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Mining Billion-node Graphs: Patterns, Generators and Tools

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CMU

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Thanks!

- Andy Yoo
- Tina Eliassi-Rad
- Brian Gallagher
- Keith Henderson
- Irene Massiat

Our goal:

Open source system for mining huge graphs:

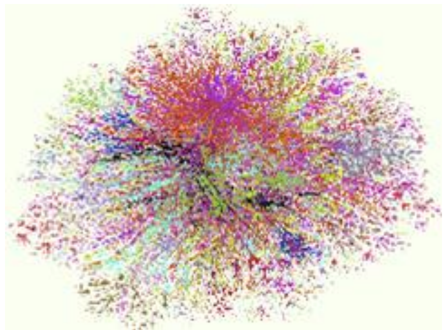
PEGASUS project (PEta GrAph mining System)

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

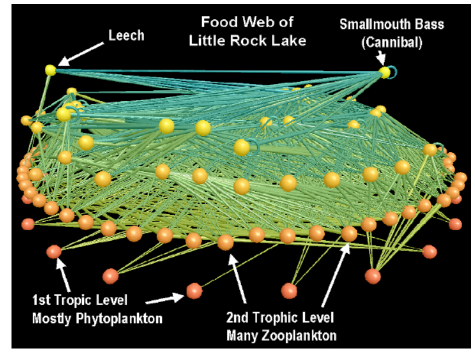
Outline

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

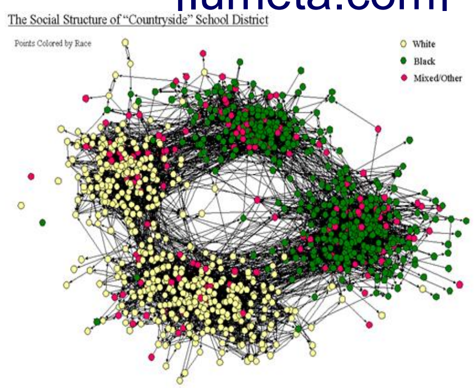
Graphs - why should we care?



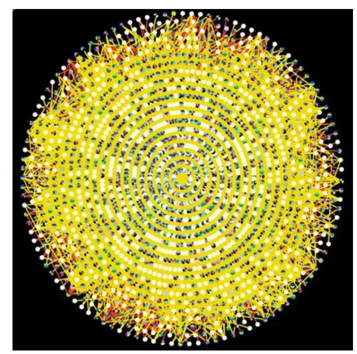
Internet Map
[lumeta.com]



Food Web
[Martinez ’91]



Friendship Network
[Moody ’01]



Protein Interactions
[genomebiology.com]

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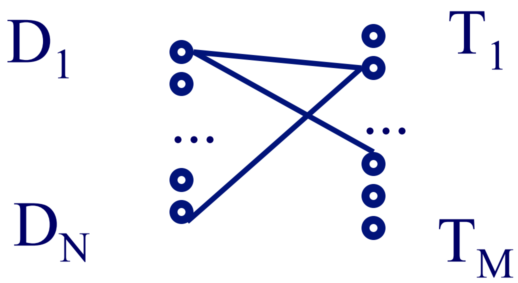
Graphs - why should we care?

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



- 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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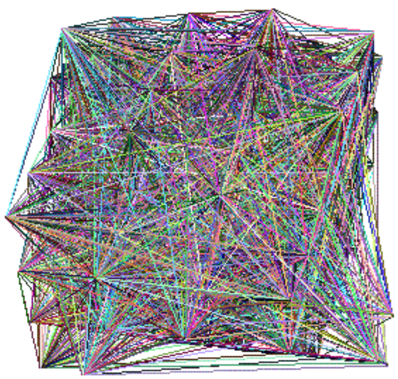
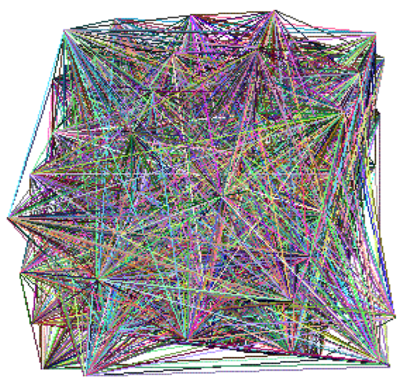
Problem #1 - network and graph mining



- 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



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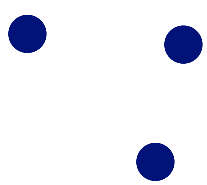
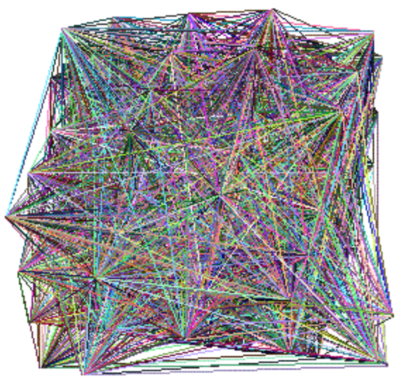
  - To spot **anomalies** (rarities), we have to discover **patterns**

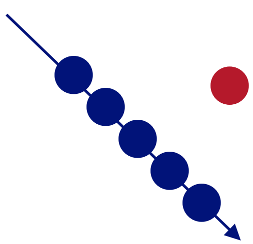


Problem #1 - network and graph mining



- 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?

Laws and patterns

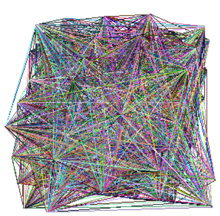
- Are real graphs random?
- A: NO!!
  - Diameter
  - in- and out- degree distributions
  - other (surprising) patterns

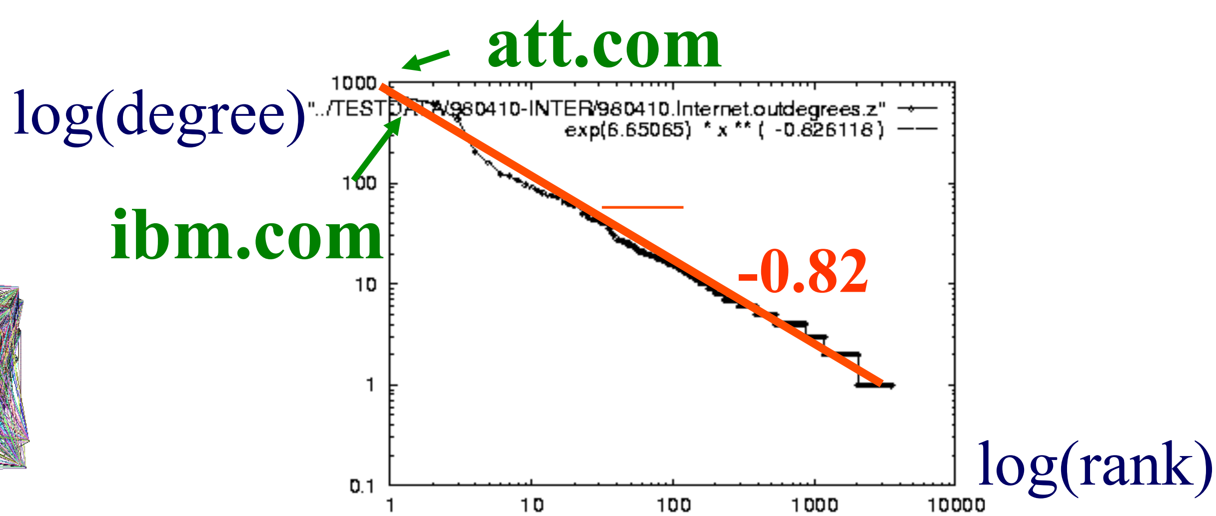
- So, let’s look at the data

Solution# S.1

- Power law in the degree distribution [SIGCOMM99]

internet domains





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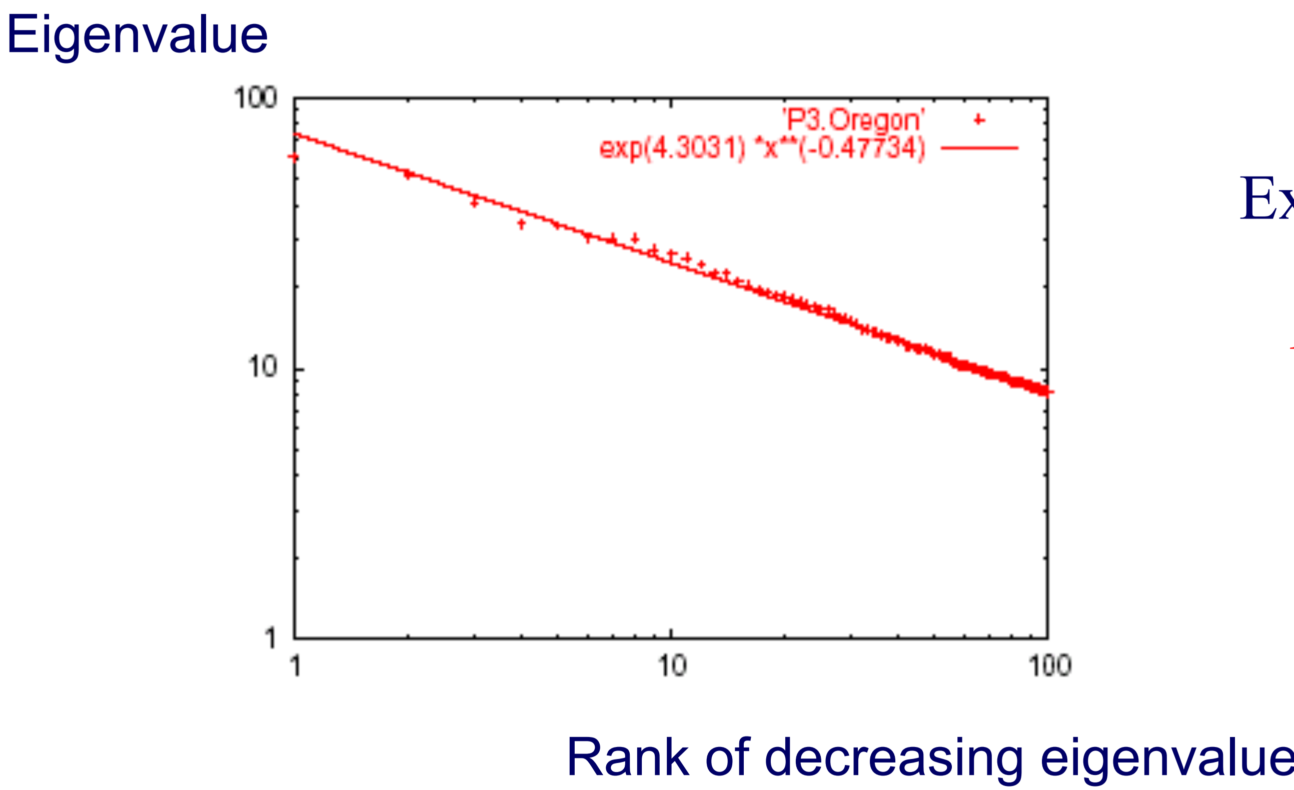
Solution# S.2: Eigen Exponent *E*



Exponent = slope

E = -0.48

May 2001

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

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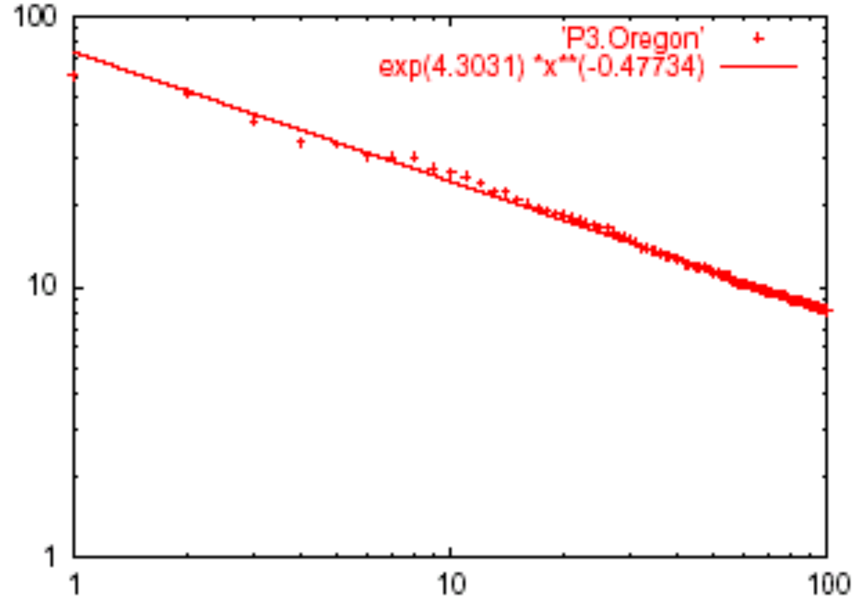
Solution# S.2: Eigen Exponent *E*

Eigenvalue



Rank of decreasing eigenvalue

Exponent = slope

$E = -0.48$

May 2001

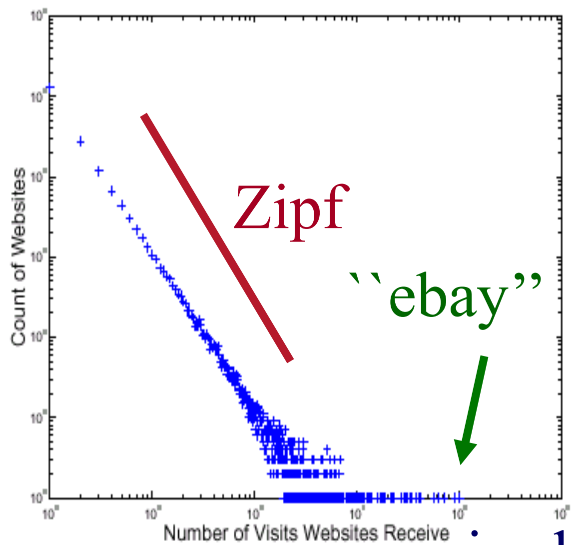
- [Mihail, Papadimitriou '02]: slope is ½ of rank exponent

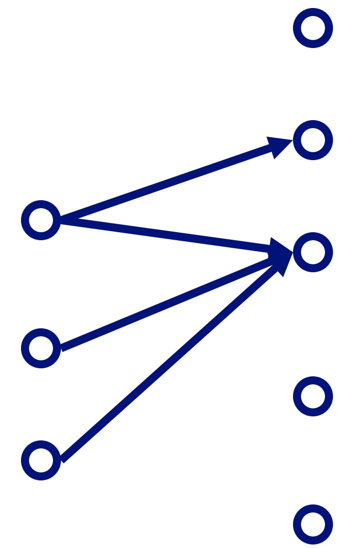
But:

How about graphs from other domains?

More power laws:

- web hit counts [w/ A. Montgomery]





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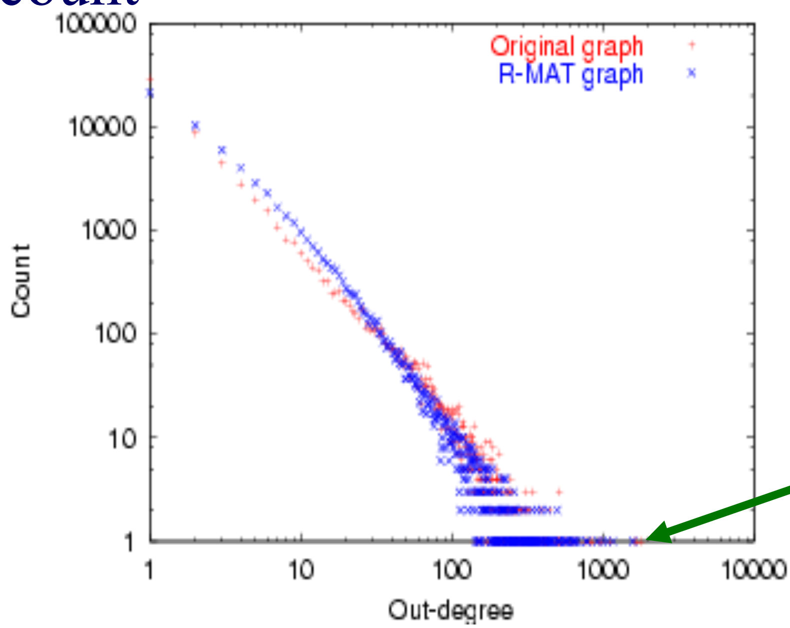
epinions.com

- 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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- Introduction – Motivation
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    - degree, diameter, eigen,
    - triangles
    - cliques
  - Weighted graphs
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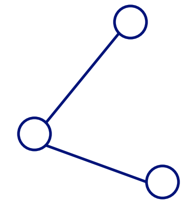
- Problem#2: Tools

Solution# S.3: Triangle 'Laws'



- Real social networks have a lot of triangles

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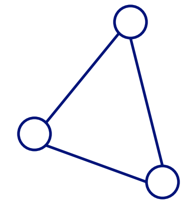
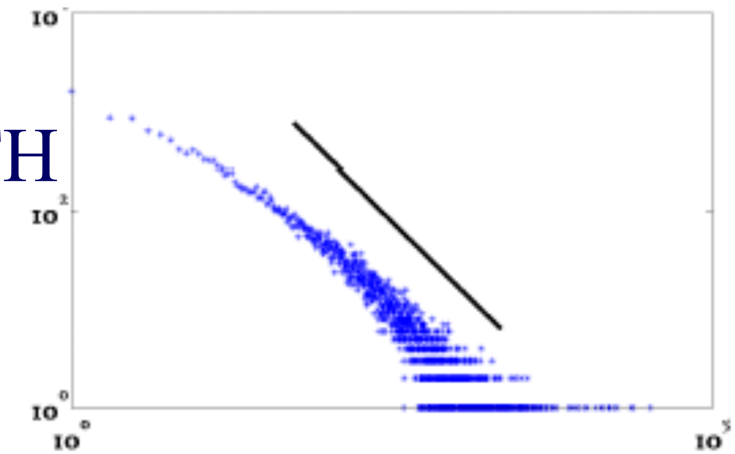
Solution# S.3: Triangle ‘Laws’

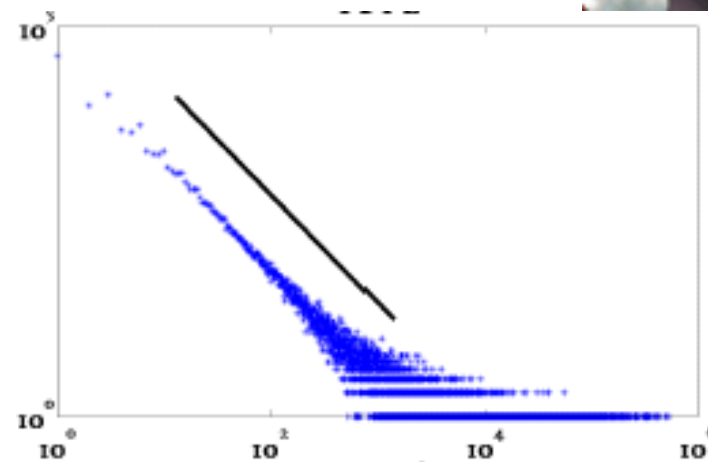


- Real social networks have a lot of triangles
  - Friends of friends are friends
- Any patterns?

