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# UNIVERSITY OF OKLAHOMA 

 GRADUATE COLLEGE
# RISKY ASSET PRICE EXPECTATION FORMATION AND EMERGENT MARKET BEHAVIORS 

A Dissertation<br>SUBMITTED TO THE GRADUATE FACULTY<br>in partial fulfillment of the requirements for the<br>degree of<br>Doctor of Philosophy

By
NICHOLAS S. TAY
Norman, Oklahoma
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RISKY ASSET PRICE EXPECTATION FORMATION AND EMERGENT MARKET BEHAVIORS

A Dissertation APPROVED FOR THE MICHAEL F. PRICE COLLEGE OF BUSINESS

BY


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# RISKY ASSET PRICE EXPECTATIONS FORMATION <br> AND <br> EMERGENT MARKET BEHAVIORS 


#### Abstract

We model how individuals with diverse beliefs form their price expectations in the light of events in a market that is perpetually novel and constantly evolving. Our model is unique in that it take into consideration the fact that people, when making decisions in an ill-defined and complex environment, will exploit their innate ability to think in fuzzy notions as well as reason inductively in these fuzzy notions. The apparatus we employ to model learning and expectations formation is the geneticfuzzy classifier system. The formulation of this apparatus, and the study of the complications that can arise when investors hold heterogeneous expectations that may change over time as well as their implications for security prices constitute the primary focus of this dissertation.

We find several interesting and intriguing results. First, results from our computer simulations reveal that market behaviors which are otherwise treated as anomalies in standard asset pricing models emerge naturally in our model. Second, our results provide support for the two diametric views held by academician and traders-that is, while academic theorists in general view the market as rational and efficient, market traders typically see the market as psychological, organic, and imperfectly efficient. Lastly, our simulations produce time series behaviors of prices and trading volume that bear strong resemblance to corresponding time series behaviors observed in real financial markets. In summary, we find 1) positive autocorrelation in trading volume, 2) positive contemporaneous correlation between trading volume and volatility, and 3) slightly excess kurtosis, ARCH-liked features, and low autocorrelation in the returns time series.


## 1. INTRODUCTION

What is finance? Campbell, Lo and MacKinlay (1997) eloquently summarized the essence of finance as a discipline in the following few sentences.

> The starting point for every financial model is the uncertainty facing investors, and the substance of every financial model involves the impact of uncertainty on the behavior of investors and, ultimately, on market prices. Indeed, in the absence of uncertainty, the problems of financial economics reduce to exercises in basic microeconomics. The very existence of financial economics as a discipline is predicated on uncertainty. (Campbell, Lo and MacKinlay 1997, p.3)

Indeed, this is the very spirit behind this dissertation. In this dissertation, we focus on the implications upon asset prices and market behaviors of an element of uncertainty that has emerged because investors are unable to form objective and precise price expectations in real financial markets ${ }^{1}$ (see Section 1.2 in this chapter). We capture this element of uncertainty with an alternative model of the process that determines how price expectations are formed. What makes our model unique is that it takes into consideration the recognized fact that investors will take advantage of their innate ability to reason inductively and analyze in fuzzy terms when they have to make decisions in a complex and ill-defined environment.

Our approach is inspired by research findings about human learning behavior from psychology and is based on techniques that have emerged from recent advances in machine learning and Artificial Intelligence research. Like most recent

[^0]contributions in this area, we are encouraged by the promise of fruitful results offered by these new methods of analysis ${ }^{2}$. The apparatus we employ to model expectations formation is a hybrid system called the genetic-fuzzy classifier ${ }^{3}$. We will argue later in this chapter that our approach will not only address the criticisms of existing learning models, but will also provide a more accurate picture of how investors actually form their expectations in real life.

It is important to accurately capture the way in which investors form their price expectations in real life because, like Shiller $(1984,1989)$ and Keynes $(1936)$, we suspect that the so called anomalies and empirical puzzles ${ }^{4}$ in real financial markets are somehow related to the manner in which price expectations are formed in real markets (see our discussion in Section 1.2). In addition, since asset prices are ultimately driven by price expectations, a model that accurately captures how expectations are shaped will help to shed light on how prices are formed in real markets.

Despite the gravity of these issues, theoretical finance and economic literature have largely ignored the need to model in a realistic manner the way that investors form their price expectations in real life ${ }^{5}$. Instead, theorists have mainly focused on

[^1]equilibrium situations in which they can design clever ways to circumvent the difficult question of how price expectations are formed. To this end, a common approach in many neoclassical models is to invoke the rational expectations argument ${ }^{6}$. But these models typically impose strong rationality assumptions about the abilities and behaviors of economic agents which some of us have found to be rather unappealing. For instance, Herbert Simon ${ }^{7}$, one of the most well known and vocal dissidents, has argued that:

A comparative examination of the models of adaptive behaviour employed in psychology (e.g. learning theories), and of the models of rational behaviour employed in economics, shows that in almost all respects the latter postulate a much greater complexity in the choice mechanisms, and a much larger capacity in the organism for obtaining information and performing computations, than do the former. Moreover, in the limited range of situations where the predictions of the two theories have been compared (See Thrall et al. 1954, Chapters 9, 10, 18), the learning theories appear to account for the observed behaviour rather better than do the theories of rational behaviour.

Both from these scanty data and from an examination of the postulates of the economic models it appears probable that, however adaptive the behaviour of organisms in learning and choice situations, this adaptiveness falls short of the ideal of 'maximizing' postulated in economic theory. Evidently, organisms adapt well enough to 'satisfice'; they do not, in general, 'optimize'.
(Simon 1992, p.39)
Despite these criticisms, many theorists have maintained that the underlying

[^2]rationality assumptions are sound because evolutionary forces in the markets will eventually select for rational behaviors ${ }^{8}$. Most of us are familiar with this argument and have in general accepted its validity. But Blume and Easley (1992) recently challenged the validity of this conventional wisdom by demonstrating clearly in several different cases that this conventional intuition in general is not valid. Yet the above hand waving by theorists is not a serious issue if the concern is equilibrium analysis. However, if the intent is to explain real market phenomena, neoclassical rationality models will undoubtedly be inappropriate because real markets can hardly be considered as equilibrium systems ${ }^{9}$.

To model expectations formation in the presence of disequilibrium, we make use of a genetic-fuzzy classifier system. ${ }^{10}$ Even though our classifier system is similar in many aspects to that used in the Santa Fe Institute Artificial Stock Market model (the SFI model), there is a crucial difference. We have allowed the economic agents in our model to use fuzzy rules of thumb instead of the more restrictive conventional rules used in the SFI model. To illustrate the difference between conventional rules and fuzzy rules, consider the following conventional rule as compared to the fuzzy rule.

[^3]Conventional Rule: If market index is greater than (0.9), then $a$ is (0.2) and $b$ is (0.8) Fuzzy Rule: If market index is (high), then $a$ is (low) and $b$ is (high)

In these rules, $a$ and $b$ are the parameters to be used in a linear forecast equation for forecasting next period price. The market index, both $a$ and $b$, and the fuzzy sets (low and high) are assumed to have been scaled to operate over the interval $[0,1]$ (also known as the universe of discourse). In our application, a fuzzy set is a mathematical mapping that transforms the magnitude of a variable into a qualitative expression that describes how large or small the variable is. This can be easily accomplished by, for instance, drawing a curve over the universe of discourse, $[0,1]$, and letting the vertical height spanned by this curve be constrained to the membership values of $[0 \%, 100 \%]$. The membership value indicates to what degree a variable is a member of a fuzzy set; a membership value of $100 \%$ will indicate a $100 \%$ member whereas a membership value of $0 \%$ will represent a non-member.

It is obvious that the difference between these two rules lies in the way the second rule uses fuzzy sets instead of crisp numbers to define the states. An apparent problem with a conventional rule is it implies a sudden and definite change in decision at the cut-off point. For instance, had the market index been a tiny fraction less than 0.9 , say market index is 0.899 , this condition in the rule will not be fulfilled and the rule will not be activated. Our introspection should convince us that we do not make such extreme decision changes over a tiny change in the relevant decision variable. In contrast, a fuzzy rule allows for a more gradual change in decision. A decline in the market index value to 0.899 will still satisfy the condition in the fuzzy rule although it
now satisfies the condition to a lesser degree. This will in turn result in a proportionate change in the values for the forecast parameters, $a$ and $b$. There are other advantages to using fuzzy rules and these will be discussed in Section 1.3.

The way our genetic-fuzzy classifier system operates is straight forward. Expectations formation is effected by a set of fuzzy rules of thumb contained in the system and learning is simulated by systematically evolving the rules with the aid of a genetic algorithm (GA). Each rule contains a set of conditions and a set of forecast parameters presented in the format "If conditions, then forecast parameters". Whenever the conditions in a fuzzy rule are matched to the prevailing state in the market, the forecast parameters in that same rule are used in a linear forecast equation to forecast next period price ${ }^{11}$. This forecast then forms the new price expectations at that point in time.

One important contribution of this work is the demonstration that behaviors which would have been considered anomalies (for instance, market crashes, mean reversion, relatively high level of trading, presence of technical trading, excessive volatility, etc.) within the standard asset pricing framework will emerge naturally in a framework where individuals are allowed to form their expectations using the approach we have proposed. Another equally intriguing result is that this model lends support to the two diametric views held by academic theorists and market traders ${ }^{12}$. Academic theorists in general see the market as rational and efficient, but market

[^4]traders typically view the market as psychological, organic, and imperfectly efficient.
Both views are certainly consistent with the behaviors we have seen in real financial markets. If we were to examine historical financial market data, we will see that financial markets, while most of the time, seem to be quite efficient, on occasions, can also exhibit moods and personality ${ }^{13}$. In addition, the statistical behaviors of the time series of prices and trading volume, arising from our simulations, are also comparable to those from real financial markets. Returns are found to have low autocorrelations and slightly excess kurtosis (although the magnitude for kurtosis is still smaller than in actual returns). The returns series also appear to exhibit the signature "ARCH" behaviors commonly seen in time series of actual stock returns. Volatility in returns are found to be contemporaneously correlated with trading volume and trading volume is autocorrelated.

To sum up, the formulation of our model, and the study of the complications that can arise when investors hold heterogeneous expectations that may change over time as well as their implications for security prices, will constitute the primary focus of this research.

The rest of this chapter is devoted to a critique of some existing learning models and a discussion of the roots of market anomalies and the motivations for our

[^5]genetic-fuzzy approach to modeling expectations formation. In Chapter 2, we present an informal tutorial on fuzzy logic and genetic algorithm. The intent of Chapter 2 is not to provide a rigorous theoretical underpinnings for these methods but to present a practical and yet intuitive approach to these methods. Chapter 3 describes the modeling of expectations formation in more details and sets up the framework of our artificial stock market model. The basic framework of the market is similar to a typical neoclassical two-asset market. The various controlled experiments that are conducted are also discussed in this chapter. Chapter 4 presents and discusses the results. Chapter 5 concludes with a summary of the main results and offers suggestions for future research.

Before we proceed any further, we would like to state that many of the ideas and views presented here are not original. They represent the collective wisdom of our predecessors in various disciplines. Nonetheless, this dissertation is unique in that it brings to bear the knowledge scattered amongst various disciplines to provide a unified approach to model economic decision making under uncertainty.

### 1.1 On the Modeling of Learning Behavior

The literature on learning has distinguished existing approaches as either based on rational learning or ad hoc learning. ${ }^{14}$ In the rational learning literature, we have models that derive learning behavior from Savage's axioms about preferences (Savage 1954). Leaming in these models occurs as individuals repeatedly update their priors

[^6]using Bayes's rule in the light of new information as they seek to maximize their expected utility under uncertainty. Since Bayesian learning is a consequence of assumptions about preferences, this approach has been referred to as rational learning ${ }^{15}$. In contrast, in the ad hoc learning literature, we have models that typically employ non-bayesian learning mechanisms borrowed from the literature on statistics, econometrics, and machine learning and Artificial Intelligence. Because there appears to be no unifying principle that underlies the construction of these models, unlike in the former case, this approach has consequently been labeled as ad hoc learning ${ }^{16}$.

Although both streams of literature, in general, acknowledge that agents are boundedly rational and face informational constraints, the learning mechanisms considered in the literature thus far are not entirely satisfactory. For instance, there are substantial evidence that Bayes theorem lacks empirical relevance and yet Bayesian learning remains a very popular approach ${ }^{17}$. Salmon (1995, p.236) suggested that, perhaps, this is because theorists still seem to be more concerned with how people

[^7]should behave rather than how they actually do behave. Salmon also pointed out that:
It seems strange from the behavioral point of view, for instance, to assume, as is the case with the standard statistical models of "rational" learning, that agents have complete knowledge of the relevant economic structure and yet are assumed to be completely ignorant of perhaps just a subset of the parameter values within that structure. ${ }^{18}$ The economic interactions that have taken place in the past to have left an individual in such an odd state are unspecified. (Salmon 1995, p.237)

In a similar vein, Bullard lamented that:
Many theorists choose to suppose that agents ignore the interaction of beliefs and outcomes-they ignore behavioral uncertainty-leading to learning schemes that are inherently misspecified (Bray 1982). The misspecification causes these decision rules to be biased, although they are often shown to converge to MMIE eventually. In fact, this kind of interpretation implies that agents in many models, since they all use the same method of forming expectations, collectively adhere to biased forecast functions-a requirement that is especially dubious considering that no agent is allowed to respecify the forecast function if the bias is detected. (Bullard 1990,p.333) ${ }^{19}$

To resolve these inconsistencies, Salmon suggested that,
A more reasonable position might be that agents' knowledge of the structure and their learning activity evolve symbiotically and the manner by which learning takes place adapts to their increased understanding of their economic environment which in turn may grow, according to economic incentives, through deliberately increased interaction with that environment. Some flexibility within the method of learning is then needed as the agent's approximation to reality improves. (Salmon 1995, p.237-238)

There are at present two methodologies in the learning literature that can potentially address these problems and they are the artificial neural networks (see Cho 1992 and

[^8]Salmon 1995) and the classifier system (see for instance Arifovic 1991, 1994, 1995, 1996, Arifovic and Eaton 1995, Arthur 1995, and Arthur et al. 1996, 1997). In comparison to the other methods (Bayesian learning, least square leaming etc.), these two approaches generally assume much less mathematical sophistication (in the conventional sense) on the part of the agents. Rather than relying on conventional mathematics or statistics, these mathematically less sophisticated agents solve complex problems using intuitive methods. But this should not be taken to imply that these agents are inferior to the mathematically more sophisticated agents in solving the complex decision problems they are faced with. In fact, we will argue in the next two sections that these intuitive methods are actually more suited to dealing with the sort of complex and ill-defined problems that the agents encountered.

Both these approaches in general allow agents to learn about the structure of their forecast functions as well as the relevant parameters of these functions. However, in an artificial neural networks, all that agents can see are the inputs and outputs to the neural networks. Learning takes place in a black box so that agents may still be unaware of what their forecast functions look like or what the relevant parameters are even if they have already learned the correct structure for their forecast functions.

In contrast, learning is transparent to the agents in a classifier system. A classifier system allows agents to hold a multitude of different forecast functions which they repeatedly test and revise as they learn from their interactions with the environment. Hence, agents know precisely what their forecast functions look like,
what the parameters are, and which of the forecast functions works best at any point in time.

Another interesting feature intrinsic in a genetic classifier system is its forward looking characteristic. A genetic classifier system constantly creates and holds on to new forecast functions which may not be useful at the present time but might become useful at some point in time in the future. This feature is not presence in an artificial neural networks which functions more like a curve fitting machine. In addition, Arthur et al. (1996) have argued that the characteristics of a genetic classifier system closely resemble the induction process that people use to make decisions when they are confronted with an ill-defined environment (see the next section).

Therefore, a classifier system is a more appealing approach than the artificial neural networks, and it is for these reasons that we have decided to use a variation of a classifier system to model expectations formation in our model.

### 1.2 Expectations Formation and Market Created Uncertainty

As yet, no intuition has been provided to explain why the approach we have proposed for modeling learning and expectations formation might explain the anomalies and transition dynamics we see in real markets. In order to understand why our model will work, we need to get to the roots of these market anomalies ${ }^{20}$. It is instructive at this point to take a step back and ask what it will take for a model to account for the market anomalies we have seen. Since models are necessarily

[^9]abstractions of the real world, their successes will ultimately hinge on incorporating those elements that are essential to explaining what they are intended to explain. Although no one knows for certain what the essential ingredients for explaining market anomalies are , empirical evidence (see Shiller 1989) seem to suggest that a certain type of market created uncertainty (see Peck and Shell 1991), intentionally sidestepped in standard asset pricing models (probably because of its analytical intractability), may potentially explain the seemingly anomalous behaviors in real financial markets.

Specifically, we are referring to the uncertainty created as a result of the interactions (either directly and/or indirectly) among heterogeneous market participants who have to learn to form their expectations in a market environment that is inherently ill-defined. The difficulty here is that under such circumstances, people will not be able to deduce their expectations logically ${ }^{21}$ (see Arthur 1994, 1995). Consequently, each market participant will have to form his price expectations based on his subjective forecast of the expectations of the rest of the market participants. When this is the case, and when no one is absolutely certain of what true fundamental values are, the market can develop a life of its own and respond in ways that are not correlated with movements in fundamental values ${ }^{22}$. According to Arthur,

[^10]... the sense he makes of the Rorschach [bold added to replace italics] pattern of market information $\mathrm{I}_{\mathrm{t}}$ is influenced by the sense he believes others may make of the same pattern. If he believes that others believe the price will increase, he will revise his expectations to anticipate upward-moving prices (in practice helping validate such beliefs). If he believes others believe a reversion to lower values is likely, he will revise his expectations downward. All we need to have self reinforcing suspicions, hopes, and apprehensions rippling through the subjective formation of expectations (as they do in real markets) is to allow that $\mathrm{I}_{1}$ contains hints-and imagined hints-of others' intentions. (Arthur 1995, p.23)

Hence, the process of expectations formation under such circumstances can be precarious. This view of the market is akin to that of Keynes's (1936, p.150). Keynes has regarded asset prices as "the outcome of the mass psychology of a large number of ignorant individuals," with professional speculators mostly trying to outguess the future moods of irrational traders, and thereby reinforcing asset price bubbles. In a similar vein, Dreman (1977, p.99) maintained that individual investors, including professionals do not form opinions on independently obtained information ${ }^{23}$. Their forecasts of future events are heavily influenced by "the thinking of the group." Similar views have also been advanced by Black (1986), De Long et al. (1989, 1990), Shiller (1984, 1989), and most recently, Soros (1994).

But what makes the problem worse is that such behavioral uncertainties diminish the incentives for arbitrage which in turn impair the market natural tendency to return itself to its fundamentals. In particular, these uncertainties create two types of risk for potential arbitrageurs. Shleifer and Summers (1990) identified these risks as identification risk and noise trader risk (future resale price risk).

Identification risk arises because uncertainty in the market makes it difficult for

[^11]potential arbitrageurs to distinguish between price movements driven by noise trader actions and price movements driven by pieces of private information which they have not yet received. Hence it is difficult for potential arbitrageurs to exploit noise traders because they can never completely assure themselves that the price movement was driven by noise, which create profit opportunities, and not by news that the market knows but they have not yet heard.

In addition, there is also the risk that price may move further from fundamental value by the end of the speculator's investment horizon. This latter risk is known as the noise trader risk or future resale price risk. On that account, an investor who knows, even with certainty, that an asset is overvalued will still take only a limited short position because noise traders may push prices even further from their fundamental values when it comes time to close the arbitrage position.

Another type of risk, fundamental risk, although not due to the market uncertainty we have discussed, can also limit arbitrage. Fundamental risk is inherent in the market. It is the possibility that the fundamental value of the stock may change against the arbitrage position before the position is closed. Even if noise traders do not move prices away from fundamental values, changes in the fundamentals themselves might move the price against the investor.

Altogether, these problems make arbitrage risky and limit arbitrage. Because arbitrage plays an "error-correction" role in the market to bring asset prices in line with their fundamental values, this role will be hampered when arbitrage is limited. As a result, asset prices may deviate from fundamental values and such deviations may
persist hence weakening whatever correlation there may have been between movements in asset prices and movements in their fundamental values.

The implication of this discussion is that when we impose the assumption of "mutual consistency in perceptions" in rational expectations models, we leave miss out the market created uncertainty outlined above which is precisely what is needed to explain the seemingly anomalous behaviors in real markets. Therefore, to account for market anomalies, we must allow the agents in our model the opportunity to form their expectations independently based on their subjective evaluations. But how do we model such expectations formation? Before we can answer this question, we need to first investigate how humans reason in situations that are ill-defined and uncertain.

We have earlier alluded to the fact that deductive reasoning will break down in an environment that is ill-defined. But if deductive reasoning will not work, how then can individuals form their expectations? Arthur et al. (1996) argues that individuals will form their expectations by induction (see also Arthur 1991, 1992, Blume and Easley 1995, Rescher 1980). So what is induction or inductive reasoning? Nicholas Rescher defined it as follows:

> Induction is an ampliative method of reasoning-it affords means for going beyond the evidence in hand in endeavor to answer our questions about how things stand in the world. Induction affords the methodology we use in the search for optimal answers.

Induction as a cognitive method proceeds by way of the systematization of question-resolving conjecture with experience, by fitting conjectural extensions sufficiently tightly into the overall setting of our other (generally tentative) commitments. Though induction always involves a leap beyond the information in hand, it only endorses these leaps when the fit is sufficiently close. (Rescher 1980, p.87)

Simply put, induction is a means for finding the best available answers to our questions that transcend the information at hand. In other words, the conclusions we draw in an induction are suggested by the data at hand rather than logically deduced from them. Logical deduction fails because the information we have at hand leave some gaps in our reasoning. In order to complete our reasoning, we fill those gaps in the least risky, minimally problematic way, as determined by plausibilistic best-fit considerations. Although this may sound like guesswork, it is really more than guess work; it is responsible estimation in the sense that we are willing to commit ourselves to the tenability of the answer which we put forth. In other words, we must find the answers to be both sensible and defensible.

Inductive reasoning follows a two-step process: possibility-elaboration and possibility-reduction. The first step involves creating a spectrum of plausible alternatives based on our experience and the information available. In the second step, these alternatives are tested to see how well they answer "the question" or how well they connect the existing incomplete premises to explain the data observed. The best fit connection is then accepted as a viable explanation for the data observed. Subsequently when new information become available or when the underlying premises change, the fit of the current connection may not be good anymore. When this happens a new alternative will take over.

So how can induction be implemented in economic models? Arthur et al. (1996) visualize induction taking place as follows. Under this scheme of rationalizing, each individual in the market continually creates a multitude of "market hypotheses"
(this corresponds to the possibility-elaboration step discussed above). These hypotheses which represent the individuals' subjective expectational models of what moves the market price and dividend are then simultaneously tested for their predictive ability in the market. In the end, those that perform well in predicting market movements will be retained and acted upon in buying and selling decisions, and the others that perform badly will be dropped (this corresponds to the possibilityreduction step). In addition, as new information enter or emerge from the market, other new hypotheses will be generated and be tested as above. This process is carried out repeatedly as individuals learn and adapt in a constantly evolving market ${ }^{24}$.

The expectations formation process we have just described can be adequately modeled by letting each individual forms his expectations using his personal geneticfuzzy classifier system. Each genetic-fuzzy classifier system contains a set of conditional forecast rules that guide the decision making. We can think of these rules as the subjective "market hypotheses" held by each individual. Inside the classifier system is a genetic algorithm that is responsible for generating new rules, testing all existing rules in the market place, and weeding out bad rules. The possibilityelaboration step is then captured by the constant formulation of new conditional forecast rules in the system and the possibility-reduction step is represented by the subsequent testing of these conditional forecast rules and the eventual removal of the bad ones. The next section will discuss in more depth the rationale behind our approach.

[^12]
### 1.3 Rationale for our Genetic-Fuzzy Approach

We have briefly touched on the motivations for using the genetic-fuzzy system back in the last two sections, we now develop a more complete argument in the following two sub-sections. The first sub-section discusses the rationale for incorporating fuzzy reasoning in the system and the second sub-section explains the reasons for using a genetic classifier system.

### 1.3.1 Why Use Fuzzy Logic?

Some cognitive psychologists have indicated that fuzzy logic offers a reasonably accurate model of the way humans think and reason, and they further suggested that perhaps our ability to efficiently process an immense amount of complex information, some of which are intrinsically vague, is the outcome of applying fuzzy logic to our reasoning and thought processes. However, for us to have confidence in using fuzzy set theory to model the way humans think and reason, there are two questions that need to be addressed. Smithson (1987) drew our attention to the following two questions. First, "are there evidence that support the hypothesis that at least some categories of human thought are fuzzy?" and second, "are the mathematical operations of fuzzy sets as prescribed by fuzzy set theory a realistic description of how humans manipulate fuzzy concepts?" For answers to these questions, we refer to the evidence cited in Smithson.

There is a considerable body of psychological research which demonstrates that prototypicality in natural semantic categories is a graded concept (e.g., Rosch (1973a), Rosch and Mervis (1975). Hersh and Caramazza (1976)), and that people widely agree and show reliability in ranking or rating the exemplarity of stimuli in semantic categories. Likewise, some anthropological research has
shown that gradedness applies across cultures. Kay and McDaniel (1975) found the fuzzy set representation of gradedness in color categories more suitable than the earlier (Berlin and Kay 1969) notions of "focus" and "boundary". Kempton (1978) was able to extend traditional cognitive anthropological folk taxonomic methods via fuzzy set methods in elicting taxonomic judgments about footwear and pottery, in two cultures. Burgess et al. (1983) discovered that the Tarhumara color-terms carry obligatory modifiers which specify the grade of membership of a stimulus in a color-category. (Smithson 1987, p. 55)

Fuzzy negation has not been very systematically critiqued either philosophically or psychologically. Hersh and Caramazza (1976) are among the few researchers to have empirically investigated the fit between subjects' own ratings of . membership in $A$ and $A^{\prime}$, and fuzzy-set predictions for membership in $A^{\prime}$. They found a high degree of correspondence between standard fuzzy negation (that is, $m_{A}=1-m_{A}$ ) and the proportion of people who indicated a stimulus was not a member of set A. However, their investigation did not use direct membership ratings and did not investigate any other kinds of fuzzy negation. (Smithson 1987, pp. 59-60)

Apparently, the standard fuzzy set account of intersection and union does not always apply to concepts that most people would agree involve conjunction and disjunction. However, at least in some cases modified versions of the theory may work well. And it is worth bearing in mind that several empirical investigations have found quite a good fit between fuzzy set operators and data. Oden (1977) found that the product operator fit better than the "min" for "and," but the difference was not large. Thole et al. (1979), on the other hand, found that the "min" fit the best (and this was confirmed in a more rigorous reanalysis in Smithson 1984). Zimmerman and Zysno's (1980) generalized connective was based on the product operator, which caused them to conclude that this operator corresponds most closely with human judgment. However, my reanalysis of their data using least-squares estimates of an alternative generalized connective indicated that the difference in fit between a connective based on "min" and one based on the product was negligible. Furthermore, in at least one application I have found that the bounded sum works best. The question of which intersection and union operators best reflect psychological reality still is open, and the answer may well turn out to be context-dependent. (Smithson 1987, pp. 64-65)

Perhaps the most interesting conceptual discussion about various multivalent and fuzzy logics for behavioral scientists is Dubois and Prades's (1980, pp. 155-169) assessment of the compatibility of several such logics with Piagetian criteria for human reasoning. Briefly, Piaget claimed that adult reasoning requires the capacity to distinguish among and relate together four kinds of transformations: (1) identity, (2) negation, (3) reciprocity, and (4) correlativity. ...

They find that the Arithmetic Rule for implication using either the min-max, product, or bounded sum operators is compatible with Piagetian criteria, but the Maxmin Rule using the min-max operator is not. ...
From this kind of evidence and ...by writers such as Gaines (1975), it appears that the Arithmetic Rule probably holds up the most consistently under conceptual scrutiny. ... Aside from apparent consistency with Piagetian theory, however, little is known about which of these logics, if any, really models human reasoning. (Smithson 1987, pp. 73-74)

All in all, the evidence presented do seem to provide support for the use of fuzzy set theory to model the way humans think and reason.

Additional evidence that are more relevant to economics are the survey findings of Katona (1975). Katona (1975) pointed out that "while most people can be induced to make a guess as to the direction of change in the near future of major macroeconomic variables, they are reluctant to give quantitative estimates of the extent of the change." Based on decades of survey research on the general public in the United States, Katona concluded that "the majority knew whether unemployment had increased or decreased in the preceding months, whether profits or retail sales had gone up or down, and also whether interest rates had risen or fallen, but did not know how much larger or smaller any of these magnitudes were." Therefore, Katona's findings also seem to suggest that people think in terms of fuzzy notions.

We turn our attention now to the other considerations that have motivated us to use fuzzy logic. The task of modeling expectations formation in an environment that is continually evolving and novel poses two unique difficulties that conventional mathematics are ill-equipped to handle. First, the problem is intrinsically ill-defined. It is ill-defined because investors who may hold diverse beliefs, clearly do not have an
objective method to form their expectations as this would require each of them to perform the impossible task of forecasting the expectations of all the other investors. Conventional mathematics is not tuned to handling ill-defined problems because we are not able to precisely define such problems in the language of conventional mathematics. And when we cannot precisely define the problems, we obviously are not going to be able to solve them. Second, inherent in this problem is a source of uncertainty that cannot be appropriately modeled by conventional probability theory. This is the vagueness that permeates human thoughts and human discourse. Since human thoughts and human discourse mold expectations, it is crucial to have a proper model of this element of uncertainty. These difficulties are not unique to our problem. They are in fact common in most complex systems, especially humanistic systems.

In order to cope with the immense burden of modeling complex systems using conventional approaches, scientists have often opted to sacrifice the realism of the models in favor of unrealistic simplifying assumptions and attribute the unmodeled portion of the systems to random noise. Although such approaches have worked well with simple mechanistic systems which can be precisely defined and where the inherent uncertainties arise primarily from random noise, such approaches are totally unsuited for modeling complex systems for the reasons discussed above as well as the common wisdom that in complex systems, we cannot hope to get meaningful results unless our assumptions are also realistic or relevant in the context being modeled. A case in point is the rational choice models in economics which we already know have been unable to account for various phenomena in the real economy.

It is in fact such difficulties that have motivated Lotfi Zadeh to develop his
fuzzy set theory. In his struggle to develop a better approach to model complex systems, Zadeh came to notice how easily humans make decision based on imprecise, non-numerical information in complex situations, and it hit upon him that at the heart of the problem is the precision that is demanded by conventional mathematics. The stumbling block in conventional mathematics is the need to precisely define a problem before we can solve it. As we have argued, in some cases, we simply are not able to precisely define the problems. The key to overcoming this stumbling block is to create a new branch of mathematics that is capable of handling imprecise or vague non-numerical data. Zadeh has clearly articulated the need for such a mathematics in his paper titled "From Circuit Theory to System Theory." In that paper, Zadeh argued that:

There is a fairly wide gap between what might be regarded as "animate" systems theorists and "inanimate" systems theorists at the present time, and it is not at all certain that this gap will be narrowed, much less closed, in the near future. There are some who feel this gap reflects the fundamental inadequacy of the conventional mathematics-the mathematics of precisely-defined points, functions, sets, probability measures, etc.-for coping with the analysis of biological systems, and that to deal effectively with such systems, which are generally orders of magnitude more complex than man-made systems, we need a radically different kind of mathematics, the mathematics of fuzzy or cloudy quantities which are not describable in terms of probability distributions. Indeed, the need for such mathematics is becoming increasingly apparent even in the realm of inanimate systems, for in most practical cases the a priori data as well as the criteria by which the performance of a man-made system is judged are far from being precisely specified or having accurately known probability distributions. (Zadeh 1962, p. 857)

The need for a mathematics of "cloudy" quantities led Zadeh to develop the concept of fuzzy sets and the related mathematics for manipulating such sets.

According to Ebrahim Mamdani, the genius of the fuzzy approach is "the possibilities of implementing 'rules of thumb' experience, intuition, heuristics, and the fact that it does not need a model of the process" (Kosko 1993, p.169). But what is even more important is a recent result from Kosko. Kosko (1992) has demonstrated clearly that fuzzy systems are universal approximators. In simple terms, it means that fuzzy systems are able to approximate general nonlinear functions to any desired degree of accuracy. This makes fuzzy systems particularly valuable for modeling complex nonlinear relationships which we either do not know how to specify or do not know how to solve analytically in the language of conventional mathematics.

The strength of fuzzy logic has attracted many compliments. For instance, Goguen remarked that:

> The inexactness of description is not a liability; on the contrary, it is a blessing in that sufficient information can be conveyed with less effort. The vague description is also easier to remember. That is, inexactness makes for greater efficiency. (Goguen 1981)

A down to earth analogy here will help to bring his point across. Suppose your friend sees a truck speeding towards you. A precise way of conveying the information to you could be, "A 6-wheeled 3-ton black truck traveling at 50 mph is accelerating towards you at a rate of 10 mph ". The fuzzy way of conveying the same information would be "Watch out! A truck is speeding towards you." It is clear how you would have preferred to be alerted under such circumstance ${ }^{25}$. The ingenuity here is that by

[^13]being less precise in our description, we can be more relevant in our communication
(given our constraints). In a similar vein, economist Riccardo Viale has argued that:
... if classical logic were accepted as the canon of deductive inferential rationality one would reach the absurdity of having to accept the countless conclusions, trivial but correct, which are implied by a set of valid premises. This would have fatal consequences for man's ability to adapt to his environment. Other inferential rules are therefore needed to select and skim significant deductions from trivial ones ... . Secondly, it is not clear why one should favor classical logic over any types of logic, which offer advantage of formalizing the concepts of possibility and necessity, or non-monotonic types of logic and "fuzzy logic," which can emulate the ambiguity, poor resolution and contradictoriness of human reasoning. (Viale 1992, pp.174-175)

The core of these observations is what Zadeh had, in his earlier work, referred to as the principle of incompatibility.
..., the essence of this principle is that as the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics. It is in this sense that precise quantitative analyses of the behavior of humanistic systems are not likely to have much relevance to the real world societal, political, economic, and other types of problems which involve humans either as individuals or in groups." (Zadeh 1973, p. 28)

Other researchers have also voiced similar sentiments. For instance, Tong pointed out that:

The [complex] process is often highly nonlinear and has large number of variables. It is often hard to discover the underlying mathematical structures, and there is often a large amount of process knowledge expressible only in linguistic terms. There are many other reasons but they all basically derive from the sheer complexity of the process ... as systems become more complex, it becomes increasingly difficult to make mathematical statements about them which are both meaningful and precise. (Tong 1978, p. 143)

[^14]To sum up, the reasons leading to our decision to use a fuzzy system are: 1) it is a better model of certain aspects of human thoughts and reasoning, 2) it is a better approach for dealing with problems that are ill-defined and inherently vague, and 3) it is a lot simpler and more efficient that a conventional system. A fuzzy system is simpler and more efficient than a conventional system because fuzzy sets allow us to compress a lot of information into very few simple fuzzy notions. This is one of the reasons why conventional expert systems have had limited success in most real world applications thus far. A conventional expert system typically requires hundreds of rules to simulate real-world situations, while in contrast, a fuzzy expert system would generally requires only tens of rules to perform similar tasks (see Moffat 1990). Given the above reasons, it is not difficult to understand why fuzzy systems have grown in popularity over the years. Zadeh foresaw more than 30 years ago that an electromechanical controller would respond better to imprecise input if its behavior was modeled on spontaneous human reasoning. Zadeh's vision has finally materialized. Fuzzy logic based controllers have proven their worth in many areas where conventional logic based controllers have failed.

### 1.3.2 Why Use a Genetic Classifier System?

The two reasons for using a genetic classifier system are: 1) it offers a general and yet robust framework for modeling decision making and leaming in a perpetually novel environment, and 2) it provides a fairly accurate representation of the reasoning systems that humans use.

The design of a classifier system is modeled after the simplistic but unusually robust survival machinery employed by living organisms. This survival machinery is evidently robust because organisms have relied on it not only to survive but to prosper for millions of years in a harsh and constantly evolving natural environment. At the heart of this machinery are two components: a stimulus-response system which tells the organisms how to behave under various conditions, and an algorithm for modifying the stimulus-response system as the organisms adapt to changes in the environment.

Our classifier system models this survival machinery as a system of fuzzy conditional action rules that are systematically evolved by a genetic algorithm (GA). A system of conditional action rules capture the essence of a stimulus-response system while a GA mimics the optimization process that takes place at the genetic level of an organism. Like the stimulus-response system, a set of fuzzy conditional action rules determines how the system should respond under various environmental conditions. This gives us a very general but simple framework for modeling complex decision making. A GA makes use of artificial production, crossover and mutation operators to systematically improve the conditional action rules as the environment changes. Chapter 2 will discuss GAs in more depth. For now, we will simply state that Holland has shown that a general and yet robust parallel search and optimization algorithm can be created from combining these three artificial genetic operators together. Holland's schema theorem basically asserts that a GA is capable of finding the optimal solutions to any optimization problem and that it will arrive at these solutions at an exponential
rate ${ }^{26}$. This result was subsequently confirmed by De Jong (1975) when he successfully applied GAs to the optimization of various complicated functions with the following characteristics: 1) continuous/discontinuous, 2) convex/nonconvex, 3) unimodal/multimodal, 4) quadratic/nonquadratic, 5) low-dimensionality/highdimensionality, and 6) deterministic/stochastic. Such strengths make a GA an invaluable tool for modeling learning.

