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Mining Large Graphs and Time Sequences: Patterns, Anomalies, and Fraud Detection

Christos Faloutsos

CMU

Thank you!

- Alkis Polyzotis

- Denise Olivera

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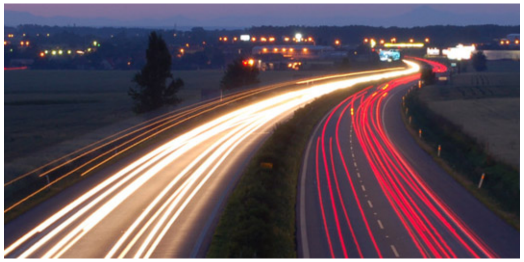
Roadmap



- Introduction – Motivation
  - Why study (big) graphs?
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
- Part#3: time sequences
- Conclusions

Graphs - why should we care?

>$10B; ~1B users

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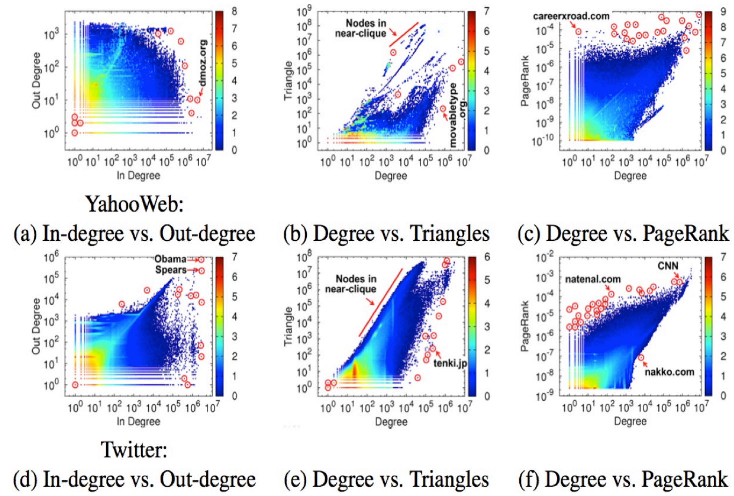
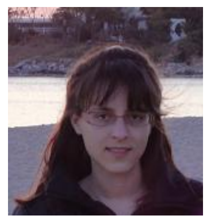
Graphs - why should we care?



~1B nodes (web sites)
~6B edges (http links)
'YahooWeb graph'



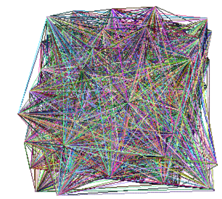
U Kang, Jay-Yoon Lee, Danai Koutra, and Christos Faloutsos. *Net-Ray: Visualizing and Mining Billion-Scale Graphs* PAKDD 2014, Tainan, Taiwan.

Graphs - why should we care?

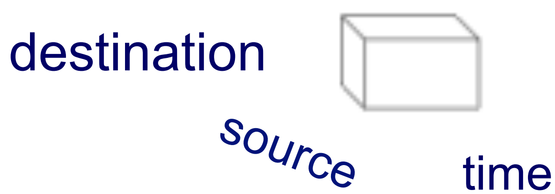
- web-log ('blog') news propagation
- computer network security: email/IP traffic and anomaly detection
- Recommendation systems
- ....

- Many-to-many db relationship -> graph

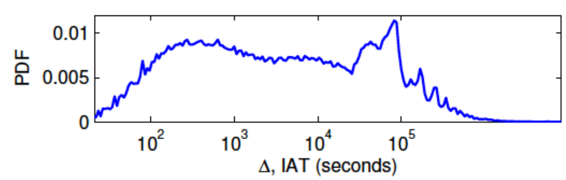
Motivating problems



- P1: patterns? Fraud detection?
- P2: patterns in time-evolving graphs / tensors



- P3: time sequences



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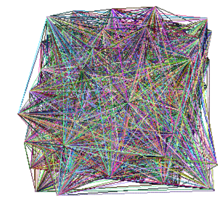
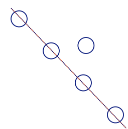


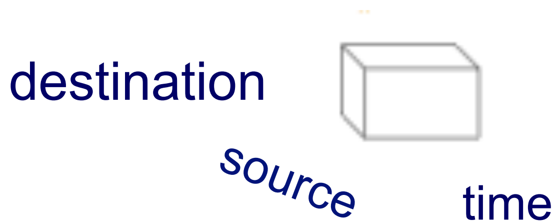
- P1: patterns? Fraud detection?



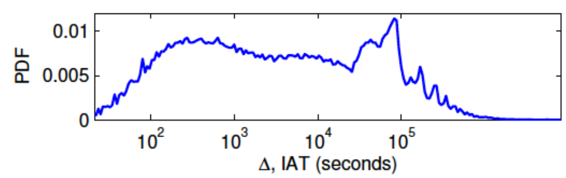
Patterns

anomalies

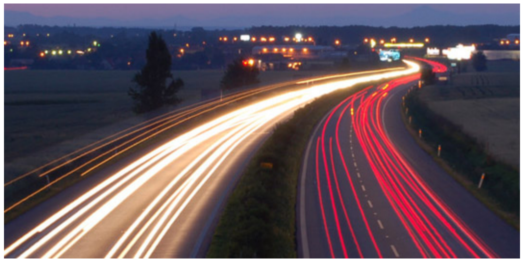
- P2: patterns in time-evolving graphs / tensors



- P3: time sequences



Roadmap



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- Part#1: Patterns & fraud detection
- Part#2: time-evolving graphs; tensors
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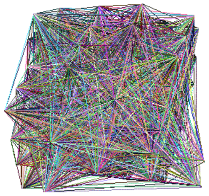
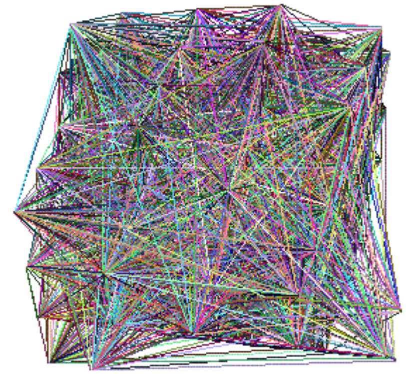


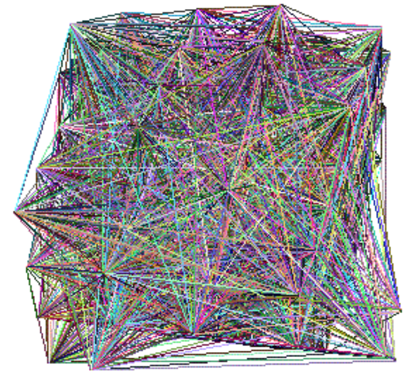
Part 1: Patterns, & fraud detection

Laws and patterns

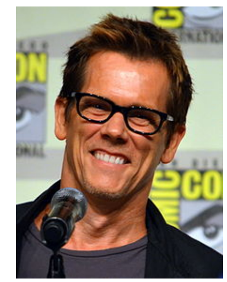


- Q1: Are real graphs random?

Laws and patterns



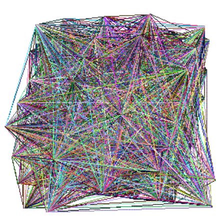
- Q1: Are real graphs random?
- A1: NO!!
  - Diameter ('6 degrees'; 'Kevin Bacon')
  - in- and out- degree distributions
  - other (surprising) patterns
- So, let's look at the data

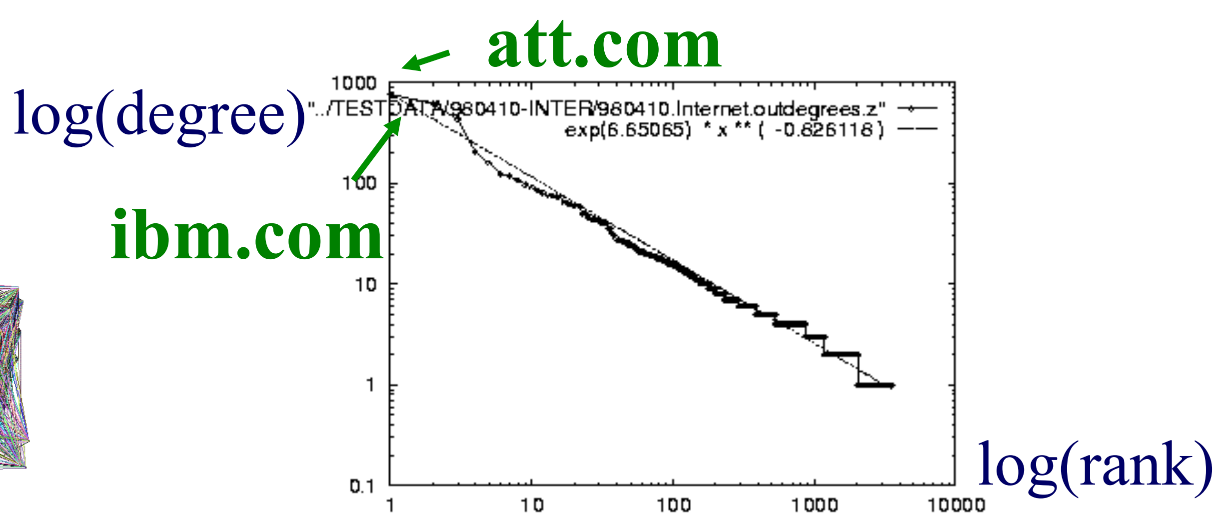


Solution# S.1

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

internet domains





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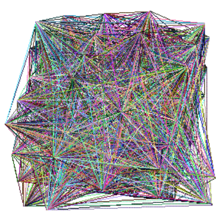
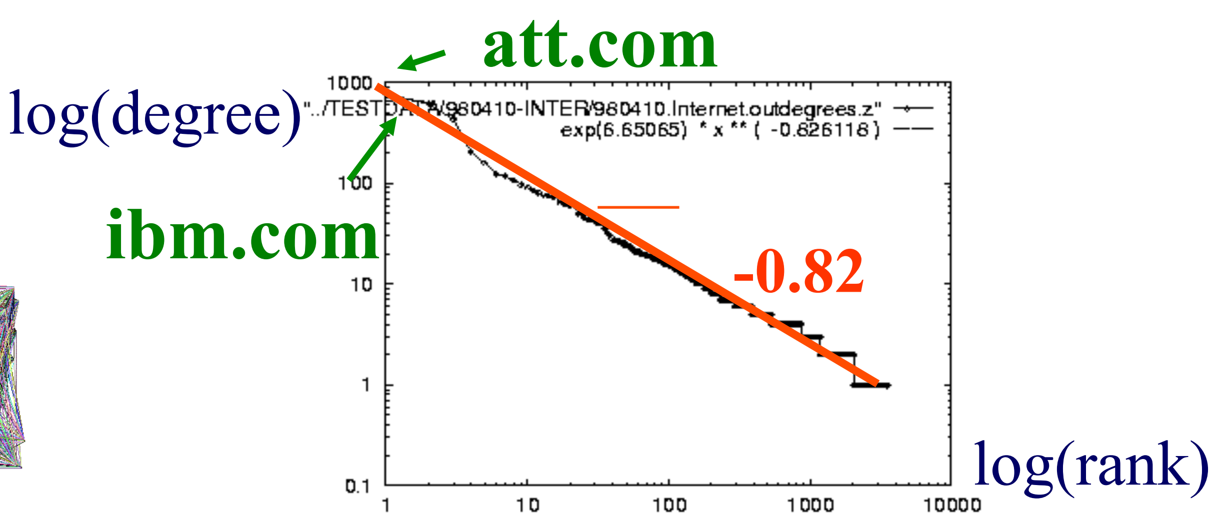
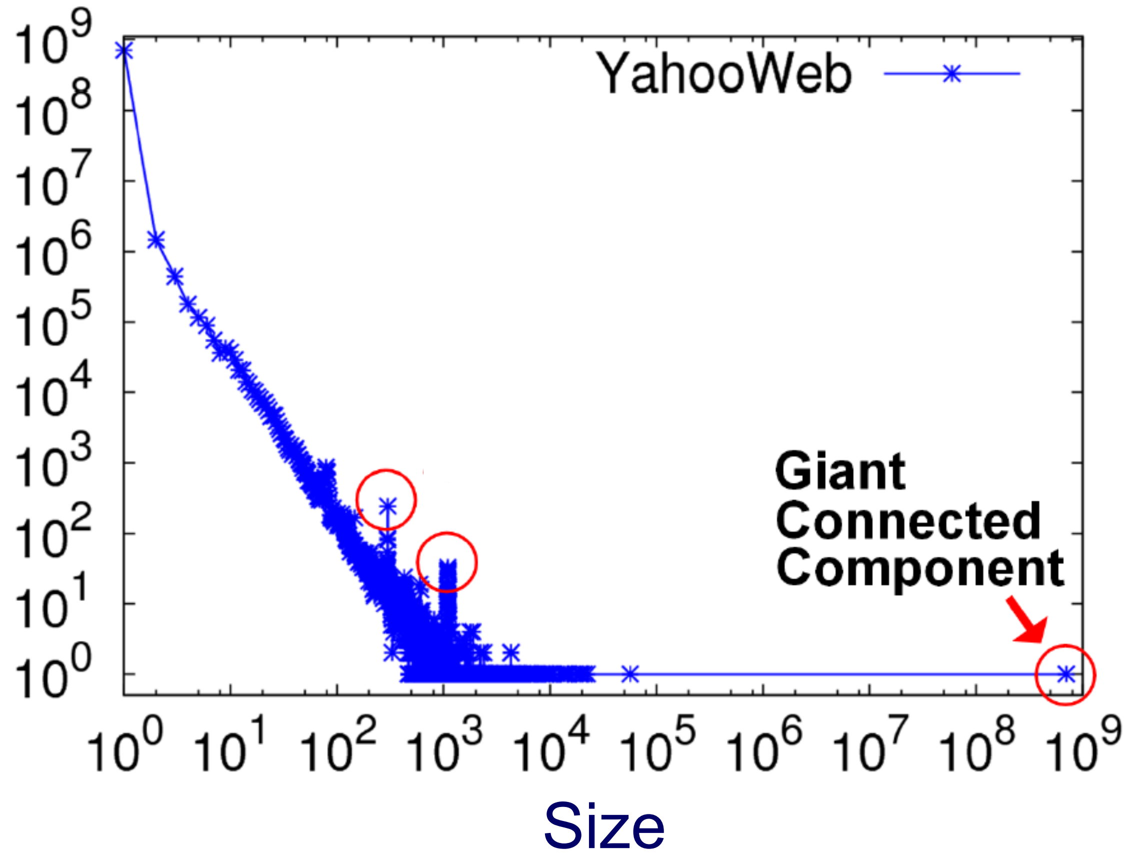




S2: connected component sizes

- Connected Components – 4 observations:

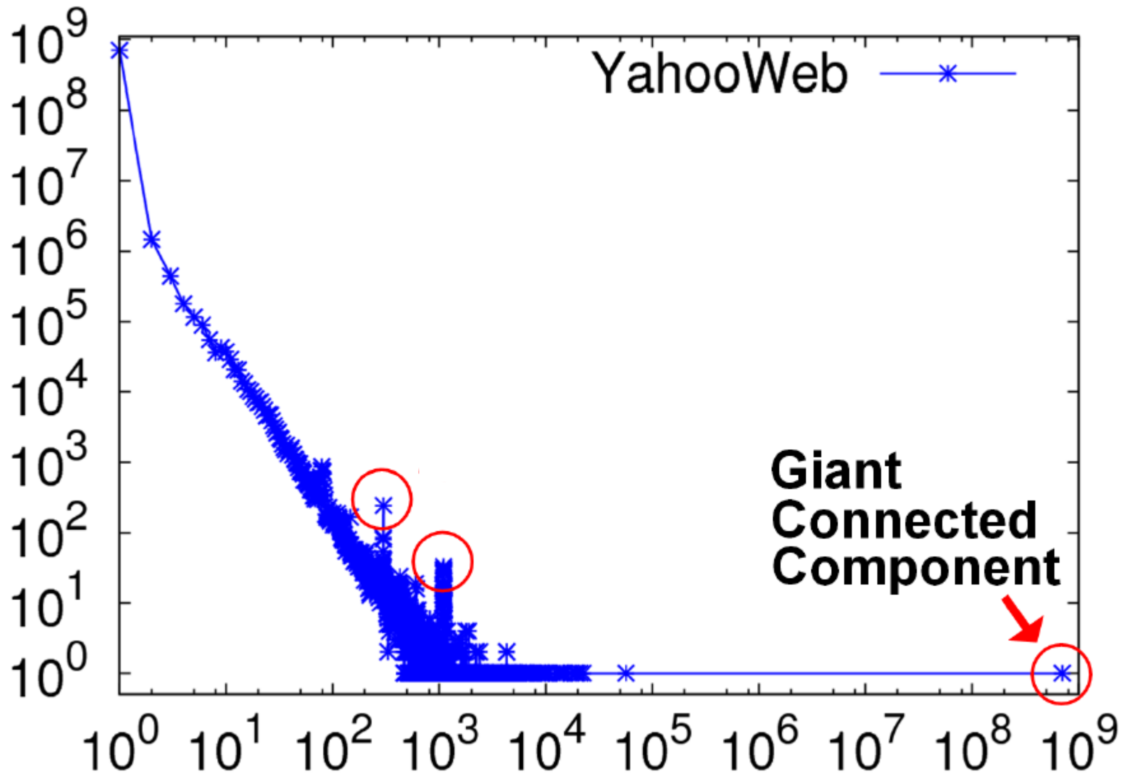


1.4B nodes
6B edges

S2: connected component sizes

- Connected Components

Count



Size

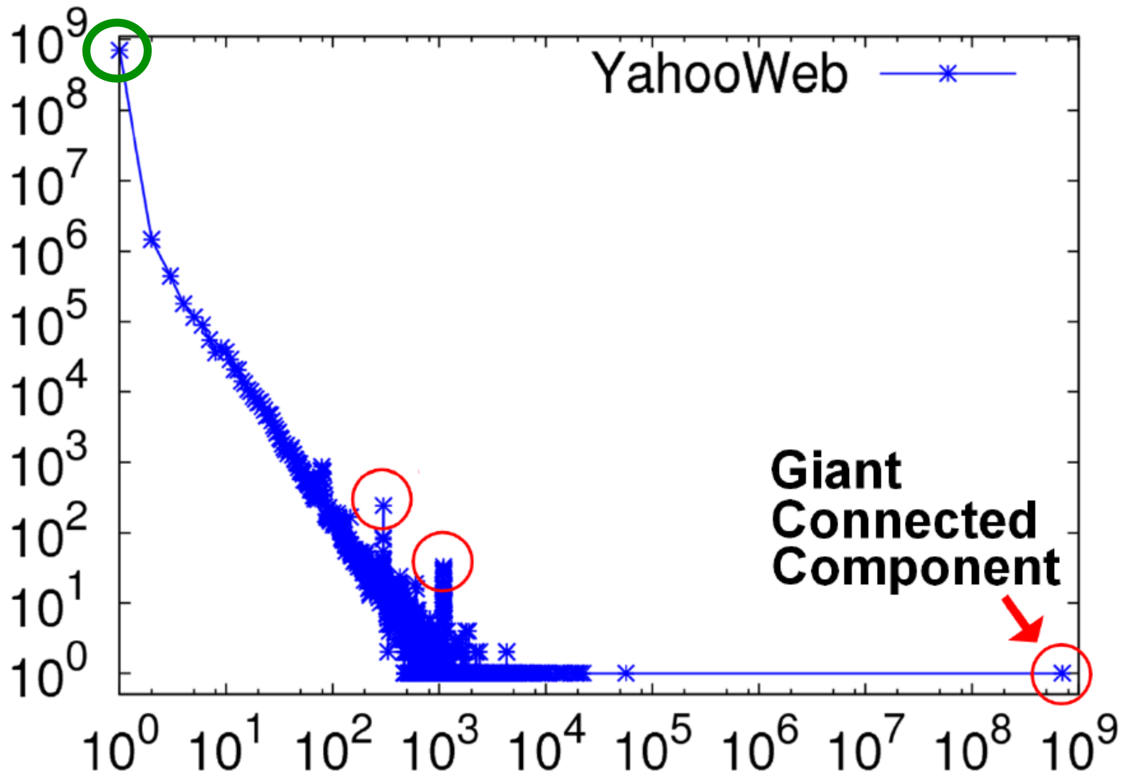
1) 10K x larger than next

S2: connected component sizes

- Connected Components

Count

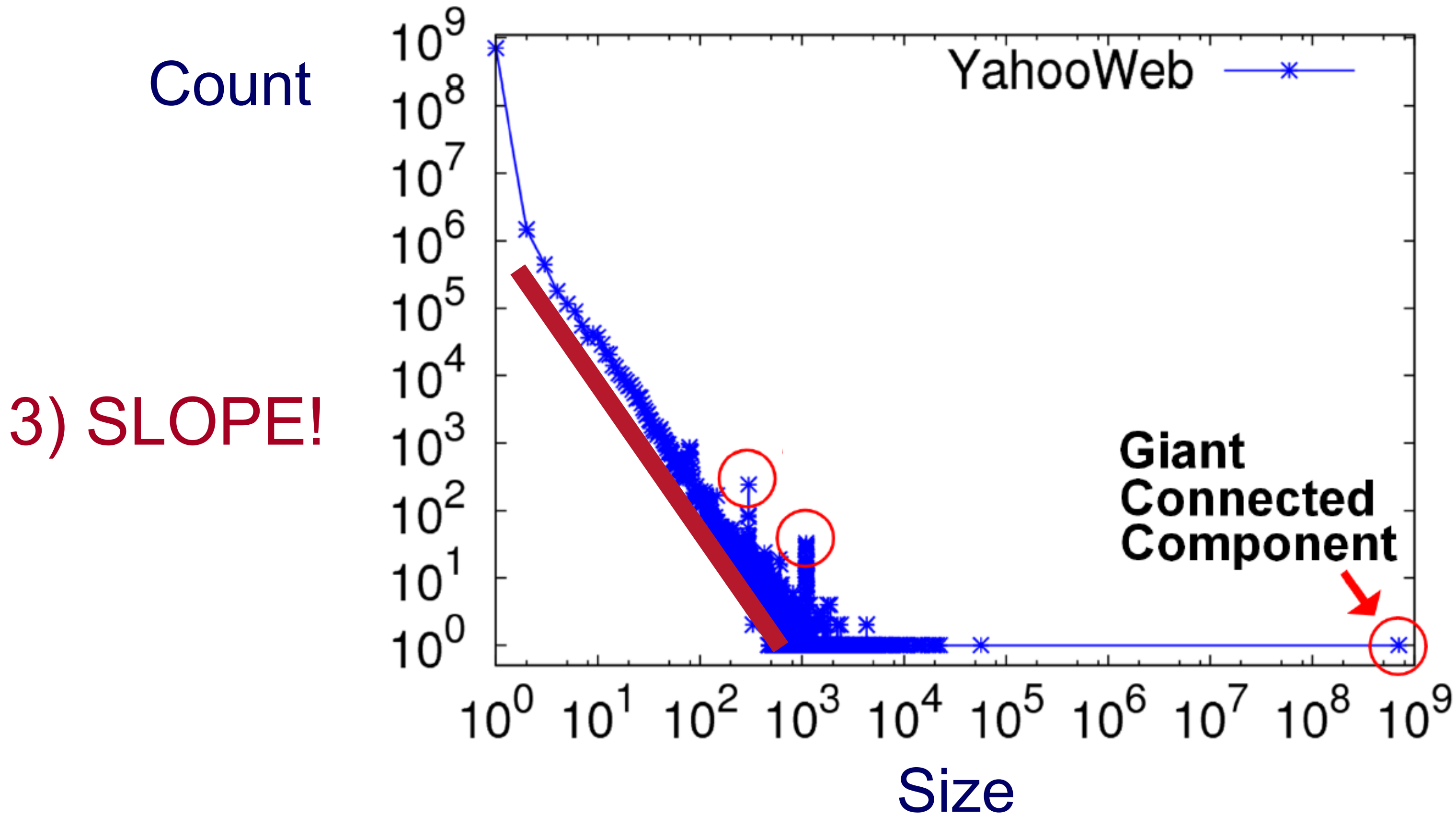
2) ~0.7B singleton nodes



Size

S2: connected component sizes

- Connected Components



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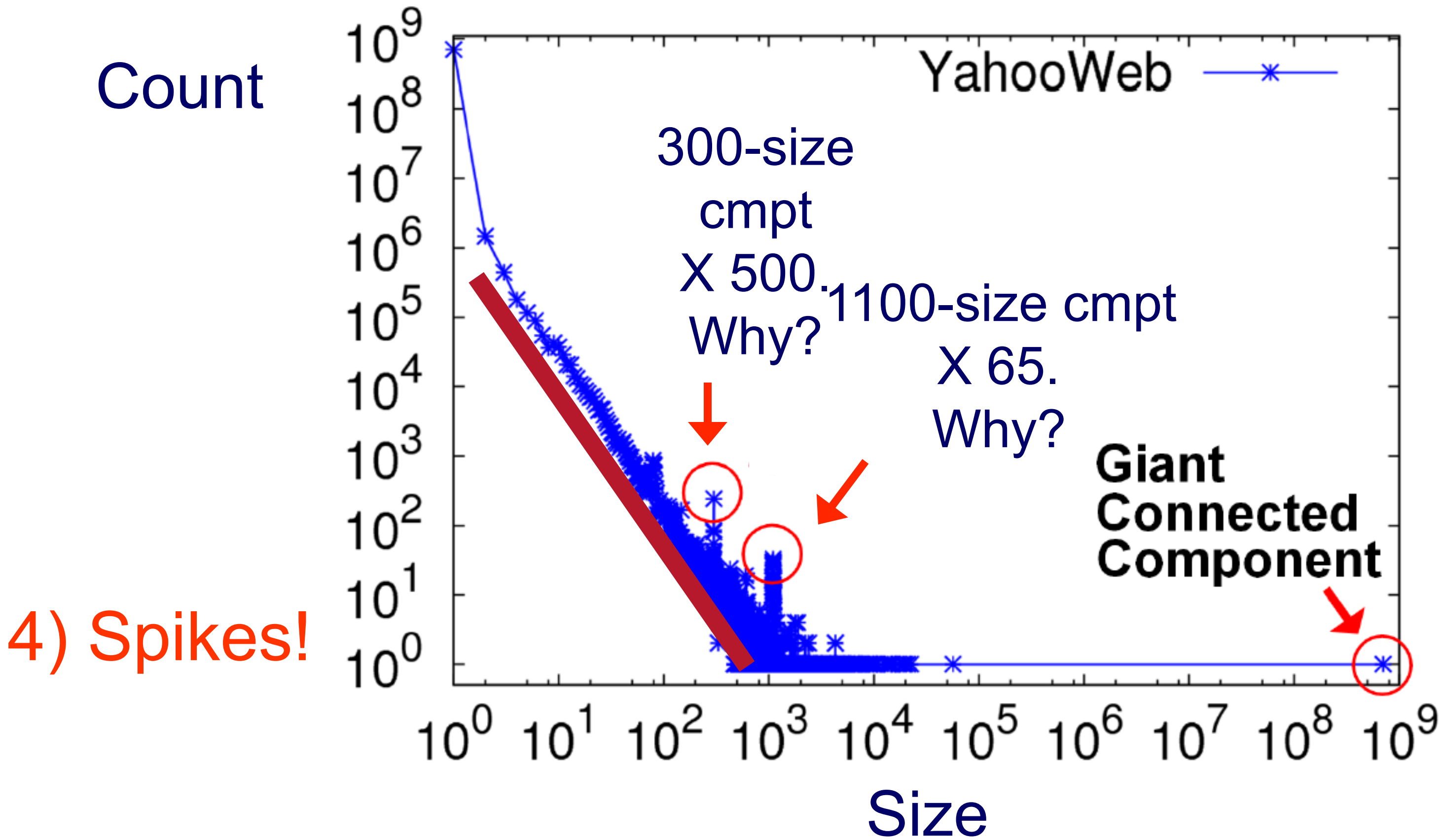
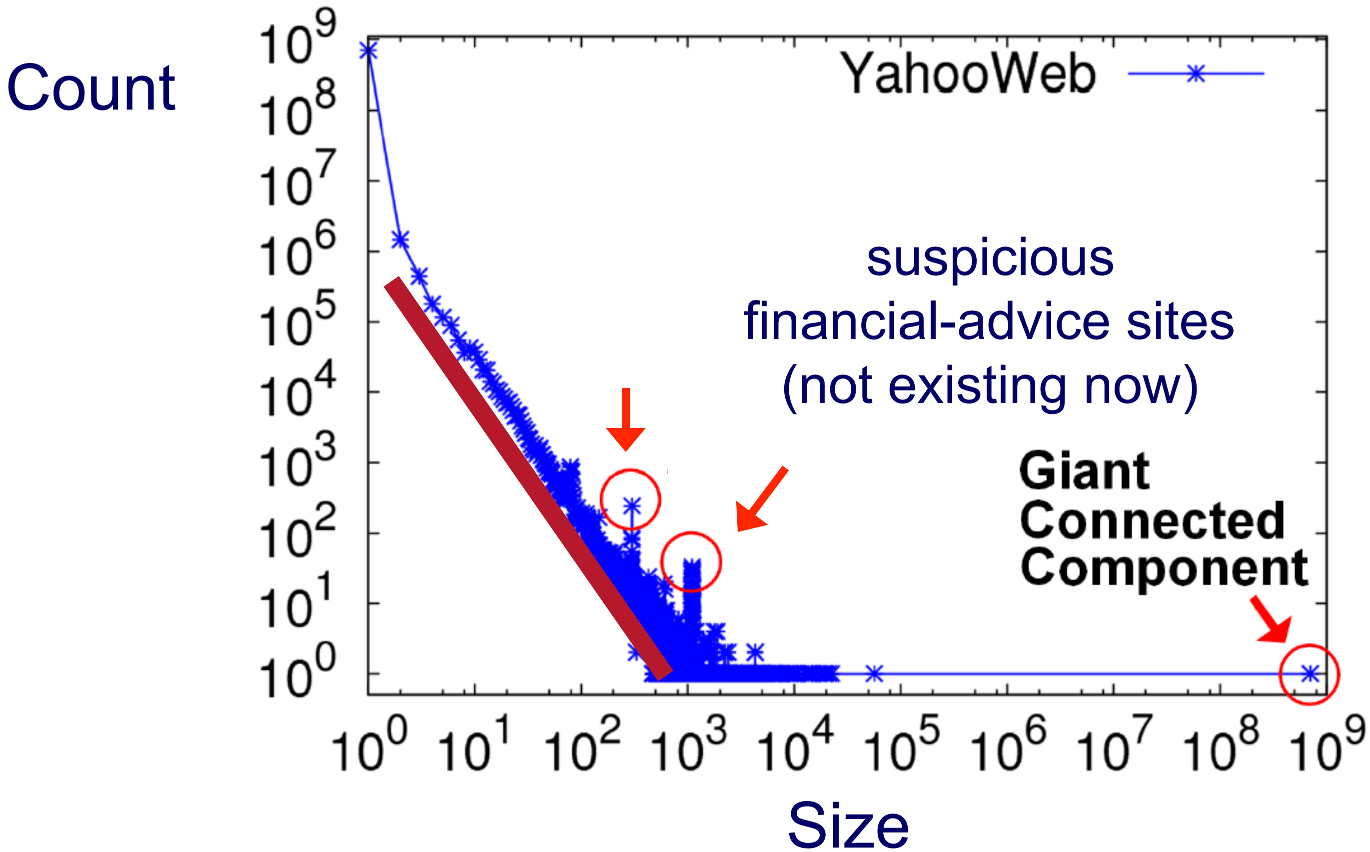


S2: connected component sizes

- Connected Components



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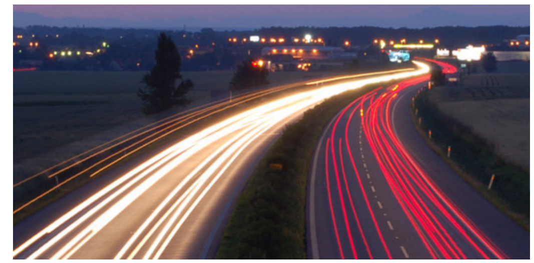

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  - Patterns: Degree; Triangles
  - Anomaly/fraud detection
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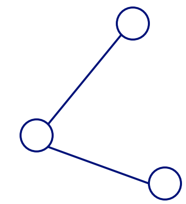
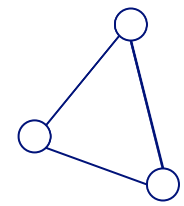
Solution# S.3: Triangle 'Laws'

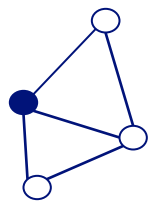


- Real social networks have a lot of triangles

Solution# S.3: Triangle ‘Laws’

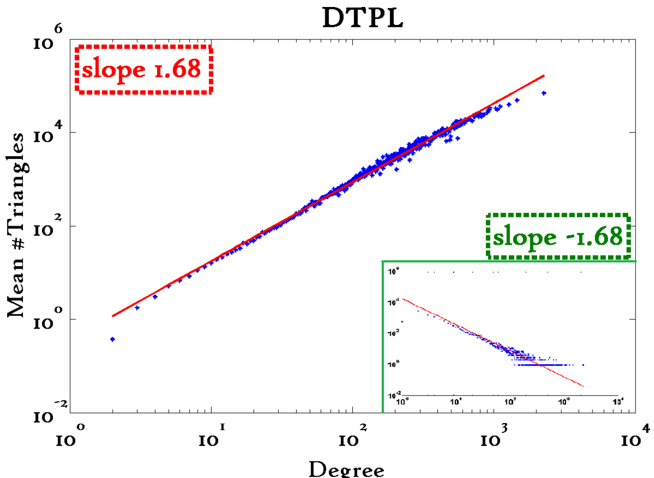


- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?
  - 2x the friends, 2x the triangles ?

