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Mining Billion-node Graphs: Patterns, Generators and Tools

Christos Faloutsos

CMU

THANK YOU!

- Prof. Lee Giles
- Louise Troxell

Our goal:

Open source system for mining huge graphs:

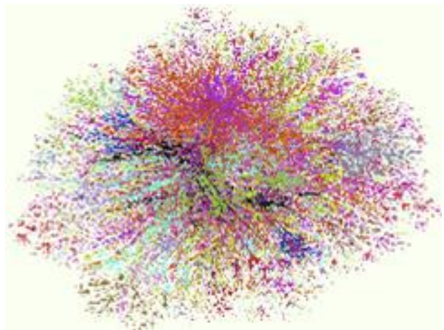
PEGASUS project (PEta GrAph mining System)

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

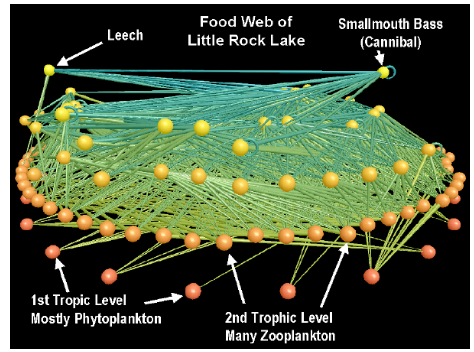
Outline

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

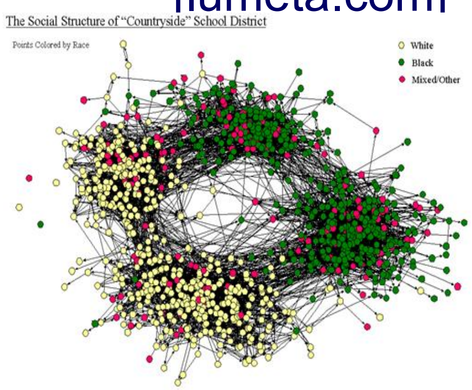
Graphs - why should we care?



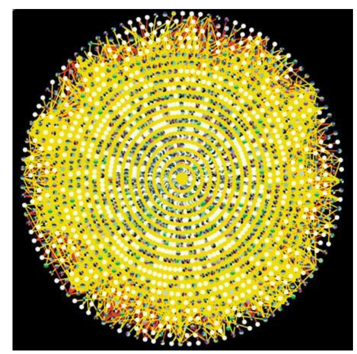
Internet Map
[lumeta.com]



Food Web
[Martinez '91]



Friendship Network
[Moody '01]



Protein Interactions
[genomebiology.com]

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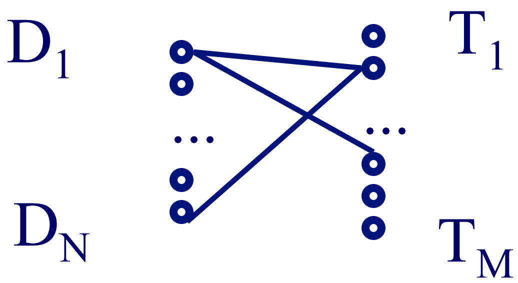
Graphs - why should we care?

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



- Citeseer: doc/authors/terms/…

- web: hyper-text graph

- ... and more:

Graphs - why should we care?

- network of companies & board-of-directors members
- ‘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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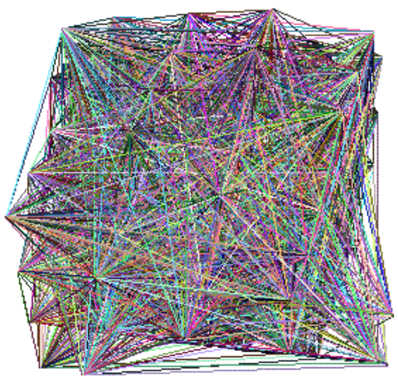
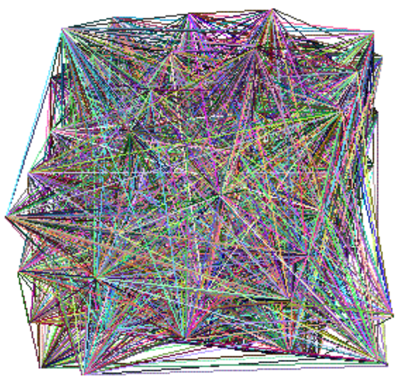
Problem #1 - network and graph mining



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

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

Problem #1 - network and graph mining



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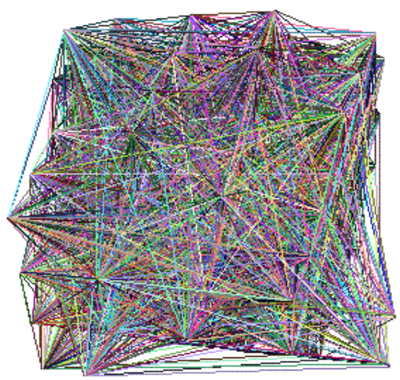
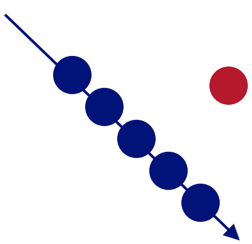
  - To spot **anomalies** (rarities), we have to discover **patterns**

Problem #1 - network and graph mining



- How does the Internet look like?
- How 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?

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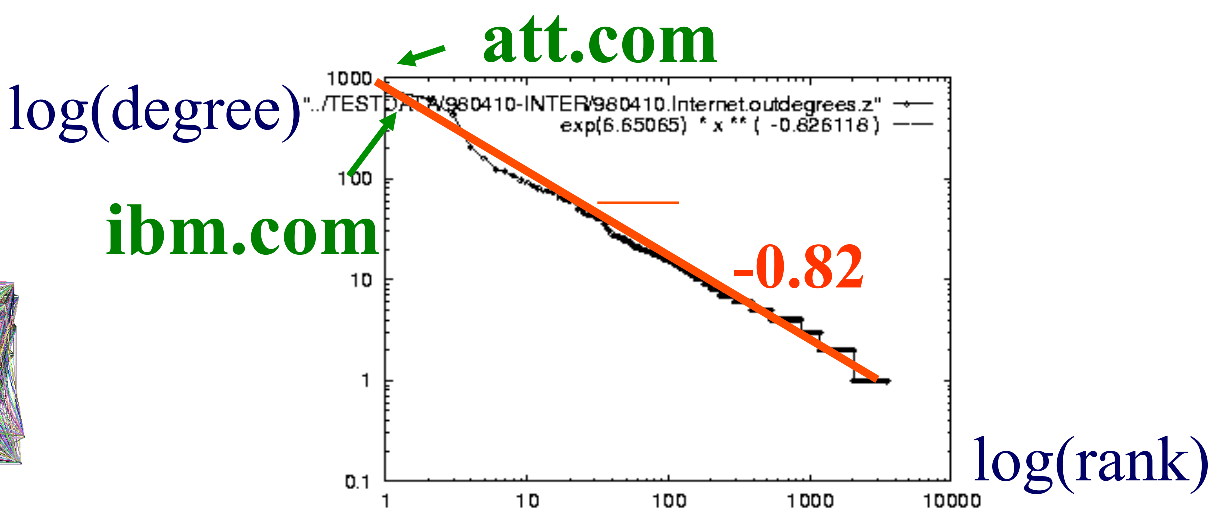
Laws and patterns

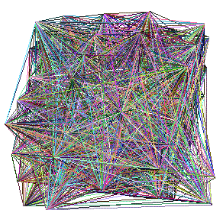
- Are real graphs random?
- A: NO!!
  - Diameter
  - in- and out- degree distributions
  - other (surprising) patterns
- So, let’s look at the data

Solution# S.1

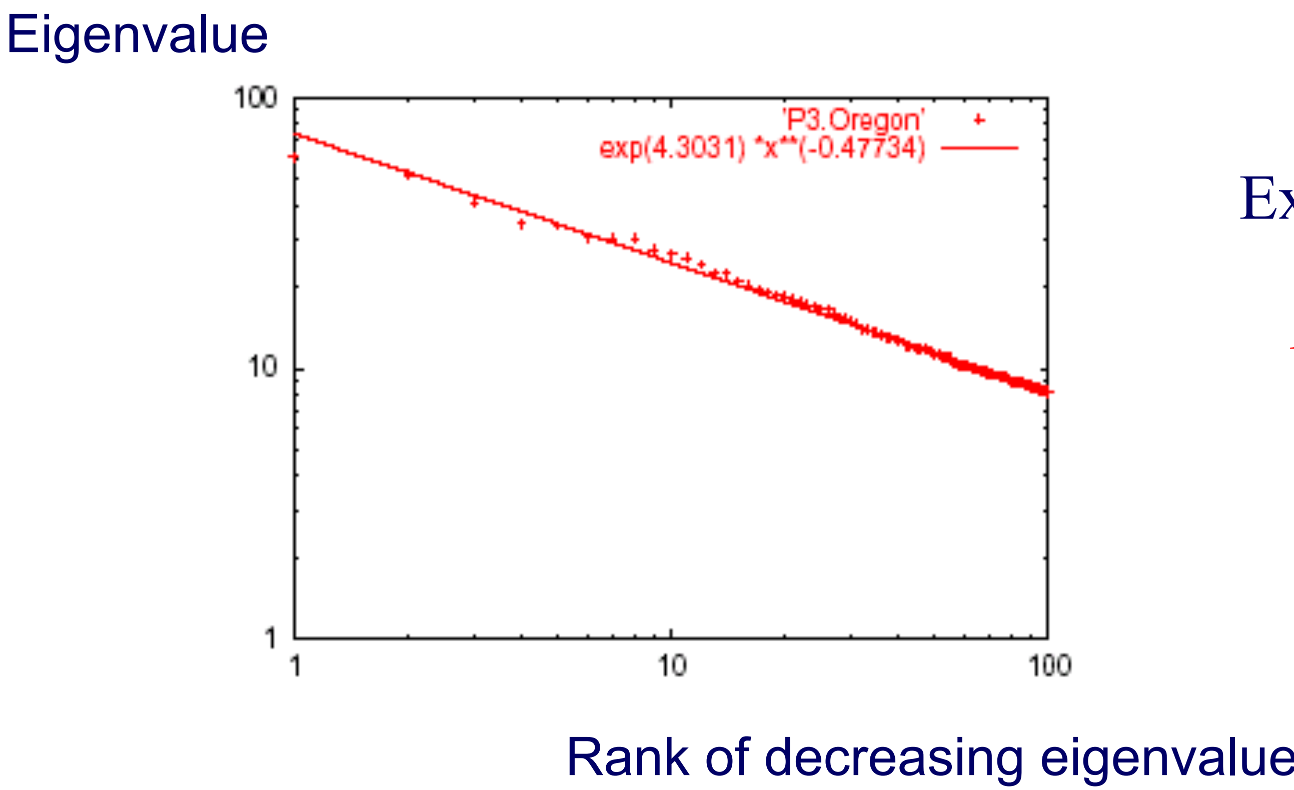
- Power law in the degree distribution [SIGCOMM99]

internet domains





Solution# S.2: Eigen Exponent *E*



Exponent = slope

E = -0.48

May 2001

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

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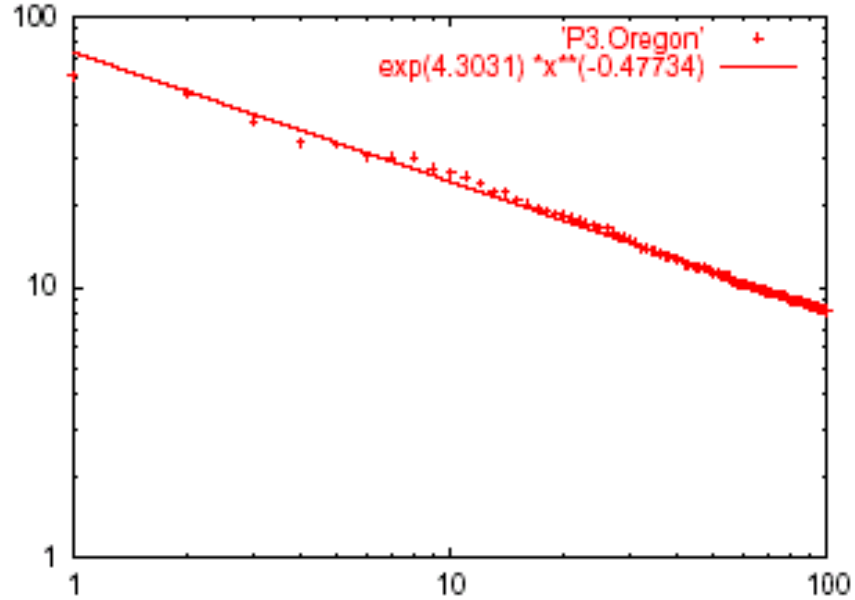
Solution# S.2: Eigen Exponent *E*

Eigenvalue



Exponent = slope

E = -0.48

May 2001

Rank of decreasing eigenvalue

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

But:

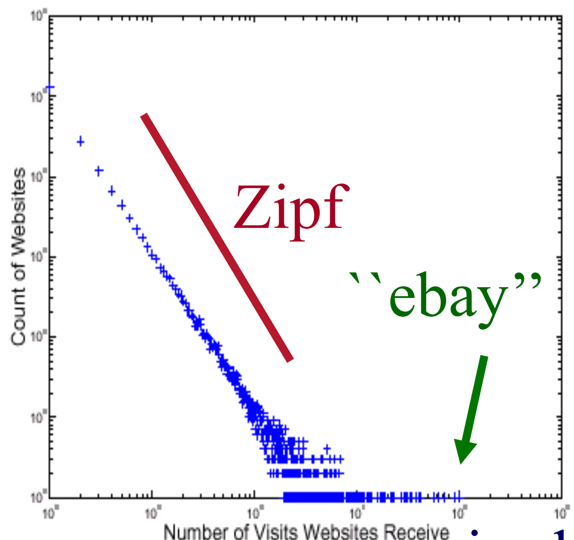
How about graphs from other domains?

More power laws:

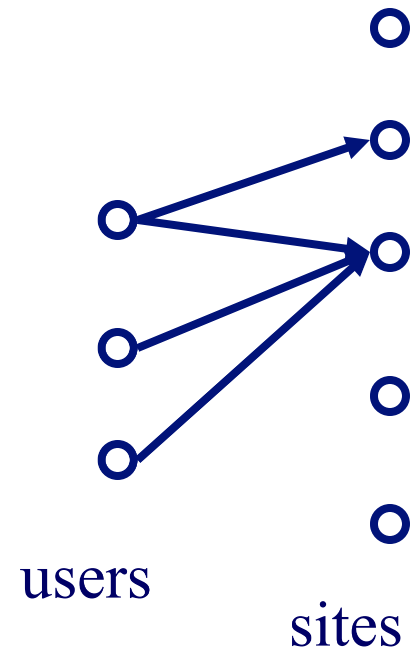
- web hit counts [w/ A. Montgomery]

Web Site Traffic

Count
(log scale)



in-degree (log scale)



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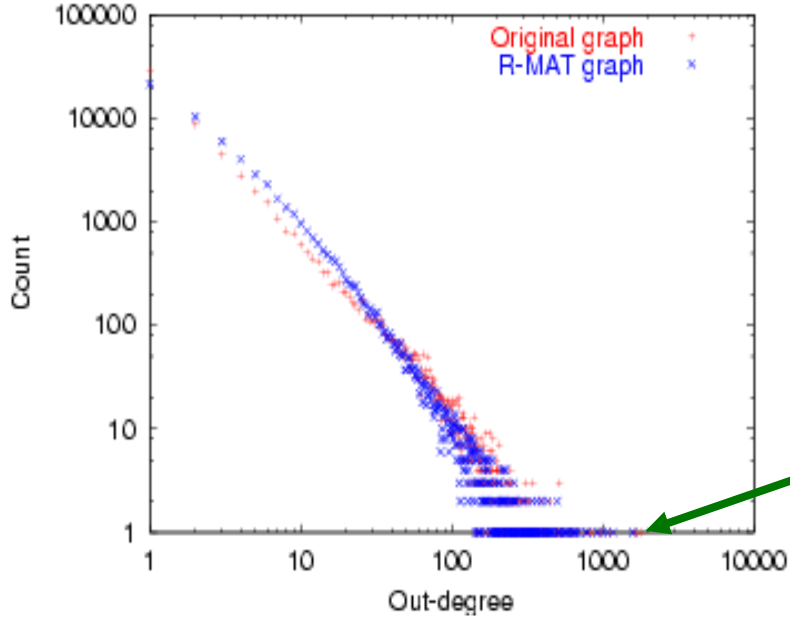
epinions.com

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

count



trusts-2000-people user

(out) degree

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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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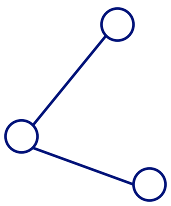
Solution# S.3: Triangle ‘Laws’



- Real social networks have a lot of triangles

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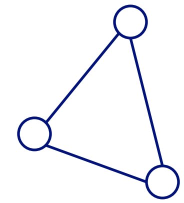
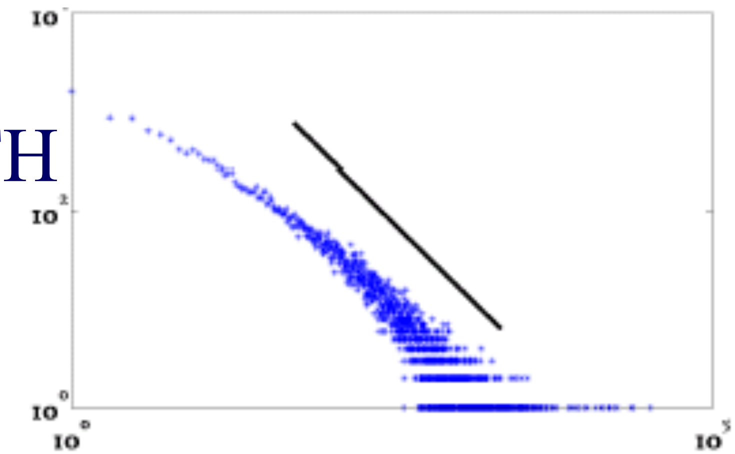
Solution# S.3: Triangle 'Laws'



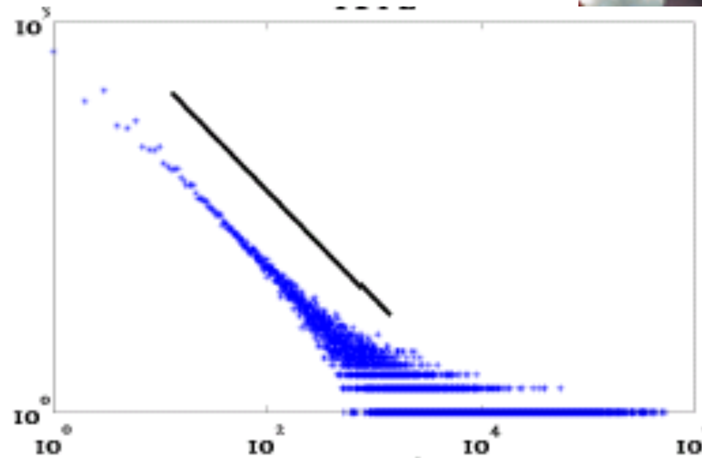
- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?

