Estimating the Shape of Covert Networks

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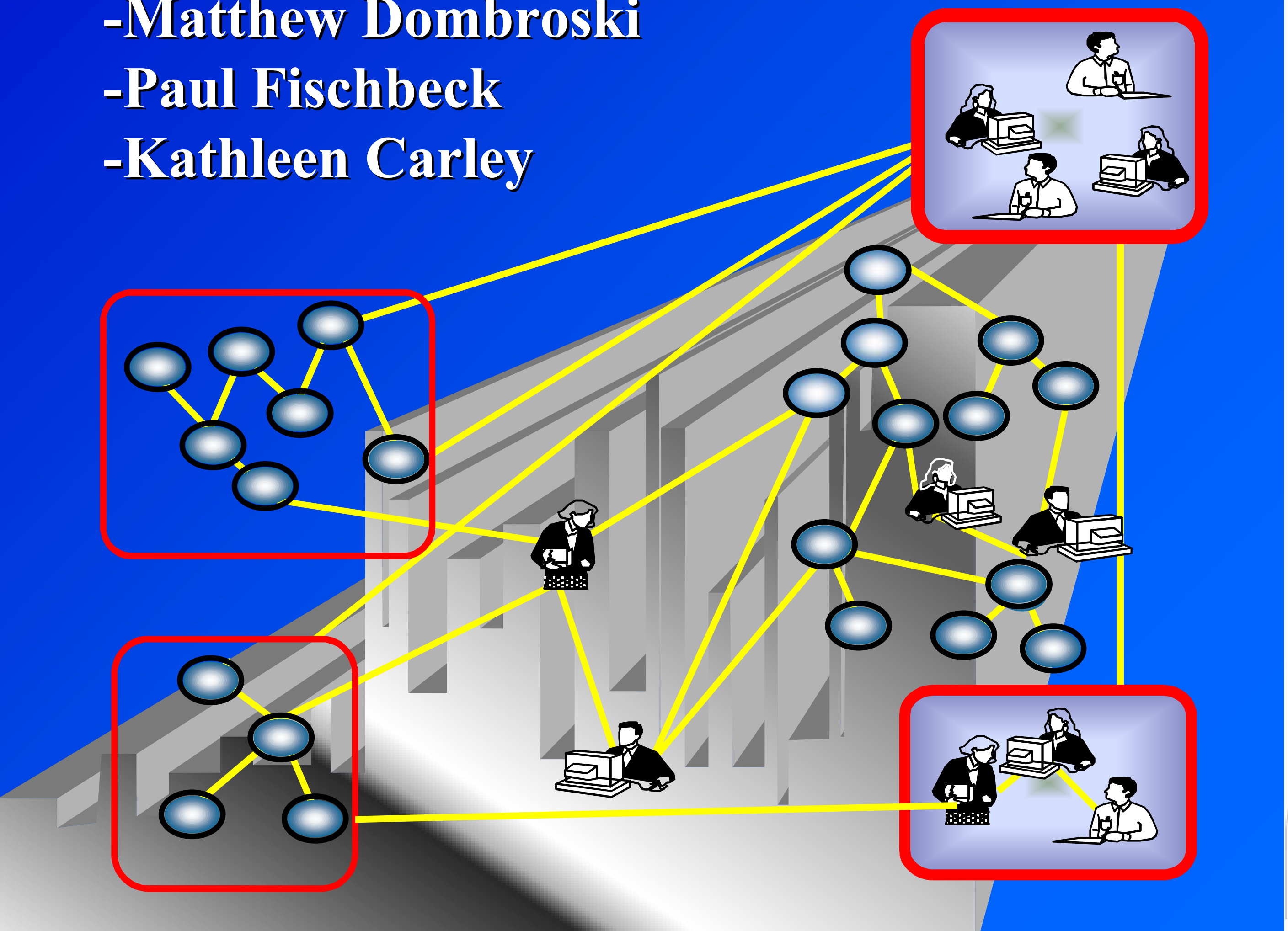

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Agenda

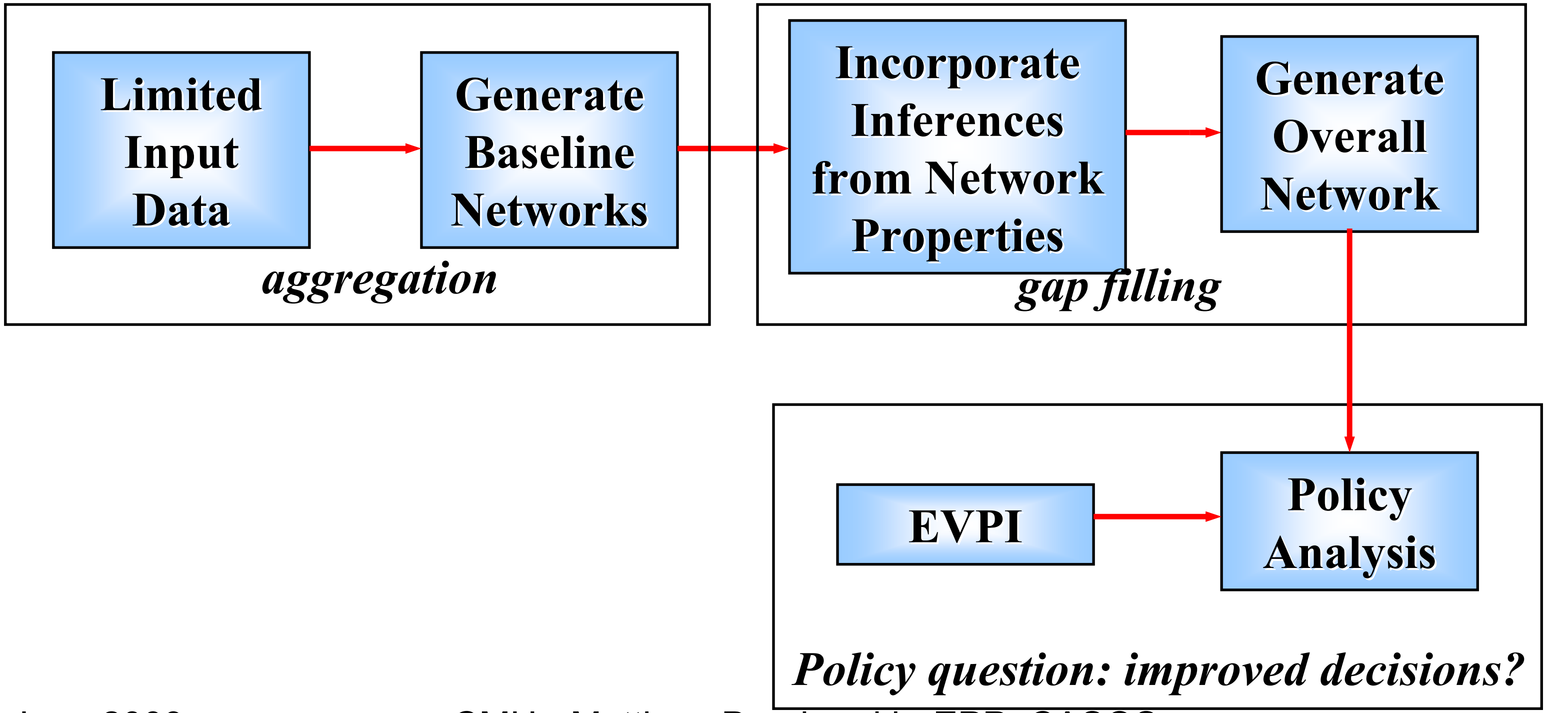
- Problem Statement
- Model Building
  - Relationship of Interest (ROI) and Aggregation
  - Network Properties
  - Empirical Data Transformation
  - Dyadic Dependency Models
- Comparison of updating models
- Command and Control Policy Analysis
  - Covert network destabilization
  - Comparison of Decision Performance Metrics versus Aggregate Network Metrics
- Conclusion and Future Research

