

Exploring Blog Graphs

Patterns and a Model for Information Propagation

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In collaboration with Jure Leskovec, Christos Faloutsos
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Long-term Goals

- How does information on the Web propagate?
- With what pattern do ideas catch on, diffuse, and decrease in popularity?
- Can we build a model for this propagation?
- How can we characterize individual blogs?

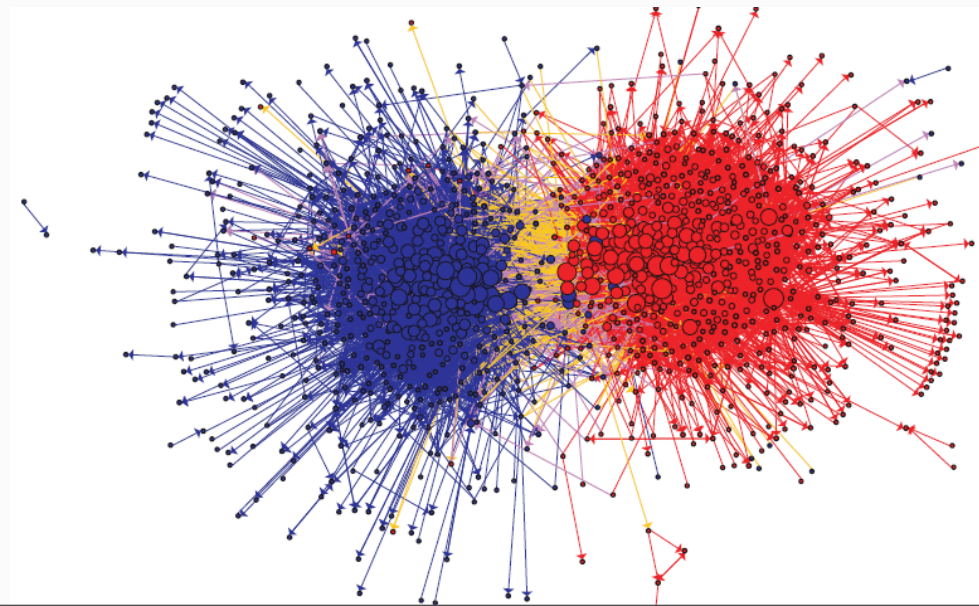
Why blogs?

- Blogs are a widely used medium of information for many topics and have become an **important mode of communication**.
- Blogs cite one another, **creating a record** of how information and ideas spread through a **social network**.
- This record is **publicly available**.

Why do we care?

- Understanding how the blog network works is important for:
 - Social issues: Political mapping, social trends and change, reactions to mass media.
 - Economic issues: Marketing, predicting commercial success, discovering links between companies.

Example: blogs in the
2004 election.
[Adamic, Glance 2005]



Immediate Goals

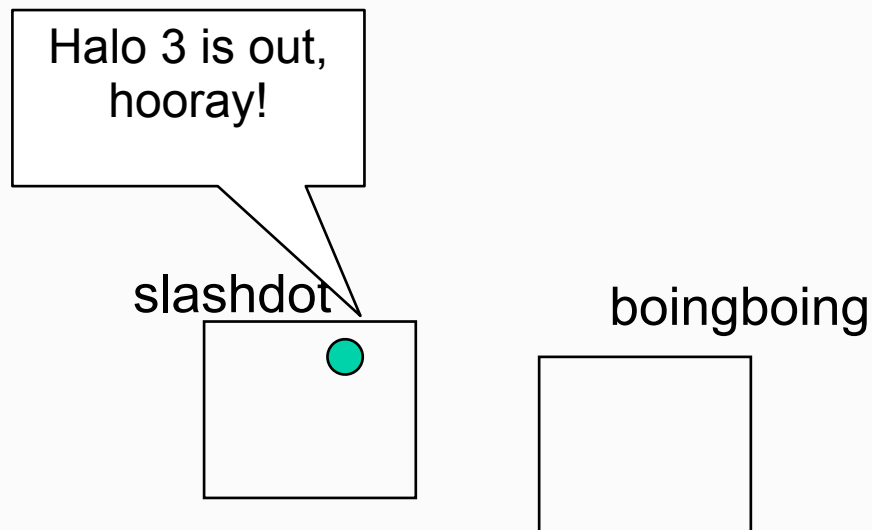
- **Q1, Temporal questions:** Does popularity have half-life? Is there periodicity?
- **Q2, Topological questions:** What topological patterns do posts and blogs follow? What shapes do cascades take on? Stars? Chains? Something else?
- **Q3, Generative model:** Can we build a generative model that mimics properties of cascades?
- **Q4, Feature extraction:** What features of blogs can we use to characterize them?

Outline

- Motivation
- Preliminaries
 - Concepts and terminology
 - Data
- Q1: Temporal Observations
- Q2: Topological Observations
- Q3: Cascade Generation Model
- Q4: Characterizing Blogs and Posts
- Discussion & Conclusions

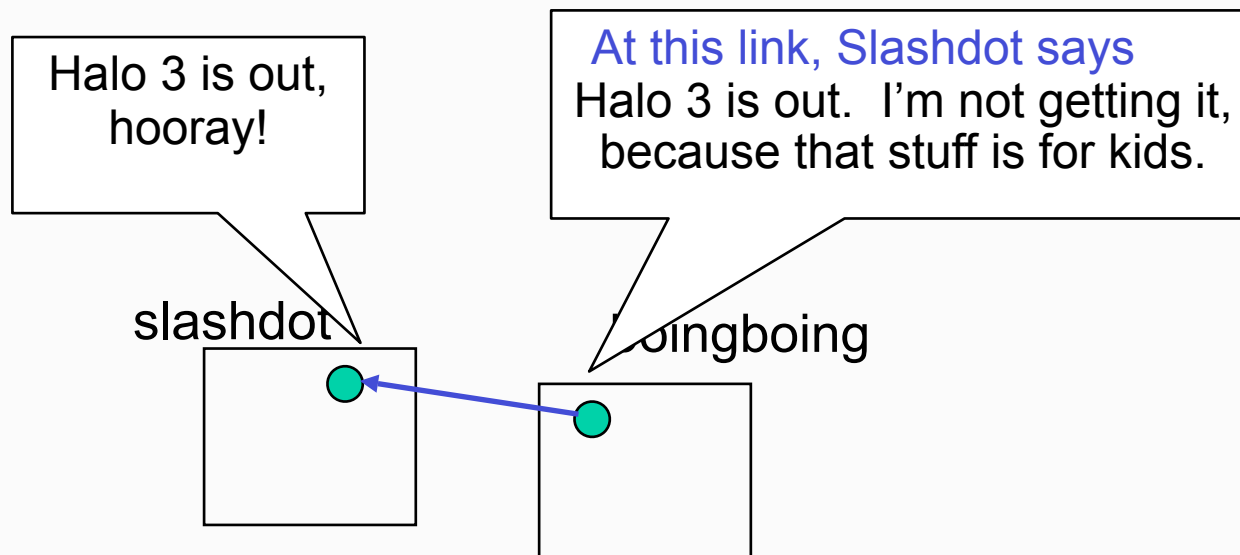
What is a blog?

- A **blog** is a frequently-updated webpage.
- A blog's author updates the blog using **posts**.
- Each post has a permanent **hyperlink**, and may contain **links** to other blog posts.

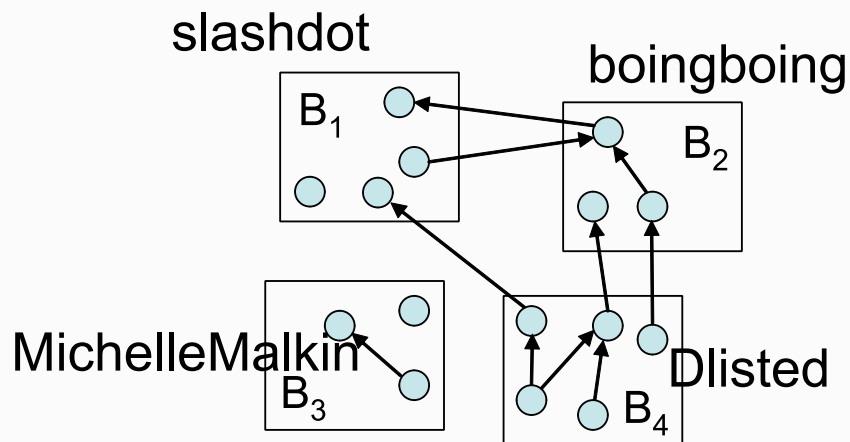


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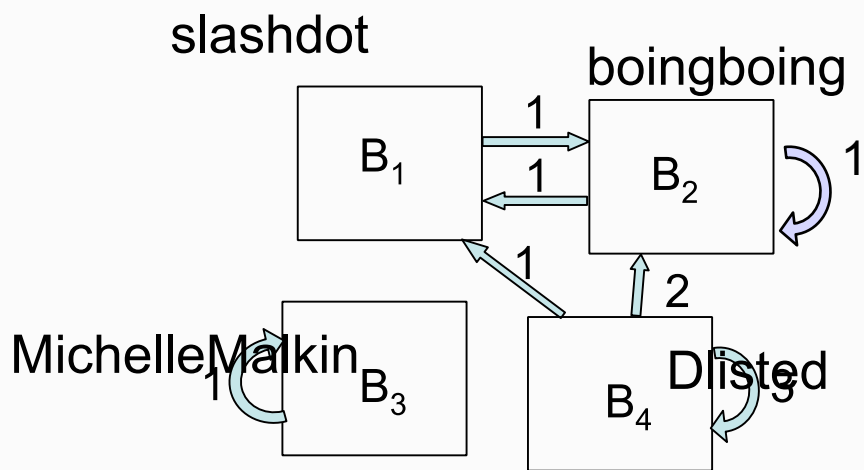
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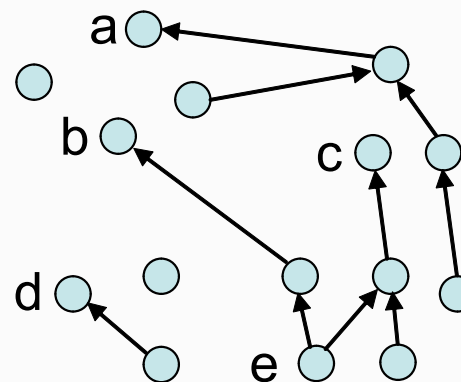
From blogs to networks



Blogosphere network



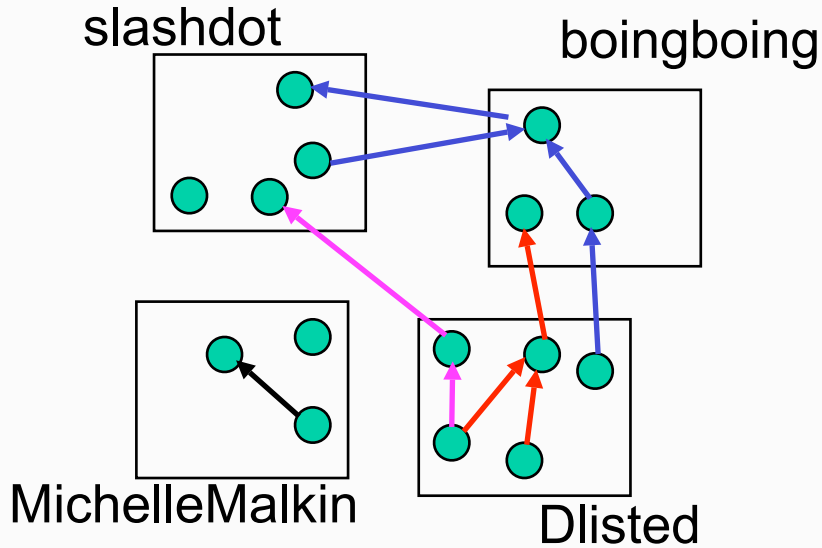
Blog network



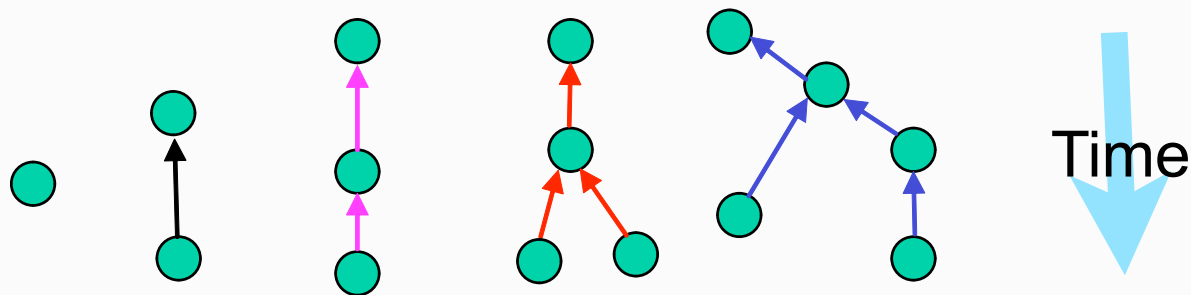
Post network¹⁰

From networks to cascades

Non-trivial vs. trivial cascades

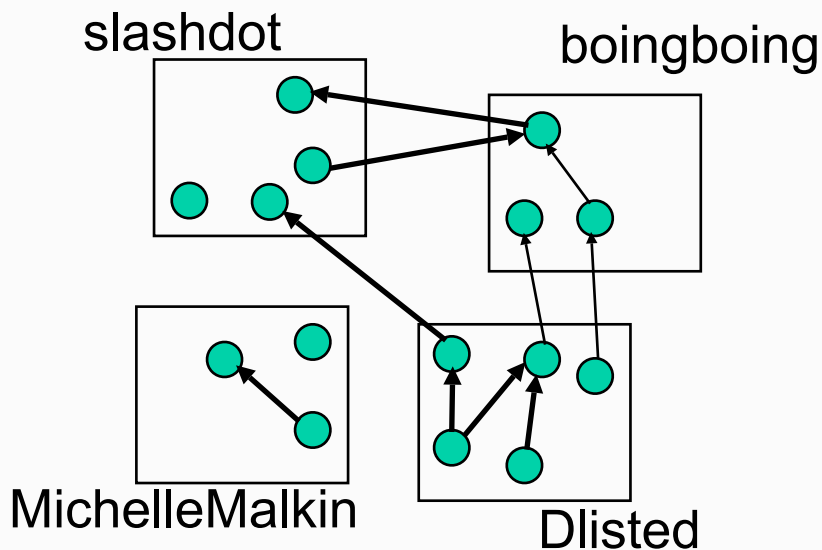


Blogosphere network



Cascades

From networks to cascades

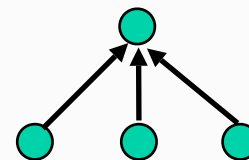
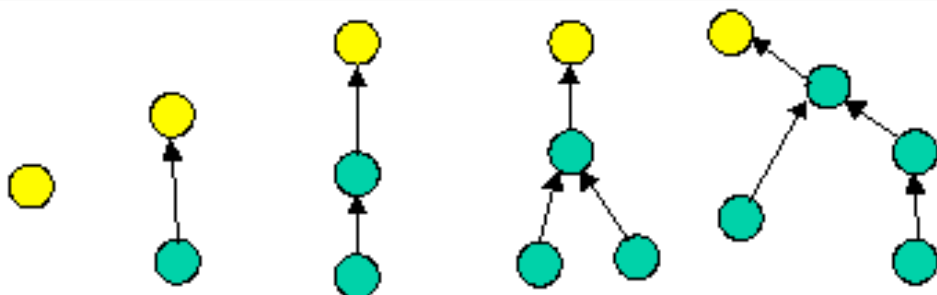


Blogosphere network

Non-trivial vs. trivial cascades

Cascade initiators are first sources of information

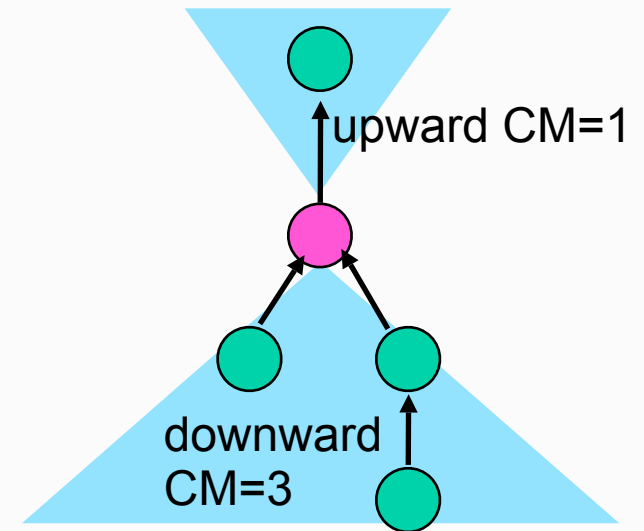
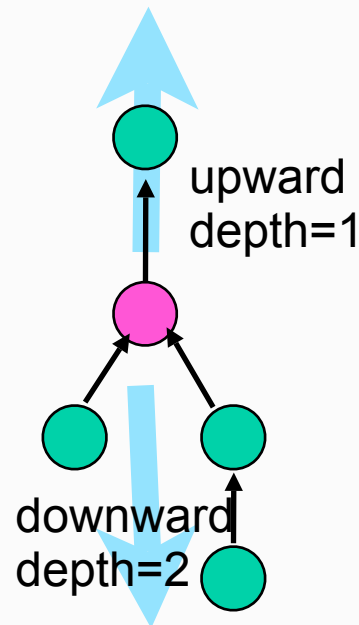
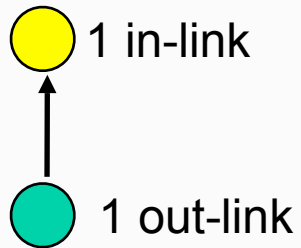
We also have stars and chains



Cascades

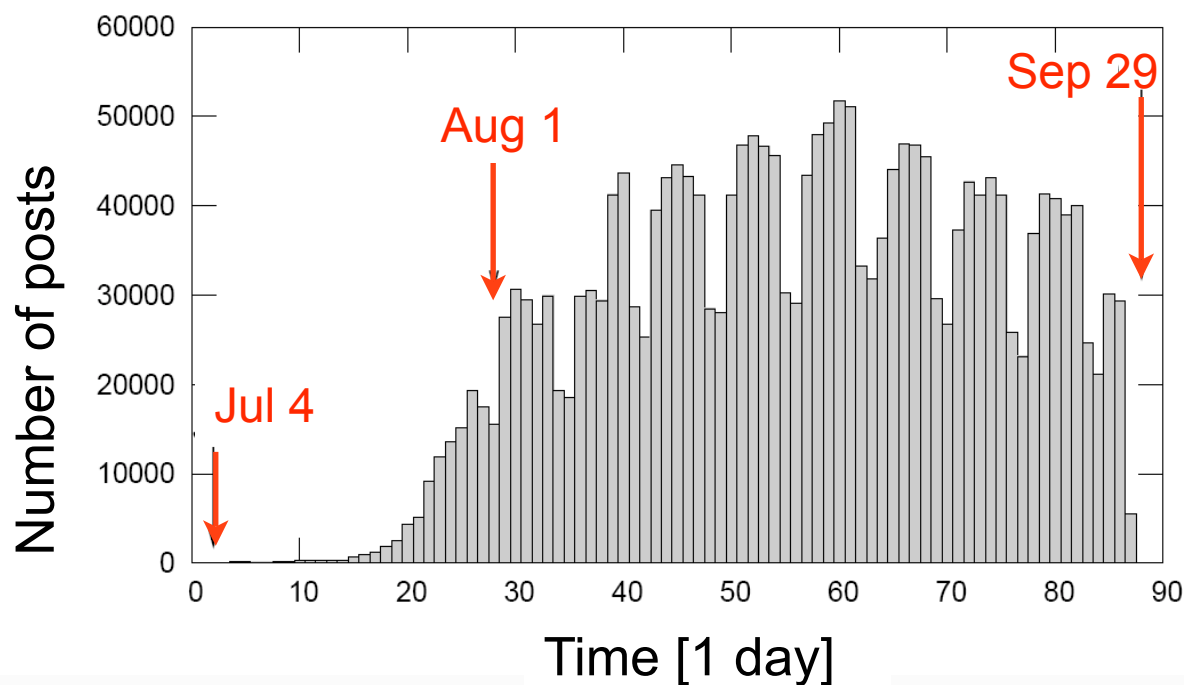
Cascades

- There are several terms we use to describe cascades:
- In-link, out-link
- Depth downwards/upwards
- Conversation mass upwards/downwards



Dataset (Nielsen Buzzmetrics)

- Gathered from **August-September 2005***
- Used set of 44,362 **blogs**, traced **cascades**
- 2.4 million **posts**, ~5 million out-links, 245,404 **blog-to-blog links**



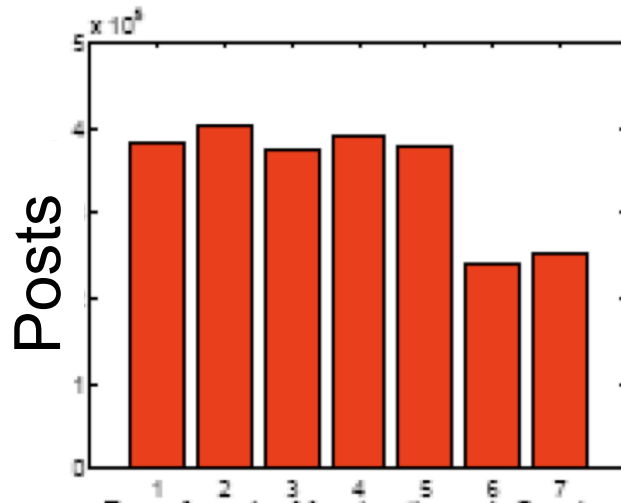
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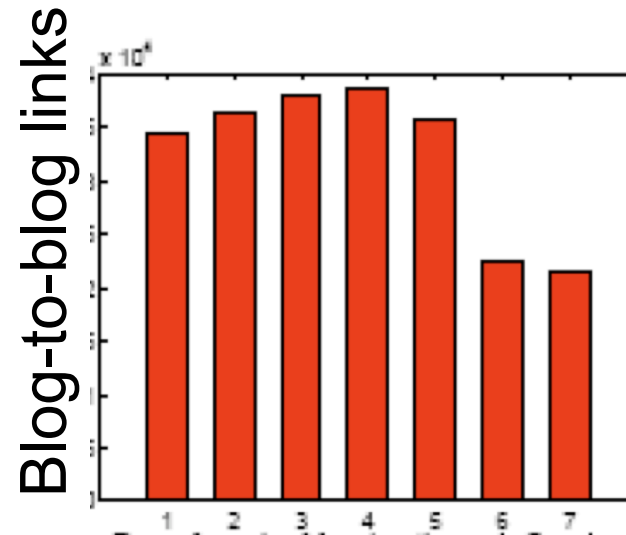
Temporal Observations

Does blog traffic behave periodically?