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

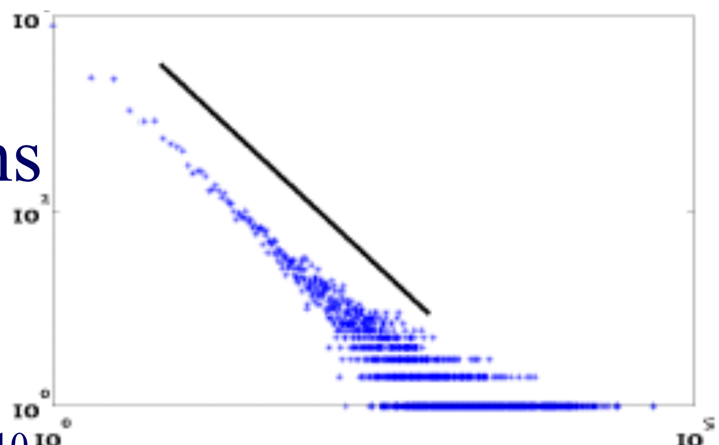
HEP-TH



ASN

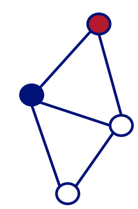


Epinions



X-axis: # of participating triangles

Y-axis: count



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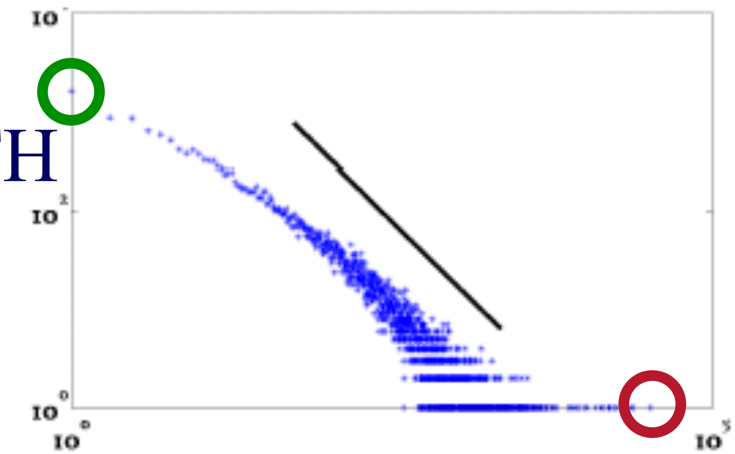
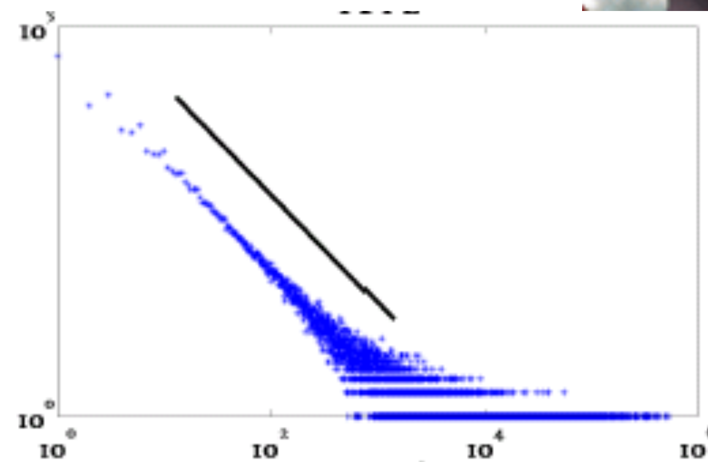
Triangle Law: #S.3
[Tsourakakis ICDM 2008]

HEP-TH





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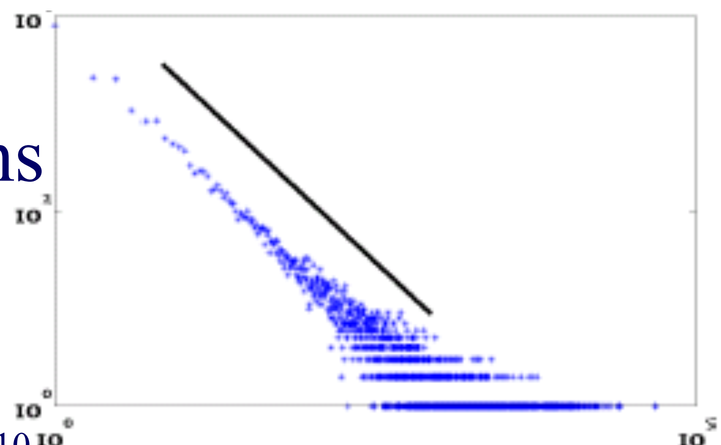

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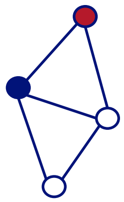
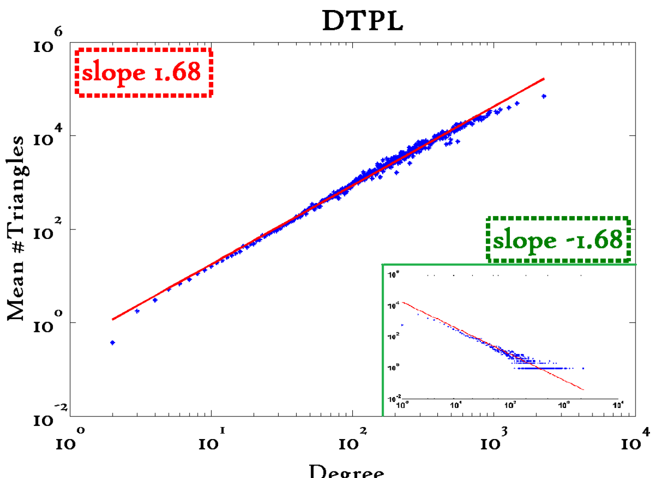
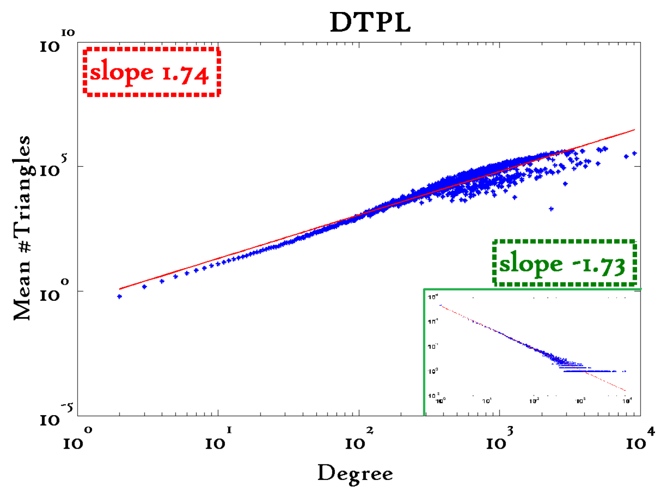


Triangle Law: #S.4
[Tsourakakis ICDM 2008]

Reuters



SN



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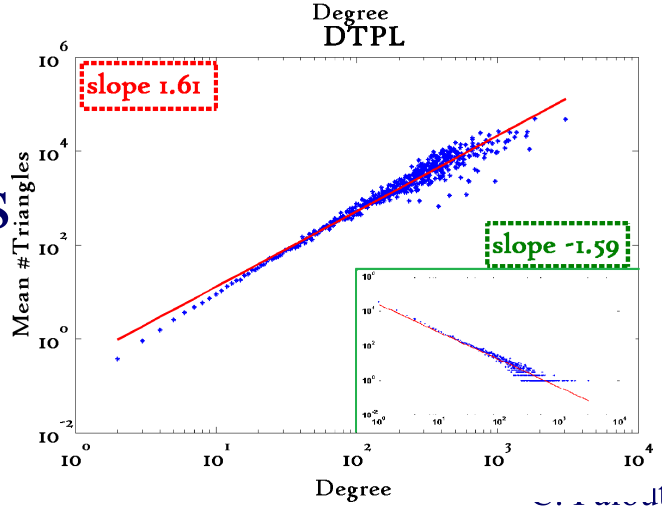

X-axis: degree

Y-axis: mean # triangles

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

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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?

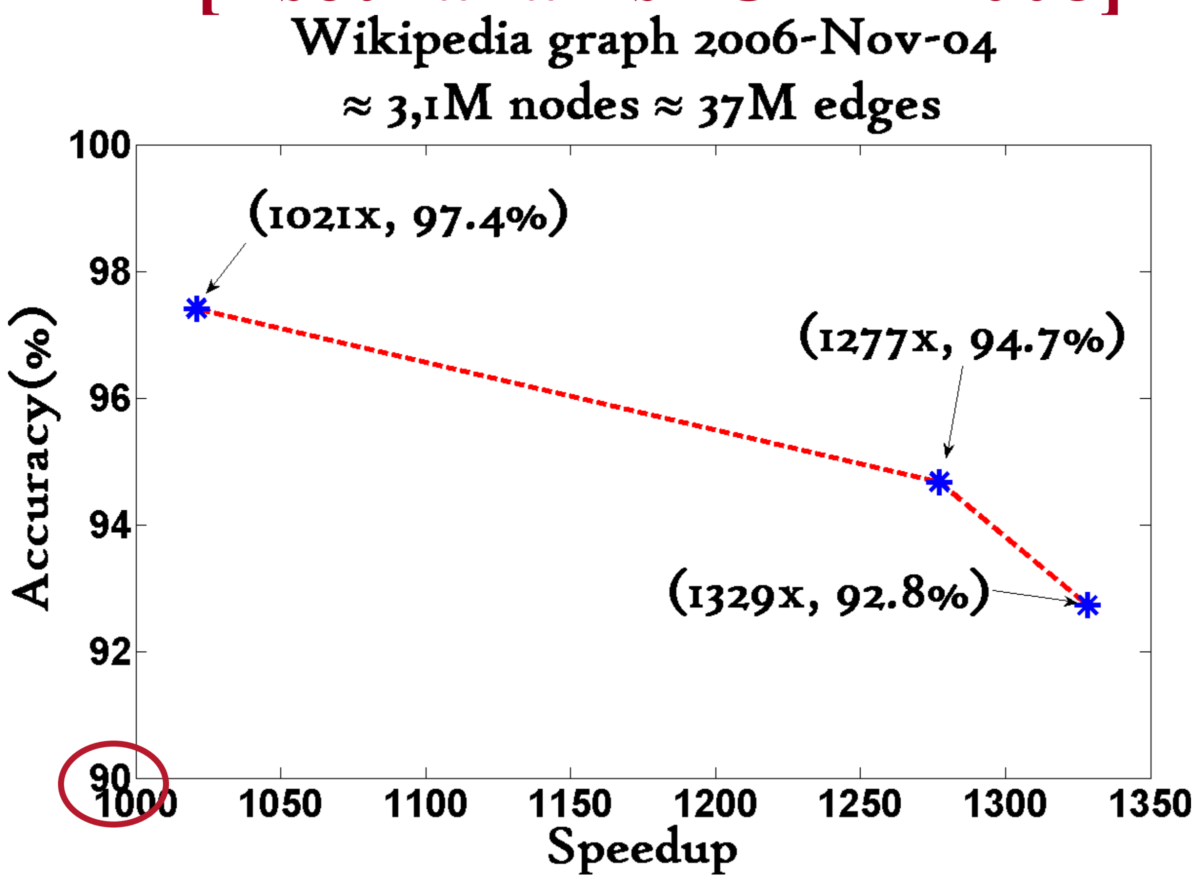
A: Yes!

#triangles = 1/6 Sum (λ_i^3)

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

details

Triangle Law: Computations [Tsourakakis ICDM 2008]



1000x+ speed-up, >90% accuracy

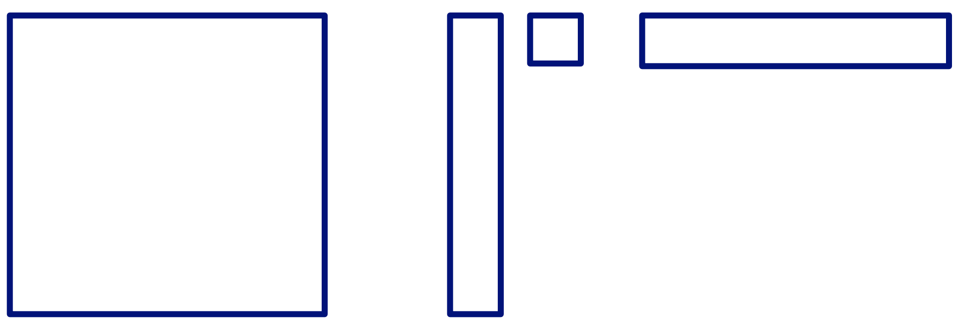
EigenSpokes

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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details

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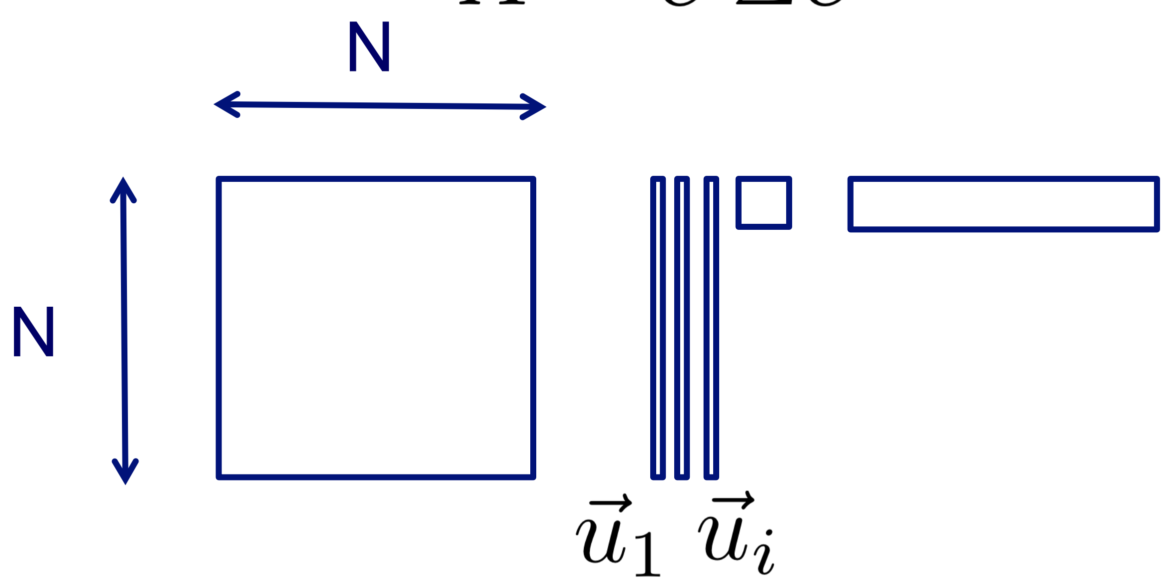
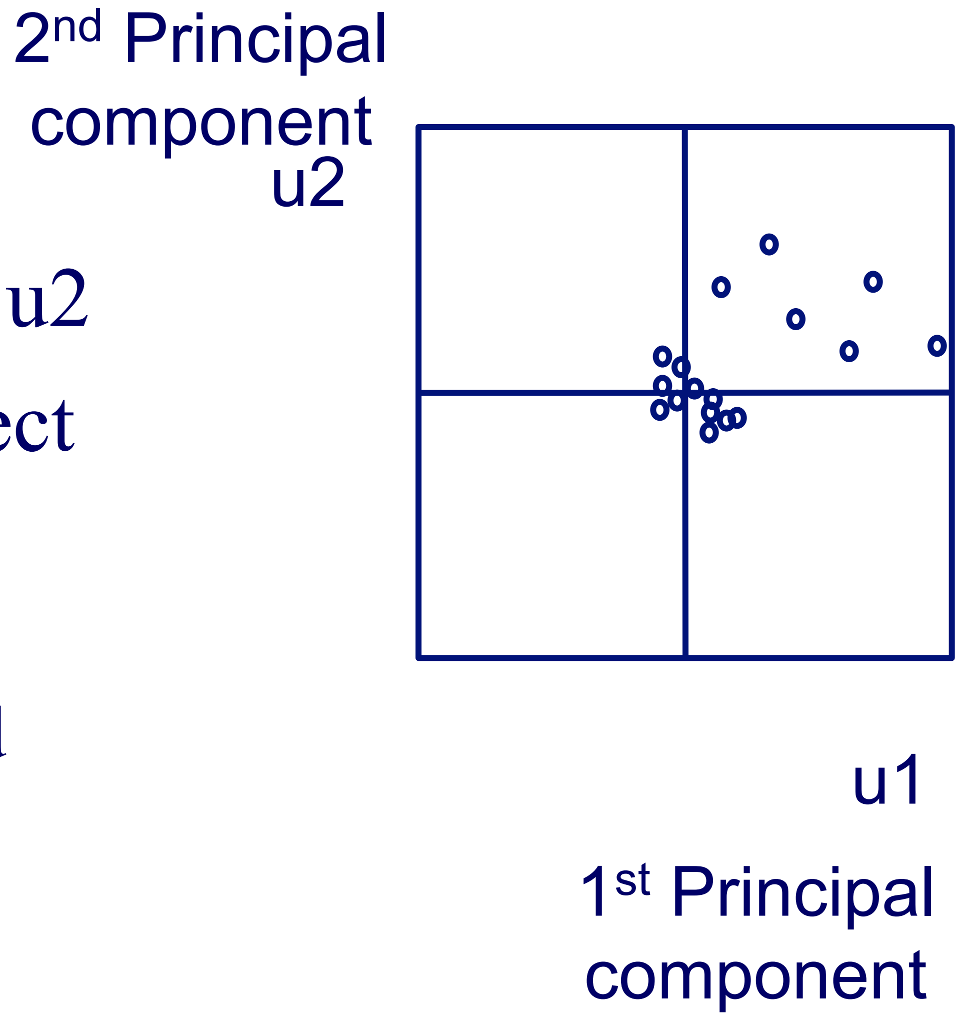


EigenSpokes

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



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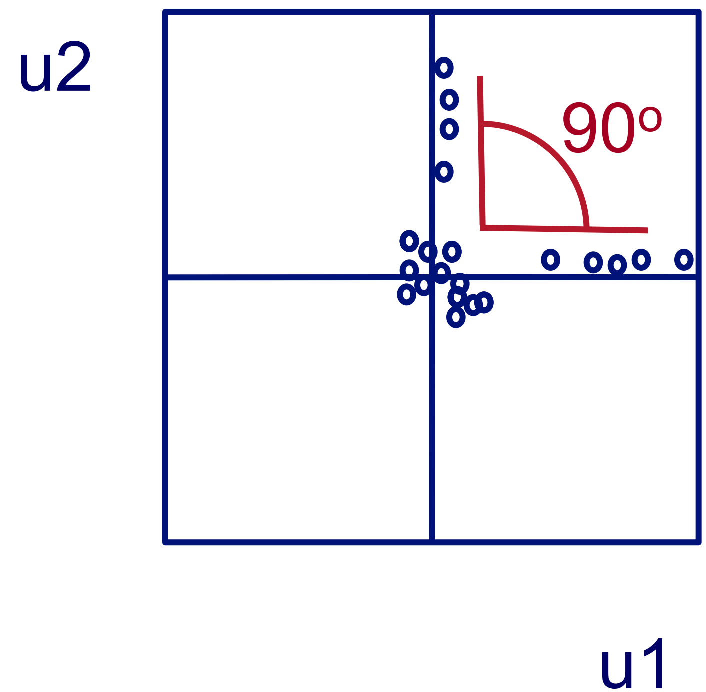
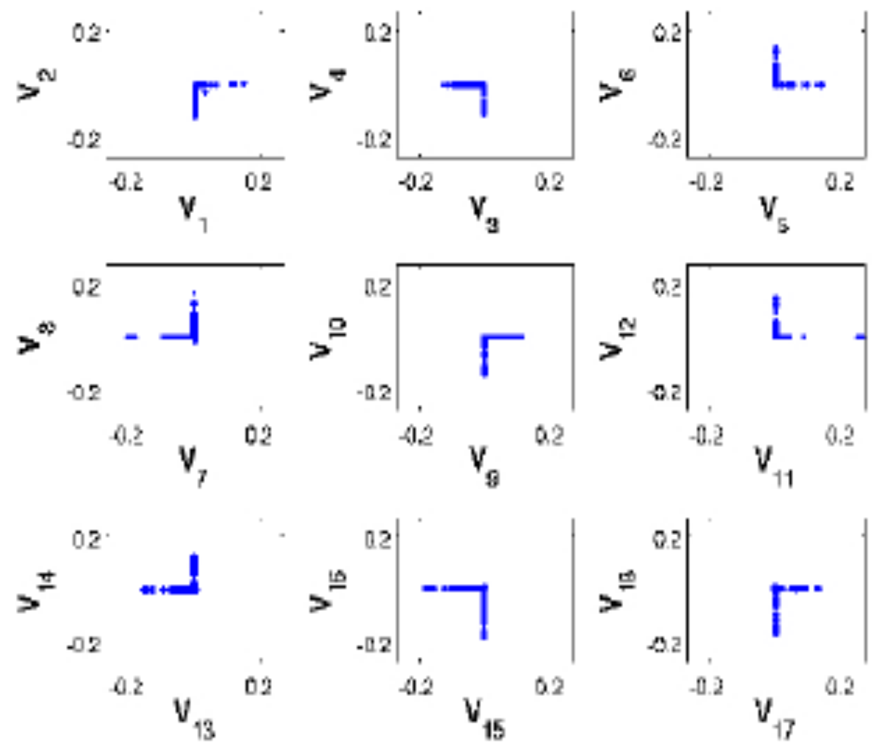


