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# Recommender Systems Research

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# Recommender Systems Research

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## Quote

“What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention, and a need to allocate that attention efficiently among the overabundance of information sources that might consume it.”

Herbert A. Simon

# Recommender Systems

- Select a subset of items based on user preferences
- Underlying algorithms range from simple keyword matching to sophisticated mining of user profiles
- Examples: top-N lists, book and movie recommenders: Amazon.com
- Reduce information overload
- Retain customers
- Increase revenue
- Now believed to be critical to sustaining the Internet economy

# Four Main Dimensions

How is the recommender system

1. modeled and designed
  - are recommendations *content-based* or *collaborative*?
2. targeted
  - to an individual, group, or topic?
3. built
4. maintained
  - online vs. offline

# Content-based Filtering

‘Since you liked *The Little Lisper*,  
you may be interested in *The Little Schemer*.’

‘Since you liked *Pride and Prejudice*,  
you also might like *Sense and Sensibility*.’

# Collaborative-filtering

Linus and Lucy like *Sleepless in Seattle*.  
Linus likes *You've Got Mail*.

---

Lucy also might like *You've Got Mail*.

# Four Main Dimensions

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What about the inherently social aspect of recommendation?



# 'Brick and Mortar' Setting

[Linus and Lucy are at *Bombay Café*, an Indian Restaurant.]

- 1 **Linus:** The menu looks enticing.
- 2 **Linus:** Since you are a returning patron, what do you recommend?
- 3 **Lucy:** Well, since you like spicy dishes, and you're not a vegetarian, you'll enjoy the Chicken Vindaloo.
- 4 **Linus:** Alright, I'll try that.

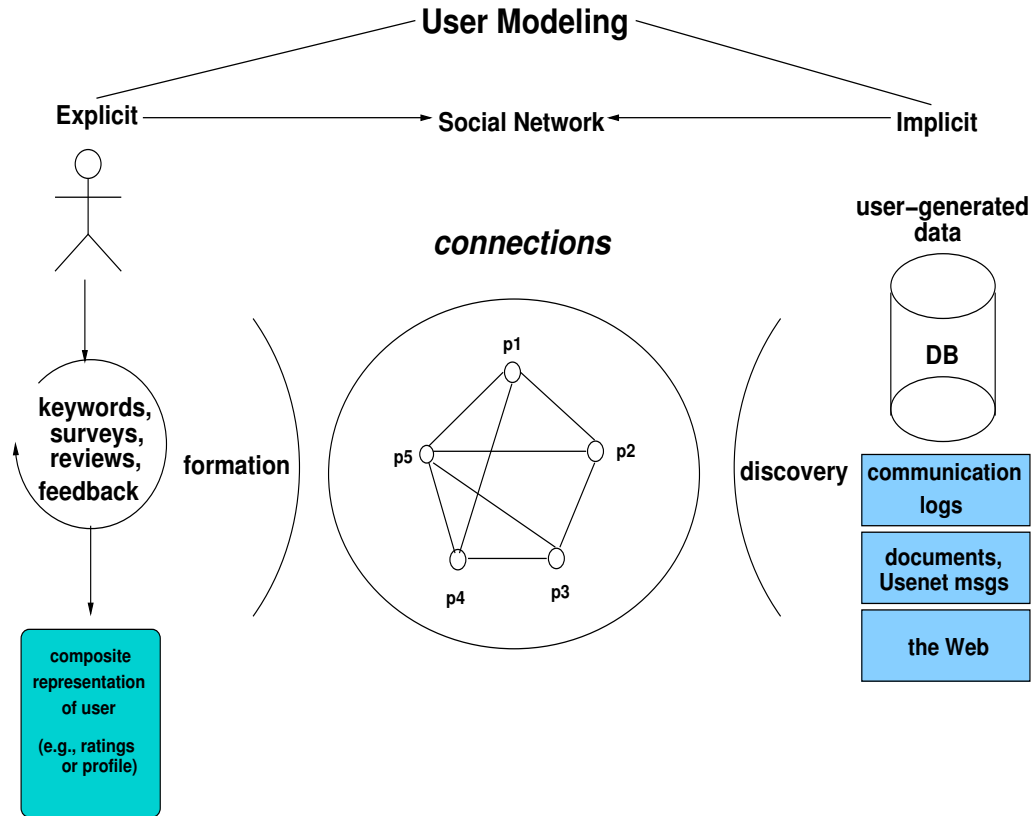
A mutually-reinforcing dynamic ensues:

- Lucy leverages her knowledge of Linus' interests into the process of recommendation.
- Linus harnesses his knowledge of Lucy's reputation to evaluate the recommendation.