Problem Statement and Motivation

- Command and Control may be able to make better decisions by determining
  - Who is in organization
  - Who is important in organization
  - How information flows through the organization
- Important applications in improving
  - Destabilization of covert and illicit organizations
  - Communication in relief and military operations with uncertain communication structure
- Most organizations have an unknown communication structure
  - Data available are often disparate and incomplete
  - High degree of uncertainty in the data
  - May not be able to fully characterize its structure

Proposed Approach

- Goal: Using a predefined relationship (dyad), construct a model that infers relationships and builds a prediction of the network quickly using limited data



Context Determines The Relationship of Interest (ROI)

- Clearly define the relationship that is of interest
  - Context dependent
    - Covert organizations (conspiring to commit an illicit act)
    - Military operations (request for resources or assistance)
  - Limits set of empirical data available for model
- Input data arrives according to Poisson process
- Quantify and distinguish input data informing ROI
  - Reliability
  - Strength of data towards relationship

Aggregation by Bayes Rule

- If L_{ij} is the event that persons *i* and *j* share the ROI
- And I_{ij} is the event that certain data is observed about the relationship between persons *i* and *j*
- Then Define: $P(I_{ij} \mid L_{ij})$ and $P(I_{ij} \mid \overline{L_{ij}})$

$$P(L_{ij} \mid I_{ij}) = \frac{P(I_{ij} \mid L_{ij})P(L_{ij})}{P(I_{ij} \mid L_{ij})P(L_{ij}) + P(I_{ij} \mid \overline{L_{ij}})P(\overline{L_{ij}})}$$

- Network priors can be assigned a priori

Incorporating Inference Using Empirical Data (cont.)

- Before constructing inference model
  - Transform empirical frequency networks into probabilities of ROI
  - Assume frequency of interaction indicates strength of relationship
- Transforming Empirical Network Data
  - Define ROI Threshold – number of interactions required to attain relationship of interest (x_{max})
  - Define marginal increase of each additional interaction to probability of ROI Transforming Empirical Network Data (λ)
- Transform interaction frequency into probabilities—

$$P(ROI) = \frac{(1 - e^{-\lambda x})}{(1 - e^{-\lambda x_{\max}})}$$

Network Transformation

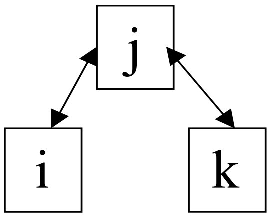
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	2	1	0	0	2	0	0	0	1	1	2	0	0	0	1	0	1	0
2	0	0	10	0	0	2	1	0	2	0	0	0	6	2	0	1	0	0	0	1
3	2	10	0	6	11	14	15	4	12	0	5	4	3	8	10	8	11	0	2	19
4	1	0	6	0	2	3	9	1	8	0	0	5	0	0	2	4	3	2	2	6
5	0	0	11	2	0	2	8	1	1	1	0	0	2	0	1	1	0	0	0	3
6	0	2	14	3	2	0	30	2	8	0	4	4	1	6	2	14	9	0	1	51
7	2	1	15	9	8	30	0	10	4	2	7	3	0	12	9	10	9	2	3	40
8	0	0	4	1	1	2	10	0	3	0	2	0	1	3	3	3	5	0	0	6
9	0	2	12	8	1	8	4	3	0	0	5	5	2	2	4	5	6	1	0	5
10	0	0	0	0	1	0	2	0	0	0	0	0	0	0	1	2	0	0	0	0
11	1	0	5	0	0	4	7	2	5	0	0	0	0	1	3	3	5	3	0	7
12	1	0	4	5	0	4	3	0	5	0	0	0	0	0	0	0	0	0	0	3
13	2	6	3	0	2	1	0	1	2	0	0	0	0	2	1	3	3	0	1	0
14	0	2	8	0	0	6	12	3	2	0	1	0	2	0	3	8	11	1	4	8
15	0	0	10	2	1	2	9	3	4	1	3	0	1	3	0	9	14	0	6	9
16	0	1	8	4	1	14	10	3	5	2	3	0	3	8	9	0	26	3	1	12
17	1	0	11	3	0	9	9	5	6	0	5	0	3	11	14	26	0	3	0	9
18	0	0	0	2	0	0	2	0	1	0	3	0	0	1	0	3	3	0	0	0
19	1	0	2	2	0	1	3	0	0	0	0	0	1	4	6	1	0	0	0	5
20	0	1	19	6	3	51	40	6	5	0	7	3	0	8	9	12	9	0	5	0

Network Transformation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	0.00	0.26	0.14	0.00	0.00	0.26	0.00	0.00	0.00	0.14	0.14	0.26	0.00	0.00	0.00	0.14	0.00	0.14	0.00
2	0.00	0.00	0.80	0.00	0.00	0.26	0.14	0.00	0.26	0.00	0.00	0.00	0.60	0.26	0.00	0.14	0.00	0.00	0.00	0.14
3	0.26	0.80	0.00	0.60	0.83	0.91	0.93	0.45	0.86	0.00	0.53	0.45	0.36	0.71	0.80	0.71	0.83	0.00	0.26	0.98
4	0.14	0.00	0.60	0.00	0.26	0.36	0.76	0.14	0.71	0.00	0.00	0.53	0.00	0.00	0.26	0.45	0.36	0.26	0.26	0.60
5	0.00	0.00	0.83	0.26	0.00	0.26	0.71	0.14	0.14	0.14	0.00	0.00	0.26	0.00	0.14	0.14	0.00	0.00	0.00	0.36
6	0.00	0.26	0.91	0.36	0.26	0.00	1.00	0.26	0.71	0.00	0.45	0.45	0.14	0.60	0.26	0.91	0.76	0.00	0.14	1.00
7	0.26	0.14	0.93	0.76	0.71	1.00	0.00	0.80	0.45	0.26	0.66	0.36	0.00	0.86	0.76	0.80	0.76	0.26	0.36	1.00
8	0.00	0.00	0.45	0.14	0.14	0.26	0.80	0.00	0.36	0.00	0.26	0.00	0.14	0.36	0.36	0.36	0.53	0.00	0.00	0.60
9	0.00	0.26	0.86	0.71	0.14	0.71	0.45	0.36	0.00	0.00	0.53	0.53	0.26	0.26	0.45	0.53	0.60	0.14	0.00	0.53
10	0.00	0.00	0.00	0.00	0.14	0.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.26	0.00	0.00	0.00	0.00
11	0.14	0.00	0.53	0.00	0.00	0.45	0.66	0.26	0.53	0.00	0.00	0.00	0.00	0.14	0.36	0.36	0.53	0.36	0.00	0.66
12	0.14	0.00	0.45	0.53	0.00	0.45	0.36	0.00	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36
13	0.26	0.60	0.36	0.00	0.26	0.14	0.00	0.14	0.26	0.00	0.00	0.00	0.00	0.26	0.14	0.36	0.36	0.00	0.14	0.00
14	0.00	0.26	0.71	0.00	0.00	0.60	0.86	0.36	0.26	0.00	0.14	0.00	0.26	0.00	0.36	0.71	0.83	0.14	0.45	0.71
15	0.00	0.00	0.80	0.26	0.14	0.26	0.76	0.36	0.45	0.14	0.36	0.00	0.14	0.36	0.00	0.76	0.91	0.00	0.60	0.76
16	0.00	0.14	0.71	0.45	0.14	0.91	0.80	0.36	0.53	0.26	0.36	0.00	0.36	0.71	0.76	0.00	1.00	0.36	0.14	0.86
17	0.14	0.00	0.83	0.36	0.00	0.76	0.76	0.53	0.60	0.00	0.53	0.00	0.36	0.83	0.91	1.00	0.00	0.36	0.00	0.76
18	0.00	0.00	0.00	0.26	0.00	0.00	0.26	0.00	0.14	0.00	0.36	0.00	0.00	0.14	0.00	0.36	0.36	0.00	0.00	0.00
19	0.14	0.00	0.26	0.26	0.00	0.14	0.36	0.00	0.00	0.00	0.00	0.00	0.14	0.45	0.60	0.14	0.00	0.00	0.00	0.53
20	0.00	0.14	0.98	0.60	0.36	1.00	1.00	0.60	0.53	0.00	0.66	0.36	0.00	0.71	0.76	0.86	0.76	0.00	0.53	0.00

