Introduction to Social Recommendation

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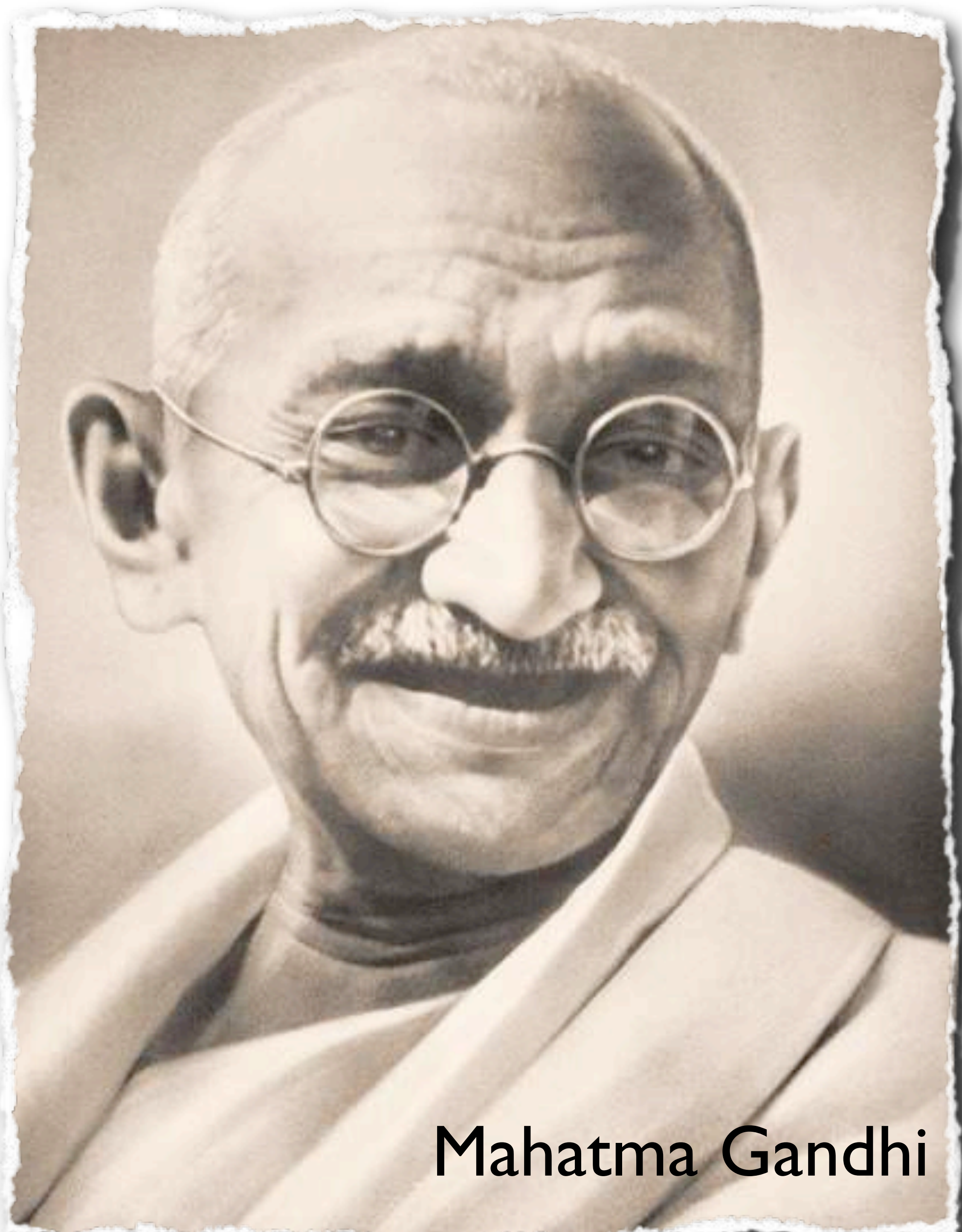
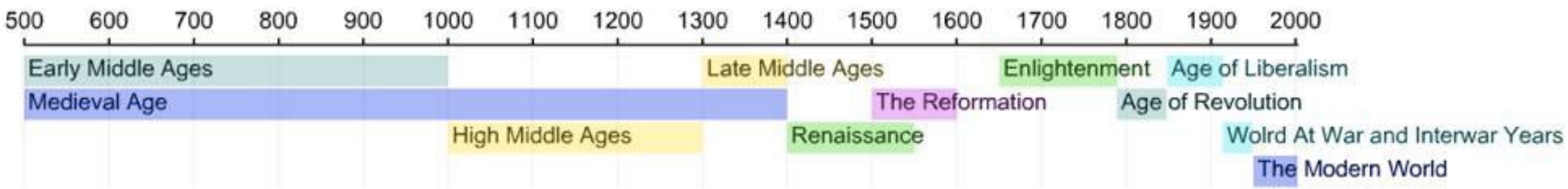


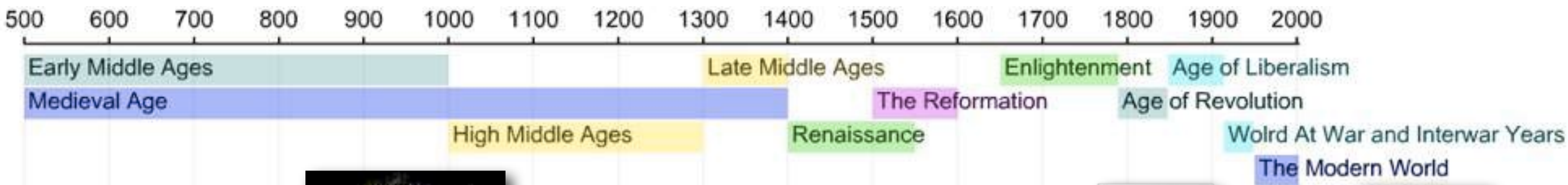
Interdependence is and ought to be as much the ideal of man as self-sufficiency.

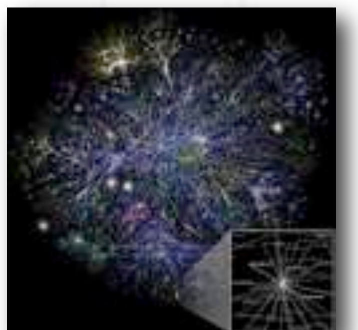
Man is a social being.

A Brief History of the World



A Brief History of the World

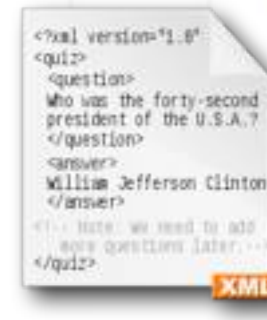




Birth of Internet

IBM Desktop PC

Apple Macintosh



Birth of XML

Time Magazine Person of the Year

1750 1945 1969 1975 1981 1983 1984 1989 1996 2004 2006

Industrial Revolution **Information Age** **Internet Age** **WWW Age** **Attention Age**

ENIAC

The MITS Altair
Apple II

Time Magazine Person of the Year

Birth of WWW

Birth of Web 2.0





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Highlights from the Journey to 1 Billion PCs
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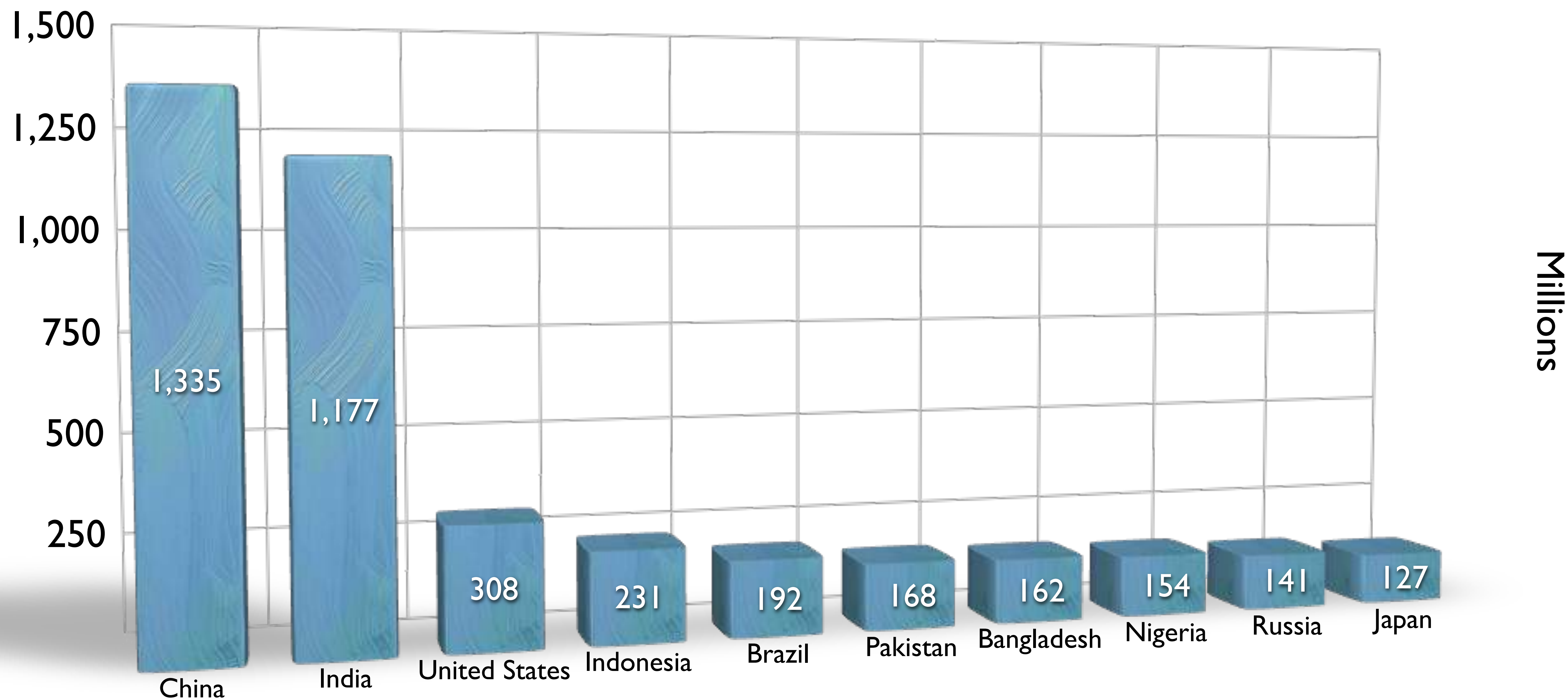
For more information, please visit http://www.intel.com

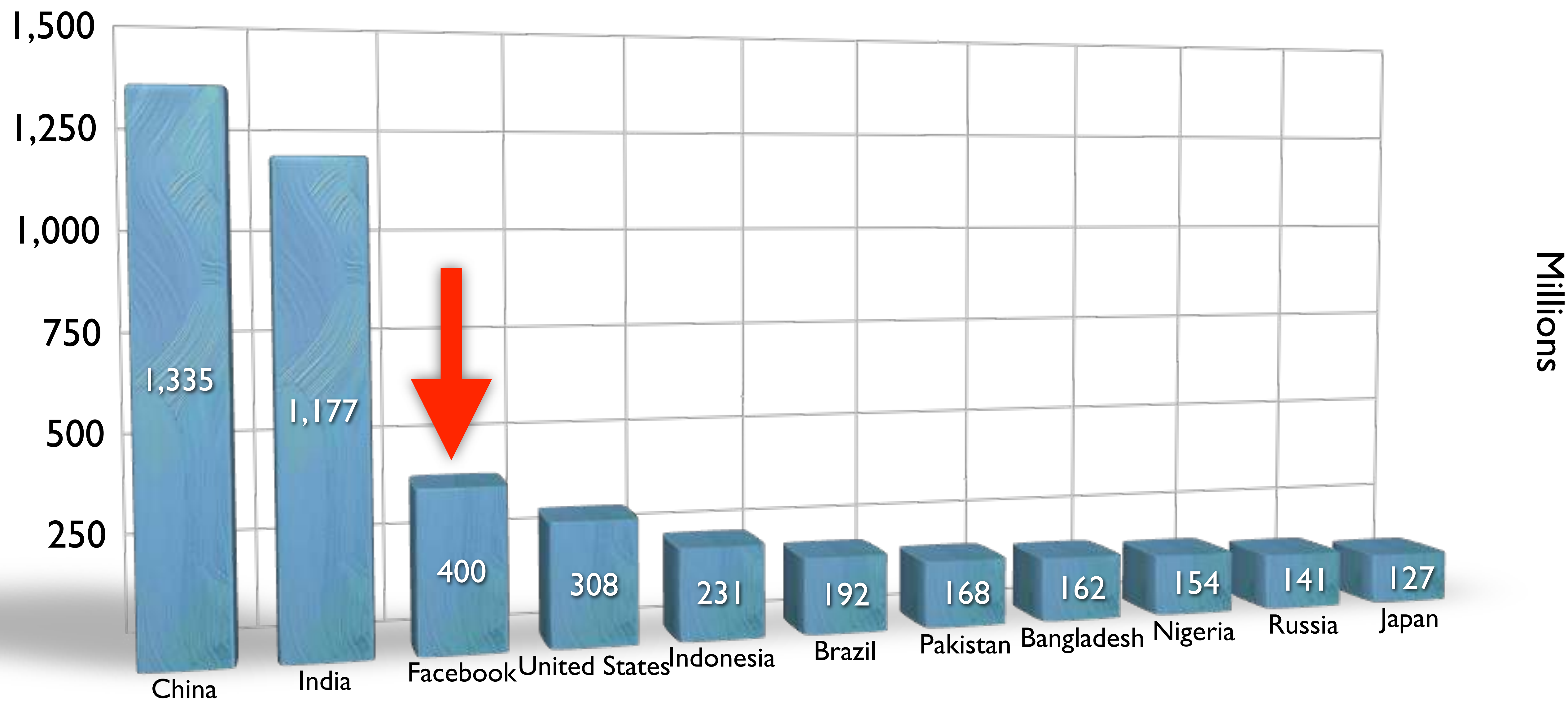
Top 10 Populations by Countries

as of July 2009

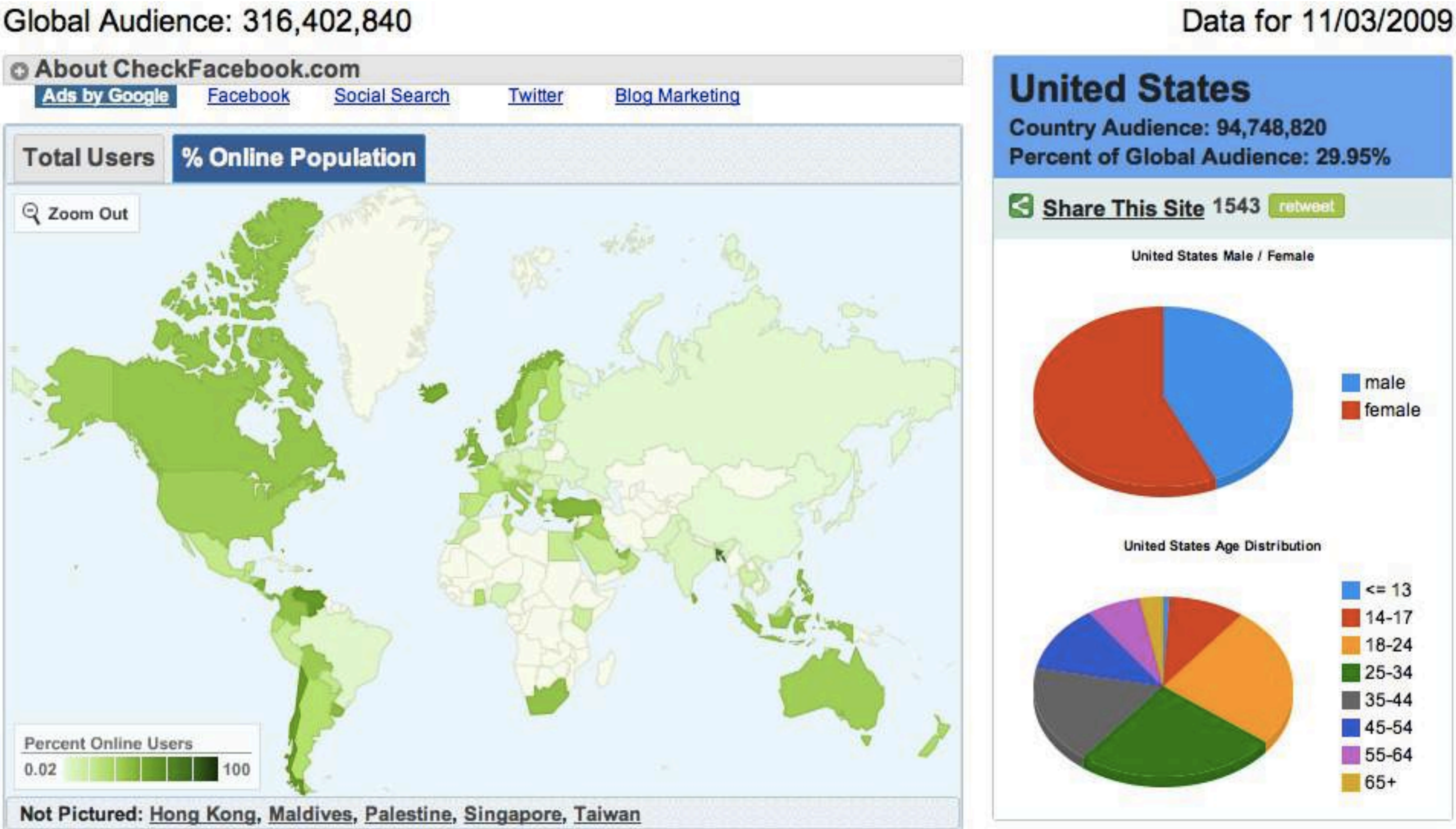


Top 10 Populations by Countries

as of February 2010



Facebook's Global Audience



Facebook's Growth Stats

Statistics

Company Figures	More than 400 million active users 50% of our active users log on to Facebook in any given day More than 35 million users update their status each day More than 60 million status updates posted each day More than 3 billion photos uploaded to the site each month More than 5 billion pieces of content (web links, news stories, blog posts, notes, photo albums, etc.) shared each week

10 Largest Countries		
1.	United States	94,748,820
2.	United Kingdom	22,261,080
3.	Turkey	14,215,880
4.	France	13,396,760
5.	Canada	13,228,380
6.	Italy	12,581,060
7.	Indonesia	11,759,980
8.	Spain	7,313,160
9.	Australia	7,176,640
10.	Philippines	6,991,040

10 Fastest Growing Over Past Week			
1.	Poland	12.46 %	137,900
2.	Thailand	10.96 %	161,300
3.	Portugal	9.81 %	80,040
4.	South Africa	9.25 %	189,080
5.	Taiwan	7.82 %	367,400
6.	Romania	7.65 %	28,060
7.	Germany	7.54 %	350,240
8.	Malaysia	7.43 %	236,840
9.	Indonesia	6.84 %	752,640
10.	Iraq	6.72 %	6,380

Global Internet Traffic

Alexa as of May 2009	China	USA	Japan	India	Brazil	Global
1	Baidu	Google	Yahoo.jp	Google.in	Google	Google
2	**QQ**	Yahoo	**FC2**	Google	**Orkut.br**	Yahoo
3	Sina	**Facebook**	Google.jp	Yahoo	Windows Live	**YouTube**
4	Google.cn	**YouTube**	**YouTube**	**Orkut.in**	Universo Online	**Facebook**
5	Taobao	**Myspace**	Rakuten	**YouTube**	**YouTube**	Windows Live
6	163	MSN	Livedoor	**Blogger**	Globo	MSN
7	Google	Windows Live	**Ameblo.jp**	Rediff	MSN	**Wikipedia**
8	Sohu	**Wikipedia**	**mixi**	**Facebook**	Google	**Blogger**
9	Youku	Craigslist	**Wikipedia**	**Wikipedia**	Yahoo	Baidu
10	Yahoo	EBay	Google	Windows Live	Terra	**Myspace**

The Brave New Words

blogger

wiki

AVATAR

頭像

tag cloud

mash-up

unfriend

tweet

blogsphere

twitterati

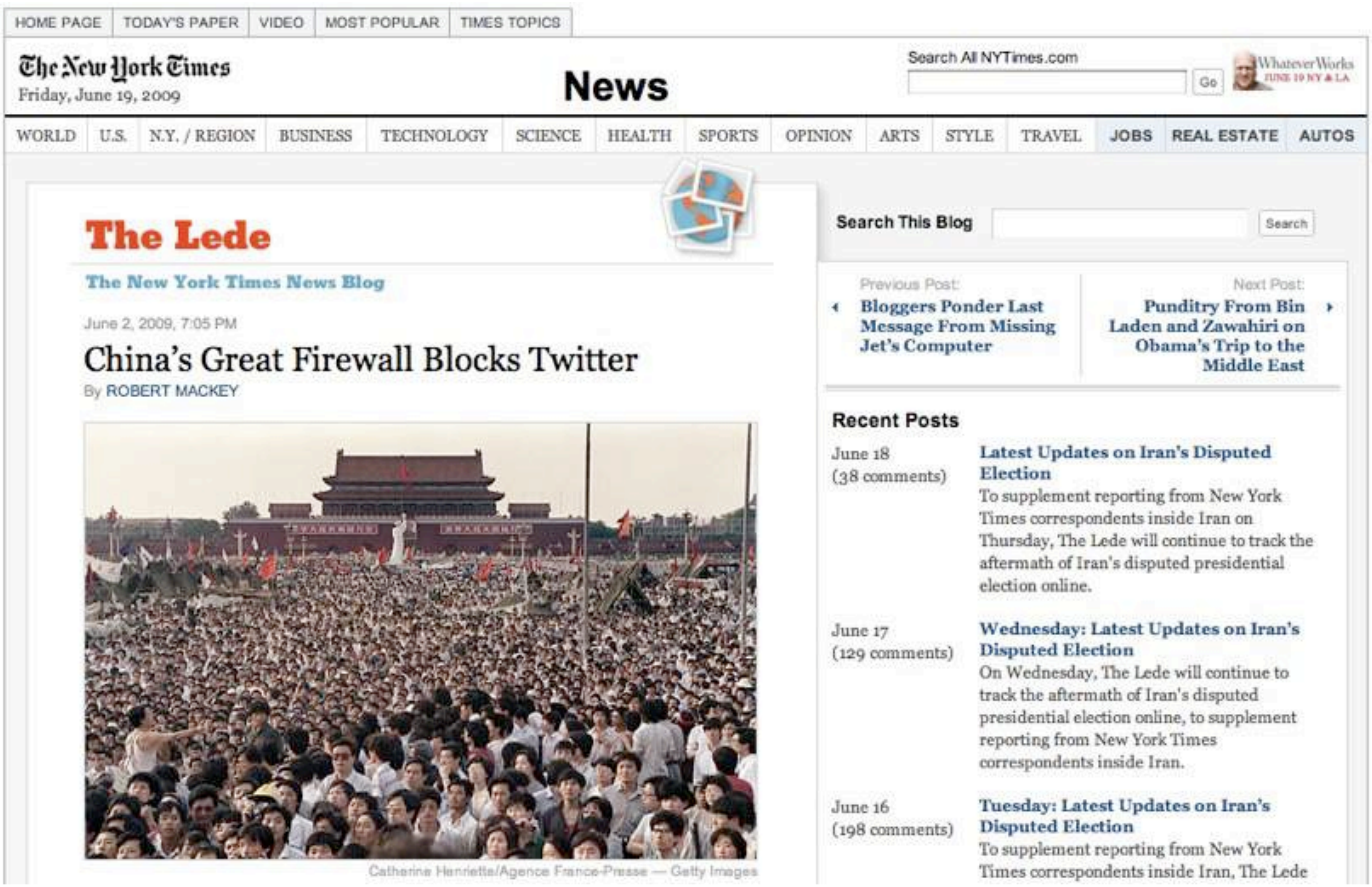
defriend

hashtags

SEXTING

Folksonomy

Twitter in Spotlight



Outline

- Introduction
- Social Search Engine
- Social Recommender Systems
- Social Media Analysis
- Conclusion

Introduction

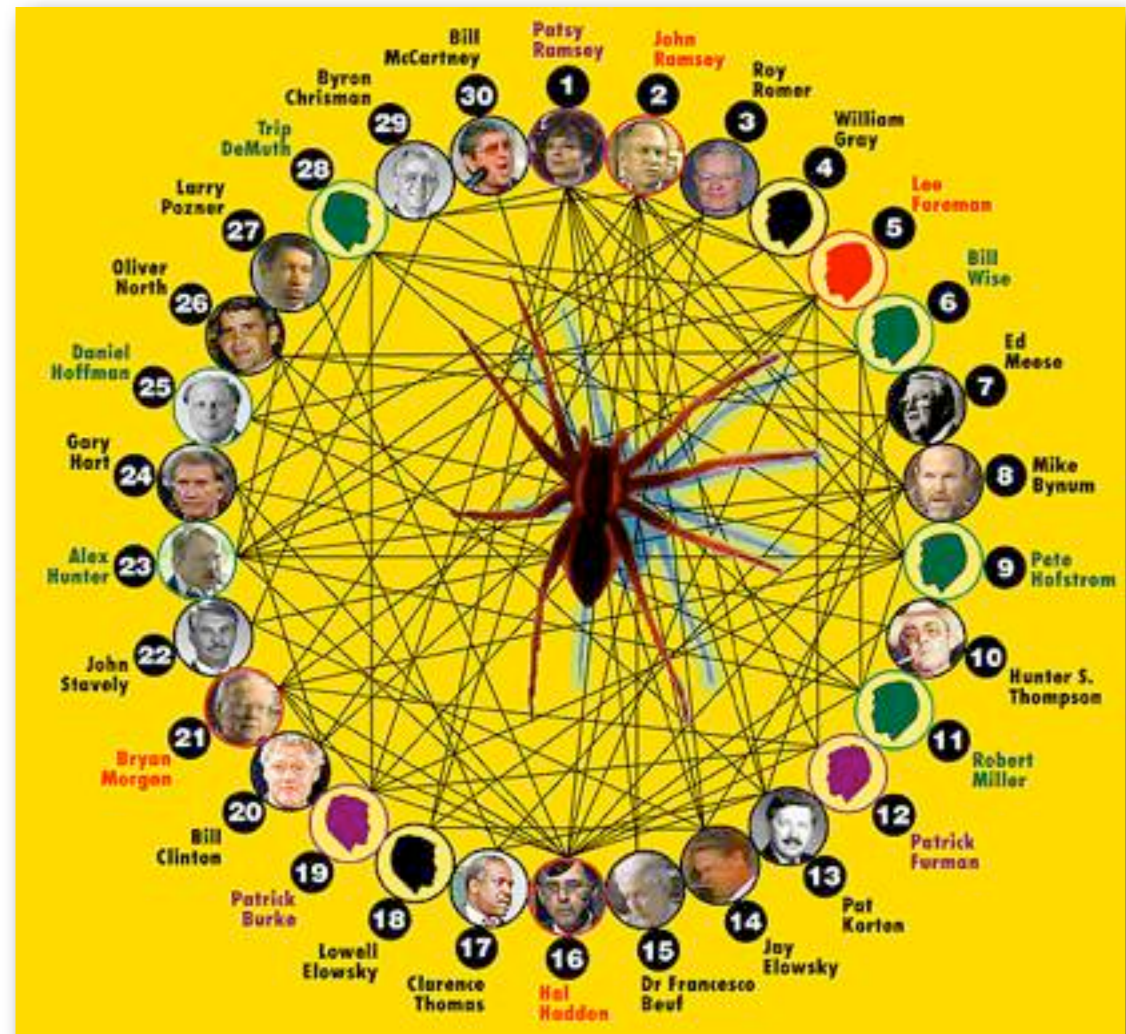
- Social Platforms
  - Social Network
  - Social Media
  - Social Games
  - Social bookmarking
  - Social News and Social Knowledge Sharing
- Techniques in Social Recommendation
- Summary

Web 2.0

- Web as a medium vs. **Web as a platform**
- Read-Only Web vs. **Read-and-Write Web**
- Static vs. **Dynamic**
- Restrictive vs. **Freedom & Empowerment**
- Technology-centric vs. **User-centric**
- Limited vs. **Rich User Experience**
- Individualistic vs. **Group/Collective Behavior**
- Consumer vs. **Producer**
- Transactional vs. **Relational**
- Top-down vs. **Bottom-up**
- People-to-Machine vs. **People-to-People**
- Search & browse vs. **Publish & Subscribe**
- Closed application vs. **Service-oriented Services**
- Functionality vs. **Utility**
- Data vs. **Value**

Social Networks

Society:
Nodes: individuals
Links: social relationship (family/work/friendship/etc.)

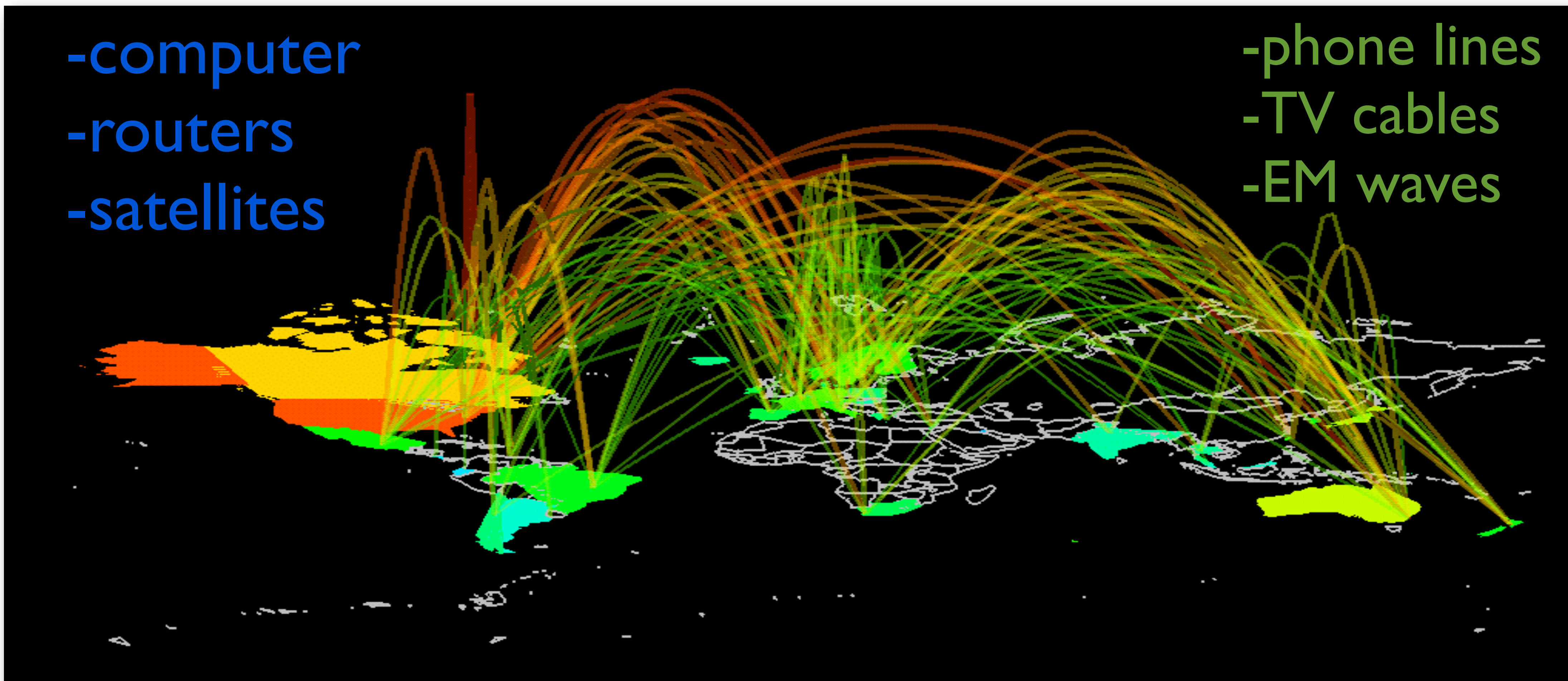


S. Milgram and John Guare: Six Degree of Separation.
Social networks: Many individuals with diverse social interactions between them.

Milgram’s Experiment

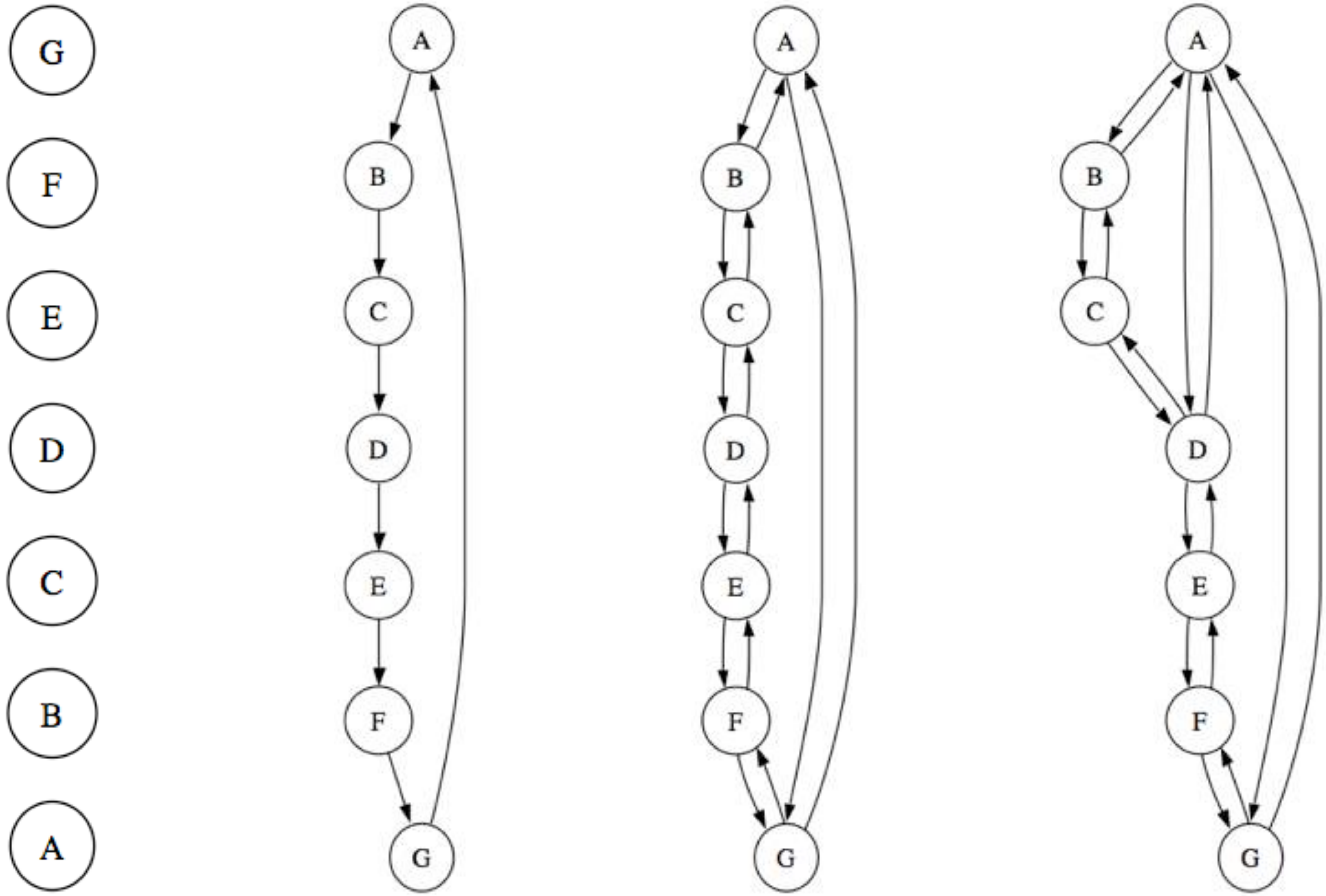
Social Networks

- The Earth is developing an electronic nervous system, a network with diverse nodes and links.

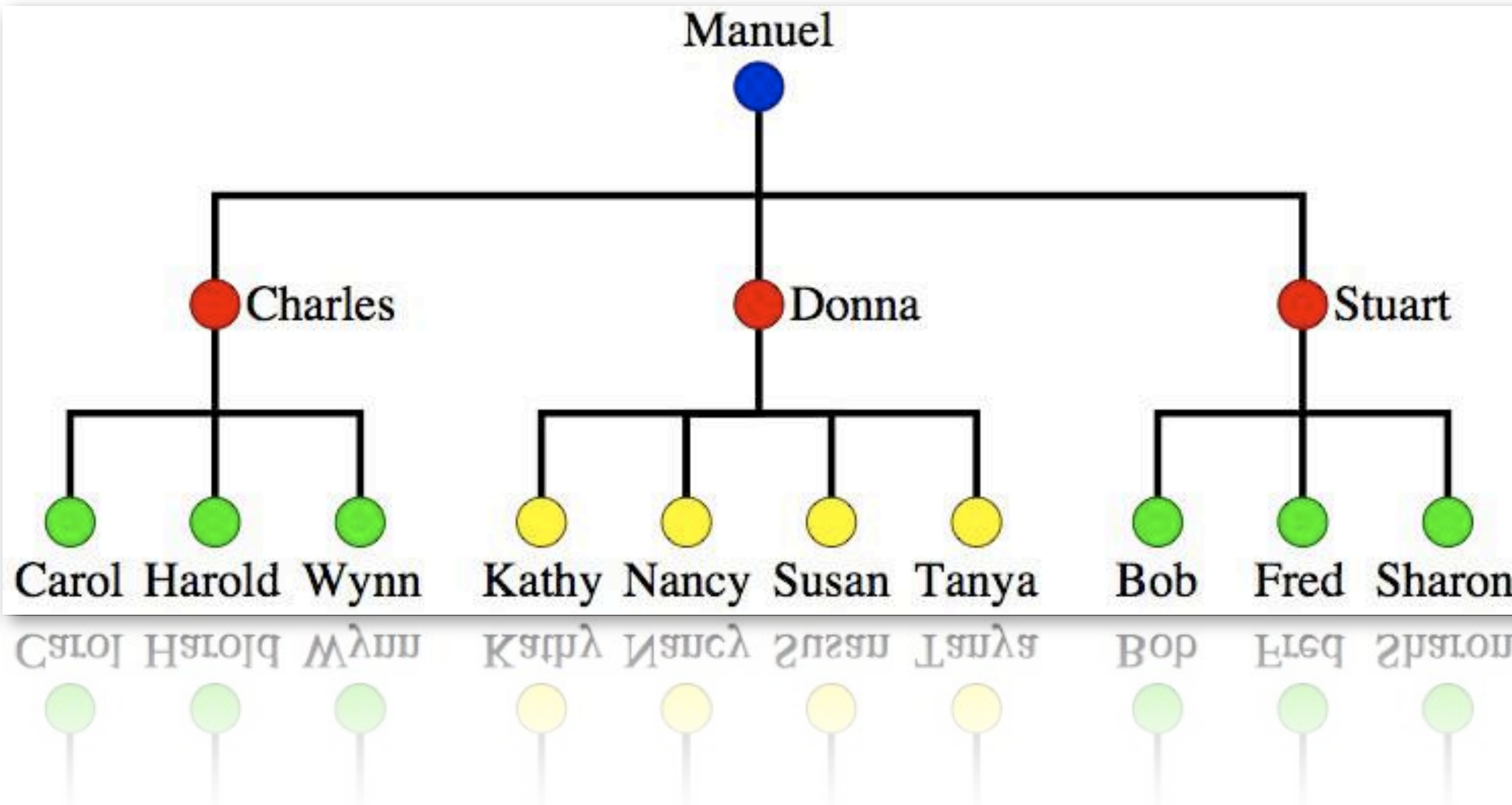


Communication networks: many non-identical components with diverse connections between them.

