
Sampling Large Graphs for Anticipatory Analysis

**Lauren Edwards*, Luke Johnson, Maja Milosavljevic, Vijay
Gadepally, Benjamin A. Miller**

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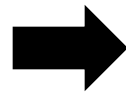
September 16, 2015



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Outline



- **Introduction**
- **Sampling Techniques**
- **Link Prediction**
- **Experimental Setup**
- **Results**
- **Summary**



Common Big Data Challenge

Users

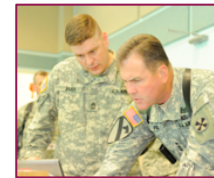
Operators



Analysts



Commanders



Rapidly increasing

- Data volume
- Data velocity
- Data variety
- Data veracity (security)

Data

Gap

Users

2000

2005

2010

2015 & Beyond

Data



OSINT



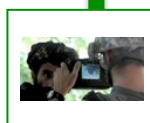
Weather



HUMINT



C2



Ground



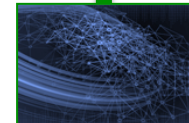
Maritime



Air



Space

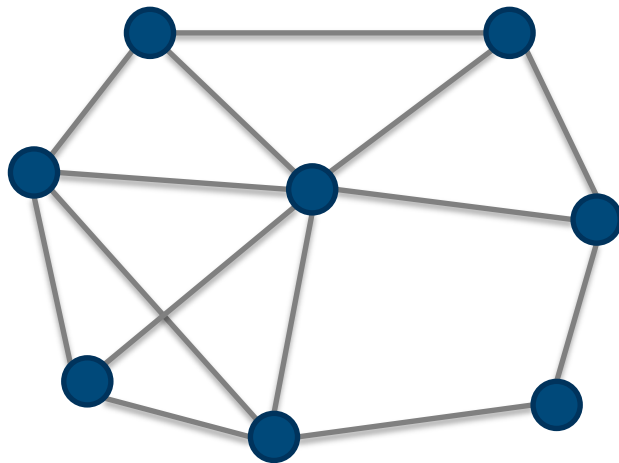


Cyber



What is a Graph?

Graphs are mathematical representations of physical or logical relationships between sets of objects



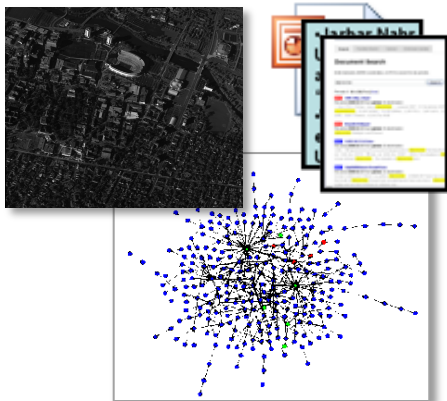
A graph is a pair of sets:

- **A set of vertices/
nodes (entities)**
- **A set of edges/links
(connections,
transactions, and
relationships)**



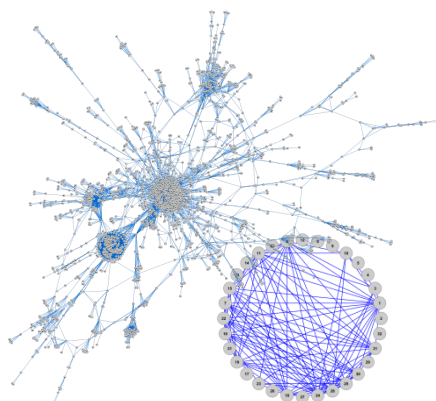
Applications of Graph Analytics

ISR



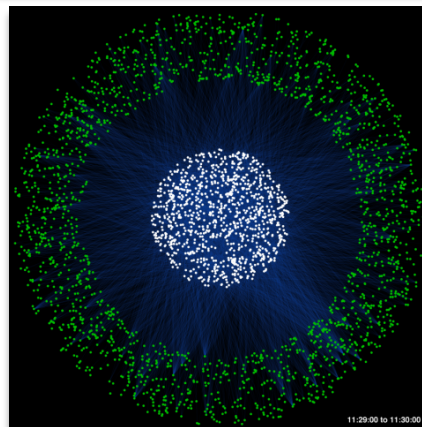
- Graphs represent entities and relationships detected through multiple data
- ~1K – 1M entities and connections
- GOAL: Identify anomalous patterns

Social



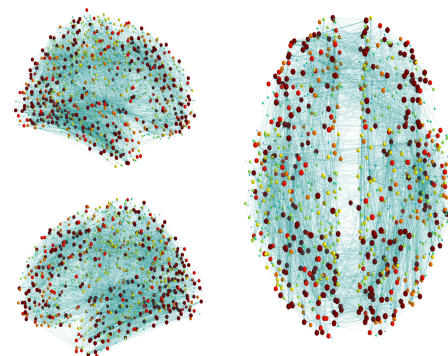
- Graphs represent relationships between individuals or documents
- ~10K – 10M individuals and interactions
- GOAL: Identify hidden social networks

Cyber



- Graphs represent communication patterns of computers on a network
- ~1M – 1B network events
- GOAL: Detect attack or malicious software

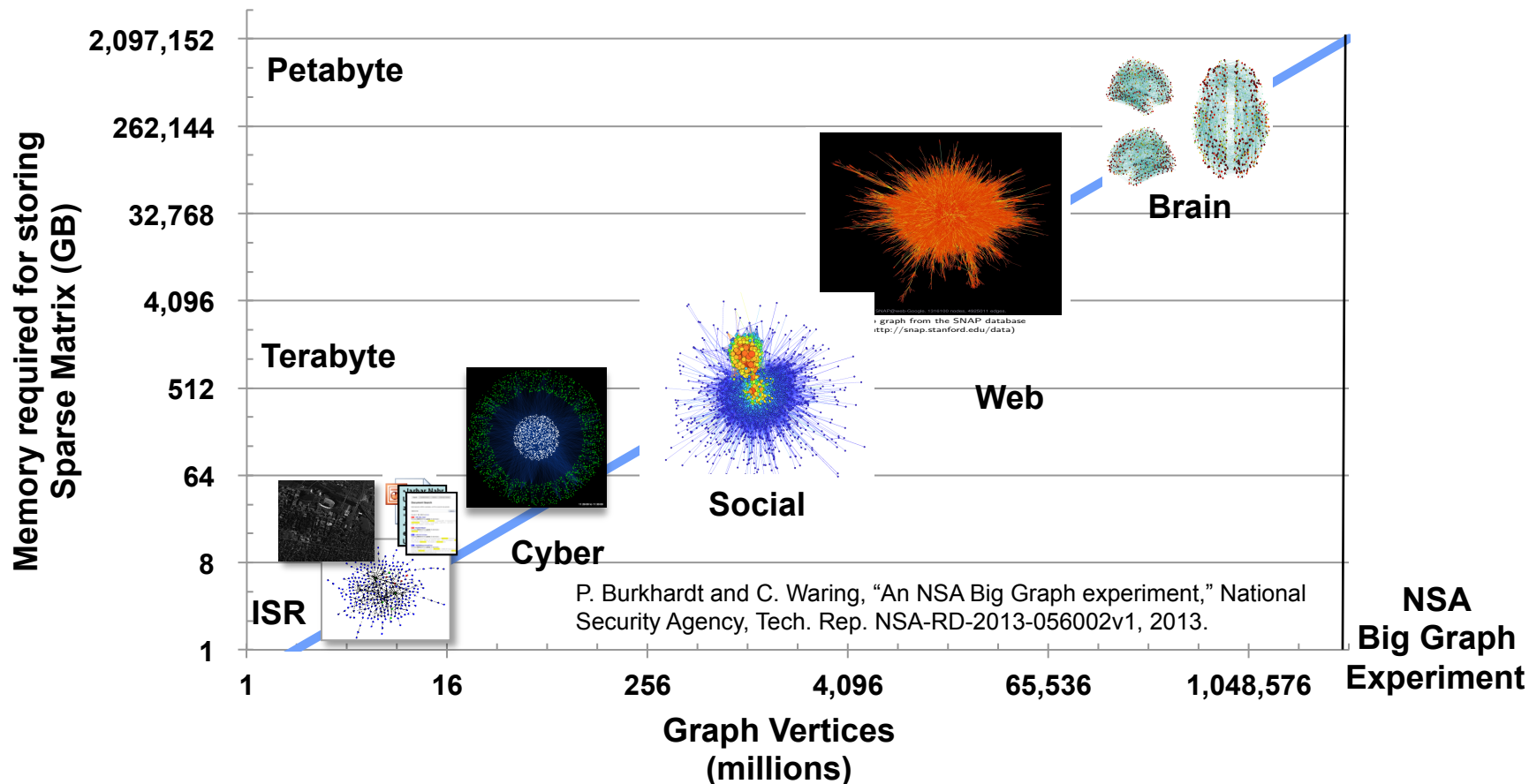
Bio



- Graphs represent connectivity between brain regions
- ~1B – 1T regions and connections
- GOAL: Detect regions affected by a neurological condition



Big Data Challenge



How can these massive graphs be leveraged to provide accurate anticipatory intelligence?

