Introduction to Social Computing

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Sand from Centuries Past Send Future Voices Fast

The Nobel Prize in Physics 2009

"for groundbreaking achievements concerning the transmission of light in fibers for optical communication"

"for the invention of an imaging semiconductor circuit – the CCD sensor"

Photo: Richard Epworth

Charles K. Kao

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Willard S. Boyle

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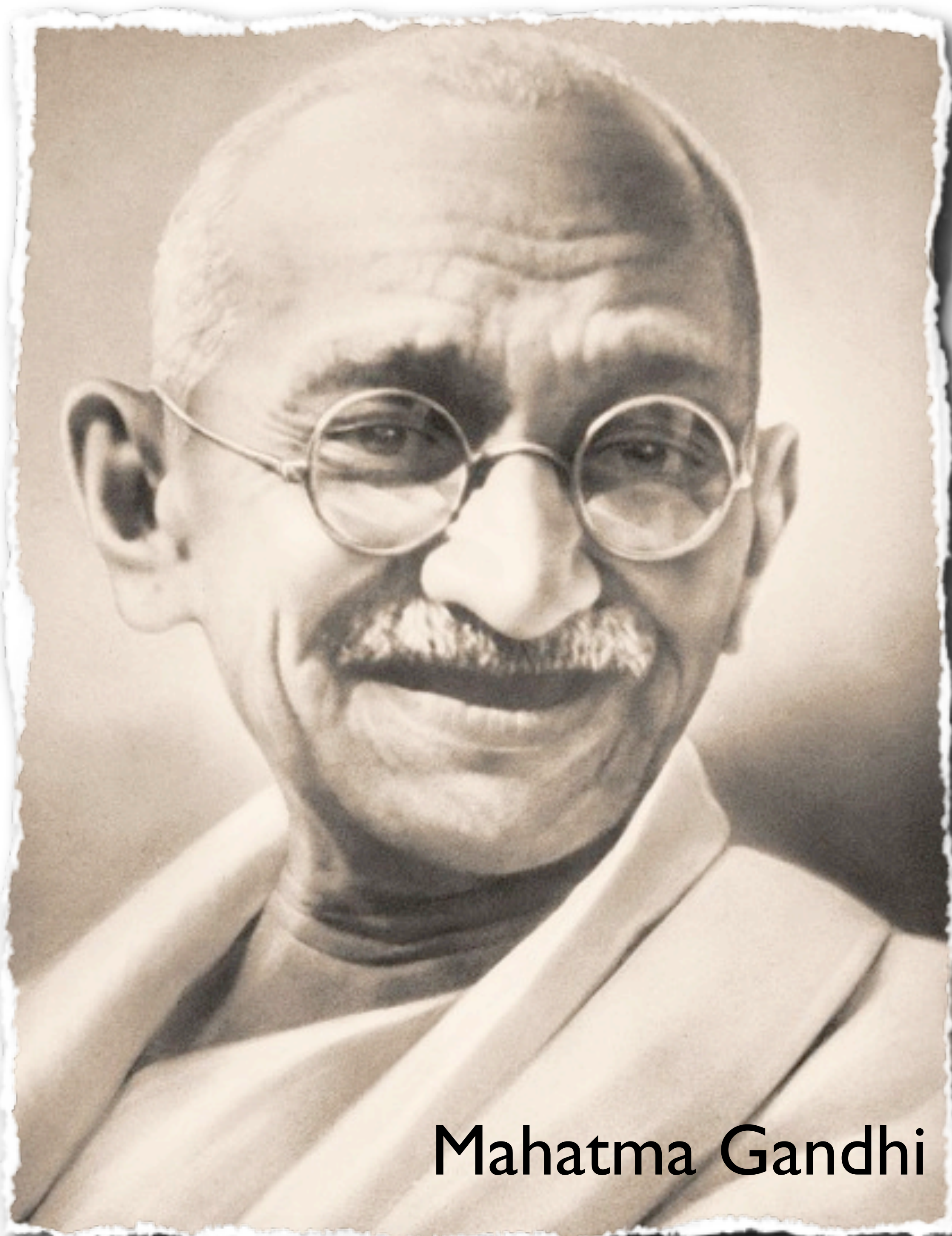
George E. Smith

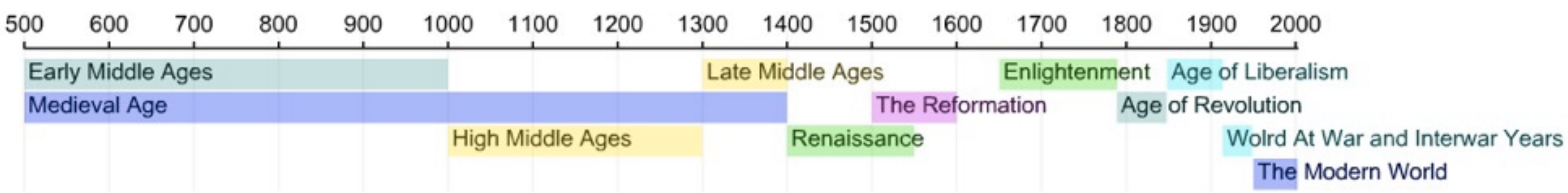


Mahatma Gandhi

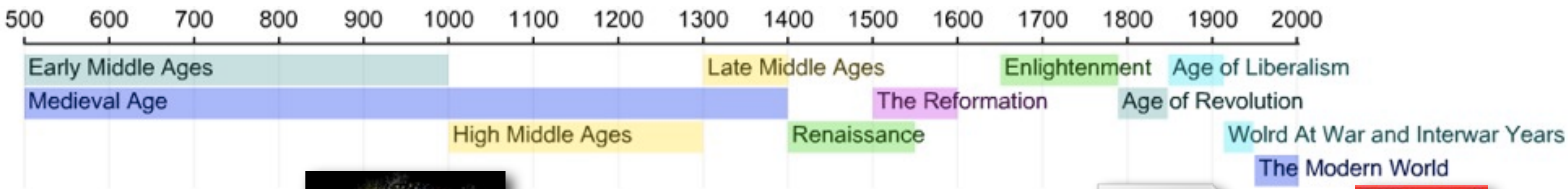
Interdependence is and ought to be as much the ideal of man as self-sufficiency.

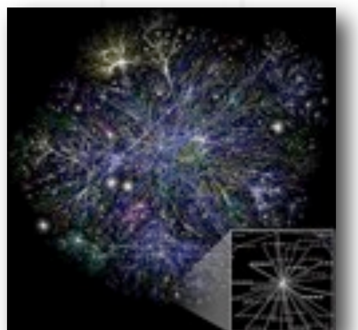
Man is a social being.

A Brief History of the World



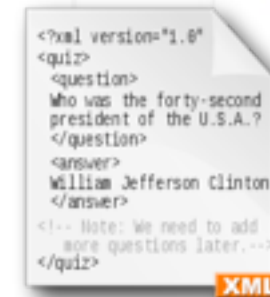
A Brief History of the World




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


intel.
revolution in evolution
Highlights from the Journey to 1 Billion PCs
1,000,000,000
900,000,000
800,000,000
700,000,000
600,000,000
500,000,000
400,000,000
300,000,000
200,000,000
100,000,000
For more information, please visit http://www.intel.com

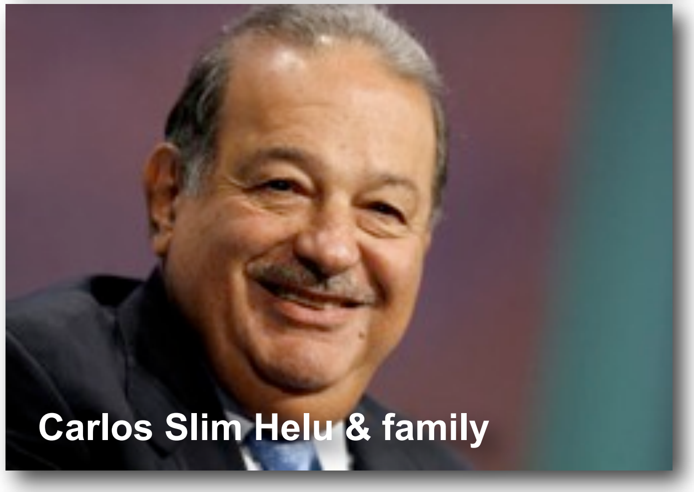
Billionaires' Shuffle

2007

Facebook in 2004.02

2008

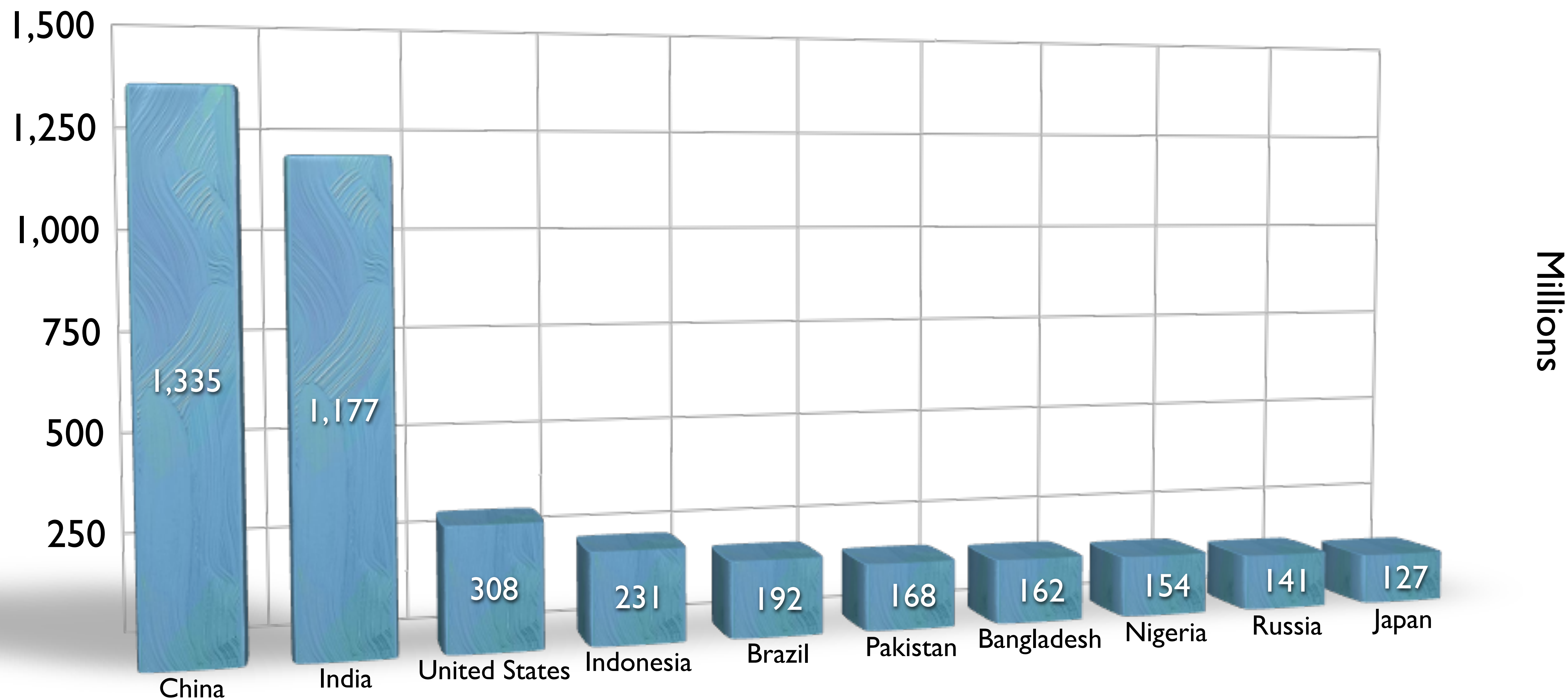
at **23** and $**1.5** billion later...



2008

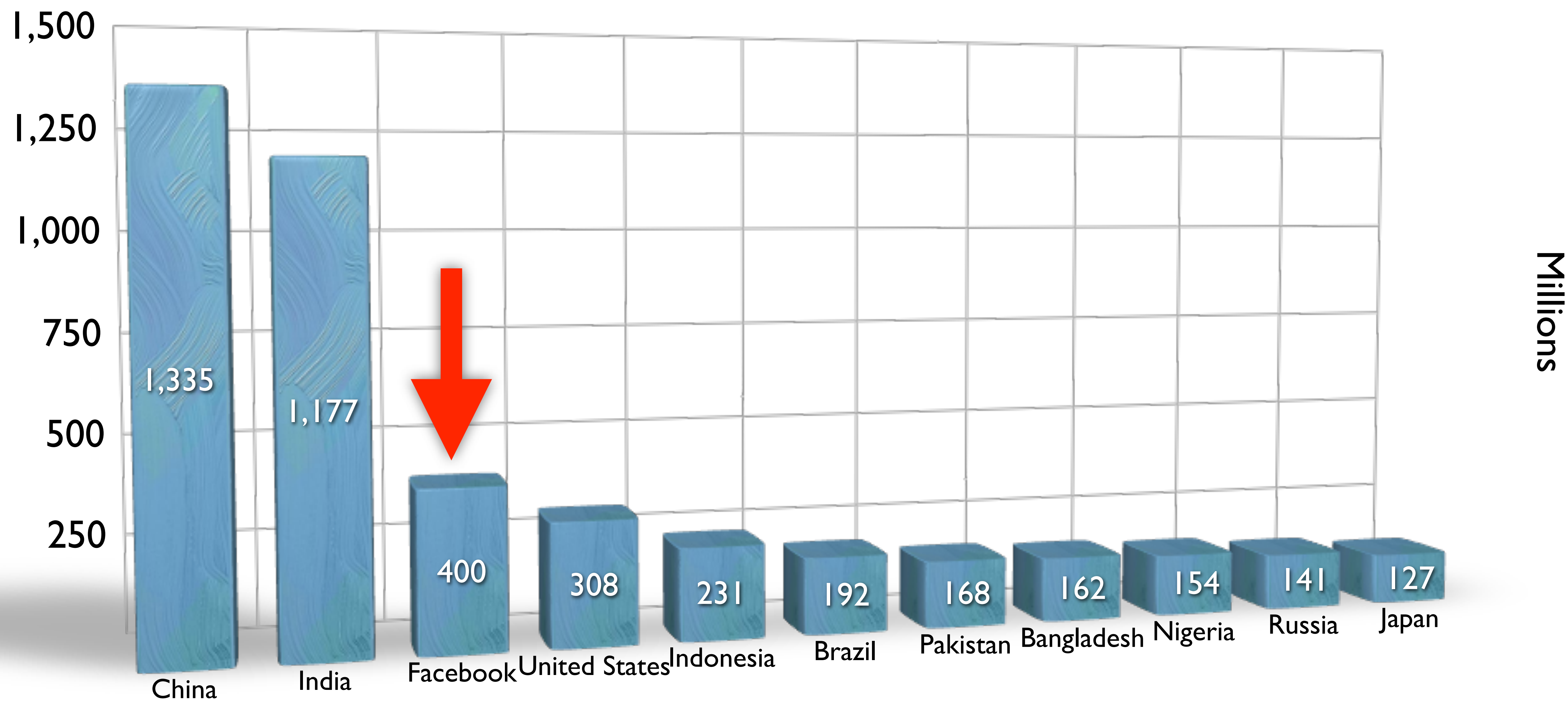
Top 10 Most Populated Countries

as of July 2009

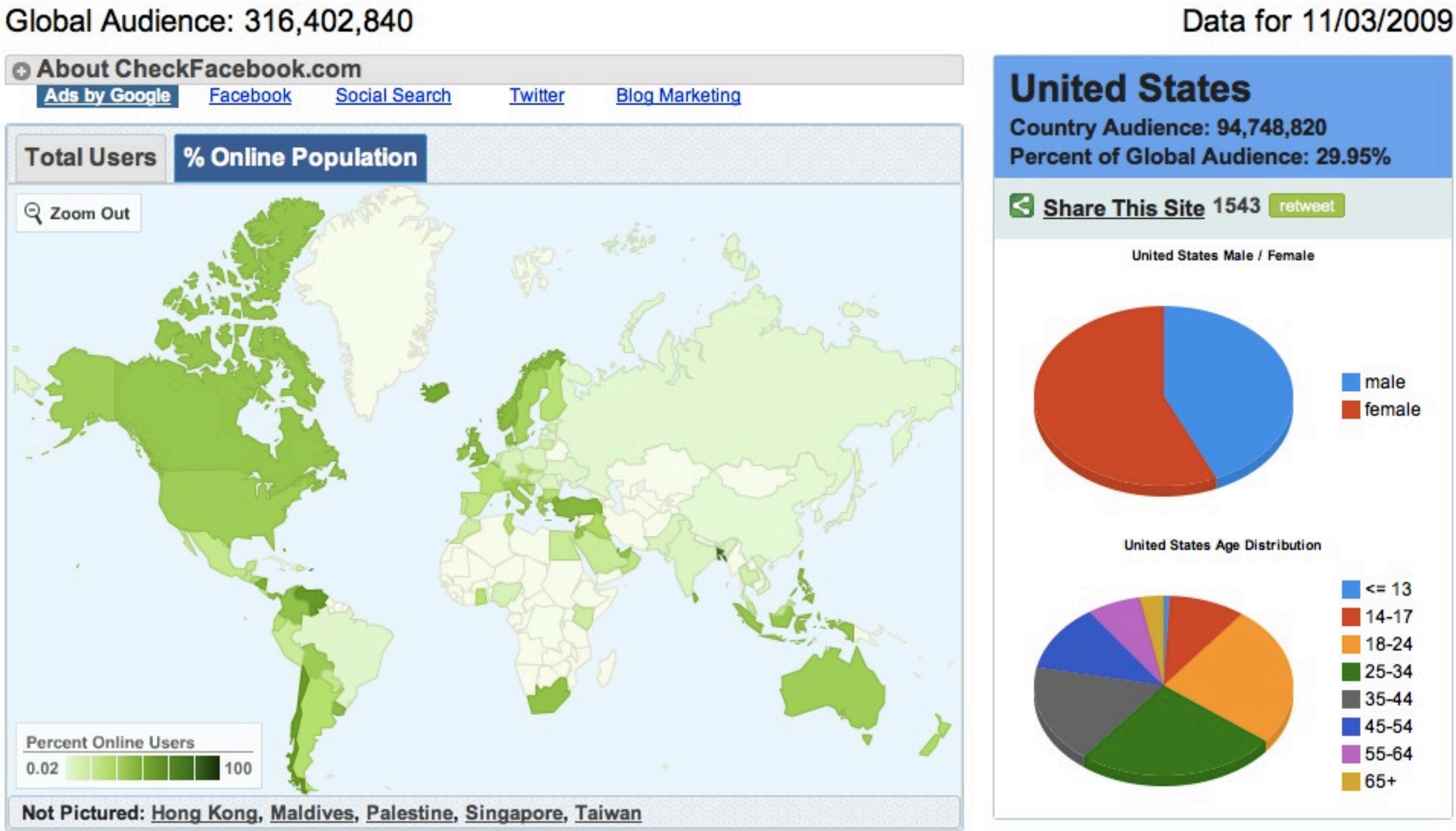


Top 10 Most Populated Countries

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

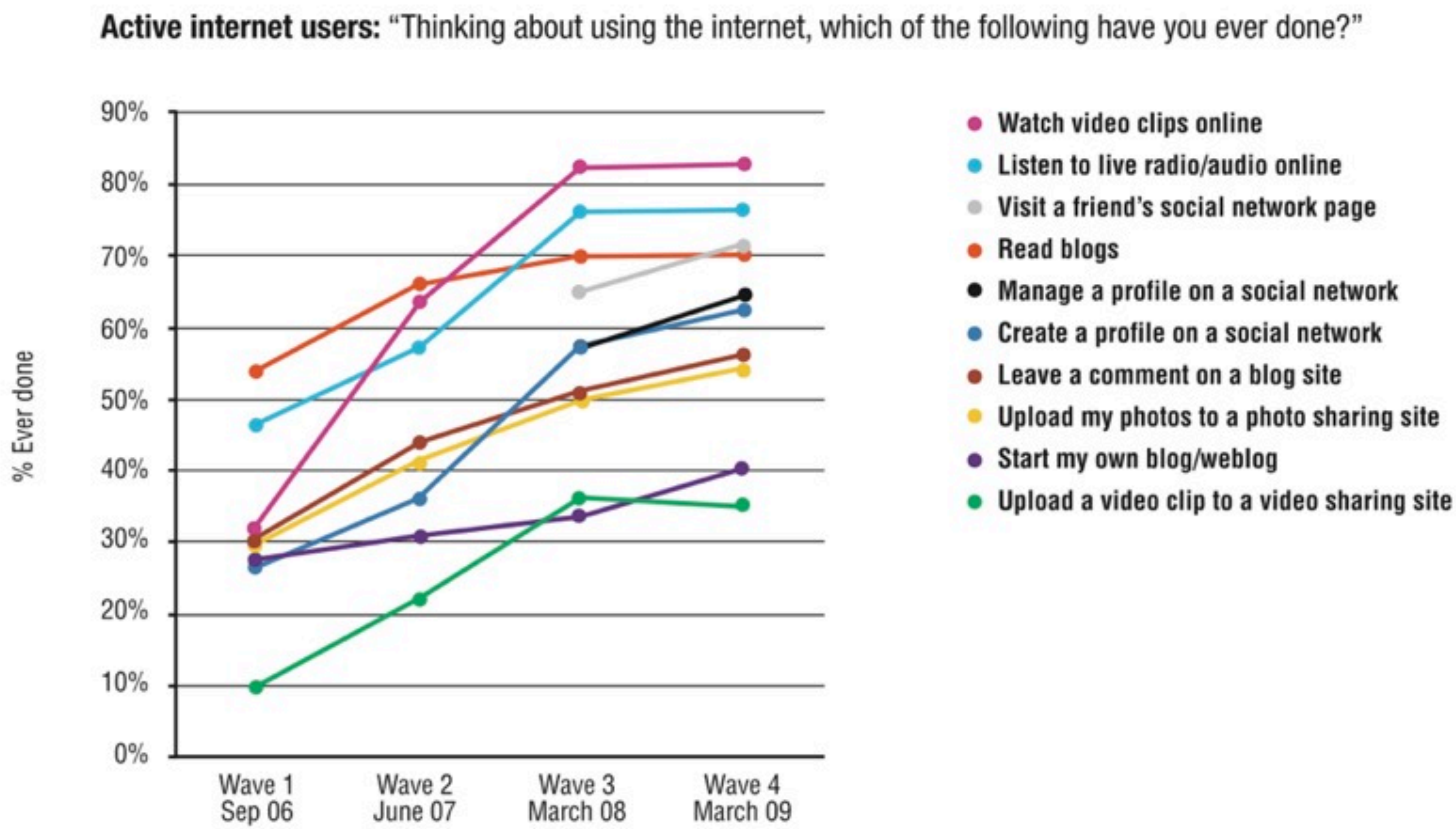
10 Fastest Growing Over Past Week			
1.	Poland	12.46 %	137,900
2.	Thailand	10.96 %	161,300
3.	Portugal	9.81 %	80,040
4.	South Africa	9.25 %	189,080
5.	Taiwan	7.82 %	367,400
6.	Romania	7.65 %	28,060
7.	Germany	7.54 %	350,240
8.	Malaysia	7.43 %	236,840
9.	Indonesia	6.84 %	752,640
10.	Iraq	6.72 %	6,380

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**

EU Commission on Social Computing

Figure 2: The growth in active usage of social computing applications

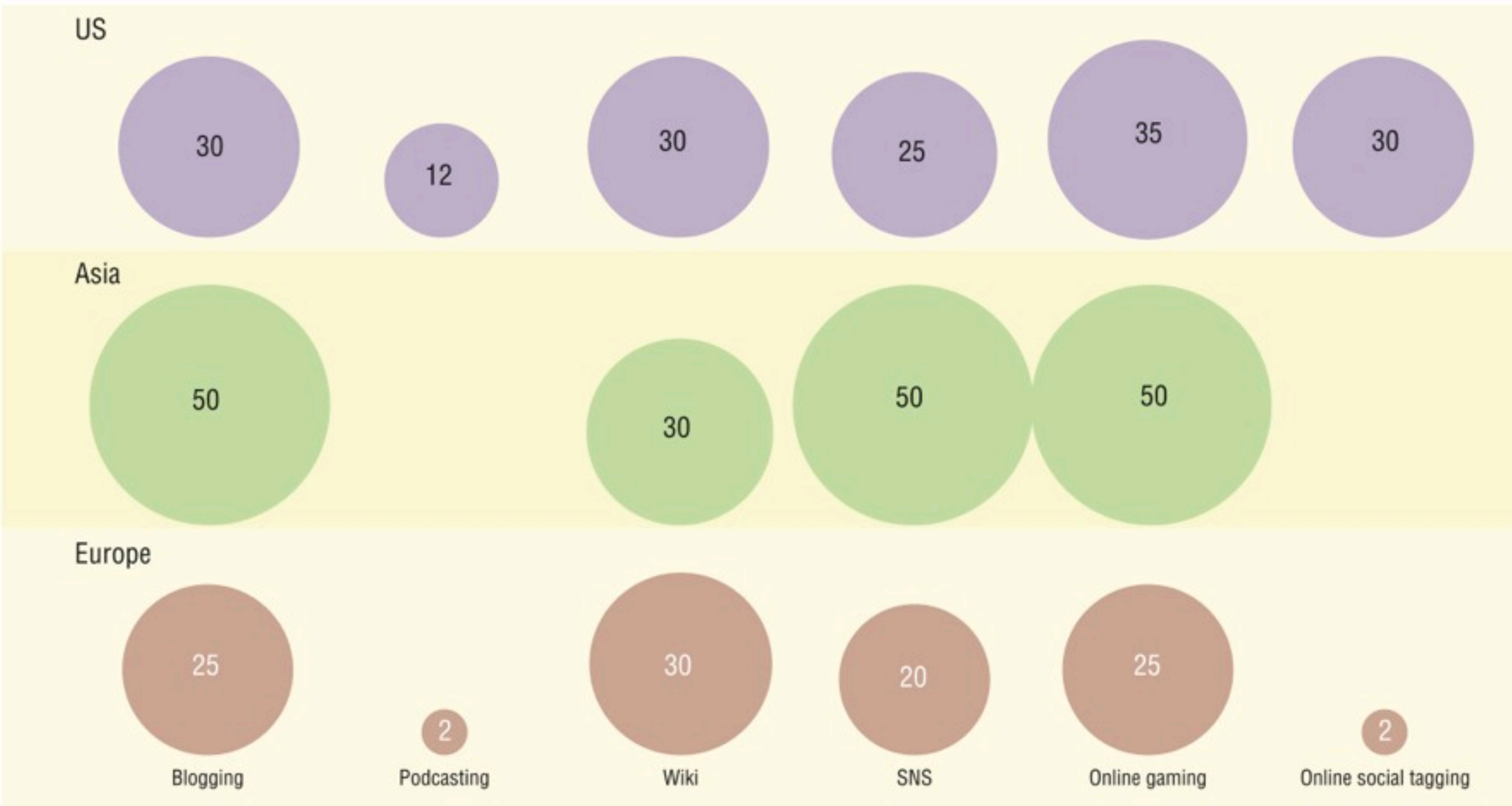


[Ala-Mutka et al. 2009]

Source: (Universal McCann, 2009)

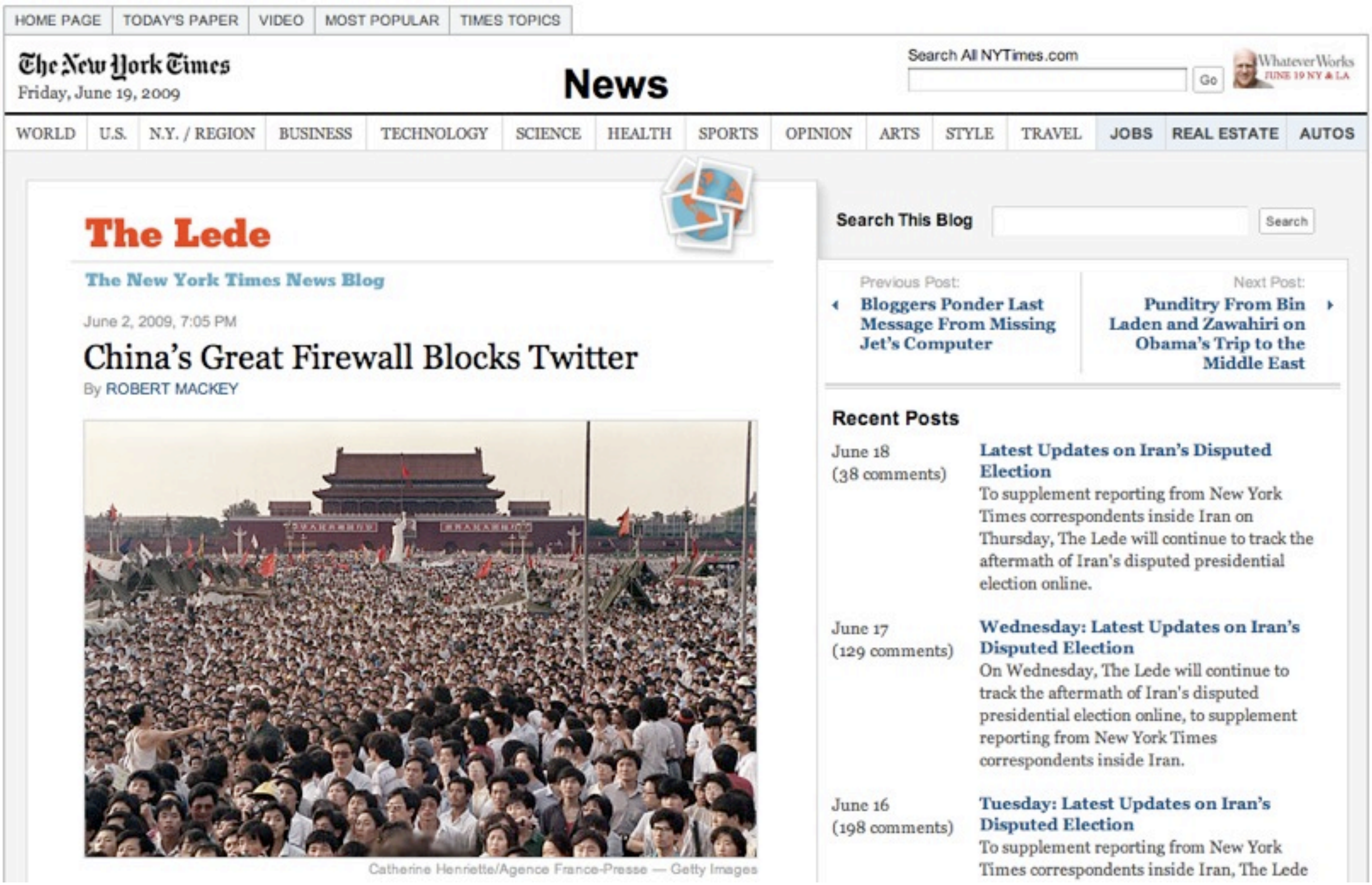
EU Commission on Social Computing

Figure 1: Adoption of Social Computing



[Ala-Mutka et al. 2009]

Twitter in Spotlight



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The New York Times
Friday, June 19, 2009

News

Search All NYTimes.com

Go

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The Lede

The New York Times News Blog

June 2, 2009, 7:05 PM

China's Great Firewall Blocks Twitter

By ROBERT MACKEY

Catherine Henriette/Agence France-Presse — Getty Images

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Search

Previous Post:
Bloggers Ponder Last Message From Missing Jet's Computer

Next Post:
Punditry From Bin Laden and Zawahiri on Obama's Trip to the Middle East

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June 18
(38 comments)
Latest Updates on Iran's Disputed Election
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

Topics in Social Computing

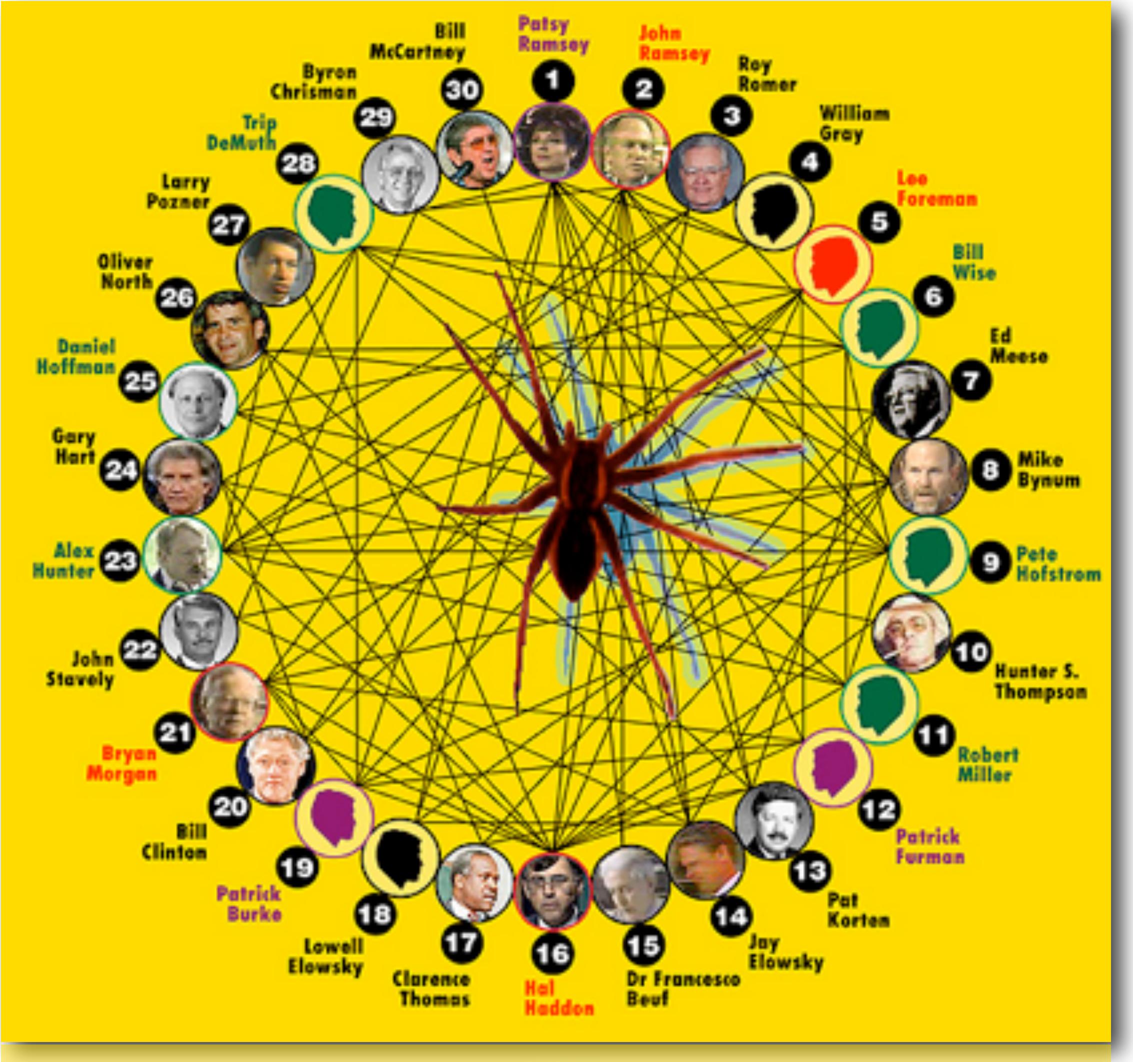
- Social Behavior Analysis and Modeling
- Social Media
- Social Network Theory and Models
- Link Analysis/Graph Mining/ Large Graph Algorithms
- Learning to Rank
- Recommender Systems/ Collaborative Filtering
- QA/Sentiment Analysis/ Opinion Mining
- Human Computation/ Crowdsourcing
- Risk, Trust, Security, and Privacy
- Monetization of Social Computing
- Software Tools and Applications
- and many, many more...