Now turning our attention to the second reason, we are interested in whether there are reasons to believe that a genetic classifier system captures certain key features of the reasoning systems humans actually use. Psychologists have argued that our mind holds two different reasoning systems ${ }^{27}$. To illustrate, consider the problem of figuring out the change at the cash register ${ }^{28}$. It is not uncommon to find that sometimes the answer will spring to our mind intuitively, but at other times we will have to do some mental arithmetic to arrive at the answer.

Sloman (1996) recently distinguished these two reasoning systems as associative and rule-based. An associative system operates reflexively and can handle both concrete images as well as abstract notions. It also allows us to produce "quick and dirty" answers based on heuristics just as in the example above. As the name

[^15]suggests, an associative system helps us make sense of new information by associating the new information with the knowledge already existing in our mind. The way an associative system processes information is analogous to the process used by police officers to compose a picture of a suspect by putting together pieces of different parts of a face based on accounts given by eye witnesses. This process allows police officers to create a picture that closely resemble what a suspect might looked like even though none of the officers may have seen the suspect before. Likewise, a similar process help us interpret new information that we may have never encountered before. People in general are unconscious of associative processing in the mind. In contrast, people are usually conscious of rule-based processing which is known to be responsible for the "logical, hierarchical and casual-mechanical" aspects of humans reasoning. Our ability to perform mathematical calculation via systematic application of rules is a good example of rule-based processing.

But how do we use these two systems and how do these two systems interact to influence our decision? Sloman maintained that the two systems do not have their own exclusive problem domain, but rather they have overlapping domains; domains that differ depending on the individual's knowledge, skill and experience. Sloman explained that:

Together, they lend their different computational resources to the task at hand; they function as two experts who are working cooperatively to compute sensible answers. One system may be able to mimic the computation performed by the other, but only with effort and inefficiency and even then not necessarily reliably. The systems have different goals and are specialists at different kinds of problems. When a person is given a problem, however, both systems may try to solve it: Each may compute a response, and those responses may not agree. (Sloman 1996, p.6)

A classifier system with conditional action rules that are evolved systematically in a parallel fashion (via a GA) resembles the associative system that Sloman talked about. There are two levels of association at play when agents use classifier systems to guide their decision making. At a macro level, agents in the model attempt to associate the rules to the states of the market they have observed by matching the conditions in the rules with the current market state.

However, what is more important is the next level of association which takes place in the background (not noticed by the agents). This is found in the GA within the classifier system where association is done at the level of the schemas. In a classifier system, rules are coded as strings of numbers. A schema is a similarity template which we can generalize from a collection of strings representing the rules. For instance, a possible schema for the strings $\{00110,00111,01110\}$ is ( $0^{*} 11^{*}$ ), where the symbol "*" represents a "wild card". Schemas are useful in that they enable a GA to quickly find general patterns that lead to better decision making.

Furthermore, in a GA, the search take places in parallel among all existing schemas. This phenomenon is known as implicit parallelism ${ }^{29}$. Both the use of schemas and the implicit parallelism make a GA very efficient in processing information.

Our mind also appears to order and reorder concepts in successively more abstract form like the schema representations in a GA. The advantages of such sub-

[^16]conceptual representations are twofold. Like the schemata in a GA, these subconceptual representations in our mind allow more efficient storage and processing of new information. Instead of having to store every piece of new information as it is, our mind can instead represent the new and perhaps complex information as subconceptual models. These sub-conceptual models serve as building blocks for bigger and more complex notions. In addition, such sub-conceptual models not only symbolize a concept but also represent some of its internal structure. They constitute an analysis of a concept. The advantage of including such analyses in a representation is to permit simpler and faster processing of reasoning ${ }^{30}$. This process is termed representational redescription by Clark and Karmiloff-Smith. Our capacity to generalize and to use analogy are all a part of this redescription process.

Once the association is done and a rule is selected, agents in our financial market model then proceed to calculate their holdings of assets in a systematic mechanical fashion. This part of the thought process resembles the rule-based system Sloman has discussed. To sum up, our artificial agents, in making their decisions, make use of the same two systems of reasoning in a cooperative fashion just as humans would in their reasoning and decision making processes.

A more general framework for studying human reasoning is the mental model framework as Garnham and Oakhill have argued recently(1994, p.341). They have urged psychologists to use this framework for unifying research on thinking and

[^17]reasoning in psychology. As a matter of fact, both the associative system and rulebased system outlined above can be interpreted in terms of a mental model framework. Mental models are cognitive views that humans construct to try to make sense of how things work. When faced with a problem, our mind constructs mental models to resolve the problem by integrating in novel ways the representations stored in our memory (the same sort of representations we have discussed previously). For instance, suppose we are given a task of supporting a coffee cup several inches above a surface using only a sheet of paper ${ }^{31}$. Solving this problem would require much more than activating the schemas for "paper" and "cup". In this case, a useful mental model might contain information about operations that can be performed with paper, the weight of the cup, and so on.

In our model, individuals' mental models of what moves prices and dividends in the market are represented by rules in a classifier system. The manner in which the rules are evolved with a GA resembles the manner in which mental models are formulated in our minds. For instance, the construction of a mental model involves an incremental updating of the representation on the basis of the present and past input. So the resultant representation in any given moment guides the interpretation of subsequent input. This gradual updating of mental models is captured by the use of the reproduction and crossover operators in a GA. In constructing a new rule (new mental model), the reproduction operator determines which existing rules (existing mental models) will be allowed to contribute to the new rule. The selection is based

[^18]on the rules' predictive ability. The crossover operator then genetically crossovers the selected rules to create a new rule. Therefore the new rule is a hybrid of those existing rules which have proven to be successful in the past, and this new rule in turn influences how the system interacts with subsequent inputs.

Another important point to keep in mind is that the rules in our classifier system do not cover all possible contingencies, and this is typical of decision-making in the real world. For instance, Hogarth (1980) has argued that:
... under most circumstances it is not reasonable to talk about finding 'all the alternatives'. The generation of alternatives is a lengthy and costly process, and one where, in real-world situations, even minimal completeness can seldom be guaranteed. Theories of optimal search can cast some light on such processes, but, because of limits on complexity, human alternative-generating behavior observed in the laboratory is usually best described as heuristic search aimed at finding satisfactory alternatives, or alternatives that represent an improvement over those previously available. (Hogarth 1980, p.5)

The manner in which we have allowed the rules to be evolved by a GA in our model is also in agreement with Hogarth's interpretation; that is, "it is a heuristic search aimed at finding satisfactorily alternatives that represent an improvement over those previously available." Recent studies in cognitive psychology suggest that this heuristic search is conducted in parallel rather than sequentially. This is captured by the parallel search characteristics intrinsic in a GA (See Rumelhart, McClelland and the PDP research group 1987, and Holland, Holyoak, Nisbett and Thagard 1986).

## 2. FUZZY LOGIC AND GENETIC ALGORITHMS

The objective of this chapter is to provide a tutorial on fuzzy logic and genetic algorithms. The intention here is not to provide a rigorous discussion of the theory of fuzzy sets ${ }^{32}$ or genetic algorithms but to present a practical and intuitive approach to these methods. The presentation will begin with fuzzy logic by introducing the concepts of fuzzy sets in Section 2.1, presenting the concepts of membership function and fuzzy logical operators in Section 2.2, illustrating how to construct a fuzzy inference system in Section 2.3, and finally, discussing recent developments in Section 2.4. This is followed by the presentation of genetic algorithms. Section 2.5 provides an overview of genetic algorithms and Section 2.6 discusses the fundamental theorem of genetic algorithms. In Section 2.7 we compare the GA to conventional optimization methods. Section 2.8 describes the basic elements in a genetic algorithm. In Section 2.9, we look at a simple application of a GA, and finally, in Section 2.10 we discuss the crux of a genetic-fuzzy classifier system.

### 2.1 What is a Fuzzy Set?

A fuzzy set differs from a classical set in that it has no well-defined boundary. To appreciate the gist of Lotfi A. Zadeh's innovation, close your eyes for a moment, and picture in your mind, a group of "old" persons around you. You will realize, in

[^19]your attempt to classify this set of "old" persons, that the boundary of this set is not "crisp". There is no clear cut-off for classifying whether a person is old or not old. For instance, we do not think of a 40 year-old person as old and a 39 year-old as not old. Instead, what we have in our mind, is a fuzzy boundary that allows for varying degree of membership to the set of "old" persons. Consequently, even though both a 39 year-old person and a 40 year-old person may be members of the set of "old" persons, they will not have the same degree of membership. The 39 year-old person would be a member of this set to a lesser degree than the 40 year-old.

Moreover, the 39 year-old and 40 year-old persons may also, at the same time, be members of the reciprocal set-the set of "young" ${ }^{33}$ persons. In this case, the 39 year-old person would be a member of the set of "young" persons to a greater degree than the 40 year-old. Therefore, within this new paradigm, an entity may belong to both a set and its complement at the same time ${ }^{34}$. It follows then that, within this paradigm, a statement like-"A 40 year-old person is old"-can no longer be an absolutely true or an absolutely false statement any more. It has to fall somewhere between false and truth. The notion of fuzzy sets has therefore extended the arena of classical two-valued Boolean logic to one where there is a gradual and perhaps even continuous transition between the false state and the truth state. Instead of absolute truth or false, "everything is [now] a matter of degree" (Kosko 1993, p. 18). Needless

[^20]to say, such gradual transition between false and truth will allow us to better represent the vague or imprecise concepts inherent in our natural language. However, as we have seen in Chapter 1, this innovation is more than just an interesting exercise in modeling imprecise linguistic concepts. It is actually an integral component of a very powerful theory for modeling complex and ill-defined systems. We will explore how it could be applied later in Section 2.3 and Section 2.10. In the next section we look at how to set up membership functions and how logical operators work on fuzzy sets.

### 2.2 Membership Function and Fuzzy Set Operators

### 2.2.1 Membership Function

We have mentioned in the last section that a fuzzy set has no well-defined boundary. To formalize the concept of fuzzy set, Zadeh (1965) introduced the notion of graded membership or a membership function. A membership function is a mathematical function that maps elements from a crisp set into real numbers in the interval [0,1]. Figure 1 and 2 illustrate the difference between a classical set and a fuzzy set of "tall" ("not tall") persons. In a classical set, an element either belongs to or does not belong to a set. Hence if we consider anyone who is at least 6' tall as "tall", and anyone who is less than 6 ' tall as "short" or "not tall", we can then represent this concept by the crisp cut-off at 6 ' in figure 1 .

This is unlike in the fuzzy world where an element can be a member of a set and its complement at the same time. "Fuzziness" is represented by drawing a curve to allow for a varying degree in tallness as shown in figure 2 . This curve is called a
membership function. The membership function tells us to what degree an element belongs to a fuzzy set. It assigns to each element in the fuzzy set a number in the interval $[0,1]$. The degree of membership in a fuzzy set can be read off the vertical axis. A membership value of 0 means that an element does not belong to the fuzzy set, and a membership value of 1 means an element is a complete member of the fuzzy set.

Take for instance, a person of height $5^{\prime} 6^{\prime \prime}$. Most would agree that this person is not very tall. By that we are merely expressing our opinion of the degree of tallness, and not whether this person is tall or not tall. In the fuzzy set representation of tall persons, this height might have a membership value of 0.6 (see figure 2 ). This means that this person is a $60 \%$ member of the set of "tall" persons (notice that this person is also a 40\% member of the set of "not tall" persons ${ }^{35}$ ). In this example, a fuzzy set has allowed us to properly describe the vague notion-"tall". In contrast, we are not able to faithfully represent this notion by probability theory. It is not the same to say that there is a $60 \%$ chance that this person is tall. By saying this, we are implying that this person could be tall or short, and it is more likely that this person is tall. Obviously, this does not capture the true meaning of what we have in mind. Hence, a vague concept is best represented by a fuzzy set.

### 2.2.2 Fuzzy Set Operators

As with conventional set theory, the concepts of complement, intersection, and union can also be defined for fuzzy sets. In the following definitions, $\mu$ denotes the

[^21]membership function and $X$ the universe of discourse ${ }^{36}$.

## Complementation (NOT)

Complementation corresponds to the logical operator "not." The complement ( $\neg \mathrm{A})$ of
a fuzzy set $\mathbf{A}$ is defined by

$$
\begin{equation*}
\mu_{\neg A}(x)=1-\mu_{A}(x), \quad x \in X \tag{2.1}
\end{equation*}
$$

## Intersection (AND)

The intersection corresponds to the logical operator "AND." The intersection of two fuzzy sets $A$ and $B$ on $X$, denoted $A \cap B$, is defined by

$$
\begin{equation*}
\mu_{A \cap B}(x)=\min \left\{\mu_{A}(x) ; \mu_{B}(x)\right\}, \quad x \in X \tag{2.2}
\end{equation*}
$$

## Union (OR)

The union corresponds to the logical operator "OR." The union of two fuzzy sets A and $B$ on $X$, denoted $A \cup B$, is defined by

$$
\begin{equation*}
\mu_{A \cup B}(x)=\max \left\{\mu_{A}(x) ; \mu_{B}(x)\right\}, \quad x \in X \tag{2.3}
\end{equation*}
$$

We illustrate these concepts by applying the above operators to two fuzzy sets, A and B. Figures 3 and 4 show the fuzzy sets A and B prior to applying these operators, and figures 5, 6 and 7 show graphically the outcomes after applying the complementation, intersection, and union operators respectively to the fuzzy sets A and B.

[^22]Having defined the fuzzy logical operators, a few comments are in order before we conclude this section. Although the above definitions are commonly used for logical operators, they are by no means the only operational definitions. Some other alternative definitions for the pair of $A N D$ and $O R$ operators are the Product operators and the Bounded Sum/Difference Operators ${ }^{37}$. However, unlike the Min-Max operators defined above, these other alternatively defined operators do not satisfy idempotency and distributivity. In addition, if there are existing errors associated with the membership grades, these alternative operators will further compound the existing errors. Fortunately, this error compounding does not happen with the use of the MinMax operators. Nevertheless, the alternatively defined $A N D$ and $O R$ operators may be preferred for other reasons. For example, the $A N D$ operator of the Product pair is useful because it resolves the Eubulidean paradox (Smithson 1987, p. 27). There are also alternative definitions for the Complementation operator and they are the Sugeno Class complements and the Yager Class complements ${ }^{38}$.

So far we have only discussed how to represent simple vague adjectives with fuzzy sets and how logical operators work on these fuzzy sets. However, our natural

[^23]As a matter of fact, the standard complementation operator we have defined is a special case of the Yager class complements; it is obtained by setting $\lambda=1$.
languages are certainly more interesting than just the plain adjectives we have considered. In our natural languages, we often use linguistic hedges such as "not very", "very", "somewhat", "more or less" etc. Zadeh refers to this class of hedges as Type I hedges and has suggested representing these linguistic hedges as operators on fuzzy sets (Zadeh 1972). The operators for representing these linguistic hedges are : Normalization, Concentration, Dilation, Contrast Intensification and Fuzzification. Zadeh has also discussed another class called Type II hedges which is used to describe hedges like "technically", "essentially", "practically" etc.. Readers interested in the modeling of these hedges may want to consult Zadeh's original paper-"A Fuzzy-SetTheoretic Interpretation of Linguistic Hedges" (Zadeh 1972). In the next section we show how the operators defined above can be used in a fuzzy inference system or a fuzzy controller to guide decision making.

### 2.3 Constructing a Fuzzy Inference System

A fuzzy inference system is a type of expert system, and like all expert systems, it is in essence a computer-based system that is designed to emulate the reasoning process of a human expert within a specific domain of knowledge. The design of a fuzzy inference system is quite simple conceptually. It consists of four modules: a fuzzification module, a fuzzy rule base, a fuzzy inference engine, and a defuzzification module. The relationships among these four modules and the working environment are illustrated in a schematic diagram in figure 8.

The fuzzification module is one of the two modules that interfaces directly
with the external environment. As the name suggests, the function of the fuzzification module is to convert the values of the relevant decision variables it has measured in the environment into appropriate fuzzy sets (actually truncated fuzzy sets). The fuzzy rule base contains a set of fuzzy decision making or control rules. These rules are typically expressed as if-then rules. For instance, one such rule might look like "If it is warm and the room is full then set the speed of the air conditioner's compressor high." The inference engine then takes the fuzzified inputs and combines them with the relevant fuzzy rules to make inferences regarding the output variables. The product of the inference engine are fuzzy outputs which will need to be transformed back into non-fuzzy values to guide decision making or for control purposes. This last step is accomplished by the defuzzification module which is the second module that interfaces directly with the external environment.

To fully appreciate the inner workings of a fuzzy inference system, let us now discuss the basic steps involved in the design of a fuzzy inference system and explore how it works in practice. For the purpose of illustration, we will consider the design of a fuzzy system for trading a stock.

The first step in the design involves identifying the relevant input and output variables and their ranges of values (which include setting up the universe of discourse), and selecting the fuzzy sets to represent the possible states of these variables. To keep things simple, we will restrict our fuzzy trading system to only two inputs-a price indicator and a volume indicator. The price indicator measures the percentage change in price, and the volume indicator measures the level of trading
volume. The price indicator and the volume indicator are allowed to have three possible states ("low", "normal" and "high") and two possible states ("normal" and "low") respectively. We assume that these two variables have been scaled to operate over the universe of discourse of $[-0.5,0.5]$ and $[0,1]$ respectively.

Next we construct membership functions for both inputs. We use three membership functions for the price indicator to represent "low" (closer to -0.5), "normal" (around 0), and "high" (closer to 0.5). For the volume indicator, we use two membership functions to represent "high" (closer to 1), and "normal" (closer to 0). Various shapes, such as triangular, trapezoidal, bell curve, sigmoid curve, etc., have been used in practice for membership functions. But the shape is generally less important than the number of membership functions and their placement. We will use the triangular membership functions for the price indicator and the trapezoidal membership functions for the volume indicator. Figures 9 and 10 show the membership functions for both inputs.

The output we want obviously is a trading decision-that is, "buy", "sell", or "hold." We will use three triangular membership functions to represent these decisions and we restrict the corresponding universe of discourse to [-1,1]. Figure 11 shows the membership functions for the trading decision. We will also assume that a defuzzified output value of less than -0.3 represents a sell decision, and of greater than 0.3 represents a buy decision. Any value between these two values will result in a decision to hold.

Having set up the fuzzy sets, we can now explore how the fuzzification module
works. Suppose that the price and volume indicators have the values of 0.2 and 0.65 respectively. To fuzzify these input values, we must first determine for each variable if the fuzzy set representing the antecedent in a given rule include the given value in its range. If it does, fuzzification entails truncating the height of this fuzzy set to the point where the input value intersects this fuzzy set. The effect of fuzzification is illustrated by the top two pictures in figures 12 tol5. Referring to figure 12, we can see that the input value of 0.2 for the price indicator has caused the corresponding fuzzy set to be truncated at a membership value $0 f 0.4$. In the case of the volume indicator, it is truncated at a membership value of 0.8 . Therefore, the effect of fuzzification is to transform the crisp input values into membership values that indicate the degree to which these values have satisfied the fuzzy antecedents in the rule. If the given input value falls outside the range of the corresponding fuzzy set in a rule, as is the case in the top left picture in figure 15 , the outcome will be a zero membership value.

The next step in the design is to construct a set of fuzzy rules to guide the trading decision. In practice, these rules are set up by consulting experts in the area we are modeling. Alternatively, these rules can also be learned from past data (see Kosko 1993, pp. 157-171, 214-222). But when neither approach is possible, the rules can be set up by trial and error. To illustrate, suppose our intention is to mimic a positive feedback trading strategy. A positive feedback strategy involves buying when there is an upward price momentum and selling when there is a downward price momentum. An upward (downward) price momentum is identified by a volume-
driven price increases (decreases). Accordingly, we can construct the rules for this strategy as follows.

Rule 1: If the price indicator is high and the volume indicator is high, then the trading decision is buy.

Rule 2: If the price indicator is normal then the trading decision is hold.
Rule 3: If the volume indicator is normal, then the trading decision is hold.

Rule 4: If the price indicator is low and the volume indicator is high, then the trading decision is sell.

The third step involves the design of the inference engine. Here we decide on how to interpret the logical connectives in the rules, the implication method and how to aggregate the outcomes from each rules. As we have mentioned earlier, there are several possible definitions for the fuzzy logical operators 'AND', 'OR' and 'NOT" (complement). For reasons discuss in the last section, we will use the Min-Max logical operators in our example. Recall that the effect of the 'AND' operator is to pick out the minimum membership value from a group of fuzzy elements connected by the 'AND' operator. Since we have used the 'AND' operator in the first and last rule above, the joint effect of the antecedents in each rule will be determined by the minimum membership values of the two fuzzy antecedents in each of these two rules. Going back to figure 12 again, the membership values for the antecedents have been determined to be 0.4 and 0.8 for the price and volume indicator respectively. Therefore, the joint effect should be a membership value of 0.4 (the minimum of the two values).

Implication involves computing the effect this joint membership value of the
antecedents has on the consequent in the same rule. There are numerous ways in which this can be achieved and one such approach is motivated by the parallels in classical logic. It is well known in classical logic (i.e. binary logic) that the truth value of $p \Rightarrow q$ is the same as either $\neg p \vee q$ or $(p \wedge q) \vee \neg p$. Alternative fuzzy implications can be derived by substituting the various definitions for the fuzzy logical operators $\wedge(A N D)$ and $\vee(O R)$ into these two expressions. Some examples are the Kleene-Dienes implication, the Lukasiewicz implication, and Zadeh implication (for more details see Driankov, Hellendoorn and Reinfrank 1993, pp.85-87).

Of all the implication operators, the most important one known in the fuzzy control literature is the Mamdani implication ${ }^{39}$. It is based on the intersection operator, i.e., $p \Rightarrow q \equiv p \wedge q$. We have used the Mamdani implication in our example. In practice, the Mamdani implication is implemented with the min operator which has the effect of truncating the height of the fuzzy set for the consequent to the joint membership value of the antecedents determined above. This explains why the bottom picture in figure 12 shows that the consequent has been truncated at the membership value of 0.4.

Figures 12 to 15 show how each rule has responded to the given input values, and the effect of implication is illustrated by the bottom picture in each of these figures. Notice that there is no logical connective in Rule 2 and 3. In these cases, the joint membership value of the antecedents is just the membership value of the only

[^24]antecedent that is present in each rule. In the case of Rule 4, although there are two antecedents, the first one is not satisfied by the given value. The first antecedent therefore yields a membership value of zero. Consequently, the joint membership value is zero and the fuzzy set for the consequent is cut off at zero. This implies therefore that the output from Rule 4 is an empty fuzzy set.

The next task that has to be performed by the inference engine is to consolidate the truncated fuzzy set from each rule. This can be accomplished by either taking the union or the intersection of all the resulting truncated fuzzy sets that represent the consequent. The choice will depend on whether we treat the rules as disjunctive or conjunctive. If we treat the rules as disjunctive, we will obtain a conclusion for a set of given input values whenever the joint membership value of the antecedents is nonzero for at least one rule. On the other hand, if we consider the rules as conjunctive, then we will obtain a conclusion only if the joint membership value of the antecedents is non-zero for all the rules. The interpretation of the rules as either disjunctive or conjunctive depends on their intended use and the way the joint membership value for the antecedents in each rule is determined. For the example we are considering, clearly we want to treat the rules as disjunctive. We therefore take the union of all the truncated fuzzy consequent. The result is the largest fuzzy set that can be formed from superimposing the truncated fuzzy sets of the consequent on each other. This final output fuzzy set is illustrated in figure 16.

The final step is to design the defuzzification module. The purpose as we have mentioned before is to convert the final fuzzy set obtained by the inference engine to a
real value so that it may be used for control purposes or guide decision making. Of the numerous defuzzification methods that have been proposed, the six most popular ones are: Centroid or Center-of-Area method, Center-of-Sums method, Center-of-LargestArea method, First-of-Maxima method, Middle-of-Maxima method, and Height defuzzification method. These defuzzification methods are illustrated in figures 17 to $22^{40}$.

In most practical applications, a major consideration in the choice of a defuzzification method is its computational complexity. The Height method, Middle-of-Maxima method and the First-of-Maxima method are the faster ones among the six methods listed above. Other considerations to keep in mind are Continuity, Disambiguity and Plausibility. Continuity will ensure that a small change in the input will not result in a large change in the output. The problem of ambiguity arises when the result of the defuzzification method is not unique. This happens when for instance the Center-of-Largest-Area method is applied to two fuzzy sets that have identical areas. A defuzzified output is considered plausible if it lies approximately in the middle of the support of the corresponding fuzzy set and has a high degree of membership in the same fuzzy set. We apply the Centroid method to our example. It is apparent from figure 16 (since the bulk of the set is concentrated on the right side), that even without carrying out the defuzzification, the decision is to buy. The calculation of the centroid gives a value of 0.333 which confirms a buy decision as

[^25]expected ${ }^{41}$. In the next section, we explore recent developments in fuzzy logic.

### 2.4 Recent Developments

It is interesting to note the following comments by Kosko on the earlier development of fuzzy logic.

Zadeh saw scientists throwing ever more math at problems and trying to think and run the business of science with the black-white reasoning that computers and adding machines used. He chose the word "fuzzy" to spit in the eyes of modern science.

The term fuzzy invited the wrath of science and received it. It forced the new field to grow up with all the problems of a "boy named Sue." The fuzzy movement in those days was a small cult and it went underground. It grew and matured without the usual support of subsidized science. That made it stronger.

Fuzzy logic did not come of age at universities. It came of age in the commercial market and leapfrogged the philosophical objections of Western Scientists. (Kosko 1993, p. 20)

As Kosko has clearly stated, the application of fuzzy logic in the commercial sector is where it gained most of its fame and subsequently caught the attention of most western academics. Over the last decade, fuzzy logic has increasingly been used in commercial applications; particularly in control systems which have to deal with vague inputs. The current interest in the commercial application of fuzzy logic was possibly triggered by two events in the 1980s; one in 1985 and another in 1987. In 1985, Shoji Miyamoto and Seiji Yasunobu of Hitachi, in their simulations,

[^26]demonstrated that a fuzzy control system is far superior than the conventional control system for the Sendai subway in Japan (see Seiji Yasunobu and Shoiji Miyamoto 1985). Although they ran into problems initially, they had a breakthrough when they realized that they should design the controller to anticipate rather than react to events as they happen. Their ideas were adopted and fuzzy systems were used to control accelerating, braking, and stopping when the line opened in 1987. The implementation was a phenomenal success.

Later in the same year (1987), at the second annual International Fuzzy Systems Association (IFSA) conference in Tokyo, Takeshi Yamakawa demonstrated the use of fuzzy control for a classic control problem-the balancing of an inverted pendulum (see Takeshi Yamakawa 1989). This is a very difficult task to accomplish with conventional control method but Yamakawa was able to maintain the pendulum upright with ease using a fuzzy controller. But that was not all. The most astonishing discovery at the conference was certainly the serendipitous demonstration that a fuzzy system can continue to function satisfactorily even when it has been degraded (McNeill and Freiberger 1993, p. 157). At the conference, a curious observer had requested Yamakawa to remove a computer board from his fuzzy control system as an attempt to investigate how the system would respond to a degradation of the information provided to the controller. The general expectations at that time were that the pendulum would drop immediately when the board was removed. However, to everyone's amazement, the pendulum continued to maintain its balance, proving forcefully that a fuzzy control system can continue to make decisions even with partial
information.
Such sensational demonstrations quickly set the stage for a broad-based
research effort in fuzzy logic. Some examples of how Fuzzy Logic has been applied in practice include ${ }^{42}$ :

- Automatic control of dam gates for hydroelectric-powerplants (Tokio Electric Power.)
- Simplified control of robots (Hirota, Fuji Electric, Toshiba, Omron)
- Camera aiming for the telecast of sporting events (Omron)
- Substitution of an expert for the assessment of stock exchange activities (Yamaichi, Hitachi)
- Preventing unwanted temperature fluctuations in air-conditioning systems (Mitsubishi, Sharp)
- Efficient and stable control of car-engines (Nissan)
- Cruise-control for automobiles (Nissan, Subaru)
- Improved efficiency and optimized function of industrial control applications (Aptronix, Omron, Meiden, Sha, Micom, Mitsubishi, Nisshin-Denki, OkuElectronics)
- Positioning of wafer-steppers in the production of semiconductors (Canon).
- Optimized planning of bus time-tables (Toshiba, Nippon-System, Keihan-Express)
- Archiving system for documents (Mitsubishi Elec.)
- Prediction system for early recognition of earthquakes (Inst. of Seismology Bureau of Metrology, Japan)
- Medicine technology: cancer diagnosis (Kawasaki Medical School)
- Combination of Fuzzy Logic and Neural Nets (Matsushita)
- Recognition of handwritten symbols with pocket computers (Sony)
- Recognition of motives in pictures with video cameras (Canon, Minolta)
- Automatic motor-control for vacuum cleaners with recognition of surface condition and degree of soiling (Matsushita)
- Back light control for camcorders (Sanyo)
- Compensation against vibrations in camcorders (Matsushita)
- Single button control for washing-machines (Matsushita, Hitatchi)
- Recognition of handwriting, objects, voice (CSK, Hitachi, Hosai Univ., Ricoh)
- Flight aid for helicopters (Sugeno)
- Simulation for legal proceedings (Meihi Gakuin Univ, Nagoya Univ.)
- Software-design for industrial processes (Aptronix, Harima, Ishikawajima-OC Engineering)
- Controlling of machinery speed and temperature for steel-works (Kawasaki Steel, New-Nippon Steel, NKK)

[^27]- Controlling of subway systems in order to improve driving comfort, precision of halting and power economy (Hitachi)
- Improved fuel-consumption for automobiles (NOK, Nippon Denki Tools)
- Improved sensitiveness and efficiency for elevator control (Fujitec, Hitachi, Toshiba)
- Improved safety for nuclear reactors (Hitachi, Bernard, Nuclear Fuel div.)

This concludes the presentation on fuzzy logic. The remaining of this chapter is devoted to discussing genetic algorithms. This next section provides an overview of genetic algorithms.

### 2.5 Genetic Algorithms-An Overview

Genetic Algorithms ${ }^{43}$ (GAs) are robust parallel search and optimization algorithms that are inspired by Darwin's notion of the "survival of the fittest" at the genetic level. At this (genetic) level, the "survival of the fittest" refers to how the "fittest" genes are sought out in nature through a combined processes of selection, crossover, and mutation. Since in principle, the search for the "fittest" genes in nature is no different from the search for optimal solutions in an optimization problem, we could potentially exploit this robust search algorithm of nature for solving very general optimization problems. But of course, this is possible only if we could represent our tentative solutions (search objects) in an optimization problem in the form of chromosome-liked objects suitable for manipulation by artificial selection, crossover and mutation operators.

[^28]In GAs, this is typically accomplished by transforming the search objects into binary strings that mimic the chromosomes. Chromosomes are entities composed of genes. If we draw an analogy between a chromosome and a binary string, then the genes in the chromosomes are like the binary bits within the binary string. The position of a gene in the chromosome is called its locus and the value taken by each gene is called its allele. Among other functions, these genes hold crucial hereditary information which can affect the development and survival of an organism. The genetic makeup of an organism is known as its genotype. Similarly, in a GA, the bits in a binary string hold important information which can determine whether the string will be selected for reproduction or be discarded. In the case of a GA, the genotype refers to the binary structure or representation of the search objects.

There is however another class of properties of an organism which also can affect the way an organism adapts and survives as the genotype does. But unlike the genotype, this set of properties is not heritable. This is the phenotype, a set of properties or behaviors which an organism acquires from its interaction with the environment (as it learns to adapt). The parallel of the phenotype in GAs is the actual representation of the search objects (i.e., that which the binary representation decode into-it could be a set of parameters, solution alternatives, or points in the solution space).

In genetics, genotype properties are inherited by future generations through iteration after iteration of the combined processes of selection, crossover, and mutation. GAs mimic this natural evolutionary process by subjecting a population of
binary strings to repeated operations which resemble those of selection, crossover and mutation. In the selection process, search objects or binary strings (chromosomes) are selected for reproduction based on their "fitness". "Fitness" in a GA is measured by how well the search objects have solved the problem at hand, or simply, by how close they approximate the true solution of the problem. Generally, the more 'fit" ones are more likely to be selected for reproduction than the less "fit" ones. Those selected for reproduction are subsequently paired off randomly and subjected to crossover. In a crossover, each pair of strings are chopped off at a randomly chosen point, and the segments from each parent are then combined to create new offspring. Although no new genes are produced, a crossover can potentially create many different combinations of truly unique strings. For instance, in human reproduction where 23 out of the 46 chromosomes from each parent are recombined and passed down to offspring, trillions of totally unique combinations can possibly be produced. In other words, trillions of truly unique individuals can be created due to crossover alone.

A numerical example here will help to provide a more definitive illustration of the effectiveness of a crossover operator. Consider a binary string with 3 bits. The entire space that can be spanned by a 3-bit binary string is: $000,001,010,011,100$, 101,110 , and 111 (the number of possible unique strings is equal to $2^{n}$, where $n$ is the number of bits). This same space could also be spanned by a crossover operator with only two linearly independent strings-i.e., two strings with different allele at each locus. For instance, consider the pair of strings 000 , and 111 in figure 23 . Using this pair of strings as the parents, figure 23 shows the possible offspring obtainable from
crossover at different points (the boxes in dark outline in figure 23 enclose the binary bits that have been crossed-over).
$\mathrm{A}, \mathrm{B}$ and C are three unique pairs of offspring obtainable from crossover at different sites. Note that the creation of $B$ requires a two point crossover, unlike that of A and C which only requires a single point crossover. It is clear from this example that a crossover operator alone (if we allow for two-point crossover) can indeed create a complete set of truly unique strings starting from only two linearly independent strings. In this case, it takes only three unique crossovers to produce a complete set of strings which span the entire space. Of course the number of times we need to crossover will vary with the length of the string. In general the number of unique crossovers needed to generate a complete set of totally unique binary strings starting from just two linearly independent strings, is equivalent to $\left(2^{n-1}-1\right)$ where $n$ is the number of bits in the string.

We have just seen that the key condition necessary for the crossover operator to span the space is to have a set of linearly independent strings at the start. When this condition is not satisfied, the crossover operator can only access a subset of the total space, and when this is the case, there is no guarantee that a crossover operator will be able to find the optimal string(s) for it(they) may lie outside the spaces which are accessible by the crossover operator. Fortunately GAs have more to offer than just crossover. The aforementioned constraint can be removed with a mutation operator. In a mutation, information held in genes are altered at random. In a binary string, this amounts to switching one or more bits in a string from 0 to 1 or vice versa.

Continuing with the previous example, if the starting strings had been 000 and 110, a mutation operator could step in, and, with some probability, alter either the first string to 001 or the second string to 111 , and in doing so create a set of unique strings to satisfy the above condition. Although this discussion has not been mathematically rigorous, it should be intuitively clear that the combined operation of crossover and mutation is indeed capable of searching the entire solution space. Therefore there should be no doubt as to the effectiveness of a GA as a search algorithm.

In most applications, the population of strings evolved in a GA is rather large and therefore will be likely to contain at least two linearly independent strings. Hence, mutation operators are not applied frequently. The probability for mutation is usually set to less than 0.01 . Another good reason for keeping the mutation probability low is to improve the final convergence behavior. If the mutation probability is set too high, the frequent perturbation will not allow the strings to settle down at the correct solution(s). On the contrary, crossover is applied more frequently, usually with a probability of about 0.7 but may be higher if necessary. Frequent crossovers are desirable as they ensure that the entire solution space is searched thoroughly for good solutions.

However, what we have established so far with the searching ability of the combination of crossover and mutation (i.e., the ability to span the entire solution space) is merely a basic requirement of any useful search strategy. It is well known that any random search strategy is also capable of searching the entire solution space with some probability. So the more pragmatic question here is whether a GA is any
better than a random search strategy. This question relates to the efficiency of a GA and will be discussed in details in the next section when we discuss the Schema Theorem.

To sum up this section, GAs are search and optimization algorithms based on natural genetics. The four key steps in a GA are: 1) encoding of initial trial solutions (search objects), 2) fitness evaluation, 3) selection for reproduction, and 4) crossover and mutation. In its search for better solutions, a GA repeats the last three of these four steps until an adequate solution has been found.

### 2.6 The Schema Theorem

The Schema theorem was constructed by Holland(1975) to make a statement about the efficiency of a GA as an optimization algorithm. This theorem asserts that in a GA the genetic makeup of a population of individuals will evolve towards that of the fitter individuals at an exponential rate, or in other words, tentative solutions will improve at an exponential rate. Goldberg (1989) has presented an excellent discussion of the Schema Theorem, and the discussion here will primarily follow his ${ }^{44}$. In relation to the previous discussion, we will stay with the binary representation, that is, we will consider only strings which are constructed over the binary alphabet $V=\{0$, 1 $\}$. We further define a schema H taken from the three-letter alphabet $\mathrm{W}=\{0,1, *\}$. where ' 0 ' and ' 1 ' are the usual binary bits and '*' represents a wildcard, or "a don't care" symbol. Schemata are simply patterns or similarity templates which we can

[^29]generalize from a collection of strings in a population. For example, consider a collection of strings $00110,00111,01110$, and 01111 . A possible schema for this population is $H=0^{*} 11^{*}$. Some other possible schema for the same set of strings are $0^{* * * *}$, and *** $1^{*}$.