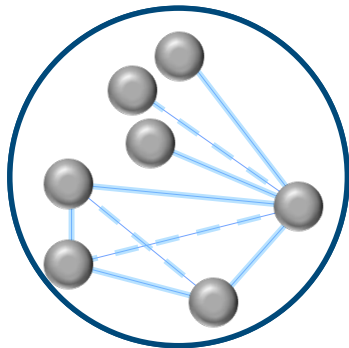


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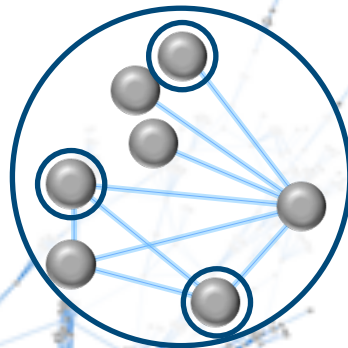
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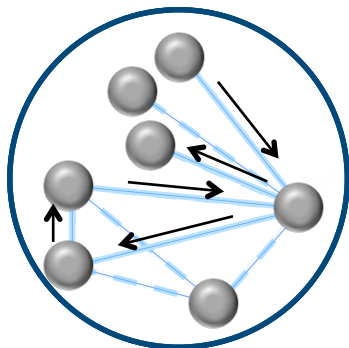
Methods for Sampling Graphs



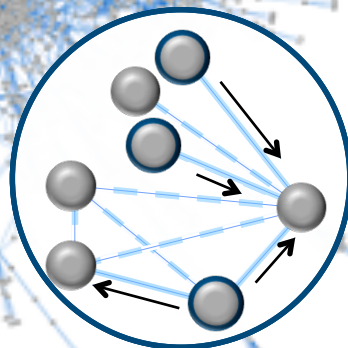
Edge sampling methods
Consider each edges individually, keep it in the sample based on some criterion



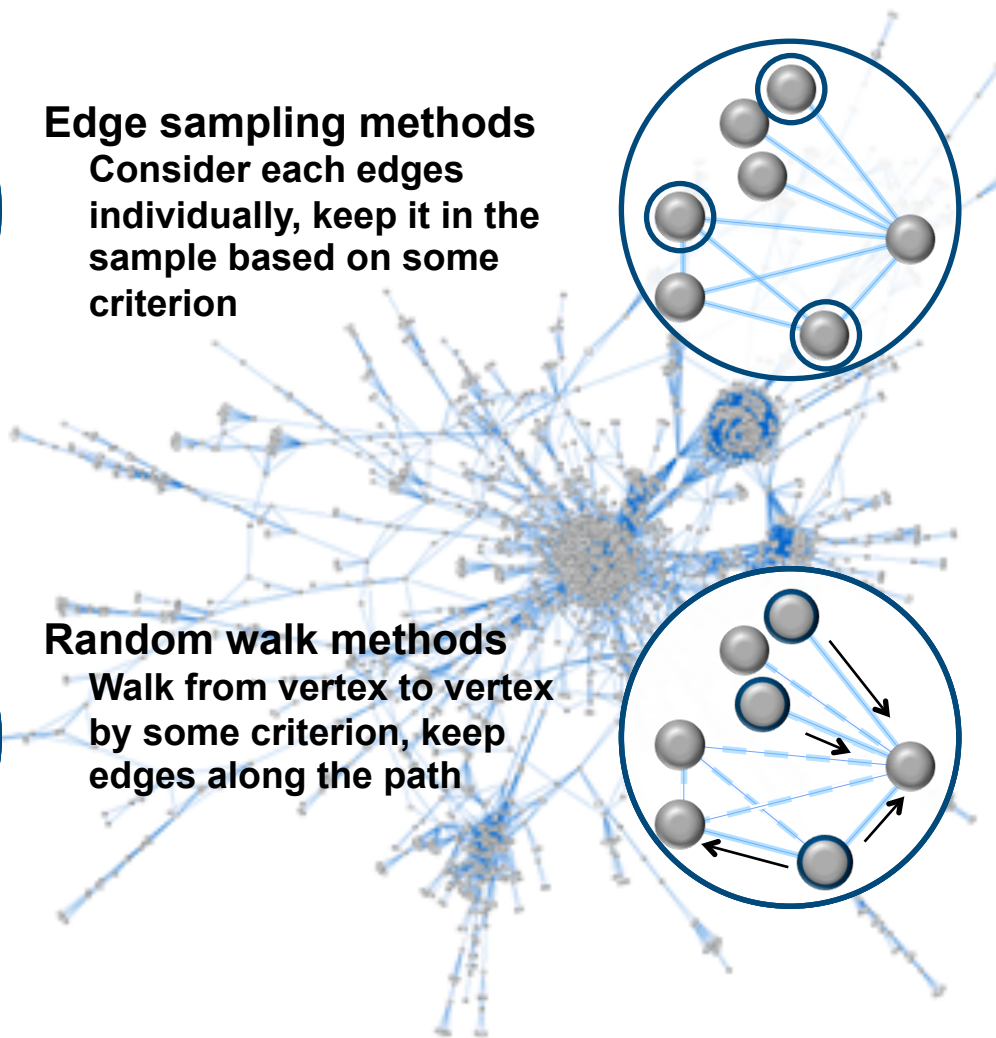
Vertex sampling methods
Sample individual vertices or local substructures



Random walk methods
Walk from vertex to vertex by some criterion, keep edges along the path



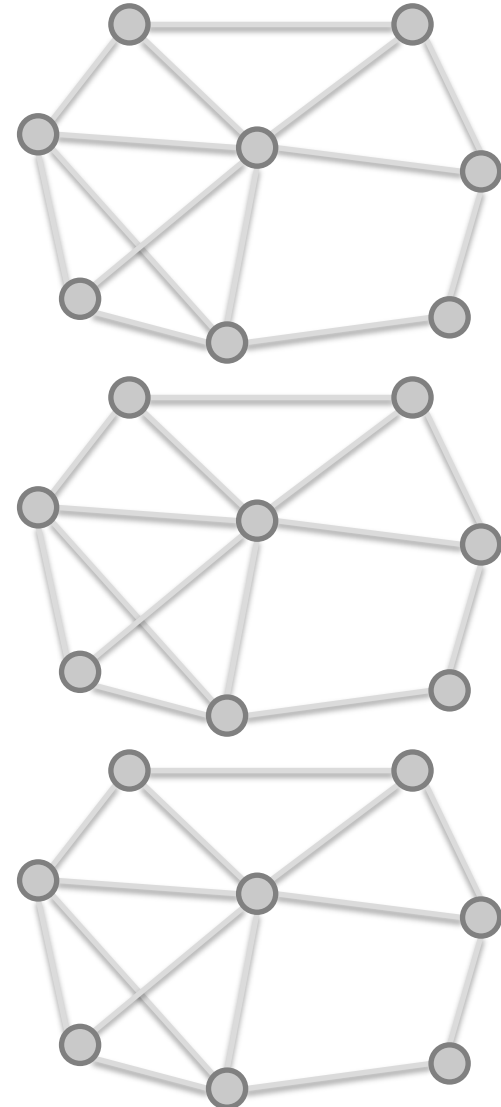
“Snowball” sampling methods
Start with a set of “seed” vertices, grow the sample from those





Methods Used

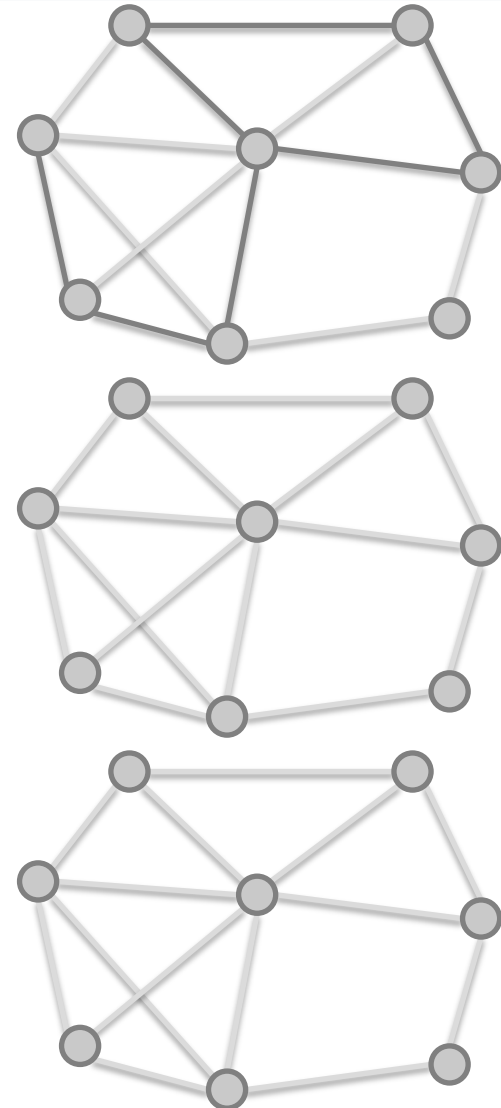
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 - Each edge in the graph has equal probability of being included in the sample
- **Popularity-Based Sampling**
 - Probability of sampling a given edge is proportional to a decreasing function of the vertex degrees
- **Wedge Sampling**
 - Choose a vertex at random, and randomly select two of its adjacent edges to be included in the sample