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

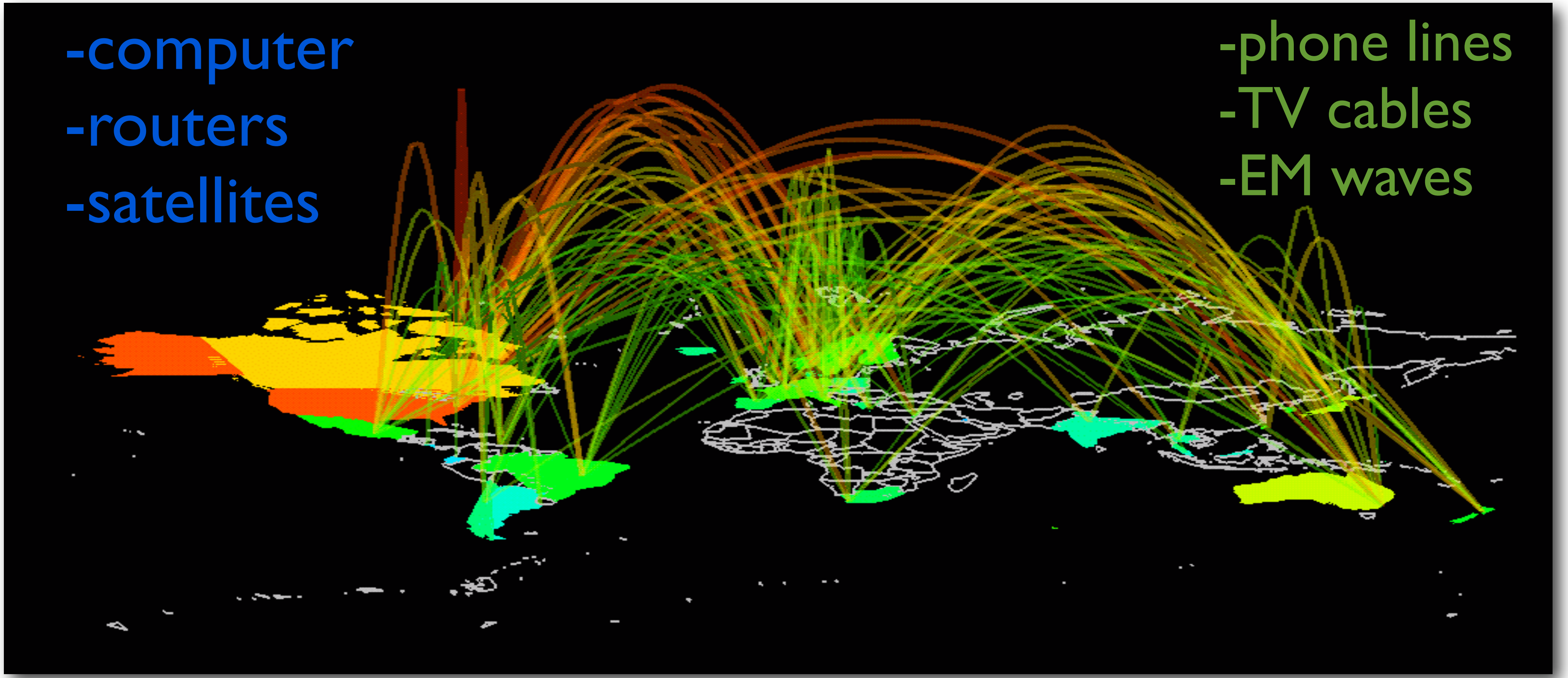
Society:
Nodes: individuals
Links: social relationship (family/work/friendship/etc.)



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

Social Networks

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



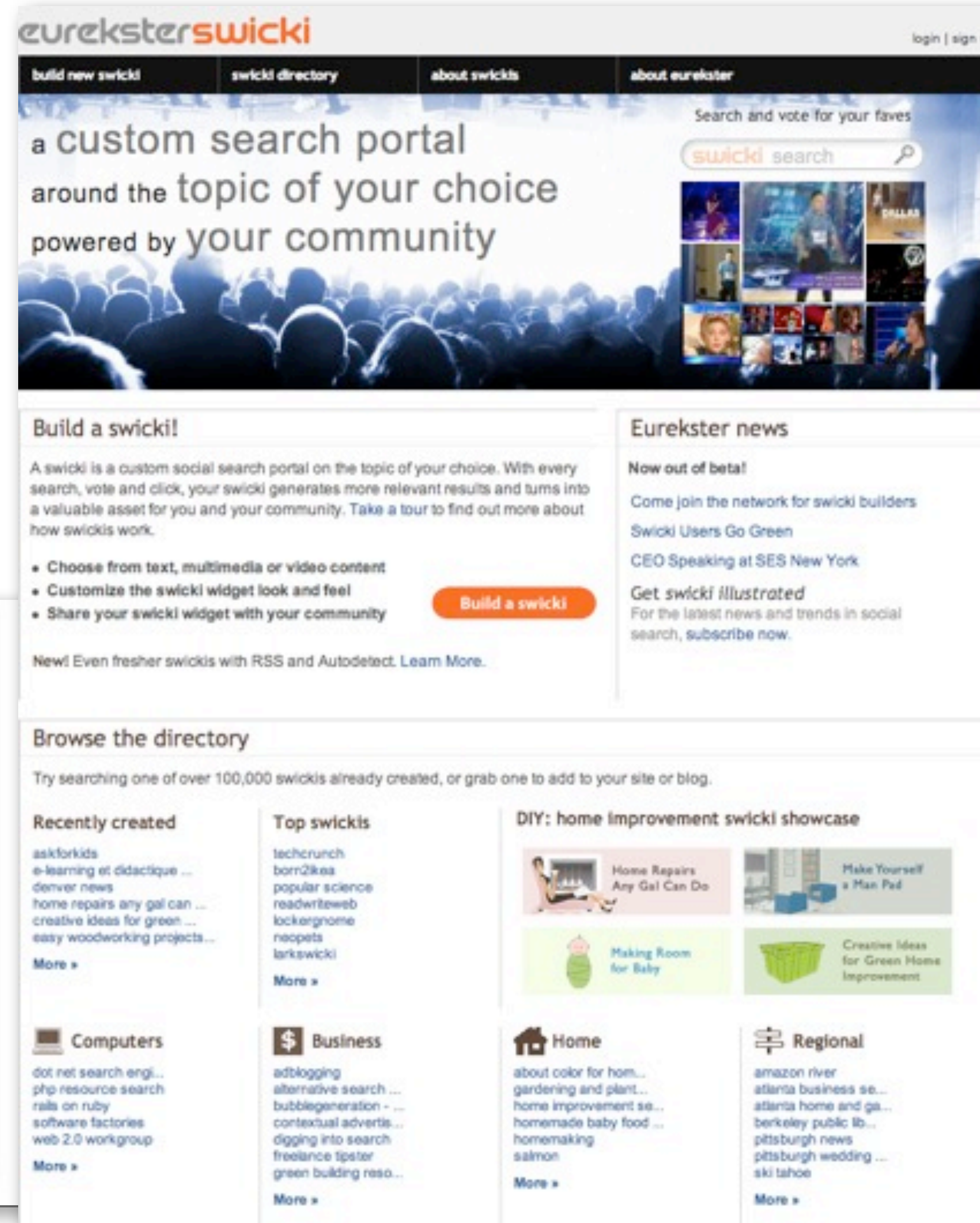
Communication networks: many non-identical components with diverse connections between them.

Social Networking Sites

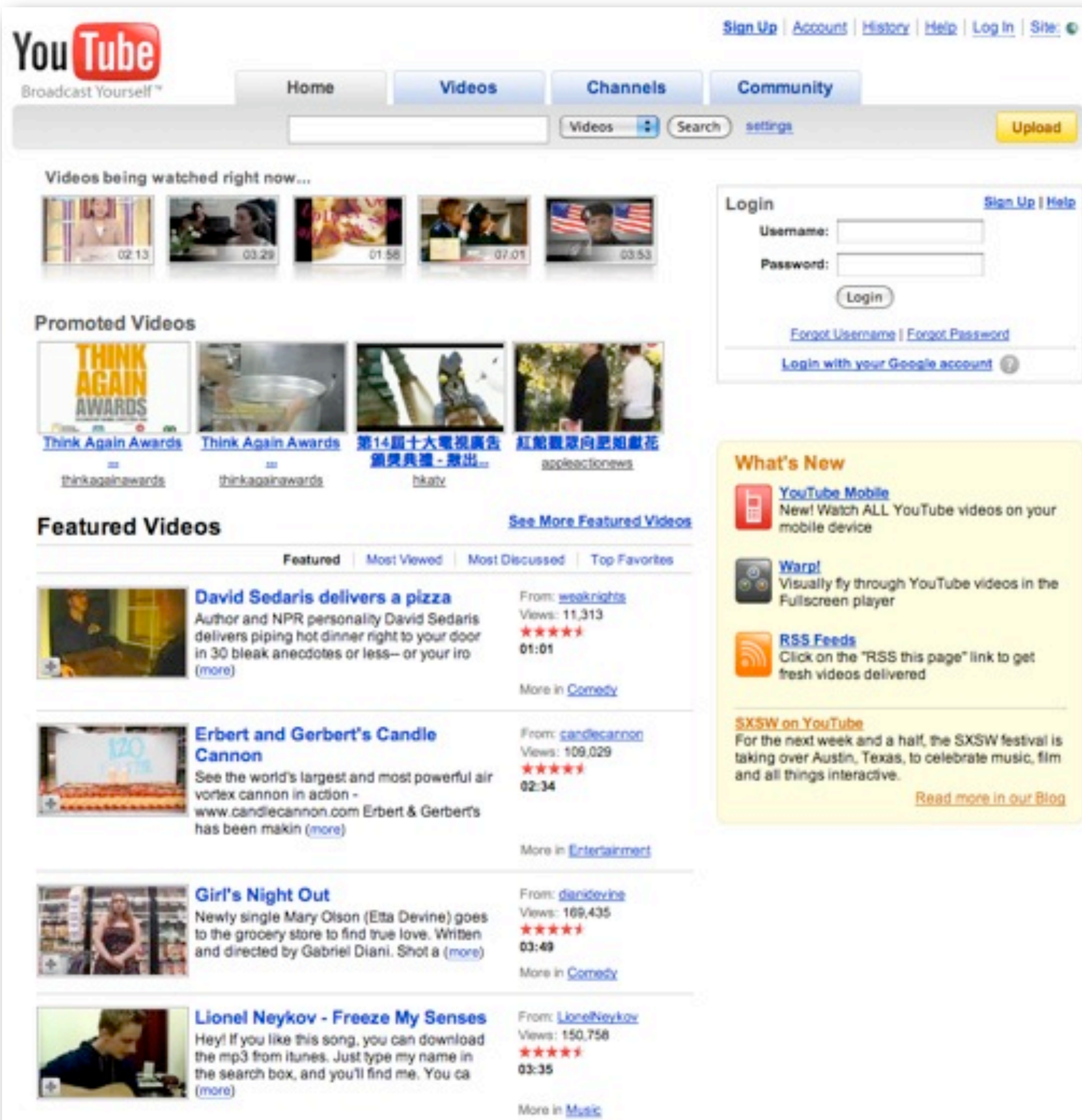
- Example of Social Networking Sites: FaceBook, MySpace, Blogger, QQ, etc.

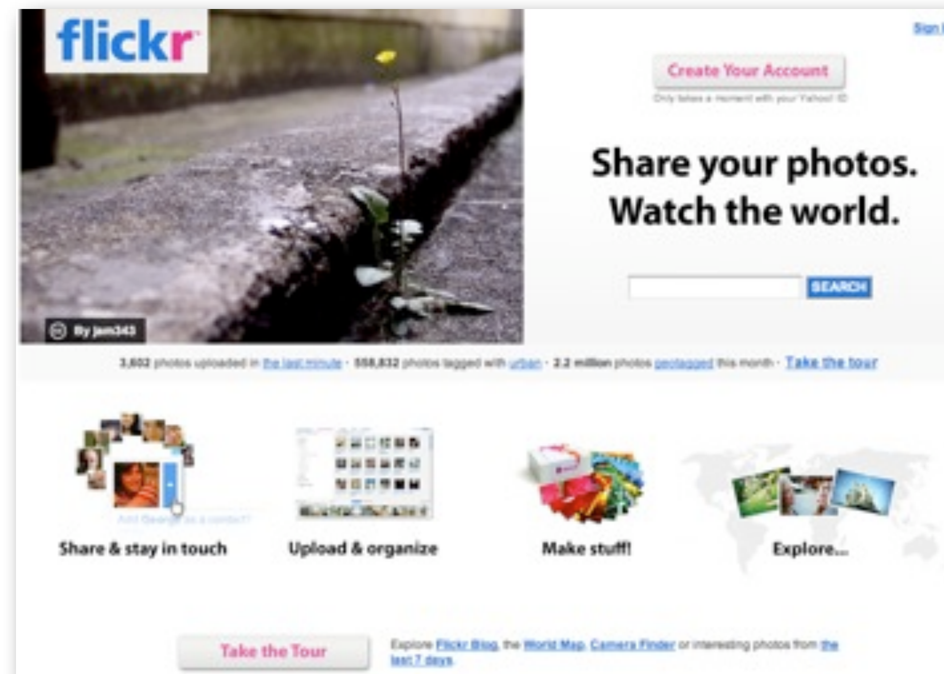
Social Search

- Social Search Engine
- Leveraging your social networks for searching

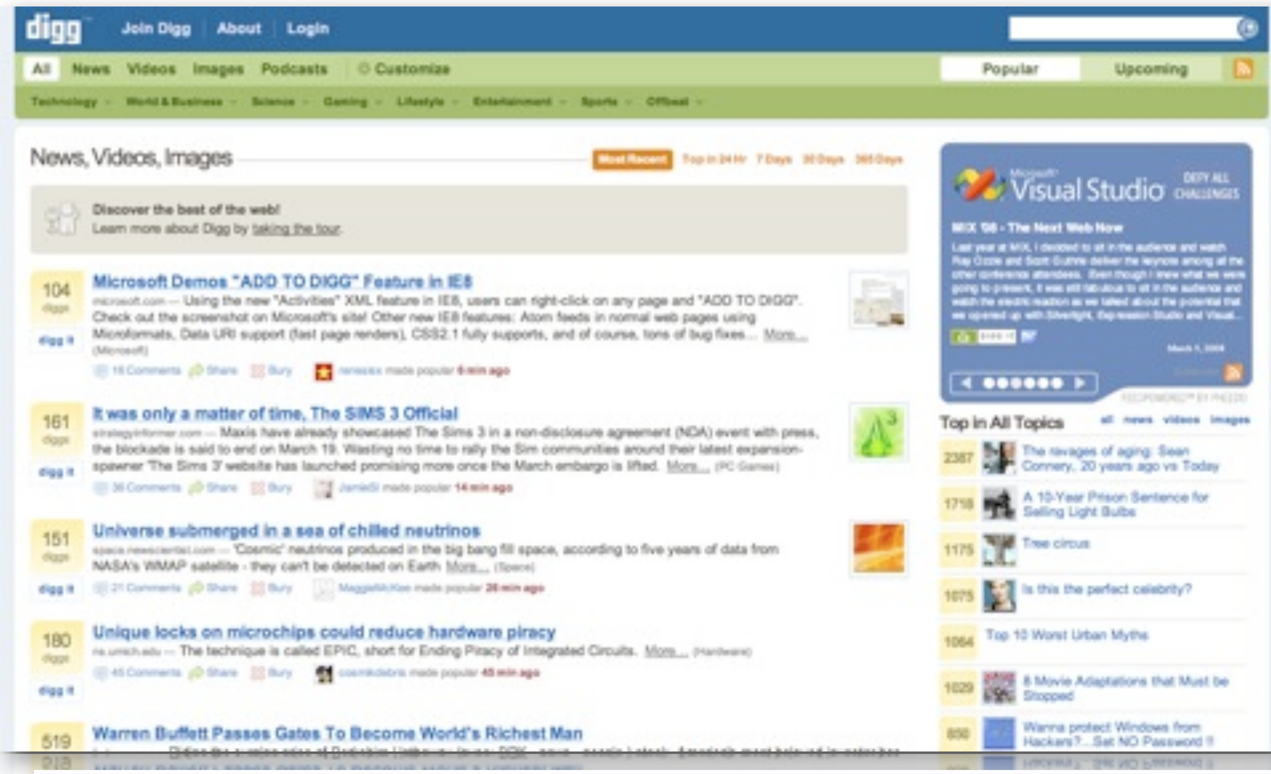


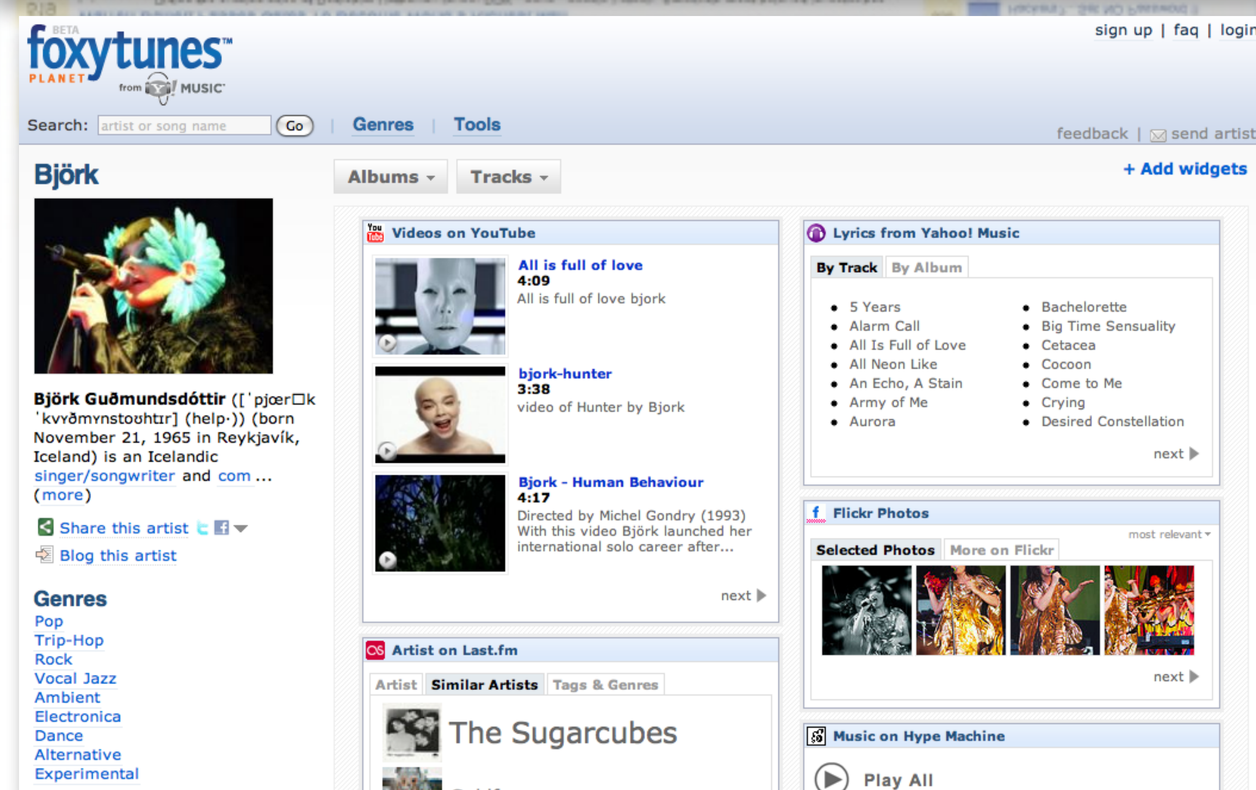
Social Media

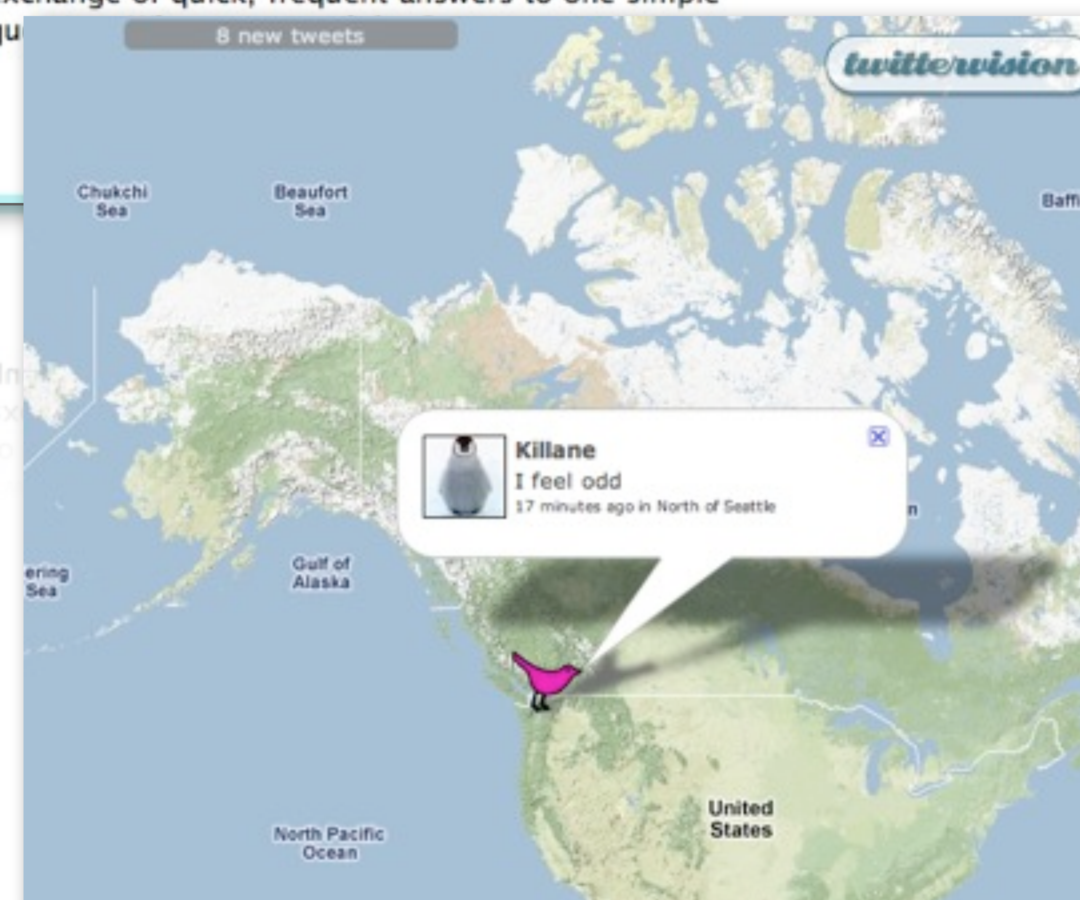




Social News/Mash Up

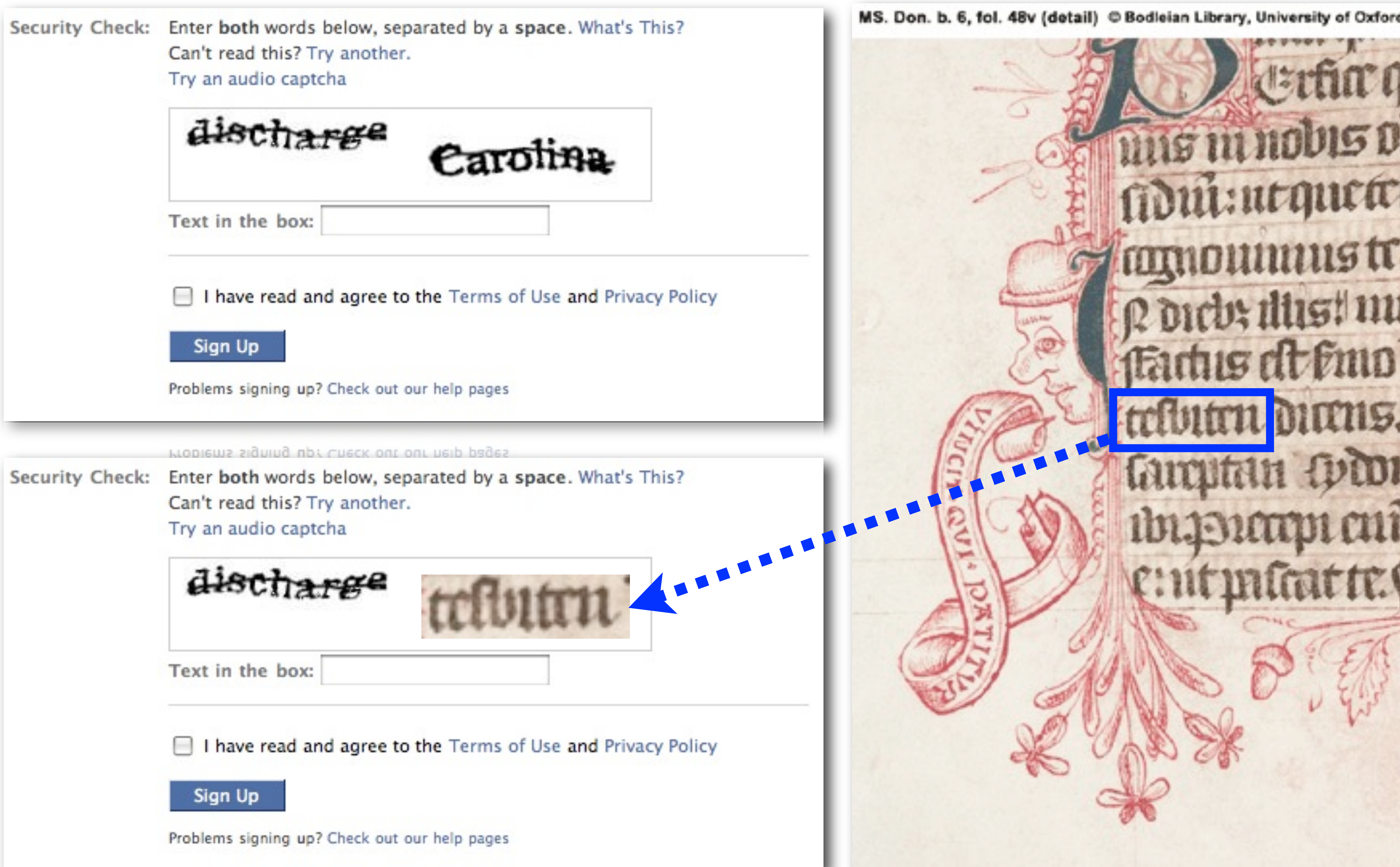






Social Knowledge Sharing

Social/Human Computation



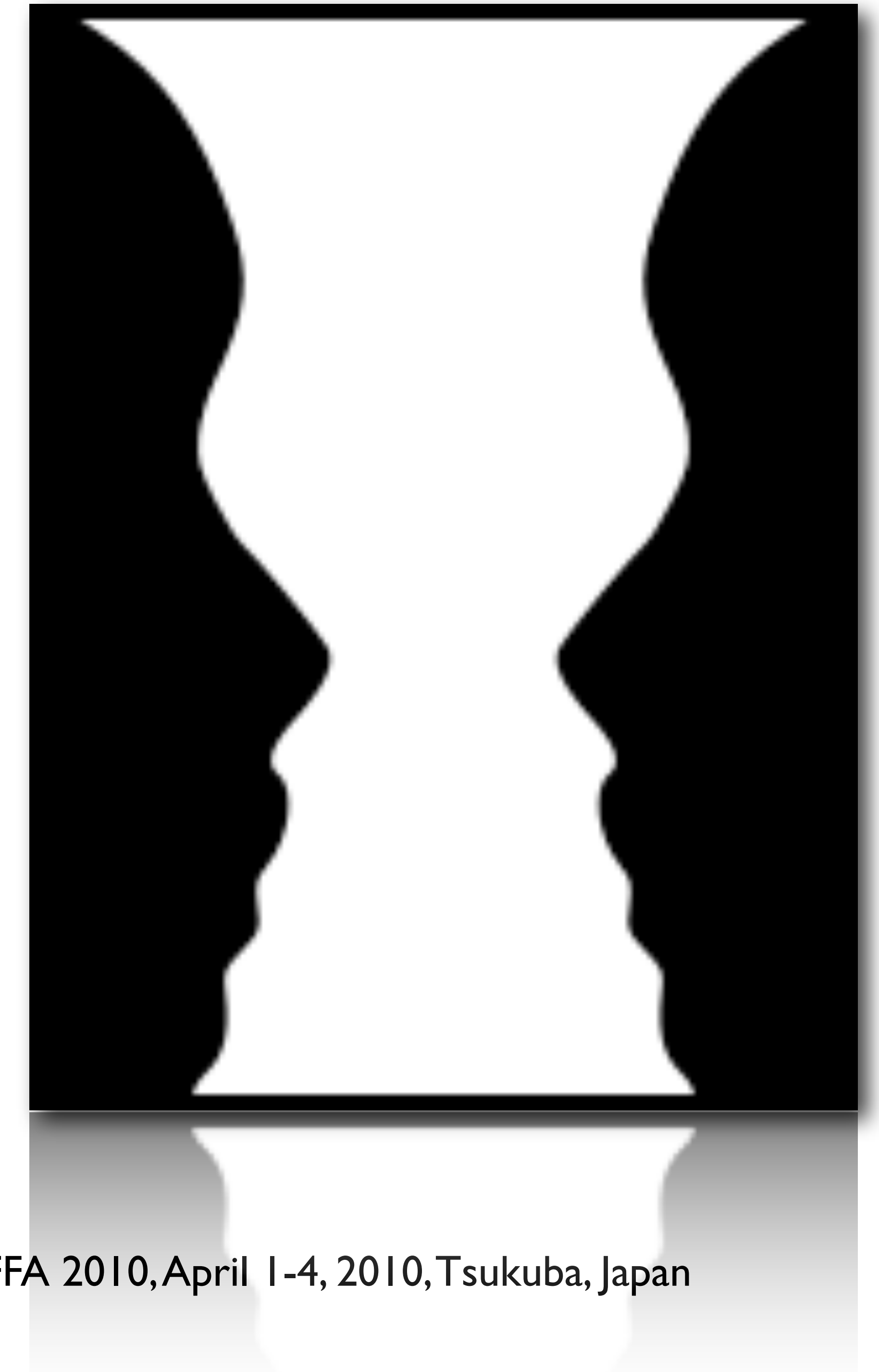
Web 2.0 Revolution

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

  Connectivity

  Collaboration

  Communities



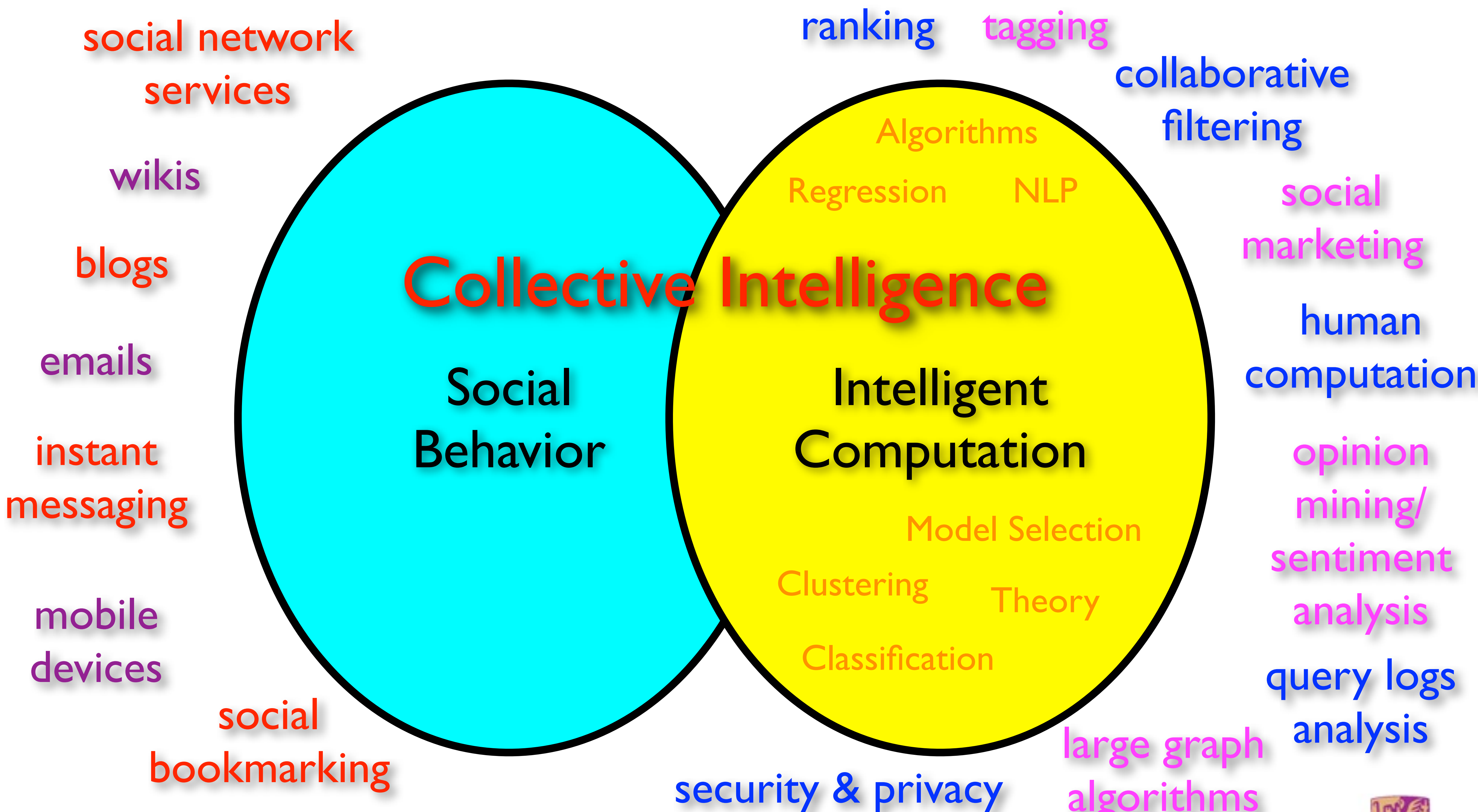
Social Relations

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 Computing



Definition of Social Computing

[wiki]

- Any Computer-mediated communication and interaction
- In the weaker sense: supporting any sort of social behavior
  - blogs, email, instant messaging, wiki, social network services, social bookmarking
- In the stronger sense: supporting "computations" that are carried out by a group of people
  - collaborative filtering, online auctions, prediction markets, reputation systems, tagging, verification games

Emerging Issues

- Theory and models
- Seach, mining, and ranking 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

Computational Perspective

- Classification, clustering, regression, etc.
- New insights on the data
  - Social relations are often hidden (latent)
  - Change data from (x, y) to $(x, c_1(x), c_2(x), \cdots, y)$
- $c(x)$ = context in *tags*, *relations*, *ratings*, etc.
- data type = *binary*, *integer*, *real*, *cardinal*, etc.