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

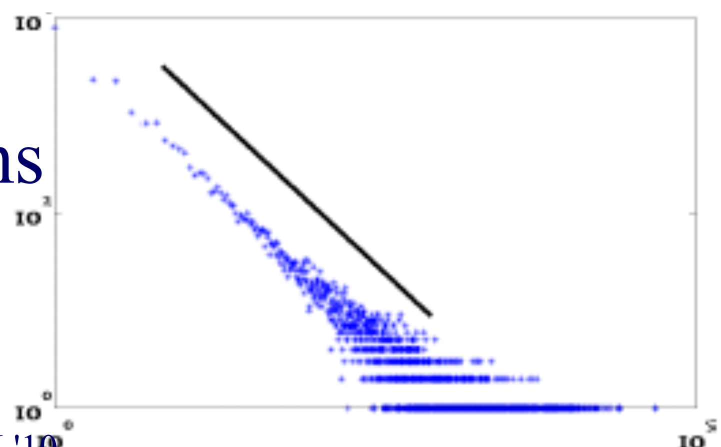
HEP-TH





ASN

Epinions



X-axis: # of Triangles
a node participates in
Y-axis: count of such nodes

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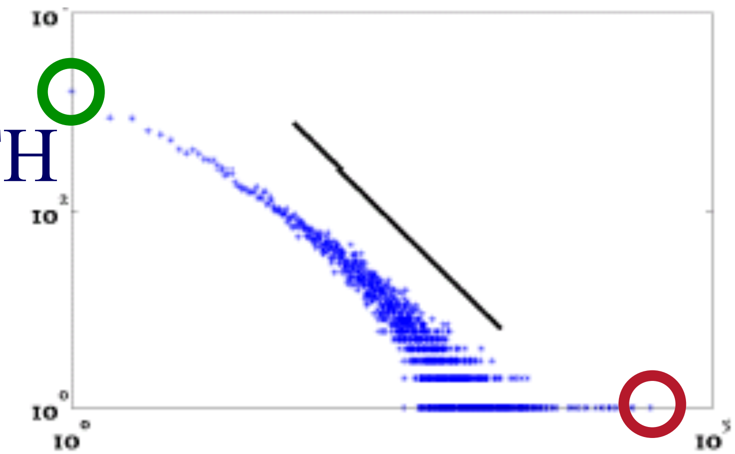
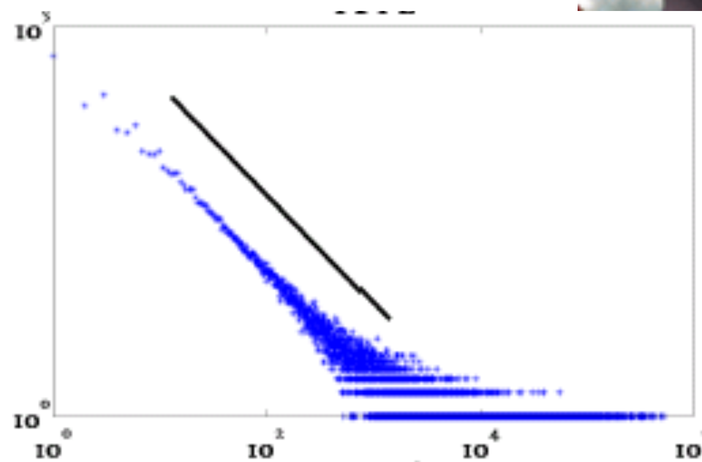
Triangle Law: #S.3
[Tsourakakis ICDM 2008]

HEP-TH





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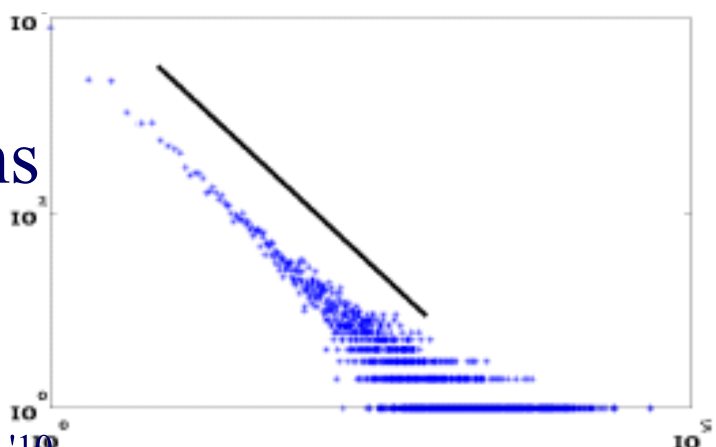

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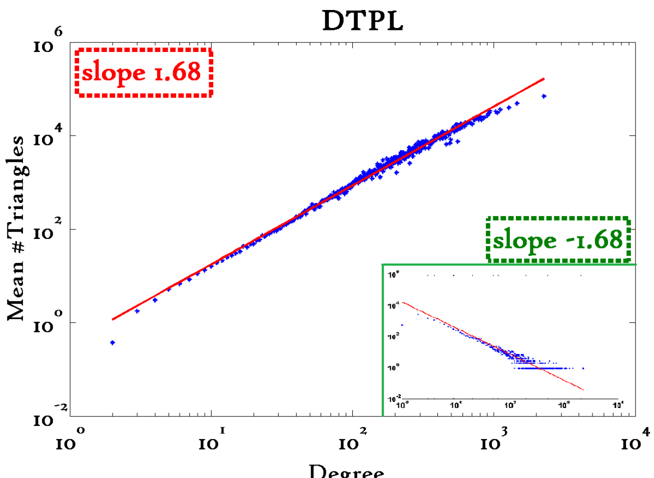
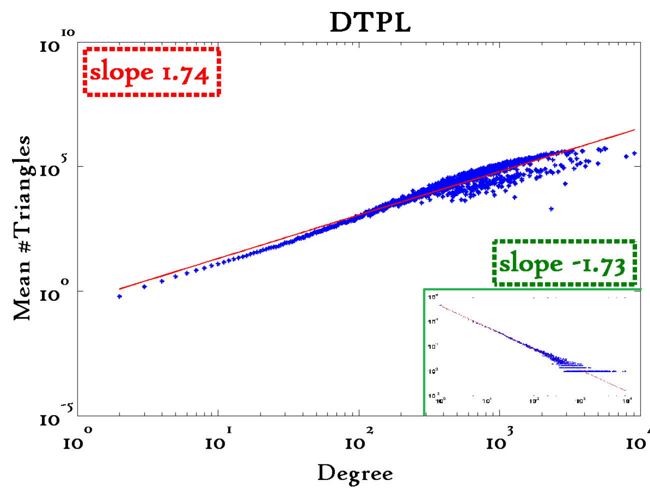
Triangle Law: #S.4
[Tsourakakis ICDM 2008]

Reuters



SN



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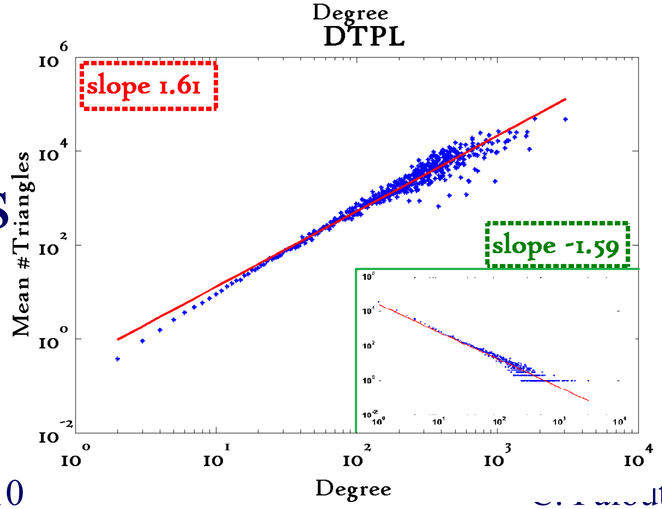

X-axis: degree

Y-axis: mean # triangles

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

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!

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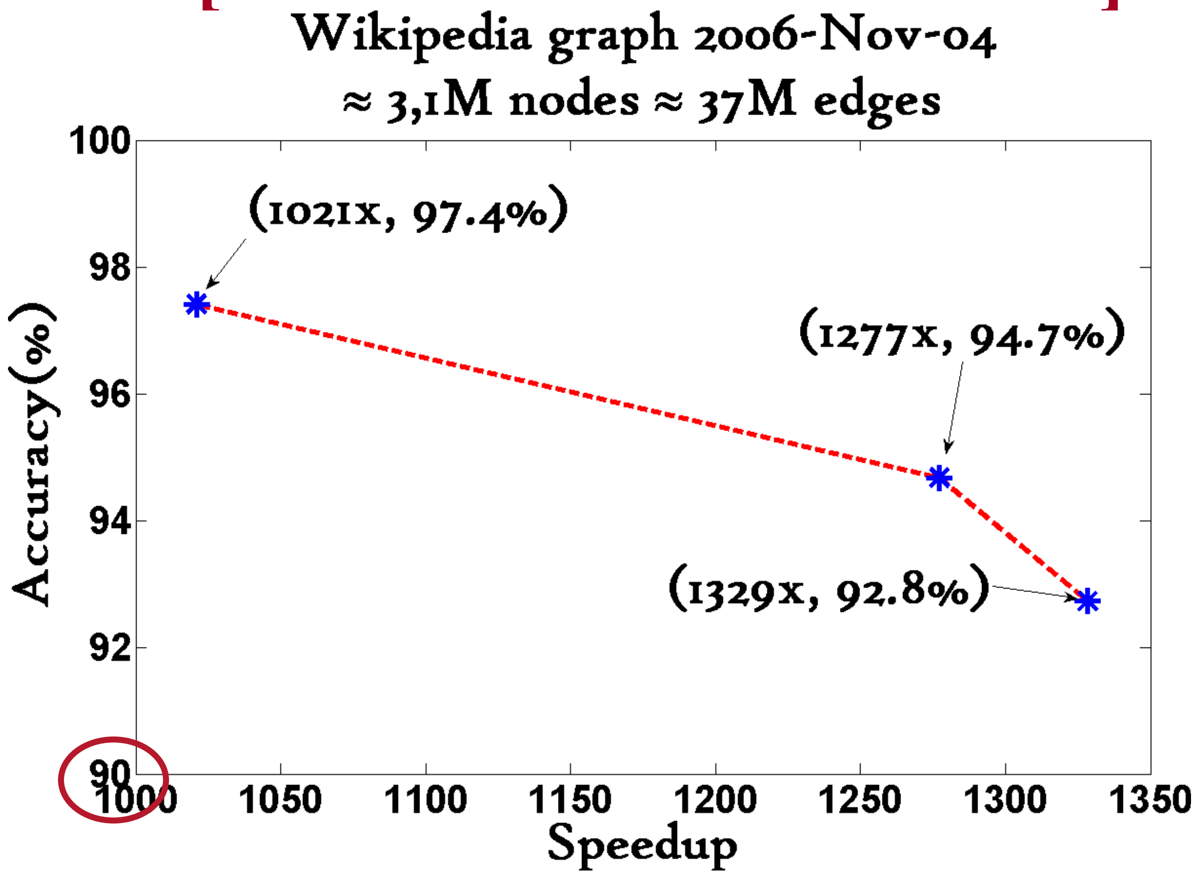
details

Triangle Law: Computations

[Tsourakakis ICDM 2008]



1000x+ speed-up, >90% accuracy

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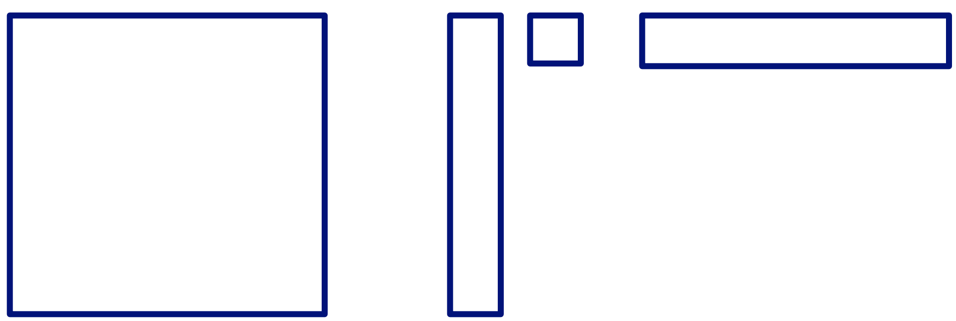
EigenSpokes

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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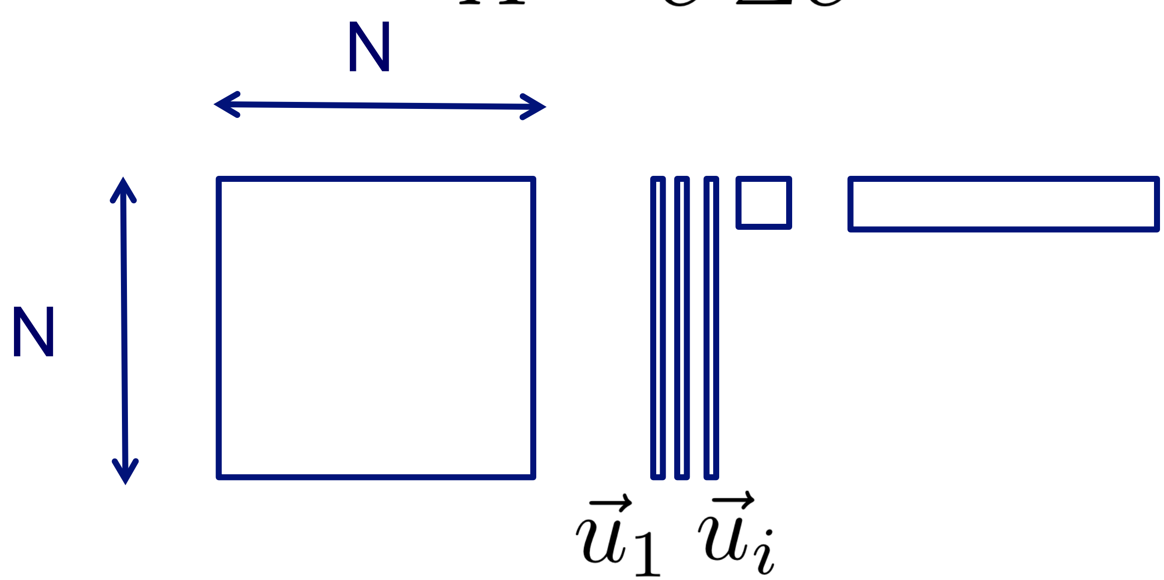

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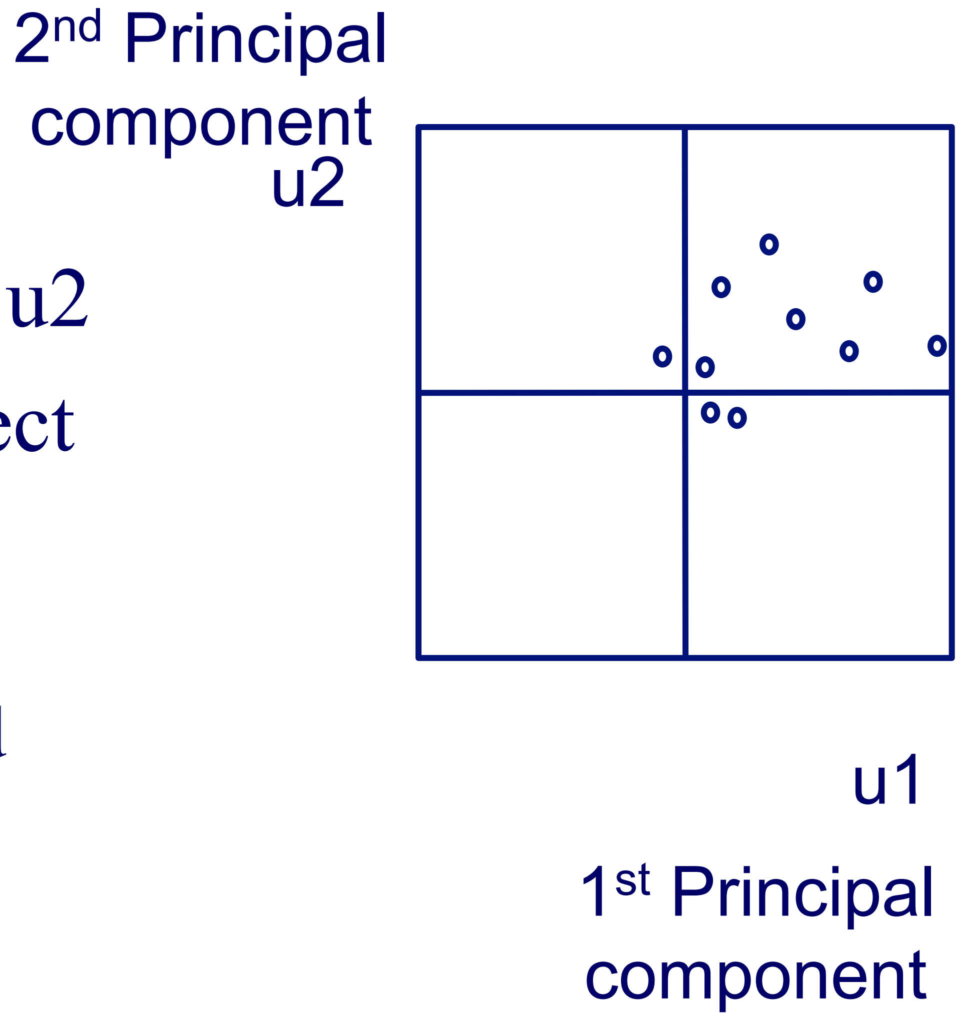
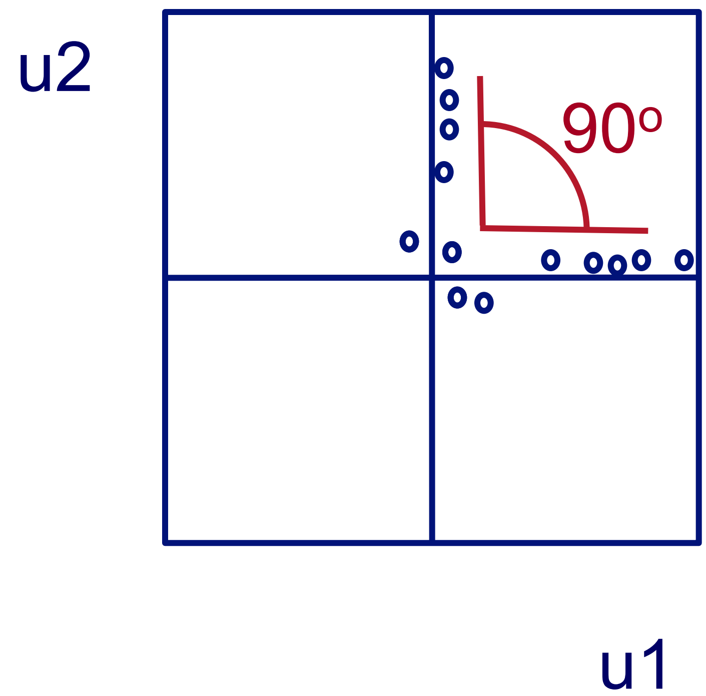
EigenSpokes

- 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 ~normal



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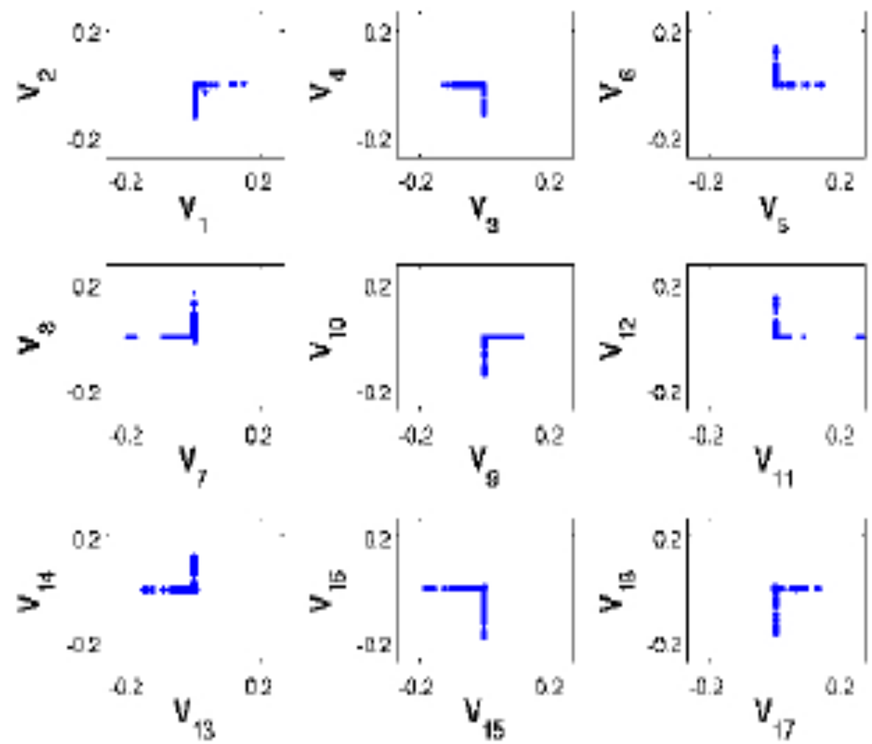
EigenSpokes - pervasiveness

