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CRITICAL NETWORKS AND DISINFORMATION

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Abstract

The spread of disinformation across both digital and physical networks has created serious challenges for public trust, decision-making, and communication strategies. This thesis builds a stochastic, path-based optimization model that focuses on maximizing the spread of accurate information under real-world uncertainty and budget constraints. The model works by planning a connected route through a network of cities, starting from a source and reaching a target, while dealing with varying travel and campaign costs across different scenarios. An application using a real-world-inspired network shows how changes in budget levels and cost assumptions impact the total number of people influenced and the number of cities reached. Results suggest that taking a conservative approach to cost assumptions allows campaigns to cover more ground and reach more people, while higher-cost or uncertain scenarios limit both reach and attendance. This work offers a flexible framework for organizing strategic communication efforts and opens the door for future research on evaluating efficiency and adapting strategies as conditions change.

Chapter 1: Introduction and Motivation

In the current intricate information landscape, the spread of disinformation greatly affects public discussions, trust in society, and decision-making in the United States. The intersection of advanced artificial intelligence technologies with widespread digital media makes it increasingly difficult to identify credible information, thereby complicating the strategic implementation of campaigns designed to counter false narratives. Tackling this urgent challenge requires careful planning, especially in the face of limited financial resources and persistent disinformation networks. Therefore, this thesis aims to enhance the strategic distribution of accurate information to maximize influence in uncertain situations while respecting budget limitations. This research adds to the existing body of work by combining path-dependent optimization with scenario-based stochastic programming, addressing a notable gap in traditional influence maximization models that frequently disregard real-world limitations and the intricacies of uncertainty. The structure of the thesis is organized as follows: in Chapter 2, relevant influence spread models and stochastic route optimization are discussed. Chapter 3 proposes a stochastic path-based influence model. Chapter 4 is an illustration of the model through an extensive real-world example and a thorough evaluation of the model's effectiveness using Data Envelopment Analysis (DEA). Chapter 5 presents final remarks and suggests directions for future research.

Chapter 2: Literature Review

The increasing prevalence of disinformation poses significant risks to network vulnerability, especially in relation to the dissemination of accurate information. Disinformation campaigns exert a profound influence on perceptions across various sectors, including public health, finance, and politics. When disseminated on online social platforms, this content can reach millions, thereby facilitating the viral spread of false propaganda [1,4,11]. Such occurrences underscore the necessity of influence maximization—defined as the enhancement of accurate information's reach—as a fundamental aspect of network optimization and highlight the importance of effective risk management and resilient strategies within organizations [6,7,12]. The challenge of influence maximization constitutes a complex optimization problem as it necessitates a careful balance between efficiency and effectiveness in mitigating disinformation while simultaneously identifying the optimal pathways for information transmission across networks [8]. In addressing real-world uncertainties, such as volatile or unspecified network parameters, stochastic programming offers a useful framework for modeling randomness. By identifying strategies in uncertain conditions, it enables the development of robust solutions for addressing these challenges [9,10]. The objective of this research is to further the understanding of these dynamics through stochastic modeling and route optimization, ultimately enhancing the capabilities to rectify disinformation and optimize the dissemination of accurate information within social networks.

Influence maximization (IM) is a well-recognized problem within the fields of network science and social network analysis, focusing on the selection of nodes within a network to maximize the spread of influence. Kempe et al. (2003) pioneered a formulation for this problem by incorporating two diffusion models: the Independent Cascade Model (ICM), wherein influence propagates stochastically, allowing active nodes to influence neighboring nodes, and the Linear Threshold Model (LTM), wherein nodes adopt influence from neighboring nodes contingent on meeting a certain threshold [12]. The research demonstrates that IM problems are NP-hard; however, the influence spread function is submodular, indicating that a greedy algorithm can approximate the optimal solution to 63% of its maximum value [14]. This revelation has propelled advancements in Monte Carlo simulations and sampling-based algorithms [15,16]. Traditional IM methodologies posit seed nodes—those that introduce new nodes into the network while maintaining their integrity—can be arbitrarily selected from within the network. This research emphasizes path-based influence spread, wherein influence propagates sequentially along a designated path rather than being freely seeded. The integration of routing constraints with IM introduces new challenges, particularly in real-world contexts where influence must be strategically sourced amid resource limitations and network unpredictability.

