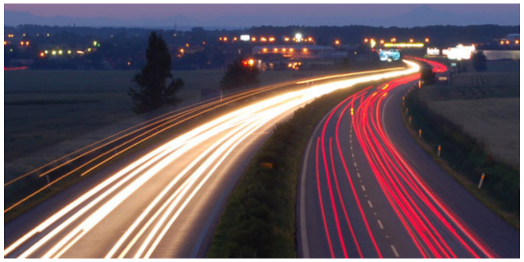
Carnegie Mellon

Anomaly detection in large graphs

Christos Faloutsos

CMU

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

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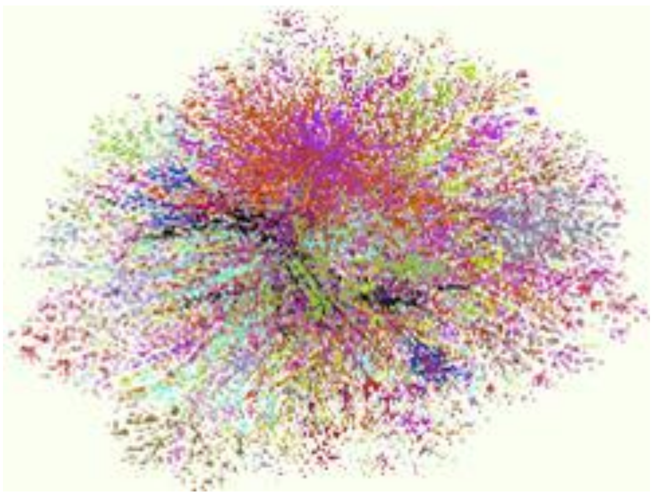
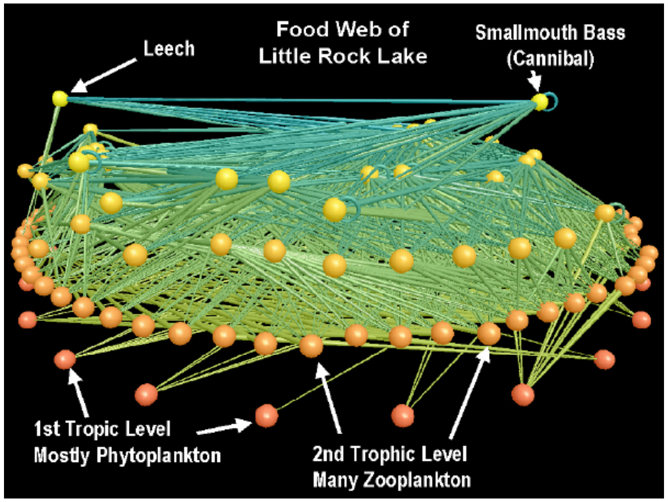
Graphs - why should we care?



Internet Map
[lumeta.com]



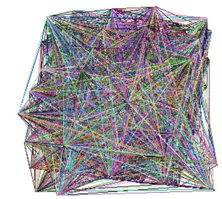
Food Web
[Martinez '91]

Graphs - why should we care?

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

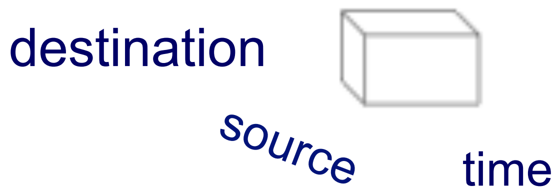
- Many-to-many db relationship -> graph

Motivating problems

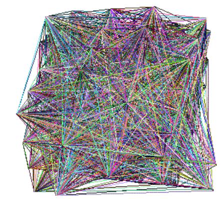


- P1: patterns? Fraud detection?

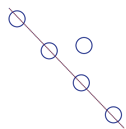
- P2: patterns in time-evolving graphs / tensors



Motivating problems



- P1: patterns? Fraud detection?

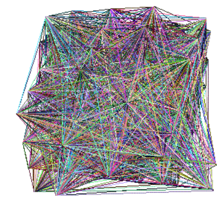


Patterns

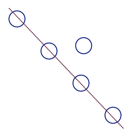
anomalies

- P2: patterns in time-evolving graphs / tensors

Motivating problems



- P1: patterns? Fraud detection?

 Patterns  anomalies*

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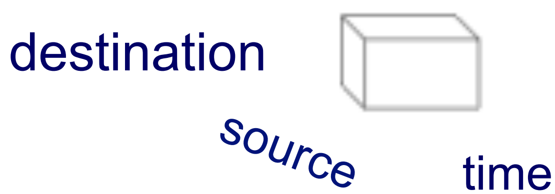
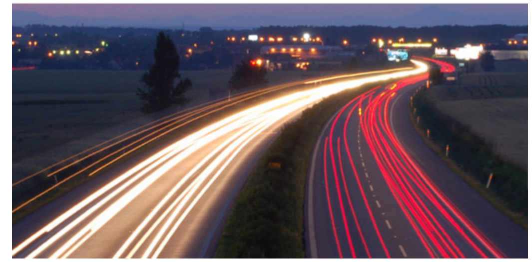


**** Robust Random Cut Forest Based Anomaly Detection on Streams*** **Sudipto Guha, Nina Mishra , Gourav Roy, Okke Schrijvers, ICML'16**

Roadmap



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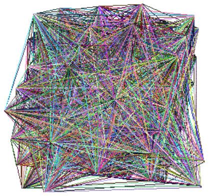
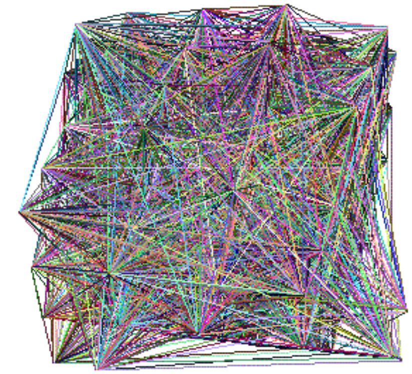


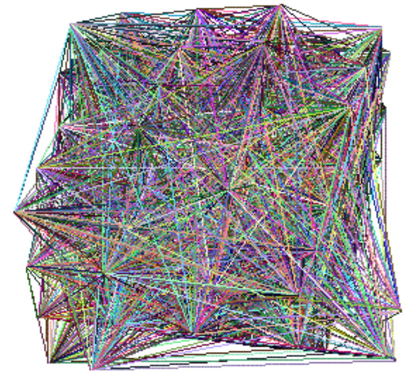
Part 1: Patterns, & fraud detection

Laws and patterns

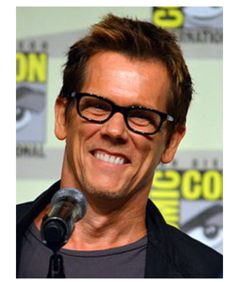


- Q1: Are real graphs random?

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

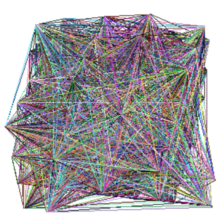
- Power law in the degree distribution [Faloutsos x 3 SIGCOMM99]

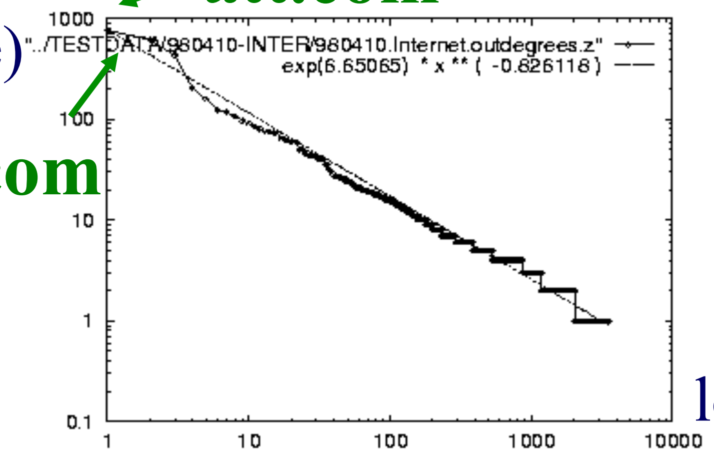
internet domains

att.com

log(degree)

ibm.com





log(rank)

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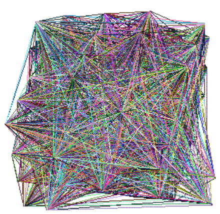
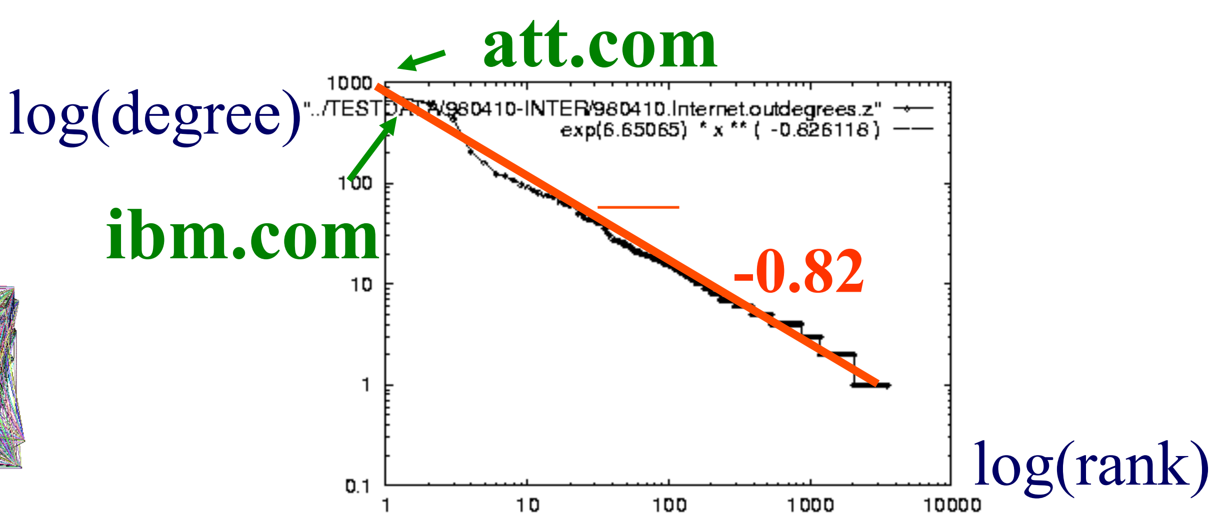
- Power law in the degree distribution [Faloutsos x 3 SIGCOMM99]

internet domains

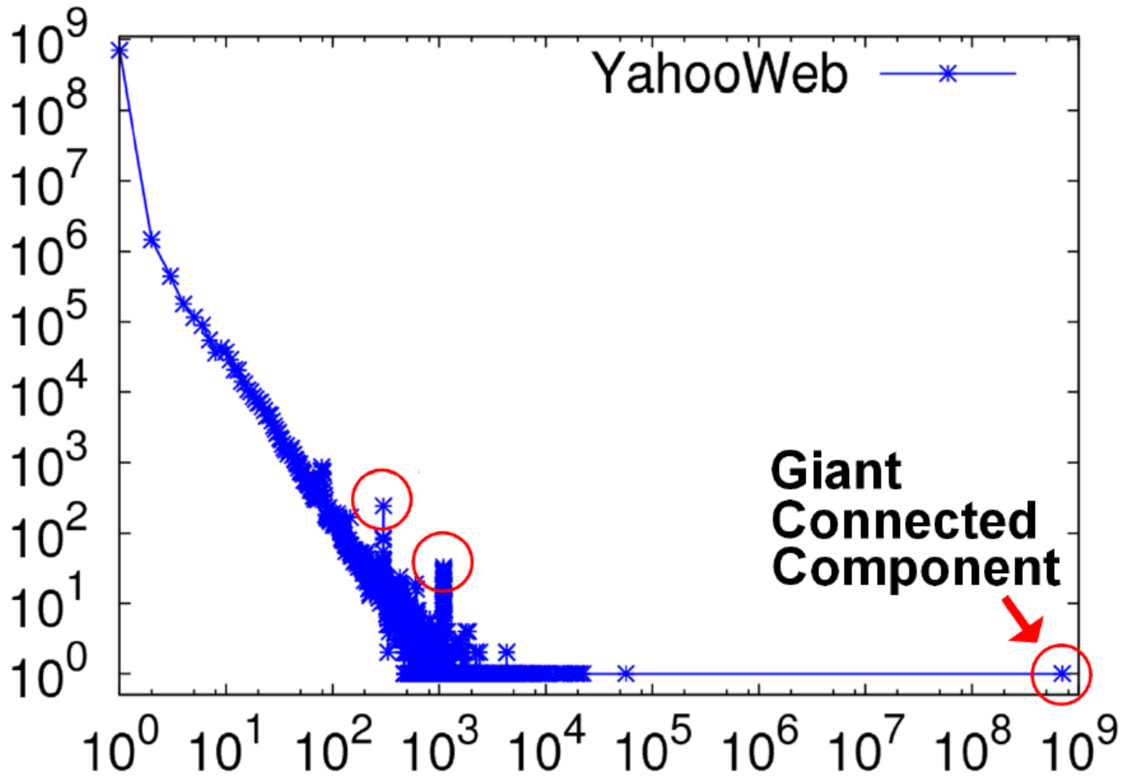




S2: connected component sizes

- Connected Components – 4 observations:

Count

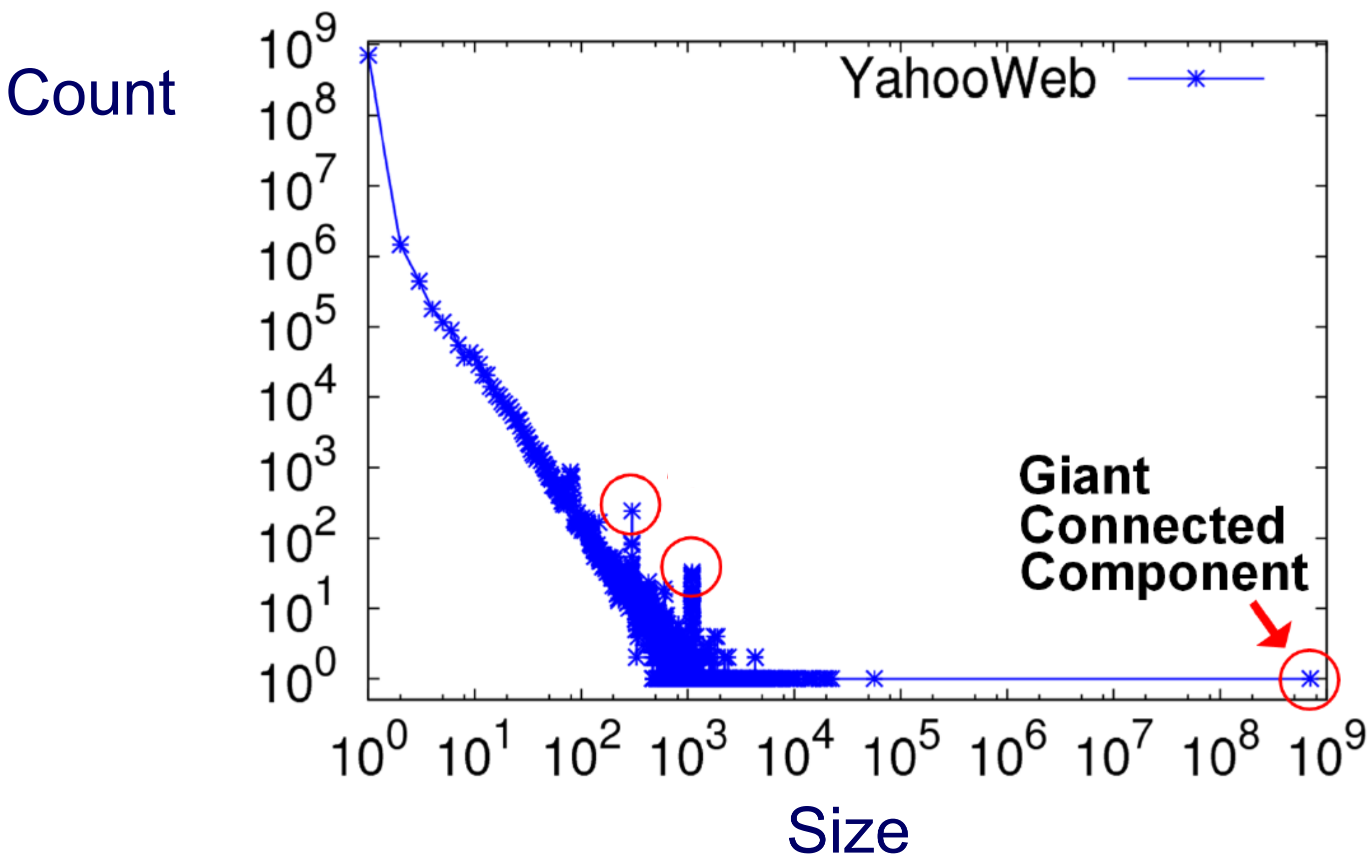


1.4B nodes
6B edges

Size

S2: connected component sizes

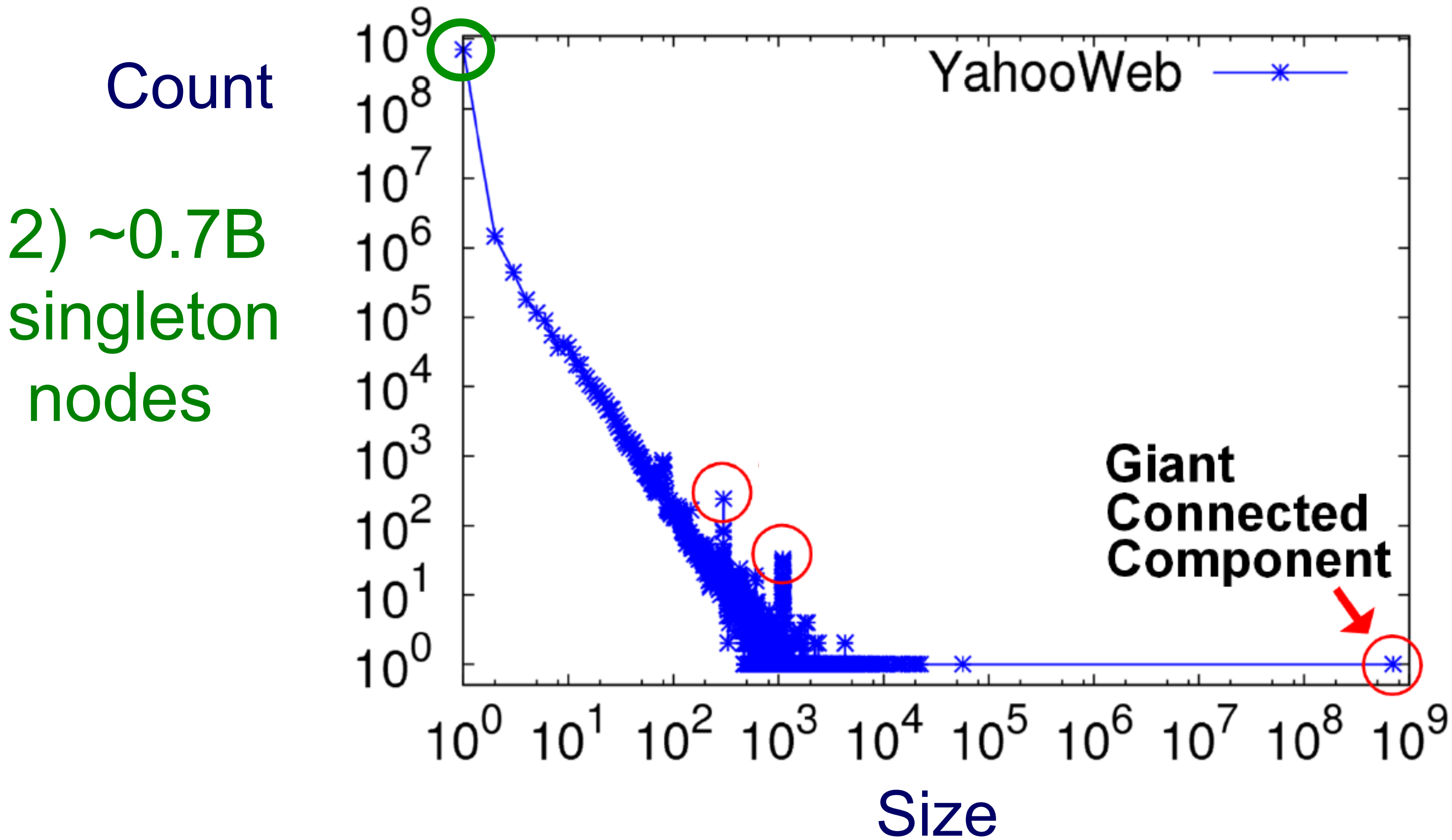
- Connected Components



1) 10K x larger than next

S2: connected component sizes

- Connected Components



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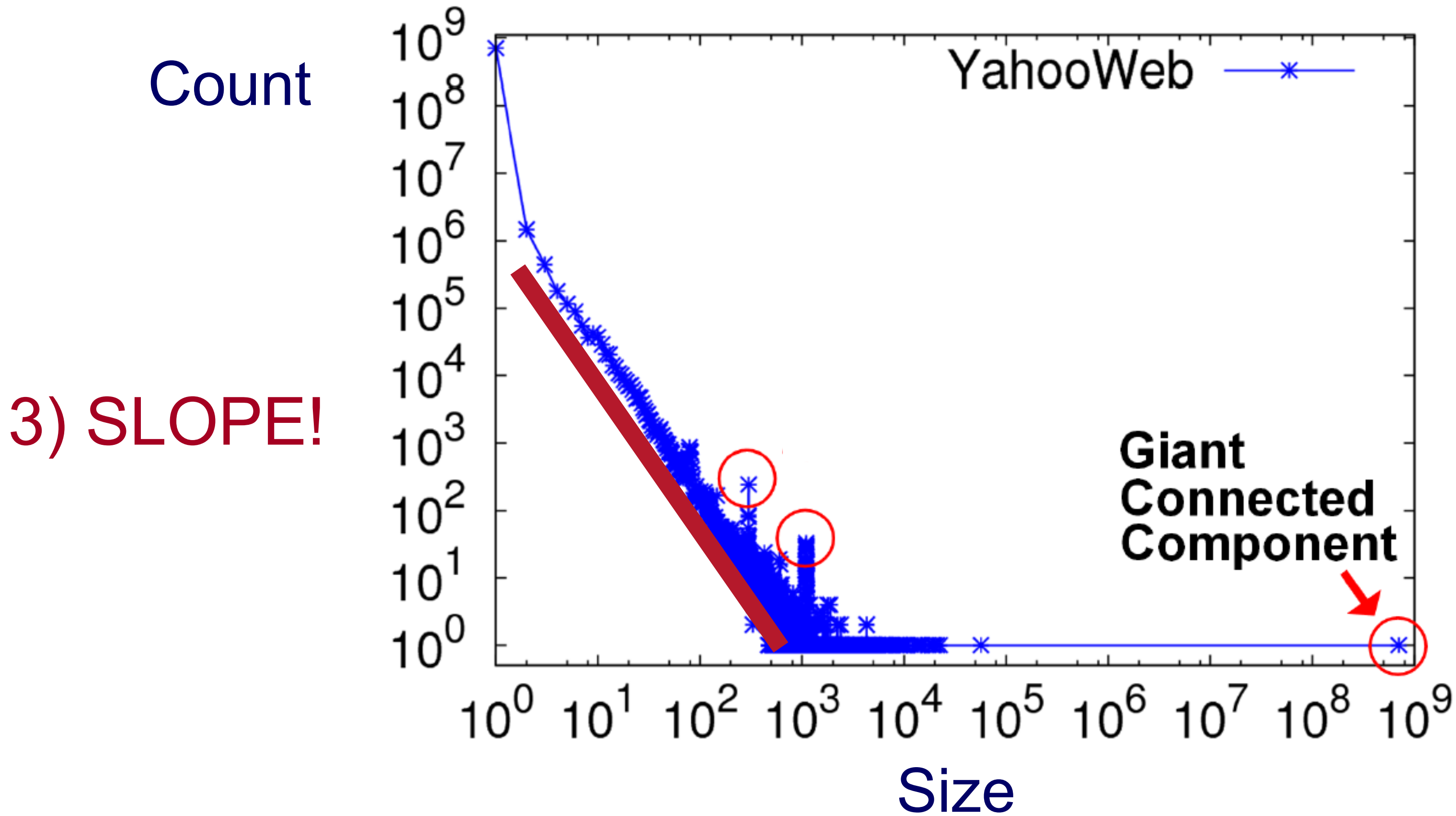