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



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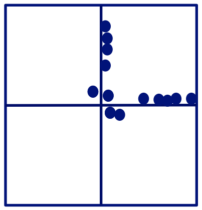
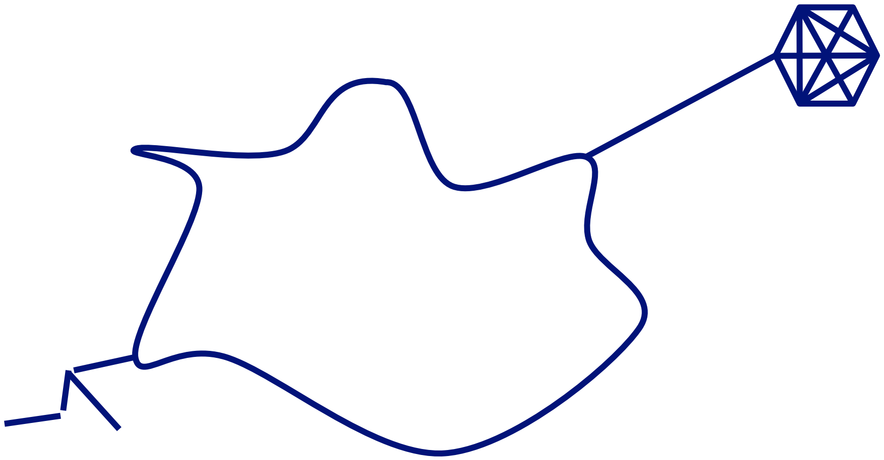
EigenSpokes - explanation



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



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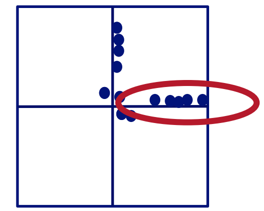

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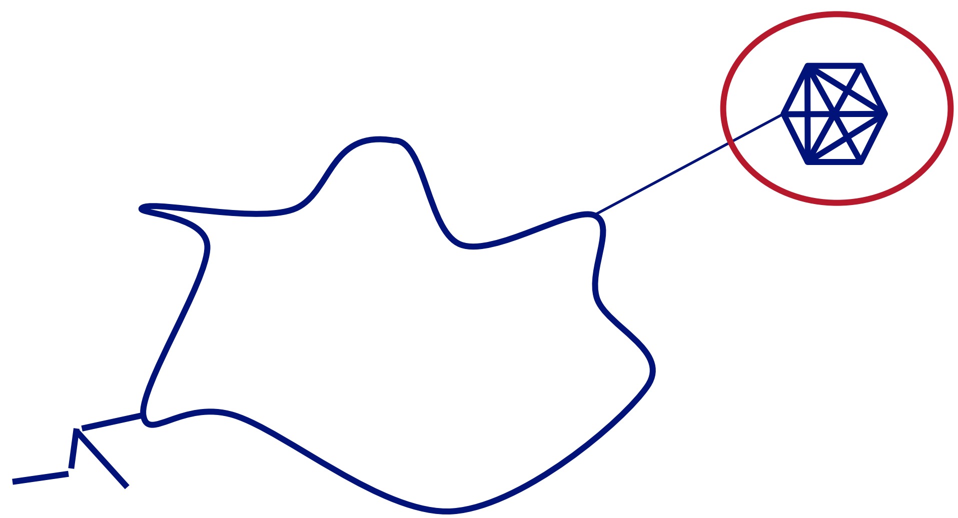

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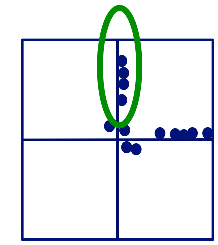

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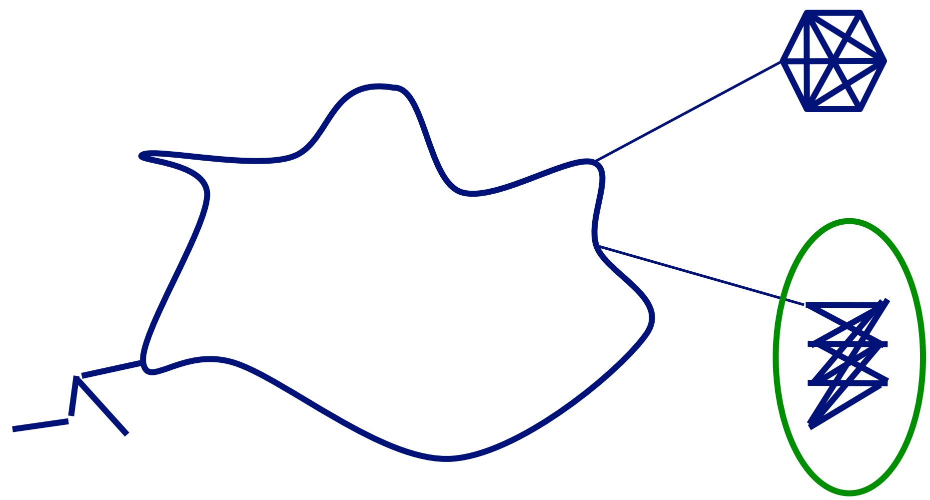

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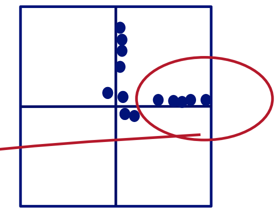

Near-cliques, or near
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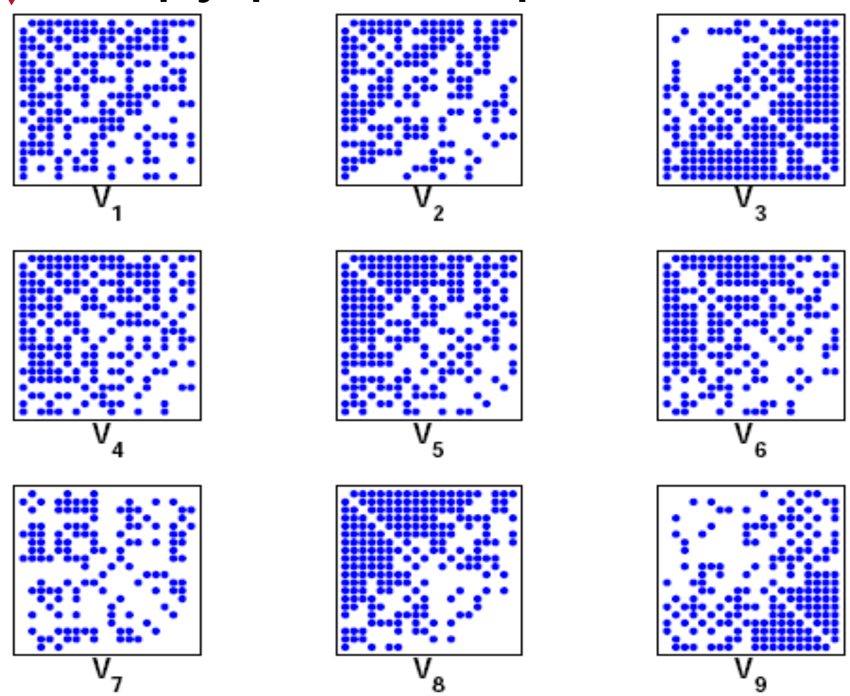
connected

spy plot of top 20 nodes



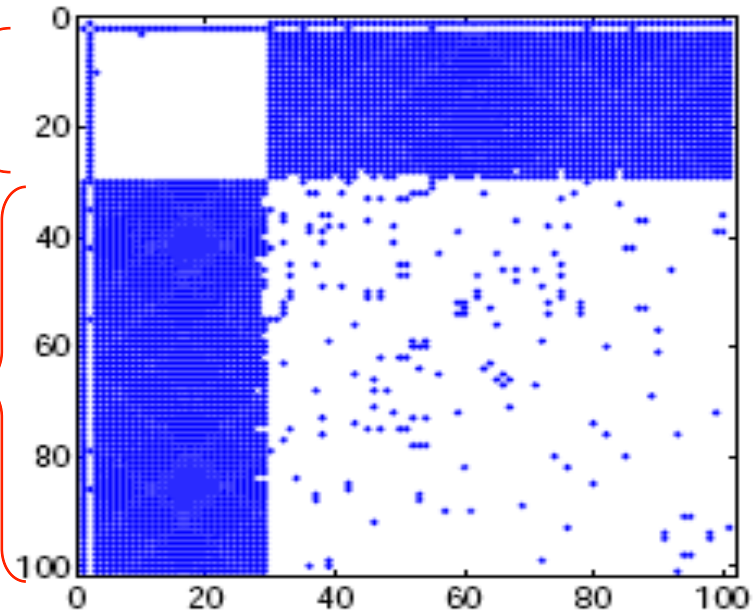
So what?

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

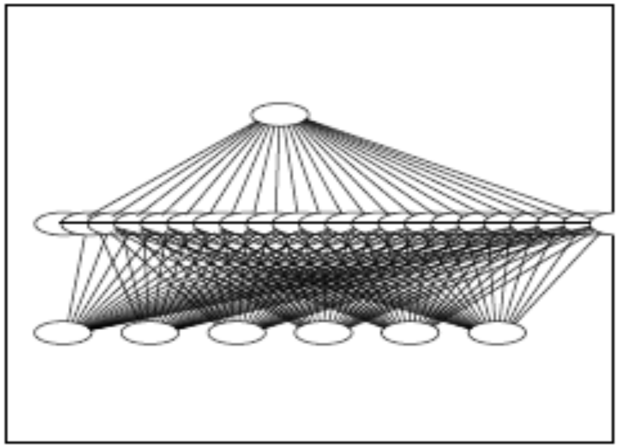
Bipartite Communities!

patents from
same inventor(s)

cut-and-paste
bibliography!



magnified bipartite community



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Observations on weighted graphs?

- A: yes - even more ‘laws’!

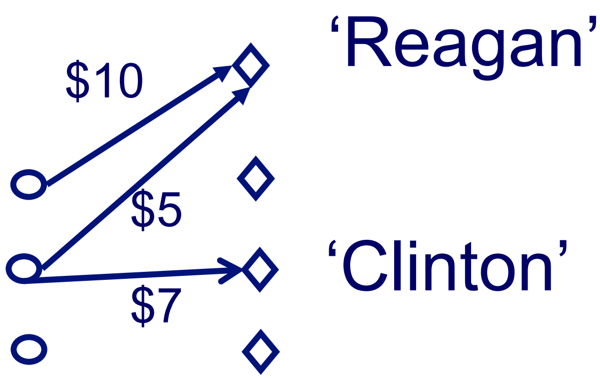
M. McGlohon, L. Akoglu, and C. Faloutsos
Weighted Graphs and Disconnected Components: Patterns and a Generator.
SIG-KDD 2008

Observation W.1: Fortification

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

Observation W.1: Fortification

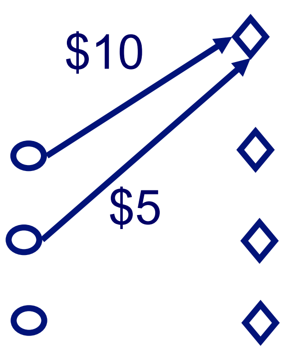
More donors, more $?



Observation W.1: fortification: Snapshot Power Law

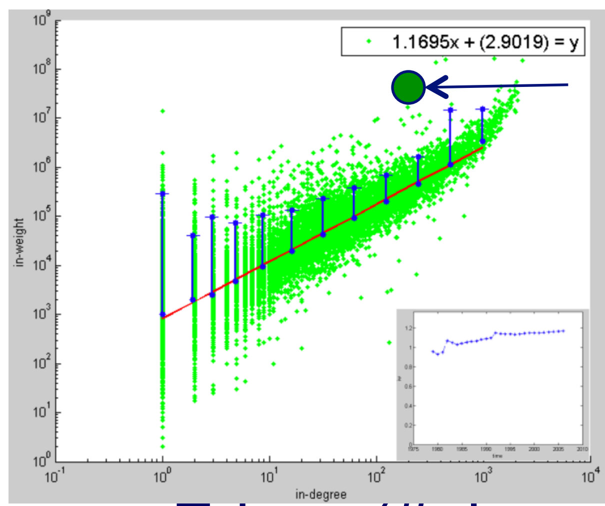
- Weight: super-linear on in-degree
- exponent 'iw': 1.01 < iw < 1.26

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



Orgs-Candidates

In-weights ($)



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

Edges (# donors)

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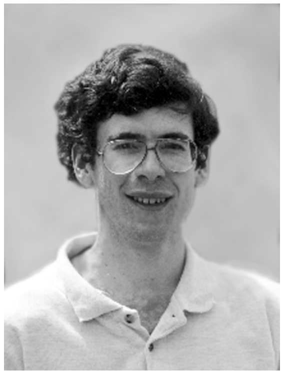
Problem: Time evolution

- 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?

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

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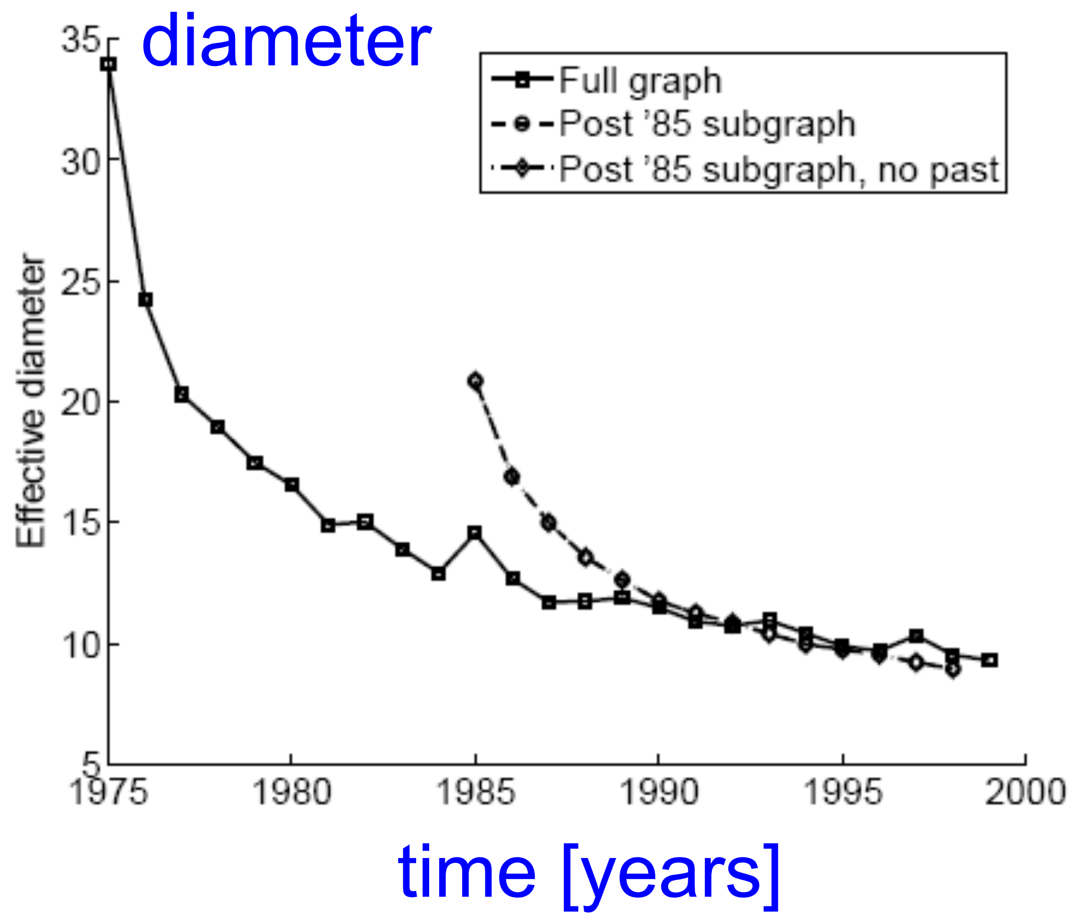
T.1 Diameter – “Patents”

- 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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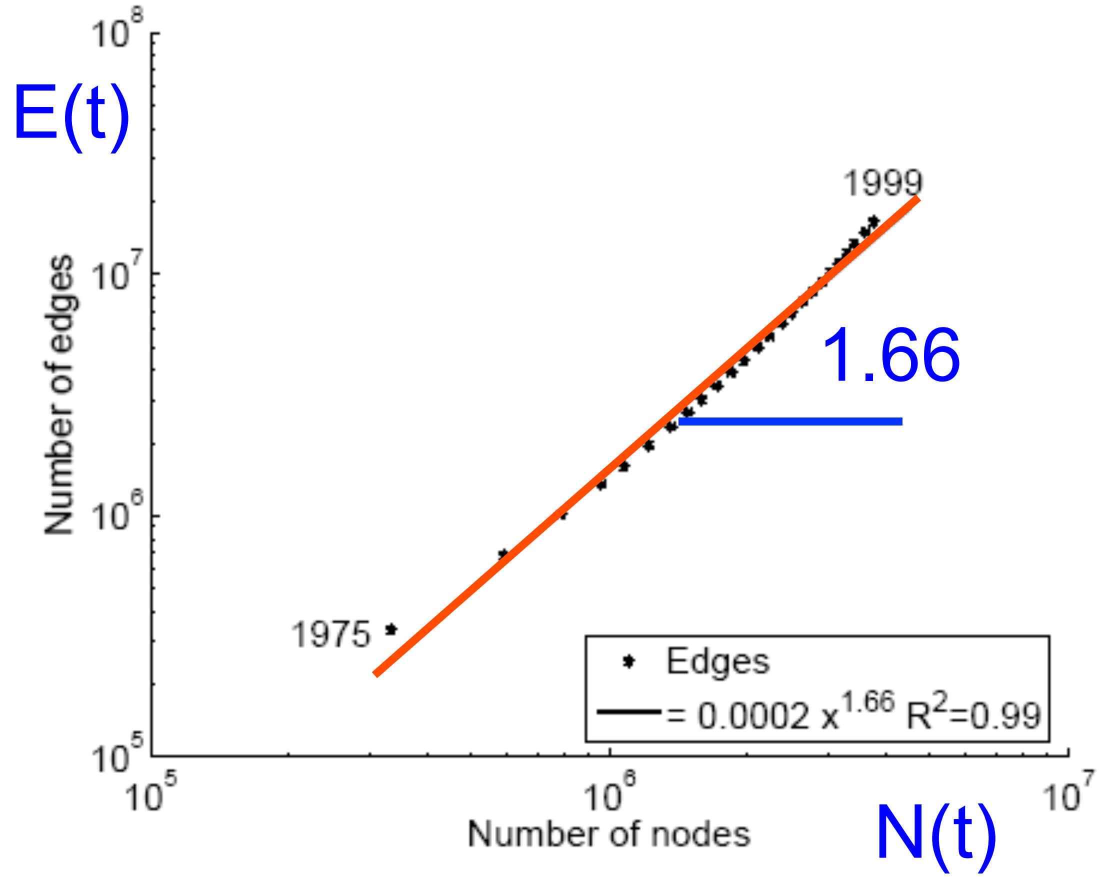
T.2 Densification – Patent Citations

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



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More on Time-evolving graphs

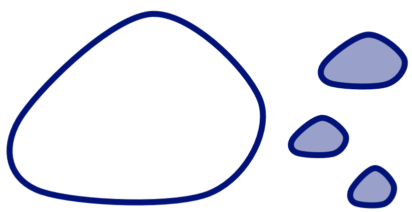
M. McGlohon, L. Akoglu, and C. Faloutsos
Weighted Graphs and Disconnected Components: Patterns and a Generator.
SIG-KDD 2008

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?