Deterministic models prove insufficient when confronted with IM challenges under uncertain conditions, wherein real-world parameters (e.g., influence probabilities and traversal costs) are not fixed but characterized as random variables across various scenarios. Scenario-based stochastic programming addresses this challenge by incorporating multiple potential realizations of uncertain factors. This approach allows for decision-making that achieves optimal outcomes, either by maximizing expected results or by satisfying constraints with high probability across various scenarios [2,13]. Stochastic programming has been applied to restrict influence rather than maximize it, in conjunction with network interdiction and protection strategies. Song and Dinh (2016) utilized stochastic optimization to allocate a finite budget for protecting arcs within a network. Their findings emphasize the need for fortification against uncertainty in rumor propagation [16]. Similarly, Wu and Küçükyavuz (2018) introduced a two-stage stochastic model for IM, showcasing how scenario-based optimization can yield optimal solutions that account for uncertainty in influence outcomes. Employing stochastic programming provides a strong framework for network influence challenges by explicitly modeling uncertainties in both propagation and costs. A scenario-based evaluation will enable us to systematically address real-world variability in influence and network constraints.

Routing problems have been extensively explored within the domains of operations research and algorithm analysis. Unlike the traditional shortest-path problem, where weights and costs remain fixed, stochastic routing problems account for a range of uncertainties regarding time and travel costs, including objectives that may vary. A common goal, however, is to identify a path that maximizes the probability of completion within budgeted time or cost [18]. When planning for an IM challenge, the core difficulty lies in optimizing the aggregation of "influence reward" along a designated route. This challenge bears resemblance to the Orienteering Problem (OP), a classic routing dilemma that integrates components from the knapsack problem by necessitating the selection of the most valuable nodes while concurrently determining the optimal visit within a travel budget (TSP-routing problem) [19]. In the scope of our research, we incorporate elements of stochastic routing and orienteering within the framework of path planning under uncertainty, where information campaigning operates under a fixed budget. Given that travel costs (associated with traversing edges) and influence costs (pertaining to influence on nodes) are uncertain, this challenge requires meticulous scenario-based decision-making to optimize influence distribution within real-world constraints [19].

The preceding review elucidates several critical gaps within the existing literature, a significant component being the absence of a path-dependent strategy. The principal function of most IM models is to select seed nodes, neglecting any prescribed path among them [15]. Furthermore, there is insufficient consideration for stochastic programming, as traditional IM approaches often presume fixed diffusion probabilities or rely on heuristics to approximate solutions without robust methods for optimizing under uncertainty [13]. Finally, there is negligible attention paid to real-world constraints, wherein many previous models oversimplify practical limitations such as time windows, travel budgets, or the opportunity cost associated with the selection of one seed node over another [16]. This research seeks to address these deficiencies by integrating path planning and influence maximization within a unified stochastic model, aimed at disseminating accurate information amidst uncertain network conditions.

Chapter 3: Stochastic Path-based Influence Model

3.1. Modeling Assumptions

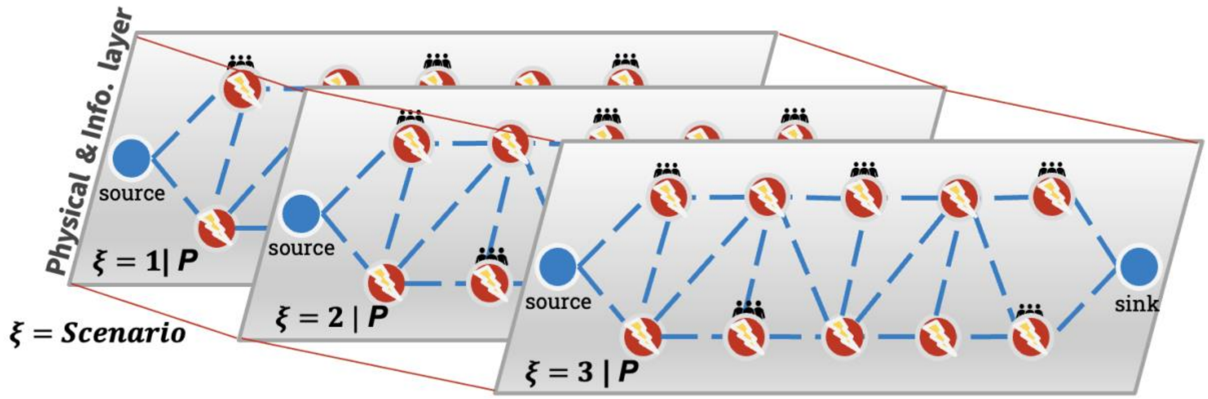

Figure 1. Maximum Influence Scenario-Path based Stochastic program Illustrated

The Figure above illustrates a new way of thinking about how to fight disinformation in real-world networks. Three different scenarios, each representing how the connections between cities and routes might change depending on how things play out. In every scenario, we start at a source where reliable information begins and aim to reach a sink, or target city, while navigating through areas already impacted by disinformation. The groups of people at each location represent the populations we're trying to influence with good information. Our model brings together both the physical side — how we move — and the information side — how ideas spread — all while working under real-world limits like budgets and travel costs. By planning for different scenarios, we can find the most effective paths to push back against disinformation and make sure our message reaches the right places, even when things don't go exactly as expected. Below are key assumptions that form the foundation of this optimization model.

