# COMPUTER SOLUTION OF THE GENERALIZED LINEAR 

## LEAST SQUARES PROBLEM USING MODIFIED

GRAM-SCHMIDT ORTHOGONALIZATION

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## PREFACE

This report describes the use of modified Gram-Schmidt orthogonalization in computer routines that find a basic approximate solution and the least squares solution of minimum Euclidean norm.to the system of equations $A X=B$, where $A$ is an $m$ by $n$ matrix or rank $r, X$ is an $n$ by $h$ matrix, and $B$ is an $m$ by $h$ matrix. $A$ can be treated as if it were of a user-specified rank, $k$.

The report includes a description of the application of the routines to (a) perform stepwise regression analysis and (b) assess the effect on the solution of decreasing the reliability of the entries in the coefficient matrix.

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## CHAPTER I

## INTRODUCTION

This report discusses the use of modified Gram-Schmidt orthogonalization for solving generalized linear least squares problems and performing stepwise regression analysis. Chapter I of this report describes some sources of generalized linear least squares problems. Chapter II presents a general discussion of the generalized linear least squares problem. The closely related problem of stepwise regression analysis is discussed in Chapter III. An algorithm constructed by E. E. Osborne (1) to solve generalized linear least squares problems and some modifications and additions that have been made to Osborne's algorithm are described in Chapter IV. A package consisting of two computer subroutines has been written to implement the algorithm described in Chapter IV. Chapter V describes test cases that were run using the package and the results of these test cases.

## Linear Least Squares Problems in Curve and Surface Fitting

One source of a generalized linear least squares problem occurs when trying to find the function,

$$
y=f(\underline{t}, \underline{c})
$$

that best (to be defined) represents a set of data points,

$$
\{y ; t\}_{i}
$$

where $y$ is the dependent variable, the $t$ are the independent variables,
the $\underline{c}$ are the coefficients to be determined (the solution vector), $f(\underline{t}, \underline{C})$ is a function from a given family of functions that is linear in $c$, and $\{y ; \underline{t}\}_{i}$ is the $i-t h$ observation. Note that $f(\underline{t}, \underline{c})$ is not necessarily linear in $t$.

For example, we may wish to represent the set of data points,

$$
"\left(t_{i}, y_{i}\right)=(2,3),(0,1),(1,1), "
$$

by a function, $f(\underline{t}, \underline{c})$, from some given family of functions, that gives the best fit. $c$ is called the vector of parameters for this family. The function that gives the best fit is taken often to be the function for which

$$
\begin{equation*}
\sum_{i=1}^{m}\left(f\left(t_{i}, c\right)-y_{i}\right)^{2} \tag{1.1}
\end{equation*}
$$

is minimized, where $m$ is the number of data points and the general form of $f(\underline{t}, \underline{c})$ has been pre-determined. This definition was proposed by Gauss (2) and is the most often used definition of the best fit (3). Finding the vector $\subseteq$ that minimizes (1.1) is called a linear least squares problem. The discrepancy, or error,

$$
f\left(t_{i}, \underline{c}\right)-y_{i}
$$

is called the i-th residual.

It will be shown that a necessary and sufficient condition for expression (1.1) to possess minima is that

$$
\frac{\partial}{\partial c_{j}}\left(\sum_{i=1}^{m}\left(f\left(t_{i}, c\right)-y_{i}\right)^{2}\right)=0
$$

for $j=1, \ldots, n$, where $n$ is the number of constants, $c_{j}$, which are to be determined.

Taking the first partial derivatives with respect to $c_{j}, j=1, \ldots, n$, we obtain

$$
\begin{equation*}
\sum_{i=1}^{m}\left(f\left(\underline{t}_{i}, \underline{c}\right)-y_{i}\right) \frac{\partial f\left(\underline{t}_{i}, \underline{c}\right)}{\partial c_{j}}=0 \tag{1.2}
\end{equation*}
$$

for $\mathrm{j}=1, \ldots, \mathrm{n}$.
If we attempt to fit the above data to a function of the form

$$
f(\underline{t}, \underline{c})=c_{1}+c_{2} t_{1},
$$

equations (1.2) generate the system of equations

$$
\begin{align*}
& 3 c_{1}+4 c_{2}=5 \\
& 4 c_{1}+10 c_{2}=7 \tag{1.3}
\end{align*}
$$

These are called the "normal equations."
Solving the normal equations, we obtain

$$
c_{1}=\frac{11}{7} \quad \text { and } \quad c_{2}=\frac{1}{14} .
$$

An equivalent way of looking at the problem of finding the curve that best fits the data is that we are trying to find the least squares solution of the overdetermined system of equations

$$
T \underline{c}=y \text {, where } T=\left[\begin{array}{ll}
1 & 3 \\
1 & 0 \\
1 & 1
\end{array}\right] \text { and } y=\left[\begin{array}{l}
2 \\
1 \\
1
\end{array}\right] \text {, }
$$

or

$$
\begin{align*}
& c_{1}+3 \cdot c_{2}=2 \\
& c_{1}+0 \cdot c_{2}=1 \\
& c_{1}+1 \cdot c_{2}=1 . \tag{1.4}
\end{align*}
$$

Problems of this form can also arise from situations unrelated to curve fitting.

There is no vector $\underline{c}$ such that (1.4) is satisfied exactly since there are more equations than variables and none of the three equations is a restatement (1inear superposition) of the other two. However, there is a point $\left(c_{1}, c_{2}\right)$ such that

$$
\left(c_{1}+3 c_{2}-2\right)^{2}+\left(c_{1}-1\right)^{2}+\left(c_{1}+c_{2}-1\right)^{2}
$$

is a minimum. That point is (11/7,1/14). This corresponds to finding a vector $\mathfrak{c}$ such that

$$
\begin{equation*}
\|T \underline{c}-y\| \tag{1.5}
\end{equation*}
$$

is a minimum, where $\|\mid \underline{c}-\underline{y}\|$ is the length (or "Euclidean norm") of the vector Tc-y. The length of the vector $\underline{w}$ is defined to be

$$
\|\underline{w}\|=\sqrt{\underline{w}^{T} \cdot \underline{w}}=\sqrt{\sum_{i=1}^{n} w_{i}^{2}}
$$

and is denoted by $||\underline{w}||$.
The $\underline{c}$ that minimizes (1.5) is the linear least squares solution of equations (1.4).

The above example had only one independent variable. In general. there can be any number of independent variables in the function that is used as the mathematical model for the curve to be fitted. An example with two independent variables is the following.

The distance of penetration of a projectile into a target depends upon the thickness and hardness of the target plate (4). A simple mathematical model might include only the thickness ( $t_{1}$ ) and hardness $\left(t_{2}\right)$ and have the linear form

$$
\hat{y}=c_{1}+c_{2} t_{1}+c_{3} t_{2}
$$

where $\hat{y}$ is an estimate of the dependent variable $y$ (penetration), and the $c_{i}$ are the coefficients to be determined.

The need to solve a generalized linear least squares problem occurs almost any time one seeks the solution of an overdetermined system of equations (one which has more equations than variables),
$A x=b$.

Only in exceptional cases can all of the equations be satisfied. We could choose a subset of the equations to be satisfied exactly. The fit of the remaining equations would be disregarded. In the least squares approach, we fit all the equations as closely as possible.

## CHAPTER II

THE GENERALIZED LINEAR LEAST SQUARES PROBLEM

Problem Definition

The definition of the generalized linear least squares problem will be given after a short discussion of systems of linear equations.

## Systems of Linear Equations

Consider the system of linear equations $\mathrm{Ax}=\underline{\mathrm{b}}$ consisting of m equations in $n$ variables. The coefficient matrix, $A$, is an $m$ by $n$ matrix, where $m$ may be less than, equal to, or greater than $n, b$ is an $m-$ component vector (the "right hand side", or vector of constants), and $\underline{x}$ is an $n$-component vector (the solution vector).

Let the $j$-th column of a matrix, $A$, be denoted by $A^{j}$. The column rank of the matrix, $A$, is defined to be the maximum number of linearly independent columns in $A$ (5). A is linearly independent of the other columns of $A$ if there do not exist constants $\alpha_{i}$ such that

$$
\sum_{\substack{i=1 \\ i \neq j}}^{n} \alpha_{i} A^{i}=A^{J}
$$

The row rank of $A$ is the number of linearly independent rows in A (5). The row rank is equal to the column rank (6). The term rank refers to the column rank throughout the remainder of this report. The rank of a matrix is less than or equal to $\min (m, n)$. If the rank
of the matrix is equal to $n$, the matrix is said to be of full rank. Exactly Determined Systems of Equations (mmn)

If $A$ is an $m$ by $n$ matrix of full rank $n$, the ordinary inverae, $A^{-1}$, of $A$, exists, and $\underline{x}-A^{-1} \underline{b}$. The solution vector $\underline{x}$ is unique (5). Underdetermined Systems of Equations ( $\mathrm{m}<\mathrm{n}$ )

If the system of equations has more variables than equations ( $m<n$ ), the system of equations is probably consistent. A system of equations is consistent if the rank of the coefficient matrix is equal to the rank of the augmented matrix ( $\mathrm{A}, \mathrm{b}$ ) (5). The rank of the system of equations is less than or equal to $m$, since any set of $m+1$ or more $m-$ component vectors is linearly dependent (5). When the number of variables is greater than the number of equations, there is a linear subspace of solutions. Two types of solutions are usually of interest in this case. They are a basic approximate solution that has at most $r$ nonzero components, where $r$ is the rank of the coefficient matrix, and the least squares solution of minimum length (Euclidean norm). These types of solutions will be described in detail in the next section.

Overdetermined Systems of Equations ( $m>n$ )

If the matrix, $A$, is an $m$ by $n$ matrix, where $m$ is greater than $n$, the system of equations $A x=b$ is most likely inconsistent since there are more equations than variables. A system of equations is inconsistent if the rank of the coefficient matrix is not equal to the rank of the augmented matrix ( $\mathrm{A}, \underline{\mathrm{b}}$ ) (5). With $\mathrm{m}>\mathrm{n}$, if the system of equations is
consistent, then $m-n$ of the equations are restatements of other equations or combinations of other equations in the aystem; they provide no new information. If the system of equations is consistent, there exists a unique vector $\underline{x}$ such that $A x=b$.

If the system of equations is inconsistent, there does not exist a vector $x$ such that $A \underline{x}=\underline{b}$. In this case, the conventional choice is to find a vector $x$ that minimizes the length of the vector $A x-b$. As mentioned previously, the length (or Euclidean norm) of a vector $w$ is defined to be

$$
\|\underline{w}\|=\sqrt{\underline{w}^{T} \underline{w}}=\sqrt{\sum_{i=1}^{n} w_{i}^{2}}
$$

and is denoted by $|\mid \underline{w} \|$. The vector $A \underline{x}-\underline{b}$ is called the "residual vector." A vector, $x$, that produces the minimum value for the length of the residual vector is called a "least squares solution." The problem of finding a solution vector that produces a residual vector of minimum length is called a "linear least squares problem."

If the rank, $r$, of $A$ is $n$, where $n$ is the number of columns in the matrix, the vector that minimizes the length of the residual vector is unique (7). If the rank, $r$, is less than $n$, there is a linear subspace (a line or hyperplane) of least squares solutions (7). The solutions can be classified by type. The two types that are usually of interest are the least squares solution of minimum length and a basic approximate solution that has at most $\dot{r}$ nonzero components, where $r$ is the rank of the coefficient matrix (1). The former is unique (7). The latter is not unique if $n>1$ (7).

A basic approximate solution is defined as follows:
$\underline{x}_{b}$ is a basic approximate solution of $A \underline{x}=\underline{b}$ if for all vectors $\underline{x}$,

$$
||A x-b|| \geq||A x-b||
$$

and $\underline{x}$ has at most $r$ nonzero components (8). Let BAS stand for basic approximate solution throughout this report.

A minimum norm solution is defined as follows:
$x_{0}$ is the least squares solution of minimum Euclidean norm if for all vectors $\underline{x}$ either

$$
\|A \underline{x}-\underline{b}\|>\left\|A \underline{x}_{0}-\underline{b}\right\|
$$

or else

$$
\|A \underline{A}-\underline{b}\|=\left\|A \underline{A}_{0}-\underline{b}\right\| \text { and }\|\underline{x}\|>\left\|\underline{x}_{0}\right\| .
$$

The second condition holds of $x$ is orthogonal to the null space of $A$; i.e., $x$ is orthogonal to every solution of $A x=0$ (1).

