Carnegie Mellon

Mining Billion-node Graphs: Patterns, Generators and Tools

Christos Faloutsos

CMU

(on sabbatical at google)

Thank you!

- Prof. Irwin King

- Priyanka Garg

Our goal:

Open source system for mining huge graphs:

PEGASUS project (PEta GrAph mining System)

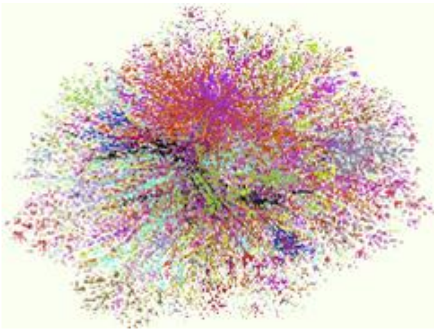
- www.cs.cmu.edu/~pegasus
- code and papers

Outline

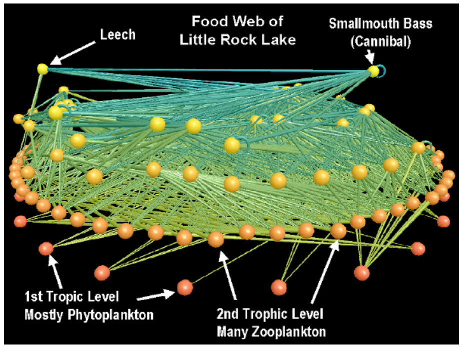
- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
- Problem#3: Scalability
- Conclusions

Carnegie Mellon

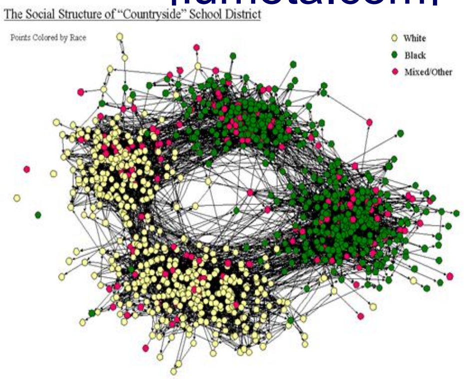
Graphs - why should we care?



Internet Map
[lumeta.com]



Food Web
[Martinez '91]

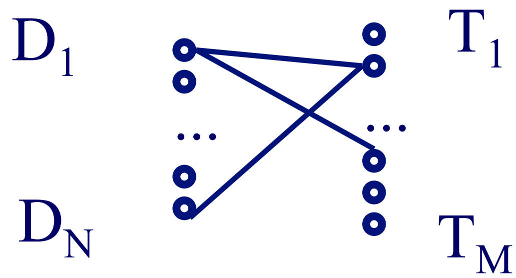


Friendship Network
[Moody '01]

- Social networks
  - (orkut, linkedIn …)
- twitter

Graphs - why should we care?

- IR: bi-partite graphs (doc-terms)



- web: hyper-text graph

- ... and more:

Graphs - why should we care?

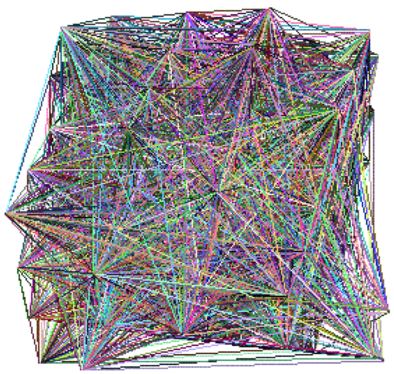
- ‘viral’ marketing
- web-log (‘blog’) news propagation
- computer network security: email/IP traffic and anomaly detection
- ....

Carnegie Mellon

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
  - Static graphs
  - Weighted graphs
  - Time evolving graphs
- Problem#2: Tools
- Problem#3: Scalability
- Conclusions

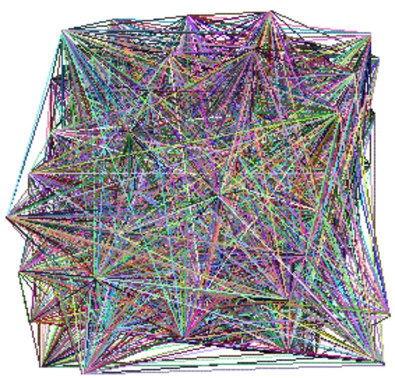
Problem #1 - network and graph mining



- What does the Internet look like?
- What does FaceBook look like?

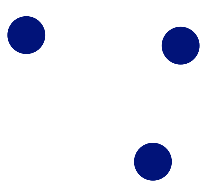
- What is ‘normal’/‘abnormal’?
- which patterns/laws hold?

Problem #1 - network and graph mining

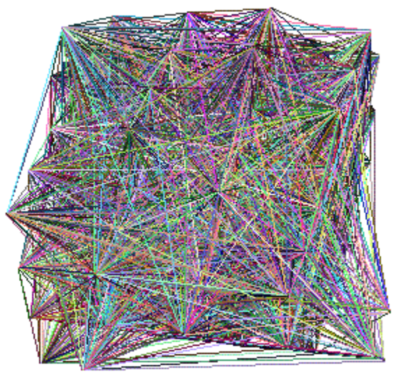


- What does the Internet look like?
- What does FaceBook look like?

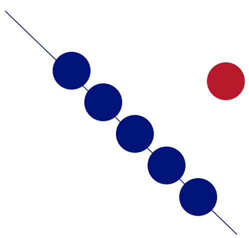
- What is ‘normal’/‘abnormal’?
- which patterns/laws hold?
  – To spot **anomalies** (rarities), we have to discover **patterns**



Problem #1 - network and graph mining



- What does the Internet look like?
- What does FaceBook look like?
- What is 'normal'/'abnormal'?
- which patterns/laws hold?
  - To spot **anomalies** (rarities), we have to discover **patterns**
  - **Large** datasets reveal patterns/anomalies that may be invisible otherwise…



Carnegie Mellon

Graph mining

- Are real graphs random?

Laws and patterns

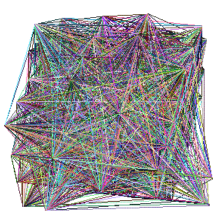
- Are real graphs random?
- A: NO!!
  - Diameter
  - in- and out- degree distributions
  - other (surprising) patterns

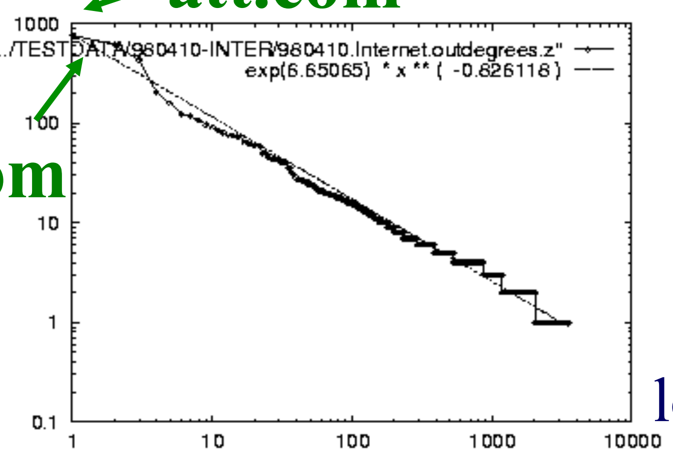
- So, let’s look at the data

Solution# S.1

- Power law in the degree distribution [SIGCOMM99]

internet domains

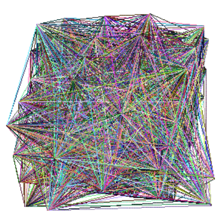


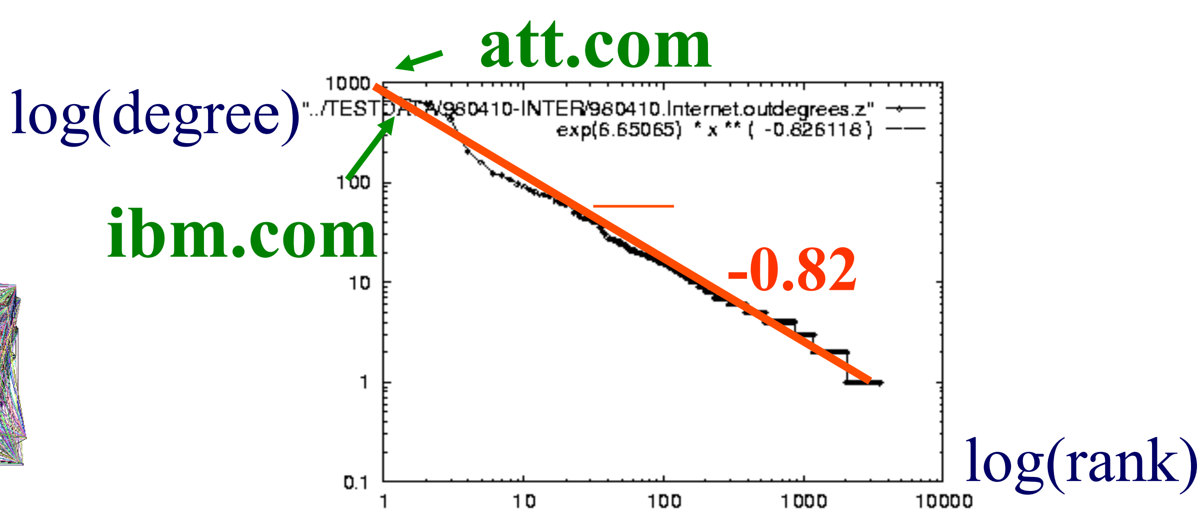


Solution# S.1

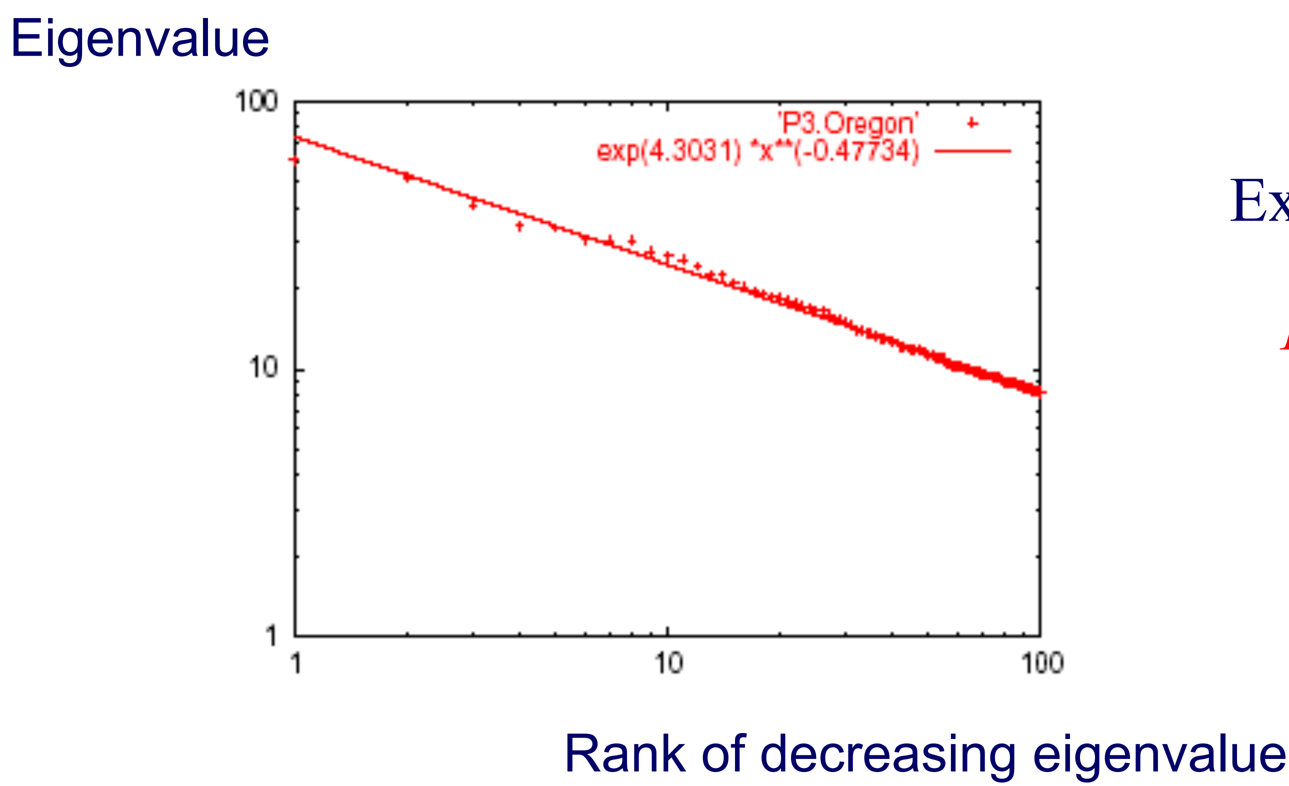
- Power law in the degree distribution [SIGCOMM99]

internet domains





Solution# S.2: Eigen Exponent *E*



Exponent = slope

$E = -0.48$

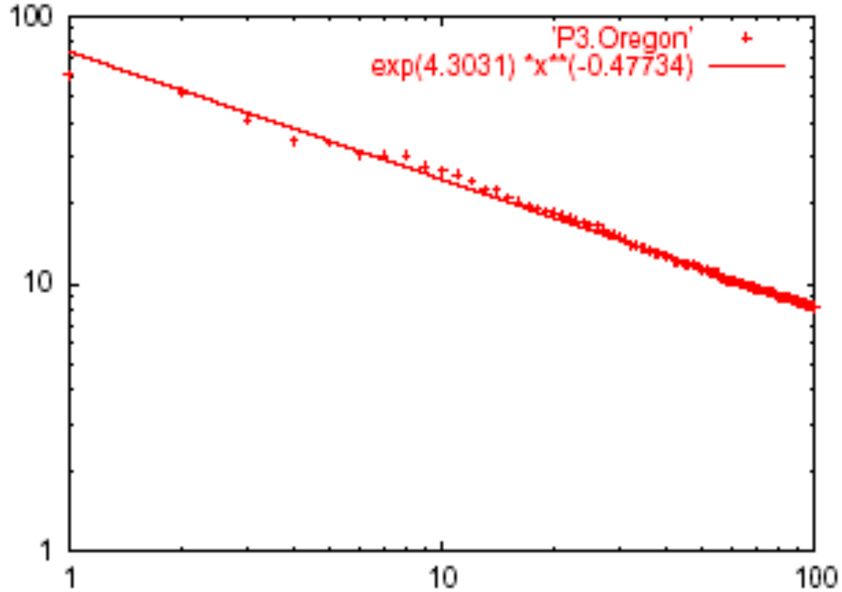
May 2001

- A2: power law in the eigenvalues of the adjacency matrix

Carnegie Mellon

Solution# S.2: Eigen Exponent *E*

Eigenvalue



Rank of decreasing eigenvalue

Exponent = slope

E = -0.48

May 2001

- [Mihail, Papadimitriou '02]: slope is ½ of rank exponent

But:

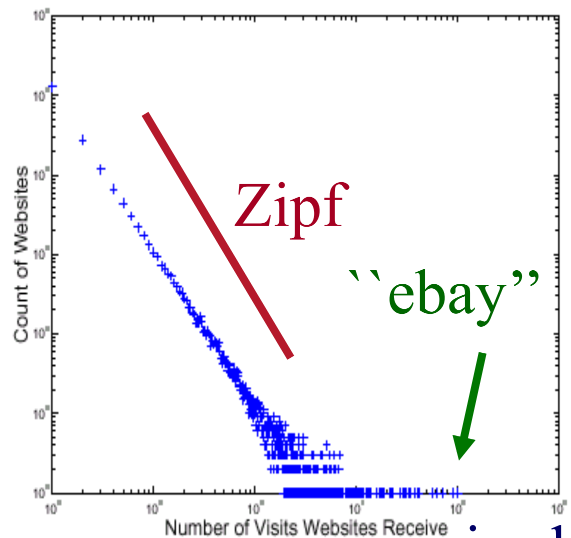
How about graphs from other domains?

More power laws:

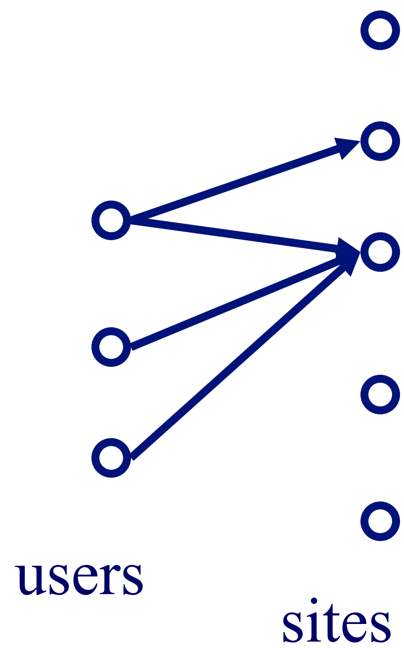
- web hit counts [w/ A. Montgomery]

Web Site Traffic

Count (log scale)



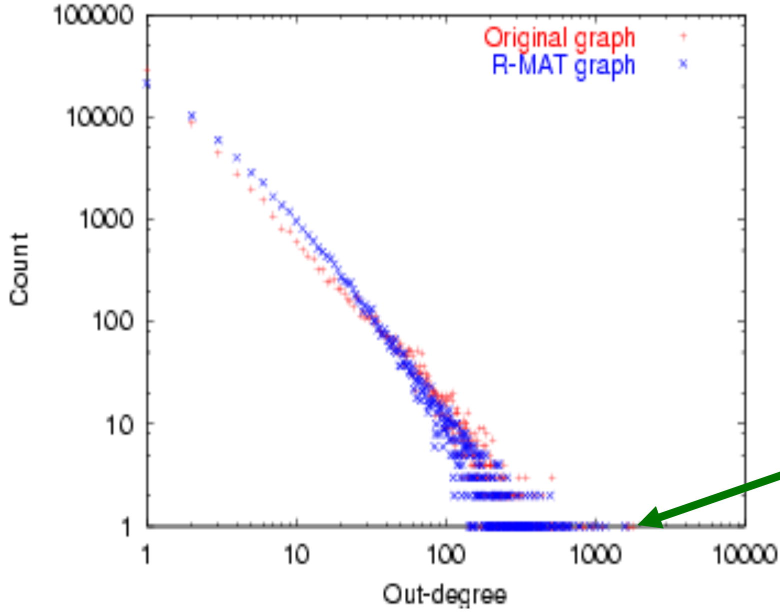
in-degree (log scale)



epinions.com

- who-trusts-whom [Richardson + Domingos, KDD 2001]

count



trusts-2000-people user

(out) degree

And numerous more

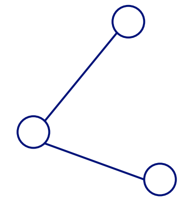
- # of sexual contacts
- Income [Pareto] –'80-20 distribution'
- Duration of downloads [Bestavros+]
- Duration of UNIX jobs ('mice and elephants')
- Size of files of a user
- …
- 'Black swans'

Carnegie Mellon

Outline

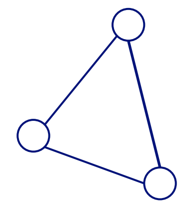
- Introduction – Motivation
- Problem#1: Patterns in graphs
  - Static graphs
    - degree, diameter, eigen,
    - triangles
    - cliques
  - Weighted graphs
  - Time evolving graphs
- Problem#2: Tools

Solution# S.3: Triangle 'Laws'



- Real social networks have a lot of triangles

Solution# S.3: Triangle 'Laws'

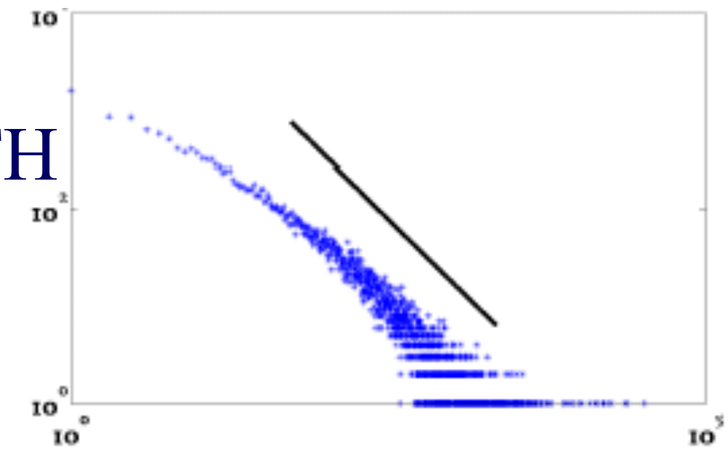


- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?

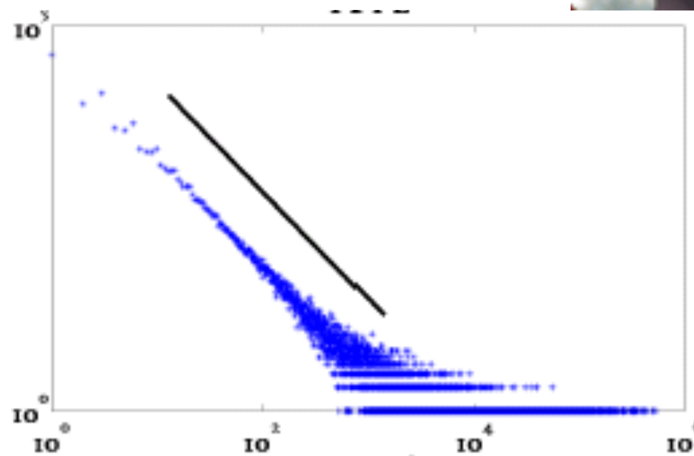
Triangle Law: #S.3

[Tsourakakis ICDM 2008]

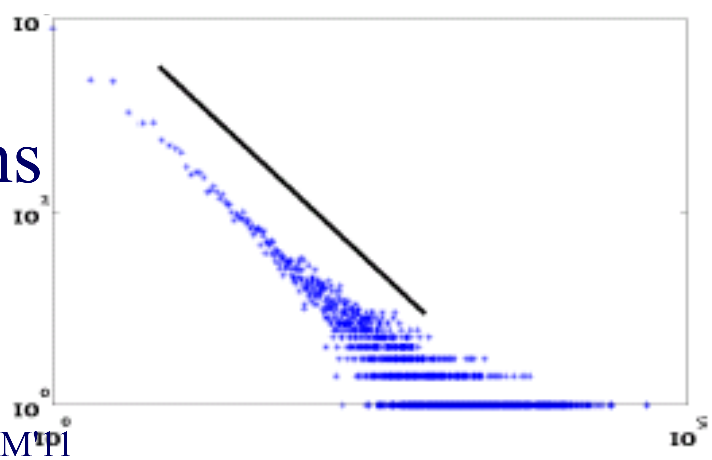
HEP-TH

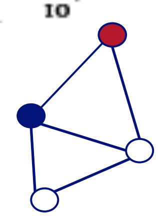


ASN



Epinions



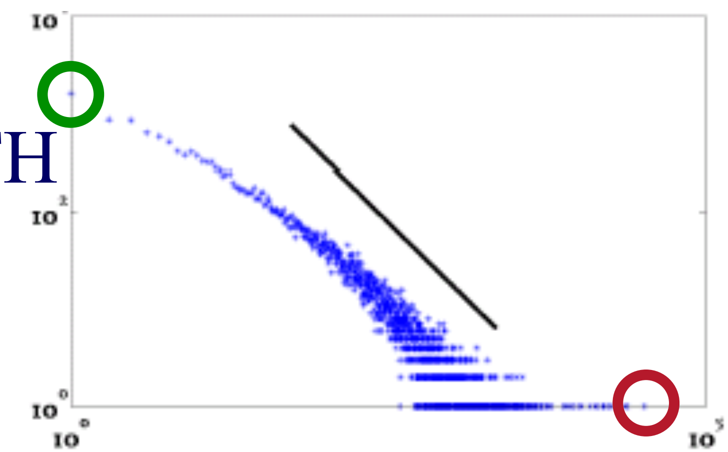


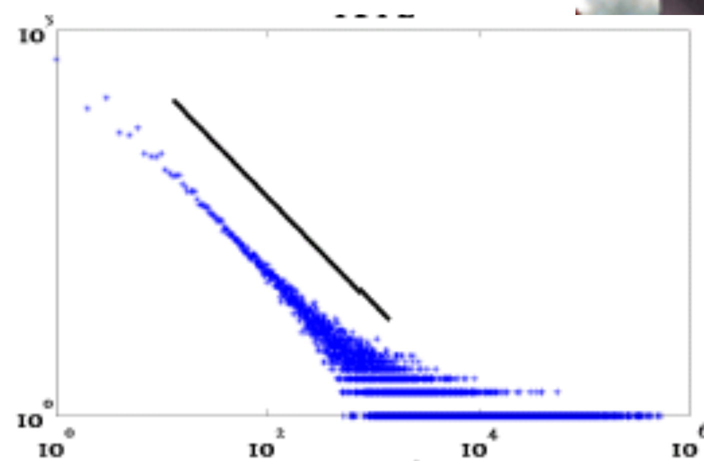
X-axis: # of participating triangles

Y: count (~ pdf)

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

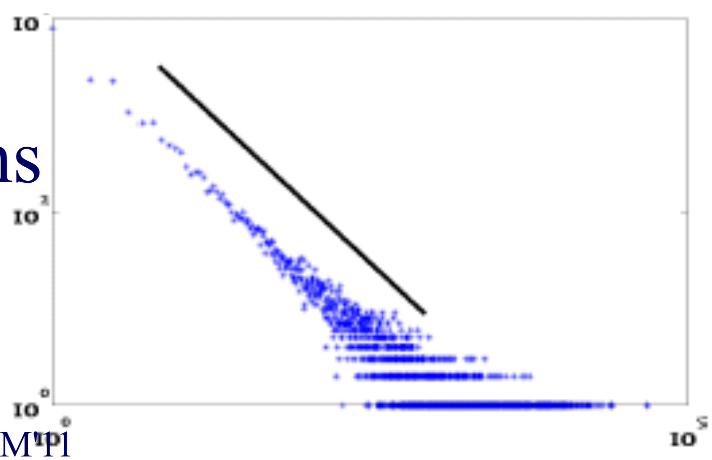
HEP-TH

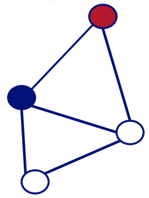




ASN

Epinions





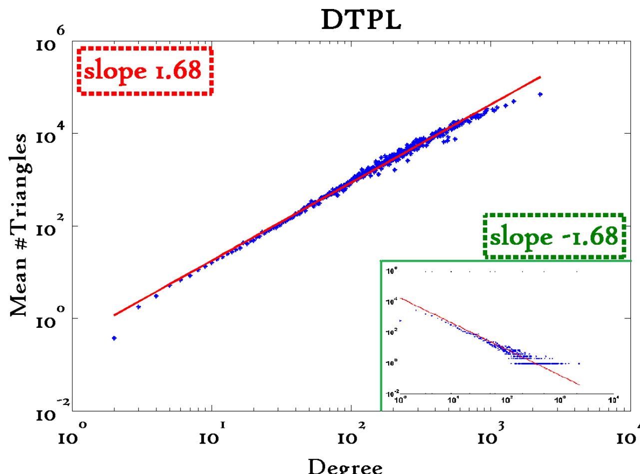
X-axis: # of participating triangles

Y: count (~ pdf)

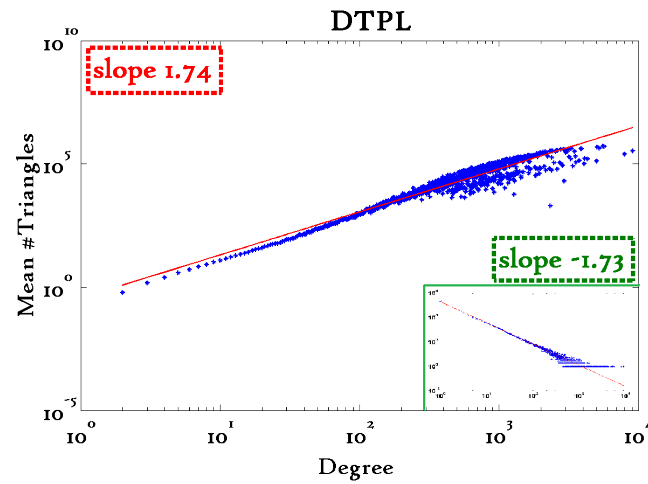
Carnegie Mellon

Triangle Law: #S.4
[Tsourakakis ICDM 2008]

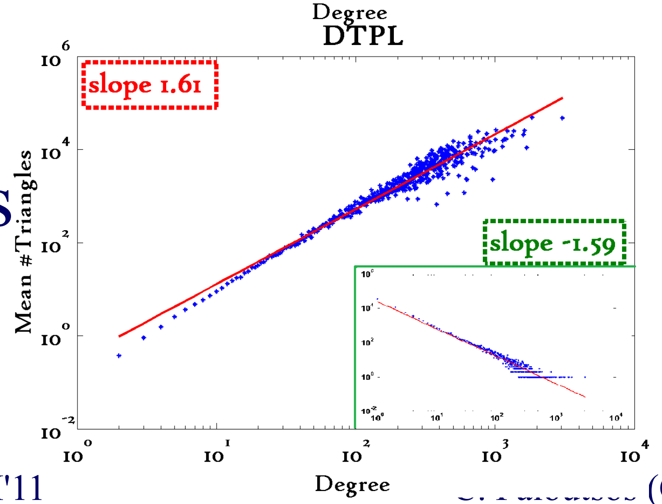
Reuters



SN



Epinions



X-axis: degree

Y-axis: mean # triangles

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

details

Triangle Law: Computations
[Tsourakakis ICDM 2008]

But: triangles are expensive to compute
(3-way join; several approx. algos)
Q: Can we do that quickly?

details

Triangle Law: Computations
[Tsourakakis ICDM 2008]

But: triangles are expensive to compute
(3-way join; several approx. algos)

Q: Can we do that quickly?