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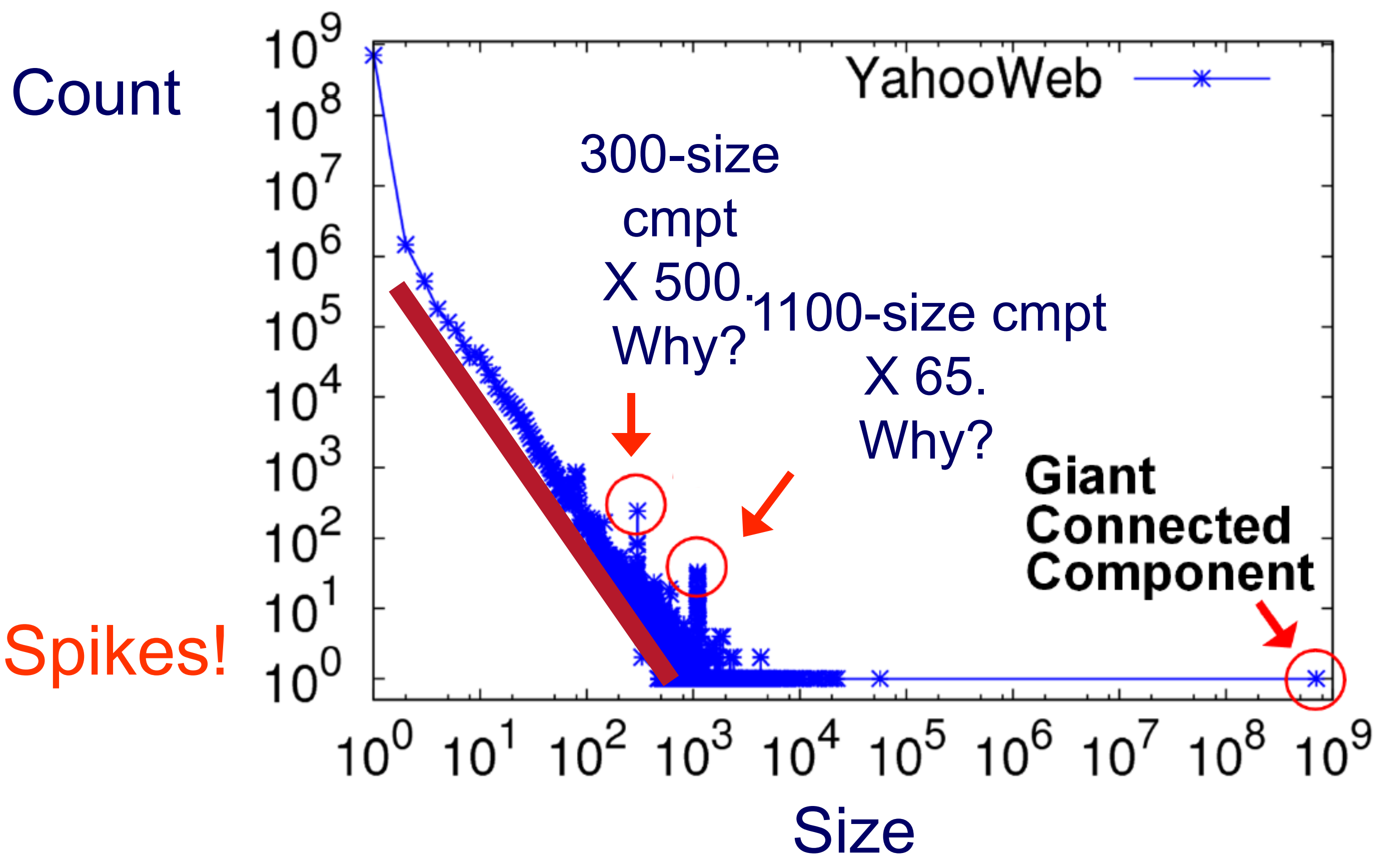
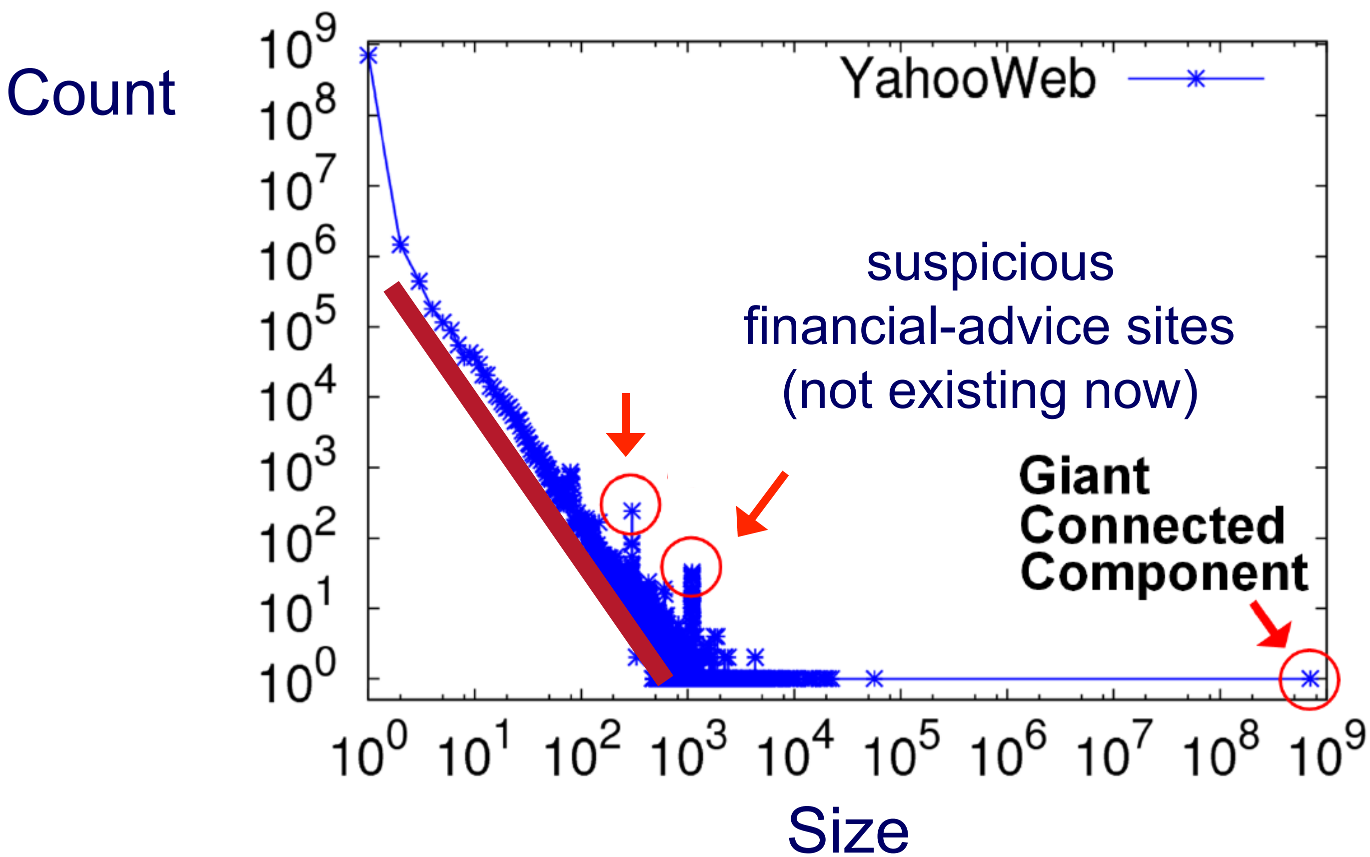


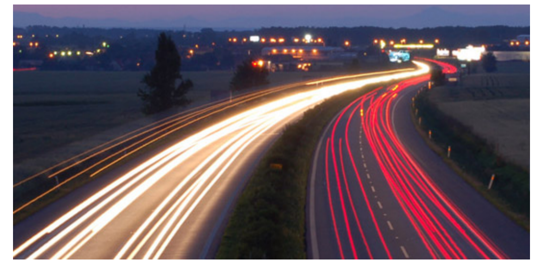
4) Spikes!

S2: connected component sizes

- Connected Components



Roadmap



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  - P1.1: Patterns: Degree; Triangles
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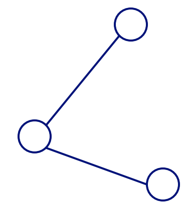
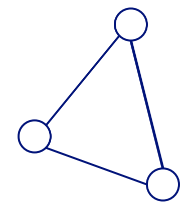
Solution# S.3: Triangle 'Laws'

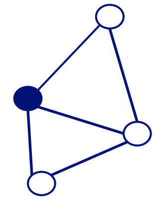


- Real social networks have a lot of triangles

Solution# S.3: Triangle 'Laws'

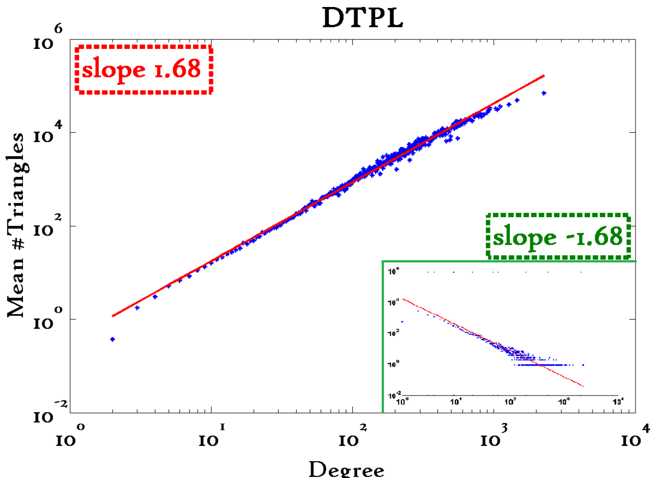


- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?
  - 2x the friends, 2x the triangles ?

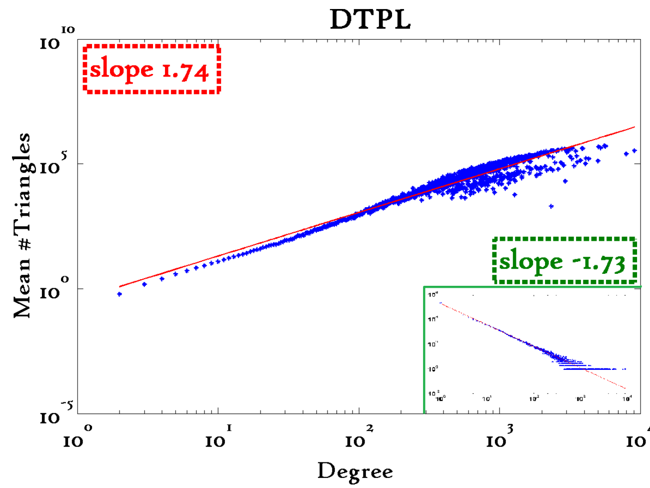


Triangle Law: #S.3
[Tsourakakis ICDM 2008]

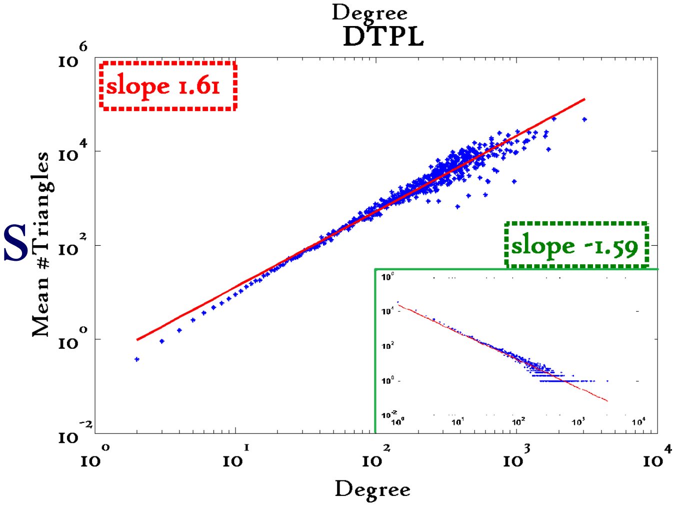
Reuters

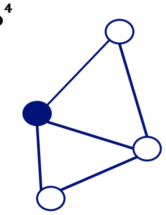


SN



Epinions



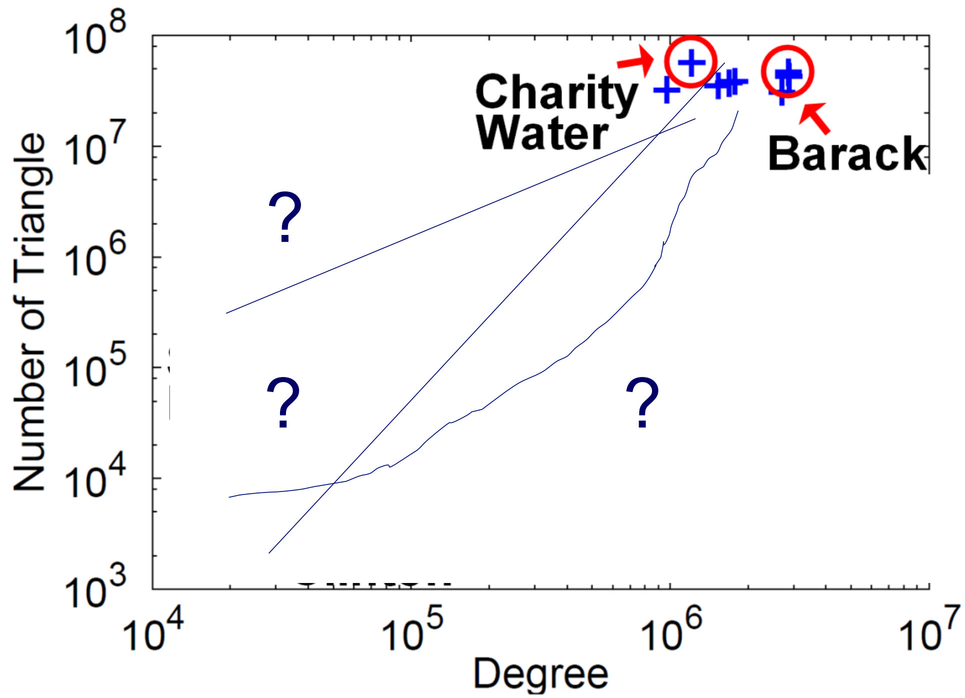


X-axis: degree

Y-axis: mean # triangles

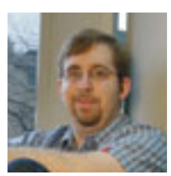
n friends -> $\sim n^{1.6}$ triangles

Triangle counting for large graphs?



Anomalous nodes in Twitter(~ 3 billion edges)

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



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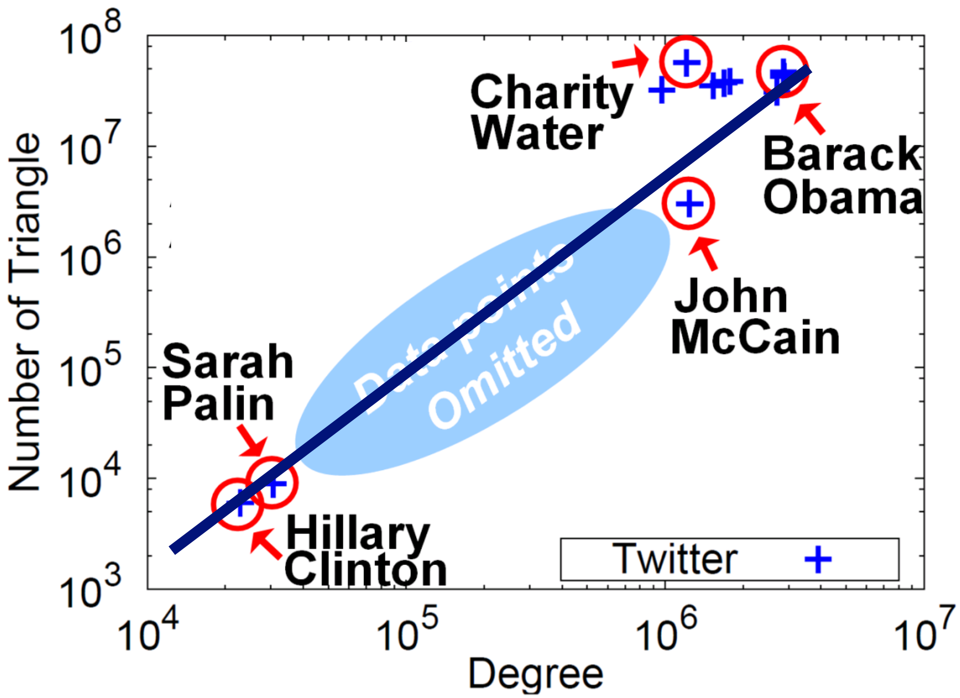

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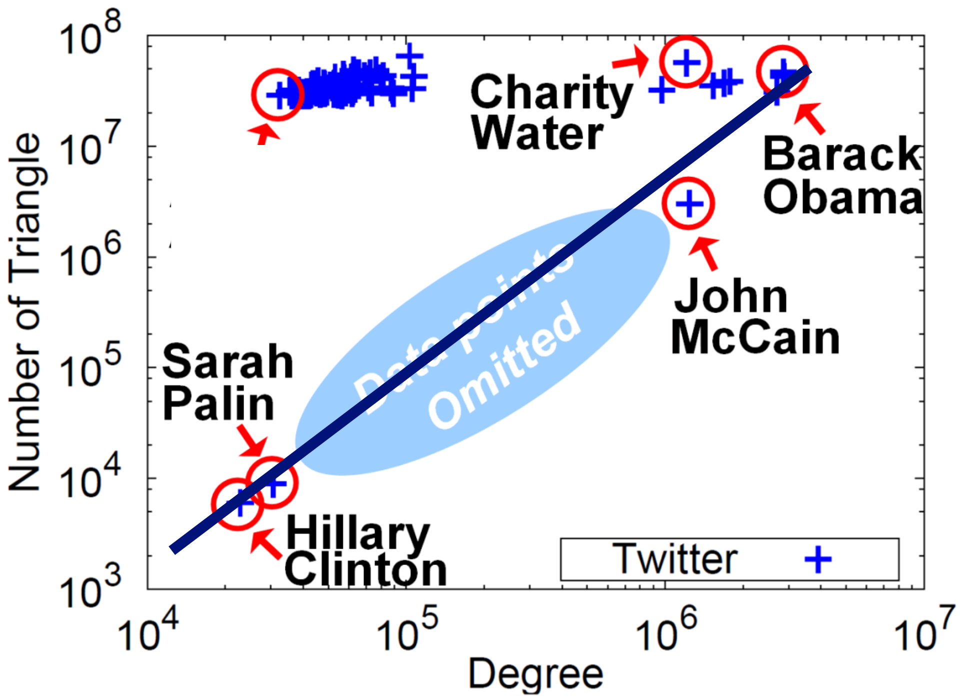

