Mining Large Graphs: Patterns, Anomalies, and Fraud Detection

Christos Faloutsos

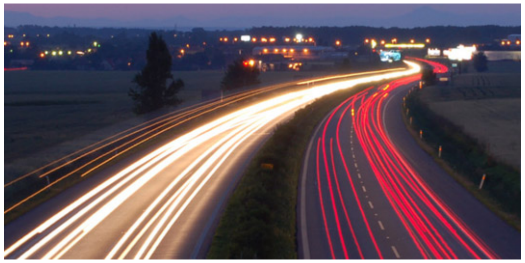
CMU

Thank you!

- Nina Balcan

- Kilian Weinberger

Roadmap



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

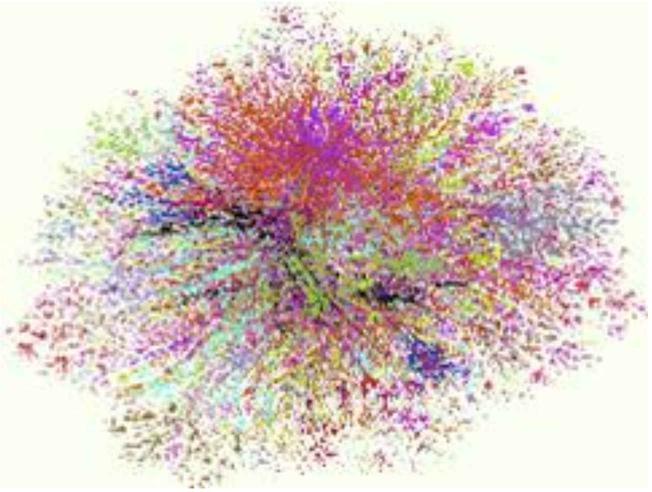
Graphs - why should we care?

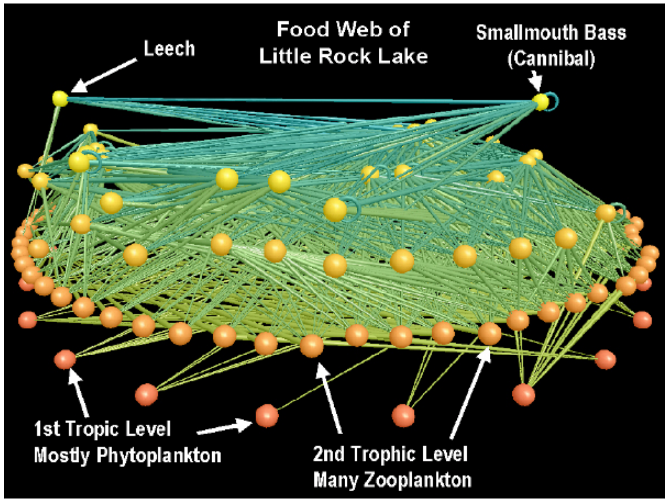
~1B nodes (web sites)
~6B edges (http links)
'YahooWeb graph'

Graphs - why should we care?

>$10B; ~1B users

Graphs - why should we care?





Internet Map
[lumeta.com]

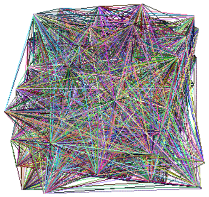
Food Web
[Martinez '91]

Graphs - why should we care?

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

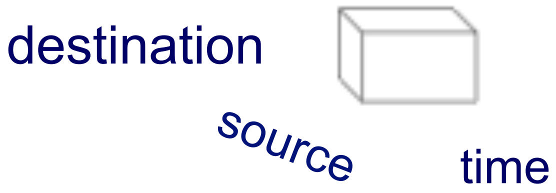
- Many-to-many db relationship -> graph

Motivating problems



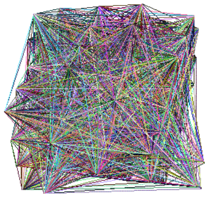
- P1: patterns? Fraud detection?

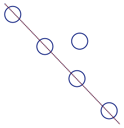
- P2: patterns in time-evolving graphs / tensors



Motivating problems

- P1: patterns? Fraud detection?





Patterns

anomalies

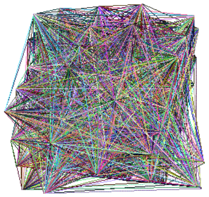
- P2: patterns in time-evolving graphs / tensors

destination

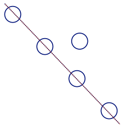
source

time

Motivating problems



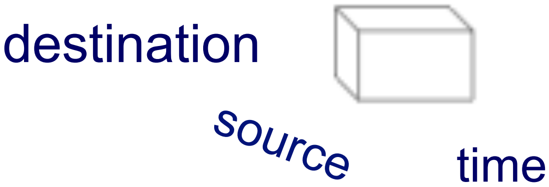
- P1: patterns? Fraud detection?



Patterns

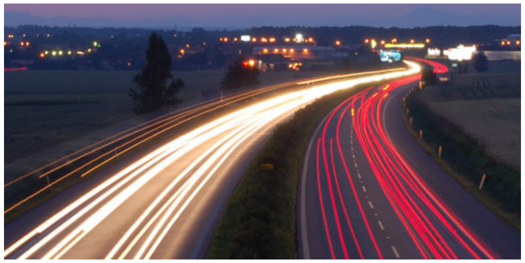
anomalies*

- P2: patterns in time-evolving graphs / tensors

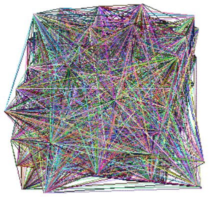


* *Robust Random Cut Forest Based Anomaly Detection on Streams* Sudipto Guha, Nina Mishra , Gourav Roy, Okke Schrijvers, ICML’16

Roadmap

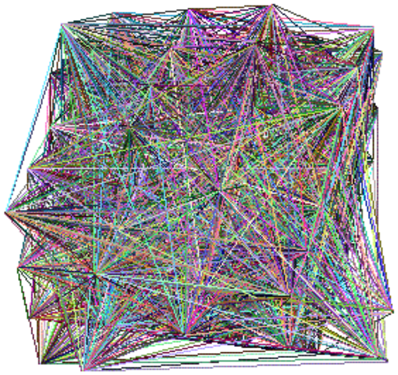


- Introduction – Motivation
  - – Why study (big) graphs?
- ➡ Part#1: Patterns & fraud detection
- Part#2: time-evolving graphs; tensors
- Conclusions



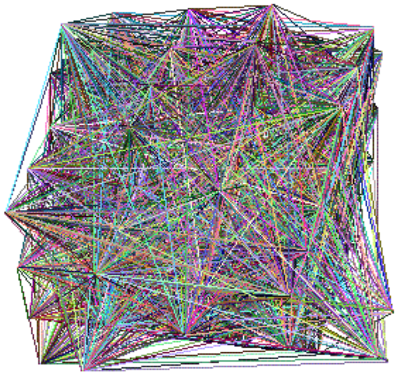
Part 1: Patterns, & fraud detection

Laws and patterns

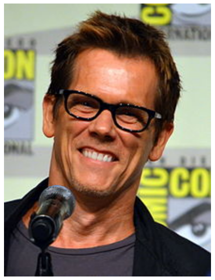


- Q1: Are real graphs random?

Laws and patterns



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



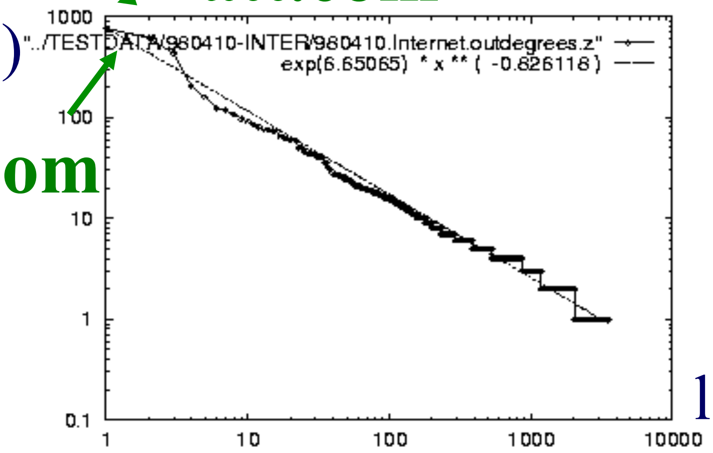
Solution# S.1

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

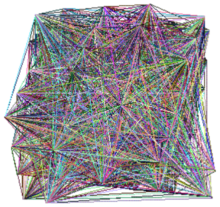
internet domains

att.com

log(degree)



ibm.com



log(rank)

Solution# S.1

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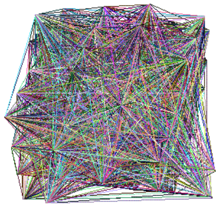
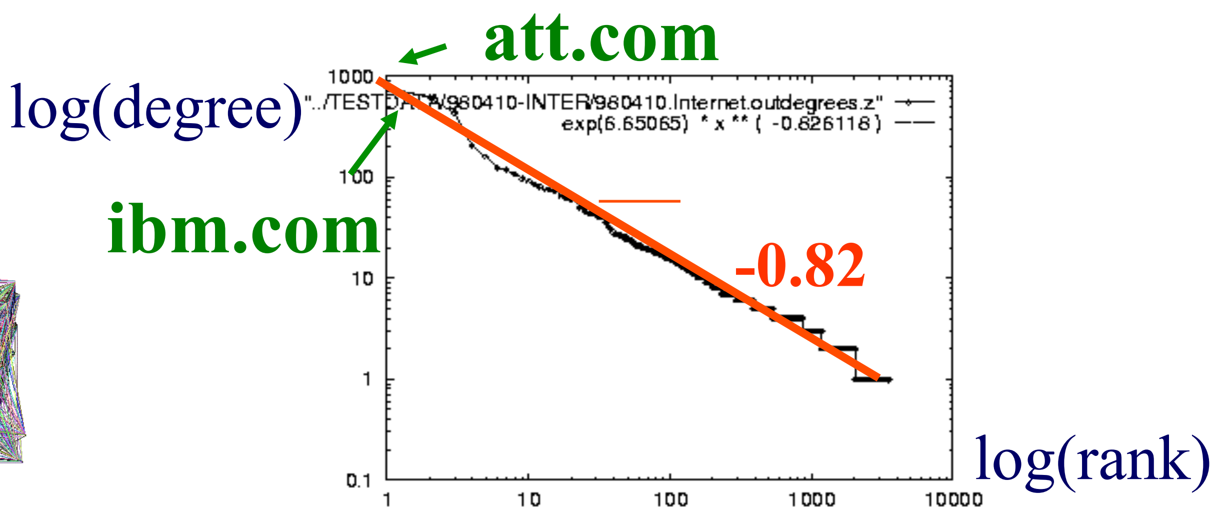
internet domains




att.com
log(degree)
ibm.com
"../TESTDATA/980410-INTER/980410.Internet.outdegrees.z"
exp(6.65065) * x ** (-0.626118)
-0.82
1000
100
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1
0.1
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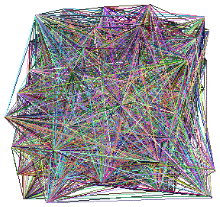
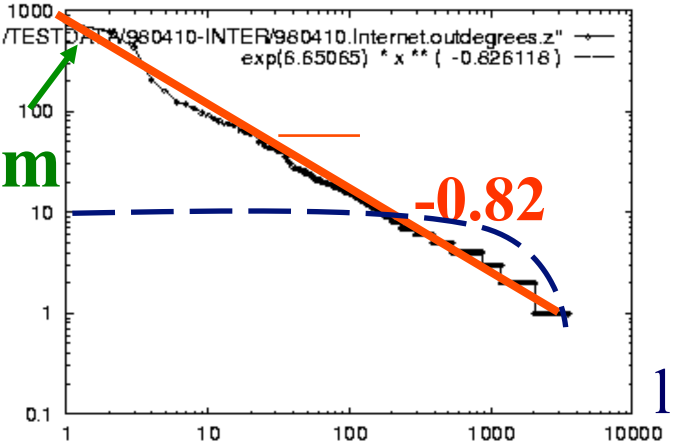
10
100
1000
10000
log(rank)

Solution# S.1

- Q: So what?

internet domains

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att.com

log(degree)

ibm.com

-0.82

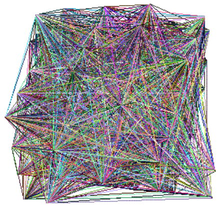
log(rank)

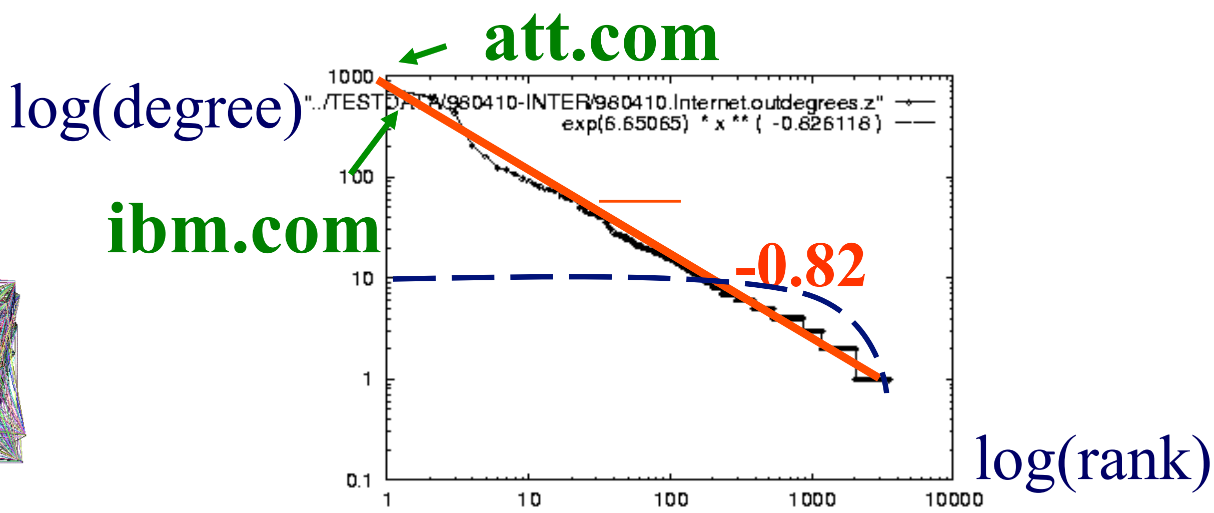
CarnegieMellon

Solution# S.1

- Q: So what?
- A1: # of two-step-away pairs: = friends of friends (F.O.F.)

internet domains

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exp(6.65065) * x ** (-0.826118)
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10
100
1000
10000

log(degree)

att.com

ibm.com

-0.82

log(rank)

Solution# S.1

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

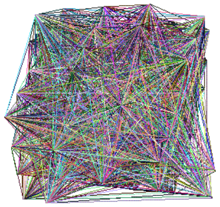
= friends of friends (F.O.F.)

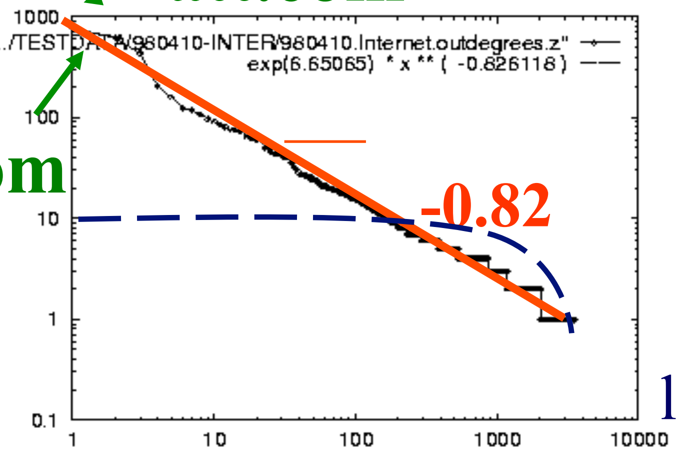
internet domains

att.com

log(degree)

ibm.com

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1000
100
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10000

-0.82

log(rank)

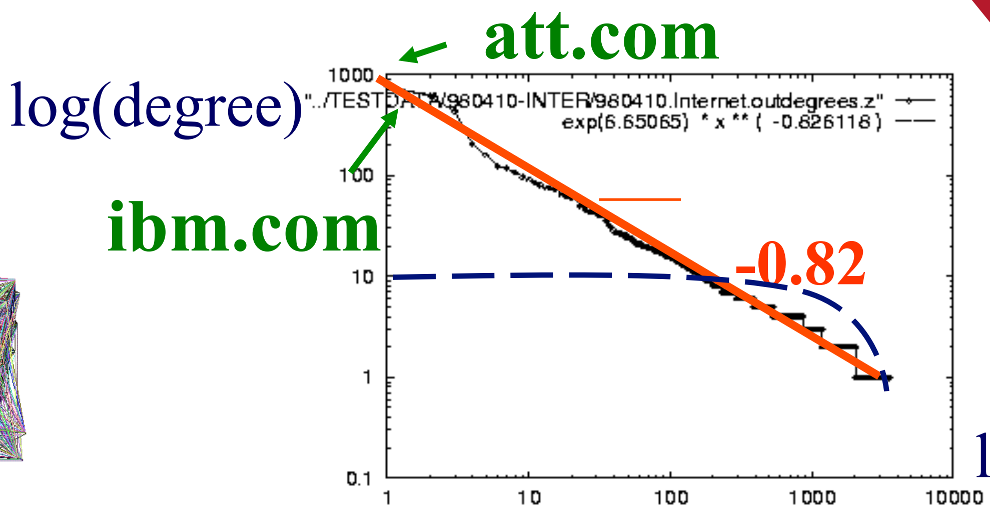
Carnegie Mellon

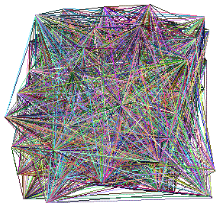
Solution# S.1

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

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

internet domains





Gaussian trap

Solution# S.1

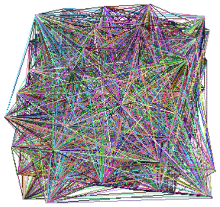
- Q: So what?
- A1: # of two-step-away pairs: O(d_max ^2) ~ 10M^2

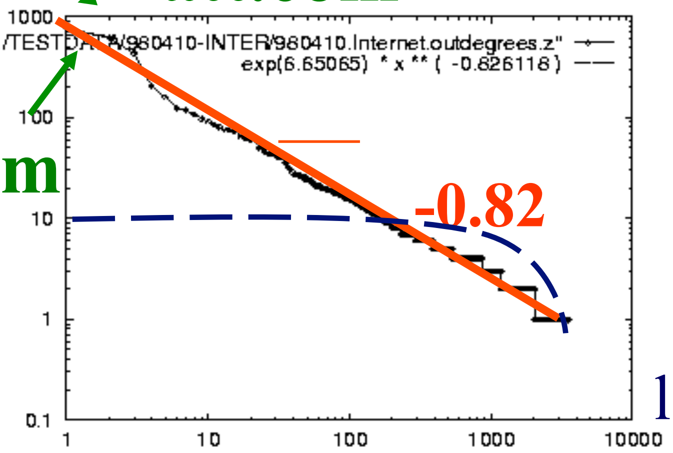
= friends of friends (F.O.F.)

⇩

~0.8PB ->
a data center(!)

internet domains

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DCO @ CMU

Gaussian trap

Solution# S.1

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

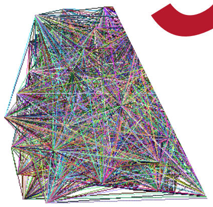
inte

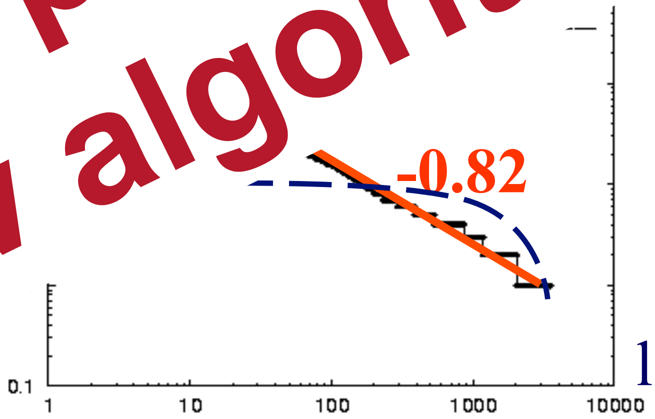
Such patterns ->
New algorithms

⇩

~0.8PB ->
a data center(!)