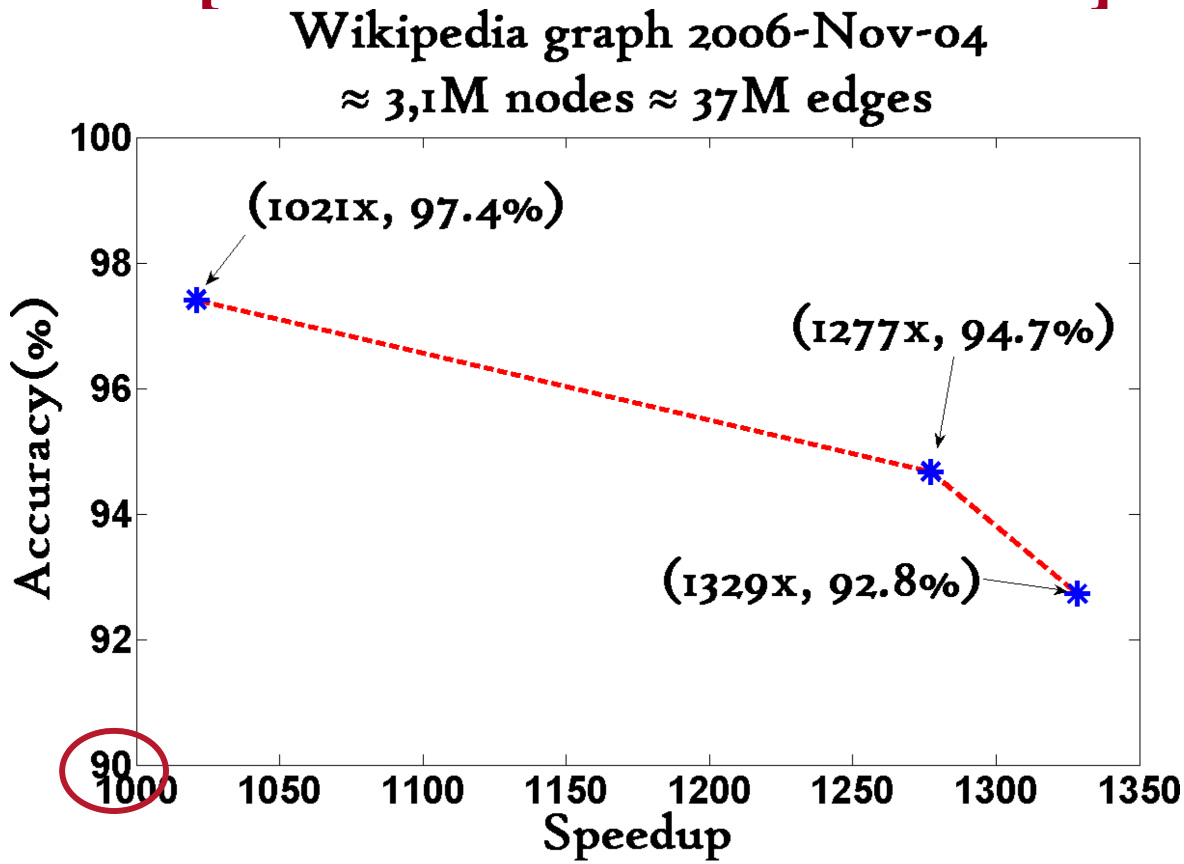
A: Yes!

#triangles = 1/6 Sum (λ_i^3)

(and, because of skewness (S2) ,
we only need the top few eigenvalues!

details

Triangle Law: Computations
[Tsourakakis ICDM 2008]



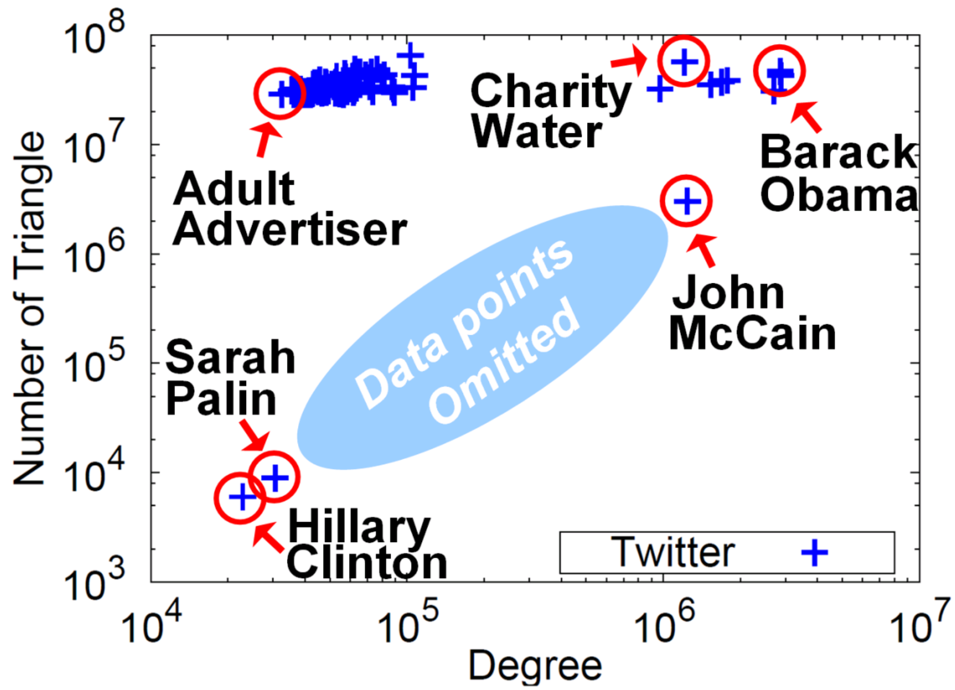
1000x+ speed-up, >90% accuracy

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]

EigenSpokes

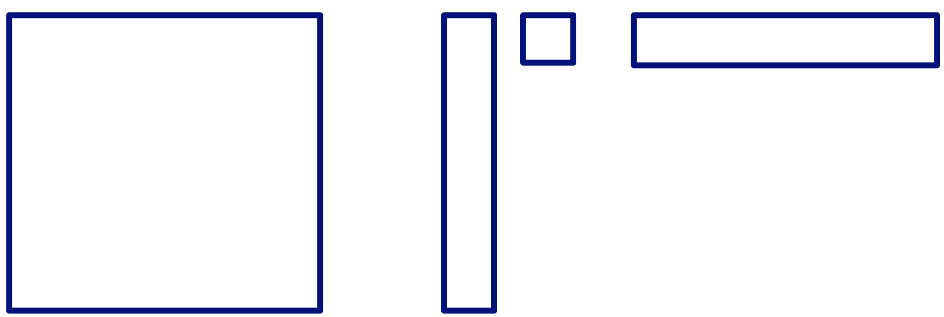
B. Aditya Prakash, Mukund Seshadri, Ashwin Sridharan, Sridhar Machiraju and Christos Faloutsos: *EigenSpokes: Surprising Patterns and Scalable Community Chipping in Large Graphs*, PAKDD 2010, Hyderabad, India, 21-24 June 2010.

Carnegie Mellon

EigenSpokes

- Eigenvectors of adjacency matrix
  - equivalent to singular vectors (symmetric, undirected graph)

$$A = U \Sigma U^T$$

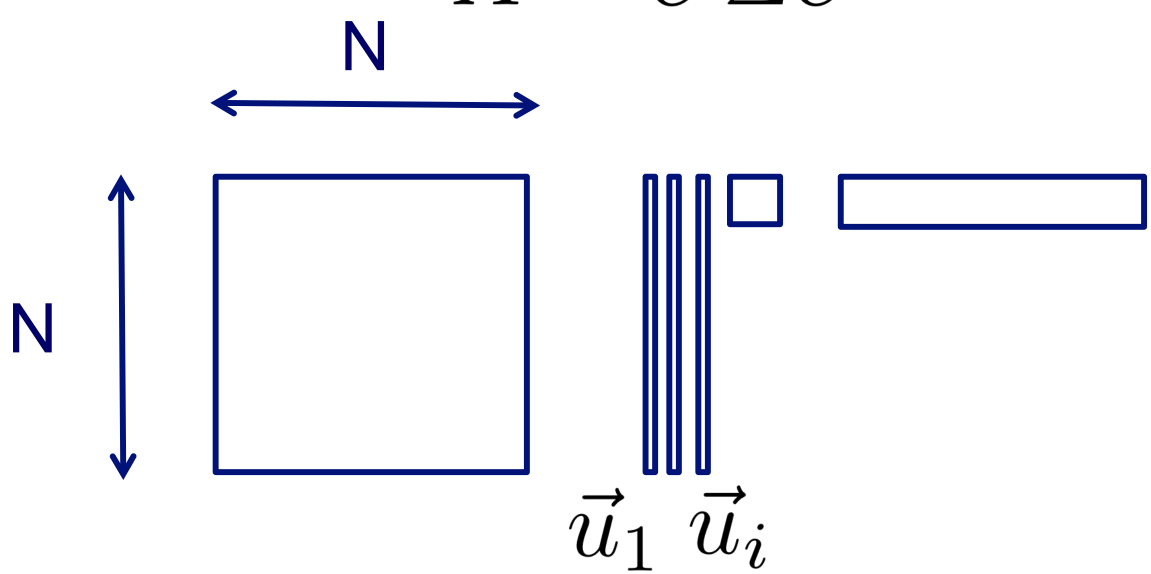


details

EigenSpokes

- Eigenvectors of adjacency matrix
  - equivalent to singular vectors (symmetric, undirected graph)

$$A = U \Sigma U^T$$

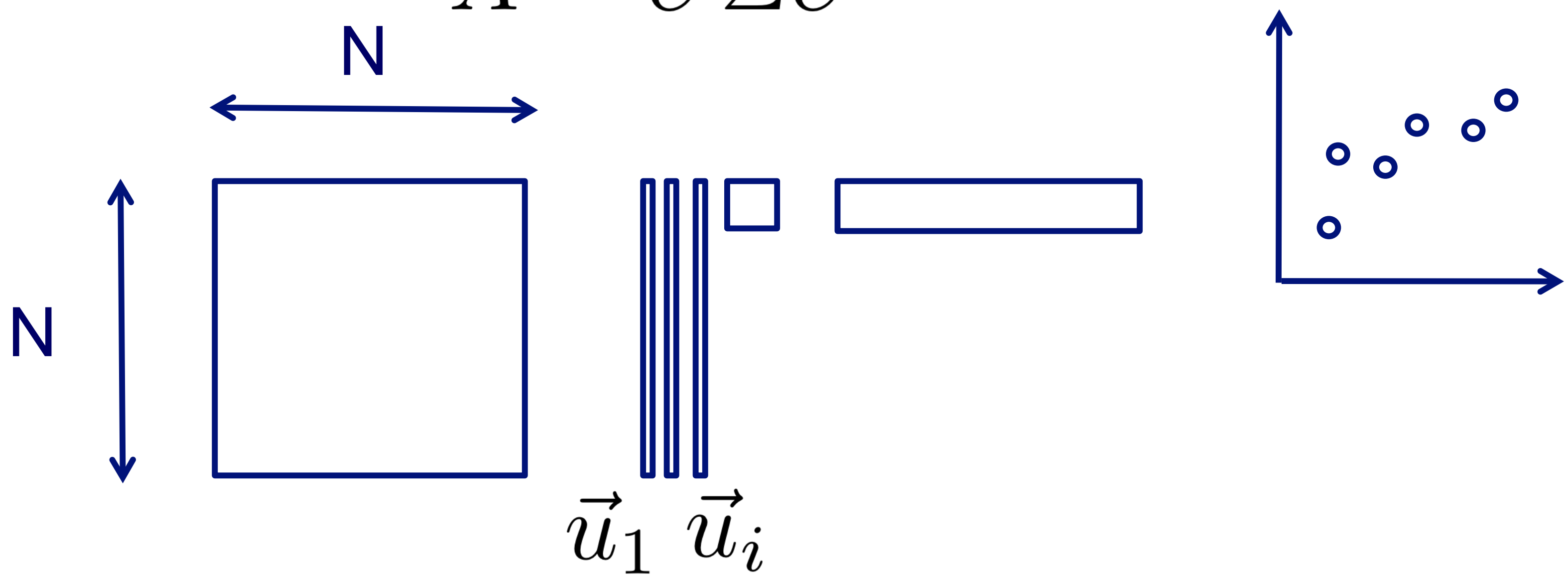


details

EigenSpokes

- Eigenvectors of adjacency matrix
  - equivalent to singular vectors (symmetric, undirected graph)

$$A = U \Sigma U^T$$

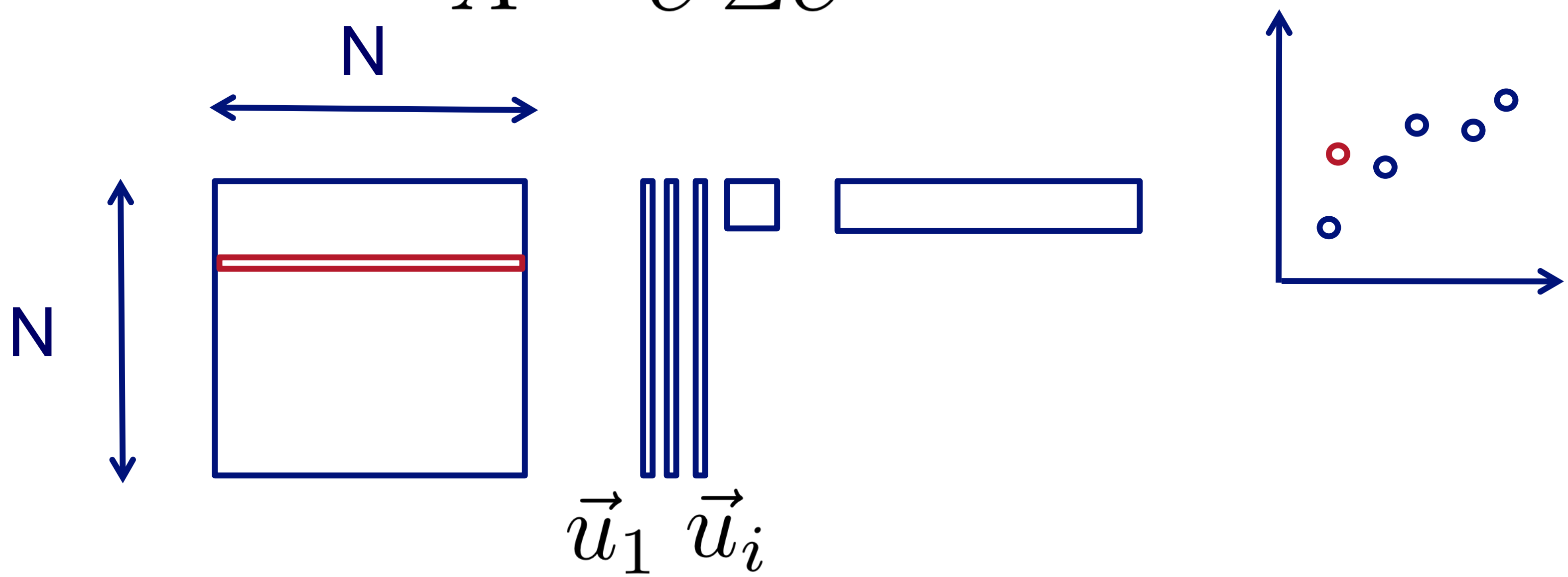


details

EigenSpokes

- Eigenvectors of adjacency matrix
  - equivalent to singular vectors (symmetric, undirected graph)

$$A = U \Sigma U^T$$

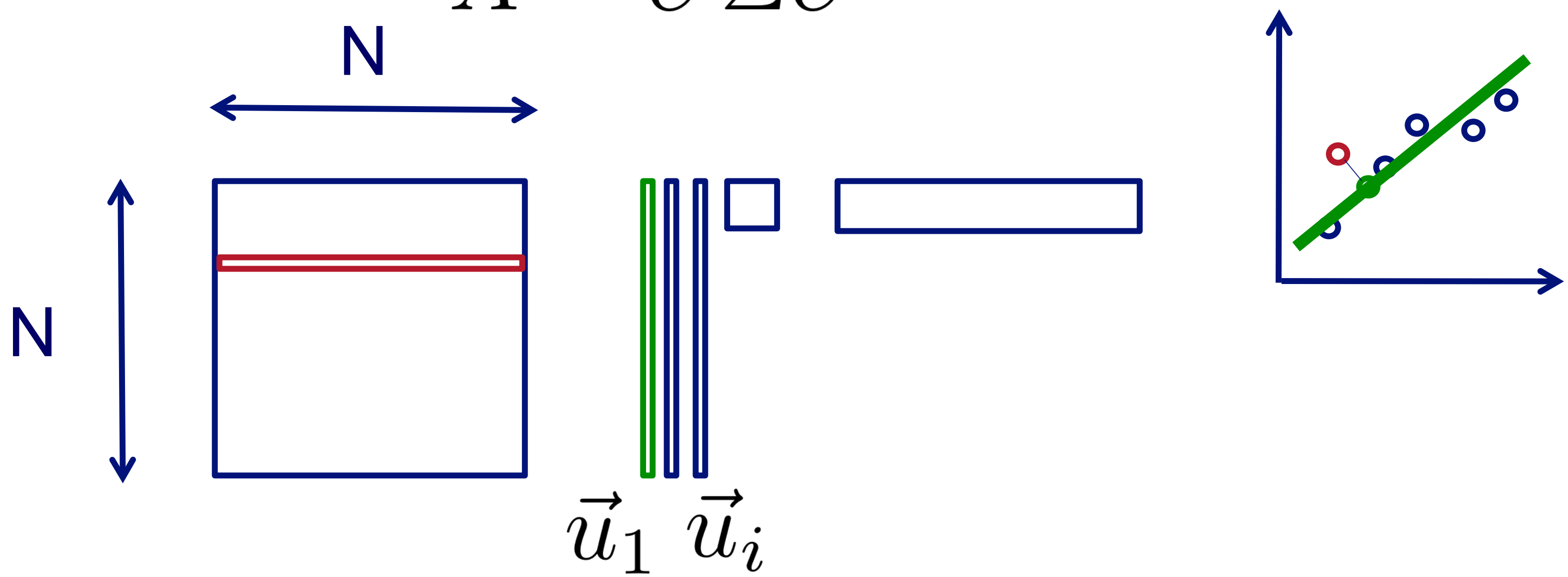


details

EigenSpokes

- Eigenvectors of adjacency matrix
  - equivalent to singular vectors (symmetric, undirected graph)

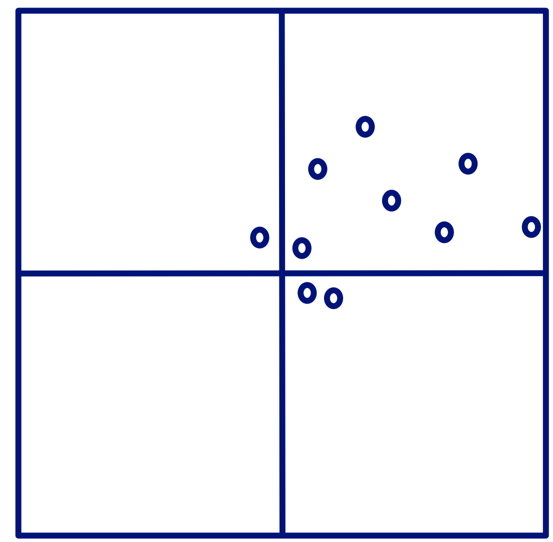
$$A = U \Sigma U^T$$



EigenSpokes

- EE plot:
- Scatter plot of scores of u1 vs u2
- One would expect
  - Many points @ origin
  - A few scattered ~randomly

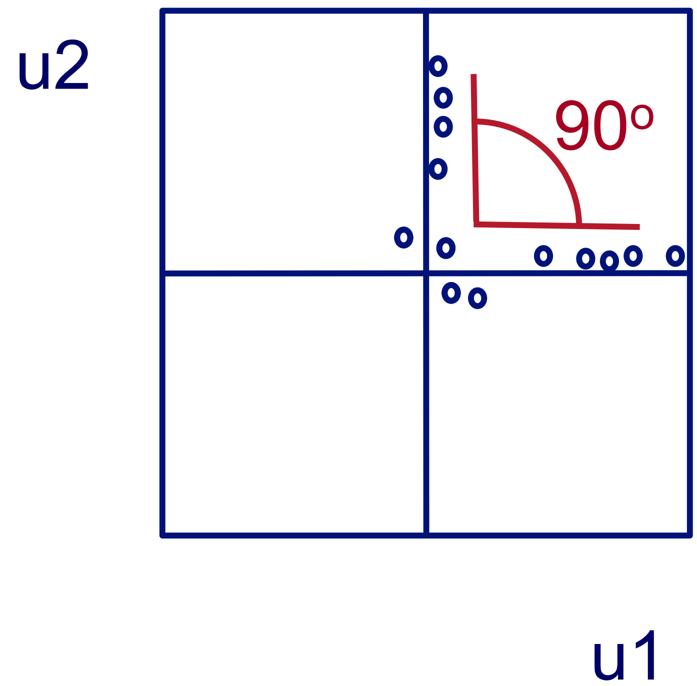
2nd Principal component
u2



u1
1st Principal component

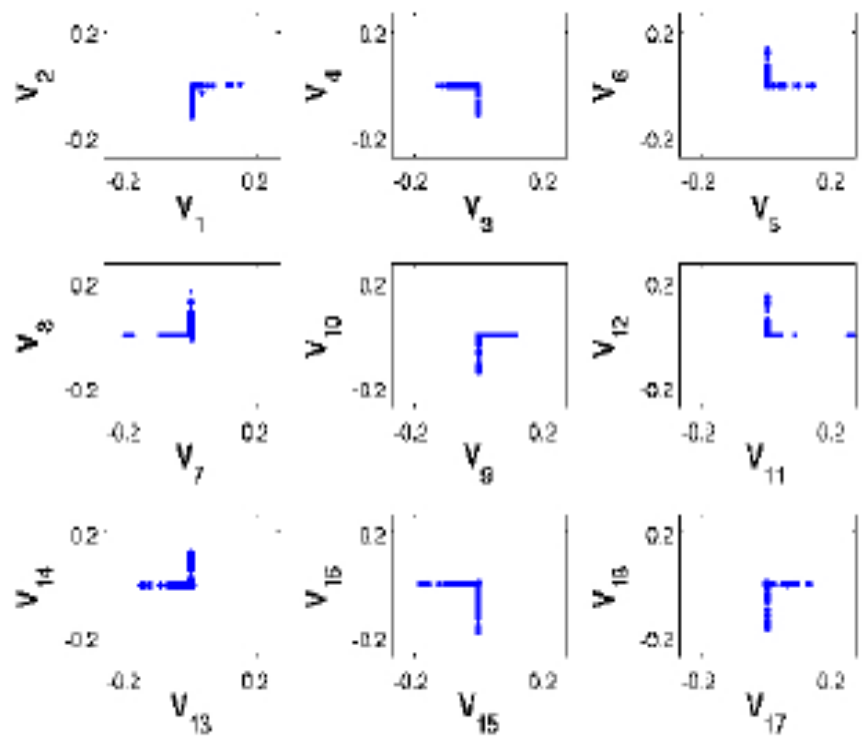
EigenSpokes

- EE plot:
- Scatter plot of scores of u1 vs u2
- One would expect
  - Many points @ origin
  - A few scattered ~randomly



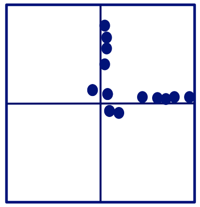
EigenSpokes - pervasiveness

- Present in mobile social graph
  - across time and space
- Patent citation graph

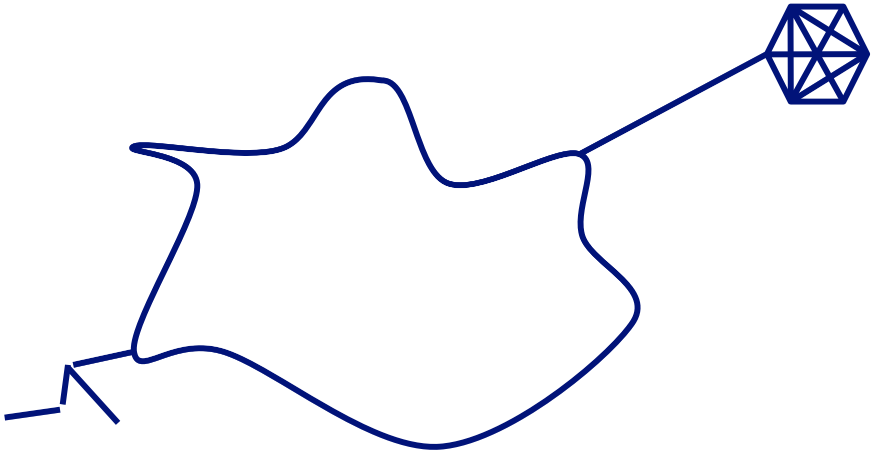


Carnegie Mellon

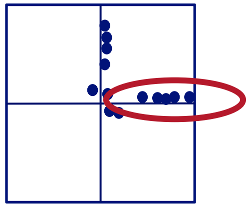
EigenSpokes - explanation



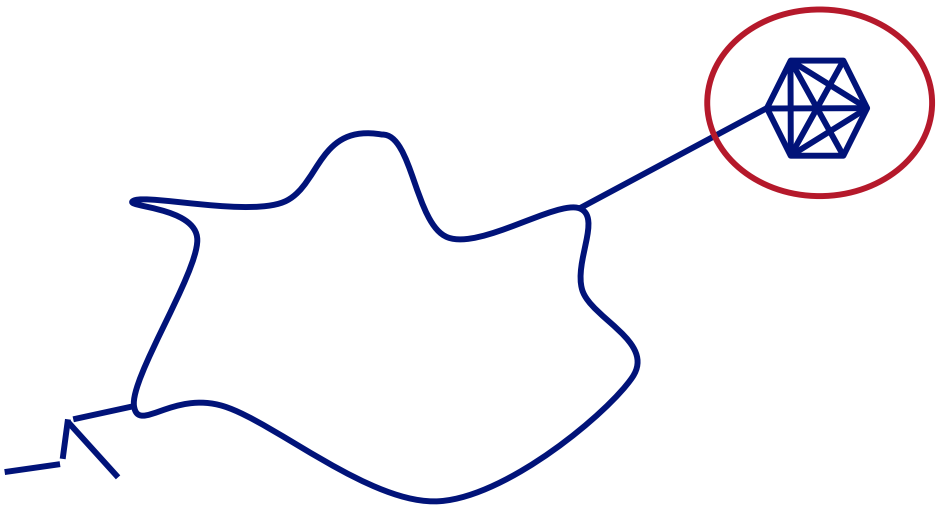
Near-cliques, or near-bipartite-cores, loosely connected



