Carnegie Mellon

Mining Large Graphs and Fraud Detection

Christos Faloutsos

CMU

Thank you!

Dr. Dragos Margineantu

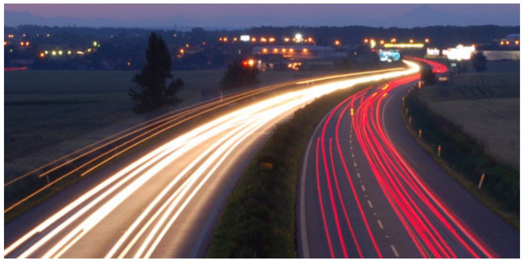
Dr. Mohammed Zaki

Kimberly Mathern

Lawrence Tingson

Carnegie Mellon

Roadmap

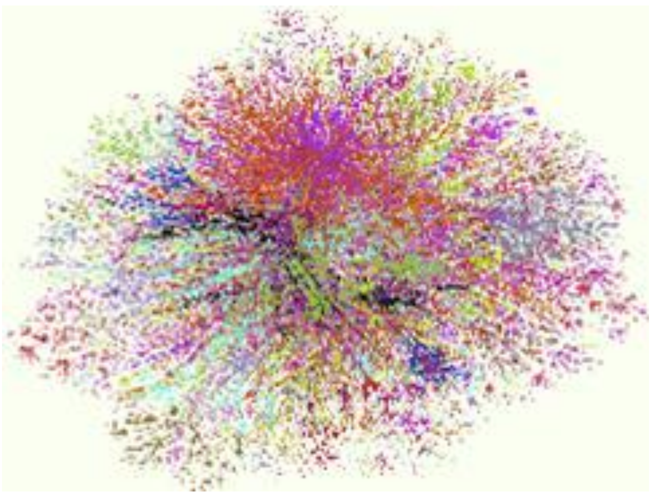


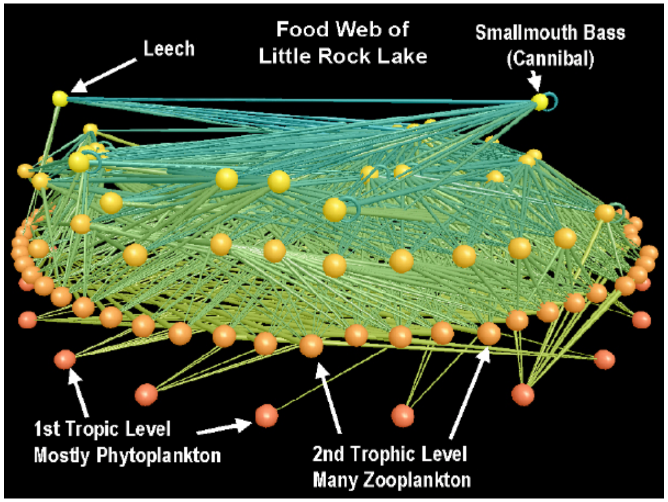
- Introduction – Motivation
  - Why study (big) graphs?
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
- Conclusions

Graphs - why should we care?

>$10B; ~1B users

Graphs - why should we care?





Internet Map
[lumeta.com]

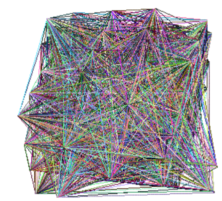
Food Web
[Martinez '91]

Graphs - why should we care?

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

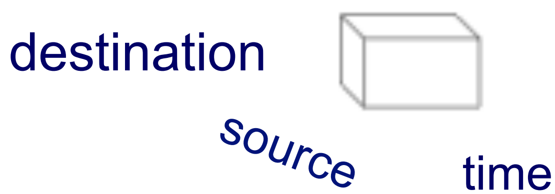
- Many-to-many db relationship -> graph

Motivating problems

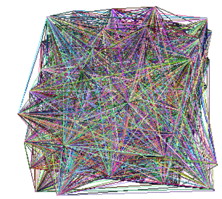


- P1: patterns? Fraud detection?

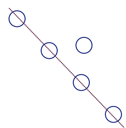
- P2: patterns in time-evolving graphs / tensors



Motivating problems



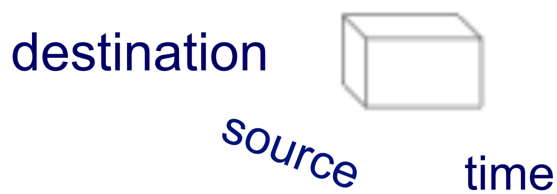
- P1: patterns? Fraud detection?



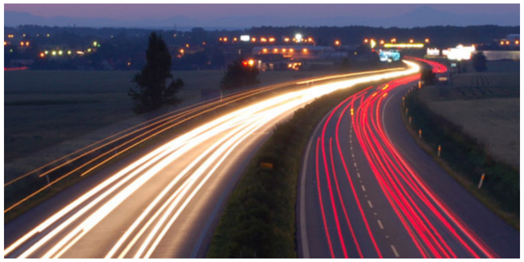
Patterns

anomalies

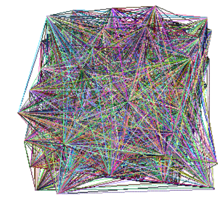
- P2: patterns in time-evolving graphs / tensors



Roadmap

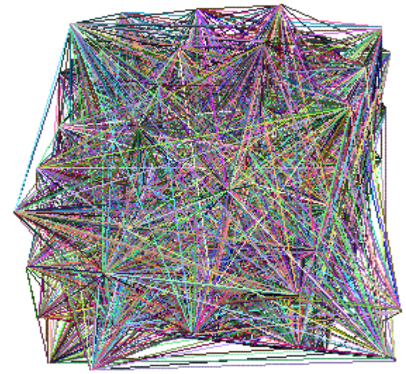


- Introduction – Motivation
  - Why study (big) graphs?
- Part#1: Patterns & fraud detection
- Part#2: time-evolving graphs; tensors
- Conclusions



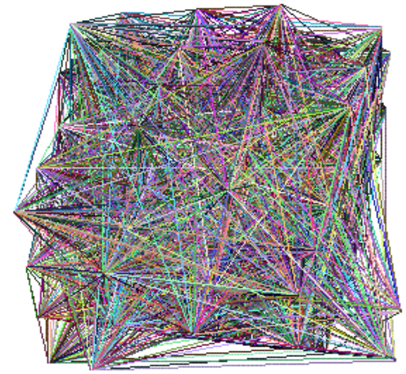
Part 1: Patterns, & fraud detection

Laws and patterns

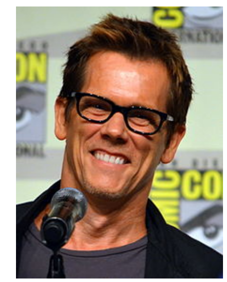


- Q1: Are real graphs random?

Laws and patterns



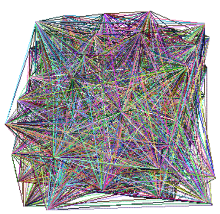
- Q1: Are real graphs random?
- A1: NO!!
  - Diameter ('6 degrees'; 'Kevin Bacon')
  - in- and out- degree distributions
  - other (surprising) patterns
- So, let's look at the data

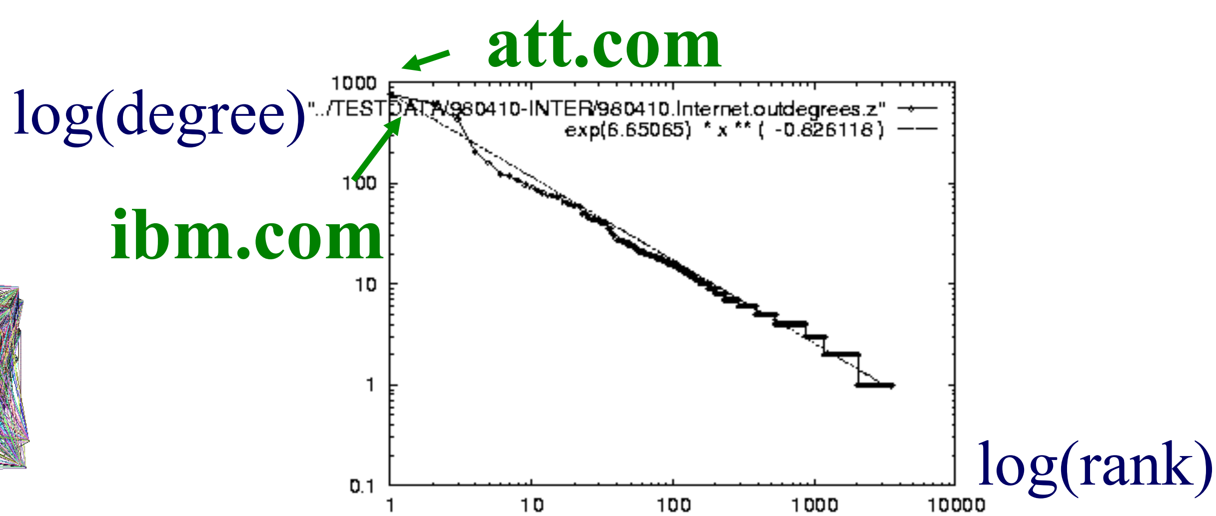


Solution# S.1

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

internet domains

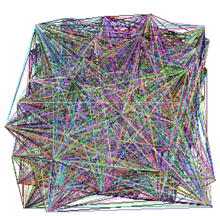


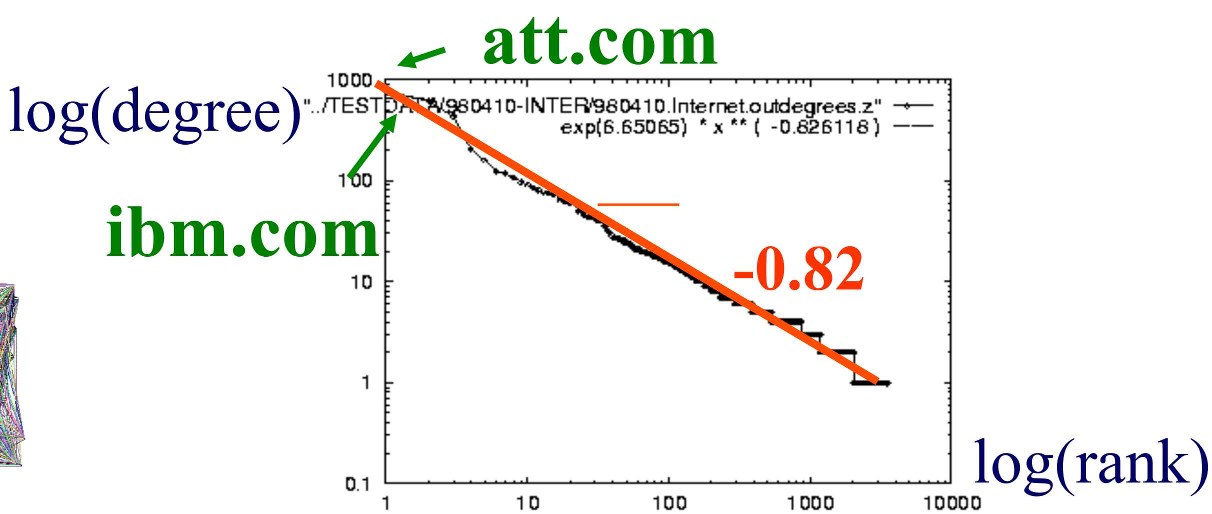


Solution# S.1

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

internet domains



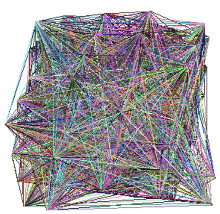


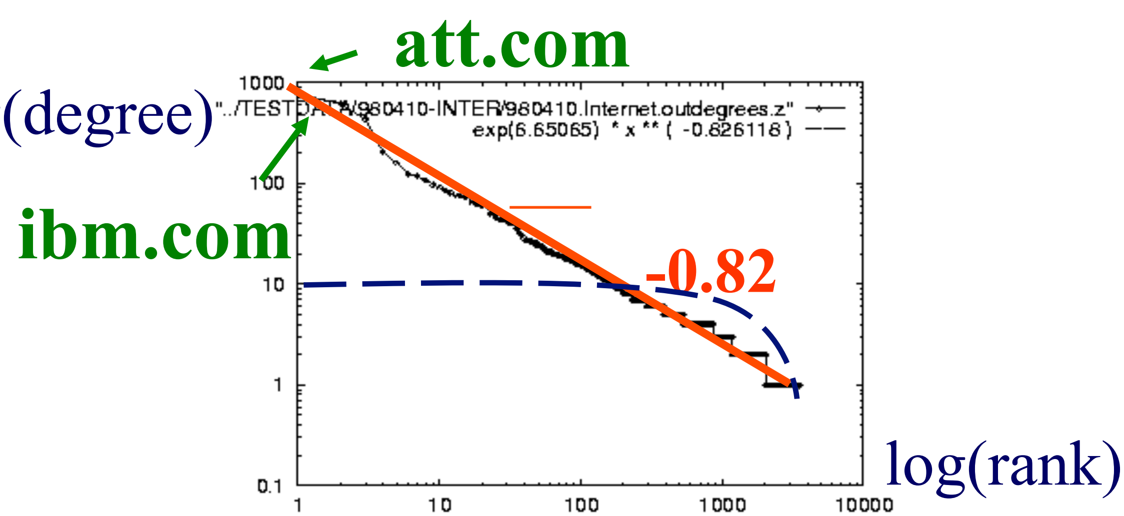
Carnegie Mellon

Solution# S.1

- Q: So what?

internet domains





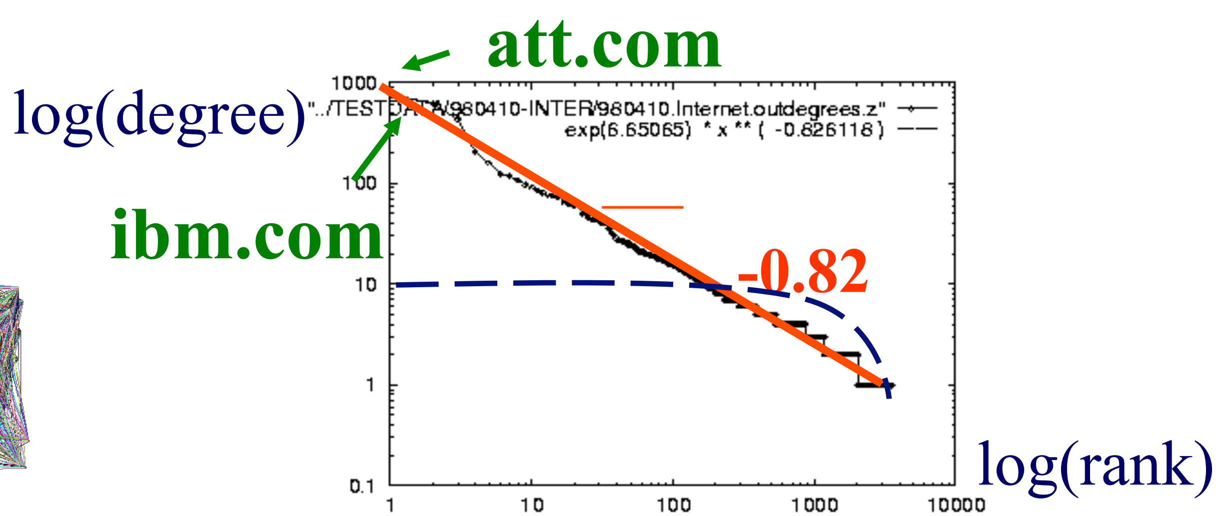
Carnegie Mellon

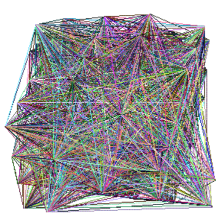
Solution# S.1

- Q: So what?
- A1: # of two-step-away pairs:

= friends of friends (F.O.F.)

internet domains



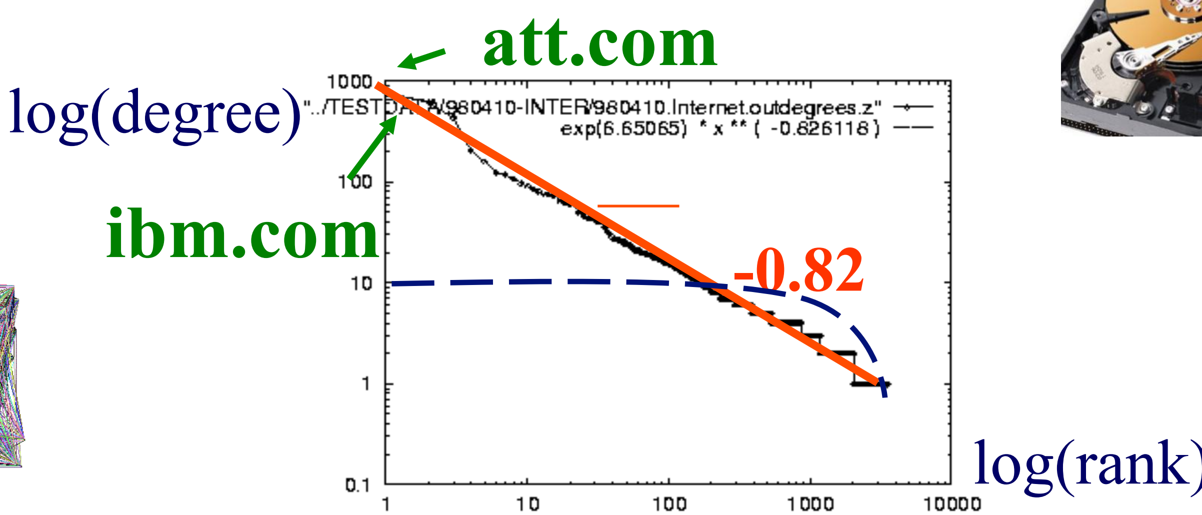


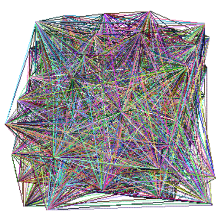
Solution# S.1

- Q: So what?
- A1: # of two-step-away pairs: 100^2 * N= 10 Trillion

= friends of friends (F.O.F.)

internet domains



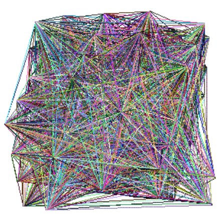


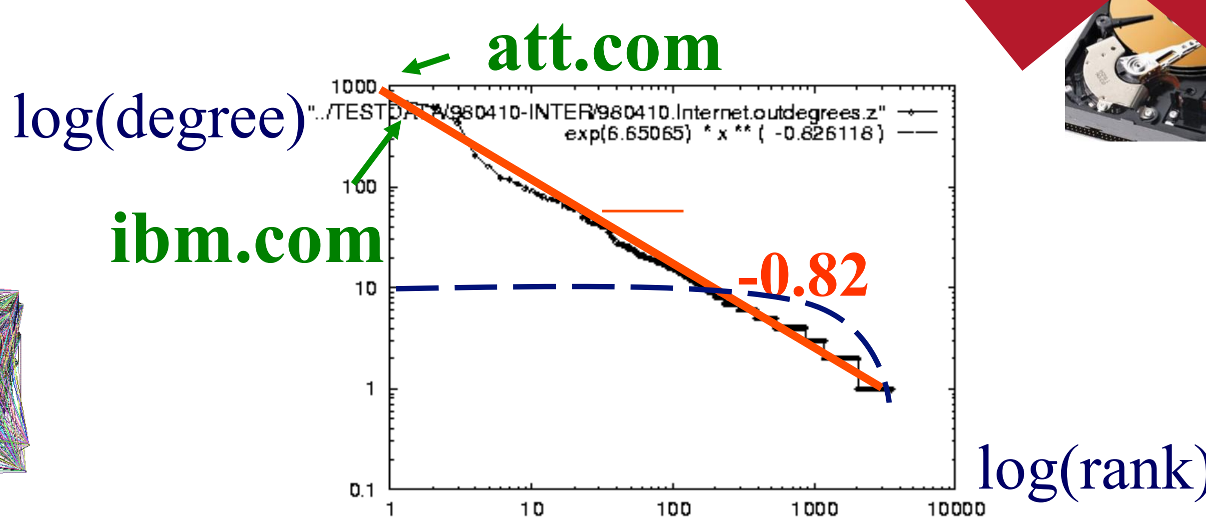
Solution# S.1

- Q: So what?
- A1: # of two-step-away pairs: 100^2 [illegible] Trillion

= friends of friends (F.O.F.)

internet domains





Gaussian trap

Solution# S.1

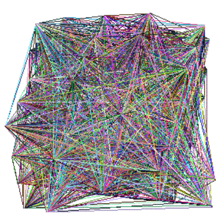
= friends of friends (F.O.F.)