1





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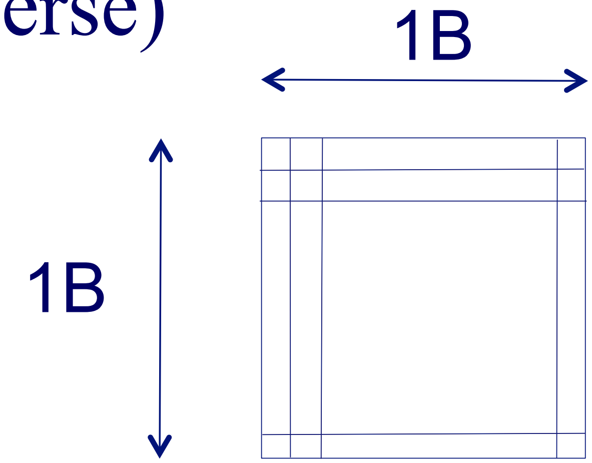
Observation – big-data:

- O(N^2) algorithms are ~intractable - N=1B

- N^2 seconds = 31B years (>2x age of universe)

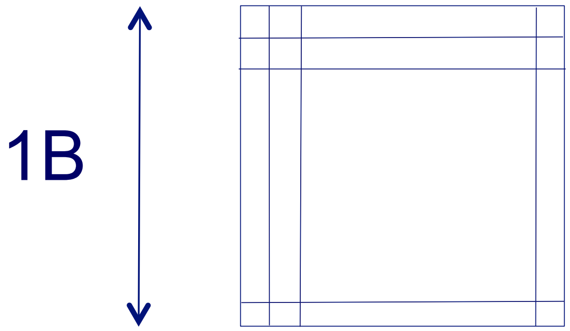


Observation – big-data:

- O(N^2) algorithms are ~intractable - N=1B

31M

- N^2 seconds = 31B years
- 1,000 machines

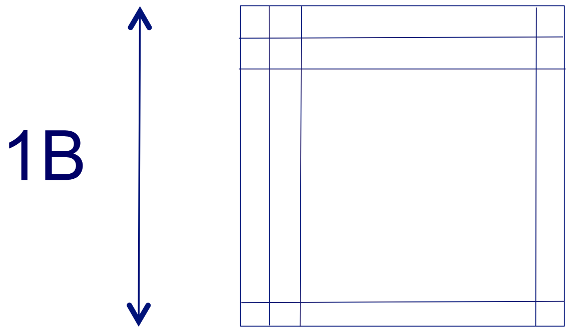


Observation – big-data:

- O(N^2) algorithms are ~intractable - N=1B

31K

- N^2 seconds = 31B years
- 1M machines



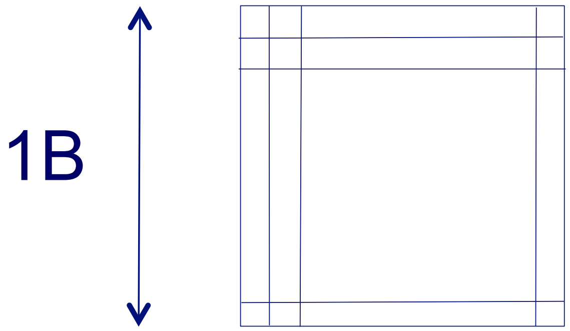
Google Y!

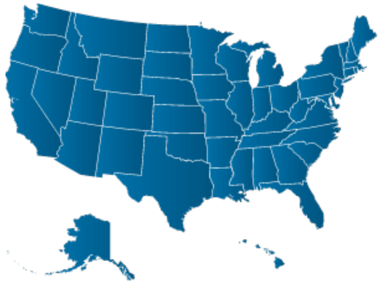
Observation – big-data:

- O(N^2) algorithms are ~intractable - N=1B

3

- N^2 seconds = 31B years
- 10B machines ~ $10Trillion





Observation – big-data:

- O(N^2) algorithms are ~intractable - N=1B

And parallelism might not help

3

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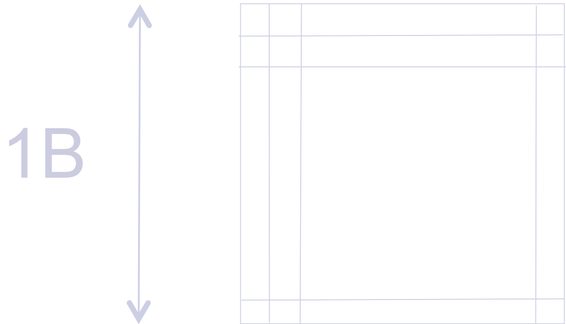
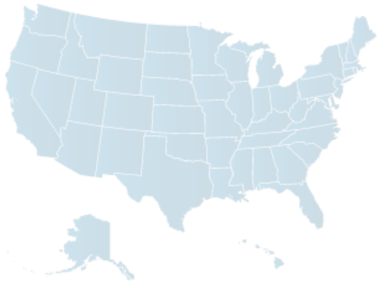
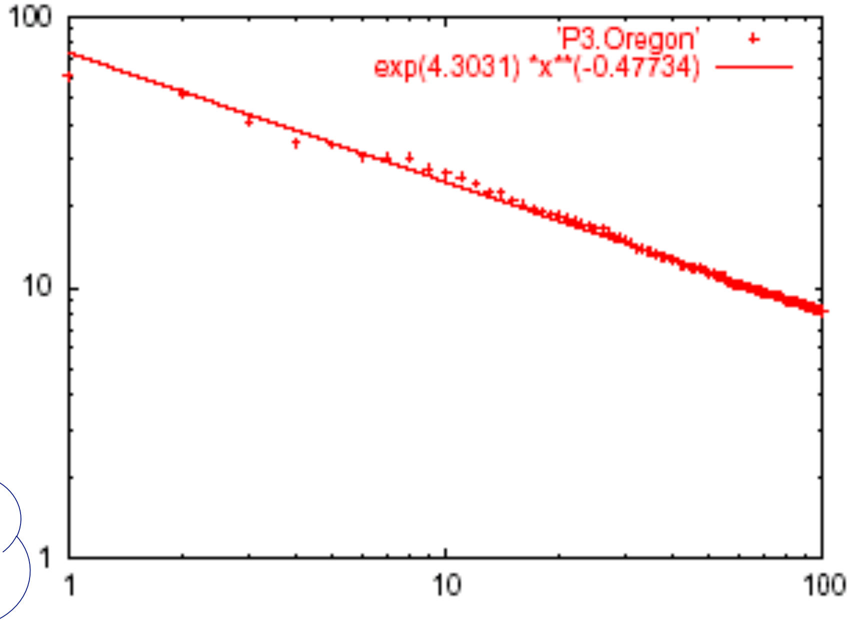




Solution# S.2: Eigen Exponent *E*



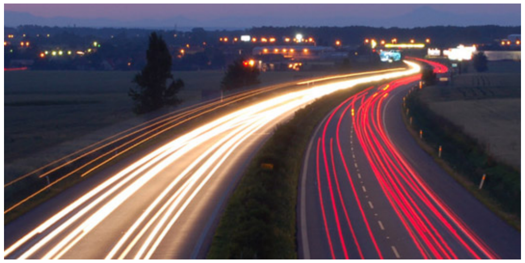
Exponent = slope

E = -0.48

A x = λ x

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

Roadmap



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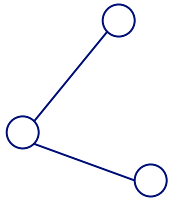
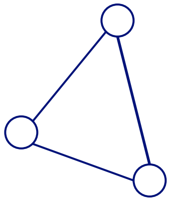
Solution# S.3: Triangle 'Laws'

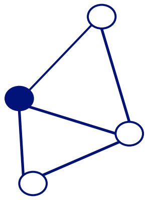


- Real social networks have a lot of triangles

Solution# S.3: Triangle ‘Laws’



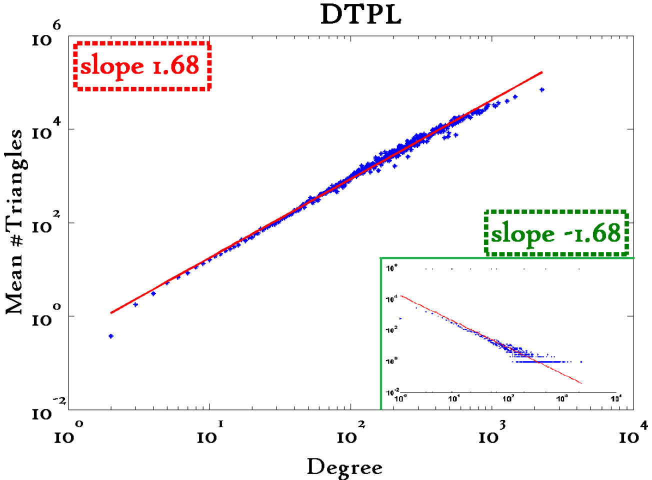
- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?
  - 2x the friends, 2x the triangles ?



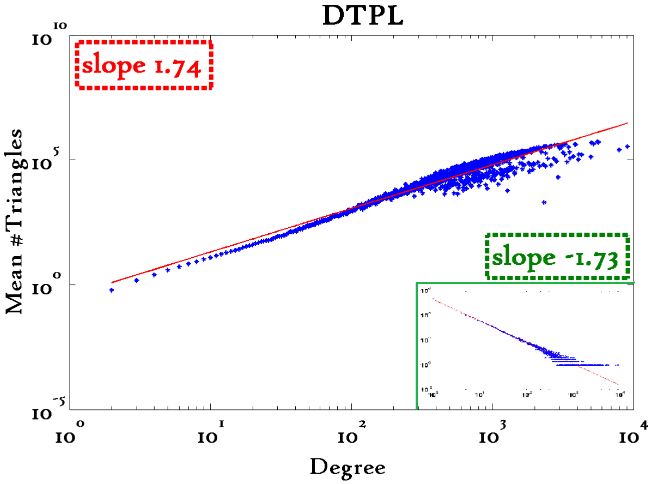
Triangle Law: #S.3

[Tsourakakis ICDM 2008]

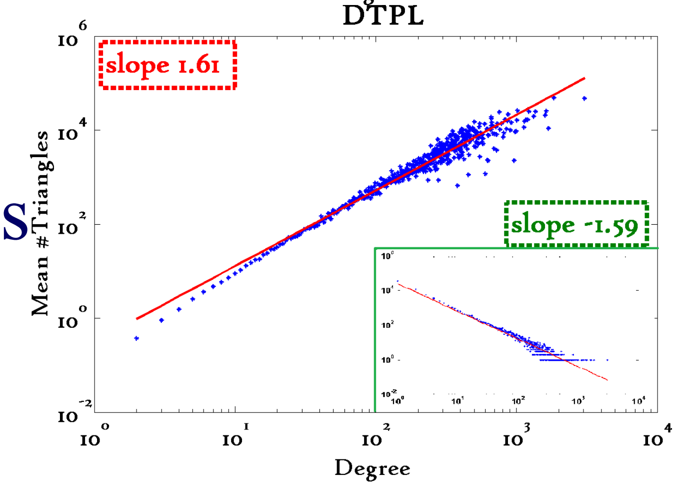
Reuters

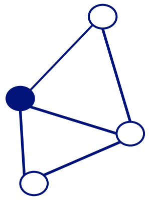


SN



Epinions





X-axis: degree

Y-axis: mean # triangles

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

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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!

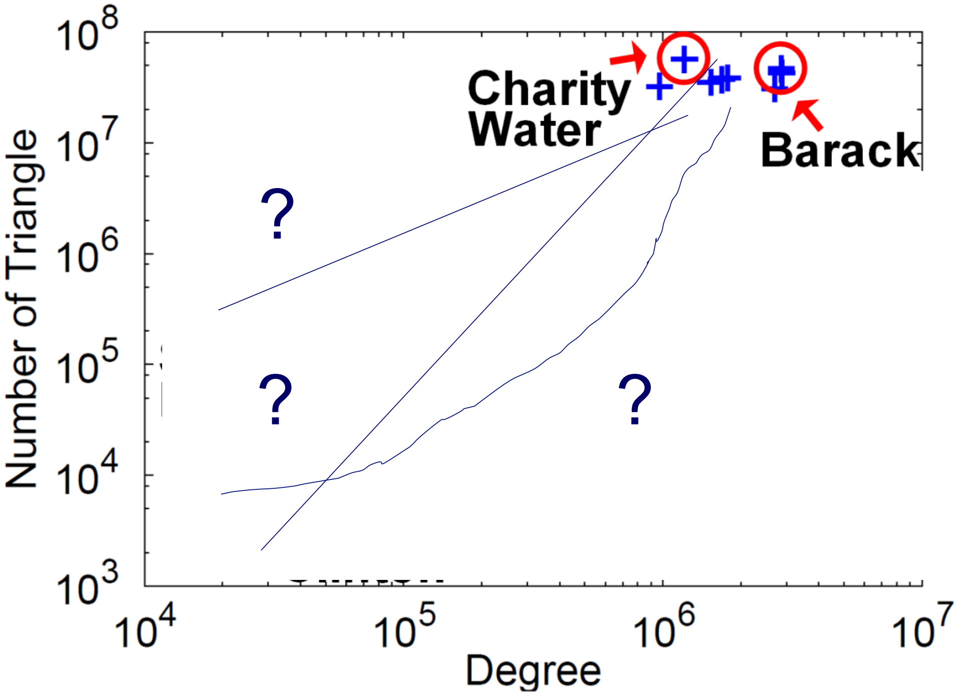
#triangles = 1/6 Sum (λ_i^3)

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

(and, because of skewness (S2) ,

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

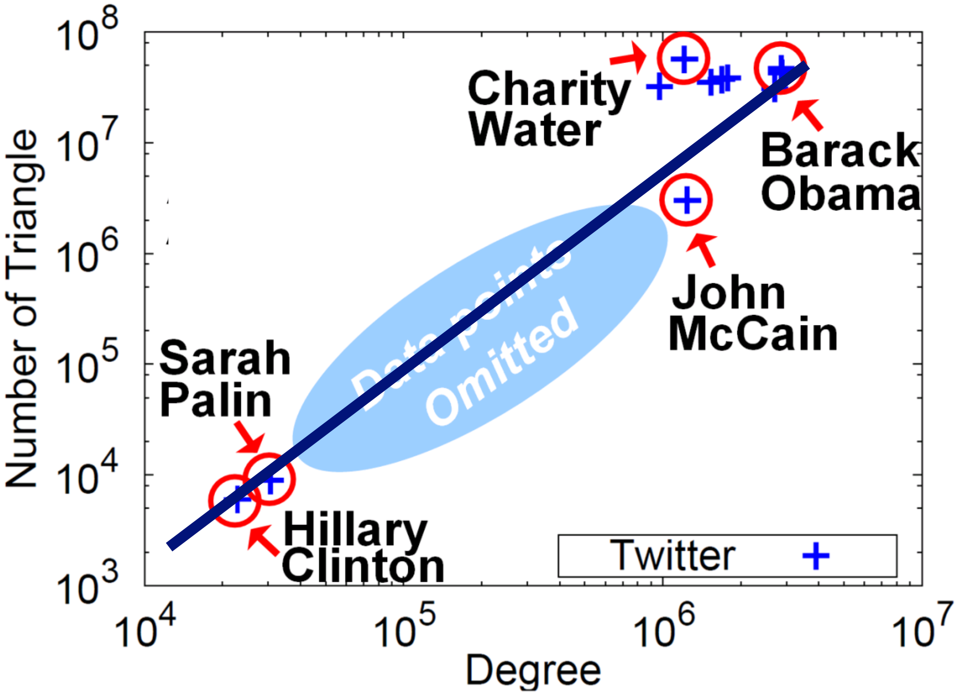
Triangle counting for large graphs?



Anomalous nodes in Twitter(~ 3 billion edges)

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

Triangle counting for large graphs?



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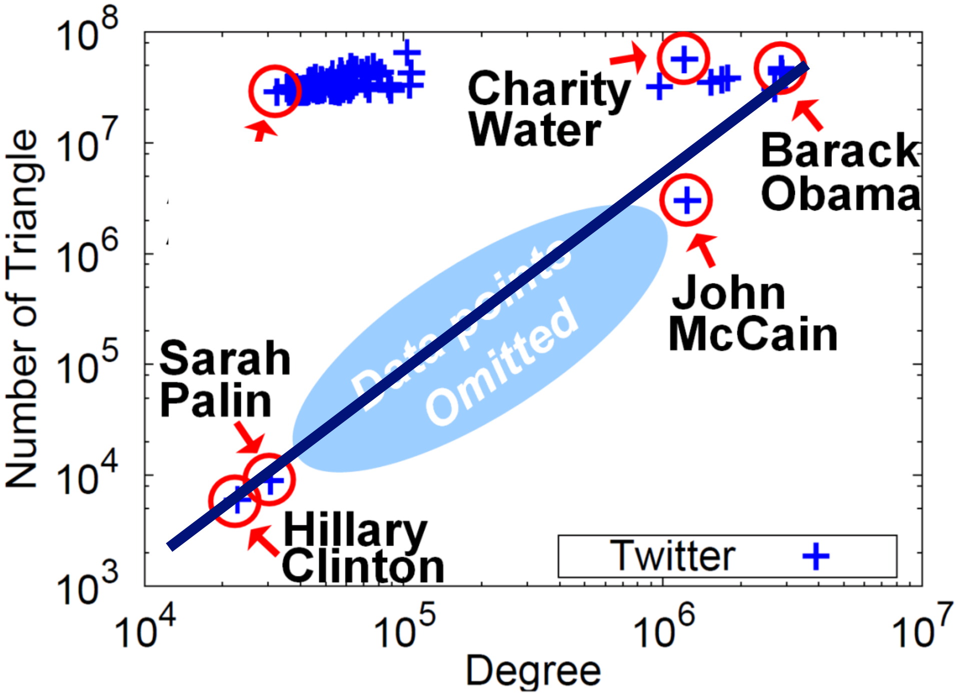

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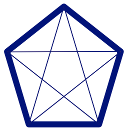

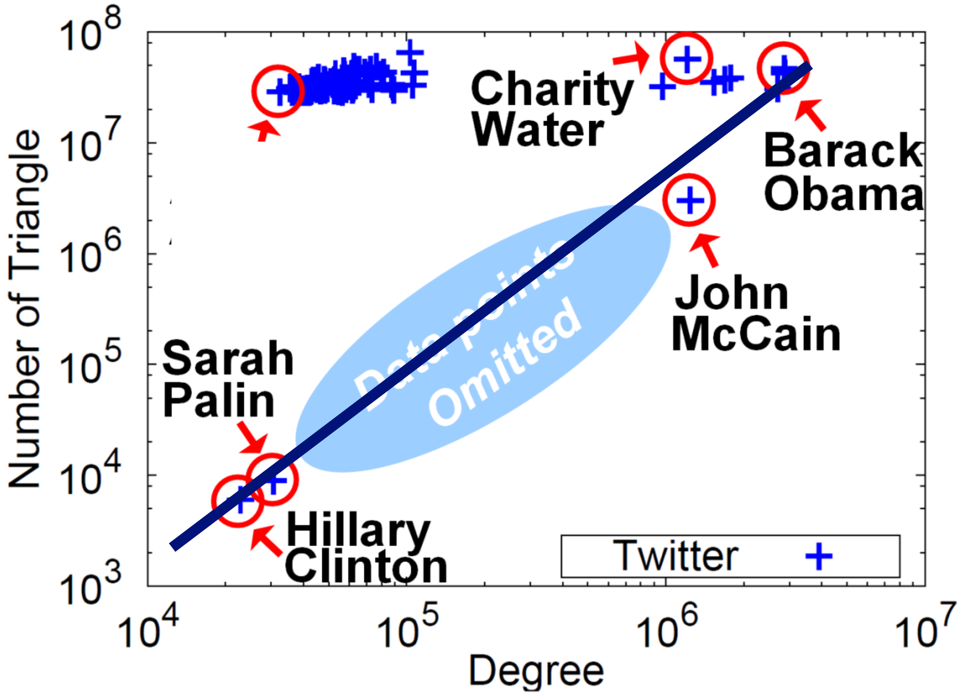

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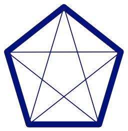