# Inherent Social Aspect

- Recommender systems attempt to emulate and automate this natural social process.
- Predictive utility relies on its representation of the recipient.
- Recommender systems involve *user modeling*.
- User models can be constructed by
  - explicitly soliciting feedback
    - \* e.g., asking users to rate products or services
  - gleaning implicit declarations of interest
    - \* e.g., through monitoring usage

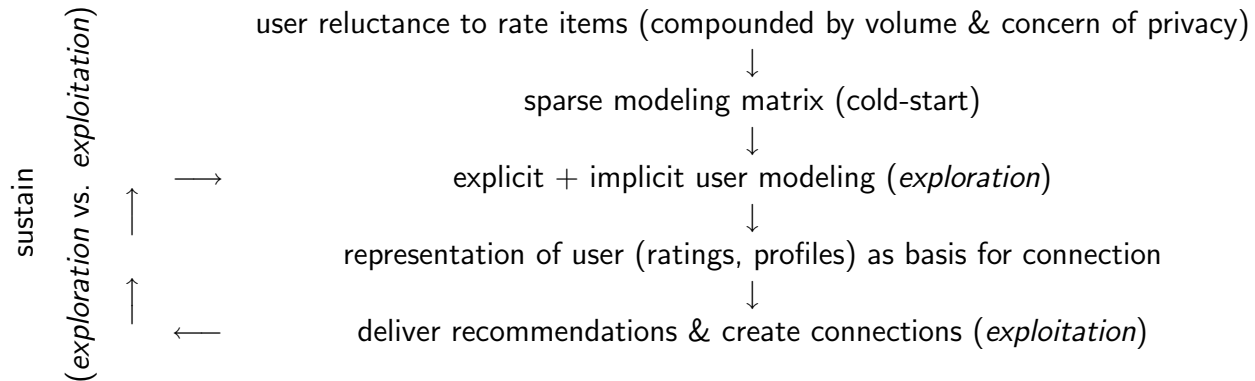
# A Connection-centric View



# Shifts in IS Research

| Concept                 | Modeling Matrix        |
|-------------------------|------------------------|
| Information retrieval   | (terms × documents)    |
| ↓                       | ↓ ↓                    |
| Information filtering   | (features × documents) |
| ↓                       | ↓ ↓                    |
| Content-based filtering | (features × artifacts) |
| ↓                       | ↓ ↓                    |
| Collaborative filtering | (people × documents)   |
| ↓                       | ↓ ↓                    |
| Recommender systems     | (people × artifacts)   |

# User Modeling Methodology for CF RSs



# Explicit User Modeling

- What kind?
  - quantitative (e.g., ratings)
  - qualitative (e.g., reviews)
- What makes it tough?
  - voluminous (and ephemeral) domains (e.g., news)
  - reluctance to evaluate artifacts
  - free-riders
  - cold-start: new user or new item
  - ‘banana’ problem (and converse)
  - users with unusual or highly specific tastes
  - users with similar interests who have rated different artifacts
  - effusivity of ratings

# Explicit User Modeling (*contd*)

- Possible solutions?
  - pay-per-use model, subscription services
  - minimum rating constraints
  - incentives
  - default votes
  - agents to rate every artifact
  - user interface approaches
  - rate clusters of items
  - hybrid approaches (collaborative and content-based)
  - use indirection
- Representative projects
  - GroupLens (Pearson's  $r$ )
  - Fab (hybrid)

# Implicit User Modeling

- Traditional approaches
  - PHOAKS (USENET News)
  - Sitemiser (bookmarks)
- Link analysis and cyber-communities
  - Social networks
    - \* Discovering shared interests
    - \* Referral Web
- Mining and exploiting structure
  - Jumping connections
  - HITS: Hubs and authorities
- Small-world networks



