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Social Fingerprinting: Identifying Users of Social Networks by their Data Footprint

The University of Tennessee
Electrical Engineering and Computer Science
Dissertation Defense

Denise Koessler Gosnell

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Is a social network user's behavior unique?

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Has social data made anonymity impossible?

87%

U.S. adults' location is known via their mobile phone

MIT T.R.

U.S. young adults carry their phone wherever they go

AT&T

96%

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Outline:

1. Define and Motivate
2. Model and Software
3. Individual Printing Algorithm
4. Community Printing Algorithm
5. Conclusions

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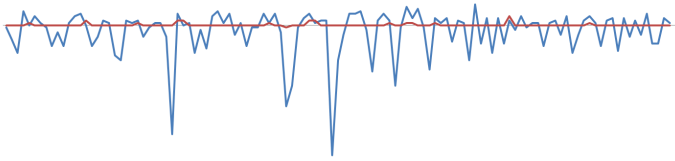
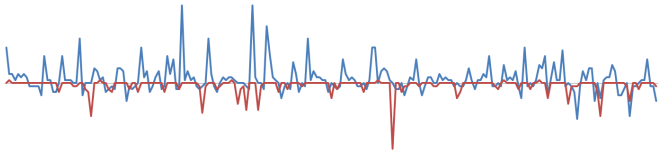
A Social Fingerprint

Social Network User A



Social Network User B



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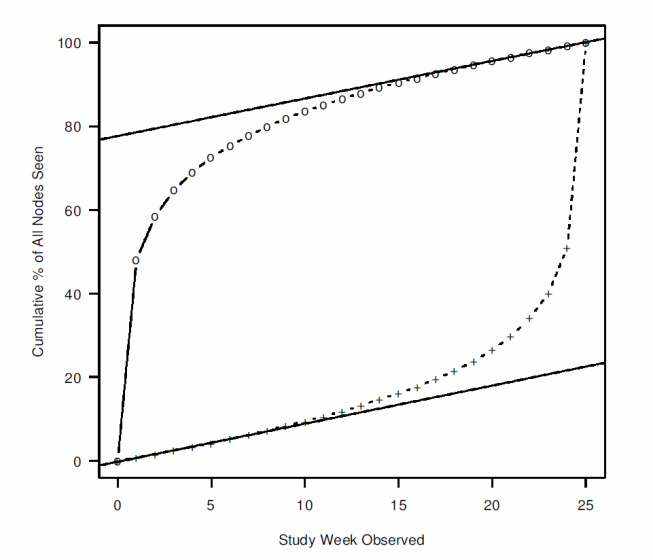
Why is this hard?



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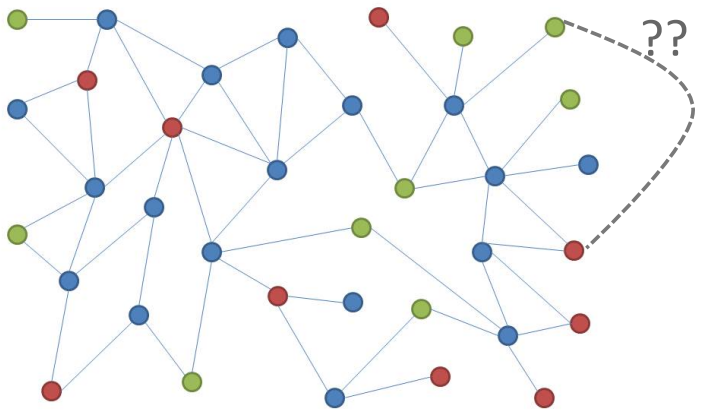
Why is this hard?



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Previous Work

ACADEMIA

- Bounds of Human Privacy, MIT
- SNAP Project, Stanford
- Graph Modeling Libraries
- Simulated topologies and statistics

INDUSTRY

- IBM Watson SMSim
- Topology Statistics
- Private Companies
- …?

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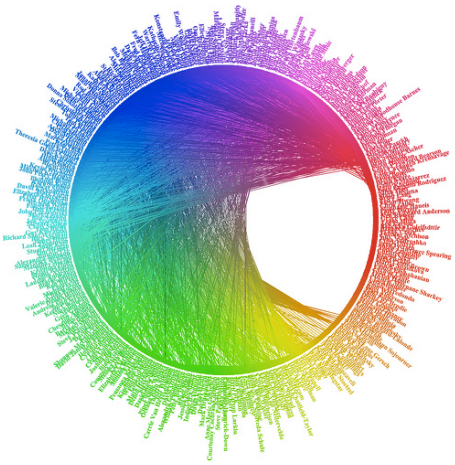
The Model

- Connectivity?
- Time?
- Multiple Edges?
- Empirical Data vs. Assumptions?



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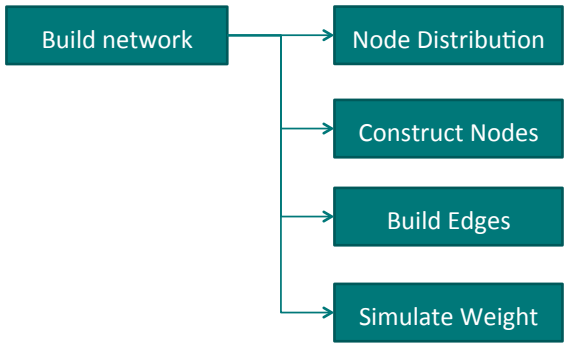
The Model