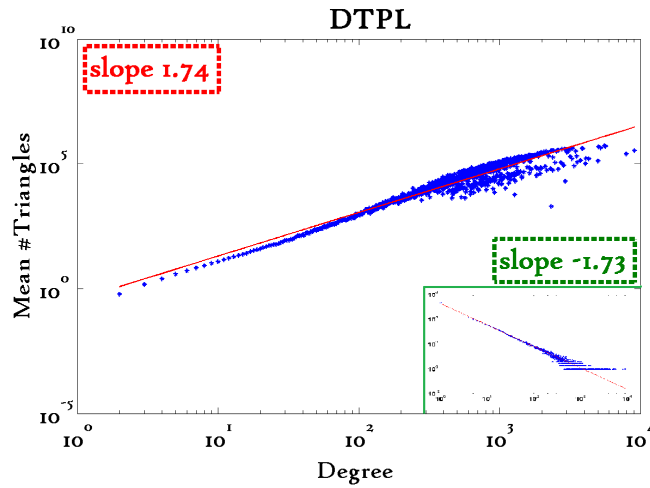


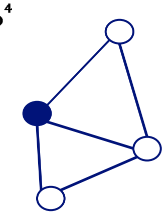
Triangle Law: #S.3
[Tsourakakis ICDM 2008]

Reuters

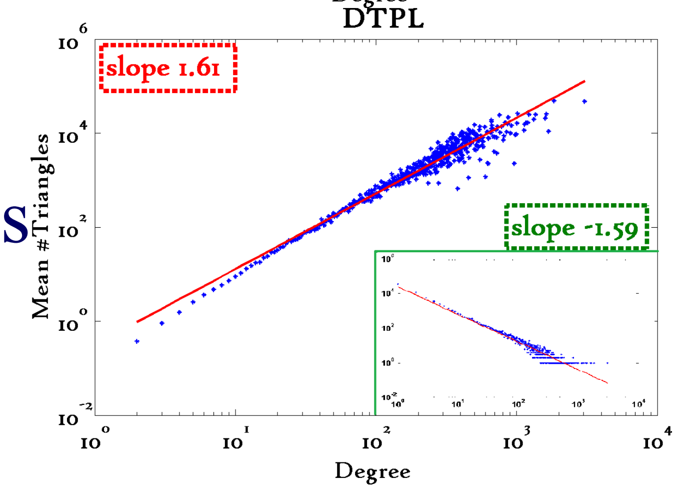


SN





Epinions

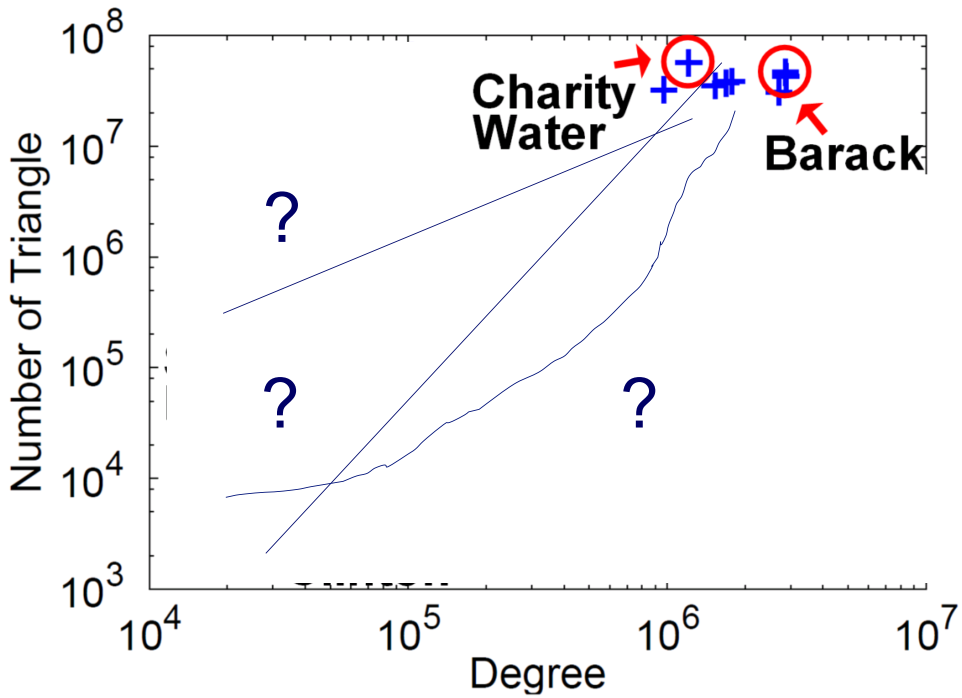


X-axis: degree

Y-axis: mean # triangles

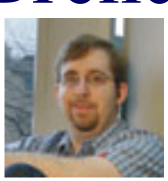
n friends -> $\sim n^{1.6}$ triangles

Triangle counting for large graphs?



Anomalous nodes in Twitter(~ 3 billion edges)

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



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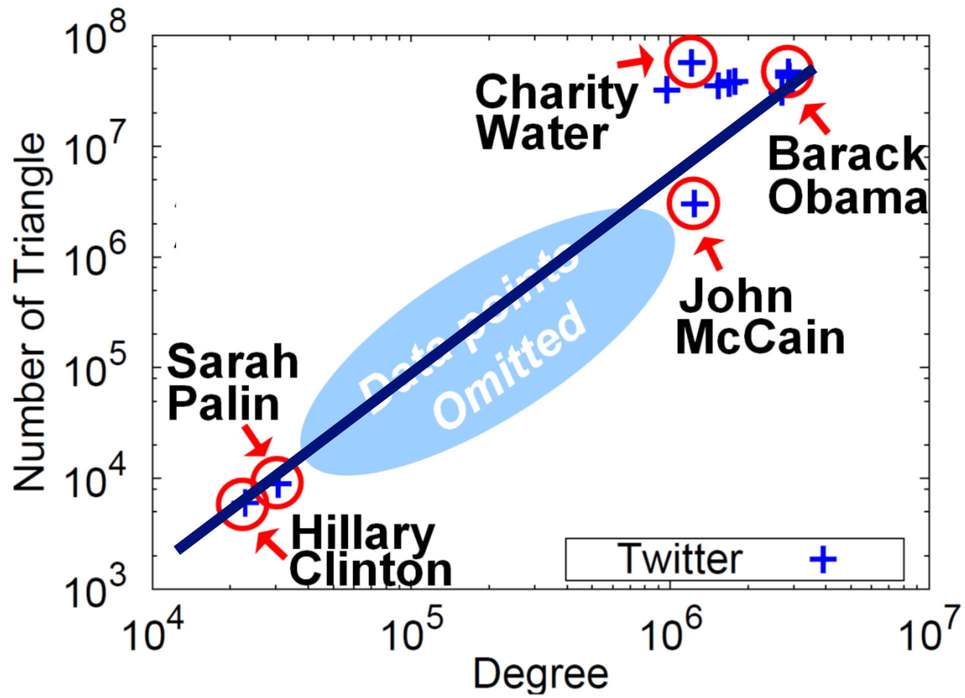

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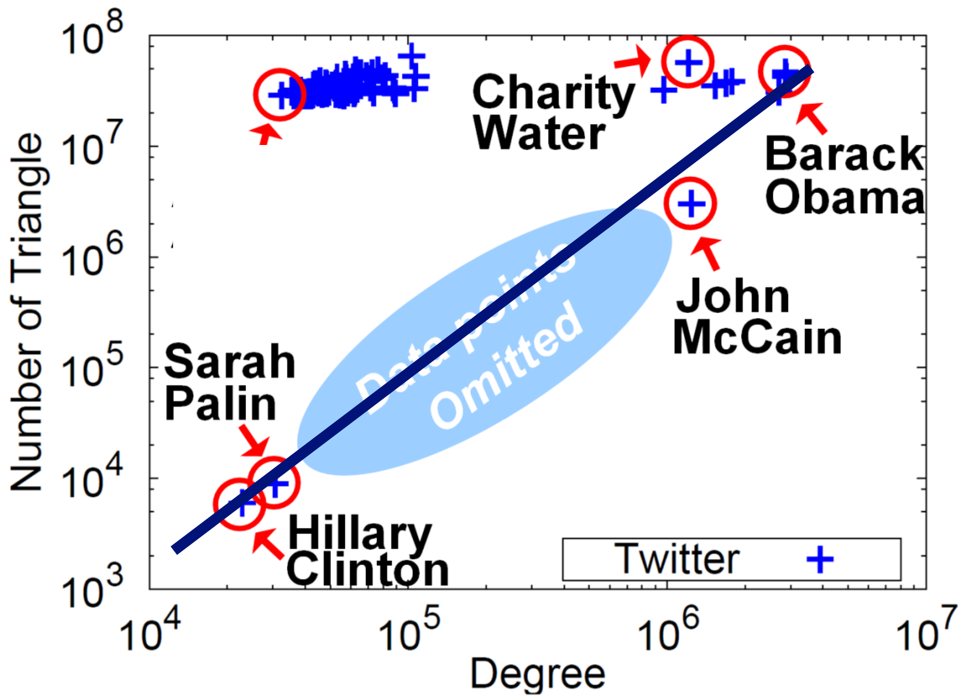

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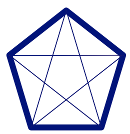

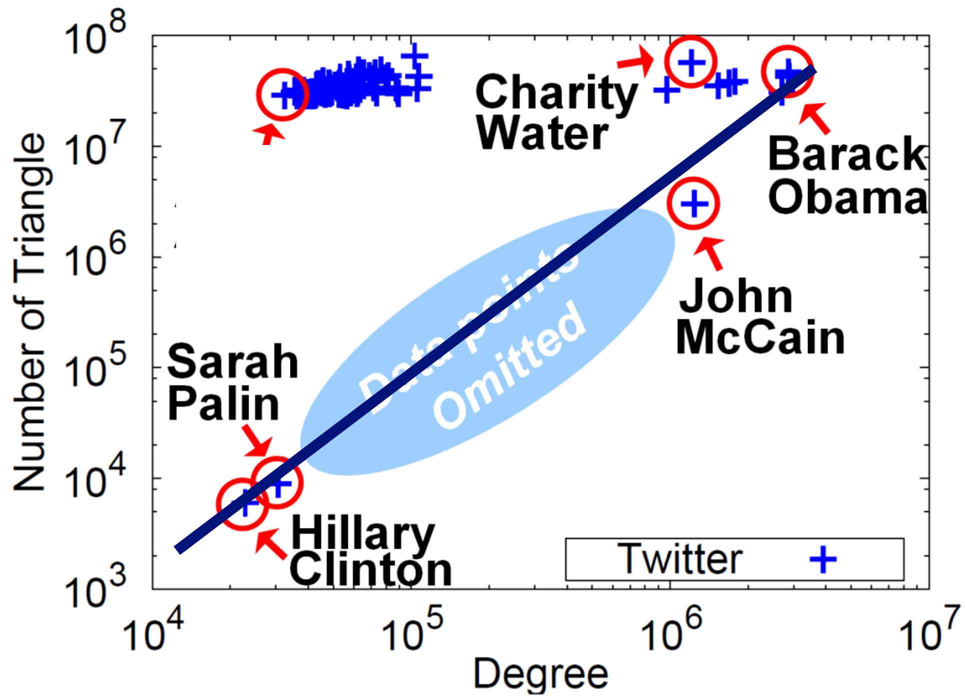

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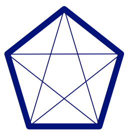

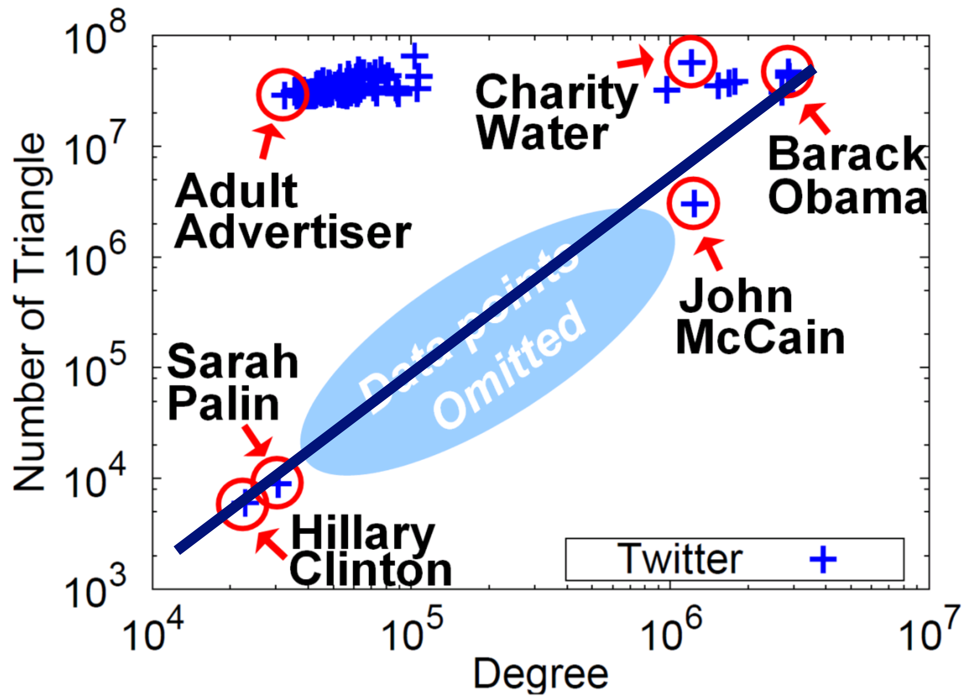

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MORE Graph Patterns

	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.