EigenSpokes - explanation

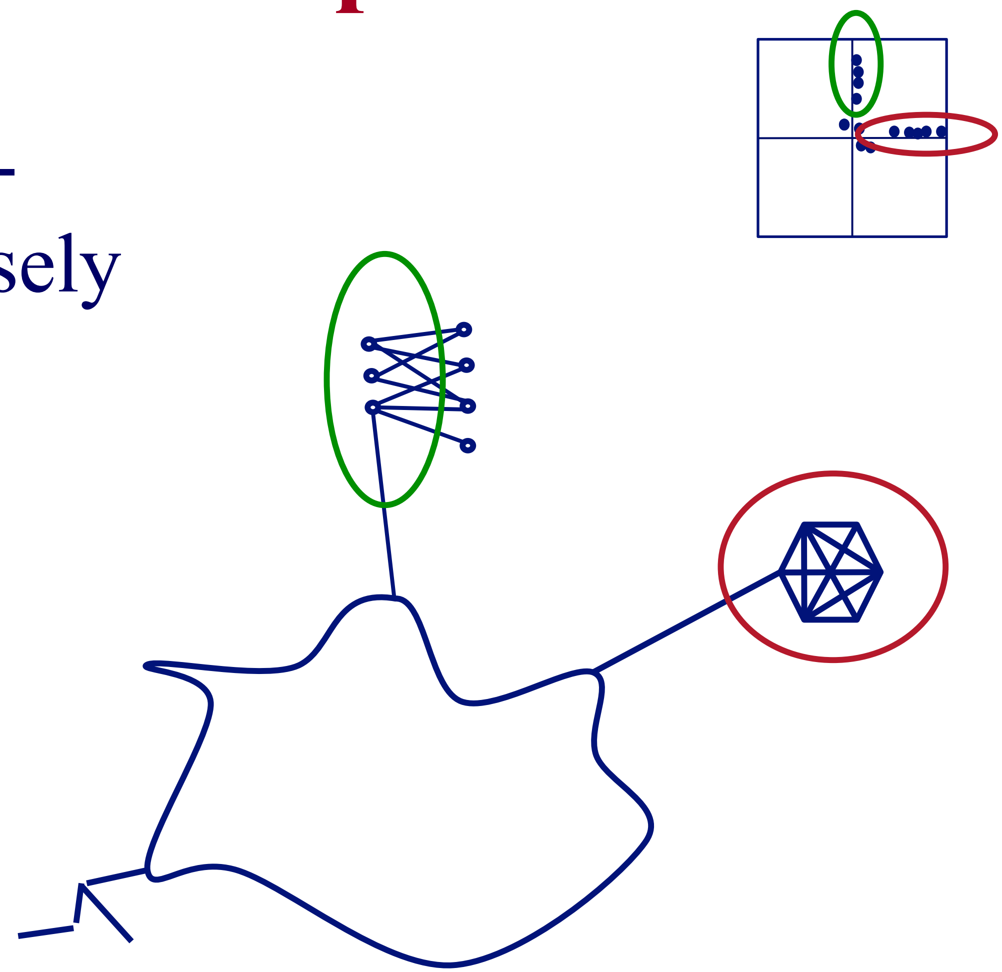


Near-cliques, or near-bipartite-cores, loosely connected

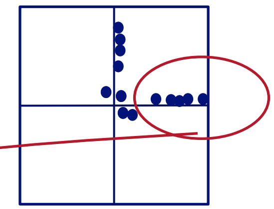


EigenSpokes - explanation

Near-cliques, or near-bipartite-cores, loosely connected

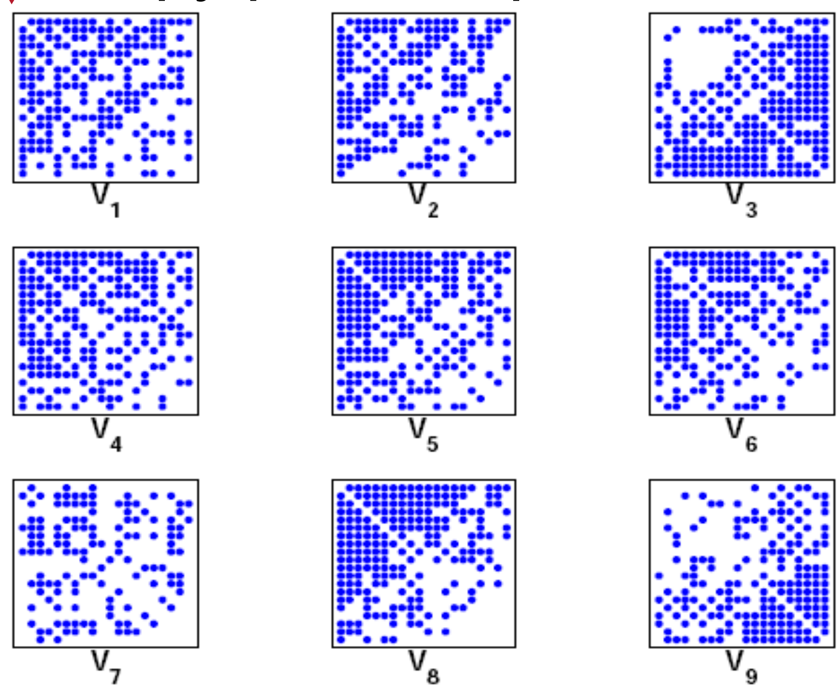


EigenSpokes - explanation



Near-cliques, or near-bipartite-cores, loosely connected

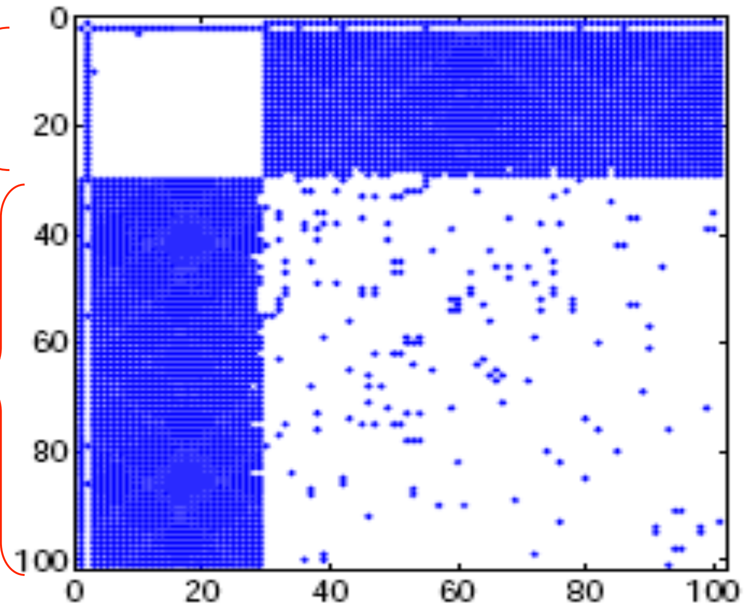
spy plot of top 20 nodes



So what?

- Extract nodes with high *scores*
- high connectivity
- Good "communities"

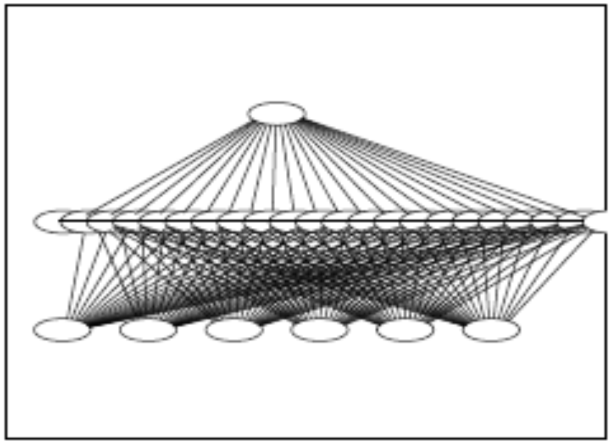
Bipartite Communities!



patents from same inventor(s)

`cut-and-paste' bibliography!

magnified bipartite community



Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
  - Static graphs
    - degree, diameter, eigen,
    - triangles
    - cliques
  - Weighted graphs
  - Time evolving graphs
- Problem#2: Tools

Observations on weighted graphs?

- A: yes - even more 'laws'!

M. McGlohon, L. Akoglu, and C. Faloutsos
Weighted Graphs and Disconnected Components: Patterns and a Generator.
SIG-KDD 2008

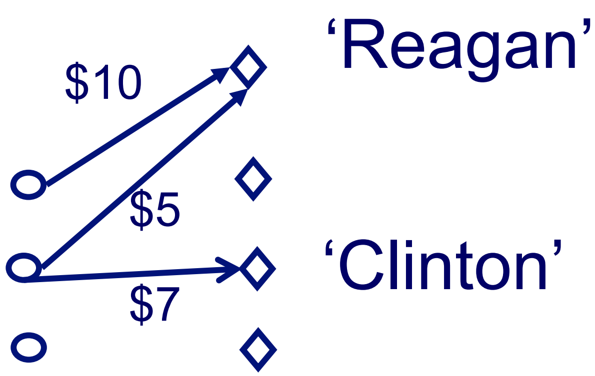
Observation W.1: Fortification

Q: How do the weights of nodes relate to degree?

Carnegie Mellon

Observation W.1: Fortification

More donors, more $?

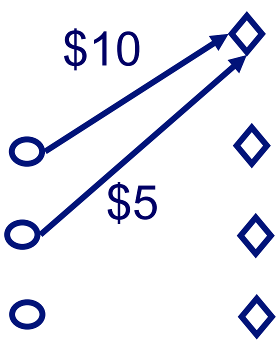


Carnegie Mellon

Observation W.1: fortification: Snapshot Power Law

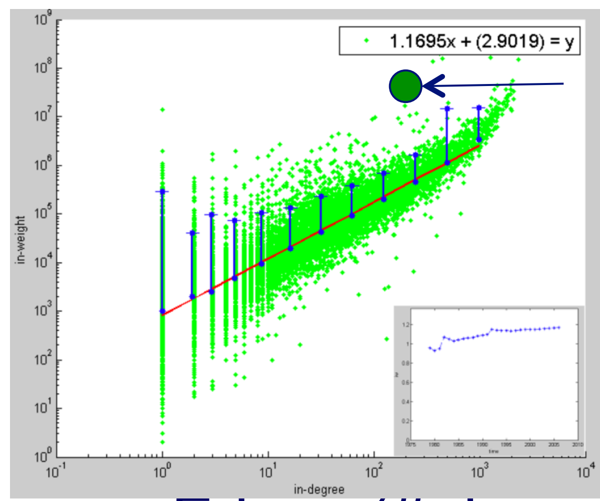
- Weight: super-linear on in-degree
- exponent ‘iw’: $1.01 < iw < 1.26$

More donors, even more $



Orgs-Candidates

In-weights ($)



e.g. John Kerry, $10M received, from 1K donors

Edges (# donors)

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
  - Static graphs
  - Weighted graphs
  - Time evolving graphs
- Problem#2: Tools
- …

Problem: Time evolution

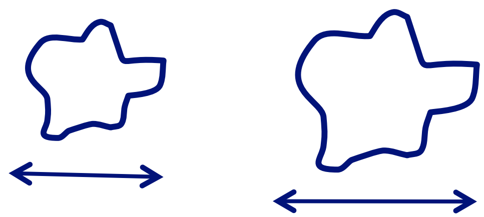
- with Jure Leskovec (CMU -> Stanford)

- and Jon Kleinberg (Cornell – sabb. @ CMU)

Carnegie Mellon

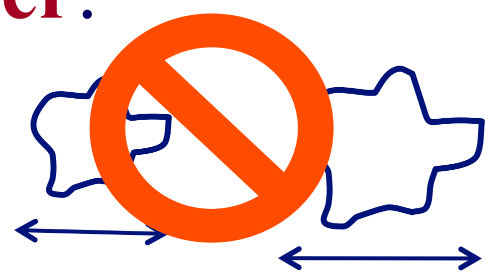
T.1 Evolution of the Diameter

- Prior work on Power Law graphs hints at **slowly growing diameter**:
  - diameter ~ O(log N)
  - diameter ~ O(log log N)
- What is happening in real data?



T.1 Evolution of the Diameter

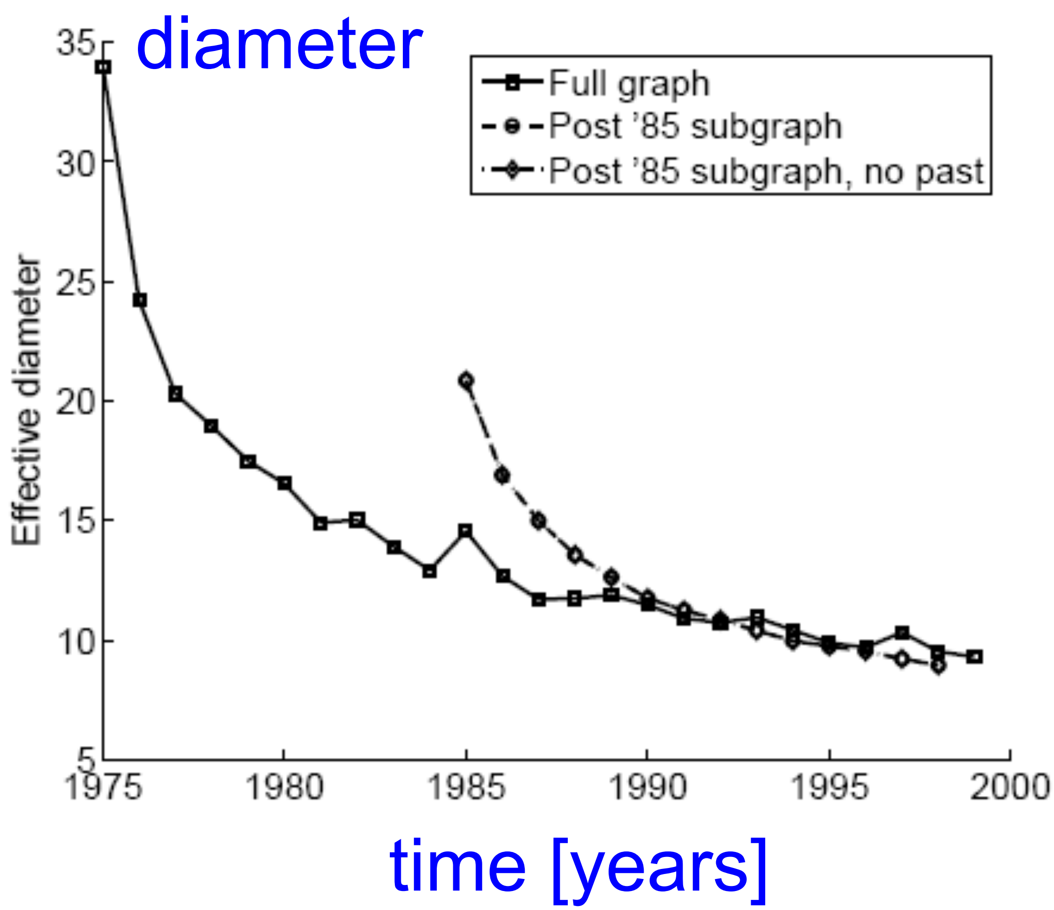
- Prior work on Power Law graphs hints at **slowly growing diameter**:
  - diameter ~ O(log N)
  - diameter ~ O(log log N)



- What is happening in real data?
- Diameter **shrinks** over time

T.1 Diameter – "Patents"

- Patent citation network
- 25 years of data
- @1999
  - 2.9 M nodes
  - 16.5 M edges



T.2 Temporal Evolution of the Graphs

- N(t) … nodes at time t
- E(t) … edges at time t
- Suppose that

$$N(t+1) = 2 * N(t)$$

- Q: what is your guess for

$$E(t+1) =?\ 2 * E(t)$$

T.2 Temporal Evolution of the Graphs

- N(t) … nodes at time t
- E(t) … edges at time t
- Suppose that

$$N(t+1) = 2 * N(t)$$

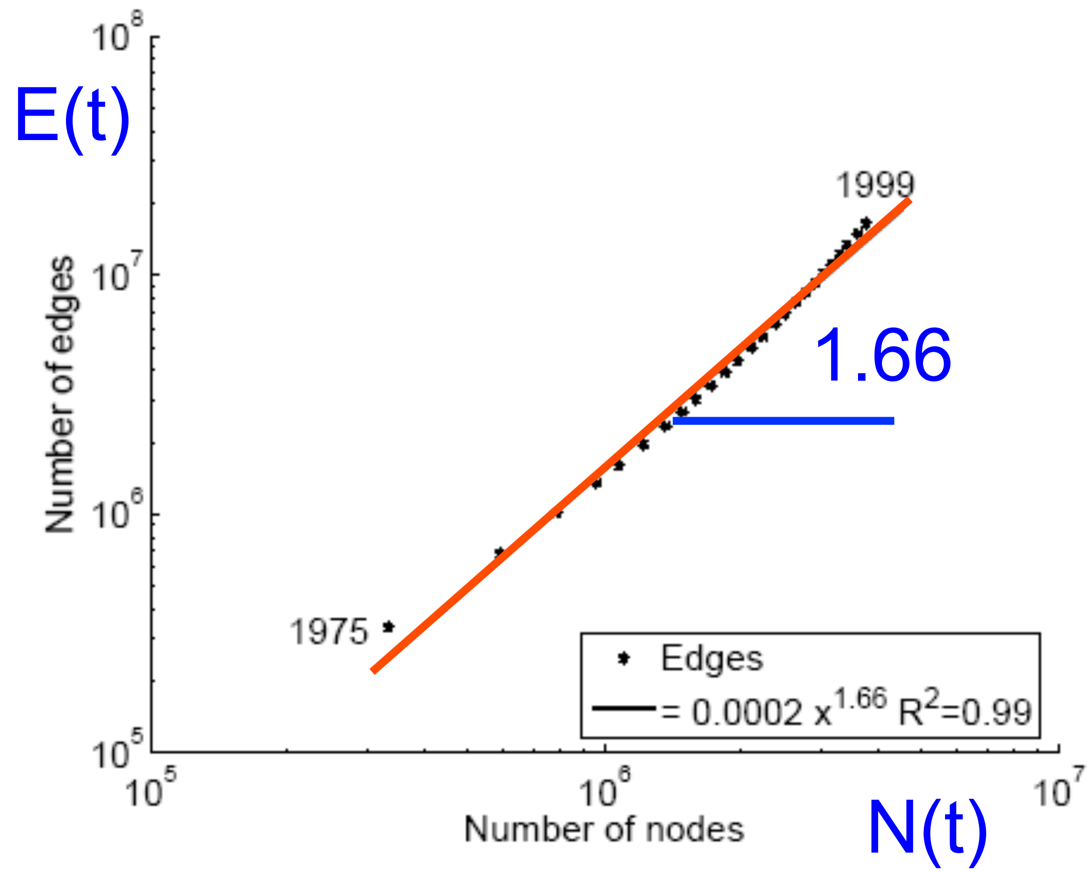
- Q: what is your guess for

$$E(t+1) \cancel{=?\ 2} * E(t)$$

- A: over-doubled!
  - But obeying the ``Densification Power Law''

T.2 Densification – Patent Citations

- Citations among patents granted
- @1999
  - 2.9 M nodes
  - 16.5 M edges
- Each year is a datapoint



Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
  - Static graphs
  - Weighted graphs
  - Time evolving graphs
- Problem#2: Tools
- …

More on Time-evolving graphs

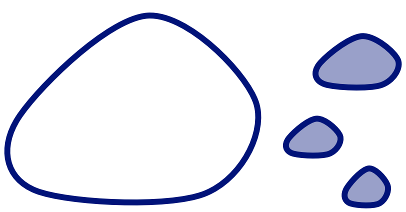
M. McGlohon, L. Akoglu, and C. Faloutsos
Weighted Graphs and Disconnected Components: Patterns and a Generator.
SIG-KDD 2008

Observation T.3: NLCC behavior

Q: How do NLCC's emerge and join with the GCC?

(``NLCC'' = non-largest conn. components)

- Do they continue to grow in size?
- or do they shrink?
- or stabilize?



Observation T.3: NLCC behavior

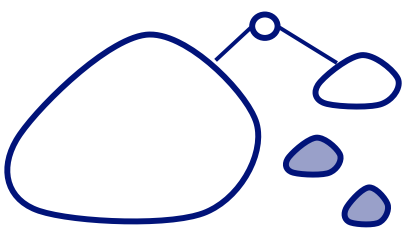
Q: How do NLCC's emerge and join with the GCC?

(``NLCC'' = non-largest conn. components)

– Do they continue to grow in size?

– or do they <u>shrink</u>?

– or stabilize?



Observation T.3: NLCC behavior

Q: How do NLCC's emerge and join with the GCC?

(``NLCC'' = non-largest conn. components)

YES – Do they continue to grow in size?

YES – or do they shrink?

YES – or stabilize?

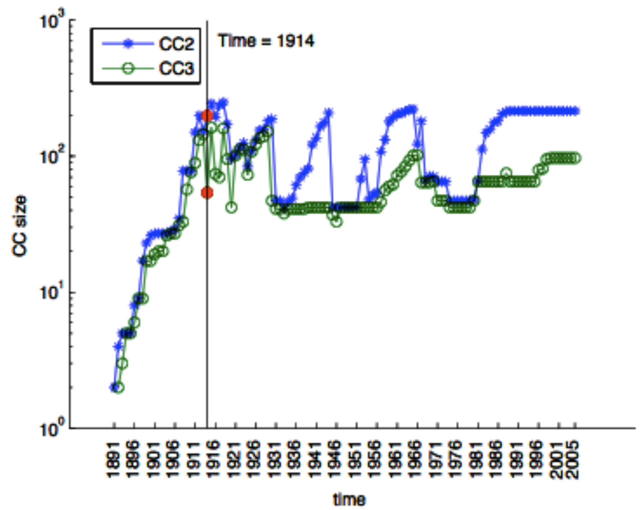
Carnegie Mellon

Observation T.3: NLCC behavior

- After the gelling point, the GCC takes off, but NLCC's remain ~constant (actually, **oscillate**).

IMDB

CC size



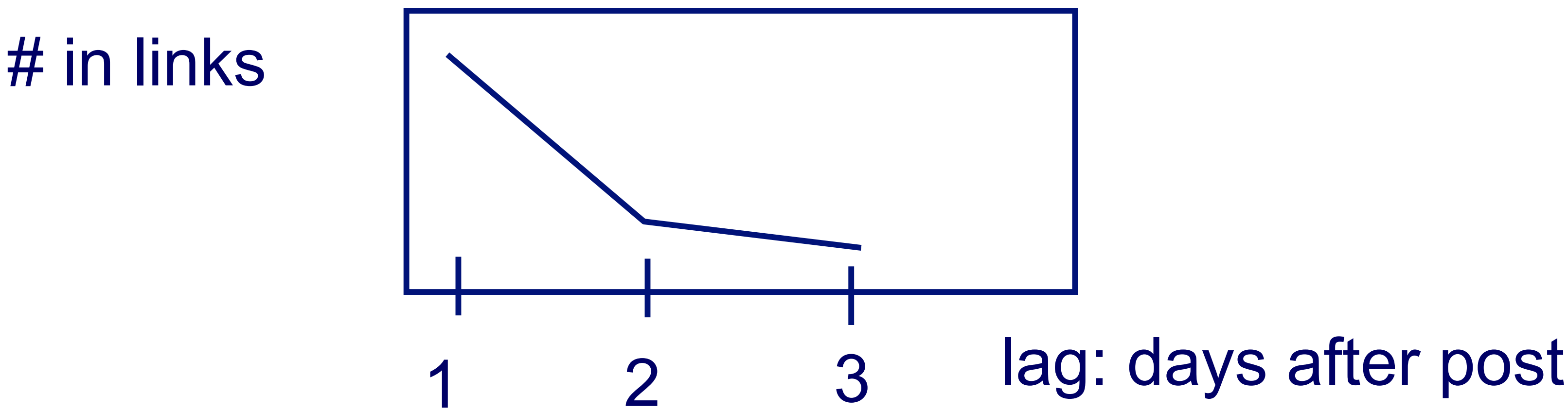
Time-stamp

Timing for Blogs

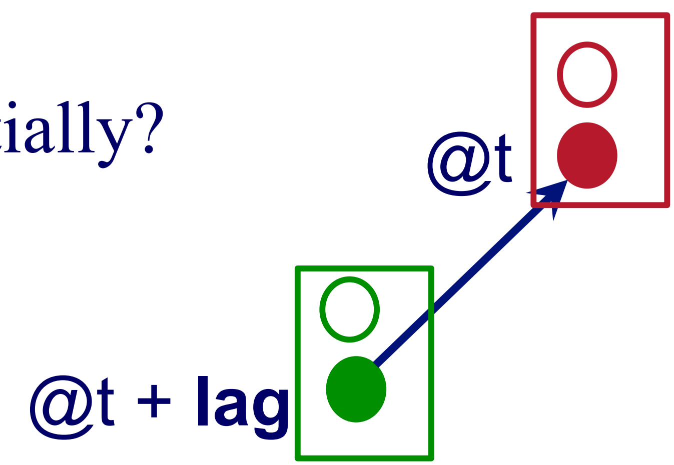
- with Mary McGlohon (CMU->Google)
- Jure Leskovec (CMU->Stanford)
- Natalie Glance (now at Google)
- Mat Hurst (now at MSR)

[SDM’07]

T.4 : popularity over time

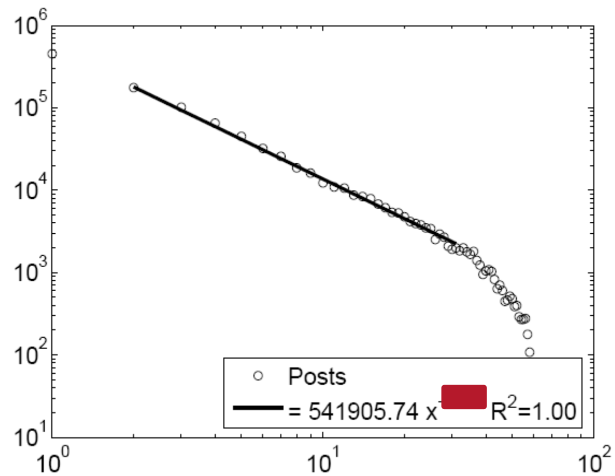


Post popularity drops-off – exponentially?



T.4 : popularity over time

in links (**log**)

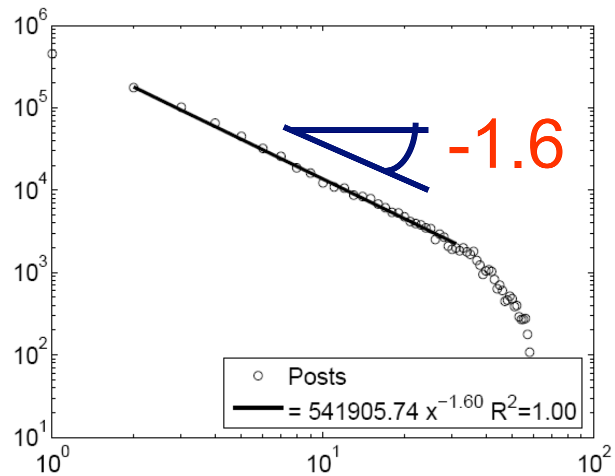


days after post (**log**)

Post popularity drops-off – exponentially?
POWER LAW!
Exponent?