Network Properties

- Triad Closure Property (Skvoretz, 1990)

If 

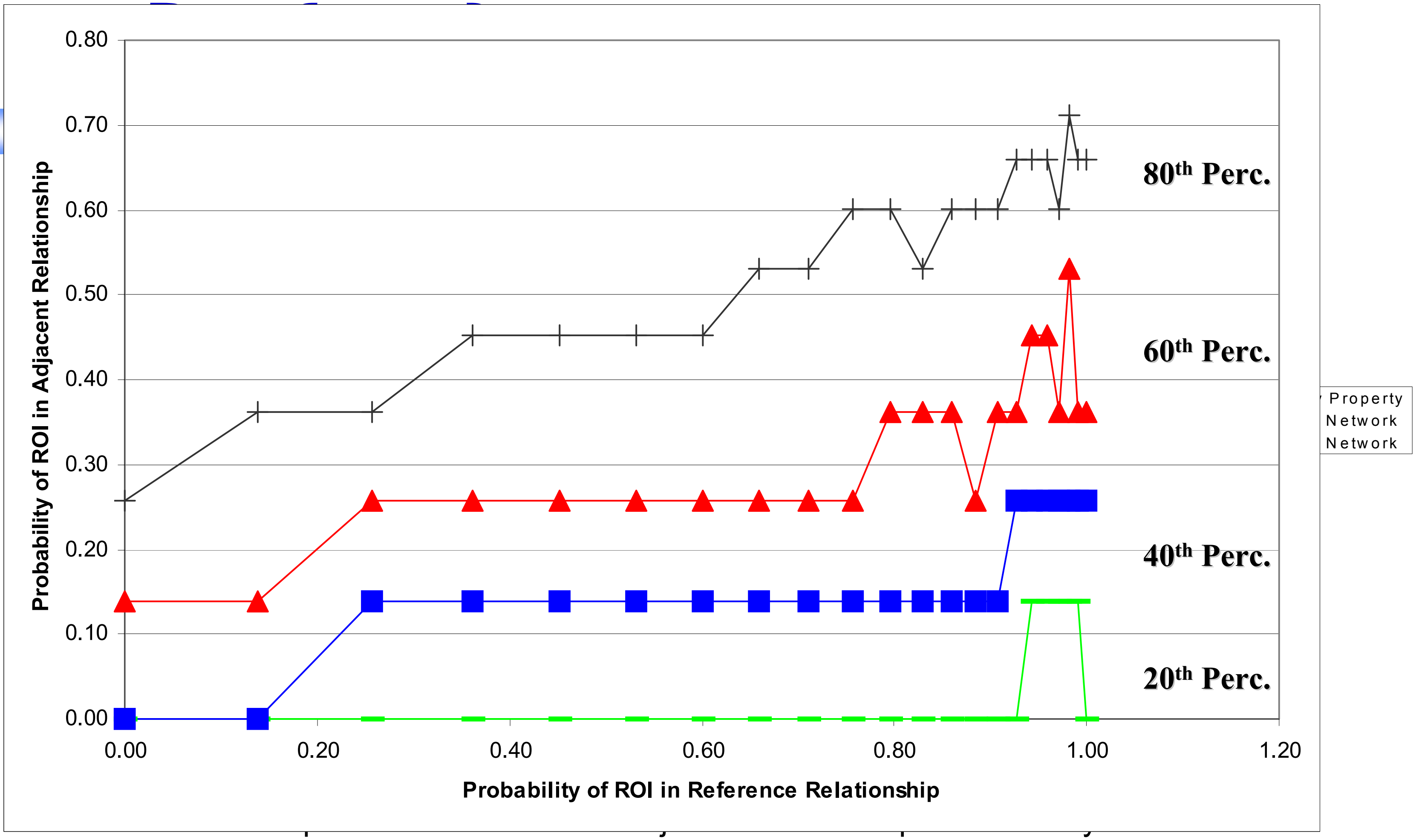
then $i \leftrightarrow k$ occurs with a probability greater than chance

- Adjacency Property
  - Corollary of triad closure that is modeled

If $i \leftrightarrow j$ occurs with probability greater than chance then $i \leftrightarrow k$

and $j \leftrightarrow k$ occur with a probability greater than chance

Incorporating Inference Using Empirical



- Model fit using neural network of 9 nodes and 3 layers (percent current error on 4000 training data points is 0.9%)

