Data-Driven Behavioral Analytics: Observations, Representations and Models

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http://www.meng-jiang.com/tutorial-cikm16.html

Tutorial in CIKM 2016, October 24, Indianapolis, IN

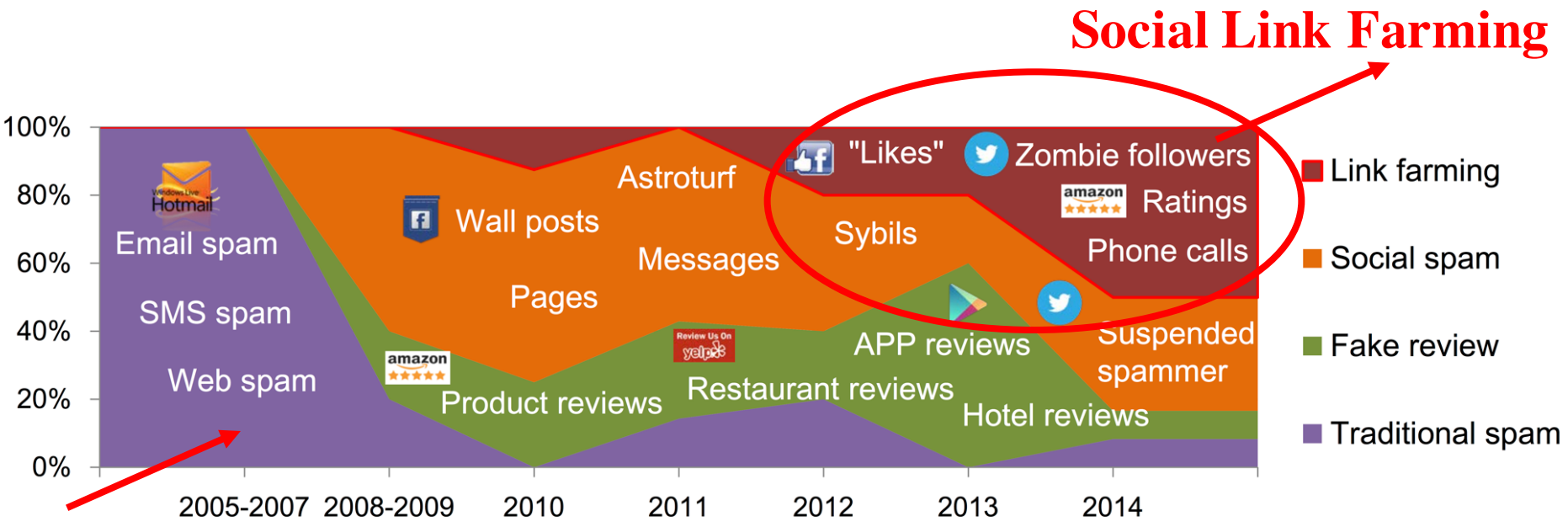
I. Mining behavior networks with social and spatiotemporal contexts

I.2. Suspicious behavior detection

Ill-gotten Facebook Likes

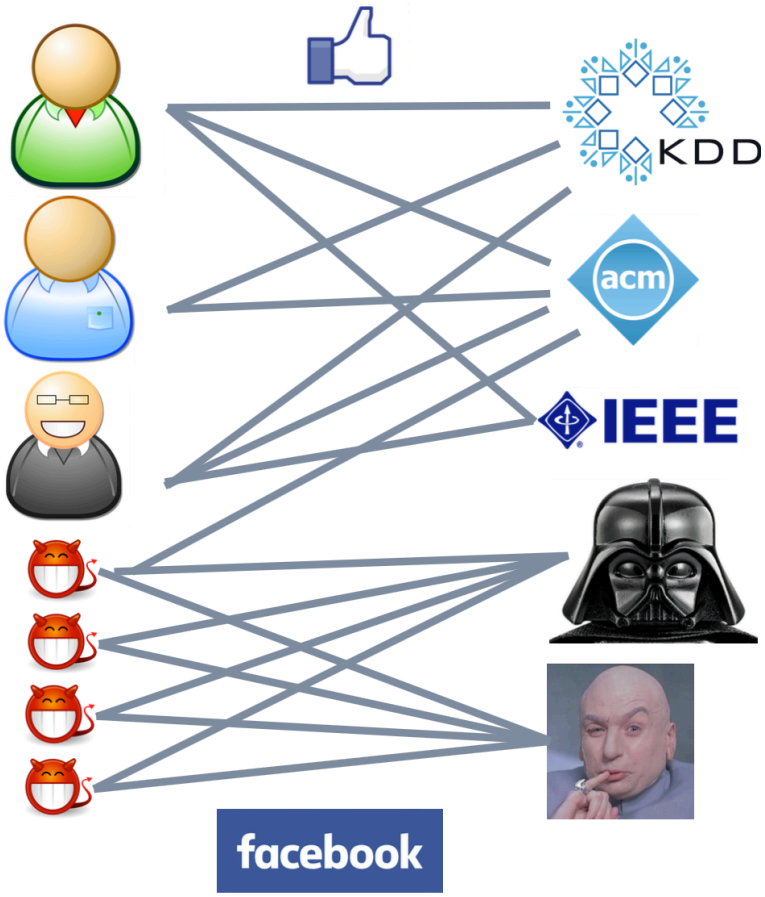
25,000 Facebook Likes	50,000 Facebook Likes	100,000 Facebook Likes	200,000 Facebook Likes
$265	$525	$1,000	$1,750
Lifetime Replacement Warranty	Lifetime Replacement Warranty	Lifetime Replacement Warranty	Lifetime Replacement Warranty
Dedicated 24/7 Customer Service	Dedicated 24/7 Customer Service	Dedicated 24/7 Customer Service	Dedicated 24/7 Customer Service
100% Risk Free, Try Us Today	100% Risk Free, Try Us Today	100% Risk Free, Try Us Today	100% Risk Free, Try Us Today
Order starts within 24 - 48 hours	Order starts within 24 - 48 hours	Order starts within 24 -48 hours	Order starts within 24 -48 hours
Order completed within 22 days	Order completed within 35 days	Order completed within 35 days	Order completed within 35 days

Suspicious Behavior Detection



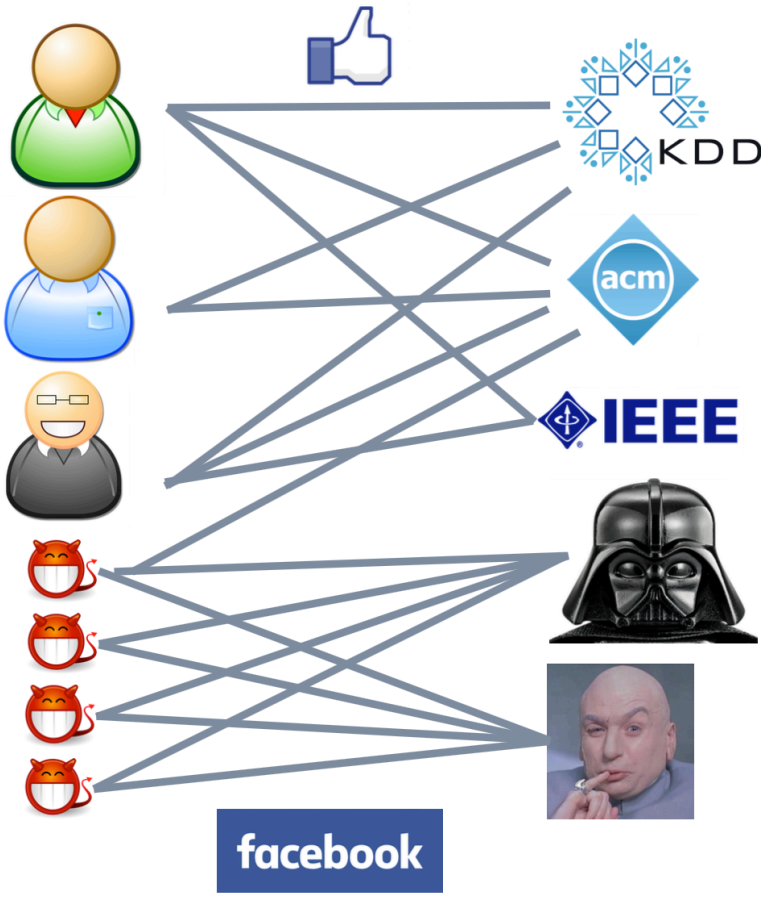
Meng Jiang, Peng Cui and Christos Faloutsos.
Suspicious Behavior Detection: Current Trends and Future Directions.
IEEE Intelligent Systems (ISSI), 2016.

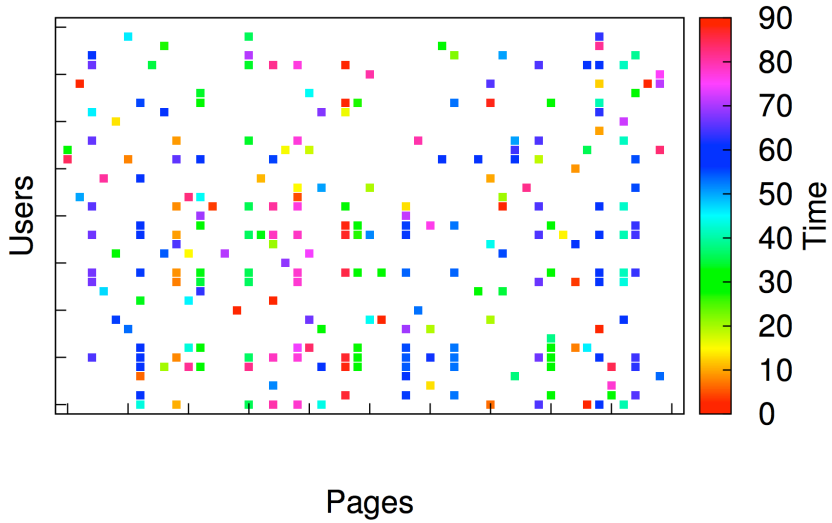
Ill-gotten Facebook Likes



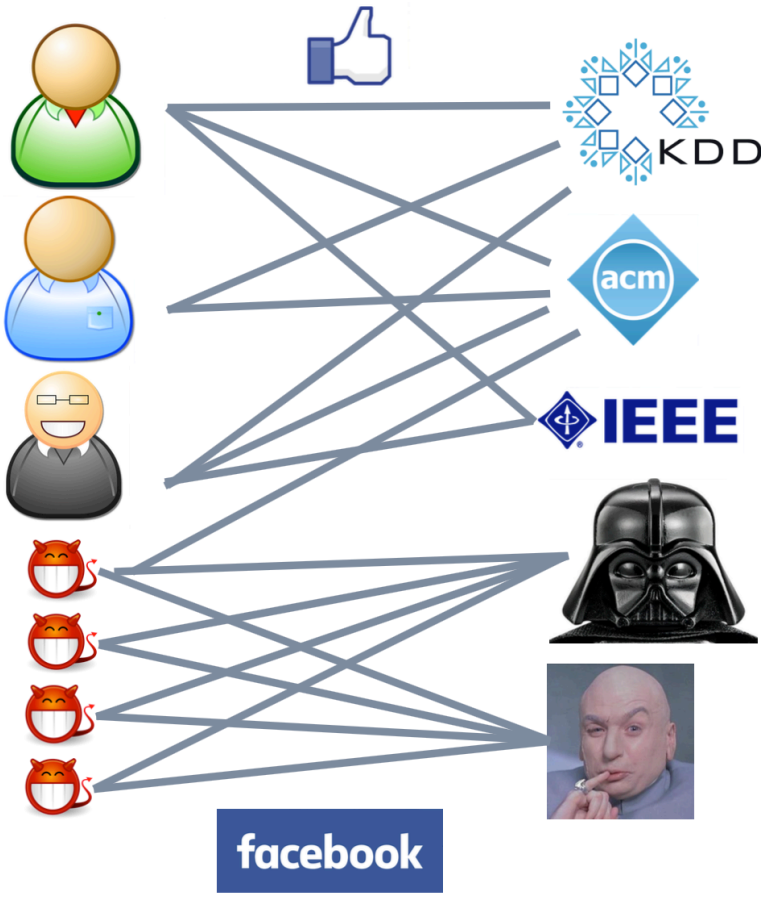
Beutel et al. **CopyCatch: Stopping Group Attacks by Spotting Lockstep Behavior in Social Neworks.** *WWW*, 2013.

