Anomaly detection in large graphs

Christos Faloutsos

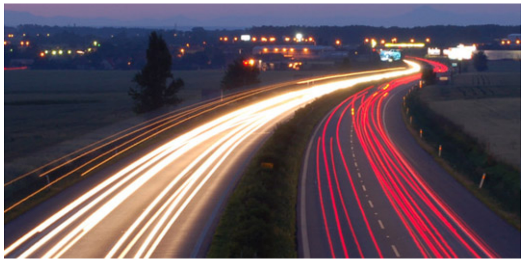
CMU

Thank you!

- Annette Jiang

- Evan Butterfield
- Tina Huang

Roadmap

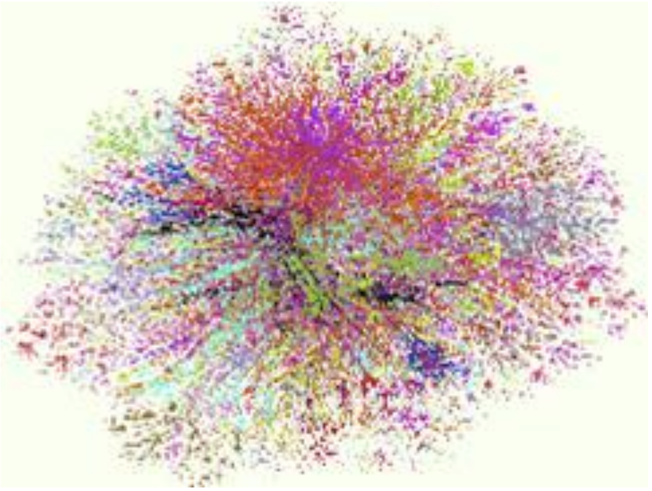


➡
- Introduction – Motivation
  - Why study (big) graphs?
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
- Conclusions

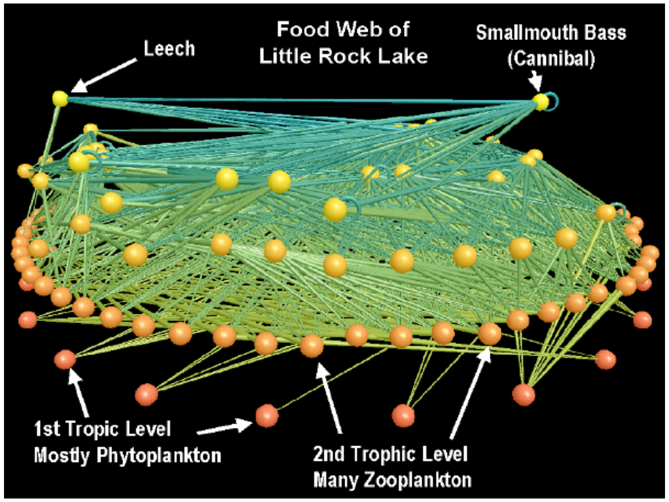
Graphs - why should we care?

>$10B; ~1B users

Graphs - why should we care?



Internet Map
[lumeta.com]



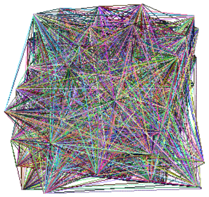
Food Web
[Martinez '91]

Graphs - why should we care?

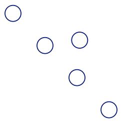
- web-log (‘blog’) news propagation YAHOO! BLOG
- computer network security: email/IP traffic and anomaly detection
- Recommendation systems NETFLIX
- ....

- Many-to-many db relationship -> graph

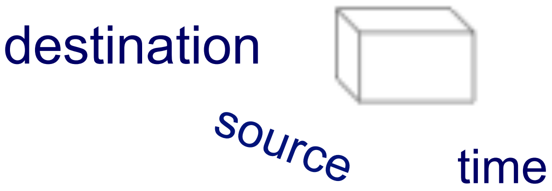
Motivating problems



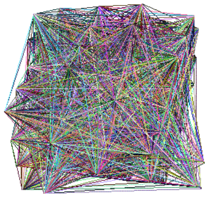
- P1: patterns? Fraud detection?



- P2: patterns in time-evolving graphs / tensors



Motivating problems



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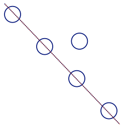
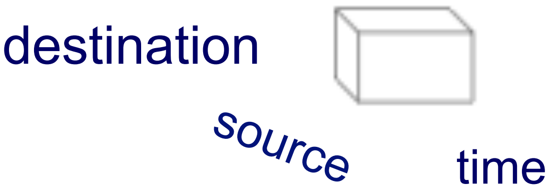


Patterns

anomalies

- P2: patterns in time-evolving graphs / tensors



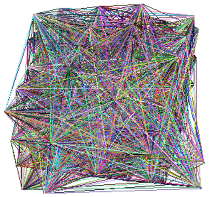
destination

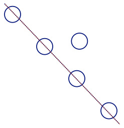
source

time

Motivating problems

- P1: patterns? Fraud detection?

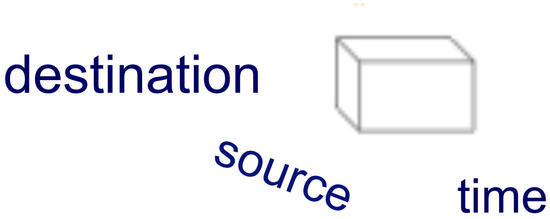




Patterns

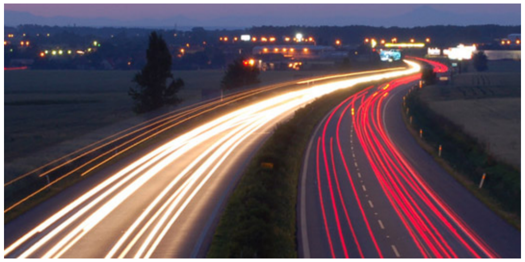
anomalies*

- P2: patterns in time-evolving graphs / tensors

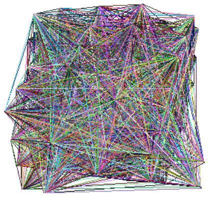


* *Robust Random Cut Forest Based Anomaly Detection on Streams* Sudipto Guha, Nina Mishra , Gourav Roy, Okke Schrijvers, ICML’16

Roadmap

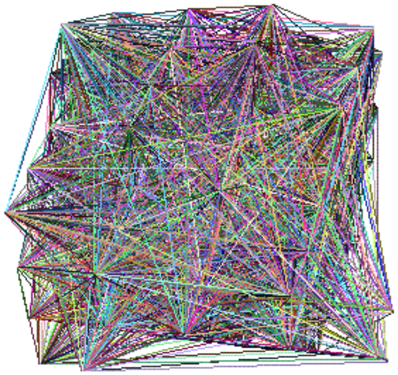


- Introduction – Motivation
  - Why study (big) graphs?
- ➡ Part#1: Patterns & fraud detection
- Part#2: time-evolving graphs; tensors
- Conclusions



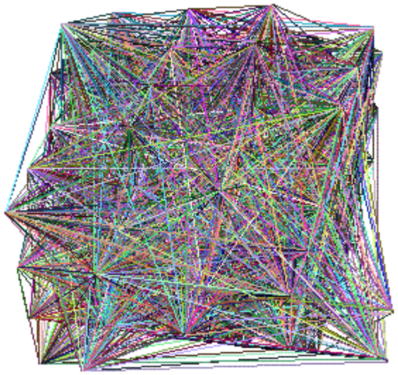
Part 1: Patterns, & fraud detection

Laws and patterns

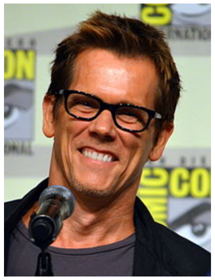


- Q1: Are real graphs random?

Laws and patterns



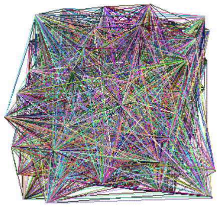
- Q1: Are real graphs random?
- A1: NO!!
  - Diameter ('6 degrees'; 'Kevin Bacon')
  - in- and out- degree distributions
  - other (surprising) patterns
- So, let's look at the data

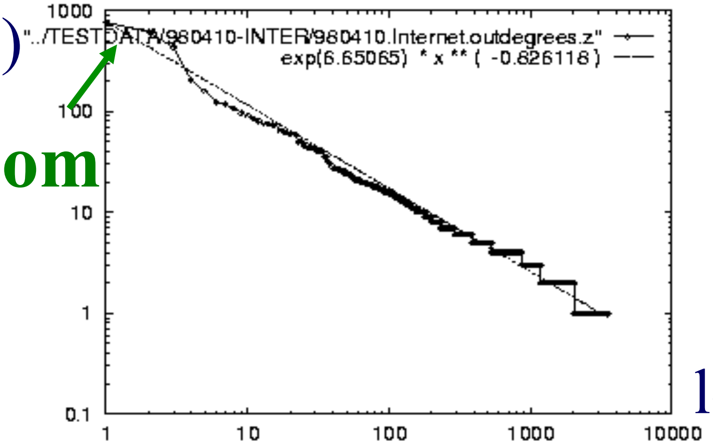


Solution# S.1

- Power law in the degree distribution [Faloutsos x 3 SIGCOMM99]

internet domains




1000
100
10
1
0.1
1
10
100
1000
10000
"../TESTDATA/980410-INTER/980410.Internet.outdegrees.z"
exp(6.65065) * x ** (-0.626118)

att.com

log(degree)

ibm.com

log(rank)

Carnegie Mellon

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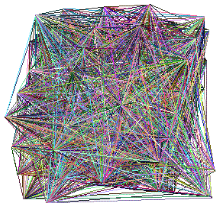
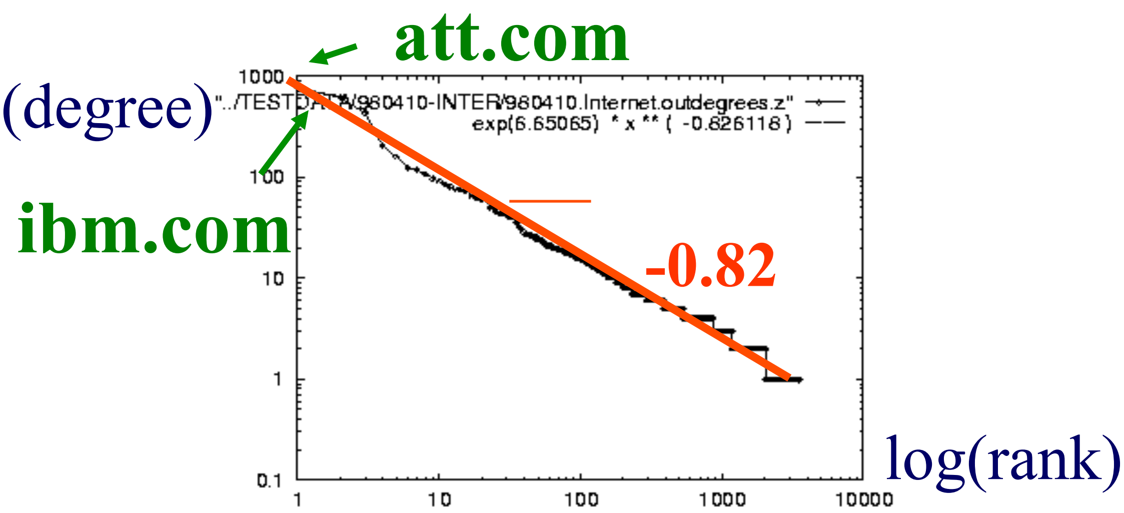
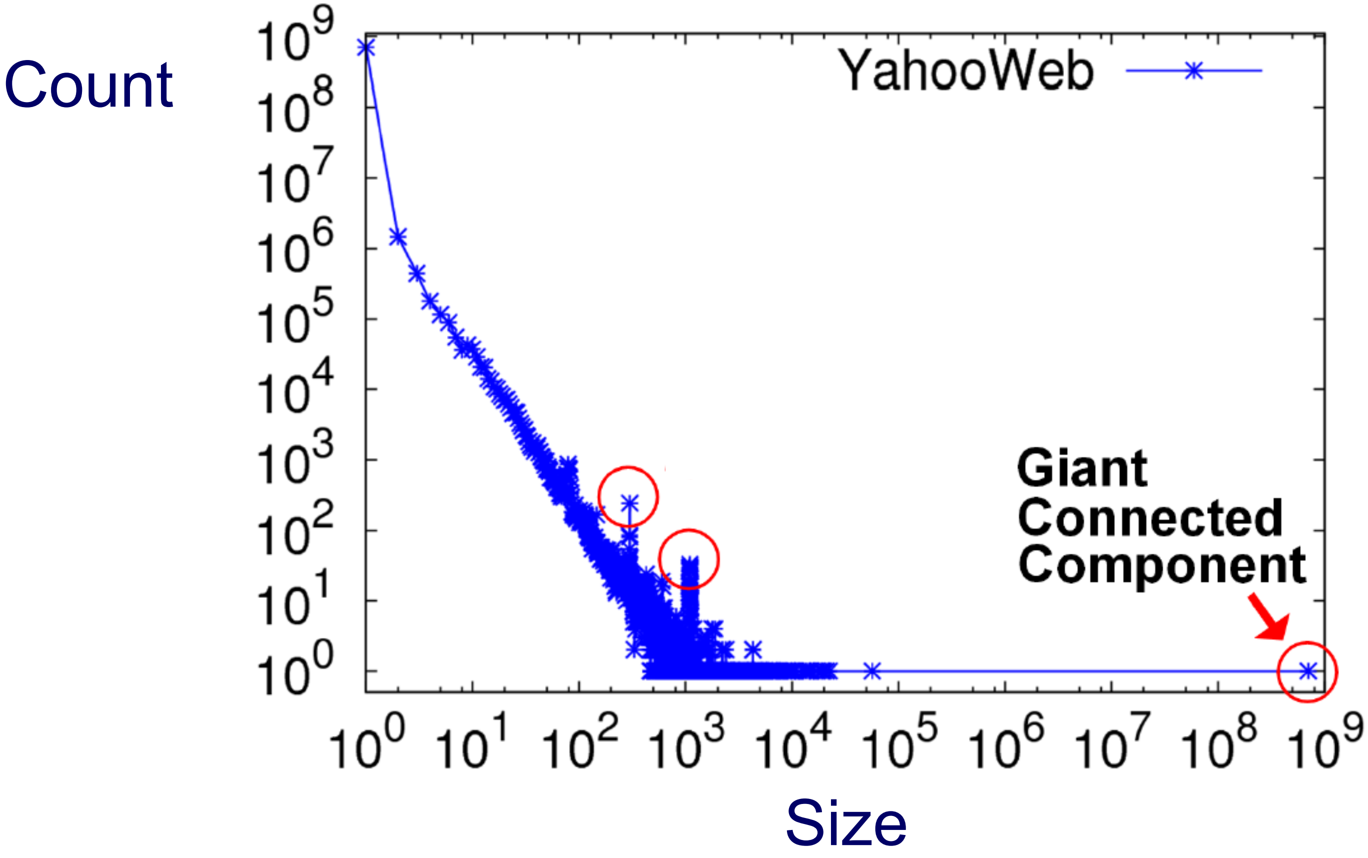



att.com
log(degree)
ibm.com
-0.82
log(rank)
"../TESTDATA/980410-INTER/980410.Internet.outdegrees.z"
exp(6.65065) * x ** (-0.826118)
1000
100
10
1
0.1
1
10
100
1000
10000

S2: connected component sizes

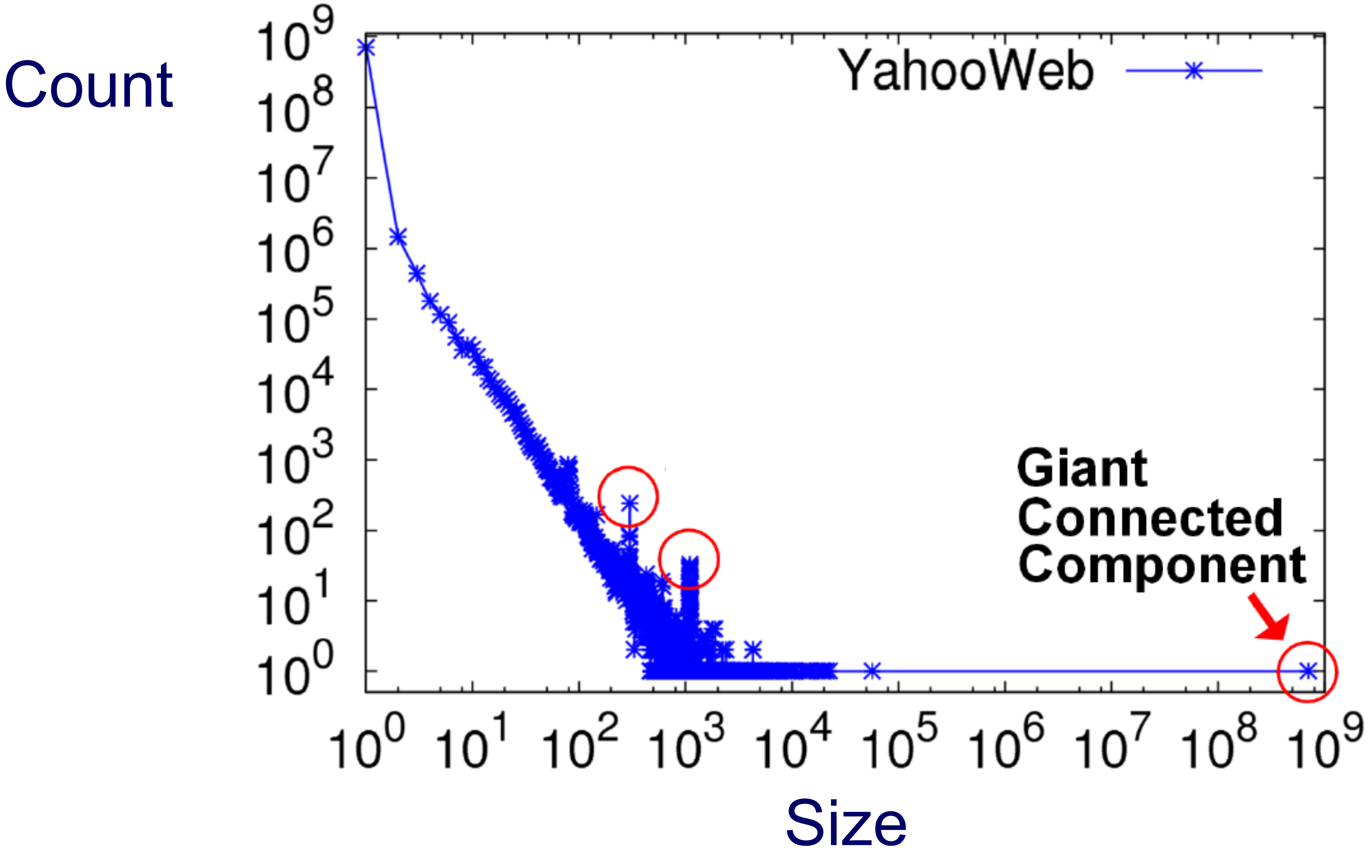
- Connected Components – 4 observations:



1.4B nodes
6B edges

S2: connected component sizes

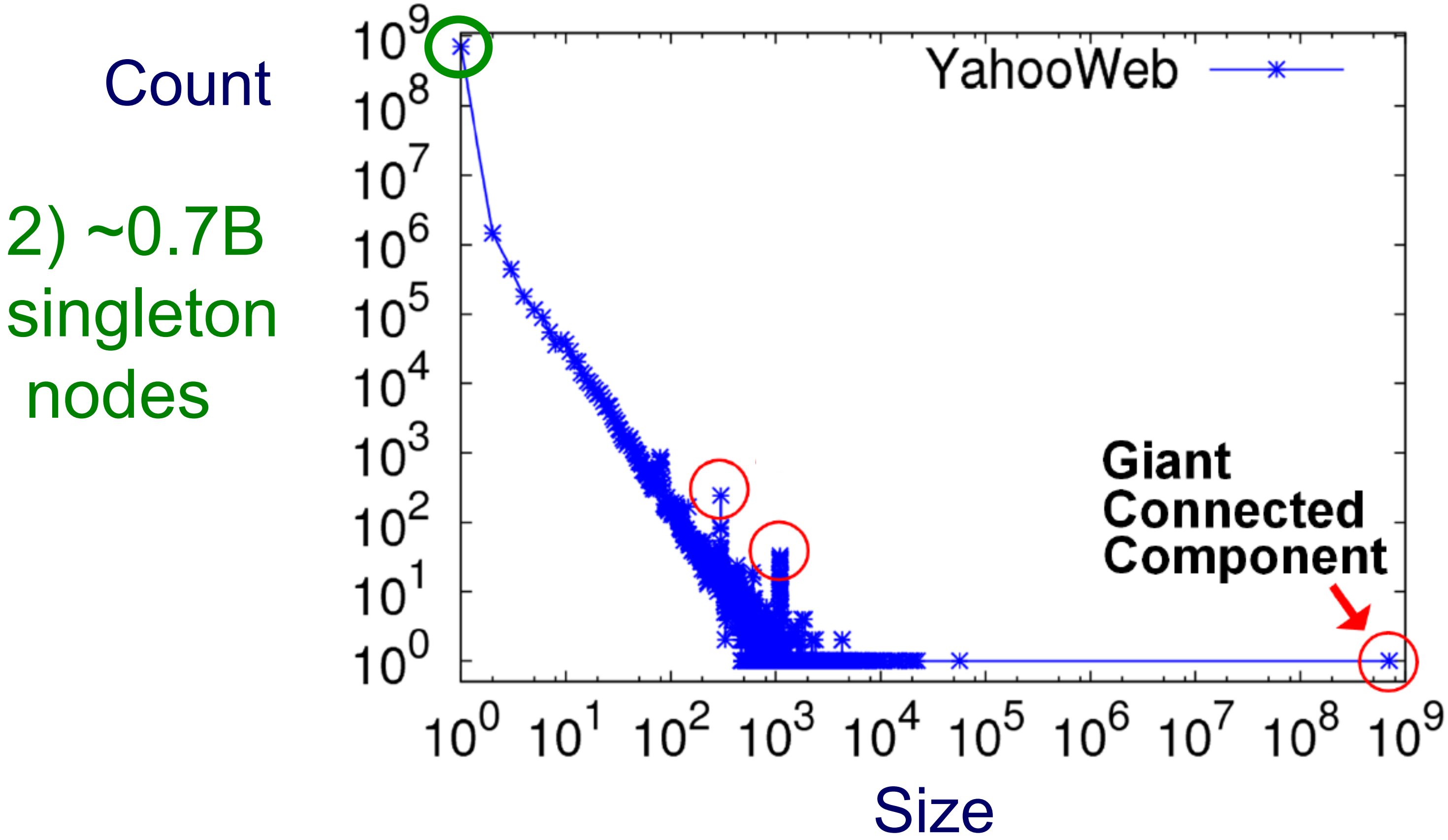
- Connected Components



1) 10K x larger than next

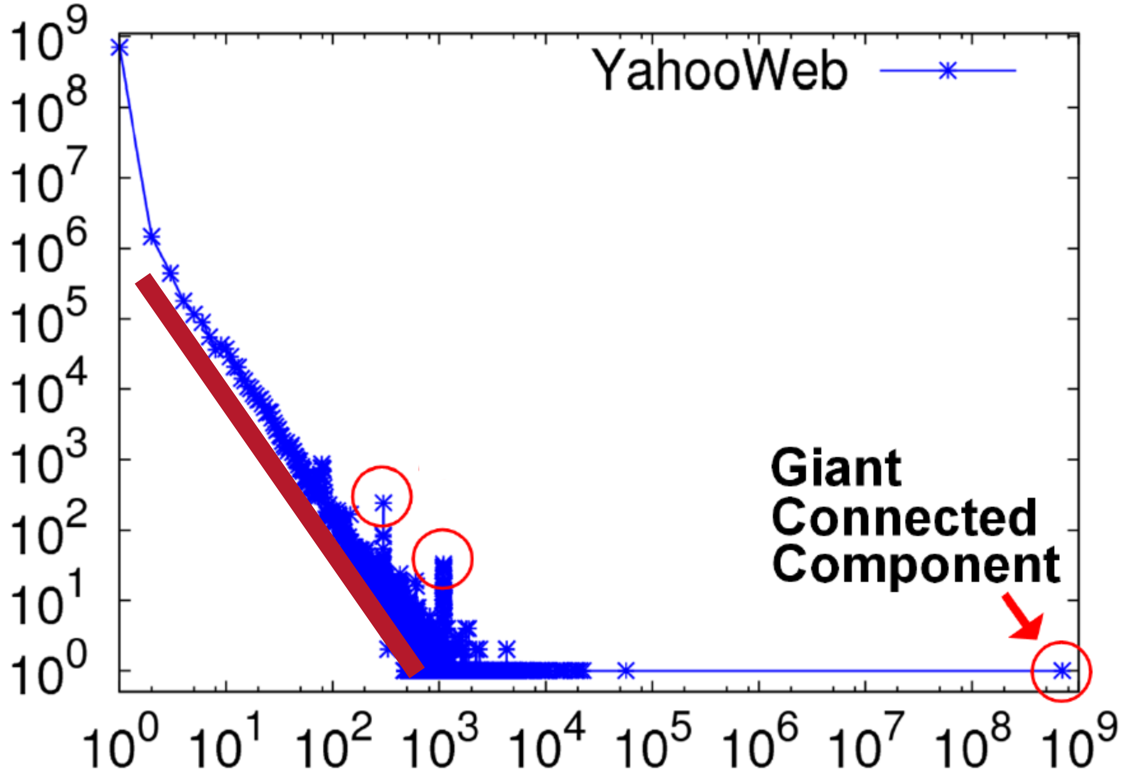
S2: connected component sizes

- Connected Components



S2: connected component sizes

- Connected Components



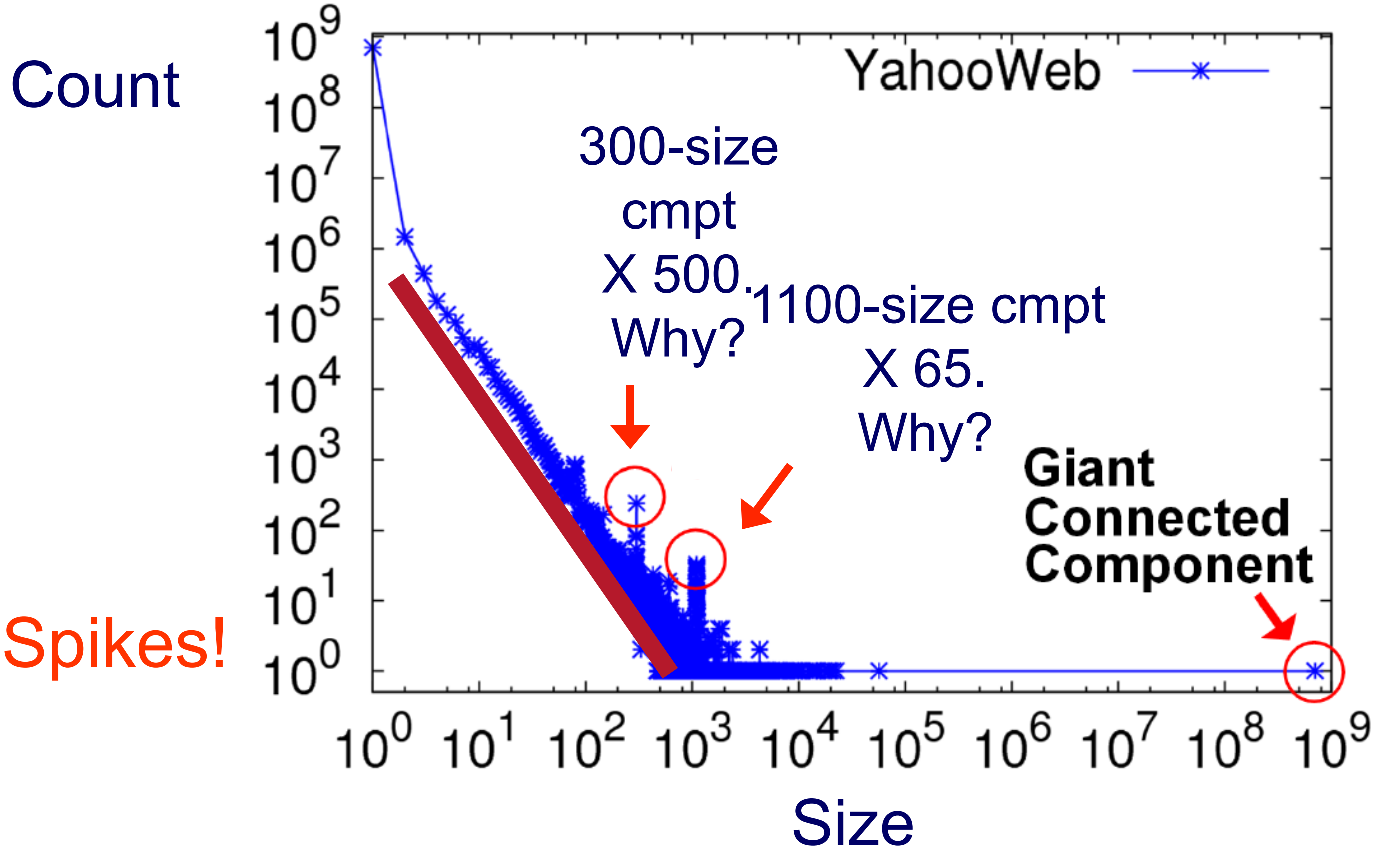
Count

3) SLOPE!

Size

S2: connected component sizes

- Connected Components



300-size cmpt X 500. Why?

1100-size cmpt X 65. Why?

Giant Connected Component

4) Spikes!