EigenSpokes - pervasiveness

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



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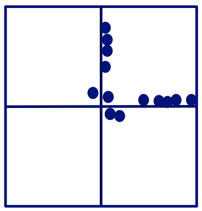
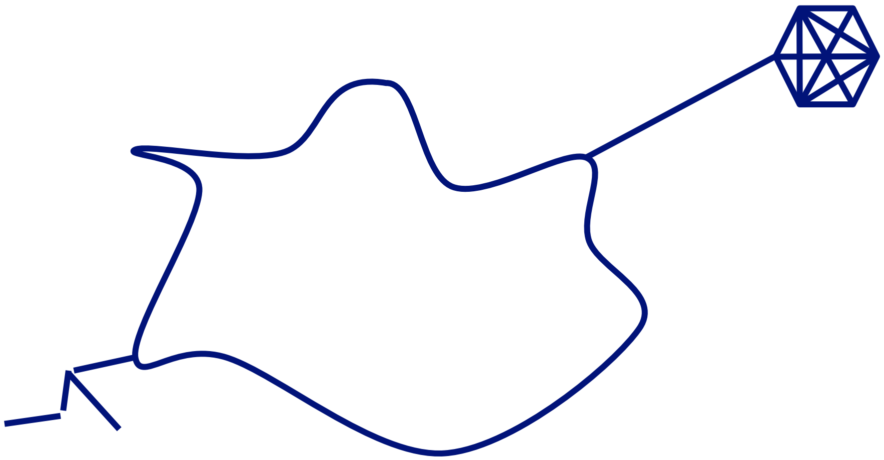
EigenSpokes - explanation



Near-cliques, or

near-bipartite-cores,

loosely connected



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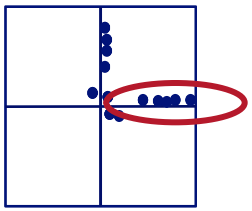

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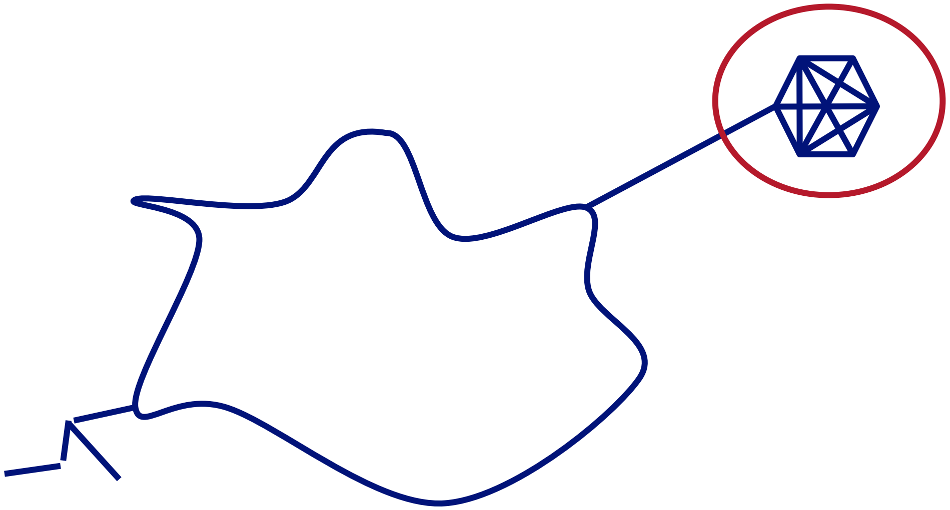

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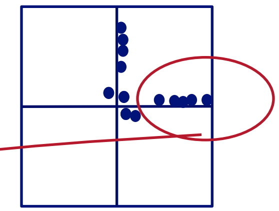

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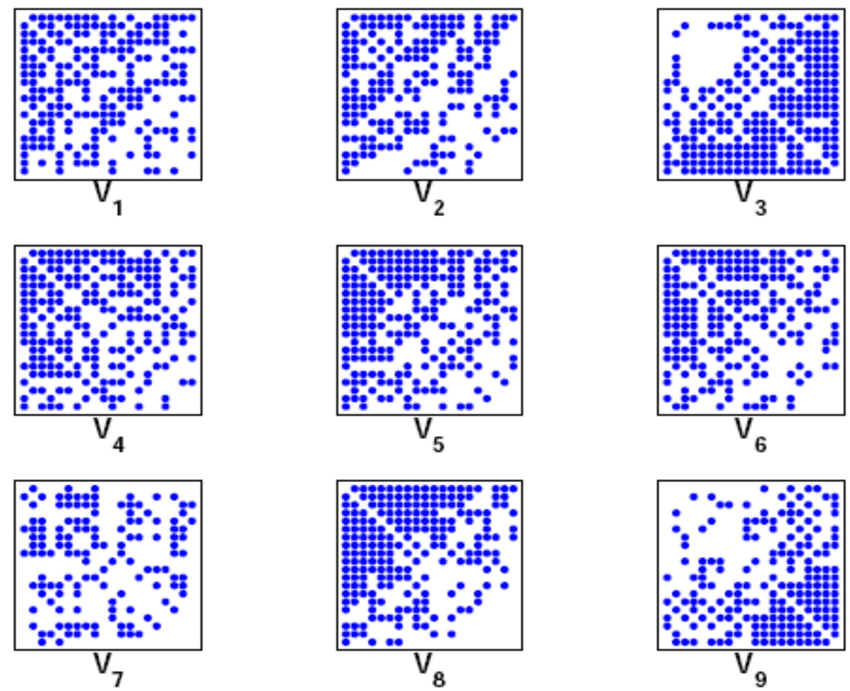
loosely connected

So what?

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

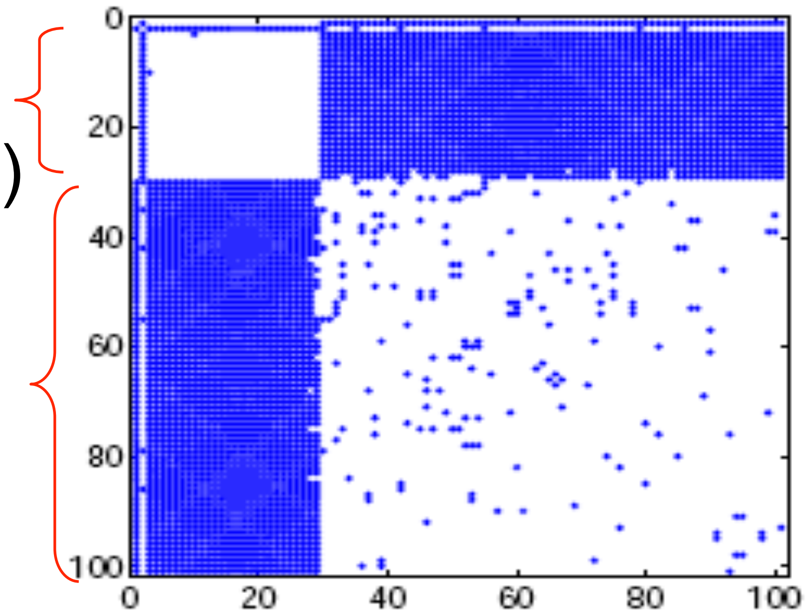
spy plot of top 20 nodes



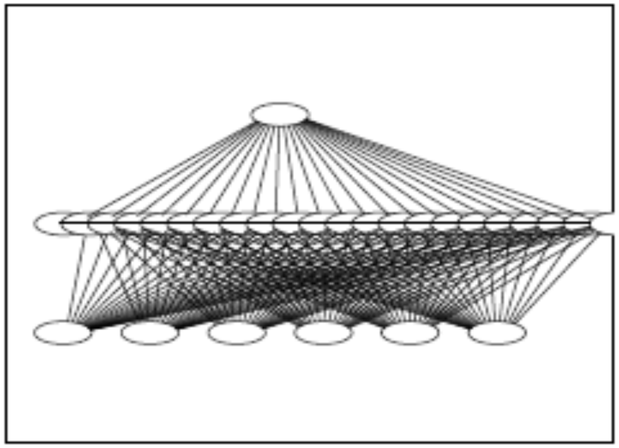
Bipartite Communities!

patents from
same inventor(s)

cut-and-paste
bibliography!



magnified bipartite community



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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

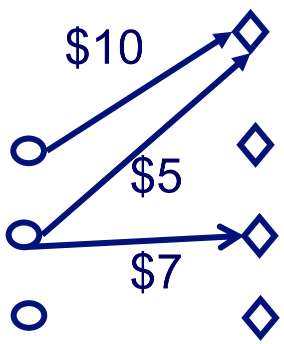
Observation W.1: Fortification

Q: How do the weights

of nodes relate to degree?

Observation W.1: Fortification

More donors, more $?



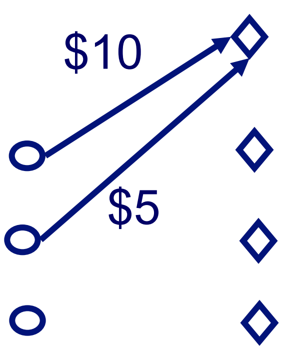
'Reagan'

'Clinton'

Observation W.1: fortification: Snapshot Power Law

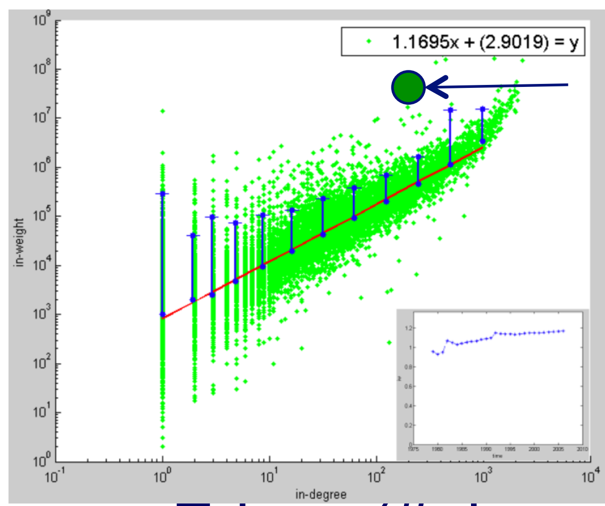
- Weight: super-linear on in-degree
- exponent ‘iw’: 1.01 < iw < 1.26

More donors, even more $



Orgs-Candidates

In-weights ($)



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

Edges (# donors)

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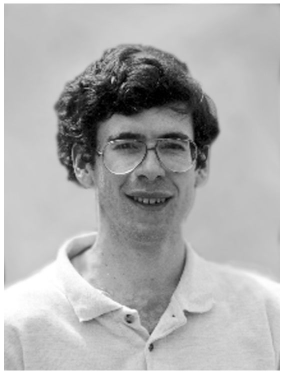
Problem: Time evolution

- 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?

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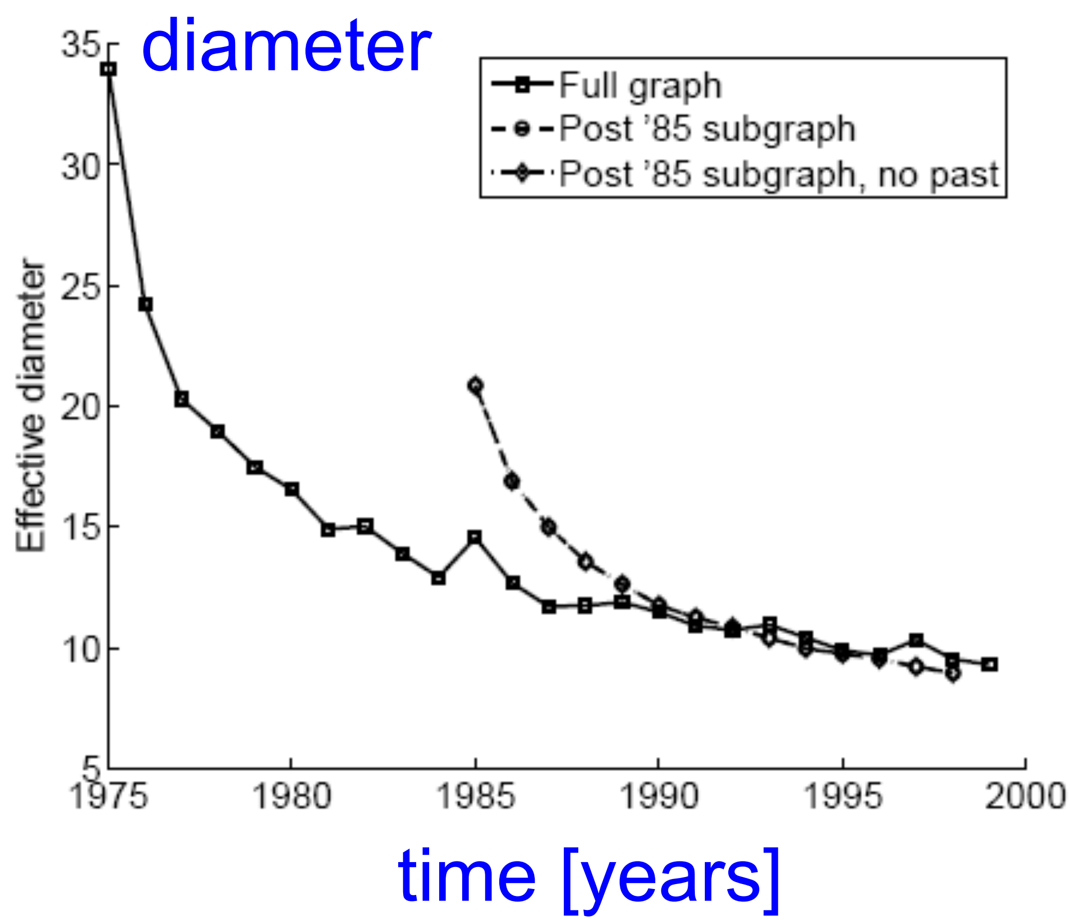
T.1 Evolution of the Diameter

- 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

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

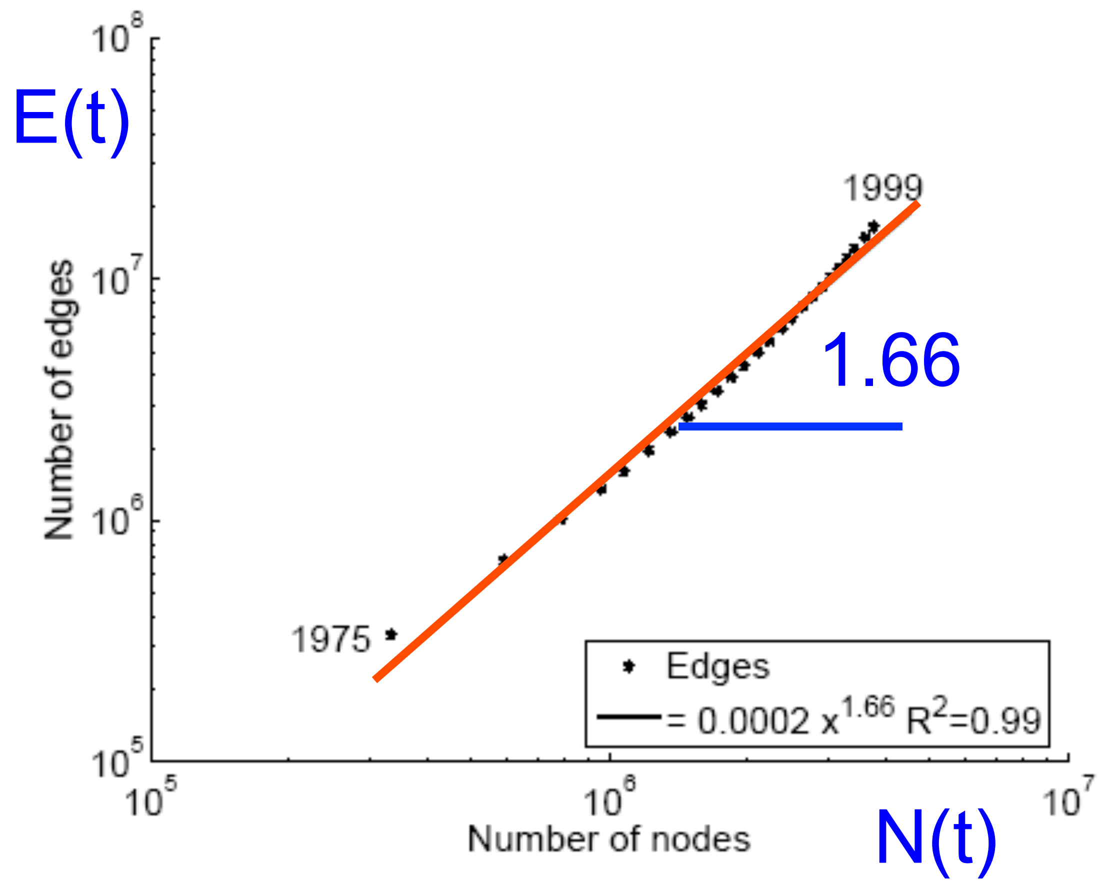
- Q: what is your guess for

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

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

T.2 Densification – Patent Citations

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



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More on Time-evolving graphs

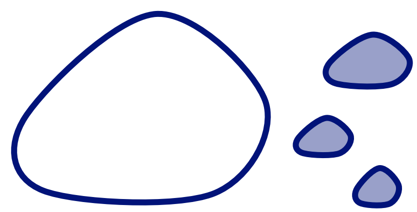
M. McGlohon, L. Akoglu, and C. Faloutsos
Weighted Graphs and Disconnected Components: Patterns and a Generator.
SIG-KDD 2008

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?