The Flow of Information

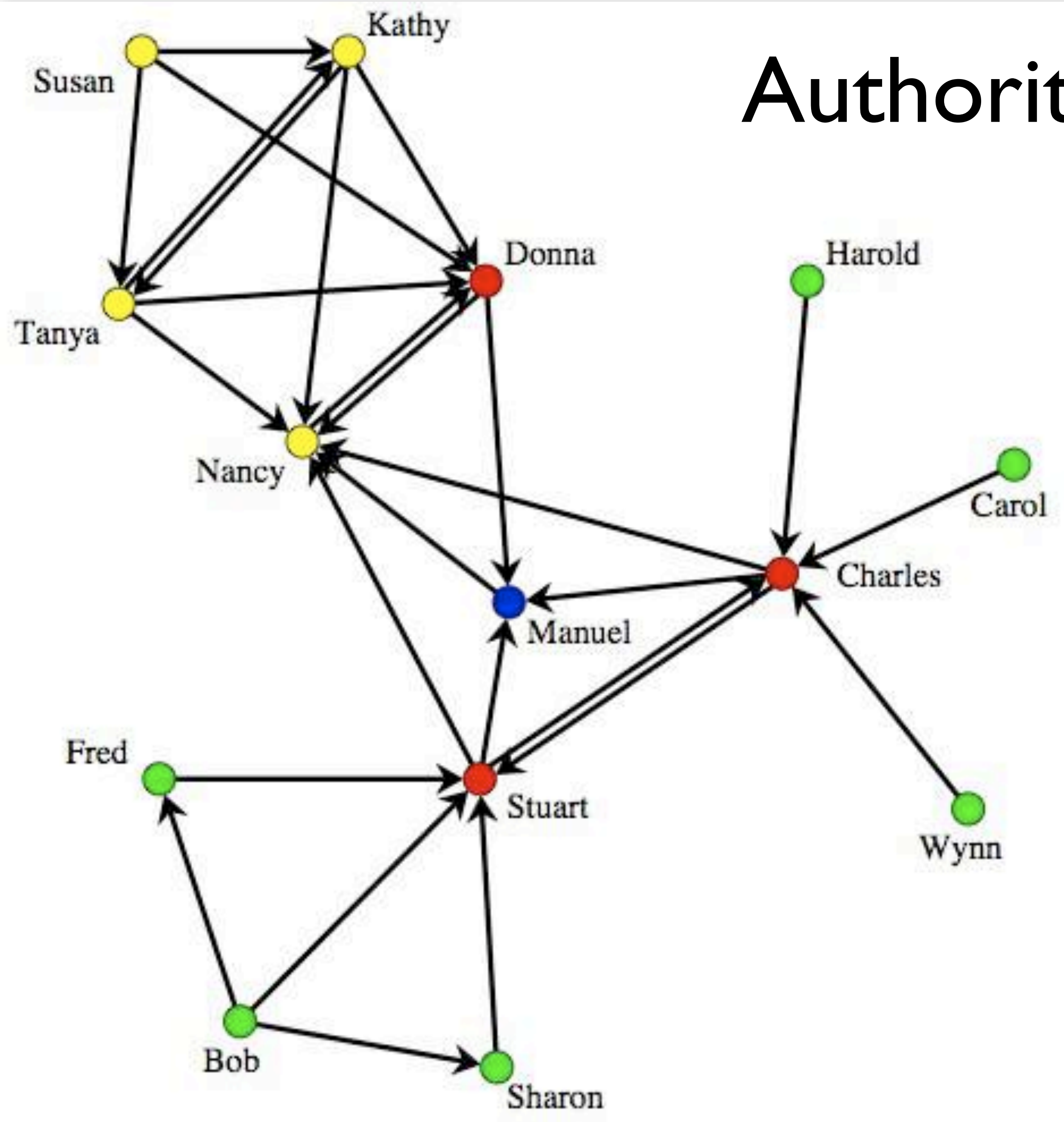


Organizational Chart



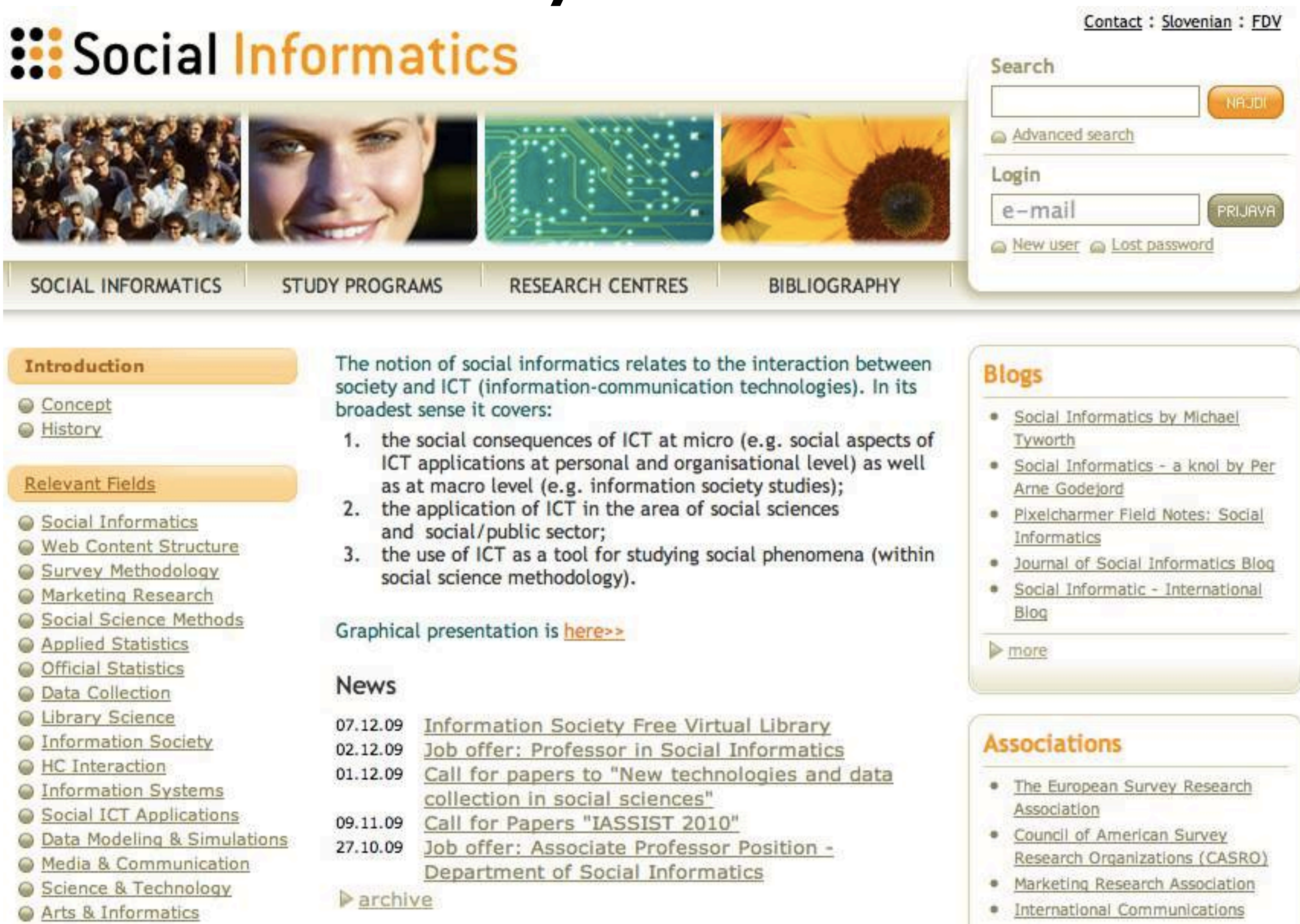
Social Network Chart

Authority vs. Importance

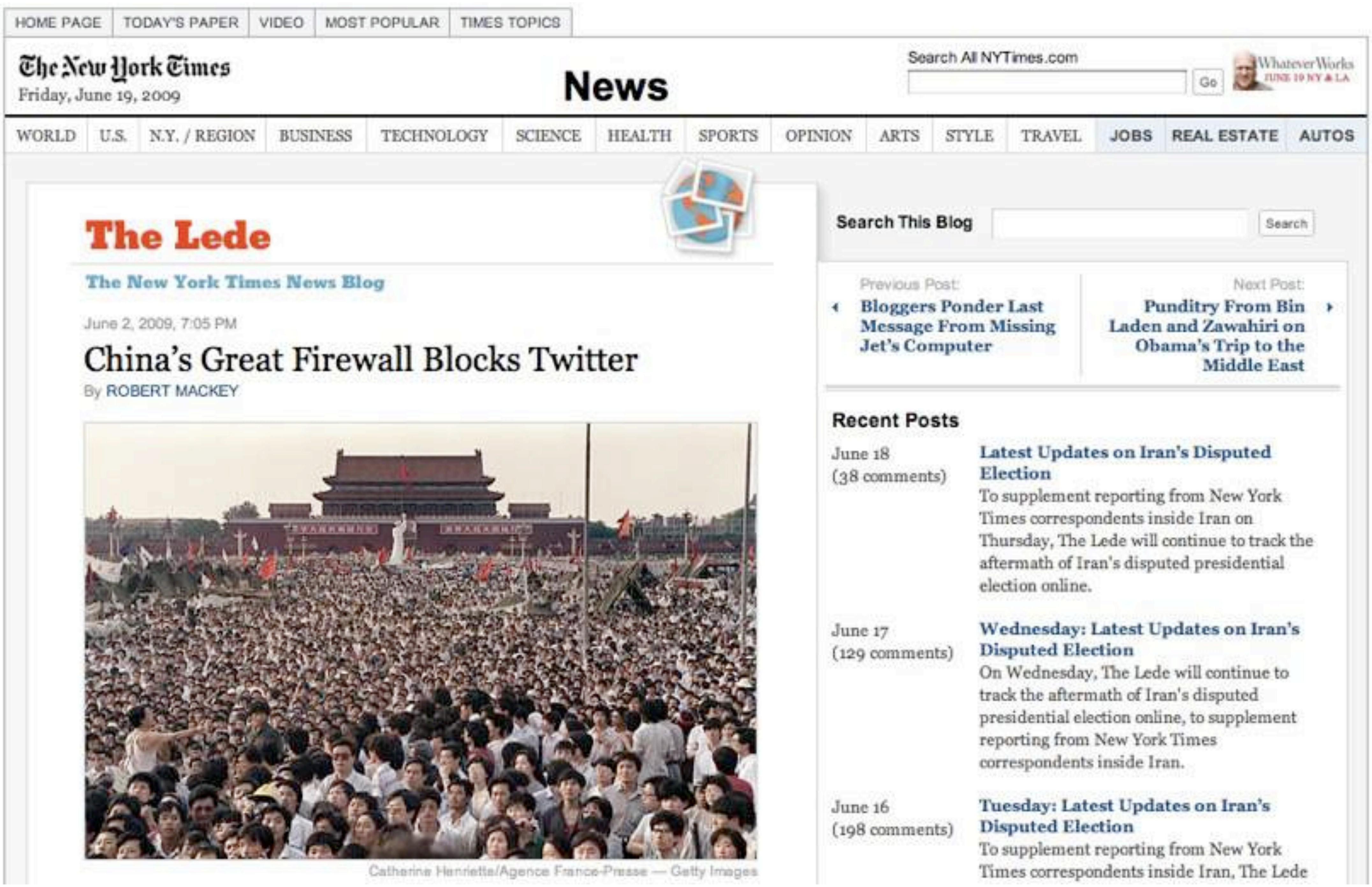


1.00	Nancy	(secretary)
0.66	Donna	(supervisor)
0.57	Manuel	(manager)
0.19	Stuart	(supervisor)
0.17	Charles	(supervisor)
0.08	Kathy	(secretary)
	Tanya	(secretary)
0.02	Fred	(auditor)
	Sharon	(auditor)
0.00	Bob	(auditor)
	Carol	(auditor)
	Harold	(auditor)
	Wynn	(auditor)
	Susan	(secretary)

Social Analytics/Informatics



Politics


HOME PAGE
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VIDEO
MOST POPULAR
TIMES TOPICS
The New York Times
Friday, June 19, 2009
News
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Go
WORLD
U.S.
N.Y. / REGION
BUSINESS
TECHNOLOGY
SCIENCE
HEALTH
SPORTS
OPINION
ARTS
STYLE
TRAVEL
JOBS
REAL ESTATE
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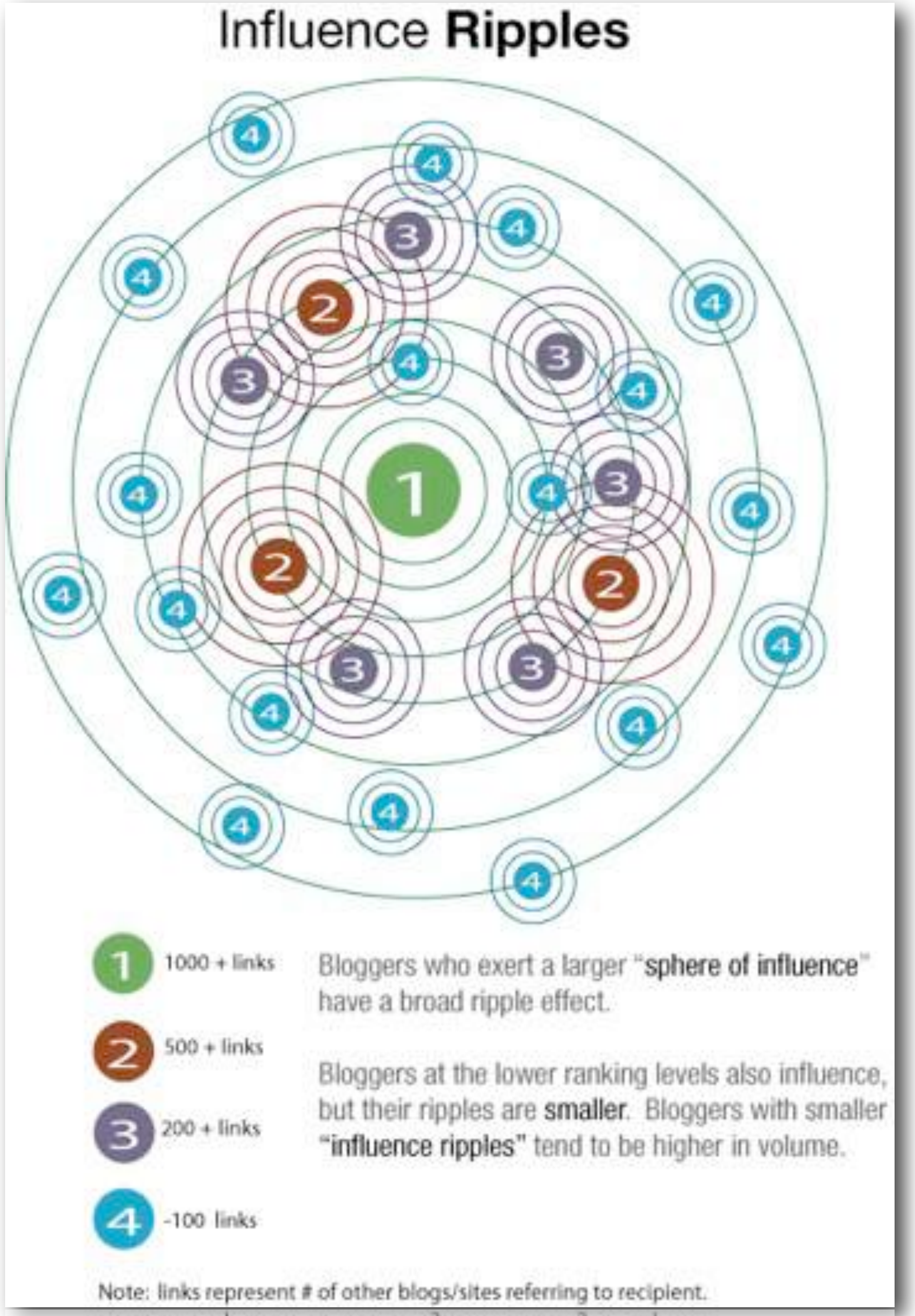
To supplement reporting from New York Times correspondents inside Iran on Thursday, The Lede will continue to track the aftermath of Iran's disputed presidential election online.
June 17
(129 comments)
Wednesday: Latest Updates on Iran's Disputed Election
On Wednesday, The Lede will continue to track the aftermath of Iran's disputed presidential election online, to supplement reporting from New York Times correspondents inside Iran.
June 16
(198 comments)
Tuesday: Latest Updates on Iran's Disputed Election
To supplement reporting from New York Times correspondents inside Iran, The Lede

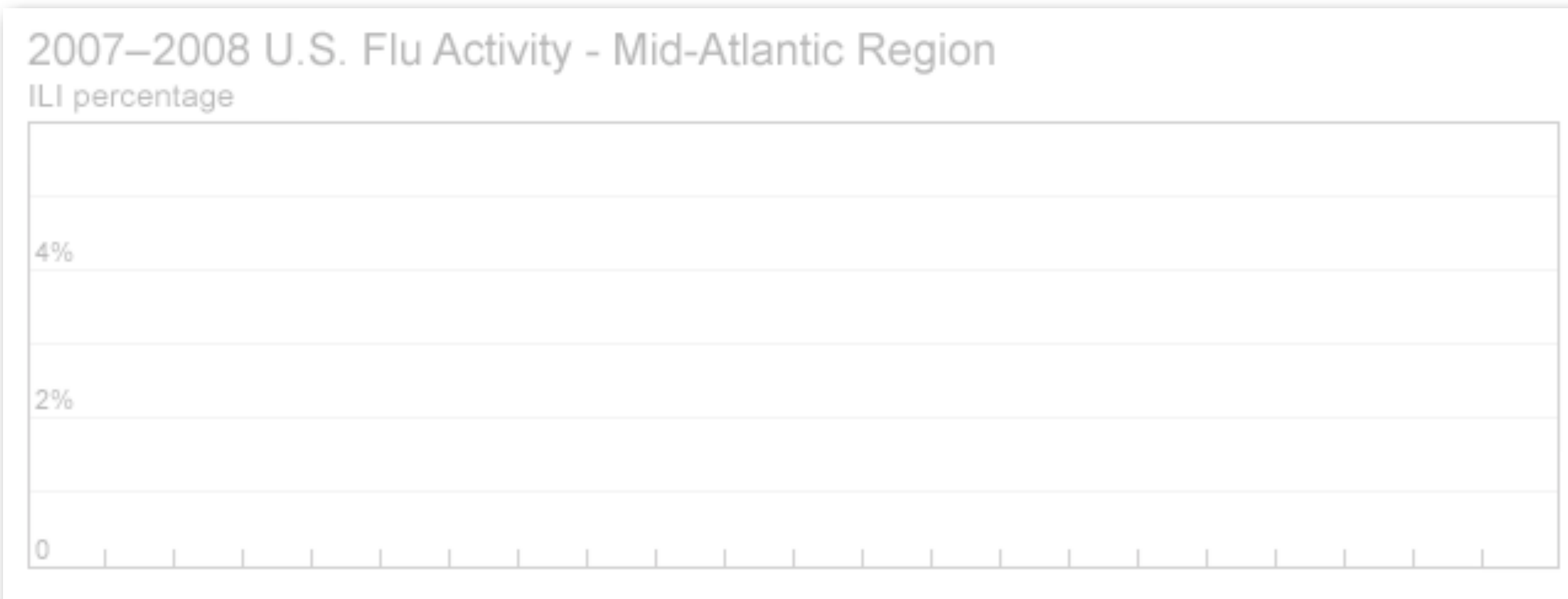
Commerce

- Social marketing
- Who are the brokers?
- Who can exert the most influence on buying/selling?
- How much should one advertise?



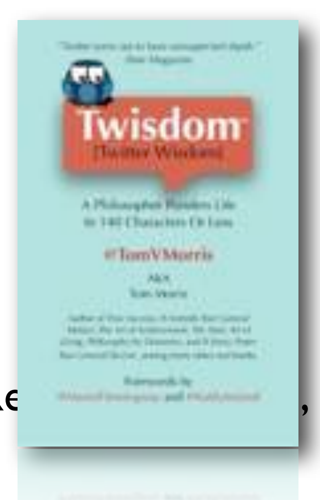
Public Health

- People's behavior can be monitored
- What is on people's mind translates to search queries
- Google predicts flu trends...



Twitter Pop Culture

- Twisdom: Twitter Wisdom
  - A Philosopher Ponders Life in 140 Characters or Less
    - "I don't know the key to success, but the key to failure is trying to please everybody." Bill Cosby Do what you know in your soul is right!
    - It is a miserable state of mind to have few things to desire, and many things to fear. – Francis Bacon
- The Longest Poem In the World-the awesome twitter poem! 956,644 verses this morning and ~4,000 a day!



The YouTube Generation

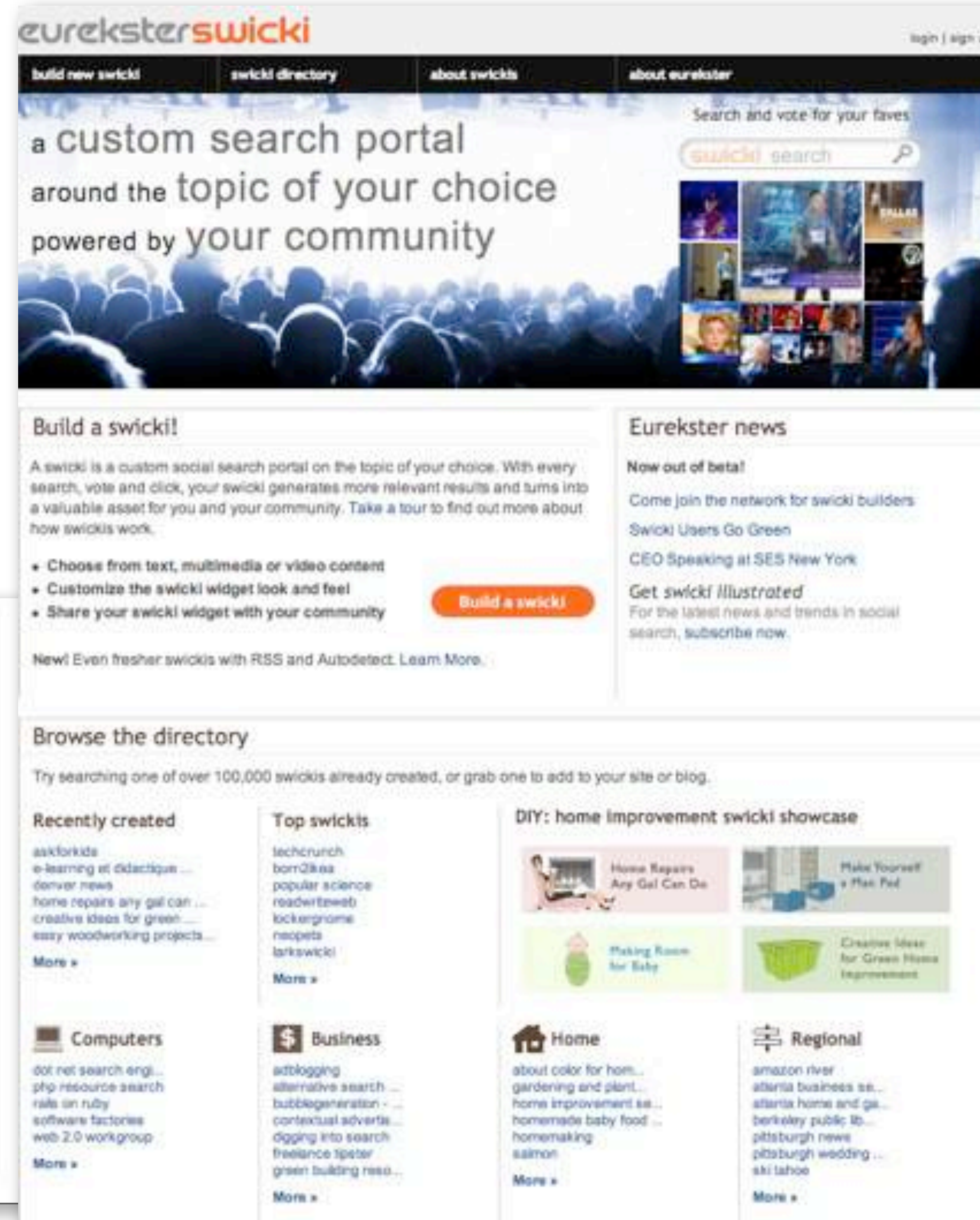
The Age of FaceBook

Social Networking Sites

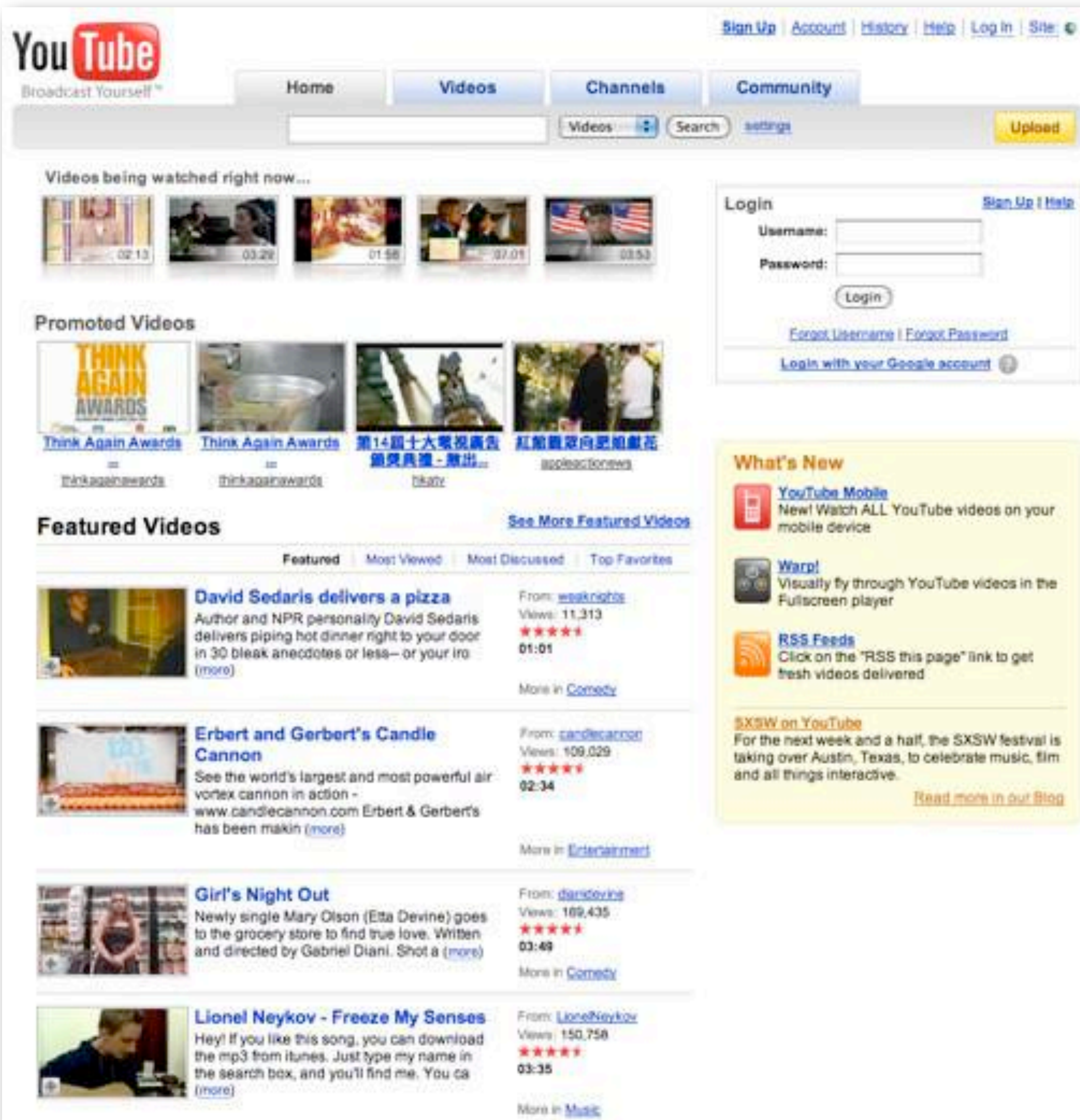
- Example of Social Networking Sites: FaceBook, MySpace, Blogger, QQ, etc.

