Discovering Opinion Spammer Groups by Network Footprints

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Introduction

- Product reviews are one major source of information.

Advertisement

Reviews

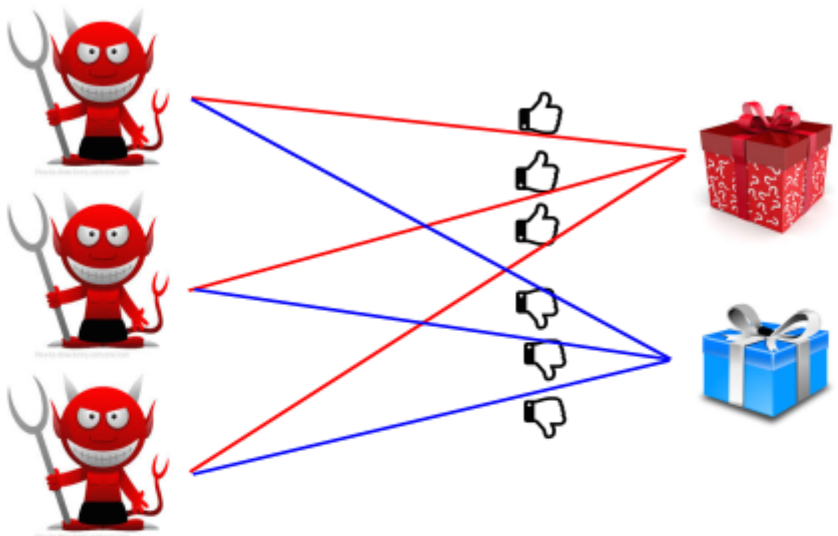
- Product reviews are important to businesses!

+1 star-rating increases revenue by 5-9%

Harvard Study by M. Luca
Reviews, Reputation, and Revenue: The Case of Yelp.com

Opinion Spam

- Opinion Spammers are hired to write fake reviews;



- Opinion spam is everywhere!
    - 14~20% in Yelp; [Mukherjee et al., ICWSM 2013]
    - 2~6% in Orbitz, Priceline, Expedia, Tripadvisor, etc. [Ott et al., WWW 2012]
- Challenges in detecting spammers:
    - Spammers camouflage, linguistic or behavioral methods might fail;
    - Lack of ground truth, difficulty in manual labeling; [Ott et al. ACL 2011]

Motivation

- Spamming in **groups** is common because:
  - Impact maximized: dominate the sentiments
  - Effort can be shared: workload split among members
  - Easier to hide: suspicious acts are balanced so no one stands out

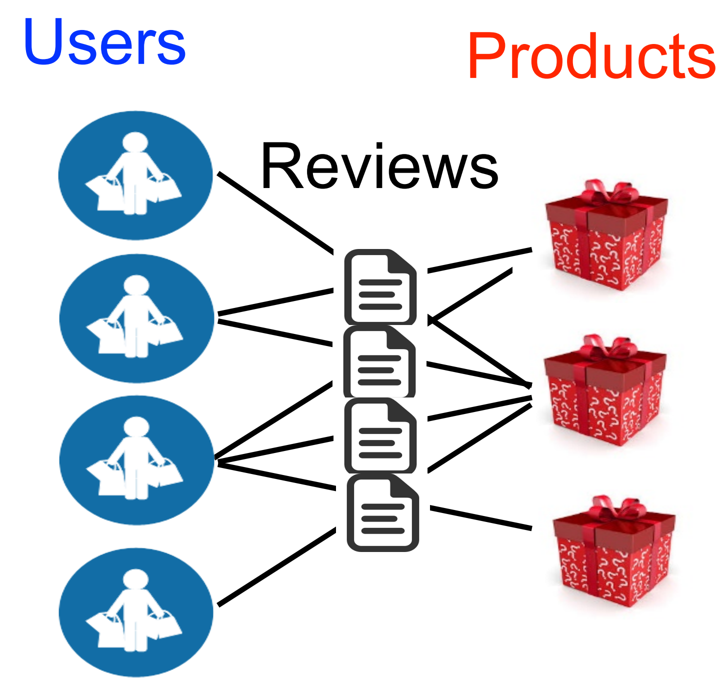
- Advantage of detecting with network footprints:
  - More **cost** for spammers to mimic local network features
  - Spammers **unaware** of the global network features

Problem Definition

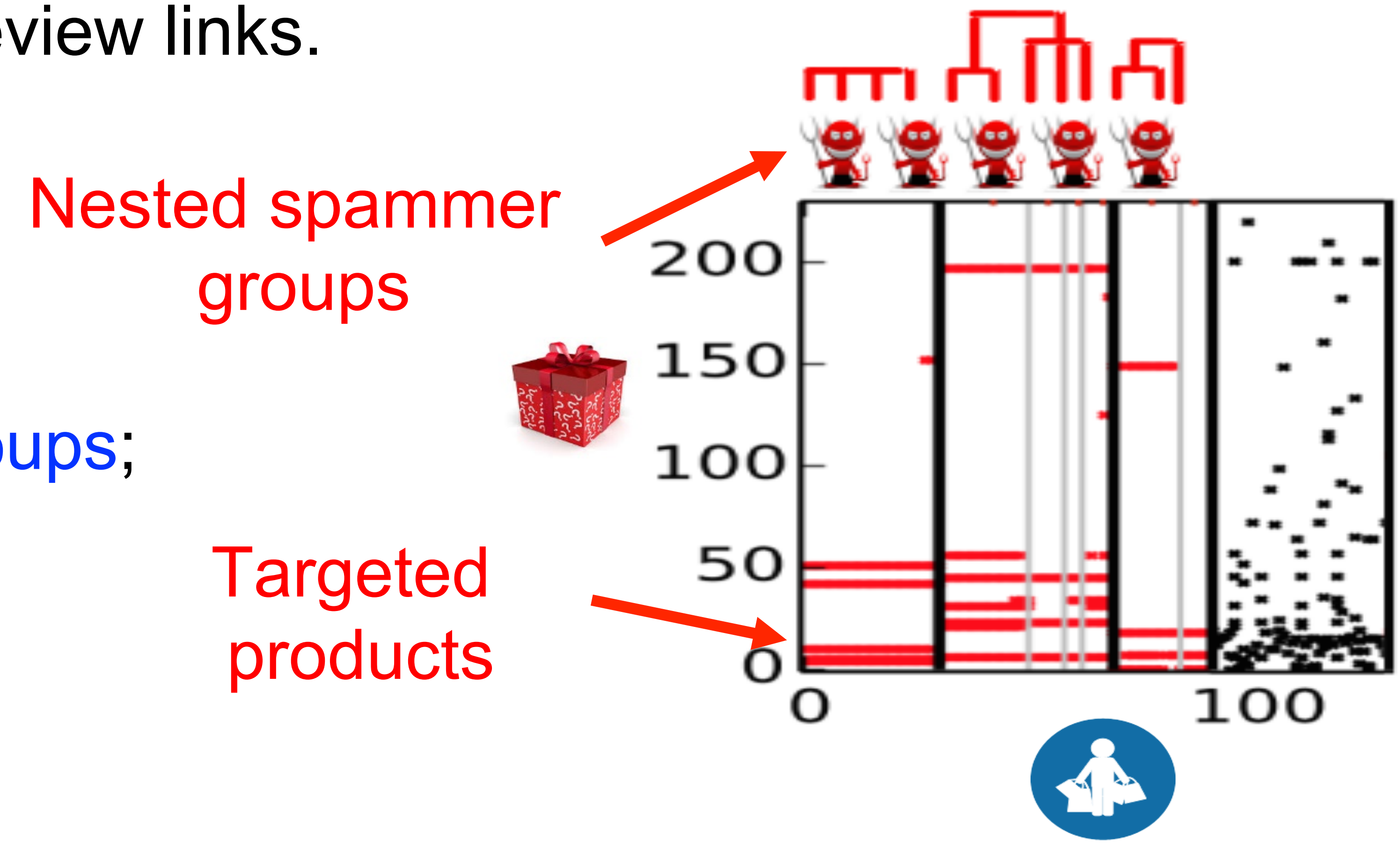
- Input:
  - A user-product bipartite review network

$$G = (U, P, E)$$

U: the set of users, P: set of products, E: set of review links.



