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Large Graph Mining

Christos Faloutsos

CMU

Thank you!

- Ed Kao
- Lori Tsoulas
- Joan Meehan-Dion

Our goal:

Open source system for mining huge graphs:

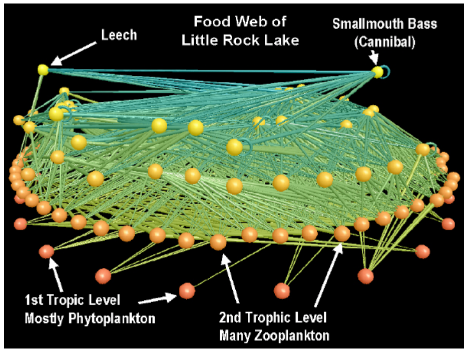
PEGASUS project (PEta GrAph mining System)

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

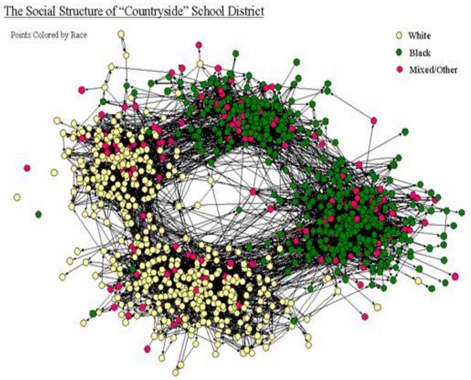
Outline

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

Graphs - why should we care?



Food Web
[Martinez '91]

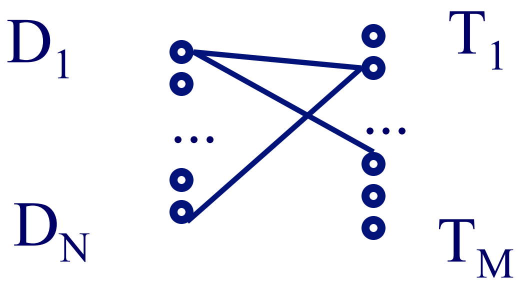


Friendship Network
[Moody '01]

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
- ....

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  - Static graphs
  - Weighted graphs
  - Time evolving graphs
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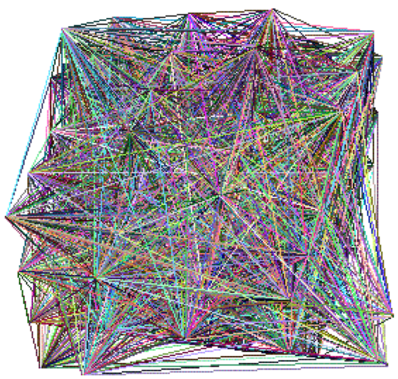
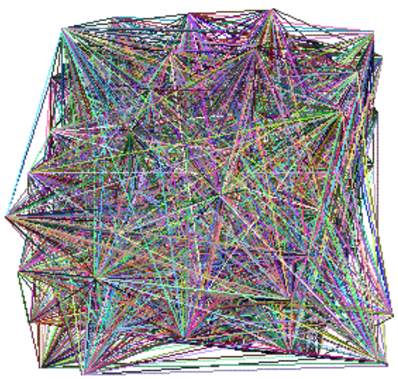
Problem #1 - network and graph mining



- 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



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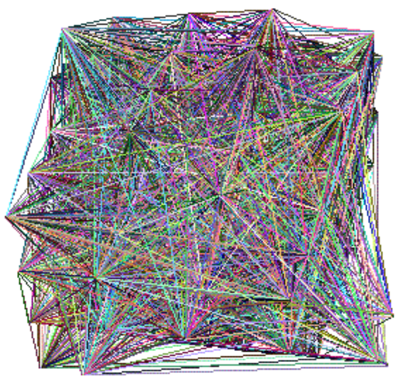

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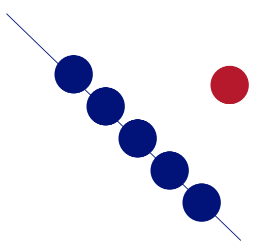
- What does FaceBook look like?

- 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

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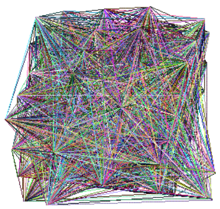
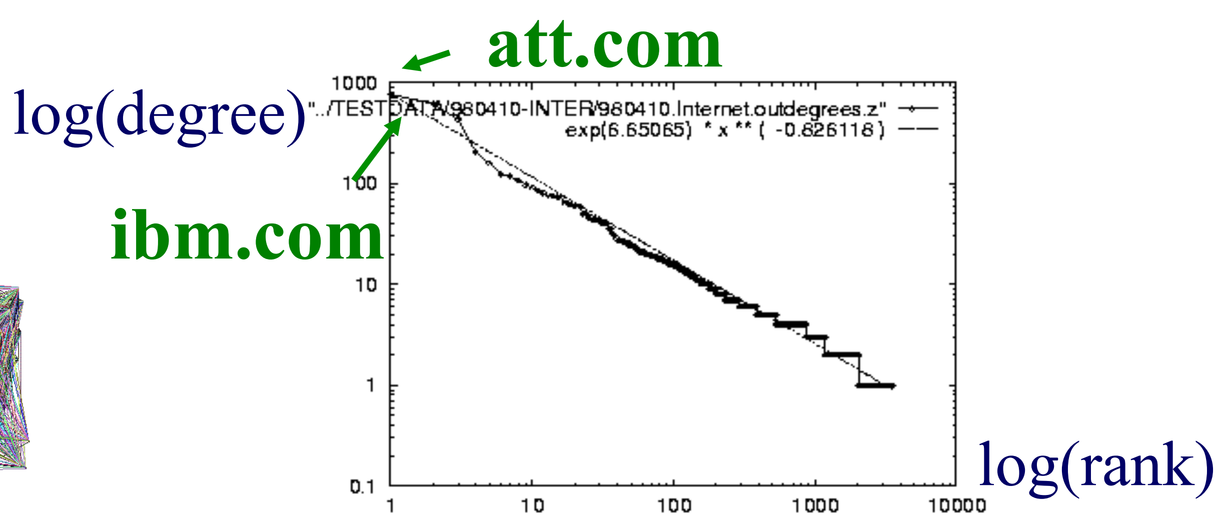
Solution# S.1

- Power law in the degree distribution [SIGCOMM99]

internet domains





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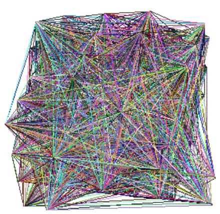

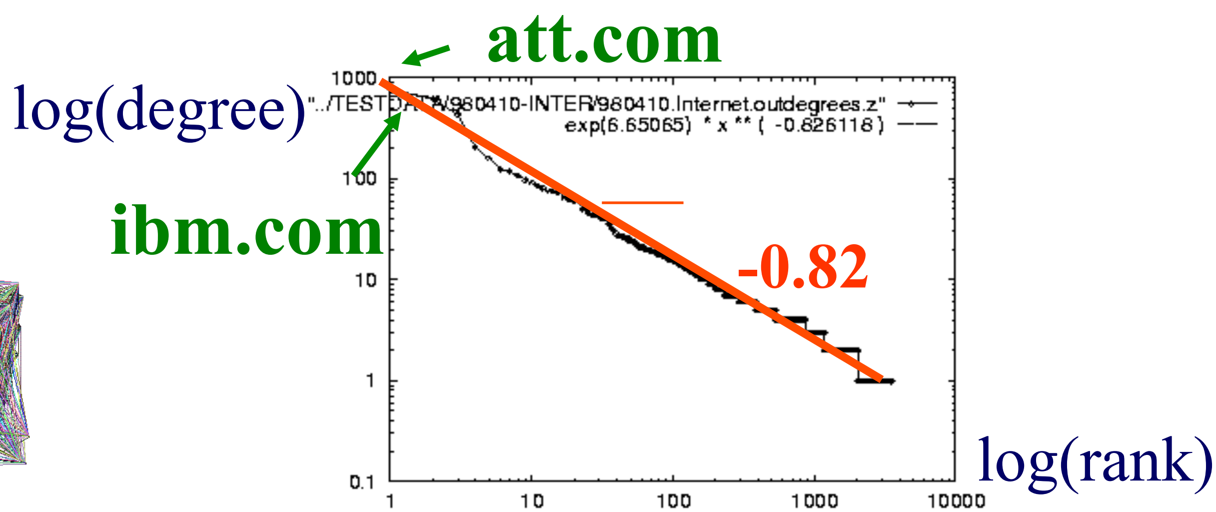

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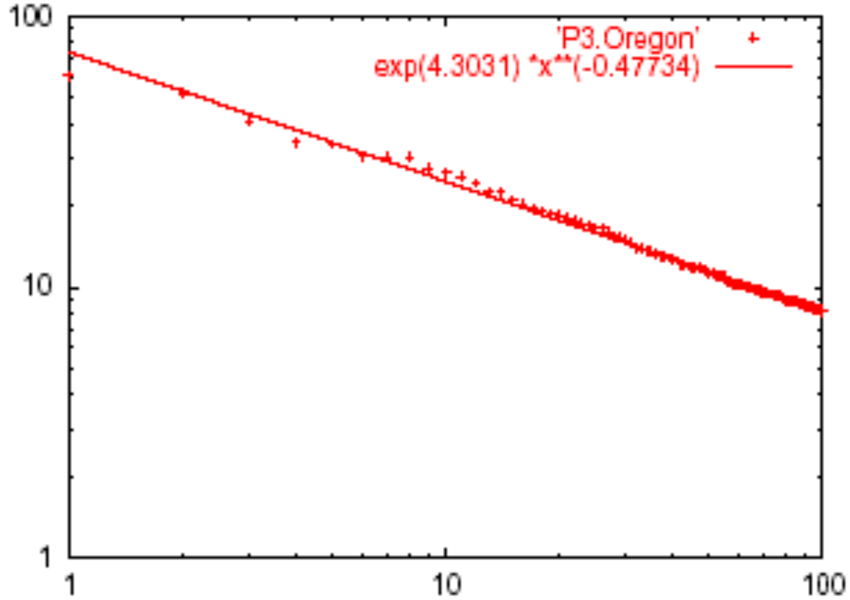
Solution# S.2: Eigen Exponent *E*

Eigenvalue



Rank of decreasing eigenvalue

Exponent = slope

$E = -0.48$

May 2001

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

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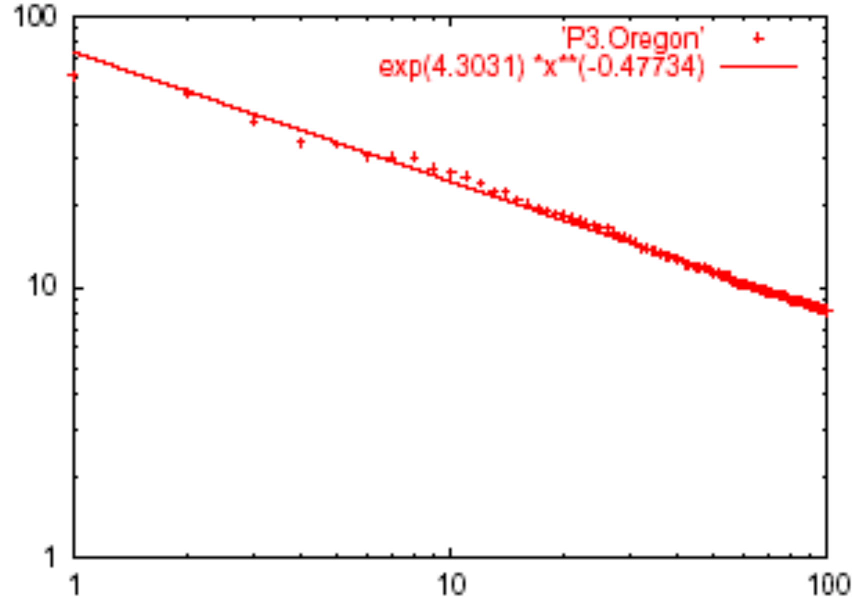
Solution# S.2: Eigen Exponent *E*

Eigenvalue



Rank of decreasing eigenvalue

Exponent = slope

$E = -0.48$

May 2001

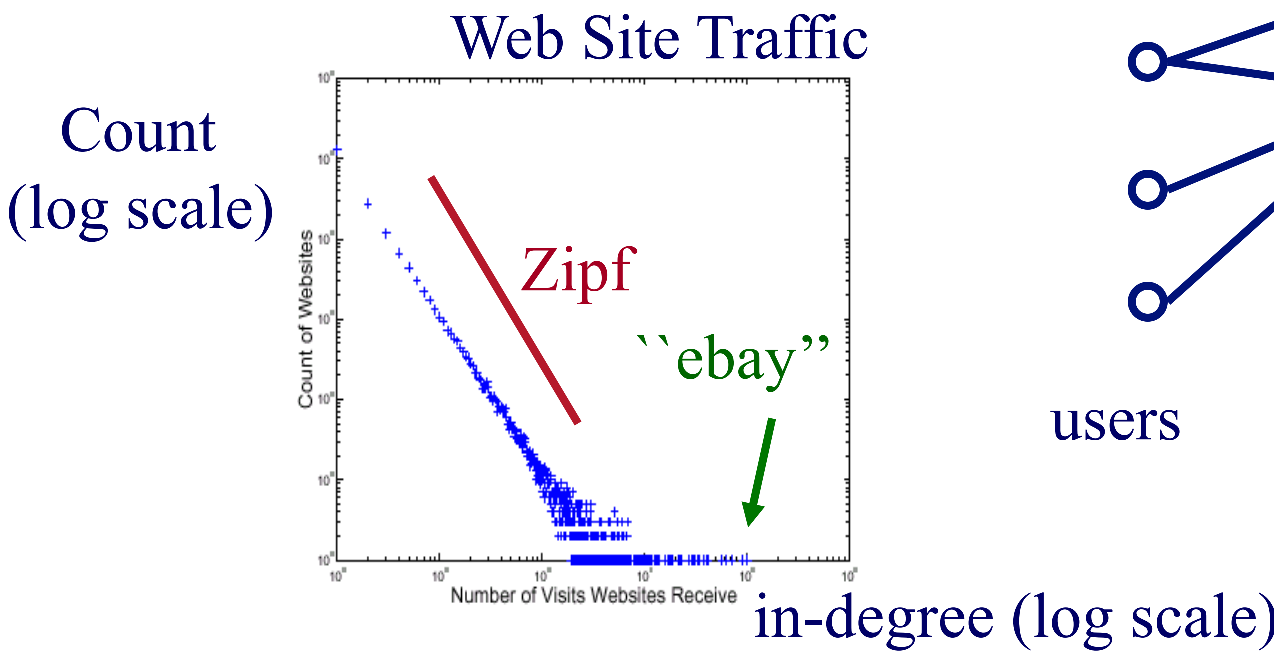
- [Mihail, Papadimitriou ’02]: slope is ½ of rank exponent

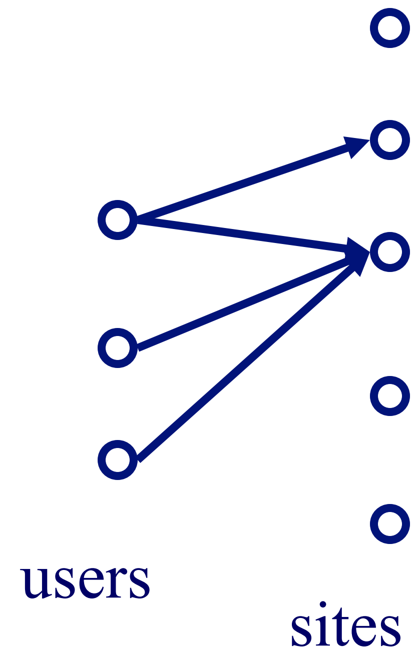
But:

How about graphs from other domains?

More power laws:

- web hit counts [w/ A. Montgomery]

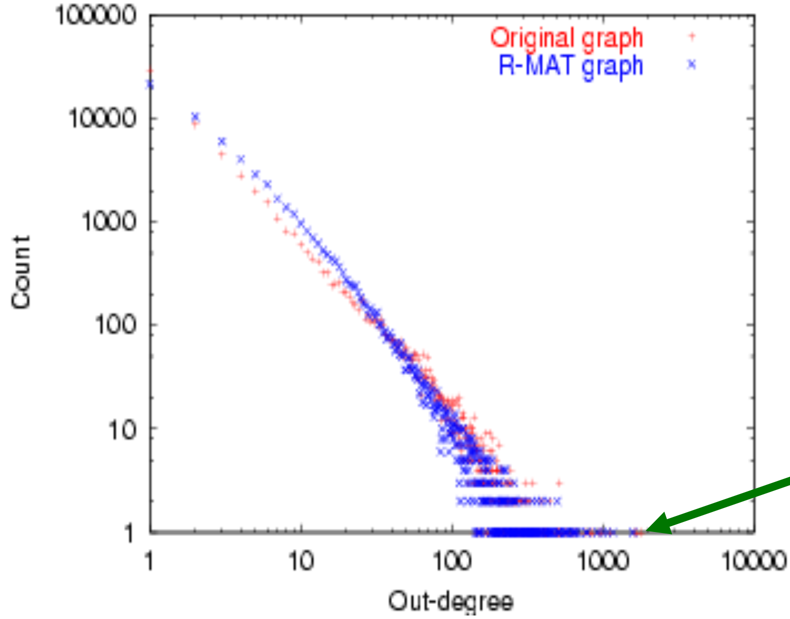




epinions.com

- 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'

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    - degree, diameter, eigen,
    - triangles
    - cliques
  - Weighted graphs
  - Time evolving graphs
- Problem#2: Tools

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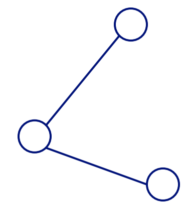
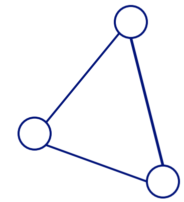
Solution# S.3: Triangle 'Laws'



- Real social networks have a lot of triangles

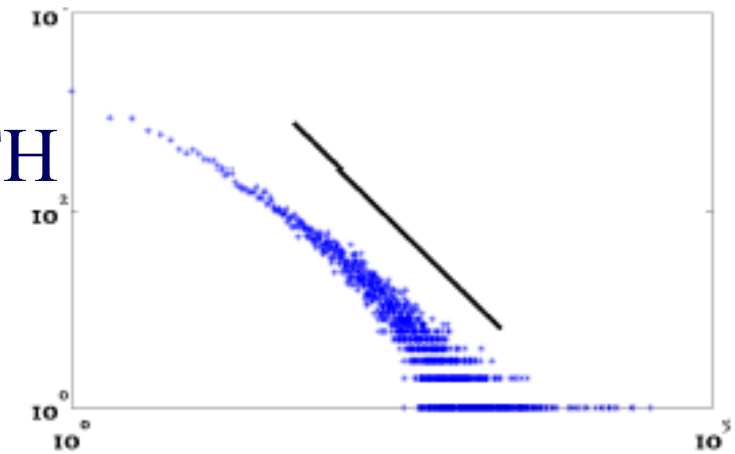
Solution# S.3: Triangle 'Laws'



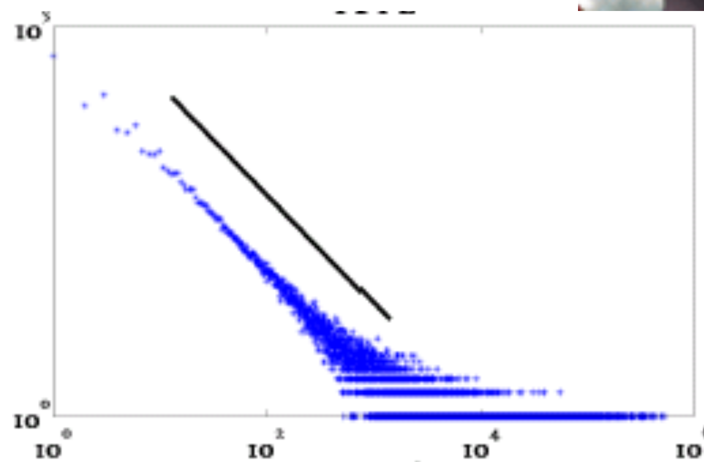
- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?

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

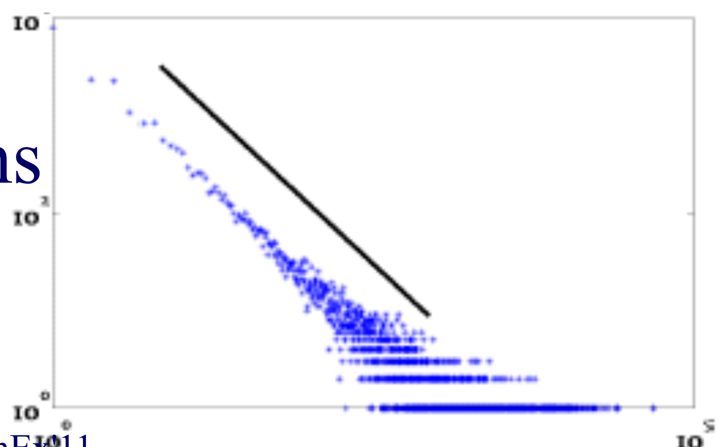
HEP-TH

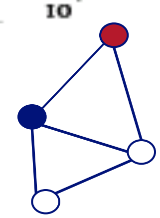


ASN



Epinions



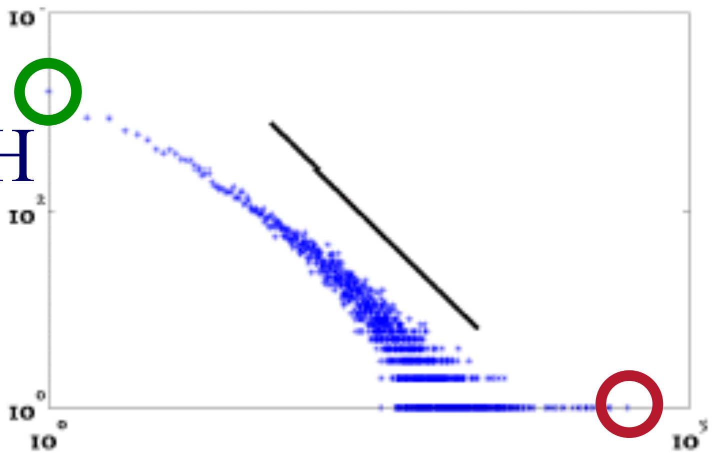


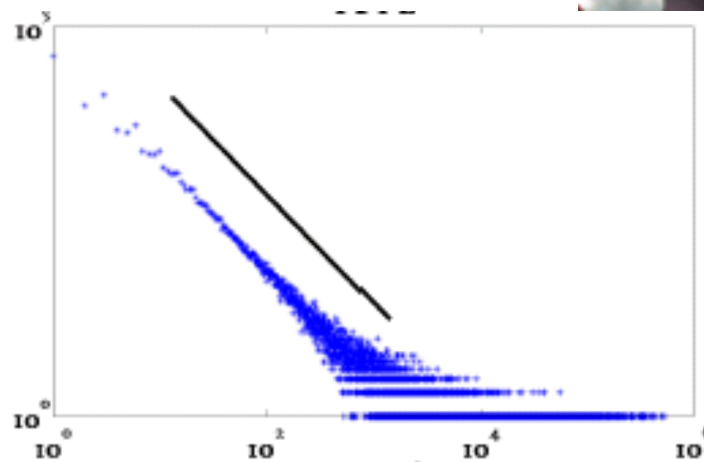
X-axis: # of participating triangles

Y: count (~ pdf)

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

HEP-TH





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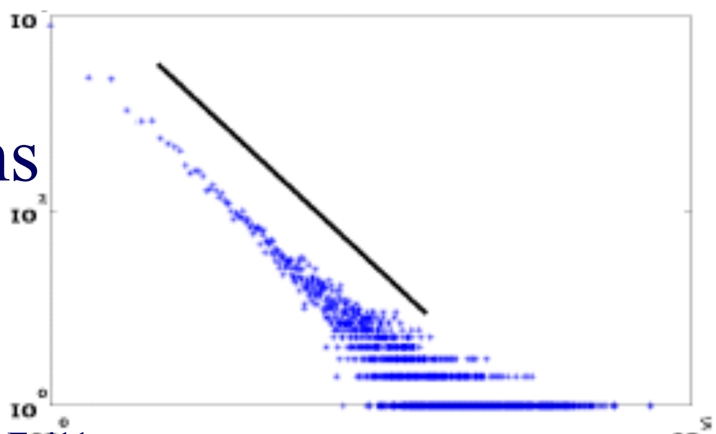

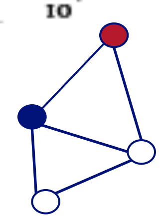

X-axis: # of participating triangles

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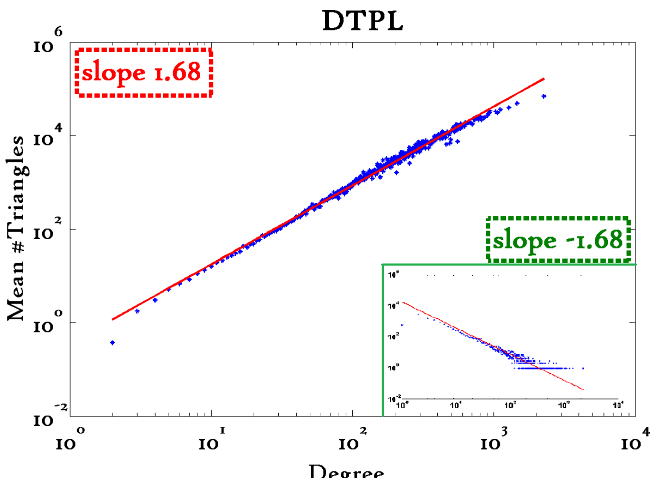
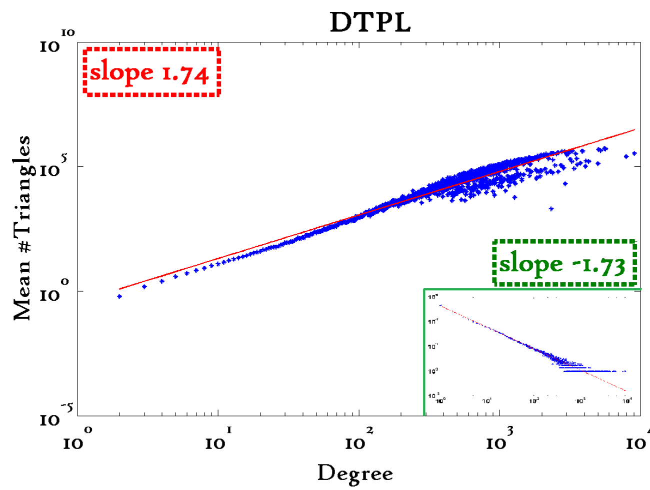
Triangle Law: #S.4
[Tsourakakis ICDM 2008]