- Posts have “weekend effect”, **less traffic** on Saturday/Sunday.



Day of week,
Mon. to Sun.

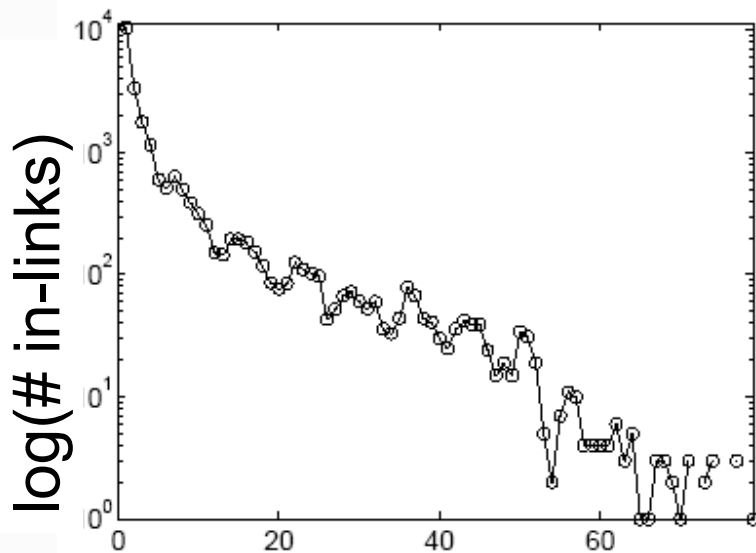


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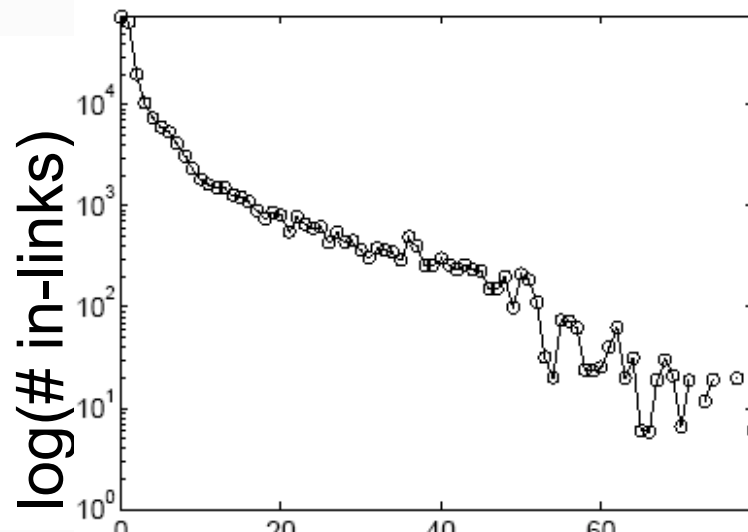
Temporal Observations

Does blog traffic behave periodically?

- Monday appears to compensate for this behavior, but it is not actually the case.
- We normalize data: $\text{count}_{\text{norm}} = \text{count} / p_d$
where p_d is percentage of links on that day.



Days after post
(Monday posts)



Same data, normalized

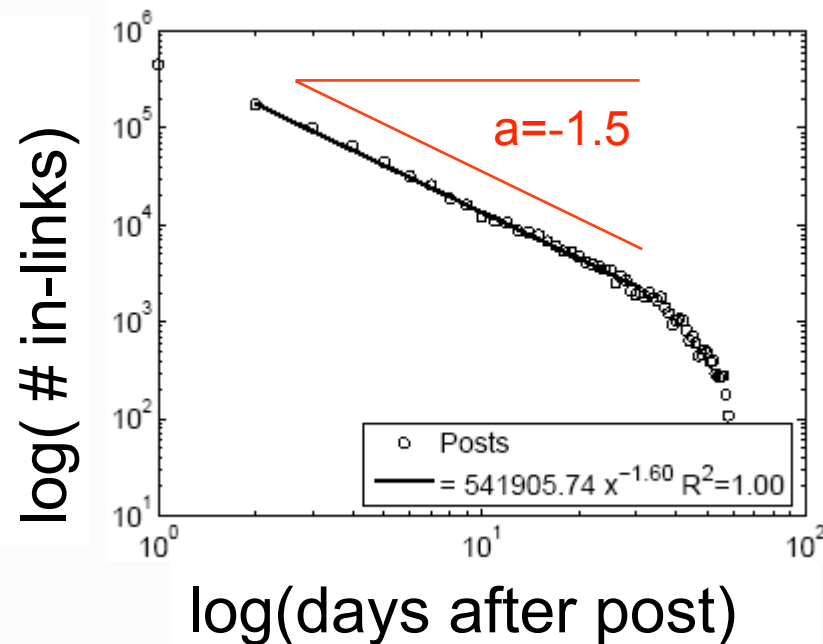
Temporal Observations

How does post popularity change over time?

Post popularity dropoff follows a power law identical to that found in communication response times in [Vazquez+2006].

Observation 1: *The probability that a post written at time t_p acquires a link at time $t_p + \Delta$ is:*

$$p(t_p + \Delta) \propto \Delta^{-1.5}$$

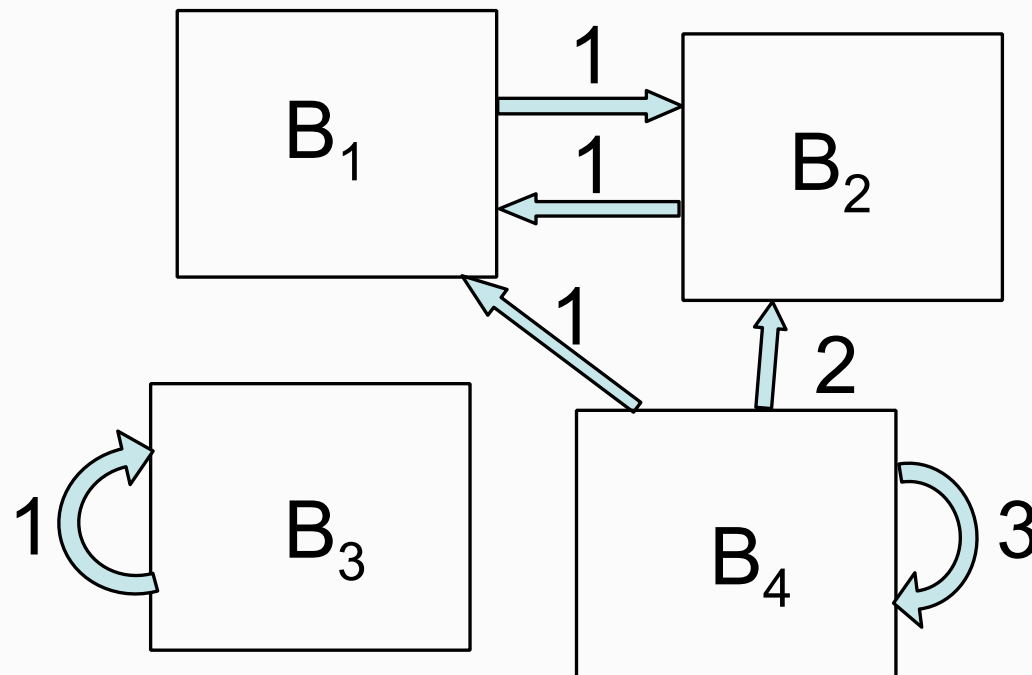


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Topological Observations

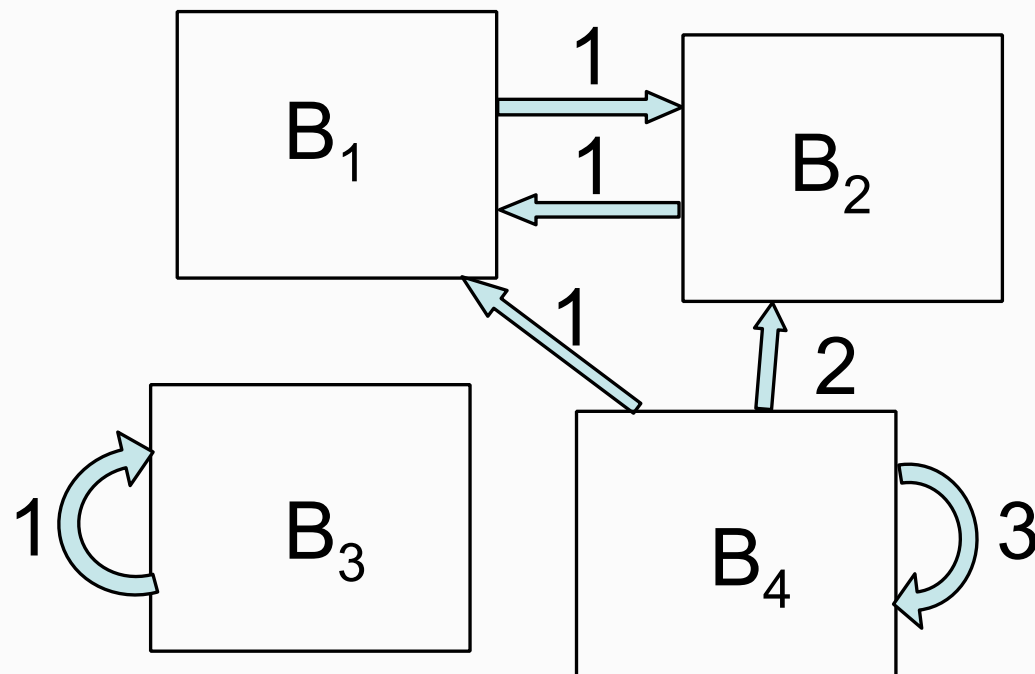
What graph properties does the blog network exhibit?



Topological Observations

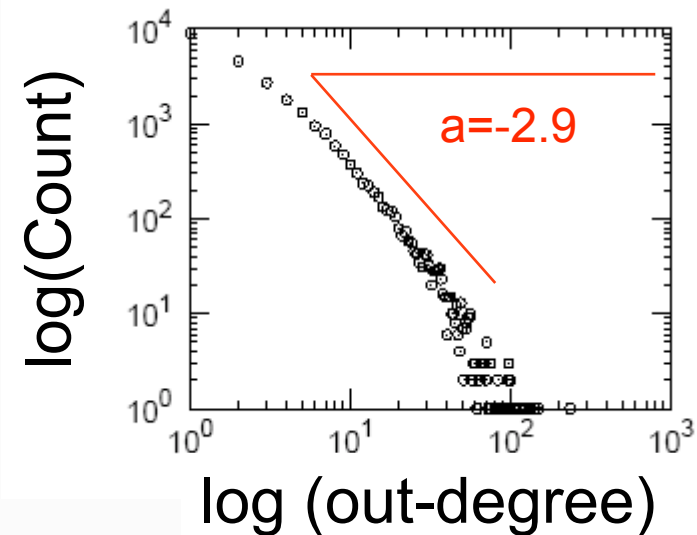
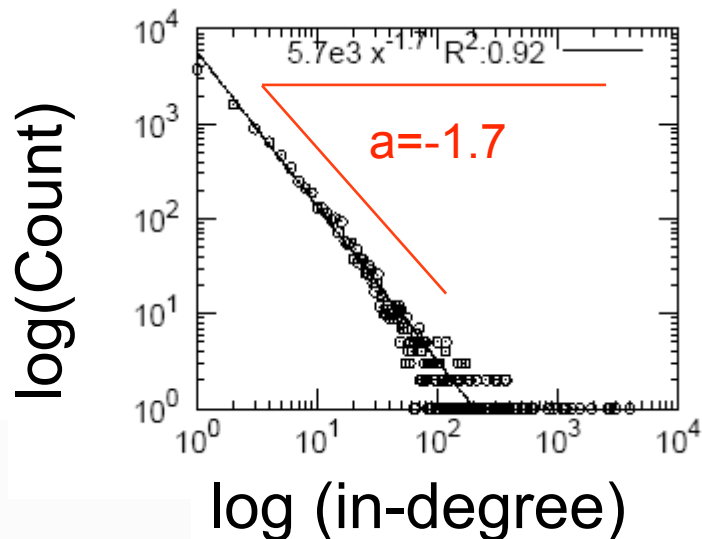
What graph properties does the blog network exhibit?

- 44,356 nodes, 122,153 edges
- Half of blogs belong to largest connected component.



Topological Observations

What laws does the blog network exhibit?



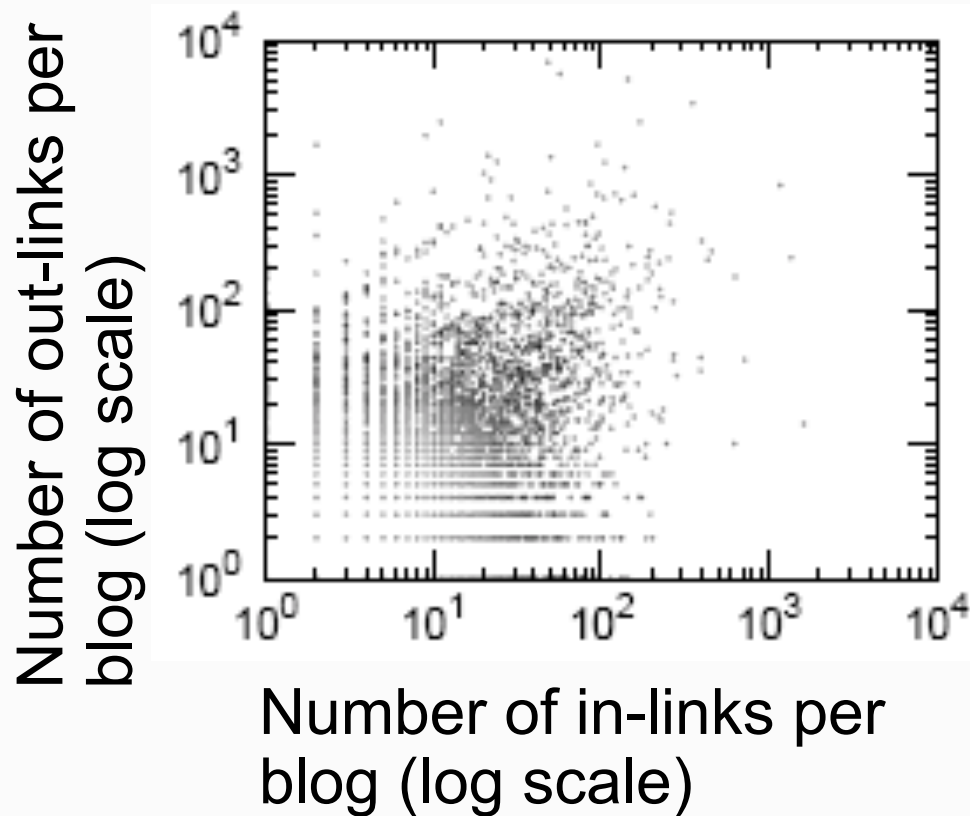
Both in- and out-degree follows a power law distribution, in-link PL exponent -1.7, out-degree PL exponent near -3.

This suggests strong **rich-get-richer phenomena**.

Topological Observations

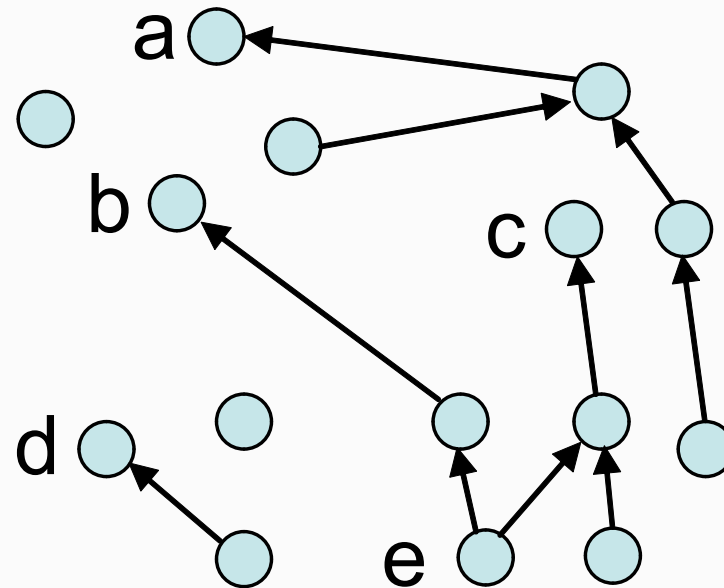
How are blog in- and out-degree related?

In-links and out-links are not correlated.
(correlation coefficient 0.16)



Topological Observations

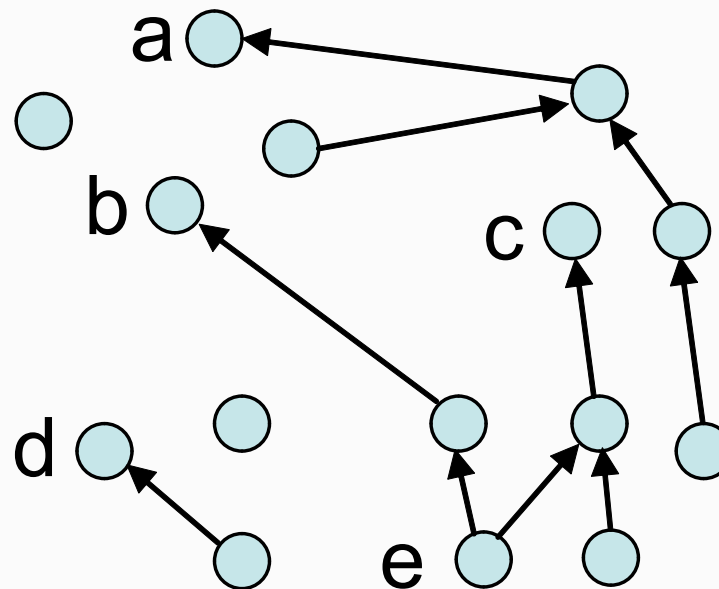
What graph properties does the post network exhibit?



Topological Observations

What graph properties does the post network exhibit?

Very sparsely connected: 98% of posts are isolated.



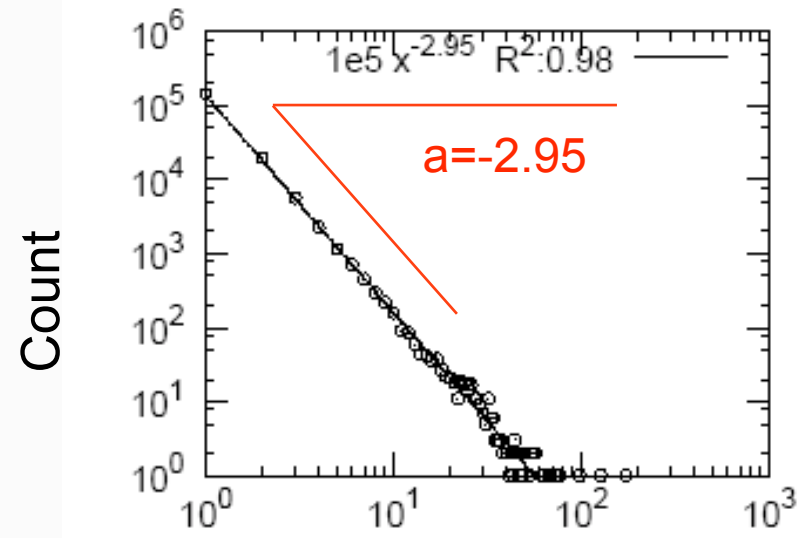
Topological Observations

What power laws does the post network exhibit?

- Both in-and out-degree follow power laws:
- In-degree has PL exponent -2.15, out-degree has PL exponent -2.95.



Post in-degree



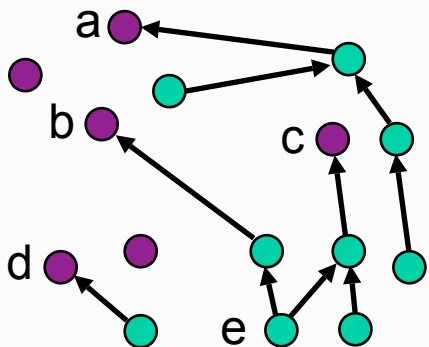
Post out-degree

Topological Observations

How do we measure how information flows through the network?

We gather *cascades* using the following procedure:

- Find all initiators (out-degree 0).