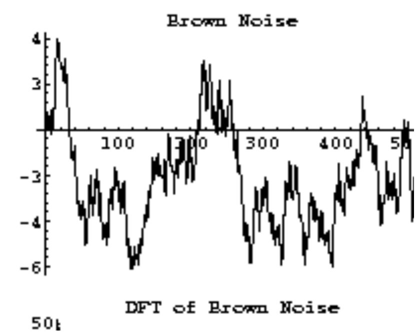
T.4 : popularity over time

in links
(**log**)



days after post
(**log**)

Post popularity drops-off – exponentially?
POWER LAW!
Exponent? -1.6
- close to -1.5: Barabasi's stack model
- and like the zero-crossings of a random walk



-1.5 slope

J. G. Oliveira & A.-L. Barabási Human Dynamics: The Correspondence Patterns of Darwin and Einstein. *Nature* **437,** 1251 (2005) . [PDF]

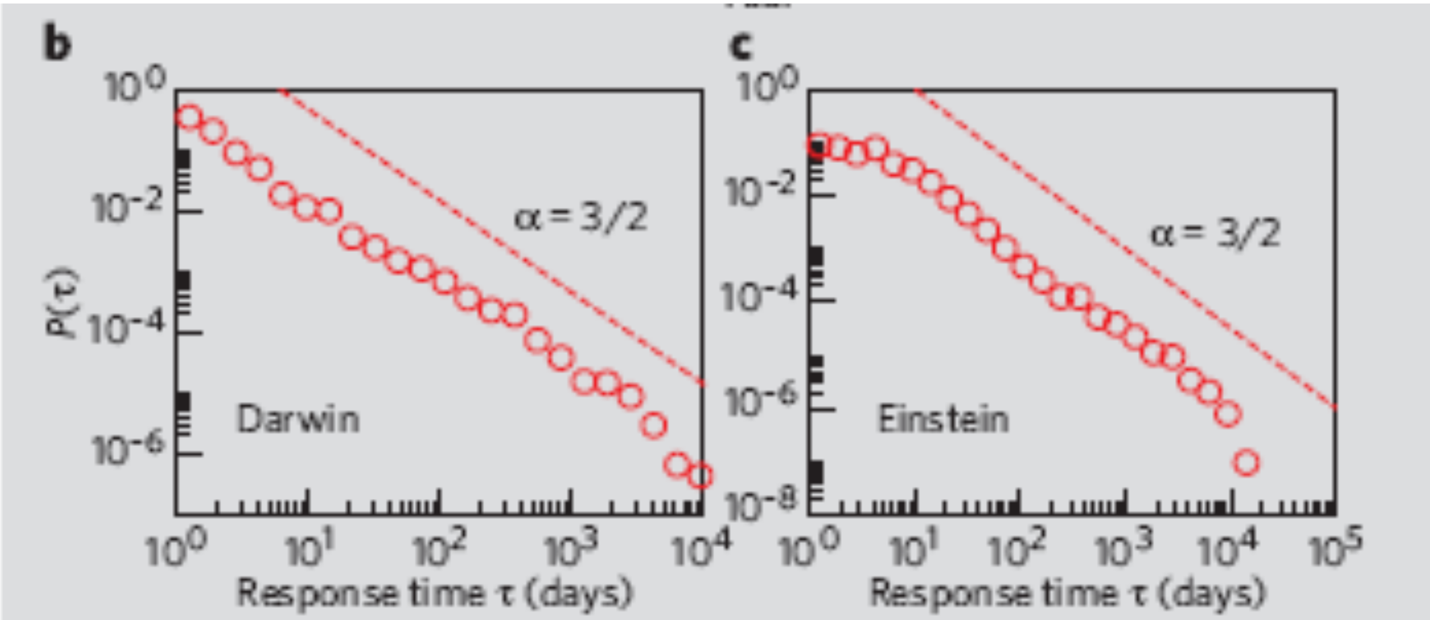


Figure 1 | The correspondence patterns of Darwin and Einstein.

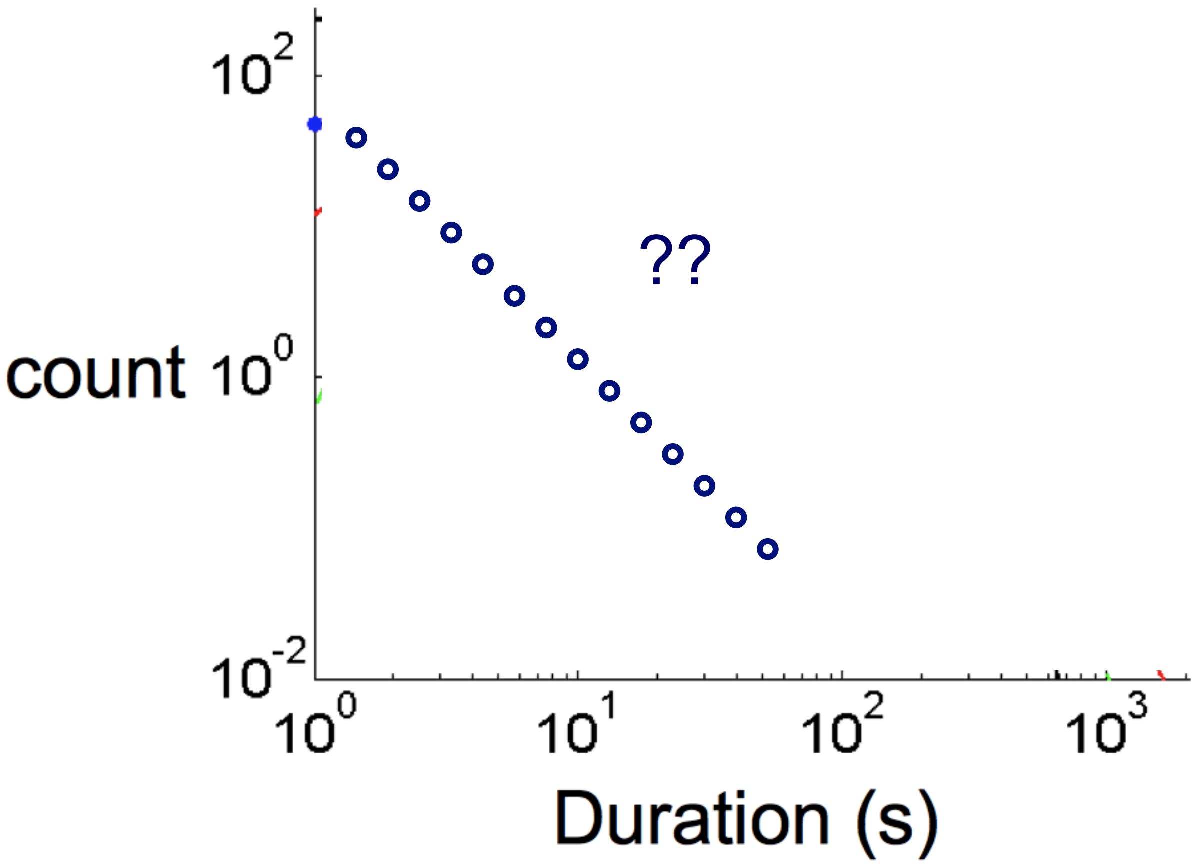
T.5: duration of phonecalls

Surprising Patterns for the Call Duration Distribution of Mobile Phone Users

Pedro O. S. Vaz de Melo, Leman Akoglu, Christos Faloutsos, Antonio A. F. Loureiro

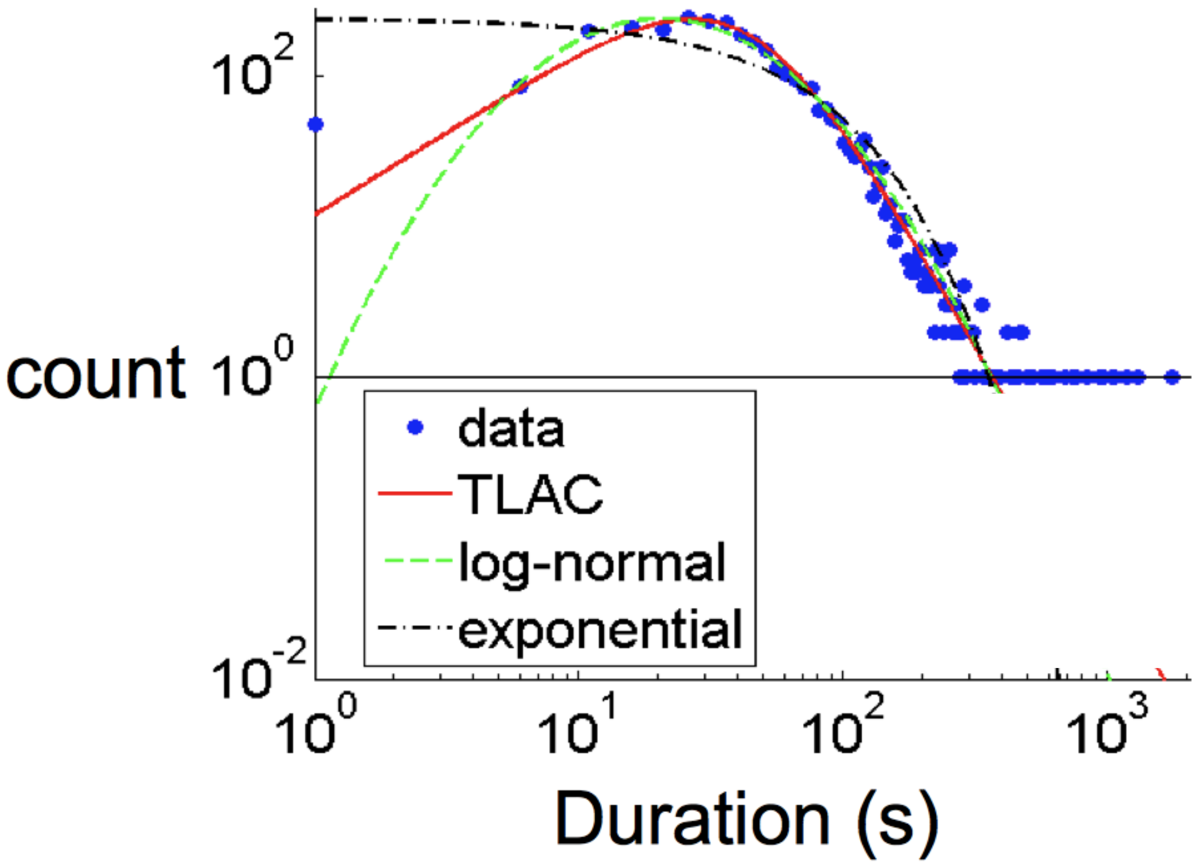
PKDD 2010

Probably, power law (?)



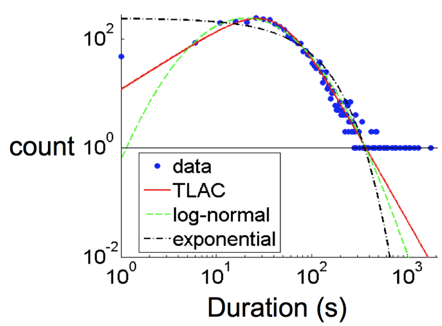
Carnegie Mellon

No Power Law!



'TLaC: Lazy Contractor'

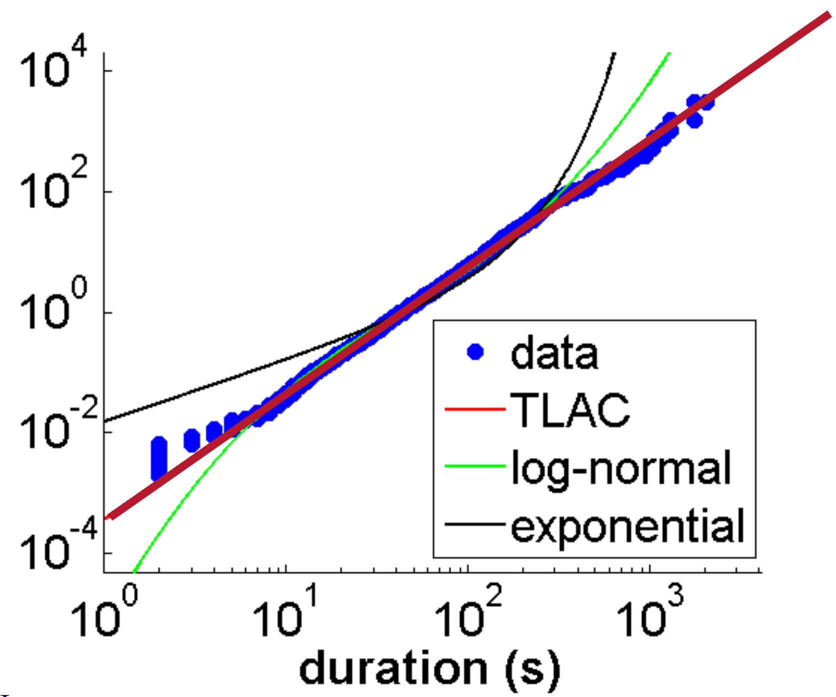
- The longer a task (phonecall) has taken,
- The even longer it will take



Odds ratio=

Casualties(<x):
Survivors(>=x)

== power law



Data Description

- Data from a private mobile operator of a large city
  - 4 months of data
  - 3.1 million users
  - more than 1 billion phone records
- Over 96% of 'talkative' users obeyed a TLAC distribution ('talkative': >30 calls)

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
  - OddBall (anomaly detection)
  - Belief Propagation
  - Immunization
- Problem#3: Scalability
- Conclusions

Carnegie Mellon

OddBall: Spotting Anomalies in Weighted Graphs

Leman Akoglu, Mary McGlohon, Christos Faloutsos

Carnegie Mellon University

School of Computer Science

PAKDD 2010, Hyderabad, India

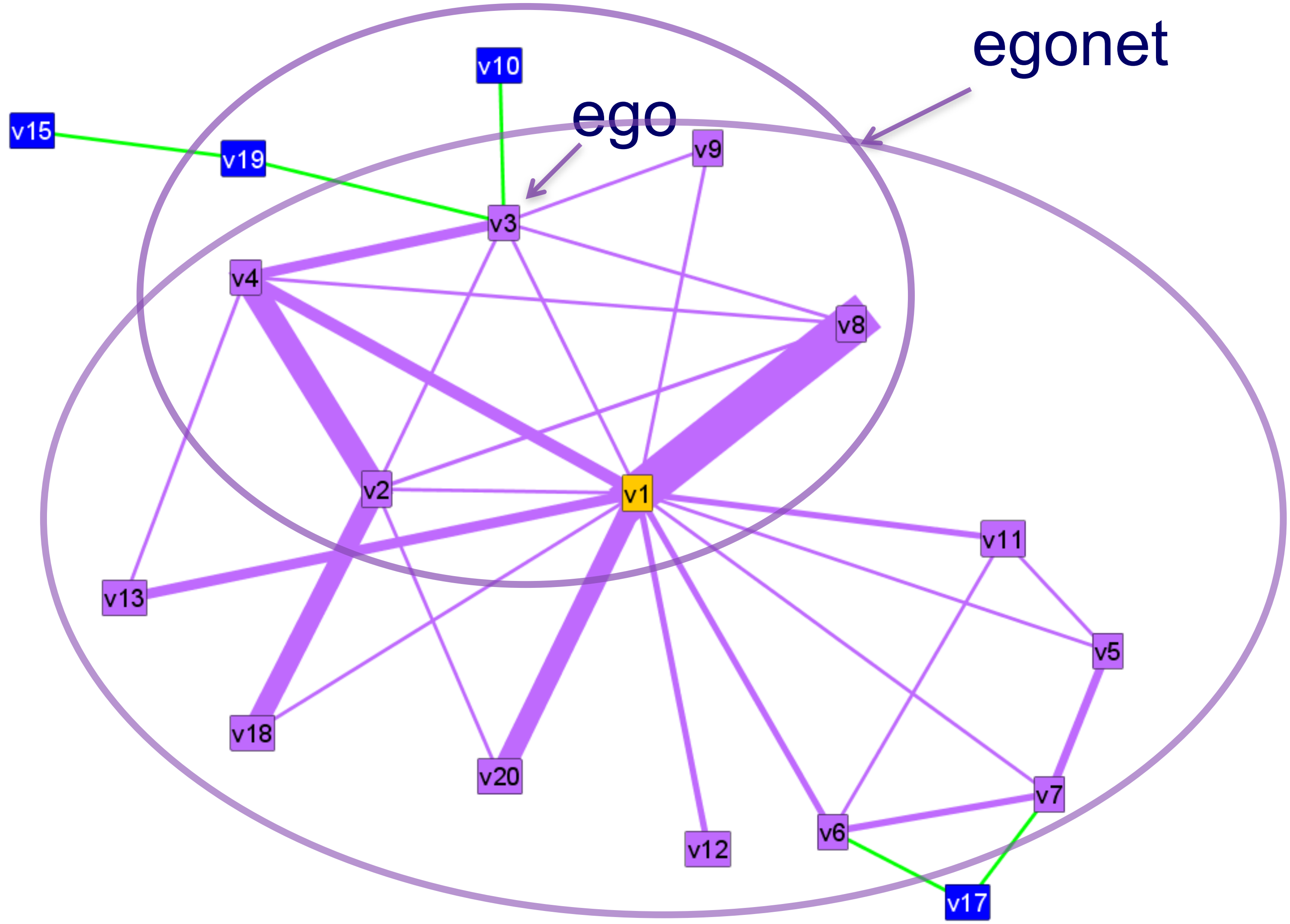
Main idea

For each node,

- extract ‘ego-net’ (=1-step-away neighbors)
- Extract features (#edges, total weight, etc etc)
- Compare with the rest of the population

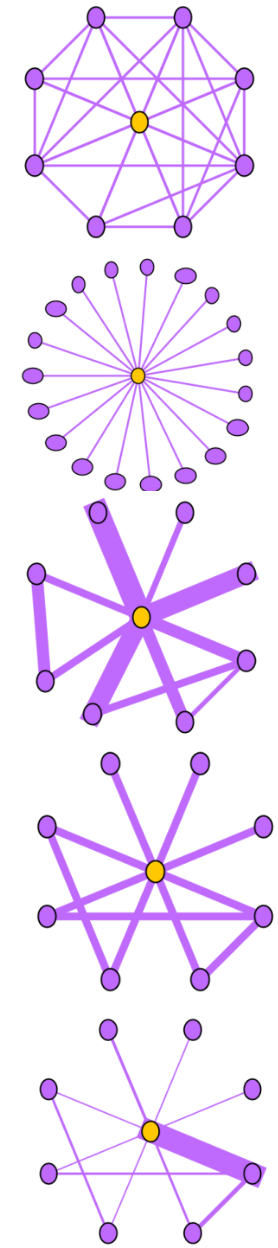
Carnegie Mellon

What is an egonet?



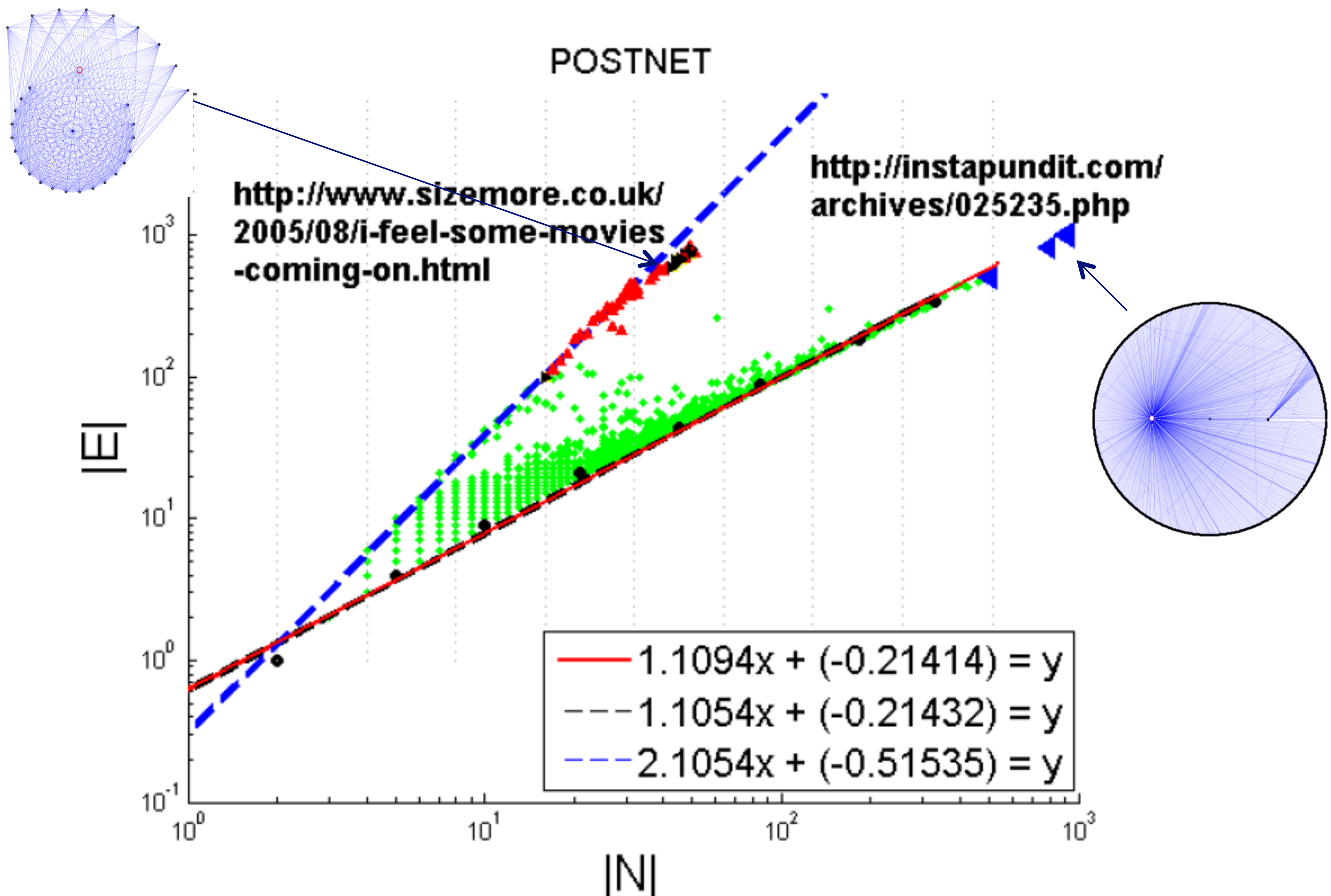
Carnegie Mellon

Selected Features



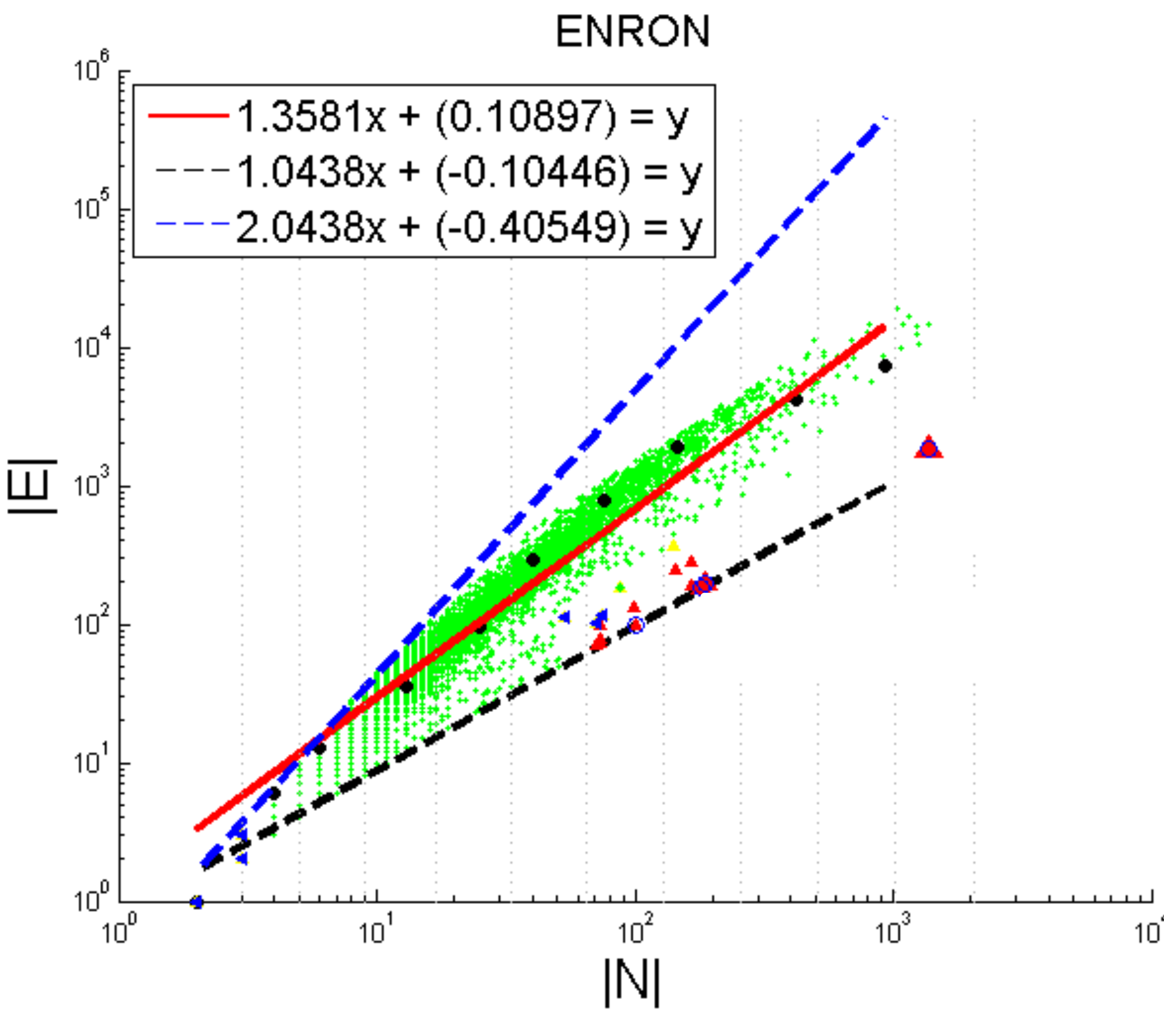
- N_i: number of neighbors (degree) of ego i
- E_i: number of edges in egonet i
- W_i: total weight of egonet i
- $\lambda_{w,i}$: principal eigenvalue of the weighted adjacency matrix of egonet I