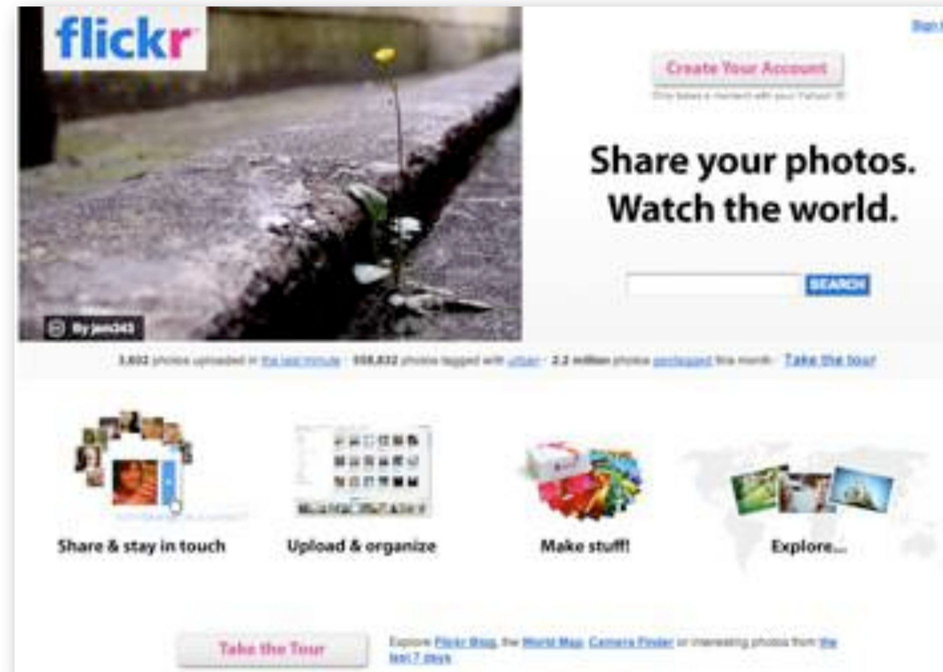
Social Search

- Social Search Engine
- Leveraging your social networks for searching



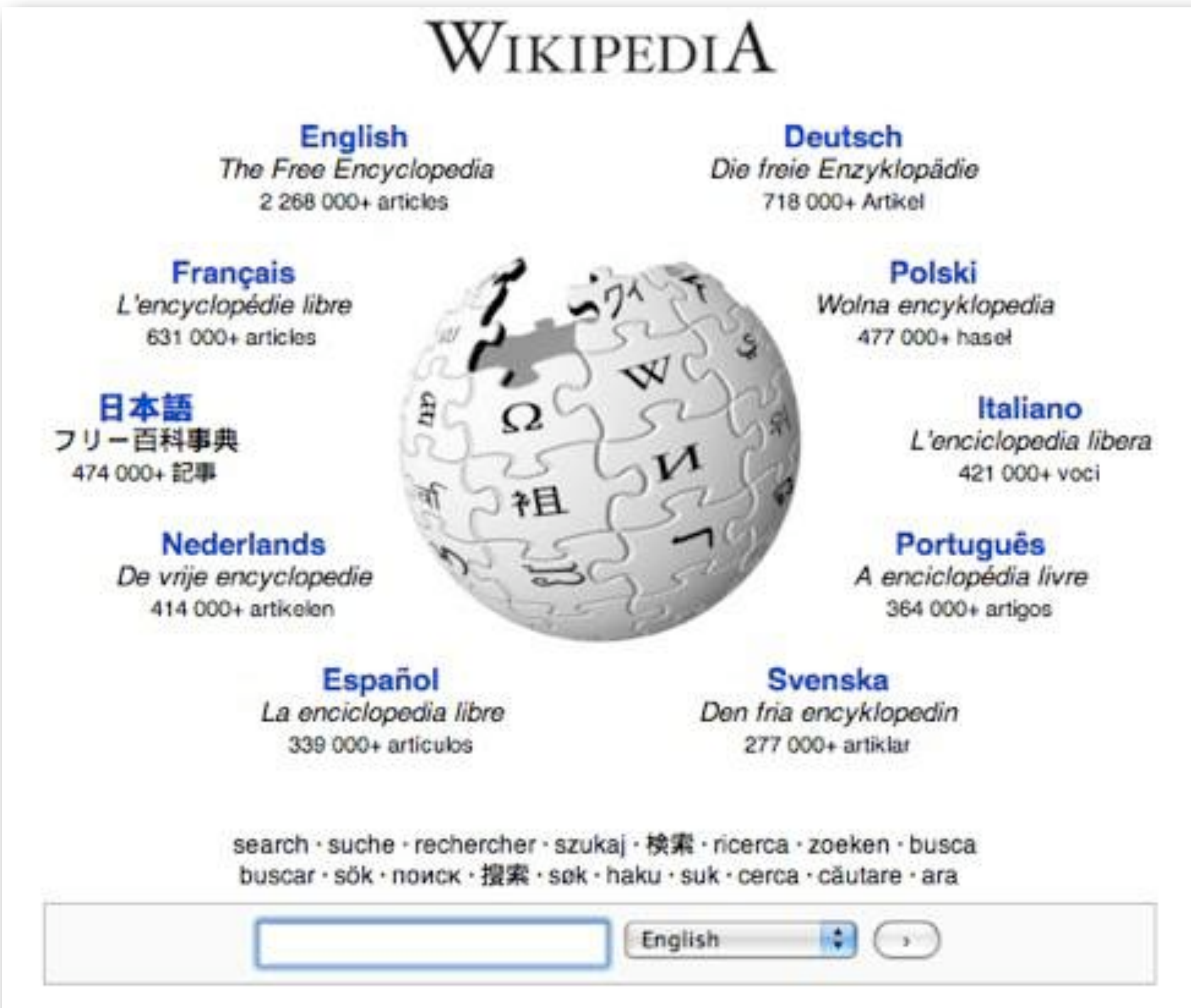
Social Media



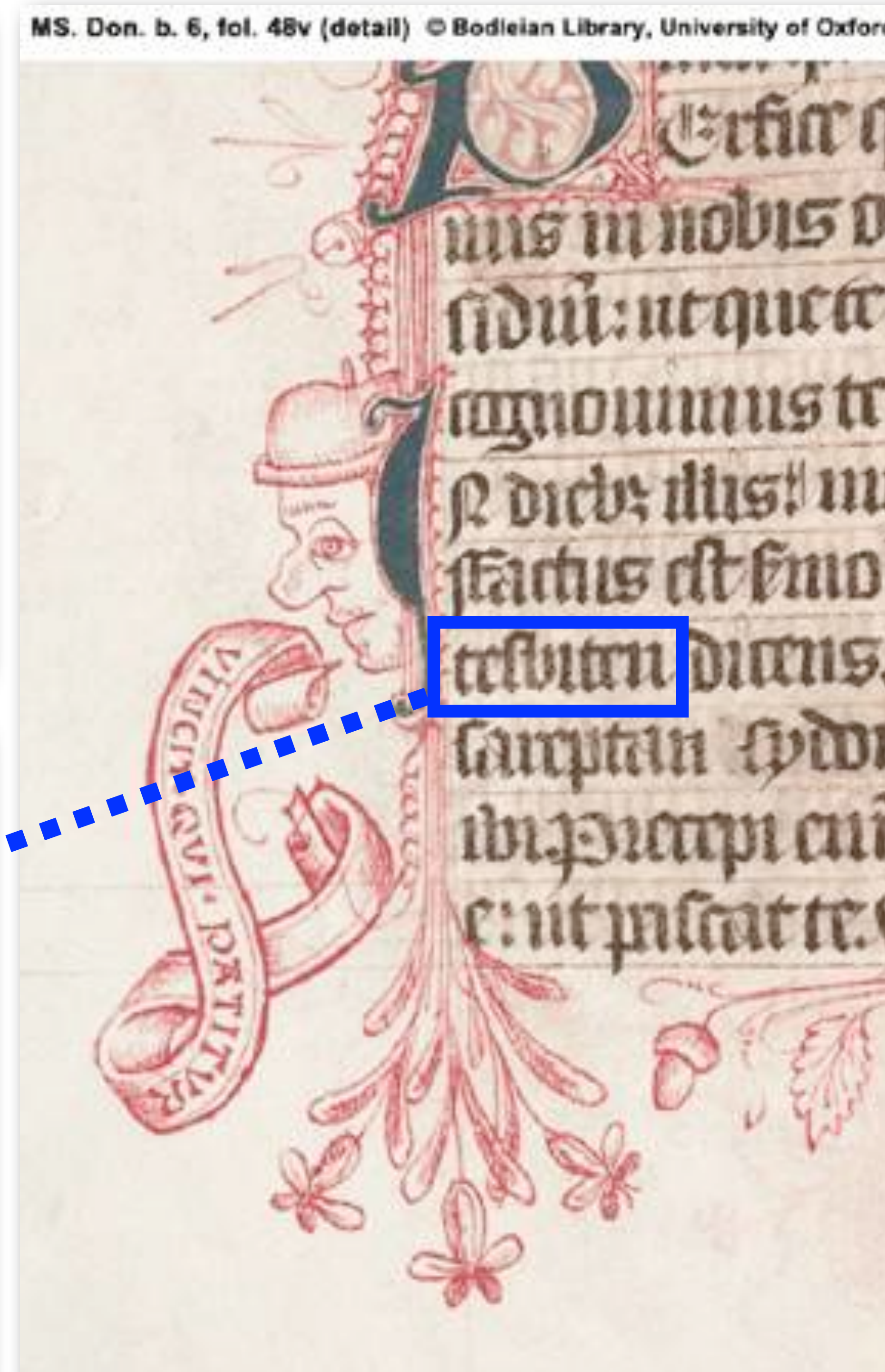


Social News/Mash Up

Social Knowledge Sharing

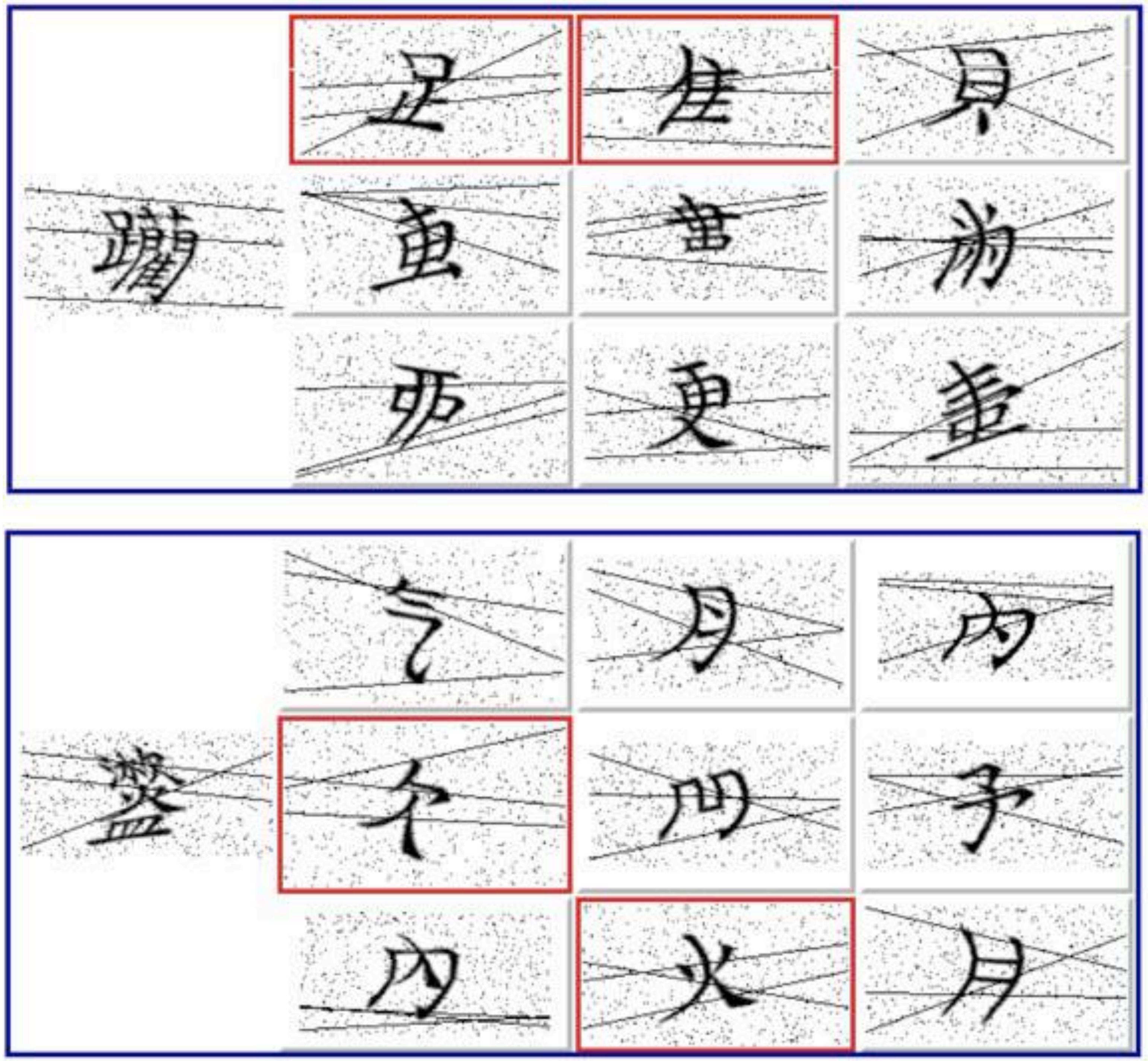


Social/Human Computation

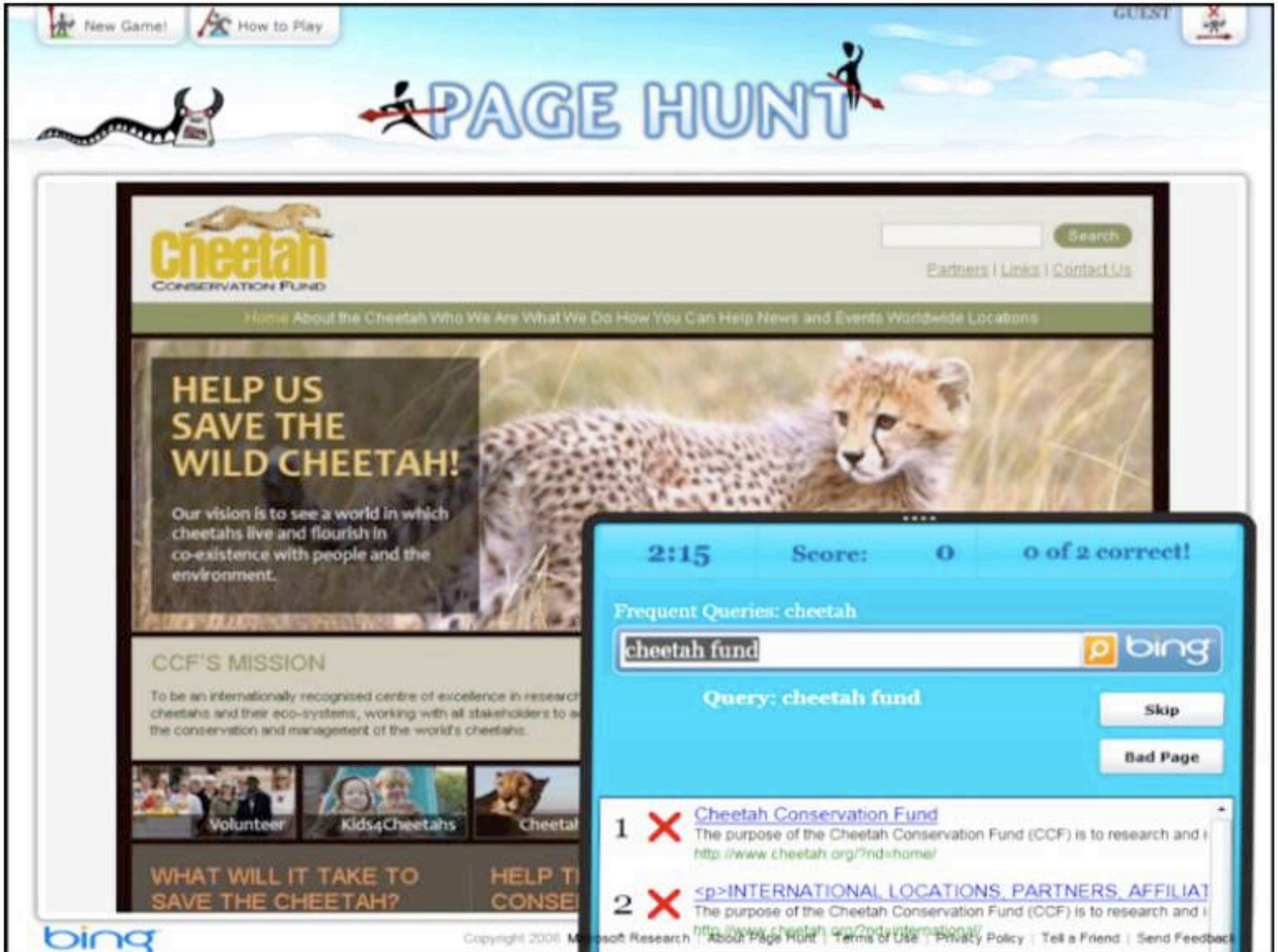


Chinese CAPTCHA

Ling-Jyh Chen, Institute of Information Science, Academia Sinica, Taipei, Taiwan



Human Computation

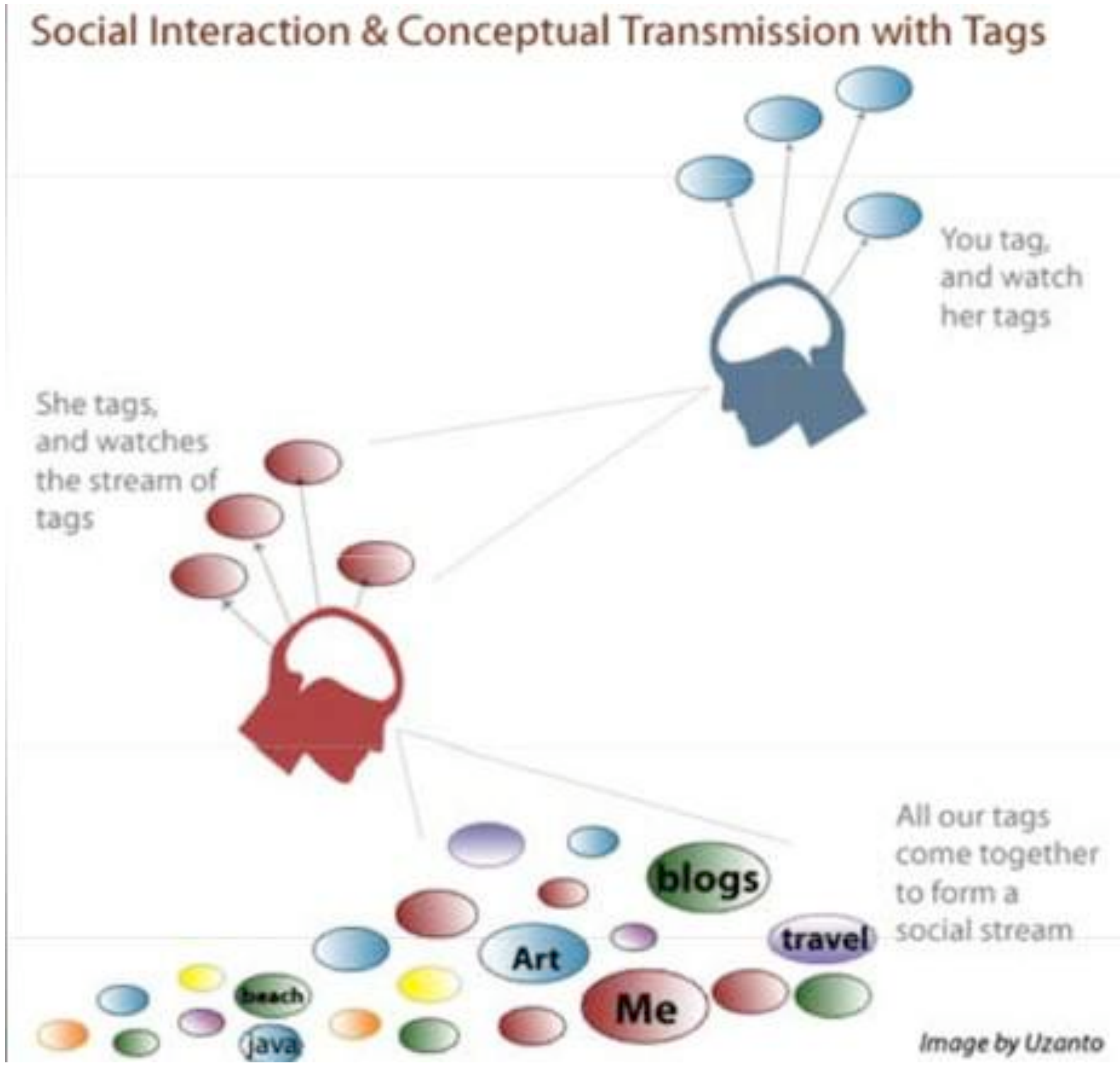


Social Bookmarking

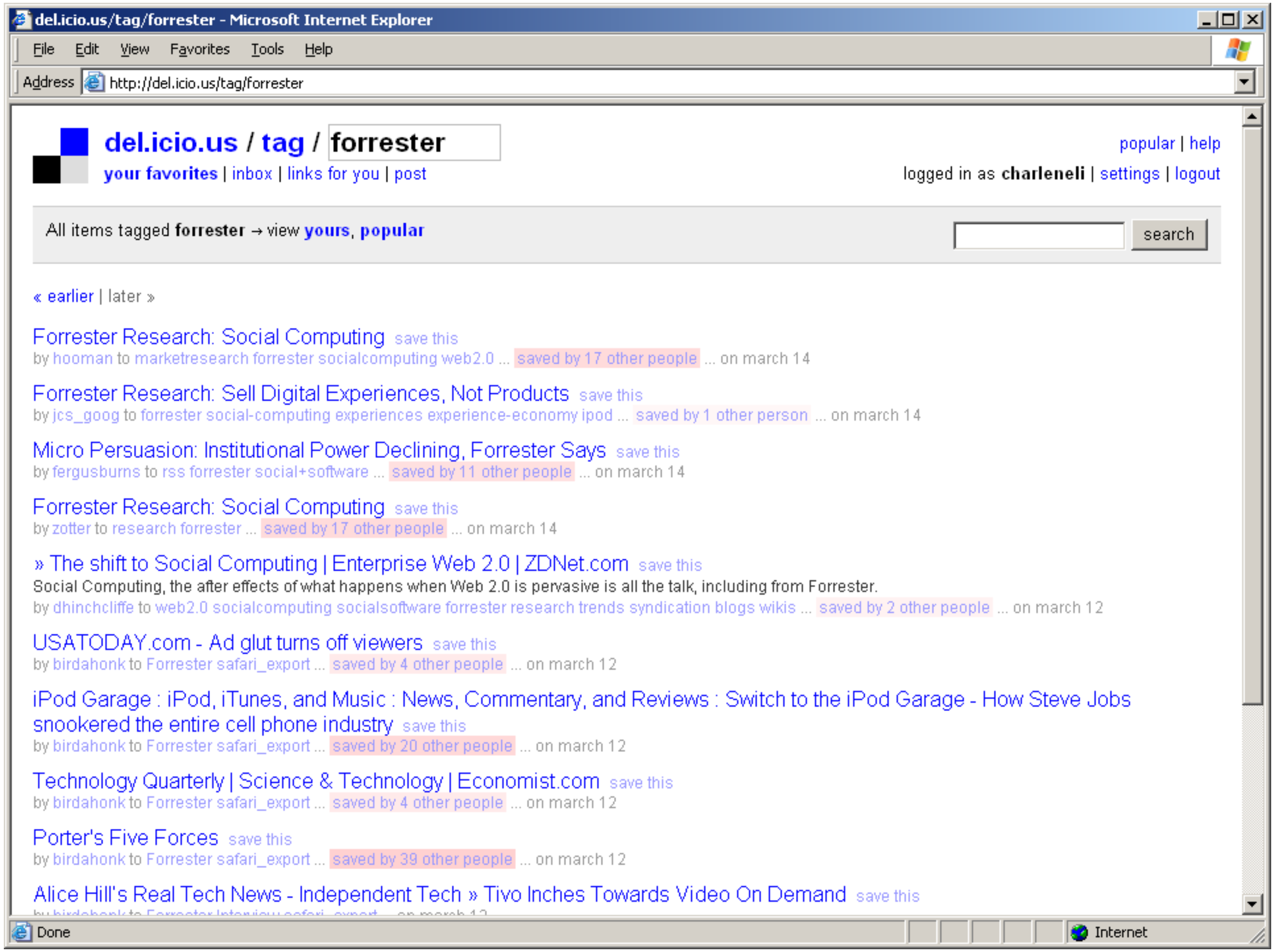
- What is a tag?
  - Descriptive metadata
  - A keyword or term associated with or assigned to a piece of information
  - User defined, created and shared
  - Many web users do it every day, with very little conscious awareness that they are "cataloging"
- What gets tagged?
  - Pictures, blog posts, video clips, catalog entries, just about anything...

Social Bookmarking

- Share one's tags
- Make the individual browsing experience a social one



Social Bookmarking in del.icio.us

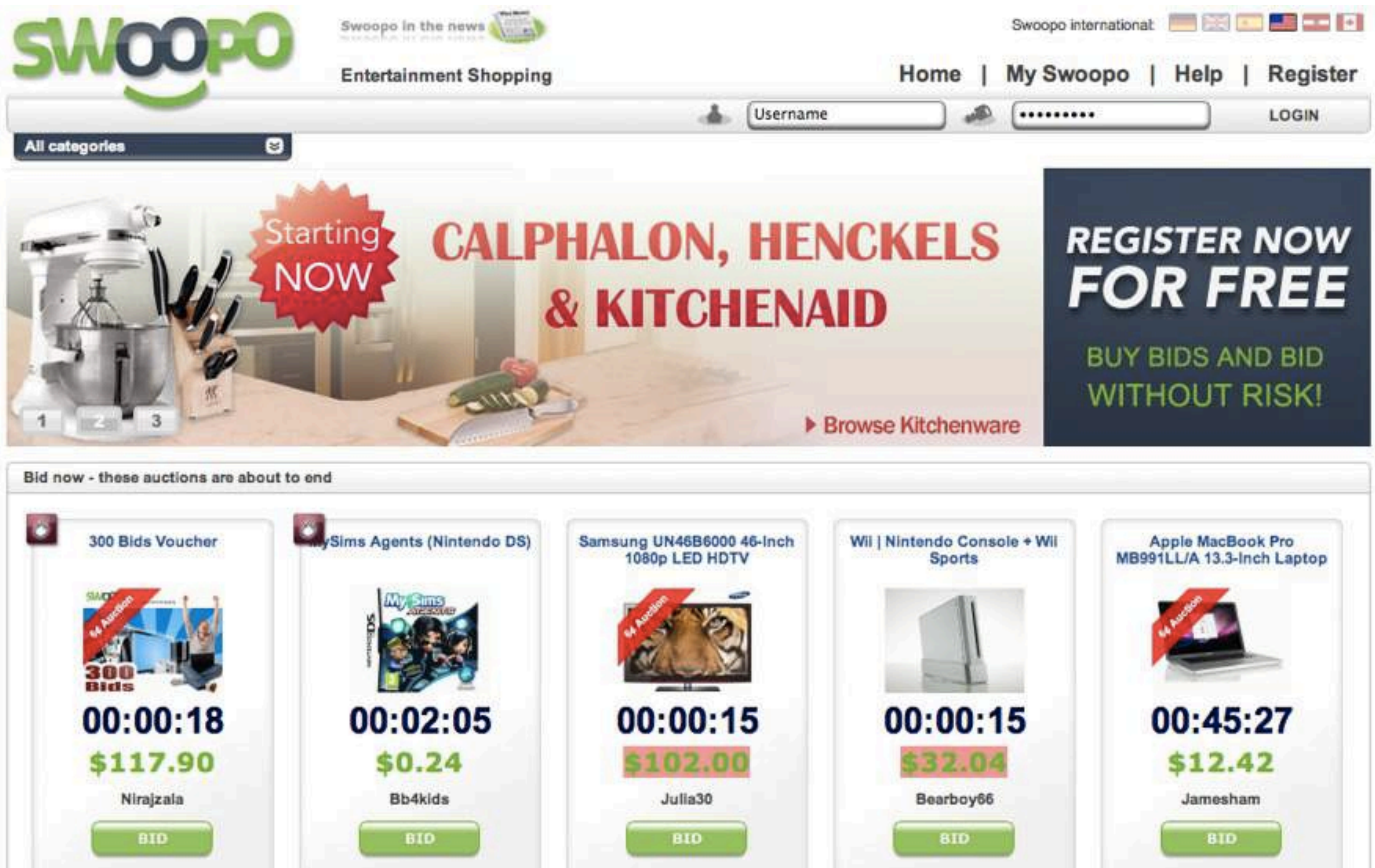


Social Bookmarking in StumbleUpon

StumbleUpon allows users to discover and rate web pages, photos, and videos. It chooses which web page to display based on the user's ratings of previous pages, ratings by his/her friends, and by the ratings of users with similar interests.

Tagging is Everywhere

Social Entertainment



Social Recommendations

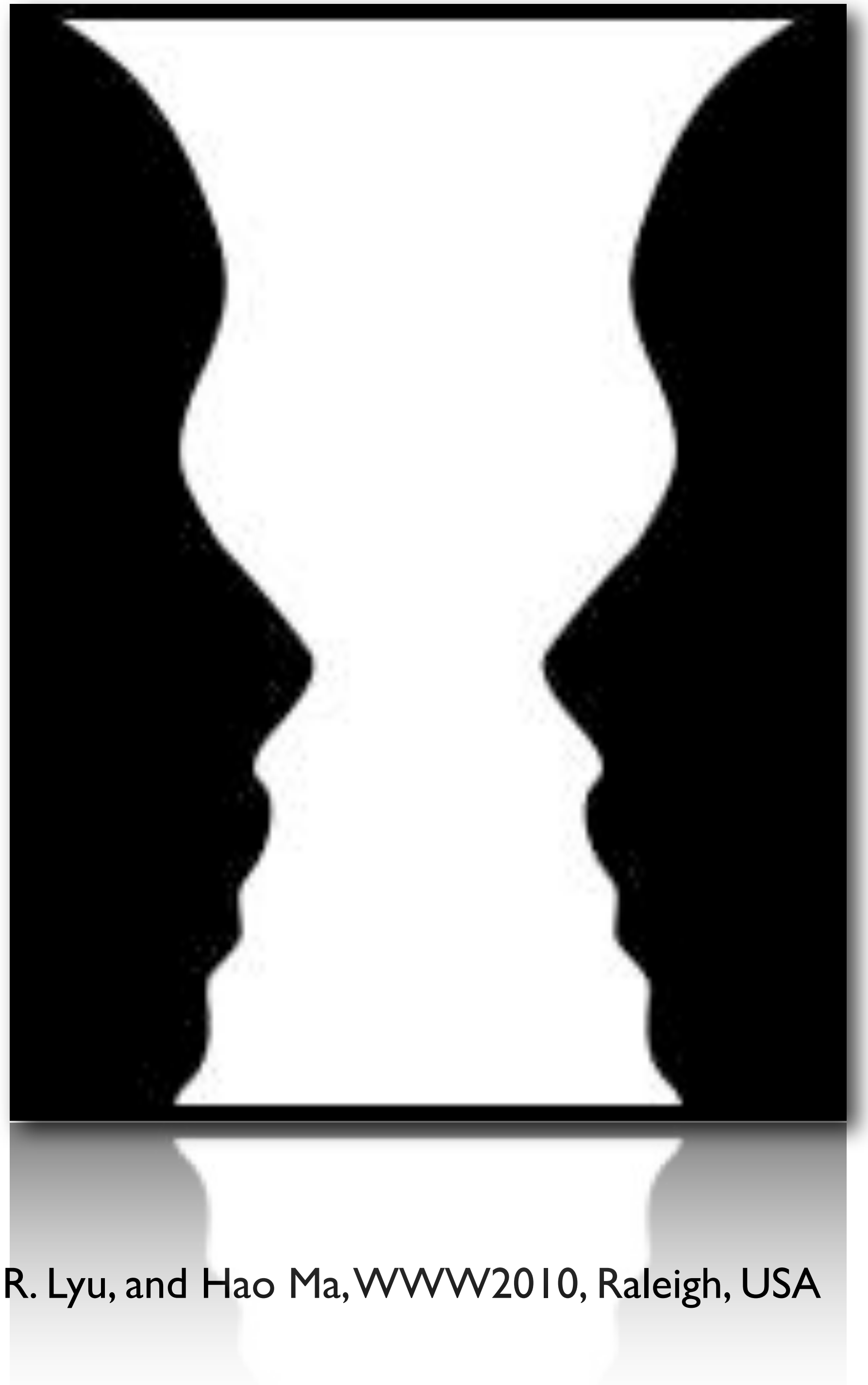
Web 2.0 Revolution

- Glocalization-think globally and act locally!
- Weblication-Web is the application!
- Three C's

Connectivity

Collaboration

Communities



Social Relations

crew
teams
populations
squad
organizations
cohorts
markets
communities
partners
groups

binary
cardinal
integer
real

presence
identity
social role
reputation
expertise
trust
ownership
accountability
knowledge

Social Recommendation

social network services

wikis

blogs

emails

instant messaging

mobile devices

social bookmarking

ranking

tagging

collaborative filtering

social marketing

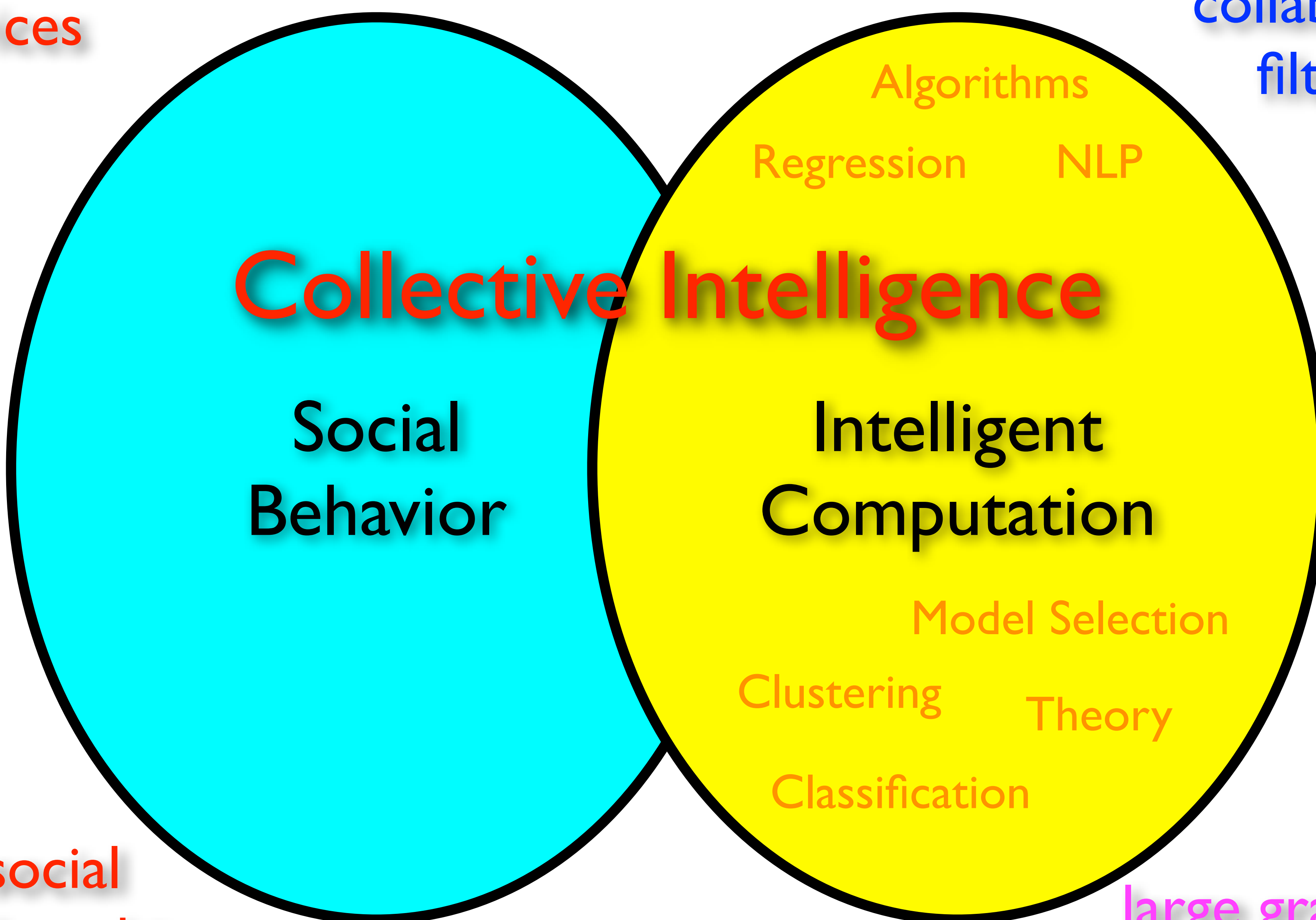
human computation

opinion mining/ sentiment analysis

query logs analysis

large graph algorithms

security & privacy



Emerging Issues

- Theory and models
- Seach, mining, ranking and recommending of existing information, e.g., spatial (relations) and temporal (time) domains
  - Dealing with partial and incomplete information, e.g., collaborative filtering, ranking, tagging, etc.
- Scalability and algorithmic issues
- Security and privacy issues
- Monetization of social interactions

Introduction

- Social Platforms
- Techniques in Social Recommendation
  - Social Network Theory
  - Graph/Link Mining
  - Collaborative Filtering
  - Machine Learning Techniques
- Summary

Social Network Theory

- Consider many kinds of networks:
  - social, technological, business, economic, content, ...
- These networks tend to share certain informal properties:
  - large scale; continual growth
  - distributed, organic growth: vertices "decide" who to link to
  - interaction restricted to links
  - mixture of local and long-distance connections
  - abstract notions of distance: geographical, content, social,…

Social Network Theory

- Do these networks share more quantitative universals?
- What would these “universals” be?
- How can we make them precise and measure them?
- How can we explain their universality?
- This is the domain of social network theory

Some Interesting Quantities

- Connected components
  - how many, and how large?
- Network diameter
  - maximum (worst-case) or average?
  - exclude infinite distances? (disconnected components)
  - the small-world phenomenon
- Clustering
  - to what extent that links tend to cluster "locally"?
  - what is the balance between local and long-distance connections?
  - what roles do the two types of links play?
- Degree distribution
  - what is the typical degree in the network?
  - what is the overall distribution?

Graph/Link Mining

- Heterogeneous, multi-relational data represented as a graph or network
  - Nodes are objects
    - Objects have attributes
    - Objects may have labels or classes
  - Edges are links
    - Links may have attributes
    - Links may be directed
- Links represent relationships and interactions between objects -- rich content for mining

What Is New For Mining

- Traditional machine learning and data mining approaches assume:
  - A random sample of homogeneous objects from single relation
- Real world data sets:
  - Multi-relational, heterogeneous and semi-structured
- Link Mining
  - Newly emerging research area at the intersection of research in social network and link analysis, hypertext and web mining, graph mining, relational learning and inductive logic programming

What is a Link in Link Mining

- Link: relationship among data
- Homogeneous networks
  - Single object type and single link type
  - Single model social networks (e.g., friends)
  - WWW: a collection of linked Web pages
- Heterogeneous networks
  - Multiple object and link types
  - Medical network: patients, doctors, disease, contacts, treatments
  - Bibliographic network: publications, authors, venues

Real life Example for Collaborative Filtering

- User's perspective
  - Lots of online products, books, movies, etc
  - Reduce my choices

- Manager's perspective

"if I have 3 million customers on the web, I should have 3 million stores on the web."

CEO of Amazon.com

More Examples

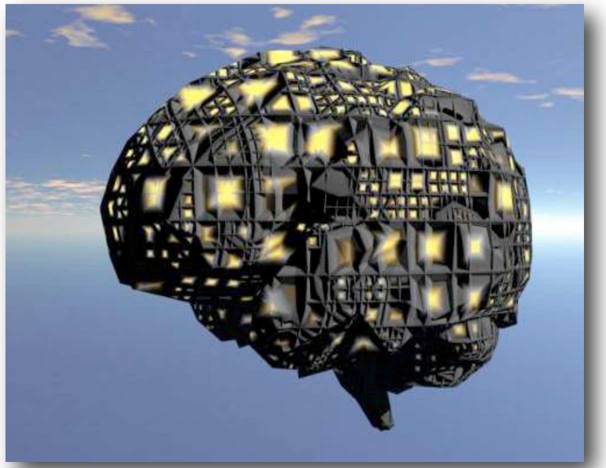
- Movielens: movies
- Moviecritic: movies again
- My launch: music
- Gustos starrater: web pages
- Jester: Jokes
- TV Recommender: TV shows
- Suggest 1.0: different products
- And much more…

How it Works?

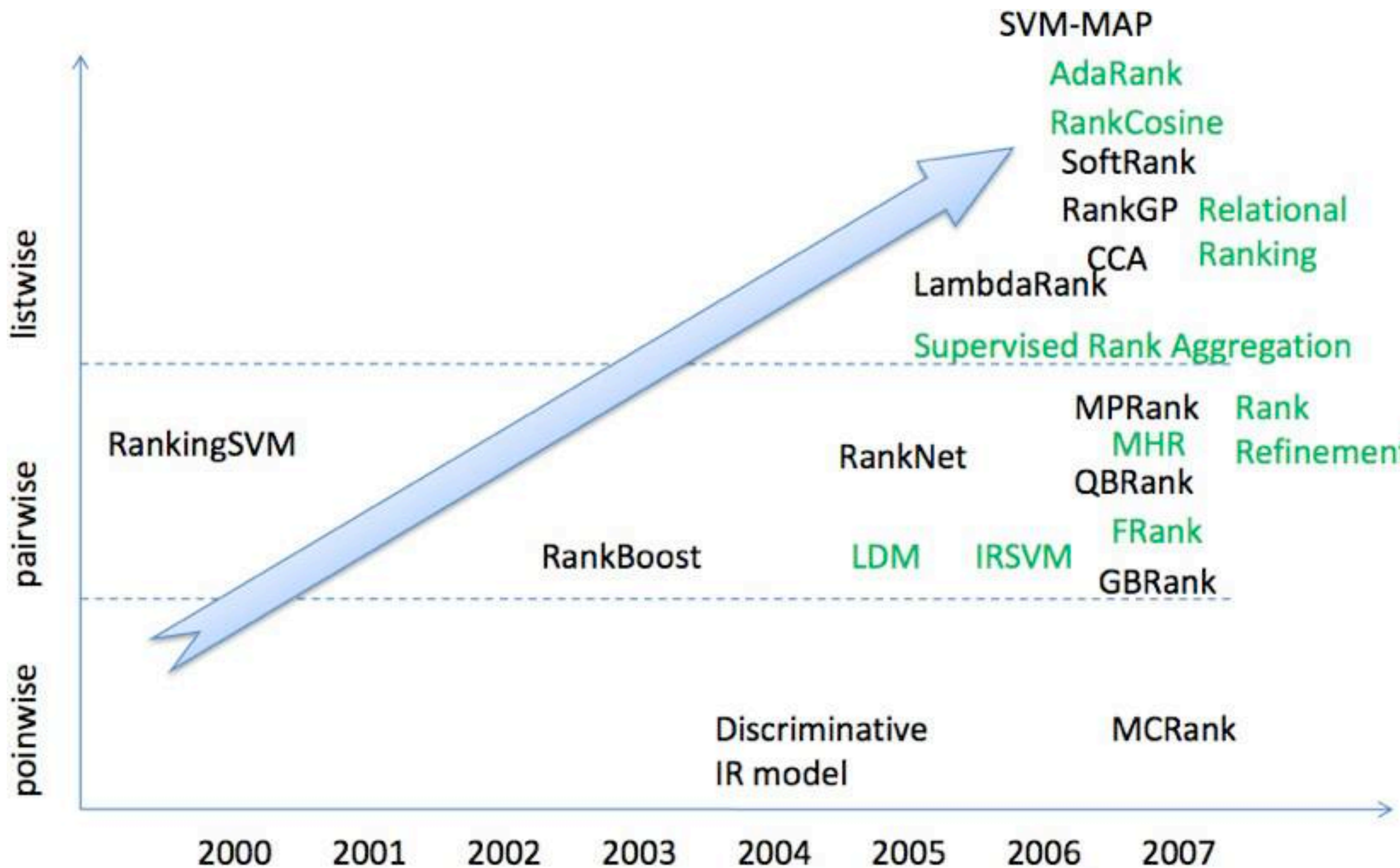
- Each user has a profile
- Users rate items
  - Explicitly: score from 1..5
  - Implicitly: web usage mining
    - Time spent in viewing the item
    - Navigation path, etc…
- System does the rest, How?
  - Look at users collective behavior
  - Look at the active user history

Machine Learning Can Help

- Machine learning is an effective tool
  - To automatically tune parameters
  - To combine multiple evidences
  - To avoid over-fitting (by means of regularization, etc.)
- Learning to Rank
  - Use machine learning technologies to train the ranking model
  - A hot research topic these years



Learning To Rank Techniques



http://research.microsoft.com/en-us/people/tyliu/default.aspx

Summary

- Social Platforms
  - Social Network
  - Social Media
  - Social games
  - Social bookmarking
  - Social News and Social Knowledge Sharing
- Techniques in Social Recommendation
  - Social Network Theory
  - Graph/Link Mining
  - Collaborative Filtering
  - Machine Learning Techniques

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Outline

- Introduction
- Social Search Engine
- Social Recommender Systems
- Social Media Analysis

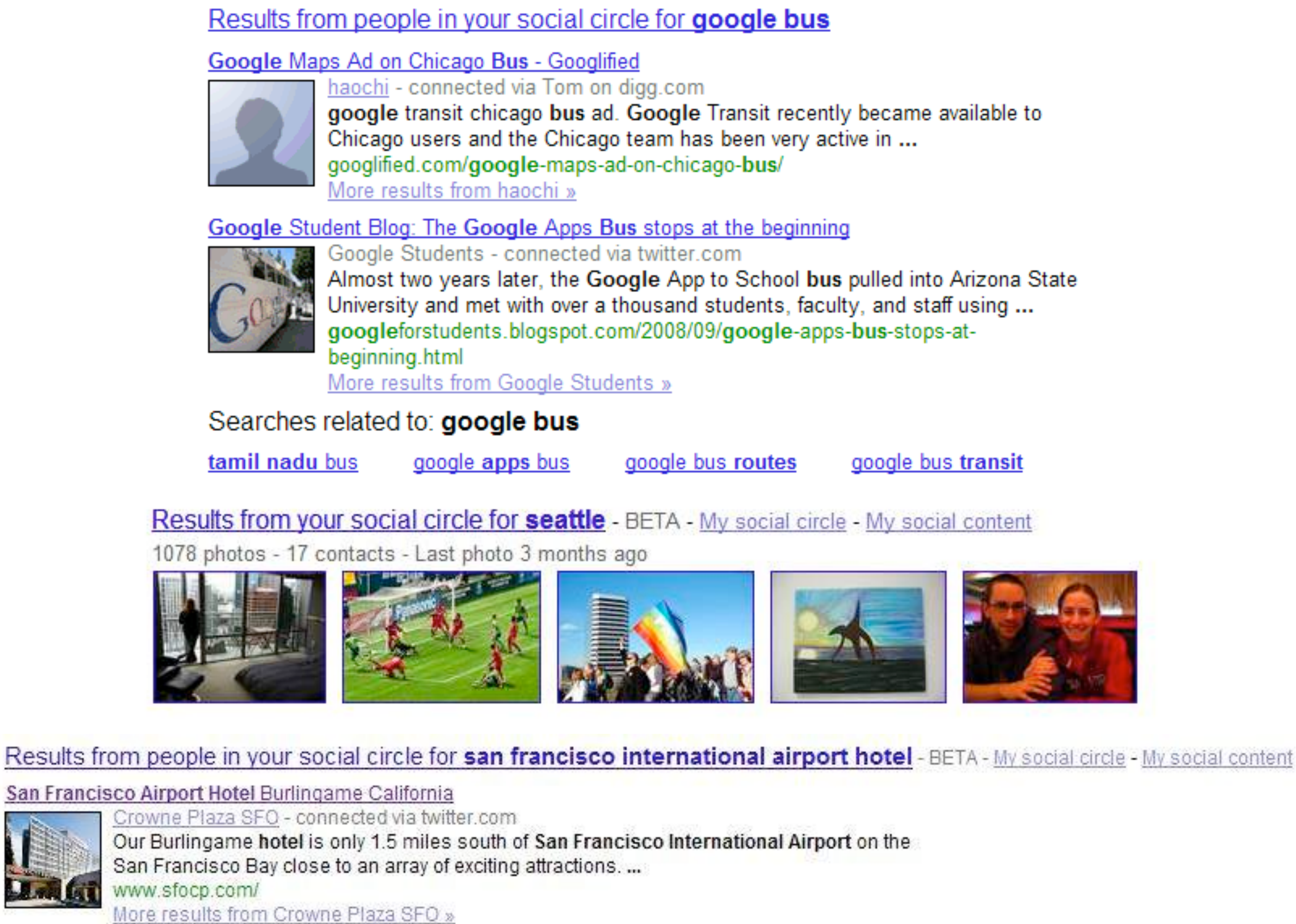
Macro Definition

- Search in
  - Shared bookmarks
  - Collaborative directories
  - Collaborative news/opinions
  - Social Q&A sites
  - etc...

Micro Definition
Leveraging Your Social Networks for Searching

Leveraging All Kinds of Web Accounts

Google's Social Search


Results from people in your social circle for **google bus**

Google Maps Ad on Chicago Bus - Googlified
haochi - connected via Tom on digg.com
google transit chicago **bus** ad. **Google** Transit recently became available to Chicago users and the Chicago team has been very active in ...
googlified.com/**google**-maps-ad-on-chicago-**bus**/
More results from haochi »

Google Student Blog: The Google Apps Bus stops at the beginning
Google Students - connected via twitter.com
Almost two years later, the **Google** App to School **bus** pulled into Arizona State University and met with over a thousand students, faculty, and staff using ...
googleforstudents.blogspot.com/2008/09/**google**-apps-**bus**-stops-at-beginning.html
More results from Google Students »

Searches related to: **google bus**

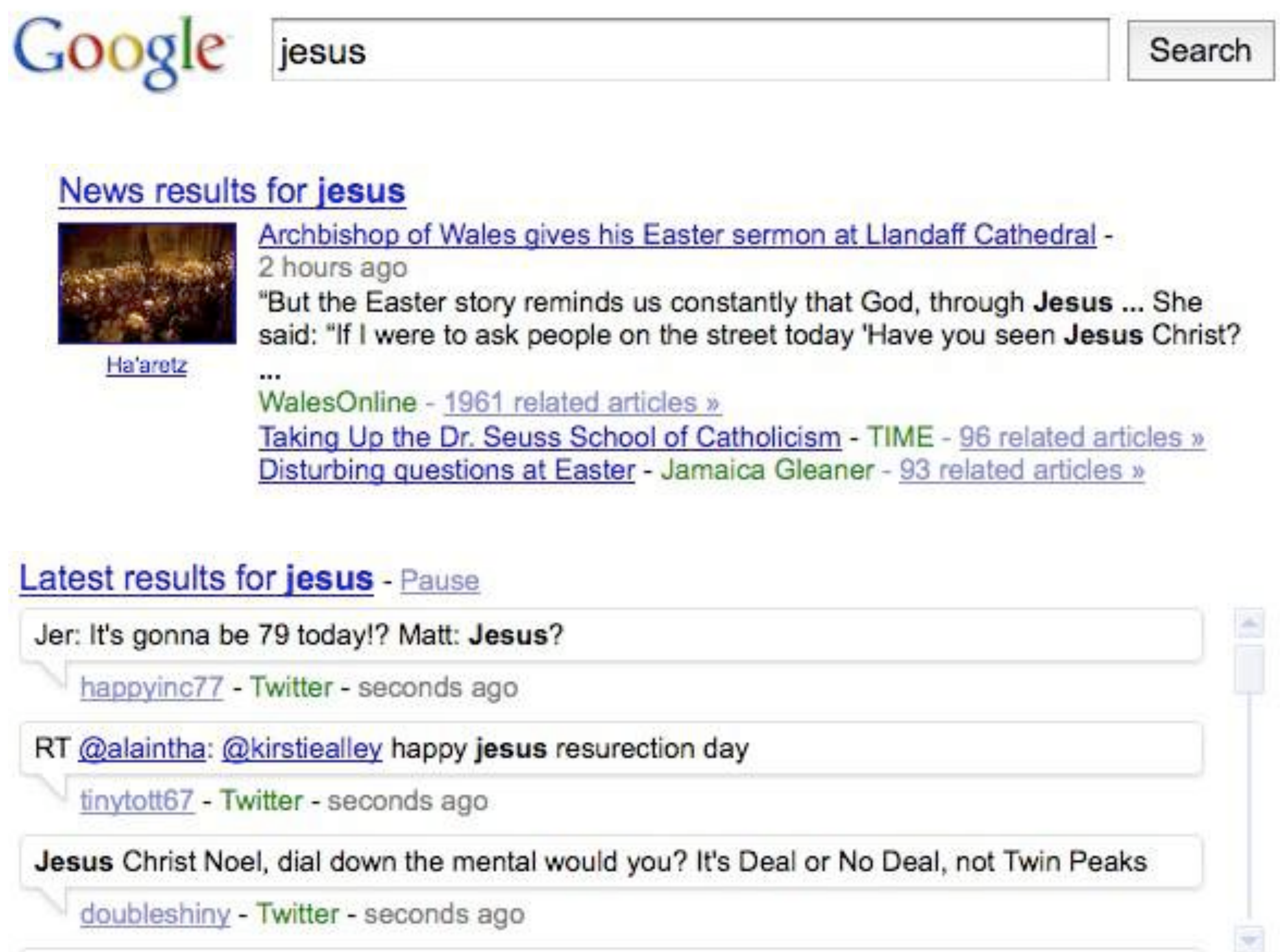
tamil nadu bus   google **apps** bus   google bus **routes**   google bus **transit**

Results from your social circle for **seattle** - BETA - My social circle - My social content
1078 photos - 17 contacts - Last photo 3 months ago

Results from people in your social circle for **san francisco international airport hotel** - BETA - My social circle - My social content

San Francisco Airport Hotel Burlingame California
Crowne Plaza SFO - connected via twitter.com
Our Burlingame **hotel** is only 1.5 miles south of **San Francisco International Airport** on the San Francisco Bay close to an array of exciting attractions. ...
www.sfocp.com/
More results from Crowne Plaza SFO »

Google's Social Search



Aardvark

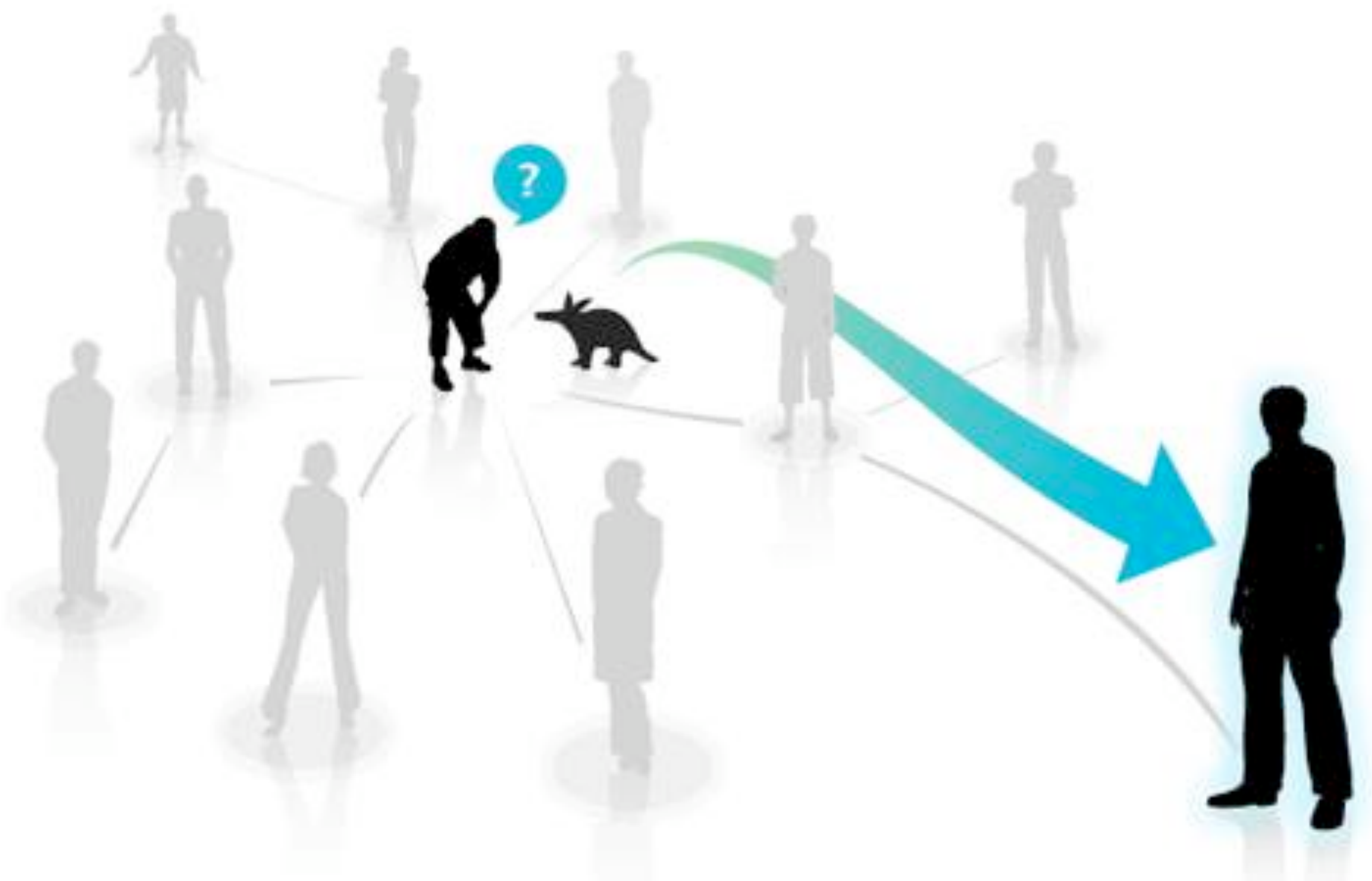

Ask a question and I'll find someone to answer
What's the best...
Example questions
Ask someone
1. Send Aardvark a question
2. Aardvark finds the perfect person to answer
3. Get their response in a few minutes
What's a great biking path around Golden Gate Park?
Sent 11:16 AM PDT
My favorite is a secret trail that takes you to the beach...
Sent 11:20 AM PDT

Evolution of Search

- Question
  - Contents
  - Machine Intelligence (Dialog systems)
  - People
  - Friends
  - Hybrid