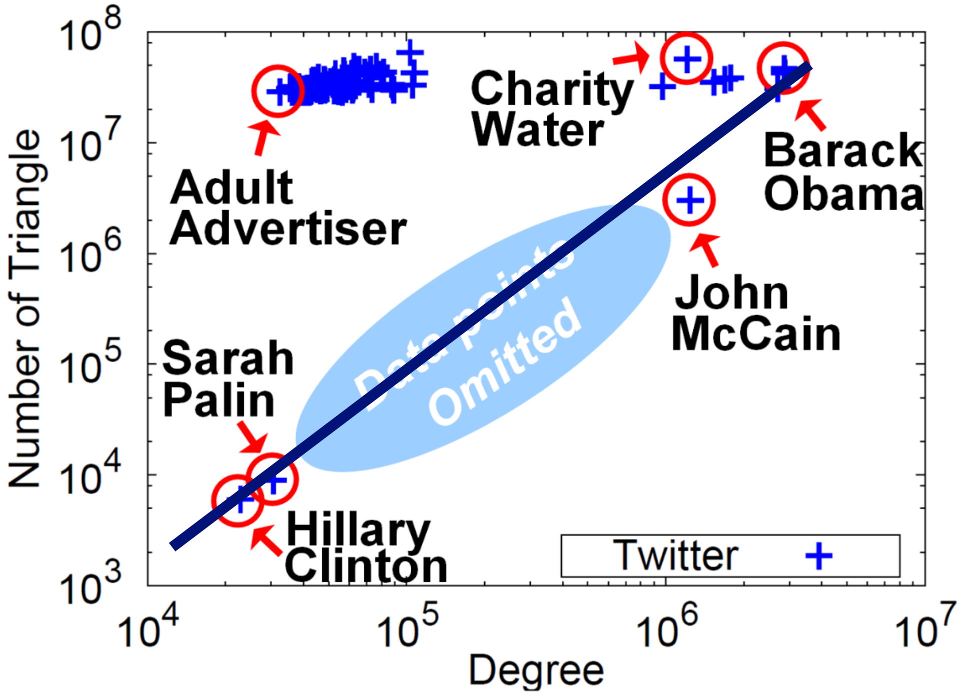

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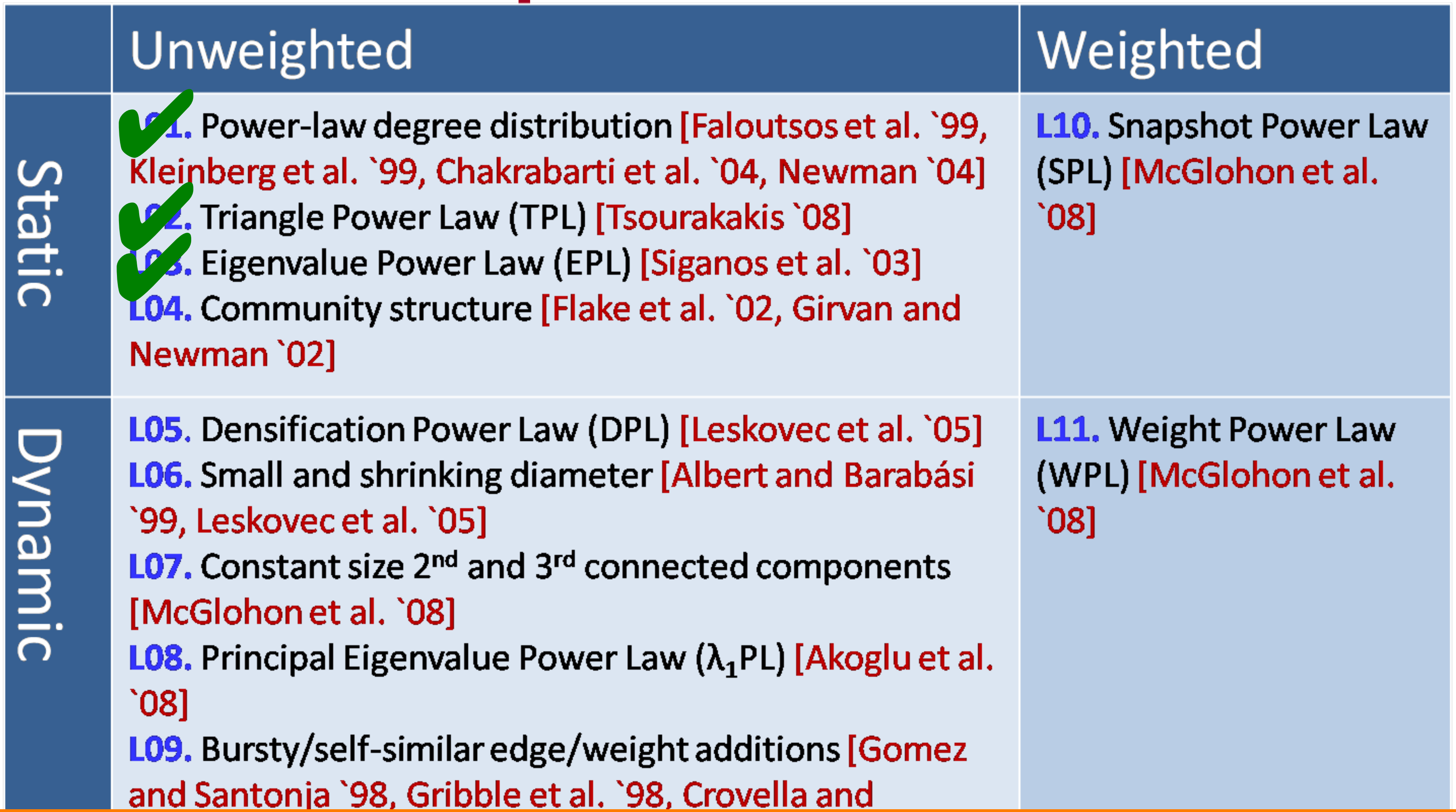
[U Kang, Brendan Meeder, +, PAKDD'11]

MORE Graph Patterns

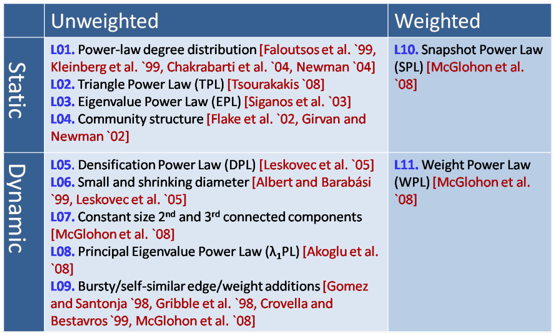


	Unweighted	Weighted
Static	✓L01. Power-law degree distribution [Faloutsos et al. `99, Kleinberg et al. `99, Chakrabarti et al. `04, Newman `04] ✓L02. Triangle Power Law (TPL) [Tsourakakis `08] ✓L03. Eigenvalue Power Law (EPL) [Siganos et al. `03] L04. Community structure [Flake et al. `02, Girvan and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

Carnegie Mellon

MORE Graph Patterns



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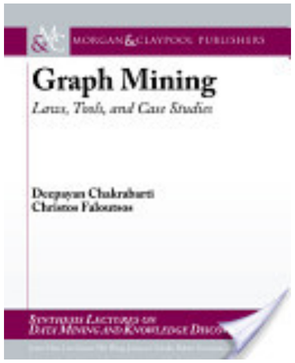
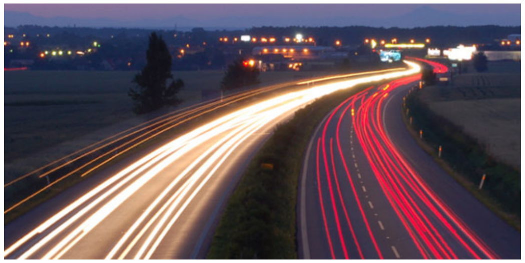
- Mary McGlohon, Leman Akoglu, Christos Faloutsos. *Statistical Properties of Social Networks.* in "Social Network Data Analytics” (Ed.: Charu Aggarwal)

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


MORGAN & CLAYPOOL PUBLISHERS
Graph Mining
Laws, Tools, and Case Studies
Deepayan Chakrabarti
Christos Faloutsos
SYNTHESIS LECTURES ON DATA MINING AND KNOWLEDGE DISCO

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

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

Patterns anomalies

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.*

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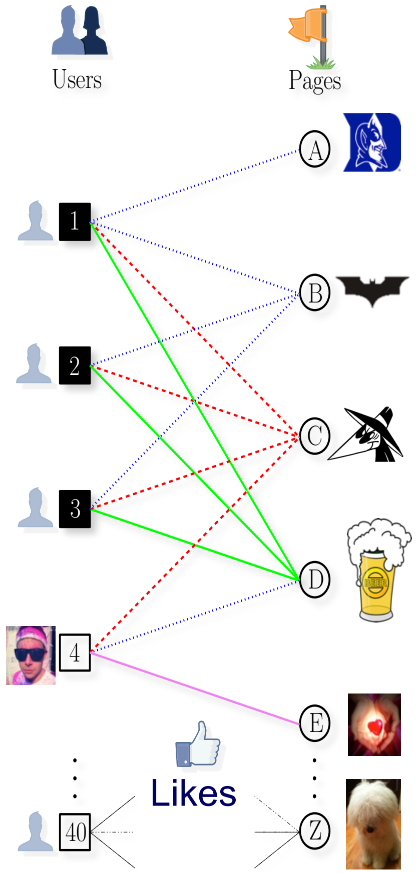
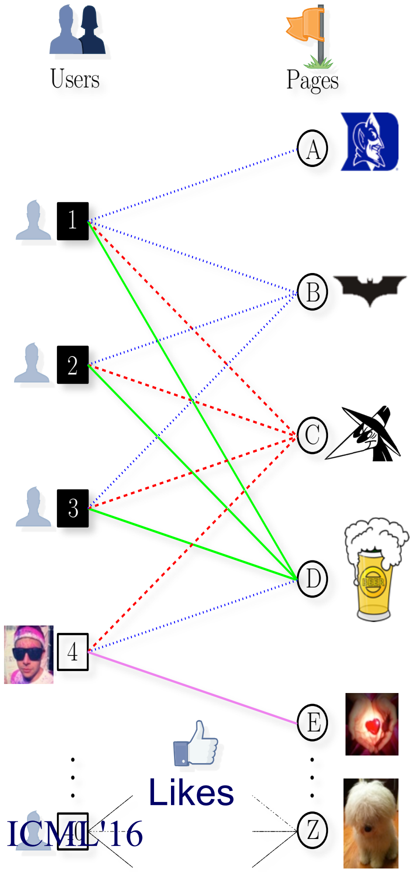


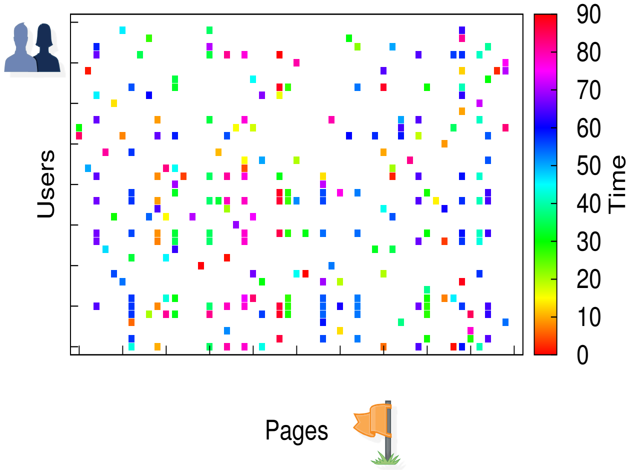
CopyCatch: Stopping Group Attacks by Spotting Lockstep Behavior in Social Networks, Alex Beutel, Wanhong Xu, Venkatesan Guruswami, Christopher Palow, Christos Faloutsos *WWW, 2013.*

Graph Patterns and Lockstep Behavior

Our intuition

- Lockstep behavior: Same Likes, same time





Graph Patterns and Lockstep Behavior

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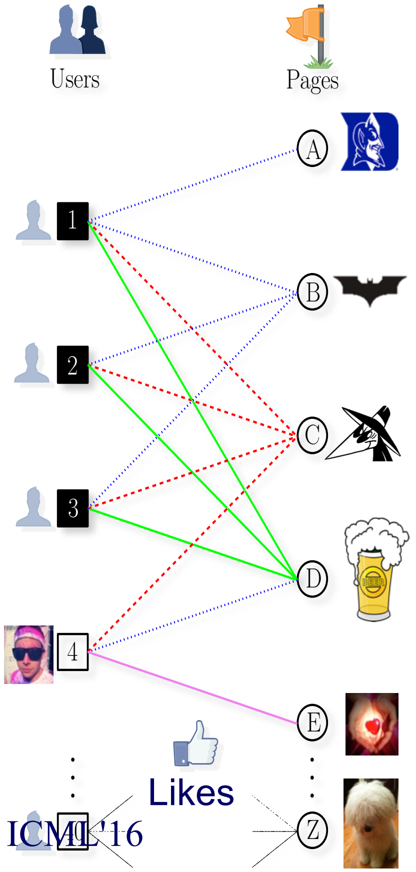

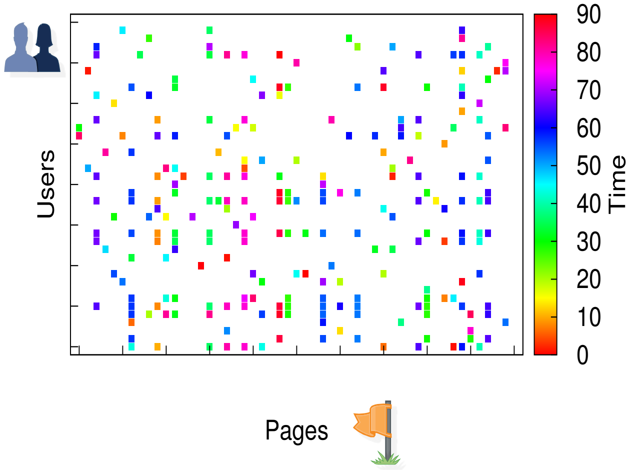

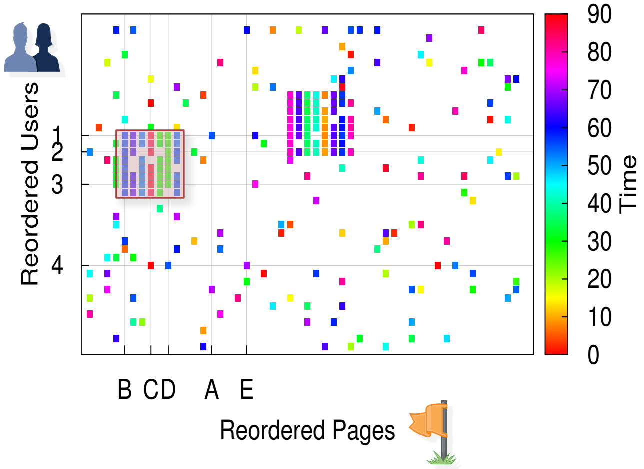

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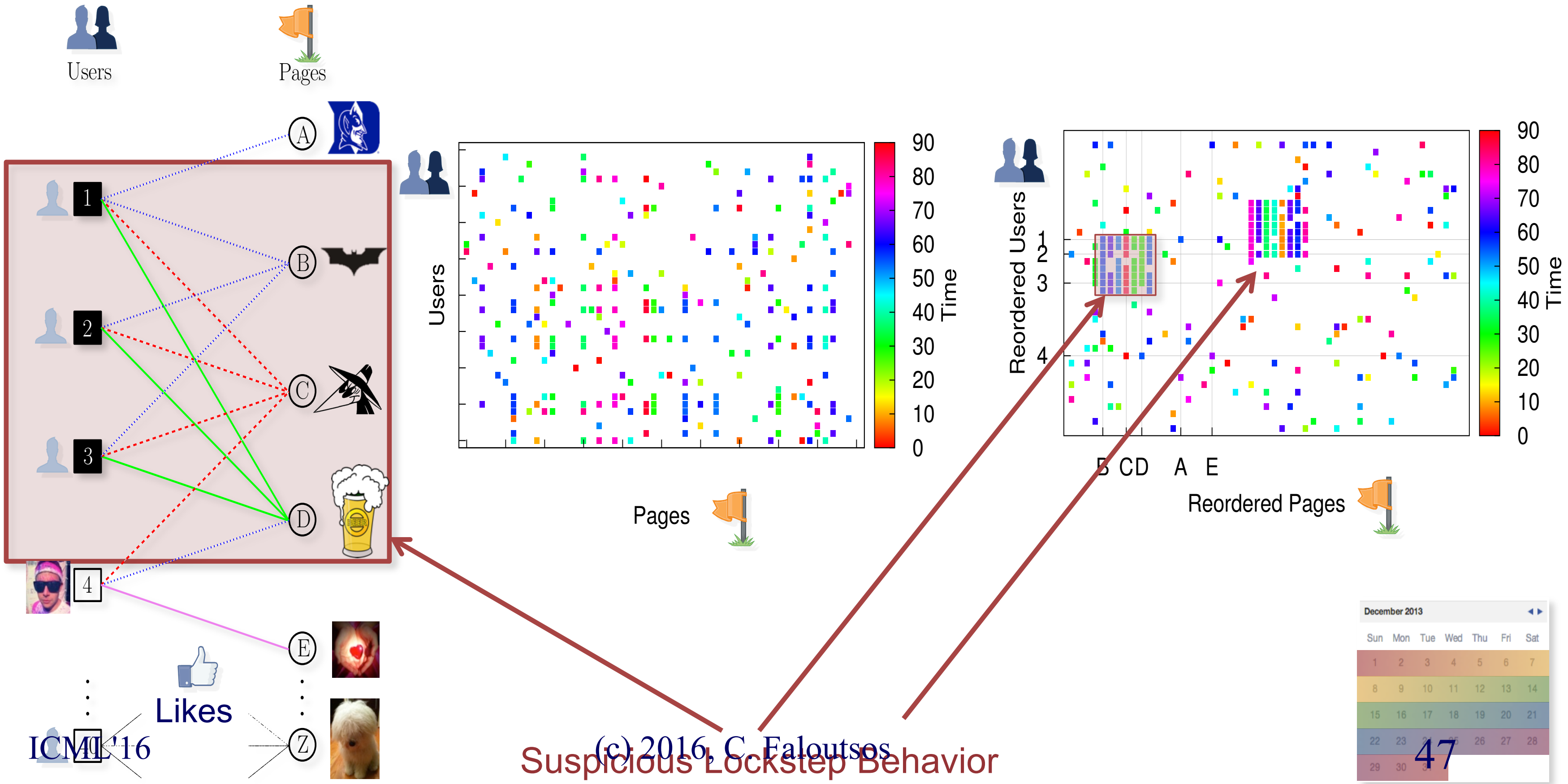
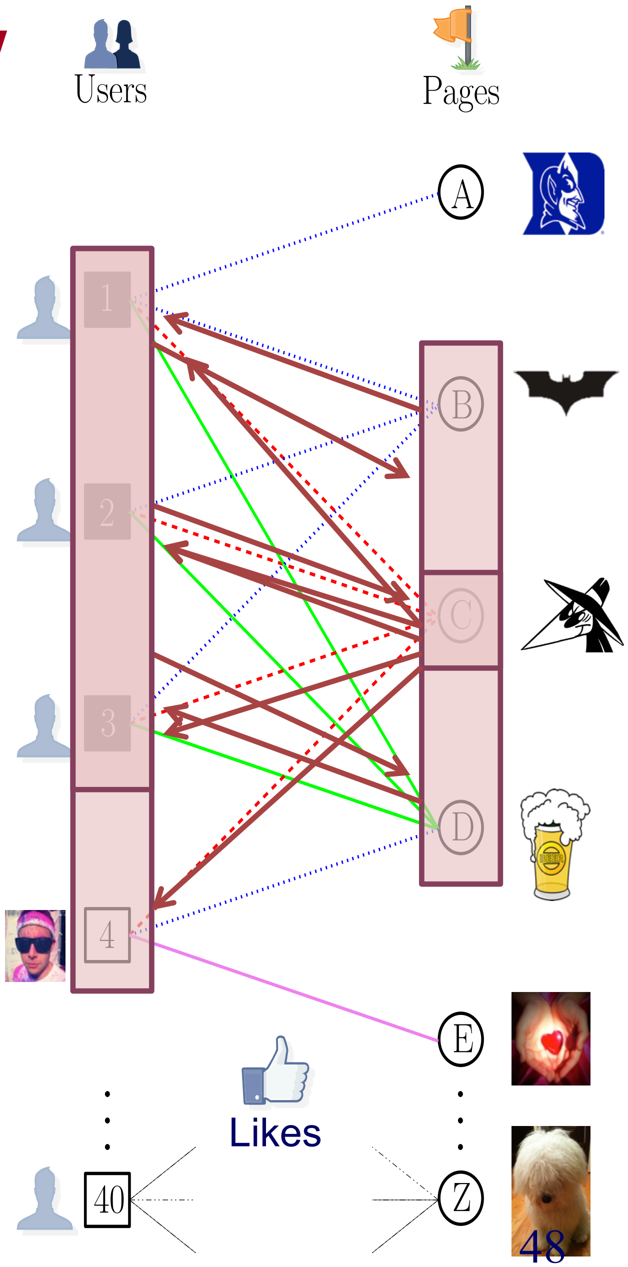


Suspicious Lockstep Behavior

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



December 2013

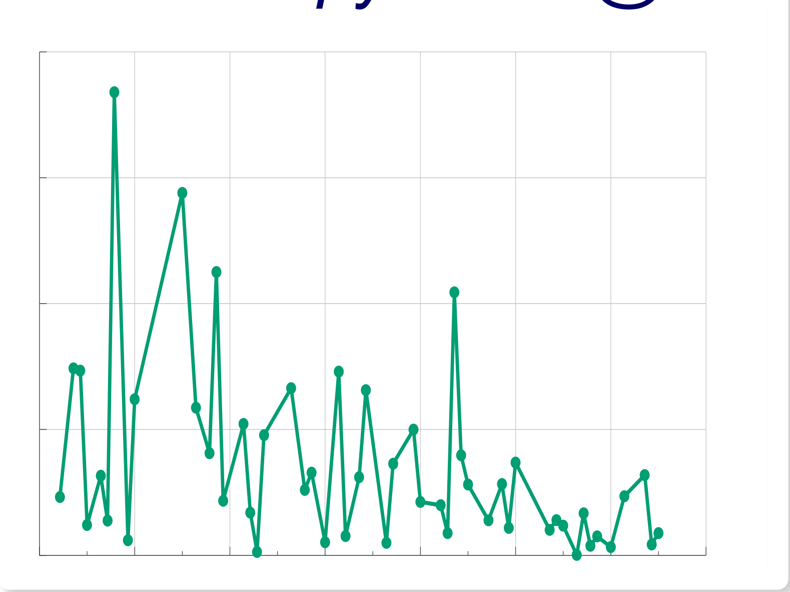
Sun	Mon	Tue	Wed	Thu	Fri	Sat
1	2	3	4	5	6	7
8	9	10	11	12	13	14
15	16	17	18	19	20	21
22	23	24	25	26	27	28
29	30	31				