- Output:
  - Nested spammer groups;
  - Targeted products;



Previous Work

- Majority: Detecting **individual** spam(mer)s:
  - Supervised methods [Feng+ ACL 2012; Jindal&Liu WSDM 2008]
  - Semi-supervised methods [Li et al., IJCAI 2011]
  - Graph-based methods [Akoglu+ ICWSM 2013; Wang+ ICDM 2011]
  - Collective classification methods; [Li et al., ICDM 2014]
- Detecting **group** spam(mer)s:
  - Linguistic, rating and temporal data to compute user suspiciousness [Xu&Zhang SDM 2015; Xu+ CIKM 2013; Mukherjee+ WWW 2012]
  - Our work only utilizes the review network

Overview: 2 main steps

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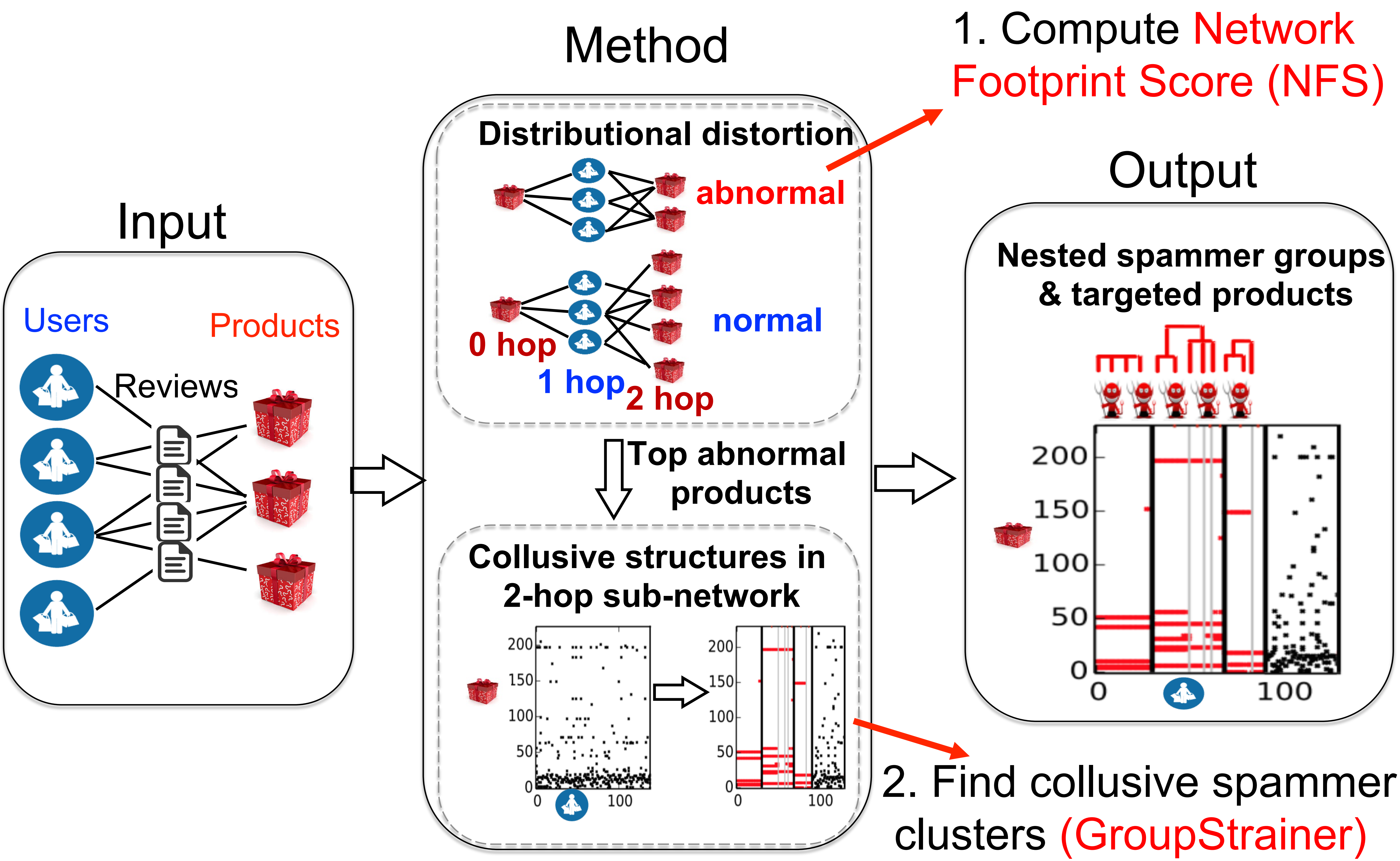

1. Network Footprint Score (NFS)

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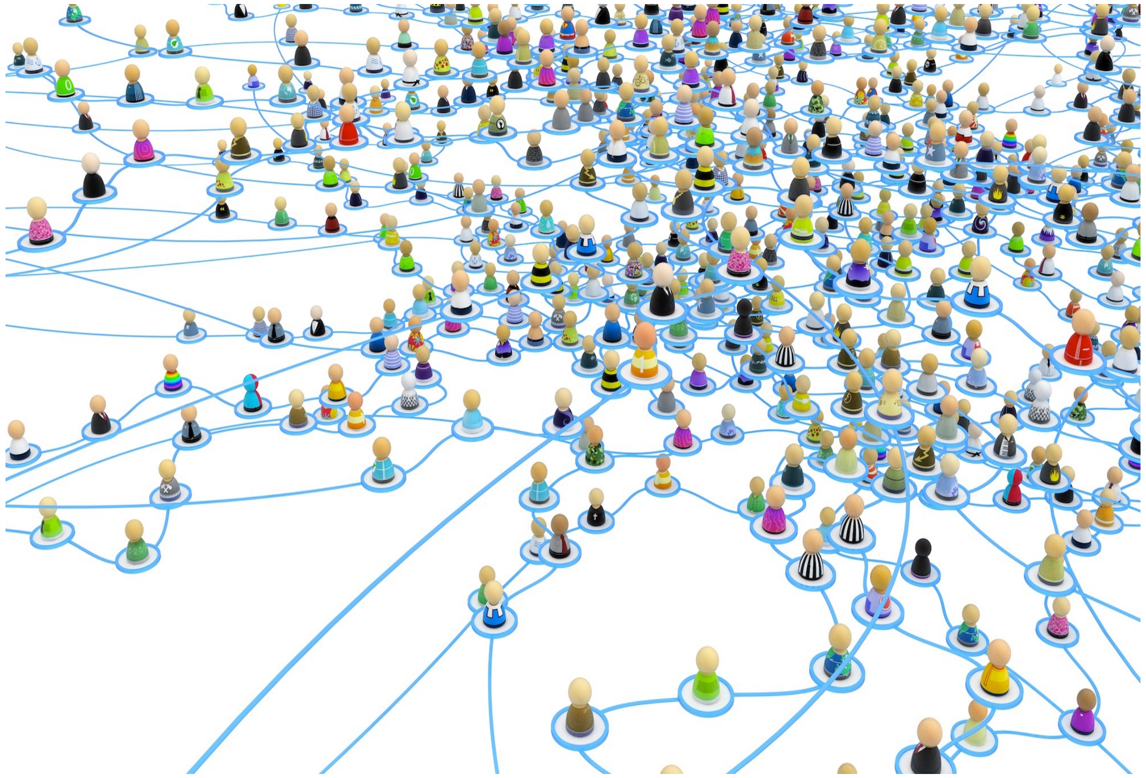
- **Observation 1:** Neighbor diversity
  - Varying levels of activities (i.e. centralities of nodes)
  - This measures the local network features



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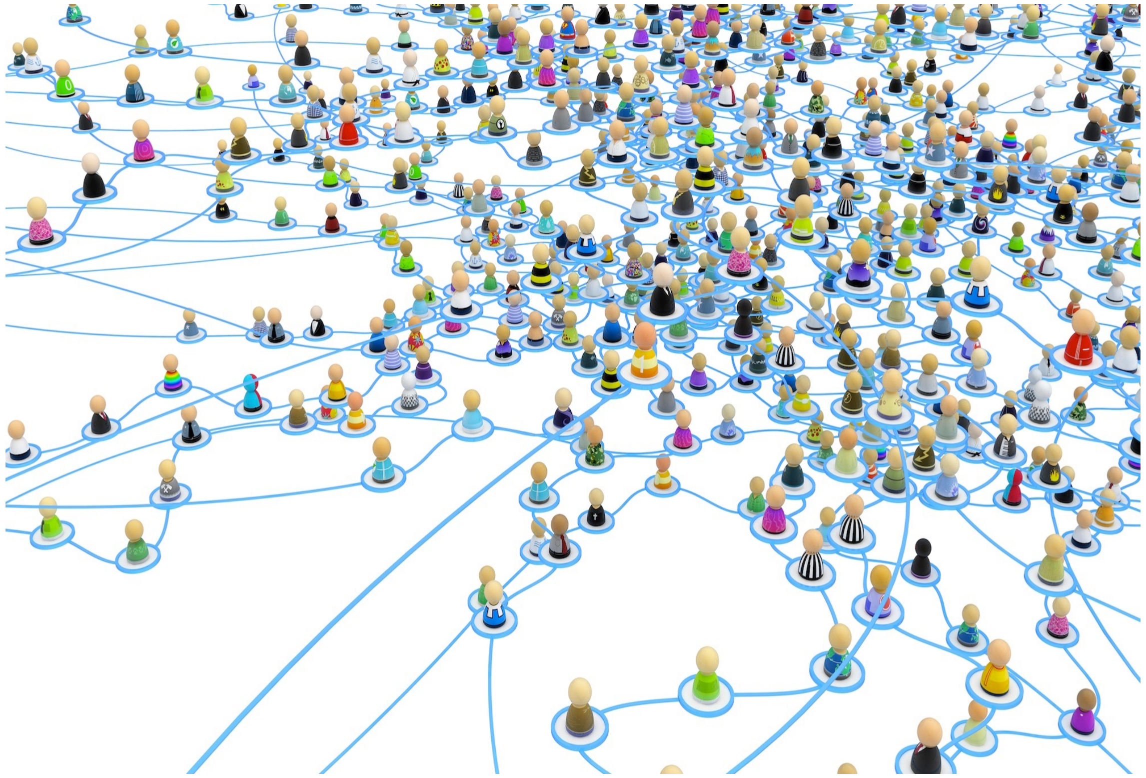