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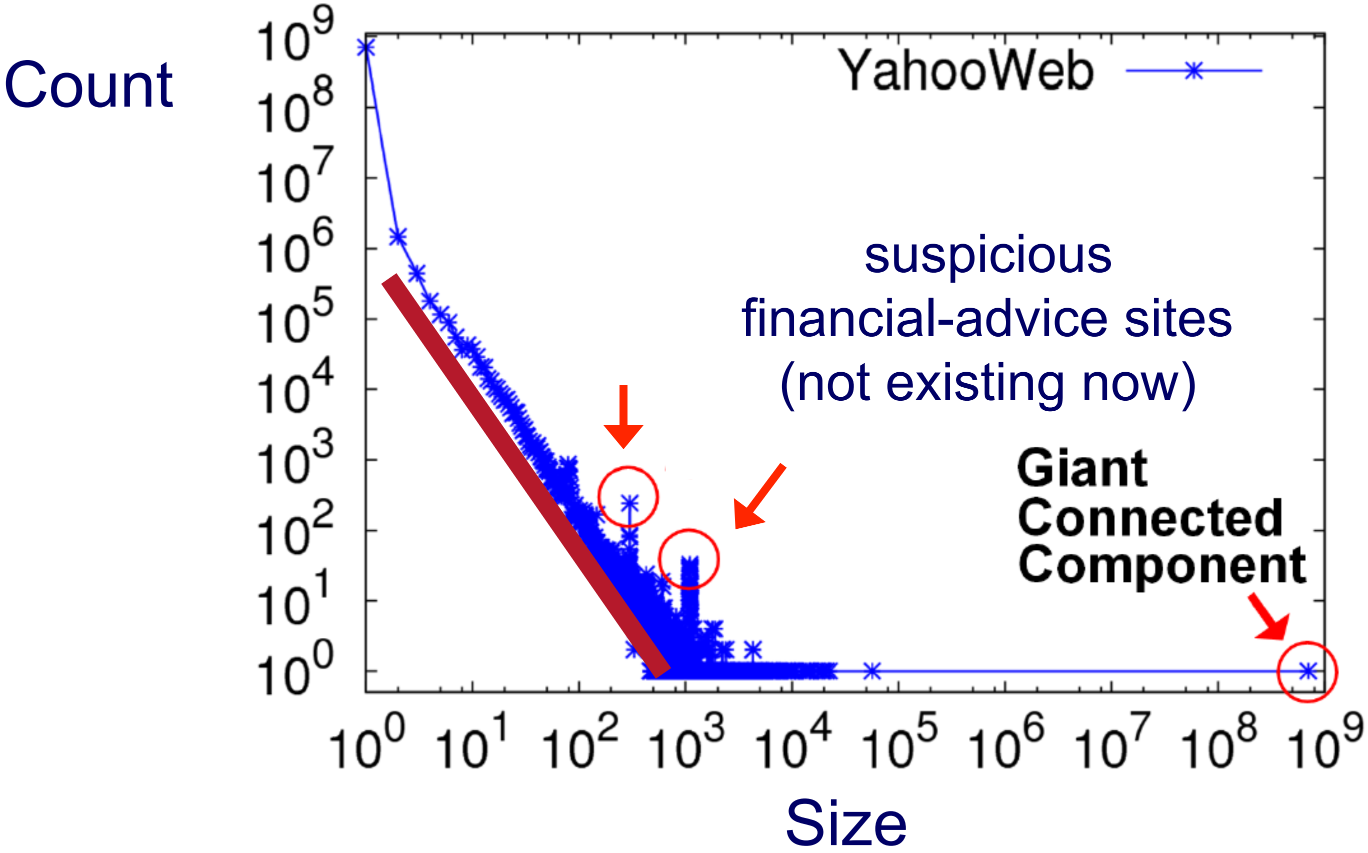
S2: connected component sizes

- Connected Components

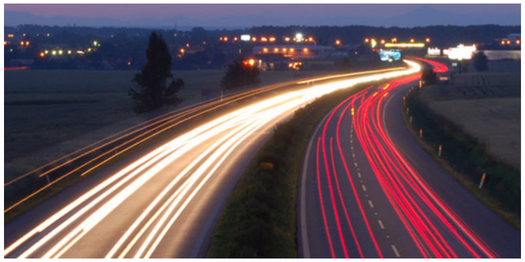


suspicious financial-advice sites (not existing now)

Giant Connected Component

(c) C. Faloutsos, 2017

Roadmap



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- Part#1: Patterns in graphs
  - ➡ P1.1: Patterns: Degree; Triangles
  - P1.2: Anomaly/fraud detection
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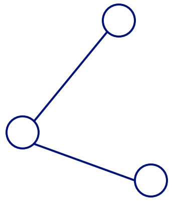
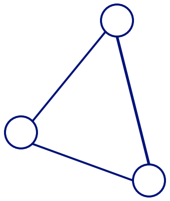
Solution# S.3: Triangle 'Laws'

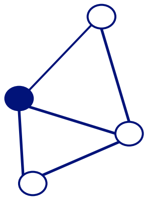


- Real social networks have a lot of triangles

Solution# S.3: Triangle 'Laws'

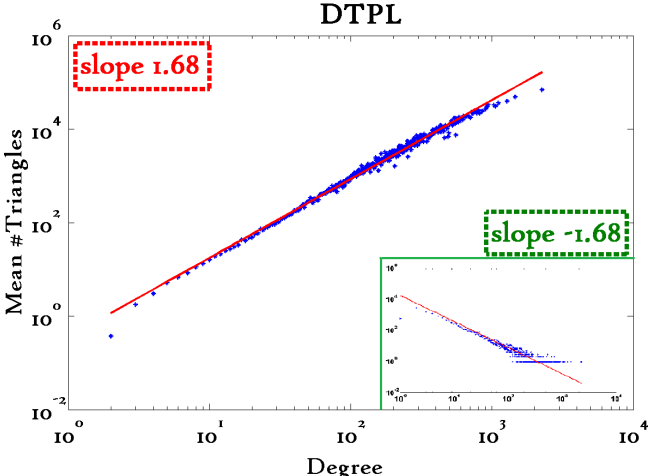


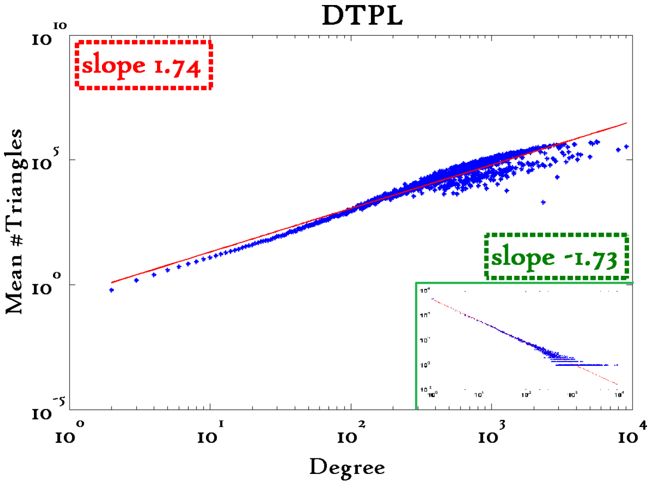
- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?
  - 2x the friends, 2x the triangles ?



Triangle Law: #S.3 [Tsourakakis ICDM 2008]

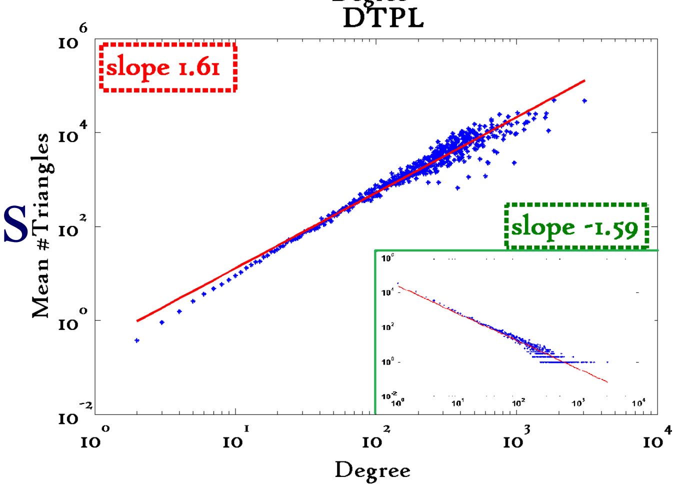
Reuters

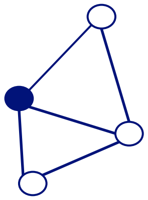




SN

Epinions



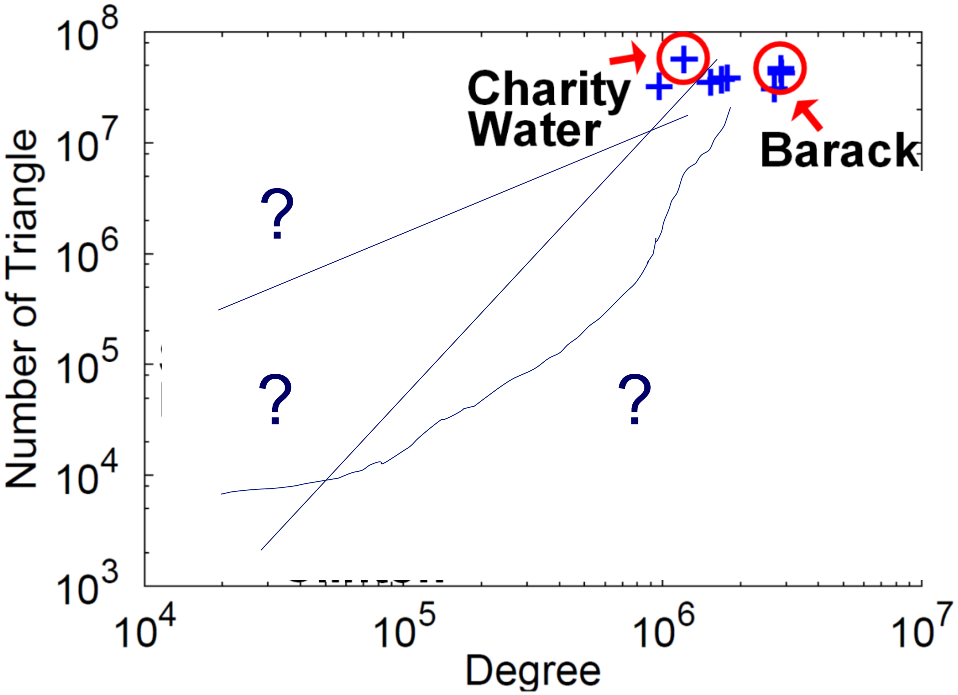


X-axis: degree

Y-axis: mean # triangles

n friends -> ~$n^{1.6}$ triangles

Triangle counting for large graphs?



Anomalous nodes in Twitter(~ 3 billion edges)

[U Kang, Brendan Meeder, +, PAKDD'11]

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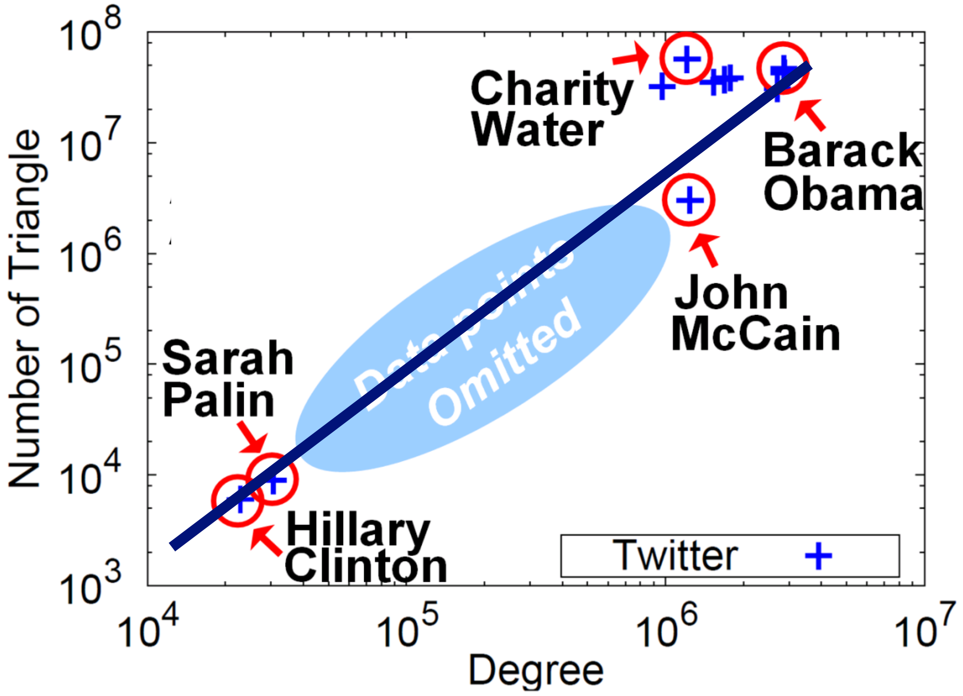

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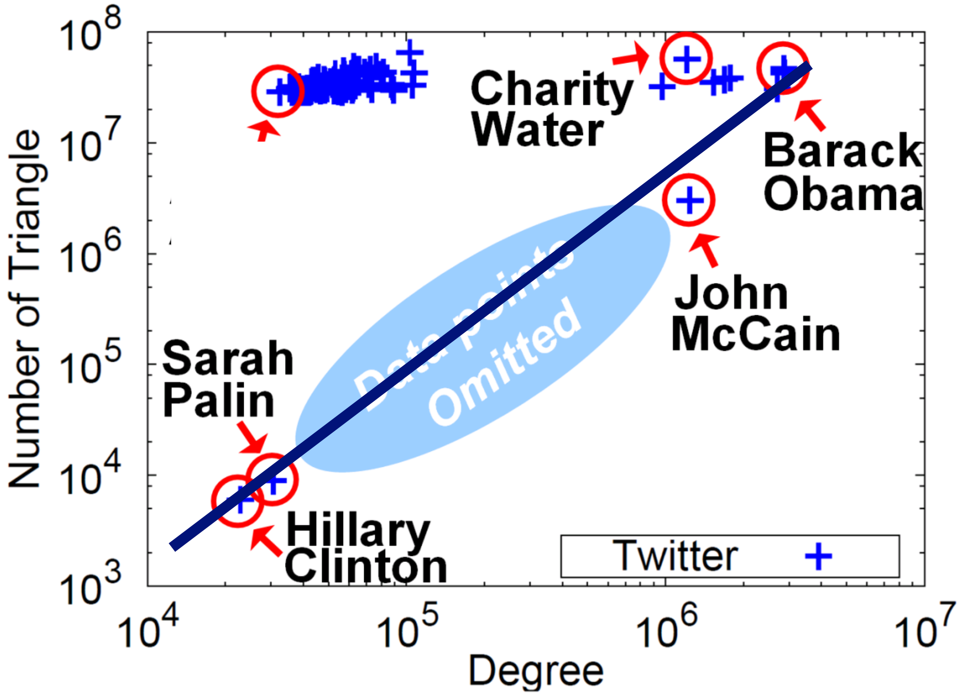

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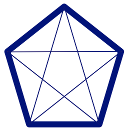

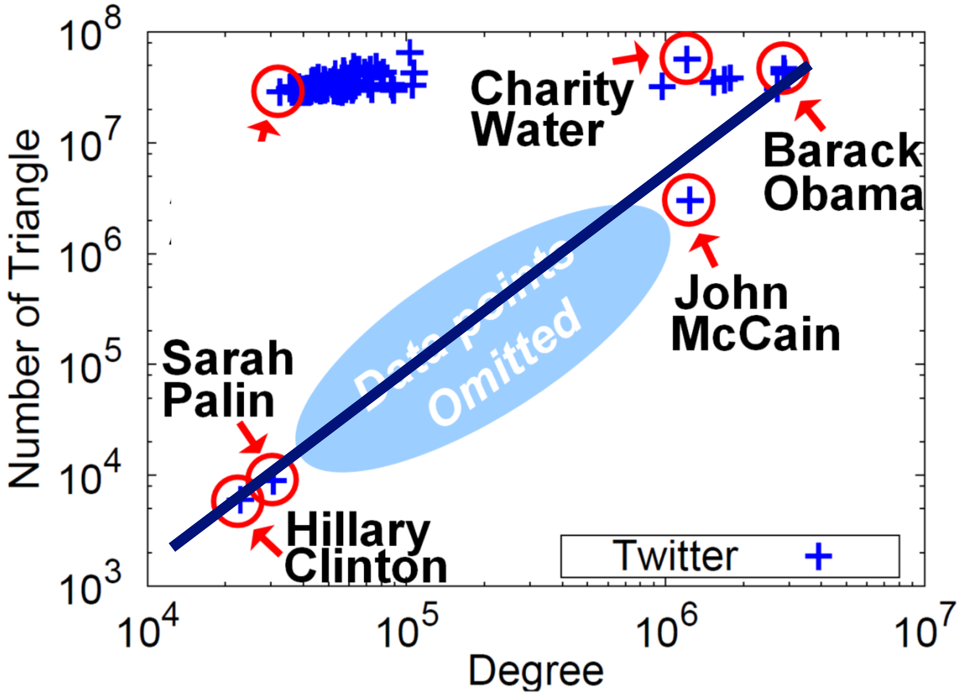

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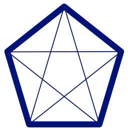

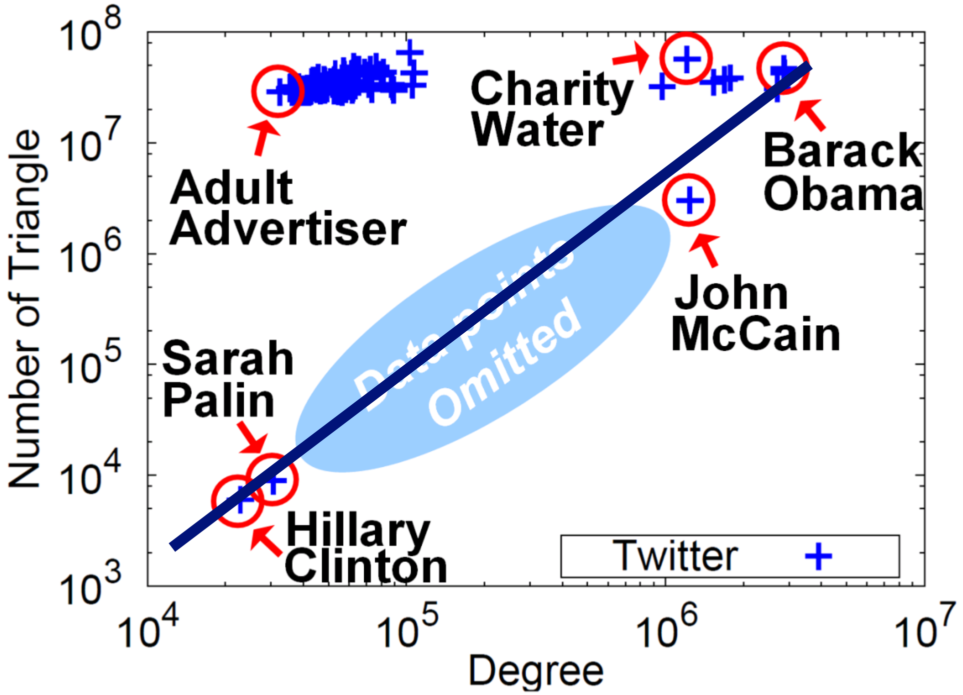

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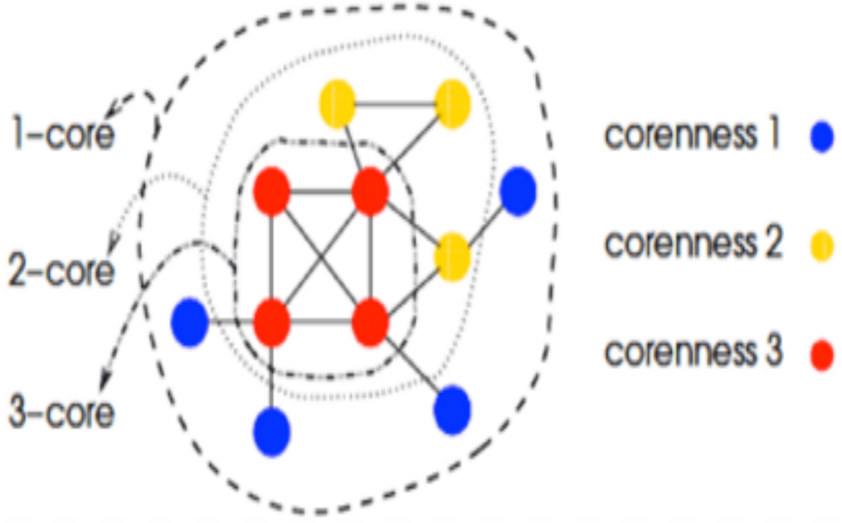
[U Kang, Brendan Meeder, +, PAKDD’11]

S4: k-core patterns - dfn

- **k-core** (of a graph)
- **degeneracy** (of a graph)
- **coreness** (of a vertex)



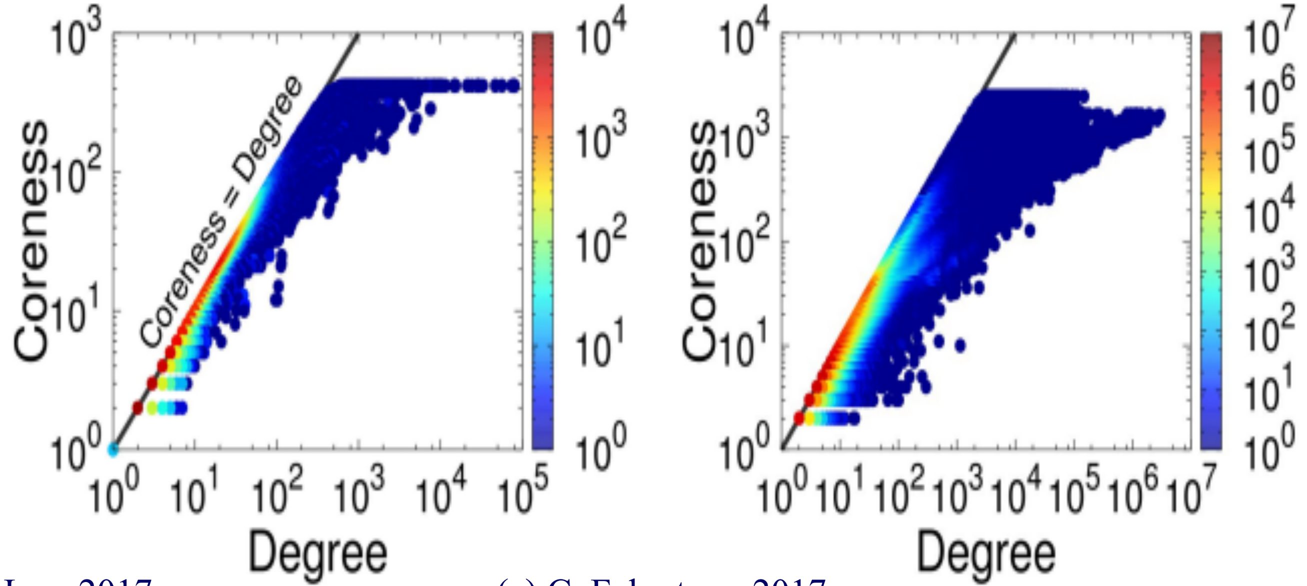
CoreScope: Graph Mining Using k-Core Analysis - Patterns, Anomalies, and Algorithms

ICDM'16 (to appear)

Kijung Shin, Tina Eliassi-Rad and CF

Mirror Pattern: Observation

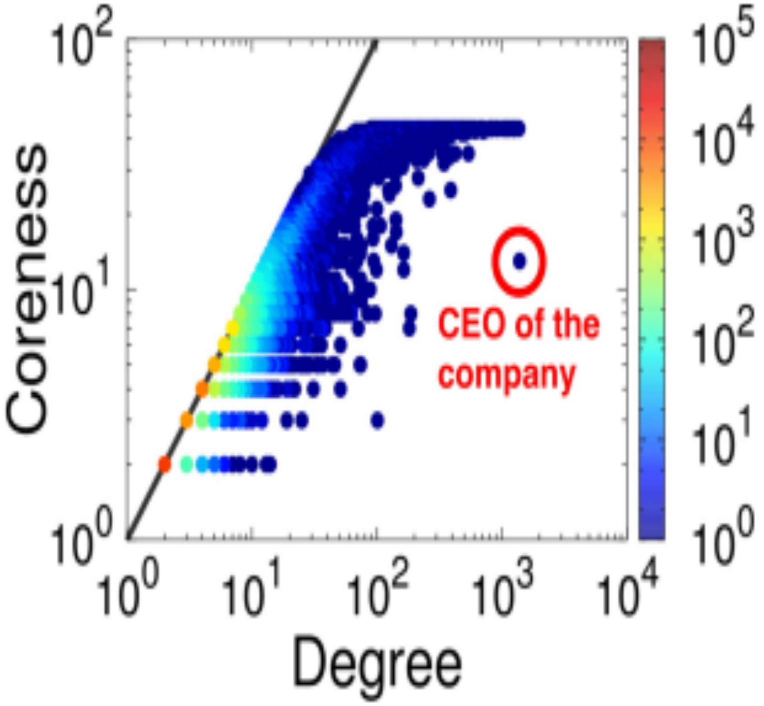
- **coreness** (of a vertex): maximum k such that the vertex belongs to the k-core
- Definition: **[Mirror Pattern]** *degree ~ coreness*



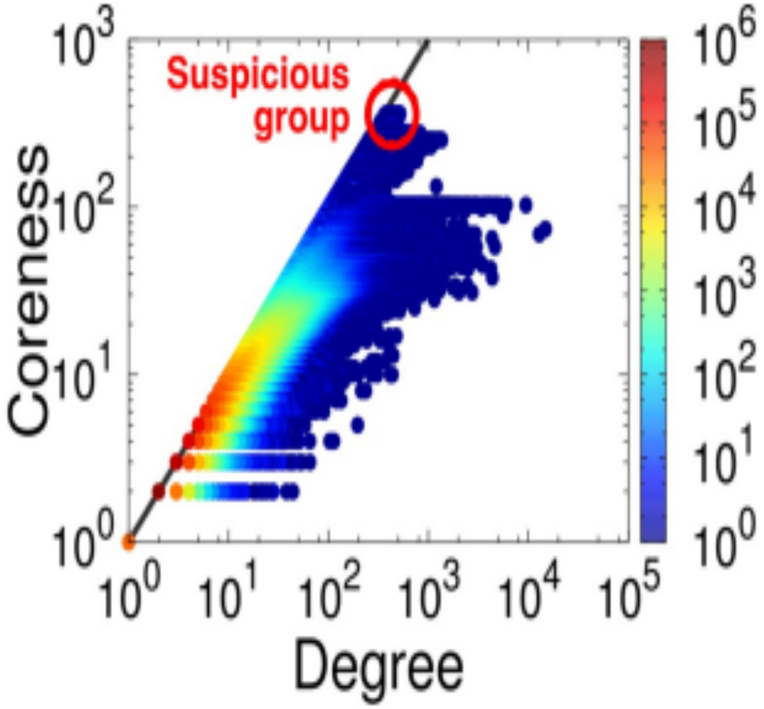
Rank correlation $\rho = 0.99$

Mirror Pattern: Application

- Exceptions are ‘strange’



Email ($\rho = 0.98$)



LiveJournal ($\rho = 0.99$)

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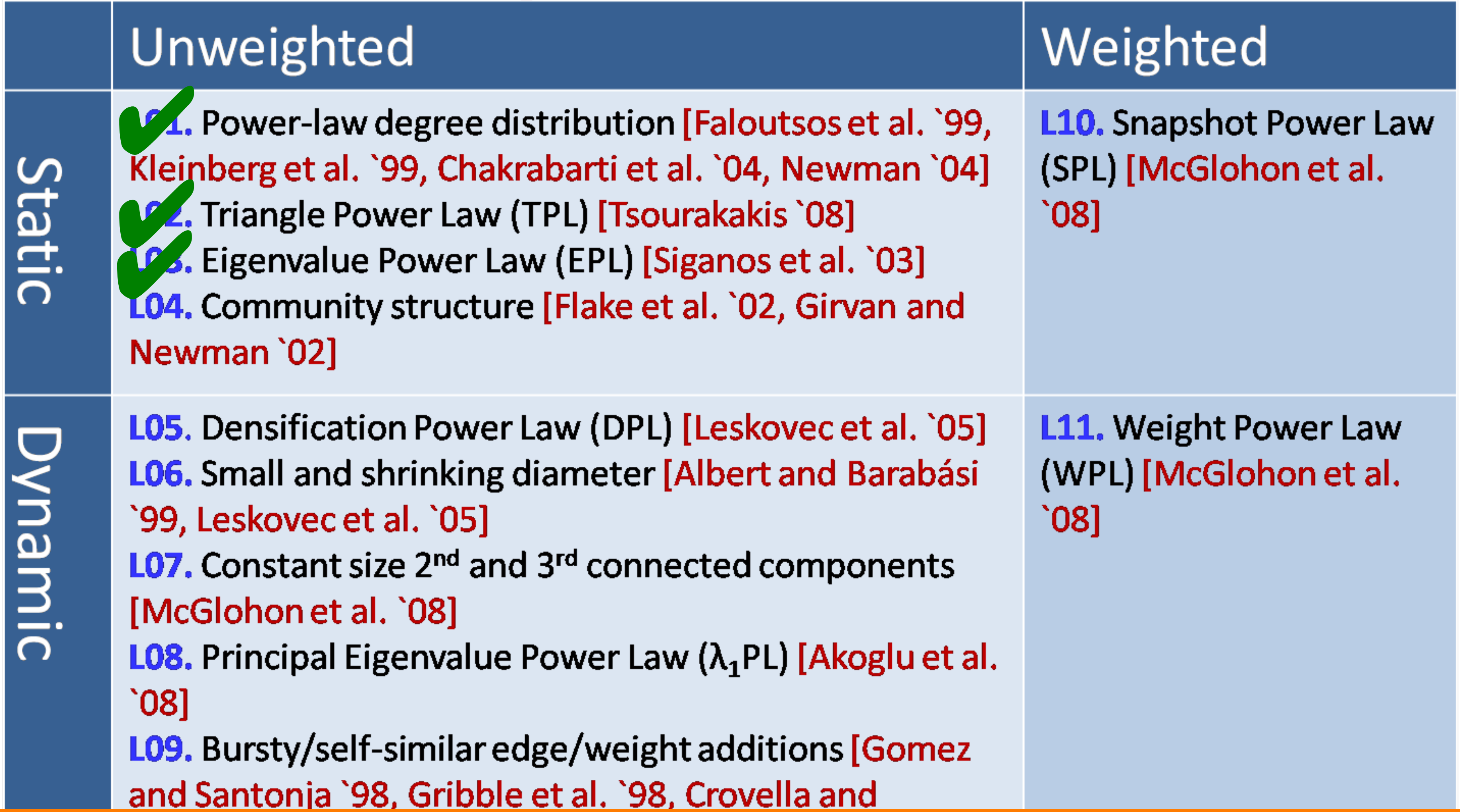
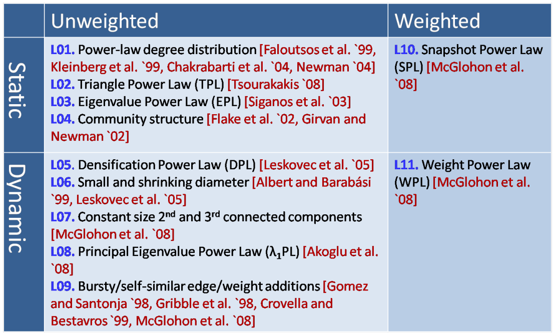
MORE Graph Patterns



	Unweighted	Weighted
Static	✓ L01. Power-law degree distribution [Faloutsos et al. `99, Kleinberg et al. `99, Chakrabarti et al. `04, Newman `04] ✓ L02. Triangle Power Law (TPL) [Tsourakakis `08] ✓ L03. Eigenvalue Power Law (EPL) [Siganos et al. `03] L04. Community structure [Flake et al. `02, Girvan and Newman `02]	L10. Snapshot Power Law (SPL) [McGlohon et al. `08]
Dynamic	L05. Densification Power Law (DPL) [Leskovec et al. `05] L06. Small and shrinking diameter [Albert and Barabási `99, Leskovec et al. `05] L07. Constant size 2nd and 3rd connected components [McGlohon et al. `08] L08. Principal Eigenvalue Power Law (λ_1PL) [Akoglu et al. `08] L09. Bursty/self-similar edge/weight additions [Gomez and Santonja `98, Gribble et al. `98, Crovella and	L11. Weight Power Law (WPL) [McGlohon et al. `08]

RTG: A Recursive Realistic Graph Generator using Random Typing Leman Akoglu and Christos Faloutsos. *PKDD*’09.