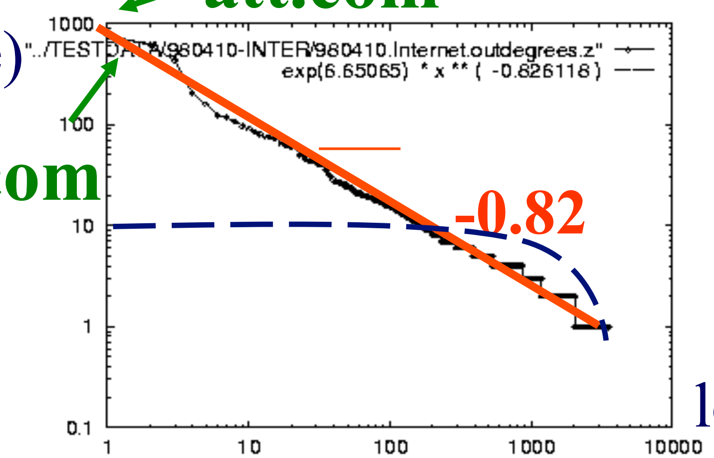
- Q: So what?
- A1: # of two-step-away pairs: O(d_max ^2) ~ 10M^2

⇩

~0.8PB ->
a data center(!)

internet domains





DCO @ CMU

Carnegie Mellon

Gaussian trap

Solution# S.1

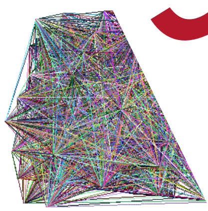
- Q: So what?
- A1: # of two-step-aw... ?) ~ 10M^2

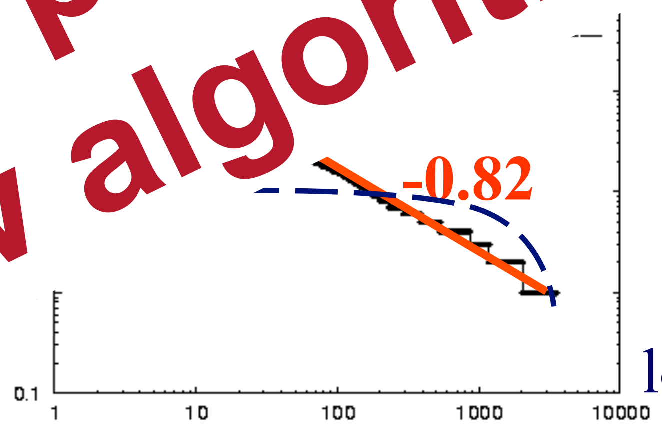
inte...

⇩

~0.8PB ->
a data center(!)

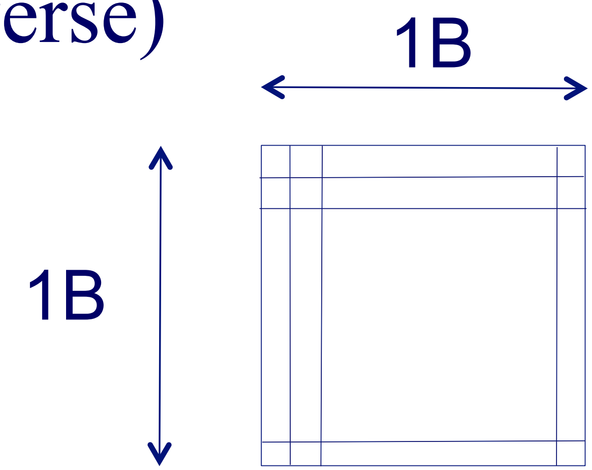
Such patterns ->
New algorithms





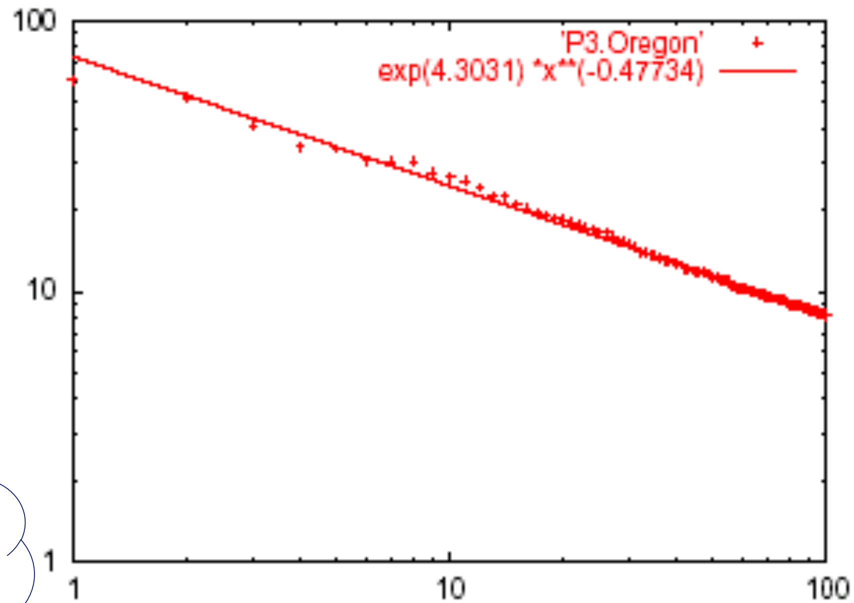
Observation – big-data:

- O(N^2) algorithms are ~intractable - N=1B
- N^2 seconds = 31B years (>2x age of universe)



Solution# S.2: Eigen Exponent *E*

Eigenvalue



Rank of decreasing eigenvalue

$A\,x = \lambda\,x$

Exponent = slope

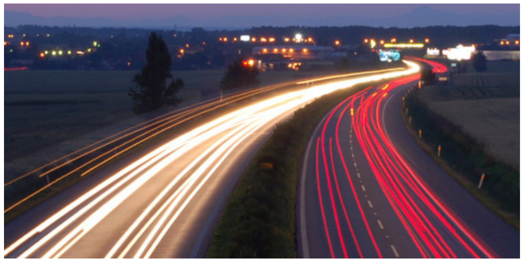
E = -0.48

May 2001

- A2: power law in the eigenvalues of the adjacency matrix ('eig()')

Carnegie Mellon

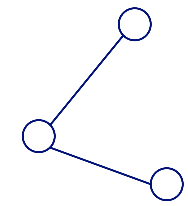
Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns: Degree; Triangles
  - Anomaly/fraud detection
  - Graph understanding
- Part#2: time-evolving graphs; tensors
- Conclusions

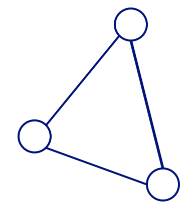
Carnegie Mellon

Solution# S.3: Triangle 'Laws'

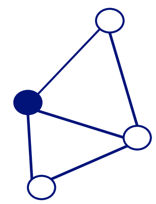


- Real social networks have a lot of triangles

Solution# S.3: Triangle 'Laws'

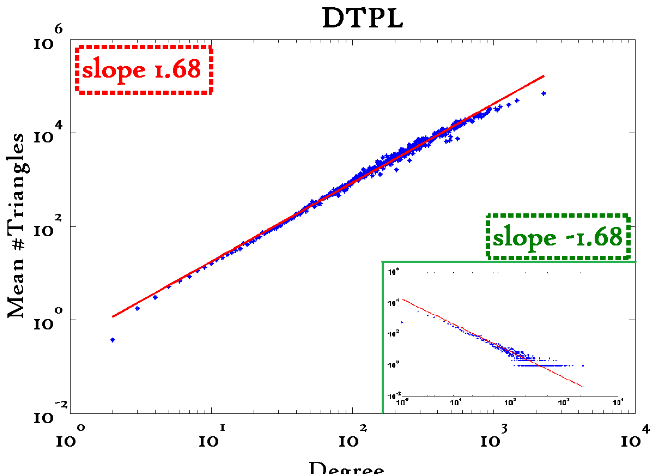


- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?
  - 2x the friends, 2x the triangles ?

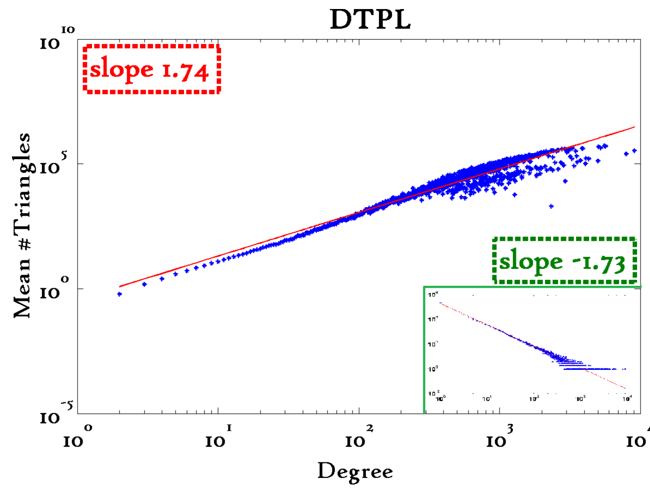


Triangle Law: #S.3
[Tsourakakis ICDM 2008]

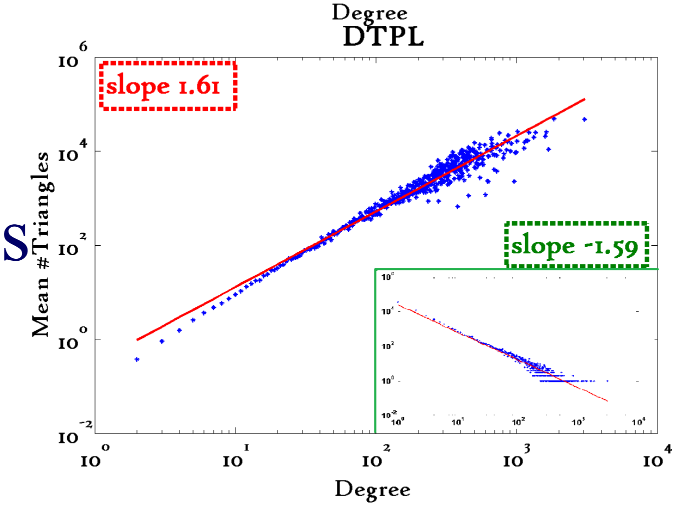
Reuters

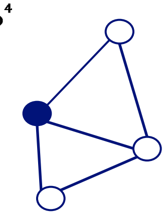


SN



Epinions





X-axis: degree

Y-axis: mean # triangles

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

Carnegie Mellon

details

Triangle Law: Computations
[Tsourakakis ICDM 2008]

But: triangles are expensive to compute

(3-way join; several approx. algos) – $O(d_{max}{}^2)$

Q: Can we do that quickly?

A:

details

Triangle Law: Computations
[Tsourakakis ICDM 2008]

But: triangles are expensive to compute

(3-way join; several approx. algos) – $O(d_{max}{}^2)$

Q: Can we do that quickly?

A: Yes!

$A x = \lambda x$

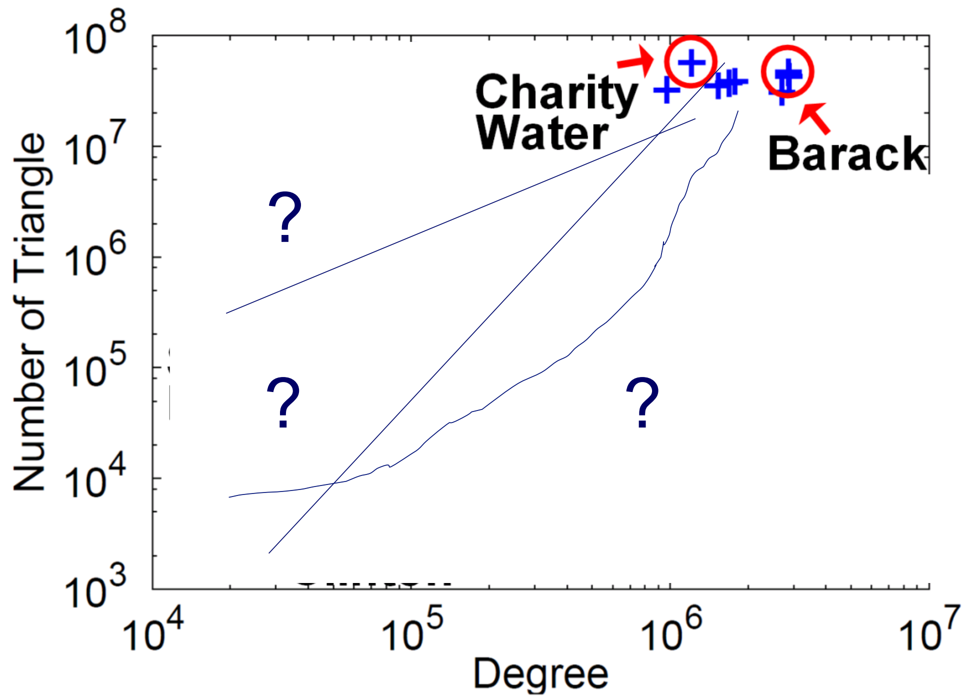
#triangles = 1/6 Sum ($\lambda_i{}^3$)

(and, because of skewness (S2) ,

we only need the top few eigenvalues! - O(E)

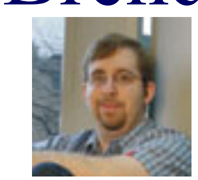
Carnegie Mellon

Triangle counting for large graphs?



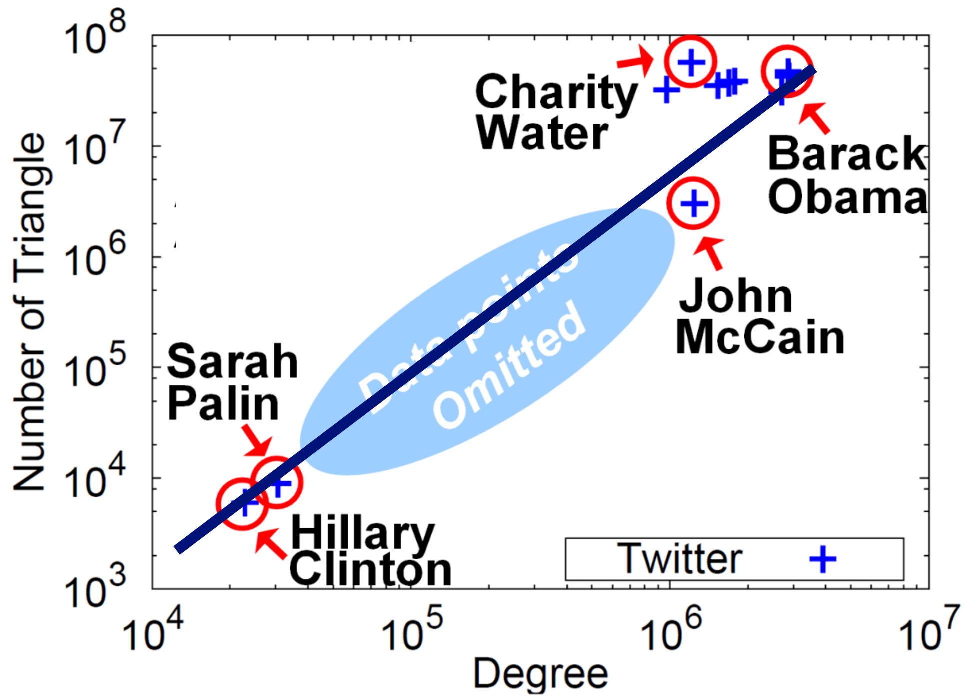
Anomalous nodes in Twitter(~ 3 billion edges)

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



Carnegie Mellon

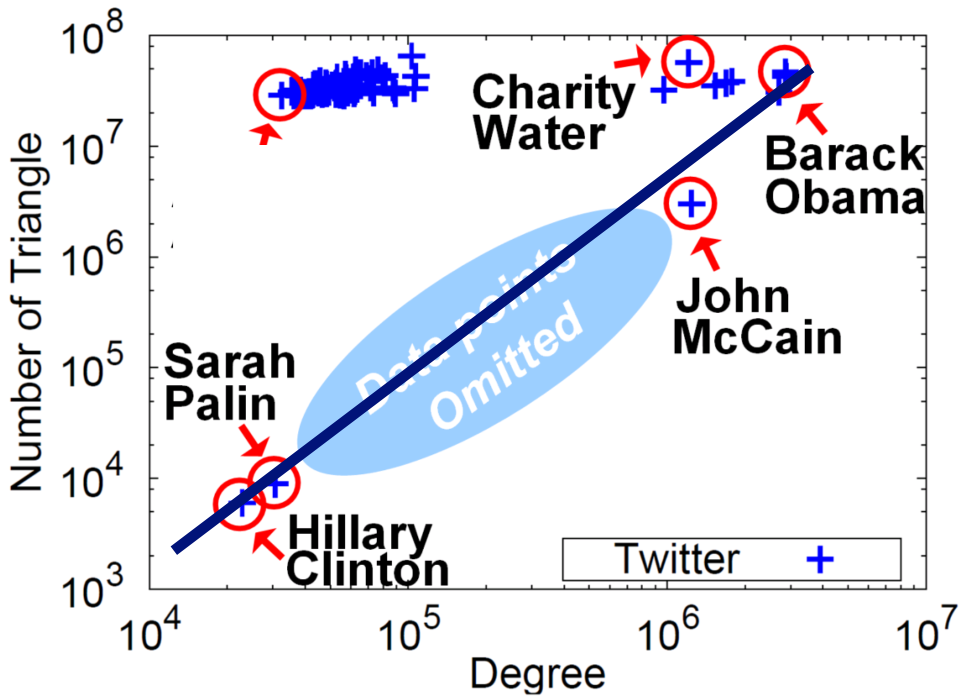
Triangle counting for large graphs?



Anomalous nodes in Twitter(~ 3 billion edges)

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

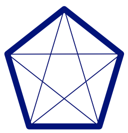
Triangle counting for large graphs?

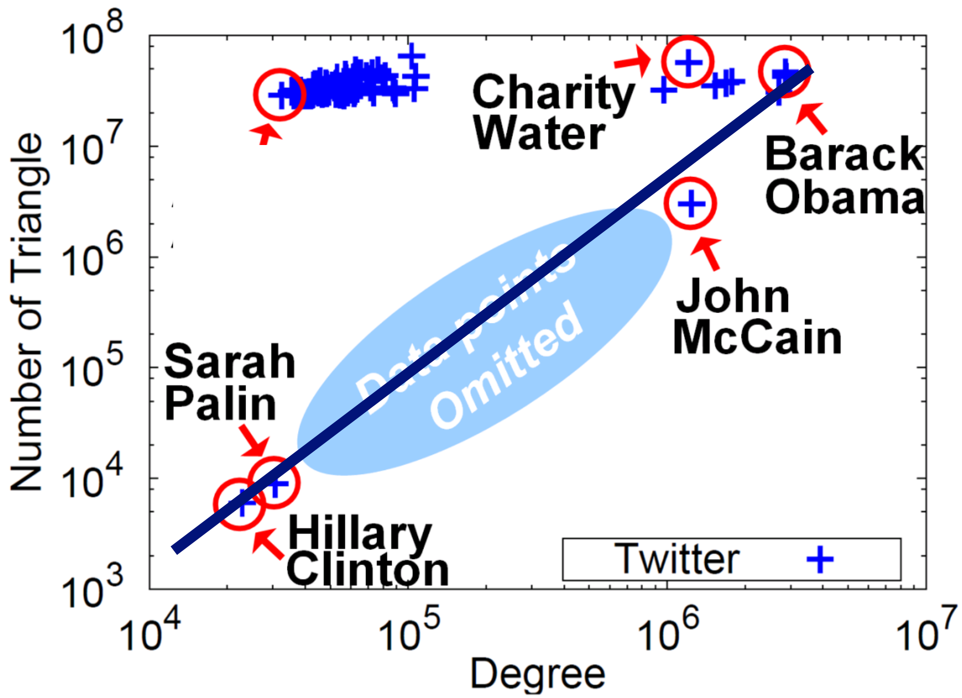


Anomalous nodes in Twitter(~ 3 billion edges)

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

Triangle counting for large graphs?