A vector $u$ is orthogonal to a vector $v$ if

$$
\underline{u}^{\mathrm{T}} \underline{v}=\sum_{i=1}^{n} u_{i} v_{i}=0
$$

Definition of the Generalized Linear Least Squares Problem

The problem of finding the solution vector, $x$, that minimizes the length of the vector $A \underline{x}-\underline{b}$, where the rank of $A$ is less than or equal to $n$, is called the "generalized linear least squares problem." The term "generalized linear least squares problem" is used to emphasize that the rank of $A$ may be less than the number of columns in $A$. In
the past, the term "linear least squares problem" was used to denote the problem of finding the vector, $\underline{x}$, that minimized the length of the vector $A \underline{x}-\underline{b}$, where $A$ was of full rank.

As mentioned previously, the solution of the system of equations Ax=b, where $A$ is an $n$ by $n$ matrix of rank $n$, can be obtained by the pre-multiplication of the right hand side by a matrix, $A^{-1}$, called the inverse of $A$. The solution of the system of equations Ax=b, where $A$ is an $m$ by $n$ matrix of rank $r(r \leq m i n(m, n))$, can be represented by the pre-multiplication of the right hand side, $\underline{b}$, by a matrix (to be defined) called the generalized inverse of $A$. It has been shown further that the generalized inverse of any complex matrix, A (not necessarily square), is unique, and, therefore, the minimum length solution is unique (7).

## Relation of the Linear Least Squares Problem to

## the Generalized Inverse of a Matrix

Penrose (7) has shown that the least squares solution of minimum Euclidean norm is unique and is represented by $x=A{ }^{@}$, where $A^{@}$ is called the generalized inverse or pseudo-inverse of $A$, $A^{@}$ is defined by the relationships

$$
\begin{aligned}
& A_{A}^{@} A=A \\
& A^{@} A A=A^{@}
\end{aligned}
$$

$$
\left(A A^{@} C^{j} \omega=A^{@} A\right.
$$

and

$$
\left(A^{@} A\right) *=A A^{@} \text {, where } A^{*} \text { is the conjugate transpose of } A \text {. }
$$

$$
A^{*}=\bar{A}^{T}=\left(A_{j 1}\right) .
$$

Rosen (8) has shown that the BAS (Basic Approximate Solution) can be represented by $\underline{x}=A^{\# \#} \underline{b}$, where $A^{\# \#}$ is defined below.

For $r=n \leq m, A^{\#}$ is equal to $A^{@}$ and $x_{b}$ is also the least squares solution of minimum Euciidean norm. For $r=n=m$,

$$
A^{\#}=A^{@}=A^{-1} .
$$

For $r<n, A^{\#}$ is not necessarily unique. For this last case, $A^{\#}$ can be defined as follows:

Let $A$ be of rank $r(r<n)$. Let $B$ consist of $r$ linearly independent columns of $A$. Let $\underline{B}$ consist of the other $n-r$ columns of $A$. For simplification, assume that $B$ consists of the first $r$ columns of $A$ so that

$$
\begin{aligned}
& A=(B, B) . \\
& B^{@}=\left(B^{*} B^{-1}\right) B^{*} \\
& A^{\sharp}=\binom{B^{@}}{0}
\end{aligned}
$$

The first $r$ rows of $A^{\# \#}$ consist of the matrix $B^{@}$. The remaining $n-r$ rows are zero.
$A^{@}$ can be expressed in terms of $B^{@}$ as follows:

$$
A^{@}=C^{*}\left(C C^{*}\right)^{-1} B^{@}
$$

where

$$
C=B^{@} A
$$

and $C^{*}$ is the conjugate transpose of $C$ (7).
It is not necessary to find $A^{@}$ or $A^{\prime \prime}$ explicitly to find the least squares solution of minimum norm or a BAS. Osborne has constructed an algorithm to find these solutions without finding $A^{@}$ or $A^{\# \#}$. His,
approach is analogous to the case of solving the system of equations Ax=b by Gaussian elimination when $A$ is an $n$ by $n$ matrix of rank $n$.

$$
\underline{x}=A^{-1} \underline{b}
$$

in this case, but $A^{-1}$ did not need to be found explicitly.

## Method

The most popular practical method for finding the least squares solution of $A \underline{x}=\underline{b}$ is to solve the normal equations,

$$
\mathrm{A}^{\mathrm{T}} \underline{\mathrm{Ax}}=\mathrm{A}^{\mathrm{T}} \underline{\mathrm{~b}}
$$

A derivation of the normal equations and a justification for their use follows.

The vector, $\underline{x}$, that minimizes $\| A \underline{x}-\underline{b}| |^{2}$ also minimizes $\|A \underline{x}-\underline{b}\|$. A necessary condition for $\|A x-b\|^{2}$ to possess a minimum is that

$$
\begin{equation*}
\frac{\partial\|A x-b \mid\|^{2}}{\partial x_{j}}=0 \text { for } j=1, \ldots, n \tag{2.1}
\end{equation*}
$$

where $n$ is the number of columns in $A$. Since $\|A \underline{x}-\underline{b}\|^{2}$ is a positive semidefinite quadratic form in $\underline{x}$ and is greater than or equal to zero for all $\underline{x},\|\dot{A x}-\underline{b}\|^{2}$ does not contain an inflection point or a maximum in an unrestricted domain (5). Therefore, the $\underline{x}$ for which equations (2.1) are satisfied must be the point where $\|A \underline{A x}-\underline{b}\|^{2}$ attains its minimum value. As mentioned above, $\|A x-\underline{b}\|^{2}$ does not contain an inflection point or a maximum in an unrestricted domain, and therefore, it is sufficient to find a vector $\underline{x}$ that satisfies (2.1) to find a minimum to $\|A \underline{x}-\underline{b}\|^{2}$.

Since

$$
\begin{aligned}
\|r\| \|^{2} & =\|A \underline{x}-\underline{b}\|^{2}=(A \underline{x}-\underline{b})^{T}(A \underline{x}-\underline{b}) \\
& =\sum_{k=1}^{m}\left(b_{k}-\sum_{i=1}^{n} x_{i} a_{k i}\right)^{2}, \quad(2.2) \\
\frac{\partial \| A x-b}{} \|^{2} & =\sum_{k=1}^{m}\left(b_{k}-\sum_{i=1}^{n} x_{i} a_{k i}\right) a_{k j}=0, j=1, \ldots, n .
\end{aligned}
$$

Equation (2.2) can be rewritten as follows:

$$
\begin{aligned}
& \sum_{k=1}^{m} b_{k} a_{k j}-\sum_{k=1}^{m} a_{k j} \sum_{i=1}^{n} a_{k i} x_{i}=0 \text { or } \\
& \sum_{k=1}^{m} a_{k j} \sum_{i=1}^{n} a_{k i} x_{i}=\sum_{k=1}^{m} b_{k} a_{k j}+j=1, \ldots, n .
\end{aligned}
$$

The above equations are called the normal equations. In matrix notation this is equivalent to

$$
\mathrm{A}^{\mathrm{T}} \underline{\mathrm{Ax}}=\mathrm{A}^{\mathrm{T}} \underline{\underline{\mathrm{~b}}}
$$

$A^{T} A$ is always symmetric and positive semi-definite (its determinant is nonnegative, as are all its eigenvalues).

Note from (2.2) that the residual vector, $r$, is orthogonal to every nonzero column of $A$, since

$$
\begin{gathered}
\left(b_{k}-\sum_{i=1}^{n} x_{i} a_{k i}\right)=r_{k}, \\
\sum_{k=1}^{m} r_{k} a_{k j}=0 \\
\text { or } \\
r^{T} A^{j}=0, j=1, \ldots, n .
\end{gathered}
$$

This will be used in the derivation of an alternate method for solving a linear least squares problem. As stated earlier, the most popular method for finding the least squares solution of minimum norm is to solve the normal equations using a method such as Gaussian elimination. There are two problems with using the normal equations to find a least squares solution of minimum norm. First, if A has rank less than $n$, $A^{T} A$ has rank less than n. A method such as Gaussian elimination would fail to find a solution. Second, the matrix $A T_{A}$ is often ill-conditioned (3). A matrix is ill-conditioned if small errors in the entries in the matrix or small errors in the solving process have a large effect on the solution obtained to the problem $\underline{A x}=\underline{b}$ for some $\underline{b}$. The degree of ill-conditioning of a matrix depends on the magnitude of the elements of the inverse of $A$. A quantity called the condition number is a measure of the ill-conditioning of $A$. The condition number is equal to $\|A\|\left\|A^{-1}\right\|$, where

$$
\begin{array}{r}
\|A\|=\max \|A \underline{x}\| \\
\|\underline{x}\|=1 \tag{9}
\end{array}
$$

The larger the condition number the greater the ill-conditioning (3). The smallest possible condition number is one. If the condition number of $A$ is cond ( $A$ ), the condition number of $A^{T} A$ is $\operatorname{cond}^{2}(A)$.

Longley (10) and Wampler (11) have done comparative studies of methods used to solve the generalized linear least squares problem. Both of them have shown examples where solving the normal equations has produced a solution vector with almost no correct digits.

Since the normal equations cannot easily be used to find the least squares solution when the coefficient matrix has a rank less
than the number of columns in the matrix, and should not be used when $\mathrm{A}^{\mathrm{T}} \mathrm{A}$ is ill-conditioned, a better method is needed. In Chapter IV a description of an algorithm developed by E. E. Osborne is presented.

A brief history of some of the methods that have been developed to find the solution to the generalized linear least squares problem is given below.

## History

As mentioned previously, if the coefficient matrix is of full rank, then the most popular method for finding the least squares solution is to solve the normal equations. If the system is ill-conditioned, solving the normal equations can produce a solution vector that is very inaccurate (10).

Orthogonalization techniques are the second most popular class of methods for solving the generalized linear least squares problem. Householder transformations or a form of the Gram-Schmidt method are used normally to do the orthogonalization (3).

## Algorithms Using Householder Transformations

E. E. Osborne (12) first proposed using Householder transformations to do orthogonalization in 1961. The method he developed was primarily for the homogeneous case $\mathrm{Ax}=\underline{0}$. His intent was to improve the accuracy of the solution he obtained. In 1965, Businger and Golub (13) proposed using Householder transformations for solving the nonhomogeneous case $\mathrm{Ax}=\underline{b}$, where A is of full rank. In 1965, Golub (14) allowed the imposition of linear equalities (a subset of equations that must be satisfied exactly). In 1967, Björck and Golub (15) added iterative improvement
of the solution to the algorithm proposed by Businger and Golub. In 1969, Hanson and Lawson (16) extended the Businger-Golub algorithm to solve systems of equations of the form $A x=b$, where $A$ is of rank $r(r \leq n)$.

## Algorithms Using Gram-Schmidt Orthogonalization

In 1964, Bauer (17) published an algorithm using modified GramSchmidt orthogonalization to solve the system of equations Ax=b. This method was good for matrices of full rank only. In 1965, Osborne (1) extended the use of modified Gram-Schmidt otrhogonalization to the case where the coefficient matrix was of rank $r$ ( $r \leq n$ ). In 1968, Björck (18) combined iterative improvement of the solution with the use of modified Gram-Schmidt orthogonalization to reduce the error in the solution of the system of equations $A x=b$, where the rank of $A$ is $r(r \leq n)$. Björck (18) has shown that modified Gram-Schmidt orthogonalization produces a somewhat more accurate solution vector than the use of Householder transformations for orthogonalization.

Programs implementing Björck's algorithm (18) and Bauer's algorithm (17) are available at Oklahoma State University, Stillwater, Oklahoma. The package consisting of the FORTRAN subroutines, LLCR and LLSQ, has been compared with the programs implementing Björck's and Bauer's algorithms. The LLCR package produced results that were as accurate or more accurate than the routines of Björck and Bauer. Björck's routine does allow the imposition of linear equalities. In practice, this option is not usually used and hence was omitted. The imposition of linear equalities can be approximated by multiplying those rows of $A$ and components of $b$ by a large weighting factor before using the package. In addition, the user of the package consisting of LLCR and

LLSQ has many options available that are not available to the user of the other routines.

## CHAPTER III

## STEPWISE REGRESSION ANALYSIS

Stepwise regression analysis is closely related to the generalized linear least squares problem described in Chapter II.

In stepwise regression analysis a curve is fitted to a set of data points,

$$
\left\{y_{i} ; t_{1}, \ldots, t_{n}\right\}_{i}, i=1, \ldots, m \text {, where }
$$

$\left\{y_{i} ; t_{1}, \ldots, t_{n}\right\}_{i}$ is the $i-t h$ observation (19). The mathematical model for the curve is called the regression equation and has the form

$$
\hat{y}_{i}=c_{0}+c_{1} t_{i 1}+c_{2} t_{i 2}+\ldots+c_{n} t_{i n}
$$

where $\hat{y}$ is an estimate of the dependent variable, $y$, the $t_{j}, j=1, \ldots, n$, are the independent variables, and the $c_{i}, i=0, \ldots, n$, are the coefficients to be determined. The $t_{j}, j=1, \ldots, n$, can represent functions of the form

$$
t_{j}=g_{j}\left(\underline{z}_{j}\right),
$$

where the functions, $\underline{g}\left(\underline{z}_{j}\right)$, do not contain the dependent variable and where the $\underline{Z}_{\mathbf{j}}$ are variables whose observed numerical values completely determine the numerical value of the $t_{j}$ (19).