Reuters



SN



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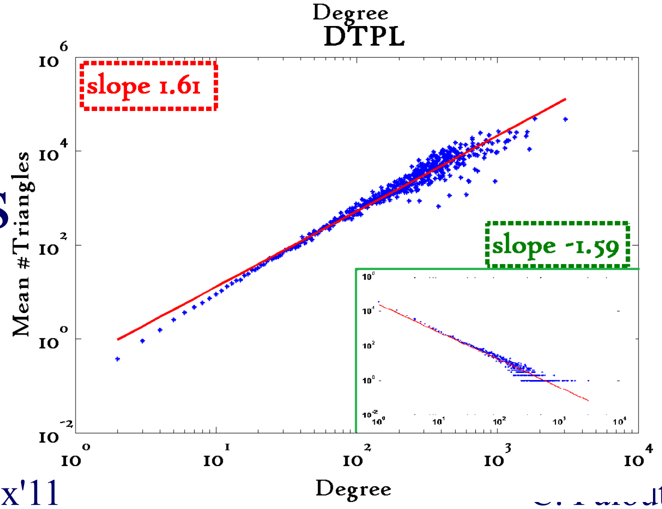


X-axis: degree

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

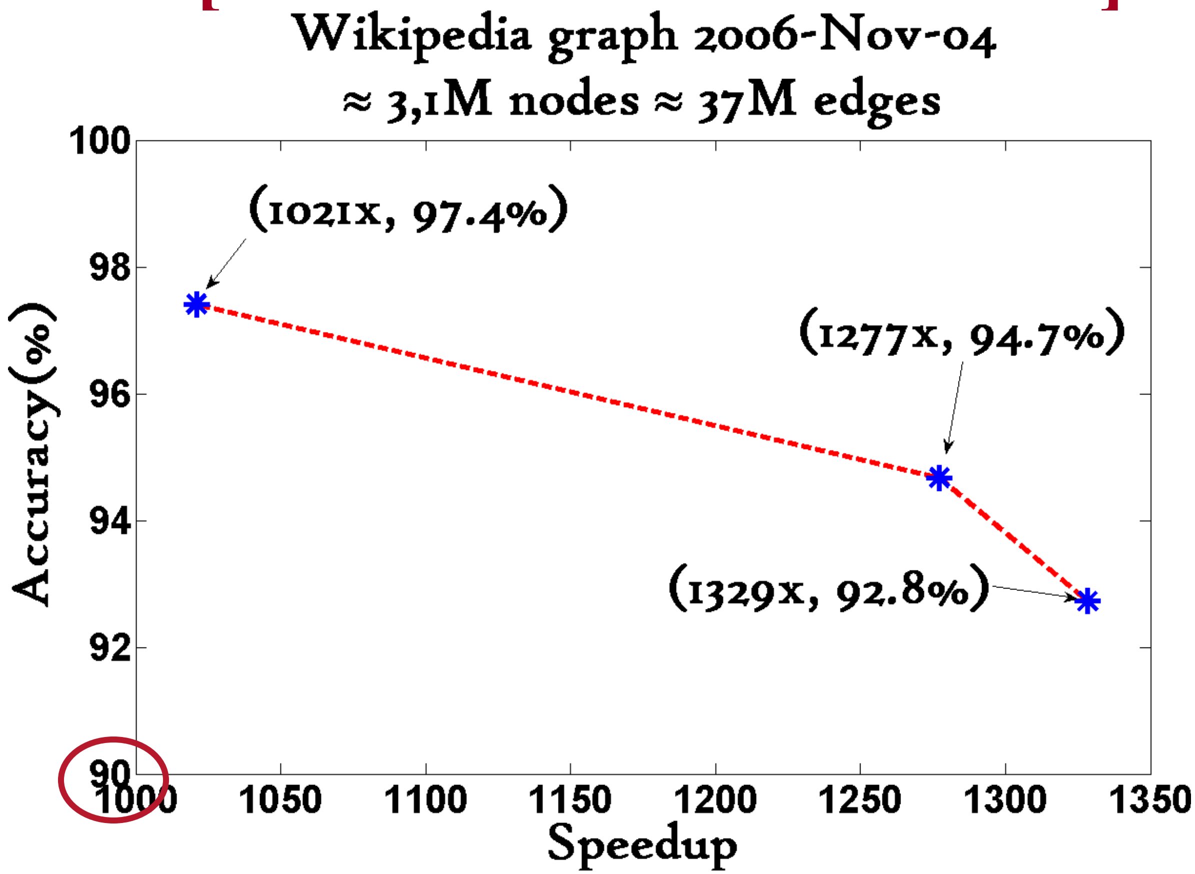
Triangle Law: Computations
[Tsourakakis ICDM 2008]

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]



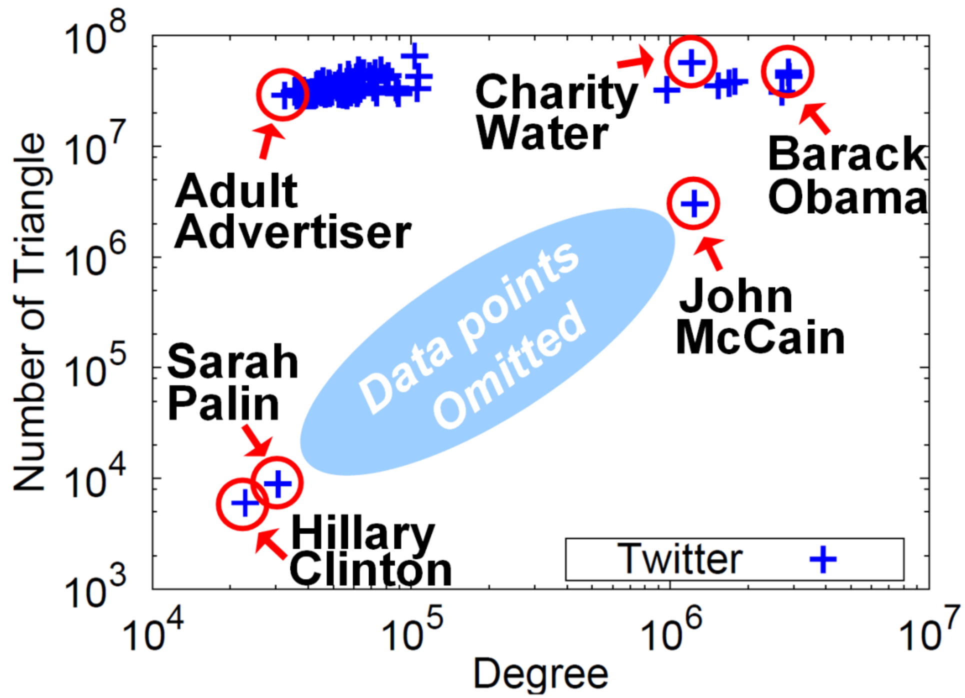
1000x+ speed-up, >90% accuracy

Triangle counting for large graphs?

Anomalous nodes in Twitter(~ 3 billion edges)

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

Triangle counting for large graphs?



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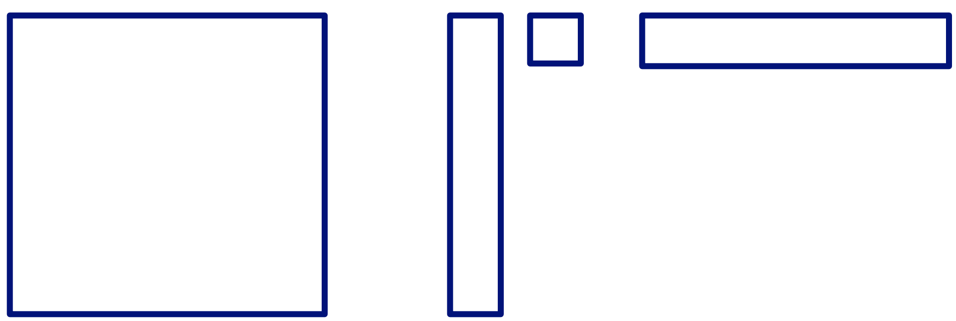
EigenSpokes

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)

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



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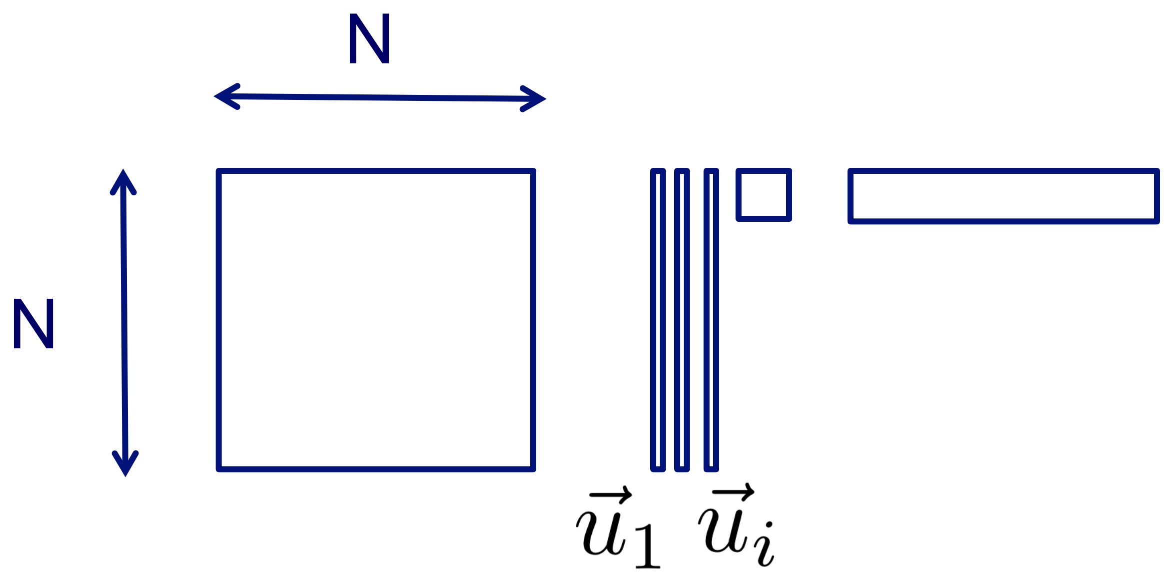

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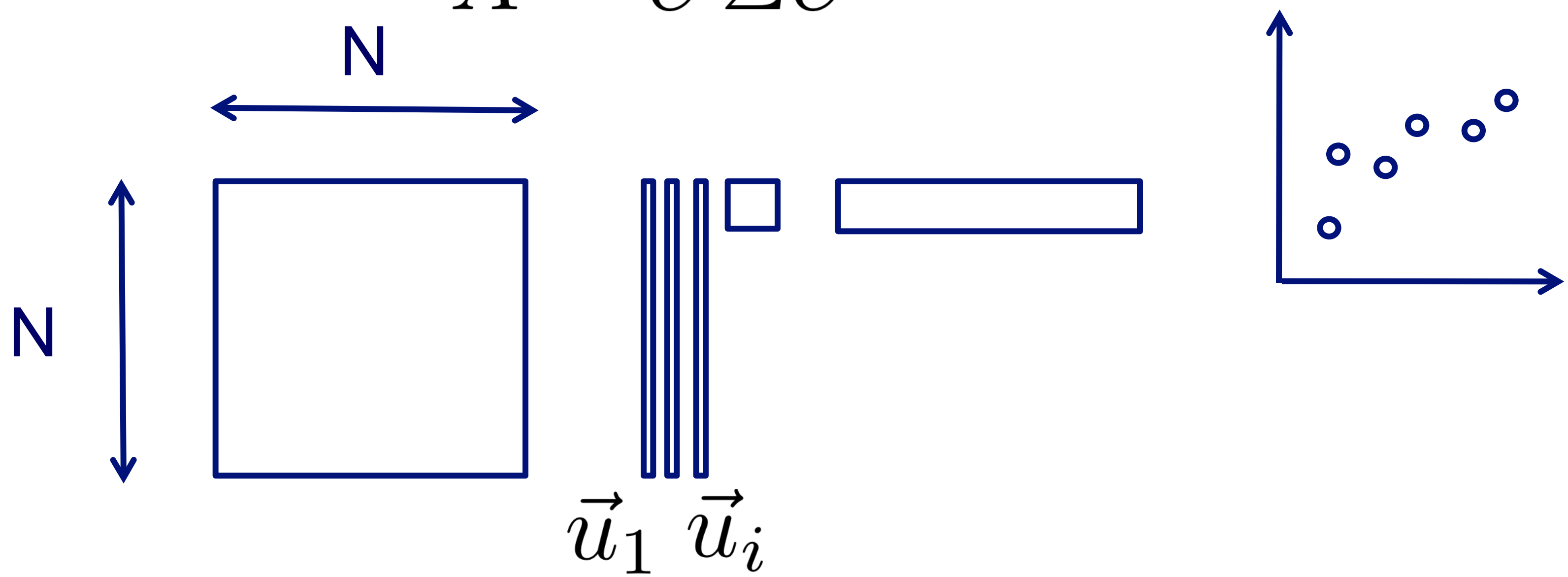

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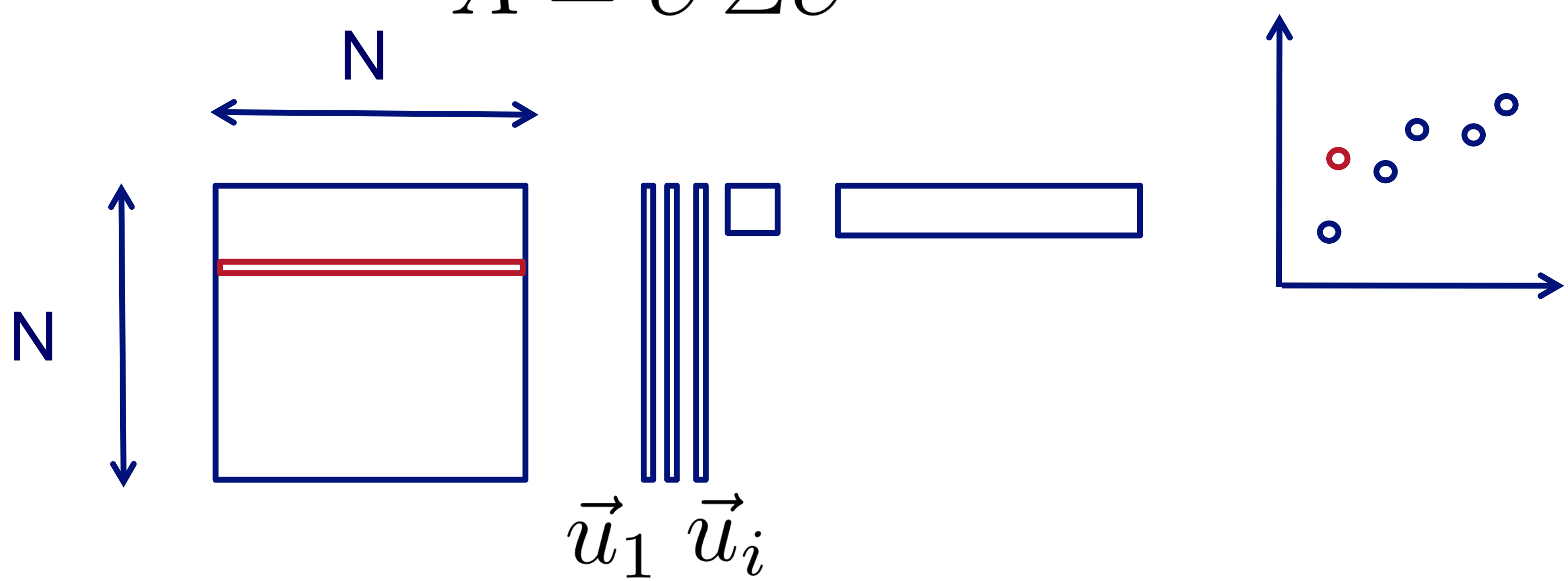

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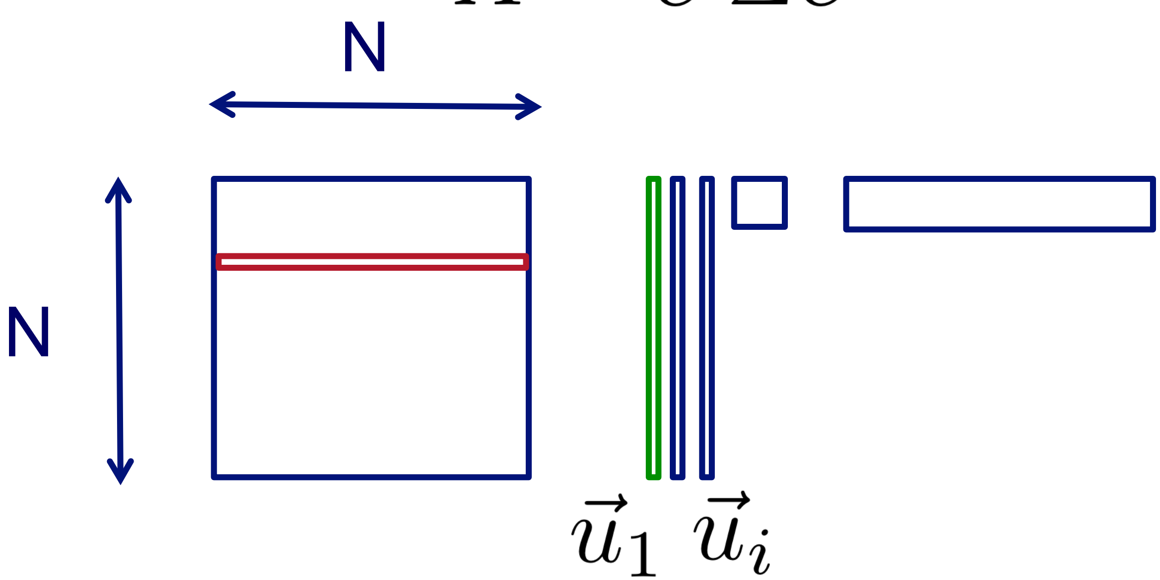
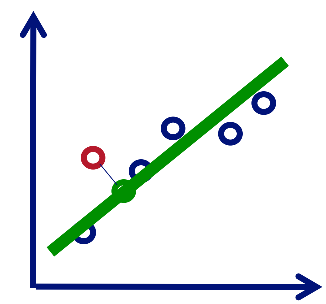
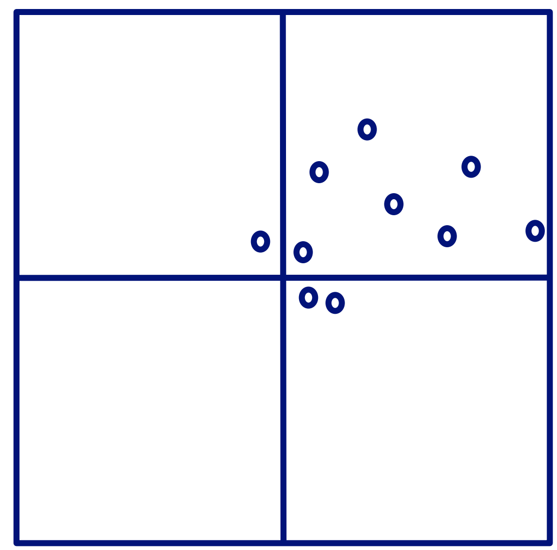




EigenSpokes

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



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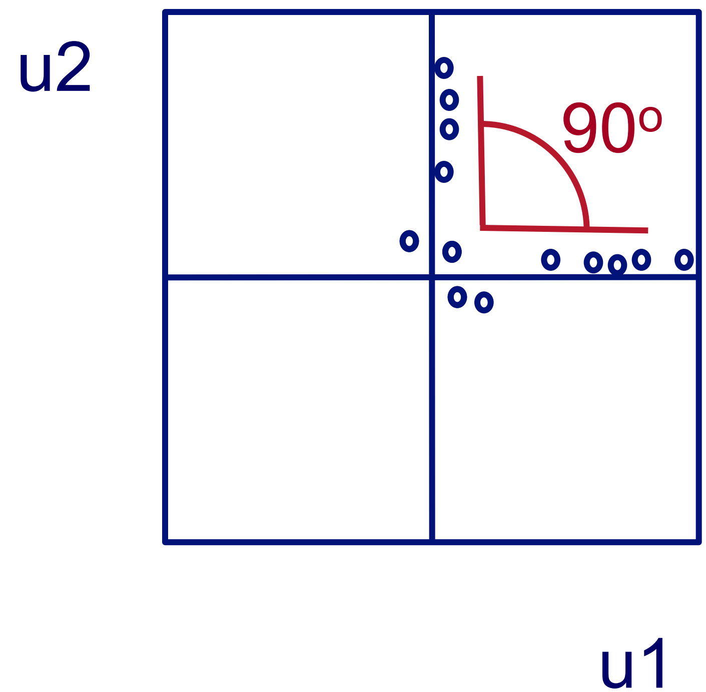
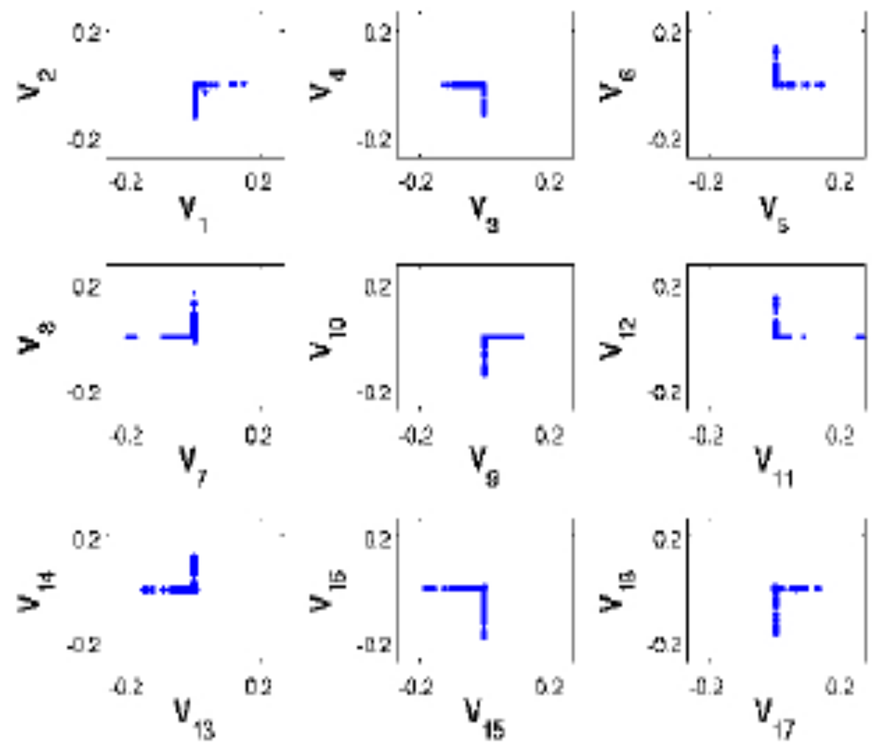


EigenSpokes - pervasiveness

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



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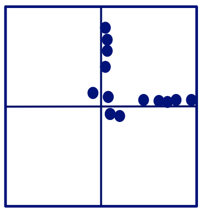
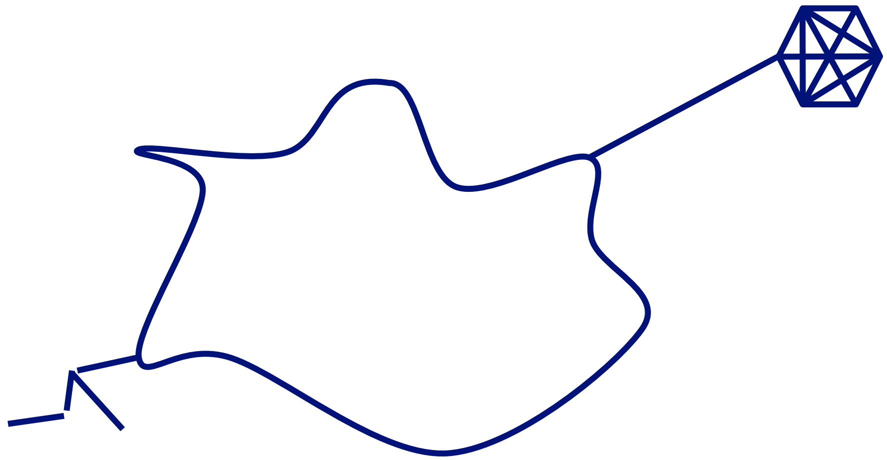
EigenSpokes - explanation



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



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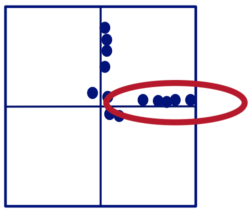

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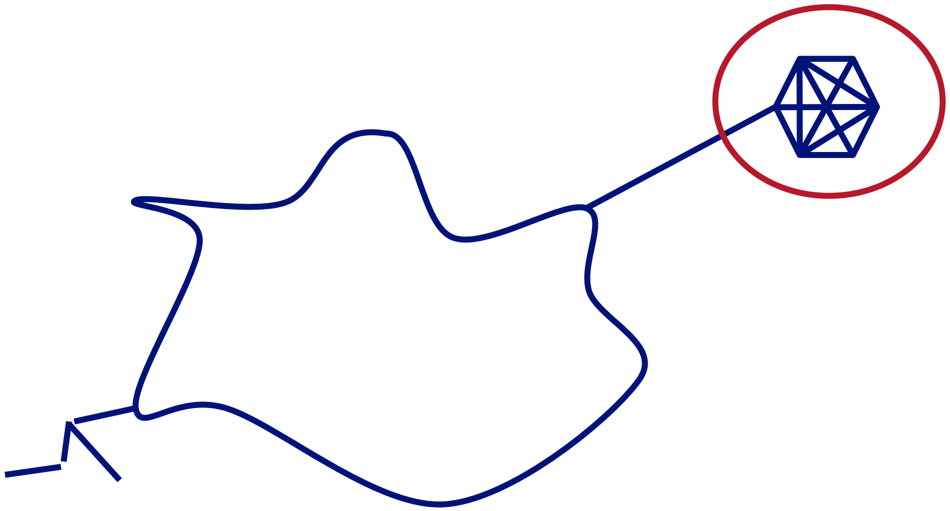