The Anatomy of A Large-Scale Social Search Engine

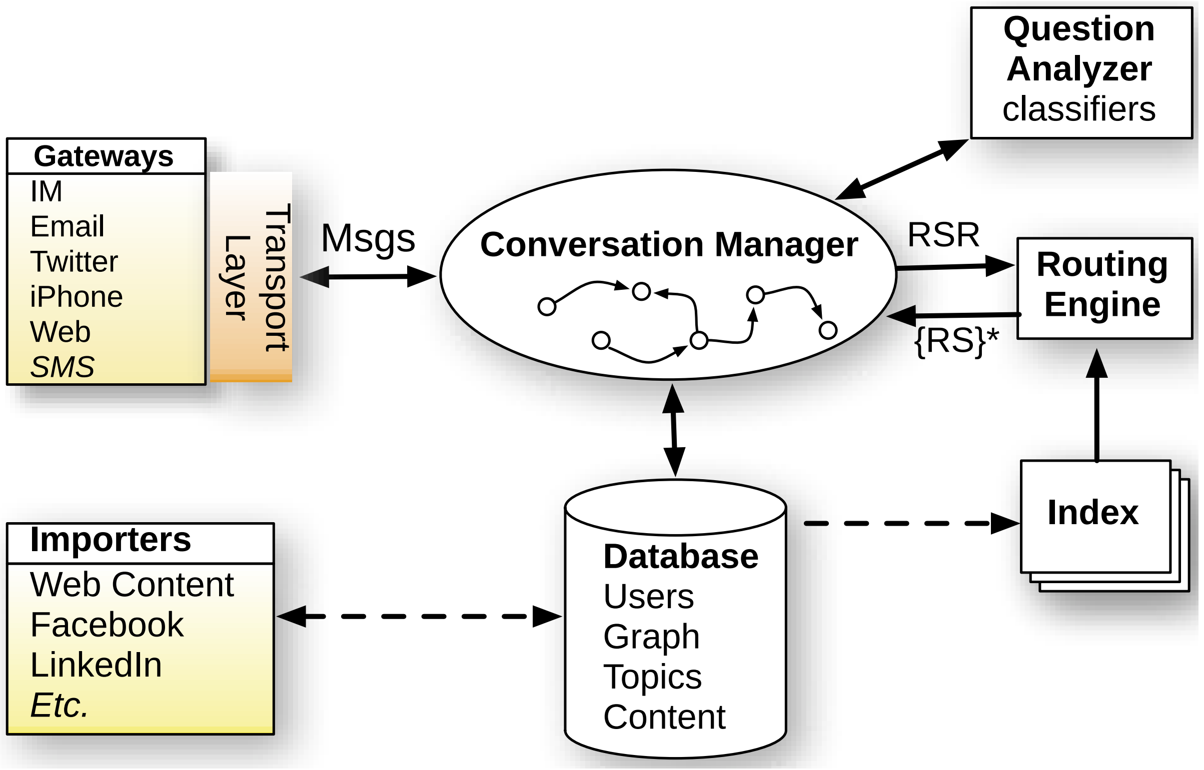
[D. Horowitz et al., WWW2010]



The Anatomy of A Large-Scale Social Search Engine

[D. Horowitz et al., WWW2010]

- Main components
  - Crawler and Indexer
  - Query Analyzer
  - Ranking Function
  - UI



The Anatomy of A Large-Scale Social Search Engine

[D. Horowitz et al., WWW2010]

- The model
  - With the topics *T*, the probability that user *i* will successfully answer question *q* is defined as

$$p(u_i|q) = \sum_{t \in T} p(u_i|t)p(t|q)$$

  - Given a question *q* from user *j*, return a ranked list of user *i* that maximizes $s(u_i, u_j, q)$

$$s(u_i, u_j, q) = p(u_i|u_j) \cdot p(u_i|q) = p(u_i|u_j) \sum_{t \in T} p(u_i|t)p(t|q)$$

The Anatomy of A Large-Scale Social Search Engine

[D. Horowitz et al., WWW2010]

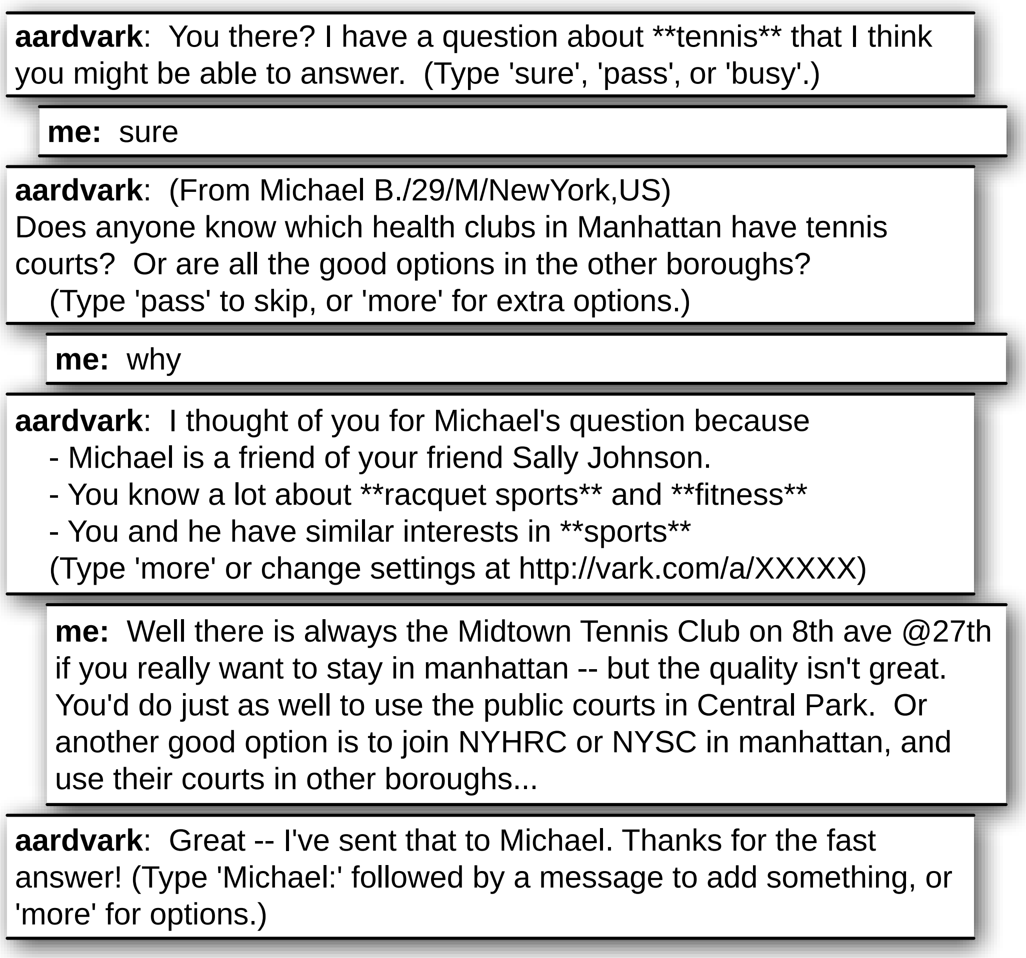


Figure 3: Example of Aardvark interacting with an answerer

Figure 4: Screenshot of Aardvark Answering Tab on iPhone

The Anatomy of A Large-Scale Social Search Engine

[D. Horowitz et al., WWW2010]

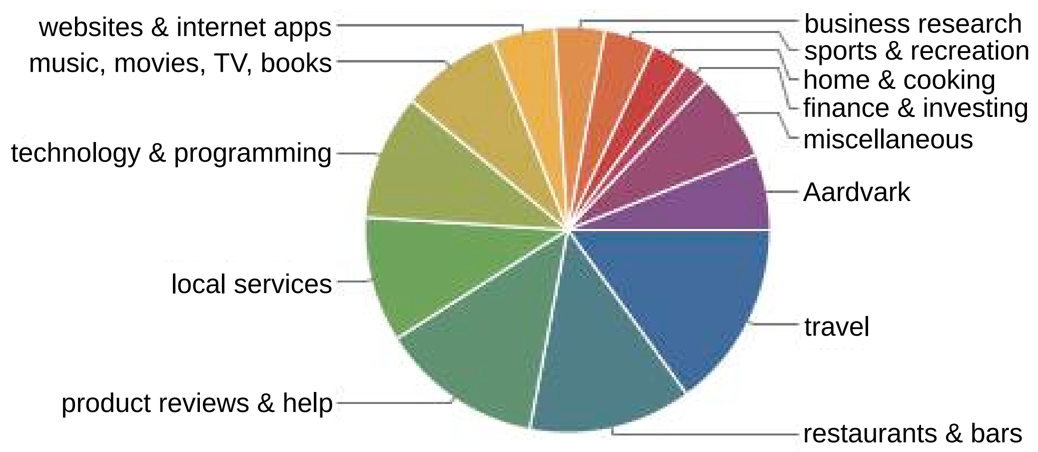


Figure 8: Categories of questions sent to Aardvark

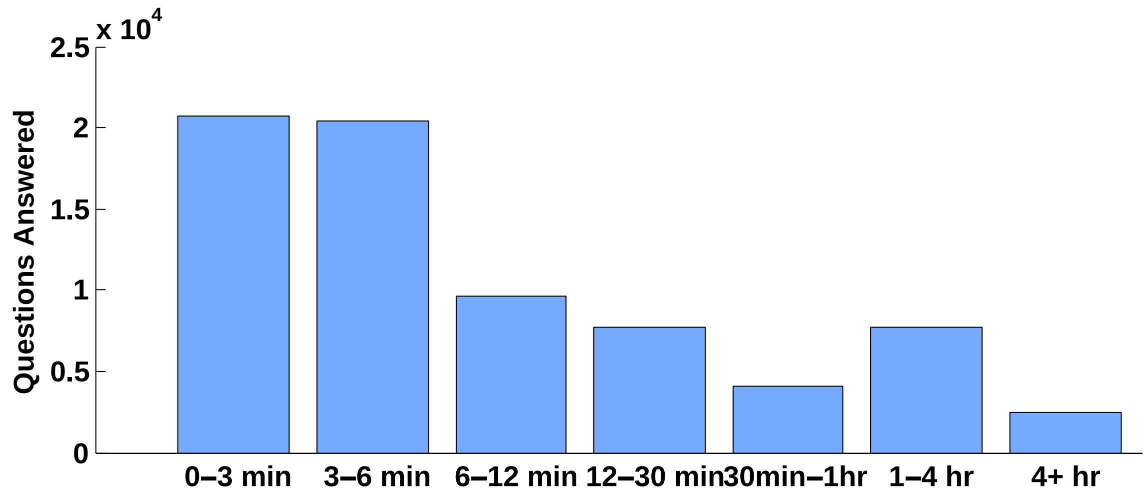


Figure 9: Distribution of questions and answering times.

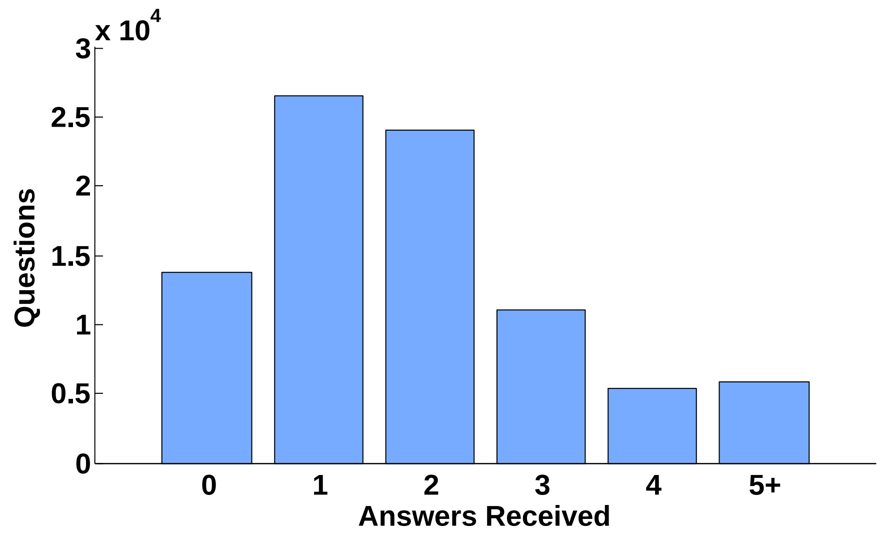


Figure 10: Distribution of questions and number of answers received.

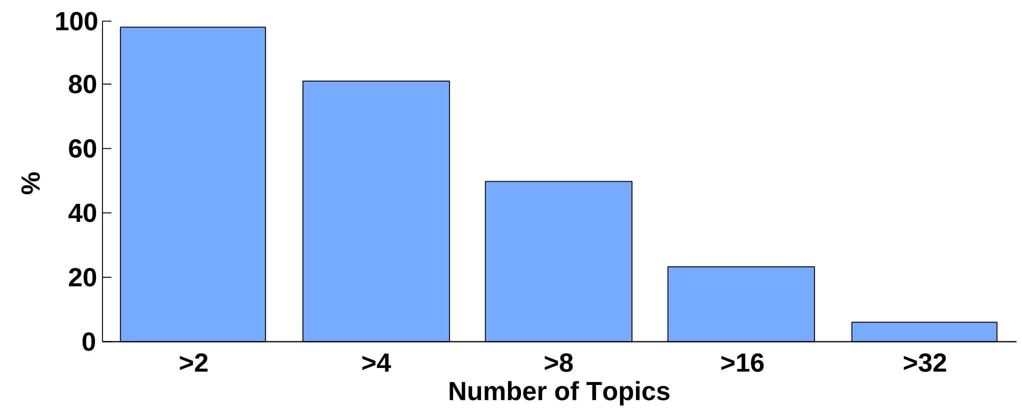


Figure 11: Distribution of percentage of users and number of topics

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Outline

- Introduction
- Social Search Engine
- Social Recommender Systems
- Social Media Analysis

Social Recommender Systems

- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems

How Much Information Is on the Web?

flickr

NETFLIX

del.icio.us

amazon.com

YouTube

facebook

WIKIPEDIA

ebay

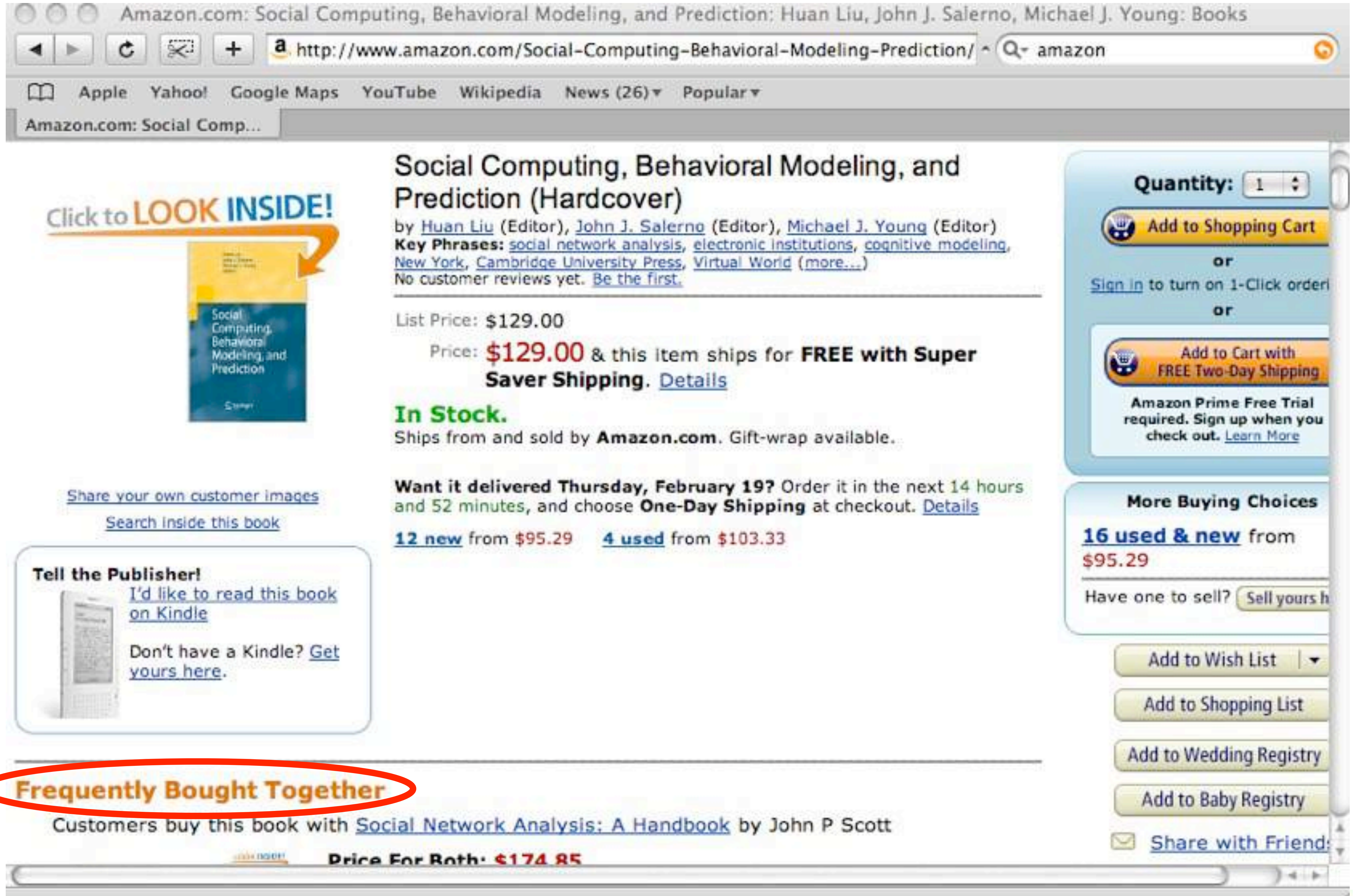
myspace.com

hulu

twitter

Information Overload

Real Life Examples



Real Life Examples

Five scales rating

★ I hate it

★★ I don't like it

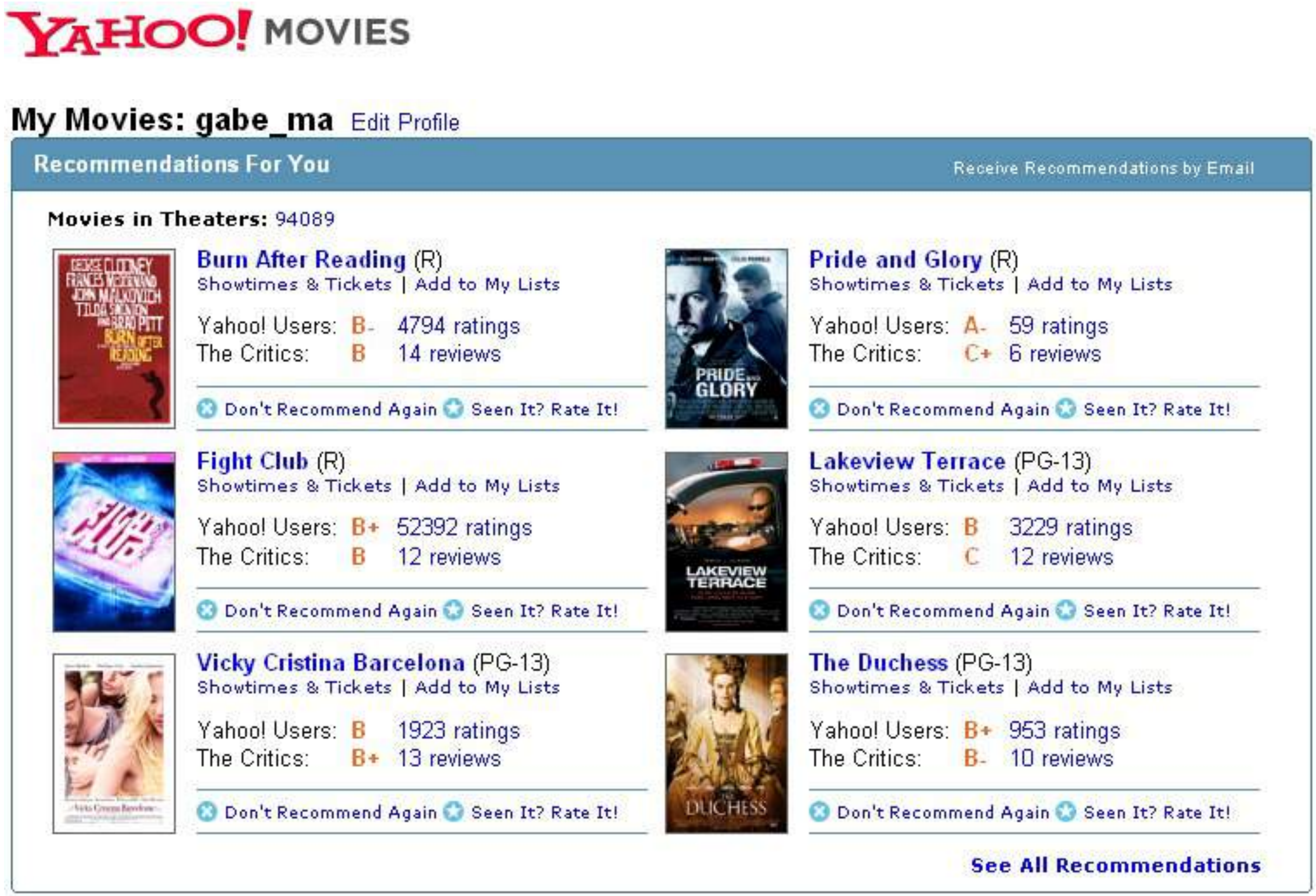
★★★ It's ok

★★★★ I like it

★★★★★ I love it

Real Life Examples

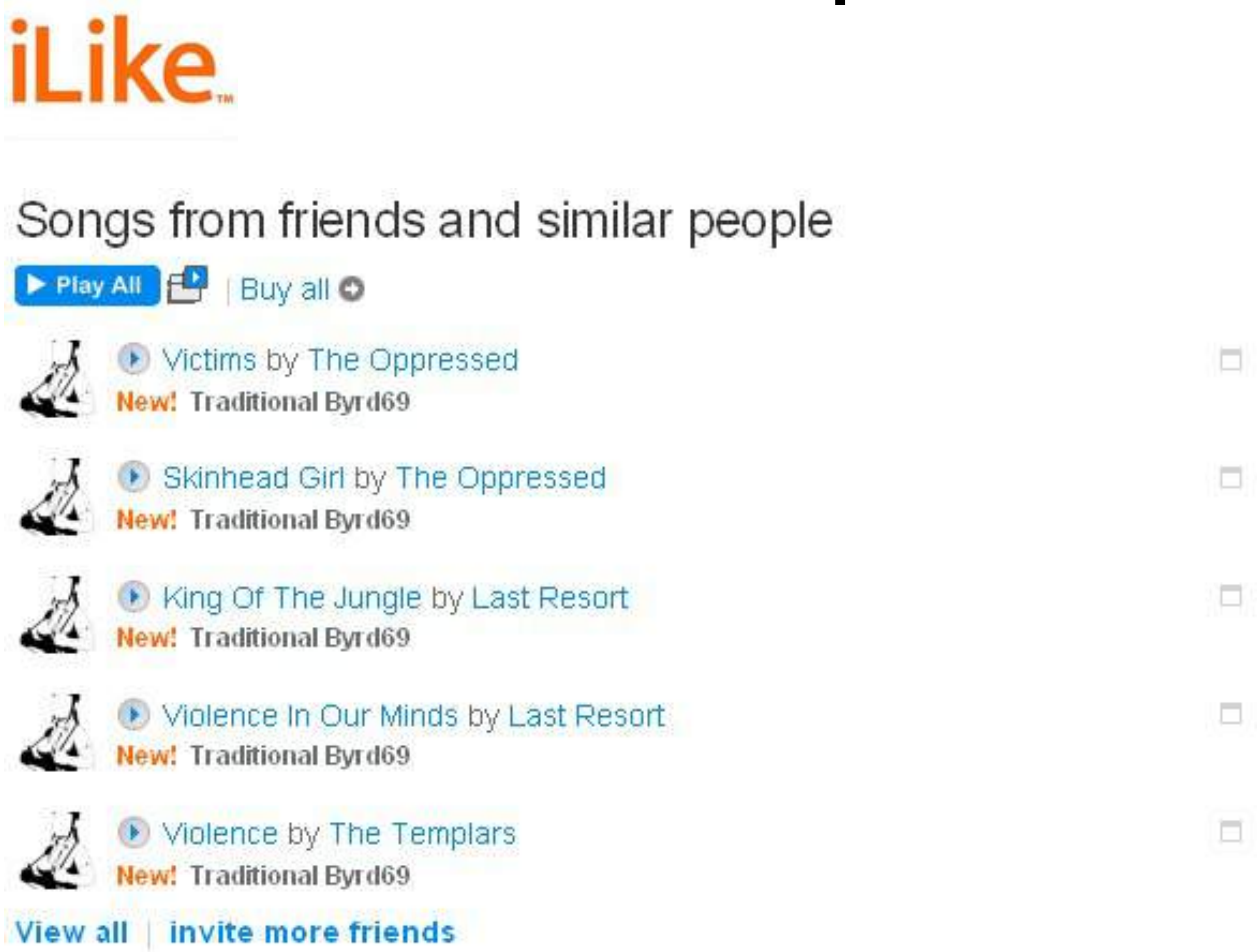
Real Life Examples



Real Life Examples

iTunes 8

Real Life Examples



Basic Approaches

- Content-based Filtering
  - Recommend items based on key-words
  - More appropriate for information retrieval
- Collaborative Filtering (CF)
  - Look at users with similar rating styles
  - Look at similar items for each item

Underling assumption: personal tastes are correlated--
Active user will prefer those items which the similar users prefer.

Framework

Items

	i_1	i_2				i_j							i_m
u_1													
u_2	1	3		4		2		5			3	4	
Users u_i		3		4		r_{ij}	3	4		3	4		4
u_n	1			3	5	2		4	1			3	

- The tasks
  - Find the unknown rating?
  - Which item should be recommended?

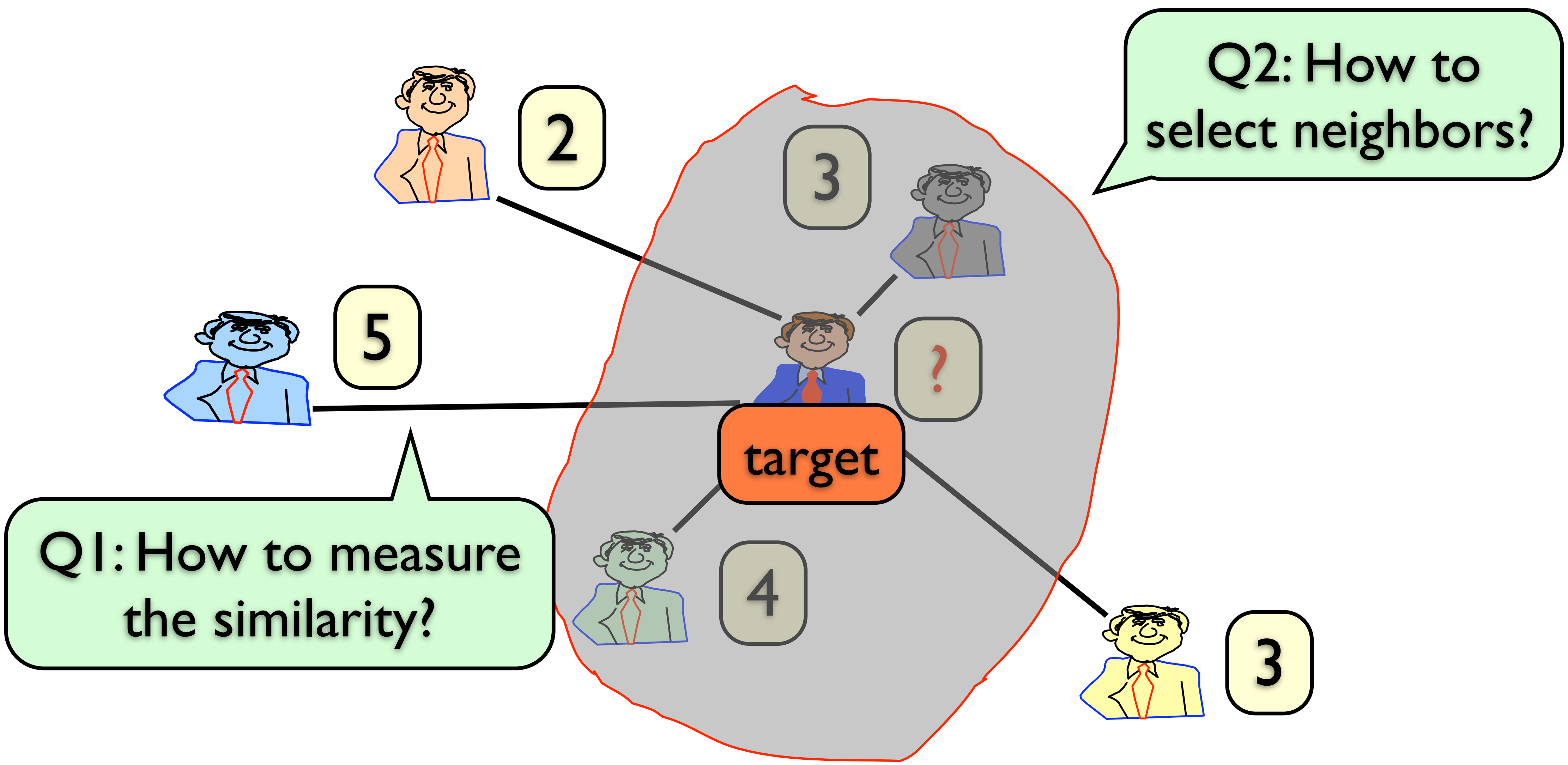
Social Recommender Systems

- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems

Collaborative Filtering

- Memory-based (Neighborhood-based)
  - User-based
  - Item-based
- Model-based
  - Clustering Methods
  - Bayesian Methods
  - Matrix Factorization
  - etc.

User-User Similarity



User-based Collaborative Filtering

Items

Users

u_1													
u_2	1	3		4		2		5			3	4	
u_3													
u_4		3		4			3	4		3	4		4
u_5													
u_6	1			3	5	2		4	1			3	

User-based Collaborative Filtering

Items

Users

u_1													
u_2	1	3		4		2		5			3	4	
u_3													
u_4		3		4			3	4		3	4		4
u_5													
u_6	1			3	5	2		4	1			3	

User-based Collaborative Filtering

Items

Users

u_1													
u_2	1	3		4		2		5			3	4	
u_3													
u_4		3		4			3	4		3	4		4
u_5													
u_6	1			3	5	2		4	1			3	

User-based Collaborative Filtering

Items

Users

u_1													
u_2	1	3		4		2		5			3	4	
u_3													
u_4		3		4			3	4		3	4		4
u_5													
u_6	1			3	5	2		4	1			3	

User-based Collaborative Filtering

Items

Users

u_1													
u_2	1	3		4		2		5			3	4	
u_3													
u_4		3		4			3	4		3	4		4
u_5													
u_6	1			3	5	2		4	1			3	

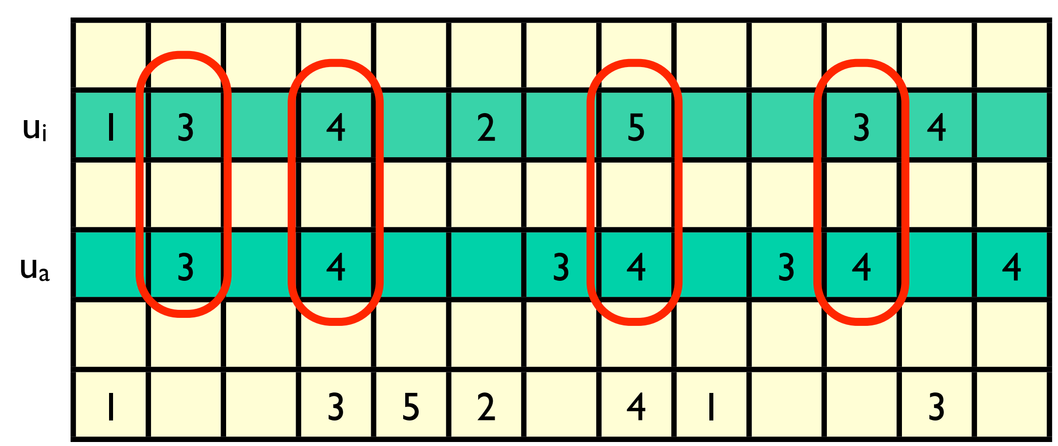
User-based Collaborative Filtering

- Predict the ratings of active users based on the ratings of similar users found in the user-item matrix
  - Pearson correlation coefficient

$$w(a,i) = \frac{\sum_j (r_{aj} - \bar{r}_a)(r_{ij} - \bar{r}_i)}{\sqrt{\sum_j (r_{aj} - \bar{r}_a)^2 \sum_j (r_{ij} - \bar{r}_i)^2}} \quad j \in I(a) \cap I(i)$$

  - Cosine measure

$$c(a,i) = \frac{r_a \cdot r_i}{||r_a||_2 * ||r_i||_2}$$



Collaborative Filtering

- Memory-based (Neighborhood-based)
  - User-based
  - Item-based
- Model-based
  - Clustering Methods
  - Bayesian Methods
  - Matrix Factorization
  - etc.

Item-Item Similarity

- Search for similarities among items
- Item-Item similarity is more stable that user-user similarity

Correlation-based Methods

[Sarwar, 2001]

- Same as in user-user similarity but on item vectors
- Pearson correlation coefficient
  - Look for users who rated both items

$$s_{ij} = \frac{\sum_u (r_{uj} - \bar{r}_j)(r_{ui} - \bar{r}_i)}{\sqrt{\sum_u (r_{uj} - \bar{r}_j)^2 \sum_u (r_{ui} - \bar{r}_i)^2}}$$

  - u: users rated both items

	i_1	i_2				i_i		i_j					i_m
u_1													
u_2	1	3		4		2		5			3	4	
u_i		3		4			3	4		3	4		4
u_n	1			3	5	2		4	1			3	

Collaborative Filtering

- Memory-based (Neighborhood-based)
  - User-based
  - Item-based
- Model-based
  - Clustering Methods
  - Bayesian Methods
  - Matrix Factorization
  - etc...

Matrix Factorization

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8
u_1	5	2		3		4		
u_2	4	3			5			
u_3	4		2				2	4
u_4								
u_5	5	1	2		4	3		
u_6	4	3		2	4		3	5

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8
u_1	5	2	**2.5**	3	**4.8**	4	**2.2**	**4.8**
u_2	4	3	**2.4**	**2.9**	5	**4.1**	**2.6**	**4.7**
u_3	4	**1.7**	2	**3.2**	**3.9**	**3.0**	2	4
u_4	**4.8**	**2.1**	**2.7**	**2.6**	**4.7**	**3.8**	**2.4**	**4.9**
u_5	5	1	2	**3.4**	4	3	**1.5**	**4.6**
u_6	4	3	**2.9**	2	4	**3.4**	3	5

$$U = \begin{bmatrix} 1.55 & 1.22 & 0.37 & 0.81 & 0.62 & -0.01 \\ 0.36 & 0.91 & 1.21 & 0.39 & 1.10 & 0.25 \\ 0.59 & 0.20 & 0.14 & 0.83 & 0.27 & 1.51 \\ 0.39 & 1.33 & -0.43 & 0.70 & -0.90 & 0.68 \\ 1.05 & 0.11 & 0.17 & 1.18 & 1.81 & 0.40 \end{bmatrix} \quad V = \begin{bmatrix} 1.00 & -0.05 & -0.24 & 0.26 & 1.28 & 0.54 & -0.31 & 0.52 \\ 0.19 & -0.86 & -0.72 & 0.05 & 0.68 & 0.02 & -0.61 & 0.70 \\ 0.49 & 0.09 & -0.05 & -0.62 & 0.12 & 0.08 & 0.02 & 1.60 \\ -0.40 & 0.70 & 0.27 & -0.27 & 0.99 & 0.44 & 0.39 & 0.74 \\ 1.49 & -1.00 & 0.06 & 0.05 & 0.23 & 0.01 & -0.36 & 0.80 \end{bmatrix}$$

Matrix Factorization

- Matrix Factorization in Collaborative Filtering
  - To fit the product of two (low rank) matrices to the observed rating matrix.
  - To find two latent user and item feature matrices.
  - To use the fitted matrix to predict the unobserved ratings.

$$\begin{pmatrix} u_{11} & \cdots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{m1} & \cdots & u_{mk} \end{pmatrix} \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{k1} & \cdots & v_{kn} \end{pmatrix}$$

User-specific latent feature vector

Item-specific latent feature column vector

Matrix Factorization

- Optimization Problem
  - Given a *m x n* rating matrix *R*, to find two matrices $U \in \mathbb{R}^{l \times m}$ and $V \in \mathbb{R}^{l \times n}$,

$$R \approx U^T V,$$

where $l < \min(m, n)$, is the number of factors

Matrix Factorization

- Models
  - SVD-like Algorithm
  - Regularized Matrix Factorization (RMF)
  - Probabilistic Matrix Factorization (PMF)
  - Non-negative Matrix Factorization (NMF)

SVD-like Algorithm

- Minimizing

$$\frac{1}{2}||R - U^T V||_F^2,$$

- For collaborative filtering

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2$$

where I_{ij} is the indicator function that is equal to 1 if user u_i rated item v_j and equal to 0 otherwise.

Regularized Matrix Factorization

- Minimize the loss based on the observed ratings with regularization terms to avoid over-fitting problem

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T V_j)^2 + \boxed{\frac{\lambda_1}{2} ||U||_F^2 + \frac{\lambda_2}{2} ||V||_F^2}$$

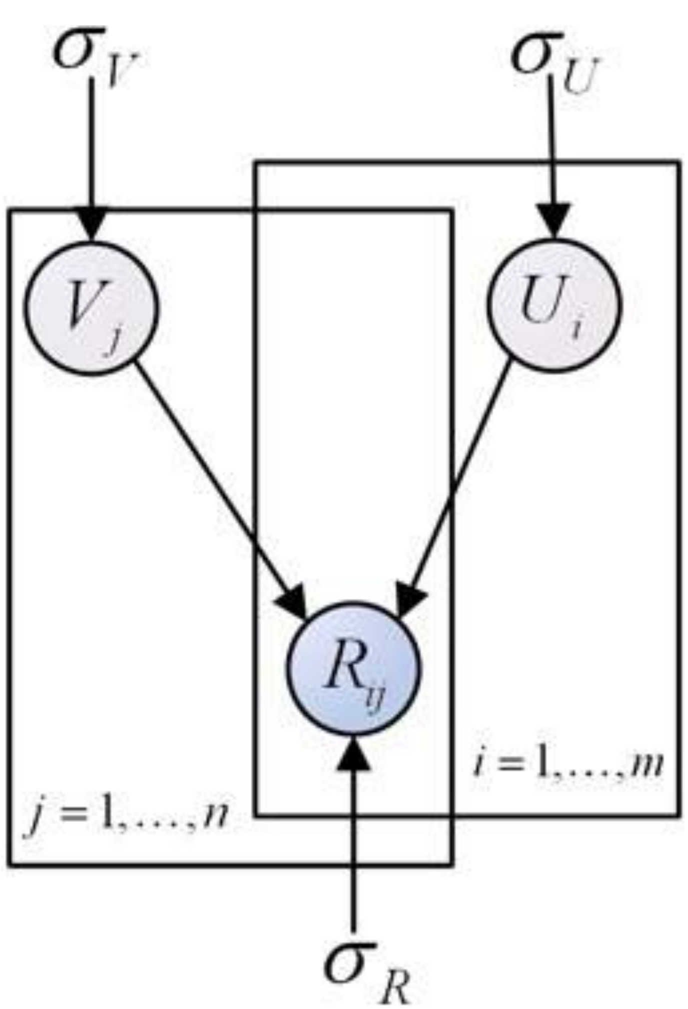
Regularization terms

where $\lambda_1, \lambda_2 > 0$.

- The problem can be solved by simple gradient descent algorithm.