A useful way to characterize a schema is to define its order and defining length. The order of a schema H , denoted by $\mathrm{O}(\mathrm{H})$, refers to the number of fixed positions present in the template. For the above example of $0^{*} 11^{*}$, the order is 3 (symbolically, we represent it as $\mathrm{O}\left(0^{*} 11^{*}\right)=3$ ). The defining length of a schema H , denoted by $\delta(\mathrm{H})$, is the number of bits between the first and last specific string position. For example, the schema $0^{*} 11^{*}$ has defining length $\delta=3$ because the last specific position is 4 and the first specific position is 1 . When there is only one specific bit like in schemata $0^{* * * *}$ and ${ }^{* * *} 1^{*}$, the defining length $\delta$ is equal to zero.

Having established convenient notations for describing the schemata, we can now focus on analyzing the net effect of the reproduction, crossover and mutation operators on the dynamics of schemata. Let $A(t)$ represents a population of binary strings at time $t$, and $m(H, t)$ represent $m$ examples of a particular schema $H$ contained within $A(t)$ at time $t$. Since reproduction involves copying strings according to their fitness values, if we denote the fitness of the $i^{\text {th }}$ string by $f_{i}$, the probability that the $i^{\text {th }}$ string will be selected for reproduction is given by $p_{i}=f_{i} / \sum_{i=1}^{N} f_{i}$. Consequently, after we have selected a new population of size $N$ with replacement from the initial population, we should on average have $\mathrm{m}(\mathrm{H}, \mathrm{t}+1)=\mathrm{m}(\mathrm{H}, \mathrm{t}) N f(H) / \sum f_{i}$
representatives of the schema H in the new population at time $\mathrm{t}+1$ where $f(H)$ is the average fitness of the strings representing schema H at time t . It is instructive to rewrite this equation in term of the average fitness of the entire population, $\bar{f}$, where $\bar{f}=\Sigma f_{j} / N$. With this substitution we obtain:

$$
\begin{equation*}
\mathrm{m}(\mathrm{H}, \mathrm{t}+1)=\mathrm{m}(\mathrm{H}, \mathrm{t}) \frac{f(H)}{\bar{f}} \tag{2.4}
\end{equation*}
$$

The effect of the reproduction operator is now obvious. Under reproduction, a particular schema grows in direct proportion to the ratio of the average fitness of the schema to the average fitness of the population. As a result, schemata with fitness values above the population average will be more represented in the next generation, while schemata with fitness values below the population average will be less represented. Keep in mind that the same phenomenon applies simultaneously to every schema H contained in a particular population A . As such, all the schemata in a population will grow or decay according to their schema averages under the operation of reproduction alone. In summary, above-average schemata grow and below-average schemata die off.

Consider now the growth of a particular schema H which remains above the average fitness by an amount $\mathrm{c} \bar{f}$ with c is a constant. The difference equation describing the growth of this schema would then be:

$$
\begin{equation*}
\mathrm{m}(\mathrm{H}, \mathrm{t}+1)=\mathrm{m}(\mathrm{H}, \mathrm{t}) \frac{\bar{f}+c \bar{f}}{\bar{f}}=(1+\mathrm{c}) \mathrm{m}(\mathrm{H}, \mathrm{t}) \tag{2.5}
\end{equation*}
$$

However, $m(H, t)$ can also be expressed as $(1+c) m(H, t-1)$ so that:

$$
\begin{equation*}
m(H, t+1)=(1+c)^{2} m(H, t-1) \tag{2.6a}
\end{equation*}
$$

Repeating this backward substitution until $t=0$ results in:

$$
\begin{equation*}
m(H, t)=m(H, 0)(1+c)^{t} \tag{2.6b}
\end{equation*}
$$

We can therefore conclude that reproduction will allocate exponentially increasing (decreasing) numbers of trials to above- (below-) average schemata.

However, reproduction alone does not promote exploration of new regions of the search space as we have discussed in the previous section. In order to encourage exploration of new regions, we need the crossover and mutation operators. To analyze the effect of crossover on the dynamics of schemata, we consider a particular string, $A$, of length $l=5$ and two representative schemata of this string:

$$
\begin{aligned}
& \mathrm{A}=01110 \\
& \mathrm{H}_{1}=* 1 * * 0 \\
& \mathrm{H}_{2}=* * * 10
\end{aligned}
$$

Both schemata $\mathrm{H}_{1}$ and $\mathrm{H}_{2}$ are represented in the string A. Assume that string A has been chosen for mating and that crossover will take place between position 3 and 4. The effect of this crossover on our two schemata $\mathrm{H}_{1}$ and $\mathrm{H}_{2}$ is illustrated below. The separator symbol $\mid$ is used to mark the crossing site.

$$
\begin{aligned}
& \mathrm{A}=011 \mid 10 \\
& \mathrm{H}_{1}=* 1 * \mid * 0 \\
& \mathrm{H}_{2}=* * * \mid 10
\end{aligned}
$$

It is obvious that unless string A is crossed-over with another string that is
identical to itself, the schema $\mathrm{H}_{1}$ will be destroyed because the 1 at position 2 and the 0 at position 5 will be placed in different offspring. In contrast, schema $\mathrm{H}_{2}$ will survive because the 1 at position 4 and the 0 at position 5 will be carried intact to a single offspring. Despite the fact that this example is rather specific, we can see that in general schema $\mathrm{H}_{1}$ is less likely to survive a crossover than schema $\mathrm{H}_{2}$ because on average the cut point is more likely to fall between the extreme fixed position. We can calculate the probability that schema $\mathrm{H}_{1}$ will be destroyed as follows. Note that $\mathrm{H}_{1}$ has a defining length of 3 . If the crossover site is selected uniformly at random among the 4 available sites, then clearly schema $\mathrm{H}_{1}$ is destroyed with probability $P_{d}=\delta\left(\mathrm{H}_{1}\right) /(l-1)$ $=3 / 4$ (or it survives with probability $P_{s}=1-P_{d}=1 / 4$ ). Likewise, the probability that schema $\mathrm{H}_{2}$ will be destroyed is $P_{d}=\delta\left(\mathrm{H}_{2}\right) /(l-1)=1 / 4$ (and the survival probability is 3/4). The survival probability for a schema H of length $l$, is in general given by $P_{s}=1-$ $\delta(\mathrm{H}) /(l-1)$. However, if crossover is applied at a probability $P_{c}$, then the total effect on the survival probability will be:

$$
\begin{equation*}
P_{s} \geq\left[1-P_{c} \frac{\delta(H)}{\ell-1}\right] \tag{2.7}
\end{equation*}
$$

Up till now we have only consider the effect of crossover. There is one more operator we have yet to consider. This is the mutation operator. Recalling that a mutation operator randomly alters a single bit with probability $P_{m}$, the survival probability of a single allele should be $\left(1-P_{m}\right)$. For a particular schema to survive a mutation, each of the $\mathrm{O}(\mathrm{H})$ fixed positions within the schema must survive. If we multiply the survival probability of each allele by itself $\mathrm{O}(\mathrm{H})$ times, we have the
survival probability of a schema of order $\mathrm{O}(\mathrm{H})$ given by: $P_{s}=\left(1-P_{m}\right)^{O(H)}$. For sufficiently small values of $P_{m}$ the schema survival probability can be approximated by $P_{s}=1-O(H) \cdot P_{m}$.

If we combined the effects of reproduction, crossover and mutation, the equation describing the growth dynamics of schemata becomes:

$$
\begin{equation*}
\mathrm{m}(\mathrm{H}, \mathrm{t}+1) \geq \mathrm{m}(\mathrm{H}, \mathrm{t}) \frac{f(H)}{\bar{f}}\left[1-P_{c} \frac{\delta(H)}{\ell-1}-O(H) \cdot P_{m}\right] \tag{2.8}
\end{equation*}
$$

This equation clearly shows that the growth of a particular schema depends primarily on 1) whether the schema is above or below the population average, 2) whether the schema has relatively short or long defining length, and 3) how specific the schema is (that is, how many fixed bits a schema has) as measured by its order, $\mathrm{O}(\mathrm{H})$. In general, less specific schemata with above-average fitness values and shorter defining lengths will enjoy exponential growth. This important conclusion is called the Schema Theorem, or the Fundamental Theorem of Genetic Algorithms ${ }^{45}$.

At this point, it is worthwhile to remind ourselves that H is only one of the many schemata that are processed by a GA simultaneously. In general Holland's implicit parallelism result shows that for a population of N strings, a GA implicitly processes on the order of $\mathrm{N}^{3}$ schemata per generation (see Goldberg 1985, and Goldberg 1989, p. 20 and 40). When we put this in perspective, a population of 100 strings will enable a GA to process on the order of a million schemata. As the GA

[^30]processes this vast collection of schemata, short, low order, above-average schemata, that represent better solutions, are given exponentially increasing representations in subsequent generations. A GA is therefore a very efficient search algorithm in comparison to purely random search strategies.

Putting this result together with our earlier illustration of GAs' effectiveness, we can conclude that GAs are indeed very robust search and optimization algorithms. De Jong (1975) has established this point conclusively when he successfully applied GAs to the optimization of complicated functions with the following characteristics: 1) continuous/discontinuous, 2) convex/nonconvex, 3) unimodal/multimodal, 4) Quadratic/nonquadratic, 5) Low-dimensionality/high-dimensionality, and 6) Deterministic/stochastic ${ }^{46}$.

Finally, these results have also emphasized two important principles to keep in mind when designing a GA code. These are:

The user should select a coding so that short, low-order schemata are relevant to the underlying problem and relatively unrelated to schemata over other fixed positions.

The user should select the smallest alphabet that permits a natural expression of the problem. (Goldberg 1989, p.80)

### 2.7 GA Versus Conventional Optimization and Search Methods

Given that we have asserted that a GA is a robust search and optimization strategy, it is natural to question whether a GA is indeed more robust than conventional search and optimization methods. Goldberg (1989) argued that

[^31]conventional optimization and search methods are inferior to GAs because they are based on sequential search and they lack a practical and robust guiding mechanism to direct the search to regions of the space which are more likely to result in fruitful outcomes.

Conventional search and optimization methods in the literature can in general be classified as calculus-based, enumerative and random ${ }^{47}$. A common theme among these conventional methods is the use of a serial approach in their search for the optimal solution. In comparison with the parallel search approach of a GA, which can process on the order of $\mathrm{N}^{3}$ schemata simultaneously (recall the implicit parallelism result), the serial approach is highly inefficient. Since many practical problems have spaces which are simply too large to be searched sequentially, it is not practical in real applications to rely on the serial approach. For example, even the highly acclaimed enumerative scheme of dynamic programming is known to break down on problems of moderate size and complexity ${ }^{48}$. In addition, the localized nature of the search in a serial approach also implies that it has the tendency to be stuck to local optimum rather than the global optimum. Such a problem does not arise in a GA which uses a parallel approach in its search for the optimal solution.

The calculus-based method is the only one among the three alternative conventional approaches that makes use of a guiding mechanism to direct its search. It

[^32]uses the derivatives of the objective function to guide the search for an optimal solution. For instance, in the "hill climbing" method, search is conducted in the direction in which the slope is the steepest (could be steepest ascent or descent depending on the nature of the problem). But, because it relies on derivatives to direct the search, this approach is not suited for working with objective functions whose derivatives are ill-defined or too difficult to evaluate. This is not a problem in a GA. In a GA, no calculation of derivatives is ever needed to direct the search. All that is needed in a GA is simply an evaluation of the objective function and the manipulation of the tentative solutions using genetic operators, and yet, tentative solutions will evolve towards better solutions at an exponential rate as we have illustrated in the last section.

Neither the enumerative nor the random algorithms employs a guiding mechanism to direct its search towards the best solution. The enumerative algorithm systematically evaluates and compare the objective function at every point in the search space to determine the optimal solution. The random search algorithm searches the entire space at random and continually keep track of the best solution found as they proceed. However, without a guiding scheme, time will be wasted in exploring unfruitful regions of the search space. Thus these two approaches will not be as efficient as a GA.

### 2.8 The Elements of a Genetic Algorithm

### 2.8.1 Encoding of Initial Trial Solutions

We have mentioned previously that the most common encoding method is to transform the tentative or trial solutions into binary strings. This transformation is straightforward for numerical value types of trial solutions and needs no further elaboration here. However, some concern has been raised regarding the representational bias in conventional binary representation because the Hamming distance between adjacent values is not constant ${ }^{49}$ (Hollstien 1971). Caruana and Schaffer (1988) have found that large Hamming distances in the standard binary representation can result in the search process being deceived hence keeping it from efficiently locating the global minimum. This problem can be resolved by the use of Gray coding which may also help to speed up convergence. As an illustration, the list in Table 1 shows the corresponding relations between Binary-coded integers and Gray-coded integers, for integers ranging from 0 to 15 . Notice that for the Gray-coded integers, adjacent integers differ by a single bit (i.e. a hamming distance of 1 ).

In practice, Gray encoding is initially applied to the entire population of strings (tentative solutions). Decoding (re-encoding) is then carried out systematically at the step right before (after) fitness evaluation. The algorithm for Gray encoding and decoding is straightforward. Let $A_{i, j}$ represents the $i^{\text {th }}$ bit in the $j^{\text {th }}$ string, and $G_{i, j}$ represents a similarly positioned bit for a Gray coded string. The algorithm is as

[^33]follows.
\[

$$
\begin{array}{ll}
\text { For Gray encoding: } & \text { if } A_{i, j} \neq A_{i, j-1} \text {, then } G_{i, j}=1 \text {, else } G_{i, j}=0  \tag{2.9}\\
\text { For Gray decoding: } & \text { if } G_{i, j}=0 \text {, then } A_{i, j}=A_{i, j-1} \text {, else } A_{i, j} \neq A_{i, j-1}
\end{array}
$$
\]

In addition to binary coding, there is an increasing interest in alternative coding strategies such as integer and real-valued representations. One argument in favor of these alternative coding strategies is they may be more convenient, more efficient or more natural than binary coding in representing the problem. For instance, Wright (1991) has argued that real-value coding is more efficient as there is no need to convert the chromosomes to phenotypes before each function evaluation. There is also no loss in precision by representing continuous values as discrete binary or other values, and there is greater freedom to use different genetic operators. The use of realvalued encodings is described in details by Michalewicz (1992) and others in the literature on evolution strategies (see for example, Back, Hoffmeister, and Schwefel 1991).

Once a decision is made on the representation, the next step is to generate an initial population of individuals (chromosomes or genotypes). Unless there is prior knowledge on what the approximate solution should be, the initial population is usually generated using a random number generator.

### 2.8.2 Fitness Evaluation

The fitness of each individual string is related to how well it satisfies the objective function. Hence a straightforward measure of relative fitness would be to
compare the raw value of the objective function contributed by each individual. However, on those occasions when the objective function is not a convenient or suitable measure of fitness, a fitness function constructed from the objective function may be used to evaluate the relative fitness of the individuals. A commonly used transformation is

$$
\begin{equation*}
F\left(x_{i}\right)=\frac{f\left(x_{i}\right)}{\sum_{i=1}^{N} f\left(x_{i}\right)} \tag{2.10}
\end{equation*}
$$

where N is the population size, $x_{i}$ is the phenotype value of individual $i$, and $f\left(x_{i}\right)$ is the fitness function or objective function. This transformation allows offspring to be selected in direct proportion to an individual's relative fitness. However, this transformation is not suited for objective functions with negative values. In such instances, instead of using the actual objective function for $f\left(x_{i}\right)$ in the above equation, a linear transformation of the actual objective function may be used (such as, $a f\left(x_{i}\right)+b$; where a and b are appropriately chosen constants). Another concern that may surface is that the range of $f\left(x_{i}\right)$ may be too wide. When this is the case, highly fit individuals in early generations can dominate the reproduction process and may cause the algorithm to result in premature convergence to some sub-optimal solution. Baker (1985) has suggested overcoming this problem by assigning fitness value according to the individuals' ranking within the population rather than basing the fitness on their raw performance. This is accomplished by using an equation similar to the following for calculating fitness.

$$
\begin{equation*}
F\left(x_{i}\right)=2-M A X+2(M A X-1)\left(\frac{x_{i}-1}{N-1}\right) \tag{2.11}
\end{equation*}
$$

MAX is typically chosen to be in the interval [1.1, 2.0] and is used for controlling the selective pressure toward the most fit individuals. $x_{i}$ is the ranking, or the position in the ordered population of individuals. As an illustration of how this transformation works, consider two individuals - the highest ranked and the lowest ranked - in a population of N individuals. The variable $x_{i}$ will be equal to N for the highest ranked and be equal to 1 for the lowest ranked. Substituting these values into the equation will give us fitness values of $M A X$ and 2-MAX respectively. The difference in fitness value between the highest ranked and the lowest ranked individual is therefore $2 M A X-2$. Using a larger value for $M A X$ will expand this difference and hence put more selective pressure in the directions of the most fit individuals, while using a smaller value for $M A X$ will do the opposite.

### 2.8.3 Selection for Reproduction

This step controls the number of offspring that each individual will contribute to the new generation. The idea here is to allow more fit individuals to contribute more offspring than the less "fit" individuals. This is in essence an artificial version of Darwin's game of the "survival of the fittest". Methods for selecting individuals usually use some form of a "roulette wheel" mechanism to probabilistically select individuals based on their fitness. The Basic Roulette Wheel Selection Method and the Stochastic Universal Sampling method are two commonly used selection techniques.

## Basic Roulette Wheel Selection

The goal of these selection techniques is to design a mechanism which will select individuals for reproduction based on their fitness values. A roulette wheel selection method accomplishes this by first dividing a roulette wheel into N sectors (where N corresponds to the total number of individuals) and then assigning to each individual a sector with an area which is proportionate to its fitness (see illustration in figure 24). In Figure 24, we see that individual 5 has the highest level of fitness, as it occupies the biggest sector. The circumference of the roulette wheel is set equal to the sum of all the individual's fitness (denoted as Sum). The process of finding an individual for mating involves, first, generating a random number in the interval [0,Sum], and then, selecting the individual whose sector spans that random number. This process is repeated until the desired number of individuals have been selected. Note that sampling is done with replacement.

Several variations of this basic roulette wheel selection method have emerged with the sole purpose of minimizing the spread and the bias in the sampling while maintaining or improving the efficiency of the algorithm. Bias is the absolute difference between an individual's actual and expected selection probability. Spread is the range in the possible number of trials that an individual may achieve. A "minimum spread" is the smallest spread that theoretically permits zero bias. Bias is therefore an indicator of accuracy, while the spread is a measure of its consistency. An efficient single-phase sampling algorithm which has a zero bias and minimum
spread is the Stochastic Universal Sampling method. This is described next.

## Stochastic Universal Sampling(SUS)

In the basic roulette wheel selection method, the process has to be repeated until the desired number of individuals have been selected. In this method, all of the individuals are selected in one step. SUS uses N equally spaced pointers, where N is the desired number of individuals. At the beginning, the population is shuffled randomly and a random number in the interval $[0, S u m / N]$ is generated, $\varphi$. The N individuals are then chosen by generating $N$ pointers spaced by 1 (i.e., $\varphi, \varphi+1, \ldots$, $\varphi+\mathrm{N}-1)$, and selecting the individuals whose fitness sectors on the roulette wheel span the positions of the pointers.

### 2.8.4 Crossover and Mutation

The individuals selected in the previous step are then subjected to crossover and mutation. The purpose of crossover and mutation is twofold - to improve the genetic structure of the individuals (or to recover those good genetic materials lost in the process) and to allow for sufficient diversity in the population genetic structure. Crossover involves slicing each chromosome into two or more segments then recombining pieces of different chromosome segments into new chromosomes. Mutation is simply the alteration of one or more bits (genes) in an individual string (chromosome).

## Crossover

Several crossover schemes are available. The main difference among the
various schemes is in the number of crossover points each allows (for e.g., single point crossover, multi-point crossover (see Spears and De Jong 1991), and uniform crossover (see Syswerda 1989)). The simplest form of crossover is the single-point crossover which is shown in figure 25. Multi-point crossover, illustrated in figure 26, is a straight forward extension of the single-point crossover. In a uniform crossover, a crossover template or mask is used to determine which parent will supply the offspring with which bits. The crossover template has the same length as the chromosome structure and contains binary bits which are created at random. Bits of ones (zeros) mean that genetic material in those positions will be supplied by the first (second) parent (see figure 27). Uniform crossover has been said to reduce the bias associated with the length of the binary representation used and the particular coding for a given parameter set.

These crossover schemes are not appropriate, however, for real-value encoded chromosomes because such an operation will not search the relevant real-valued space efficiently or, worse yet, invalid values may be produced as a result of the operation. Instead of crossover operators, other recombination operators are used for real-value encoded chromosomes (such as an intermediate recombination operator, or a linear recombination operator). An intermediate recombination operator produces offspring according to the following:

$$
\begin{equation*}
O_{i}=P_{i} \bullet \alpha\left(P_{j}-P_{i}\right) \tag{2.12}
\end{equation*}
$$

where the $P \mathrm{~s}$ are the parents, $O \mathrm{~s}$ are the offsprings, and $\alpha$ is a scaling factor chosen
randomly from a uniform distribution over some interval, usually $[-0.25,1.25]$ (see Muhlenbein and Schlierkamp-Voosen 1993). A linear recombination operator is a special case of the intermediate recombination operator. The scaling factor, $\alpha$, is a constant for the linear recombination operator, instead of a random value.

## Mutation

Mutation is a random process where one allele of a gene is replaced by another to produce a new genetic structure. In a binary representation, this involves the switching of chosen bit(s) from 1 to 0 or vice versa. In GAs, mutation is applied at random with low probability, typically in the range 0.001 and 0.01 , and it modifies elements in the chromosomes. The role of mutation is often seen as providing a guarantee that the probability of searching any given string is always positive and will never be zero. Mutation acts as a safety net to recover good genetic material that may be lost through the action of selection and crossover. With non-binary representations, mutation is achieved by either perturbing the gene values or random selection of new values within the allowed range. In general it has been found that for codings more complex than binary, high mutation rates can be both desirable and necessary (see Tate and Smith 1993, Wright 1991, Janikow and Michalewicz 1991).

As for actually building the new generation, the newly made individuals are usually simply inserted into the new population and the process is repeated until the new population is of the desired size. More elaborate strategies have been devised in which, for instance, an offspring is inserted into the new population only if it is fitter than its parents or if it is sufficiently different from the rest of the population (anti-
crowding). Several replacement strategies have been proposed to maintain genetic diversity in order to prevent the GA from converging prematurely (Eshelman and Schaffer 1991). Most of these methods depend on a similarity measure between individuals. In the next section, we discuss the application of a GA to find the minimum of a function.

### 2.9 A Simple Application of a GA

In this Section, we look at how a GA can be used to solve a simple optimization problem. The problem we will consider is the minimization of the function $f(x)=x^{2}$, where $0 \leq x \leq 10$. This function is displayed in figure 28. It is clear that the minimum of this function occurs at $x=0$, and $f(0)=0$. With such a trivial problem as an example, our intention is of course, not to demonstrate the power of a GA ${ }^{50}$. My purpose here is twofold: 1 ) to show the structure of a GA computer program and to relate it to the discussion in the previous section, and 2) to make sense of the GA simulation results from the perspective of the Schema Theorem.

This section is divided into two subsections. The first part discusses the key steps in the GA computer program that we have used to solve the above problem-the minimization of $f(x)=x^{2}$. The second part discusses the results from the simulation.

[^34]
### 2.9.1 A GA computer program

We discuss below a simple MATLAB program for solving this minimization problem. The subroutines in the program are taken from the Genetic Algorithm Toolbox for use with MATLAB developed by Chipperfield et al.(1995) at the University of Sheffield. Rather than going through every step of our GA code ${ }^{51}$, we will focus only on the crucial steps and relate it to the discussion in the previous section.

Figure 29 shows the result of the GA simulations. It is clear from the plot that the crossover and mutation operators are very effective as the GA converges very quickly (after about 70 generations, less than 10 seconds running time on a Pentium $120)$ to the correct solution.

## Explaining The Key Steps In Our GA Program

1. Initialization of population.

Chrom = [ones (NIND, NVAR*PRECI)]
NIND $=20$, is the number of individuals in the population
$\mathrm{PRECI}=8$, sets the length of each individual string
NVAR $=1$, is the number of variables encoded in each string.
This statement generates a matrix, Chrom, of size 20x8, containing 20
strings of ones. Each string has a length of 8 bits. Note that we have intentionally set the starting population to a collection of strings of ones, which is the furthest in hamming distance to the correct solution of strings of zeros, to demonstrate the effectiveness and efficiency of the crossover

[^35]and mutation operators in searching the solution space. We will see in the next subsection that the population converges rather quickly to the correct solution.
2. Evaluate initial population.

```
temp \(=b s 2 r v\) (Chrom, FieldD)
ObjV \(=\) temp * temp
```

The first statement uses the routine $b s 2 r v$ to convert the binary strings into real-valued decimal numbers and store them as temp (temp is the variable denoted as $x$ in the objective function). FieldD is the field description. It contains information about the variable and provides an option for Gray coding. For reasons discussed earlier, Gray coding was used in the simulation.

The second statement calculates the value of the objective function for each decoded string (recall that the objective function is $x^{2}$ )
3. Assign fitness-value to entire population

Fitn $V=\operatorname{ranking}(O b j V)$
Here fitness is assessed using the routine ranking which ranks the individuals and subsequently transforms the relative ranking to fitness values using linear ranking with a selective pressure of 2 . The parameter $M A X$ is set to 2. So the equation for fitness calculation reduces to: $F\left(x_{i}\right)=2\left[\frac{x_{i}-1}{N-1}\right]$ where N is equal to 20 , and $x_{i}$ is the ranking that runs
from 1 to 20. This implies that the fitness values assigned will follow the following sequence (in order of increasing ranking):
$\left[\begin{array}{lllllllll}0.1053 & 0.2105 & 0.3158 & 0.4211 & 0.5263 & 0.6316 & 0.7368 & 0.8421 & 0.9474\end{array}\right.$
1.05261 .15791 .26321 .36841 .47371 .57891 .68421 .78951 .8947 2.0000]

Note also that in a situation where subsets of strings are identical, the fitness value for each string in each subset of identical strings is determined by the average fitness value of the subset. For instance if the strings ranked 1,2 , and 3 are identical, then the fitness value is: $(0.1053+0.2105+0.3158) / 3$. Ranking in this routine is designed for minimization of objective functions. Hence if we have a maximization problem, we will need to recast the problem as a minimization prior to using the ranking routine.
4. Select individuals for breeding

SelCh $=$ select ('sus', Chrom, FitnV, GGAP)
This step uses the routine select to pick out individuals for breeding based on the individual's fitness. The method employed here is the Stochastic Uniform Sampling method which was discussed in the previous section.
5. Recombine selected individuals (crossover)

SelCh = recombin ('xovsp', SelCh, 0.7)
recombin allows for different crossover operations. In our case, we chose the 'xovsp', which is the single point crossover. The crossover probability
is set to $70 \%$. This routine actually uses a lower level routine which performs a uniform crossover. With appropriately specified options, it will behave like a single point crossover (i.e. the mask will contain a substring of zeros next to a substring of ones).
6. Perform mutation on offspring

SelCh $=$ mut $($ SelCh, 0.003 $)$
Mutation changes the bits in the population of strings and the mutation probability is set to $0.3 \%$ in this case.
7. Evaluate offspring

$$
\begin{aligned}
& \text { temp1 = bs2rv (SelCh, FieldD) } \\
& \text { ObjVSel = temp1 * temp1) }
\end{aligned}
$$

This is similar to step 2 above.
8. Reinsert offspring into current population
[Chrom ObjV] = reins (Chrom,SelCh,1,1,ObjV,ObjVSel)
reins allows two options for offspring to be reinserted back into the population. One option is to allow offspring to replace parents uniformly at random. Another option is to allow offspring to replace least fit parents.

Here, the latter option is used. $O b j V$ and $O b j V S e l$ contain the fitness values of the parents and the offspring respectively.

### 2.9.2 Simulation Results

Figure 29 shows that the objective function converges very quickly to the correct solution of zero (after about 70 generations which take less than 10 seconds to
run on a Pentium 120). Table 2-4 show how the population of strings evolve over time. The population consists of 20 individual strings, and the crossover and mutation probabilities were set to 0.7 and 0.003 respectively. The length of each string, which determines the precision of the binary representation, was set to 8 bits. we also used a generation gap of 0.9 , which mean that new individuals totaling $90 \%$ of the population are created and reinserted into the population at each generation.

We observed in Section 2.6 that in general, schemata which have fitness values above (below) that of the average fitness of the population should grow (decay) exponentially. In Table 2, we see that at Generation 10, the more fit strings are those which belong to the schema $[* * * * 0 * * *]$ (keep in mind that the purpose is to minimize the objective function, so the more fit strings will have lower $f(x)$ values). Five generations later, at Generation 15, the entire population has converged to the schema $[* * * * 0 * * *$ ] confirming the prediction of the Schema Theorem. In Table 3, at Generation 35, note that the more fit schema is the one that has a zero in the last position, i.e. $\left[00^{* *} 0 * * 0\right]$. Just as the Schema Theorem predicted the population again converges to this schema by Generation 55. At Generation 55, a new schema with better fitness value has been discovered. This schema puts an additional zero in the third position. Following the evolution to Generation 60, we see again that the population has quickly converged to this new schema. This is the same pattern that we see over and over again as we trace the evolution of the population over time. The conclusion we can draw from these observations is exactly what the Schema Theorem has predicted, that is, in a genetic algorithm tentative solutions improve at an
exponential rate.

### 2.10 A Genetic Fuzzy Classifier System

We have argued earlier in this chapter that fuzzy logic allows us to construct much better control systems than we can achieve using conventional mathematical control theory. However, the quality of a fuzzy control system, like most rule-based systems, ultimately relies on a good set of control rules (among other factors). Unfortunately a fuzzy system is not capable of learning these rules on its own. This self-leaming ability is not as crucial in applications in which the operating environment is fairly stable and does not evolve over time. But for applications to situations in which the environment is constantly evolving, for instance, our economy, a fuzzy control system with a fixed set of control rules is likely to be less effective.

To overcome this particular limitation of a fuzzy system, various approaches have been developed. One fruitful approach involves the use of a neural network to learn the rules over time. Although this approach has been successful, it has an important disadvantage which we have already discussed back in Chapter 1. In a neural network, the learning that is taking place happens in a black box and it is not transparent to the modeler. For that reason, the modeler will have no intuitive feel as to why the control system may behave in the way it has. In light of this criticism, the GA approach has been proposed. In a Genetic-Fuzzy classifier system, a GA is used to evolve the fuzzy inference rules through a combined process of reproduction, crossover and mutation. The advantage of GA over neural network is it affords
complete transparency to the process which is going on. This transparency allows the modeler to check on whether the evolution that is taking place or the rules themselves, is sensible or not, and it in turn provides the modeler an opportunity to take appropriate actions to correct the model whenever it is necessary.

There are two obvious ways in which a GA can be implemented to evolve the fuzzy inference rules. One way is to manipulate the antecedents or consequent in each rule directly. Suppose we have the following two rules (chromosomes):

R1: If the price indicator is high and the volume indicator is high, then the trade is buy.

R2: If the price indicator is low and the volume indicator is low, then the trade is hold.

Applying crossover can, for instance, result in the formation of the following two rules:

R1': If the price indicator is high and the volume indicator is low, then the trade is buy.
$\mathrm{R}^{\prime}$ : If the price indicator is low and the volume indicator is high, then the trade is hold.

Notice that the antecedents in bold have been swapped between the two rules. On the other hand applying mutation to a rule, let's say R1, can give us:
$\mathrm{R} 1^{\prime \prime}$ : If the price indicator is normal and the volume indicator is high, then the trade is buy.

Another possibility is to use a GA to evolve the parameters that define the fuzzy sets representing the fuzzy antecedents or consequent. Consider the fuzzy set in figure 30. This fuzzy set can be formalized by the following equation:

$$
\begin{equation*}
\mu(x)=\frac{x}{(1-a)}-\frac{a}{(1-a)}, \quad a \leq x \leq 1.0 \tag{2.13}
\end{equation*}
$$

Since the parameter ' $a$ ' is just a numerical value, the implementation of a GA to evolve this parameter is straight forward. We have a choice of either casting its value in binary representation or keeping it in its original real-valued representation. The steps involved are similar to what we have described in Section 2.9. The objective function will be determined by what this fuzzy set is to be used for.

In practice, to facilitate easy coding, the linguistic fuzzy rules in a geneticfuzzy classifier are usually transformed into bit strings. Consider the fuzzy rule base we have constructed in Section 2.3.

Rule 1: If the price indicator is high and the volume indicator is high, then the trade is buy.

Rule 2: If the price indicator is normal then the trade is hold.
Rule 3: If the volume indicator is normal, then the trade is hold.
Rule 4: If the price indicator is low and the volume indicator is high, then the trade is sell.

This set of rules may for instance be represented by the matrix in figure 31. The numbers in the first two columns represent the states of the antecedents, which are the price and volume indicators respectively. The third column captures the state of the consequent which is the trading decision. The fourth column gives the weight assigned to each rule in the rule base, and the last column specifies the type of logical operator in use. Consider the first column. Since the price indicators can have three possible outcomes, that is, "low", "normal", and "high", these can be denoted by " 1 ",
" 2 ", and " 3 " respectively. So a " 3 " in the first column would mean that the price indicator is "high" while a " 2 " would imply that the price indicator has been normal. A " 0 " means that this antecedent is absent from the rule. The same explanation also applies to the second column and the third column. In the second column, since the volume indicator can only be "normal" or "high", we denote these membership functions by " 1 " and " 2 " respectively. In the third column, " 1 ", " 2 " and " 3 " are used to denote "sell", "hold" and "buy" respectively. The ' 1 s ' in the fourth column means that all the rules are given equal weighting. Finally in the last column, a ' 1 ' stands for the ' $A N D$ ' operator and a ' 2 ' stands for an ' $O R$ ' operator. In the next chapter, we will discuss in more depth how we have implemented a genetic-fuzzy classifier system to model the learning behavior of artificial economic agents in our model.

## 3. MODEL AND EXPERIMENTS

We have argued in Chapter 1 that in order to account for the anomalies and empirical puzzles in real financial markets, we must have an accurate model of the process that determines how price expectations are formed. In particular, we emphasized that such a model must take into consideration the fact that investors will rely on their innate abilities to reason inductively and analyze in fuzzy terms ${ }^{52}$. We subsequently justified that a genetic-fuzzy classifier system can faithfully capture these traits. In this chapter we will discuss in details how we have adapted the geneticfuzzy classifier system to accomplish this goal. To illustrate that our intuition is a plausible explanation for market anomalies, we populate an artificial stock market with agents who form their expectations using the genetic-fuzzy classifier system and we investigate the implications of this expectations formation mechanism on market dynamics ${ }^{53}$. The basic framework of our artificial stock market is borrowed from a typical neoclassical two-asset market.

Section 3.1 will describe the structure of this artificial stock market in more details. In Section 3.2, we discuss in depth how we have adapted a genetic-fuzzy classifier to model the process that generates price expectations in the market. Section 3.3 will outline the various controlled experiments we have conducted to illustrate that our intuition is indeed plausible.

[^36]
### 3.1 The Market Environment

What we have in mind is a neoclassical two-asset market very similar to that of Bray (1982) or Grossman and Stiglitz (1980) except for a little twist; we deviate from these traditional models by allowing agents in our model to form their expectations inductively using a genetic-fuzzy classifier system in the manner we have outlined in

## Chapter 1.

The only two tradeable assets in the market are a risky stock and a risk-free bond. We assume that the risk-free bond is in infinite supply and it pays a constant interest rate r. But only $N$ units of the risky stock are available, and each pays a dividend of $d_{t}$, which is driven by an exogenous stochastic process $\left\{d_{t}\right\}$ not known to the agents. The dividend process is arbitrary; and in the Santa Fe Institute experiments, Arthur et al. $(1996,1997)$ have considered the following AR(1) process ${ }^{54}$

$$
\begin{equation*}
d_{t}=\bar{d}+\rho\left(d_{t-1}-\bar{d}\right)+\varepsilon_{t}, \tag{3.1}
\end{equation*}
$$

where $\varepsilon_{t}$ is Gaussian, i.i.d., has zero mean, and variance $\sigma_{\varepsilon}^{2}$. The subscript, $t$, indexed time. We assume that time is discrete and we have an infinite horizon.

There are $N$ heterogeneous agents in the market. These agents form their expectations individually and independent of each other. In other words, they do not communicate their buying or selling intentions to each other. Thus, they will quite

[^37]likely hold different expectations from each other. Other than the heterogeneity in their expectations, these agents are otherwise identical to each other. They all share a similar constant absolute risk aversion (CARA) utility function $U(W)=-\exp (-\lambda W)$. At each period, upon observing the information available to them, they will make decisions on their desired holdings of each of the two assets to maximize their utilities.