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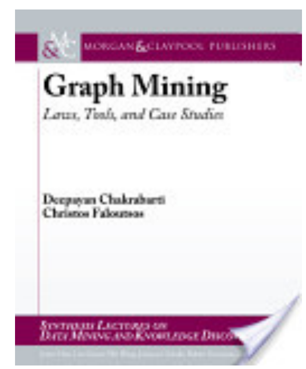
- Mary McGlohon, Leman Akoglu, Christos Faloutsos. *Statistical Properties of Social Networks.* in "Social Network Data Analytics" (Ed.: Charu Aggarwal)

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

http://www.cs.cmu.edu/~christos/TALKS/16-06-19-ICML/

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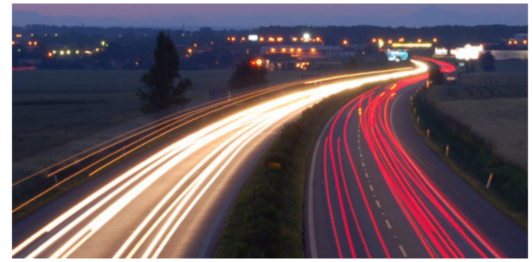
Roadmap



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  - Patterns
  - Anomaly / fraud detection
    - Spectral methods (‘fBox’)
    - Belief Propagation
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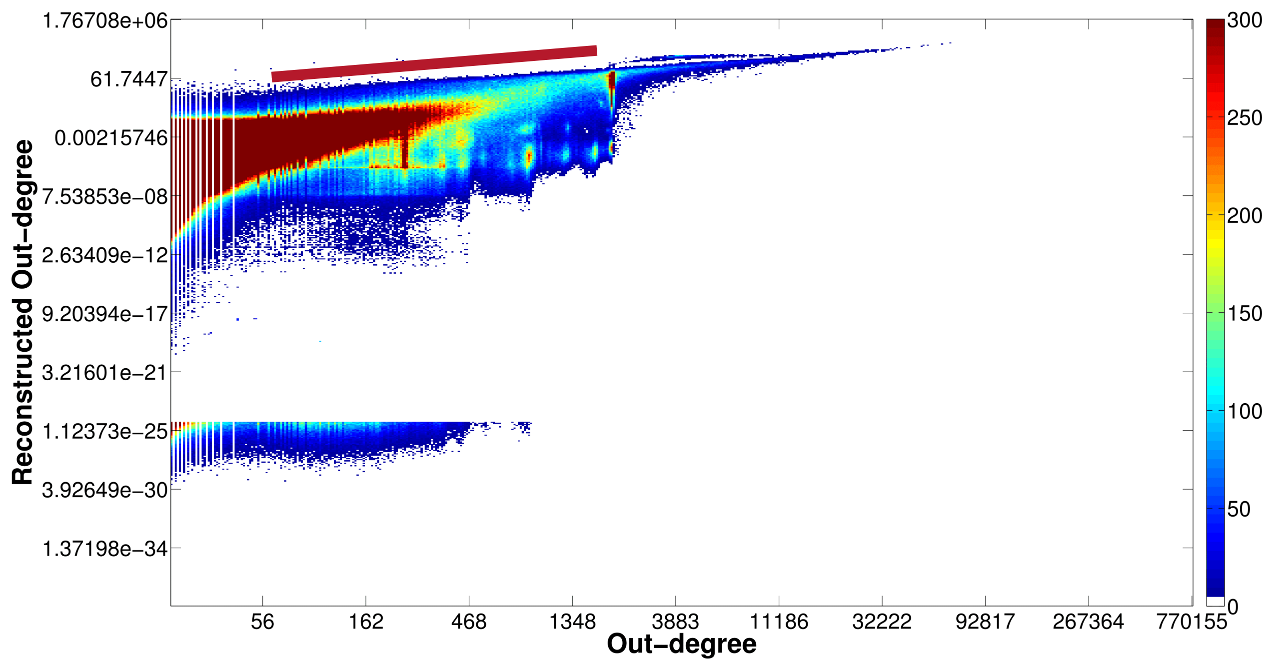
Problem: Social Network Link Fraud

Target: find “stealthy” attackers missed by other algorithms

Clique

41.7M nodes
1.5B edges

Bipartite
core



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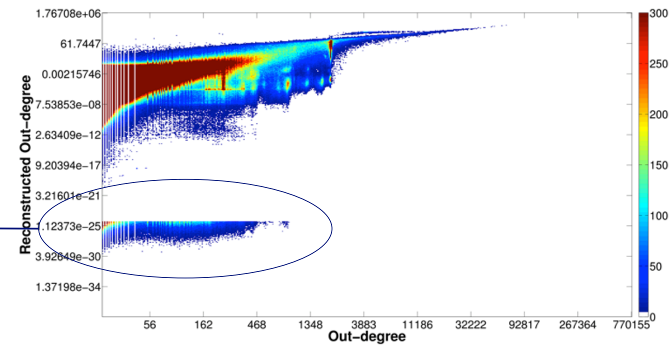
Lekan Olawole Lowe @loweinc 26 Jul 09
Sign up free and Get 400 followers a day using http://tweeteradder.com

Lekan Olawole Lowe @loweinc 26 Jul 09
Get 400 followers a day using http://www.tweeterfollow.com



Takeaway: use *reconstruction error* between true/latent representation!

Neil Shah, Alex Beutel, Brian Gallagher and Christos Faloutsos. *Spotting Suspicious Link Behavior with fBox: An Adversarial Perspective.* ICDM 2014, Shenzhen, China.

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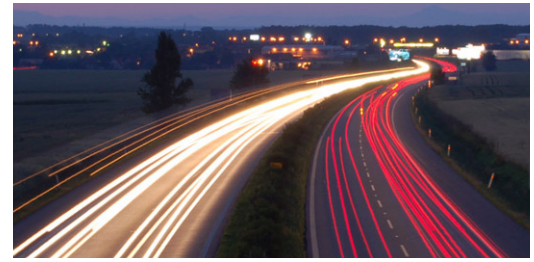
Roadmap



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    - CopyCatch
    - Spectral methods (‘fBox’, **suspiciousness**)
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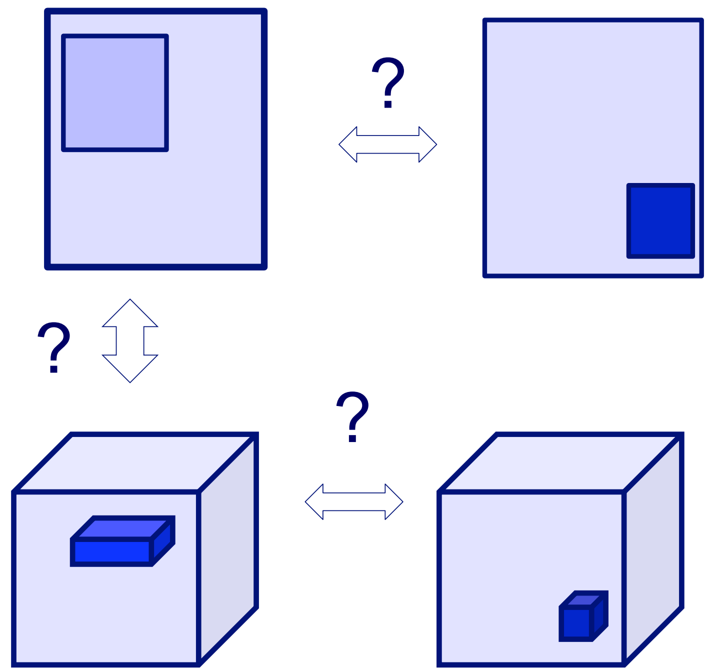
Suspicious Patterns in Event Data

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.

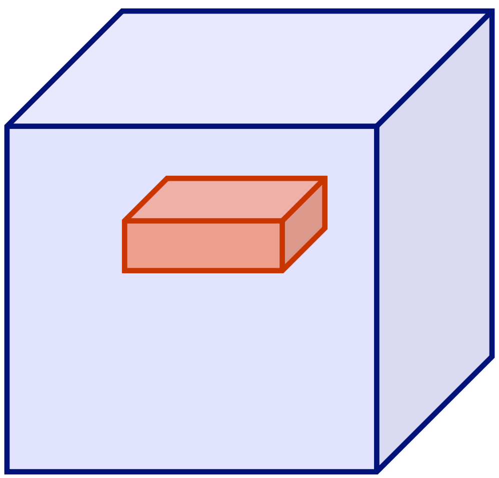
Suspicious Patterns in Event Data

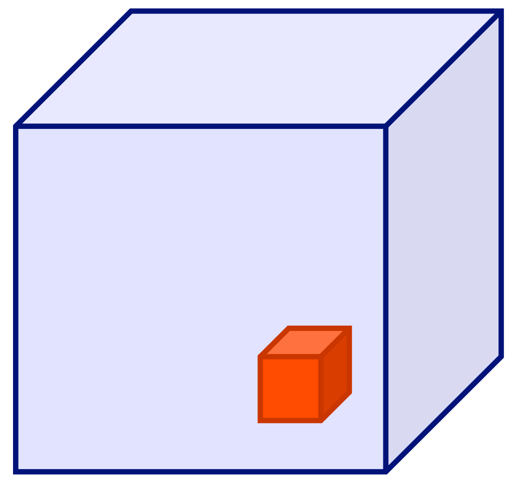
Which is more suspicious?

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

vs.

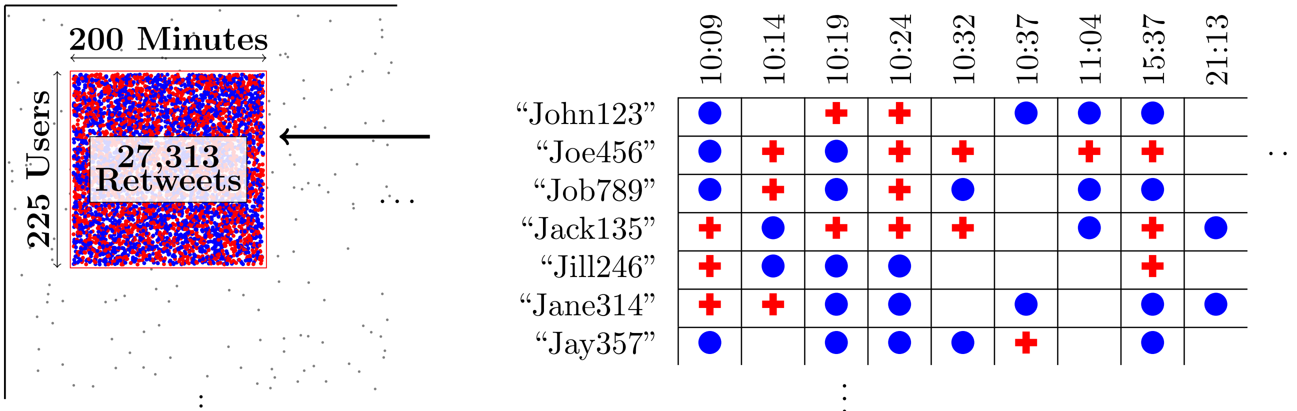
225 Users
Retweeting same 1 tweet
15 times each
All in 3 hours
All from 2 IP addresses





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

Suspicious Patterns in Event Data



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

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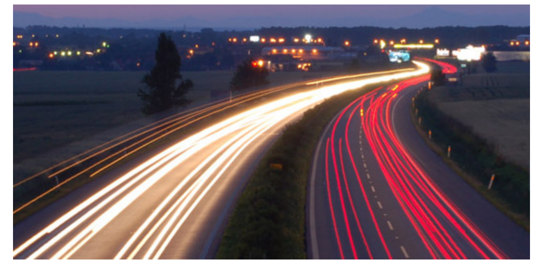
Roadmap



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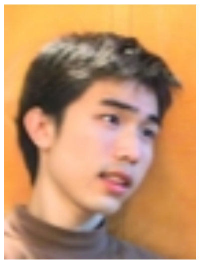
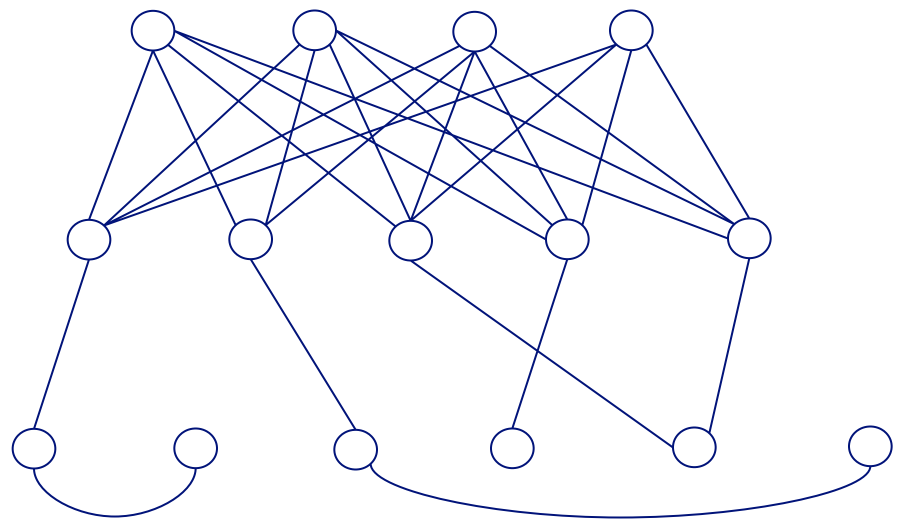
E-bay Fraud detection

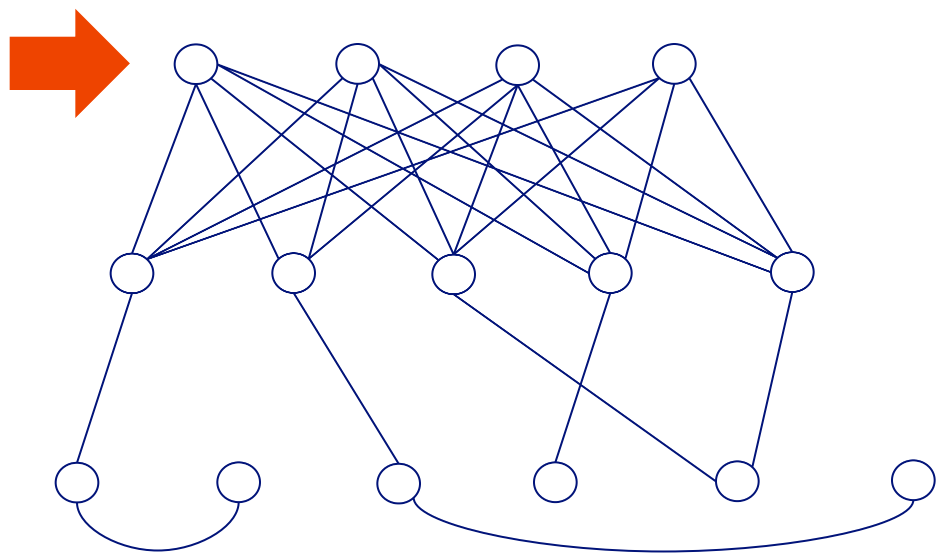


w/ Polo Chau &
Shashank Pandit, CMU
[www'07]