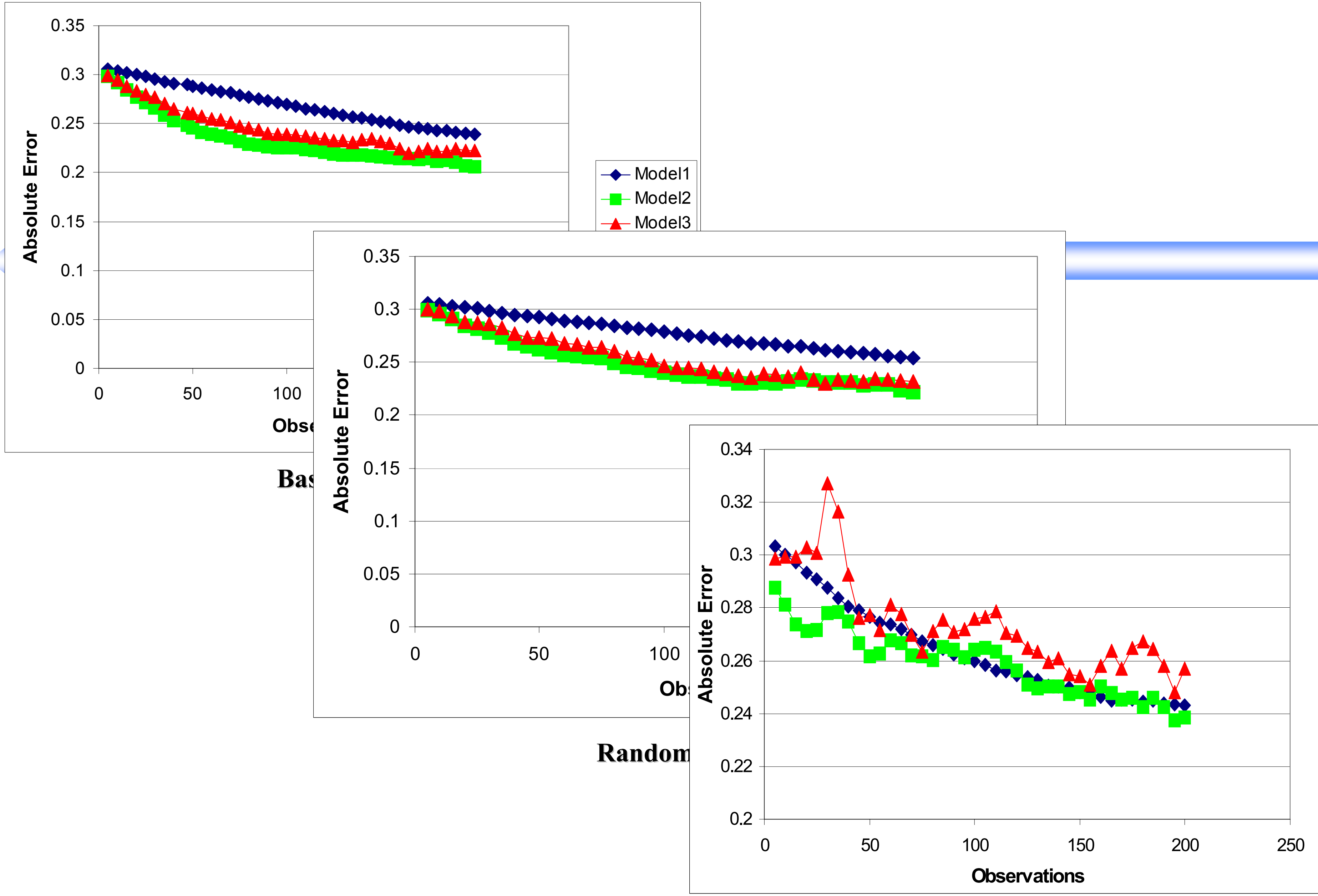
Several Possible Implementations of Model

- Three inference models constructed:
  - Model 1-Direct update dyads using incoming information and Bayes Rule only (control model)
  - Model 2-Model 1 plus indirect inferencing only on immediately adjacent relationships using inference model
  - Model 3-Model 2 plus indirect inferencing on all other relationships using inference model

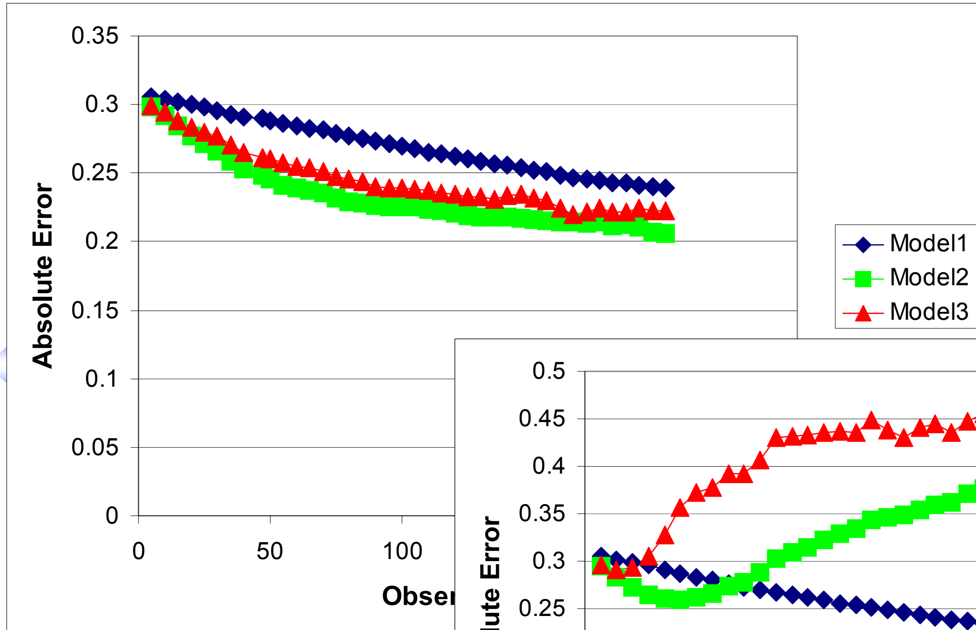
Performance of Models Compared Using Simulation

- Sample data (20 of 58 nodes), perform an update, calculate performance, another update
- Constant uniform prior (0.2)
- Reconstruct by varying:
  - Input data accuracy
  - Proportion of information supporting existence of ROI (0.5)
- Performance Metric
  - Absolute Error (sum of prediction probability minus actual probability)

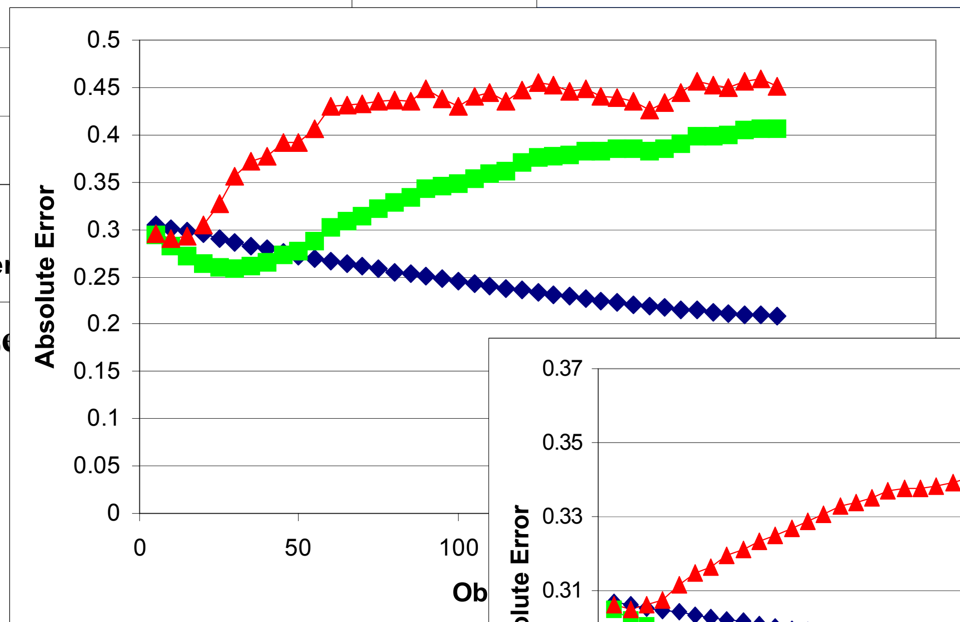
$$\text{Absolute Error} = \left(\sum_{i>j}\sum_{j=1}^{N} abs(p_{ij} - A_{ij})\right)$$



