Part 3: Case Studies
Outline

- **Part 1:** How do networks form, evolve, collapse?
- **Part 2:** What tools can we use to study networks?
- **Part 3:** Case studies
  - How do ideas diffuse through a network?
  - How to detect communities?
  - How do we detect anomalies in networks?
Part 3: Case Studies

● Q4: How do ideas diffuse through a network?
  – Cascades
  – Epidemiological modeling of cascades
  – Outbreak detection

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● Q6: What sort of anomaly detection can we perform?
  – Fraud detection on E-bay
  – Spam detection
Cascading Behavior in Large Blog Graphs

How does information propagate over the blogosphere?

J. Leskovec, M. McGlohon, C. Faloutsos, N. Glance, M. Hurst. Cascading Behavior in Large Blog Graphs. SDM 2007.
Immediate Goals

- **Temporal questions:** Does popularity have half-life?
- **Topological questions:** What topological patterns do posts and blogs follow? What shapes do cascades take on? Stars? Chains? Something else?
- **Models:** Can we build a generative model that mimics properties of cascades?
Cascades on the Blogosphere

Blogosphere
blogs + posts

Blog network
links among blogs

Post network
links among posts

Cascade is graph induced by a
time ordered propagation of
information (edges)
Blog data

- 45,000 blogs participating in cascades
- All their posts for 3 months (Aug-Sept ‘05)
- 2.4 million posts
- ~5 million links (245,404 inside the dataset)
Temporal Observations

*How does post popularity change over time?*

- Does popularity decay at a constant rate?

- With an exponential ("half life")?
Temporal Observations

How does post popularity change over time?

Post popularity dropoff follows a power law...

\[ \log(\text{# in-links}) = a \log(\text{days after post}) \]
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:

$p(t_p + \Delta) \propto \Delta^{-1.5}$
What is topology of blogs?

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

In- and out-degree follow power law distribution. In-degree exponent -1.7, out-degree exponent -3.

Strong rich-get-richer phenomena.
Post Network

2.4M nodes, 250K edges

Both in- and out-degree follow power laws. In-degree exponent -2.1, out-degree exponent -3.
Topological patterns: Cascades

- Procedure for gathering cascades:
  - Find all initiators (nodes with out-degree 0)
  - Follow in-links
  - Produces directed acyclic graph
  - Count cascade shapes (use our multi-level graph isomorphism testing algorithm)
Topological Observations

How do we measure how information flows through the network?

Common cascade shapes extracted using algorithms in [Leskovec, Singh, Kleinberg; PAKDD 2006].
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:

$$p(n) \propto n^{-2}$$
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).
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 $\beta$ determines how easily spreading conversations are.
  - [Hethcote2000]
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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.
1. Randomly pick a blog to infect, add node to cascade
Cascade Generation Model

2. Infect each in-linked neighbor with probability $\beta$. 

$B_1 \rightarrow B_2 \rightarrow B_3 \rightarrow B_4$
Cascade Generation Model

2. Infect each in-linked neighbor with probability $\beta$. 

\[ B_1 \xrightarrow{\text{INFECT}} B_2 \xrightarrow{\text{DO NOT INFECT}} B_3 \xrightarrow{\text{INFECT}} B_4 \]
3. Add infected neighbors to cascade.
Cascade Generation Model

4. Set “old” infected nodes to uninfected.
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Experimental Results

Generative model produces realistic cascades

$\beta=0.025$

Most frequent cascades
Conclusions

● Temporal observations
  – Post popularity-dropoff follows power law (exponent= -1.5)

● Topological observations
  – Power-laws in degree distribution, cascade sizes
  – “Stars” are more common than “chains”

● Cascade generating model
  – Based on epidemiology
  – Matches frequent cascades, size power laws
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Outbreak detection

- Problems of finding sources of contamination in water networks and finding “hot” stories on blogs are isomorphic.
  - Minimize time to detection, population affected
  - Maximize probability of detection.
  - Minimize sensor placement cost.