The Stochastic Path-based Influence Model uses the following assumptions:

- Due to scheduling flow, the campaign must follow a connected path from a designated starting point (Reno, NV) to an endpoint (Bangor, ME), visiting cities along the way.
- Disinformation has affected the network already and is stagnant (not spreading).
- The travel cost between locations (plane routes) is uncertain and varies across different probabilistic scenarios.
- The cost of visiting each city (campaign) is also scenario-dependent.
- The campaign has a total budget B in USD, which limits the number of locations and routes that can be visited. The expected budget across all scenarios must be within the total available budget.
- The selected path must form a continuous route from a source node (starting point) to a terminal node (target).
- Each node has an estimated number of attendees and cost to hold an information campaign.
- If selected to visit a city, every person that is estimated to attend is influenced.
- The objective function is based on expected influence spread, considering different probabilistic cost scenarios.
- The of probabilities are for each scenario are cumulative and must sum to one.

3.2. Notation

Table 1. SPIM Sets, Parameters and Decision Variables

Notation	Description
Sets	
N	Set of cities for information stops
A	Set of routes where (i, j) ∈ A, represents route from i to j
S	Set of scenarios , for each k ∈ S representing possible realizations of uncertain costs. indexed by k
$\boldsymbol{\varphi}$	Source node
$\boldsymbol{\vartheta}$	Sink node
Parameters	
$\mathbf{p_k}$	Probability of scenario k ∈ S such that $\sum_{\mathbf{k} \in \mathbf{S}} \mathbf{p_k} = \mathbf{1}$
$\mathbf{c_{ij}^k}$	Cost in dollars of traversing arc under scenario
$\mathbf{c_i^k}$	Cost in dollars of visiting node i ∈ N under scenario
$\mathbf{d_i}$	Influence value of visiting Node
B	Total available budget
Decision Variables	
$\mathbf{x_{ij}}$	Equal to 1 if link is on the selected path, binary
$\mathbf{z_i}$	Equal to 1 if is visited on the selected path, binary

3.3. Objective function

As discussed earlier, the purpose of this Model is to maximize influence throughout a network. We need a binary variable that informs whether we visited a city to achieve this.

$$\mathbf{Max} \sum_{\mathbf{i} \in \mathbf{N}} \mathbf{d_i z_i} \qquad (1)$$

Eq. 0 seeks to maximize the influence at each city for all cities in the network by integrating (multiplying) the binary node (0 or 1) with the influence population at that respective city to keep track of influence score.

3.4. Constraints

Constraint 3.4.1 ensures that while traversing the network, we must stay within our budgeted amount for each scenario. This includes traveling on arcs and the cost to be at each node. However, each scenario's expected cost must also be within budget. It balances fiscal responsibility with opportunity, leveraging weighted scenarios to provide a more realistic environment than single-scenario approaches.

$$\sum_{k \in S} p_k \left[c_i^s z_i + \sum_{j:(i,j) \in A} c_{ij}^s x_{ij} \right] \leq B \qquad , \forall i \in N \qquad (3.4.1)$$

Constraints 3.4.2 and 3.4.3 explain that our source node and sink node must be one. This helps the model understand that we must start at the source and sink nodes, establishing the endpoints necessary for a properly defined path.

$$z_{\varphi} = 1 \qquad (3.4.2)$$

$$z_{\vartheta} = 1 \qquad (3.4.3)$$

Constraint 3.4.4 establishes that the source node has one additional outgoing arc compared to its incoming arcs, which ensures the path starts from the source node. Constraint 3.4.5 requires that the sink node receive precisely one more arc than it sends out, which ensures the path will complete at the sink node.

$$\sum_{j:(\varphi,j) \in A} x_{\varphi j} - \sum_{j:(j,\varphi) \in A} x_{j\varphi} = 1 \qquad (3.4.4)$$

$$\sum_{j:(\vartheta,j) \in A} x_{\vartheta j} - \sum_{j:(j,\vartheta) \in A} x_{j\vartheta} = 1 \qquad (3.4.5)$$