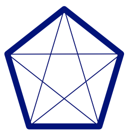


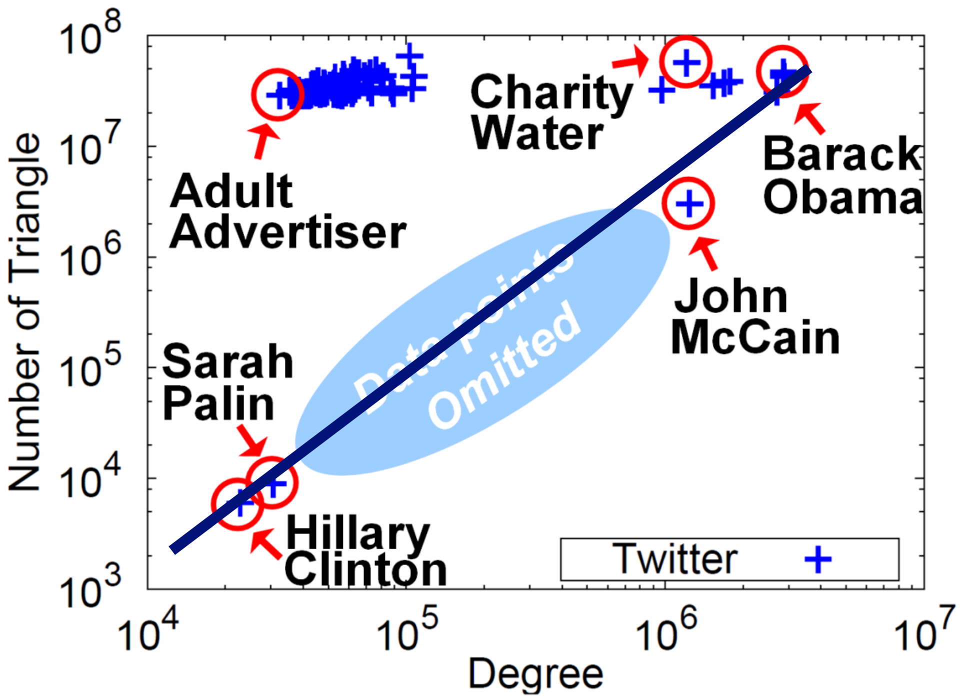


Anomalous nodes in Twitter(~ 3 billion edges)

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

Triangle counting for large graphs?





Anomalous nodes in Twitter(~ 3 billion edges)

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

MORE Graph Patterns

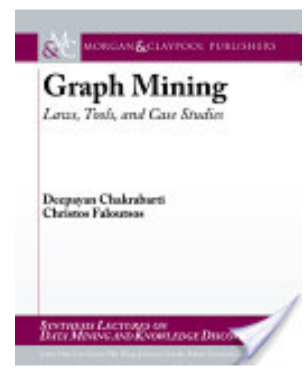
	Unweighted	Weighted
Static	**L01.** Power-law degree distribution [Faloutsos et al. `99, Kleinberg et al. `99, Chakrabarti et al. `04, Newman `04] **L02.** Triangle Power Law (TPL) [Tsourakakis `08] **L03.** Eigenvalue Power Law (EPL) [Siganos et al. `03] **L04.** Community structure [Flake et al. `02, 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 2$^{nd}$ and 3$^{rd}$ 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

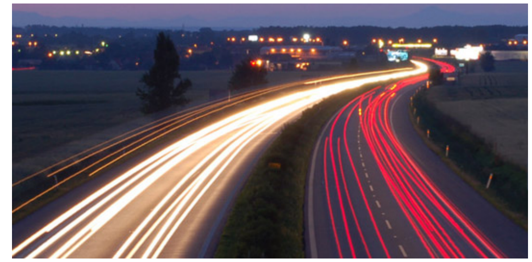
	Unweighted	Weighted
Static	L01. Power-law degree distribution [Faloutsos et al. `99, Kleinberg et al. `99, Chakrabarti et al. `04, Newman `04] L02. Triangle Power Law (TPL) [Tsourakakis `08] L03. Eigenvalue Power Law (EPL) [Siganos et al. `03] L04. Community structure [Flake et al. `02, Girvan and Newman `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 Bestavros `99, McGlohon et al. `08]	L11. Weight Power Law (WPL) [McGlohon et al. `08]

- 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



- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns
  - Anomaly / fraud detection
    - CopyCatch
    - Spectral methods ('fBox')
    - Belief Propagation

Patterns  anomalies

- Part#2: time-evolving graphs; tensors
- Conclusions

Carnegie Mellon

Fraud

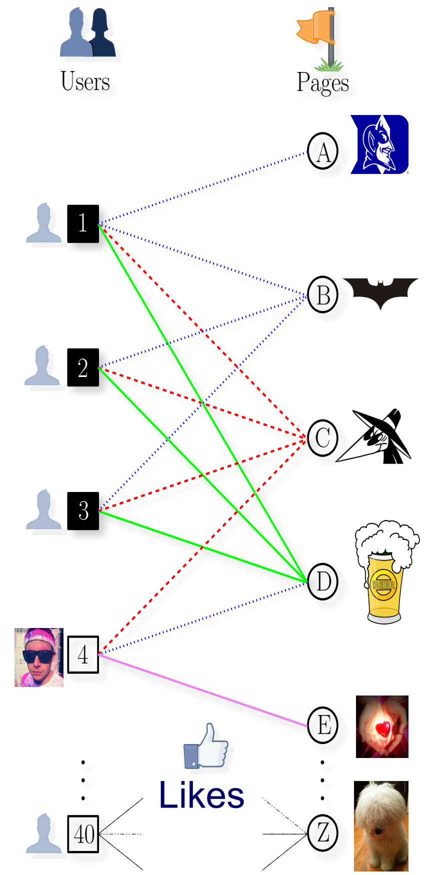
- Given
  - Who ‘likes’ what page, and when
- Find
  - Suspicious users and suspicious products

CopyCatch: Stopping Group Attacks by Spotting Lockstep Behavior in Social Networks, Alex Beutel, Wanhong Xu, Venkatesan Guruswami, Christopher Palow, Christos Faloutsos *WWW, 2013.*

Carnegie Mellon

Fraud

- Given
  - Who 'likes' what page, and when
- Find
  - Suspicious users and suspicious products

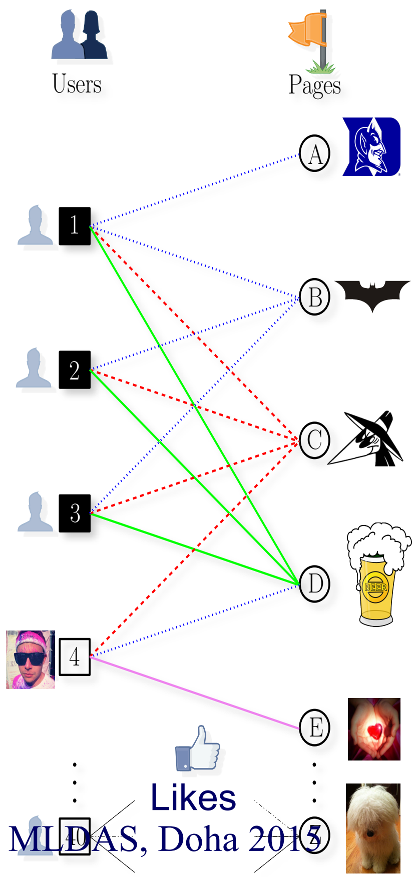


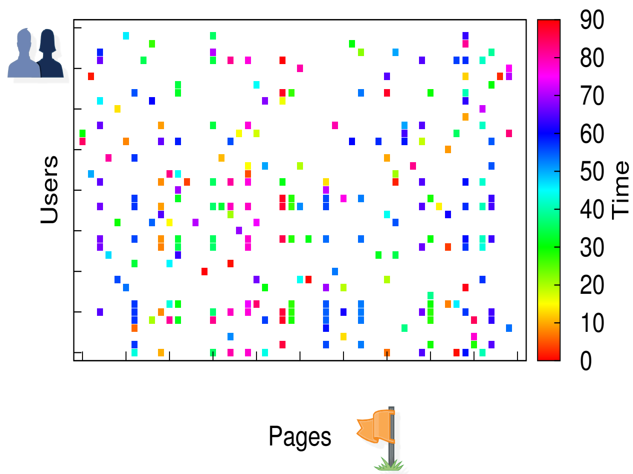
CopyCatch: Stopping Group Attacks by Spotting Lockstep Behavior in Social Networks, Alex Beutel, Wanhong Xu, Venkatesan Guruswami, Christopher Palow, Christos Faloutsos *WWW, 2013.*

Graph Patterns and Lockstep Behavior

Our intuition

- Lockstep behavior: Same Likes, same time



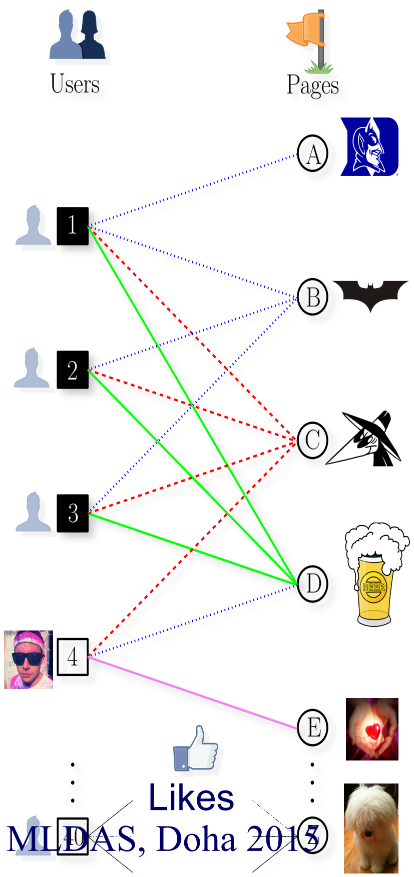


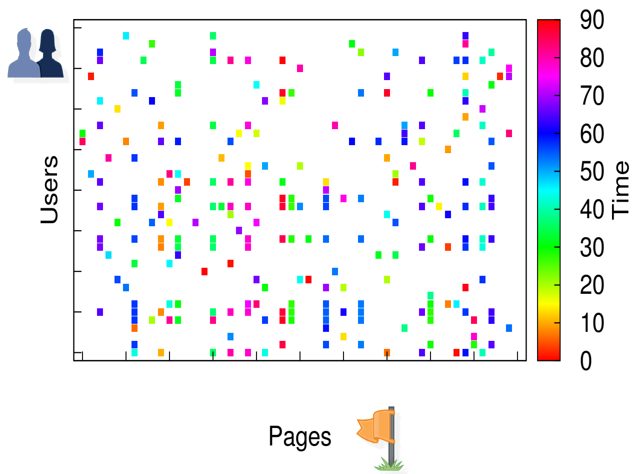
Carnegie Mellon

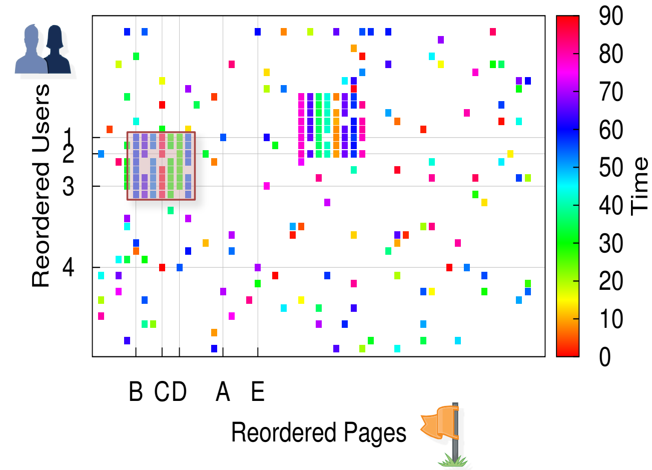
Graph Patterns and Lockstep Behavior

Our intuition

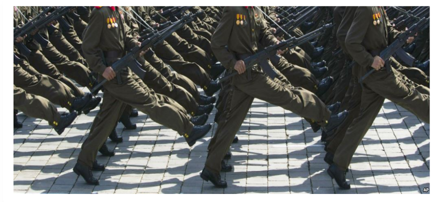
- Lockstep behavior: Same Likes, same time





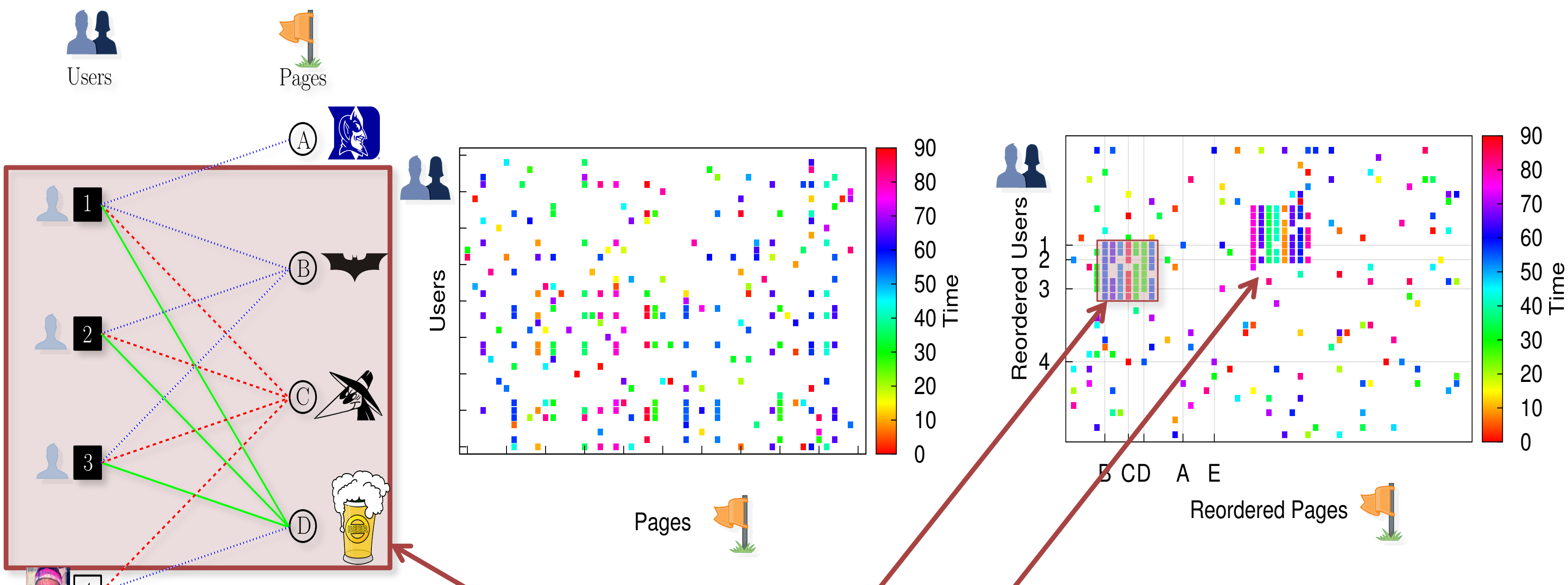


Graph Patterns and Lockstep Behavior



Our intuition

- Lockstep behavior: Same Likes, same time

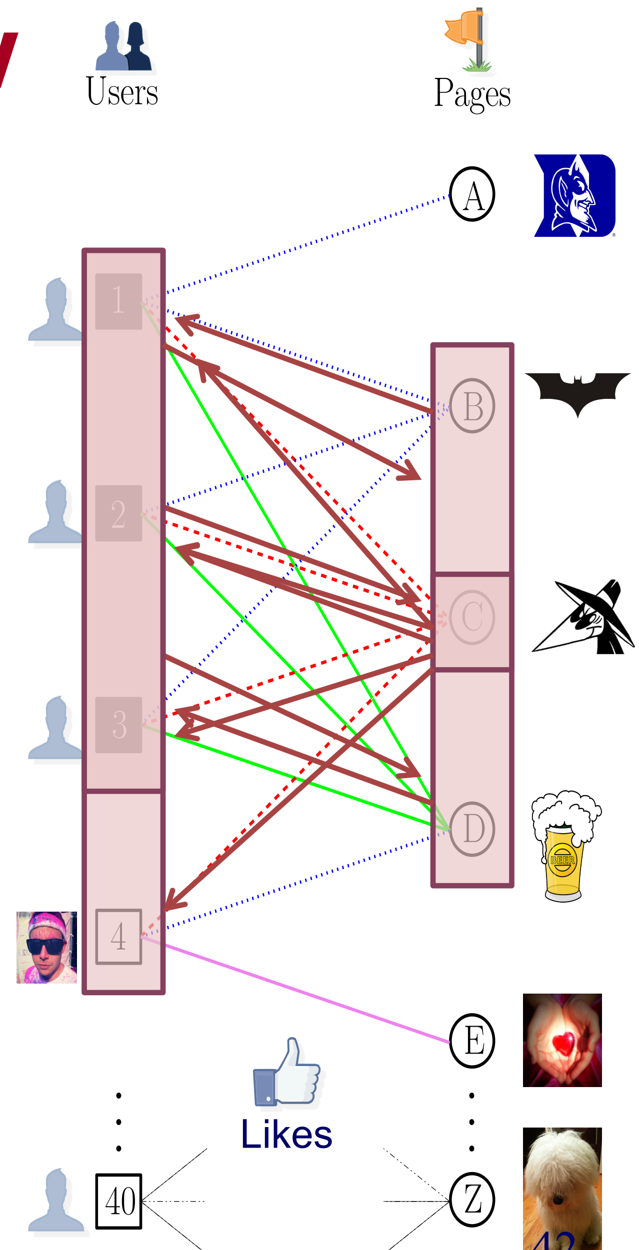


Carnegie Mellon

MapReduce Overview

- Use Hadoop to search for many clusters in parallel:

1. Start with randomly seed
2. Update set of Pages and center Like times for each cluster
3. Repeat until convergence



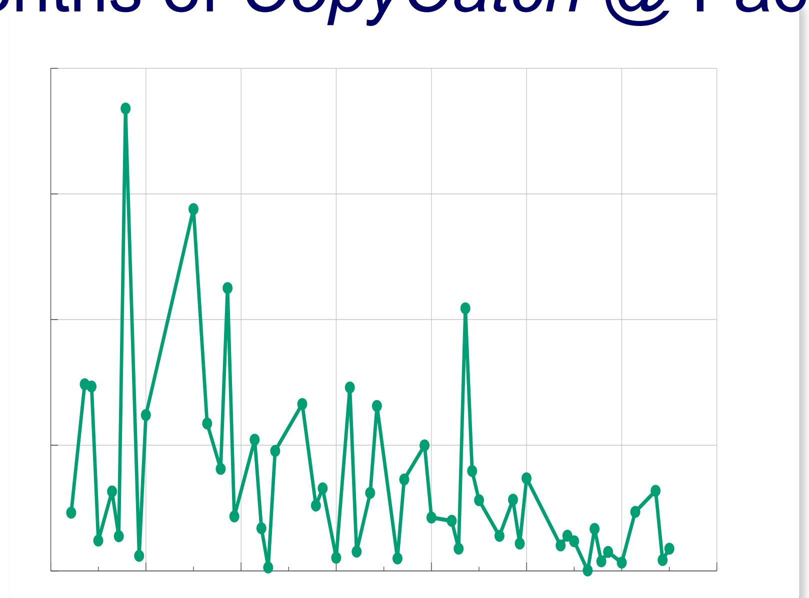
Carnegie Mellon

Deployment at Facebook

- *CopyCatch* runs regularly (along with many other security mechanisms, and a large Site Integrity team)

