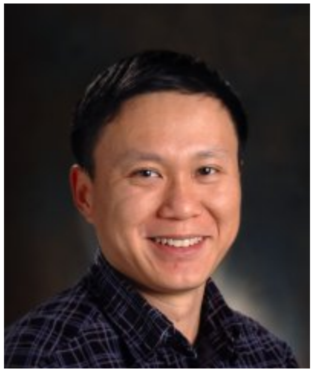
Carnegie Mellon

Large Graph Mining

Christos Faloutsos

CMU

Thank you!



- Jian Pei

- Alexandra Fedorova

- Heather Anders

Our goal:

Open source system for mining huge graphs:

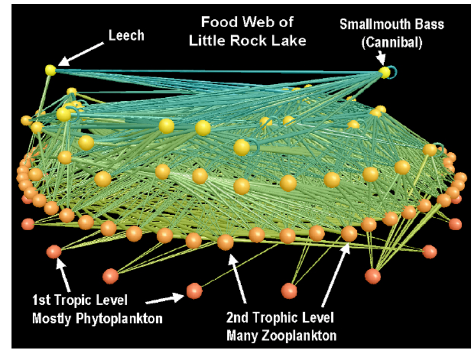
PEGASUS project (PEta GrAph mining System)

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

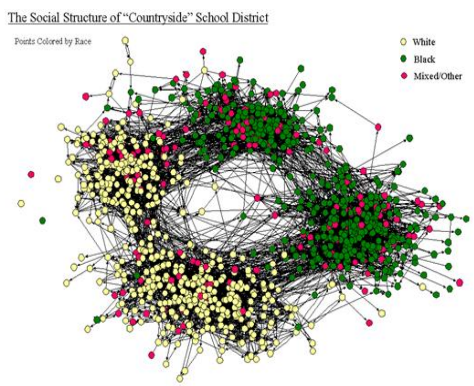
Outline

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

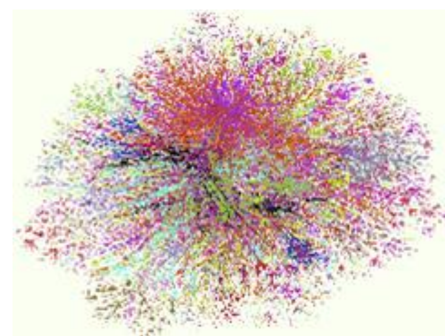
Graphs - why should we care?



Food Web
[Martinez '91]



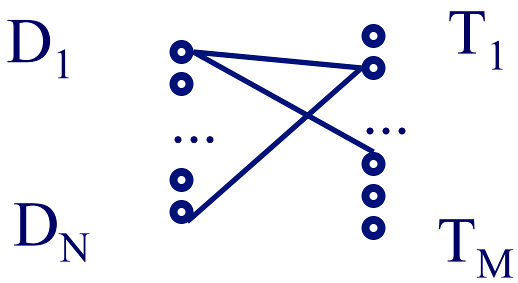
Friendship Network
[Moody '01]



Internet Map
[lumeta.com]

Graphs - why should we care?

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



- web: hyper-text graph

- ... and more:

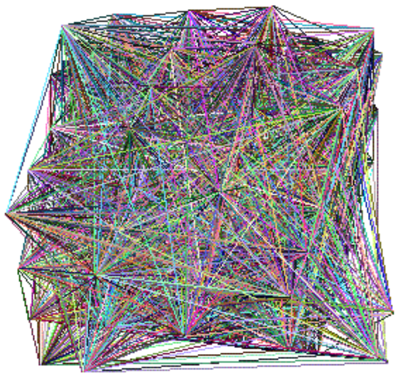
Graphs - why should we care?

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

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

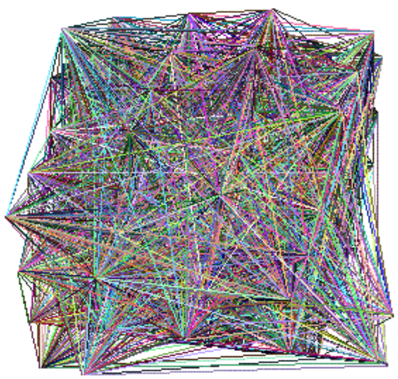


- What does the Internet look like?
- What does FaceBook look like?

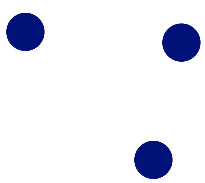
- What is 'normal'/'abnormal'?
- which patterns/laws hold?

Carnegie Mellon

Problem #1 - network and graph mining

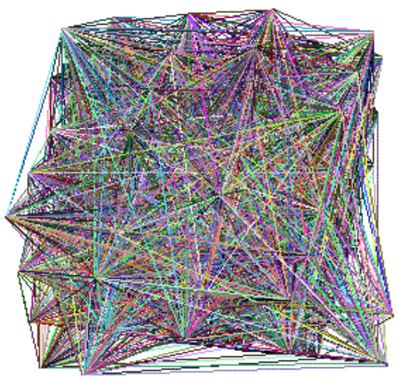


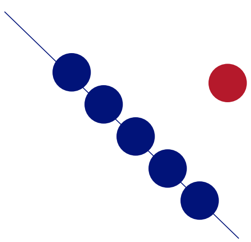
- What does the Internet look like?
- What does FaceBook look like?
- What is 'normal'/'abnormal'?
- which patterns/laws hold?
  - To spot **anomalies** (rarities), we have to discover **patterns**



Carnegie Mellon

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…

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

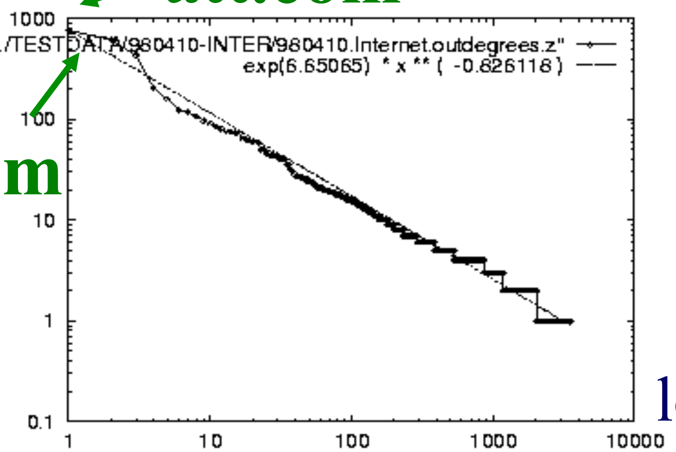
- Power law in the degree distribution [SIGCOMM99]

internet domains

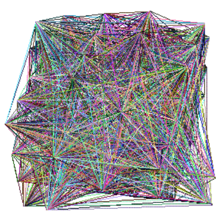
att.com

log(degree)

ibm.com



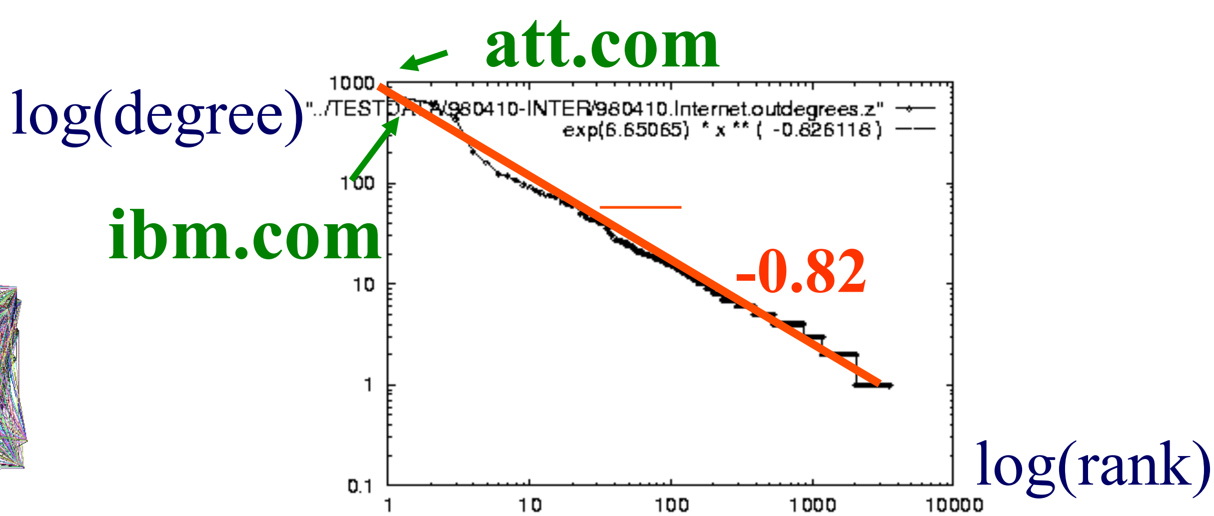
log(rank)

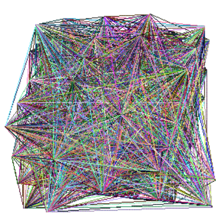


Solution# S.1

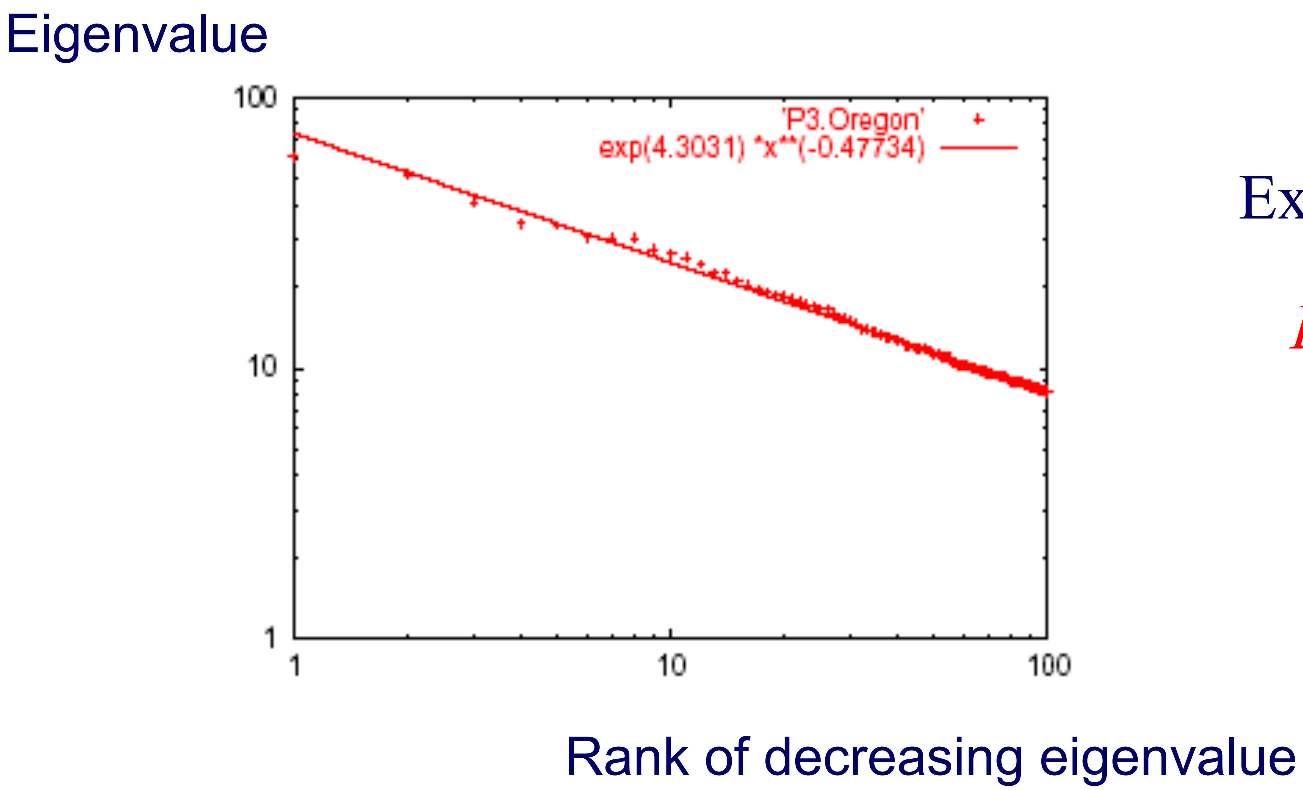
- Power law in the degree distribution [SIGCOMM99]

internet domains





Solution# S.2: Eigen Exponent *E*



Exponent = slope

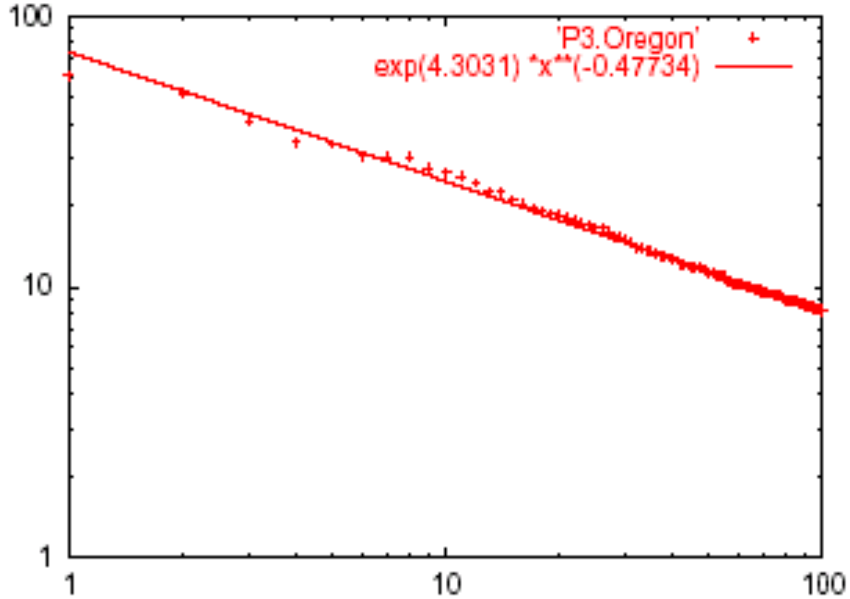
$E = -0.48$

May 2001

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

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:

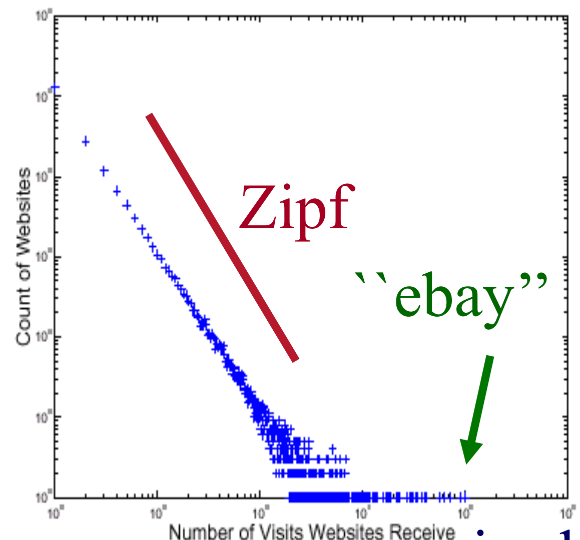
How about graphs from other domains?

More power laws:

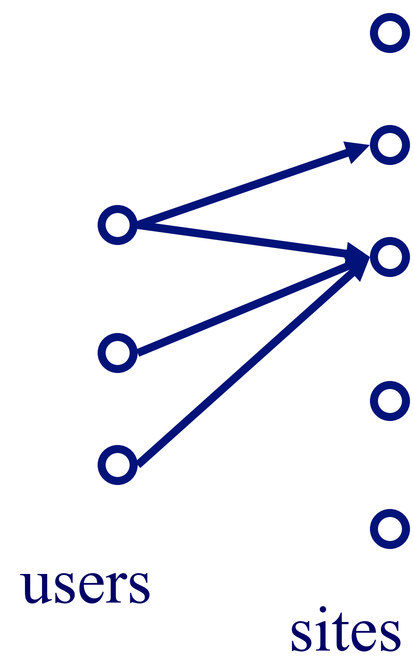
- web hit counts [w/ A. Montgomery]

Web Site Traffic

Count
(log scale)



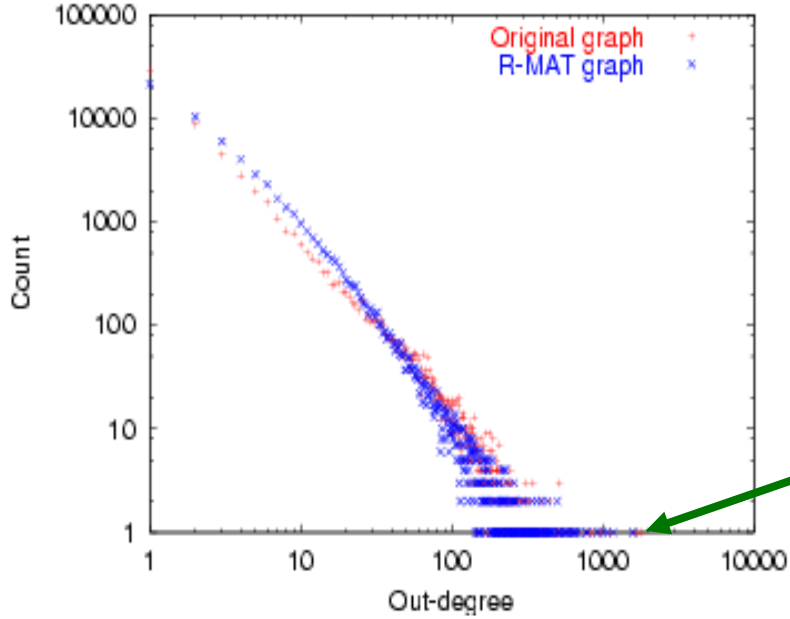
in-degree (log scale)



epinions.com

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

count



trusts-2000-people user

(out) degree

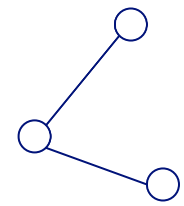
And numerous more

- # 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'

Outline

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

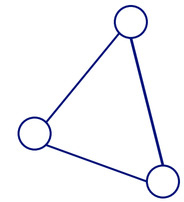
Solution# S.3: Triangle 'Laws'



- Real social networks have a lot of triangles

Carnegie Mellon

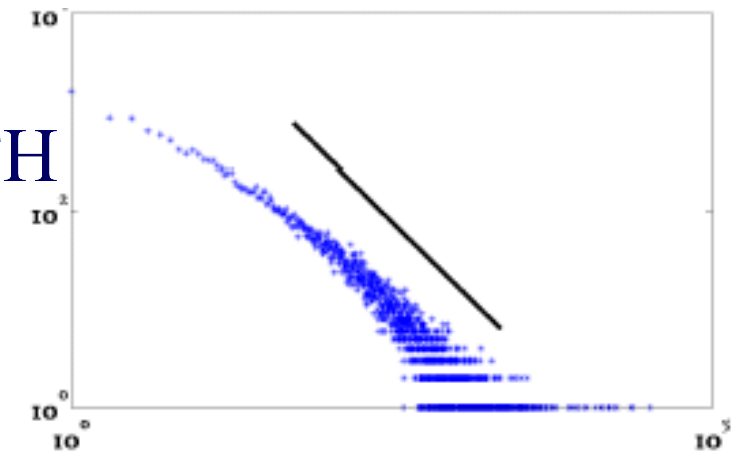
Solution# S.3: Triangle 'Laws'



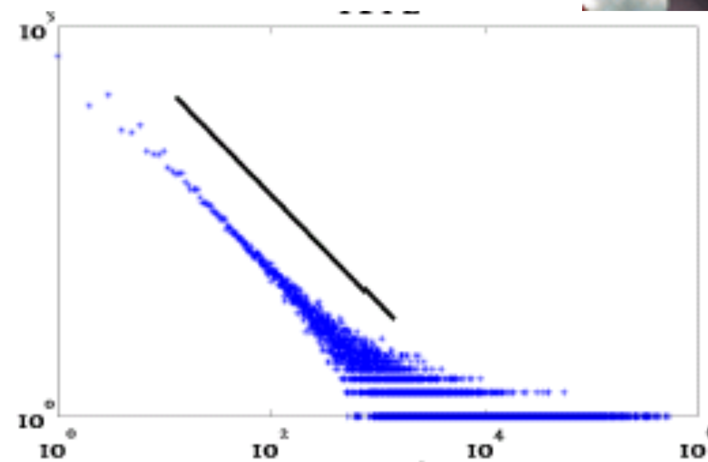
- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?

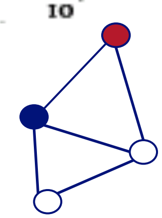
Triangle Law: #S.3
[Tsourakakis ICDM 2008]

HEP-TH

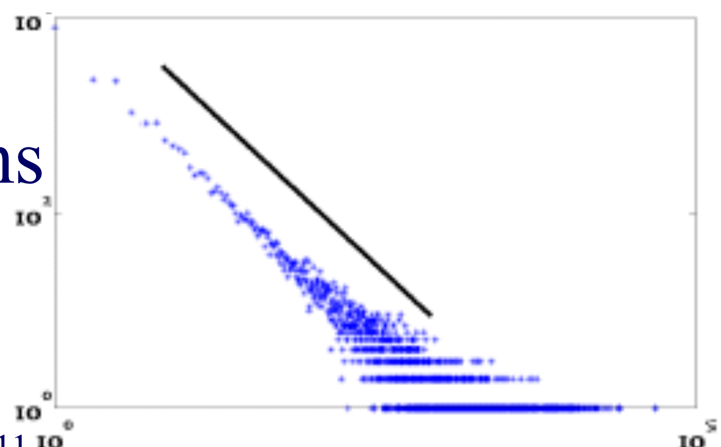


ASN





Epinions

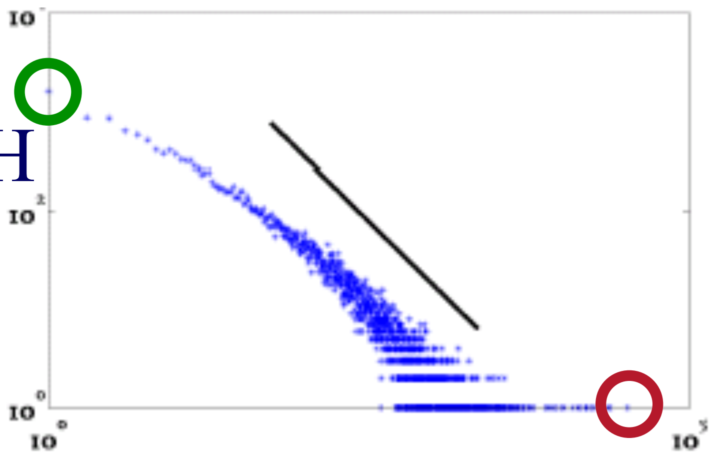


X-axis: # of participating triangles

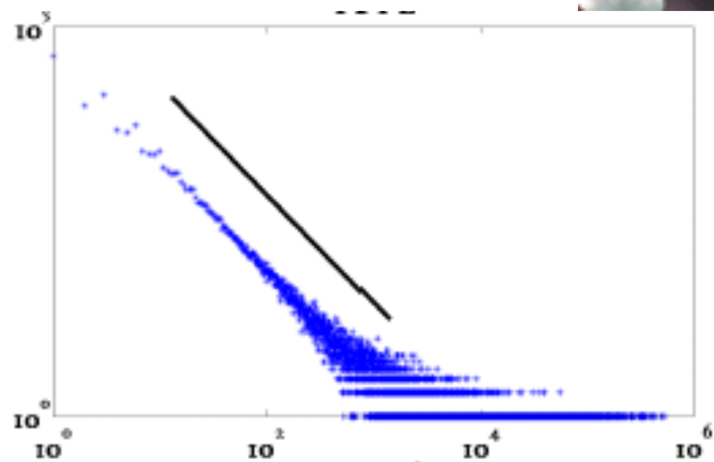
Y: count (~ pdf)

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

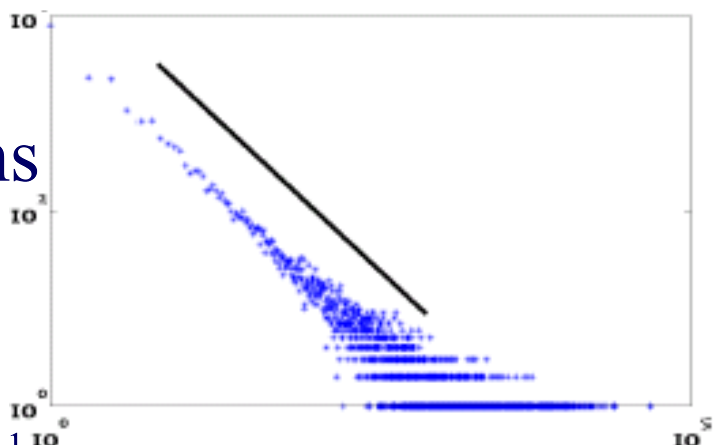
HEP-TH

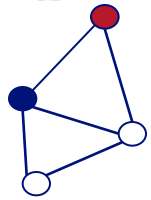


ASN



Epinions





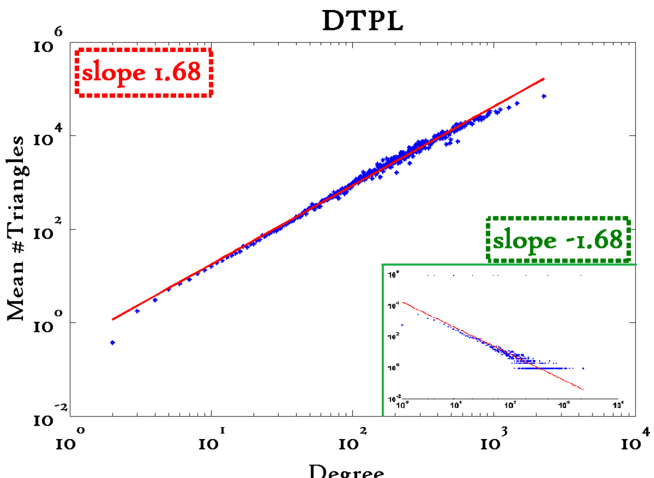
X-axis: # of participating triangles

Y: count (~ pdf)