Topics in Social Computing

- Social Behavior Analysis and Modeling
- Social Media
- Social Network Theory and Models
- Link Analysis/Graph Mining/ Large Graph Algorithms
- Learning to Rank
- Recommender Systems/ Collaborative Filtering
- QA/Sentiment Analysis/ Opinion Mining
- Human Computation/ Crowdsourcing
- Risk, Trust, Security, and Privacy
- Monetization of Social Computing
- Software Tools and Applications
- and many, many more...

Human Computation

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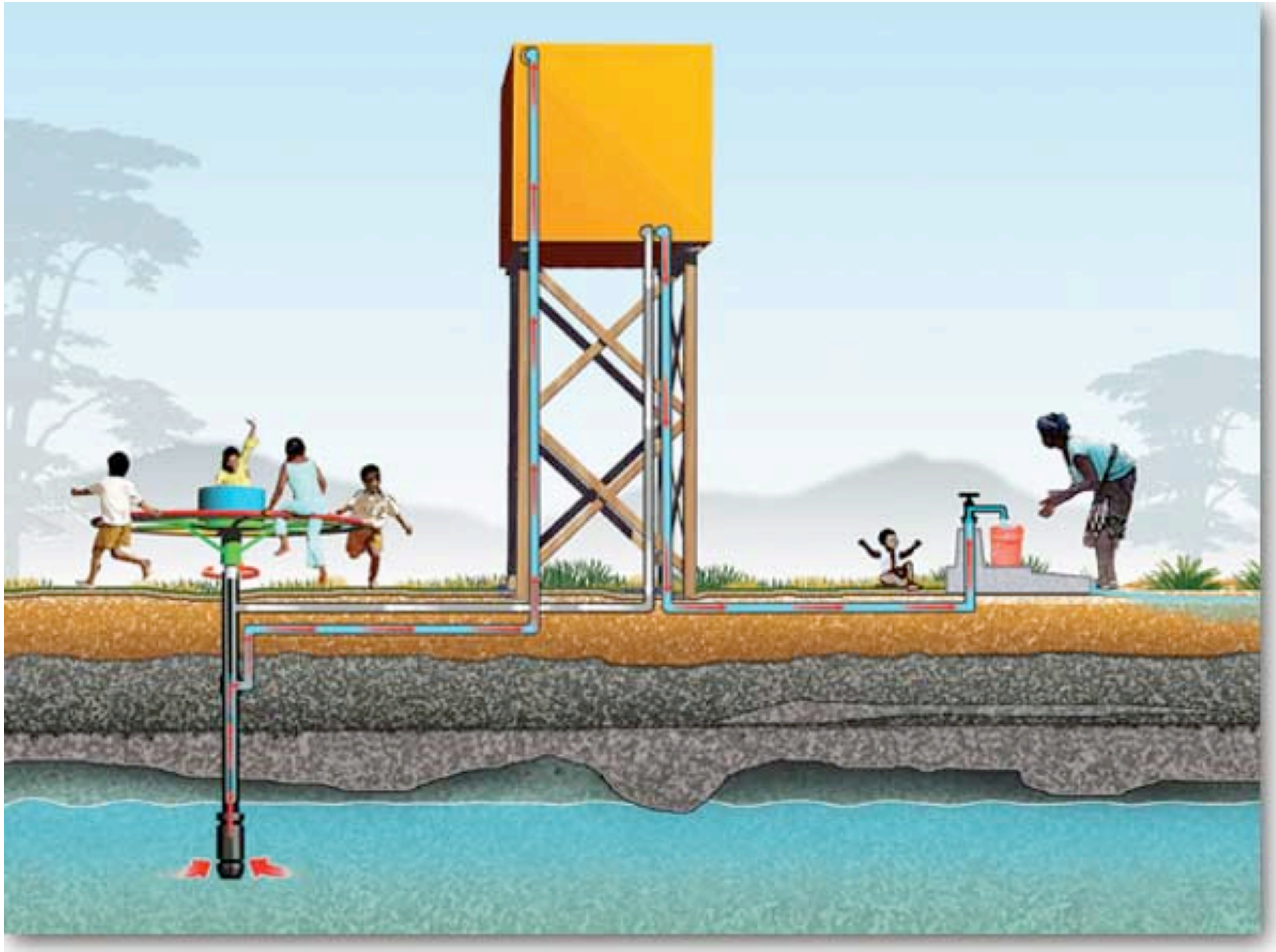
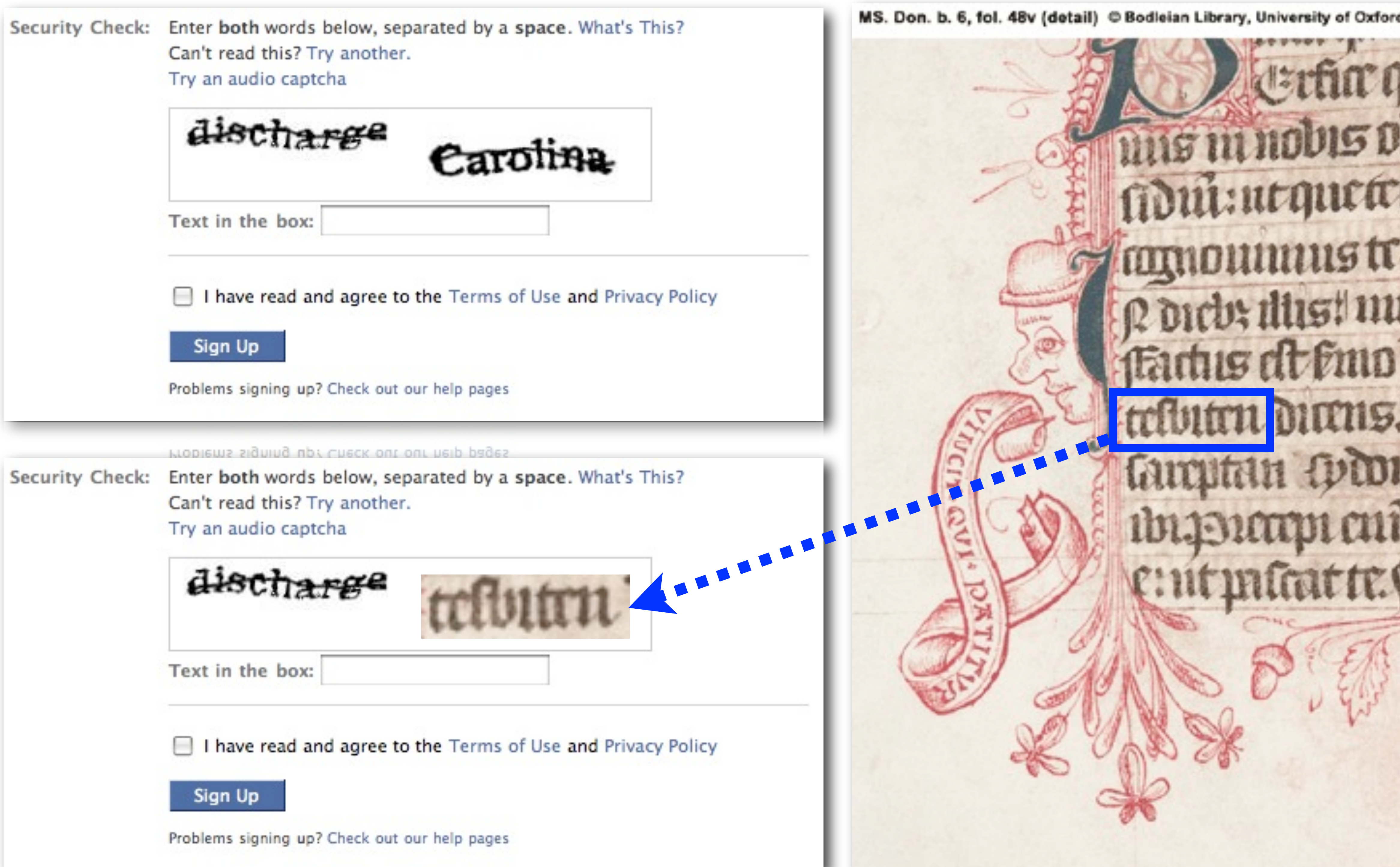
Playing/Having Fun ⟵?⟶ Work/Computation

Idea of Human Computation

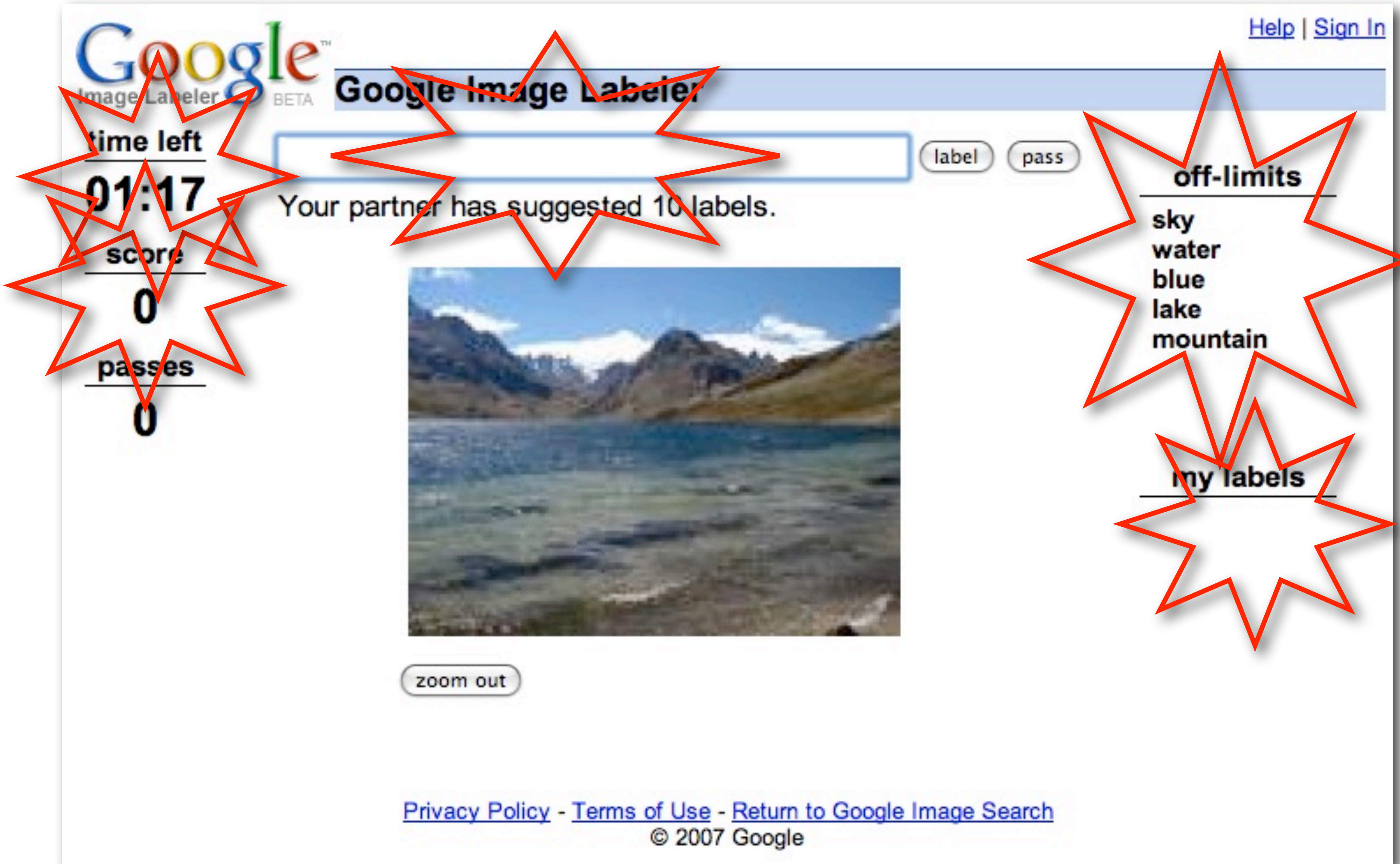


- Take advantage of people's desire to be entertained and perform useful tasks as a side effect

Social/Human Computation



Human Computation



Why Is It Important?

- Some statistics (July 2008)
  - 200,000+ players have contributed 50+ million labels.
  - Each player plays for a total of 91 minutes.
  - The throughput is about 233 labels/player/hour (i.e., one label every 15 seconds)
- Idea behind
  - Solve some problems which are difficult to be solved by computers.
  - Take advantage of people's desire to be entertained.
  - Produce useful metadata as a by-product.

Games With A Purpose

- **Matchin**
  - Image search by aesthetic value
- **Babble**
  - Translate foreign language into English
- **InTune**
  - Tags songs with description text
- **Squigl**
  - Image segmentation
- **Verbosity**
  - Database of common knowledge description

Background

- Human Computation Systems (HCS) aim to solve Artificial Intelligence (AI) problems through the human human interactions

- In order to ensure the collected information to be useful, we have to:

1. guarantee the quality of collected information
2. attract more people to contribute information

Types of HCS

- The categories of the human computation systems are:
  1. Initiatory Human Computation
  2. Distributed Human Computation
  3. Social Game-based Human Computation with volunteers or paid engineers
  4. Social Game-based Human Computation with online players

Initiatory Human Computation (1)

- Objective: To complete some tasks that are natural for humans but difficult for computers even computation power increased rapid recently
- Example (1): CAPTCHA
  - A computer generated challenge-response test
  - Objective: To distinguish humans from computers using a common sense problem

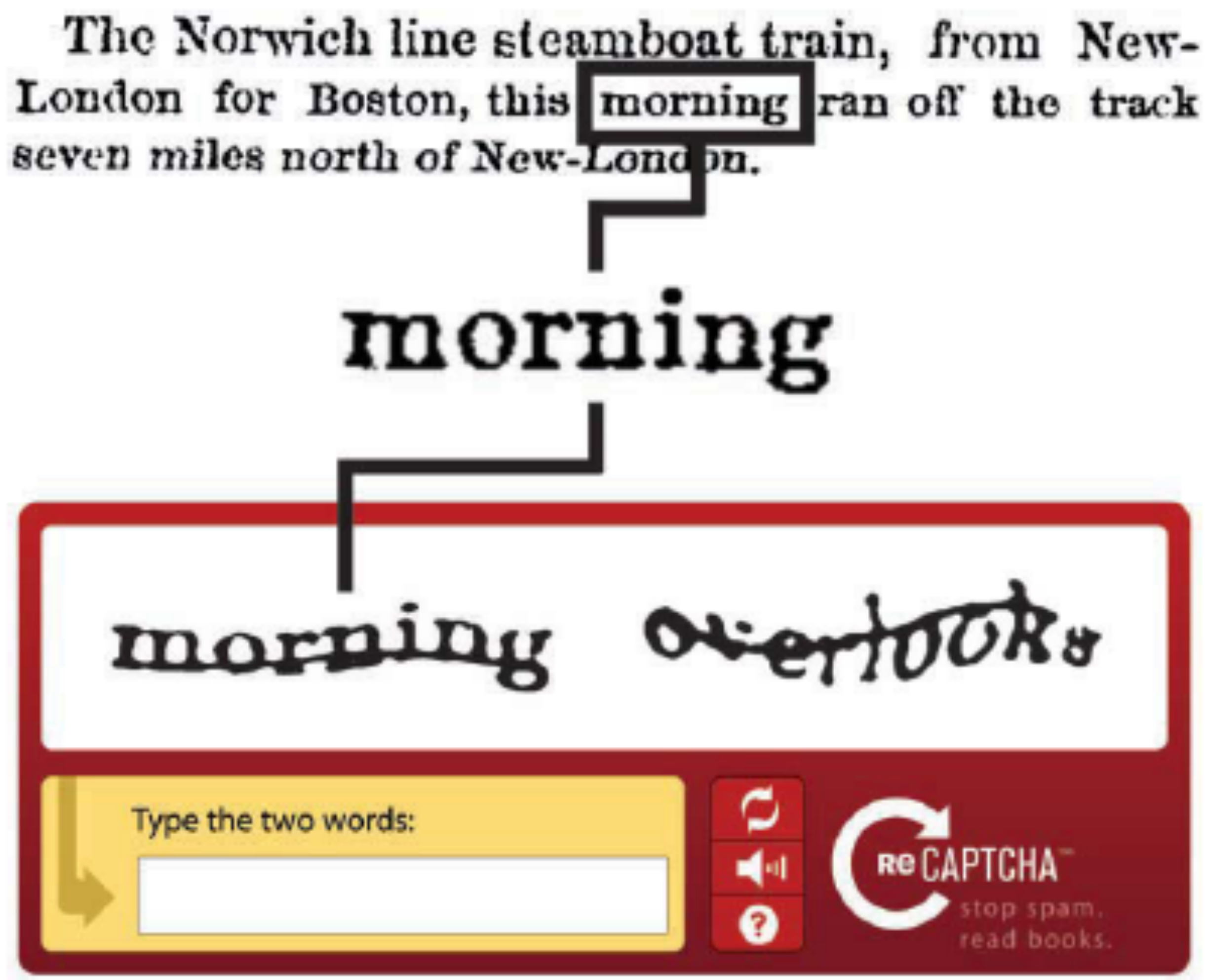
The Yahoo! CAPTCHA.

Initiatory Human Computation (2)

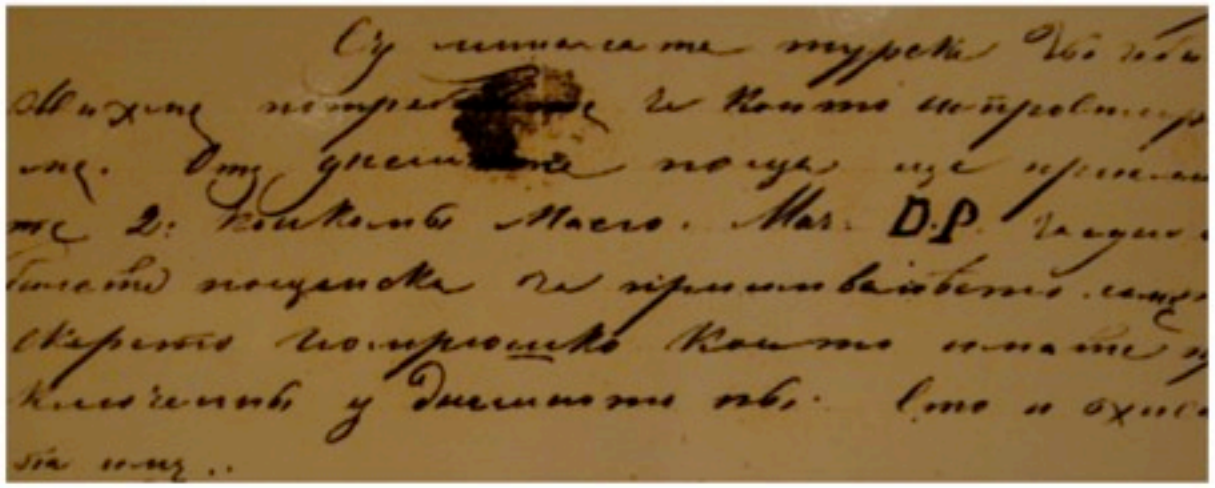
- Example (2): reCAPTCHA
  - Objective: To produce valuable common sense knowledge to improve the OCR quality in digitizing books
  - Combining two words: one identified word; and one unidentified word
  - If a user recognizes the identified word, the answer to the unidentified word is assumed to be correct

Initiatory Human Computation (3)

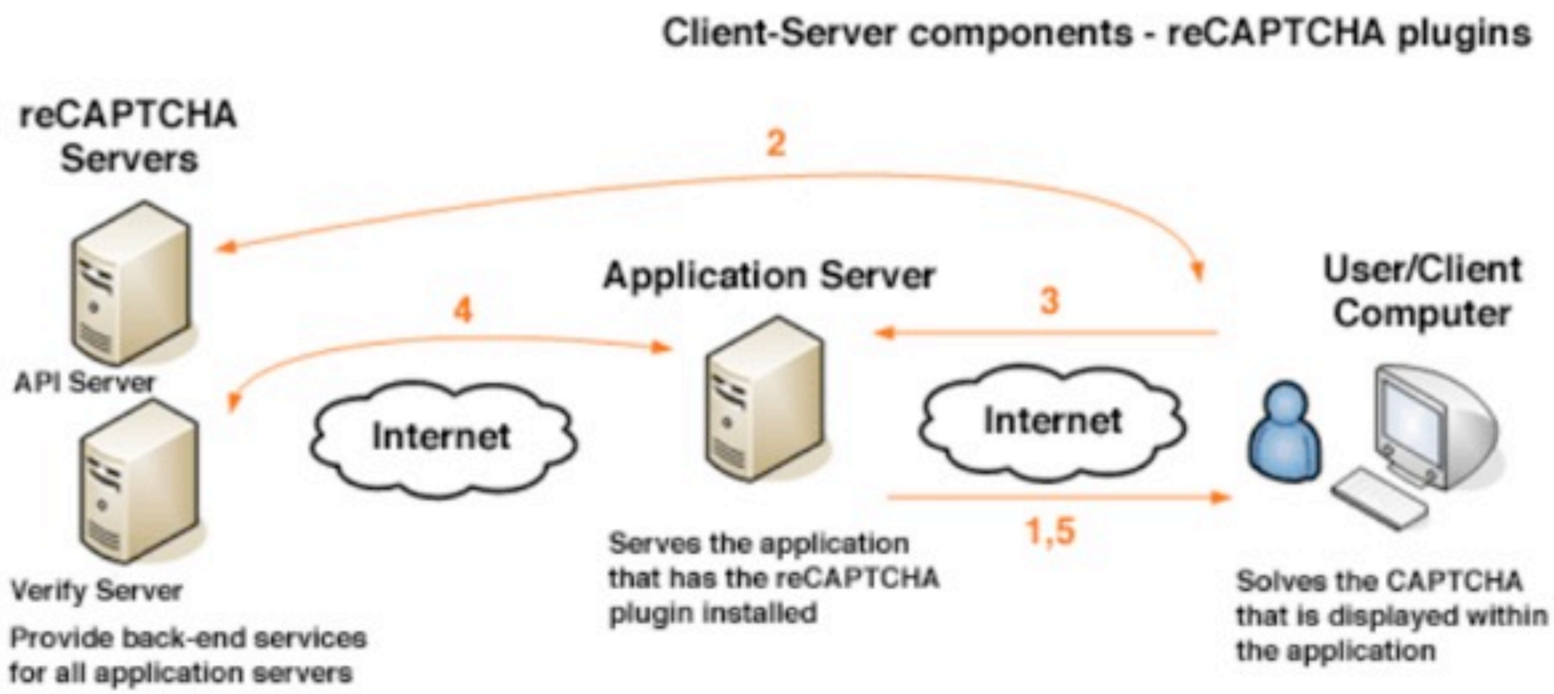
- Example (2): reCAPTCHA



reCAPTCHA

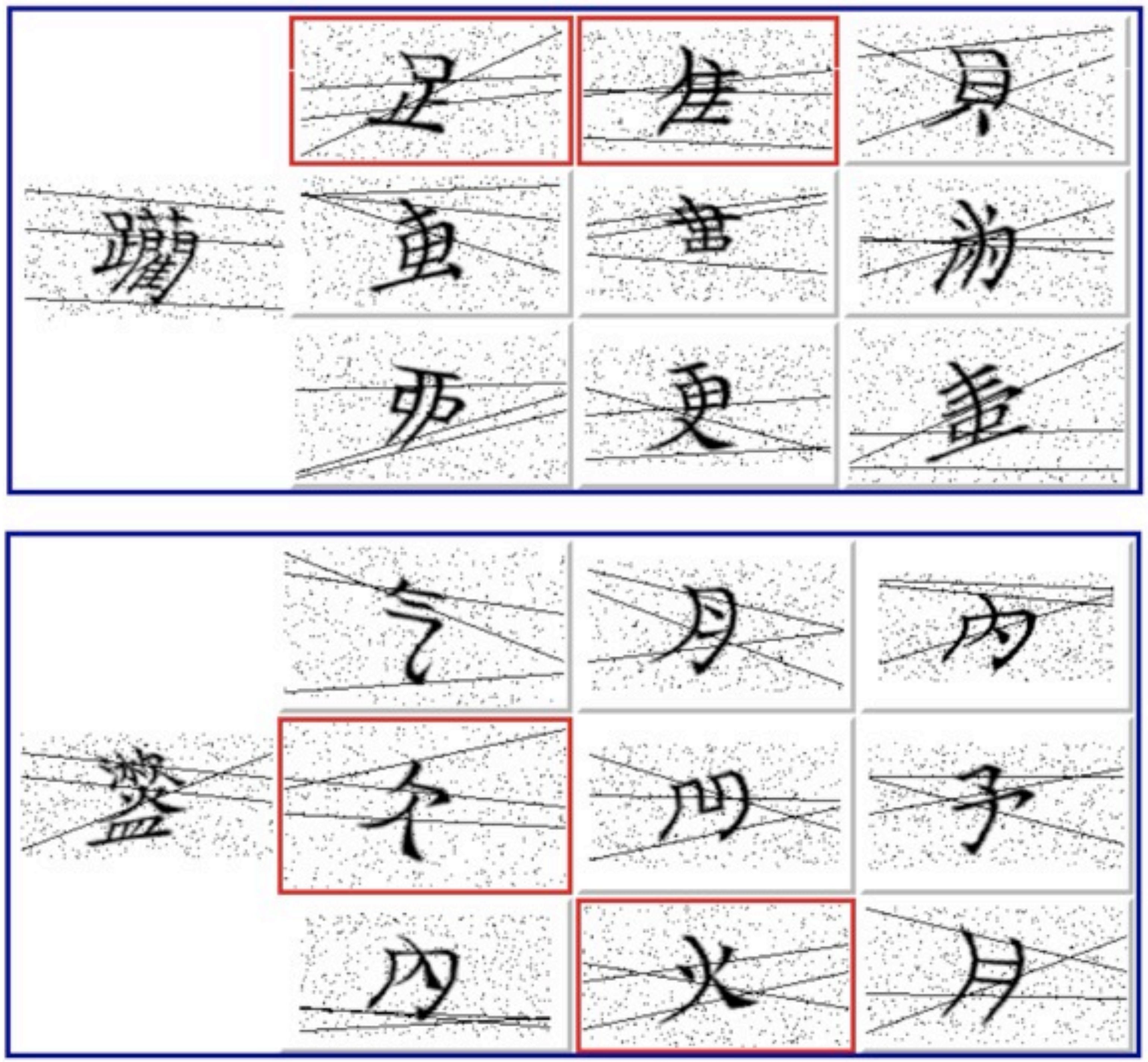



olcott
have
Type the two words:
reCAPTCHA™
stop spam.
read books.
Submit
The words above come from scanned books.
By typing them, you help to digitize old texts.