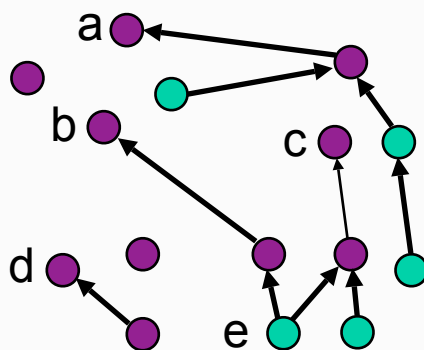
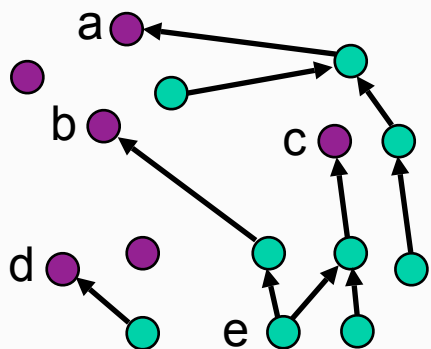


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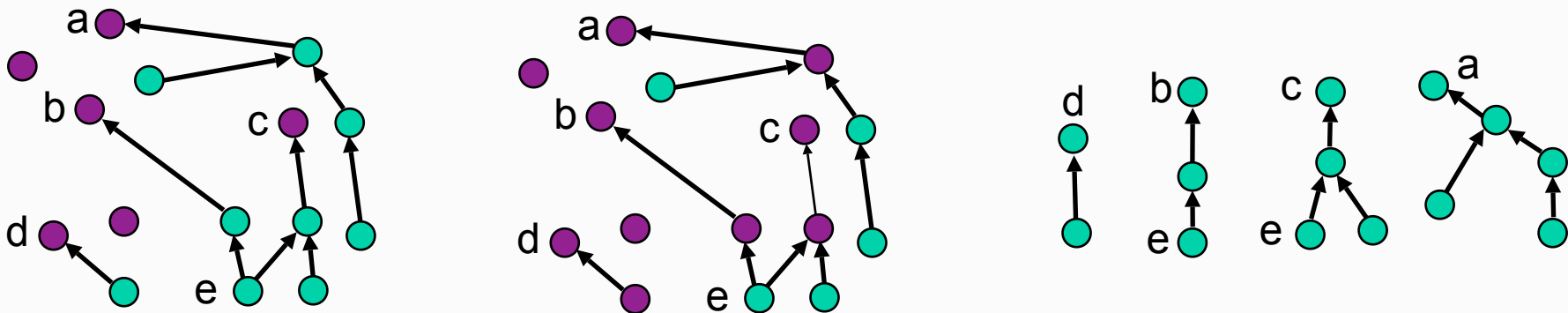


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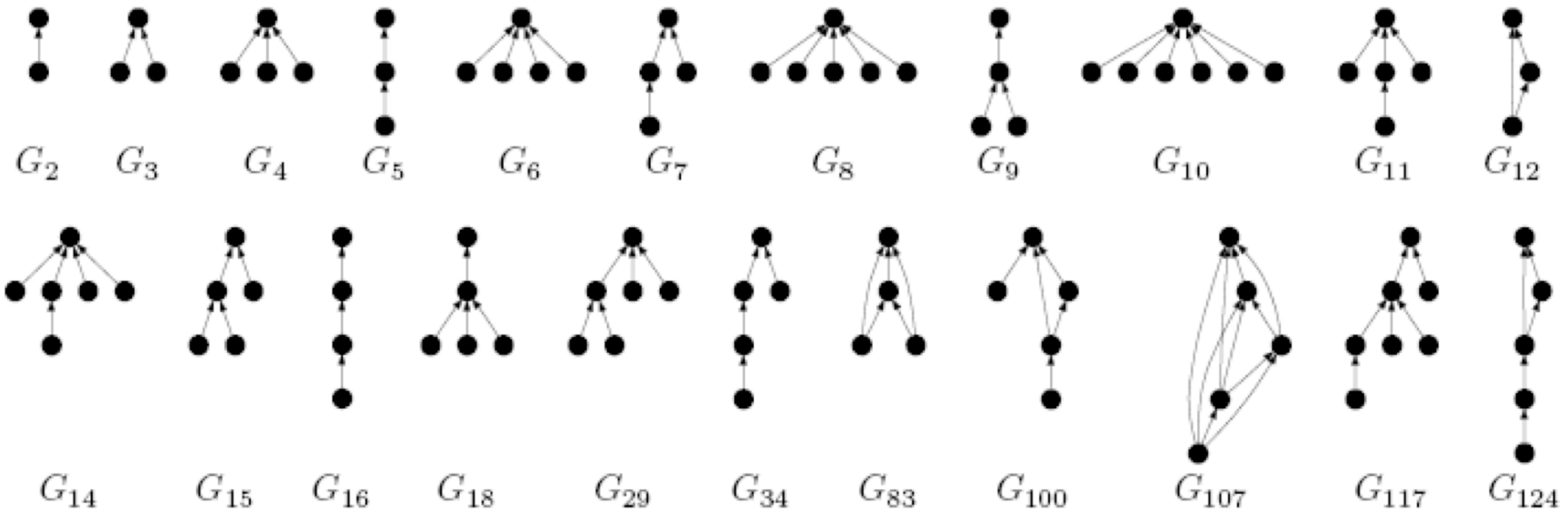
- Find all initiators (out-degree 0).
- Follow in-links.
- Produces directed acyclic graph.



Topological Observations

How do we measure how information flows through the network?

Common cascade shapes are extracted using algorithms in [Leskovec+2006].



Topological Observations

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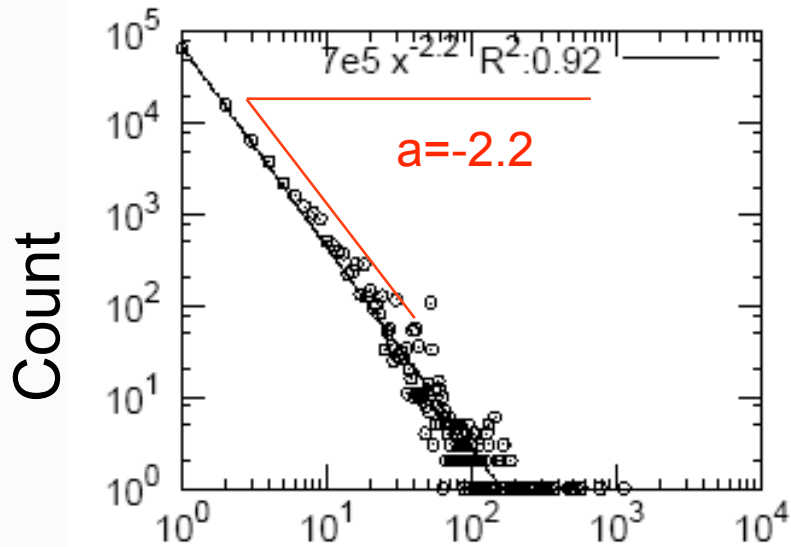
We work with a bag of cascades— each cascade is a disconnected subgraph.

We now explore some graph properties of cascades.

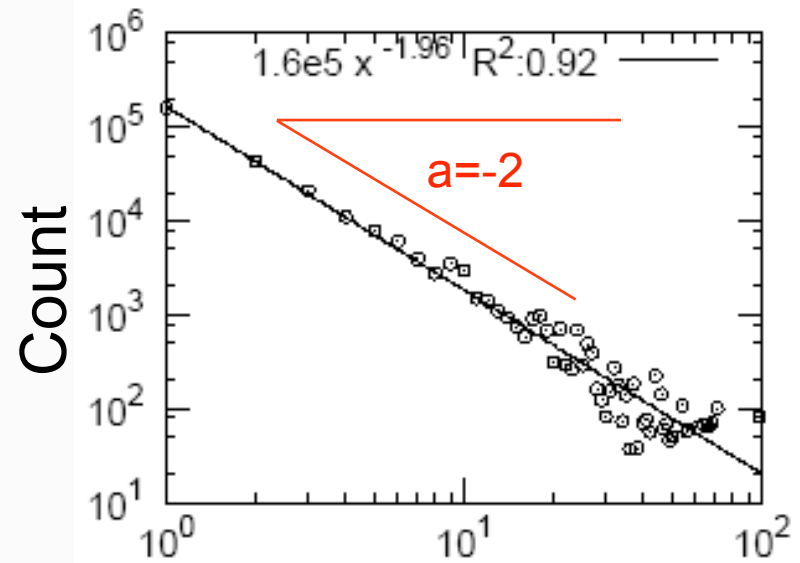
Topological Observations

What graph properties do cascades exhibit?

As before, in- and out-degree in bag of cascades follow power laws.



Cascade node in-degree



Cascade node out-degree

Topological Observations

What graph properties do cascades exhibit?

Cascade size distributions also follow power law.

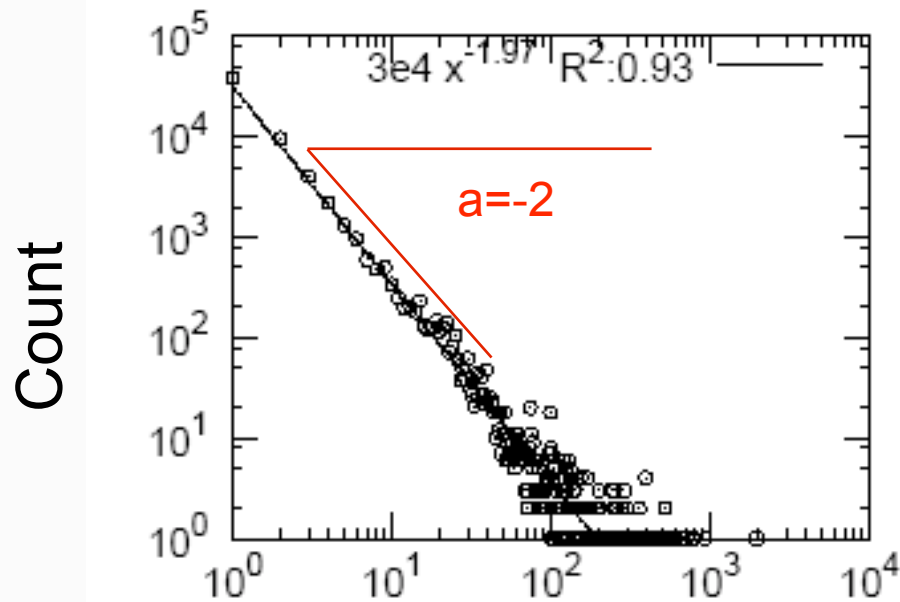
Topological Observations

What graph properties do cascades exhibit?

Cascade size distributions also follow power law.

Observation 2: *The probability of observing a cascade on n nodes follows a Zipf distribution:*

$$p(n) \propto n^{-2}$$



Cascade size (# of nodes)

Topological Observations

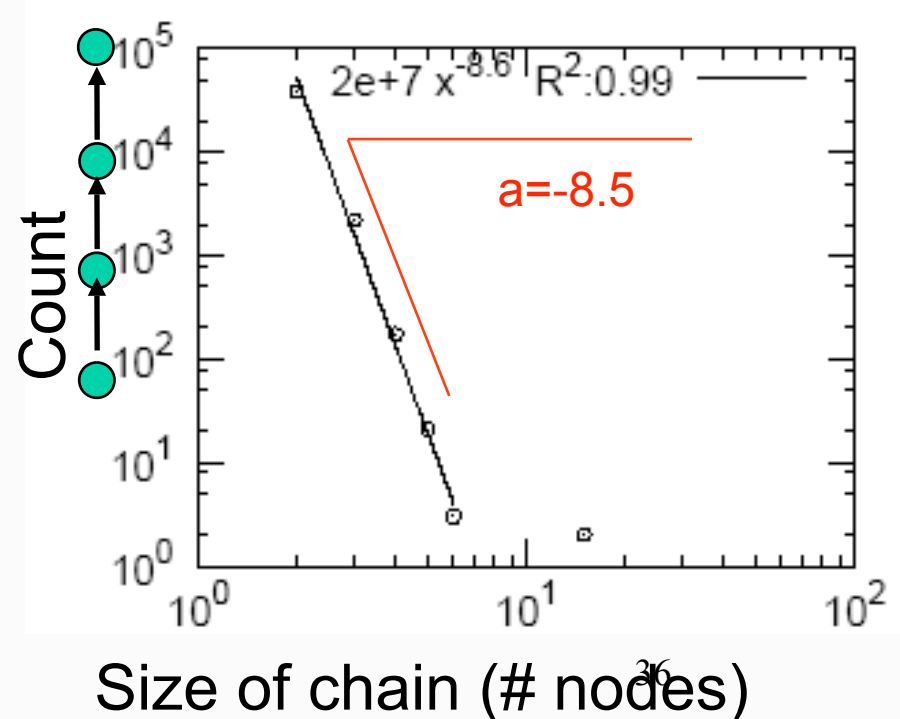
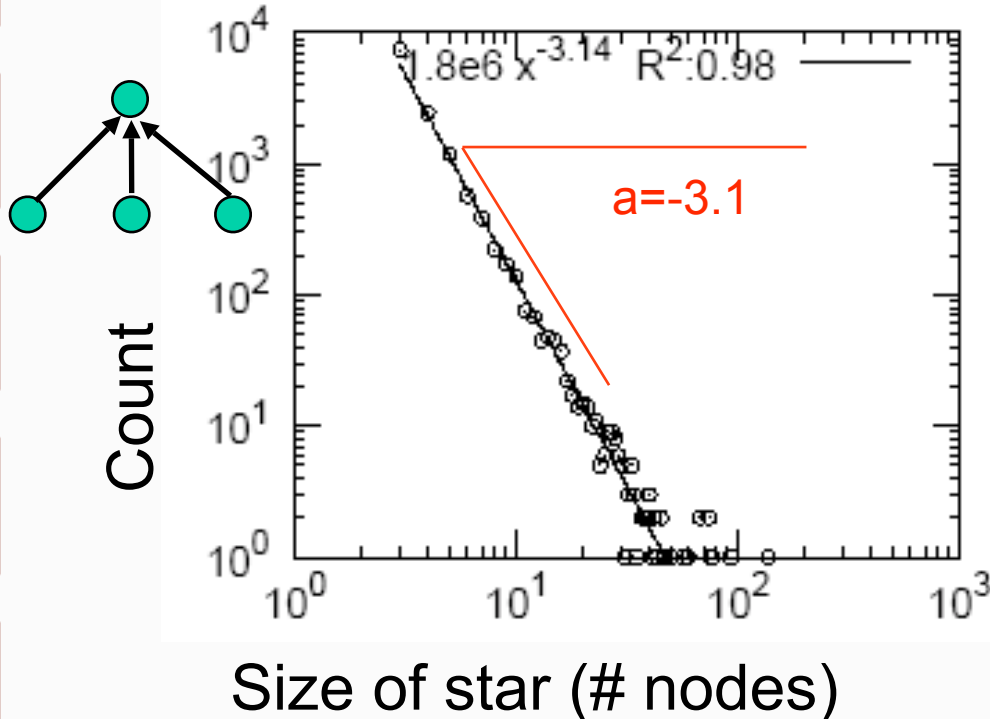
What graph properties do cascades exhibit?

Stars and chains also follow a power law, with different exponents (star -3.1, chain -8.5).

Topological Observations

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 - What shapes and patterns do cascades take on?
- Q3: Cascade Generation Model
 - Epidemiological Background
 - Proposed Model
 - Experimental Validation
- Q4: Characterizing Blogs and Posts
- Discussion & Conclusions
- Future Work

Epidemiological models

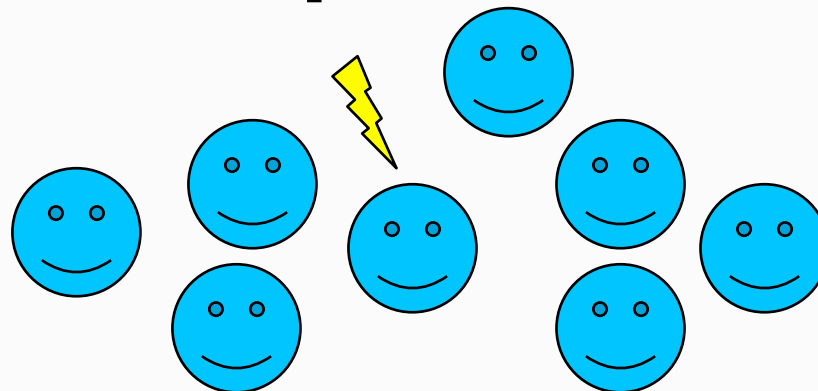
- We consider modeling cascade generation as an **epidemic**, with ideas as viruses.
- We use the SIS (flu-like) model:
 - At any time, an entity is in one of two states: **susceptible** or **infected**.
 - One parameter β determines how easily spreading conversations are.
 - [Hethcote2000]

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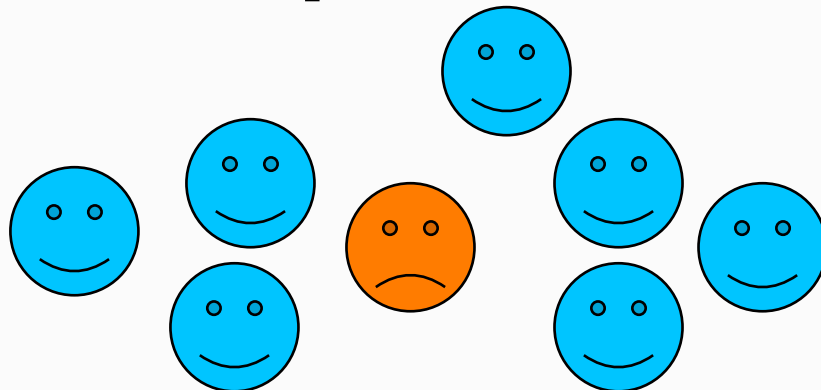
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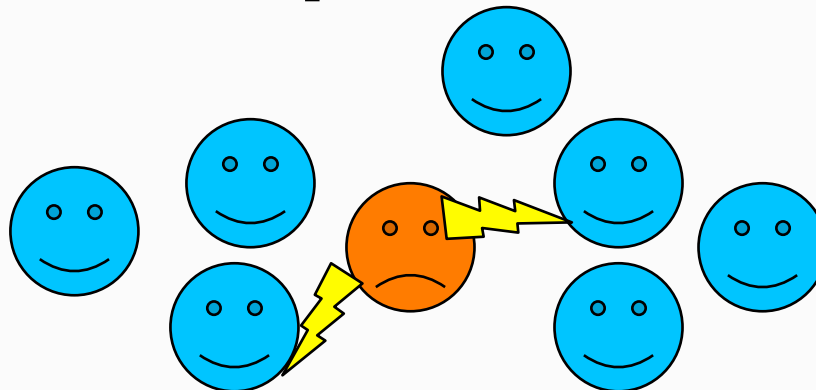
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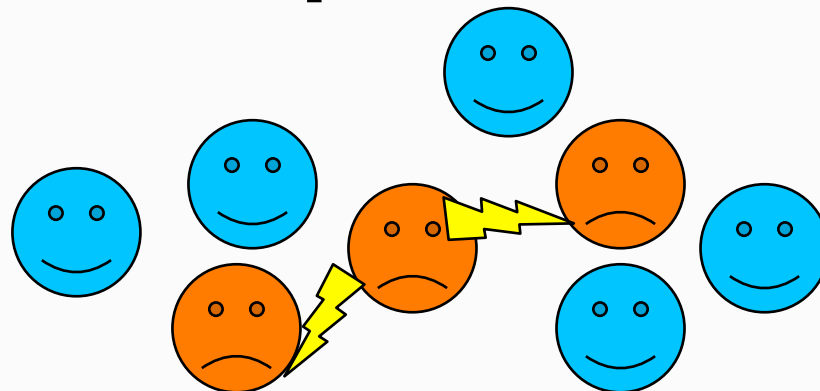
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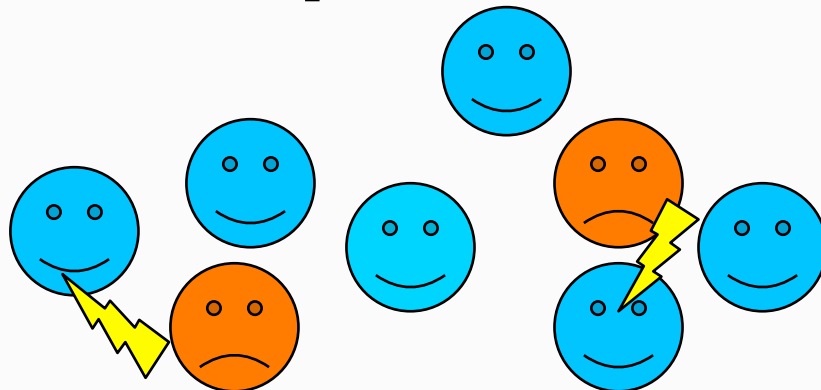
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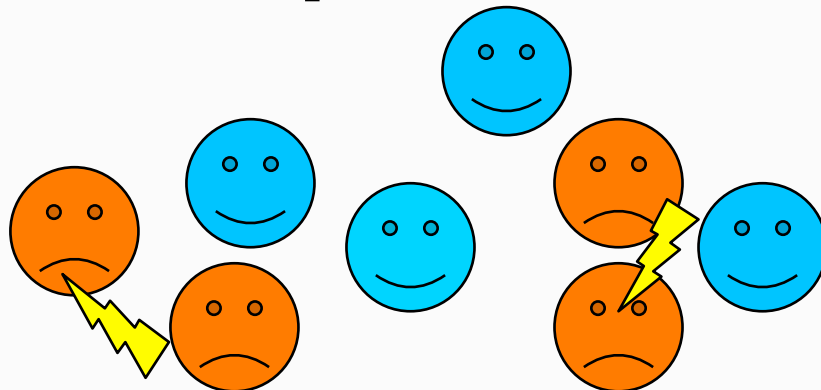
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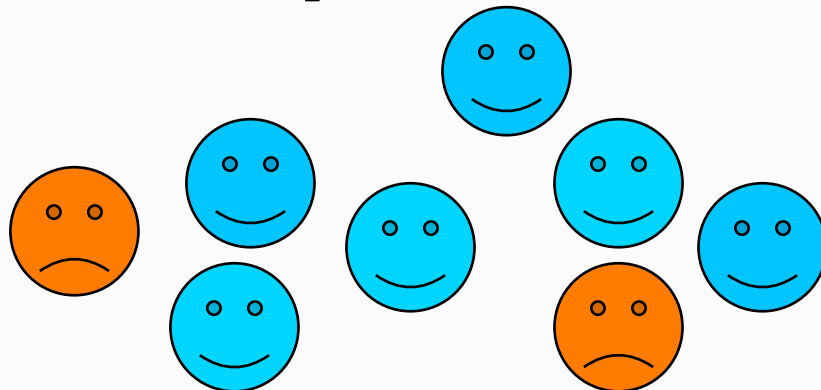
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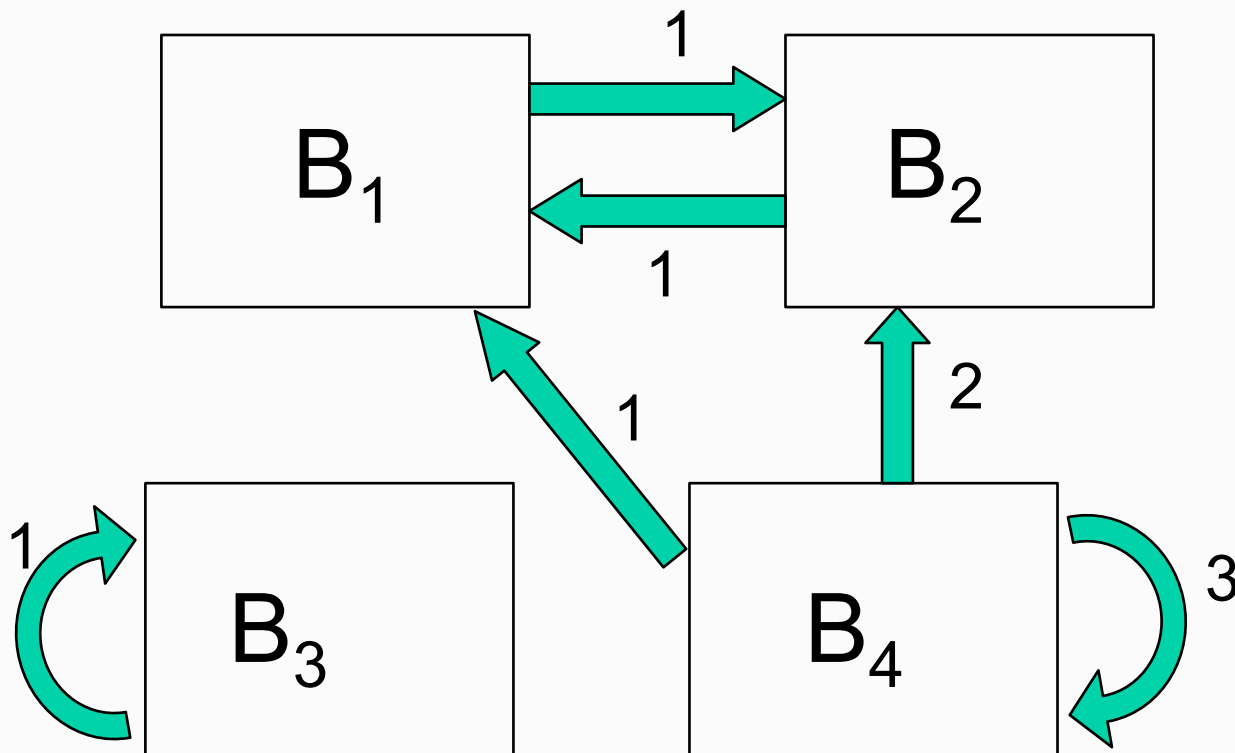
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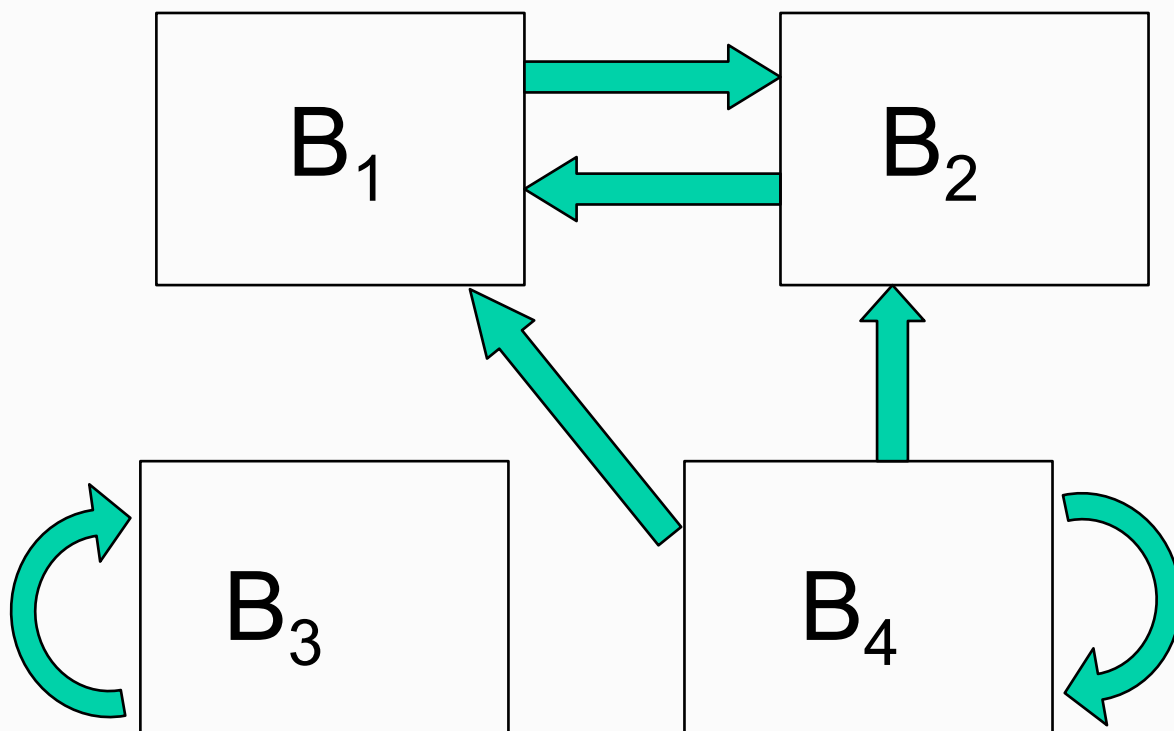
Cascade Generation Model