McGlohon, Faloutsos ICWSM 2008
CELF: Main idea

- Given a graph $G(V,E)$
- and a budget of $B$ sensors
- and data on how contaminations spread over the network:
  - for each contamination $i$ we know the time $T(i, u)$ when it contaminated node $u$
- Minimize time to detect outbreak
- **CELF** algorithm uses submodularity and lazy evaluation

J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, J. VanBriesen, N. Glance. "Cost-effective Outbreak Detection in Networks" KDD 2007
Blogs: Comparison to heuristics

Benefit (higher=better)
“Best 10 blogs to read”

http://www.cs.cmu.edu/~jure/blogs/blogs-uc-pa.html

NP - number of posts, IL- in-links, OLO- blog out links, OLA- all out links

| k | PA score | Blog                     | NP  | IL   | OLO  | OLA  |
|---|----------|--------------------------|-----|------|------|------|
| 1 | 0.1283   | http://instapundit.com   | 4593| 4636 | 1890 | 5255 |
| 2 | 0.1822   | http://donsurber.blogspot.com | 1534| 1206 | 679  | 3495 |
| 3 | 0.2224   | http://sciencepolitics.blogspot.com | 924 | 576  | 888  | 2701 |
| 4 | 0.2592   | http://www.watcherofweasels.com | 261 | 941  | 1733 | 3630 |
| 5 | 0.2923   | http://michellemalkin.com | 1839| 12642| 1179 | 6323 |
| 6 | 0.3152   | http://blogometer.nationaljournal.com | 189 | 2313 | 3669 | 9272 |
| 7 | 0.3353   | http://themodulator.org   | 475 | 717  | 1844 | 4944 |
| 8 | 0.3508   | http://www.bloggersblog.com | 895 | 247  | 1244 | 10201|
| 9 | 0.3654   | http://www.boingboing.net | 5776| 6337 | 1024 | 6183 |
| 10| 0.3778   | http://atrios.blogspot.com | 4682| 3205 | 795  | 3102 |
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• Cascades take on different shapes (sorted by frequency):

How can we use cascades to identify communities?
PCA on cascade types

- Perform PCA on sparse matrix.
- Use log(count+1)
- Project onto 2 PC...

~9,000 cascade types

|       | slashdot | boingboing |
|-------|----------|------------|
| ...   | 4.6      | 2.1        | .09       |
| ...   | 3.2      | 1.1        | 3.4       | .07       |
| ...   | 4.2      | ...        |
| ...   | 5.1      | ...        |
| ...   | 2.1      | 1.1        |
| ...   | .67      | ...        |
| ...   | .01      | ...        |
PCA on cascade types

- Observation: Content of blogs and cascade behavior are often related.

- Distinct clusters for “conservative” and “humorous” blogs (hand-labeling).

M. McGlohon, J. Leskovec, C. Faloutsos, M. Hurst, N. Glance. Finding Patterns in Blog Shapes and Blog Evolution. ICWSM 2007.
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Community Factorization

- Yun Chi, Shenghuo Zhu, Xiaodan Song, Junichi Tatemura, Belle L. Tseng. Structural and temporal analysis of the blogosphere through community factorization. KDD 07

- Main idea: Use tensor factorization to identify subgraphs over time.
Community Factorization Results

- Hurricane Katrina community
- Blog info community
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E-bay Fraud detection

Dectects ‘non-delivery’ fraud: seller takes $$ and disappears

Shashank Pandit, Duen Horng Chau, Samuel Wang, and Christos Faloutsos. NetProbe: A Fast and Scalable System for Fraud Detection in Online Auction Networks WWW 07.
E-bay Fraud detection - NetProbe

Suspected fraudster — this user has been behaving much like the other suspects by trading with the similar sets of possible accomplices.
Idea: ‘Accomplices’, and Belief Propagation

- 3 types of nodes: honest, fraud, accomplices
- ‘Accomplices’ never do fraud
  - give high ratings to fraudsters-to-be

Belief propagation intuition:

- If I am honest, my neighbors are either honest or ‘accomplices’
- If I’m an accomplice, my neighbors are either honest or fraud
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Spam detection

- Kolari, Java, Finin, 2006:
- Studying link structure can help detect spam in blogs.
- Splogs may deviate from power law degree distribution found in authentic blogs.
Conclusion

- Presented patterns found in real graphs (power-law degrees, giant connected component, densification, shrinking diameter)
- Demonstrated tools to solve problems (matrix tools, tensors, self-similarity)
- Showed some examples of using these tools for applications to social media (viral marketing, community detection, anomaly detection).
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● Epidemiology and viral marketing

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