Sensor Reliable Conditionals (0.8, 0.1)

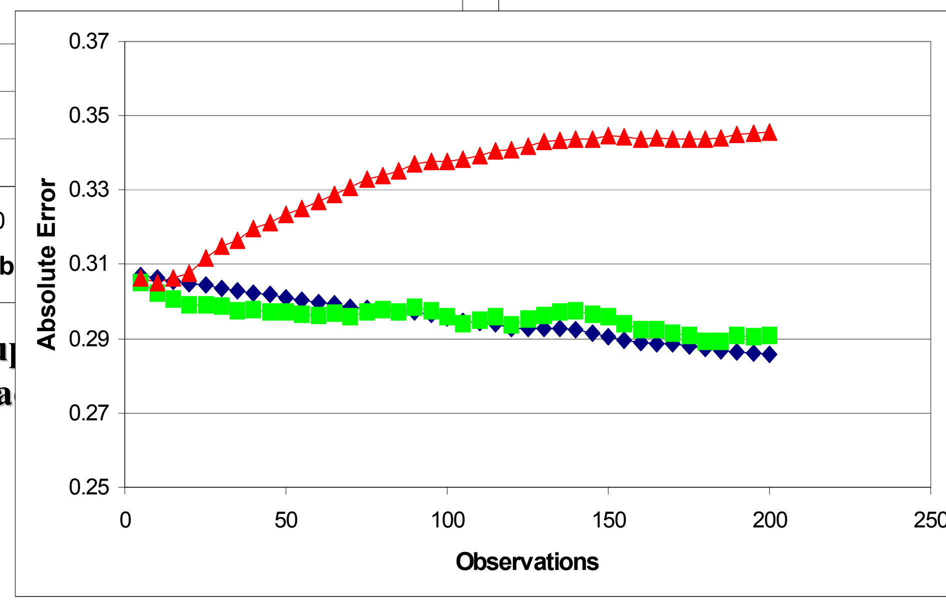


Base



0.8 P(observing dyad su

0.2 P(observing non dya



0.2 P(observing dyad supporting information)

0.8 P(observing non dyad supporting information)

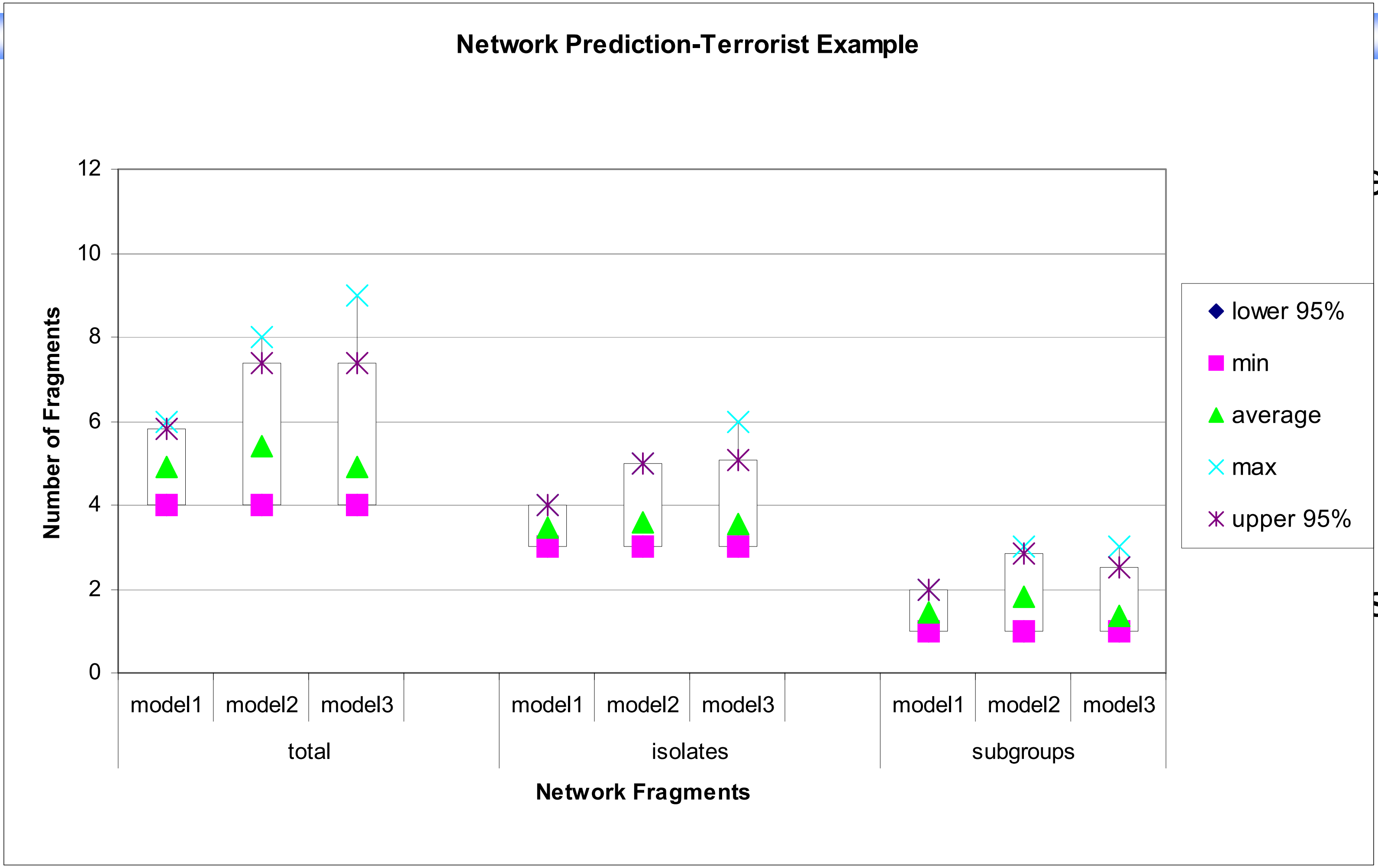
Conclusions from Simulations

- Inference model results are mixed
- Under conditions of balance between positive and negative tie input data and random or moderately accurate conditionals
  - Performance on Absolute Error is relatively good for inference models
  - After about 400 updates, base model outperforms inference models
- Under conditions of imbalance
  - Base model outperforms inference models for nearly all updates
  - Inference over/under predicts the network
- Under conditions of accurate conditionals
  - Models are indistinguishable

Policy Analysis

- What does this mean for command and control decisions?
- C2 Terrorist Example
  - C2 must make a decision of who to remove from network of conspirators using models
  - Get Network prediction after *x* updates
  - Estimate the *n* most critical individuals to remove from network
  - Remove them from network
  - Assess how many fragments the network is broken into
- Compare the number of fragments across different model implementations

Policy Analysis
Scenario-Covert Networks (cont.)