0. Begin with Blog Net.



Cascade Generation Model

0. Begin with Blog Net, but ignore edge weights.



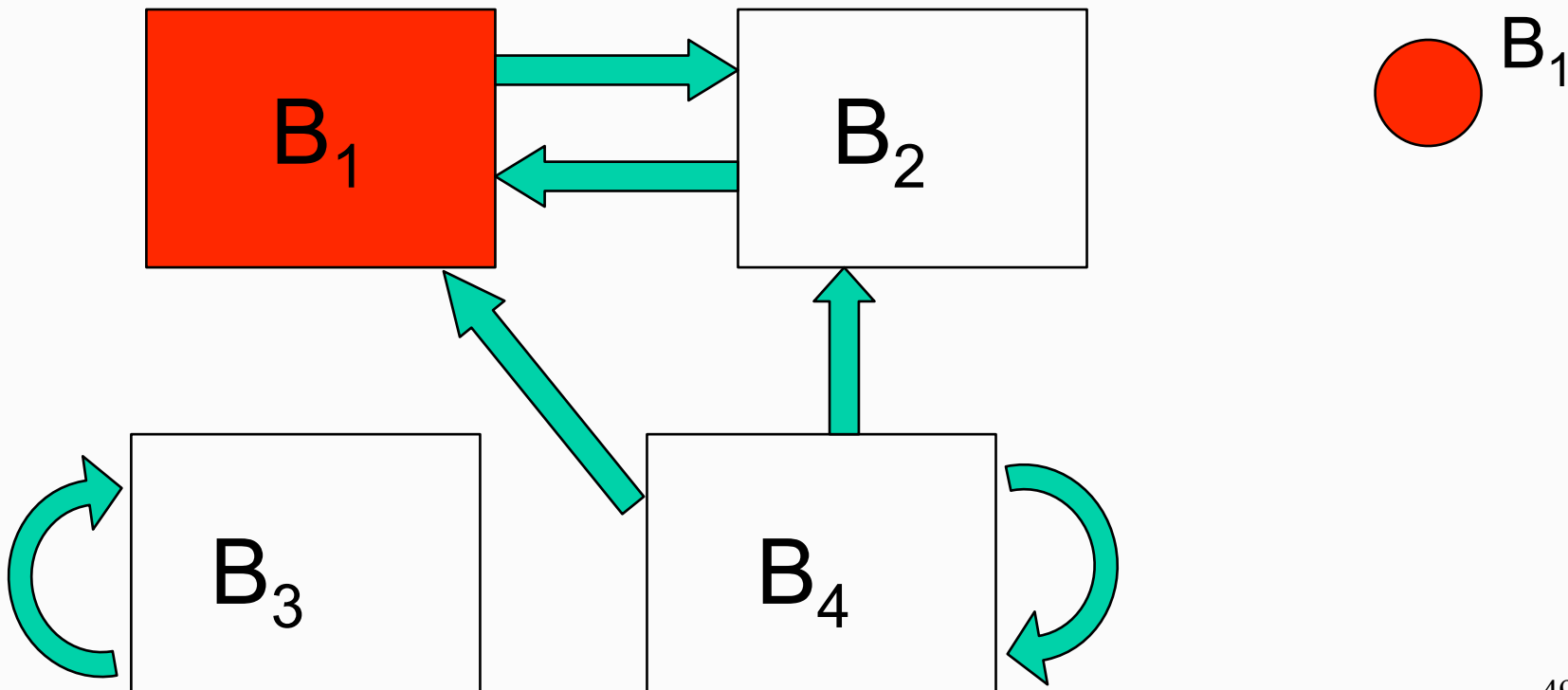
Example—

*B1 links to B2,
B2 links to B1,
B4 links to B2
and B1, as well
as itself*

*B3 is isolated,
linking to itself.*

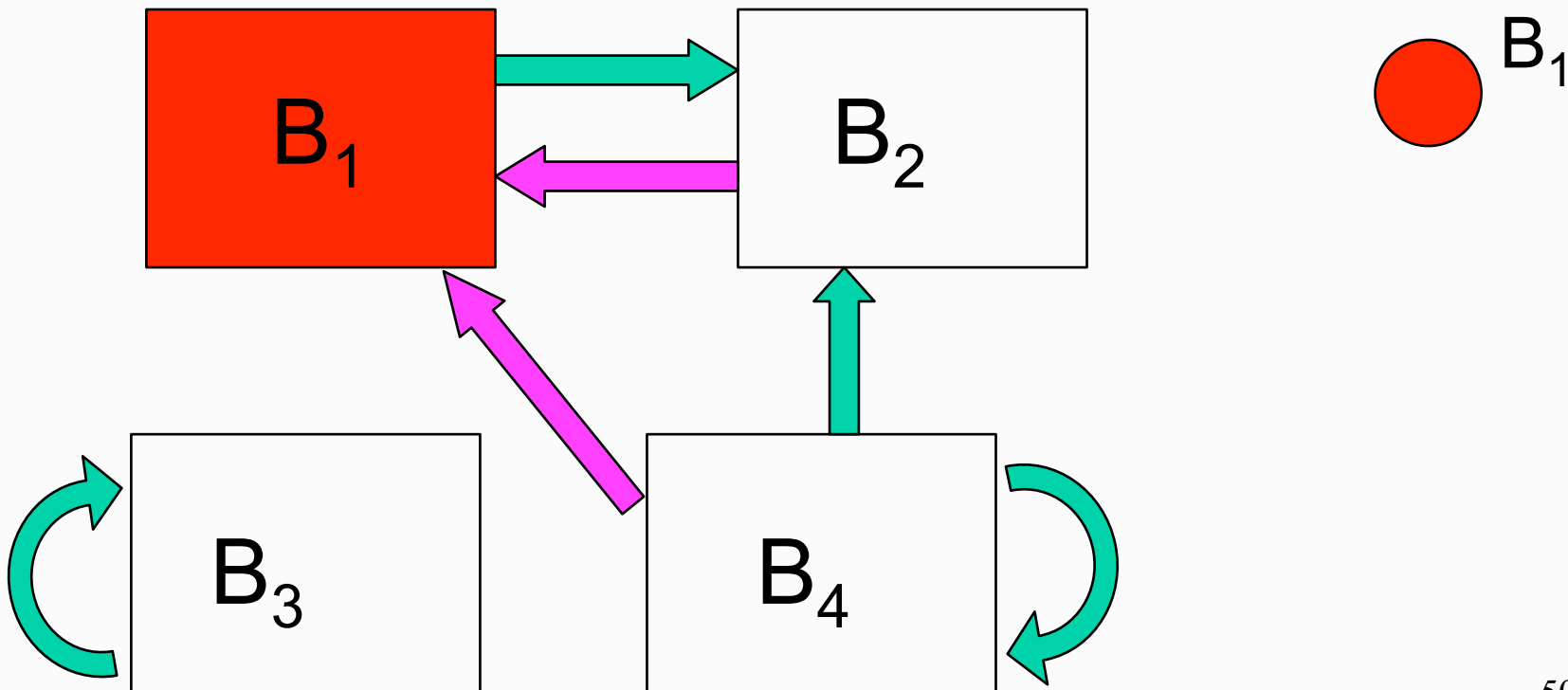
Cascade Generation Model

1. Randomly pick a blog to infect, add node to cascade



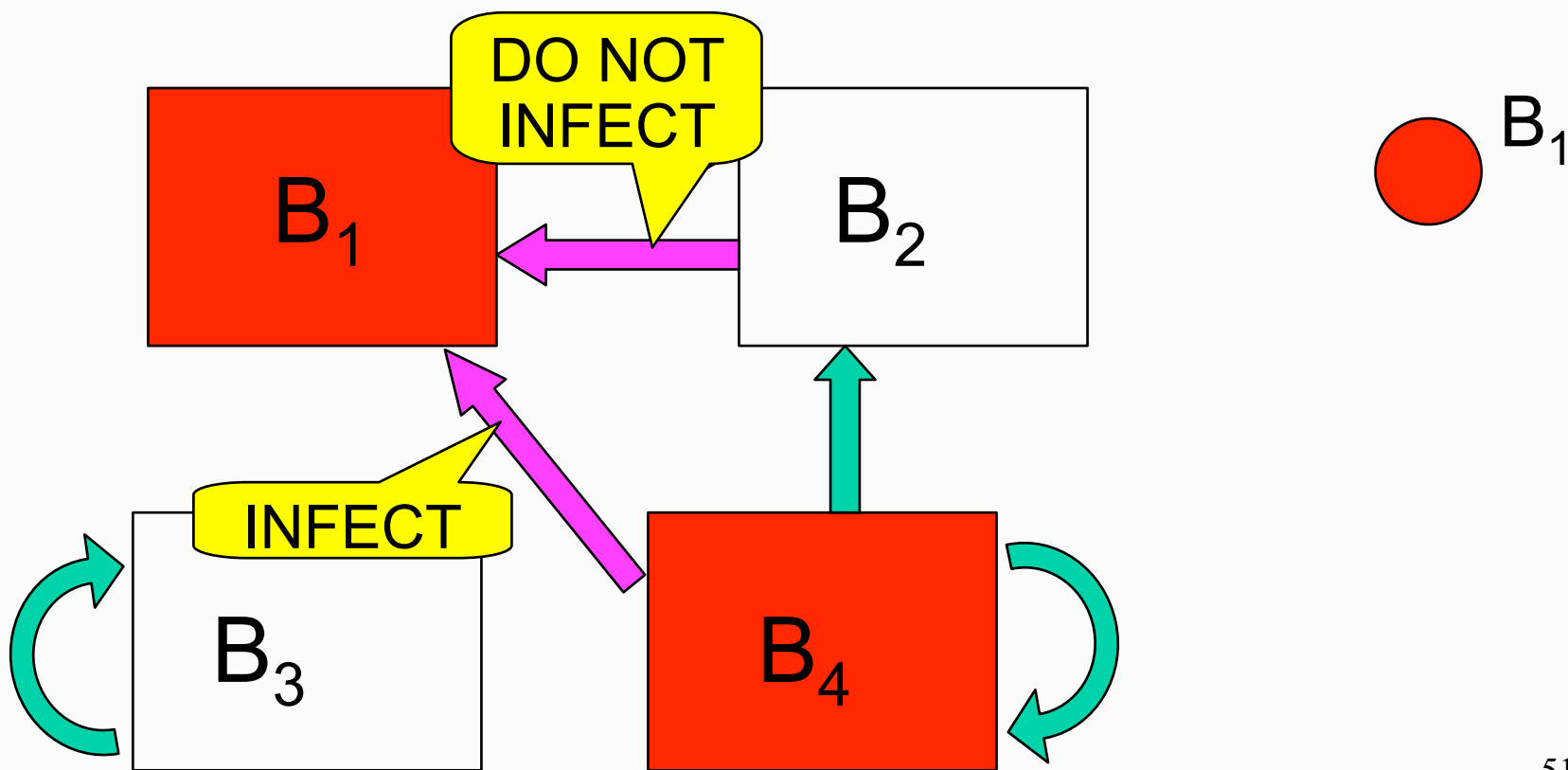
Cascade Generation Model

2. Infect each in-linked neighbor with probability β .



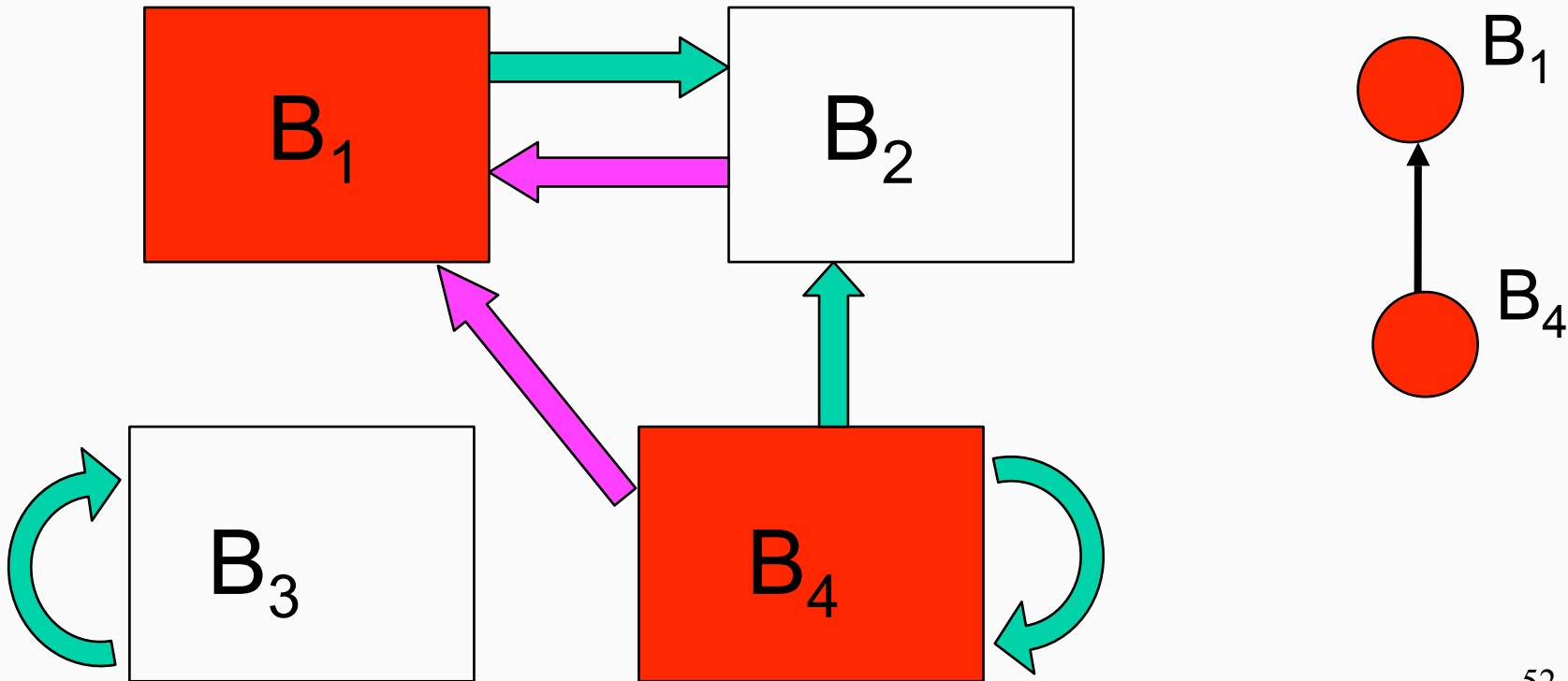
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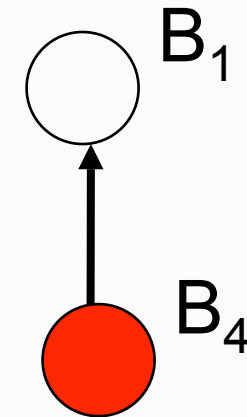
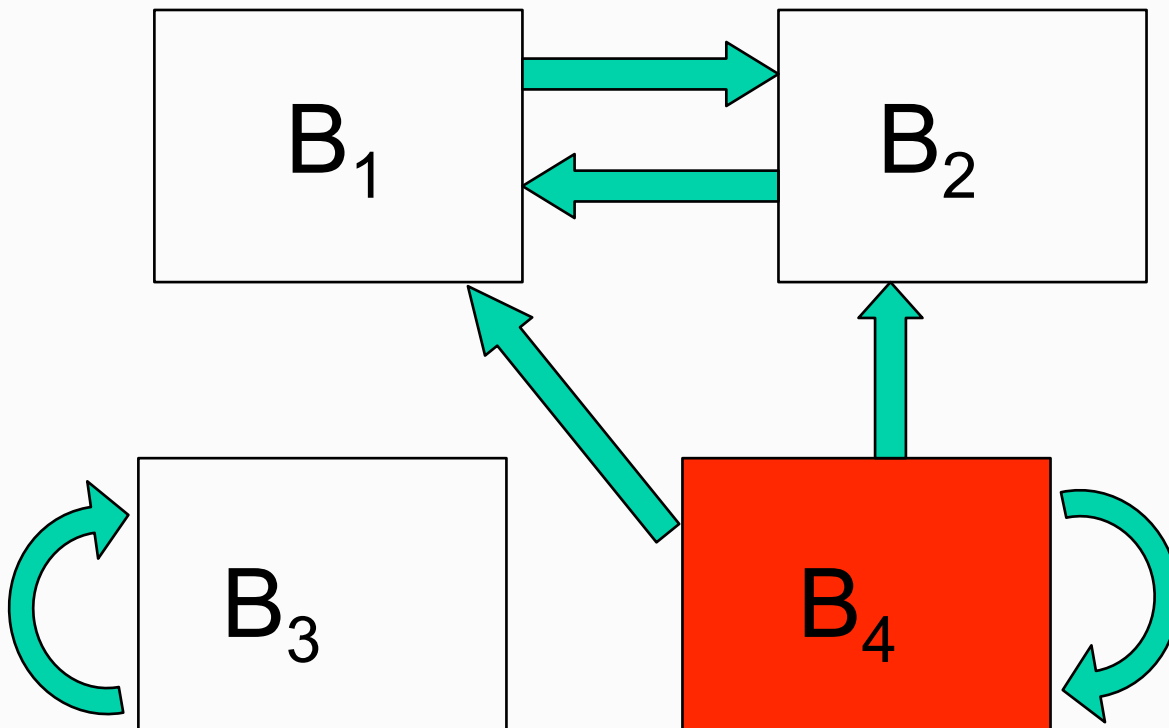
Cascade Generation Model