- Quantification:
  - Shannon Entropy (H) of neighbors' centrality;

p: centrality density histogram

i: index of products

$$H_c(i) = -\sum_{k=1}^{K} p_k^{(i)} \log p_k^{(i)}$$

c: type of centrality (Degree or Pagerank)

k: index of bins

1. Network Footprint Score (NFS)

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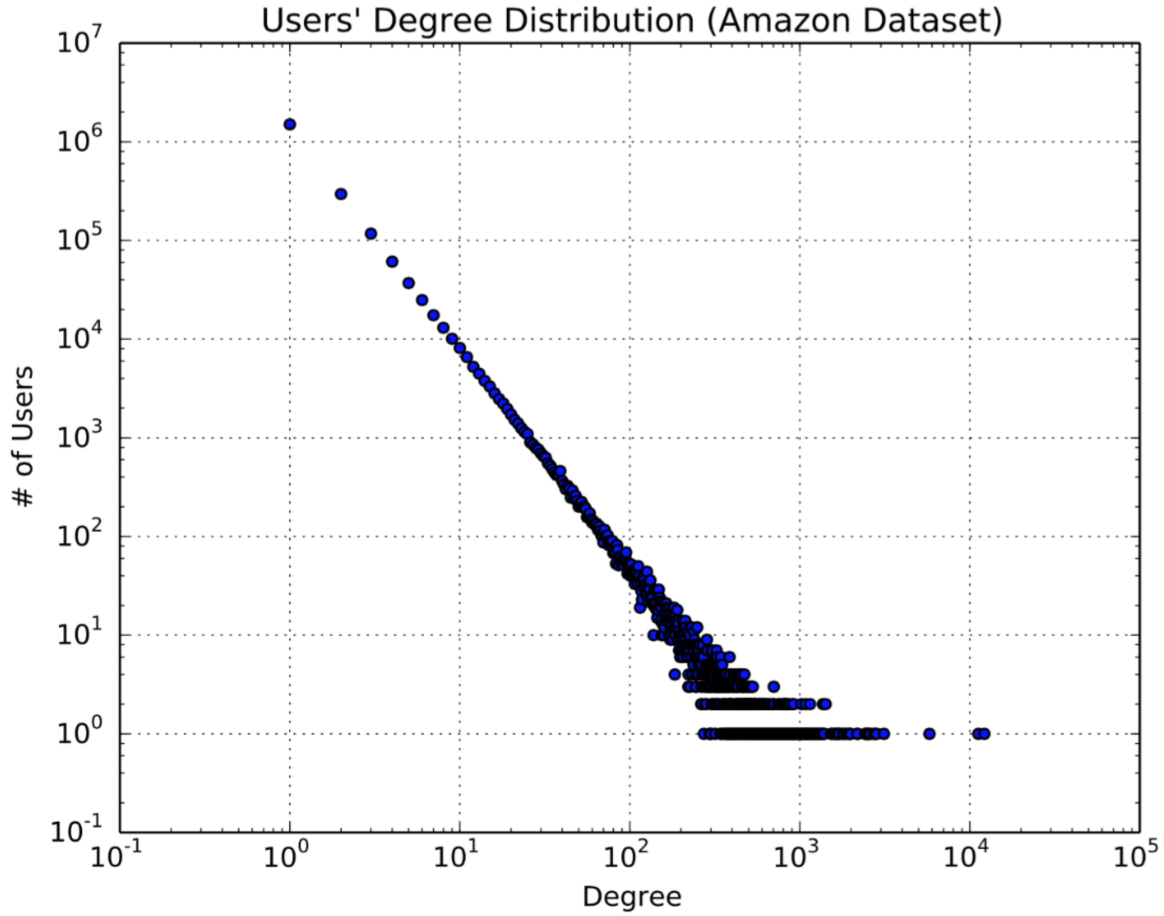
- **Observation 2:** Self-similarity
  - Graph portions should have similar distribution as the whole graph

    → Product's neighbors should follow power-law-like distribution as the global distribution of all users;



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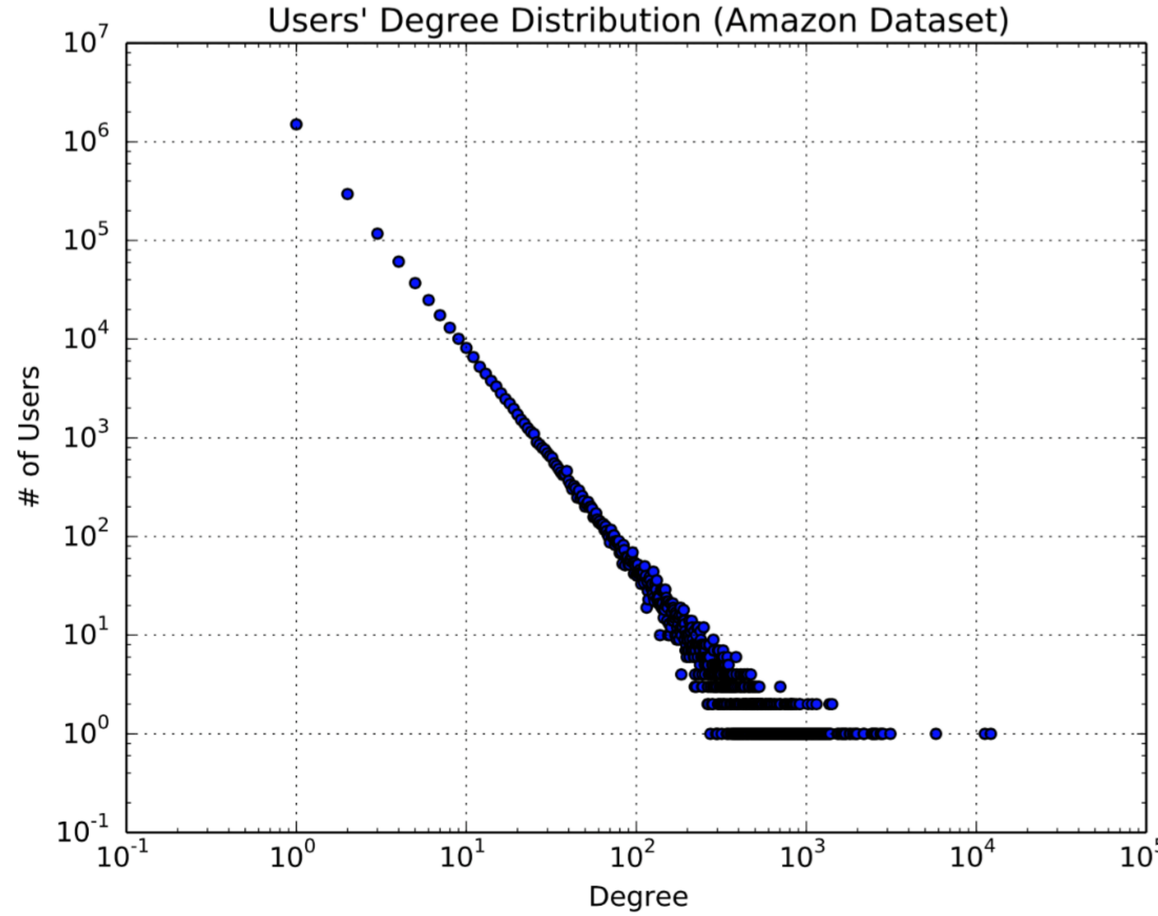


- Quantification:
  - KL-Divergence (*KL*) between neighbors and all users'

