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How to detect epidemics and influential blogs?

Currently: Carnegie Mellon

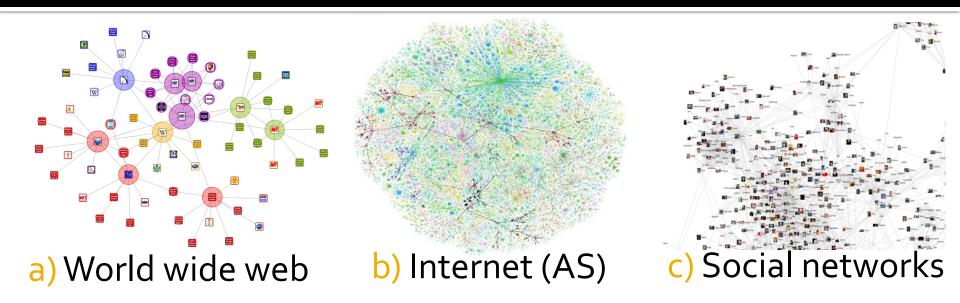


Networks: Rich data

- Today: Large on-line systems have detailed records of human activity
 - On-line communities:
 - Facebook (64 million users, billion dollar business)
 - MySpace (300 million users)
 - Communication:
 - Instant Messenger (~1 billion users)
 - News and Social media:
 - Blogging (250 million blogs world-wide, presidential candidates run blogs)
 - On-line worlds:
 - World of Warcraft (internal economy 1 billion USD)
 - Second Life (GDP of 700 million USD in '07)

Opportunities for **impact** in **science** and **industry**

Networks: Rich and massive data

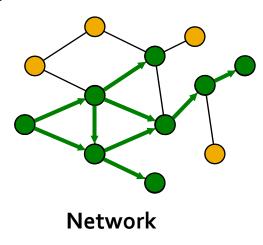


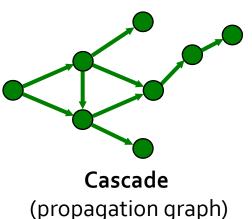
We need massive network data for the patterns to emerge:

- MSN Messenger network [WWW '08]
 - 240M people, 255B messages, 4.5 TB data
- Blogosphere
 - 60M posts, 120M links

Diffusion and Cascades

- Behavior that cascades from node to node like an epidemic
 - News, opinions, rumors
 - Word-of-mouth in marketing
 - Infectious diseases
- As activations spread through the network they leave a trace - a cascade



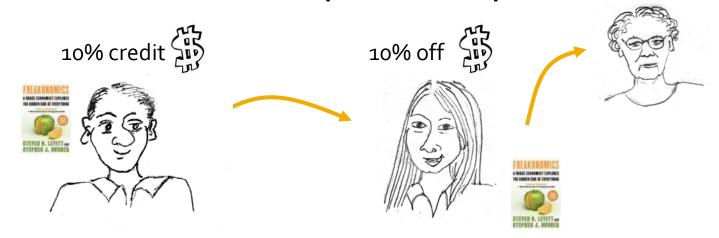


Talk outline

- Where do cascades occur?
 - On the Web we can actually observe and measure a number of cascades
- What do cascades look like?
 - How do information and influence spread?
- How to detect who is influential?
 - Effective and efficient algorithms
 - Saving lives

Setting 1: Viral marketing

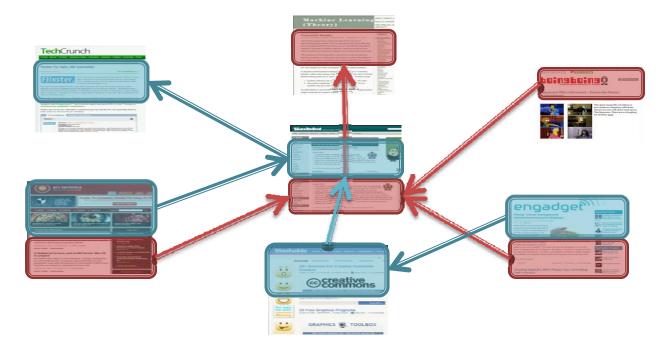
 People send and receive product recommendations, purchase products