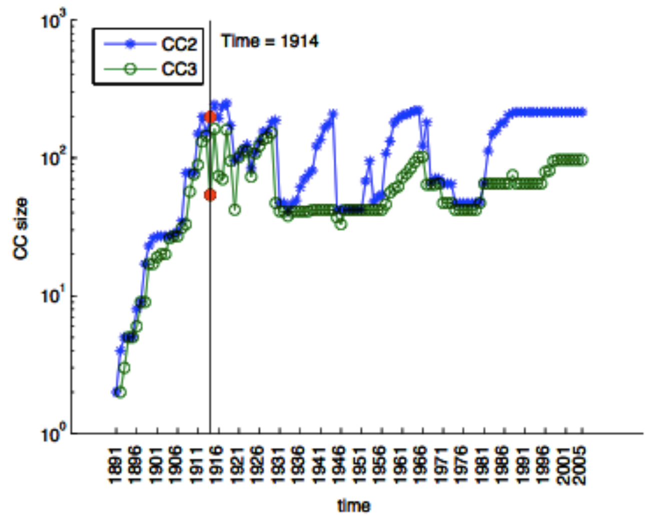


Observation T.3: NLCC behavior

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

IMDB

CC size



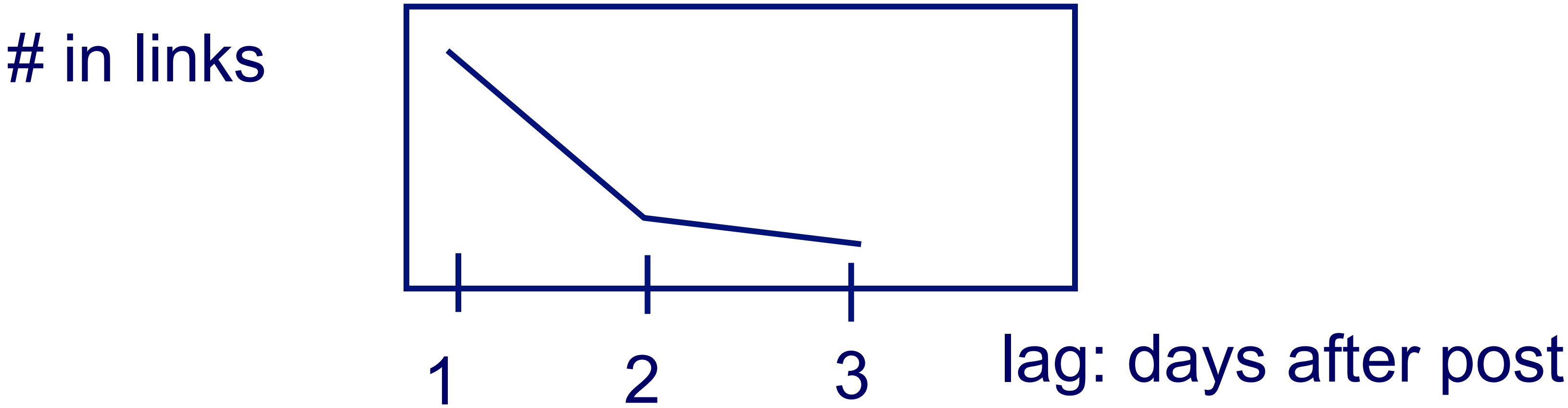
Time-stamp

Timing for Blogs

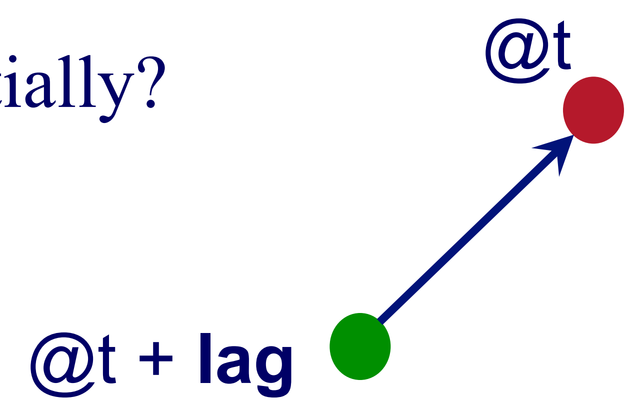
- with Mary McGlohon (CMU)
- Jure Leskovec (CMU->Stanford)
- Natalie Glance (now at Google)
- Mat Hurst (now at MSR)

[SDM’07]

T.4 : popularity over time

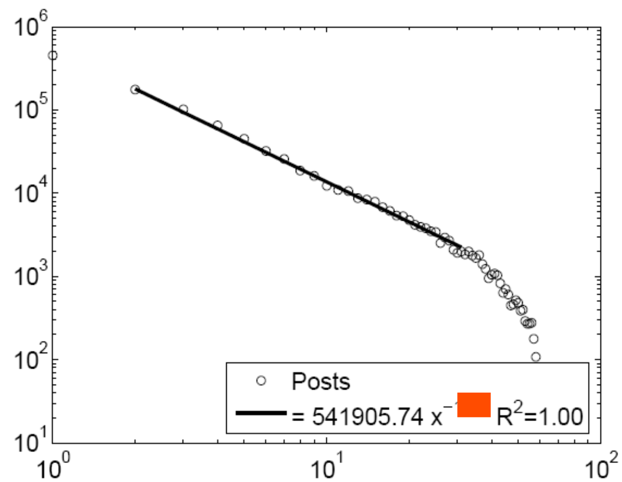


Post popularity drops-off – exponentially?



T.4 : popularity over time

in links (**log**)



days after post (**log**)

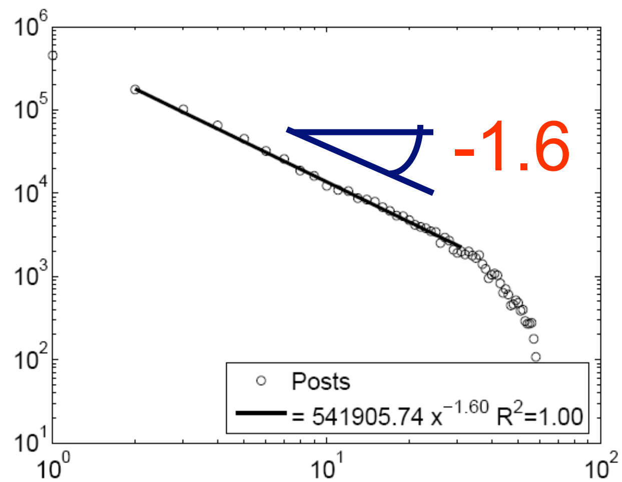
Post popularity drops-off – exponentially?

POWER LAW!

Exponent?

T.4 : popularity over time

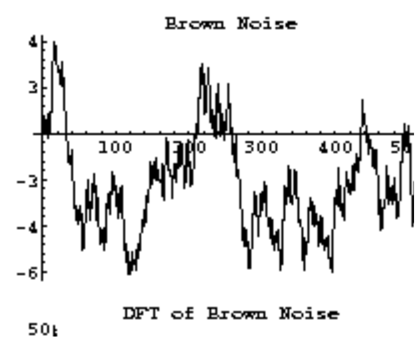
in links
(**log**)



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



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Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
  - CenterPiece Subgraphs; G-Ray
  - OddBall (anomaly detection)
  - PEGASUS
- Problem#3: Scalability
- Conclusions

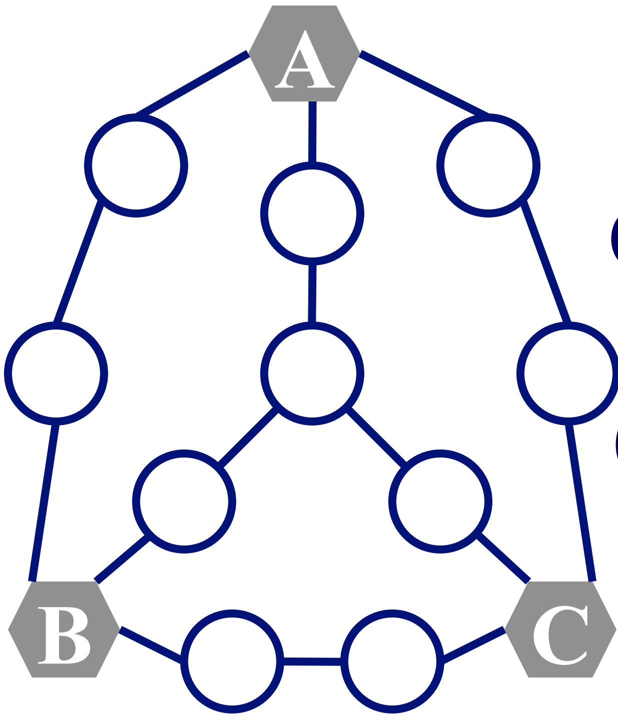
CenterPiece Subgraphs

- Hanghang TONG et al, KDD’06

Center-Piece Subgraph Discovery

[Tong+ KDD 06]

Input



Original Graph

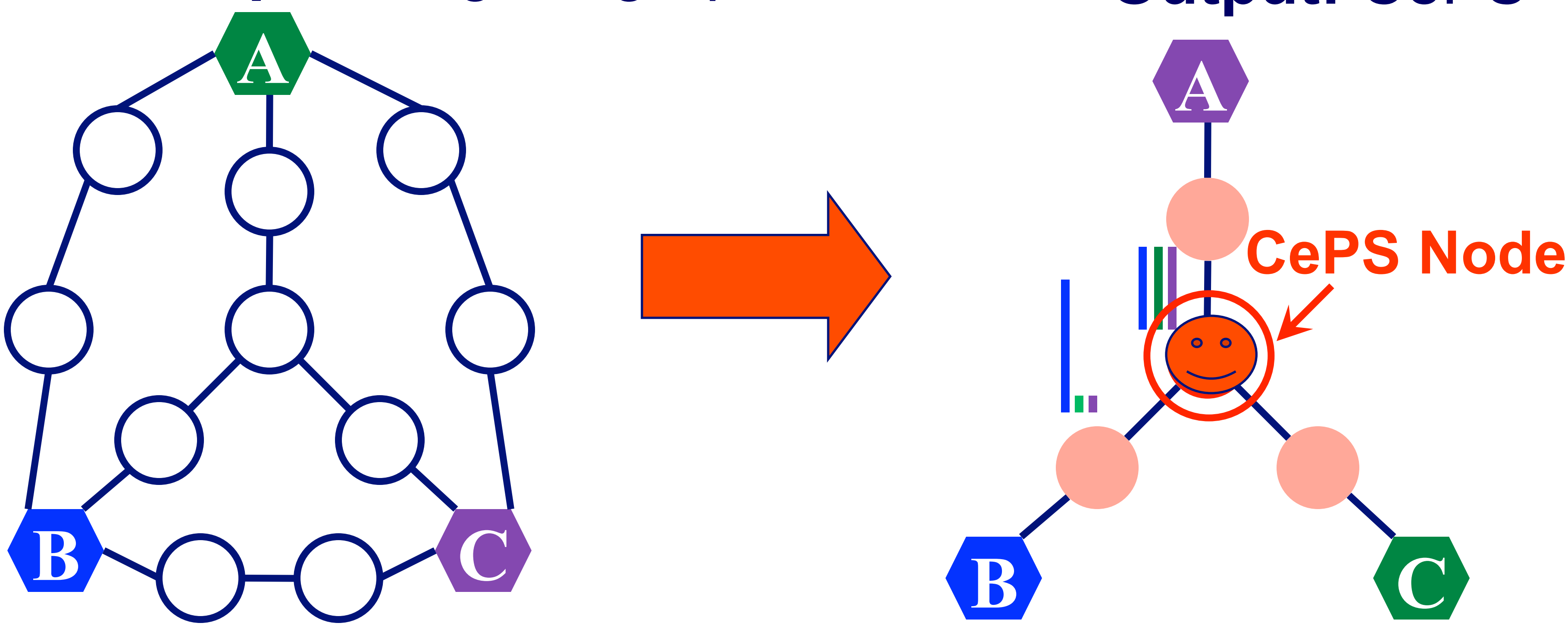
Q: Who is the most central node wrt the black nodes?
(e.g., master-mind criminal, common advisor/collaborator, etc)

Center-Piece Subgraph Discovery

[Tong+ KDD 06]

Input: original graph

Output: CePS



Q: How to find hub for the query nodes?

A: Combine proximity scores (RWR)

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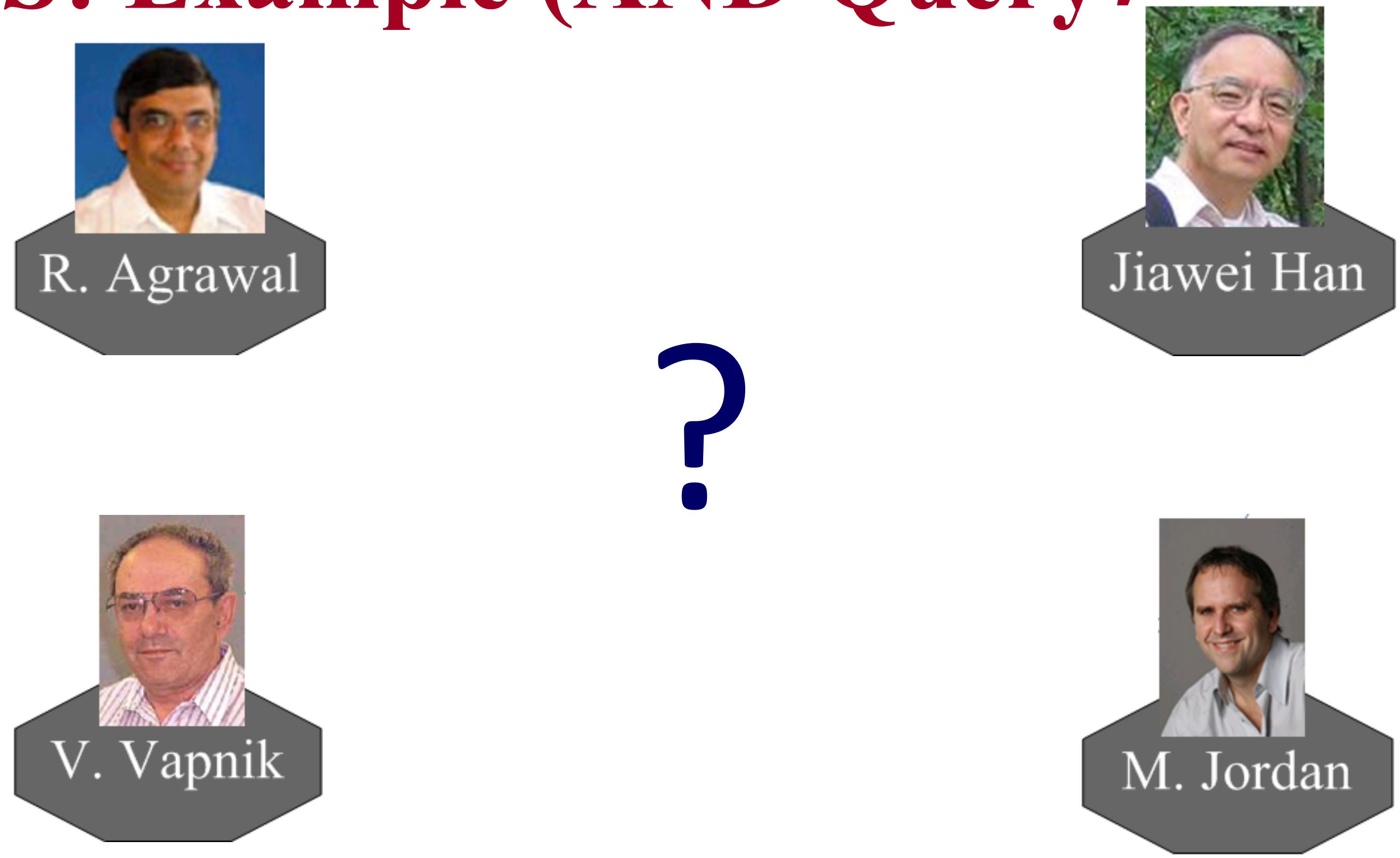
CePS: Example (AND Query)

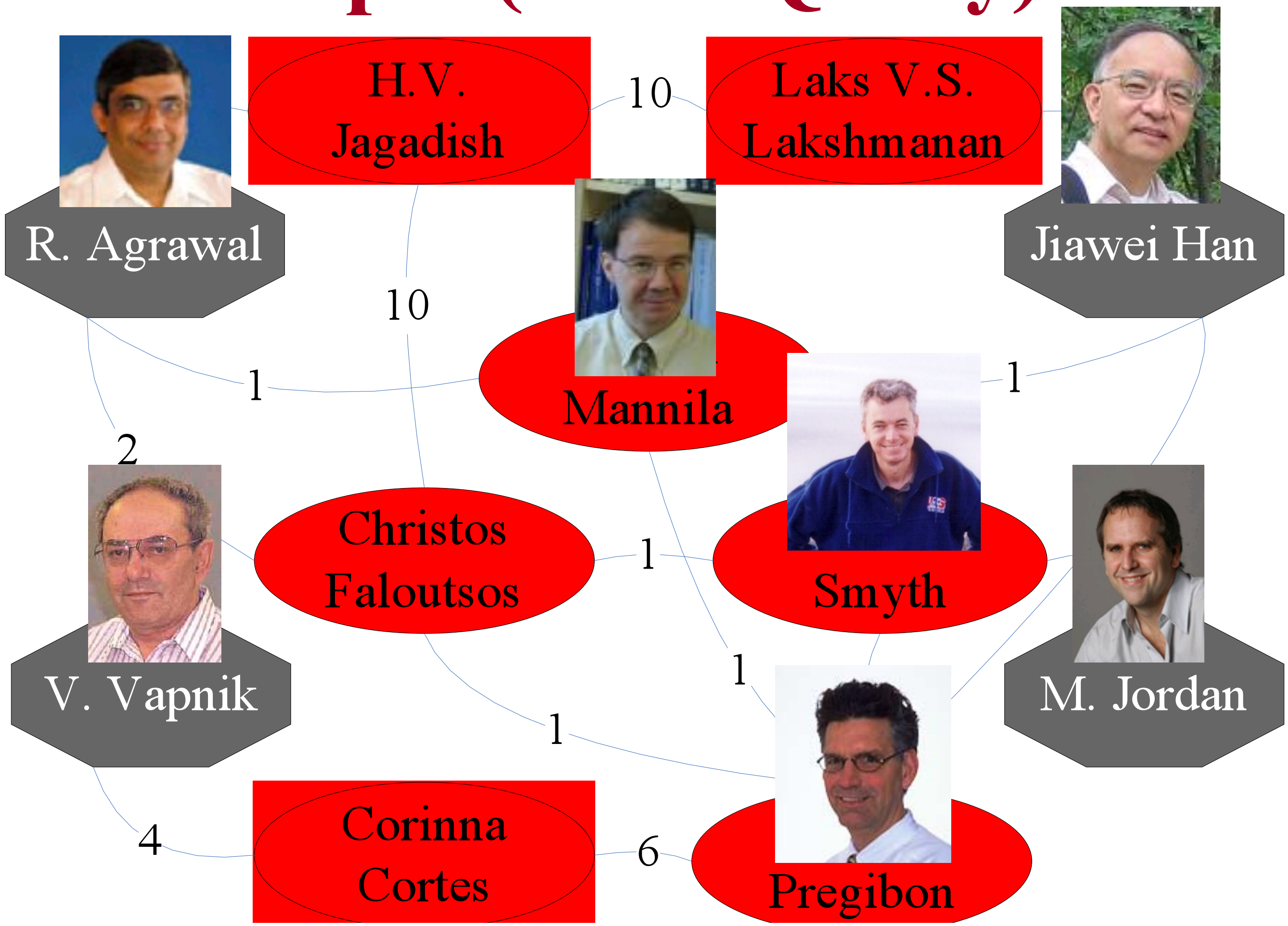


DBLP co-authorship network:

-400,000 authors, 2,000,000 edges

Code at: http://www.cs.cmu.edu/~htong/soft.htm

CePS: Example (AND Query)



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- Conclusions

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Graph X-Ray: Fast Best-Effort Pattern Matching in Large Attributed Graphs