Constraints 3.4.4-3.4.6 play a crucial role in our model, ensuring that the number of arriving arcs aligns with the number of departing arcs for every node, except the source and sink. These constraints are not just imports, but vital components of our approach. They guarantee a smooth, continuous route from the source to the destination, eliminating unnecessary interruptions or delays. Moreover, they prevent the formation of isolated loops that don't connect with the primary path, thereby enhancing the efficiency of our model.

$$\sum_{\mathbf{i}:(\mathbf{i},\mathbf{j})\epsilon\, \mathbf{A}} \mathbf{x_{ij}} = \sum_{\mathbf{k}:(\mathbf{j},\mathbf{k})\epsilon\, \mathbf{A}} \mathbf{x_{jk}} \qquad , \forall \mathbf{j} \in \mathbf{N}\backslash\{\boldsymbol{\varphi}, \boldsymbol{\vartheta}\} \qquad (3.4.6)$$

The constraints labeled 3.4.7 and 3.4.8 ensure that any chosen path between two points includes stops at both locations, mirroring real-world scenarios. A genuine stop is mandatory during transit between two points, reflecting the practicality of our model. These rules eliminate imaginary travel paths, which fail to reflect accurate routes, ensuring that all paths we select link to authentic information campaign events. Without these constraints, the model could propose routes that do not match actual campaign visits, highlighting the practical implications of this work.

$$\mathbf{x_{ij}} \leq \mathbf{z_i} \qquad , \forall (\mathbf{i}, \mathbf{j}) \in \mathbf{A} \qquad (3.4.7)$$
$$\mathbf{x_{ij}} \leq \mathbf{z_j} \qquad , \forall (\mathbf{i}, \mathbf{j}) \in \mathbf{A} \qquad (3.4.8)$$

The initial regulation requires that all locations visited apart from the starting point must have a defined path leading to them, ensuring the comprehensiveness of our model. Constraints 3.4.9 and 3.4.10 further ensure all locations visited during the campaign route must have an exit path to another location except the final stop according to the second rule. Combining these rules prevents the model from selecting important locations that are not part of the campaign's travel route. These rules generate a campaign schedule that ensures that each chosen stop can be accessed and leads to another valid location. The optimizer could select high-impact locations lacking feasible travel routes, creating an unworkable campaign schedule, underscoring the need for a comprehensive approach.

$$\mathbf{z_i} \leq \sum_{\mathbf{j:(i,j)\epsilon\, A}} \mathbf{x_{ij}} \qquad , \forall \mathbf{i} \ \epsilon \ \mathbf{N} \backslash \{\boldsymbol{\varphi}, \boldsymbol{\vartheta}\} \qquad (3.4.9)$$

$$\mathbf{z_i} \leq \sum_{\mathbf{j:(j,i)\epsilon\, A}} \mathbf{x_{ji}} \qquad \forall \mathbf{i} \ \epsilon \ \mathbf{N} \backslash \{\boldsymbol{\varphi}, \boldsymbol{\vartheta}\} \qquad (3.4.10)$$

Constraint 3.4.11 governs subtour elimination, meaning that there are no cycles formed among a strict subset of nodes without including the source and sink nodes. this drives the solution to form a single connected path rather multiple disconnected loops throughout the network.

$$\sum_{\mathbf{i\epsilon\, S}} \sum_{\mathbf{j\epsilon\, S}} \mathbf{x_{ij}} \leq |\mathbf{S}| - \mathbf{1} \qquad \forall \mathbf{S} \subset \mathbf{N}, \mathbf{2} \leq |\ \mathbf{S}\ | \leq |\ \mathbf{N}\ | - \mathbf{1} \qquad (3.4.11)$$

Constraints 3.4.11 & 3.4.12 ensure that each decision variable is binary throughout the entire network.

$$\mathbf{x_{ij}} \in \{\mathbf{0}, \mathbf{1}\} \qquad , \forall (\mathbf{i}, \mathbf{j}) \in \mathbf{A} \qquad (3.4.12)$$

$$\mathbf{z_i} \in \{\mathbf{0}, \mathbf{1}\} \qquad , \mathbf{i} \in \mathbf{N} \qquad (3.4.13)$$

Chapter 4: Application

4.1. Structure of the System

In this section, we explore the methodology developed in the earlier chapters through a hands-on example of an information campaign route optimization. The analysis includes a network of potential stops and their respective rally costs, which are key to scheduling the information campaign. This network features 78 potential locations for informational rally stops, called nodes, and 140 travel paths, known as arcs, that connect them. Together, this framework creates an existing information campaign network that helps us identify hotspots for spreading information. We estimate attendance in each city based on its population. Each node represents a unique location that can host a campaign event, while each arc outlines the travel routes between these spots. This network naturally establishes a sequence for our campaign stops, ensuring the route flows smoothly. We assign rally costs to each travel path to accurately reflect the expenses and logistics involved in moving from one stop to the next. These costs take into account travel time, monetary expenses, and strategic factors, all of which play a role in optimizing the route. Additionally, we estimated expenses based on the operational costs of using an entire aircraft (like the Boeing 737 and 757). The map illustrating the optimization network across the U.S. is presented below.