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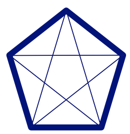

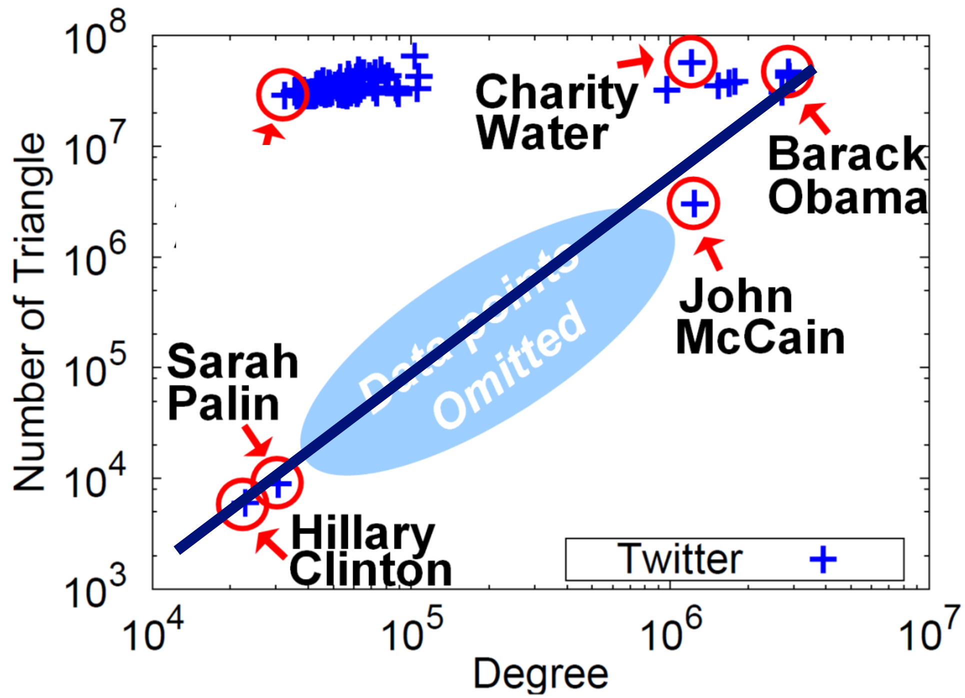

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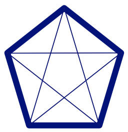

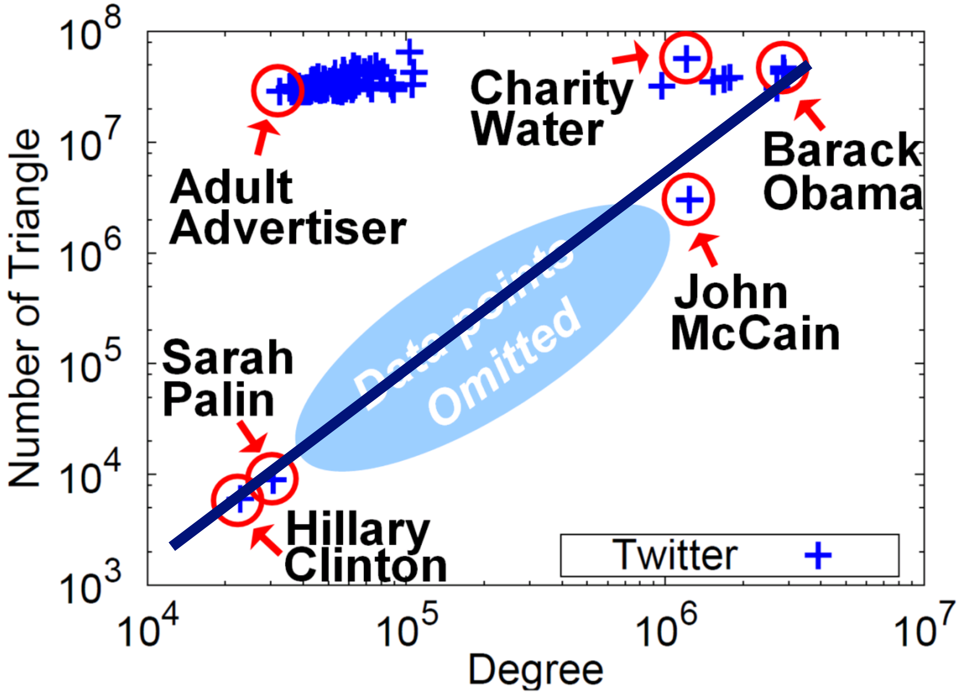

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MORE Graph Patterns

	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

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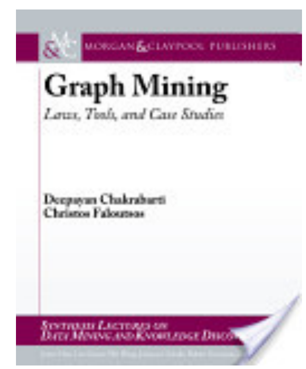
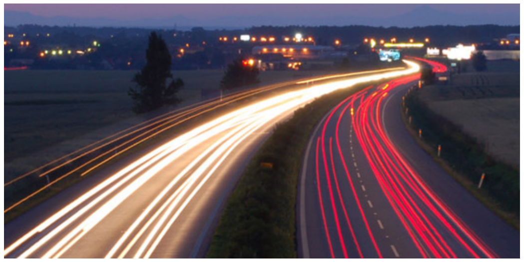
- Mary McGlohon, Leman Akoglu, Christos Faloutsos. *Statistical Properties of Social Networks.* in "Social Network Data Analytics" (Ed.: Charu Aggarwal)

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

Roadmap



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  - P1.2: Anomaly / fraud detection
    - No labels – spectral
    - With labels: Belief Propagation
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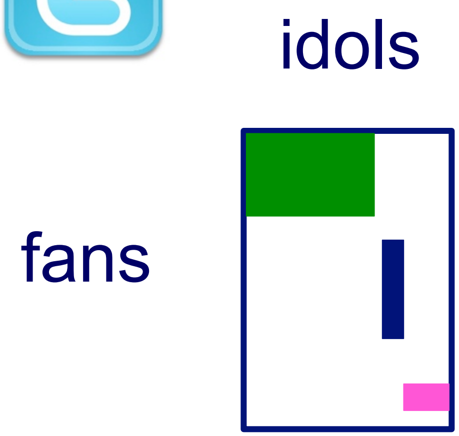
Patterns  anomalies

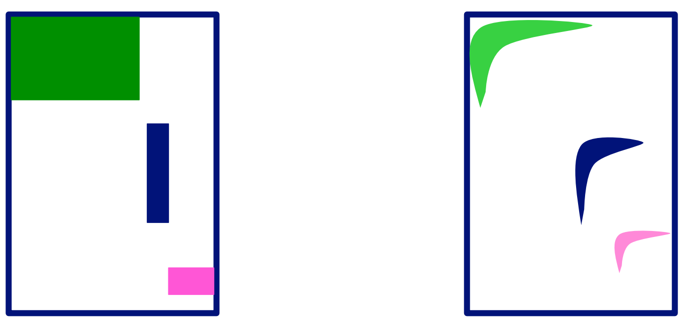
How to find ‘suspicious’ groups?

- ‘blocks’ are normal, right?



Except that:

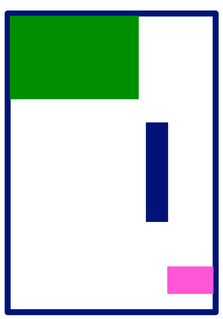
- ‘blocks’ are normal, right?
- ‘hyperbolic’ communities are more realistic [Araujo+, PKDD’14]

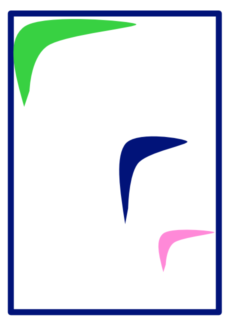


Except that:

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

Q: Can we spot blocks, easily?





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Except that:

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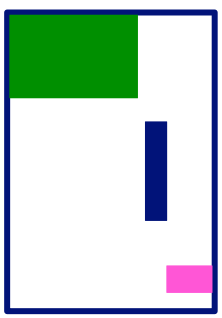
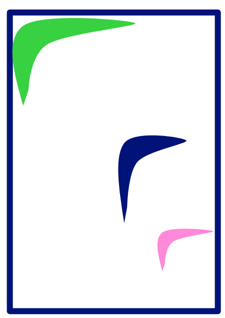
Q: Can we spot blocks, easily?

A: Silver bullet: SVD!



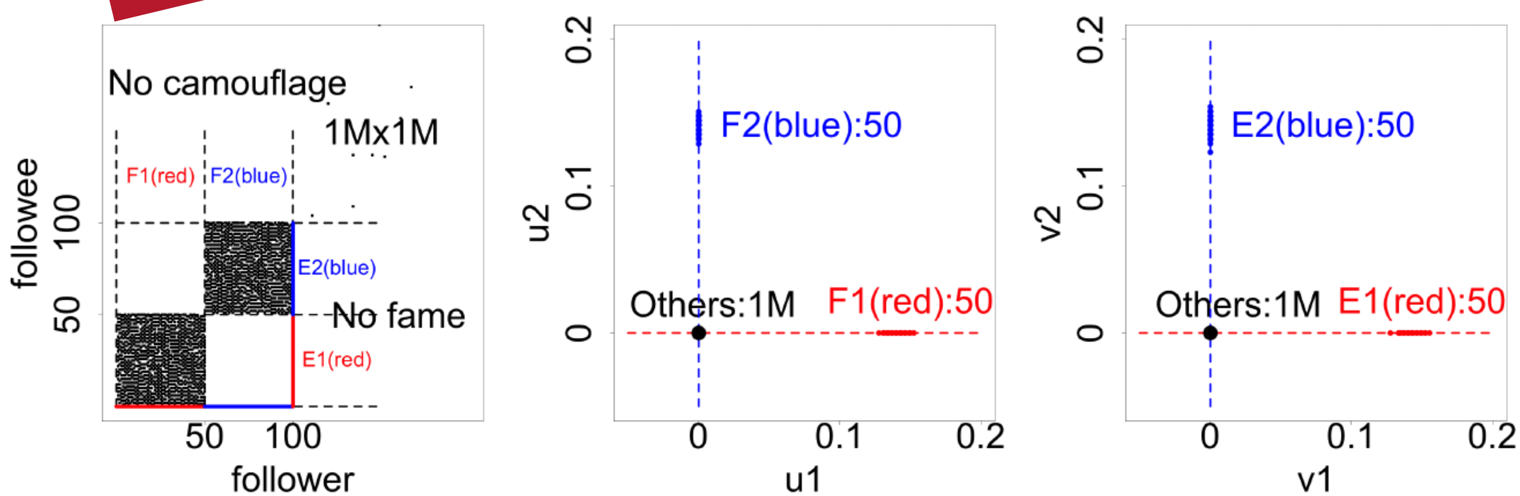


Lockstep and *Spectral S*[...]*ace Plot*

Press 'SVD';
Look for spokes

- Case #1
- "

A[...] Spectral Subspace Plot

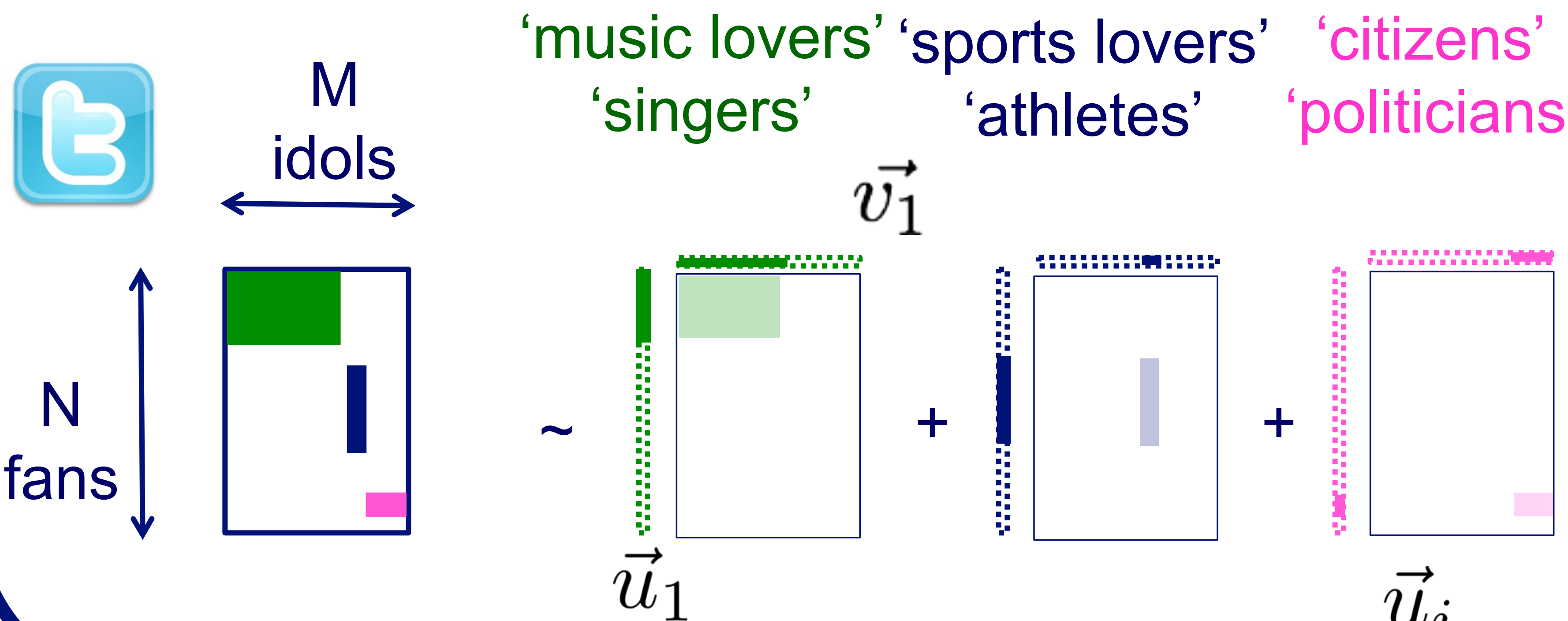


Rule 1 (short "rays"): two blocks, high density (90%), no "camouflage", no "fame"

DETAILS

Crush intro to SVD

- Recall: (SVD) matrix factorization: finds blocks



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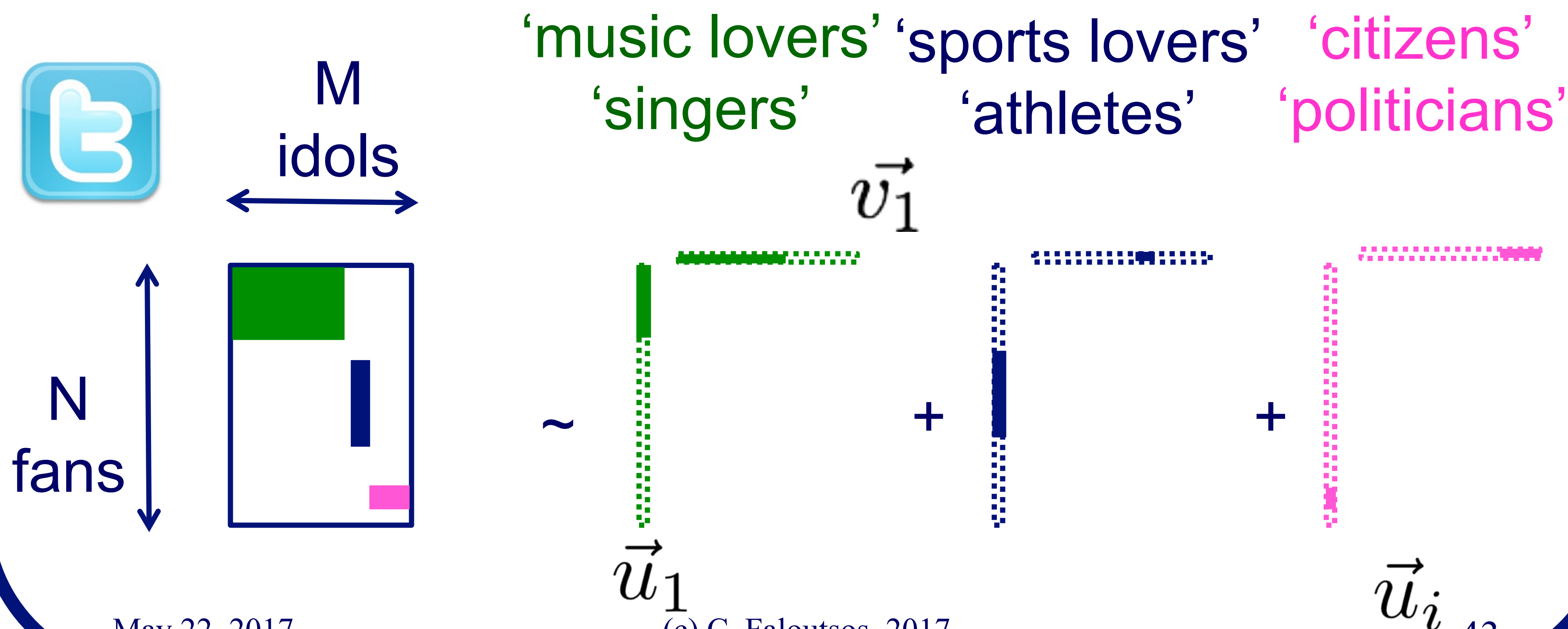

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Inferring Strange Behavior from Connectivity Pattern in Social Networks

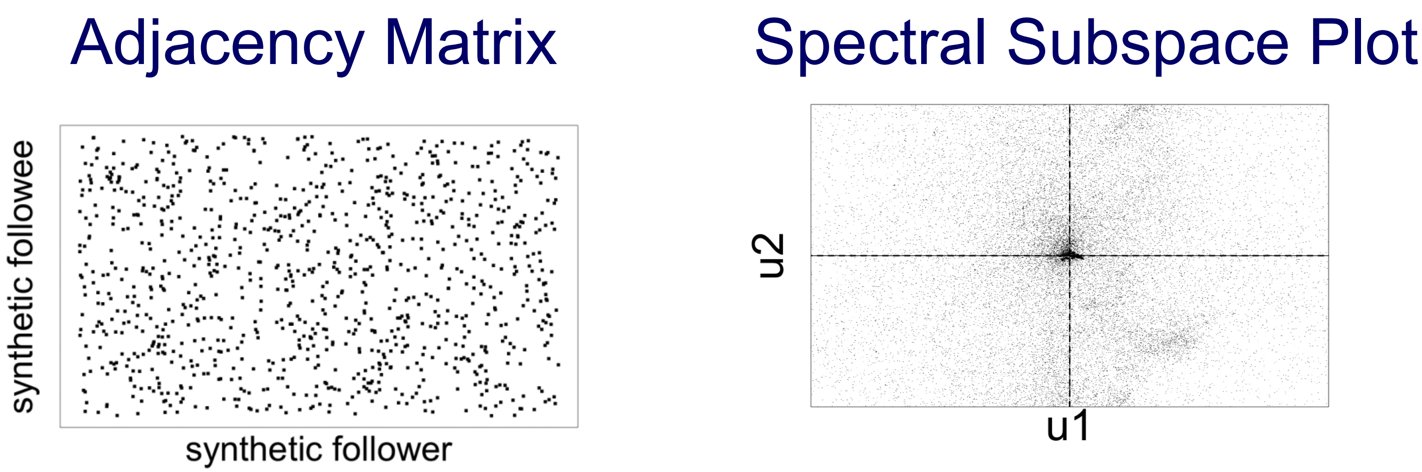
PAKDD'14

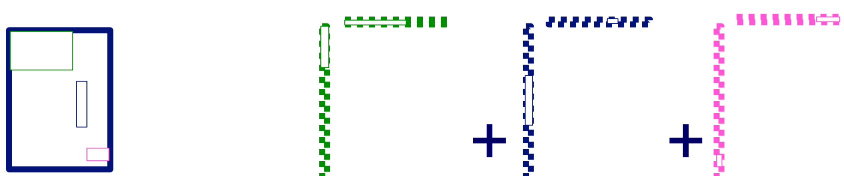


Meng Jiang, Peng Cui, Shiqiang Yang (Tsinghua)
Alex Beutel, Christos Faloutsos (CMU)