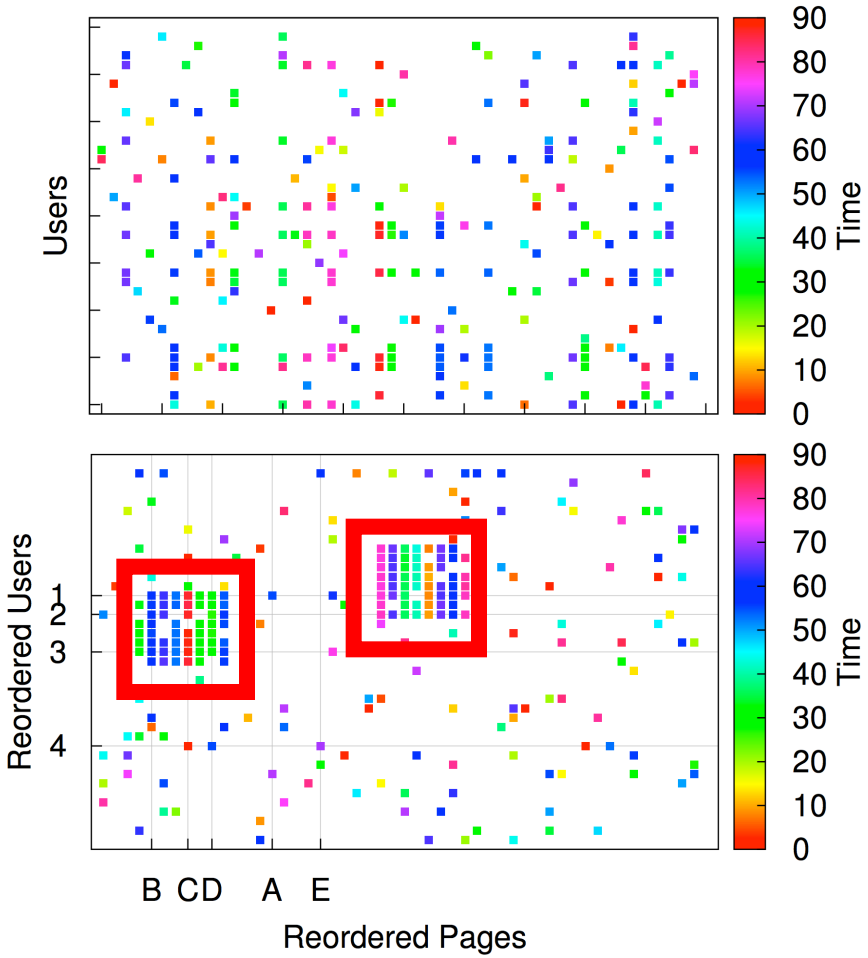
Observation: Graphical View





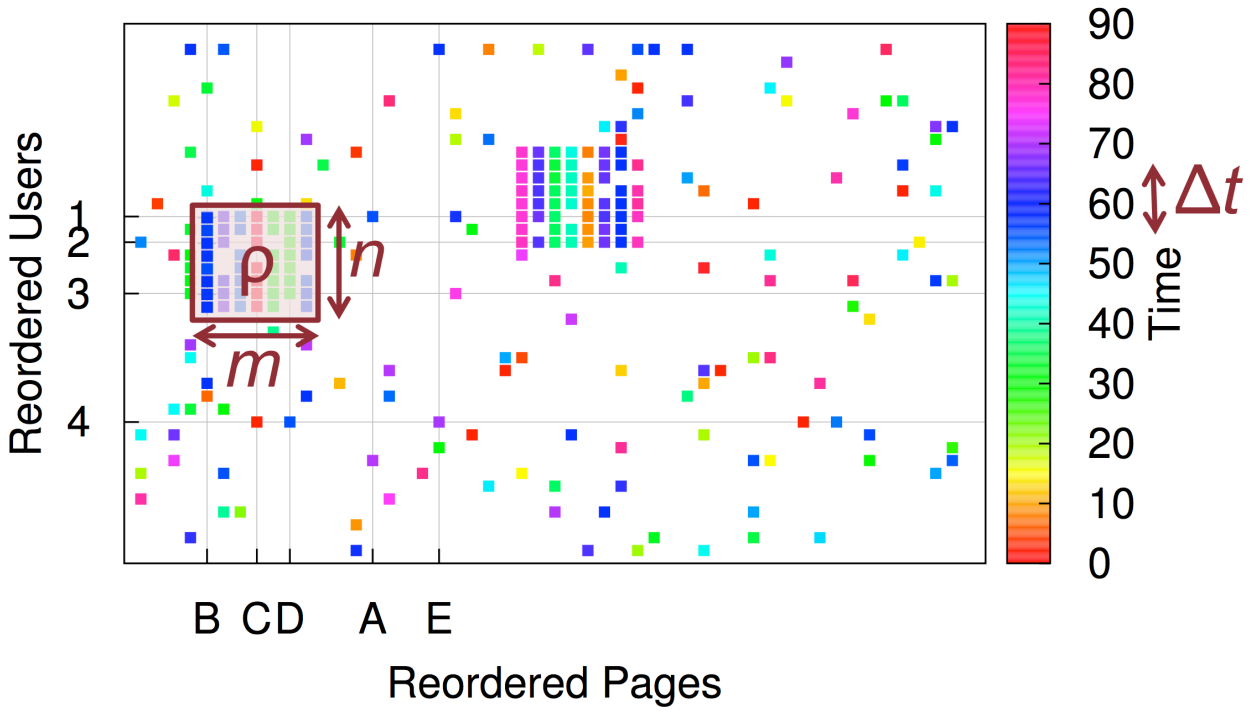
Observation: Reorder Matrix



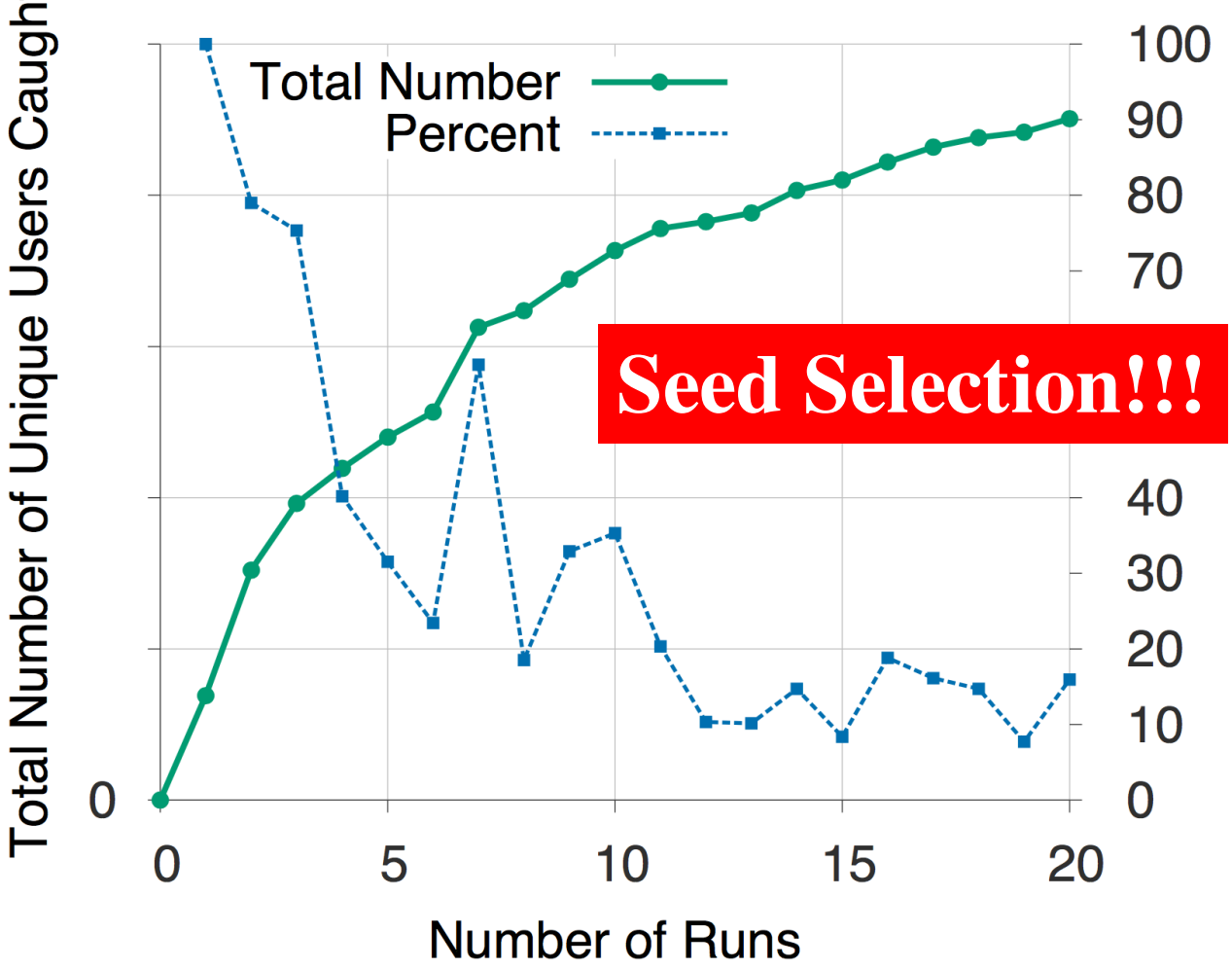


Algorithm: Seed + Search

- **CopyCatch**
  - "Near Bipartite Core": n users, m Pages, ϱ, Δt



Experimental Result

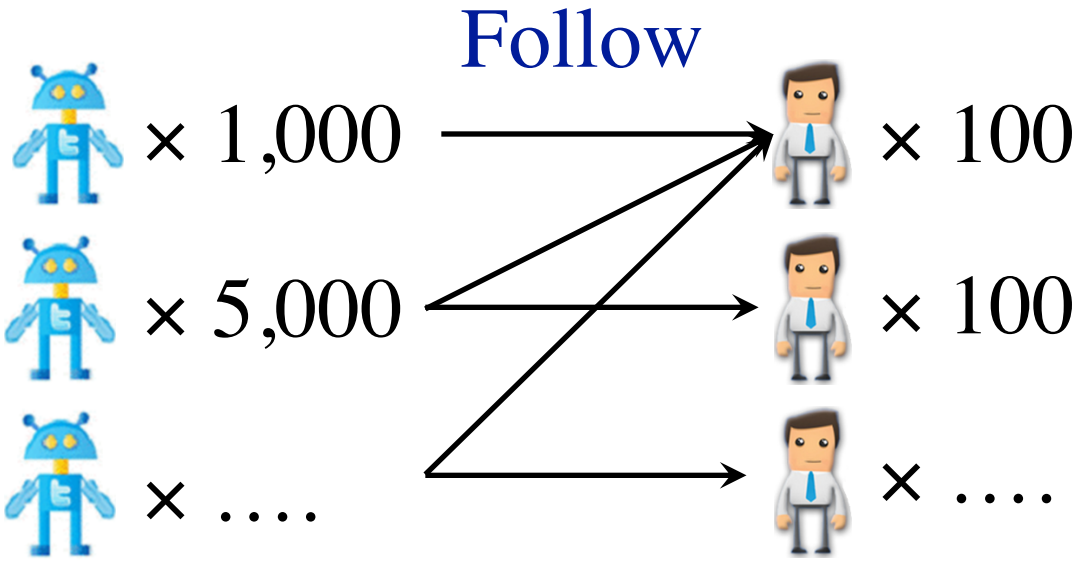


Serious Problem in Weibo

Experience-driven approaches:

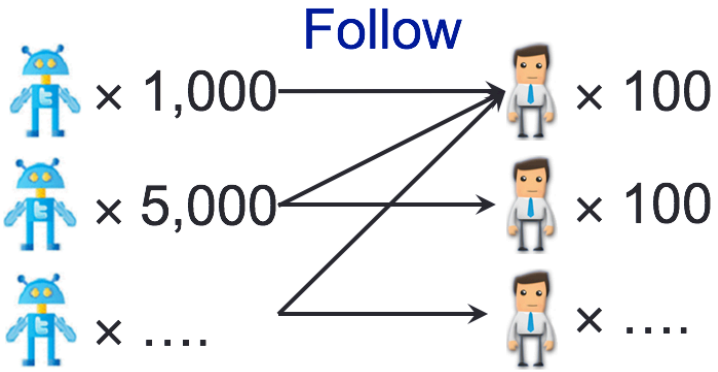
features of #followees, #hashtags, #URLs…

Zombie Followers

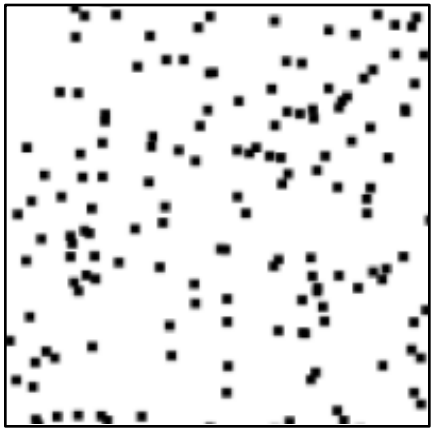


Jiang et al. **Inferring Strange Behavior from Connectivity Pattern in Social Networks.** *PAKDD*, 2014.

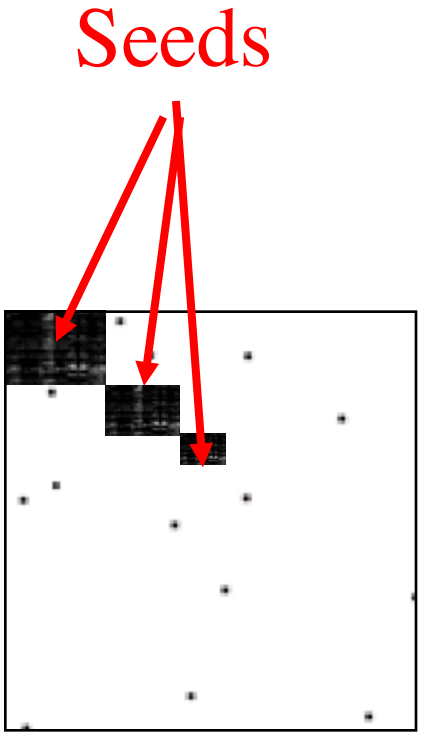
Observation: Reorder Matrix



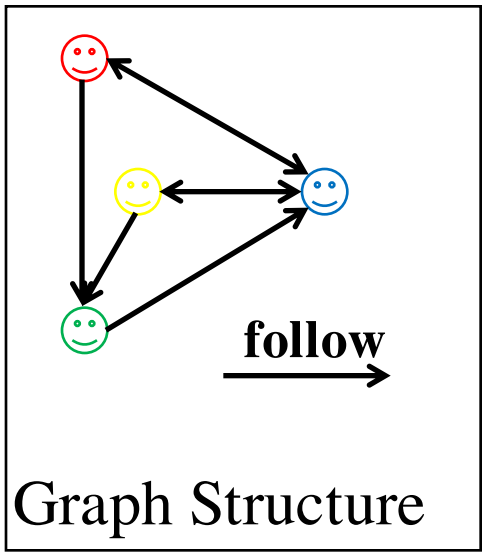
Given

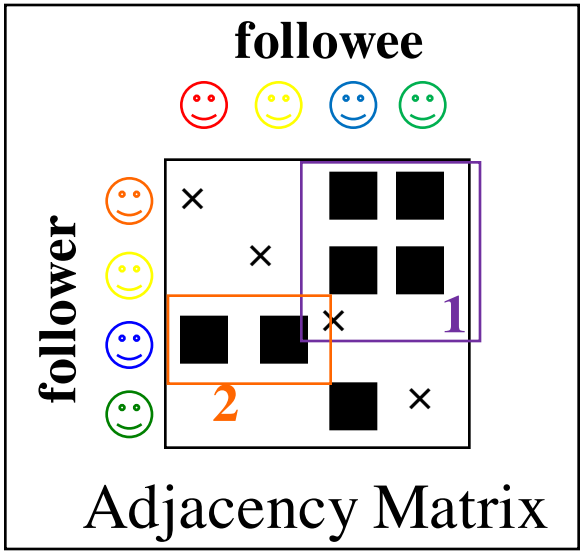


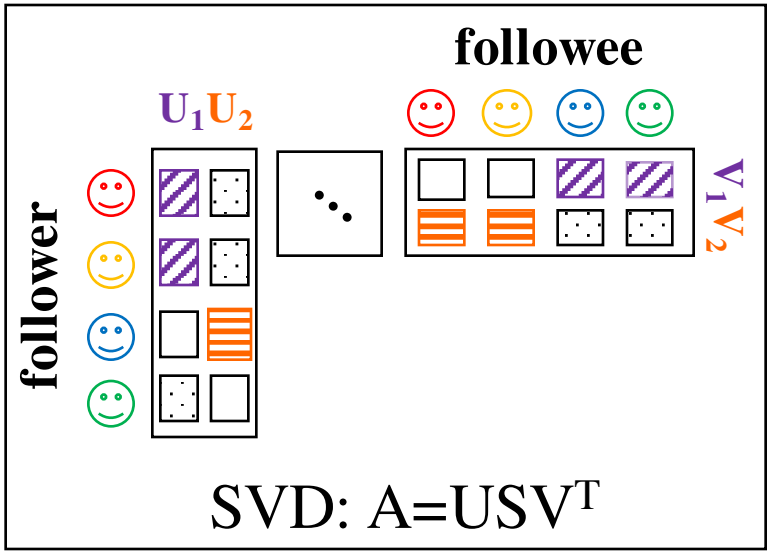
Reorder



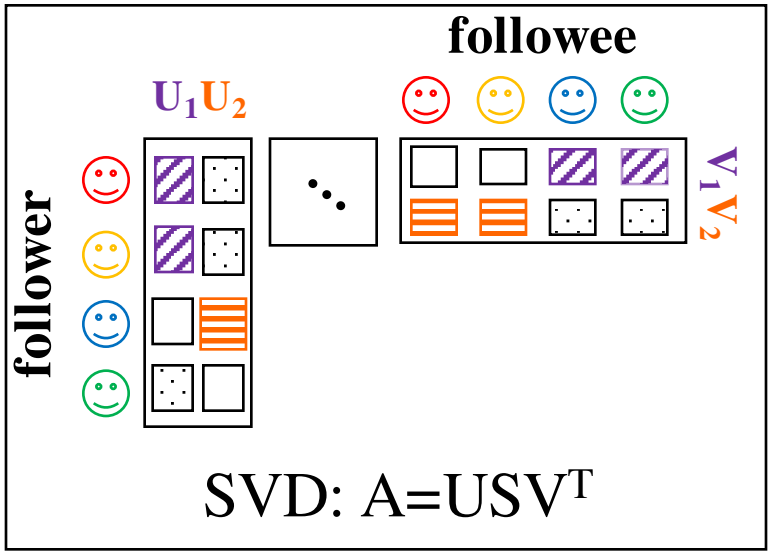
Representation: SVD Reminder



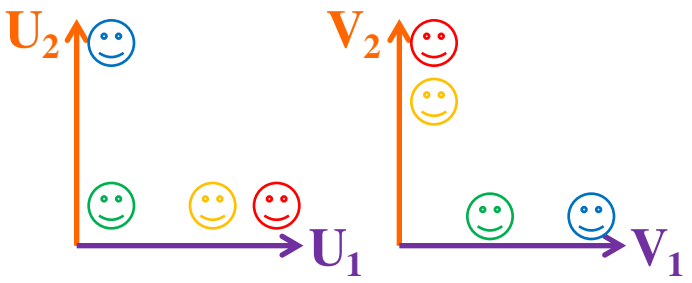




Representation: Spectral Subspace



Pairs of singular vectors:

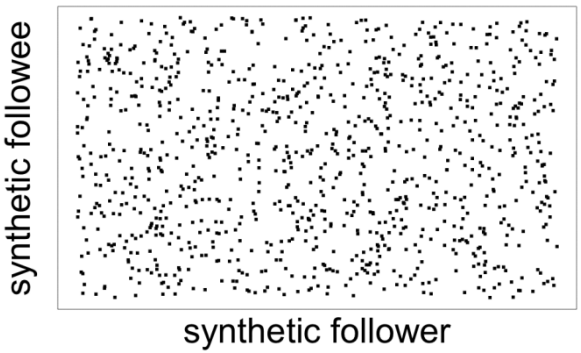


"Spectral Subspace Plot"

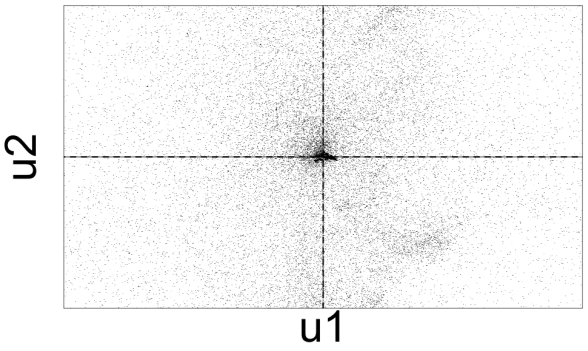
Spectral Subspace Plot: Case #0

- NO lockstep behavior: Scatter

Adjacency Matrix



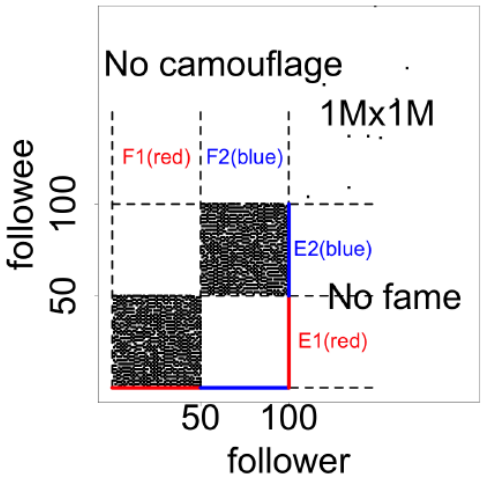
Spectral Subspace Plot



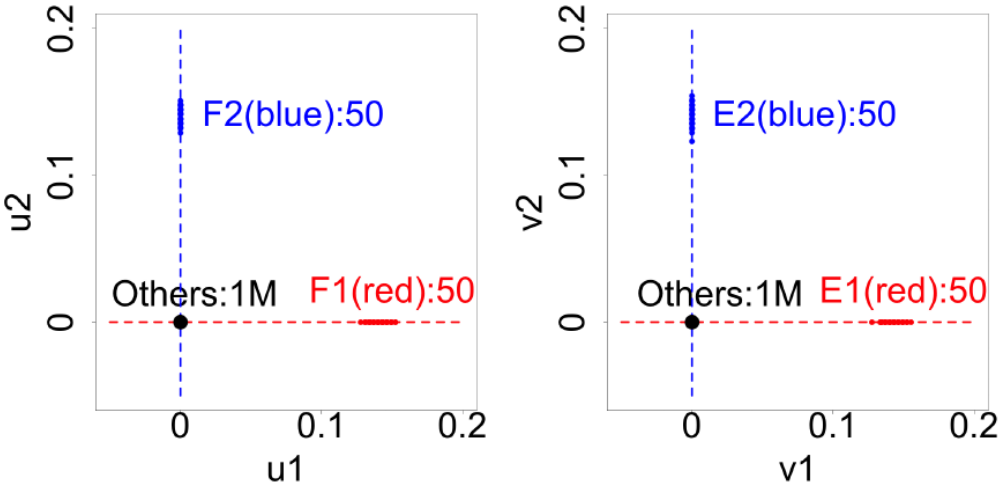
Spectral Subspace Plot: Case #1

- Non-overlapping lockstep: "Rays"

Adjacency Matrix



Spectral Subspace Plot

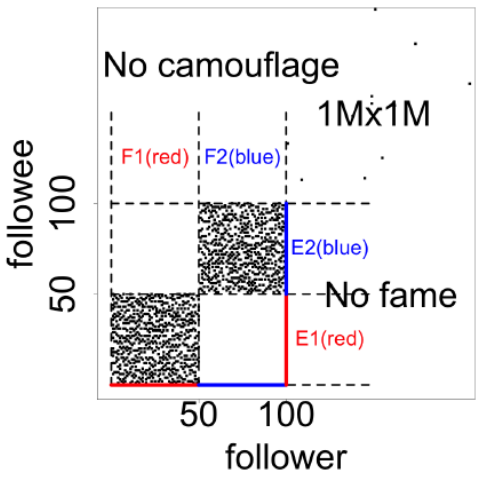


Rule 1 (short "rays"): two blocks, high density (90%), no "camouflage", no "fame"

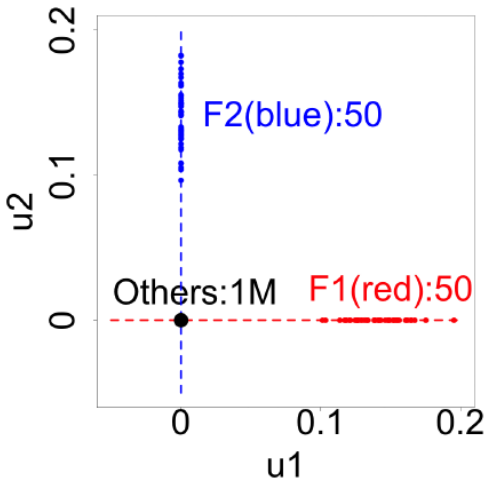
Spectral Subspace Plot: Case #2

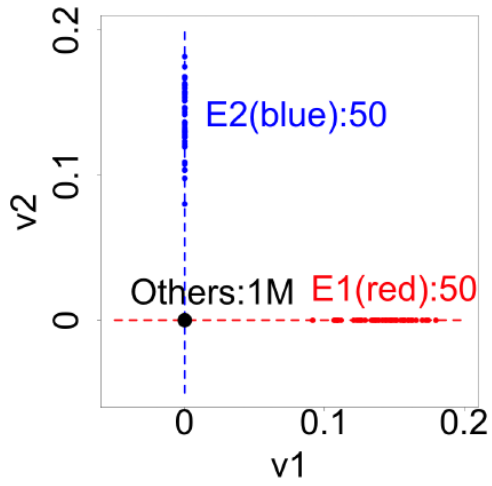
- Non-overlapping: Low density, Elongation

Adjacency Matrix



Spectral Subspace Plot



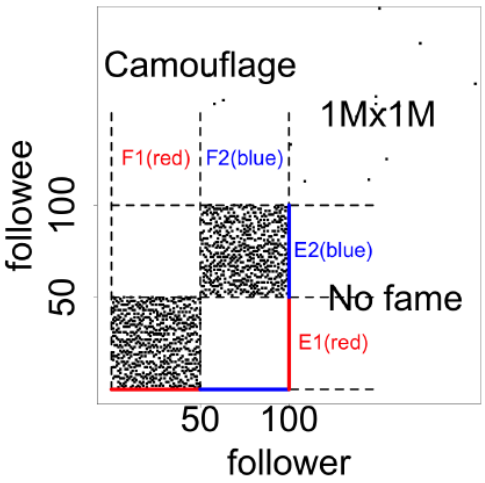


Rule 2 (long "rays"): two blocks, low density (50%), no "camouflage", no "fame"

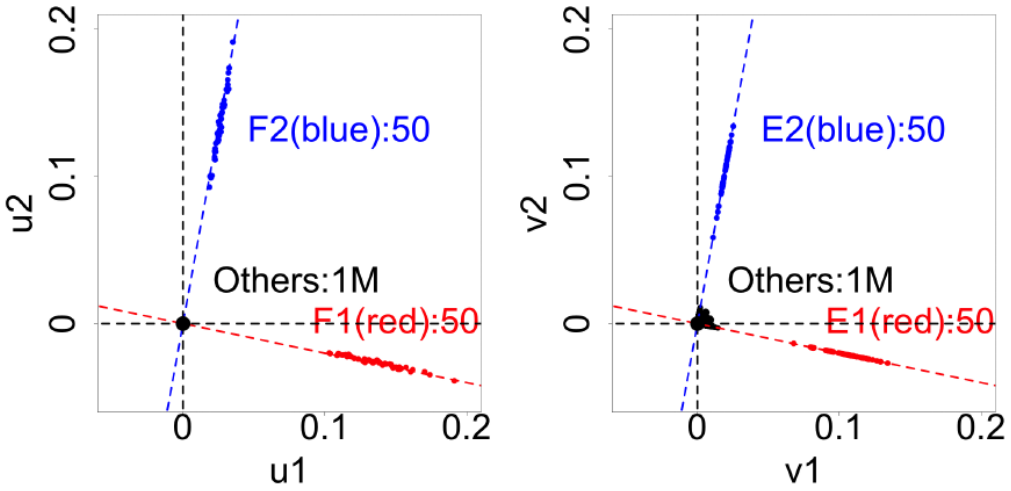
Spectral Subspace Plot: Case #3

- Non-overlapping: Camouflage/Fame, Tilting

Adjacency Matrix



Spectral Subspace Plot

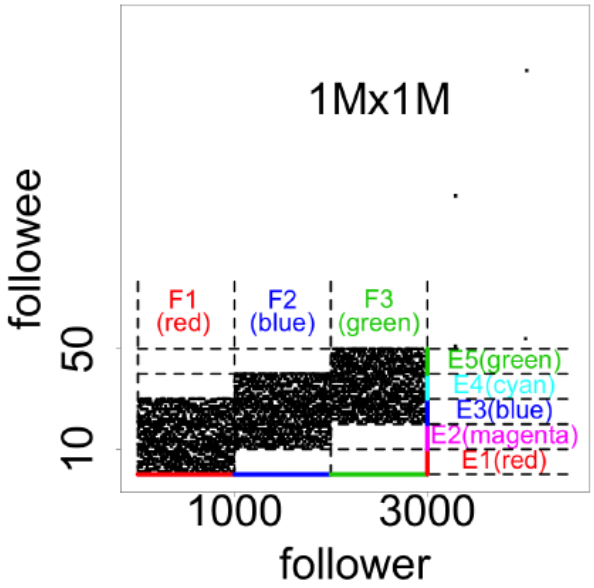


Rule 3 (tilting "rays"): two blocks, with "camouflage", no "fame"

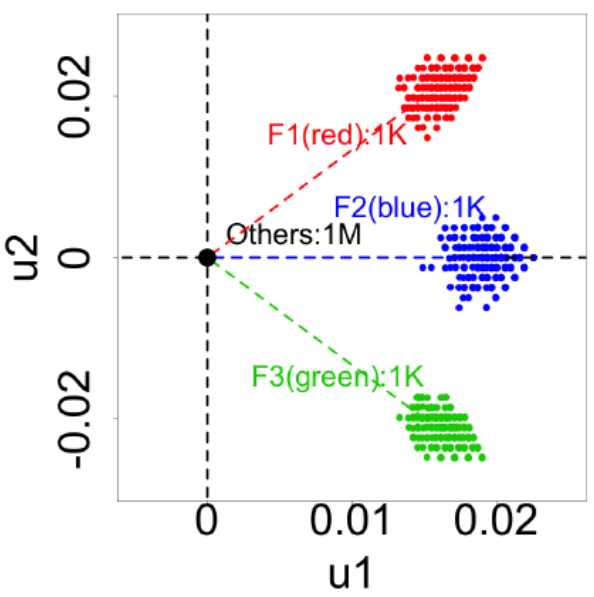
Spectral Subspace Plot: Case #4

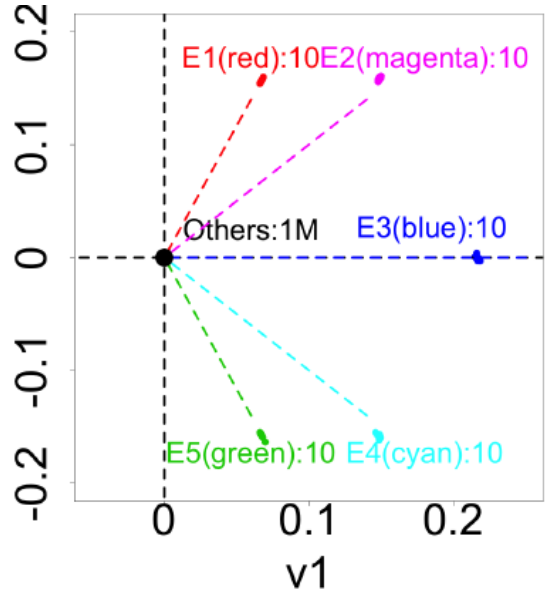
- Overlapping: "Staircase", "Pearls"