MORE Graph Patterns



	Unweighted	Weighted
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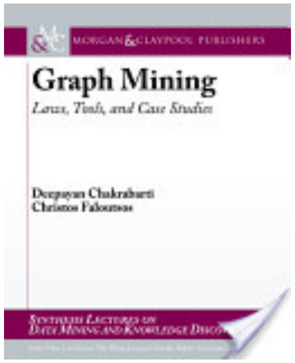
- Mary McGlohon, Leman Akoglu, Christos Faloutsos. *Statistical Properties of Social Networks.* in "Social Network Data Analytics” (Ed.: Charu Aggarwal)

- Deepayan Chakrabarti and Christos Faloutsos, *Graph Mining: Laws, Tools, and Case Studies* Oct. 2012, Morgan Claypool.



MORGAN & CLAYPOOL PUBLISHERS

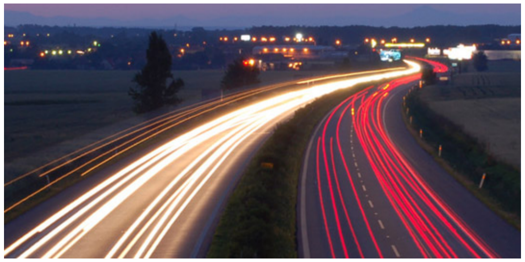
Graph Mining

Laws, Tools, and Case Studies

Deepayan Chakrabarti
Christos Faloutsos

Synthesis Lectures on Data Mining and Knowledge Discovery

Roadmap



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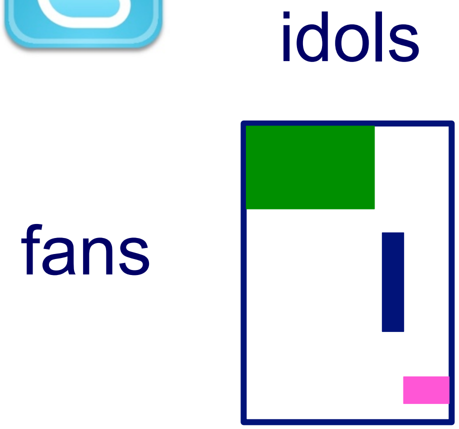
  - P1.1: Patterns
  - P1.2: Anomaly / fraud detection
    - No labels – spectral
    - With labels: Belief Propagation
- Part#2: time-evolving graphs; tensors
- Conclusions

Patterns

anomalies

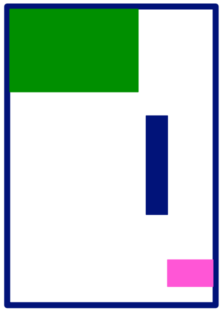
How to find ‘suspicious’ groups?

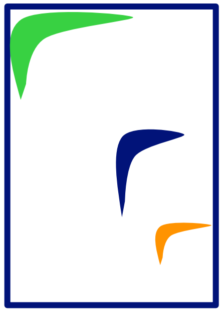
- ‘blocks’ are normal, right?



Except that:

- ‘blocks’ are normal, right?
- ‘hyperbolic’ communities are more realistic [Araujo+, PKDD’14]

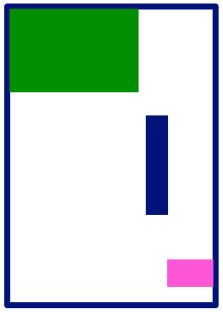


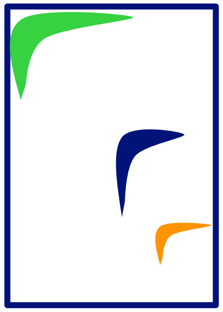


Except that:

- ‘blocks’ are usually suspicious
- ‘hyperbolic’ communities are more realistic [Araujo+, PKDD’14]

Q: Can we spot blocks, easily?



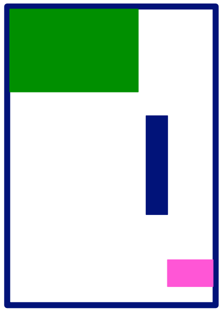


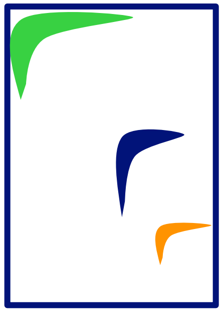
Except that:

- ‘blocks’ are usually suspicious
- ‘hyperbolic’ communities are more realistic [Araujo+, PKDD’14]

Q: Can we spot blocks, easily?

A: Silver bullet: SVD!

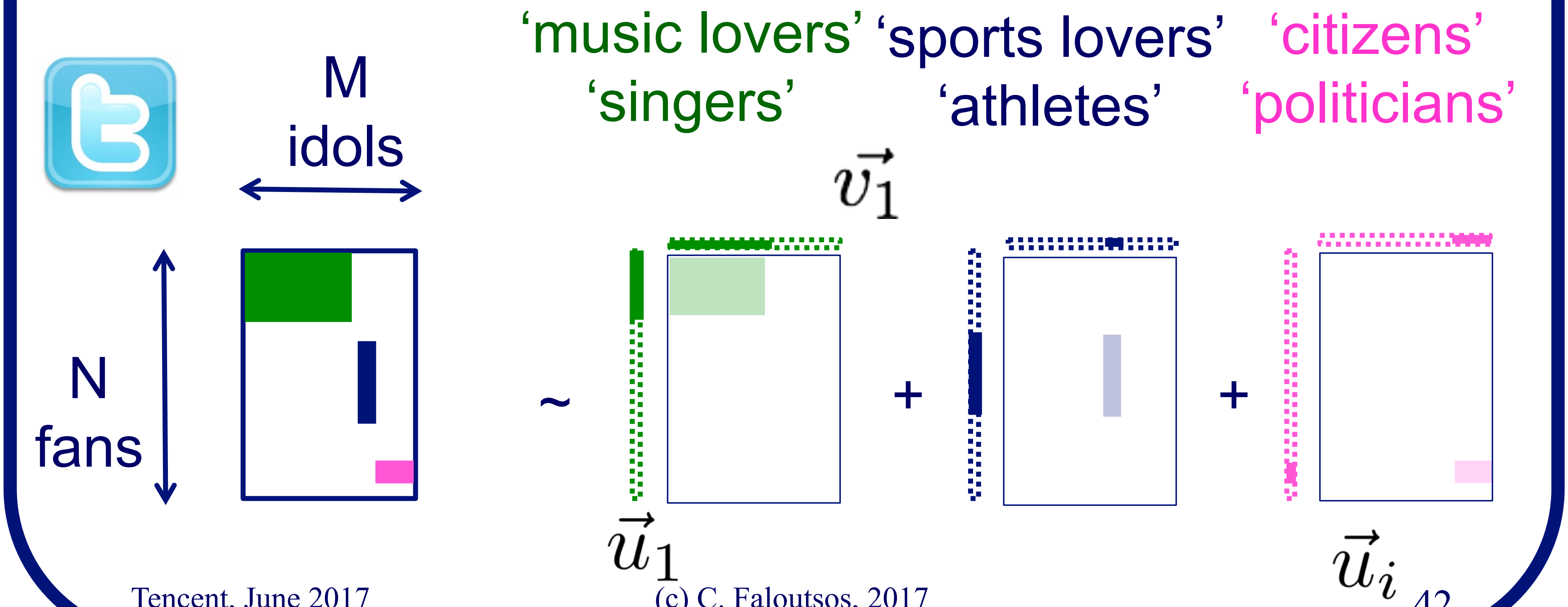




DETAILS

Crush intro to SVD

- Recall: (SVD) matrix factorization: finds blocks



DETAILS

Crush intro to SVD

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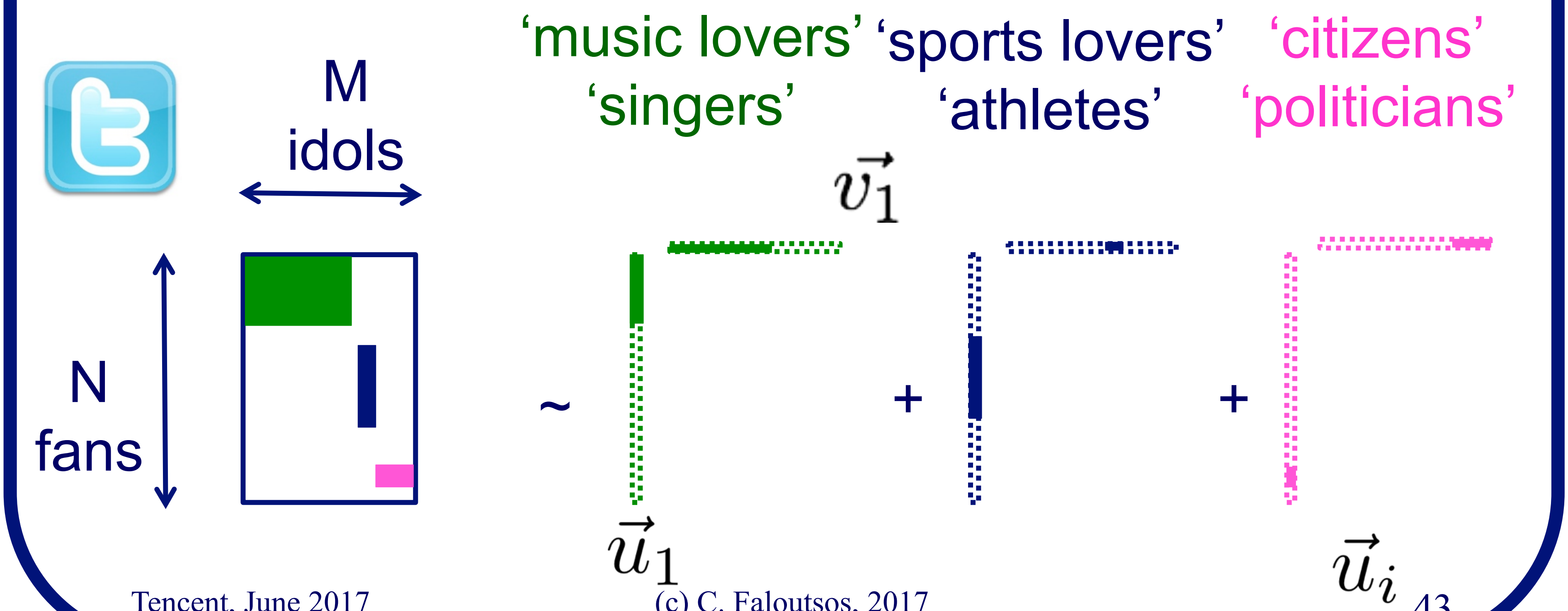


Carnegie Mellon

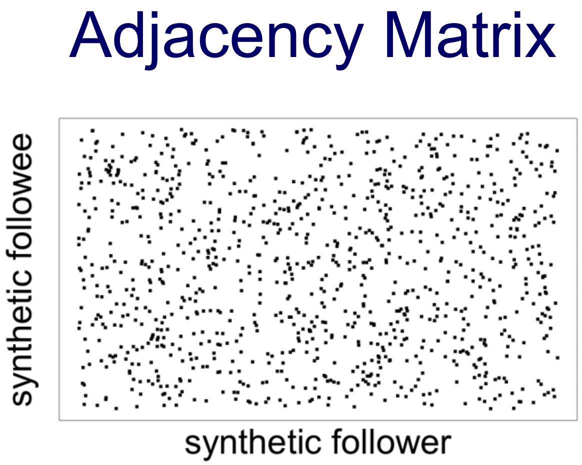
Inferring Strange Behavior from Connectivity Pattern in Social Networks
PAKDD'14

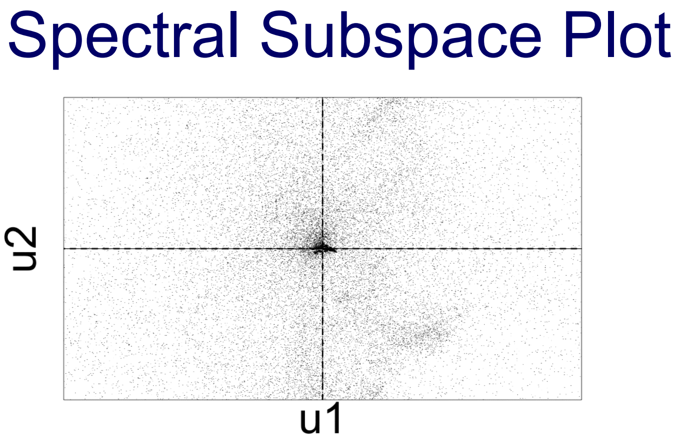
Meng Jiang, Peng Cui, Shiqiang Yang (Tsinghua)

Alex Beutel, Christos Faloutsos (CMU)

Lockstep and *Spectral Subspace Plot*

- Case #0: No lockstep behavior in random power law graph of 1M nodes, 3M edges
- Random ↔ “Scatter”

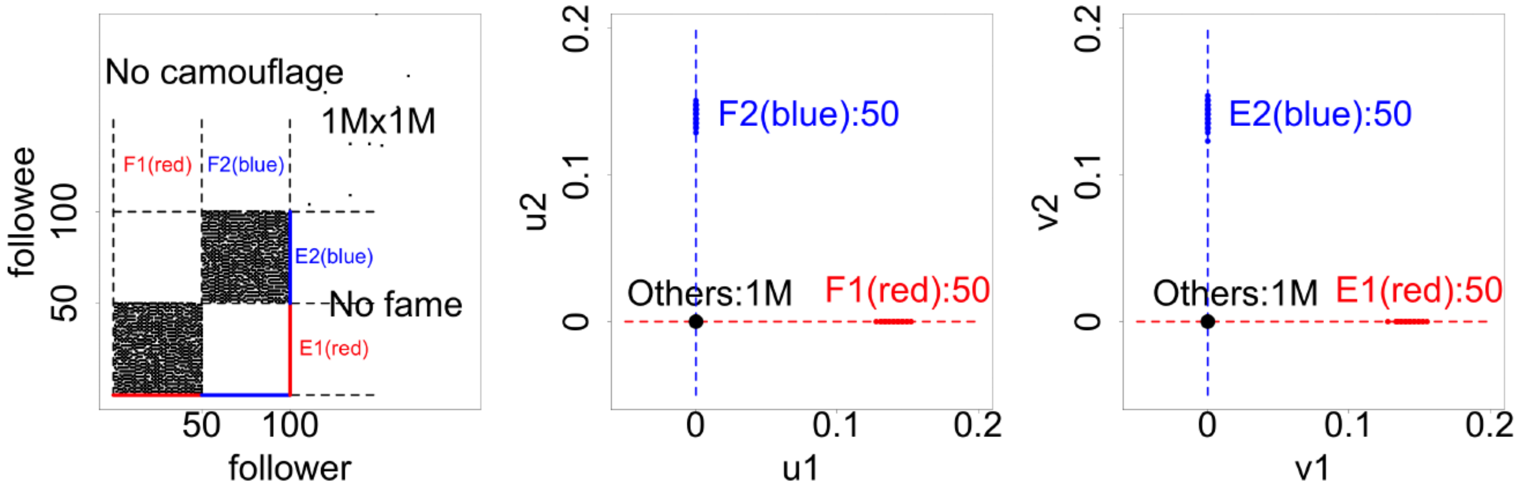




Lockstep and *Spectral Subspace Plot*

- Case #1: non-overlapping lockstep
- "Blocks" ⟷ "Rays"

Adjacency Matrix Spectral Subspace Plot



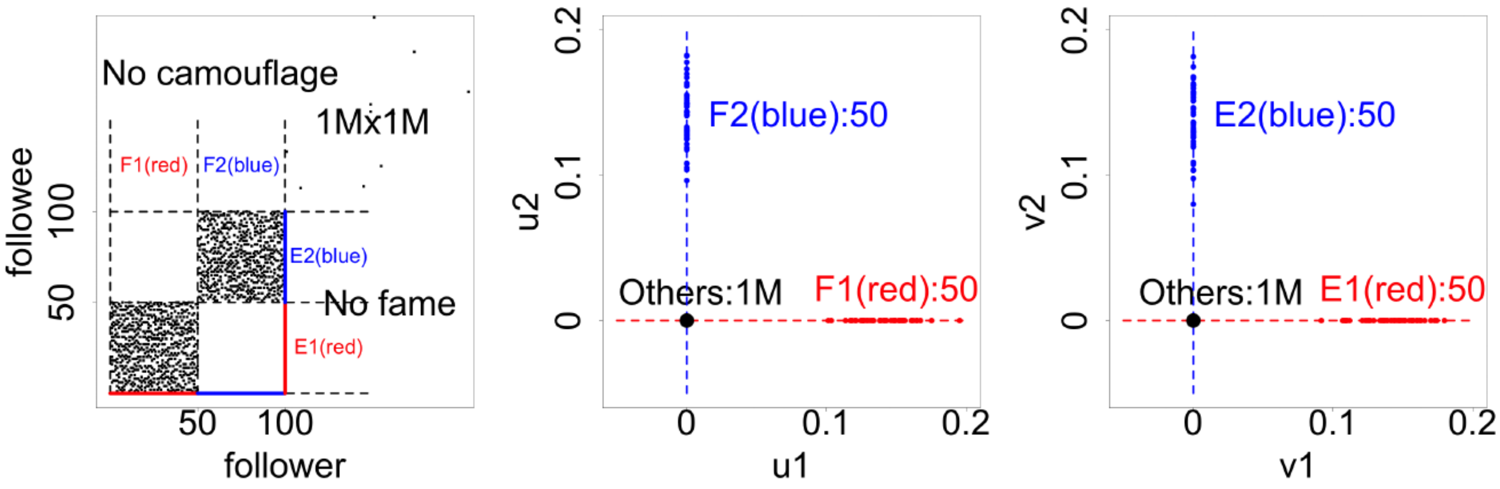
Rule 1 (short "rays"): two blocks, high density (90%), no "camouflage", no "fame"

Lockstep and *Spectral Subspace Plot*

- Case #2: non-overlapping lockstep
- "Blocks; low density" ⟷ Elongation

Adjacency Matrix

Spectral Subspace Plot

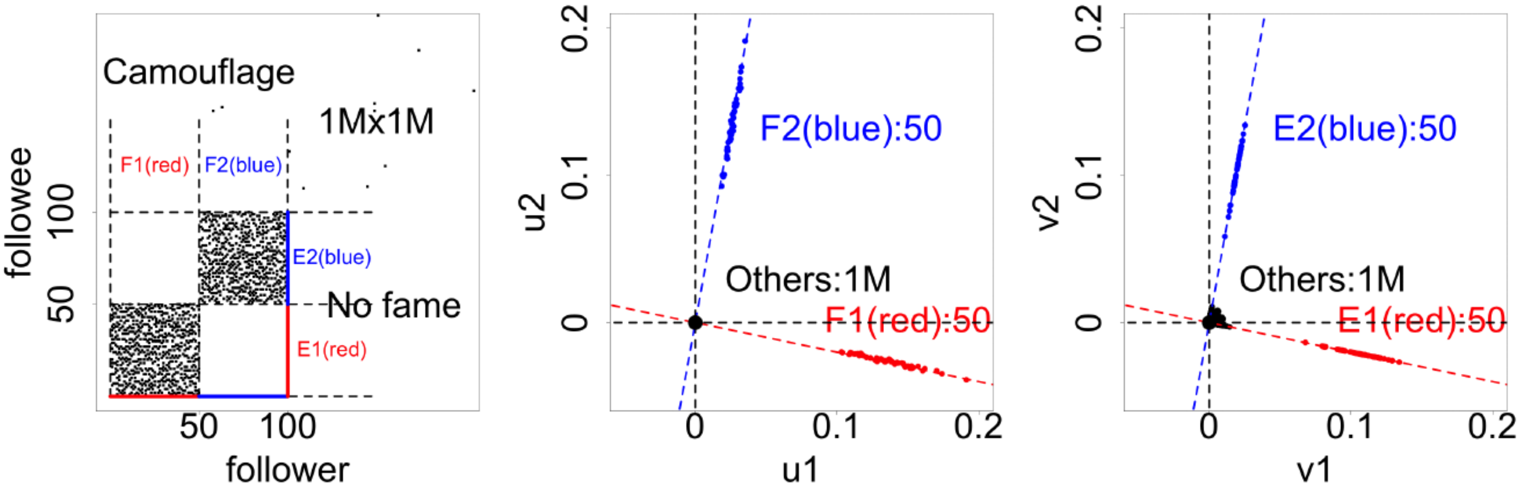


Rule 2 (long "rays"): two blocks, low density (50%), no "camouflage", no "fame"

Lockstep and *Spectral Subspace Plot*

- Case #3: non-overlapping lockstep
- “**Camouflage**” (or “Fame”) ⟷ Tilting “Rays”

Adjacency Matrix Spectral Subspace Plot

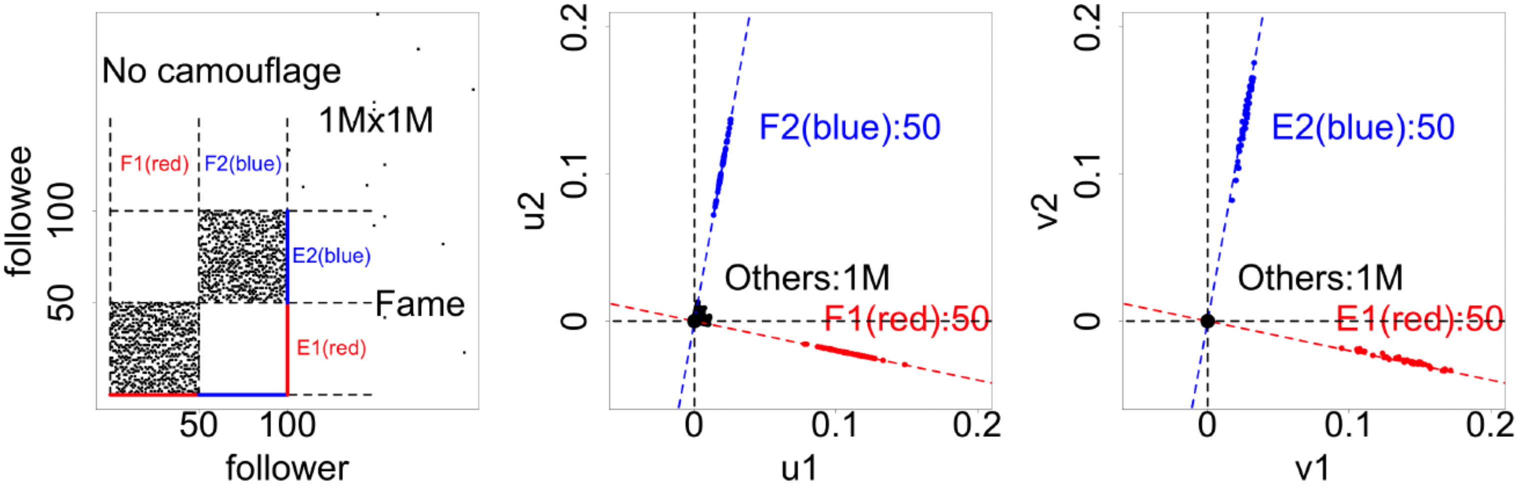


Rule 3 (tilting “rays”): two blocks, with “camouflage”, no “fame”

Lockstep and *Spectral Subspace Plot*

- Case #3: non-overlapping lockstep
- "Camouflage" (or "**Fame**") ⟵⟶ Tilting "Rays"

Adjacency Matrix Spectral Subspace Plot



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

Carnegie Mellon

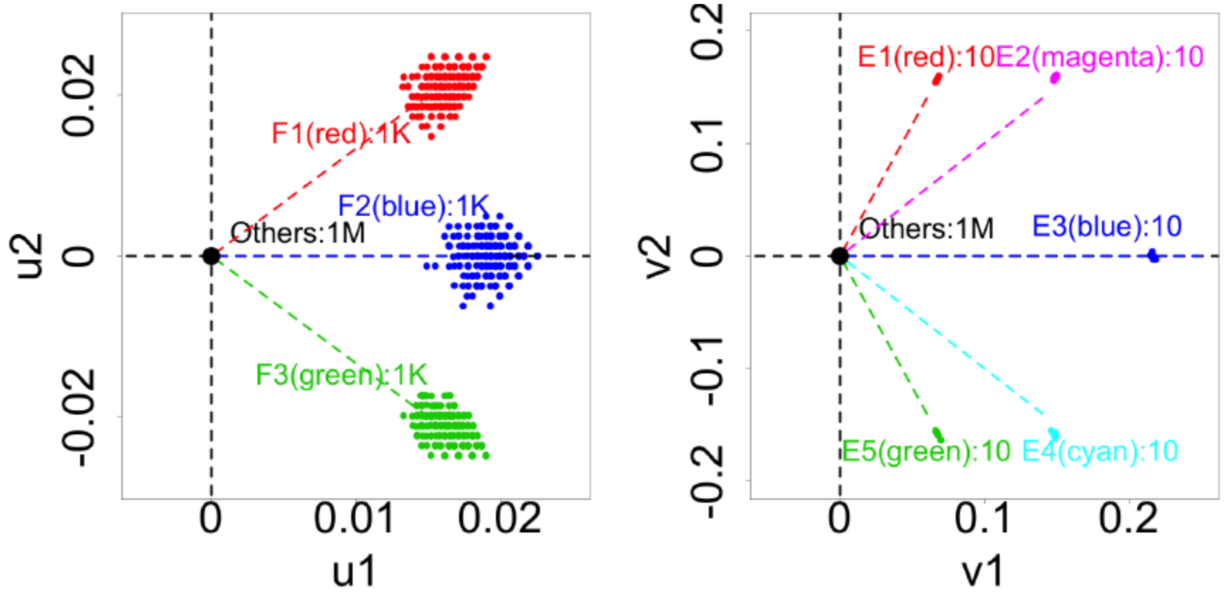
Lockstep and *Spectral Subspace Plot*

- Case #4: ? lockstep
- "?" ⟷ "Pearls"

Adjacency Matrix

?