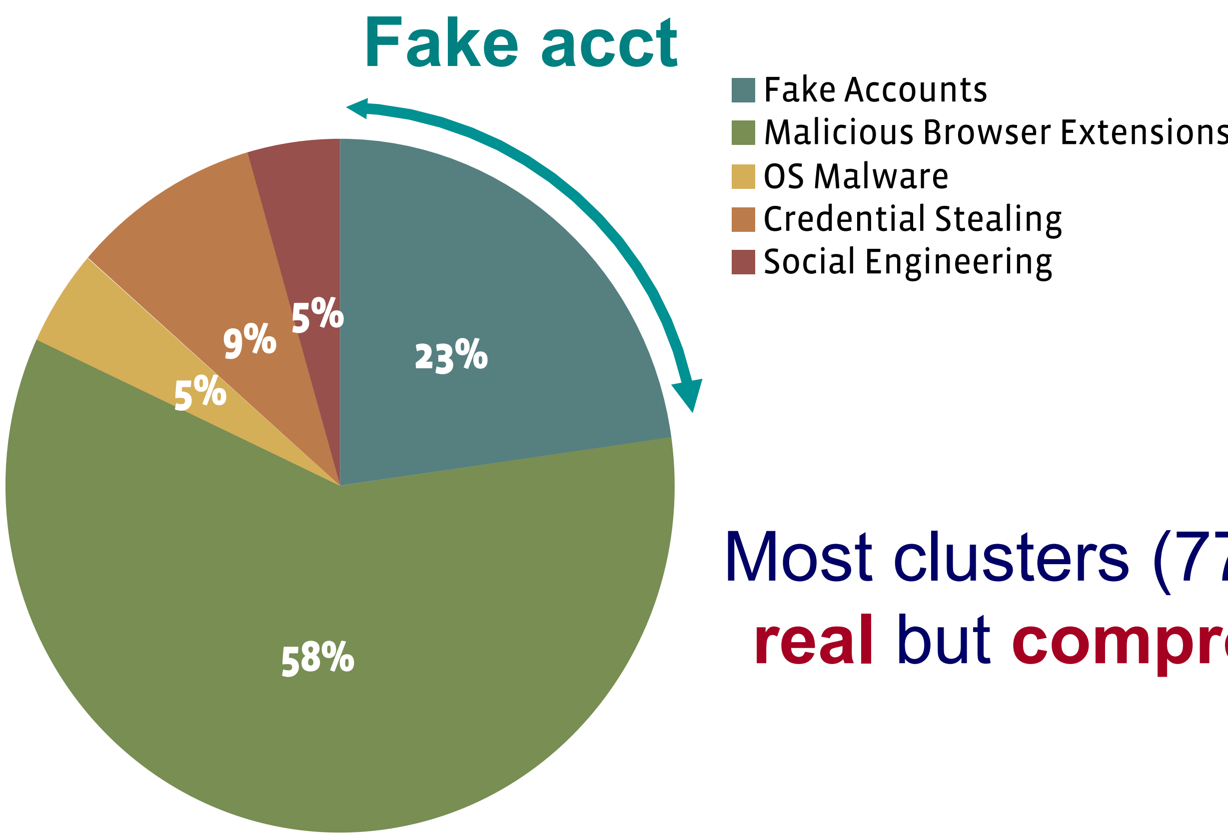
3 months of *CopyCatch* @ Facebook

#users caught



time

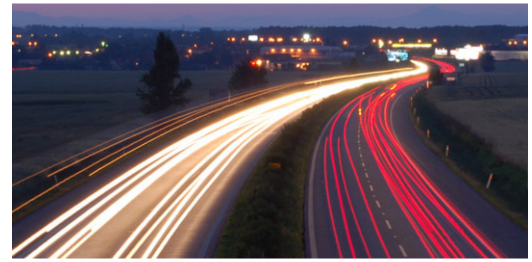
Deployment at Facebook



Most clusters (77%) come from **real** but **compromised** users

Manually labeled 22 randomly selected *clusters* from February 2013

Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns
  - Anomaly / fraud detection
    - CopyCatch
    - Spectral methods ('fBox')
    - Belief Propagation
- Part#2: time-evolving graphs; tensors
- Conclusions

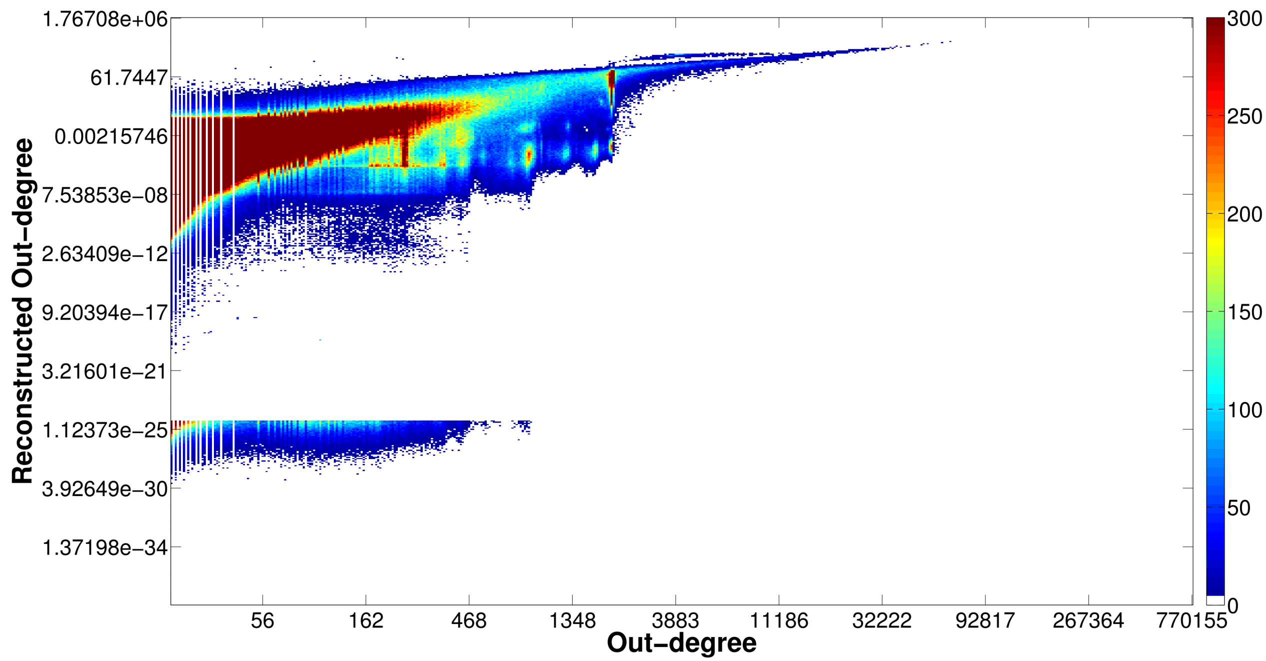
Problem: Social Network Link Fraud

Target: find "stealthy" attackers missed by other algorithms

Clique

41.7M nodes
1.5B edges

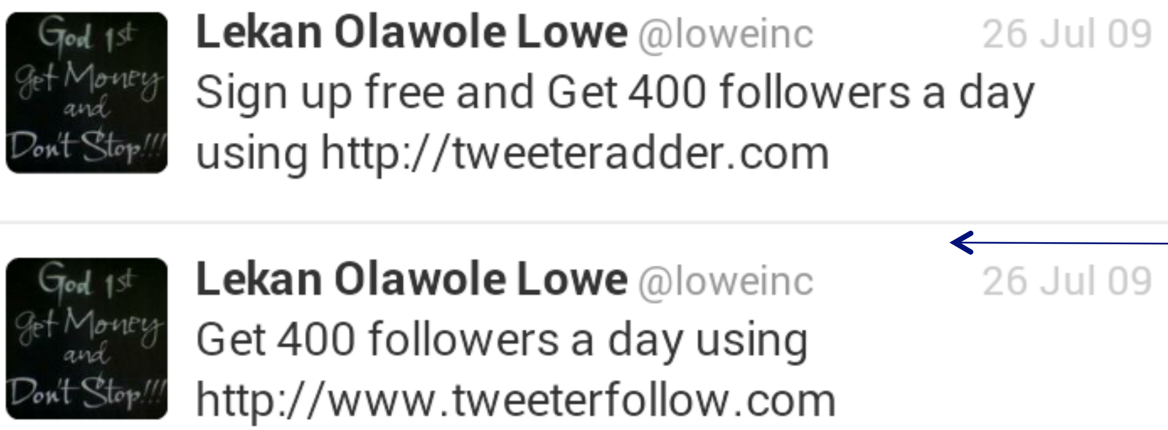
Bipartite
core

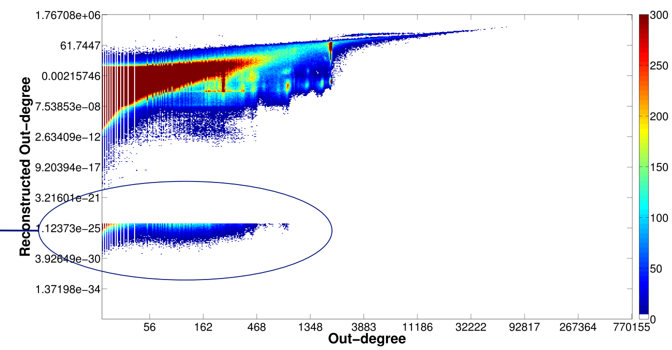


Carnegie Mellon

Problem: Social Network Link Fraud

Target: find “stealthy” attackers missed by other algorithms

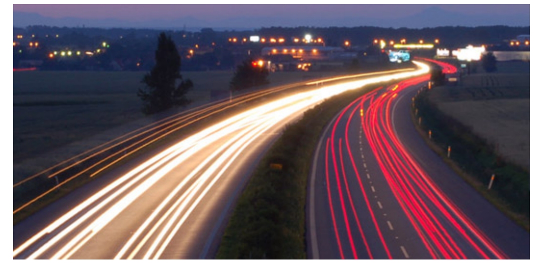




Takeaway: use *reconstruction error* between true/latent representation!

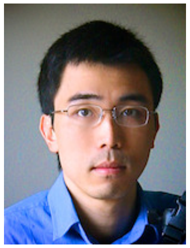
Neil Shah, Alex Beutel, Brian Gallagher and Christos Faloutsos. *Spotting Suspicious Link Behavior with fBox: An Adversarial Perspective.* ICDM 2014, Shenzhen, China.

Roadmap

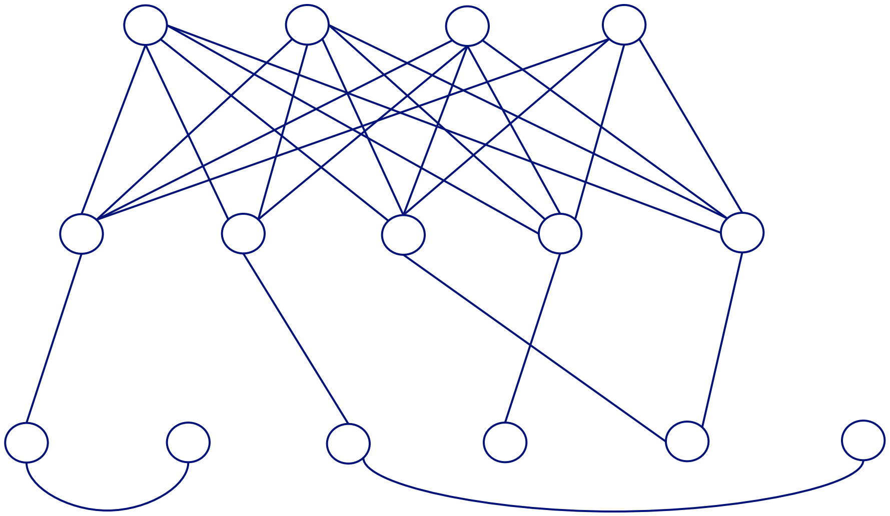


- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns
  - Anomaly / fraud detection
    - CopyCatch
    - Spectral methods (‘fBox’)
    - Belief Propagation
- Part#2: time-evolving graphs; tensors
- Conclusions

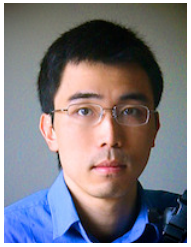
E-bay Fraud detection

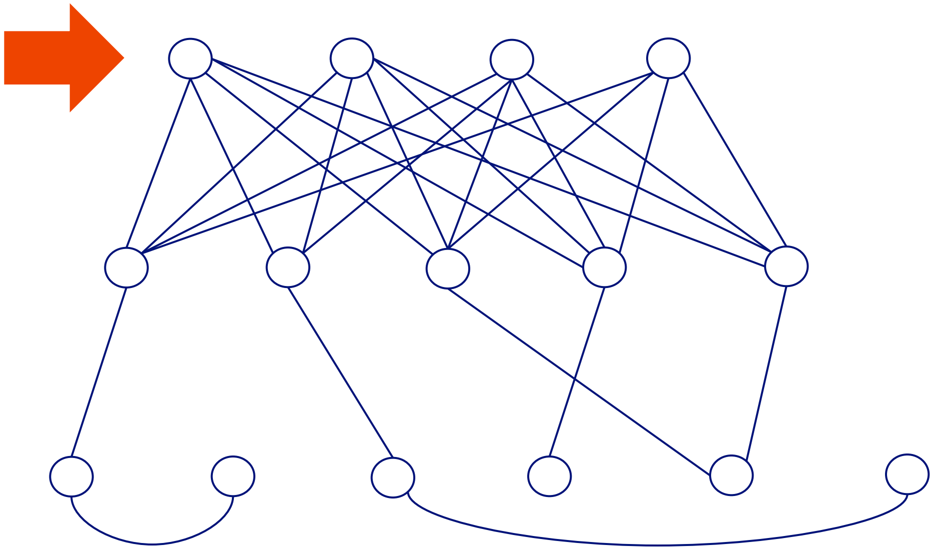


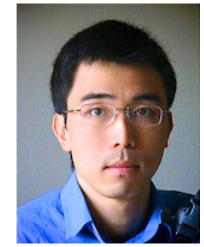
w/ Polo Chau &
Shashank Pandit, CMU
[www'07]



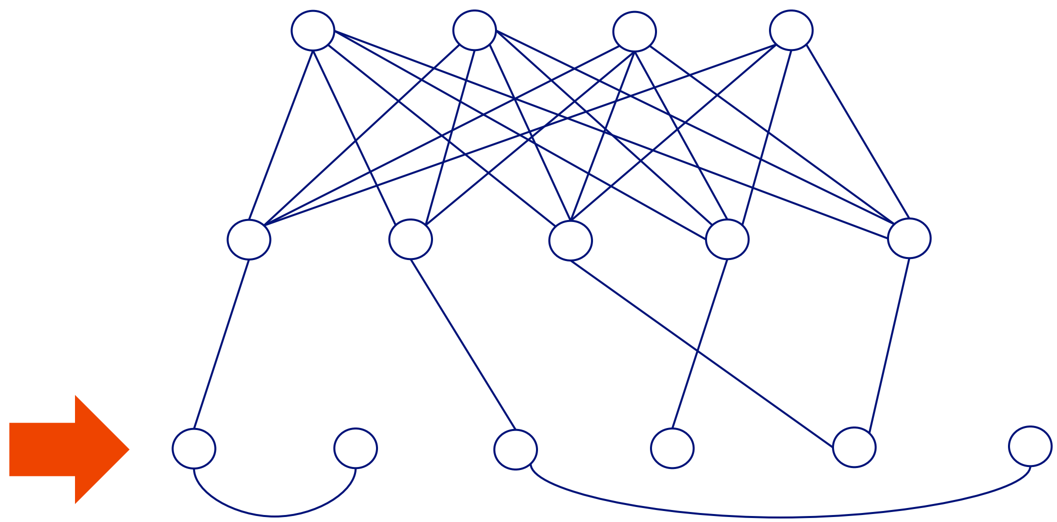
E-bay Fraud detection





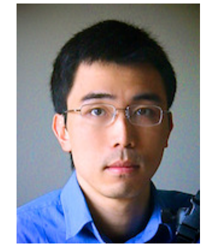


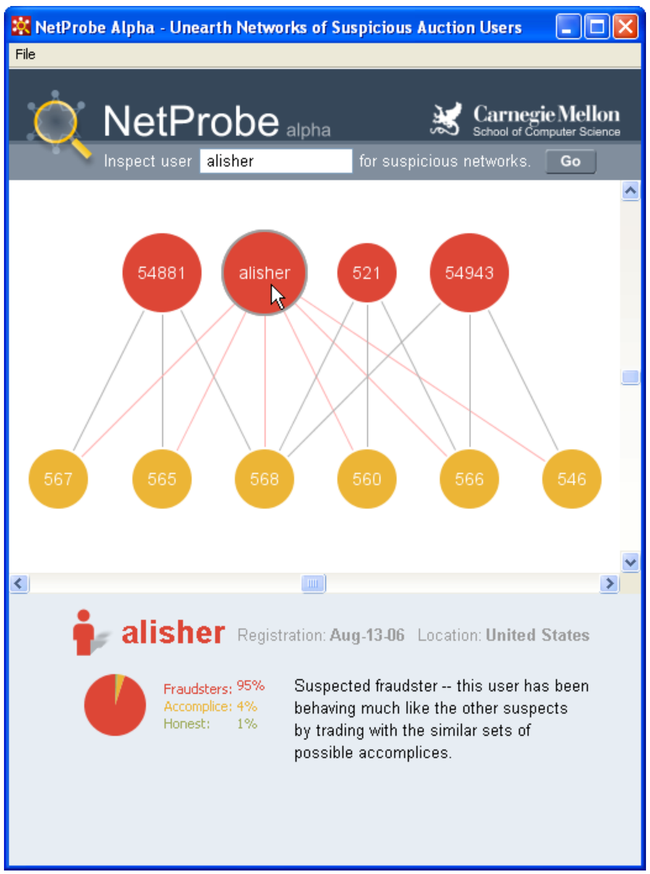
E-bay Fraud detection

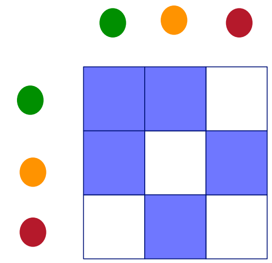


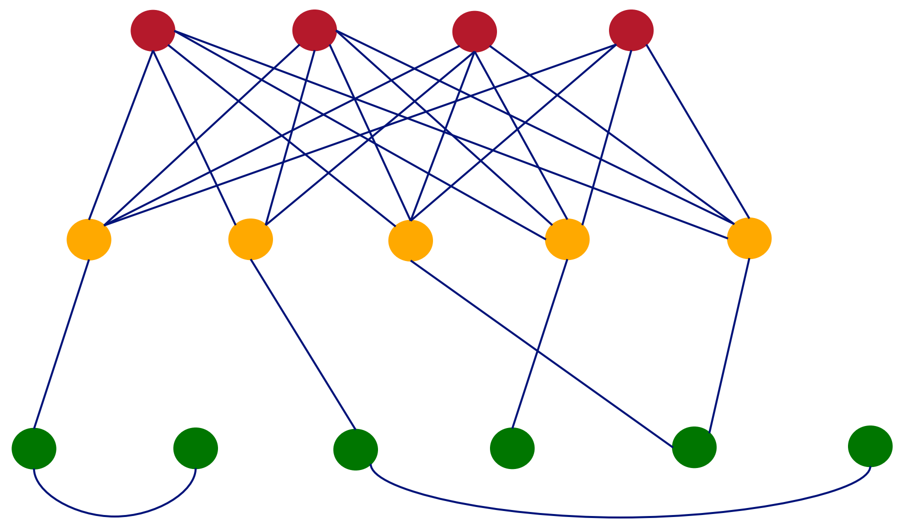
Carnegie Mellon

E-bay Fraud detection - NetProbe

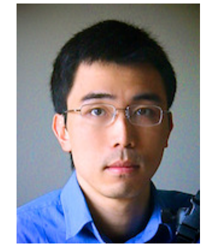








Popular press



USA TODAY

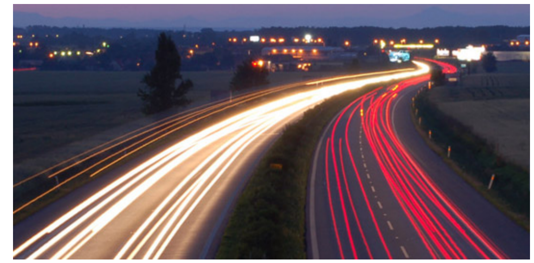
The Washington Post

Los Angeles Times

And less desirable attention:

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

Roadmap



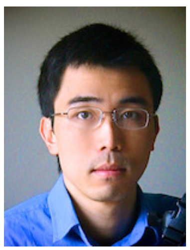
- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns
  - Anomaly / fraud detection
    - CopyCatch
    - Spectral methods ('fBox')
    - Belief Propagation; antivirus app
- Part#2: time-evolving graphs; tensors
- Conclusions

Carnegie Mellon

PATENT PENDING

Polonium: Tera-Scale Graph Mining and Inference for Malware Detection

SDM 2011, Mesa, Arizona



symantec.

symantec.