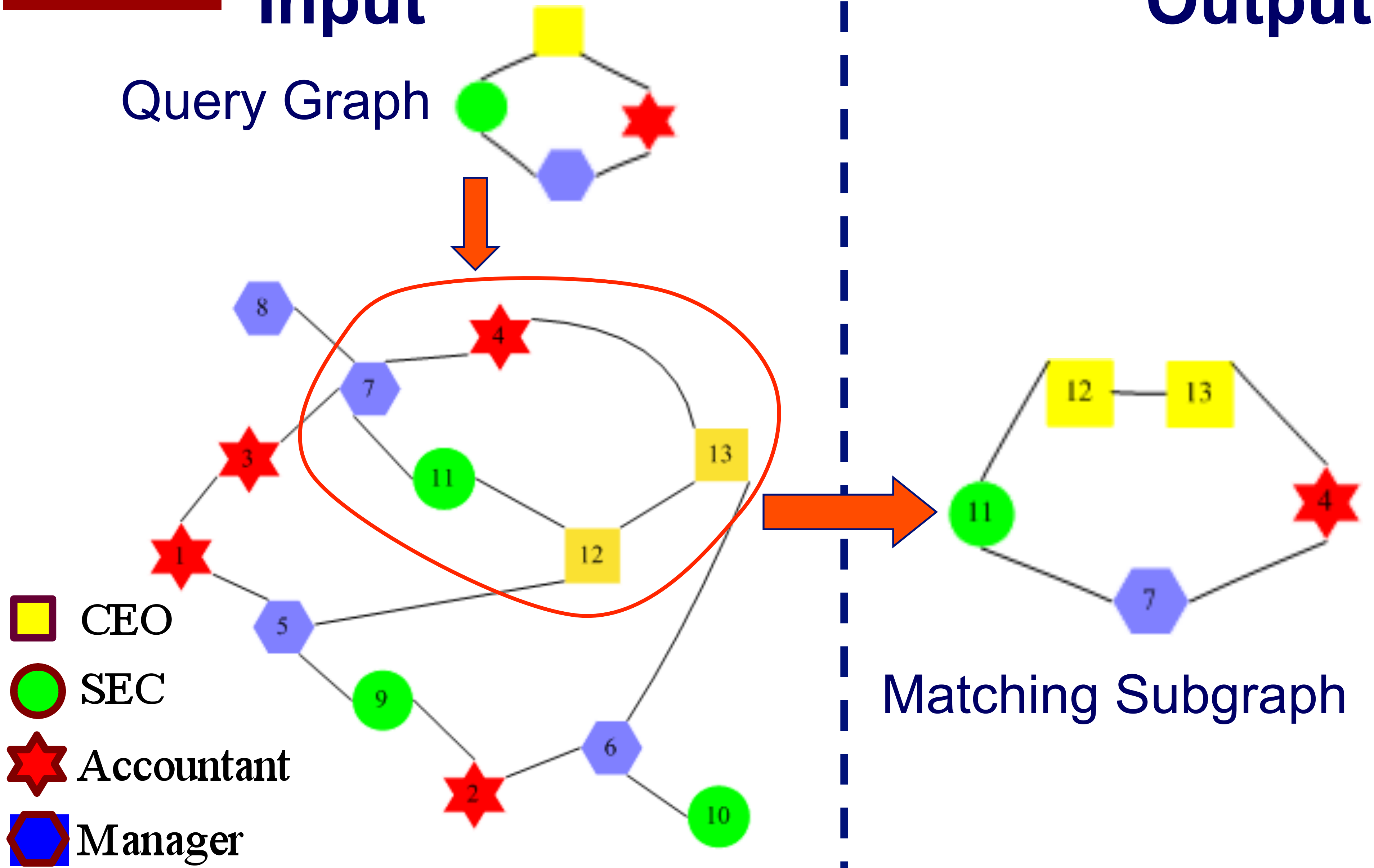
Hanghang Tong, Brian Gallagher, Christos Faloutsos, Tina Eliassi-Rad

KDD'07

Carnegie Mellon

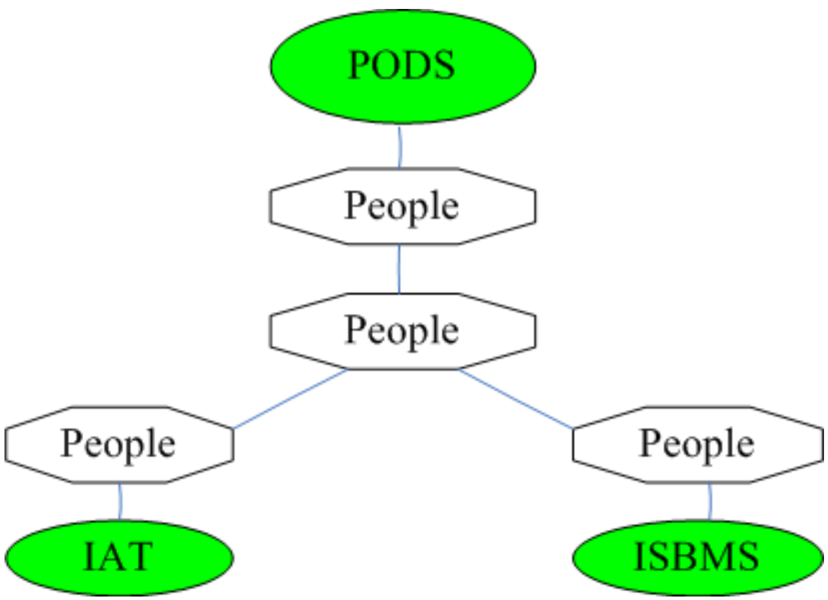
Input

Output

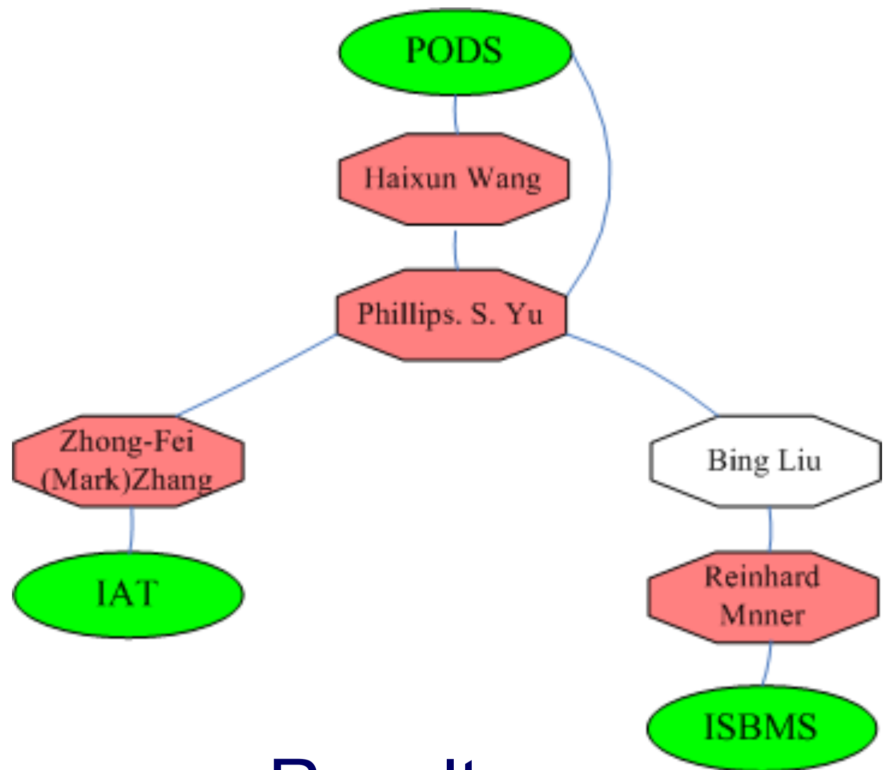


Attributed Data Graph

Effectiveness: star-query



Query



Result

Outline

- Introduction – Motivation
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  - OddBall (anomaly detection)
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OddBall: Spotting Anomalies in Weighted Graphs

Leman Akoglu, Mary McGlohon, Christos Faloutsos

Carnegie Mellon University

School of Computer Science

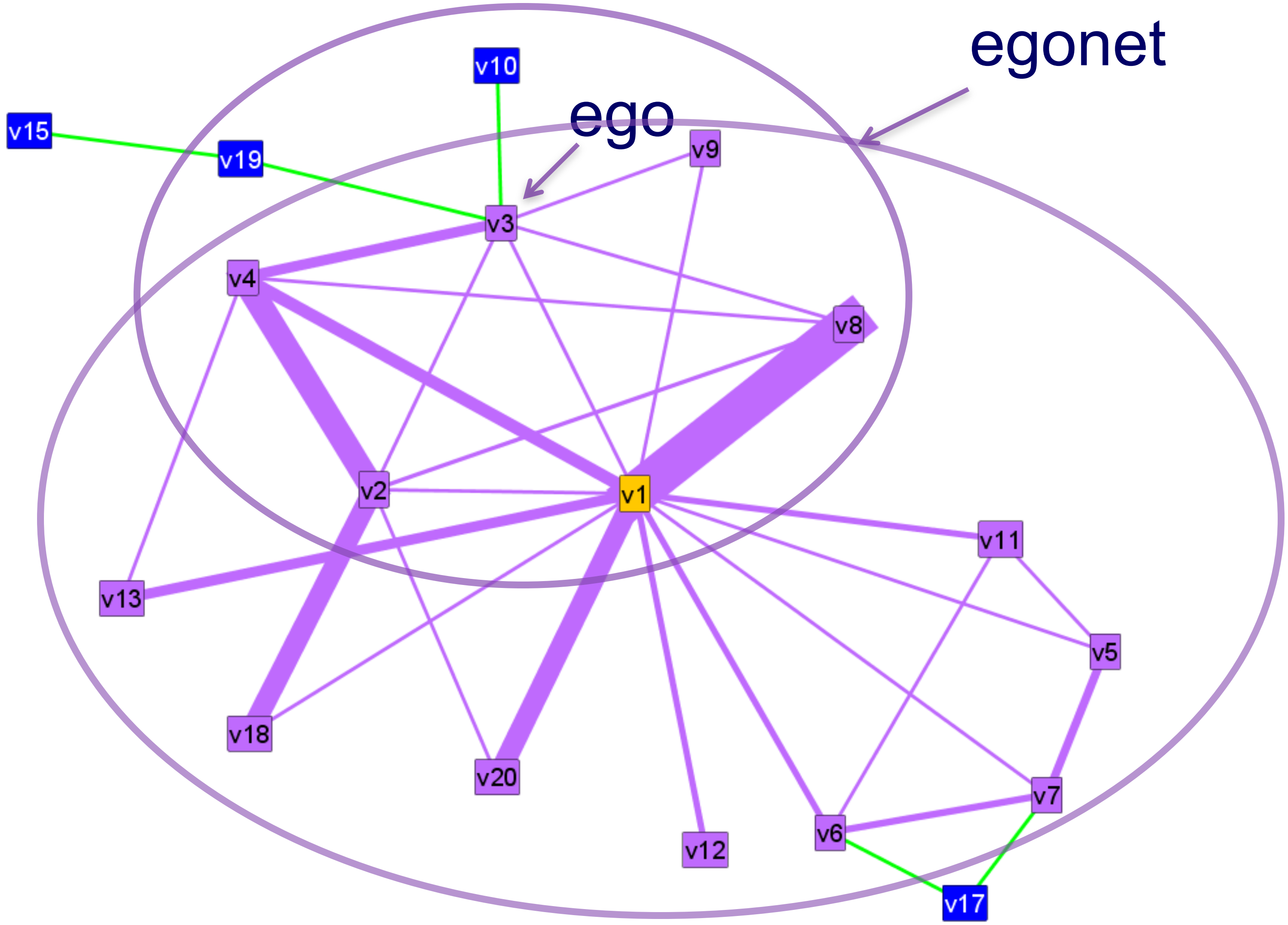
To appear in PAKDD 2010, Hyderabad, India

Main idea

For each node,

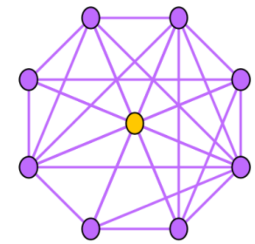
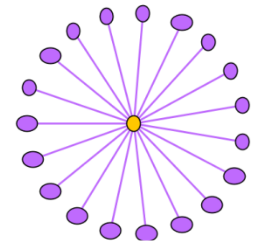
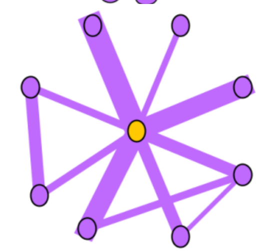
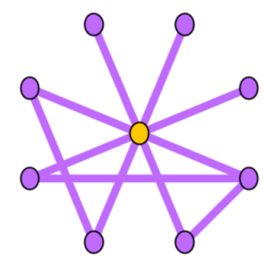
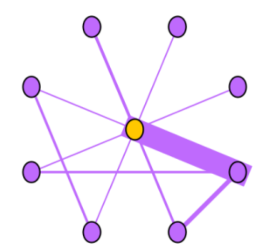
- extract ‘ego-net’ (=1-step-away neighbors)
- Extract features (#edges, total weight, etc etc)
- Compare with the rest of the population

What is an egonet?

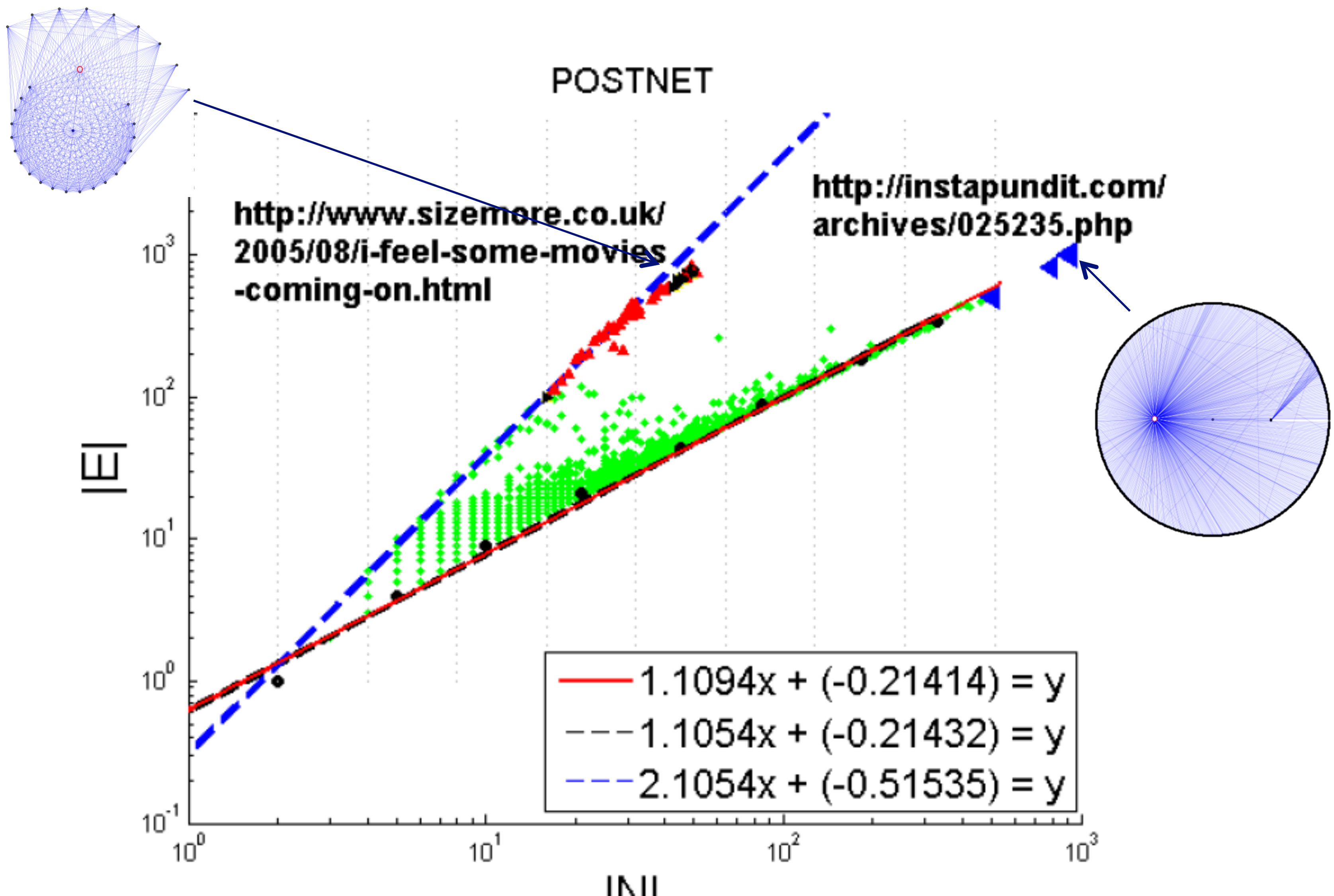


Selected Features

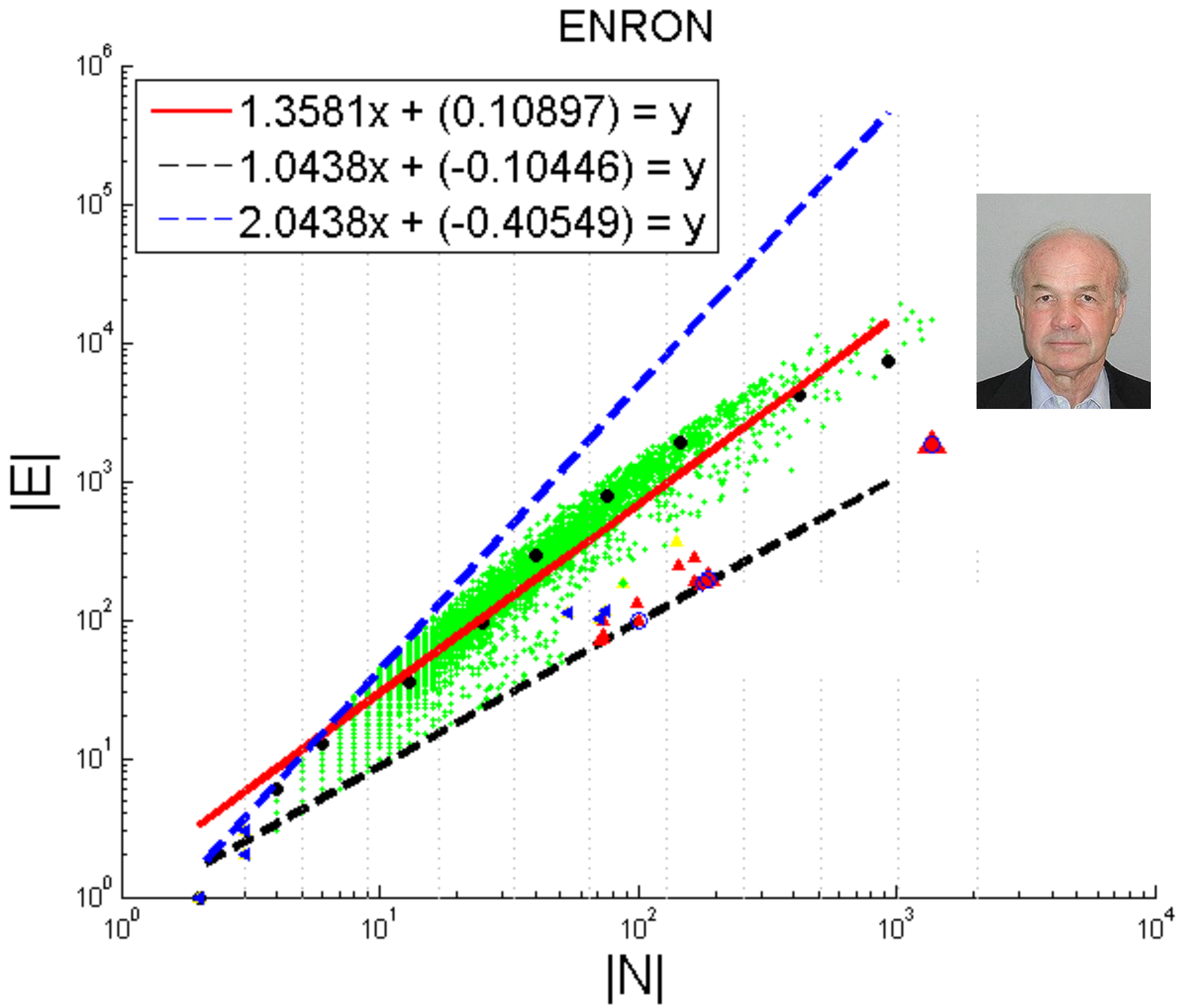
- N_i: number of neighbors (degree) of ego i
- E_i: number of edges in egonet i
- W_i: total weight of egonet i
- $\lambda_{w,i}$: principal eigenvalue of the weighted adjacency matrix of egonet I

Near-Clique/Star



Near-Clique/Star



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Outline – Algorithms & results