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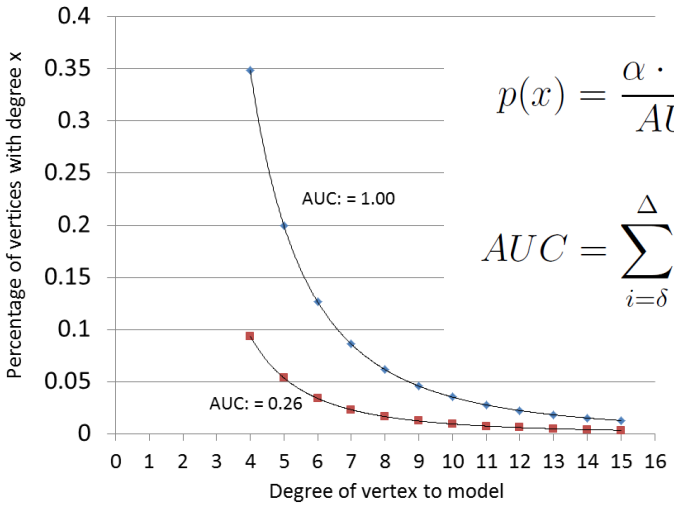
Scale-free Distribution



$$p(x) = \frac{\alpha \cdot x^{-\beta}}{AUC}$$

$$AUC = \sum_{i=\delta}^{\Delta} \alpha \cdot i^{-\beta}$$

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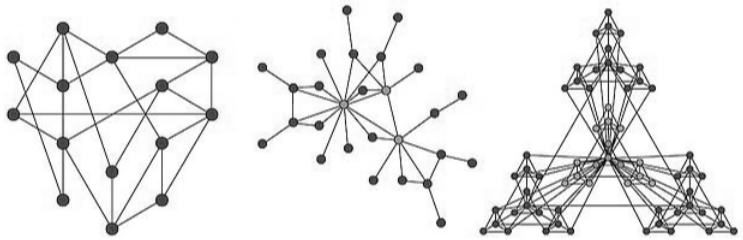
The Base Model

Scale-Free Graph



Random Graph

Hierarchical Graph

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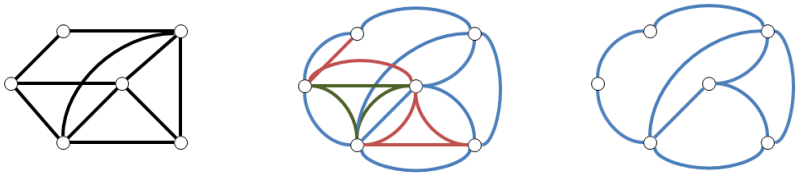
Multiple Edges



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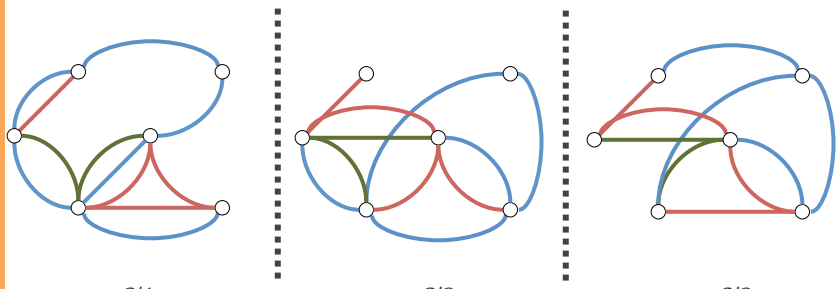
Dynamic Edges



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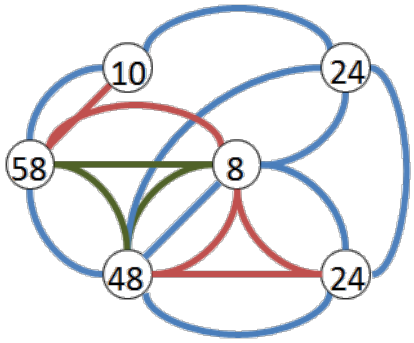
Simulating Edge Weights



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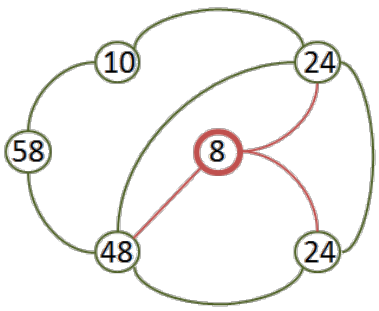
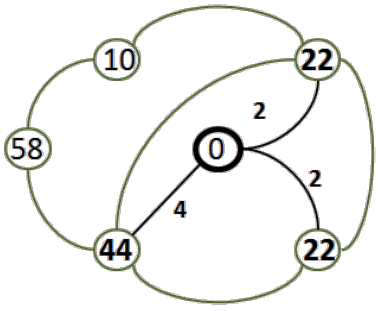
Maximal Diffusion Algorithm





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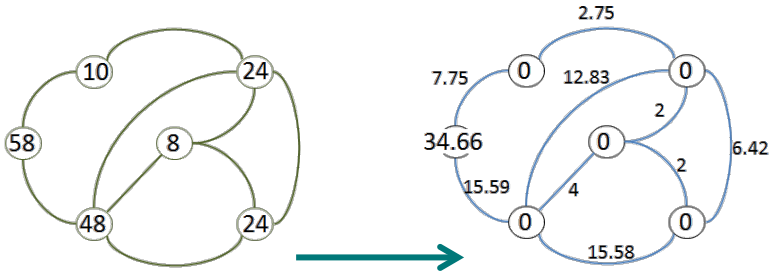
Maximal Diffusion Algorithm



Capacity constraints: $\sum_{v_j \in N(v_i)} w(e(i,j)) \leq c_{i,b}$

Flow conservation: $r_{i,b} + \sum_{v_j \in N(v_i)} w(e(i,j)) = c_{i,b}$

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Maximal Diffusion Algorithm

Result: A fractional estimation of an optimally weighted graph via the diffusion of node capacity.
Input: time step t and edge type b;
Sort all nodes such that $c^t_{i,b} \leq c^t_{i+1,b}$;
for *each* $v_i \in V(G)_{sorted}$ **do**
  Initialize: $r^t_{i,b} = c^t_{i,b}$;
  Determine total community capacity C of v_i;
    $C = \sum_{v_j \in N(v_i)} c^t_{j,b}$;
  where $N(v_i) = \{v_j \in V(G^t) | e(i,j)^t_b \in E(G^t)\}$;
  for *each* $v_j \in N(v_i)$ **do**
    $w = c^t_{i,b} \cdot \frac{c^t_{j,b}}{C}$;
    $e(i,j)^t_b = w$;
    $c^t_{j,b} = c^t_{j,b} - w$;
    $r^t_{i,b} = r^t_{i,b} - w$;
  end
  Sort all nodes starting from v_i such that $c^t_{i,b} \leq c^t_{i+1,b}$;
end