Stepwise regression is used when it is desired to represent the dependent variable in terms of as few of the independent variables as possible. When the dependent variables are highly correlated, the
simple regression model may be considerably simplified by eliminating some of the variables. In the stepwise procedure one variable is added to the mathematical model at a time (19). Thus, the intermediate equations

$$
\begin{aligned}
\hat{y} & =c_{0} \\
\hat{y} & =c_{0}^{\prime}+c_{1}^{\prime} t_{i_{1}} \\
\hat{y} & =c_{0}^{\prime \prime}+c_{1}^{\prime \prime} t_{i_{1}}+c_{2}^{\prime \prime} t_{i_{2}} \\
& . \\
& .
\end{aligned}
$$

are obtained. Note the $i_{1}$ is not necessarily equal to 1 , $i_{2}$ is not necessarily equal to 2 , etc.

An important property of the stepwise procedure is based on the fact that a variable may be significant at an early stage but may become insignificant after several other variables are entered in the equation. A variable that is not highly correlated with the other variables in the regression equation at an early stage may be highly correlated with variables that enter the regression equation later, thereby reducing its significance. The stepwise procedure permits the insignificant variable (highly correlated variable) to be removed from the regression equation. The test to decide if any variable is to leave or enter the regression equation is a statistical test, namely the $F$-test. The $F$-test measures the degree of linear correlation among variables in the regression equation (20). If a variable is too highly correlated with the other variables in the regression equation, it will be removed or not allowed to enter.

The decision as to which variable is to enter the regression equation
is a numerical decision. The variable added to the regression equation at each step is the one that makes the greatest improvement in the fit of the curve as measured by the length of the residual vector; i.e., it is the one that produces the shortest residual vector. At each stage of the stepwise procedure, the least squares solution is found for the variables entered in the regression equation at that point (19).

Stepwise regression does not necessarily produce the solution vector with the residual vector of minimum length. All that is assured is that given $k$ variables in the regression equation, the next variable to enter the equation is the variable whose addition to the model produces the solution vector for which the length of the residual vector is minimized.

Some packages that are called stepwise regression packages do not have the ability to delete variables from the regression equation. Stepwise regression without the deletion of variables is called IVOR (Independent Variable Ordering by Regression Sum of Squares) (4) or "forward selection" (19). Some packages that include only forward selection are the IBM 360 Scientific Subroutine Package (21), the BioMedical (BMD) stepwise regression programs (22), and the package that implements the methods described in the next chapter.

Deletion of variables from the regression equation was not implemented because of the following reasons.

First, there is no standard statistical test that best calculates the linear correlation among variables in the regression equation for all cases. The F-test assumes that the standard deviations of all the variables are equal. If the standard deviations are not all equal, the F-test may not give an accurate calculation of the linear correlation among the variables.

Second, when a variable is deleted from the regression equation, the system of equations must be returned to the state in which it would have been if the variable had never entered the regression equation. When orthogonalization is used to do stepwise regression, this state must be constructed. The construction of this state can be inaccurate. The LLCR package was written to provide an accurate means to solve generalized linear least squares problems and to perform stepwise regression (IVOR).

Third, cycling may occur when variables are deleted from the equation. A group of variables may alternately enter and leave the regression equation. For example, variable $t_{f_{1}}$ may enter the regression equation followed by $t_{i_{2}}$ 's entry. $t_{i_{1}}$ may be deleted from the regression equation followed by $t_{i_{2}}$ 's deletion from the regression equation. $t_{i_{1}}$ may reenter the regression equation followed by $t_{i_{2}}$ 's reentry into the regression equation. This pattern may continue until something extra-ordinary happens to stop the process such as exceeding the time limit or the job.

An attempt will be made to implement deletion of variables from the regression equation in the future.

CHAPTER IV

THE USE OF MODIFIED GRAM-SCHMIDT ORTHOGONALIZATION TO
SOLVE THE GENERALIZED LINEAR LEAST SQUARES PROBLEM

The generalized linear least squares problem consists of finding the solution vector $x$ to the system of equations, Ax=b, that minimizes the length of the residual vector $A x-b$.
E. E. Osborne (1) has constructed a method for solving the generalized Iinear least squares problem based on the fact that (a) the residual vector for a linear least squaras solution is orthogonal to every nonzero column of $A$ and $(b)$ the least squares solution of minimum norm is orthogonal to the null space of $A$; i.e., orthogonal to every solution of $A x=0$

Osborne's algorithm consists of three phases. During the first phase of the algorithm, the numerical rank of the system of equations is found and a decomposition of the coefficient matrix into the product of an orthogonal matrix and a permuted unit upper triangular matrix is determined. During the second phase, a BAS (Basic Approximate Solution) is found. During the third phase, the minimum norm solution is found. Before the three phases of the algorithm are discussed, a definition of numerical rank will be given.

As mentioned in Chapter II, the rank of a matrix is equal to the number of linearly independent columns in $A$. $A^{j}$, the j-th column of $A$, is linearly dependent on the other columns of $A$ if there exist constants $\alpha_{i}$ such that

$$
\sum_{i=1}^{n} \quad \alpha \nmid A^{i}=A^{j}
$$

Osborne's algorithm considers a column, $A^{j}$, to be linearly dependent on other columns of $A$ if there exist constants $\alpha_{j}$ suck that

$$
\frac{\left\|A^{j}-\sum_{\substack{i=1 \\ i \neq j}} \alpha_{j} A^{i}\right\|<\varepsilon}{\left\|A^{j}\right\|}
$$

where $\varepsilon$ is set by the user of the algorithm, as a measure of the relative error he will tolerate. In practice, $\varepsilon$ is: $\geq \delta$, where $\delta$ is the smallest number such that

$$
\text { 1. }+\delta>1 .
$$

in single precision real arithmetic on the computer being used. For example, on the IBM $360 / 65$. $\delta \approx 9.6 \times 10^{-7}$.

The numericil rank of $A$ is the number of linearly independent columns in $A$, where the definition of linear dependency is the numerical one given in (4.1).

```
Osborne's Algorithm
```


## Phase I

Phase I of Osborne's algorithm consists largely of elementary column operations performed on the matrix,

$$
\binom{\mathrm{A}}{\mathrm{R}}
$$

where $R$ is an $n$ by $n$ identity matrix, that produces a decomposition
of the form $A=A_{N} R^{-1}$ and determines the numerical rank of $A$. If the numerical rank of $A$ if $r^{*}$, $r^{*}$ columns of $A_{N}$ will be made mutually orthogonal using modified Grampchraidt orthogonalization. A description of $R_{N}$ is given later in this section.

The transformation of

$$
\binom{A}{R}
$$

into the matrix

$$
\binom{\mathrm{A}_{\mathrm{N}}}{\mathrm{R}_{\mathrm{N}}}
$$

by modified Gram-Schmidt orthogonalization will be described now.
In modified Gram-Schmidt orthogonalization of a matrix of full rank, the second column is orthogonalized with respect to the first column, the third column is orthogonalized with respect to the first and second columns, ..., the n-th column is orthogonalized with respect to all the other columns of $A$, where $n$ is the number of columns in $A$.

If the matrix has a numerical rank less than the number of columns, the lengths of some of the columns will become $\leftrightarrows E$ during the orthogonalization process (1). No attempt should be made to orthogonalize these columns with respect to the other columns of the coefficient matrix.

In order to keep track of the columns that remain to be orthogonalized, if any, Osborne reordered the colums of the partially orthogonalized coefficient matrix so that the first $k$ columns of the modified A matrix contain the k columns that have been made mutually orthogonal,
for $k=1, \ldots, r^{*}=$ numerical rank of $A$. A vector,

$$
\rho=\left(\left\|A^{2}\right\|^{2},\left\|A^{2}\right\|^{2}, \ldots,\left\|A^{n}\right\|^{2}\right)
$$

also is set up at the beginning of the algorithm. Whenever columns of the modified matrix,

$$
\binom{\mathrm{A}}{\mathrm{R}}
$$

are interchanged, corresponding components of $\rho$ are interchanged.
The $k-t h$ step of the modified Gram-Schmidt orthogonalization procedure is described below.

For $k=1, \ldots, r * x$ the numerical rank of $A$, the quantities

$$
\begin{aligned}
& d_{k}=\left|\left|A_{k-1}^{k}\right|\right|^{2} \\
& \alpha_{k j}=\left(A_{k-1}^{k} \cdot A_{k-1}^{j}\right) / d_{k} \\
& A_{k}^{j}=A_{k-1}^{j}-\alpha_{k j} A_{k-1}^{k} \\
& R_{k}^{j}=R_{k-1}^{j}-\alpha_{k j} R_{k-1}^{k}, \quad k+1 \leq j \leq n,
\end{aligned}
$$

where $A_{0}=A$ and $R_{Q}=I$, are calculated.
A vector representation for the orthogonalization of two vectors in 2-space is shown in Figure 1 (23). The orthogonal projection of on $\alpha$ is made. The orthogonalized vectors are $\beta^{\prime}$ and $\alpha$, where $\beta^{\prime}=\beta-\alpha$. $\beta^{\prime}$ is orthogonal to $\alpha$.

Let

$$
\binom{A_{K}}{R_{k}}
$$



Figure 1. Geometrical Representation of the Orthogonalization of 2 vectors in 2 -space.
be used to designate the state of the matrix

$$
\because\binom{A}{R}
$$

after each step $k, k=1, \ldots$, numerical rank of $A$, of the algorithm. At this point (1), $k$ colums have been made mutually orthogenal and

$$
\begin{aligned}
A= & A_{k} R_{k}^{-1} \\
& \text { or } \\
A_{k}= & A R_{k}
\end{aligned}
$$

The quantities

$$
t(j)=\left\|A_{k}^{j}\right\|^{2} / \rho(j)
$$

are calculated for $j=k+1, \ldots, n$, where $A^{j}$ is the $j-t h$ column of $A$.

If

$$
t(j) \leq \varepsilon \quad \text { for } j=k+1, \ldots, n,
$$

the numerical rank of $A$ is $k$ and $A_{N}=A_{k}$. The numerical rank is the first $k$ for which

$$
t(j) \leq \varepsilon \quad \text { for } j=k+1, \ldots, n .
$$

If

$$
t(j)>\varepsilon \quad \text { for any } j, j=k+1, \ldots, n,
$$

the $j$ for which $t(j)$ is the maximum is found. Column $j$ of

$$
\binom{A_{k}}{R_{k}}
$$

is interchanged with column $k+1$ of

$$
\binom{A_{k}}{R_{k}}
$$

The j-th component of $\rho$ is interchanged with the ( $k+1$ )-st component of $\rho$. The selection of the column to become the ( $k+1$ )-st column of $A_{k+1}$ is called Osborne pivoting throughout the remainder of the report.

Once the numerical rank, $r^{*}$, of the matrix is determined, the $n-r *$ vectors that have a length $\leq \varepsilon$ are considered to be zero vectors. The last $n-r^{*}$ columns of $R_{r *}$ are made mutually orthogonal. The operations described above produce the matrix

$$
\binom{A_{N}}{R_{N}}
$$

$\mathrm{R}_{\mathrm{N}}$ has the following properties (1):
(i) $\quad \operatorname{det} R_{N}= \pm 1$,
(ii) $A=A_{N} R_{N}$ or $A_{N}=A R_{N}^{-1}$
(iii) $R_{N}$ is obtainable by permuting rows of an upper triangular matrix all of whose diagonal elements are unity.
(iv) The vectors $R_{N}^{r^{*+1}}, R_{N}^{r^{*+2}}, \ldots, R_{N}^{n}$ form an orthogonal basis for the null space of A (1).

## Phase II

The basic approximate solution is found during phase II. The procedure to find the basic approximate solution is based on the fact that the residual vector for a linear least squares solution is orthogonal to every nonzero column of the coefficient matrix. The development of a method to find the basic approximate solution will be given now.