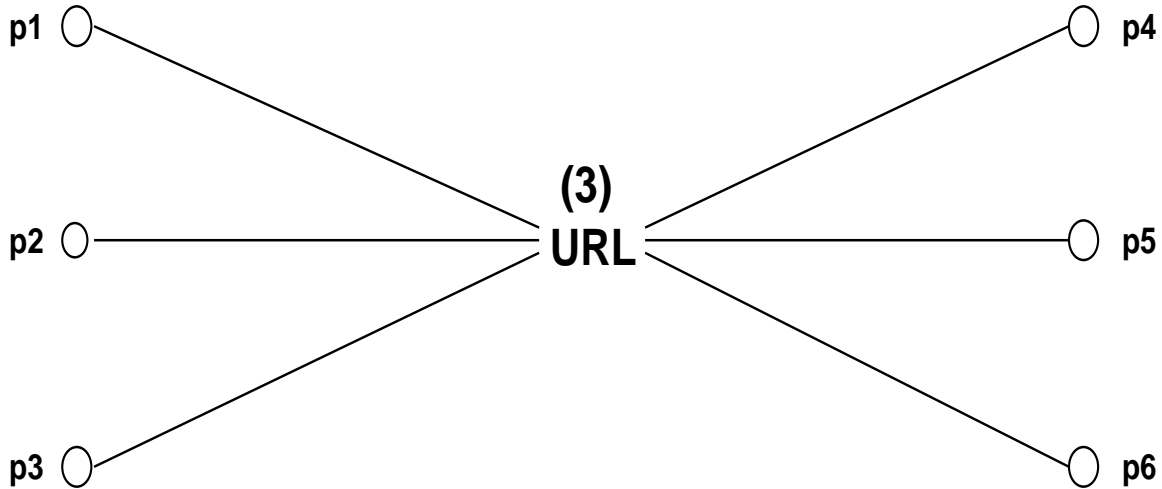
# What are implicit declarations of interest?

- Clickstream data, (web) access logs, 'footprints'
- Time spent on a product page
- UI events: scrolling, highlighting
- Transaction data, shopping carts
- Hyperlinks
- Bookmarks