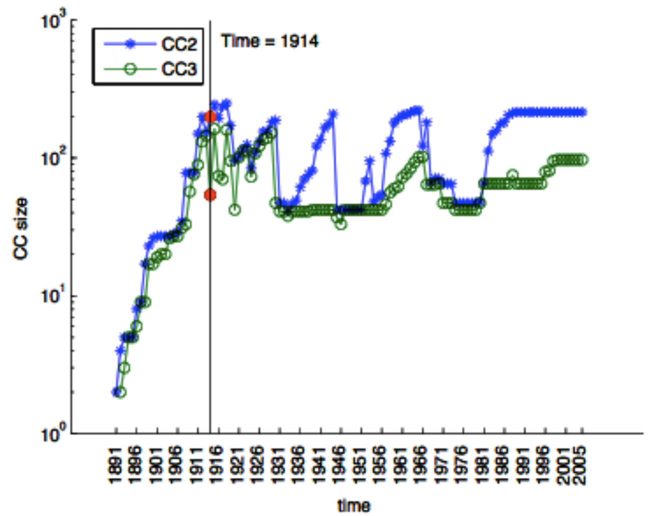


Observation T.3: NLCC behavior

- 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]

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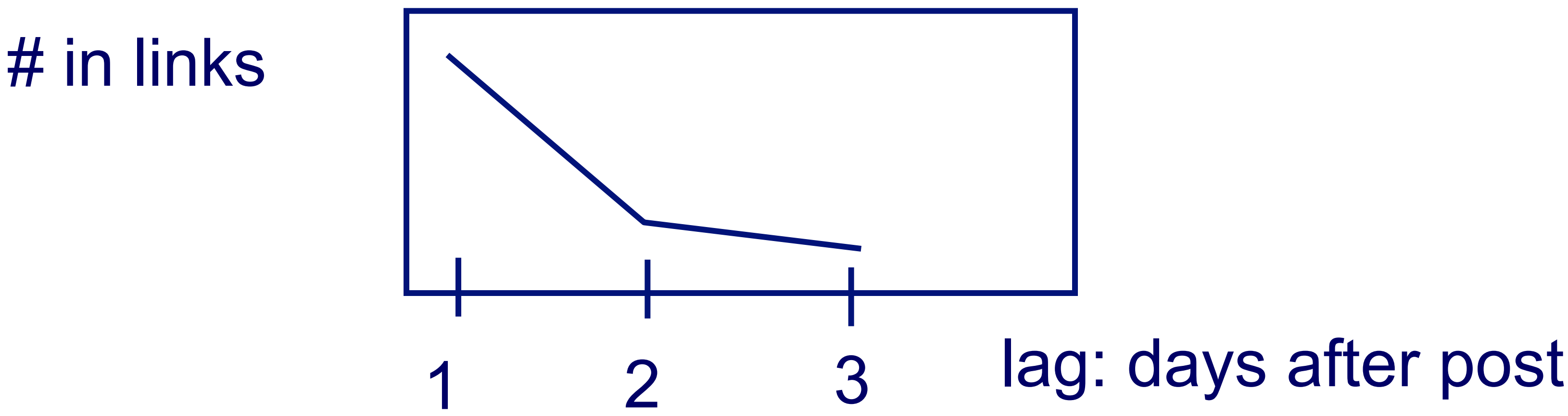
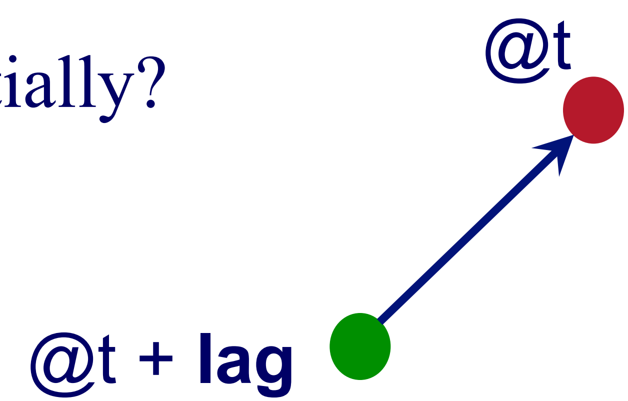
T.4 : popularity over time



Post popularity drops-off – exponentially?



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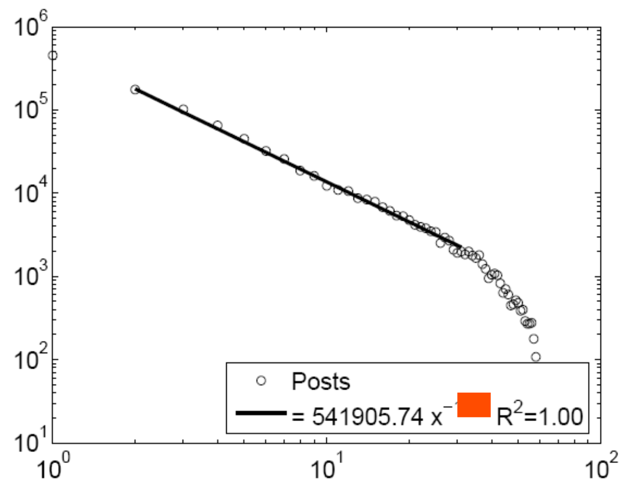
T.4 : popularity over time

in links (**log**)



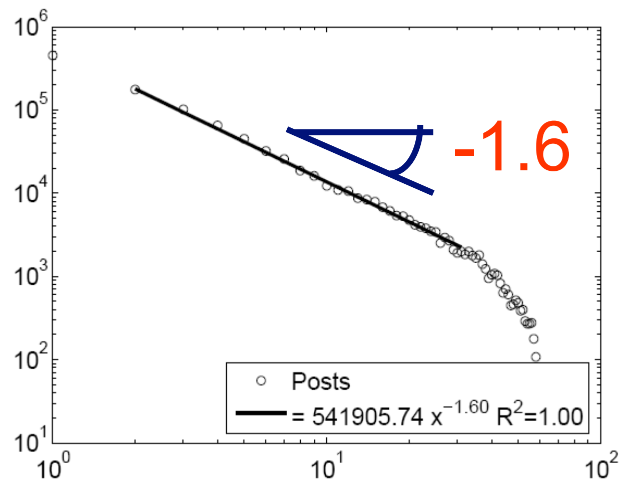
days after post (**log**)

Post popularity drops-off – exponentially?

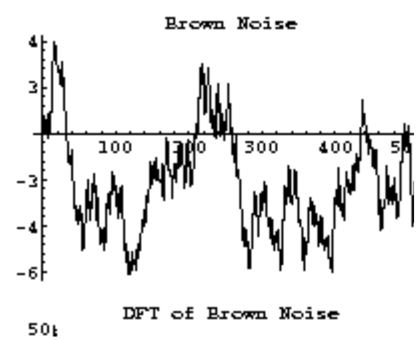
POWER LAW!

Exponent?

T.4 : popularity over time



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

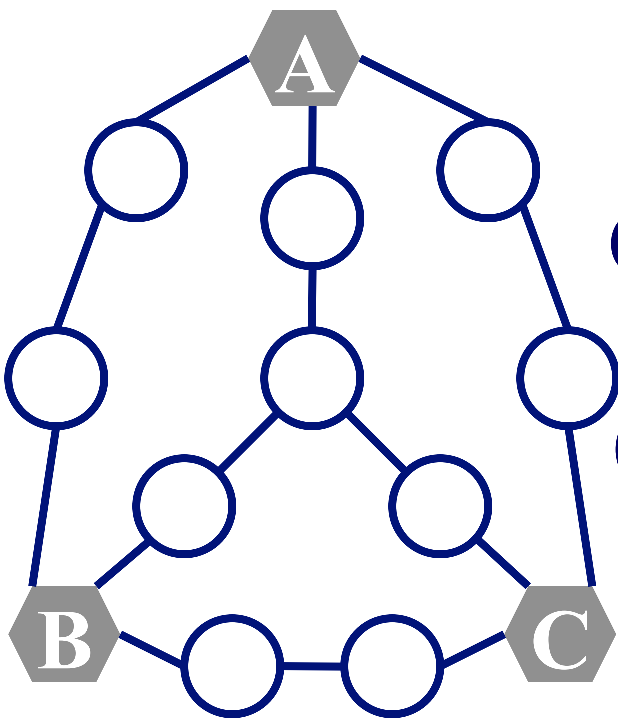
CenterPiece Subgraphs

- 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)

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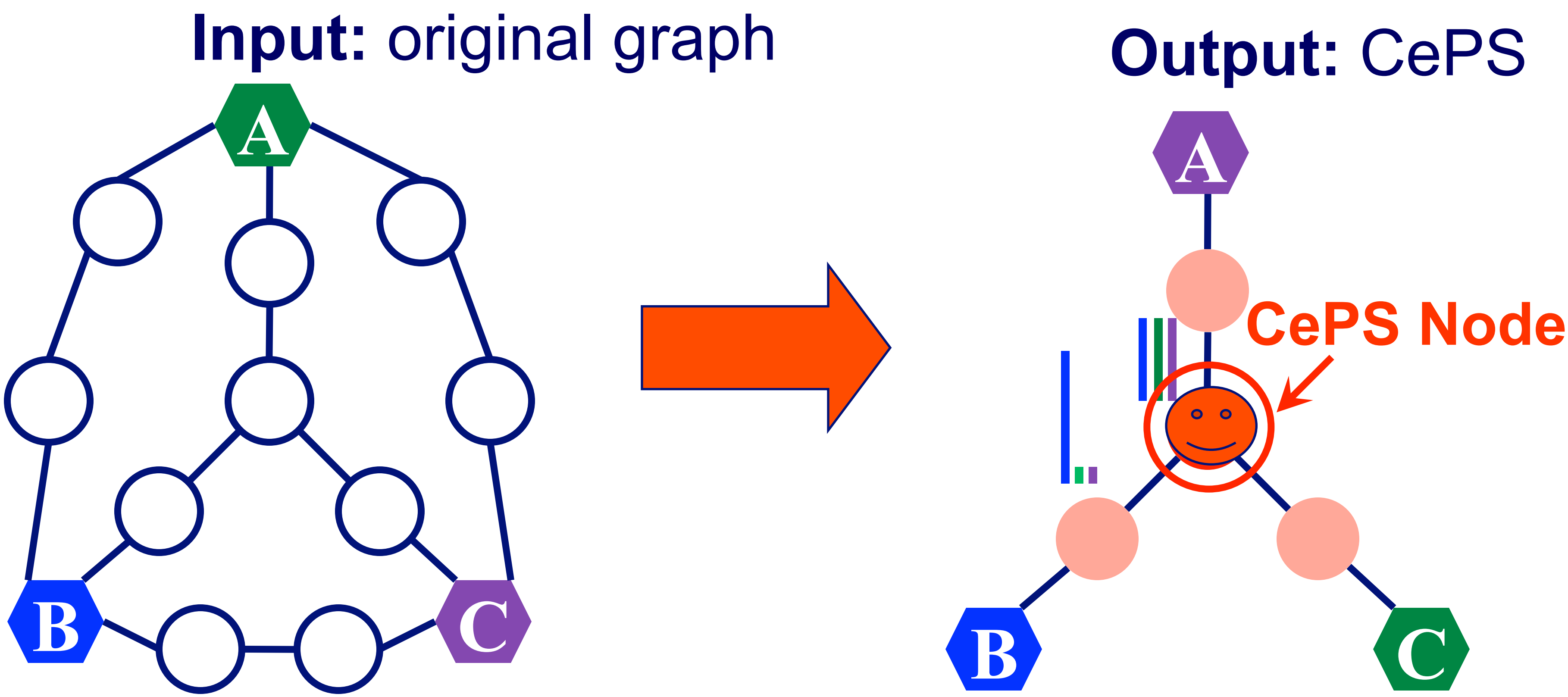
Center-Piece Subgraph Discovery

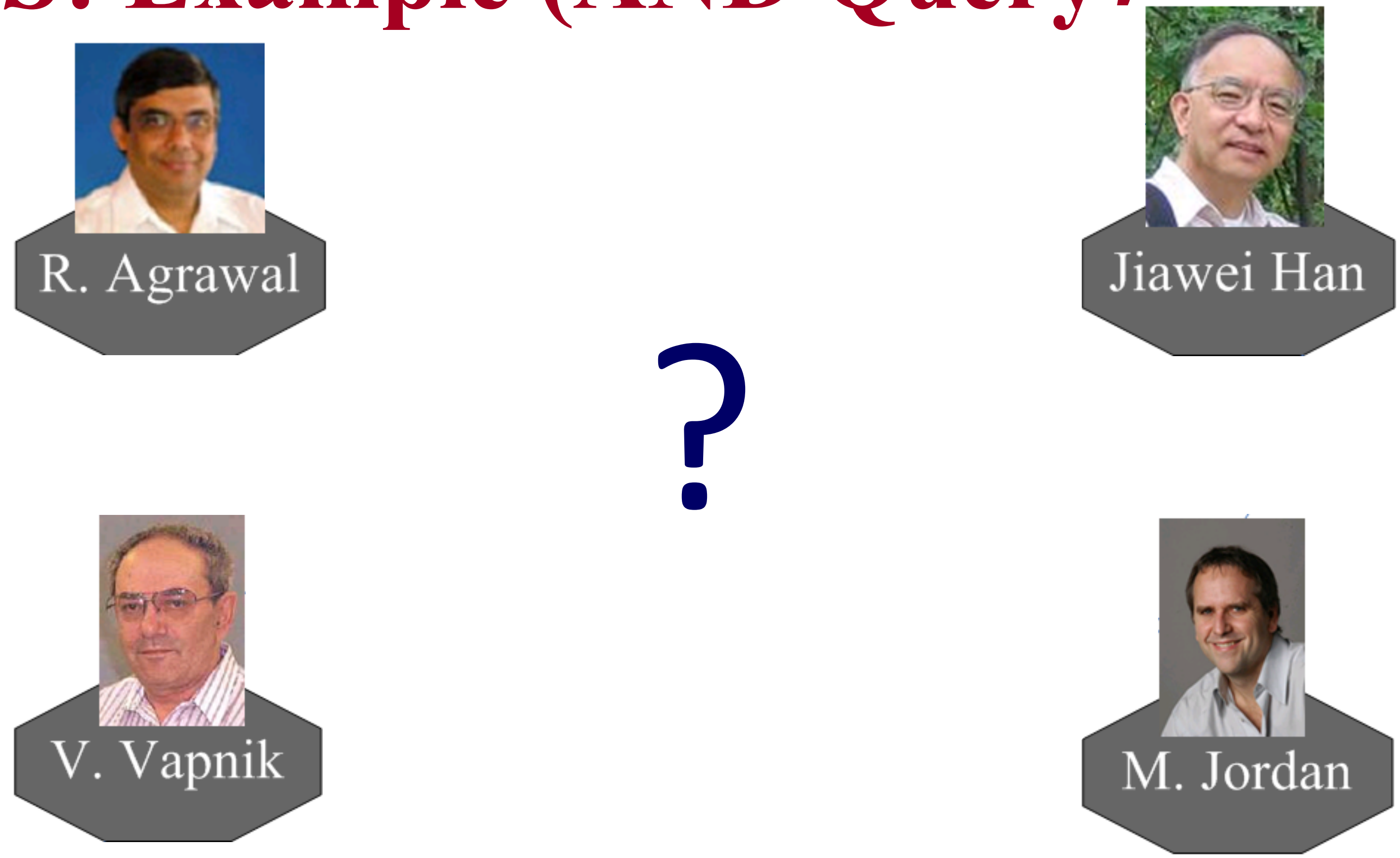
[Tong+ KDD 06]



Q: How to find hub for the query nodes?

A: Combine proximity scores (RWR)

CePS: Example (AND Query)

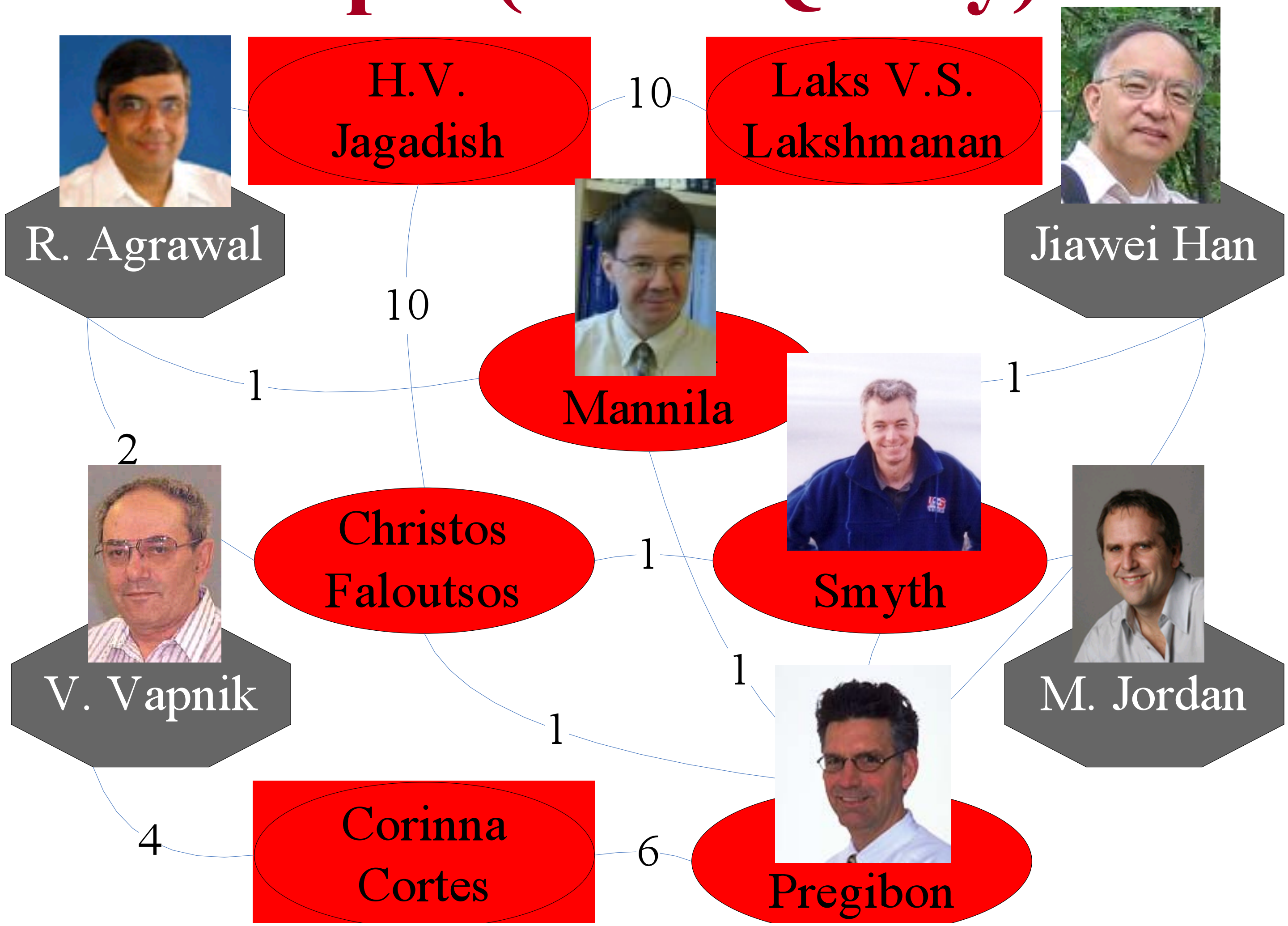


DBLP co-authorship network:

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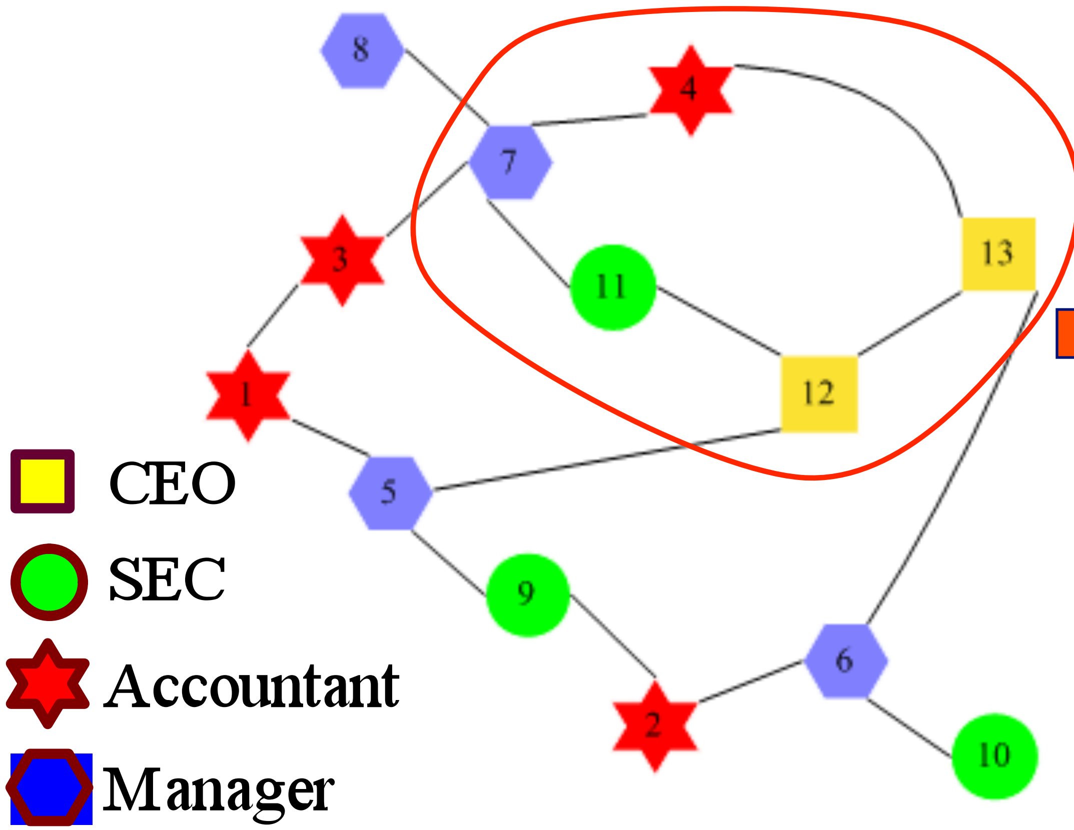
Graph X-Ray:
Fast Best-Effort Pattern Matching in Large Attributed Graphs

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

KDD'07

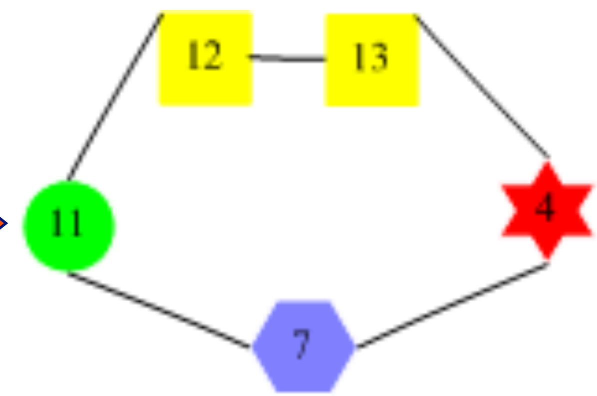
Input

Query Graph



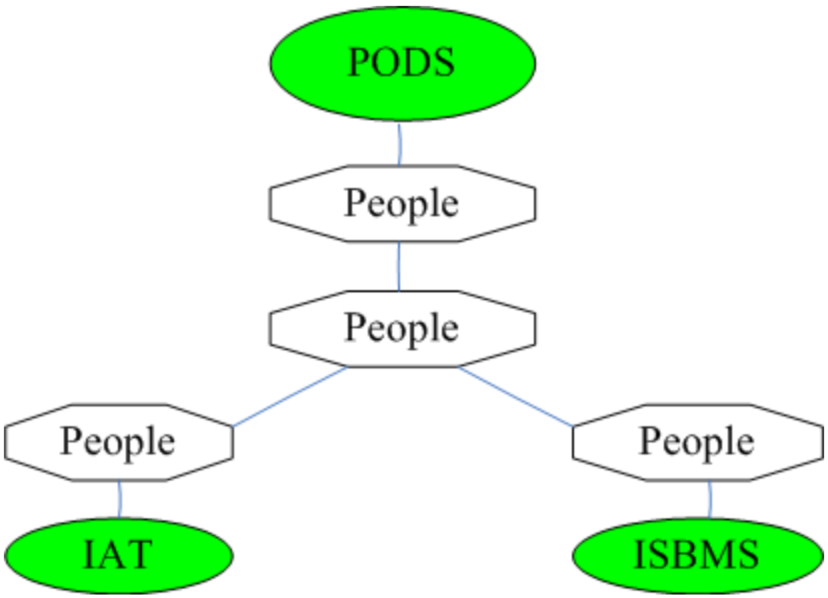
Attributed Data Graph

Output

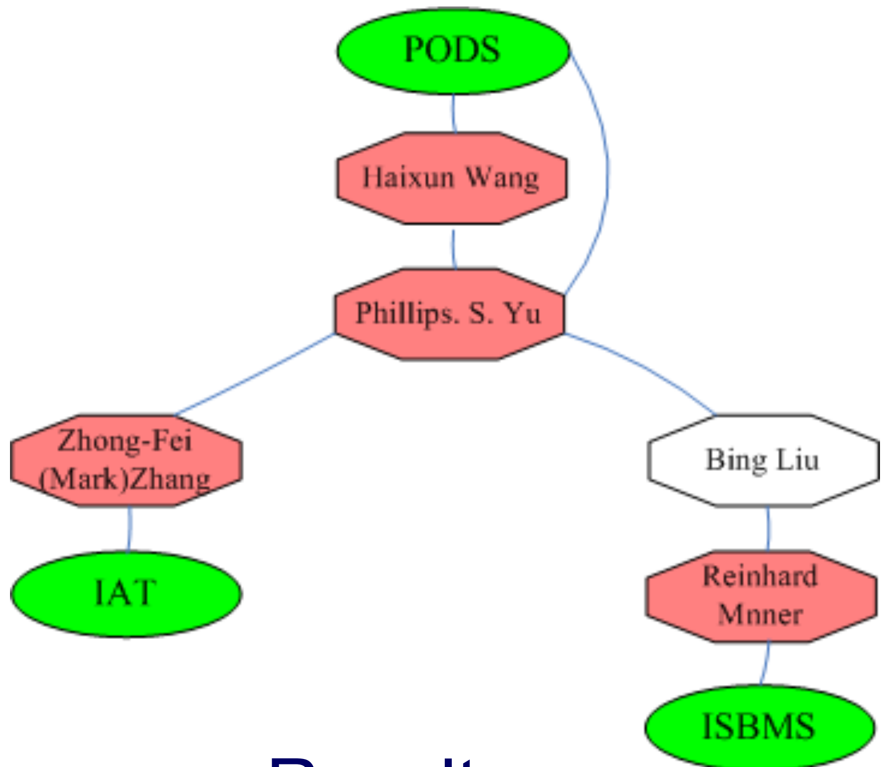


Matching Subgraph

Effectiveness: star-query



Query



Result

Outline

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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

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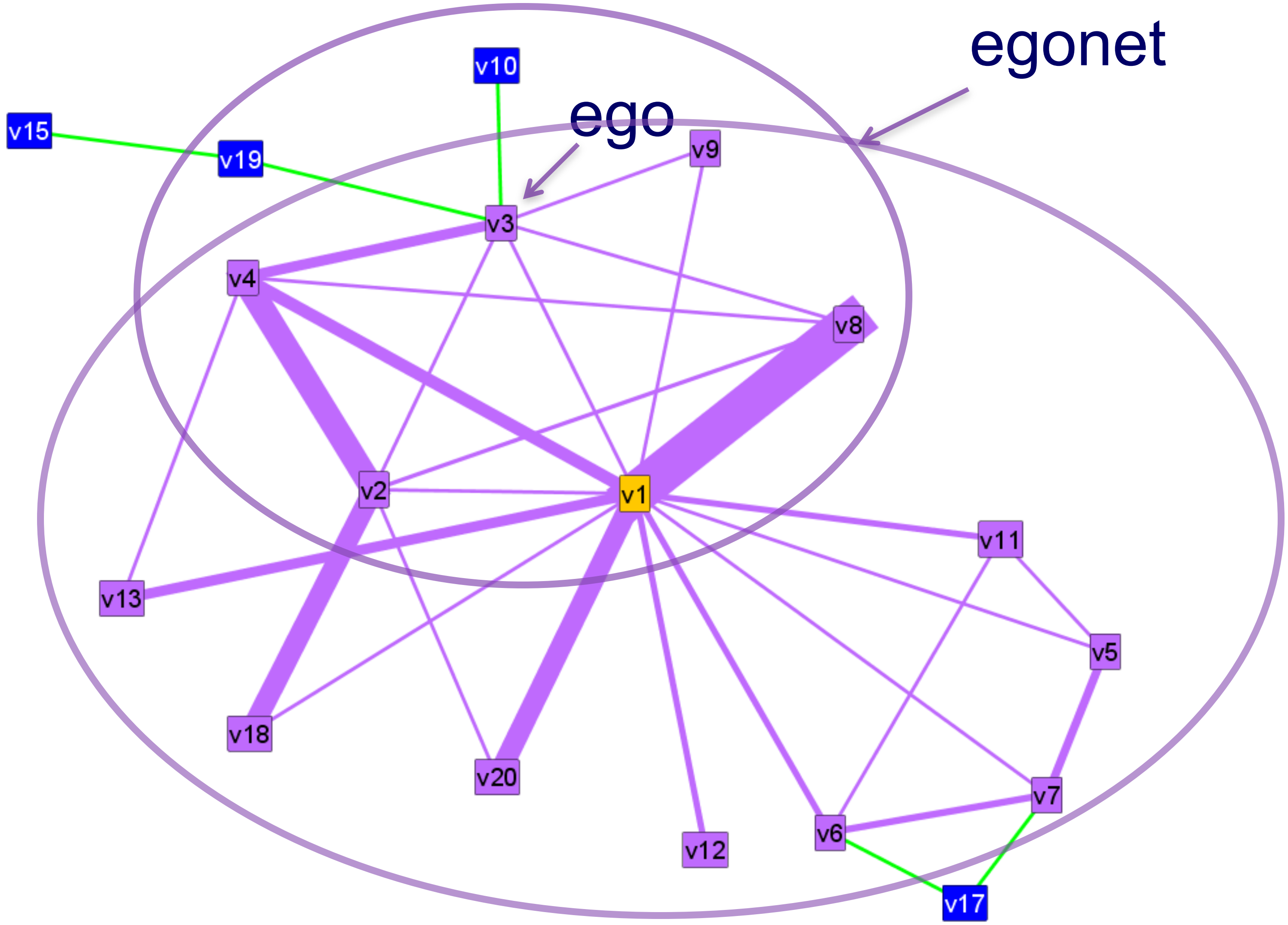
What is an egonet?



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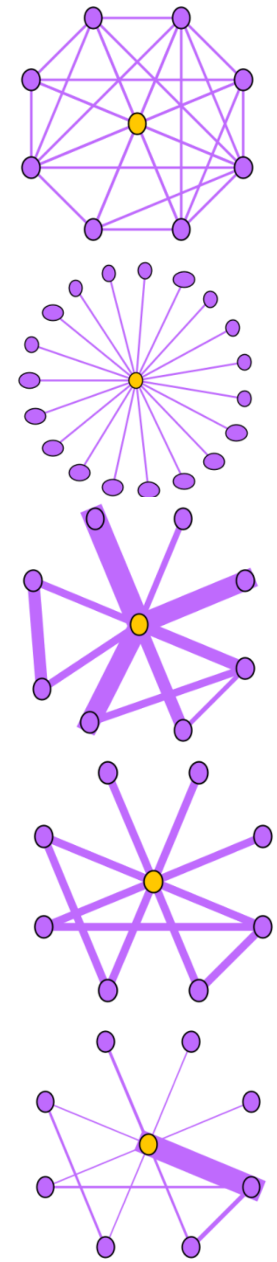
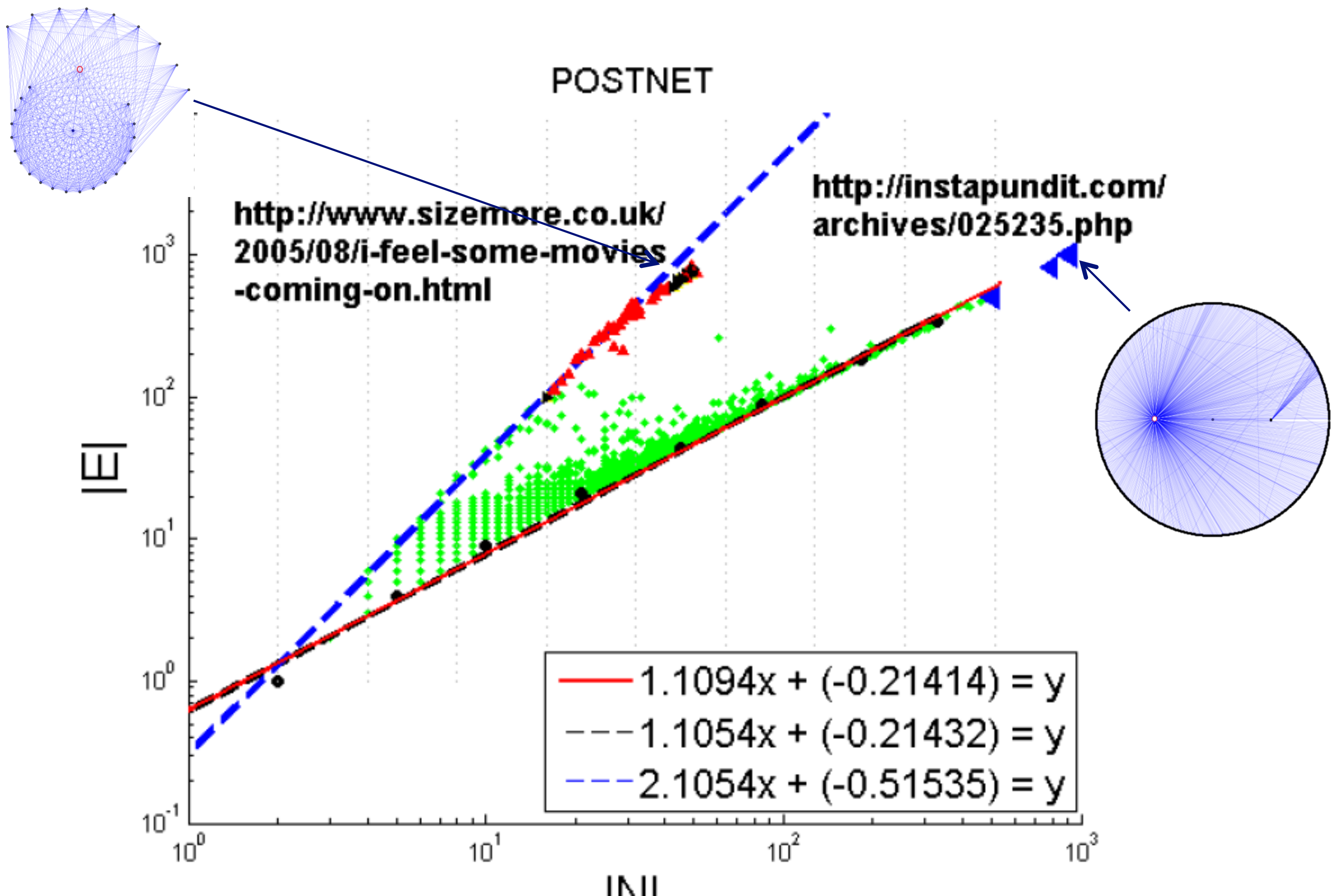
Selected Features

- 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



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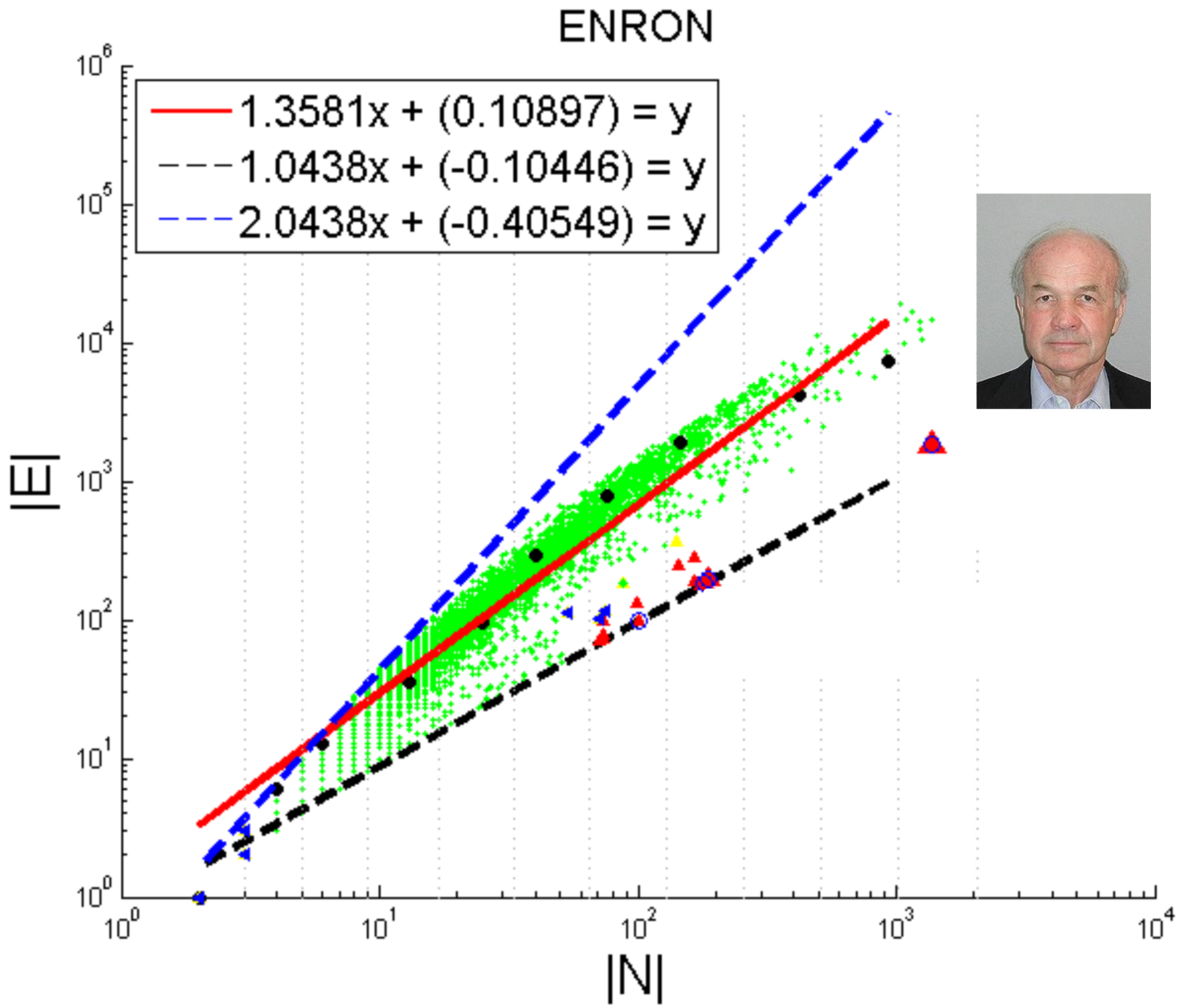