Near-Clique/Star

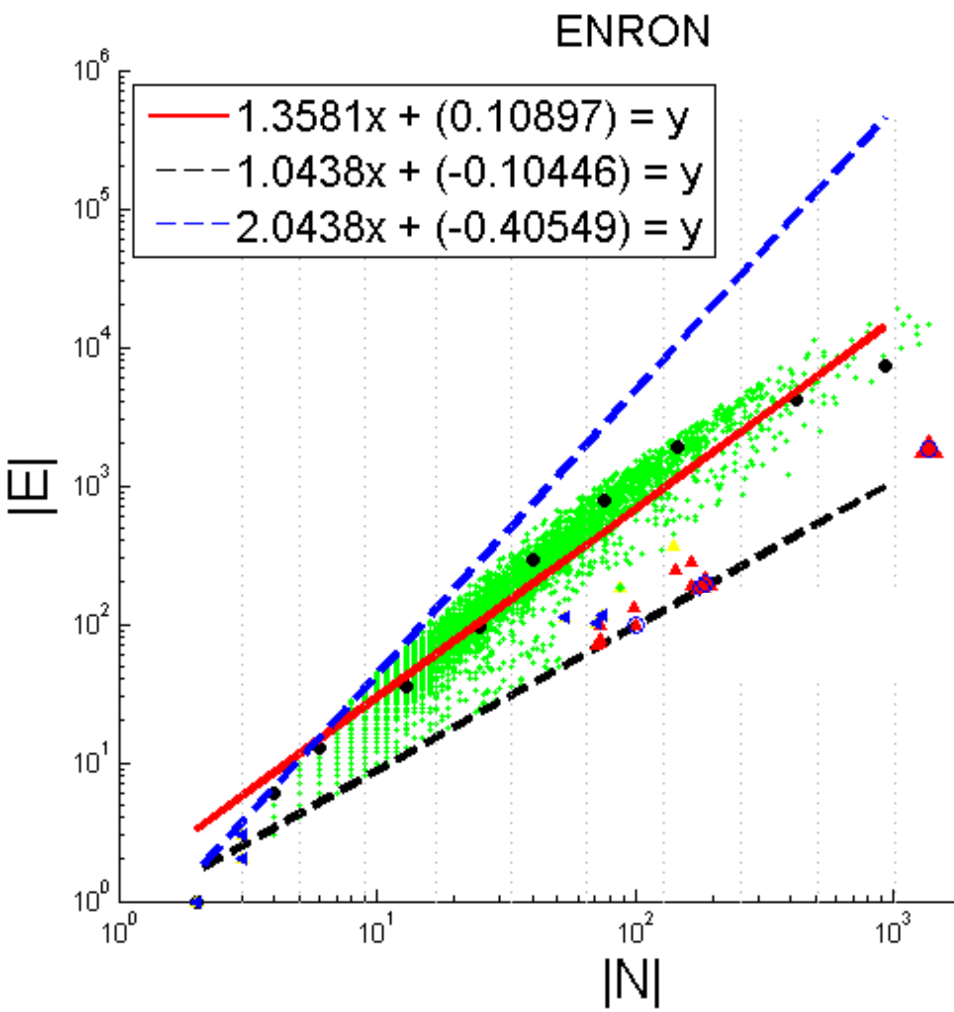


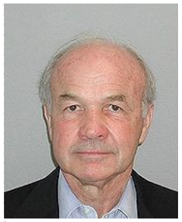
Carnegie Mellon

Near-Clique/Star



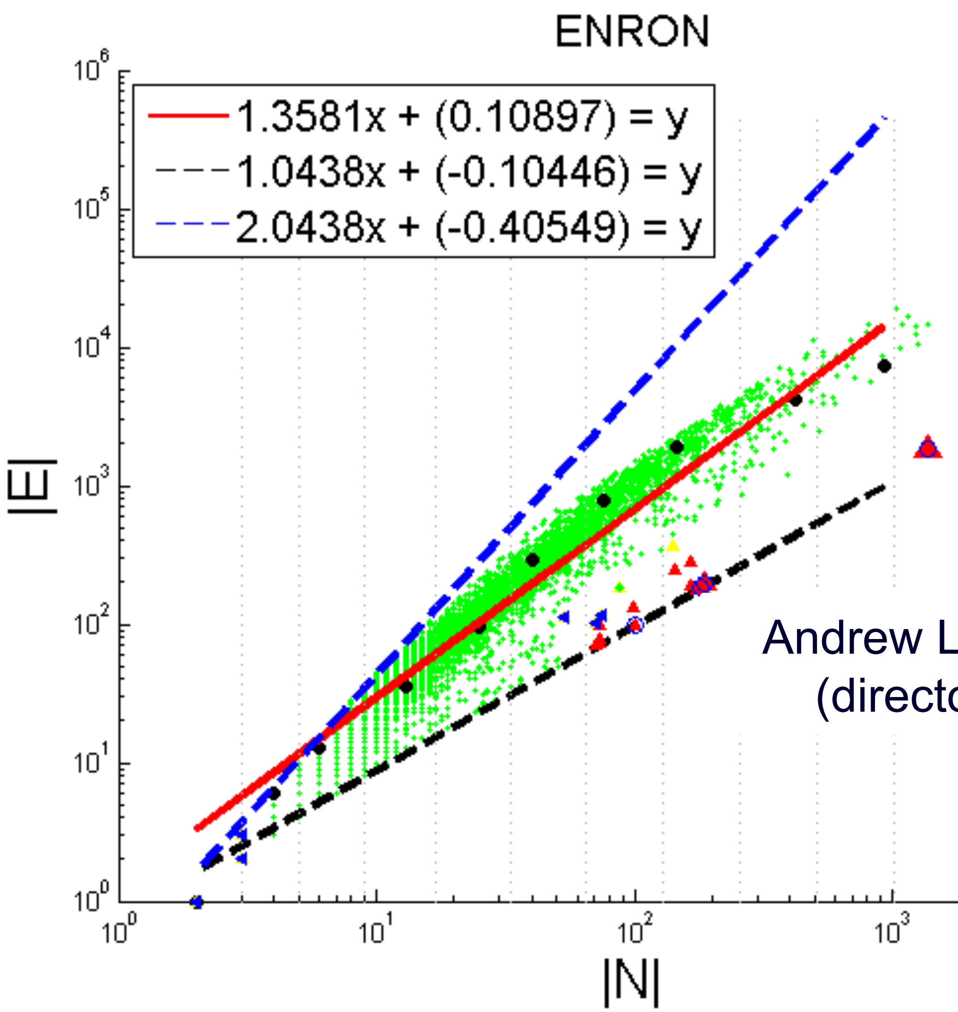
Near-Clique/Star

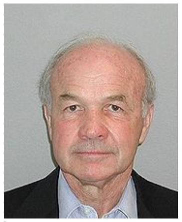




Kenneth Lay (CEO)

Near-Clique/Star





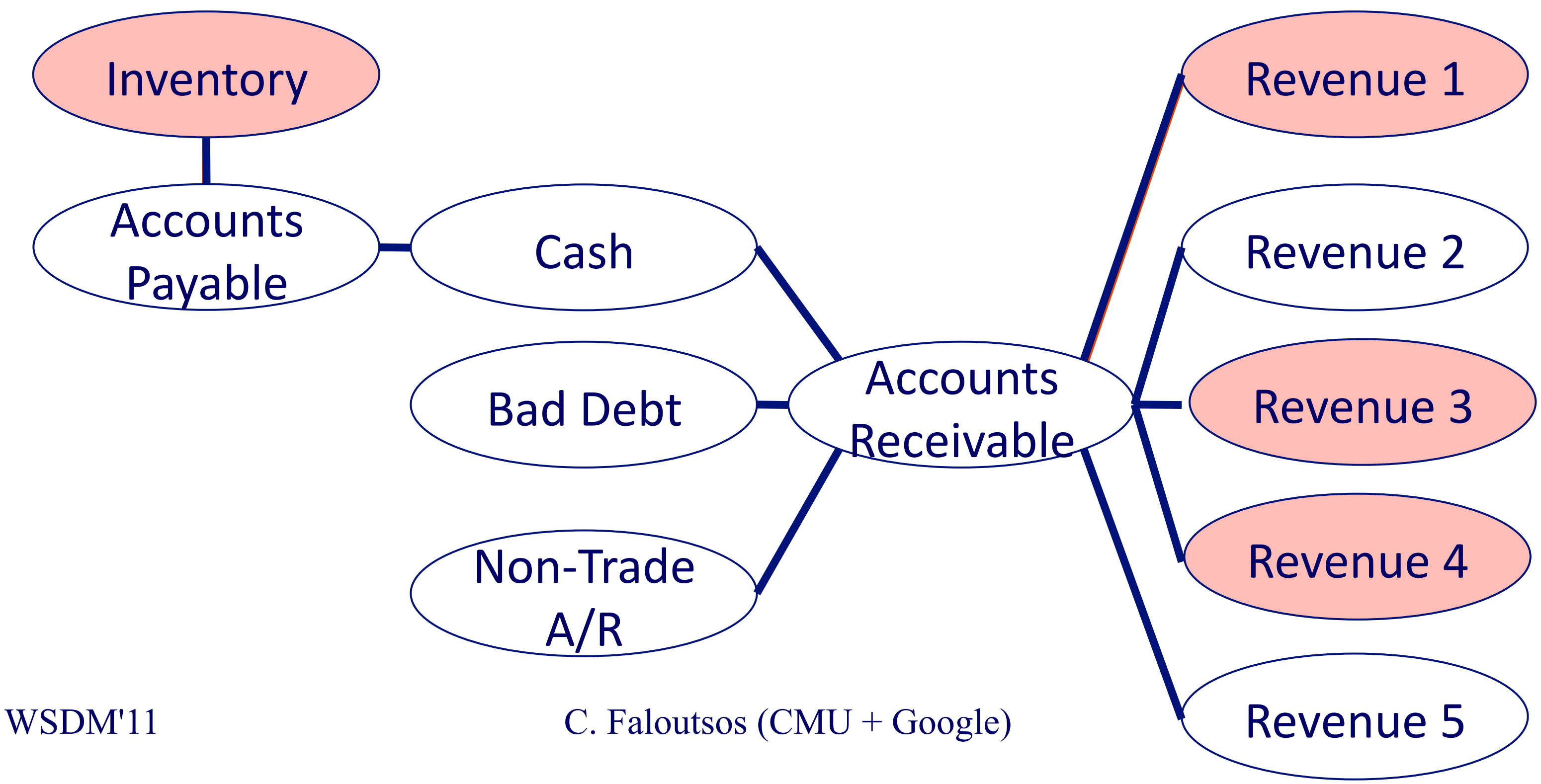
Kenneth Lay
(CEO)

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
  - OddBall (anomaly detection)
  - Belief Propagation
  - Immunization
- Problem#3: Scalability
- Conclusions

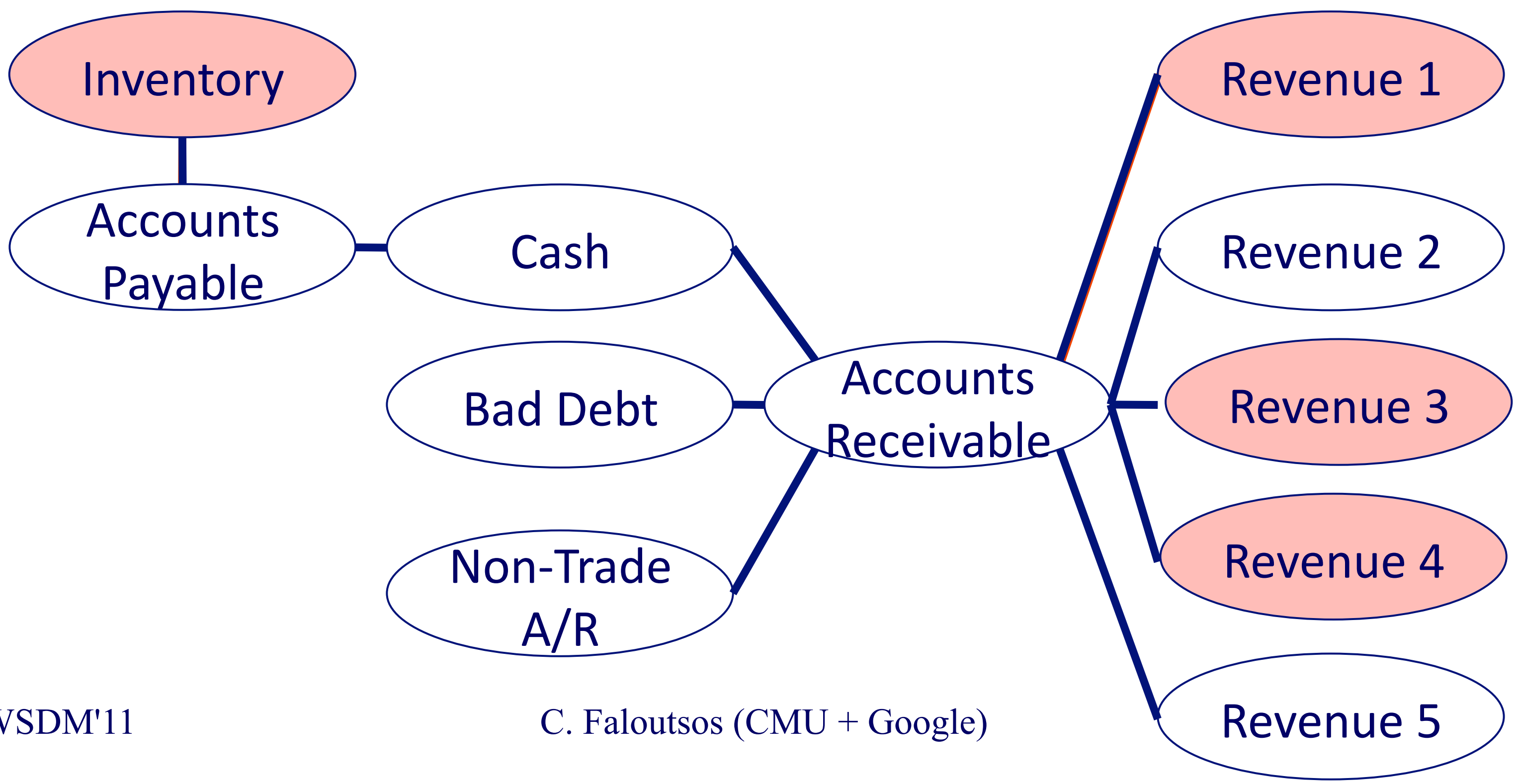
Fraud detection

- Problem: Given network and noisy domain knowledge about weakly-suspicious nodes (flags), which nodes are most risky?



Fraud detection

- Flags: eg, too many round numbers, etc



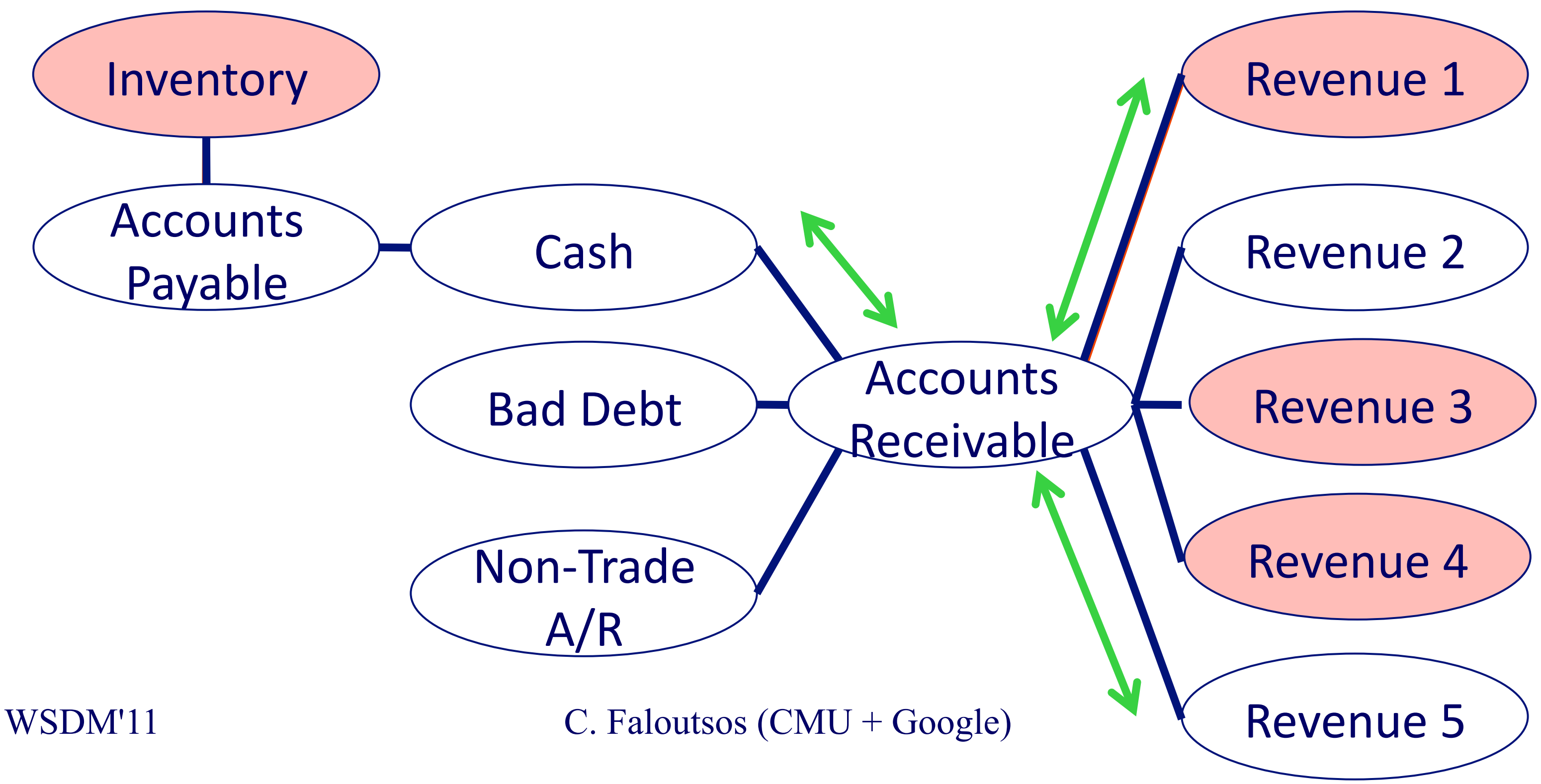
Solution: Belief Propagation

- Solution: Social Network Analytic Risk Evaluation
  - Assume homophily between nodes ("guilt by association")
  - Use belief propagation (message passing)
  - Upon convergence, determine end risk scores.

[SNARE: McGlohon+, KDD'09]

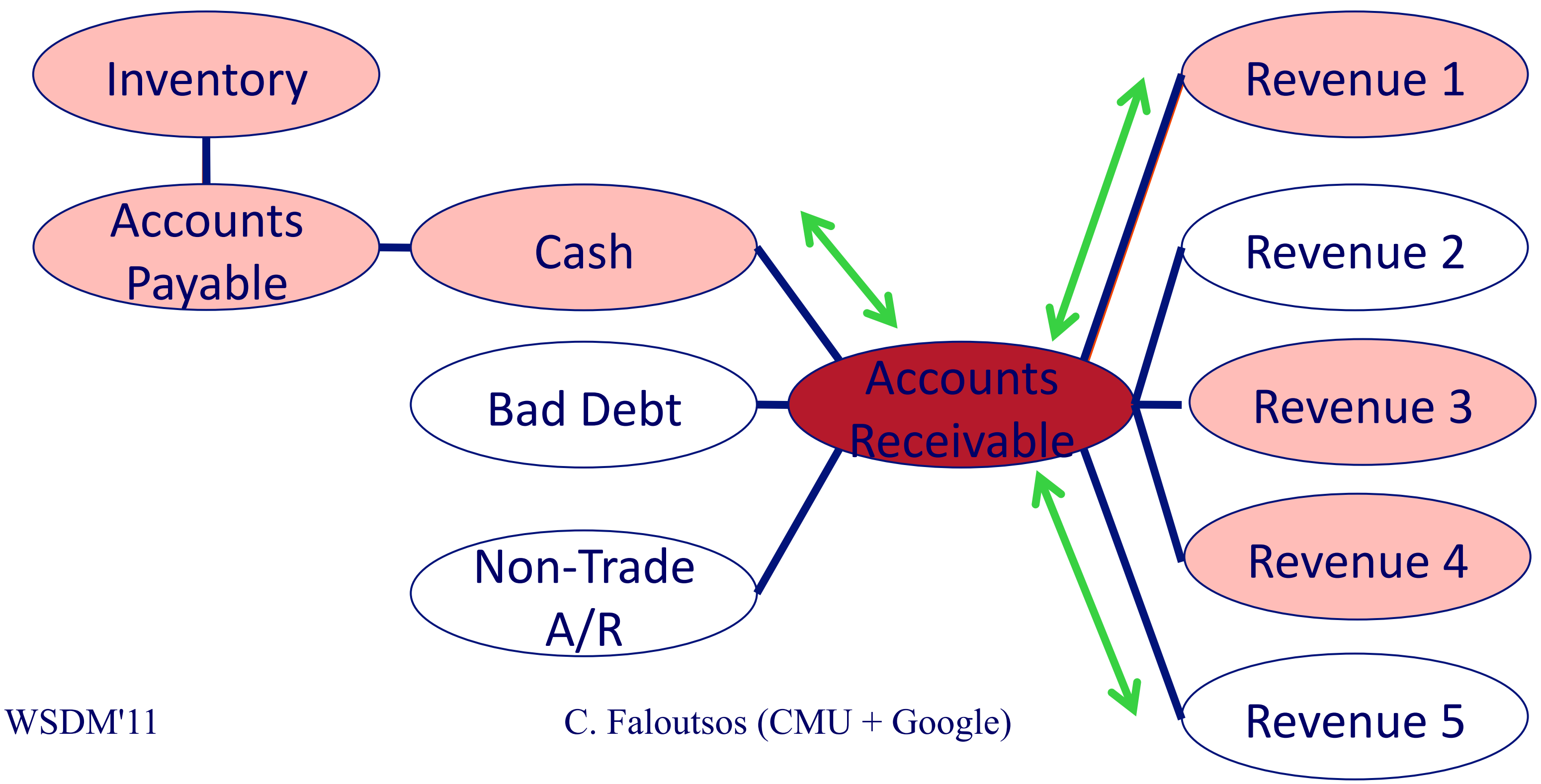
Fraud detection

- Problem: Given network and noisy domain knowledge about suspicious nodes (flags), which nodes are most risky?



Fraud detection

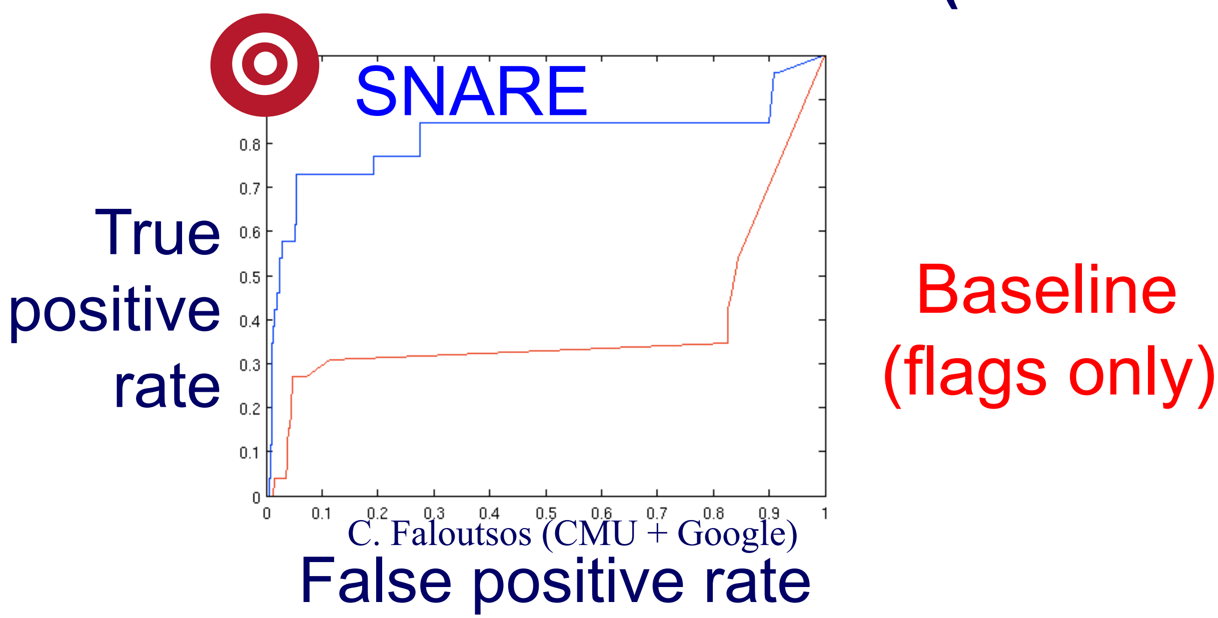
- Problem: Given network and noisy domain knowledge about suspicious nodes (flags), which nodes are most risky?



BP and ‘SNARE’

- Accurate – significant improvement over base
- Flexible - Can be applied to other domains
- Scalable - Linear time
- Robust - Works on large range of parameters

Results for accounts data (ROC Curve)



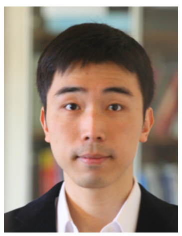
How to do B.P. on large graphs?

A: [U Kang, Polo Chau, +, ICDE’11], to appear

Carnegie Mellon

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

SDM 2011, Mesa, Arizona



Polo Chau
Machine Learning Dept

symantec.

Carey Nachenberg
Vice President & Fellow

symantec.

Jeffrey Wilhelm
Principal Software Engineer

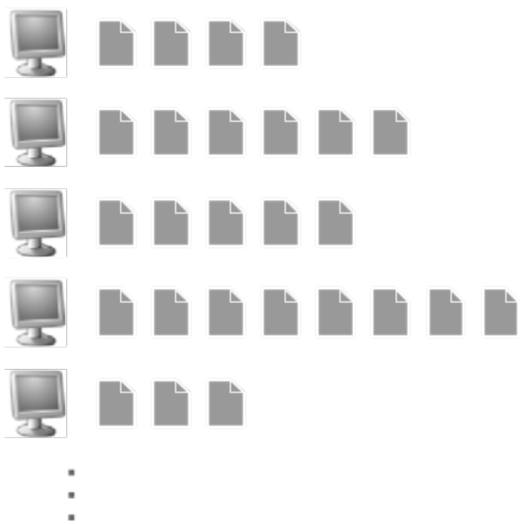
symantec.

Adam Wright
Software Engineer

Prof. Christos Faloutsos
Computer Science Dept

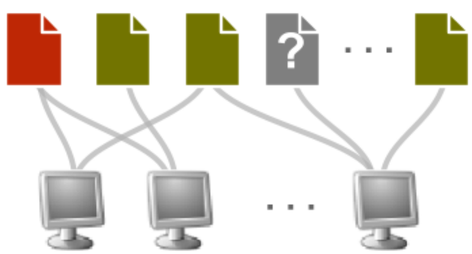
Ca

The Data



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

- 50+ million machines
- 900+ million executable files

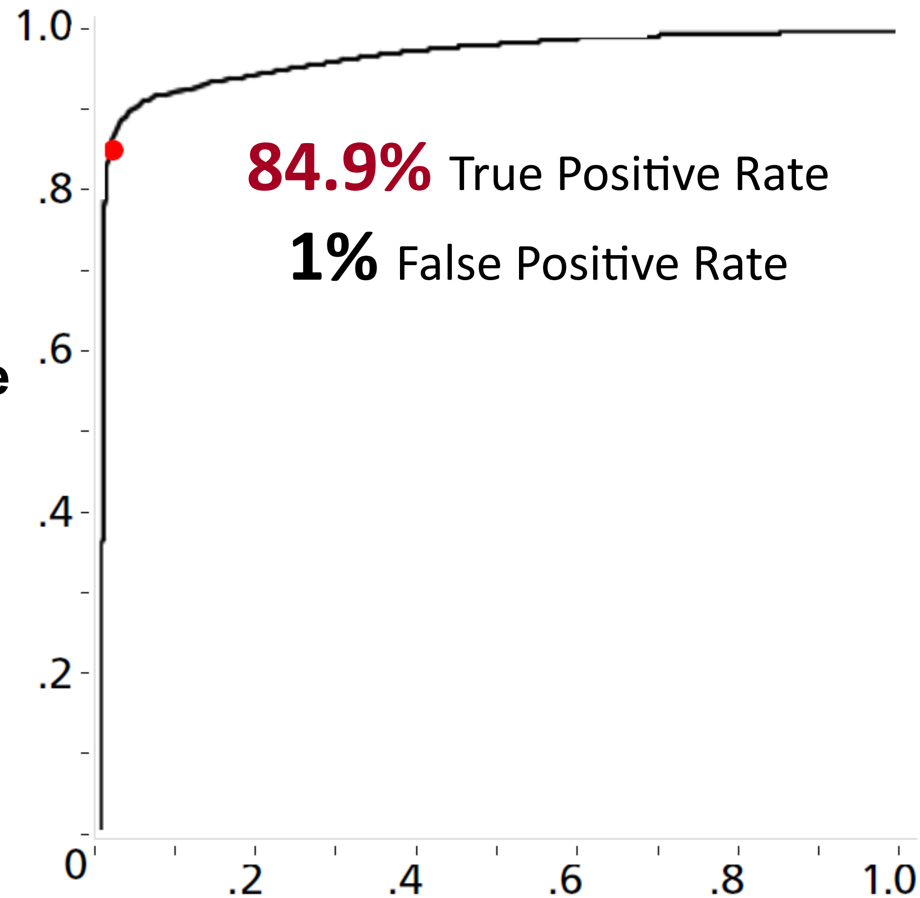


Constructed a machine-file bipartite graph (0.2 TB+)

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

One-Iteration Results

for files reported by four or more machines



True Positive Rate

% of malware correctly identified

False Positive Rate

% of non-malware wrongly labeled as malware

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
  - OddBall (anomaly detection)
  - Belief propagation
  - Immunization
- Problem#3: Scalability -PEGASUS
- Conclusions

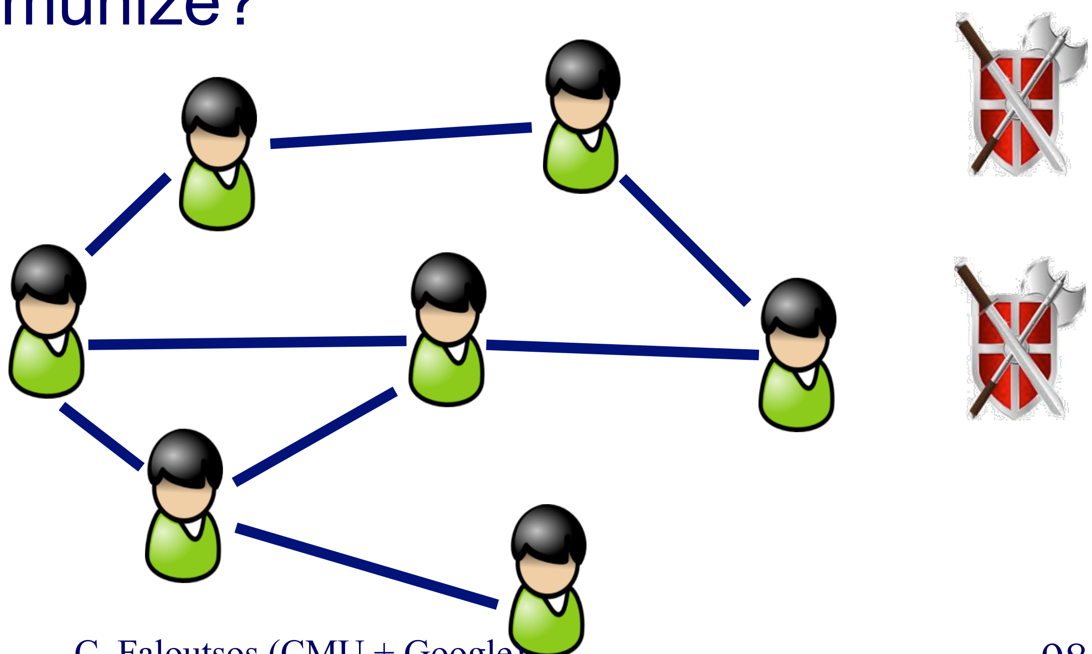
Immunization and epidemic thresholds

- Q1: which nodes to immunize?
- Q2: will a virus vanish, or will it create an epidemic?