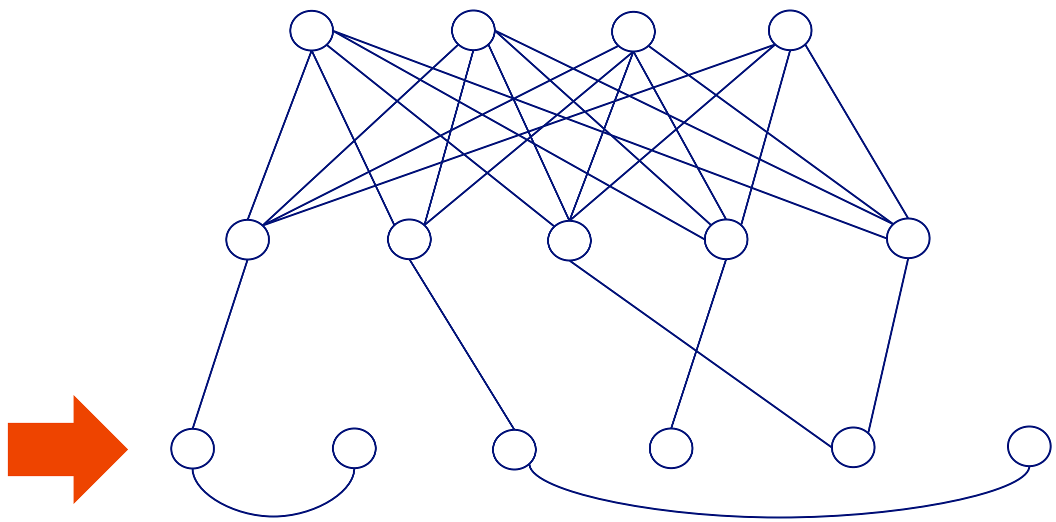


Carnegie Mellon

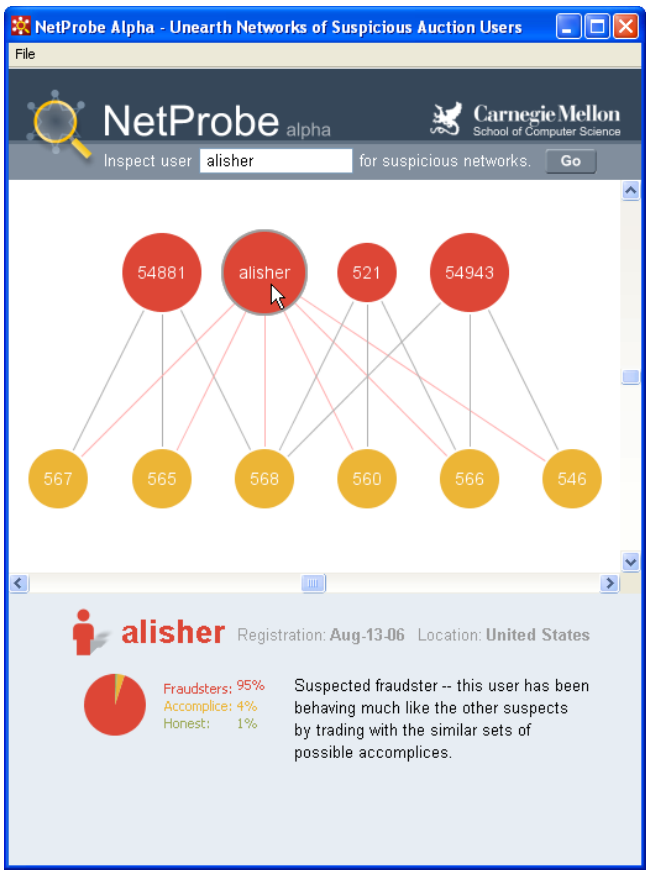
E-bay Fraud detection

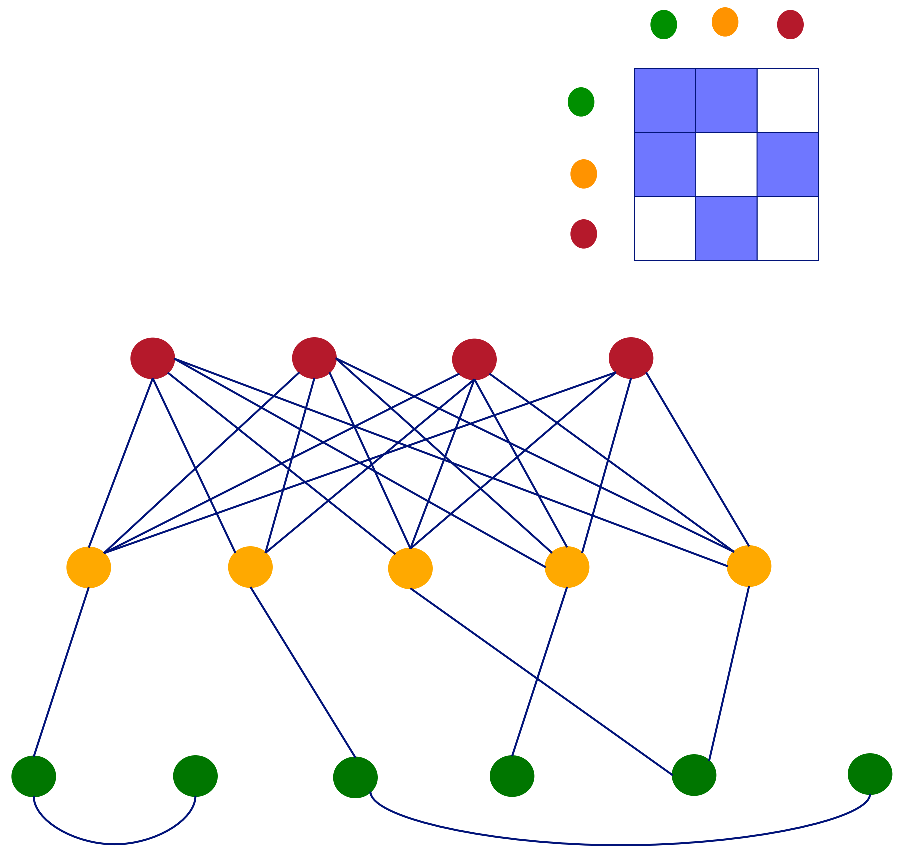


E-bay Fraud detection



E-bay Fraud detection - NetProbe





Popular press

USA TODAY

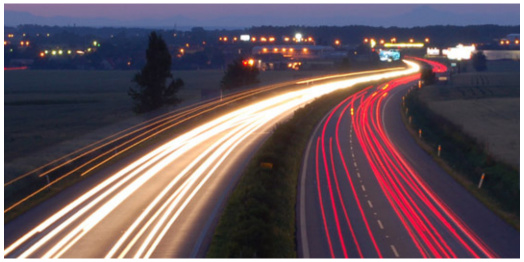
The Washington Post

Los Angeles Times

And less desirable attention:

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

Roadmap

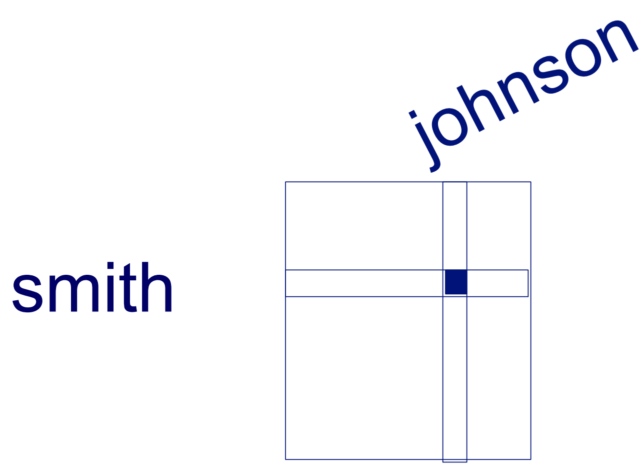


- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
  - P2.1: time-evolving graphs
  - [P2.2: with side information (‘coupled’ M.T.F.)
  - Speed]
- Part#3: time sequences
- Conclusions

Part 2: Time evolving graphs; tensors

Graphs over time -> tensors!

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



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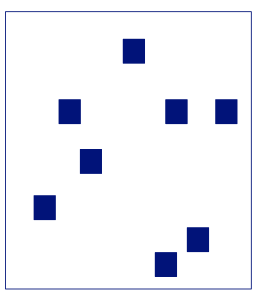

Graphs over time -> tensors!

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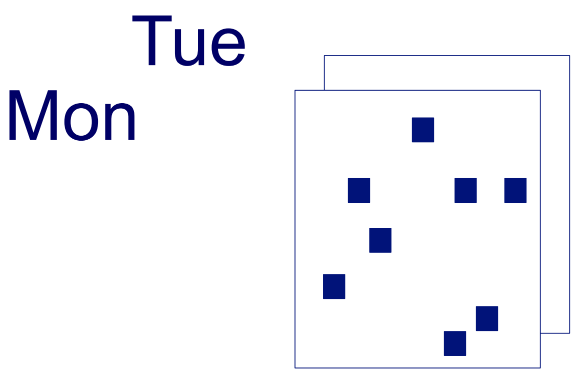

Graphs over time -> tensors!

- Problem #2.1:
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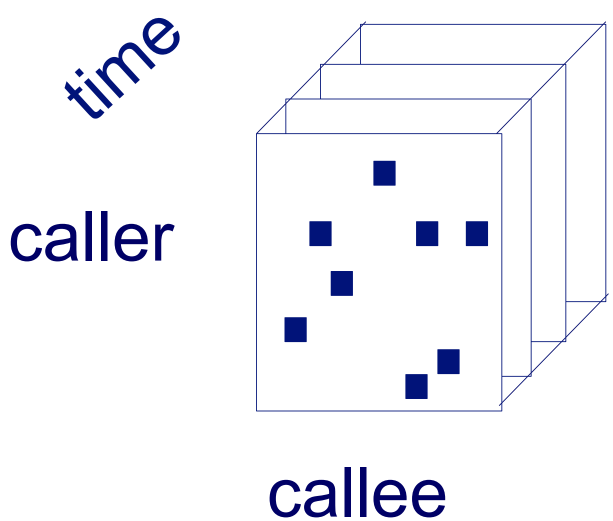

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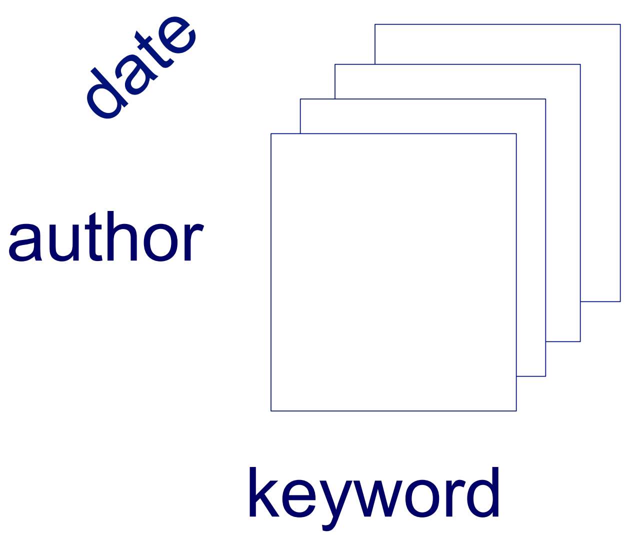
Graphs over time -> tensors!

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



MANY more settings, with >2 'modes'

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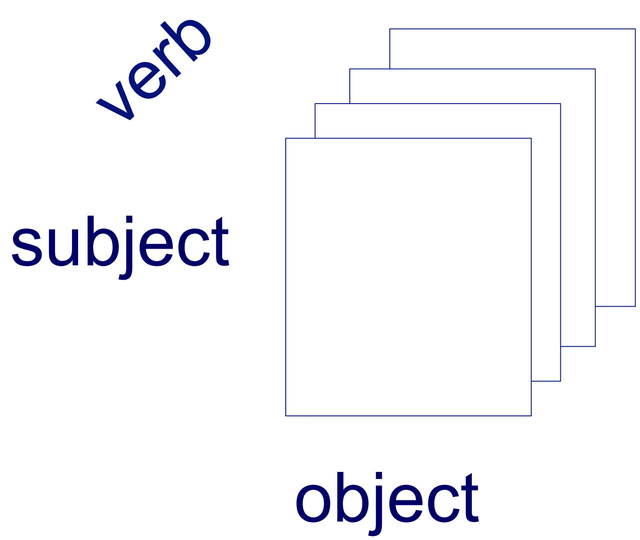
Graphs over time -> tensors!

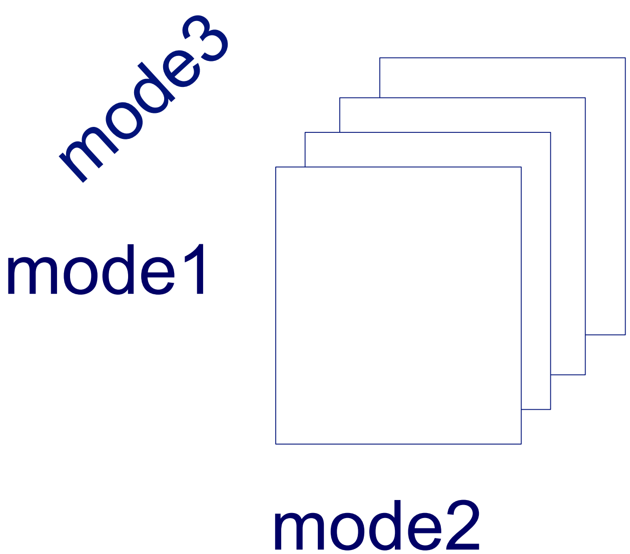
- Problem #2.1'':
  - Given subject – verb – object facts
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

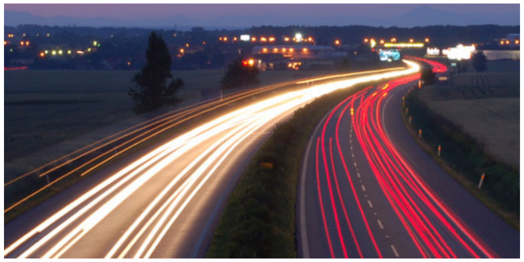
Graphs over time -> tensors!

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



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

Roadmap



- Introduction – Motivation
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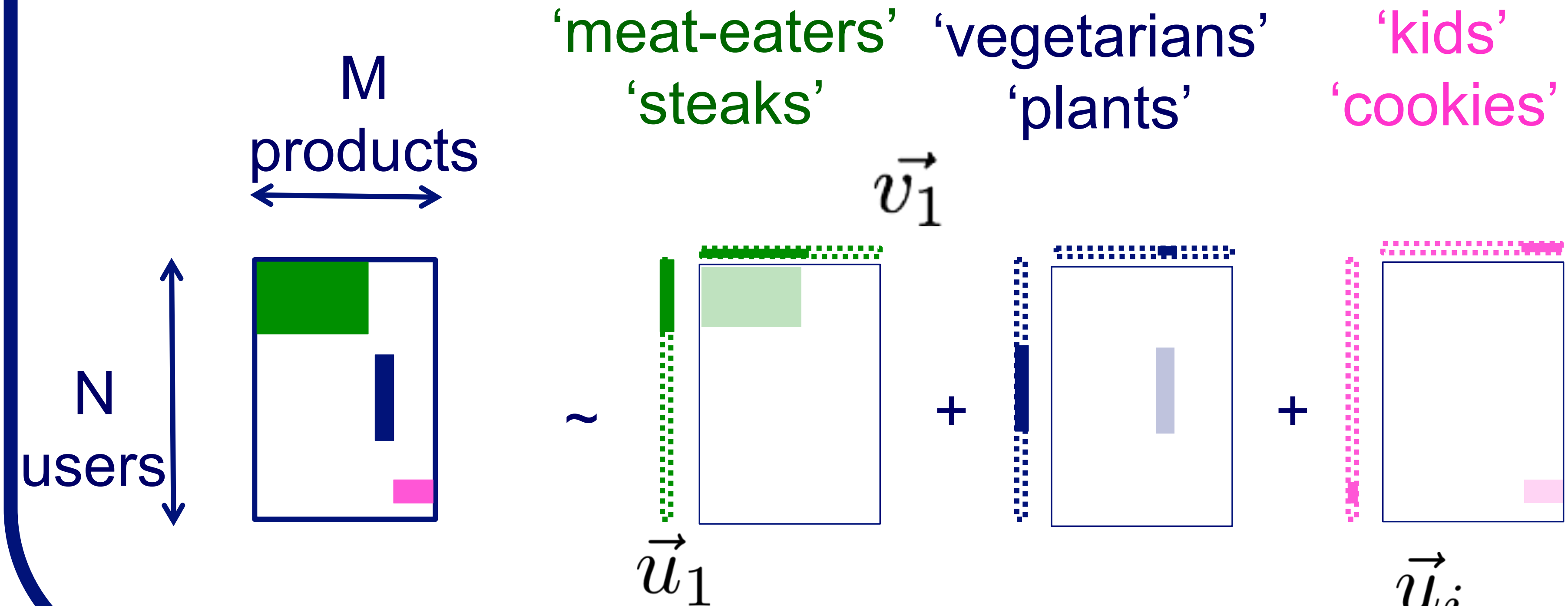
  - Speed]
- Conclusions