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Degree Distr.	old	old
Pagerank	old	old
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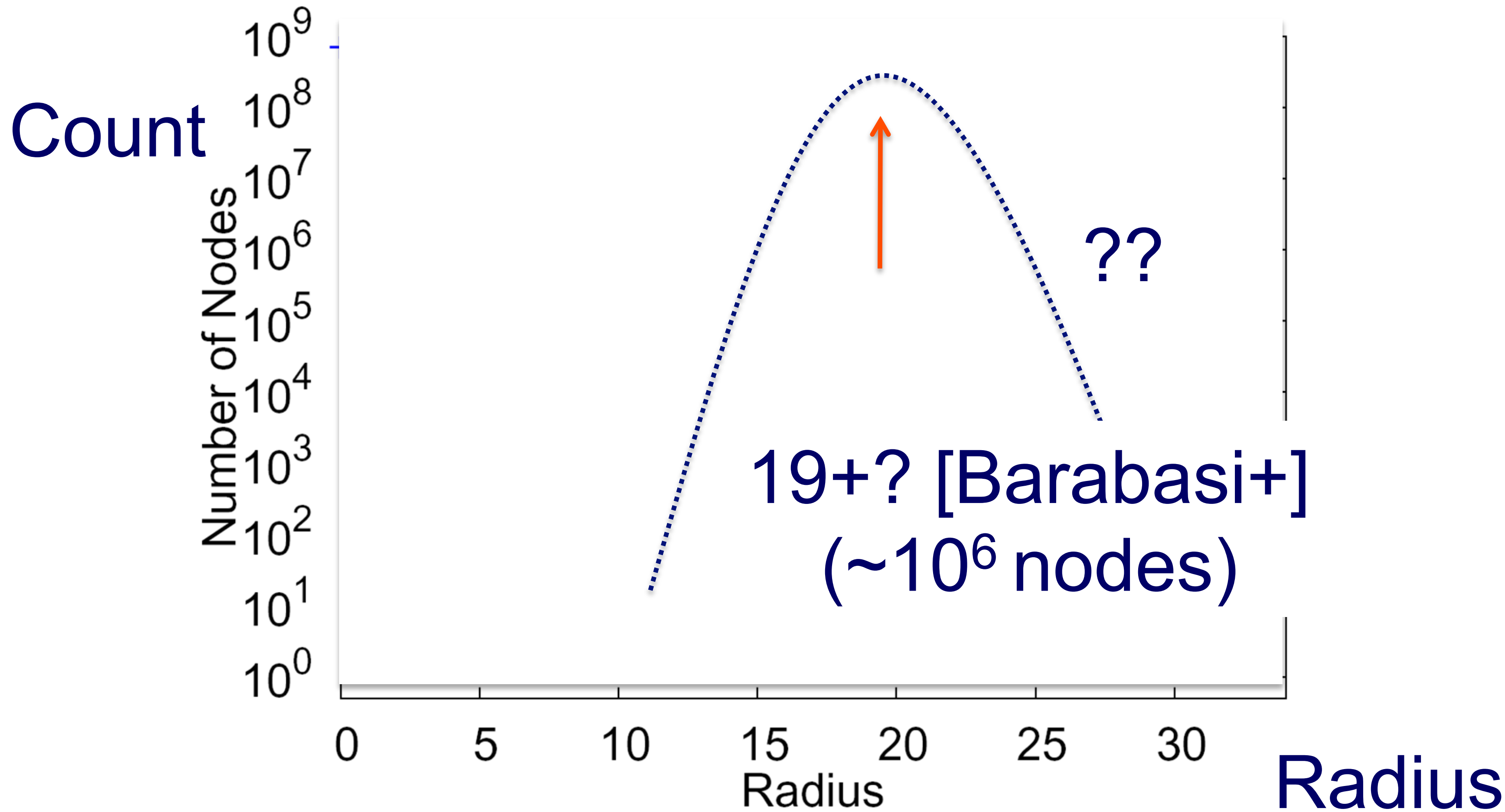
Conn. Comp	old	**DONE**
Triangles	**DONE**	
Visualization	**STARTED**	

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



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

- Largest publicly available graph ever studied.

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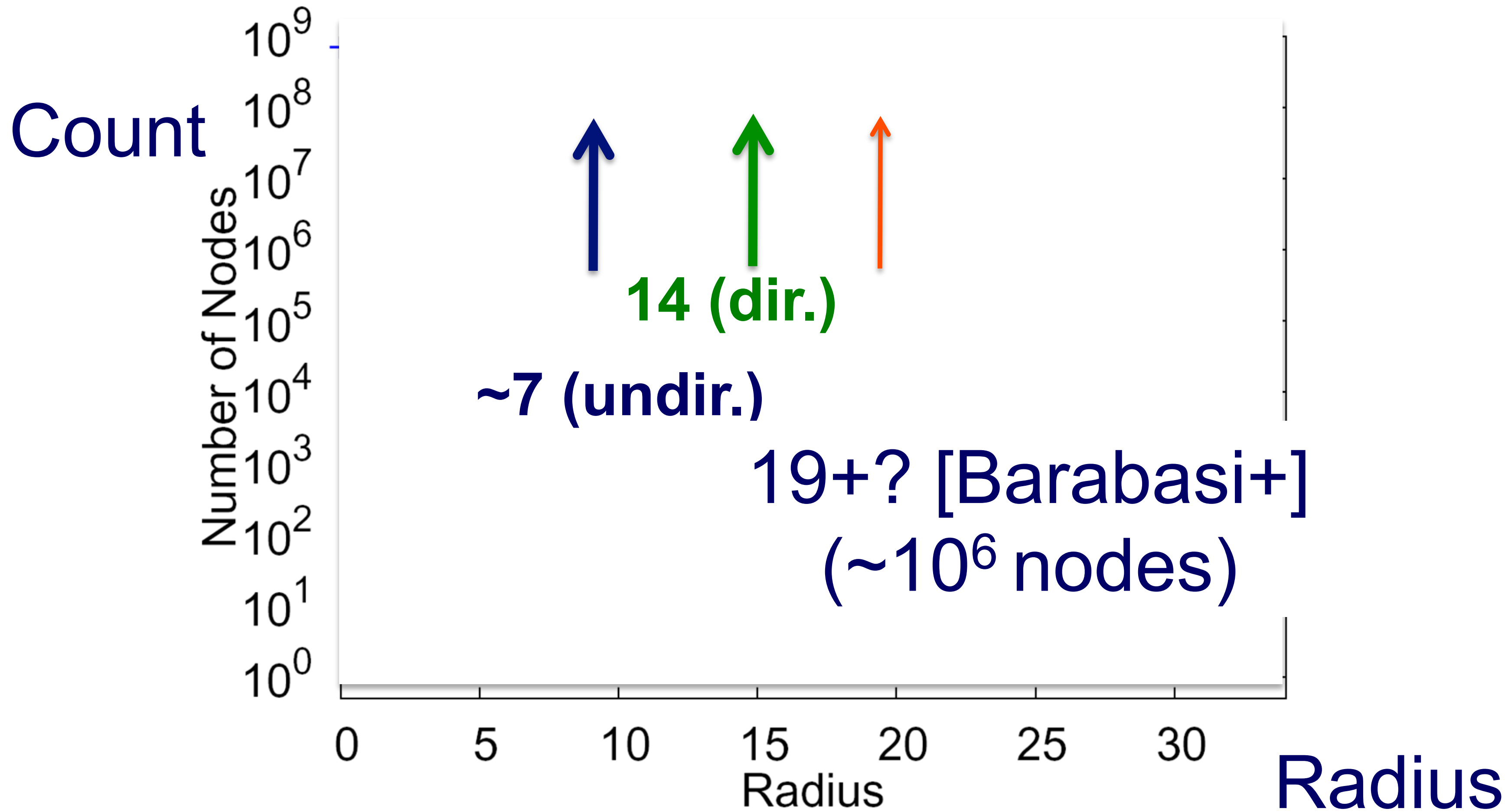

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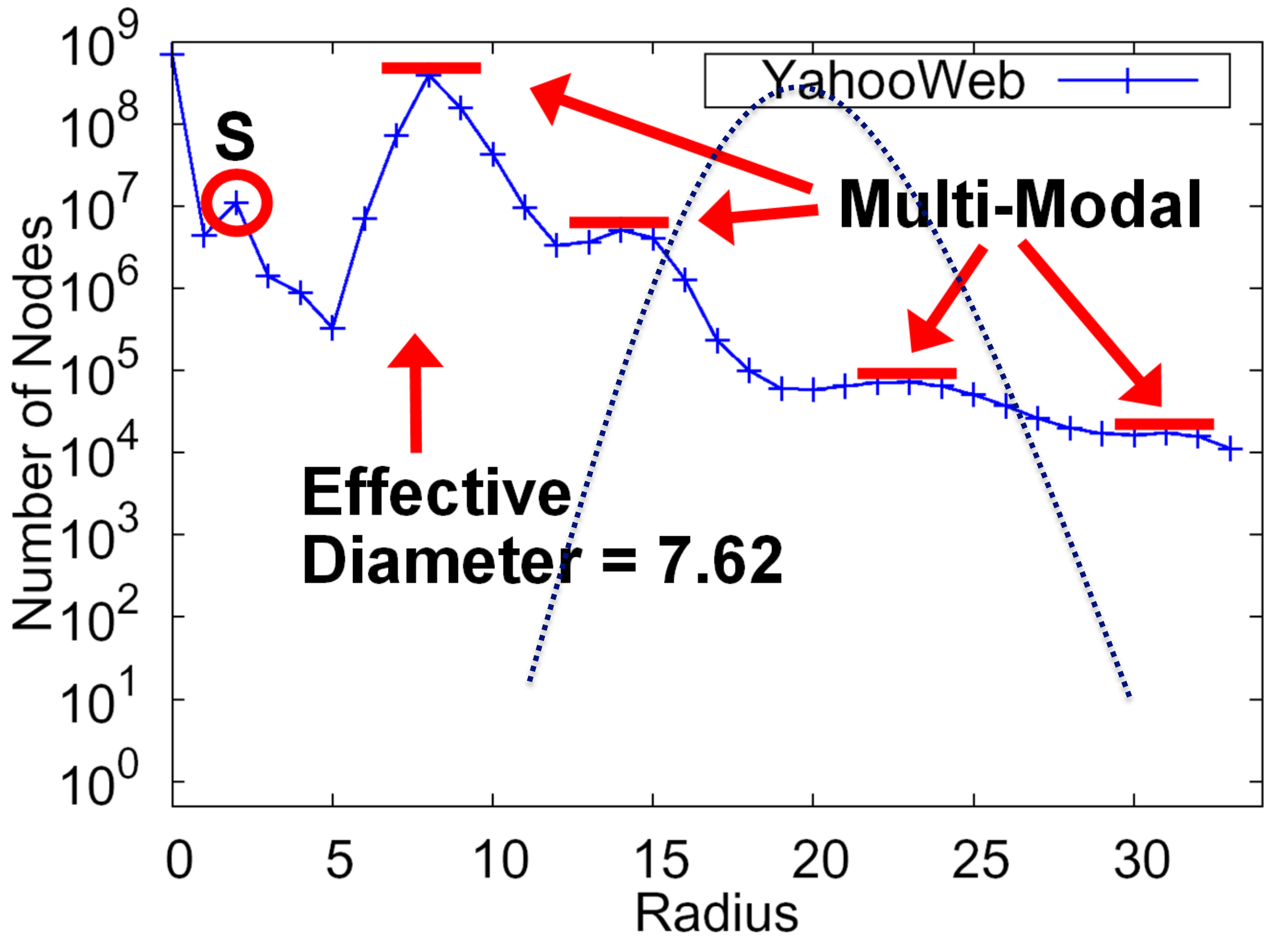
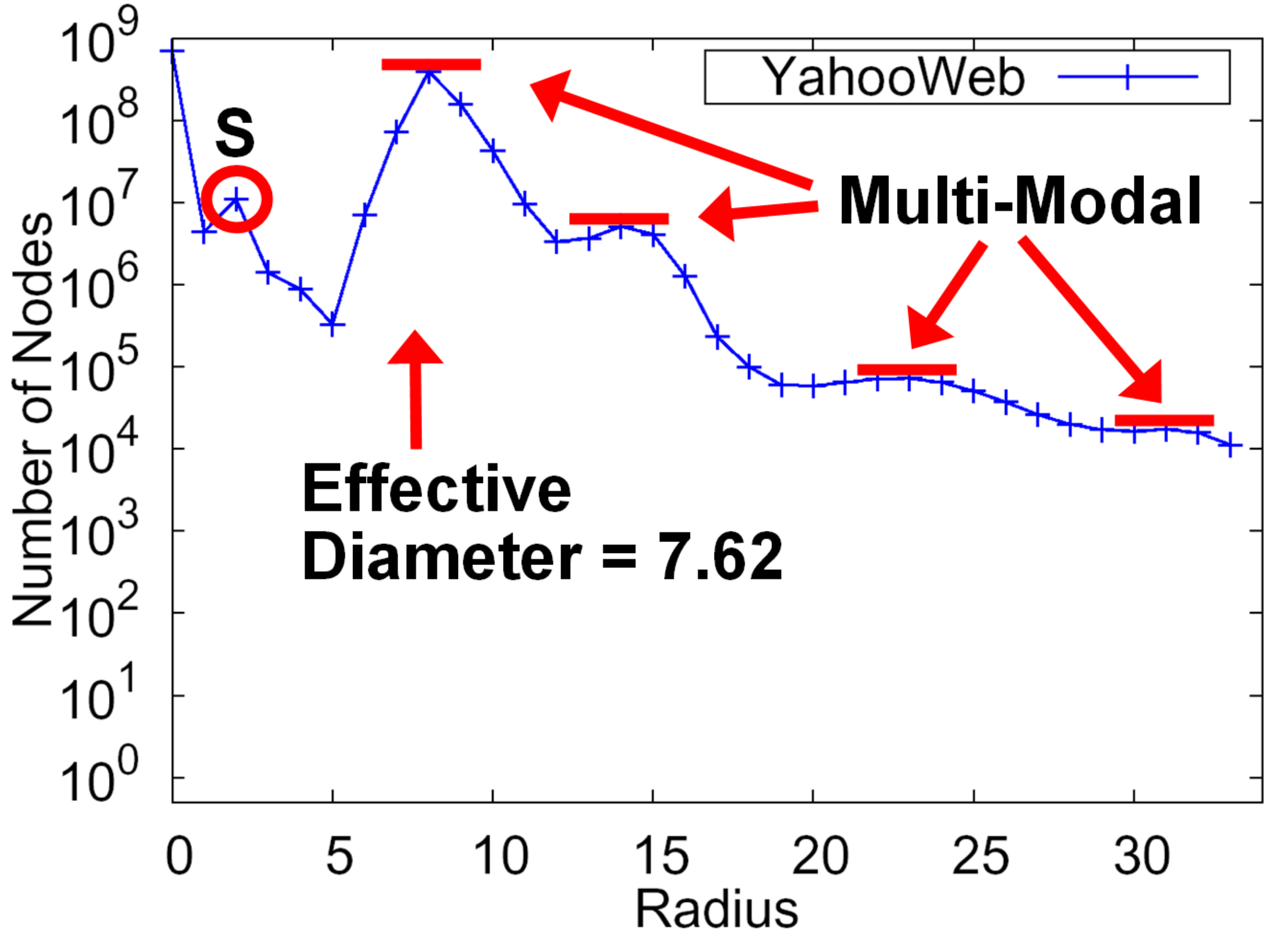


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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



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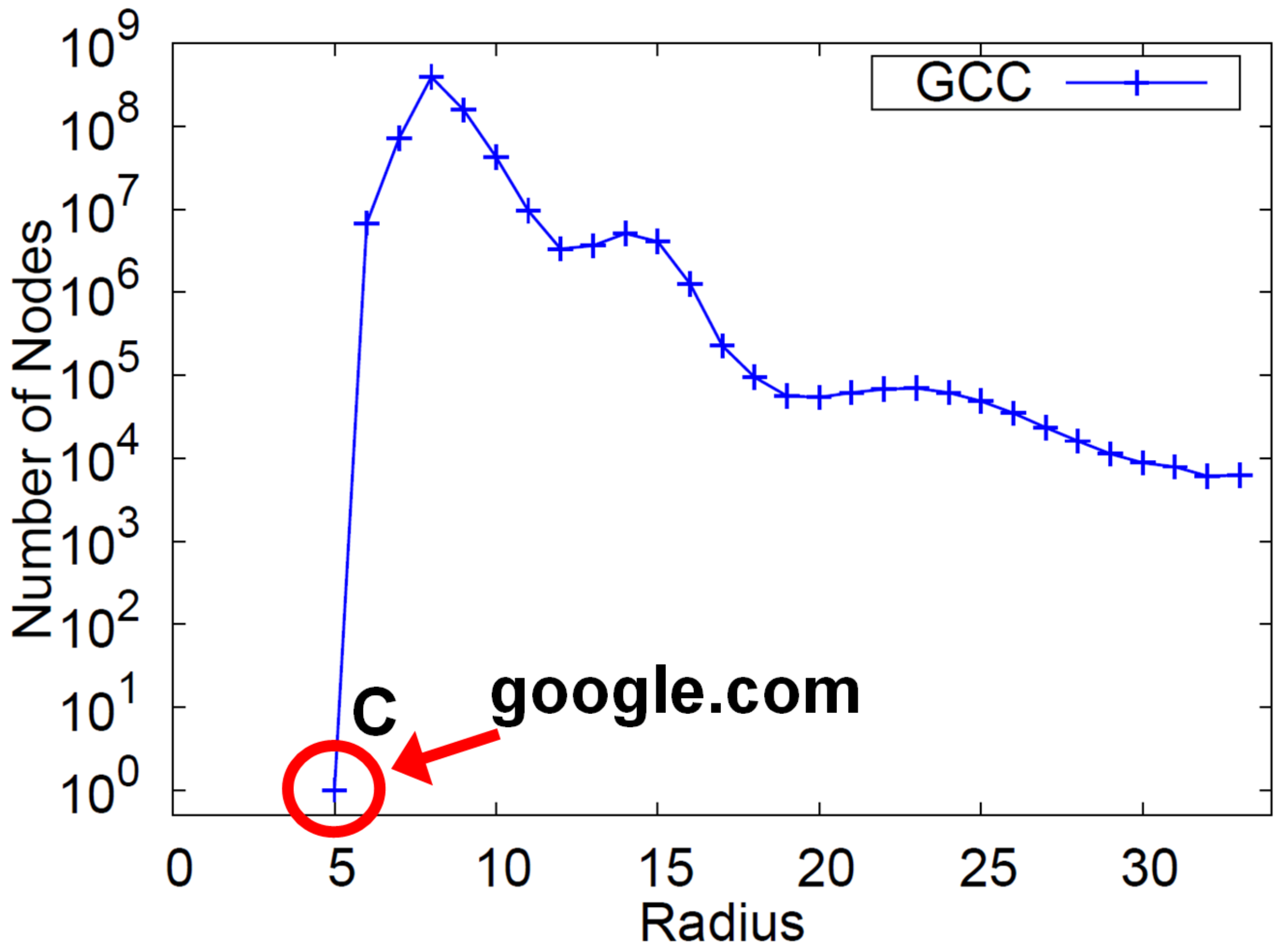
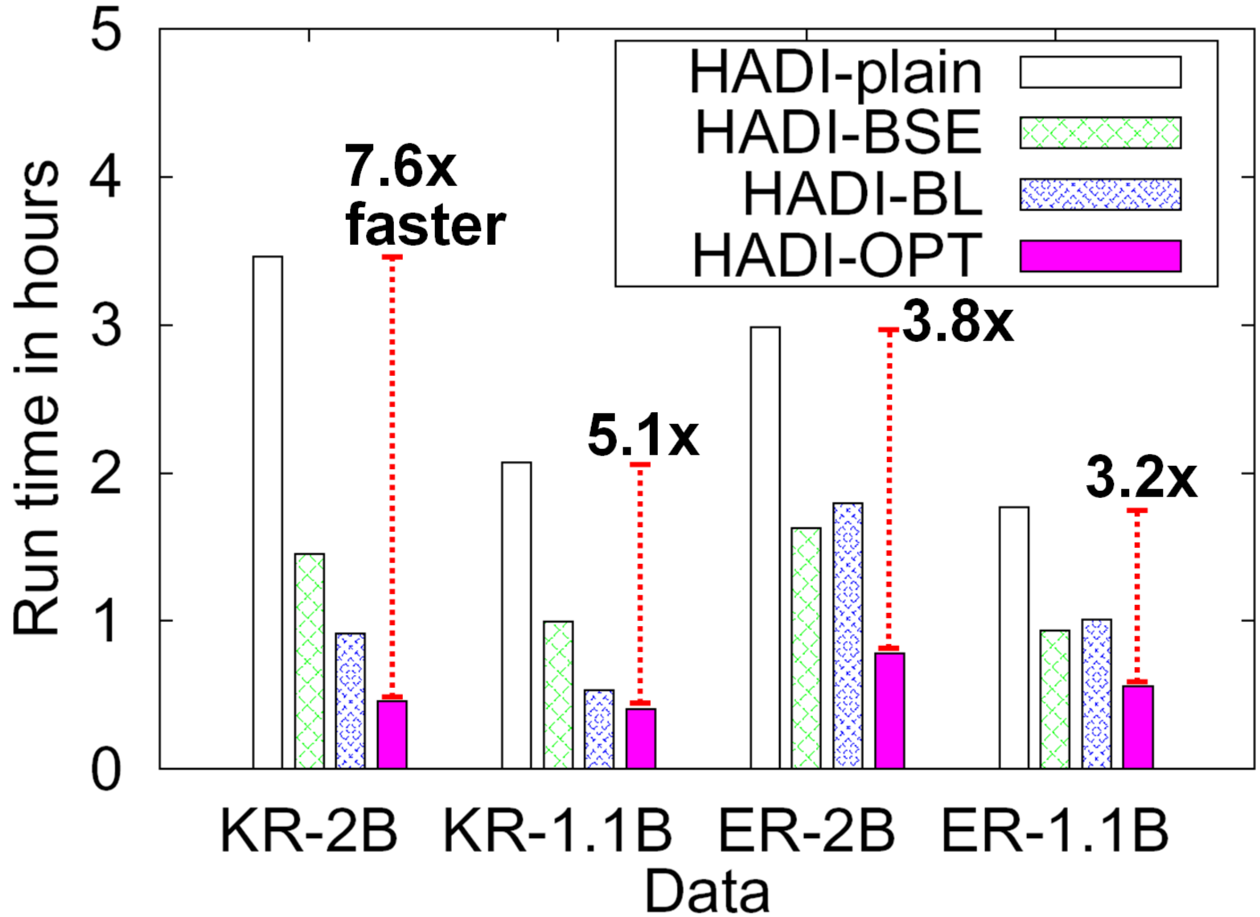


Radius Plot of **GCC** of YahooWeb.

details



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

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Outline – Algorithms & results

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Degree Distr.	old	old
Pagerank	old	old
Diameter/ANF	old	DONE
Conn. Comp	old	DONE
Triangles	DONE	
Visualization	STARTED	

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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).