P^(i)^: centrality histogram of product *i*'s neighbors

Q: centrality histogram of all users

$$KL_c(P^{(i)}\|Q) = \sum_k p_k^{(i)} \log \frac{p_k^{(i)}}{q_k}$$

c: type of centrality (Degree or Pagerank)

k: index of bins

1. Network Footprint Score (NFS)

- NFS: integrating 4 observations

$$f(H(i)) = P(H \leq H(i))$$

i: index of products

$$f(KL(i)) = 1 - P(KL \leq KL(i))$$

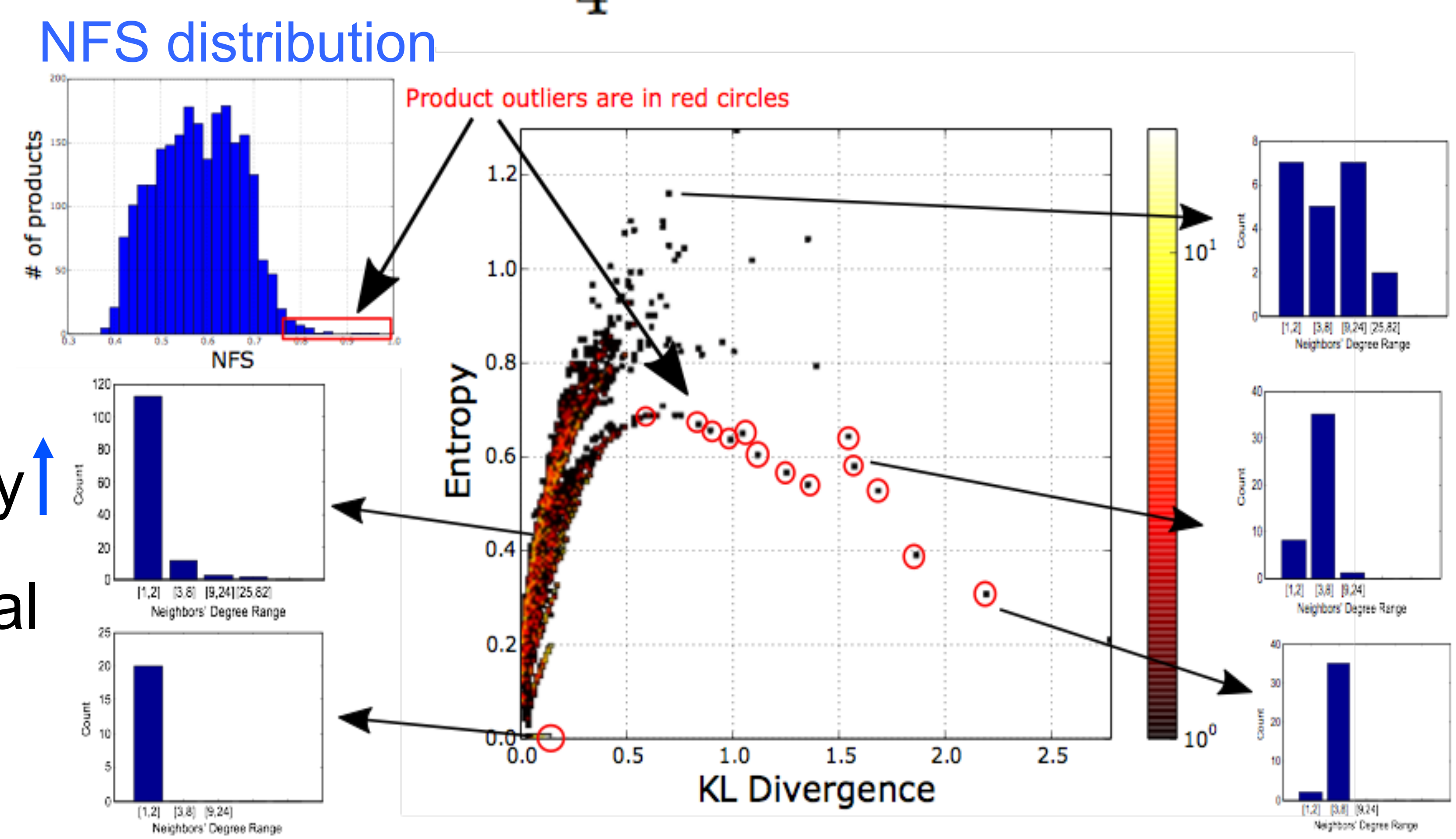
$$NFS(i) = 1 - \sqrt{\frac{f(H_{deg}(i))^2 + f(H_{pr}(i))^2 + f(KL_{deg}(i))^2 + f(KL_{pr}(i))^2}{4}}$$

- Interpretation:

  Entropy ↓ Abnormality ↑

  KL Divergence ↑ Abnormality ↑

  Right-bottom: more abnormal



Degree entropy vs. KL-divergence in iTunes

2. GroupStrainer

- Induce local **sub-network**:
  1. k products with highest NFS, **k** chosen by mixture modeling [Gao et al. ICDM 2006]
  2. Induce a 2-hop sub-network: **k** abnormal products as seeds

Distribution of NFS

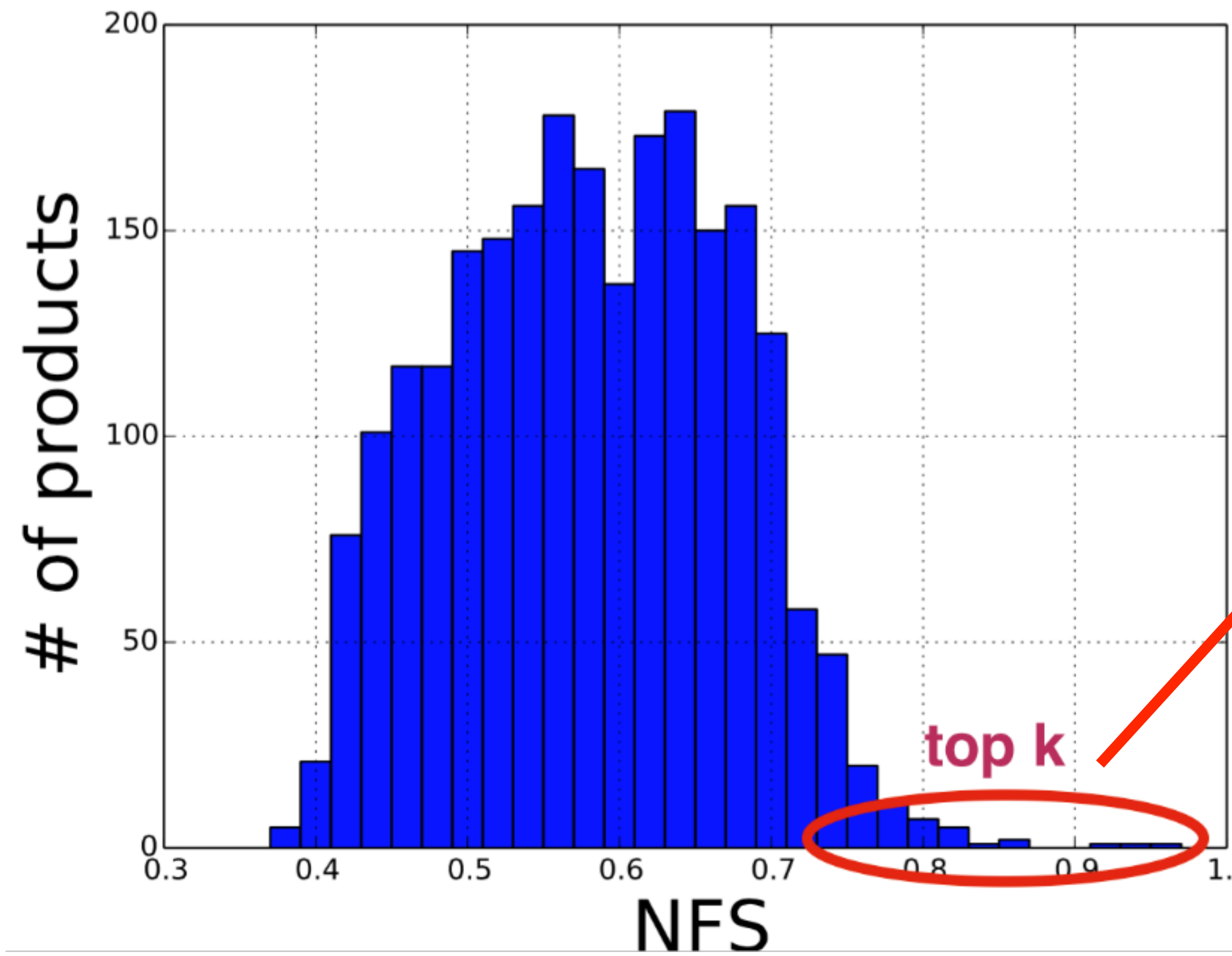
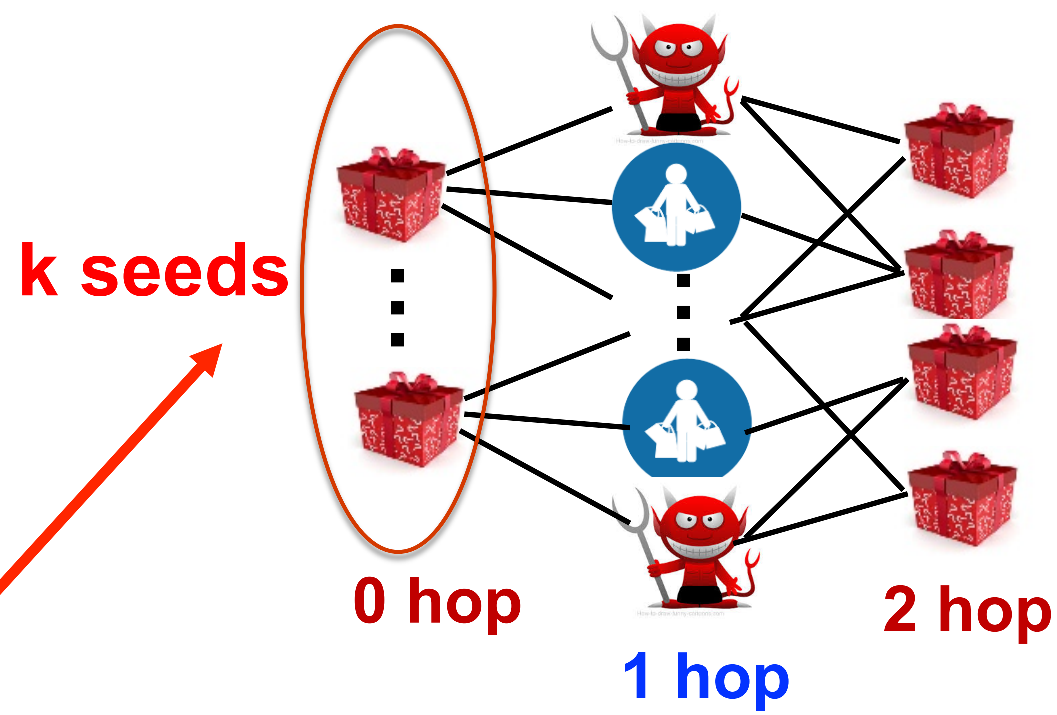