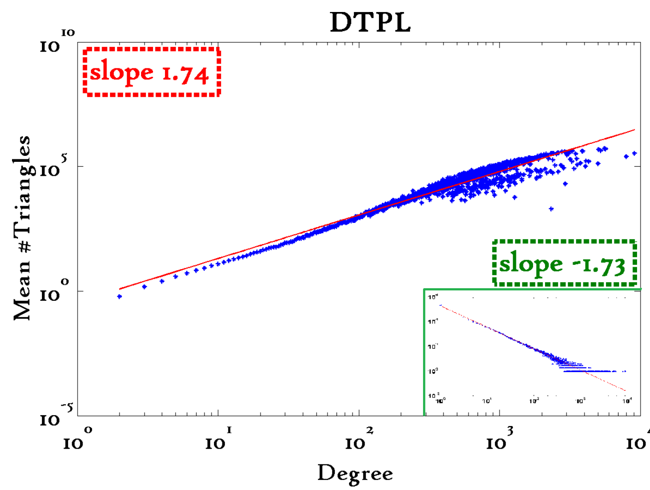
Carnegie Mellon

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

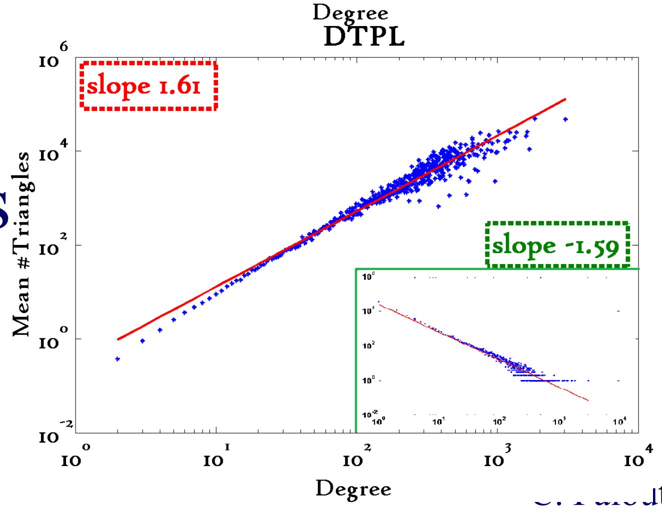
Reuters



SN



Epinions



X-axis: degree

Y-axis: mean # triangles

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

Carnegie Mellon

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

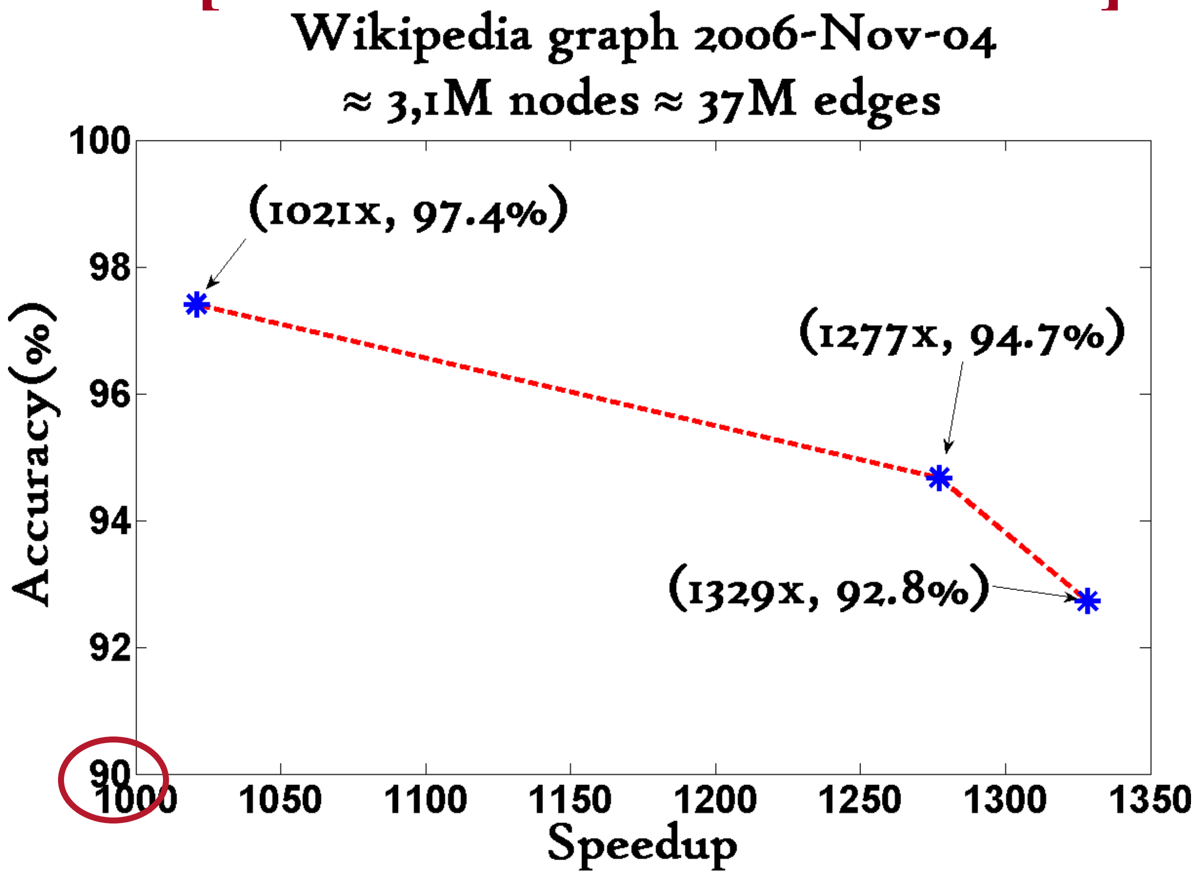
Triangle Law: Computations
[Tsourakakis ICDM 2008]

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!

Carnegie Mellon

details

Triangle Law: Computations [Tsourakakis ICDM 2008]



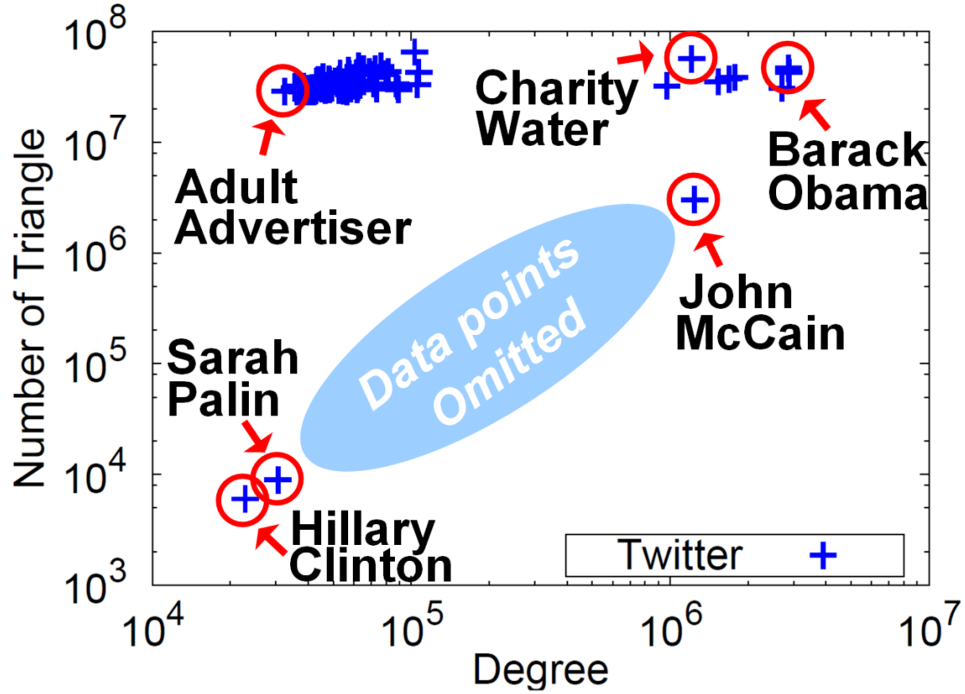
1000x+ speed-up, >90% accuracy

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]

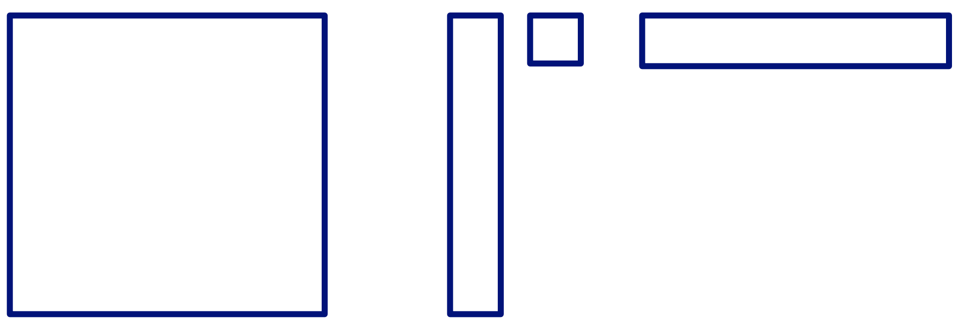
EigenSpokes

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.

EigenSpokes

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

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

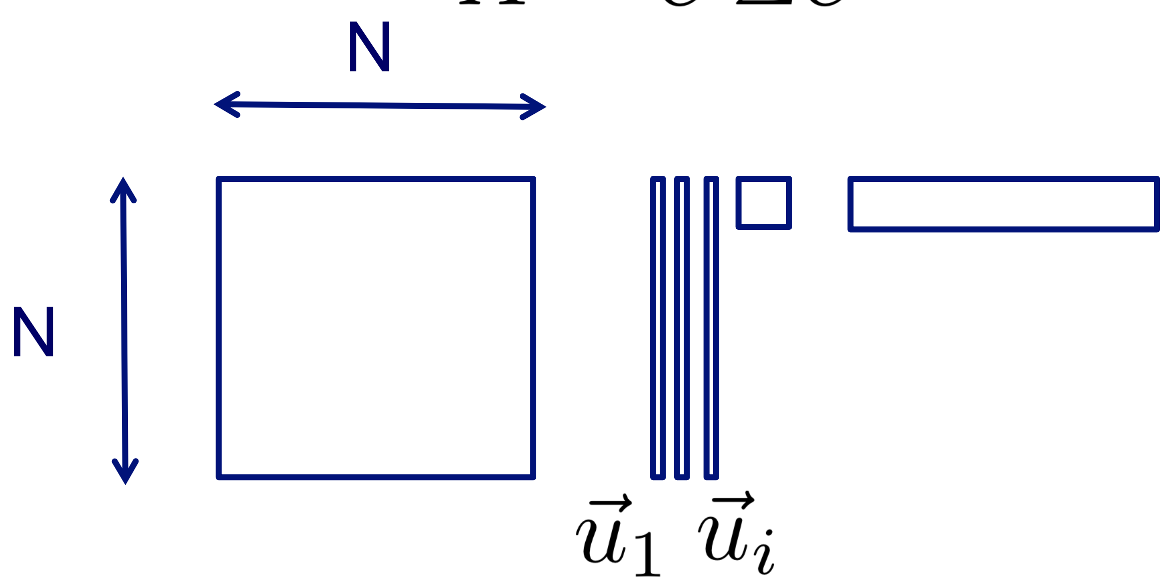


details

EigenSpokes

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

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

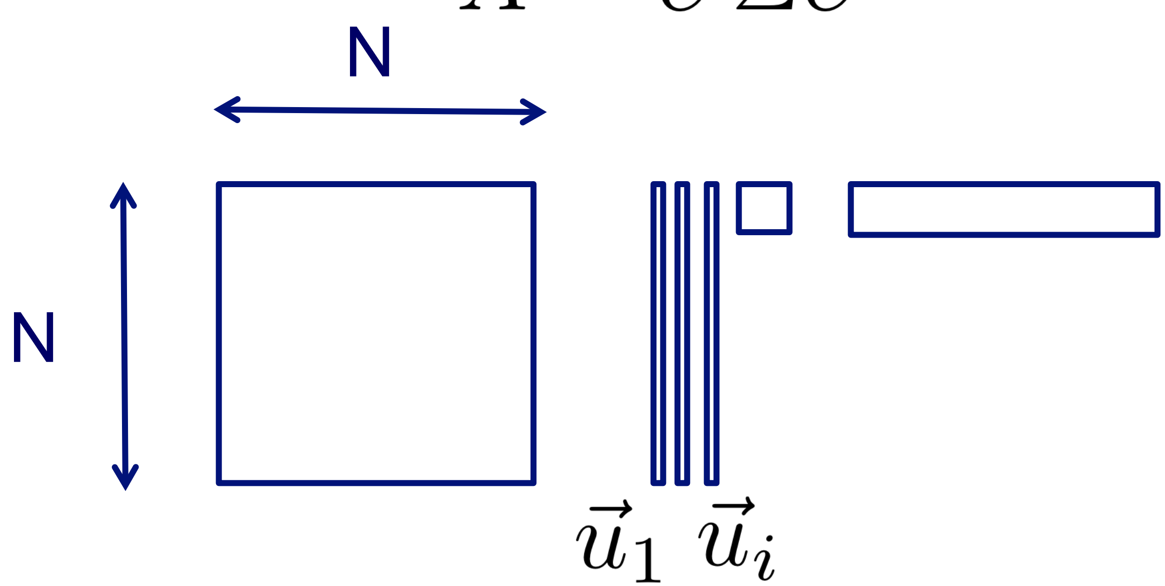


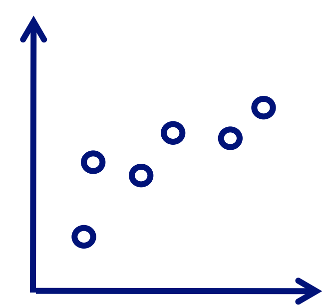
details

EigenSpokes

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

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





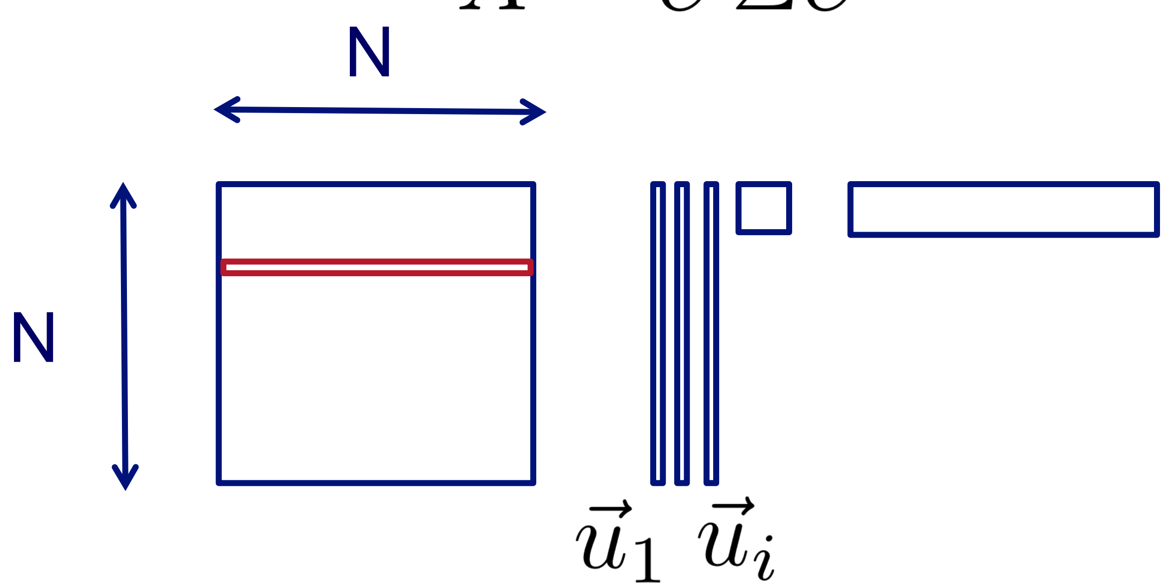
Carnegie Mellon

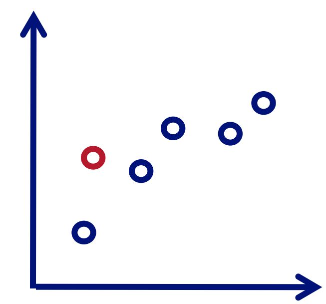
details

EigenSpokes

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

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





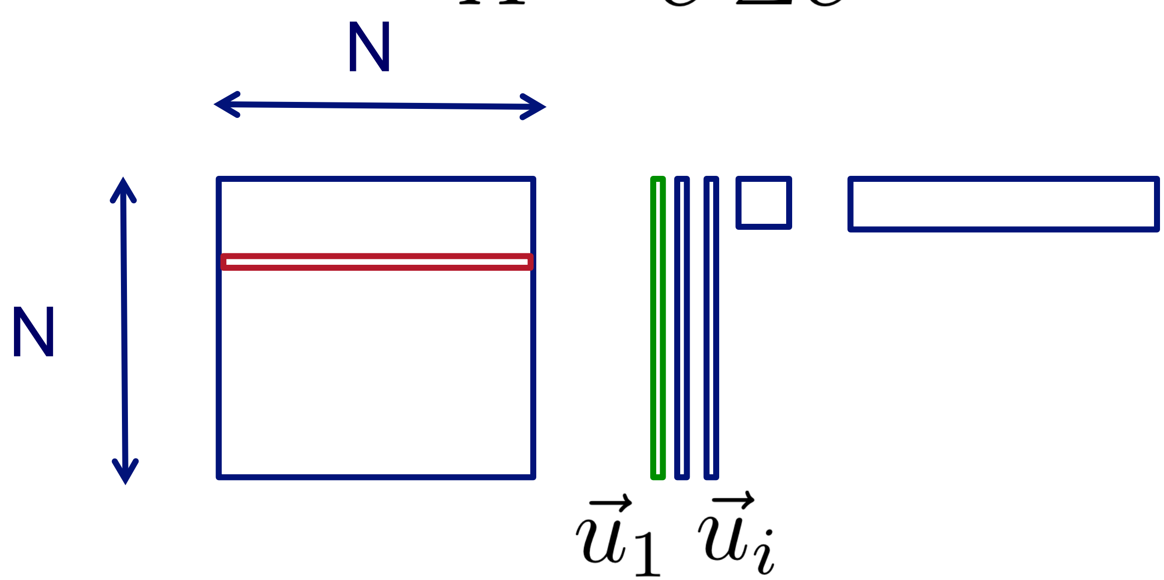
Carnegie Mellon

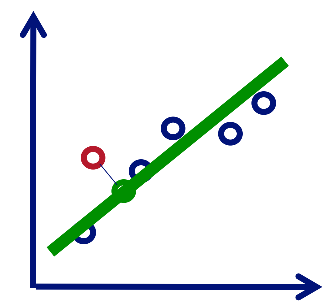
details

EigenSpokes

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

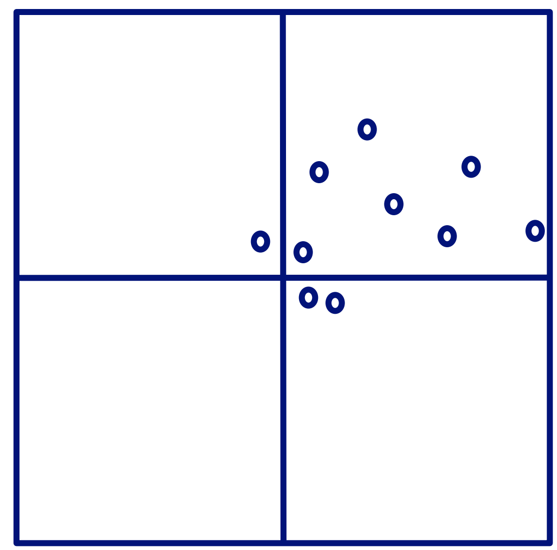
$$A = U \Sigma U^T$$





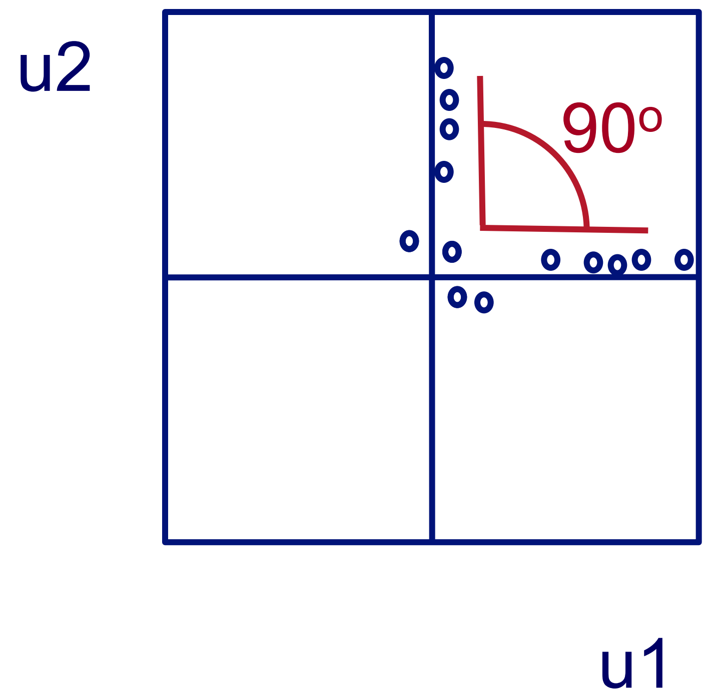
EigenSpokes

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



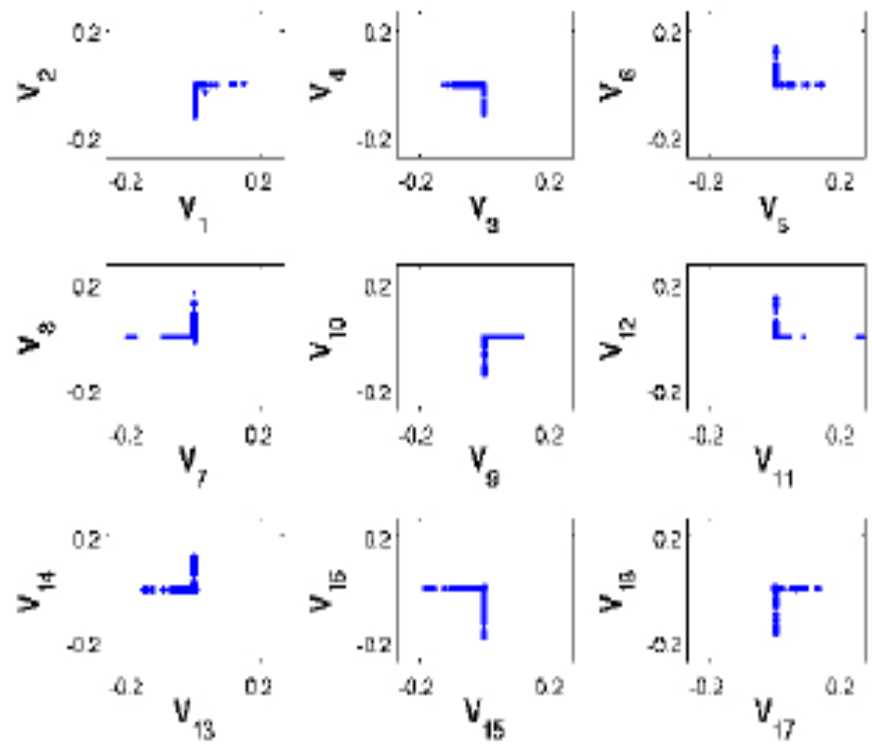
EigenSpokes

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

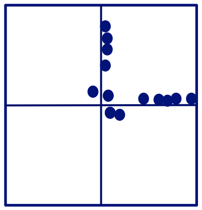


EigenSpokes - pervasiveness

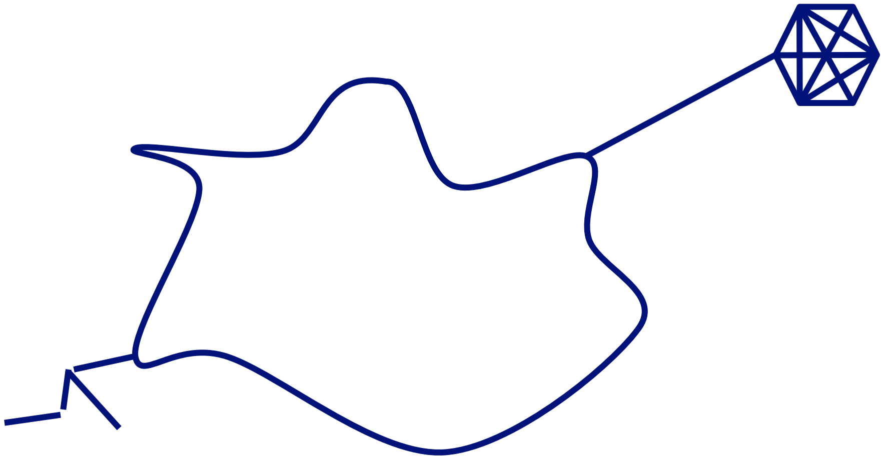
- Present in mobile social graph
  - across time and space
- Patent citation graph