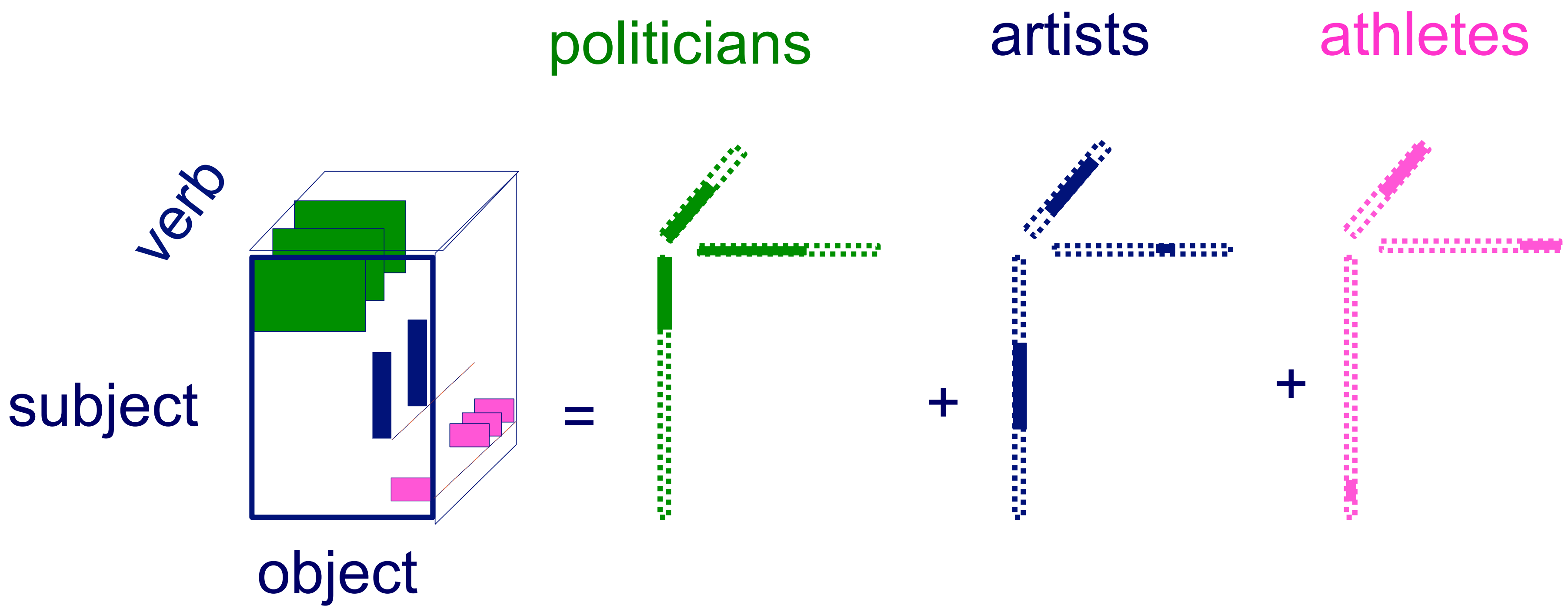
Answer to both: tensor factorization

- Recall: (SVD) matrix factorization: finds blocks



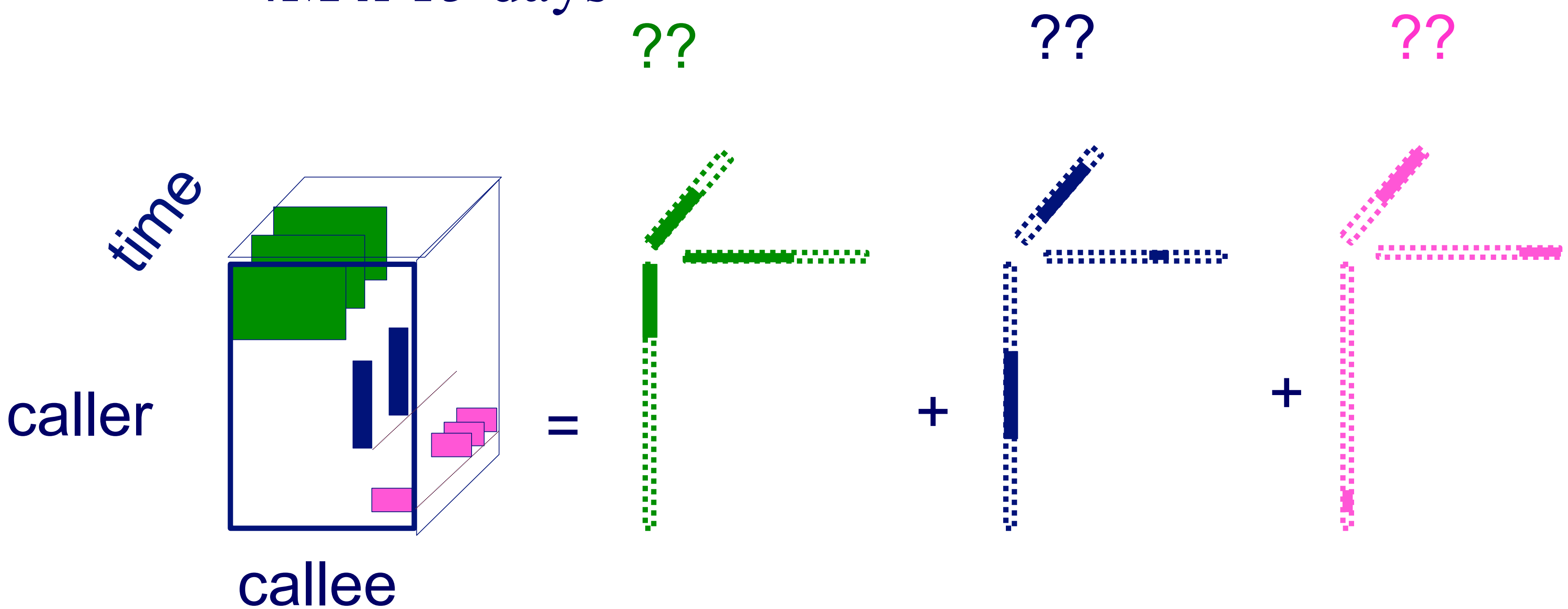
Answer to both: tensor factorization

- PARAFAC decomposition

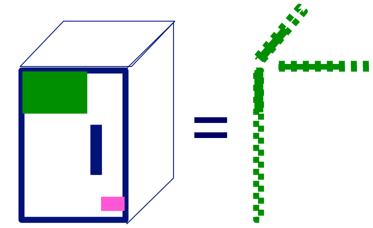


Answer: tensor factorization

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

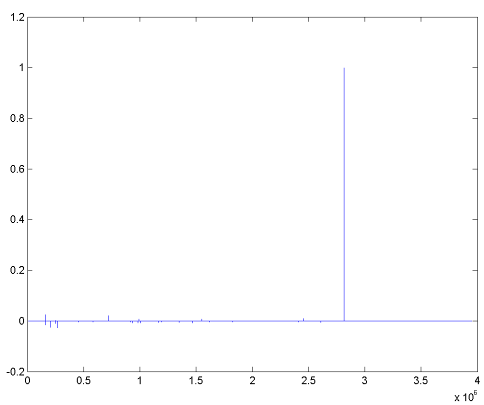


Anomaly detection in time-evolving graphs

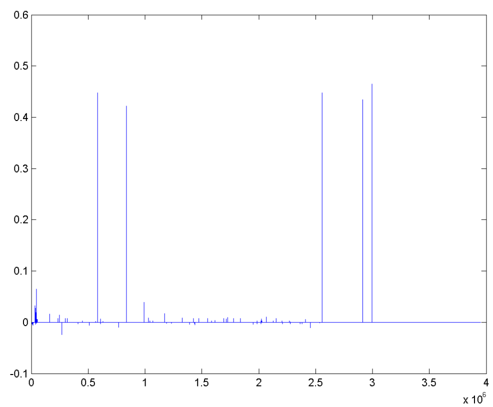


- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks

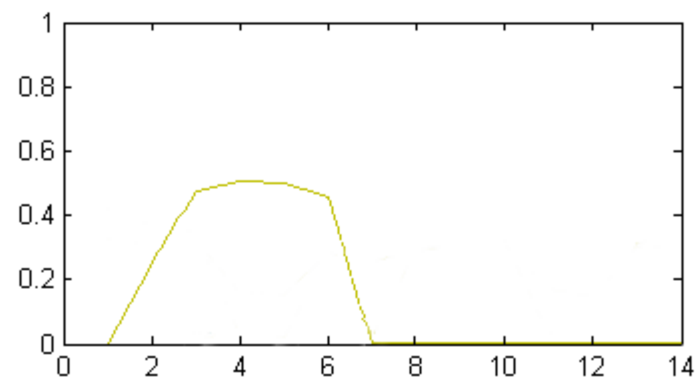
1 caller



5 receivers



4 days of activity



~200 calls to EACH receiver on EACH day!

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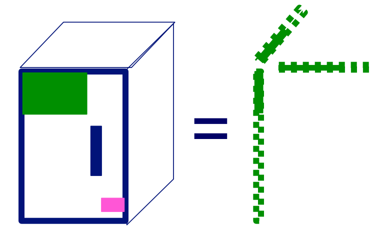
Anomaly detection in time-evolving graphs



- Anomalous communities in phone call data:
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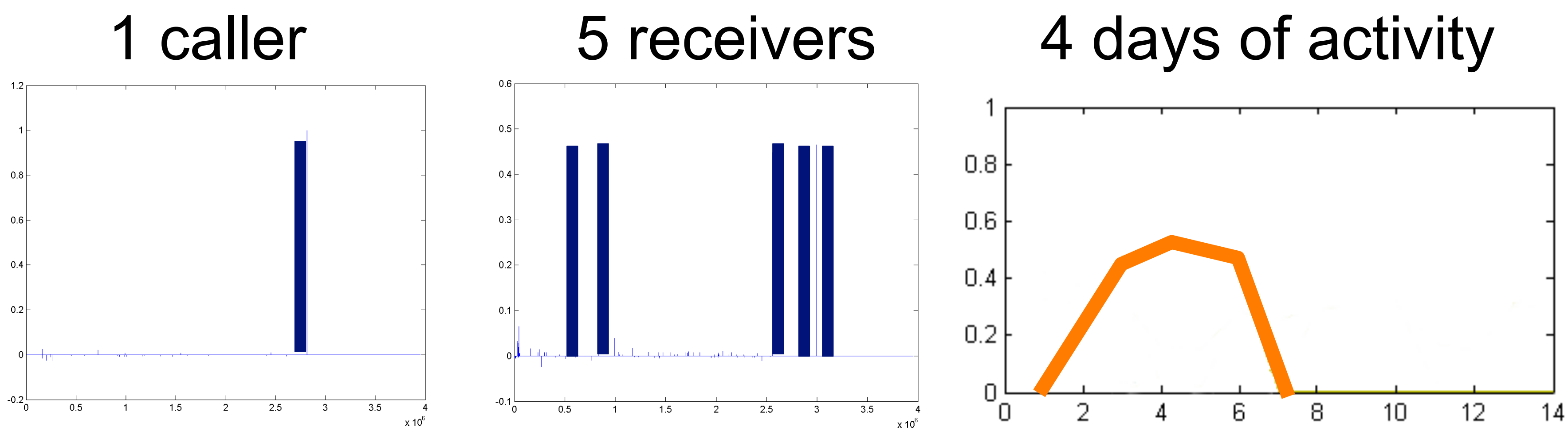

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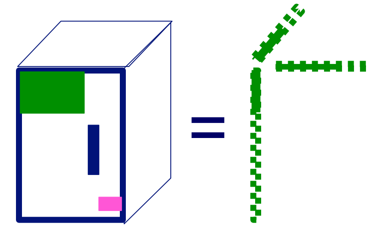
Anomaly detection in time-evolving graphs

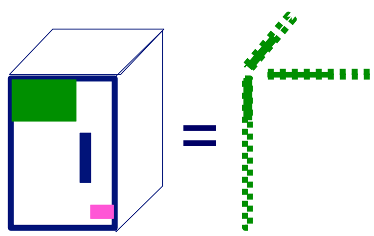


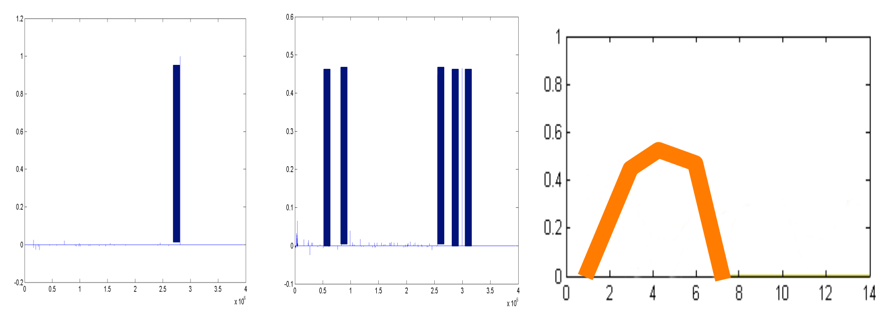
- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks

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.

Part 2: Conclusions

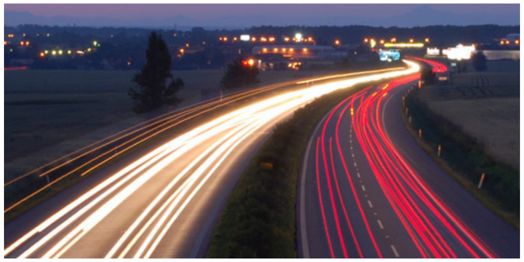
- Time-evolving / heterogeneous graphs -> tensors
- PARAFAC finds patterns
- (GigaTensor/HaTen2 -> fast & scalable)





Part 3:
Time sequences

Roadmap



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- Part#3: time sequences
- Acknowledgements and Conclusions

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

Carnegie Mellon

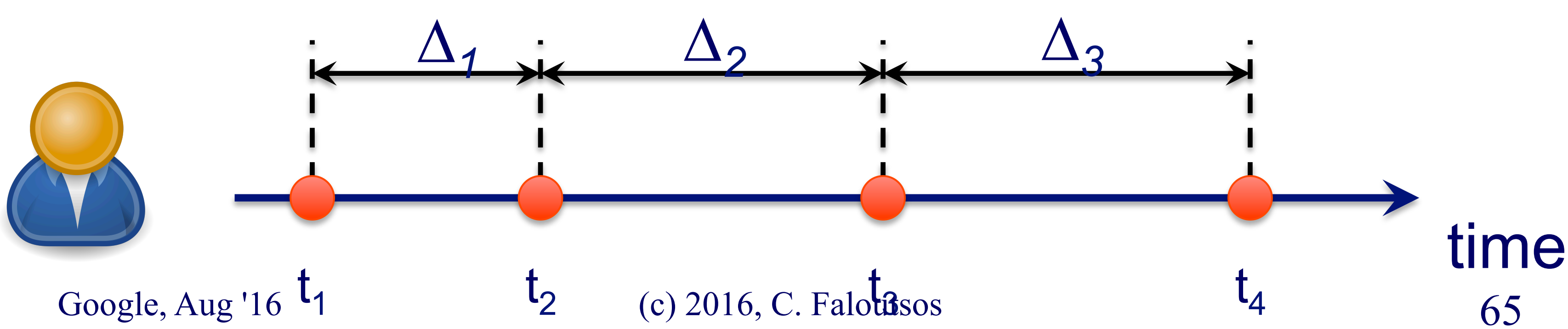
Pattern Mining: Datasets

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

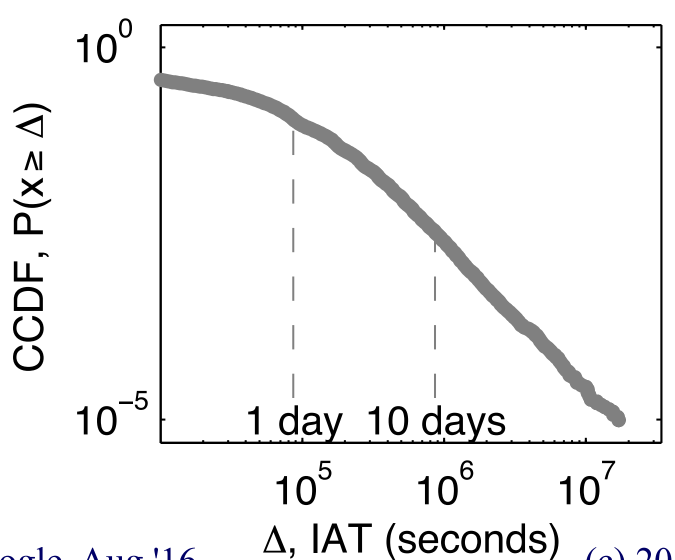


Pattern Mining

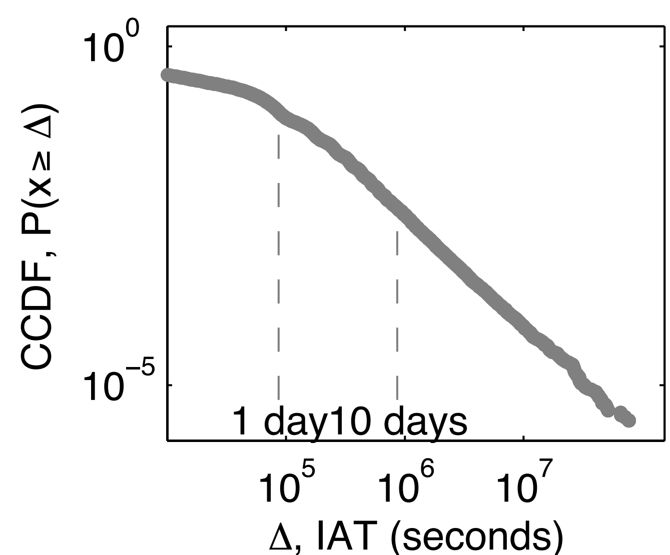
Pattern 1: Distribution of IAT is heavy-tailed