Deployment at Facebook

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

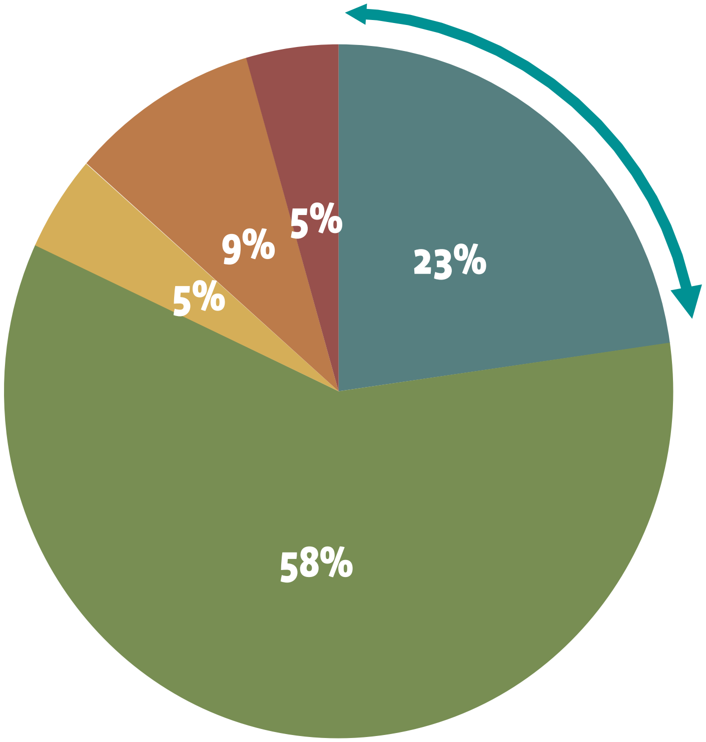
3 months of *CopyCatch* @ Facebook

#users caught



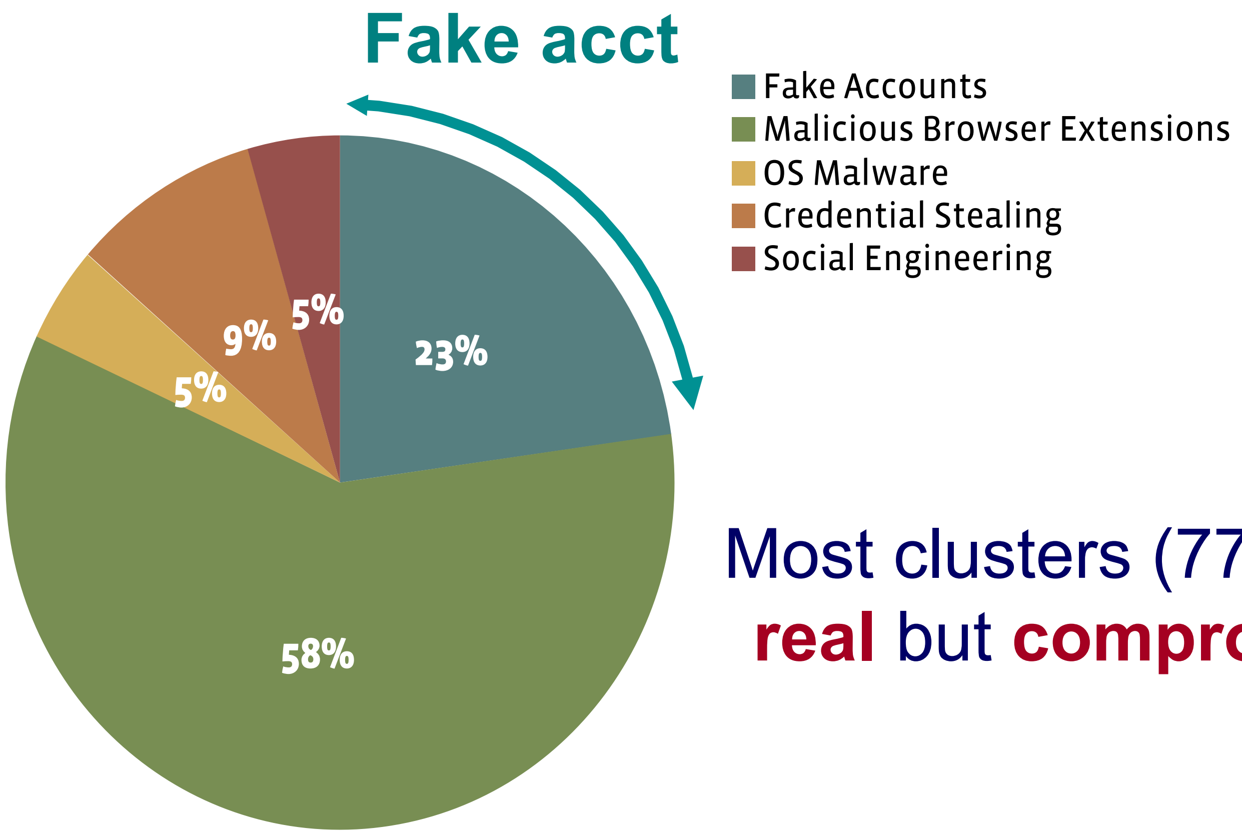
time

Deployment at Facebook



Manually labeled 22 randomly selected *clusters* from February 2013

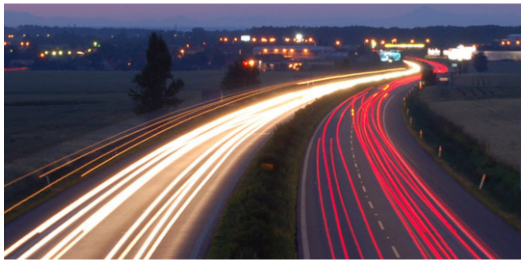
Deployment at Facebook



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

Manually labeled 22 randomly selected *clusters* from February 2013

Roadmap



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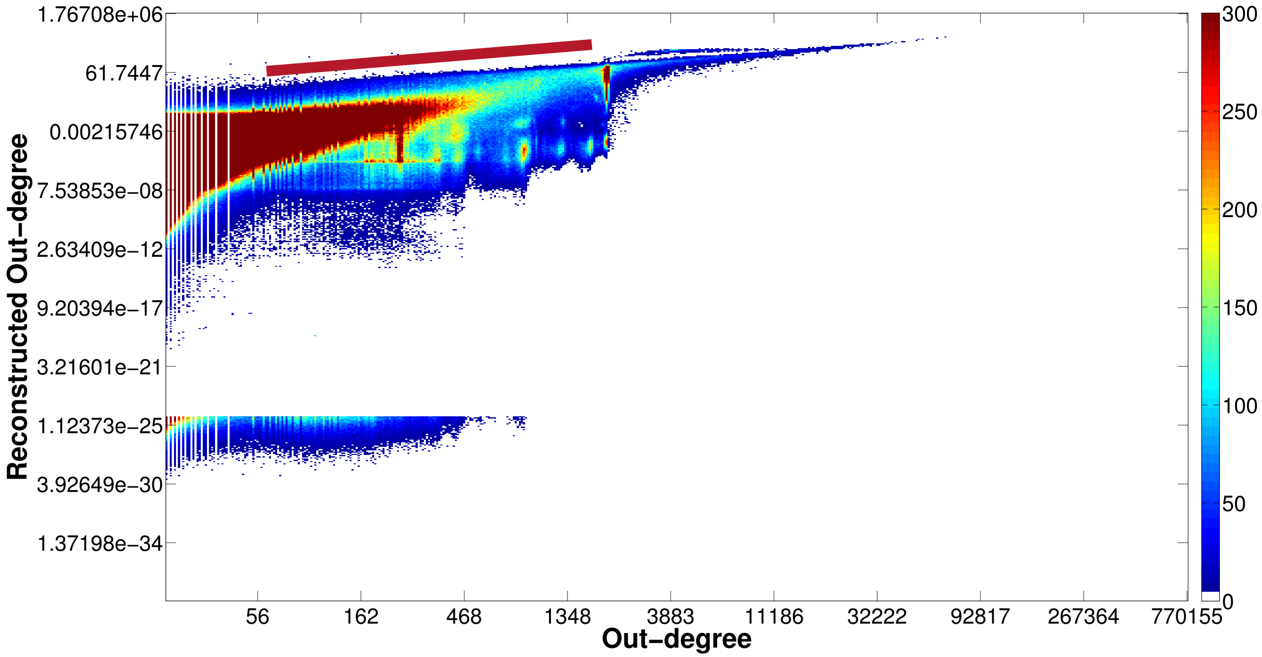
Problem: Social Network Link Fraud

Target: find "stealthy" attackers missed by other algorithms

Clique

41.7M nodes
1.5B edges

Bipartite
core



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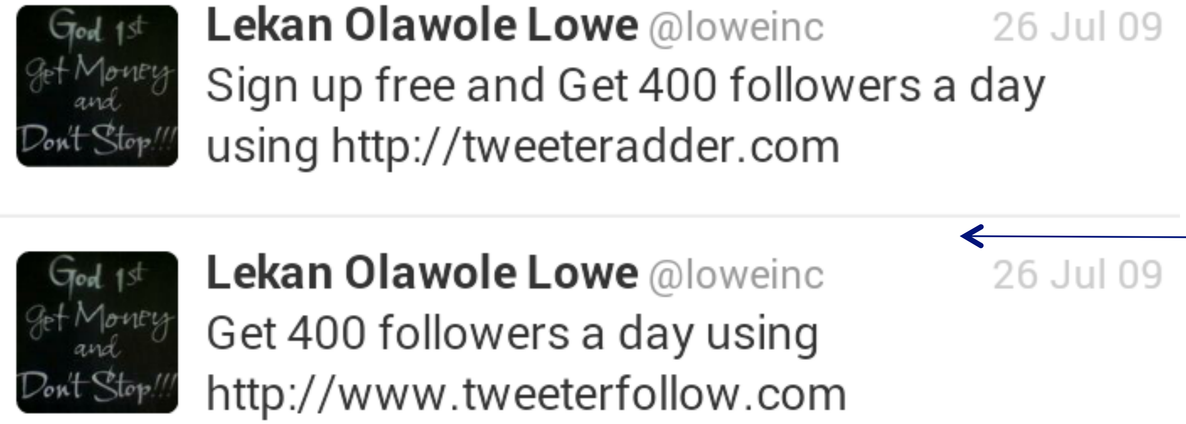
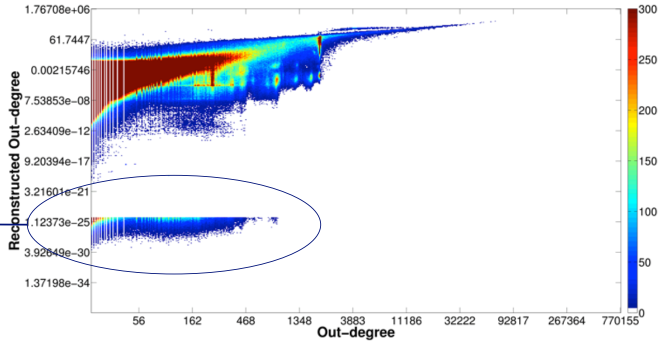


Lekan Olawole Lowe @loweinc 26 Jul 09

Sign up free and Get 400 followers a day using http://tweeteradder.com

Lekan Olawole Lowe @loweinc 26 Jul 09

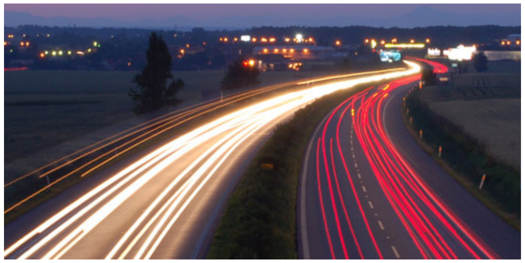
Get 400 followers a day using http://www.tweeterfollow.com



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.

Roadmap



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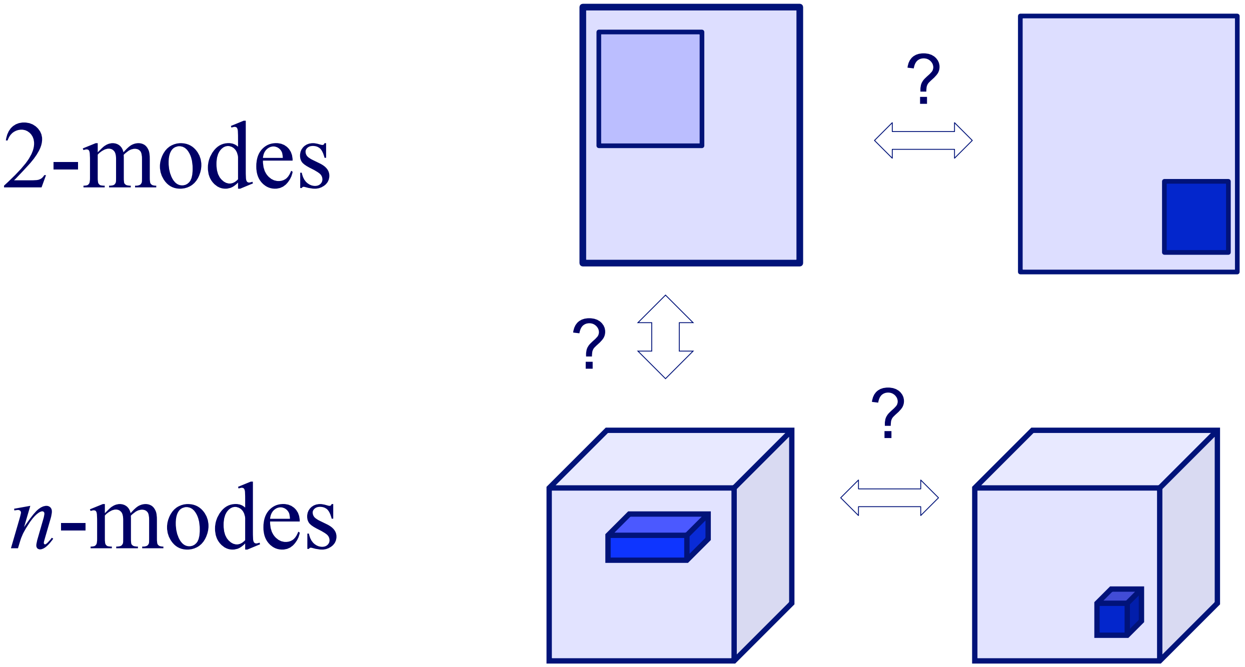
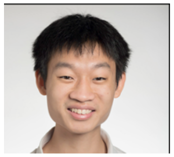
Suspicious Patterns in Event Data





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.

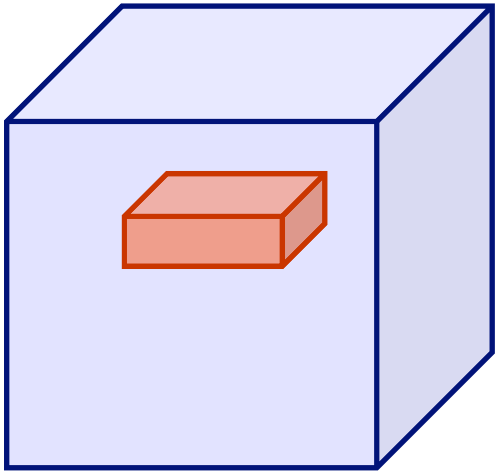
Suspicious Patterns in Event Data

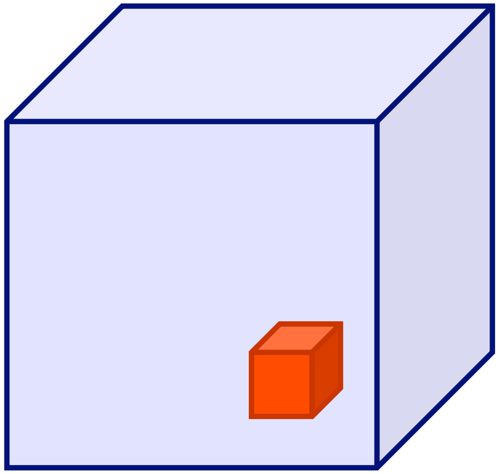
Which is more suspicious?

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

vs.

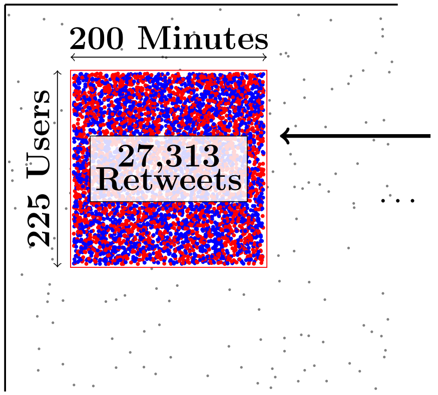
225 Users
Retweeting same 1 tweet
15 times each
All in 3 hours
All from 2 IP addresses





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

Suspicious Patterns in Event Data



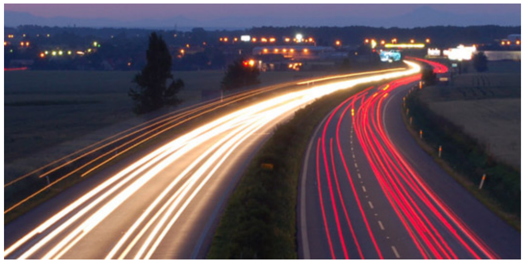
	10:09	10:14	10:19	10:24	10:32	10:37	11:04	15:37	21:13
"John123"	●		✚	✚		●	●	●	
"Joe456"	●	✚	●	✚	✚		✚	✚	
"Job789"	●	✚	●	✚	●		●	●	
"Jack135"	✚	●	✚	✚	✚		●	✚	●
"Jill246"	✚	●	●	●				✚	
"Jane314"	✚	✚	●	●		●		●	●
"Jay357"	●		●	●	●	✚		●	

. . .

Retweeting: "Galaxy Note Dream Project: Happy Happy Life Traveling the World"

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

Roadmap



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Carnegie Mellon

Problem dfn:

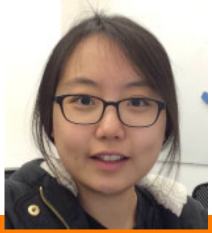
e.g.

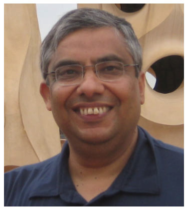
	ears	fins	stripes	lungs	gills	carnivore	...
salmon		●			●		
tiger	●		●	●		v ●	
jaguar	●			●		●	
tuna		●			●		
lion	●			●		●	
⋮							

	ears	lungs	carnivore	stripes	fins	gills	...
lion	●	●	●				
tiger	●	●	●	●			
jaguar	●	●	●				
tuna					●	●	
salmon					●	●	
⋮							

Problem definition

- **Given** a large binary matrix of facts of *(object, property)* pairs
- **Find** *groupings* of the facts and the *order* of transmission
- To **optimize** 'student effort' (**->** incremental learning curve, '*ALOC'*)





Bryan Hooi, Hyun Ah Song, et al, "*Matrices, Compression, Learning Curves: Formulation, and the GroupNTeach Algorithms*", PAKDD 2016 *is for student learning, and how do*

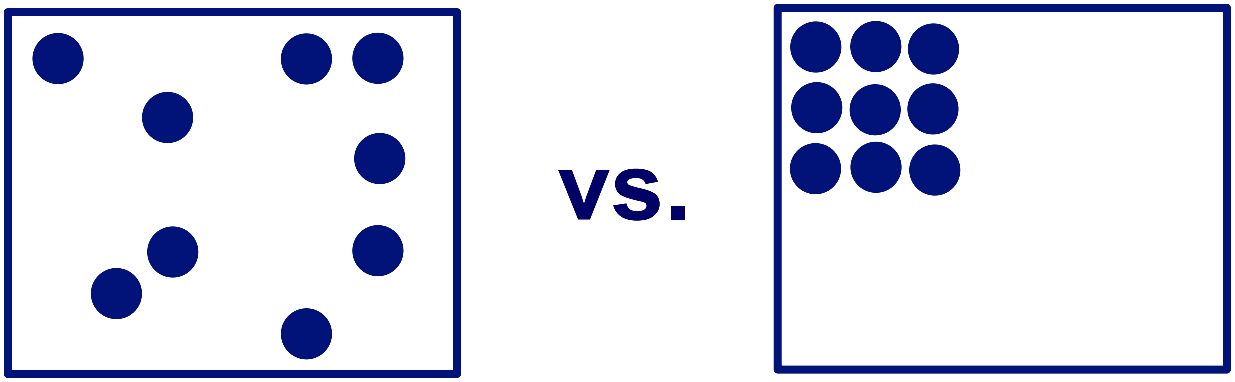
Details:

Given a large binary matrix of objects and properties, re-order rows and columns,