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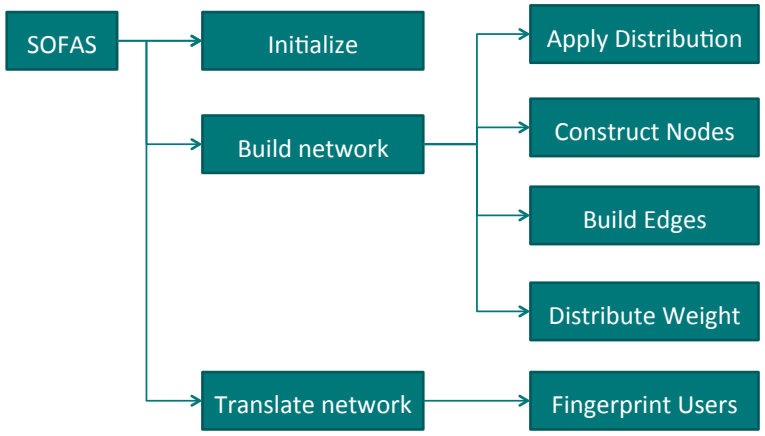
SOcial Fingerprint Analysis Software (SOFAS)



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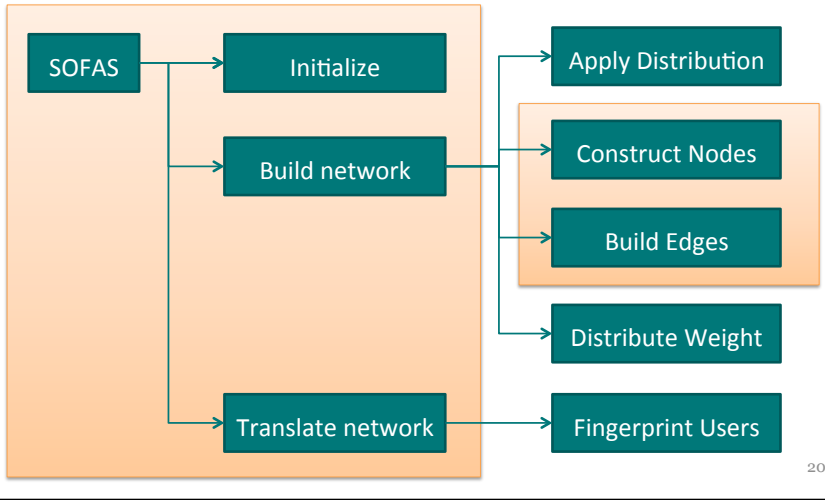
SOFAS: Phases 1 & 2



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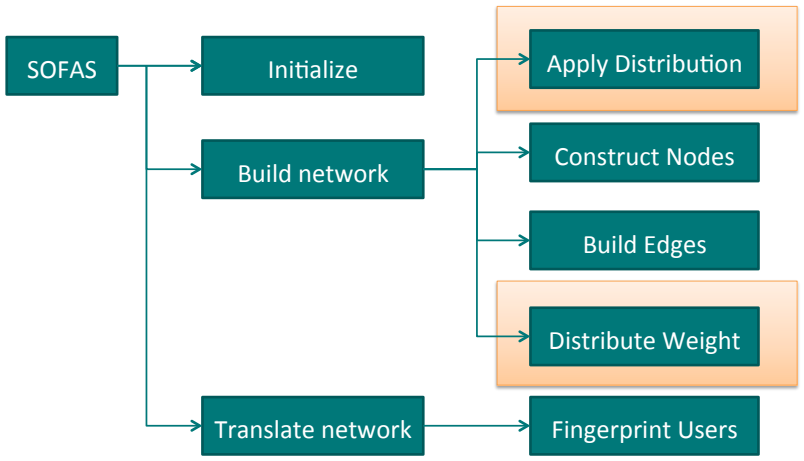
SOFAS: Phases 3 and 4



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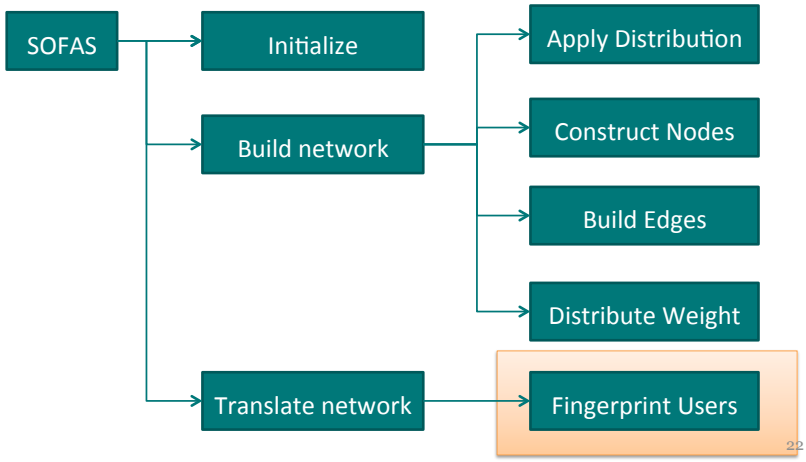
SOFAS: Phase 5