# PHOAKS

**recommenders**

**recipients**



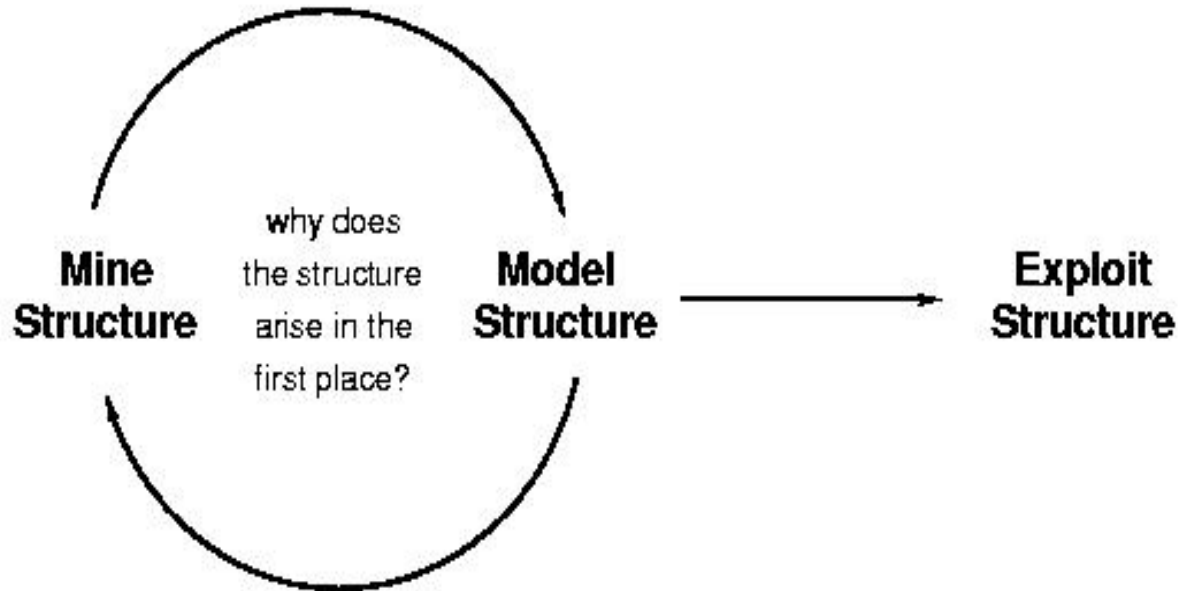
# Link Analysis and Cyber-communities

- Discovering shared interests
  - Used e-mail logs to mine connections
  - Closeness

$$InterestDistance(n_1, n_2) = \frac{|(C(n_1) \cup C(n_2)) - (C(n_1) \cap C(n_2))|}{|(C(n_1) \cup C(n_2))|}$$

- Referral Web
  - Used close proximity of names in webpages
  - Queries:
    - \* Referral chains: ‘What is my relationship to Marvin Minsky?’
    - \* Search for experts: ‘What colleagues of mine, or colleagues of colleagues of mine know about simulated annealing?’
    - \* Proximity search: ‘List documents on the topic *annealing* by people close to Scott Kirkpatrick.’

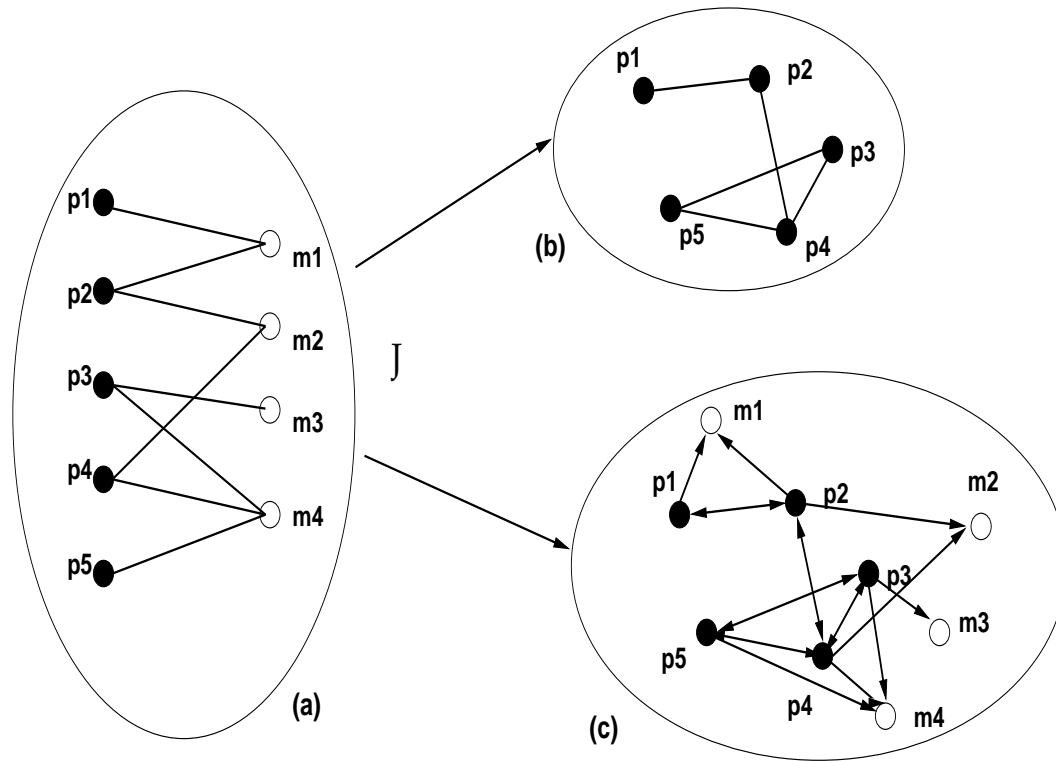
# Mining and Exploiting Structure: Theme