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

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



Reddit Users



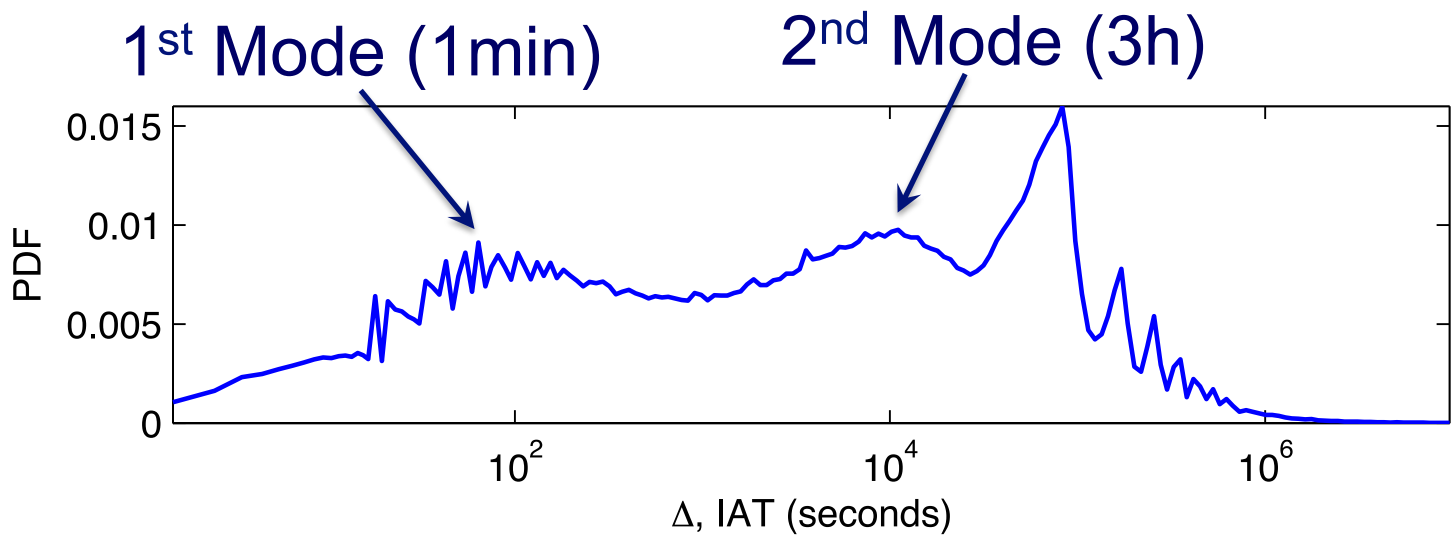
Twitter Users

Pattern Mining

Pattern 2: Bimodal IAT distribution

'Active'/ 'resting' periods

Log-binned histogram of postings IAT



Twitter Users

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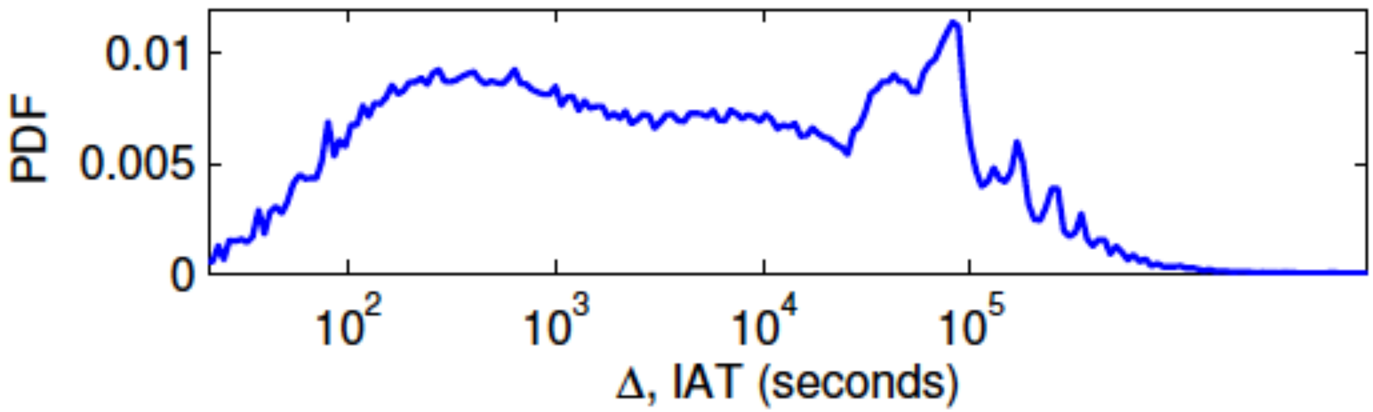
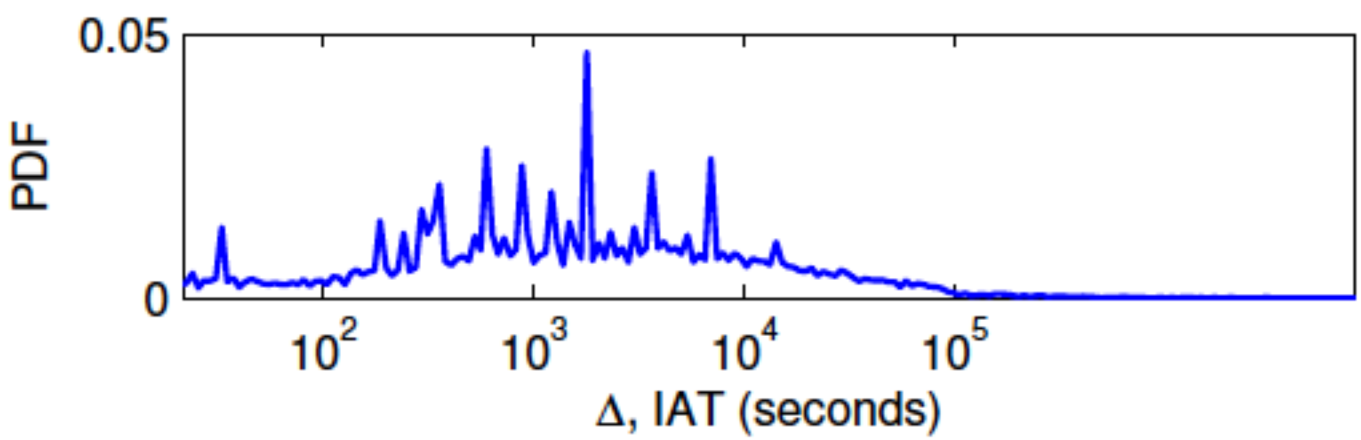
Human? Robots?

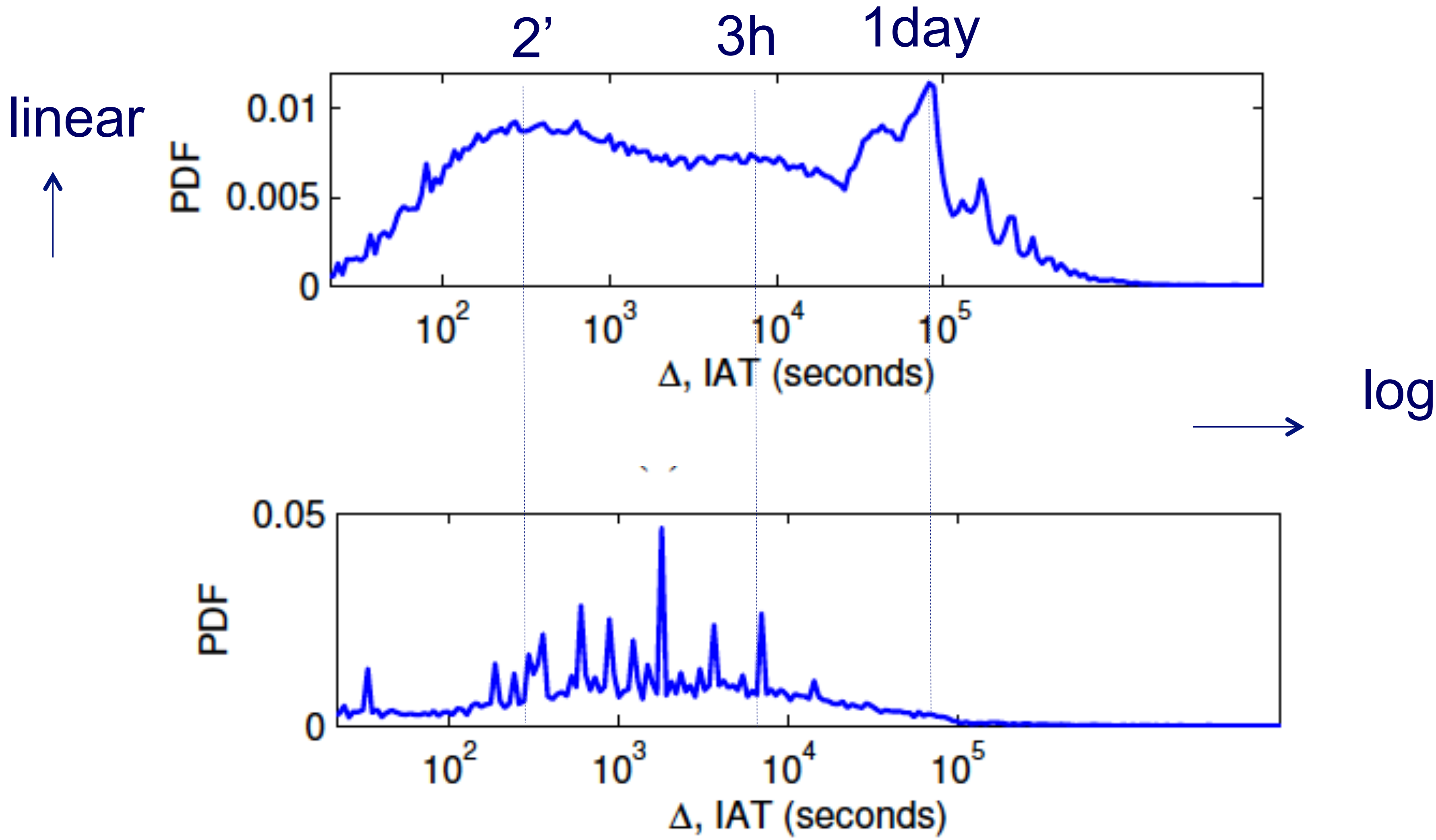
linear ↑



log →



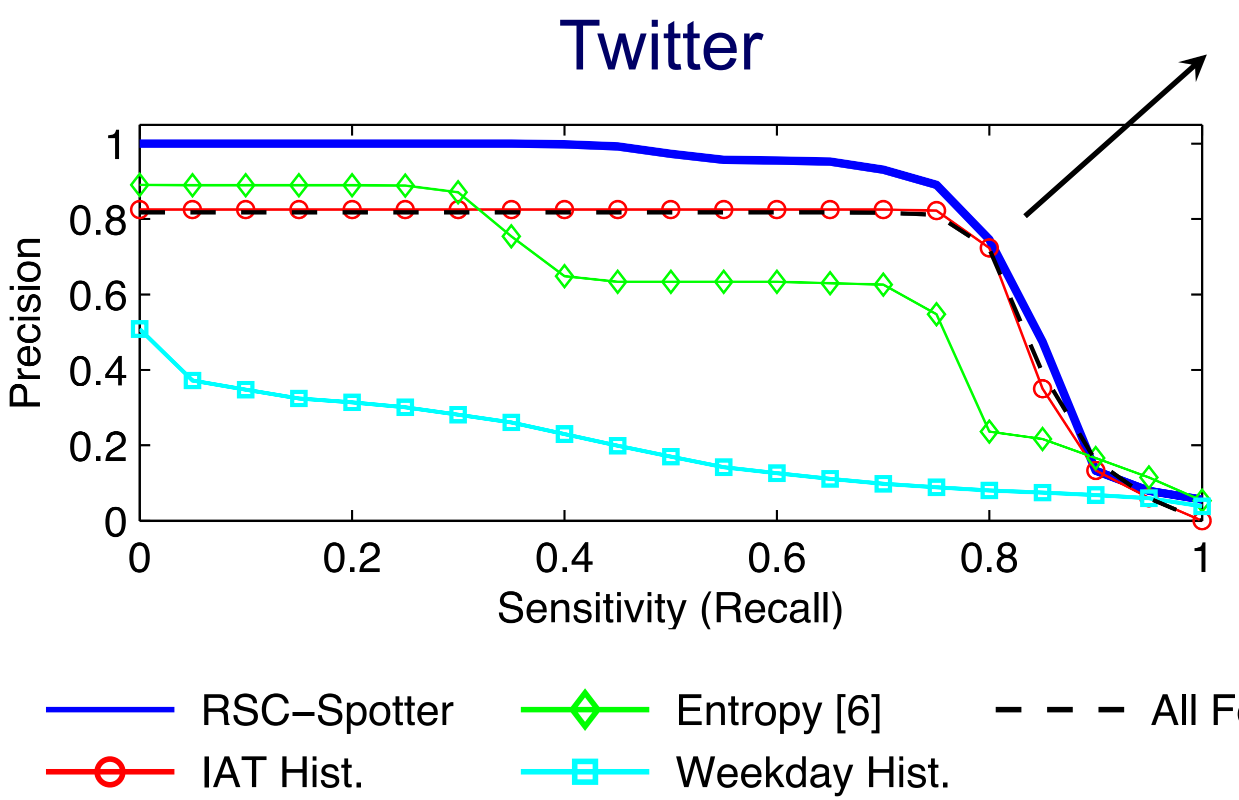
Human? Robots?



Experiments: Can RSC-Spotter Detect Bots?