3. Add infected neighbors to cascade.



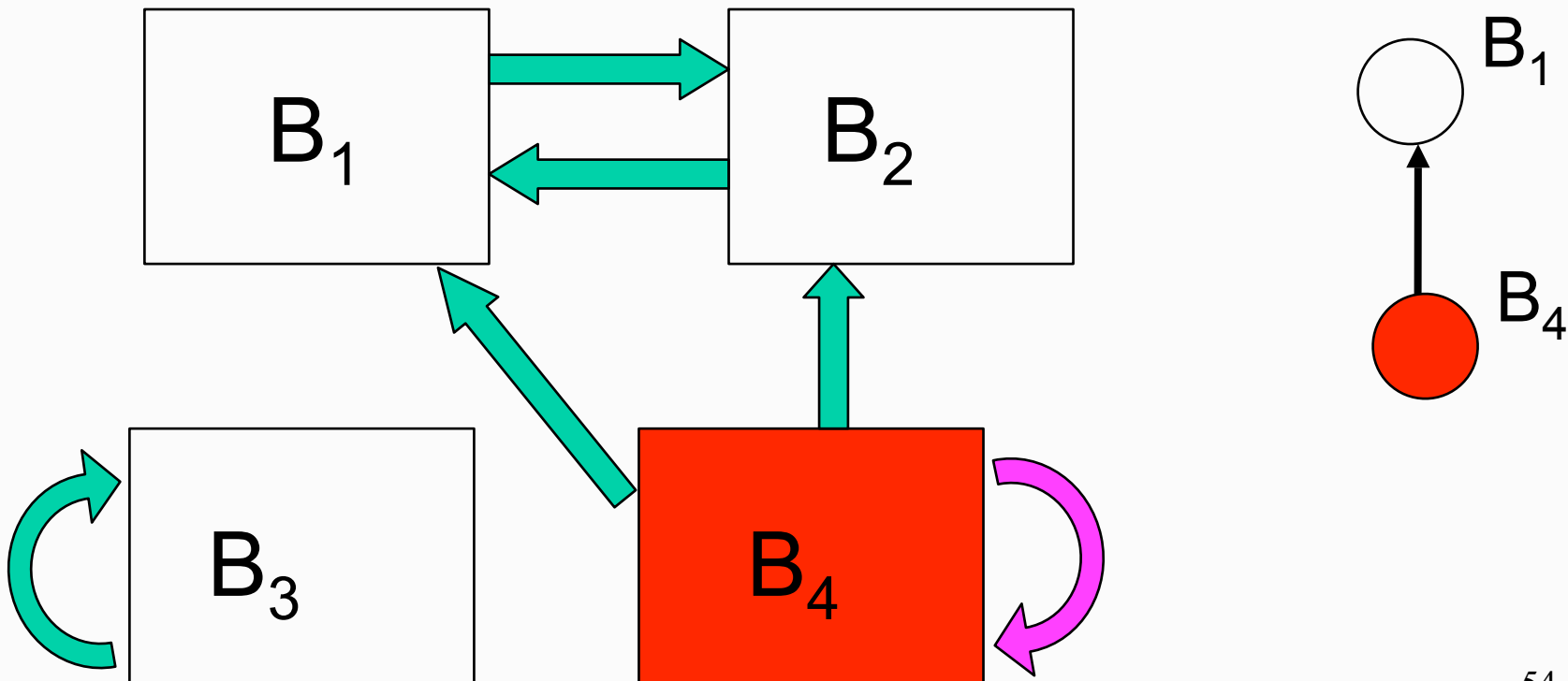
Cascade Generation Model

4. Set “old” infected nodes to uninfected.



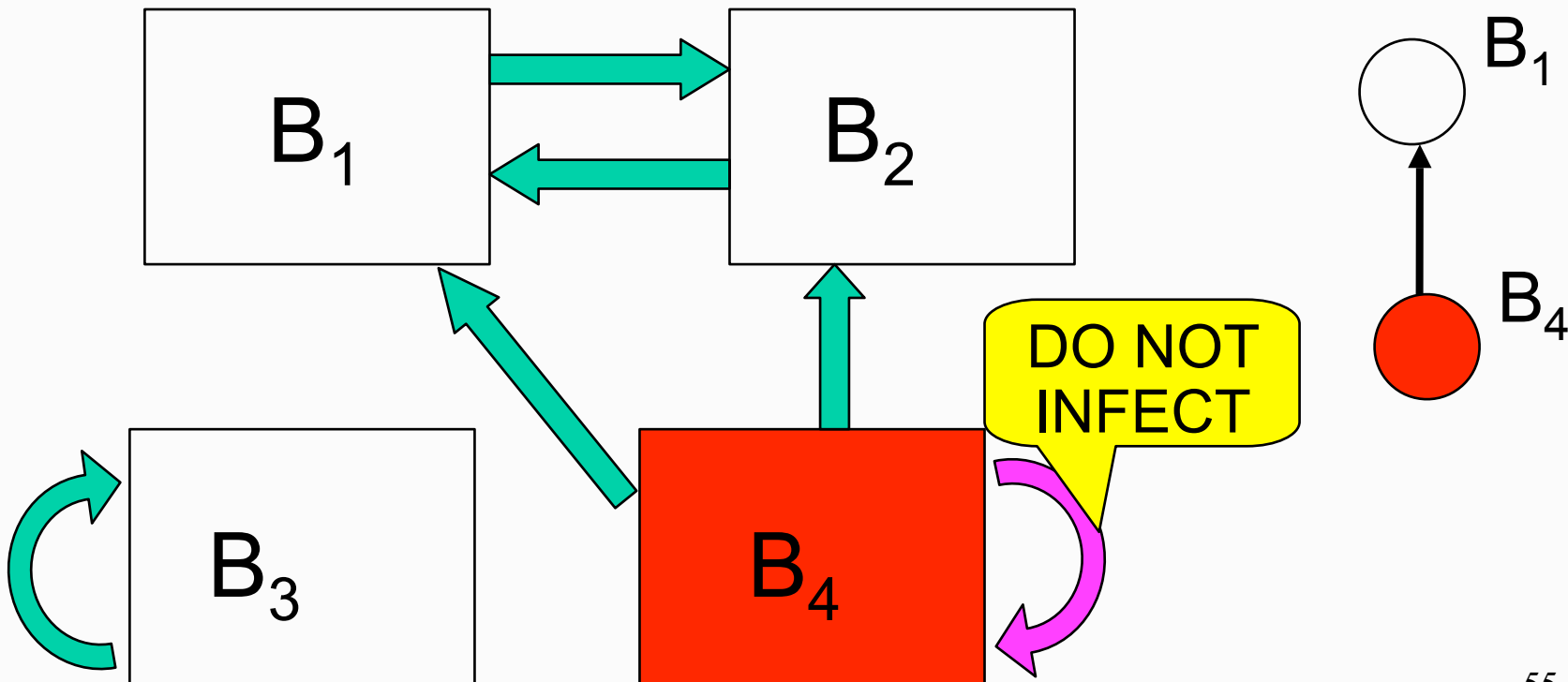
Cascade Generation Model

4. Set “old” infected nodes to uninfected. Repeat steps 2-4 until no nodes are infected.



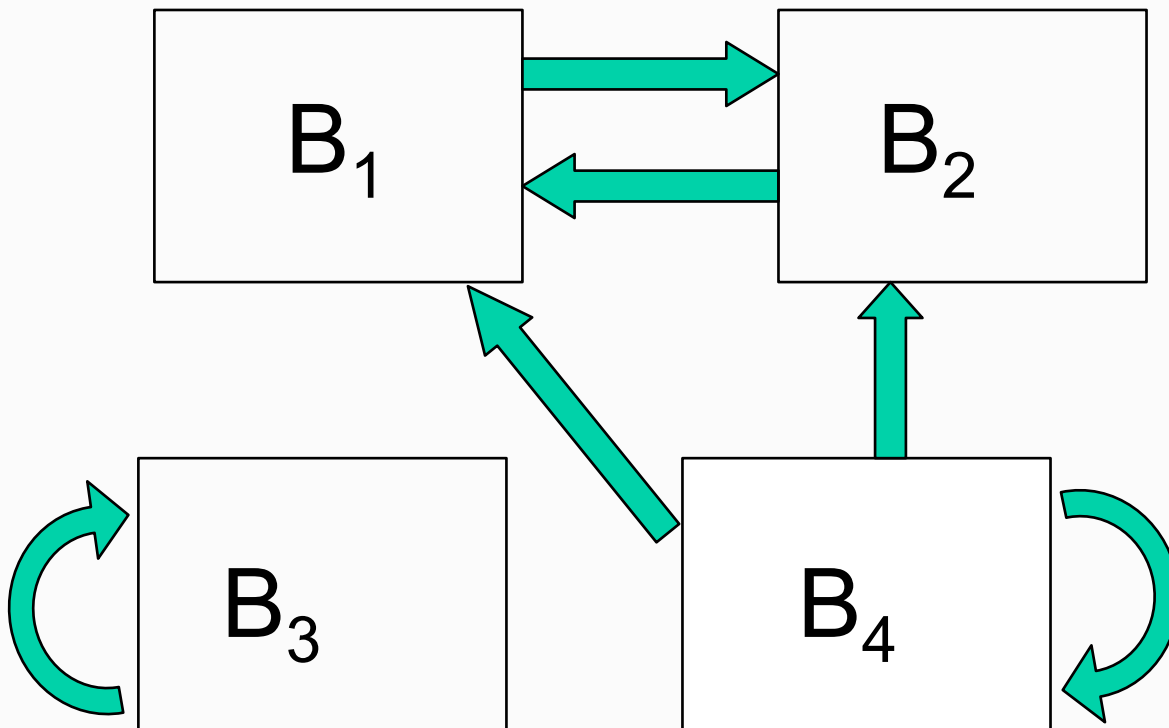
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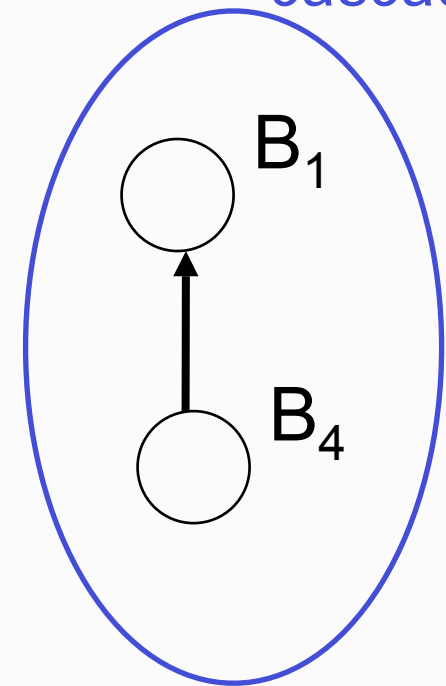


Cascade Generation Model

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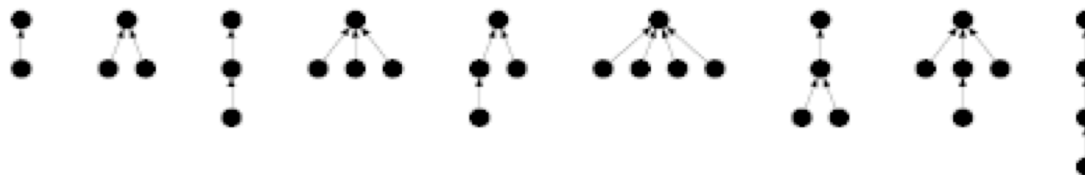
Completed cascade!



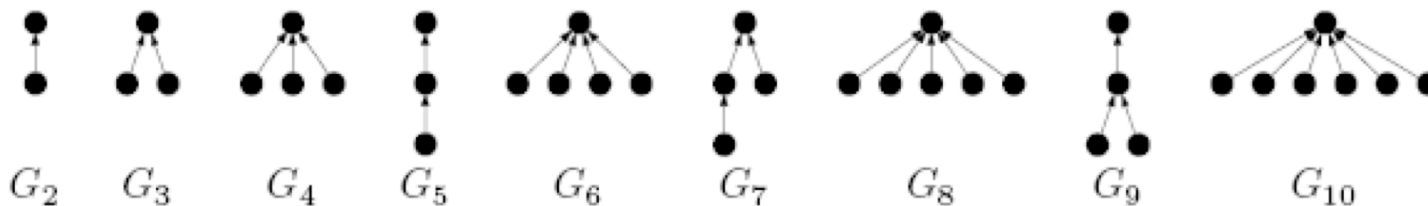
CGM matches observations

- After trying several values, we decide on $\beta=.025$.
- 10 simulations, 2 million cascades each
- **Most frequent cascades:** 7 of 10 matched exactly.

model

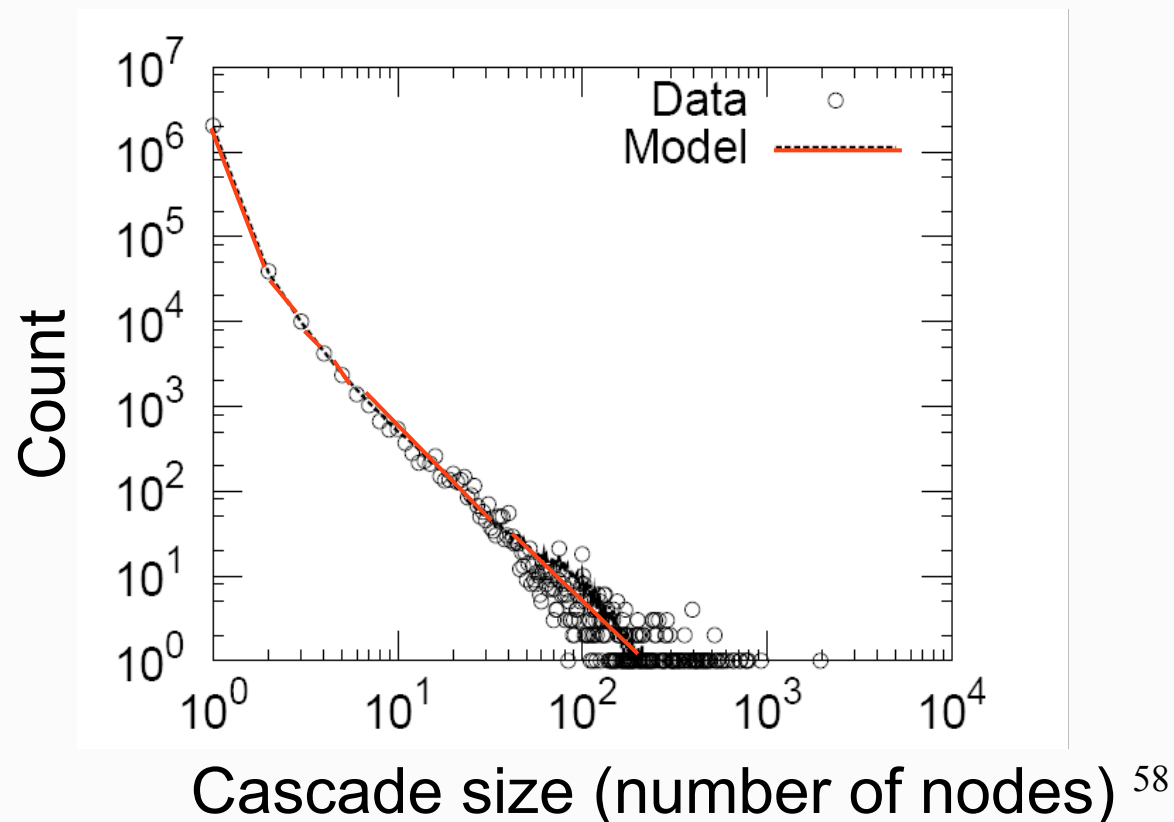


data



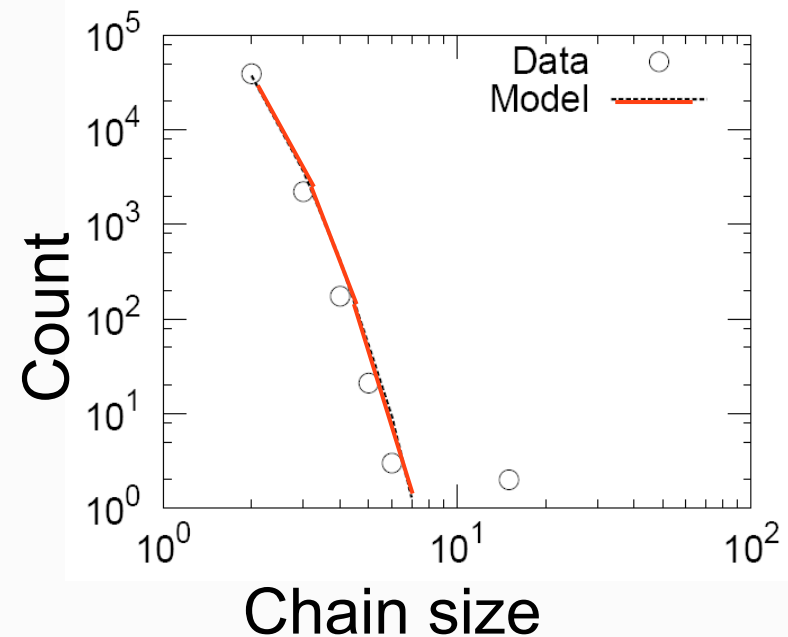
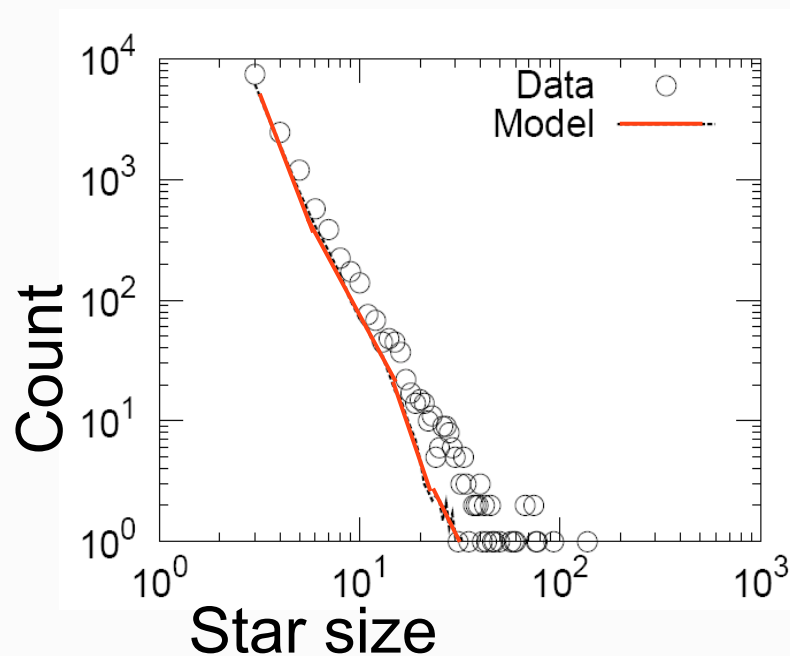
CGM matches observations

Cascade size in this model also follows a power law-- the model distribution is shown with the real data points.



CGM matches observations

- Stars and chains both follow power laws, close to those observed in real data.



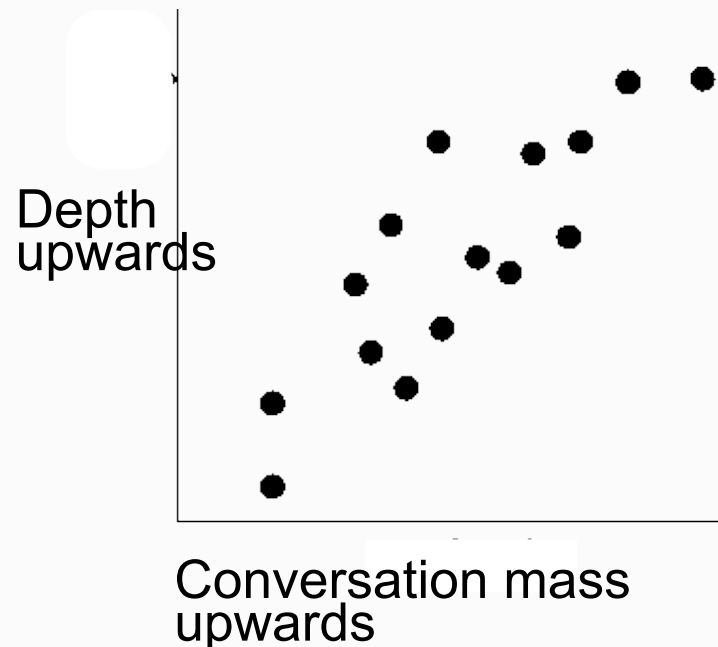
Outline

- Motivation
- Preliminaries
- Q1: Temporal Observations
- Q2: Topological Observations
 - What are graph properties for blog networks?
 - What shapes and patterns do cascades take on?
- Q3: Cascade Generation Model
- Q4: Characterizing Blogs and Posts**
- Discussion & Conclusions
- Future Work

Preliminaries- PCA

- We will work with very high-dimensional data (~9,000 dimensions).
- **Principal Component Analysis** is a method of dimensionality reduction.

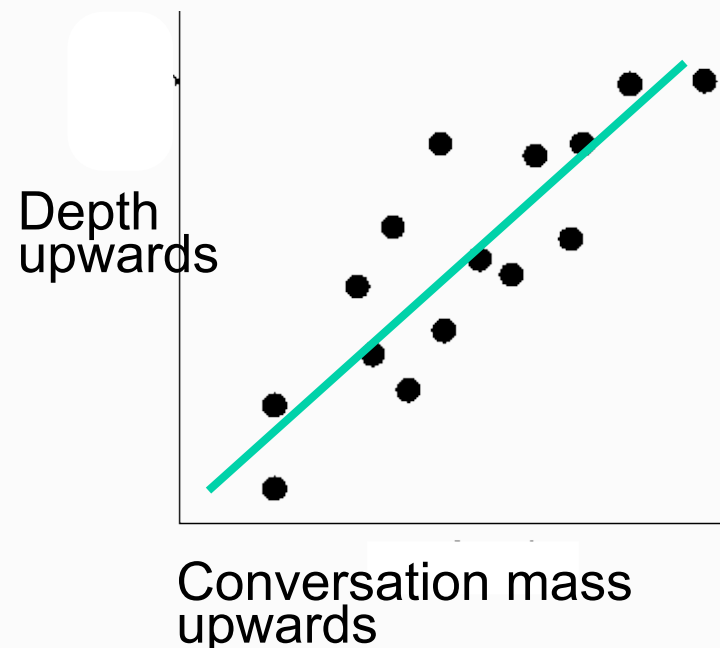
Hypothetically,
for each blog...



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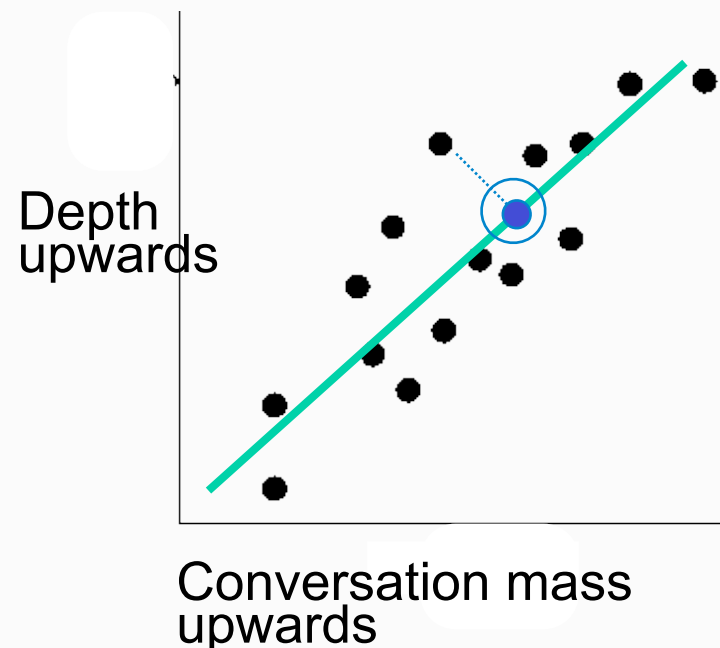
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Hypothetically,
for each blog...