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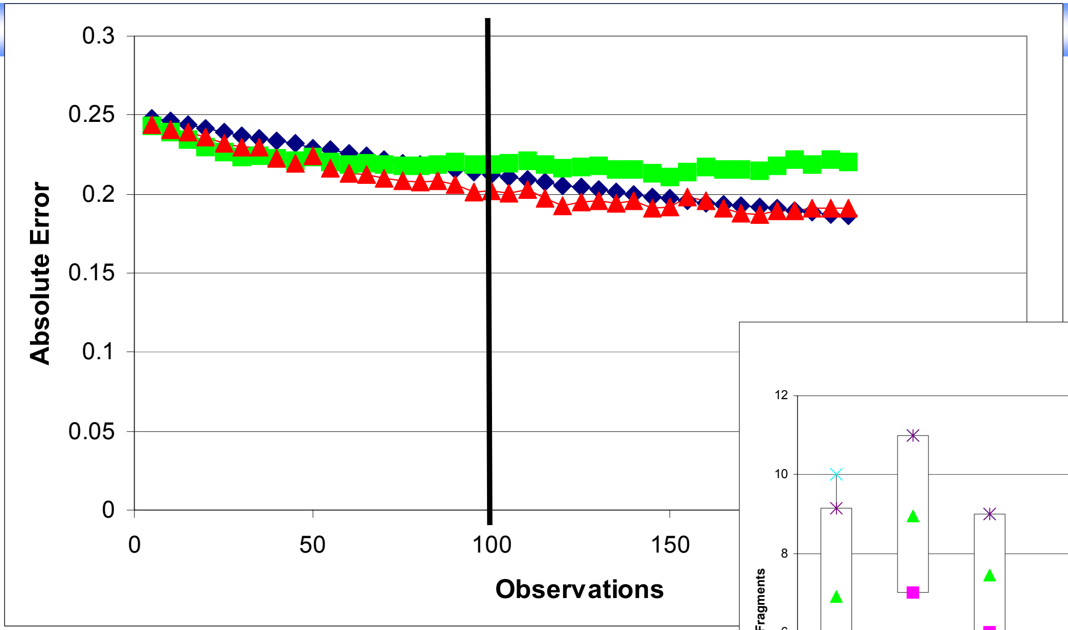
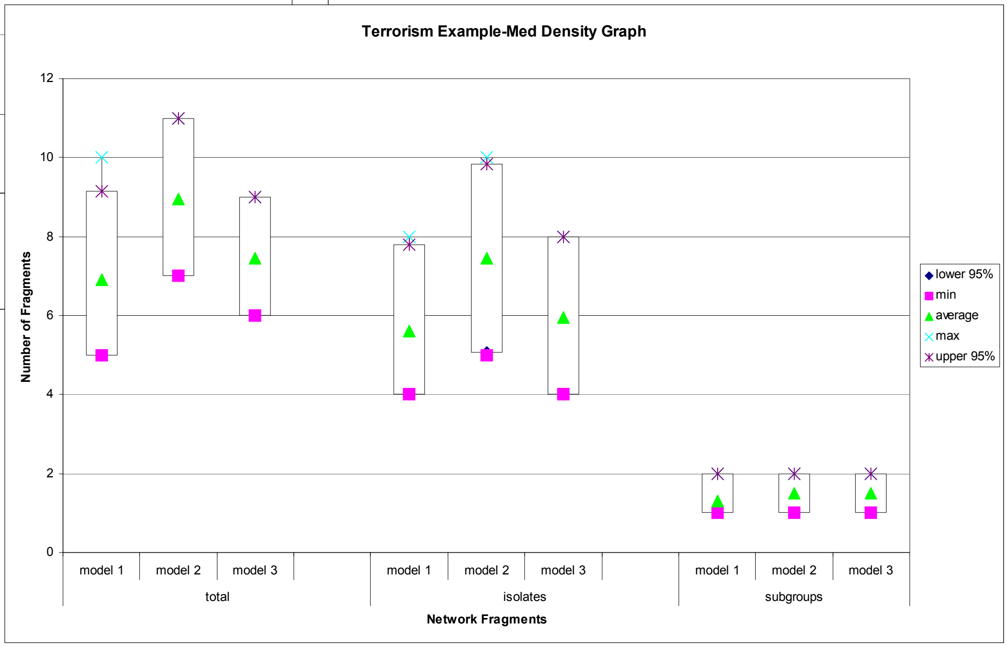
A Comparison of Simulation Performance Metrics to Decision Metrics



Mid Density Network



Network Match Performance Versus Decision Performance

- Conduct a paired t-test for each network prediction for absolute error and fragments
- Null Hypotheses:
  - E(absolute error$_1$ - absolute error$_2$) = 0, E(fragments$_1$ – fragments$_2$) = 0
  - E(absolute error$_1$ - absolute error$_3$) = 0, E(fragments$_1$ - fragments$_3$) = 0
  - E(absolute error$_2$ - absolute error$_3$) = 0, E(fragments$_2$ – fragments$_3$) = 0

Hypothesis	Mean Value	Standard Deviation	T-value	Dof	Significance Level
$-(Abs_1 - Abs_2)$	0.95	16.8	0.25	19	> 0.1
$Frag_1 - Frag_2$	-2.05	1.19	-7.70	19	< 0.001
$-(Abs_1 - Abs_3)$	-1.67	15.3	-0.48	19	> 0.1
$Frag_1 - Frag_3$	-0.55	1.19	-2.07	19	0.025 < S < 0.05
$-(Abs_2 - Abs_3)$	-2.60	3.01	-3.87	19	< 0.001
$Frag_2 - Frag_3$	1.50	1.15	5.85	19	< 0.001

Conclusions

- Good/bad performance on simulation metric does not imply good/bad performance in C2 decision space
  - Absolute Error recommends 3 over 2, but 2 = 1 and 3 = 1
  - Fragments recommends 2, 3, then 1
- Decision metrics may predict performance better than aggregate network metrics
  - Fragments is a better measure of the actual decision we will make
  - Absolute error is one step abstracted from the decision
- C2 decisions can benefit from a model
  - Care must be taken in evaluating performance of such models
  - Slight improvement in the number of fragments generated
  - Errors when too many updates occur

Future Work

- Explore the relationship between other C2 decision metrics and aggregate network metrics
  - Improving Communication for Military Operations
    - Network prediction indicates where communication is weak
    - Add dyads to force individuals to communicate better
    - Expected number of individuals to learn a new fact
  - Vaccination Strategies Against a Contagious Disease
- Develop more rigorous model using triad closure
- Characterize several different types of models for different types of networks
  - Work relationships
  - Friend relationships