Adjacency Matrix



Spectral Subspace Plot





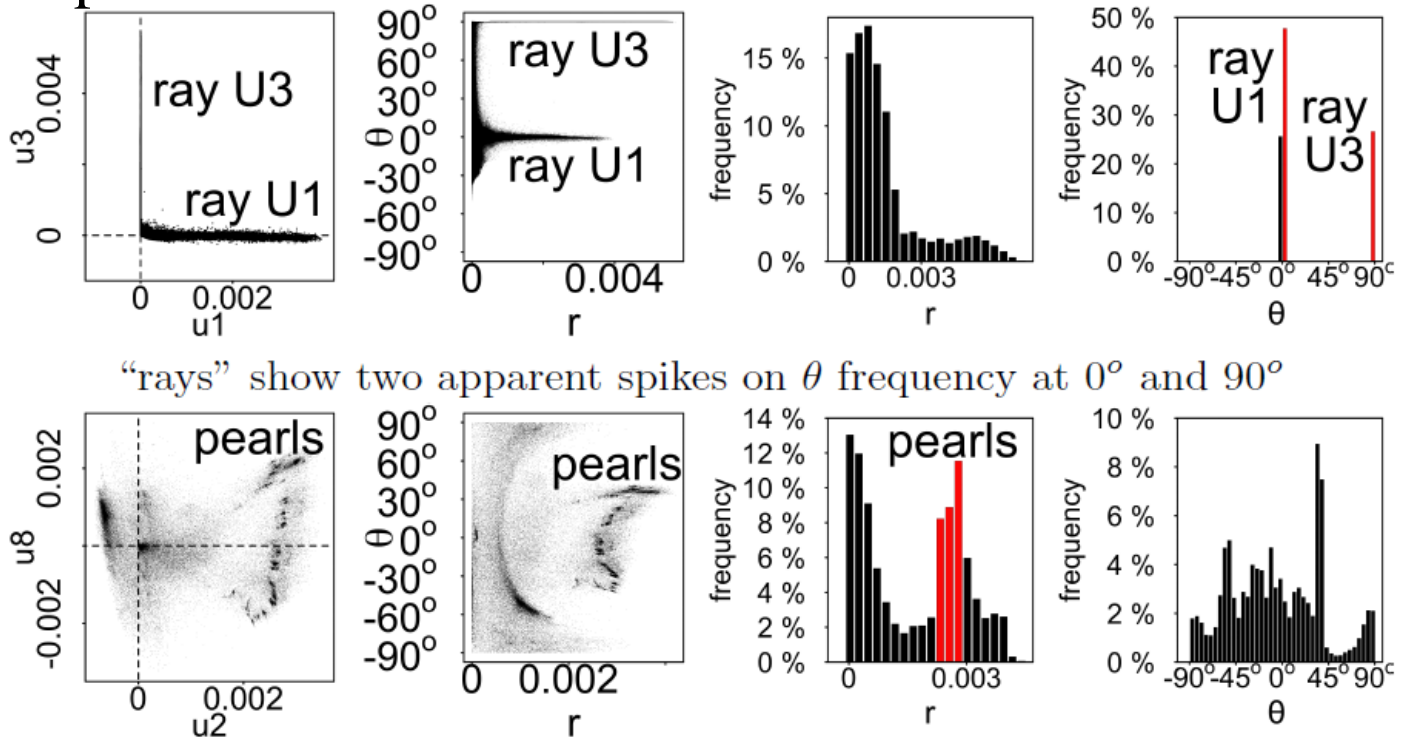
Rule 4 ("pearls"): a "staircase" of three partially overlapping blocks.

Algorithm: Reading & LockInfer

Spectral Subspace Plot

Polar Coordinate Transform

Histograms



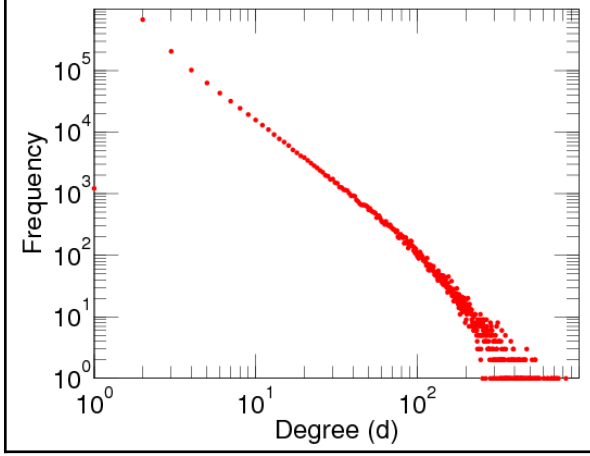
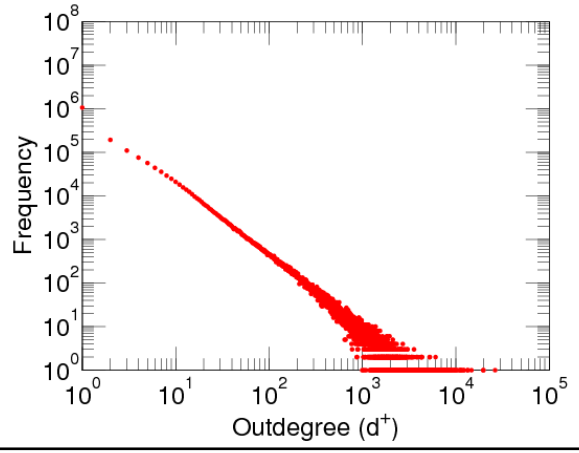
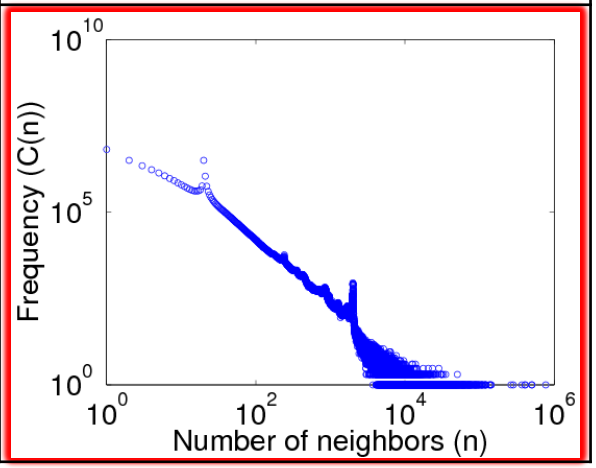
"rays" show two apparent spikes on θ frequency at 0^o and 90^o

"pearls" show a spike on r frequency at a much-greater-than-zero value

High precision but low recall!!!

Out-Degree Distributions

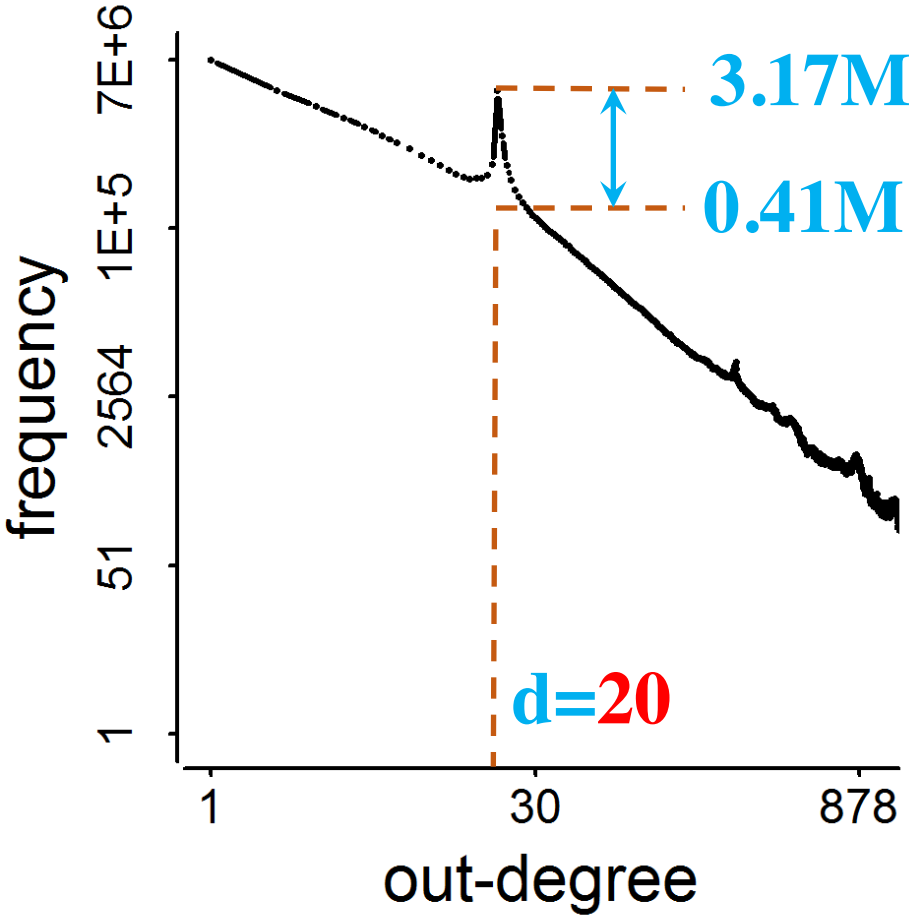
- **Power-law distribution** [Faloutsos *et al*. SIGCOMM; Broder *et al*. Computer Networks; Chung *et al*. PNAS]

DBLP **Author**-publication	**Flickr** **User**-user	**Twitter** **Who**-follows-whom
		

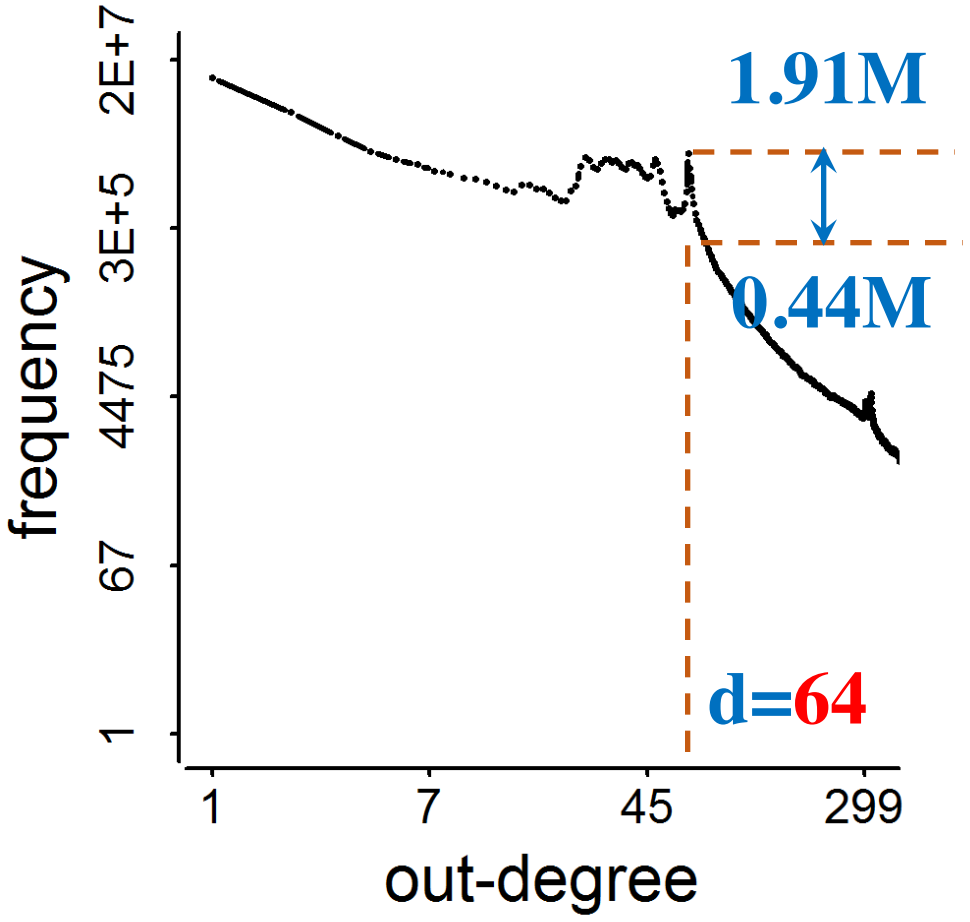
[konect.uni-koblenz.de/networks/]

Spikes!

2009 41M

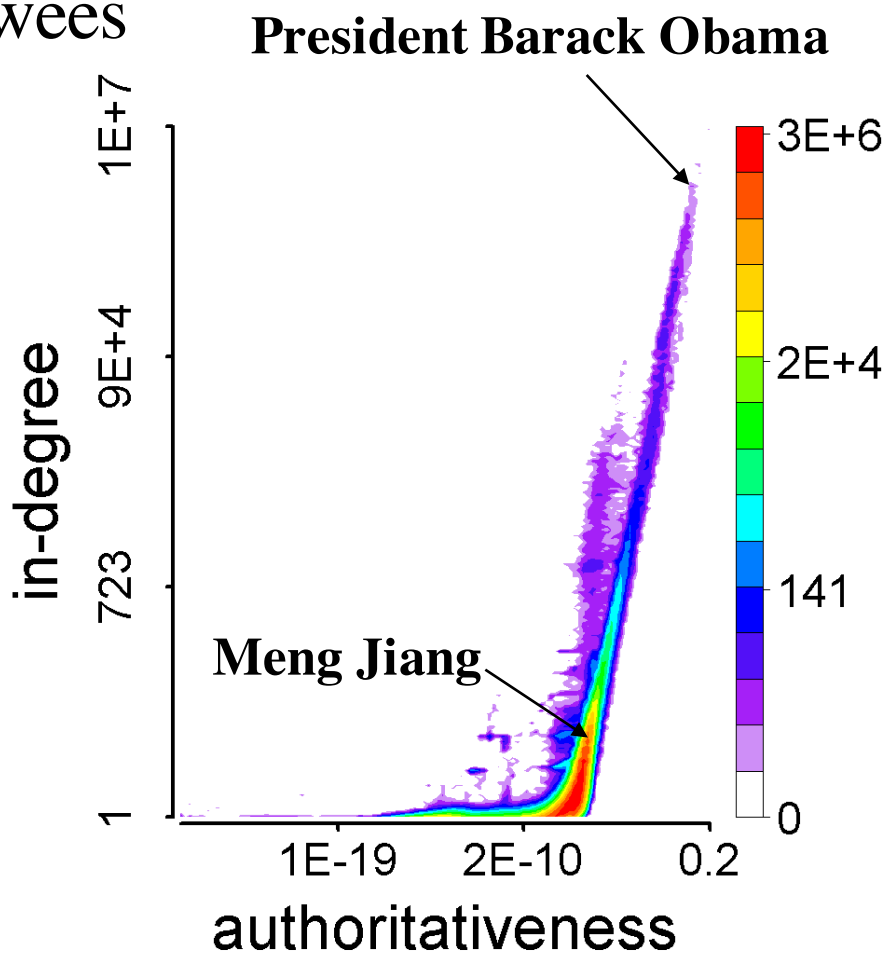


2011 117M



Observation: How They Behave

- Feature space of followees [Kleinberg. JACM]