Client-Server components - reCAPTCHA plugins
reCAPTCHA Servers
2
Application Server
4
3
User/Client Computer
API Server
Internet
Internet
Verify Server
Provide back-end services for all application servers
Serves the application that has the reCAPTCHA plugin installed
1,5
Solves the CAPTCHA that is displayed within the application

Chinese CAPTCHA

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

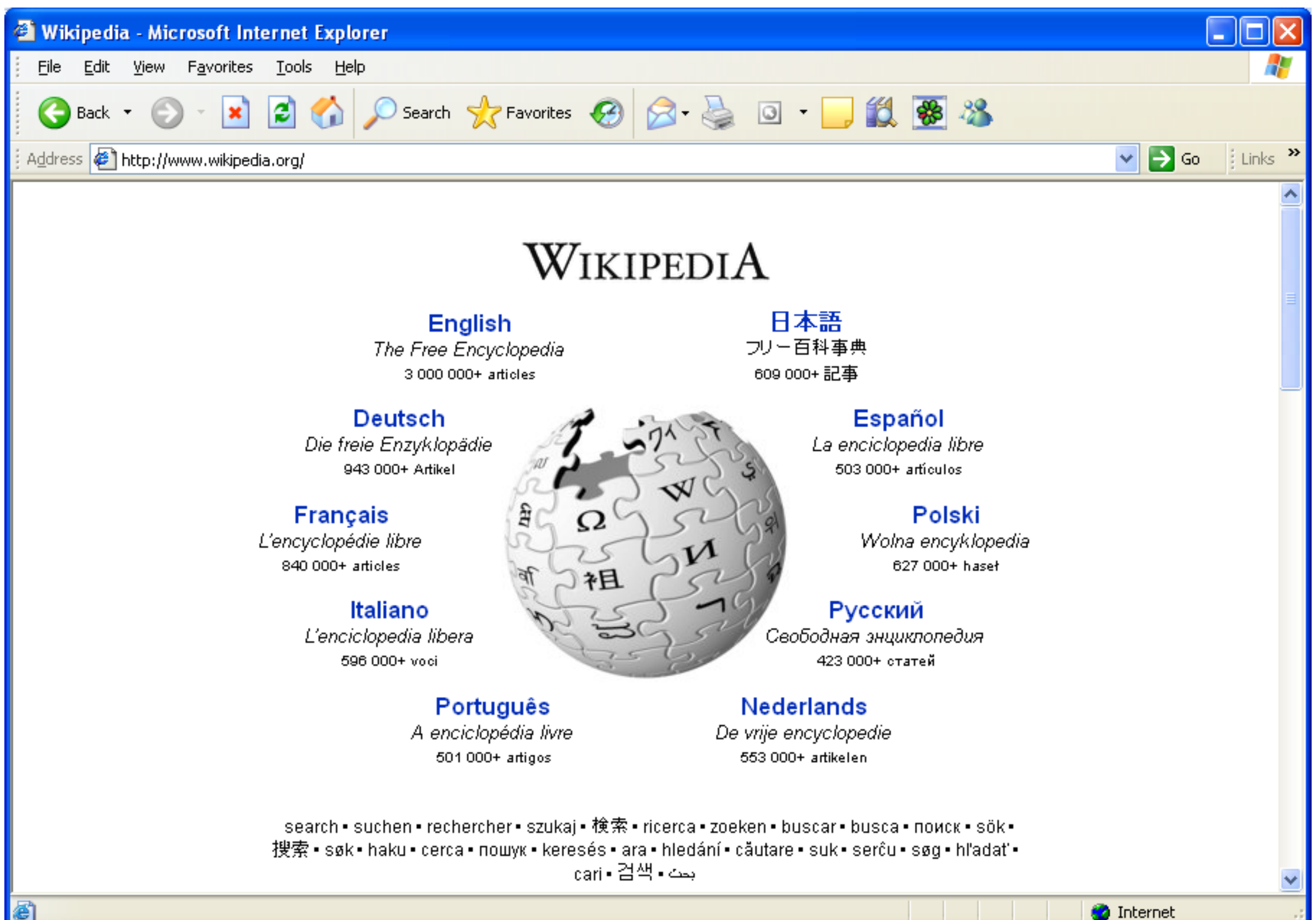


Distributed Human Computation (1)

- Objective: To encourage a huge population of Internet users to contribute to solve the difficult AI problems
- Example (1): Razor
  - To use human votes to determine if a given email is spam (anti-spam mechanism)
- Example (2): Proofreader
  - To give a (small) portion of the image file and corresponding text (generated by OCR) side-by-side to a human proofreader

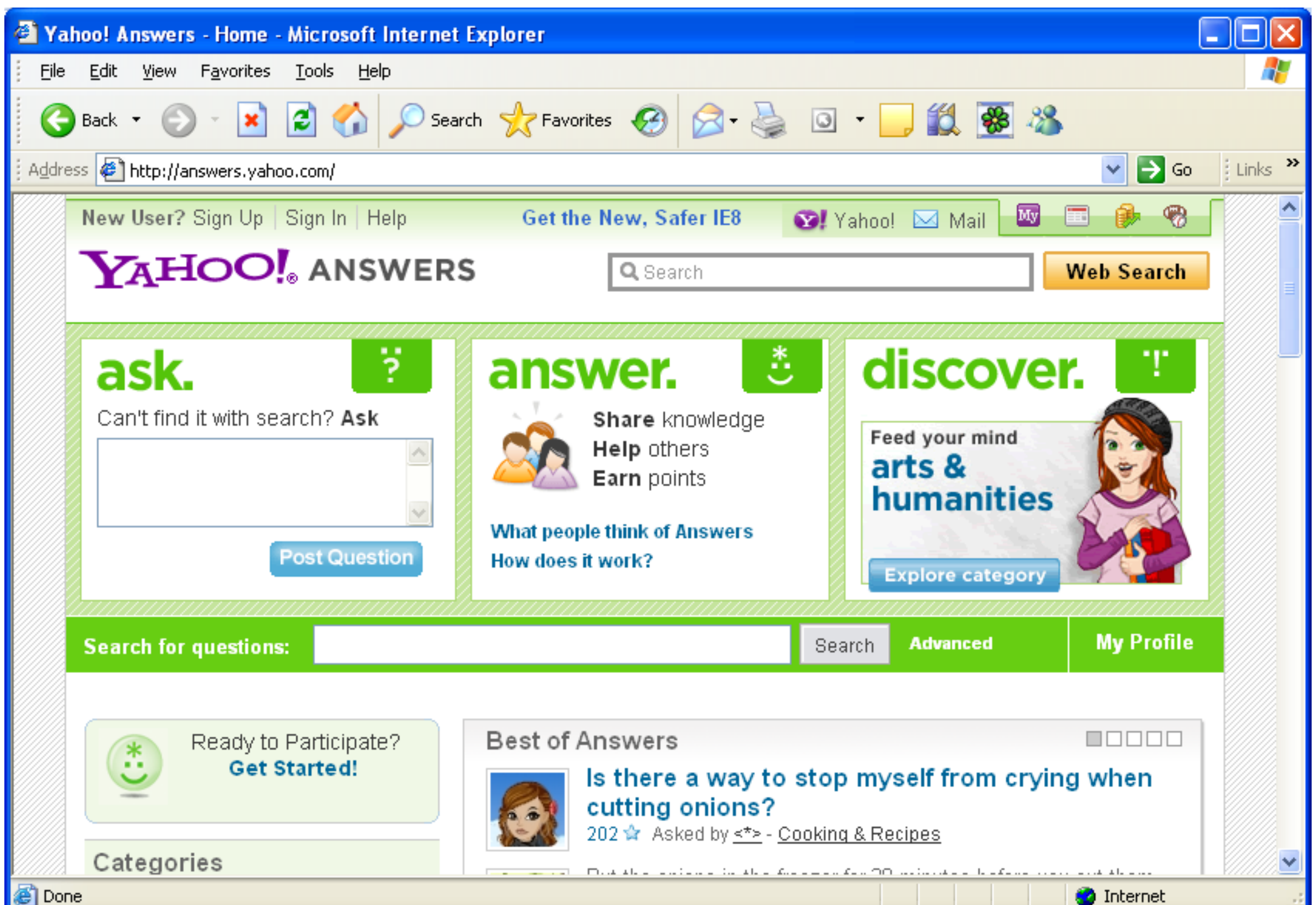
Distributed Human Computation (2)

- Example (3): Wikipedia
  - The collective knowledge is distributed in that essentially almost anyone can contribute to the Wiki



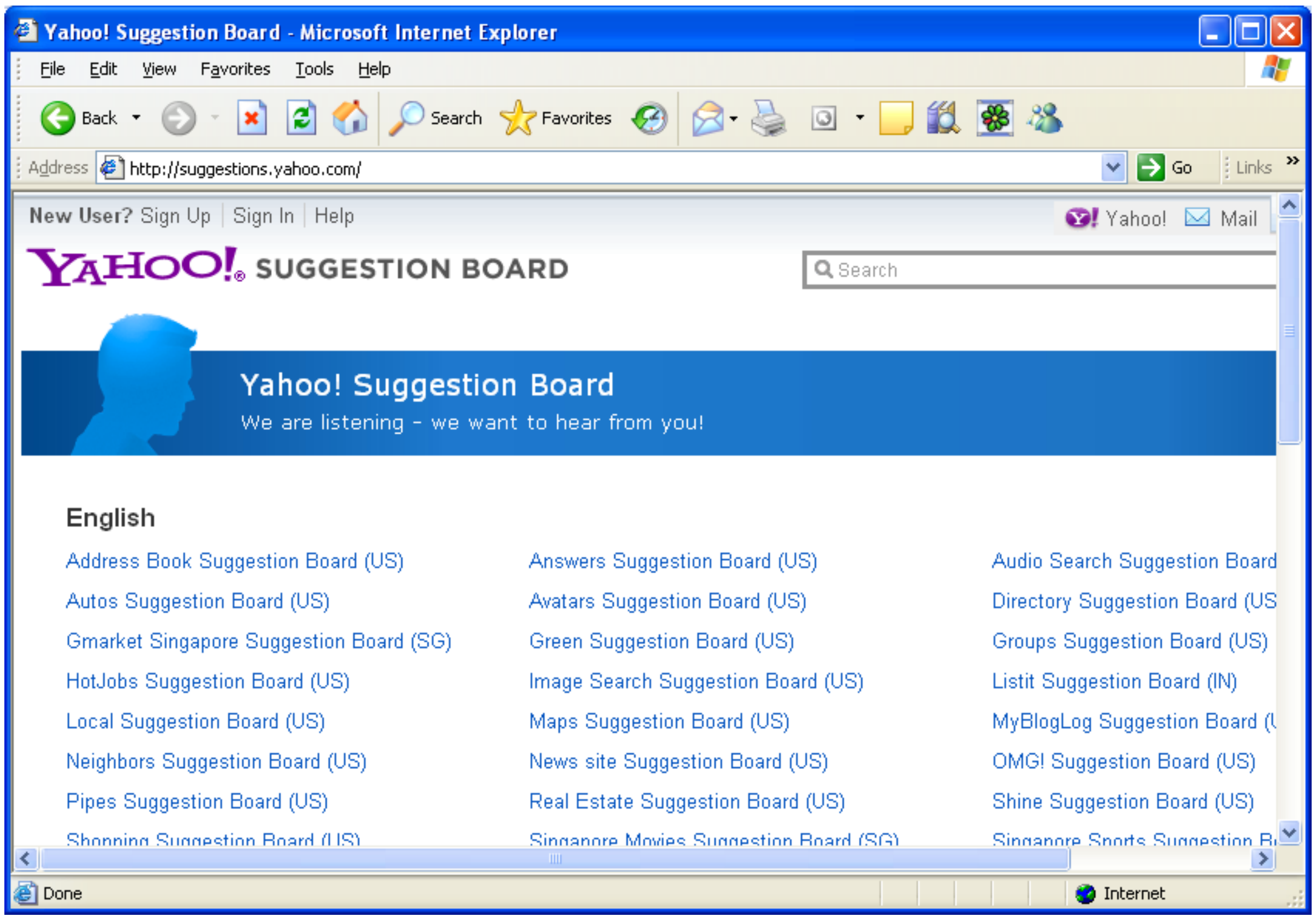
Distributed Human Computation (3)

- Example (4): Yahoo! Answers
  - To provide automated collection of human reviewed data at Internet-scale



Distributed Human Computation (4)

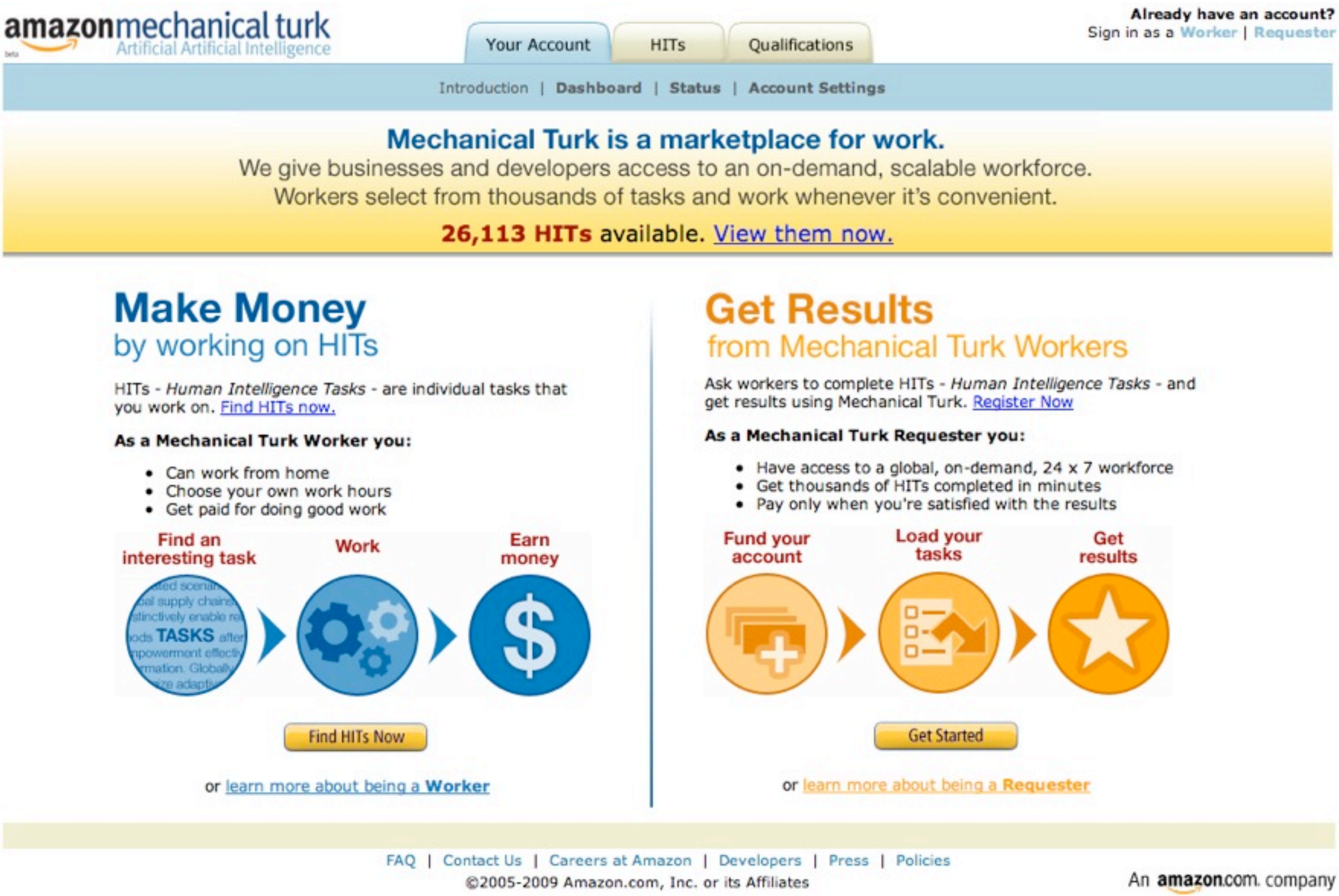
- Example (5): Yahoo! Suggestion Board
  - An Internet-scale feedback and suggestion system



Distributed Human Computation (5)

- Example (6): Amazon Mechanical Turk
  - It provides monetary rewards for tasks
- Example (7): LabelMe
  - A web-based tool for image annotation
  - Anybody can annotate image using it. You can only have access to the database once you have annotated a certain number of images.
- Example (8): 43Things
  - To collect goals from users and help them to find other users who have similar goals
- Example 9: MajorMiner
  - Music annotation game

Amazon Mechanical Turk



Example of Mechanical Turk

Answer a short survey

1. What is your gender?

- ○ Male
- ○ Female

2. What is your age?

[ ]

3. Which of the following best describes your highest achieved education level?

[Some High School ▾]

4. What is the total income of your household?

- Less than $12,500
- $12,500 - $24,999
- $25,000 - $37,499
- $37,500 - $49,999

5. What is your favorite type of TV Show? (select all that apply)

- ☐ Sports
- ☐ Situational Comedies
- ☐ Drama
- ☐ News
- ☐ Music Videos

Find the Website Address for this Restaurant

- For this restaurant below, enter the website address for the official website of the restaurant
- Include the full address, e.g. http://www.thecheesecakefactory.com
- Do not include URLs to city guides and listings like Citysearch.

Restaurant Name: **${name}**

Address: **${address}**

Phone Number: **${phone}**

Website:

[ ]

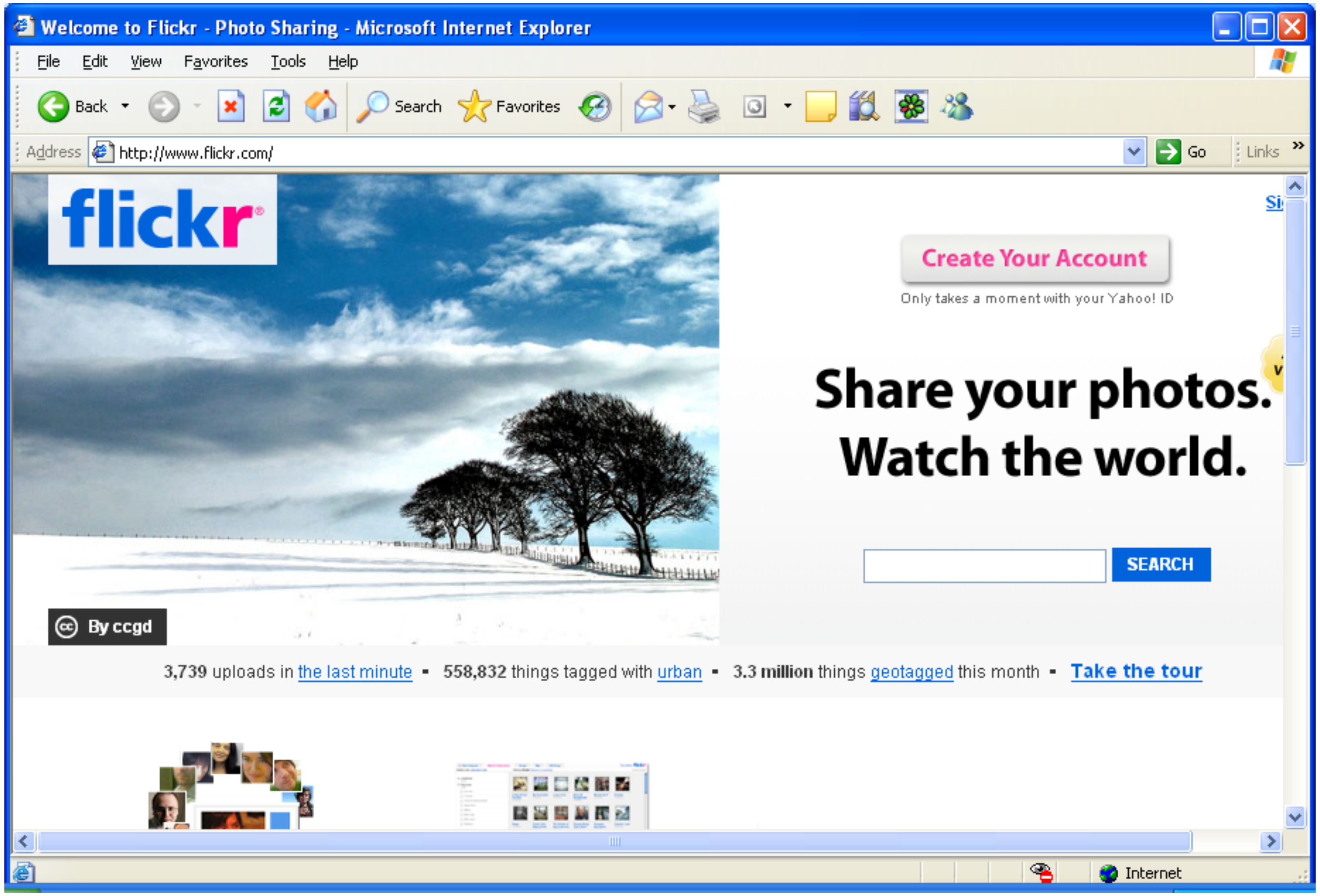
Please provide any comments you may have below, we appreciate your input!

[ ]

[Submit]

Distributed Human Computation (6)

- Example (10): Yahoo's flickr
  - It is a photo-sharing site with captions being used as photo tags



Social Game-based Human Computation with Volunteers or Paid Engineers (1)

- Recently social games were proposed to collect accurate information from players as a side effect of their playing
- The players are volunteers or paid engineers
- Disadvantages:
    - Rely on online volunteers or paid engineers to enter information explicitly
    - Unable to scale up the system due to high cost
    - No validation mechanism to guarantee that the information collected is accurate

Social Game-based Human Computation with Volunteers or Paid Engineers (2)

- Most of the games at early stage aimed to collect commonsense knowledge.
- Example (1): Cyc
  - To collect information from the input by paid knowledge engineers
- Example (2): Open Mind
  - To collect common sense knowledge from people to develop intelligent software
  - Shortcoming: was too reliant on the unpaid volunteers to donate their time to contribute information

Social Game-based Human Computation with Volunteers or Paid Engineers (3)

- Example (2): Open Mind

Social Game-based Human Computation with Volunteers or Paid Engineers (4)

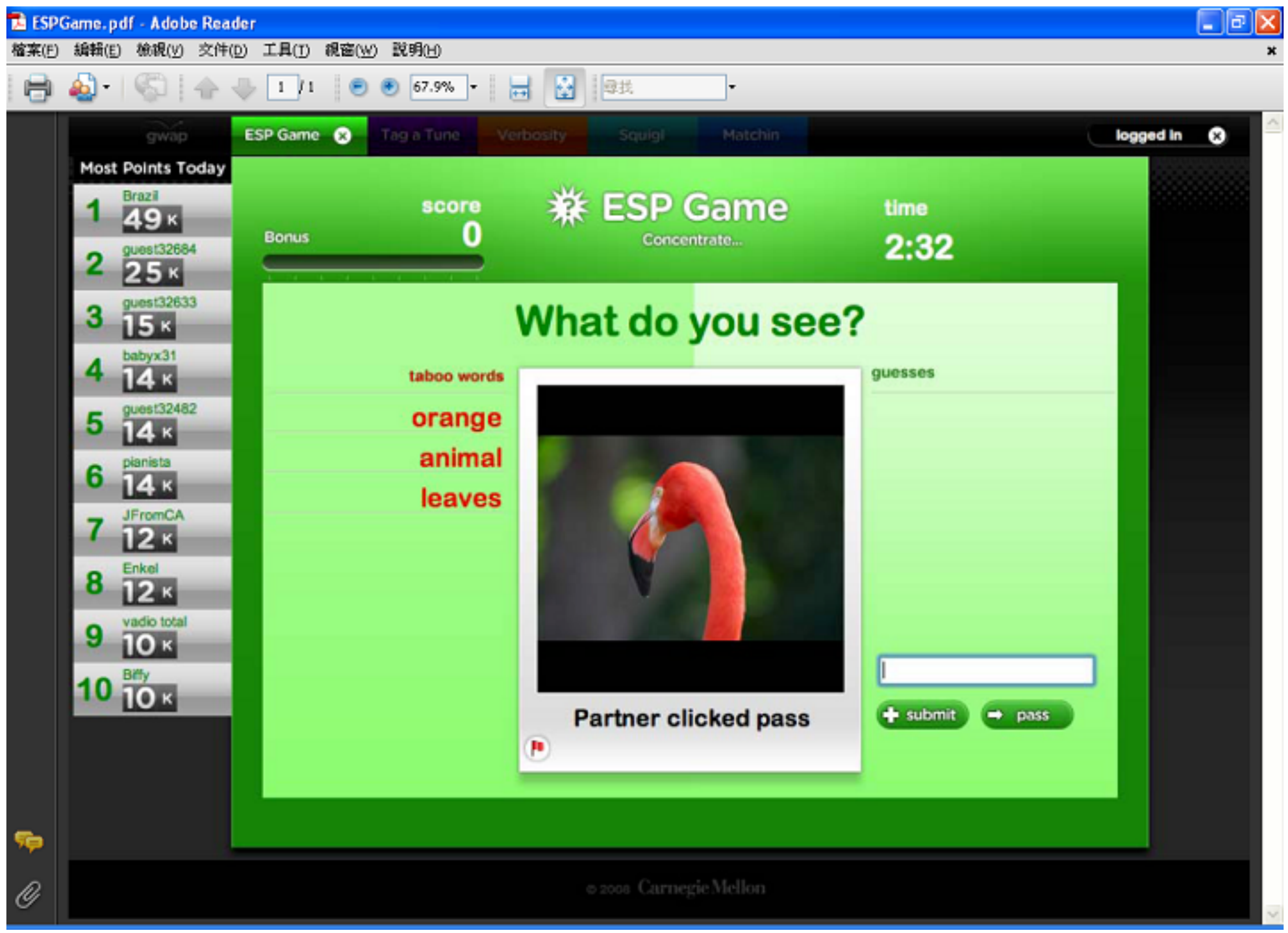
- Example (3): Mindpixel
  - Reward those Internet users who consistently validate a fact inline with the other users
  - Shortcoming: the cost is high!
- Example (4): Wildfire wally
  - To solve the maximum clique problem
  - Shortcoming: rely on unpaid volunteers to donate their time to contribute information

Social Game-based Human Computation with Online Players (1)

- Later, social games were proposed to collect information from the players as a side effect of their playing
- Advantage:
  - It encouraged more Internet users to contribute information to solve the AI problems because of the increasingly popularity of online game
- TWO important factors for collecting information effectively from players through a social game:
  - Guarantee the quality of collected information
  - Maintain the enjoyment of players in the game

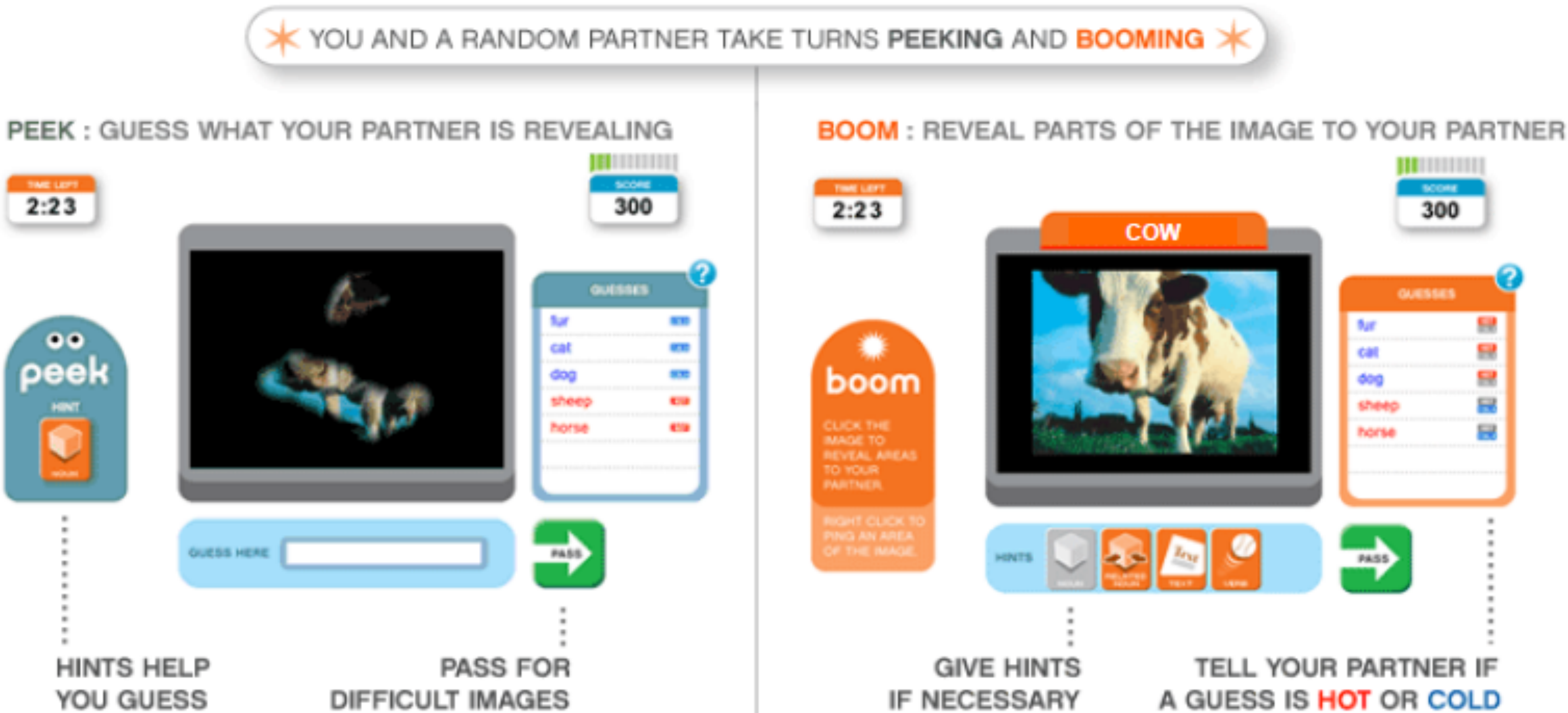
Social Game-based Human Computation with Online Players (2)

- To collect text information from images
  - Examples (1): ESP game



Social Game-based Human Computation with Online Players (3)

- To collect text information for images:
  - Examples (2): Peekaboom



Social Game-based Human Computation with Online Players (4)

- To collect commonsense knowledge:
  - Examples (3): Verbosity

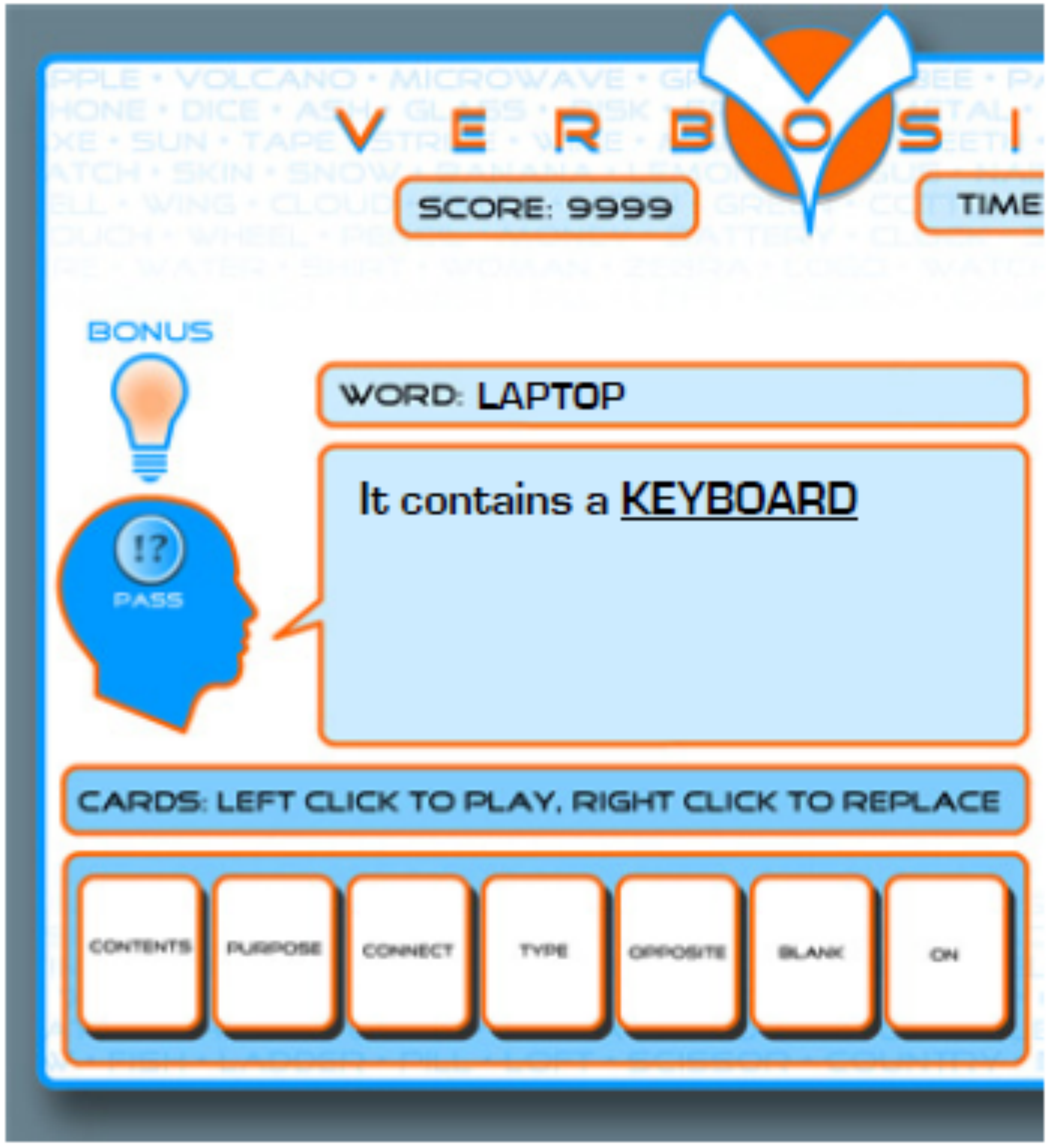
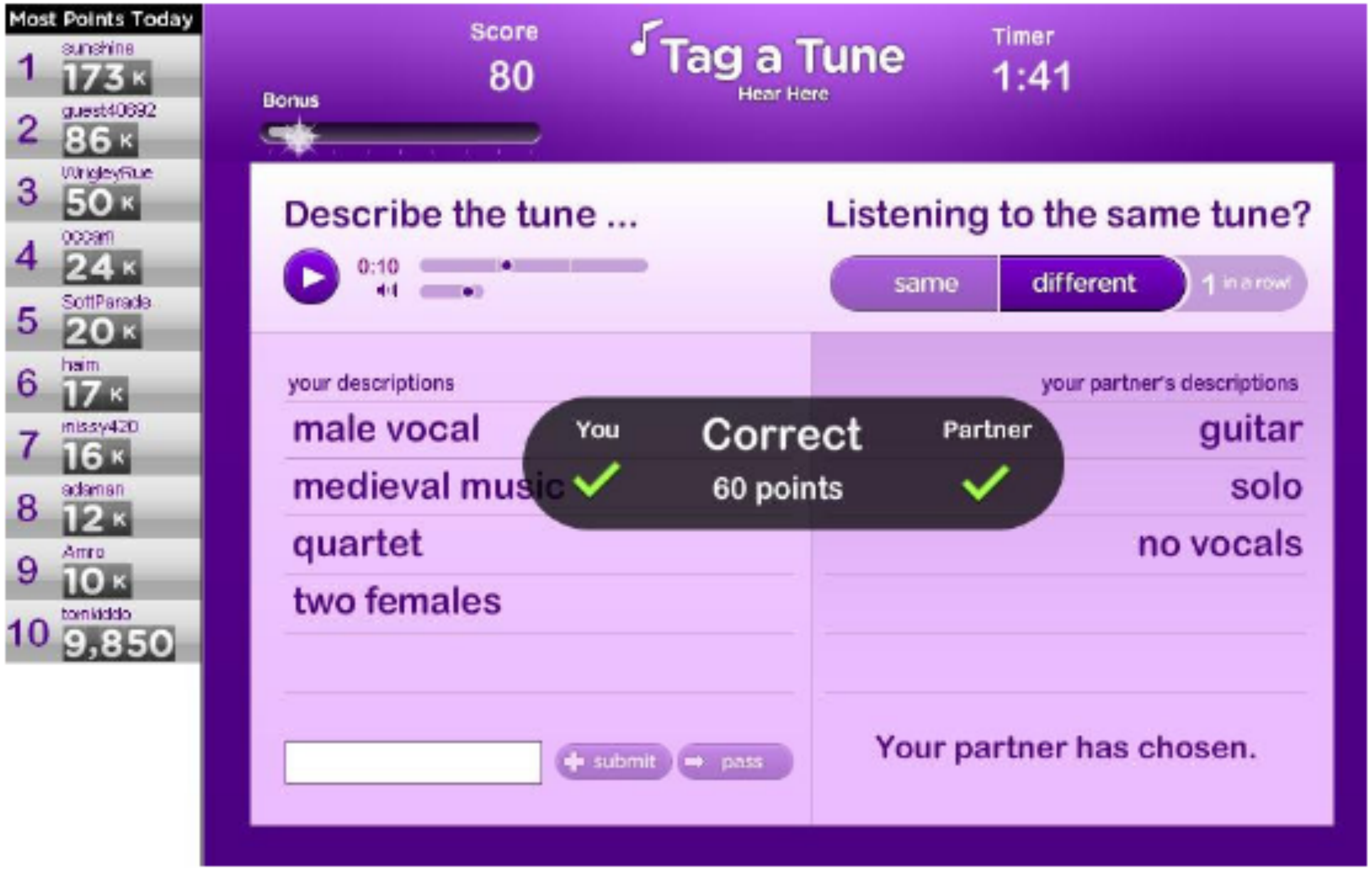


Figure 1. Part of the Narrator's screen.