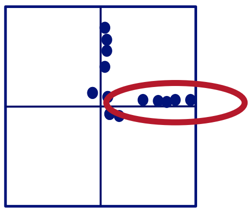
EigenSpokes - explanation



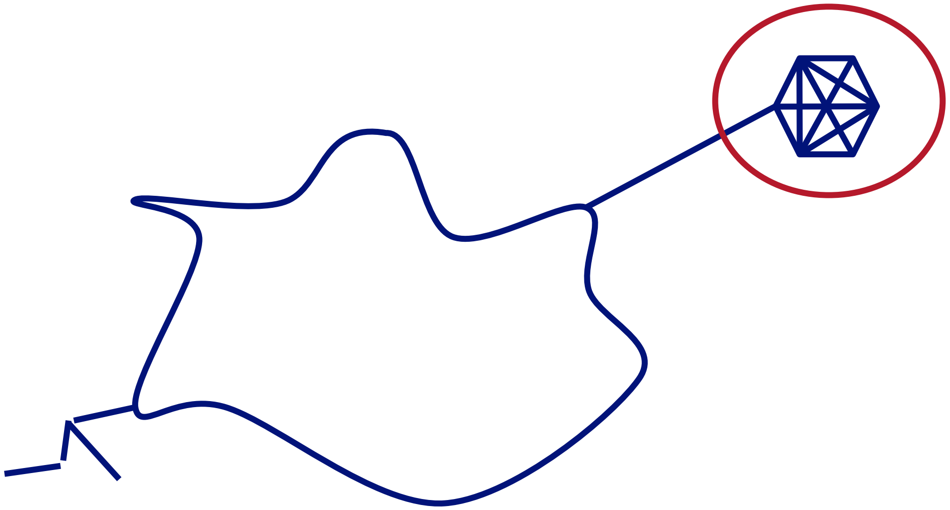
Near-cliques, or near-bipartite-cores, loosely connected



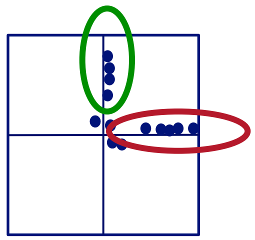
EigenSpokes - explanation



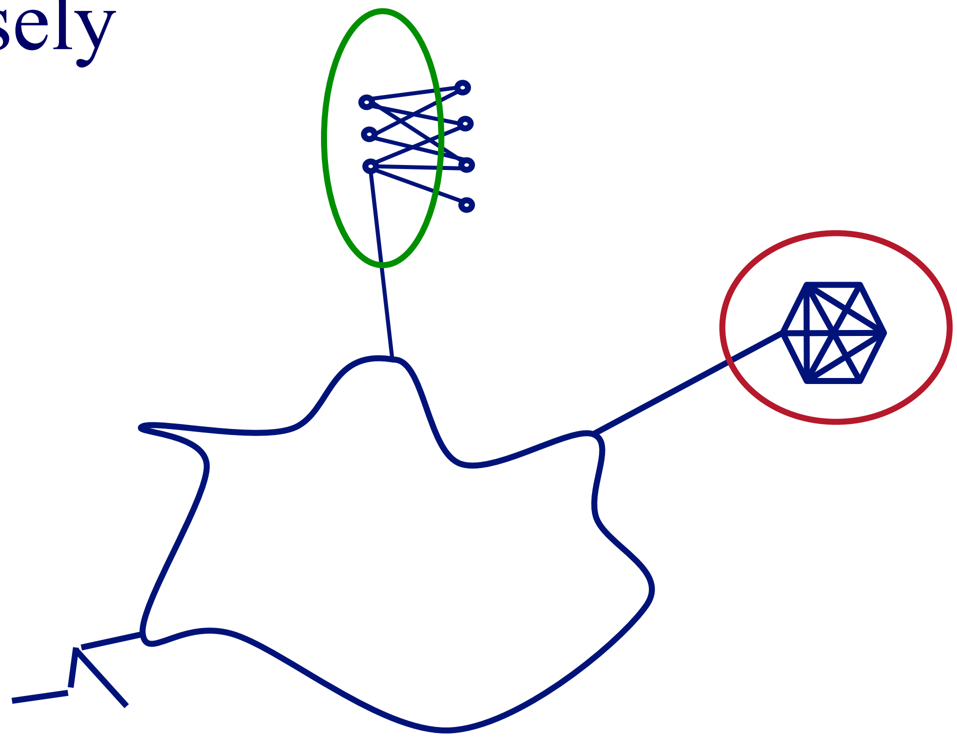
Near-cliques, or near-bipartite-cores, loosely connected



EigenSpokes - explanation



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

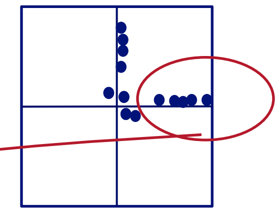


EigenSpokes - explanation

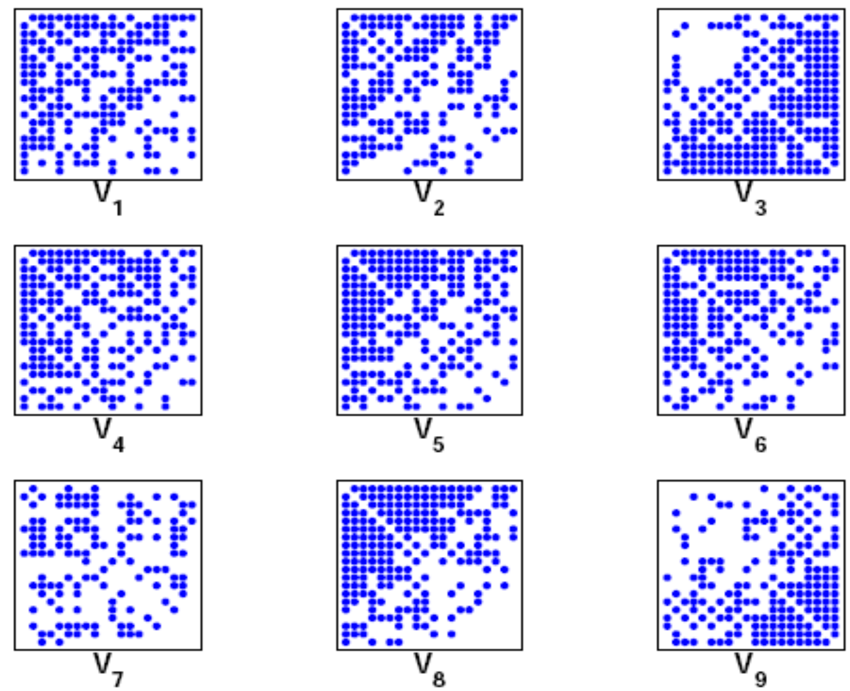
Near-cliques, or near-bipartite-cores, loosely connected

So what?

- Extract nodes with high *scores*
- high connectivity
- Good “communities”



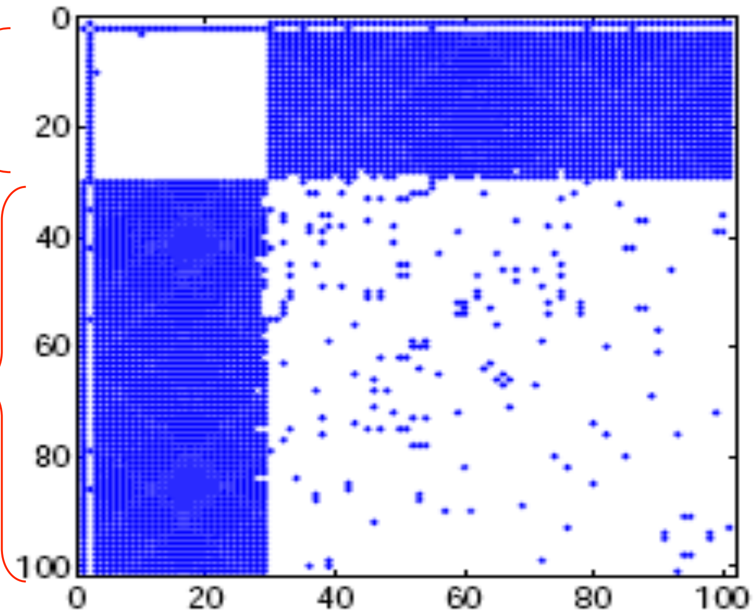
spy plot of top 20 nodes



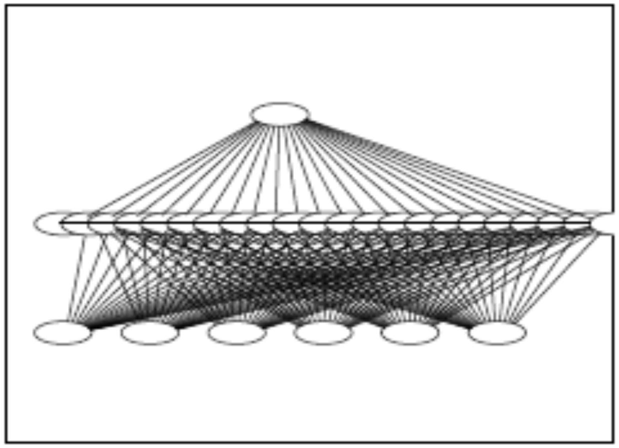
Bipartite Communities!

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

Carnegie Mellon

Observations on weighted graphs?

- A: yes - even more 'laws'!

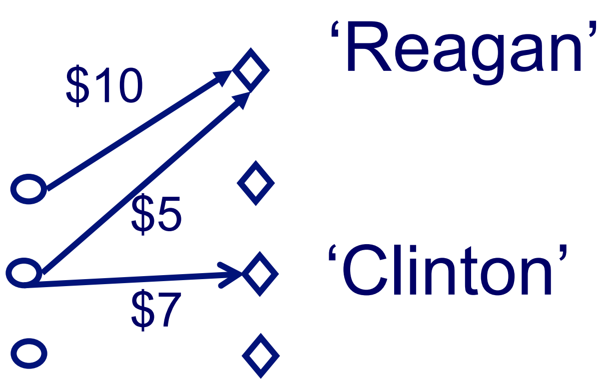
M. McGlohon, L. Akoglu, and C. Faloutsos
Weighted Graphs and Disconnected Components: Patterns and a Generator.
SIG-KDD 2008

Observation W.1: Fortification

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

Observation W.1: Fortification

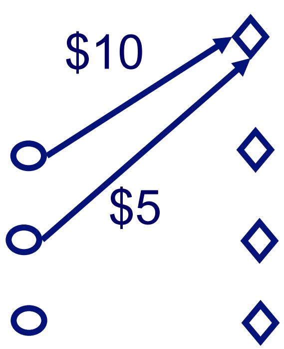
More donors, more $?



Observation W.1: fortification: Snapshot Power Law

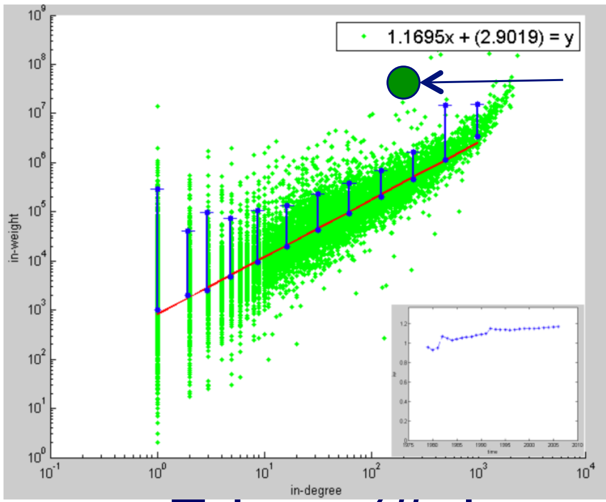
- Weight: super-linear on in-degree
- exponent ‘iw’: 1.01 < iw < 1.26

More donors,
<u>even</u> more $



In-weights ($)

Orgs-Candidates



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

Edges (# donors)

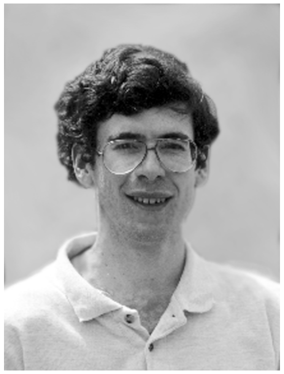
Outline

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

Problem: Time evolution

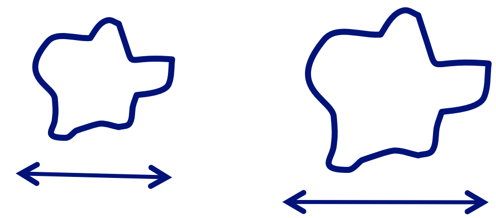
- with Jure Leskovec (CMU -> Stanford)

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



T.1 Evolution of the Diameter

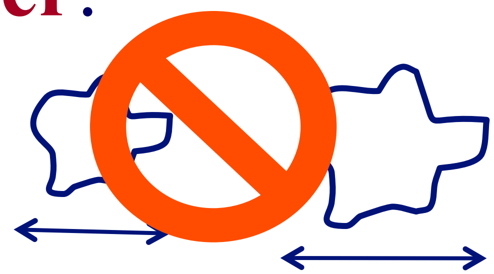
- Prior work on Power Law graphs hints at **slowly growing diameter**:
  - diameter ~ O(log N)
  - diameter ~ O(log log N)



- What is happening in real data?

T.1 Evolution of the Diameter

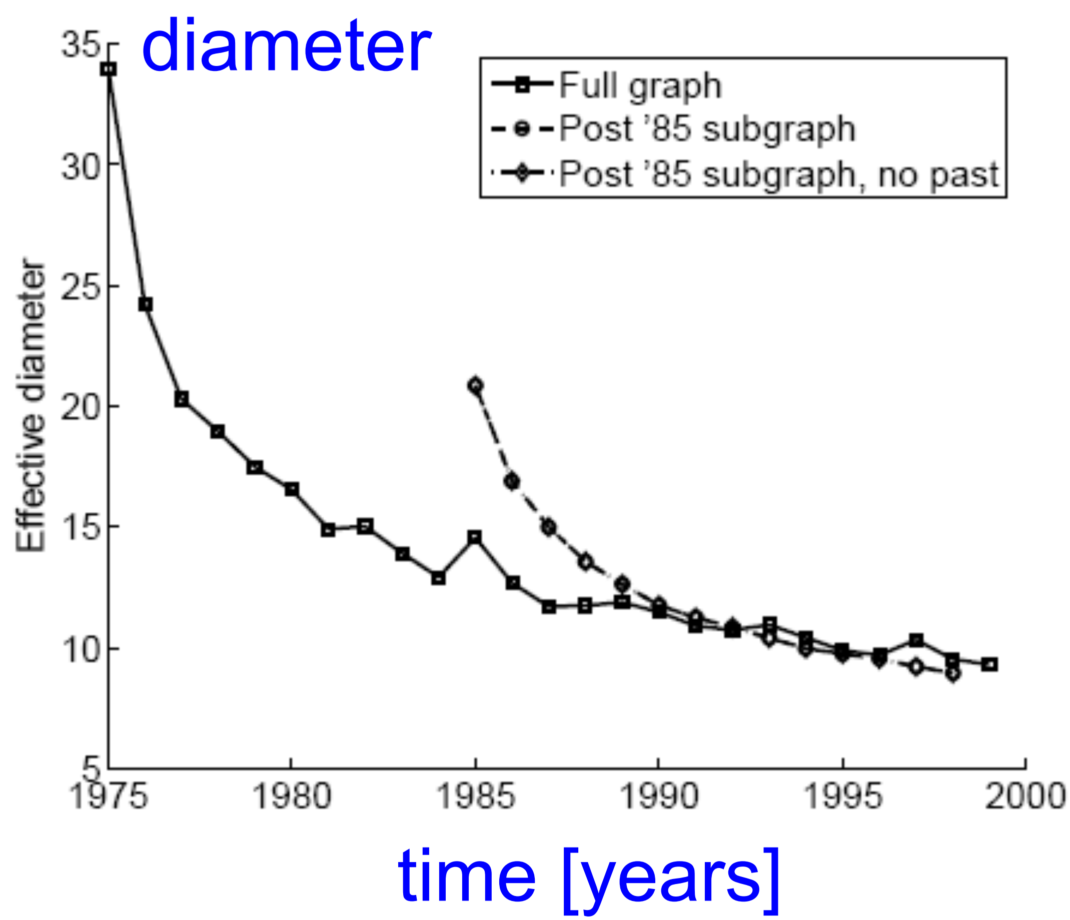
- Prior work on Power Law graphs hints at **slowly growing diameter**:
  - diameter ~ O(log N)
  - diameter ~ O(log log N)



- 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

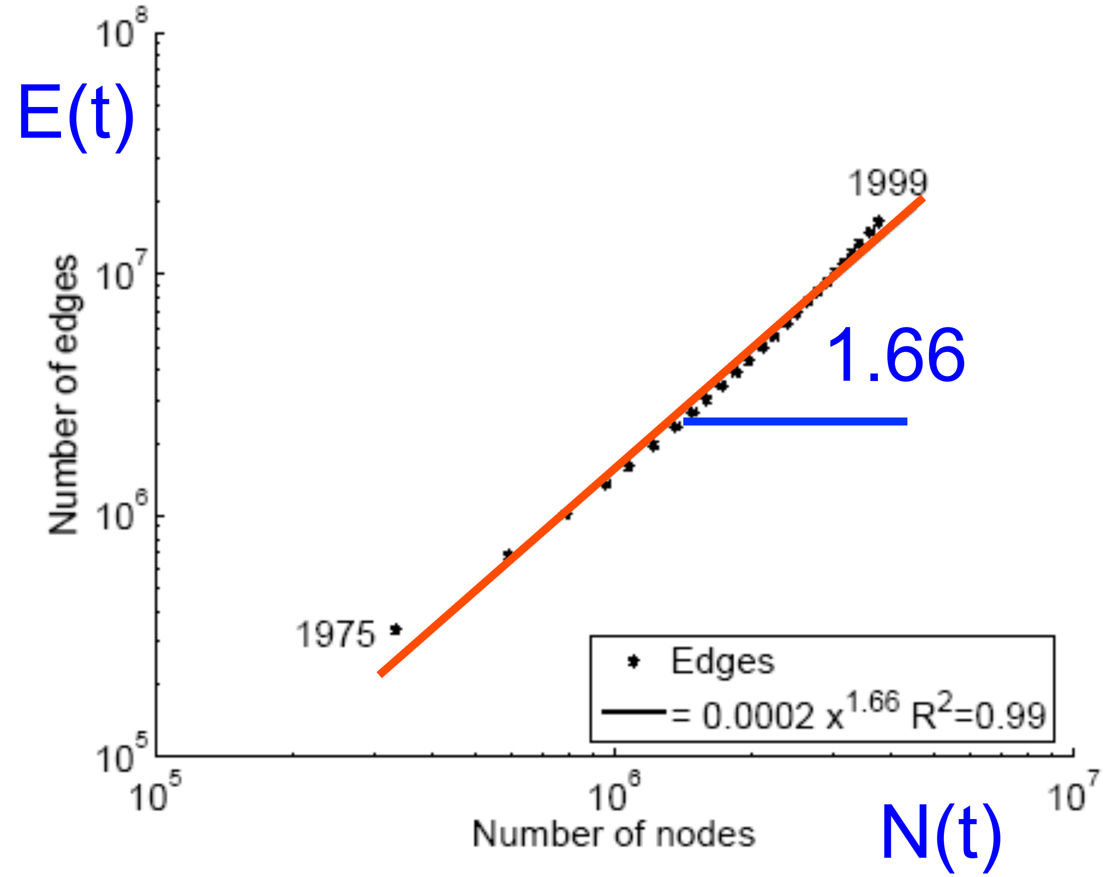
  E(t+1) =? 2 * E(t)

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

Carnegie Mellon

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

Carnegie Mellon

Observation T.3: NLCC behavior

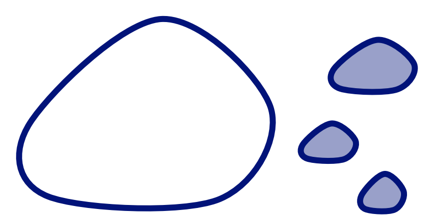
Q: How do NLCC's emerge and join with the GCC?

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

– Do they continue to grow in size?

– or do they shrink?

– or stabilize?



Observation T.3: NLCC behavior

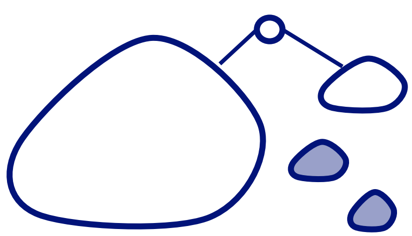
Q: How do NLCC's emerge and join with the GCC?

(``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?

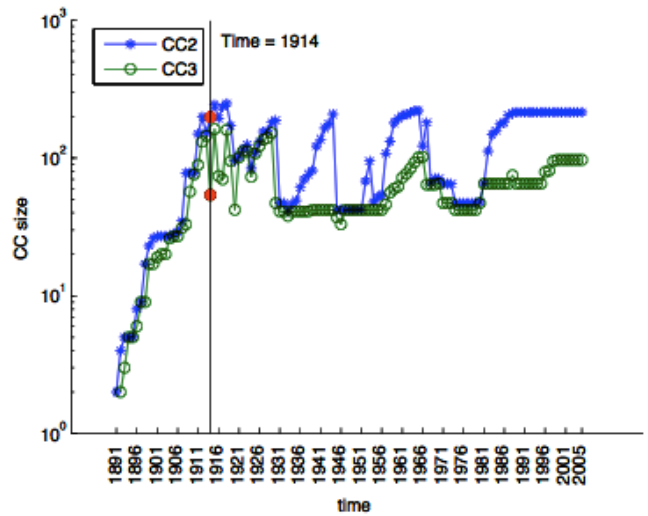
YES – or stabilize?

Observation T.3: NLCC behavior

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

IMDB

CC size



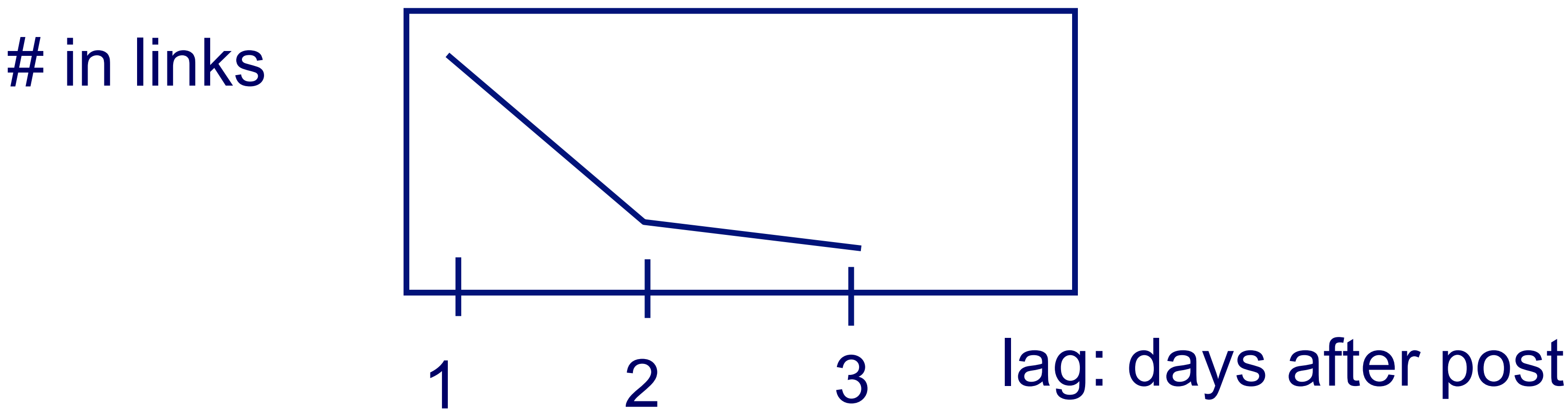
Time-stamp

Timing for Blogs

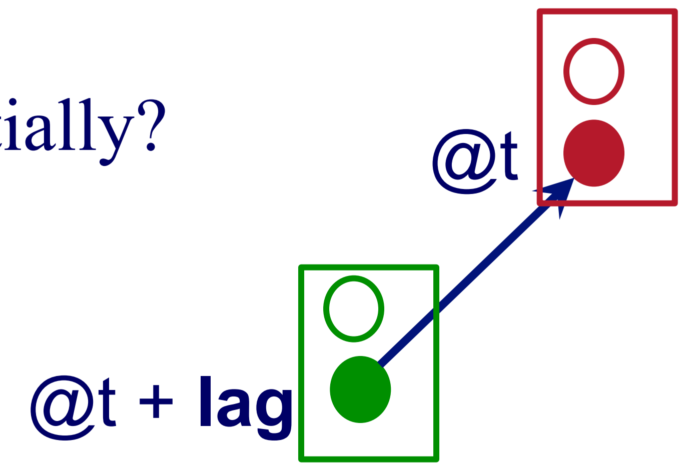
- with Mary McGlohon (CMU->Google)
- Jure Leskovec (CMU->Stanford)
- Natalie Glance (now at Google)
- Mat Hurst (now at MSR)

[SDM’07]

T.4 : popularity over time

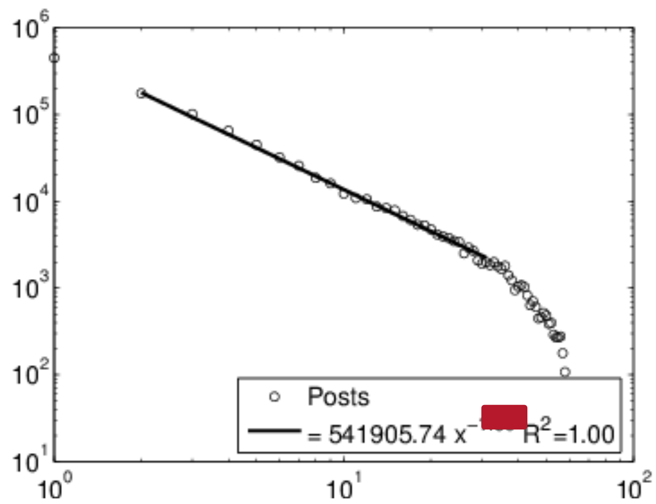


Post popularity drops-off – exponentially?