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Degree Distr.	old	old
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Diameter/ANF	old	**DONE**
Conn. Comp	old	**DONE**
Triangles	**DONE**	
Visualization	**STARTED**	

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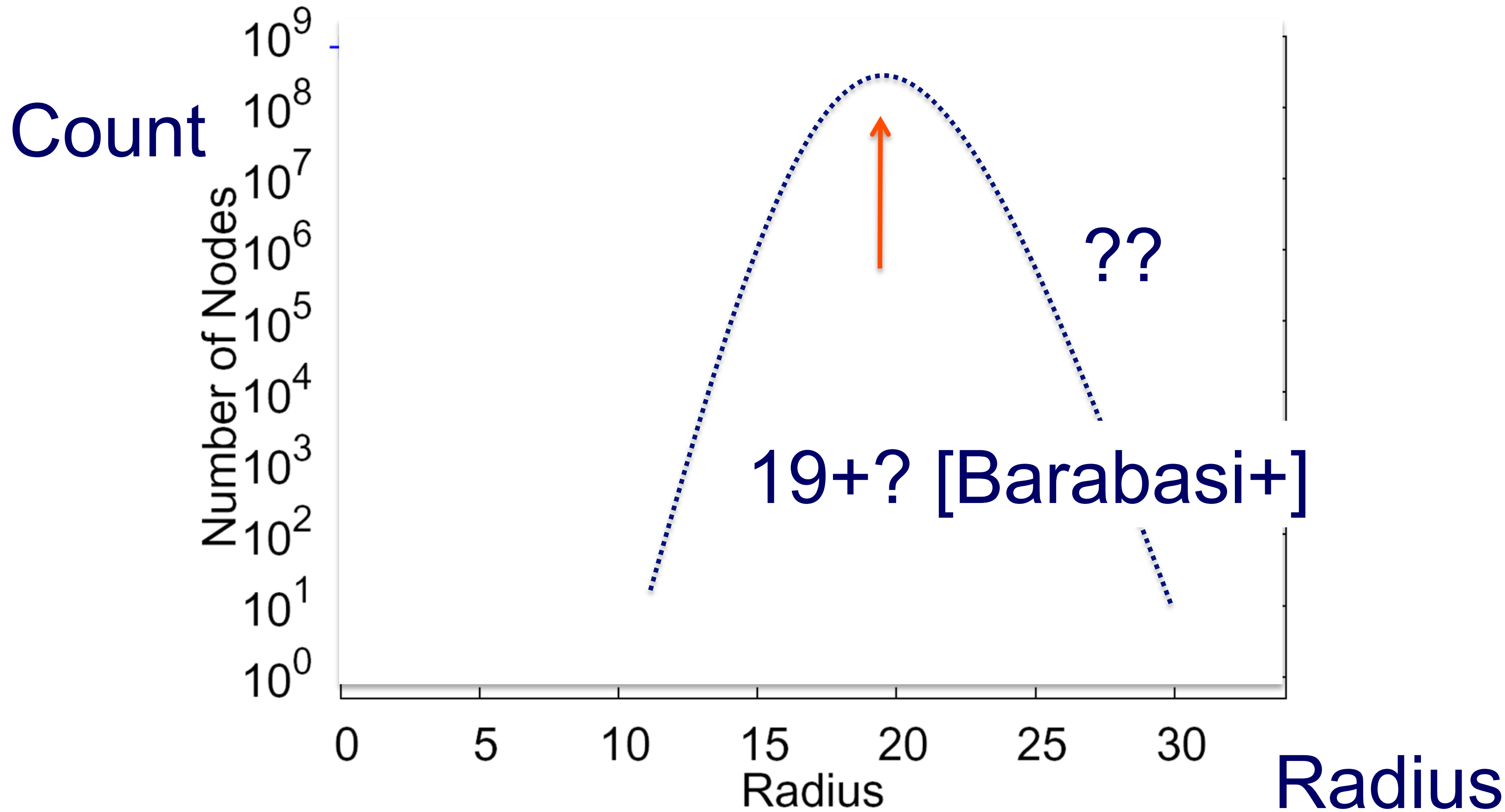
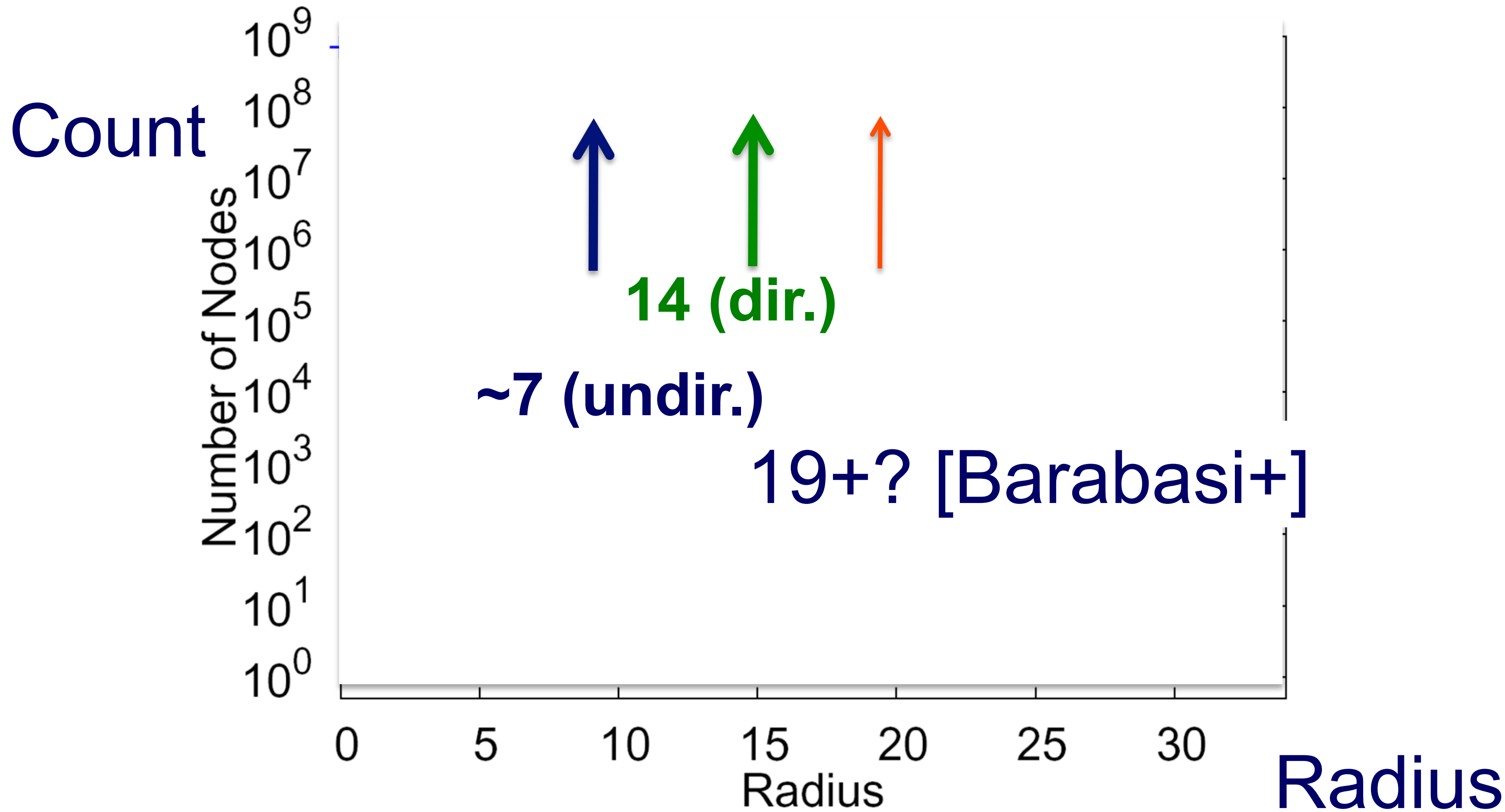
HADI for diameter estimation

- *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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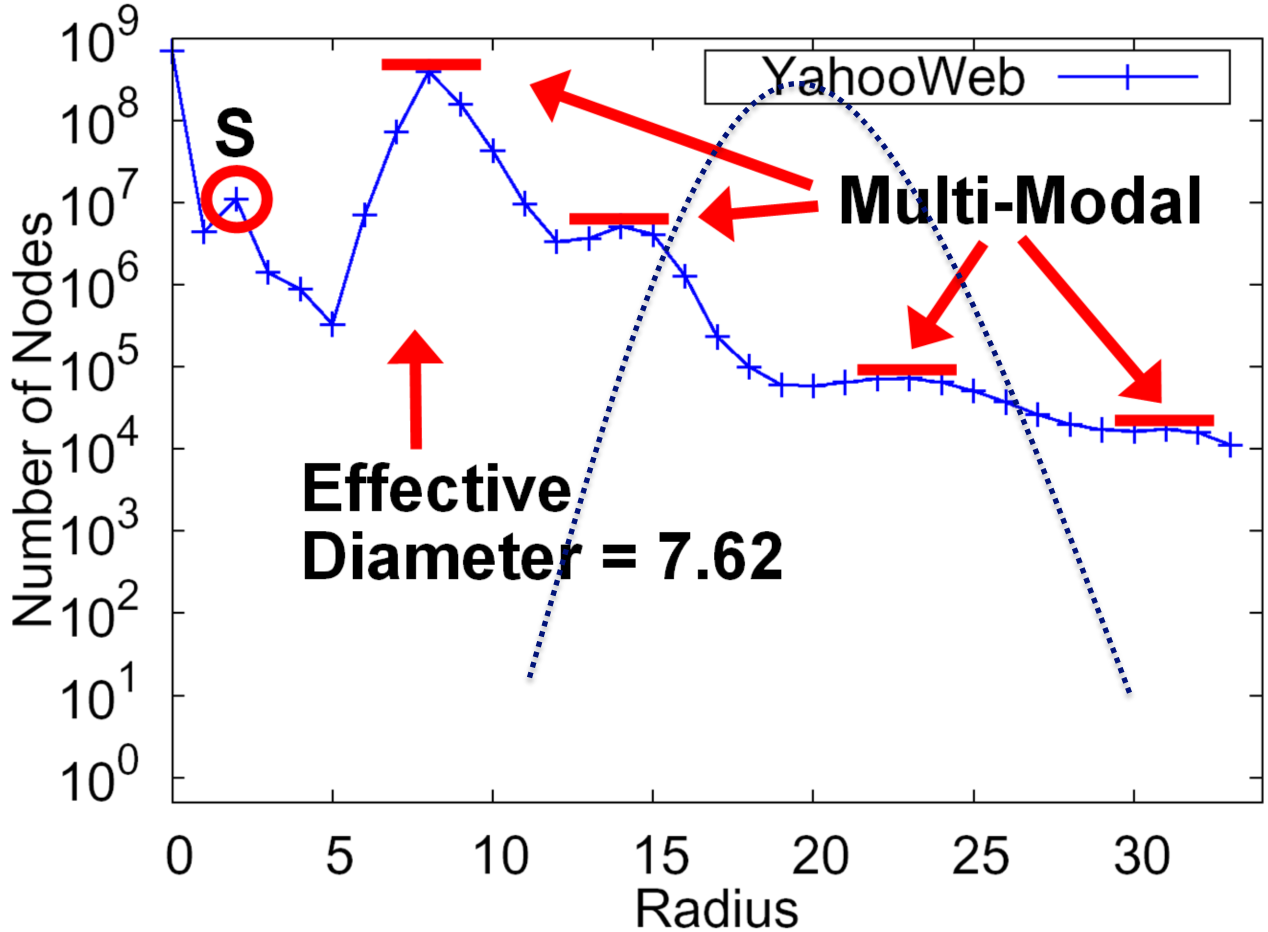
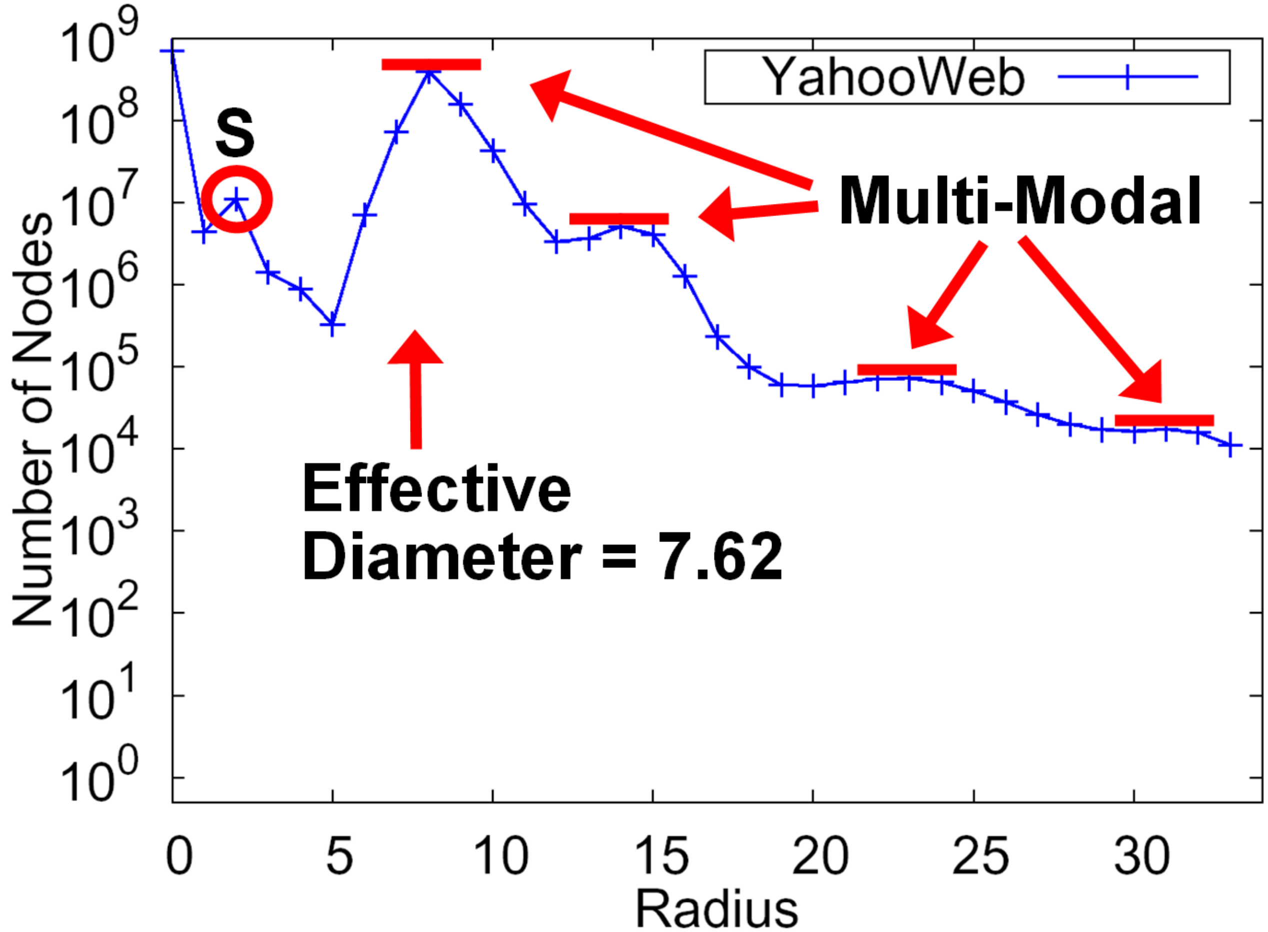


YahooWeb graph (120Gb, 1.4B nodes, 6.6 B edges)

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



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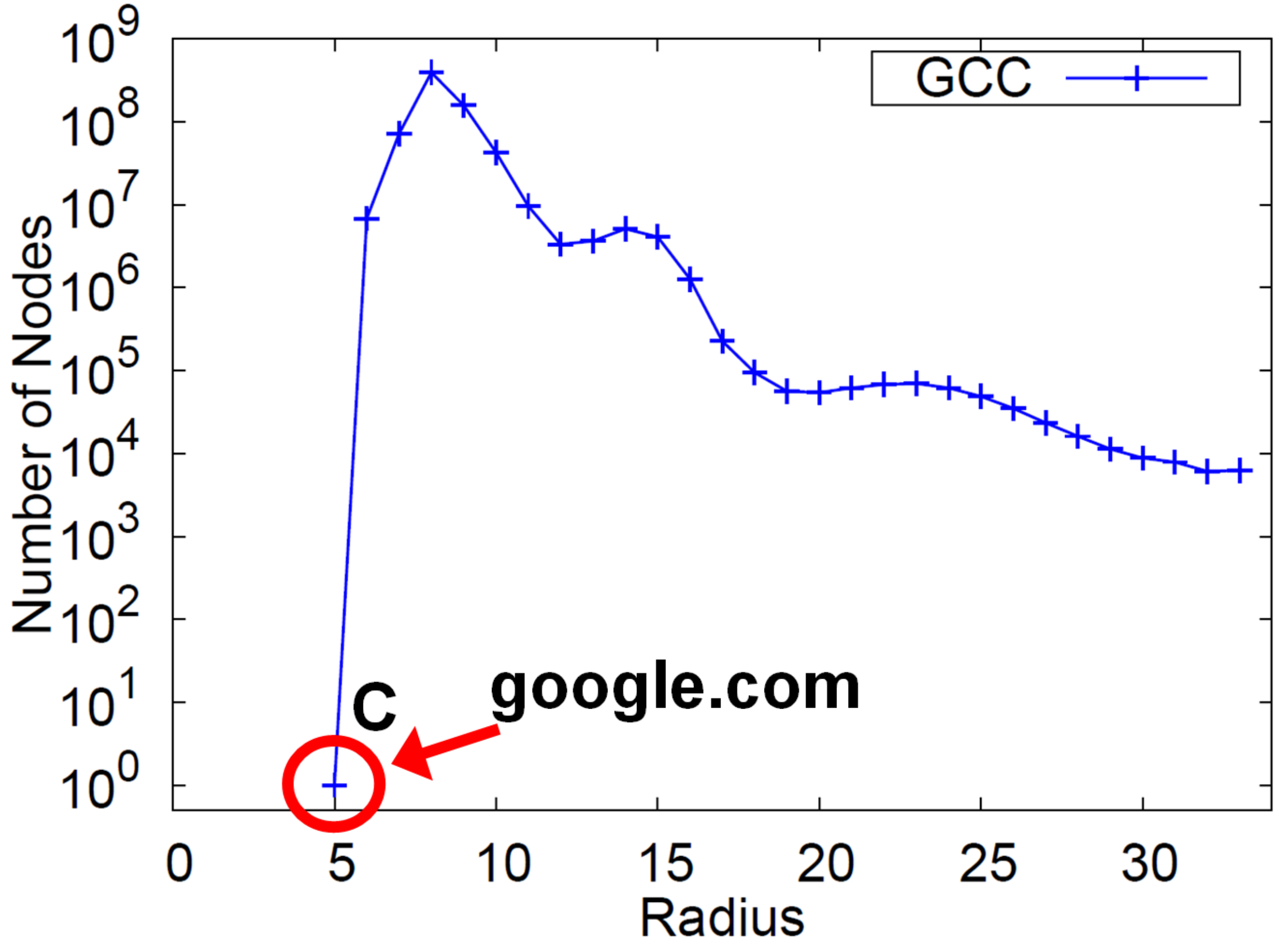

Radius Plot of **GCC** of YahooWeb.