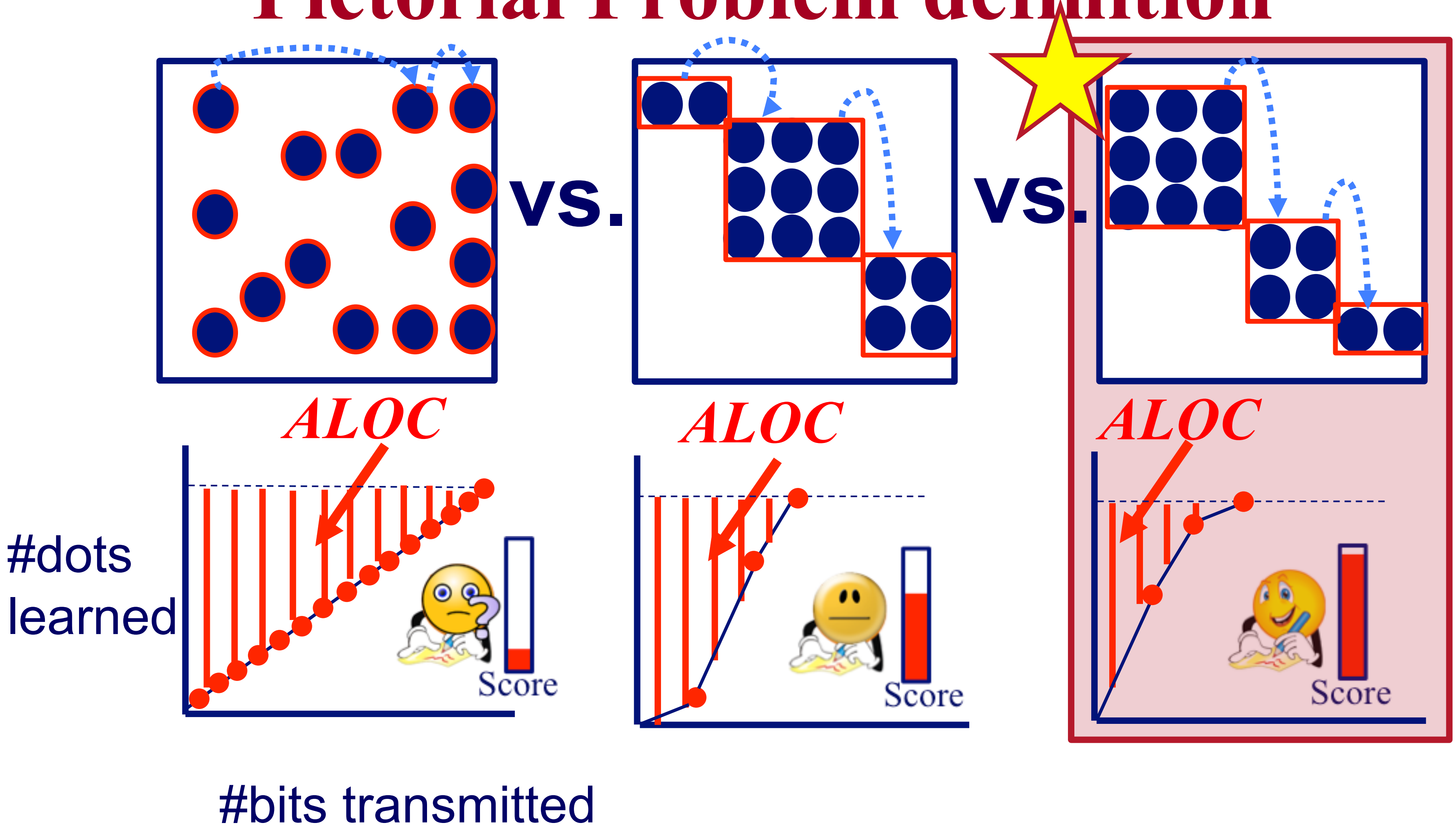
***G1. Metric** for better encoding of matrix for student learning?*

***G2**. How do we construct **language** to describe it?*

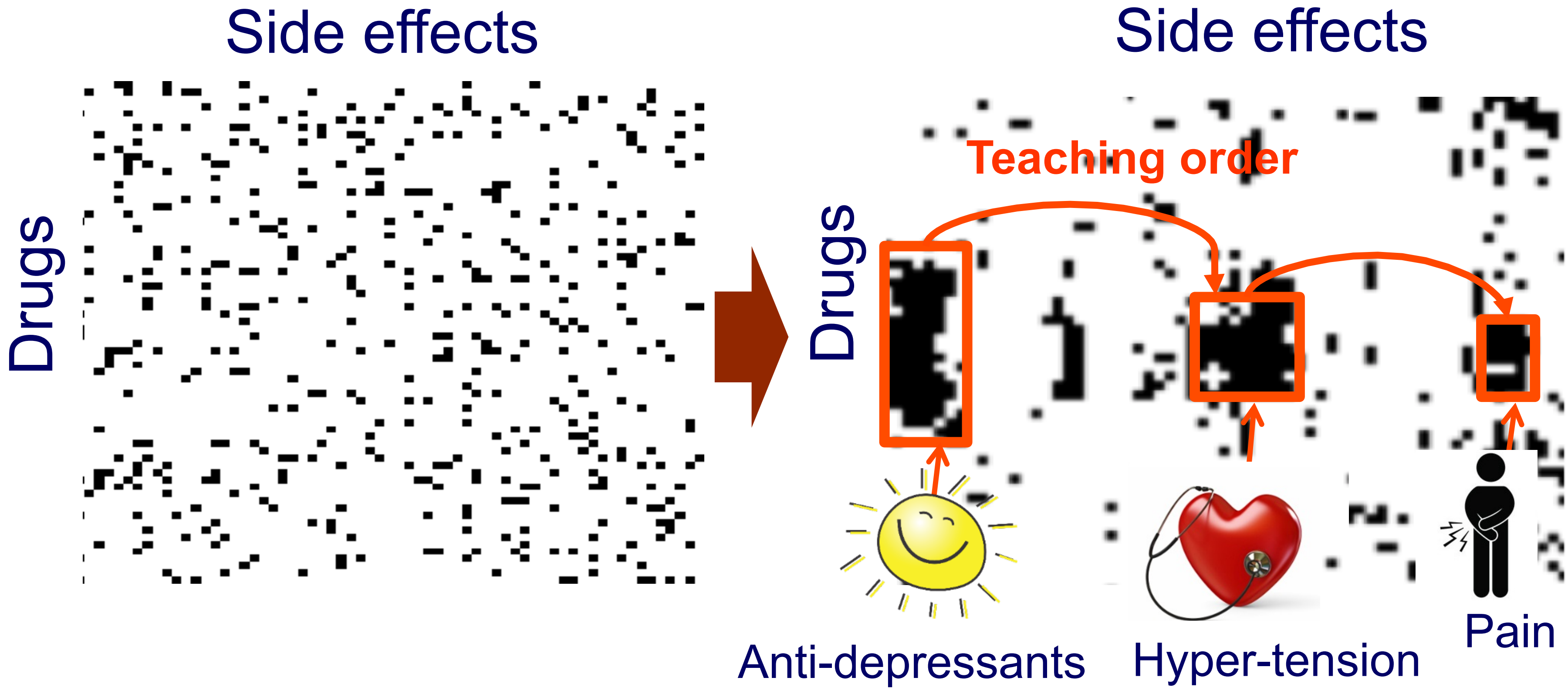
***G3.** How do we **optimize** this metric?*



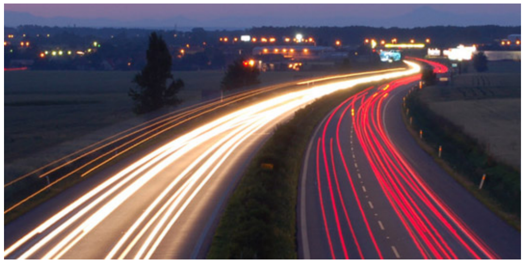
Pictorial Problem definition



Results


Side effects
Drugs
Side effects
Drugs
Teaching order
Anti-depressants
Hyper-tension
Pain

Roadmap



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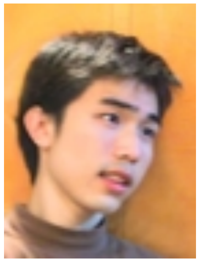
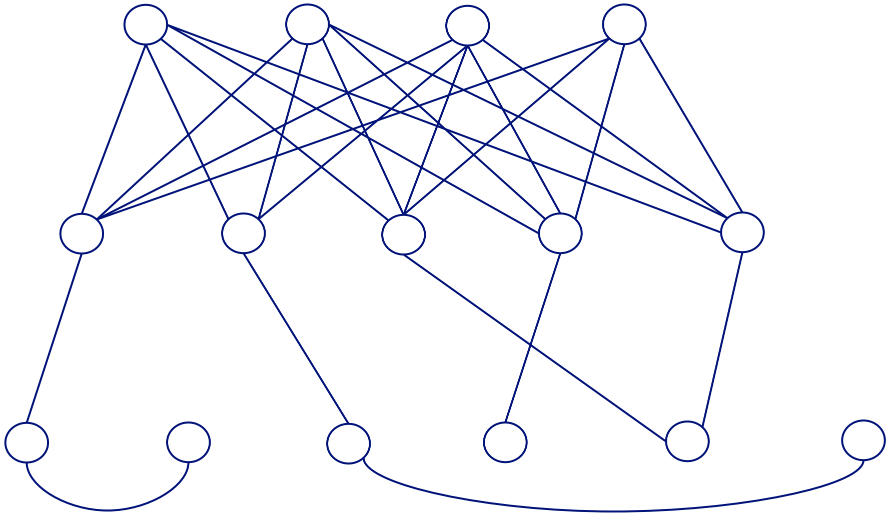
E-bay Fraud detection



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



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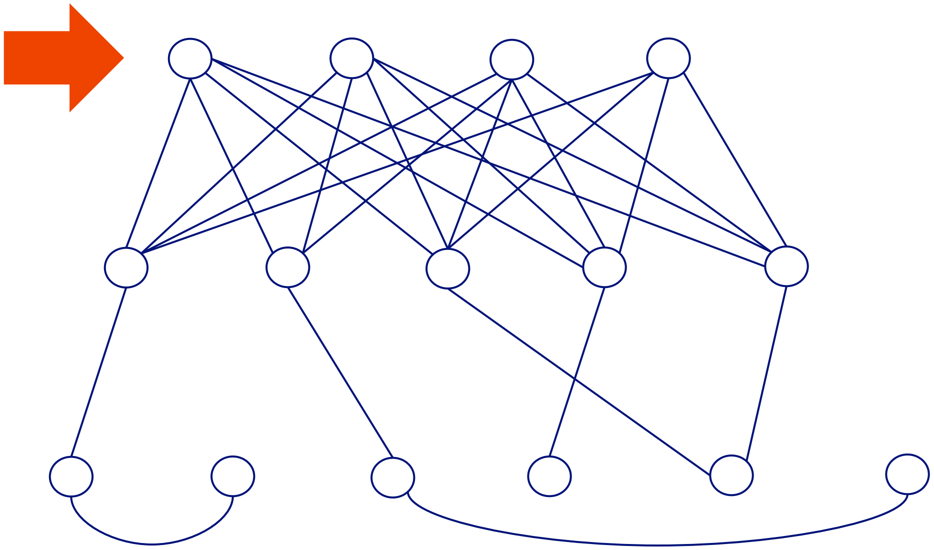

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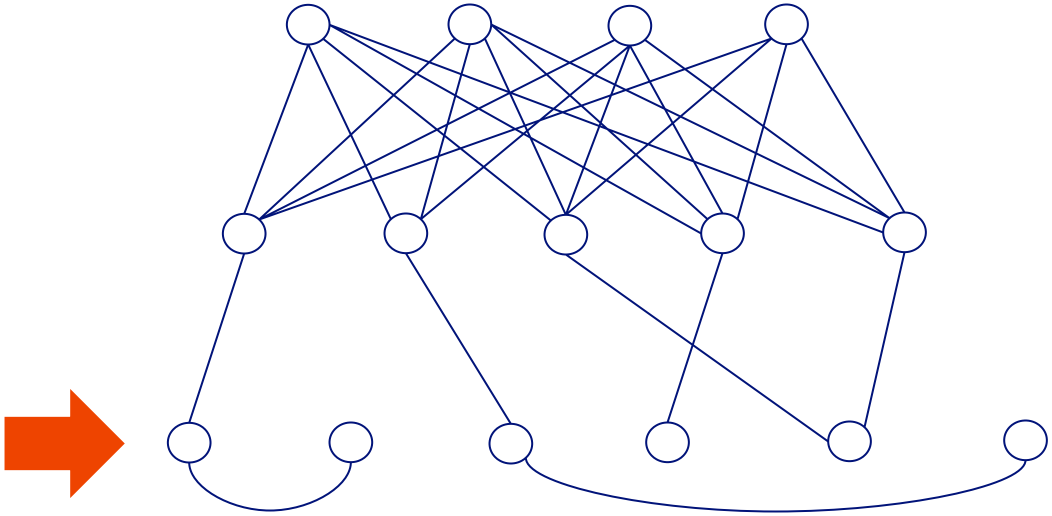
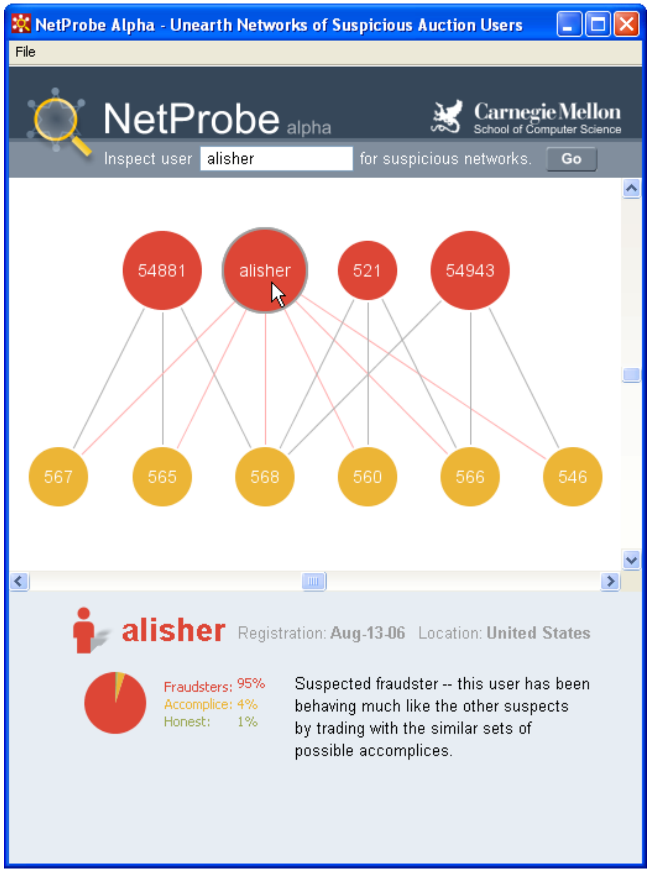


E-bay Fraud detection - NetProbe



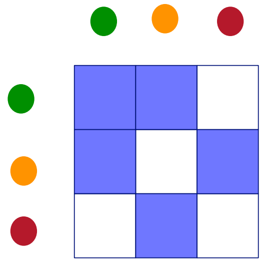
NetProbe Alpha - Unearth Networks of Suspicious Auction Users

Inspect user alisher for suspicious networks. Go

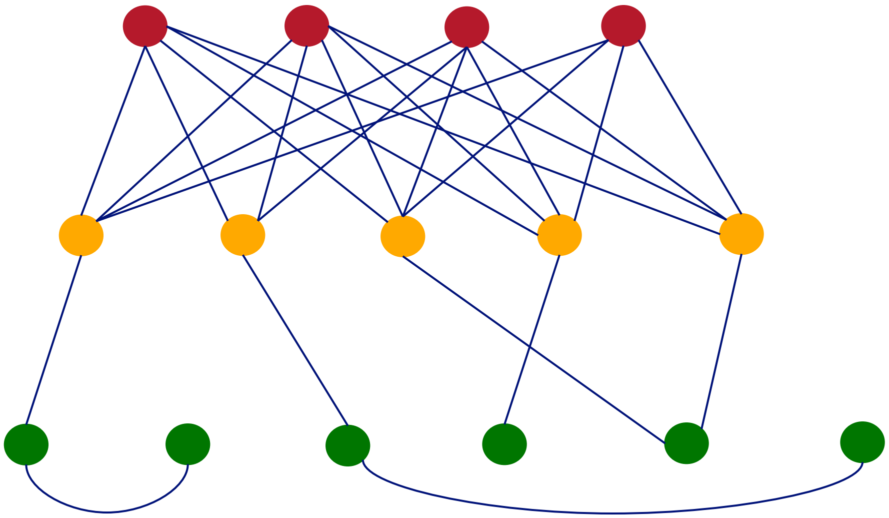
alisher Registration: Aug-13-06 Location: United States

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

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



	🟩	🟧	🟥
🟩	🟦	🟦	
🟧	🟦		🟦
🟥		🟦	



Popular press

USA TODAY

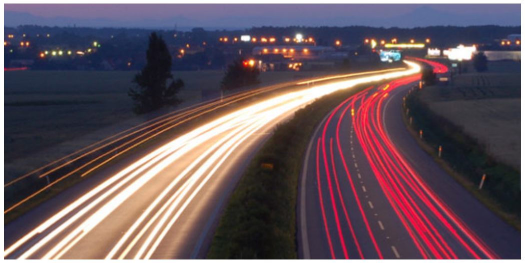
The Washington Post

Los Angeles Times

And less desirable attention:

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

Roadmap



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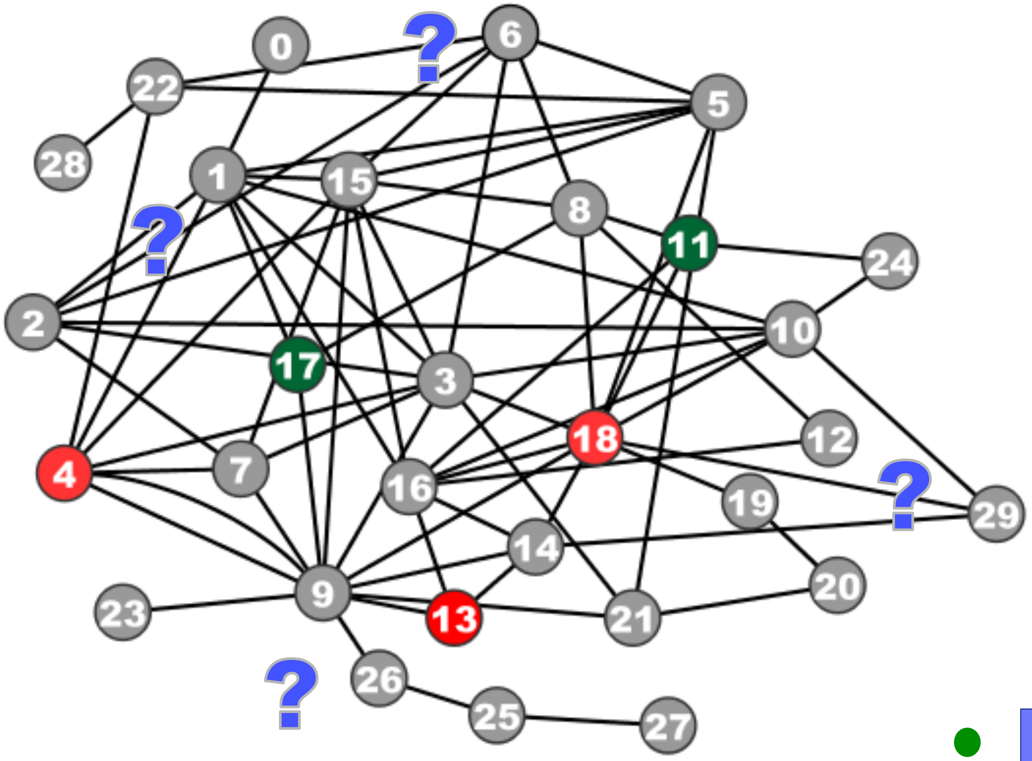
Unifying Guilt-by-Association Approaches: Theorems and Fast Algorithms

Danai Koutra
U Kang
Hsing-Kuo Kenneth Pao

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

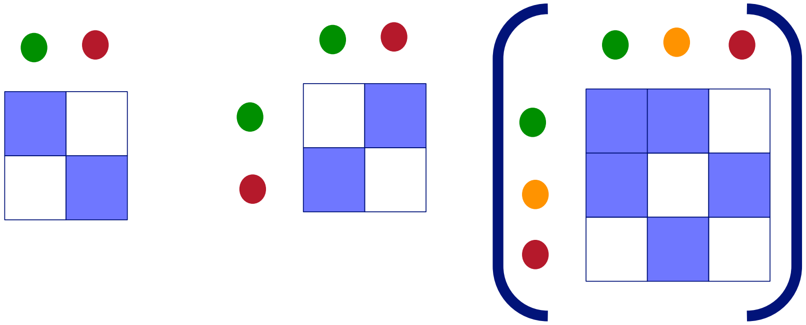
ECML PKDD, 5-9 September 2011, Athens, Greece

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*')

Google

- SSL (Semi-supervised learning)
  - minimize the differences among neighbors
- BP (Belief propagation)
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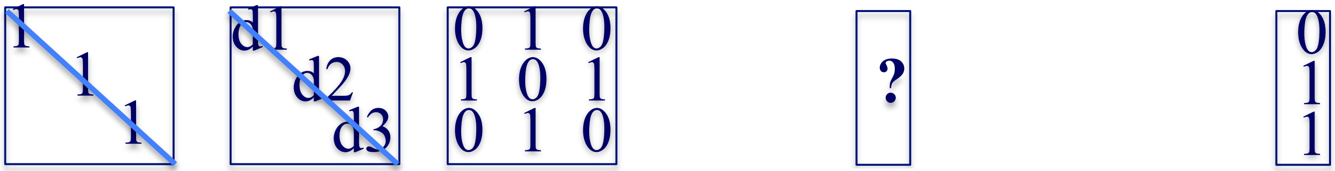
Correspondence of Methods