T.4 : popularity over time

in links
(**log**)

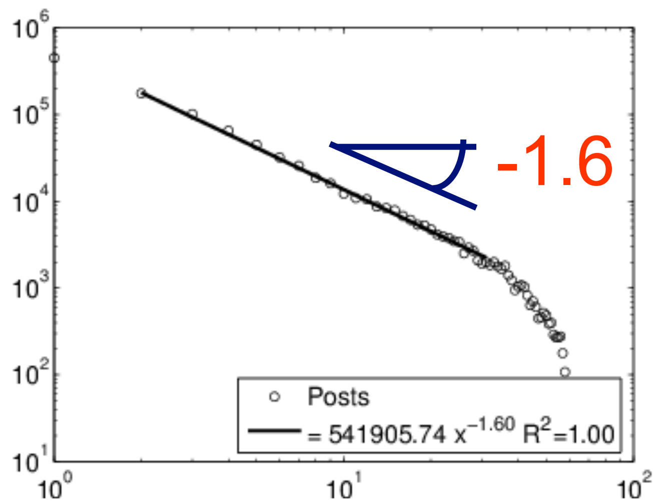


days after post
(**log**)

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

T.4 : popularity over time

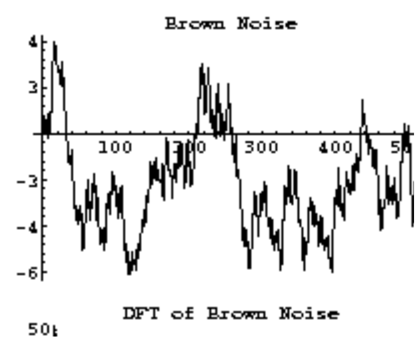
\# in links (**log**)



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]

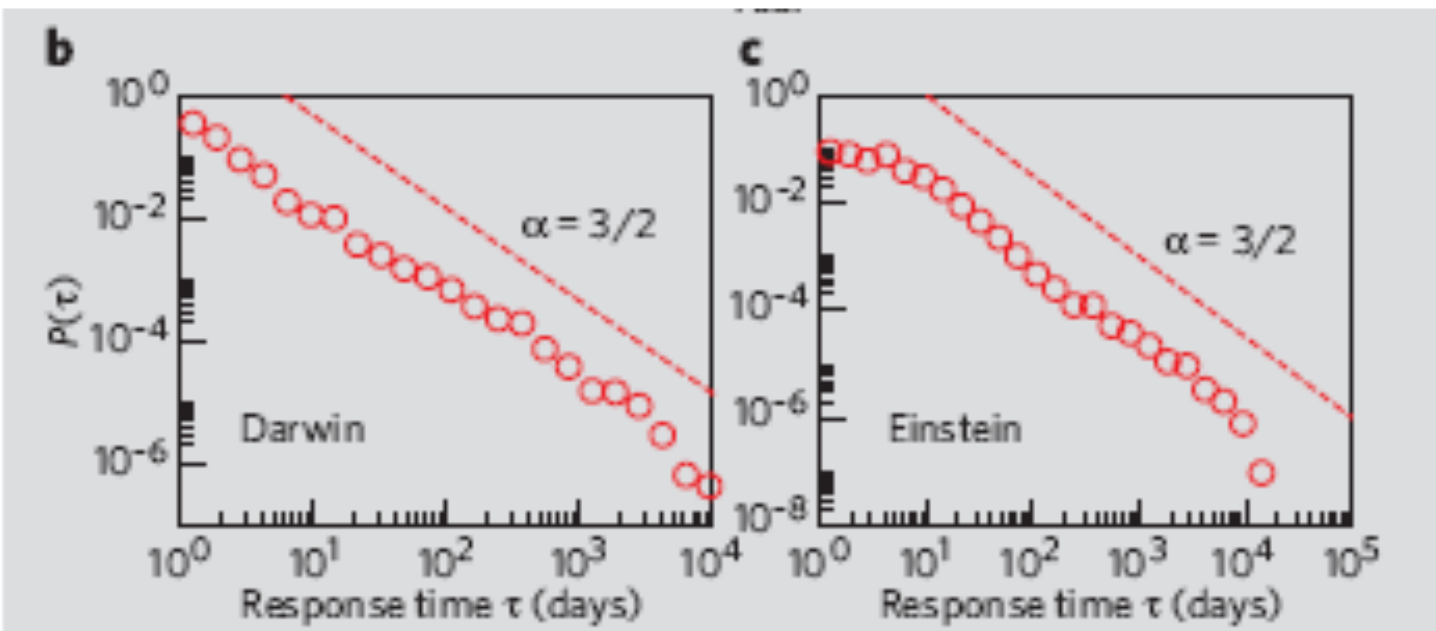


Figure 1 | The correspondence patterns of Darwin and Einstein.

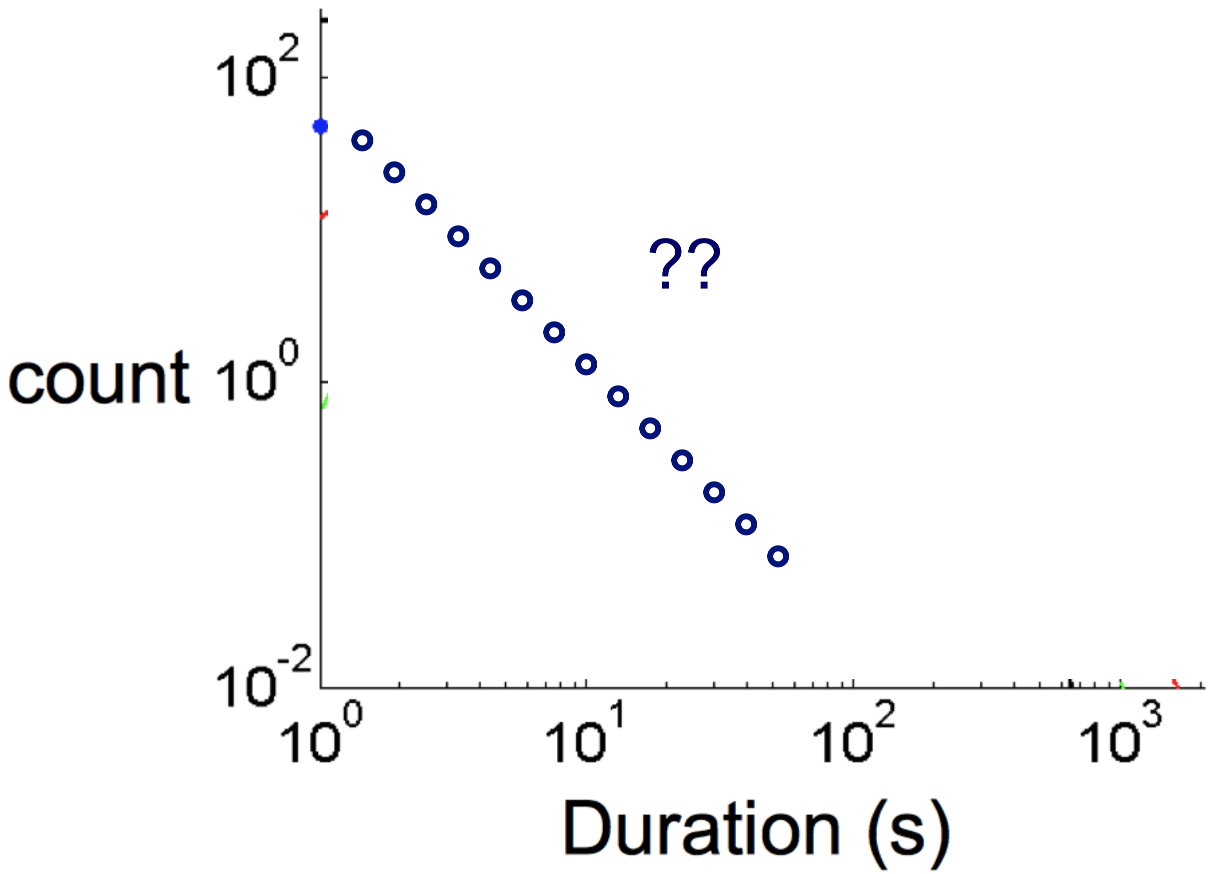
T.5: duration of phonecalls

Surprising Patterns for the Call Duration Distribution of Mobile Phone Users

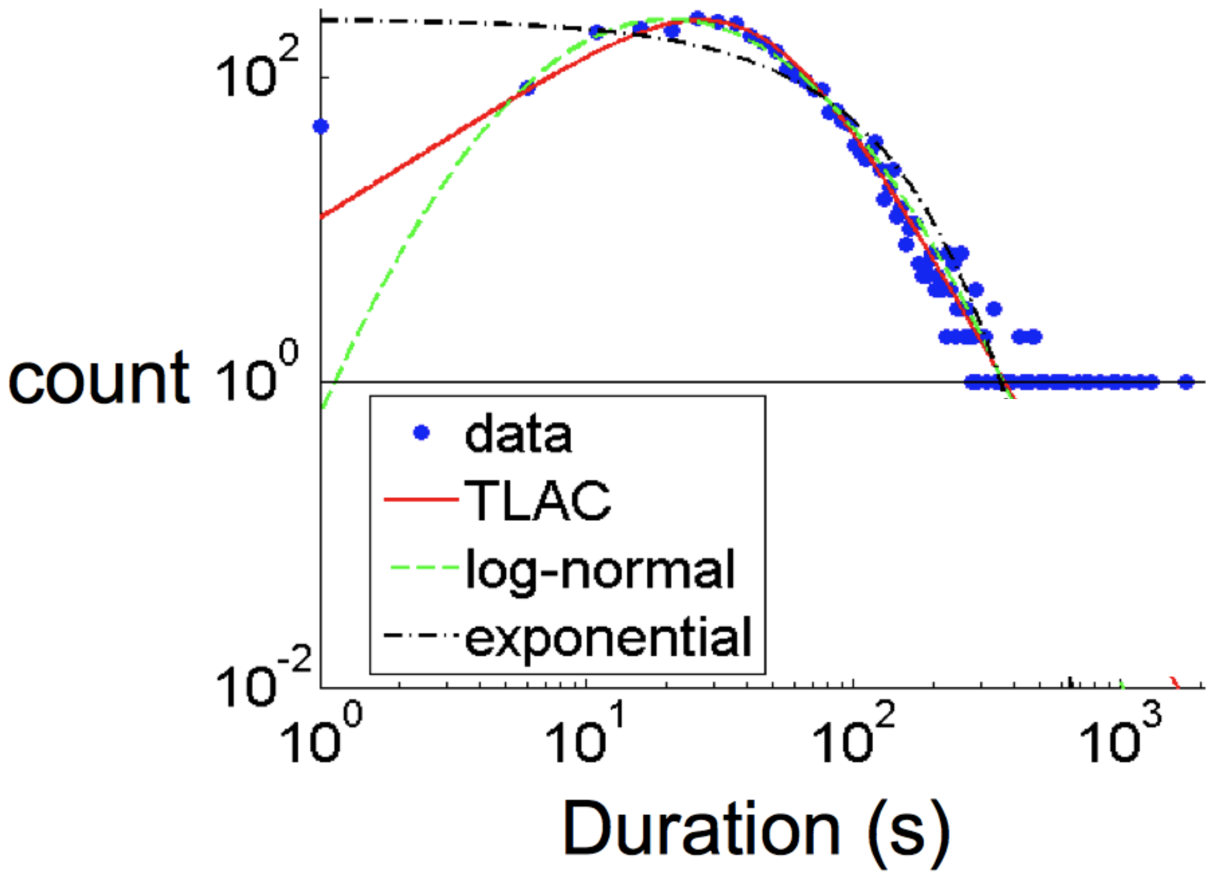
Pedro O. S. Vaz de Melo, Leman Akoglu, Christos Faloutsos, Antonio A. F. Loureiro

PKDD 2010

Probably, power law (?)

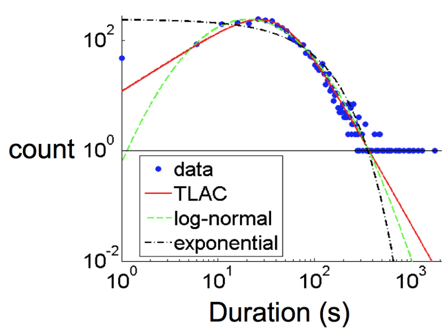


No Power Law!


count
10^2
10^0
10^{-2}
10^0
10^1
10^2
10^3
Duration (s)
data
TLAC
log-normal
exponential

‘TLaC: Lazy Contractor’

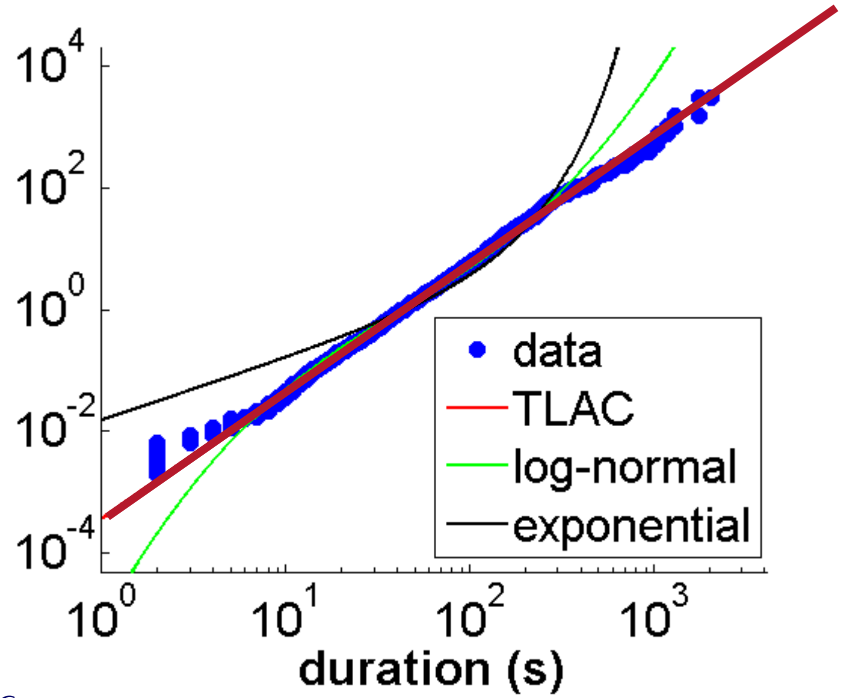
- The longer a task (phonecall) has taken,
- The even longer it will take



Odds ratio=

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

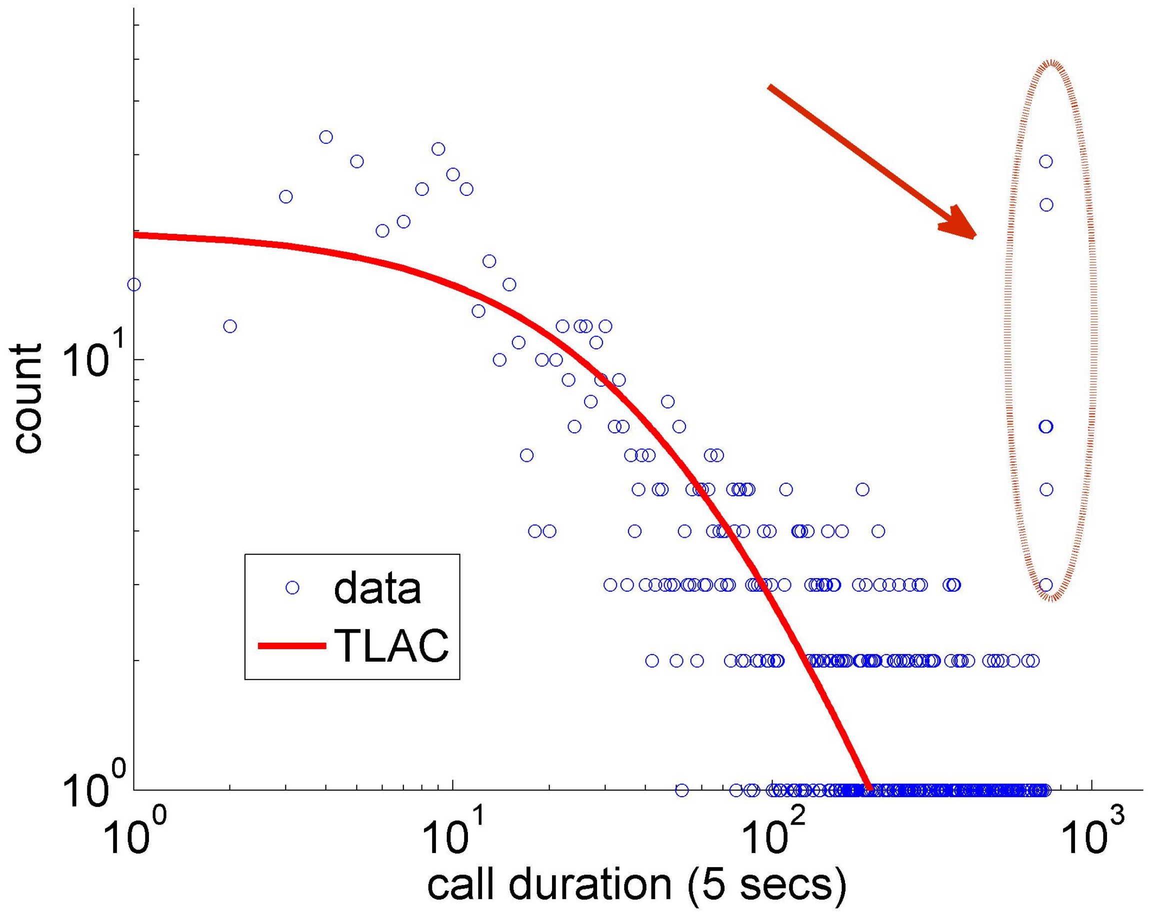
== power law



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)

Outliers:



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

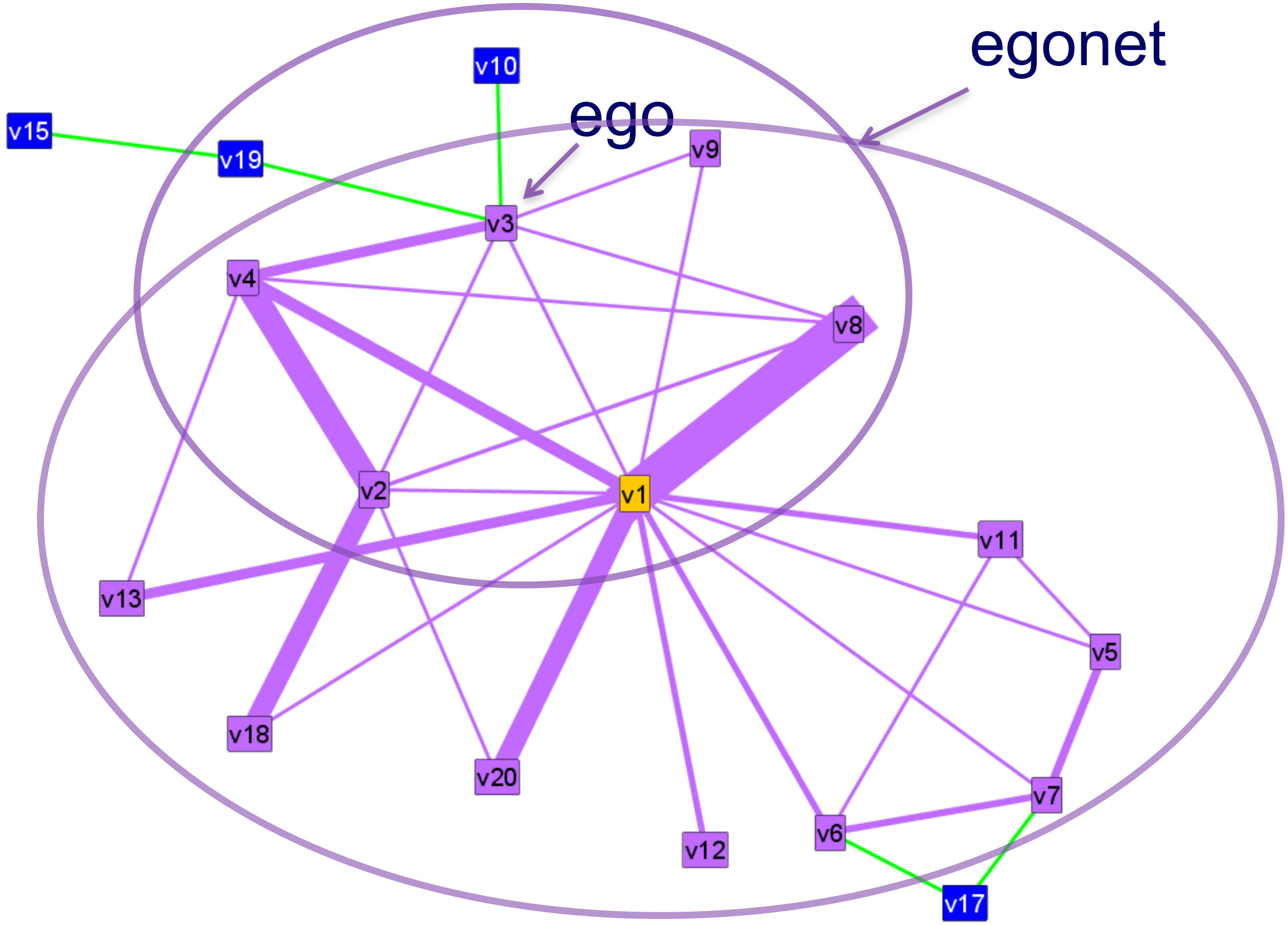
PAKDD 2010, Hyderabad, India

Main idea

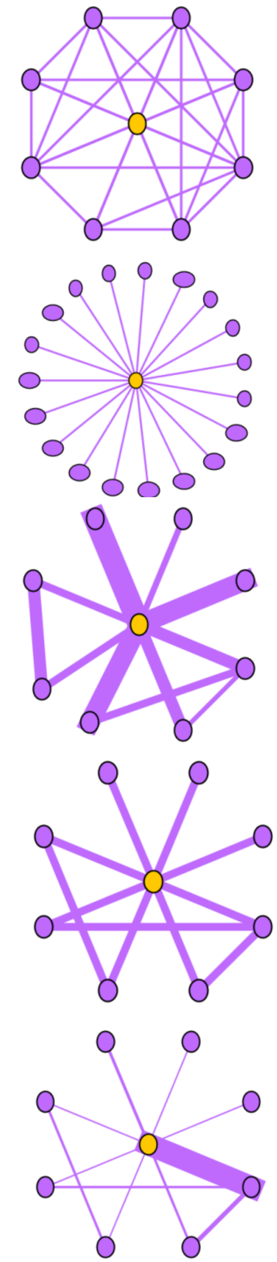
For each node,

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

What is an egonet?