If the vector

$$
\binom{-\underline{b}}{\underline{0}}
$$

is appended to the matrix
the matrix

$$
\begin{aligned}
& \binom{A R_{N}}{R_{N}}, \\
& \left(\begin{array}{cc}
A R_{N} & \underline{-b} \\
R_{N} & \underline{0}
\end{array}\right)
\end{aligned}
$$

results. This matrix is post-multiplied by the ( $n+1$ ) by ( $n+1$ ) matrix

$$
\left(\begin{array}{ll}
\mathrm{I} & \underline{\mathrm{u}} \\
0 & 1
\end{array}\right)
$$

which will orthogonalize - $\underline{b}$ with respect to the first $r^{*}$ columns of $A R_{N}$ - The matrix

$$
\left(\begin{array}{cc}
A R_{N} & A R_{N} \underline{u}-\underline{b} \\
R_{N} & R_{N} \underline{u}
\end{array}\right)
$$

results. Since $R_{N}$ is nonsingular and the residual vector $A R_{N-b}$ is orthogonal to every nonzero column of $A R_{N}, R_{N}$ u is a least squares solution of $A \underline{x}=\underline{b}$. According to Rosen's definition (8), it is a basic approximate solution. This follows from properties (i) and (iii) above and from the fact that $R_{\mathrm{N}} \mathrm{u}$ is a linear combination of the first $\mathrm{r}^{*}$ columns of $R_{N}$. Therefore, $R_{N u}$ has at most $r *$ nonzero components (1).

## Phase III

In phase III, the minimum length solution is found by computing a least squares solution that is orthogonal to the null space of $A$; i.e., orthogonal to every solution of $A x=0$.

The following discussion shows how the minimum length solution is found from the basic approximate solution.

If the matrix

$$
\left(\begin{array}{cc}
A R_{N} & A R_{N} \underline{u}-\underline{b} \\
R_{N} & R_{N} \underline{\underline{u}}
\end{array}\right)
$$

is post-multiplied by the $(n+1)$ by ( $n+1$ ) matrix

$$
\left(\begin{array}{ll}
\mathrm{I} & \mathrm{~V} \\
0 & 1
\end{array}\right)
$$

which will orthogonalize $R_{N} \underline{\sim}$ with respect to the last $n-r^{*}$ columns of $R_{N}$, where $r^{*}$ is the numerical rank of $A$, the matrix

$$
\left(\begin{array}{cc}
A R_{N} & A R_{N}(\underline{v}+\underline{u})-\underline{b} \\
R_{N} & R_{N}(\underline{v}+\underline{u})
\end{array}\right)
$$

is obtained. The first $r^{*}$ components of $\underline{v}$ are zero and the last $n-r^{*}$ columns of $A$ are considered to be zero vectors. Therefore,

$$
A R_{N} \mathrm{Y}=0
$$

and $A R_{N}(\underline{v}+\underline{u})$ is orthogonal to the nonzero columns of $A R_{N}$. Thus, $R_{N}(\underline{v}+\underline{u})$ is a least squares solution of $A \underline{x}=\underline{b} . R_{N}(\underline{v}+\underline{u})$ is orthogonal to the null space of $A$, and, therefore, is the unique least squares solution of minimum length (1).

## Mathematical Summary of the Algorithm

The complete algorithm can be described mathematically as follows:

$$
\begin{aligned}
& A_{N}^{1}=A^{1} \\
& R_{N}^{1}=R^{1} \\
& R_{N}^{k}=R^{k}-\sum_{j=1}^{k-1}\left(\frac{A_{N}^{j} \cdot A^{k}}{A_{N}^{j} \cdot A_{N}^{j}}\right) R^{j} \\
& A_{N}^{k}=A^{k}-\sum_{j=1}^{k-1}\left(\frac{A_{N}^{j} \cdot A^{k}}{A_{N}^{j} \cdot A_{N}^{j}}\right) A^{j} \text { for } k=2, \ldots, r^{*},
\end{aligned}
$$

where $r^{*}$ is the numerical rank of A.

$$
\begin{aligned}
& R_{N} \underline{u}=-\sum_{j=1}^{r *}\left(\frac{A_{N}^{j} \cdot(-\underline{b})}{A_{N}^{j} \cdot A_{N}^{j}}\right) R_{N}^{j} \\
& R_{N}(\underline{u}+\underline{v})=R_{N} \underline{u}-\sum_{j=r^{*}+1}^{n}\left(\frac{R_{N}^{j} \cdot\left(R_{N} u\right)}{R_{N}^{j} \cdot R_{N}^{j}}\right) R_{N}^{j} .
\end{aligned}
$$

The routines that have been implemented to solve the generalized linear least squares problem employ the algorithm constructed by Osborne. Certain modifications in Osborne's method have been made and several additional features have been added.

## Modification and Additions

The major addition to Osborne's algorithm was the ability to do IVOR (Independent Variable Ordering by Regression Sum of Squares)-stepwise regression without the deletion of variables from the regression equation. In addition, the coefficient matrix can be treated as if it had a pre-specified rank, the initial BAS and minimum length solutions can be iteratively refined, and the error matrix, $\left(A^{T} A\right)^{-1}$, is calculated for matrices of full rank.

IVOR

Earlier in the chapter it was stated that after r* steps of the algorithm constructed by Osborne, r* columns of the coefficient matrix are mutually orthogonal. After $k$ steps of the algorithm, $k$ columns of the coefficient matrix are mutually orthogonal. Let the state of the coefficient matrix be designated by $A_{k}$.

$$
A_{k}=A R_{k} \quad \text { or } A=A_{k} R_{k}^{-1} .
$$

If

$$
\binom{-\underline{b}}{\underline{0}}
$$

is appended to

$$
\binom{A R_{k}}{R_{k}}
$$

the matrix

$$
\left(\begin{array}{cc}
A R_{k} & -\underline{b} \\
R_{k} & \underline{0}
\end{array}\right)
$$

results. If the resulting matrix is post-multiplied by the ( $n+1$ ) by $(n+1)$ matrix,

$$
\left(\begin{array}{ll}
I & \underline{u} \\
0 & 1
\end{array}\right)
$$

that will orthogonalize - b with respect to the first $k$ columns of $A R_{k}$, the matrix

$$
\left(\begin{array}{cc}
A R_{k} & A R_{k} \underline{u}-\underline{b} \\
R_{k} & R_{k} \underline{u}
\end{array}\right)
$$

results. $R_{k \underline{u}}$ has $k$ nonzero components since $\operatorname{det} R_{k}= \pm 1, R_{k}$ is obtainable by permuting the rows of an unit upper triangular matrix, and $R_{k} \underline{u}$ is a linear combination of the first $k$ columns of $R_{k}$. The $k$ nonzero components of $R_{k} \underline{u}$ are the regression coefficients for the $k$ variables that have entered the regression equation. The ( $k+1$ )-st variable to enter the regression equation is found as follows:

For each variable not in the regression equation, we predict the
length of the residual vector that would be obtained if the variable were entered in the regressioquation. The length of the residual vector can be predicted by calculating

$$
\left\|\left(A R_{k} \underline{u}-\underline{b}\right)-\left(\frac{A_{k}^{t} \cdot\left(A R_{k}{ }^{u}-b\right)}{A_{k}^{t} \cdot a_{k}^{t}}\right) A_{k}^{t}\right\|
$$

for each variable $t$ that is not in the regression equation. The variable that will produce the residual vector of the shortest length is the variable to enter the regression equation.

## Solving the System of Equations for a Pre-ßpecified Rank

The coefficient matrix can be treated as if it were of a prespecified rank, $k$. If the numexical rank is less than $k$, the minimum norm solution is found; otherwise $k$ colums of the coefficient matrix are made mutually orthogonal. Osborne's method (1) of column selection is used to choose those $k$ columns. The remaining columns of the coefficient matrix are treated as if they are zero vectors. The last $n-k$ columns of $R_{k}$ then are made mutually orthogonal, where $n$ is the number of columns in the coefficient matrix. Orthogonalizing only $k$ columns of the coefficient matrix when the rank of the coefficient matrix is not less than $k$ corresponds to increasing the value of $\varepsilon$ until the numerical rank of the coefficient matrix is equal to $k$. This might be used on an accurate computer such as the CDC 6600 to predict the solution that could be found on a less accurate computer such as the IBM 360.
$E$ is the value used to determine if a column is a Inear combination of other columns in the coefficient matrix. The system of equations can be solved for several ranks during one run of the implemented routines: This corresponds to solving the system of equations for a range of $\varepsilon$.

## Iterative Improvement of the Initial Solutions

Roundoff error in the calculation of a solution vector often makes the solution vector inaccurate. If ${\underset{x}{c}}^{\text {is }}$ the calculated answer and $\underline{x}_{t}$ is the true answer,

$$
\underline{x}_{c}+\Delta \underline{x}=\underline{x}_{t}
$$

and

$$
\begin{gathered}
A \underline{x}_{t}=\underline{b} \text { or } A(\underline{x}+\Delta \underline{x})=\underline{b} \\
A \Delta \underline{x}=\underline{b}-A x_{c}
\end{gathered}
$$

Iterative improvement of the initial BAS and minimum length solutions has been implemented to improve their accuracy. The interative improvement procedure is described as follows (1):
(i) Let $x_{i}$ be the initial solution.
(ii) Calculate the vector $\underline{m}=\underline{b}-\mathrm{Ax}_{\mathrm{i}}$ in double precision.
(iii) Solve the system of equations

$$
A \Delta \underline{x}_{i}=\underline{r}_{i} .
$$

(v)

If

$$
\left|\left|\underline{x}_{i+1}-x_{i}\right|\right| /\left|\left|\underline{x}_{i+1}\right|\right| \leq \varepsilon_{1}
$$

where $\varepsilon_{1}$ is greater than or equal to $\left\{, \underline{x}_{i+1}\right.$ is accapted as the solution to $\mathrm{Ax}=\underline{b}$.
$\delta$ is the smallest floating point number such that $1 .+\delta>1$. in the computer.

## Calculation of the Error Matrix

The matrix $R_{N}$ generated by the orthogonalization process described above can be used to obtain the error matrix, $\left(A_{A}\right)^{-1}$, if $A$ is of full rank.

The derivation of the error matrix from $R$ follows.

$$
\begin{aligned}
& A=A_{N} R_{N}{ }^{-1 "} \\
& \left(A^{T}\right)^{-1}=\left[\left(A_{N} R_{N}^{-1}\right)^{T}\left(A_{N} R_{N}^{-1}\right)\right]^{-1} \\
& =\left[\left(R_{N}^{-1}\right)^{T} \cdot A_{N}^{T} A_{N} R_{N}^{-1}\right]^{-1} \\
& =\left[\left(R_{N}^{-1}\right)^{T} D R_{N}^{-1}\right]^{-1} \\
& =R_{N} D^{-1}\left(\left(R_{N}^{-1}\right)^{T}\right)^{-1} \\
& =R_{N} D^{-1}\left(\left(R_{N}^{-1}\right)^{-1}\right)^{T} \\
& =R_{N} D_{N}^{-1} R_{N}^{T} \quad D \text { is a diagonal matrix. }
\end{aligned}
$$

## Polynomial Fitting

The LLCR package can be used to fit a polynomial to a set of data points,

$$
\{y ; t\}_{1}
$$

where $y$ is the dependent variable, $t$ is the independent variable, and
$\{y ; t\}_{i}$ is the i-th observation.
The mathematical model for the curve would have the form

$$
\hat{y}=c_{0}+c_{1} t+c_{2} t^{2}+\ldots+c_{n} t^{n}
$$

where $\hat{y}$ is an estimate of $y$ and the $c_{j}, j=0, \ldots, n$, are the coefficients to be determined. When the package is used to fit a polynomial to a set of data points, one variable is entered into the mathematical model at a time. The variables are entered in the following order:

$$
t, t^{2}, t^{3}, \ldots, t^{n}
$$

Entering the variables in the above order is called sequential selection. When the variables are entered sequentially, the intermediate equations

$$
\begin{aligned}
y & =c_{0} \\
y & =c_{0}^{\prime}+c_{1}^{\prime} t \\
y & =c_{0}^{\prime \prime}+c_{1}^{\prime \prime} t+c_{2}^{\prime \prime} t^{2} \\
y & =c_{0}^{\prime \prime \prime}+c_{1}^{\prime \prime \prime} t+c_{2}^{\prime \prime \prime} t^{2}+c_{3}^{\prime \prime \prime} t^{3} \\
& .
\end{aligned}
$$

are obtained. The user can decide if he wishes to represent the data by a polynomial of a lesser degree.

## CHAPTER V

RESULTS AND CONCLUSIONS

Test Problems and Verification

A package consisting of the routines LLCR and ILSQ has been written In Standard FORTRAN (24) to implement Osborne's method (1). for solving the generalized linear least squares problem, Since the routines can solve a system of equations for multiple right hand sides during one run of the program, the generalized inverse of an arbitrary matrix can be found accurately and efficiently. In addition, the user of the package can perform IVOR (Independent Variable Ordering by Regression Sum of Squares)--stepwise regression without the deletion of variables from the regression equation. The user also can study efficiently the effects on the solution vector of decreasing the reliability of the entries in the coefficient matrix, The error matrix, $\left(A^{T} A\right)^{-1}$, is calculated for systems where the coefficient matrix is of full rank.