Carnegie Mellon

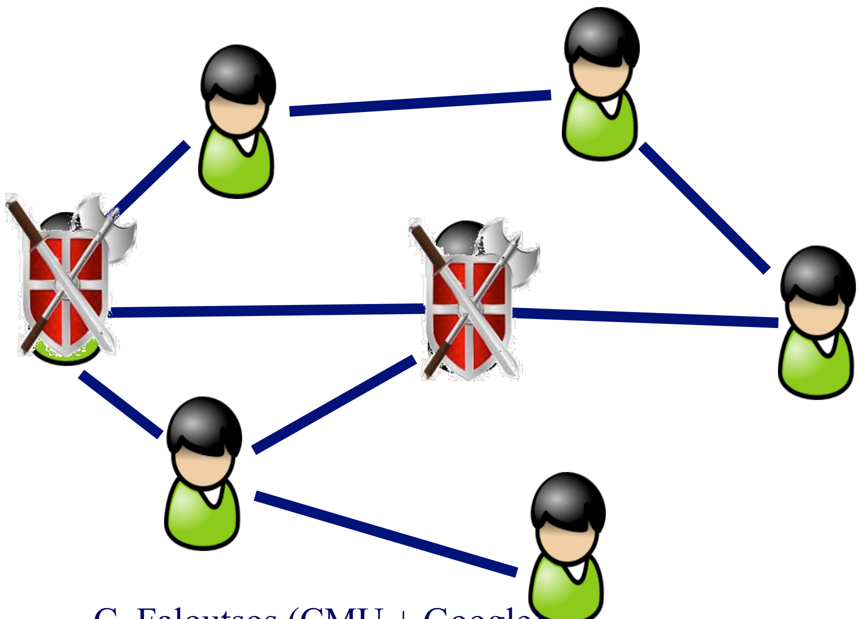
Q1: Immunization:

- Given
  - a network,
  - k vaccines, and
  - the virus details
- Which nodes to immunize?



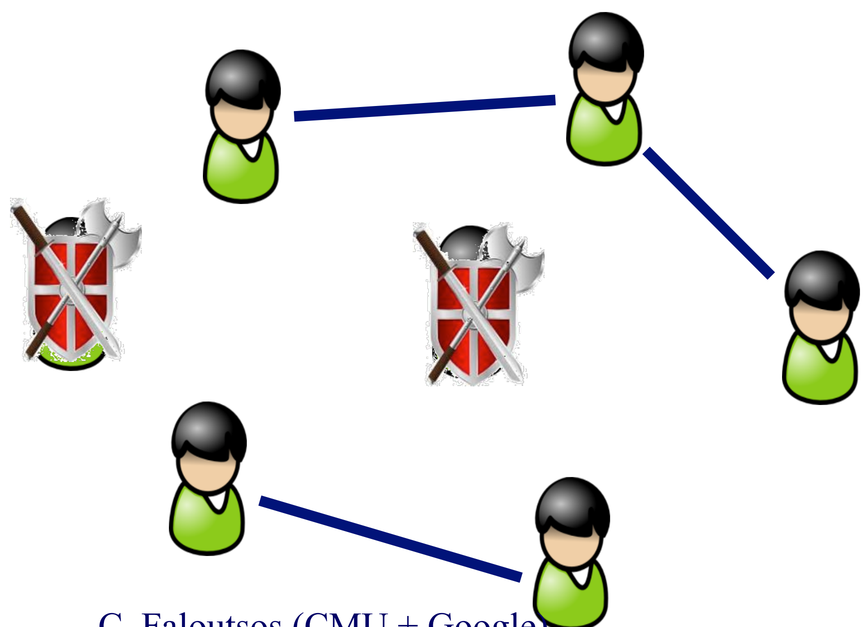
Q1: Immunization:

- Given
    - a network,
    - k vaccines, and
    - the virus details
- Which nodes to immunize?



Q1: Immunization:

- Given
  - a network,
  - k vaccines, and
  - the virus details
- Which nodes to immunize?

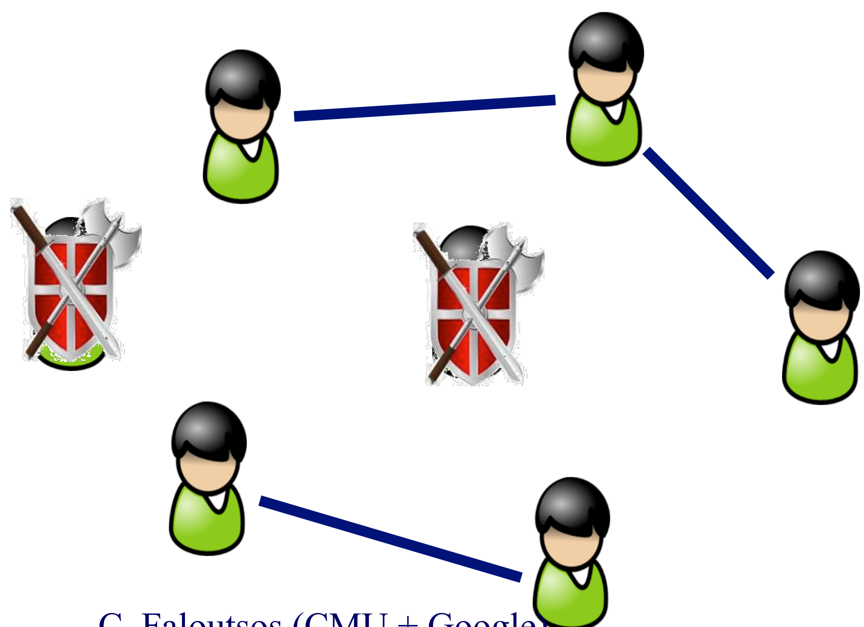


Carnegie Mellon

Q1: Immunization:

- Given
  - a network,
  - k vaccines, and
  - the virus details
- Which nodes to immunize?

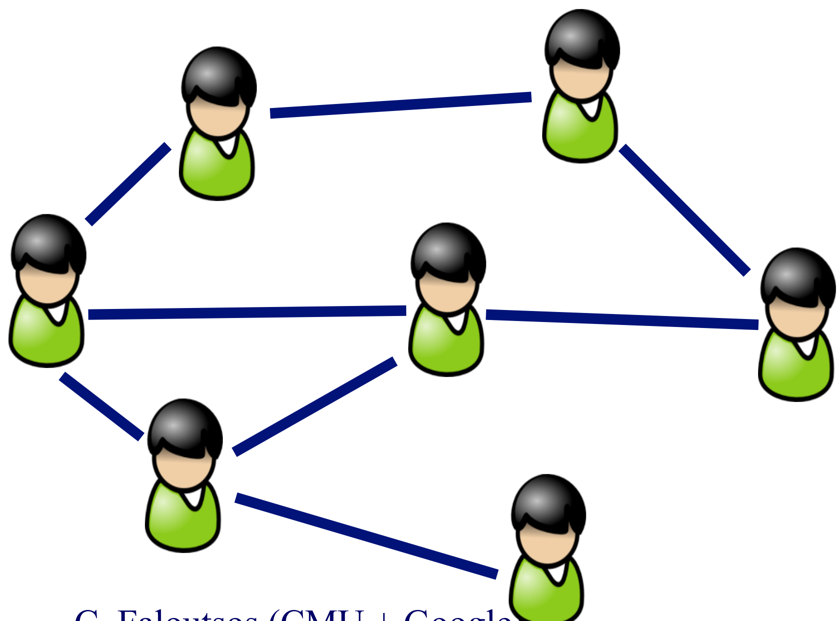
A: immunize the ones that maximally raise the `epidemic threshold' [Tong+, ICDM'10]



Q2: will a virus take over?

- Flu-like virus (no immunity, 'SIS')
- Mumps (life-time immunity, 'SIR')
- Pertussis (finite-length immunity, 'SIRS')

β: attack prob
δ: heal prob

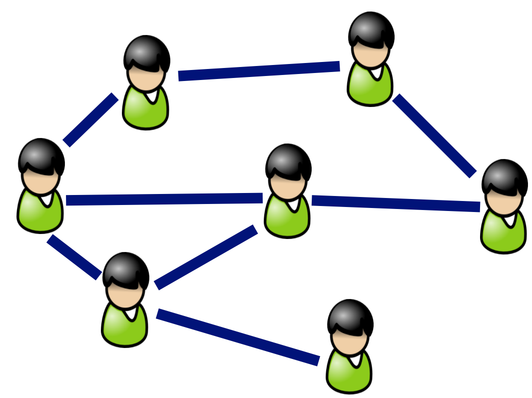


Q2: will a virus take over?

- Flu-like virus (no immunity, 'SIS')
- Mumps (life-time immunity, 'SIR')
- Pertussis (finite-length immunity, 'SIRS')

β: attack prob
δ: heal prob

A: depends on connectivity
(avg degree? Max degree?
variance? Something else?

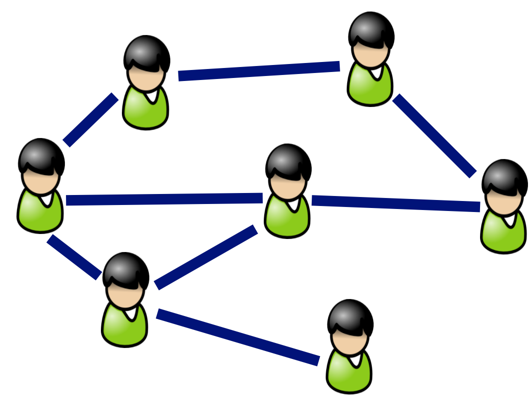


Q2: will a virus take over?

- Flu-like virus (no immunity, 'SIS')
- Mumps (life-time immunity, 'SIR')
- Pertussis (finite-length immunity, 'SIRS')

β: attack prob
δ: heal prob

A: depends on connectivity:
ONLY on first eigenvalue



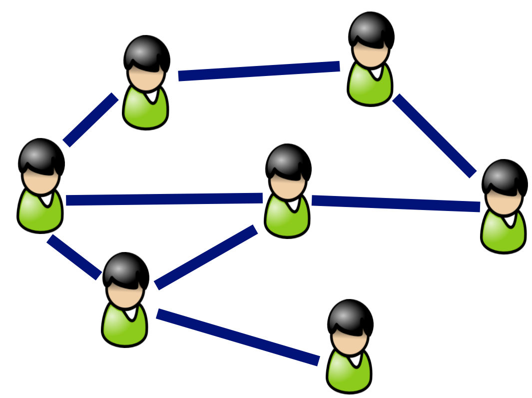
A2: will a virus take over?

- For **all** typical virus propagation models (flu, mumps, pertussis, HIV, etc)
- The **only** connectivity measure that matters, is

  $1/\lambda_1$

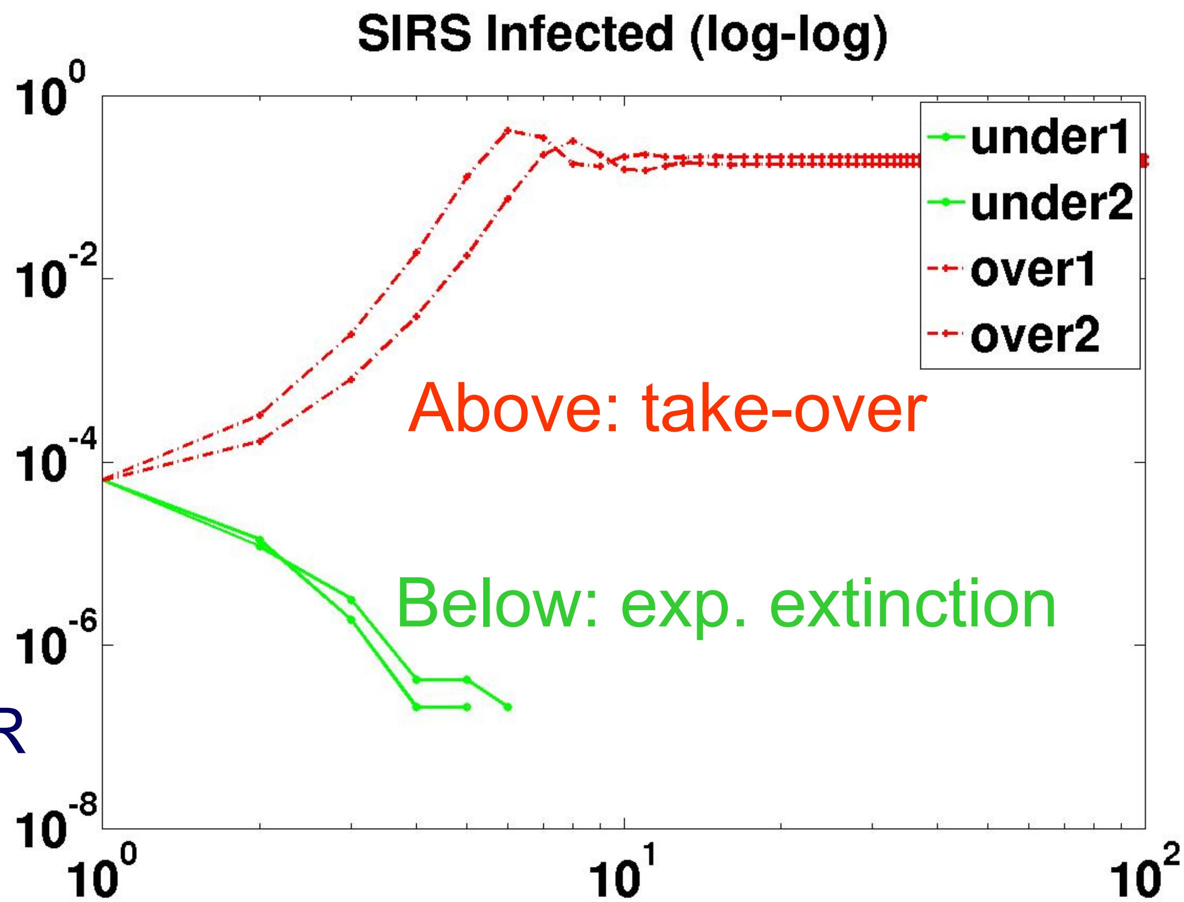
  the first eigenvalue of the adj. matrix

  [Prakash+, arxiv]



A2: will a virus take over?

Fraction of infected



Time ticks

Graph:
Portland, OR
31M links
1.5M nodes

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
  - OddBall (anomaly detection)
  - Belief propagation
  - Immunization
- Problem#3: Scalability -PEGASUS
- Conclusions

Scalability

- Google: > 450,000 processors in clusters of ~2000 processors each [Barroso, Dean, Hölzle, *“Web Search for a Planet: The Google Cluster Architecture”* IEEE Micro 2003]
- Yahoo: 5Pb of data [Fayyad, KDD’07]
- Problem: machine failures, on a daily basis
- How to parallelize data mining tasks, then?
- A: map/reduce – hadoop (open-source clone) http://hadoop.apache.org/

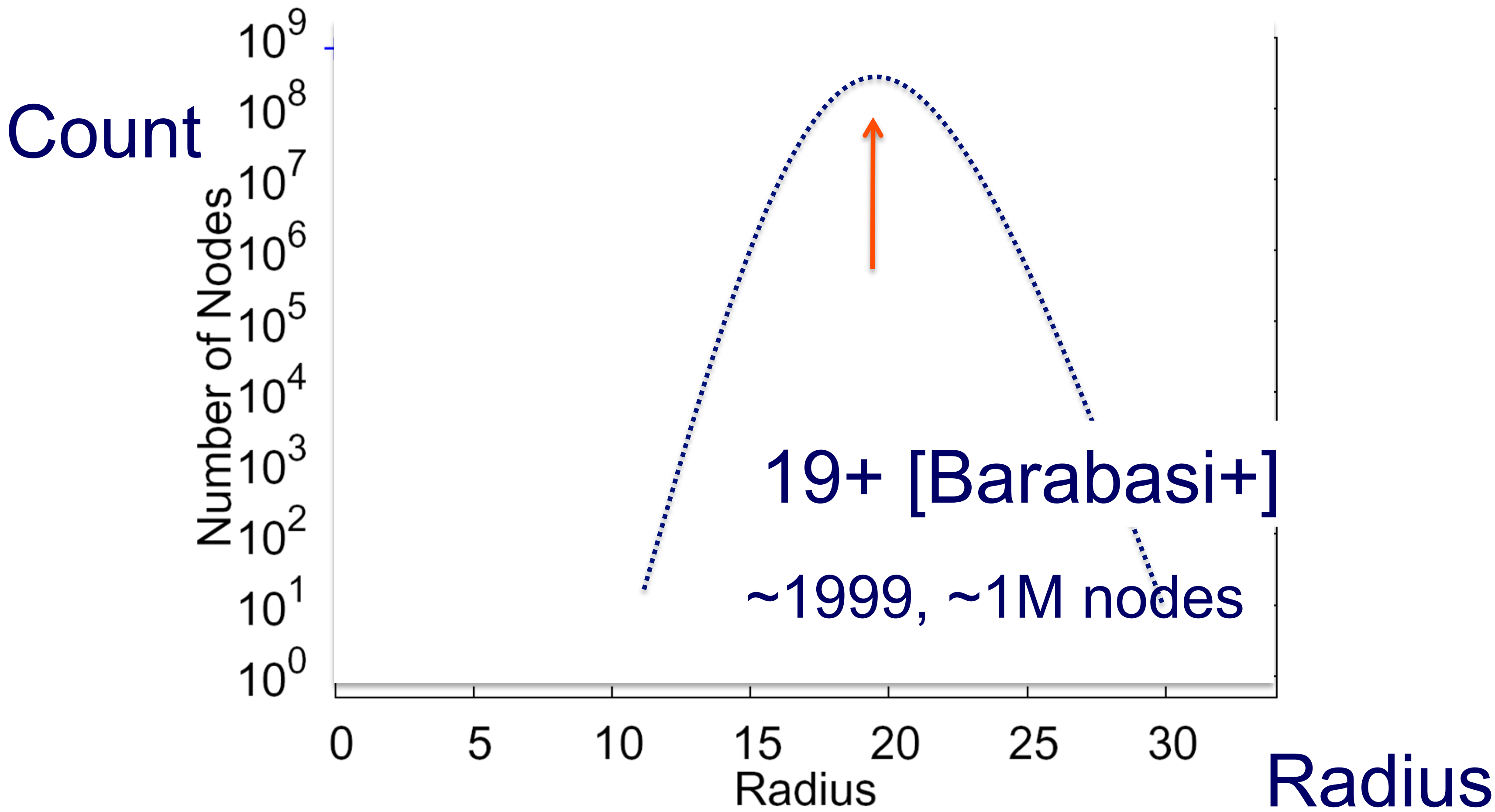
Outline – Algorithms & results

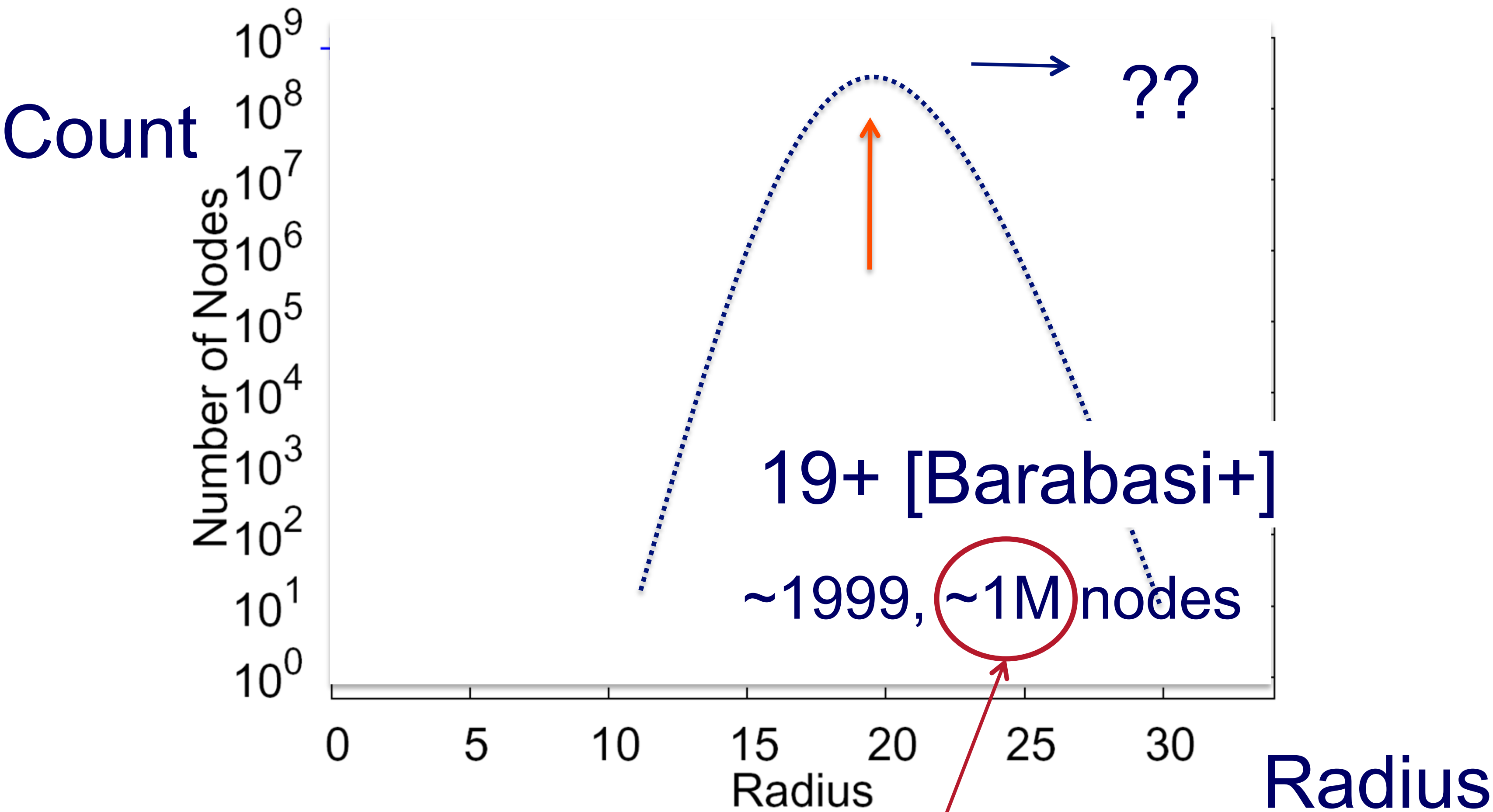
	Centralized	Hadoop/ PEGASUS
Degree Distr.	old	old
Pagerank	old	old
Diameter/ANF	old	**HERE**
Conn. Comp	old	**HERE**
Triangles	**done**	
Visualization	**started**	

Carnegie Mellon

HADI for diameter estimation

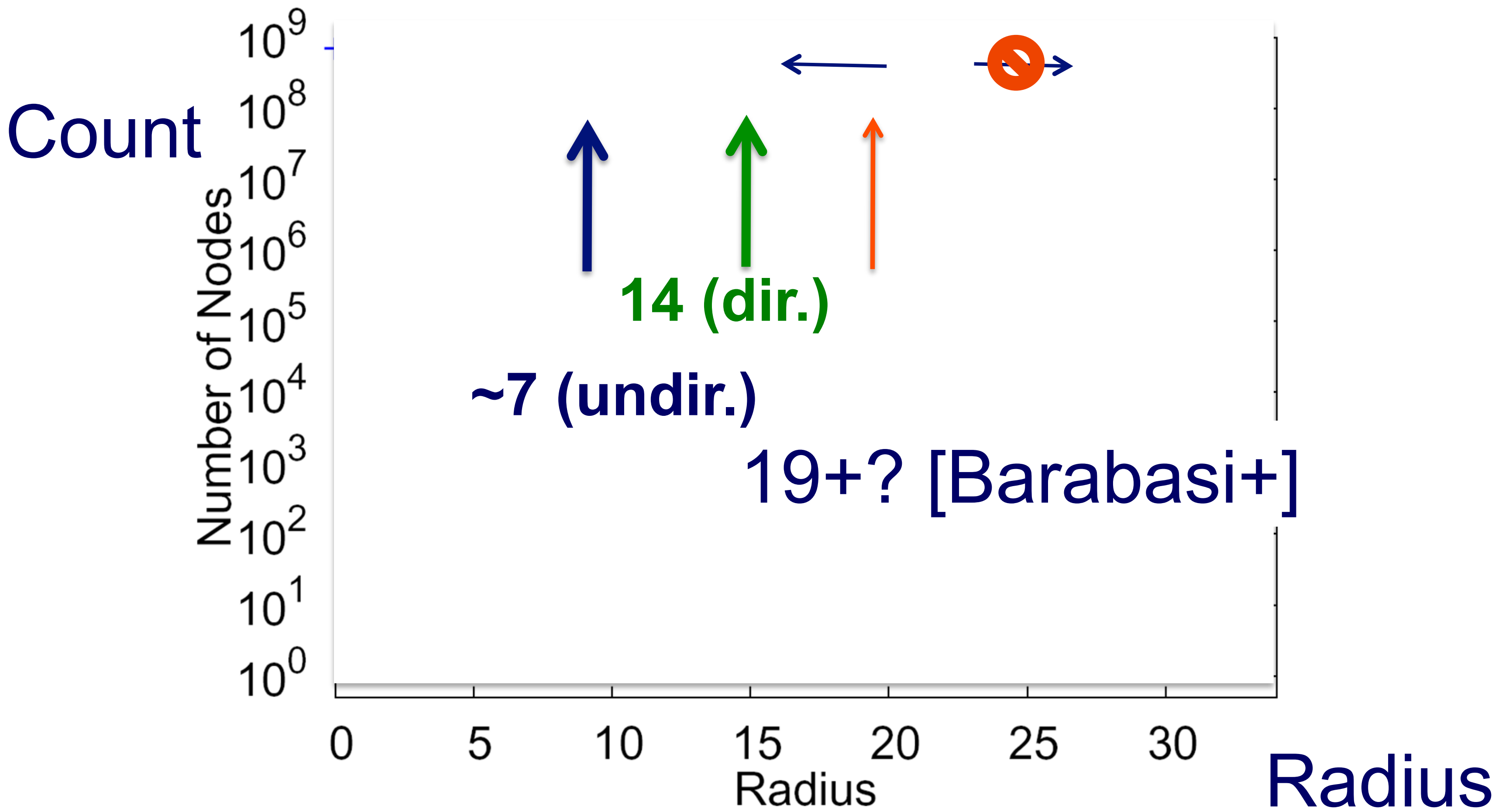
- *Radius Plots for Mining Tera-byte Scale Graphs* **U Kang**, Charalampos Tsourakakis, Ana Paula Appel, Christos Faloutsos, Jure Leskovec, SDM'10
- Naively: diameter needs **O(N**2)** space and up to O(N**3) time – **prohibitive** (N~1B)
- Our HADI: linear on E (~10B)
  - Near-linear scalability wrt # machines
  - Several optimizations -> 5x faster