EigenSpokes - explanation

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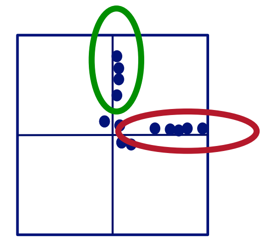

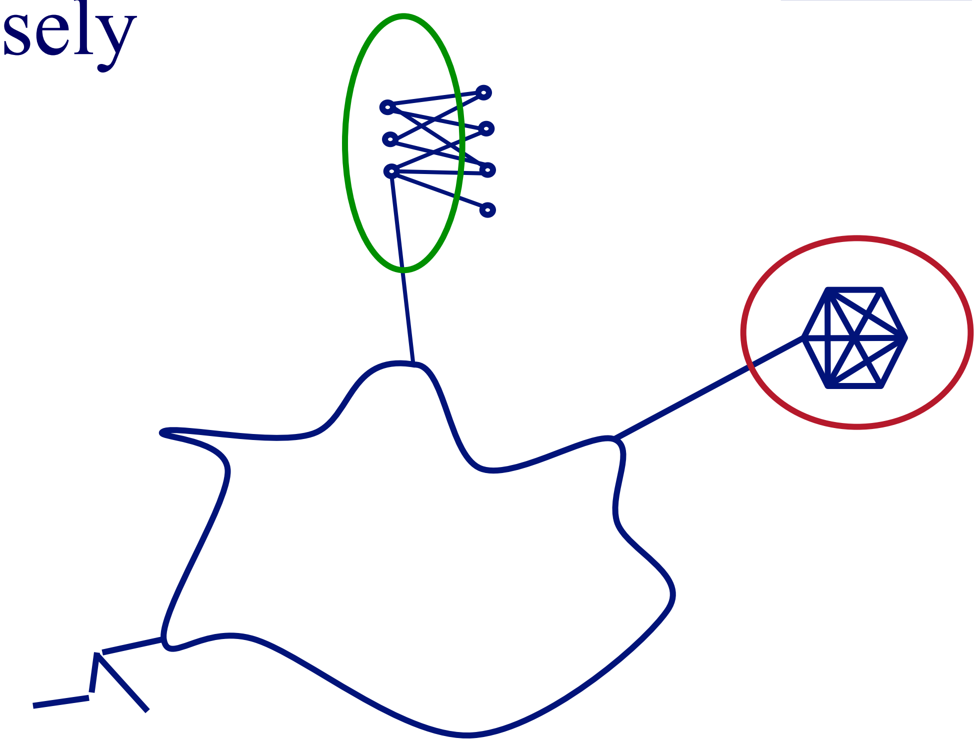

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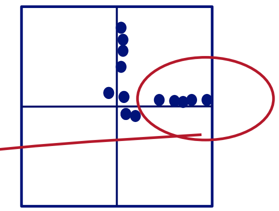
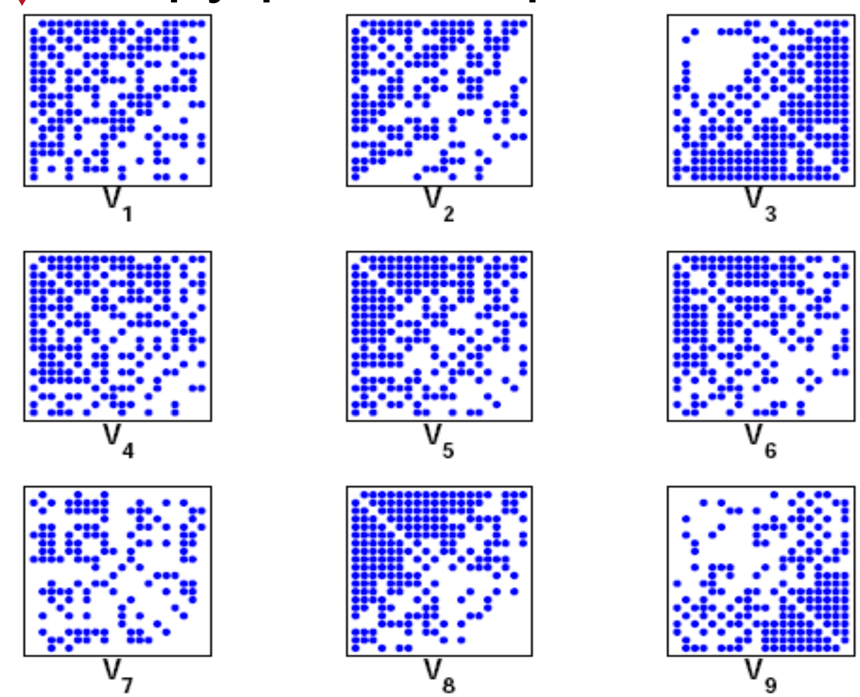


Near-cliques, or near-bipartite-cores, loosely connected

spy plot of top 20 nodes



So what?

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

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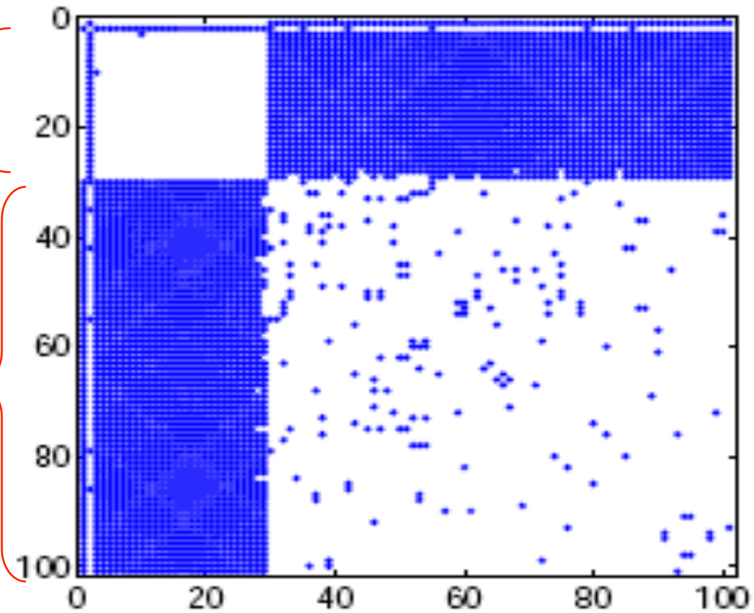
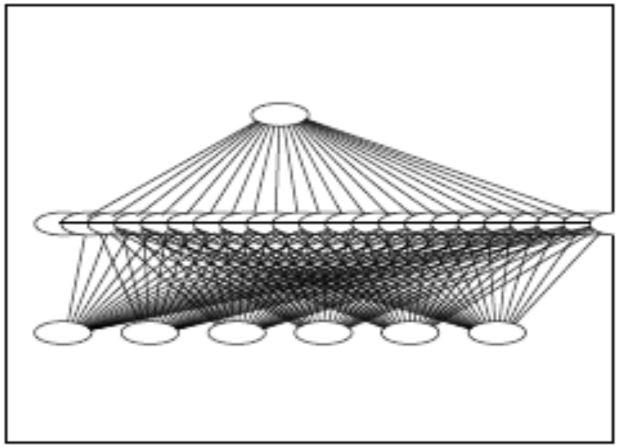
Bipartite Communities!



patents from same inventor(s)

`cut-and-paste' bibliography!

magnified bipartite community



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    - 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?

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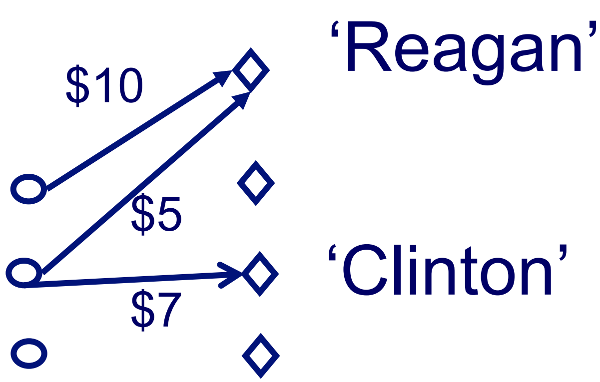
Observation W.1: Fortification

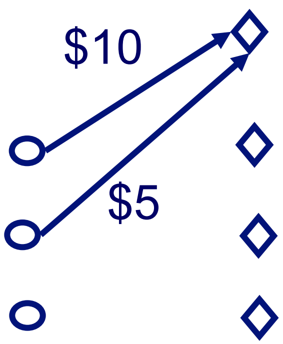
More donors, more $?



Observation W.1: fortification: Snapshot Power Law

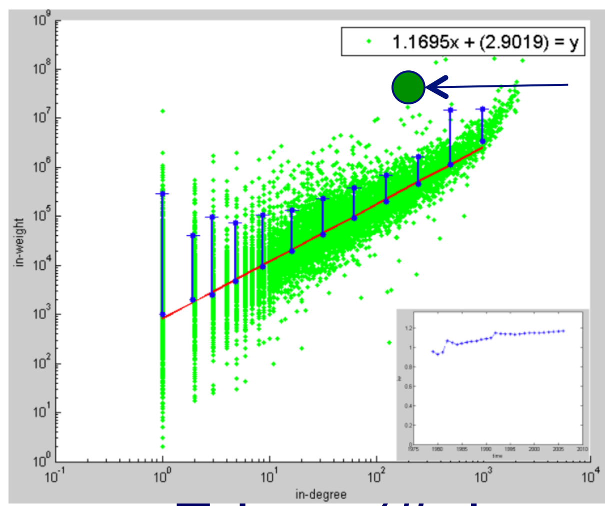
- Weight: super-linear on in-degree
- exponent ‘iw’: 1.01 < iw < 1.26

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



In-weights ($)

Orgs-Candidates



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

Edges (# donors)

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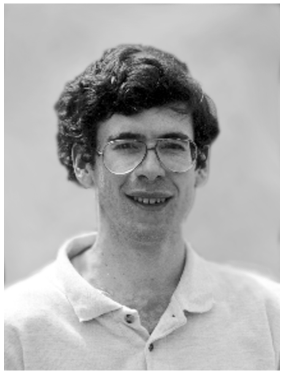
Problem: Time evolution

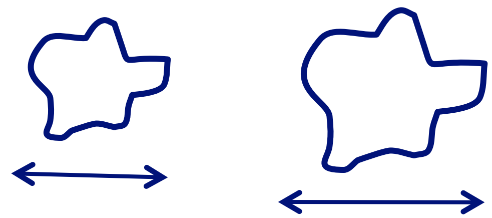
- with Jure Leskovec (CMU -> Stanford)

- 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

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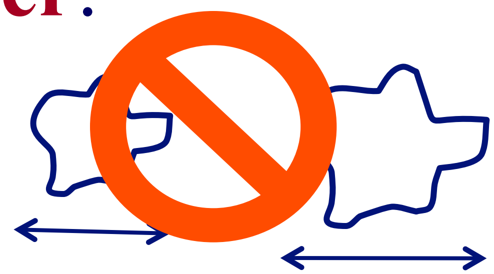
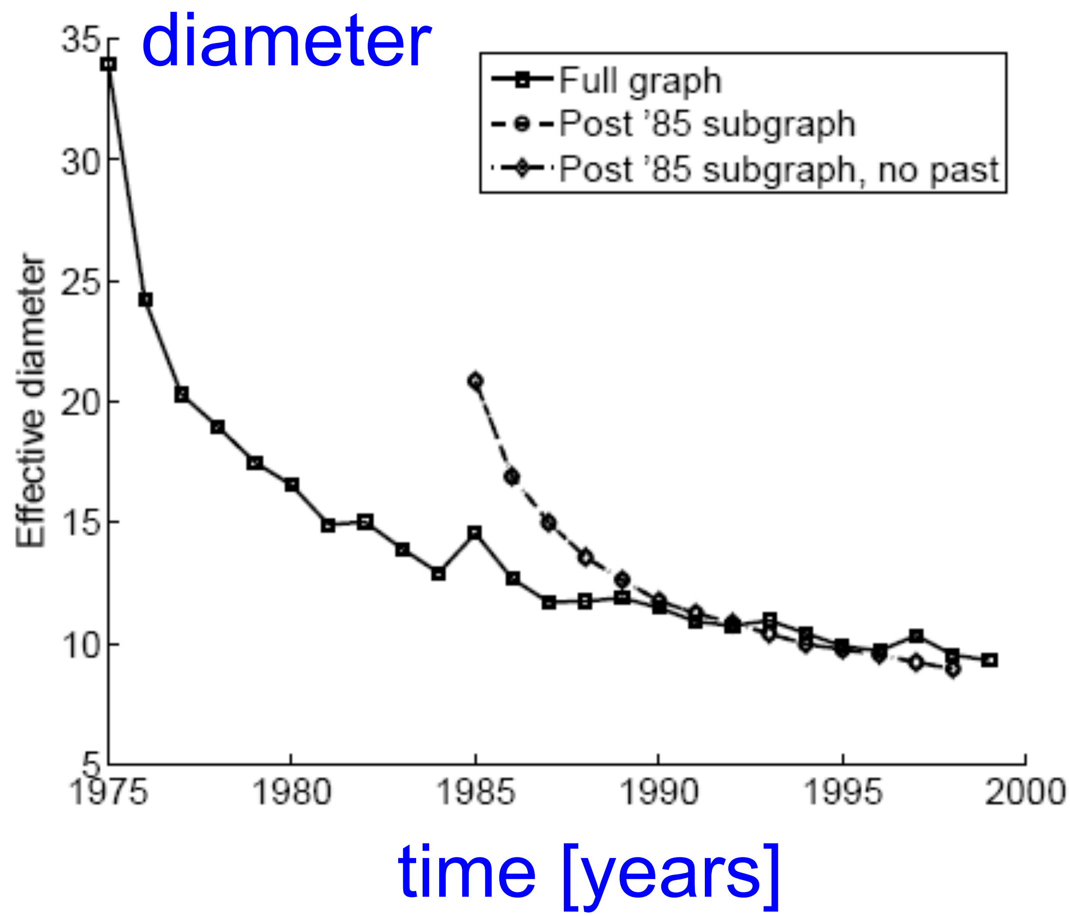


- What is happening in real data?
- Diameter **shrinks** over time

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''

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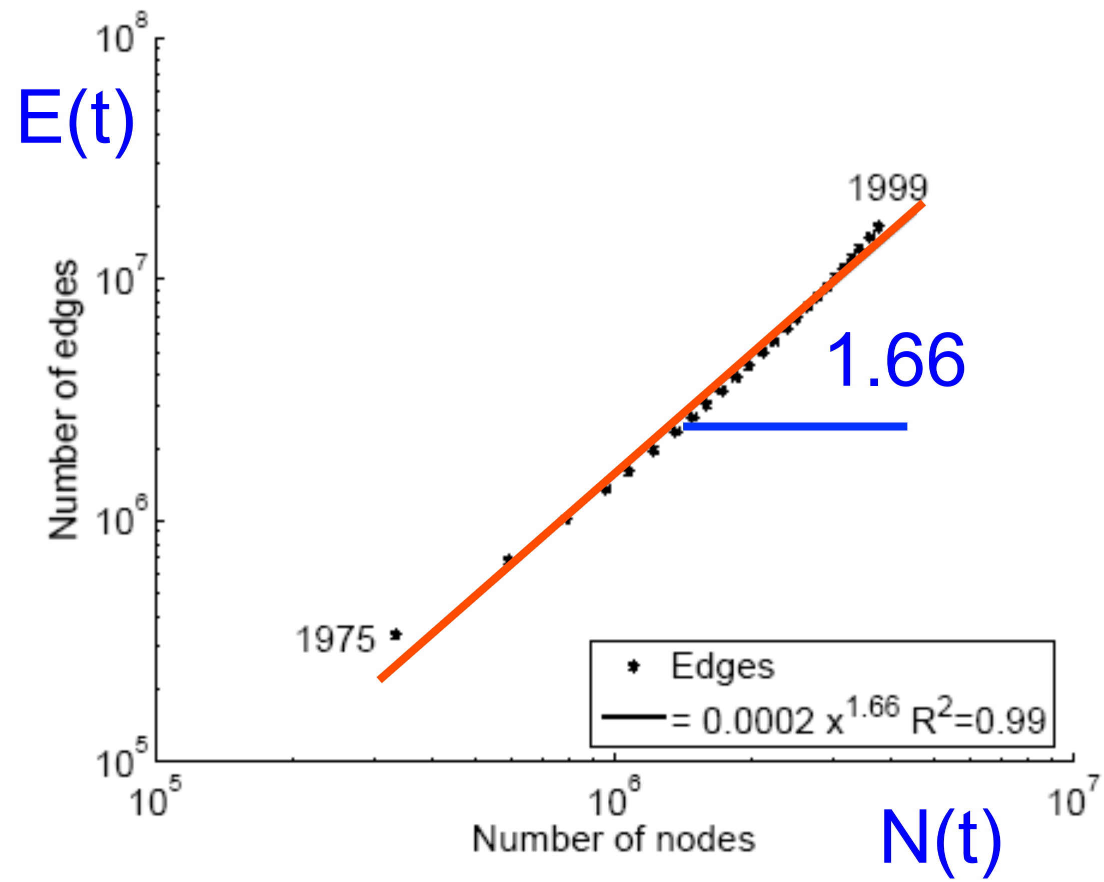
T.2 Densification – Patent Citations

- 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

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Observation T.3: NLCC behavior

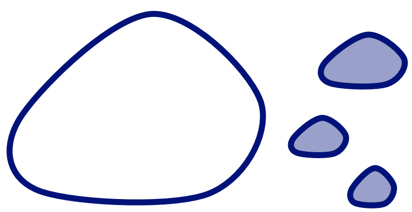
Q: How do NLCC's emerge and join with the GCC?

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

– Do they continue to grow in size?

– or do they shrink?

– or stabilize?



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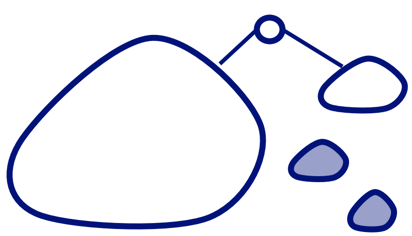

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Observation T.3: NLCC behavior

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?

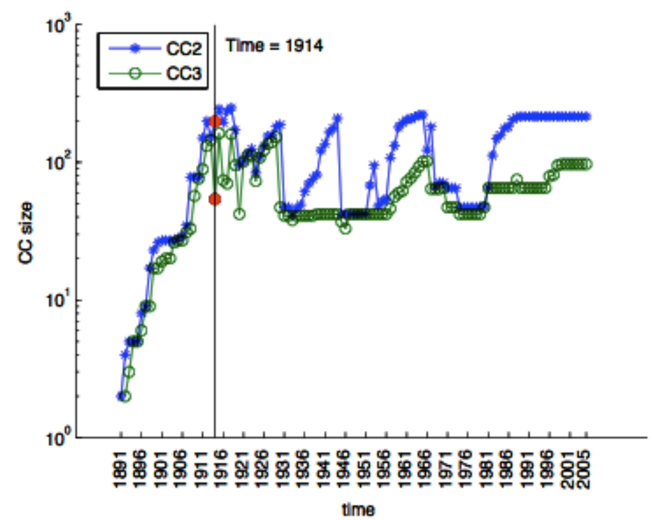
YES – or stabilize?

Observation T.3: NLCC behavior

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

IMDB

CC size



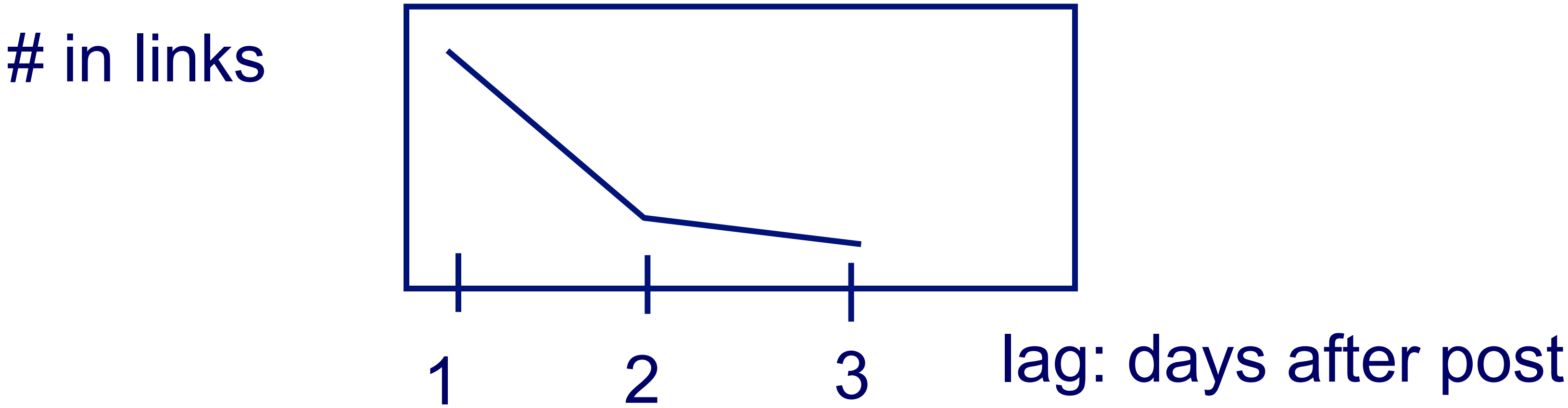
Time-stamp

Timing for Blogs

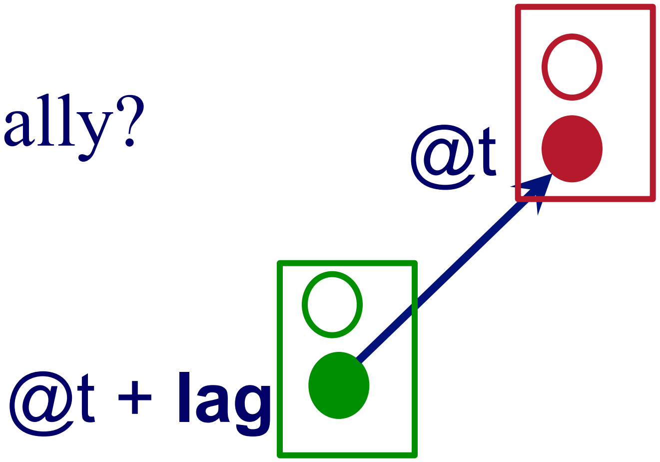
- with Mary McGlohon (CMU->Google)
- Jure Leskovec (CMU->Stanford)
- Natalie Glance (now at Google)
- Mat Hurst (now at MSR)

[SDM’07]

T.4 : popularity over time

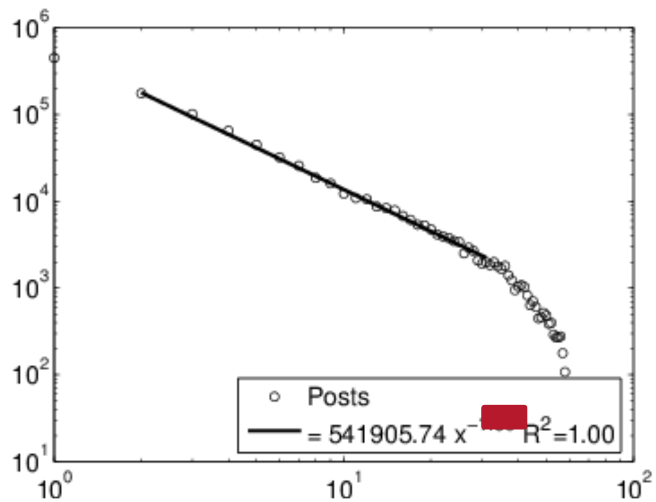


Post popularity drops-off – exponentially?