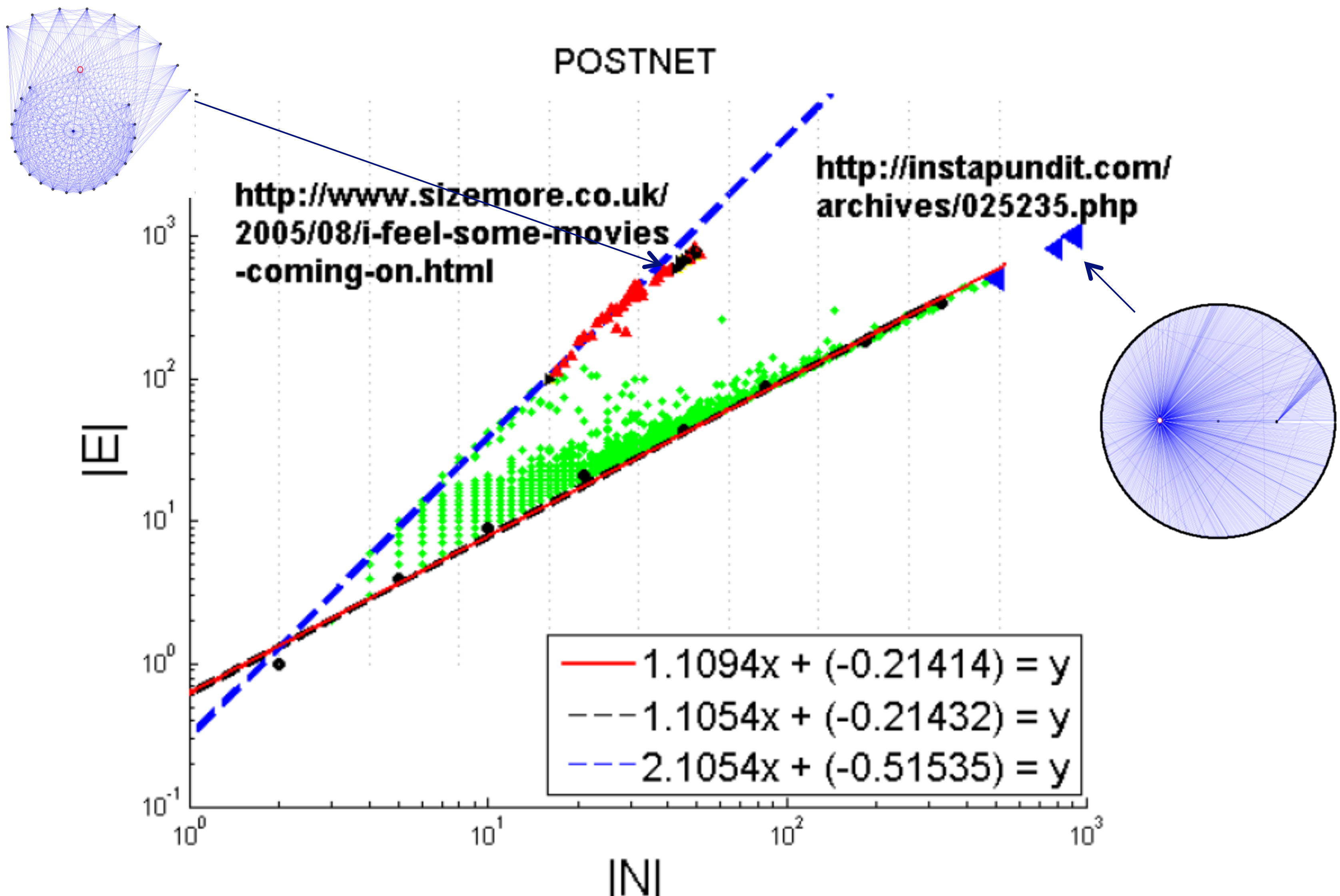
Selected Features



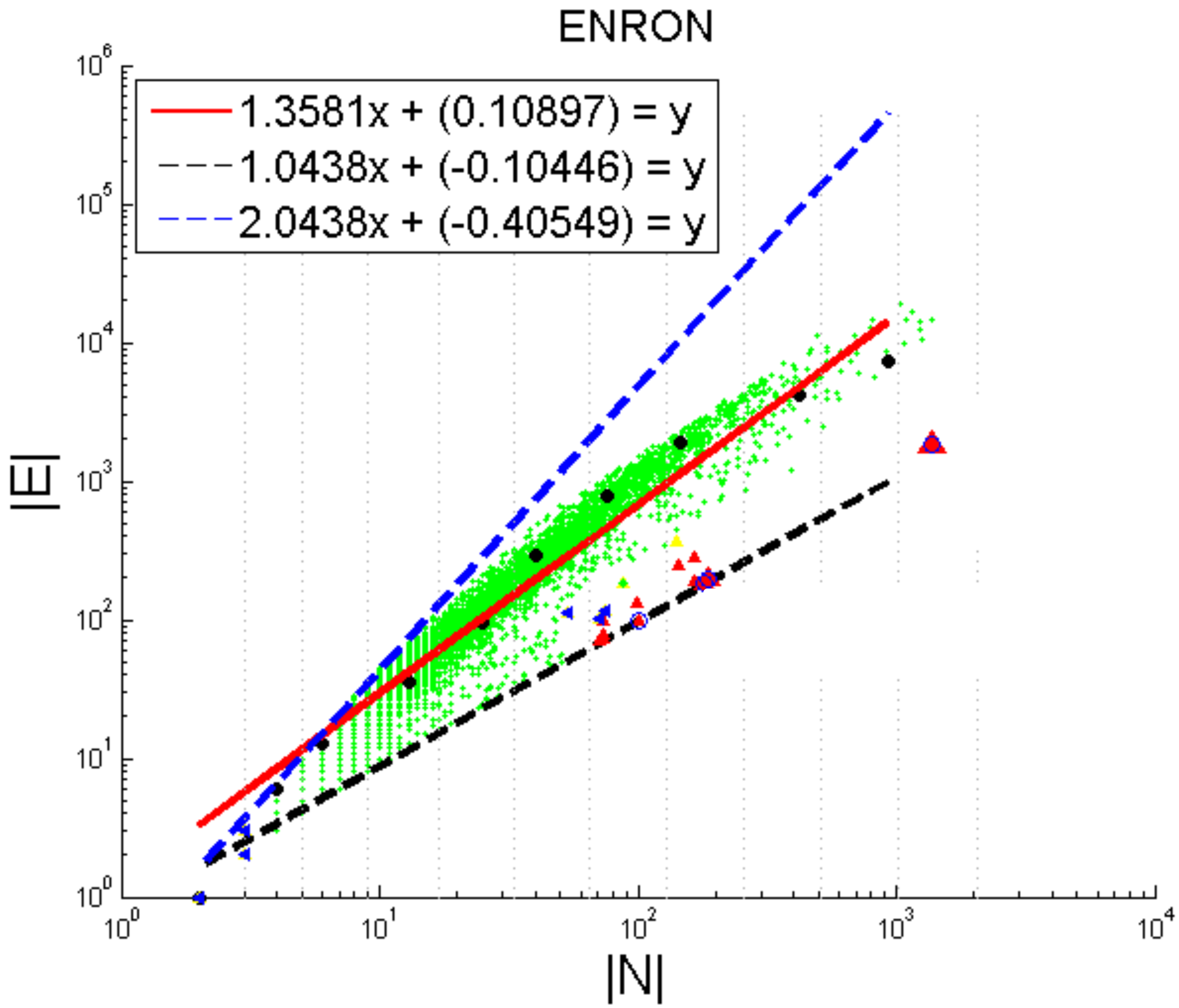
- N_i: number of neighbors (degree) of ego i
- E_i: number of edges in egonet i
- W_i: total weight of egonet i
- $\lambda_{w,i}$: principal eigenvalue of the weighted adjacency matrix of egonet I

Carnegie Mellon

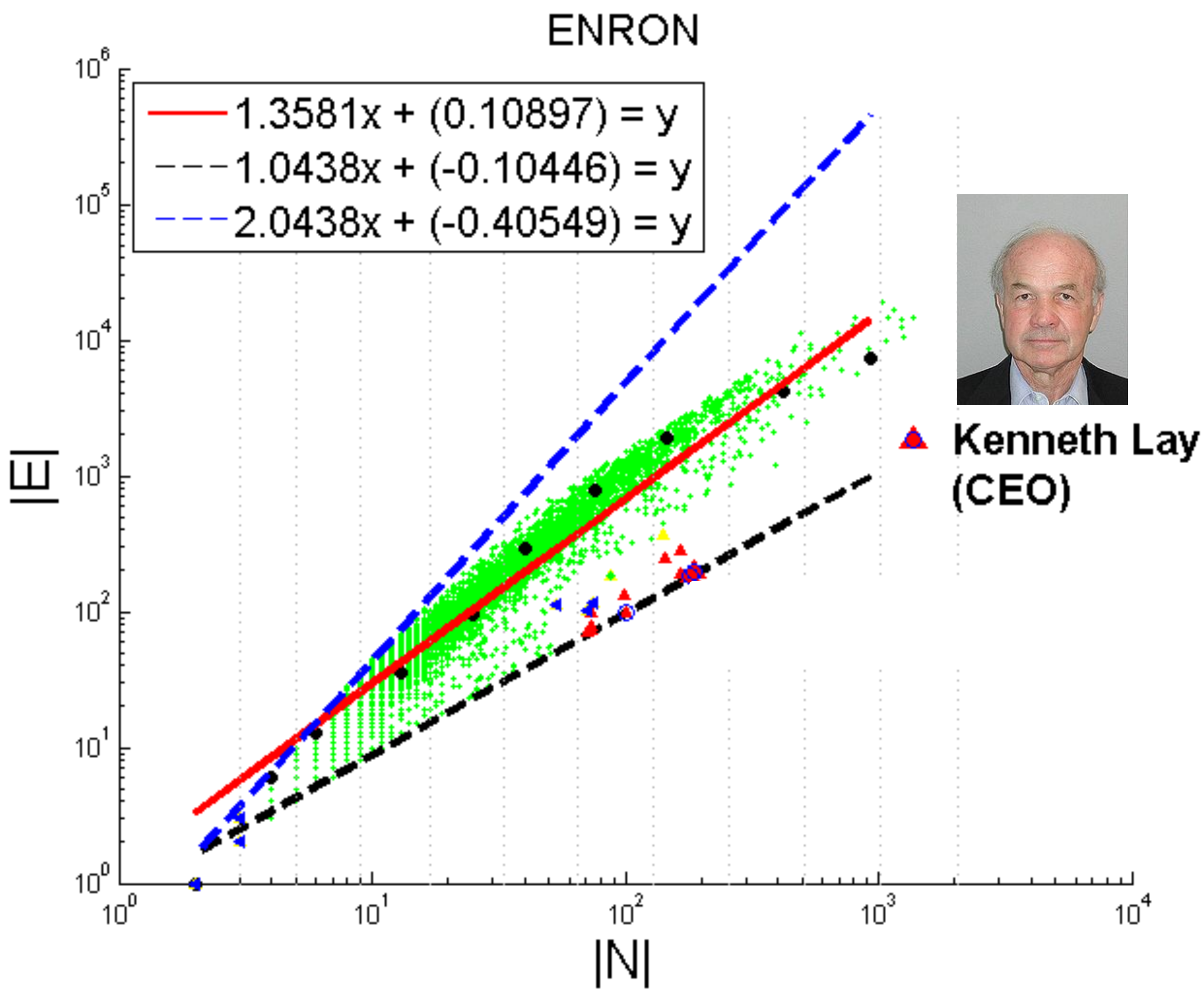
Near-Clique/Star



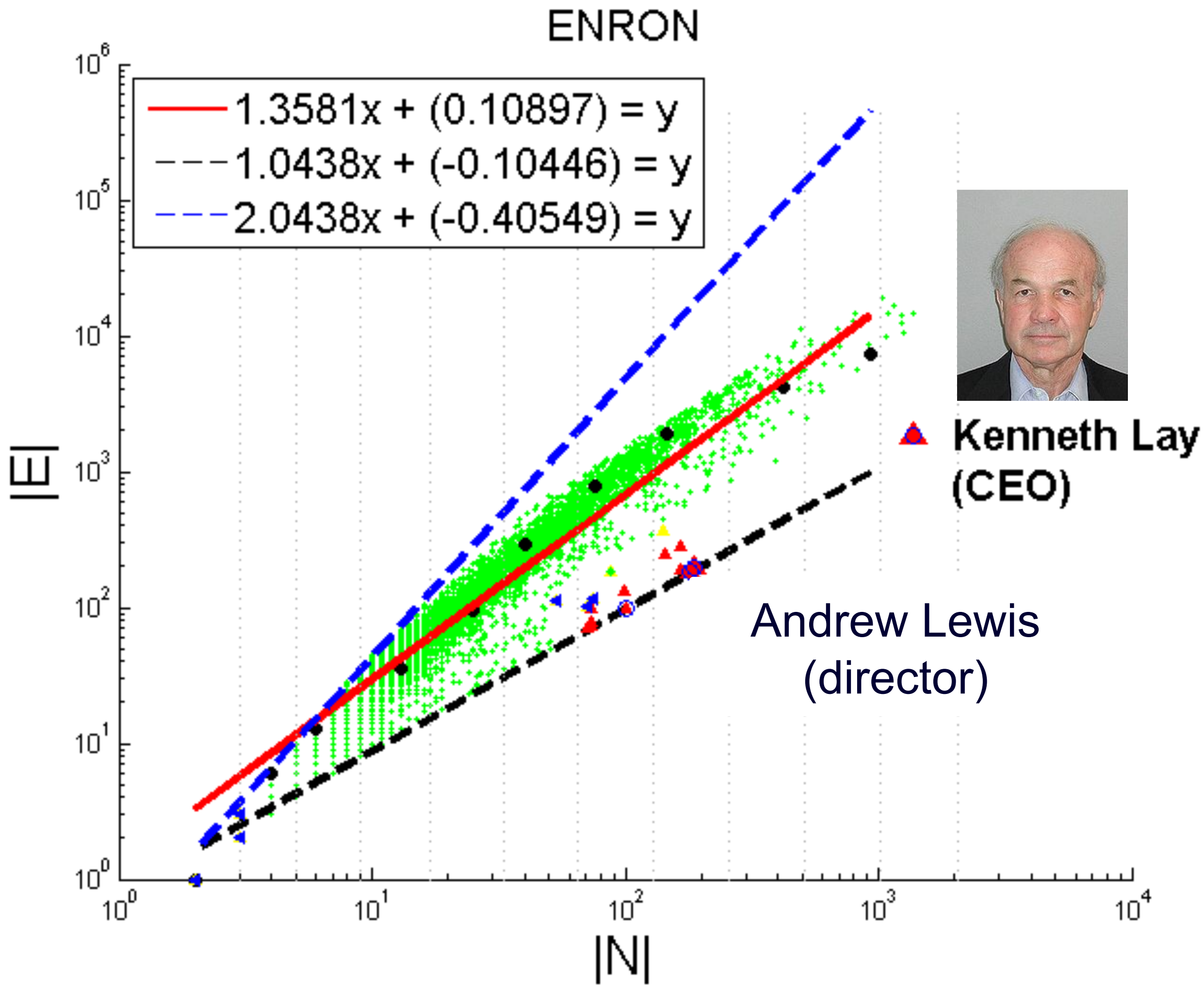
Near-Clique/Star



Near-Clique/Star



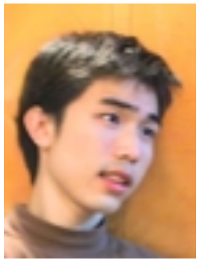
Near-Clique/Star



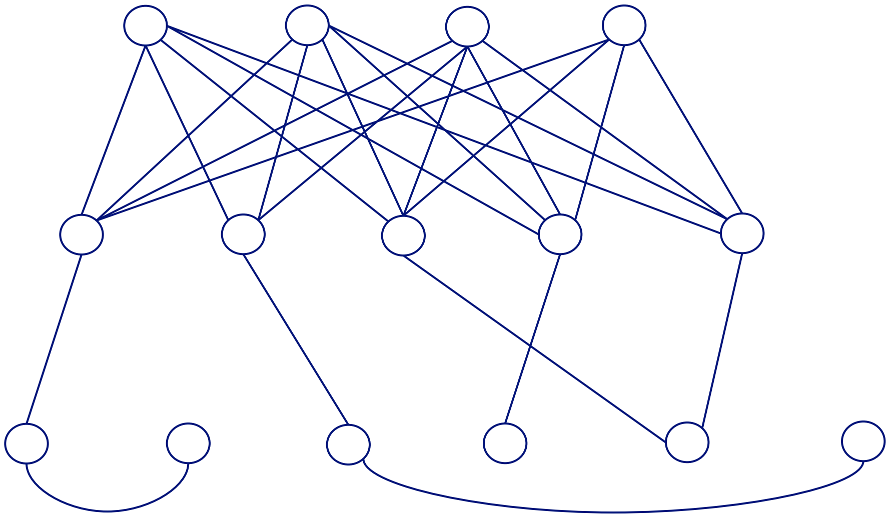
Outline

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

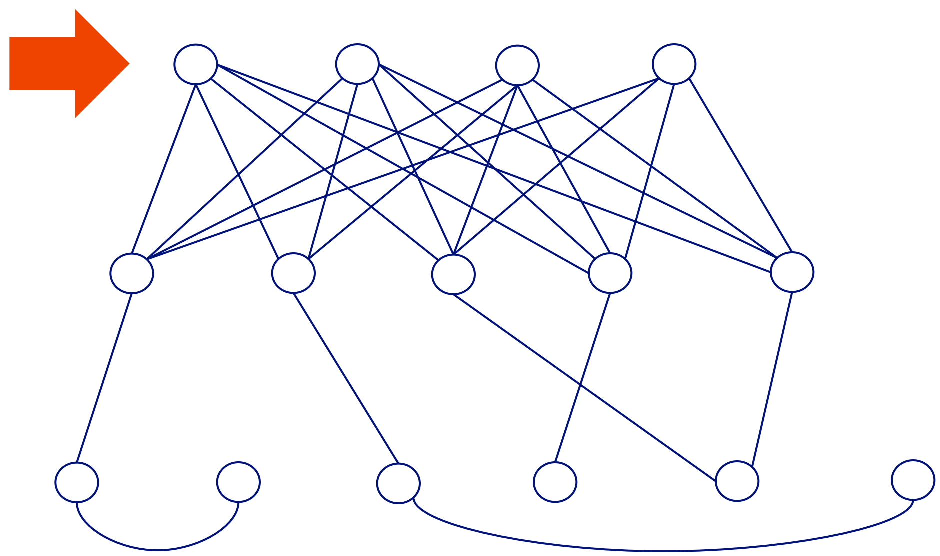
E-bay Fraud detection



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

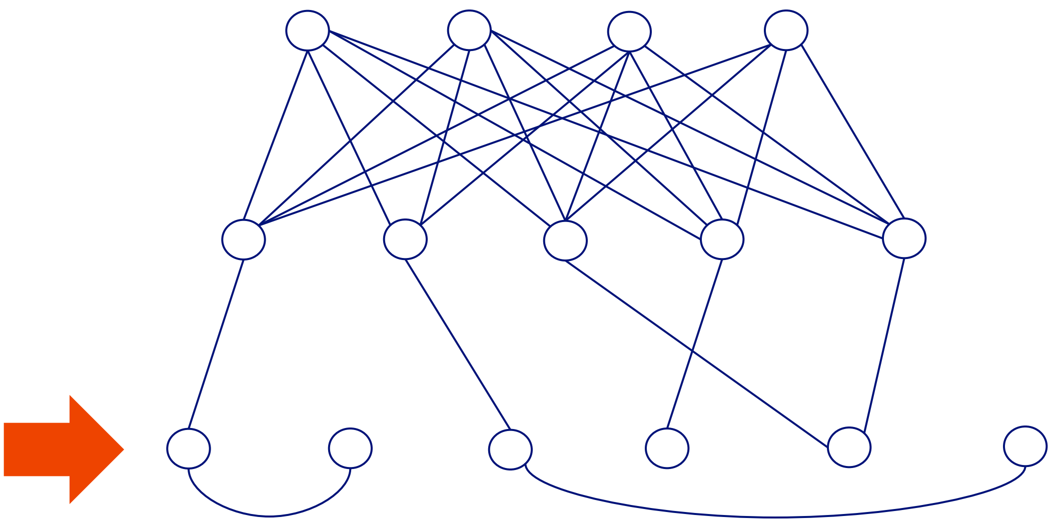


E-bay Fraud detection

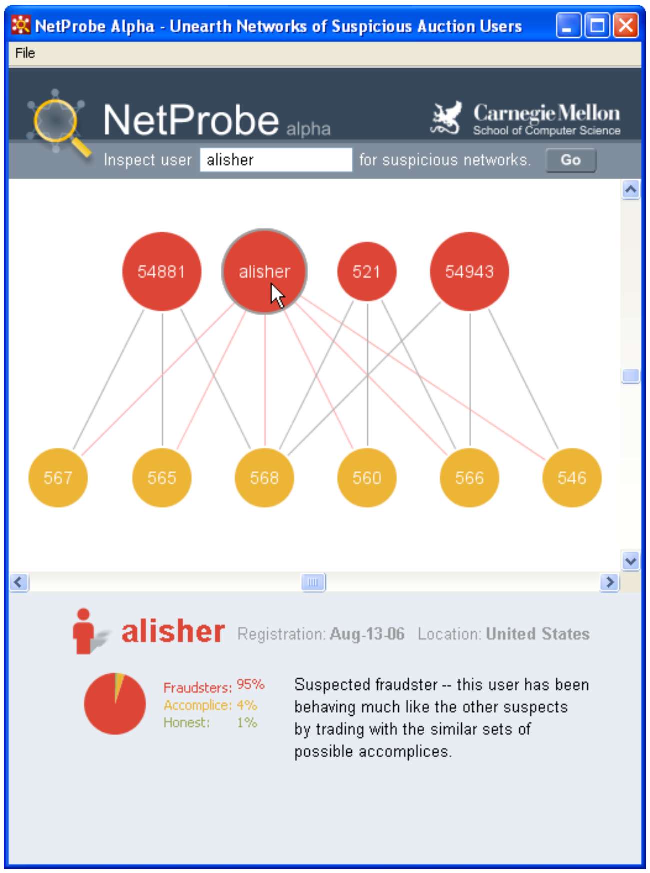


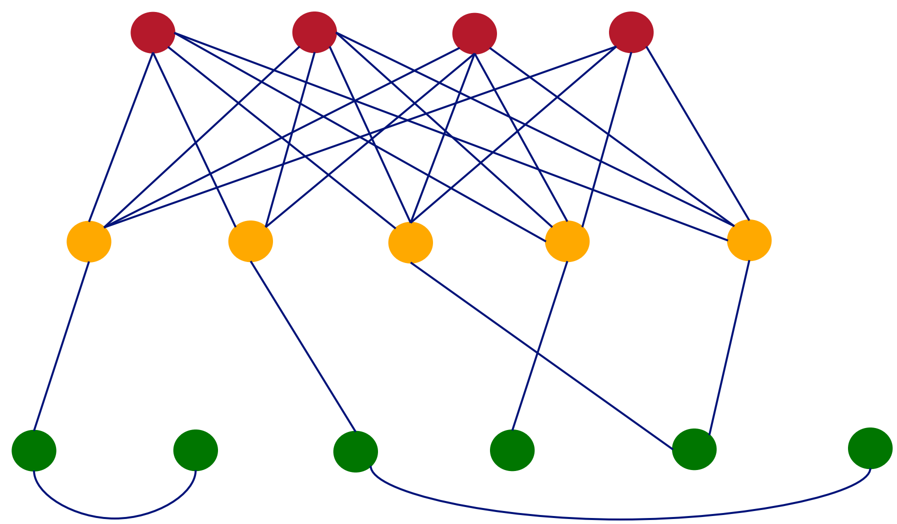
Carnegie Mellon

E-bay Fraud detection



E-bay Fraud detection - NetProbe





Popular press

USA TODAY

The Washington Post

Los Angeles Times

And less desirable attention:

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

Carnegie Mellon

Outline

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

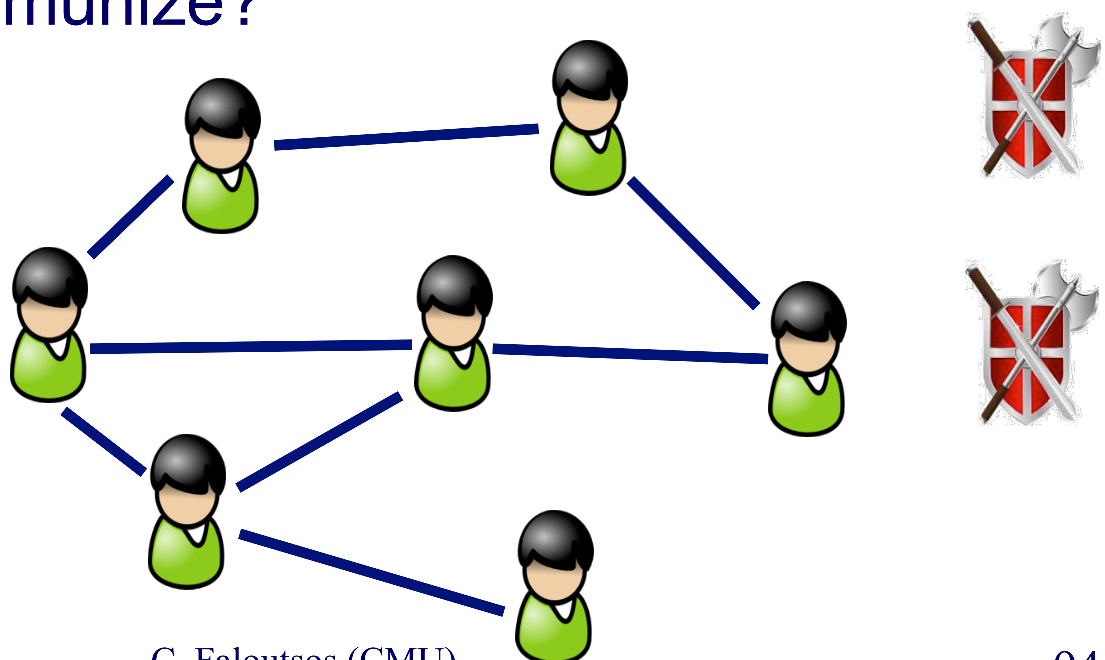
Carnegie Mellon

Immunization and epidemic thresholds

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

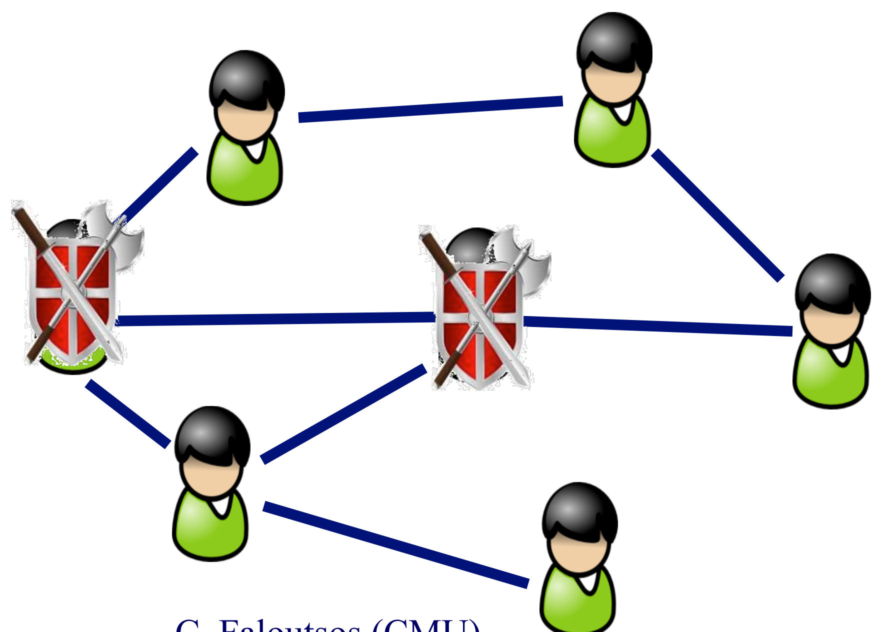
Q1: Immunization:

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



Q1: Immunization:

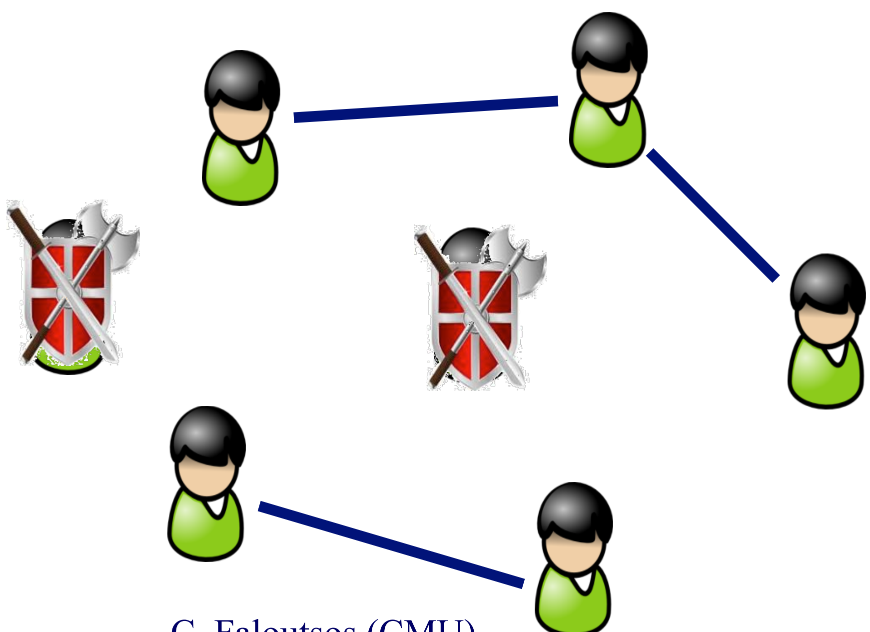
- Given
  - a network,
  - k vaccines, and
  - the virus details
- Which nodes to immunize?