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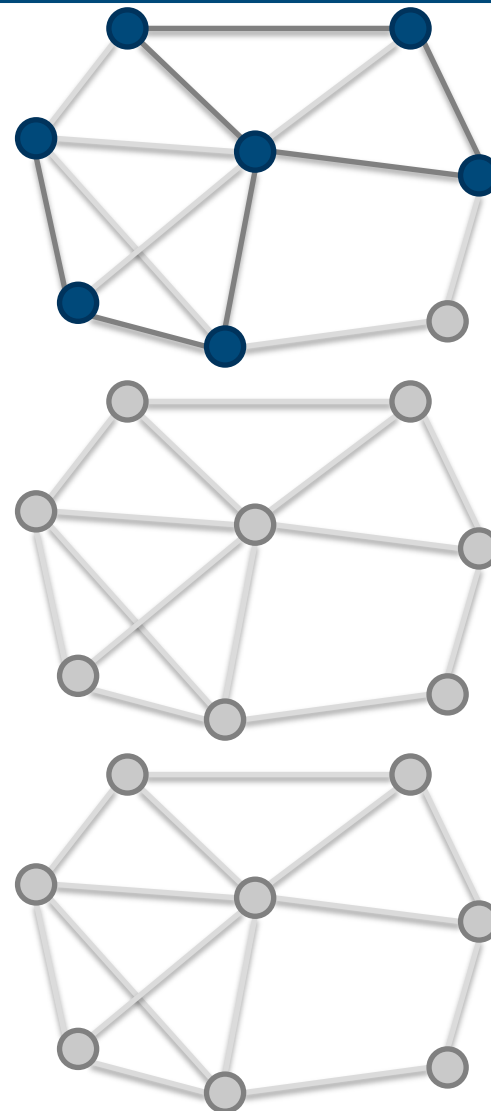
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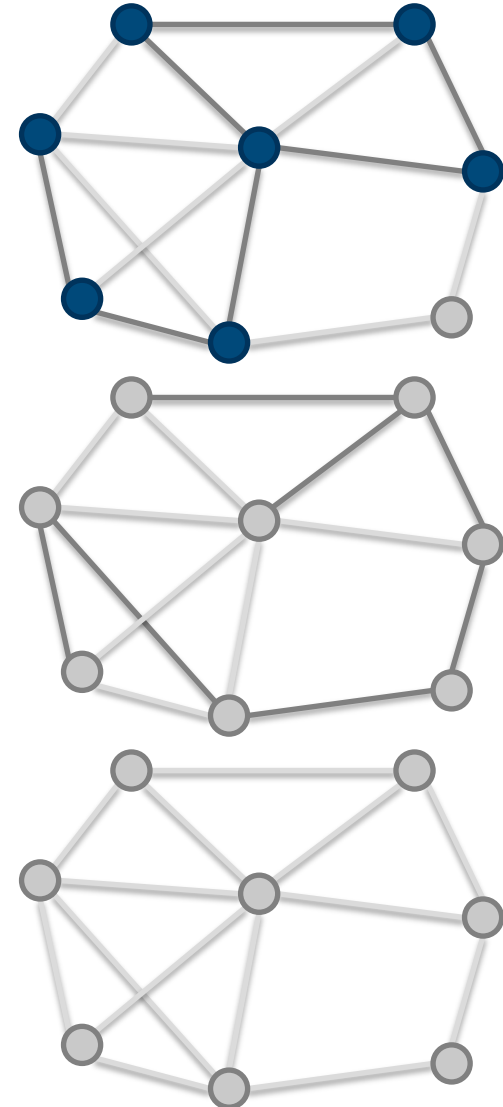
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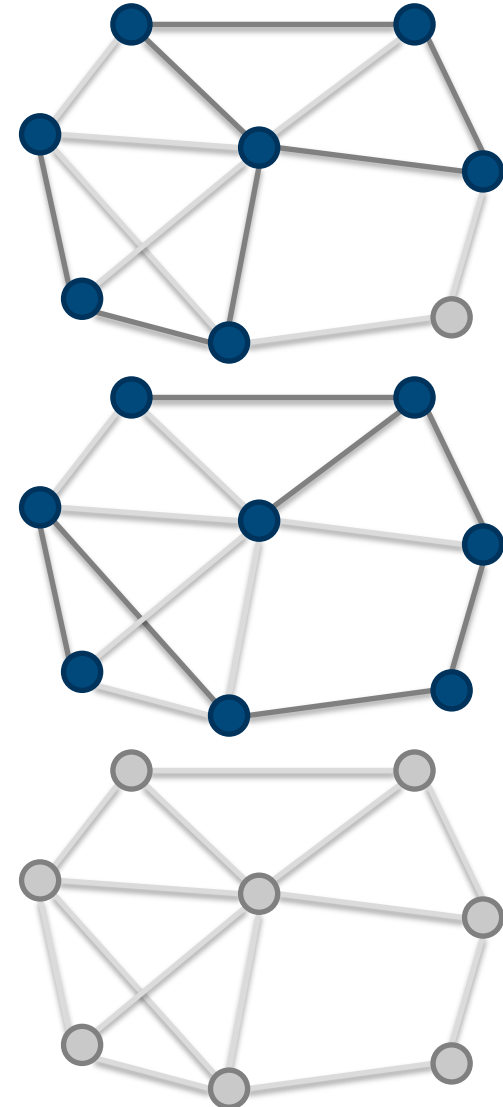
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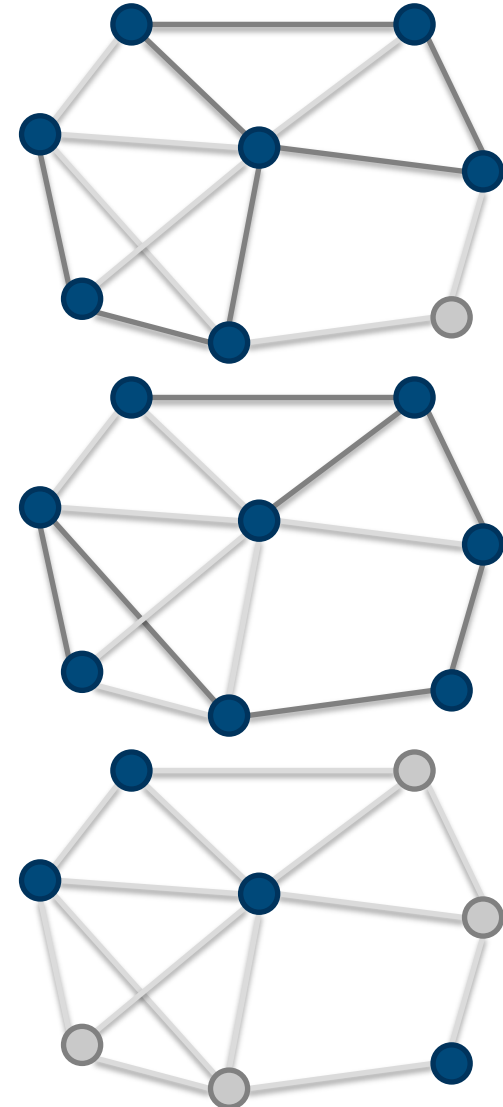
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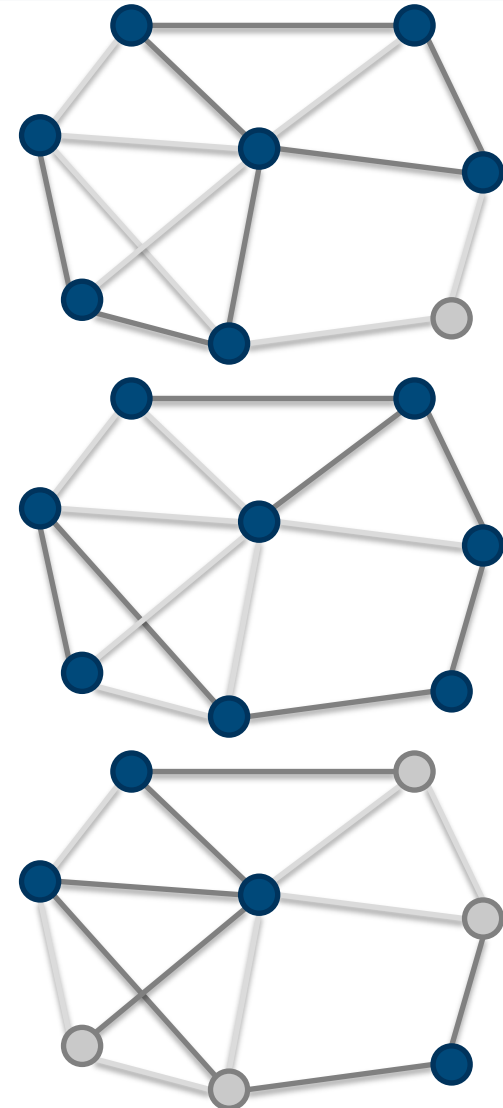
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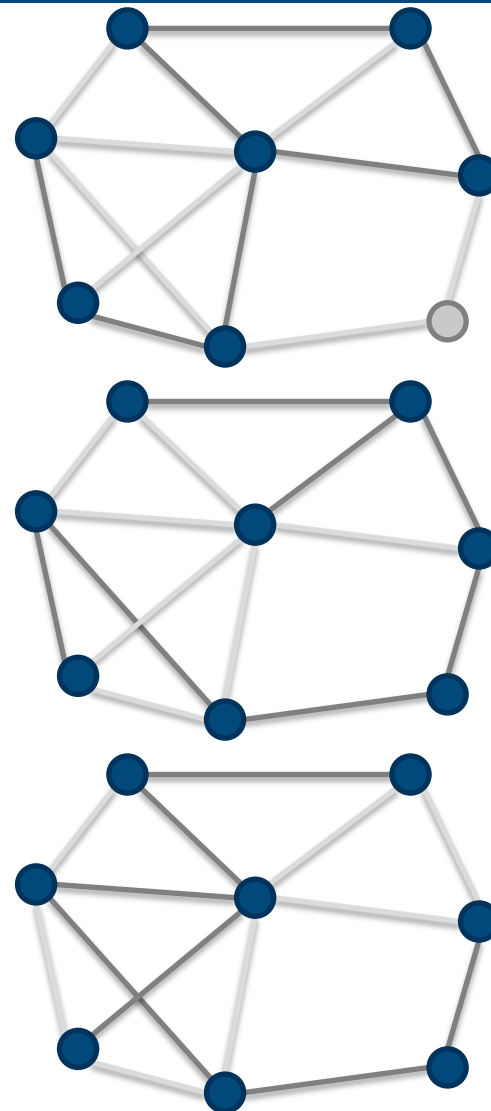
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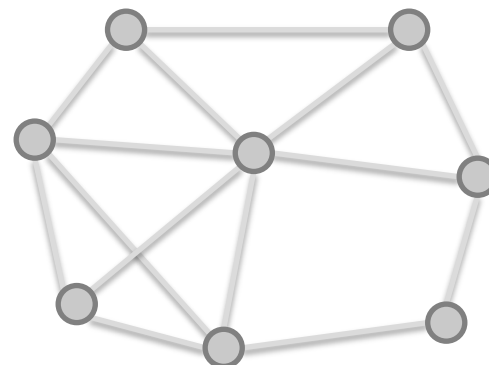
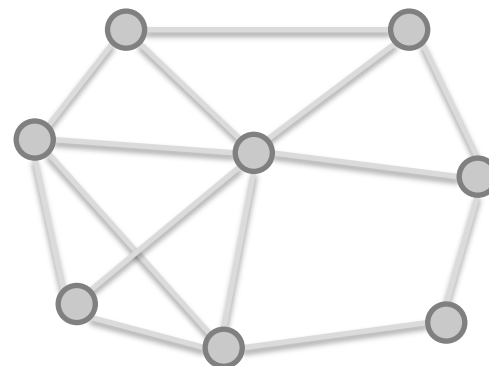
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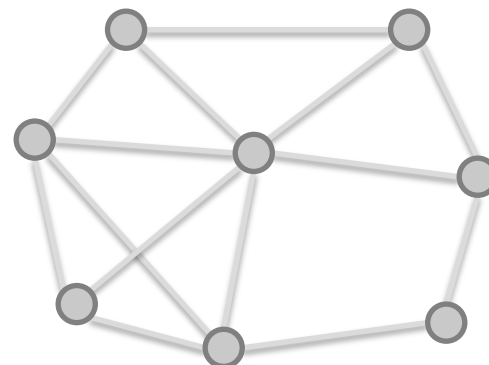
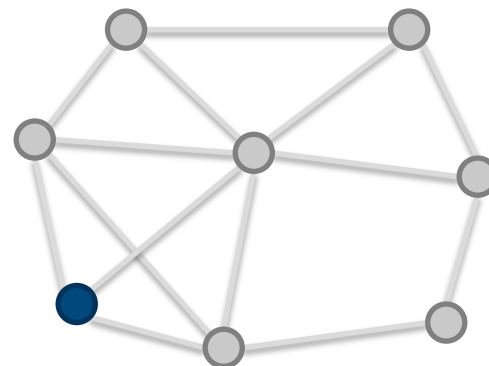