Precision vs. Sensitivity Curves

Good performance: curve close to the top



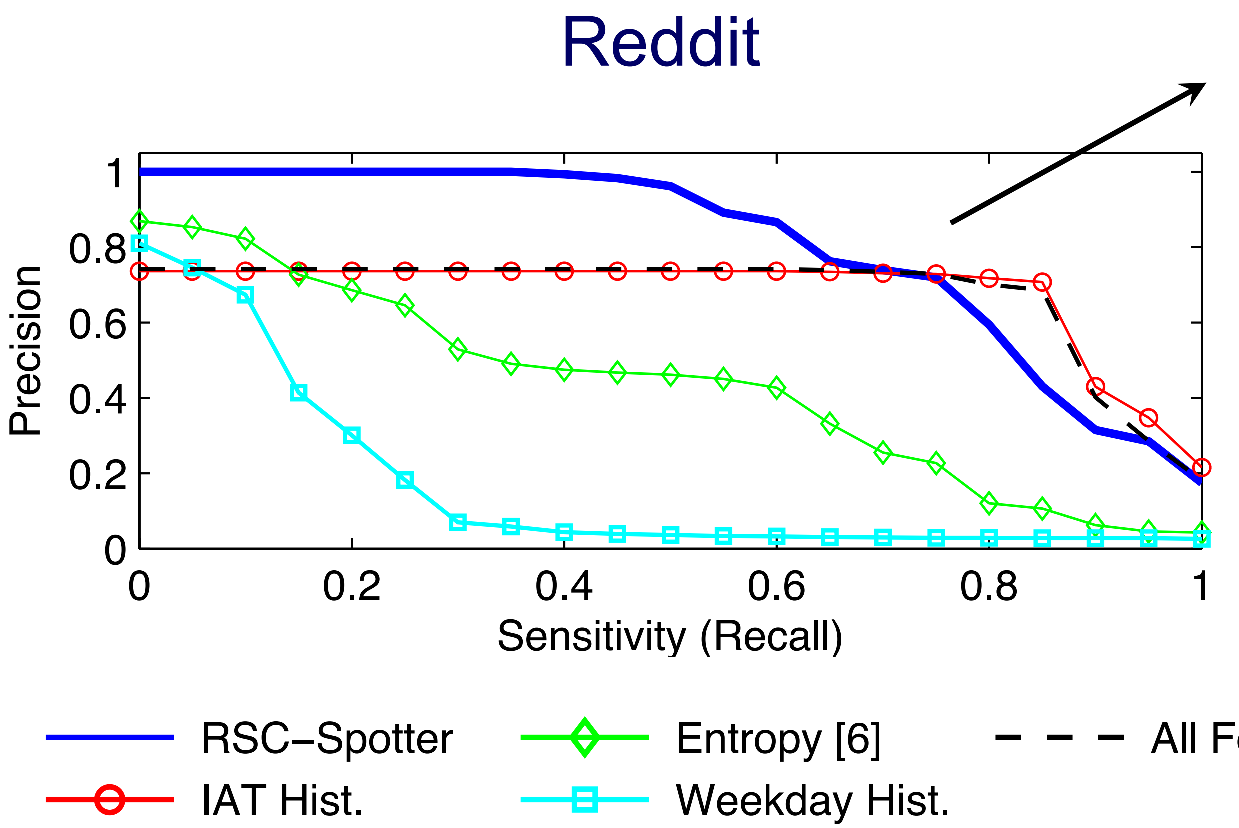
Precision > 94%
Sensitivity > 70%

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

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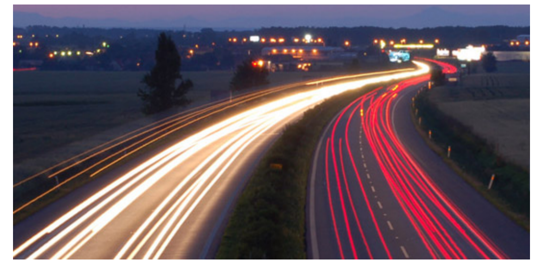
Roadmap



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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

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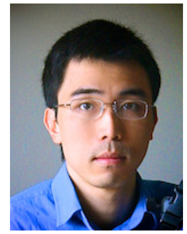
Cast

Akoglu, Leman

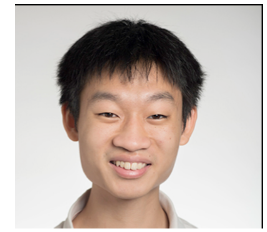
Araujo, Miguel

Beutel, Alex



Chau, Polo

Eswaran, Dhivya

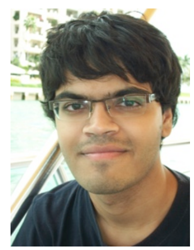


Hooi, Bryan

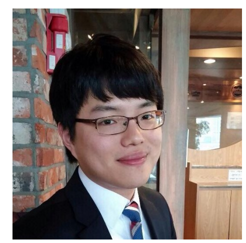
Kang, U

Koutra, Danai

Papalexakis, Vagelis



Shah, Neil

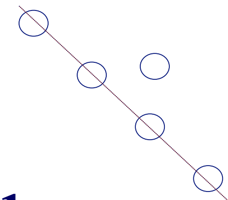


Shin, Kijung

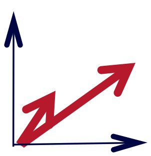
Song, Hyun Ah

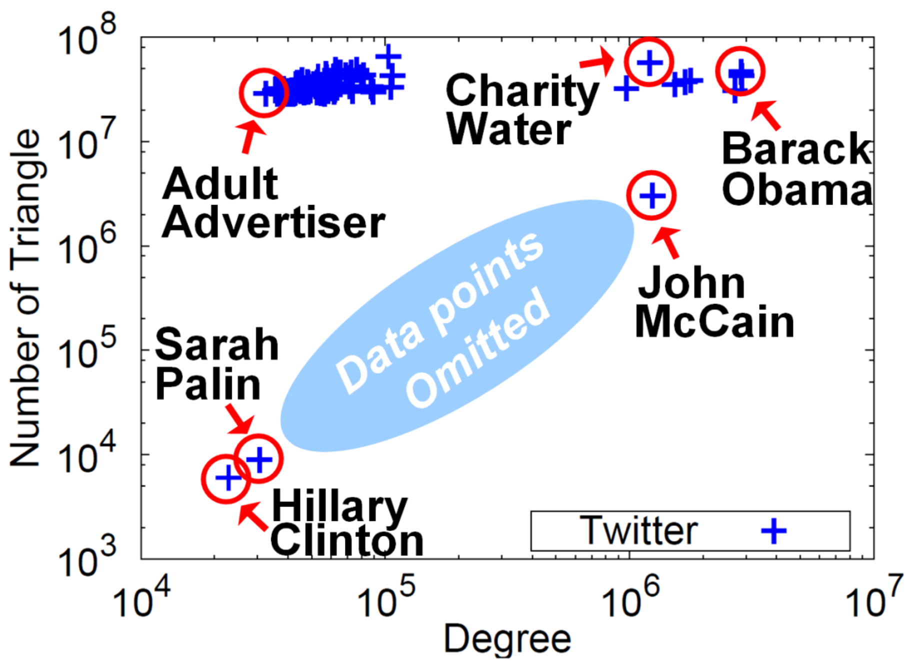
CONCLUSION#1 – Big data

- **Patterns**  **Anomalies**



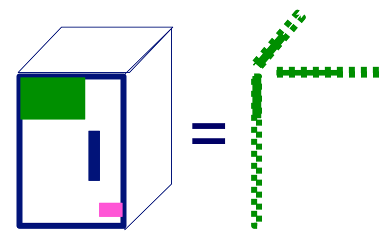
- **Large** datasets reveal patterns/outliers that are invisible otherwise

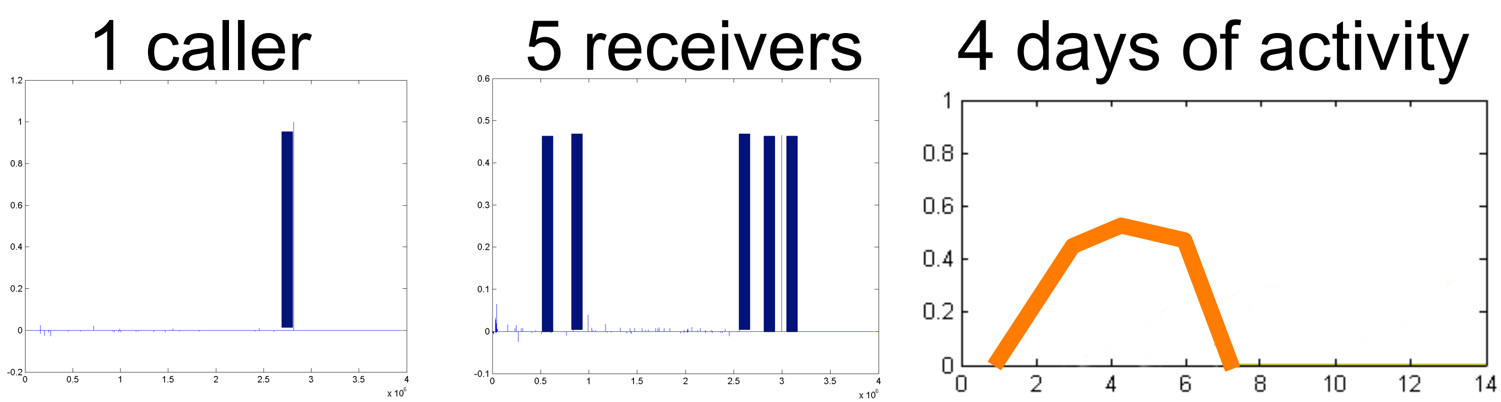




CONCLUSION#2 – tensors

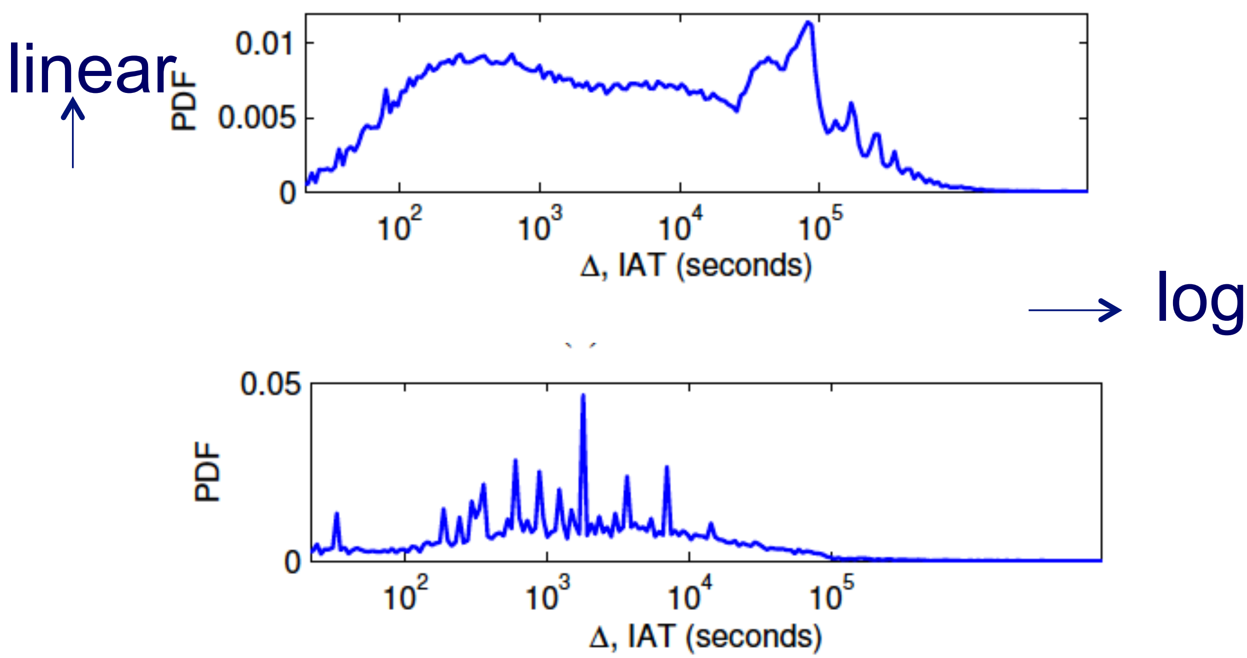
- powerful tool



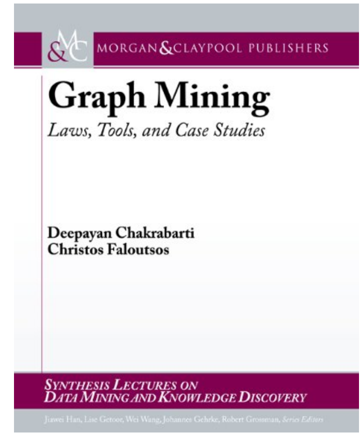


Conclusion#3

- Different footprints of real vs ‘robot’ users



References



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

- *Graph-based Anomaly Detection and Description: A Survey*, Leman Akoglu, Hanghang Tong, Danai Koutra
- http://arxiv.org/abs/1404.4679

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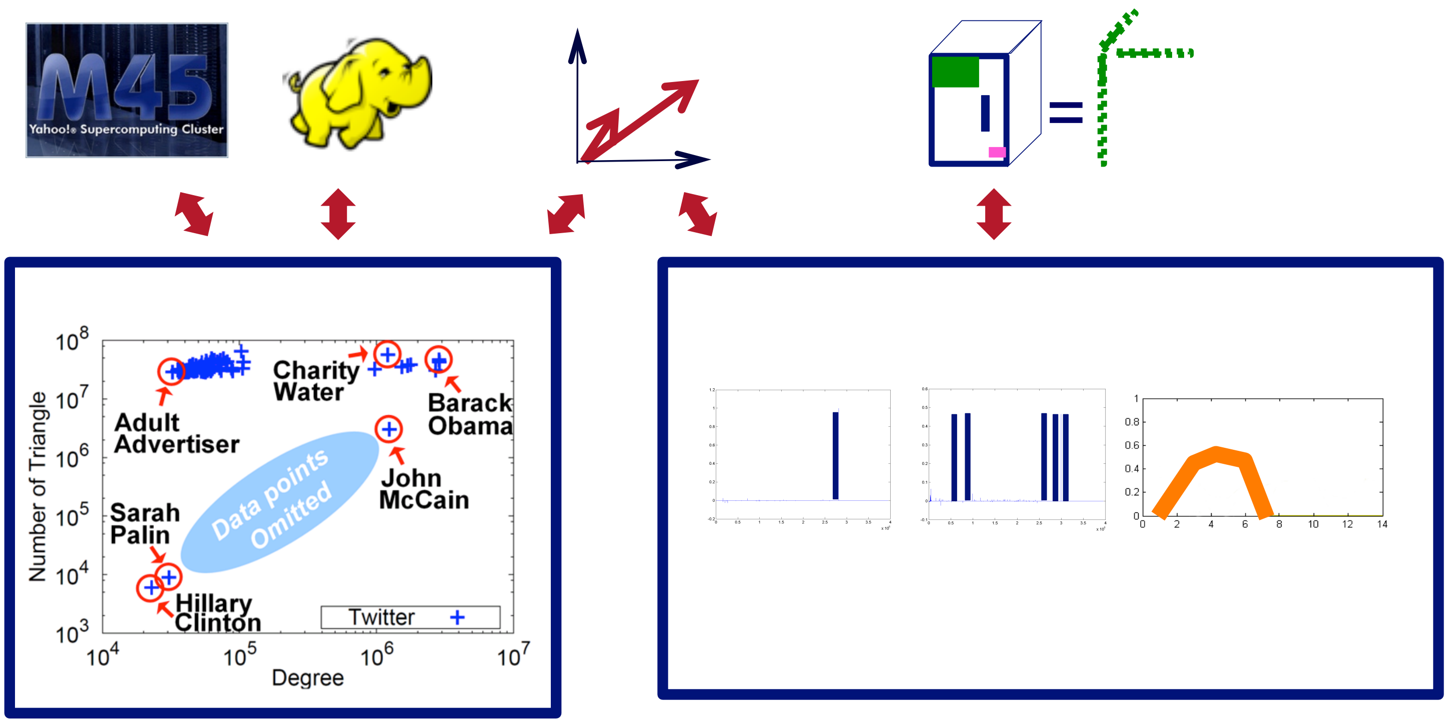
TAKE HOME MESSAGE:

Cross-disciplinarity



Thank you!

Cross-disciplinarity