Polo Chau
Machine Learning Dept

Carey Nachenberg
Vice President & Fellow

Jeffrey Wilhelm
Principal Software Engineer

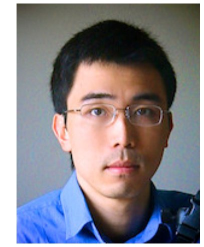
symantec.

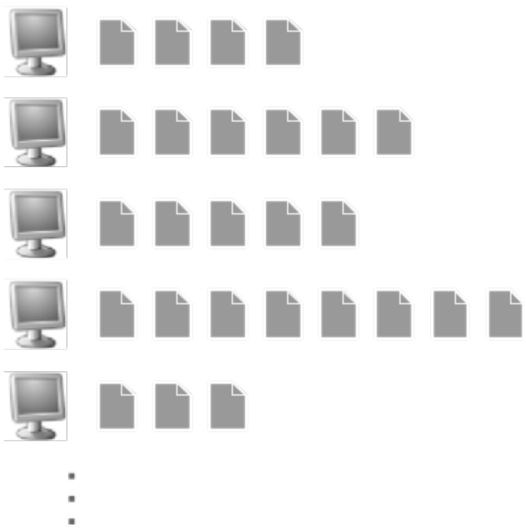
Adam Wright
Software Engineer

Prof. Christos Faloutsos
Computer Science Dept

Carnegie Mellon

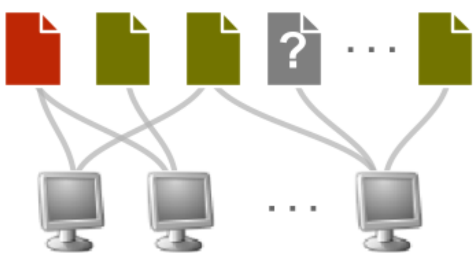
Polonium: The Data





60+ terabytes of data *anonymously* contributed by participants of worldwide *Norton Community Watch* program

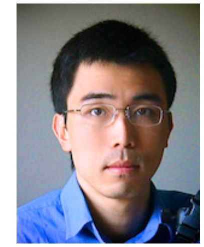
- 50+ million machines
- 900+ million executable files



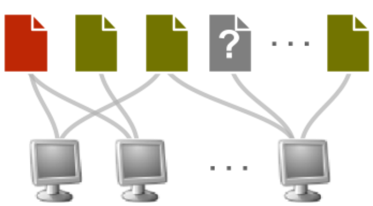
Constructed a machine-file bipartite graph (0.2 TB+)

- 1 billion nodes (machines and files)
- 37 billion edges

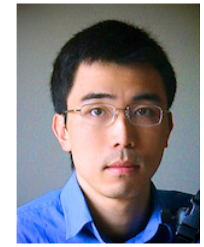
Polonium: Key Ideas



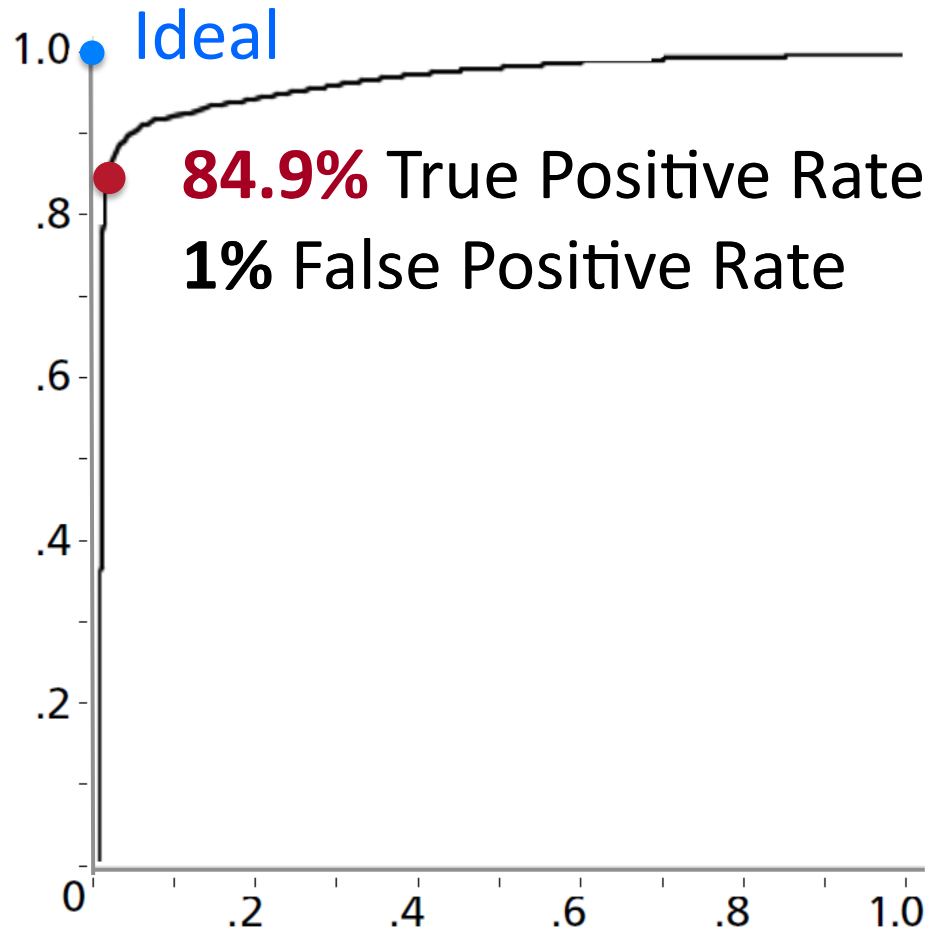
- Use Belief Propagation to propagate domain knowledge in machine-file graph to detect malware
- Use "guilt-by-association" (i.e., homophily)
  - E.g., files that appear on machines with many bad files are more likely to be bad
- Scalability: handles 37 billion-edge graph



Carnegie Mellon



Polonium: One-Interaction Results

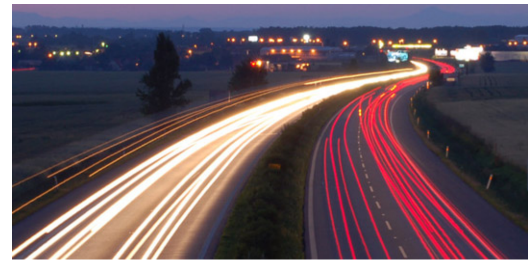


True Positive Rate
% of malware correctly identified

False Positive Rate
% of non-malware wrongly labeled as malware

Carnegie Mellon

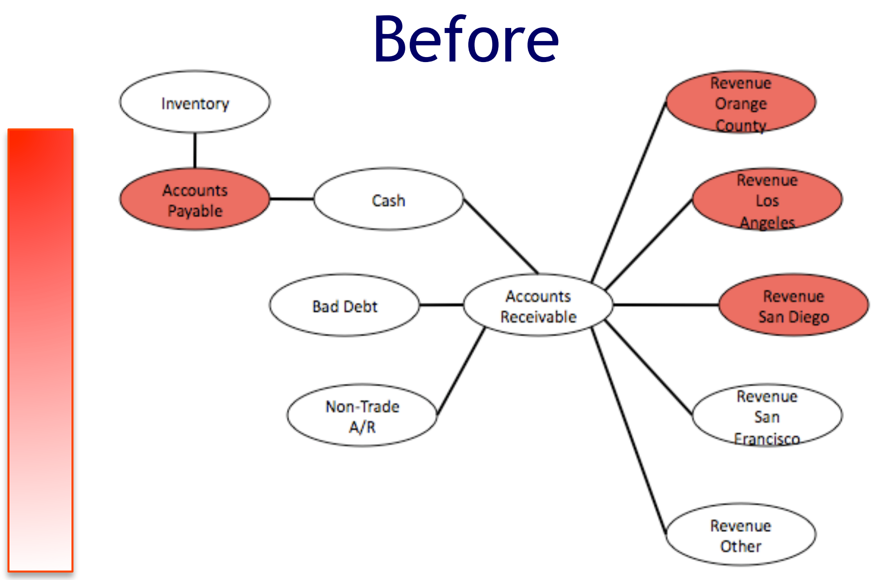
Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns
  - Anomaly / fraud detection
    - CopyCatch
    - Spectral methods ('fBox')
    - Belief Propagation; financial fraud
- Part#2: time-evolving graphs; tensors
- Conclusions

Network Effect Tools: SNARE

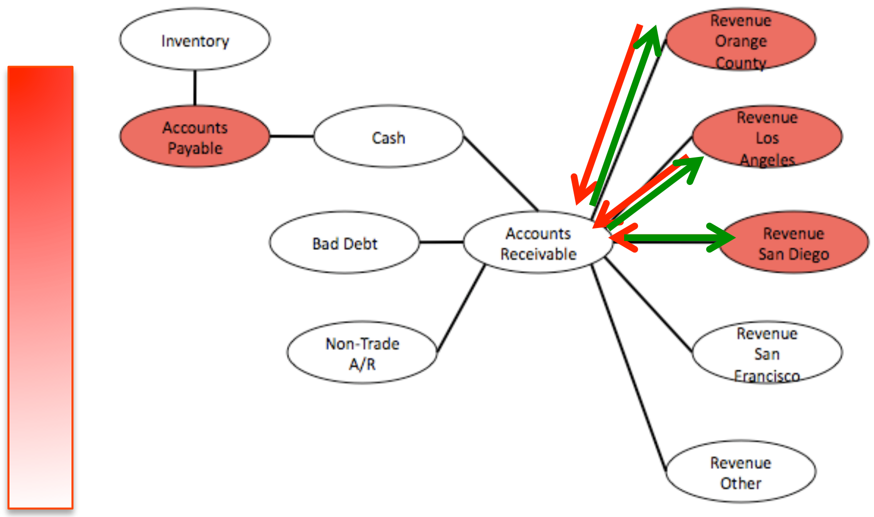
- Some accounts are sort-of-suspicious – how to combine weak signals?



Network Effect Tools: SNARE

- A: Belief Propagation.

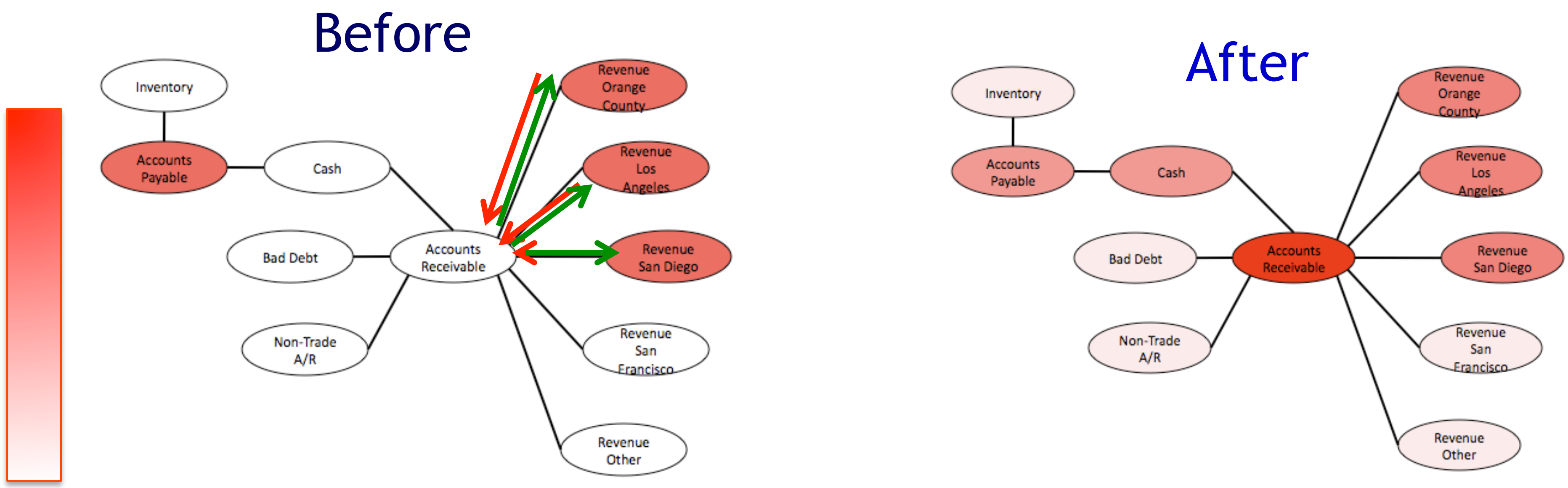
Before



Carnegie Mellon

Network Effect Tools: SNARE

- A: Belief Propagation.

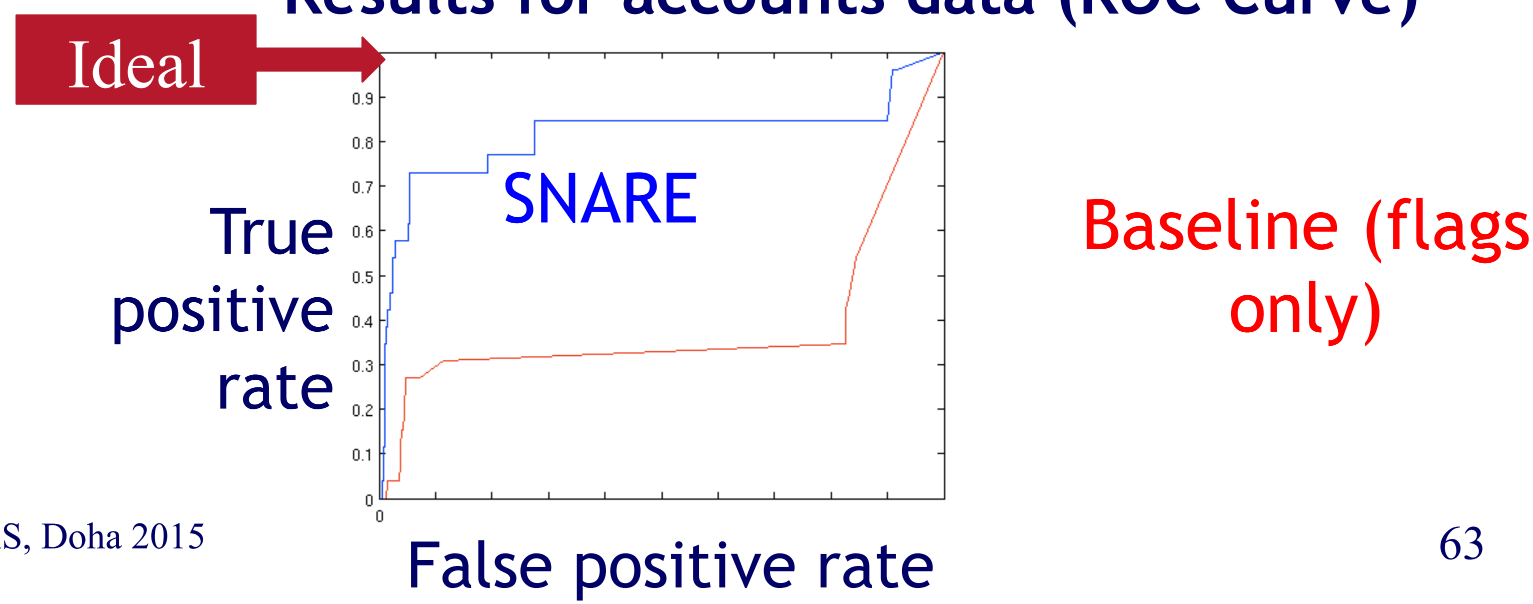


Mary McGlohon, Stephen Bay, Markus G. Anderle, David M. Steier, Christos Faloutsos: *SNARE: a link analytic system for graph labeling and risk detection*. KDD 2009: 1265-1274

Network Effect Tools: SNARE

- Produces improvement over simply using flags
  - Up to 6.5 lift
  - Improvement especially for low false positive rate

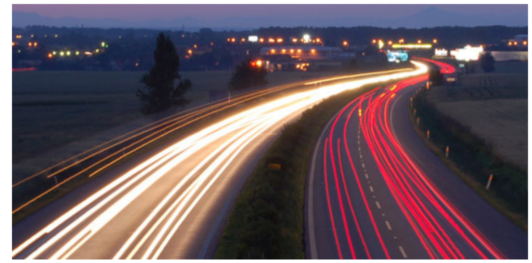
Results for accounts data (ROC Curve)



Network Effect Tools: SNARE

- Accurate- Produces large improvement over simply using flags
- Flexible- Can be applied to other domains
- Scalable- One iteration BP runs in linear time (# edges)
- Robust- Works on large range of parameters

Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
  - Patterns
  - Anomaly / fraud detection
    - CopyCatch
    - Spectral methods (‘fBox’)
    - Belief Propagation; fast computation & unification
- Part#2: time-evolving graphs; tensors
- Conclusions

Carnegie Mellon

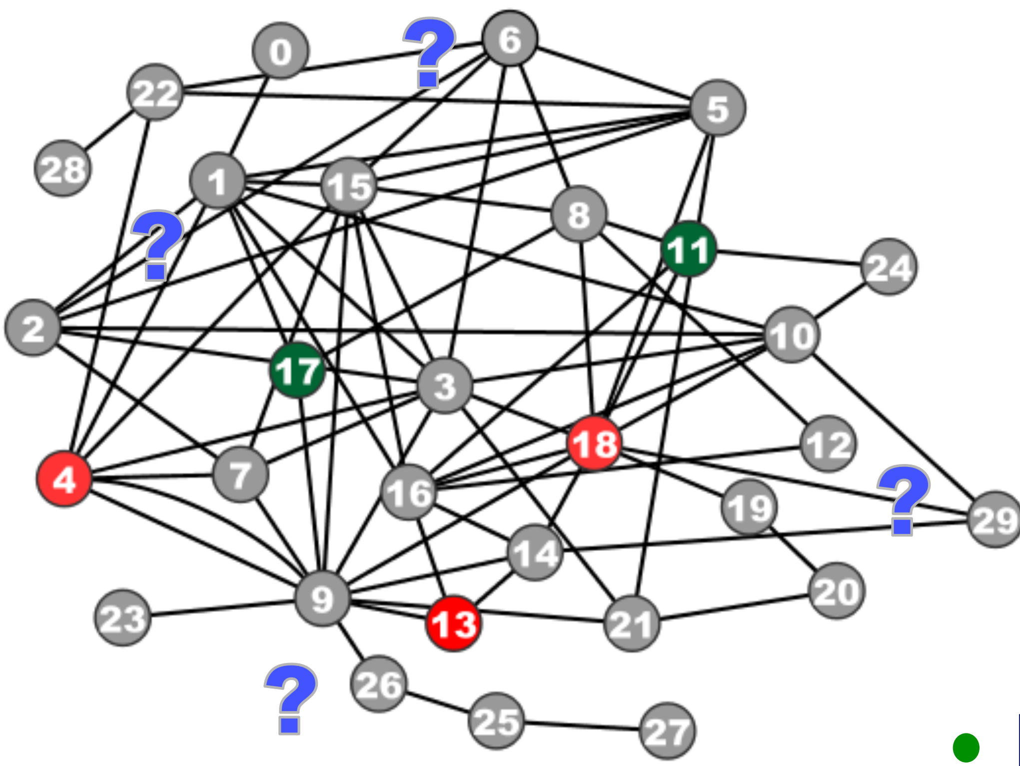
Unifying Guilt-by-Association Approaches: Theorems and Fast Algorithms