Lockstep and *Spectral Subspace Plot*

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

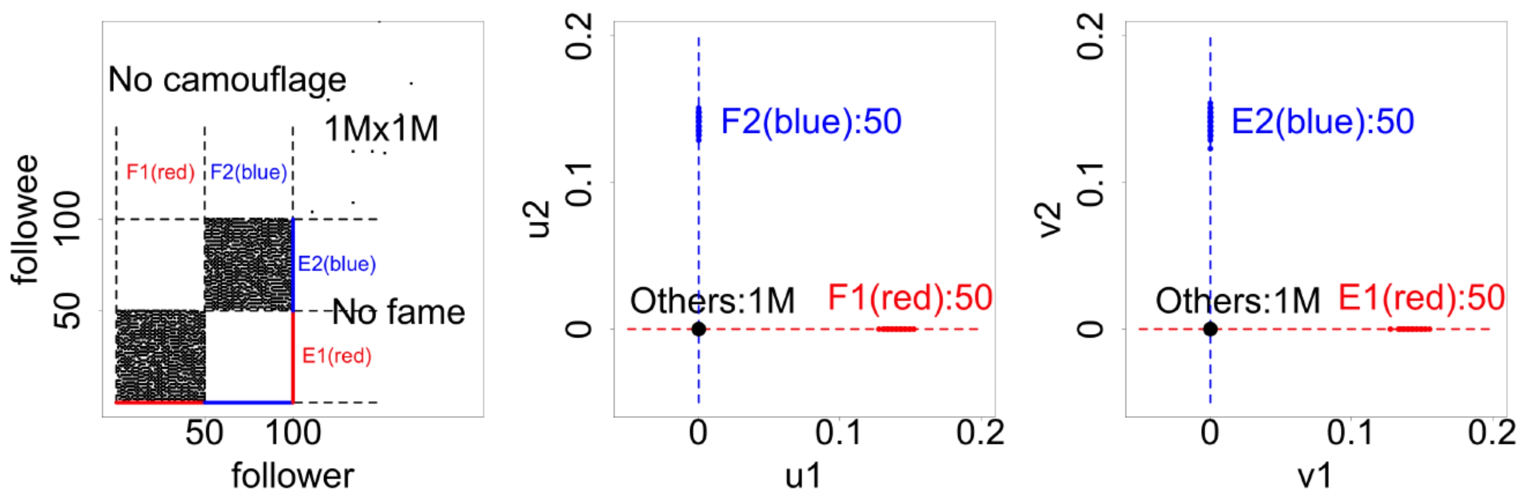




Lockstep and *Spectral Subspace Plot*

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

Adjacency Matrix　　Spectral Subspace Plot

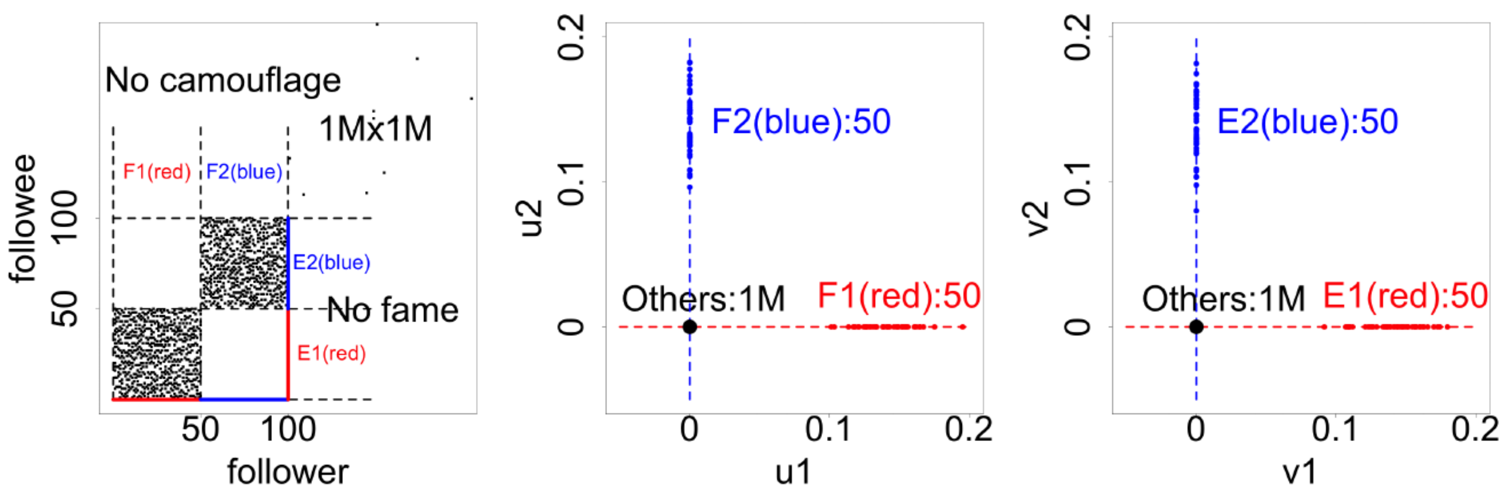


Rule 1 (short "rays"): two blocks, high density (90%), no "camouflage", no "fame"

Lockstep and *Spectral Subspace Plot*

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

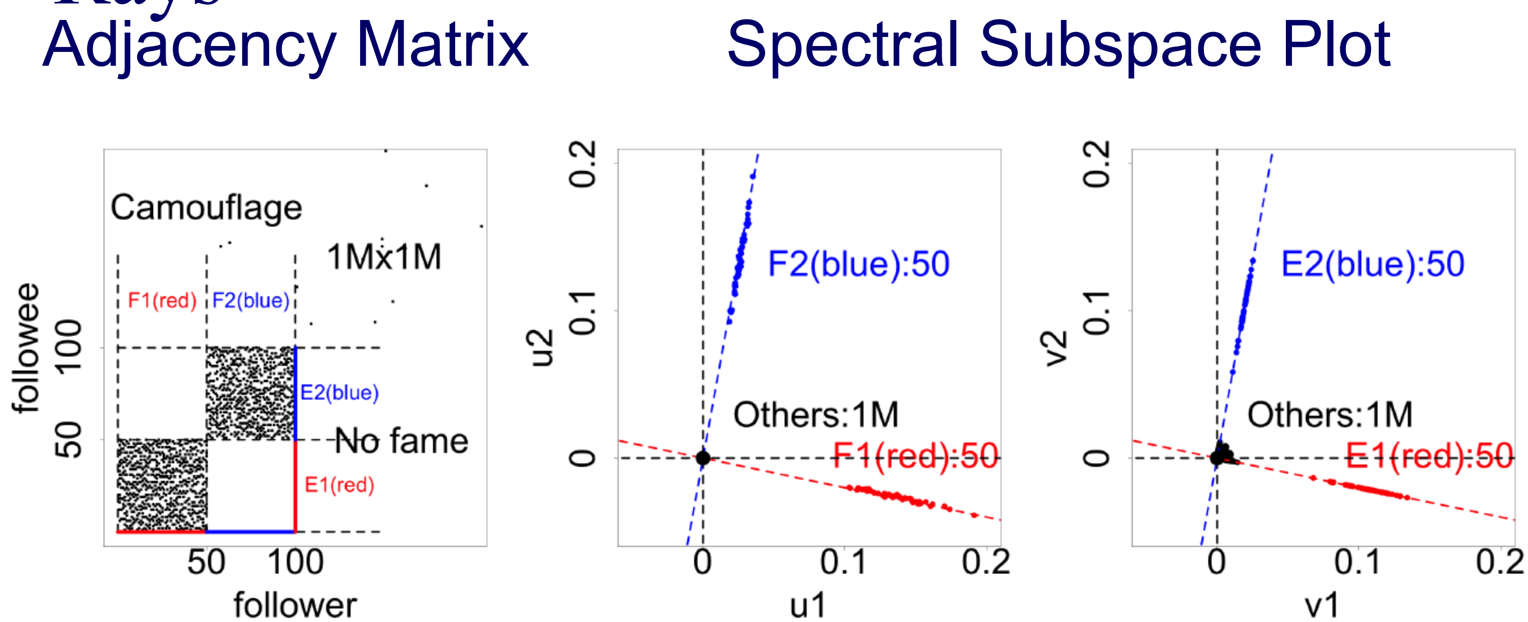
Adjacency Matrix　　Spectral Subspace Plot



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"



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

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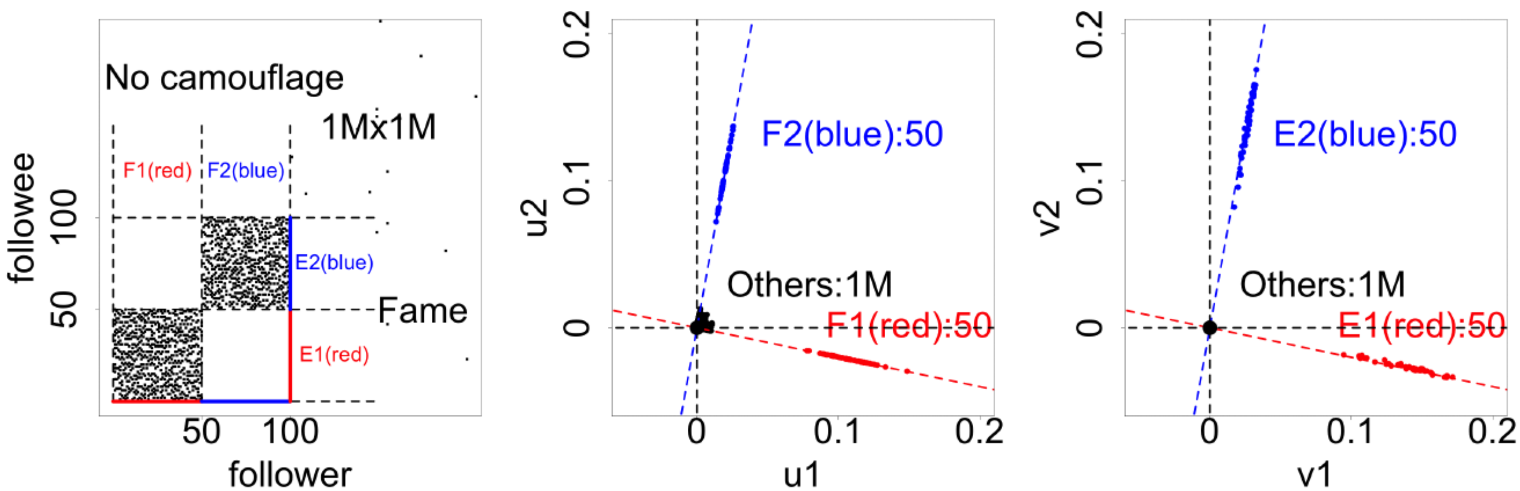
Lockstep and *Spectral Subspace Plot*

- 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"

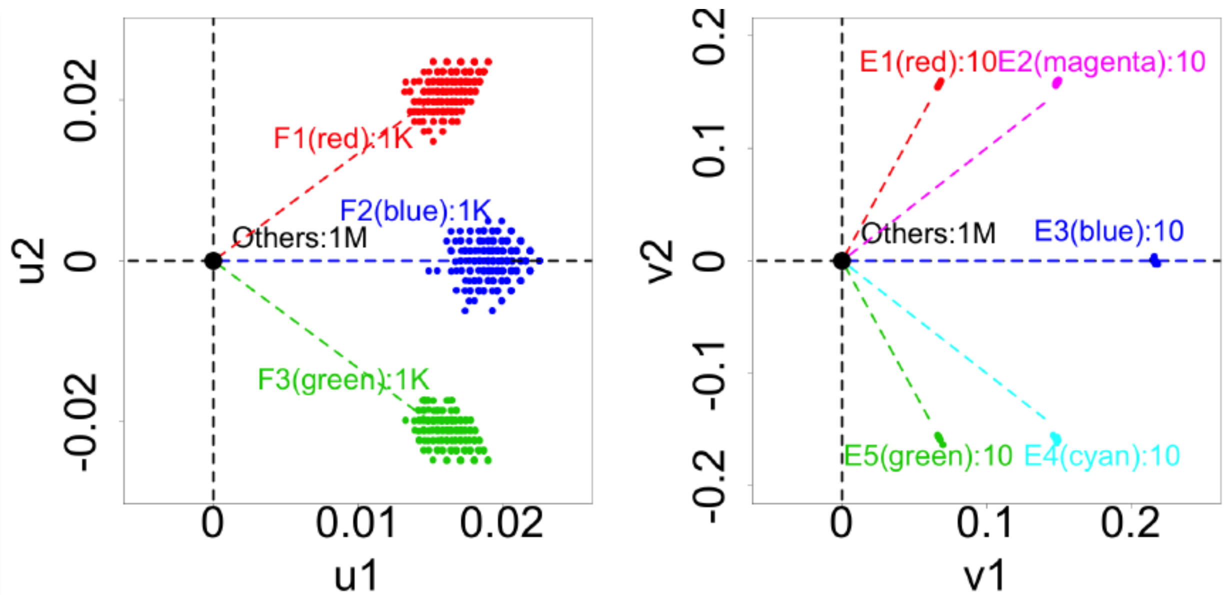
Lockstep and *Spectral Subspace Plot*

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

Adjacency Matrix

?

Spectral Subspace Plot



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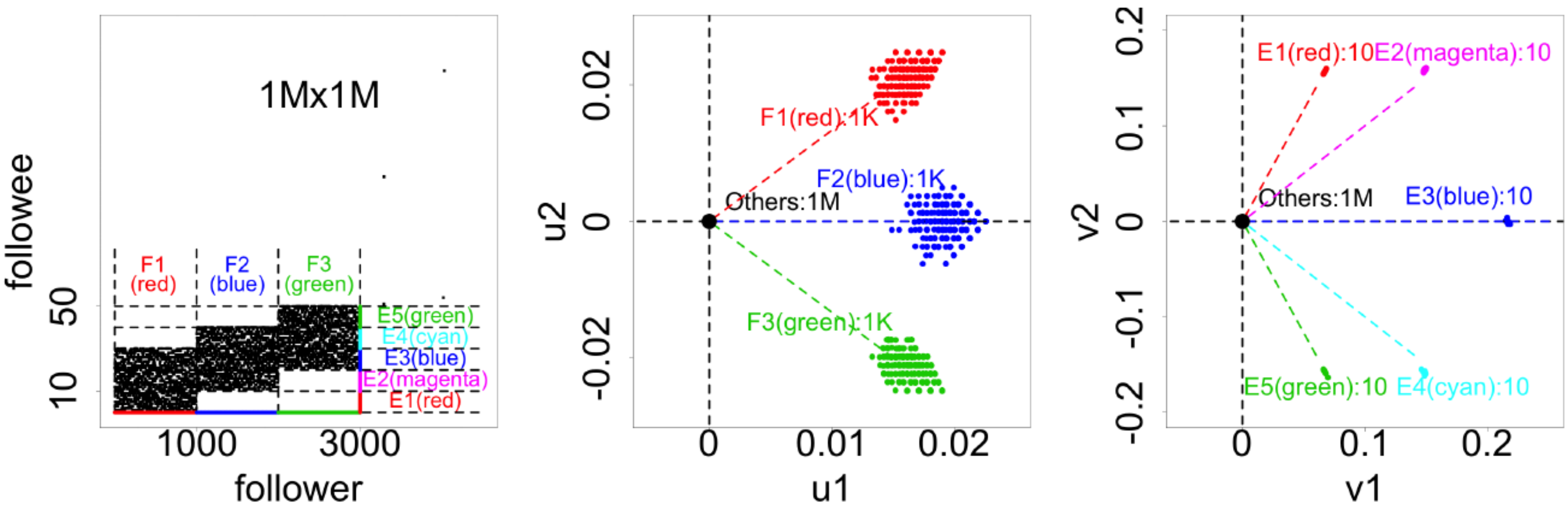
Lockstep and *Spectral Subspace Plot*

- Case #4: **overlapping** lockstep
- **"Staircase"** ⟷ "Pearls"

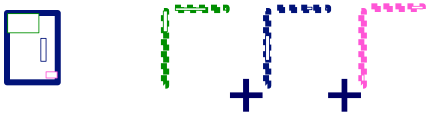
Adjacency Matrix | Spectral Subspace Plot



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

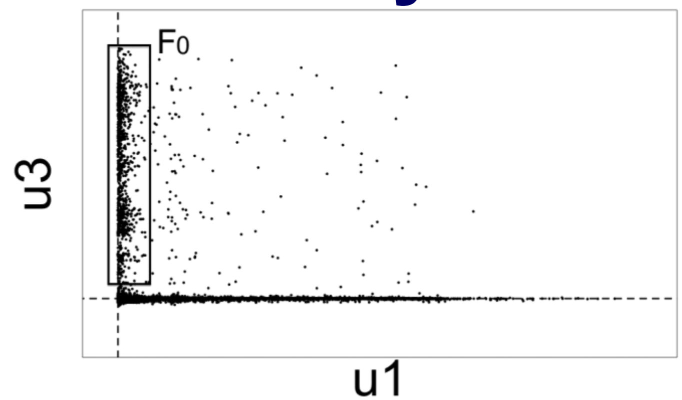
Dataset

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

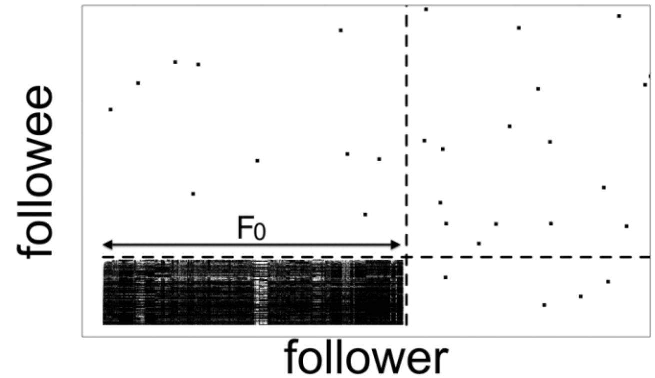


Real Data

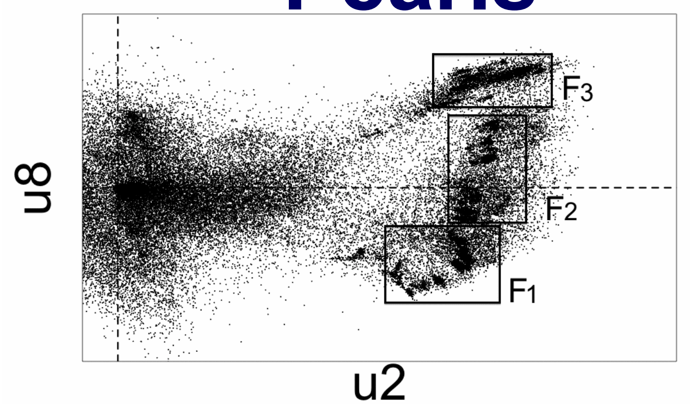
"Rays"



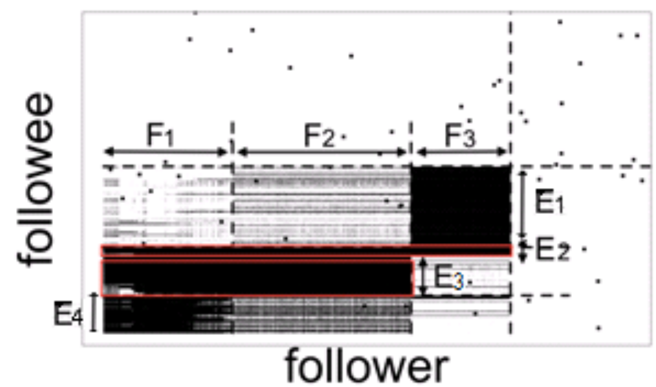
"Block"



"Pearls"

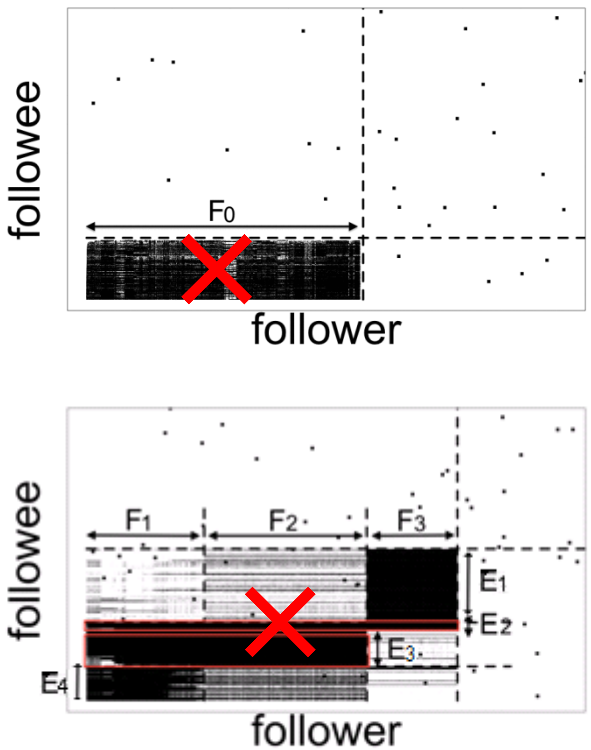


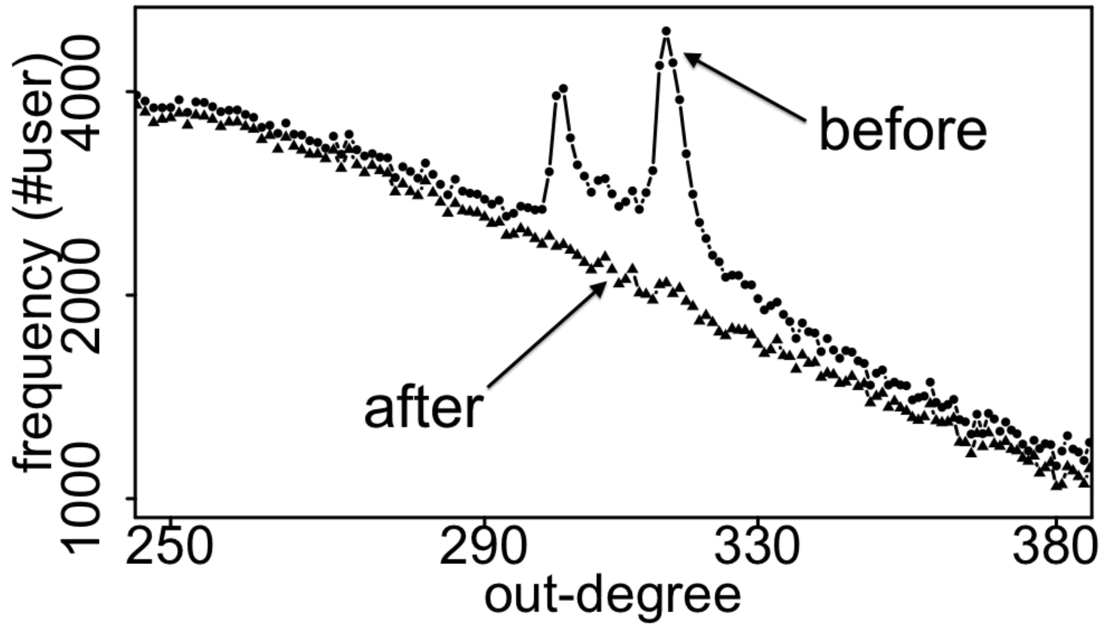
"Staircase"