Assuming that agent $i$ 's predictions at time $t$ of the next period's price and dividend are normally distributed with (conditional) mean, $E_{i, 1}\left[p_{t+1}+d_{t+1}\right]$ and variance, $\sigma_{t, i, p+d}^{2}$, then agent $i$ 's demand, $x_{i, t}$, for holding shares of the risky asset is given by ${ }^{55}$ :

$$
\begin{equation*}
x_{i, t}=\frac{E_{i, t}\left[p_{t+1}+d_{t+1}\right]-p_{t}(1+r)}{\lambda \sigma_{i, t, p+d}^{2}}, \tag{3.2}
\end{equation*}
$$

where $p_{t}$ is the price of the risky asset at time $t$, and $\lambda$ is the degree of relative risk aversion. Since total demand must equal the total number of shares issued for the market to clear,

$$
\begin{equation*}
\sum_{i=1}^{N} x_{i, t}=N \tag{3.3}
\end{equation*}
$$

This last equation closes the model and determines the clearing price, $p_{t}$, in equation

[^38]Now let us turn our attention to the timing of the various events in the model. The current dividend, $d_{t}$, is announced at the start of time period $t$, and this is public information. Agents then form their expectations of the next period's price and dividend $E_{i, t}\left[p_{t+1}+d_{t+1}\right]$ based on this information and other general information on the state of the market (which includes the historical dividend sequence $\left\{\ldots d_{t-2}\right.$, $\left.d_{t-1}, d_{t}\right\}$ and price sequence $\left\{\ldots p_{t-2}, p_{t-1}\right\}$. Once their price expectations are established, agents will use equation (3.2) to calculate their desired holdings of the two assets. This information is in turn conveyed to a Walrasian auctioneer who then declares a price $p_{t}$ that will clear the market. The sequence is then repeated. One final thing to keep in mind is that in the process, agents keep track of the forecasting abilities of their genetic-fuzzy classifiers which they have relied upon to generate their price expectations. As agents learn about the forecasting abilities of these classifiers, those unreliable classifiers will be weeded out to make room for classifiers with new and perhaps better rules.

### 3.2 Modeling the Formation of Expectations

The structure of our genetic-fuzzy classifier is based on the design of the classifier system originally developed by Holland (see Goldberg 1989, Holland and Reitman 1978, or Holland et al. 1989). At the heart of a Holland's classifier system are three essential components: a set of conditional action rules, a credit allocation system (Holland called this the Bucket Brigade algorithm) and a genetic algorithm (GA). The behavior of the system ultimately is determined by its rules. Each rule
contains a set of conditions and an action or a combination of actions. Its operation is straightforward. Whenever the prevailing state in the environment matches all the conditions in a rule, the system adopts the actions prescribed in the rule. The function of the credit allocation system is to systematically keep track of the relative effectiveness of each rule in the classifier. This information is in turn used to guide a GA in the invention of new rules and the elimination of ineffective rules. Together they make it possible for the system to learn about the environment and adapt to innovations in the environment.

The genetic-fuzzy classifier we have employed to model expectations formation is a simple modification of the Holland's classifier system. We replace the conventional rules in Holland's classifier with fuzzy rules to create our genetic-fuzzy classifier. These fuzzy rules still use a similar condition-action format as the conventional rules, but they differ from the conventional rules in that the conditions and actions are now described by fuzzy terms rather than precise terms.

Recall that what we want to get out of the system are price expectations. We accomplish this by replacing the "action" part of the rules with a set of forecast parameters. These forecast parameters are then substituted in a linear forecasting equation to generate the price expectations we are after. The forecast equation we have used is:

$$
\begin{equation*}
E_{t}\left(p_{t+1}+d_{t+1}\right)=a\left(p_{t}+d_{t}\right)+b, \tag{3.4}
\end{equation*}
$$

where $a$ and $b$ are the forecast parameters to be obtained from the activated rule, and
the variables $p_{t}$ and $d_{t}$ are the price and dividend at time, $t$. Therefore, the format of the rules now looks like,

## If conditions then forecast parameters.

Here is an example of such a rule,
If $\{$ price/fundamental value $\}$ is low, then $a$ is low and $b$ is high.
But before a GA can operate on these rules, we must transform them into bits strings.
We use five bits to specify the conditions in a rule. These five bits represent five market descriptors and they include one fundamental factor and four other technical factors. We use another two bits to represent the forecast parameters $a$ and $b$. Altogether, we use a string of seven bits to represent each conditional forecast rule ${ }^{56}$.

### 3.2.1 Conditions and Forecast Parameters

Specifically, the five market descriptors we have used for the conditional part of a rule are: $p * r / d, p / M A(5), p / M A(10), p / M A(100)$, and $p / M A(500)$. The variables $r, p$ and $d$ are the interest rate, price, and dividend respectively. The variable $M A(\mathrm{n})$ in the denominator denotes a n -period moving average of prices. We organize the positions of the five bits so that they refer to the market descriptors in the same order as above ${ }^{57}$. Thus, the first bit reflects the current price in relation to the current dividend and it indicates whether the stock is above or below the fundamental value at

[^39]the current price. Clearly this is a "fundamental" bit. The remaining four bits, bits 25, are "technical" bits which indicate whether a trend in the price is under way. These "technical" bits will be ignored if useless and acted upon if the technical-analysis trend actually emerges.

To transform these market descriptors into fuzzy sets, we need to set up appropriate universe of discourse and decide on the number and type of fuzzy sets to use for each of these market variables. We set the universe of discourse for each of these variables to $[0,1]^{58}$. We let the possible states of each market descriptor be represented by a set of four membership functions-two trapezoidal and two triangular fuzzy sets, and we label them as "low", "moderately low", "moderately high" and "high". The shapes and locations of these fuzzy sets along the universe of discourse are as illustrated in figure 32. When we represent these fuzzy sets as bits, they are coded as " 1 ", " 2 ", " 3 " and "4" for "low", "moderately low", "moderately high" and "high" respectively. A " 0 " is reserved to record the absence of a fuzzy set. A " 0 " has the same interpretation as the "\#" (don't care) symbol used by Arthur et al. (1996, 1997).

To give an example, if the conditional part of the rule is coded as [011302], this would mean that $p * r / d$ and $p / M A(100)$ are not present in the conditional part of the rule, and that $p / M A(5)$ are "low", $p / M A(10)$ is "moderately high" and $p / M A(500)$ is "moderately low". In other words, this corresponds to a state in which

[^40]the market price is less than $M A(5)$ but somewhat greater than $M A(10)$ and is slightly less than $M A(500)$. As long as the prevailing state in the market matches the conditions for $p / M A(5), . p / M A(10)$, and $p / M A(500)$, the conditional part of the rule will be fulfilled and this rule will be activated regardless of what the values for $p^{*} r / d$ and $p / M A(100)$ might be (which is why we said that a " 0 " is like a "don't care" symbol).

However, we need to point out that because these market descriptors are intrinsically fuzzy, the conditions described by them will be likely to match many states in the market. Hence, what really matters is the degree to which each of these conditions is fulfilled and not so much whether each condition is indeed matched or not matched by the prevailing state.

Now we turn to the modeling of the forecast part of the rule. We allow the possible states of each forecast parameter to be represented by five fuzzy sets. The fuzzy membership functions used for this purpose are a Z-shaped function, three Gaussian functions and a S-curve function. These fuzzy sets are labeled as "low", "moderately low", "average", "moderately high", and "high". The universe of discourse for parameter, $a$ and $b$, are set to $[0.65,1.25]$ and $[-12,22]$ respectively ${ }^{59}$. The shapes and locations of these fuzzy membership functions are as illustrated in figures 33 and 34 . When we represent these fuzzy sets as bits, we code them as "1", "2", "3", "4" and "5" for "low", "moderately low", "average", "moderately high", and

[^41]"high" respectively. An example will make this clear. If the forecast part of the rule is coded as [25], it means that the forecast parameters $a$ is "moderately low" and $b$ is "high". Following from the example above, when we put together the conditions and the forecast parameters, we will get a complete rule which we would code as: [0130 $2 \mid 25]$. In general, we can write it as: $\left[x_{1}, x_{2}, x_{3}, x_{4}, x_{5} \mid y_{1}, y_{2}\right]$, where $x_{1}, x_{2}, x_{3}, x_{4}, x_{5} \in\{0,1,2,3,4\}$ and $y_{1}, y_{2} \in\{1,2,3,4,5\}$. Although it is not explicit in our notation, we have used the "OR" operators as the logical connectives among the conditions. We should therefore interpret the rule $\left[x_{1}, x_{2}, x_{3}, x_{4}, x_{5} \mid y_{1}, y_{2}\right]$ as:
\[

$$
\begin{gathered}
\text { "If } p^{*} r / d \text { is } x_{1} \text { or } p / M A(5) \text { is } x_{2} \text { or } p / M A(10) \text { is } x_{3} \text { or } \\
p / M A(100) \text { is } x_{4} \text { or } p / M A(500) \text { is } x_{5} \text {, then } a \text { is } y_{1} \text { and } b \text { is } y_{2} \text { " }
\end{gathered}
$$
\]

### 3.2.2 Fuzzy Rule Bases As Market Hypotheses

A genetic-fuzzy classifier contains a set of fuzzy rules that jointly determines what the price expectations should be for a given state of the market. We call a set of rules a rule base. Each rule base represents an investor's tentative hypothesis of the market and it is supposed to stand for a complete and consistent belief. This point needs further clarification.

Take for instance a fuzzy rule like "If $p * r / d$ is high than $a$ is low and $b$ is high". This rule by itself does not make much sense as a hypotnesis because it does not specify what the forecast parameters should be for other contingencies, for example the case where $p^{*} r / d$ is "low", "moderately low" or "moderately high". We will need three additional rules to cover these other possible states in order to form a
complete belief. For this reason, we have designed the rule base so that each rule base contains four fuzzy rules. In evolving these rules with a GA, care is also taken to ensure that the rules in the same rule base will never be inconsistent with each other ${ }^{60}$. That is, we cannot have rules that share identical conditions and yet suggest different forecast parameters within the same rule base. Figure 35 shows an example of a rule base, coded as a set of four bit strings, that is both complete and consistent.

However we do allow each agent in our model to work in parallel with several distinct rule bases. To be specific, we have allowed each agent in our model to work with three rule bases. The implication of this is that, at any given moment, agents may entertain several different market hypotheses in their minds. Hence, it is quite possible that each agent may derive several different price expectations at any given time. To sort out which of these price expectations to believe, an agent looks at the relative forecast accuracies of these rule bases and act on the one that has recently proven to be the most accurate. Sub-section 3.2.4 discusses how we measure forecast accuracies and calculate the fitness values of rule bases. In the next sub-section, we take a look at a simple example to illustrate how the system works.

### 3.2.3 An Example

To demonstrate how our genetic-fuzzy expectational system works, consider a simple fuzzy rule base with the following four rules.

If $0.5^{*} p / M A(5)$ is low then $a$ is average and $b$ is moderately high.

[^42]If $0.5^{*} p / M A(5)$ is moderately low then $a$ is moderately high and $b$ is high. If $0.5^{*} p / M A(5)$ is high then $a$ is low and $b$ is low.

If $0.5^{*} p / M A(5)$ is moderately high then $a$ is high and $b$ is high.
Now suppose that the current state in the market is given by $p=80, d=10$, and $M A(5)=100$. This gives us, $0.5 \times p / M A(5)=0.4$. The response of each rule and the resultant fuzzy sets for the two forecast parameters, given this state of the market, are illustrated in Figures 36-41. In particular, pay attention to the responses for the $1^{\text {st }}, 3^{\text {rd }}$ and $4^{\text {th }}$ rules. In these cases, the membership value for those fuzzy sets representing $p / M A(5)$ is zero since 0.4 is outside their domains, consequently the forecast parameters associated with these rules will also have zero membership values. Thus, only the $2^{\text {nd }}$ rule contributes to the resultant fuzzy sets for the forecast parameters $a$ and $b$. When we defuzzify these resultant fuzzy sets using the Centroid method, we obtain 1.1 and 19.6 for the parameters ' $a$ ' and ' $b$ ' respectively. This is illustrated in figures 40 and 41. Substituting these forecast parameters into equation (3.4) gives us the forecast for the next period price and dividend
of: $E(p+d)=1.1(80+10)+19.6=118.6$.

### 3.2.4 Forecast Accuracies and Fitness Values

Forecast accuracy is measured by the inverse of $e_{t, i, j}^{2}$. The variable $e_{t, i, j}^{2}$. is the moving average of squared forecast error and is defined as:

$$
\begin{equation*}
e_{t, i, j}^{2}=(1-\theta) e_{t-1, i, j}^{2}+\theta\left[\left(p_{t+1}+d_{t+1}\right)-E_{t, i, j}\left(p_{t+1}+d_{t+1}\right)\right]^{2}, \tag{3.5}
\end{equation*}
$$

where $\theta$ is a weight (a constant), subscript $i$ and $j$ denote the $i^{\text {th }}$ individual and the $j^{\text {th }}$
rule base, and $t$ indexes the time. In each period, agents refer to $e_{t, i, j}^{2}$ to decide which price expectations to believe and act upon.

The variable $e_{t, i, j}^{2}$ is also used for two other purposes. First, it is used as a proxy for the forecast variance $\sigma_{t i, j}^{2}$ which is needed to solve equation (3.2). This equation tells the agents how many risky shares to hold in each period. Second, it contributes to the fitness measure which is defined as:

$$
\begin{equation*}
f_{t, i, j}=-e_{t, i, j}^{2}-\beta s . \tag{3.6}
\end{equation*}
$$

The parameter $\beta$ is a constant and $s$ is the specificity. Specificity is the number of bits which are set (i.e., not 0 's) in the conditional part of a rule base. The parameter $\beta$ is introduced to penalize specificity. The purpose is to discourage agents from carrying bits that are superfluous or redundant. Thus, the more specific the conditions are in a rule base, the lower its fitness will be, keeping other things constant. The net effect of this is to ensure that a bit is used only if agents genuinely find it useful in predictions and in doing so introduces a weak drift towards the all 0 's configuration. The fitness measure is used to guide the selection of rule bases for 'crossover' and 'mutation' in the GA. A GA creates new rule bases by "mutating" the values in the rule base array, or by "crossover"-combining part of one rule base array with the complementary part of another ${ }^{61}$. In general, the more fit ones will be more likely to reproduce whereas

[^43]the less fit ones will have higher probability of being eliminated.

### 3.2.5 Recapitulate

Our model begins with a dividend, $d_{t}$, announced publicly at time period $t$. Based on this information and the various moving averages of historical market price, agents generate several different price expectations using their genetic-fuzzy classifiers. They forecast next period's price and dividend $\left(E_{i, t}\left[p_{t+1}+d_{t+1}\right]\right)$ by using the forecast parameters from the rule base that has proven to be the most accurate recently. With this expectation and its variance, they use equation (3.2) to calculate their desired stock holdings. This information is then passed on to a Walrasian auctioneer who calculates a price to clear the market. Once the market clears, the next period's price and dividend are revealed and the accuracies of the rule bases are updated.

Learning in the model happens at two different levels. On the surface, learning happens rapidly as agents experiment with different rule bases and over time discover which rule bases are accurate and worth acting upon and which should be ignored. At a deeper level, learning takes place on a slower time scale as a GA from time to time discards unreliable rule bases to make room for new ones through crossover and mutation. The new, untested rule bases that are created from time to time will not cause disruptions because they will be acted upon only if they prove to be accurate. This avoids brittleness and provides what machine-learning theorists call "gracefulness" in the learning process.

### 3.3 Experiments

This section describes the controlled experiments we have conducted to demonstrate that our intuiton about the roots of market anomalies and empirical puzzles in real financial markets is plausible. In these experiments, we kept almost all of the model's parameters the same so that comparisons can be made of the market outcomes using the model under identical conditions with only controlled changes. The primary control parameter is the learning frequency.

Learning frequency refers to the frequency at which a GA is invoked in the model. When the leaming frequency is high, a GA is invoked more frequently and agents will revise their rule bases more often. On the contrary, when it is low, a GA is invoked less often, so agents will revise their rule bases at a slower pace. Recall that agents are not able to use deductive reasoning to shape their price expectations. Instead, they use inductive reasoning which basically amounts to formulating tentative hypotheses and testing these hypotheses again and again in the market. Under such a scheme, it is intuitively clear that the learning frequency will play a key role in determining the structure of the rule bases and how well the agents are able to coordinate their price expectations. When the learning frequency is high, agents will be revising their beliefs quite frequently so they will be unlikely to have adequate time to fully explore whether their market hypotheses are consistent with those belonging to the other agents. At the same time, if agents revise their hypotheses at shorter horizon, their hypotheses will also be likely to be based on the transient shorter horizon features of the time series of market variables. These factors together make it difficult for
agents to converge on an equilibrium price expectation even if it is present. In contrast, when the learning frequency is low, agents will have more time between revising their rule bases to explore their hypotheses. Furthermore, their hypotheses will also tend to be based on the longer horizon features in the time series of market variables. Consequently, agents are more likely to locate an equilibrium price expectation if it is present in the market.

In our core experiments (see description below) we used the dividend process given by the $A R(1)$ process we have presented as equation (3.1) in Section 3.1. In addition to these core experiments, we have also investigated the impacts of an alternative dividend process on market outcomes. We are interested in investigating whether agents in our model are able to learn and adapt in an environment that exhibits regular patterns. In particular, we looked at an alternative variation of the $A R(1)$ dividend process that exhibits cyclical behaviors. This was accomplished by adding a cyclical drift term to the AR(1) process. We intentionally set the period of the cycle so that only the "slow learning" ${ }^{62}$ agents will have the opportunity to observe a complete cycle of the dividend process between revising their rule bases. The "fast-learning" agents on average will not have the opportunity to observe the complete cycle of the dividend process between revising their hypotheses. We then studied the impacts of the frequency of learning on market outcomes under this altemative dividend process.

### 3.3.1 Core Experiments

What we called the core experiments are the controlled experiments that have

[^44]been conducted by Arthur et al. (1997). We do this so that we will have some benchmarks to compare our results. In these experiments, the only parameter that changes is the learning frequency. The model's parameters that are common to all these experiments are tabulated in Table 5. We conducted two sets of experiments; one for a learning frequency, $k=250$, where the agents learn on average once every 250 time periods and the other for a learning frequency, $k=1000$, where they learn on average once every 1000 periods. We will follow Arthur et al. (1997) in referring these two cases as "fast learning" and "slow learning". In these experiments, learning takes place asynchronously for the agents. In other words, not all the agents in the model will update their rule bases simultaneously.

We began with a random initial configuration of rules and we ran each experiment for 200,000 periods to allow asymptotic behavior to emerge if it is present. Subsequently, starting with the configuration attained at $t=200,000$ we ran an additional 10,000 periods to collect the data for statistical analysis. We repeat the simulations 20 times under different random seeds to collect cross-sectional statistics.

### 3.3.2 Experiment With An Alternative Dividend Process

We also investigated the impacts on market outcomes of an dividend process with the following specification:

$$
\begin{equation*}
d_{t}=4 * \operatorname{Sin}(0.0065 \cdot t)+\bar{d}+\rho\left(d_{t-1}-2 * \operatorname{Sin}(0.03 \cdot t)-\bar{d}\right)+\varepsilon_{t} \tag{3.7}
\end{equation*}
$$

The added cyclical drift term will cause the dividend to oscillate with a magnitude of $+/-4$ from its mean. The period of a complete cycle is about 970 time periods. Thus,
those agents who are learning at a frequency, $k=1000$, will on average observe about one complete cycle before they revise their beliefs. In contrast, those agents who are learning at the higher frequency of $k=250$, will on average observe only about $1 / 4$ cycle before they revise their beliefs.

## 4. RESULTS

Simulation results from our experiments show that our model is able to generate behaviors that bear strong resemblance to many of the anomalies that have been observed in real financial markets. We discuss these results in the following sections. For ease of exposition, we will refer to the high learning frequency experiment and low learning frequency experiment as the "fast learning" and "slow learning" cases respectively. In addition, we will let REE stands for Rational Expectation Equilibrium.

### 4.1 Statistical Analysis and Times Series Behaviors

This section looks at the behaviors of market variables averaged over the 20 runs.

### 4.1.1 Asset Price and Return

Figure 42 and 43 present snapshots of observed price behavior over typical windows for both experiments. These graphs present the price series over a shortened window, so that the visual relation between the market price and the REE price is not obscured by the compression necessary when presenting the entire history. These graphs seem to suggest that the market price is more volatile than the REE price.

To make a more precise statement, we compute the mean and standard deviation for the market price across the 20 runs for both sets of experiments and we present this result in the first two rows in Table 6. Judging from the standard deviation alone, it is clear that the market price in both sets of our experiments are
more volatile than the REE price, hence confirming our observation above ${ }^{63,64}$. We also noted that the market price in the fast learning case is more volatile than the market price in the slow learning case. The higher volatility in asset price in the former case can be attributed to the more frequent revision of rules by agents in this set of experiments. Another reason is that the rules in the fast learning case are more likely to be based on the transient shorter horizon features in the time series of market variables. This then makes it necessary for the agents to employ different rule bases to form their expectations at different times. This regular switching in the agents' beliefs can give rise to higher volatility because they need time to adapt to the changes. This effect is more pronounced in the experiment with the cyclical dividend process. We will say more about this below.

The remaining rows in Table 6, except for the last row, looks at the behavior of the residual series $\left(\varepsilon_{t}\right)$ obtained from regressing the market price and dividend as follows.

$$
\begin{equation*}
p_{t+1}+d_{t+1}=a+b\left(p_{t}+d_{t}\right)+\varepsilon_{t+1} \tag{4.1}
\end{equation*}
$$

We know that in the homogeneous REE, the residual series should be independent and identically distributed as $N(0,4)$, for the dividend process we have used ${ }^{65}$. This means that the theoretical standard deviation for $\varepsilon_{t}$ should be 2. Furthermore, under a

[^45]gaussian distribution its kurtosis should be zero. We compare these theoretical results to those in the third and fifth rows in Table 6. It is apparent from the values in the third row that the residual series from both sets of experiments are more volatile than their theoretical counterpart. The fifth row shows that that the residuals from the fast learning experiment exhibit slightly excess kurtosis. Although this is consistent with the fact that real asset returns are leptokurtotic, the magnitude is still smaller than those for daily asset returns.

To facilitate comparison with real data, we present summary statistics for Disney, Exxon, IBM and Intel in Table 7. ${ }^{66}$ These results were computed from daily data over the last five and a half years, from January 1993 to June 1998. It is obvious from the third row in Table 7 that the magnitude of excess kurtosis is much larger in these data.

The sixth row in Table 6 looks at the autocorrelation in the residuals. This value will tell us if there are any linear structure remaining in the residuals. Our result shows that there is little autocorrelation remaining. This corresponds to the low autocorrelations for actual stock returns presented in the fourth row of Table 7.

Several authors have shown that security returns exhibit conditional timevarying variability (for instance, Engle 1982, Bollerslev 1986, Bollerslev, Chou and Kroner 1992, Glosten, Jaganathan, and Runkle 1994, Nelson 1991). We therefore test for ARCH dependence in the residuals in row 7 and 8 on Table 6 . We test for this in two different ways. In row 7 , we investigate the first order autocorrelation in squared

[^46]residuals. In row 8, we perform the ARCH LM test proposed by Engle (1982). Both of these tests reveal that there are ARCH dependence in the residuals. However, the effect is more pronounced for the fast learning case. In this case, all of the 20 runs rejected the null hypothesis of "no ARCH" at the $95 \%$ confidence level in our ARCH LM tests. In the slow learning case, only $15 \%$ of the runs rejected the null. The first order autocorrelation of the squared residuals is a little larger than the slow learning case, and it is barely significant at the $95 \%$ confidence level.

The last row in Table 6 compares the mean excess return for the fast learning and slow learning experiments. ${ }^{67}$ The mean excess return is higher for the fast learning case with a value of $3.15 \%$ as compared with $2.71 \%$ in the slow learning case. There is therefore an increase in the equity premium in the fast leaming case. Both these values are higher than the estimated value for the REE case which is $2.52 \%$.

### 4.1.2 Trading Volume

Figure 44 and 45 show snapshots of observed trading volume over a typical window for both the fast learning and slow learning cases. Clearly, trading volume is not zero. As a matter of fact, we find that the volume of trades, on occasions, can be as high as $40 \%$ of the total number of shares available in the market ${ }^{68}$. But on average, for the fast learning case, the volume traded is about $2.53 \%$ of the total number of shares available in the market. In the slower learning case, the average

[^47]volume traded is 0.1637 shares which is about one fourth the value of the fast learning case. The summary statistics for volume are presented in Table 8.

Figure 46 and 47 plot the volume autocorrelations for both the fast learning and slow learning experiments. In these two plots, the broken lines are one standard deviation away from the continuous line which is the mean. These plots shows that the trading volume is autocorrelated. This result lines up well with the positive autocorrelations usually found in time series of the volume traded for common stocks ${ }^{69}$. To compare, we plot the volume autocorrelations for Disney, Exxon, IBM and Intel in figure 48. The features in these two plots are strikingly similar.

Figure 49, 50 and 51 look at the cross correlation between volume traded and volatility. In figure 49 and 50, the cross correlation is between volume traded and squared residuals. In figure 51, which shows the results for actual stocks, we take the squared returns to be the volatility and we compute the cross correlation between it and the volume traded. We find that volume traded is contemporaneously correlated with volatility for both the fast and slow learning cases but the results is stronger for the former. Again, these results are strikingly similar to those for actual securities presented in figure 51.

### 4.1.3 Market Efficiency

Figure 52 plots a snapshot of the difference between the REE price and the market price over a typical window. This plot displays periods in which the market appears to be rather efficient and the market price tracks the REE price quite well. But

[^48]this is intersperse with sporadic wild fluctuations where the market price would break away from the REE price and do something different for a short period of time. This is most apparent in the fast learning case. This result implies that the market moves in and out of various states of efficiency. The figure also shows that the market price has a tendency to return near to the REE price. Such behaviors are common in real financial markets.

### 4.1.4 Dividend Process with Cyclical Drift Term

The dividend process we look at oscillates with a magnitude that is equal to $40 \%$ its long run mean value. We have intentionally set the period of the oscillatory term such that only the slow learning agents have the opportunity to observe the complete cycle between revising their rules. Figure 53 displays the behavior of the dividend process. The shaded regions in figure 53 and the next few figures mark the periods for the oscillations. The duration of each period is about 970 time periods.

Our results in general reveal that the leaming mechanism used by the agents is quite robust. Agents are able to track the REE price quite well despite the large oscillatory disturbances ${ }^{70}$. Figure 58 plots the difference between the REE price and the market price. It is clear that the slow learning agents perform better than the fast learning agents in tracking the REE price. This is also evident in figures 56 and 57

[^49]which show close up the time series behaviors of the market price relative to the REE price.

When there are persistent oscillatory features in the time series for market price and dividend, agents must employ rule bases that are sensitive to such periodic fluctuations. Agents will most likely have to rely on several different rule bases in order to keep up with the periodic fluctuations. For instance, agents may hold rule bases for the up hill phase, the down hill phase and the turning point phase of the cycle. Figure 54 and 55 display snapshots of the time series behaviors of the forecast parameters ' $a$ ' and ' $b$ '. The oscillatory behaviors in these time series suggest that the agents systematically rotate the rule bases they have used to form their forecast in order to keep up with the periodic changes in the market.

Figure 59 plots the time series of volume traded. It is interesting to note that trading are clustered near the tuming point phases of the cycle. This makes sense because the turning points are where the market price makes the most drastic change during its course. The trading volume in the fast learning case is higher than that for the slow learning case. This is expected because those agents who revise their rule bases frequently tend to focus on the short horizon features in the time series and therefore will be likely to construct expectations that tend to over-estimate the movements of market price, especially at the turning point.

### 4.2 Long Run Behaviors

This section focuses on the behaviors of some variables over the 200,000 time
periods. Figures 60 and 61 show the percentage of bits set for the two sets of experiments. The percentage of bits set refer to the non-zero bits averaged over all the rule bases held by the agents in each period. In the case of the fundamental bits set, we consider only the bits in the first position, and we calculate the fraction of the nonzero fundamental bits over all the available fundamental bits. In a similar fashion, we compute the fraction of technical bits set by taking into consideration only the second, third, fourth and fifth bits in each rule base. Figures 60 and 61 portray the behaviors for the fundamental bits set and the technical bits set respectively. The results show that these bits did not converge to zeros even after a relatively long time. This indicates that there is strong persistence in the use of both fundamental and technical information despite the fact that the market price seems to track the REE price quite well (this is evident in figures 62 and 63$)^{71}$. Keep in mind that these information should have been irrelevant if the agents were in a Homogeneous REE.

Figures 62 and 63 portray the convergence behaviors of the average of each of the forecast parameters-' $a$ ' and ' $b$ ', in each period. It is clear that the mean values of the parameters approach quite close to the theoretical HREE values of 9.5 and 4.5 for ' $a$ ' and ' $b$ ' respectively.

[^50]
## 5. SUMMARY AND CONCLUSIONS

This dissertation argues that the so called market anomalies can be explained by allowing agents in the model to form their expectations in a manner akin to how investors would form their expectations in real life. In particular, because the environment that investors operate in is ill-defined, they will have to rely on their innate abilities to analyze in fuzzy terms and reason inductively. We showed that these traits can be faithfully captured by a genetic-fuzzy classifier system. We subsequently asserted that we should be able to account for some of the documented anomalies and empirical puzzles by allowing agents in our model to form their price expectations using a genetic-fuzzy classifier. The model we have constructed was indeed capable of replicating some of the anomalies and stylized time series behaviors we have seen in real financial markets.

Although we did not intentionally try to calibrate our market to fit real data, we are pleased that some of the results quantitatively came out to be relatively closed to those in real financial data. We are referring to the results for volume autocorrelations and volume and volatility cross-correlations. However, there are other aspects of our results that are not entirely satisfactory. In particular, we find the kurtosis in the returns series to be too low. We have some idea on how to improve on this aspect of the model. We suspect that it is partly related to how we have set up the fuzzy sets for the conditional part of a rule. During our simulations we have observed that the market indicators tend to vary between the value of 0.4 and 0.6 . The location of our
fuzzy membership functions along the universe of discourse are not particular sensitive to changes within the range of 0.4 and 0.6 . We can improve the sensitivity by adding more membership functions within this range, while at the same time making those existing membership functions operating within this range to be narrower.

Nevertheless, this alone might not be sufficient to generate the rather large kurtosis we see in real data. We think it will be helpful to introduce some means for agents to coordinate their price expectations directly. In a separate paper, Scott and I (see Linn and Tay 1998) have proposed such a model. We develop a model of investor behavior based on endogenous influence through interaction. In that model, the individual trader's choice of which way to trade depends upon the level of uncertainty present in the market, the extent of agreement on the direction of trade reflected in the choices of other traders, and on the extent of price persistence at the time of the decision. We feel that combining the present model with a model like the one we have just described will probably give us the best chance at explaining the huge kurtosis we see in real financial markets. But we are not motivated merely by the end results. The approach we have suggested is also grounded on the behavior we typically see in real markets. That is, investors do not act alone, they do communicate with each other, and to some extent their communication will influence their trading behaviors.

So far, we have only focused on the time series behaviors of a few market variables. As a whole, our model can also account for several anomalies in real
market qualitatively. First, our model can give rise to rather active trading. Second, our model seems to support the views of both academician and market traders.

Academic theorists in general view the market as rational and efficient. But market traders typically see the market as psychological and imperfectly efficient. In our model, we find that the market moves in and out of various states of efficiency. This is obvious in figure 52. Furthermore, we find that by slowing down the speed of learning, the market can approach the efficiency of a REE. Third, we find evidence of ARCH effects in the returns, low autocorrelation in returns, and persistent technical trading behaviors. All in all, we were able to account for several features in the real markets and our results are consistent with what Arthur et al. have found.

## BIBLIOGRAPHY

Alchian, A. A. "Uncertainty, Evolution, and Economic Theory." Journal of Political Economy 58 (1950): 211-221.

Arifovic, J. "Leaming By Genetic Algorithms In Economic Environments." Ph.D. diss., University of Chicago, 1991.

Arifovic, J. "Genetic Algorithm Learning and the Cobweb Model." Journal of Economic Dynamics and Control 18 (1994): 3-28.

Arifovic, J. "Genetic Algorithms and Inflationary Economies." Journal of Monetary Economics 36 (1995): 219-243.

Arifovic, J. "The Behavior of the Exchange Rate in the Genetic Algorithm and Experimental Economies." Journal of Political Economy 104 (1996): 510-541.

Arifovic, J. and C. Eaton. "Coordination Via Genetic Learning." Computational Economics 8 (1995): 181-203.

Arrow, K. J. "Rationality of Self and Others in an Economic System." Journal of Business 59 (1986): S385-S398.

Arrow, K. J. and F. Hahn. General Competitive Analysis. San Francisco.: Holden-Day, 1971.

Arthur, W. B. "Designing Economic Agents that Act Like Human Agents: A Behavioral Approach to Bounded Rationality." American Economic Review 81 (1991): 353-359.

Arthur, W. B. "On Learning and Adaptation in the Economy." Working Paper 92-07038, Santa Fe Institute, 1992.

Arthur, W. B. "Inductive Reasoning and Bounded Rationality." American Economic Review 84 (1994): 406-411.

Arthur, W. B. "Complexity in Economic and Financial Markets." Complexity 1 (1995): 20-25.

Arthur, W. B., B. LeBaron, and R. Palmer. "Time Series Properties of an Artificial Stock Market." SSRI Working Paper 9725, University of Wisconsin, Madison, 1997.

Arthur, W. B., J. H. Holland, B. LeBaron, R. Palmer, and P. Tayler. "Asset Pricing Under Endogeneous Expectations in an Artificial Stock Market." Working Paper 96-12-03, Santa Fe Institute, 1996.

Back, T., F. Hoffmeister, and H. P. Schwefel. "A Survey of Evolution Strategies." Proceedings of the International Conference on Genetic Algorithm 4 (1991): 210.

Baker, J. E. "Adaptive Selection Methods for Genetic Algorithms." Proceedings of an International Conference on Genetic Algorithms and Their Applications 1 (1985): 101-111.

Bauer, P., Nouak, S. and R. Winkler. <HTTP://www.flll.uni-linz.ac.at:80/fuzzy /fuzzy.html>, 1996

Baumol, W.J., and R. E. Quandt. "Rules of Thumb and Optimally Imperfect Decision Rules." American Economic Review 54 (1964): 23-46.

Bellman, R. E. Adaptive Control Processes: A Guided Tour. Princeton, NJ: Princeton University Press,1961.

Beltratti, A. and S. Margarita. "Evolution of Trading Strategies Among Heterogeneous Artificial Economic Agents." Technical Report, Instituto di Ecoomia G. Prato, Universta di Torino, 1992.

Berlin, B. and P. Kay. Basic Color Terms: Their Universality and Evolution. Berkeley: University of Califormia Press, 1969.

Bethke, A. D. "Genetic Algorithms as Function Optimizers." Ph.D. diss., University of Michigan, 1981.

Black, F. "Noise." Journal of Finance 41 (1986): 529-544.
Blume, L. E. and D. Easley. "Evolution of Market Behavior." Journal of Economic Theory 58 (1992): 9-40.

Blume, L. E. and D. Easley. "Rational expectations and rational learning." Working Paper, Department of Economics, Comell University,1993

Blume, L. and D. Easley. "What Has the Rational Learning Literature Taught Us?." In Learning and Rationality in Economics, eds. A. Kirman, and, M. Salmon. Cambridge: Basil Blackwell,1995.

Bollerslev, T. "Generalized Autoregressive Conditional Heteroskedasticity." Journal
of Econometrics 31 (1986): 307-327.
Bollerslev, T, R. Y. Chou, and K. F. Kroner. "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence." Journal of Econometrics 52 (1992): 559.

Bray, M. M. "Learning, Estimation and the Stability of Rational Expectations." Journal of Economic Theory 26 (1982): 318-339.

Bray, M. M. and D. M. Kreps. "Rational Learning and Rational Expectations." In Essays in Honour of K. J. Arrow, eds. W. Heller, R. Starr and D. Starett. Cambridge: Cambridge University Press, 1986.

Bray, M. M. and N. E. Savin. "Rational Expectations and Equilibria, Learning and Model Specification." Econometrica 54 (1986): 1129-1160.

Brock, W. A., Lakonishok, J. and B. LeBaron. "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." Journal of Finance 47 (1992): 1731-1764.

Bullard, J. "Rethinking Rational Expectations." In Acting Under Uncertainty: Multidisciplinary Conceptions, ed. George M. Von Furstenberg, 325-354. Norwell, MA: Kluwer Academic Publishers, 1990.

Burgess, D., W. Kemption, and R. E. MacLaury. "Tarahumara Color Modifiers: Category Structure Resaging Evolutionary Change." American Ethnologist 10 (1983): 133-149.

Campbell, J. Y. and R. Shiller. "Stock Prices, Earnings and Expected Dividends." Journal of Finance 63 (1988a): 661-676.

Campbell, J. Y. and R. Shiller. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors." Review of Financial Studies 1 (1988b): 195277.

Campbell, J. Y., A. W. Lo, and A. Craig MacKinlay. The Econometrics of Financial Markets. Princeton, NJ: Princeton University Press, 1997.

Caruana, R. A. and J. D. Schaffer. "Representation and Hidden Bias: Gray Vs. Binary Coding." Proceedings of the 6th International Conference on Machine Learning (1988): 153-161.

Cho, I. K. "Perceptrons Play the Repeated Prisoner's Dilemma." Working Paper, University of Chicago, September, 1992.

Chipperfield, A., P. Fleming, H. Pohlheim, and C. Fonseca. Genetic Algorithm Toolbox For Use With MATLAB. Department of Automatic Control and Systems Engineering, University of Sheffield, 1995.

Cox, E. The Handbook of Fuzzy Systems. New York: Academic Press, 1994.
Cutler, D. M., J. M. Poterba, and L. H. Summers. "What Moves Stock Prices?." Journal of Portfolio Management 15 (1989): 4-12.

Cutler, D. M., J. M. Poterba, and L. H. Summers. "Speculative Dynamics." Review of Economic Studies 58 (1991): 529-546.

Cyert, R. M. and DeGroot, M. M. "Rational Expectations and Bayesian Analysis." Journal of Political Economy 82 (1974): 521-536.