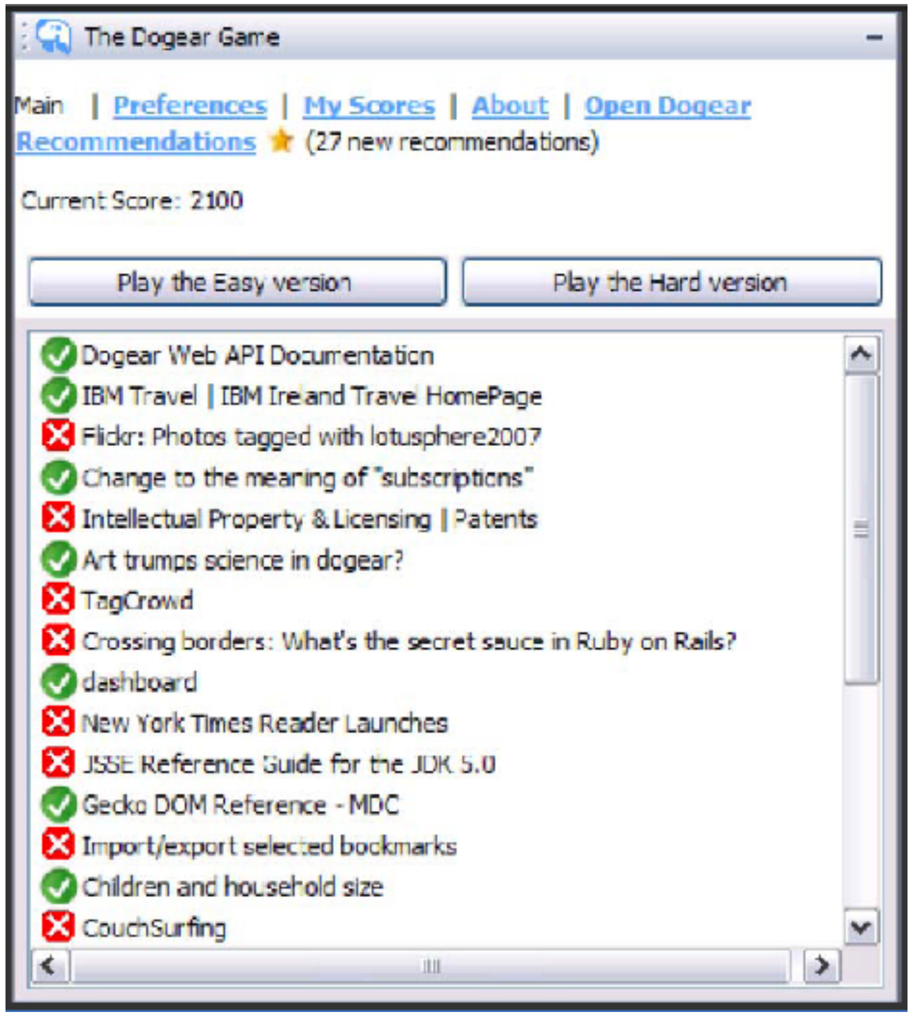
Social Game-based Human Computation with Online Players (5)

- To collect subjective descriptions of sounds and music:
  - Example (4): Tagatune



Social Game-based Human Computation with Online Players (6)

- To learn colleagues' bookmarks in an organizational goal:
  - Example (5): Dogear Game



Social Game-based Human Computation with Online Players (7)

- To tag locations in the real world through gameplay in mobile social games:
  - Example (6): Gopher guessing game

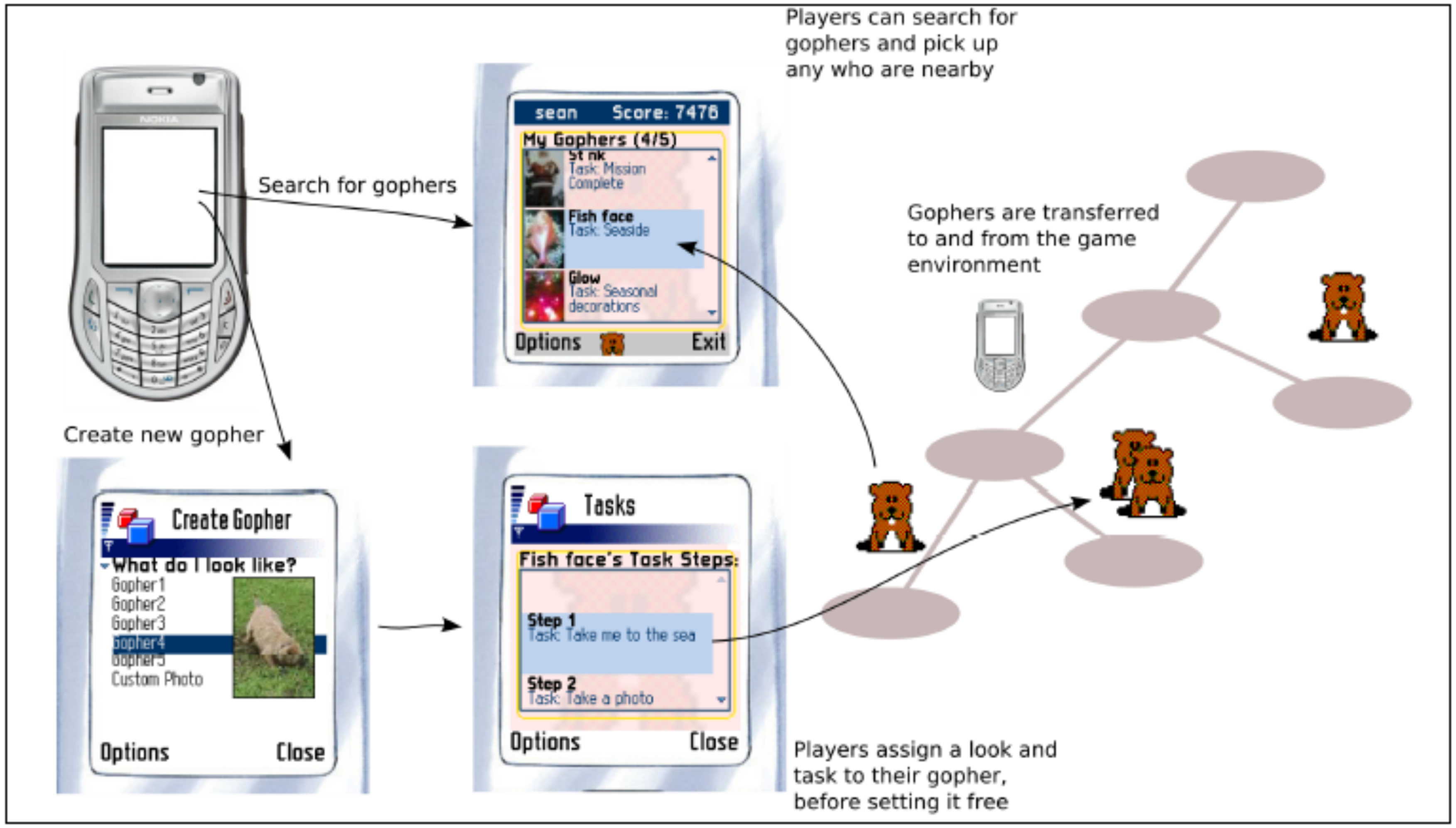


Figure 1. Real world experience, acquiring gophers

Social Game-based Human Computation with Online Players (8)

- To tag locations in the real world through gameplay in mobile social games:
  - Example (7): Gopher guessing game

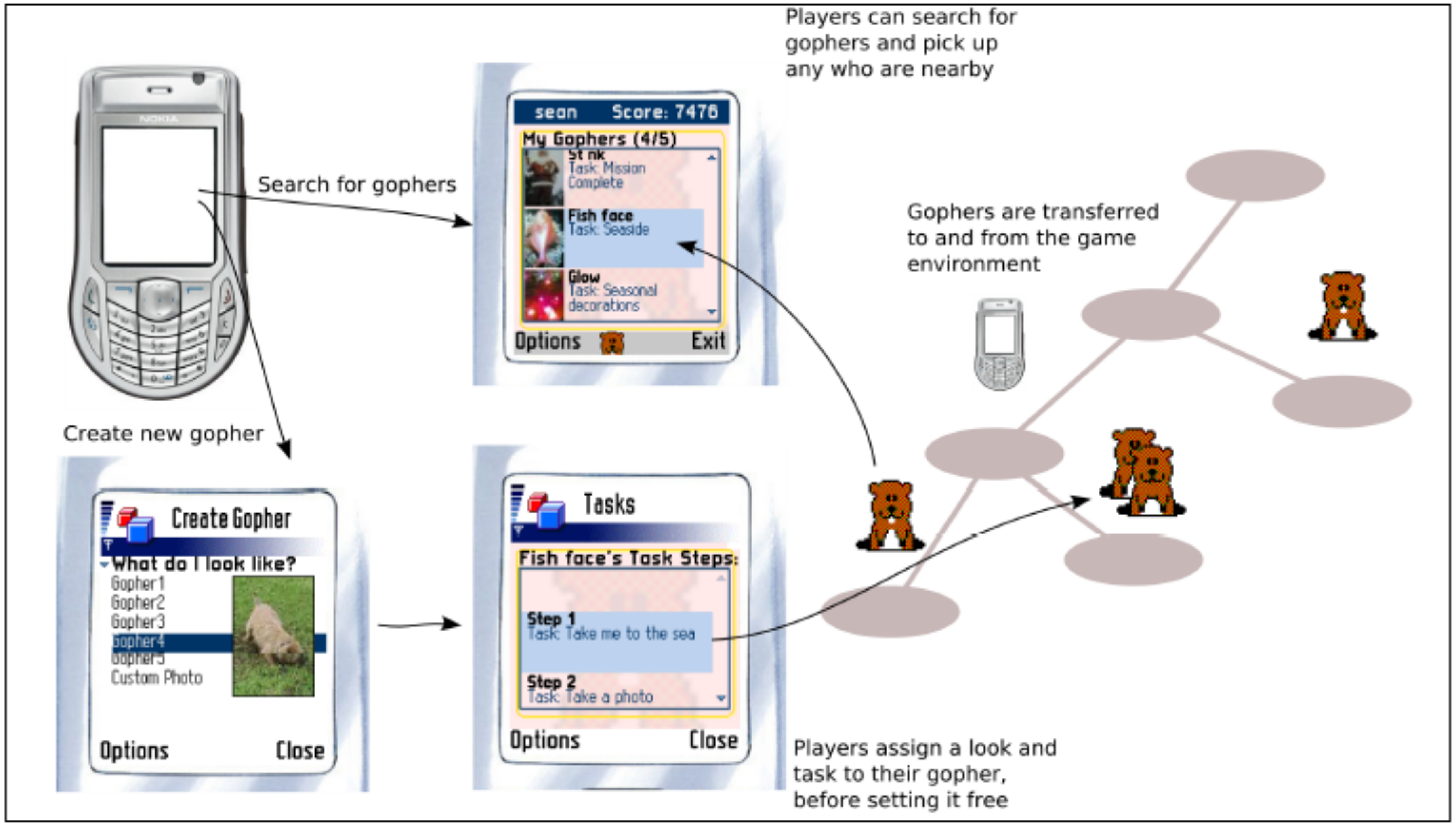


Figure 1. Real world experience, acquiring gophers

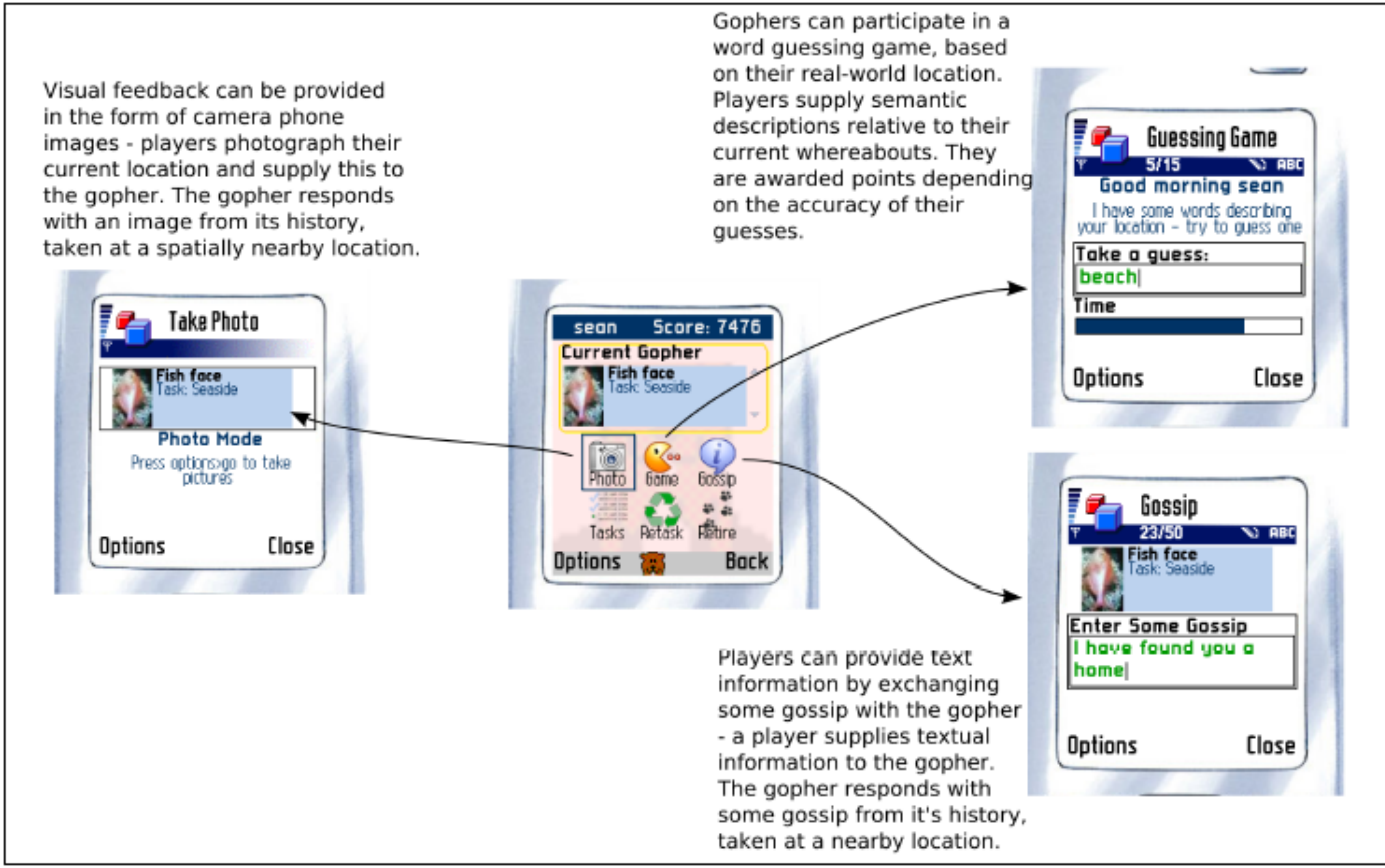
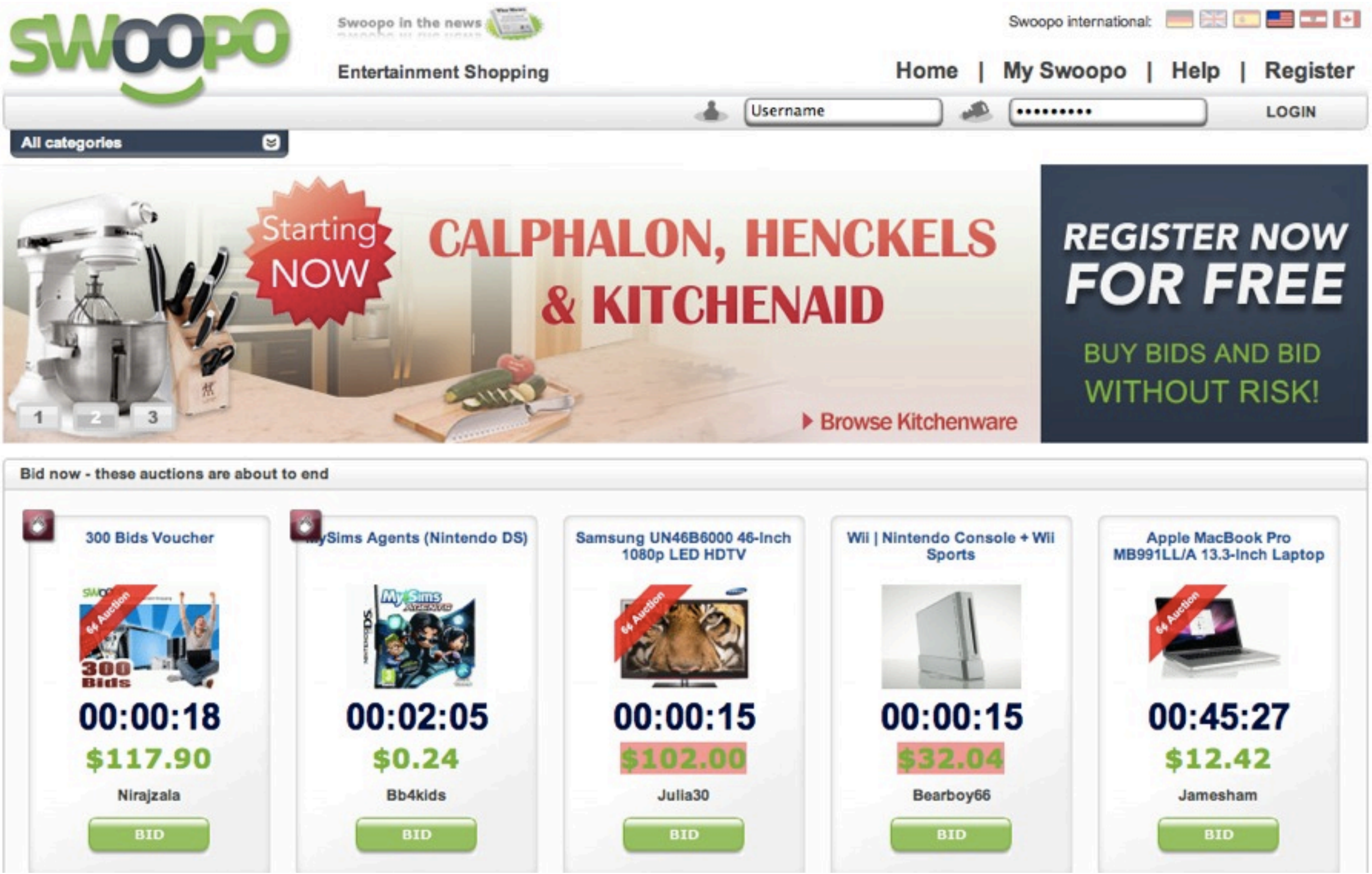


Figure 2. Real world experience, interacting with gophers

Entertainment Shopping



Categorization of Social Games

TABLE I
CATEGORIZATION OF SOCIAL GAMES

Game Structure	Verification Method	Game Mechanism
Output-agreement	Symmetric	Collaborative or Hybrid
Input-agreement	Symmetric	Collaborative or Hybrid
Inversion-problem	Asymmetric	Collaborative or Competitive or Hybrid
Output-optimization	Symmetric or Asymmetric	Collaborative or Competitive or Hybrid

Summary

TABLE II
CATEGORIZATION OF SOCIAL GAMES WITH EXAMPLES

Game Structure	Verification Method	Game Mechanism	Player Requirement		Examples
			Num of Player	Game Play	
Output-agreement	Symmetric	Collaborative	2	Synchronous	ESP, Matchi, Squigl, OntoGame
		Hybrid	Multi-players	Synchronous	Common Consensus, Social Heroes
		Hybrid	Multi-players	Asynchronous	Gopher Game
Input-agreement	Symmetric	Collaborative	2	Synchronous	TagATune
		Hybrid	N/A	N/A	N/A
Inversion-problem	Asymmetric	Collaborative	1 or 2	Synchronous	Peekaboom, Verbosity
		Competitive	2	Asynchronous	Dogear, CyPRESS, CARS
		Hybrid	1 or Multi-players	Synchronous	Phetch
Output-optimization	Symmetric	Collaborative	2	Synchronous	Restaurant Game
		Competitive	N/A	N/A	N/A
		Hybrid	Multi-players	Synchronous	Diplomacy

Crowsourcing

Sheng-Wei (Kuan-Ta) Chen, Institute of Information Science, Academia Sinica, Taipei, Taiwan

- Crowdsourcing = Crowd + Outsourcing
- Soliciting solutions via open calls to large-scale communities
  - INNOCENTIVE
  - oDesk
  - Amazon Mechanical Turk - Marketplace for work
  - Yahoo! Answers
  - Wikipedia

What Are Crowdsourceable?

- Software development - USD $25,000 per job
- Data entry - USD $4.4 per hour
- Image tagging - USD $0.04 per image
- General questions - points on Yahoo! Answers
- Image understanding - USD $0.01 to $0.02 per task
- Human action recognition - USD $0.01 per task
- Linguistic annotations (word similarity) - USD $0.2 per 30 word pairs

Multimedia QoE Assessment

- Quality of Experience (QoE) = User's subjective satisfaction about a service (multimedia content)
- To provide end-user experience, we measure the QoE of multimedia content, e.g, image, voice, video, etc.
  - Efficiency vs. Reliability
  - Objective evaluation approach
  - Subjection evaluation approach

Evaluation Approaches

- Objective Evaluation
    - Cannot capture all the QoE dimensions that may affect users' experiences
    - Cannot include external factors, e.g., quality of headsets, distance between the viewer and the display
- Subjective Evacuation
    - Opinions, e.g., 1=bad, 2=poor, 3=fair, 4=good, and 5=excellent
    - Difficult to define the ordinal scales concisely
    - Difficult to verify users' scoring results

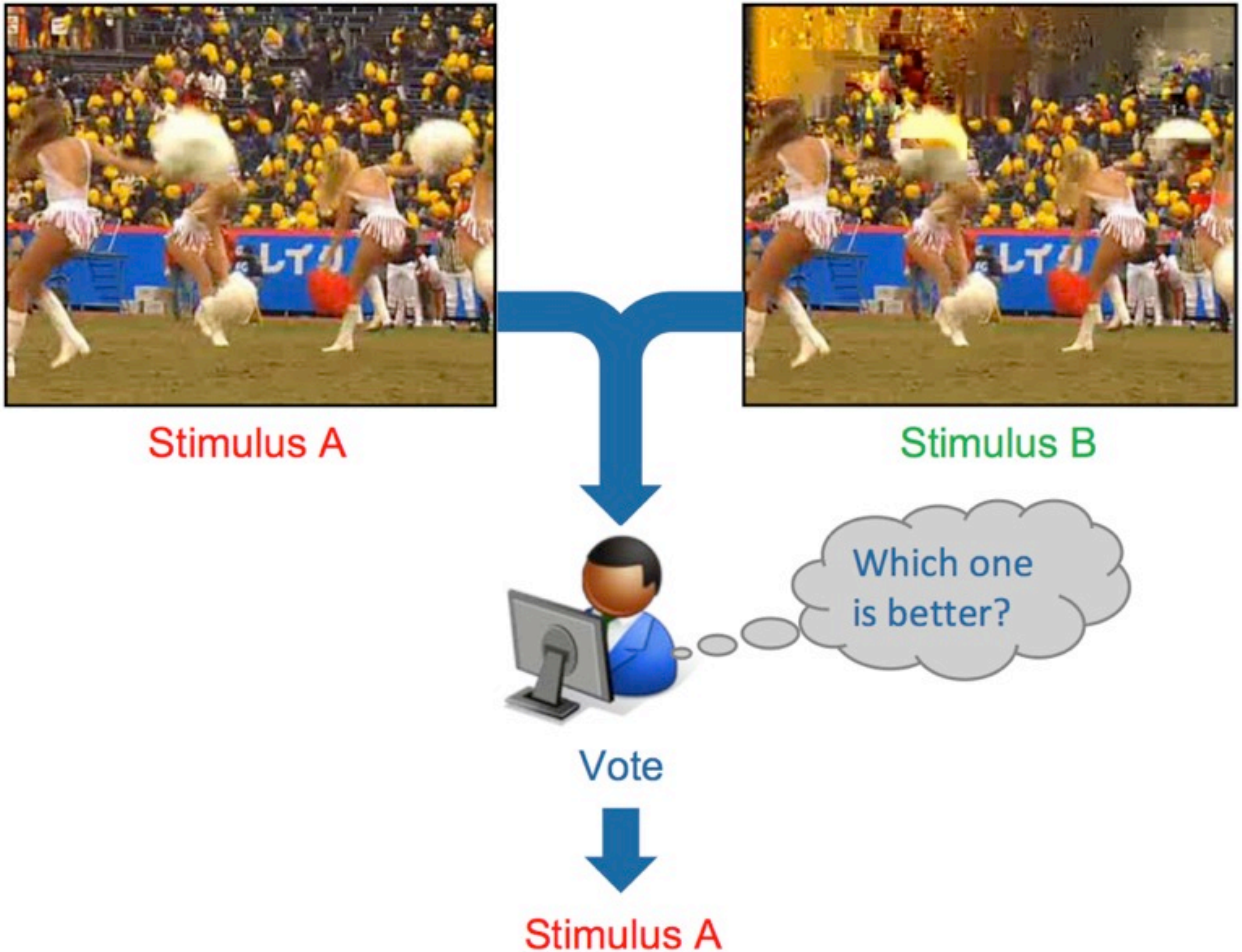
Drawbacks of Subjective Evaluation

- High economic cost
  - Participant payment
- High labor cost
  - Supervision labor
- Physical space/time requirements
  - Transportation cost
  - Laboratory space
  - Difficult to find motivated participants

Crowdsourcing Challenges

- Not every Internet user is trustworthy
  - Experiments without supervision so no quality assurance
  - Increased variance and bias
  - Need to find a way to detect problematic inputs!

Paired Comparison Test



Features of Paired Comparison

- Generalizable across a variety of multimedia applications
- Simple comparative judgement
- Interval scale QoE scores can be calculated
- Verifiable users' feedback

Verification of Users' Inputs

- Transitivity property
  - If A > B and B > C then A should be > C
- Transitivity Satisfaction Rate (TSR)

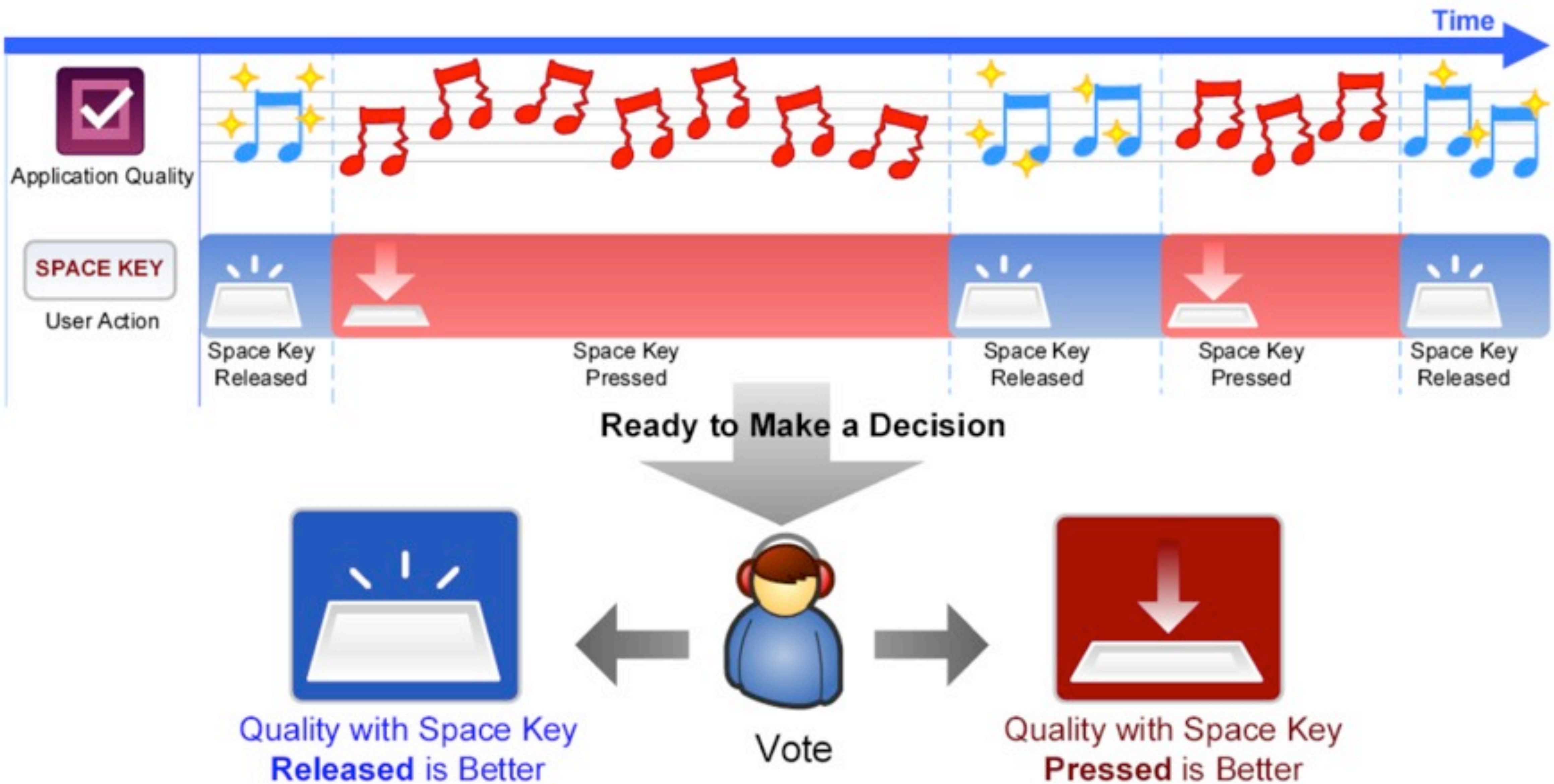
$$\frac{\#\text{ of triples satisfy the transitivity rule}}{\#\text{ of triples the transitivity rule may apply to}}$$

- Detect inconsistent judgements from problematic users
  - TSR = 1 => perfect consistency
  - TSR >= 0.8 => generally consistent
  - TSR < 0.8 => judgement are consistent

Experiment Design

- Suppose our task is to evaluate the effect of n audio processing algorithms, e.g., audio encoding
  - Select an audio clip (source clip) as the evaluation target
  - Apply the *n* algorithms to the source clip and generate *n* different versions of the clip (test clips)
  - Create an Adobe Flash-based system for users to evaluate the *n* test clips
  - A user need to perform 2 out of *n* paired comparison

Concept Flow of Acoustic QoE Evaluation



Which One is Better?

Participant Source

- Laboratory
  - Recruit part-time workers at an hourly rate of USD $8
- MTurk
  - Post experiments on the Mechanical Turk web site
  - Pay the participant USD $0.15 for each qualified experiment
- Community
  - Seek participants on the website of Internet community with 1.5 million members
  - Pay the participant an amount of virtual currency that was equivalent to USD $0.01 for each qualified experiment

Evaluation of the Framework

- Three participant sources
  - Laboratory
  - Amazon Mechanical Turk
  - Community
- Each with different cost structure
- Compare the cost required by each participant and the data quality produced

- The first **crowdsourcable** QoE evaluation framework
- Users' inputs can be **verified**
  - the transitivity property: A > B and B > C ➔ A > C
  - detect inconsistent judgements from problematic users
- Experiments can thus be outsourced to Internet crowd
  - **lower monetary cost**
  - **wider participant diversity**
  - **maintaining the evaluation results' quality**

Case Study	Experimenter Source	Total Cost (dollar)	# Rounds	# Person	Qualified Rate	Cost / Round (cent)	Time / Round (sec)	Avg. TSR
MP3 Bit Rate	Laboratory	50.97	1440	10	67%	3.54	16	0.96
	MTurk	7.50	750	24	47%	1.00	9	0.96
	Community	1.03	1,470	93	54%	0.07	25	0.96

Chen et al, "A Crowdsourceable QoE Evaluation Framework for Multimedia Content," *Proceedings of ACM Multimedia 2009*.

