



# Beyond Pagerank: Network Effects Between Web Entities (WWW 2005 Panel Discussion)

Soumen Chakrabarti  
IIT Bombay

[www.cse.iitb.ac.in/~soumen](http://www.cse.iitb.ac.in/~soumen)

# Web entities, relations, economy

- Information entities: page, ad, href, iframe
- Real-life artifacts: goods, services—these live in complex attribute spaces
- Actors: searcher, author, search engine, vendor, ad author, ad server
- Many interconnected relations
  - wrote(author,href), received(person,email), paid(vendor,adserver,money), bookmarked(searcher,href,datetime), bought(searcher,product),...
- Emails, blogs, Friendster, Orkut, Tribe, LinkedIn, Yahoo360, del.icio.us, ...

# Research efforts

How to model interactions and use models for well-motivated optimization problems?

- Network value of customers [Domingos+2001, Kempe+2003]
- Viral marketing, network epidemics and spectral analysis [Wang+2003]
- Effect of ranking monopolies on social networks [Baeza-Yates+2002, Cho+2004, Chakrabarti+2005, Pandey+2005]
- Recommender systems: content-based, collaborative, cold-start [Schein+2002]

# Targeting highly networked customers

Probability of a given reaction of  $i$ -th customer in a social network

Known reaction of pilot customers

Search for  $\mathbf{M}$  to maximize expected lift in profit

$\Pr(X_i | \mathbf{X}^k, \mathbf{Y}, \mathbf{M})$  Bitvector of marketing campaign over all nodes

Attributes of marketed item and/or relations to attributes of customer  $i$

$$ELP(\mathbf{X}^k, \mathbf{Y}, \mathbf{M}) = \sum_i R_i \Pr(X_i = 1 | \mathbf{X}^k, \mathbf{Y}, \mathbf{M}) - |\mathbf{M}|c$$

Reward/revenue for converting potential customer  $i$  to purchase

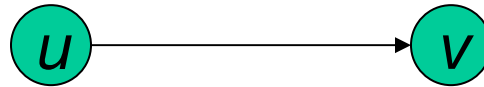
One-shot, greedy, and hill-climbing search for the best  $\mathbf{M}$

Number of 1s in  $\mathbf{M}$

Cost of advertising to one customer (may not be constant)

# Epidemics and eigenvalues

If infected, infects each neighbor with probability  $\beta$  every time step



If infected, heals with probability  $\delta$  every time step

$$1 - p(v, t) = (1 - p(v, t-1))(1 - r(v, t-1)) + p(v, t-1)(1 - r(v, t-1))\delta$$

Pr v infected at  $t$ 
Pr v gets infection at  $t-1$

$$1 - r(v, t) = \prod_{(u,v) \in E} (1 - \beta p(u, t-1))$$

Pr no neighbor gives infection

$$\mathbf{p}(t) = ((1 - \delta)\mathbf{I} + \beta \mathbf{E})\mathbf{p}(t-1) = \mathbf{S}\mathbf{p}(t-1), \text{ say}$$

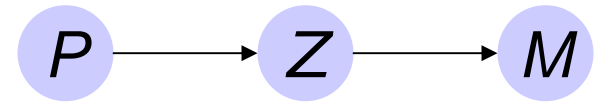
Approximate linear propagation model

$\mathbf{p}(t)$  dies down to zero as  $t \rightarrow \infty$  if  $\lambda_1(\mathbf{S}) < 1$ , which happens if

$$\delta / \beta > \lambda_1(\mathbf{E})$$

# Hidden links in recommender systems

Is person  $p$  likely to enjoy movie  $m$ ?



← Person	Movies →			
	0	?	0	1
1	1	0	0	1

$$\Pr(p, m) = \sum_z \Pr(p) \Pr(z | p) \Pr(m | z)$$

Person  $p$  chooses hidden “genre”  $z$

Genre induces distrib over movies

Exploit additional linkage: find movies with casting similar to that of movies user has liked before