T.4 : popularity over time

in links
(**log**)

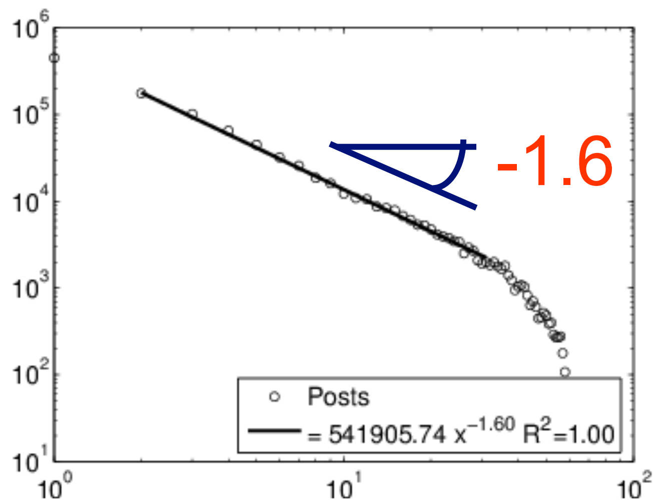


days after post
(**log**)

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

T.4 : popularity over time

in links
(**log**)



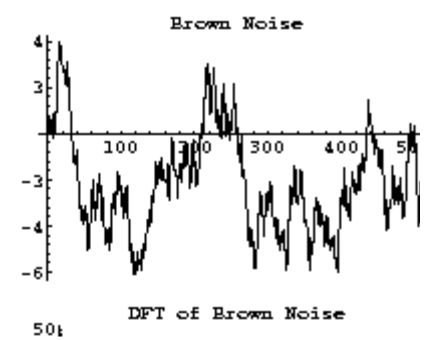
days after post
(**log**)

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]

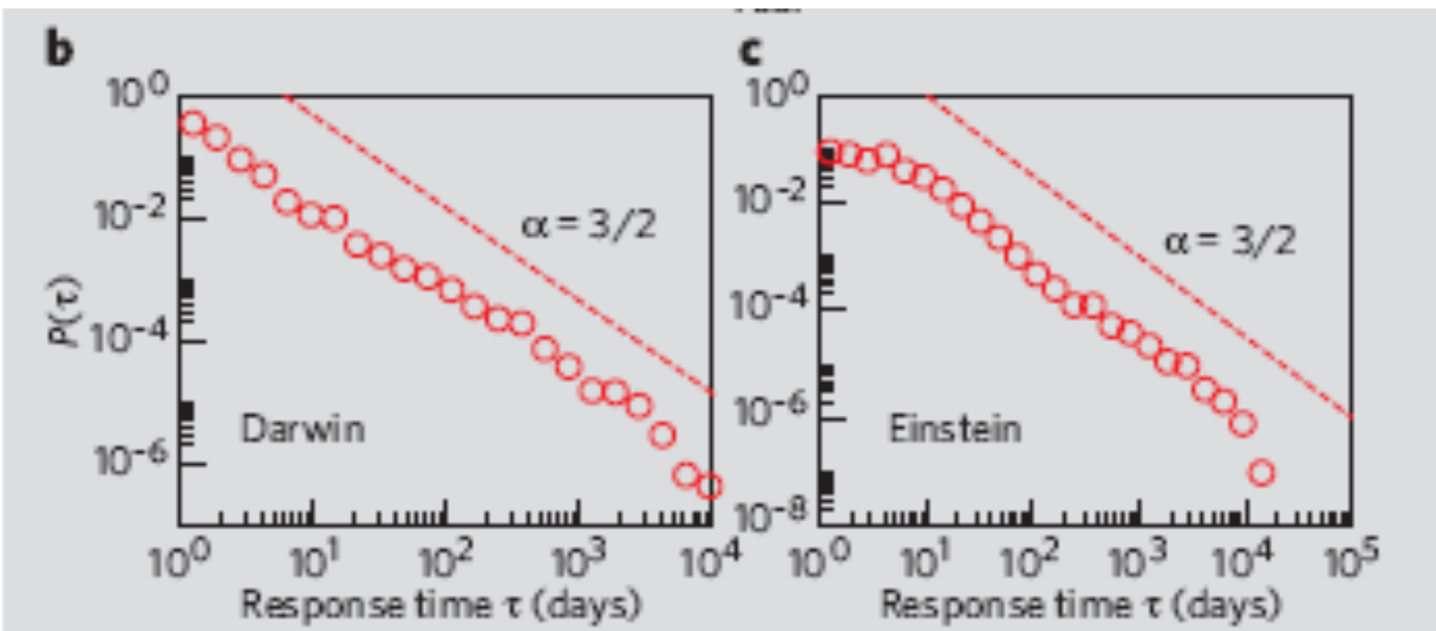


Figure 1 | The correspondence patterns of Darwin and Einstein.

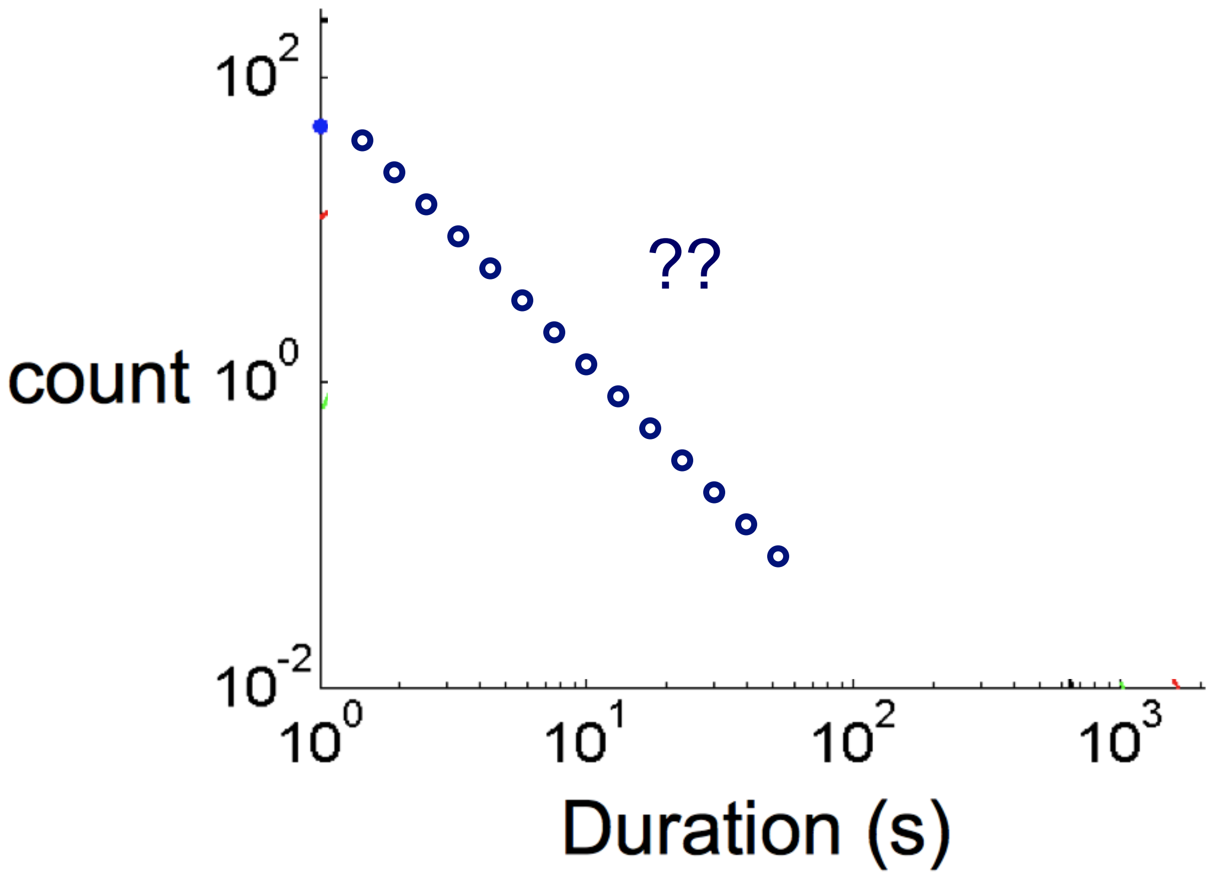
T.5: duration of phonecalls

Surprising Patterns for the Call Duration Distribution of Mobile Phone Users

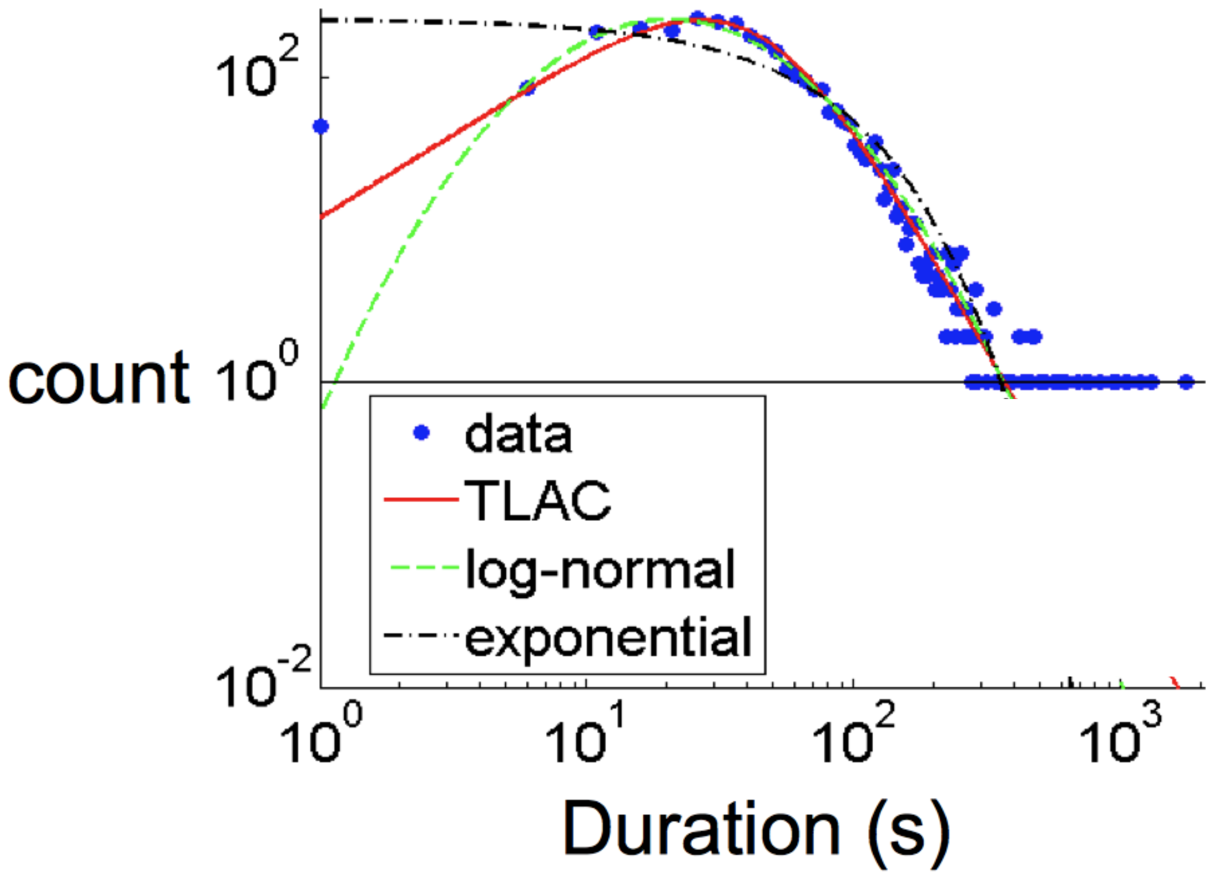
Pedro O. S. Vaz de Melo, Leman Akoglu, Christos Faloutsos, Antonio A. F. Loureiro

PKDD 2010

Probably, power law (?)

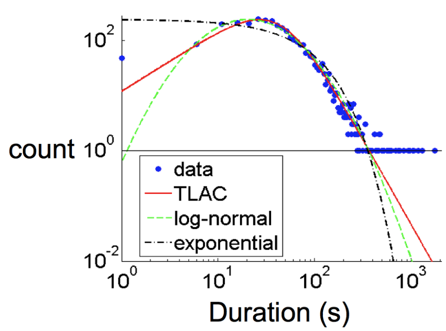


No Power Law (yet)



‘TLaC: Lazy Contractor’

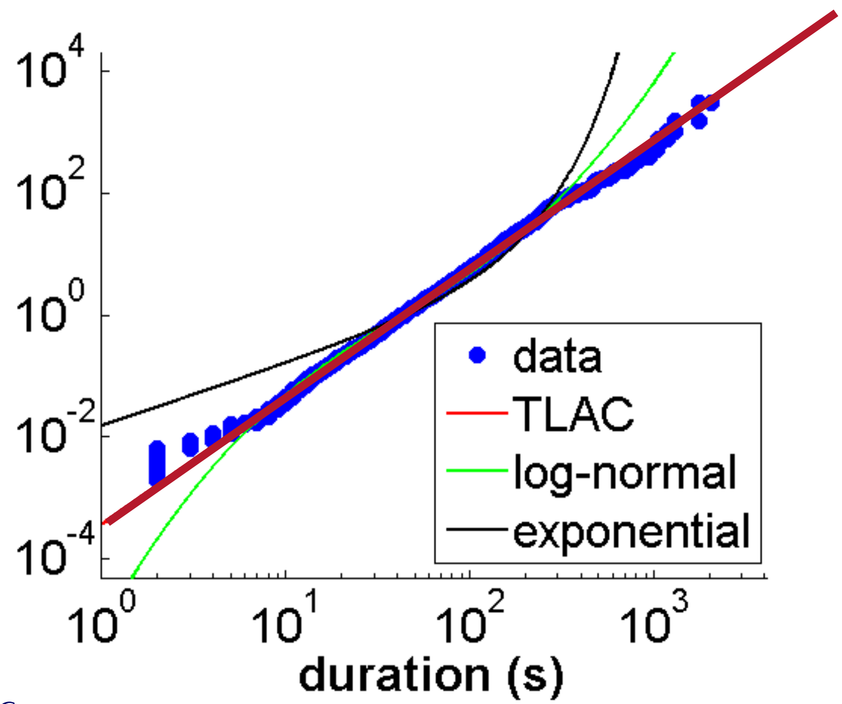
- The longer a task (phonecall) has taken,
- The even longer it will take



Odds ratio=

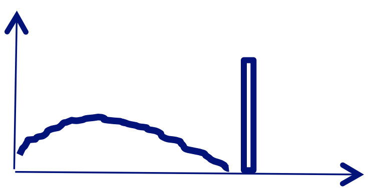
Casualties(<x): Survivors(>=x)

== 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)
- Rest 4%: ~



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Outline

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

teasers

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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

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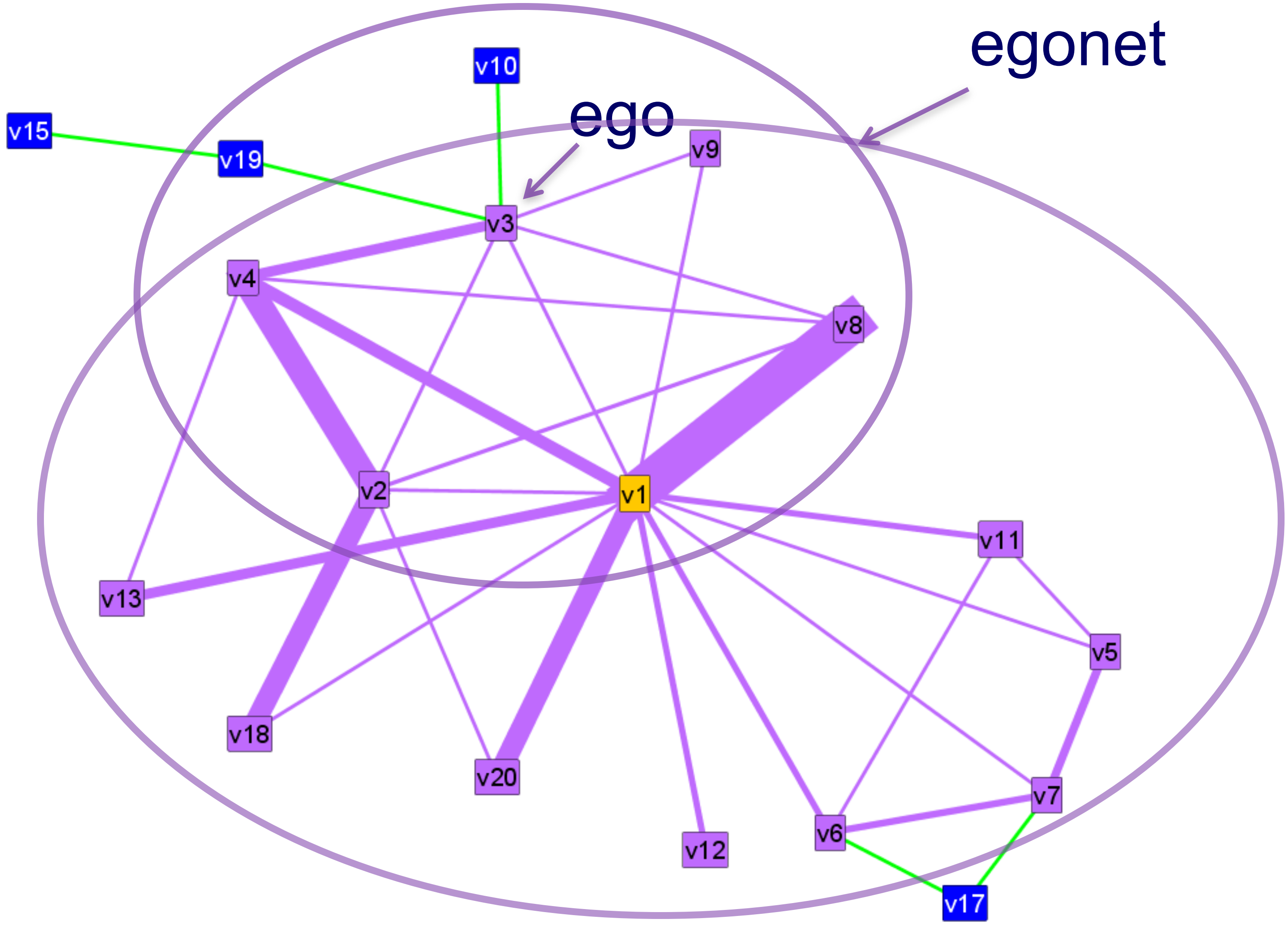
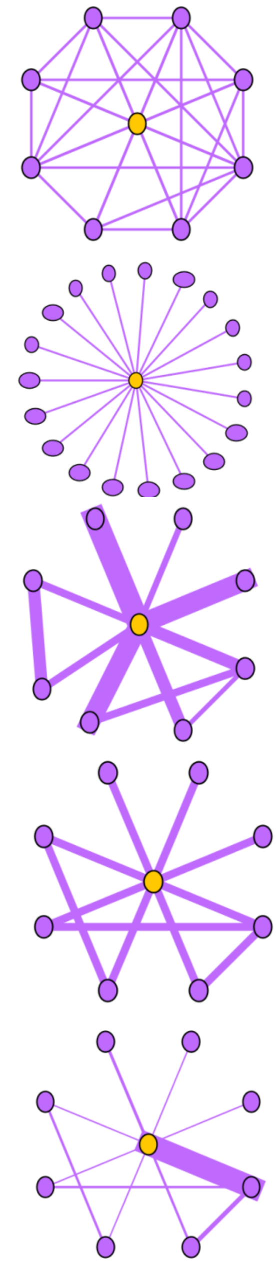
What is an egonet?



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

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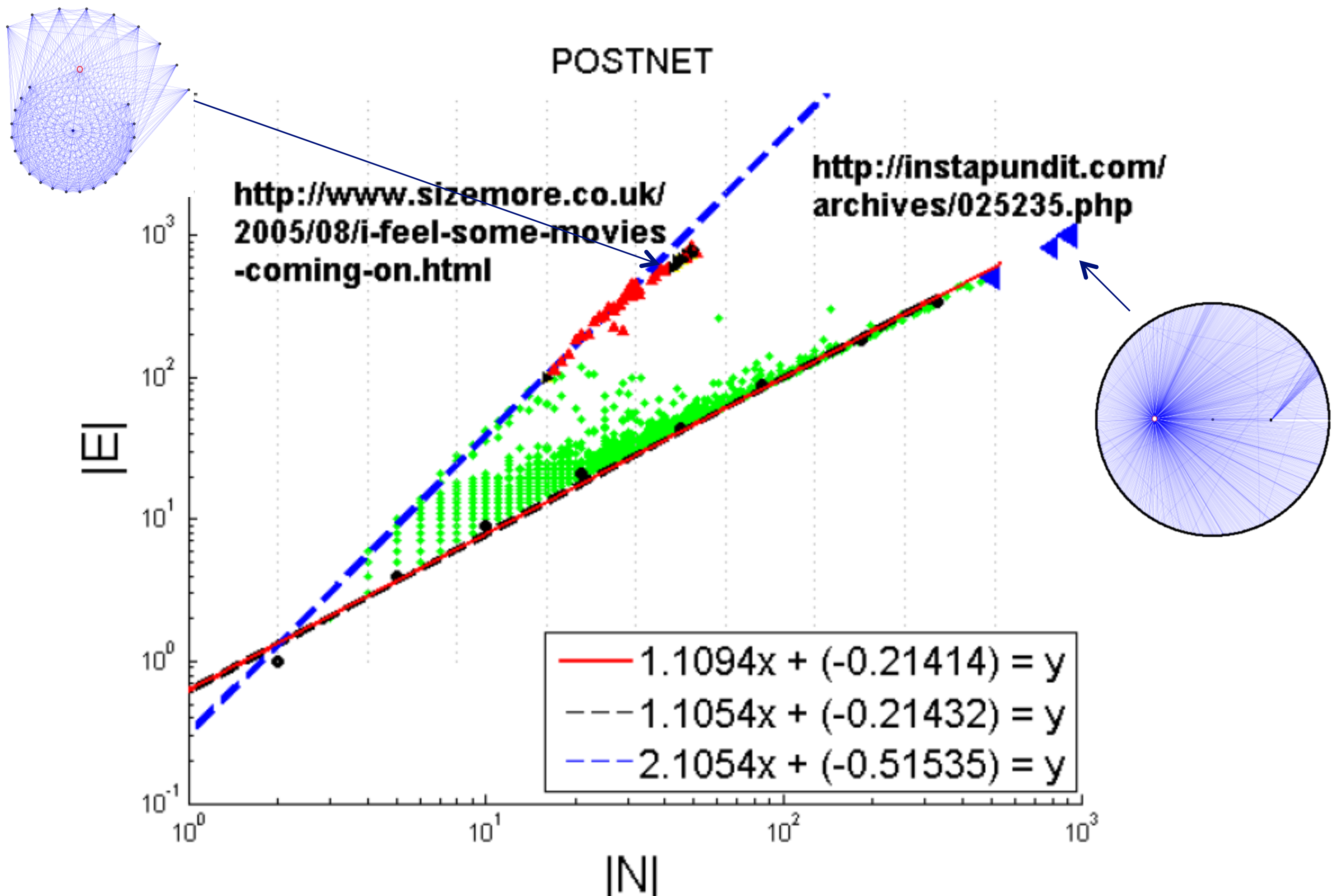
Near-Clique/Star



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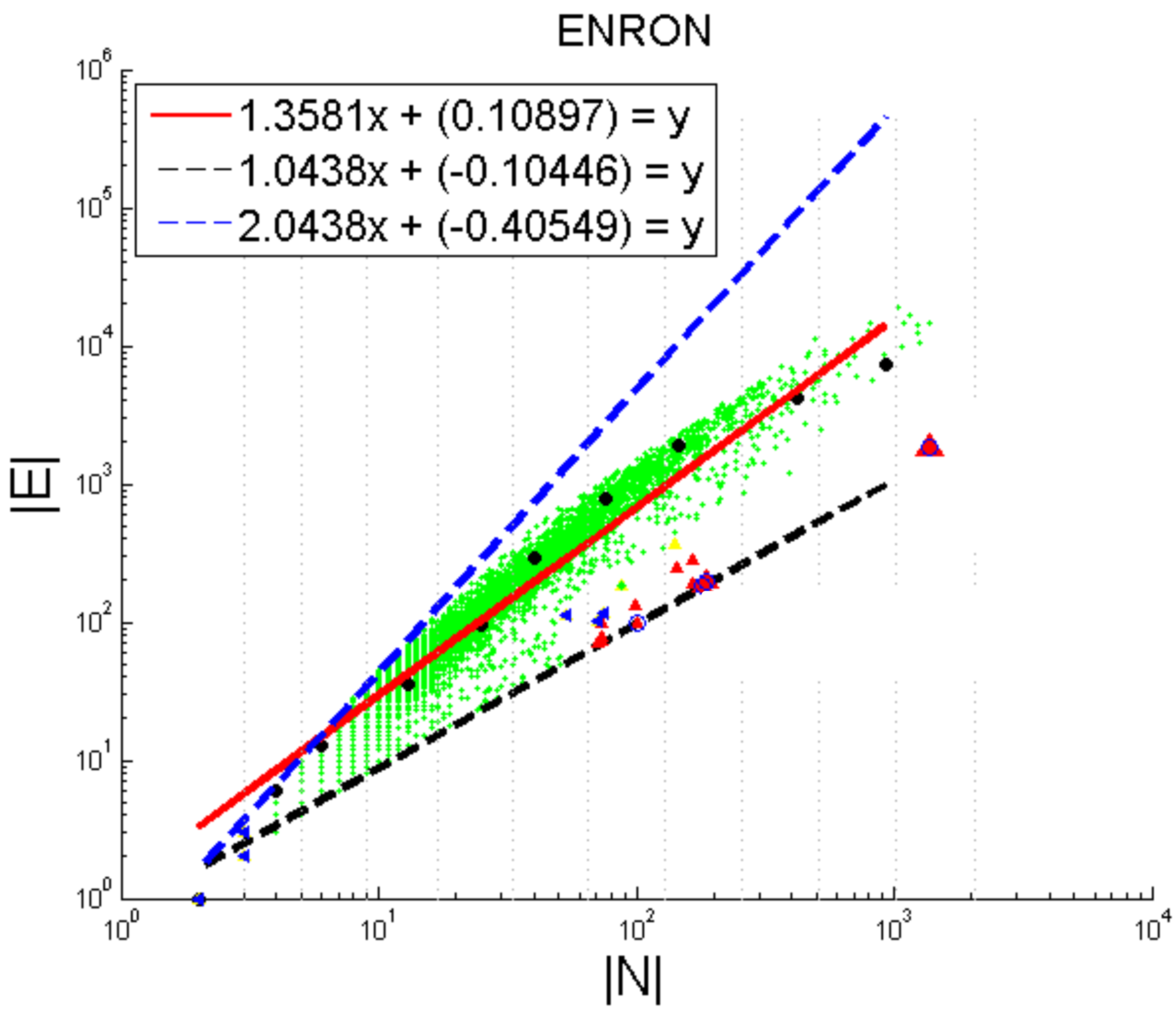