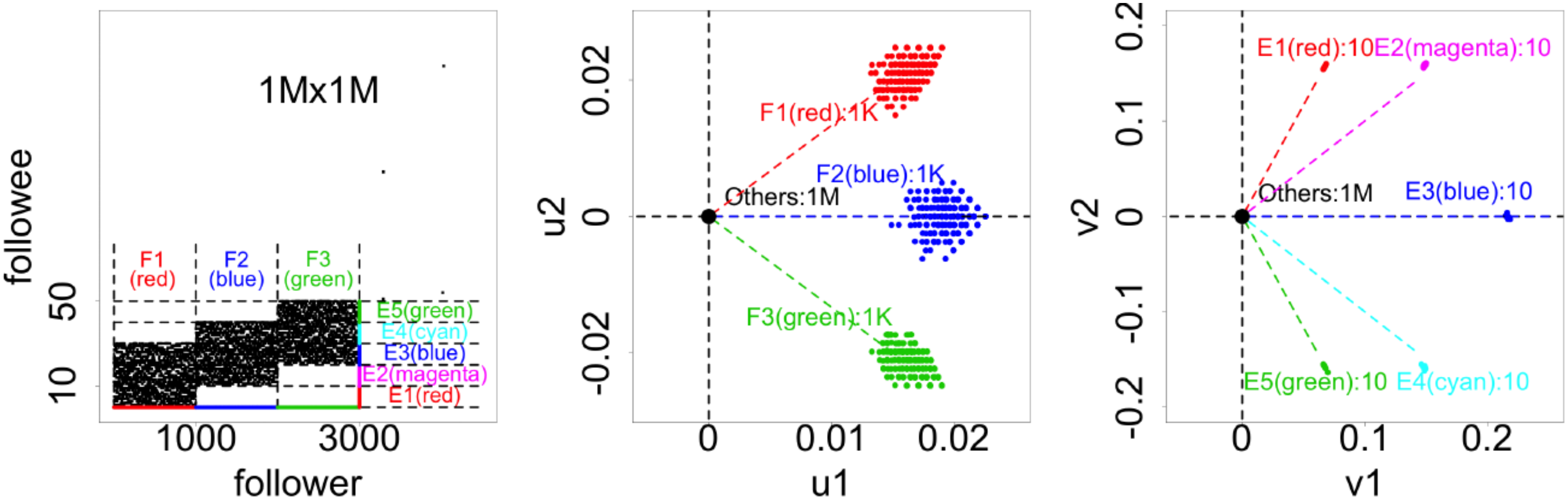
Spectral Subspace Plot



Lockstep and *Spectral Subspace Plot*

- Case #4: **overlapping** lockstep
- “**Staircase**” ↔ “Pearls”

Adjacency Matrix   Spectral Subspace Plot



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

Dataset

- Tencent Weibo
- 117 million nodes (with profile and UGC data)
- 3.33 billion directed edges

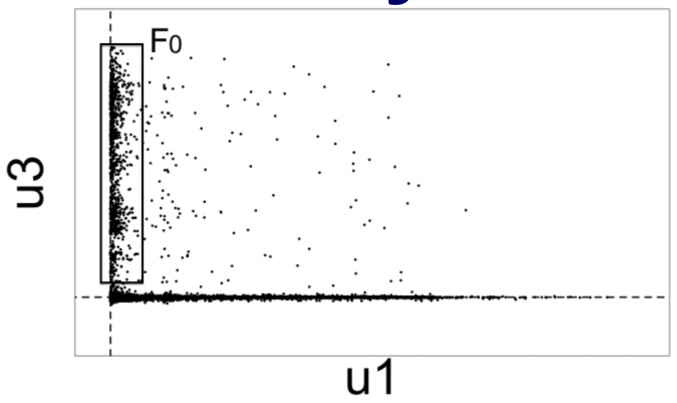
樱冢lily
洗着衣服看了一晚上的圣斗士，是有多宅啊！！！
5分钟前 阅读(15)

杨茜
应大家要求写游记啦,论坛已经置顶啦,欢迎去踩~www.16fan.com"超勇敢沙巴游记"
29分钟前 阅读(59)

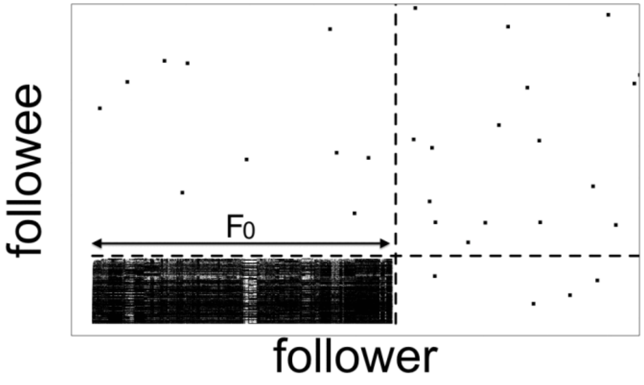
WIS护肤
男生脸上的痘印吧，当然是要把干净！力荐WIS：http://url.cn/Nucyw2 没痘印才叫帅！

Real Data

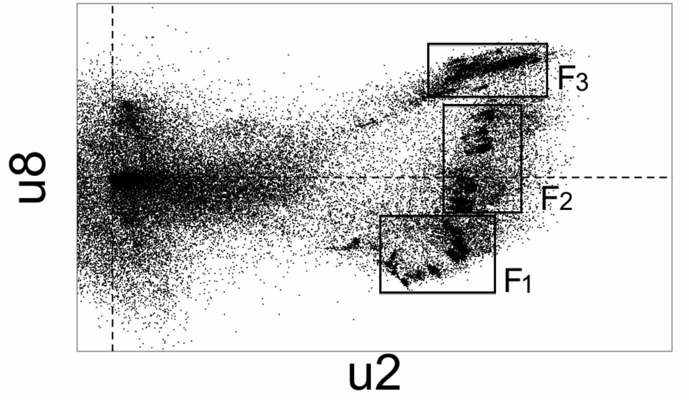
“Rays”



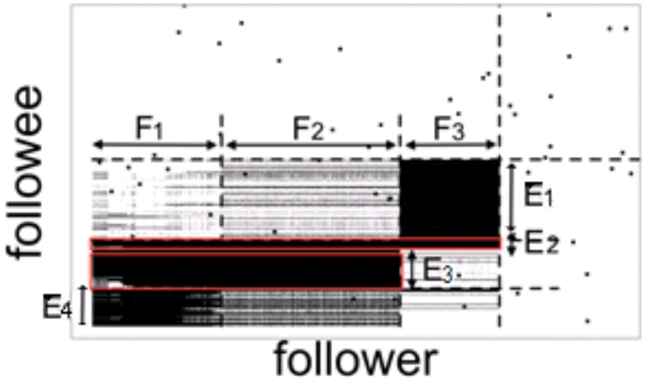
“Block”



“Pearls”

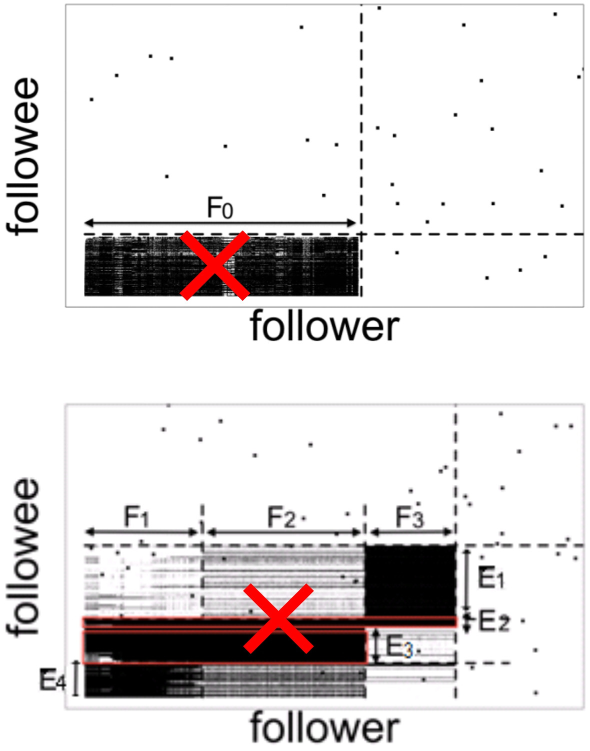


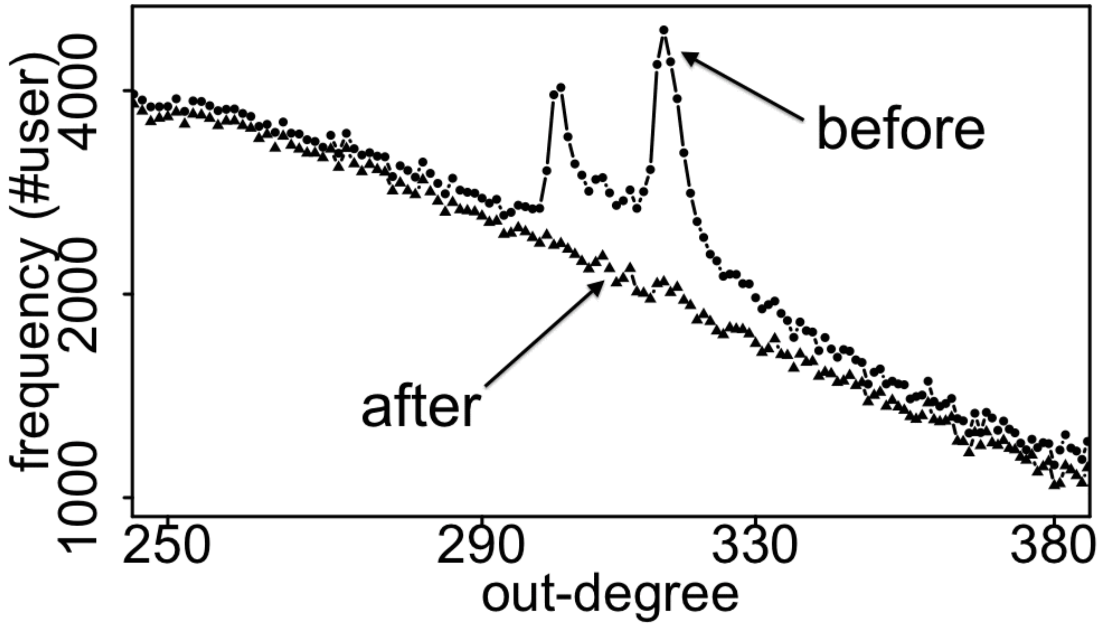
“Staircase”



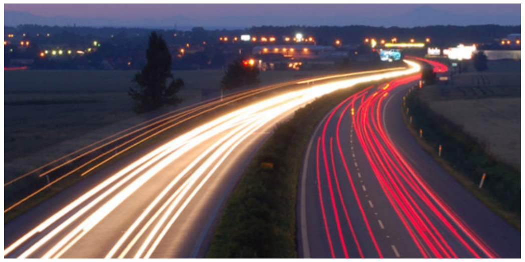
Real Data

- Spikes on the out-degree distribution





Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
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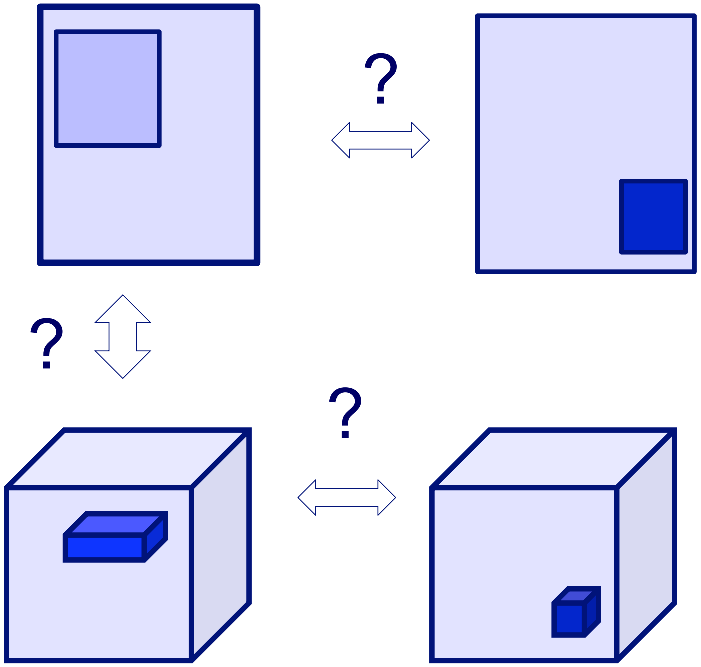
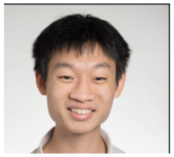
  - P1.2: Anomaly / fraud detection
    - No labels – spectral methods
      - ➡ **Suspiciousness**
    - With labels: Belief Propagation
- Part#2: time-evolving graphs; tensors
- Conclusions

Suspicious Patterns in Event Data

2-modes

n-modes





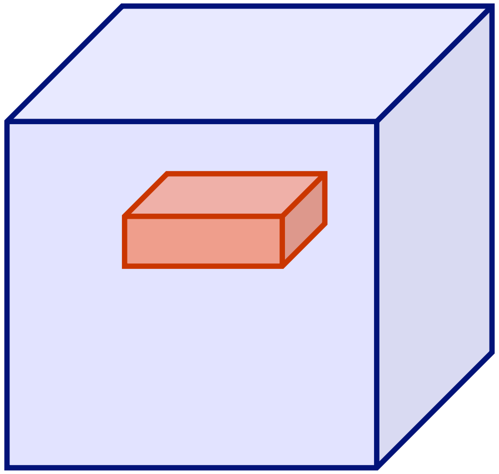
A General Suspiciousness Metric for Dense Blocks in Multimodal Data, Meng Jiang, Alex Beutel, Peng Cui, Bryan Hooi, Shiqiang Yang, and Christos Faloutsos, *ICDM*, 2015.

ICDM 2015

Suspicious Patterns in Event Data

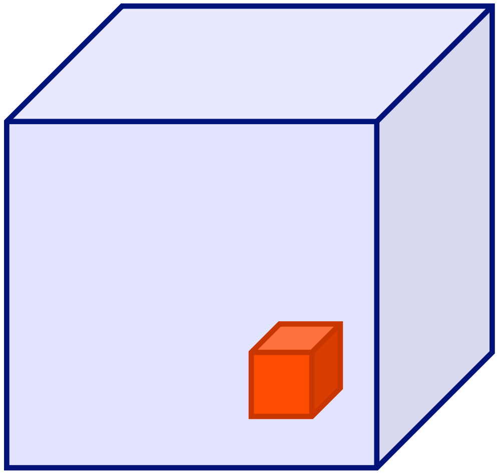
Which is more suspicious?

20,000 Users
Retweeting same 20 tweets
6 times each
All in 10 hours



vs.

225 Users
Retweeting same 1 tweet
15 times each
All in 3 hours
All from 2 IP addresses



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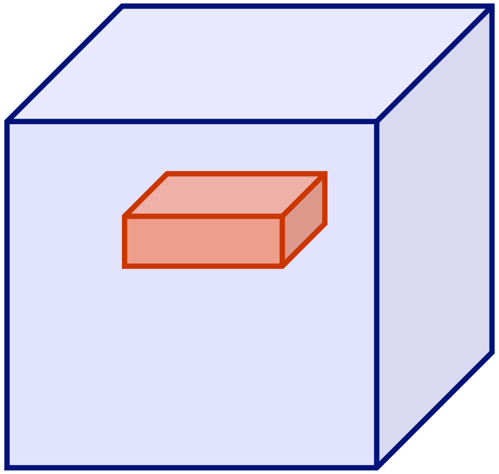

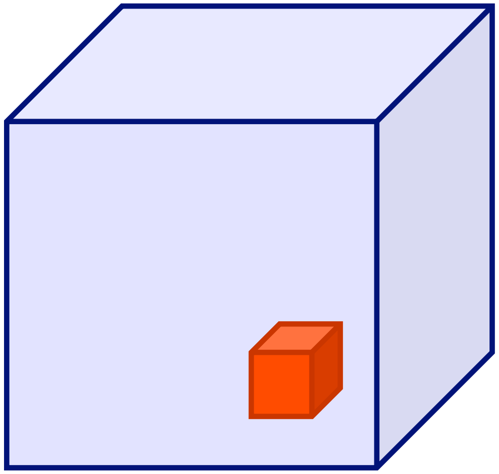

Answer: volume * $D_{KL}(p|| p_{background})$

Suspicious Patterns in Event Data

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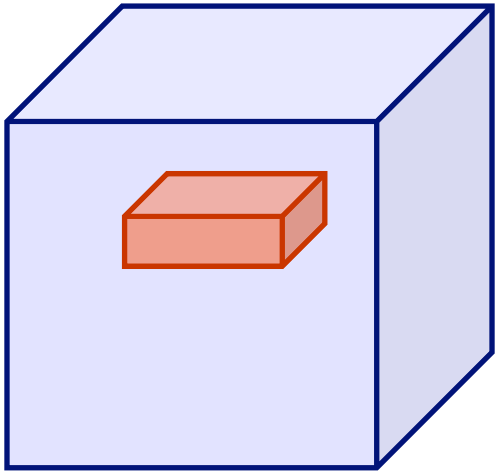
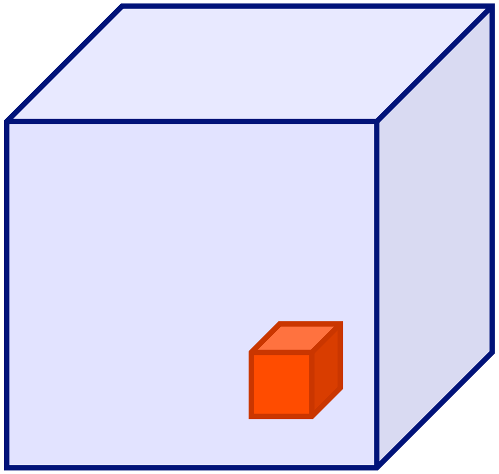


size

contrast



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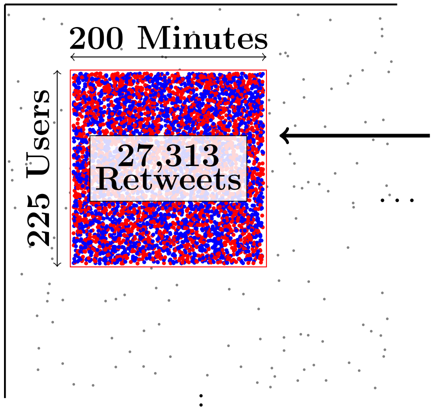
Suspicious Patterns in Event Data

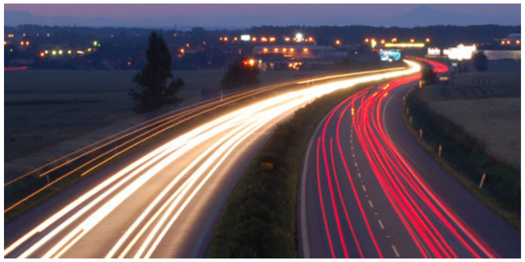


	10:09	10:14	10:19	10:24	10:32	10:37	11:04	15:37	21:13	
“John123”	●		+	+		●	●	●		
“Joe456”	●	+	●	+	+		+	+		. . .
“Job789”	●	+	●	+	●		●	●		
“Jack135”	+	●	+	+	+		●	+	●	
“Jill246”	+	●	●	●				+		
“Jane314”	+	+	●	●		●		●	●	
“Jay357”	●		●	●	●	+		●		
	⋮									

Retweeting: “Galaxy Note Dream Project: Happy Happy Life Traveling the World”

	#	User×tweet×IP×minute	Mass c	Suspiciousness
CrossSpot	1	14×1×2×1,114	41,396	1,239,865
	2	225×1×2×200	27,313	777,781
	3	8×2×4×1,872	17,701	491,323
HOSVD	1	24×6×11×439	3,582	131,113
	2	18×4×5×223	1,942	74,087
	3	14×2×1×265	9,061	381,211

Roadmap



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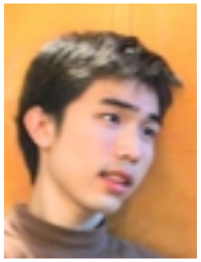
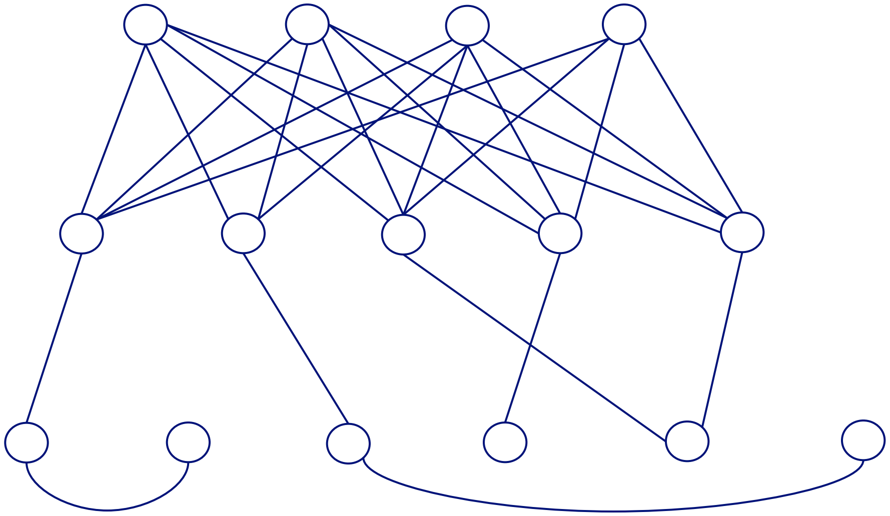
E-bay Fraud detection



w/ Polo Chau &
Shashank Pandit, CMU
[www'07]



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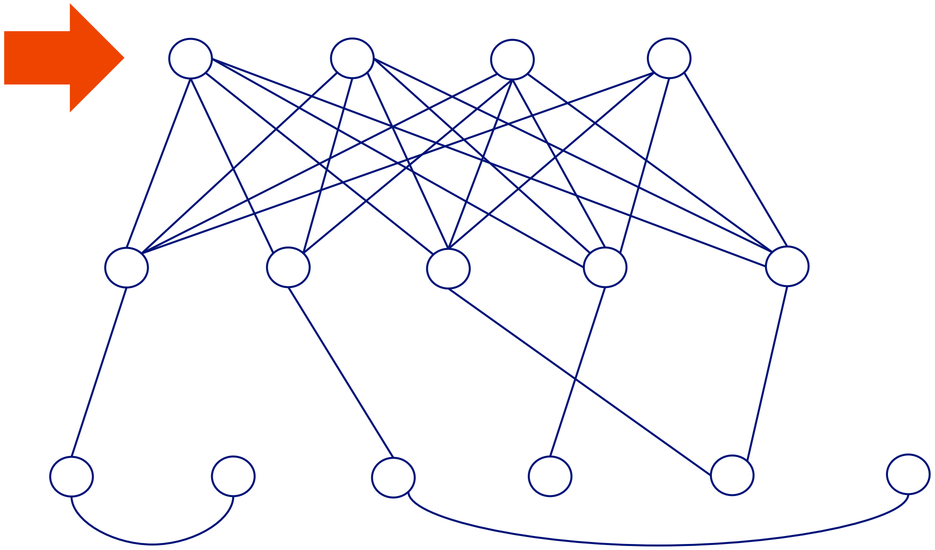
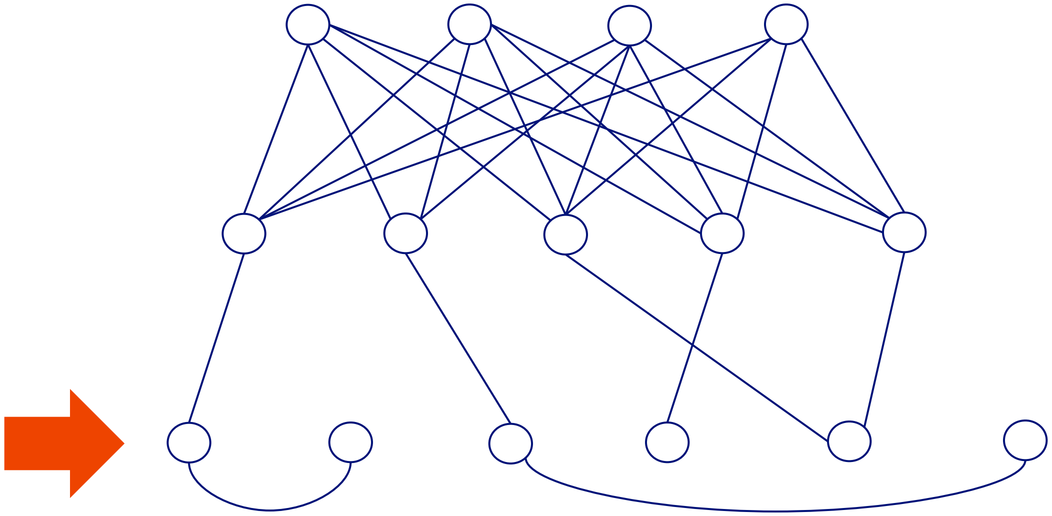
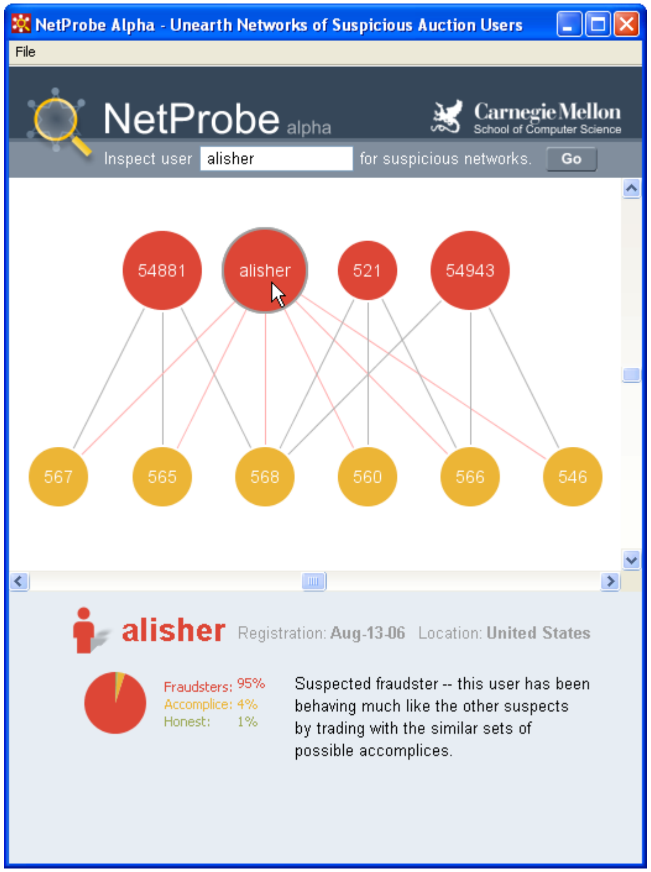


Carnegie Mellon

E-bay Fraud detection



E-bay Fraud detection - NetProbe



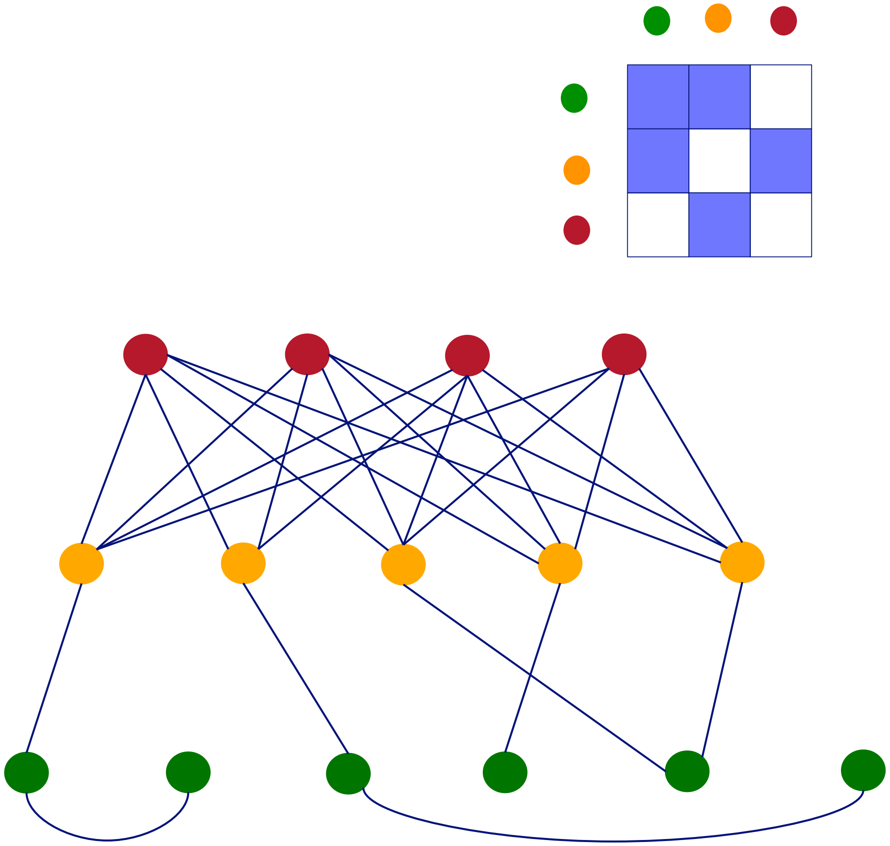
NetProbe Alpha - Unearth Networks of Suspicious Auction Users
File
NetProbe alpha
Carnegie Mellon
School of Computer Science
Go
54881
alisher
521
54943
567
565
568
560
566
546

Inspect user alisher for suspicious networks.

alisher Registration: Aug-13-06 Location: United States

Fraudsters: 95%
Accomplice: 4%
Honest: 1%

Suspected fraudster -- this user has been behaving much like the other suspects by trading with the similar sets of possible accomplices.



Popular press

USA TODAY

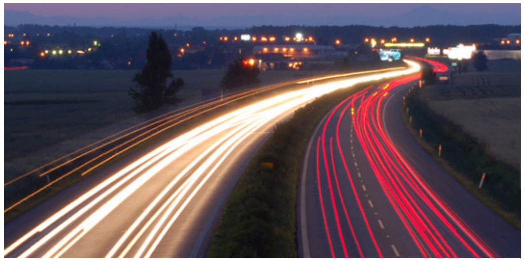
The Washington Post

Los Angeles Times

And less desirable attention:

- E-mail from ‘Belgium police’ (‘copy of your code?’)