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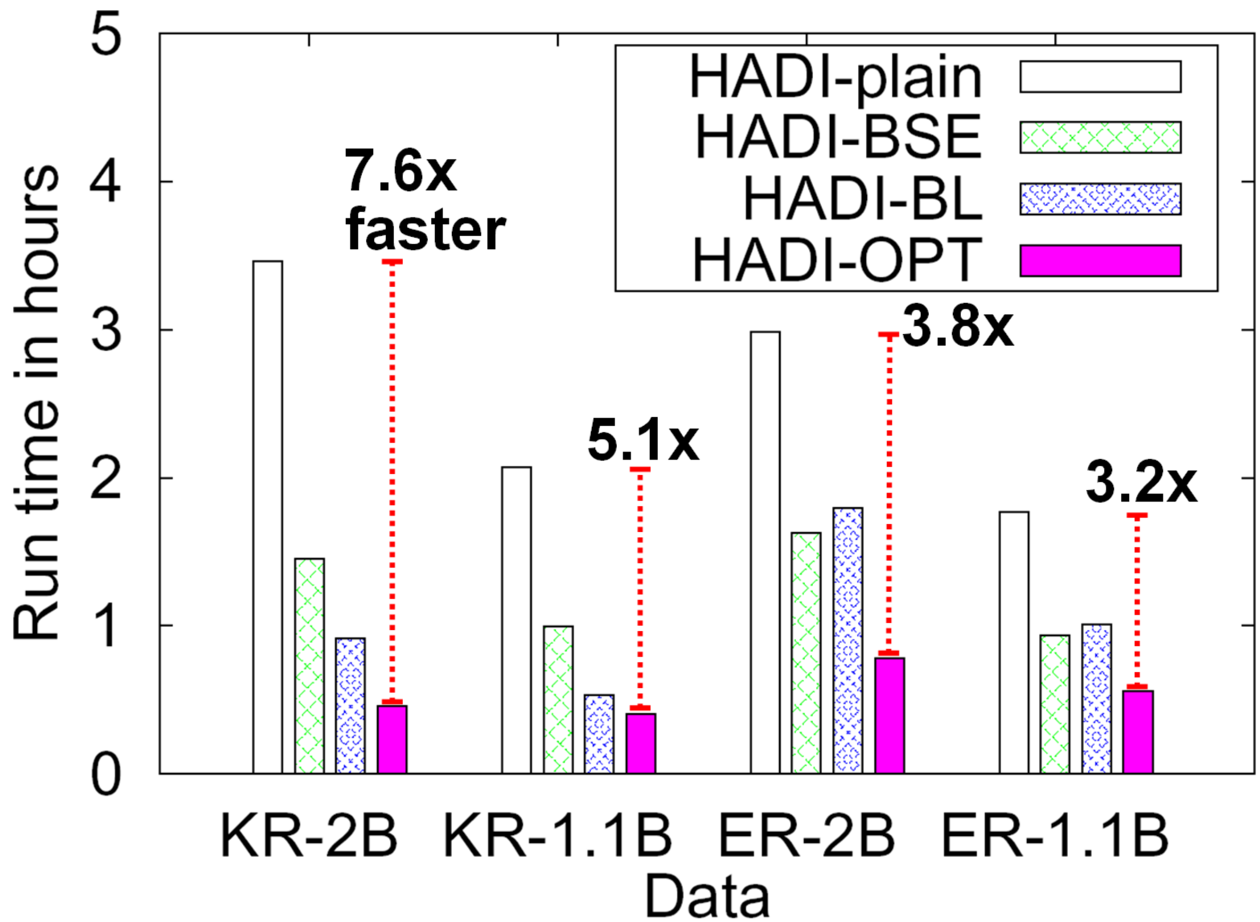
details



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

Generalized Iterated Matrix Vector Multiplication (GIMV)

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

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Generalized Iterated Matrix Vector Multiplication (GIMV)

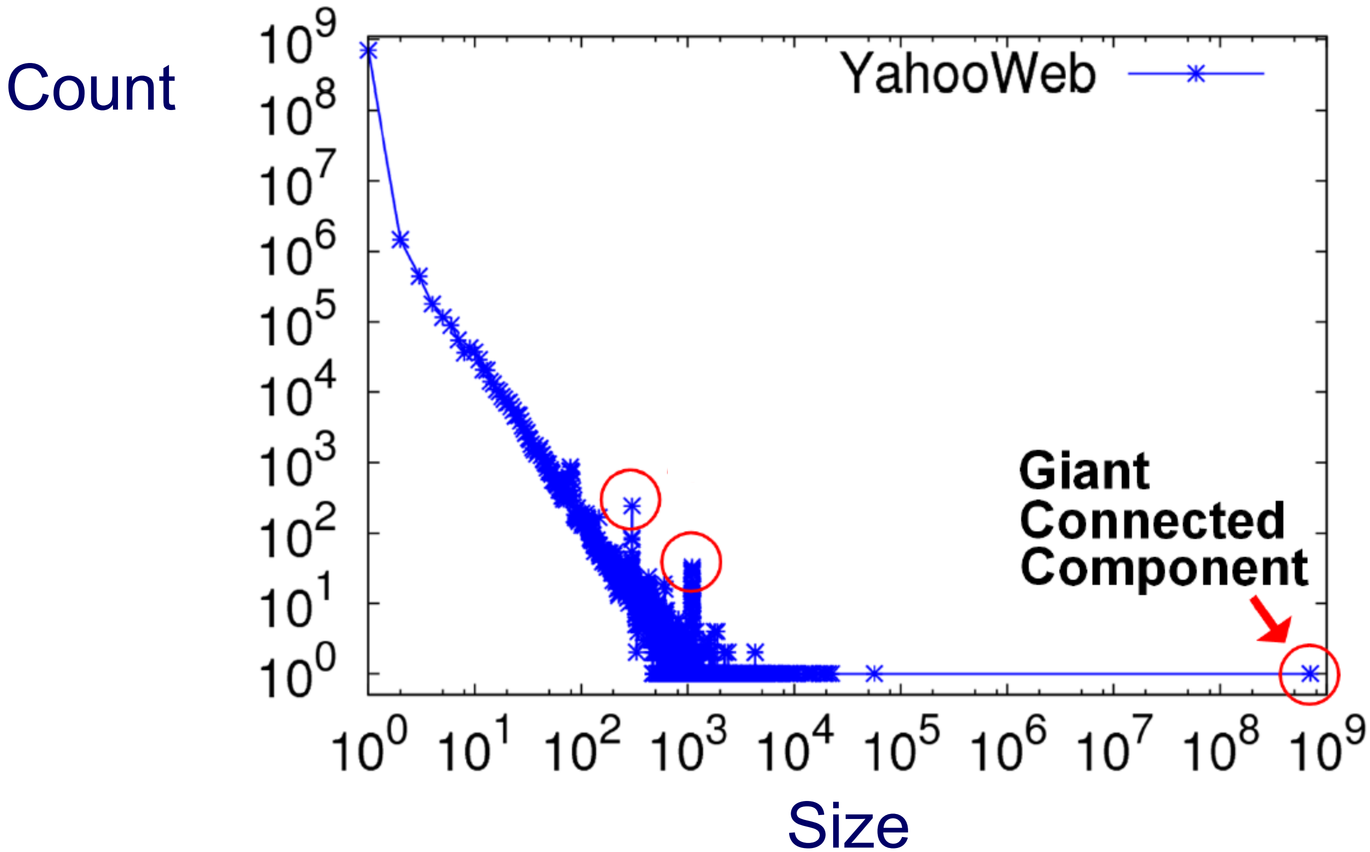
details

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

Matrix – vector Multiplication (iterated)

Example: GIM-V At Work

- Connected Components



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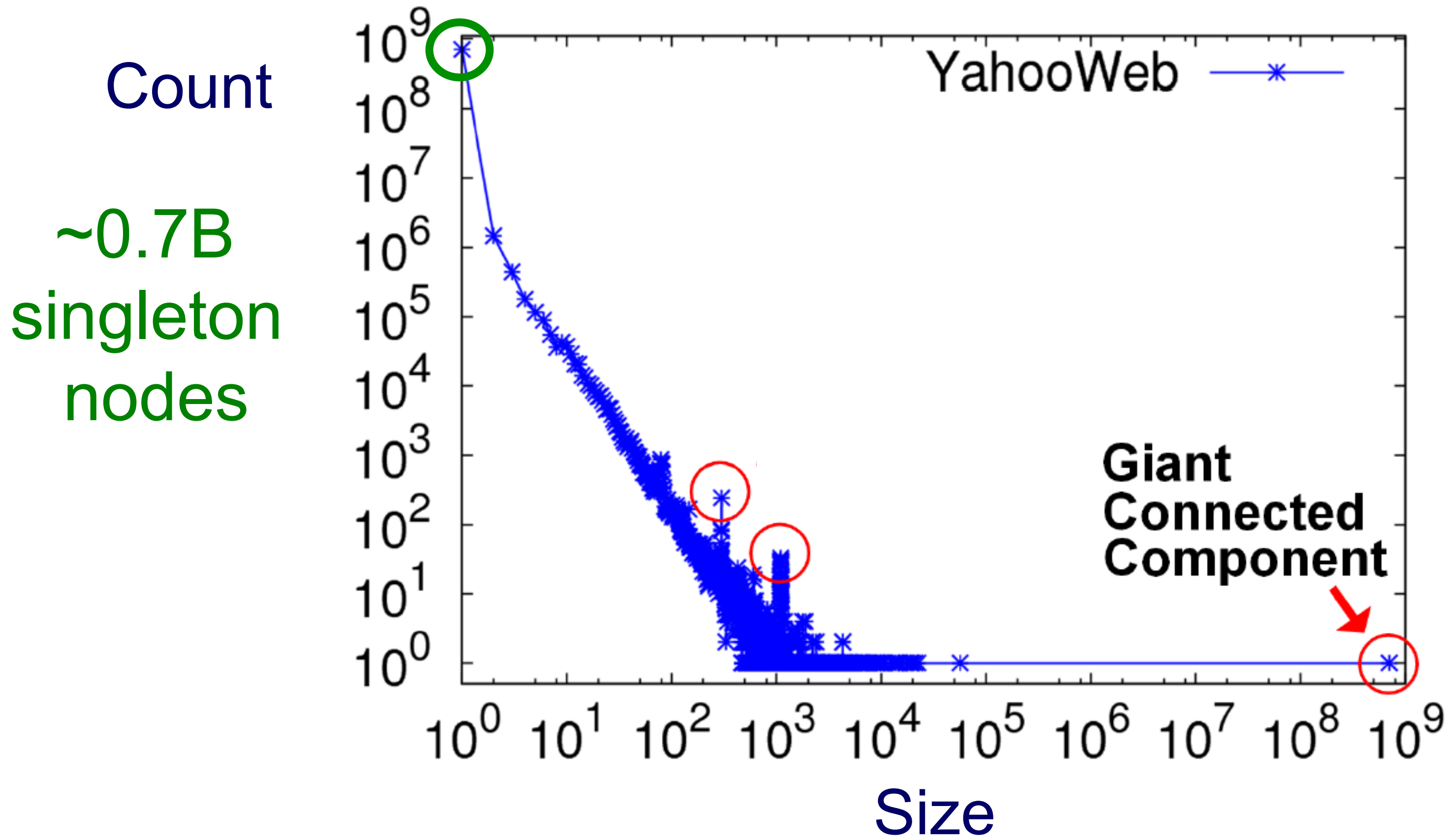
Example: GIM-V At Work

- Connected Components



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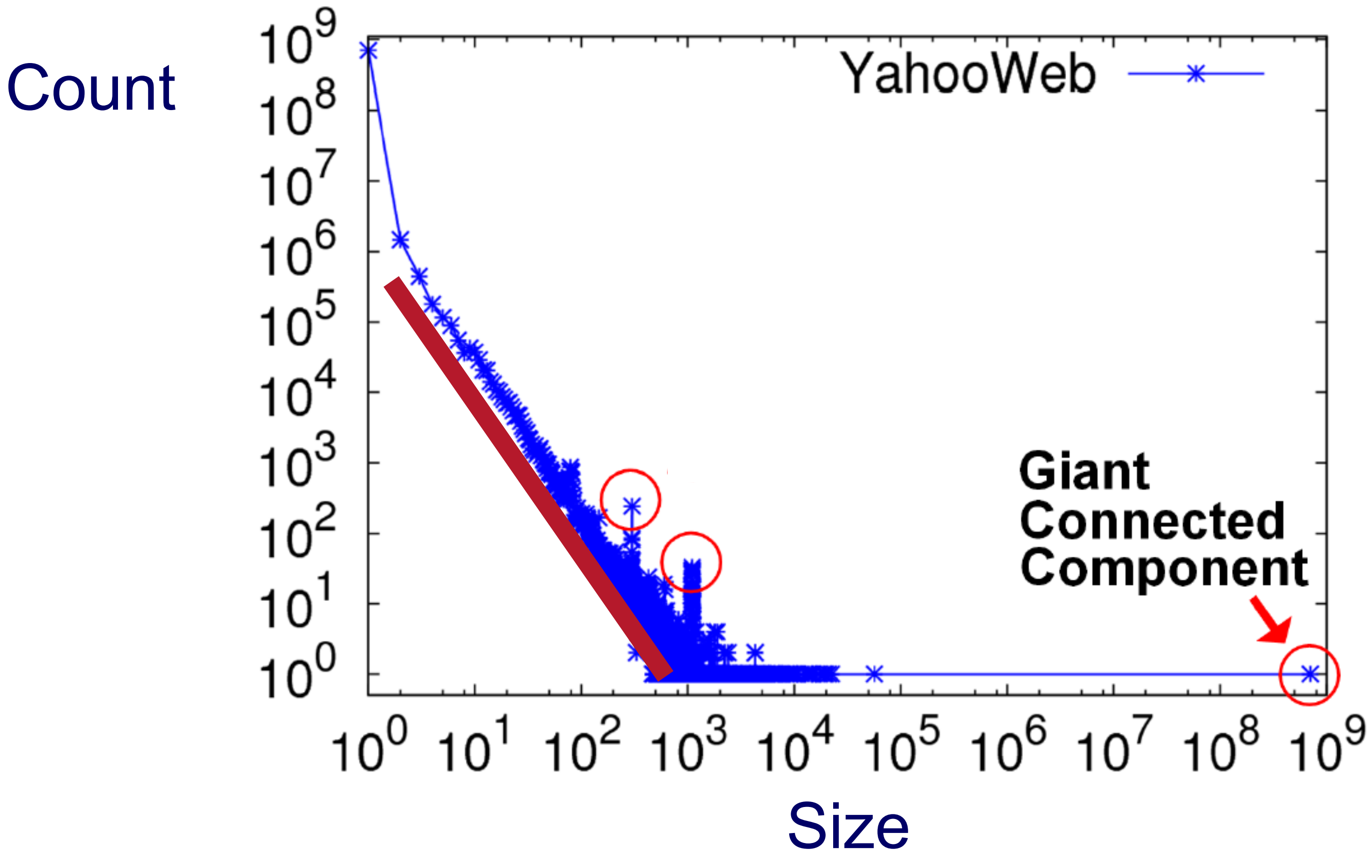
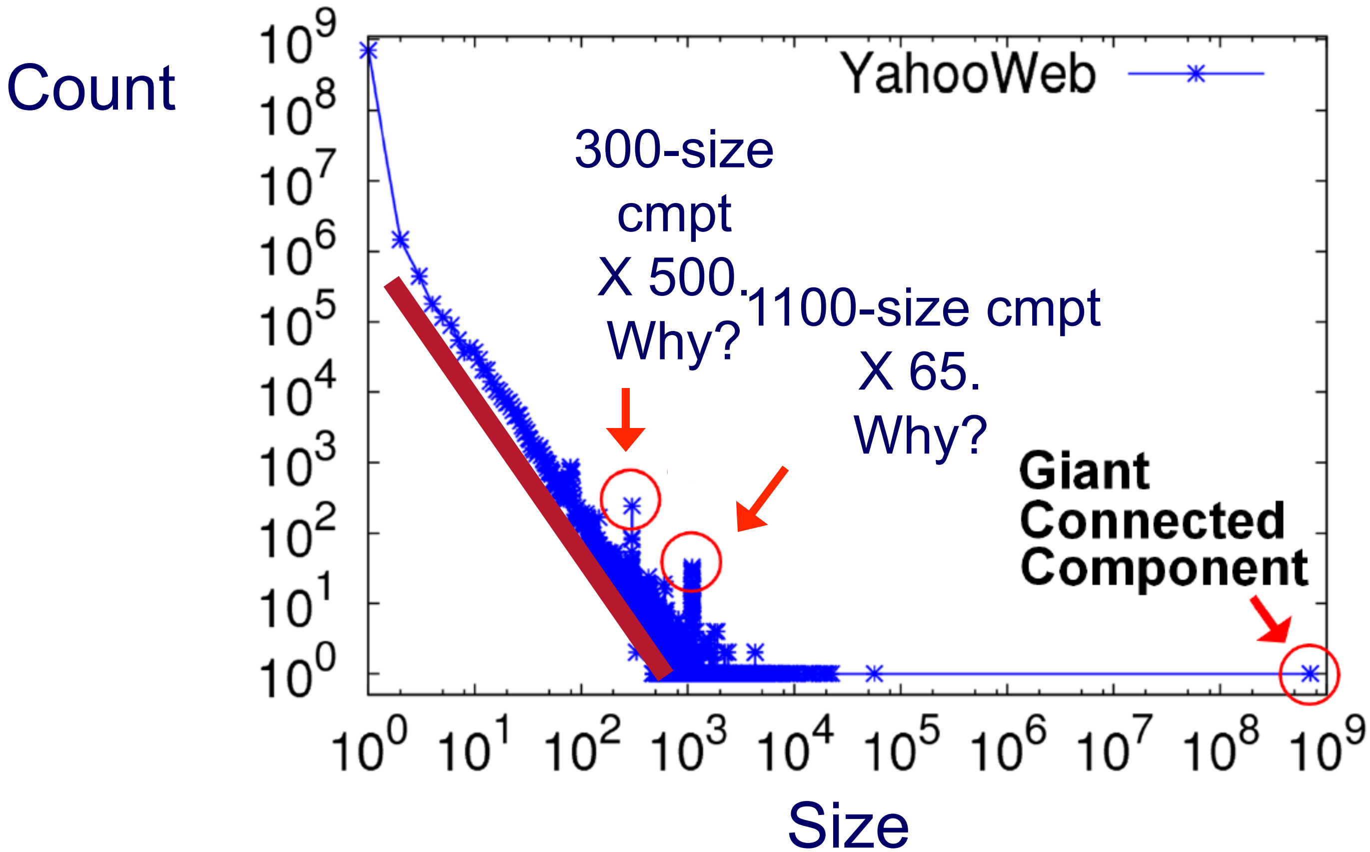
Example: GIM-V At Work