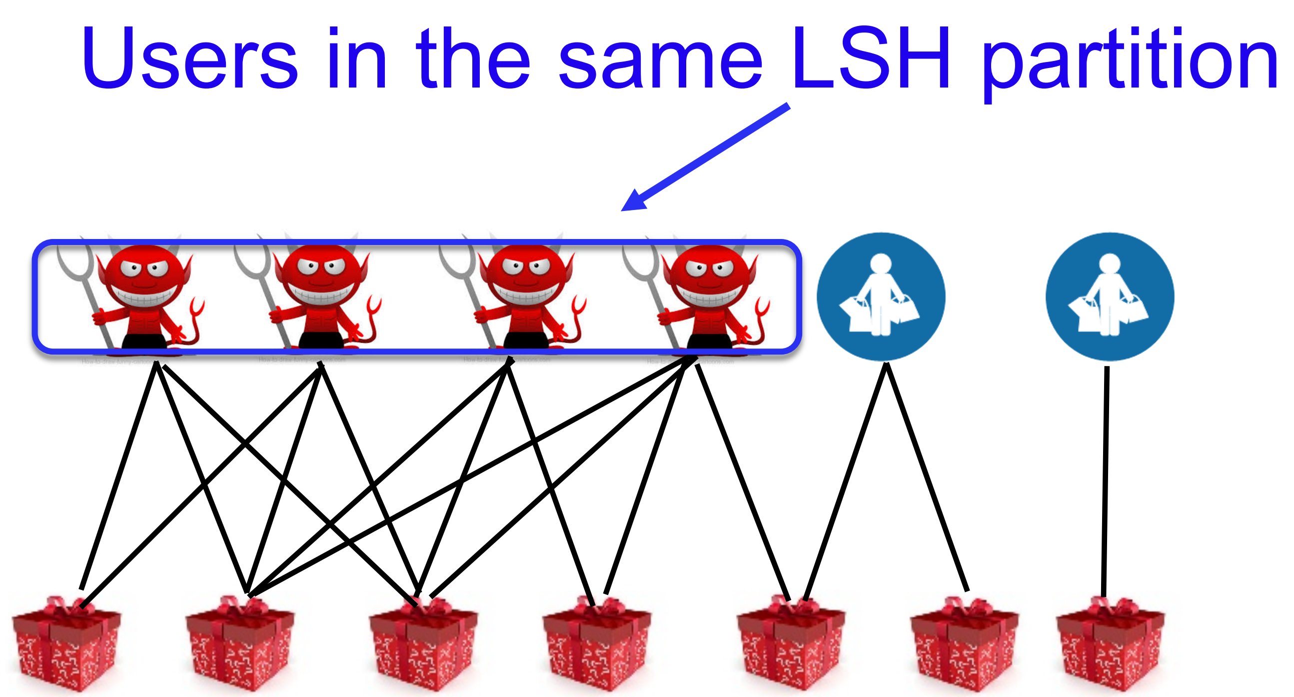
Fig4: 2-hop induced sub-network



2. GroupStrainer

- Efficient clustering
  1. Init similarity thresholds

     $S = \{s_1, s_2, \ldots, s_n\}$
  2. For each iteration i, use Locality Sensitive Hashing (LSH) to partition users
  3. In each partition, merge user groups if all pair-wise similarities are larger than s_i
  4. Terminate if no new merges, otherwise go to step 2



Example illustrating GroupStrainer

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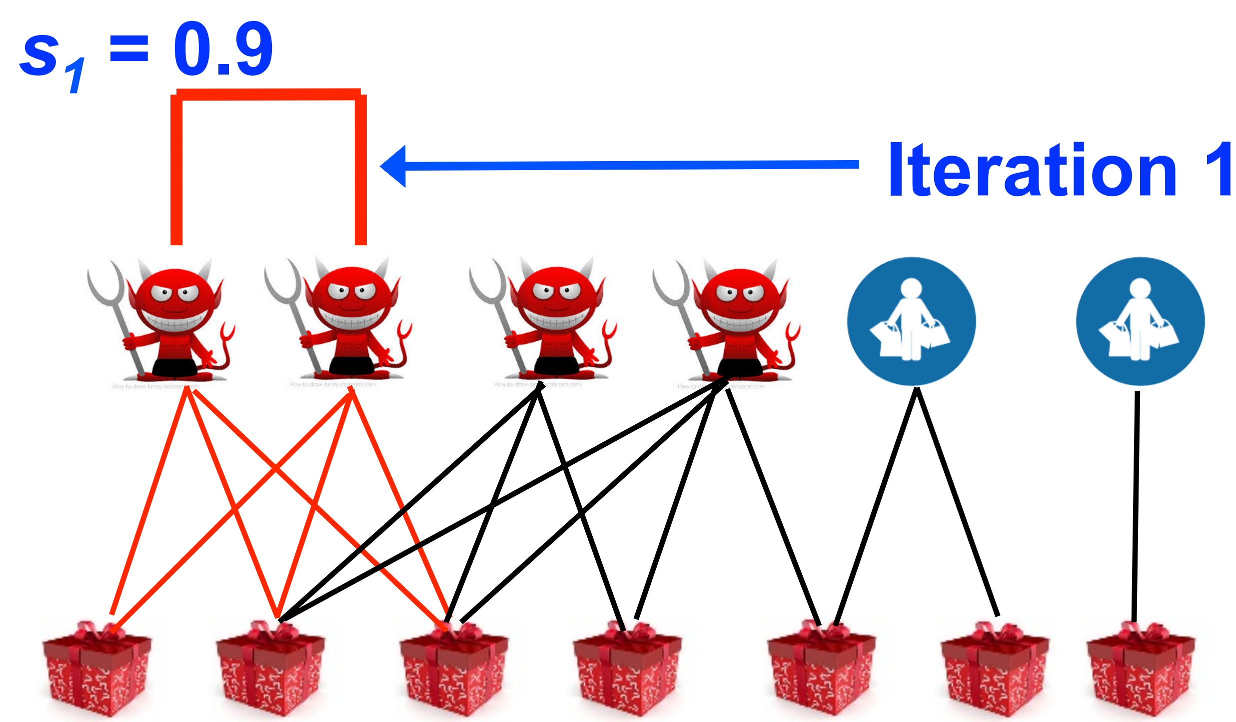

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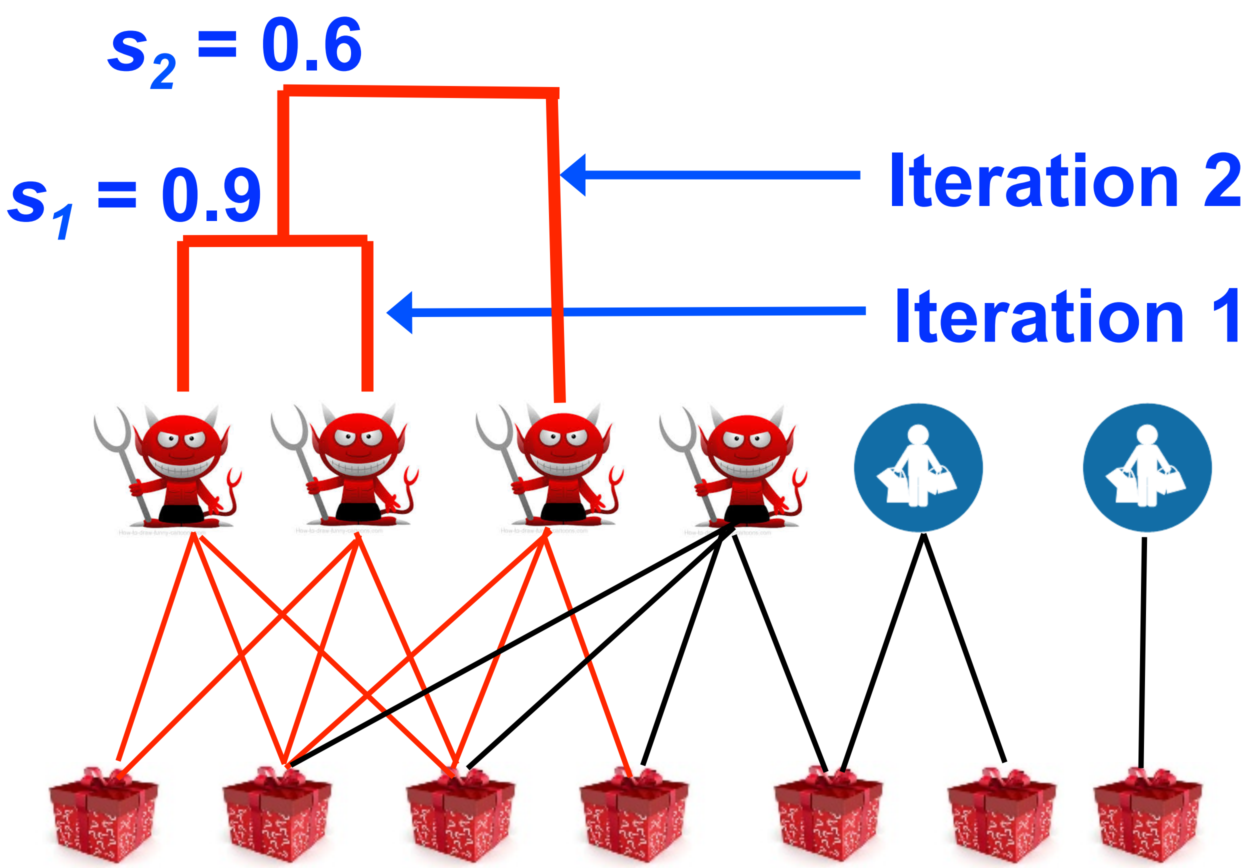