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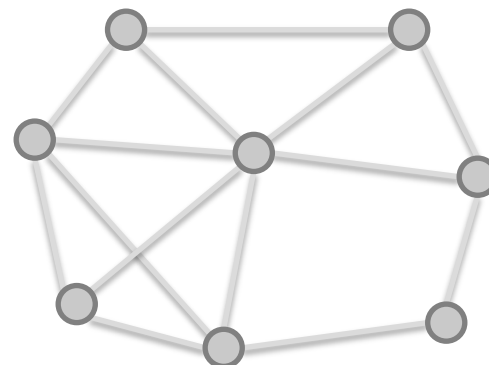
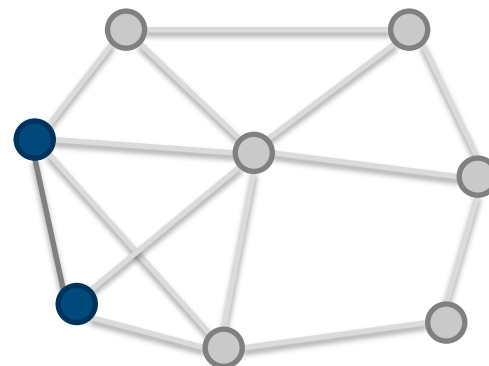
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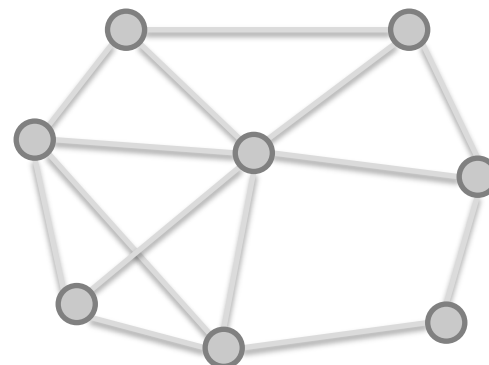
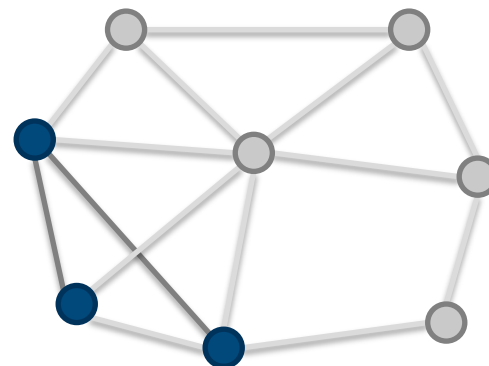
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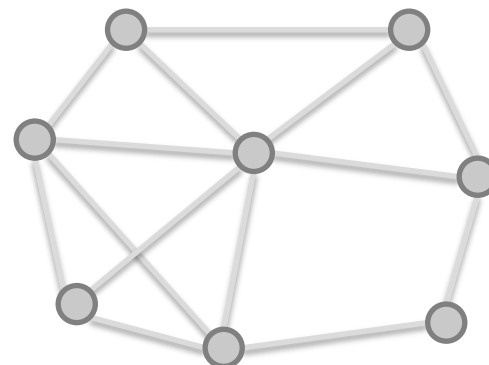
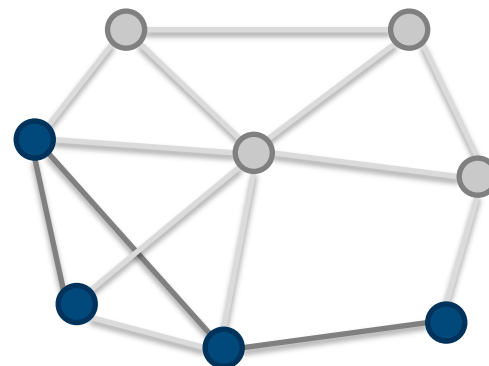
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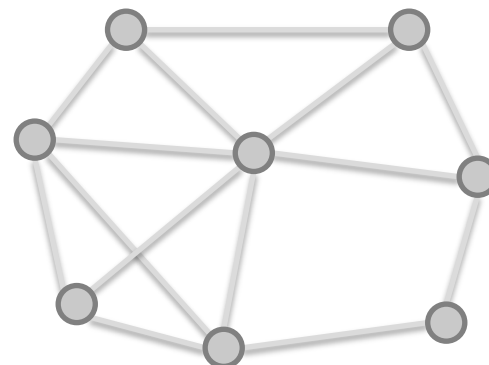
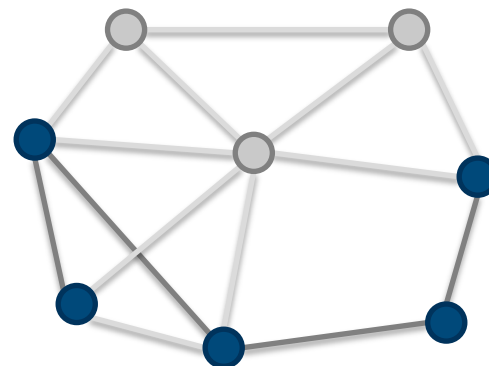
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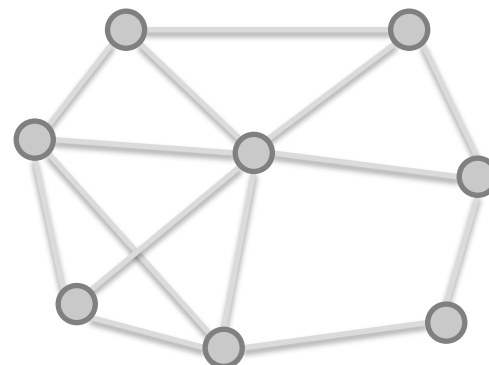
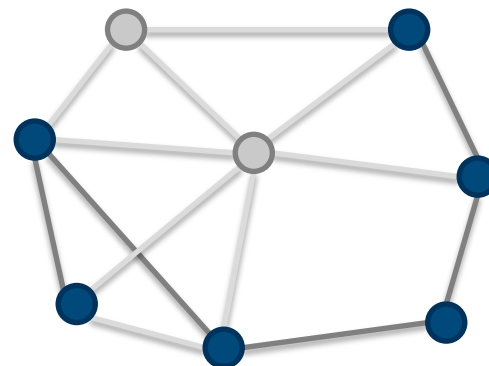
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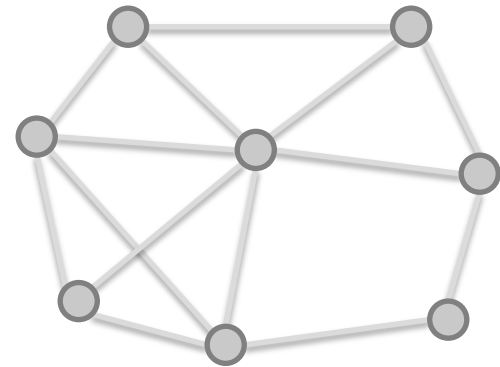
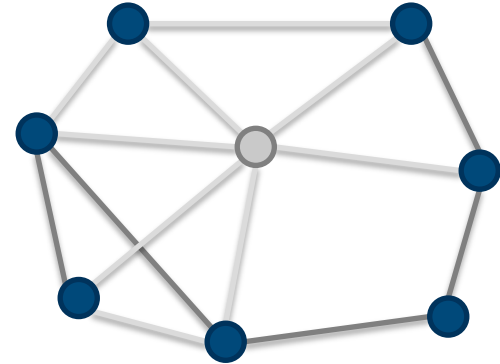