Probabilistic Matrix Factorization

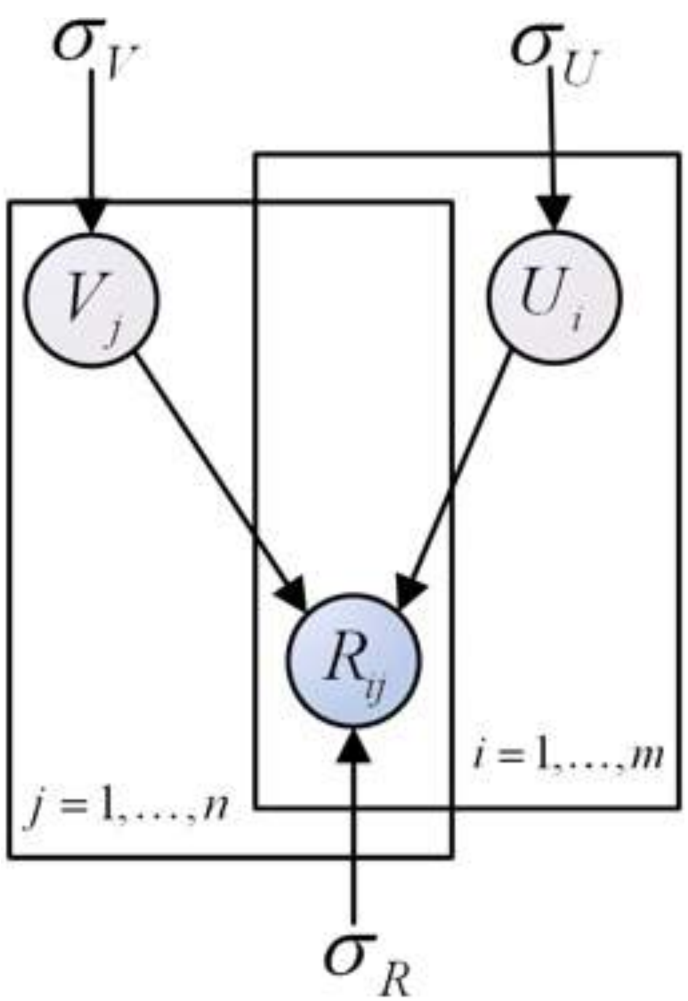
- PMF
  - Define a conditional distribution over the observed ratings as:



$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \left[\mathcal{N}\left(R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$

Probabilistic Matrix Factorization

- PMF
  - Assume zero-mean spherical Gaussian priors on user and item feature:

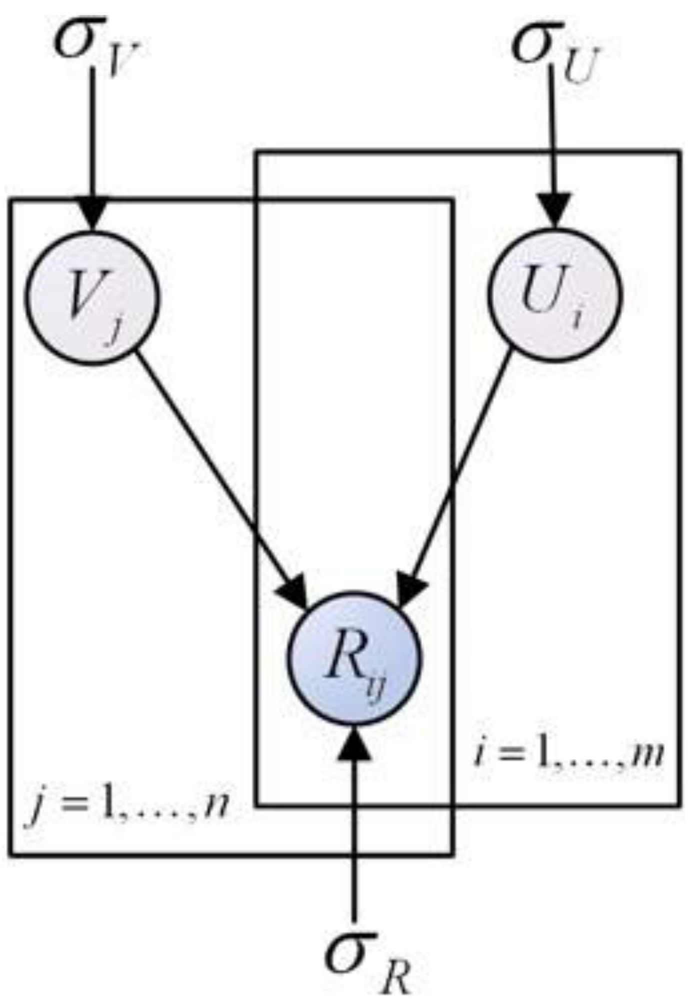


$$p(U|\sigma_U^2) = \prod_{i=1}^{m} \mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I})$$

$$p(V|\sigma_V^2) = \prod_{j=1}^{n} \mathcal{N}(V_j|0, \sigma_V^2 \mathbf{I})$$

Probabilistic Matrix Factorization

- PMF
  - Bayesian inference



$$\begin{aligned} p(U,V|R,\sigma_R^2,\sigma_U^2,\sigma_V^2) &\propto p(R|U,V,\sigma_R^2)p(U|\sigma_U^2)p(V|\sigma_V^2) \\ &= \prod_{i=1}^{m}\prod_{j=1}^{n}\left[\mathcal{N}\left(R_{ij}|g(U_i^T V_j),\sigma_R^2\right)\right]^{I_{ij}^R} \\ &\times \prod_{i=1}^{m}\mathcal{N}(U_i|0,\sigma_U^2\mathbf{I}) \times \prod_{j=1}^{n}\mathcal{N}(V_j|0,\sigma_V^2\mathbf{I}). \end{aligned}$$

Non-negative Matrix Factorization

- NMF
  - Given an observed matrix Y, to find two non-negative matrices U and V
  - Two types of loss functions
    - Squared error function

$$\sum_{ij}(R_{ij} - U_i^T V_j)^2$$

    - Divergence

$$D(R||U^T V) = \sum_{ij}(R_{ij}\log\frac{R_{ij}}{U_i^T V_j} - R_{ij} + U_i^T V_j)$$

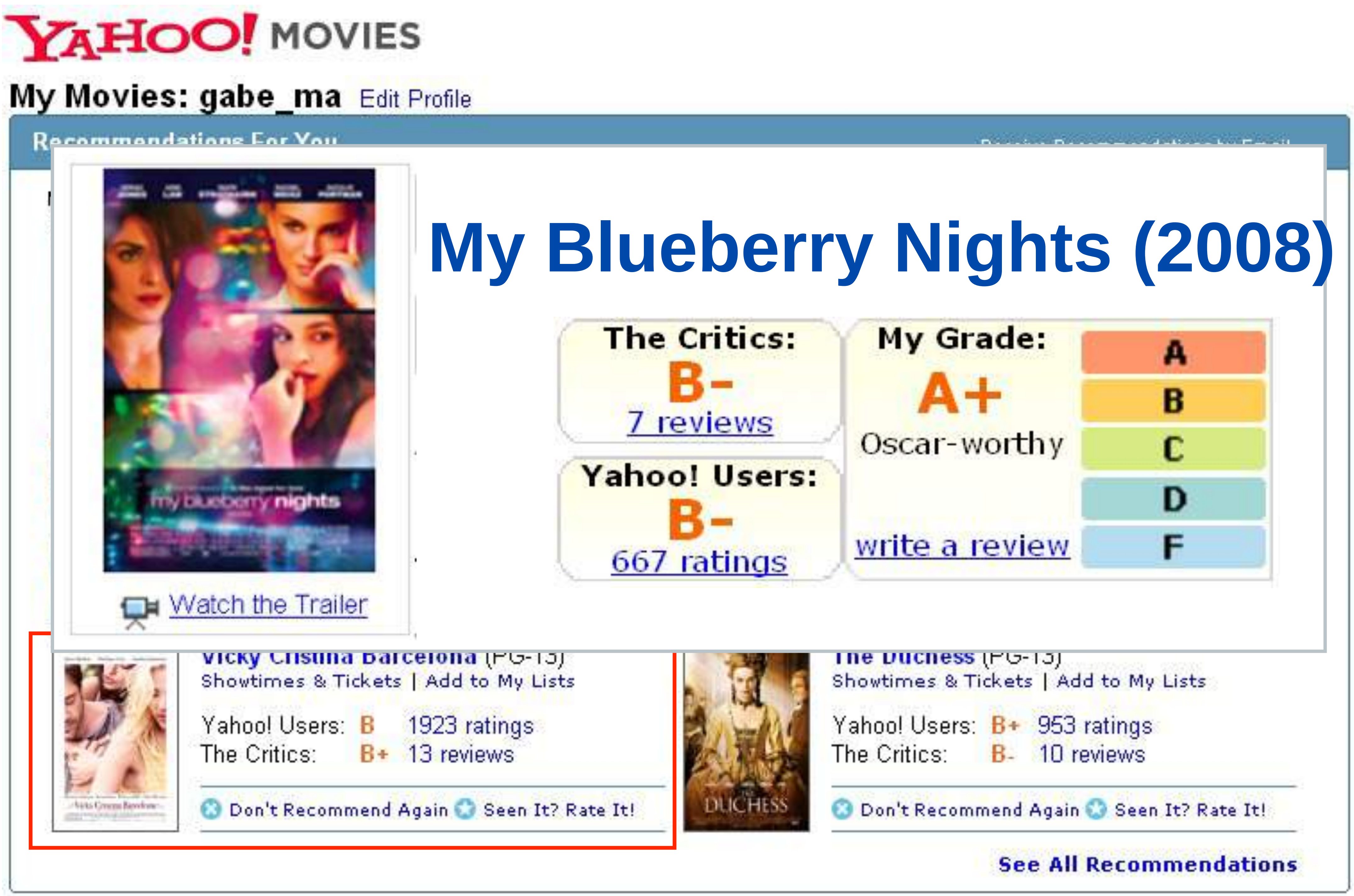
- Solving by multipicative updating rules

Social Recommender Systems

- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems

Challenges

- Data sparsity problem



Challenges

My Movie Ratings

The Pursuit of Happyness (PG-13, 1 hr. 57 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B+ 38992 ratings
The Critics: B- 13 reviews

My Rating: A+

Finding Nemo (G, 1 hr. 40 min.)
Buy DVD | Add to My Lists

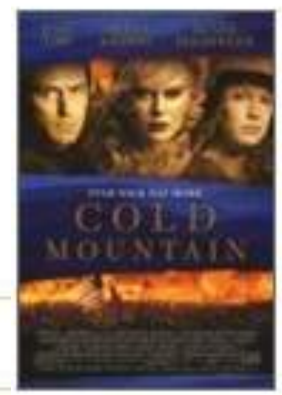
Yahoo! Users: B+ 137394 ratings
The Critics: A- 14 reviews

My Rating: A

My Blueberry Nights (PG-13, 1 hr. 30 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B- 756 ratings
The Critics: B- 7 reviews

My Rating: A+



Cold Mountain (R, 2 hrs. 35 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B 38986 ratings
The Critics: B+ 10 reviews

My Rating: B+

The Lord of the Rings: The Fellowship of the Ring
Buy DVD | Add to My Lists

Yahoo! Users: A- 110957 ratings
The Critics: A 15 reviews

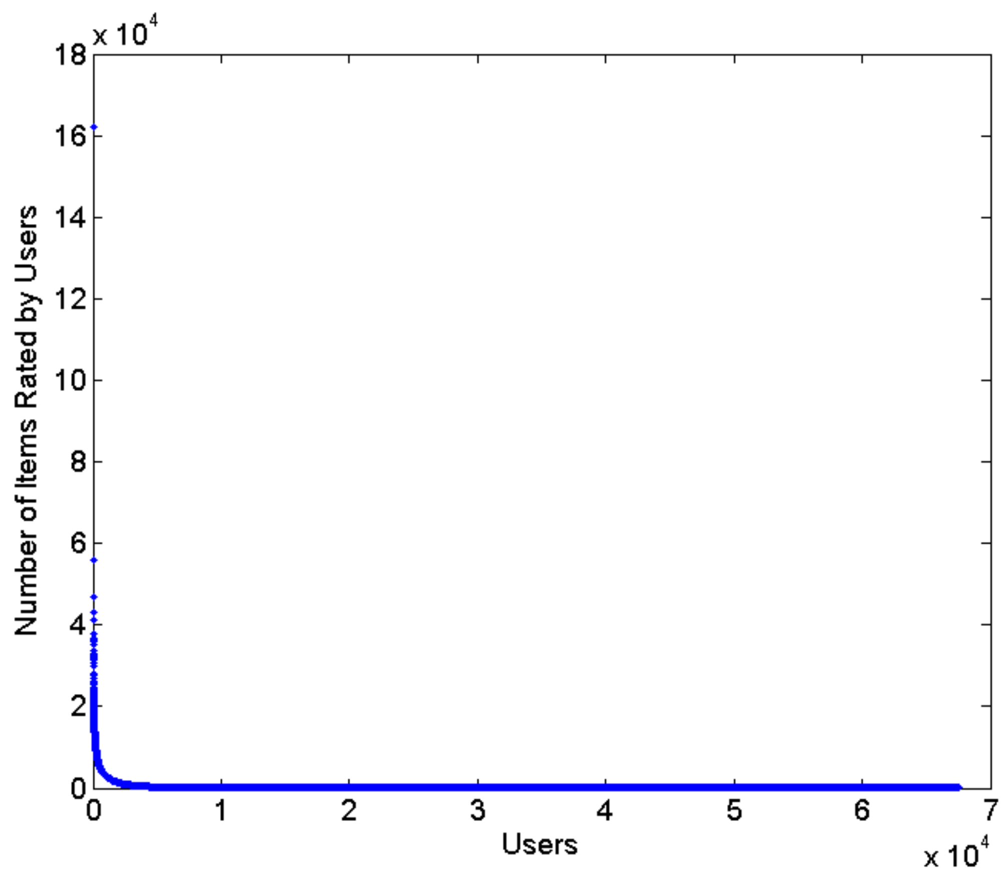
My Rating: A

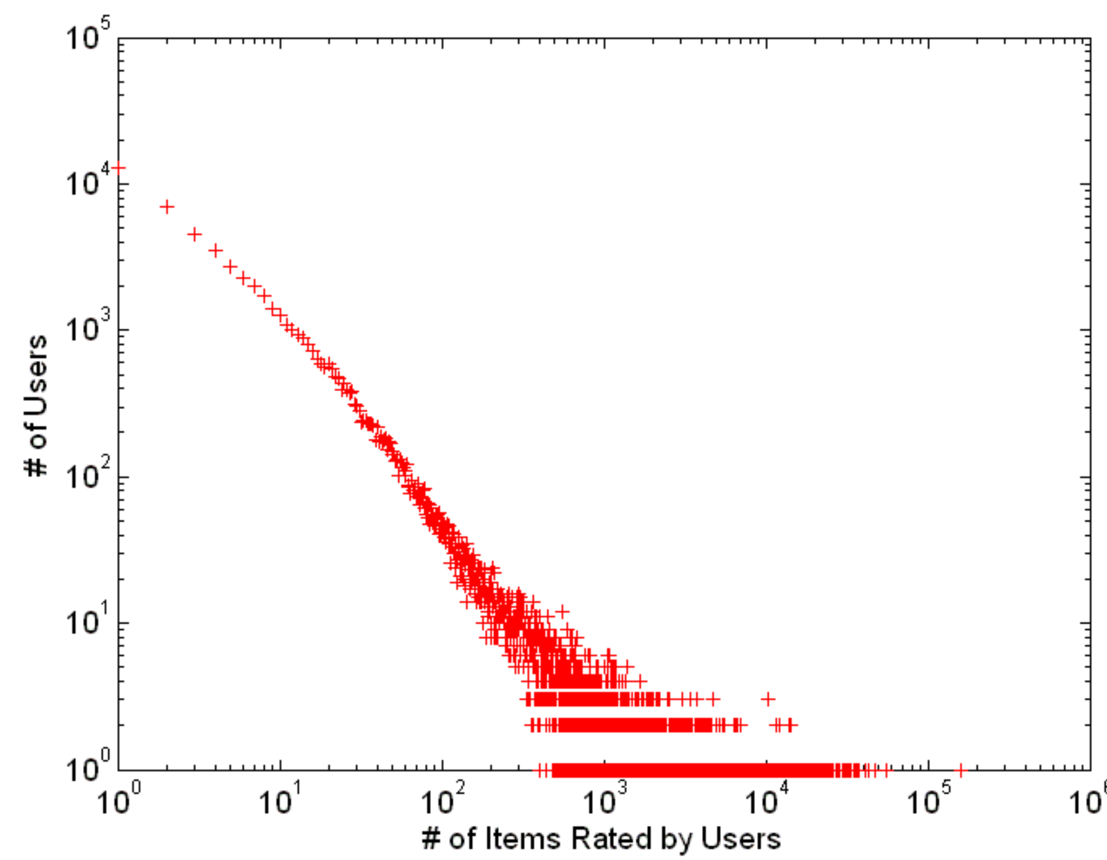
Shrek 2 (PG, 1 hr. 32 min.)
Buy DVD | Add to My Lists

Yahoo! Users: B+ 150368 ratings
The Critics: B 15 reviews

My Rating: B

Number of Ratings per User



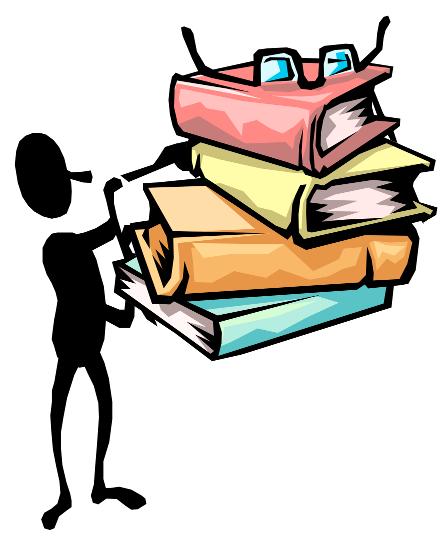


Extracted From Epinions.com

114,222 users, 754,987 items and 13,385,713 ratings

Challenges

- Traditional recommender systems ignore the social connections between users



Recommendations from friends

Social Recommendation Using Probabilistic Matrix Factorization

[Hao Ma, et al., CIKM2008]

Motivations

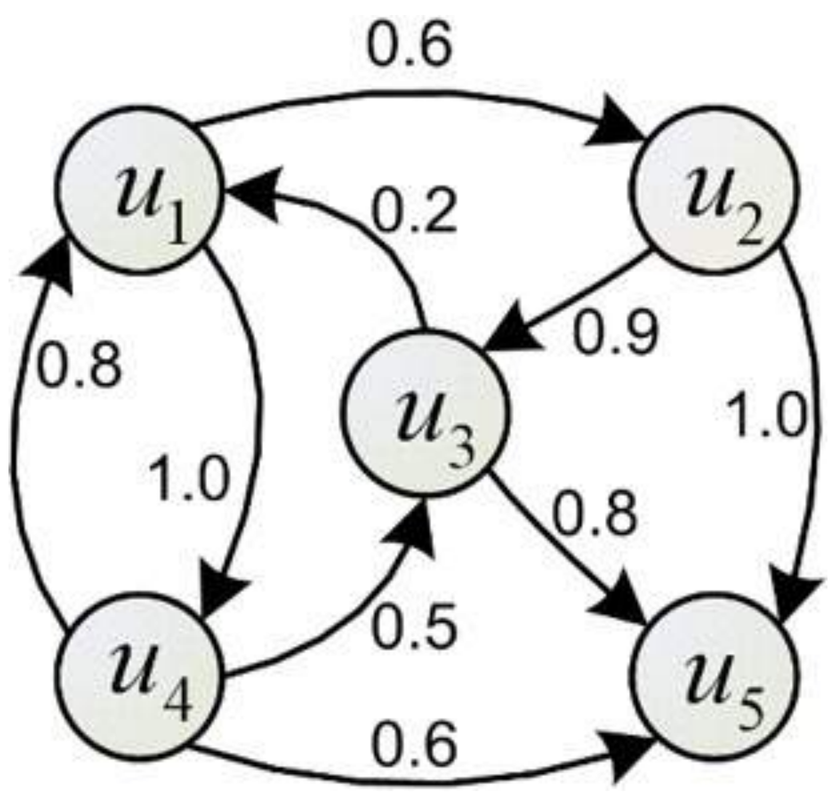
- "Yes, there is a correlation - from social networks to personal behavior on the web"

  Parag Singla and Matthew Richardson (WWW'08)

  - Analyze the who talks to whom social network over 10 million people with their related search results
  - People who chat with each other are more likely to share the same or similar interests

- To improve the recommendation accuracy and solve the data sparsity problem, users' social network should be taken into consideration

Problem Definition



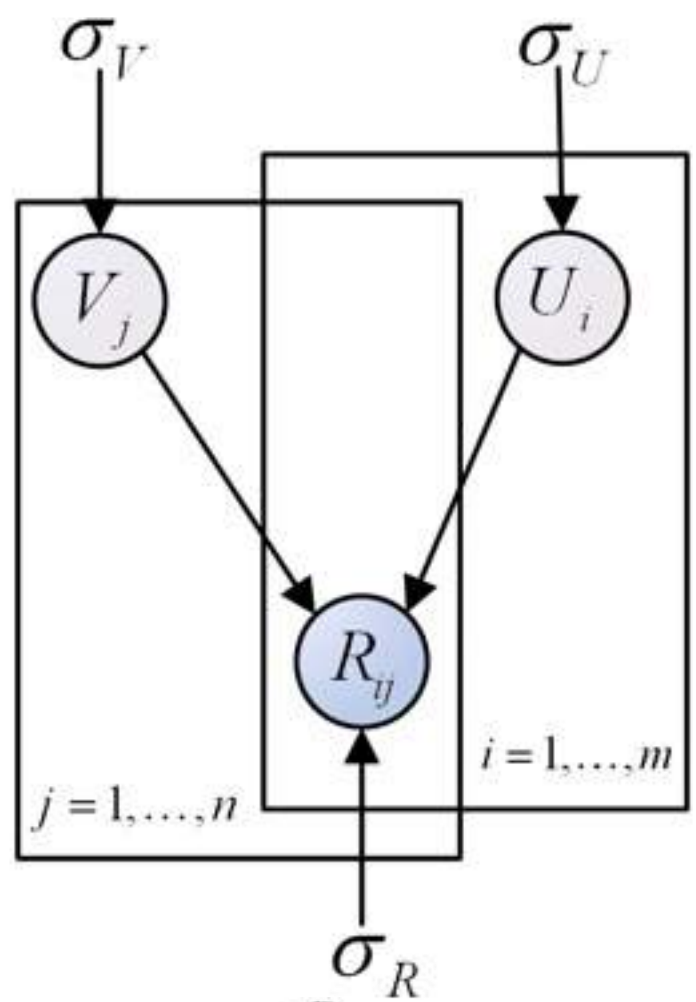
Social Trust Graph

	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3

User-Item Rating Matrix

User-Item Matrix Factorization

	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3



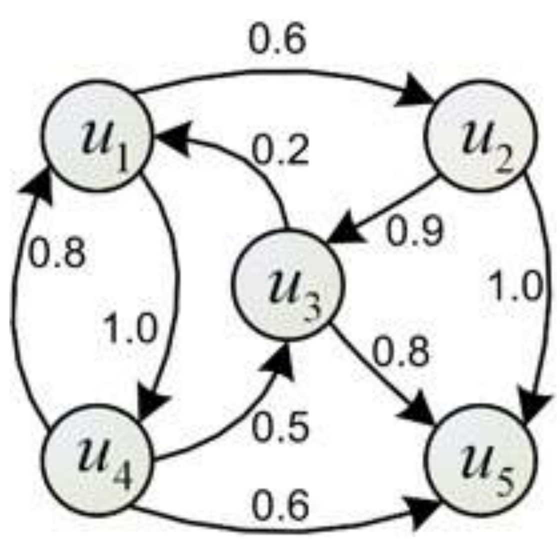
$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \left[\mathcal{N}\left(R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$

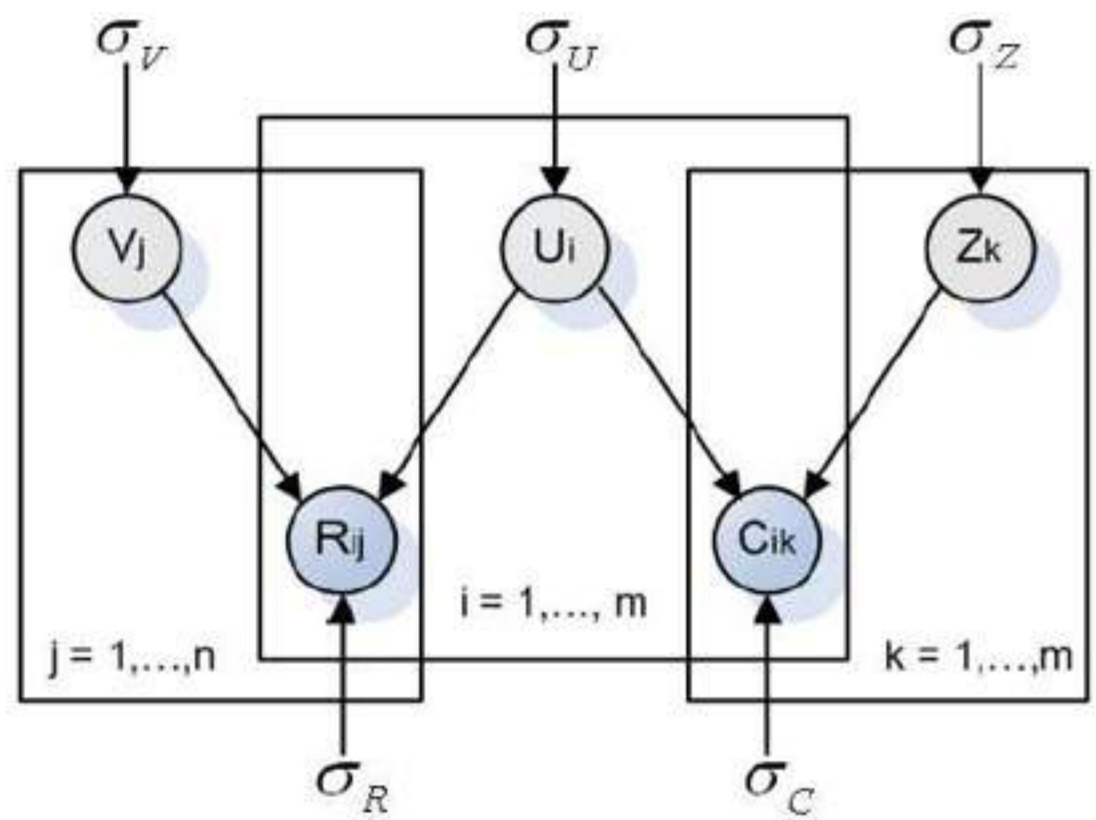
$$p(U|\sigma_U^2) = \prod_{i=1}^{m} \mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I}) \qquad p(V|\sigma_V^2) = \prod_{j=1}^{n} \mathcal{N}(V_j|0, \sigma_V^2 \mathbf{I})$$

R. Salakhutdinov and A. Mnih (NIPS'08)

SoRec

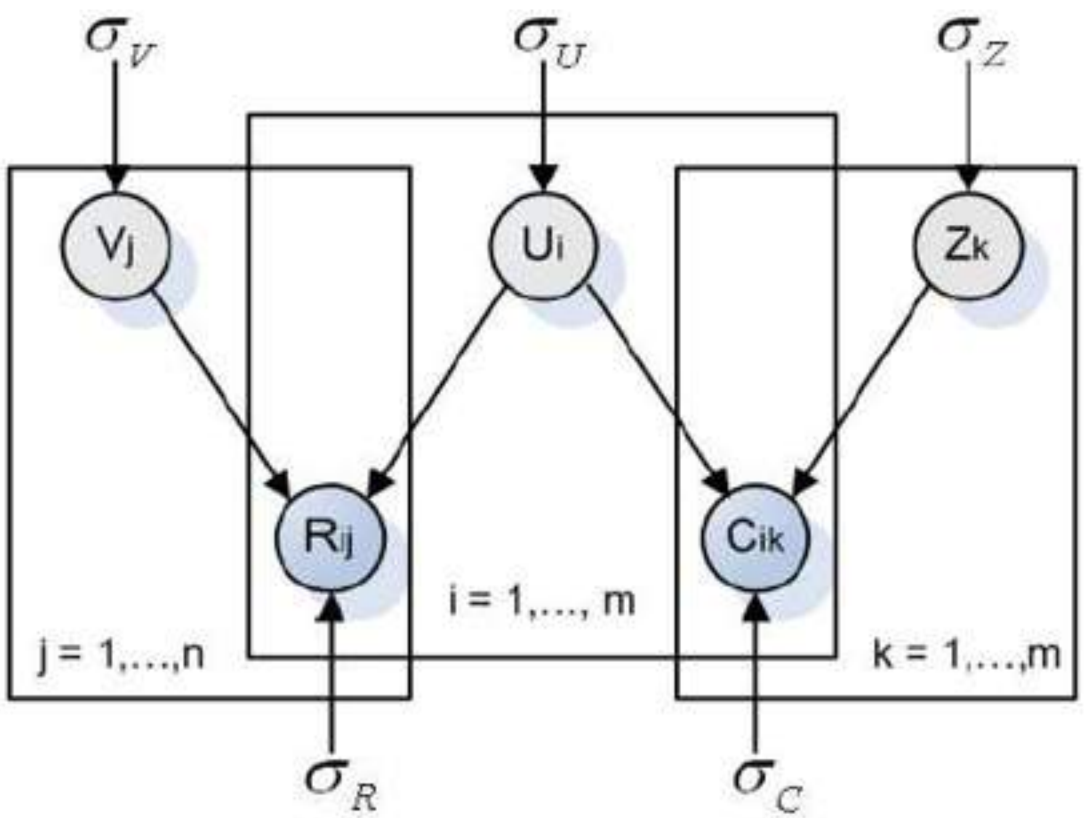
	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3





SoRec

SoRec



$$p(R|U,V,\sigma_R^2) = \prod_{i=1}^{m}\prod_{j=1}^{n}\mathcal{N}\left[\left(r_{ij}|g(U_i^T V_j),\sigma_R^2\right)\right]^{I_{ij}^R}$$

$$p(C|U,Z,\sigma_C^2) = \prod_{i=1}^{m}\prod_{k=1}^{m}\mathcal{N}\left[\left(c_{ik}|g(U_i^T Z_k),\sigma_C^2\right)\right]^{I_{ik}^C}$$

$$p(U|\sigma_U^2) = \prod_{i=1}^{m}\mathcal{N}(U_i|0,\sigma_U^2\mathbf{I}) \quad p(V|\sigma_V^2) = \prod_{j=1}^{n}\mathcal{N}(V_j|0,\sigma_V^2\mathbf{I})$$

$$p(Z|\sigma_Z^2) = \prod_{k=1}^{m}\mathcal{N}(Z_k|0,\sigma_Z^2\mathbf{I})$$

$$\mathcal{L}(R,C,U,V,Z) =$$
$$\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^R (r_{ij} - g(U_i^T V_j))^2 + \frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^C (c_{ik}^* - g(U_i^T Z_k))^2$$
$$+ \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2 + \frac{\lambda_Z}{2}\|Z\|_F^2,$$

SoRec

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial U_i} &= \sum_{j=1}^{n} I_{ij}^{R} g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij}) V_j \\
&+ \lambda_C \sum_{j=1}^{m} I_{ik}^{C} g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^{*}) Z_k + \lambda_U U_i, \\
\frac{\partial \mathcal{L}}{\partial V_j} &= \sum_{i=1}^{m} I_{ij}^{R} g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij}) U_i + \lambda_V V_j, \\
\frac{\partial \mathcal{L}}{\partial Z_k} &= \lambda_C \sum_{i=1}^{m} I_{ik}^{C} g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^{*}) U_i + \lambda_Z Z_k,
\end{aligned}
$$

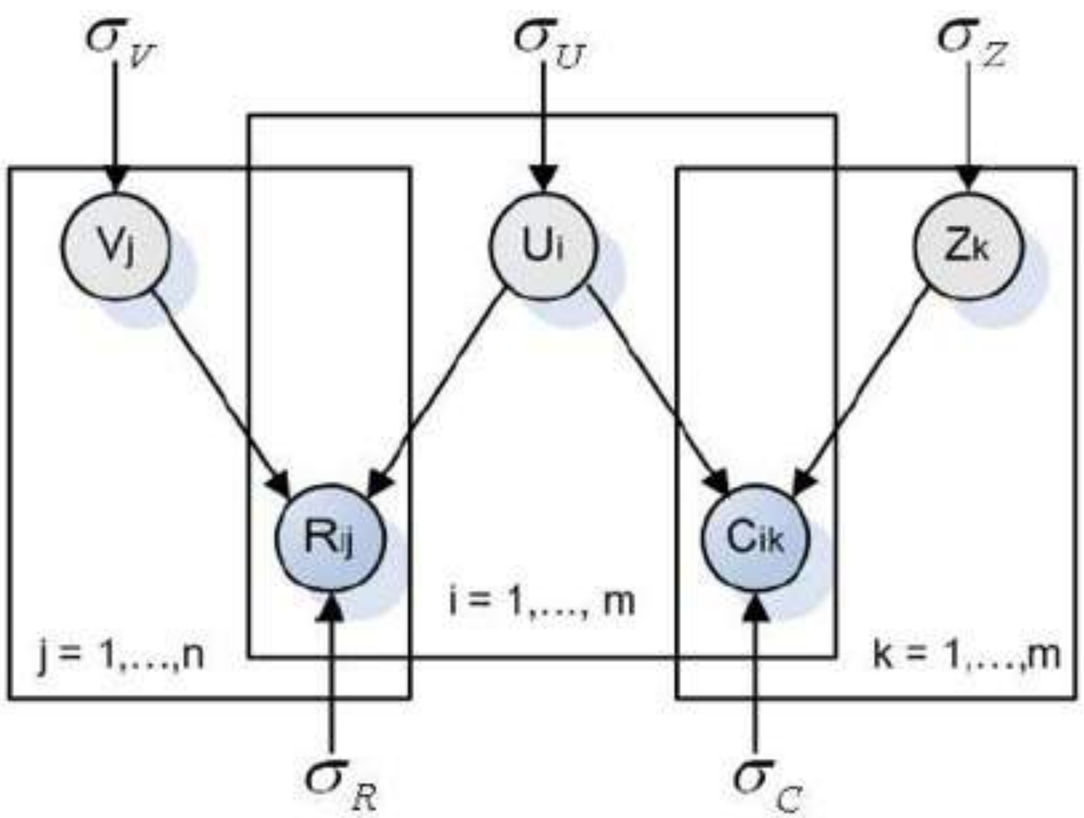
Complexity Analysis

- For the Objective Function $O(\rho_R l + \rho_C l)$
- For $\frac{\partial \mathcal{L}}{\partial U}$ the complexity is $O(\rho_R l + \rho_C l)$
- For $\frac{\partial \mathcal{L}}{\partial V}$ the complexity is $O(\rho_R l)$
- For $\frac{\partial \mathcal{L}}{\partial Z}$ the complexity is $O(\rho_C l)$
- In general, the complexity of our method is linear with the observations in these two matrices

Disadvantages of SoRec

- Lack of interpretability

- Does not reflect the real-world recommendation process

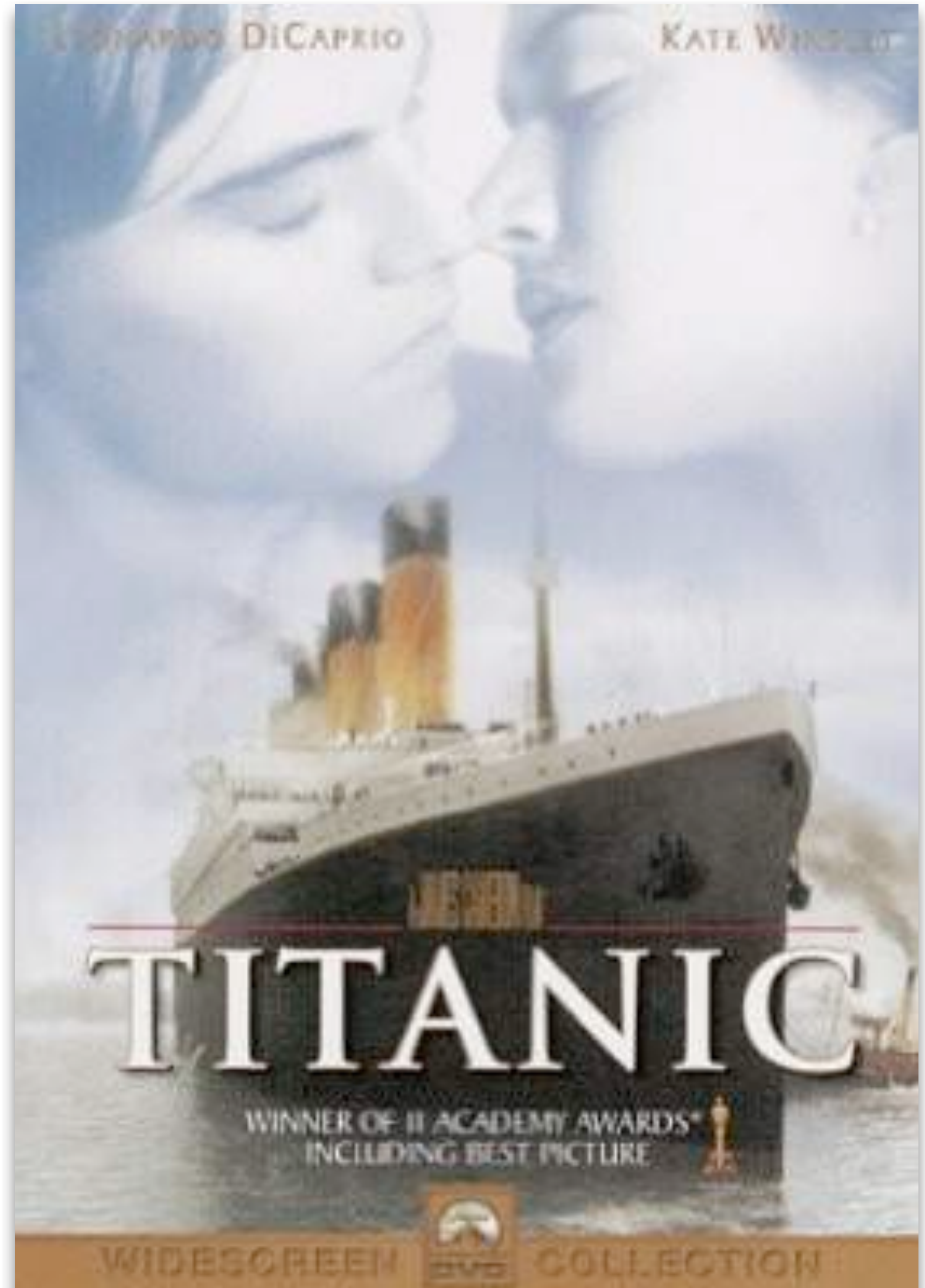


SoRec

Learning to Recommend with Social Trust Ensemble

[Hao Ma, et al., SIGIR2009]

1st Motivation

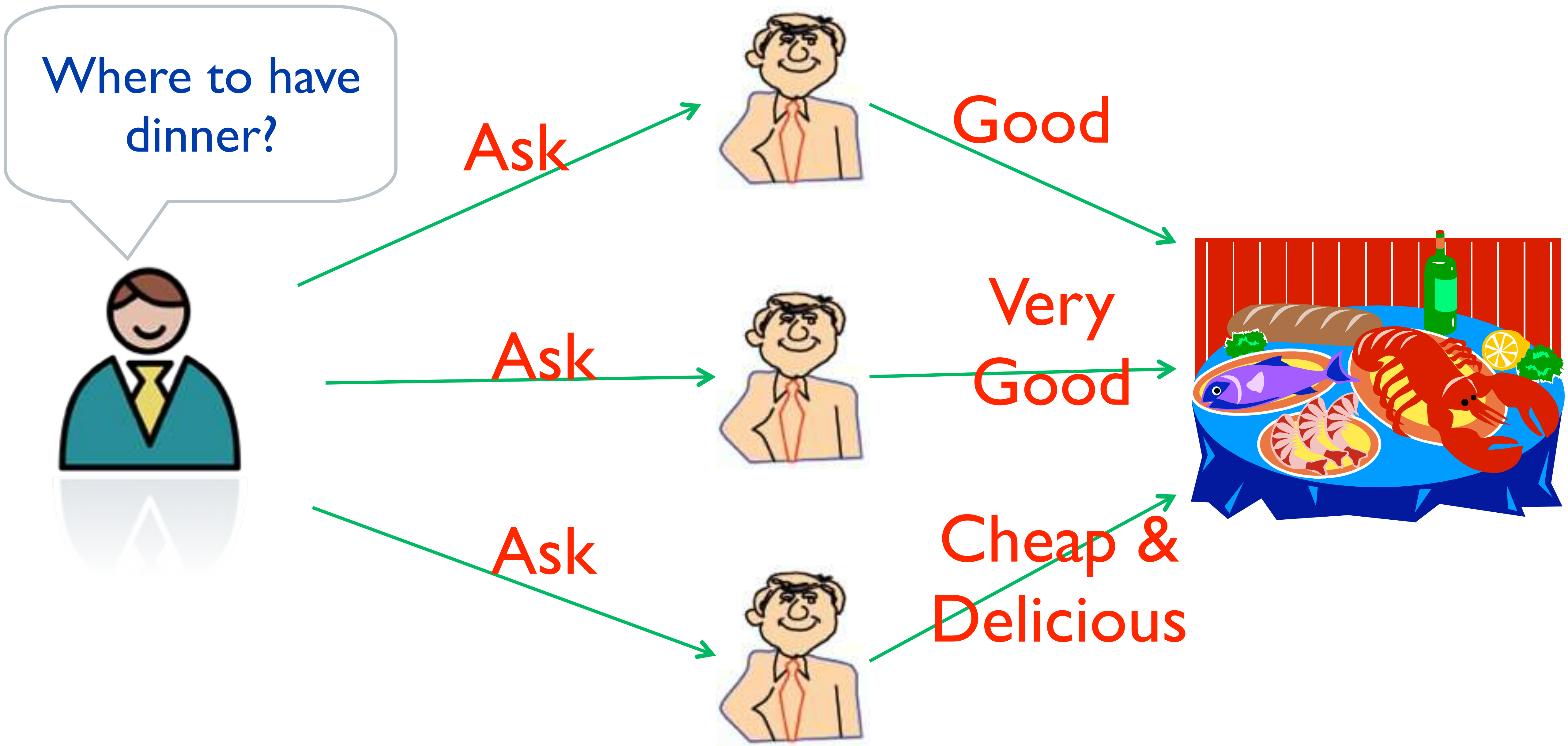


1st Motivation

1st Motivation

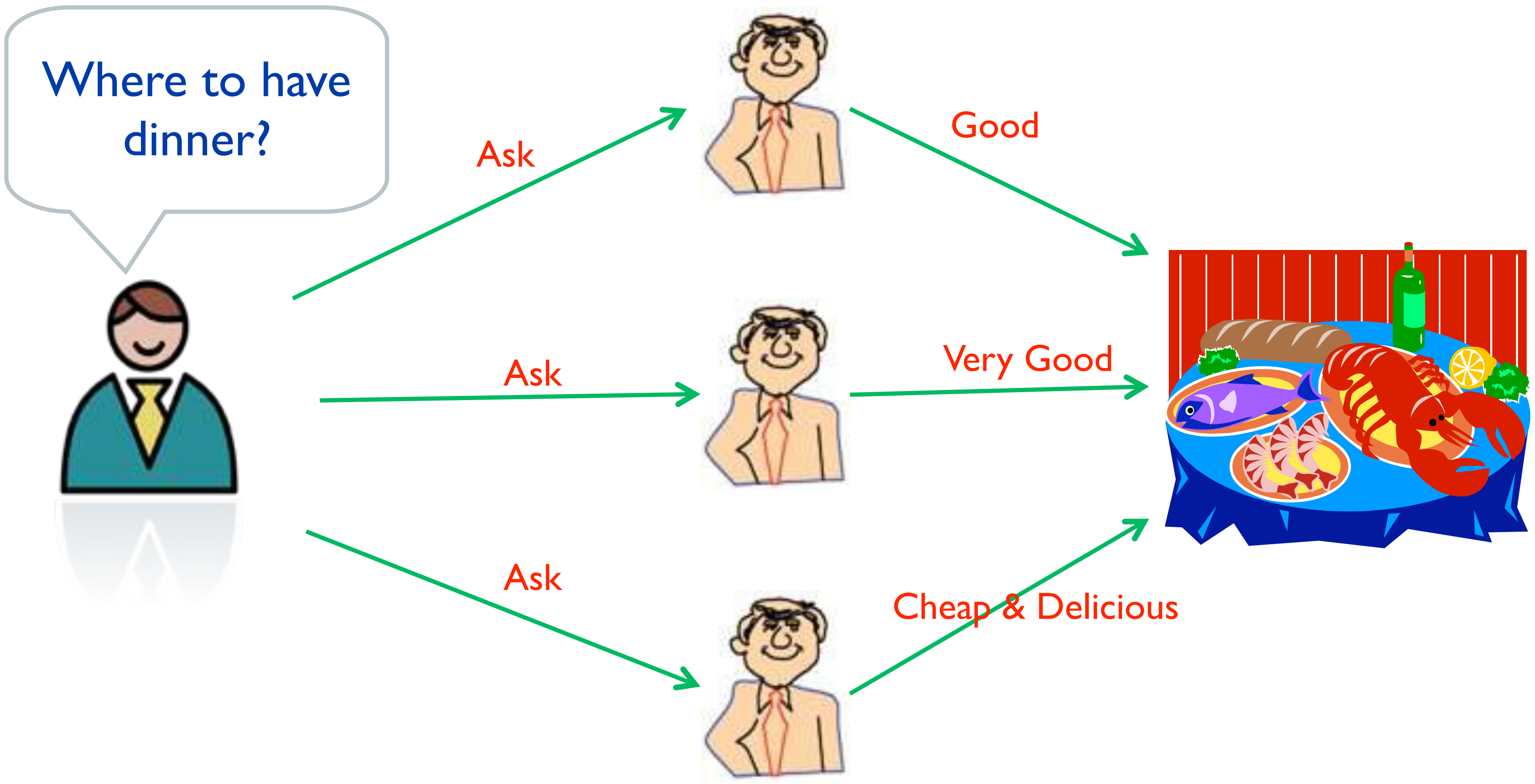
- Users have their own characteristics, and they have different tastes on different items, such as movies, books, music, articles, food, etc.