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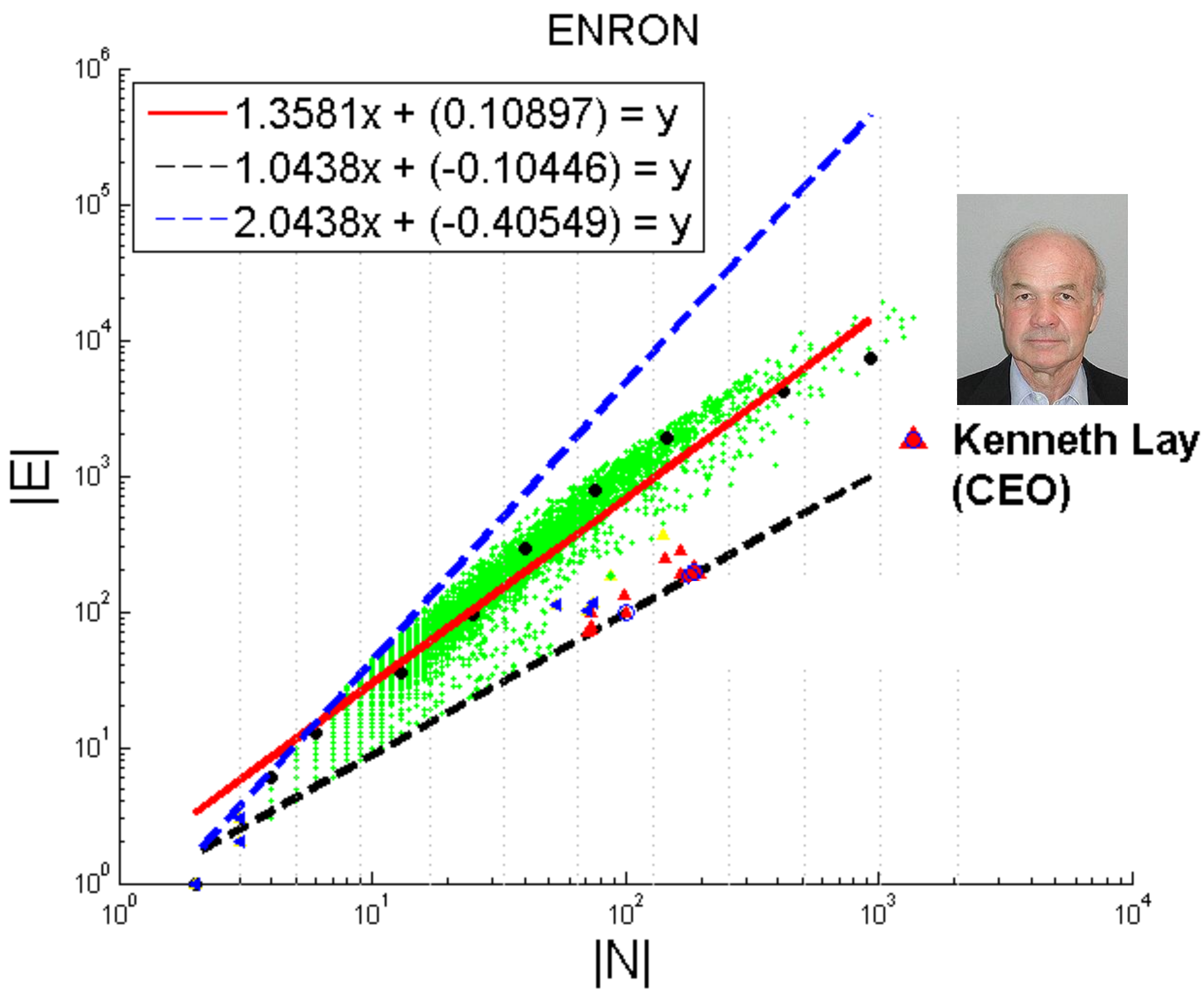

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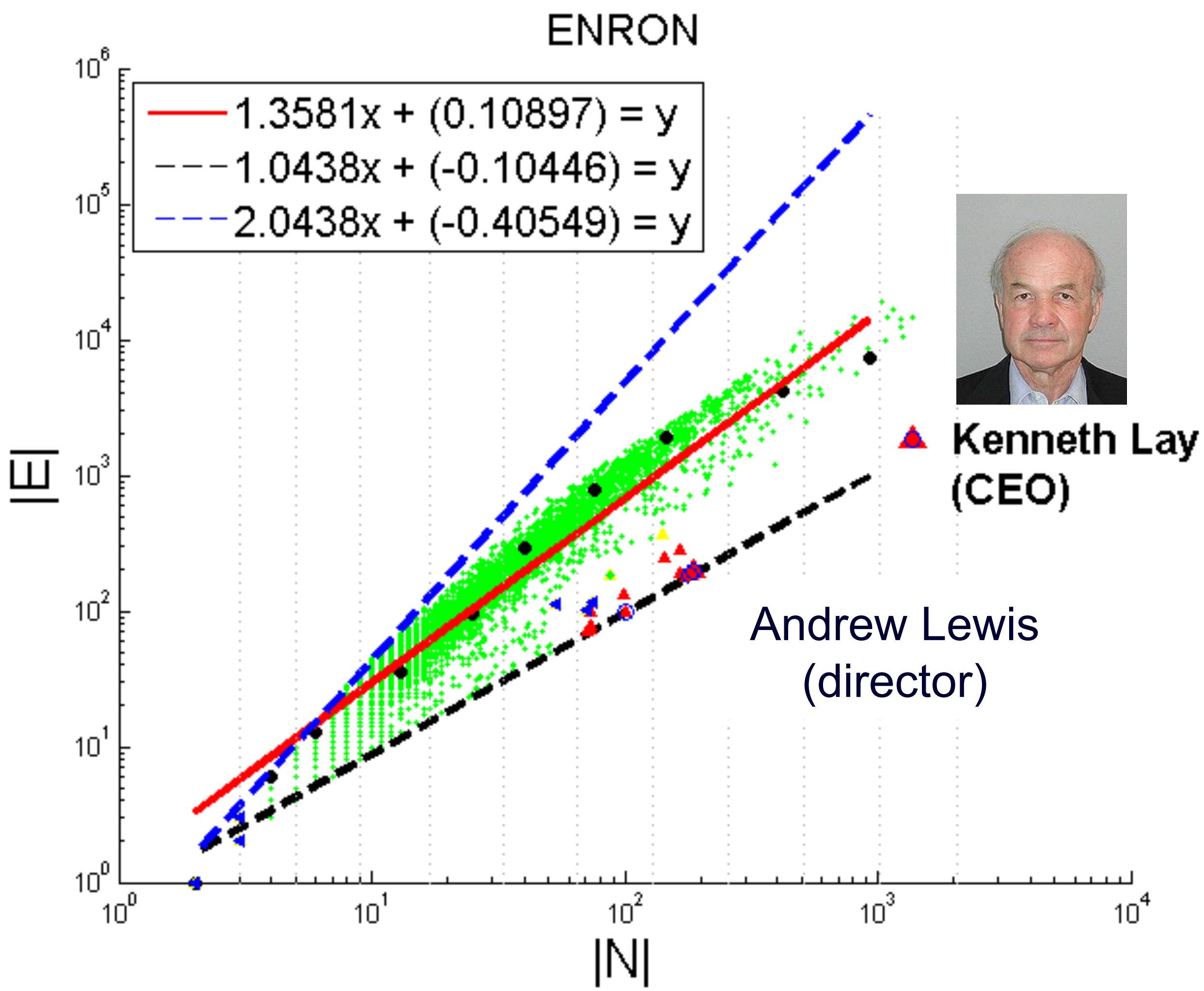

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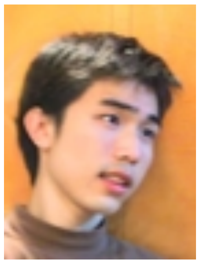
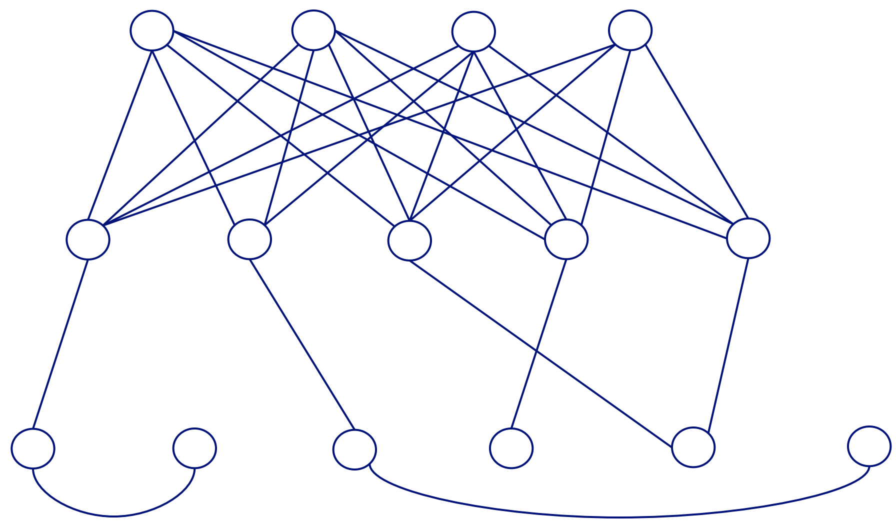
E-bay Fraud detection



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



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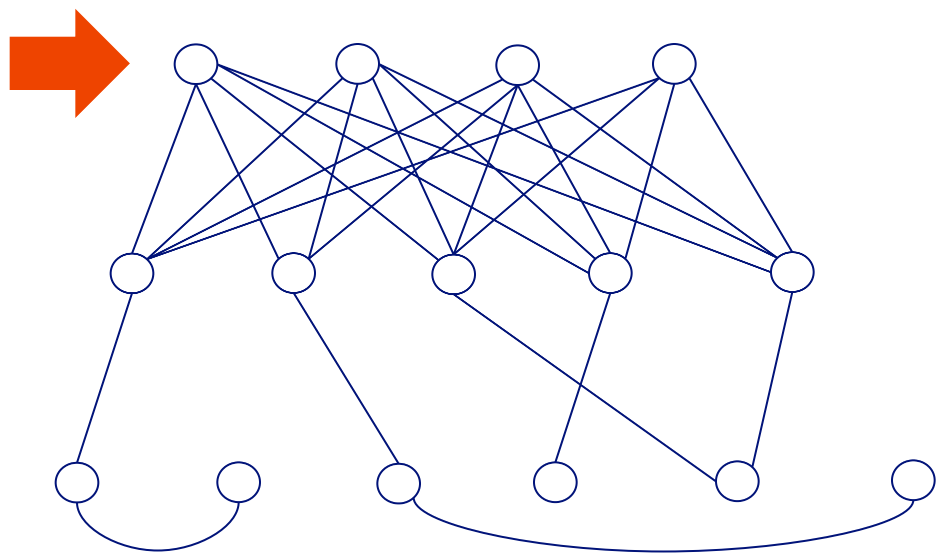

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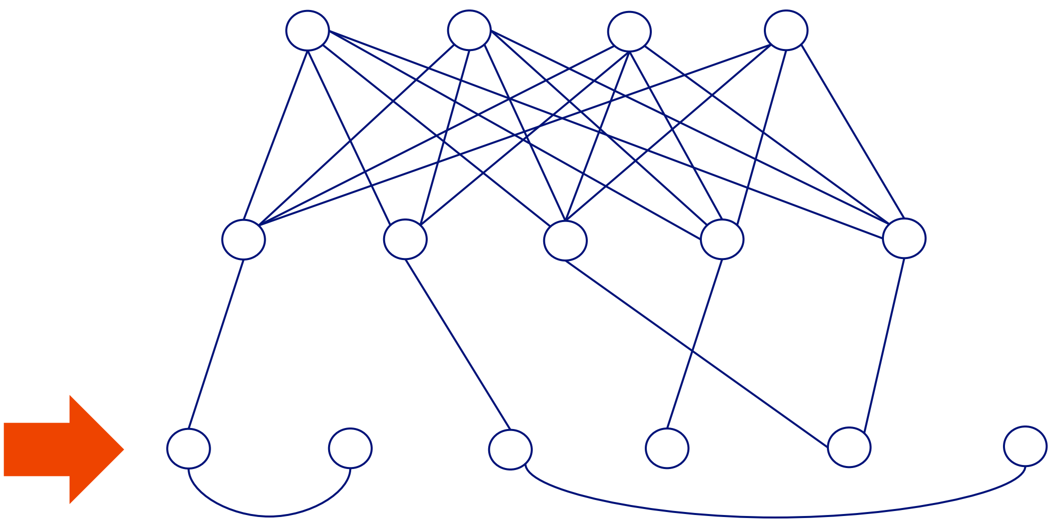
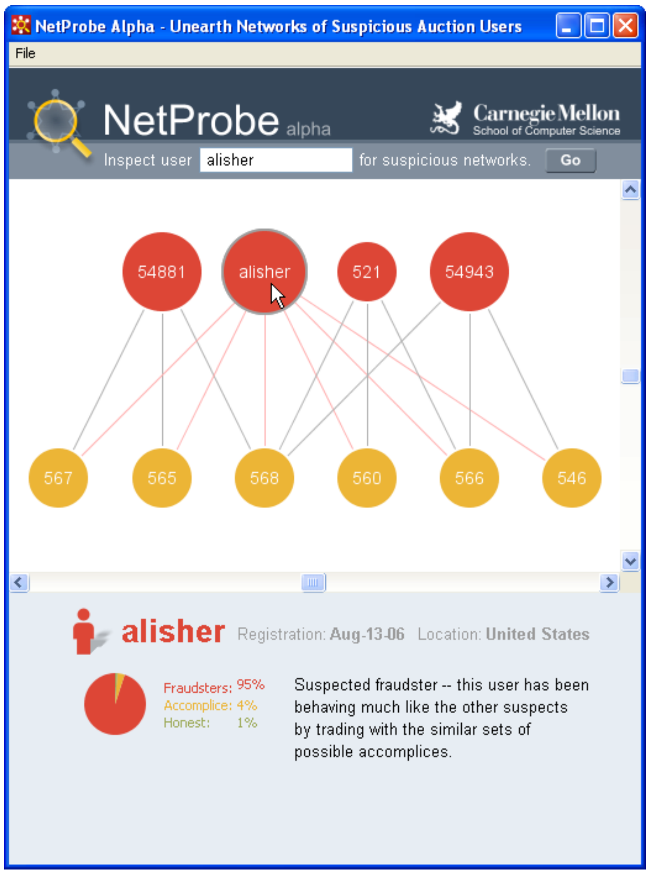
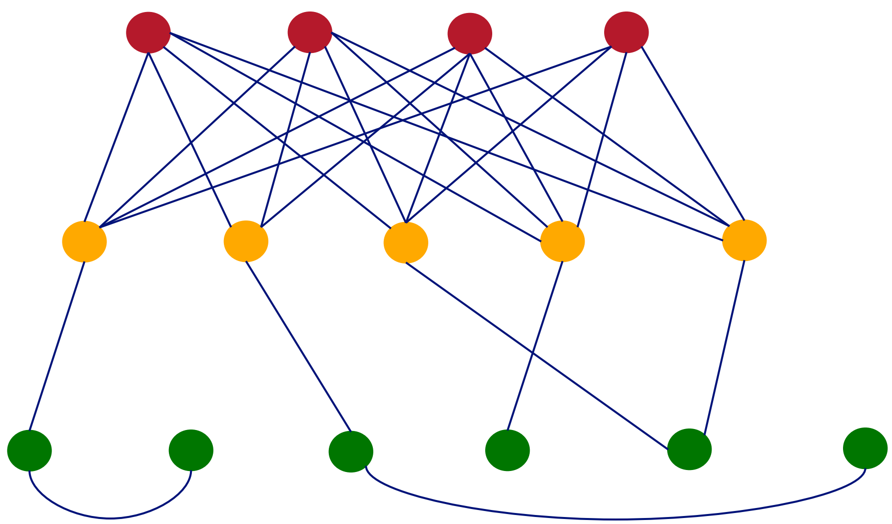


E-bay Fraud detection - NetProbe





Popular press

USA TODAY

The Washington Post

Los Angeles Times

And less desirable attention:

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

Outline

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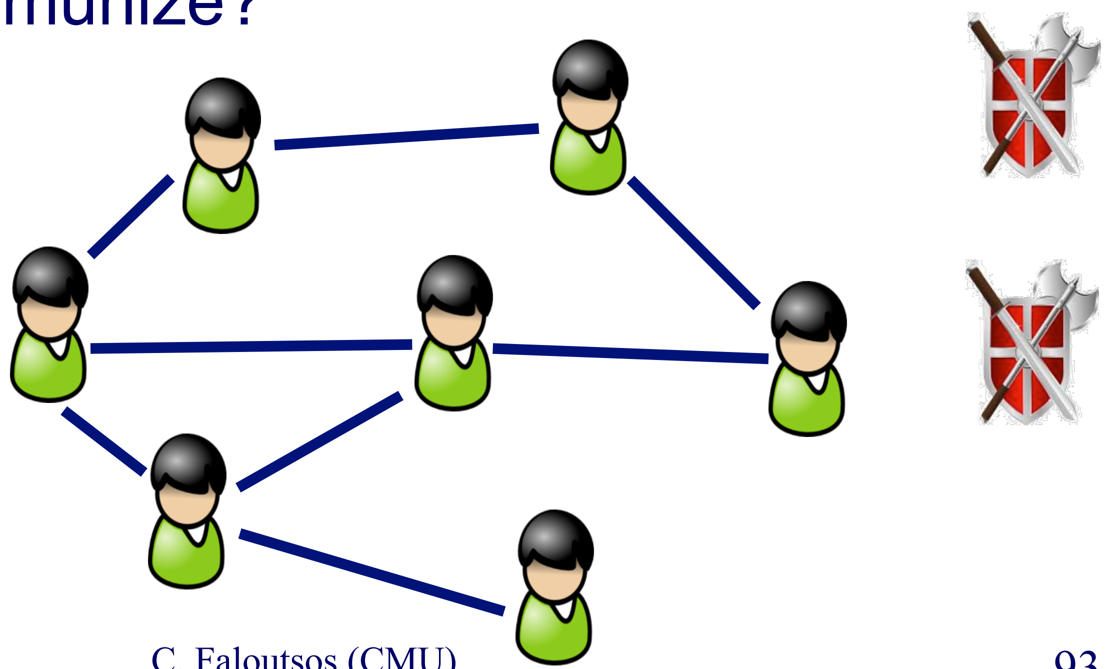
Immunization and epidemic thresholds

- 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?



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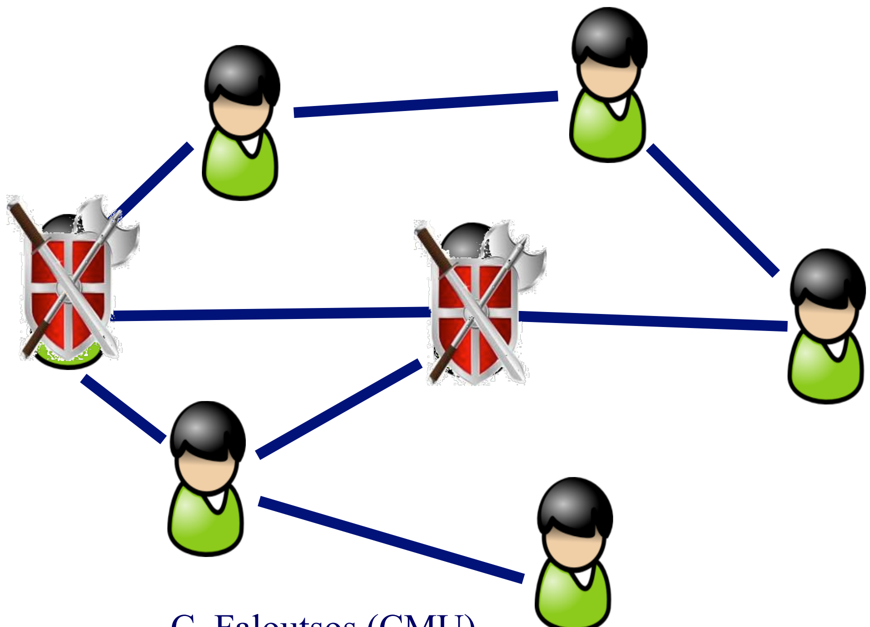

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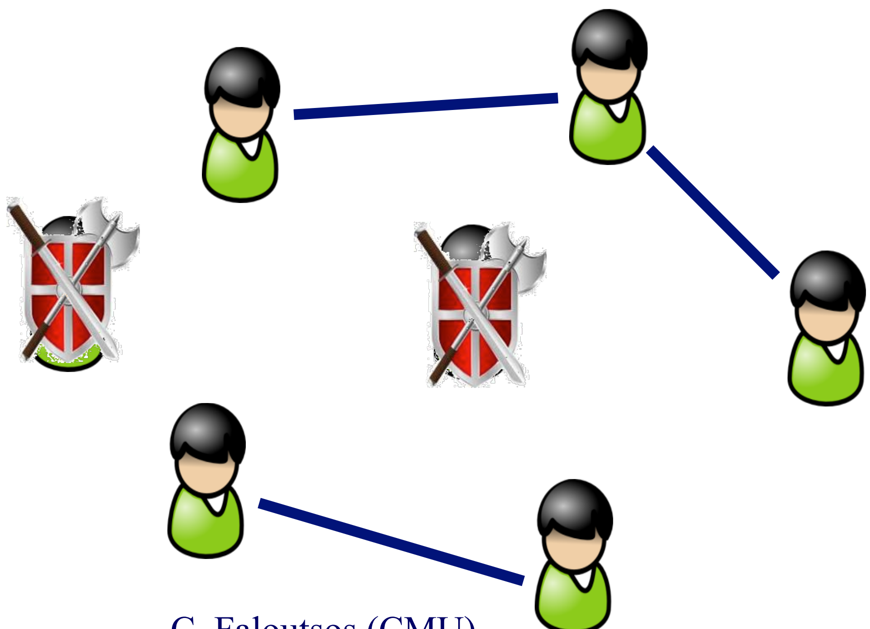
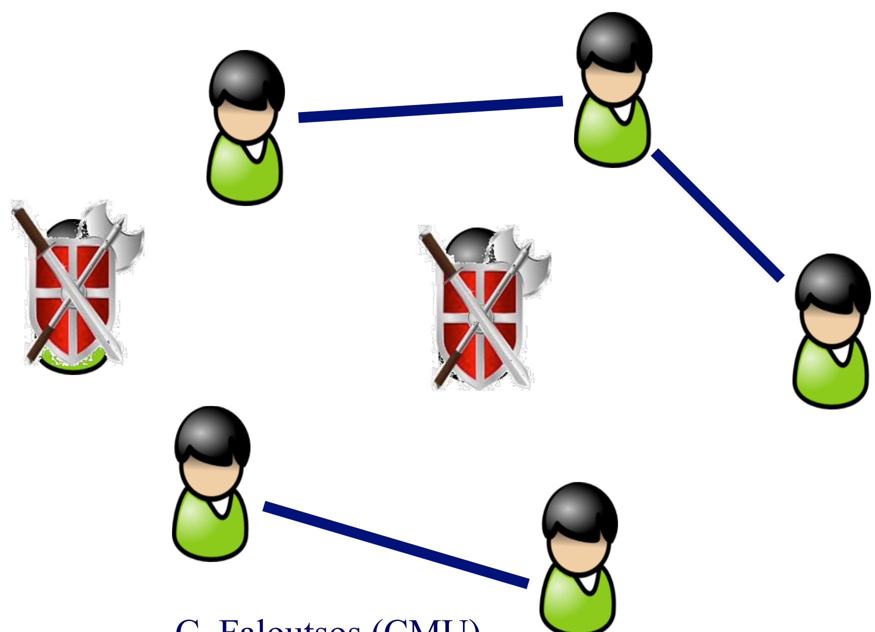


Q1: Immunization:

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

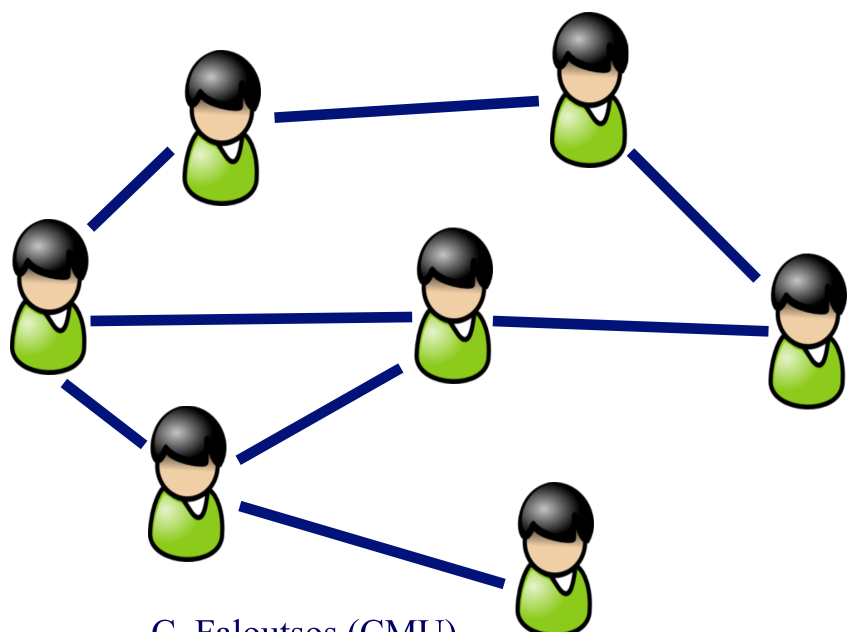
A: immunize the ones that maximally raise the `epidemic threshold' [Tong+, ICDM'10]



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



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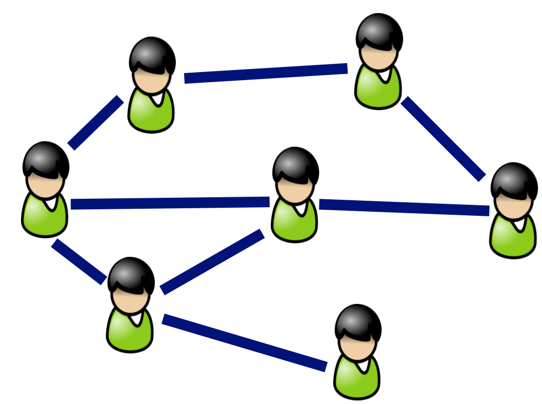
- Pertussis (finite-length immunity, ‘SIRS’)

β: attack prob
δ: heal prob

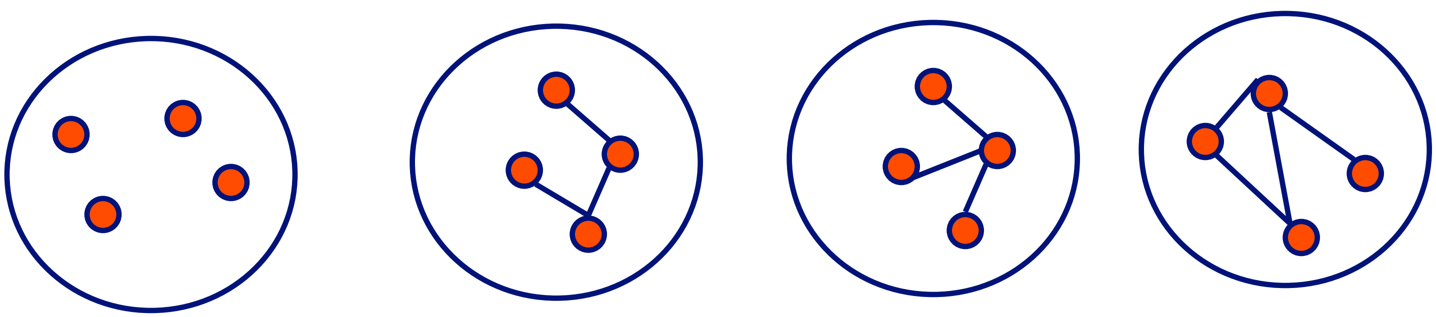
A: depends on connectivity
(avg degree? Max degree?
variance? Something else?