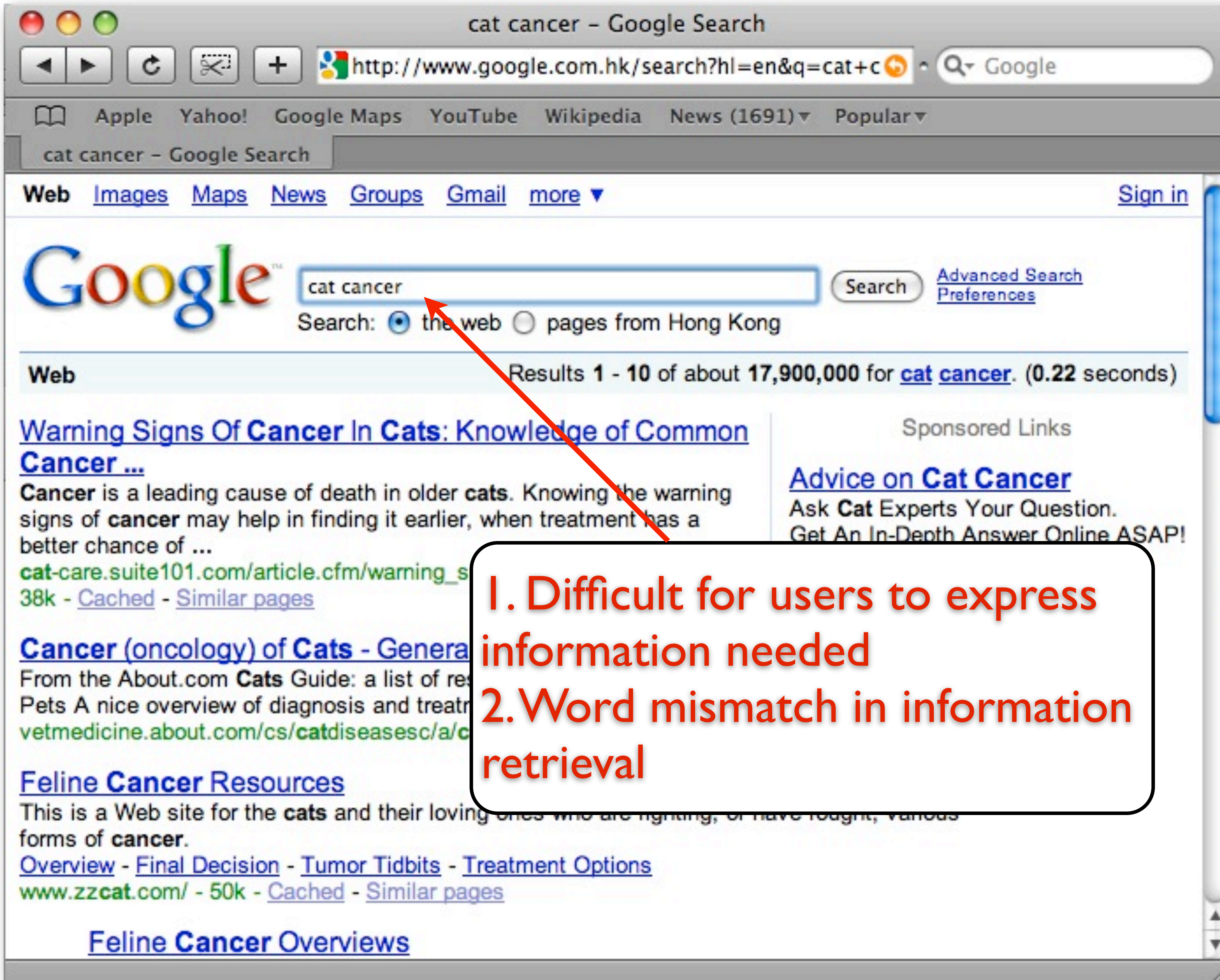
Summary

- Human computation is useful can be effective in performing intelligent tasks where computers cannot
- Crowdsourcing provides a new paradigm and a new platform for scientific research
- New applications, new methodologies, and new businesses are emerging with the aid of human computing/crowdsourcing

Query Suggestion

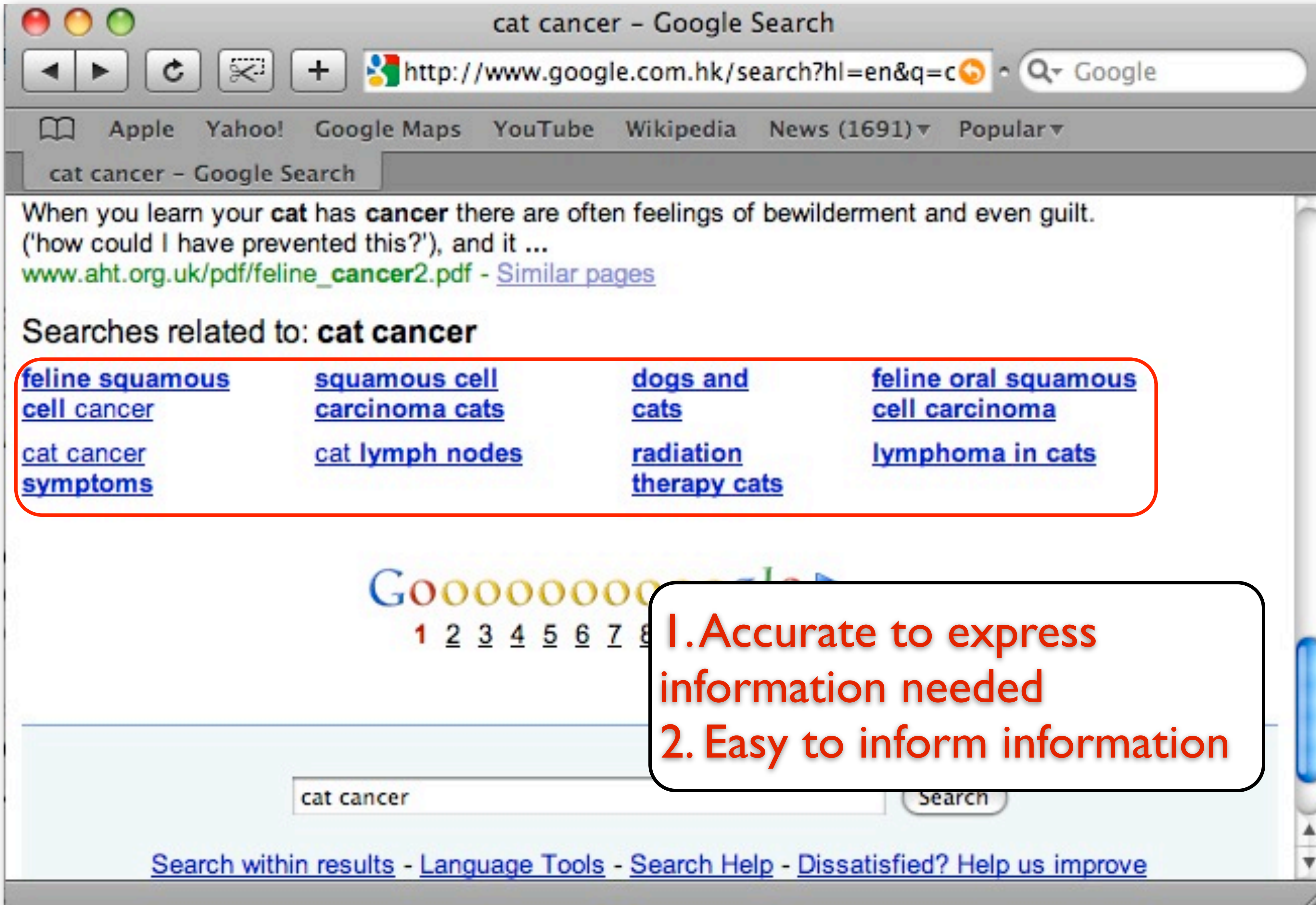
Irwin King
Department of Computer Science and Engineering
The Chinese University of Hong Kong
http://www.cse.cuhk.edu.hk/~king

Motivation



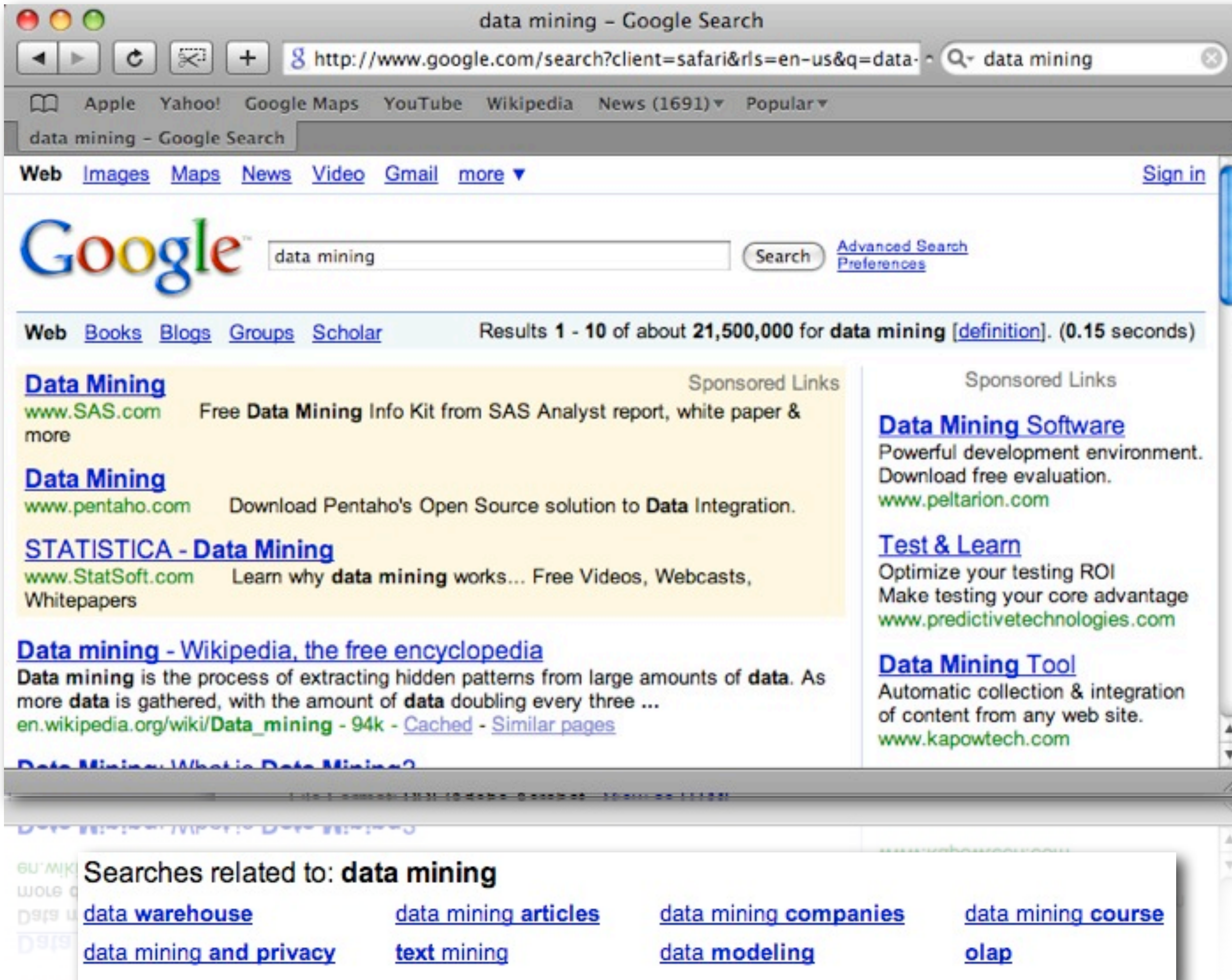
1. Difficult for users to express information needed
2. Word mismatch in information retrieval

Motivation



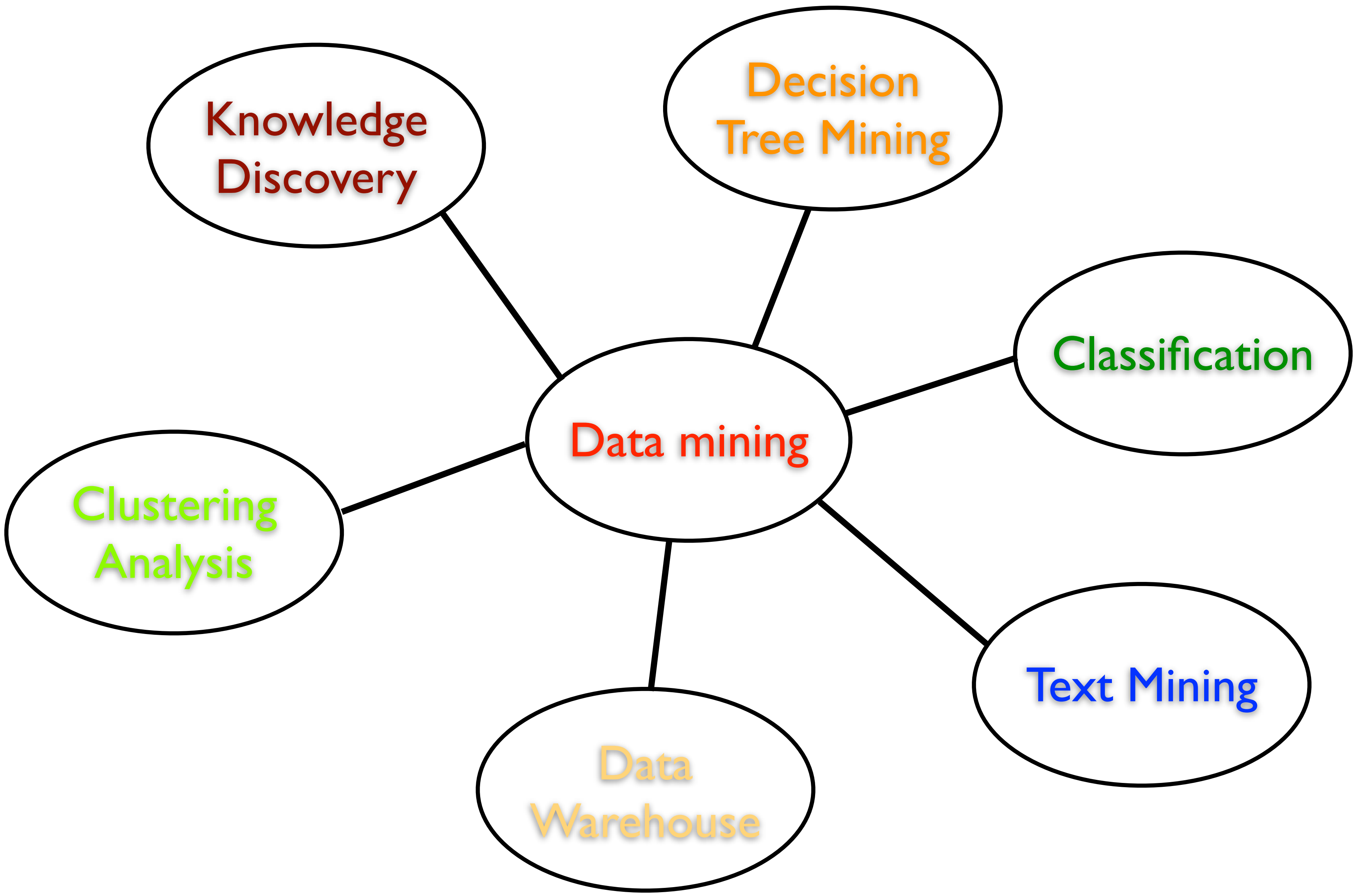
1. Accurate to express information needed
2. Easy to inform information

Motivation


data mining – Google Search
http://www.google.com/search?client=safari&rls=en-us&q=data-
data mining
Apple Yahoo! Google Maps YouTube Wikipedia News (1691) Popular
data mining – Google Search
Web Images Maps News Video Gmail more
Sign in
Google
data mining
Search
Advanced Search
Preferences
Web Books Blogs Groups Scholar
Results 1 - 10 of about 21,500,000 for data mining [definition]. (0.15 seconds)
Sponsored Links
Data Mining
www.SAS.com Free Data Mining Info Kit from SAS Analyst report, white paper & more
Data Mining
www.pentaho.com Download Pentaho's Open Source solution to Data Integration.
STATISTICA - Data Mining
www.StatSoft.com Learn why data mining works... Free Videos, Webcasts, Whitepapers
Data mining - Wikipedia, the free encyclopedia
Data mining is the process of extracting hidden patterns from large amounts of data. As more data is gathered, with the amount of data doubling every three ...
en.wikipedia.org/wiki/Data_mining - 94k - Cached - Similar pages
Sponsored Links
Data Mining Software
Powerful development environment. Download free evaluation.
www.peltarion.com
Test & Learn
Optimize your testing ROI
Make testing your core advantage
www.predictivetechnologies.com
Data Mining Tool
Automatic collection & integration of content from any web site.
www.kapowtech.com
Searches related to: data mining
data warehouse
data mining articles
data mining companies
data mining course
data mining and privacy
text mining
data modeling
olap

Challenges

- Word mismatch: people often use different words to describe concepts in their queries than authors use to describe the same concepts in their documents.



Challenges

- Queries contain ambiguous and new terms
  - apple: "apple computer" or "apple pie"?
  - NDCG:?
- Users tend to submit short queries consisting of only one or two words
  - almost 20% one-word queries
  - almost 30% two-word queries

- Users may have little or even no knowledge about the topic they are searching for!

Classes of Suggestion Relevance

[Jones, 2006]

- Precise rewriting
    - The rewritten form of query matches user's intent
- Approximate rewriting
    - The rewritten form has a direct close relationship to the topic described by the initial query
- Possible rewriting
    - The rewritten form either has some categorical relationship to the initial query or describes a complementary product
- Clear mismatch
    - The rewritten form has no clear relationship to user's intent

Example Queries and Query-suggestion

Class	Score	Examples		
Precise rewriting	1	automotive insurance	$\mapsto$	automobile insurance
		corvette car	$\mapsto$	chevrolet corvette
		apple music player	$\mapsto$	apple ipod
		apple music player	$\mapsto$	ipod
		cat cancer	$\mapsto$	feline cancer
		help with math homework	$\mapsto$	math homework help
Approximate rewriting	2	apple music player	$\mapsto$	ipod shuffle
		personal computer	$\mapsto$	compaq computer
		hybrid car	$\mapsto$	toyota prius
		aeron chair	$\mapsto$	office furniture
Possible rewriting	3	onkyo speaker system	$\mapsto$	yamaha speaker system
		eye-glasses	$\mapsto$	contact lenses
		orlando bloom	$\mapsto$	johnny depp
		cow	$\mapsto$	pig
		ibm thinkpad	$\mapsto$	laptop bag
Clear mismatch	4	jaguar xj6	$\mapsto$	os x jaguar
		time magazine	$\mapsto$	time and date magazine

Typical Query Suggestion

[Jinxi Xu, 1996]

- Global analysis
  - Selects expansion terms on the basis of the information on the whole document set
  - Relatively robust
  - Expensive in terms of disk space and computer time
- Local analysis
  - Formulate expansion terms based on top-ranked results
  - Relatively efficient
  - Perform badly for queries with few relevant documents

Query Suggestion Using Clickthrough Data

- Query logs recorded by search engines

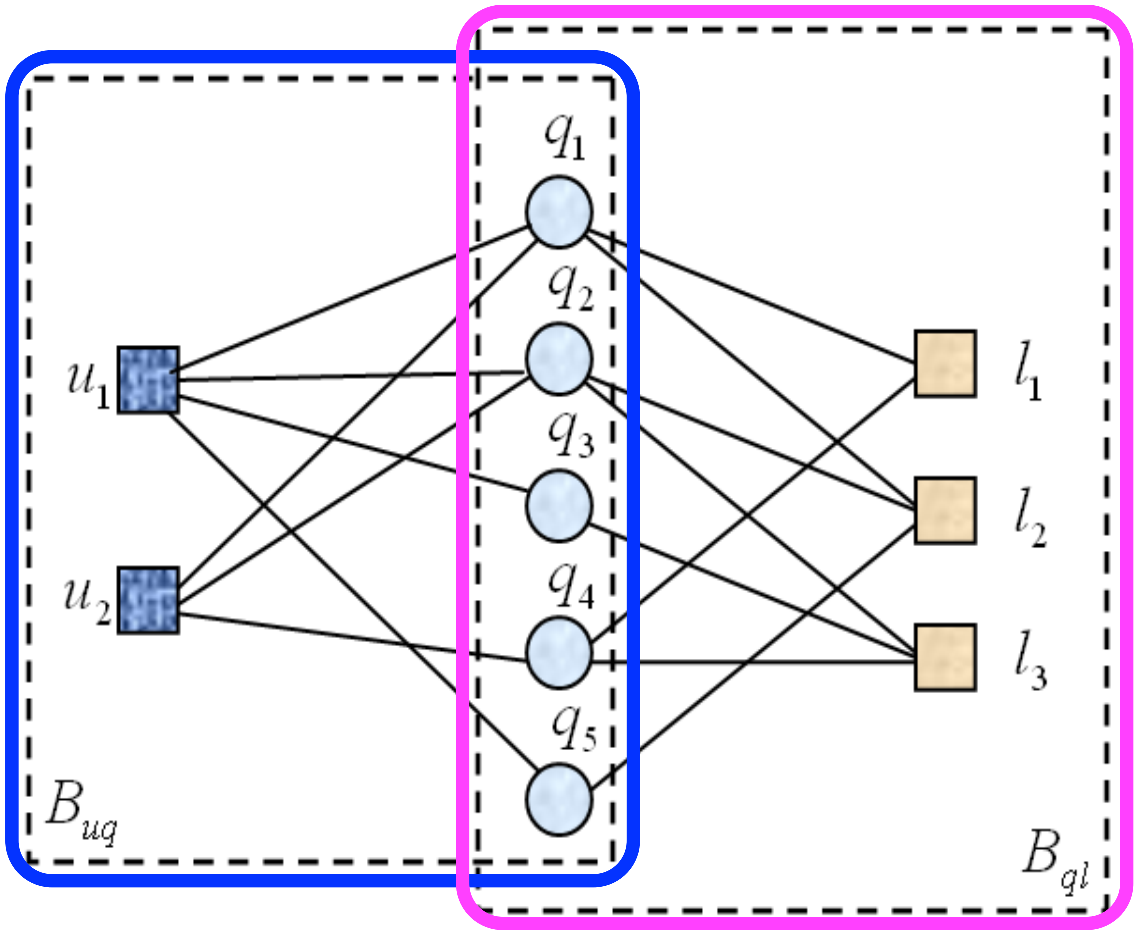
$$\langle u, q, l, r, t \rangle$$

Table 1: Samples of search engine clickthrough data

ID	Query	URL	Rank	Time
358	facebook	http://www.facebook.com	1	2008-01-01 07:17:12
358	facebook	http://en.wikipedia.org/wiki/Facebook	3	2008-01-01 07:19:18
3968	apple iphone	http://www.apple.com/iphone/	1	2008-01-01 07:20:36
...	...	...	...	...

- Users' relevance feedback to indicate desired/preferred/target results

Joint Bipartite Graph



$B_{uq} = (V_{uq}, E_{uq})$
$V_{uq} = U \cup Q$
$U = \{u_1, u_2, ..., u_m\}$
$Q = \{q_1, q_2, ..., q_n\}$
$E_{uq} = \{(u_i, q_j)|$ there is an edge from u_i to $q_j\}$
is the set of all edges.
The edge (u_i, q_j) exists in this bipartite graph if and only if a user u_i issued a query q_j.

$B_{ql} = (V_{ql}, E_{ql})$
$V_{ql} = Q \cup L$
$Q = \{q_1, q_2, ..., q_n\}$
$L = \{l_1, l_2, ..., l_p\}$
$E_{ql} = \{(q_i, l_j)|$ there is an edge from q_i to $l_j\}$
is the set of all edges.
The edge (q_j, l_k) exists if and only if a user u_i clicked a URL l_k after issuing an query q_j.

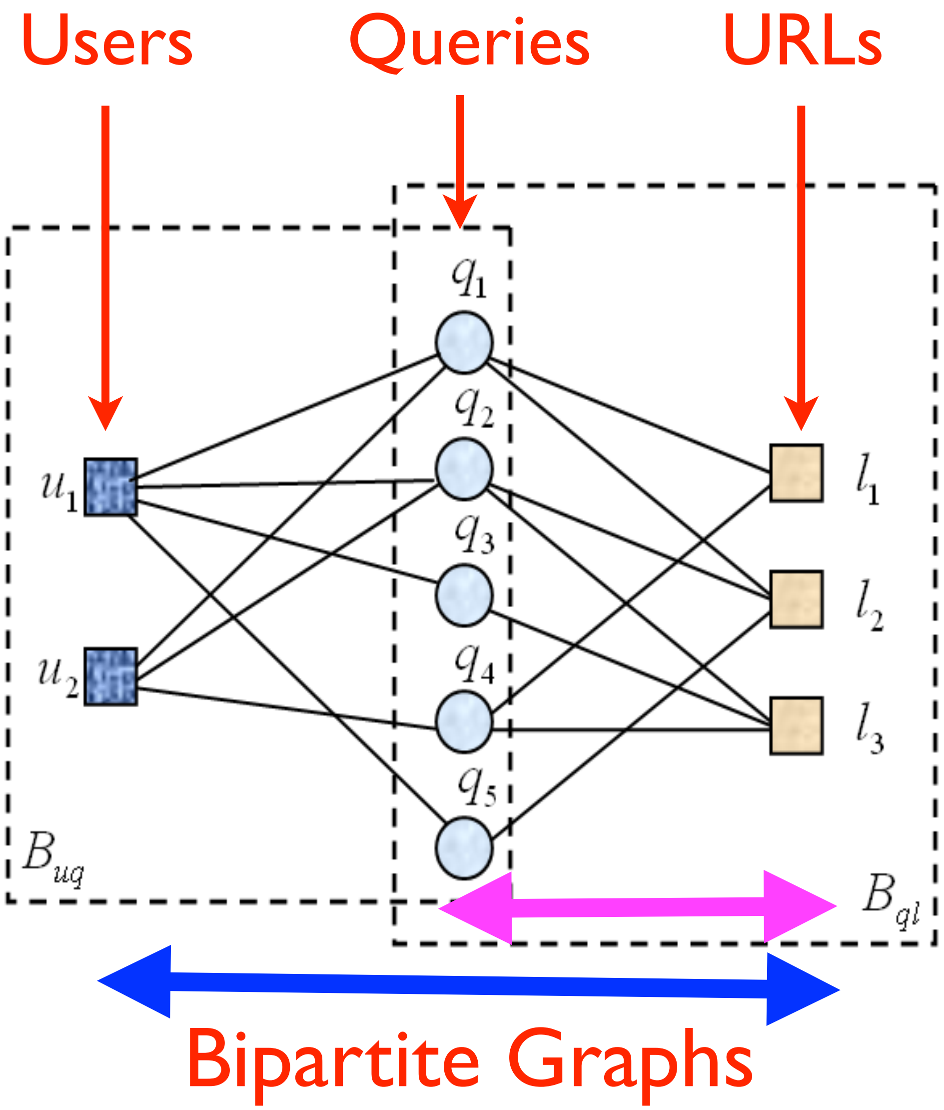
Key Points

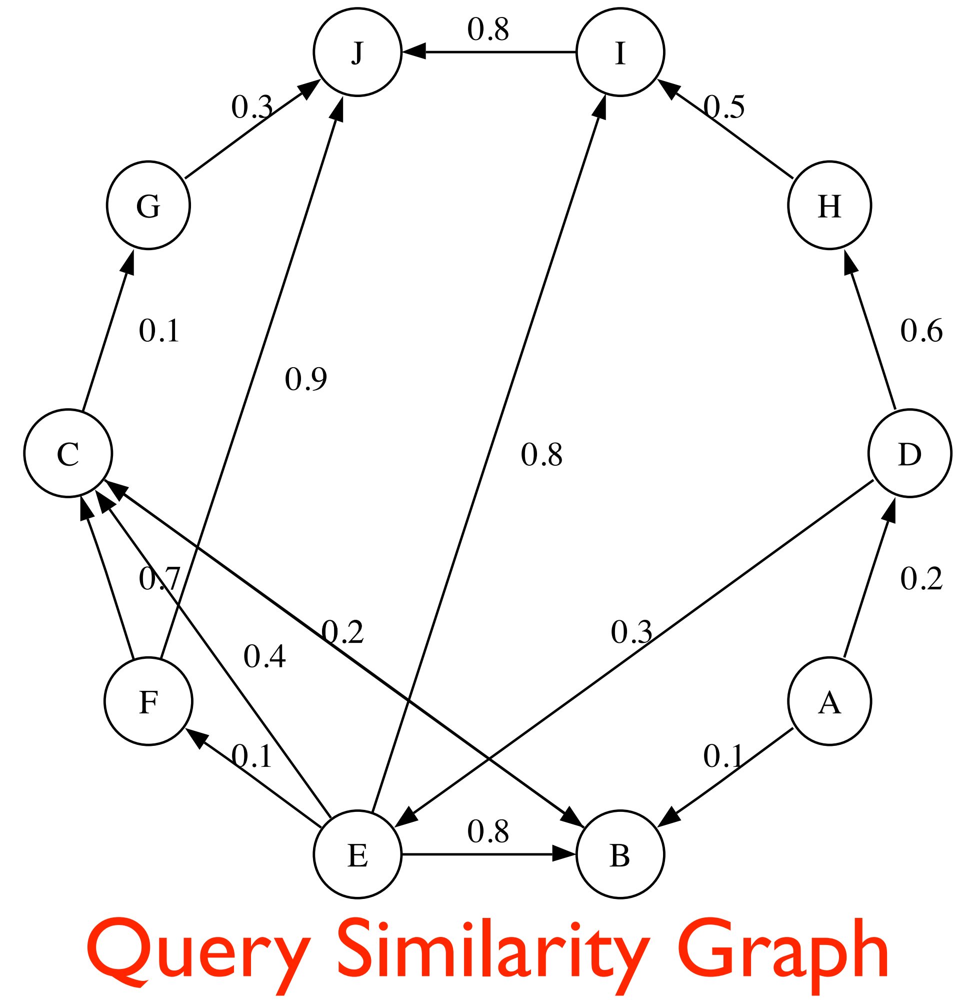
- Two-level latent semantic analysis

Level 1

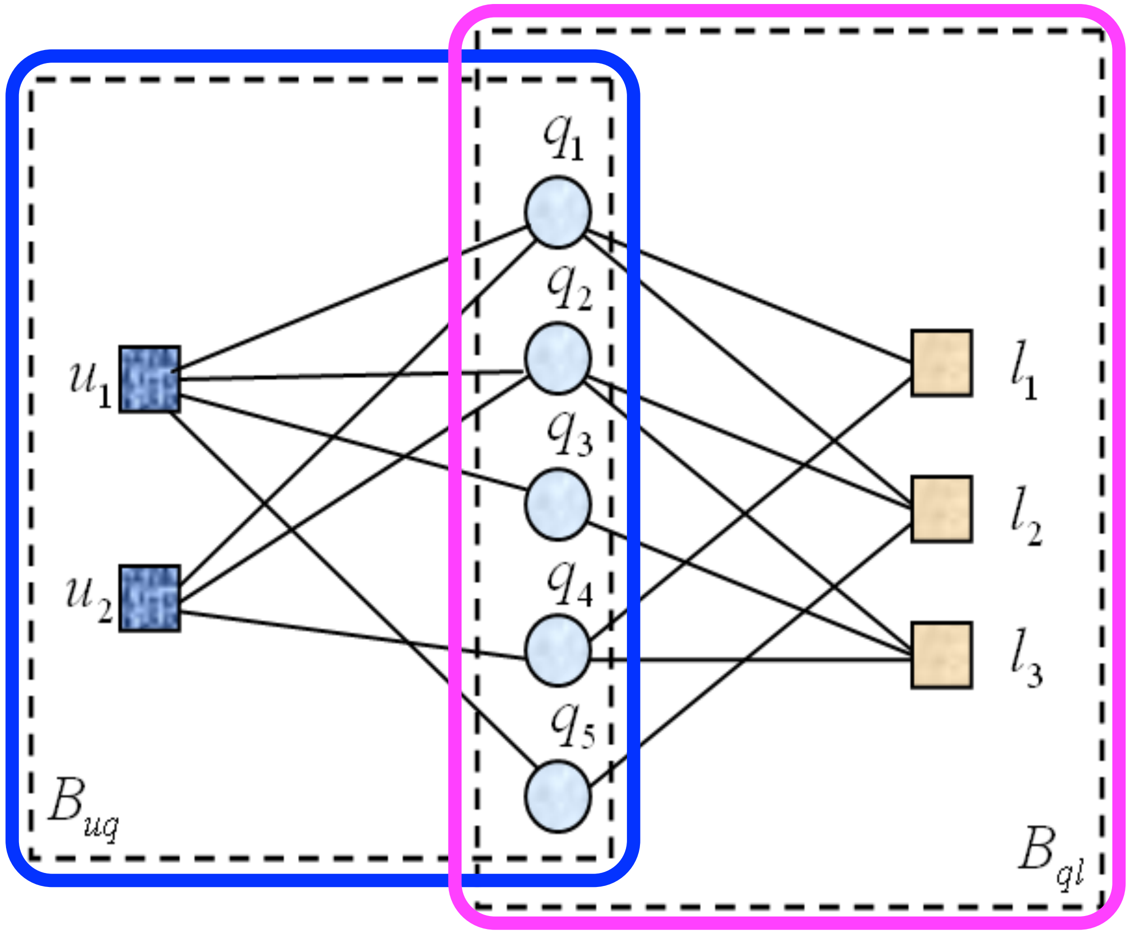
Level 2

  - Consider the use of a joint user-query and query-URL bipartite graphs for query suggestion
  - Use matrix factorization for learning query features in constructing the Query Similarity Graph
  - Use heat diffusion for similarity propagation for query suggestions