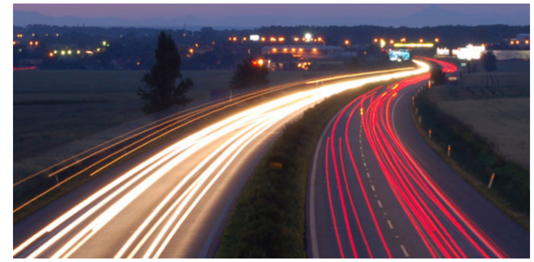
Real Data

- Spikes on the out-degree distribution





Roadmap



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

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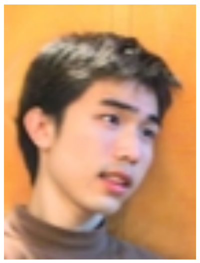
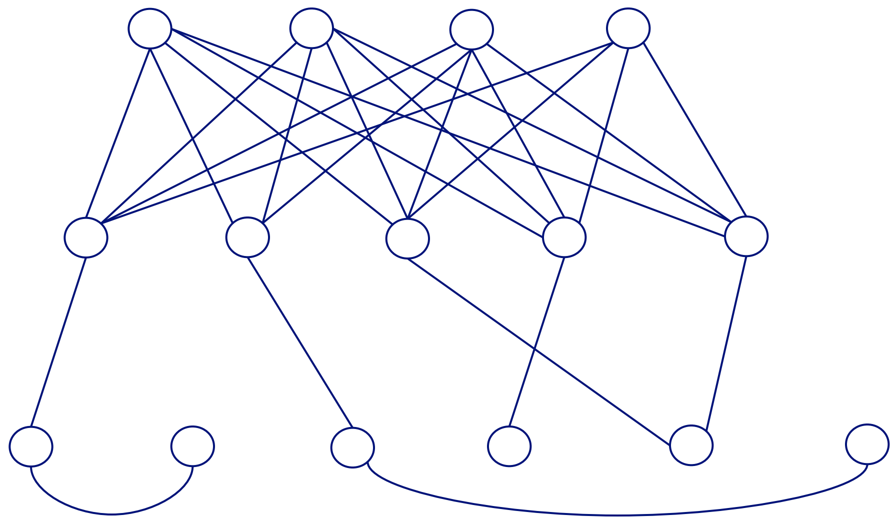
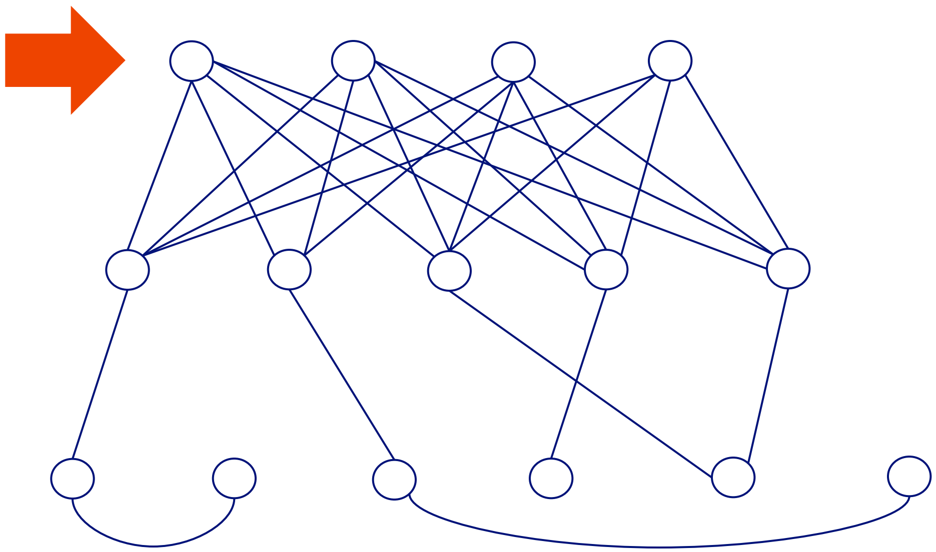
E-bay Fraud detection



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



E-bay Fraud detection



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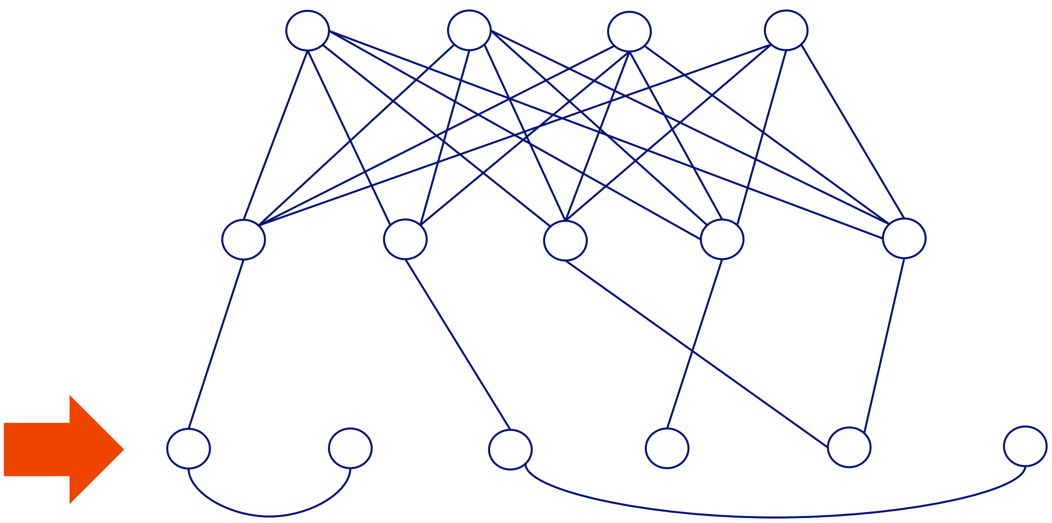
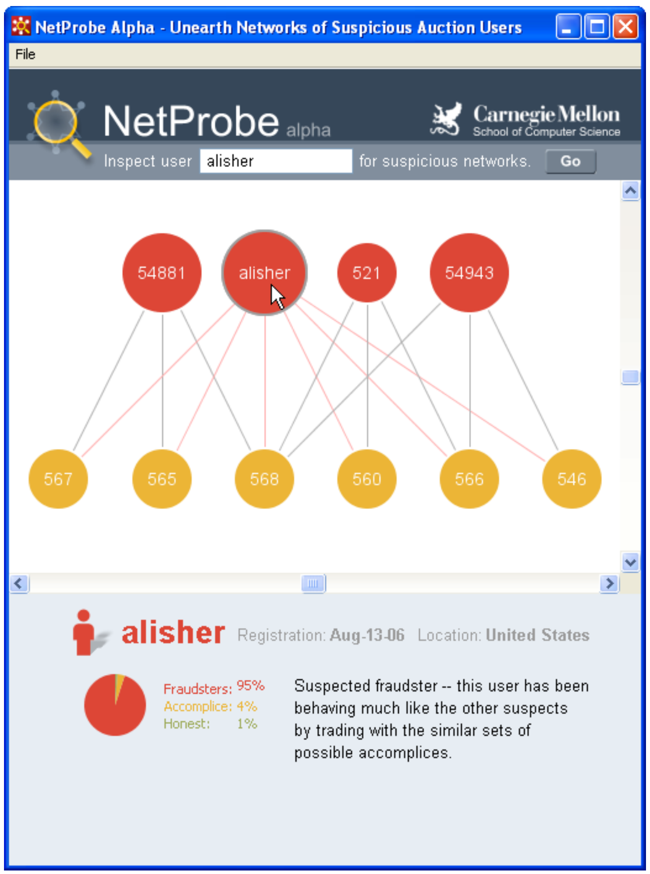
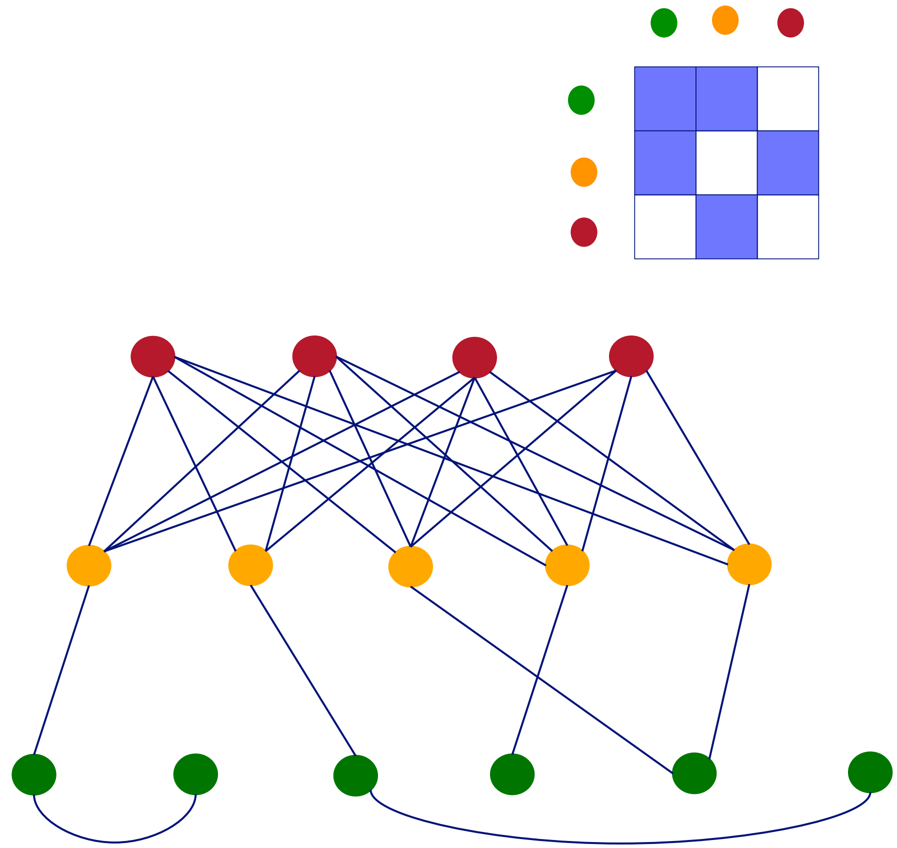
E-bay Fraud detection



E-bay Fraud detection - NetProbe





Popular press

USA TODAY

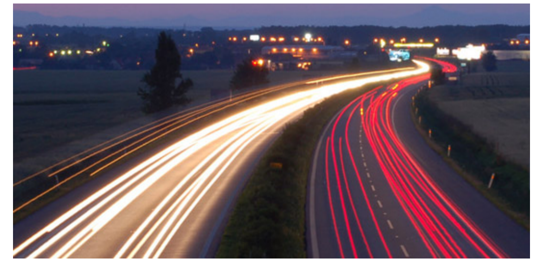
The Washington Post

Los Angeles Times

And less desirable attention:

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

Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns
  - Anomaly / fraud detection
    - No labels - Spectral methods
    - w/ labels: Belief Propagation – closed formulas
- Part#2: time-evolving graphs; tensors
- Conclusions

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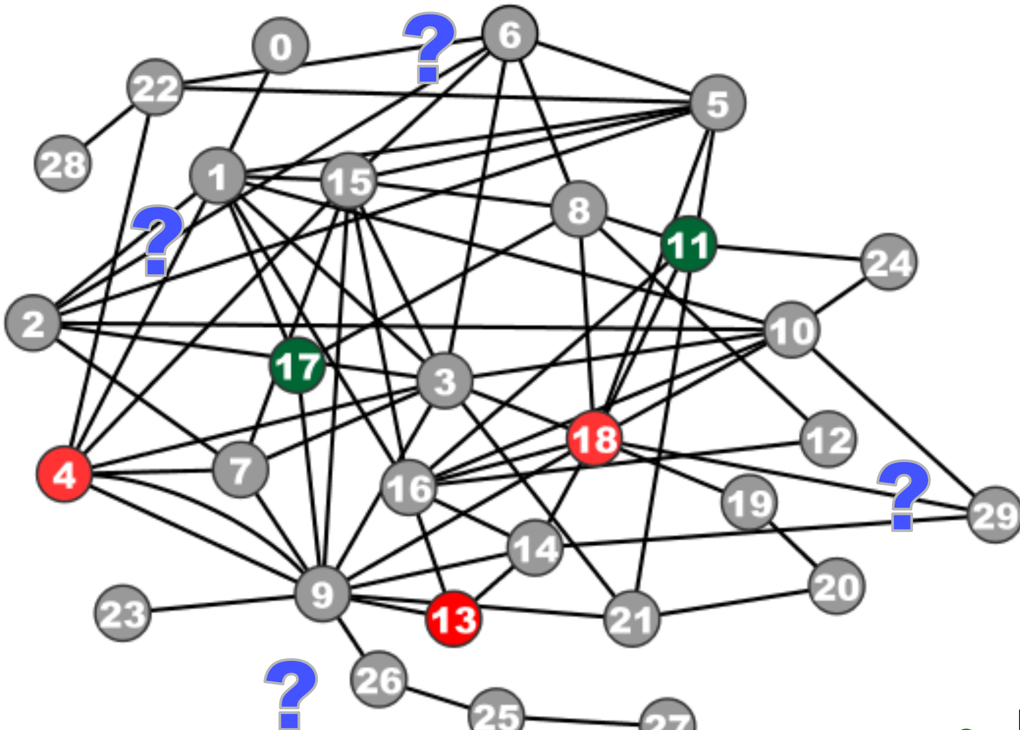
Unifying Guilt-by-Association Approaches: Theorems and Fast Algorithms

Danai Koutra
U Kang
Hsing-Kuo Kenneth Pao

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

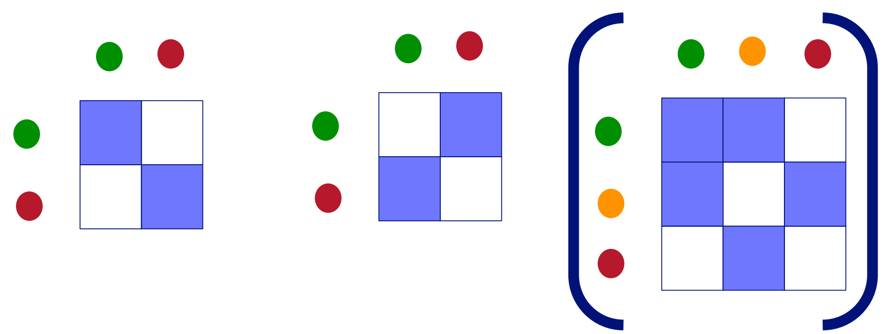
ECML PKDD, 5-9 September 2011, Athens, Greece

Problem Definition: GBA techniques



Given: Graph; & few labeled nodes

Find: labels of rest (assuming network effects)



Correspondence of Methods

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

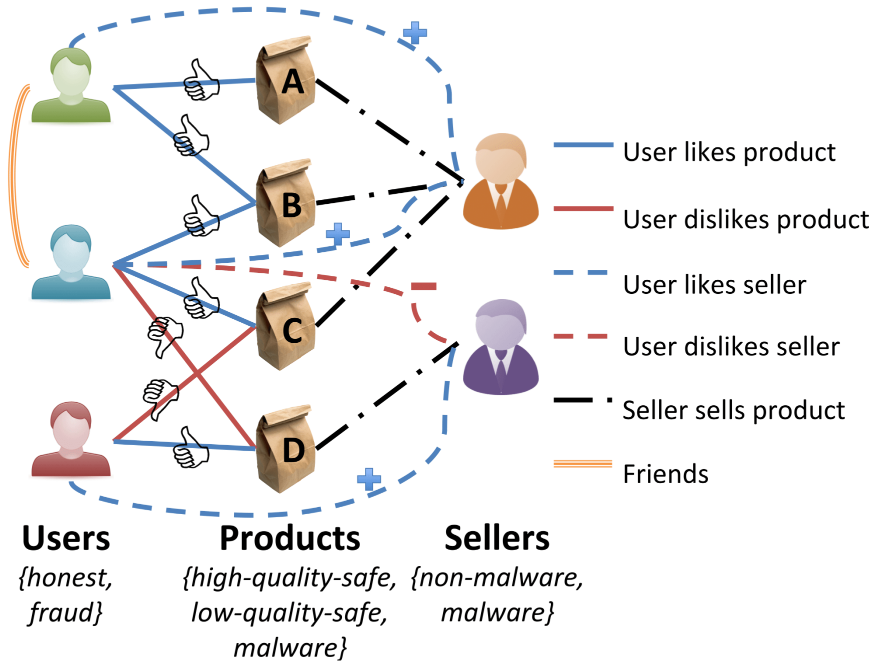
$$\begin{bmatrix} 1 & & \\ & 1 & \\ & & 1 \end{bmatrix} \quad \begin{bmatrix} d1 & & \\ & d2 & \\ & & d3 \end{bmatrix} \quad \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} \\ ? \\ \\ \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

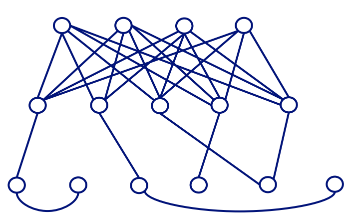
adjacency matrix

final labels/ beliefs

prior labels/ beliefs

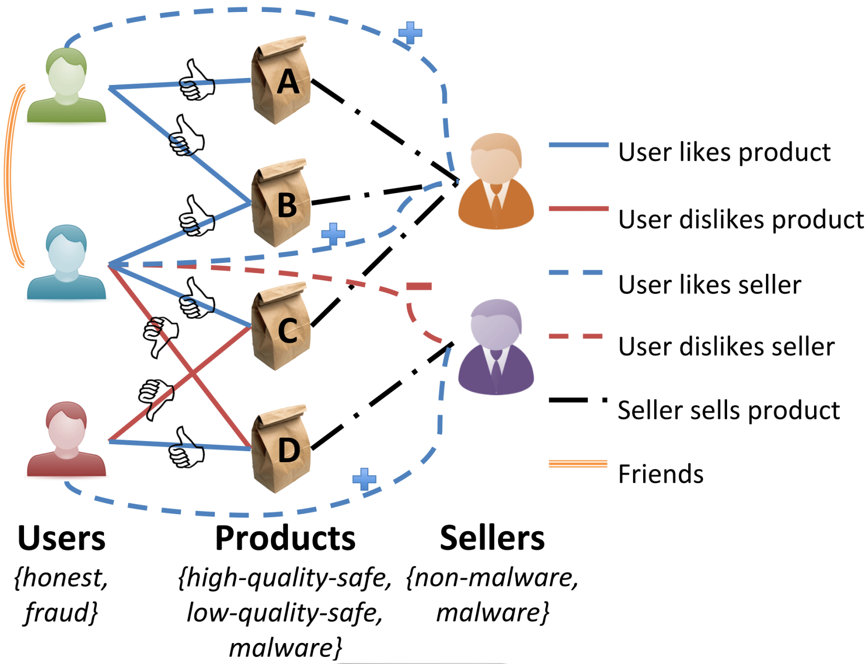
Problem: e-commerce ratings fraud





- **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



- **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



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

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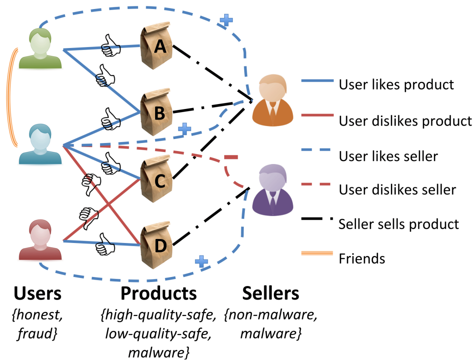
Problem: e-commerce ratings fraud



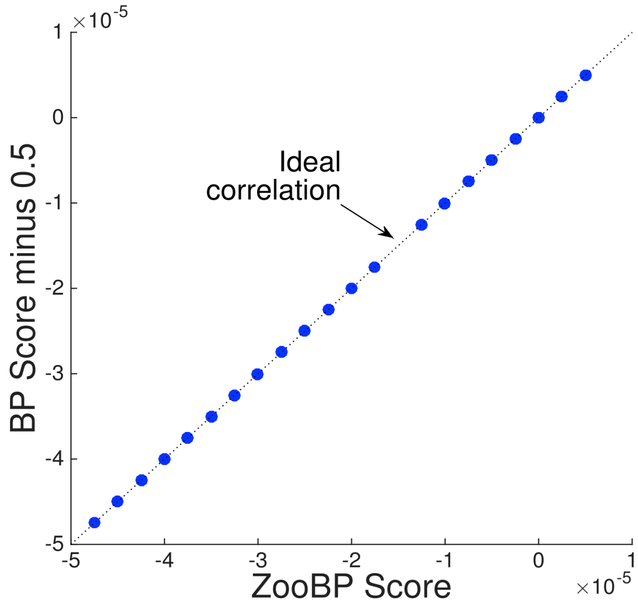
Theorem 1 (ZooBP). *If* $\mathbf{b}, \mathbf{e}, \mathbf{P}, \mathbf{Q}$ *are constructed as described above, the linear equation system approximating the final node beliefs given by BP is:*

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

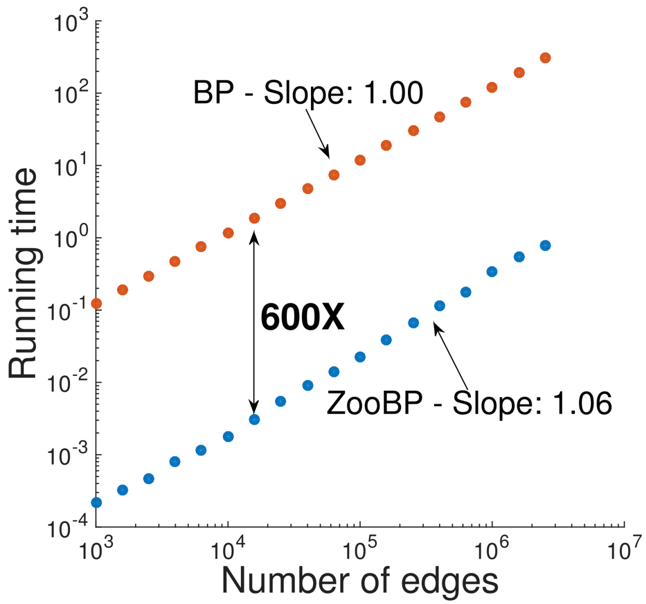
Dhivya Eswaran, Stephan Günnemann, Christos Faloutsos, "*ZooBP:* Belief Propagation for Heterogeneous Networks", VLDB 2017

ZooBP: features

Fast; convergence guarantees.