Roadmap



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Carnegie Mellon

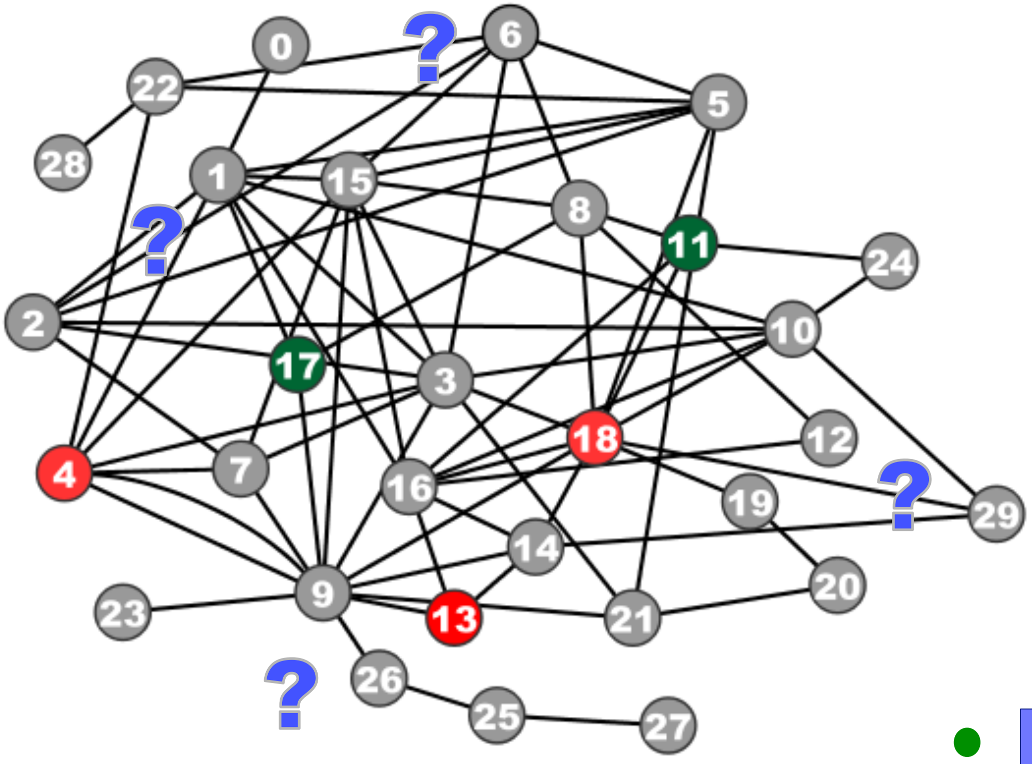
Unifying Guilt-by-Association Approaches: Theorems and Fast Algorithms

Danai Koutra
U Kang
Hsing-Kuo Kenneth Pao

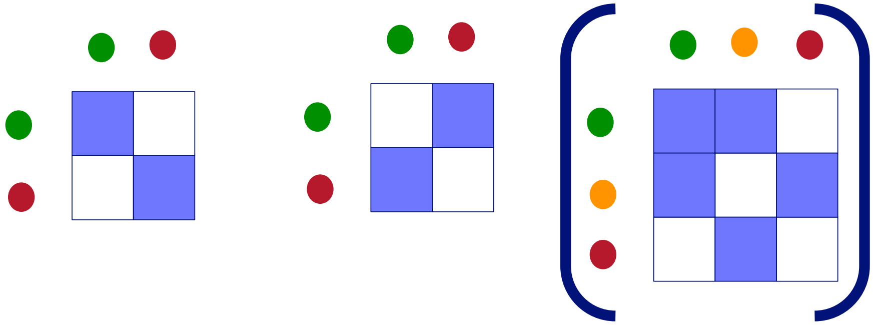
Tai-You Ke
Duen Horng (Polo) Chau
Christos Faloutsos

ECML PKDD, 5-9 September 2011, Athens, Greece

Problem Definition: GBA techniques



Given: Graph; &
few labeled nodes
Find: labels of rest
(assuming network effects)



Are they related?

- RWR (Random Walk with Restarts)
  - google's pageRank ('*if my friends are important, I'm important, too*')

Google

- SSL (Semi-supervised learning)
  - minimize the differences among neighbors
- BP (Belief propagation)
  - send messages to neighbors, on what you believe about them

Are they related? YES!

- RWR (Random Walk with Restarts)
  - google's pageRank ('*if my friends are important, I'm important, too*')
- SSL (Semi-supervised learning)
  - minimize the differences among neighbors
- BP (Belief propagation)
  - send messages to neighbors, on what you believe about them

Correspondence of Methods

Method	Matrix	Unknown	known
RWR	$[\mathbf{I} - c\ \underline{\mathbf{AD}}^{-1}]\ \times$	$\mathbf{x}\ =$	$(1\text{-}c)\mathbf{y}$
SSL	$[\mathbf{I} + a(\mathbf{D} - \underline{\mathbf{A}})]\ \times$	$\mathbf{x}\ =$	$\mathbf{y}$
FABP	$[\mathbf{I} + a\,\mathbf{D} - c'\underline{\mathbf{A}}]\ \times$	$\mathbf{b_h}\ =$	$\boldsymbol{\phi}_\mathbf{h}$

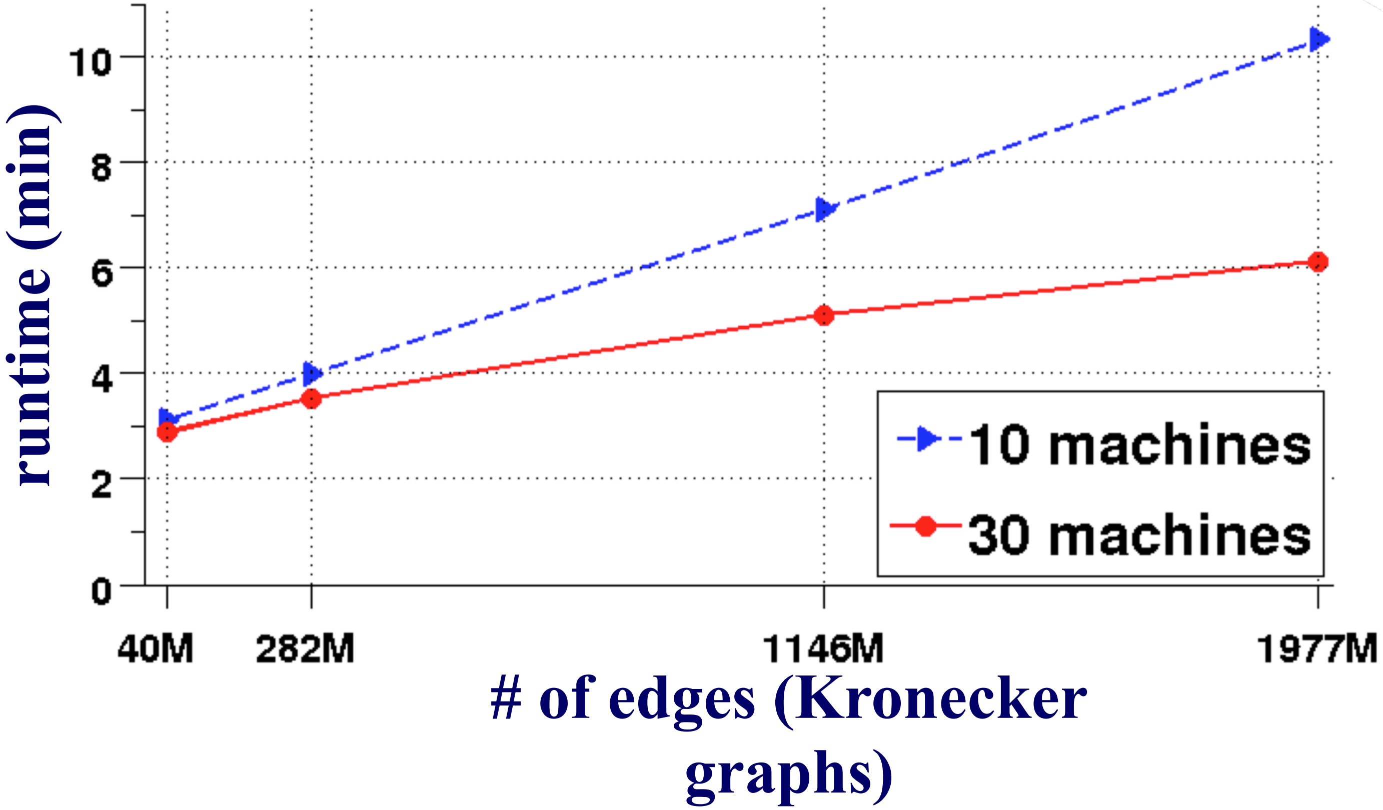
$$\begin{bmatrix}1&&\\&1&\\&&1\end{bmatrix}\quad\begin{bmatrix}d1&&\\&d2&\\&&d3\end{bmatrix}\quad\begin{bmatrix}0&1&0\\1&0&1\\0&1&0\end{bmatrix}\quad\begin{bmatrix}?\end{bmatrix}\quad\begin{bmatrix}0\\1\\1\end{bmatrix}$$

adjacency matrix

final labels/ beliefs

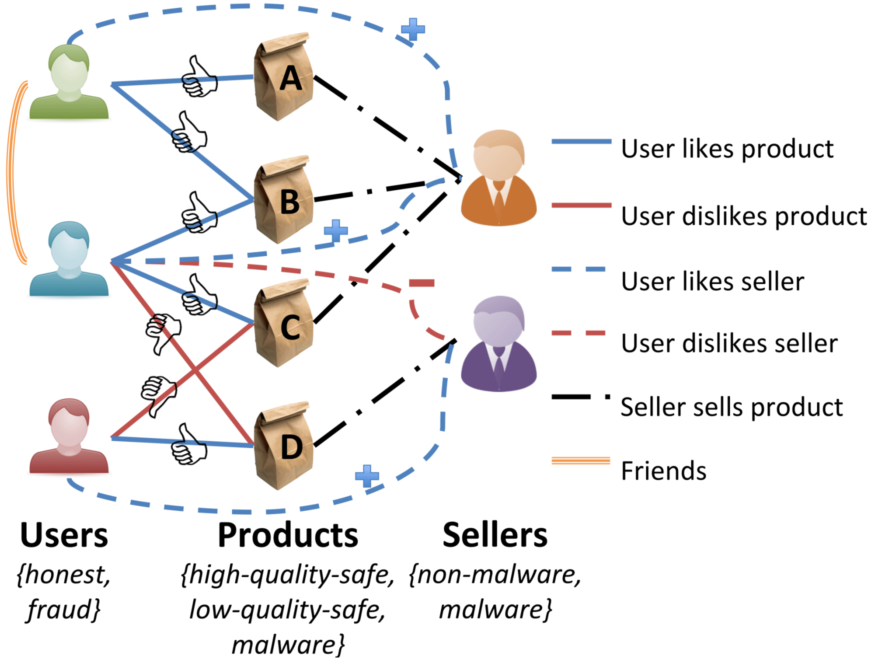
prior labels/ beliefs

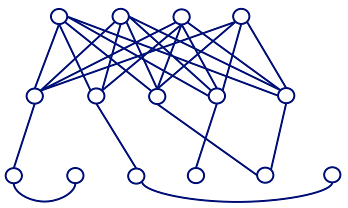
Results: Scalability



FABP is **linear** on the number of edges.

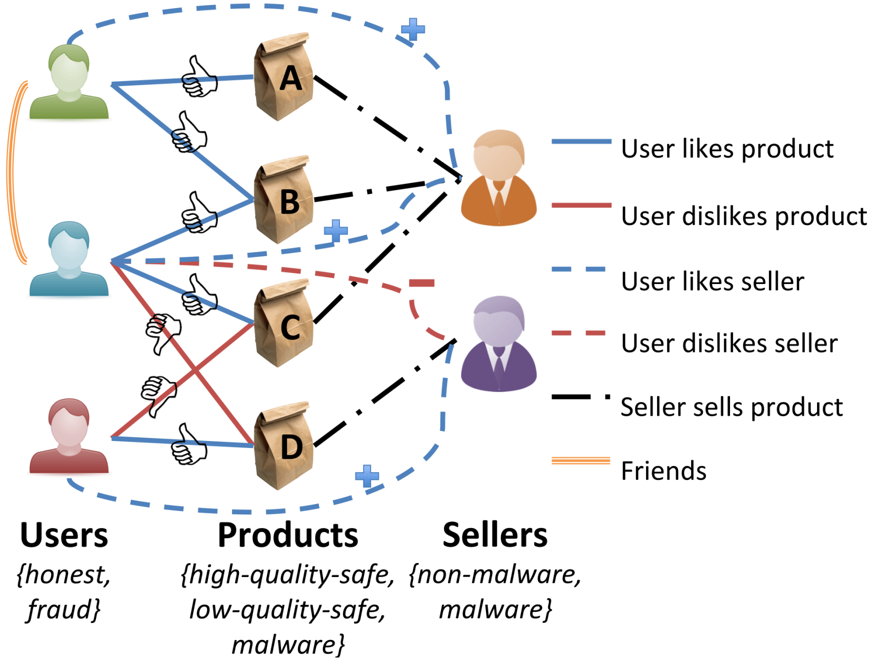
Problem: e-commerce ratings fraud





- **Given** a **heterogeneous** graph on users, products, sellers and positive/negative ratings with “seed labels”
- **Find** the top *k* most fraudulent users, products and sellers

Problem: e-commerce ratings fraud



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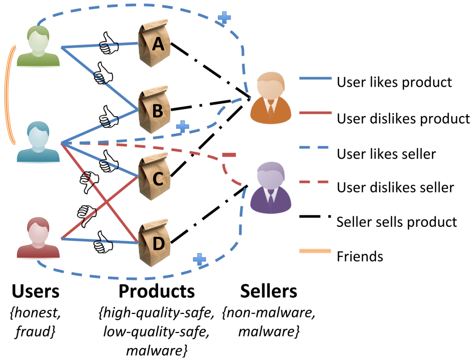
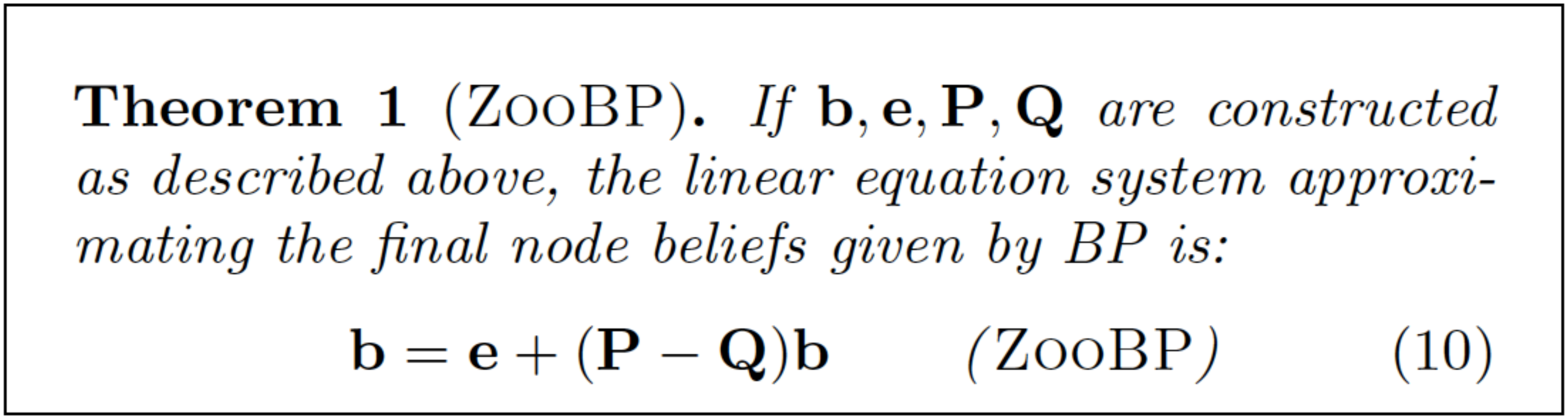
- **Find** the top *k* most fraudulent users, products and sellers

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, “*ZooBP:* Belief Propagation for Heterogeneous Networks”, In submission to VLDB 2017

Problem: e-commerce ratings fraud





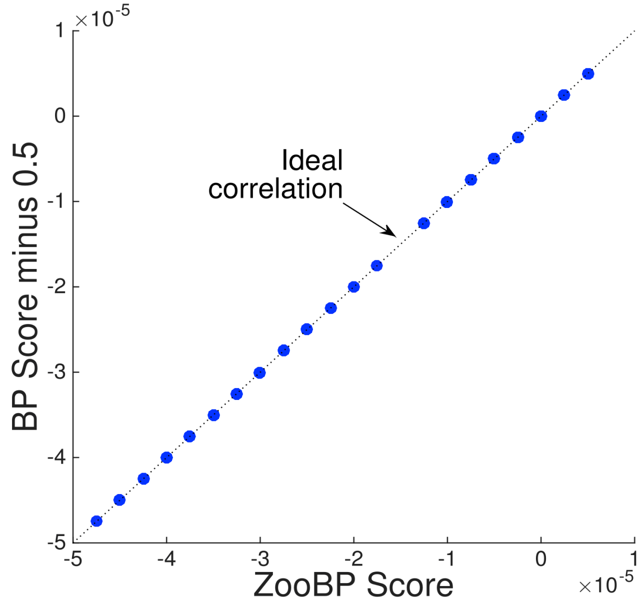
Theorem 1 (ZooBP). *If* $\mathbf{b}, \mathbf{e}, \mathbf{P}, \mathbf{Q}$ *are constructed as described above, the linear equation system approximating the final node beliefs given by BP is:*

$$\mathbf{b} = \mathbf{e} + (\mathbf{P} - \mathbf{Q})\mathbf{b} \qquad \textit{(ZooBP)} \qquad (10)$$

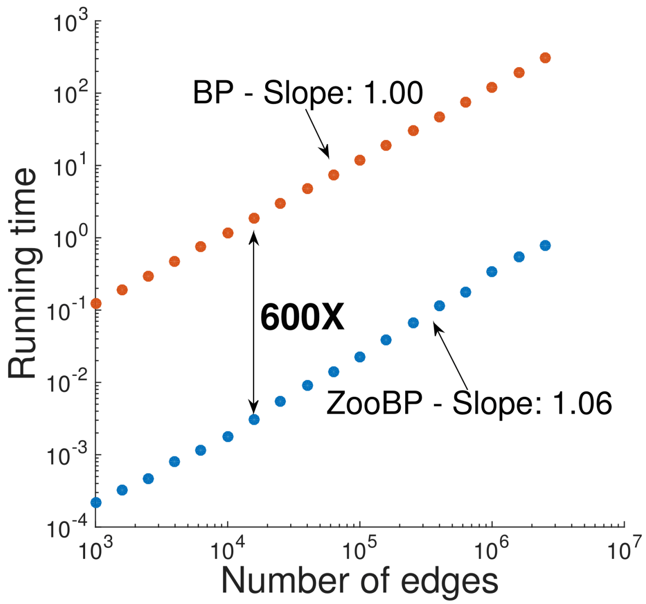
Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", In submission to VLDB 2017

ZooBP: features

Fast; convergence guarantees.



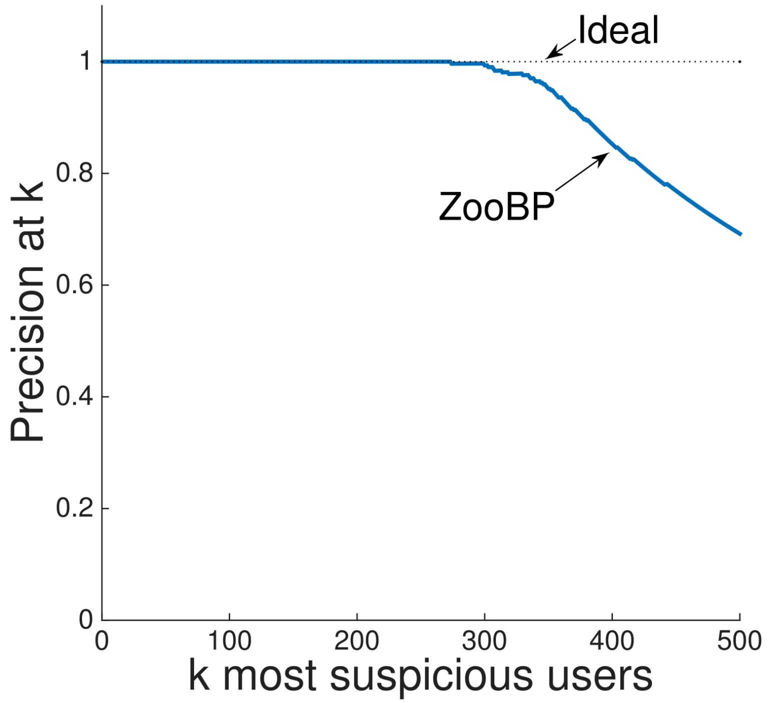
Near-perfect accuracy



linear in graph size

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", In submission to VLDB 2017

ZooBP in the real world

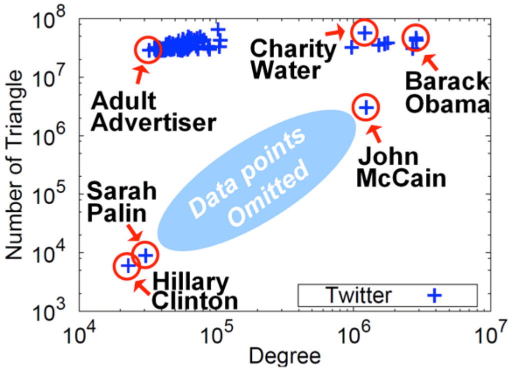


- Near 100% precision on top 300 users (Flipkart)
- Flagged users: suspicious
  - 400 ratings in 1 sec
  - 5000 good ratings and no bad ratings

Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", In submission to VLDB 2017

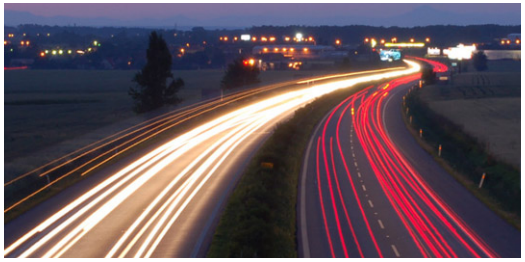
Summary of Part#1

- *many* patterns in real graphs
  - Power-laws everywhere
  - Long (and growing) list of tools for anomaly/ fraud detection



Patterns anomalies

Roadmap

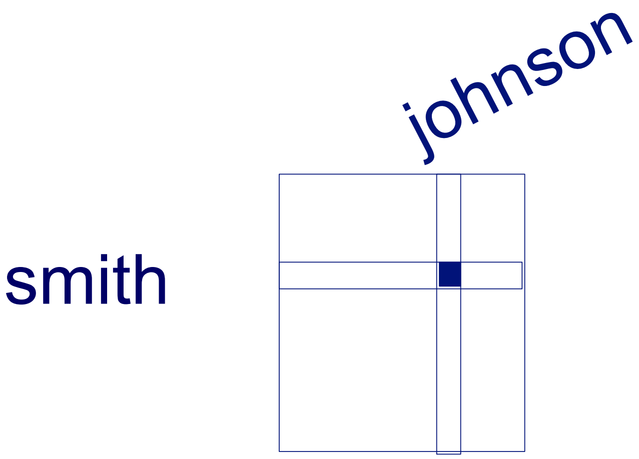


- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs
  - ➡ P2.1: tools/tensors
  - P2.2: other patterns
- Conclusions

Part 2: Time evolving graphs; tensors

Graphs over time -> tensors!

- Problem #2.1:
  - Given who calls whom, and when
  - Find patterns / anomalies



Graphs over time -> tensors!

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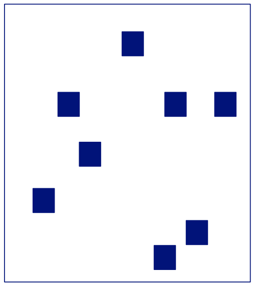

Graphs over time -> tensors!

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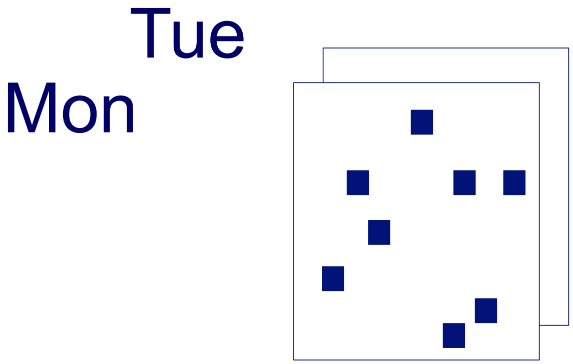
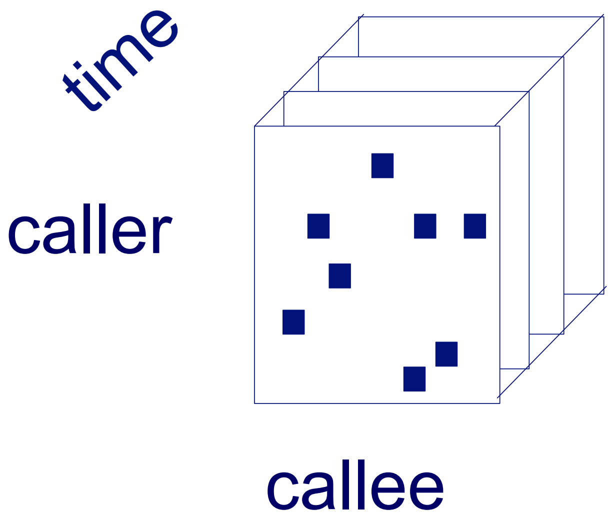


Carnegie Mellon

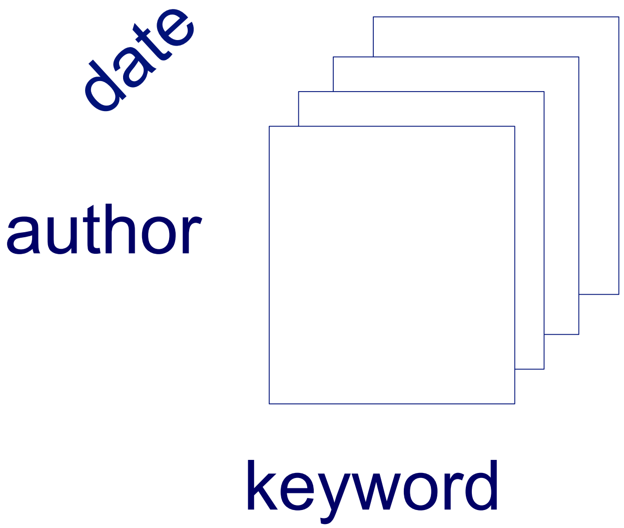
Graphs over time -> tensors!

- Problem #2.1:
  - Given who calls whom, and when
  - Find patterns / anomalies



Graphs over time -> tensors!

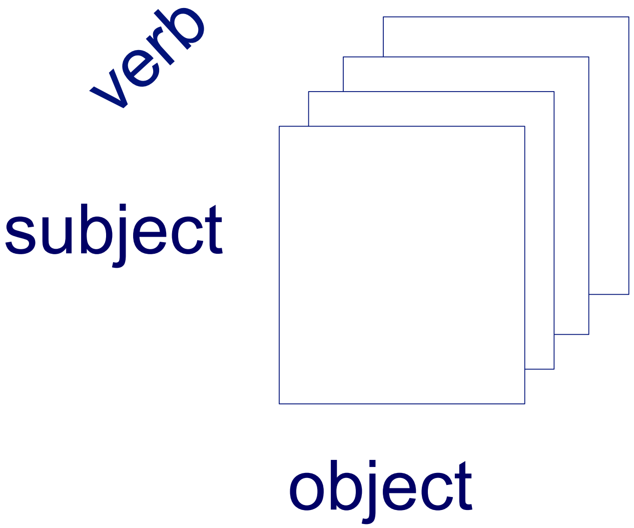
- Problem #2.1':
  - Given author-keyword-date
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

Graphs over time -> tensors!

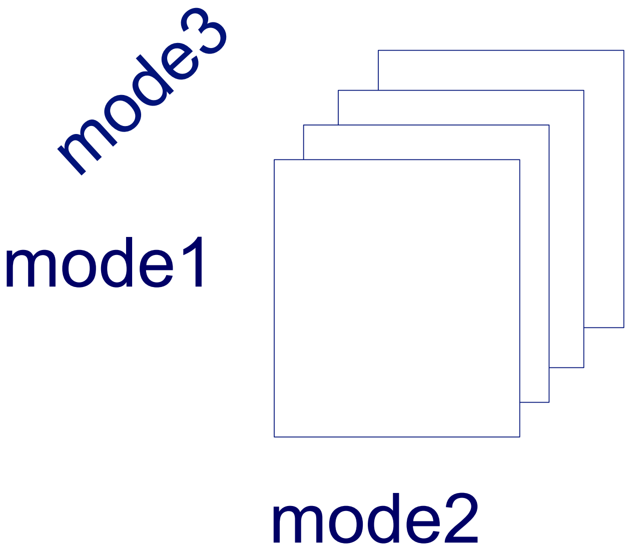
- Problem #2.1'':
  - Given subject – verb – object facts
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

Graphs over time -> tensors!