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)

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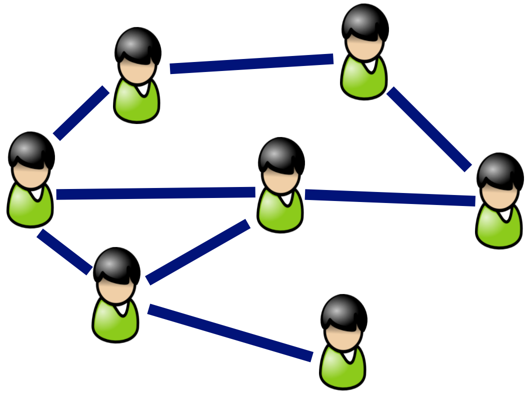
A2: will a virus take over?

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

$1/\lambda_1$

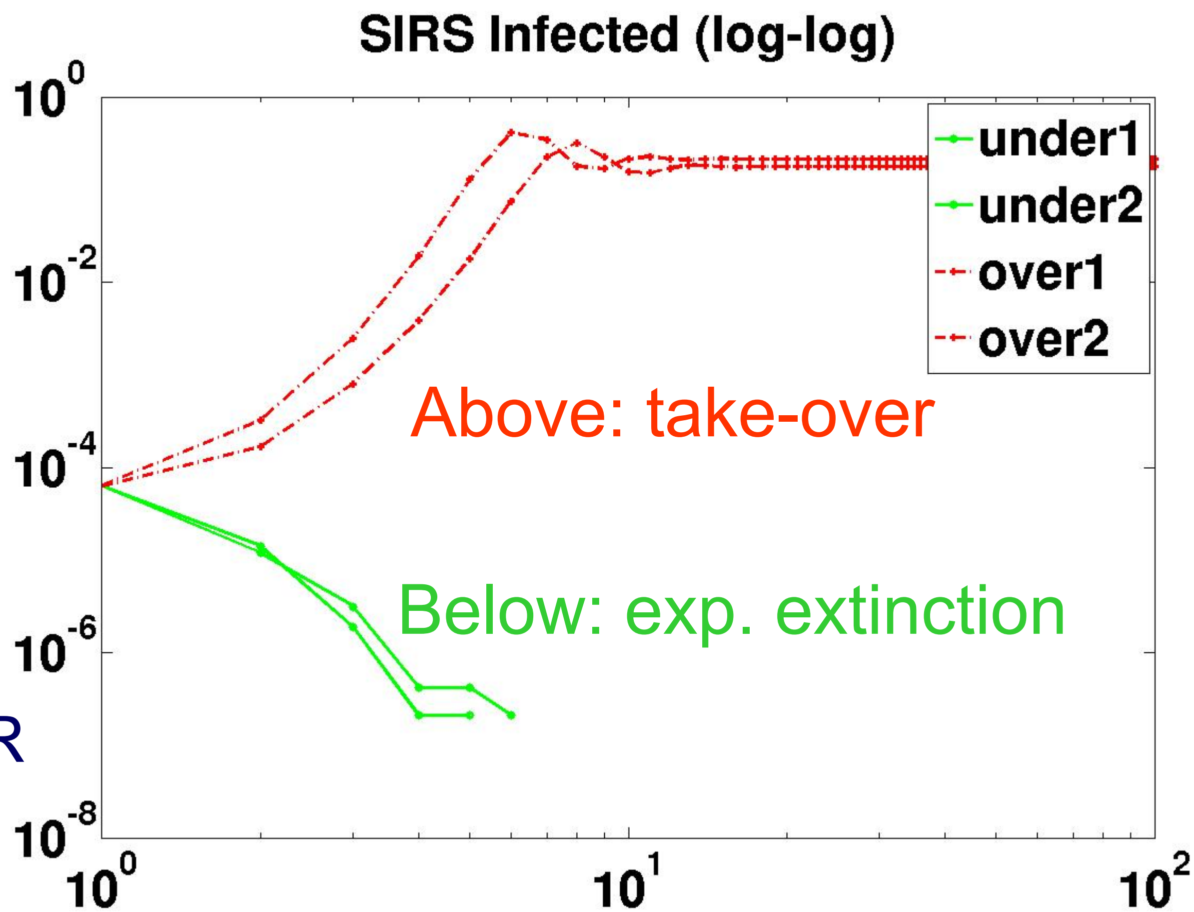
the first eigenvalue of the adj. matrix

[Prakash+, '10, arxiv]



A2: will a virus take over?

Fraction of infected



Time ticks

Graph:
Portland, OR
31M links
1.5M nodes

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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/

hadoop

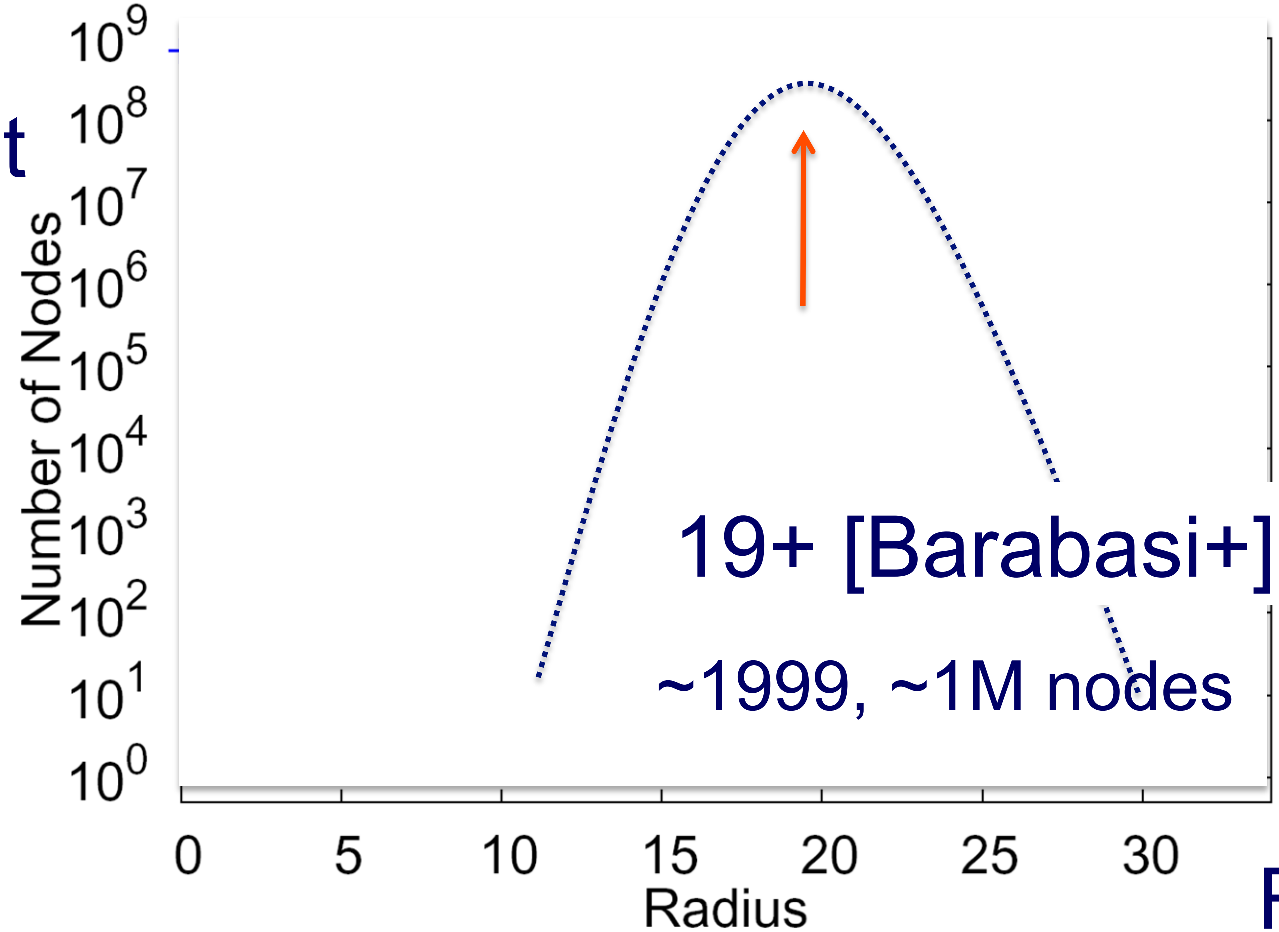
Outline – Algorithms & results

	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

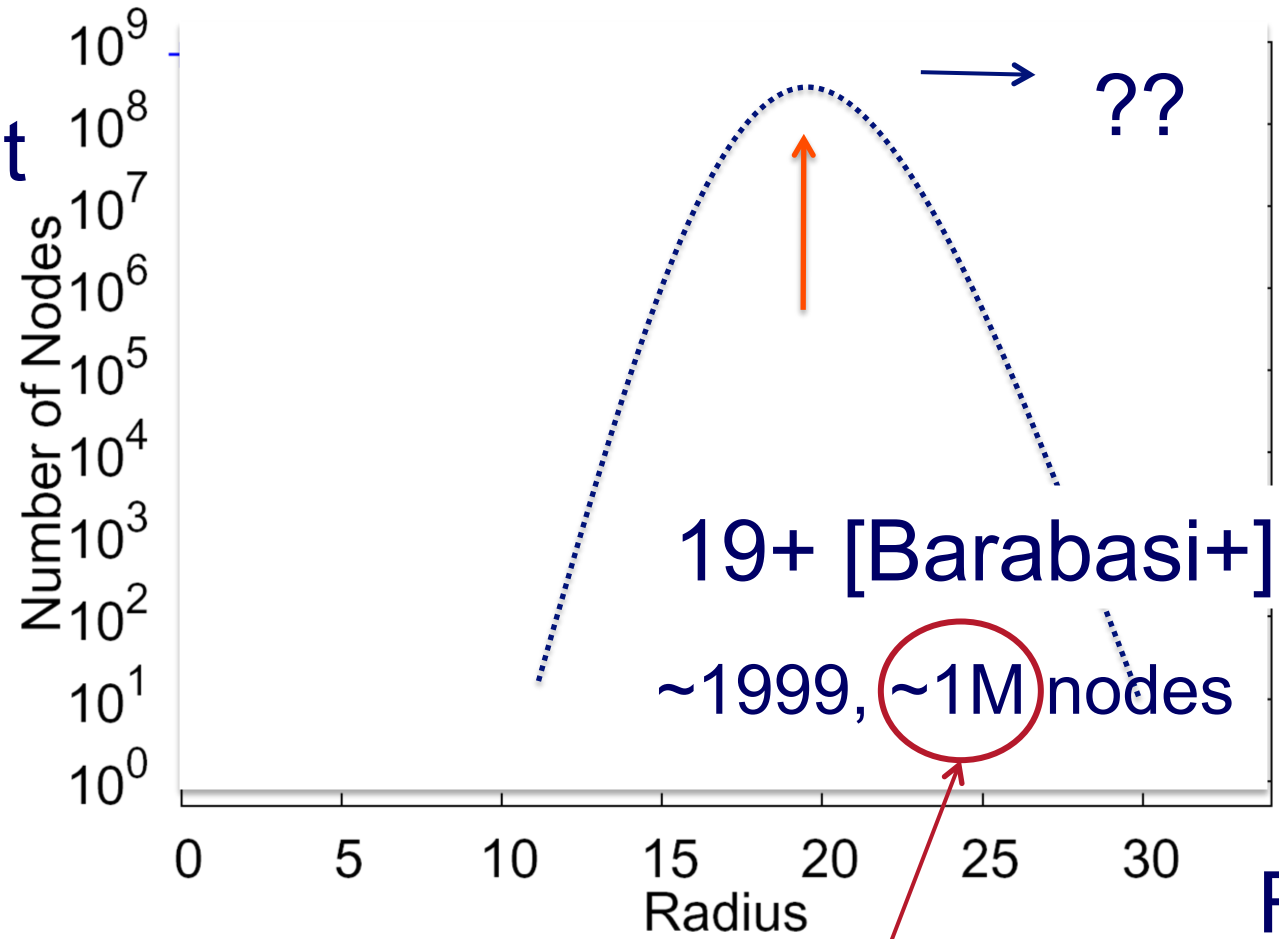


19+ [Barabasi+]

~1999, ~1M nodes

Radius

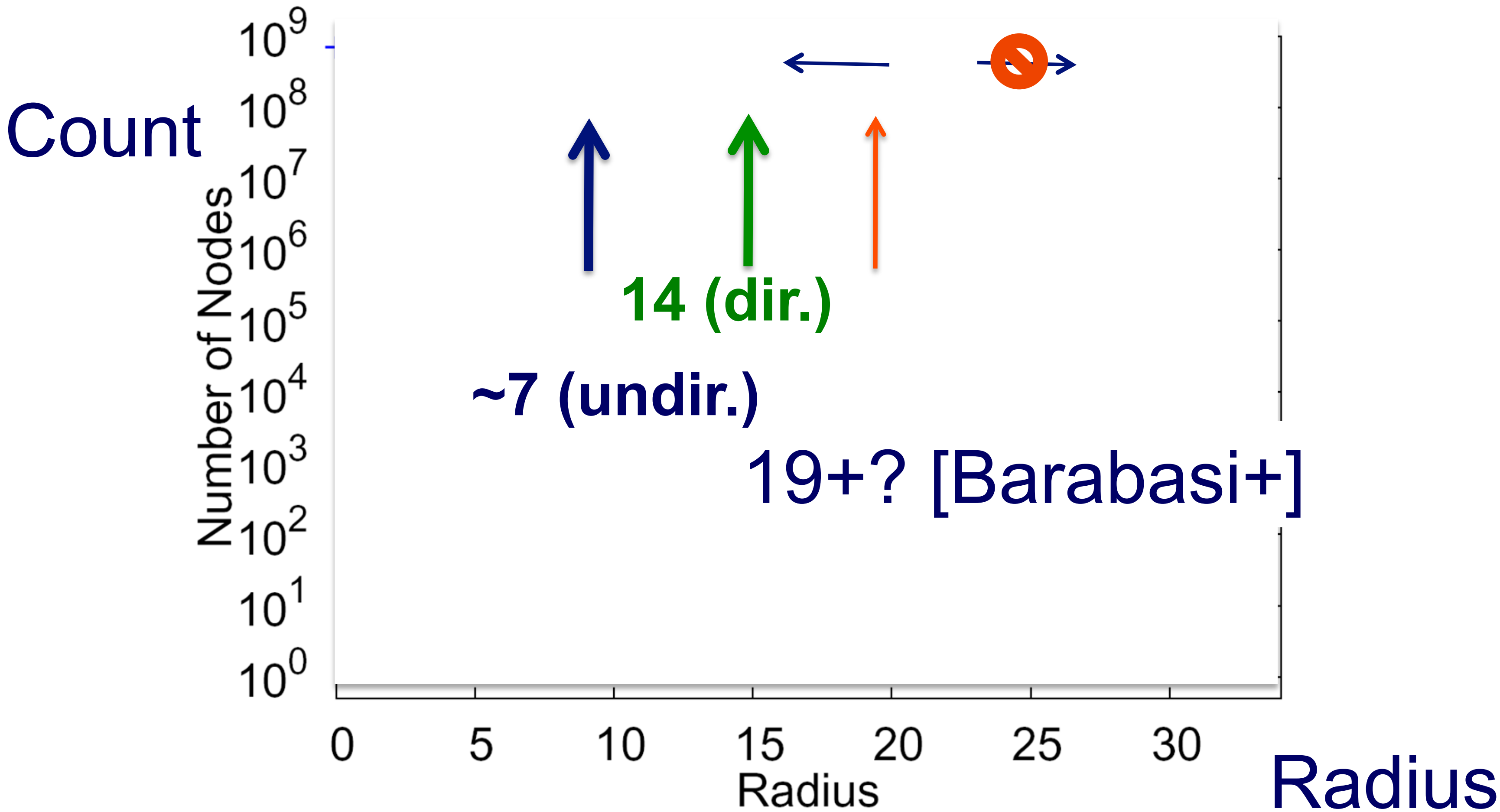
Count



Radius

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

- Largest publicly available graph ever studied.



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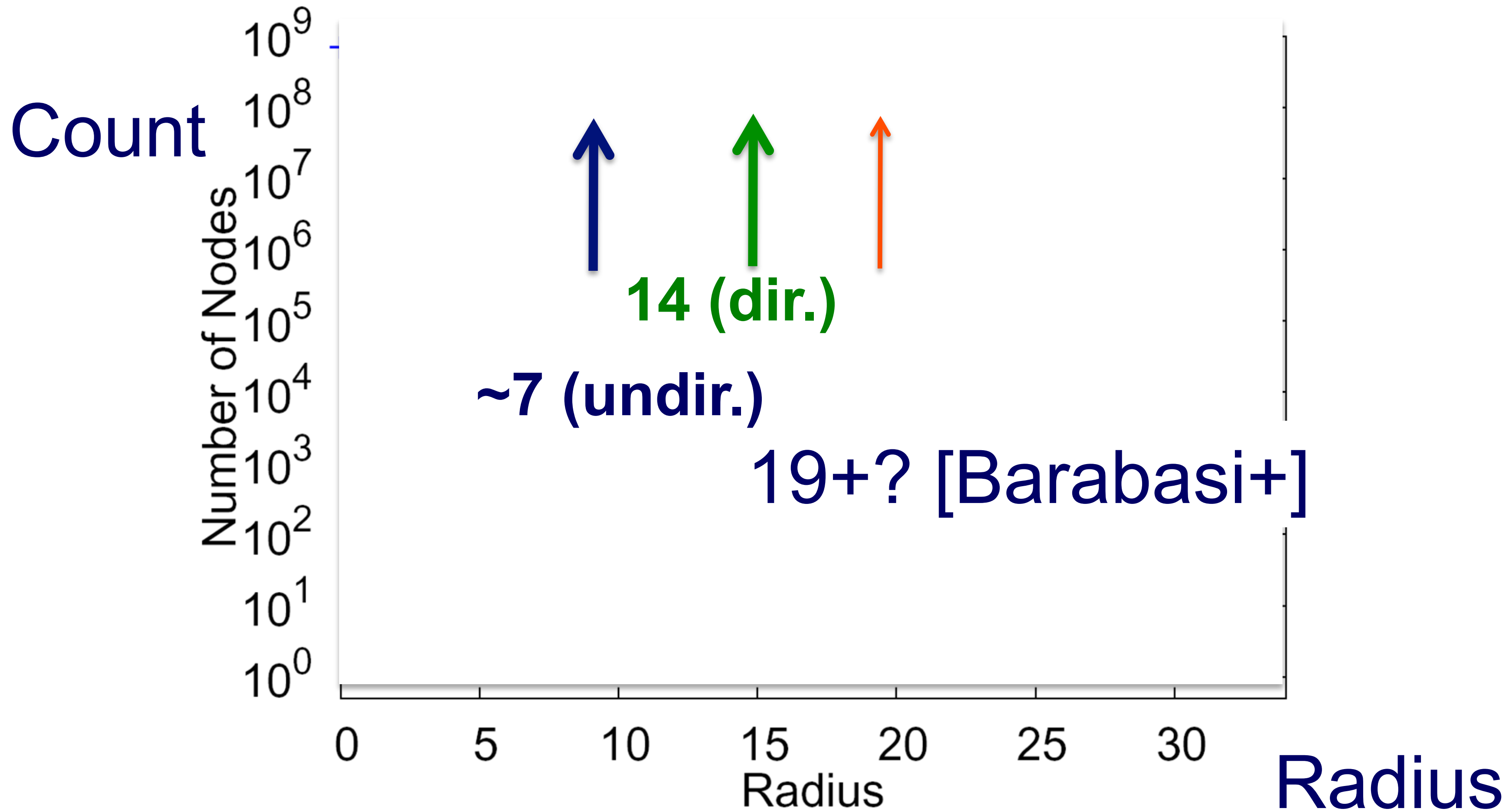
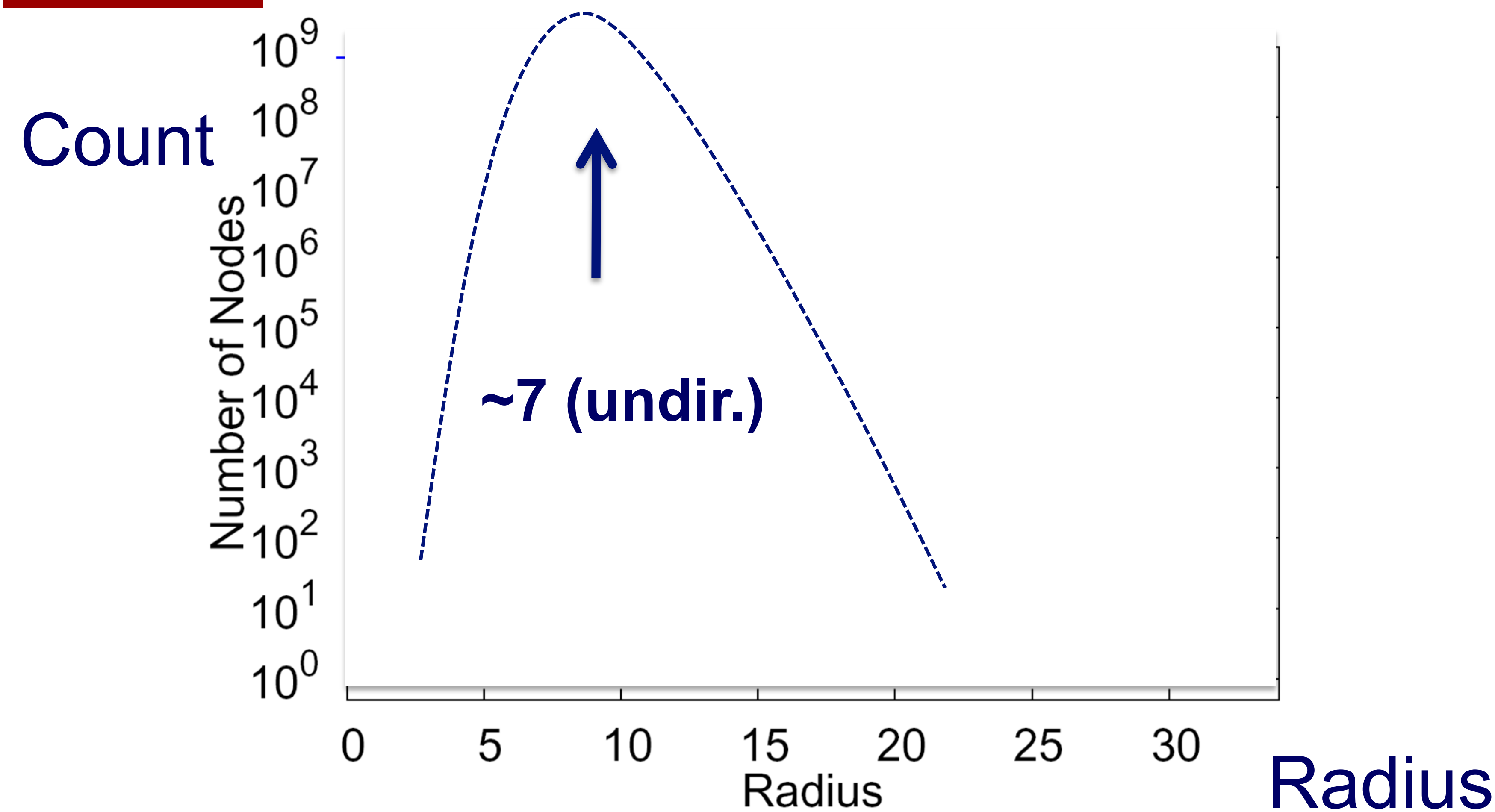
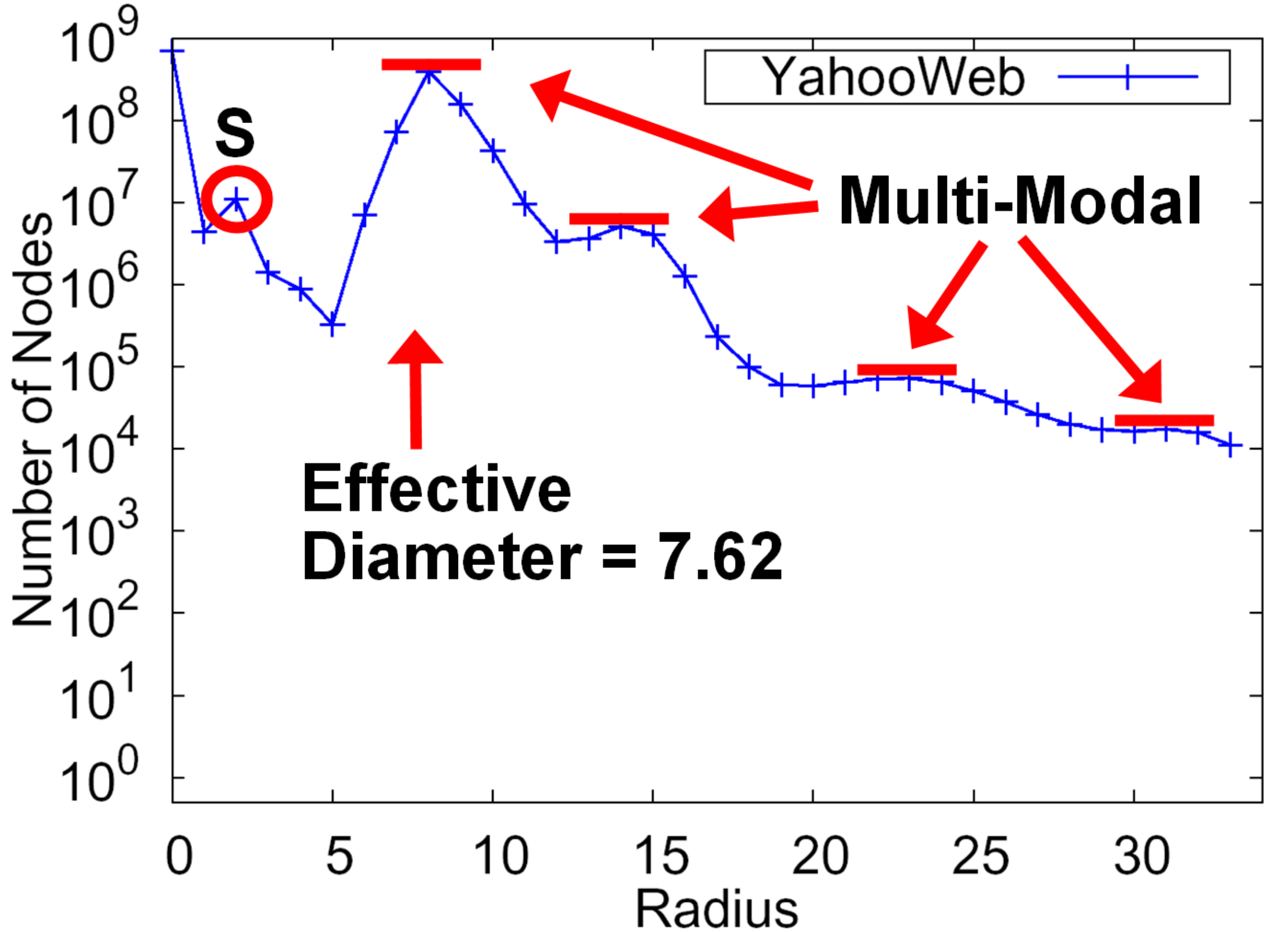