Near-perfect accuracy



linear in graph size

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

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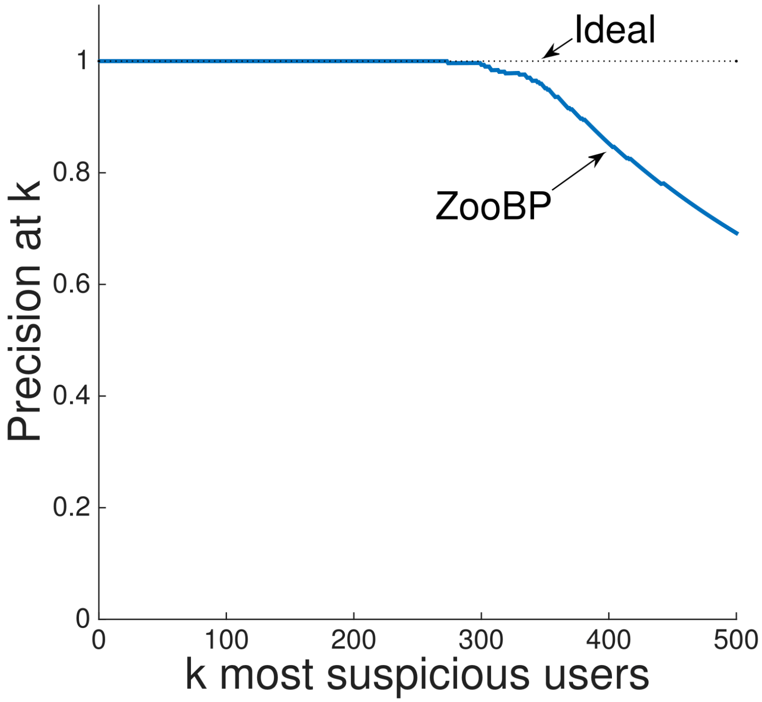
ZooBP in the real world

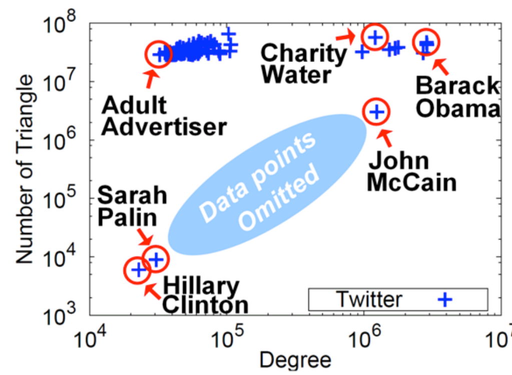


- Near 100% precision on top 300 users (Flipkart)
- Flagged users: suspicious
  - 400 ratings in 1 sec
  - 5000 good ratings and no bad ratings

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

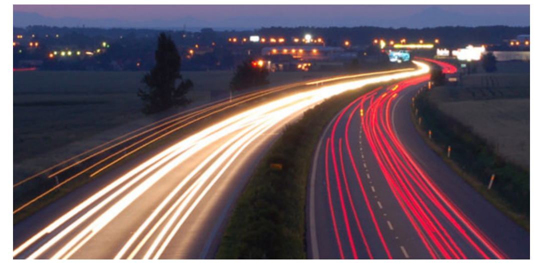
Summary of Part#1

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



Patterns  anomalies

Roadmap

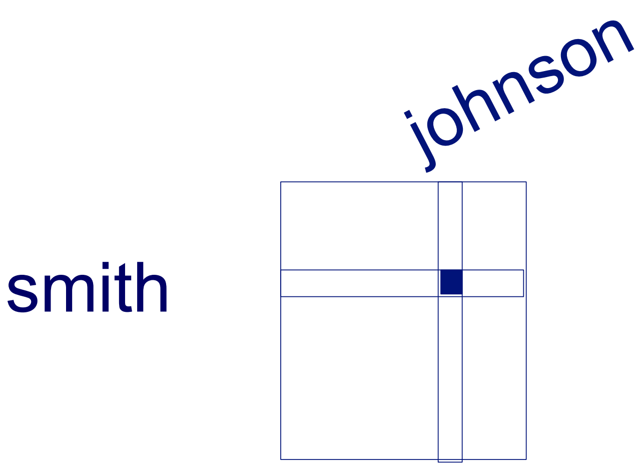


- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs
  - P2.1: tools/tensors
  - P2.2: other patterns
- Conclusions

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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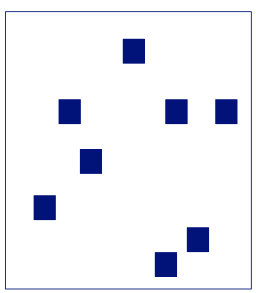

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Graphs over time -> tensors!

- Problem #2.1:
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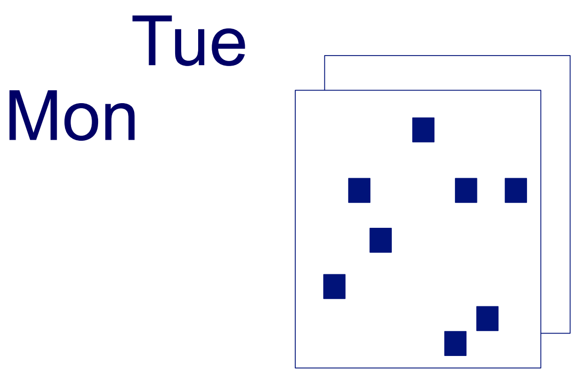

Graphs over time -> tensors!

- Problem #2.1:
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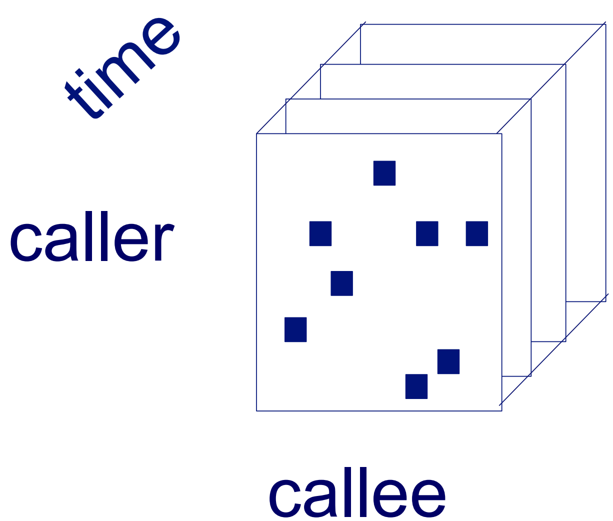
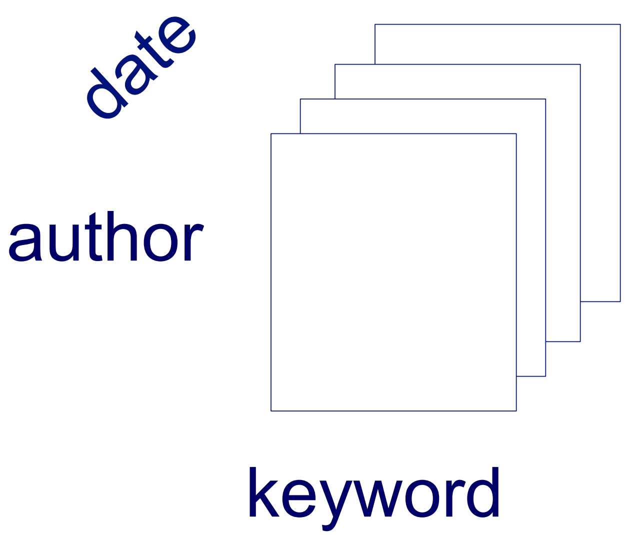


Graphs over time -> tensors!

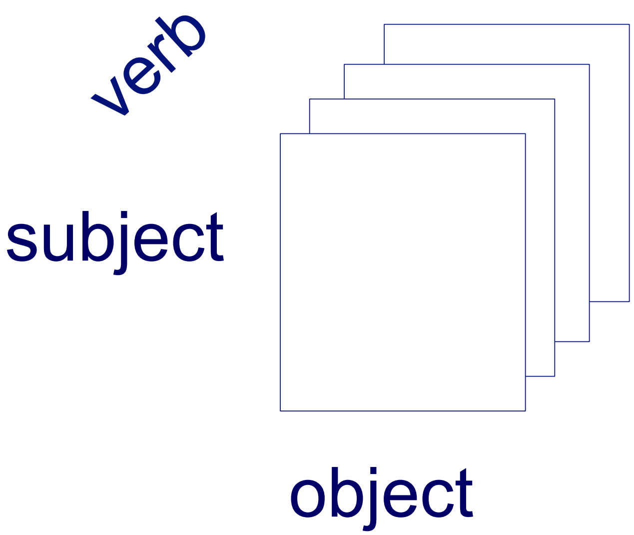
- Problem #2.1':
  - Given author-keyword-date
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

Graphs over time -> tensors!

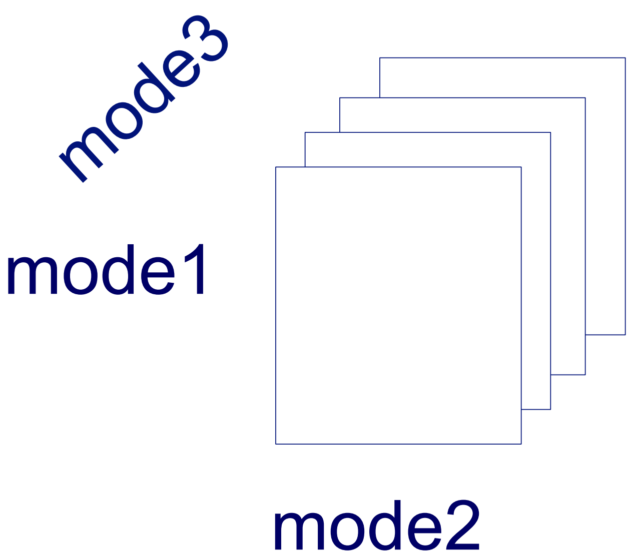
- Problem #2.1'':
  - Given subject – verb – object facts
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

Graphs over time -> tensors!

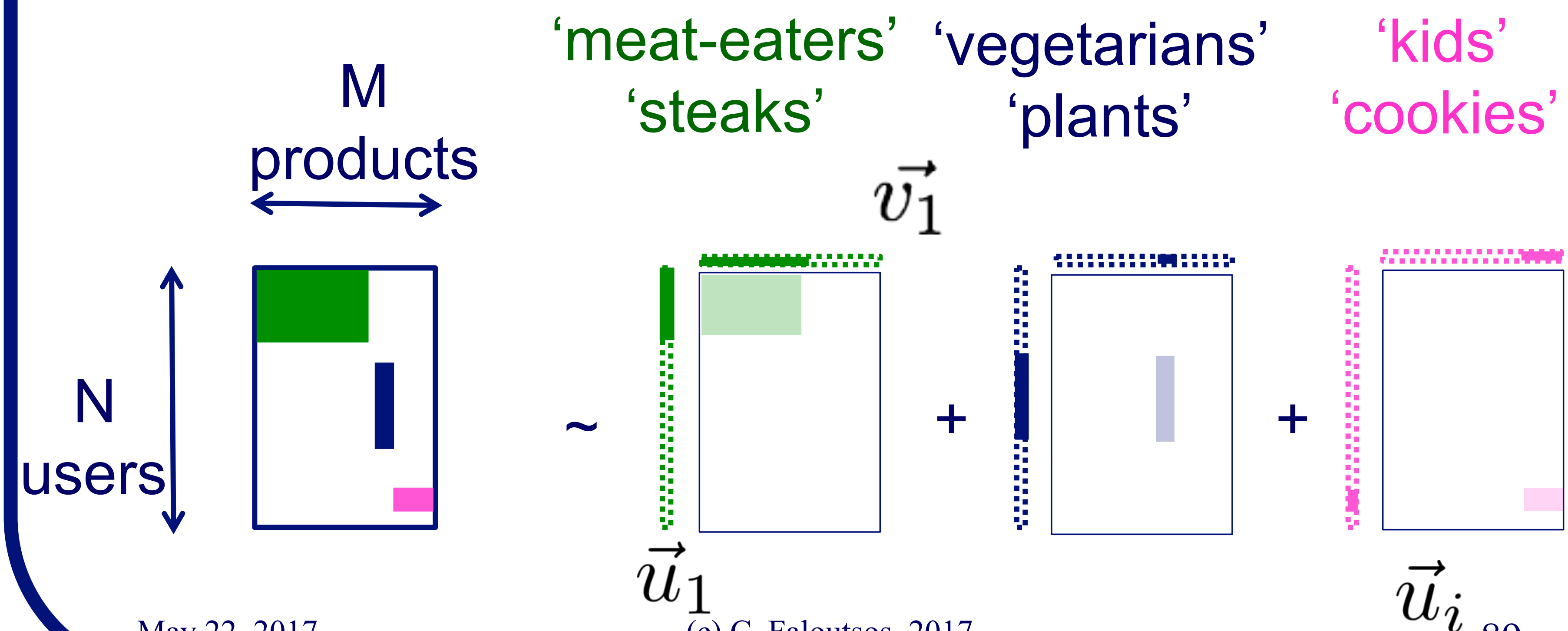
- Problem #2.1''':
  - Given <triplets>
  - Find patterns / anomalies



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

Answer : tensor factorization

- Recall: (SVD) matrix factorization: finds blocks



Answer: tensor factorization

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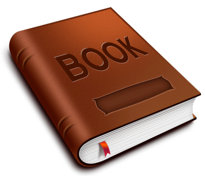
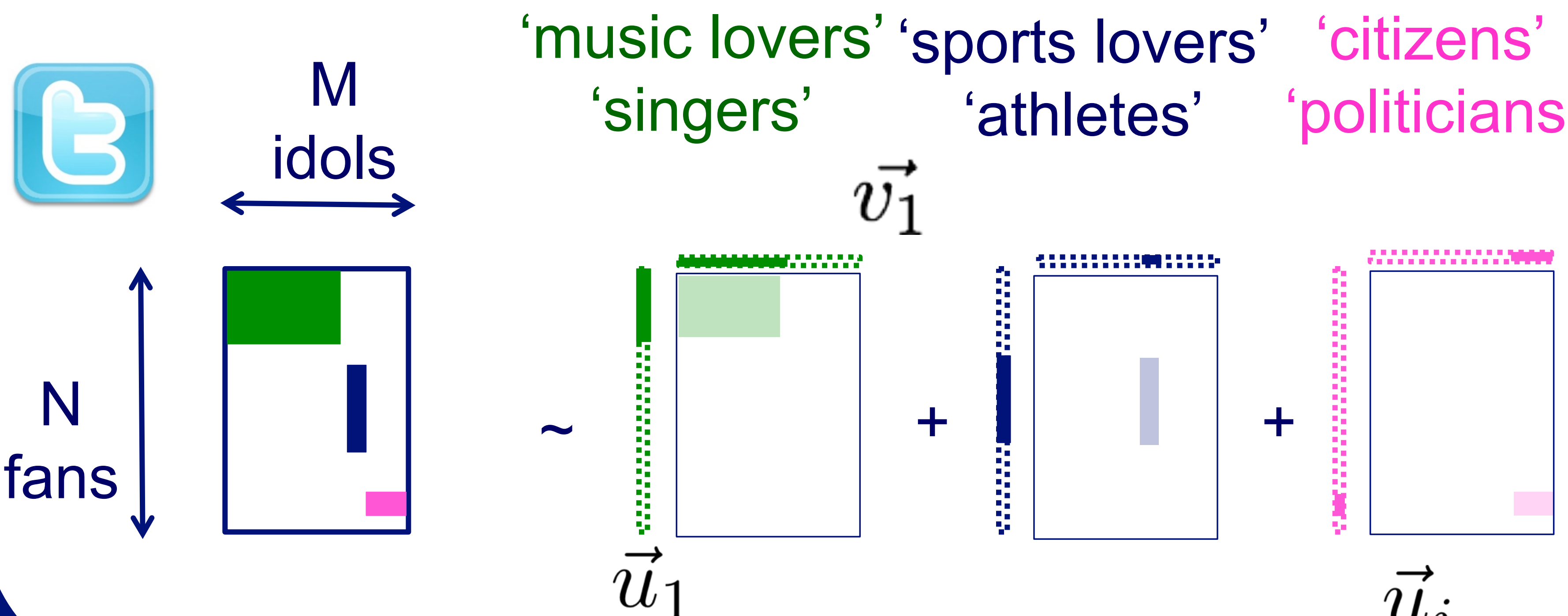