Preliminaries- PCA

Details

We can represent any real $N \times M$ matrix X as $X = U \Lambda V^t$

$$\begin{matrix} & \mathbf{X} & & \mathbf{U} & & \mathbf{\Lambda} & & \mathbf{V}^t \\ \left[\begin{array}{ccccc} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{array} \right] & = & \left[\begin{array}{cc} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{array} \right] & \mathbf{X} & \left[\begin{array}{cc} 9.64 & 0 \\ 0 & 5.29 \end{array} \right] & \mathbf{X} & \left[\begin{array}{ccccc} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{array} \right] \\ & & & & & & & \mathbf{v}^1
 \end{matrix}$$

Preliminaries- PCA

Details

- Reduce dimensionality by setting all other components of Λ to zero.

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \times \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \times \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

Preliminaries- PCA

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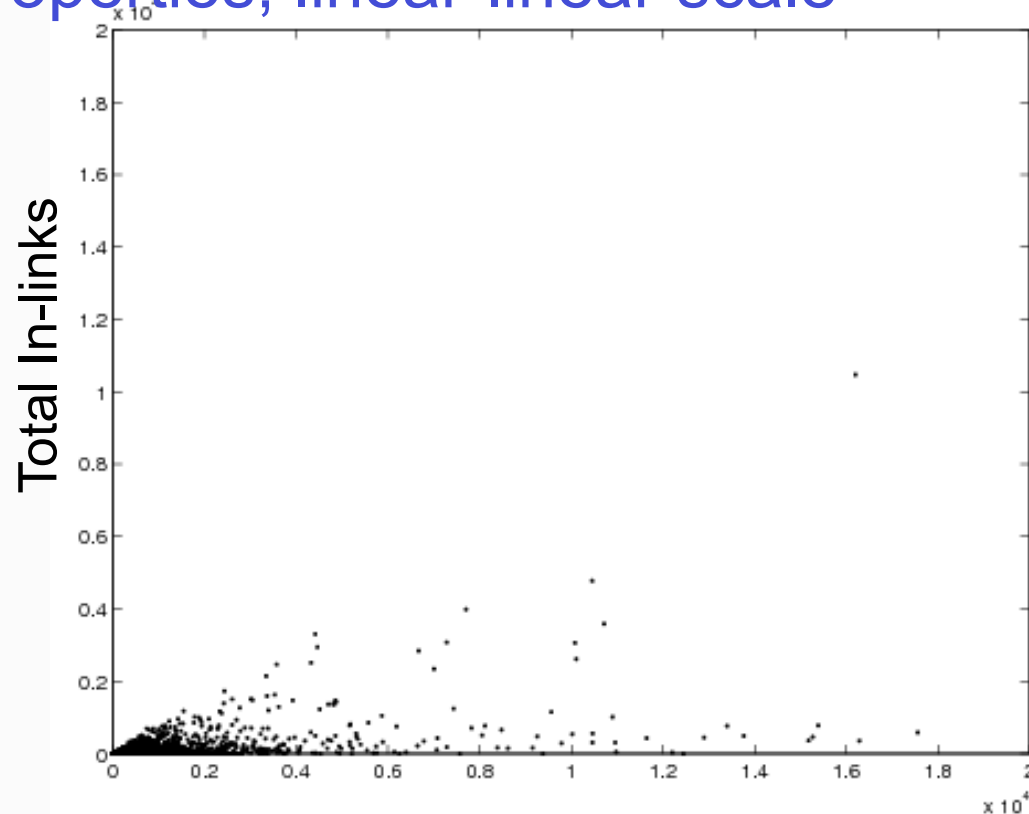
$$\begin{bmatrix} 0 & 0 \\ 2 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \sim \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \times \begin{bmatrix} 9.64 & 0 \\ 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

Reference: Fukunaga, K. (1990). *Introduction to Statistical Pattern Recognition*, Academic Press.

Preliminaries- Regularizing data

- Not everything in life is normally distributed. 😊

Blog properties, linear-linear scale

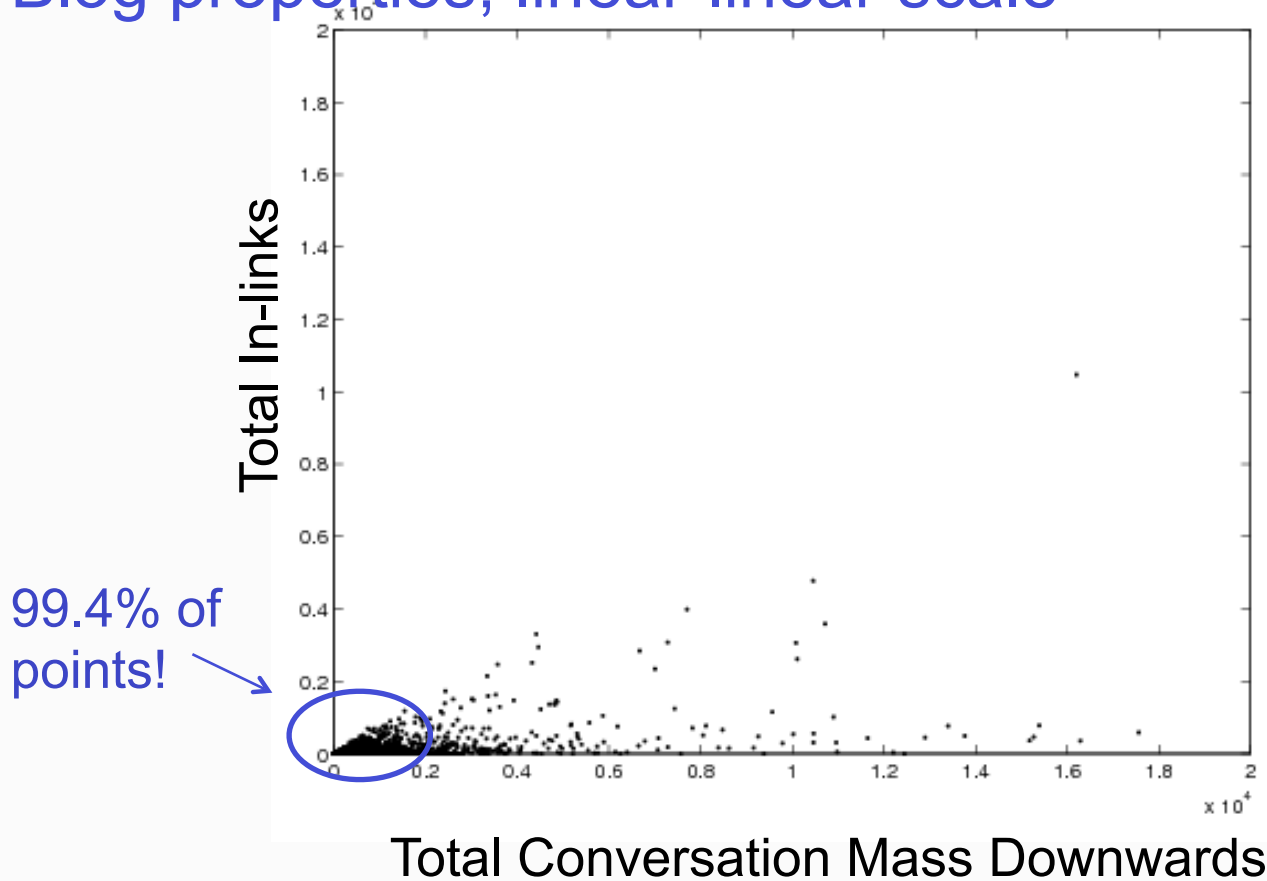


Total Conversation Mass Downwards

Preliminaries- Regularizing data

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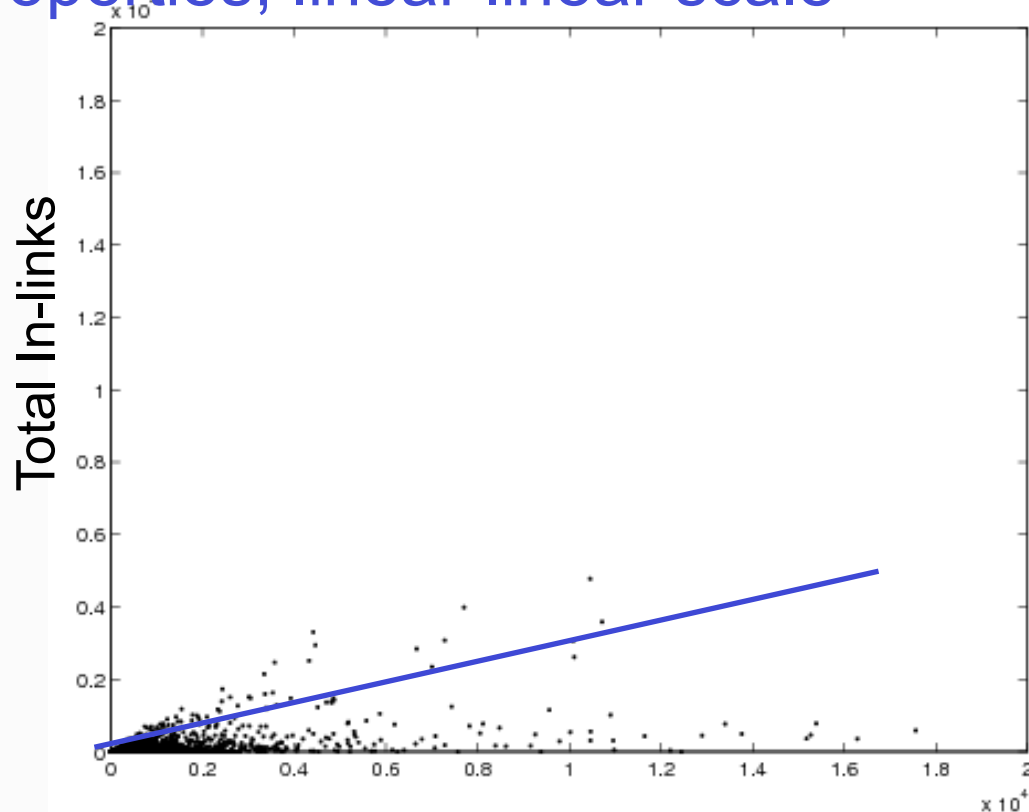
Blog properties, linear-linear scale



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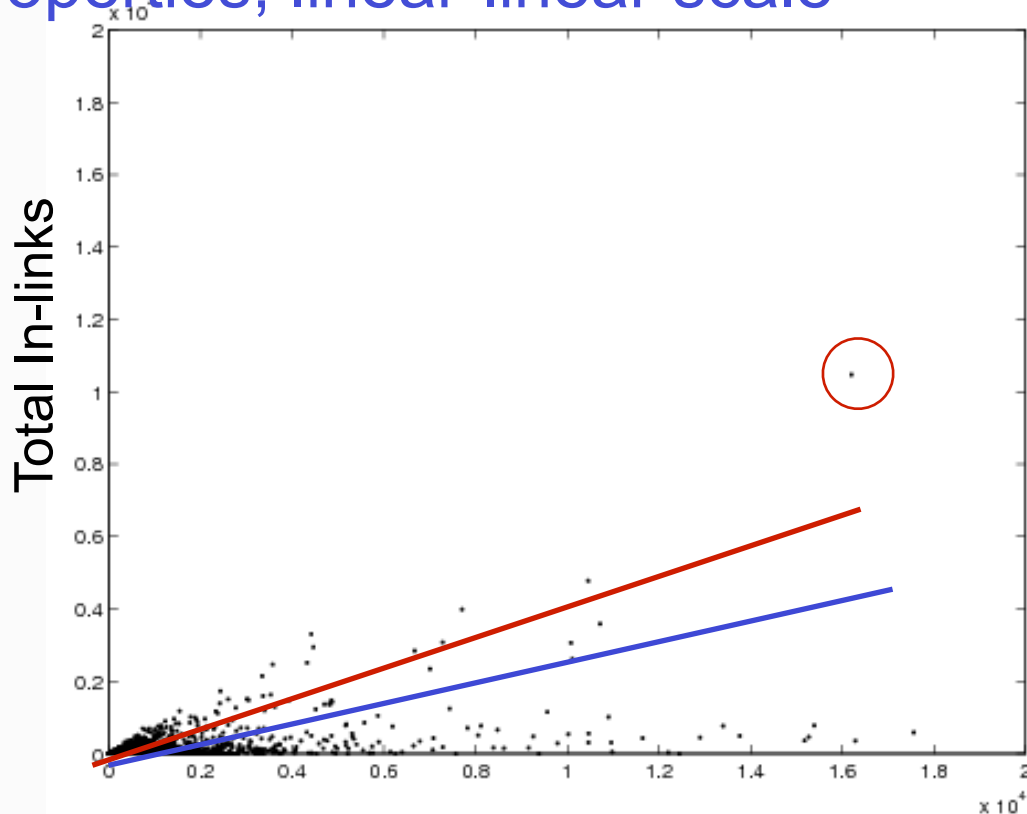
Try to fit a line...

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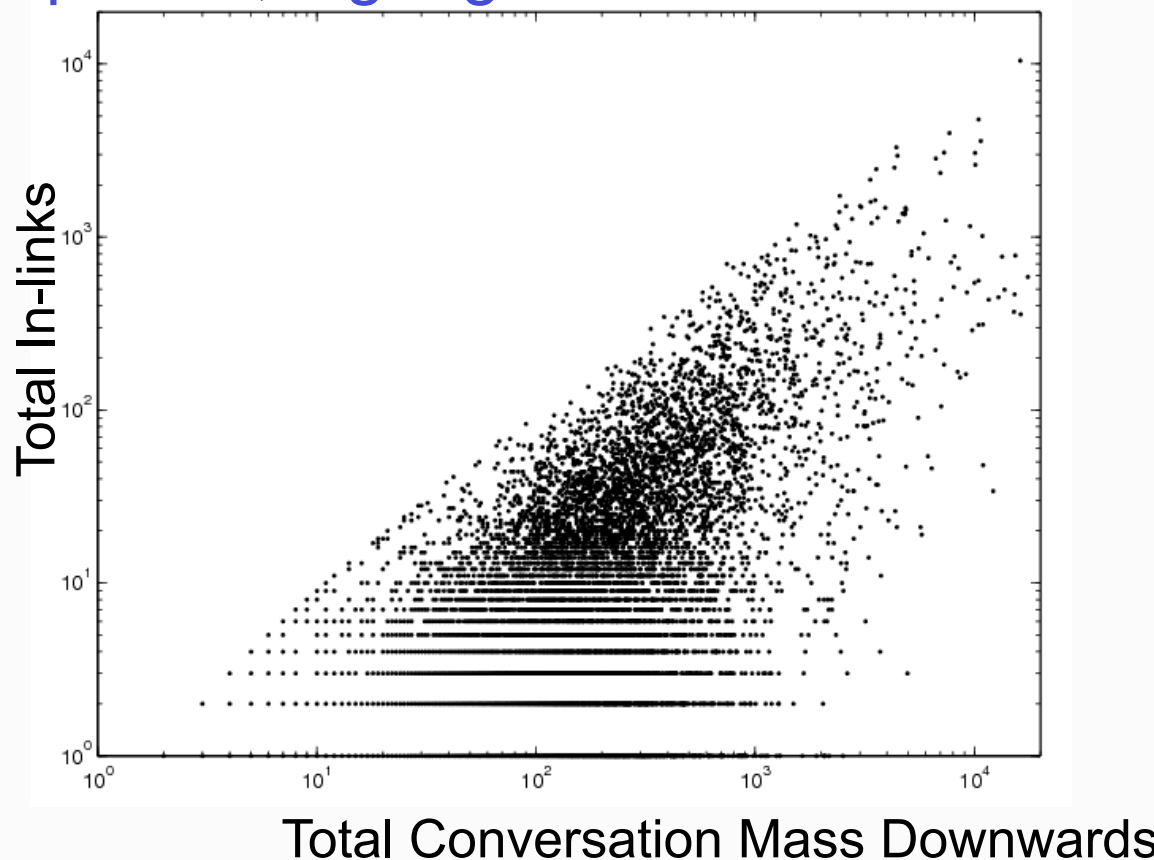
Try to fit a line...

Outliers dramatically affect fit.

Preliminaries: Regularizing data

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- Therefore, we propose to take $\log(\text{count}+1)$.

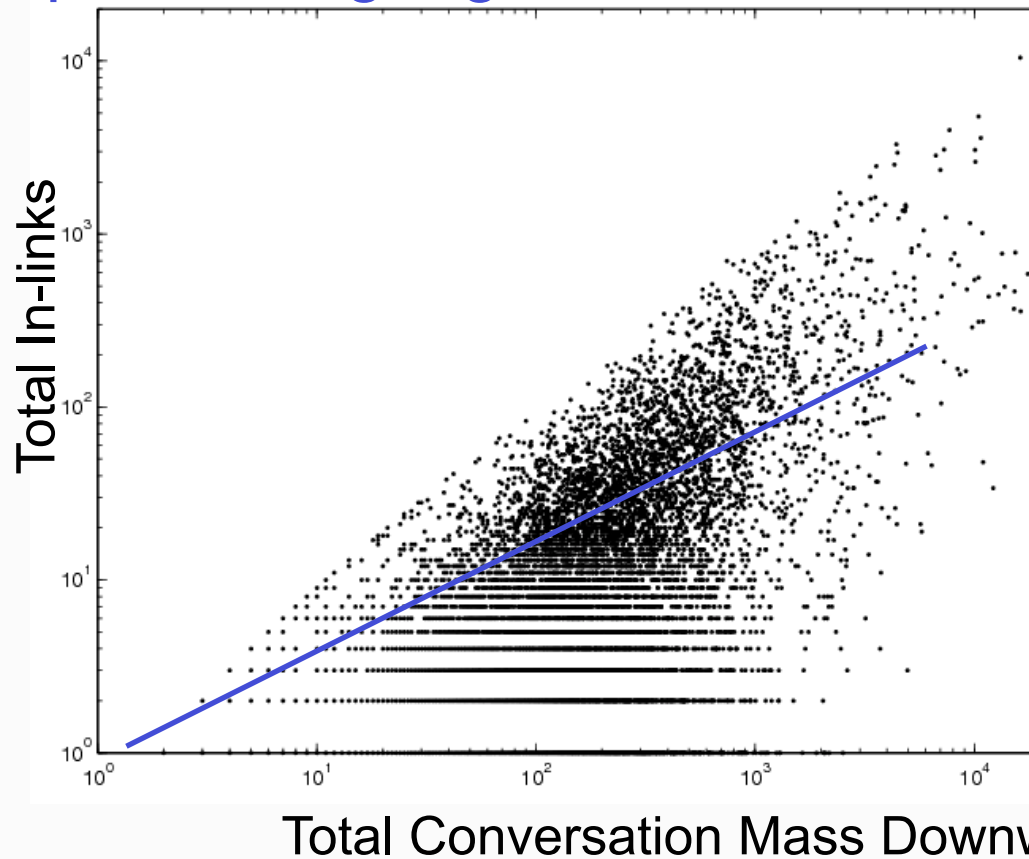
Blog properties, log-log scale



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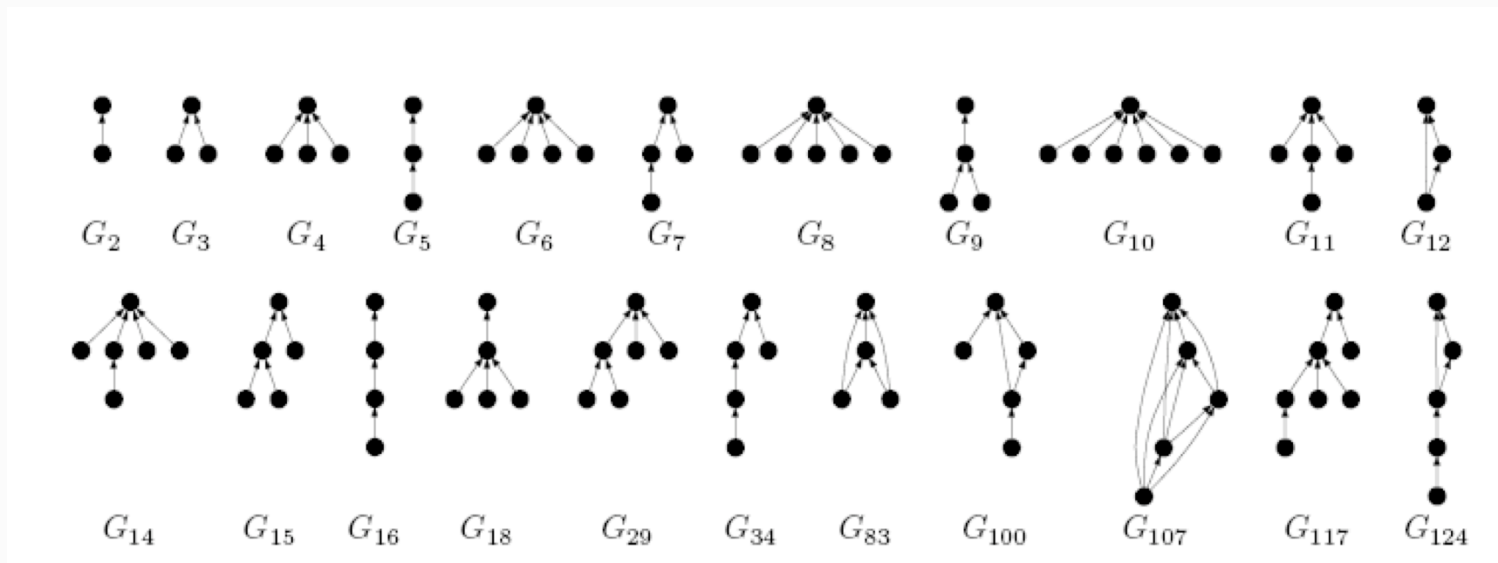
Blog properties, log-log scale



Outliers' effects are minimized.

- *Suppose we want to cluster blogs based on content. What features do we use per blog?*

- *Suppose we want to cluster blogs based on content. What features do we use per blog?*
- Try cascade shapes.