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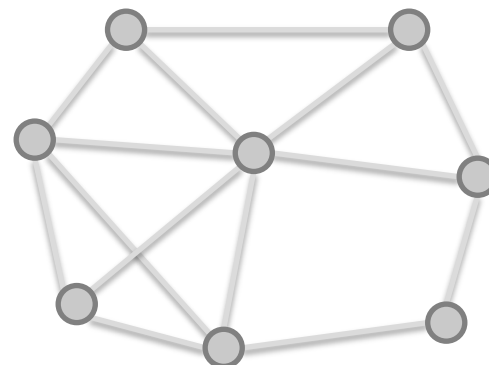
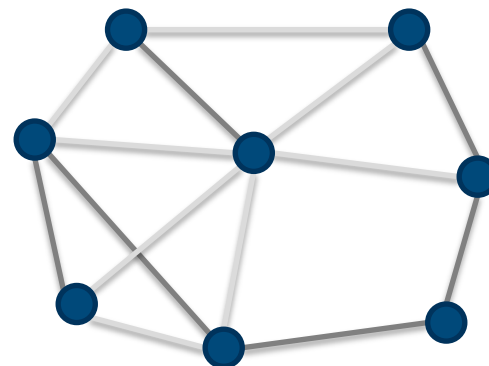
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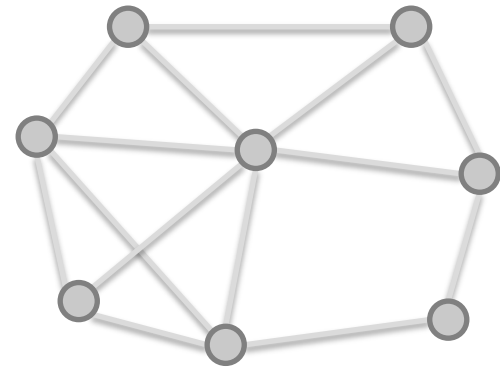
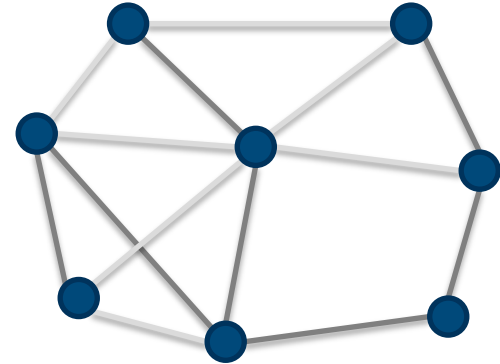
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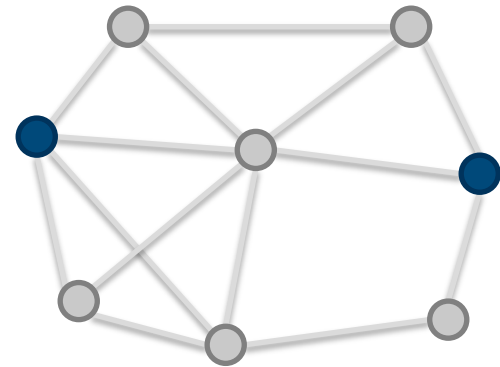
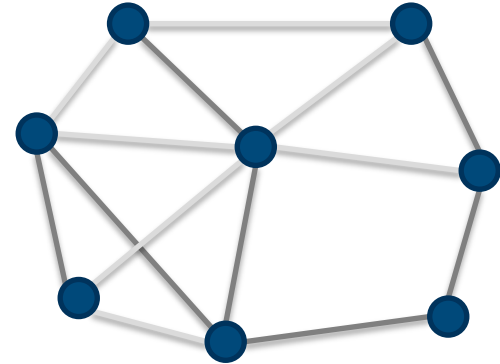
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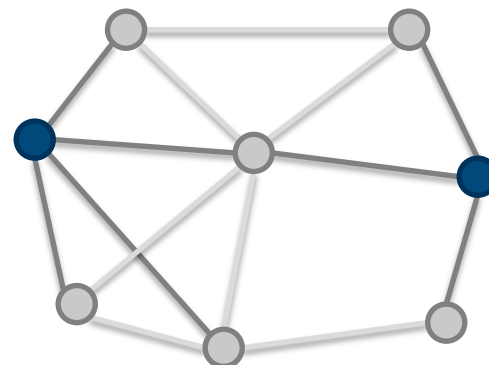
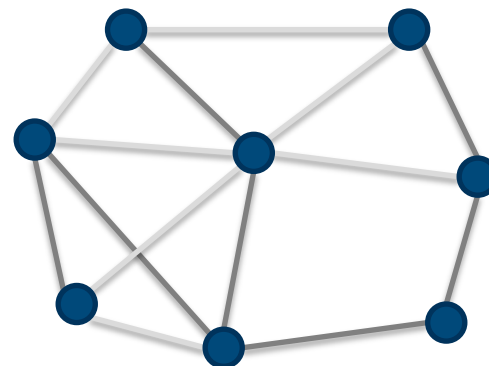
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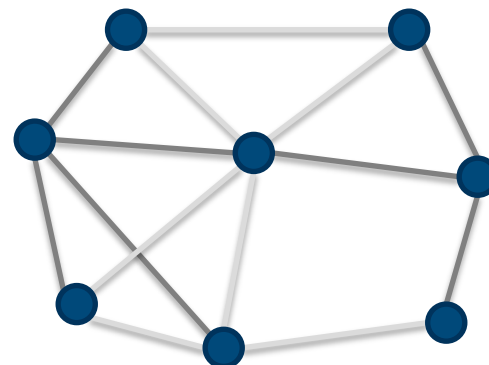
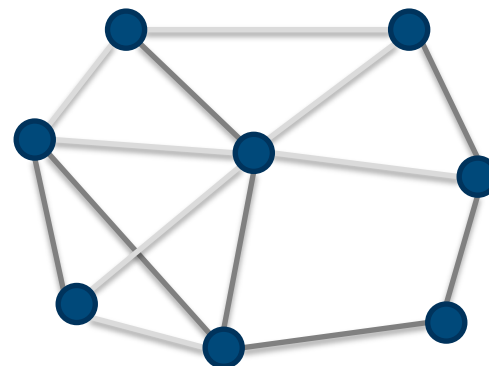
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Selected methods comprise a broad array of network sampling techniques