Questions and Comments

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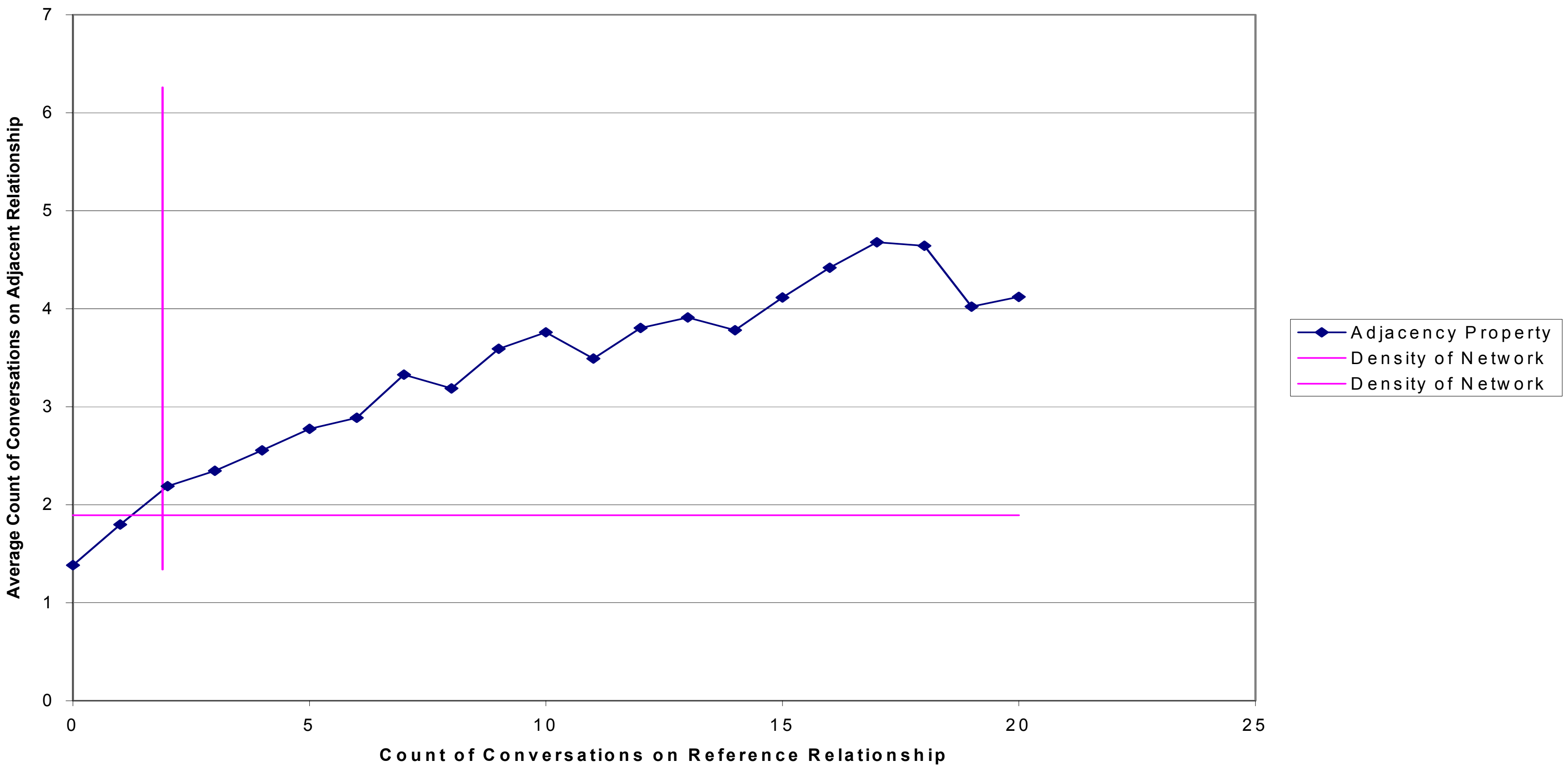
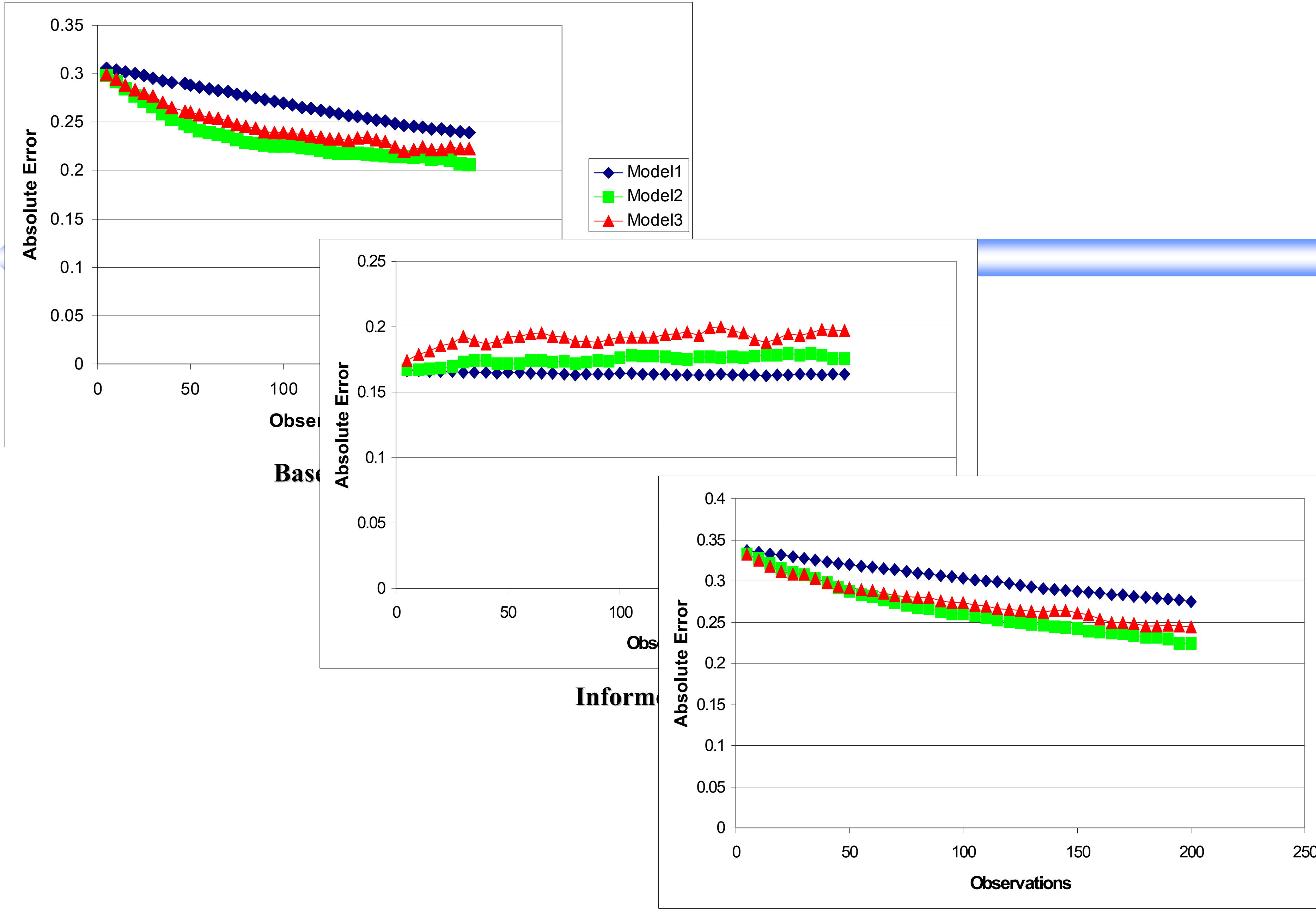
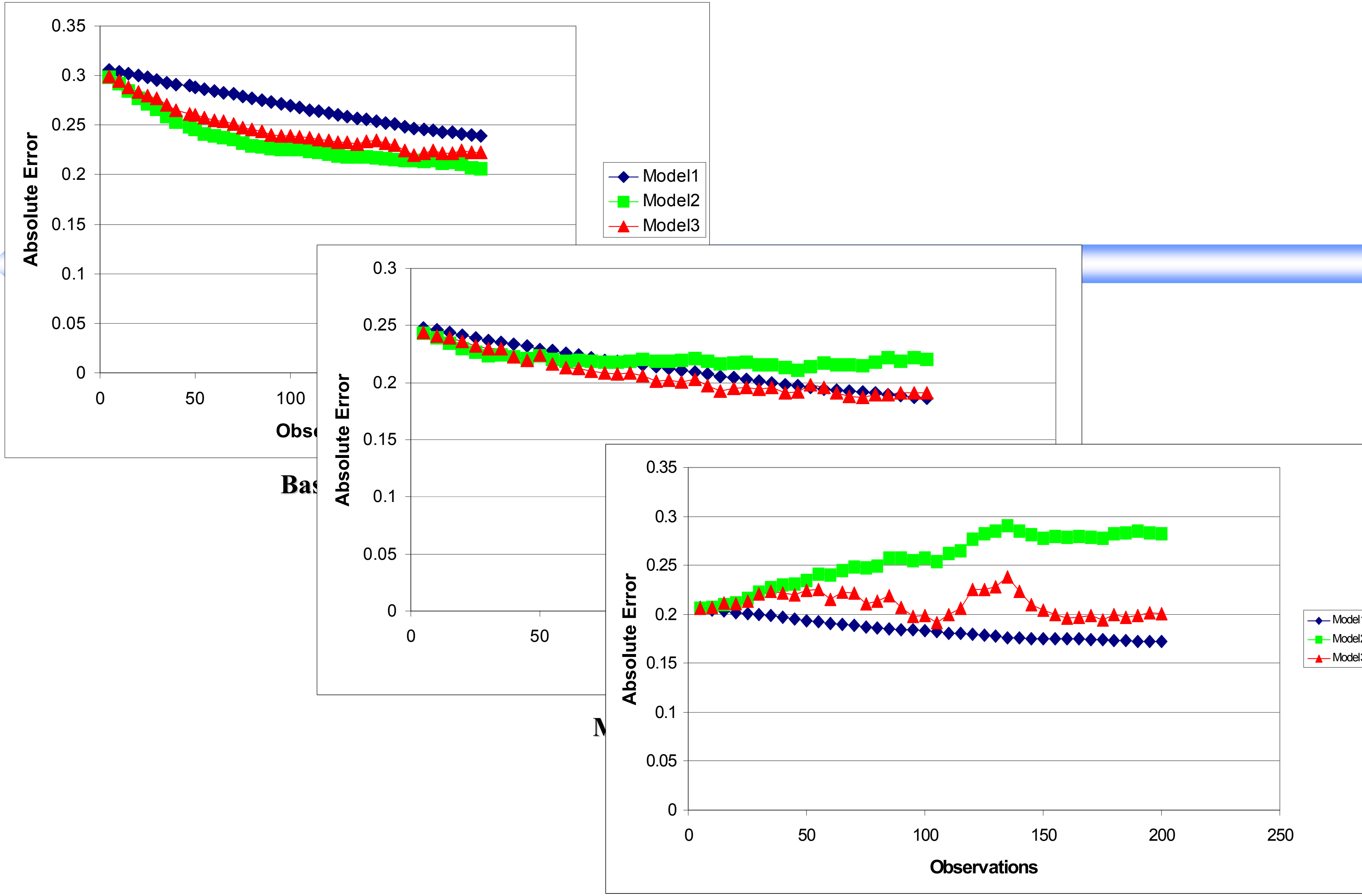
Incorporating Inference Using Empirical Data