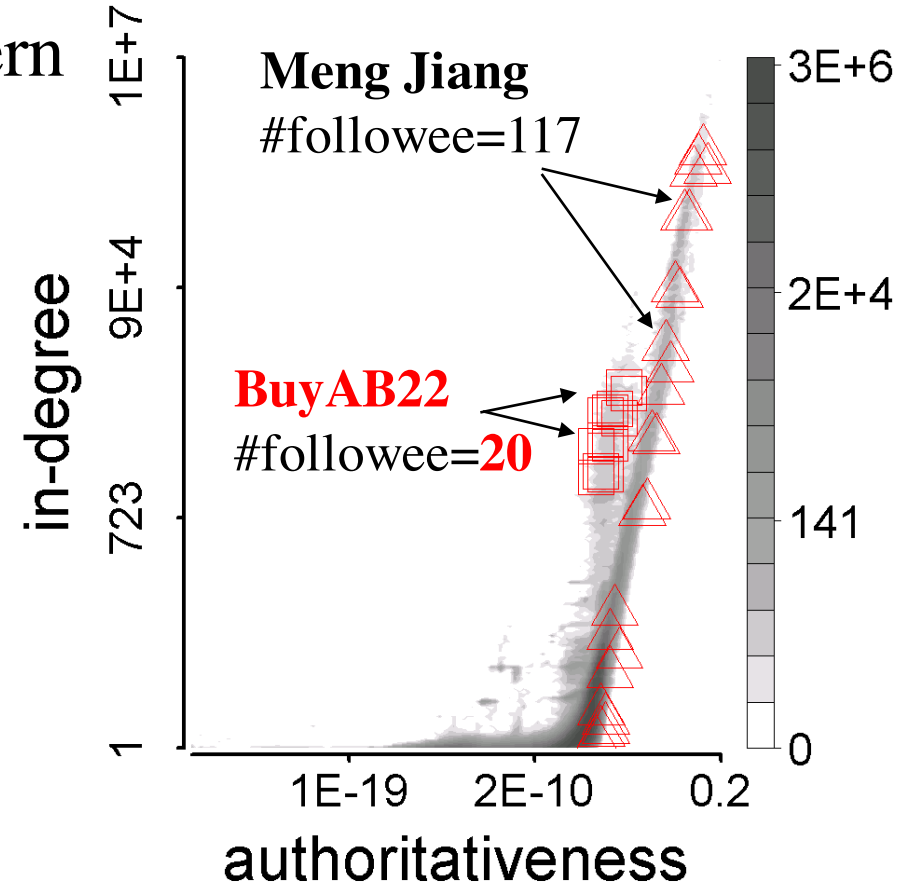
Observation: How They Behave

- Who are their followees?
- Their behavioral pattern
  - **Synchronized**

Similar with each other

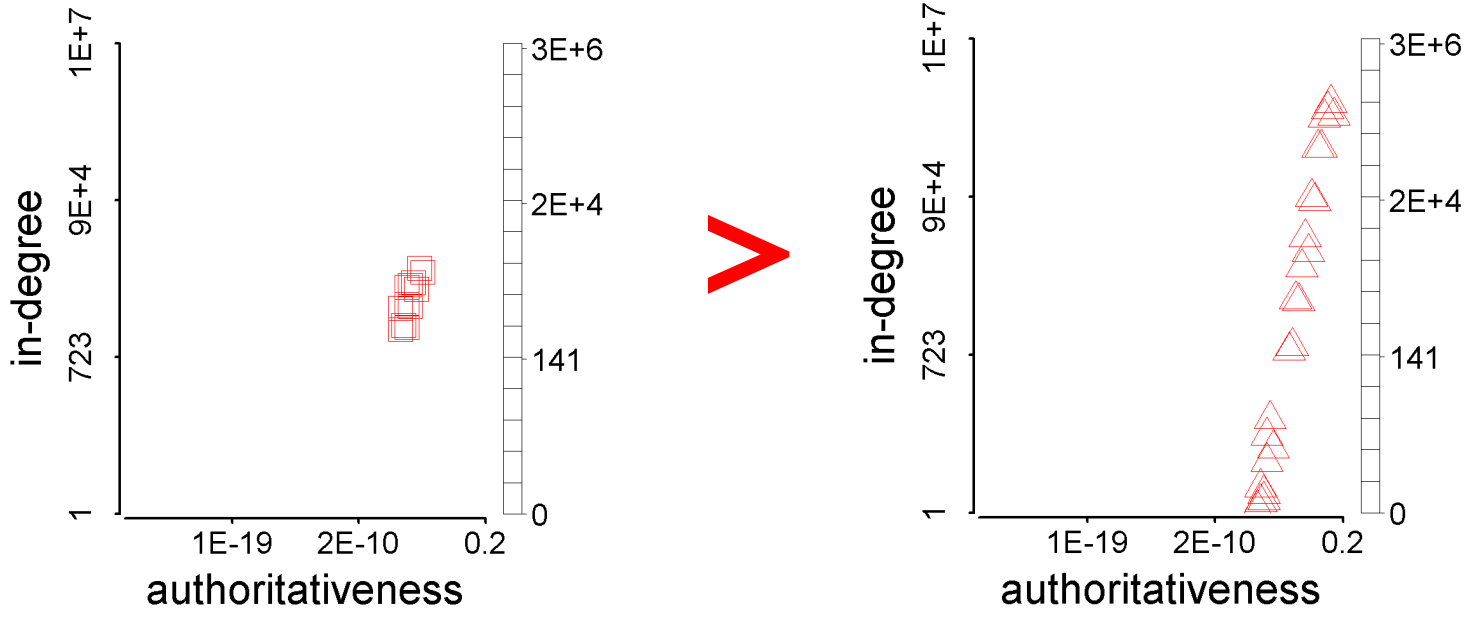
  - **Abnormal**

Different from the majority



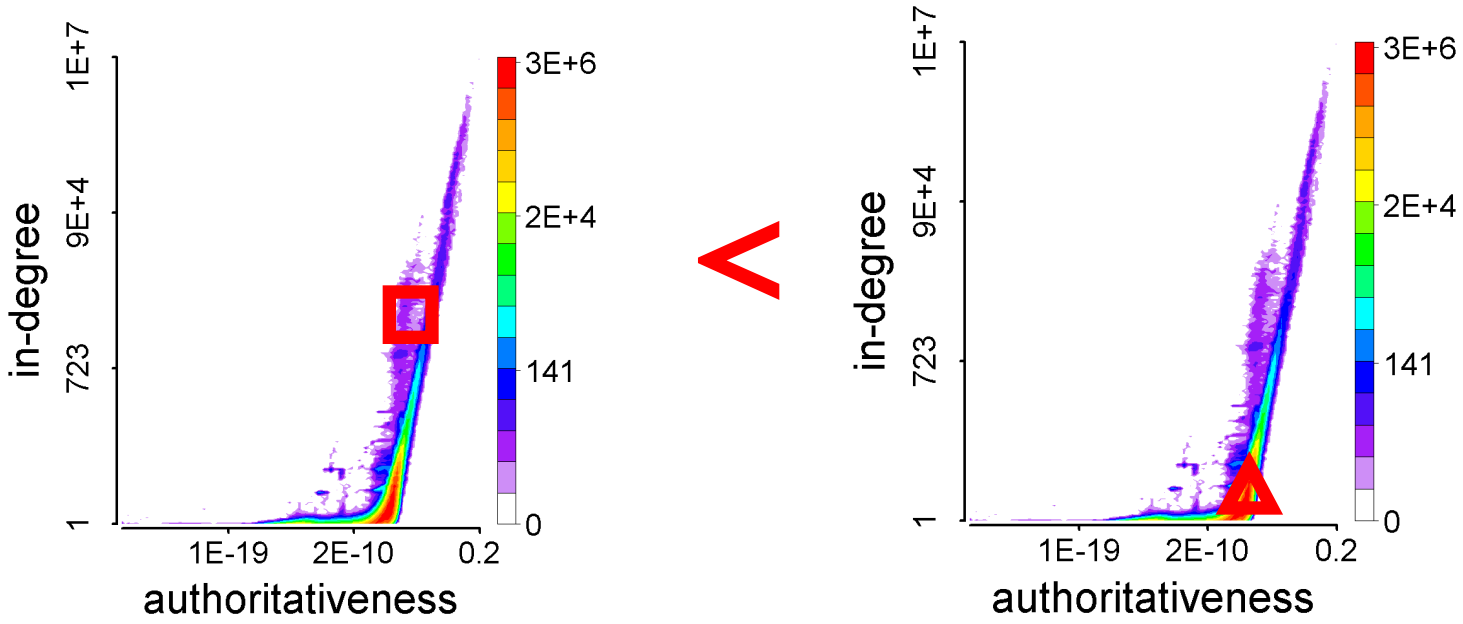
Represent Synchronicity

$$sync(u) = \frac{\sum_{(v,v') \in \mathcal{F}(u) \times \mathcal{F}(u)} \mathbf{p}(v) \cdot \mathbf{p}(v')}{d(u) \times d(u)}$$

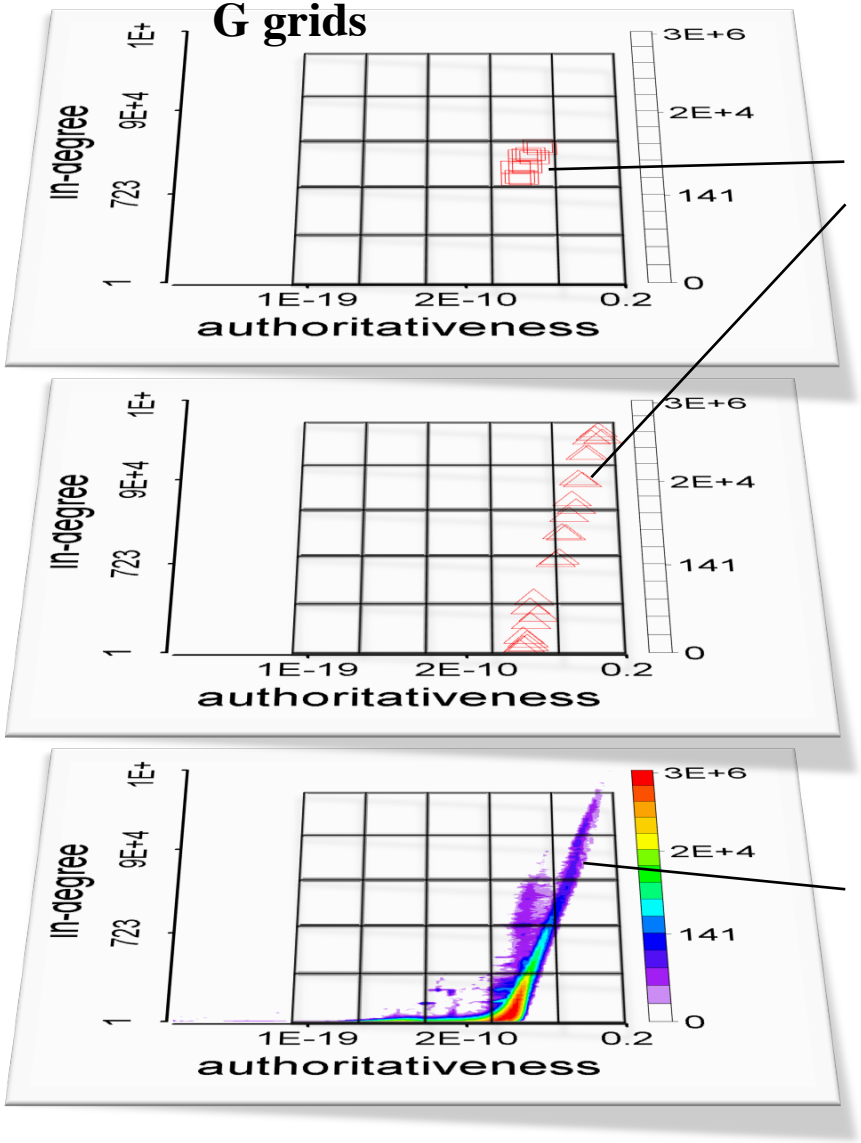


Represent Normality

$$norm(u) = \frac{\sum_{(v,v') \in \mathcal{F}(u) \times \mathcal{U}} \mathbf{p}(v) \cdot \mathbf{p}(v')}{d(u) \times N}$$



Theorem: Synchronicity vs. Normality



fp_g: #foreground points in grid **g**
$\sum fp_g = F = d(u)$ (#followees of **u**)

Given normality

$$n = \sum(fp_g/F)\,(bp_g/B) = \sum f_g b_g,$$

find minimal synchronicity

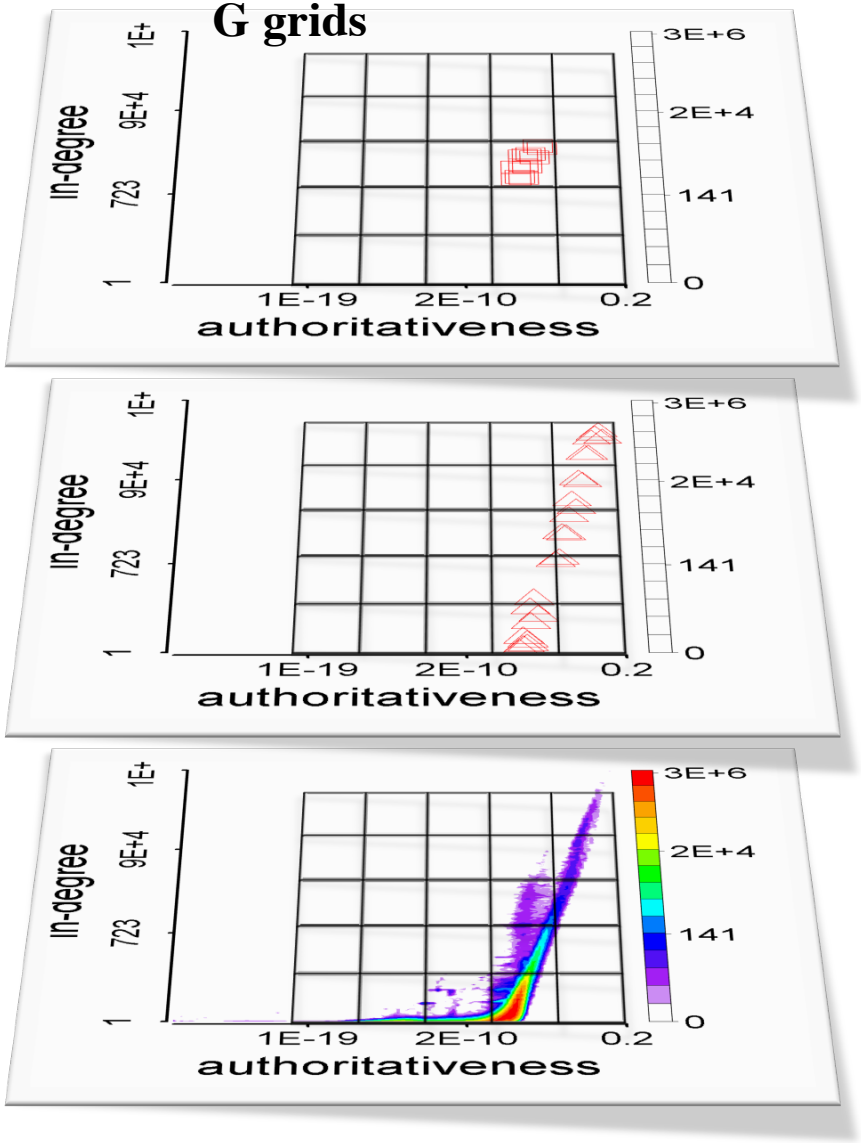
$$s = \sum(fp_g/F)\,(fp_g/F) = \sum f_g^2$$

where

$$\sum f_g = 1, \sum b_g = 1$$

bp_g: #background points in grid **g**
$\sum bp_g = B = N$ (#all users)

Theorem: Synchronicity vs. Normality



Solution.