<u>Data:</u> Large online retailer: 4 million people,
 16 million recommendations, 500k products

Setting 2: Blogosphere

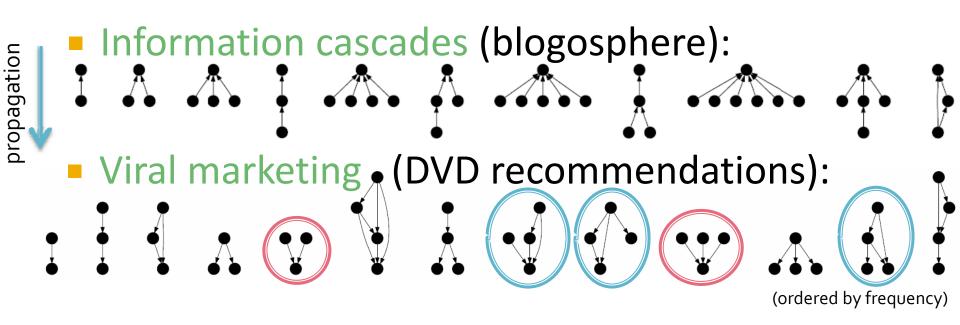
 Bloggers write posts and refer (link) to other posts and the information propagates



Data: 10.5 million posts, 16 million links

What do cascades look like?

Are they stars? Chains? Trees?

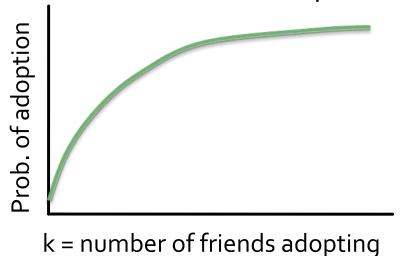


- Viral marketing cascades are more social:
 - Collisions (no summarizers)
 - Richer non-tree structures

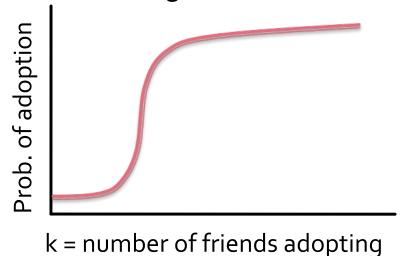
Human adoption curves

- Prob. of adoption depends on the number of friends who have adopted [Bass '69, Granovetter '78]
- What is the shape?

Distinction has consequences for models and algorithms



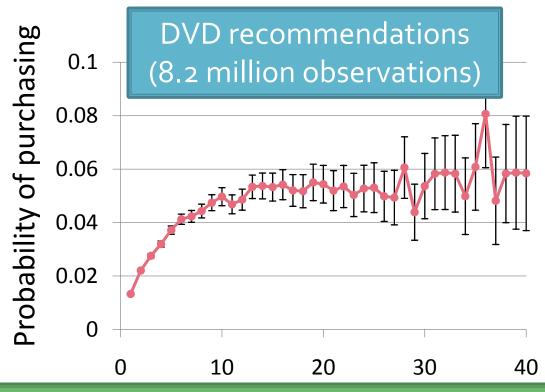
Diminishing returns?



Critical mass?

To find the answer we need lots of data

Adoption curve: Validation

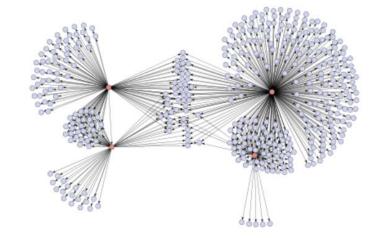


Adoption curve follows the **diminishing returns**. Can we exploit this?