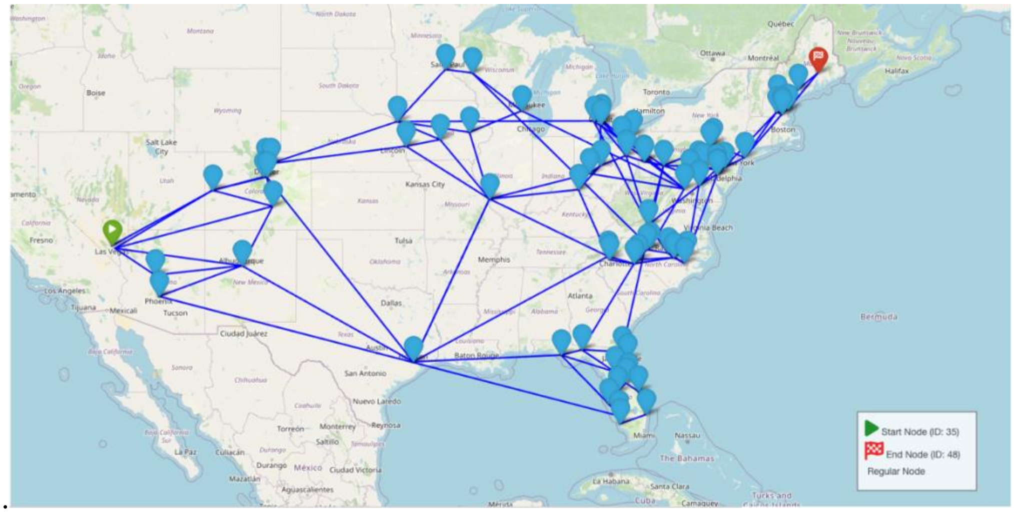

Figure 2. Optimization Network

4.2. Model Parameters

The budget parameters were not defined arbitrarily. A preliminary analysis utilizing the model presented in Chapter 3 for a singular scenario (absent of a probabilistic approach) indicated a consistent linear trend in the total amount of influence. The x-axis illustrates a range of budgets from \$2.5 million to \$5 million. The y-axis, depicted in blue, represents the amount of influence, while the other y-axis portrays the marginal return, which is defined as the number of attendees per million as a measure of efficiency. Budgets under \$2.5 million yielded no solutions; in contrast, budgets over \$5 million showed a steady increase with no significant characteristics. Therefore, a scenario-based stochastic program will focus on testing various budgets in Table 2.

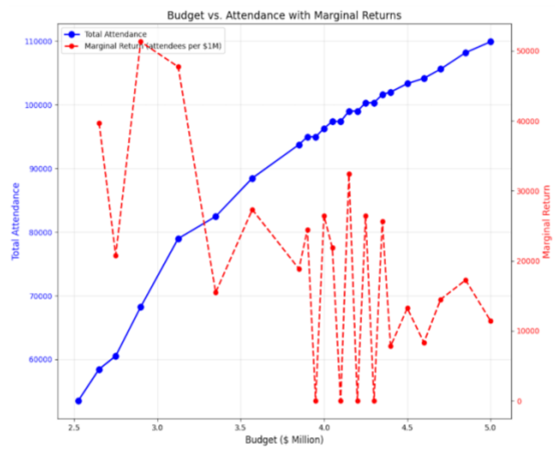

Figure 3. Marginal Return & Optimal Influence on Various Budgets for Deterministic

Budget
$2,525,000
$2,650,000
$2,750,000
$2,900,000
$3,125,000
$3,350,000
$3,570,000
$3,850,000
$4,100,000
$4,350,000
$4,600,000
$4,850,000

Table 2. Range of Budgets

The scenario probabilities were chosen arbitrarily to illustrate the following structure: [conservative probability, most likely probability, expensive probability]. The conservative scenario has probabilities of [.50, .35, .15]. The most likely scenario, which may be cheaper, has probabilities of [.35, .50, .15], while the most likely scenario that may be expensive has probabilities of [.15, .50, .35]. Finally, the expensive scenario presents probabilities of [.15, .35, .50]. Table 3 presents the sets of optimization models that are executed independently, corresponding to various budgets and scenarios to ensure robustness. This means we are optimizing 48 realizations of this model.