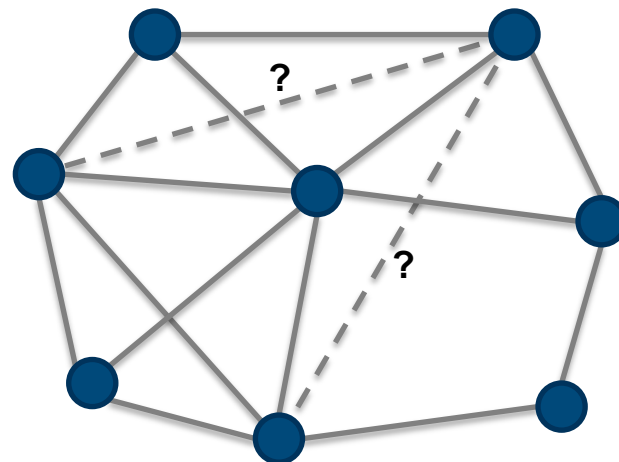
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Link Prediction

- **Scenario:** Two vertices currently do not share an edge
- **Question:** How likely are these vertices to form a connection in the near future?
- **Examples:**
 - How likely is a connection to be formed between two people in a social network?
 - How likely are two political entities to engage in diplomatic or military conflict?

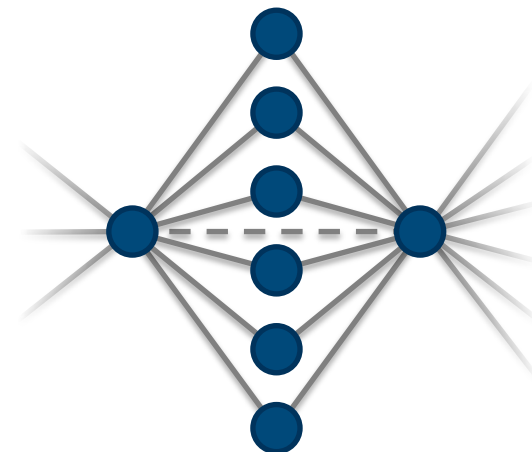


Link prediction: Anticipation of new connections that currently do not exist

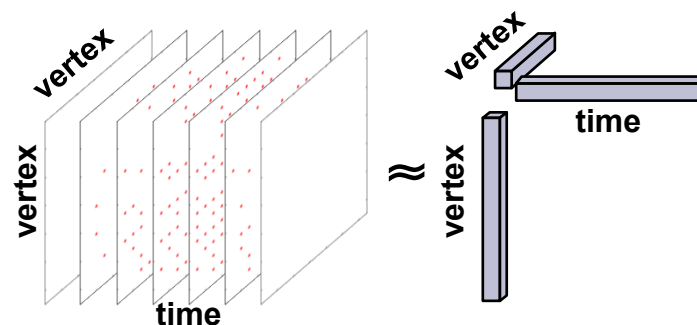


Link Prediction Statistics

- **Common neighbors**
 - Vertices with more neighbors in common are more likely to connect
- **Jaccard's coefficient**
 - Normalize common neighbors by total number of neighbors
- **Low-rank approximation**
 - Use a low-rank approximation for the square of the adjacency matrix
- **Tensor decomposition**
 - Break data into vertex-vertex-time factors, extrapolate along temporal axis



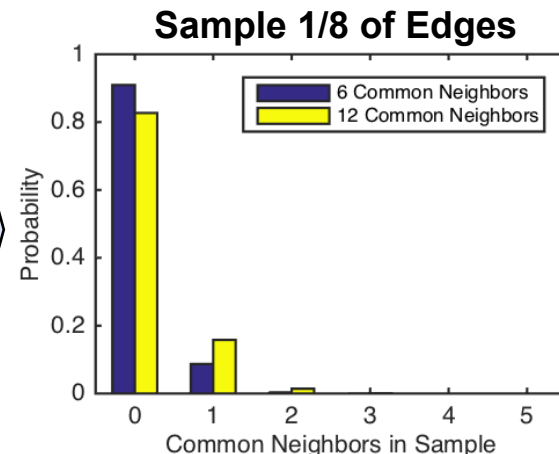
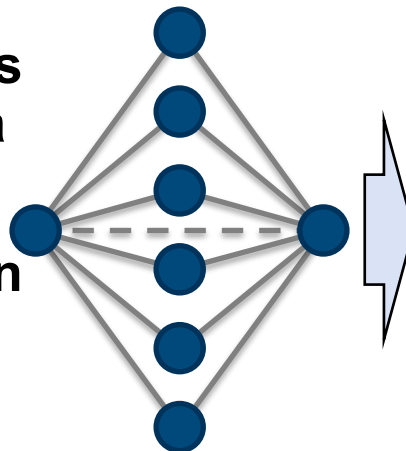
$$A^2 \approx U \Sigma^2 U^T$$



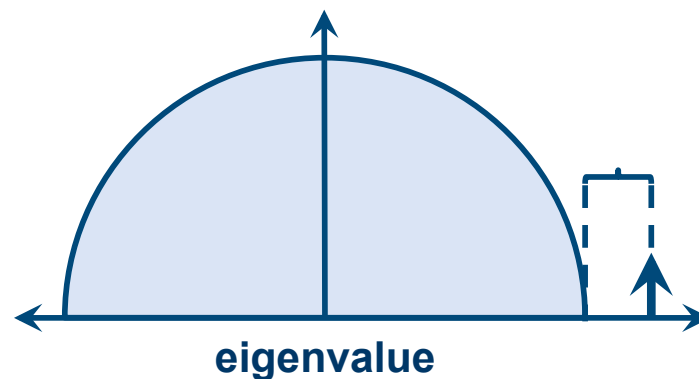


How Does Sampling Hurt?

- If edge sampling probability is p , probability of maintaining a common neighbor is p^2
- This “smears” the distribution of common neighbors, inhibiting detection



- For eigenvector-based techniques, removing edges causes the distribution of eigenvalues to contract
- The outlier eigenvalues, which provide the most information, contract more quickly