Danai Koutra
U Kang
Hsing-Kuo Kenneth Pao

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

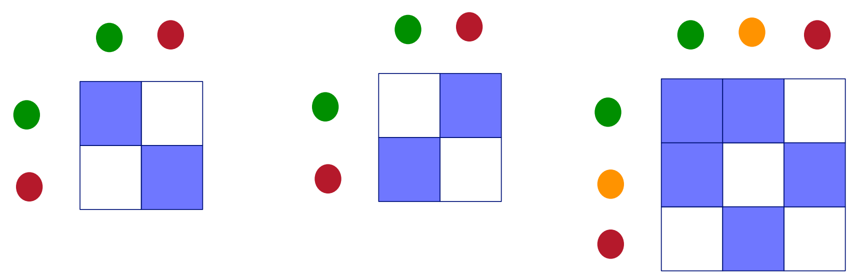
ECML PKDD, 5-9 September 2011, Athens, Greece

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*')
- 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	$[\mathbf{I} - c\ \underline{\mathbf{AD}^{-1}}]$	$\times$	$\mathbf{x}$	$=$	$(1-c)\mathbf{y}$
SSL	$[\mathbf{I} + a(\mathbf{D} - \underline{\mathbf{A}})]$	$\times$	$\mathbf{x}$	$=$	$\mathbf{y}$
FaBP	$[\mathbf{I} + a\,\mathbf{D} - c'\underline{\mathbf{A}}]$	$\times$	$\mathbf{b_h}$	$=$	$\boldsymbol{\phi}_\mathbf{h}$

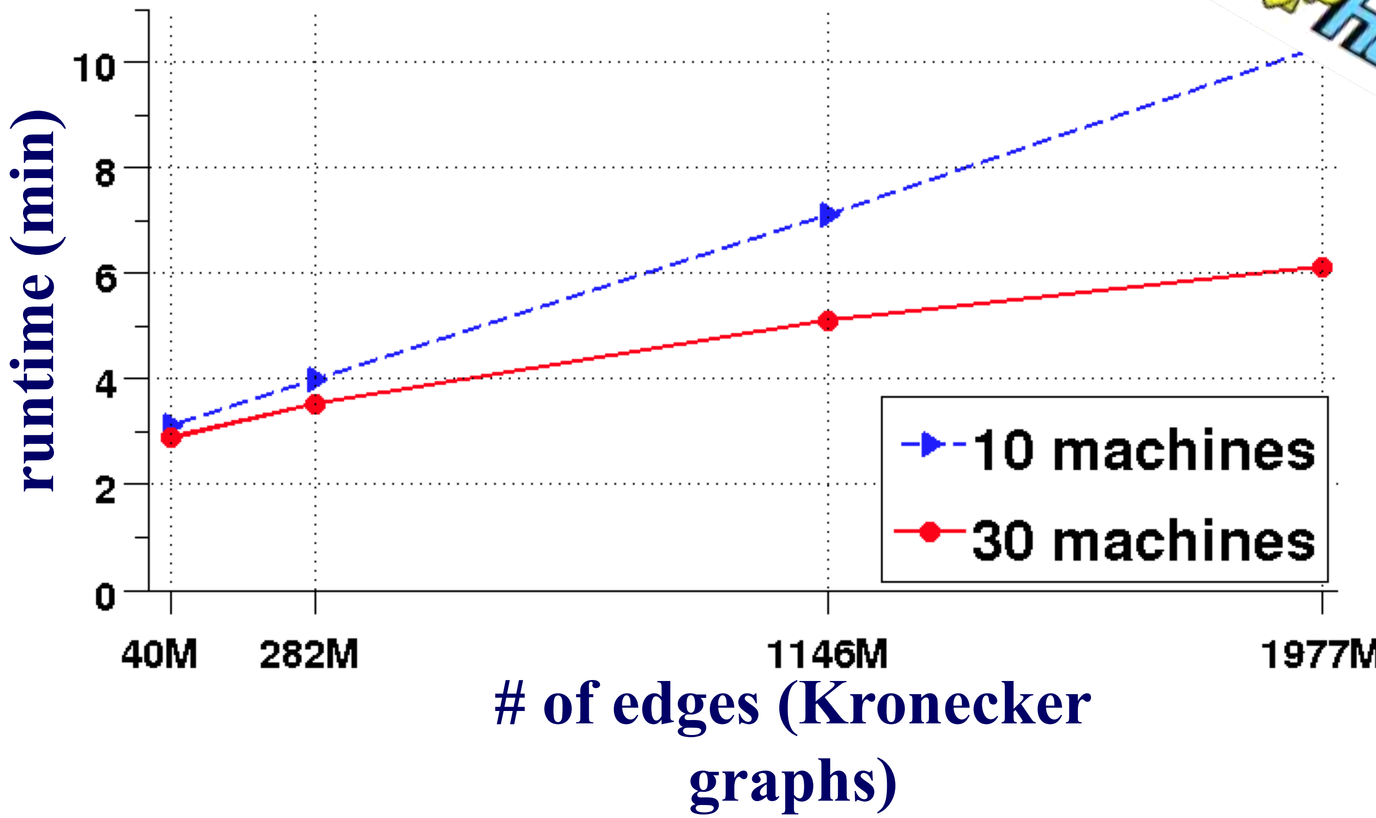
$$\begin{bmatrix} 1 & & \\ & 1 & \\ & & 1 \end{bmatrix} \quad \begin{bmatrix} d1 & & \\ & d2 & \\ & & d3 \end{bmatrix} \quad \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} ? \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

adjacency matrix

final labels/ beliefs

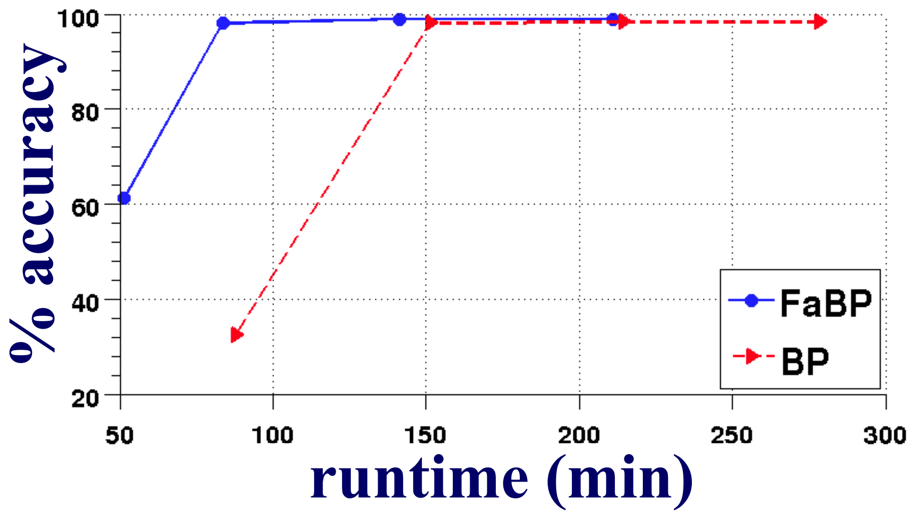
prior labels/ beliefs

Results: Scalability



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

Results: Parallelism



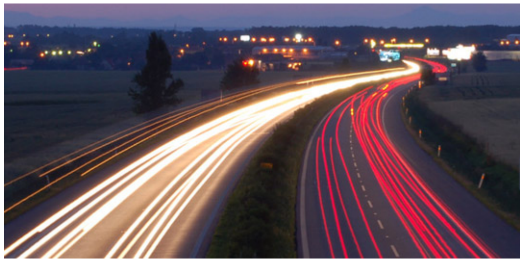
FABP **~2x faster**
& wins/ties on **accuracy.**

Summary of Part#1

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

Patterns  anomalies

Roadmap

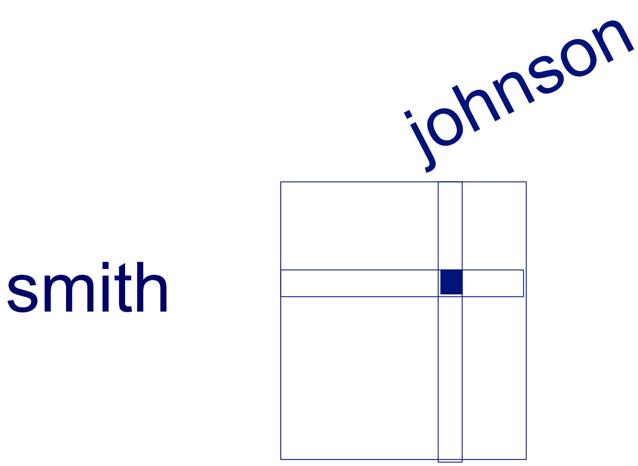


- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
- Conclusions

Part 2: Time evolving graphs; tensors

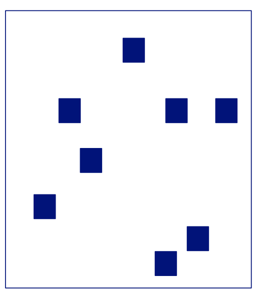
Graphs over time -> tensors!

- Problem #2:
  - Given who calls whom, and when
  - Find patterns / anomalies



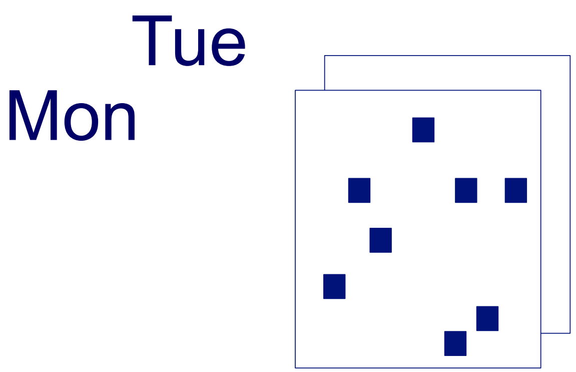
Graphs over time -> tensors!

- Problem #2:
  - Given who calls whom, and when
  - Find patterns / anomalies



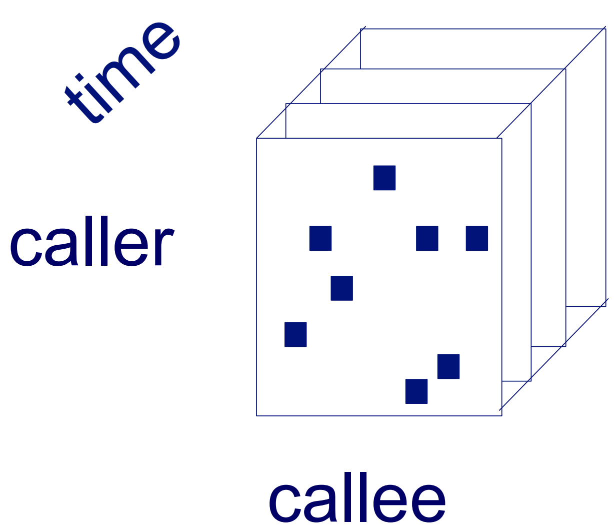
Graphs over time -> tensors!

- Problem #2:
  - Given who calls whom, and when
  - Find patterns / anomalies



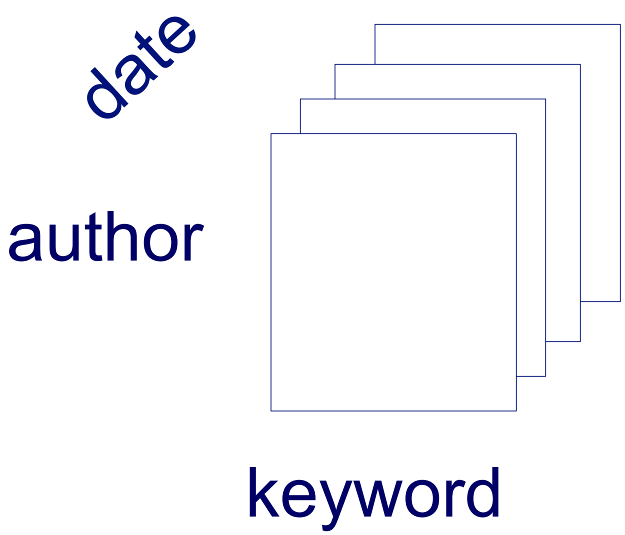
Graphs over time -> tensors!

- Problem #2:
  - Given who calls whom, and when
  - Find patterns / anomalies



Graphs over time -> tensors!

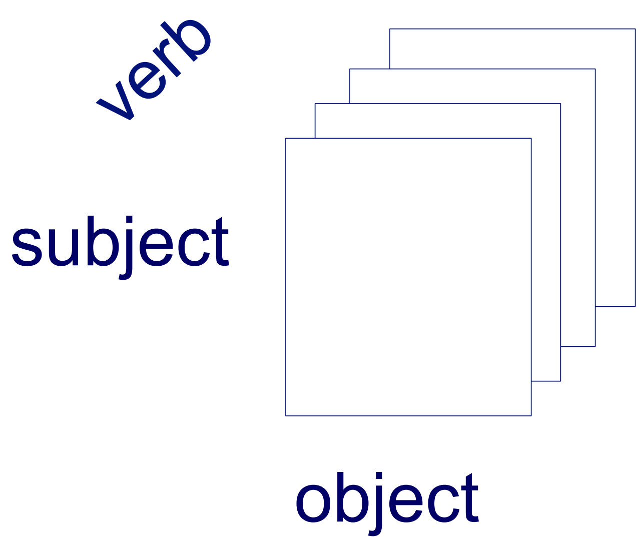
- Problem #2':
  - Given author-keyword-date
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

Graphs over time -> tensors!

- Problem #2'':
  - Given subject – verb – object facts
  - Find patterns / anomalies

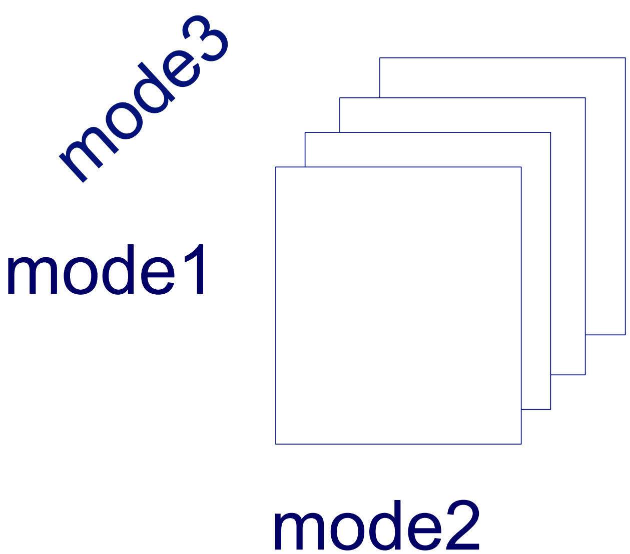


MANY more settings, with >2 'modes'

Carnegie Mellon

Graphs over time -> tensors!

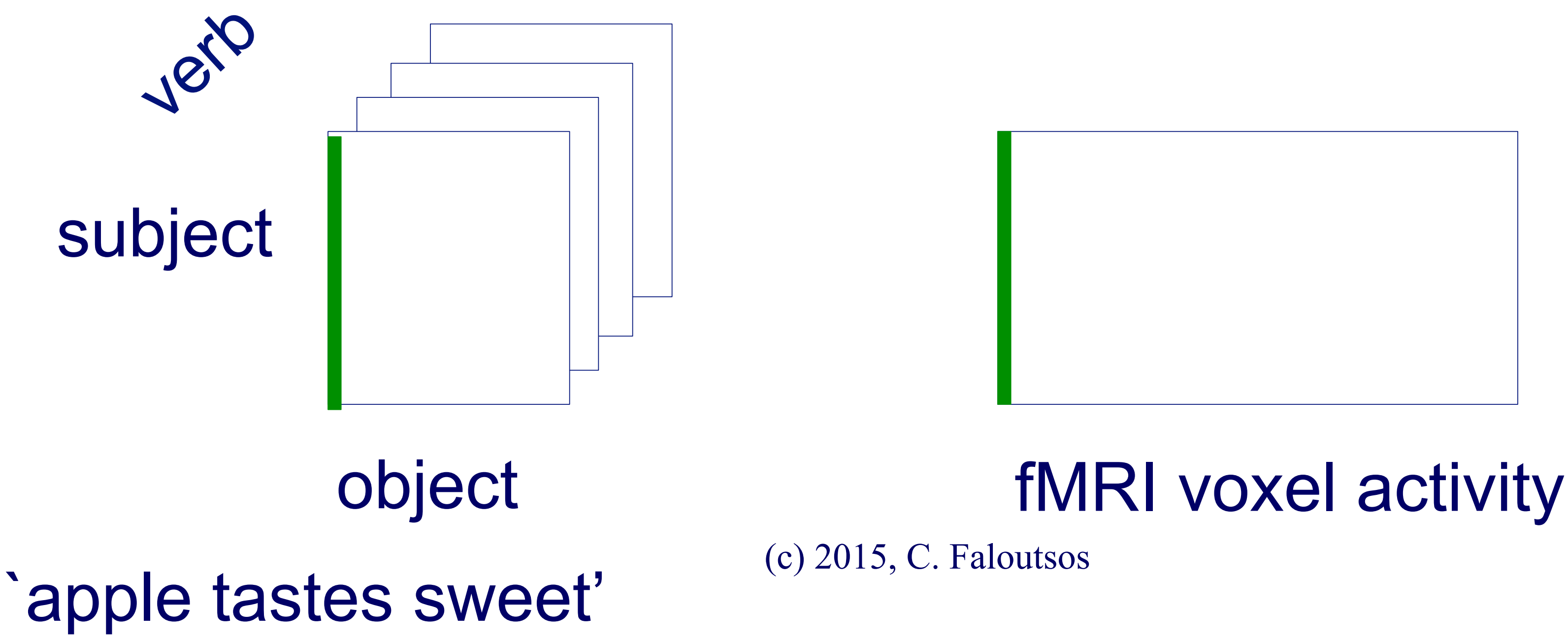
- Problem #2''':
  - Given <triplets>
  - Find patterns / anomalies



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

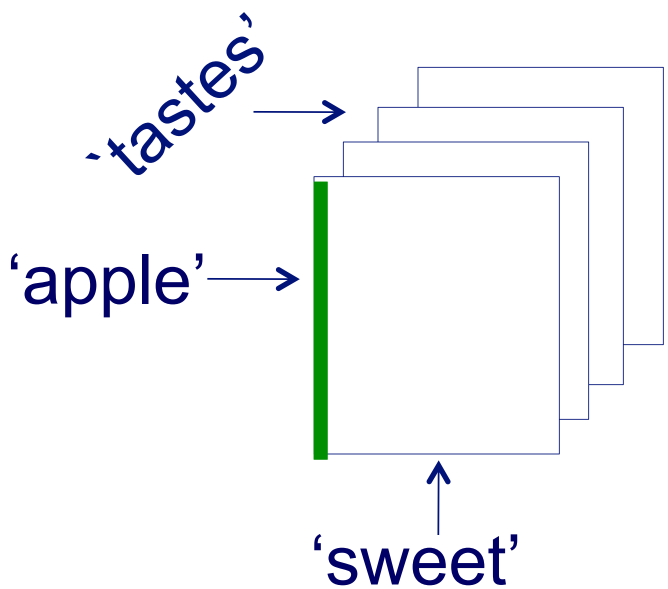
Graphs & side info

- Problem #2a: coupled (eg., side info)
  - Given subject – verb – object facts
    - And voxel-activity for each subject-word
  - Find patterns / anomalies