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

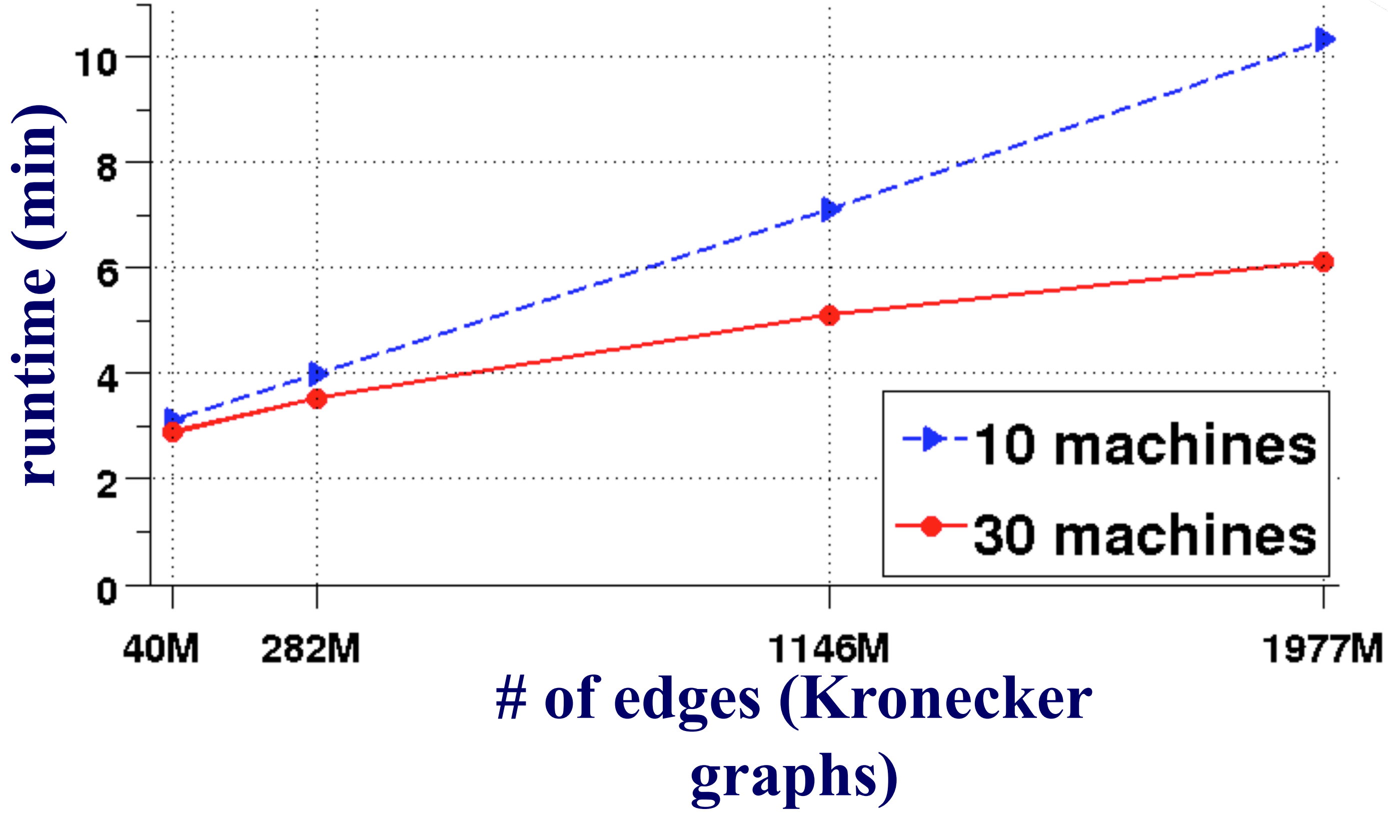


adjacency matrix

final labels/ beliefs

prior labels/ beliefs

Results: Scalability



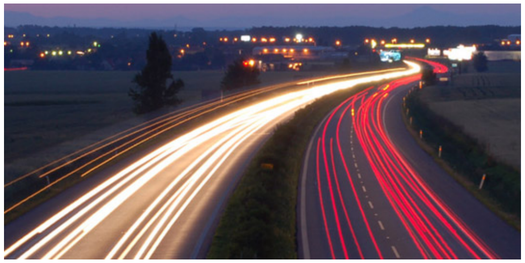
FABP is **linear** on the number of edges.

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

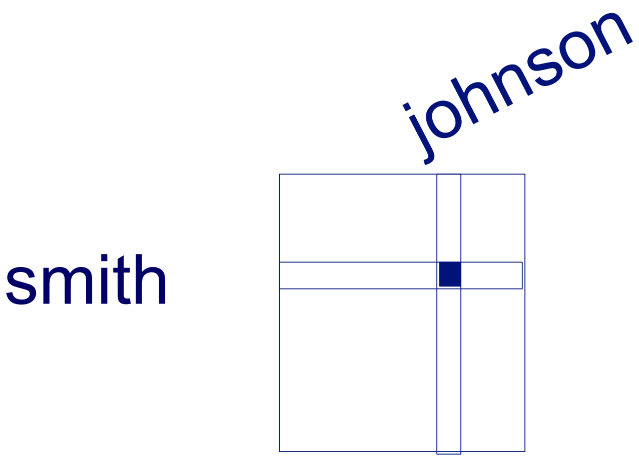


- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
  - ➡ P2.1: time-evolving graphs
  - [P2.2: with side information (‘coupled’ M.T.F.)
  - Speed]
- Conclusions

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!

- Problem #2.1:
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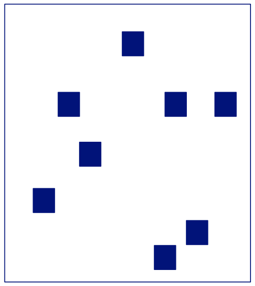
  - Find patterns / anomalies



Carnegie Mellon

Graphs over time -> tensors!

- Problem #2.1:
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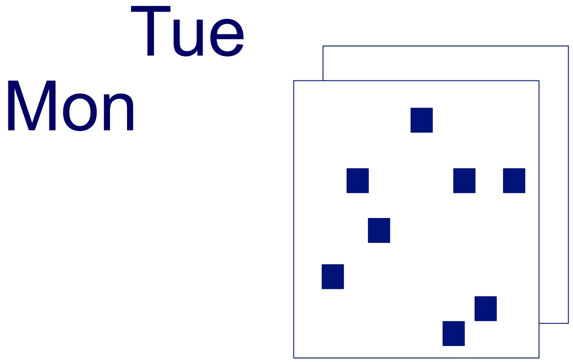
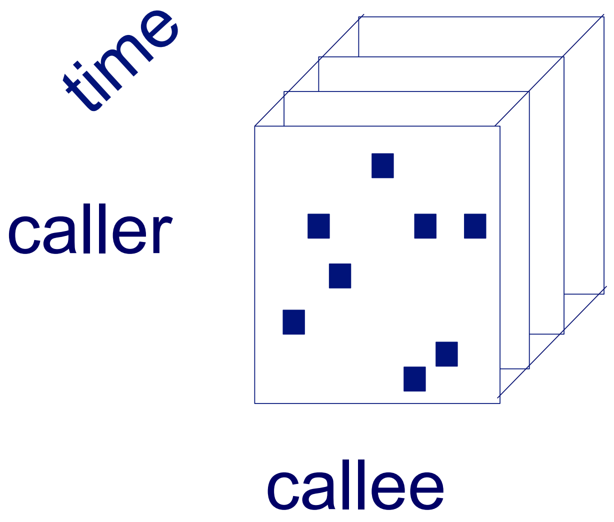
  - Find patterns / anomalies



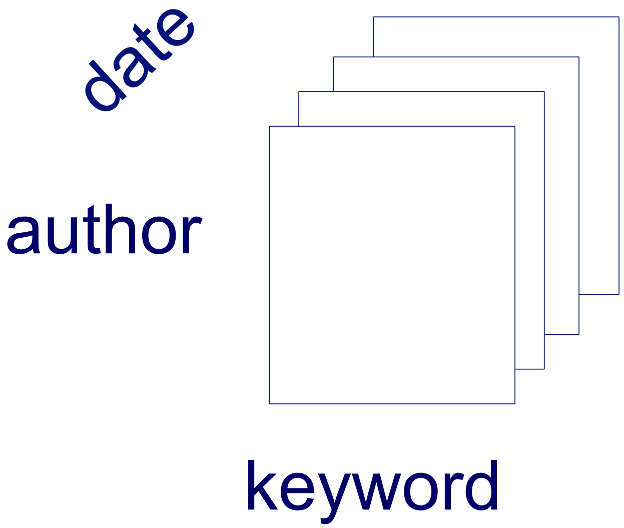
Graphs over time -> tensors!

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



Graphs over time -> tensors!

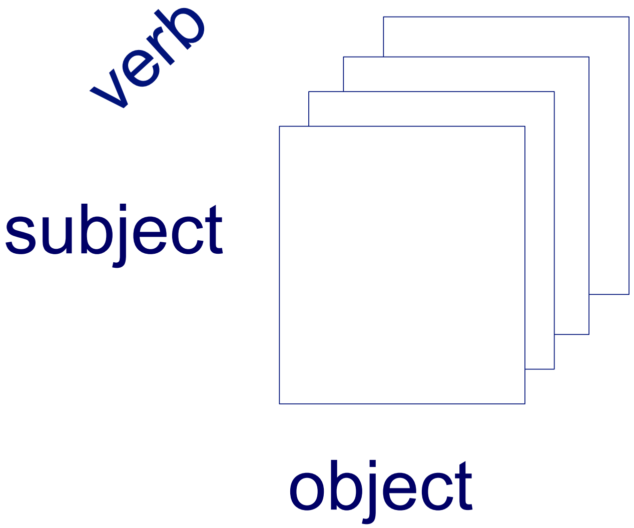
- Problem #2.1':
  - Given author-keyword-date
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

Graphs over time -> tensors!

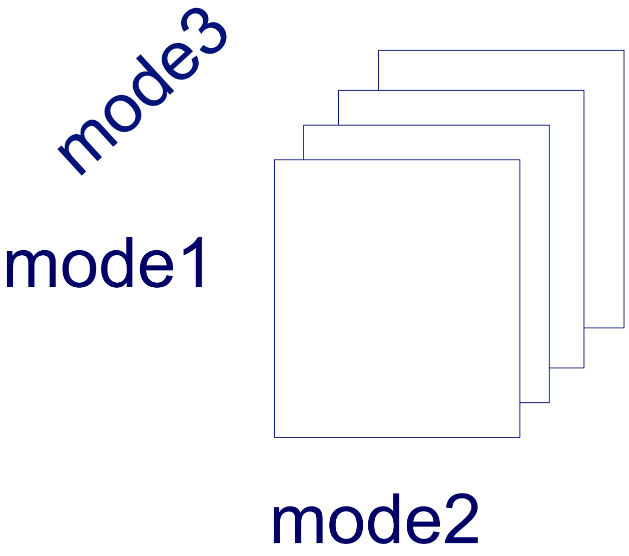
- Problem #2.1'':
  - Given subject – verb – object facts
  - Find patterns / anomalies



MANY more settings, with >2 'modes'

Graphs over time -> tensors!

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

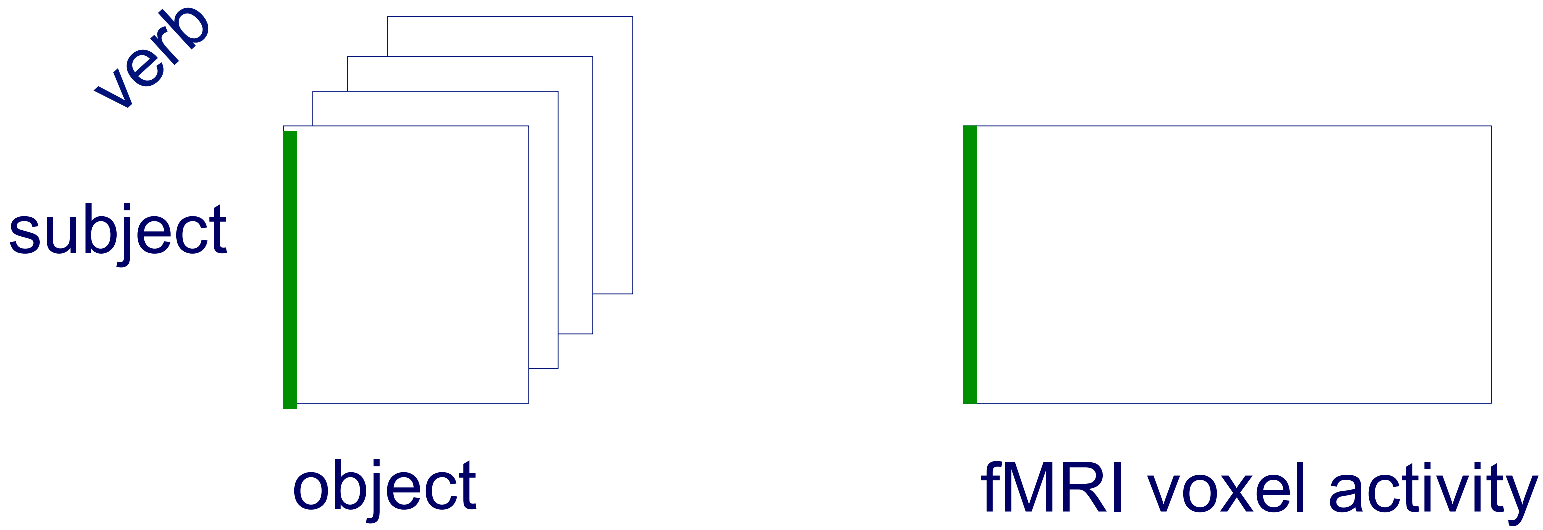


MANY more settings, with >2 'modes' (and 4, 5, etc modes)

SKIP

Graphs & side info

- Problem #2.2: coupled (eg., side info)
  - Given subject – verb – object facts
    - And voxel-activity for each subject-word
  - Find patterns / anomalies

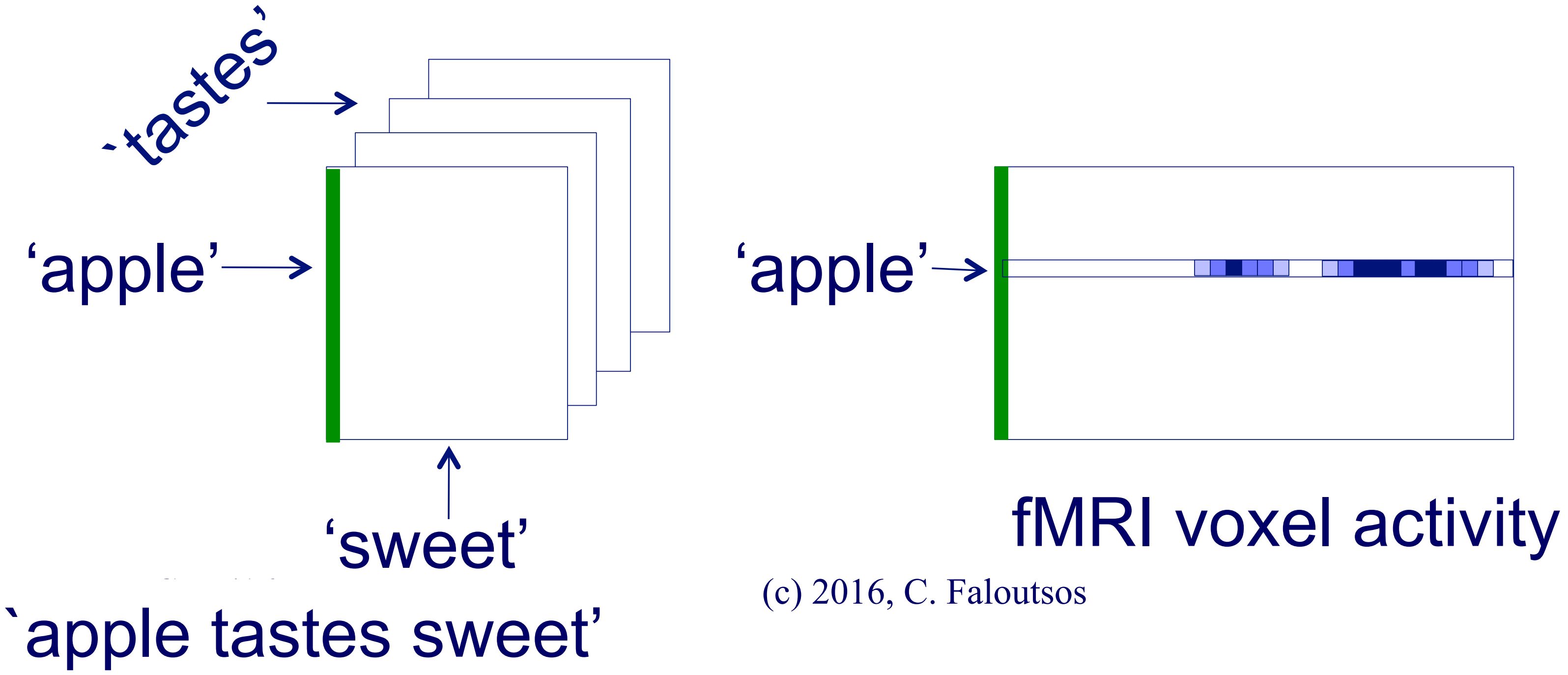


`apple tastes sweet'

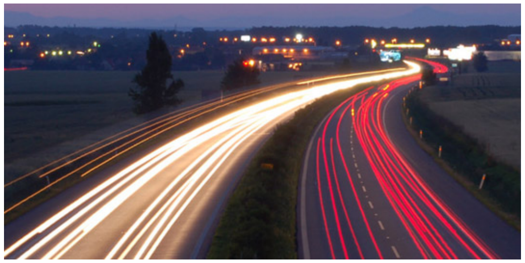
SKIP

Graphs & side info

- Problem #2.2: coupled (eg., side info)
  - Given subject – verb – object facts
    - And voxel-activity for each subject-word
  - Find patterns / anomalies



Roadmap



- Introduction – Motivation
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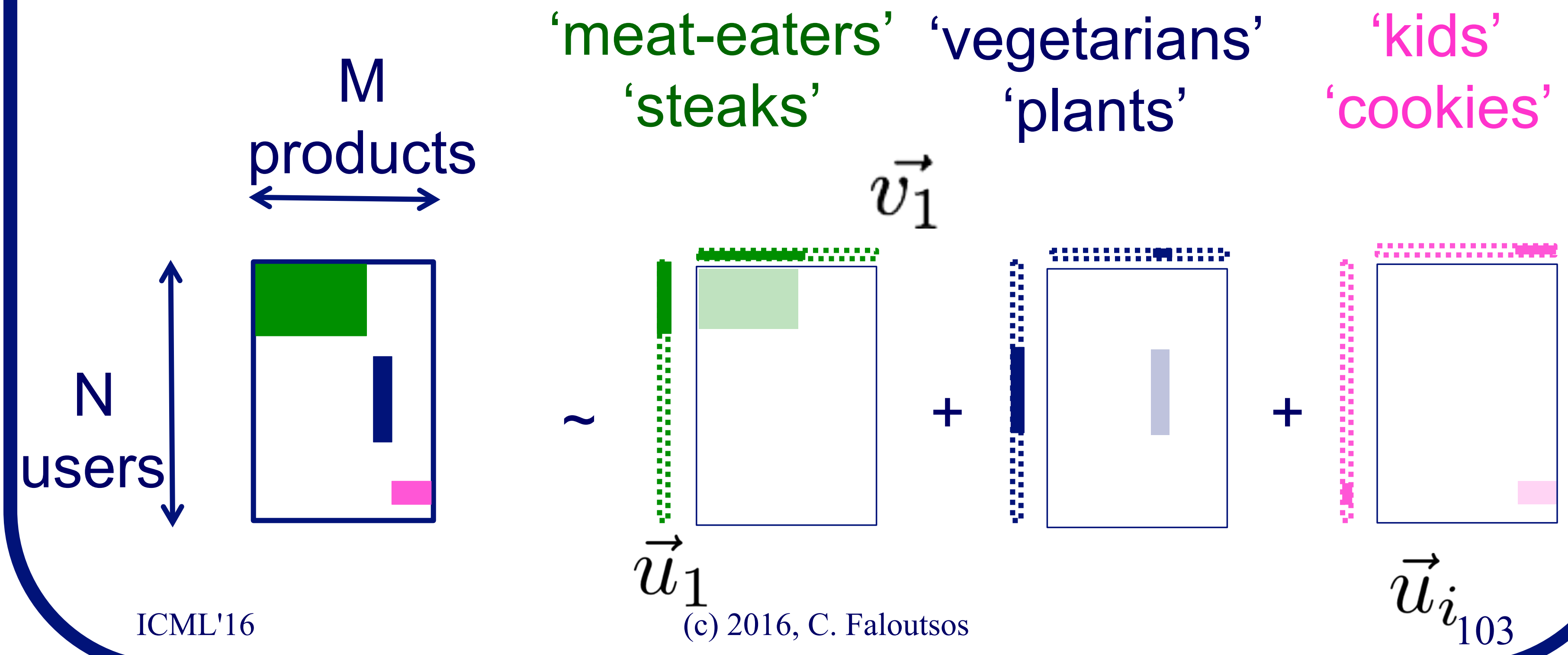
  - P2.1: time-evolving graphs
  - [P2.2: with side information (‘coupled’ M.T.F.)
  - Speed]
- Conclusions