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details

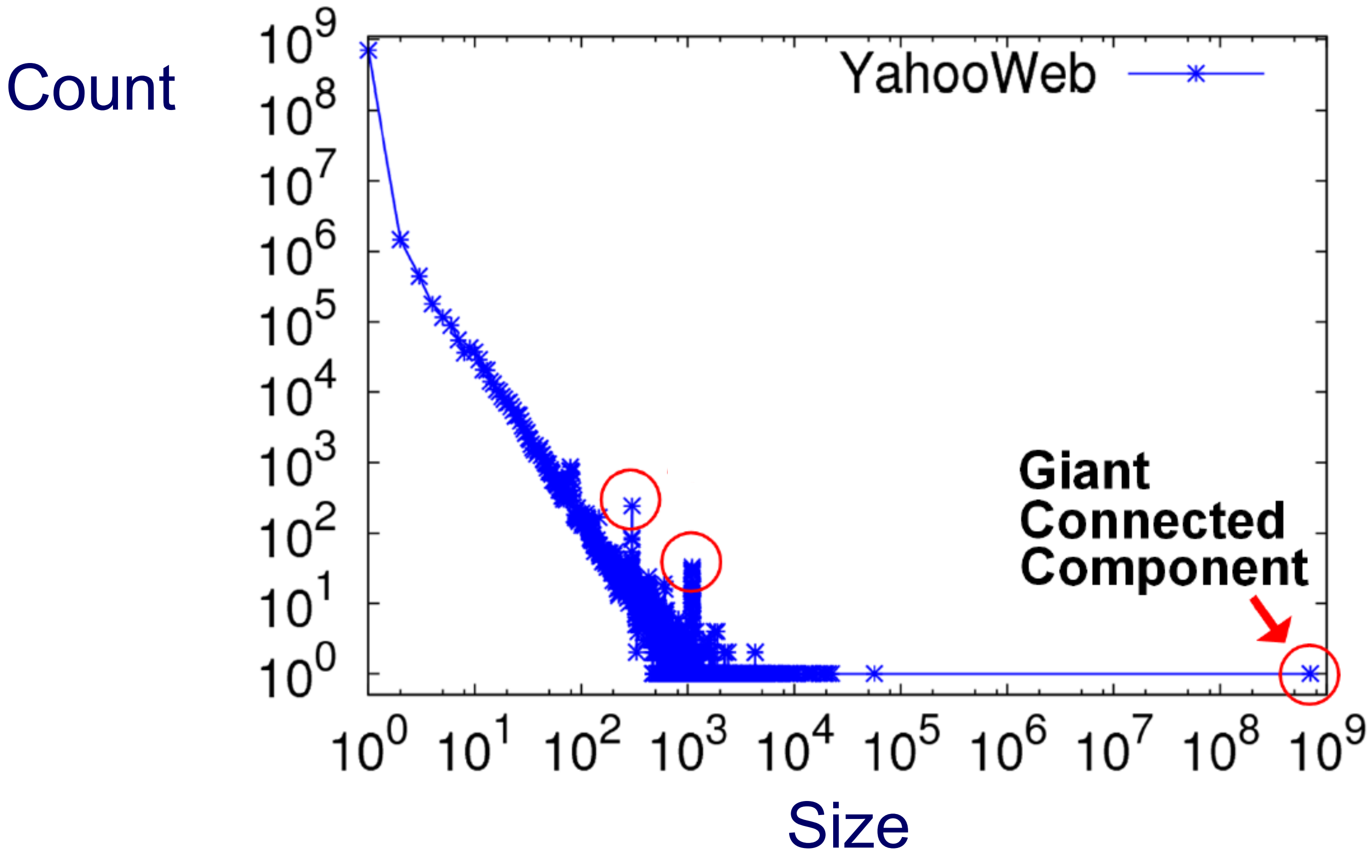
Generalized Iterated Matrix Vector Multiplication (GIMV)

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

Matrix – vector Multiplication (iterated)