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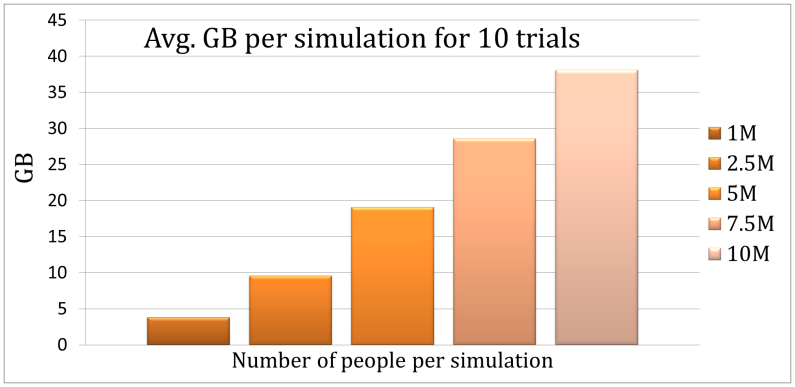
SOFAS: Memory Performance



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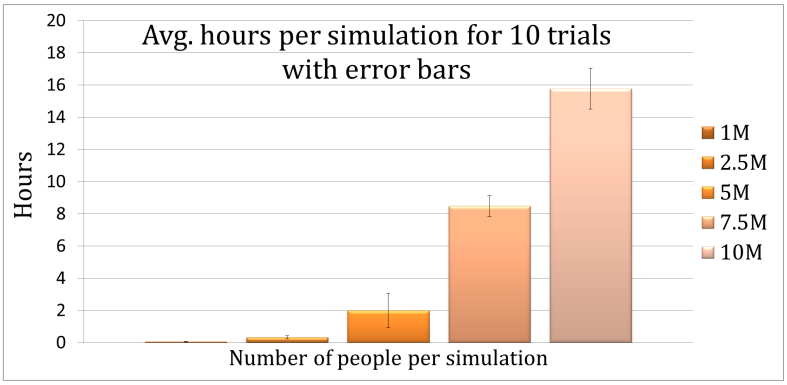
SOFAS: Time



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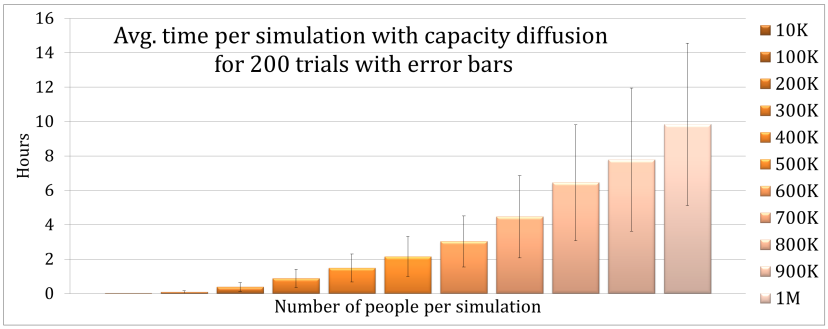
SOFAS: Diffusion Time



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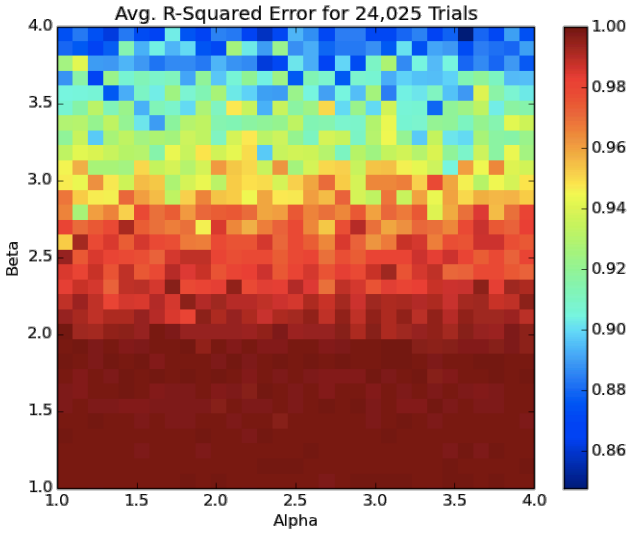
SOFAS: Distribution Error



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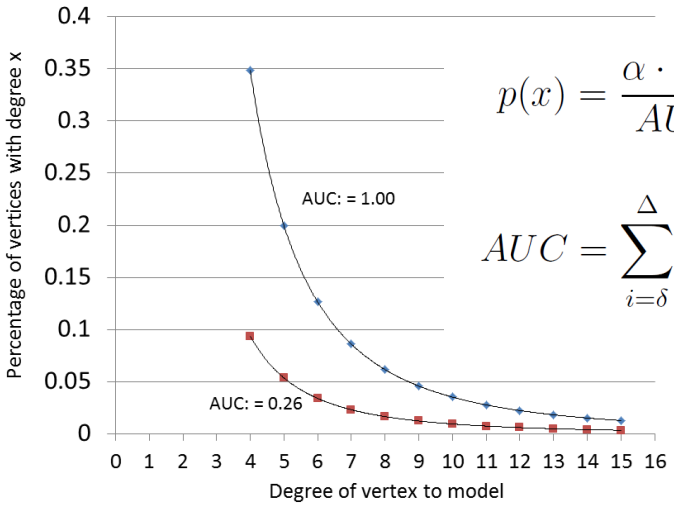
Scale-free Distribution



$$p(x) = \frac{\alpha \cdot x^{-\beta}}{AUC}$$

$$AUC = \sum_{i=\delta}^{\Delta} \alpha \cdot i^{-\beta}$$

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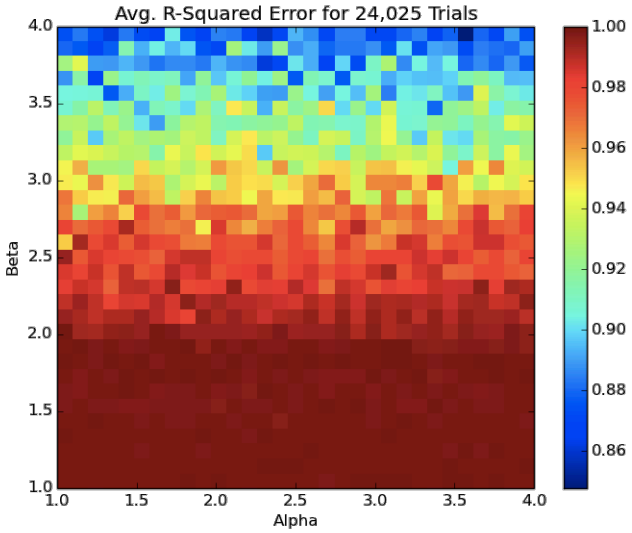
SOFAS: Distribution Error