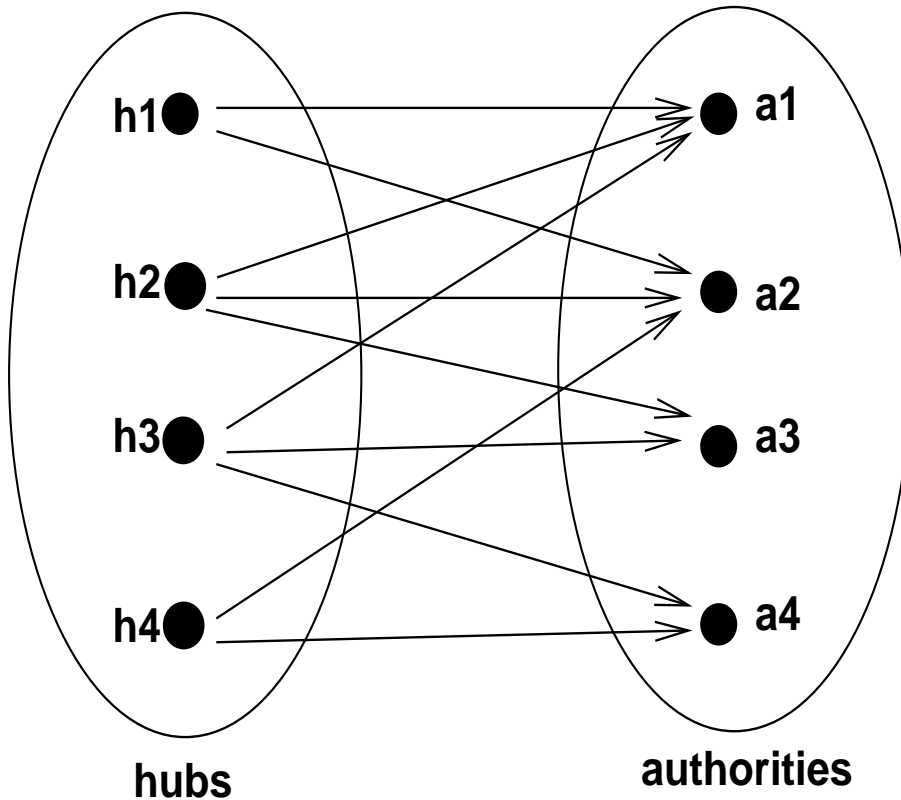
# Mining and Exploiting Structure (*contd*)

- Affiliation networks vs. social networks
  - actor-movie collaboration graph
  - author-paper collaboration graph
- What structure can be mined?
  - degree distribution
  - connectivity
- Examples:
  - Jumping Connections
  - HITS: Hubs and authorities

# Jumping Connections

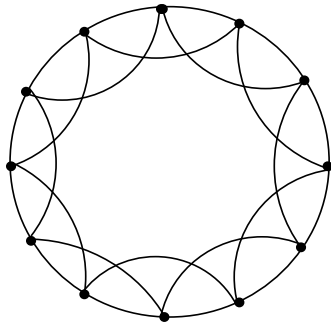


# HITS: Hubs and Authorities

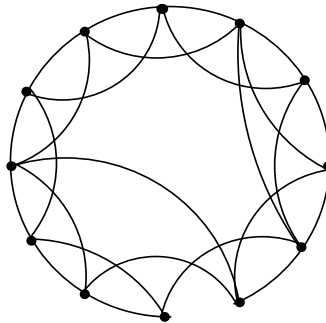


# Small-world Networks

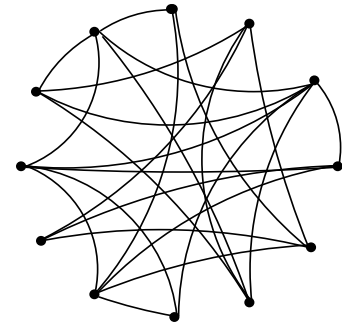
Regular Network



Small-World Network



Random Network



$p = 0$



$p = 1$

Increasing randomness



# Discovering Social Networks

| <b>Concept</b>                                   | <b>Implicit declaration of interest</b>  | <b>Algorithm or System</b>                                    |
|--|--|---|
| Traditional Approaches to Implicit User Modeling | URLs in Usenet news<br>bookmarks   | PHOAKS<br>Sitseer   |
| Link Analysis and Cyber-Communities              | e-mail logs<br>web documents   | Discovering Shared Interests<br>Referral Web                  |
| Mining and Exploiting Structure                  | movie ratings datasets<br>hits-buffs, half bow-tie<br>web link topology<br>hubs and authorities<br>bow-tie | Jumping Connections<br><br>PageRank (Google)<br>HITS (CLEVER) |
| Small-world Networks                             | actor collaborations<br>author collaborations<br>infectious disease<br>the web                             | Oracle of Bacon<br>DBLP                                       |