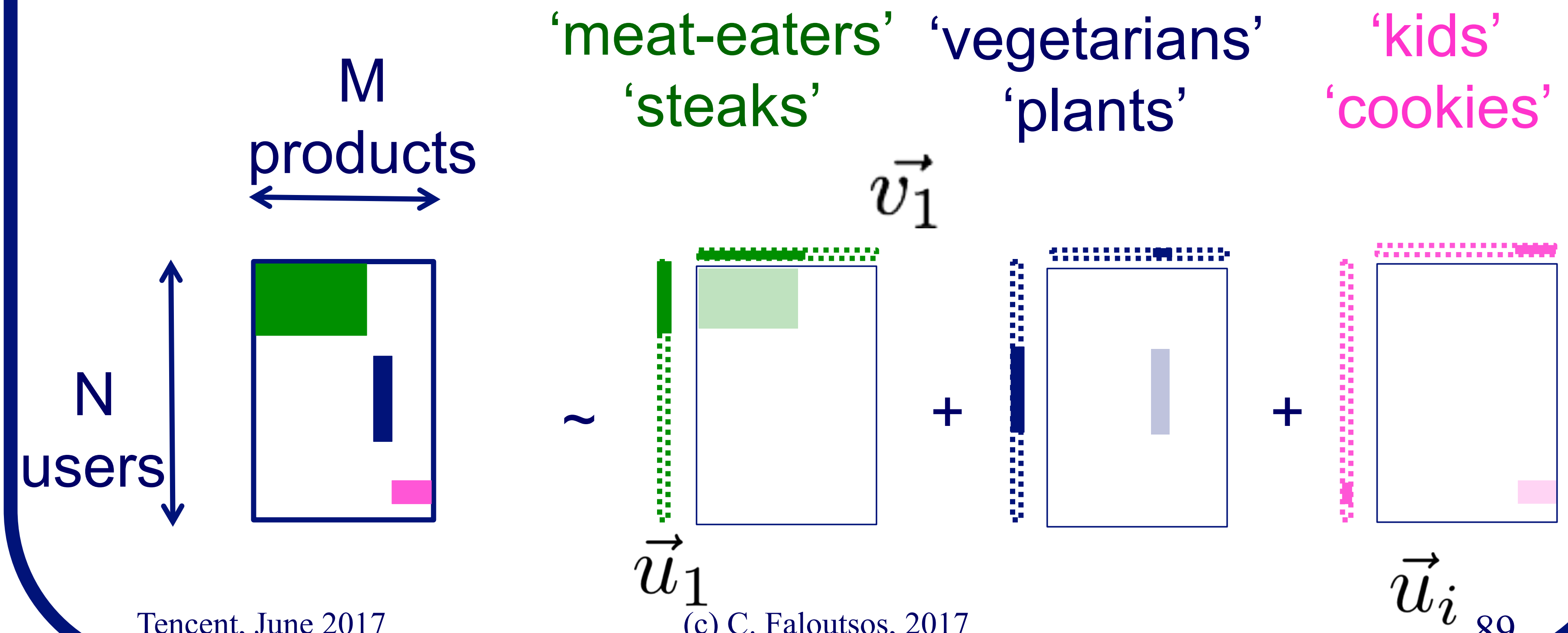
- Problem #2.1''':
  - Given <triplets>
  - Find patterns / anomalies



MANY more settings, with >2 'modes' (and 4, 5, etc modes)

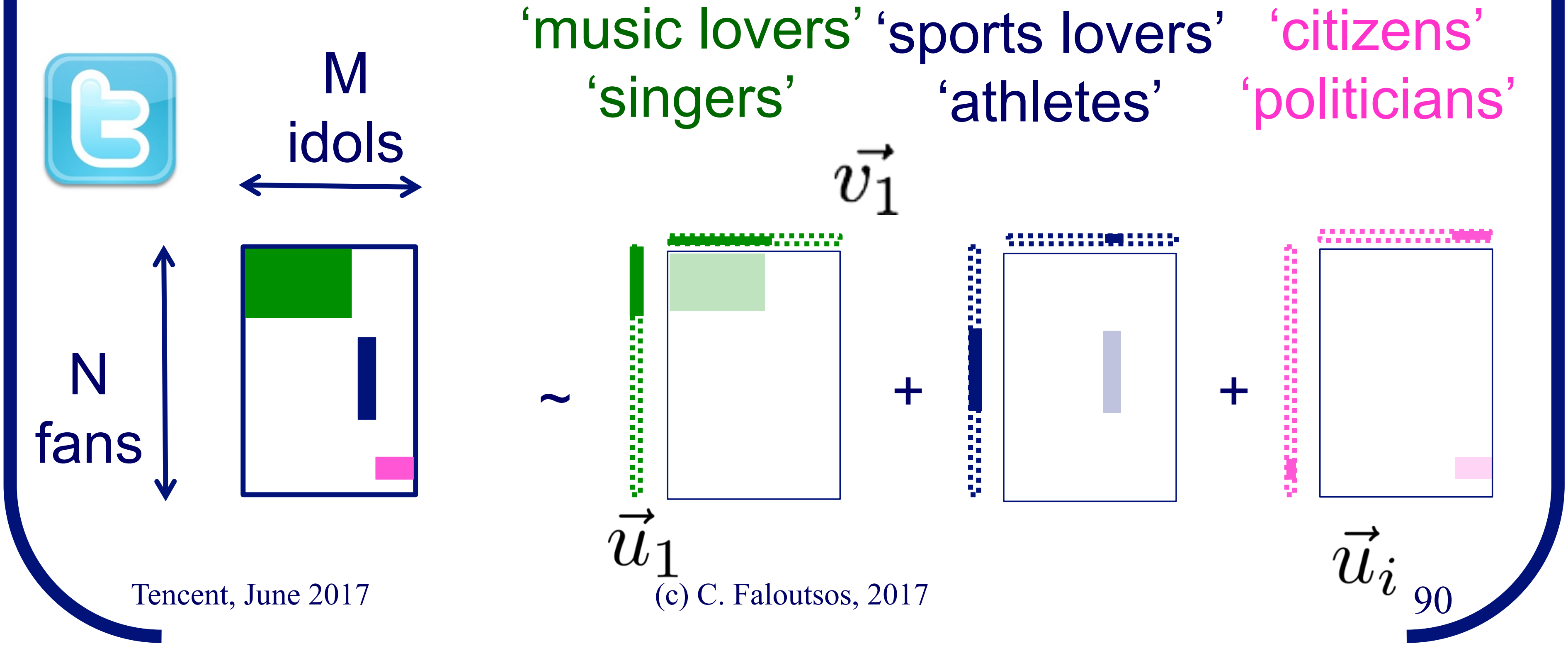
Answer : tensor factorization

- Recall: (SVD) matrix factorization: finds blocks



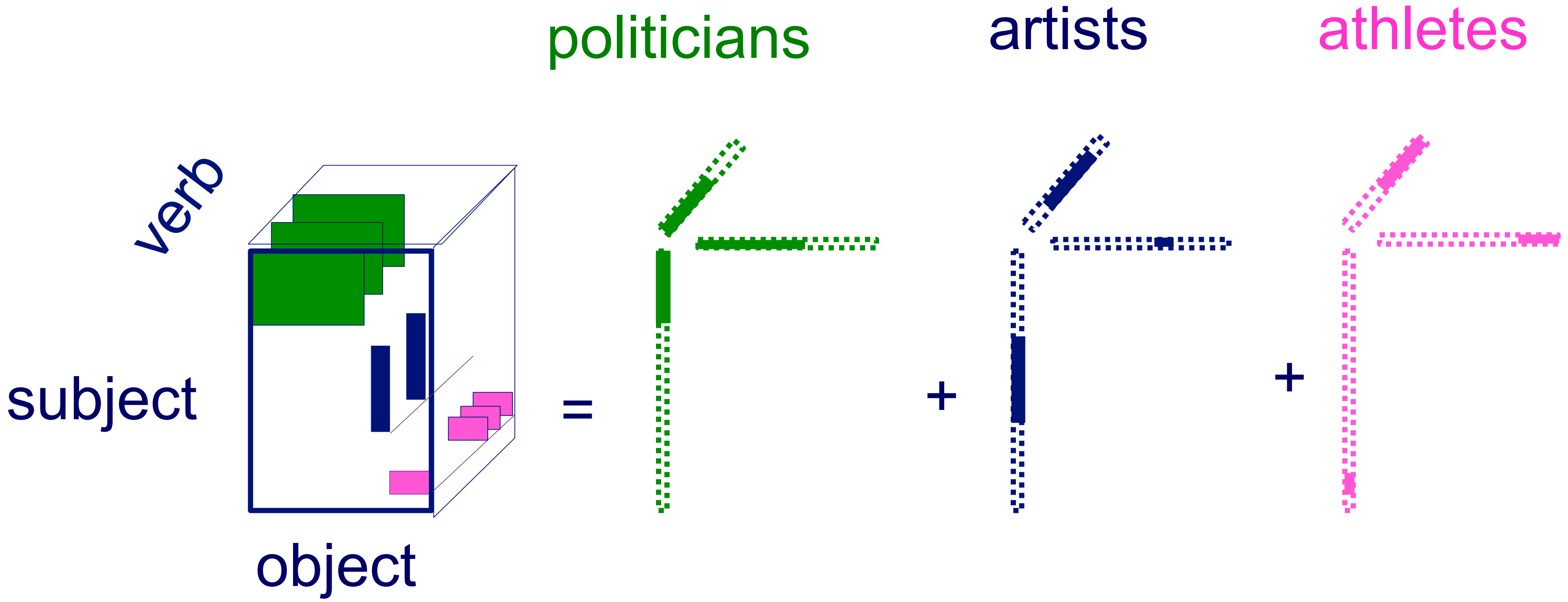
Crush intro to SVD

- Recall: (SVD) matrix factorization: finds blocks



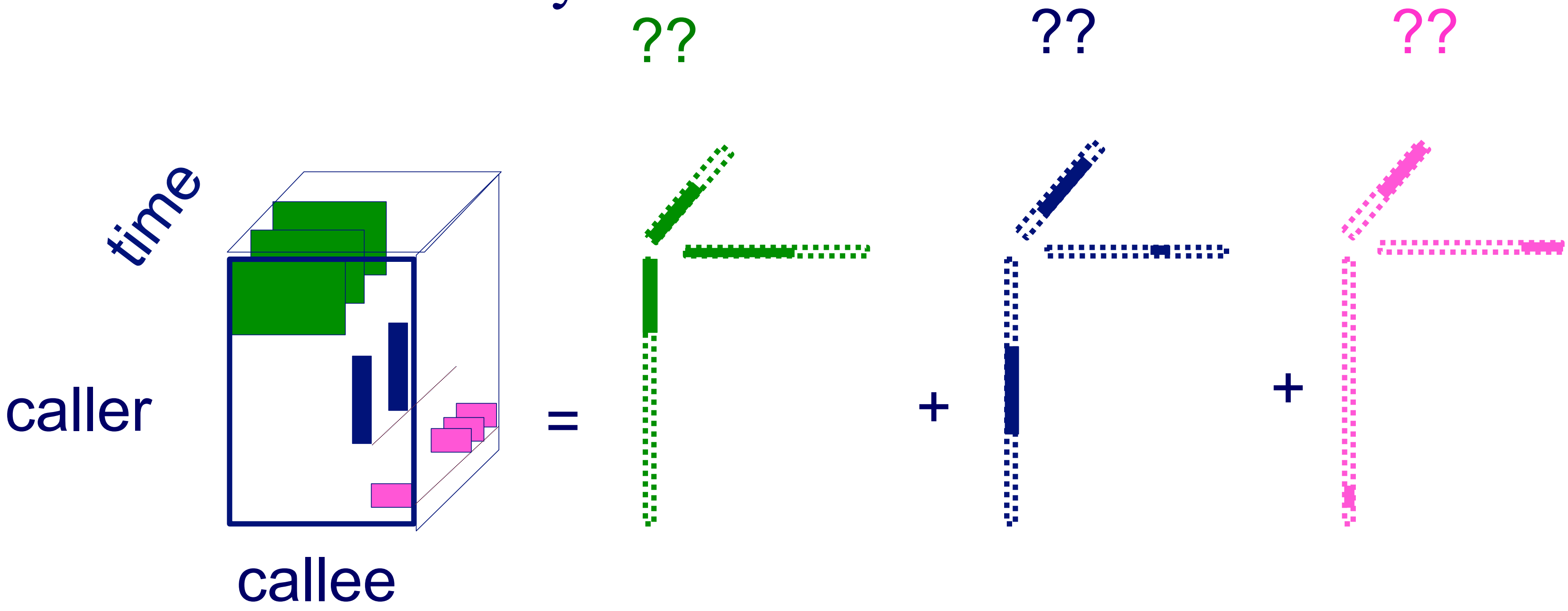
Answer: tensor factorization

- PARAFAC decomposition

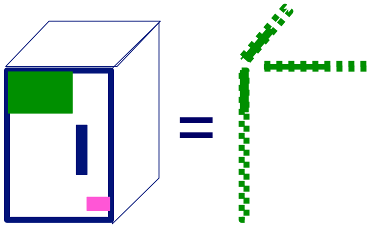


Answer: tensor factorization

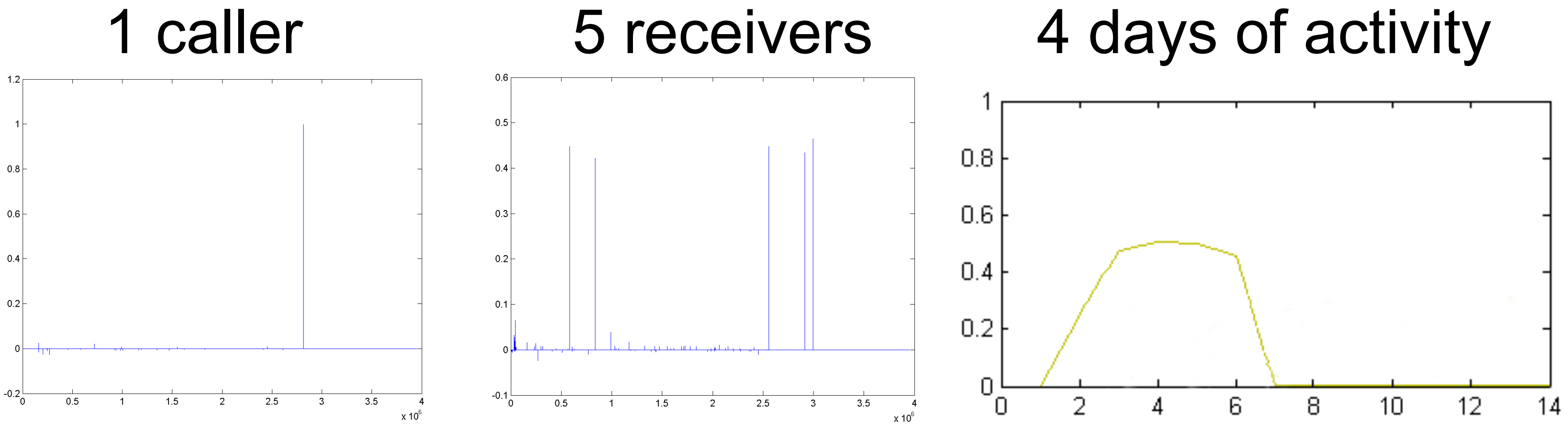
- PARAFAC decomposition
- Results for who-calls-whom-when
  - 4M x 15 days



Anomaly detection in time-evolving graphs



- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks

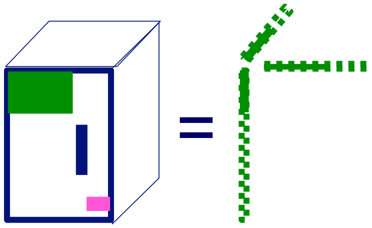

1 caller

5 receivers

4 days of activity

~200 calls to EACH receiver on EACH day!

Anomaly detection in time-evolving graphs



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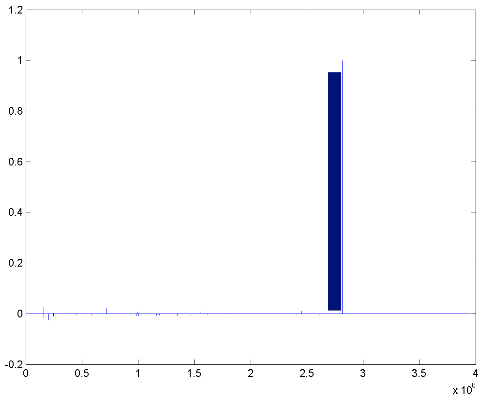
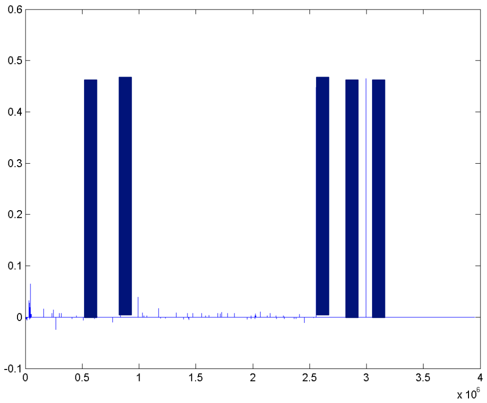
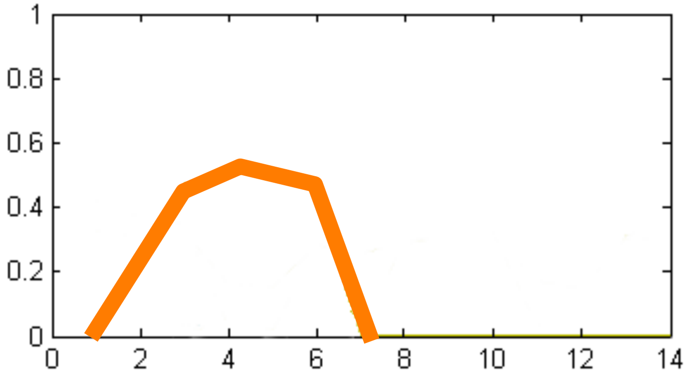


5 receivers

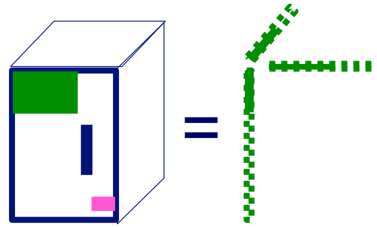


4 days of activity



~200 calls to EACH receiver on EACH day!

Anomaly detection in time-evolving graphs



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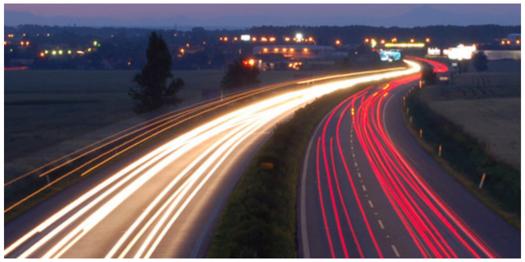
  - European country, 4M clients, data over 2 weeks

Miguel Araujo, Spiros Papadimitriou, Stephan Günnemann, Christos Faloutsos, Prithwish Basu, Ananthram Swami, Evangelos Papalexakis, Danai Koutra. *Com2: Fast Automatic Discovery of Temporal (Comet) Communities*. PAKDD 2014, Tainan, Taiwan.

Roadmap



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- Conclusions

USP
Universidade
de São Paulo

筑波大学
University of Tsukuba

Carnegie
Mellon
University

KDD 2015 – Sydney,
Australia

RSC: Mining and Modeling Temporal Activity in Social Media

Alceu F. Costa* Yuto Yamaguchi Agma J. M. Traina

Caetano Traina Jr. Christos Faloutsos

*alceufc@icmc.usp.br

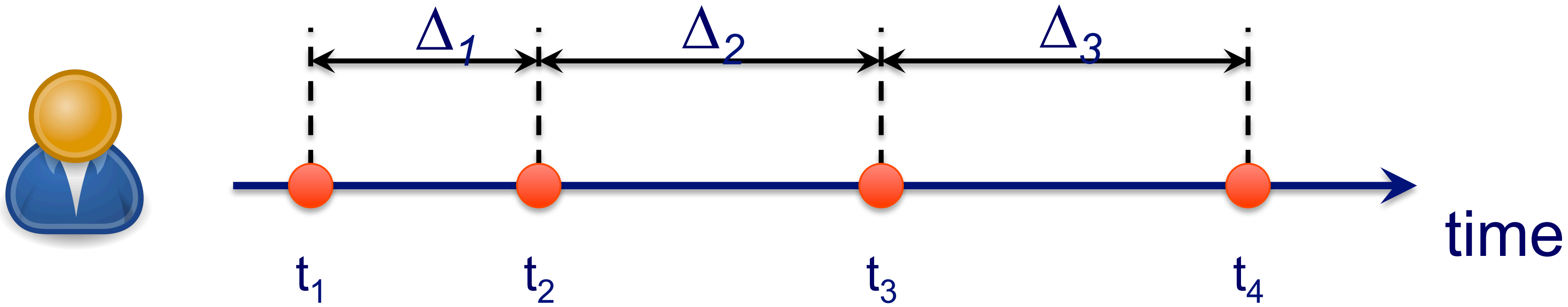
Pattern Mining: Datasets

Reddit Dataset	Twitter Dataset
Time-stamp from comments	Time-stamp from tweets
21,198 users	6,790 users
20 Million time-stamps	16 Million time-stamps

For each user we have:

Sequence of postings time-stamps: $\boldsymbol{T} = (t_1, t_2, t_3, \ldots)$

Inter-arrival times (IAT) of postings: $(\Delta_1, \Delta_2, \Delta_3, \ldots)$

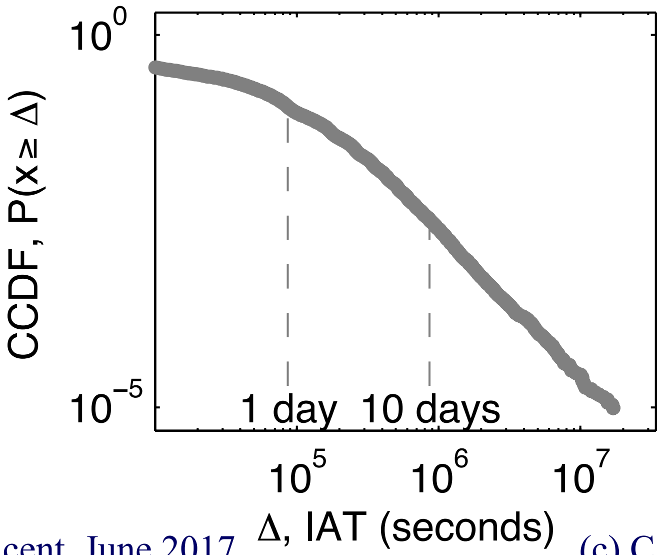


Pattern Mining

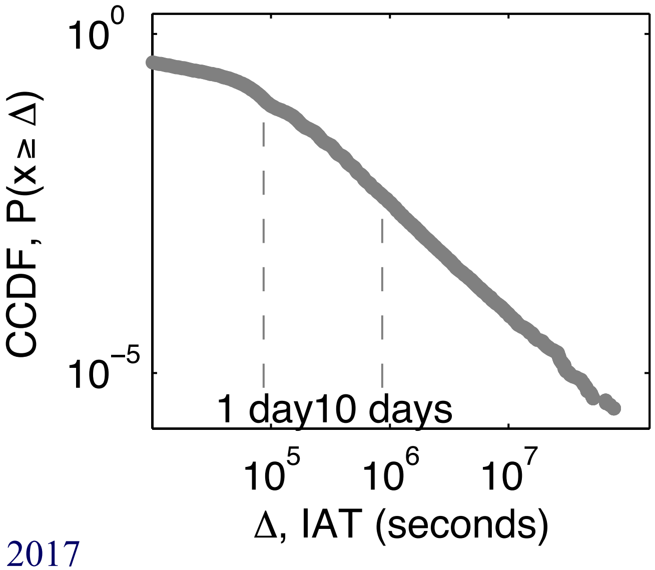
Pattern 1: Distribution of IAT is heavy-tailed

Users can be inactive for long periods of time before making new postings

IAT Complementary Cumulative Distribution Function (CCDF) (log-log axis)



Reddit Users



Twitter Users

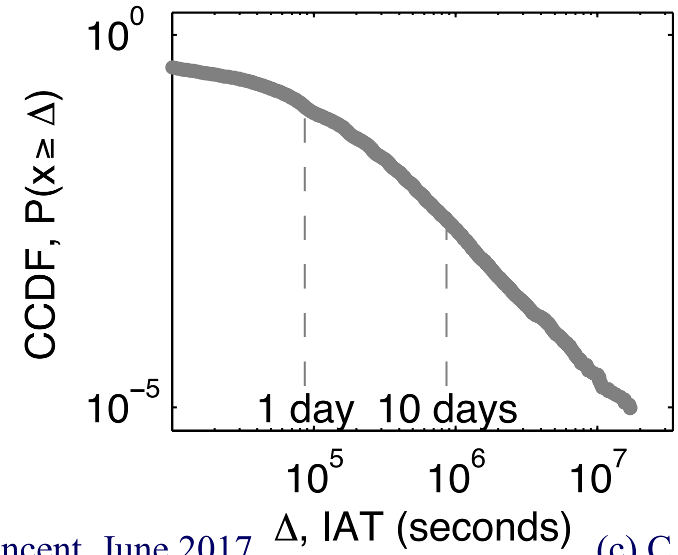
Pattern Mining

Pattern 1: Distribution of IAT is heavy-tailed

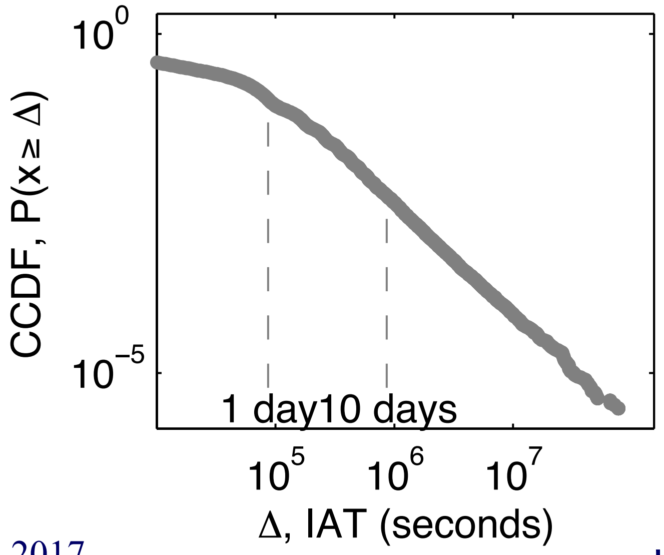
Users can be inactive for long periods of time before making new postings

No surprises – Should we give up?

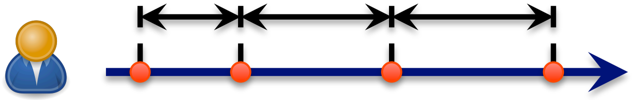
IAT Com n (CCDF)



Reddit Users

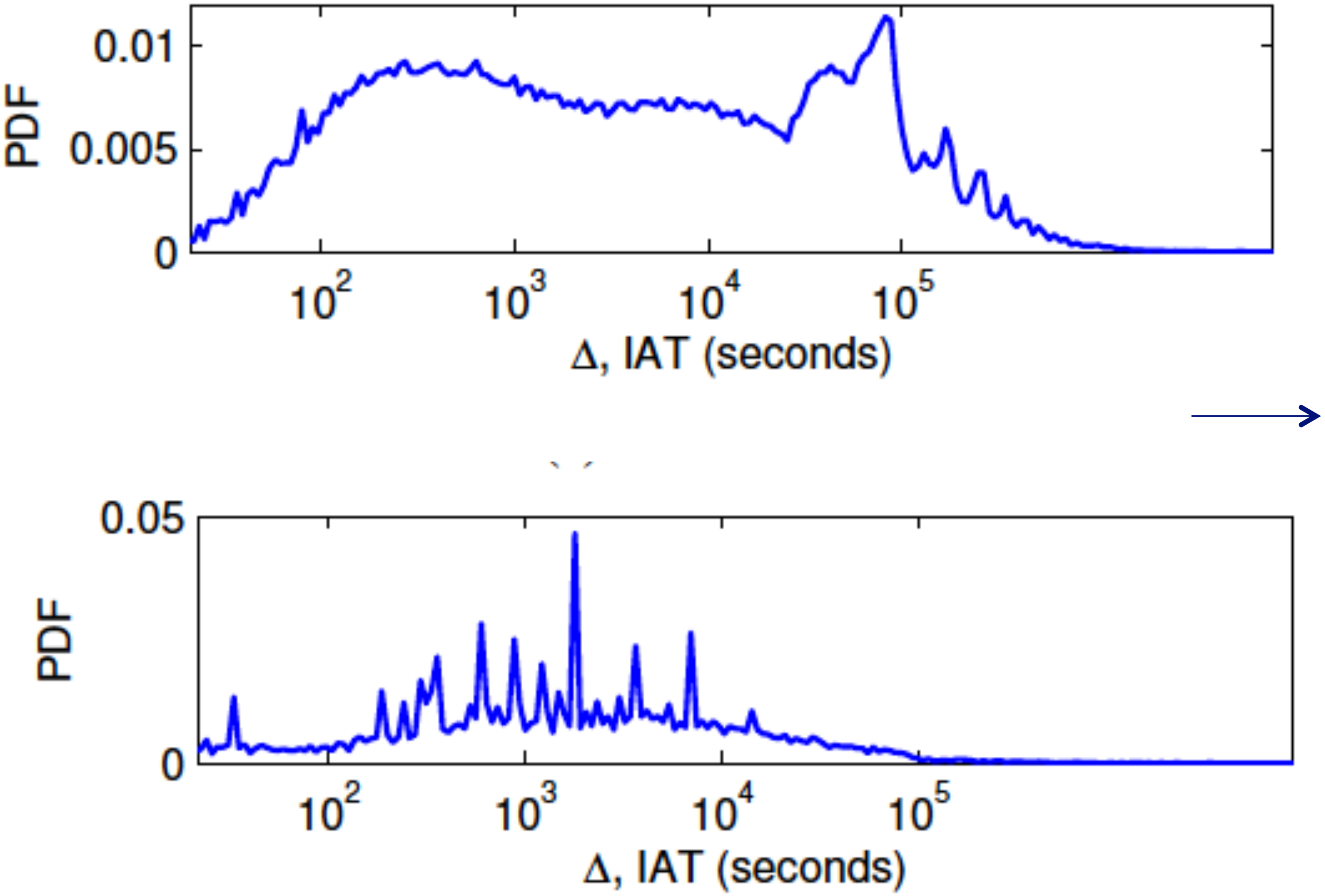


Twitter Users

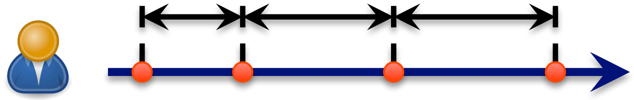


Human? Robots?