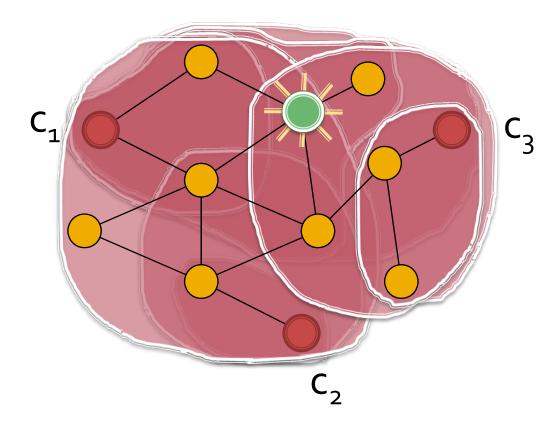
Later similar findings were made for group membership [Backstrom-Huttenlocher-Kleinberg 'o6], and probability of communication [Kossinets-Watts 'o6]

Cascade & outbreak detection

- Blogs information epidemics
 - Which are the influential/infectious blogs?
- Viral marketing
 - Who are the trendsetters?
 - Influential people?
- Disease spreading
 - Where to place monitoring stations to detect epidemics?



The problem: Detecting cascades



How to quickly detect cascades as they spread?

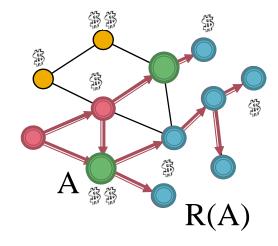
Two parts to the problem

Cost:

 Cost of monitoring is blog dependent (big blogs cost more time to read)

Reward:

 Minimize the number of people that that know the story before we do



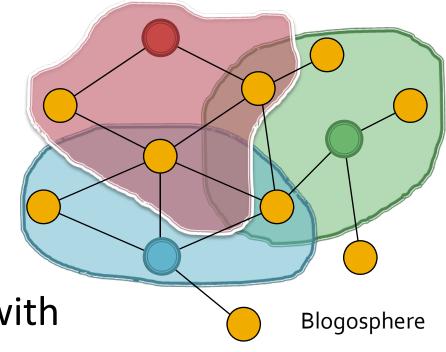
The solution: Covering blogs

= Given a budget (e.g., of 3 blogs)

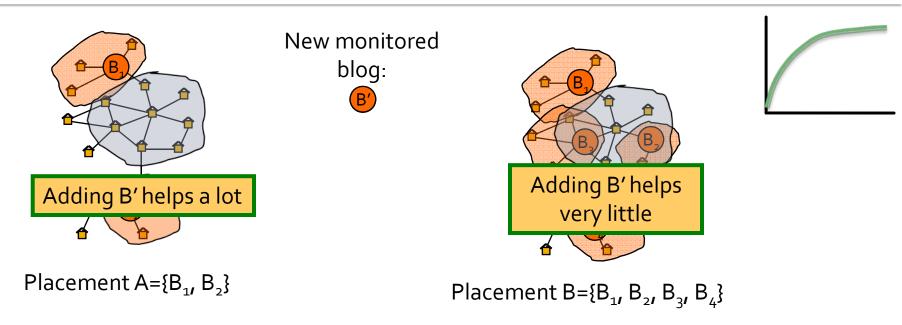
Select blogs to cover the most of the blogosphere?

= Bad news: Solving this exactly is NP-hard

Good news: <u>Theorem</u>:
 Our algorithm CELF can
 do it in linear time and with
 factor 3 approximation



Problem structure: Submodularity



- Gain of adding a node to small set is larger than gain of adding a node to large set
- Submodularity: diminishing returns, think of it as "concavity")

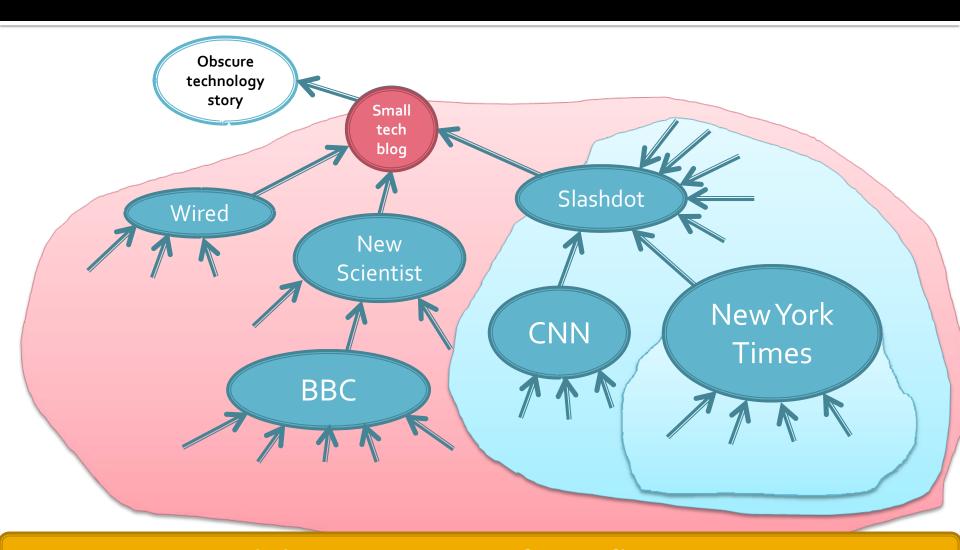
Back to the Question...