Cyert, R. M. and M. M. DeGroot. Bayesian Analysis and Uncertainty in Economic Theory. Totowa, NJ: Rowman and Littlefield, 1987.

Davis, L. Handbook of Genetic Algorithms. New York: Van Nostrand Reinhold, 1991.
DeCanio, S. J. "Rational Expectations and Learning from Experience." Quarterly Journal of Economics 93 (1979): 47-57.

De Jong, K. A. "An Analysis of the Behavior of a Class of Genetic Adaptive Sytems." Ph.D. diss., University of Michigan, 1975.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. "The Size And Incidence of the Losses from Noise Trading." Journal of Finance 44 (1989): 681-696.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." Journal of Finance 45 (1990): 379-396.

Demsetz, H. "Rationality, Evolution and Acquisitivenss." Economic Inquiry 34 (1996): 484-496.

Dreman, D. Psychology and the Stock Market: Investment Strategy Beyond Random Walk. New York: Amaco, 1977.

Dreman, D. The New Contrarian Investment Strategy. New York: Random House, 1982.

Driankov, D., H. Hellendoorn and M. Reinfrank. An Introduction to Fuzzy Control. New York: Springer Verlag, 1993.

Dubois, D., and H. Prade. Fuzzy Sets and Systems: Theory and Applications. New York: Academic Press, 1980.

Easley, D. and N. Kiefer. "Controlling a Stochastic Process With Unknown Parameters." Econometrica 56( 1989): 963-978.

Edelman, G. M. Neural Darwinism. New York: Basic Books, 1987.

Edwards, W. "Conservation in Human Information Processing." In Formal Respresentation of Human Judgement, ed. B. Kleinmuntz. New York: Wiley, 1968.

Engle, R. F. "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation." Econometrica 50 (1982): 987-1007.

Eshelman, L. J. and J. D. Schaffer. "Preventing Premature Convergence by Preventing Incest." In Proceeding of the Fourth International Conference on Genetic Algorithms. San Mateo: Morgan Kaufmann, 1991

Evans, G. "Expectational Stability and the Multiple Equilibria Problem in Linear Rational Expectations Models." Quarterly Journal of Economics 100 (1985): 1217-1234.

Evans, G. "The Fragility of Sunspots and Bubbles." Journal of Monetary Economics 23 (1989): 297-318.

Fama, E. F. "Efficient Capital Markets: II." Journal of Finance 46 (1991): 1575-1618.
Fama, E. F. and K. R. French. "Permanent and Temporary Components of Stock Prices." Journal of Political Economy 96 (1988): 246-273.

Friedman, M. Essays in Positive Economics. Chicago, IL: University of Chicago Press, 1953.

Frydman, R. "Sluggish Price Adjustments and the Effectiveness of Monetary Policy Under Rational Expectations." Journal of Money, Credit, and Banking 13 (1981): 94-104.

Gaines, B. R. "Stochastic and Fuzzy Logics." Electronic Letters 11 (1975): 188-189.
Gaines, B. R., L. A. Zadeh, and H. J. Zimmerman. "Fuzzy Sets and Decision

Analysis." TIMS/Studies in the Management Science 20 (1984): 3-4.
Gamham, A. and J. Oakhill. Thinking and Reasoning. Cambridge: Blackwell Publisher, 1994

Gennotte, G. and H. Leland. "Market Liquidity, Hedging and Crashes." American Economic Review 80 (1990): 999-1021.

Glosten, L. R., R. Jagannathan, and D. Runkle. "Relationship Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks." Northwestern University, Mimeo, 1989.

Goguen, J. A. "Concept Representation in Natural and Artificial Languages: Axioms, Extensions and Applications for Fuzzy Sets." In Fuzzy Reasoning and its Applications, eds. E. H. Mamdani and B. Gaines, 67-115. New York: Academic Press, 1981.

Goldberg, D. E. "Optimal Initial Population Size for Binary-Coded Genetic Algorithms." TCGA Report No. 85001, University of Alabama, Tuscaloosa, The Clearinghouse for Genetic Algorithms, 1985.

Goldberg, D. E. Genetic Algorithms in Search, Optimization and Machine Learning. Reading, MA: Addison-Wesley, 1989.

Grefenstette, J. J. ed. Proceedings of the International Conference on Genetic Algorithms and Their Applications. Hillsdale: Lawrence Erlbaum Associates, 1985.

Grefenstette, J. J. ed. Genetic algorithms and their applications: Proceedings of the Second International Conference on Genetic Algorithms. Hillsdale: Lawrence Erlbaum Associates, 1987.

Grether, D. M. "Testing Bayes Rule and the Representativeness Heuristic: Some Experimental Evidence." Journal of Economic Behavior and Organization 17 (1992): 31-57.

Grossman, S. J. "On the Efficiency of Competitive Stock Markets Where Traders Have Diverse Information." Journal of Finance 31 (1976): 573-585.

Grossman, S. and J. E. Stiglitz. "On the Impossibility of Informationally Efficient Markets." American Economic Review 70 (1980): 393-408.

Hersch, H. M. and A. A. Caramazza. "A Fuzzy Set Approach to Modifiers and Vagueness in Natural Language." Journal of Experimental Psychology: General

Hinton, G. E. "Mapping Part--Whole Hierachies Into Connectionist Networks." Artificial Intelligence 46 (1990): 47-76.

Hogarth, R. M. Judgement and Choice: The Psychology of Decision. New York: Wiley, 1980.

Holland, J. H. "Hierarchical Descriptions of Universal Spaces and Adaptive Systems." In Essays on Cellular Automata, ed. A. W. Burks. Urbana, IL: University of Illinois Press, 1970a.

Holland, J. H. "Robust Algorithms for Adaptation Set in General Format Framework." Proceedings of the IEEE Symposium on Adaptive Processes Decision and Control. XVII (1970b): 5.1-5.5.

Holland, J. H. "Processing and Processors for Schemata." In Associative Information Processing, ed. E. L. Jacks, New York: American Elsevier, 1970c.

Holland, J. H. Adaptation in Natural and Artificial Systems. Ann Arbor, MI: University of Michigan Press, 1975.

Holland, J. H. "Genetic Algorithms and Classifier Systems: Foundations and Future Directions." Genetic Algorithms and their Applications: Proceedings of the Second International Conference on Genetic Algorithms (1987) 82-89.

Holland, J. H. "Genetic Algorithm." Scientific American (July 1992): 66-72.
Holland, J. H., K. J. Holyoak, R. E. Nisbett, and P. R. Thagard eds. Induction: Processes of Inference, Learning, and Discovery. Cambridge: MIT Press, 1989.

Holland, J. H. and J. Reitman. "Cognitive Systems Based on Adaptive Algorithms." In Pattern-Directed Inference Systems. New York: Academic Press, 1978.

Hollstien, R. B. "Artificial Genetic Adaptation in Computer Control Systems." Ph.D. diss., University of Michigan, 1971.

Jacklin, C. J., A. W. Kleidon, and P. Pfleiderer. "Under Estimation Of Portfolio Insurance and the Crash of October 1987." Review of Financial Studies 5 (1992): 35-63.

Janikow, C. Z. and Z. Michalewicz. "An Experimental Comparison of Binary and Floating Point Representations in Genetic Algorithms." Proceedings of the International Conference on Genetic Algorithm 4 (1991): 31-36.

Kahneman, D., P. Slovic, and A. Tversky. "Judgement Under Uncertainty: Heuristics and Biases." Cambridge: Cambridge University Press, 1982.

Karpov, J. M. "The Relation Between Price Changes and Trading Volume: A Survey." Journal of Financial and Quantitative Analysis 22 (1987): 109-126.

Katona, G. "Psychological Economics." New York: Elsevier, 1975.
Kay, P. and C. McDaniel. "Color Categories As Fuzzy Sets." Working Paper \#44, Berkeley: Language Behavior Research Laboratory, University of California, 1975.

Kempton, W. "Category Grading and Taxonomic Relations: A Mug is a Sort of a Cup." American Ethnologist 5 (1978): 44-65.

Keynes, J. M. The General Theory of Employment, Interest and Money. London: Macmillan, 1936.

Kiefer, N. M. and Y. Nyarko. "Control of a Linear Regression Process With Unknown Parameters." In Dynamic Econometric Modeling, Proceedings of the Third International Symposium in Economic Theory and Econometrics, eds. W. A. Barnett, E. R. Berndt and H. White. Cambridge: Cambridge University Press, 1988.

Kiefer, N. M. and Y. Nyarko. "Optimal Control of an Unknown Linear Process with Learning." International Economic Review 30 (1989): 571-586.

Kirman, A. and M. Salmon, eds. Learning and Rationality in Economics. Cambridge: Basil Blackwell, 1995.

Klir, G. J. and T. A. Folger. Fuzzy Sets, Uncertainty, and Information. Englewood Cliffs, NJ: Prentice Hall, 1988.

Klir, G. J. and B. Yuan. Fuzzy Sets and Fuzzy Logic: Theory and Applications. Upper Saddle River, NJ: Prentice Hall, 1995.

Kosko, B. Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence. Englewood Cliffs: Prentice Hall, 1992.

Kosko, B. Fuzzy Thinking: The New Science of Fuzzy Logic. New York: Hyperion, 1993.

Leroy, S. F. and R. D. Porter. "Stock Price Volatility: Tests Based on Implied

Variance Bounds." Econometrica 49 (1981a): 97-113.
Leroy, S. F. and R. D. Porter. "The Present-Value Relation: Tests Based on Implied Variance Bounds." Econometrica 49 (1981b): 555-574.

Linn, S. C. and B. E. Stanhouse. "The Economic Advantage of Least Squares Leaming in a Risky Asset Market." Journal of Economics and Business 49 (1997): 303319.

Linn, S. C. and N. S. Tay. Investor Interaction and the Dynamics of Security Prices." CFS Working Paper, Finance Division, University of Oklahoma, 1998.

Lo, A. W. and A. C. Mackinlay. "Stock Prices Do Not Follow Random Walk: Evidence From a Simple Specification Test." Review of Financial Studies 1 (1988): 41-66.

Lucas, R. E. Jr. "Adaptive Behavior and Economic Theory." Journal of Business 59 (1986): 401-426.

Marcet, A. and T. J. Sargent. "The Fate of Systems With Adaptive Expectations." American Economic Review 78 (1988): 168-172.

Marcet, A. and T. J. Sargent. "Convergence of Least Squares Learning Mechanism in Self Referential Linear Stochastic Models." Journal of Economic Theory 48 (1989a): 337-368.

Marcet, A. and T. J Sargent. "Convergence of Least Squares Learming in Environments With Hidden State Variables and Private Information." Journal of Political Economy 97 (1989b): 1306-1322.

Marcet A. and T. J. Sargent. "Least Square Learning and the Dynamics of Hyperinflation." In Economic Complexity: Chaos, Sunspots, Bubbles and Nonlinearity, eds. W. A. Barnett, J. Geweke and K. Shell. Cambridge: Cambridge University Press, 1989c.

McLennan, A. "Incomplete Learning in a Repeated Statistical Decision Problem." Working Paper, University of Minnesota, 1987.

McNeill, D. and P. Freiberger. Fuzzy Logic. New York: Simon and Schuster, 1993.
Michalewicz, Z. Genetic Algorithm + Data Structure $=$ Evolution Programs. North Holland: Springer Verlag, 1992.

Mirman, L., A. Postlewaite and R. Kihistrom. "Experimental Consumption and the
'Rothschild Effect'." In Bayesian Models in Economic Theory, eds. M. Boyer and R. E. Kihlstrom. 1984.

Mitchell, M. An Introduction to Genetic Algorithms. Cambridge, MA: MIT Press, 1995.

Moffat, S. "Fuzzy Thinking." Fortune (17 December 1990): 173-174.
Muhlenbein, H. and D. Schlierkamp-Voosen. "Predictive Models for the Breeder Genetic Algorithm: I. Continuous Parameter Optimization." Evolutionary Computation 1 (1993): 25-49.

Nelson, D. "Conditional Heteroskedasticity in Asset Returns: A New Approach." Econometrica 59 (1991): 347-70.

Nelson, R. and S. Winter. An Evolutionary Theory of Economic Change. Cambridge: Harvard University Press, 1982.

Nyarko, Y. "Bayesian Rationality and Leaming Without Common Priors." C. V. Starr Center for Applied Economics Working Paper 90-45, New York University, 1990.

Nyarko, Y. "Bayesian Learning Without Common Priors and Convergence to Nash Equilibrium." C. V. Starr Center for Applied Economics Working Paper 91-6, New York University, 1991a.

Nyarko, Y. "Learning in Mis-Specified Models and the Possibility Of Cycles." Journal of Economic Theory, 51 (1991b) 416-427.

Oden, G. C. "Integration of Fuzzy Logical Information." Journal of Experimental Psychology (General) 106 (1977): 565-575.

Palmer, R. G., W. B. Arthur, J. H. Holland, B. LeBaron, and P. Tayler. "Artificial Economic Life: A Simple Model of A Stock Market." Physica D, 75 (1994): 264-274.

Peck, J. and K. Shell. "Market Uncertainty: Correlated And Sunspot Equilibria In Imperfectly Competitive Economies." Review of Economic Studies 58 (1991): 1011-1029.

Prescott, E. "The Multiperiod Control Problem Under Uncertainty." Econometrica 40 (1972): 1043-1058.

Radner, R. "Existence of Equilibrium of Plans, Prices, and Price Expectations."

Econometrica 40 (1972): 289-304.

Rescher, N. Induction: An Essay on the Justification of Inductive Reasoning Pittsburgh: University of Pittsburgh Press, 1980.

Rosch, E. "Natural Categories." Cognitive Psychology 4 (1973a): 328-350.
Rosch, E. "On The Internal Structure of Perceptual and Semantic Categories." In Cognitive Development and the Acquistion of Language, ed. T. E. Moore. New York: Academic Press, 1973b.

Rosch, E. and C. B. Mervis. "Family Resemblance: Studies in the Internal Structure of Categories." Cognitive Psychology 7 (1975): 573-605.

Rothschild, M.. "A Two-Armed Bandit Theory of Market Pricing." Journal of Economic Theory 9 (1974): 185-202.

Rumelhart, D. E., J. L., McClelland, and, the PDP Research Group, eds. "Parallel Distributed Processing. Cambridge: MIT Press, 1987

Salmon, M. "Bounded Rationality and Learning: Procedural Learning." In Learning and Rationality in Economics, eds. A. Kirman and M. Salmon, 236-274. Cambridge: Basil Blackwell, 1995.

Savage, L. J.. "The Foundations of Statistics." New York: Wiley, 1954
Sargent, T. J. "Bounded Rationality in Macroeconomics." Oxford: Clarendon Press, 1993.

Schneider, W., and R. M. Shiffrin.. "Controlled and Automatic Human Information Processing: I. Detection, Search, and Attention." Psychological Review 84 (1977): 1-66.

Shastri, L. and V. Ajjanagadde. "From Simple Associations to Systematic Reasoning: A Connectionist Representation of Rules, Variables and Dynamic Bindings Using Temporal Synchrony." Behavioral and Brain Science 16 (1993): 417-494.

Shiller, R. J. "Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?" American Economic Review 71 (1981): 421-436.

Shiller, R. J. "Stock Prices and Social Dynamics." Brookings Papers on Economic Activity 2 (1984): 457-498.

Shiller, R. J.. "The Volatility Debate. American Journal of Agricultural Economics."

70 (1988): 1057-1063.
Shiller, R. J. "Market Volatility." Cambridge, Mass: MIT Press, 1989.
Shleifer, A., and, L. H. Summers. "The Noise Trader Approach to Finance. Journal of Economic Perspectives, 4 (1990): 19-34.

Simon, H. A.. "Administrative Behavior." New York: Macmillan, 1947.
Simon, H. A.. "A Behavioral Model of Rational Choice." Quarterly Journal of Economics 69 (1955): 99-118.

Simon, H. A.. "Models of Man: Social and Rational." New York: Wiley. 1957.
Simon, H. A.. "Theories of Decision Making in Economics. American Economic Review 49 (1959): 253-283.

Simon, H. "From Substantive to Procedural Rationality." In S. J. Latsis ed., Method and Appraisal in Economics, Cambridge: Cambridge University Press, 1976; reprinted in Models of Bounded Rationality, Boston: MIT Press, 1982.

Simon, H. A. "Models of Bounded Rationality." Cambridge: MIT Press, 1982
Simon, H. A. "Rationality in Psychology and Economics." In Rational Choice: The Contrast Between Economics and Psychology, eds. R. Hogarth and M. Reder, 25-40. Chicago: University of Chicago Press, 1986.

Simon, H. A., M., Egidi, R., Marris, and R. Viale.. Economics, Bounded Rationality and the Cognitive Revolution. Vermont: Edward Elgar, 1992.

Sloman, S.A.. "The Empirical Case for Two Systems of Reasoning." Psychological Bulletin 119 (1996): 3-22.

Smithson, M. 'Multvariate Analysis Using 'And' and 'Or'." Journal of Mathematical Social Science 7 (1984): 231-251.

Smithson, M.. "Fuzzy Set Analysis for Behavioral and Social Sciences. New York: Springer Verlag, 1987.

Smolensky, P. "On the Proper Treatment of Connectionism." Behavioral and Brain Science 11 (1988):1-23.

Soros, G. The Alchemy of Finance: Reading the Mind of the Market. New York: J. Wiley, 1994.

Spears, W. M., and, K. A. De Jong. "An Analysis of Multi-Point Crossover." In Foundations of Genetic Algorithms, ed. J. E. Rawlins, (1991) 301-315.

Sweeney, R. J. "Beating the Foreign Exchange Market." Journal of Finance 41 (1986): 163-182.

Sweeney, R. J. "Some New Filter Rule Tests: Methods and Results." Journal of Financial and Quantitative Analysis 23 (1988): 285-300.

Syswerda, S. "Uniform Crossover in Genetic Algorithms." Proceedings of the International Conference on Genetic Algorithm 3 (1989): 2-9.

Taylor, M. and H. Allen. "The Use of Technical Analysis in the Foreign Exchange Market." Journal of International Money and Finance 11 (1992): 304-314.

Tate, D. M., and A. E. Smith. "Expected Allele Convergence and The Role of Mutation in Genetic Algorithms." Proceedings of the International Conference on Genetic Algorithm 5 (1993): 31-37.

Thole, U., H.J., Zimmermann, and P. Zysno. "On the Suitability of Minimum and Product Operators for the Intersection of Fuzzy Sets." Fuzzy Sets and Systems 2 (1979): 167-180.

Thrall, R. M., C. H. Coombs, and R. L. Davis (eds.). Decision Processes. New York: Wiley, 1954.

Tong, R. M. "Synthesis of Fuzzy Models for Industrial Processess--Some Recent Results." International Journal of General Systems 4 (1978): 2-10.

Townsend, R. M. "Market Anticipation, Rational Expectations and Bayesian Analysis." International Economic Review 19 (1978): 481-494.

Townsend, R. M. "Forecasting the Forecasts of Others." Journal of Political Economy 91 (1983a): 545-588.

Townsend, R. M. "Equilibrium Theory With Learning and Disparate Expectations: Issues and Methods." In Individual Forecasting and Aggregate Outcomes, eds. R. Frydman and E. S. Phelps. Cambridge: Cambridge University Press, 1983b.

Tversky, A. and D. Kahneman. "Judgement Uncertainty: Heuristics And Biases." Science 185 (1974): 1124-1130.

Varian, H. R. "What Use is Economic Theory?" Working Paper, Department of

Economics, University of Michigan, 1993.
Viale, R. "Cognitive Constraints of Economic Rationality." In Economics, Bounded Rationality and the Cognitive Revolution, eds. H. A. Simon., M. Egidi, R. Marris, and R. Viale, 174-193. Brookfield, Vermont: Edward Elgar, 1992.

Vose, M. D. "Generalizing the Notion of Schema in Genetic Algorithms." Artificial Intelligence 50 (1991): 385-396.

Woodford, M. "Learning to Believe in Sunspots." Econometrica 58 (1990): 277-307.
Wright, A. H. "Genetic Algorithms for Real Parameter Optimization." In Foundations of Genetic Algorithms, ed. J. E. Rawlins. San Mateo: Morgan Kaufmann, 1991.

Yamakawa, T. "Stabilization of an Inverted Pendulum by a High-Speed Fuzzy Logic Controller." Hardware System, Fuzzy Sets and Systems 32 (1989): 161-180.

Yasunobu, S., and S. Miyamoto. "Automatic Train Operation System by Predictive Fuzzy Control." In Industrial Applications of Fuzzy Control, ed. M. Sugeno. New York: North Holland, 1985.

Zadeh, L. A. "From Circuit Theory to System Theory." Proceedings of the Institute of Radio Engineers 50 (1962): 856-865.

Zadeh, L. A. "Fuzzy Sets." Information and Control 8 (1965): 338-353.
Zadeh, L. A. "A Fuzzy-Set-Theoretic Interpretation of Linguistic Hedges." Journal of Cybernetics 2 (1972): 4-34.

Zadeh, L. A. "Outline of a New Approach to the Analysis Of Complex Systems and Decisions Processes." IEEE Transactions on Systems, Man, and Cybernetics 1 (1973): 28-44.

Zimmermann, H. J. and P. Zysno. "Latent Connectives in Human Decision Making." Fuzzy Sets and Systems 4 (1980): 37-51.

## FIGURES

Membership Value


Fig. 1. Classical Sets of Tall and Not-Tall person

## Membership Value



Fig. 2. Fuzzy Sets of Tall and Not-Tall person


Fig. 3. Fuzzy Set A


Fig. 4. Fuzzy Set B


Fig. 5. Fuzzy Set for Not-A ( $\neg \mathrm{A})$


Fig. 6. Fuzzy Set for Intersection: $\mathrm{A} \cap \mathrm{B}(\mathrm{A} \mathbf{A N D} B)$


Fig. 7. Fuzzy Set for Union : AUB (A OR B)


Fig. 8 A Schematic Diagram of A Fuzzy Inference System


Fig. 9. Fuzzy Sets for Input 1: Price Indicator


Fig. 10. Fuzzy Sets for Input 2: Volume Indicator


Fig. 11. Fuzzy Sets for Output: Trading Decision


Fig. 12. Response of Rule 1


Fig. 13. Response of Rule 2


Fig. 14. Response of Rule 3


Fig. 15. Response of Rule 4

## Membership Value



Fig. 16. Aggregate Output/Defuzzification


Fig. 17. Centroid Defuzzification Method


Fig. 18. Center of Sum Defuzzification Method


Fig. 19. Height Defuzzification Method


Fig. 20. First-of-Maxima Defuzzification Method


Fig. 21. Middle-of-Maxima Defuzzification Method


Fig. 22. Center-of-Largest Area Defuzzification Method

| Parent 1 | 1 | 1 | 1 |
| :---: | :---: | :---: | :---: |
| Parent 2 | 0 | 0 | 0 |
| Offspring A1 | 1 | 1 | \% |
| Offspring A2 | 0 | 0 | \% |
| Offspring B1 | 1 | 9. | 1 |
| Offspring B2 | 0 | \$1 | 0 |
| Offspring Cl | \$ | 1 | 1 |
| Offspring C2 | 1 | 0 | 0 |

Fig. 23. Spanning of parameter space by Crossover operator


Fig. 24. A Roulette Wheel


Fig. 25. Single-Point Crossover


Fig. 26. Multi-Point Crossover

| Parent 1 | $=$ | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Parent 2 | $=$ | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| MASK | $=$ | $\mathbf{0}$ | $\mathbf{0}$ | $\mathbf{1}$ | $\mathbf{1}$ | $\mathbf{0}$ | $\mathbf{0}$ | $\mathbf{1}$ | $\mathbf{1}$ | $\mathbf{0}$ | $\mathbf{0}$ |
| Offspring 1 | $=$ | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 |
| Offspring 2 | $=$ | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |

Fig. 27. Uniform Crossover


Fig. 28. Plot of $f(x)=x^{2}$


Fig. 29. Result of GA simulation

Membership Value


Fig. 30. Fuzzy Set for Input $x$
$\left|\begin{array}{lllll}3 & 2 & 3 & 1 & 1 \\ 2 & 0 & 2 & 1 & 1 \\ 0 & 1 & 2 & 1 & 1 \\ 1 & 2 & 1 & 1 & 1\end{array}\right|$

Fig. 31. A Fuzzy Rule Base Coded in Bit Strings


Fig. 32. Fuzzy Sets for the States of the Market Descriptors


Fig. 33. Fuzzy Sets for Forecast Parameter ' $a$ '


Fig. 34. Fuzzy Sets for Forecast Parameters ' $b$ '

|  | Conditions |  |  |  | Forecast <br> Parameters |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0 | 0 | 2 | 3 | 3 | 5 |  |
| 4 | 0 | 0 | 1 | 4 | 1 | 3 |  |
| 2 | 0 | 0 | 4 | 2 | 2 | 4 |  |
| 3 | 0 | 0 | 3 | 1 | 5 | 1 |  |$|$

Fig. 35. A Complete and Consistent Rule Base


Fig. 36. Response of $1^{\text {st }}$ Rule



Fig. 37. Response of $2^{\text {nd }}$ Rule




Fig. 38. Response of $3^{\text {rd }}$ Rule




Fig. 39. Response of $4^{\text {th }}$ Rule


Fig. 40. Resultant Fuzzy Set for Forecast Parameter ' $a$ '


Fig. 41. Resultant Fuzzy Set for Forecast Parameter ' $b$ '


Fig. 42. Time Series Record of the Market Price Vs. the REE Price Over a Typical Window in the High Learning Frequency Case

—— Market Price ..... REE Price

Fig. 43. Time Series Record of the Market Price Vs. the REE Price Over a Typical Window in the Low Learning Frequency Case


Fig. 44. Time Series Record of the Volume Traded Over a Typical Window in the High Leaming Frequency Case


Fig. 45. Time Series Record of the Volume Traded Over a Typical Window in the Low Learning Frequency Case


Fig. 46. Volume Autocorrelations in the High Learning Frequency Case


Fig. 47. Volume Autocorrelations in the Low Learning Frequency Case


Fig. 48. Volume Autocorrelations for Disney, Exxon, IBM and Intel


Fig. 49. Cross Correlation Between Volume and Volatility in the High Learning Frequency Case


Fig. 50. Cross Correlation Between Volume and Volatility in the Low Learning Frequency Case


Fig. 51. Cross Correlation Between Volume and Volatility for Disney, Exxon, IBM and Intel


Fig. 52. Time Series Record of the Difference between the Market Price and the REE Price Over a Representative Window


Fig. 53 Time Series Record of the Cyclical Dividend Process Over a Typical Window


Fig. 54 Time Series Record of the Forecast Parameters Over a Typical Window for the High Learning Frequency Case with a Cyclical Dividend Process


Fig. 55 Time Series Record of the Forecast Parameters Over a Typical Window for the Low Learning Frequency Case with Cyclical Dividend Process


Fig. 56 Time Series Record of the REE Price and the Market Price Over a Typical Window for the High Learning Frequency Case with Cyclical Dividend Process


Fig. 57 Time Series Record of the REE Price and the Market Price Over a Typical Window for the Low Learning Frequency Case with Cyclical Dividend Process


Fig. 58 Time Series Record of the Difference Between the REE Price and Market Price Over a Typical Window Under a Cyclical Dividend Process


- High Frequency ..... Low Frequency

Fig. 59 Time Series Record of the Volume Traded Over a Typical Window Under a Cyclical Dividend Process

Fraction of Bits Set


Fig. 60 Time Series Record of Fraction of Fundamental Bits Set

Fraction of Bits Set


Fig. 61 Time Series Record of Fraction of Technical Bits Set


Fig. 62 Time Series Record of the Average of Forecast Parameter ' $a$ '


Fig. 63 Time Series Record of the Average of Forecast Parameter ' $b$ '

## TABLES

TABLE 1

Relations between Gray and Binary representation

|  | Binary |
| :---: | :---: |
| (10) | 0000 |
| (hill' | 0001 |
| "013 | 0011 |
| bils | 0010 |
| als | 0110 |
| '1] | 0111 |
|  | 0101 |
| 13, | 0100 |
| 包边 | 1100 |
|  | 1101 |
|  | 1111 |
|  | 1110 |
|  | 1010 |
|  | 1011 |
|  | 1001 |
|  | 1000 |

TABLE 2

Evolution of the population of strings over time

Generation 5
Generation 10
Generation 15

|  |  |  |  |  |  |  |  | $\begin{gathered} \hline f(x) \\ \hline 6.7 \\ \hline \end{gathered}$ |  |  |  |  |  |  |  | $\mathrm{f}(\mathrm{x})$ |  |  |  |  |  |  |  |  | $\frac{f(x)}{6.5}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |  |  |  |  | 1 |  |  | 1 | 6.7 |  |  |  | 1 | 0 | 1 | 1 | 1 |  |  |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 |  | 11 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 |  | 11 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 11 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 |  | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 |  | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 11 | 0 | 1 | 1 | 1 | 6.5 |  | 1 |  | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 11 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 11 | 0 | 1 | 1 | 1 | 6.5 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 11 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 6.5 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 6.5 |  | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6.7 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |  | 6.5 |

TABLE 3

Evolution of the population of strings over time

Generation 25
Generation 35
Generation 55

| Generation 25 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | Generation 55 |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  |  | f(x) |  |  |  |  |  |  |  |  | $\mathrm{f}(\mathrm{x})$ |  |  |  |  |  |  | $\mathrm{f}(\mathrm{x}$ |  |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 |  | 0 | 1 |  | 0 |  | 1 | 0 | 1.4 | 0 |  |  | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 10 | 0 | 1 | 1 | 1 | 1.5 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 3.6 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 10 | 0 | 1 | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1.5 | 0 | 0 | 01 | 0 | 1 | 1 | 0 | 1.1 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 10 | 0 | 1 | 1 | 0 | 1.4 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 10 | 0 | 1 | 1 | 0 | 1.4 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 |  |  | 1 | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 10 | 0 | 1 | 1 | 0 | 1.4 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 6.5 | 0 | 0 | 1 | 10 | 0 | 1 | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 3.6 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 6.5 | 0 | 0 | 1 |  | 0 |  | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 1 | 0 |  | 1 | 0 | 1.4 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1.4 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 3.5 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1.4 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 3.6 | 0 | 0 | 1 | 1 | 0 |  | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 | 1 | 0 |  | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 3.6 | 0 | 0 | 1 |  | 0 |  | 1 | 1 | 1.5 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 3.5 | 0 | 0 | 1 |  | 0 |  | 1 | 0 | 1.4 | 0 | 0 | 11 | 0 | 1 | 1 | 0 | 1.4 |

TABLE 4

Evolution of the population of strings over time

Generation 60

|  |  |  |  |  |  |  |  | f(x) |  |  |  |  |  |  | $\mathrm{f}(\mathrm{x})$ |  |  |  |  |  |  |  | $\mathrm{f}(\mathrm{x})$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 3.9 |  |  | 0 | 0 |  | 0 | 0.0 | 0 | 0 | 0 |  |  |  | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 00 | 0 | 0 | 0 | 11 | 0.08 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 00 | 0 | 0 |  | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 0 | 0 | 0 |  | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 0 | 0 | 0 |  | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |  | 0.1 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 00 | 0 | 0 |  | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 00 | 0 | 0 |  | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 00 | 0 | 0 |  | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0.1 |  | 00 | 0 | 0 | 0 | 11 | 0.08 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 |  |  | 0 | 0 | 0 | 10 | 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 |  | 00 | 0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 |  | 0 | 0 | 0 | 0 | 11 | 0.08 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1.1 |  | 0 | 0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 | 0 | 00 | 0 | 0 | 0 | 11 | 0.08 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 |  | 00 | 0 | 0 | 0 | 10 | 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  | 0.0 |
| 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1.1 |  |  | 0 |  |  | 0 | 0.0 | 0 | 0 | 0 | 0 |  | 0 | 0 |  | 0.0 |

## TABLE 5

## Common Parameter Values in the Experiments

| $N W$ |
| ---: | :--- |

[^51]TABLE 6

Summary Statistics of Market Price and Residuals

| Variables | Fast Learning Experiment | Slow Learning Experiment | REE (Theoretical) |
| :---: | :---: | :---: | :---: |
| Price ( $P_{\nu}$ ) |  |  |  |
| Mean ( $\bar{P}$ ) | 75.6795 | 78.8940 | 80.000 |
| Std. Dev. $\left(\sigma_{P}\right)$ | 5.9420 | 5.7674 | 5.528 |
| Residual ( $\varepsilon_{t}$ ) |  |  |  |
| Standard Deviation | $\begin{gathered} 2.0950 \\ (0.0107) \end{gathered}$ | $\begin{gathered} 2.0160 \\ (0.02080) \\ \hline \end{gathered}$ | 2.0 |
| Excess Kurtosis | $\begin{gathered} 0.0839 \\ (0.0849) \end{gathered}$ | $\begin{gathered} 0.0563 \\ (0.04232) \end{gathered}$ | 0.0 |
| $\rho_{1}\left(\varepsilon_{t}\right)$ | $\begin{gathered} 0.1097 \\ (0.0867) \end{gathered}$ | $\begin{gathered} 0.0555 \\ (0.01612) \\ \hline \end{gathered}$ | 0.0 |
| $\rho_{1}\left(\varepsilon_{t}^{2}\right)$ | $\begin{aligned} & \hline 0.0387^{* *} \\ & (0.01382) \\ & \hline \end{aligned}$ | $\begin{gathered} -0.0120 \\ (0.00730) \\ \hline \end{gathered}$ | 0.0 |
| ARCH LM(1) ${ }^{\text {I }}$ | $\begin{gathered} \text { 18.1886*** } \\ {[1.00]} \\ \hline \end{gathered}$ | $\begin{aligned} & 1.9471 \\ & {[0.15]} \end{aligned}$ |  |
| Mean Excess Return ${ }^{2}$ | $\begin{gathered} 3.154 \% \\ (0.2527) \end{gathered}$ | $\begin{aligned} & \hline 2.710 \% \\ & (0.0336) \end{aligned}$ | 2.5\% |

The numbers in parenthesis are the standard errors.
The numbers in square bracket are the percentage of the number of tests that reject the null hypothesis of "no ARCH".
${ }^{1}$ The number for the ARCH LM (1) tests are the mean of the $\chi^{2}$-statistics for the 20 runs.
${ }^{2}$ Excess Return is calculated as $\frac{\left(p_{t+1}+d_{t+1}-p_{t}\right)}{p_{t}}-r_{f}$.
** denotes significance at the $2 \%$ confidence level.
*** denotes significance at the $1 \%$ confidence level.

TABLE 7

Summary Statistics of Returns
for Disney, Exxon, IBM, and Intel

| Variables | Disney | Exxon | IBM | Intel |
| :---: | :---: | :---: | :---: | :---: |
| Return $\left(R_{t}\right)$ |  |  |  |  |
| Mean | 0.00085 | 0.00067 | 0.00130 | 0.00100 |
|  |  |  |  |  |
| Standard Deviation | 0.01548 | 0.01221 | 0.01930 | 0.02296 |
|  |  |  |  |  |
| Excess Kurtosis | 2.8444 | 1.9933 | 5.2202 | 3.4910 |
|  |  |  |  |  |
| $\rho_{1}\left(R_{t}\right)$ | -0.031 | -0.101 | -0.019 | 0.033 |
|  | $(0.244)$ | $(0.000)$ | $(0.492)$ | $(0.227)$ |
| $\rho_{1}\left(R_{t}^{2}\right)$ | 0.045 | 0.110 | 0.073 | 0.069 |
|  | $(0.097)$ | $(0.000)$ | $(0.007)$ | $(0.011)$ |
| ARCH LM(1) | 2.7949 | 64.9086 | 7.3189 | 7.8167 |
|  | $(0.095)$ | $(0.000)$ | $(0.007)$ | $(0.005)$ |

The numbers given in parenthesis are the $p$-values.

* denotes significance at the $10 \%$ confidence level.
denotes significance at the $1 \%$ confidence level.