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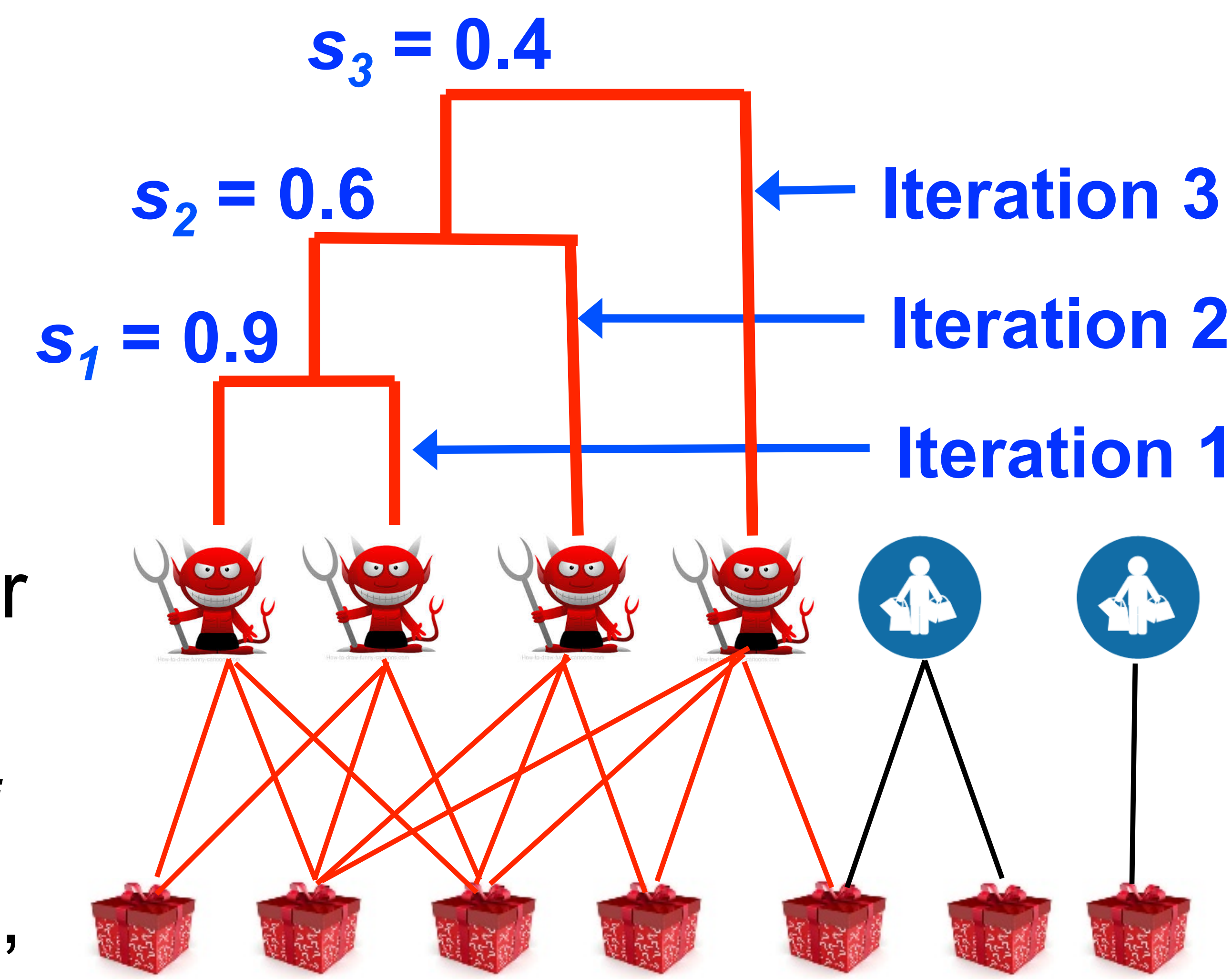

Example illustrating GroupStrainer

Datasets

- **Synthetic** datasets: (4 datasets, various generators and sizes)
  - Chung-Lu Generator [Chung et al., Internet Mathematics, 2003]
  - Random Typing Generator (RTG) [Akoglu et al., PKDD, 2009]
- **Real-world** datasets:
  - iTunes [Akoglu et al., ICWSM 2013]
  - Amazon [Jindal and Liu, WSDM 2008]

Table 1. Summary of synthetic and real-world datasets used in this work.

	Synthetic Data				Real-world Data	
	Chung-Lu1	Chung-Lu2	RTG1	RTG2	iTunes	Amazon
# of users	532,742	2,133,399	604,520	876,627	966,808	2,146,074
# of products	157,768	665,381	604,805	876,950	15,093	1,230,916
# of edges	1,299,059	5,191,053	3,097,342	4,644,572	1,132,329	5,838,061

NFS on Synthetic Graphs

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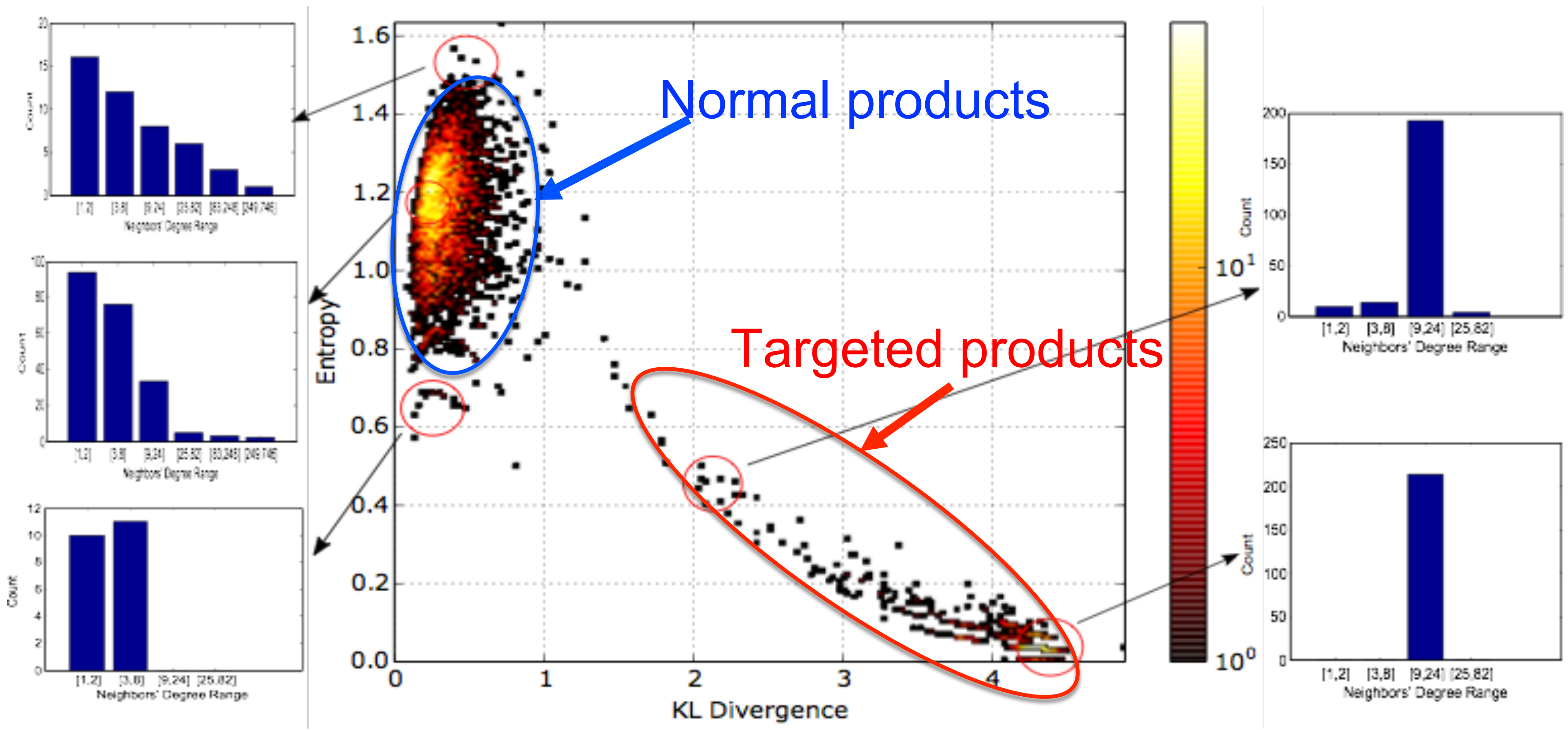
- Different region, different shape of centrality histograms



Degree Entropy vs. KL Divergence in Chung-Lu1
(10% pop. Camouf.)