Budget	Set 1	Set 2	Set 3	Set 4
$2,525,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$2,650,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$2,750,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$2,900,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$3,125,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$3,350,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$3,570,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$3,850,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$4,100,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$4,350,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$4,600,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]
$4,850,000	[.50, .35, .15]	[.15, .50, .35]	[.35, .50, .15]	[.15, .35, .50]

Table 3. Robust optimization

4.3. Results

Figure 3 illustrates the variation in total attendance as budget levels increase across different probability scenarios (Conservative, Expensive, Most Likely-Conservative Chance, Most Likely-Expensive Chance). Clear trends emerge, showing that the Conservative scenario consistently results in the highest total attendance at all budget levels, followed by the Expensive scenario, while the Most Likely scenarios generally produce lower attendance. This indicates that using conservative cost assumptions may optimize attendance outcomes compared to other scenarios, especially at elevated budget levels.

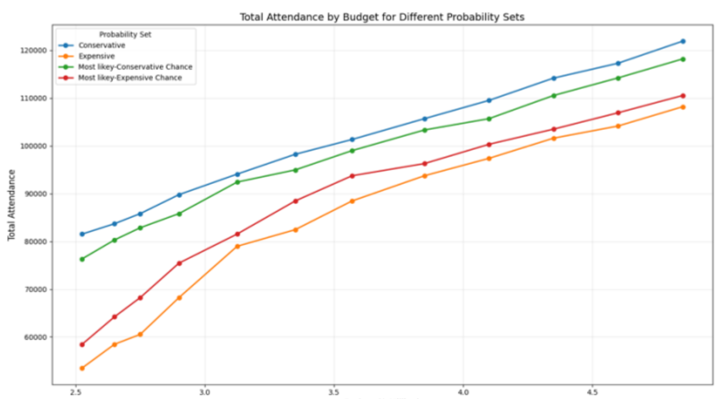

Figure 4. Total Attendance by Budget for Different Probability Sets

Figure 4 illustrates the link between the allocated budget and the number of cities targeted across various probability sets. The Conservative scenario notably distinguishes itself, targeting substantially more cities as the budget rises, which suggests that a conservative cost approach enables wider geographic reach. In contrast, the Most Likely and Expensive scenarios exhibit minimal growth and relatively steady patterns in city selection, indicating that higher per-city costs limit the capacity to expand geographically.

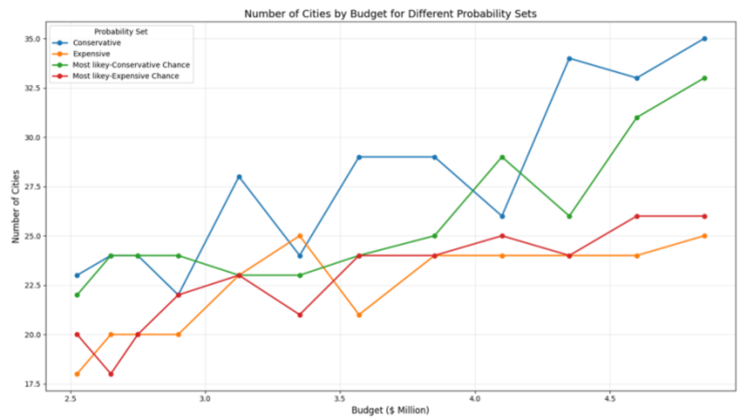

Figure 5. Number of Cities by Budget for Different Probability Sets

In summary, these plots clearly illustrate that under conservative budget assumptions, campaigns not only reach more attendees overall but also extend to more cities, maximizing the geographical impact of available resources. Conversely, higher-cost scenarios restrict attendance and geographical reach, demonstrating important trade-offs to consider when making strategic budget decisions. Figures 5-8 show the optimal route per budget and scenario.