- Connected Components



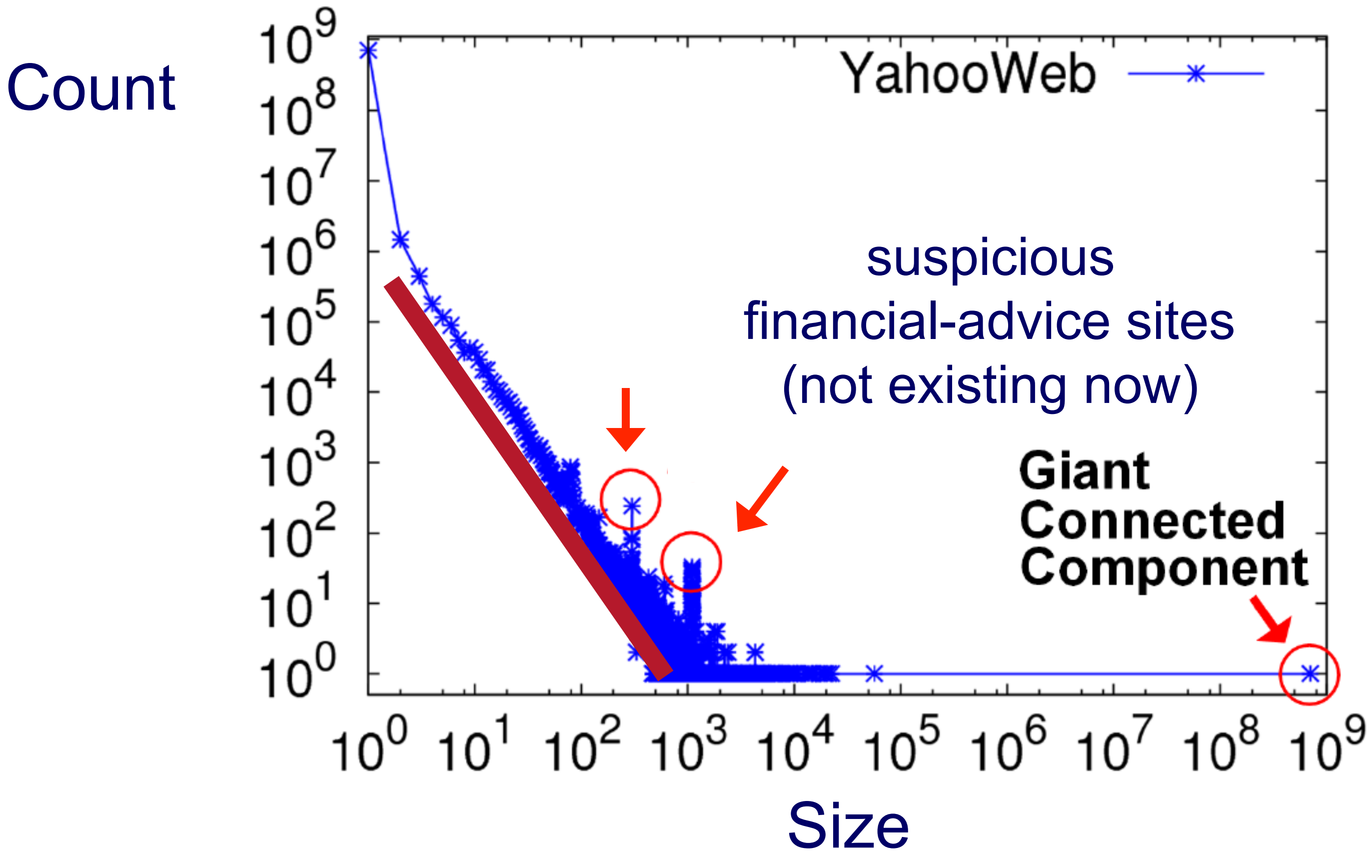
Example: GIM-V At Work

- Connected Components



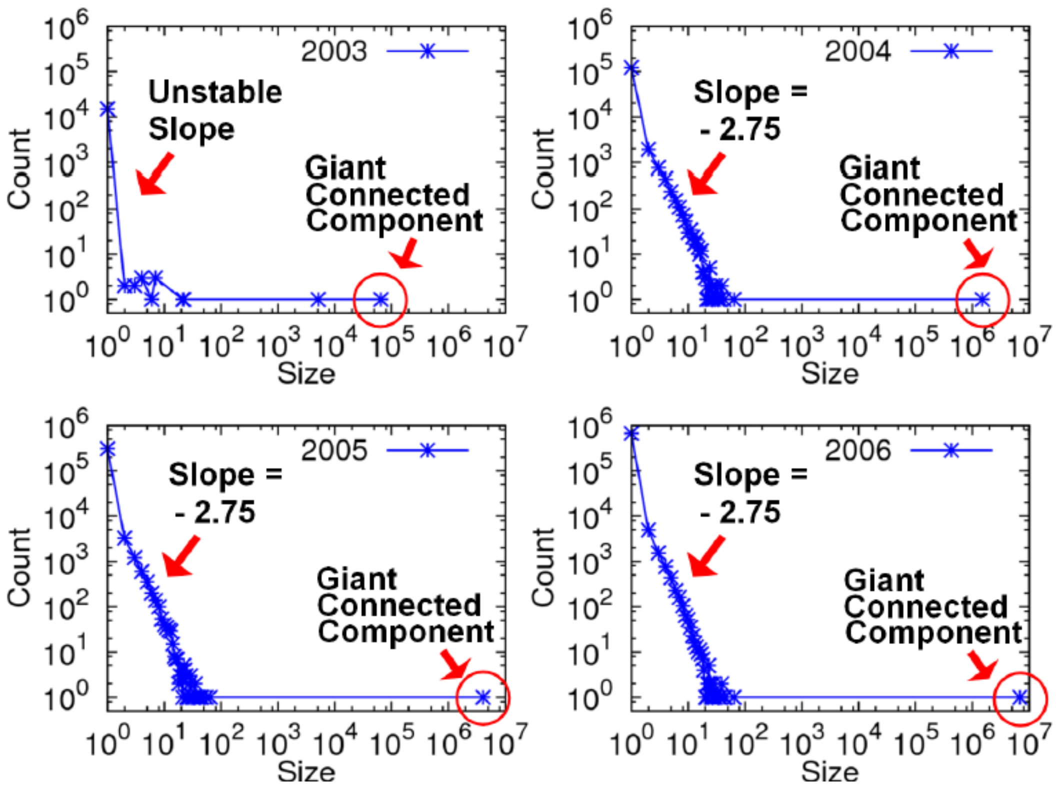
Example: GIM-V At Work

- Connected Components



GIM-V At Work

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



Stable tail slope
after the gelling point

Outline – Algorithms & results

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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)

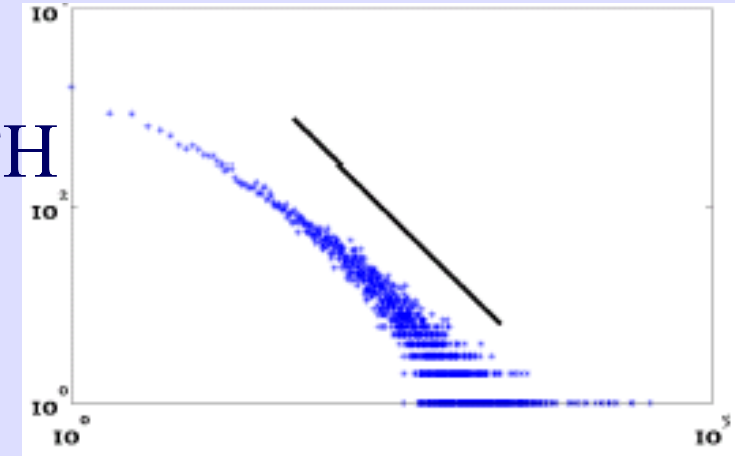
(and, because of skewness, we only need the top few eigenvalues!

Mentioned already

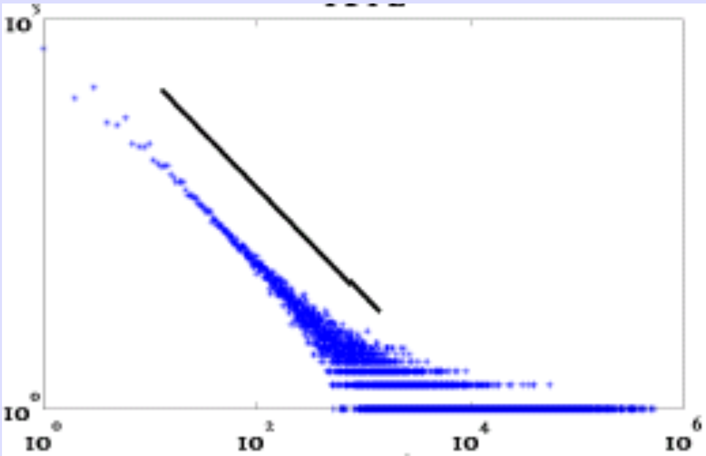
Triangle Law: #1

[Tsourakakis ICDM 2008]

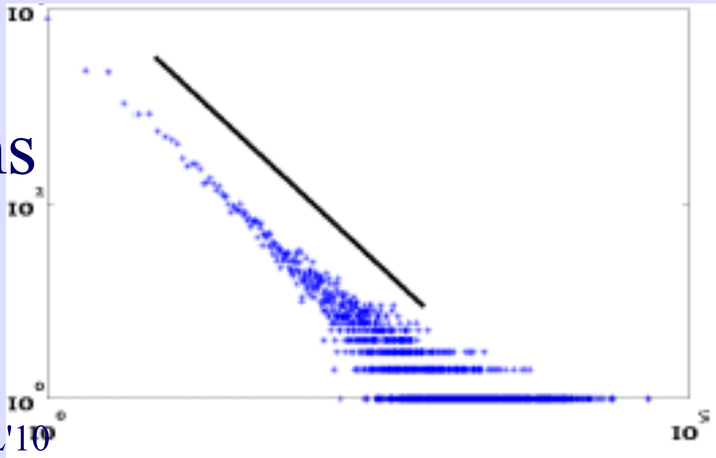
HEP-TH



ASN



Epinions



X-axis: # of Triangles
a node participates in
Y-axis: count of such nodes

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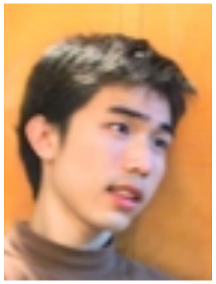
Visualization: ShiftR



- *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.

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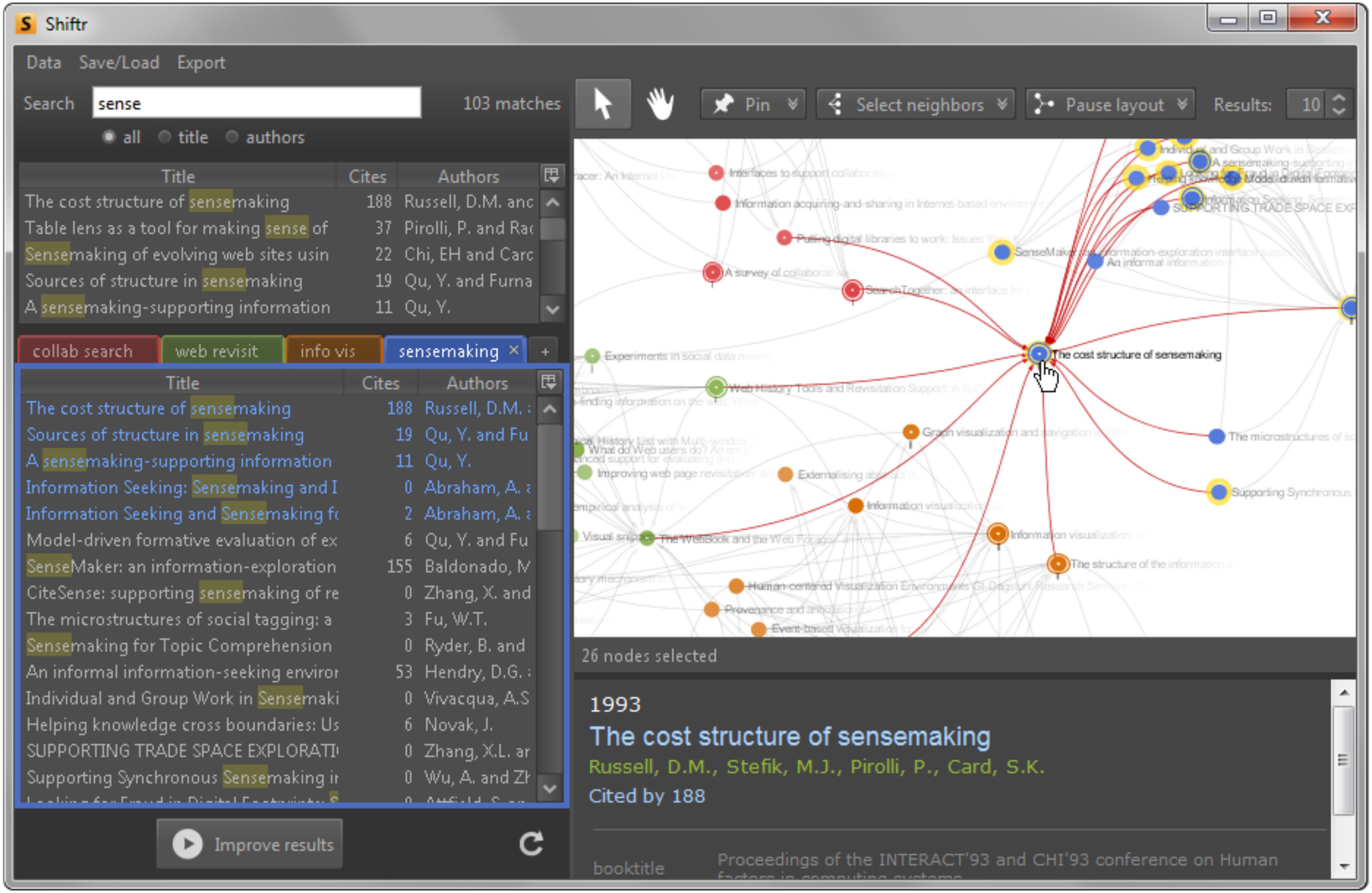

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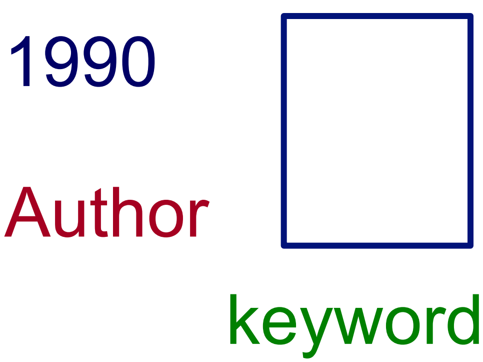
Other topics - part#1 - tools

- 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]

Tensors

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



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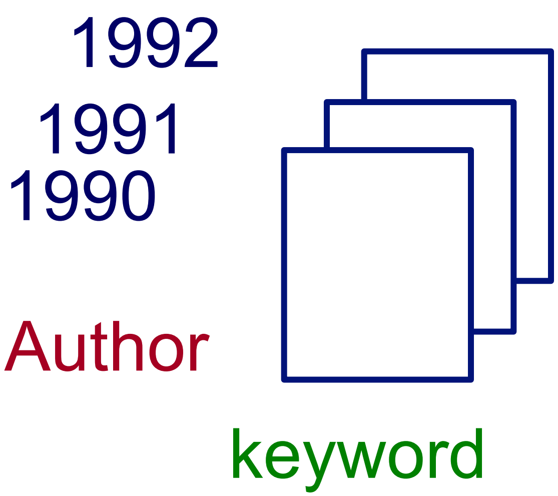

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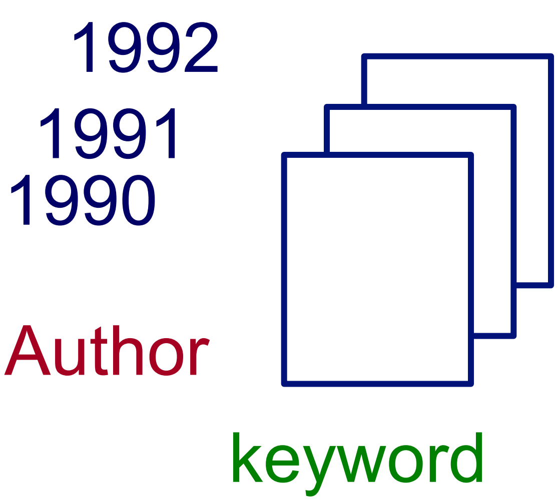
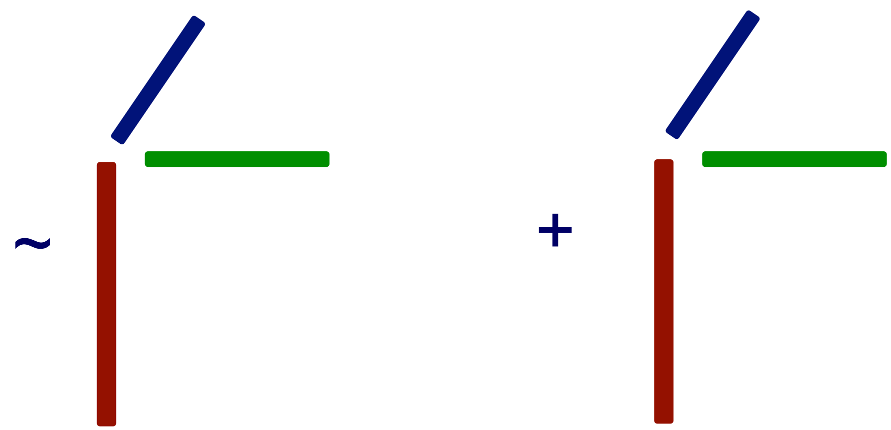


PARAFAC tensor decomposition
(generalization of SVD)



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Other topics – part#2 - generators

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

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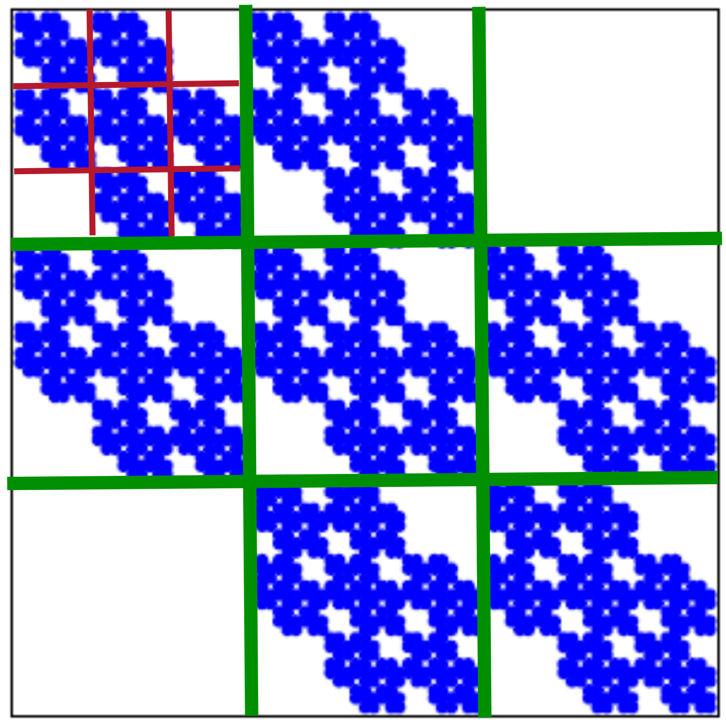
Kronecker Product – a Graph

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

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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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OVERALL CONCLUSIONS – low level:

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

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)

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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

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References

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

References

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

References

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

References

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

Joint papers with LLNL

- Keith Henderson, Tina Eliassi-Rad, Spiros Papadimitriou, Christos Faloutsos: HCDF: A Hybrid Community Discovery Framework. SDM 2010:754-765
- Hanghang Tong, Yasushi Sakurai, Tina Eliassi-Rad, Christos Faloutsos: Fast mining of complex time-stamped events. CIKM 2008:759-768
- Jimeng Sun, Charalampos E. Tsourakakis, Evan Hoke, Christos Faloutsos, Tina Eliassi-Rad: Two heads better than one: pattern discovery in time-evolving multi-aspect data. Data Min. Knowl. Discov. (DATAMINE) 17(1) :111-128 (2008)

Joint papers with LLNL

- Jimeng Sun, Charalampos E. Tsourakakis, Evan Hoke, Christos Faloutsos, Tina Eliassi-Rad: Two Heads Better Than One: Pattern Discovery in Time-Evolving Multi-aspect Data. ECML /PKDD 2008:22
- Duen Horng Chau, Christos Faloutsos, Hanghang Tong, Jason I. Hong, Brian Gallagher, Tina Eliassi-Rad: GRAPHITE: A Visual Query System for Large Graphs. ICDM Workshops 2008:963-966

Joint papers with LLNL

- Brian Gallagher, Hanghang Tong, Tina Eliassi-Rad, Christos Faloutsos: Using ghost edges for classification in sparsely labeled networks. KDD 2008:256-264
- Hanghang Tong, Christos Faloutsos, Brian Gallagher, Tina Eliassi-Rad: Fast best-effort pattern matching in large attributed graphs. KDD 2007:737-746

Project info

www.cs.cmu.edu/~pegasus

PROJECT PEGASUS

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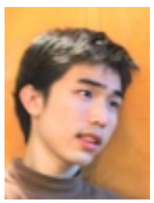




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Thanks to: LLNL (DE-AC52-07NA27344, +)
NSF, CTA-INARC; Yahoo (M45), IBM, SPRINT, INTEL, HP