Carnegie Mellon

Q1: Immunization:

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

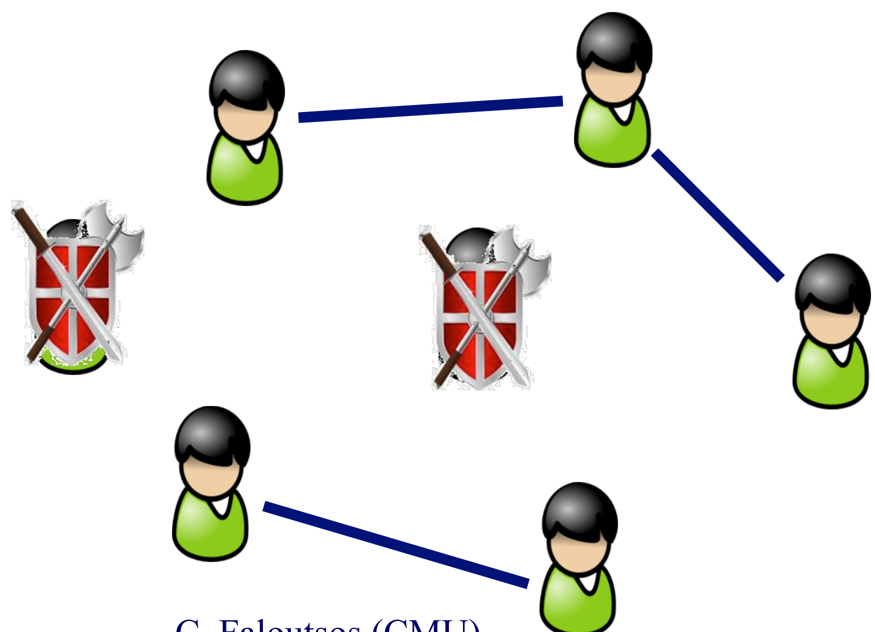


Carnegie Mellon

Q1: Immunization:

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

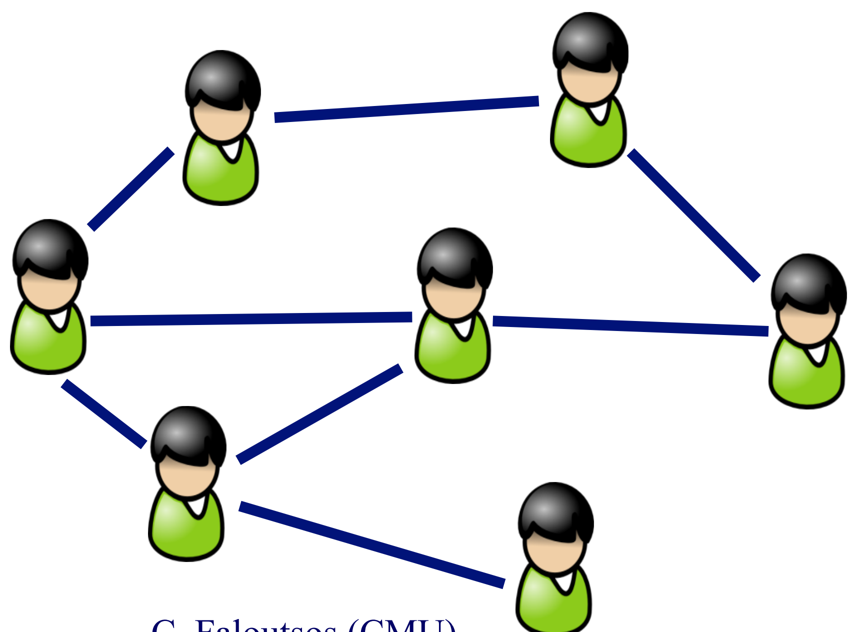
A: immunize the ones that maximally raise the `epidemic threshold' [Tong+, ICDM'10]



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

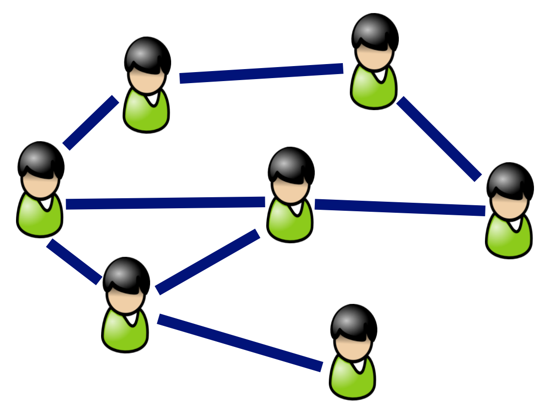


Q2: will a virus take over?

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

β: attack prob
δ: heal prob

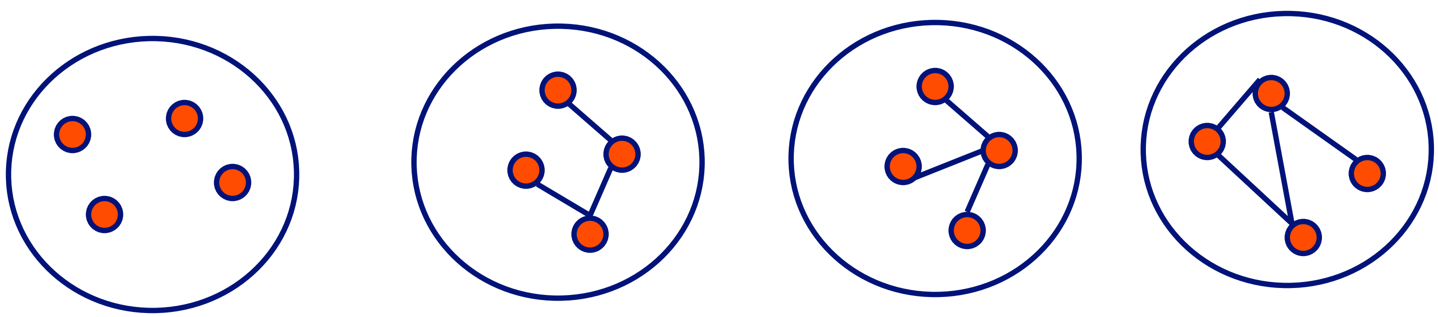
A: depends on connectivity
(avg degree? Max degree?
variance? Something else?



Epidemic threshold τ

What should τ depend on?

- avg. degree? and/or highest degree?
- and/or variance of degree?
- and/or third moment of degree?
- and/or diameter?



Epidemic threshold

- [Theorem] We have no epidemic, if

$$\boxed{\beta/\delta < \tau = 1/\lambda_{1,A}}$$

Epidemic threshold

- [Theorem] We have no epidemic, if

epidemic threshold

recovery prob.

$$\boxed{\beta/\delta < \tau = 1/\lambda_{1,A}}$$

attack prob.

largest eigenvalue of adj. matrix ***A***

Proof: [Wang+03] (for SIS=flu only)

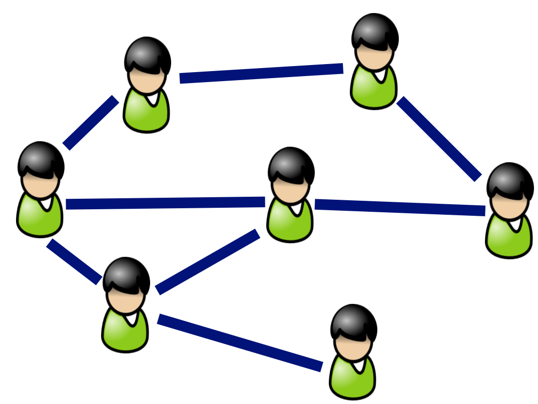
A2: will a virus take over?

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

  $1/\lambda_1$

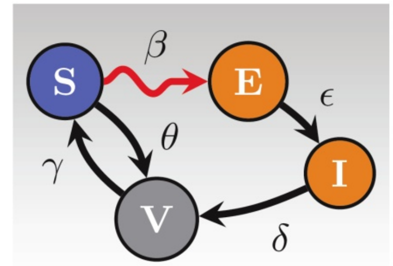
  the first eigenvalue of the adj. matrix

  [Prakash+, ‘10, arxiv]



Carnegie Mellon

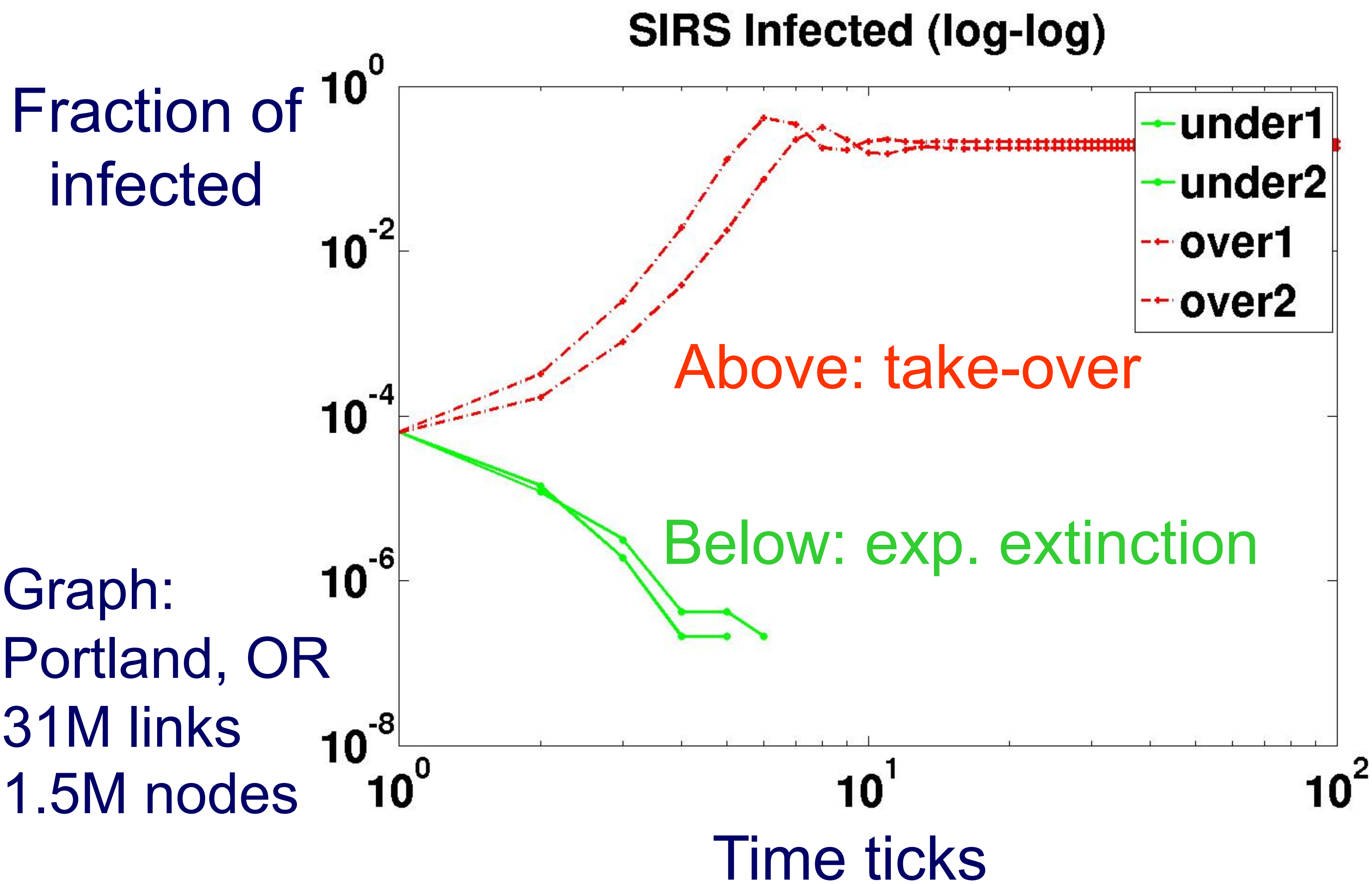
Thresholds for some models



- s = *effective strength*
- $s < 1$: *below threshold*

Models	Effective Strength (s)	Threshold (tipping point)
SIS, SIR, SIRS, SEIR	$s = \lambda \, . \left(\frac{\beta}{\delta}\right)$	
SIV, SEIV	$s = \lambda \, . \left(\frac{\beta\gamma}{\delta(\gamma+\theta)}\right)$	$s = 1$
$SI_1I_2V_1V_2$ (**H.I.V.**)	$s = \lambda \, . \left(\frac{\beta_1 v_2 + \beta_2 \varepsilon}{v_2(\varepsilon + v_1)}\right)$	

A2: will a virus take over?

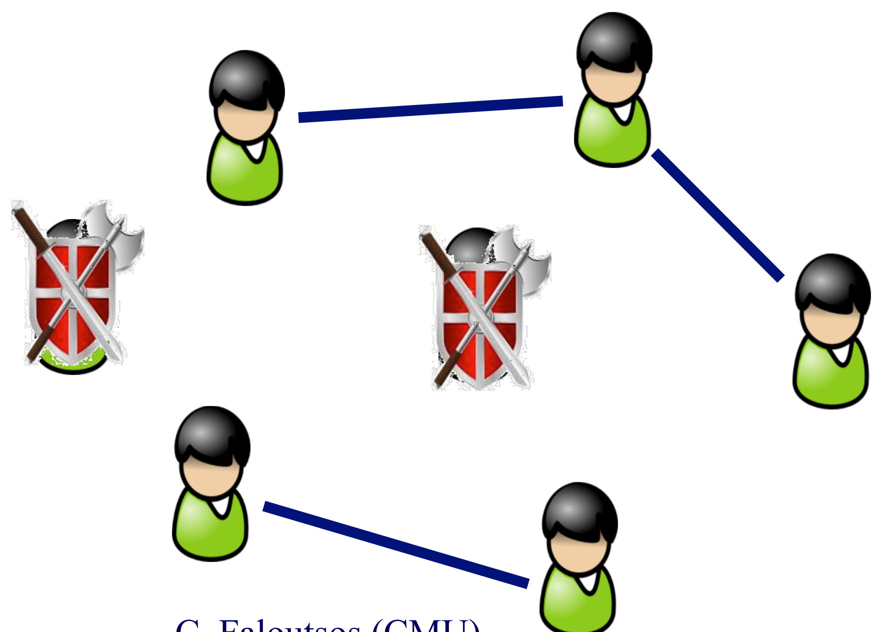


Graph:
Portland, OR
31M links
1.5M nodes

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]

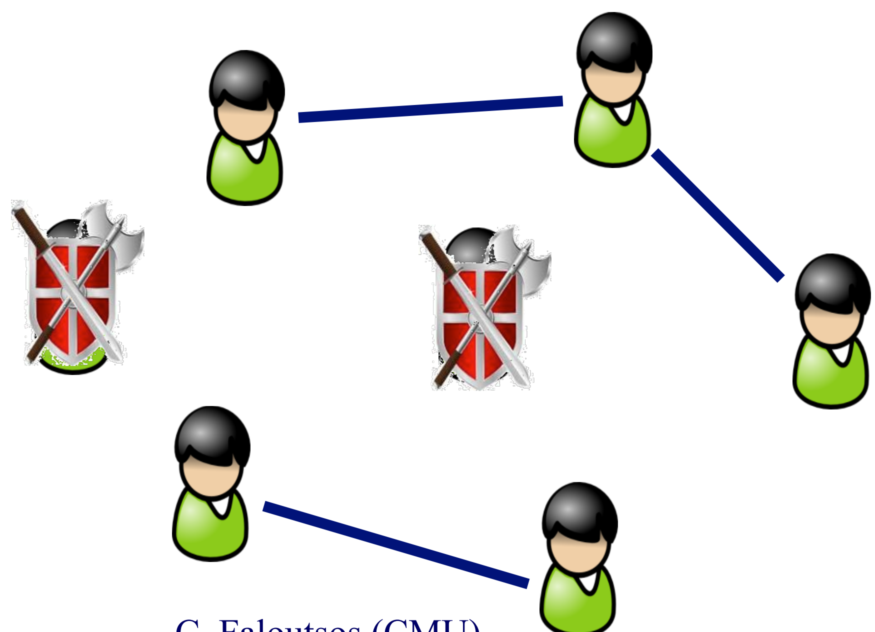


Q1: Immunization:

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

A: immunize the ones that

Max eigen-drop $\Delta\lambda$ for any virus!



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/

Carnegie Mellon

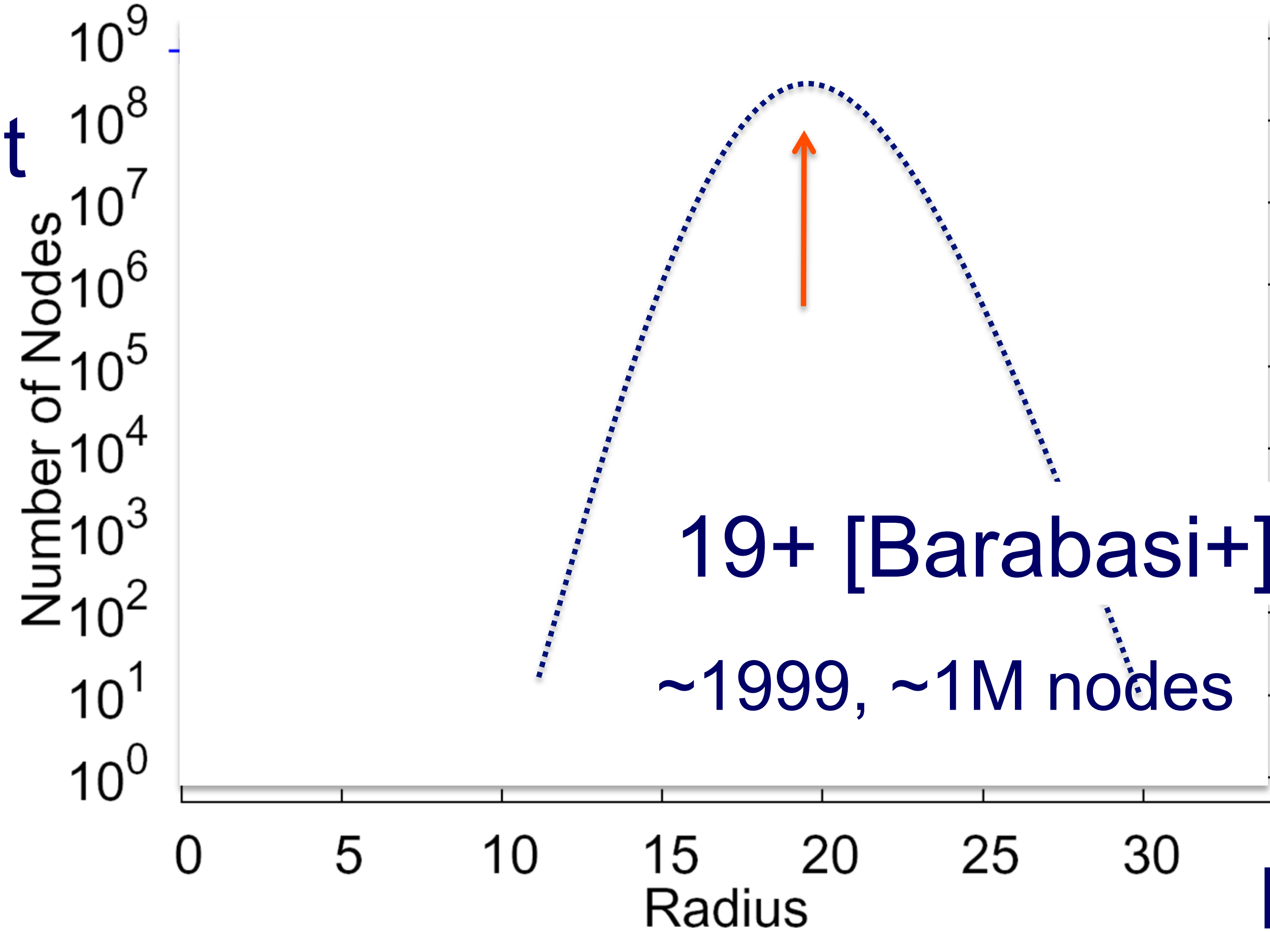
Outline – Algorithms & results

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

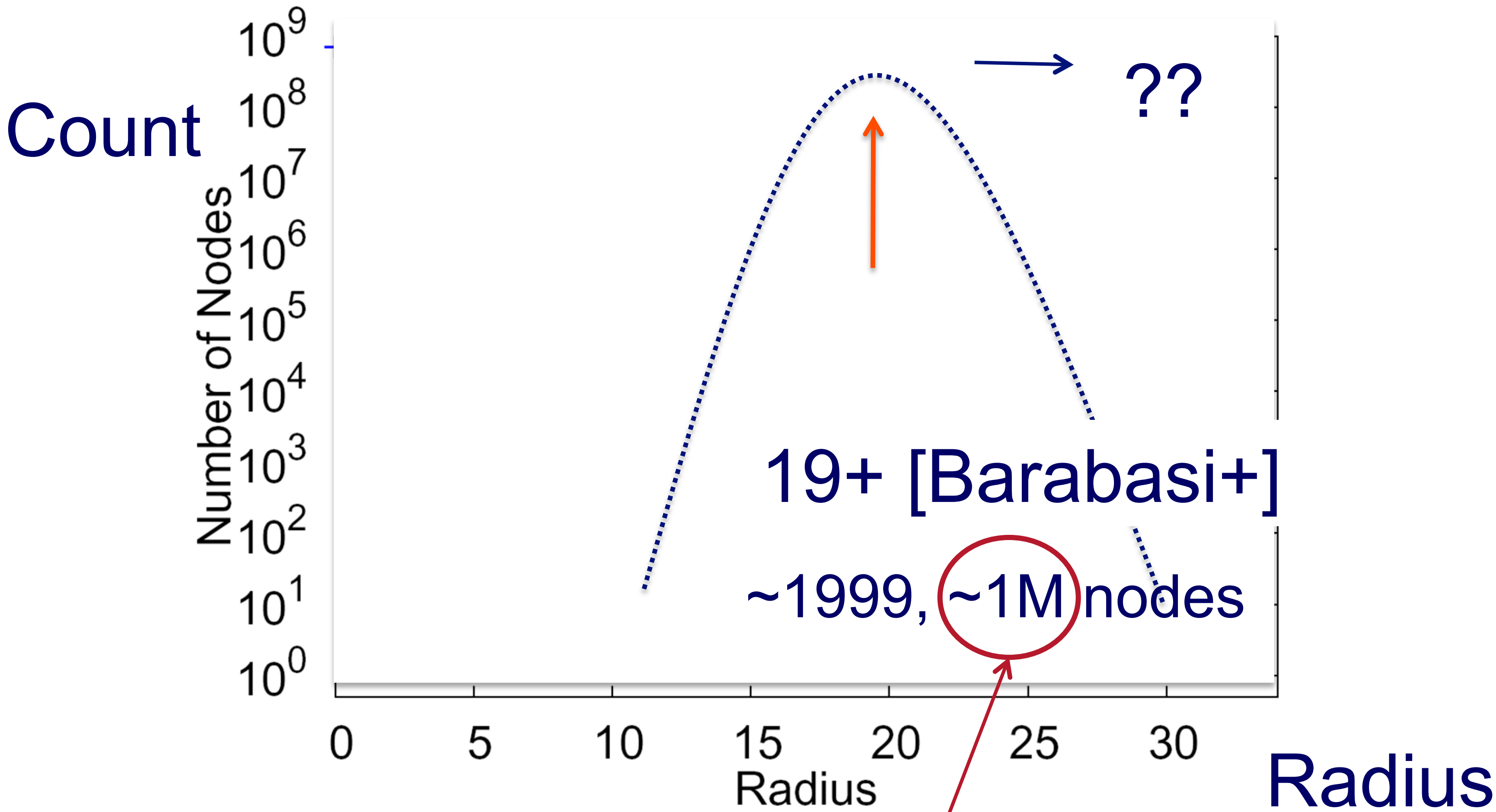
HADI for diameter estimation

- *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



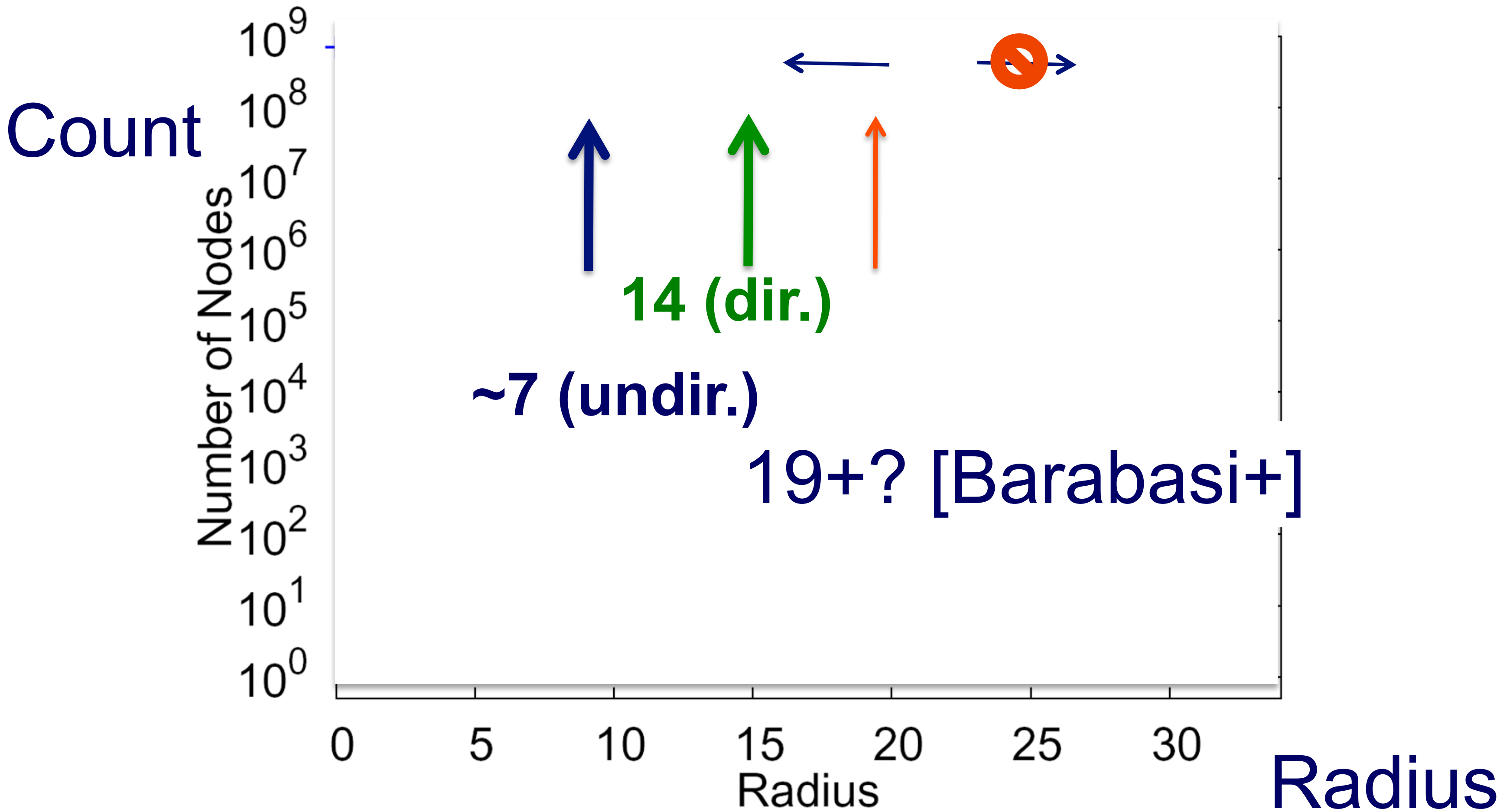
Radius



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

- Largest publicly available graph ever studied.