Each of the above uses has been tested on the IBM $360 / 65$ at Oklahoma State University, Stillwater, Oklahoma. The results are 1isted below.

Using the Package to Find the Generalized
Inverse of an Arbitrary Matrix

The generalized inverse of an arbitrary matrix, A, can be found by solving the set of equations $A X=I$, where $A$ is an $m$ by matrix, $X$
(the generalized inverse of $A$ ) is an $n$ by $m$ matrix, and $I$ is an $m$ by $m$ identity matrix.

The generalized inverse of a 6 by 4 zero matrix was found exactly in one iteration. Many routines for solving an arbitrary system of equations will not handle the case where the coefficient matrix has a rank of zero.

The generalized inverse of the matrix

$$
\left[\begin{array}{cccc}
1 . & -1 . & 3 . & 1 . \\
2 . & 4 . & 5 . & 1 . \\
-1 . & 2 . & -1 . & 1 . \\
4 . & 1 . & 9 . & 1 .
\end{array}\right]
$$

was found to full single precision accuracy without iterating the solution. This example was taken from Rosen (8). The generalized inverse was found to be

$$
\left[\begin{array}{rrrr}
-.21153 & .04487 & -.22435 & .05769 \\
-.19230 & .19230 & .03846 & -.03846 \\
.08653 & -.00320 & .01602 & .06730 \\
.50961 & -.09294 & .46474 & -.04807
\end{array}\right]
$$

Using the Package to Find the Solution Vector
for an Arbitrary System of Equations

Example 1. The first example was taken from Rosen's article (8). The system consisted of

$$
\left[\begin{array}{rrrr}
1 . & -1 . & 3 . & 1 . \\
2 . & 4 . & 5 . & 1 . \\
-1 . & 2 . & -1 . & 1 . \\
4 . & 1 . & 9 . & 1 .
\end{array}\right]\left[\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3} \\
x_{4}
\end{array}\right]=\left[\begin{array}{l}
1 . \\
3 . \\
2.5 \\
2.5
\end{array}\right]
$$

Using an $\varepsilon$ of $.16 \times 10^{-5}$, the rank of the system was found to be three. Full single precision accuracy was obtained without iterating the solution. The lengths of the residual vector for the basic approximate solution (BAS) and the minimum length solution were both .5. The lengths of the BAS vector and the minimum length solution vector were 1.607 and 1.451 , respectively. The BAS vector was

$$
\left[\begin{array}{c}
.07692 \\
.38462 \\
0 \\
1.5577
\end{array}\right]
$$

The minimum length solution vector was

$$
\left[\begin{array}{r}
-.49359 \\
.38462 \\
.28526 \\
1.27240
\end{array}\right]
$$

Example 2. The second system of equations that was used to test the package had a coefficient matrix consisting of the first five columns of a 6 by 6 inverse Hilbert matrix and a right hand side chosen to generate a solution vector of ( $1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}$ ). The matrix,

$$
\left[\begin{array}{ccccc}
1 & \frac{1}{2} & \frac{1}{3} & \cdots & \frac{1}{\mathrm{~m}-1} \\
\frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \cdots & \frac{1}{\mathrm{~m}} \\
\frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \cdots & \frac{1}{\mathrm{~m}+1} \\
\vdots & \vdots & \cdots & & \cdot \\
\vdots & \cdot & \cdot & & \cdot \\
\frac{1}{m-1} & \frac{1}{m} & \frac{1}{m+1} & \cdots & \frac{1}{2 m-1}
\end{array}\right]
$$

is the Hilbert matrix of order m.
The inverse of the Hilbert matrix was used because each of the entries in it is an integer and can be represented in a computer exactly if the precision of the computer is large enough (3). Therefore, the effect of roundoff error on the solution vector can be studied. This system of equations is fairly 111-conditioned, getting worse with larger m.

Full single precifion accuracy was achieved when the solution was iterated. The results of the run are shown in Table I.

The implementation of Björck's routine (18) required five iterations to obtain this accuracy. Only three iterations were required with LLCR and LLSQ.

Example 3. The third test case consisted of the last six columns of an 8 by 8 inverse Hilbert matrix with a right hand side chosen to produce the solution vector $\left(\frac{1}{3}, \frac{1}{4}, \frac{1}{5}, \frac{1}{6}, \frac{1}{7}, \frac{1}{8}\right)$.

This system is extremely ill-conditioned. As mentioned previously, when a system is ill-conditioned, small errors in the entries in the input coefficient matrix or in the solution process cause a large

TABLE I

SOLUTION OF THE SYSTEM OF EQUATIONS CONSISTING OF THE FIRST FIVE COLUMNS OF A 6 BY 6 INVERSE HILBERT MATRIX AND A RIGHT HAND SIDE CHOSEN TO GENERATE THE SOLUTION $\operatorname{VECTOR}\left(1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}\right)$

| Iteration Number | Solution Vector | Length of the Residual Vector |
| :---: | :---: | :---: |
| 0 | . 9558830 | 1.043110 |
| , | . 4843262 |  |
|  | . 3263453 |  |
|  | . 2468576 |  |
|  | . 1988596 |  |
| 1 | . 9997082 | . 4102879 |
|  | . 4999225 |  |
|  | . 3333055 |  |
|  | . 2499895 |  |
|  | . 1999996 |  |
| 2 | . 9999999 | .1591172 |
|  | . 4999998 |  |
|  | . 3333333 |  |
|  | . 2499999 |  |
|  | . 2000000 |  |
| 3 | . 9999999 | . 2431152 |
|  | . 4999999 |  |
|  | . 3333333 |  |
|  | . 2499999 |  |
|  | . 2000000 |  |

change in the solution vector (3). The condition number of a matrix is a measure of the ill-conditioning of the system. The smallest possible condition number is unity. The system in the present examye has a condition number of $10^{8}$.

Using an $\varepsilon$ of $.16 \times 10^{-5}$ and doing all calculations in single precision, the numerical rank was determined to be four. Full single precision accuracy was achieved after iteration of the solution. The rank was not determined to be six as there was considerable truncation error in forming inner products due to the low precision of the IBM 360 .

Table II contains the results of the run.

TABLE II
SOLUTION OF THE SYSTEM OF EQUATIONS CONSISTING OF THE LAST SIX COLUMNS OF AN 8 BY 8 INVERSE hILbERT MATRIX AND A RIGHT HAND SIDE CHOSEN
to generate the solution vector

$$
\left(\frac{1}{3}, \frac{1}{4}, \frac{1}{5}, \frac{1}{6}, \frac{1}{7}, \frac{1}{8}\right)
$$

| Iteration <br> Number | Minimum <br> Length <br> Solution <br> Vector | Length of the <br> Residual Vector <br> for the Minimum <br> Length Solution | Basic <br> Approximate <br> Solution <br> Vector | Length of the <br> Residual <br> Vector for <br> the BAS |
| :---: | :---: | :---: | :---: | :---: |
| 0 | -.09663224 | 155.1612 | -.1880930 | 97.75385 |
|  | .03279249 |  | -.6149425 | -.00001407021 |

Björck's routine failed to find a solution for this example. It must be emphasized again that obtaining a numerical rank of four was not a failure of the routines but was caused by the low precision of
the computer on which the test case was run.

Example 4. The fourth test case consisted of the first five elements of each of the first three rows of a 6 by 6 inverse Hilbert matrix with the right hand side ( $463,-13860,97020$ ). Both the basic approximate solution vector and the minimum norm solution vector are of interest since the number of equations is less than the number of variables.

Table III contains the results of the run.

TABLE III

SOLUTION OF THE SYSTEM OF EQUATIONS CONSISTING OF
THE FIRST FIVE ELEMENTS OF EACH OF THE FIRST THREE ROWS OF A 6 BY 6 INVERSE HILBERT MATRIX WITH

A RIGHT HAND SIDE
( $463,-13860,97020$ )

| Iteration Number | Minimum Norm Solution Vector | Square of the Length of the Residual Vector | Basic Approximate Solution Vector |
| :---: | :---: | :---: | :---: |
| 0 | $\begin{gathered} .02615530 \\ -.08060956 \\ -.002280064 \\ .07264209 \\ .1280568 \end{gathered}$ | .009011976 | $\begin{aligned} & 1.583456 \\ & .2777886 \\ & 0 \\ & 0 \\ & .07685214 \end{aligned}$ |
| 1 | $\begin{gathered} .02614972 \\ -.08058983 \\ -.002287482 \\ .07262659 \\ .1280463 \end{gathered}$ | . 0009218131 |  |
| 2 | $\begin{gathered} .02614973 \\ -.08058983 \\ -.002287471 \\ .07262659 \\ .1280463 \end{gathered}$ | . 0005667009 |  |
| 3 | $\begin{gathered} .02614974 \\ -.08058983 \\ -.002287467 \\ .07262659 \\ .1280463 \\ \hline \end{gathered}$ | . 0004688033 |  |

## Using the Package to Perform IVOR

The package consisting of LLCR and LLSQ was used to perform IVOR on oxygen solubility data. The mathematical model for this curve is defined below.

```
Let }\mp@subsup{z}{1}{}=\mathrm{ absolute temperature,
    z}\mp@subsup{\mathbf{z}}{2}{=}=\mathrm{ salinity of seawater,
    y = log of the solubility of oxygen in sea water,
```

    and the model be described by
    $$
\begin{gathered}
\hat{y}_{i}=\left(a_{i 1}+a_{i 2} / z_{i 1}+a_{i 3} \ln \left(z_{i 1}\right)+a_{i 4} z_{i 1}+a_{i 5^{z_{i 1}}}+\ldots\right) \\
\left(b_{i 1}+b_{i 2} z_{i 2}+\ldots\right)
\end{gathered}
$$

so that

$$
\begin{array}{rlrl}
t_{i 1} & \equiv 1, & c_{1} & \equiv a_{1} b_{1} \\
t_{i 2} & \equiv z_{i 2}, & c_{2} \equiv a_{2} b_{2} \\
t_{i 3} \equiv 1 / z_{i 1}, & c_{3} \equiv a_{2} b_{1} \\
t_{i 4} \equiv z_{i 2} / z_{i 1}, & c_{4} \equiv a_{2} b_{2} \\
t_{i 5} \equiv \ln \left(z_{i 1}\right), & c_{5} \equiv a_{3} b_{1} \\
t_{i 6} \equiv z_{i 2} l_{n}\left(z_{i 1}\right), & c_{6} \equiv a_{3} b_{2} \\
t_{i 7} \equiv z_{11}, & c_{7} \equiv a_{4} b_{1} \\
t_{i 8} \equiv z_{i 2} z_{i 1}, & c_{8} \equiv a_{4} b_{2} \\
\text { etc. } & \text { etc, }
\end{array}
$$

Table IV contains the results of the IVOR analysis. The results of a stepwise regression analysis of this data appears in an article by Weiss (25). In his analysis, only eight of the twelve variables in the model were entered in the regression equation because the sum of the squares of the residuals divided by the number of degrees of

TABLE IV

## RESULTS OF THE IVOR ANALYSIS OF THE OXYGEN SOLUBILITY DATA

| Number of <br> Variables <br> in the | Number <br> of the <br> Variable <br> Entered | Length of <br> the Basic <br> Solution <br> Vector | Length of <br> the Residual <br> Vector for <br> the Basic <br> Solution | Length of <br> the Minimum <br> Solution <br> Vectort | Length of <br> Residual <br> Vector <br> for the <br> Minimum <br> Norm |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 2 | $.4040704 \times 10^{5}$ | 2419.978 | $.1014893 \times 10^{5}$ | 7617.572 |
| 2 | 1 | $.9049813 \times 10^{5}$ | 981.9752 | $.1028102 \times 10^{5}$ | 6018.982 |
| 3 | 7 | $.8972010 \times 10^{5}$ | 212.4384 | $.1031885 \times 10^{5}$ | 7818.671 |
| 4 | 3 | $.3168621 \times 10^{7}$ | 82.10176 | $.1091479 \times 10^{5}$ | 4422.227 |
| 5 | 8 | $.1634972 \times 10^{7}$ | 28.52036 | $.1092203 \times 10^{5}$ | 4558.884 |
| 7 | 12 | $.1634366 \times 10^{7}$ | 27.99304 | $.1097797 \times 10^{5}$ | 3548.216 |
| 8 | 4 | $.1033133 \times 10^{9}$ | 26.44726 | $.1103234 \times 10^{5}$ | 3473.011 |
| 9 | 9 | $.1005459 \times 10^{8}$ | 26.06484 | $.1197020 \times 10^{5}$ | 2147.965 |
| 10 | 5 | $.1540121 \times 10^{9}$ | 25.942180 | $.1205483 \times 10^{5}$ | 454.9831 |
| 11 | 6 | $.2658320 \times 10^{11}$ | 25.50685 | $.1207378 \times 10^{5}$ | 29.94534 |
| 12 | 10 | $.3464215 \times 10^{11}$ | 25.27790 | $.2317320 \times 10^{8}$ | 42.48019 |

freedom ( $\mathfrak{m}-n$ ) failed to decrease after eight variables had entered the equation. This was caused by the use of the normal equations to perform the stepwise regression analysis.