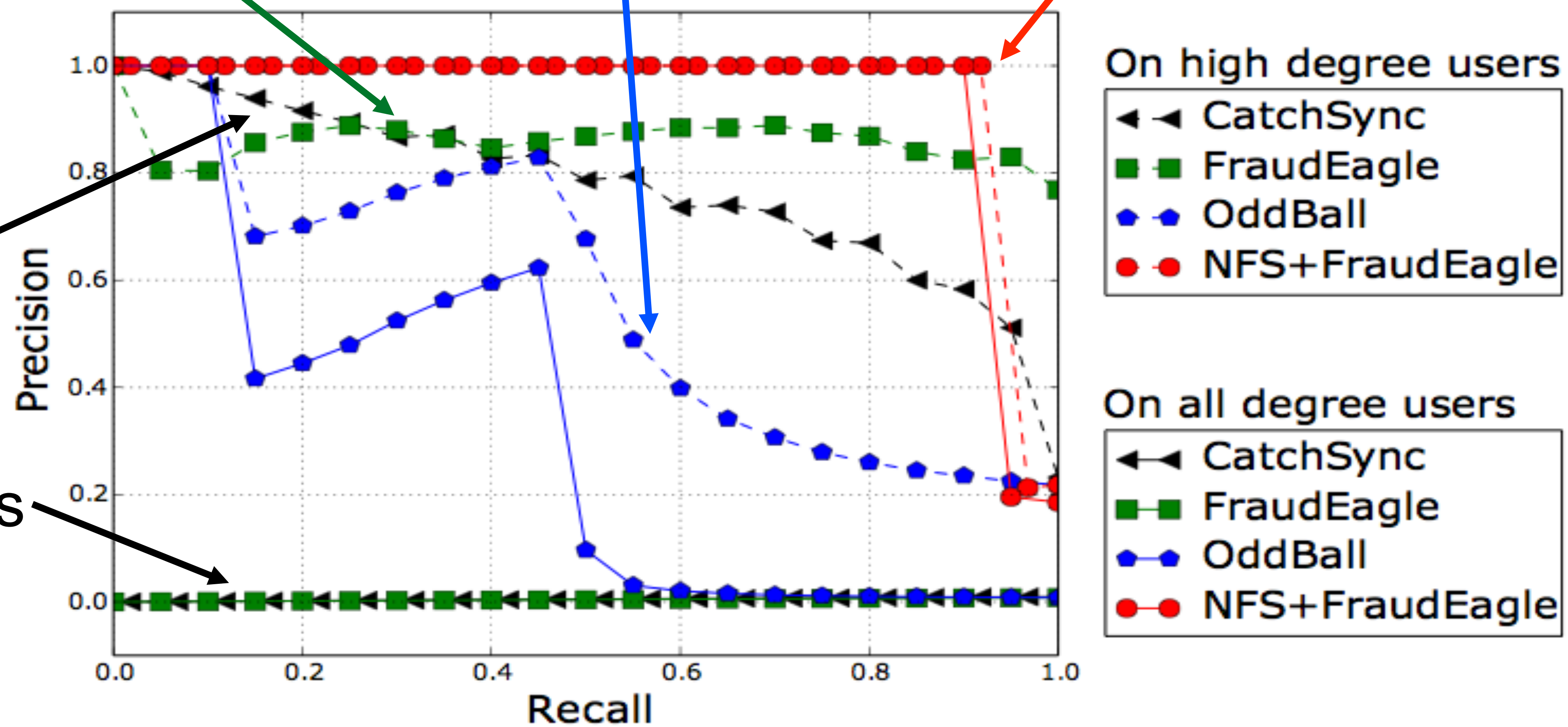
NFS on Synthetic Graphs

FraudEagle:
- Label propagation

OddBall:
- Detects near-cliques and star shapes

NFS + FraudEagle
- Solid line: all users
- Dash line: high-deg users

CatchSync
- Good on high-degree users
- Poor on all users



AUC of **Pre-Rec curve** on RTG2 (30% random camouflage)

NFS on Synthetic Graphs

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AUC of Pre-Rec Curve (Range [0, 1]; larger is better)

Dataset	Camouf.	HDP	Oddball[3]	CatchSync[16]	FE[1]	NFS+FE
Chung-Lu1	10% Pop.	6170	0.990/0.937	1.000/0.009	0.570/0.569	1.000/1.000
	30% Pop.	6172	0.997/0.973	1.000/0.008	0.570/0.570	1.000/1.000
	10% Rand.	6205	0.982/0.886	1.000/0.007	0.552/0.552	1.000/1.000
	30% Rand.	6266	0.881/0.386	0.957/0.007	0.532/0.526	1.000/1.000
Chung-Lu2	10% Pop.	25306	0.977/0.943	1.000/0.002	0.294/0.294	1.000/1.000
	30% Pop.	25302	0.995/0.988	1.000/0.002	0.294/0.294	1.000/1.000
	10% Rand.	25330	0.955/0.887	1.000/0.002	0.280/0.279	1.000/1.000
	30% Rand.	25392	0.711/0.374	0.982/0.002	0.261/0.256	1.000/0.977
RTG1	10% Pop.	17771	0.945/0.852	1.000/0.008	0.176/0.176	1.000/1.000
	30% Pop.	17766	0.929/0.842	0.997/0.007	0.176/0.176	1.000/1.000
	10% Rand.	17780	0.918/0.803	0.995/0.007	0.168/0.168	1.000/1.000
	30% Rand.	17843	0.637/0.367	0.878/0.007	0.163/0.158	0.952/0.950
RTG2	10% Pop.	25658	0.906/0.778	1.000/0.005	0.129/0.129	1.000/1.000
	30% Pop.	25658	0.879/0.746	1.000/0.005	0.129/0.129	1.000/1.000
	10% Rand.	25678	0.877/0.741	0.987/0.005	0.123/0.123	1.000/1.000
	30% Rand.	25716	0.577/0.331	0.778/0.005	0.119/0.115	0.952/0.951

AUC on high-degree users

AUC on all users

GroupStrainer on Synthetic Graphs

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- Synthetic data generator **(SCI, ε)**:
  - Collusion with **Spammer Collusion Index (SCI) =** camouflage index

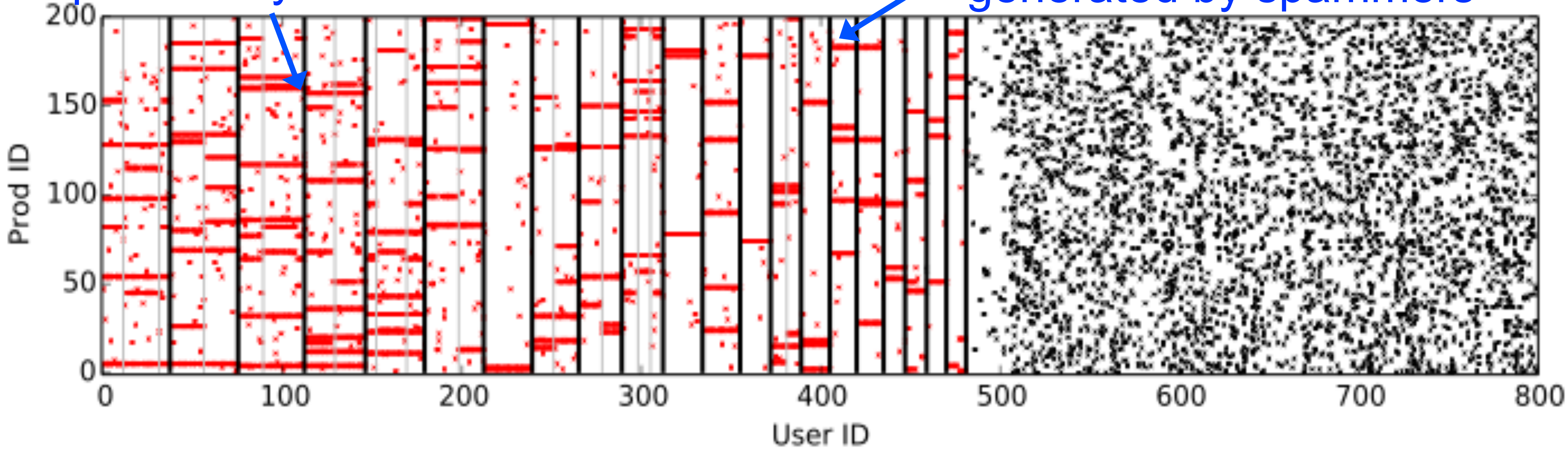
$$SCI(g) = \sum_{g_i, g_j \subset g, i \neq j} \frac{|t(g_i) \cap t(g_j)|}{|t(g_i) \cup t(g_j)|} / \binom{n}{2}$$

SCI equivalent to avg Jaccard similarity of groups' targets sets

  - **ε:** fraction of noise reviews (i.e. camouflage) over spam reviews.