Count
Number of Nodes
10^9
10^8
10^7
10^6
10^5
10^4
10^3
10^2
10^1
10^0
0
5
10
15
20
25
30
Radius
19+ [Barabasi+]
~1999, ~1M nodes
Radius



YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

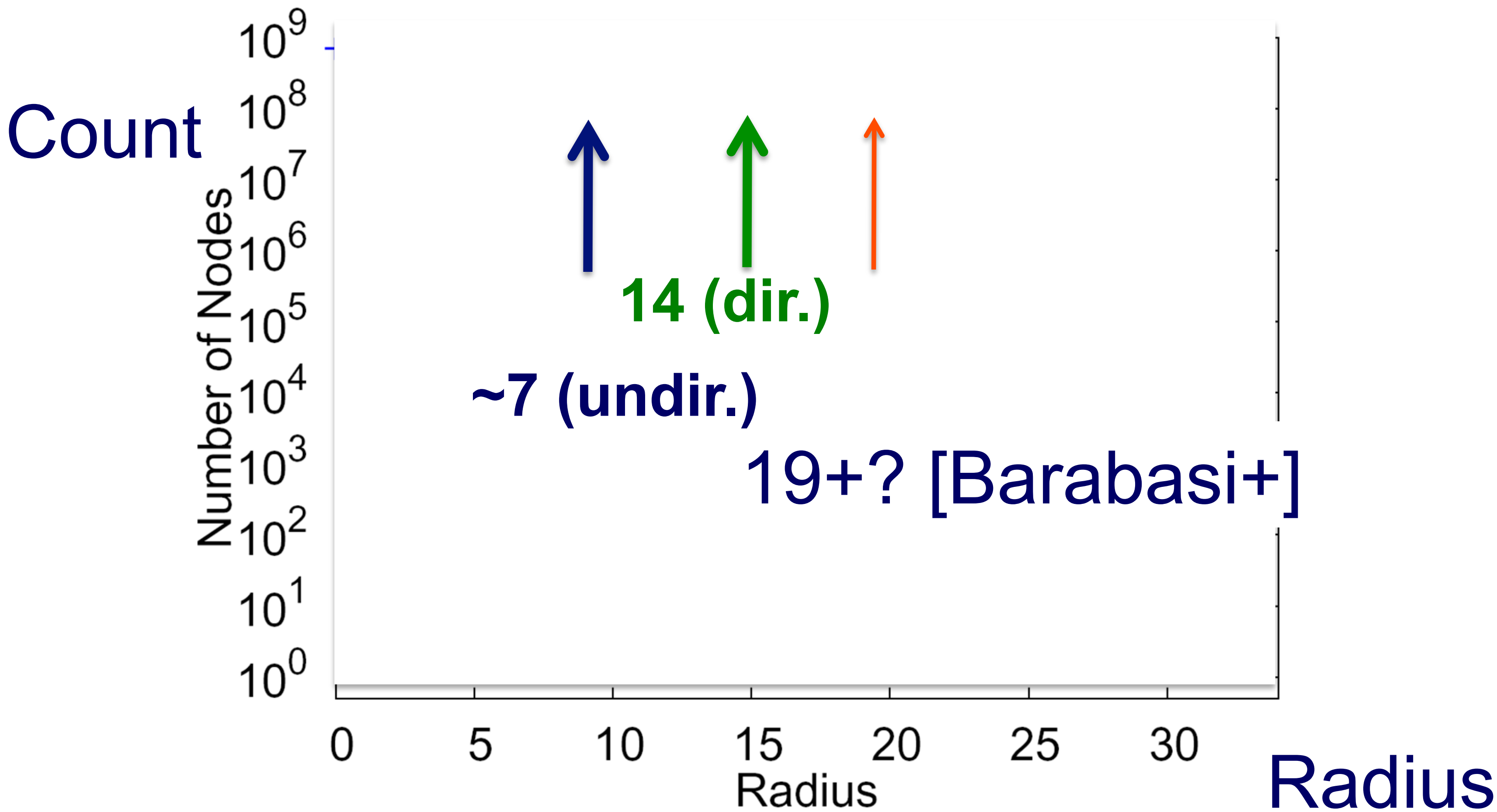
- Largest publicly available graph ever studied.



YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

- Largest publicly available graph ever studied.

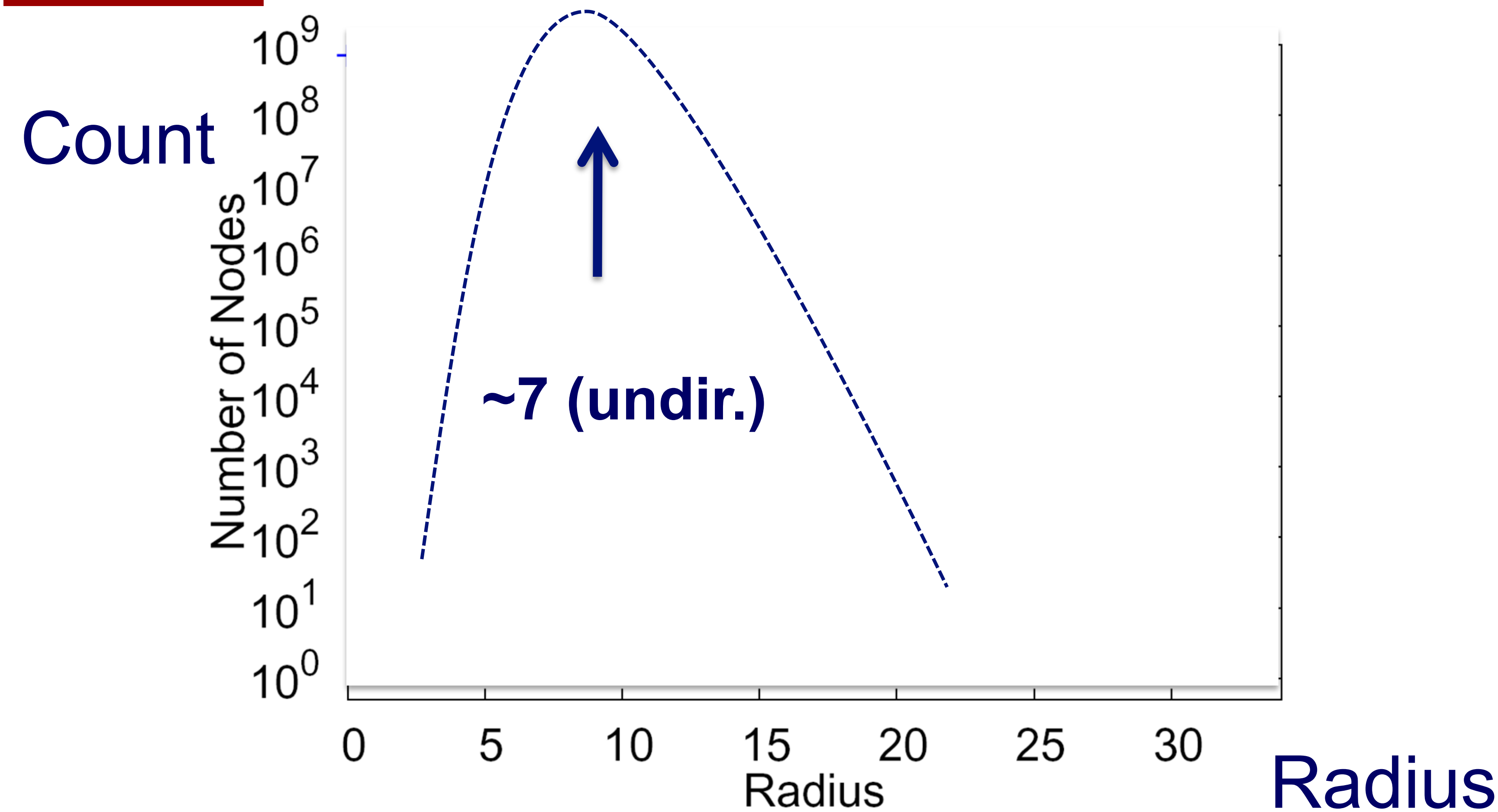
Carnegie Mellon



YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

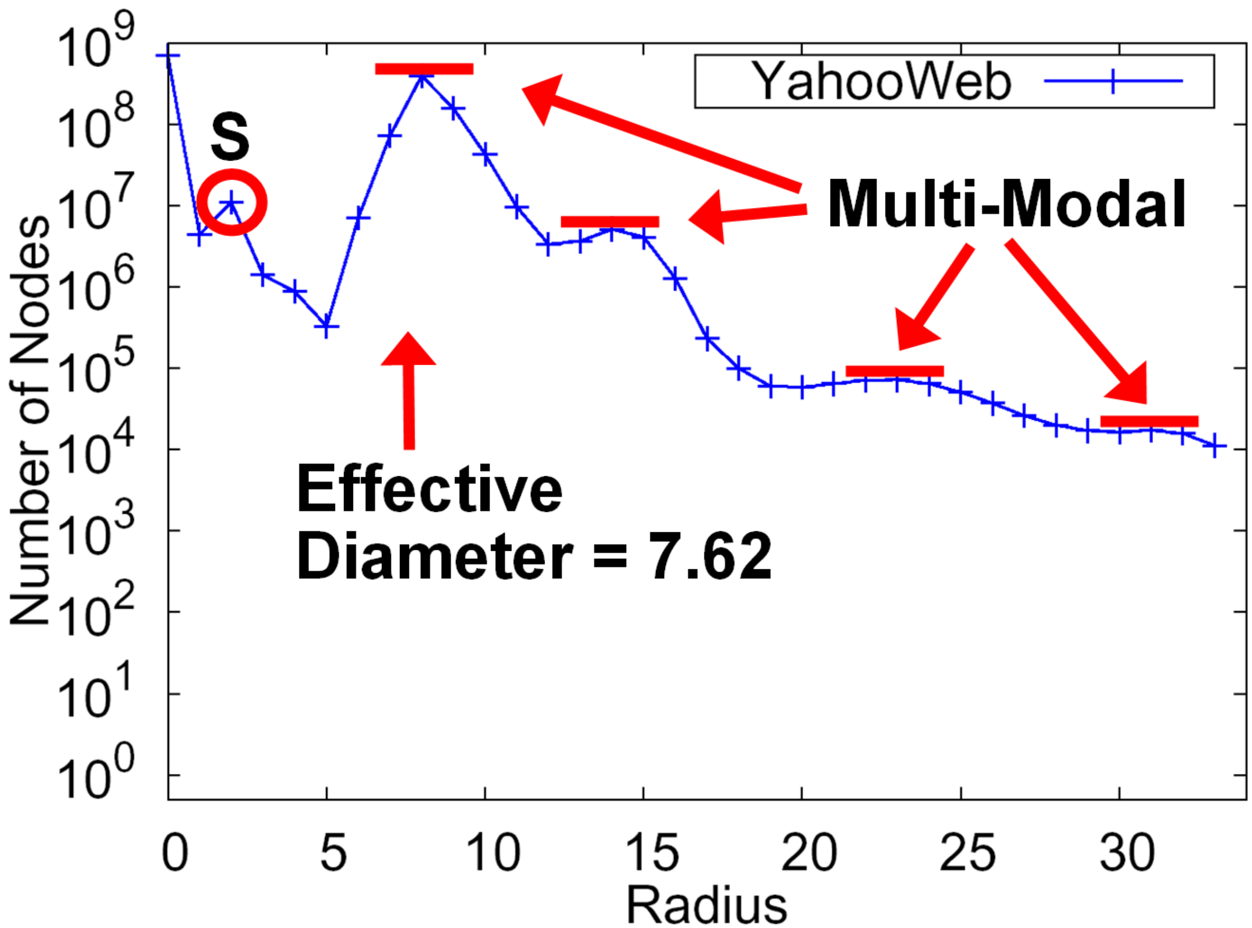
- 7 degrees of separation (!)
- Diameter: shrunk

Carnegie Mellon



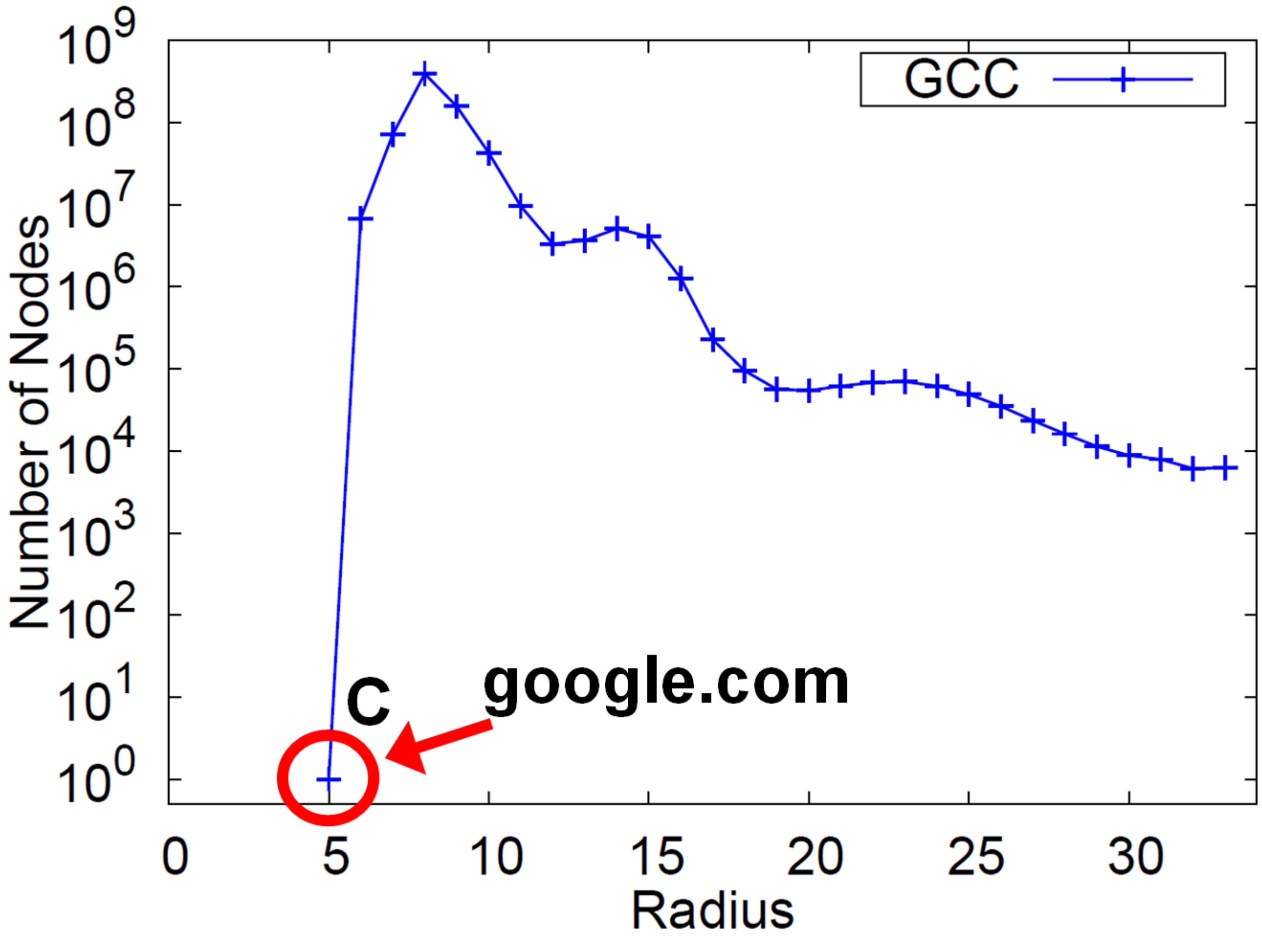
YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

Q: Shape?

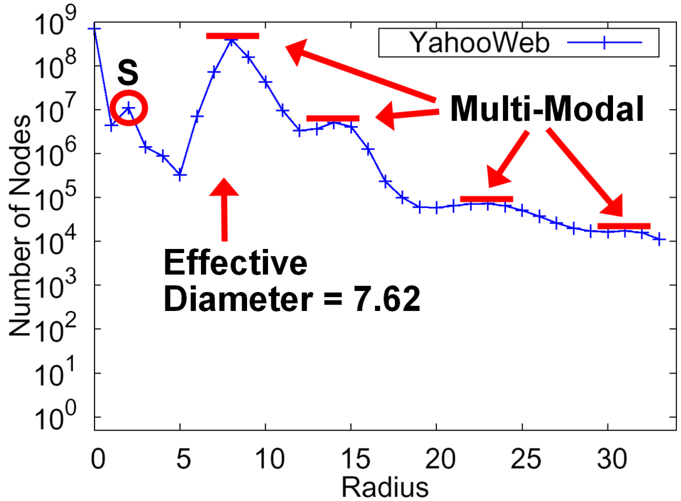


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

- effective diameter: surprisingly small.
- Multi-modality (?!)

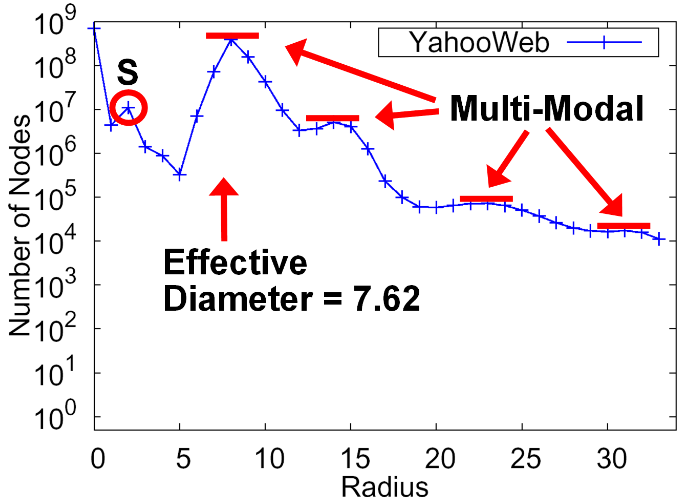


Radius Plot of **GCC** of YahooWeb.

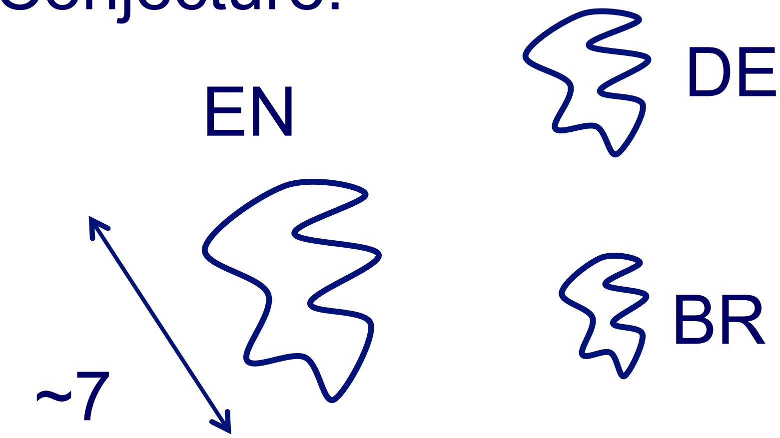


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

- effective diameter: surprisingly small.
- Multi-modality: probably mixture of cores .

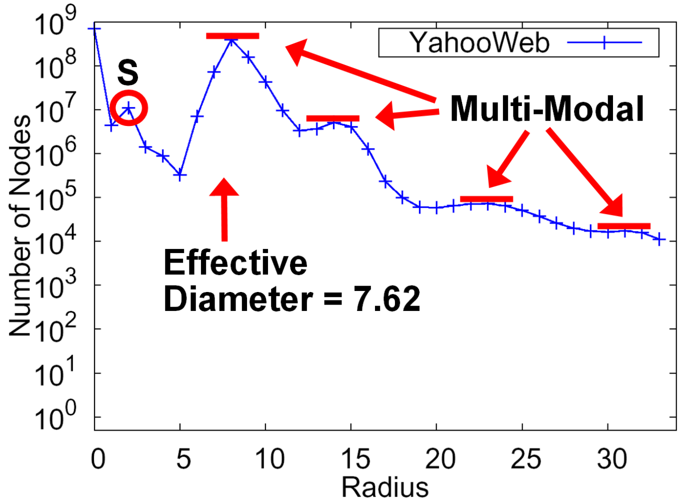


Conjecture:

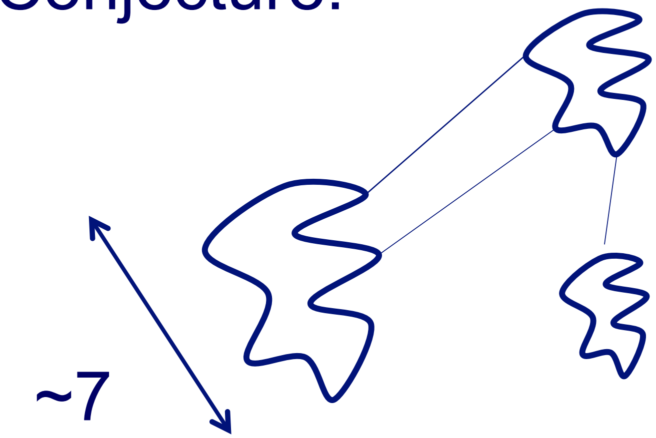


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

- effective diameter: surprisingly small.
- Multi-modality: probably mixture of cores .



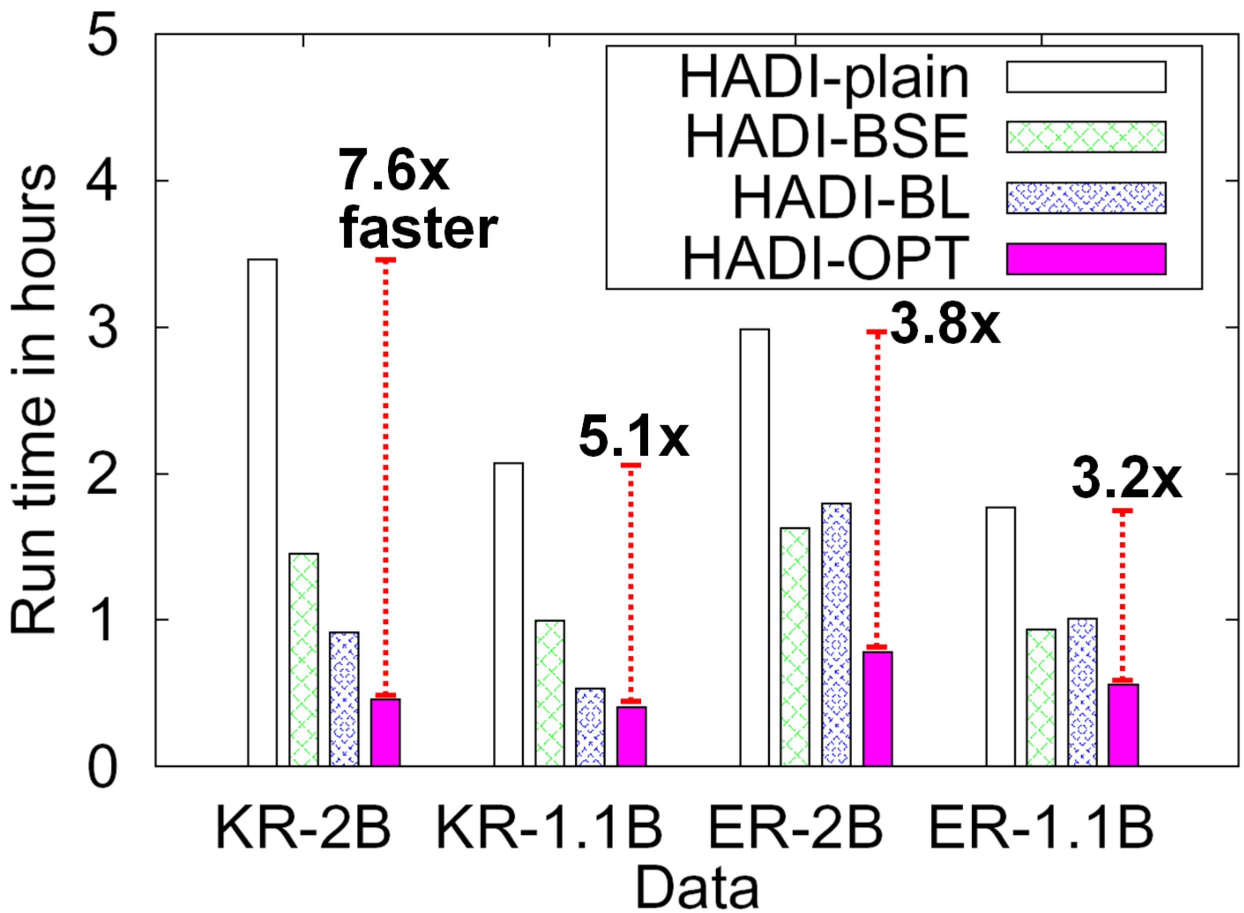
Conjecture:



YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

- effective diameter: surprisingly small.
- Multi-modality: probably mixture of cores .

details



Running time - Kronecker and Erdos-Renyi Graphs with billions edges.