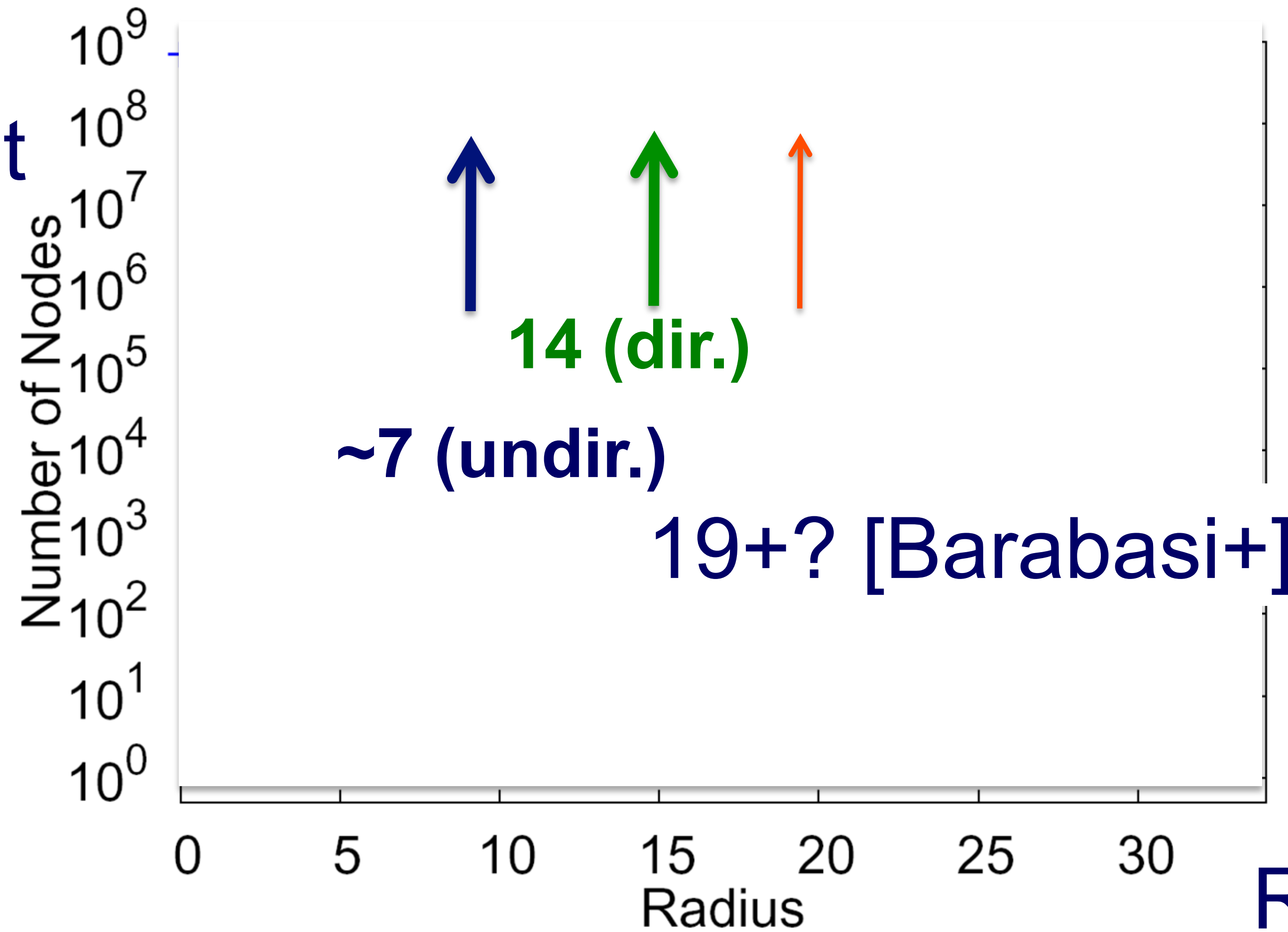
Carnegie Mellon



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

- Largest publicly available graph ever studied.

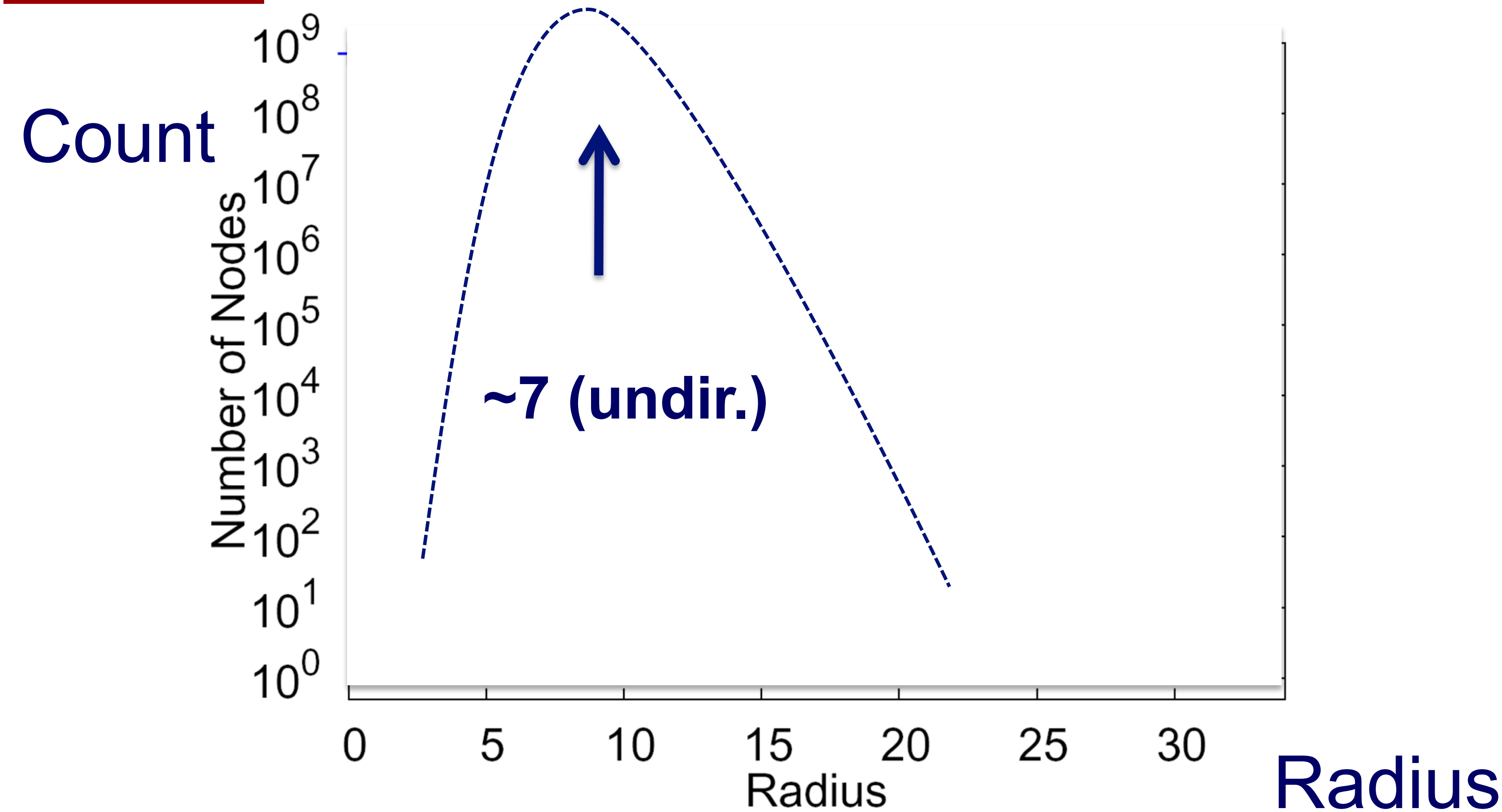
Count



Radius

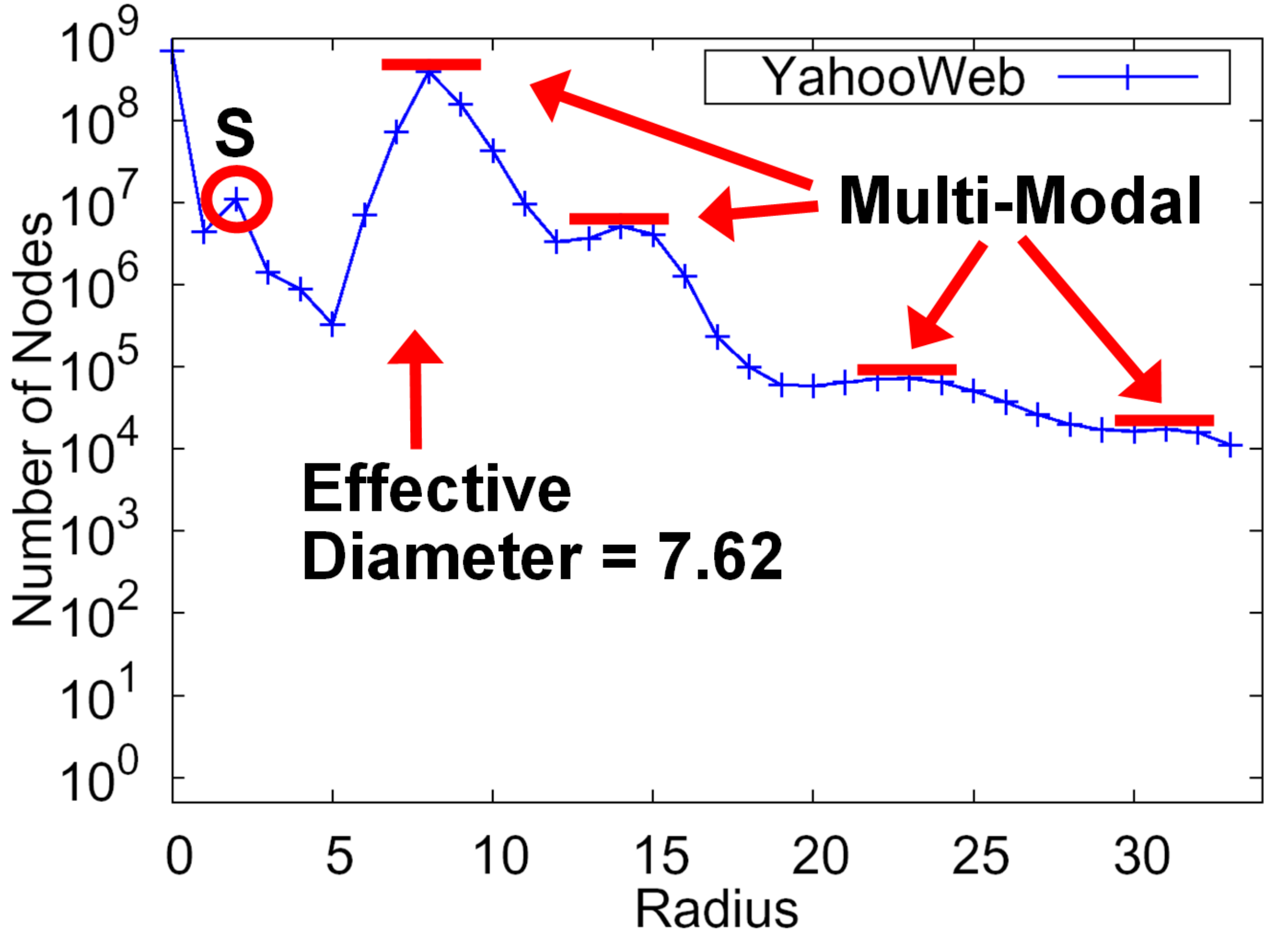
YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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



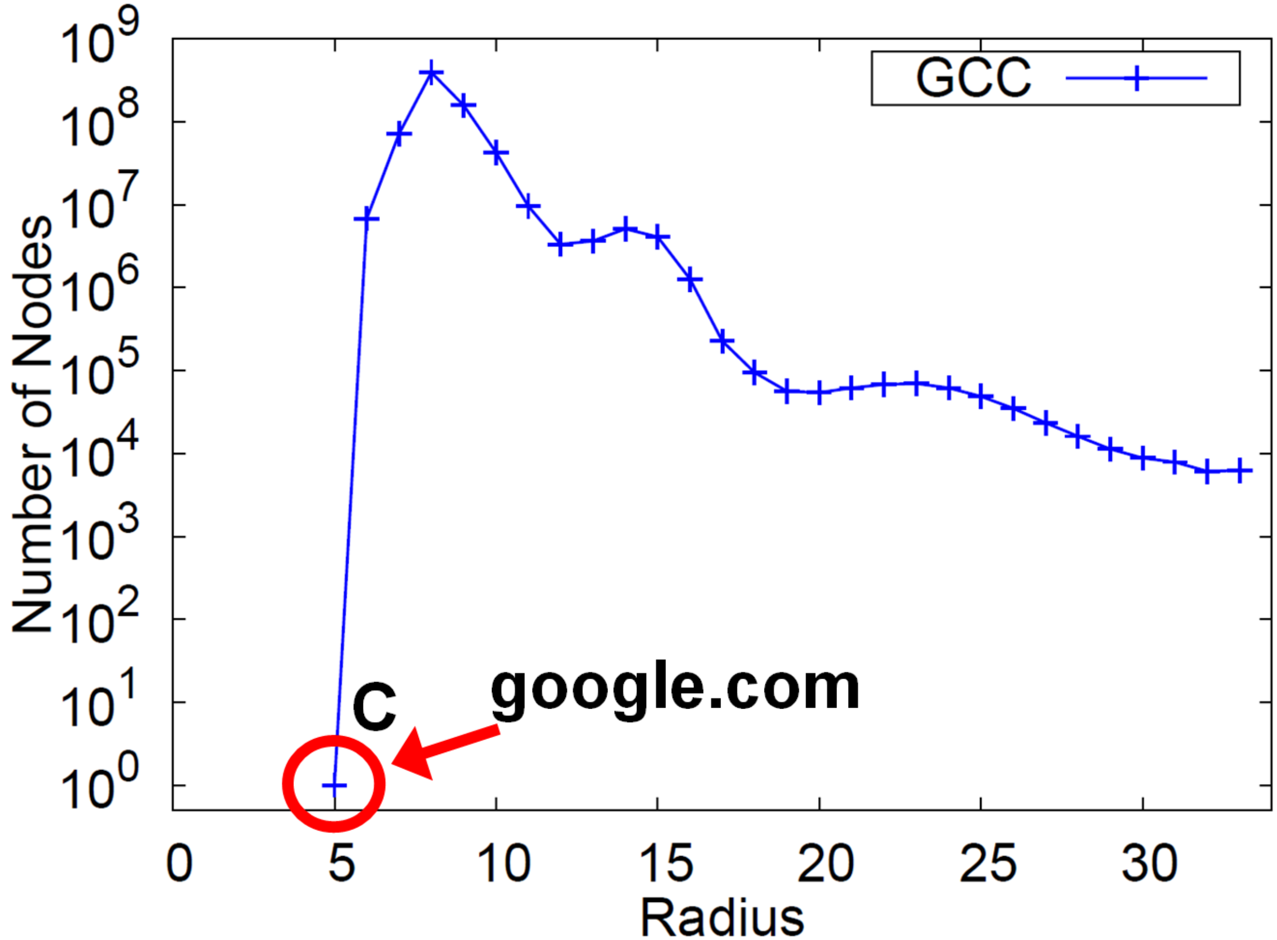
YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

Q: Shape?

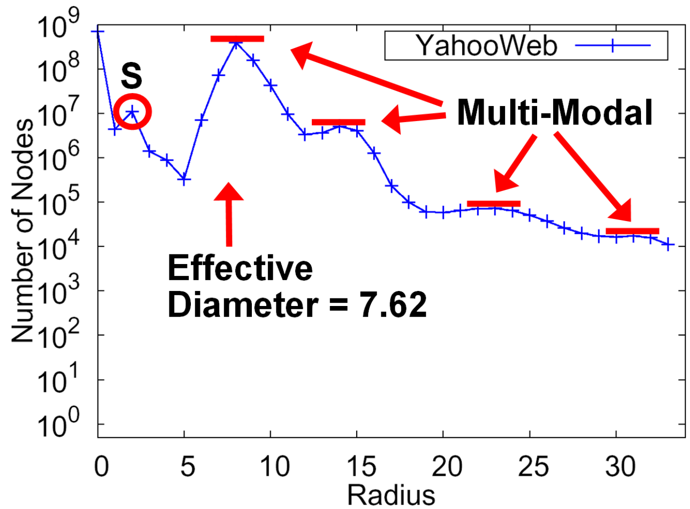


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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

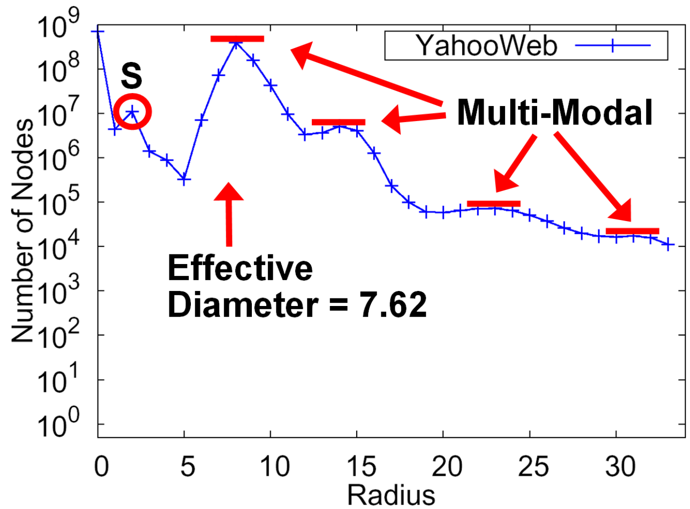


Radius Plot of **GCC** of YahooWeb.

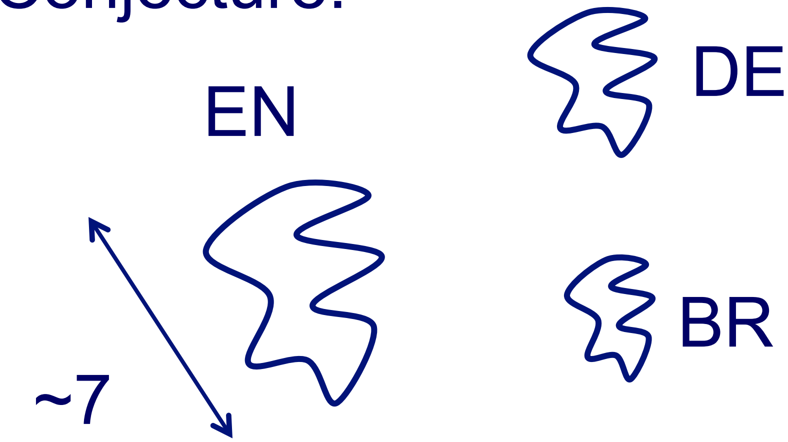


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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



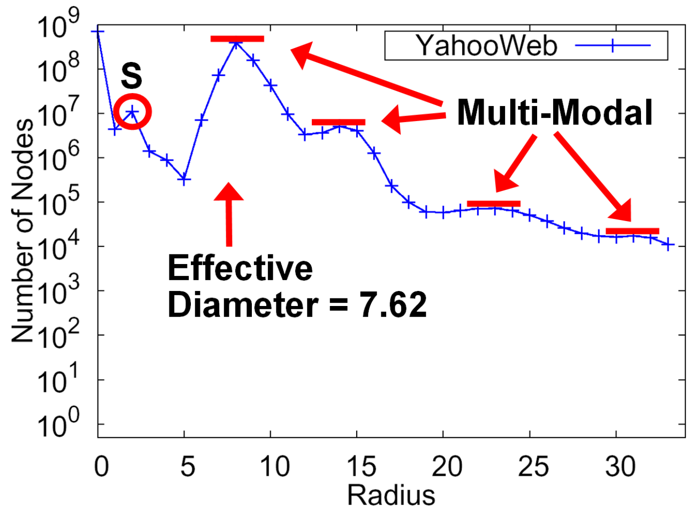
Conjecture:



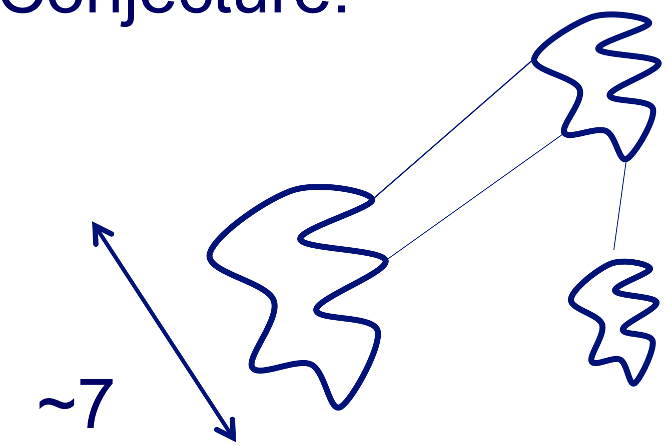
YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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

Carnegie Mellon



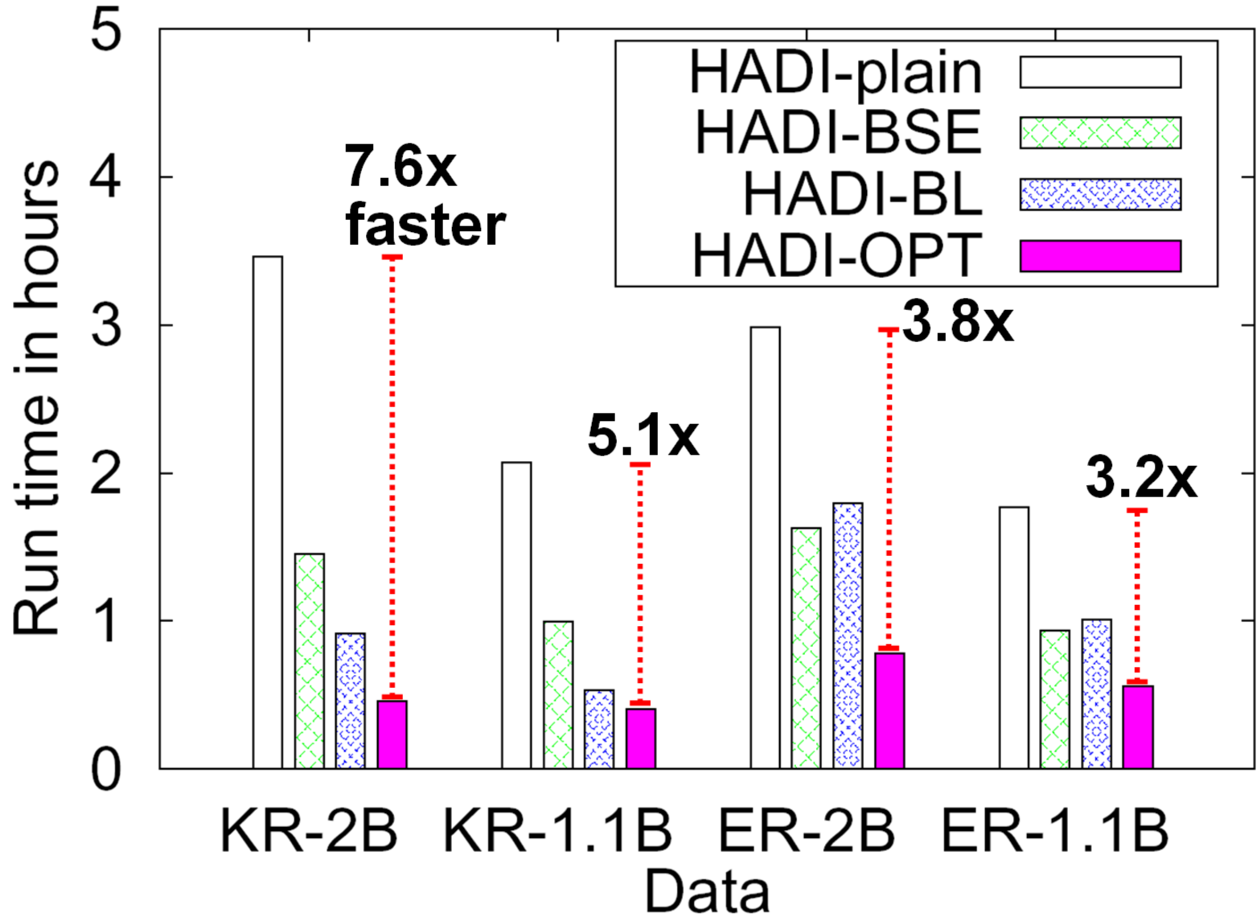
Conjecture:



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		HERE
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).