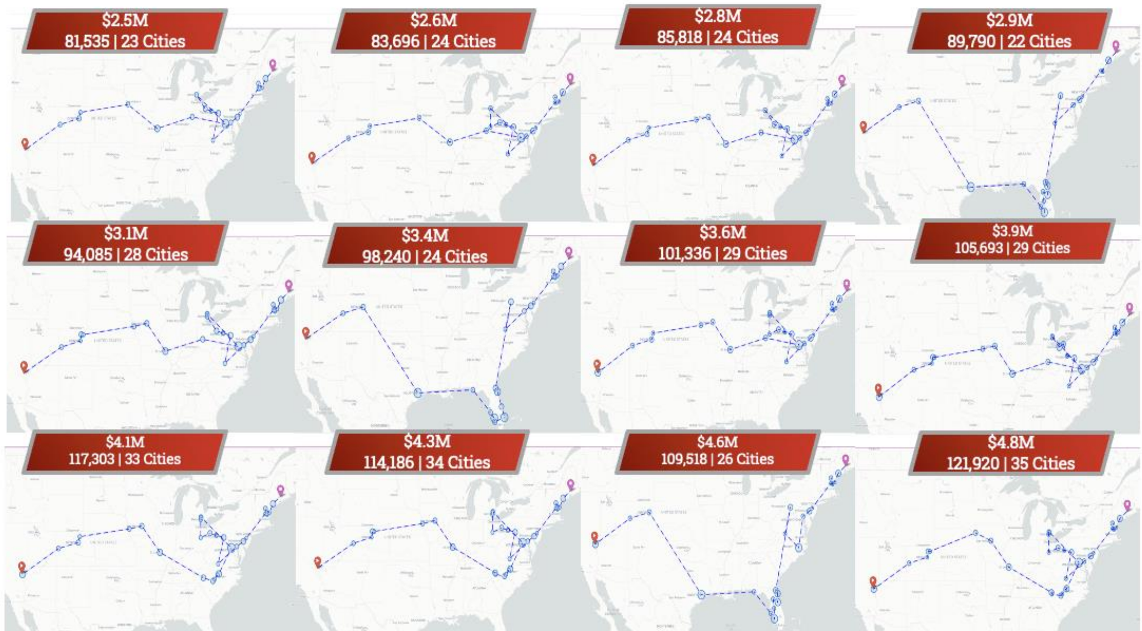

Figure 6. Conservative Solutions Illustrated [.50, .35, .15]

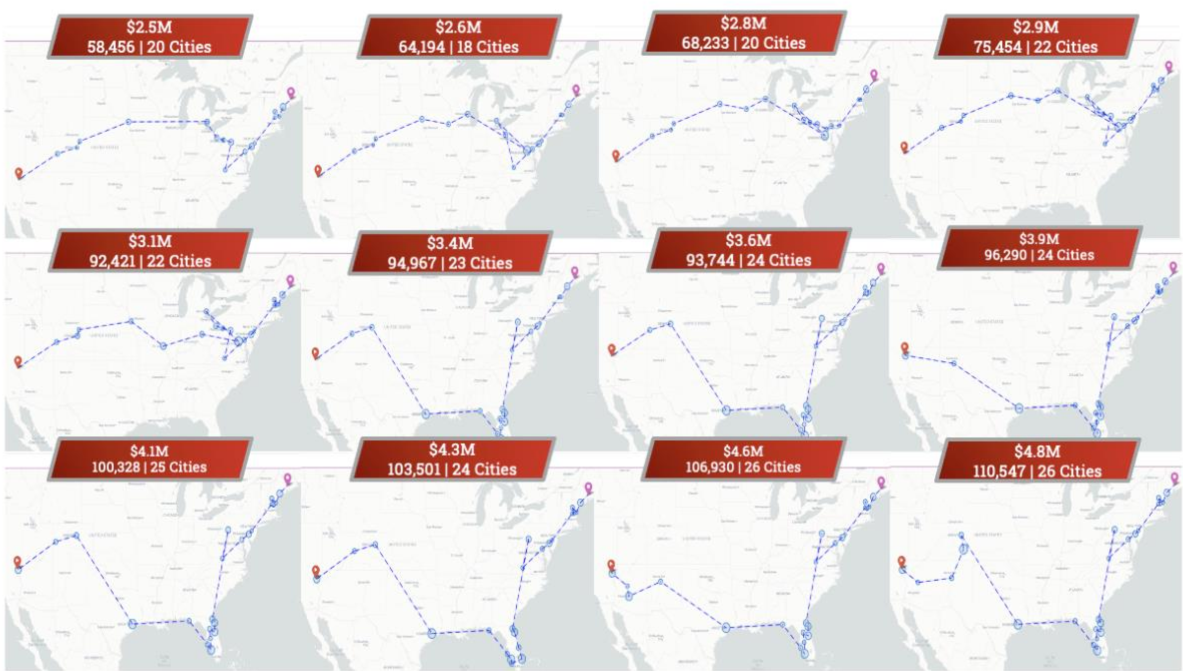

Figure 7. Most Likely with a Chance of Being Expensive Solution Illustrated [.15, .50, .35]

Figure 8. Most Likely with a Chance of Being-a Cheaper Solution [.35, .50, .15]