Crush intro to SVD

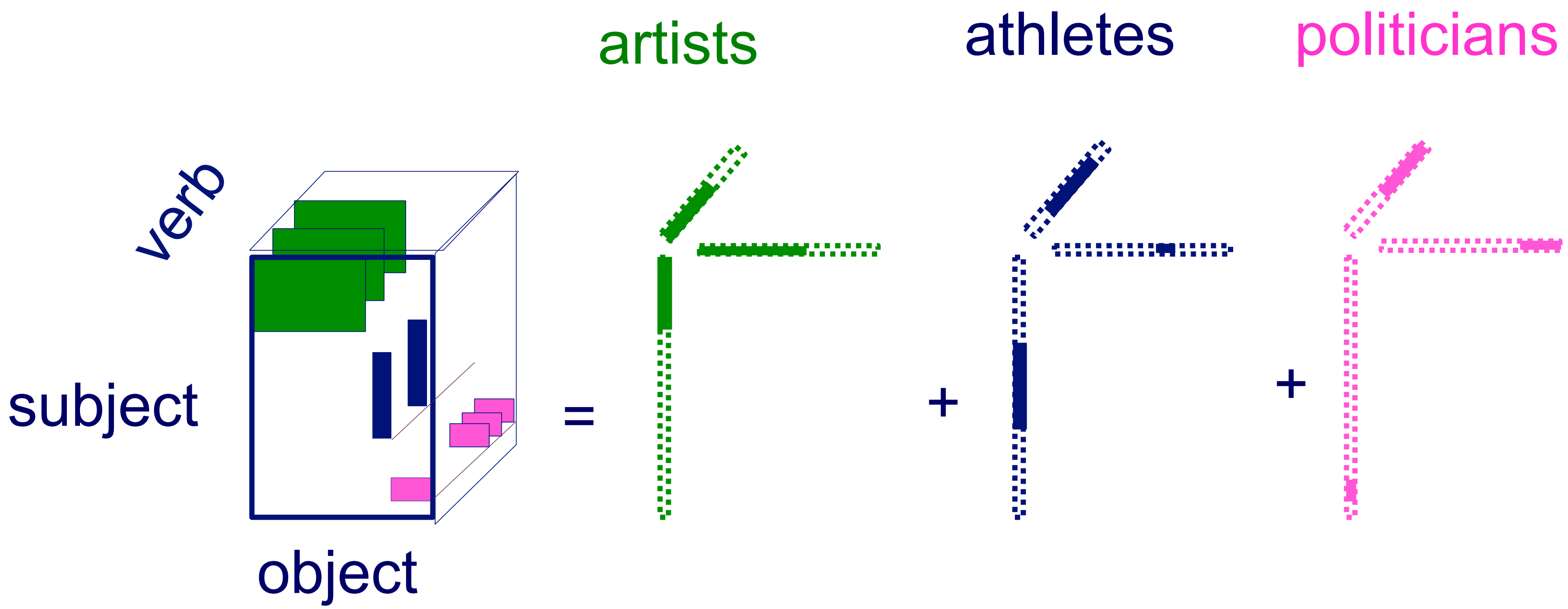
DETAILS

- Recall: (SVD) matrix factorization: finds blocks



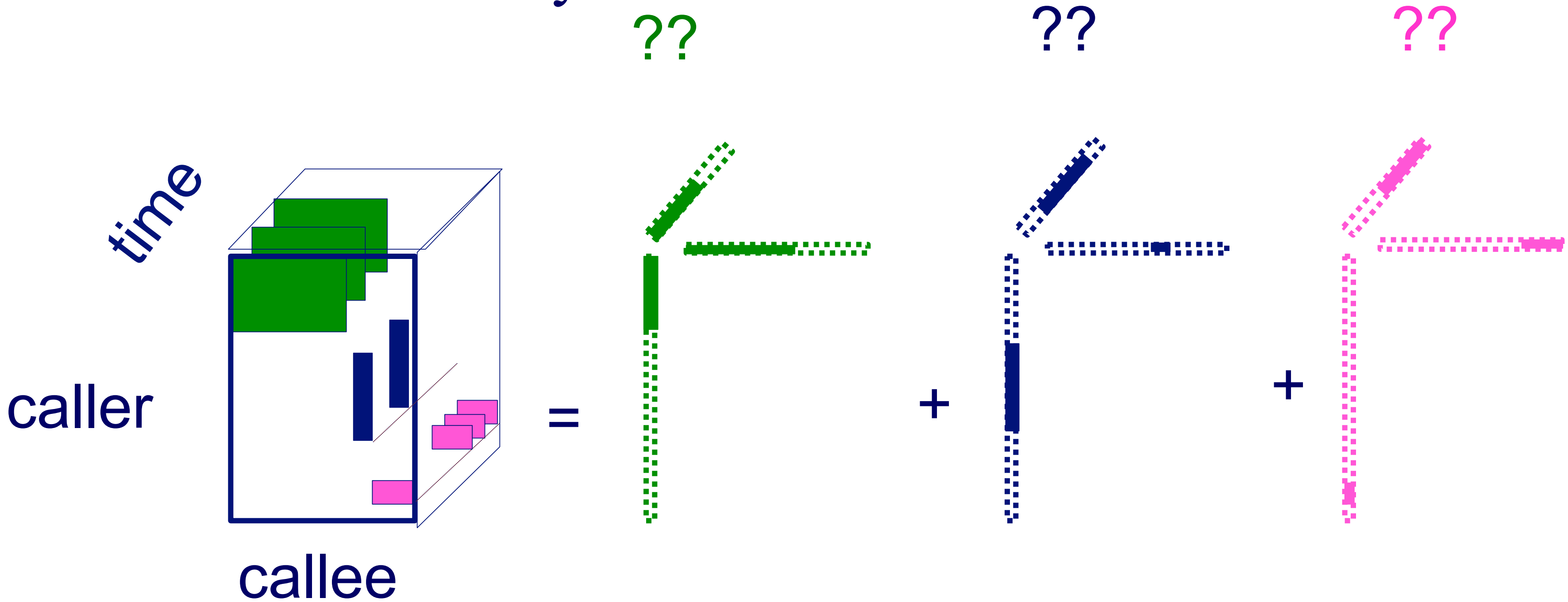
Answer: tensor factorization

- PARAFAC decomposition

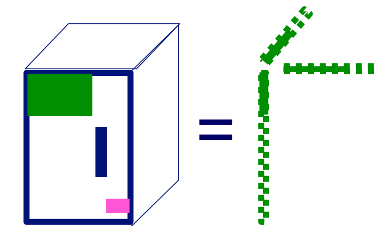


Answer: tensor factorization

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

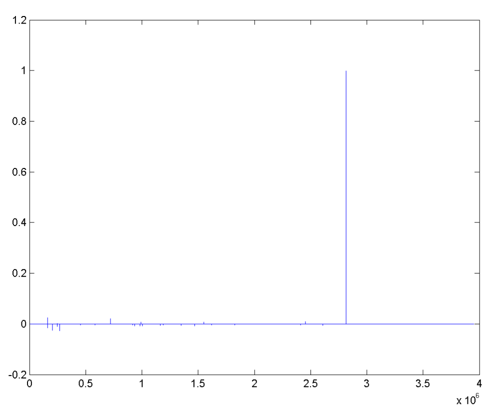


Anomaly detection in time-evolving graphs

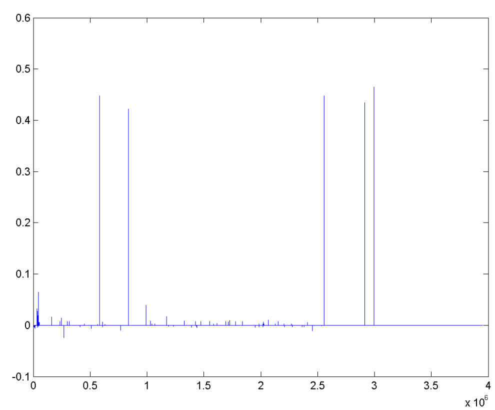


- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks

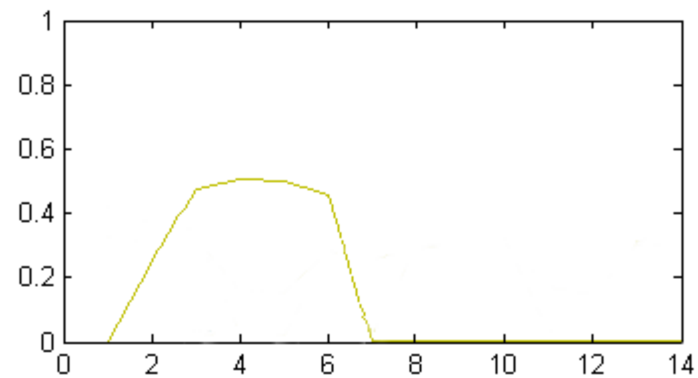
1 caller



5 receivers



4 days of activity



~200 calls to EACH receiver on EACH day!

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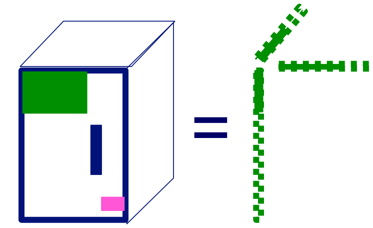
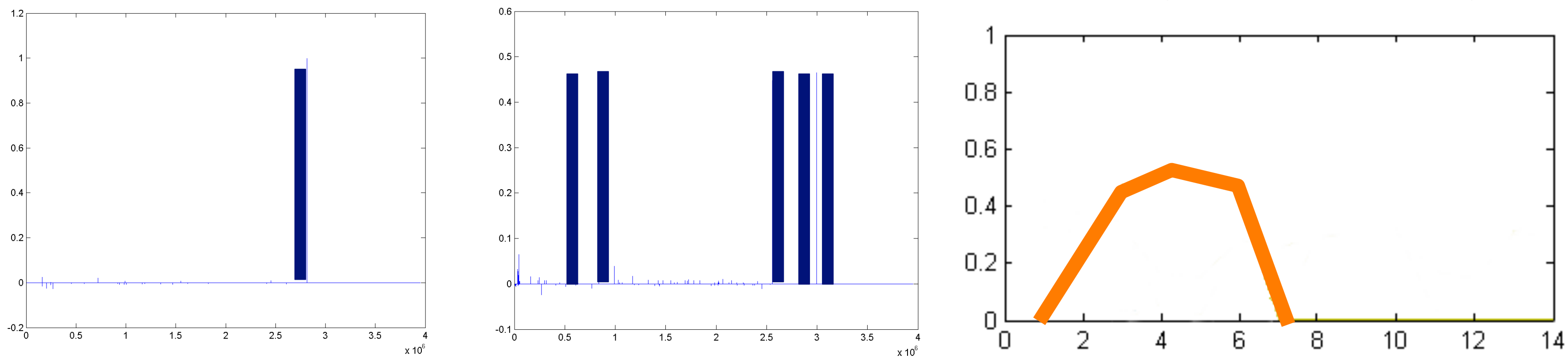
Anomaly detection in time-evolving graphs



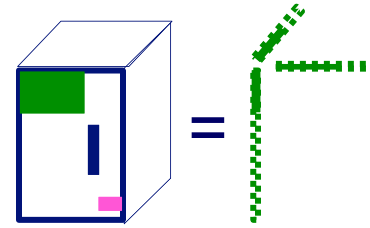
- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks

1 caller | 5 receivers | 4 days of activity



~200 calls to EACH receiver on EACH day!

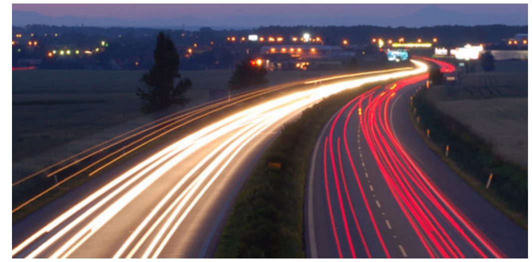
Anomaly detection in time-evolving graphs



- Anomalous communities in phone call data:
  - 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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  - P2.2: other patterns – inter-arrival time
- Conclusions

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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

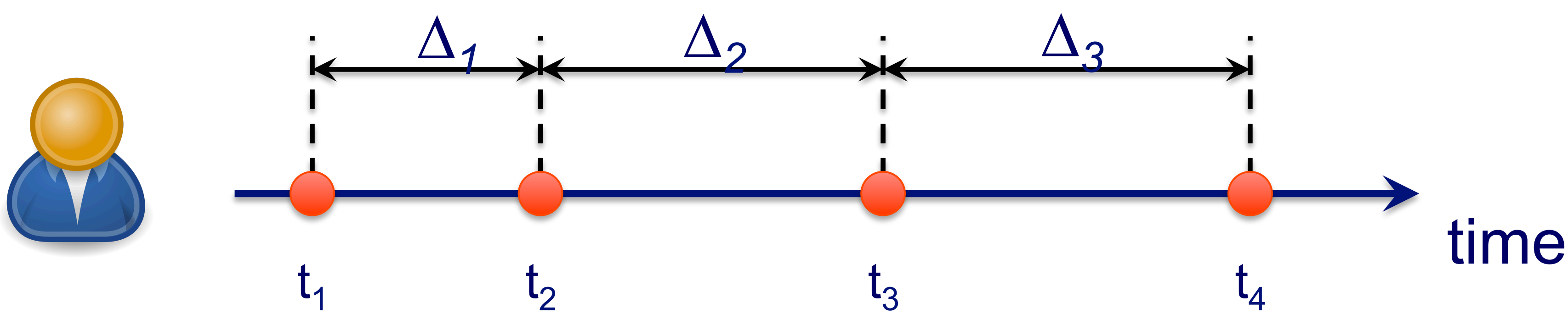
Pattern Mining: Datasets

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: $(\Delta_1, \Delta_2, \Delta_3, \ldots)$

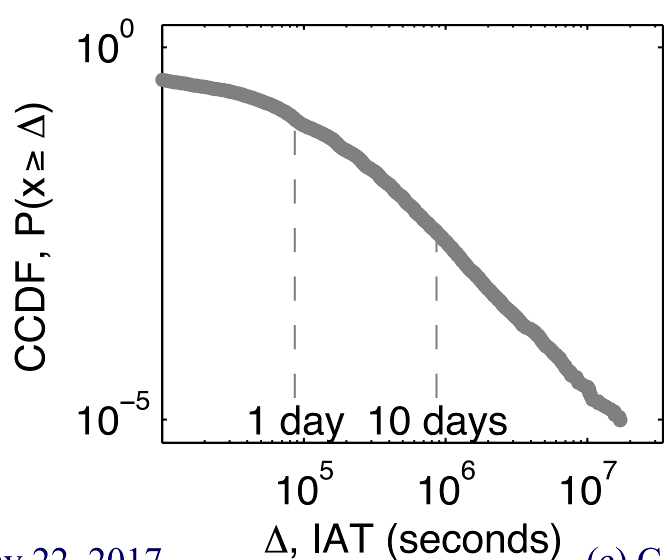


Pattern Mining

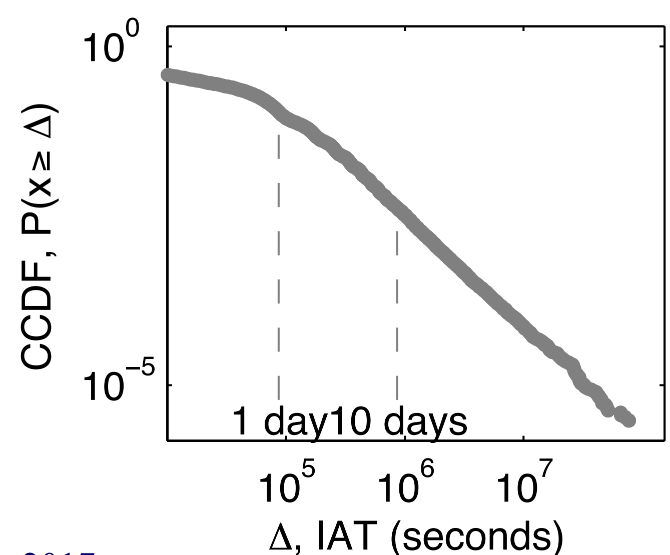
Pattern 1: Distribution of IAT is heavy-tailed

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

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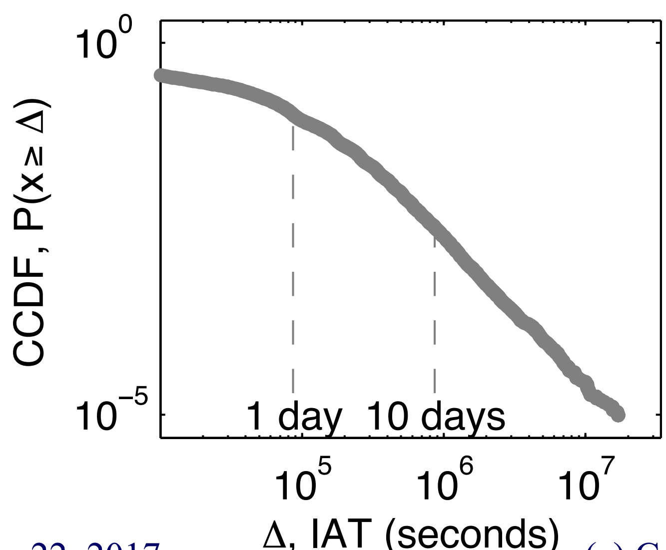
Pattern Mining

Pattern 1: Distribution of IAT is heavy-tailed

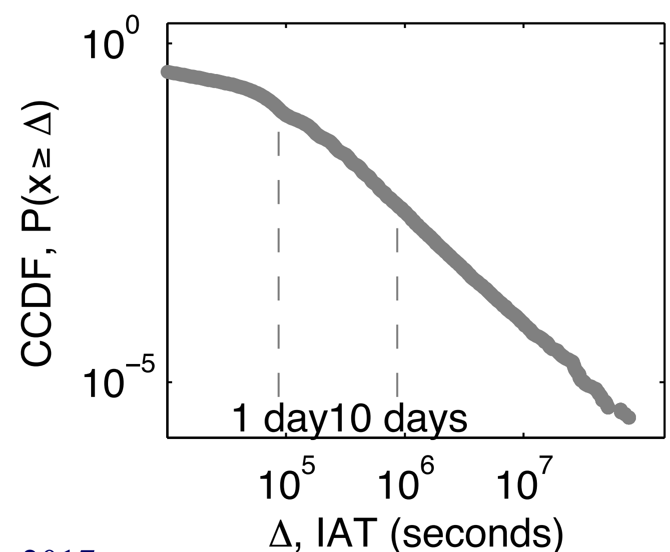
Users can be inactive for long periods of time before making new postings

No surprises – Should we give up?

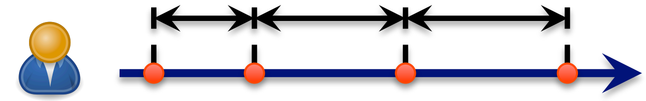
IAT Com... n (CCDF)



Reddit Users

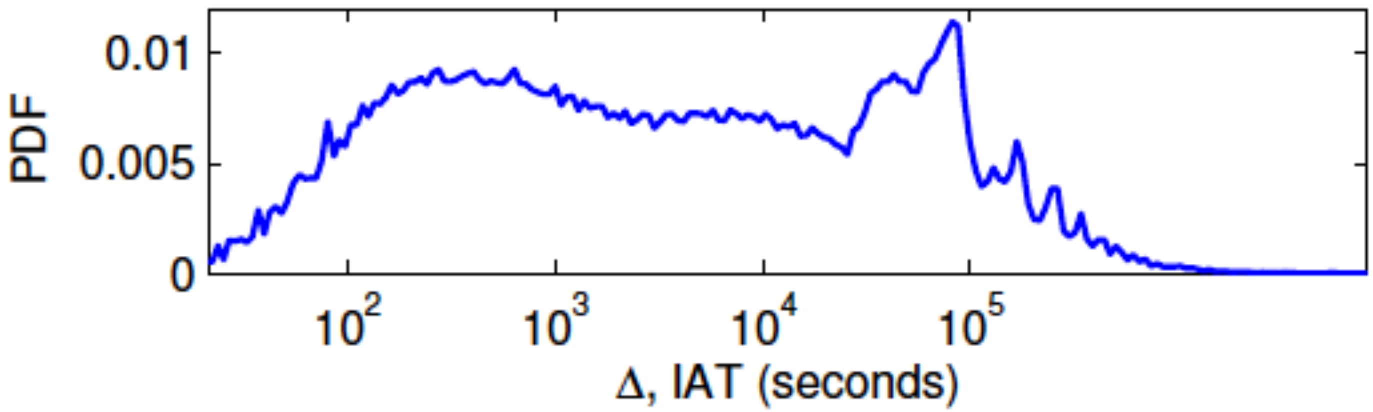


Twitter Users

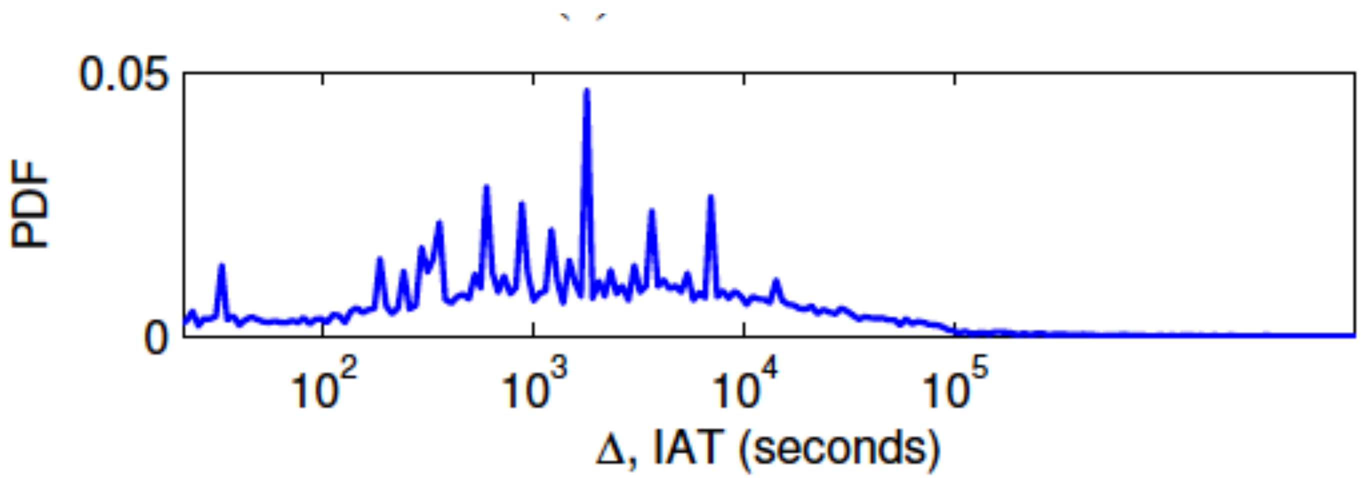


Human? Robots?

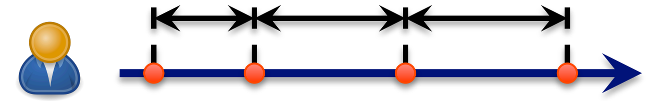
linear



log

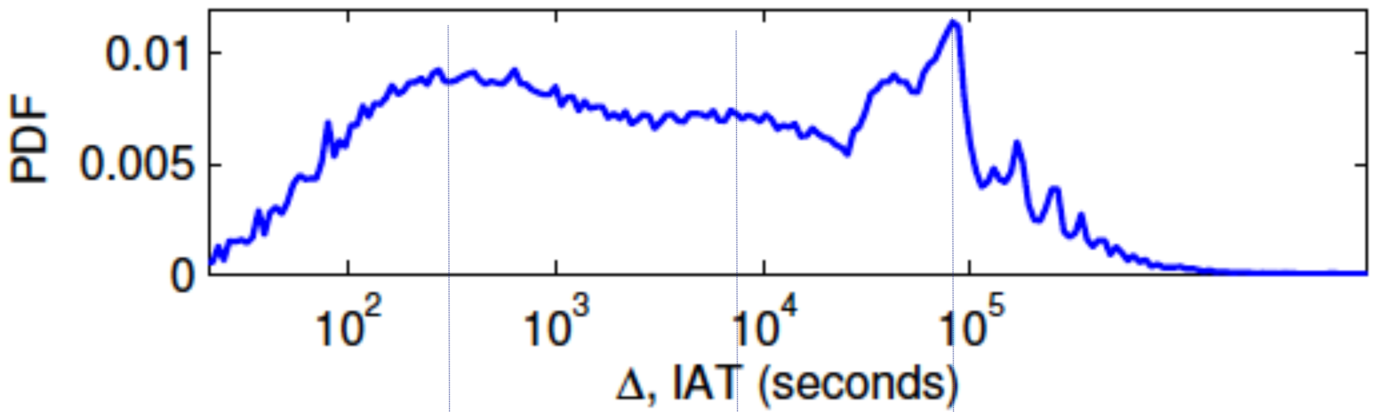


Human? Robots?