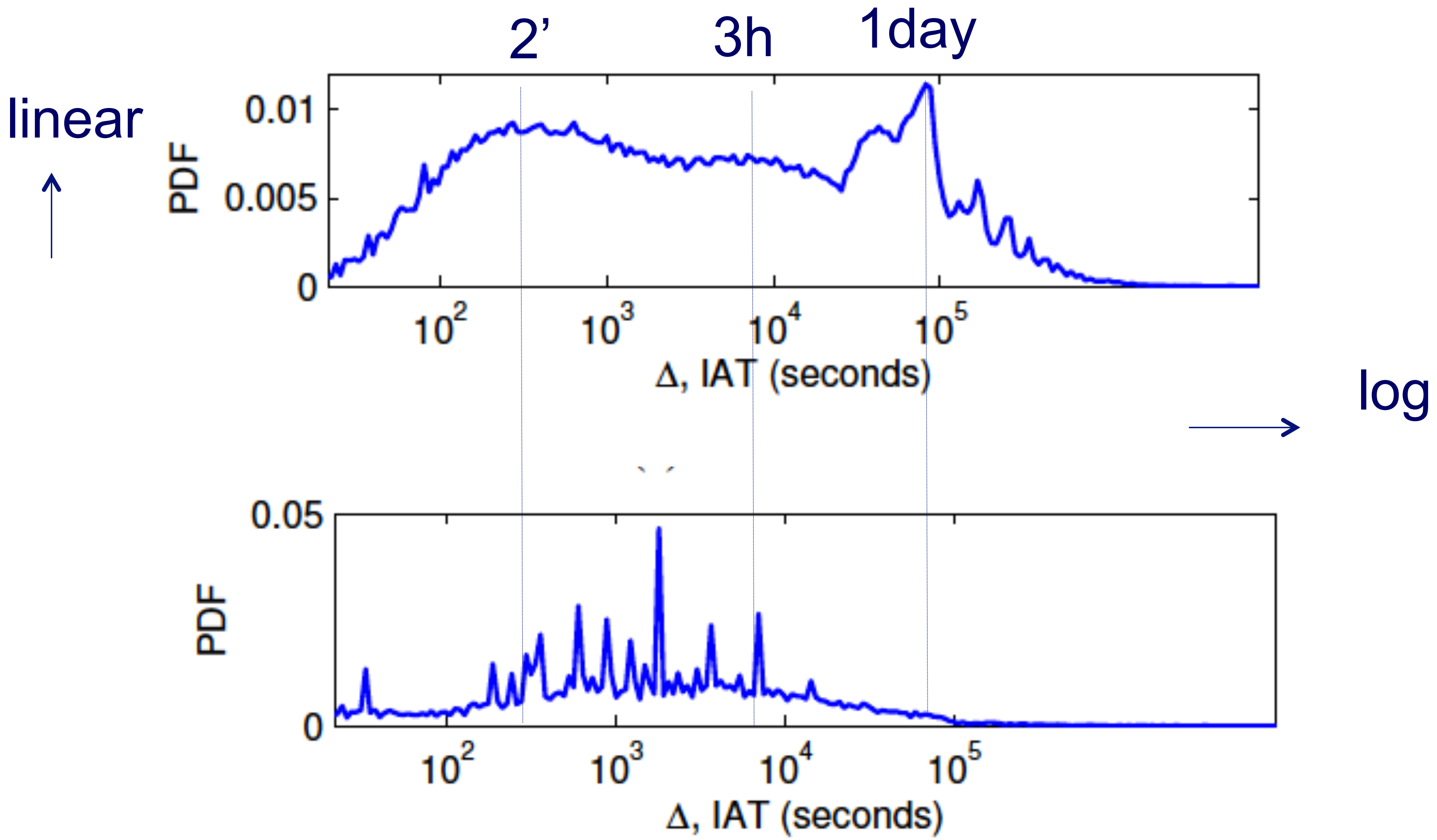
linear



log



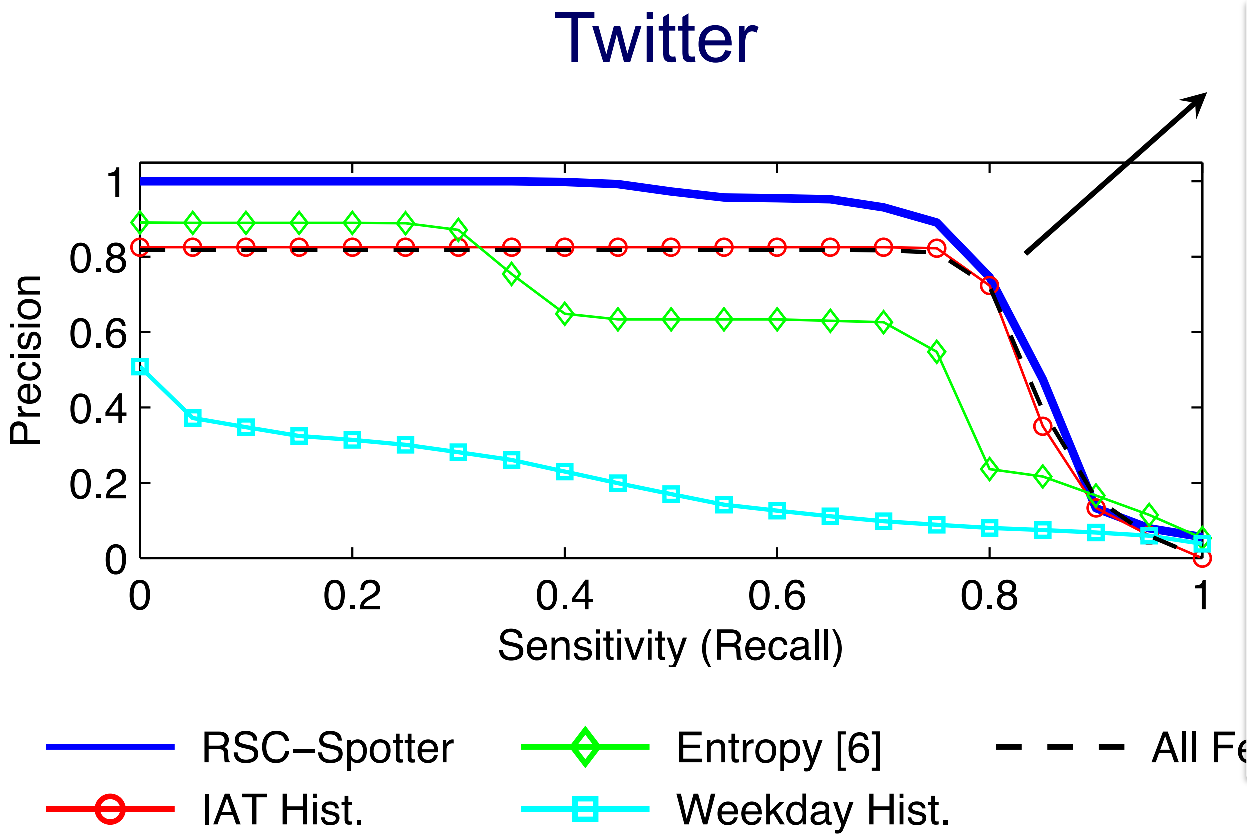
Human? Robots?



Experiments: Can RSC-Spotter Detect Bots?

Precision vs. Sensitivity Curves

Good performance: curve close to the top



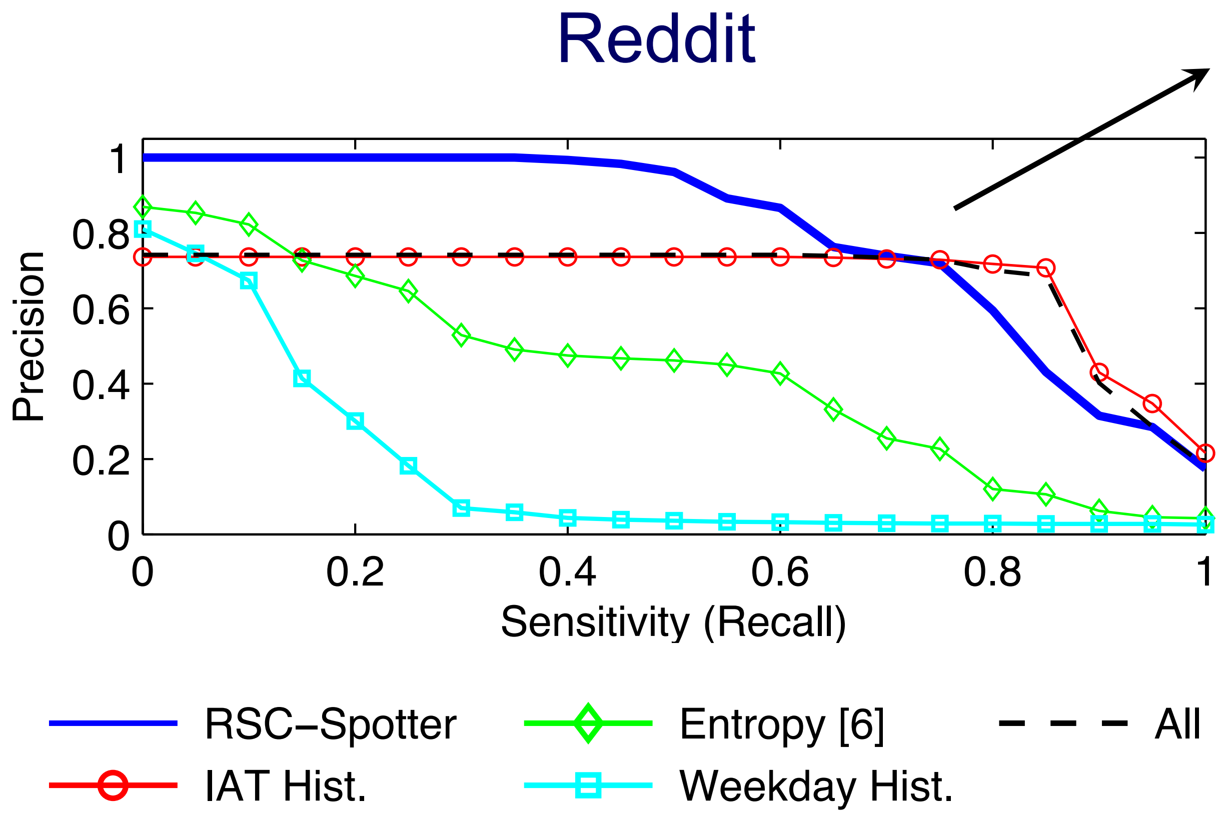
Precision > 94%
Sensitivity > 70%

With strongly imbalanced datasets
# humans >> # bots

Experiments: Can RSC-Spotter Detect Bots?

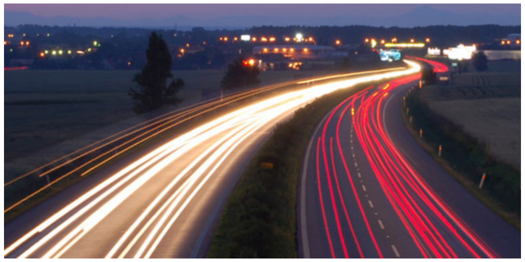
Precision vs. Sensitivity Curves

Good performance: curve close to the top



Precision > 96%
Sensitivity > 47%
With strongly imbalanced datasets
# humans >> # bots

Roadmap



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- Part#1: Patterns in graphs
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  - P2.1: tools/tensors
  - P2.2: other patterns
    - inter-arrival time
    - ➡ Network growth
- Conclusions

Beyond Sigmoids: the NetTide Model for Social Network Growth and its Applications

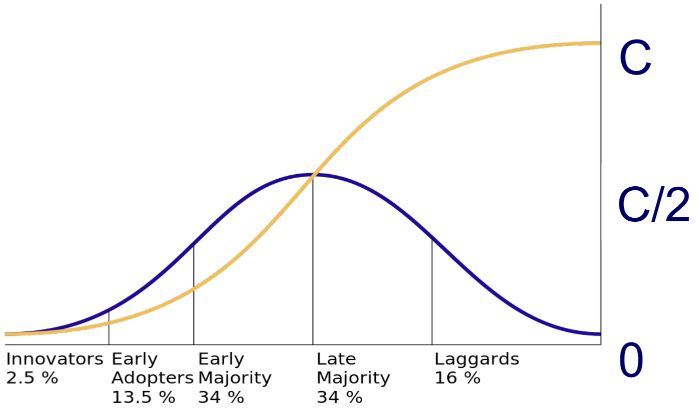
KDD'16

Chengxi Zang 臧承熙, Peng Cui, CF

PROBLEM: n(t) and e(t), over time?

- n(t): the number of nodes.
- e(t): the number of edges.
- E.g.:
  - How many members will have next month?
  - How many friendship links will have next year?

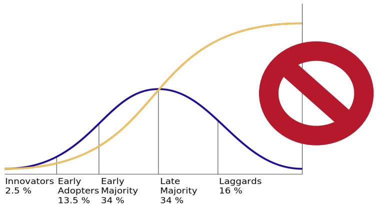
- Linear?
- Exponential?
- Sigmoid?

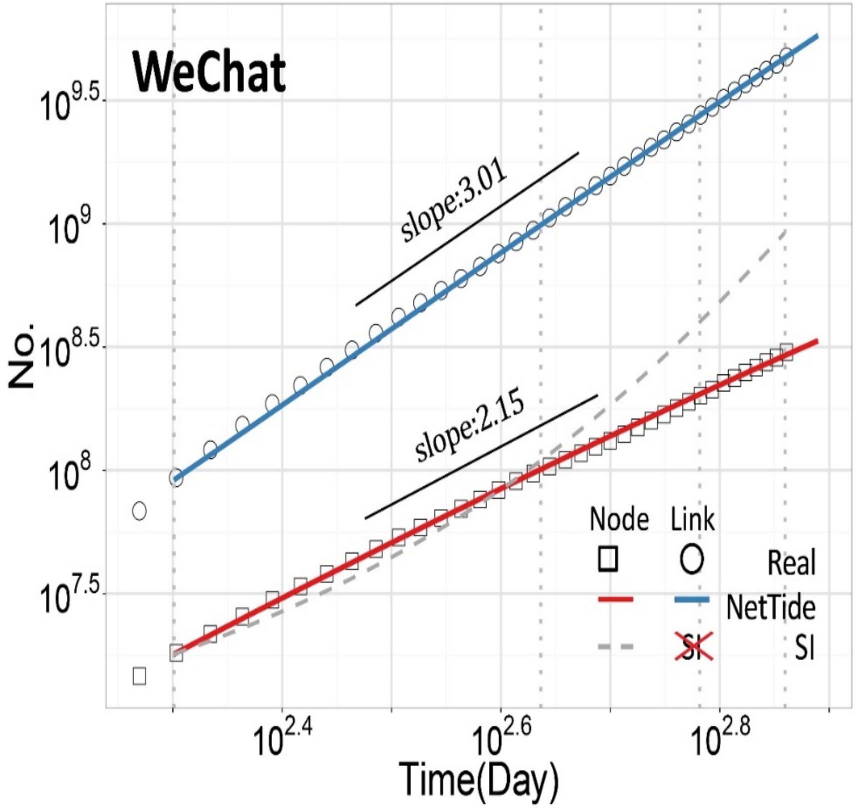


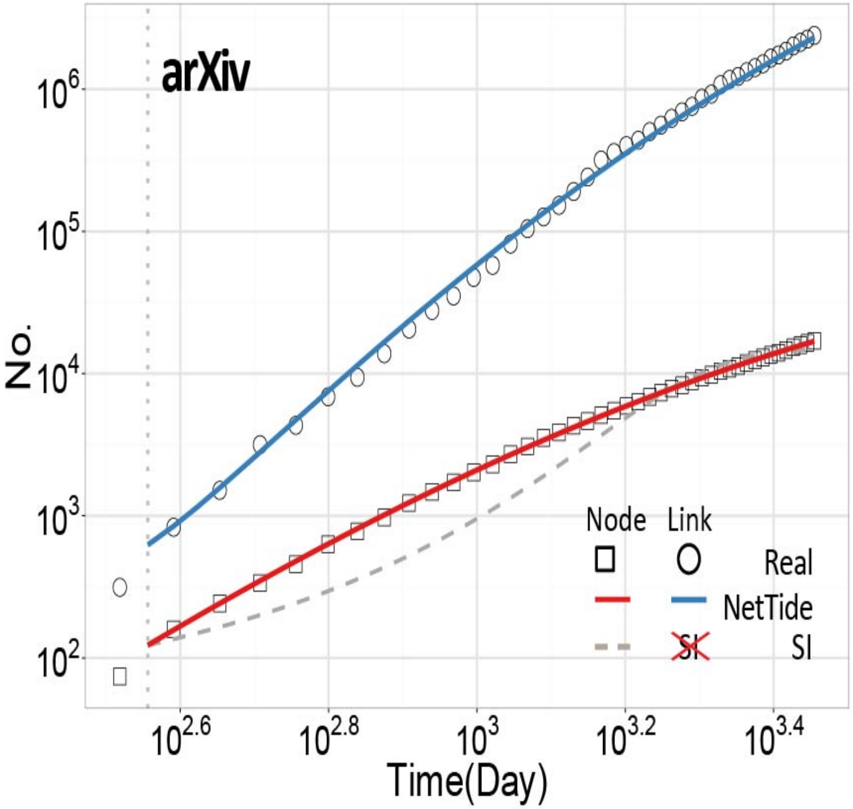
Datasets

- **WeChat 2011/1-2013/1 300M nodes, 4.75B links**
- ArXiv 1992/3-2002/3 17k nodes, 2.4M links
- Enron 1998/1-2002/7 86K nodes, 600K links
- Weibo 2006 165K nodes, 331K links

A: Power Law Growth







Cumulative growth（Log-Log scale）

Carnegie Mellon

Details

Proposed: NetTide Model

- Nodes n(t)

$$\frac{dn(t)}{dt} = \frac{\beta}{t^{\theta}} n(t)(N - n(t))$$

- Links e(t)

$$\frac{de(t)}{dt} = \frac{\beta'}{t^{\theta}} n(t)\left(\alpha(n(t) - 1)^{\gamma} - \frac{e(t)}{n(t)}\right) + 2\frac{dn(t)}{dt}$$

Details

NetTide-Node Model

$$dn(t)/dt = \beta/t^{\theta}\, n(t)(N-n(t))$$

- Intuition:
  - Rich-get-richer
  - Limitation
  - Fizzling nature

$\left.\begin{array}{l}\text{Rich-get-richer}\\ \text{Limitation}\end{array}\right\}$ = SI; ~Bass

Details

NetTide-Node Model

$$\frac{dn(t)}{dt} = \frac{\beta}{t^{\theta}} \, n(t) \, \left(N - n(t)\right)$$

#nodes(t)