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Social Fingerprinting:

Identifying the Individual

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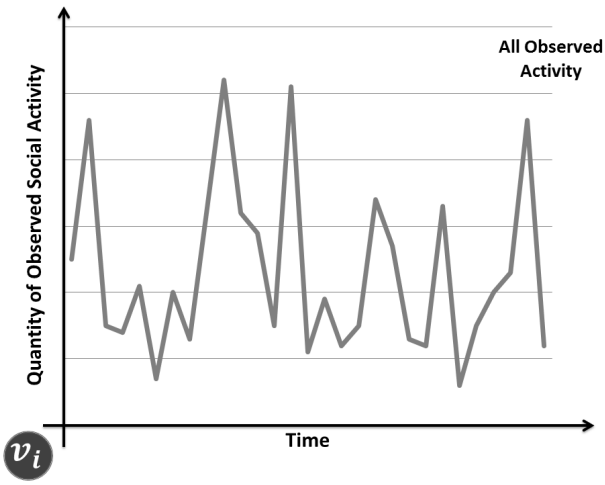
The Theory



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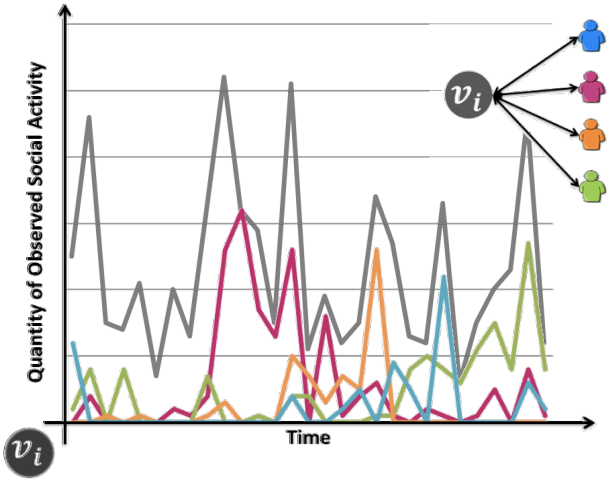
The Theory



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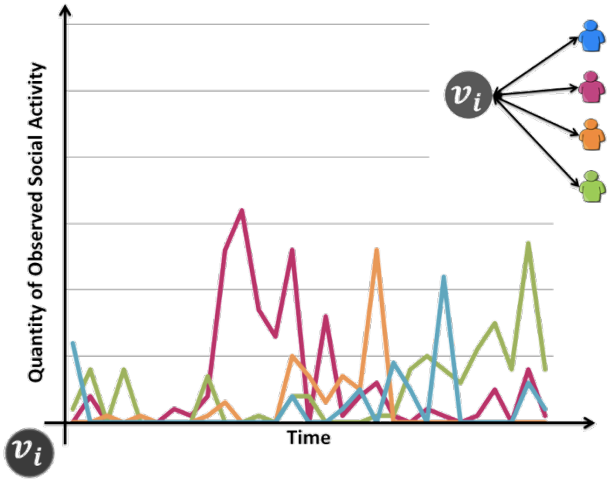
The Theory



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Social Fingerprint Procedure:

1. For each person, construct a neighborhood graph
2. Given the neighborhood graph, determine candidate prints
3. Rank the prints
4. Evaluate

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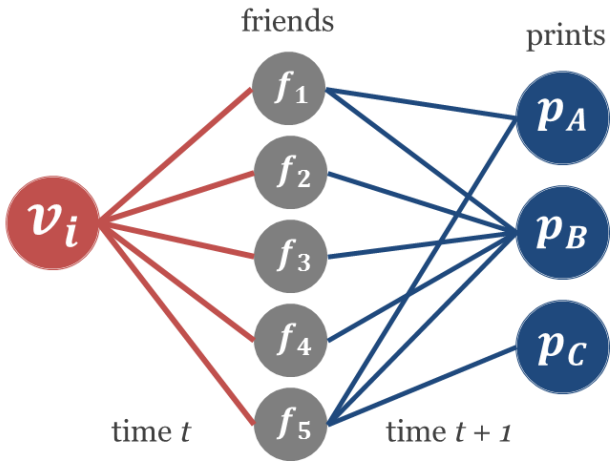
Print Construction



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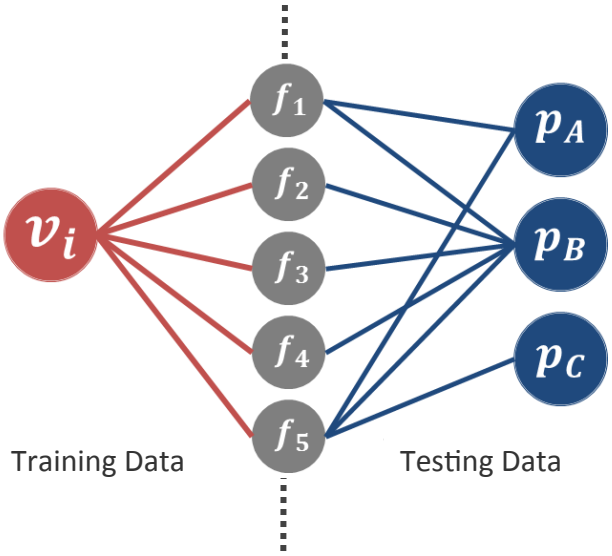
Print Construction