2nd Motivation



2nd Motivation

- Users can be easily influenced by the friends they trust, and prefer their friends' recommendations.



Motivations

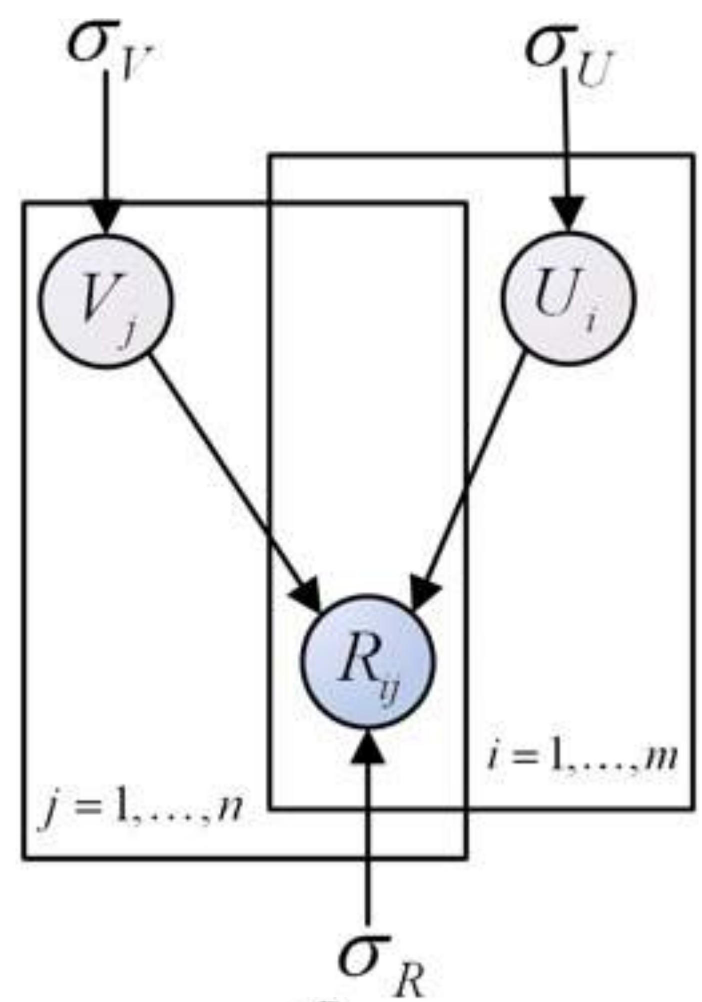
- Users have their own characteristics, and they have different tastes on different items, such as movies, books, music, articles, food, etc.

- Users can be easily influenced by the friends they trust, and prefer their friends' recommendations.

- One user's final decision is the balance between his/her own taste and his/her trusted friends' favors.

User-Item Matrix Factorization

	v_1	v_2	v_3	v_4	v_5	v_6
u_1		5	2		3	
u_2	4			3		4
u_3			2			2
u_4	5			3		
u_5		5	5			3



$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \left[\mathcal{N}\left(R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$

$$p(U|\sigma_U^2) = \prod_{i=1}^{m} \mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I}) \qquad p(V|\sigma_V^2) = \prod_{j=1}^{n} \mathcal{N}(V_j|0, \sigma_V^2 \mathbf{I})$$

[R. Salakhutdinov, et al., NIPS2008]

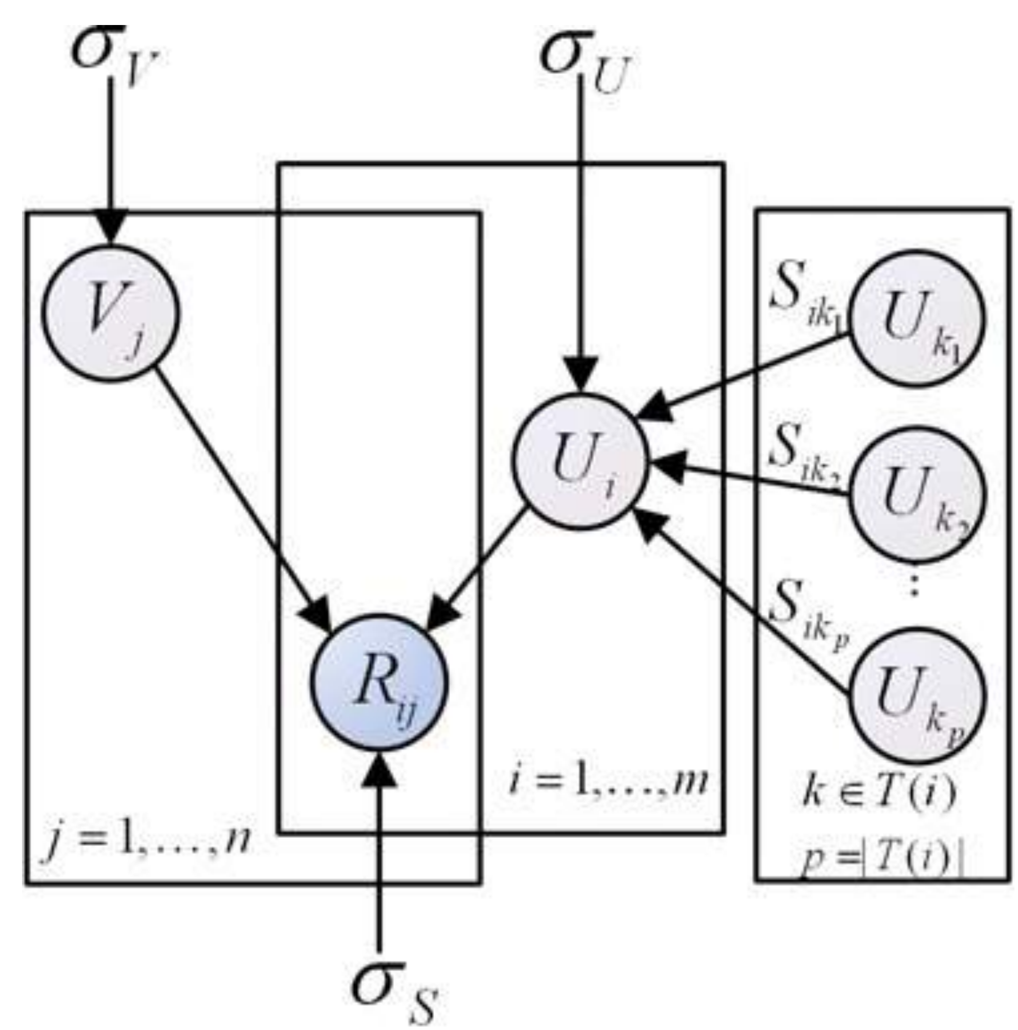
Recommendations by Trusted Friends

$$\widehat{R}_{ik} = \frac{\sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}}{|\mathcal{T}(i)|}$$

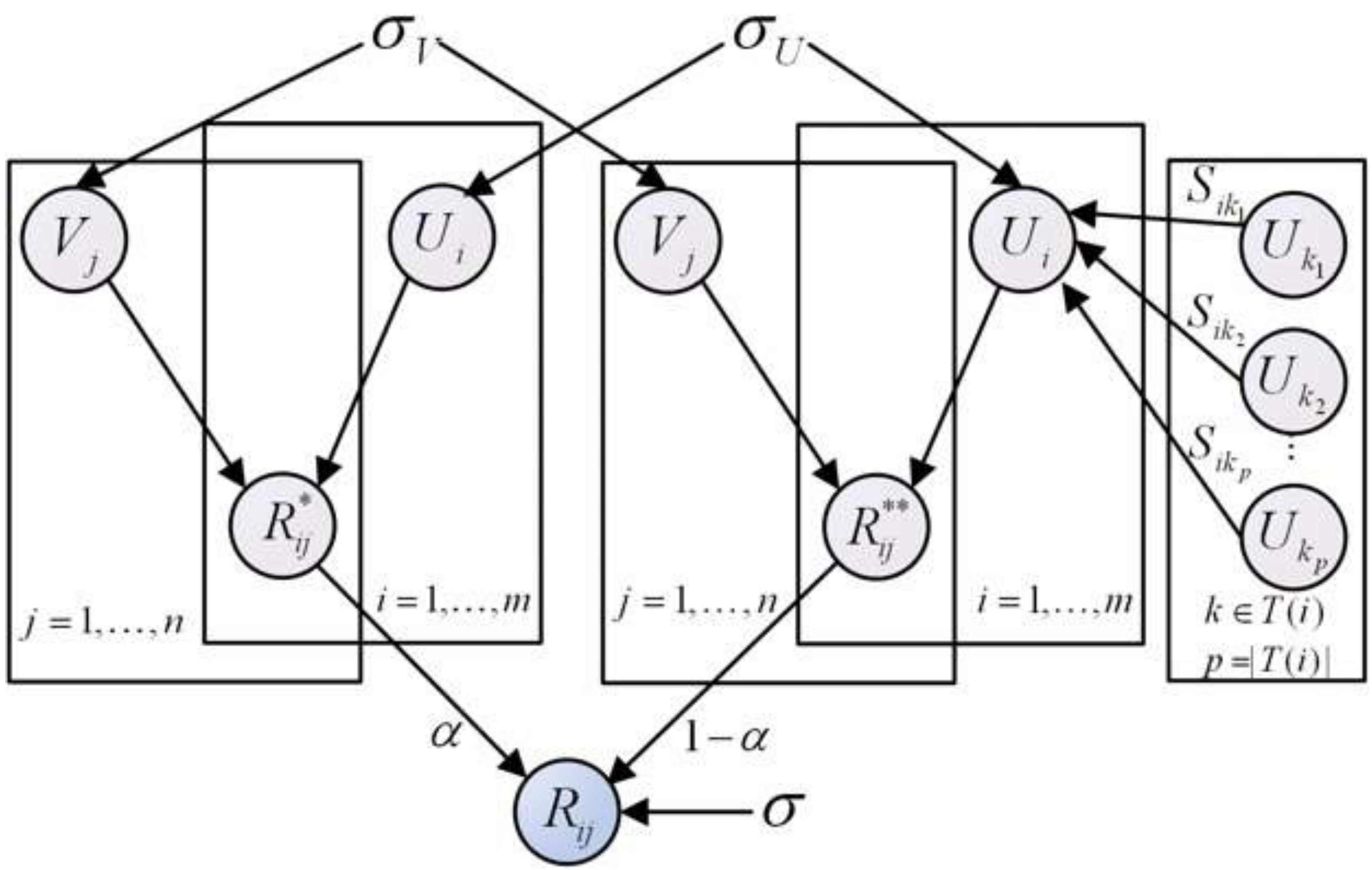
$$\widehat{R}_{ik} = \sum_{j \in \mathcal{T}(i)} R_{jk} S_{ij}$$

$$p(R|S, U, V, \sigma_R^2) =$$

$$\prod_{i=1}^{m} \prod_{j=1}^{n} \left[\mathcal{N} \left(R_{ij} | g(\sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j), \sigma_S^2 \right) \right]^{I_{ij}^R}$$



Recommendation with Social Trust Ensemble



$$\prod_{i=1}^{m} \prod_{j=1}^{n} \left[\mathcal{N}\left(R_{ij} | g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j), \sigma^2 \right) \right]^{I_{ij}^R}$$

Recommendation with Social Trust Ensemble

$$\mathcal{L}(R,S,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(R_{ij} - g(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j))^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2, \qquad (15)$$

$$\frac{\partial\mathcal{L}}{\partial U_i} = \alpha\sum_{j=1}^{n} I_{ij}^{R} g'(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j)V_j \times (g(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j) - R_{ij}) + (1-\alpha)\sum_{p\in\mathcal{B}(i)}\sum_{j=1}^{n} I_{pj}^{R} g'(\alpha U_p^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(p)} S_{pk}U_k^T V_j) \times (g(\alpha U_p^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(p)} S_{pk}U_k^T V_j) - R_{pj})S_{pi}V_j + \lambda_U U_i,$$

$$\frac{\partial\mathcal{L}}{\partial V_j} = \sum_{i=1}^{m} I_{ij}^{R} g'(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j) \times (g(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j) - R_{ij}) \times (\alpha U_i + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T) + \lambda_V V_j,$$

Complexity

- In general, the complexity of this method is linear with the observations the user-item matrix

Epinions Dataset

- 51,670 users who rated 83,509 items with totally 631,064 ratings
- Rating Density 0.015%
- The total number of issued trust statements is 511,799

Metrics

- Mean Absolute Error and Root Mean Square Error

$$MAE = \frac{\sum_{i,j} |r_{i,j} - \widehat{r}_{i,j}|}{N}$$

$$RMSE = \sqrt{\frac{\sum_{i,j} (r_{i,j} - \widehat{r}_{i,j})^2}{N}}$$

Comparisons

Table III: Performance Comparisons (A Smaller MAE or RMSE Value Means a Better Performance)

Training Data	Metrics	Dimensionality = 5						
		UserMean	ItemMean	NMF	PMF	Trust	SoRec	RSTE
90%	MAE	0.9134	0.9768	0.8738	0.8676	0.9054	0.8442	**0.8377**
	RMSE	1.1688	1.2375	1.1649	1.1575	1.1959	1.1333	**1.1109**
80%	MAE	0.9285	0.9913	0.8975	0.8951	0.9221	0.8638	**0.8594**
	RMSE	1.1817	1.2584	1.1861	1.1826	1.2140	1.1530	**1.1346**

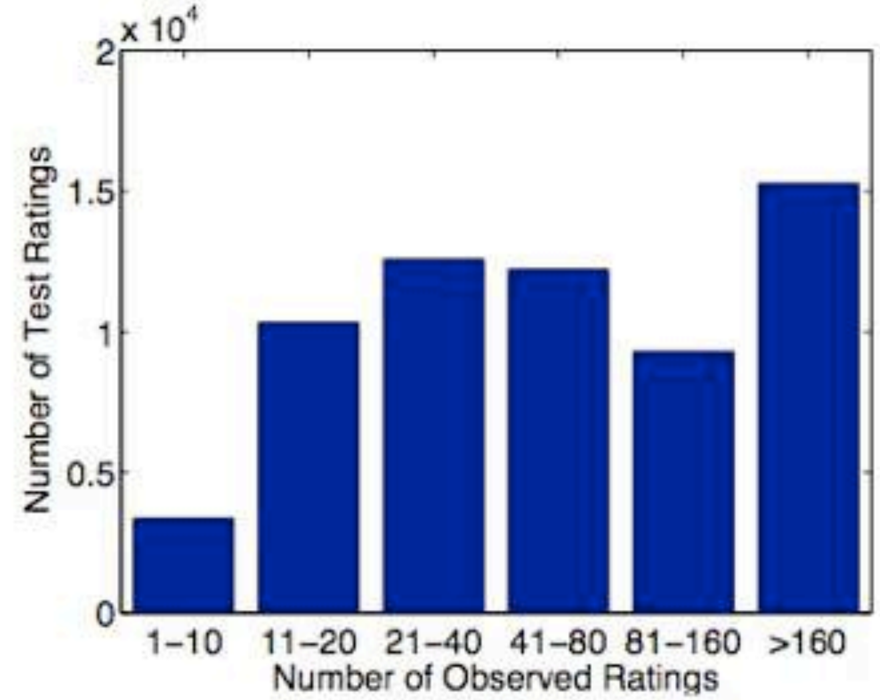
Training Data	Metrics	Dimensionality = 10						
		UserMean	ItemMean	NMF	PMF	Trust	SoRec	RSTE
90%	MAE	0.9134	0.9768	0.8712	0.8651	0.9039	0.8404	**0.8367**
	RMSE	1.1688	1.2375	1.1621	1.1544	1.1917	1.1293	**1.1094**
80%	MAE	0.9285	0.9913	0.8951	0.8886	0.9215	0.8580	**0.8537**
	RMSE	1.1817	1.2584	1.1832	1.1760	1.2132	1.1492	**1.1256**

NMF --- D. D. Lee and H. S. Seung (Nature 1999)
PMF --- R. Salakhutdinov and A. Mnih (NIPS 2008)
SoRec --- H. Ma, H. Yang, M. R. Lyu and I. King (CIKM 2008)
Trust, RSTE --- H. Ma, I. King and M. R. Lyu (SIGIR 2009)

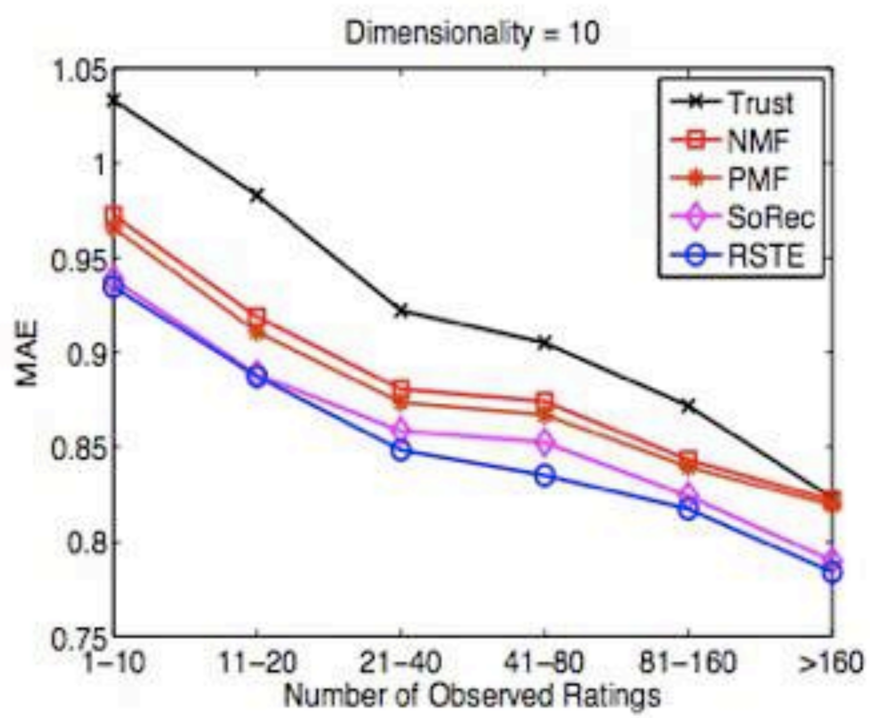
Performance on Different Users

- Group all the users based on the number of observed ratings in the training data
- 6 classes: "1 − 10", "11 − 20", "21 − 40", "41 − 80", "81 − 160", "> 160",

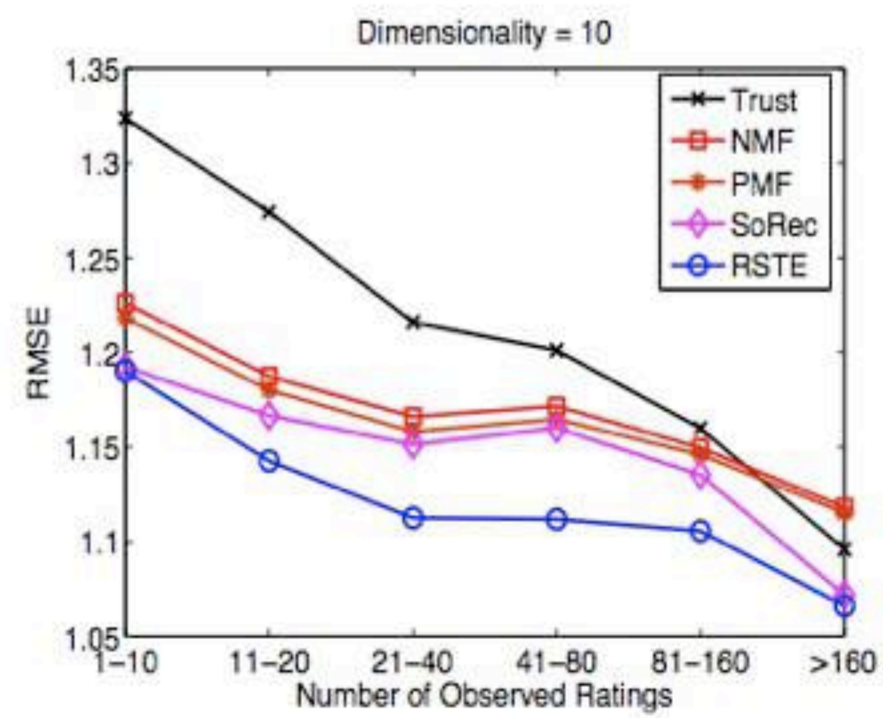
Performance on Different Users



(a) Distribution of Testing Data (90% as Training Data)

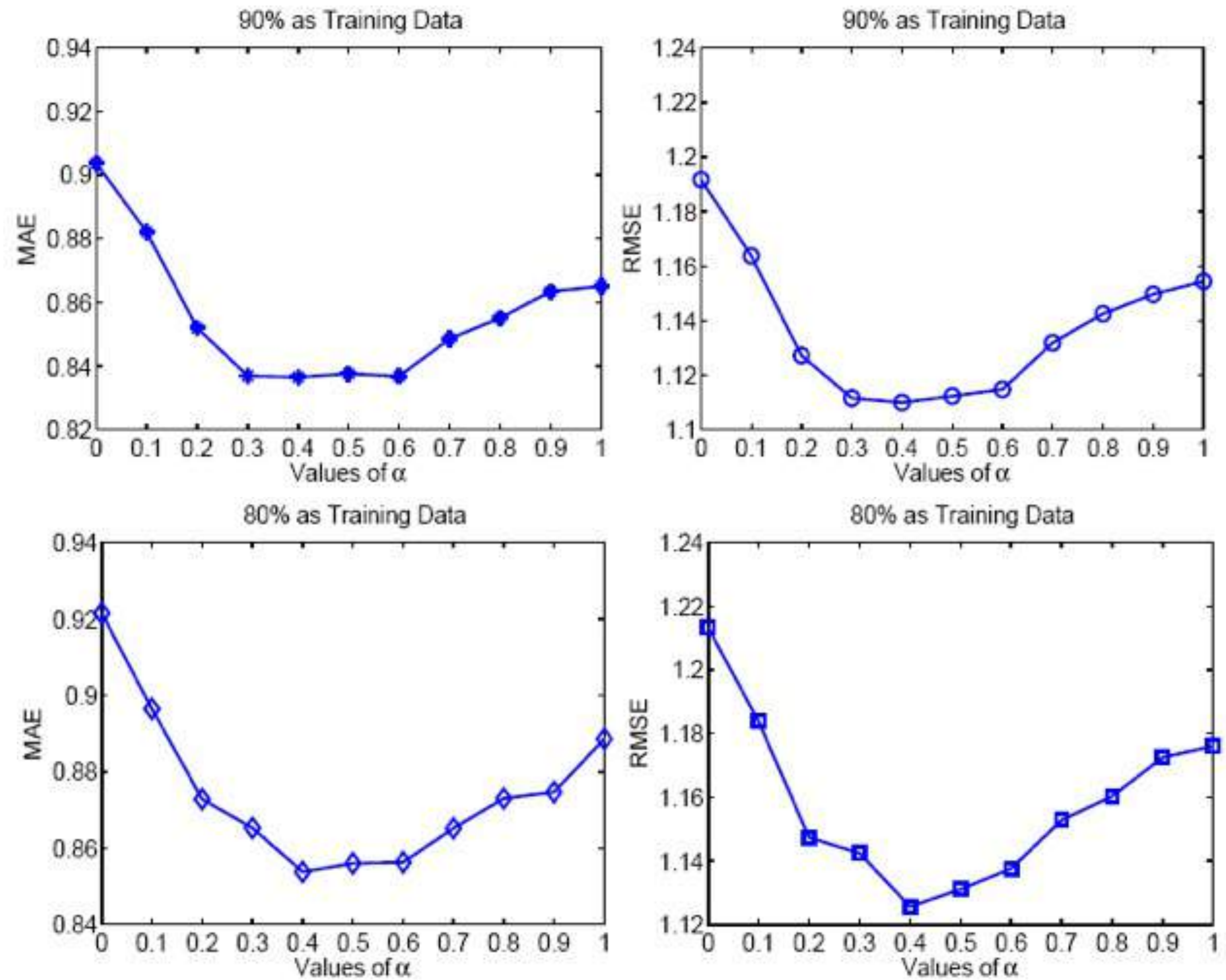


(b) MAE Comparison on Different User Rating Scales (90% as Training Data)



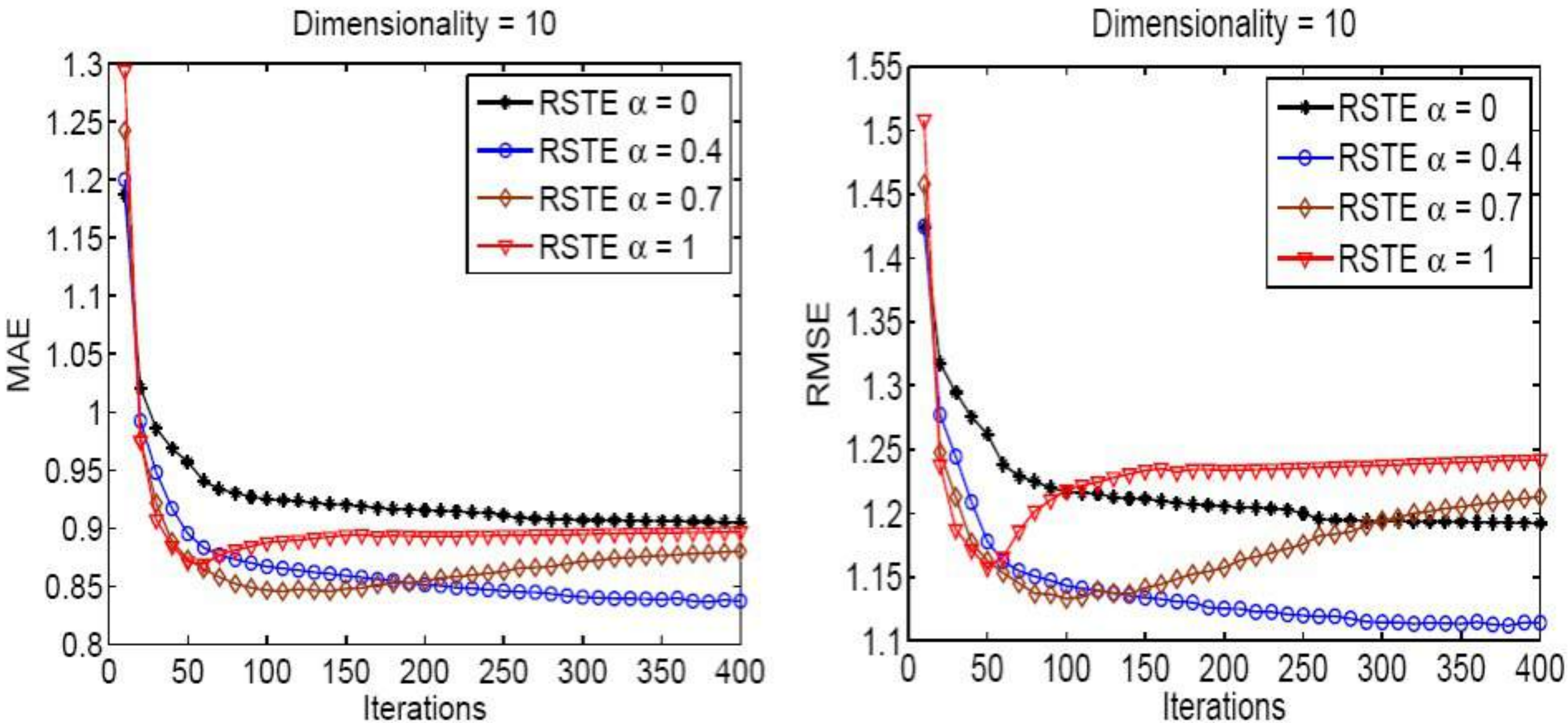
(c) RMSE Comparison on Different User Rating Scales (90% as Training Data)

Impact of Parameter Alpha



Impact of Parameter α (Dimensionality = 10)

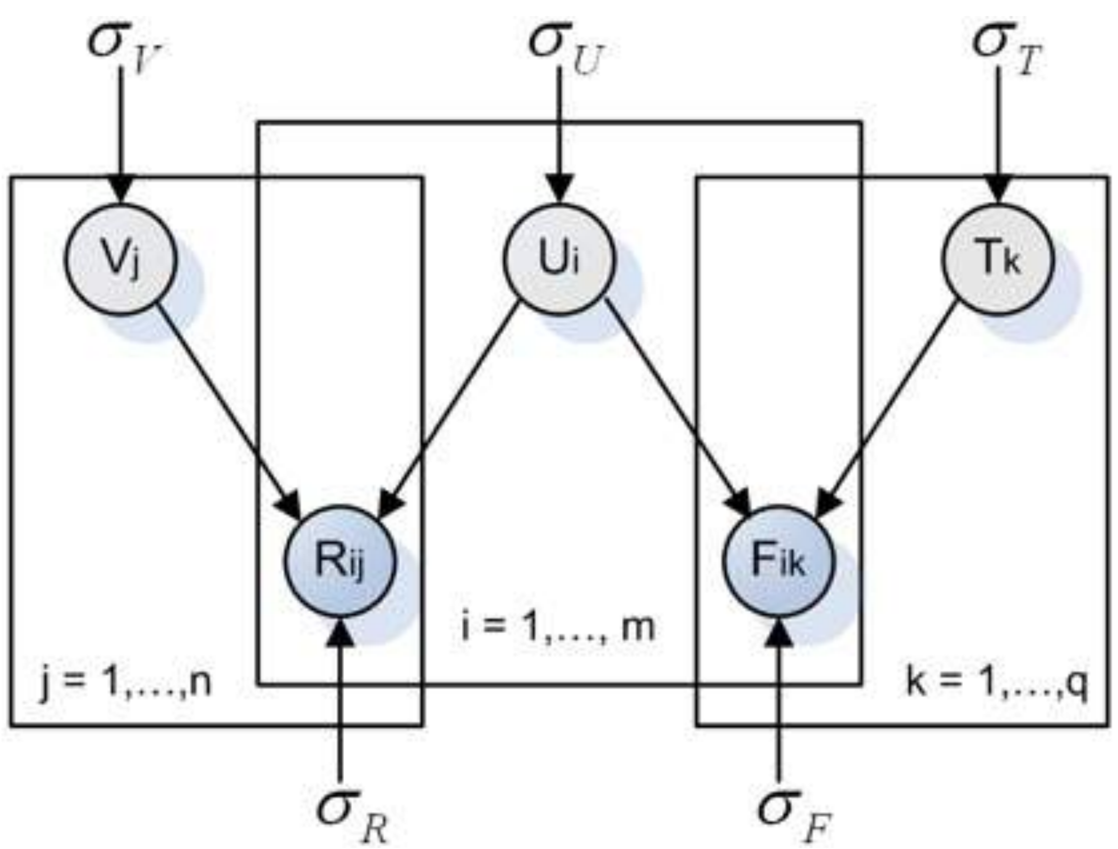
MAE and RMSE Changes with Iterations

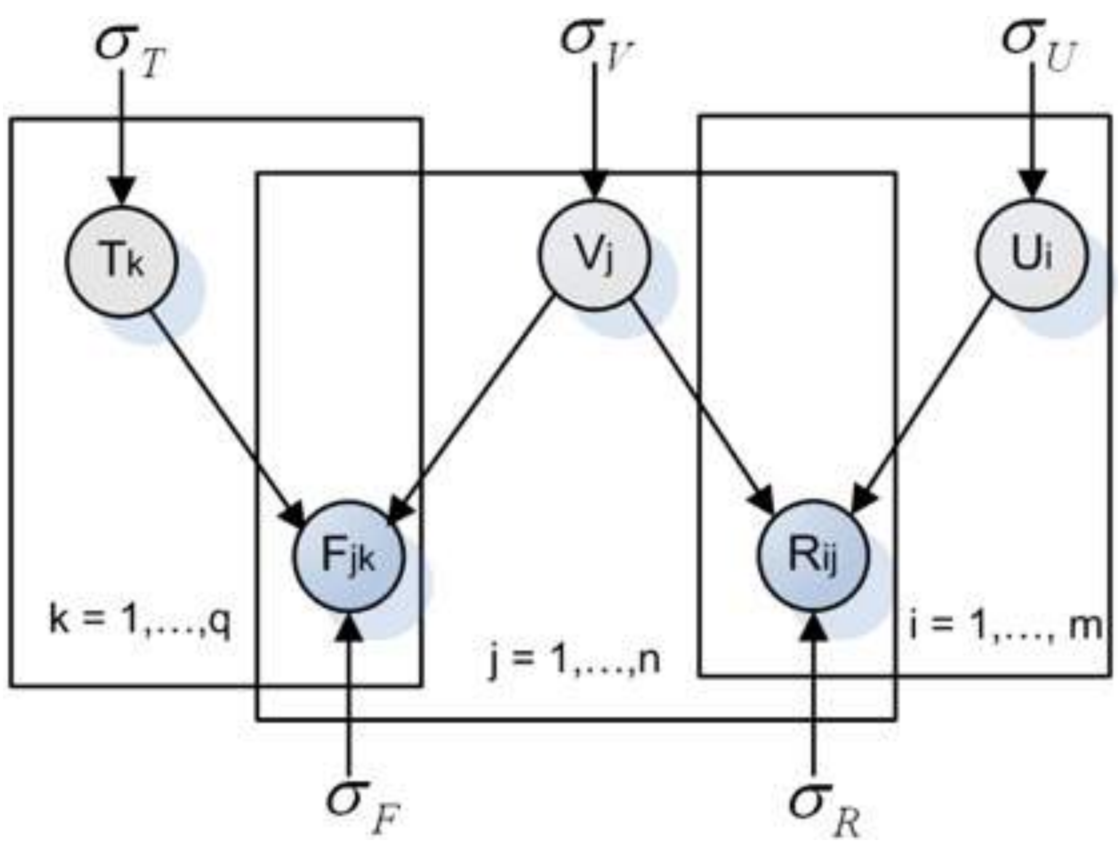


90% as Training Data

Further Discussion of SoRec

- Improving Recommender Systems Using Social Tags





MovieLens Dataset

71,567 users, 10,681 movies,

10,000,054 ratings, 95,580 tags

Further Discussion of SoRec

- MAE

Table V: MAE comparison with other approaches on MovieLens dataset (A smaller MAE value means a better performance)

Methods		80% Training	50% Training	30% Training	10% Training
User Mean		0.7686	0.7710	0.7742	0.8234
Item Mean		0.7379	0.7389	0.7399	0.7484
5D	SVD	0.6390	0.6547	0.6707	0.7448
	PMF	0.6325	0.6542	0.6698	0.7430
	SoRecUser	0.6209	0.6419	0.6607	0.7040
	SoRecItem	**0.6199**	**0.6407**	**0.6395**	**0.7026**
10D	SVD	0.6386	0.6534	0.6693	0.7431
	PMF	0.6312	0.6530	0.6683	0.7417
	SoRecUser	0.6197	0.6408	0.6595	0.7028
	SoRecItem	**0.6187**	**0.6395**	**0.6584**	**0.7016**

Further Discussion of SoRec

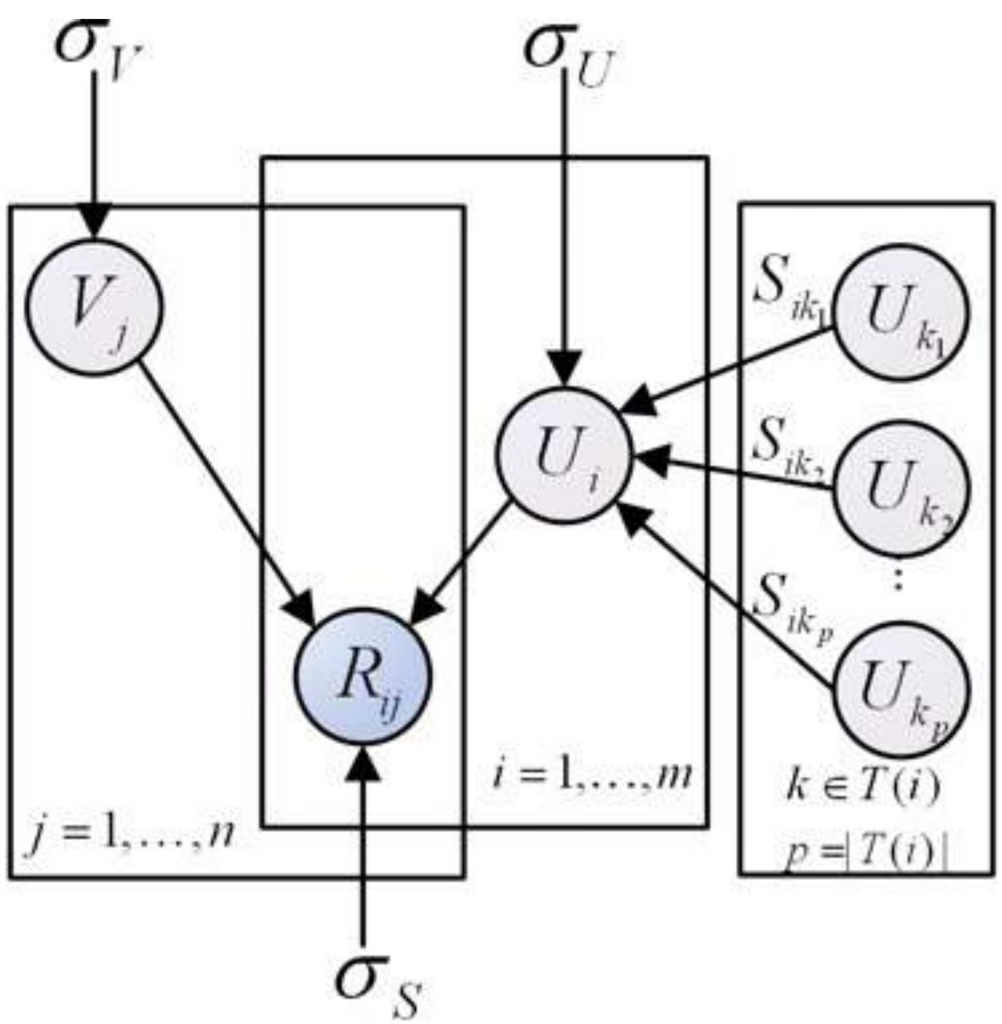
- RMSE

Table VI: RMSE comparison with other approaches on MovieLens dataset (A smaller RMSE value means a better performance)

Methods		80% Training	50% Training	30% Training	10% Training
User Mean		0.9779	0.9816	0.9869	1.1587
Item Mean		0.9440	0.9463	0.9505	0.9851
5D	SVD	0.8327	0.8524	0.8743	0.9892
	PMF	0.8310	0.8582	0.8758	0.9698
	SoRecUser	0.8121	0.8384	0.8604	0.9042
	SoRecItem	**0.8112**	**0.8370**	**0.8591**	**0.9033**
10D	SVD	0.8312	0.8509	0.8728	0.9878
	PMF	0.8295	0.8569	0.8743	0.9681
	SoRecUser	0.8110	0.8372	0.8593	0.9034
	SoRecItem	**0.8097**	**0.8359**	**0.8578**	**0.9019**

Further Discussion of RSTE

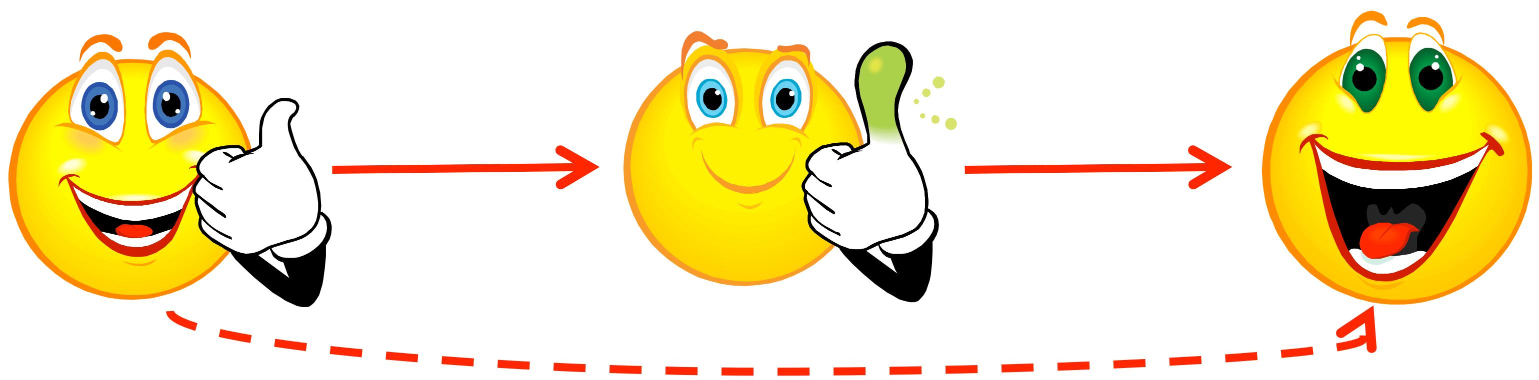
- Relationship with Neighborhood-based methods



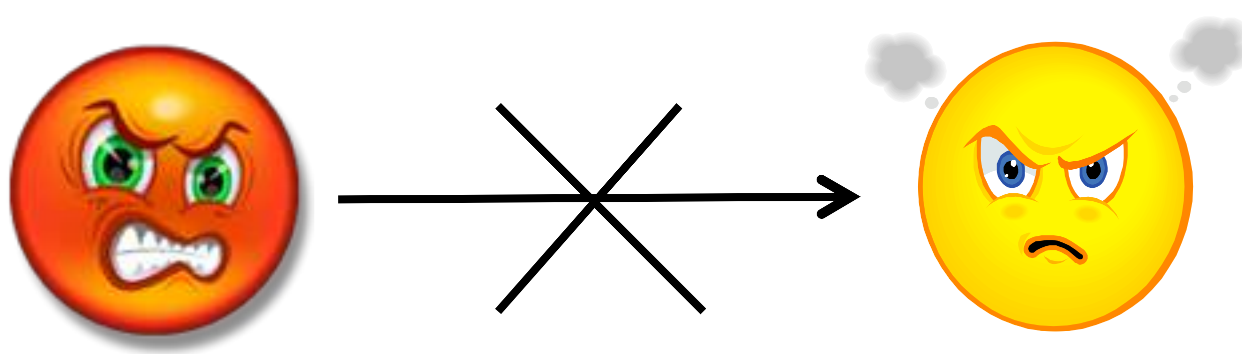
- The trusted friends are actually the explicit neighbors
- We can easily apply this method to include implicit neighbors
- Using PCC to calculate similar users for every user

What We Cannot Model Using SoRec and RSTE?