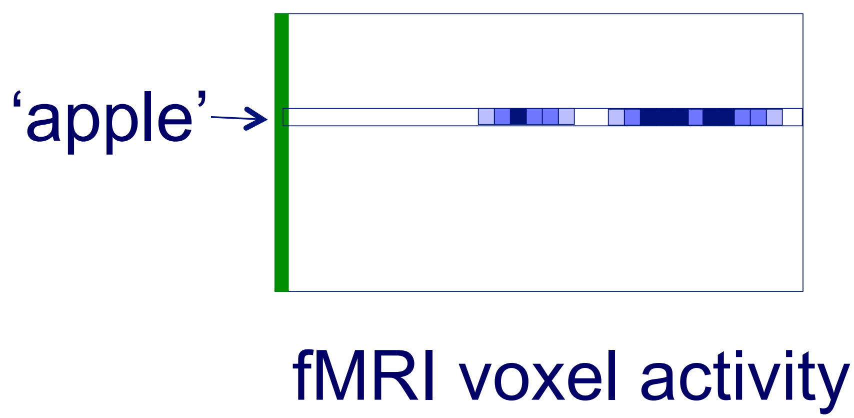


Graphs & side info

- Problem #2a: coupled (eg., side info)
  - Given subject – verb – object facts
    - And voxel-activity for each subject-word
  - Find patterns / anomalies

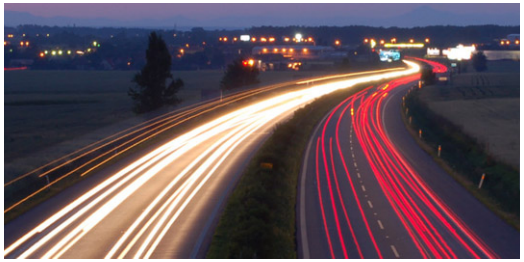


`apple tastes sweet'



Carnegie Mellon

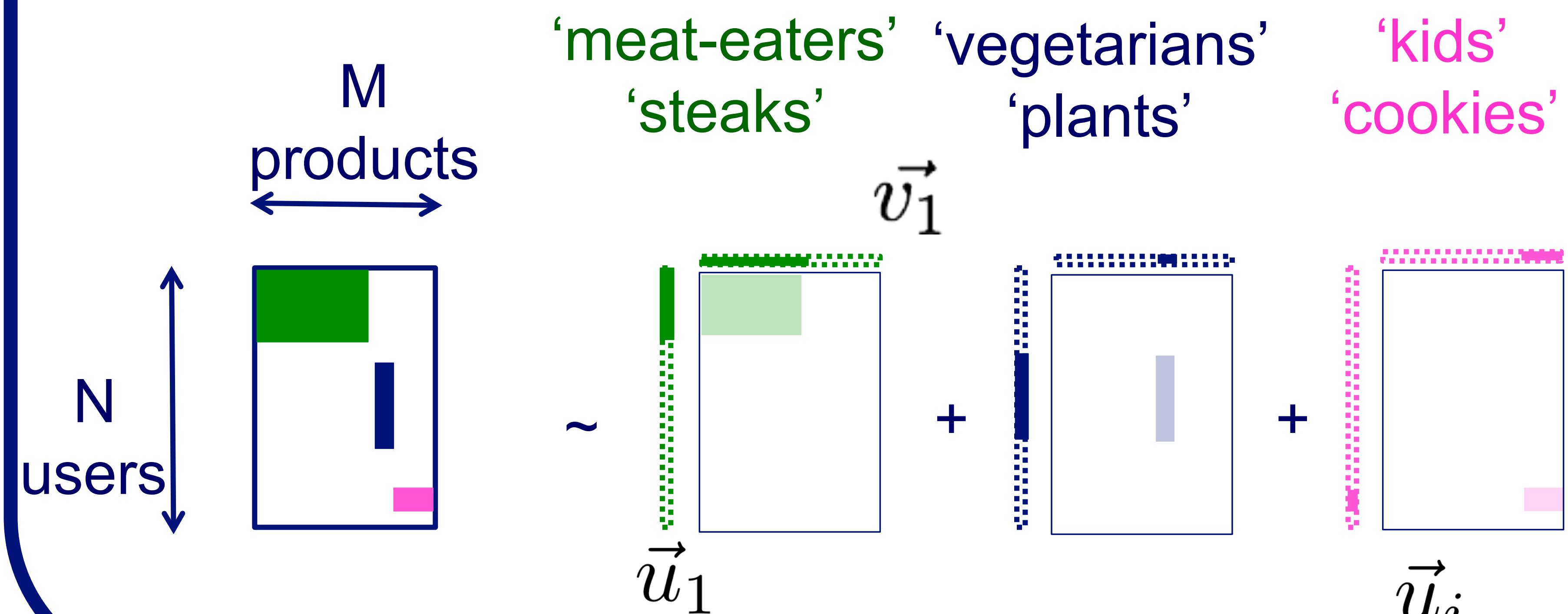
Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
  - Intro to tensors
  - Results
  - Speed
- Conclusions

Answer to both: tensor factorization

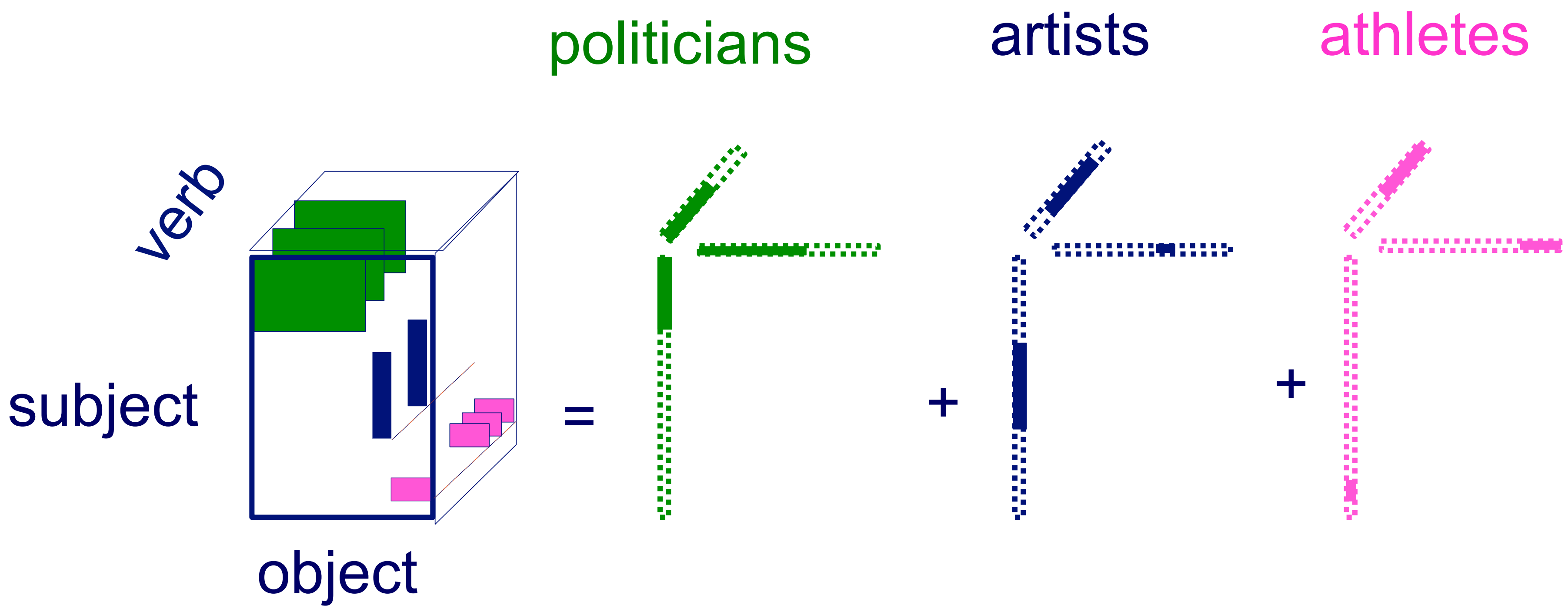
- Recall: (SVD) matrix factorization: finds blocks



Carnegie Mellon

Answer to both: tensor factorization

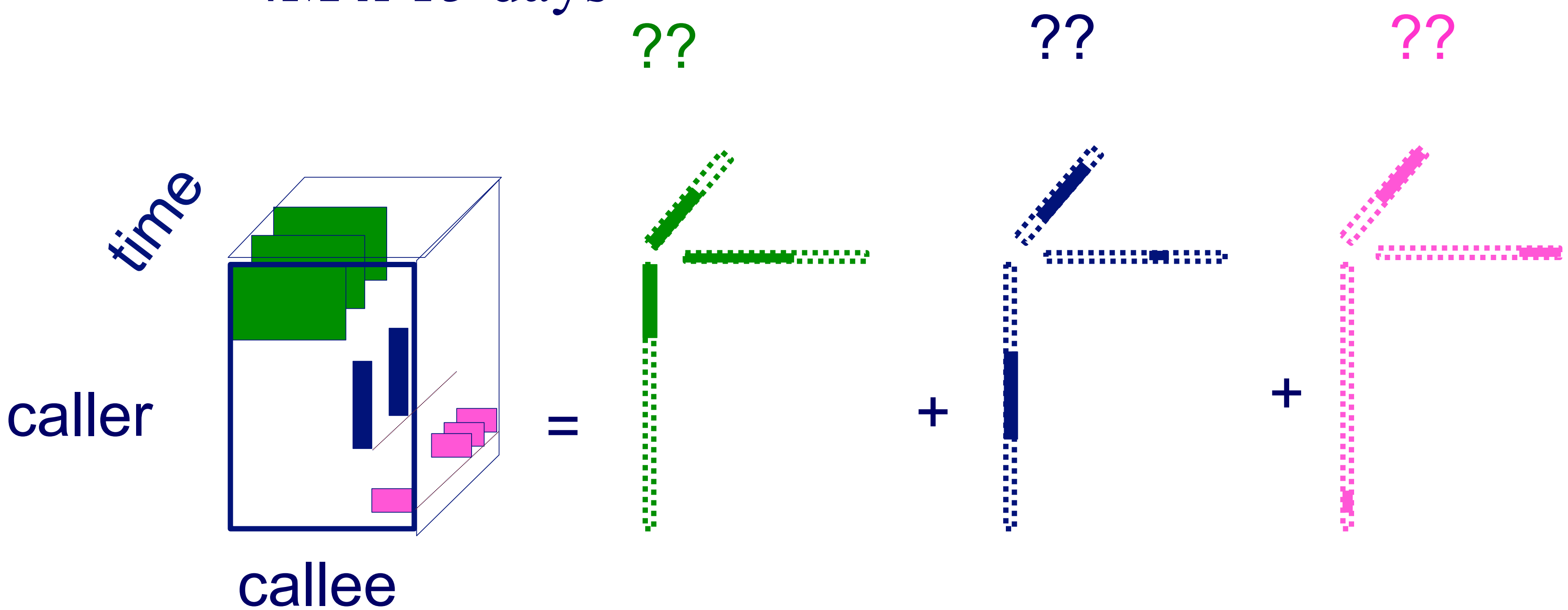
- PARAFAC decomposition



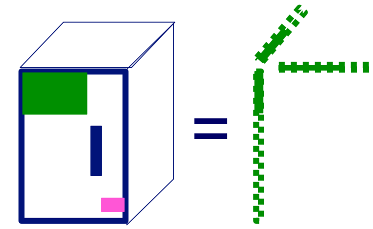
Carnegie Mellon

Answer: tensor factorization

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

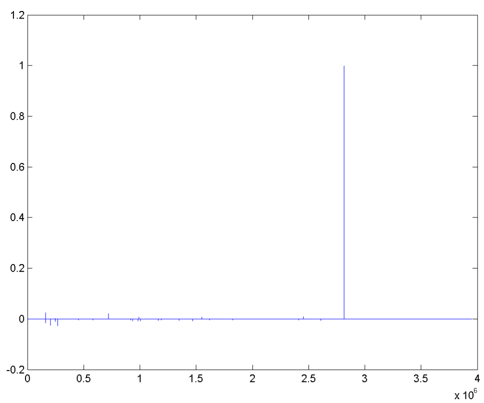


Anomaly detection in time-evolving graphs

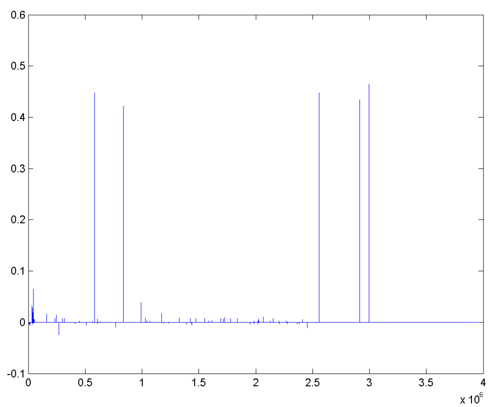


- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks

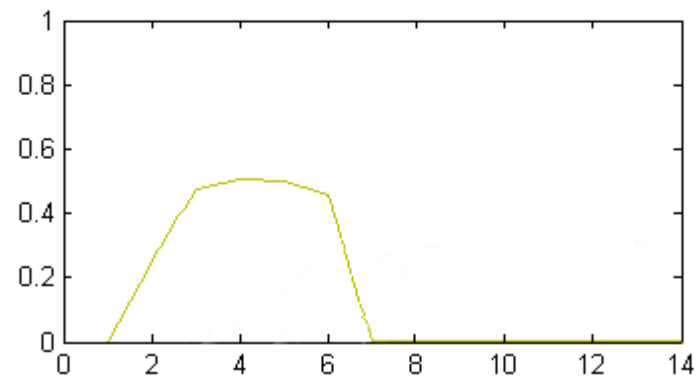
1 caller



5 receivers



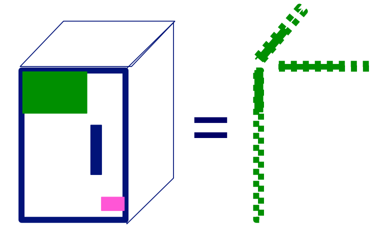
4 days of activity



~200 calls to EACH receiver on EACH day!

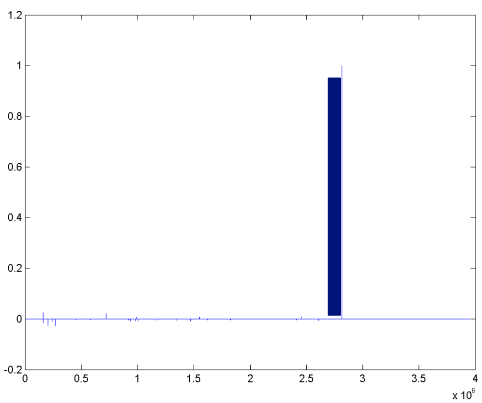
Carnegie Mellon

Anomaly detection in time-evolving graphs

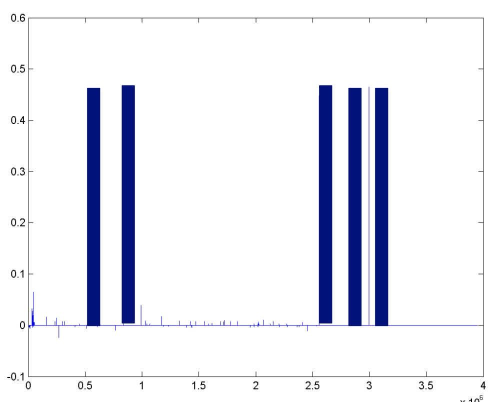


- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks

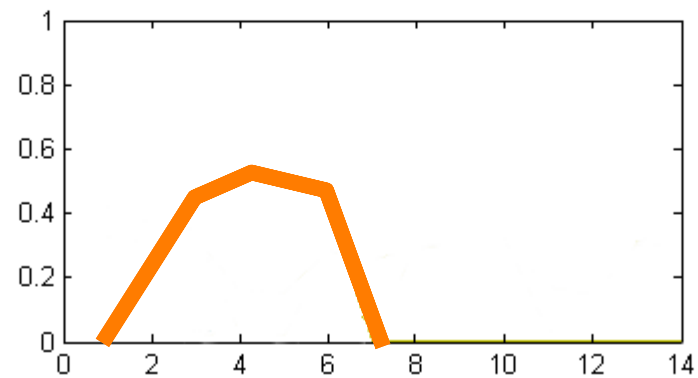
1 caller



5 receivers

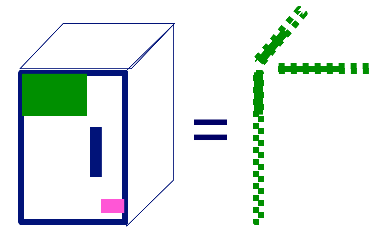


4 days of activity

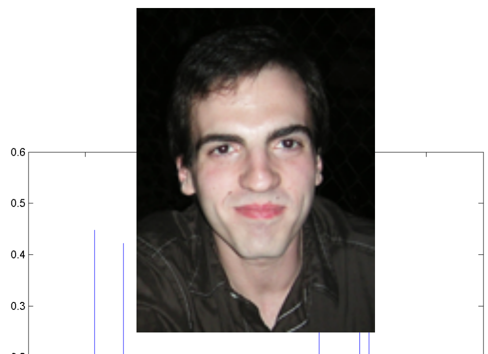


~200 calls to EACH receiver on EACH day!

Anomaly detection in time-evolving graphs

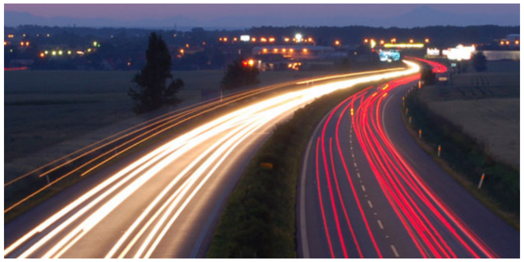


- Anomalous communities in phone call data:
  - European country, 4M clients, data over 2 weeks



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

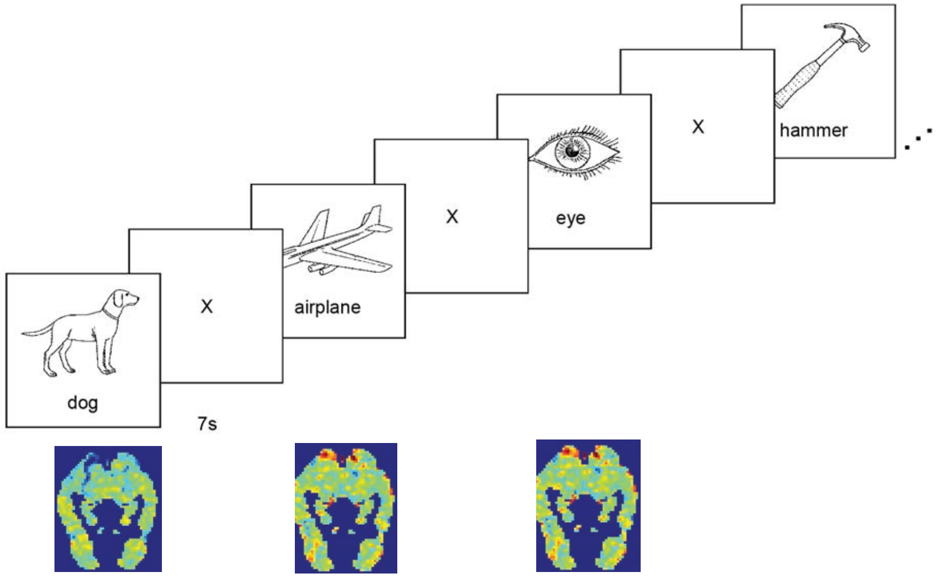


- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
  - Intro to tensors
  - Results
  - Speed
- Conclusions

Carnegie Mellon

Neuro-semantics

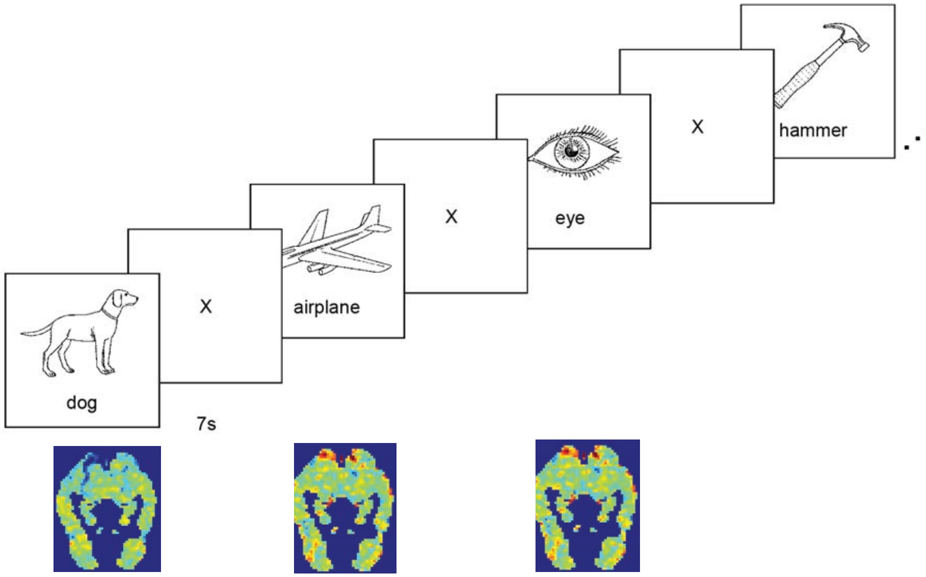
- **Brain Scan Data***
  - 9 persons
  - 60 nouns
- **Questions**
  - 218 questions
  - 'is it alive?', 'can you eat it?'