Twelve variables were entered in the regression equation by the LLCR package. The length of the residual vector continued to decrease with each variable added to the regression equation.

Note that with all twelve variables in the regression equation,
the length of the solution vector was $.3202155 \times 10^{11}$ with a residual vector of length 25.12197. The length of the solution vector with seven variables in the regression equation was $.1033133 \times 10^{8}$ with a residual vector of length 26.44726 . Thus, with a modest increase in the length of the residual vector, a large decrease in the length of the solution vector was obtained.

In Chapter II, it was stated that if the true rank of the coefficient matrix is less than the number of columns, there is a linear subspace of solution vectors with a residual vector of some minimum length. Among all the vectors in that subspace, there is a unique vector of minimum length (7). All the components of this vector are nonzero. An attempt was made to consider the variables not entered in the regression equation to be linear combinations of the variables represented in the regression equation. The least squares solution of minimum length was then calculated as if the coefficient matrix had a rank equal to the number of variables in the regression equation. The length of each of these solution vectors was considerably less than the length of the basic approximate solution vector (BAS) for the same rank. The lengths of the residual vectors were unacceptably high in most cases. Table IV contains the results of this analysis.

## Using the Package to Test the Effects of Decreasing the

## Precision of the Entries in the Coefficient Matrix

As mentioned in Chapter IV, the user can request that the coefficient matrix be treated as if it had a rank equal to $k$. This corresponds to increasing the value of $\varepsilon$ until the rank of the coefficient matrix is $k$, where $\varepsilon$ is the value used to determine the numerical rank
of the coefficient matrix. If the true numerical rank is less than the rank requested, the true minimum length solution is found. If not, $n-k$ columns of the coefficient matrix are considered to be linear combinations of the $k$ columns that are chosen to be made mutually orthogonal; the minimum norm solution for rank $k$ is found.

The ability to specify a rank enables the user to test the effect on the solution vector of measuring the entries in the coefficient matrix less accurately. During one run of the package, the solution vectors for each choice of rank ranging from one to min(m,n) can be found. This corresponds to finding the solution to the generalized linear least squares problem for a range of $E$. Osborne's method of column selection is used to select the columns to be made mutually orthogonal when the package is used for this purpose.

The solution vectors for a range of ranks were found for the oxygen solubility data. Table $V$ contains the results of the analysis.

Note that for ranks ten and eleven, the length of the minimum length solution vectors greatly decreased with only a moderate increase in the length of the residual vector. For example, the minimum length solution vector's length was $.12072 \times 10^{5}$ with a residual vector of length 26.1 for rank ten. For rank eleven, the minimum length solution bector's length was $.3462100 \times 10^{7}$ with a residual vector of length 25.6 . In contrast, when IVOR was performed and eleven variables had entered the regression equation, the length of the solution vector was $.3464215 \times 10^{11}$ with a residual vector of length 25.3 . When ten variables had entered the regression equation, the length of the solution vector was $.1033 \times 10^{8}$ with a residual vector of length 25.5 .

If the user's objective is to obtain the best trade-off between

TABLE V
ANALYSIS OF OXYGEN SOLUBILITY DATA
USING OSBORNE PIVOTING

| Rank | Basic <br> Variable <br> Entered <br> in the <br> Equation | Length of the Basic Solution Vector | Length of the Residual Vector for the BAS | Length of the Minimum Nom Solution Vector | Length of the Residual Vector for the Minimum Norm Solutior |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | $.21612785 \times 10^{5}$ | $.4380520 \times 10^{4}$ | $.1008446 \times 10^{5}$ | . $8425207 \times 10^{4}$ |
| 2 | 10 | $.1614233 \times 10^{5}$ | $.4168454 \times 10^{4}$ | $.102177 \times 10^{5}$ | . $7203746 \times 10^{4}$ |
| 3 | 11 | $.161299 \times 10^{5}$ | . $4164684 \times 10^{4}$ | $.102470 \times 10^{5}$ | $.5419911 \times 10^{4}$ |
| 4 | 4 | . $1649864 \times 10^{5}$ | $.1013336 \times 10^{4}$ | $.1045335 \times 10^{5}$ | . $2508875 \times 10^{4}$ |
| 5 | 5 | . $1652604 \times 10^{5}$ | . $9690841 \times 10^{3}$ | . $1051180 \times 10^{5}$ | . $1671074 \times 10^{4}$ |
| 6 | 12 | . $1652779 \times 10^{5}$ | . $9588091 \times 10^{3}$ | . $1051873 \times 10^{5}$ | $.1564966 \times 10^{4}$ |
| 7 | 7 | . $1724977 \times 10^{5}$ | . $8021976 \times 10^{2}$ | $.1118416 \times 10^{5}$ | . $250944 \times 10^{4}$ |
| 8 | 6 | $.1724570 \times 10^{5}$ | . $7149151 \times 10^{2}$ | $.1127042 \times 10^{5}$ | . $236241 \times 10^{4}$ |
| 9 | 9 | . $1724276 \times 10^{5}$ | . $7111963 \times 10^{2}$ | . $1196991 \times 10^{5}$ | $.1190856 \times 10^{4}$ |
| 10 | 8 | $.1723771 \times 10^{5}$ | . $2611948 \times 10^{2}$ | $.1207238 \times 10^{5}$ | . $2611625 \times 10^{2}$ |
| 11 | 2 | . $6880348 \times 10^{7}$ | . $2565849 \times 10^{2}$ | . $3462101 \times 10^{7}$ | . $2565829 \times 10^{2}$ |
| 12 | 3 | $.3202155 \times 10^{11}$ | . $2512197 \times 10^{2}$ | $.3202155 \times 10^{11}$ | $.2512197 \times 10^{2}$ |

the length of the solution vector and the length of the residual vector, the package should be run once with IVOR and once with Osborne pivoting.

## Comparison of Methods

The package consisting of LLCR and LLSQ appears to be the first accurate IVOR (stepwise regression) package for ill-conditioned systems of equations. Until this time, stepwise regression packages have
solved the normal equations,

$$
A^{T} A \underline{x}=A^{T} \underline{b} .
$$

The normal equations are often very ill-'conditioned, making double precision calculations necessary (3). Longley (10) has shown examples where essentially no correct digits were obtained when the normal equations were solved. In addition, refinement of the intermediate solutions is available with this package.

For ill-conditioned systems using modified Gram-Schmidt orthogonalIzation produces a much more accurate solution vector than using the normal equations to solve a linear least squares problem. For a mathematical comparison of the accuracy of the methods, see article's by Björck (26), Golub (27), and Wampler (11).

Number of Operations and Storage Requirements

If the coefficient matrix is of full rank, the package requires approximately $\mathrm{mn}^{2}$ multiplications and $m+m+n^{2}+2 n$ storage locations to calculate the linear least squares solution of minimum norm when iterative refinement of the solution is not performed. This should be contrasted with $2 \mathrm{mn}^{2}+\frac{4 n^{3}}{3}$ single precision multiplications and $\mathrm{n}^{2}$ storage locations needed for forming and solving the normal equations in double precision (24).

If iterative refinement is performed, another $m(n+1)$ storage locations are required. An additional $n^{2}+k n$ locations are needed if the system is solved for more than one rank, where $k$ is the number of ranks for which the system is solved.

If the coefficient matrix is of deficient rank, $r$ *, the number of multiplications necessary for finding the solution is $\mathrm{mn}^{2}-\left(\mathrm{n}-\mathrm{r}^{*}-1\right)(\mathrm{m}+\mathrm{n})$ multiplications. The storage requirements are the same as for the full rank case.

When the package is used to perform IVOR, the number of operations necessary to add the $k$-th variable to the regression equation is $2 m\left(n-k+\frac{m a}{2} 3 n k+n^{2}\right)$. The total number of operations would be $4 m^{2} n^{2}+m n^{3}-n$. Approximately $(n+2)^{2}\left(m+\frac{3 n}{2}\right)$ operations are required for stepwise regression using the normal equations (19). If double precision calculations are necessary to obtain single precision accuracy, the comparison is more favorable.

The user of the LLCR package should consider putting all the floating point variables in double precision when solving an ill-conditioned system of equations. Refinement of the initial solutions would be ineffective so no more storage would be required than would be when the calculations were done in single precision with the initial solutions being refined. $\delta$ should be chosen so that $1 . D 0+\delta>1 . D 0$ when doing all calculations in double precision. The solution process is slower when all calculations are done in double precision; the results should be more accurate, however.

There are advantages to being able to solve the system of equations for a range of ranks during one run of the LLCR package instead of using a routine like Björck's. Beginning with a guess, several runs might be necessary to find the $\varepsilon$ to produce the desired rank. In addition, if the results were sought for a range of ranks, Björck's routine would require that the first h-l colums of the coefficient matrix be orthogonalized for each rank $h$ for which the solution was
desired. The LLCR package requires that only one column of the coefficient matrix be orthogonalized after the solution vector for the first rank is found. $2 n^{2}$ additional words are required for this feature, however.

Table VI contains a list of the various uses of the package, and the method of column selection, the ranks for which the system is solved, and the extra storage required for each use.

## Summary

Routines have been written that use modified Gram-Schmidt orthogonalization to solve the generalized linear least squares problem. Both a basic approximate solution and the least squares solution of minimum Euclidean norm are found. Improvement in the accuracy of the solutions by means of iterative refinement of the initial solutions is available to the user of these routines. Full single-precision accuracy in the solutions is obtained when iterative improvement of the solutions is performed and the parameter that is used to determine the numerical rank of the system is at least as great as the relative accuracy of the computer on which the package is run. The error matrix, $\left(A^{T} A\right)^{-1}$, is returned for systems of full rank.

The routines can be used to determine efficiently and accurately the generalized inverse of an arbitrary matrix, A. This is accomplished by solving the system of equations

$$
A X=I
$$

for the matrix $X . I$ is an $m$ by identity matrix, where $n$ is the number of rows in the matrix $A$. The generalized inverse, $X$, is an $n$

## TABLE VI

USES OF THE PACKAGE CONSISTING OF LLCR AND LLSQ

| Problem | Method of Column Selection | The Solution will be found for Ranks | Amount of Extra Storage Needed |
| :---: | :---: | :---: | :---: |
| To calculate the generalized inverse of $A$, an $m$ by $n$ matrix | Osborne pivoting | the numerical rank of A | $\mathrm{m}(\mathrm{m}-1)$ |
| To find the solution of an arbitrary <br> system of equations, $A x=\underline{b}$ | Osborne pivoting | the numerical <br> rank of A | none |
| To perform stepwise regression without the deletion of variables | IVOR | 1 to the numerical rank of the coefficlent matrix | $2 n^{2}$ |
| To study the effect of decreasing the reliability of the entries in the coefficient matrix (solve the system for a range of ranks) | Osborne pivoting | 1sjsnumerical rank of A (a range for $f$ is chosen by the user) | $2 n^{2}$ |
| To find the best trade-off between the length of the solution vector and the residual vector | IVOR and Osborne pivoting | 1 to the numerical rank of $A$ | $2 n^{2}$ |
| ```To fit a polynomial to a set of data points``` | Sequential selection | 1 to the degree of the polynomial | $2 n^{2}$ |

by m matrix, where $n$ is the number of columns in $A$.
IVOR, or forward selection, has been implemented. IVOR corresponds to stepwise regression without the deletion of variables from the regression equation. The package appears to be the first accurate stepwise regression package for ill-conditioned problems.

The coefficient matrix can be treated as if it had a user-specified rank, $k$. This corresponds to increasing the value of the parameter that is used to determine the numerical rank of the coefficient matrix until the rank is $k$. This facility can be used to test the sensitivity of the solution vector to decreased precision of the entries in the coefficient matrix.