TABLE 8
Summary Statistics of Trading Volume

| Variables | Fast Learning <br> Experiment | Slow Learning <br> Experiment |
| :---: | :---: | :---: |
| Mean | 0.6326 | 0.1637 |
|  | $(0.0775)$ | $(0.0409)$ |
| Maximum | 10 | 6.206 |
| Minimum | 0.01497 | 0.0 |

APPENDIX

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# -SOLUTIONEOR A LINEAR HOMOGENEOUS RATIONAL 

## EXPECTATIONS EOUILIBRIUM

Recall that the dividend process and the demand are given by:

$$
\begin{gathered}
d_{t}=\bar{d}+\rho\left(d_{t-1}-\bar{d}\right)+\varepsilon_{t} \\
x_{i, \lambda}=\frac{E_{i, r}\left[p_{t+1}+d_{t+1}\right]-p_{t}(1+r)}{\lambda \sigma_{i, t, p+d}^{2}}
\end{gathered}
$$

Now to solve for a homogeneous linear rational expectations equilibrium, we conjecture that price is a linear function of the dividend, that is,

$$
p_{t}=f d_{t}+e
$$

This allows us to write the conditional expectation and conditional variance of
$\left(p_{t+1}+d_{t+1}\right)$ as

$$
\begin{aligned}
E_{i, r}\left[p_{t+1}+d_{t+1}\right]=E_{i, r}\left[(1+f) d_{t+1}+e\right] & =E_{i, l}\left[(1+f)\left(\bar{d}+\rho\left(d_{t}-\bar{d}\right)+\varepsilon_{t+1}\right)+e\right] \\
& =(1+f)\left(\bar{d}+\rho\left(d_{t}-\bar{d}\right)\right)+e \\
\operatorname{Var}_{i, t}\left[p_{t+1}+d_{t+1}\right]=\operatorname{Var}_{i, t}\left[(1+f) d_{t+1}+e\right] & =\operatorname{Var}_{i, s}\left[(1+f)\left(\bar{d}+\rho\left(d_{t}-\bar{d}\right)+\varepsilon_{t+1}\right)+e\right] \\
\sigma_{p+d}^{2} & =\operatorname{Var}_{i, t}[(1+f) \varepsilon]=(1+f)^{2} \sigma_{\varepsilon}^{2}
\end{aligned}
$$

In equilibrium, each agent must hold the same number of shares (since all the agents are equally risk averse). Given that the total number of shares is equal to the total number of agents, each agent must hold only one share at all times when they are in equilibrium. This allows us to set the demand equation to one. We can then substitute into the demand equation the above expression for the one-period ahead forecast to get,

$$
1=\frac{(1+f)\left(\bar{d}+\rho\left(d_{t}-\bar{d}\right)\right)+e-\left(f d_{t}+e\right)(1+r)}{\lambda \sigma_{p+d}^{2}}
$$

Since the LHS is a constant, there must not be any dependence on time on the RHS, so terms containing $d_{t}$ must vanish. This leads us to

$$
\begin{gathered}
(1+f) \rho-(1+r) f=0 \\
f=\frac{\rho}{(1+r-\rho)}
\end{gathered}
$$

To solve for ' $e$ ', we substitute $f$ back into the demand equation and set it to 1 to get .

$$
e=\frac{\bar{d}(f+1)(1-\rho)-\gamma \sigma_{p+d}^{2}}{r}
$$

Now to obtain the relationship between the forecast parameters ' $a$ ' and ' $b$ ' in our model and these HREE parameters, we write the one-period ahead optimal forecast for price and dividend as:

$$
E\left(p_{t+1}+d_{t+1}\right)=\rho\left(p_{t}+d_{t}\right)+(1-\rho)[(1+f) \bar{d}+e]
$$

Comparing this equation to $E\left(p_{t+1}+d_{t+1}\right)=a\left(p_{t}+d_{t}\right)+b$, it is obvious that

$$
\begin{aligned}
& a=\rho \\
& b=(1-\rho)[(1+f) \bar{d}+e]
\end{aligned}
$$



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female - reduces gencler to enentilized Identities on the netions lineer. path frow inmine victin or Goddess to maccultne nationotate.
Chattorjee treces tha devolopment through antheolonial to postcolontal Indian nationalimer. In order to protect a cense of thatr ownidentity ha the hace of colonhal power, he argues, malienoum colondzed comamuntites separate the metorial and spiritual The matertal fane domatn of the cutilde' of the econony and of stelecrnt, of eclence and technology, domath where the Went had proved its ouportorty and the Eant had bearing the ensenthl mark of cultural identity. The greater onef succens In imitating Western oklis in the materda dometn, therofore, the greater the need to preserve the distinctness of one's apirtival culture" ( $)$.

Woman becomes the allogortcal name for a speatic historicel fallurer the fallure to coordinate the political or the ontological whth the
eplatomological within an undivided agency" (BSy) This hature is both
essentially gendered and unavoldable as tha model itcoll seemingty
forecloses the ponsiblity of albernative national identities.
Reading national identity in these gendered terms means that II the
nation an magined community, then as Chatterjee notes, "(e)ven our
Imaginatione remain forever colonized" (5). Colonization occurs through
the Fetaphor of the family and its gendered senifien of the notion. The paternal candy eflectively fuses two narratives of notional hdentity legat political and cthinte. Whereas tee legilpolitical nation logitimates 伎ell on the busts of history, terttory, and, minodern fiberal tarne, the promise - protect privete difference han ruturn for prablice alleglance, the etherde nation "t enen as a fletive muper-fanily, and ht boaste podigrees and genealogles to back up its chims. thee nation can trace its roots to an Heputed conmon ancevtry and-therclore it nuenters are brothers and chters or at hast coushas, differmatiated by fanily thes from outeldare In the cose of Indlia, that thetortc anolnts a state created by decree with a notion of national solldarity ustied mere th oppoition to the Britilh then 4n othnte linguldic, or relifious purity or cohestons

Rumhdief responee to this model is to rendor it both heral and tantanticso that we are forced te see how in is constructed and to account for our own roliance on tu saleen underscores thatity when he looks back on the we of independent indlas:
there was an extra feotivel on the calnndar, a new nyyth to colebrate. because natlon which had never prevlousty exdsted was about to wha It freedon, catupulting ue into a world which, aktough h had tive thousand years of hutory, although it had invented the game of chess and traded with Middle Kingdon Eeypt, was nevertholess quite lmaginarys into a mythicil had, country which would never exdet except by the efforts of a phenomenal collective will - except in a drean we all agreed to dreamner(129)
Here Rundie collapes the distinction betwean postcolonial Indlats Hythe and poltical formation in intorsperses passages such as the coe above whe officill state thelonts making teney to megine Nohre or, Mohandas K. Gundh as national fathers or Indira Condhis Benergency as a parental responet to the nation's dilficult adolescence (when, as the explatned her suepenslon of civil and politicel nights during the Bmergency, There cones a time ha the Hhe of the nation when hard decistons have to be takeny.
Mohendas Gandil was htanoll adept at fuelne coneltating oymbole of the nation into those of a mpposedty cenential hachan identity to lagithente and bolster the cuuse of nutionalish. Although he launched hes polticel moveanent from the cly of Ahmedabadi and was himeelf educted abroad, as welhry, he cratted his polmical idantity as
 which Gandhi "reversed priortles, and enbraced the very values the
 composed his own partorale, and used it both to dirupt the order and
 Indian elites and middie clases. He brought the nationalist ldea from the
 countryede he constructed a new topography of India, defined not by the rellway trackes that linked clises but by the routse that corsnected viliagess (125). This strategy does not detract from the sincerty of Candifi commitment to political eelf-determination through rurel Hes rather, I
exempllifes the way in which the gendered model of the nation (here
.
figured es the oppoition between rural lifit and pacilication on the one
 for polutical resiotance.
While Rushdiet own deal traeg of India corresponds more
closely to Nohruit viston of a epecilicaly Indlan modernity than it does to Gendhif ruril vibion, he does sot condenan Gandhte nationsilist
progrean Inotead, Ruahtile warns of the daryers of conflating the poltical and the nythe through the fagure of Indin Candh. Whan she appears in Milnight's Ccilldren as the Widow, the is bot Prine Minatar and the Mother goddass. Kall dknown for her dentructive powers) 10 In has study
 blacknes befeweled by cruldrenis corpses, eerpents and skull and her

 temper her excesses when ohe threatens to destroy the world she helped

 Indiat matriarchal Hyth - that the was croated to sive the gods from thetr more powerful enemies, but having done so, the continued on a rampease of uncontrollable killing whech could only be stopped by her husband Shiva lying down in front of her" (55). Kinsley reade more flexpelity in that inneg, notige that she oftea appears to be dancing on top of the prostrate or even corpse-like Shiva. In both cisen the remaling the nythologicel embodiment of unrestrained feminine fury.
Kalif counterpert in Purvath, the goddess of domesticlty who softens Shivi's destructiveness and who, in Kinsleys worde "persuaded or
provoked han into creating a chili, who wa necessary for the
preservation of the world (4i). chiva and Parvati as the other two moot mportant of midnight's childrun provide a parallel context for the figure of Katil the novel Stuva galeents enemy, rivil, and widndght twhat and Parvati is saleem's one true elly, whose hation with Shiva producee Aedan Csaleemis surrogate son and the representative of the next

## generation of Indian independence).

Indira Candin es Kalilirst appears to saleemin in drean. Dressed in the colors of the netional nas and foreshadowng the future che has in store for mildnight's ctildren, the Whdow
stitu on hygh chatr the chatr ingreen the seat in black the Widow's
hat hes a contre-parting it in green on the left and on the right
black. High as the aky the chatr is green the seat is black the
Widow's arm is long as doath its skin it green the fingernalle are long and charp and black. Between the walle the chlldren green the walls are green the Widow'b arin counes saaking down the snake fis green the children scream the fingernall are black they scrutch the Widowt arnn hanting see the children run and screan the
Widow's hand curts round them green and black. (249)
Wih this melevolent image, Rushdie denounces Indira Gandhits
attempts to legitimate her power - maptured in the slogan "indira is
Indla" - through mythic refierences which place her own haroh menoures
within the context of Phndutim and tw "reconcliation of extremess erotic
passion and ascetie remunciation, frenated motion and unnovins colm, violence and pessivity."11 By refering to her only the Widow, Reahditie Instetw weh reconclifition is impoesthe her unurpation of treditionally mesculinized tate power and cexaral power goes unchecked in the absence of a husband. Shive in the novel eerves not as her husband but as her son

 (destruction) and Parval (benevolencel), he dows so to warn of these shetoricol and metaphorical ployes at the same time, by verpting these relighous figures according morttal statua, he reinforces a patriarchal critique of Indire Gandhil's authority. ${ }^{12}$ While Parvet does give birth to
 in one of the Whdow's camprigns. Wifely obedience and loyalty are no malch for unrestrained, insatioble fominine appetite for power. Rather than serve to define and protect some form of inclusive indlan
community, these references ultimately mythologine authoritarian rule
 ideotomy.
What we eee in thls example - both in the role Candhi defines for hemelf and Rushdiels characterization of it - is an attempt to bridey precolonial and post-colonial identities through the metaphor of the family tree. By representing herself atmultancously tmeless and modorn, Indira Gandly legitinates her power through a seamless construction of Indian tientity, one thet connects, in Chatterfeo't terms, splitual and
materid domains. She is "Mother India" in its mythle and modern form.

As both the danghter of Noltru and, through her mardiage the namesake
 nuar nyythe statas, indira represents the contemporary ecion of a lineage
 Mata) she hepes to cepptalize on the beneficent ansocidions with the Image.

Wherens the language of the fanily should describe a nationat communtry that is contmuons and united, in Midmight's Childrew tut reveats the dosive for those attributes and their cost The Widow ues her power to suppress figurative and Hertal challenges to her anthorty: dhe dhmueses partionent, surpends civil rughten, and, true to Rushdiets motaphor, sterillzes the childrea of midndghts independence to drain theon of their magk and fertility. Saleem, Hle Rushdie, wavess botwees thit hopeless view of nodern Indin, where the onty "purpoee of Midnght's Chiltren might be annililiation" (274), and the endless posalbilites for alternative storiee permeating the narrative formitself.

We see another example of the centrality and fatlure of the family metaphor at the highpoint of Seleem's powers when he nightiy comenes the Midnight Childrant Conterence (MCC) acting tresshator, partlanentarian, president, and dj. for all the voices in his heed of the children born at the moment of Indiat tndependence. Upon recegnining his power to fume into and connect all the thought communications of midnight's children, Saleem concelve of himeilf en foundation for an ideal bourgeols public ephere "I had in mindin sort of loose confederation of equals all point of view eiven equal exprestion" (253).



 chlldrend, whose denled birthright has conderaned hum to He on the to destroy enamies and to father an untold number of illegittinate


 partictpatmry public ophere commences, it finctured by power strugeles, Saleen's mind), is Almost a soon as this microcom of a secular and
 deltneating the ephere from othern, and of creating a neutral, equal epace commauntoations, the crildrea are motivated by cot-4nterest), of

 moderntty.

 dnos ex mankuos vuope esmosup pus feesodiovecu suprusu

 чрмим ui


birth of the now mation Stive dierupts it wh nidicule and contumpt In
reepone to saleumbs search for the common good, his rivil thunders,
 thing in the whole hiter-loeplag world got reasoln, yamitu(Mou got to get what you con, do whet you can willa tu, and then you got to cile. That's renson, fich boy. Everything elve is only mother-sloephng vinue (263-4). Salnen eventually frils at mefintaining the alleglance of his "rbinges' in this national family and the conference, reflected In saleems own body, gradually dislategrates. La an tronic twitt on the fanily metaphor and its capacity for "mother-sleopings and "usteter-teeptng" corruption, ghiva
 Indira Canchis son, Rethy) and thereby escaptng ite ultimate effects Fis lasting logacy is the horde of clildren he fathers (before voluntadiy undergolng sterilizationd including Aadam, his son with Parvatit (his Ugurative sister in the fanally of midnught's chilidren).
 reconcliation of extremer' are domesticated through the nation as
 while Parvat dies in the Widow's destruction of the magiclans' ghetto. By juxtaposing the Widow and the MCC, Rumidie show how the nation

 the necesoly of metaphor in creating a sense of belonging. The novel stope short of providing altematives to the model it criticives, although it offers the inveginative eppece for such an alternative to exist.
*
Redhalribhines and Chattrije cill for a recognition of comenunal
Identhies outide the spectrue detined by the Enlightenment erblect end
hui notion identities which eay form the bads for alturnative
conetructions of national idenity. Chatterjeets histortographic projeet
Intlegent bralding of an iden of community whth the concept of cuptitr
23n. Insteed of beginaing to read thoden postcolonial nationalime
according to Westem standarte of politiel organization, he looks at
colonial era (6). Thus in a ruformulation of the traditional gender roles
used to tubstantite national identity, the inner or sptitual domain
becomes the foundation for alternative modernities
This approach, combined with Radhakrishnante instotence on
roading nation and gender simultaneousty, suggesta a way out of the
dilemun posed by Jameson's approach to nettonal allogory and
Chaterfeet own duallstic model. Here the comnections between the
budinal or paivate and the national are nelther refuted nor ovaluated
solely in terms of thet relationahup to the imperial century rathex,
eltemative historiographtes expand and eritique the category of the
theorije community foundational to Inditan modernity, however, Chattuife end on a rote of dimppoliatments

The frony h, of course, that thit other merretive is agein vilentily Interrupted once the postcolondal notion otate attocupts to neume It journey alons the trujectory of worldhistorical development. The modern otate, cmbedded it is whth the univereal nerrative of capital, cannot recognter within ita furlediction any form of comamualty except the elngle, deterninte, dempornphicelly cmumerable form of the nation. It must therefore subluynte 5 necestary by the of otate violance, alil uch aspirations of communky identity. These other appiration in turn cen sive to henealves a hiltorically vaild funtification orly by datwing an alternative nationhood with dehts to an alternative ctate (238) He concludes that efforts to de-colontze the imegination of the modern postcolonial national sublect are ulttmatwly thwarted by an mability to theortze mation and community simultaneously. ${ }^{14}$ Modernly inelin in this reading becomes grnonymove with eublect-nation idemiticutions cefined by ementialized genders and capital expansion.

Rushdie does not offer succesful mediating communitien in the uubject-nation relationstup he makes the relationchip ithelf suspect through it Hiteralization. Ac Chatterjee predicten communitles tise the magidang' ghetto - home of "corfurers and contortionitte and juggers and faldre" (451) who "disbolleved, with the absolute certainty of Muslonisteby-trade, in the posibility of mogic" (462) - which challenge the Whdow' mythic oteture are destroyed; thoee which flourhh, wach as
the pickle fuctory, eupport the prevaiting Ideolowy of cconomic growth and -
The trenstormation of saleemis childheod home Mothwolds

## Etate into the plckle factory, utte of hit current Herary and cullinery

 endeavor, hillustrates how that ideolony is domesticated and malntatned.
 them, that the ontire contumb be retotned by the new owneras and that the
 An Methwold mitended, his estate (In addtion to his unacknowledged

## tathering of Saleena) exerts his influence long ather independence,

## determining much of the flevor of Salem's chlldhood Wingdom":

## the Intate, Mpthwoldis Extate, for chengherg them. Every evening at

 stx they are out in there garden, celebrating the cocktral hour, and when Wilian Methwold connes to call they oltp etfortesty inte нмй transformation, is mumbling under his breath Listen carefulty: Willan Methwold. All well (113)
Whan family fortunes decline in political, relliglous and econome turmoll, group of enturpritng industrialinheg women inhertt the estate
 version of the British construction of Bombay) and later the plckle factory.
 the factory under his odd aurse Mary Pareira by day and witter by ndght


#### Abstract

Ahnough geographiculy croular, Saleemis path traces the hnear clevalopment of the modernizing nation-thete the legacy of Mothwold and his estate. What has cranged in the procest, howvere, the gendering of public and privete words rather than the phallic power which provalls, as the wromen control the proces of captalimation Methwodd begen.

The trensformation of the domeetic into the commercial has a revislonary potentill h terns of the cendered olfenfiers of the nation an canily metaphor. That potential is limited however, by the depletion of the "formuldble" and "trong arrued" women who took over Methwold"s Eetete marting thetr erdewor whith a pluk obelik, and by Saloumb own indstence it remining of the conter of the otory the preserver of hutory ${ }^{18}$


## 

As bridgee between readere, wubject, and natione the narrators are succestul to the extent that they can define themofves as epokencent for the nation in order to naturalive the nation a fanily metuphor. Challenges to that metaphor apper cirnultaneously as challenges to the narnaves authority and, thue, to our own ruading plemure such that we work with them to preserve the illuslon of marrative authorty. When we identify whth the narratore in the role, they function as cinenstic sutures, roles thet eern particularly appropriate for an author who honors the Bombay flin industry with cinematic images languoge, and proceses of identilication. ${ }^{16}$ In Midmight" Chillren, the posseathrough honges wach
 denote pasing of the years" (4i4) and chaptars "hade oute" Rushdile creates a relatonship between wext and reader that is both constructed and real when he havite readere ho approach the cerreen unill the frages cimsolve and "the tlumion indis rentity" (19n. We are urged to surrender ourselves temponanty to the we witht to a nim in a darkened theeter.

Rushdie makes thit relitiondtp seductive through magic realism whith destubliates conflation of the hantaticol, historical, and qauotldax we enter a wordd where mandxy depends on our willygnest to accede to the tuterdependence of the fratastic and the "reel." Slince the novel refuses any retum to mecure epletemological or ontological foundation, we must roly on the torns the narritive provides for ove identifications At the same the, Midmight's Children and The Moer": Last Stek are Mutoriceily grounded and motivated. Magic realism forces te to recognize, howevor, that we conceptenalise our hitories through decologtcily-leden metaphora, that identificution takes place in the (Lacendan) Lenaginery: While we cen never step outuide of the bellef that atructure our reditles we can loam to recognize our complicity with those sfantiflng yyetems.

Ruphdieb novels can meen ance profoundly misogynist and elf. critical They present the autharitative masculine mfod constituting and constructing the narrative of the modern nation agatmet woll an for a sensual, anteriol, fominine ground. Saleem and the Moor are Mterally writing for their lives and their text mbotitute for children they connot
independence suowment, "the story of Indian nationalism is ermed from histaricel grep, with its vistual exciston of Gandhly role in the


 the thory jumps from the Amitioar massacre of 1919 (when General Dyer historical "riuhn" in tis dronich of indian independence, for example,
 tunpotence, and impending distrtegration moct the ideology of the

 balanced once more - the base of my boocoles triangle is secure. Ihower at inepiration. it is enly when she returns to care for fina that he saye, I am





 himeoll and Aot Ue, his fellow pritoner, conforter, end consdence who
 fathes. Whilo stieem witter for Padma, hit female audtence and

里
the book that document its sat outcome, and the most dramatis
The eracure te not the seme critigue of rutionallen Rushale meke through the character of the Widow, there authortiarian nationalitim, rationalized in mythic terna, works in the name of puity to cupprus dfference In the example above eliding Condhian political forces of nationalisn (while noting the rellgious factionalism among indlans) has two distinct eftectse it privilgge Juwhuntal Nhtru's vition of Indian


the Frime Mintster and his coblnet, however, he rentinds us of his ow callulity:
Re-reading wiy work I drocvered an error in dhonology. The cesesination of Mahatma Candh occurs, in thes pages on the
 *- ap on anu the wrong thme.
Does one error lnvilldate the entive fabic? Ami I ee far gones
 everythan - to rewrite the whole history of wy time purely in order to place myedil in a central rolet (198)
Ahhough he is quite willing to keep himeif at the center of the story at all costs, Seleem's questions serve a reminder that other sources of knowledge (as well ather kind of poltical nationaliza, such a
Nehruil) exdet, though withen the text only he can provide access to them.



 theoretboulty than practically, Rushdie presente an egregions exanple of
 the protngondst (132). While the iden that point-ot-view narrution could we heve sutured over this inturnton by occupytat andiar locus to that of threatened matruston of the narrator's wolo and pleasure (joulssmen) once
 nerration the protugontst give unfothered view of events, thereby
 Eushdte cuploys two kumy suturing bechniques datuned by Bdtan

which we all every dry stempt to reed the world (2s).




 (n)otody no conutry, has monopoly of untruth (3). As Devid - 3nherweaving Ihtorical and his own foctonal rendertng of events that civor of another he axphosizes 组 hi parodies of oftciat mistortes and


## cwen the sulure itweli (by addreest the reader directy) hinte to the

## Gssures undertying of our devire for narrative coheston

Point-ol-view narrution tu the novel promete the identificution
 By contreating the feminine cadiences deitre for ctuple hnearity with the narretors' convoluted and metephortcol textes the reader marks ha or her
 When selecen, fiustrated by Pedmat demand for a more etraightiorward tale, whes for "a more dlecerning audience, someone who would
understand the need for rhythm pactng, the cubtle introduction of minor
 the contemporary reader.
The eecond narrative mechalque, netr-fletion, works in oppostion to point-of-view narration to allen the reader with the author at the expenee of the flltional mubject. Ruphdie does the by regularty addresing the reader in a voice which does not quite match that of the ostenulble narrator. In Tha Meor's Last Stgh Rushdle writee And se for the yarn of the Moor if I were forced to choone between logete and chillhood meenory, between heed and hoart then curey in spite of all the foregolng. Id go alone with the tale (85-9). The passage rends contextually as the Moor's musting on what to believe about his patt though it may aloo read
 "eo along with the tale." At other timen, the novel addremes the reader

please, your horses, the mete-namutor inglits to ward off inpatience and In an example tron Mudnight's Children, Rushdte and/as Saleen seen to speak in tanden when the narrator describes the metaphorical powibithtes of midnught's chuldreat
Reality con have a metaphorical contents that does not make H sess real A thousend and one children wore borms there were a thousand and one possbilutes which had never been present in one place at one than befores and there were a thousand med one clead endh Midndght chlldren can be made to represent many things, according to your point of view; they can be seen athe last throw of everything antiquated and retrogresive fin owr myth.



 Rather than enabling the reader to experience the plounure of identifiction with the protagonith, meta-niction, according to Mrney,
 In" rather than "consumers of the text (140)) the resulting pleasure moks it odgine in the metatextual stratey heall. In the quote above, we can indulee with soleem in a philosophical moment which defends his own narrative or we can separate ourselves from Saleem and foln with

-- fromer emo suopur ay
eptatemological purtity in narrating the nation, a leck which correpponds to
 expatriate life, they do not reconstruct a homogeneous Wetem tradition: allustons stem no doubt at least in part from Betitsh cchooling and reflection of Rushdio's own pitiliged meterancy. While Rueshdies polition responelbility for counteracting imperallism, a edrinduigent
 meemared by Western standards. Aljen Ahmed, for example, cthes plaral.7t reed ertically, the puzzle reprotuces the terms of Jamesonts


 midnight" - of independent india - wth "extarnal" clues. In the neme of







Rushile in dectphering the puardee of Indian independence. What we
 the novels Rushdie insist that they dont work in ay laind of exact

 refy on tivislon of moterial end eplitual masculle and ceninh "polve the nddle of udinght posed by he chopecters in this way, we
 Moor to how whe Indit Toolik hike In the familut lexn both we norrattve coheston on more than one level We boo for galoen and the





 challuge the ruder complacont rumpton of a shale perrpective vit

 che hat reading ringer perhup cipped fron the centance of ryy own





 - pha pu mory is "(m)emorye truth, because memory has its own spectal und. It



 mnconconclous, we beome aware of tit processe and thelr depandonce 4пиu
 ypal alulerunce between our own corporen coordinates and those of the



 *) P1ou ( Pa


In MLIMHight's Chilldreme menory Is melther truetworthy nor noutadgic but it is producive even ol cally forth nuptures in coherent moljectivity and national identity. Memory implict heterogenolity holds the promise for plurelisen which the text itsoll athempts to delliver. As Joseph Swarn argues, menory fie the epere "the reproductive cycle of ant" only reproductive copacity Saleen retam and Rushdie can ofler (260). Just Siverman outhines in her aesthetic theory how the aesthetic works through the othuilotion of "new" and barted menories to displace the sublect from normative ildantifications, the novel we tee how menory/s productive capadty - creating its own truthe, timnulating the narrative presenting other ways of seelag es well the terus of its own critique $=$ erves as anticlote to national purity.

Ruchdia recogntas the danger implicit in mach a reading of turning his aesthetic (with ths selective memories) Into an escape from history rather then an entry into it. Hie notes in Imagimary Honalands, for Instance, that "maginative truth is etmoltaneously honourable and suopect (10), though he defends his "broken mirror" of mamory a ueful reflection of the "Provilional nature of all truthr" (12). Corra ralees the question more polniediy in his dlecuspion of Rushdie aesthatic principles "to bend Indian Hif this way or that to make us believe in the Hustons of tilepathy or in metaphors that new to come Merolly true and always to remember what reallty fe. The lluston becomes not an aspect of the country's corruption but a comment on ine (146). Whilie this strategy aims to make us "think critically not only about Indian polltice and identity but alvo about the terrible seductive force of Saloemis $=$ of
ตujprod of sueaios ofl
were wiped out" 413), bsoth puritying and nearly lethal. While the blow wars with Paldetan the was "only wiped clean whilst others, lees fortunate




 The memortes which fuel Saleem's overflowing btory may replicate the history than in showing how we can understand one through the other.
 and history chare a set of ofgnifiers and anages through which we see the than despite hibldinal wimmilation to crente pleasure, that both aesthetices

 that the privilegtng of intellect over emotion necesoarily linits the



 Corris defintion of Rushdiets anthetic principle sa ueful one,

## 8



cutarrestared to harocence and pudty" (419-20) initalily provides relied from the wetghty inheritance it turn into a "eeceding from hatory" and, wht it poiltcel responsiblilys. Bat how conventent tht annetia haw much in excusest saleen hater axclatms looking back on his ehiting . pothical alleglances and his wertime activttes (420). Ammedna halptates hio ulthate politicel subuntulon (he becomes a cltizen and soldter of Fakdotan) and reduces him to his most bastc dectres Hilh extraordinary
 dog by Puitstanil forces during the cecond wer (reselting in the hadependesce of Bangladesh) wthe Indla.

## wartime mision in the jungte, without hope of betne found and divorced

 from all ties to their former IIves and from the type of memories which of thetr own fantades instead of tylnte to rencue thenselves by remembertig who they are and what thetr responsibiltios anthi be, they

 growing traneparence that "they understood that the was the last and
 fooling them into using up their dreams, so that ate their drean-mit seeped
 disipation of thetr dreams parallels the Widow's sterlization campaign,


$-3$
-

threater to turn Salenas into "upecks of vololese dust" (352)) Becasee in dratnage He the orighas of the cracks my hapless, pulverized body, drelned above ned below, began to creck becmusit was dried cut PSO. To corstall the surfacing of lack that threatens both his and the mationts unity, he splins memories into a national and porsosal narrative of unty. Dedny Padma's temporary absence, for axample, he complatng *A balance has been upsety 1 feel cracks widening down the lengeth of my body; becuse suddenly I am alone, whathout my necesary eat, and ut inat onough' (177). While the narrative process can only delay Saleenis inevitable break-up, Rushalie intends ite form, modeiled on the oral narrative, to capture "the Indian talent for non-stop self-
regeneration. The form - multitudinous, hinting at the infinile

personal tragedy" (1H, 16).
Aesthetic form has a stmillar sustainine and procreative function in
The Moort: Last Stegh Ahhough the novel begins as the Moor's chrondele
ouf чим чри
revelation that he is haprisoned by his mother's former protege, Vasco
echehorezade of me A long my tale hold his interest he would let me Tive" (421) Other parallels with Mhuight: Childrew abound; diunting The Moor's Last Sidh a lind of nequel to the chronide of capltal and nusitive expandion that are at once the notionis only hopes and greatest thent Saleem and Aadan (now Adma) reappear, allont whth the foudshing plickle factory in contemporary Bombay. Compettion for the role of Mother Indle repurfaces in expunded form to hndude not fuat Indin Gendh and vartous Findu goddesess, but also a fim star and her movie role, Moort moother, Auroxa, and his lover, Ume Meanwhile the hutorical puraners of molats story have grown to inctude early Portuguese oplee trader and Mporth conqueross on one end and the ase of information and fuld capten on the other.

IFMiduight's Chillirem chronlcles both the yoarning for a pure and ctable identity and ifs inevitable fallure, The Moor's Lest Sigh inventigates inpurity in all its forme it dot in how love of country erotidees the nation any metaphor, rusulting in a meemungty cadins array of cexul, economle, politicol, and rolliglous corruptions, At the same time, the movel, like Mulnight's Childrem, fe a paean to the revolatory potential of the aesthetic. Through the lmage of the petimpsest, which runs throughout the novel to charecterter the city, market, paintings, poltuce, and chartecine Runhdie indits thet aesthetic texty can reveal what usually remine hidden, that within their impurites He other truths.

The Moor is our guide through a sertes of false Edens in which the "romantic myth of the pluril, hybrid nation" (227) give way to "dibauchery and crime" (303). Desconded from Cochin Jews, Moorth

Sultan, Chribtians, and, dendicounty, perhaps Prime Minister Noluru
 not 2 shwpot, angerel cur. I ww - whath the word these dayst utomisel. Yesirs a real Bombay mix' (104). Borm a decade alter independence, he represents the chy Hedy, hus own fantaticel growth rete (he ages at twice the avorge opeed) a mirror of urban eprawt "I grew ha all cirections, willy-nilly. My father we bis men but by the of ten wy houldes had grown wider than his coate I was a whyernper freed of all legai restratnts, a one-man popalation oxploslon, amegalopolis, a ohtrripplig. button-popplay Hulk" (180).

The Moor's embodiment of Bombay provide indight Into the kind of Indian modernity Rushdle pries. The city, whose lont Iutlory of commencial and industral growth sets it apart from the modernty of the natlon-statet bureaucracy in New Deilh or the colonial history of Calcutten wa "the great powerhouse of hndian economic moderndzation"; it "bocane permmently lodyed in the popular lmaghation," according to Khinanh, "a a totem of modern India theif (130). It mexture of economic growth, cosmopolitentime and congsted class diversty finds its
 Hocited there. Perticulaty in a nation with whlespread mithericy and 22,000 distinct dialects film provides the kind of cocmmon cultural ground necesery for an imagined national community that Benedict Anderson accibes to print capitullinn. The Moor, we thail see, hisuelif located at the intrrection of thes hoets of national identity represented by and in Bombay, eubodying both their promises and tallures.al

In addition to his accelerated developnent theor is dibtinguished by his deformed right hand. Leve soloure nove, this deformity symbolie and substitutes for the phallic power the narrutor wantw yout never wholly achleve, particularly after he, too, becomes Hapotent As Siverman notes ha Mele Subfectivity at Marging, Ideologicil conatetency depends upon the allgmment of phallic power with the mals cexul organ In making thet nituphorical connection iteral in the text Ruphlie once agan make avalleble for conscious erutiny. The leck which "drainge above and dratnge balow" occastoned in Salcent replaced here by the Moof's indblity to acsume his legacy the only eon of Aurera and Abnhtum, to pass on fie trudition of economic growth (thek wealth comes from a long history of splce trading) and Imaghative nemewal they possess.

Once again the tmage of Mother India deternanes the contemporary teras of that legacy. The Moor, who invelts hemother and tredes an erotictred relatlonshlp whth her for a doomed affir with multo personality Uma, is disinhertied for his dialoyalty and cast into the underwerld from the Eden of his mother's arthote salon. The cost of losing his mothers love, or of forsaknng it, H He tidentity. Fudting humeelf In the hidden bowels of the centrel fifl beneath the city he thought he knew in its entirety, he dreamit "that ny ukin was indeed coming away trom ny body, I had creaned so long ago that it would But in this verkon of the draam, ny peeling akin took whit it all elements of my personality, I wa becoming nobody, nothing or, rather, I wat becoming What had been mede of me. I was what the Wurcler saw, what ny nose
melled on my body, whet the rats were beghnome whth growing ewhersasin, to appronch. I wes scum" (2s5). Without the protective and unifying image of Aurorn, the Moor finds himent at the clisposal of competing ideological factions

This texsion, between the croticization of the nation as famply and the need for the metaphor hn matnuining a conee of selt, m replayed throughout the nove. What varies however, the tinaee of Mother Indil hercell. The followin scene fluptrates the centrulty of the nation as Camily metephor on the lovel of plot and otructures well as the wey in which Rushdie trungifgure it berna Auruen, whose pabntirge prement her son's He againdt an exprealontt national backdrop presldes over one of her infenous solstas. Within the novel a whole, she represents an irreverent and urben allernative to Indire Candhis "Indiris indim" and the ht film Mother Indind feminine eymbolics (which rely on fenages of Hhedu nyythology and nual aplatit). At the party, Auron addresses the leading lady of Mether Indle, who playe Radha, and her husband Sunul who playe the wayward son Birdex

The flut time I saw that plcture I took one look at your Bad Son, Bifur and I thought, O boy, what a handsome guy - too much clazle, 100 much chlill, bring water. He may be a thief and a bounder, but that is some A-class loverboy good. And now look you have gone and marry-o'ed him! What eexy Ives you movie people leadofy: to marry your own mon, I wear, wowie.
Deapite the guests' shocked protestations regarding the difference between Fictions" and "flesh and blood;" Aurora indist on conflating tham:

Hindu nationalism. According to Nalind Natarafan in her analyole of the

fim, actually made in 1957, the year of the fictitious Moor's bith, achieves Che nation conily narrative embodied by the maternal Image. The 4tmportance an inage of national identity, and the wider validity of
This stratey forces readers to reconsider readng of the fin thell,
than the others. any of thee incarnations of Mother Indla has a grenter clath on "reality"
 relatlonahtp of Aurove and the Moor, to auggent the fitm verston) in order and its actors with a fictutious storyling (made in the clee of the widely recognined national icon produced by the Elombay filus inductry) In this caeme Ruyhdi intertwhes the actuel flin (arguably the most (cev) ndppowupe endpeo 514 whith the subeldiary theme of fritudden love added on. But what







-wu snowiof en
Twon in the placure, but, 1 knew rifhe off that bad Biftu had the hate ber
dentity fir coopted and forgotten in her maeriage to her Flinda co-than
 Sita with all of the tredutional colf-emerificing virtues ascribed to these women. We hive, then, a nationalist articulation of Findar rellighon and culture focutin on the figure of a Mulim actrems" (B) . Rumhints hand, the flumb hage of Mother fadia is complicit wtuk rather an opponitional to the dominnmi Wectern model of the nation fandly. While Mothar hadlie nught ceean to provide the beots for charnative national Identificetions, beeed on the epplit betweon fempinaized tratition and mascullinired modenity, hn fact that lmage works to promote both mafortarian politics and the normative ideatibentons of the Oedipod complex.

In the novel, Rushdie play off and subverts thentiarity of the ime of Mother Indil by revealing the palimpsest of conflicting meanings it contains. lnstand of one stable inage of Mother india which pre-dates and survives colonial expertence and includes (consumes) all of the nation's rellytons and tongues, we are fovced to choose between competing Imagen. With the exception of Indiri Gandly, noreoever, at in the Itm nome of thow lunges is represented by flinda women. Juth how elastic is the image. Rushdie seems to be asking. How far whil it bend to accommodate the phurility of the nation while estil matatatulay a eense of national belonging anmable to the value of the Hindu mafority?

On one level of the plot, Rushdie contrests Indira Gandh's authoritarientan with the plurality of Auron's painting noting that, as discuesed previously, they are mutually exclumive ideologicaliy and public
a
another, depending on polmicol expedinnc, thereby emptying them all of
 interest. Once again, Reshdie polints to the dangers of abmindoning a metaphor of belonging to Hind dipparata idantiths together. Alihough traditional Mother milia worls ta confunction wth a patidenchal ideology. without that innge - or a subetitucte for il - identity becomen a pliant tool in service of eelipromotion. Umile asumption of the Mother Indin innege, in this regard, fanctione amelagousty 10 the tumstornation chiccumed emarier of traditional communel identifcettions, bued on
religilon or ante, for indtance, into velicles for national political

## ecendency.

Deoplie her apparent politicel irrelevance during Indire Candblts rulh, Aurorat remains the moot important alternative to the rural matrlarch of the fallm and to Candht's own authoritarianism. Whereas Mother Indie ideailize the Indian peemant womani.as bride, mother, and producere of conss as long-affeding, stacent lovine rodemptive, and conservatively wedded to the malatanance of the sodial statuen quo," Aursen, the Moor says, "was a dity girth, perthaps the ctiy girt, musch the mcemation of the amartyboots metropolis as Mothee India was village

the commopotitan Bombay film industry and itm most popular product.
Weallity, headtronge and vhlonery, Aurosa refuses to bend her
 tradtion as a matter of course - from her marriaet to the Jewthh duty



 As a member of an (elite) economic, relighou, and othric minodty,
 Irnagined, not as fxed property" (167). The image of Indla promoted by constratned circumstancees its strength was not deological intemety, "Nehru's idea of indiannes emerged through laprevised responses to

 modernity of forging diverne cultural traditions into a mecular unity. The trateg a a epecticelly Indian respone to the problem posed by



 than the legal and burneucratic protection of mdividual utght guaranteed



 by Noluru, of a secular Inclia conmantited to protecting tit diveres Prume Mintster), she rempins commited to the ideal image, promulpated her many lovers (rangfing from a Hindu mationalint leader to the firut.
intornationallzation of languages and lumge nather than ther plurai or hybud corms. The gunilial and cultural contexte of both Una and Adam are etther wholly fabnicated (on Umat part) or ellided (Aden's quent mythic parentoge from Shive and Purvath and hus rearthe by Saloen and the pickle factory women remain the concors of Midulght's Childnen rather than this novel).

