# On the Performance of Percolation Graph Matching 

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## Privacy of Networks

- Adversary has:
- Anonymized network: unlabeled graph
- Side information: labeled graph - similar but not identical

```
anonymized social network
```



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side information
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matching nodes by structure only

## Graph Matching Applications

- Social networks:
- Correlating different domains

- Security:
- Identifying computer viruses by function-call patterns
- Computer vision:
- Segment adjacency graph to find similar images


## $\boldsymbol{G}(\boldsymbol{n}, \boldsymbol{p} ; \boldsymbol{s})$ Sampling Model

Generator $G=G(n, p)$ sampled ( $s$ )
$\square$ not sampled ( $1-s$ )

## $\boldsymbol{G}(\boldsymbol{n}, \boldsymbol{p} ; \boldsymbol{s})$ : Two Correlated $\boldsymbol{G}(\boldsymbol{n}, \boldsymbol{p s})$ 's



## Result 1: GM is Easy with $\infty$ Resources

- Theorem [PG11]:
- For the $G(n, p ; s)$ matching problem, if

$n p s$ : $E$ [degree] of $G_{1,2} \quad$ penalty for dissim of $G_{1,2}$
then $G_{1,2}$ can be perfectly matched a.a.s.
- Interpretation:
- Surprisingly weak condition: degree growing faster than $\sim \log n$ enough to break anonymity
- Decrease with $s$ only quadratic

Mappings and Edge Mismatch

$$
\Delta\left(\pi_{0}\right)=0 \quad \Delta(\pi)=2
$$

## Approach

- Assumption:
- Attacker has infinite computational power
- Can try all possible mappings $\pi$ and compute edge mismatch function $\Delta(\pi)$
- Question:
- Are there conditions on $p, s$ such that

$$
P\left\{\pi_{0} \text { unique } \quad \min \quad \text { of } \Delta(\pi)\right\} \rightarrow 1
$$

- If yes: adversary would be able to match vertex sets only through the structure of the two networks!
- Note:
- $G(n, p ; s)$ model: statistically uniform, low clustering, degree distribution not skewed -> conjecture: harder than real networks


## Result 2: Graph Matching with Seeds



## Questions

- How many seeds are needed?
- Is there a phase transition?
- How efficiently can we match?
- Tuning parameters?


Figure 2. The fraction of nodes re-identified depen sharply on the number of seeds. Node overlap: 25 Edge overlap: 50\%

From [A. Narayanan, V. Shmatikov, "De-anonymizing social networks", IEEE Symp. on Security and Privacy, 2009]

## Percolation Graph Matching Algorithm



## Result: Seed Set Size Threshold for $\boldsymbol{G}(\boldsymbol{n}, \boldsymbol{p} ; \boldsymbol{s})$

- Theorem 2: phase transition in \# seeds a
- For $n^{-1} \ll p s^{2} \ll s^{2} n^{-\frac{4}{r} \text { : }}$
- If $\frac{a}{a_{c}} \rightarrow \alpha<1$, final map is $o(n)$ w.h.p.

$$
\text { If } \frac{a}{a_{c}}>\alpha>1, \text { final map is } n-o(n) \text { w.h.p. }
$$

- Seed set size threshold:
- $a_{c}=\left(1-r^{-1}\right)\left(\frac{(r-1)!}{n\left(p s^{2}\right)^{r}}\right)^{1 /(r-1)}$
- Slowly densifying network: constant $r$
- Growth of $a_{c}$ : a bit less than linear
- $p=\log n / n, s$ fixed $\rightarrow a_{c} \propto n(\log n)^{-r /(r-1)}$


## Bootstrap Percolation for $\boldsymbol{G}(\boldsymbol{n}, \boldsymbol{p})$

Activation from $r$ neighbors

[S. Janson, T. Luczak, T. Turova, T. Vallier, Bootstrap Percolation on the Random Graph $G(n, p)$, Annals Applied Prob., 22(5), 2012]

## Giant Component: Branching Process



## Bottleneck in Bootstrap Percolation

consumption > production
production > consumption


## Simulation of PGM with $\boldsymbol{G}(\boldsymbol{n}, \boldsymbol{p} ; \boldsymbol{s})$ Network



## Simulation of PGM with $\boldsymbol{G}(\boldsymbol{n}, \boldsymbol{p} ; \boldsymbol{s})$ Network



## Slashdot Social Network



## Result 3: Getting Started

- How to find seeds? [PFG13]
- Efficient (polynomial) algorithm to generate seed set
- Does not work for $G(n, p)$
- Real graphs:
- More heterogeneous than $G(n, p)$ : degree skew, transitivity
- Provides features for nodes



## Finding Seeds: Bayesian Framework



## Seed: Bayesian Framework



Node: $U_{2}$
Network sampling model:
Fingerprint:
( $X_{1}=4$,
$D_{1,1}=1$,
$D_{1,2}=3$ )
Fingerprint:
( $X_{1}=1$,
$D_{1,1}=4$,
$D_{1,2}=2$ )

Fingerprint:
$\left(X_{2}=3\right.$,
$D_{2,1}=3$,
$\left.D_{2,2}=1\right)$
Fingerprint:
( $X_{2}=3$,
$D_{2,1}=1$,
$D_{2,2}=3$ )

Jointly MAP matching:
Best bipartite matching $\pi$ s.t. max P(all matched correctly | all fingerprints)

## Conclusion

- Graph matching problem:
- Social networks: privacy; merging
- Model as noisy graph isomorphism problem
- How much information in network structure?
- $G(n, p ; s)$ random graph model:
- Parsimonious: density ( $p$ ), similarity ( $s$ )
- Information-theoretic characterization of feasible region condition is quite mild
- Percolation Graph Matching algorithm:
- Simple algorithm, propagating evidence over node pairs
- Actually works very well in practice; parsimonious ( $r$ )
- Analysis:
- Sharp phase transition in seed set size (a), confirms empirical observation