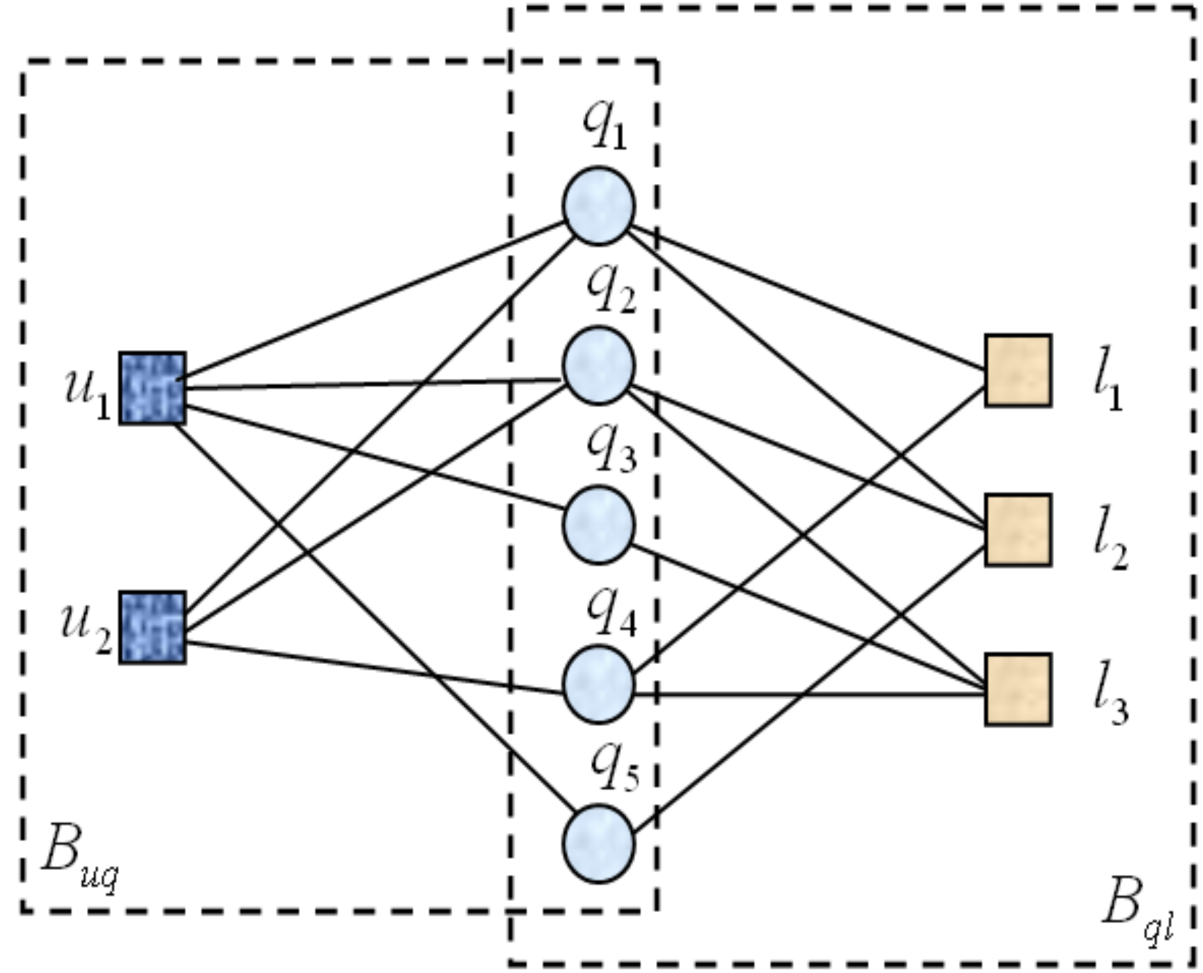
- Queries are issued by the users, and which URLs to click are also decided by the users
- Two distinct users are similar if they issued similar queries
- Two queries are similar if they are issued by similar users



r_{ij}^*	Normalized weight, how many times u_i issued q_j
s_{jk}^*	Normalized weight, how many times q_j is linked to l_k
U_i	L-dimensional vector of user u_i
Q_j	L-dimensional vector of query q_j
L_k	L-dimensional vector of URL l_k

$$\begin{aligned}\mathcal{H}(R,U,Q) &= \min_{U,Q} \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^R (r_{ij}^* - g(U_i^T Q_j))^2 \\ &+ \frac{\alpha_u}{2}\|U\|_F^2 + \frac{\alpha_q}{2}\|Q\|_F^2\end{aligned}$$

$$\begin{aligned}\mathcal{H}(S,Q,L) &= \min_{Q,L} \frac{1}{2}\sum_{j=1}^{n}\sum_{k=1}^{p} I_{jk}^S (s_{jk}^* - g(Q_j^T L_k))^2 \\ &+ \frac{\alpha_q}{2}\|Q\|_F^2 + \frac{\alpha_l}{2}\|L\|_F^2\end{aligned}$$



$$\mathcal{H}(S, R, U, Q, L) = \frac{1}{2}\sum_{j=1}^{n}\sum_{k=1}^{p} I_{jk}^{S}(s_{jk}^{*} - g(Q_j^T L_k))^2 + \frac{\alpha_r}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(r_{ij}^{*} - g(U_i^T Q_j))^2 + \frac{\alpha_u}{2}\|U\|_F^2 + \frac{\alpha_q}{2}\|Q\|_F^2 + \frac{\alpha_l}{2}\|L\|_F^2,$$

- A local minimum can be found by performing gradient descent in U_i, Q_j and L_k

Gradient Descent Equations

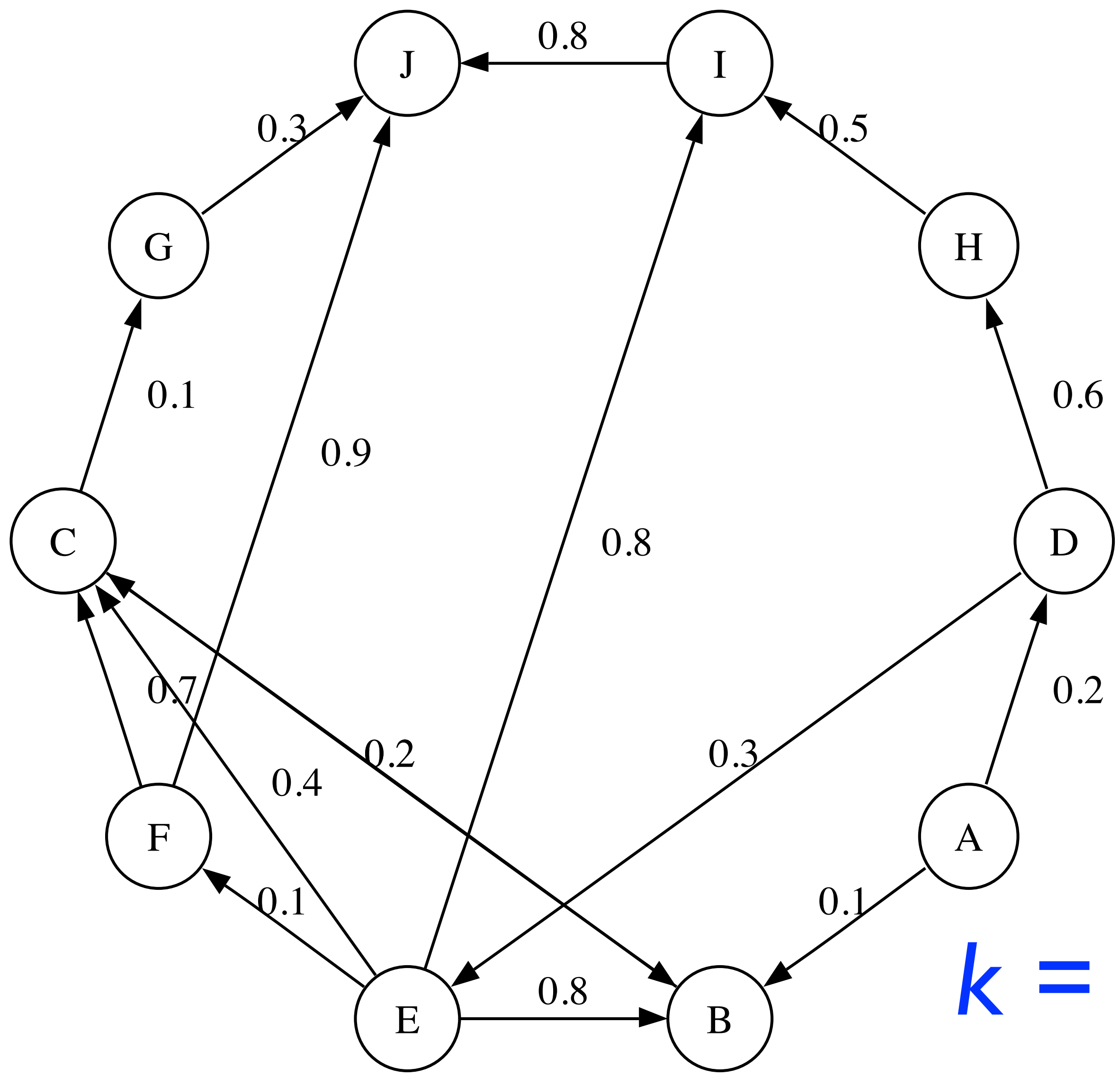
$$\frac{\partial \mathcal{H}}{\partial U_i} = \alpha_r \sum_{j=1}^{n} I_{ij}^{R} g'(U_i^T Q_j)(g(U_i^T Q_j) - r_{ij}^{*}) Q_j + \alpha_u U_i,$$

$$\boxed{\begin{aligned}\frac{\partial \mathcal{H}}{\partial Q_j} &= \sum_{k=1}^{p} I_{jk}^{S} g'(Q_j^T L_k)(g(Q_j^T L_k) - s_{jk}^{*}) L_k \\ &+ \alpha_r \sum_{i=1}^{m} I_{ij}^{R} g'(U_i^T Q_j)(g(U_i^T Q_j) - r_{ij}^{*}) U_i + \alpha_q Q_j,\end{aligned}}$$

$$\frac{\partial \mathcal{H}}{\partial L_k} = \sum_{j=1}^{n} I_{jk}^{S} g'(Q_j^T L_k)(g(Q_j^T L_k) - s_{jk}^{*}) Q_j + \alpha_l L_k,$$

Only the Q matrix, the queries' latent features, is being used to generate the query similarity graph!

Query Similarity Graph



$k = 4$

- Similarities are calculated using queries' latent features
- Only the top-k similar neighbors (terms) are kept

Similarity Propagation

- Based on the Heat Diffusion Model
- In the query graph, given the heat sources and the initial heat values, start the heat diffusion process and perform *P* steps
- Return the Top-*N* queries in terms of highest heat values for query suggestions

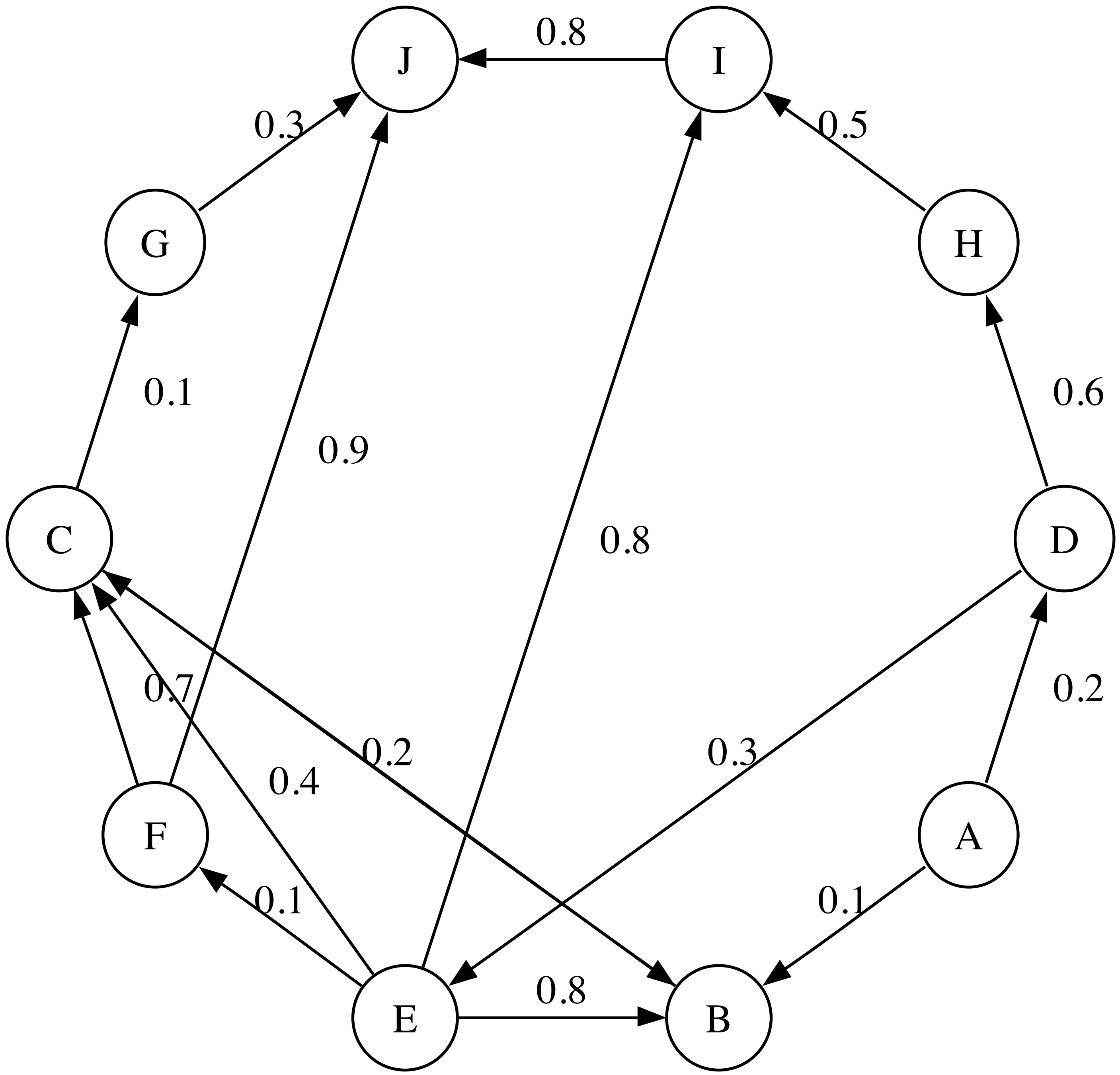
Heat Diffusion Model

- Heat diffusion is a physical phenomena
- Heat flows from high temperature to low temperature in a medium
- Heat kernel is used to describe the amount of heat that one point receives from another point
- The way that heat diffuse varies when the underlying geometry varies

$$\boxed{\rho C_P \frac{\partial T}{\partial t} = Q + \nabla \cdot (k \nabla T)}$$

ρ	Density
C_P	Heat capacity and constant pressure
$\frac{\partial T}{\partial t}$	Change in temperature over time
Q	Heat added
k	Thermal conductivity
∇T	Temperature gradient
$\nabla \cdot \mathbf{v}$	Divergence

Heat Diffusion Process



Similarity Propagation Model

$$\frac{f_i(t+\Delta t)-f_i(t)}{\Delta t} = \alpha\left(-\frac{\tau_i}{d_i} f_i(t) \sum_{k:(q_i,q_k)\in E} w_{ik} + \sum_{j:(q_j,q_i)\in E} \frac{w_{ji}}{d_j} f_j(t)\right) \quad (1)$$

$$\mathbf{f}(1) = e^{\alpha\mathbf{H}}\mathbf{f}(0) \quad (2)$$

$$H_{ij} = \begin{cases} w_{ji}/d_j, & (q_j,q_i)\in E, \\ -(\tau_i/d_i)\sum_{k:(i,k)\in E} w_{ik}, & i=j, \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

$$\mathbf{f}(1) = e^{\alpha\mathbf{R}}\mathbf{f}(0), \quad \boxed{\mathbf{R} = \gamma\mathbf{H} + (1-\gamma)\mathbf{g}\mathbf{1}^T} \quad (4)$$

α	Thermal conductivity
d_i	Heat value of node i at time t
$f_i(t)$	Heat value of node i at time t
w_{ik}	Weight between node i and node k
$\mathbf{f}(0)$	Vector of the initial heat distribution
$\mathbf{f}(1)$	Vector of the heat distribution at time 1
τ_i	Equal to 1 if node i has outlinks, else equal to 0
γ	Random jump parameter, and set to 0.85
$\mathbf{g}$	Uniform stochastic distribution vector

Discrete Approximation

- Compute $e^{\alpha \mathbf{R}}$ is time consuming
- We use the discrete approximation to substitute

$$\mathbf{f}(1) = \left(\mathbf{I} + \frac{\alpha}{P}\mathbf{R}\right)^{P} \mathbf{f}(0)$$

- For every heat source, only diffuse heat to its neighbors within *P* steps
- In our experiments, *P* = 3 already generates fairly good results

Query Suggestion Procedure

- For a given query *q*

1. Select a set of *n* queries, each of which contains at least one word in common with *q*, as heat sources
2. Calculate the initial heat values by

$$f_{\hat{q}_i}(0) = \frac{|\mathcal{W}(q) \cap \mathcal{W}(\hat{q}_i)|}{|\mathcal{W}(q) \cup \mathcal{W}(\hat{q}_i)|}$$

q = "Sony"
"Sony" = 1
"Sony Electronics" = 1/2
"Sony Vaio Laptop" = 1/3

3. Use $\mathbf{f}(1) = e^{\alpha \mathbf{R}} \mathbf{f}(0)$ to diffuse the heat in graph
4. Obtain the Top-*N* queries from $\mathbf{f}(1)$

Physical Meaning of α

- If set α to a large value
  - The results depend more on the query graph, and more semantically related to original queries, e.g., travel => lowest air fare
- If set α to a small value
  - The results depend more on the initial heat distributions, and more literally similar to original queries, e.g., travel => travel insurance

Experimental Dataset

Data Source	Clickthrough data from AOL search	After Pre-Processing
Collection Period	March 2006 to May 2006 (3 months)	
Lines of Logs	19,442,629	
Unique user IDS	657,426	192,371
Unique queries	4,802,520	224,165
Unique URLs	1,606,326	343,302
Unique words		69,937

Pre-processing

- Computer set-up
  Intel Pentium D CPU, 3.0 Gz, Dual Core with 1G memory
- Keep valid words which contains only ‘a’, ‘b’,…, ‘z’ and spaces
- Remove those queries which appear less than three times

Query Suggestions

Table 2: Examples of LSQS Query Suggestion Results ($k = 50$)

Testing Queries	Suggestions				
	$\alpha = 10$			$\alpha = 1000$	
	Top 1	Top 2	Top 3	Top 4	Top 5
michael jordan	michael jordan shoes	michael jordan bio	pictures of michael jordan	nba playoff	nba standings
travel	travel insurance	abc travel	travel companions	hotel tickets	lowest air fare
java	sun java	java script	java search	sun microsystems inc	virtual machine
global services	ibm global services	global technical services	staffing services	temporary agency	manpower professional
walt disney land	world of disney	disney world orlando	disney world theme park	disneyland grand hotel	disneyland in california
intel	intel vs amd	amd vs intel	pentium d	pentium	centrino
job hunt	jobs in maryland	monster job	jobs in mississippi	work from home online	monster board
photography	photography classes	portrait photography	wedding photography	adobe elements	canon lens
internet explorer	ms internet explorer	internet explorer repair	internet explorer upgrade	microsoft com	security update
fitness	fitness magazine	lifestyles family fitness	fitness connection	womens health magazine	family fitness
m schumacher	schumacher	red bull racing	formula one racing	ferrari cars	formula one
solar system	solar system project	solar system facts	solar system planets	planet jupiter	mars facts
sunglasses	replica sunglasses	cheap sunglasses	discount sunglasses	safilo	marhon
search engine	audio search engine	best search engine	search engine optimization	song lyrics search	search by google
disease	grovers disease	liver disease	morgellons disease	colic in babies	oklahoma vital records
pizzahut	pizza hut menu	pizza coupons	pizza hut coupons	papa johns pizza coupon	papa johns
health care	health care proxy	universal health care	free health care	great west healthcare	uhc
flower delivery	global flower delivery	online florist	flowers online	send flowers	virtual flower
wedding	wedding guide	wedding reception ideas	wedding decoration	unity candle	centerpiece ideas
astronomy	astronomy magazine	astronomy pic of the day	star charts	space pictures	comet

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Privacy and Trust in Social Networks

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Privacy and Trust Tradeoff

- Privacy
- Need legal rights
- Reveal more data to trustworthy people

- Trust
- Provide access rights
- Gain trust through open sensitive data

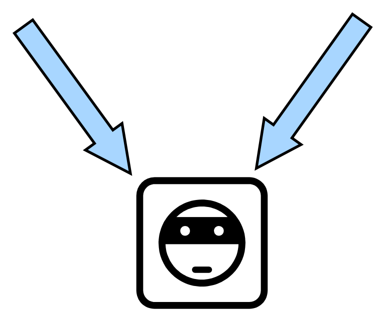
Motivation

Published table

Age	Zip.	Salary
17	12k	1000
19	13k	1010
20	14k	1020
24	16k	50000
29	21k	16000
34	24k	24000
39	36k	33000
45	39k	31000

Voter registration list

Name	Age	Zip.
Andy	17	12k
Bill	19	13k
Ken	20	14k
Jane	23	15k
Nash	24	16k
Joe	29	21k
Sam	34	24k
Linda	39	36k
Mary	45	39k



An adversary

Fact: 87% of Americans can be uniquely identified by {Zipcode, gender, date-of-birth}.

k-anonymity

[Sweeney, 2001]

	Age	Zip.	Salary
Andy	17	12k	1000
	19	13k	1010
	20	14k	1020
	24	16k	50000
	29	21k	16000
	34	24k	24000
	39	36k	33000
	45	39k	31000

(a) The microdata

Group ID	Age	Zip.	Salary
1	[17,24]	[12k,16k]	1000
1	[17,24]	[12k,16k]	1010
1	[17,24]	[12k,16k]	1020
1	[17,24]	[12k,16k]	50000
2	[29,34]	[21k,24k]	16000
2	[29,34]	[21k,24k]	24000
3	[39,45]	[36k,39k]	33000
3	[39,45]	[36k,39k]	31000

(b) Generalization

A group

Not sure about the salary of Andy now!

- *k*-anonymity
  - Divide tuples into groups
  - Each group has at least *k* tuples

Problem with *k*-anonymity

[Machanavajjhala, 2001]

	Non-Sensitive			Sensitive
	Zip Code	Age	Nationality	Condition
1	13053	28	Russian	Heart Disease
2	13068	29	American	Heart Disease
3	13068	21	Japanese	Viral Infection
4	13053	23	American	Viral Infection
5	14853	50	Indian	Cancer
6	14853	55	Russian	Heart Disease
7	14850	47	American	Viral Infection
8	14850	49	American	Viral Infection
9	13053	31	American	Cancer
10	13053	37	Indian	Cancer
11	13068	36	Japanese	Cancer
12	13068	35	American	Cancer

Microdata

	Non-Sensitive			Sensitive
	Zip Code	Age	Nationality	Condition
1	130**	< 30	*	Heart Disease
2	130**	< 30	*	Heart Disease
3	130**	< 30	*	Viral Infection
4	130**	< 30	*	Viral Infection
5	1485*	≥ 40	*	Cancer
6	1485*	≥ 40	*	Heart Disease
7	1485*	≥ 40	*	Viral Infection
8	1485*	≥ 40	*	Viral Infection
9	130**	3*	*	Cancer
10	130**	3*	*	Cancer
11	130**	3*	*	Cancer
12	130**	3*	*	Cancer

A 4-anonymous table

What about we know a person's Zip Code = 13053 and Age = 31?

In this case, we can conclude his/her disease is Cancer.

l-diversity

[Machanavajjhala, 2001]

	Non-Sensitive			Sensitive
	Zip Code	Age	Nationality	Condition
1	13053	28	Russian	Heart Disease
2	13068	29	American	Heart Disease
3	13068	21	Japanese	Viral Infection
4	13053	23	American	Viral Infection
5	14853	50	Indian	Cancer
6	14853	55	Russian	Heart Disease
7	14850	47	American	Viral Infection
8	14850	49	American	Viral Infection
9	13053	31	American	Cancer
10	13053	37	Indian	Cancer
11	13068	36	Japanese	Cancer
12	13068	35	American	Cancer

Microdata

	Non-Sensitive			Sensitive
	Zip Code	Age	Nationality	Condition
1	1305*	≤ 40	*	Heart Disease
4	1305*	≤ 40	*	Viral Infection
9	1305*	≤ 40	*	Cancer
10	1305*	≤ 40	*	Cancer
5	1485*	> 40	*	Cancer
6	1485*	> 40	*	Heart Disease
7	1485*	> 40	*	Viral Infection
8	1485*	> 40	*	Viral Infection
2	1306*	≤ 40	*	Heart Disease
3	1306*	≤ 40	*	Viral Infection
11	1306*	≤ 40	*	Cancer
12	1306*	≤ 40	*	Cancer

A 3-diverse table

- *l*-diversity
  - Divide tuples into groups
  - Each group has at least *l* different sensitive values

(*k*, e)-anonymity

[Zhang, 2007]

	ID	Quasi-identifiers			Sensitive
tuple ID	name	age	zipcode	gender	salary
1	Alex	35	27101	M	$54,000
2	Bob	38	27120	M	$55,000
3	Carl	40	27130	M	$56,000
4	Debra	41	27229	F	$65,000
5	Elain	43	27269	F	$75,000
6	Frank	47	27243	M	$70,000
7	Gary	52	27656	M	$80,000
8	Helen	53	27686	F	$75,000
9	Jason	58	27635	M	$85,000

Microdata

		Quasi-identifiers			Sensitive
group ID	tuple ID	age	zipcode	gender	salary
1	1	[31-40]	271*	*	$56,000
1	2	[31-40]	271*	*	$54,000
1	3	[31-40]	271*	*	$55,000
2	4	[41-50]	272*	*	$65,000
2	5	[41-50]	272*	*	$75,000
2	6	[41-50]	272*	*	$70,000
3	7	[51-60]	276*	*	$80,000
3	8	[51-60]	276*	*	$75,000
3	9	[51-60]	276*	*	$85,000

A 3-diverse table

Though the salary in group 1 is different, we are sure that Alex's salary is around 55,000

- (*k*, e)-anonymity
  - Each group has at least *k* tuples
  - Difference between the maximum and minimum values must be at least e

Outline

- What is privacy and trust?
- Privacy in social network
  - Basic privacy requirement
  - Privacy in graph
- Trust in social network
- Reference

Possible Attacks on Anonymized Graphs

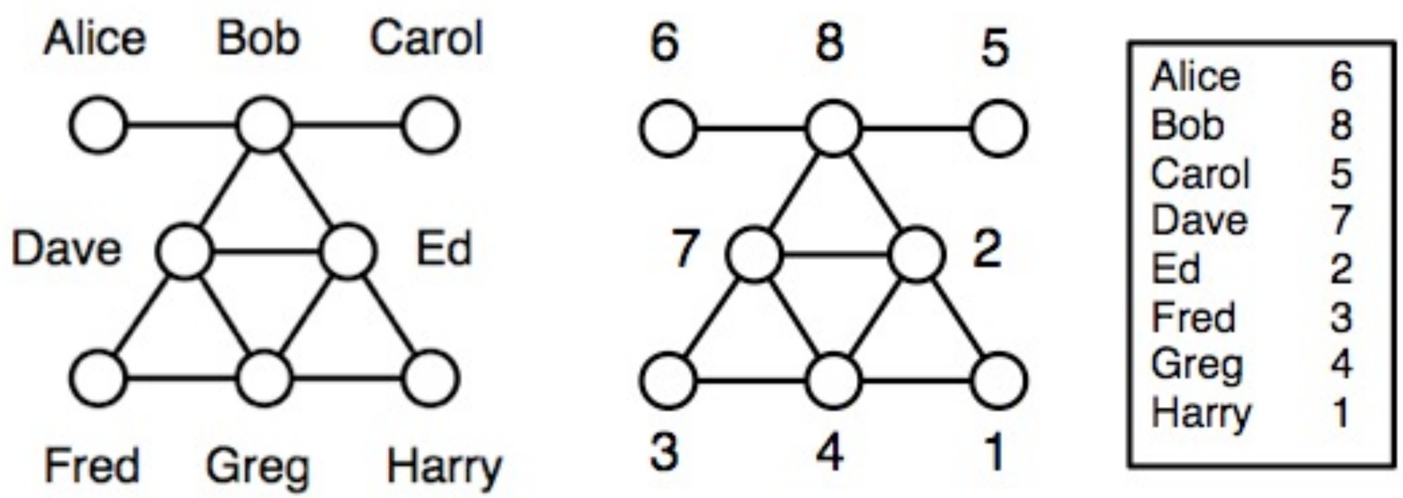
- Attack method [Michael Hay, 2008]
  - Identify by neighborhood information
  - It includes
    - Vertex Refinement Queries
    - Sub-graph Queries
    - Hub Fingerprint Queries

Possible Attacks on Anonymized Graphs

- Attack types [Lars Backstrom, 2008]
  - Active Attacks
    - Create a small number of new user accounts linking with other users before the anonymized graph is generated
  - Passive Attacks
    - Identify themselves in the published graph
  - Semi-passive Attacks
    - Create necessary link with other users

Vertex Refinement Queries

[Michael Hay, 2008]



(a) graph

Node ID	$\mathcal{H}_0$	$\mathcal{H}_1$	$\mathcal{H}_2$
Alice	ϵ	1	$\{4\}$
Bob	ϵ	4	$\{1, 1, 4, 4\}$
Carol	ϵ	1	$\{4\}$
Dave	ϵ	4	$\{2, 4, 4, 4\}$
Ed	ϵ	4	$\{2, 4, 4, 4\}$
Fred	ϵ	2	$\{4, 4\}$
Greg	ϵ	4	$\{2, 2, 4, 4\}$
Harry	ϵ	2	$\{4, 4\}$

(b) vertex refinements

Equivalence Relation	Equivalence Classes
$\equiv_{\mathcal{H}_0}$	$\{A, B, C, D, E, F, G, H\}$
$\equiv_{\mathcal{H}_1}$	$\{A, C\}$ $\{B, D, E, G\}$ $\{F, H\}$
$\equiv_{\mathcal{H}_2}$	$\{A, C\}\{B\}\{D, E\}\{G\}\{F, H\}$
$\equiv_{\mathcal{A}}$	$\{A, C\}\{B\}\{D, E\}\{G\}\{F, H\}$

(c) equivalence classes

H*'s computation is linear in the number of edges in the graph!

Summary

- Data privacy and security is a real and serious issue
- *k*-Anonymity and *l*-Diversity could help but may not be watertight
- Anonymizing graphs through graph generalization, node partitioning, and graph summarization

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Learning To Rank

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Learning to Rank

- Booming Search Industry

Learning to Rank

- Given query q and set of docs $d_1, ...d_n$
  - Find documents relevant to q
  - Typically expressed as a ranking on $d_1, ...d_n$
  - Are social signals important?