Aurosth painther reflect the chaging fortunes of her fundy and the nation, withun and egainat the lunge of Mother India Her "career" bughe with the mural she palnts acros her roon after her mother Bollets death diupels the ldylice trance of chuldhood. The murail incorporates the torles of her chillhood without thelr martiting glowe Vasco de Gama, her ancestor, arriving in Indin, mencing epices and money; the Last Suppor with her fumily member attending thetr faating ourvints the masons of the Tal Mahal losing thelr hand to prevent any finer constructions the approaching war for independences erotic temple imagary through a ctuld's eye and her own fanciful gode.

Lke the crewd that ewallow Saleen Smai h Milnight's Chillirem and Rushate himself in The Ridlle of Midnight, the mural drow Aurorets astounded father "onward" Into "the crowd whithout boundariest: Aurori had composed her giant work in much a wey that the tmage of her own family had to fight thelr way through this hyperabundance of innegery, the was sugeting thet the privacy of Cobral Idland was an illusion and this mountin, this hive, this endlesty metephoric line of humarity wa the truth" (60). It was Mother indiu in all her manllestations = Mother India with her garthnees and her
Inextaustible motion, Mother India who loved and batraped and ate and
 pasilonte confoining and eternil quarrel stretched lomg beyond the

 murdi in recogntition of the hack that con maver bo mate good, the
 depictions of histodes and identities offer the only posilthe compenantion. Aurom pursues the joint political and aesthetic vislom throughoul the rest of har Hie, riotng to promanence as both an artitt and agtator for a



 caught between "Vasco Mrandals playful influence, his fondness for lmaghary worlds whose only naturel law was his own soverolen Whimeicality, and Abrahanis dogmatic insittence on the inportance, at that historical juncture, of a clearaighted naturallsm that would help
 materythy "the national longing for form" that ditives The Ruille of
Milnight and Midntght's Childrem, presented in another medium.
 vymbol of power and fratility, these deplctions of the Moor's hand (and

 portrats of herseff and the Moor in which hit deformed hand, otherwibe a only con sus well as of the dawn the personifles, Aurora patnte eroticised.
 long history: alow, in Wis depletion as Sultan Boabdi (the last Sultan of Cramada) from reprecentetive of the notion and as a whedow hato the family's defleting bat "dynumbly, all focus on the Moor. He functions not only as a
 dark partod (1981-1987, froen the Moots dheinheritance throuede the




U pray ou royime evp profeq yoen 04 poox dtpychs and triptychs the mult-hceted dimenslons of the real and the




 keep It validuOnly don't go to the English. We have had enough of them Whe giver him a pasport whith a Spanich visa and one-way tcket "Always
 them. Even after the Energency forever end that period of hopetuiness phuralim, and throughout her hife Aurrara urges the Moor to search for
 (eve) nea
or on top of. Call it Polimpstine. And above it allt the palace,

 the fort on top. Place where worlds collide, flow in and out of one








 of otrength Thut strength hos lonte here rems loyvil to his mother
 were, orchitectural relarences to Indla's politicel history stretching frox the Moorth inverion (which brought Ltan to India) to the Mughal capire (with the Tal Mahn) to colocial power to the current meet of the central state government. Hie crrculates the image of the Red Fort in an attempt to sccomptith aestheticully whan Nehru tuded polticitity: to forge yyubols of a united india which ohnaltaneousty refled ite complicated past Awne of the meed for mybolle idmothoction to componsate for the lick of historical unity, Nohru hamedi' inaugurated the state nitual of nulstug the national fies from the fort on ench anriversary of independence. The led Fort thus forces the reeders into the conflicted areni of momory and forgetting toutllned by Benedlet Andereon in Inagined Commuritien, making identification wh the unified nation a matter of suspended disbeliot.

Khithani describes the ritual flaz-reding (15) as fust one aspect of Nehru' program to create a foundation for Inclian national identity. Nolru also pursued this progeam through the exercise of state power, thell a legacy of the polltical arena left over fircen the Brithh Ref, and through his hetory, The Discovery of Indla (1946). In both cases Kidinand writes, Nehru Irelied on a compelling if imaghary, story of the Indian port, told a tale of cultural mixing and fusion, a civilizational tandency towtirds undfication that would realize iteelf within the frame of a modern nation state He located this atory of an internol impulise towneds Indian undty withh a larger etory of the movement of wortd hetory, namative of diverse peoples coming to deternine thetr own futures and to

Dempthe the trunsformative polentiol of these reworked hangen of
********* national identity, Pushdie never completily abendons the paternalintic nation as famaly model of Indian hetory. In Midmight's Culliven, Rumbite regularty asociateo hithory with Saleemis diefigurement. Prom his staritization to the epreading of the crecks to an arrey of other scont dibfegurution plagums saleem an it plagues the nation "tite has been transmuted into grotesquery by the truption into it of histary" (6I). Rualdie encournges us to read the Moors dibfigurement ase atmilar conflation of personal and nationel ditemter: "Banished from the ratural, what cholce did I have but to embrace the oppoetio? Which it to ayy. unnaturalisen, the only real bm of these backto-front and jebberwocky days. Pliced beyond the Pate, would you not seek to make lyht of the Dank? Just ca. Moraes Zogolby, expelled from his ettory, tumbled towards history" (b).

Ruphdieb crutiden of the effecte of hetory on the subject-nation derve not from a destre to separate nesthetics and history, bet fron the
 devotion from his mother to Unim (colnciding with the Energency). Aurerat printings turn dark and threatening. In place of the multiple world fading hand out of one anotherg the paints jesed nseures swallowing up her fantuatical creatares and show the fort crumblateg inte rubte. Craduelly her style becone more naturalitic as ohe chow hersely watching the Moor watching Une 1 reveds Aurorats eelf-consectous awareness of her ebblag power to hold his love and alloglance.

After Una engheere the Moor's expulston from his fandiy. Auronat aesthetic cye truflis hin into the underwodd where the watches hli decline with increastag horror. He later sees himeelf hin theee last paluting "(m)otherloanohte previous metaphorical role as andmer of oppostien, a standerd-beerer of plurallien, ceneln to stand as a nymbol however approximate - of the nuw nation, and buing transtormed, Insteed, into a sern-alligerical figure of decay" (302).

To survive in the underworld bereath the cosmopollunisen of Bornbuy, he leans to wee his doformed hand a club, entorchut the will of a Hindu nationatht leader. Here we find, what Norman Ruch colli in hile rewiew of the novel, m mordant reflection on the final outlook for relligious nationalism hn lidia, whose most cheering conclusion that any hope for the downfall of that insttution lies in the infinite mercenary corruptiblity of the humen eprecies" (7). The only escape fron the underworld is, paradoxicely, up trurough its ranks of corruption At the
$1$

Aurora crading air. Abrahan, incensed by this apparent insult to his wife
 Aurorat pallunpsentar Lintinlly connulssioned by Abrahan in 1947 to do a
© ( )
(cIc) ерхй congivenees, he is in the forgeground, "oost in mimbo lile a wandertng same penel but not reconcled. While ahe holds out her hend in appropretates for his own atory, showe mother and sen recunted in the
 through Aurora and Vasco Mirandais paintinge. Aurorabs final palating,


Jut as Rushdie ruprosents the differences between Nolru and
(-EDI) 4раианисо
annex its moderuity and distribute the beneftis of it to ana, cloved
 indernolly homogenove communities, anch insulated from the






oves apys ay
Chithani unpports this comparison, he ctise Ruatudie ha his anolysib of

comes too linte to save hin from imprieosment. He find hamsell locked
Moorusalen, but an ughy, pretentiove house" (409). This realization
 tmpremsions had beea llusory, and the allusion hed already thed.d. The emerges from the tlinion: "No, it wam not a mirecte, efter all, my first her. Gradually the Moor rees the rulgarity of the innages and docay
 explodes (351). The Moor locates Mranda ensconced in what appean to be
 Alhamber" Auroris four stolen paintinge. "Go find your preclow he loven the Moor travels to Spein, hoping to find in Murandis Little when, seelding to escape from the collapae of his facility enplire and the dty
 difference of its hetorion and culturel substance. corruption, in Rushdiles view) of cuptialiner. Both dmin an methetic of phuralimen by fthes comamentariantam and the heterrational epreed (end between Aurost, Üma and Mrrada, ho repretents the dad challinge to
 luncting his career as an innermationally renowned munnlist of atiports
 Alhambra, O , The Moer's Last Sish - over the refected Madonat tableme. the Unluchy cot-Zogepbld, Lent Sultim of Gremeda, Seem Daparting trow the



Mrandit vengeful obseeton While Aol U works each day to uncover
the madonne portralt of Aurosa from beneoth Mirundate celf-portult, the
Moor his forced to record hiv hilly history al his own 7at afeh*
The Moorf pligrimge ends in falure beceuse he funds "an and-
Jruedose not a home but an eway. A place that did not bind, but clisolved (3s). The fontasy world Miranda created to enliven the

Moort crildhood (and atleviate the celt-doult caueed by his delormity) cunsot sestath him now, nor mubstitute for the healing power of the: matumal tmage. Ultimatuly only Aurorat eedhetic vilione, with thitr zelding of history, myth, and tmagtration, ane mend his physical and prychological wounda. Here the narrative himitates the potental of the palimpsest as an aethettc form. After Auroris death, Mirandal destruction of hie portritit of her, the theft and loss of her own paintings only the text thelf retains her image(l).

Ruhdie present allernatives to Aurorets seculer phurallise bound by the maternal metaphor an nothing more than fale Edens. In addition to the relyious atingulatien Rushdie countermands for obvious reasons, he present unscrupalous and unrestrained captelilization as yet another
national aftiction. Adan and Abroham epilomize this most recent.
corruption Last ceen as aninfint in the pldkl factory of Midnight's. Children, Adwm reappears here as the symbol of the globel market At
only 17, he has amased a privite fortune with hid buslness oavvy and
 and opportuntiy: His commercial fletr seduce Abrahen who adopts hin huto the fanilly and butness

Wore golas to put our footprimt on the world; beaned Abrahath proud of knowing the worde new connotation "What riligers thee locals are with thetr culk of the rule of Ranal Not Ren Rayha but RAM Tryja-that in cour ace in the hole'
"Not fam but RAM I recognised at once the young fillow's sloganistng touch ${ }^{\text {. }}$
Thee we a nuw Ad in Bden" the Moor writes attor he is diplaced by the aloption. The future hed arrived. There was a genoration wating to ininctit the earth, caring nothing for old-tinners concerns dedicated to the purselt of the now, speiking the future's strung, blaty, affectles speech - quit a change from our molodramatic garan-mnaala exclanations" (343). The ditthnction the Moor maker between his own cros-cultural borrowing and Haeage and Adamis Internationaliem partllels the arguwent Ruahdie makes for his own discurstve hybridity.

Adam's fntemational tongue meske new form of corporate colonialinn dedicated to the growing empiee of capital. Iths memos quickly becmene legendary. To optimi manpower utilisetion, engendering of a we-leeling is key; they typically eadi. Further encouragement was given to the Idea that each employee should offer monthly 'evaluations' of his fellows' strengthe and weaknesse - thus tuming the building hinto a tower of hypercitical
tecturical profossional class, Bangalore fis the home of many of the laxgest


 the underwordd and the changlay politicel climate in Bombayh we find diecused previousty (with respect to the parallel storylines of the Moor in


workheg when people start meeing the stringe" he tell the Moor. To helli
I had a damn ine run. Have abloody apple (13n). The wealth bogin to emege does Abraham feel regrets The magie stops been, 隼 you follow my Hee, illogicam" (187). Only atter the foundations of accupted no responsiblity in case of ith-heilth or infury. It woald have practice, eatd ancient Abraham, cucking wheezily. But naturally we for thetr work Nobody ever hoard of paying upooke until we began the golng eo far - O phillanthrophtel - to pay them mall amount of cah construction sttes epringing up on every inch of the new land, and even opportunity, Thering many phantoms an courld to work on the hage (that in the otreet dwellers) do not exdet, Abrahaen and his collieagues see:


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(overty hausy-wagy, ecrethy stabby-wably) ineaks "We will be a
malthational corporations operating fninda. While Indh provides huhty tratned relatively incxpensive Labor for corporations euch as EM and Hewlet-Packird, they, in turn, offer workers saleries uncmatchable in other parts of the country or other suctor of the ecomony. simee these corporations wheld nan economie power whin both corrhas with it and produce international identifications, the chy itsill "hat becone the capital of Nor-Rendent liadianfand] this new chas too has ascestondst undestanding of the itee of indin" (148).

The innge of talse Eden, economic polnicil and cesthetic, whose Idyilic vells are eventually etripped away apportions blane for comruption on Indian themeetver ruther than on outuide forces. Those "requestered, earpented, Edendolnfernal private undverses" (15) that enclose the Moort Canaly history are of priviloge and opportuatty equandered by ereed and corruption As allernatuly (eltte) minorly and national repreventative, the Moor indists that there are no pure hneages and that oll bear rupponibulty for the nation's the His Moorth Hineege does not absolve the maforty from political responsiblity; mastend it draw attention to the epread of neo-colonialisuin in business and politics

The Moor with whon he is conthnilly compared, Boubdi, Lat Sulkan of Cranadi, effectively ended his empine by botraylng his father and then copltulating to the Sparnch. Rushdie in dearly aware of the ironias of colonillisun intersecting in the Sultan's story: Boabdil the het trace of Arub power in Europe which once competed with Vasco de Came for trade routes to Asla and which otrotched from the beerian Penineula to the Sutante of Delh, and his decine nemals the aggrandizement of Spanich
and Portygue global power. These two colonill narrative imtarect in
 ntarded voyag to Indil, attends the ceremon marking Boabdili abdication to Cathollic rule over Granado in 1401, thue markine the beginning of a whole other colondal nerretive2

The Moor benre the wolght of colonial hetory, yet insints upon chlung responsiblity for nutional affire rether than aturbuting then to the legacles of that pest and all the while he getann him futh in his noothest parionat embrace of phuruty. As he departs with his etuffed day Jawharlal ( a sad commentary on the Prime Ministers legacy) from Bombay for Spaln, for example, he ruminates on Macualay's 1858 "Minate on Education" wh ith encupsulation of Brhish colonial mentallyy concluding "a closs of Meceulay's Mmutemen' tindlims educated by the Crithlh to feclithte colonitationl would hate the bet of Indian. We this Cnalyl were not, had never been, that clase The beot, and worot, were in un and foughtin us, they fought in the land at linge la some of un, the word turupheds but still we could cuy - and eay truthhullity - that we had loved the bext (376).

The love that perseveres at the end of the novel for for Auronits mangrelized Mother India Just Aal Ux palnstakingly unveile her irom buneeth the Suttanis fmate, Moor trie to reconstruct her in his narrative Yet Aurora hai alreaty died, the phining will be destroyed before it is restored, and, Rushalie has strown throughout thext, the Inage of Mother Indin is at once redemptive, feroclous and rubniestve. This concludon, much like Aurora' chilldhood murri, focuse attention
on the hack that can never be filled and, therefore, on the aesthetic
 Chilirents optimises in the narrativet productive form, The Moor's Last Sigh retalns hope in the aesthetict cuppelty for timnghative renewal and penterating viston, powers whach depend upon an acknowledgenent of the lack they try to overcome.
The centinual romender of heck has a productive function the

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 distance and deferral comes through the whinting norrative perpectives. and the trope of the pelimpsest which always hints at another vision lytug
 the revilionay potential of dittance and deferral stems from the way, momory functions is aesthetic texts. Whether by uncovering otherwise repressed mamories or instiling "new" munvoriss in the unconsciots, silvermen argue, aesthotic texts open up path of identification which are normally forselosed by the dominmet fiction.
In The Meer's Last Sigh Rushcle constructs the living presence of
 history rufutee to conforn to a nostaligle vilion of a unified past. Since. aesthatic value depends upon pleasure and destre, when a text ettmulates

natae this pousble through the nation thunly inetaphor whose canllionty havites our Identulication with at Autough that metaphor atteupte to domesticte diffrence han order to create a undfed netional Identity, by showing the process of domentortion twork, both in success and hifures he callt enttention to itw newly expmoded range of Identhemtions In beconting conselous of that expanded rangen we mey Ilarn to idealiet what is outshde of ourvilve. Disturce and coferrel tere the conctuions necesmery for this ex-corpordive Ideelization and, therefore identilication The anethetic can listervone $h$ these normetive procueses by olmultaneousty allowheg conecious "ecrutiny" of their terne and unconecious 緔idinal otimulation necesery for identificationa.

Stivernan describes the proces of ev-corporative identitication in tume of sublemation. Following Lacan, she defines sublimation the "shift away Irom the happosstble non-object of destre which is produced whin entry hinto language and the Yading of the reat to a nameable and spectic object ${ }^{\text {T}}$. That new object becomes laden with the responsilility of "makk sood the cublects heck" Narrutive or aesthetic compannation, thea, offers the subject innges with which to catify his or her foundetional destress "When one treatisen object in this way, one of course idealiess it. To cublimate theus to confer ideality on that someone or comething through which the subfect articulates his or her ineffable deedrer (73).

Rather than view the Moorts "atomised" Identity and hie defornity as follurre in his bld to represent the modern nation, or an fillures of the nation heelf, Rushdie asks us to make a postive identifiction botween
*
the Moor and lindie through prectedy the smane termas In onder to do sa,
we must reconsider the ternes of notional hdentity itselt Shece the Moor ends up disinhertied, impotent, and exlled he falls to complete the equation of paternty, progress, and power whth which we started. Similarly, the novel refutes attempts at locating national Identity whthen a ceninized, nythic epphere stnce the hanes of Mother motia are nother


## tuodel What remains is the aeothetic unvering of memortes and






 creculation.
 Sigh, that we night "hope to awaken, renewed and joyht, hato a botter

 for the aesthetic images of ourselves we sanction and condemn. The


sense of the actuallization of state power) and aesthetic limitations of Rushotiet pluralist ideal.

Nohru's tremendous oftes a etatesman, particulary an Indin's first
Prime Minitter, was his recognition of the need to create both an inea of Indla aviltable for collective Identification and a state apparatus and agmen capable of rewerding subpect for that identuication in thetr dally
 cere, and so forth, In the realm of the imaginary, Nehra, ike icuatile, adopted the mingeg of the palimpset as a metaphor for hidian heterogenelty and unity: "india' he wrote in The Discovery of Indly, - onwas ithe an anclent pellmpeest on which layer upon layer of thought and neverle had been hnscribed, and yet no mucceeding layer had complotely hdden or eraed what had been witten previously. Nehru used that image as part of his effort to construct (come would eay fabricate)

 the dawn of civilization.24

It would be unfair to read the decline of the Congres Party and the

 tallure of tmagination. Whether attributed to the immense tak of coverudat dose to a billion people or to spectic poitical fallures the fact that indlia retain grose inequalites of wealth, education, and opportunity provides an unpetus for political unrest. In other worde disparities.

offer factitate subjects withdrawal Gron the nation' loundling ideoloyy. Moreoever, alkhough the extmples from The Moer's Les Sigt diceused above foem on the relationshp between Rurhdiet aenthetic and Nohru': urban modernity, it is huportant to renember that the ldea of India was founded on the collaboretive villons of Nelbre and Gandin ant thus on uban and rural identiflections.

In drawing atteation to these two condituative tenets of modern India - the idea of unty awnime poltutel (nutional) expremion and the jolnt eet of dendifcetion proffered by the "founding fatherser "Nohru and Candil - I want to emphedze the access they give us to the nature of the nationis lack. Both Judth Butler and Wiham Connolly, in thetr poychoanalytic and polticil analyees of how the state exarciee power to maintan the allegiance of fto citlaen, otress the problem inherent in the legitimation of that power. Whilie the nation, as an ideal, manucurates the subject's desire for and, thui idendfication with it, the state (the actualty of that ideal) will alway fat shon and eubatitute coercive power for it The mathonehpy between the notionts ideal and courctve powess creates a parallel set of powers withtn its dtizen-subjects. As Butler explains (and as diccused in Chapter One) an ideal such as mation set the former cubjection (assujetissement) to the symbollc order that makes poselble the nubject (self-) exprestong at the cume time, it constituta a subject capable of widding power (pouvoith. The state Butter argues, at once promotes its status as an ideal and "cultivates melanchollia among its cittaony" in order to exercle it power. Citzens, memwhite, constituted in terme of


 mastration by a Findu miltunt, who thought Gendh too pro-Mevian,
 what made India poosible also profoundly diminished the intograil value


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 of plarility farough Saloun's narrative supertulty, Aurorib ingeinative




novituale loes.
the iden forever try to astiffy the devtes opurred by the innugural and
Cendld from the otory of hadian independence (ee Bremnan remerks), the privileglexy of an urbm modernity thet dimeltaneoudy meglects the condtitons of rumal Indiont (although it ahow the negative effectro of modentration and captellimu, perticulaty on the urben poor), and the
 noveth, however, is that ther sociel critiques - of copitalim, milituant roligious fundementulivi, and narrutives of purtity - sometimes appear in the alltoo-fandilis terms of ettunte and relighous otereotyphes, fa the divilive terme the novels otherwiee content. Ruehdiots hopa, ilike Nelirits, is for an Indian pluralien that will provide a vialle alternative vilon of the modern nation. He outined
 it best representis is a woederfal demonstration of multiplictyy tite a wonderful demonatration of how people of completely different backgrounds and fatths and idens can live together and form a compolte culture which is greater then the mam of the parts." Hhe own writang attempts to ceptuse that mulliplicity through excese and famboyance
 nerrative plesarres of ins mesthetic, thas, provide the compensation for and identification with the terms of the ideal nation. More importinnty, it that methetic excess whidh footers the kind of erticol distance mecoseary for conectous, and therefore ethical idensfications.
While these teenung narrutives work syytiotically, their poltitical affectere more amblyuous The difference underscorss the limitations of
the aesthetcic in challenging the prevalling eocial order. In the cese of The

There were many tenes fin the monthe after his bugan that I oudd to nyed that I no longer withed to be a writue. I melt that everything I had pat into the act boine $e^{1}$ writer had fulld, had otuphy been frvalldated by what had happened Yoa wrte out of what you think of as your best eety the best there is in you II the uphot of thet that the whole phanet thinks of you a complete bantard, you wonder what its about, what 4 was tor, and why do 1 . Pile attumpt to cesculbe diflerent worlds In term of each other ts
 mongrer world, plural nation, or textual paltmpeest. Much of thene, his overt metaphors bring our propudices and otherwise naturalized Ideologies to the fore, nubling us to look anew at then Thus the gradual cracking of Saleem in Milinight's Chllaren or the Oectipal joken in The Meor's Last Steh promote humor and underetanding, mether than outrage. In the case of rellgion howeve, The Satamic Vorees "event" makes clear, readers ere les willing to forgive, perhaps, a stmilar btecary play. There we see that the pleasure and compensetion prombed by the aesthetic is thwarted by the very losees it reeke to assuage.

Given all the , it is dificult to understand why Rushdie would turn in The Moer"s Last Sish to the Agure of Abrahan to tather and to represent capltalitst corruption. Even though Rushdie's metaphon are always sugestive rather then prescriptive, ustag the Jewish patriarch to epitomiza the inherent dangers of rampant, corrupt capitallisn seans too convenlently to exacerbate antisemitic ertereotypes funhdie's critique of capitalism in based in part on is homogeniming effect on caltural
diflerence it devaluting of the hitorical and material component of
 cubfect mation and languge retnforces ethuic and relighous minimities and expands the reahin fin whech they opente Perheps the problean of lmagining alternative imajes of subfect and nation meaks the Hmith, both our own and Rushdile of coming to lerms ether polttically or cesthetically whth our foundational loses for as Saloen way, New mytis re needed; but that none of my budnem (346)

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Blate, Clad Rendent Alien. Ontaria, Canada Penguin Books, 1986.

Reviece 13. T-2 (1991) 193-219.
October 28 (Spy and Mans The Amblvalence of Colonial Dhecourse."
-Th Loention of Culture New York Routhedge 1994.

Ehabha, Homi K Nation Narrutlon New Yorks Routlodeg, 1990
Druce Rotbing. Minnempolife Univerity of Minnemotian 1993. 173 -208.




Becker Carol (ed), The Subverroe limaghmatlowis Artbotb, Seciety, enad



 Pres 199

Booker, M. Keth Beauty and the Beast Dualinn as Dupotimn he the Fiction of Salman Rusholia.' English Litanary Histery 57.4 (Whater 1900); 977.997.

Booth Wana The Cowpeny We keq. An Ethice of Piction. Berkeley: Undventty of Colliforda Press, 195

Erenna, Thmothy. Commpolitas and Celebrities" Luce Cluss 31.1 (1999) 1-19.
-India, Nationallem, and Other Rallures. The Sout Athathc Qumaterly 8.1 (Winter 1988) 131-14G
-Salman Rusludle and Thid World: Myt Notlow. New York st Martin's Pret 1989.

Brodhead, Rechard Hi. The School of Hawthorma. New York Oxford Univerthy Pres, 19e6.

Brooken Denld. An Interview whth Shban Rushdie. Hellx 19 (1984) 58 69.

Bruner, Jereme Actual Minds, Pessithe Worlds Canbridge: Harvard Untversity Pres, 1986.

Buefl, Frederick National Culture and the Nan Clobal System Baltimores Johns Hopkin Univernty Prees, 1994

Butler, Juduh Bodies Thet Matter: On Dive Discurstive Linult of "Sex." New Yorke Routledege, 1923
-Excliable Speck 1 Polttics of the Performation. New York Routledee. 1997.

[^54] Halperin Nev Yorks Roulledge 199 .


Tuth Dennts From Nowbury to Saluan Rushdies Teachny the Iupertalisw EA. Lobert Gidong. Nevorks Mertint Pres. $1991: 64$

Complein, Ehne. Bryond Controveryy Vita Noupent and saturan
Carter-Sanborm Kisth We Murder Who We Were Iasuilue nat the


Ceruth, Cotly, Undehind Expertonces Truwn, Narwitce, and History. Balthonores The Joh Hopkin Univertity Prese 1906

Caton, Louin F. Tomante Sruseles The Bldungsroman and Mother Daughter Bonding in lamaica Xencat's Aunle Iofn. MELUS 213 (Fil 1900: $125-142$

## Cnysit hloward Tm Art of Iudsument Oxford Besil Biackwit, 1989.

Chakrabarty, Dipesh. Poscoloriality and the Artifice of Ingtory: Whe Speak for Indian' Thest? Representalloms 37 (1992) 1-26.

Chatterjee, Pertha. The Nation It Praenents Colonial und

- Nathonally Thowst and Colondil Worlls A Dertuatme Discourse?

Chrisman, Lavra Ti Imperisl Unconscious" Critical Owarterty 323 (1990): 38-55.

Curistian, Barbara. "Community and Natures The Novel of Tont




路

Connolly, Widana
-PeItcel Theory Modernity. New York Benl backwoll, 15es.
Cormw-Gles JoAnne. Atro-Anesicun Critcksin ment Western

Ctghton, S nnd L. Shepiro. An Exclustve Talk with Saluan Heuhdie" News wect (12 Februnry 1990) 46-4.
Cronin Hechard. The Indian Englloh Novet ki and Mlinleht' Crobly, Chultina Dealing wht Driferences Fewintst Therive Pollticul Rd, Iudtu Butier and Joan W. Scott Routiedge New York, 192. 130-143.
Cunntinhanh Volentue. Nosin是 Out the Indion Really: Tine Literary Supplewemt. 15 May 1981: 3s.
Danta Arthur C. Mugha Art: The Nation (Pobruary 2/9, 1998)64-6\%.
Dayd, Samir. Talking Disty Salman Rushathe Midnistits Chilinen." Colloge Englth S44 (Aprin 1992), 431435
Dugbrick, Maria Trafticking Cuture in Postcolonial Lterature:.
 SPAN (October 1992): 60-7n

Darida, Jacques. Economiments." Diecritics vol 11 Oune 1983) 3-25. -The Truth in Puinting. Truns, Ceofr Bennumgton and lan Mcleod. Chicago: Untversity of Chicago Prese 1887.

Dinwwaney, Anuradha Author(ix)kag Midndett's Chlldren and Shawe Literature of the Idiam Dlaspertat Edemanuel S. Nelson New Yorke Cruempood Prese, 1992. $157=167$.
Dublote W.BE. The souls of Black Folk New York stenet 1969.
Dutx, Jean Piarre. "Magle Realimen in Midadghts Culldren".
Connuenuedth Espay and Studies : 1 (Auturn 1985): 57-3.
 Symposium. Bd. Luigl Sampletro. Millant Dimperio Editore Novere,
Hagloton, Terry. The Ileology of the Aesthotic. Oxford: Bawil Blackwell, Esonwanne, Uzo. Race' and Hermaneatice Peradigm Shth-From Scientific to Hermeneutic Understanding of Race A/ricom Americam Re0lew 25. 4 (1992) 565-581.
Ewing, Kathertne Pratt Arguing Sainthood: Moderutty, Poychoamalysts, and Islan. Durham: Duke Untversty Prese, 1997.
Fanon, Frantz. Black Stin, White Mesk, Trans, Chartes Lam Markmam. New York Grove Press, 1909.
Grove Press, 1963.

Tenton, Janues Keepling up with Solmen Ruchdie. The New Yor* Revie of tooke38( (28 March 1991), 2034

Feroun Jusswall. Chifion Sarts The Pighta of South Aten heundqrants


Phaney, Brian Suture in Literary Analyds. LTT: Litowture Interpredathem Theory v. 2 (1990) 131-144

Fischer, Michael MJ. MEhnicity and the Pos-Modern Arts of Menory:"
 Cufiord and George Marcus Betkeley! Universty of Colifornia Prest 1186. 124-233.
 Midmelthe Cuildrem. The Commowerdith Novel in Engish 5.1 Spring 1992): 38-45.

Thetcher, D.M. (ed) Readine Rushice Propectives on the Fiction of Salwn Rushdie. Allanteg Rodoph 1994

Plectwer, Richurd Meorim Spalm. Berkeley: Univeraly of Callforela Prese 199

Forster, L M. A Passuge te Indian New Yorke Hincourt Brace 1924
Froud, Slgmand. The Frend Reader, Ed. Peter Cey, New York W. W. Norton $\mathrm{CO}_{4} 195$.
-The Interpretastion of Dreams. Tund and ced James Strachey. New York: Avon Booke, 1965.
-Mose Monothelome Tranel Katherime Jones New York Alred A. Knopl 1989.

Friedlander, Saul, Geulle Arad, and Dan Diner (eds). Histery and Memory: Studie in Represutation of the Past. Bloomingtone Indlena University Press, 1994.

Fues, Diana Eswntidity Speedng: Feminlam, Nature O Difference. Now York: Routledge, 1989.
-ILenHfication Papers, New York Routledge, 1995.

Caten Honry Loult, Ir. Figures in Blicke Worde, Stgu, ant the "Reciat" Self. Oxford: Oxford Univerity Prest 1987.
-(ed.) "Race" Writine min Difermen Univirely of Chicago Prese Chenge, 1985

CTre Signifyine Monlegr A Theory of Ancom-Americem Litrrany Criticism Oxfords Oxford Undventy Press, 1983.

Glendenatng, Victorla "A Novelint in the Country of the Miad-" Sumdey Timen Odober 25, 1881:2
 Undverity of Chicago Prese 1997.
"Callu Exile, Call it Immelgration." Review of Jusulme. Ne Yort Time Boo Reden 10 Septmber 1989.9.

Gramed, Antonia, Solection from Prisom Notetroks. Ed. and trant. Quintin Hoare and Ceoffrey Nowdi Smith. New York Intarnational Publishers 1971.

Greene, Coyle "Pemindet Fiction and the Use of Momory". Signs 16:2 (1991):200-321.

Grosbbere Lawrence "Culturel Suudies and/In New Worldse" In Ruces Identiy, mud Representidion in Educotion. Ed Cameron MoCuthy and Warren Crichlow. New York Routledge 1993. 89-103.

Habermat, Juygen. The Philosephicel Discoure of Mollority. Candridees MII Prese 1978
-The Structural Tramsformation of the Puble Sphere. Trand Thomas Burger with Frederick Lawrence Combridge: MIT Prese 1991.

Haflenden John. Noweilsts In Interviede. New York Metheren, 1985
Hall Stuart "Ethendiy: identliy and Difforence." Redical America 22.4 (1991):920.
n
Culture Relevislon Discourse-Encoding and Decoding" In Studying
1993 $20-34$

Hervey, David. The Condilion of Pestmedernity. Oxford Blackwelt 1990.
 Healey, Both. Mosalc vs. Molting Pot." New York Times Book Reolew.
Heath, Staphen. Questione of Cinema. Mloomingtons Indiana Univerolty
Prese 1901.
Hendersor, Mae Gwendolyn, speaking in Tongues: Dialogicu, Dialecticus, and the Black Woman Writerts Iradtuon." Reading Black, Reanims.
 and the Migrant as Story-Teller.' SPAN: Journal of the South Prodfic Ansociation for Cownonwhelth Litherature and Langunge Stultien, 29
Holston, James and Asjua Appadural "Citles and Citzennhip." Pubic Culture 8.2 (Winter 1966): 187-204.
Homans, Margaret Women of Color Writers and Feminist Theory:
New Litevery Histery 251 (Winter 1994): $73-94$
hook, bell. Chooring the Margh as a Sproe of Radical Oponnes.: Yeurnime Rece, Gender Cultural Poldice Bostoms South Rad Proes 1090.

Mutcheon, Linda A Poetice of Postuodurnime New Yorks Routhedes 198
 7.

Irving Ti The Rushdie Confrontution A Clash in Voluen' Iowa Review 20. 1 (Winter 1990): 175-184.
lyer, Nalin. Amearicin/Indians Motaphors of the Sell in uharati Mudcherfeis The Holder of the World.' ARIEL 27A (1990)29-44.

Inanson, Frederic The Political Uncomecieus Theor Cornell Untvertty Pross 1981.
-Third World Literture in the Ere of Multhntional Copitalhen. Social Text 15 (Fall 1900): 6-88

Joyce, James. A Portraft of the Artist an Youme Mam Now York Penguth, 1964.

Juan-Novarro, Santiago. The Dielogit Imagination of Salman Ruchdie and Cartos Fuentes National Allogories and the Sceme of Writing in Mhdmight's Chilliren and Cridtobed Nonate: Neotellcen 20.2 (1994): 257. 311

Juenwalla, Feroza Beyond Indlannesse The Sylituc Concerne of Midnifht's Children" The pournel of Imation Writine in Engilish 122 Ouly 1984) 26-47.

Kammen, Michuel. Mystle Chords of Momory: The Trameformation of Tredtion Amertem Culture New Yorke Knopt 199.

Kasson, John F. Amusimg the Mullon New York Fin Hand 1978.
Kouman, Micheel T. "Author from Three Countries" Nev York Times Boak Review (November 13, 1983), 3, 22-23.


 Creenwood Press 1992 70.77.
Khinanh, Suntl. The Mee of Indila. New Yorks Farnir, Strans Croux, 1997.
Kinsley, David Hindu Gellesser Visions of the Droder Foudulue in the Hindm Rellgtow Tradthlem. Berkeley! Untversity of Callifornla Press, 1986.
Kolodny, Annette. Thi Integrity of Menory: Creating a New Literary Hitory of the United States. Americen Iterature 57 (1985): 291307.
 AREL: 1 Reedeve of internation Ewgish Litwature 262 (April 1905): 4i.
Krishnaswamy, Revath. Mythalogtes of Migraney Postcoloniallism, Postuodermsm and the Politice of (Dis)location" ARIEL: A Reote of International English Literuture 26.1 (Ganamy 1995k 12s.146.
Lacen, Jacques, Ecrits: A Selection. New York: W.W. Norton, 19n.

- Four Fundamental Concepts of Poycho-Analysiar Bd. Jacques-Alain Miler. Trant. Alan Sheriden. New Yorks W.W. Norton and Con 1981
Lakshmil Vilay. "Rushdiefs Fictions The World Beyond the Looking Clase "In Reworidines: The Litarature of the Indian Diaqpona. Ed.
Emmanuel \& Nelson. Now York: Creanwood Press 1992 149-150.


## Laplanche, J. and J-B. Pontalis The Language of Prycheamalyols. New

 York W.W. Norton, 1973.Lamerug Nell Postcolonializen and the Dilemma of Nationallems Alpaz Ahmad's Citique of Third-Worldism." Diaspopa 23 (1993): 373-400. Loong, Llow-Geok "Bharatit Mukherfee'. Intemational Literature in James Press, 1991. 487-500.
Levine, Coorge (ed). Meology and Aesthetice. New Brunswid, N:
Rutyers University Prens, 1994

Liddte Joanna and Renna Josti. Duughters of moleperelener Gender, Coste nd Chen lind Londons Zed Books, 1986

Lha, Shuley Ceok-Lin "Asweying the Cold; or, Contesting the Grounds of Astam-Amextcon Literature. Ne Levery Histery 24 (193): $147-169$

Lppcombt, Dovid. Cought ha Strange Middle Ground Contesting
 163-109.