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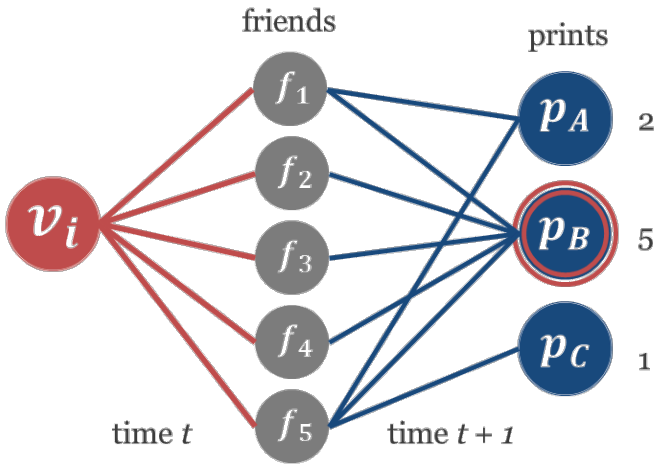
Intersection Score



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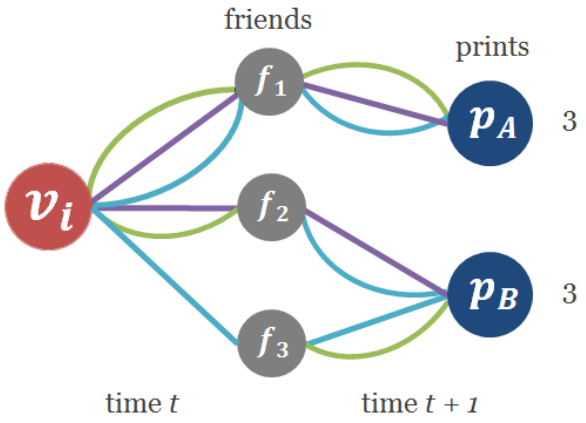
Subgraph Matching



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All Ranking Functions

Edge Based

- Absolute Difference
- Percent Difference
- Euclidean Distance
- Euclidean Distance, threshold based
- Euclidean Distance, inverse sum

Node Based

- Intersection
- Graph Matching
- Hamming Distance

Ensemble Style

- BCS
- Olympic Score

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Graph Prints: Test Cases

- Number of People: 1K, 10K, 100K
- Length of time: 6
- Attrition on relationships: varies
- Training/Testing Split: varies
- Model Types: Binary and Weighted
- Total trials: 57,000 example graphs

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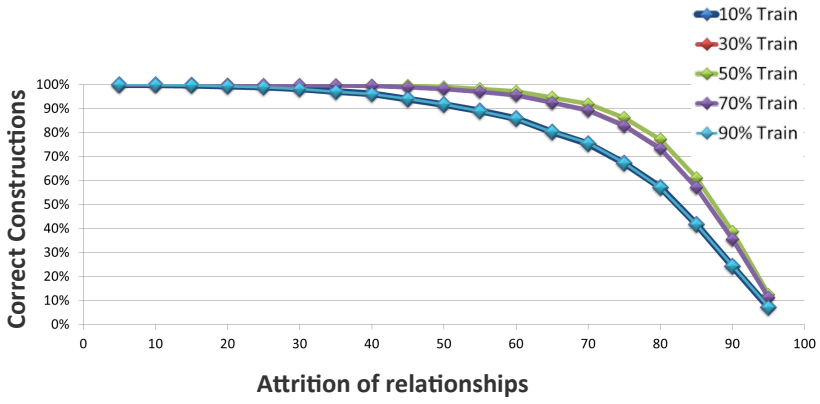
Validation of Approach



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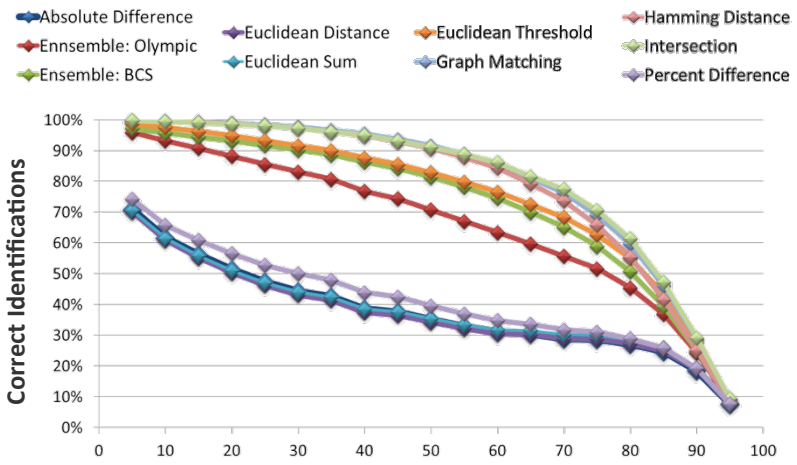
Ranking Function Performance



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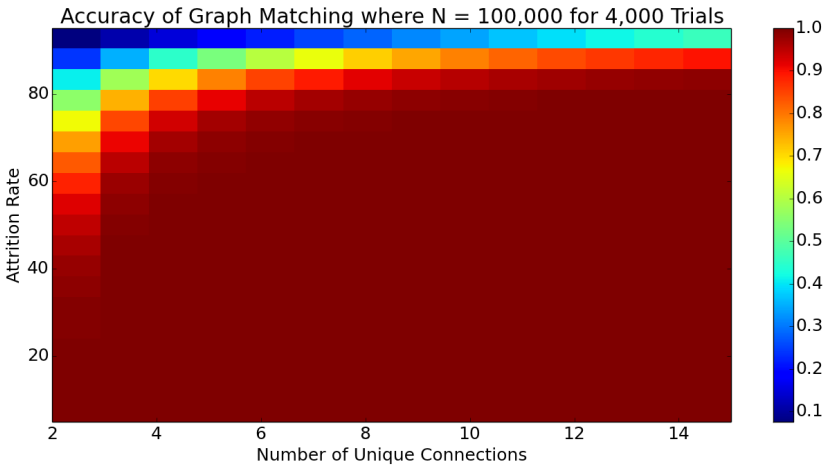
Best of the Best