CascadeType

- Perform PCA on sparse matrix.
- Use $\log(\text{count}+1)$
- Project onto 2 PC...

~9,000 cascade types

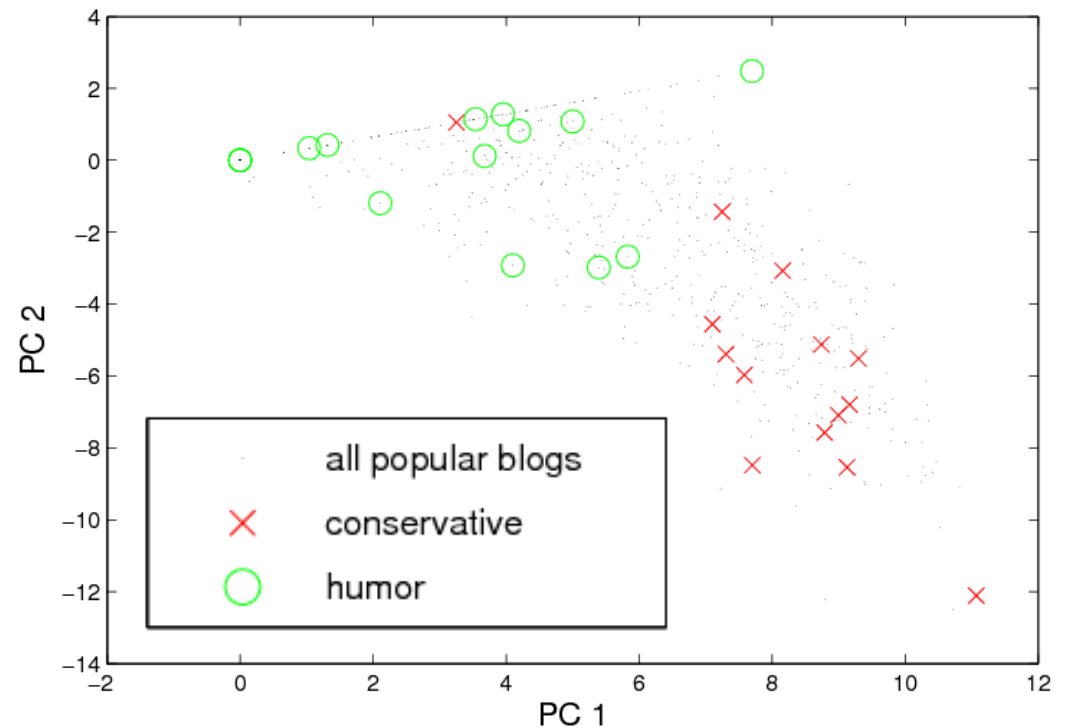


~44,000 blogs

<i>slashdot</i>	4.6	2.1	.09			
<i>boingboing</i>	3.2	1.1		3.4	.07	
...	4.2					
...	5.1					
...	2.1		1.1			
...	.67			.07		
...	.01					

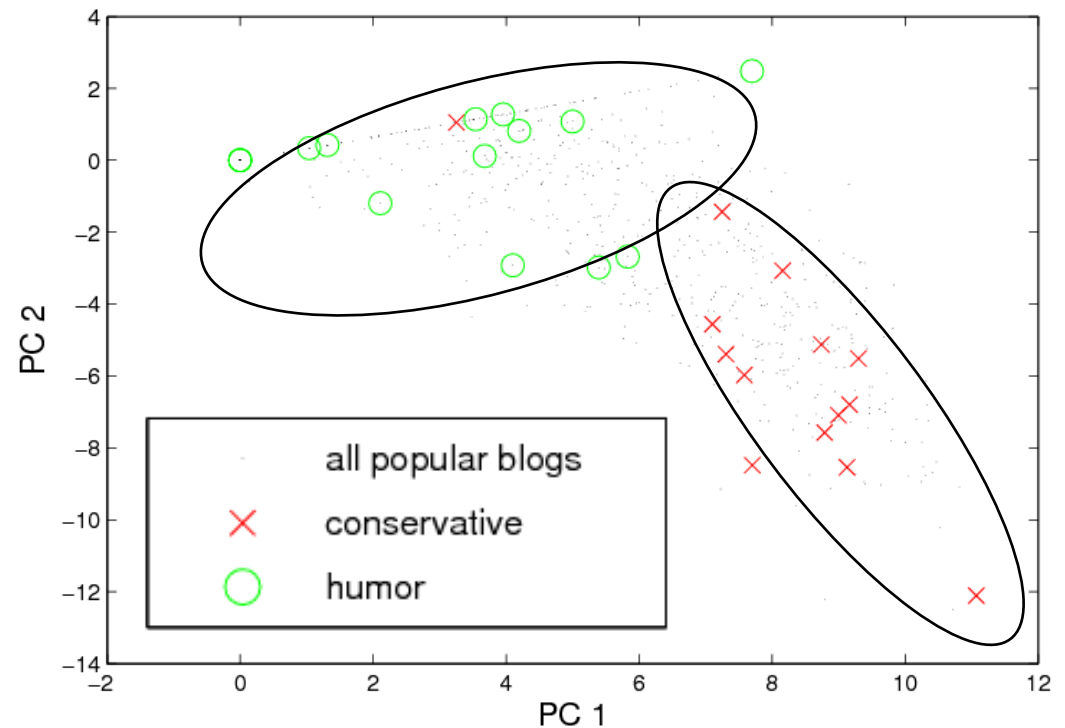
CascadeType: Results

- Observation: Content of blogs and cascade behavior often related.
- Distinct clusters for “conservative” and “humorous” blogs (hand-labeling).



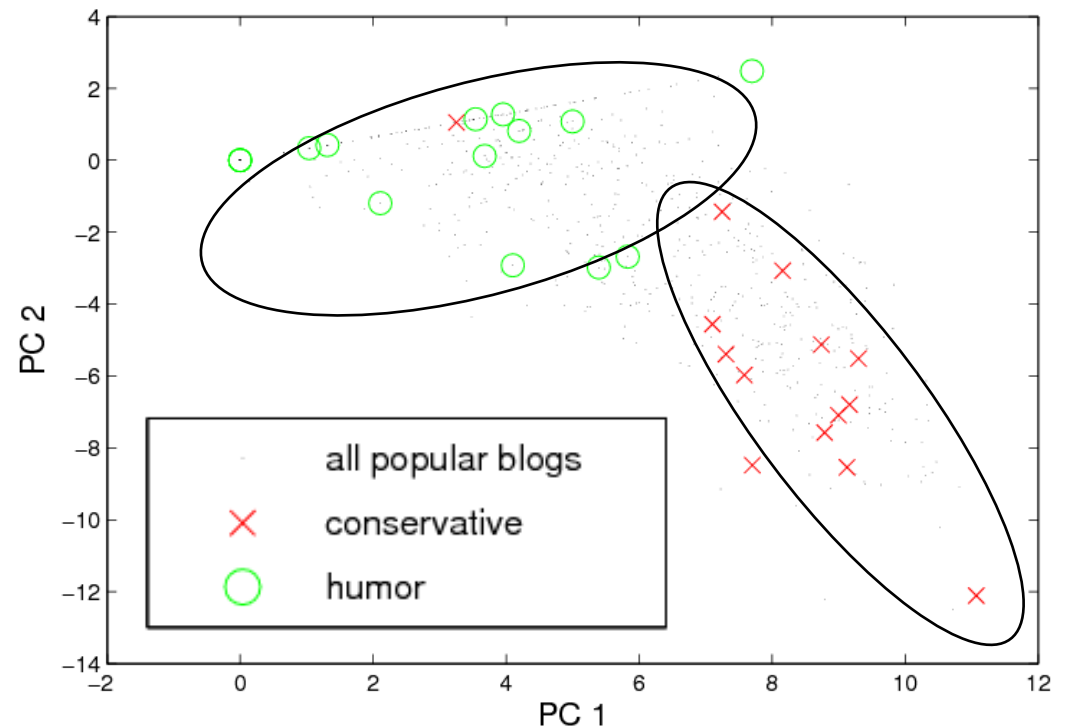
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- Suppose we want to cluster blog posts. What features do we use?
- Try **post features**. (number in-links, conversation mass, depth...)

PostFeatures

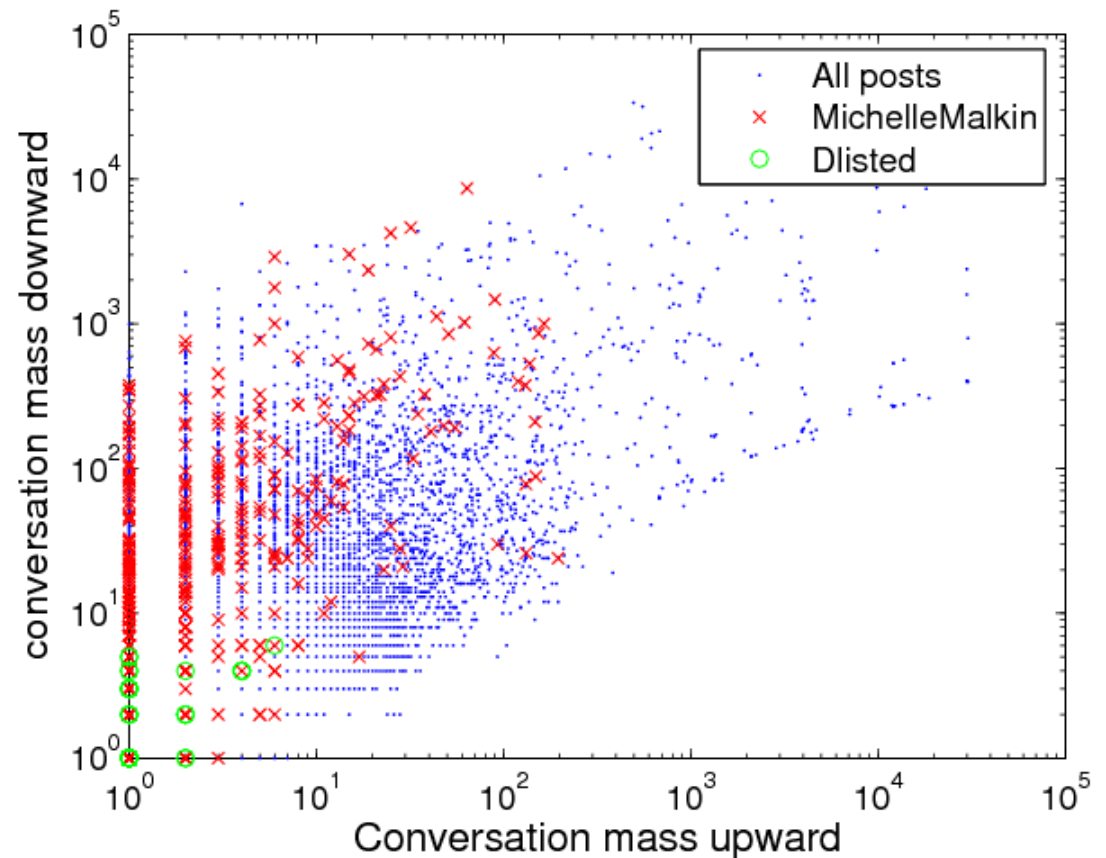
~2,400,000 posts

	# in-links	#out-links	CM up	CM down	depth up	depth down
<i>slashdot-p001</i>	4.5					
<i>slashdot-p002</i>	.3	2.2				
...	.2	4.5				
...	1.2	2.4				
<i>boingboing-p001</i>	4.2	6.2				
<i>boingboing-p002</i>	.6	1.1				
...	.1	.6				

Run
PCA...

PostFeatures: Results

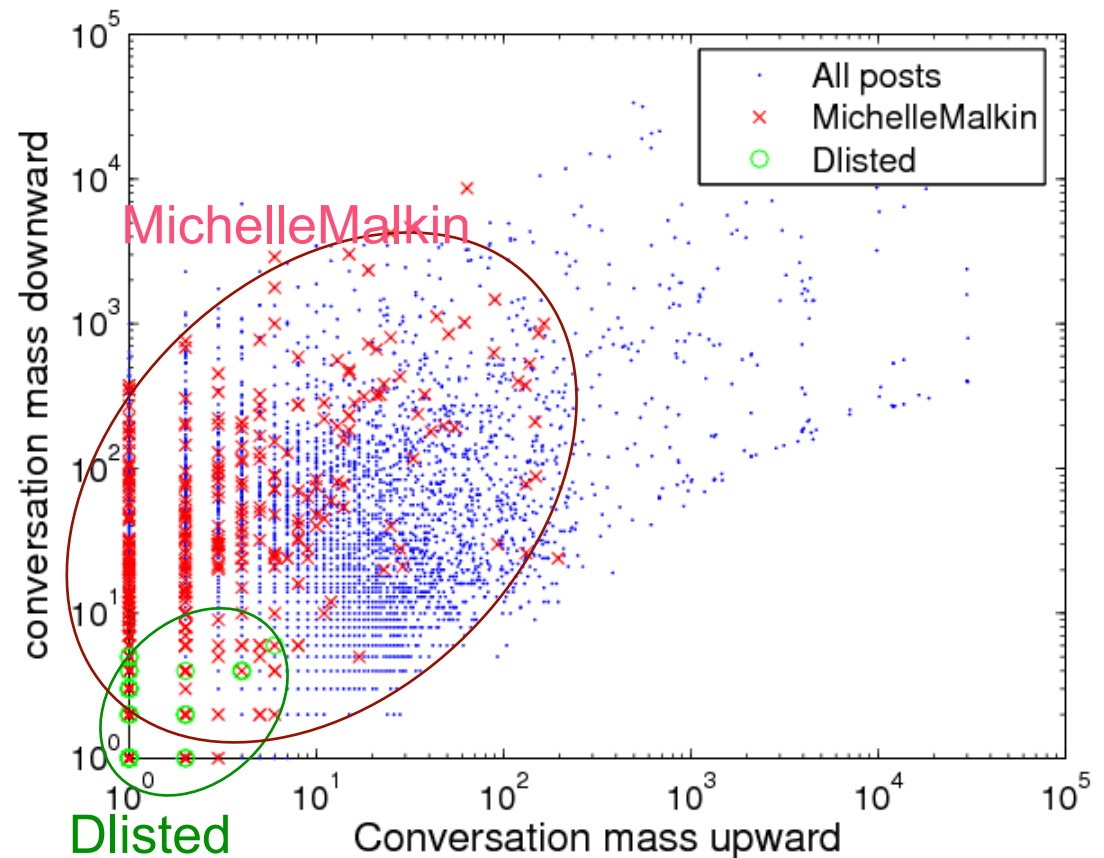
- Observation: Posts within a blog tend to retain similar network characteristics.



PostFeatures: Results

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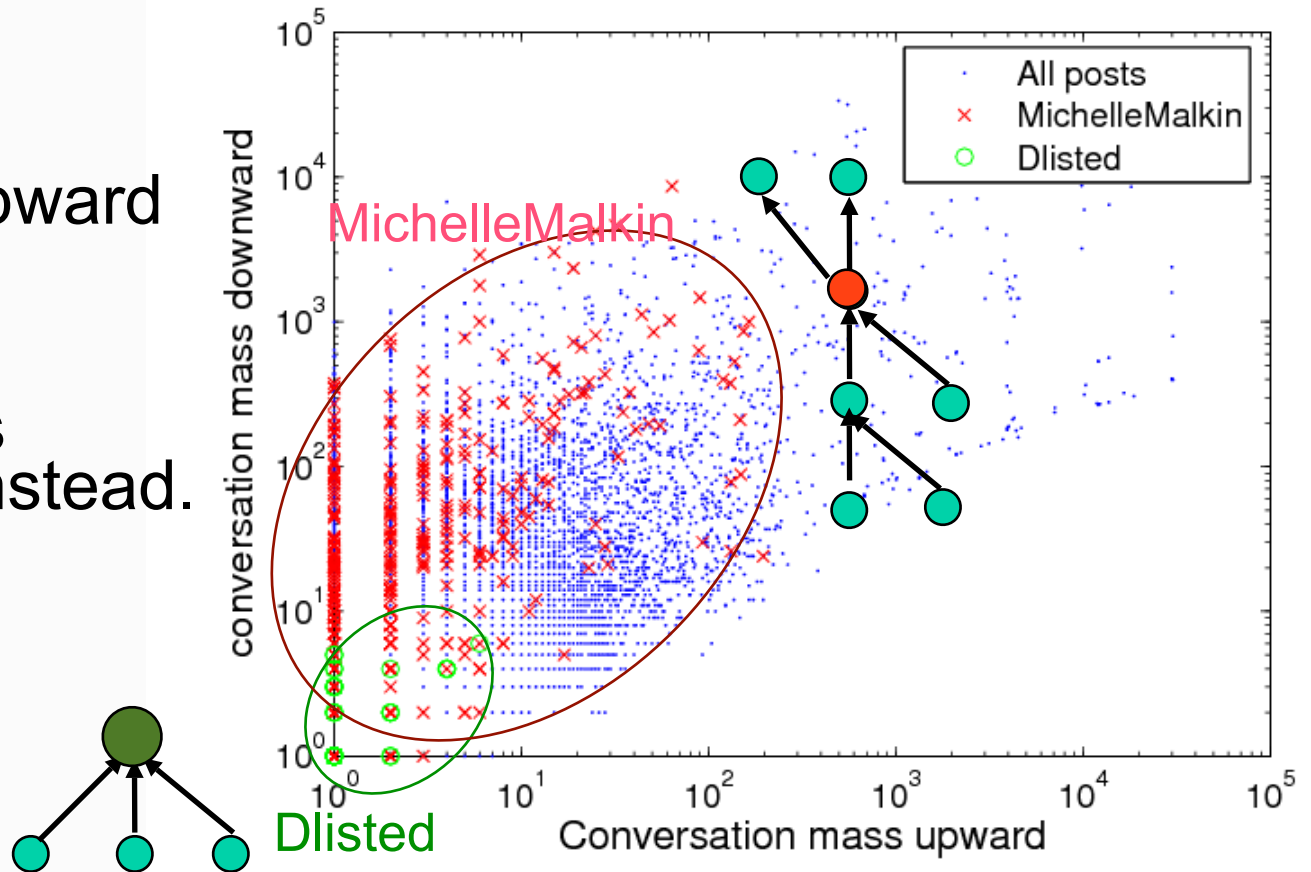
- PC1 ~ CM upward
- PC2 ~ CM downward
- We show this scatter plot instead.



PostFeatures: Results

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- PC1 ~ CM upward
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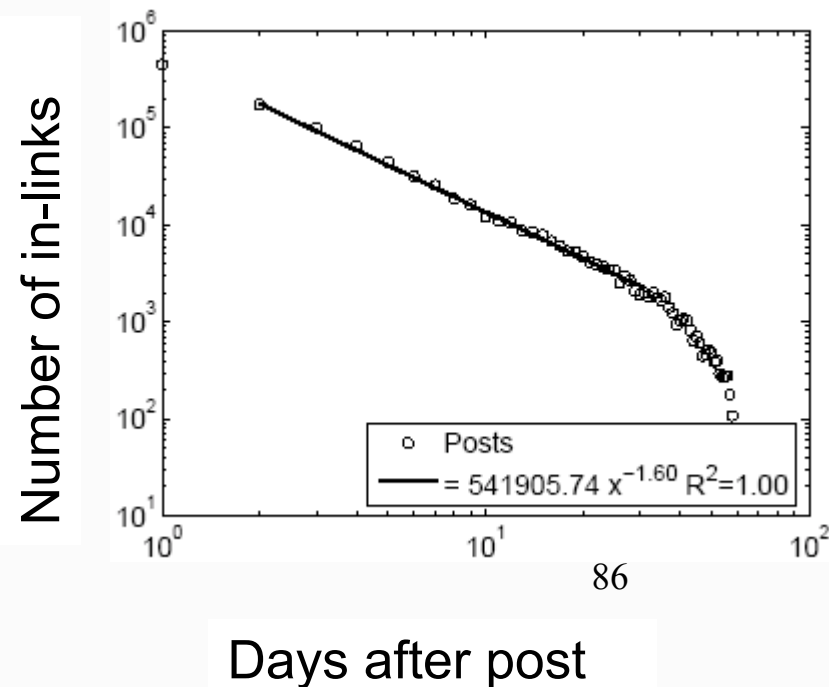
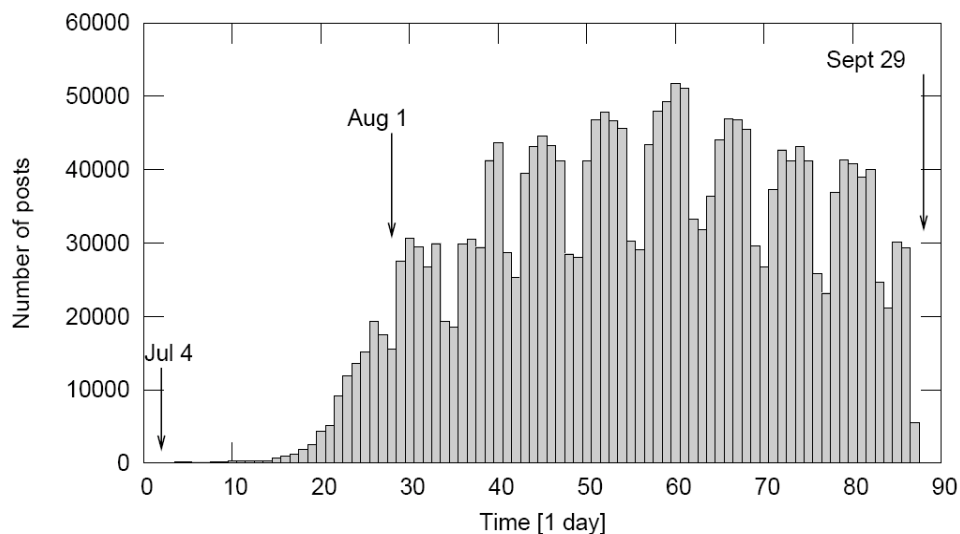


Results in brief

- Analyzed one of largest available collections of blog information. (10GB)
- Two networks: “Post network” and “blog network”.
- Discovered several properties of the networks.
- Also analyzed properties of “cascades”.
- Presented generative model for cascades.
- Using cascades and post features, were able to successfully cluster blogs by type.