= I have 10 minutes. Which blogs should I read to be most up to date?

= Who are the most influential bloggers?



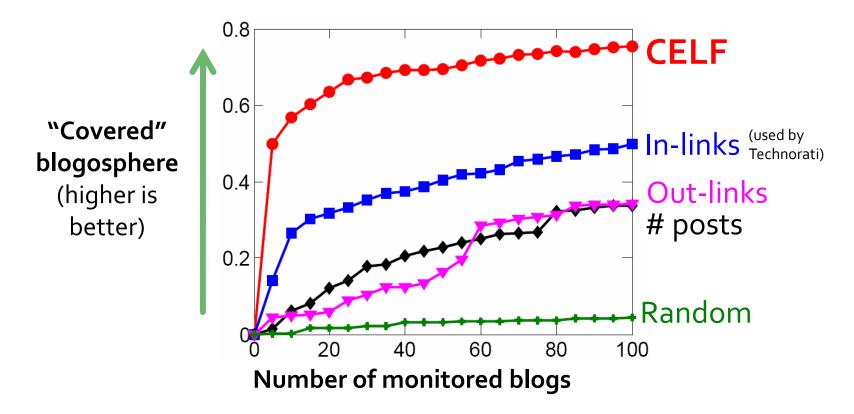
A single story propagates...



Sooner we read the story, more of its influence area we cover

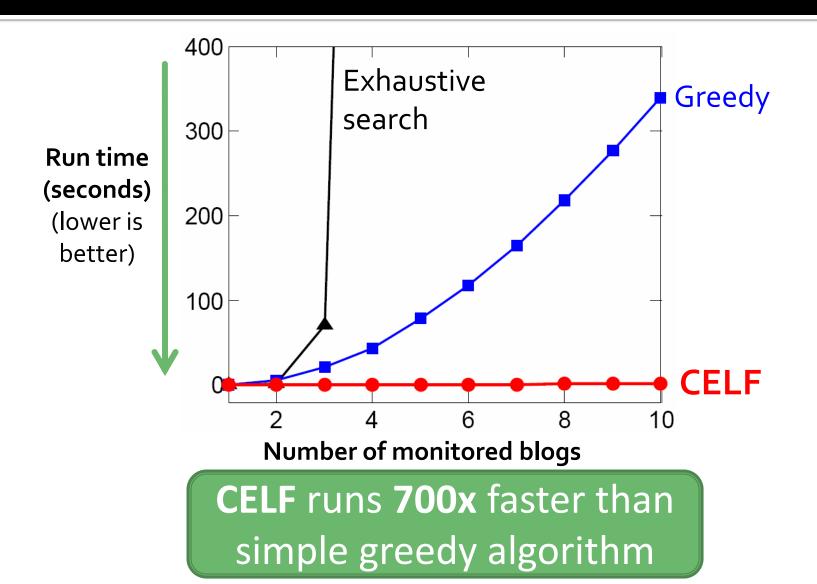
Blogs: Information epidemics

Which blogs should one read?