- Propagation of trust



- Distrust



Recommend with Social Distrust

[Hao Ma, et al., RecSys2009]

Distrust

- Users' distrust relations can be interpreted as the "dissimilar" relations
  - On the web, user Ui distrusts user Ud indicates that user Ui disagrees with most of the opinions issued by user Ud.

Distrust

$$\max_U \frac{1}{2}\sum_{i=1}^{m}\sum_{d\in\mathcal{D}^+(i)} S_{id}^{\mathcal{D}}\|U_i - U_d\|_F^2$$

$$\begin{aligned}\min_{U,V}\mathcal{L}_{\mathcal{D}}(R,S^{\mathcal{D}},U,V) &= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^R(R_{ij}-g(U_i^T V_j))^2 \\ &+ \frac{\beta}{2}\sum_{i=1}^{m}\sum_{d\in\mathcal{D}^+(i)}(-S_{id}^{\mathcal{D}}\|U_i-U_d\|_F^2) \\ &+ \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2.\end{aligned}$$

Trust

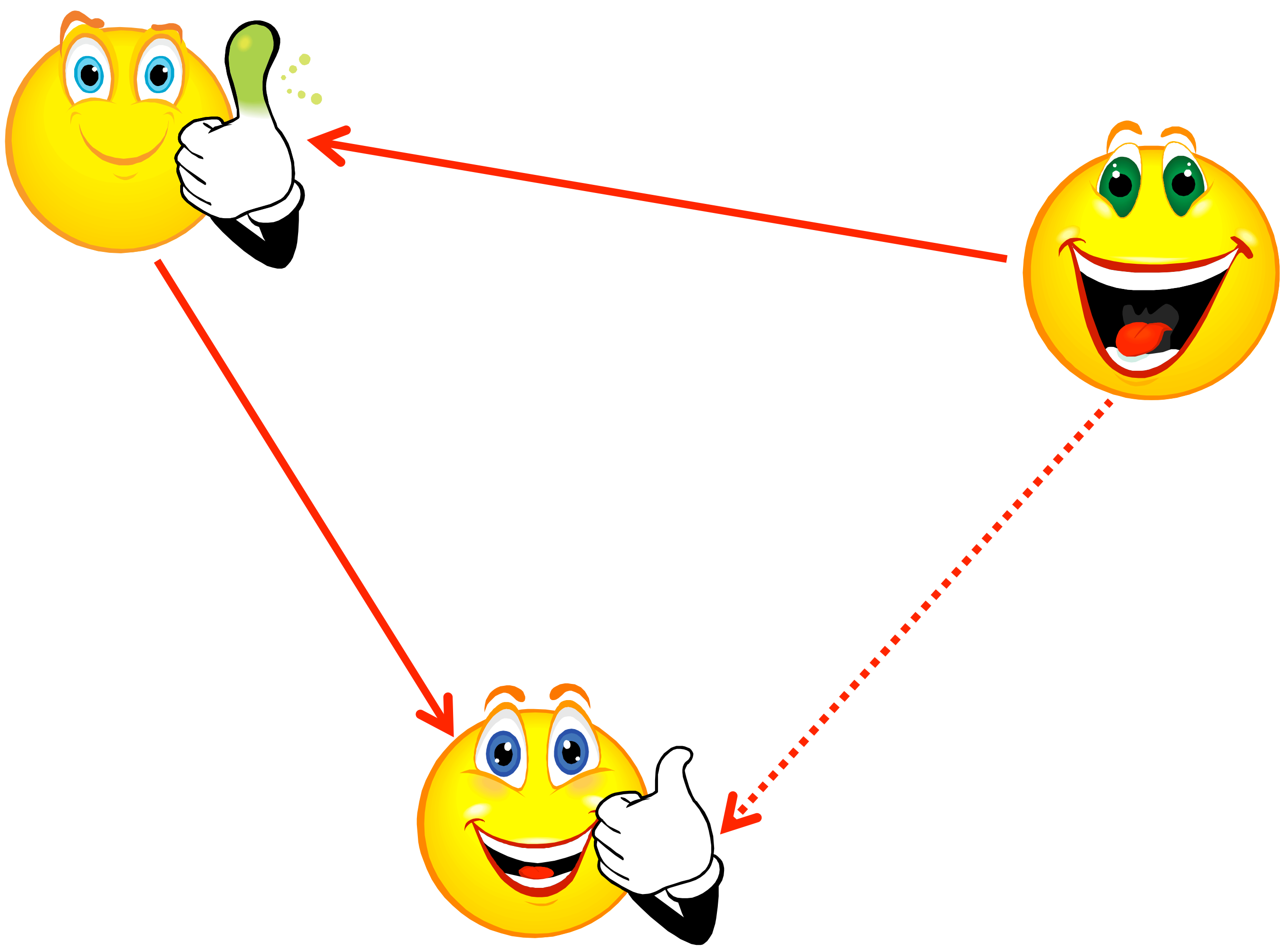
- Users' trust relations can be interpreted as the "similar" relations
    - On the web, user Ui trusts user Ut indicates that user Ui agrees with most of the opinions issued by user Ut.

Trust

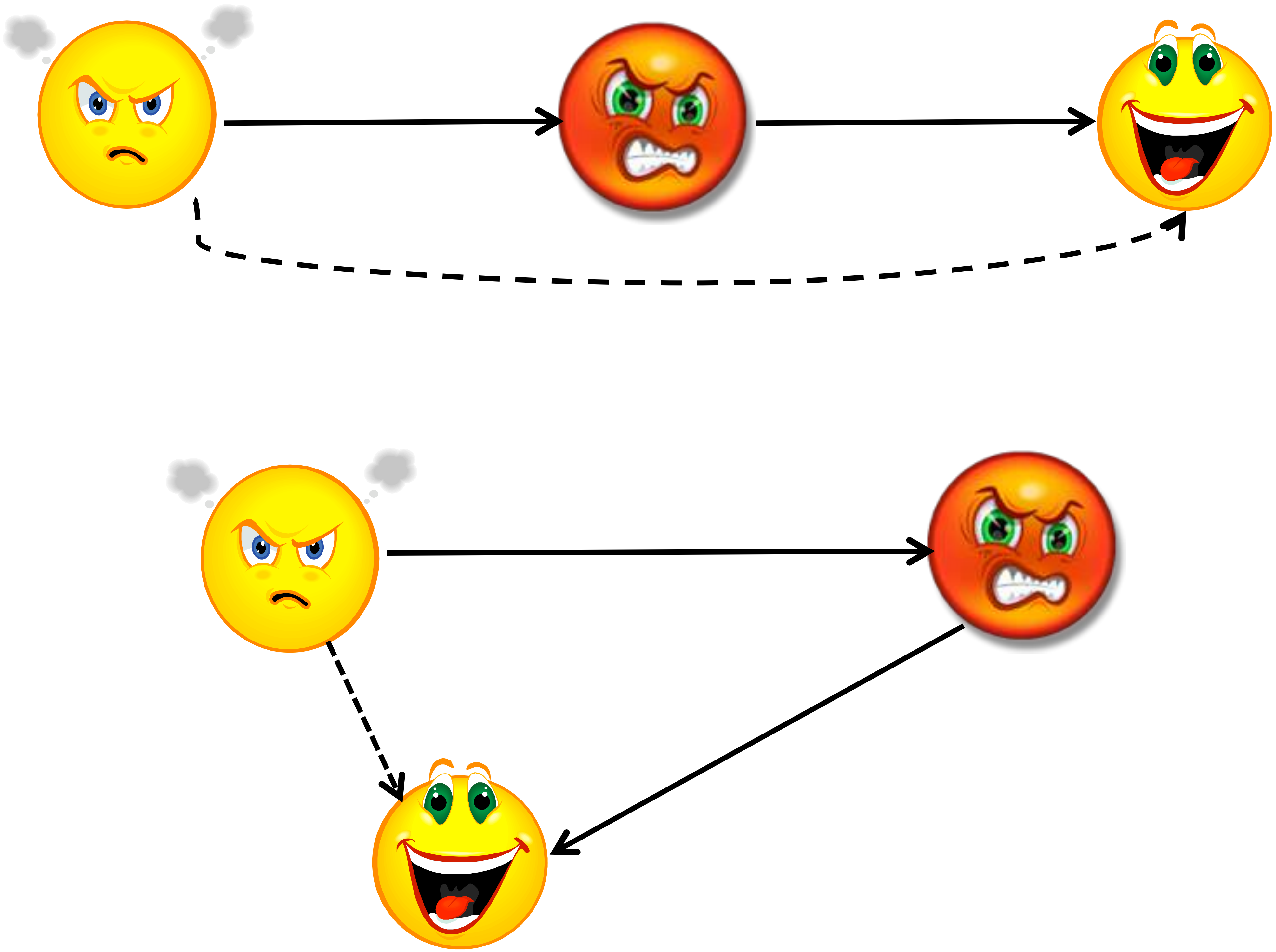
$$\min_{U} \frac{1}{2} \sum_{i=1}^{m} \sum_{t \in \mathcal{T}^{+}(i)} S_{it}^{\mathcal{T}} \|U_i - U_t\|_F^2$$

$$\begin{aligned}\min_{U,V} \mathcal{L}_{\mathcal{T}}(R, S^{\mathcal{T}}, U, V) &= \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}^{R} (R_{ij} - g(U_i^T V_j))^2 \\ &+ \frac{\alpha}{2} \sum_{i=1}^{m} \sum_{t \in \mathcal{T}^{+}(i)} (S_{it}^{\mathcal{T}} \|U_i - U_t\|_F^2) \\ &+ \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2.\end{aligned}$$

Trust Propagation



Distrust Propagation?



Experiments

- Dataset - Epinions
- 131,580 users, 755,137 items, 13,430,209 ratings
- 717,129 trust relations, 123,670 distrust relations

Data Statistics

Table 1: Statistics of User-Item Rating Matrix of Epinions

Statistics	User	Item
Min. Num. of Ratings	1	1
Max. Num. of Ratings	162169	1179
Avg. Num. of Ratings	102.07	17.79

Table 2: Statistics of Trust Network of Epinions

Statistics	Trust per User	Be Trusted per User
Max. Num.	2070	3338
Avg. Num.	5.45	5.45

Table 3: Statistics of Distrust Network of Epinions

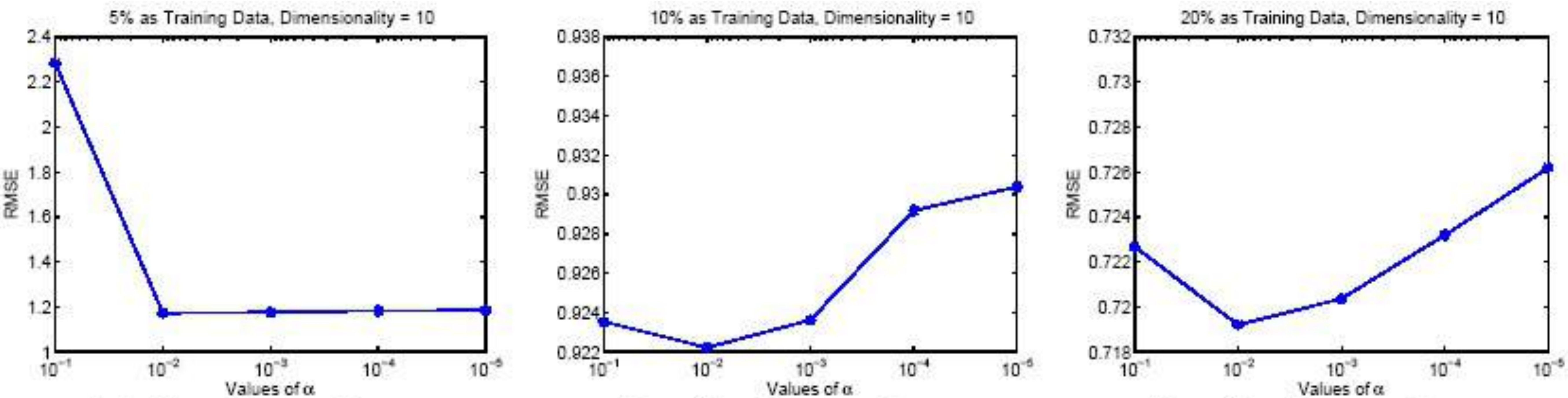
Statistics	Distrust per User	Be Distrusted per User
Max. Num.	1562	540
Avg. Num.	0.94	0.94

Experiments

RMSE

Dataset	Traning Data	Dimensionality	PMF	SoRec	RWD	RWT
Epinions	5%	5D	1.228	1.199	1.186	**1.177**
		10D	1.214	1.198	1.185	**1.176**
	10%	5D	0.990	0.944	0.932	**0.924**
		10D	0.977	0.941	0.931	**0.923**
	20%	5D	0.819	0.788	0.723	**0.721**
		10D	0.818	0.787	0.723	**0.720**

Impact of Parameters



(a) 5% as Training Data (b) 10% as Training Data (c) 20% as Training Data

Figure 6: Impact of Parameter α

Alpha = 0.01 will get the best performance!

Parameter beta basically shares the same trend!

Social Recommender Systems

- Introduction
- Collaborative Filtering
- Trust-aware Recommender Systems
- Social-based Recommender Systems

Comparison

- Trust-aware Recommender systems
    - Trust network
    - Trust relations can be treated as "similar" relations
    - Few dataset available on the web

- Social-based Recommender Systems
    - Social friend network, mutual relations
    - Friends are very divers, and may have different tastes
    - Lots of web sites have social network implementation

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Outline

- Introduction
- Social Search Engine
- Social Recommender Systems
- Social Media Analysis

Social Media Analysis

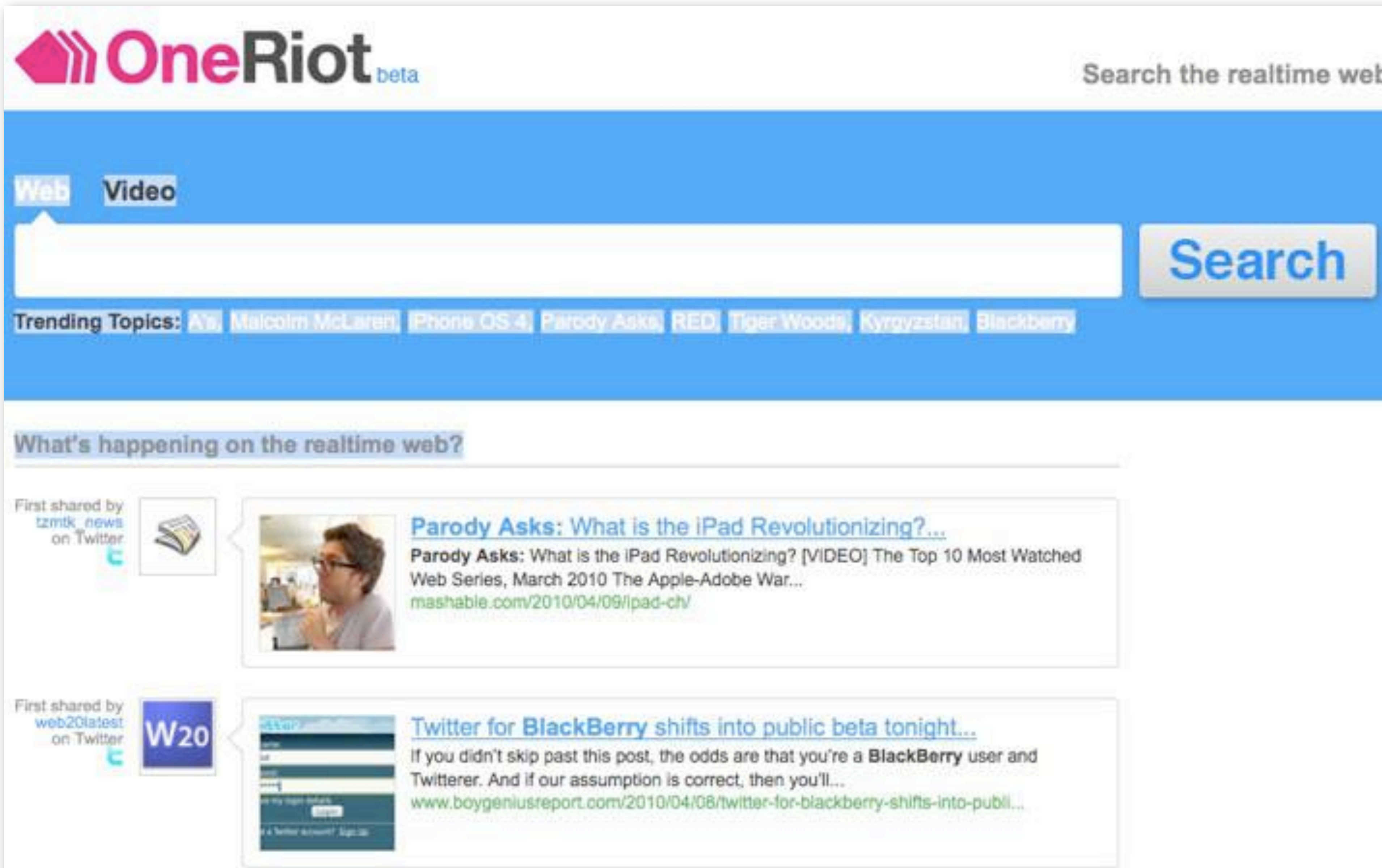
- Social Media Ranking
- Tag Recommendation
- News Recommendation
- User Recommendation
- Twitter-powered Recommendation

Social Media Ranking

- Pulse Rank - OneRiot
- Reddit Algorithm
- Digg Algorithm
- Google's Page Rank

Pulse Rank - OneRiot

- A realtime web search engine, which archives and makes searchable news, videos and blogs being discussed on the web, ordered to reflect current social relevance.



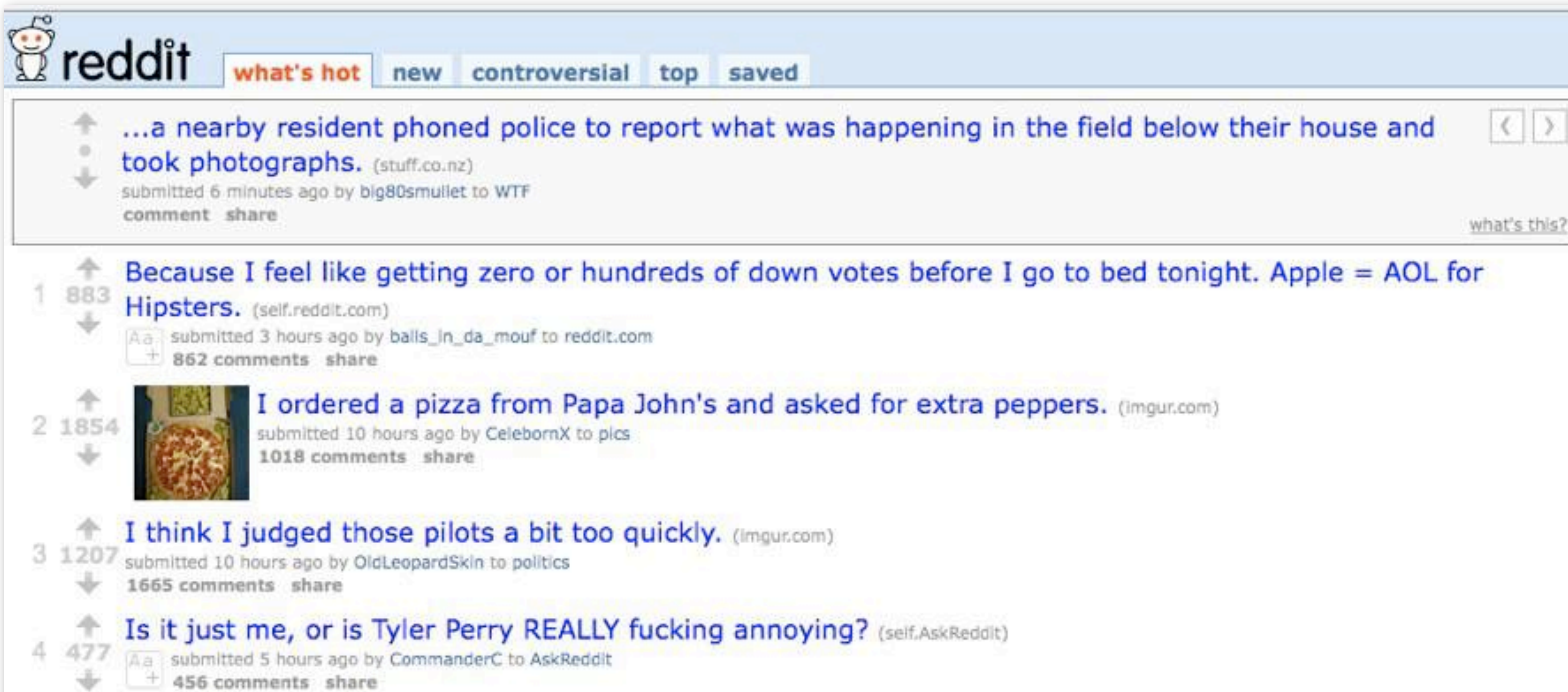
Pulse Rank - OneRiot

- "Pulse Rank" algorithm looks at dozens of factors that give "weight" to certain results
  - **Freshness**: Is the most recently published content necessarily the most relevant?
  - **Domain Authority:** An article about Obama on New York Times should weight higher than the article on my blog.
  - **People Authority**: Who is sharing this link on the social web?
  - **Acceleration**: Is this page increasing in hotness or decreasing in hotness?

From http://blog.oneriot.com/content/2009/06/oneriot-pulse-rank/

Reddit Algorithm

- **Reddit** is a social news website on which users can post links to content on the Internet. Other users may then vote the posted links up or down, causing them to become more or less prominent on the reddit home page.



Reddit Algorithm

- Time differences

$$t_s = A - B$$

- Differences of the up votes and down votes

$$x = U - D$$

$$y = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \qquad z = \begin{cases} |x| & \text{if } |x| \geq 1 \\ 1 & \text{if } x < 1 \end{cases}$$

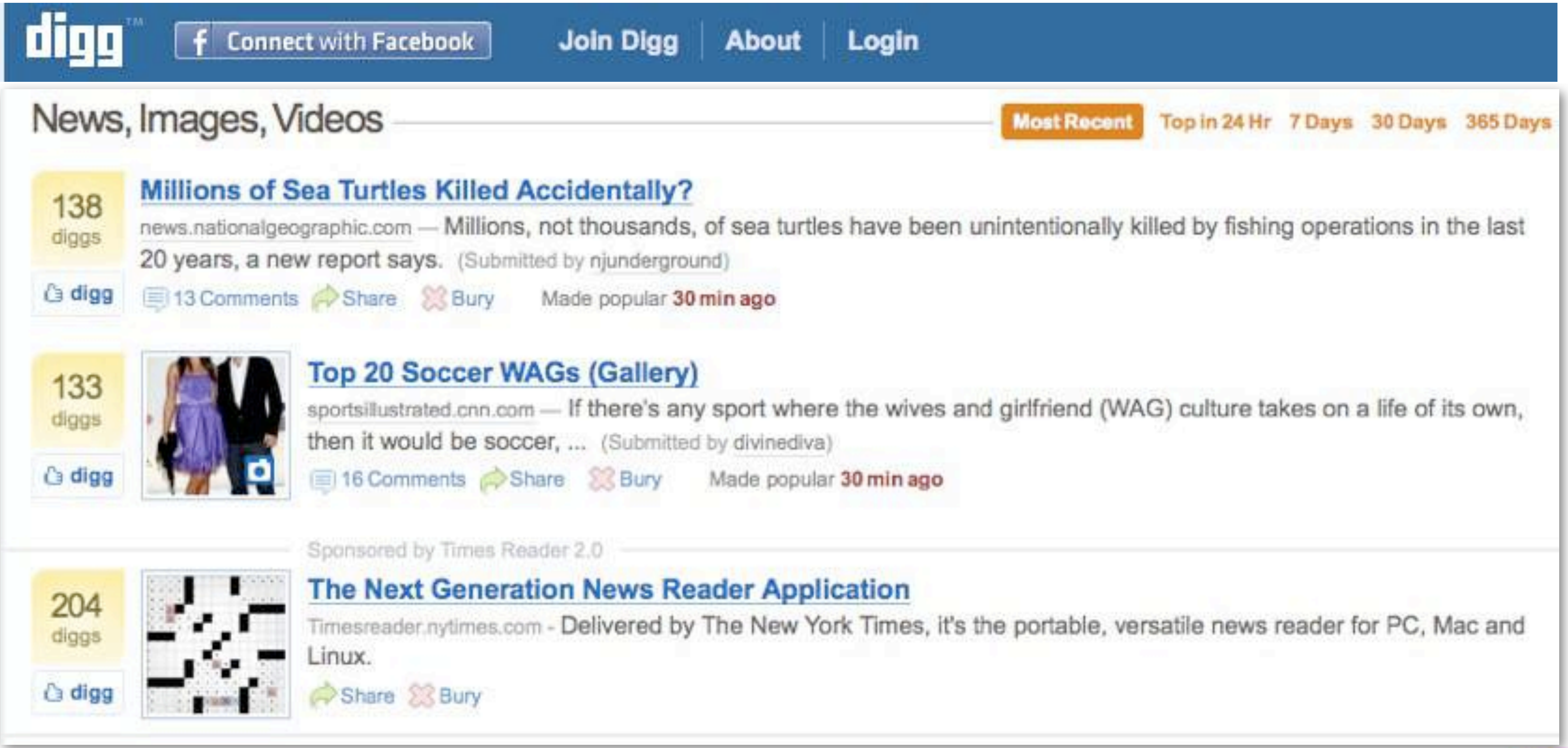
- Ranking functions

$$f(t_s, y, z) = \log_{10} z + \frac{y t_s}{45000}$$

From http://uggedal.com/reddit.cf.algorithm.png

Digg Algorithm

- A social news website made for people to discover and share content from anywhere on the Internet, by submitting links and stories, and voting and commenting on submitted links and stories



Digg Algorithm

- The rapidity of the votes
  If you get 40-50 votes (no matter what users digg) in the first 30 minutes, you're probably on the frontpage.
- The rank of the users that vote the article
  The highest it is on the top list, the better.
- The number of comments, and the positive diggs that each article receives
  If you have a lot of negative rated comments that can hurt more then help actually.
- The number of buries your story gets
- The submitted / promoted stories ratio of the users that vote
  If 12-14 users with at least a 70% ratio, vote your article, you can make the frontpage much easier.

From http://www.seopedia.org/tips-tricks/social-media/the-digg-algorithm-unofficial-faq/

How Google Ranks Tweets

How Google Ranks Tweets

- The key is to identify "reputed followers"
- You earn reputation, and then you give reputation
- One user following another in social media is analogous to one page linking to another on the Web. Both are a form of recommendation
- Page Rank on follow graph

From http://www.technologyreview.com/web/24353/?a=f

Social Media Analysis

- Social Media Ranking
- Tag Recommendation
- News Recommendation
- User Recommendation
- Twitter-powered Recommendation

Why users tag?

- Tagging means something specific to the user
- It is easy -- anyone can do it
- Finding things on the Internet
- Serendipitous discovery
- It is social
- New ways to share and discover

Why need Tag Recommendation?

- User tags contain noises
- Automating the tagging process
- Assisting users to tag

Flickr Tag Recommendation based on Collective Knowledge

[B. Sigurbjörnsson, et al., WWW2008]

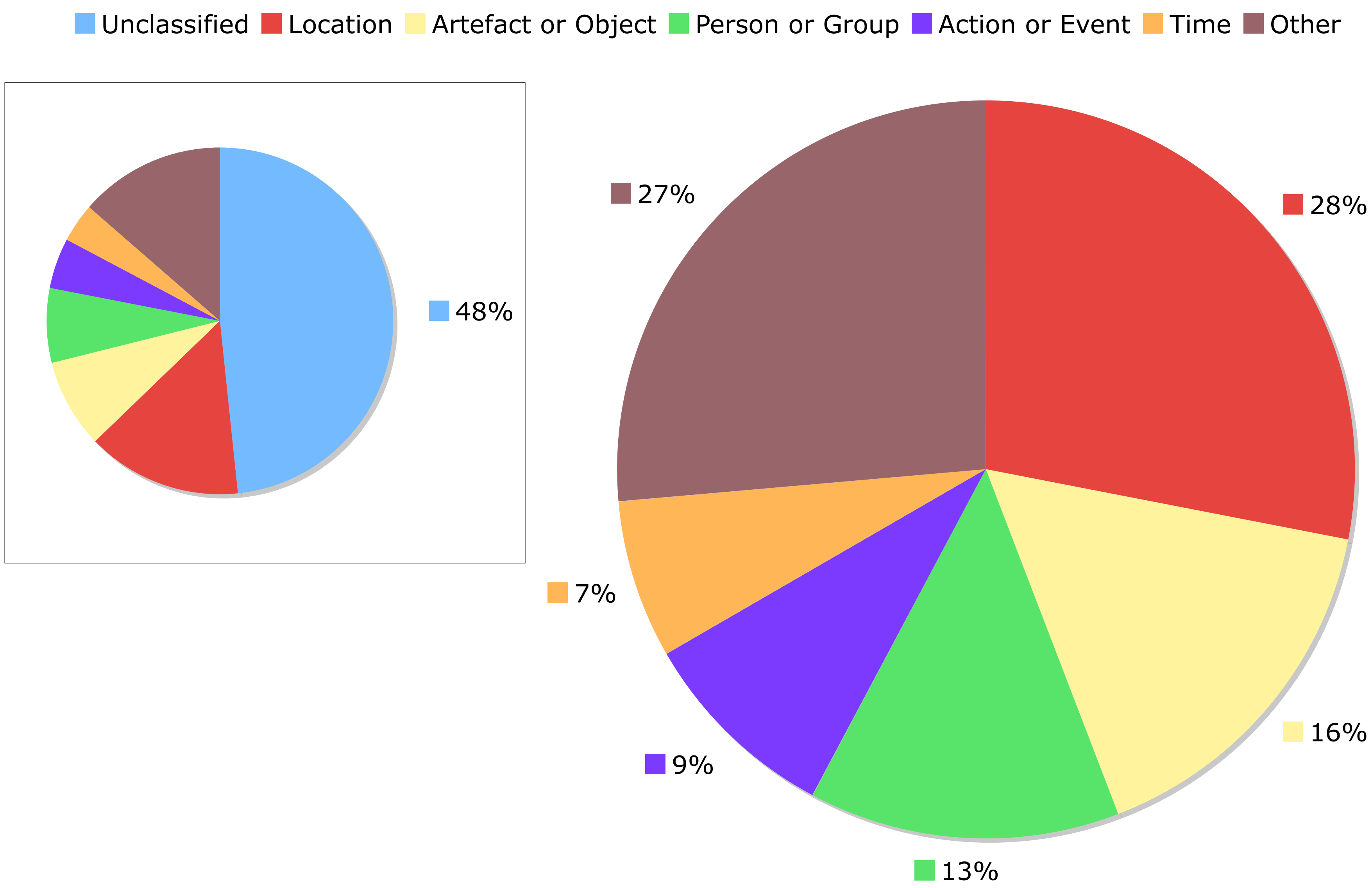


Figure 3: Most frequent WordNet categories for Flickr tags.

Flickr Tag Recommendation based on Collective Knowledge

[B. Sigurbjörnsson, et al., WWW2008]

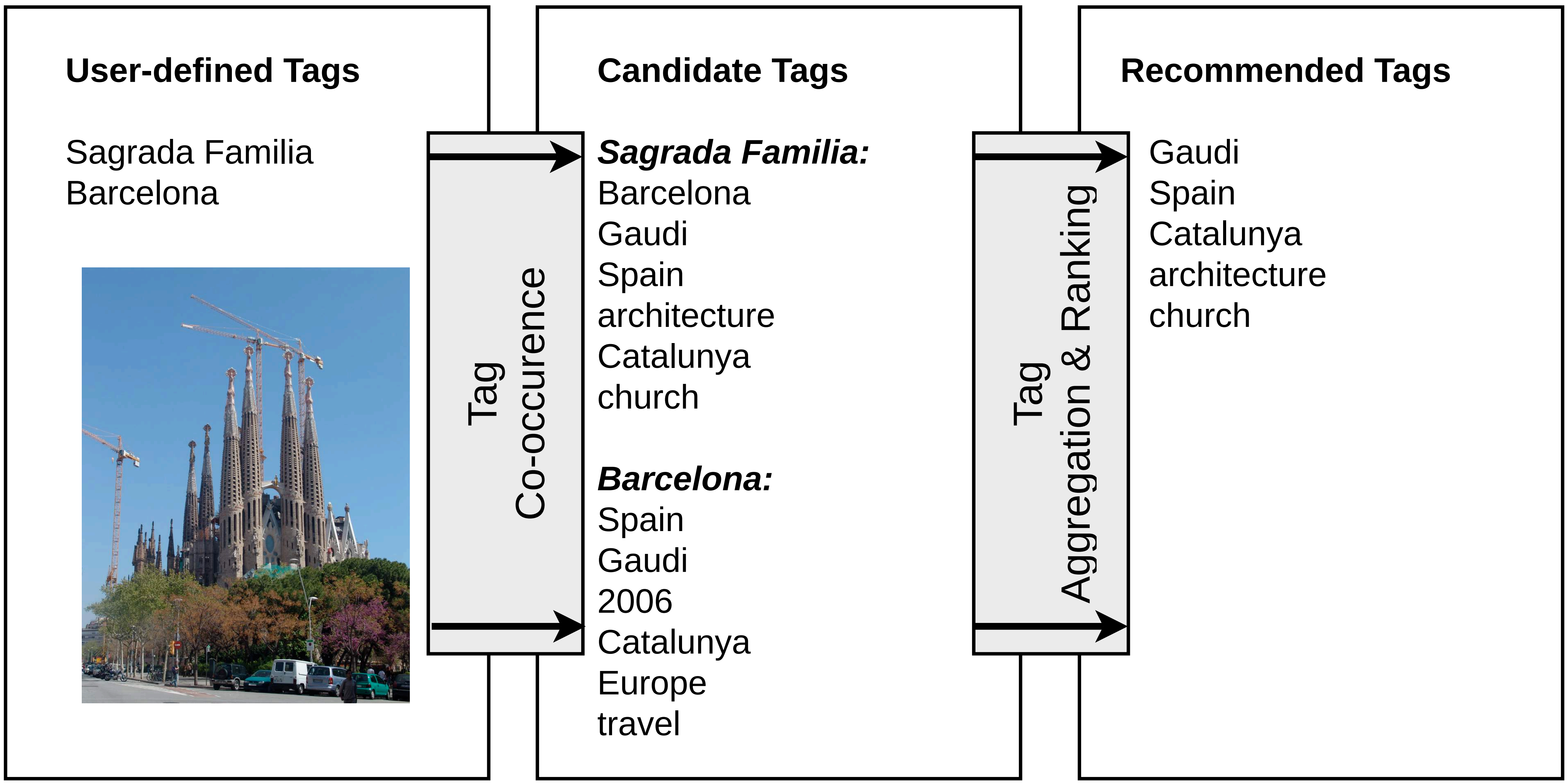
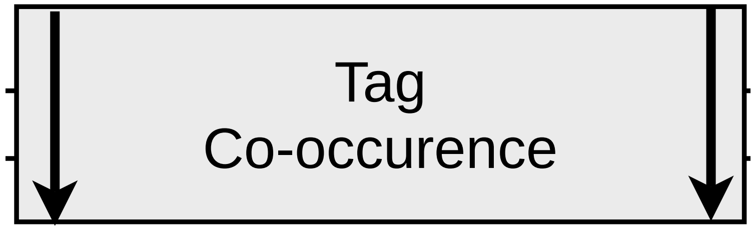


Figure 4: System overview of the tag recommendation process.

Flickr Tag Recommendation based on Collective Knowledge

[B. Sigurbjörnsson, et al., WWW2008]



- Define the Tag Co-occurrence between two tags to be the number of photos where both tags are used in the same annotation

- Symmetric measure: Jaccard Coefficient

$$J(t_i, t_j) := \frac{|t_i \cap t_j|}{|t_i \cup t_j|}$$

- Asymmetric measure:

$$P(t_j|t_i) := \frac{|t_i \cap t_j|}{|t_i|}$$

Flickr Tag Recommendation based on Collective Knowledge

[B. Sigurbjörnsson, et al., WWW2008]

Tag: Eiffel Tower

Symmetric Meature:

Tour Eiffel
Eiffel
Seine
La Tour Eiffel
Paris

Good at identifying equivalent tags

Aymmetric Meature:

Paris
France
Tour Eiffel
Eiffel
Europe

Good at suggesting diverse tags

Flickr Tag Recommendation based on Collective Knowledge

[B. Sigurbjörnsson, et al., WWW2008]

- Aggregation

  - Vote
    - The voting strategy computes a score for each candidate tag c

$$vote(u,c) = \begin{cases} 1 & \text{if } c \in C_u \\ 0 & \text{otherwise} \end{cases}$$

A score is therefore computed as

$$score(c) := \sum_{u \in U} vote(u,c)$$

  - Sum
    - The summing strategy sums over the co-occurrence values of the tags

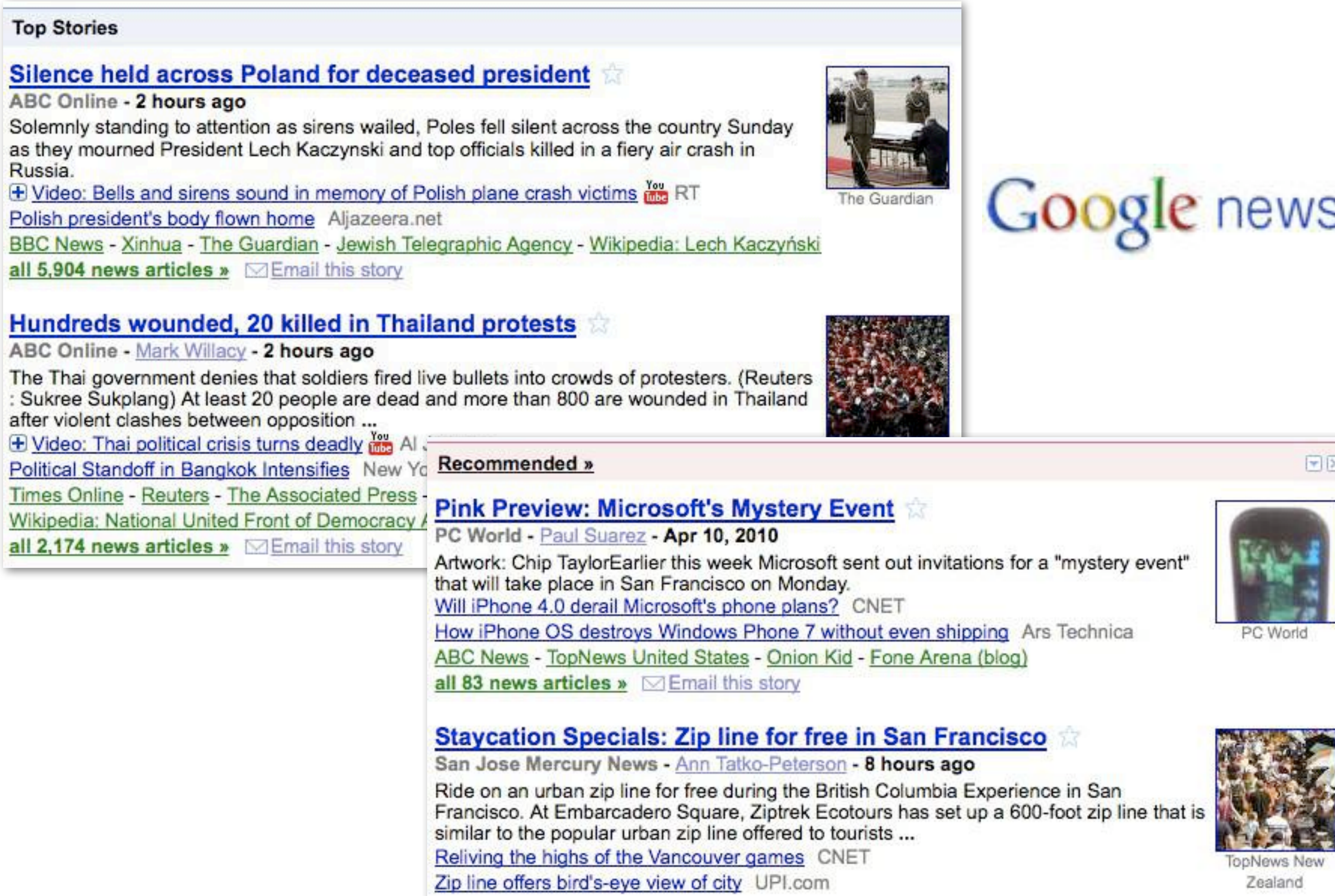
$$score(c) := \sum_{u \in U} (P(c|u) \quad \text{, if } c \in C_u)$$

where P(c|u) calculates the asymmetric co-occurrence values, and u is the user defined tags

Social Media Analysis

- Social Media Ranking
- Tag Recommendation
- News Recommendation
- User Recommendation
- Twitter-powered Recommendation

Google News Recommendation



Google news

News Recommendation

- Online news reading has become very popular
- Web provides access to news articles from millions of sources around the world
- Key challenge: help users find the articles that are interesting to read

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

- News click logs analysis
  - Data
    - Google News, over 12-month period, from 2007/07/01 to 2008/06/30
    - Randomly sampled 16,848 users from users who made at least 10 clicks per month
    - Users are from more than 10 different countries and regions