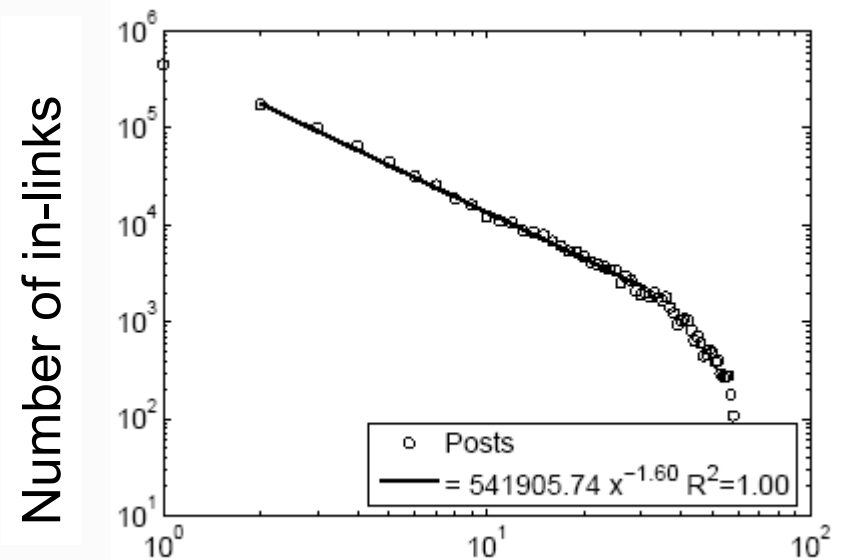
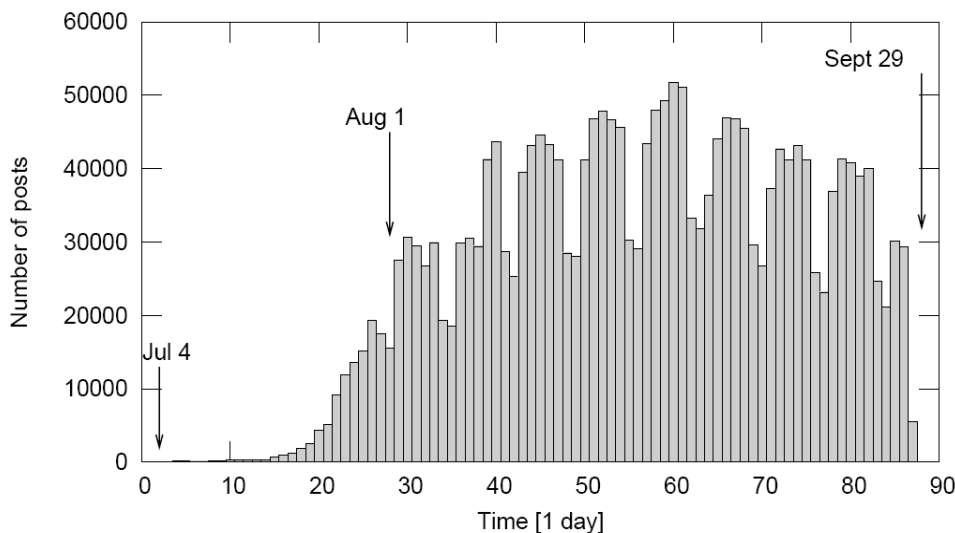
Immediate questions: answered

- *Q1, Temporal questions: Does popularity have half-life? Is there periodicity?*



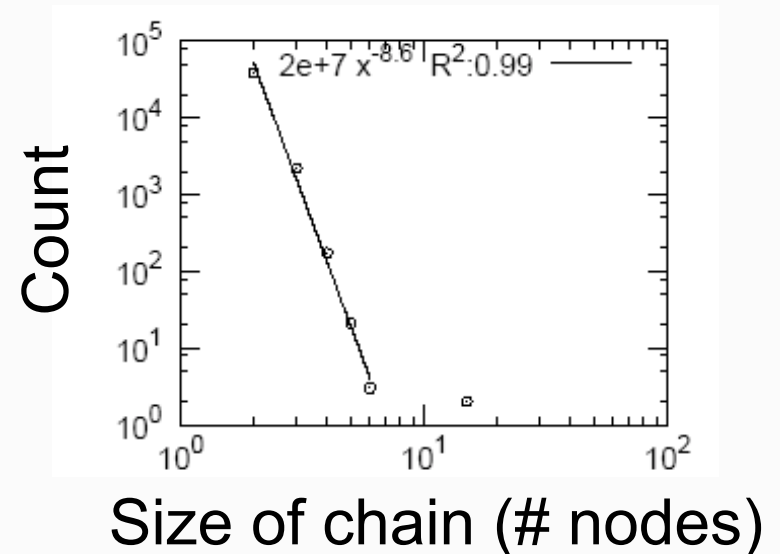
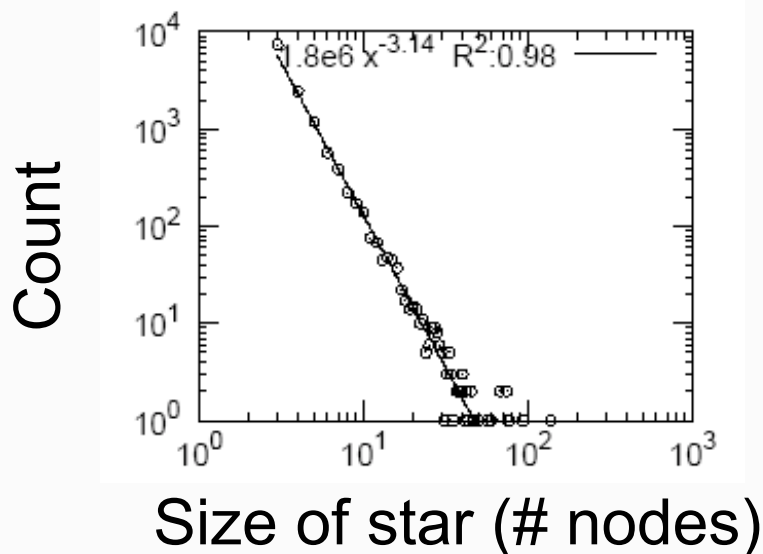
Immediate questions: answered

- *Q1, Temporal questions: Does popularity have half-life? Is there periodicity?*
 - Popularity drops off with power law.
 - Weekly periodicity (“weekend effect”).



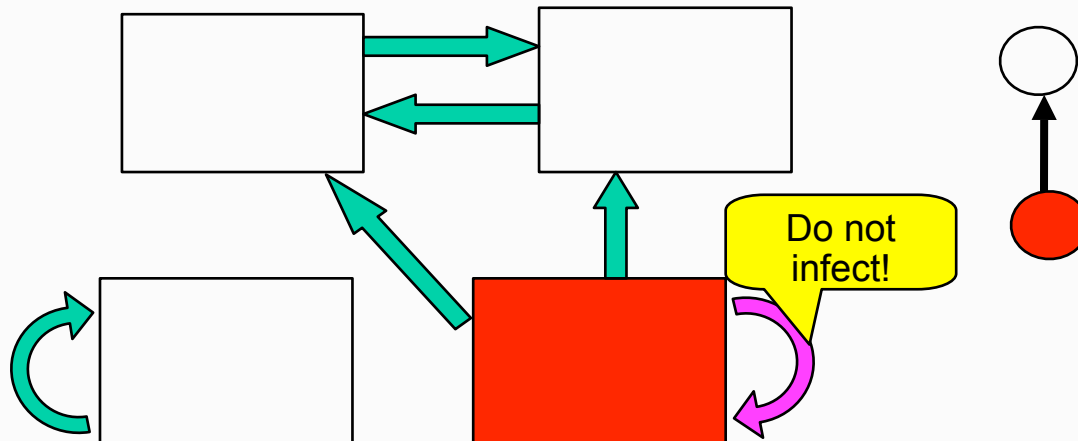
Immediate questions: answered

- Q2, Topology: What topological patterns do posts and blogs follow?
- What shapes to cascades take on? Stars? Chains? Something else?
 - Degree distribution, cascade size are power laws.
 - Stars are more common than chains.



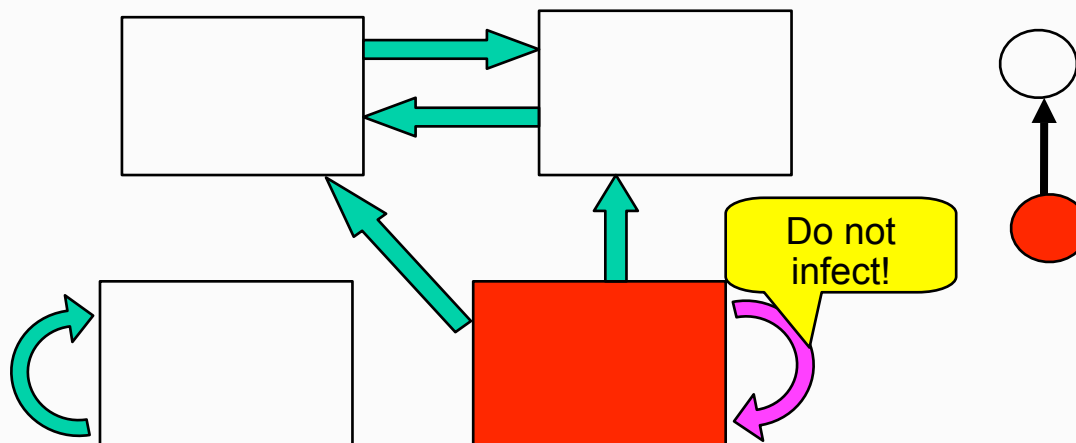
Immediate questions: answered

- Q3, *Can a simple model replicate this behavior?*



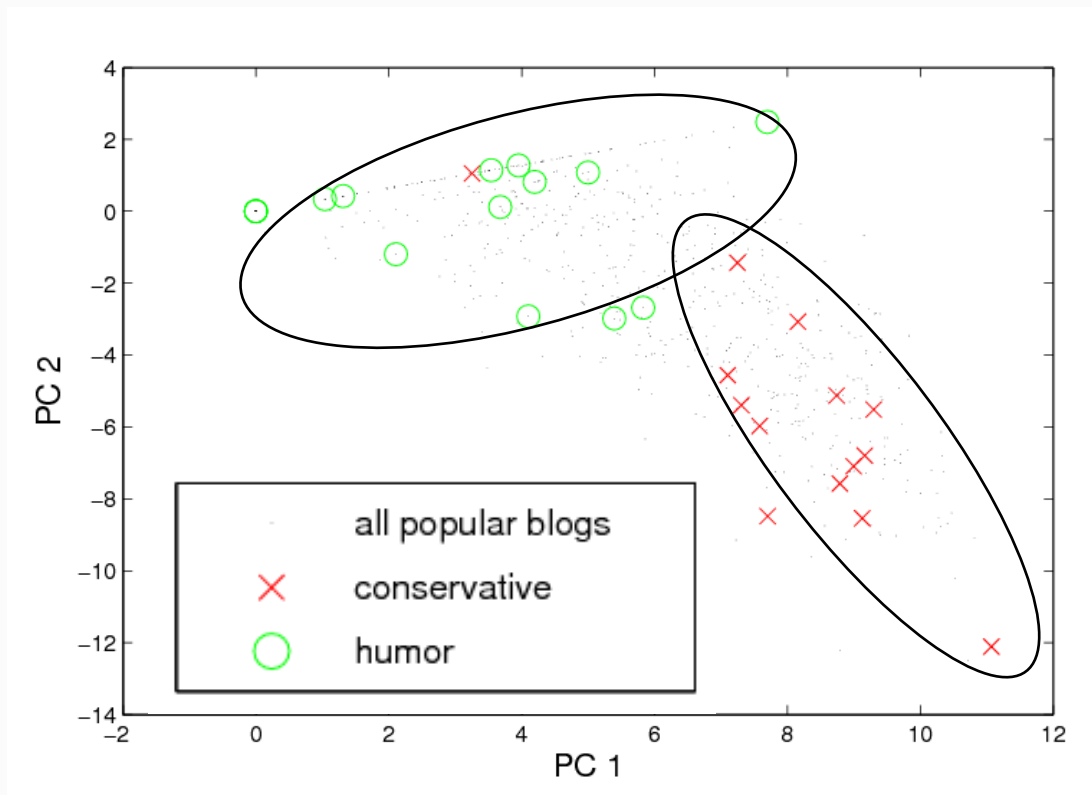
Immediate questions: answered

- Q3, *Can a simple model replicate this behavior?*
 - *Yes. Epidemiological (flu-like) model.*
 - *Single parameter.*
 - *Fits data surprisingly well.*



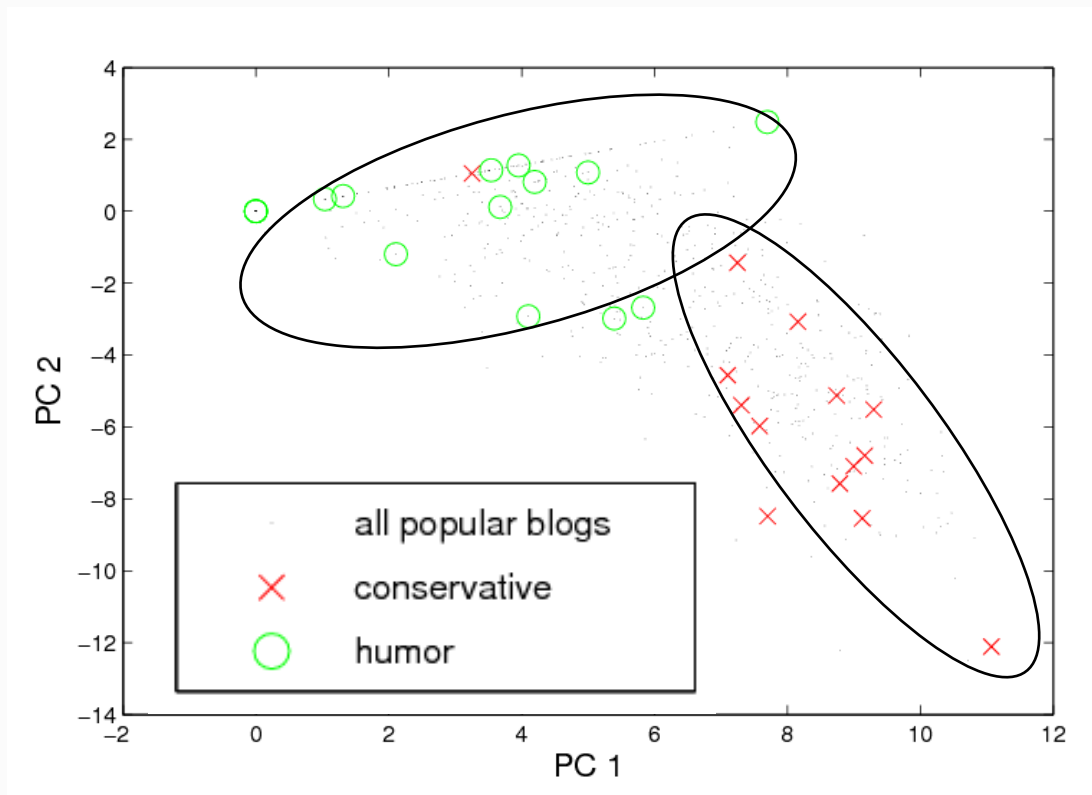
Immediate questions: answered

- Q4, *Can we characterize blogs and posts?*



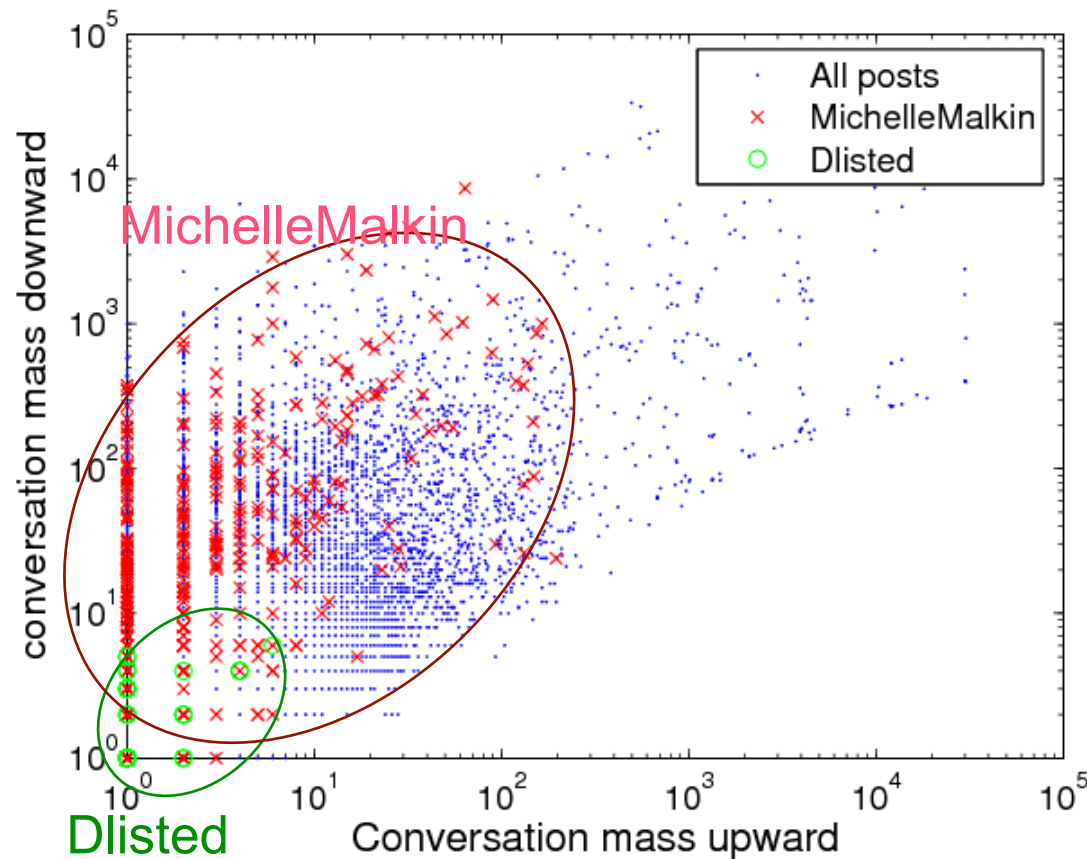
Immediate questions: answered

- Q4, *Can we characterize blogs and posts?*
 - *Yes. We used PCA based on cascade types to successfully cluster blogs by genre.*



Immediate questions: answered

- Q4, *Can we characterize blogs and posts?*
 - *We also used post features (conversation mass) to cluster individual posts into the blogs they belong.*



Future work and applications

- Blogs are just part of the picture.
 - Q: What is a more immediate snapshot of what is on Internet users' minds?

Future work and applications

- Blogs are just part of the picture.
 - Q: What is a more immediate snapshot of what is on Internet users' minds? (besides Twitter)



Future work and applications

- Blogs are just part of the picture.
 - Q: What is a more immediate snapshot of what is on Internet users' minds?
 - A: **Search**.
 - This raises more questions:
 - Do major blog posts influence search (particularly for products) and ad click-through?
 - Can we use trends in blogs and search to forecast product popularity?
 - Can we adapt to trends to match users with ads which would most interest them?

Related work

- For explanation of SIS model:
 - [Hethcote2000] H.W. Hethcote. The mathematics of infectious diseases. *SIAM Rev.*, 42(4):599–653, 2000.
- For algorithms for extracting cascade shapes:
 - [Leskovec+2006] J. Leskovec, A. Singh, and J. Kleinberg. Patterns of influence in a recommendation network. PAKDD 2006.
- For some modeling of power laws:
 - [Vazquez+2006] A. Vazquez, J. G. Oliveira, Z. Dezso, K. I. Goh, I. Kondor, and A. L. Barabasi. Modeling bursts and heavy tails in human dynamics. *Physical Review E*, 73:036127, 2006.

Questions?

Ranking blogs by PostFeatures

- Conversation mass up/down gives a better understanding of the blog posts than in-links and out-links.
- Therefore, we may choose to rank blogs based on these attributes.

Blogs ranked by CM vs in-links

Top blogs by conversation mass

- 1 michellemalkin.com
- 2 boingboing.net
- 3 imao.us (75)
- 4 captainsquartersblog.com/mt
- 5 instapundit.com
- 6 radioequalizer.blogspot.com (53)
- 7 powerlineblog.com
- 8 waxy.org/links
- 9 washingtonmonthly.com
- 10 kottke.org/reminder

Top blogs by in-links

- 1 boingboing.net
- 2 michellemalkin.com
- 3 instapundit.com
- 4 waxy.org/links
- 5 kottke.com/reminder
- 6 patriotdaily.com (11)
- 7 captainsquartersblog.com/mt
- 8 powerlineblog.com
- 9 washingtonmonthly.com
- 10 petashon.com (30)

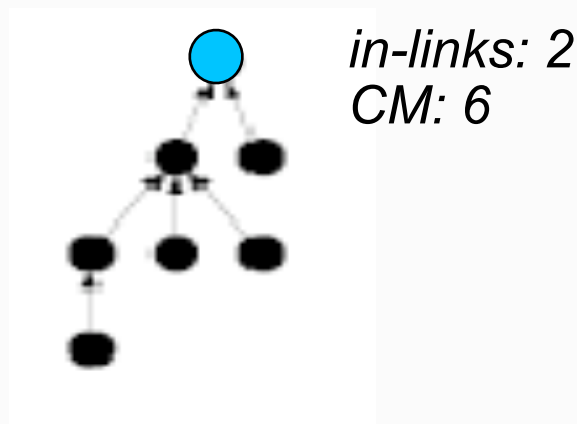
Blogs ranked by CM vs in-links

Top blogs by conversation mass

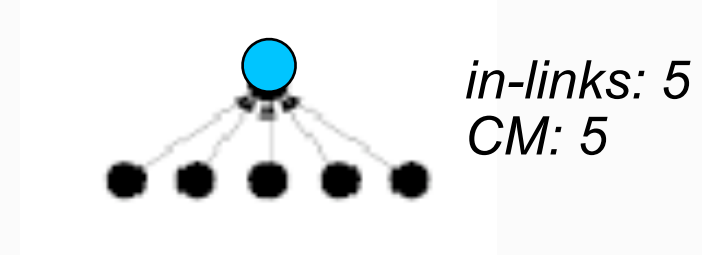
- 1 michellemalkin.com
- 2 boingboing.net
- 3 [imao.us \(75\)](http://imao.us)
- 4 captainsquartersblog.com/mt

Top blogs by in-links

- 1 boingboing.net
- 2 michellemalkin.com
- 3 instapundit.com
- 4 waxy.org/links



.....
[10 petashon.com \(30\)](http://petashon.com)



- Perhaps IMAO has longer cascades, just fewer inlinks.
- While petashun has “stars”.