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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

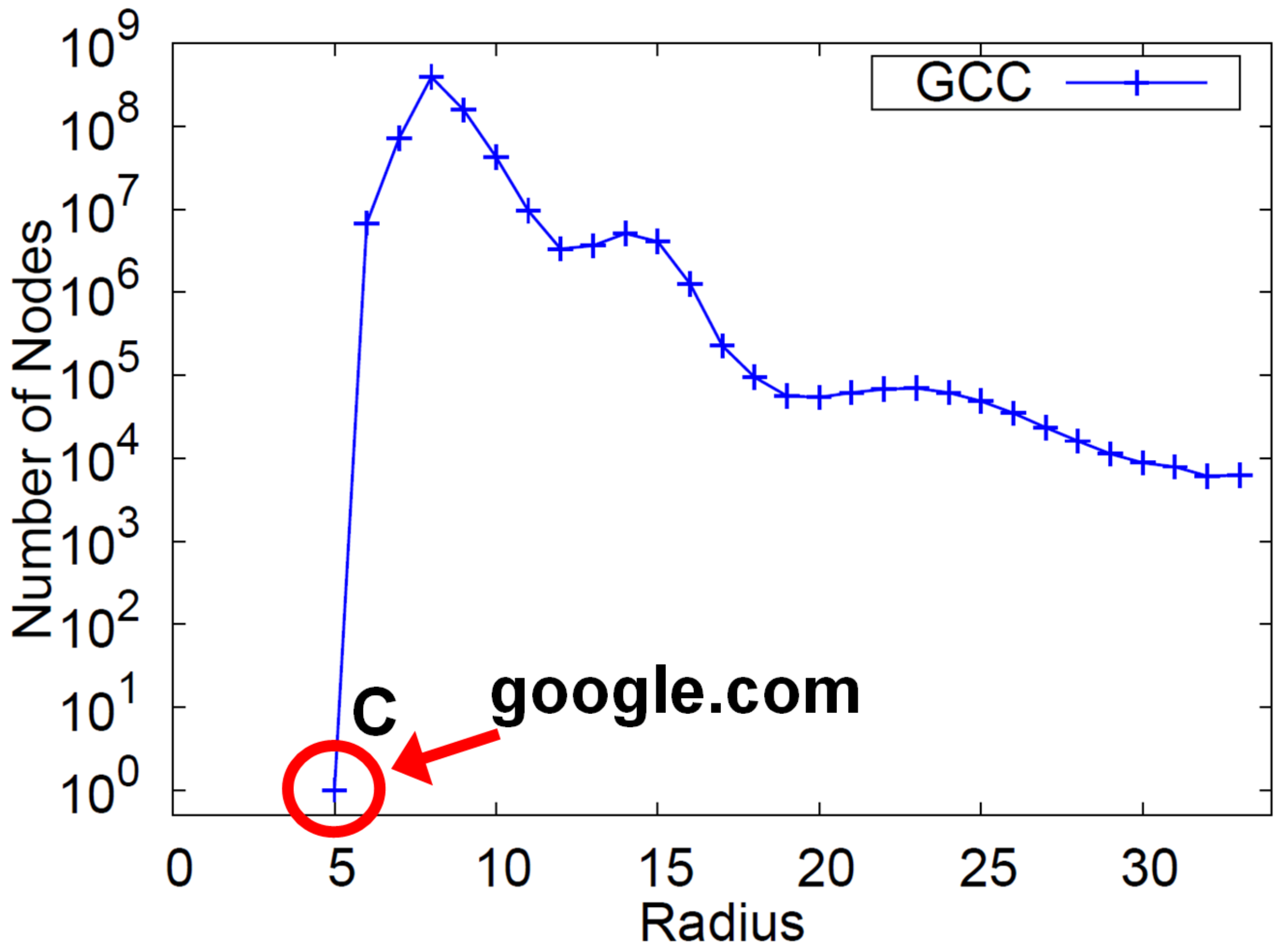


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)
Q: Shape?

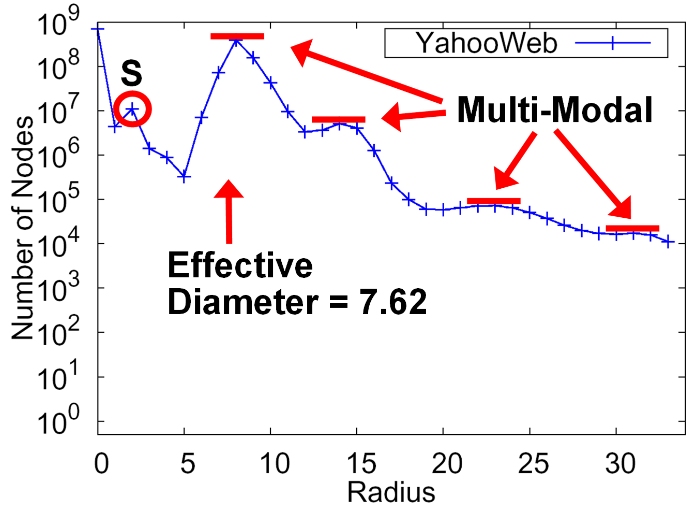


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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

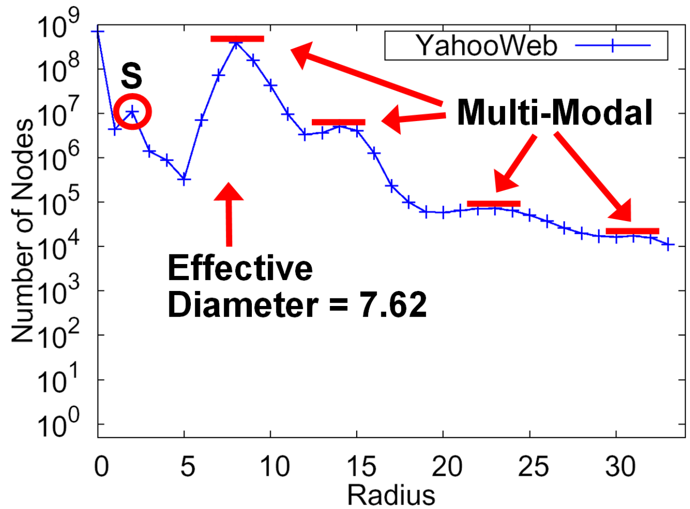


Radius Plot of **GCC** of YahooWeb.

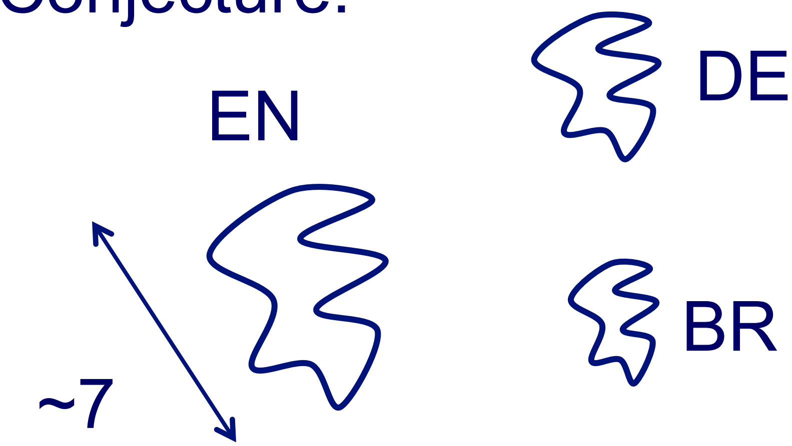


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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



Conjecture:



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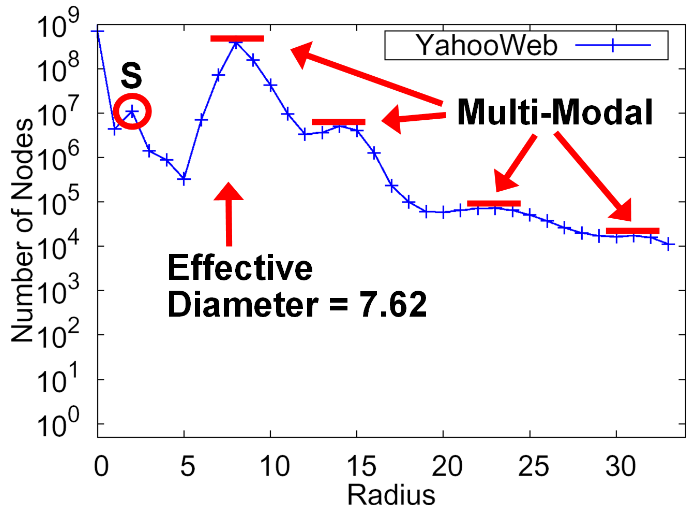

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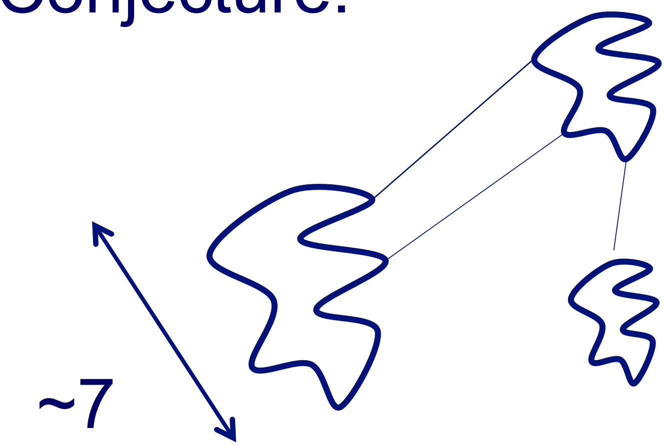

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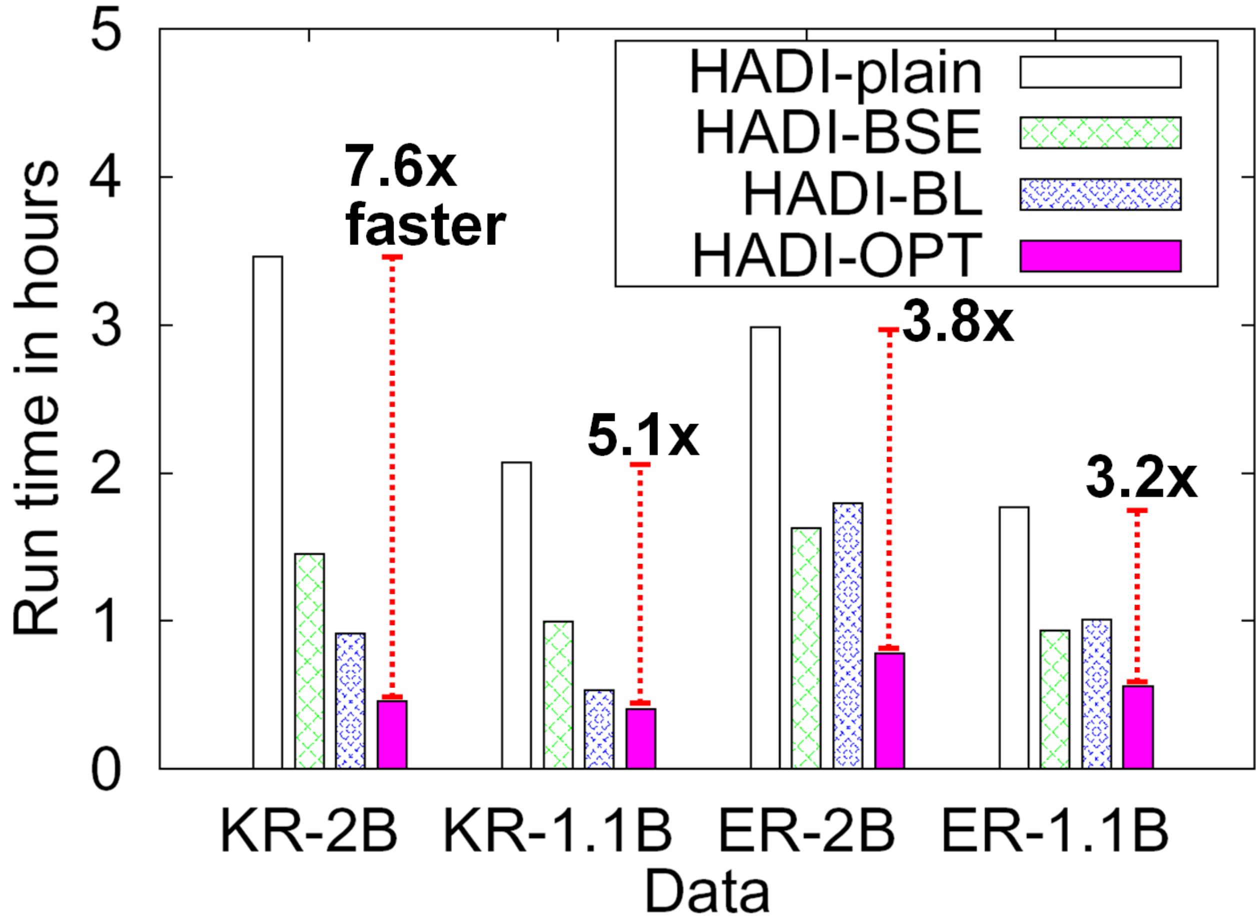
details



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

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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).

details

Generalized Iterated Matrix Vector Multiplication (GIMV)

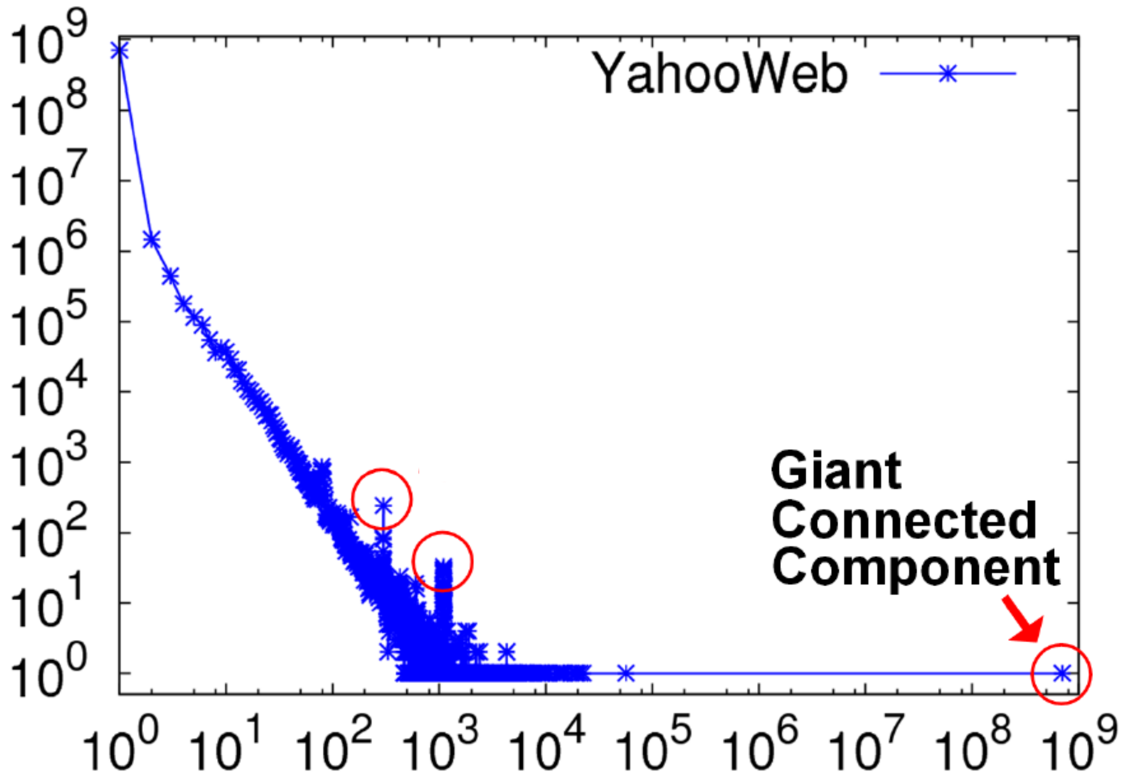
- PageRank
- proximity (RWR)
- Diameter
- Connected components
- (eigenvectors,
- Belief Prop.
- …)

Matrix – vector Multiplication (iterated)

Example: GIM-V At Work

- Connected Components – 4 observations:

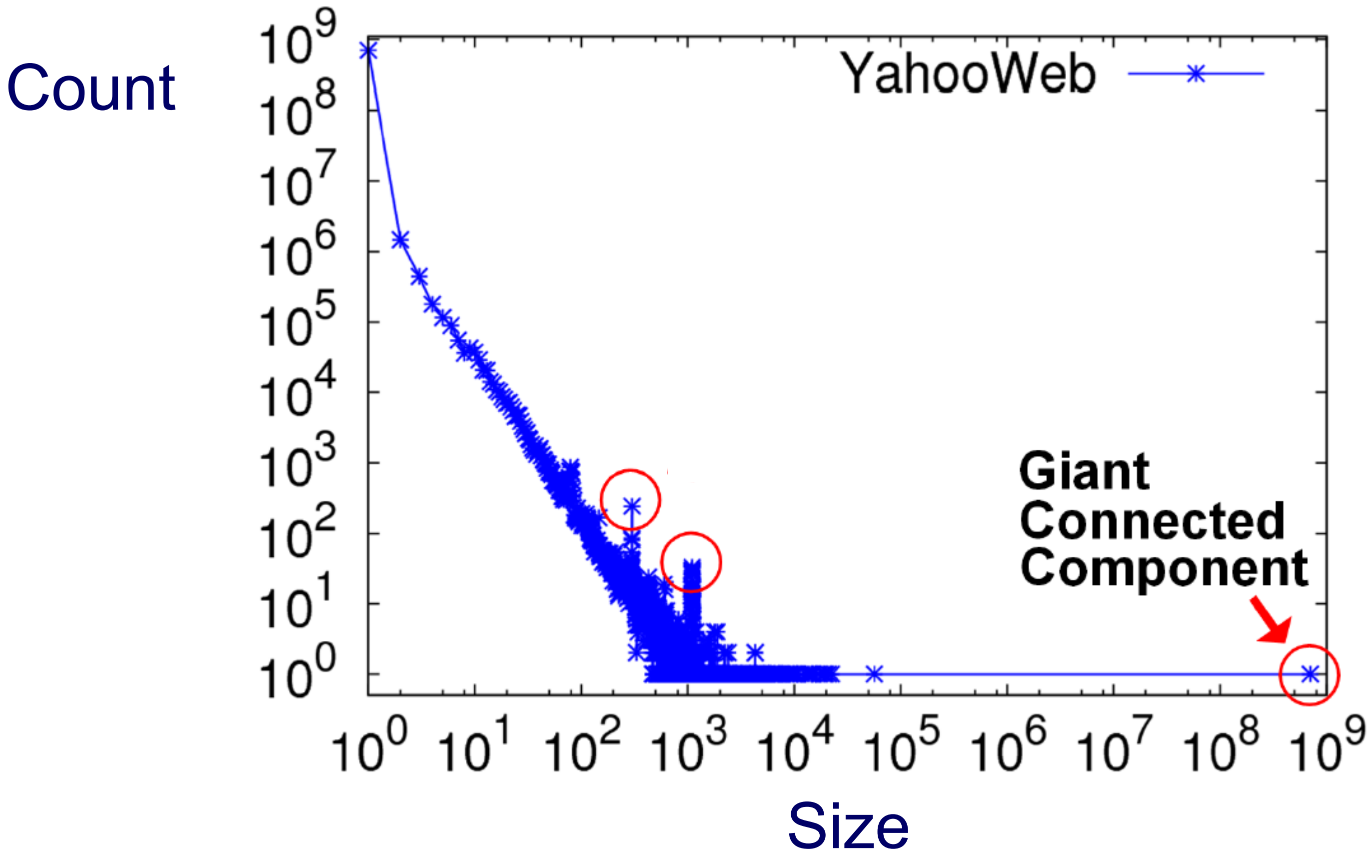
Count



Size

Example: GIM-V At Work

- Connected Components



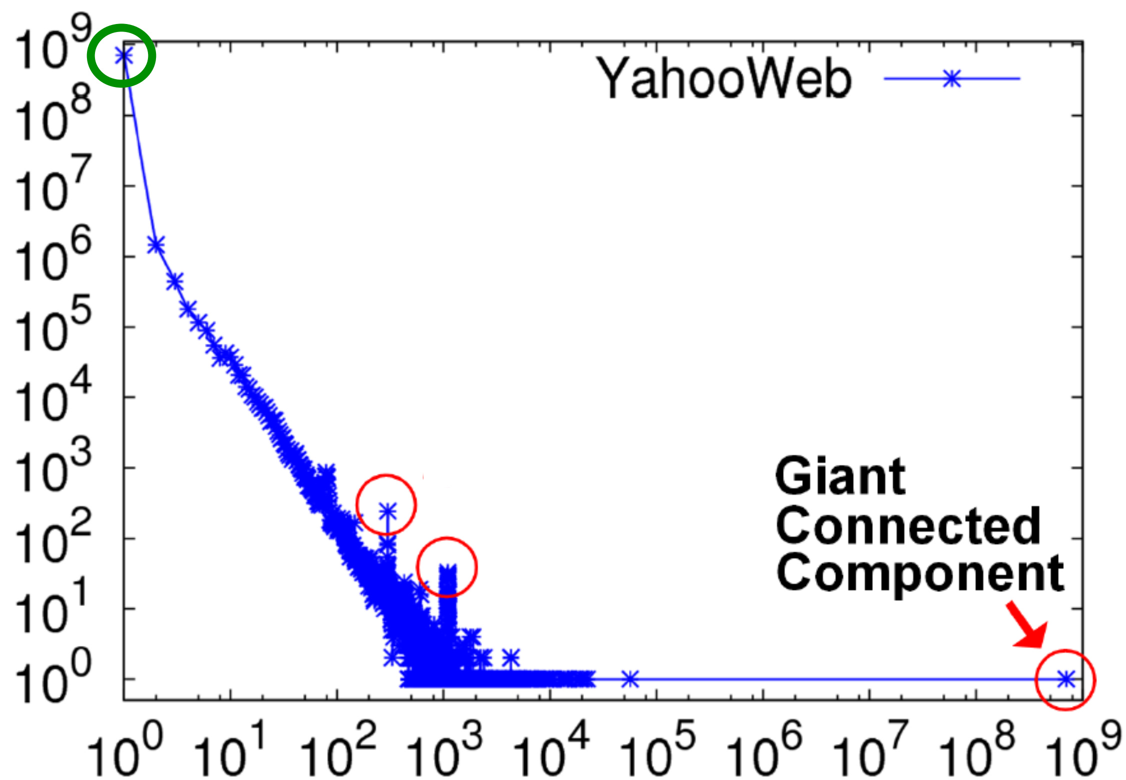
1) 10K x larger than next

Example: GIM-V At Work

- Connected Components

Count

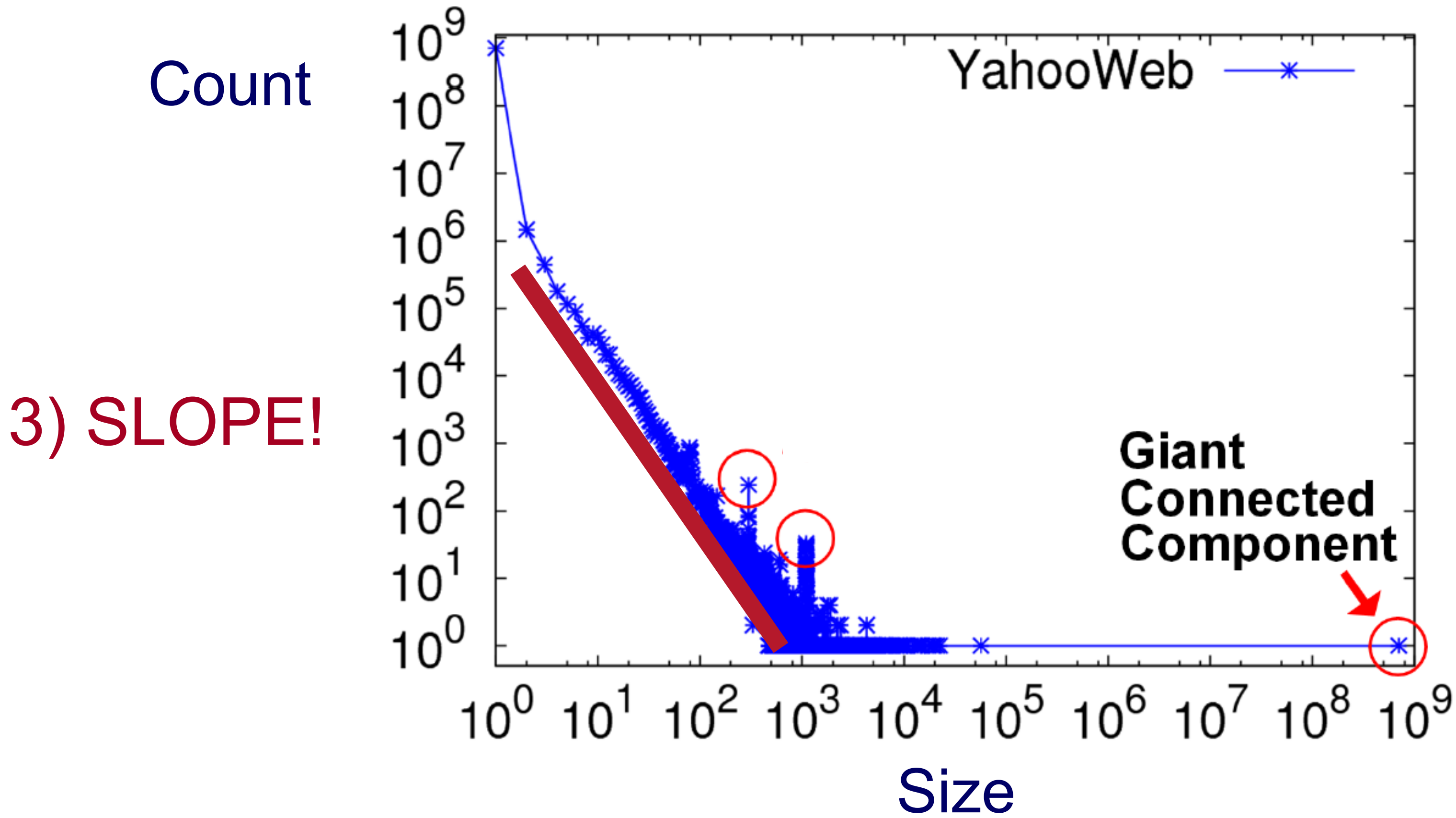
2) ~0.7B singleton nodes



Size

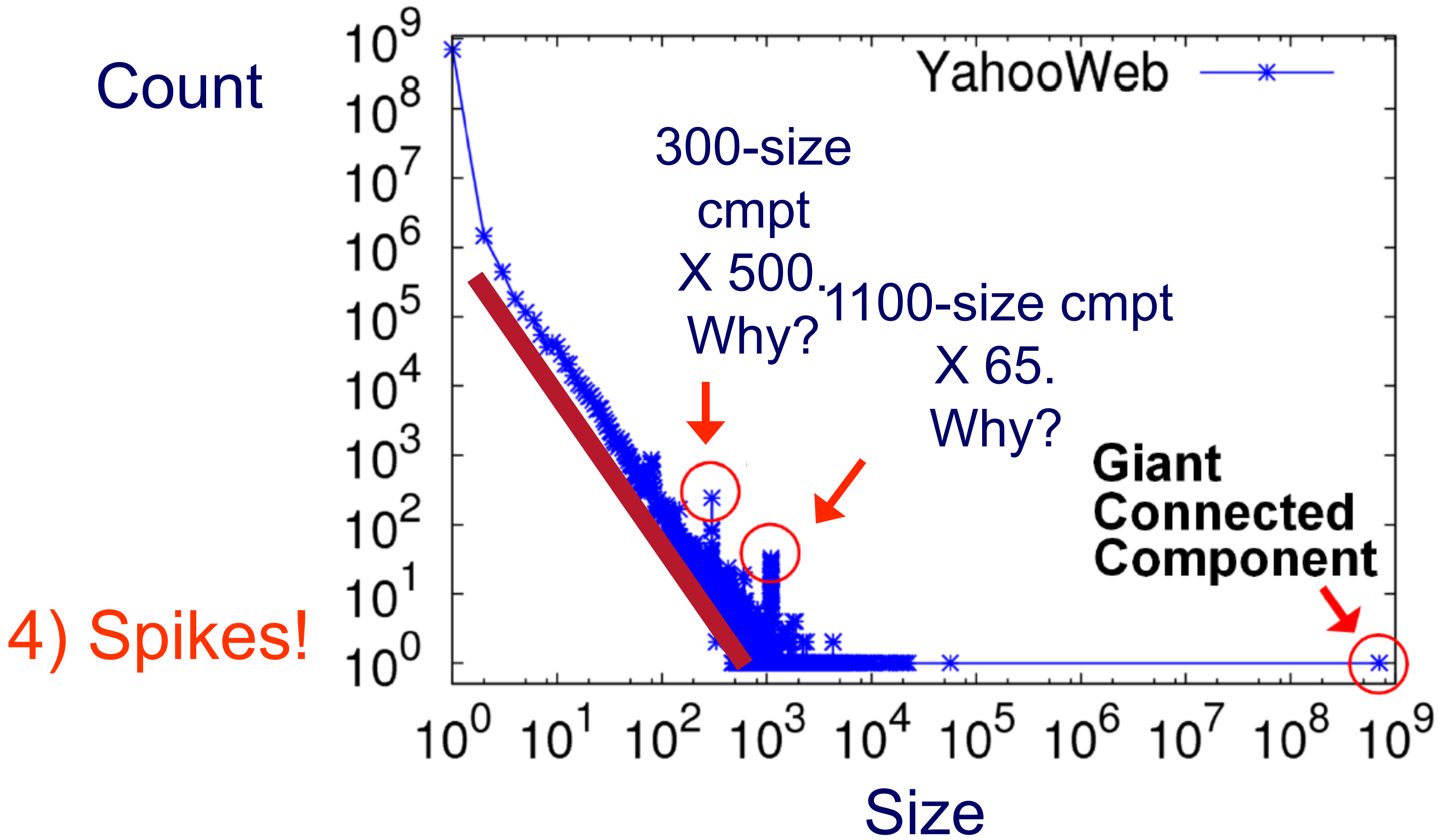
Example: GIM-V At Work

- Connected Components



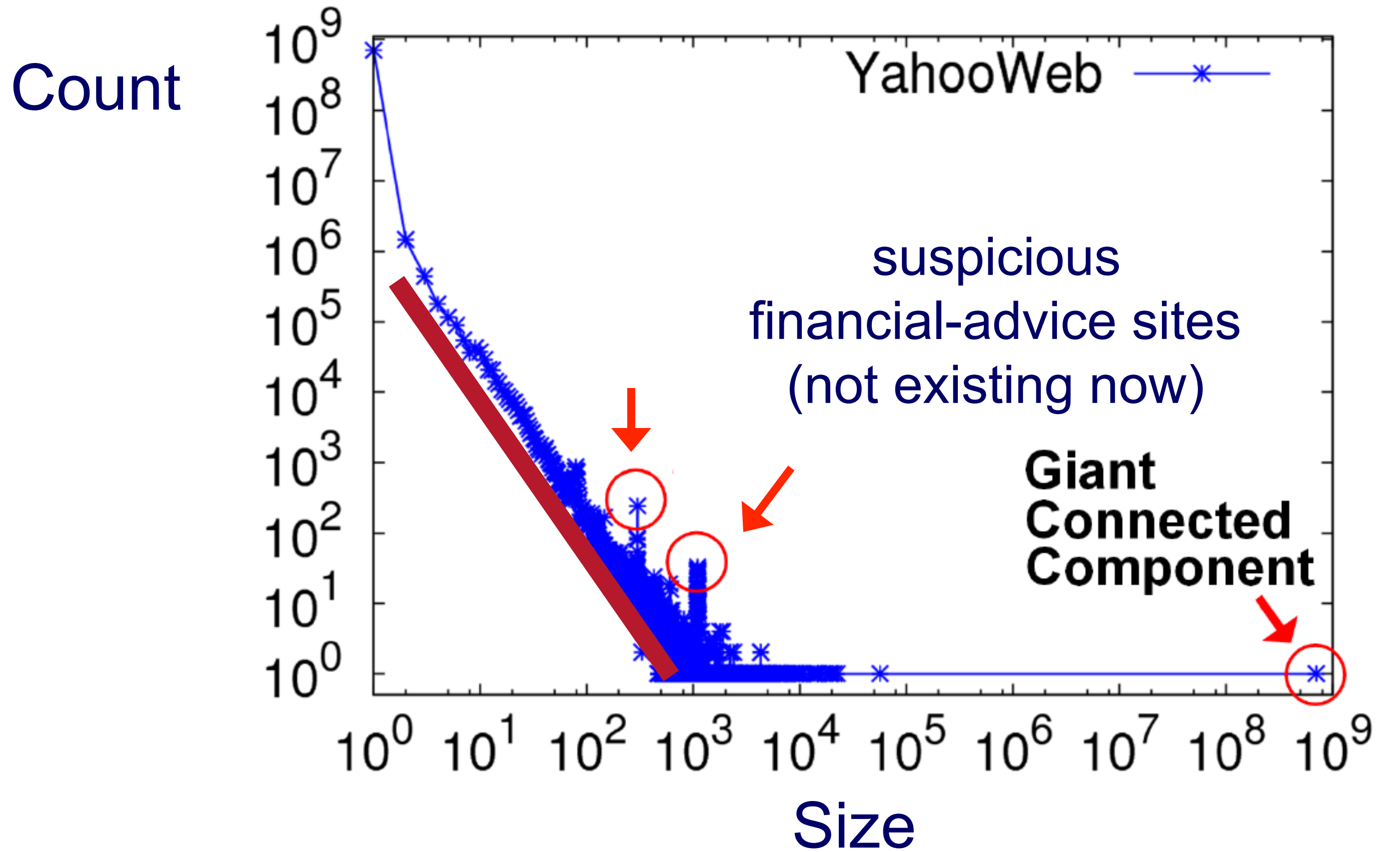
Example: GIM-V At Work

- Connected Components



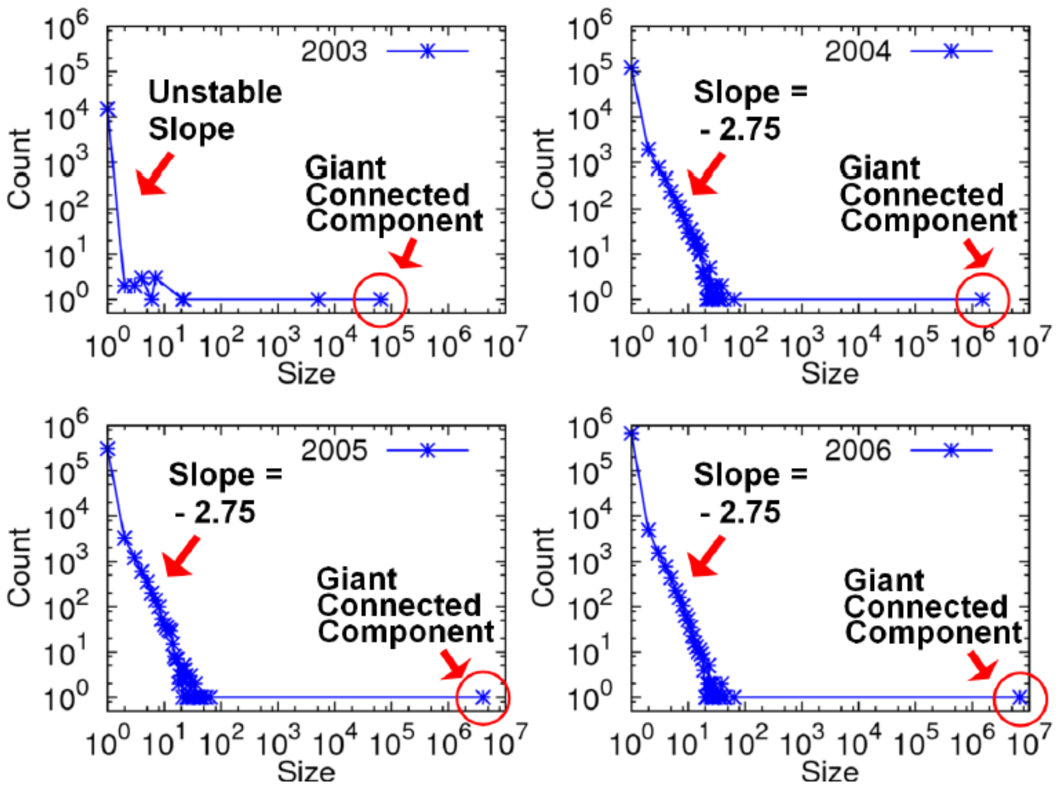
Example: GIM-V At Work

- Connected Components



GIM-V At Work

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



Stable tail slope
after the gelling point

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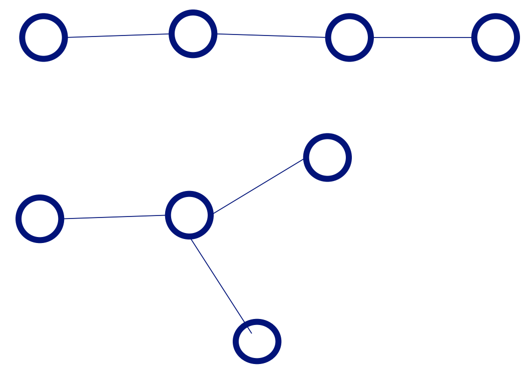
What do NLCC's look like?

- Chains?
- Stars?
- General trees?
- Cliques?
- Miniature versions of the GCC?
- Something else?

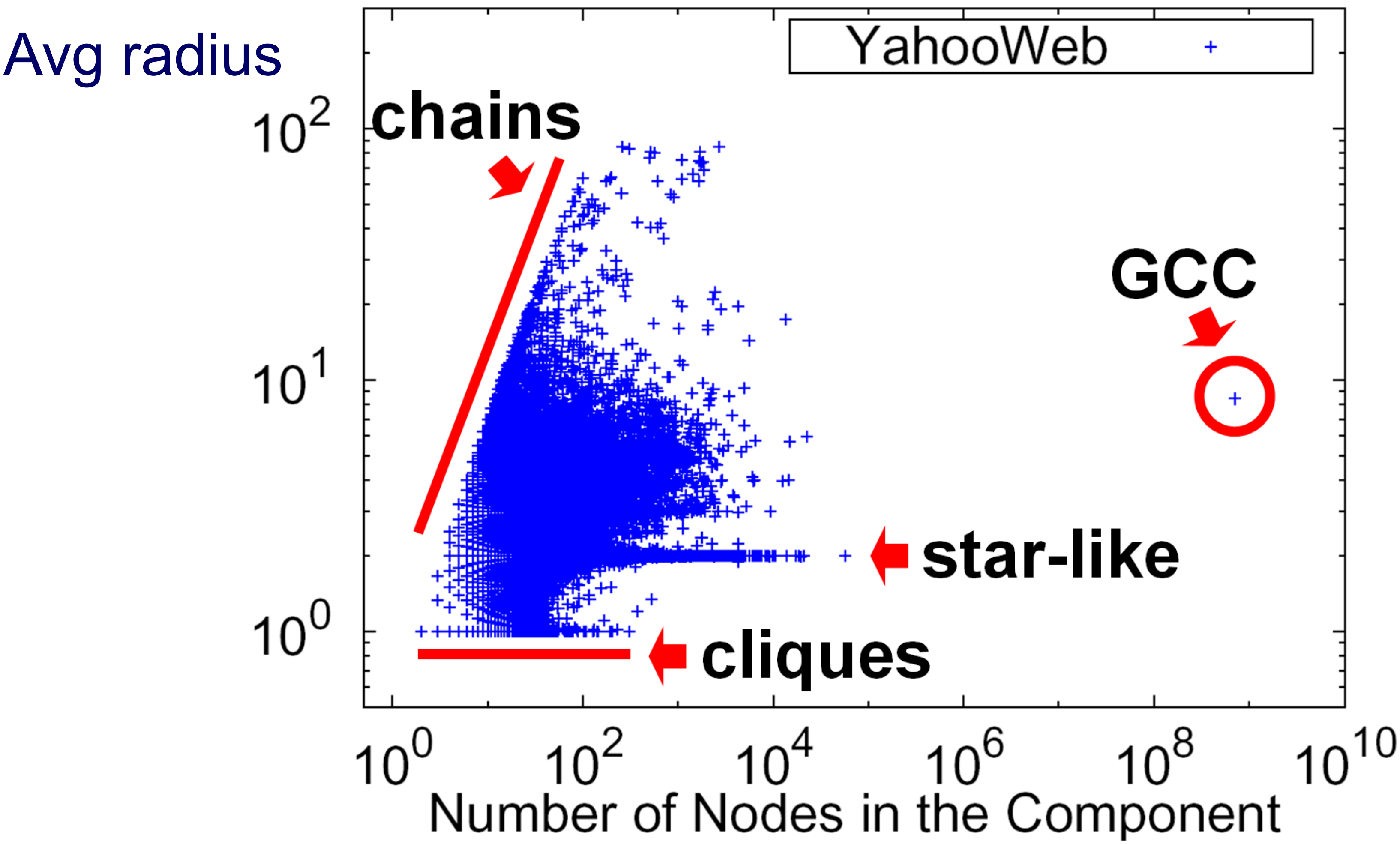


Answer:

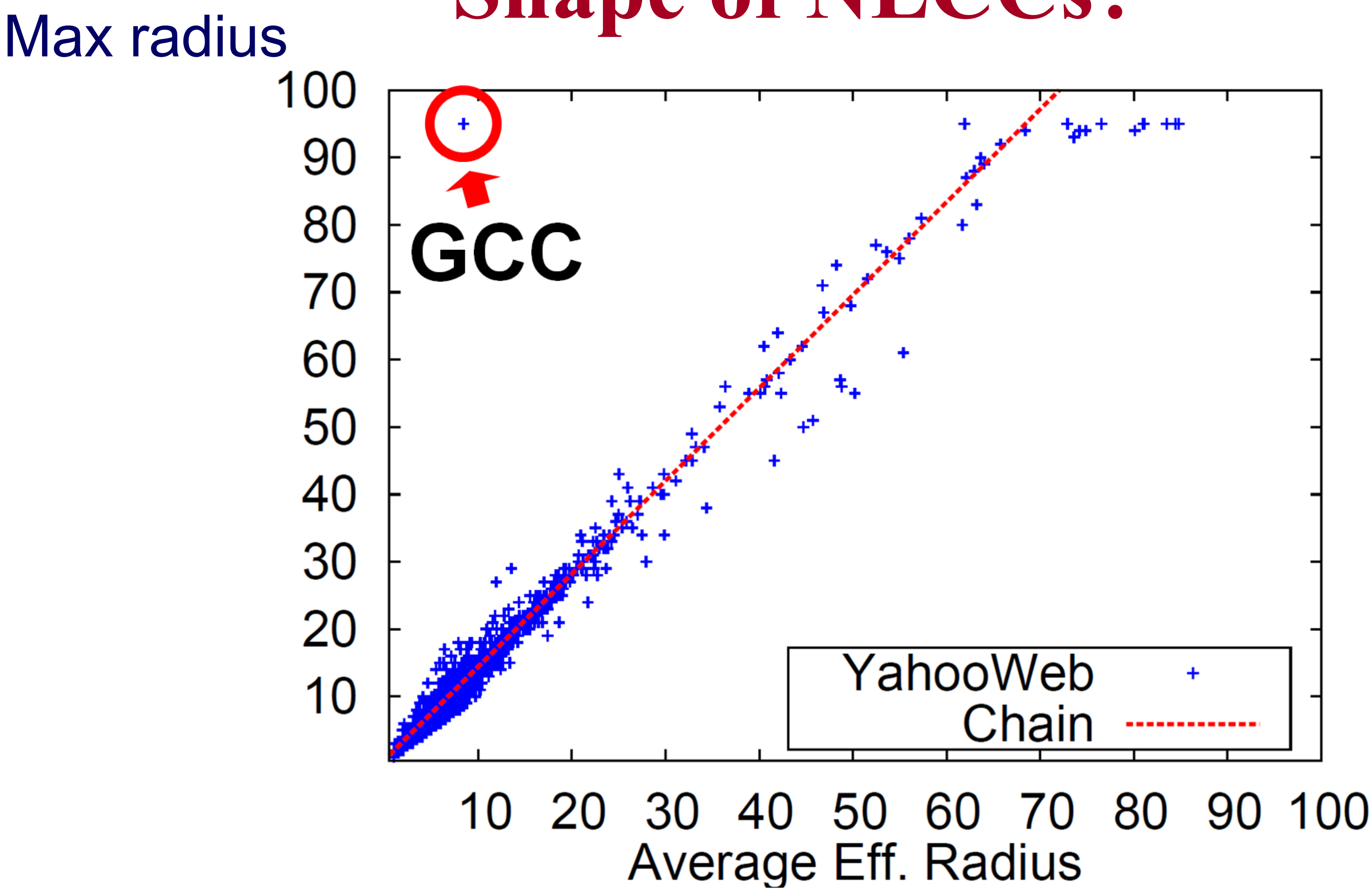
- A mixture
- Mostly, chain-like (but a bit ‘thicker’)

- *Patterns on the Connected Components of Terabyte-Scale Graphs*. U Kang, Mary McGlohon, Leman Akoglu, and Christos Faloutsos. ICDM 2010, Sydney, Australia.

Shape of NLCCs?

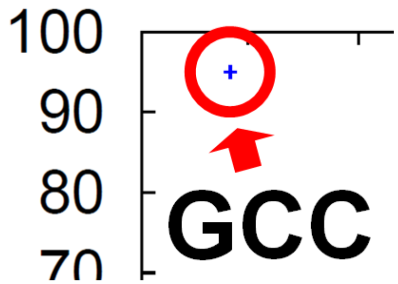


Shape of NLCCs?



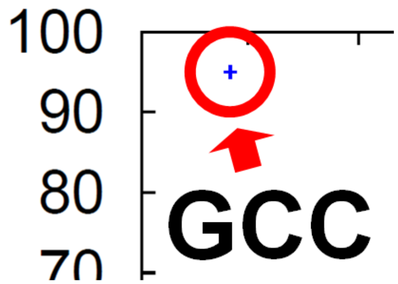
Shape of NLCCs?

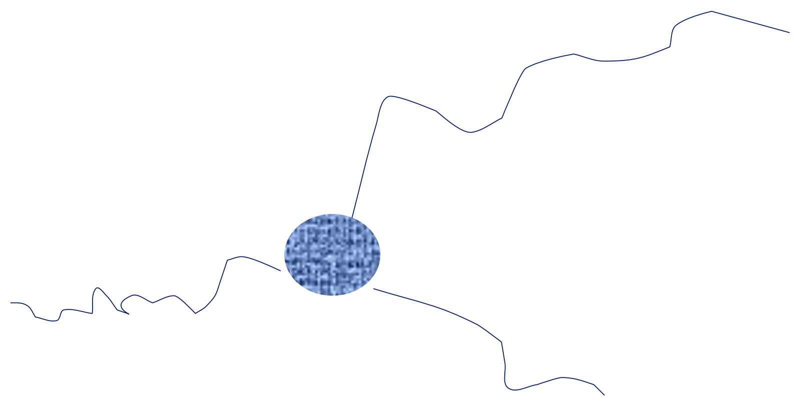
Max radius



Shape of NLCCs?

Max radius





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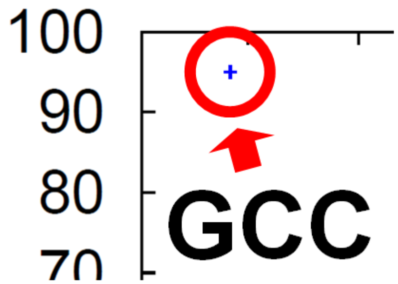

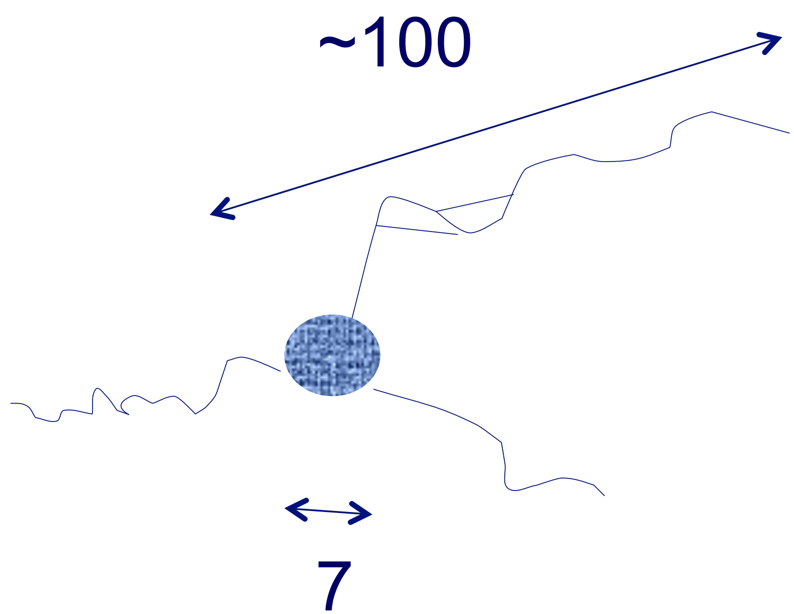

Outline

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

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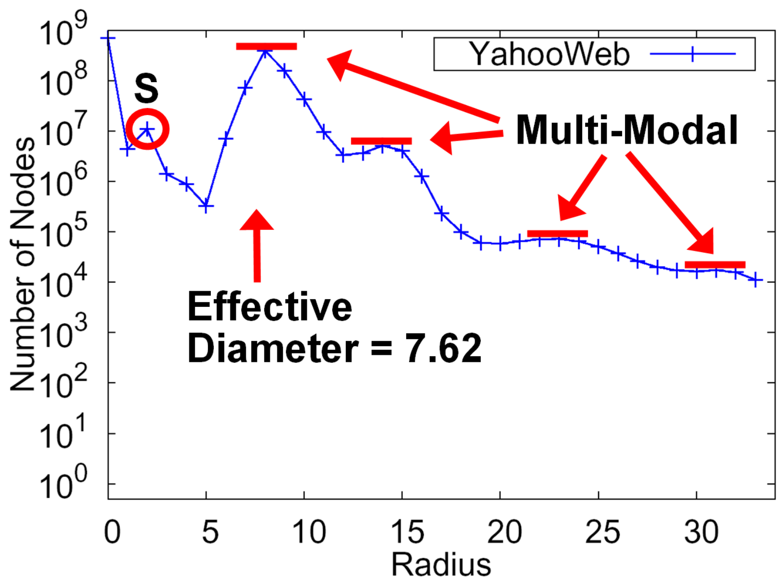
OVERALL CONCLUSIONS – low level:

- 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



(Topics not mentioned here)

- Anomalies; fraud detection
- Immunization; epidemic thresholds

- Generators (Rmat/Kronecker, ‘random typing’; agent-based)
- Time-evolving graphs (tensors, wavelets)
- Community detection (MDL)

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Project info

www.cs.cmu.edu/~pegasus

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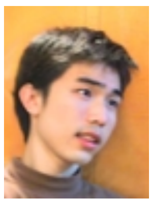
Prakash, Aditya

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