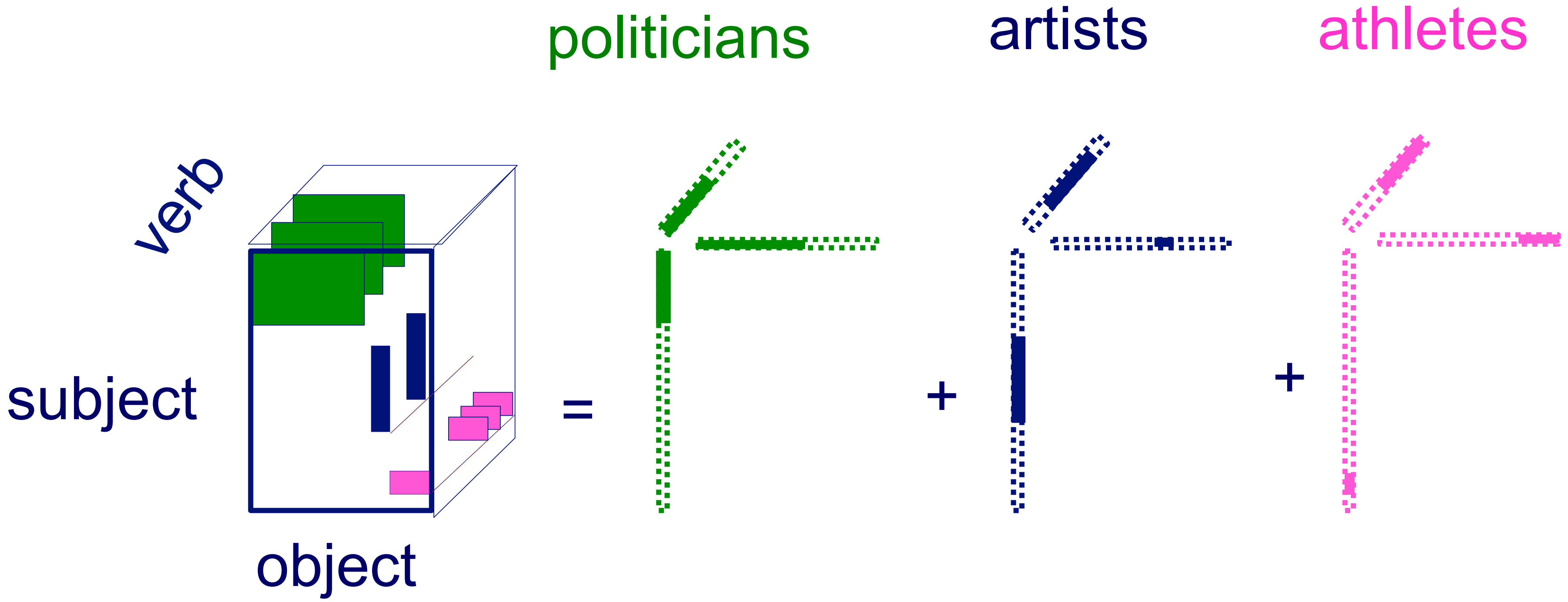
Answer to both: tensor factorization

- Recall: (SVD) matrix factorization: finds blocks



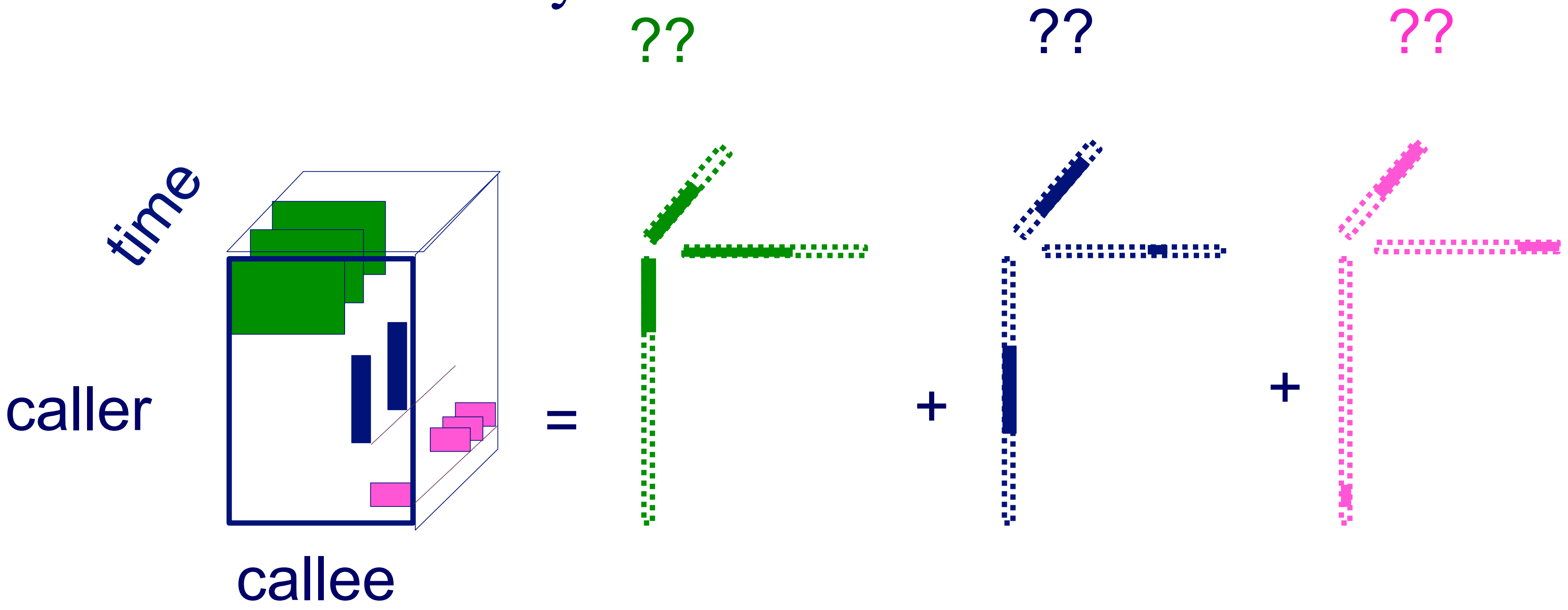
Answer to both: tensor factorization

- PARAFAC decomposition



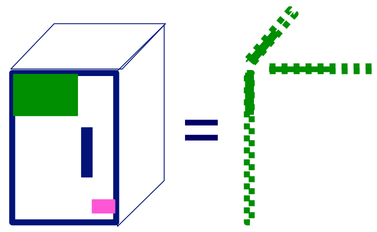
Answer: tensor factorization

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

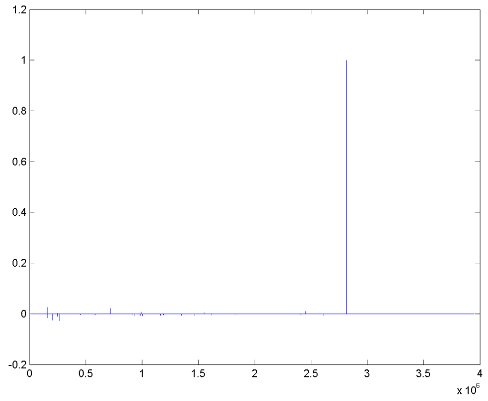


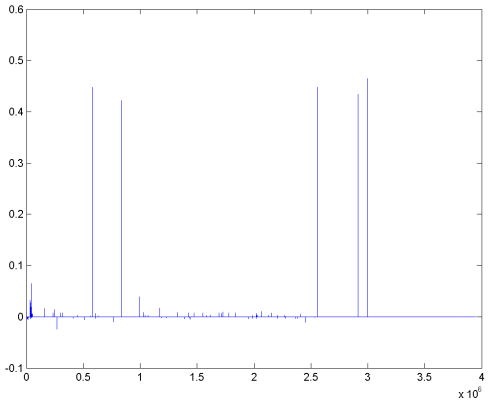
Carnegie Mellon

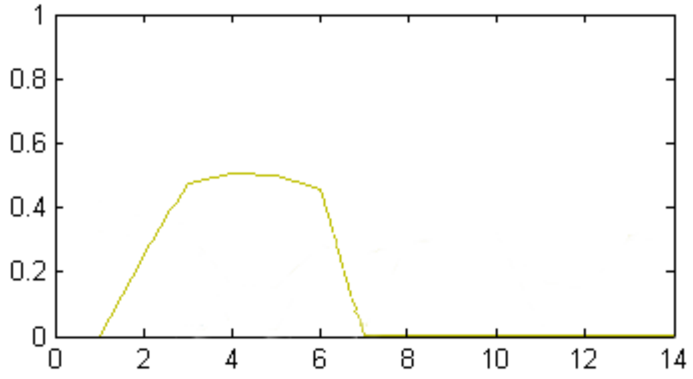
Anomaly detection in time-evolving graphs



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

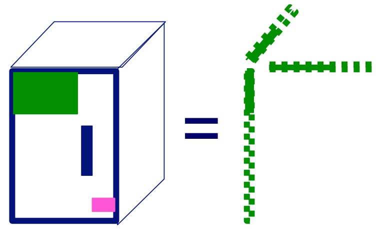

1 caller


5 receivers


4 days of activity

~200 calls to EACH receiver on EACH day!

Anomaly detection in time-evolving graphs



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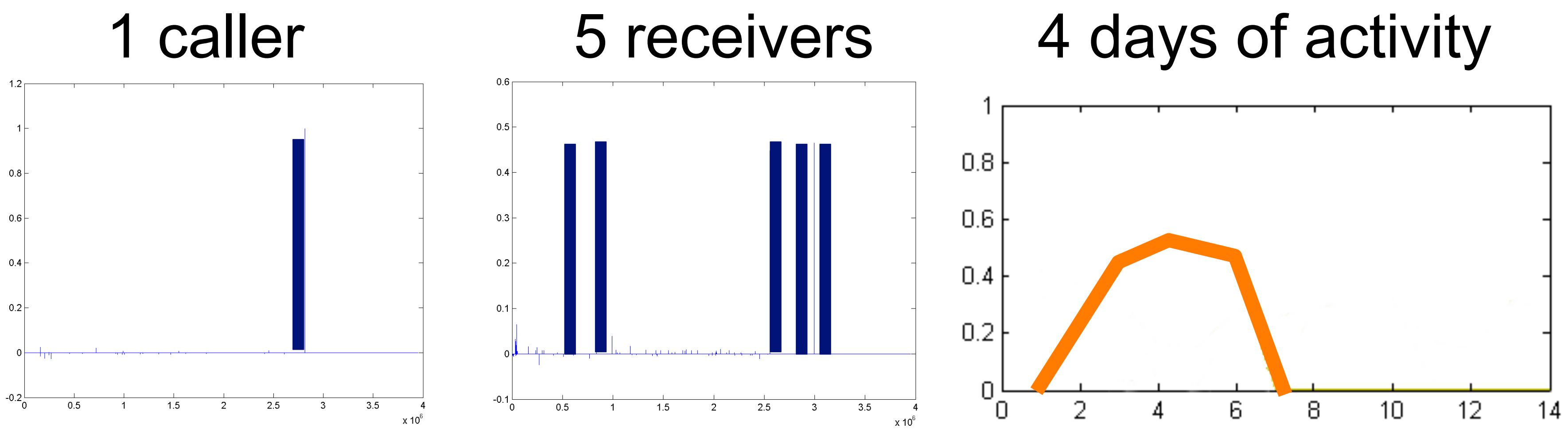
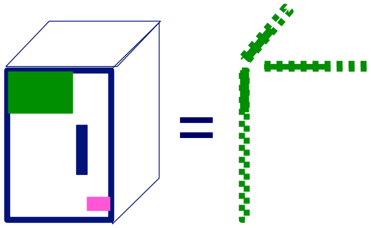


~200 calls to EACH receiver on EACH day!

Carnegie Mellon

Anomaly detection in time-evolving graphs



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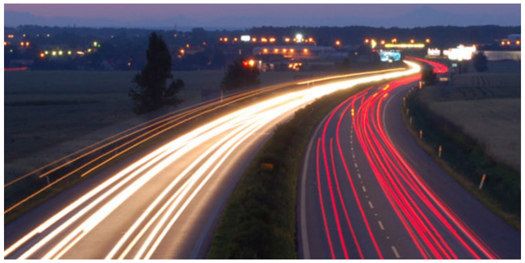
Miguel Araujo, Spiros Papadimitriou, Stephan Günnemann, Christos Faloutsos, Prithwish Basu, Ananthram Swami, Evangelos Papalexakis, Danai Koutra. *Com2: Fast Automatic Discovery of Temporal (Comet) Communities*. PAKDD 2014, Tainan, Taiwan.

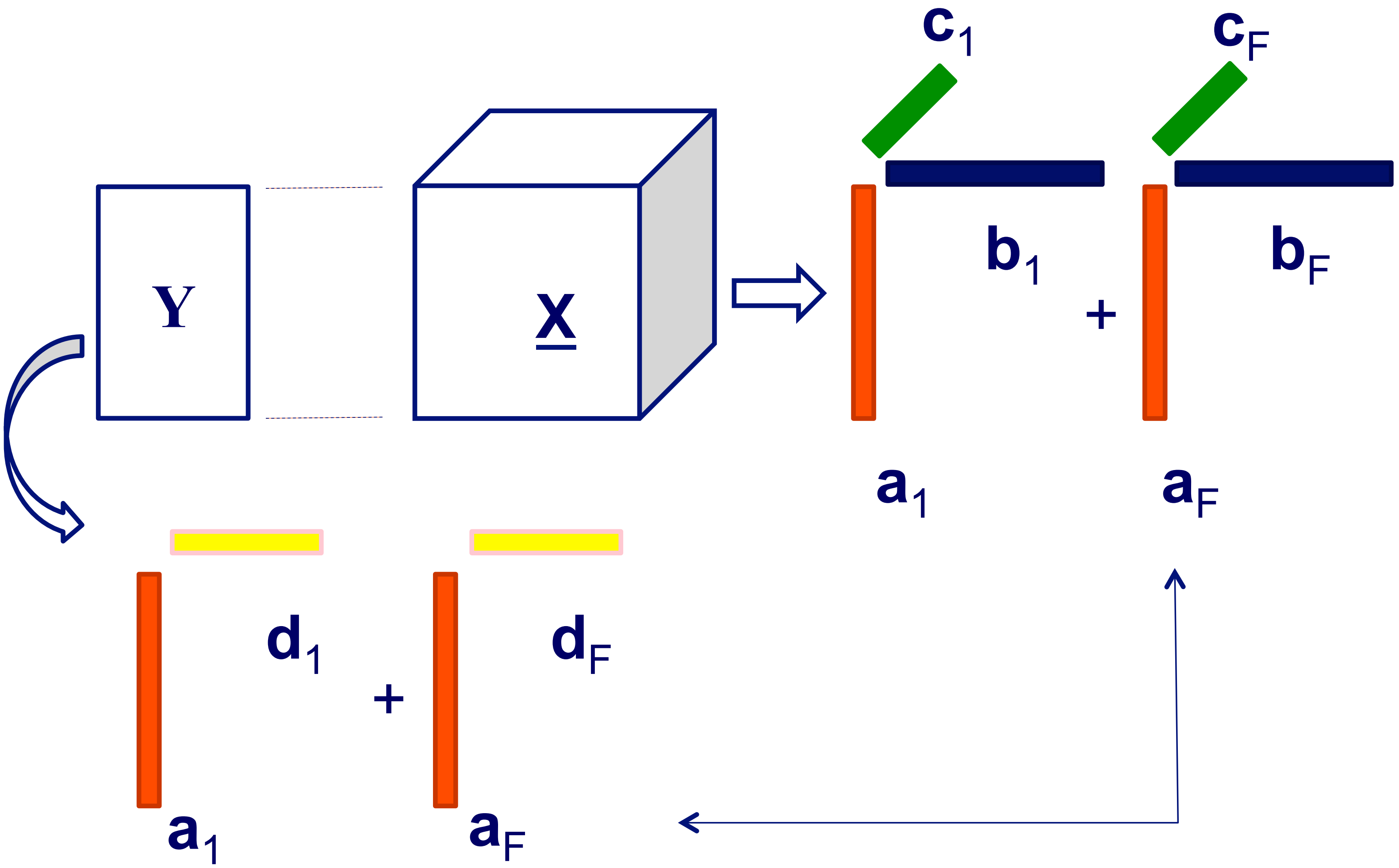
SKIP

Roadmap



- Introduction – Motivation
- Part#1: Patterns in graphs
- Part#2: time-evolving graphs; tensors
  - P2.1: Discoveries @ phonecall network
  - [P2.2: Discoveries in neuro-semantics
  - Speed]
- Conclusions

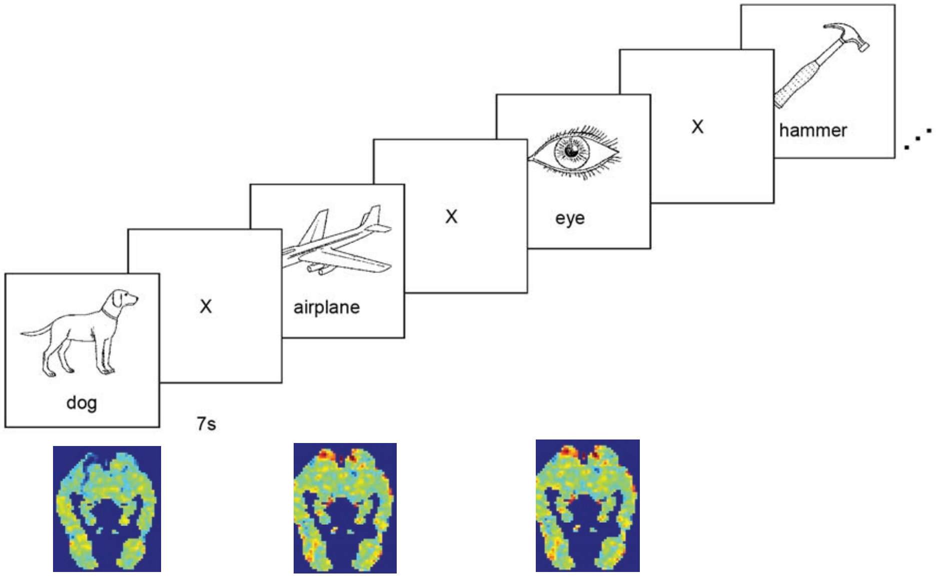
Coupled Matrix-Tensor Factorizat SKIP (CMTF)



Neuro-semantics

SKIP

- **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

SKIP

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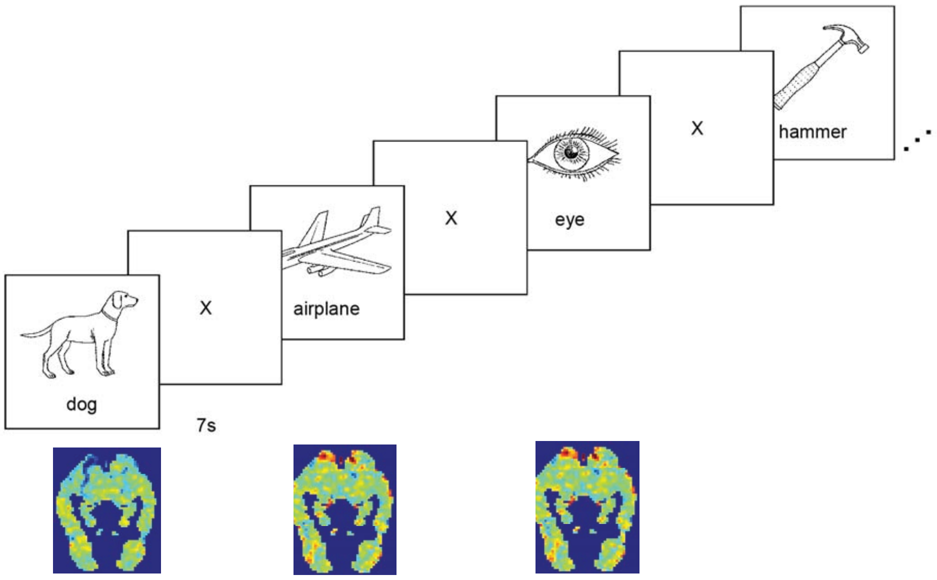

Patterns?