*Mitchell et al. *Predicting human brain activity associated with the meanings of nouns*. Science,2008. Data@ www.cs.cmu.edu/afs/cs/project/theo-73/www/science2008/data.html

Neuro-semantics

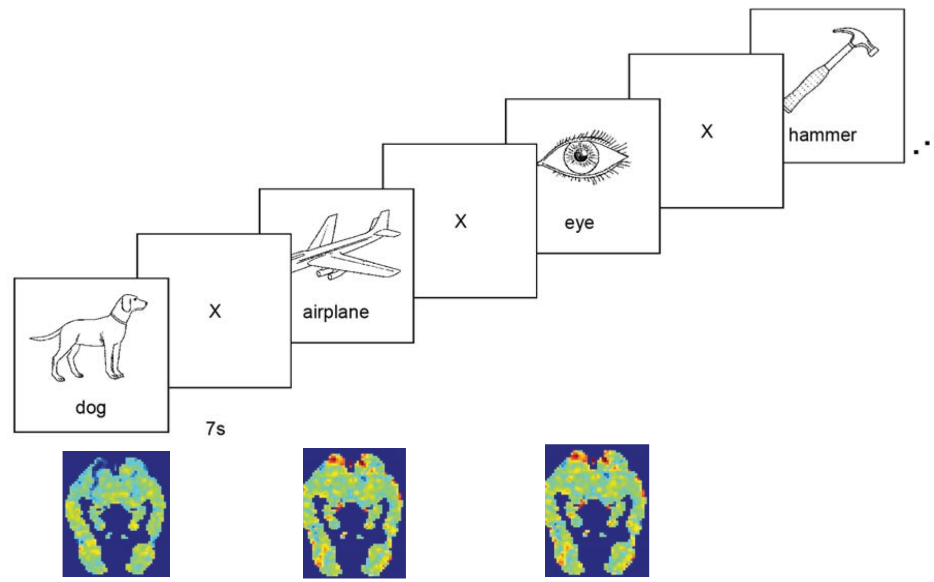
- **Brain Scan Data***
  - 9 persons
  - 60 nouns
- **Questions**
  - 218 questions
  - 'is it alive?', 'can you eat it?'



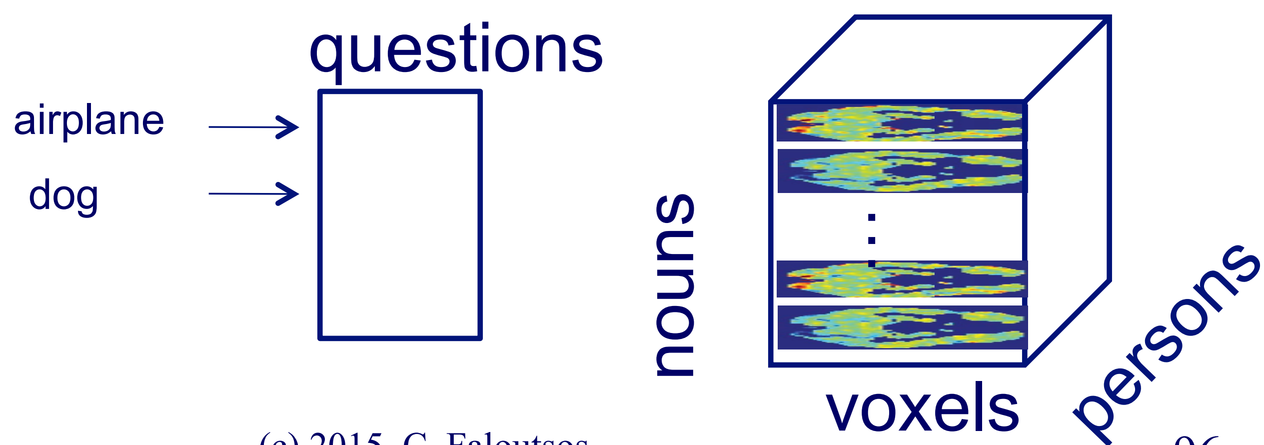
Patterns?

Neuro-semantics

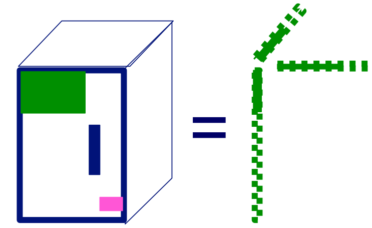
- **Brain Scan Data***
  - 9 persons
  - 60 nouns
- **Questions**
  - 218 questions
  - 'is it alive?', 'can you eat it?'



Patterns?



Neuro-semantics

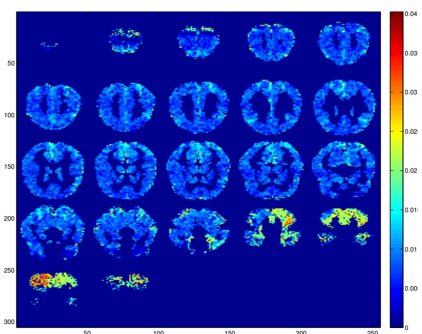


Nouns

beetle
pants
bee

Questions

can it cause you pain?
do you see it daily?
is it conscious?



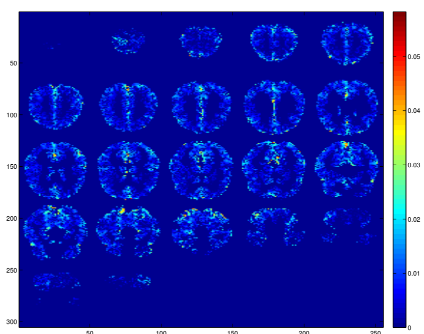
Group1

Nouns

bear
cow
coat

Questions

does it grow?
is it alive?
was it ever alive?



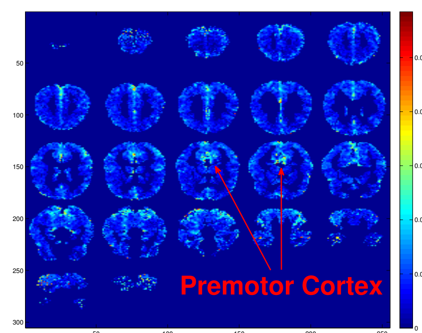
Group 2

Nouns

glass
tomato
bell

Questions

can you pick it up?
can you hold it in one hand?
is it smaller than a golfball?



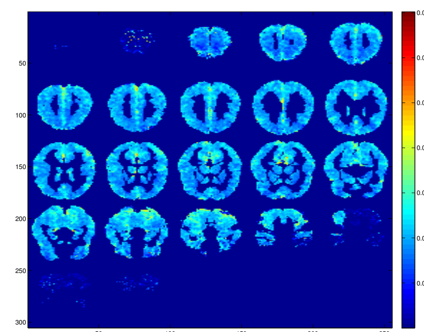
Group 3

Nouns

bed
house
car

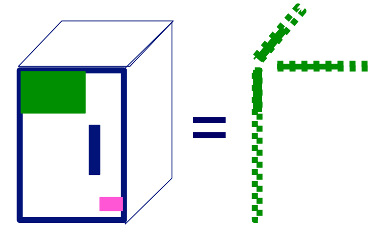
Questions

does it use electricity?
can you sit on it?
does it cast a shadow?



Group 4

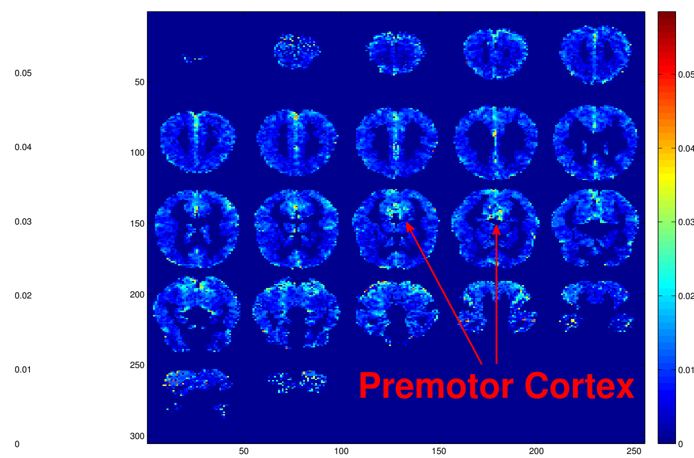
Neuro-semantics



Small items -> Premotor cortex

Nouns
glass
tomato
bell

Questions
can you pick it up?
can you hold it in one hand?
is it smaller than a golfball?'



Group 3

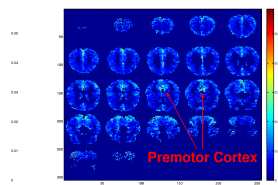
Carnegie Mellon

Neuro-semantics

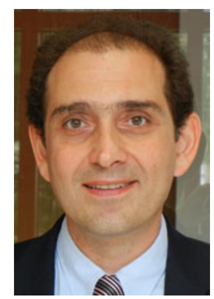
Small items -> Premotor cortex

Nouns
glass
tomato
bell

Questions
can you pick it up?
can you hold it in one hand?
is it smaller than a golfball?'

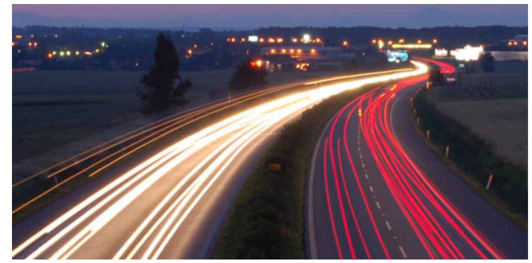


Group 3



Evangelos Papalexakis, Tom Mitchell, Nicholas Sidiropoulos, Christos Faloutsos, Partha Pratim Talukdar, Brian Murphy, *Turbo-SMT: Accelerating Coupled Sparse Matrix-Tensor Factorizations by 200x*, SDM 2014

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

Project info: PEGASUS

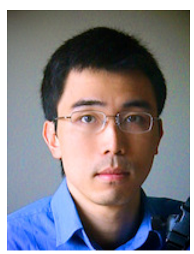
www.cs.cmu.edu/~pegasus

Results on large graphs: with Pegasus + hadoop + M45

Apache license

Code, papers, manual, video

Prof. U Kang



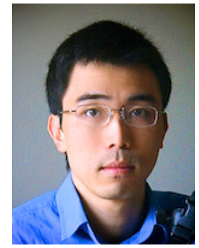
Prof. Polo Chau

Cast

Akoglu, Leman

Araujo, Miguel

Beutel, Alex



Chau, Polo

Kang, U

Koutra, Danai

Lee, Jay Yoon

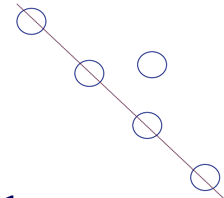
Prakash, Aditya

Papalexakis, Vagelis

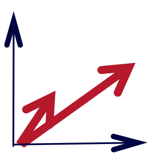
Shah, Neil

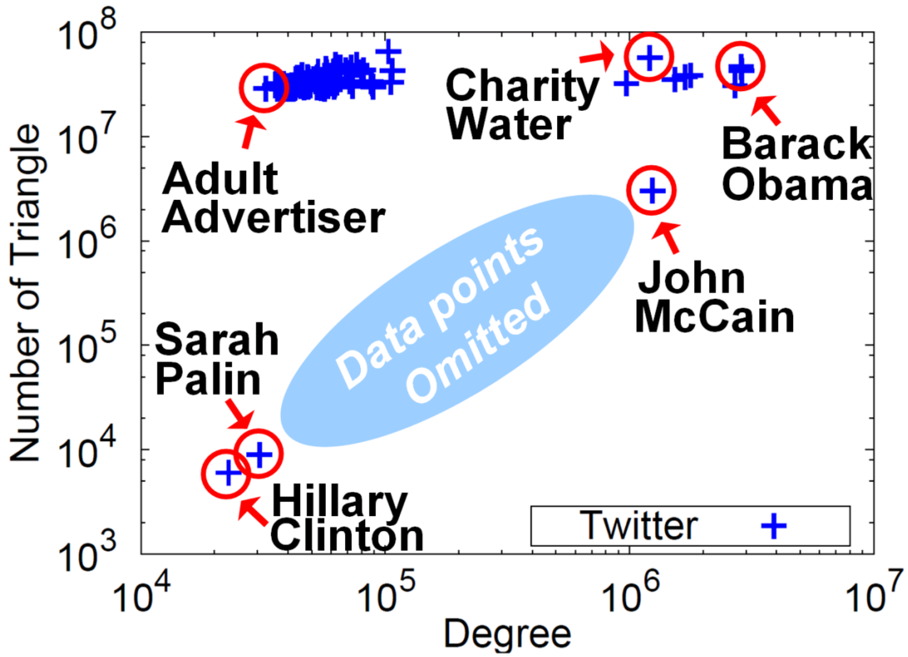
CONCLUSION#1 – Big data

- **Patterns**  **Anomalies**



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





CONCLUSION#2 – tensors

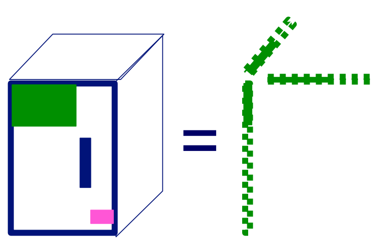
- powerful tool

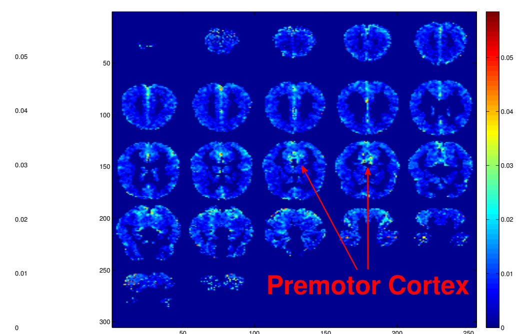
Nouns

glass
tomato
bell

Questions

can you pick it up?
can you hold it in one hand?
is it smaller than a golfball?'

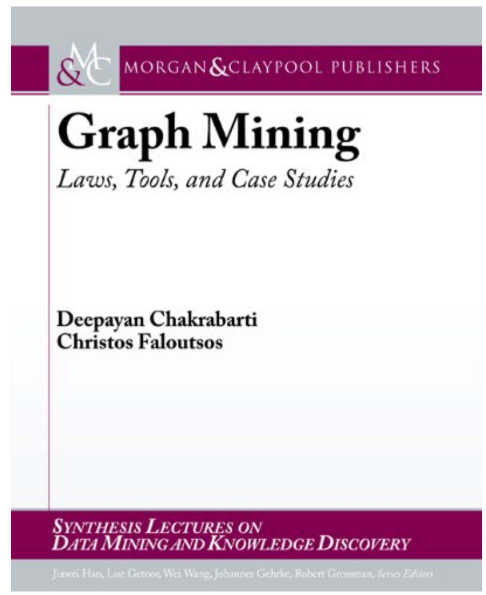




Group 3

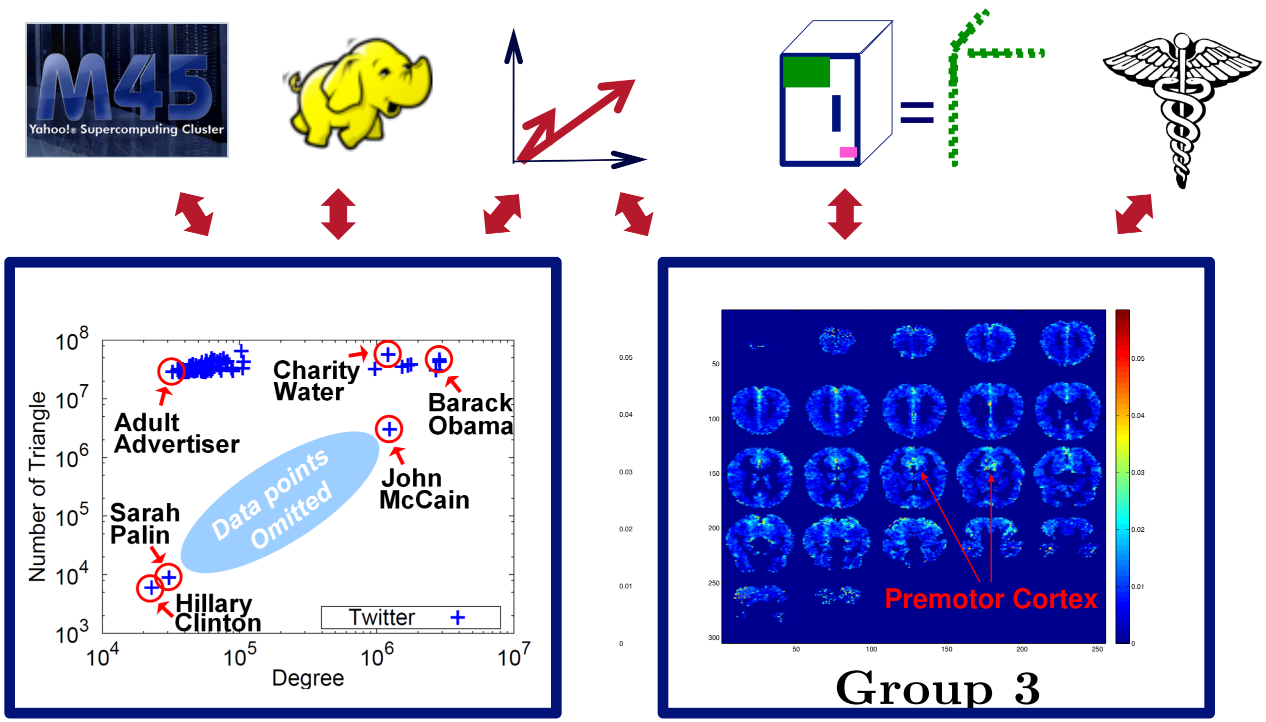
References

- 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



Carnegie Mellon

Thank you!

Cross-disciplinarity