Lagrange multiplier:

minimize $s(f_g) = \sum f_g^2$

subject to $\sum f_g = 1, \sum f_g b_g = n$

Lagrange function:

$F(f_g, \lambda, \mu) = (\sum f_g^2) + \lambda(\sum f_g - 1) + \mu(\sum f_g b_g - n)$

Gradients:

$$\begin{cases} \nabla_{f_g} F = 2 f_g + \lambda + \mu b_g = 0 \\ \nabla_{\lambda} F = \sum f_g - 1 = 0 \\ \nabla_{\mu} F = \sum f_g b_g - n = 0 \end{cases}$$

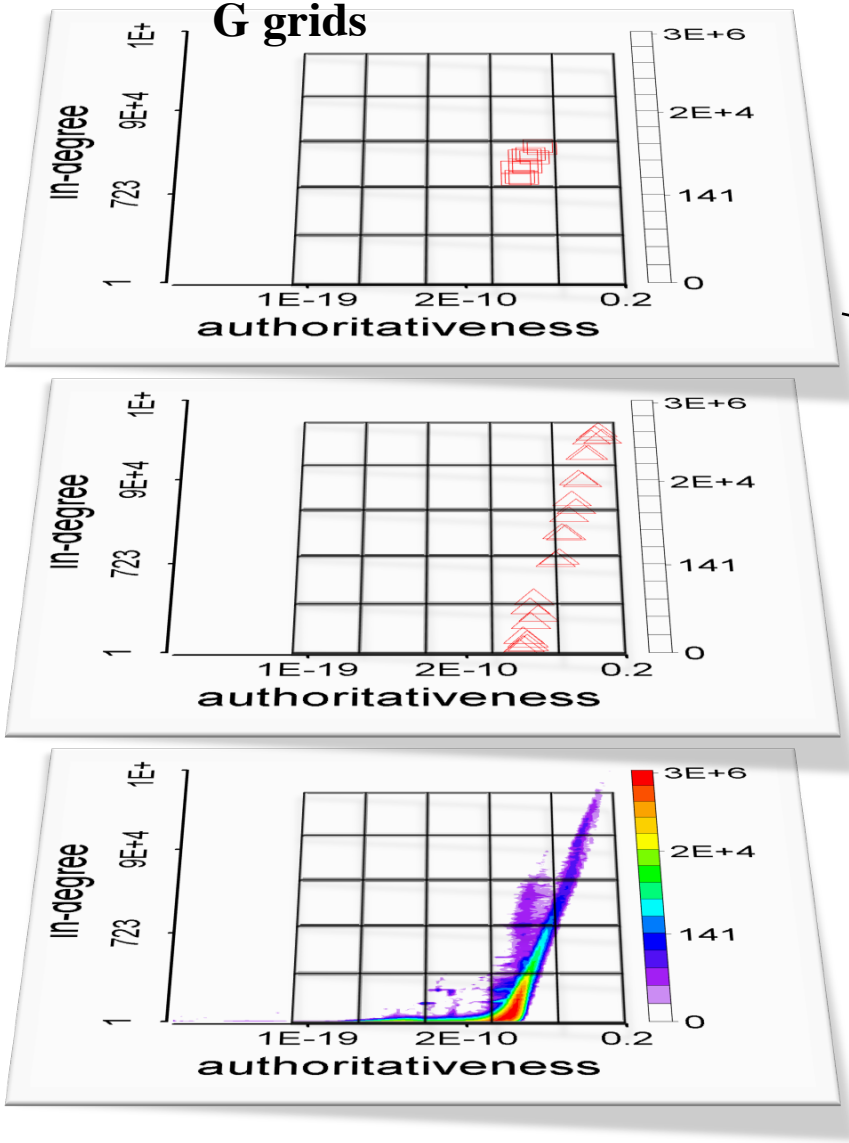
$$\begin{cases} 2 + \lambda G + \mu = 0 & \times \Sigma \\ 2n + \lambda + \mu s_b = 0 & \times b_g \Sigma \\ 2 s_{min} + \lambda + \mu n = 0 & \times f_g \Sigma \end{cases}$$

where $s_b = \sum b_g^2$.

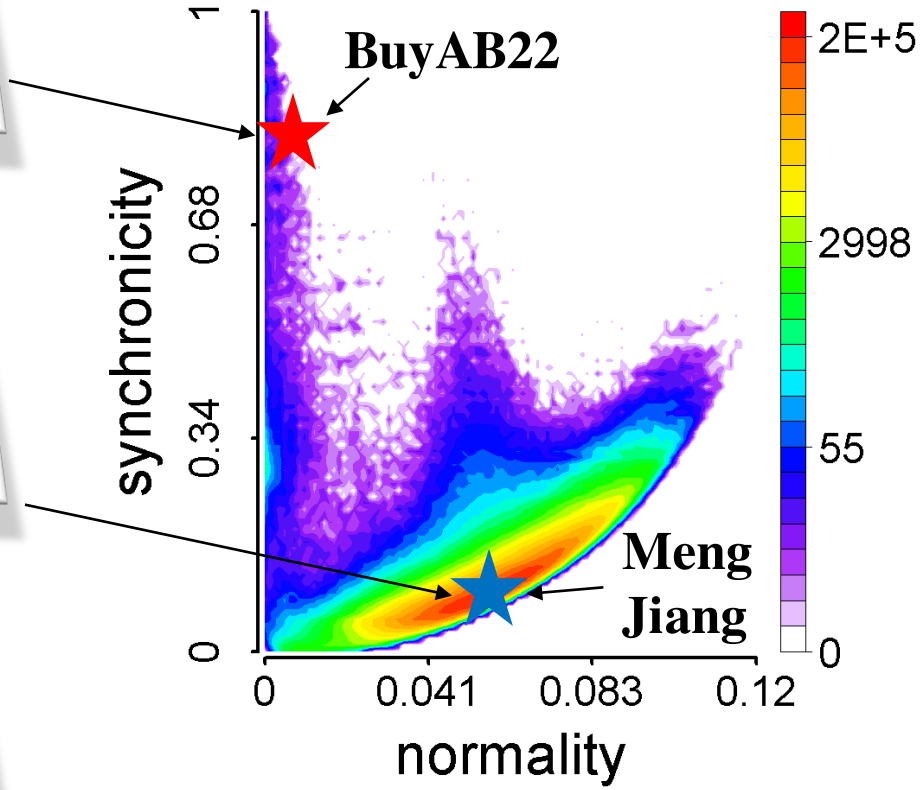
Therefore,

$$s_{min} = \frac{-G n^2 + 2n - s_b}{1 - G s_b}$$

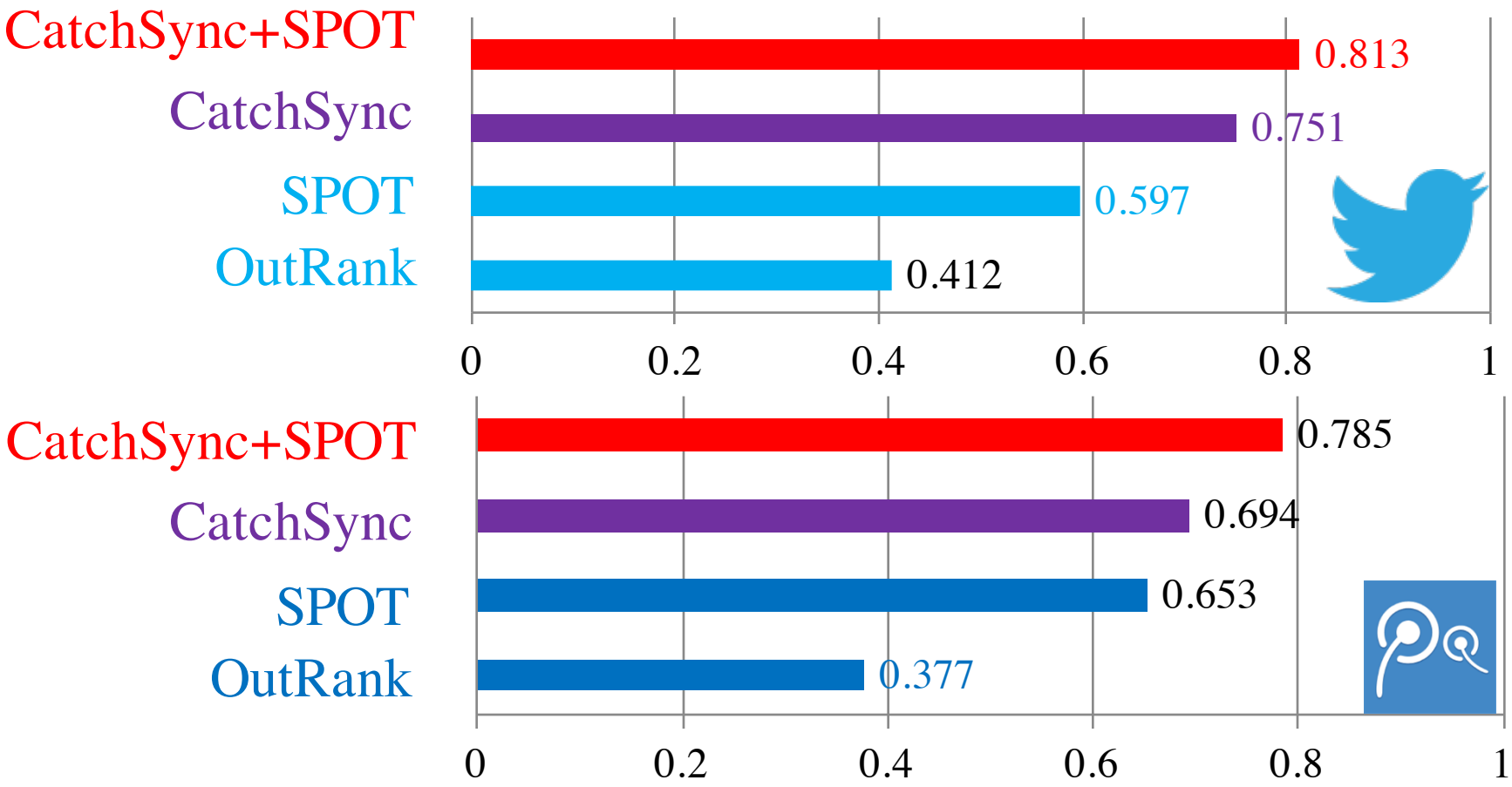
CatchSync Algorithm



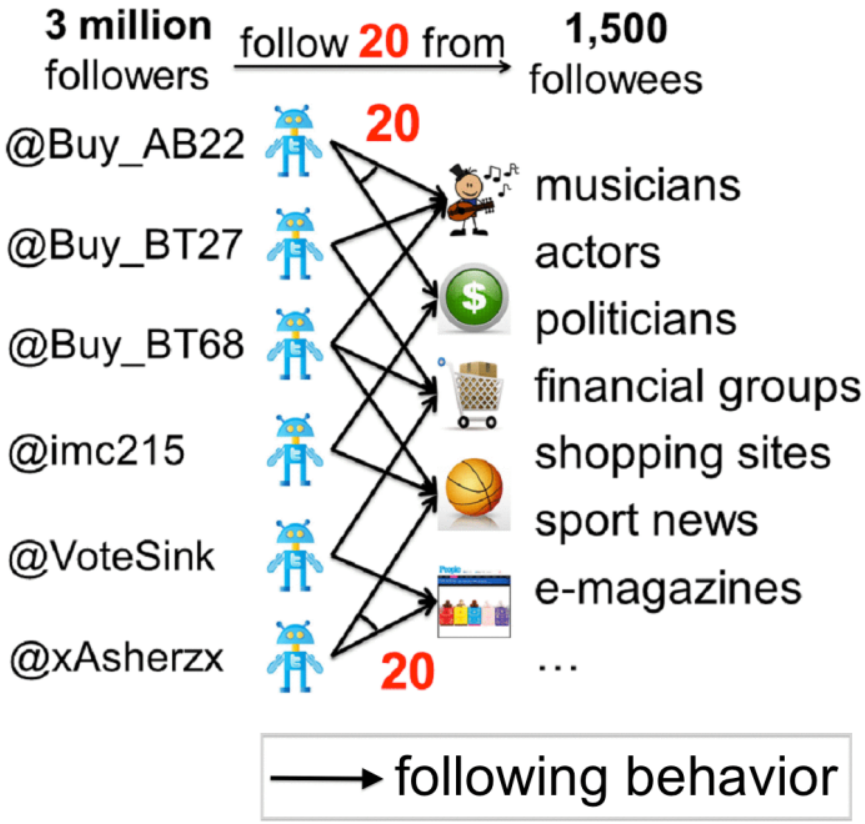
$$s_{min} = \frac{-G\,n^2 + 2\,n - s_b}{1 - G\,s_b}$$