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

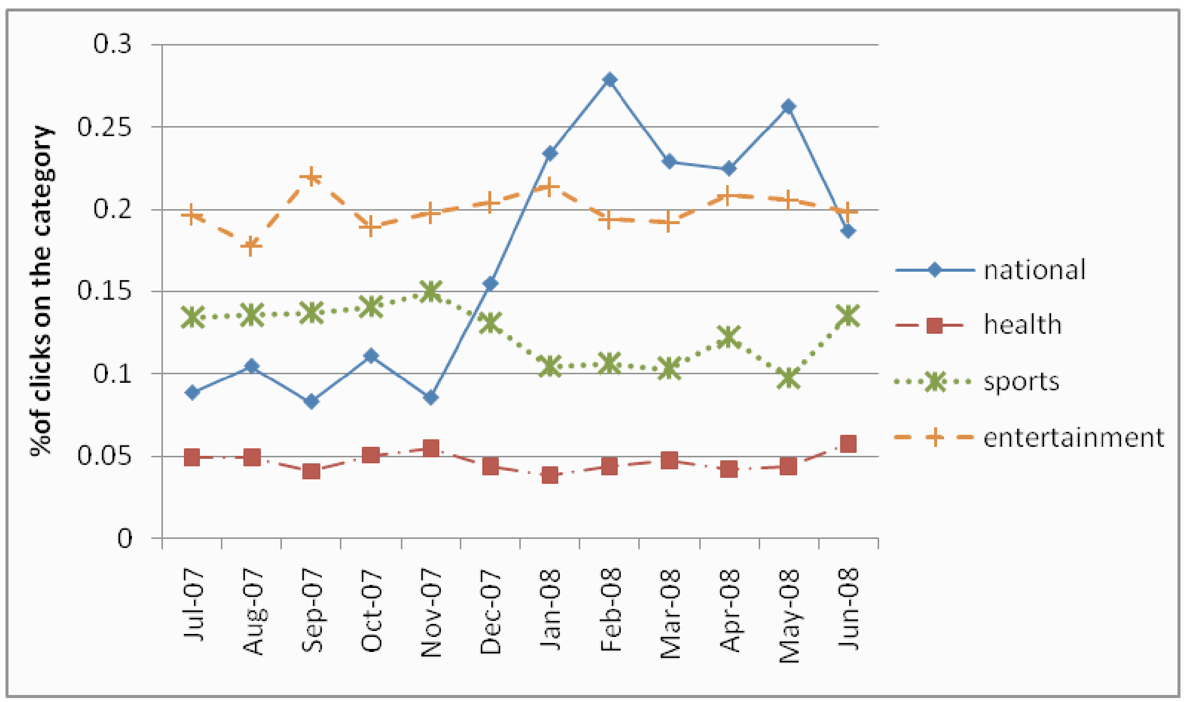


Figure 2. Interest distribution of US users over time

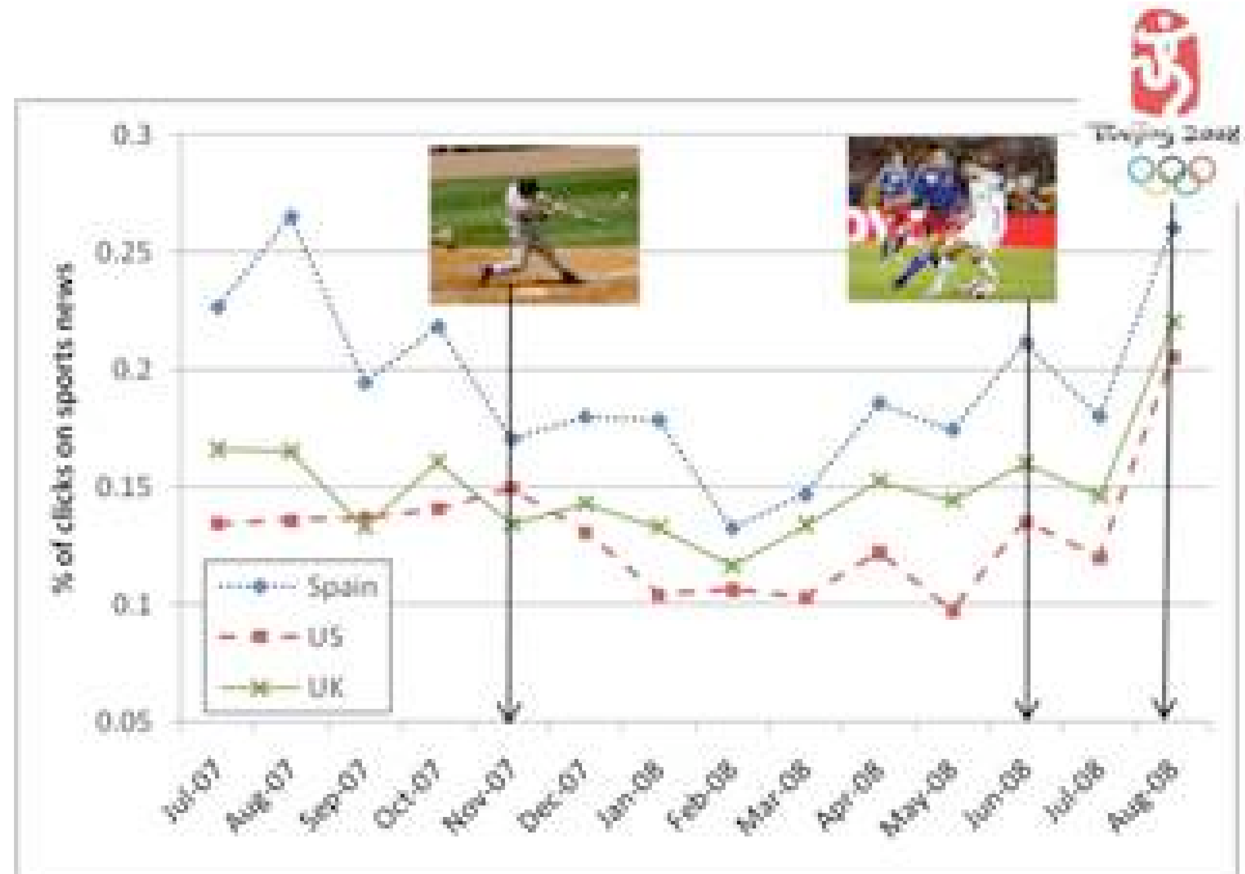


Figure 3. Change of interests in sports news over time

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

- Observations
  - The news interests of individual users do change over time
  - The click distributions of the general public reflect the news trend, which correspond to the big news events
  - There exists different news trends in different locations
  - To a certain extent, the individual user's news interests correspond with the news trend in the location that the users belongs to

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

- Bayesian Framework for User Interest Prediction
  - Predicting user's genuine news interest
    - For a specific time period t in the past, the genuine interest of a user in topic category c_i is modeled as

$$p^t(click \mid category = c_i)$$

    - Using Bayesian rule

$$interest^t(category = c_i) = p^t(click \mid category = c_i)$$

$$= \frac{p^t(category = c_i \mid click)\, p^t(click)}{p^t(category = c_i)}$$

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

- Bayesian Framework for User Interest Prediction
  - Combining predictions of past time periods

$$interest(category = c_i) = \frac{\sum_t \left(N^t \times interest^t(category = c_i)\right)}{\sum_t N^t}$$

$$= \frac{\sum_t \left(N^t \times \frac{p^t(category = c_i \mid click) p^t(click)}{p^t(category = c_i)} \right)}{\sum_t N^t}$$

N^t is the total number of clicks by the user in time period t

  - Assume $p^t(click)$ is a constant, then we get

$$interest(category = c_i)$$

$$= \frac{p(click) \times \sum_t \left(N^t \times \frac{p^t(category = c_i \mid click)}{p^t(category = c_i)} \right)}{\sum_t N^t}$$

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

- Bayesian Framework for User Interest Prediction
  - Predicting user's current news interest
    - Use the click distribution of the general public in a short current time period (e.g. in the past hour), represented as $p^0(category = c_i)$, by using Bayesian rule:

$$p^0(category = c_i \mid click) = \frac{p^0(click \mid category = c_i)\, p^0(category = c_i)}{p^0(click)}$$

    - Estimate $p^0(click \mid category = c_i)$ with genuine interests $interest(category = c_i)$

$$p^0(category = c_i \mid click) \propto \frac{interest(category = c_i)\, p^0(category = c_i)}{p(click)} \propto \frac{p^0(category = c_i) \times \sum_t \left(N^t \times \frac{p^t(category = c_i \mid click)}{p^t(category = c_i)} \right)}{\sum_t N^t}$$

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

- Bayesian Framework for User Interest Prediction
  - Predicting user's current news interest
    - Adding a set of virtual clicks G, which is set to be 10 in the system. It can be regarded as a smooth factor.

$$p^0(category = c_i \mid click)$$

$$\propto \frac{p^0(category = c_i) \times \left(\sum_t \left(N^t \times \frac{p^t(category = c_i \mid click)}{p^t(category = c_i)} \right) + G \right)}{\sum_t N^t + G}$$

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

- Live traffic experiment
  - Experiments conducted on a fraction (about 10,000 users) of the live traffic at Google News
  - Users were randomly assigned to a control group and a test group. Two groups have the same size
  - Control group uses old recommendation algorithm, while the test group uses the proposed recommendation algorithm

Personalized News Recommendation Based on Click Behavior

[J. Liu, et al., IUI2008]

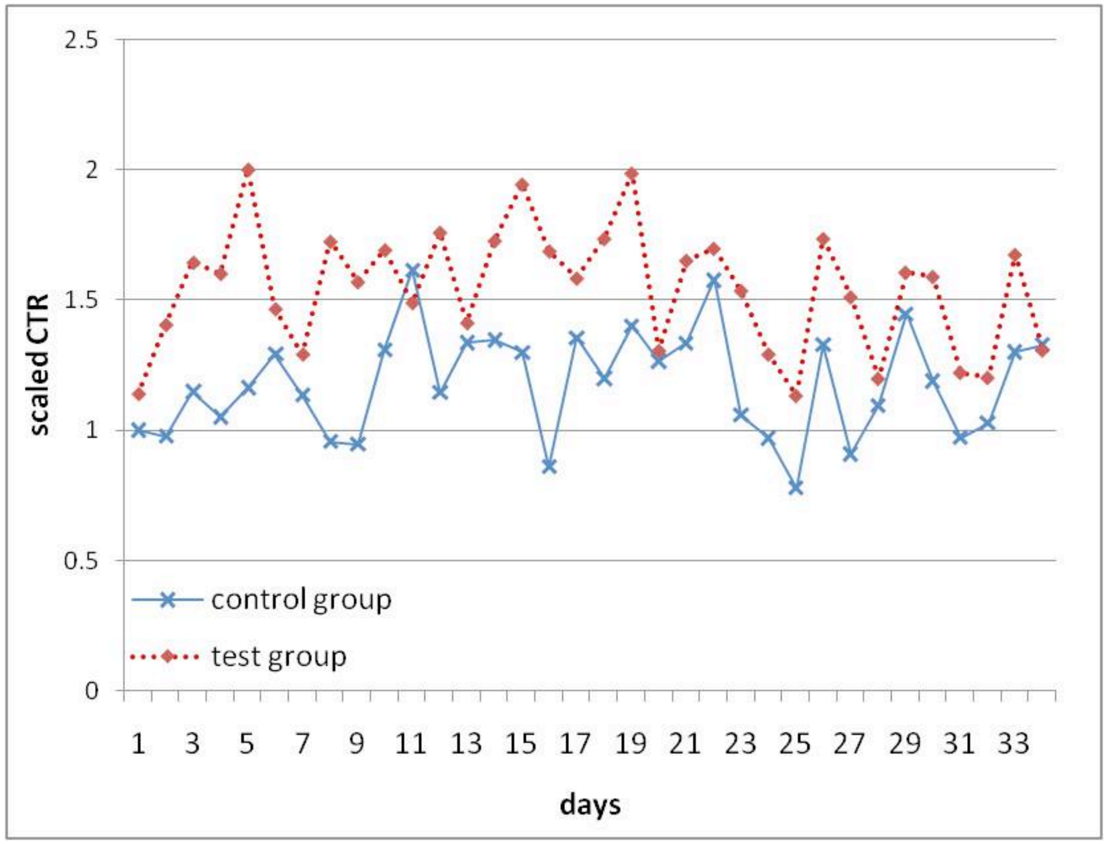


Figure 4. CTR of the recommended news section

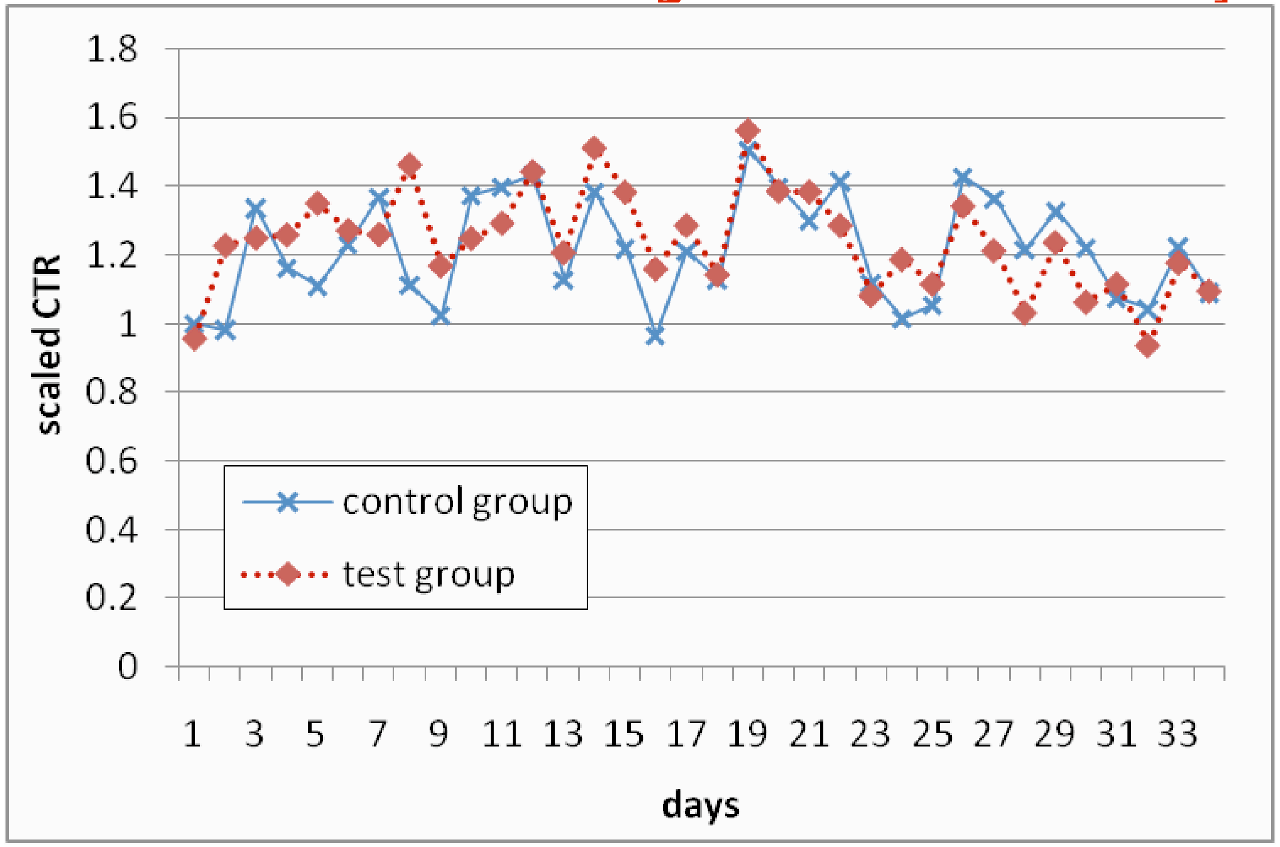


Figure 5. CTR of the Google News homepage

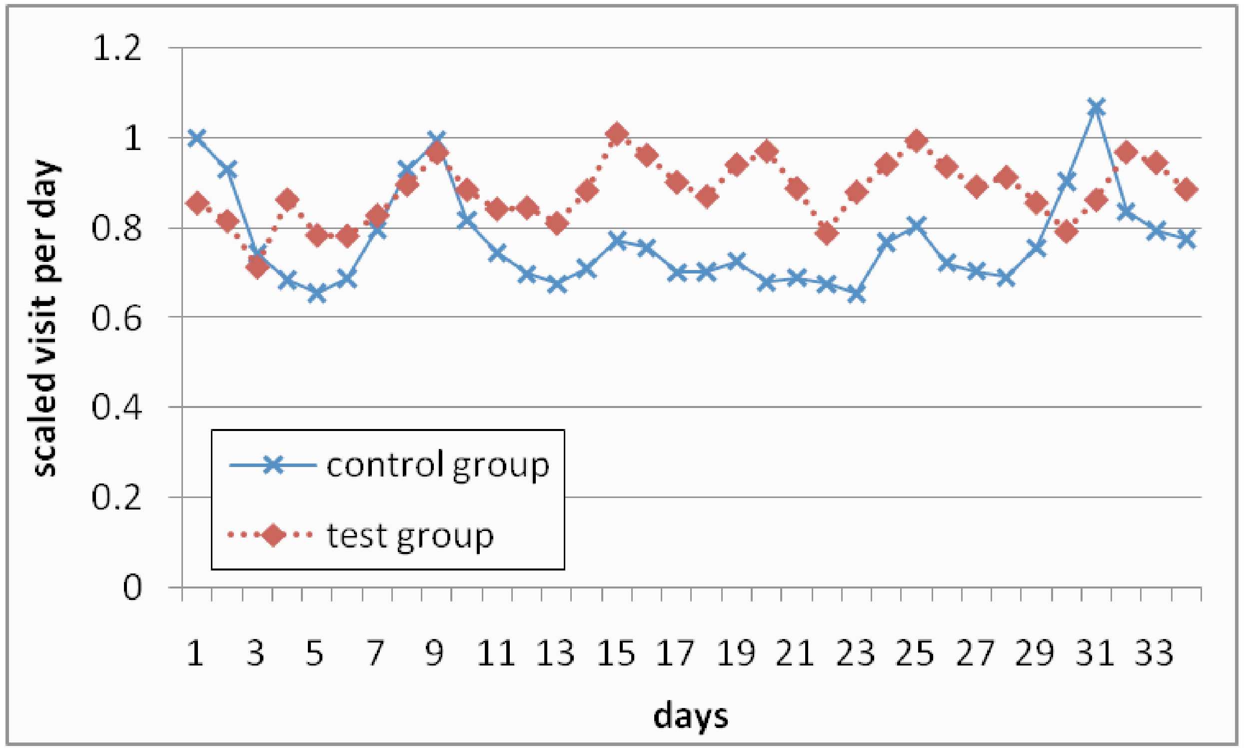


Figure 6. Frequency of website visit per day

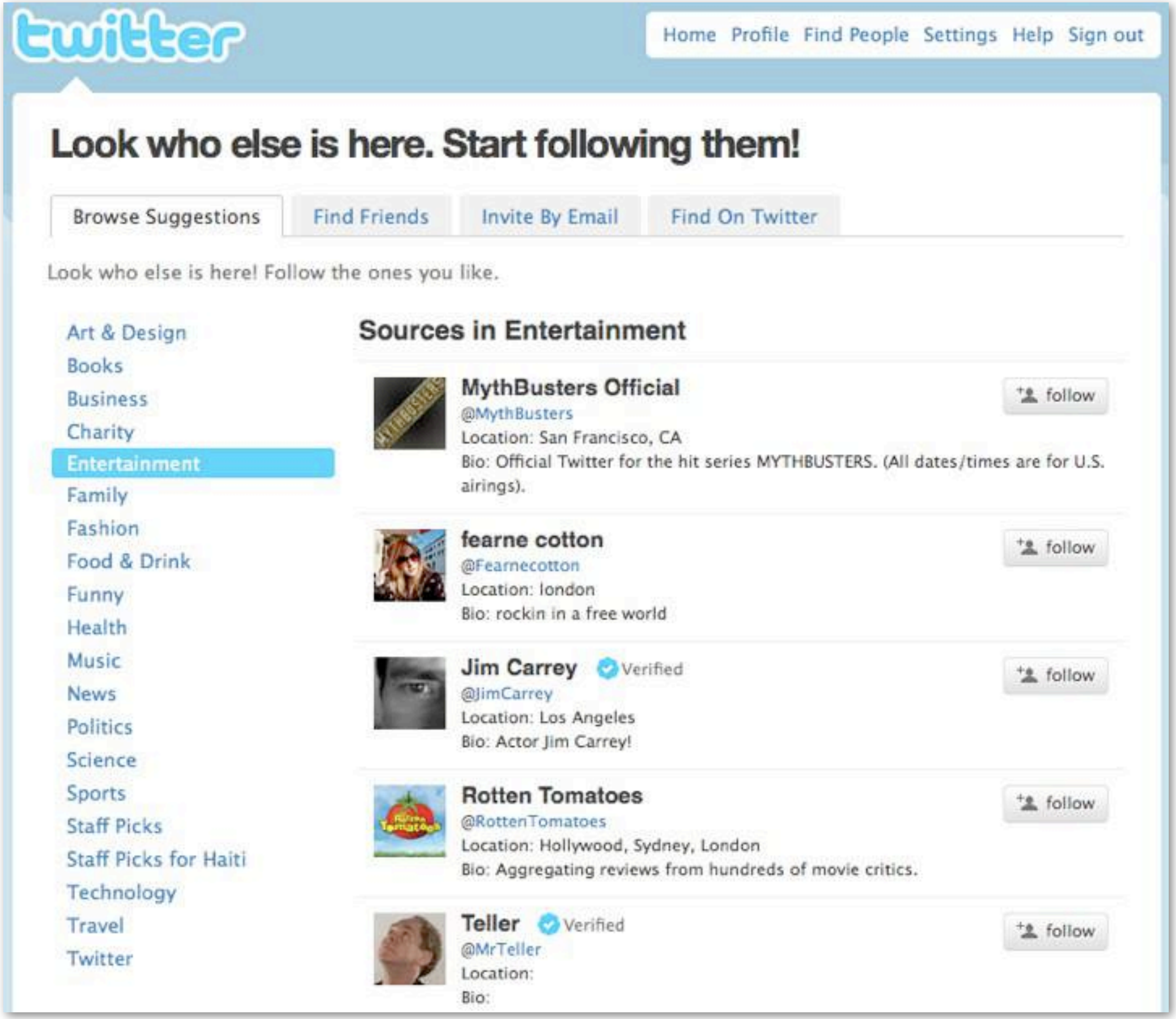
Social Media Analysis

- Social Media Ranking
- Tag Recommendation
- News Recommendation
- User Recommendation
- Twitter-powered Recommendation

User Recommendation

- Facebook Service - People You May Know
  - Based on “friend-of-a-friend” approach

User Recommendation



“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

- On social networking site, people recommendation algorithms are designed to help users:
  - Find known, offline contacts
  - Discover new friends
- Both are changeling problems

"Make New Friends, but Keep the Old" - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

- Two research questions:
  - How effective are different algorithms in recommending people as potential friends?
  - Can a people recommender system effectively increase the number of friends a user has?

"Make New Friends, but Keep the Old" - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

- Test bed
  - Beehive, an enterprise social networking site within IBM
- Four different algorithms are tested
- The survey was targeted at a group of 500 users who were asked to answer questions related to their friending behavior

“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

- Algorithms

1. Content Matching
   - Based on the intuition that “if we both post content on similar topics, we might be interested in getting to know each other”
   - Based on TFxIDF method
2. Content-plus-Link (CplusL)
   - Enhances the content matching algorithm with social link information derived from social network structure
   - Based on the intuition that “By disclosing a network path to a weak tie or unknown person, the recipient will be more likely to accept the recommendation.”

“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

- Algorithms

3. Friend-of-Friend (FoF)
   - Only leverages social network information of friending
   - Based on the intuition that “if many of my friends consider Alice a friend, perhaps Alice could be my friend too”
4. SONAR
   - Based on the SONAR system, which aggregates social relationship information from different public data sources within IBM: (1) Organizational chart; (2) Publication database; (3) Patent database; (4) Friending system; (5) People tagging system; (6) Project wiki; and (7) Blogging system.

“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

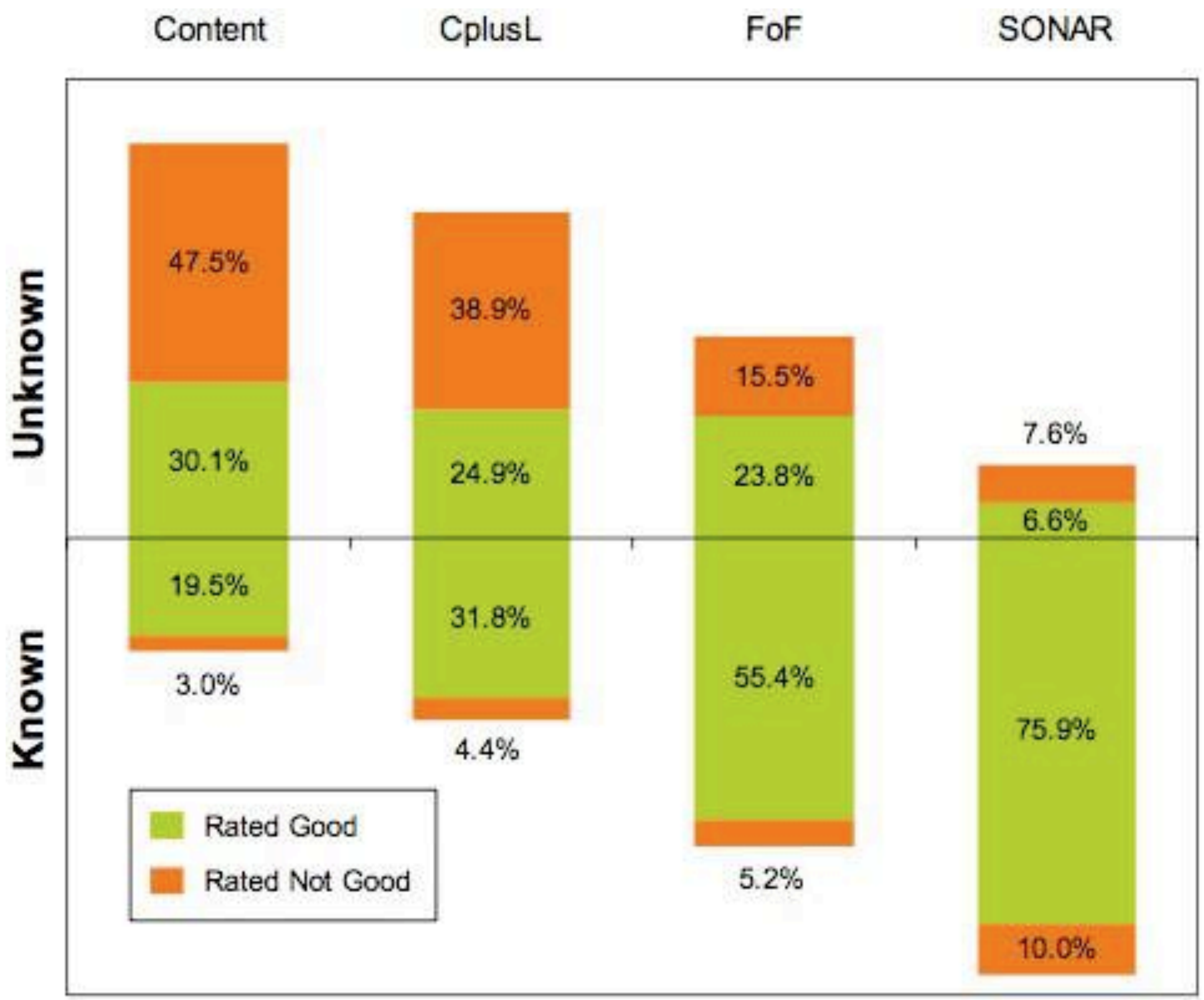


Figure 1. Known vs. unknown, Good vs. not good.

“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

	Content	CplusL	FoF	SONAR
Content		52.8%	1.8%	8.3%
CplusL			3.3%	9.6%
FoF				13.1%

Table 1. Overlap ratios between recommendations generated by different algorithms.

“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

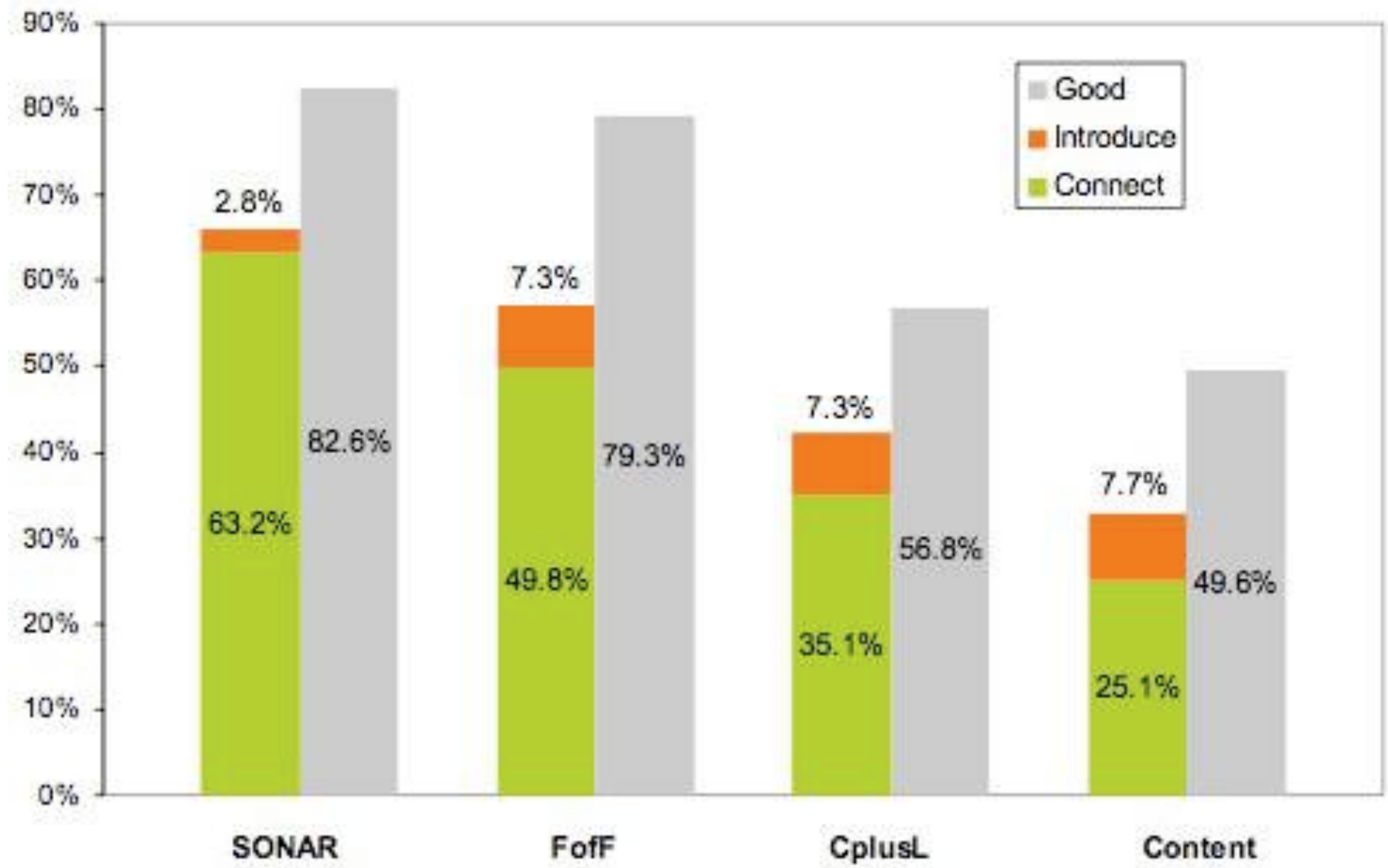


Figure 2. Good recommendations that resulted in actions.

“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

[Jilin Chen, et al., CHI2009]

SONAR	FoF	CplusL	Content
59.7%	47.7%	40.0%	30.5%

Table 2. Recommendations resulting in connect actions.

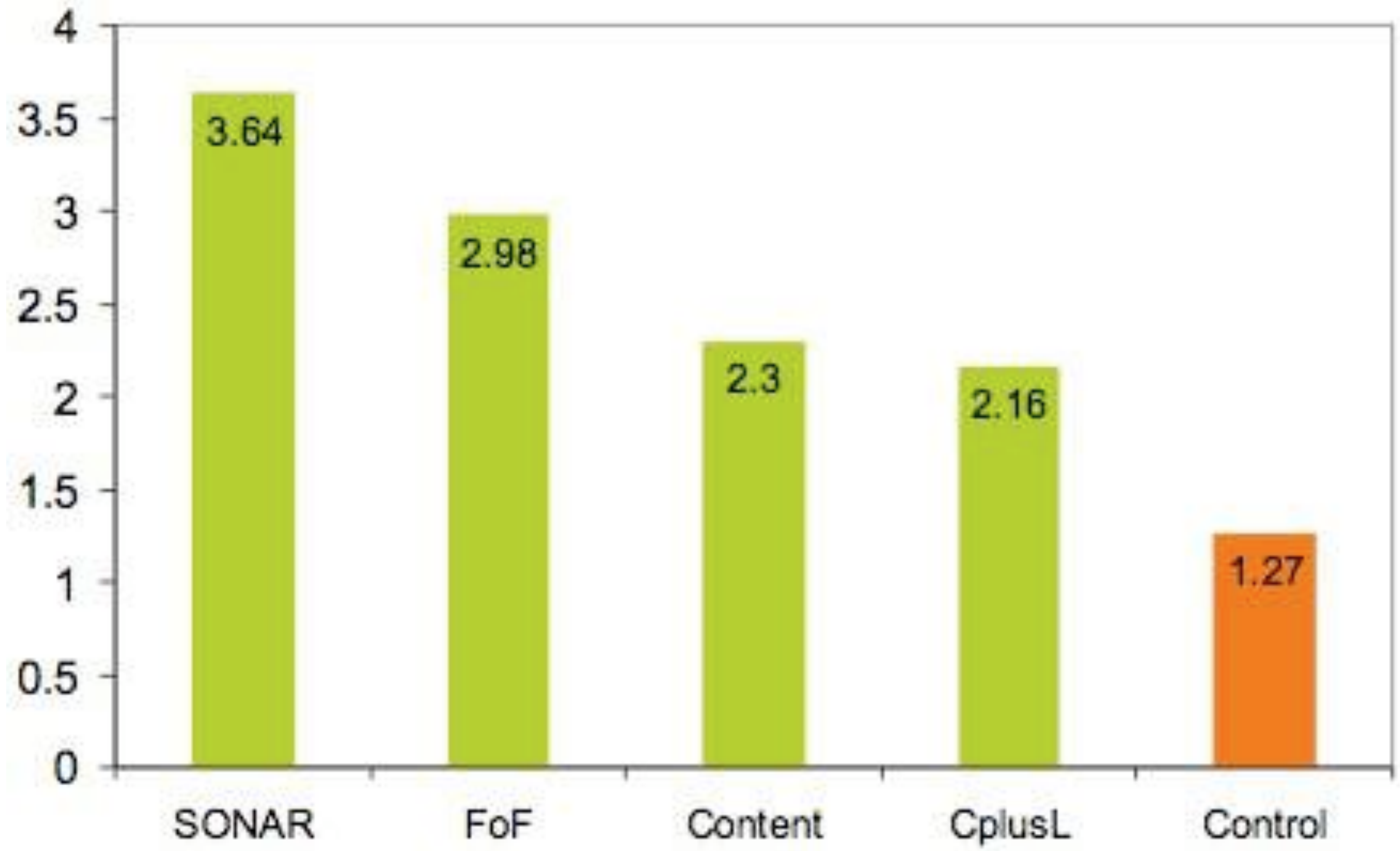


Figure 4. Increase in number of friends.

“Make New Friends, but Keep the Old” - Recommending People on Social Networking Sites

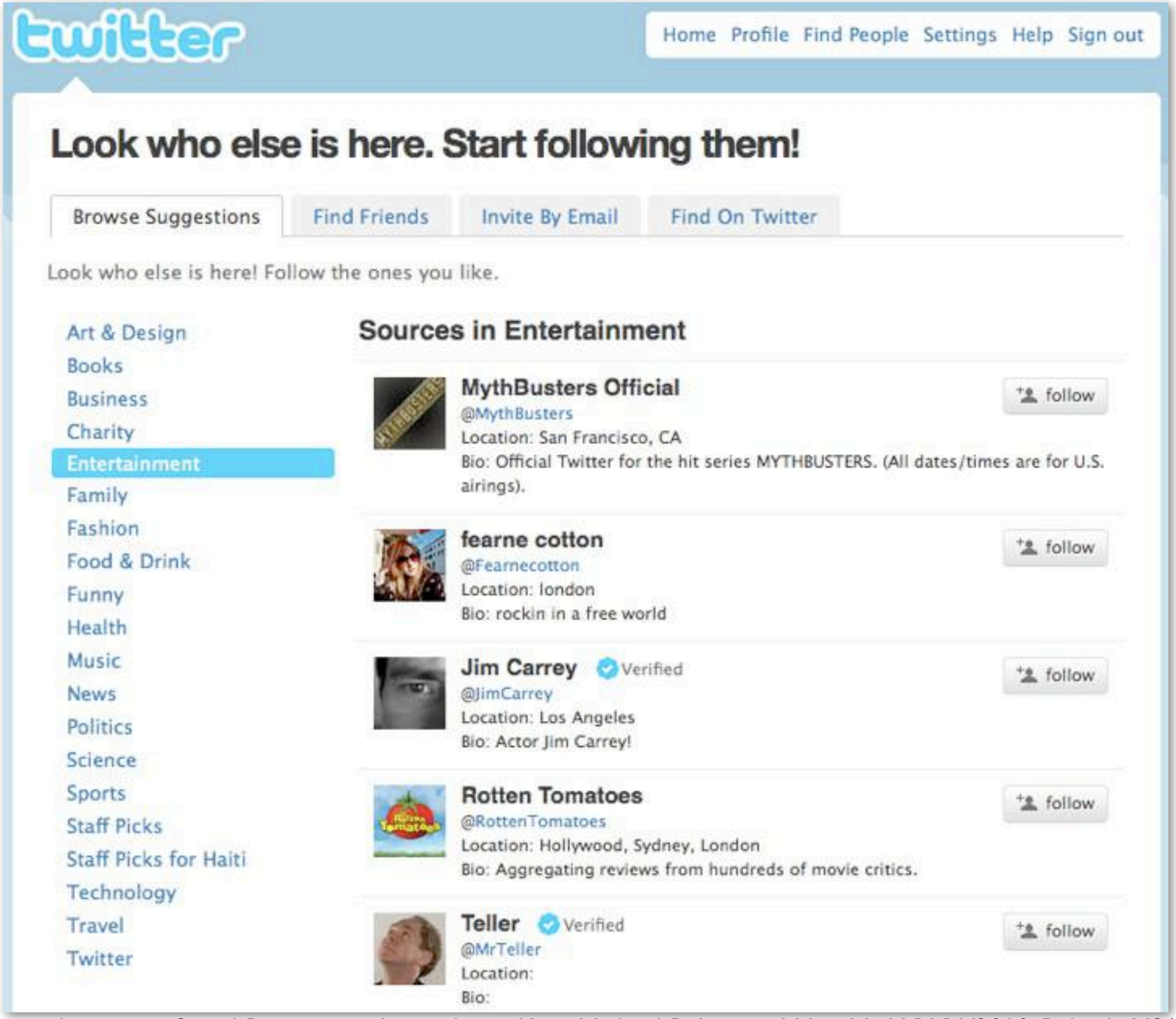
[Jilin Chen, et al., CHI2009]

- Conclusions
  - Relationship based algorithms (FoF and SONAR) outperform content similarity ones (Content and CplusL) in terms of user response
  - Relationship based algorithms are better at finding known contacts whereas content similarity algorithms were stronger at discovering new friends

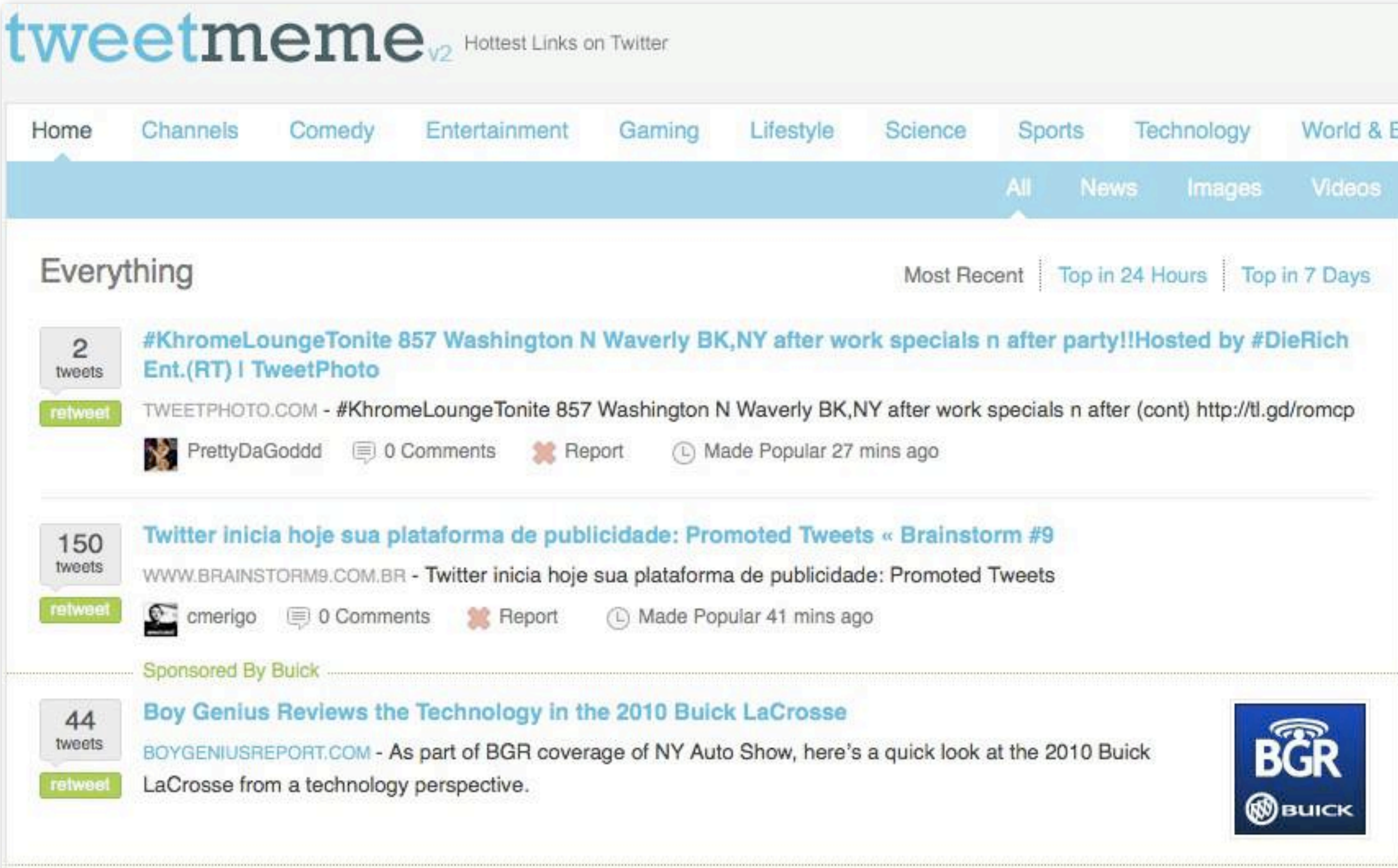
Social Media Analysis

- Social Media Ranking
- Tag Recommendation
- News Recommendation
- User Recommendation
- Twitter-powered Recommendation

Twitter Recommendation Engine



Twitter-powered Recommendation



Twitter-powered Recommendation

Twitter-powered Recommendation

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