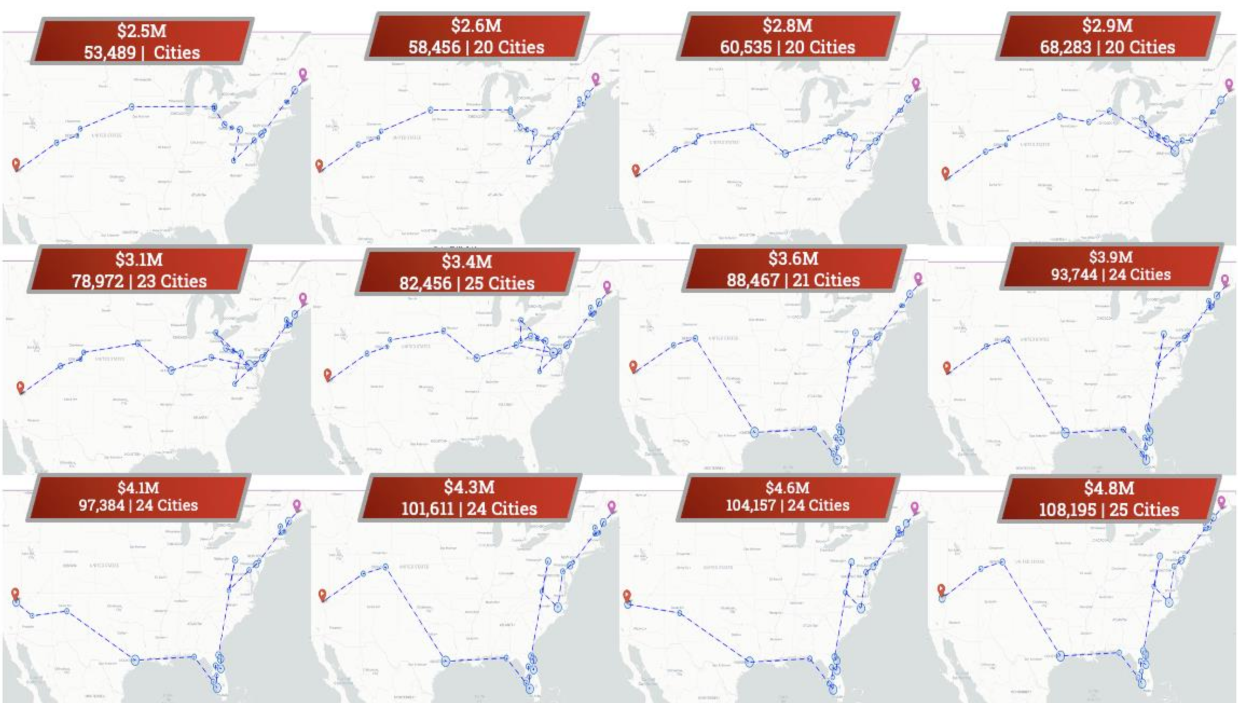

Figure 9. Expensive Scenario Solution Illustrated [.15, .35, .50]

Chapter 5: Conclusion

5.1. Limitations and Future Work

This thesis addresses the pressing challenge of disinformation by introducing an innovative stochastic path-based influence model that integrates influence maximization with routing constraints in uncertain conditions. The study, which utilized comprehensive scenario-based optimization, demonstrated that conservative budget assumptions led to optimal outcomes, resulting in increased attendance and a broader geographic reach compared to scenarios characterized by higher uncertainty or cost. While the research made significant contributions, including a robust methodological framework and practical implications for strategic information planning, it also encountered limitations, such as fixed assumptions regarding attendance and a simplified representation of disinformation dynamics. Future research should explore real-time adaptive optimization strategies and incorporate dynamic information propagation models to tackle emerging threats more effectively, such as the independent cascade model. In summary, this study provides essential insights and methodological tools for managing resources and enhancing strategic communication efforts against disinformation in challenging environments.

5.2. Future Work With Data Envelopment Analysis

In future work, applying Data Envelopment Analysis (DEA) could offer a powerful way to evaluate how efficiently different information campaign strategies perform across various scenarios. DEA would enable direct comparisons of campaigns by examining both the inputs, such as budget and travel costs, and the outputs, like the total number of people influenced or cities reached. Constructing an efficiency frontier could illustrate which strategies make the best use of their resources and which ones are falling short. It would also be valuable to extend DEA to accommodate variable returns to scale, allowing for fairer comparisons among campaigns of different sizes and structures. Beyond assessing traditional campaign routes, DEA could also evaluate other strategies for disseminating trustworthy information, such as targeted online outreach, social media interventions, or hybrid physical-digital efforts. Overall, integrating DEA into this framework could provide stronger insights into how various resource decisions and communication approaches impact campaign success, offering a clearer path for designing better strategies in uncertain environments.

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