- Bernard and Killworth (1976) fraternity brother network
  - Observed number of interactions between 58 individuals over a week
  - Average interactions between individuals-1.89, min-0, max-51

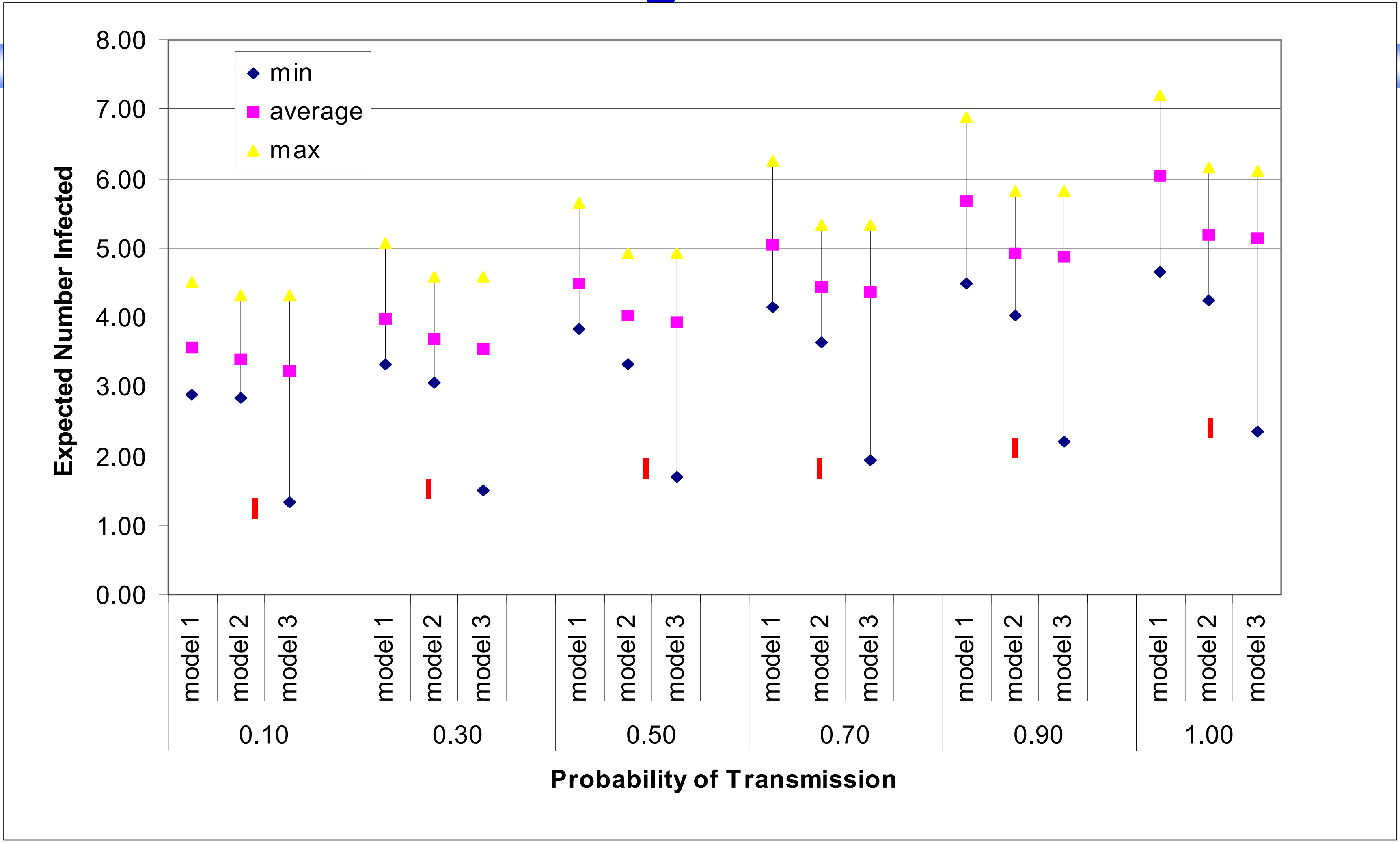


Misinformed Prior



Low Density Network

Policy Analysis
Scenario-Contagious Diseases



Policy Analysis
Scenario 3-Relief Organizations