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Social Fingerprinting:

Picking the individual out of crowd

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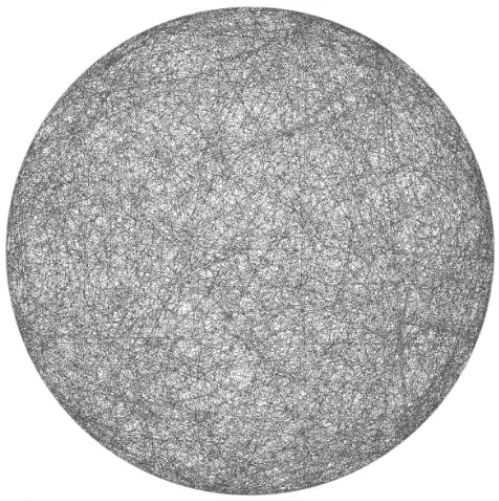
What does this look like?



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Social Fingerprint Procedure:

1. Construct matrix A and query vector(s)
2. Semidiscrete Decomposition of matrix A to yield rank-*k* approximation
3. Compute new query vectors
4. Rank the vectors w.r.t. cosine similarity
5. Evaluate

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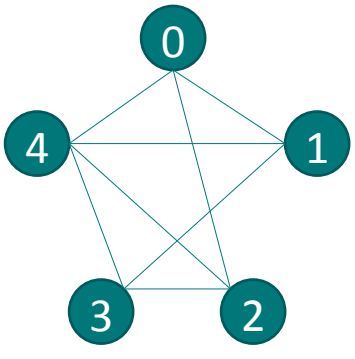
Construction:



Time *t*

$$\begin{array}{c} \\ p_0 \\ p_1 \\ p_2 \\ p_3 \\ p_4 \end{array} \begin{array}{c} \begin{array}{ccccc} p_0 & p_1 & p_2 & p_3 & p_4 \\ \downarrow & \downarrow & \downarrow & \downarrow & \downarrow \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

Binary: *A[i,j]* → the presence of the relationship

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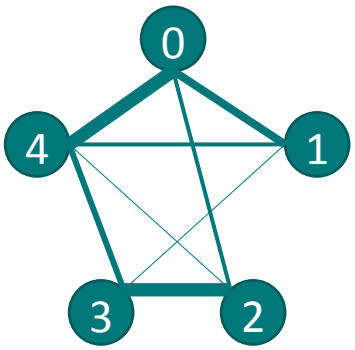
Construction:



Time *t*

$$\begin{array}{c} \\ p_0 \\ p_1 \\ p_2 \\ p_3 \\ p_4 \end{array} \begin{array}{c} \begin{array}{ccccc} p_0 & p_1 & p_2 & p_3 & p_4 \\ \downarrow & \downarrow & \downarrow & \downarrow & \downarrow \end{array} \\ \begin{bmatrix} 0 & 5 & 2 & 0 & 9 \\ 5 & 0 & 0 & 1 & 2 \\ 2 & 0 & 0 & 9 & 1 \\ 0 & 1 & 9 & 0 & 4 \\ 9 & 2 & 1 & 4 & 0 \end{bmatrix} \end{array}$$

Term Frequency: *A[i,j]* → the *strength* of the relationship

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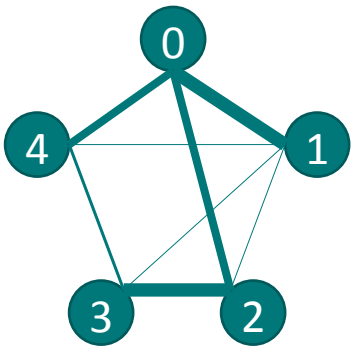
Construction: Query Vectors



Time *t + 1*

$$\begin{array}{ccccc} q_0 & q_1 & q_2 & q_3 & q_4 \\ \downarrow & \downarrow & \downarrow & \downarrow & \downarrow \end{array}$$
$$\begin{bmatrix} 0 \\ 9 \\ 4 \\ 0 \\ 3 \end{bmatrix} \begin{bmatrix} 9 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 0 \\ 9 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 9 \\ 0 \\ 2 \end{bmatrix} \begin{bmatrix} 3 \\ 1 \\ 0 \\ 2 \\ 0 \end{bmatrix}$$

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Semidiscrete Decomposition (SDD)
[Kolda and O'Leary 1998]

$$A_{nxn} \approx U_{nxk} \cdot \sum_{kxk} \cdot V_{nxk}$$

$$U_{i,j} \in \{-1,0,1\}$$

$$\sum_{i,i} = \sigma_i$$

$$V_{i,j} \in \{-1,0,1\}$$

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Validation: $q^{t+1}[j]*V^{(t)}[i]$

	V[0]	V[1]	V[2]	V[3]	V[4]
q[0]	**0.8467**	0	0	0.5319	0
q[1]	0.0704	**0.9859**	0.9859	0.1516	0.9859
q[2]	0.2095	**0.9778**	**0.9778**	0	**0.9778**
q[3]	0.2454	0	0	**0.9693**	0
q[4]	0.1414	**0.9899**	**0.9899**	0	**0.9899**

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SDD: Test Cases

- Number of People: 100, 500 or 1,000
- Length of time: 12
- Attrition on relationships: 37%
- Low Rank Approximation rank: varies
- Training/Testing Split: varies
- Total trials: 84,000