## A SELECTED BIBLIOGRAPHY

(1) Osborne, E. E. "Smallest Least Square Solutions of Linear Equations." J. SIAM Numer. Anal. Ser. B., Vol. 2 (1965), 300-307.
(2) Gauss, C. F. "Theoria Combinations Observationum Erroribus Minimis Obnoxiae." Werke, Vol. 4 (1873), 3-93r
(3) Forsythe, G. and C. B. Moler. Computer Solution of Linear Systems. Englewood Cliffs, New Jersey: Prentice-Hall, Inc.; 1967.
(4) Abt, K., Gemmill, G., Herring, T. and R. Shade. "DA-MRCA: A FORTRAN IV Program for Multiple Linear Regression." Naval Weapons Laboratory Report No. 2035, 1966.
(5) Cooper, L. and D. Steinberg. Introduction to Methods of Optimization. Philadelphia: W. B. Saunders Company; 1970.
(6) Hadley, G. Linear Algebra. Reading, Massachusetts: AddisonWesley; 1961.
(7) Penrose, R. "On Best Approximate Solutions of Linear Matrix Equations." Proc. Cambridge Philos. Soc., Vol. 52 (1956), 17-19.
(8) Rosen, J. B. "Minimum and Basic Solutions to Singular Linear Systems." J. Soc. Indust. App1. Math., Vo1. 12 (1964), 156-161.
(9) Fox, L. An Introduction to Numerical Linear Algebra. New York: Oxford University Press; 1965.
(10) Longley, J. "An Appraisal of Least Squares Problems for the Electronic Computer from the Point of View of the User." JASA, Vol. 62 (1967), 819-841.
(11) Wampler, R. "A Report on the Accuracy of Some Widely Used Least Squares Programs." JASA, Vol. 65 (1970), 528-532.
(12) Osborne, E. E. "On Least Squares Solutions Linear Equations." J. Assoc. Comput. Mach., Vo1. 8 (1961), 628-636.
(13) Businger, P. and G. Golub. "Linear Least Squares Solutions by Householder Transformations." Numer. Math., Vol. 7 (1965) 269-276.
(14) Golub, G. 'Numerical Methods for Solving Linear Least Squares Problems." Numer. Math., Vol. 7 (1965), 206-216.
(15) Björck, A. and G. H. Golub. "Iterative Refinement of Linear Least Squares Solutions by Householder Transformation." BIT, Vol. 7 (1967), 323-337.
(16) Hanson, R. J. and C. L. Lawson. "Extensions and Applications of the Householder Algorithms for Solving Linear Least Squares Problems." Mathematics of Computation, Vol. 23 (1969), 787-812.
(17) Bauer, F. L. "Elimination with Weighted Row Combinations for Solving Linear Equations and Least Squares Problems." Numer. Math., Vol. 7 (1964), 338-352.
(18) Björck, A. "Iterative Refinement of Linear Least Squares Solutions II." BIT, Vol. 8 (1968), 8-30.
(19.) Efroymson, M. A. "Multiple Regression Analysis." in Mathematical Methods for Digital Computers (Ralston, A. and H. S. Wilfe, Ed.). New York: John Wiley and Sons, Inc.; 1960.
(20) Dixon, W. and F. Massey. Introduction to Statistical Analysis. New York: McGraw-Hill; 1957.
(21) System/360 Scientific Subroutine Package (360A-CM-03X) Version III Programmer's Manual, IBM H20-0205. White Plains, New York: IBM Corporation Technical Publications Dept.; 1971.
(22) BMD Biomedical Computer Programs (Dixon, W. J., Ed.). Berkeley, California: University of California Press; 1968.
(23) Summers, D. L. and D. D. Babb. "Unfolding Pulse-Height Distributions by Vector Analysis." in Applications of Computers to Nuclear and Radiochemistry. Washington, D. C.: Atomic Energy Commission; 1962.
(24) USA Standard FORTRAN. ANSI Standard X3.9-1966. New York: American National Standards Institute; 1966.
(25) Weiss, R. F. "The Solubility of Nitrogen, Oxygen, and Argon in Water and. Seawater." Deep-Sea Research, Vol. 17 (1970), 721.
(26) Björck, A. "Solving Linear Least Squares Problems by Gram-Schmidt Orthogonalization." BIT, Vol. 7 (1967), 1-21.
(27) Golub, G. "Matrix Decompositions and Statistical Calculations." in Statistical Computations. New York: Academic Press; 1969.

## APPENDIX A

COMPUTER LISTINGS OF LLCR AND LLSQ

SUBROUTINE LLCR (A,LA,R,LRE,SAVE,LSAV,X,RHO,RHOM, SA,ERR,RES,V,XOLD, LLCROOIO
\#SALPH, LSAL, NR,NC, BASIC, NRHS, XSAVEI
LLCR 0020
C
DATE MARCH 1,1972
BRIEF DESCRIPTION OF THIS PROGRAM..

LLCR0030
C

BRIEF DESCRIPTION OF THIS PROGRAM.....
THIS ROUTINE WILL GIVE THE SOLUTION OF MINIMUM NQRM TO THE
LLCR0040

C
GENERAL LINEAR LEAST SQUARES PROBLEM. MODIFIED GRAM-SCHMIOT ORTHOGONALIZATION IS USED TO OBTAIN THIS SOLUTION.

LLCR0060
LLCR 0070
LLCR 0080
LLCR 0090

1. THE FOLLONING OPTIONS HAVE BEEN IMPLEMENTED.

LLCR0100

1. THE SOLUTIONS FOR MULTIPLE RIGHT HAND SIDES WITH A SINGLE

LiCROLIO
COEFFICIEMT MATRIX CAN BE FOUND DURING ONE CALL TO THE ROUTINE.
2. REFINEMENT OF THE INITIAL BASIC APPROXIMATE AND INITIAL MINIMUM NORM SOLUTIONS IS AVAILABLE.

LLCR0140
3. THE ERROR MATRIX, THE INVERSE OF THE PRODUCT OF THE COEFFICIENT

LLCRO150
LLCR 0160
LLCROIT0
4. THE BASIC SOLUTIONS CAN BE PRINTED.

LLCR 0180
ASSUME THAT THE RANK OF THE COEFFICIENT MATRIX IS IRANK, WHERE LLCRO190
IRANK IS LESS THAN THE NUMBER OF COLUMNS IN THE COEFFICIENT MATRIX.LLCRO2OO THE BASIC SOLUTION OBTAINED IS THE SOLUTION WITH AT MOST IRANK LLCROZIO
NONZERO COMPONENTS THAT GIVES THE MINIMUM EUCLIDEAN NORM. LLCRO220
5. THE USER CAN REQUEST THAT IVOR, INOEPENDENT VARIABLIE ORDERING

LLCR0230 BY REGRESSION SUM OF SQUARES, BE PERFORMED. IVOR CORRESPONDS TO LLCRO240 PERFORMING STEPWISE REGRESSION WITHOUT REMOVING A VARIABLE FROM LLCRO250 THE REGRESSION EQUATION ONCE IT HAS ENTERED THE REGRESSION EQUATION.
6. THE USER CAN REQUEST THAT THE COEFFICIENT MATRIX BE TREATED AS IF IT HAD A RANGE OF RANKS, KRBEG THROUGH KREND. IF THE RANK REQUESTED IS GREATER THAN THE NUMERICAL RANK OF THE SYSTEM LLCR0260 LLCR0270 LLCR0280 LLCR 0290
(DETERMINED BY THE RELATIVE ACCURACY EPSI, A MESSAGE IS PRINTED. LLCRO300
LLCR 0310
IN THE AUTHOR-S M.S. REPORT IDEPARTMENT OF COMPUTING AND INFORMATION
SCIENCES, OKLAHOMA STATE UNIVERSITY; MAY, 19721.
LLCR0320

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REFERENCES....
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    E. E. OSBORNE, JOURNAL OF THE SIAM 12 (1965) 300 LLCR0370
    LLCR0360
J. B. ROSEN, JOURNAL OF THE SIAM 12 (1964) 156 LLCR0380
G. GOLUB, NUMERISCHE MATHEMATIK 7 (1965) 206
JOHN R. RICE, MATHEMATICS OF COMPUPATION $20(1966) 325$ LLCRO400
LLCR 0390
A. BJORCK, BIT 7 (1967) 257 LLCR0410
A. BJORCK, BIT 8 (1968) 8 LLCR0420
A. BJORCK, BIT 7 (1967) 1
LLCR 0430
LLCR 0440
DESCRIPTION OF SUBROUTINES CALLED.....
LLCROM50
LLCR 0470
LLCR 0480
LLCR 0490
DESCRIPTION OF VARIABLES....
LLCR0500
C INPUT VARIABLES....

A -- THE NR BY NCOLS AUGMENTED MATRIX THE NRHS RIGHT HAND SIDES ARE CONCATENATED WITH THE NR BY NC COEFFICIENT MATRIX TO FORM THE AUGMENTED MATRIX. THE FIRST IRANK COLUMNS OF A ARE MADE MUTUALLY ORTHOGONAL. THE NEXT (NC-IRANK) COLUMNS ARE
INPUT VARIABLES.....