Neuro-semantics

SKIP

- **Brain Scan Data***
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  - 60 nouns
- **Questions**
  - 218 questions
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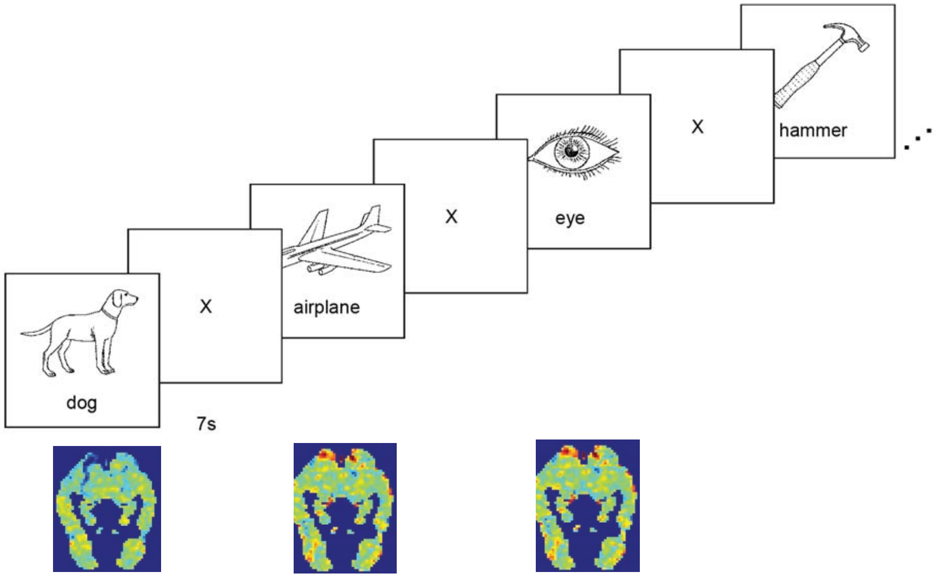
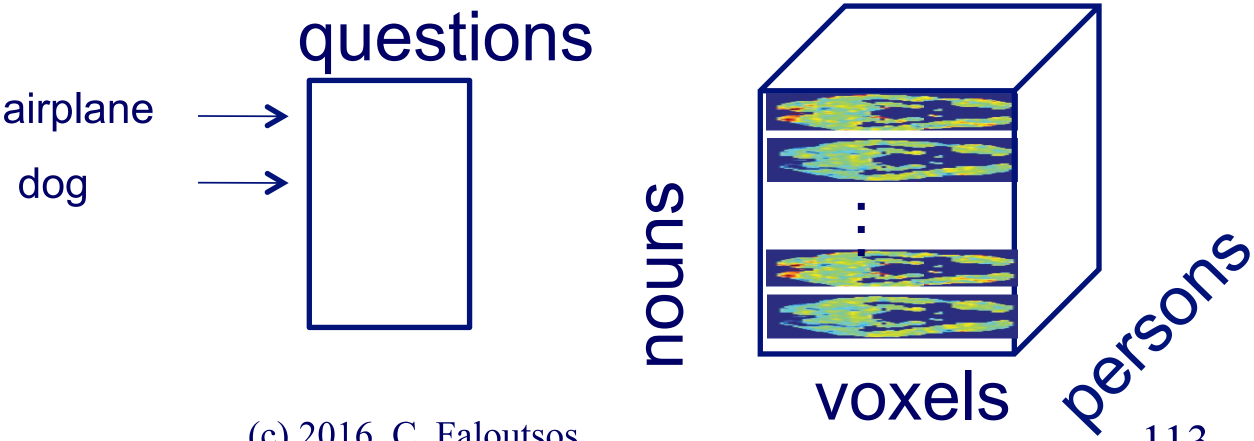


Patterns?



Neuro-semantics

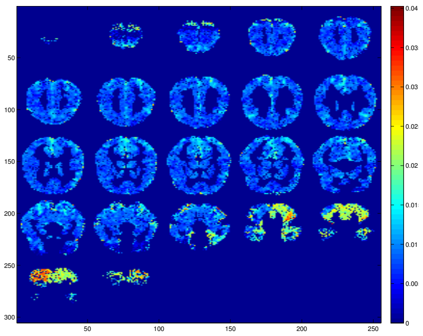
SKIP

Nouns

beetle
pants
bee

Questions

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



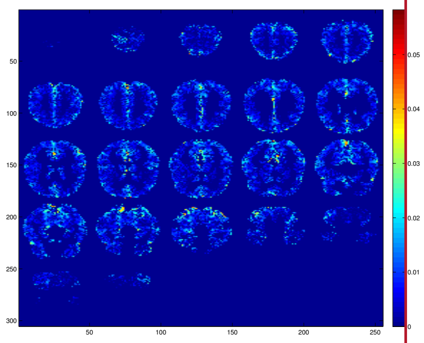
Group1

Nouns

bear
cow
coat

Questions

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



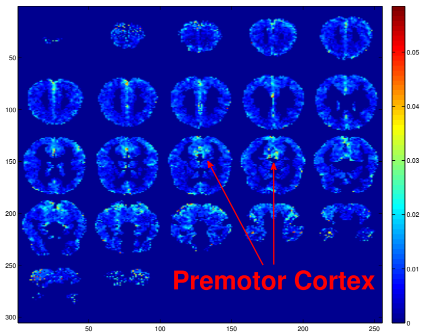
Group 2

Nouns

glass
tomato
bell

Questions

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



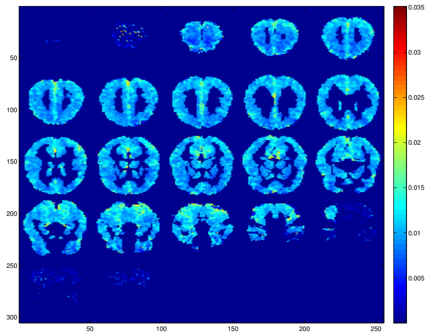
Group 3

Nouns

bed
house
car

Questions

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



Group 4

Neuro-semantics

SKIP

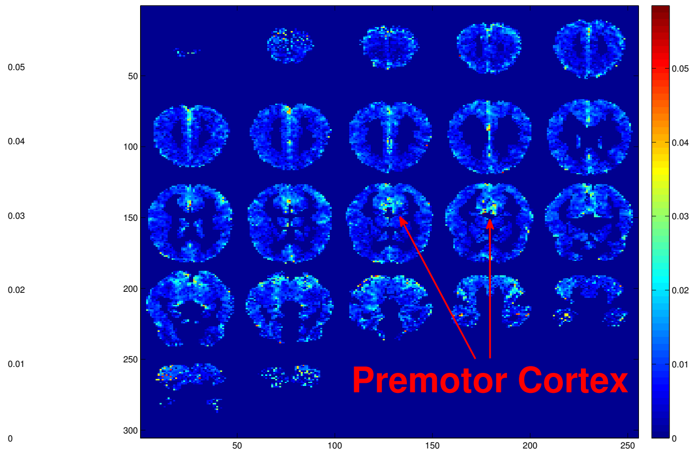
Small items -> Premotor cortex

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

Neuro-semantics

SKIP

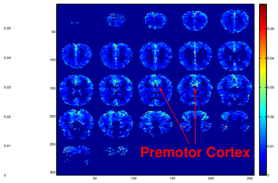
Small items -> Premotor cortex

Nouns

glass
tomato
bell

Questions

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

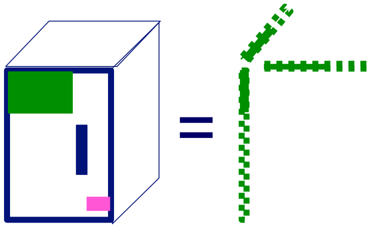


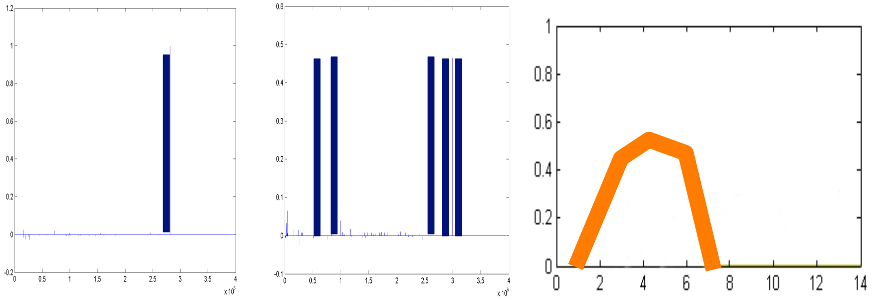
Group 3

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

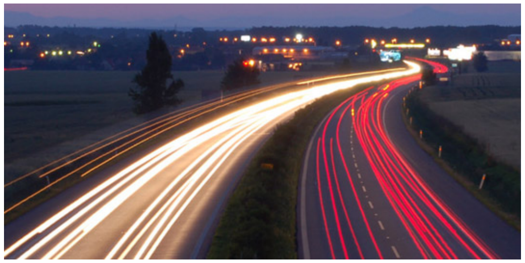
Part 2: Conclusions

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





Roadmap



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

Thanks

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

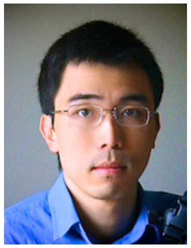
Thanks to: NSF IIS-0705359, IIS-0534205, CTA-INARC; Yahoo (M45), LLNL, IBM, SPRINT, Google, INTEL, HP, iLab

Cast

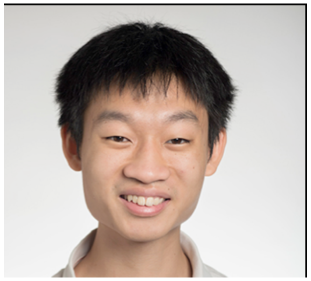
Akoglu, Leman

Araujo, Miguel

Beutel, Alex



Chau, Polo



Hooi, Bryan

Kang, U

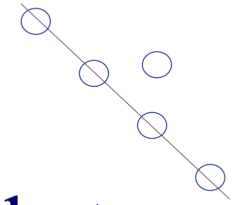
Koutra, Danai

Papalexakis, Vagelis

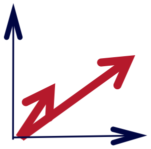
Shah, Neil

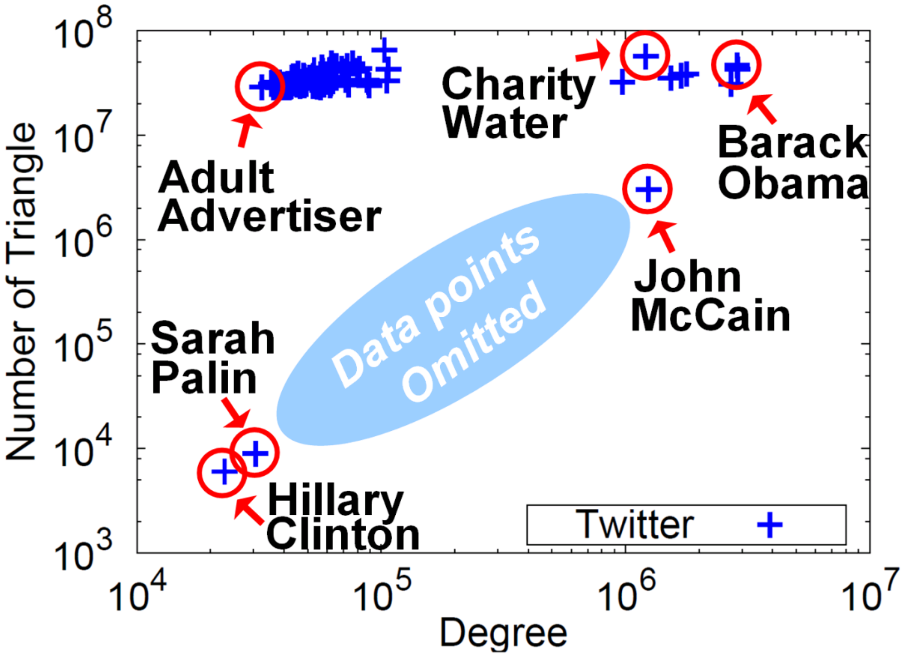
Song, Hyun Ah

CONCLUSION#1 – Big data



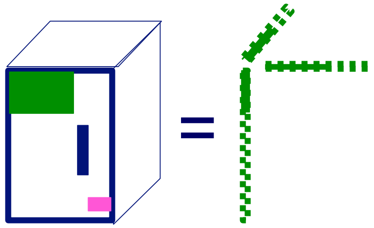
- **Patterns** **Anomalies**
- **Large** datasets reveal patterns/outliers that are invisible otherwise

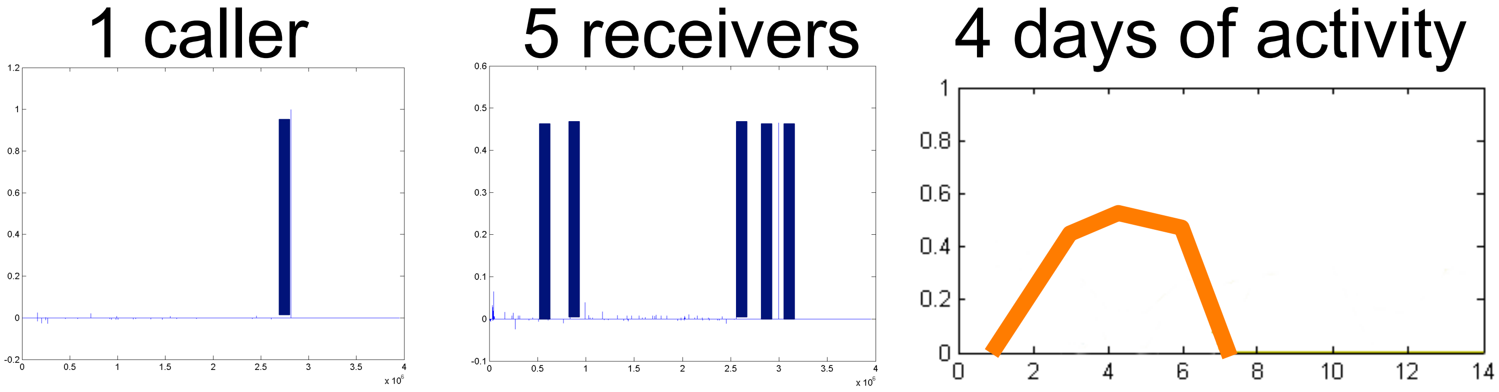




CONCLUSION#2 – tensors

- powerful tool





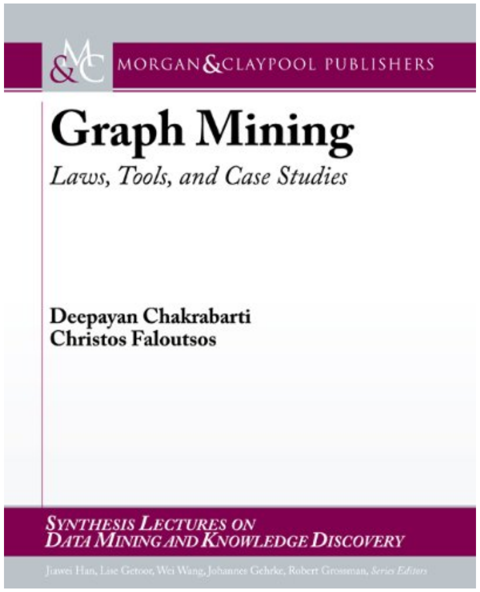
1 caller

5 receivers

4 days of activity

References

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



MORGAN & CLAYPOOL PUBLISHERS

Graph Mining

Laws, Tools, and Case Studies

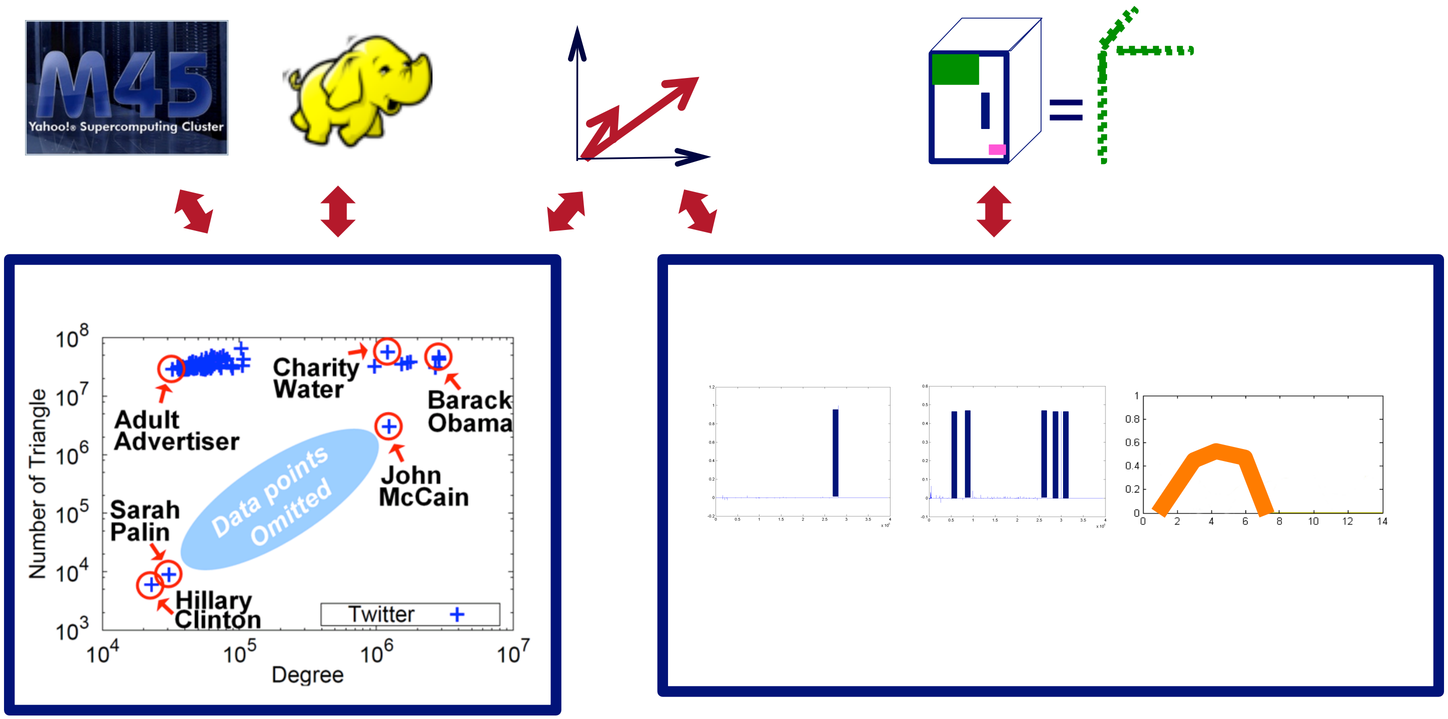
Deepayan Chakrabarti
Christos Faloutsos

SYNTHESIS LECTURES ON DATA MINING AND KNOWLEDGE DISCOVERY

Jiawei Han, Lise Getoor, Wei Wang, Johannes Gehrke, Robert Grossman, *Series Editors*

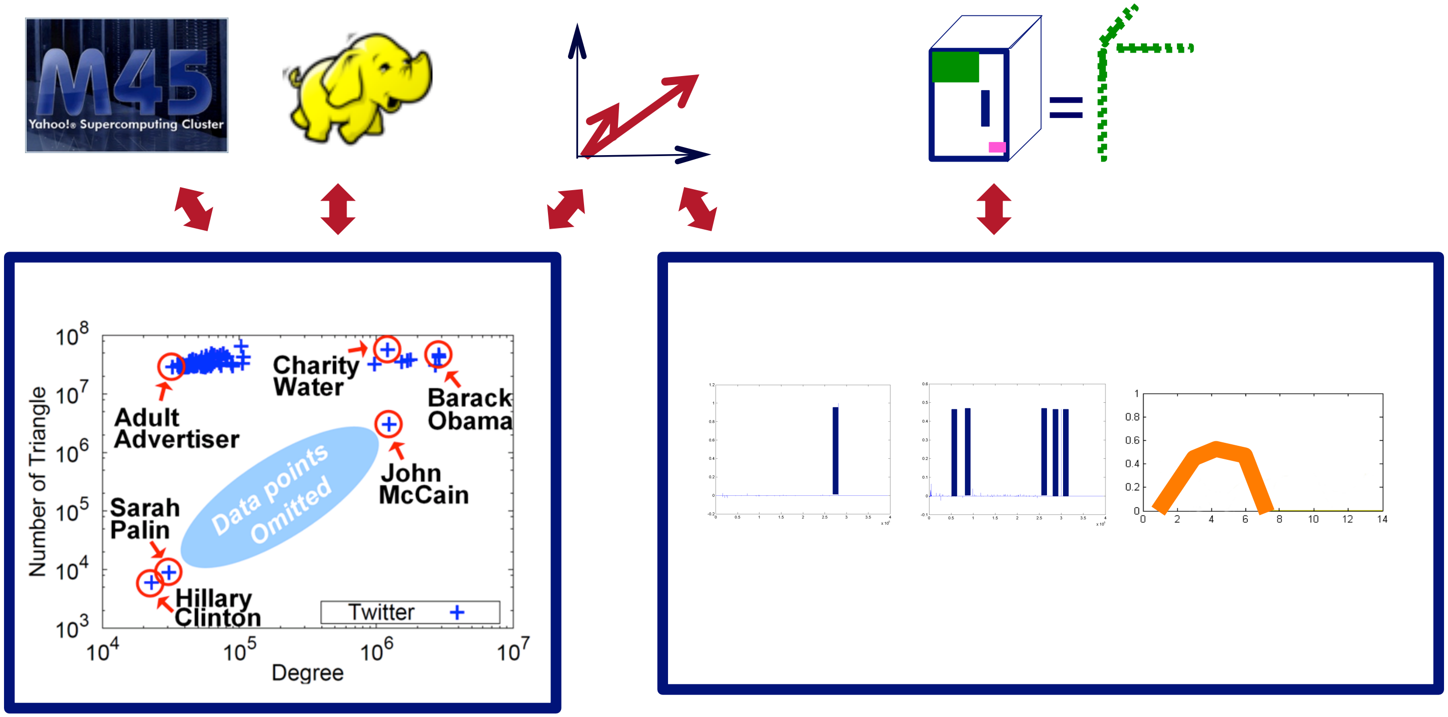
TAKE HOME MESSAGE:

Cross-disciplinarity



Thank you!

Cross-disciplinarity



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