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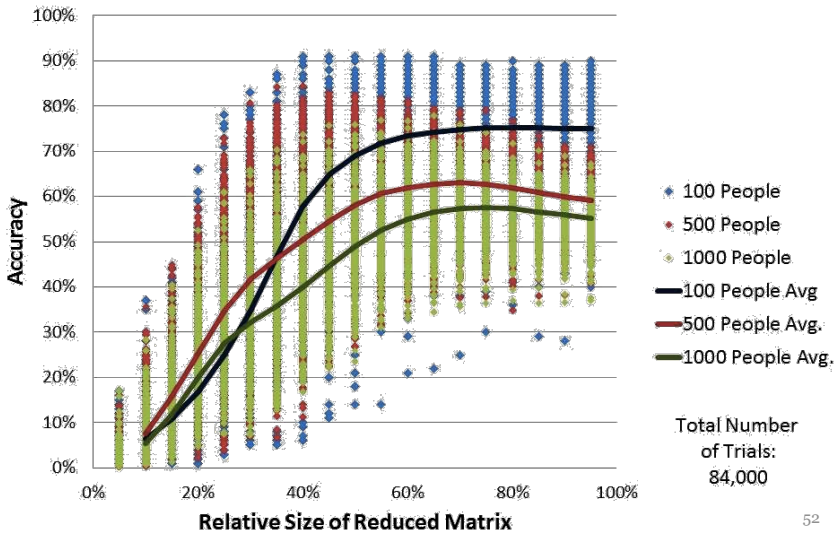
Binary Model Results



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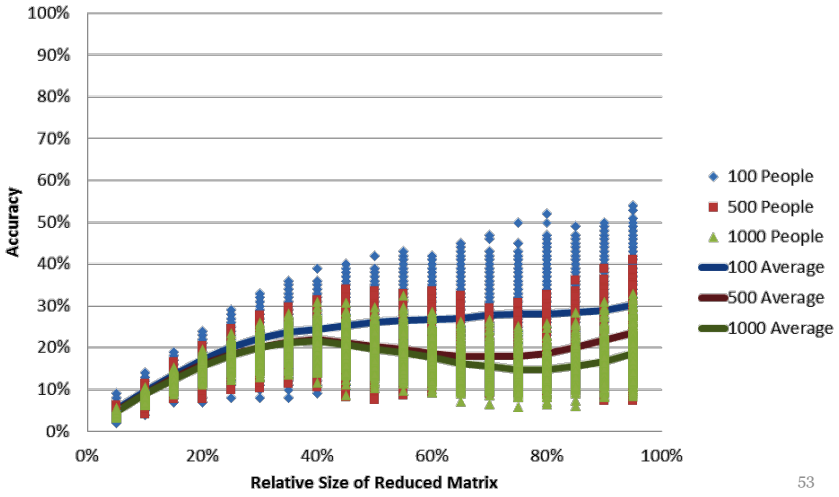
Weighted Model Results



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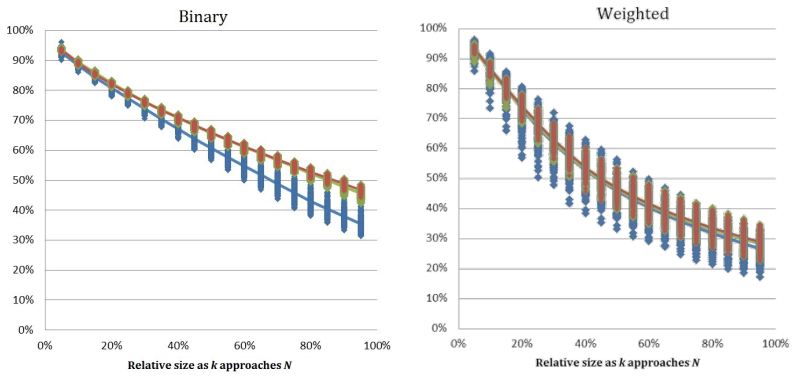
Binary vs Weighted Model Error



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SDD: Case Study

- Number of People: 100
- Length of time: 12
- Attrition on relationships: 37%
- Low Rank Approximation rank: 75%
- Training/Testing Split: 50/50

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SDD: Case Study Results

- Binary Model Accuracy: 81%
- Weighted Model Accuracy: 27%

	WM: Incorrect	WM: Correct
BM: Incorrect	12	7
BM: Correct	61	20

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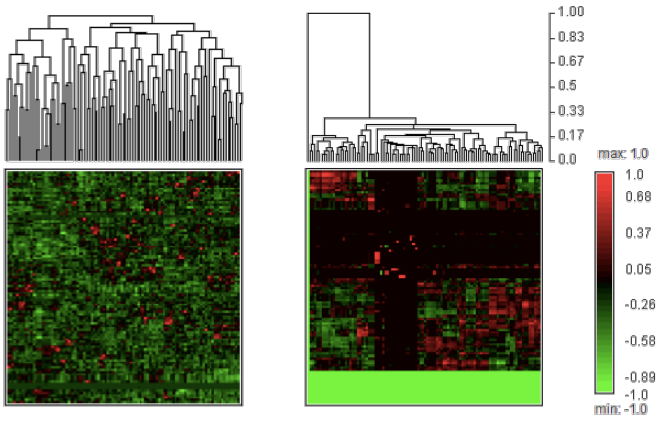
Model Insights



Binary Model Similarity Matrix

Weighted Model Similarity Matrix

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Accomplishments and Contributions

- Introduced a novel problem
- Created and released a modeling environment: SOFAS
- Modeled and defined first approaches for social fingerprint identification

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Open Research

- New models for social fingerprint detection
- Additional features and graph statistics of the SOFA software
- Fingerprint Evasion

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pokitdok

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Social Fingerprinting:
Identifying Users of Social Networks by their Data Footprint

The University of Tennessee
College of Engineering Dissertation Defense
Dr. Denise Koessler Gosnell, PhD Computer Science
(Nerdery)