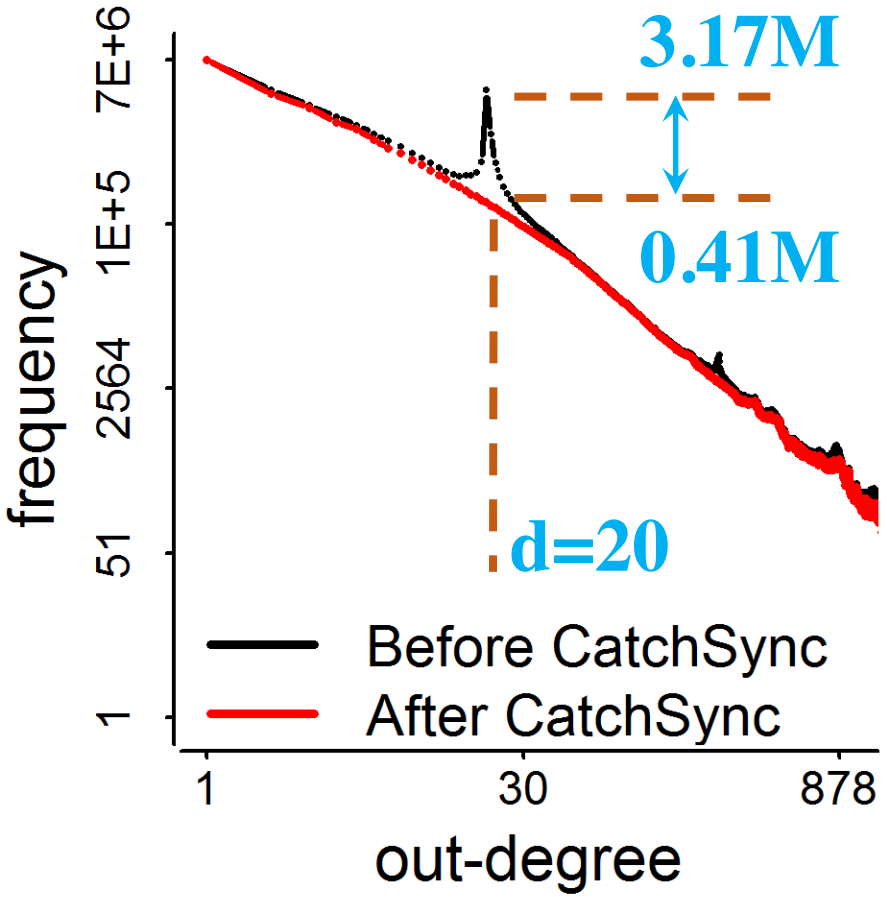


Experimental Results



Experimental Results





Impact

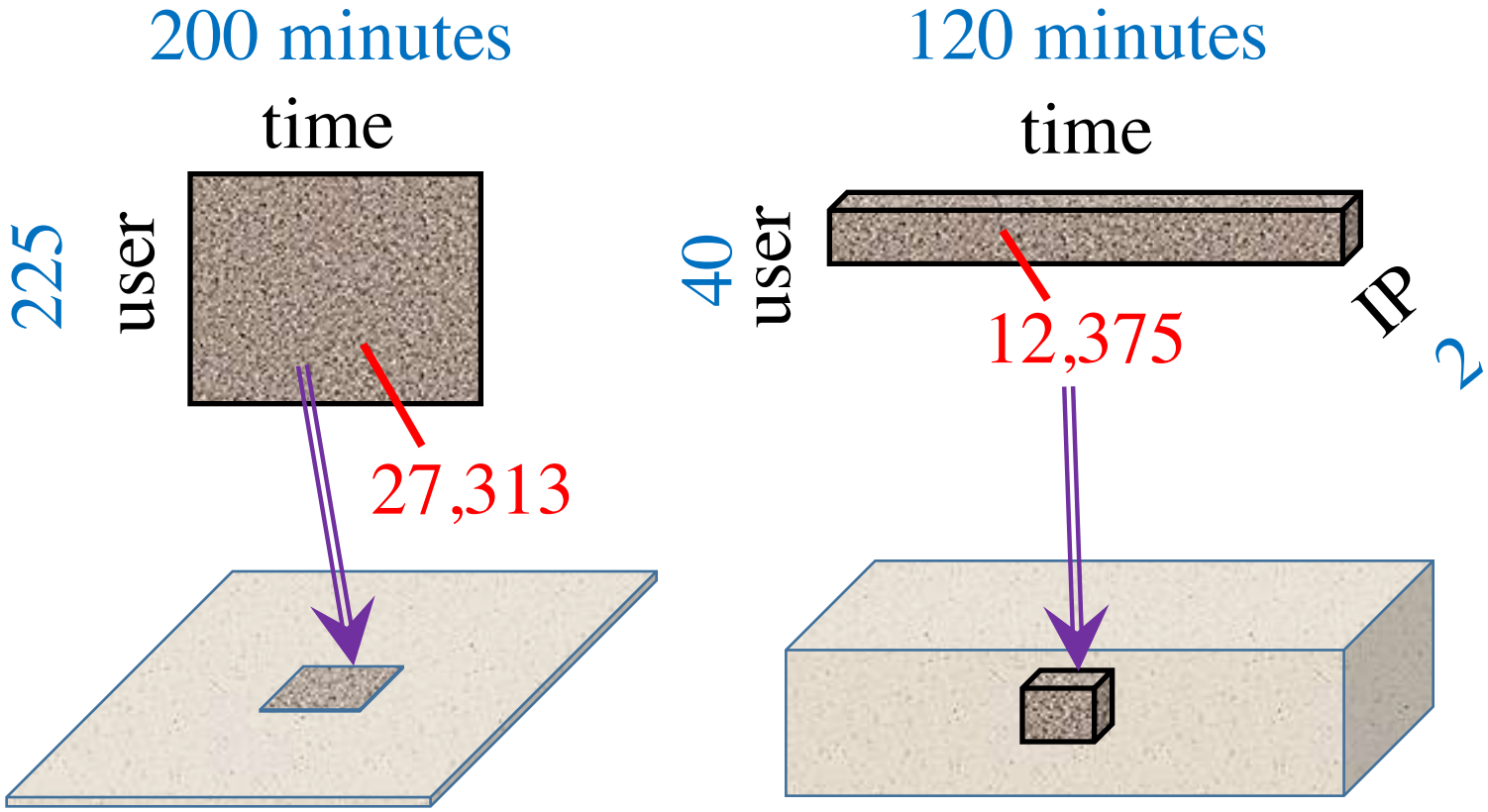
- **M. Jiang**, P. Cui, A. Beutel, C. Faloutsos and S. Yang. "CatchSync: Catching Synchronized Behavior in Large Directed Graphs" in **KDD'14 Best Paper Finalist**, Aug 2014. (#citations = **36**)
- Taught in
  - **CMU 15-826:** Multimedia Databases and Data Mining
  - **UMich EECS 598:** Graph Mining and Exploration at Scale
  - **ASONAM'16 Tutorial:** "Identifying Malicious Actors on Social Media" by S. Kumar, F. Spezzano, V.S. Subrahmanian
- Deployed in Weibo? Unfortunately, in July 2014…

Observation: Spatiotemporal Contexts

Dataset	Dimension/Mode				Mass
Weibo's Retweeting	User	Root ID	IP	Time (min)	#retweet
	29.5M	19.8M	27.8M	56.9K	211.7M
Weibo's Trending (Hashtag)	User	Hashtag	IP	Time (min)	#tweet
	81.2M	1.6M	47.7M	56.9K	276.9M
Network attacks (LBNL)	Src-IP	Dest-IP	Port	Time (sec)	#packet
	2,345	2,355	6,055	3,610	230,836

Jiang et al. **A General Suspiciousness Metric for Dense Blocks in Multimodal Data.** *ICDM*, 2015.

Dense Block Indicates Suspiciousness

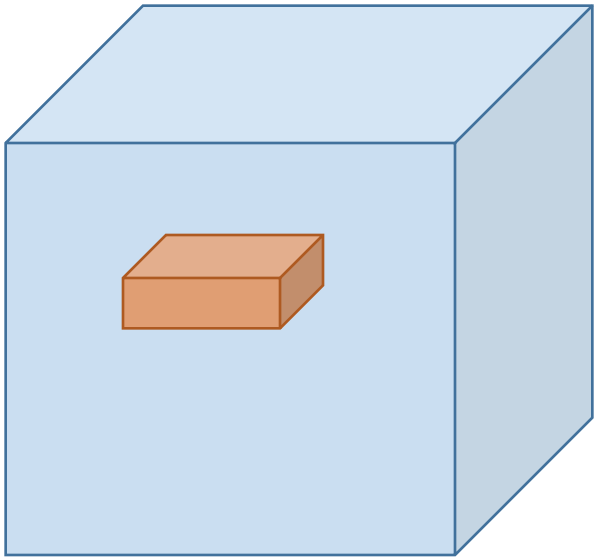


Q: Which is more suspicious?

We need a metric to evaluate the suspiciousness.

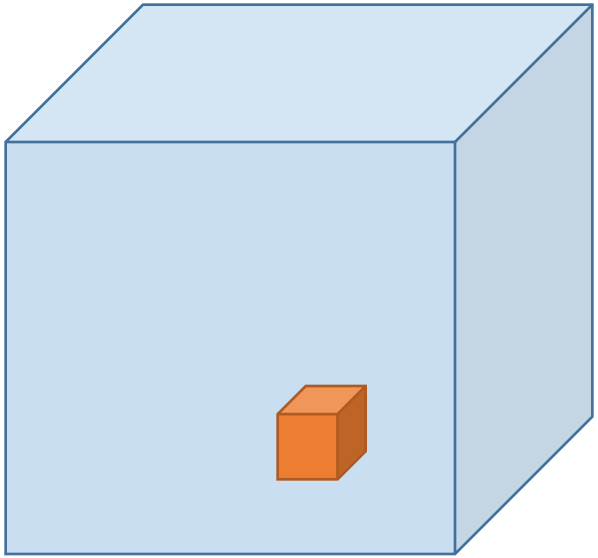
Criteria for Suspiciousness Metric

What properties are required of a good metric?



$N_1 \times N_2 \times N_3$

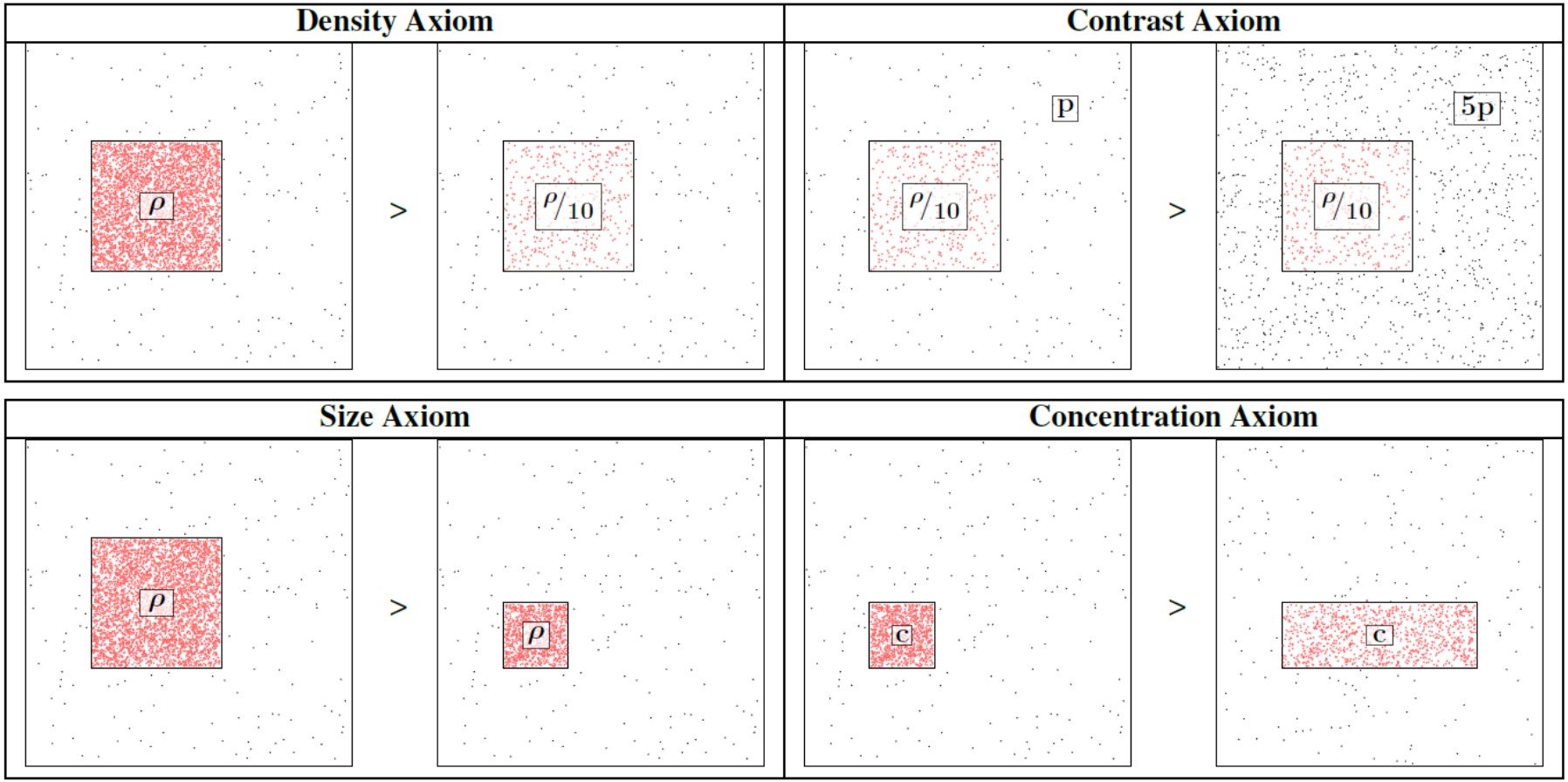
Count data with total "mass" C



$f\left(\begin{array}{c} n_1 \times n_2 \times n_3 \\ \text{mass } c \\ \text{density } \varrho \end{array}\right)$ vs $f\left(\begin{array}{c} n'_1 \times n'_2 \times n'_3 \\ \text{mass } c' \\ \text{density } \varrho' \end{array}\right)$

Axioms: 1 to 4

$$c_1 > c_2 \iff f(\mathbf{n}, c_1, \mathbf{N}, C) > f(\mathbf{n}, c_2, \mathbf{N}, C)$$

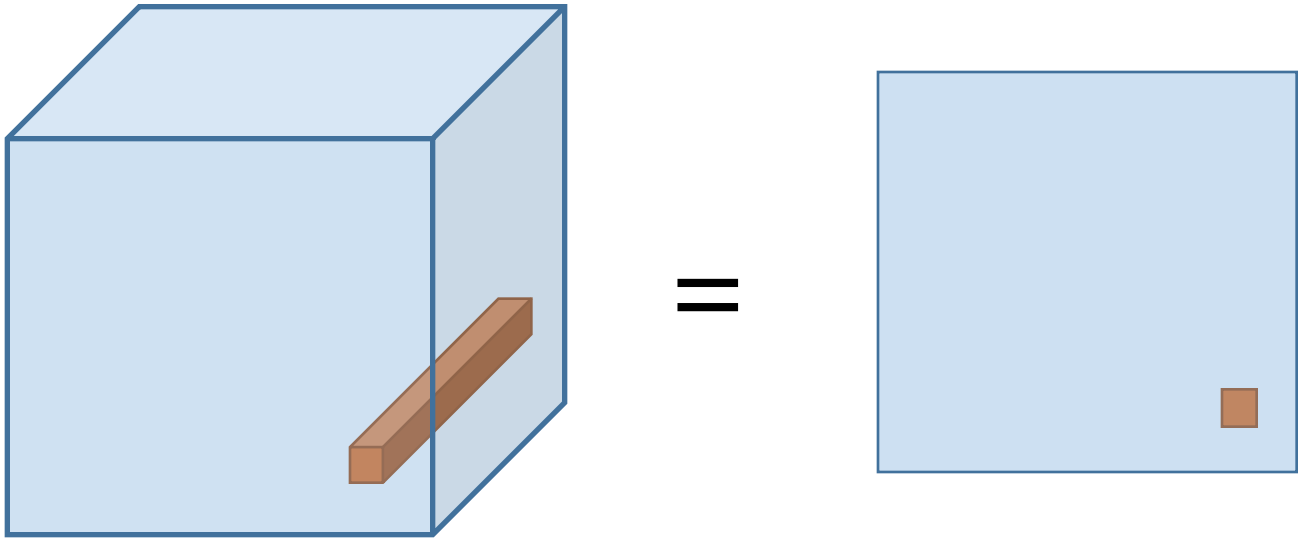


$$p_1 < p_2 \iff \hat{f}(\mathbf{n}, \rho, \mathbf{N}, p_1) > \hat{f}(\mathbf{n}, \rho, \mathbf{N}, p_2)$$