Generalized Iterated Matrix Vector Multiplication (GIMV)

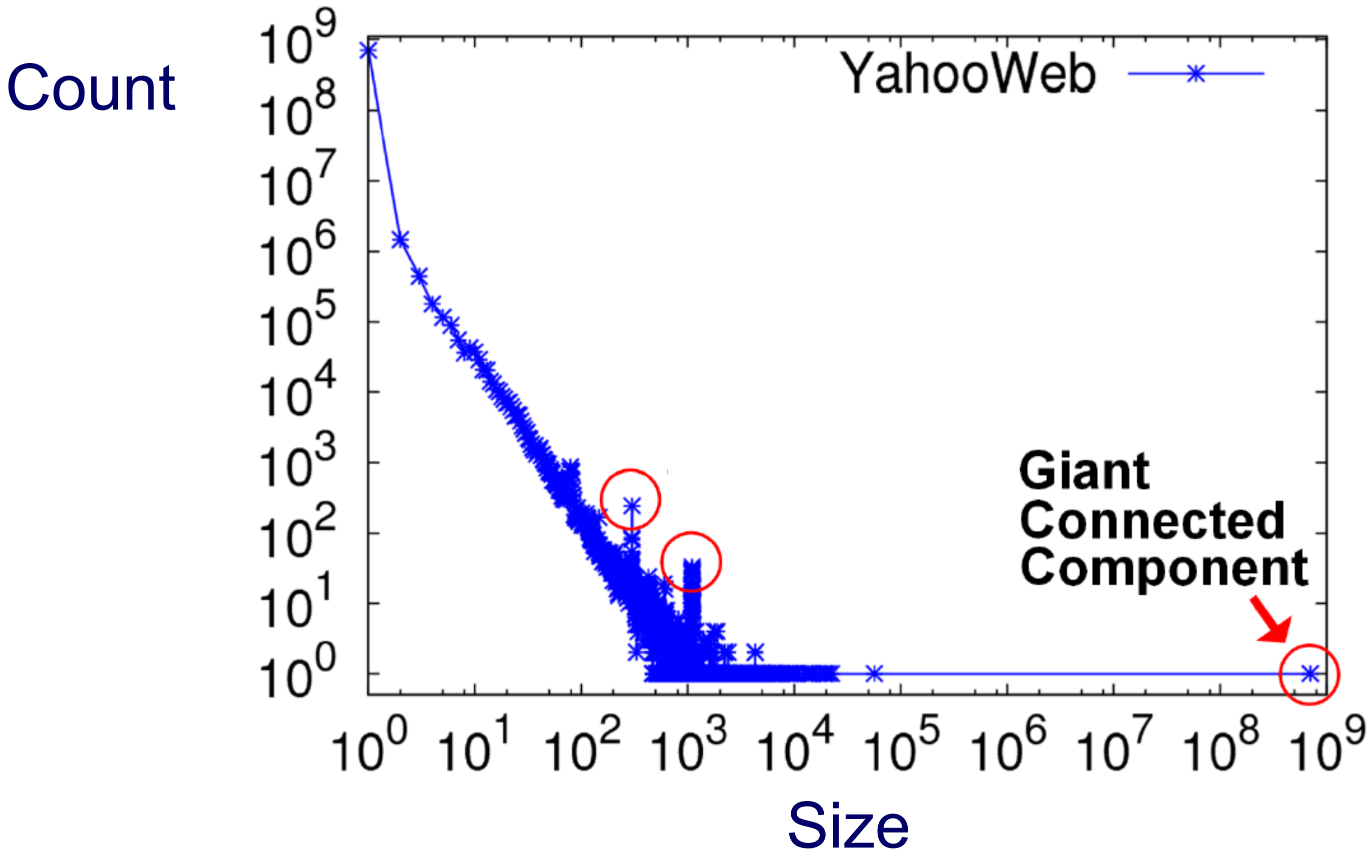
details

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

Matrix – vector Multiplication (iterated)

Example: GIM-V At Work

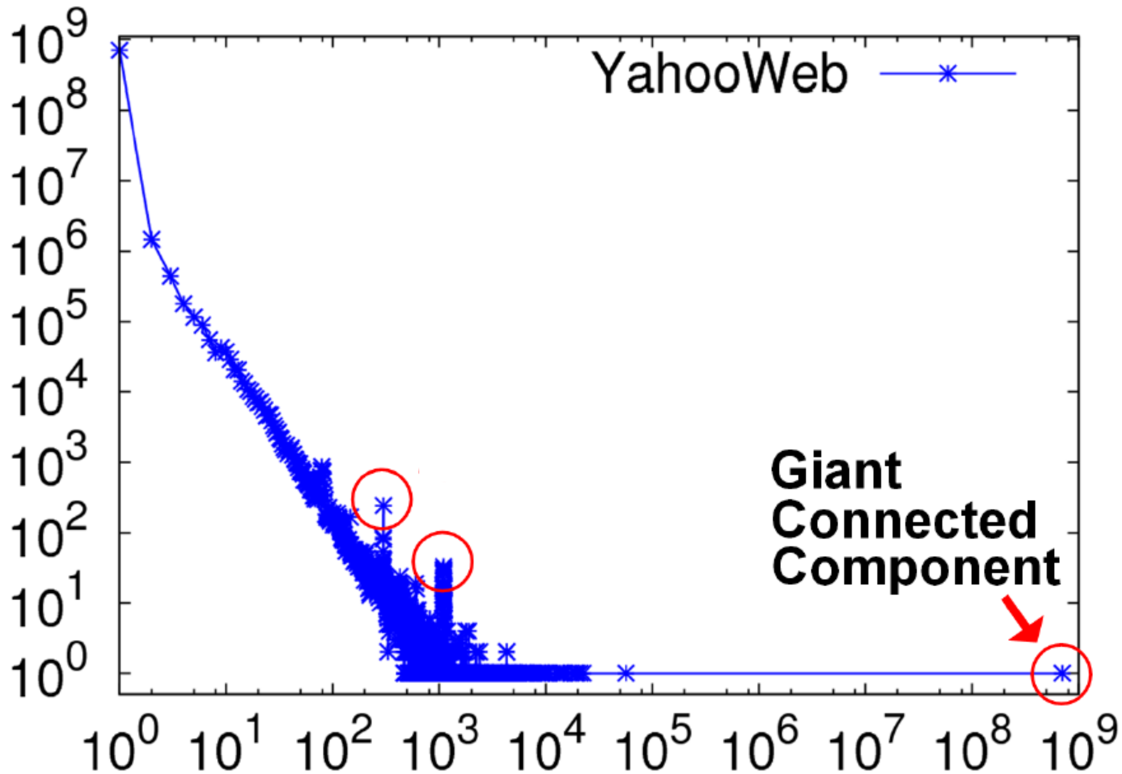
- Connected Components – 4 observations:



Example: GIM-V At Work

- Connected Components

Count



Size

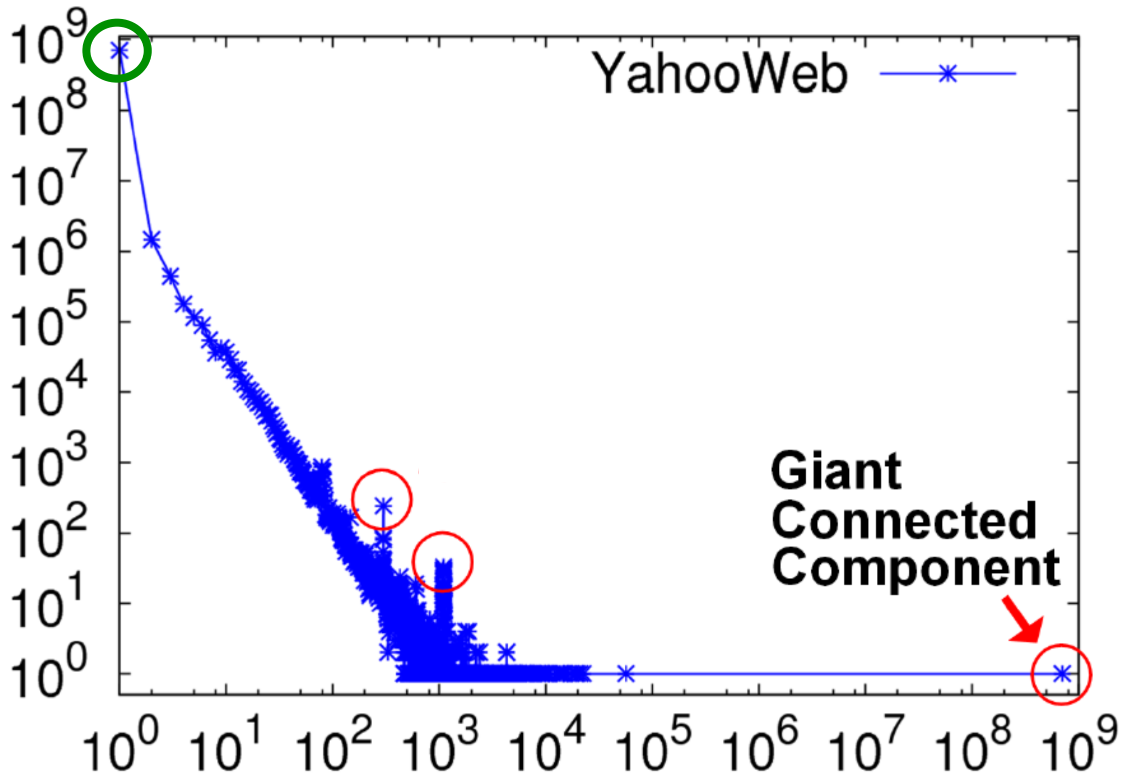
1) 10K x larger than next

Example: GIM-V At Work

- Connected Components

Count

2) ~0.7B singleton nodes



Size

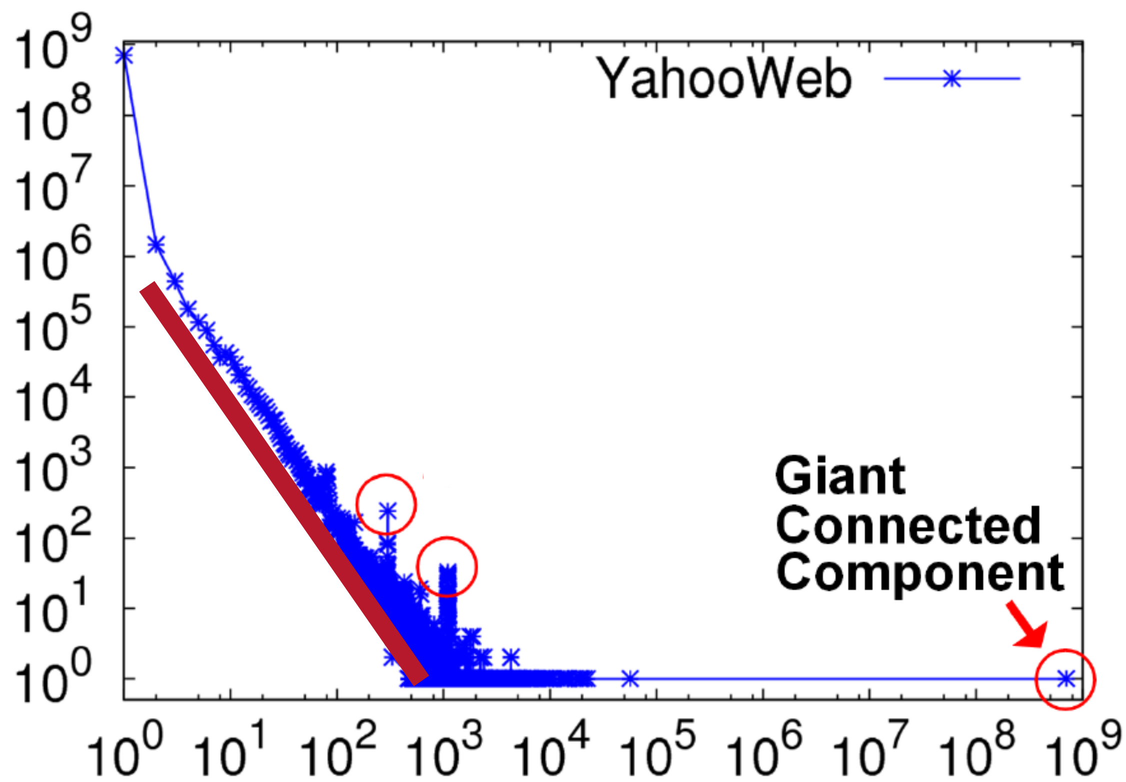
Carnegie Mellon

Example: GIM-V At Work

- Connected Components

Count

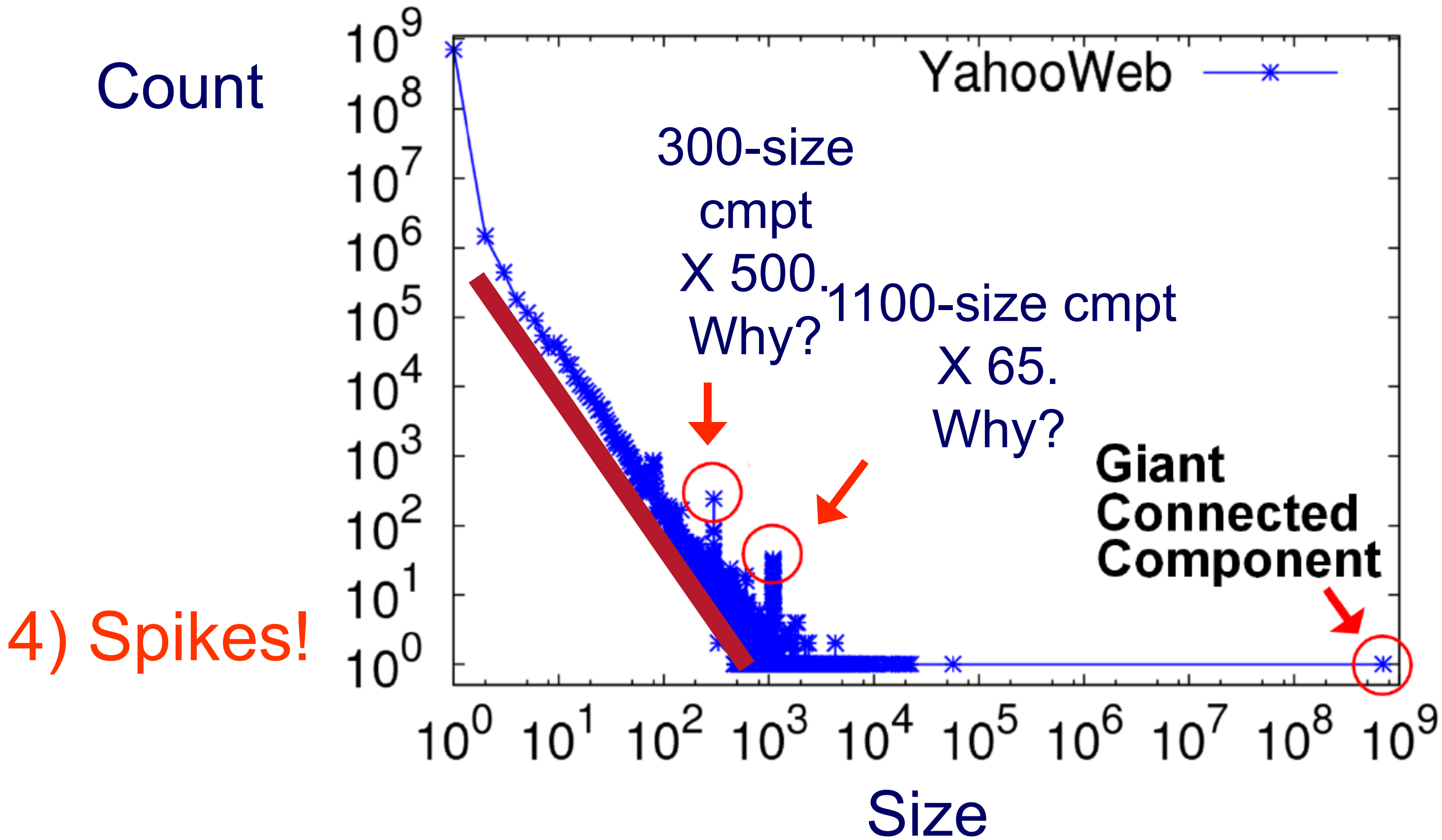
3) SLOPE!



Size

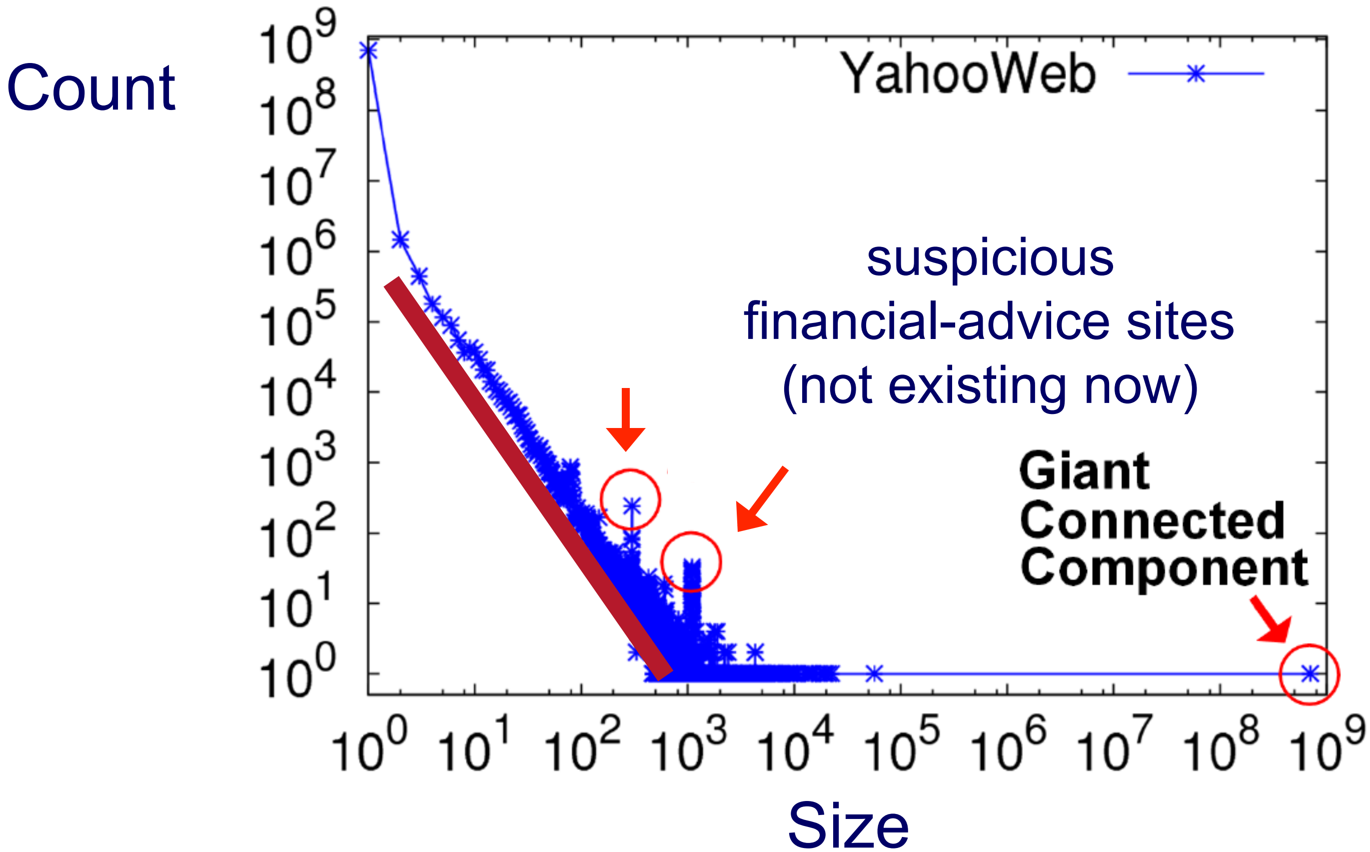
Example: GIM-V At Work

- Connected Components



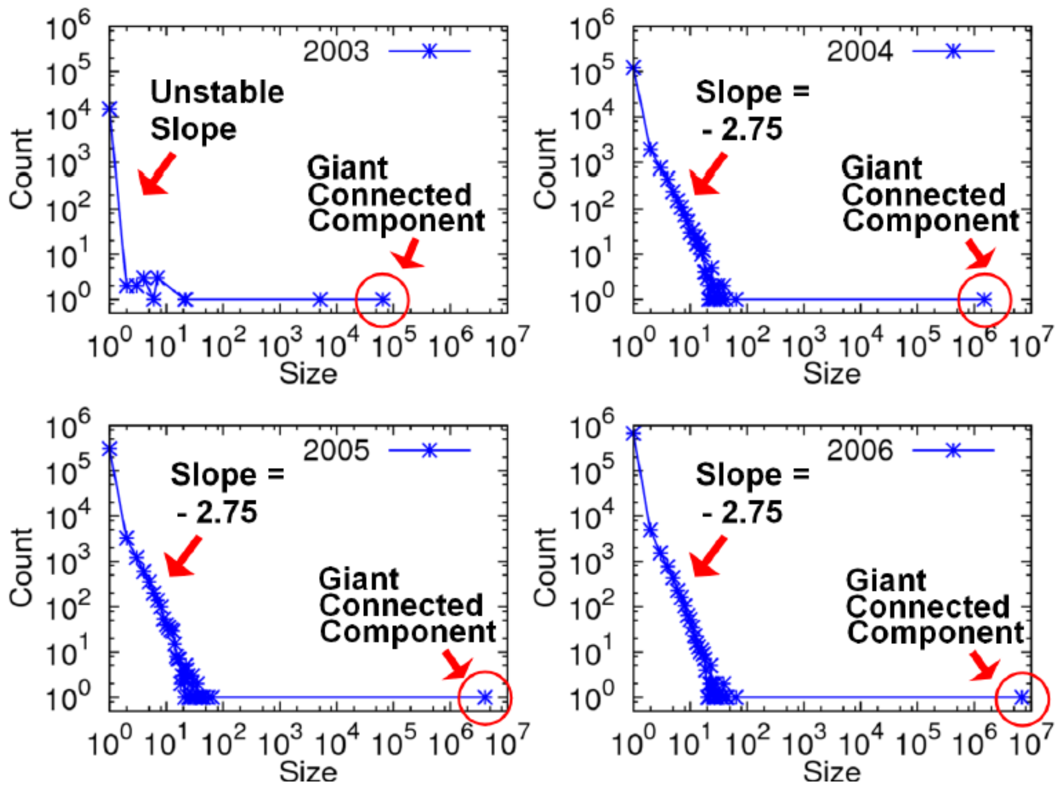
Example: GIM-V At Work

- 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

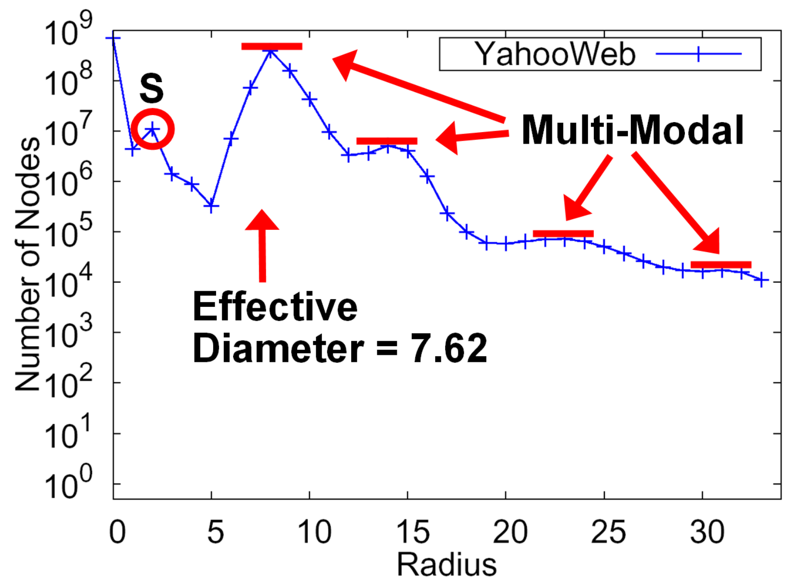
- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
- Problem#3: Scalability
- Conclusions

OVERALL CONCLUSIONS – low level:

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

OVERALL CONCLUSIONS – high level

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



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

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

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

Carnegie Mellon

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

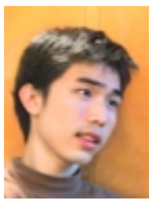
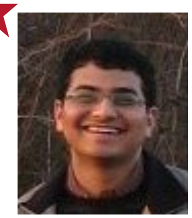
Project info

www.cs.cmu.edu/~pegasus

Chau, Polo

Koutra, Danae

Prakash, Aditya

★  ★     ★  

Akoglu, Leman

Kang, U

McGlohon, Mary

Tong, Hanghang

★ **Out, next year**

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