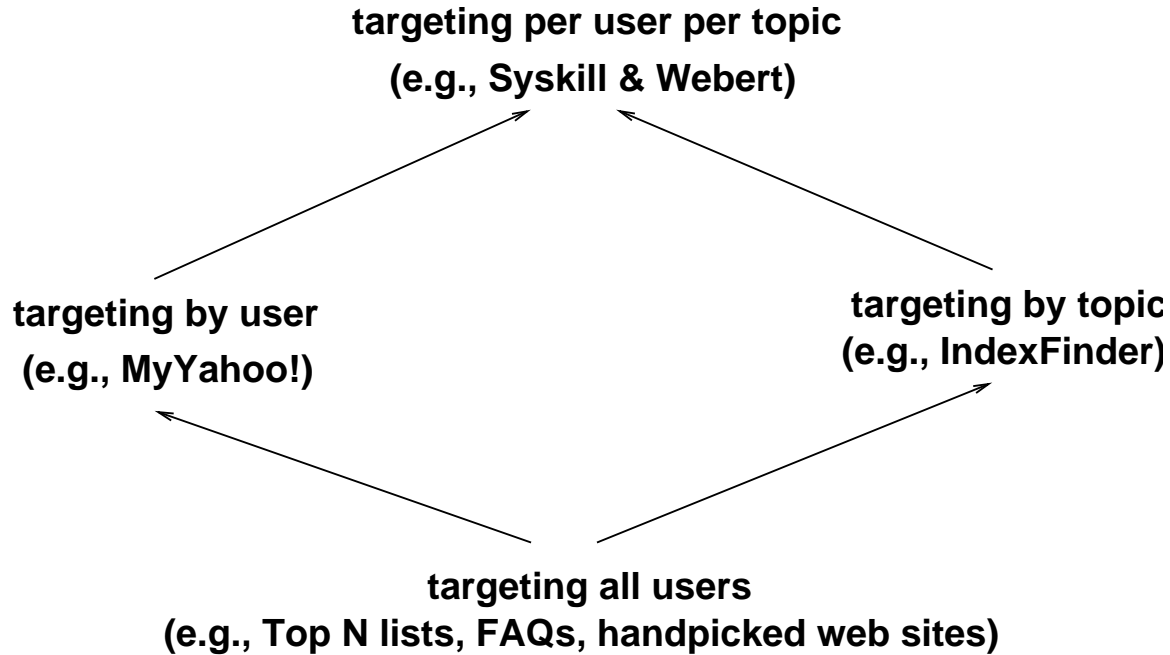
# Take away

- Purely structural information can be very instructive.
- These properties are found in nature (self-generating and self-organizing systems) and not merely an artifact of an idealized world.
- In what ways can we exploit these properties for recommendation?

# Broadening Issues

- Evaluation
  - Functional vs. human-oriented evaluations
  - Is there something in between?
- Targeting
  - Answers the question ‘for whom are we building this system?’
- Privacy and trust
  - Broader than one user and one system
  - Concept of a *weak-tie*
- Shilling
  - Involves inundating the system with data intended to coerce it to artificially recommend the perpetrator’s products more often than those of a competitor.
  - Algorithms to detect when a system is being shilled

# Targeting



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# Conclusions

- Recommenders are systems that *connect* people.
- The question is 'do they bring people together by *explicitly* or *implicitly* modeling them?'
- Approaches for discovering self-organizing social networks constitute the primary thrust in current RS research.
- Evaluation is challenging with the human in the loop.
- We are trying to make a science out of recommendation.

# Recommender Systems Research

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