For more info see our website: www.blogcascades.org

CELF: Scalability



www.blogcascades.org

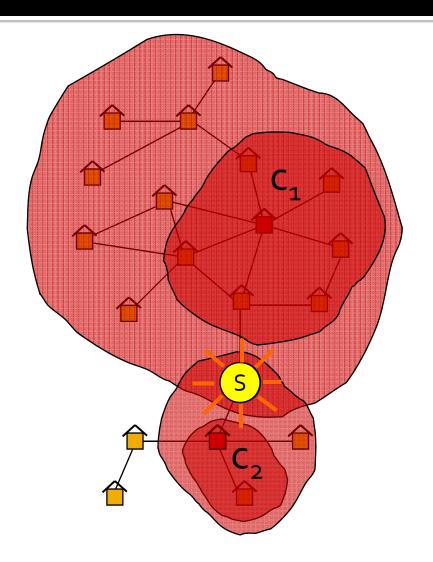
So, who is influential? What should I read?

k	Score	Blog	Posts	InLinks	OutLinks
1	0.13	http://instapundit.com	4593	4636	5255
2	0.18	http://donsurber.blogspot.com	1534	1206	3495
3	0.22	http://sciencepolitics.blogspot.com	924	576	2701
4	0.26	http://www.watcherofweasels.com	261	941	3630
5	0.29	http://michellemalkin.com	1839	12642	6323
6	0.32	http://blogometer.nationaljournal.com	189	2313	9272
7	0.34	http://themodulator.org	475	717	4944
8	0.35	http://www.bloggersblog.com	895	247	10201
9	0.37	http://www.boingboing.net	5776	6337	6183
10	0.38	http://atrios.blogspot.com	4682	3205	3102
11	0.39	http://lawhawk.blogspot.com	1862	463	6597
12	0.40	http://www.gothamist.com	6223	3324	17172
13	0.41	http://mparent7777.livejournal.com	25925	199	47933
14	0.42	http://wheelgun.blogspot.com	1174	128	939
15	0.43	http://gevkaffeegal.typepad.com/the_alliance	302	428	2481

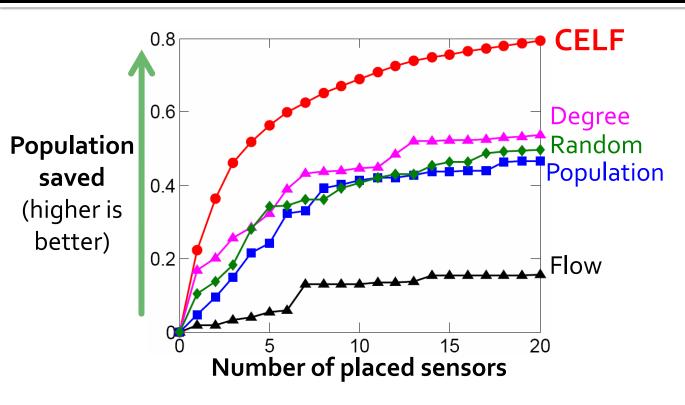
Same problem: Water Network

Given:

- a real city water distribution network
- data on how contaminants spread over time
- Place sensors (to save lives)
- Problem posed by the US Environmental Protection Agency



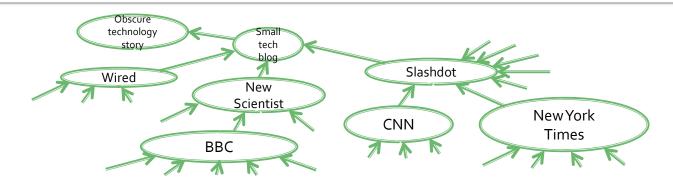
Water network: Results

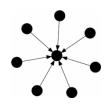


 Our approach performed best at the Battle of Water Sensor Networks competition

Author	Score		
CMU (CELF)	26		
Sandia	21		
U Exter	20		
Bentley systems	19		
Technion (1)	14		
Bordeaux	12		
U Cyprus	11		
U Guelph	7		
U Michigan	4		
Michigan Tech U	3		
Malcolm	2		
Proteo	2		
Technion (2)	1		

Conclusion and connections





- How do news and information spread
 - New ranking and influence measures for blogs
 - Recommendations and incentives
 - Diffusion of topics (news, media)
- Predictive models of information diffusion
 - Social Media Marketing
- How to design better systems incorporating diffusion and incentives



References

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