| $\begin{aligned} & \mathbf{C} \\ & \mathbf{C} \end{aligned}$ | LA | -- | THE first dimension of the a array | LLCR0600 <br> LLCR 0610 |
| :---: | :---: | :---: | :---: | :---: |
| C |  |  | (LA MUST BE. GE. NR.) | LLCR0620 |
| C | LRE | -- | THE FIRST DIMENSION OF THE R AND ERR ARRAYS | LLCR0630 |
| C |  |  | (LRE MUST DE .GE. NC.) | LLCR 0640 |
| C | LSAV | -- | THE FIRST DIMENSION OF THE ARRAY SAVE | LLCR 0650 |
| C |  |  | ILSAV MUST BE. GE. NR IF ITERATIVE IMPRQVENENT OF Thel | LLCR 0660 |
| C |  |  | SOLUTION IS REQUESTED. LSAY SHOULD EQUAL 1 | LLCR0670 |
| C |  |  | OTHERNISE.) | LLCR 0680 |
| C | LSAL | -* | THE FIRST DIMENSION OF THE ARRAY SALPH | LLCR 0690 |
| C |  |  | (LSAL MUST BE GE. NC IF THE PROBLEM IS TO BE SOLVED | LLCR 0700 |
| C |  |  | FOR MORE THAN ONE RANK. LSAL SHOULD EQUAL 1 | LLCR0710 |
| C |  |  | OTHERWISE. | LLCR0720 |
| C | EPS 1 | $\cdots$ | THE CONVERGENCE CRITERION FOR THE ITERATIYE IMPROVE- | LLCR0730 |
| C |  |  | MENT OF THE SOLUTION | LLCR0740 |
| C |  |  | EACH COMPONENT IN THE FINAL SOLUTION VECTOR WILL | LLCR0750 |
| C |  |  | DIFFER FROM THE CORRESPONDING COMPONENT IN THE | LLCR0760 |
| C |  |  | PREVIOUS SOLUTION VECTOR BY NO MORE THAN EPSI | LLCR0770 |
| C |  |  | TIMES THE COMPONENT IN THE FINAL SOLUTION VECTOR. | LLCR0780 |
| C | EPS |  | THE VALUE USED TO DETERMINE IF A COLUMN IN THE | LLCR 0790 |
| C |  |  | COEFFICIENT MATRIX IS A LINEAR COMBINATION DF OTHER | LLCR0800 |
| C |  |  | COLUMNS IN THE COEFFICIENT MATRIX | LLCR0810 |
| C |  |  | NEITHER EPS NOR EPSI SHOULD BE LESS THAN THE PRODUCT | LLCR 0820 |
| C |  |  | Of the base and the relative accuracy of the machine | LLCR0830 |
| C |  |  | BEING USED. | LLCR0840 |
| C | NR | -- | THE NUMBER OF EQUATIONS IN THE SYSTEM | LLCR0850 |
| c |  |  | (NUMBER OF ROWS OF A) | LLCR0860 |
| C | NC | -* | THE NUMBER OF INDEPENDENT VARIABLES | LLCR0870 |
| C |  |  | (NUMBER OF COLUMNS OF A BEFORE IT IS AUGMENTED) | LLCR0880 |
| C | NRHS |  | THE NUMBER OF RIGHT HAND SIDES | LLCR0890 |
| C |  |  | (NRHS MUST BE.GE. 1.) | LLCR0900 |
| C | IPIV |  | =-1 NO PIVOTING IS PERFORMED. | LLCR 0910 |
| C |  |  | $=0$ OSBORNE PIVOTING IS PERFDRMED. | LLCR0920 |
| C |  |  | - 1 IVOR IS PERFORMED. | LLCR0930 |
| C |  |  | SEE THE ARTICLE BY OSBORNE FOR A DESCRIPTION OF | LLCR 0940 |
| C |  |  | OSBORNE PIVOTING. | LLCR0950 |
| C | I SW |  | $=1$ If THE SQUARE OF THE NORM IS TO BE RECOMPUTED USINGI | LLCR0960 |
| C |  |  | INNER PRODUCTS | LLCR0970 |
| C |  |  | OTHERWISE. THE SQUARE OF THE NORM IS RECOMPUTED | LLCR 0980 |
| C |  |  | USING THE METHOD PROPOSED BY OSBORNE. | LLCR0990 |
| C | IREF |  | $=1$ IF THE INITIAL SOLUTION IS TO BE REFINED | LLCR1000 |
| C |  |  | \# O IF THE SOLUTION. IS NOT TO BE REFINED BUT THE | LLCR 1010 |
| C |  |  | RESIDUAL VECTOR IS TO BE CALCULATED | LLCR 1020 |
| C |  |  | =-1 THE SOLUTION IS NOT TO BE REFINED AND THE RESIDUAL | LLCR 1030 |
| C |  |  | VECTOR CANNOT BE CALCULATED | LLCR 1040 |
| C |  |  | (SAVE AND a are the same matrix.l | LLCR 1050 |
| C | NTRAC. |  | $=-1$ ERROR MESSAGES ONLY ARE PRINTED. | LLCR 1060 |
| C |  |  | $=0$ THE FINAL SOLUTIGN VECTORS AND THE RANK OF THE | LLCR 1070 |
| C |  |  | COEFFICIENT MATRIX ARE PRINTED IN ADDITION TO THE | LLCR 1080 |
| C |  |  | ABOVE. | LLCR 1090 |
| C |  |  | $\pm 1$ THE INTERMEDIATE SOLUTION VECTORS, THE RESIDUAL | LLCR1100 |
| C | - |  | VECTORS FOR EACH INTERMEDIATE SOLUTION AND THE | LLCR1110 |
| C |  |  | FINAL SOLUTION, AND THE ERROR MATRIX ARE PRINTED | LLCR1120 |
| C |  |  | IN ADDITION TO THE ABOVE. | LLCR1130 |
| c |  |  | $=2$ THE ORIGINAL COEFFICIENT MATRIX, THE ORIGINAL | LLCR 1140 |
| C |  |  | RIGHT HAND SIDES, AND THE DECOMPOSITION MATRIX AREL | LLCR 1150 |
| C |  |  | PRINTED IN ADDITION TO THE ITEMS LISTEO ABOVE. | LLCR1160 |
| C | KW | -- | THE STANDARD OUTPUT UNIT NUMBER | LLCR1170 |
| C | KRBEG,KREND | -- | AN ATTEMPT WILL BE MADE TO SOLVE THE SYSTEMS OF | LLCR 1180 |
| C |  |  | EQUATIONS AS IF THE COEFFICIENT MATRIX HAD A RANK OF | LLCR1190 |






```
    330 RES(IR)=-RES(IR) LLCR 3600
        IFIIRANK I 400,400,340
LlCR3610
    340 DO 380 Iml,IRANK
    DOT=VZERO
    DO 350 J=1,NR
    350 DOT=DOT+A(J,Il**RES(J)
        ALPHA=DOT/RHO(I)
    DO 360 J=I.NR
    360 RES(J)=RES(J)-ALPHA*A(J,I)
    OO 370 Jx1.NC
    370 V(J)=V(J)-ALPHA*R(J.I)
    380 CONTINUE
    IF(KSW)440,390,390
    390 IFIIRANK-NC 1400,440,400
    400 IRNK P=IRANK+1
    DO 430 I=IRNKP,NC
    DOT=VZERO
    00 410 J=1.NC
    410 DOT=DOT+R(J,I)*V(J)
C ....
J)
RHOM(II CAN NEVER BE ZERO THEORETICALLY OR
NUMER ICALLY.
        ALPHA=DOT/RHOM(I)
        DO 420 J=1,NC
    420 V(J)=V(J)-ALPHA*R(J.I)
    430 CONTINUE
C
    .... CALCULATE THE NEW SOLUTION VECTOR.
    440 00 450 I=I,NC
        XOLD{I}=x{I)
    450 X(I)=X(I)+V(I)
C....
    DO 500 1=1,NC
        DIF=X(I)-XOLD(I)
        IF(DIF)460;470,470
    460 DIF=-DIF
    470 XOLD(I)=X(I)
        IF(XOLD(I))480,490,490
    480 XOLD(I)=-XOLD(I)
    490 IFIDIF-EPSI*XOLD(I):500,500,240
    500 CONTINUE
        IF(KSH)540,510,540
    510 IF{IPIV-1)520,540,520
    520 NO=KRANK-KRBEG+1
        KK=K-NC
        DO 530 KL=1,NC
    530 XSAVE{KL,KK,NO) =X(KL)
    540 [F(NTRAC)670,550,550
    550 WRITE(KW,860)KNT
        NO=K-NC
        IF(IREF)630,560,560
C ....
CALCULATE THE RESIDUAL VECTOR.
    560 00 580 I=1,NR
        DRES=VZERO
        DO 570.J=1.NC
        DINT=X(J)
        DINTP=SAVE(I,J)
    570 DRES=DRES+DINTP*DINT
    DSAVE=SAVE(I,K)
    580 RES\II=DSAVE-DRES
        IF(NTRAC-2)600,590,600
    590 WRITE{KW,770)NO,(RES\1),I=1,NR)
LLCR 3610
LLCR3620
LLCR 3630
LLCR 3640
LLCR 3650
LLCR 3660
LLCR3670
LLCR 3680
LLCR 3690
LLCR 3700
LLCR3710
LLCR 3720
LLCR3730
LLCR 3740
LLCR 3750
LLCR 3760
LLCR 3770
LLCR3780
LLCR 3790
LLCR3800
LLCR 3810
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LLCR 3840
LLCR 3850
LLCR3860
LLCR3870
LLCR 3880
LCR3890
LLCR3900
UCR3910
LLCR 3920
LLCR 3930
LLCR 3940
LLCR 3950
LLCR 3960
LLCR3970
LLCR 3980
LLCR 3990
LLCR 4000
LLCR 4010
LLCR 4020
LLCR4030
LLCR 4040
LLCR 4050
LLCR4060
LLCR 4070
LLCR4080
LLCR 4090
LLCR4100
LLCR4110
LCR4120
LLCR4130
LLCR4140
LLCR 4150
LLCR 4160
LLCR4170
LLCR4180
LLCR4190
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## APPENDIX B

SAMPLE OUTPUT FROM THE PROBLEM CONSISTING OF THE FIRST FIVE COLUMNS OF A 6 BY 6 INVERSE HILBERT MATRIX AND A RIGHT HAND SIDE CHOSEN TO GENERATE THE SOLUTION VECTOR

$$
\left(1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}\right)
$$


start iterating the gasic solution
iteration o










| -0.1110306E 00 |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
| THE | SOLUTION TO THE SYSTEM $0.9997082 E 00$ | $\begin{aligned} & \text { EM FOR RIGHT HAND SIDE } \\ & 0.4999225 \mathrm{E} 00 \end{aligned}$ | $\begin{array}{ll} \text { NUMBER } & 1 \\ 0.3333055 E & 00 \end{array}$ | 0.2499895E 00 | $0.1999967 E 00$ |
| Iteration 2 |  |  |  |  |  |
| the | $\begin{aligned} & \text { RESIDUAL VECTOR FOR RIGHT HAND SIDE NUMBER } \\ & \begin{array}{ll} -0.2093315 E-03 & 0.5882978 \mathrm{E}-02 \\ 0.4262781 \mathrm{E}-01 & \end{array} \end{aligned}$ |  | $\begin{gathered} 1 \mathrm{IS} \\ -0.3905296 \mathrm{E}-01 \end{gathered}$ | 0.1000857 OO | -0.1091981E 00 |
| the length of the residual vectior is or 0.1591172 l 00 |  |  |  |  |  |
| the | SOLUTION TO THE SYSTEM 0.9999990 E 00 | EM for right hand side 0.4999998 EO | $\begin{array}{ll} \text { NUMBER } & 1 \\ 0.3333333 E & 00 \end{array}$ | 0.2499999 EO | 0.2000000E 00 |
| ITERATION |  |  |  |  |  |
| THE | $\begin{aligned} & \text { RESIDUAL VECTOR FOR RIG } \\ & -0.3291368 E-03 \\ & 0.6493306 \mathrm{E}-01 \end{aligned}$ | ght hand side number $0.9074807 \mathrm{E}-02$ | $\begin{gathered} 115 \\ -0.5993128 E-01 \end{gathered}$ | $0.1531076 E 00$ | -0.1666510E 00 |
| the lengit of the residual vector for the final solution is $0.2431152 e 00$ the souare of the length of the residual vector for the final solution is o.5910502e-01 |  |  |  |  |  |
| the | final soluticn to the s $0.9999999 E 00$ | system for the right $0.4999999 E 00$ | HAND SIDE NUMBER 0.3333333 E 00 | $\begin{aligned} & 1 \\ & 0.2499999 E \quad 00 \end{aligned}$ | 0.2000000 E 0 |
| THE | length of the final solution vector is |  | 0.1209797E 01 |  |  |
| the error matrix |  |  |  |  |  |
|  | 0.2461610 E 00 | 0.7977712E-01 | $0.3363910 \mathrm{E}-01$ | 0.1456363E-01 | 0.5140688E-02 |
|  | $0.7977712 \mathrm{E}-01$ | $0.2632471 \mathrm{E}-01$ | 0.1121059E-01 | 0.4884373E-02 | 0.1731764E-02 |
|  | 0.3363910E-01 | 0.1121059E-01 | 0.4800081E-02 | 0.2098641E-02 | $0.745888 \mathrm{BE}-03$ |
|  | $0.1456363 \mathrm{E}-01$ | $0.4884373 \mathrm{E}-02$ | 0.2098641E-02 | 0.9195909E-03 | 0.3273471 E-03 |
|  | 0.5140688E-02 | $0.1731764 \mathrm{E}-02$ | $0.7458888 \mathrm{E}-03$ | 0.3273471E-03 | 0.1166535E-03 |

## APPENDIX C

SETTING THE INPUT VARIABLES FOR
LLCR AND LLSQ

The following flow chart and tables will give the user of the LLCR package the information he needs to set the FORTRAN variables needed by the package. A complete description of the calling sequence is given in Appendix A.

The first group of variables are usage independent. They should be set at the values given below for every problem solved by the package. Table VII contains the FORTRAN variables in the group and the corresponding values.

TABLE VII

SETTING THE USAGE INDEPENDENT FORTRAN VARIABLES NEEDED BY THE LICR PACKAGE

| FORTRAN Variables | Values |
| :--- | :---: |
| KREND | $\leq n, \geq$ KRBEG |
| EPS | $\geq \delta$ |
| EPS1 | $\geq \delta$ |
| NR | $m$ |
| NC | $n$ |
| LA | $\geq m$ |
| LRE | $\geq n$ |

$n$ is the number of columns in the coefficient matrix, $m$ is the number of rows in the coefficient matrix, and $\delta$ is the relative accuracy of the computer.

The values at which the second group of variables are set depends upon the amount of extra storage available for the program, the accuracy desired for the final solutions, and the amount of extra execution time the user is willing to sacrifice. Figure 2 contains a flow chart that
will show the user how to set this group of variables.


Figure 2. Setting the Usage Dependent FORTRAN Variables

The third group of varłables are usage dependent; these variables will be set differently for different usages of the package. The appropriate value for each variable in this group for each usage is given in Table VIII.

TABLE VIII

SETTING THE USAGE DEPENDENT VARIABLES NEEDED
BY THE LLCR PACKAGE

| Program Usage | IPIV | KRBEG | NRHS | LSAL |
| :--- | :---: | :---: | :---: | :---: |
| To solve a system or systems of <br> equations AXmB | 0 | $\mathfrak{n}$ | h | 1 |
| To perform IVOR or "forward <br> selection" | 1 | 1 | 1 | $\geq \mathfrak{n}$ |
| To solve AX=B while treating |  |  |  |  |
| the entries In A as if they |  |  |  |  |
| had a variable precision |  |  |  |  |
| To fit a polynomial to data | 0 | $\geq 1$ | h | $\geq \mathfrak{n}$ |
| To calculate a generalized | -1 | 1 | 1 | $\geq \mathfrak{n}$ |
| inverse | 0 | $\mathfrak{n}$ | m | 1 |

The tables and flowchart: given above and the information given in Appendix A should should enable the user to work with LLCR and LLSQ with relative ease. The routines are also documented internally with comment cards.

> VITA
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> Candidate for the Degree of
> Master of Science

Thesis: COMPUTER SOLUTION OF THE GENERALIZED LINEAR LEAST SQUARES PROBLEM USING MODIFIED GRAM-SCHMIDT ORTHOGONALIZATION

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