First, fit a person-actor model from training data

$$\Pr(p, a) = \sum_z \Pr(p) \Pr(z | p) \Pr(a | z)$$

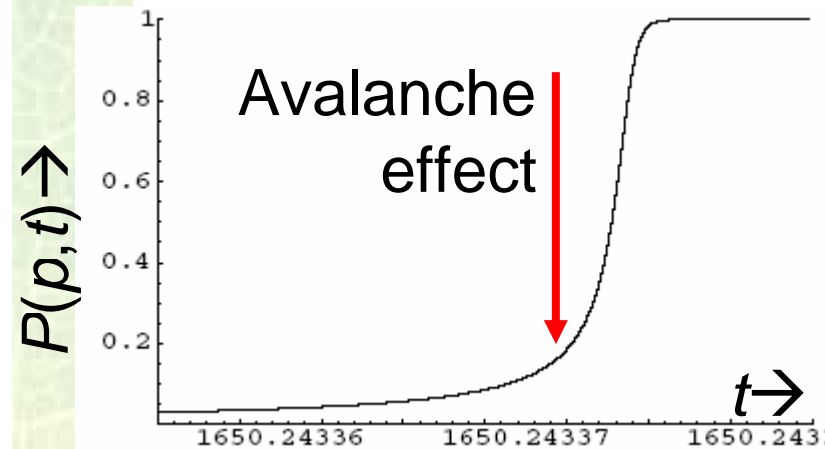
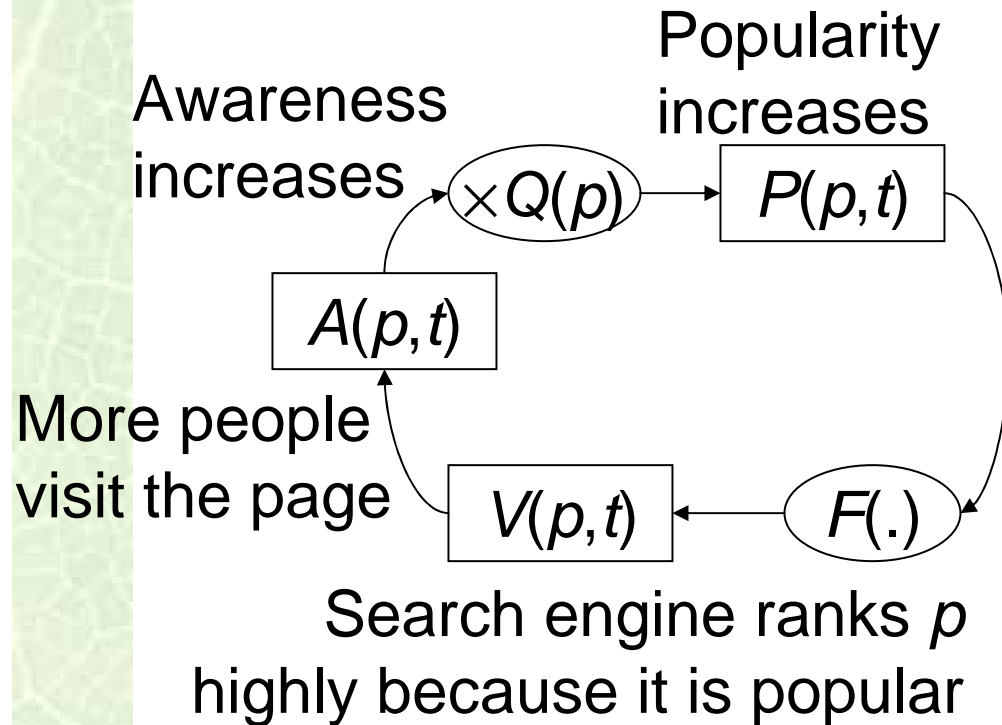
Next, “fold in” a movie via EM

Final recommendation

$$\begin{cases} \Pr(z | a, m) \propto \Pr(a | z) \Pr(z | m) \\ \Pr(z | m) \propto \sum_a [a \in m] \Pr(z | a, m) \end{cases}$$

$$\Pr(p | m) = \sum_z \Pr(z | m) \Pr(p | z)$$

# Positive feedback and “Googearchy”



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Soumen Chakrabarti IIT Bombay

Usual power-law behavior

Degree distribution under Googearchy



Celebrities on "bestseller list"

“Unintended consequences” of promotions owing to dynamic network effects

# Challenges

- Tractable yet reliable models
  - Many types of entities, relations, quantities
  - Simplify without losing the essence
- Large-scale clean-room experiments tough
  - Parameter settings can leave permanent effect
  - Long-term observation, control groups
- Highly non-linear dynamical systems
  - Explosive/logistic growth, burstiness, competition
- Data privacy, capture, scaling
  - Distributed ownership, willful distortions