Axiom 5: Cross Dimensions

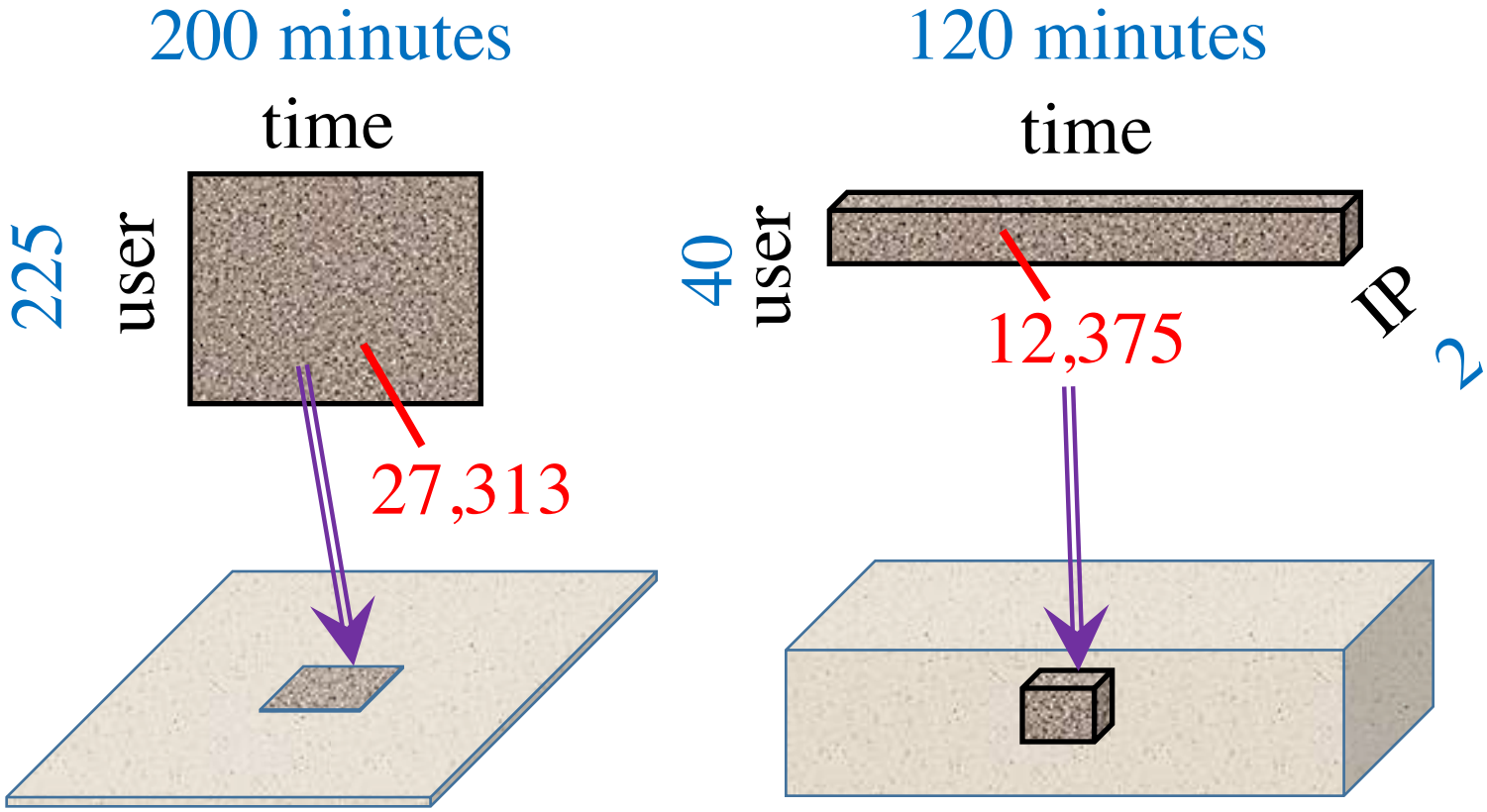
$$f_{K-1}\left([n_k]_{k=1}^{K-1}, c, [N_k]_{k=1}^{K-1}, C\right) = f_K\left(([n_k]_{k=1}^{K-1}, N_K), c, [N_k]_{k=1}^{K}, C\right)$$

Not including a mode is the same as including all values for that mode.



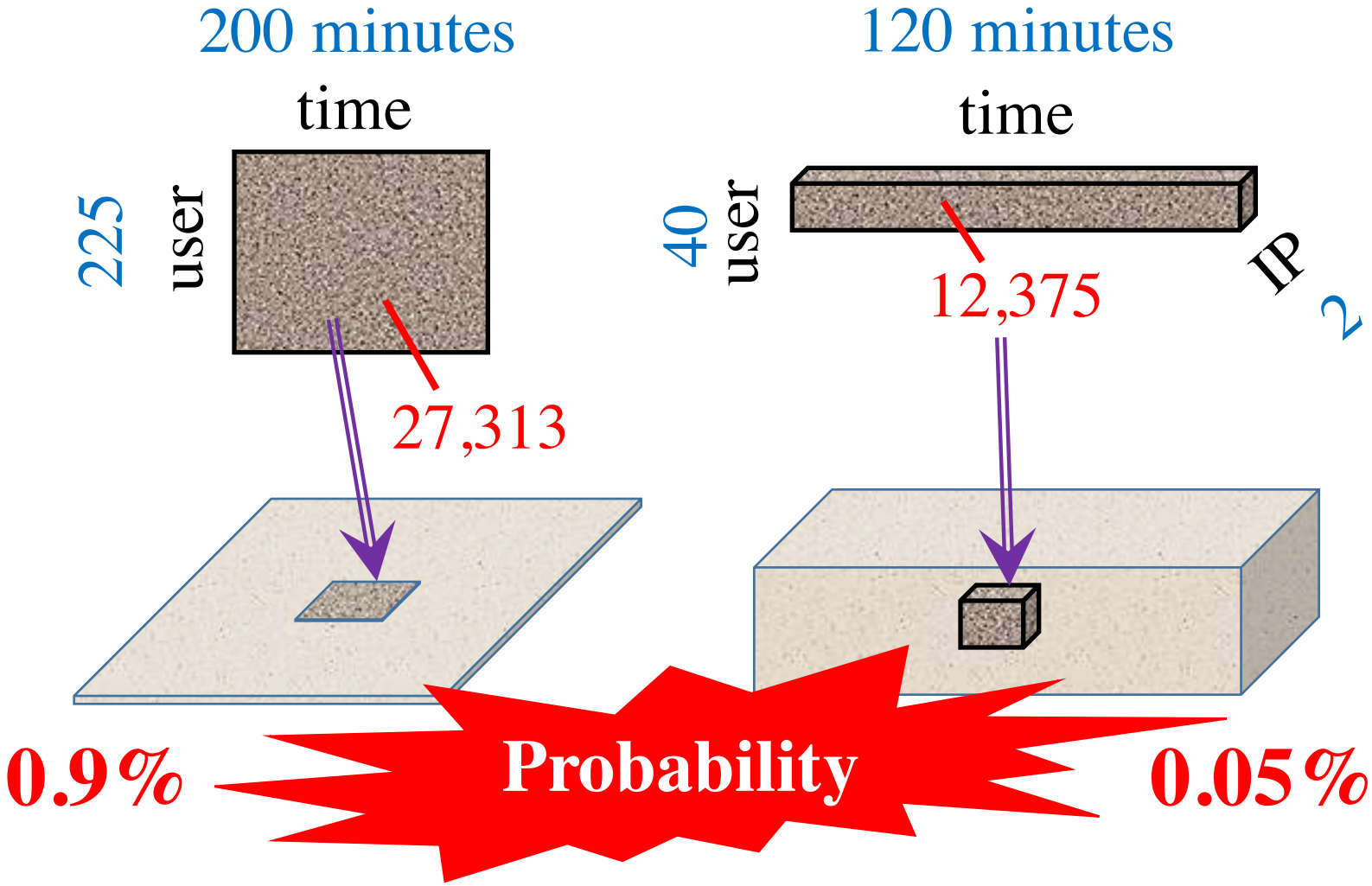
- New information (more modes) can only make our blocks more suspicious

Scoring the Suspiciousness



Q: Which is more suspicious?

Scoring the Suspiciousness



A General Suspiciousness Metric

- Negative log likelihood of block's probability

$$f(n, c, N, C) = -\log\left[Pr(Y_n = c)\right]$$

Lemma *Given an $n_1 \times \cdots \times n_K$ block of mass c in $N_1 \times \cdots \times N_K$ data of total mass C, the suspiciousness function is*

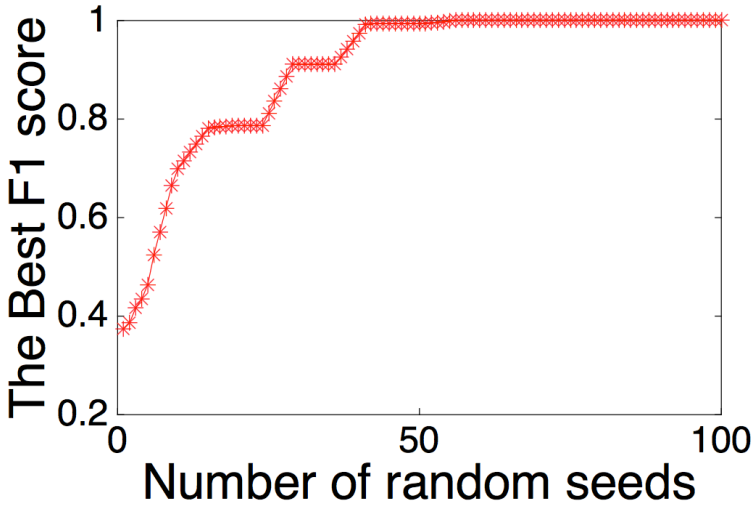
$$f(\mathbf{n}, c, \mathbf{N}, C) = c(\log \frac{c}{C} - 1) + C \prod_{i=1}^{K} \frac{n_i}{N_i} - c \sum_{i=1}^{K} \log \frac{n_i}{N_i}$$

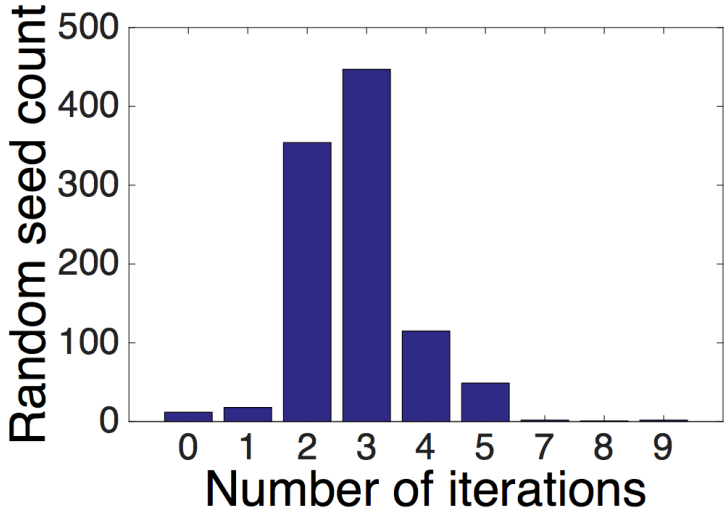
Using ρ as the block's density and p is the data's density, we have the simpler formulation

$$\hat{f}(\mathbf{n}, \rho, \mathbf{N}, p) = \left(\prod_{i=1}^{K} n_i\right) D_{KL}(\rho || p)$$

CrossSpot Algorithm

- Local search to maximize the metric
  - Start with seed blocks
  - Parameter-free: iteratively update the blocks
  - Scalable: parallelize to multiple machines





Advantages

	Method	Scores Blocks	Axioms: Density 1	Size 2	Concentration 3	Contrast 4	Multi-modal 5
Metrics	**SUSPICIOUSNESS**	✔	✔	✔	✔	✔	✔
	Mass	✓	✓	✗	✗	✗	✓
	Density	✓	✓	✗	✓	✗	✗
	Average Degree [9]	✓	✓	✗	✗	✗	N/A
	Singular Value [10]	✓	✓	✓	✓	✗	✗
Methods	**CROSSSPOT**	✔	✔	✔	✔	✔	✔
	Subgraph [30, 10, 36]	✓	✓	✓	✓	✗	N/A
	CopyCatch [6]	✓	✓	✓	✓	✗	N/A
	EigenSpokes [31]	✗	N/A				
	TrustRank [14, 8]	✗	N/A				
	BP [28, 1]	✗	N/A				

Results: Dense Block Detection

- Synthetic data
  - 1,000×1,000×1,000 of 10,000 random data
  - Block#1: 30×30×30 of 512 3 modes
  - Block#2: 30×30×1,000 of 512 2 modes
  - Block#3: 30×1,000×30 of 512 2 modes
  - Block#4: 1,000×30×30 of 512 2 modes

	Recall				Overall Evaluation		
	Block #1	Block #2	Block #3	Block #4	Precision	Recall	F1 score
HOSVD (r=20)	93.7%	29.5%	23.7%	21.3%	**0.983**	0.407	0.576
HOSVD (r=10)	91.3%	24.4%	18.5%	19.2%	0.972	0.317	0.478
HOSVD (r=5)	85.7%	10.0%	9.5%	11.4%	0.952	0.195	0.324
CrossSpot	**100%**	**99.9%**	**94.9%**	**95.4%**	0.978	**0.967**	**0.972**

Results: Tweeting Hashtags

User × hashtag × IP × minute	Mass c	Suspiciousness
582 × 3 × 294 × **56,940**	5,941,821	111,799,948
188 × 1 × 313 × **56,943**	2,344,614	47,013,868
75 × 1 × 2 × 2,061	689,179	19,378,403

User ID	Time	IP address (city, province)	Tweet text with hashtag
USER-D	11-18 12:12:51	IP-1 (Deyang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-E	11-18 12:12:53	IP-1 (Deyang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-F	11-18 12:12:54	IP-2 (Zaozhuang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-E	11-18 12:17:55	IP-1 (Deyang, Shandong)	**#Li Ning - a weapon with a hero#** good support activities!
USER-F	11-18 12:17:56	IP-2 (Zaozhuang, Shandong)	**#Li Ning - a weapon with a hero#** good support activities!
USER-D	11-18 12:18:40	IP-1 (Deyang, Shandong)	**#Toshiba Bright Daren#** color personality test to find out your sense...
USER-E	11-18 17:00:31	IP-2 (Zaozhuang, Shandong)	**#Snow#** the Samsung GALAXY SII QQ Service customized version...
USER-D	11-18 17:00:49	IP-2 (Zaozhuang, Shandong)	**#Toshiba Bright Daren#** color personality test to find out your sense...
USER-F	11-18 17:00:56	IP-2 (Zaozhuang, Shandong)	**#Li Ning - a weapon with a hero#** good support activities!

Results: Network Attacks

	#	Src-IP × dst-IP × port × second	Mass c	Suspiciousness
CROSSSPOT	1	411 × 9 × 6 × **3,610**	47,449	552,465
	2	533 × 6 × 1 × **3,610**	30,476	400,391
	3	5 × 5 × 2 × **3,610**	18,881	317,529
	4	11 × 7 × 7 × **3,610**	20,382	295,869
HOSVD	1	15 × 1 × 1 × 1,336	4,579	80,585
	2	1 × 2 × 2 × 1,035	1,035	18,308
	3	1 × 1 × 1 × 1,825	1,825	34,812
	4	1 × 13 × 6 × 181	1,722	29,224

Summary

- Ill-gotten Facebook Likes, Zombie Followers
- **Observations, Representations, Models**
  - **CopyCatch:** Catching ill-gotten Likes by core search
  - **LockInfer:** Adding seed selection before search
  - **CatchSync:** Catching smart zombie followers with high recall (recovering power-law distributions)
  - **CrossSpot:** Defining suspiciousness across dimensions

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Thank you!

Data-Driven Behavioral Analytics:
Observations, Representations and Models