Widely-used Judgement

- Pointwise
  - Binary judgment (Relevant vs. Irrelevant)
  - Multi-valued discrete (Perfect > Excellent > Good > Fair > Bad)
- Pairwise
  - Pairwise preference
    - Document A is more relevant than document B w.r.t. query q
- Listwise
  - Partial or total orders
  - Could be mined from click-through logs

Conventional Ranking Models

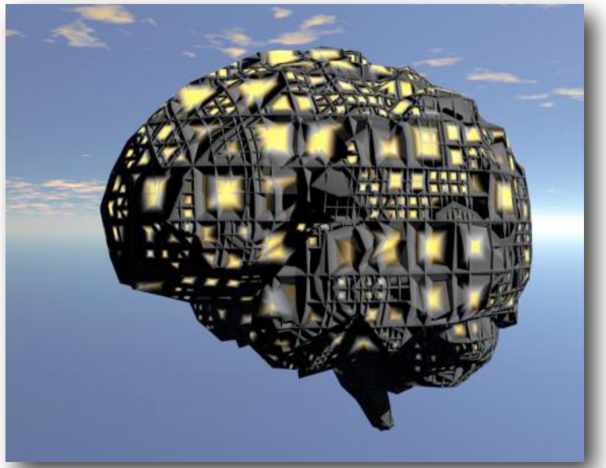
- Content relevance
  - Boolean model, extended Boolean model, etc.
  - Vector space model, latent semantic indexing (LSI), etc.
  - BM25 model, statistical language model, etc.
  - Span based model, distance aggregation model, etc.
- Page Quality
  - Link analysis: HITS, PageRank, TrustRank, etc.
  - Log mining: DirectHITS, BrowseRank, etc

Discussion on Conventional Models

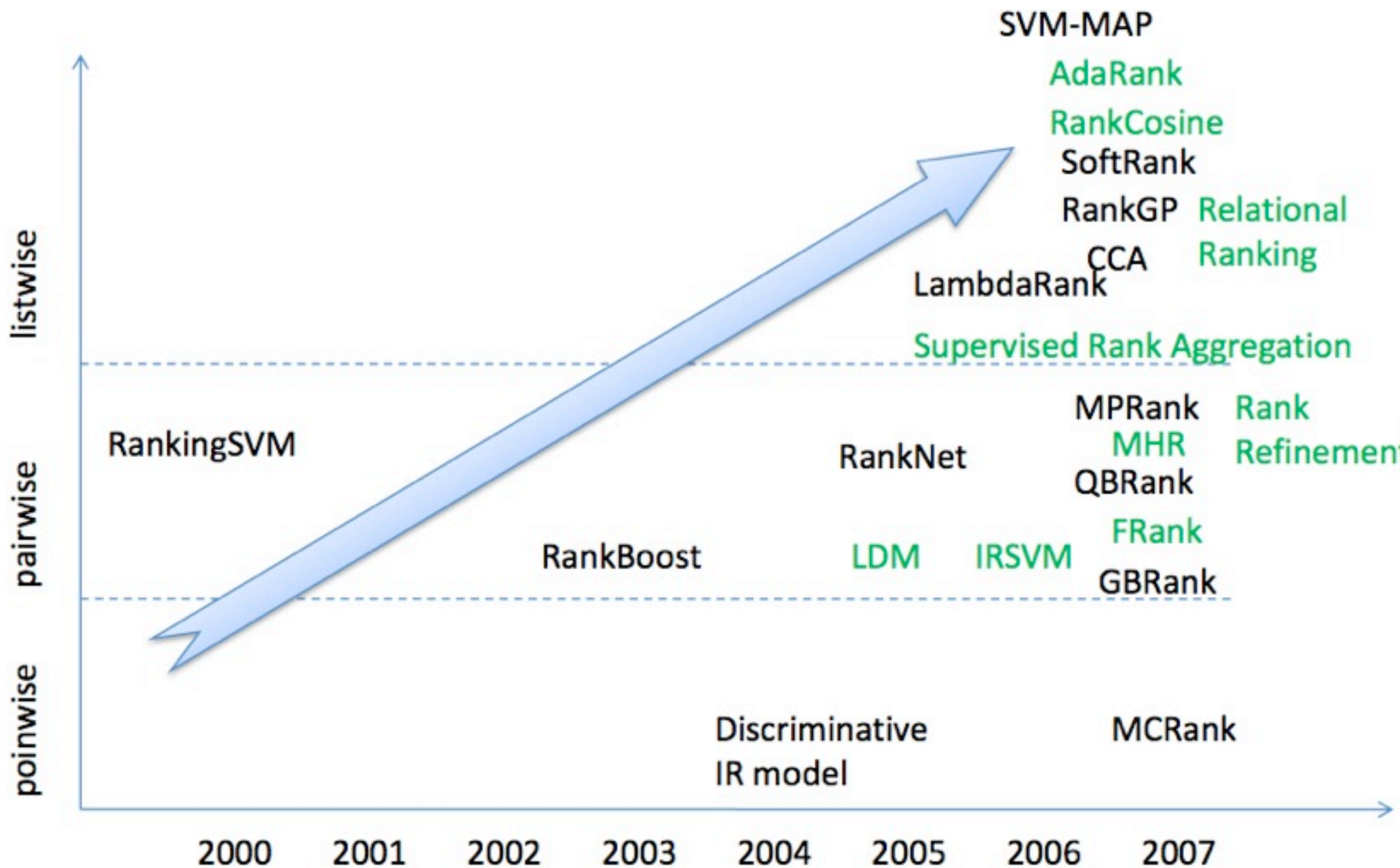
- For a particular model
  - Manual parameter tuning is usually difficult, especially when there are many parameters.
- For comparison between two models
  - Given a test set, it is difficult/unfair to compare two models if one is over-tuned while the other is not.
- For a collection of models
  - There are hundreds of models proposed in the literature.
  - It is non-trivial to combine them to produce a even more effective model

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

Resources

- LETOR benchmark: a package of benchmark data sets for learning to rank, released by Microsoft Research Asia.
- Current LETOR baselines
  - Ranking SVM
  - RankBoost
  - AdaRank
  - Multiple hyperline ranker
  - FRank
  - ListNet

Define Metric

A metric on a set X is a function (called the distance function or simply distance)

$$d : X \times X \to \mathcal{R} \tag{1}$$

where $\mathcal{R}$ is the set of real numbers. For all $x, y, z \in X$, this function is required to satisfy the following conditions:

1. $d(x, y) \geq 0$ (non-negativity)
2. $d(x, y) = 0$ if and only if $x = y$ (identity of indiscernible)
3. $d(x, y) = d(y, x)$ (symmetry)
4. $d(x, z) \leq d(x, y) + d(y, z)$ (subadditivity or triangle inequality)

Define Ranking

A ranking is a relationship between a set of items. Weak order or total preorder.

A total order is a binary relation on some set X. The relation is transitive, antisymmetric, and total. If X is totally order under $\leq$, then the following statemetns hold for all a, b, and c in X:

- If $a \leq b$ and $b \leq a$ then $a = b$ (antisymmetry);
- If $a \leq b$ and $b \leq c$ then $a \leq c$ (transitivity);
- $a \leq b$ or $b \leq a$ (totality).

IR Evaluation

- Objective
  - Evaluate the effectiveness of a ranking model
- A standard test set
  - Contain a large number of (randomly sampled) queries, their associated documents, and the labels (relevance judgments) of these documents.
- A measure
  - Evaluate the effectiveness of a ranking model for a particular query.
  - Average the measure over the entire test set to represent the expected effectiveness of the model.

Ranking Evaluation

- Binary judgment
  - Relevant vs. Irrelevant
- Multi-level ratings
  - Excellent > Good > Fair > Poor
- Pairwise preferences
  - Document *A* is more relevant than document *B* with respect to query *q*

Measures

- Precision--measure of exactness
- Recall--measure of completeness
- They are usually linked closely together
- Often, there is an inverse relationship between Precision and Recall
- Increasing one at the cost of reducing the other, e.g., increase its Recall by retrieving more documents, at the cost of increasing number of irrelevant documents retrieved (decreasing Precision)

Confusion Matrix

- True positives
- True negatives
- False positives
- False negatives

		actual value		
		p	***n***	**total**
prediction outcome	***p'***	True Positive	False Positive	P'
	n'	False Negative	True Negative	N'
	total	P	N	

In Classification

- Precision–the number of true positives divided by the total number of elements labeled as belonging to the positive class

$$\text{Precision} = \frac{tp}{tp + fp} \tag{1}$$

It can also be interpreted as the probability that a (randomly selected) retrieved document is relevant.

- Recall–the number of true positives divided by the total number of elements that actually belong to the positive class.

$$\text{Recall} = \frac{tp}{tp + fn} \tag{2}$$

Recall in this context is also referred to as the True Positive Rate. It can also be interpreted as the probability that a (randomly selected) relevant document is retrieved in a search.

In Classification

- True Negative Rate

$$\text{True Negative Rate} = \frac{tn}{tn + fp} \tag{1}$$

- Accuracy

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn} \tag{2}$$

In Information Retrieval

- Precision
  - In classification, precision for a class is the number of true positives divided by the total number of elements labeled as belonging to the positive class
  -

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|} \quad (1)$$

  - Precision takes all retrieved documents into account
  - Precision can also be evaluated at a given cut-off-rank. This is called precision at n or P@n.
- Recall
  - Recall is the fraction of the documents that are relevant to the query that are successfully retrieved.

$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|} \quad (2)$$

Fall-Out

- Fall-Out–the proportion of non-relevant documents that are retrieved, out of all non-relevant documents available:

$$\text{Fall-Out} = \frac{|\{\text{non-relevant documents}\} \cap \{\text{ retrieved documents}\}|}{|\{\text{non-relevant documents}\}|} \tag{1}$$

F-Measure

- F-Measure–Weighted harmonic mean of precision and recall.

$$F = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{1}$$

This is also known as the F_1 measure since recall and precision are evenly weighted.

For the general F_β measure (for non-negative real values of β):

$$F_\beta = (1 + \beta^2) \cdot \frac{\text{Precision} \cdot \text{Recall}}{\beta^2 \cdot \text{Precision} + \text{Recall}} \tag{2}$$

The F_2 measure weights recall twice as much as precision, and the $F_{0.5}$ measure weights precision twice as much as recall.

Average Precision and Recall

- Average Precision of Precision and Recall–it emphasizes returning more relevant earlier. It is average of precisions computed after truncating the list after each of the relevant documents in turn:

$$\mathrm{AP} = \frac{\sum_{r=1}^{N} (\mathrm{P@}r \times \mathrm{rel}(r))}{\text{number of relevant documents}} \tag{1}$$

  where r is the rank, N the number retrieved, rel() a binary function on the relevance of a given rank, and P@r precision at a given cut-off rank, r.

Example

Given the list of seven retrieved documents as, $\{r_1, nr_2, nr_3, r_4, r_5, nr_6, r_7\}$ where r_i are relevant documents and nr_j are non-relevant documents. The Average Precision is then

$$\mathrm{AP} = \frac{1}{4} \cdot \left(\frac{1}{1} + \frac{2}{4} + \frac{3}{5} + \frac{4}{7} \right) \approx 0.67 \tag{1}$$

Evaluation Measures

- MAP (Mean Average Precision)–averaged AP over all queries in the test set
- NDCG (Normalized Discounted Cumulative Gain)
- MRR (Mean Reciprocal Rank)
  - For query q_i, rank position of the first relevant document: r_i
  - MRR: average of $1/R_i$ over all queries
- WTA (Winner-Take-All)
  - If top ranked document is relevant: 1; otherwise 0
  - Average over all queries

Discounted Cumulative Gain

DCG is a measure of effectiveness of a Web search engine algorithm or related applications, often used in information retrieval. DCG measures the usefulness, or gain, of a document based on its position in the result list. The gain is accumulated cumulatively from the top of the result list to the bottom with the gain of each result discounted as lower ranks.

- Assumptions
  - Highly relevant documents are more useful when appearing earlier in a search engine result list (have higher ranks)
    - Highly relevant documents are more useful than marginally relevant documents, which are in turn more useful than irrelevant documents.

Cumulative Gain

Cumulative Gain (CG) is the predecessor of DCG and does not include the position of a result in the consideration of the usefulness of a result set. It is the sum of the graded relevance values of all results in a search result list. The CG at a particular rank position p is

$$\mathrm{CG}_p = \sum_{i=1}^{p} rel_i \tag{1}$$

where rel_i is the graded relevance of the result at position i.

The value computed with the CG function is unaffected by changes in the ordering of search results, i.e., moving a highly relevant document d_i above a higher ranked, less relevant, document d_j does not change the computed value for CG.

Discounted Cumulative Gain

Discounted Cumulative Gain (DCG) The premise of DCG is that highly relevant documents appearing lower in a search result list should be penalized as the graded relevance value is reduced logarithmically proportional to the position of the result. The discounted CG accumulated at a particular rank position p is defined as

$$\mathrm{DCG}_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i} \tag{1}$$

The logarithmic reduction factor has not shown any theoretical justification. An alternative formulation of DCG places much stronger emphasis on retrieving relevant documents sooner using a power distribution and is formulated as

$$\mathrm{DCG}_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2(1+i)} \tag{2}$$

The function is equivalent to the previous DCG function when the relevance values of documents are binary, i.e., $rel_i \in \{0, 1\}$.

The summation $\sum_{i=1}^{p}$ is cumulating, the term $2^{rel_i} - 1$ is the gain, and the term $\log_2(1+i)$ is the position discount.

Normalizing DCG

Search result lists vary in length depending on the query. Comparing a search engine's performance from one query to the next cannot be consistently achieved using DCG alone, so the cumulative gain at each position for a chosen value of p should be normalized across queries. This is done by sorting documents of a result list by relevance, producing an ideal DCG (IDCG) at position p. For a query, the normalized discounted cumulative gain, or nDCG, is computed as:

$$\mathrm{nDCG}_p = \frac{\mathrm{DCG}_p}{\mathrm{IDCG}_p} \tag{1}$$

Note that in a perfect ranking algorithm, the DCG_p will be the same as the IDCG_p producing an nDCG of 1.0.

Example

Presented with a list of documents in response to a search query, an experiment participant is asked to judge the relevance of each document to the query. Each document is to be judged on a scale of 0-3 with 0 meaning irrelevant, 3 meaning completely relevant, and 1 and 2 meaning "somewhere in between". For the documents ordered by the ranking algorithm as

$$D_1, D_2, D_3, D_4, D_5, D_6$$

the user provides the following relevance scores:

$$\mathrm{CG}_p = \sum_{i=1}^{p} rel_i = 3 + 2 + 3 + 0 + 1 + 2 = 11$$

Changing the order of any two documents does not affect the CG measure.

Example

DCG is calculated as follows:

i	rel_i	$\log_i$	$\frac{rel_i}{\log_2 i}$
1	3	N/A	N/A
2	2	1	2
3	3	1.59	1.887
4	0	2.0	0
5	1	2.32	0.431
6	2	2.59	0.772

Now a switch of D_3 and D_4 results in a reduced DCG so a more relevant document is discounted more by being placed in a lower rank.

Example

To normalize DCG values, an ideal ordering for the given query is needed. For this example, that ordering would be the monotonically decreasing sort of the relevance judgments provided by the experiment participant, which is:

$$3, 3, 2, 2, 1, 0$$

The DCG of this ideal ordering, or IDCG, is then:

$$\mathrm{IDCG}_6 = \frac{\mathrm{DCG}_6}{\mathrm{IDCG}_6} = \frac{8.09}{8.693} = 0.9306$$

so the DCG_6 of this ranking is

$$\mathrm{DCG}_6 = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i} = 3 + (2 + 1.887 + 0 + 0.431 + 0.772) = 8.09$$

Properties of Ranking in IR

- Loss function should be defined on ranked list w.r.t. a query
- Relative order is important
- Position sensitive
- Rank based evaluation

Categorization

- Pointwise
  - Input: single documents
  - Output: scores or class labels
  - Discriminative model for IR, McRank, ...
- Pairwise
  - Input: document pairs
  - Output: partial order preference
  - Ranking SVM, RankBoost, RankNet, FRank, ...
- Listwise
  - Input: document collections
  - Output: ranked document list
  - LambdaRank, AdaRank, SVM-MAP, RankCosine,...

Pointwise Approach

- Reduce ranking to regression or classification on single documents
- Discriminative Model
  - Treat relevant documents as positive examples, while irrelevant documents as negative examples
  - Learning algorithms
    - Maximum Entropy
    - Support Vector Machines

Document Features

$\sum_{q_i \in Q \cap D} \log(c(q_i, D))$	$\sum_{q_i \in Q \cap D} (\log(\frac{\lvert C \rvert}{c(q_i, C)}))$
$\sum_{i=1}^{n} \log(1 + \frac{c(q_i, D)}{\lvert D \rvert})$	$\sum_{i=1}^{n} \log(1 + \frac{c(q_i, D)}{\lvert D \rvert} idf(q_i))$
$\sum_{q_i \in Q \cap D} \log(idf(q_i))$	$\sum_{i=1}^{n} \log(1 + \frac{c(q_i, D)}{\lvert D \rvert} \frac{\lvert C \rvert}{c(q_i, C)})$

where $c(w, D)$ represents the raw count of word w in document D, C represents the collection, n is the number of terms in the query, $|\cdot|$ is the size-of function and $idf(\cdot)$ is the inverse document frequency.

- Vector space model (or term vector model) uses a vector of indexed words to represent a document.
- Each dimension corresponds to a separate term
- If a term (keyword, phrase, etc.) occurs in the document, its value in the vector is non-zero.
- The dimensionality of the vector is the number of words in the vocabulary.

Relevancy Ranking

Relevancy rankings of documents in a keyword search can be calculated, using the assumptions of document similarities theory, by comparing the deviation of angles between each document vector and the original query vector where the query is represented as same kind of vector as the documents. In practice, it is easier to calculate the cosine of the angle between the vectors instead of the angle:

$$\cos\theta = \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{||\mathbf{v}_1||||\mathbf{v}_2||} \tag{1}$$

A cosine value of zero means that the query and document vector are orthogonal and have no match (i.e. the query term do not exist in the document being considered). See cosine similarity for further information.

Term Frequency

The **term count** in the given document is simply the number of times a given term appears in that document. This count is usually normalized to prevent a bias towards longer documents (which may have a higher term count regardless of the actual importance of that term in the document) to give a measure of the importance of the term ti within the particular document d_j. Thus we have the **term frequency**, defined as follows.

$$\mathrm{tf}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{1}$$

where $n_{i,j}$ is the number of occurrences of the considered term (t_i) in document d_j, and the denominator is the sum of number of occurrences of all terms in document d_j.

Inverse Document Frequency

The **inverse document frequency** is a measure of the general importance of the term (obtained by dividing the number of all documents by the number of documents containing the term, and then taking the logarithm of that quotient).

$$\mathrm{idf}_i = \log \frac{|D|}{|\{d : t_i \in d\}|} \tag{1}$$

with

- $|D|$: total number of documents in the corpus
- $|\{d : t_i \in d\}|$: number of documents where the term t_i appears (that is $n_{i,j} \neq 0$). If the term is not in the corpus, this will lead to a division-by-zero. It is therefore common to use $1 + |\{d : t_i \in d\}|$ Then

$$\text{tf-idf}_{i,j} = \mathrm{tf}_{i,j} \times \mathrm{idf}_i \tag{2}$$

A high weight in tf–idf is reached by a high term frequency (in the given document) and a low document frequency of the term in the whole collection of documents; the weights hence tend to filter out common terms. The tf-idf value for a term will always be greater than or equal to zero.

Maximum Entropy (ME) Model

- Principle of Maximum Entropy is to model all that is known and assume nothing about that which is unknown.
- Choose a model consistent with all facts, but otherwise as uniform as possible.

ME Probability function is defined as:

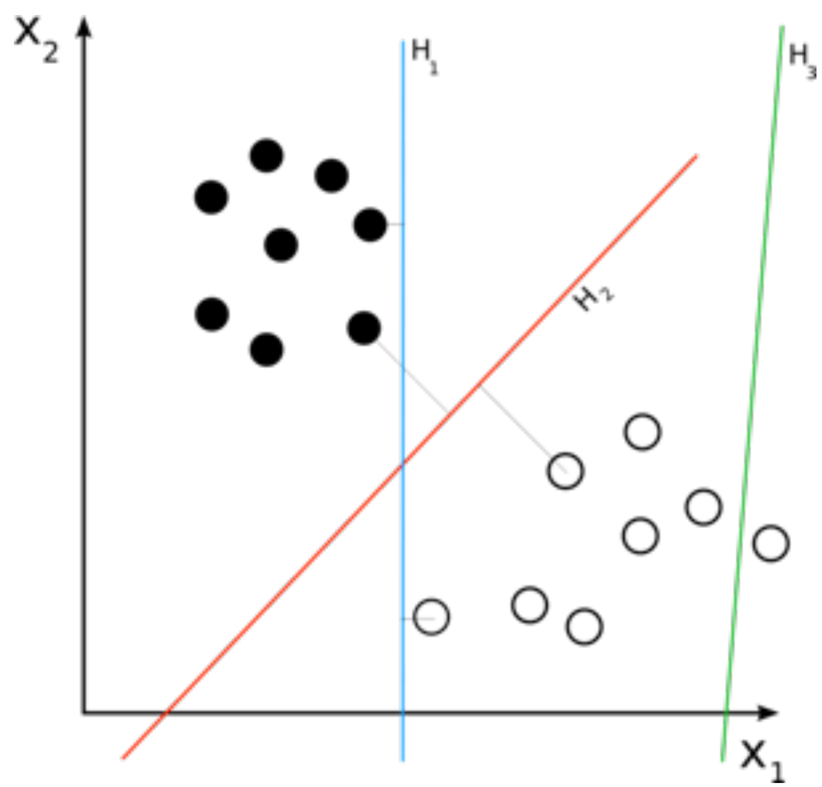
$$P(R|D,Q) = \frac{1}{Z(Q,D)} \exp(\sum_{i=1}^{n} \lambda_{i,R} f_i(D,Q)) \tag{1}$$

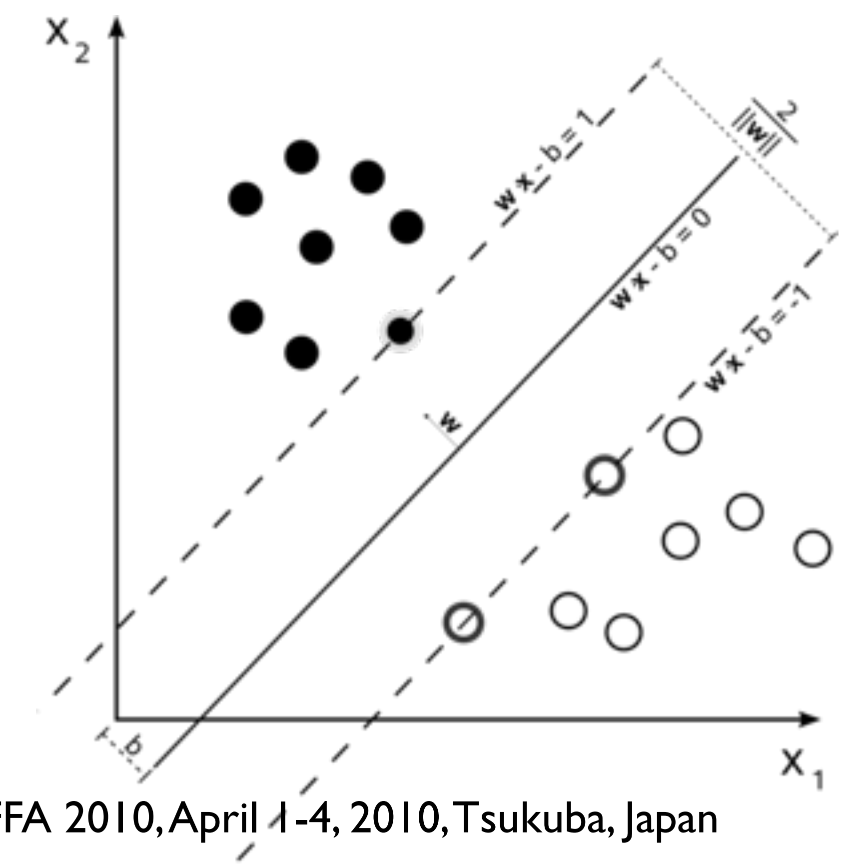
where $Z(Q,D)$ is a normalizing constant, $f_i(D,Q)$ are the feature functions of the document with weights $\lambda_{i,R}$ and n is the number of features. One can use the log-likelihood ratio as the scoring function:

$$\log \frac{P(R|D,Q)}{P(\bar{R}|D,Q)} = \sum_{i=1}^{n} (\lambda_{i,R} - \lambda_{i,\bar{R}}) f_i(D,Q) \tag{2}$$

Support Vector Machine

- A support vector machine constructs a hyperplane or set of hyperplanes in a high-dimensional space, which can be used for classification, regression or other tasks.
- A good separation is achieved by the hyperplane that has the largest distance to the nearest training datapoints of any class.





SVM Formalization

We are given some training data, a set of points of the form

$$\mathcal{D} = \{(\mathbf{x}_i, c_i) | \mathbf{x}_i \in \mathcal{R}^p, c_i \in \{-1, 1\}\}_{i=1}^{n} \tag{1}$$

where the c_i is either 1 or -1, indicating the class to which the point $\mathbf{x}_i$ belongs. Each $\mathbf{x}_i$ is a p-dimensional real vector. We want to find the maximum-margin hyperplane which divides the points having $c_i = 1$ from those having $c_i = -1$. Any hyperplane can be written as the set of points $\mathbf{x}$ satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0, \tag{2}$$

where $\cdot$ denotes the dot product. The vector $\mathbf{w}$ is a normal vector: it is perpendicular to the hyperplane. The parameter $\frac{b}{||\mathbf{w}||}$ determines the offset of the hyperplane from the origin along the normal vector $\mathbf{w}$.

We want to choose the $\mathbf{w}$ and b to maximize the margin, or distance between the parallel hyperplanes that are as far apart as possible while still separating the data. These hyperplanes can be described by the equations

$$\mathbf{w} \cdot \mathbf{x} - b = 1, \tag{3}$$

and

$$\mathbf{w} \cdot \mathbf{x} - b = -1, \tag{4}$$

SVM Formalization

By using geometry, we find the distance between these two hyperplanes is $\frac{2}{||\mathbf{w}||}$, so we want to minimize $||\mathbf{w}||$. As we also have to prevent data points falling into the margin, we add the following constraint: for each i either

$$\mathbf{w} \cdot \mathbf{x} - b \geq 1 \text{ for } \mathbf{x}_i \tag{1}$$

of the first class or

$$\mathbf{w} \cdot \mathbf{x} - b \leq 1 \text{ for } \mathbf{x}_i \text{ of the second.} \tag{2}$$

This can be rewritten as:

$$c_i(\mathbf{w} \cdot \mathbf{x} - b) \geq 1 \text{ for all } 1 \leq i \leq n. \tag{3}$$

We can put this together to get the optimization problem:

$$\min_{\mathbf{w},b} \quad ||\mathbf{w}|| \tag{4}$$

$$\text{subject to} \quad c_i(\mathbf{w} \cdot \mathbf{x}_i - b) \geq 1 \text{ for any } i = 1, \ldots, n. \tag{5}$$

SVM

Thus if $\mathbf{f}(D, Q)$ is the vector of features, then the discriminant function is given by

$$g(R|D, Q) = \mathbf{w} \cdot \phi(\mathbf{f}(D, Q)) + b, \tag{1}$$

where

- $\mathbf{w}$ is the weight vector in kernel space that is learnt by the SVM from the training exmaples,
- $\cdot$ denotes inner product
- b is a constant
- ϕ is the mapping from input space to kernel space

The equation $g(R|D, Q) = 0$ represents the equation for the hyperplane in the kernel space.

The value of the discriminant function $g(R|D, Q)$ for an arbitrary document D and a query Q is proportional to the perpendicular distance of the document's augmented feature vector $\phi(\mathbf{f}(D, Q))$ from the separating hyper-plane in the kernel space.

Pairwise Approach

- No longer assume absolute relevance
- Reduce ranking to classification on document pairs w.r.t. the same query
- RankNet
  - Use Neural Network as model, and gradient descent as algorithm, to optimize the cross-entropy loss.
  - Evaluate on single documents: output a relevance score for each document w.r.t. a new query.

Ranking with Neural Nets

- Don't need to learn ordinal regression (mapping points to actual rank values); just need to map features to reals
- Train system on pairs (where first point is to be ranked higher or equal to second)
- However must evaluate on single points
- Use cross entropy cost => probabilistic model
- Use gradient descent

RankNet: Notes

- 5 human judged levels of relevance (“bad”, ... , “perfect”)
- A net with (number of features) inputs and one output
- Sort documents by the score that their feature vectors (which are computed from query + doc + other data)
- Compute NDCG on a set-aside validation set, keep the net that gives the best validation NDCG

RankNet Conclusions

- RankNet is simple to train
- RankNet is fast in test phase
- RankNet gives good results
- For pair-based probability costs (e.g., click rates!) RankNet is very well suited to the problem.
- However, the cost function used is not NDCG: the latter is optimized only indirectly, using a validation set.

Listwise Approach

- Instead of reducing ranking to regression or classification, perform learning directly on document list.
  - Directly optimize IR evaluation measure
    - AdaRank, SVM-MAP, SoftRank, LambdaRank, RankGP, ...
  - Define listwise loss functions
    - RankCosine, ListNet, ListMLE, ...

Concluding Remarks

- Social Computing is here to stay!
- Relations are important!
- Discovering new paradigms by blending different social media and interactions
- Be concerned about computational techniques to search, rank, and mine data and information to achieve collective intelligence/wisdom

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On-Going Research

Machine Learning

- Heavy-Tailed Symmetric Stochastic Neighbor Embedding (NIPS'09)
- Adaptive Regularization for Transductive Support Vector Machine (NIPS'09)
- Direct Zero-norm Optimization for Feature Selection (ICDM'08)
- Semi-supervised Learning from General Unlabeled Data (ICDM'08)
- Learning with Consistency between Inductive Functions and Kernels (NIPS'08)
- An Extended Level Method for Efficient Multiple Kernel Learning (NIPS'08)
- Semi-supervised Text Categorization by Active Search (CIKM'08)
- Transductive Support Vector Machine (NIPS'07)
- Global and local learning (ICML'04, JMLR'04)

On-Going Research

Web Intelligence/Information Retrieval

- A Generalized Co-HITS Algorithm and Its Application to Bipartite Graphs (KDD'09)
- Entropy-biased Models for Query Representation on the Click Graph (SIRIR'09)
- Effective Latent Space Graph-based Re-ranking Model with Global Consistency (WSDM'09)
- Formal Models for Expert Finding on DBLP Bibliography Data (ICDM'08)
- Learning Latent Semantic Relations from Query Logs for Query Suggestion (CIKM'08)
- RATE: a Review of Reviewers in a Manuscript Review Process (WI'08)
- MatchSim: link-based web page similarity measurements (WI'07)
- Diffusion rank: Ranking web pages based on heat diffusion equations (SIGIR'07)
- Web text classification (WWW'07)

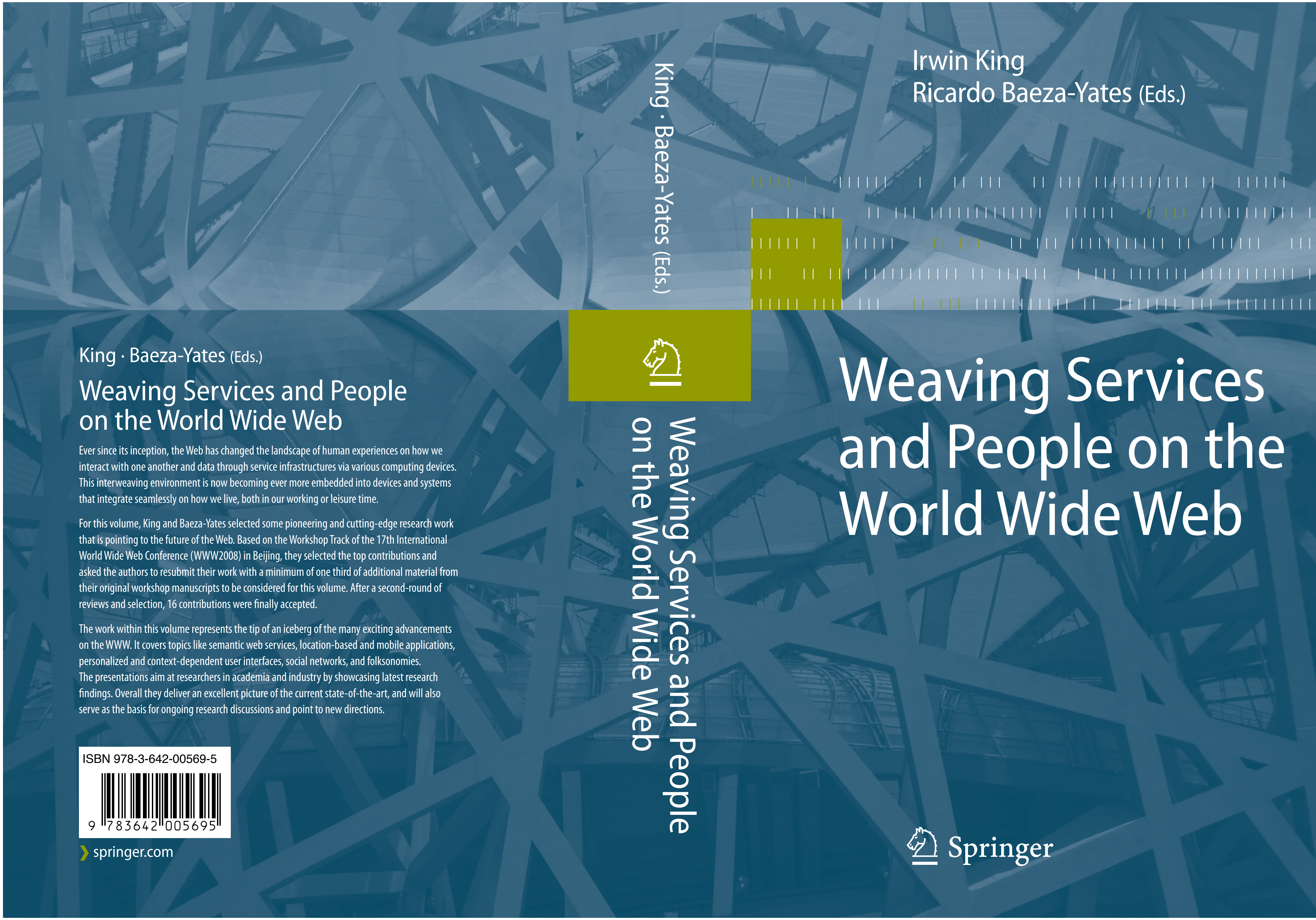
On-Going Research

Recommender Systems/Collaborative Filtering

- Learning to Recommend with Social Trust Ensemble (SIRIR'09)
- Semi-Nonnegative Matrix Factorization with Global Statistical Consistency in Collaborative Filtering (CIKM'09)
- Recommender system: accurate recommendation based on sparse matrix (SIGIR'07)
- SoRec: Social Recommendation Using Probabilistic Matrix Factorization (CIKM'08)

Human Computation

- A Survey of Human Computation Systems (SCA2009)
- Mathematical Modeling of Social Games (SIAG2009)
- An Analytical Study of Puzzle Selection Strategies for the ESP Game (WI'08)
- An Analytical Approach to Optimizing The Utility of ESP Games (WI'08)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