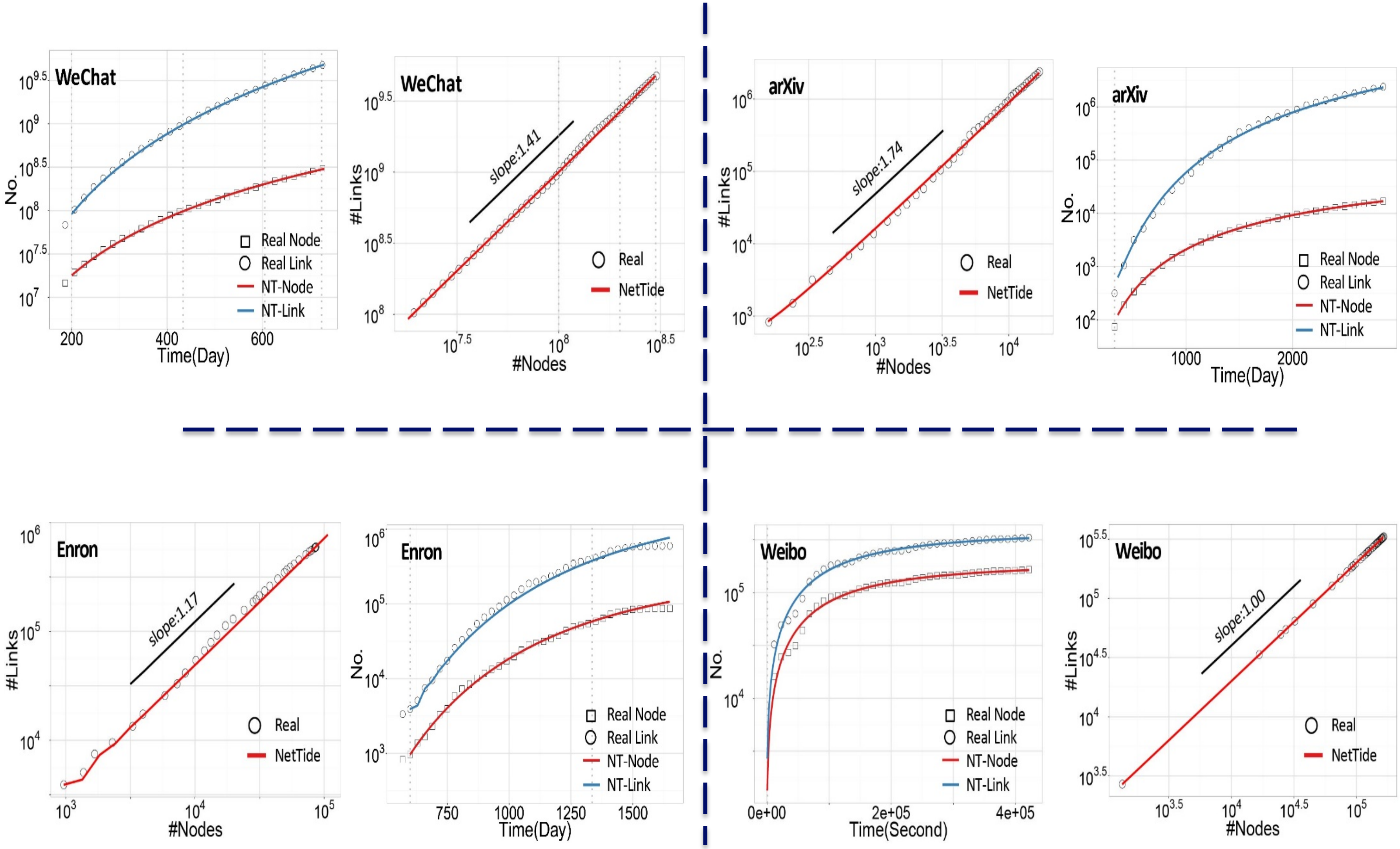
Total population

- Intuition:
  - Rich-get-richer
  - Limitation
  - Fizzling nature

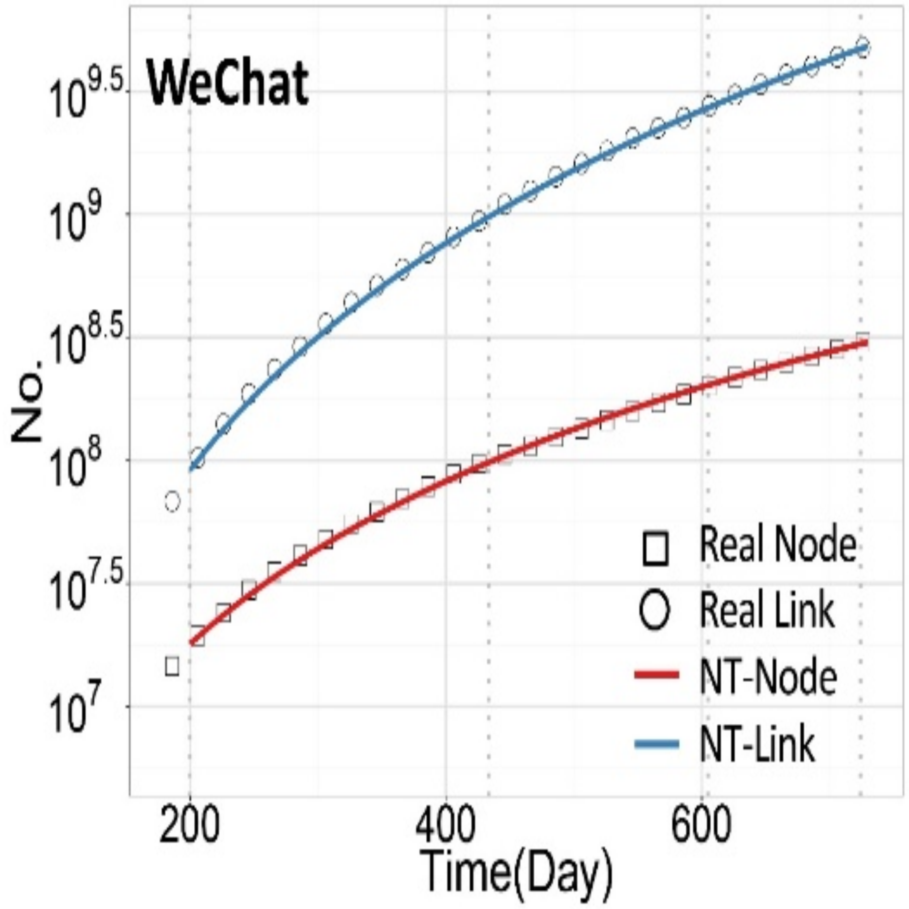
= SI; ~Bass

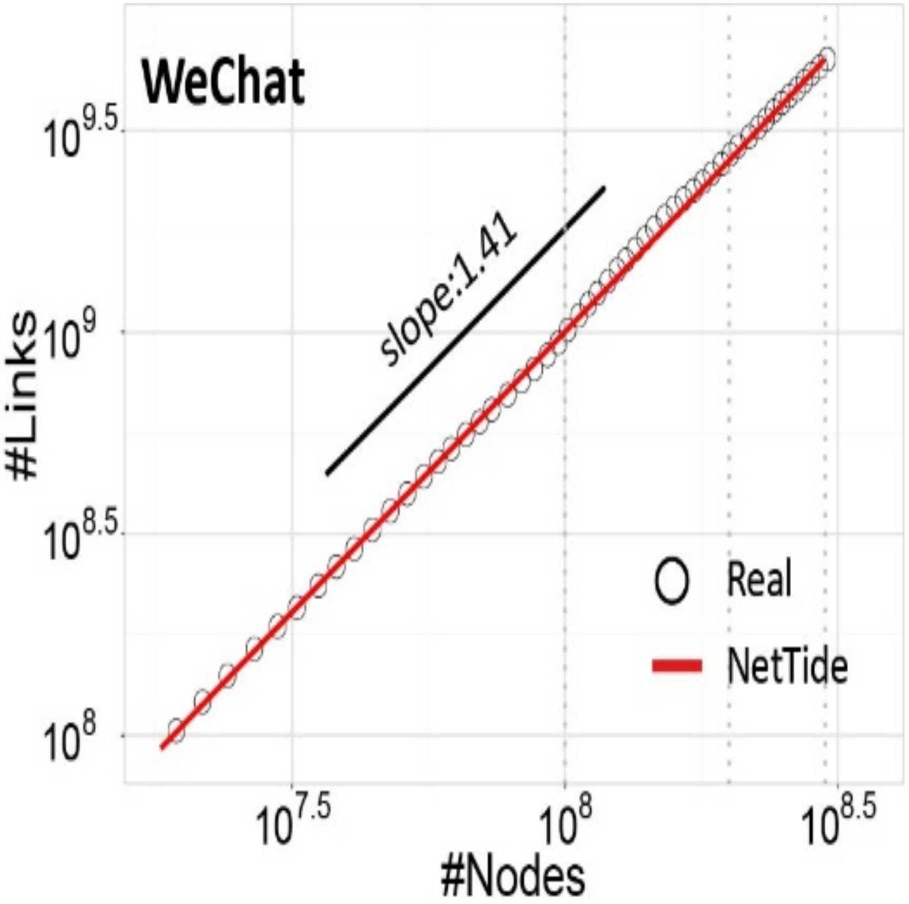
Carnegie Mellon

Results: Accuracy

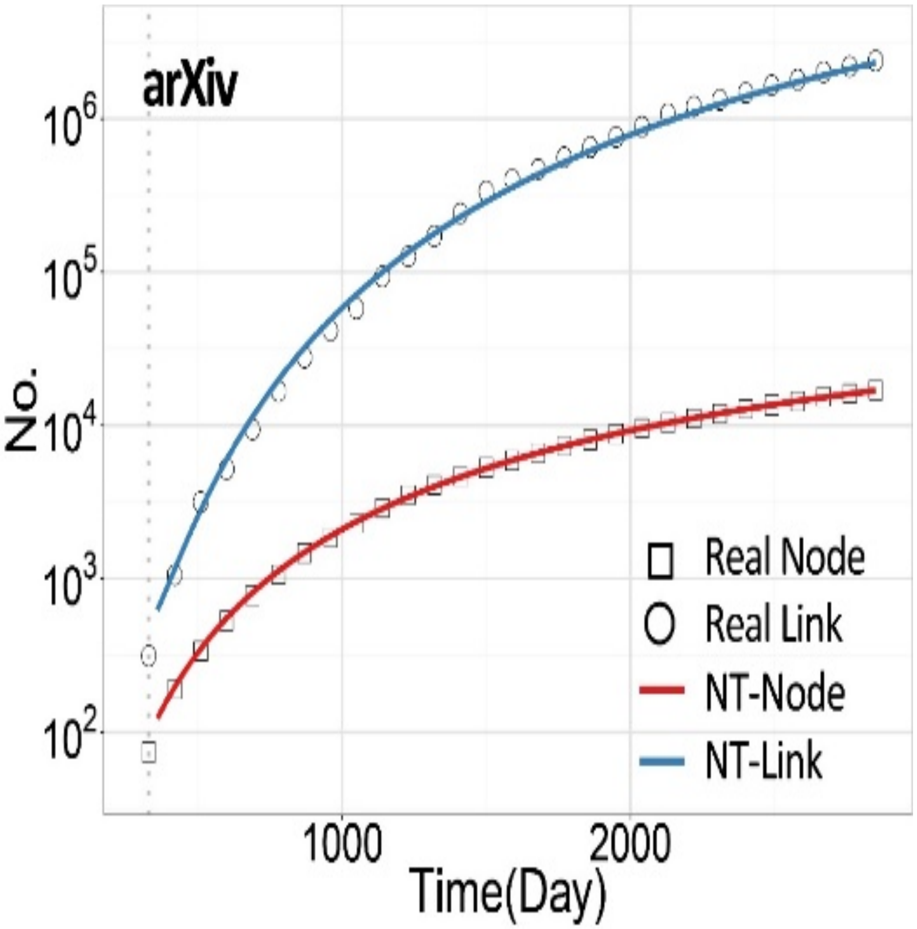


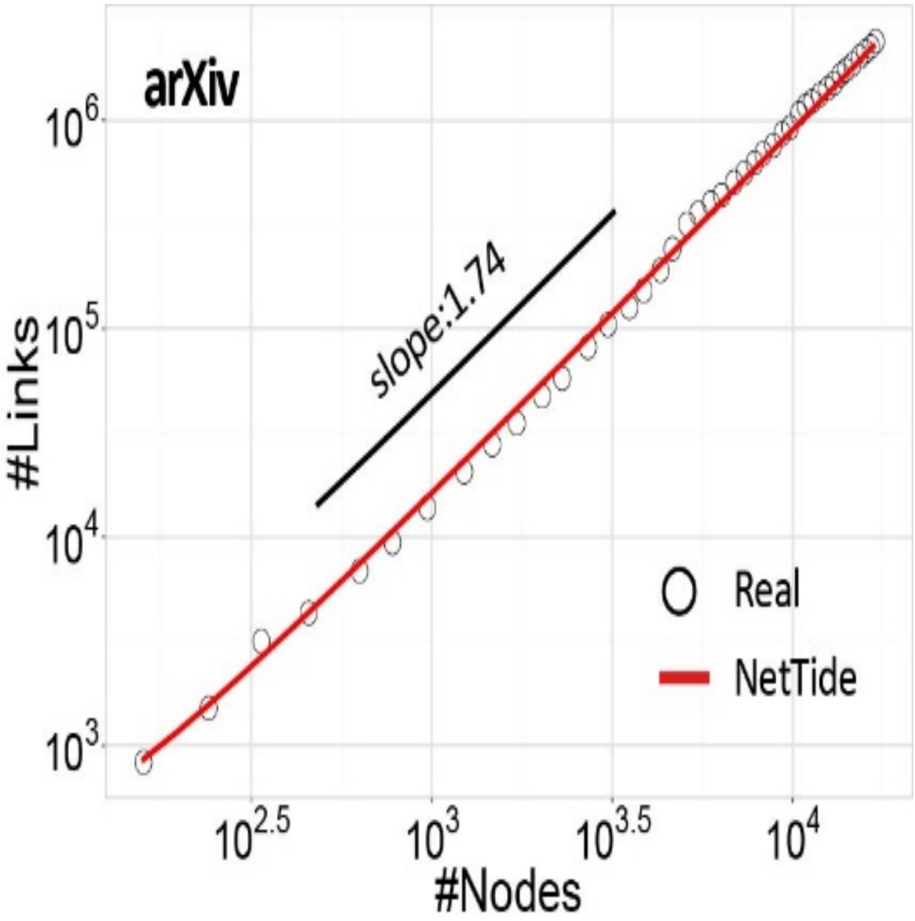
Results: Accuracy



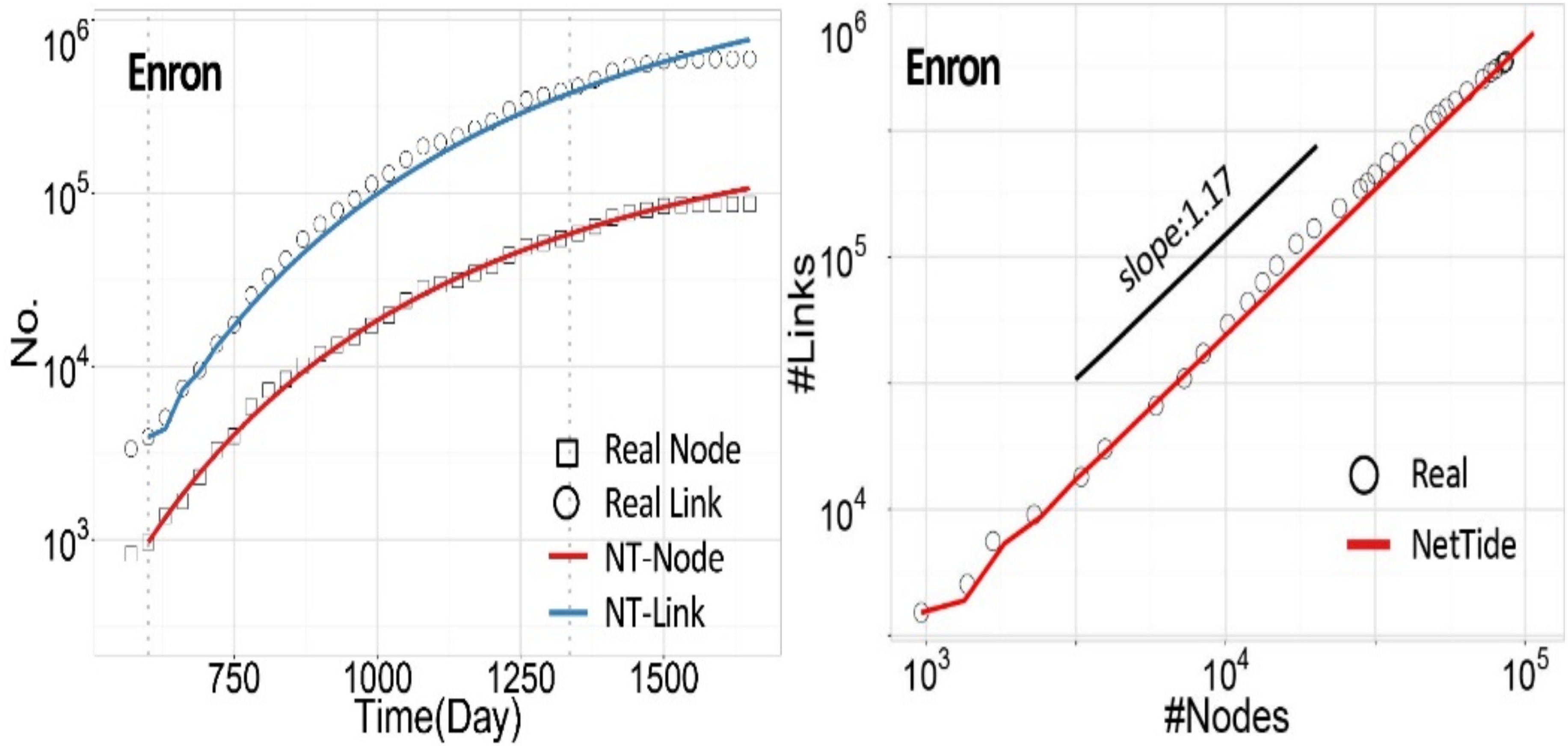


Results: Accuracy

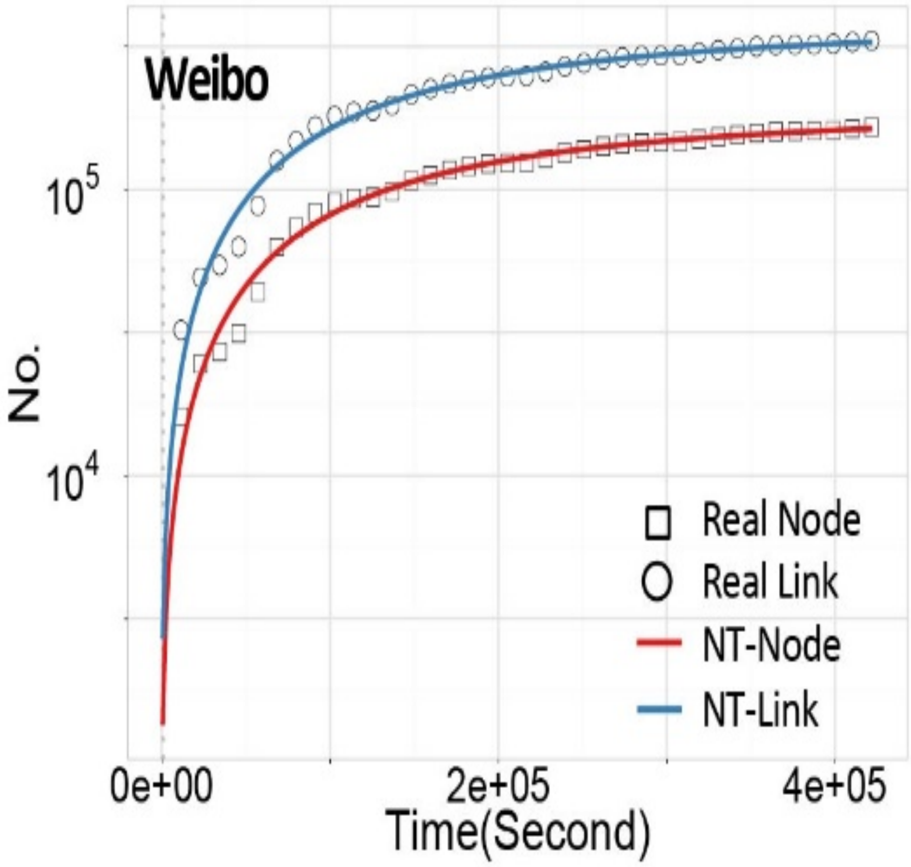


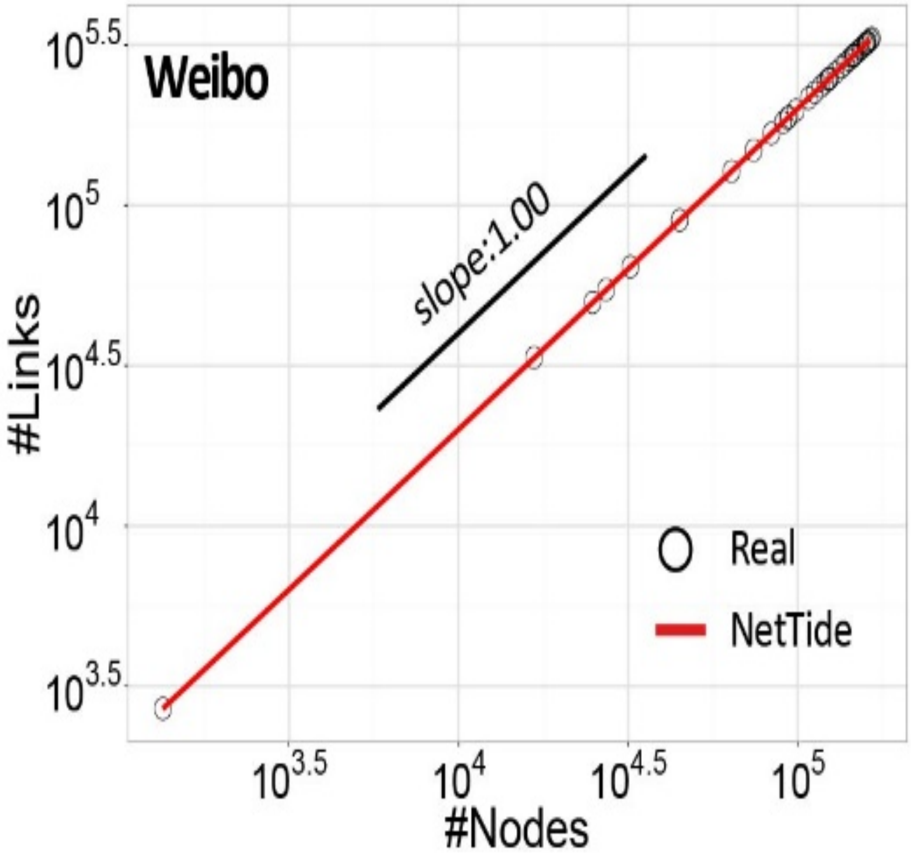


Results: Accuracy



Results: Accuracy

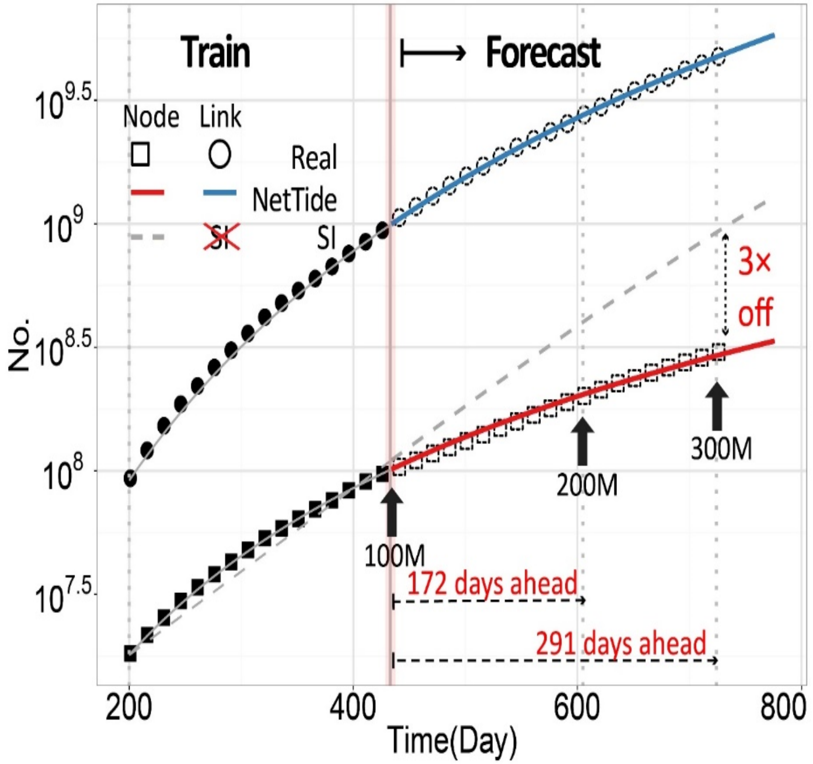


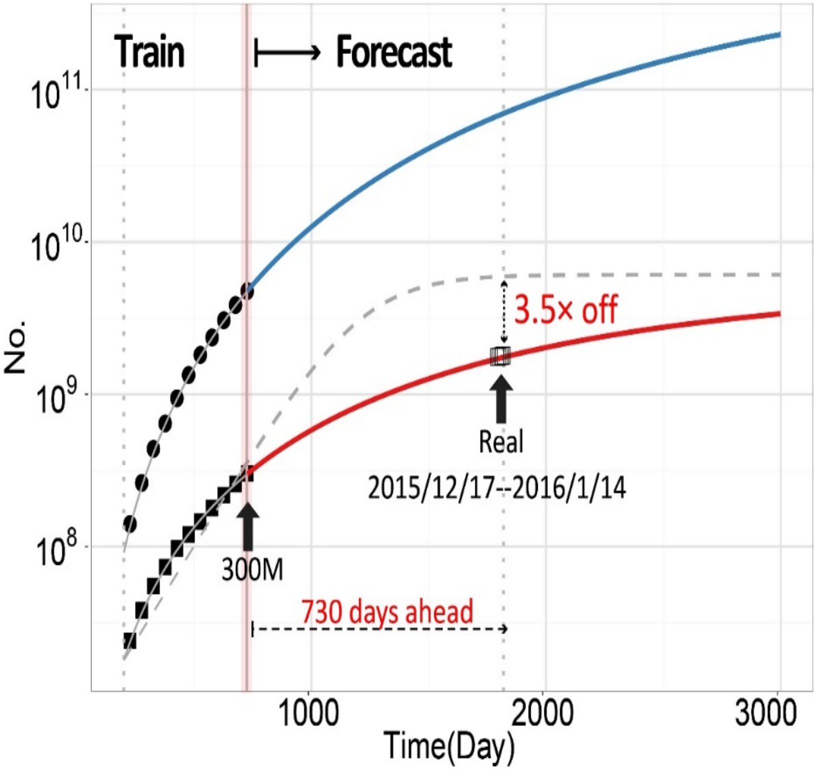


Results: Forecast

WeChat from 100 million to 300 million

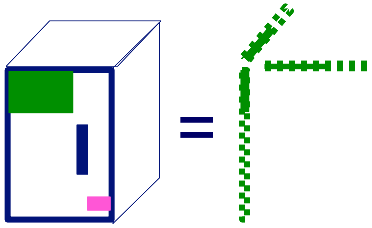
730 days ahead

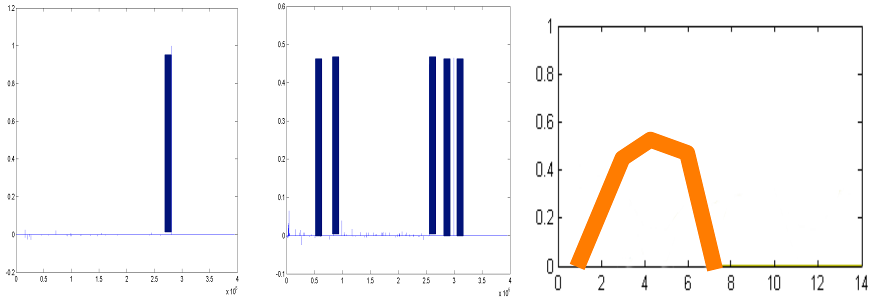




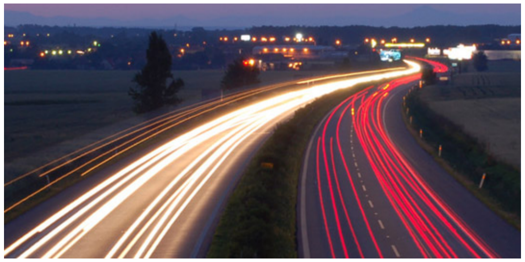
Part 2: Conclusions

- Time-evolving / heterogeneous graphs -> tensors
- PARAFAC finds patterns
- Surprising temporal patterns (P.L. growth)





Roadmap



- Introduction – Motivation
  - Why study (big) graphs?
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
- ➡ Acknowledgements and Conclusions

Thanks

Disclaimer: All opinions are mine; not necessarily reflecting the opinions of the funding agencies

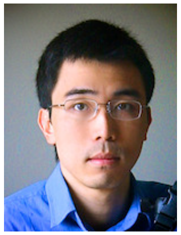
Thanks to: NSF IIS-0705359, IIS-0534205, CTA-INARC; Yahoo (M45), LLNL, IBM, SPRINT, Google, INTEL, HP, iLab

Cast

Akoglu,
Leman

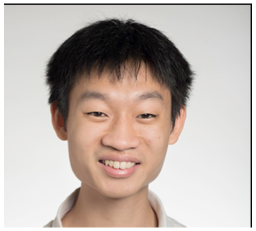
Araujo,
Miguel

Beutel,
Alex



Chau,
Polo

Eswaran,
Dhivya



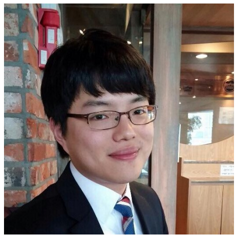
Hooi,
Bryan

Kang, U

Koutra,
Danai

Papalexakis,
Vagelis

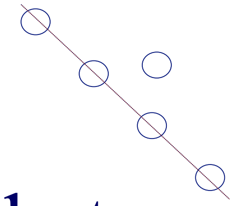
Shah,
Neil



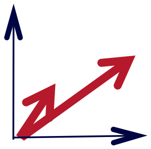
Shin,
Kijung

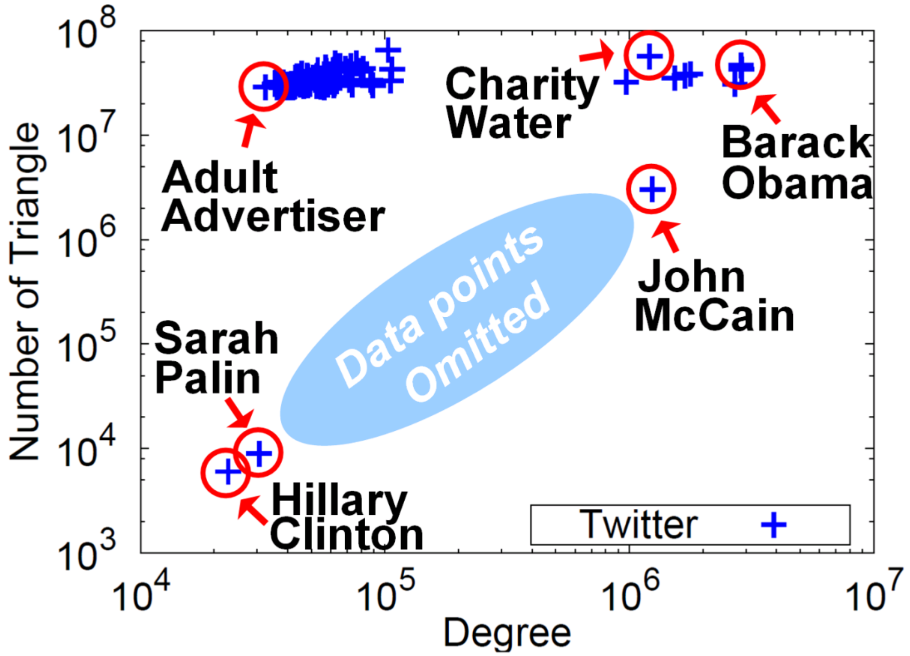
Song,
Hyun Ah

CONCLUSION#1 – Big data



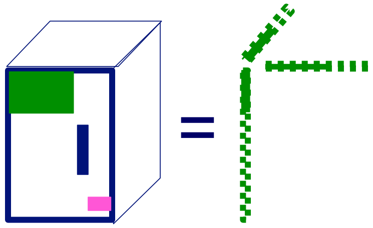
- **Patterns** **Anomalies**
- **Large** datasets reveal patterns/outliers that are invisible otherwise

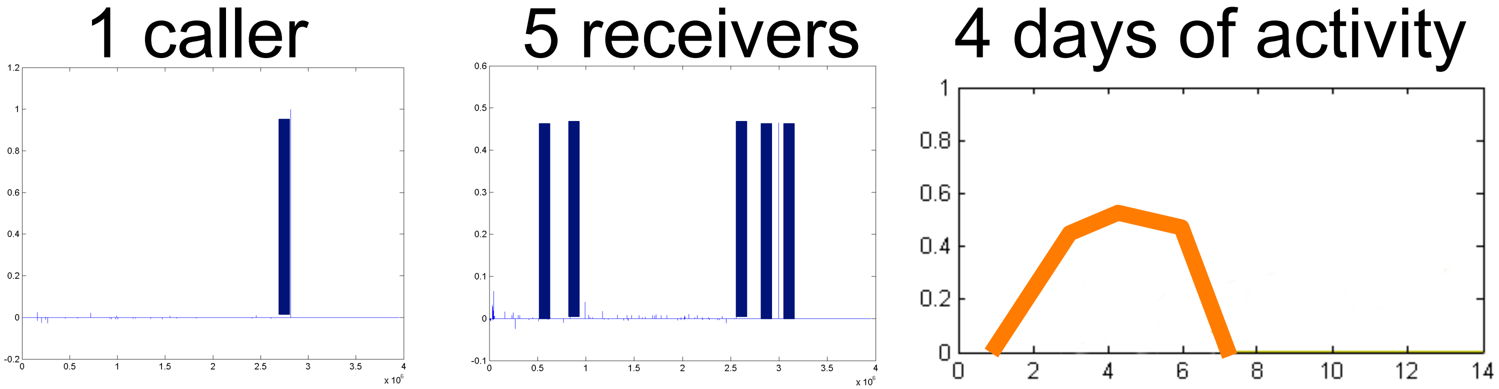




CONCLUSION#2 – tensors

- powerful tool



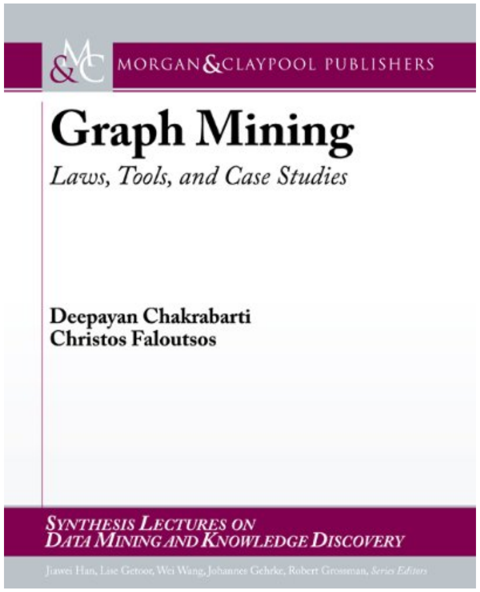

1 caller

5 receivers

4 days of activity

References

- D. Chakrabarti, C. Faloutsos: *Graph Mining – Laws, Tools and Case Studies*, Morgan Claypool 2012
- http://www.morganclaypool.com/doi/abs/10.2200/S00449ED1V01Y201209DMK006



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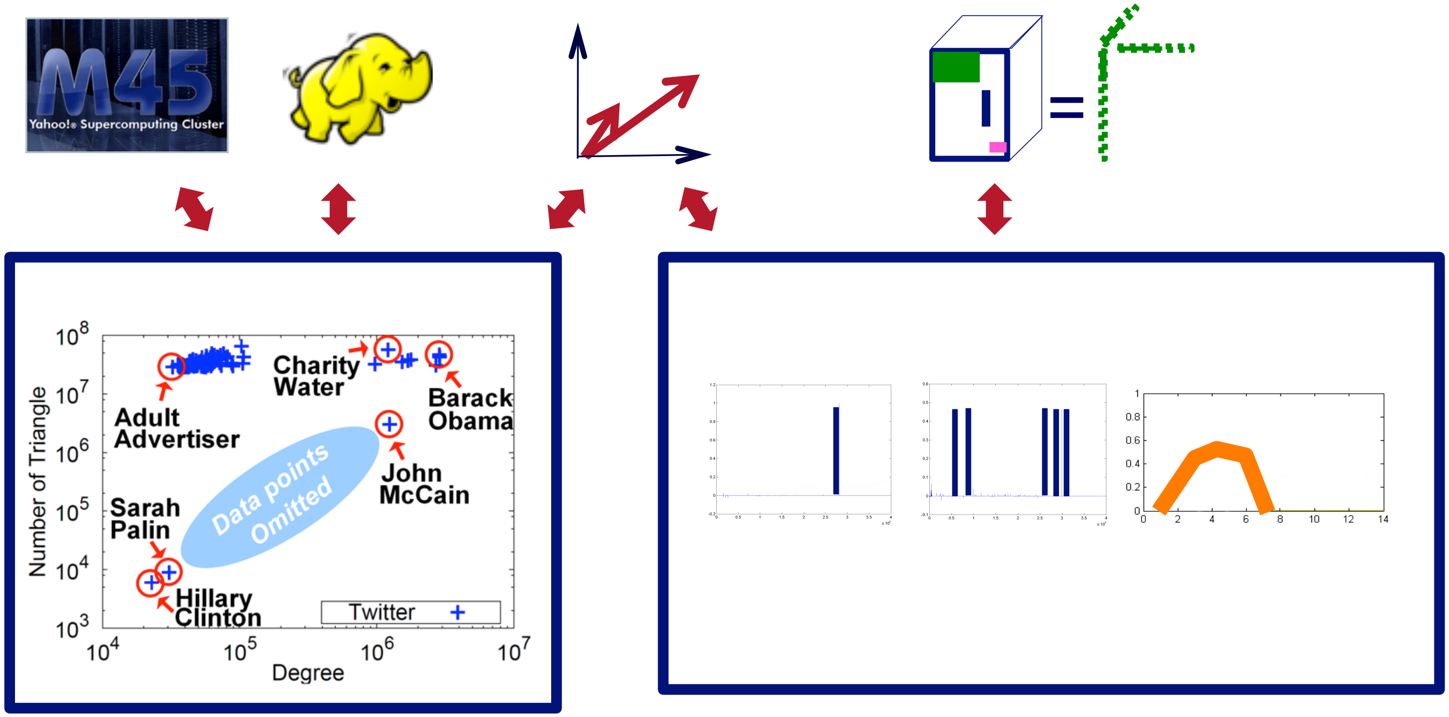
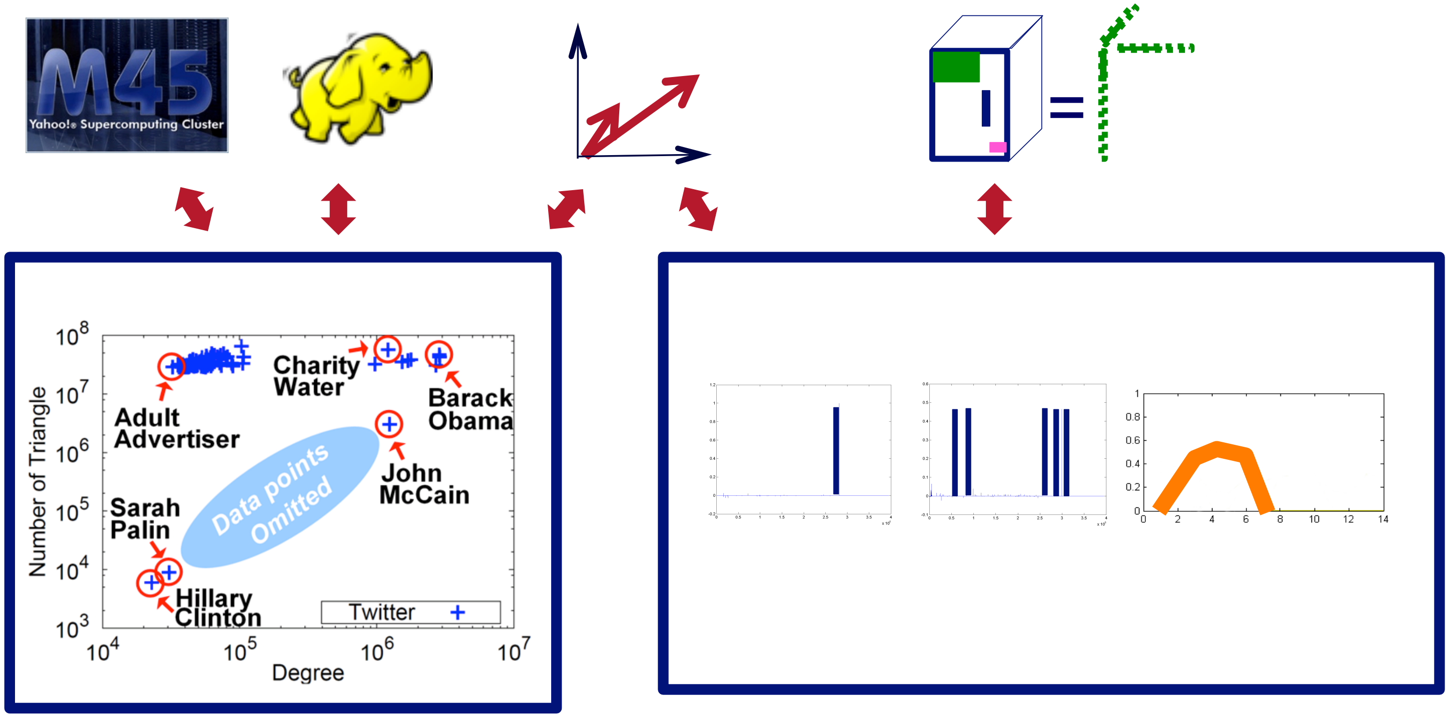
TAKE HOME MESSAGE:

Cross-disciplinarity



Thank you!

Cross-disciplinarity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Yahoo!® Supercomputing Cluster
=
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Degree
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Adult Advertiser
Charity Water
Barack Obama
John McCain
Sarah Palin
Hillary Clinton
Data points Omitted
Twitter +