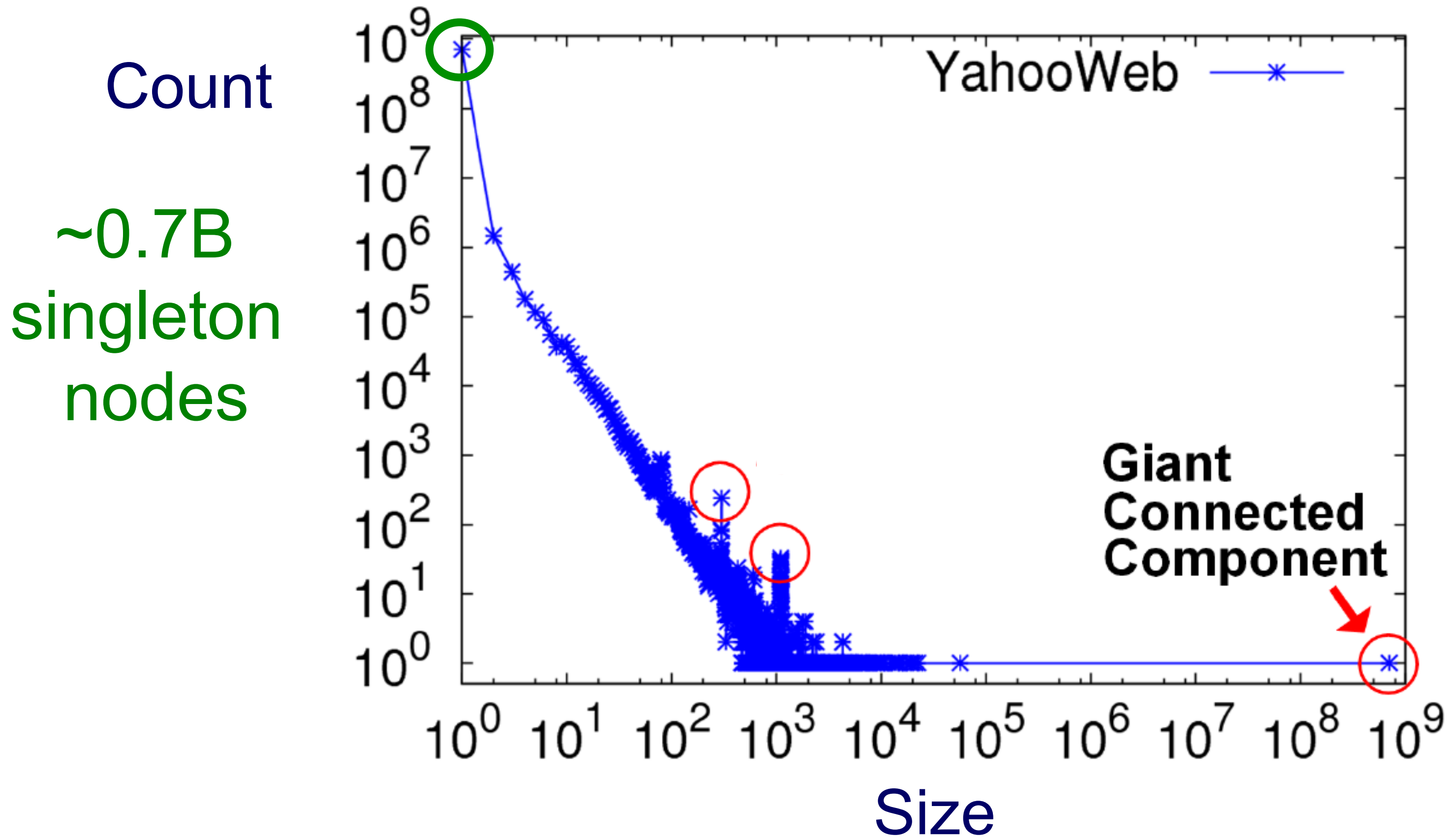
Example: GIM-V At Work

- Connected Components



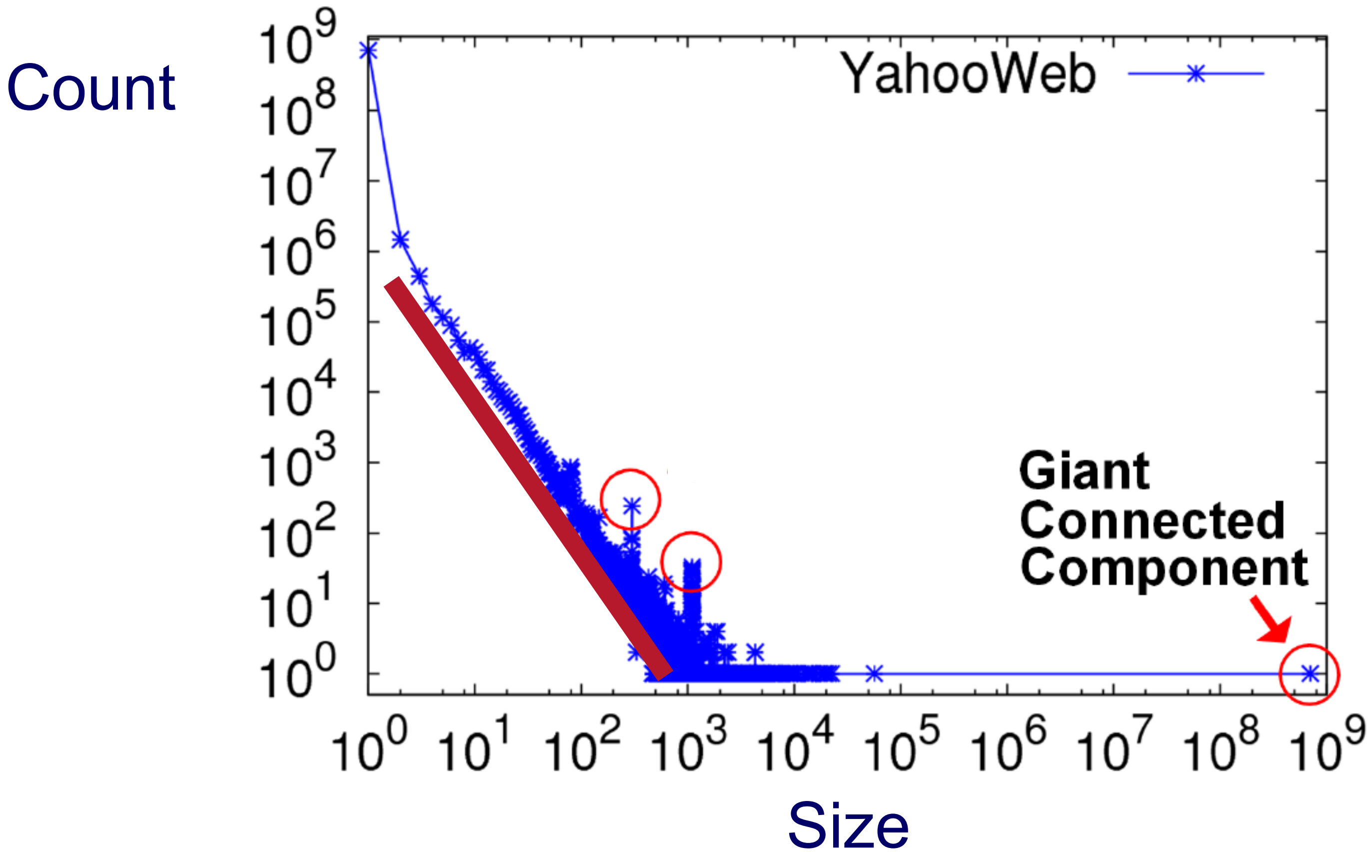
Example: GIM-V At Work

- Connected Components



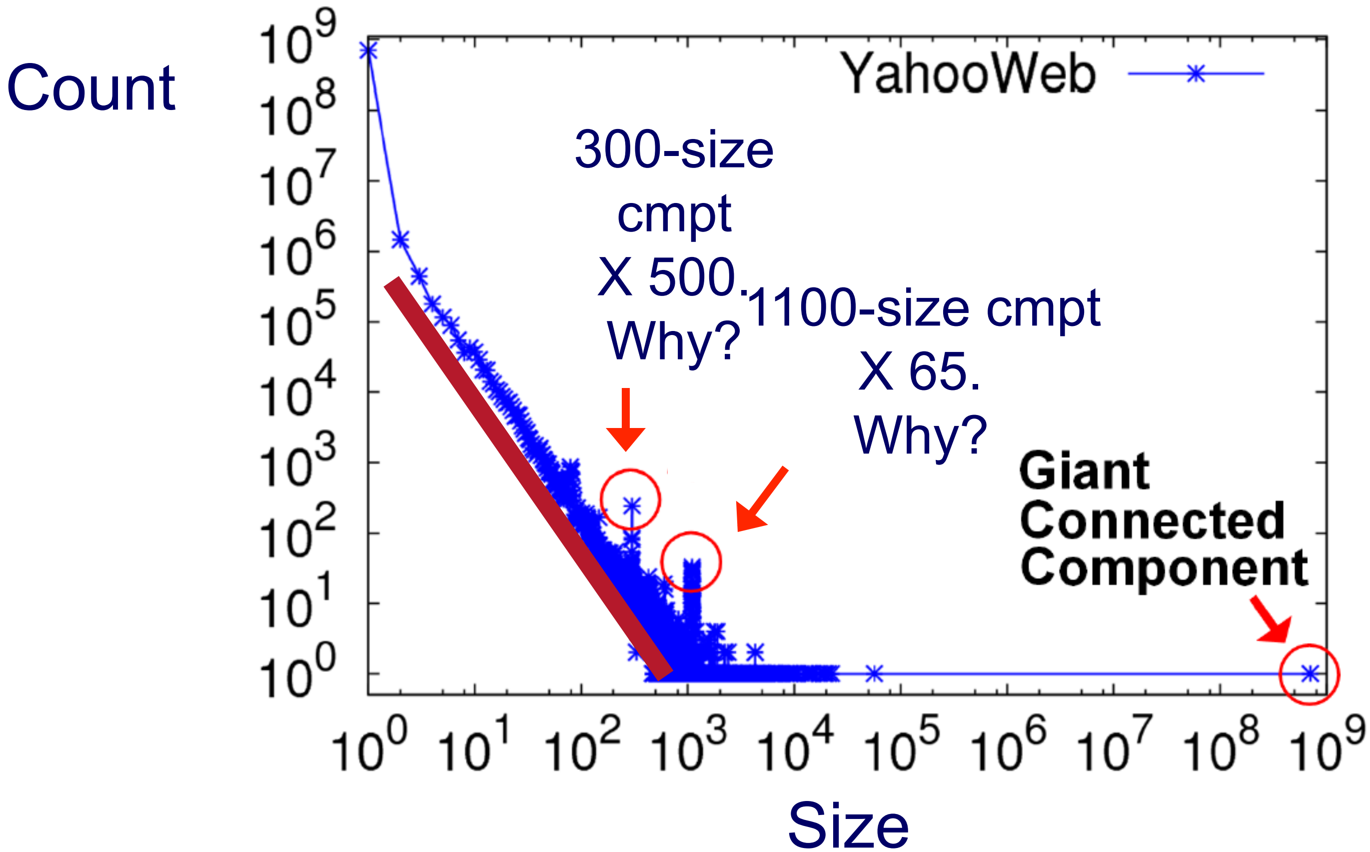
Example: GIM-V At Work

- Connected Components



Example: GIM-V At Work

- Connected Components



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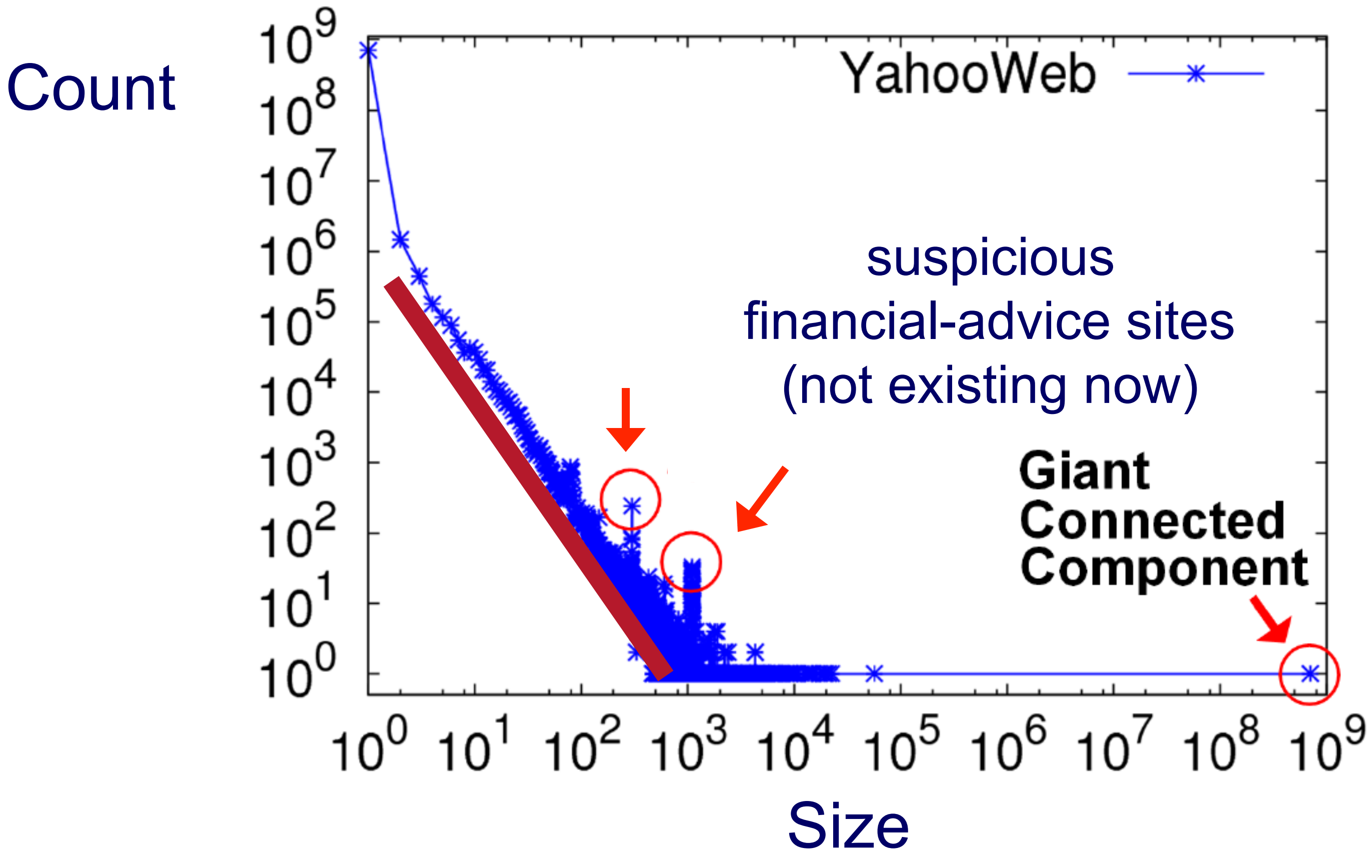
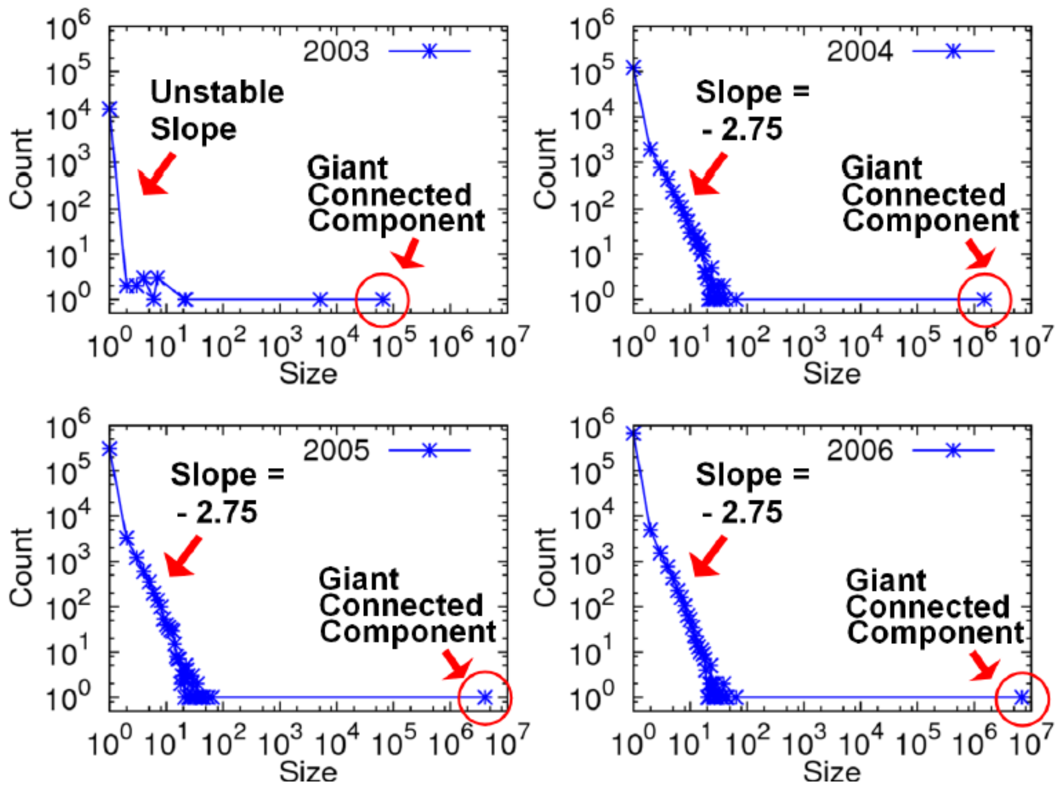
Example: GIM-V At Work

- 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 – Algorithms & results

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Conn. Comp	old	**DONE**
Triangles	**DONE**	
Visualization	**STARTED**	

Mentioned already

Triangles : 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, we only need the top few eigenvalues!

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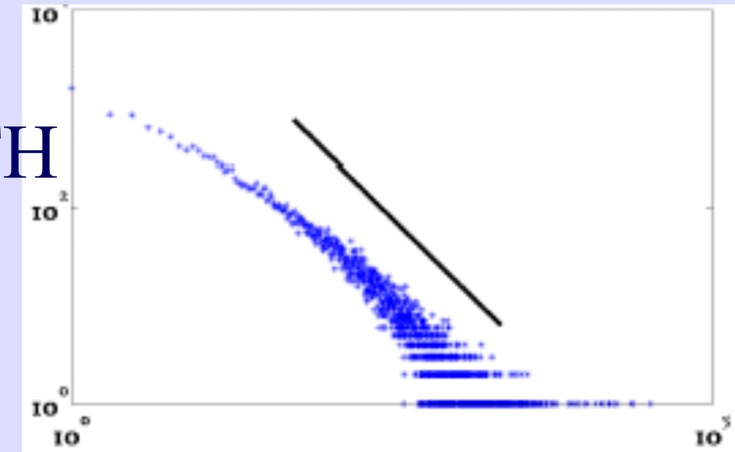
Mentioned already

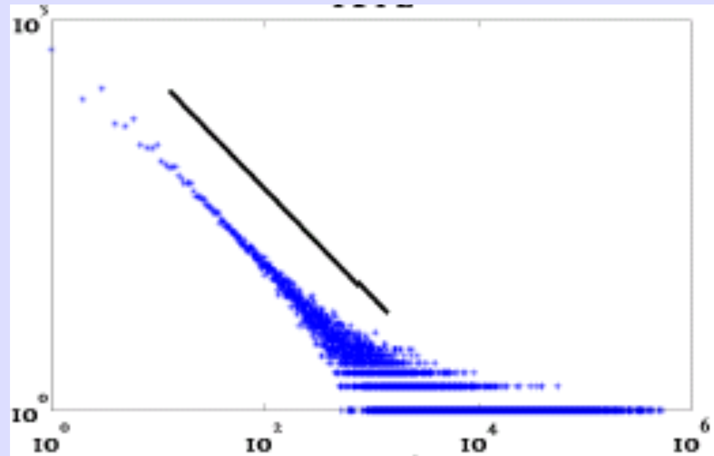
Triangle Law: #1

[Tsourakakis ICDM 2008]

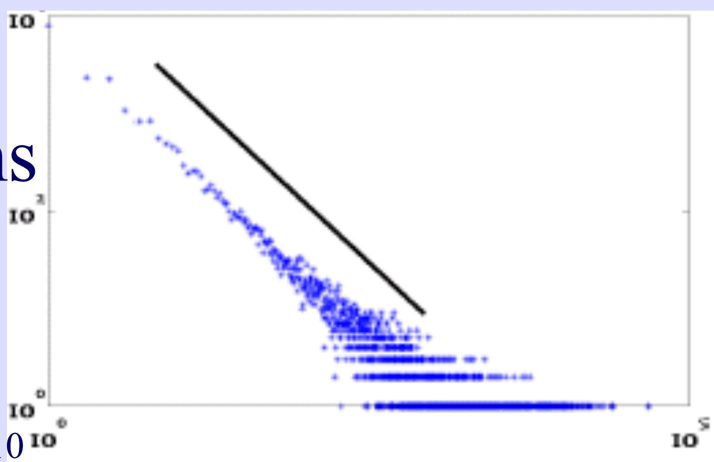
HEP-TH



ASN



Epinions



X-axis: # of Triangles a node participates in

Y-axis: count of such nodes

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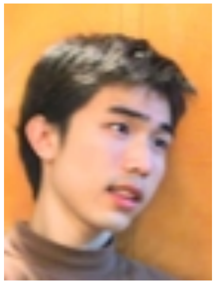
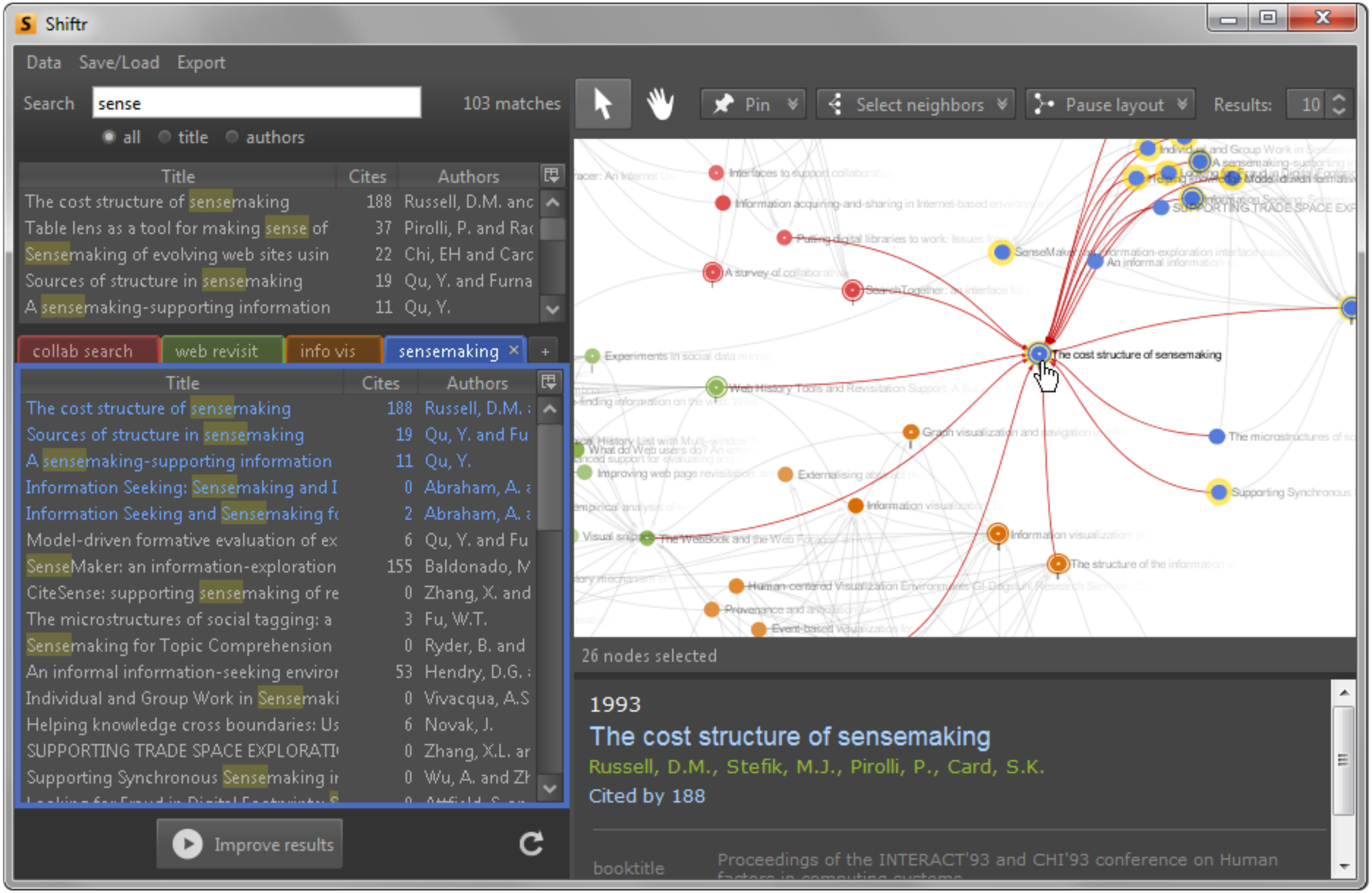
Visualization: ShiftR



- *Supporting Ad Hoc Sensemaking: Integrating Cognitive, HCI, and Data Mining Approaches*
  Aniket Kittur, **Duen Horng (‘Polo’) Chau**, Christos Faloutsos, Jason I. Hong
  Sensemaking Workshop at CHI 2009, April 4-5. Boston, MA, USA.


Shiftr
Data
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Title
Cites
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The cost structure of sensemaking
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Table lens as a tool for making sense of
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Sensemaking of evolving web sites usin
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Sources of structure in sensemaking
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A sensemaking-supporting information
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Qu, Y. and Fu
SenseMaker: an information-exploration
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Baldonado, M
CiteSense: supporting sensemaking of re
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Zhang, X. and
The microstructures of social tagging: a
3
Fu, W.T.
Sensemaking for Topic Comprehension
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Ryder, B. and
An informal information-seeking enviror
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Hendry, D.G.
Individual and Group Work in Sensemaki
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Vivacqua, A.S
Helping knowledge cross boundaries: Us
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Novak, J.
SUPPORTING TRADE SPACE EXPLORATI
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Zhang, X.L. ar
Supporting Synchronous Sensemaking ir
0
Wu, A. and Zh
Improve results
The cost structure of sensemaking
26 nodes selected
1993
The cost structure of sensemaking
Russell, D.M., Stefik, M.J., Pirolli, P., Card, S.K.
Cited by 188
booktitle
Proceedings of the INTERACT'93 and CHI'93 conference on Human

Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
- Problem#3: Scalability
- (additional topics, skipped)
- Conclusions

Other topics - part#1 - tools

- Community detection – how many?
  - Cross-Associations [Chakrabarti +, KDD 2004]
- Time-evolving graphs
  - Tensors [Sun+, KDD'06],
  - [Kolda+ ICDM'05]
  - GraphScope [Sun+, KDD'07]
- Graph compression
  - CUR decomposition [Sun+ SDM'07]

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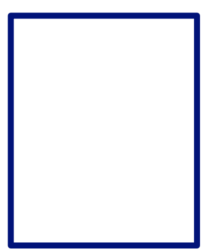
Tensors

- Adjacency matrices, stacked (over time, and/or edge-type – ‘composite networks’)



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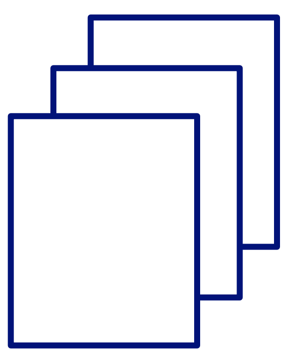
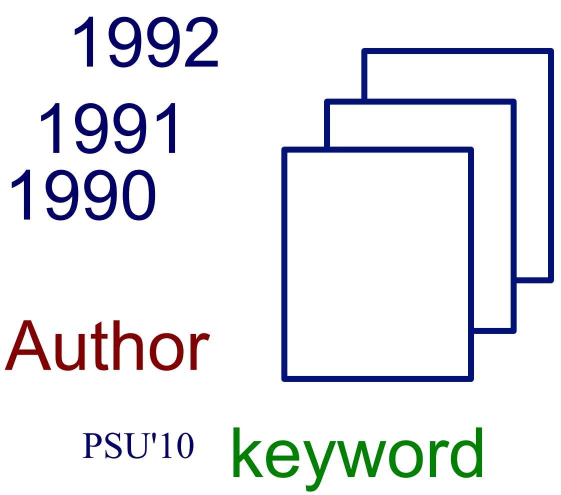
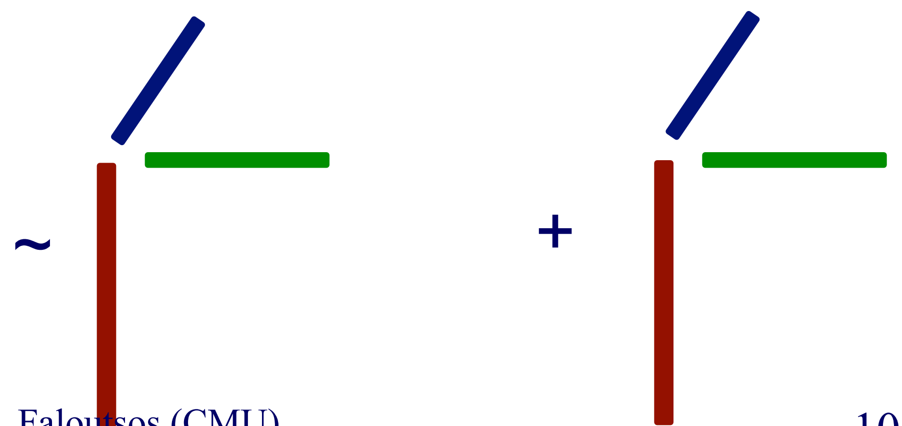


Tensors

- Adjacency matrices, stacked (over time, and/or edge-type – ‘composite networks’)

PARAFAC tensor decomposition (generalization of SVD)





Other topics – part#2 - generators

- Kronecker [PKDD'05];
- Random Typing [Akoglu+, PKDD'09]

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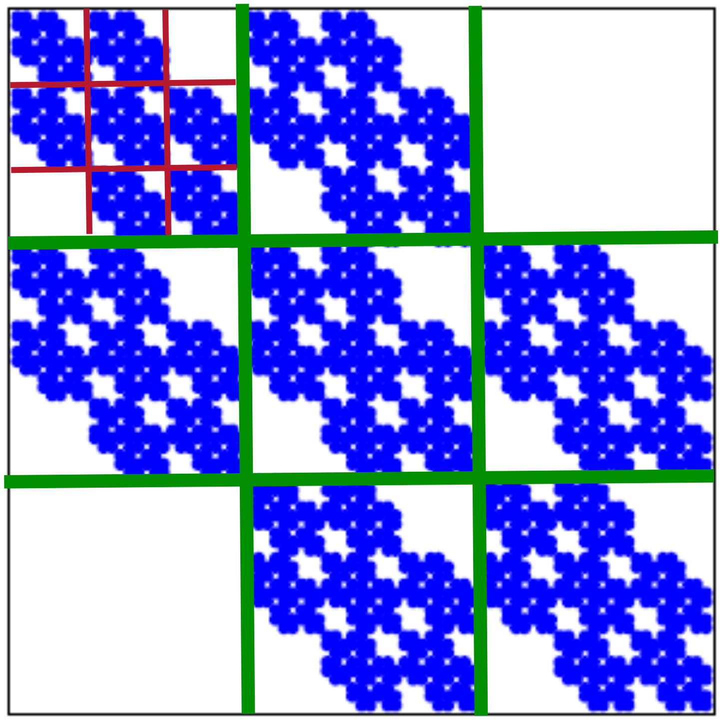
Kronecker Product – a Graph

- One of most realistic generators, with **provable** properties



Other topics - part#3 – virus propagation

- Epidemic threshold for SIS: depends **only** on first eigenvalue of adjacency matrix

$$\lambda_1$$

- [Chakrabarti+, TISSEC'07]

Other topics - part#3 – virus propagation

- Ditto for epidemic threshold for
  - SIR (mumps – lifetime immunity)
  - SEIR (incubation)
  - MSEIR (temp. immunity by birth)
  - S I1 I2 R (HIV)
- In all cases, the epid. threshold depends on

$$\lambda_1$$

- [B.A. Prakash ++, 2010]
- http://arxiv.org/abs/1004.0060

Other topics - part#3 – virus propagation

- Immunization policies [Tong+, under review]
- Drinking water sensor placement [KDD’07]

More info

Tutorial on graph mining: KDD'09

(w/ Gary Miller and C. Tsourakakis)

www.cs.cmu.edu/~christos/TALKS/09-KDD-tutorial/

Tutorial on tensors: SIGMOD'07

(w/ T. Kolda and J. Sun):

www.cs.cmu.edu/~christos/TALKS/SIGMOD-07-tutorial/

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Outline

- Introduction – Motivation
- Problem#1: Patterns in graphs
- Problem#2: Tools
- Problem#3: Scalability
- (additional topics, skipped)
- Conclusions

OVERALL CONCLUSIONS – low level:

- Several new **patterns** (fortification, triangle-laws, conn. components, etc)
- New **tools**:
  - CenterPiece Subgraphs, G-Ray, anomaly detection (OddBall)
- **Scalability**: PEGASUS / hadoop

OVERALL CONCLUSIONS – high level

- Large datasets may reveal patterns/outliers that would be invisible otherwise
- Terrific opportunities
  - Large datasets, easily(*) available PLUS
  - s/w and h/w developments
- Promising collaborations between DB/Sys, AI/Stat, sociology, marketing, epidemiology, ++

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Project info

www.cs.cmu.edu/~pegasus

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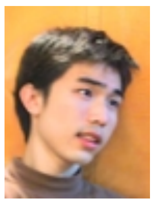

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