Outline – Algorithms & results

	Centralized	Hadoop/ PEGASUS
Degree Distr.	old	old
Pagerank	old	old
Diameter/ANF	old	**HERE**
Conn. Comp	old	**HERE**
Triangles		done
Visualization	**started**	

Generalized Iterated Matrix Vector Multiplication (GIMV)

PEGASUS: A Peta-Scale Graph Mining System - Implementation and Observations.
U Kang, Charalampos E. Tsourakakis, and Christos Faloutsos.
(ICDM) 2009, Miami, Florida, USA.
Best Application Paper (runner-up).

details

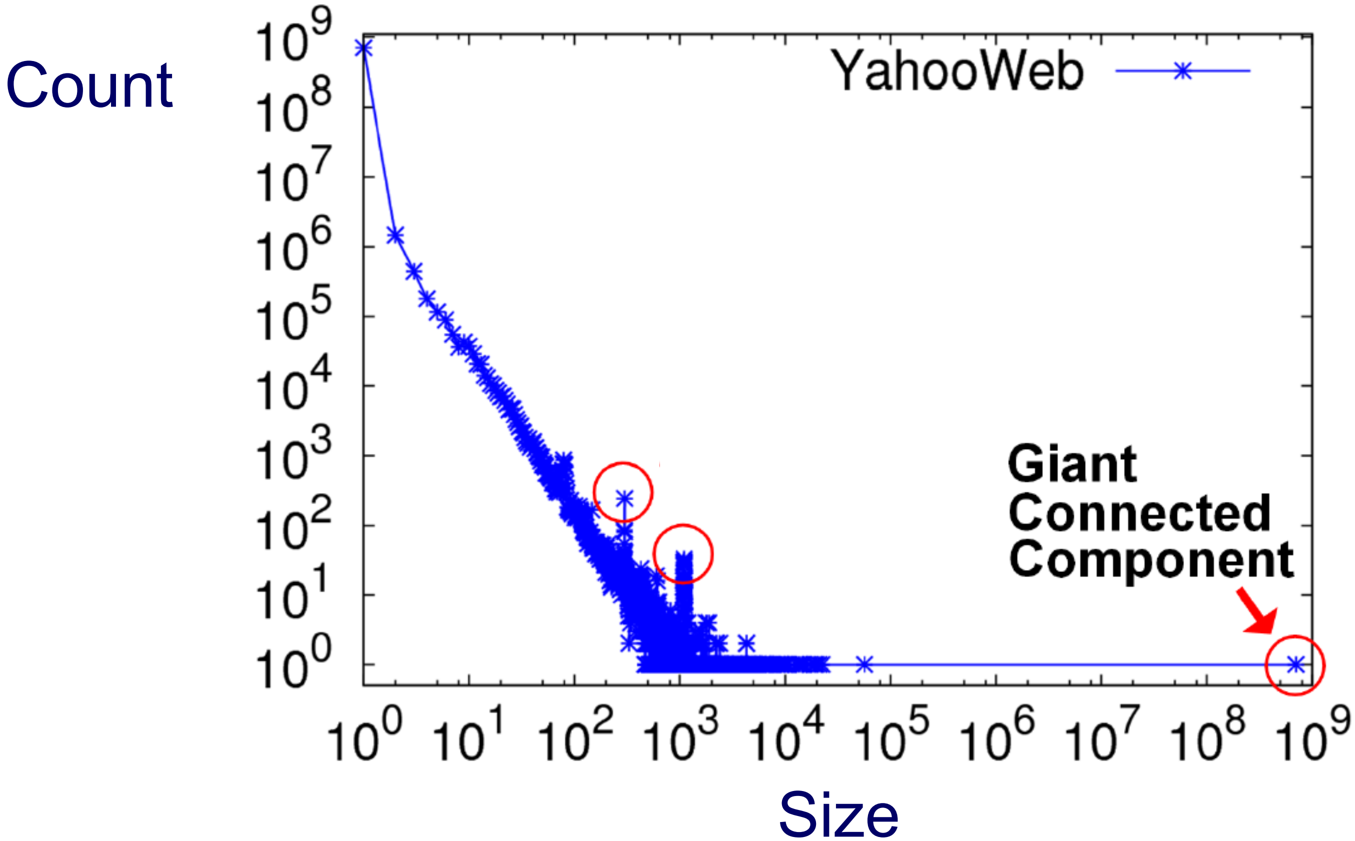
Generalized Iterated Matrix Vector Multiplication (GIMV)

- PageRank
- proximity (RWR)
- Diameter
- Connected components
- (eigenvectors,
- Belief Prop.
- …)

Matrix – vector Multiplication (iterated)

Example: GIM-V At Work

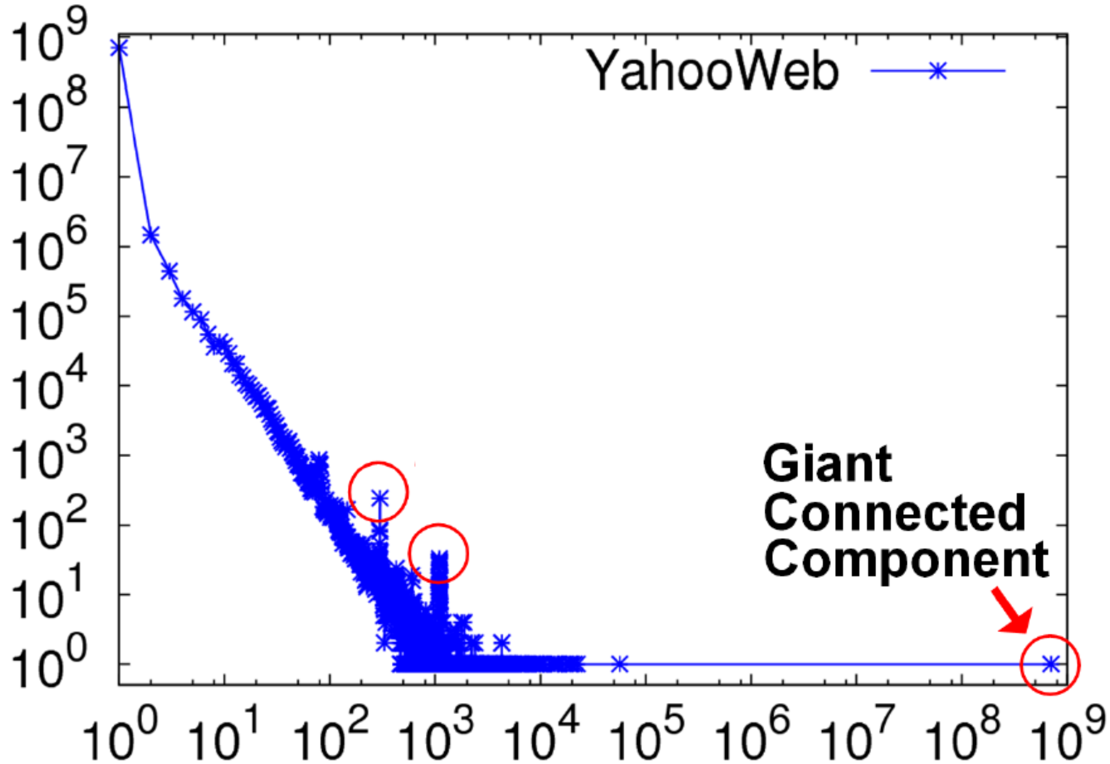
- Connected Components – 4 observations:



Example: GIM-V At Work

- Connected Components

Count



Size

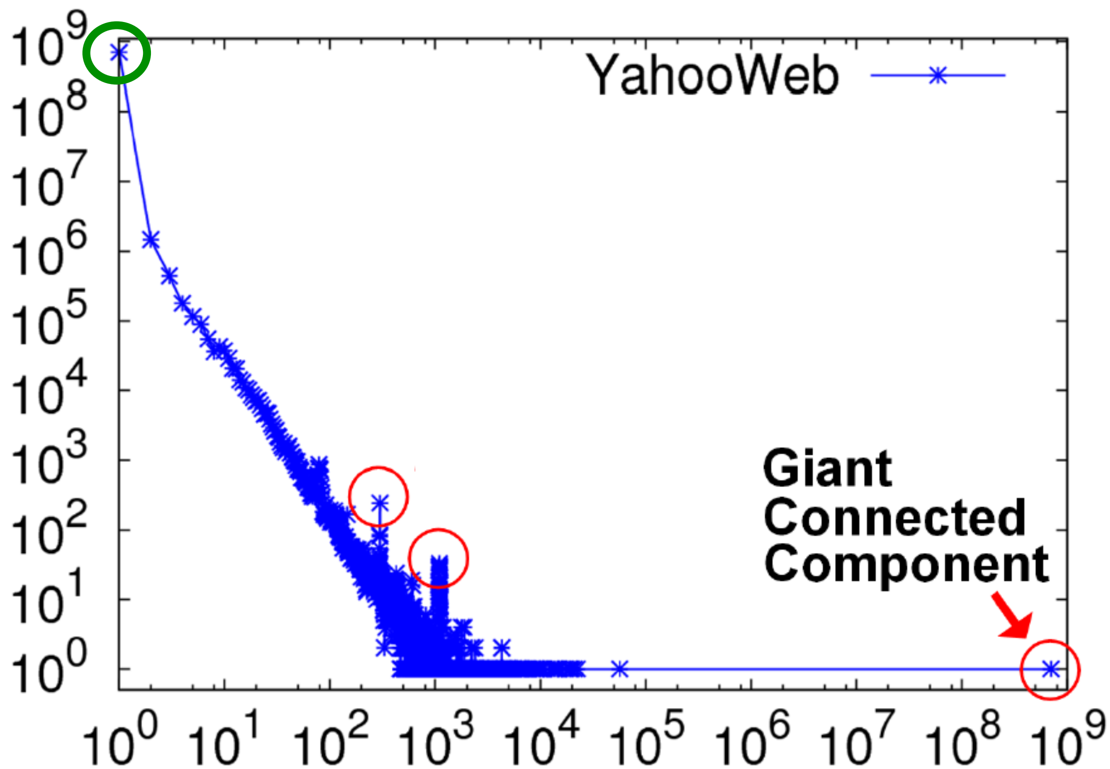
1) 10K x larger than next

Example: GIM-V At Work

- Connected Components

Count

2) ~0.7B singleton nodes



Size

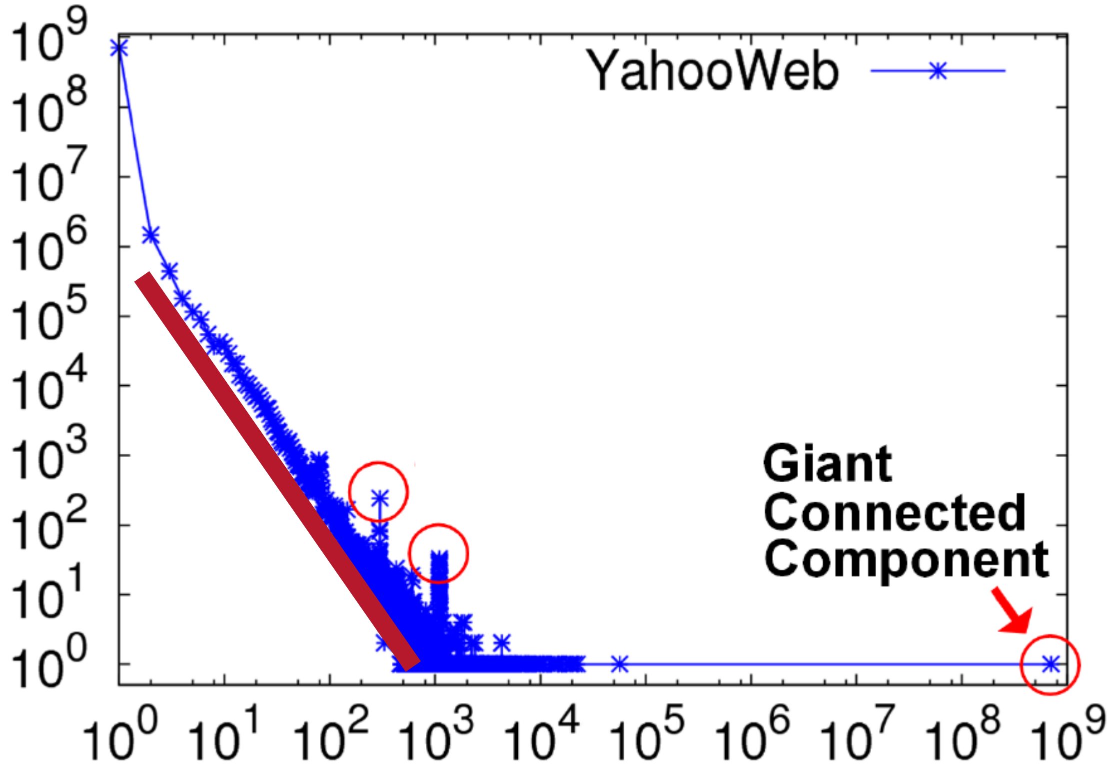
Carnegie Mellon

Example: GIM-V At Work

- Connected Components

Count

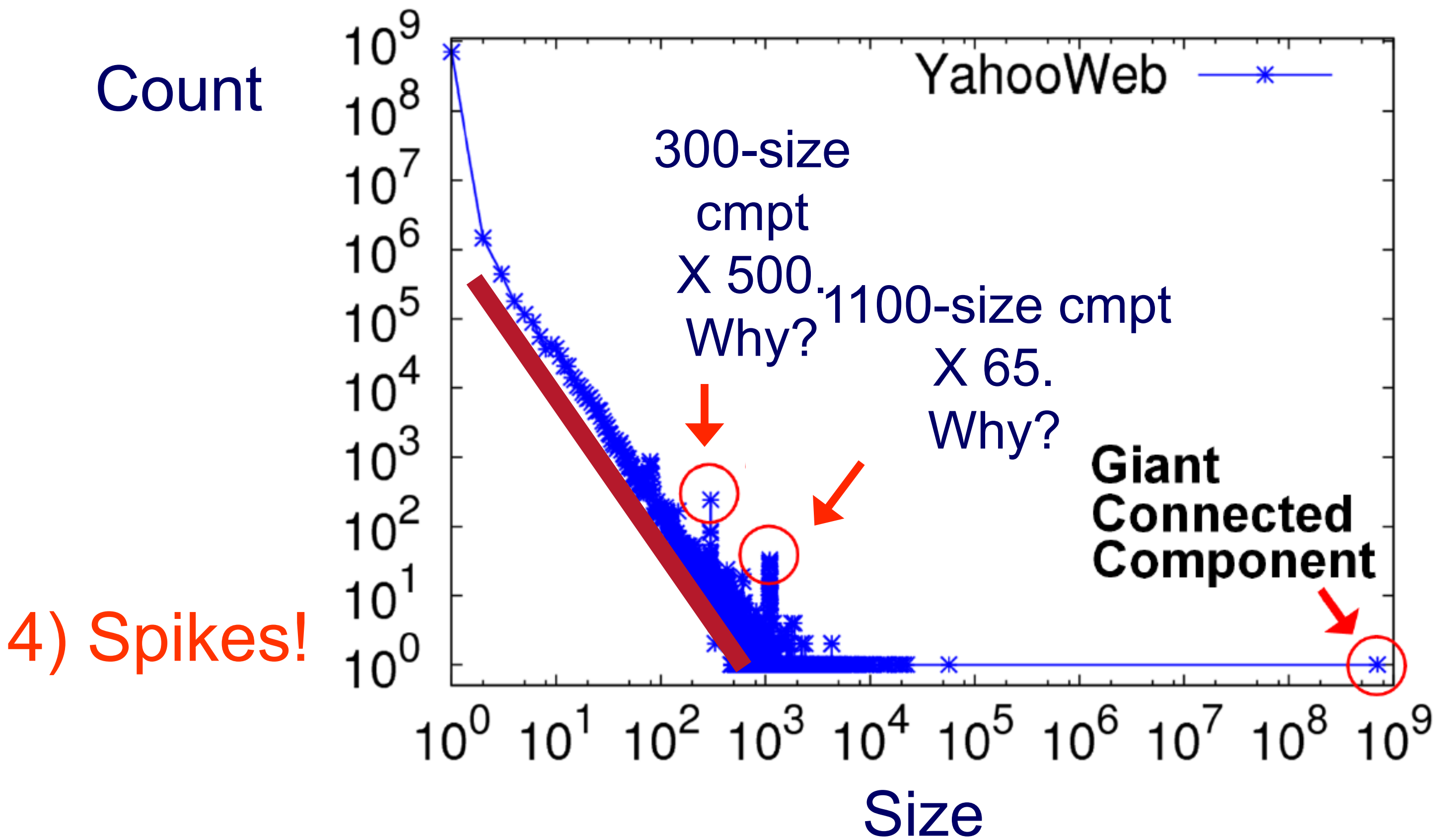
3) SLOPE!



Size

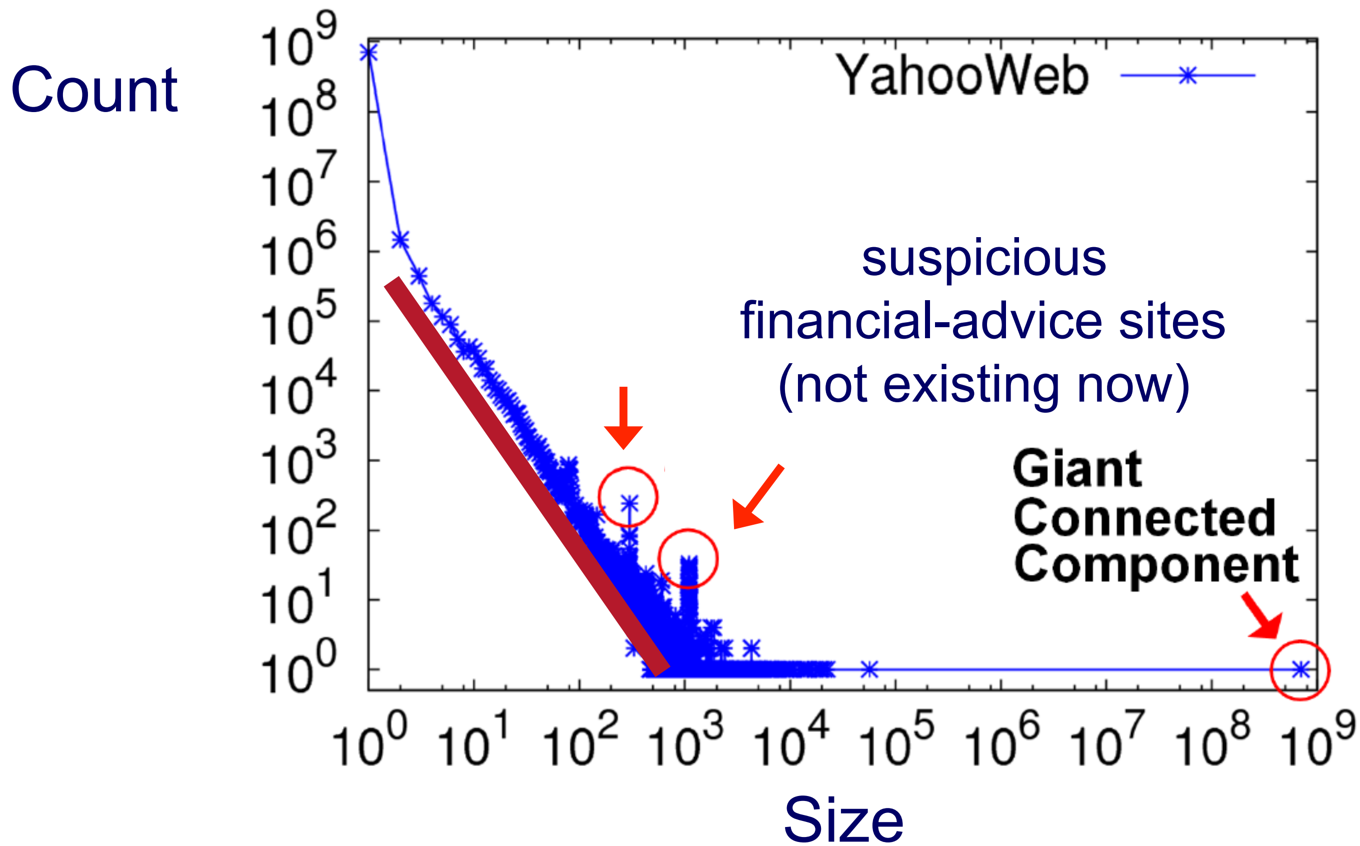
Example: GIM-V At Work

- Connected Components



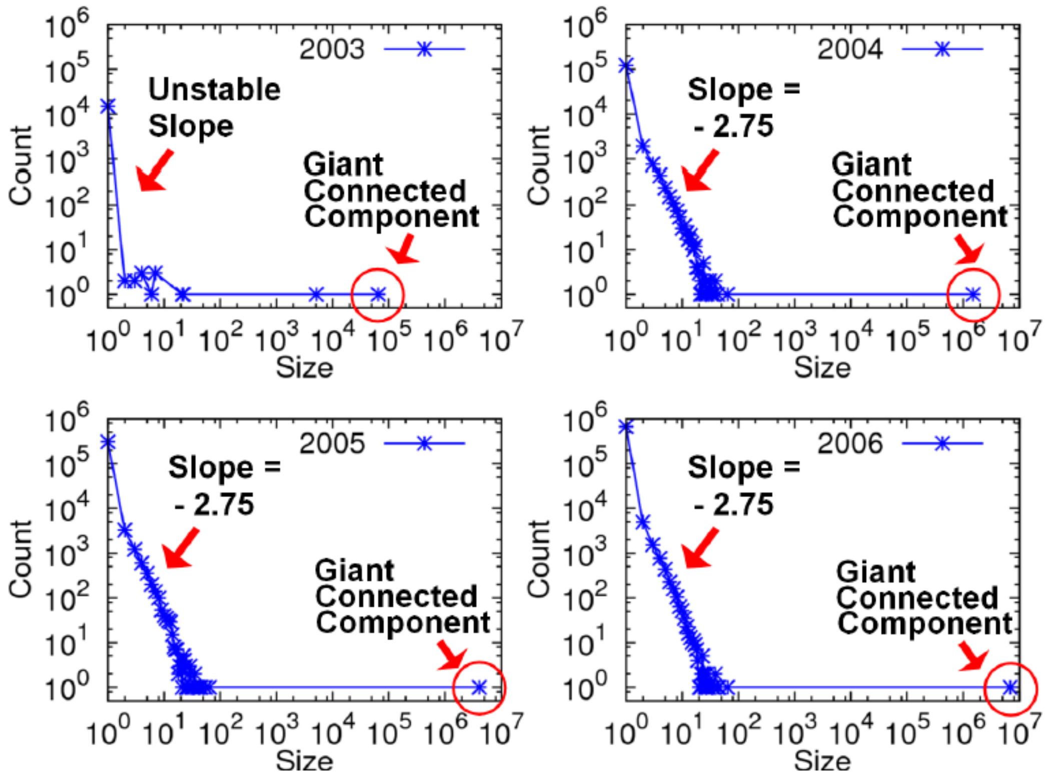
Example: GIM-V At Work

- Connected Components



GIM-V At Work

- Connected Components over Time
- **LinkedIn: 7.5M nodes and 58M edges**



Stable tail slope
after the gelling point

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
- Problem#3: Scalability
- Conclusions

Carnegie Mellon

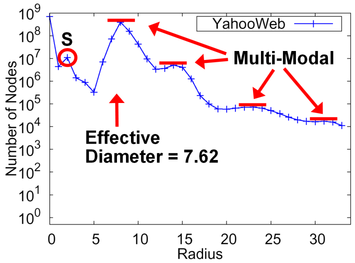
OVERALL CONCLUSIONS – low level:

- Several new **patterns** (fortification, triangle-laws, conn. components, etc)
- New **tools**:
  - anomaly detection (OddBall), belief propagation, immunization
- **Scalability**: PEGASUS / hadoop

Carnegie Mellon

OVERALL CONCLUSIONS – high level

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



- Terrific opportunities
  - Large datasets, easily(*) available PLUS
  - s/w and h/w developments

References

- Leman Akoglu, Christos Faloutsos: *RTG: A Recursive Realistic Graph Generator Using Random Typing*. ECML/PKDD (1) 2009: 13-28

- Deepayan Chakrabarti, Christos Faloutsos: *Graph mining: Laws, generators, and algorithms*. ACM Comput. Surv. 38(1): (2006)

References

- Deepayan Chakrabarti, Yang Wang, Chenxi Wang, Jure Leskovec, Christos Faloutsos: *Epidemic thresholds in real networks.* ACM Trans. Inf. Syst. Secur. 10(4): (2008)

- Deepayan Chakrabarti, Jure Leskovec, Christos Faloutsos, Samuel Madden, Carlos Guestrin, Michalis Faloutsos: *Information Survival Threshold in Sensor and P2P Networks*. INFOCOM 2007: 1316-1324

Carnegie Mellon

References

- Christos Faloutsos, Tamara G. Kolda, Jimeng Sun: *Mining large graphs and streams using matrix and tensor tools*. Tutorial, SIGMOD Conference 2007: 1174

References

- T. G. Kolda and J. Sun. *Scalable Tensor Decompositions for Multi-aspect Data Mining*. In: ICDM 2008, pp. 363-372, December 2008.

References

- Jure Leskovec, Jon Kleinberg and Christos Faloutsos *Graphs over Time: Densification Laws, Shrinking Diameters and Possible Explanations*, KDD 2005 (Best Research paper award).
- Jure Leskovec, Deepayan Chakrabarti, Jon M. Kleinberg, Christos Faloutsos: *Realistic, Mathematically Tractable Graph Generation and Evolution, Using Kronecker Multiplication*. PKDD 2005: 133-145

Carnegie Mellon

References

- Jimeng Sun, Yinglian Xie, Hui Zhang, Christos Faloutsos. *Less is More: Compact Matrix Decomposition for Large Sparse Graphs*, SDM, Minneapolis, Minnesota, Apr 2007.
- Jimeng Sun, Spiros Papadimitriou, Philip S. Yu, and Christos Faloutsos, *GraphScope: Parameter-free Mining of Large Time-evolving Graphs* ACM SIGKDD Conference, San Jose, CA, August 2007

References

- Jimeng Sun, Dacheng Tao, Christos Faloutsos: *Beyond streams and graphs: dynamic tensor analysis*. KDD 2006: 374-383

References

- Hanghang Tong, Christos Faloutsos, and Jia-Yu Pan, *Fast Random Walk with Restart and Its Applications*, ICDM 2006, Hong Kong.
- Hanghang Tong, Christos Faloutsos, *Center-Piece Subgraphs: Problem Definition and Fast Solutions*, KDD 2006, Philadelphia, PA

References

- Hanghang Tong, Christos Faloutsos, Brian Gallagher, Tina Eliassi-Rad: Fast best-effort pattern matching in large attributed graphs. KDD 2007: 737-746

Carnegie Mellon

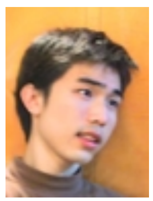
Project info

www.cs.cmu.edu/~pegasus

Chau, Polo

McGlohon, Mary

Tong, Hanghang



Akoglu, Leman

Kang, U

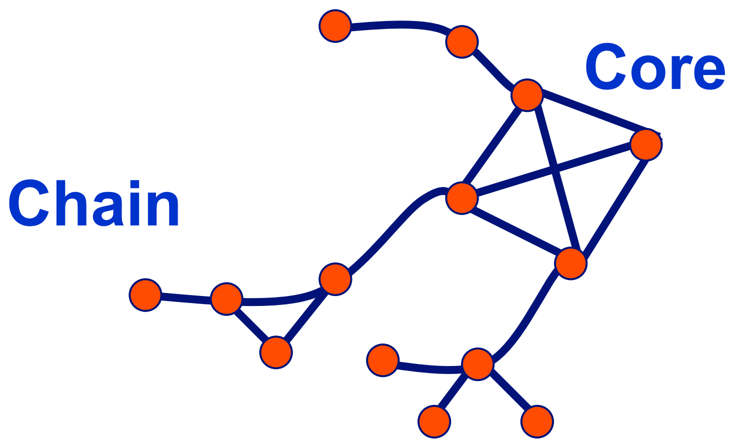
Prakash, Aditya

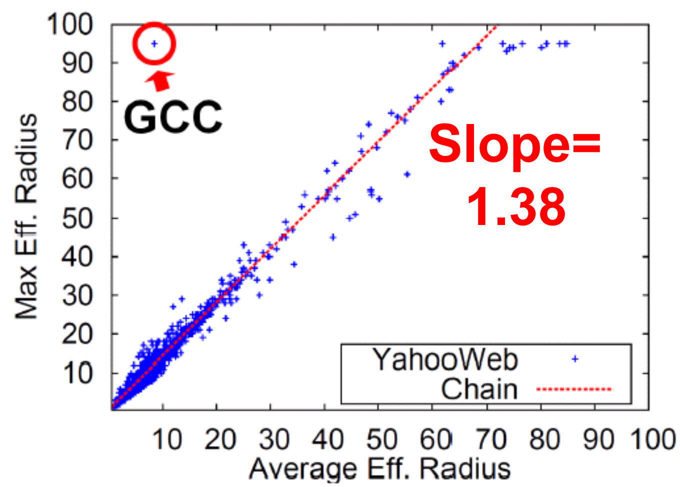
Thanks to: NSF IIS-0705359, IIS-0534205, CTA-INARC; Yahoo (M45), LLNL, IBM, SPRINT, Google, INTEL, HP, iLab

Extras

Radius of Connected Component

- What are the patterns of radii in connected components?





GCC looks like a 'kite'♪

Chain-like disconnected components