Low, Cail Chine-Llang In a Free Stater Pos-Coloxialimen and Postmodernden h Bharatu Mukhorjeis Fretion" Women: A Culturel Revicw 41 (Spring 1993): E-18

Marzorat, Corald. "Salnuan Rushdie Flition' Enobatled Infidel" The Nev Yort Time Magualme. 29 Jansimy 1909 24

Masom, Roger Burford. Sahmen Rushdie" PN Rexiew 15.4 (1989): 15-19.
MoClintock, Anne. Impertal Luether: Race, Conder Sexud Sexty in the Colondal Context. New York Routiedge, 193.
-"No Longer in Puture Heaven: Cender, Race and Nationalism." Dangerons Llalsons: Conder, Nation, and Postcoloulal Perepectione Ed. Anne McClintock, Aamine Muft, and Eli Shohat Mhneqpolies Universty of Minnesot Prese 1997. 89-112

Meer, Aneena Charat Mukheflee An Interview.' (OMB 29 (1989):4645.

- "Galnan Rushdien An Interview.' BOMB Interolews. New York New Art Publications, 1992 61-74.

Mesud, Clatre. The Euperor's Tear: Review of The Holder of the Werld Times Literary Supplement, 12 Novenber 1998: 23.

Micheth, Walter Bent Rece into Cultures A Critical Cenealogy of Cultural Idendity." Crittcel Impury 18(1992):053658.

Miler, Donald. Omuppotence and lis Enemtes" Thid Text 11 (1990) 135-43.
Miler, Jacque-Ainh suture (elements of the logle of the stenifient):
Screen 18 (Whuter 1977-7): 2434

Morley, David and Kevin tobine (eda) Spuces of Heritye Clebul Merla, Electronic Lembecpes Culturni Bomenden New Yorks Routhedge
Mortson Tond Beloved Now York Pheme Books 193\%.
-Sula New Yorte Phume Book, 1973.
Mouffe, Chantal "Cutsenohtp and Polltical ldentity: October 61 (Sumaner 1992): 2532.
Mukherfee Arun. Towards an Aesthetics of Oppositions Enars ou Literature, Criticlsm,
Willam-Wallace, 198. Cultural Imperhilism. Stratord, Ontertos Nuname Naiace 1900
Mukherjee, Arun P. Characturixation in Saman (qushdieb Midnisht Children Rreaking out of the Hold of Realism and Sectlng the
 Mukherjee, Bheret. Ance the Ratwe Whe Cluts Batse Mother lones 153 (April4ay 1990: 25-31,61-65.
C-Conquerins Americe ofth harnil Mukherfee: Videocnseste.
-A Convertation with VS Natpaut WHa Robent ioyer
Stume und 50-51 (Fral 1980-Winter 1931) 153-171.
-Darkuess New York Fawcet Crut, 1985
-Days Nishts Culcutta Wh Clark Hhats Now Yorke Doubleday CO. 1977.
-A Four-Hundred-Year-Old Woman
-The Iolder of Whe Wil Nuw York Pawcet Colunntine, 1993.

- Tinundrant Whting Cive Us You Moximaltetw New You The Book Review, Auguct 2s, 1983, 1, 22-29.
-Aa Intarview whith Bharati Mukherfe' With Alison B Carb. Massachusetts Review 24 (1985): 645654
- An Intorview whith Barsti Mukherfee. Wien Michael Comnell, Jesie Grearson and Tom Grime Revi 203 (Spring 1900) 732

Cmin Interview with Bhardi Mukhergee" Whth Ceoli Hancock Connilim Fictiom Maguzin 59 (May 198\%; 30-4.
-"An Interview with Bharni Mukharjea' View 20.5 (1990).
-"Aa Inviolbia Woman'. Saturday Nighte6 (March 1981): 30-40.

- Iasmine Nuw Yodk Peweett Crest 1989.
-Lene H to Me. Now York Alfred A Knopf, 1997.
-The Middlemen ond Other Storles. New York Pawcett Cret 128.
-Prophet and Loss Sahnan Rushdte's Meration of Souls "Village Volce Litenary supplement. 72 (Match 1990\%:9-12
-The Sornow and The Terrore The Hewntin Lugacy of the Air Indla Tregedy. Whth Clask Blate Markhm, Ontario: Viking Pexguin, 1987.
-The Therre Daughter. New York Feweet Crest, 1971.
—WIfe New York Taweett Crest, 1975
Mulvey Laura "Vhual Pleasure and Narrative Cinema.' Screen, 16.3 (1973): 8-18.

Nalk, M. K. A Life in Frogments The Fate of Identity hn Midnight's Children. Indiem Lerary Rewlew 3.3 (October 1985) 63-65.

Nataralan, Nalind Women, Nation, and Narration in Mindightte Children ${ }^{*}$ Scittere Hegomomies. Ed. Inderpal Grewail and Caren Kaplan. Minneapollis University of Minnesota Press 1994
 191.

Needban, Arurcha Ding weney. The Poitics of Post-Colontal lidentiyy Salman Rushde." Muscichusett Review 204 (Winter 1988-1002): 609-24

Negt Oskar and Aloxander Kluge. The Public Sphere and Expertewce. Minureppolic Univerdty of Mimnesotia Prese 19 P

Nebson, Cecil. New Endlishes, New Discoursen, New Epeech Acta World Endilehess Journol of Ewitis as Imternathonal Linguge 10.3 (Wint 1991): 317-323.

Nelson, Bremamuel 8. Bhanti Mutherfees Criticut Perepecthees Nev York Griland Publithing, lic, 1928

- Thanala Markanday, Mharati Mukherjee, and the Indiaa Immigrant Expertence' Toronto South Adan Reolew (Whter 199): 19.
- Troubled Journeye Indian Imulgrant Experdence 鱼 Kamala Markandaylt Nowhere Mam and Bhirati Mukherfee's Darkness" From Conmmenedth to Pot-Colonial. Ed. Anna Rutherford. Sydney. Australla: Dangaroo Prees, 1992: 53-59.

Nietzeche, Priedrich. "On the Truth and Lies in a Nommoral Sanse" Phillosephy Truth Selections from Nietaschis notubots of the Eierly 1870' . Ed, and trunst Danill Breareale. New Jersey: Humanities Prese 1979. 79-10.

Nussbaum, Martha C Pootic Iustice The Lherory Inaghation and Public Life Bontone Bracen Prese, 1905.

Ondaate, Mcheel "Michael Ondatyen Interview by Lhada Flatcheon." Other Solitules. Cmmadim Multicultural Fictionn Bd. Lida Hulchoon and Marion Richmond. Torontor Oxford Univerdty Press 1900. 196-202

Parameswaran, Uma "Handcuffed to FHetory, Salman Rushdiet Art." AREL: A Reolew of Imternational Emgelish Litersture 144 (October 1983). 3445 .

- Lapt He Raturning Chidet: Seleem Sinaif Inaction in Solman Rushdie't Miduligt's Children.' The Literary Criterion 183 (1989):57-6t.
 xu zal Rachakrihnan, $R$. Nationalism, Cender, and the Narrative of ldeotity.

 Midneghtre Children':" ARIEL: A Recle of International Engelish
Literature 252 (April 1994 ): 91-107. Price, David W. Salinan Rushdies "Use and Abuse of Fistory' in
 Prokenh, Gyan. Writing Post-Orienteltet Hhtorles of the Third Word:
Penpective from Indian Historiograptry" Companattee Studies in
Sodety and History 322 (Apdl 1990) 3 3s-40s.
 Plwiniskd, David I. Losing EDen Mo Modern Bombay: Rushdile's.


## (Decumber 21, 1995): 73-82 <br> (Decumber 21, 1995): 73-92 Washington." The Ne Yor Reolew of Booky

Pinctney, Darryl High Cottom Now Yorks Penguhn, 1992

Litruyy Criterion 183 (1983) 1922
Pattanaynk, Chandrabhenu, Intwrview with Salnan Rushale" The



Roo, KA AR And and the Prathe Mindghets Children- Worli Litereture
Today 56 (Winter 1982): 181. Tolay 56 (Whinter 1982) 181.
Rao, Mathemadana. Quest for Idontity: A Study of the Narrative in
Relmenechnelder, Dioter. Hiotory and the Individual in Andta Dosals Clent Leght of Day and Solunan Ruehdle's Mudulght's Childroen." World Llerature Wititen in Emgitish 22.1 (Winter 1934): 190-200. Renan, Ronest Qures-ce qu'une nationT Onures Complates (Part, Mertin Thoma Natiow Nurratlen Bd Hond K Bhabla Now York Routieden, 1990: 8-22
Robbing, Bruce (ed). Intellectuals: Aesthetics, Polltics, Acudomics. Minneapolts Untversity of Minnesota, 1990

- Mrtroduction" The Phantom Public Sphere Miraeapollse Univervity
Rombes, Nicholas $\mathrm{D}_{4}$ Jr. The Satanic Verses as a Cinumatic Narrattve." LheraturefFilm Quarterly 21.1 (1993): 47.53.
Rosen Jonathan "Our Jerusalem. "The New Yer Thaes Boek Rcolee. 23 June 1996: 92
Rons Bruee M. Rememberins Pernowal Past: Dascriptions of Autoblognaphical Memery. New Yorke Oxford Universty Pres, 199.
Rose Jean W. Interview with Salman Rushdie" Contrmperery Authors
Roy, Anindo. The Aesthetics of an (Un)willing Inemigrant: Bharati Mukherjeets Days and Nights in Catculta and Jasmine." Bhartit Mulherfee: Criticel Porspections. Netbor, Emmenuel \& New Yorks Garland Publishing Ince, 1993.

Rubenstonn Roberta conndarter Sefo Conder, Culture, Ficthen Unane Univeraly of Mhole Pres, 19s:

Ruch, Norman. Doomed ha Bombay." Review of The Moor's Last Sight The Nev Yow Tiw Reo Revid, hanuary 14, 1996\%.

Ruhhdie, Solnan Damene, This (the Ordental scene for Youl The New Yorker (lun 23 \& 30, 1997) 50-64.

- A Dangerous Art Form Thu World Took Reve 1 (198) 3 3.
-EDet, Wet Now York Pontheon Books 1994.
-In Conversations Tretions are Lie that Tell the Truth Wh Cunser Crus. The Listener (27 fune 1885): 1415.
-Coodnees The Ammicun Neurots' Th NaHiou 242 (22 March 1986) 34
- Hinaginary Homelands. New Yorke Penguin Books 199.
-The Indian Writer En England."The Ey of the Beholder Indian Writin th Emgitin. Ed. Mangle Butcher. London Commonweelth Inetitute, 1983, 75-83.
-Intorview.' National Public Radio, All Thing Considered Januery 17, 199
- Interview. National Public Radio, Tale of Nation lanuary 15, 19\%6
-Introduction" AH, Tarlq, An Indiam Dynasty. Now York C. P. Putnant Sone 1985.
—Minhtht's Chillown Now Yokk Pengum Booka, 1980.
—"Mudight's Childrew and Shewe." Rumpipi7 (1985): 1-19.
-"Introduction" Minverwork 50 Year of Imdiaw Writing, 194-1997. EC. with Elzabeth Wert. New York Marry Holt and $\mathrm{CO}, 1997$. vil-x.
—Th Moor's Last S4h. New York: Pmathoon Books, 1998.
-Th Riddle of Midnefhe Public Medla Viee, 1985.
- Balman Rushalia With Cherlote Corrwall Writen Tal* - Iteas of Our Thwe Writre hin Conversation Sertes. ICA Video, 1090.
- Salman Ruldise The Satame Verses' When W. L. Webb Writers Tullt - Lens of Our Time. Widters in Converwation Serfes. ICA Cuardinn Vidre, 1599.

> RustomiHCorns Roshnt Expatriates Innenigrantis, and Liternture Three South Astan Women Whters. Masechusetts Rectew 29.4 Cumener 1980265565

Qage Vic The Cod-chaped Holli Salman Rushote and the Myth of Orighe. Himeceriam Stwite In Eugllth 22 (1991):921.

Gaid, Edward Third World Intellectuals and Metropolitan Culture:" Rarlan 93 (Winter 1990): 27-50.

The Worli, Tex Critle Cmbidga, MA: Harvard Undverelty Prees 1923.

Saldivar, fore The Dialectics of Our America: Cementogy, Cultural

Sangari, Kumkun The Polutics of the Posslble Cultural Collique (Fall 198) 157-186

SantWade, Arviadre and Karon Marguertit Redel Refahtiontu the Self. Inumgrant Women in Bharat Mukhofeet New World." Studles in Short Fiction v. 29 (19\%): 11-17.

Scary chaina The Boly h paine The Maldug end Unmathis of the World. New Yoks Oxford Univerity Prees, 198.

Son, Suchimith. Mewory, Language, and Soclety in Salman Rumblipe Haroum sen Sthen Sten "Contemporary Literiture 36.4 (Whater 1905) 654-675.

Scott, Jom W. "Muiticulturalimin and the Poltice of Identity: October 61 (1994) 1219.
 Haroun and the gen of stortes." Contempovary Literature 364 (Winter 1990) 654.67.

Sennett Richard. The Ilendity Myth' The New Yort Thes Jonuery 30 , $1294 \mathrm{P}^{17}$.

Soth Sunt After Miduight. Imdin Todey (1) April 1983) 1367.
 Review $1.2(1900): 30-53$.

Sholenar, Polly. Home Trethes Bhareat Mulherfee, Wortd Chiven. Volce Literary Supplemento June 1983 19.
 1922
-The Subfect of Seutotics Now Youk Oxford Umlverthy Pres 1988
-TMreshold of Vishle World. New York Routledge, 1993.
Stigh, Amruyth Josoph T. Skerrett, Jry and Robert E. Hogan (ed.). Memory - Cultural Politics Nrw Appremehes Awertew Elonic Literatures. Botom: Northeastern Univerity Pres, 199.
-Memory, Narrathoe, O Ilen itiy: New Approsches in Ethuic Americom Litaraturem Bostont Northenstern Untverity Prent 1994

Stngh, Sushlla. Selman Rushdte' Nowell Grow Pantasy to Reallty. Commonwealth Review 11 (1980): $111-23$.
glemon, Stophen. Post-Colonial Allegory ad the Iransformation of History. Tournal of Commomuolth Litriature 23. 1 (198): 157-168.

8mith, Anthony D. Natiomal Ulenitty. Renor Univeritty of Las Vegat Pres 199.

Santh, Colin "The Undeurable Lightnews of Salman Ruphdig." Selected Papers of the 10th Annual Conference on Comunonwealth Literature and Larguage Studies, Kondesteln, 11-14 June 1987. Critced Apprometw to the New Literatures in Emglich Ed. Dieter Rlemenechnolder. Eseen Die Blau (ade 1989. 104-115.

Splegelman Art Mmus. A Suroker" Then It Au Here My Treubles

## Coman

New York Pantheon, 1091.
Splliers, Hortense I. "All the Thunge You Could Be by Now, I Gierausad Froudit Wif We Your Mothert Pychomalyols ned Race. Coundiry 2 225 (Iull 1906) 78141.
-Comparntive Americam Lleutities: Rece, Sex, ad Nationally im the Modem Text. New Youk loutledge 1991.
-Manais Beby, Papab Maybe Dlacritics 172 (Sunmer 107): 65-8.
Splvak, Guyatr Chakravorty: Outside in thenchine Machma. Nuw York Routtedys, 1993.
-The Post-Colonlal Critic. Ed Surh Hertyn. New Yorks toutledge 1900.
--"Reading The Satanic Verese" Public Culture 21 (Fell 1909); 79-99.
Sivestav, Aruna The Erupire Wrute Backi: Language and Fibtory in Shame and Munight's Childrem." IPat the Lust Post Theortahin PostColonialism and Post-Moderntem Bditinn Adarn and Htelen Tinn Aberte: Univecolty of Cidgary Pres 1930. 65-7\%.

St Andrews B. A. Co-Wanderent Kogawa and Mukherpee New Inumgrant Writerne" World Lterature Todey 06.1 (1992) 56-58.
stemberg, Fybil Bharat Mukherfes." Publisher's Weathy 25 Auguet 1929.46-47.

Suleri, Sara Contraband Hhtortes Salmen Rushdie and the Emboditnent of Blasphemy. Yale Revicw 7\% 4 (Sumuner 1909), 604-124.
-The Rhetorlc of Exdish India Chicugo Univerdty of Chiongo Preen 1992

Sunder Rajan, Rafonwari. Real and Imaghed Wowem: Cender, Culture and Postcoleniallsw. Now York: Routlidge, 1993.

Cwann, Joxeph Elast I East and Wed West Satman Rushdies Mldudemt" Chlldrew en Indian Novel." Worl Liteveture Writte in Emelisi 25. 2 (Aubumn 1980): 359362.

Tapphay Crig. South Asi/North America New Dwelling and the Paster in Rumerlding: The Liternture of the Indian Dhepporio. Ed. Imanuel S Nelbon Westport, C1I Creouwcod Pres, 1922 35-4



Tharoor, Shash Inder Frow Mhlulght Millonhum. Now York Arcade Publishine 1997.

Tomplin, Jane Sensutiond Destune The Culturai Wort of Americm Fictlom, 1790-1 4 a. New York Onford Univerdty Press, 12ss:

Vhwanathan Gauri. Masts of Conquest Literary Study and Britioh Rule In Indha. New York Columbin Univertity Pree 1909.

Walcott, Derrk Collectel Peems, 1948-1984. New York Noonday Prese, 192.

Wall, Cheryh A (ed.), Changine Our Own Werds Eswys m Criticism, Theory, and Writhy by Black Women. New Brunewick Rutgers Untversity Proes 1990.

Woltom Jean Re-Phacing Race han (White) Peychomalytic Dlecourne Founding Nartatives of Femindm.' Critical Imquiry 21 (Gumemer 1998):775-804.

Warner, Mchael The Mas Publle and the Mass Subject. In The Phantow Public Sphere Ed. Bruee Robblins. Minneapolis University of Mmnesota, 1993. 234-236.

Wieneling, Leon Midughtw Other Chlldren New Republic (December 1983): 32-34.

Weet, Cornel "Black Culture and Postmodernlena" Remading History. Ed. Barbara Kruger and Phil Mriani. Seattler Bey Preas, 1989. $87-96$
-The Diemua of the Black intolltectual.' Breekty Breadi Insurgent Bleck hutellectual LIT EA beil hooks and Cornel West Bowtons South Find Preen 1991. 131-146.
-Tace Motten New York Vintage Books 199
Whte, Jonathan Politics and the Individual in the Moderniot Historical Novel. Rocusting the Werlis Writime After Colondalisma caltimores The Johas Hophin University Pres, 1993 209 -240.

Wickranagamage, Crunen. Relocetion as Positive Act The Imenlgrant Experlence hn Bharat Mukhetfee's Novels" Diaspere 22 (19024); 171-200
 Quarterly 263 (Autumn 1984) 2337.
Wolpert, Stanley: A New Hetory of India Now York Oxtord Untverelty Proen 1923

Yates Frunces Amelha The Art of Memery. Chlougor Cuicego Unlverdity Preen 1966.

Zurck Sluvol Looking Aury: An Iniveduction to Decques Licien Threugh Popular Cuiture Cambridgen MIT Prus, 1901.
-The Sublime Object of Lleclogy. New Yorke Vere, 1089.


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[^0]:    ${ }^{1}$ It is important to point out that this breakdown in our ability to form objective price expectations is not due to limitations in our computational ability; it happens because the problem is inherently ill-defined making it impossible for us to pin down a price expectations from a sea of many plausible price expectations that everyone can agree upon objectively. We will say more about this in Section 1.2.

[^1]:    ${ }^{2}$ Varian (1993, p.1) argued that the recent upsurge in interest in this and other traditionally difficult research questions is most likely due to the availability of better methods of analysis that promise researchers more fruitful ways of addressing these questions.
    ${ }^{3}$ See Cox (1994).
    ${ }^{4}$ Some examples are market crashes, mean reversion, relatively high level of trading, presence of technical trading, excess volatility, volatility clustering etc. These behaviors are curious from the stand point of standard neoclassical models with strong underlying rationality assumptions.
    ${ }^{5}$ Varian (1993) has argued that this is because theorists did not have the right tools to address the problem and it is not because they are not interested in the problem.

[^2]:    ${ }^{6}$ This entails making strong rationality assumptions so that every agents in the model will arrive at the same price expectations. Another common approach in neoclassical models is to assume a tatonnement process, see Arrow and Hahn (1971).
    ${ }^{7}$ Furthermore, according to Simon:
    Neoclassical economic theory assumes that the problem agenda, the way in which problems are represented, the values to be achieved (utility function), and the alternatives available for choice have all been given in advance. It has no systematic way of explaining how problems get on the agenda ..., what is it that people value and how values change, or how action alternatives are created ... . Hence it is incapable of creating a genuine economic dynamics. (Simon et al. 1992, p.5).

    For more information, see the bounded rationality works of Herbert Simon-Simon 1947, 1955, 1957, 1959, 1976, 1982, 1986, Simon et al. 1992.

[^3]:    ${ }^{8}$ See for instance the arguments of Alchian (1950), Friedman (1953), or a recent discussion of Alchian's contribution to economics by Demsetz (1996).
    ${ }^{9}$ Kenneth Arow, one of the pioneer architects of the neoclassical framework, recently raiseds the concern that "the attainment of equilibrium (inevitably) requires a disequilibrium process", and in the presence of disequilibrium it will not be meaningful to talk about rational behavior in the sense defined in neoclassical theory (Arrow 1986, p.S387).
    ${ }^{10}$ A Classifier system is a machine learning system that is capable of learning syntactically simple rules so that it may operate in an arbitrary environment. What we have done differently is to replace the conventional rules typically found in these systems with fuzzy rules.

[^4]:    ${ }^{11}$ The forecasting equation we will use is: $E_{( }\left(p_{t+1}+d_{t+1}\right)=a\left(p_{t}+d_{t}\right)+b$.
    ${ }^{12}$ This is the same result obtained by Arthur et al. 1996, 1997, and Palmer et al. 1994 in their Santa Fe Institute Artificial Stock Market Model.

[^5]:    ${ }^{13}$ This is especially evident during market crashes. One good example is the recent market crash on October 27, 1997. On that day, the Dow Jones Industrial Average suffered its biggest point drop in history. This occurred despite the fact that fundamentals of the United States economy are strong (and have been for the past several years) and the prospects for continued growth, with low inflation and low unemployment, are equally great. On the following day, October 28, 1997, the U.S. stock markets soared back with the Dow Jones Industrial Average posting its biggest point gain in history amid record volume.

[^6]:    ${ }^{14}$ Sargent (1993) and Kirman and Salmon (1995) provide good reviews of recent learning models in economics.

[^7]:    ${ }^{15}$ Examples of rational learning models include the earlier works of Prescott (1972), Cyert and DeGroot (1974) (section titled "Consistent Model"), Rothschild (1974) and Townsend (1978), and more recent works of Frydman (1981), Townsend (1983a, 1983b), McLennan (1987), Mirman et al., (1984), Bray and Kreps (1986), Easley and Kiefer (1989), Kiefer and Nyarko (1988, 1989), and Blume and Easley (1993) among many others.
    ${ }^{16}$ Examples of ad hoc learning models include Radner (1972), Cyert and DeGroot (1974) (section titled "Inconsistent Model"), DeCanio (1979), Evans (1985), Bray and Savin (1986), Lucas (1986), Marcet and Sargent (1988, 1989a, 1989b, 1989c), Nyarko (1990, 1991a, 1991b), Woodford (1990), Linn and Stanhouse (1997), etc.
    ${ }^{17}$ Kahneman et al. (1982) show that likelihoods and preferences expressed by individual experimental subjects do not satisfy the coherence properties that are necessary for the existence of subjective probabilities. Moreover they are found to update probabilities but they do not appear to use information efficiently in that posterior probabilities differ quantitatively and systematically from those predicted by the use of Bayes's rule (Nelson and Winter 1982, Edwards 1968, Tversky and Kahneman 1974, Cyert and DeGroot 1987). Grether (1992) also describes experiments in which it seems clear that individuals systematically fail to take "proper" account of prior probabilities.

[^8]:    ${ }^{18}$ Often for instance the "regression parameters" are assumed to be unknown but the residual variance is assumed to be known.
    ${ }^{19}$ MMIE refers to Mills-Muth implicit expectations. Bullard gives it a special name to distinguish it from the concept of rational expectations. The intention is to emphasize that there is a process that drives the formation of MMIE. Mathematically, it is described by: $\mathrm{X}_{\mathrm{rs}}=\mathrm{E}_{\mathrm{r}}\left(\mathrm{X}_{\mathrm{tr}}\right)$, where $\mathrm{X}^{*}$ is the forecast of X , and $\mathrm{E}_{1}$ is the mathematical expectations operator based on information available at time $t$.

[^9]:    ${ }^{20}$ We should emphasize that the so called market anomalies are not really anomalies per se. They are called "anomalies" only because they cannot be explained by standard asset pricing models.

[^10]:    ${ }^{21}$ Arthur finds that in markets where individuals form their expectations heterogeneously, deductive reasoning will not provide any closure and will result in indeterminacy (see also discussions by Arrow 1986, Blume and Easley 1995).
    ${ }^{22}$ Gennotte and Leland (1990), and Jacklin, Kleidon and Pfleiderer (1992) have demonstrated that uncertainty among market participants about the proportions of investors who follow various investment strategies is sufficient to produce market crashes, even if investors rationally update their beliefs over time.

[^11]:    ${ }^{23}$ See also Dreman (1982).

[^12]:    ${ }^{24}$ See also a related discussion by Baumol and Quandt (1964).

[^13]:    ${ }^{25}$ To give a second analogy, suppose you are given the task of explaining in 300 words the contents of a 10 page essay. This can be accomplished by lifting sentences out of the essay to make up the 300 words, or by writing a 300 words summary for the 10 pages essay. The first approach (analogous to the conventional approach) would be very precise because the sentences are exact duplicate of those in the essay, however, its content would be not as relevant or as meaningful as it

[^14]:    will merely contain a collection of scattered thoughts. On the contrary, the second approach (analogous to the fuzzy logic approach) would not be as precise, but its content will be more meaningful as it will attempt to connect the ideas in the entire essay and make sense out of it. The latter approach will not be as precise because in the summary you will need to use words or phrases that encompass a fuzzier and larger set of thoughts (see Zadeh 1973, pp. 28-29).

[^15]:    ${ }^{26}$ See for instance, Holland (1992), Goldberg (1989) and the discussion in Section 2.6 of this dissertation.
    ${ }^{27}$ However, psychologists have yet to agree on a precise definition of these two systems, or on where to draw the line that distinguishes one system from the other. For instance, Smolensky (1988) distinguishes these systems as intuitive processor versus conscious rule interpreter, Hinton (1990) calls it intuitive and rational processors, Schneider and Shiffrin (1977) use the terms automatic and controlled processing, Evans (1989) describes them as perceptually based matching process and linguistic-logical process, and Shastri and Ajianagadde (1993) distinguish them as reflexive and reflective reasoning.
    ${ }^{28}$ This example is from Sloman (1996, p.1).

[^16]:    ${ }^{29}$ Holland has shown in his Schema theorem that the implicit parallelism inherent in a GA allows it to process on the order of $\mathrm{N}^{3}$ schemata per generation where N is the number of strings in the population. To put this in perspective, if we have 100 strings, a GA will process on the order of a million schemata.

[^17]:    ${ }^{30}$ This is the same reason why a GA so efficient. This will become obvious after our discussion of the Schema Theorem in Chapter 2.

[^18]:    ${ }^{31}$ This example is from Holland et al. (1989).

[^19]:    ${ }^{32} \mathrm{Klir}$ and Folger (1988) have shown that an isomorphism exists between logic and set theory. As such the term fuzzy logic and fuzzy set theory will be used interchangeably. To be more precise, some may argue that it is really a fuzzy subset theory and not fuzzy set theory. However, like the majority, we prefer to use the term fuzzy set theory. Both Klir and Folger (1988) and Klir and Yuan (1995) are good introductory text on fuzzy sets theory.

[^20]:    ${ }^{33}$ "Young" is taken to be synonymous with "not old" (i.e. the complementary set) here.
    ${ }^{34}$ Such inconsistency would not have survived in the Boolean logic paradigm for Boolean logic requires an entity to be either a member (truth) or not a member (false) of a set, and cannot permit any overlap between a set and its complement - "truth" and "false". It is therefore interesting to note how such seemingly inconsistent ideas can fit in nicely within the fuzzy set paradigm.

[^21]:    ${ }^{35}$ See Section 2.2.2 for the relationship between a set and its complement.

[^22]:    ${ }^{36}$ The universe of discourse of any fuzzy set $A$ in $X$ is defined to be the set of points in $X$ for which the membership function for $A$ is positive).

[^23]:    ${ }^{37}$ Product Operators
    $A N D: \mu_{A \cap B}(x)=\mu_{A}(x) \bullet \mu_{B}(x) ; \quad \mathbf{x} \in \mathbf{X}$
    OR: $\mu_{A \cup B}(x)=\mu_{A}(x)+\mu_{B}(x)-\mu_{A}(x) \bullet \mu_{B}(x) ; \quad \mathrm{x} \in \mathrm{X}$
    Bounded Sum/Difference Operators
    $A N D: \mu_{A \cap B}(x)=\max \left\{0, \mu_{A}(x)+\mu_{B}(x)-1\right\} ; \quad \mathrm{x} \in \mathrm{X}$
    $O R: \mu_{A \cup B}(x)=\min \left\{1, \mu_{A}(x)+\mu_{B}(x)\right\} ; \quad x \in X$
    ${ }^{38}$ Sugeno Class Complements: $\quad \mu_{-A}(x, \lambda)=\frac{1-\mu_{A}(x)}{1+\lambda \mu_{A}(x)}, \quad x \in X$
    Yager Class Complements: $\quad \mu_{-1}(x, \lambda)=\left(1-\mu_{1}(x)^{\lambda}\right)^{1 / \lambda}, \quad x \in X$

[^24]:    ${ }^{39}$ The Mamdani implication is important because it will not have "interaction." Basically, this means that it will produce the same result regardless of whether it uses composition based inference or individual rule based inference. See Driankov, Hellendoorn and Reinfrank (1993, pp.101-102).

[^25]:    ${ }^{40}$ See Driankow, Hellendoorn and Reinfrank (1993, pp.132-141) for details on how to carry out these calculations.

[^26]:    ${ }^{41}$ The equation for calculating the Centroid is given by:

    $$
    u^{*}=\frac{\int u \cdot \mu(u) d u}{\int \mu(u) d u}
    $$

    where $u^{\cdot}$ is the centroid, $u$ are values within the domain of the final fuzzy set, and $\mu(u)$ is the membership value for a given $u$.

[^27]:    ${ }^{42}$ These examples are from Bauer, Nouak, and Winkler 1996, and Kosko 1993, pp. 184-187.

[^28]:    ${ }^{43}$ GA is the brainchild of John H. Holland at the University of Michigan (see Holland 1970a, 1970b, 1970c, and 1975). The initial ideas were first conceived by Holland in the early 1960s. Robust is used here to mean efficient and efficacious. We will follow Goldberg's (1989) footsteps in justifying that a GA is indeed efficient and efficacious later. Davis (1991) is a good reference for GAs.

[^29]:    ${ }^{4}$ See also the original work of Holland (1975). For a quick overview see Mitchell (1995). Vose (1991) has a generalization of schema and genetic algorithms.

[^30]:    ${ }^{45}$ This result has been rigorously proven in theory (see Holland 1970b, 1970c, 1975, and 1987, and Bethke 1981).

[^31]:    ${ }^{46}$ See also Grefenstette $(1985,1987)$ for demonstrations of the robustness of GAs.

[^32]:    ${ }^{47}$ We need to distinguish between a random search strategy and other methods that make use of randomness. For instance, a GA uses randomness but is not what we would called a random search strategy. That is, although it has some degree of randomness, a GA's search is not directionless.
    ${ }^{48}$ Bellman (1961) called this the "curse of dimensionality".

[^33]:    ${ }^{49}$ Hamming distance is used here to refer to the number of bits that separates two binary integers. For instance if we compare the strings 0101 and 0111 , there is a hamming distance of 1 between them because only one bit needs to be flipped to make the two strings identical.

[^34]:    ${ }^{50}$ Besides, as we have mentioned earlier, more definitive and careful experiments confirming the robustness of GAs have already been conducted by De Jong (1975). There is very little incremental value in carrying out such a demonstration here.

[^35]:    ${ }^{51}$ The GA code is a simple modification of the SGA code in the toolbox.

[^36]:    ${ }^{52}$ To recap, investors have to rely on inductive reasoning because the ill-defined environment they operate in prohibits the use of deductive reasoning. The use of fuzzy notions is necessary because it allows investors to efficiently process the immense amount of information that enters the market.
    ${ }^{53}$ Our model is based on the Santa Fe Artificial Stock Market model by Arthur et. al $(1996,1997)$. Another work that investigates similar issues is Beltratti and Margarita (1992).

[^37]:    ${ }^{54}$ Besides studying the outcomes under this dividend process, part of our experiments also include investigating the consequences of alternative dividend processes on the model's behaviors. Specifically, we have investigated the consequences of including a cyclical drift term as well as a linear growth drift term in the dividend process. More will be said about these alternative processes in Section 3.3.

[^38]:    ${ }^{55}$ This optimal demand function is derived from the first order condition of expected utility maximization of agents with CARA utility under the condition that the forecasts follow a Gaussian distribution (see Grossman 1976 for details). But when the distribution of stock prices is non-Gaussian (as we will see in our simulations) the above connection to the maximization of a CARA utility function no longer exists, so in these cases we simply take this demand function as given.

[^39]:    ${ }^{56}$ In practice, we have two additional bits to denote the weight of each rule in a Rule Base and the logical connective used in the conditions of the rules. The interpretation of these two bits has already been discussed in Section 2.10. In our experiment, we have kept the weights the same and we have used the logical ' $O R$ ' operator in all the rules.
    ${ }^{57}$ In other words, the five bits for the conditional part of a rule would be arranged according to:
    [ $\left.p^{*} r / d p / M A(5) p / M A(10) p / M A(100) p / M A(500)\right]$

[^40]:    ${ }^{58}$ When we set the universe of discourse to the interval [ 0,1$]$, we have implicitly multiplied each of the market descriptors by 0.5 . So if a market descriptor is equal to 0.5 , it means that market price is exactly equal to the benchmark that is referred to in the market descriptor.

[^41]:    ${ }^{59}$ These intervals are chosen so that the HREE (homogeneous rational expectation equilibrium) values are centered in these intervals.

[^42]:    ${ }^{60}$ Nonetheless, fuzzy logic does allow for internal inconsistency if we were to compare it to Boolean logic. Recall that we have argued in Chapter 2 that a variable may be a member of both a set and its complement.

[^43]:    ${ }^{61}$ Note that in our experiment, we do not allow crossover to happen between different agents.
    Crossover only takes place among the rule bases held by the same agent. We do this so that we can investigate how agents learn by observing only the common information in the market and not by exchanging ideas with each other.

[^44]:    ${ }^{62}$ The slow (fast) learning agents are those who revise their hypotheses less (more) frequently.

[^45]:    ${ }^{63}$ We estimated the standard deviation of the REE price to be 5.4409.
    ${ }^{64}$ For evidence on volatility of market price and related tests, see Leroy and Porter (1981a, 1981b) and Shiller (1981). Shiller (1988) is a discussion of the volatility debate..
    ${ }^{65}$ Note that $\sigma_{p+d}^{2}=(1+f)^{2} \sigma_{\varepsilon}^{2}=[\rho /(1+r-\rho)]^{2} \sigma_{c}^{2}$. This result is derived in Appendix A. This equation will give us a variance of 4 when we substitute into this equation the parameter values listed on Table 5 .

[^46]:    ${ }^{66}$ There stocks were selected to present the results for a variety of the major industries in the economy.

[^47]:    ${ }^{67}$ Excess Return is calculated as $\frac{\left(p_{t+1}+d_{t+1}-p_{t}\right)}{p_{t}}-r_{f}$.
    ${ }^{68}$ In the experiments, we have placed an upper bound on the number of shares that can be traded at 10 shares per period, which represents $40 \%$ of the number of shares available in the market.

[^48]:    ${ }^{69}$ See Karpov (1987).

[^49]:    ${ }^{70}$ Under the alternative dividend process, the conventional Rational Expectations Equilibrium (REE) will not make sense because conventional REE is a static concept. Nonetheless, it is intuitively clear that a dynamic equilibrium can exist. This will be an equilibrium in which every agents correctly forecast the ups and downs in the market at each point in time. Our results seem to suggest that this is what the agents are trying to achieve. We should also point out that our calculation of the REE price is still based on the parameters derive under the previous conditions. For ease of exposition, we will continue to refer to it as the REE price although we recognize that it does not make sense to talk about a REE.

[^50]:    ${ }^{71}$ See Brock, Lakonishok and LeBaron (1992), Sweeney (1986, 1988) and Taylor and Allen (1992) for evidence on technical trading. For evidence on the predictive value of Price-Dividend ratio see Campbell and Shiller (1988a, 1988b). For predictability in the market in general, see Campbell, Lo and MacKinlay (1997). See also the related works of Cutler et. al (1989, 1991), Fama and French (1988), Fama (1991) and Lo and Mackinlay (1988).

[^51]:    ${ }^{1}$ This is the probability that an agent will have one of his rule bases subjected to mutation. When a particular rule base is selected for mutation, the probability that each bit is mutated is 0.03 , and the probability that a bit will be transformed from 0's to non-0's or vice versa is 0.5 .

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[^54]:    -Gender Troubles Founduland the Submersion of Identily. New York: Rontledes. 1990