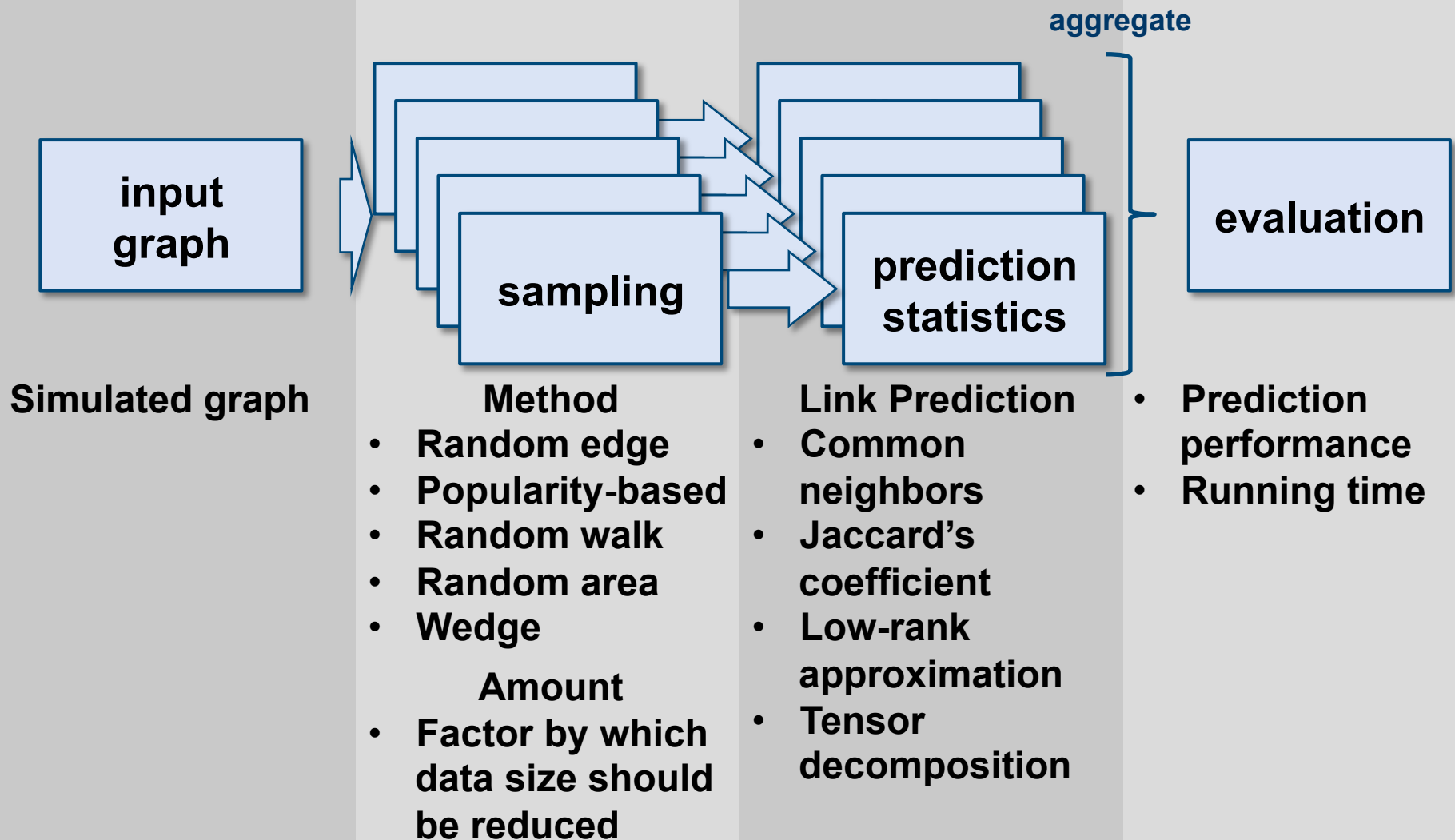


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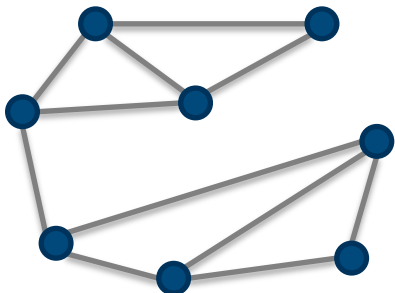
Experiments



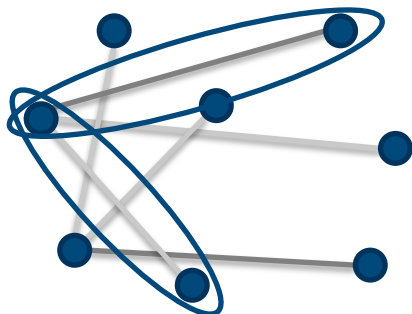


Simulation Setup

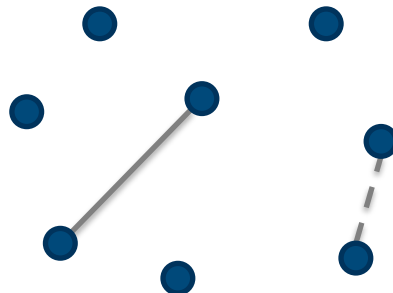
Graph at time t



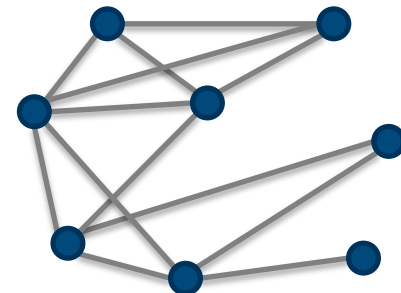
Normalized common neighbors



Random changes



Graph at time $t+1$

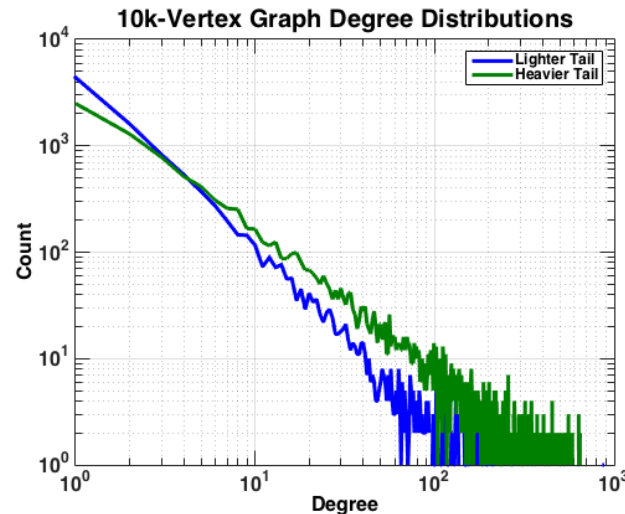


- **BTER Model: Simulate graphs evolving over several time steps**
- **First time step: Create a graph from a generative model**
- **Future time steps:**
 - **Compute common neighbors**
Normalize using cosine similarity
Randomly select based on scores
 - **Create new random edges from generative model**
Simulates “chance” encounters
 - **Randomly remove edges**



Simulated Graphs

- Approximately 10,000 vertices, average degree of 17, 5% increase in edge count per time step
- Two degree distributions: one lighter tailed and one heavier tailed

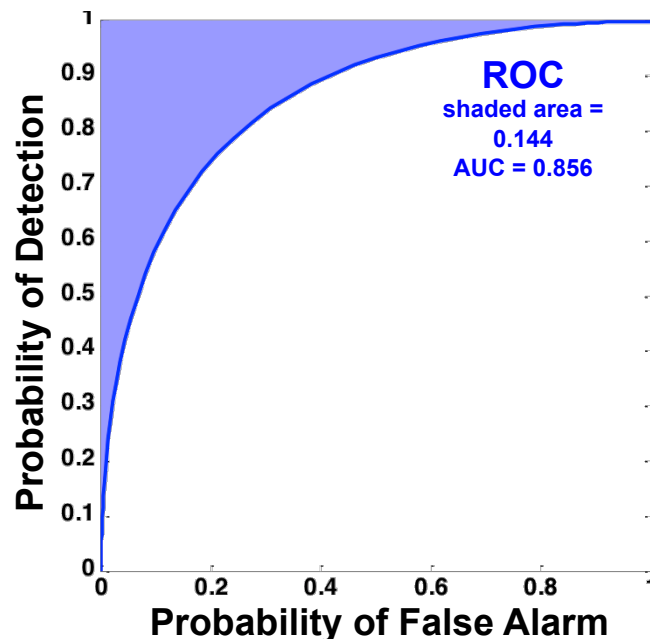


Variations designed to determine most robust sampling methods



Performance Metrics

- **Area under the ROC curve (AUC)**
 - Measure area under the receiver operating characteristic (ROC) curve, which maps false alarm rate to detection rate
- **Running time**
 - Time required (in Matlab implementation) to compute prediction statistics
- **Memory Footprint**
 - Storage required for prediction statistics



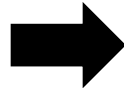
Fundamental metrics for anticipatory network analytics:

- Predictive performance
- Latency
- Computing resource use



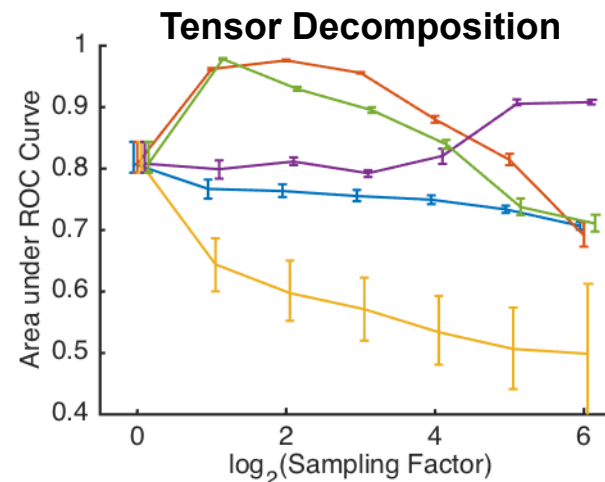
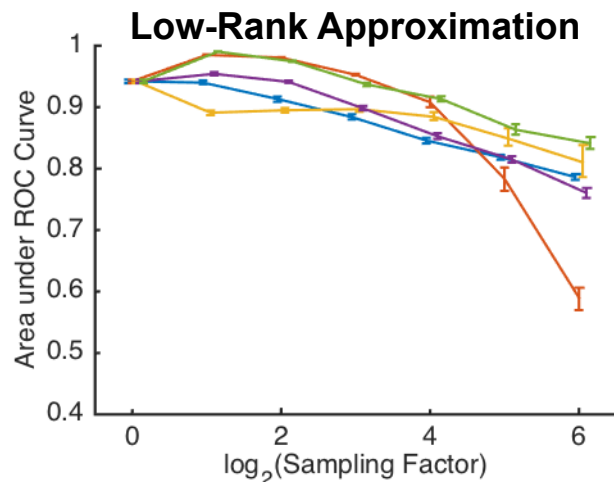
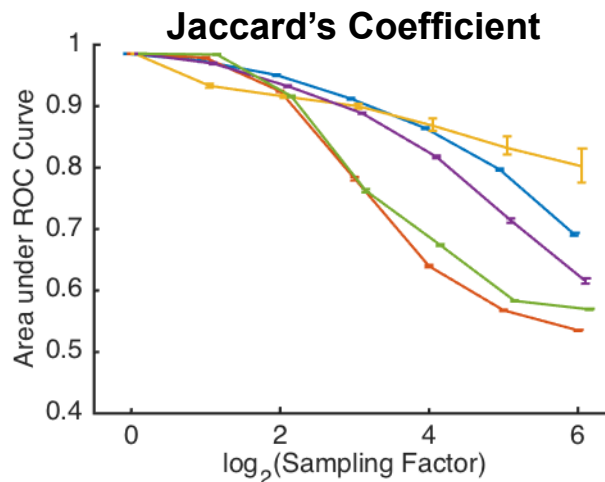
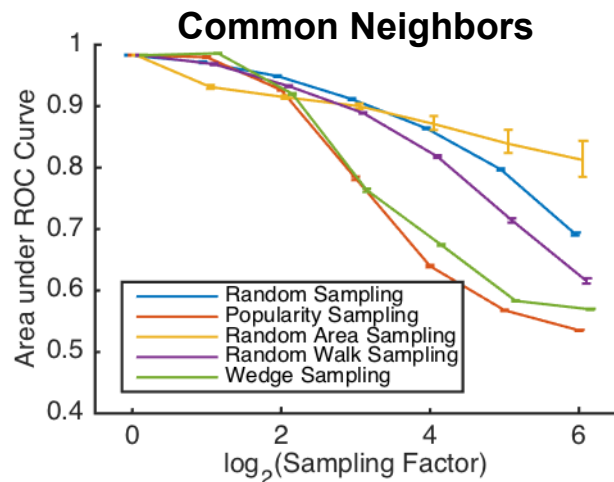
Outline

- Introduction
- Sampling Techniques
- Link Prediction
- Experimental Setup
- Results
- Summary





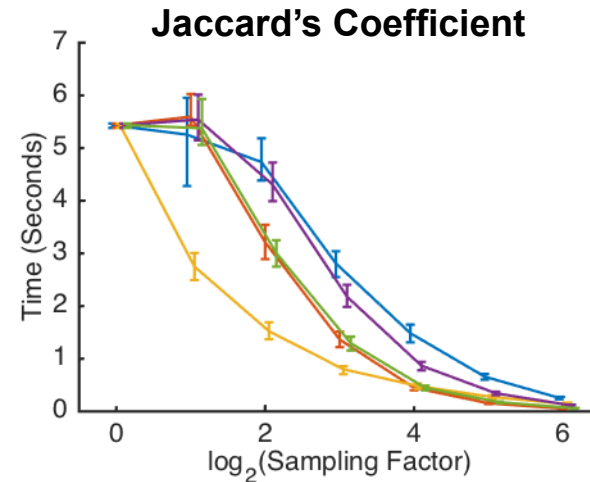
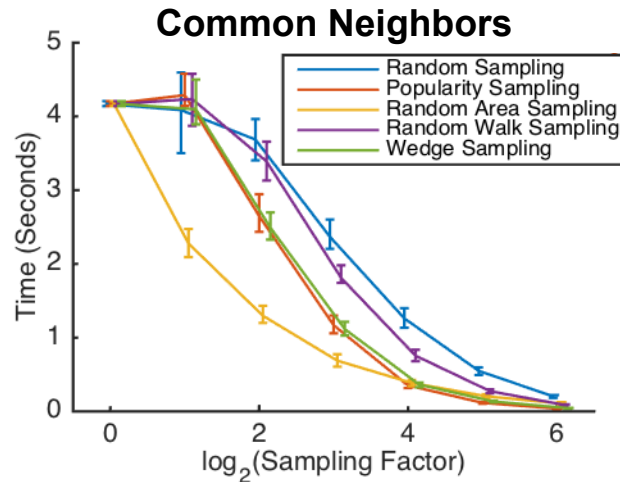
Link Prediction in Baseline Simulation



- **Common neighbors and Jaccard's coefficient are virtually identical**
- **Random area sampling has the most significant initial performance drop in all cases**
- **Random walk sampling improves AUC at a higher sampling factor with tensor factorization**



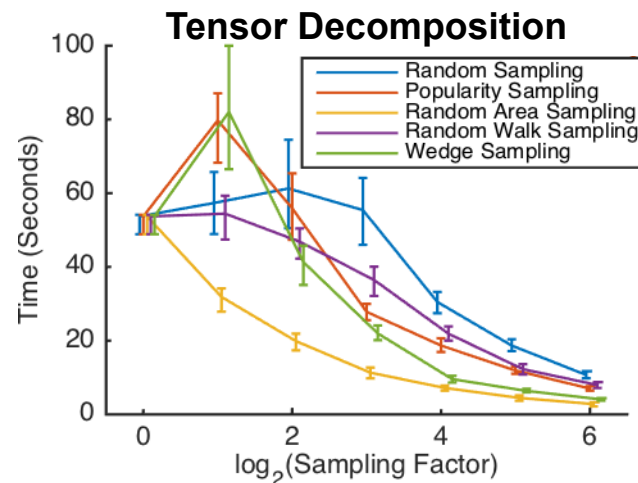
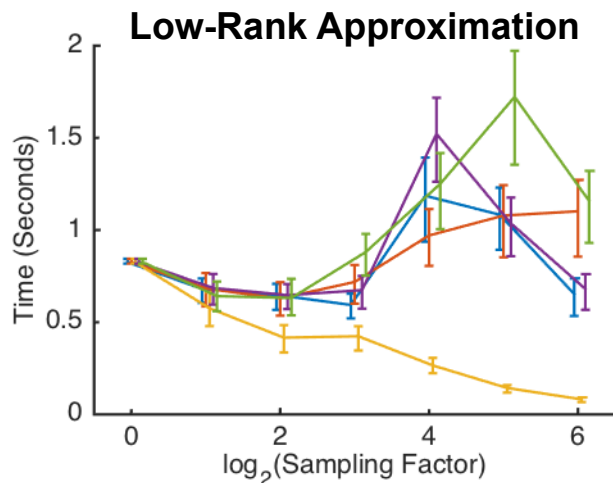
Time for Link Prediction



- **Common neighbors and Jaccard: time is substantially reduced as sampling becomes more aggressive**
- **Best initial decrease is with random area sampling**
 - However, this comes with the biggest decrease in predictive performance



Time for Link Prediction

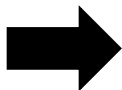


- **Low Rank: time increases with higher sampling rates**
 - Changes in the distribution of eigenvalues alters convergence rate
- **Tensor: High sampling rates significantly reduces runtime**
- **Random area sampling produces high number of isolated vertices, reduces the dimensionality of the adjacency matrix**



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Summary

- **Network analytics are of tremendous importance for anticipatory analytics**
 - **Forecast future connections**
- **Networks of interest are often extremely large, and data sampling enables computation on a dataset of a reasonable size**
- **Study considered the effect of sampling on anticipatory network analytics**
 - **Random edge sampling is typically the most stable**
 - **Random area sampling loses performance the fastest**
- **Promising areas for future work: test on larger simulated and real graph data, investigate emergent community detection, aggregate samples for higher predictive capabilities, integration with high-performance graph analytics hardware**



Backup