Spammer groups separated by black bars

Red dots : reviews generated by spammers



Output of GroupStrainer on synthetic dataset (SCI = 0.5, ε = 0.2)

GroupStrainer on Synthetic Graphs

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Performance of GroupStrainer for varying ε and SCI

Normalized Mutual Information (NMI) (range [0,1]; larger, better)

Corresponding similarity threshold

Dataset	SCI = 1.0	SCI = 0.9	SCI = 0.8	SCI = 0.7	SCI = 0.6	SCI = 0.5	SCI = 0.4
$\epsilon = 0$	1.000/0.95	1.000/0.70	1.000/0.65	1.000/0.65	0.997/0.65	1.000/0.60	0.948/0.55
$\epsilon = 0.2$	0.994/0.65	0.997/0.55	1.000/0.60	0.995/0.60	0.998/0.55	0.990/0.60	0.980/0.50
$\epsilon = 0.4$	0.993/0.50	1.000/0.55	0.993/0.55	0.998/0.55	0.994/0.55	0.988/0.55	0.980/0.50
$\epsilon = 0.6$	0.989/0.55	0.998/0.50	0.991/0.50	0.991/0.55	0.996/0.50	0.995/0.50	0.984/0.45
$\epsilon = 0.8$	0.984/0.50	0.987/0.50	0.989/0.50	0.993/0.50	0.977/0.45	0.991/0.50	0.976/0.45

NMI is large even if large noise & little collusion

Performance on Real Datasets

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All detected groups found suspicious (synchronized behaviors) in at least one aspect of time, rating, text

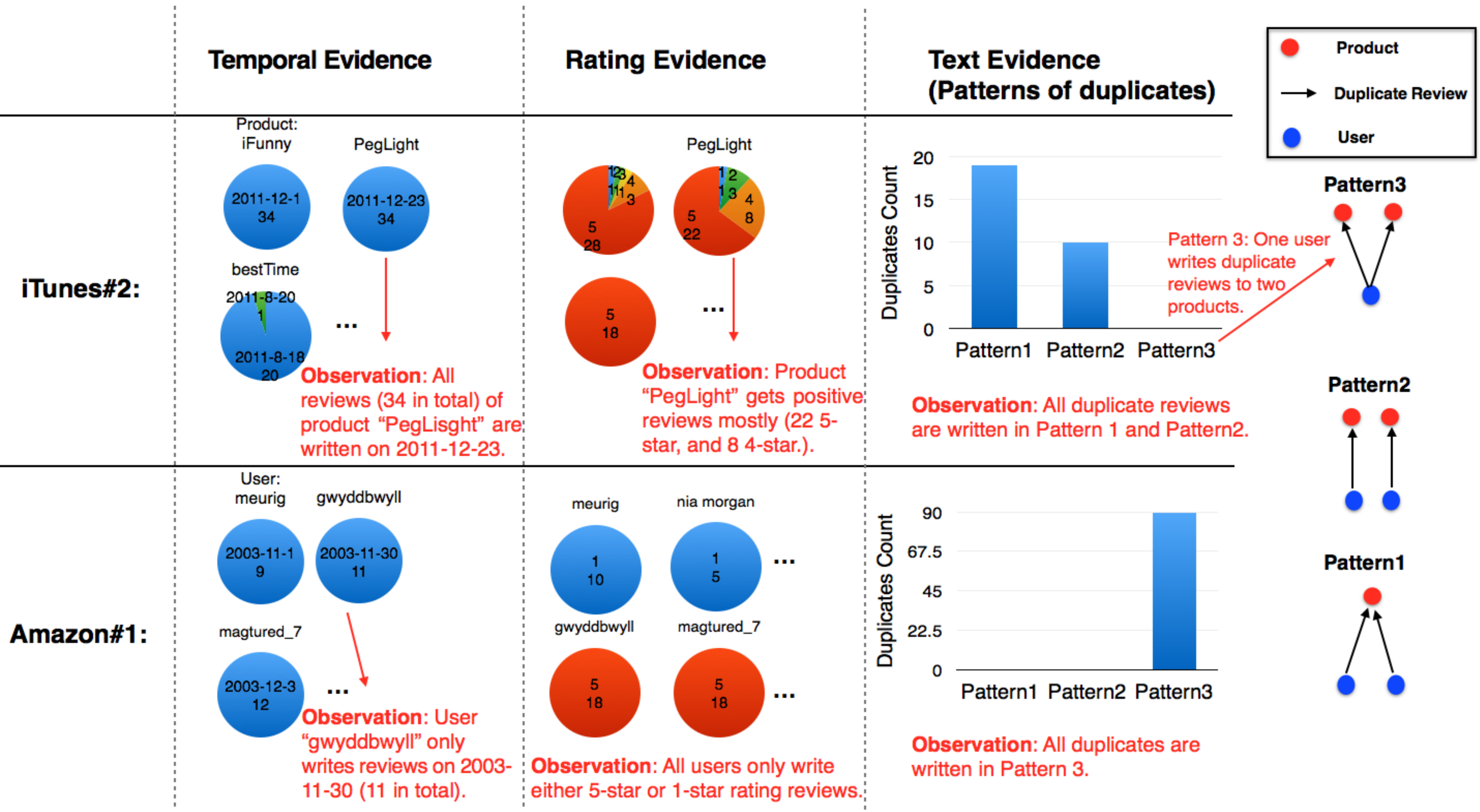
List of detected groups in Amazon

P: products, *U*: users, *t*: time, *: rating star, Dup: duplicates

Misnomer

	iTunes					Amazon				
ID	#P	#U	t, ⋆	*Dup*	Developer	#P	#U	t, ⋆	*Dup*	Category, Author
1	5	31	s, c	51/154	all same	10	20	c, c	90/138	Books, all same
2	8	38	c, s	29/202	2 same	4	12	s, c	32/47	Books, all same
3	4	61	s, c	34/144	all inaccessible	7	9	c, c	44/60	Books, all same
4	4	17	c, s	0/68	1 inaccessible	7	19	s, c	5/88	Books, all same
5	5	102	c, s	8/326	different	23	42	c, c	2/468	Music, all same
6	6	50	s, c	4/173	all same	8	17	s, c	9/73	Books, 4/8 same
7	2	56	c, c	12/112	different	6	18	s, c	4/94	Movies&TV, all same
8	4	42	c, c	8/112	2 same					
9	6	67	s, c	0/137	all same					

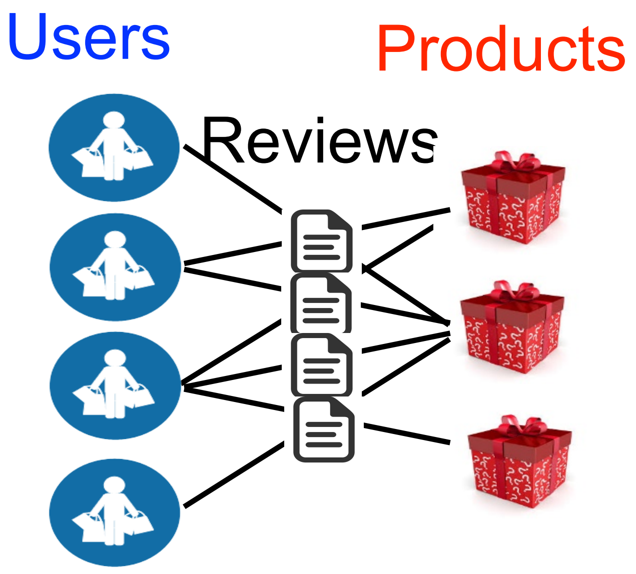
Case Study



Abundant evidence of suspicious behaviors in various patterns

Conclusion

- Two-step method to detect **spammer groups**:
  - 1. NFS: a measure of suspiciousness for products based on network footprints
  - 2. GroupStrainer: an efficient clustering algorithm to detect collusive spammers
- **Advantages**: unsupervised detection, adversarial robustness, sensemaking, and efficiency
- Validated on both synthetic and real-world data



Thank you!

Code and Data available:

http://www3.cs.stonybrook.edu/~juyye/

http://www3.cs.stonybrook.edu/~datalab/