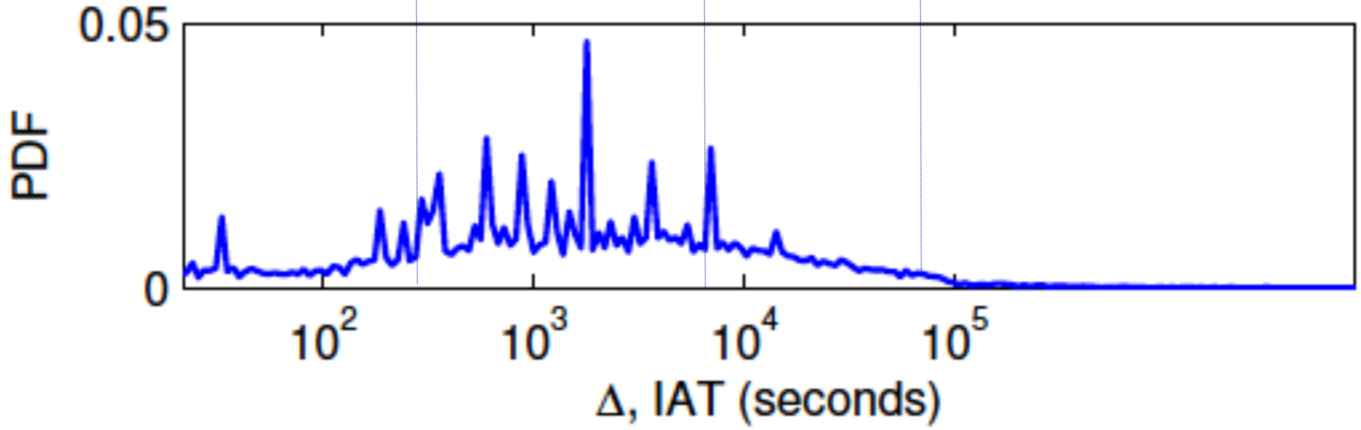


2’ 3h 1day

linear



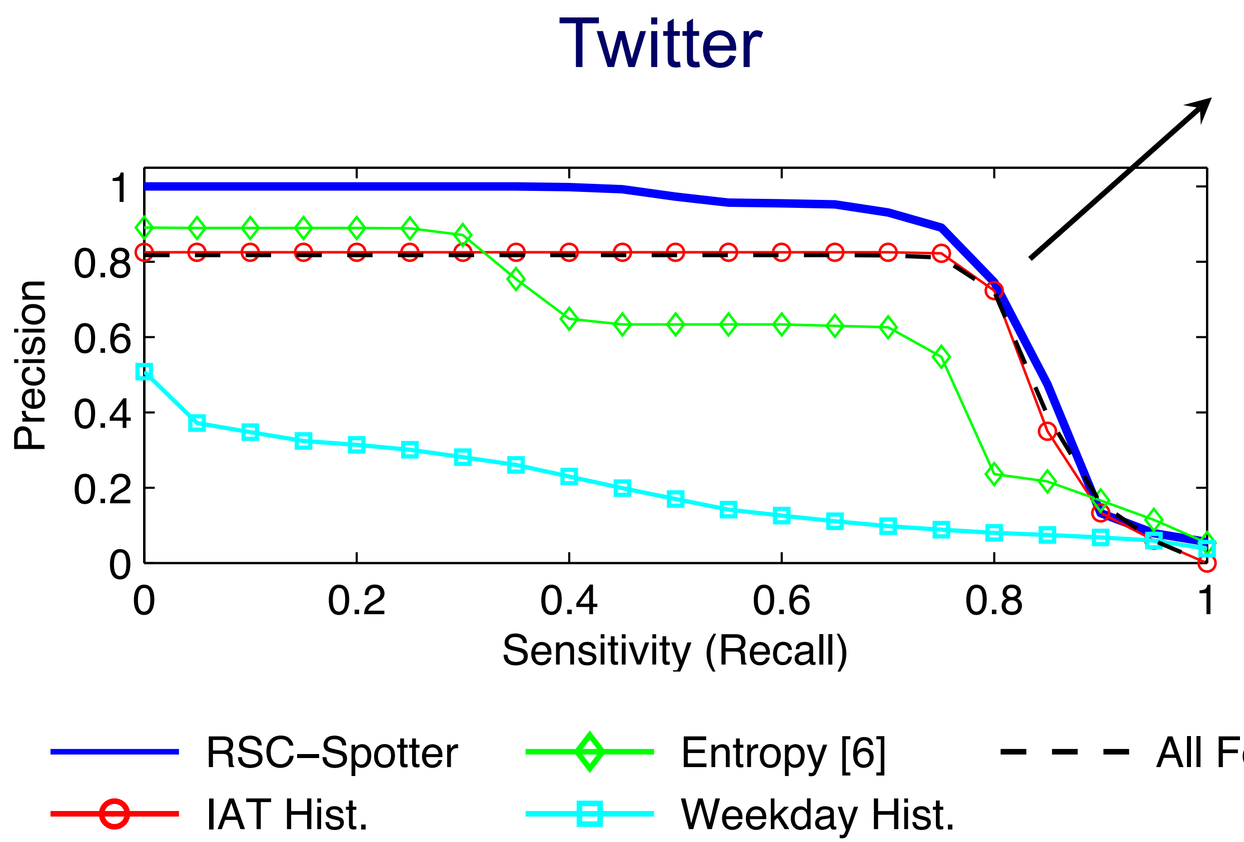
log



Experiments: Can RSC-Spotter Detect Bots?

Precision vs. Sensitivity Curves

Good performance: curve close to the top



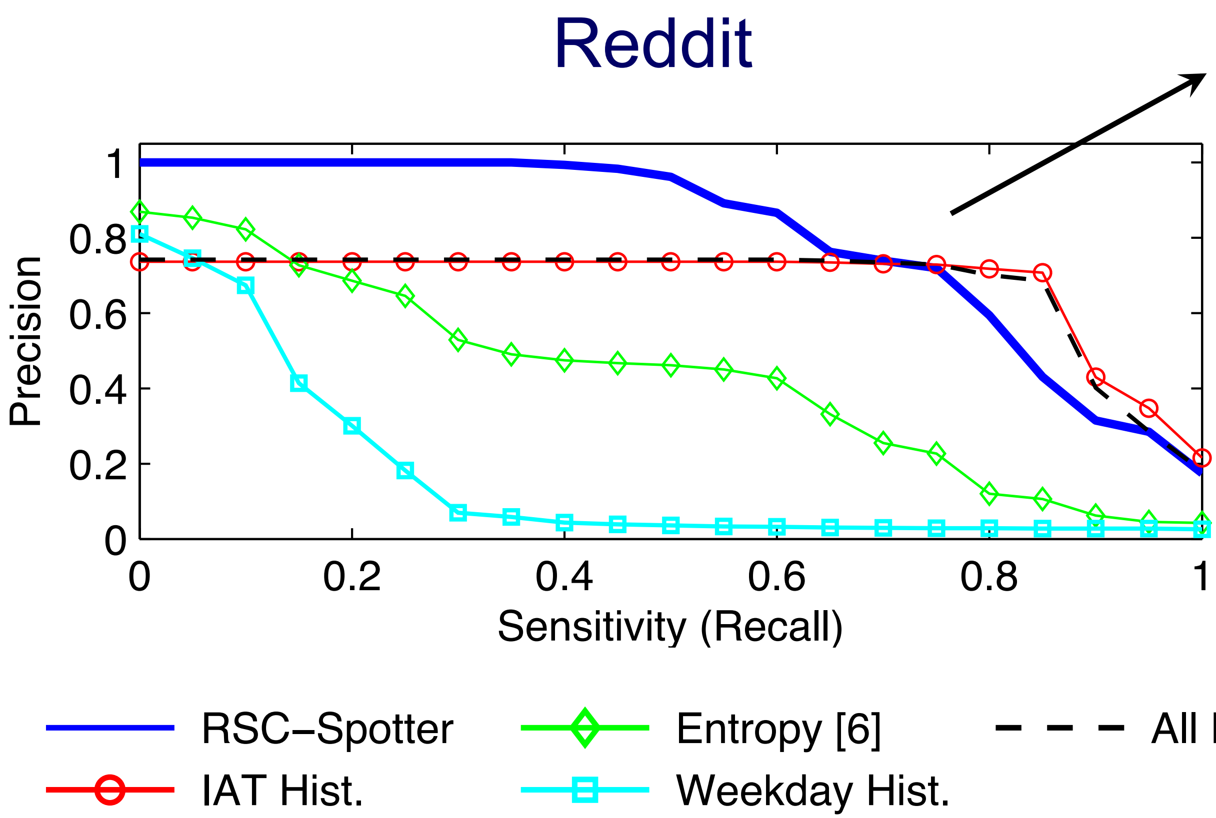
Precision > 94%
Sensitivity > 70%

With strongly imbalanced datasets
humans >> # bots

Experiments: Can RSC-Spotter Detect Bots?

Precision vs. Sensitivity Curves

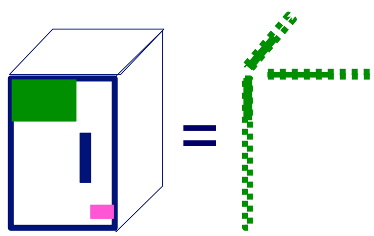
Good performance: curve close to the top

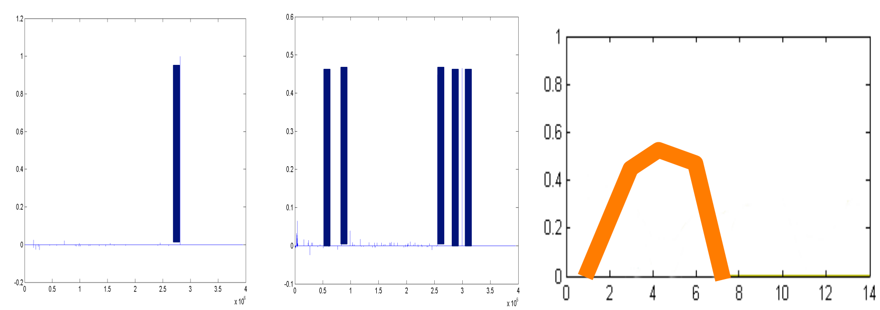


Precision > 96%
Sensitivity > 47%
With strongly imbalanced datasets
humans >> # bots

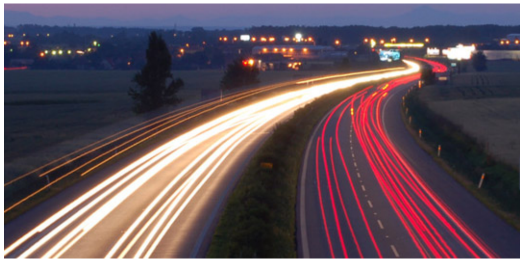
Part 2: Conclusions

- 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

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Thanks

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

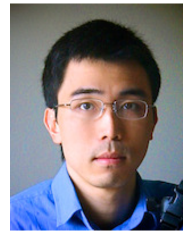
Thanks to: NSF IIS-0705359, IIS-0534205, CTA-INARC; Yahoo (M45), LLNL, IBM, SPRINT, Google, INTEL, HP, iLab

Cast

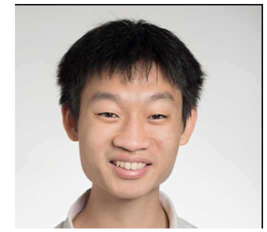

Akoglu, Leman


Araujo, Miguel


Beutel, Alex


Chau, Polo

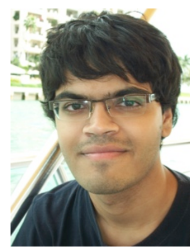

Eswaran, Dhivya


Hooi, Bryan


Kang, U


Koutra, Danai

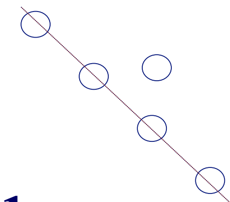

Papalexakis, Vagelis


Shah, Neil

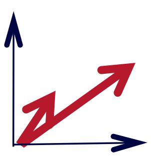

Shin, Kijung

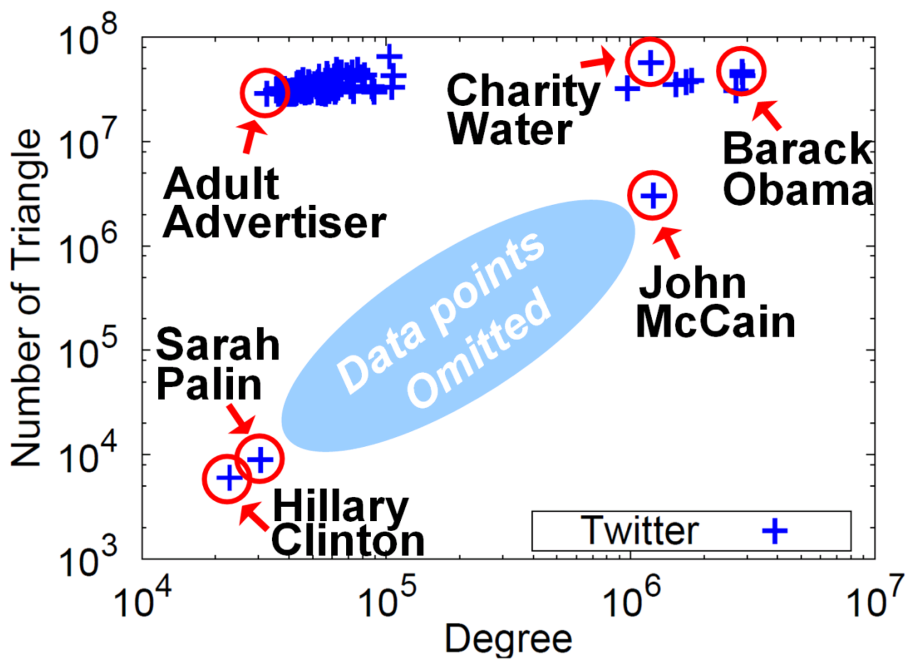

Song, Hyun Ah

CONCLUSION#1 – Big data



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





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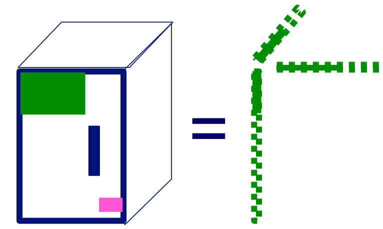
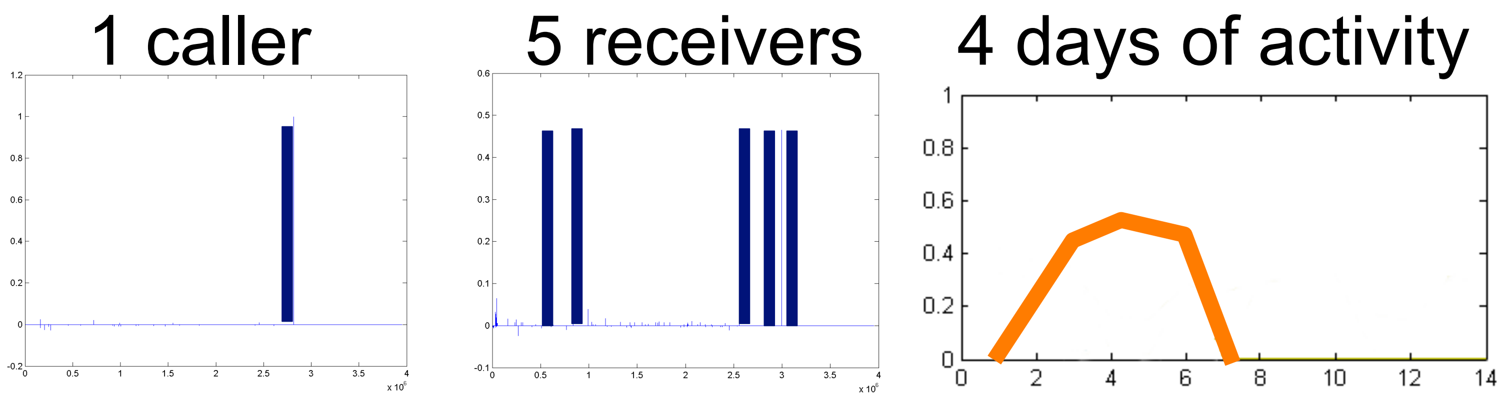
CONCLUSION#2 – tensors

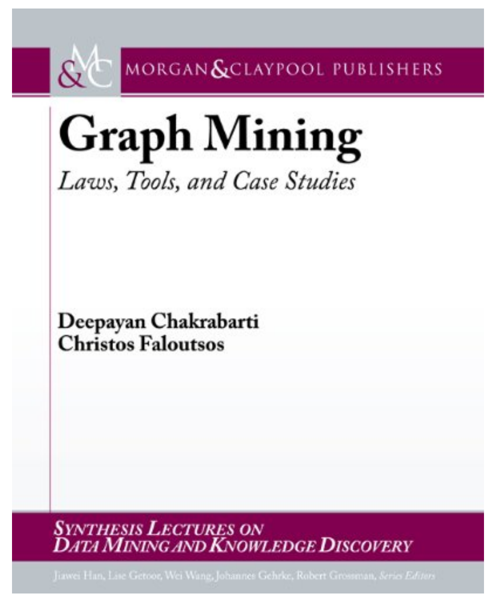
- powerful tool





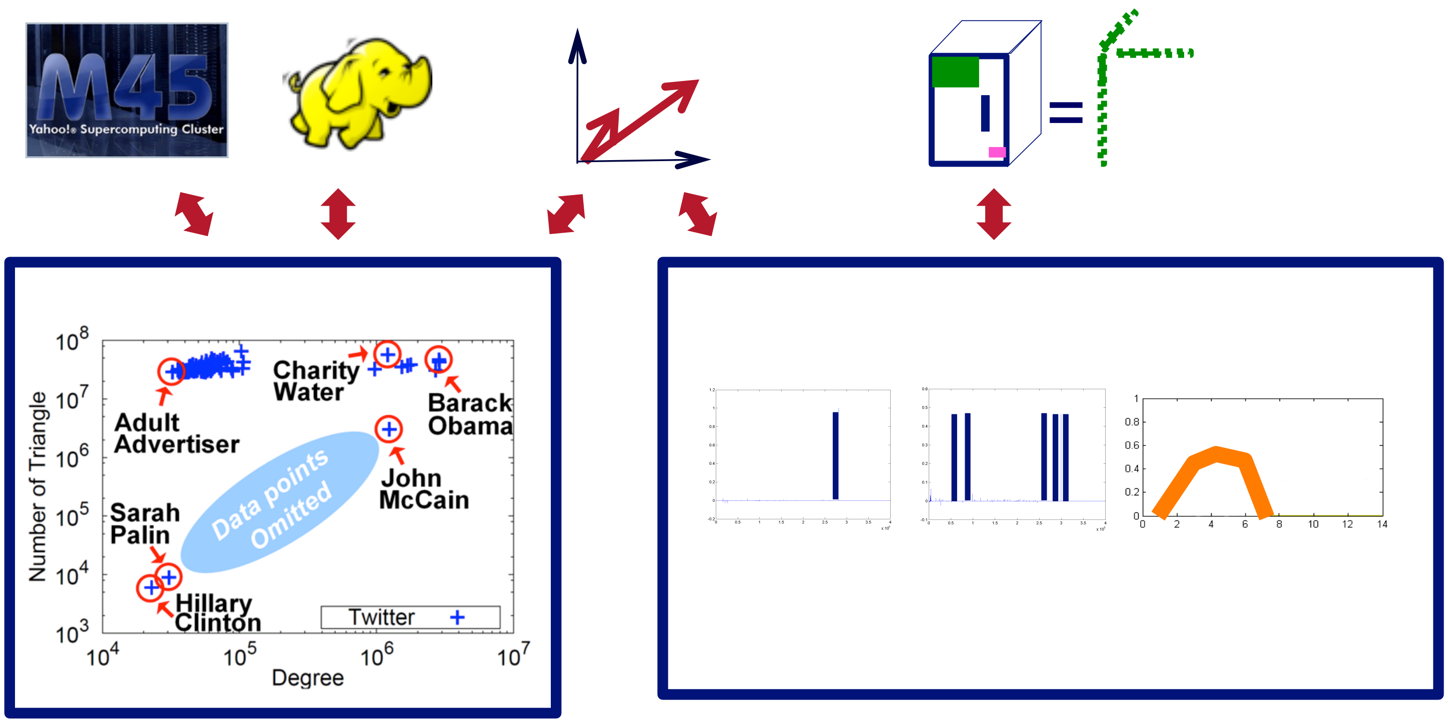
References

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



TAKE HOME MESSAGE:

Cross-disciplinarity



Thank you!

Cross-disciplinarity