Social Network Analysis

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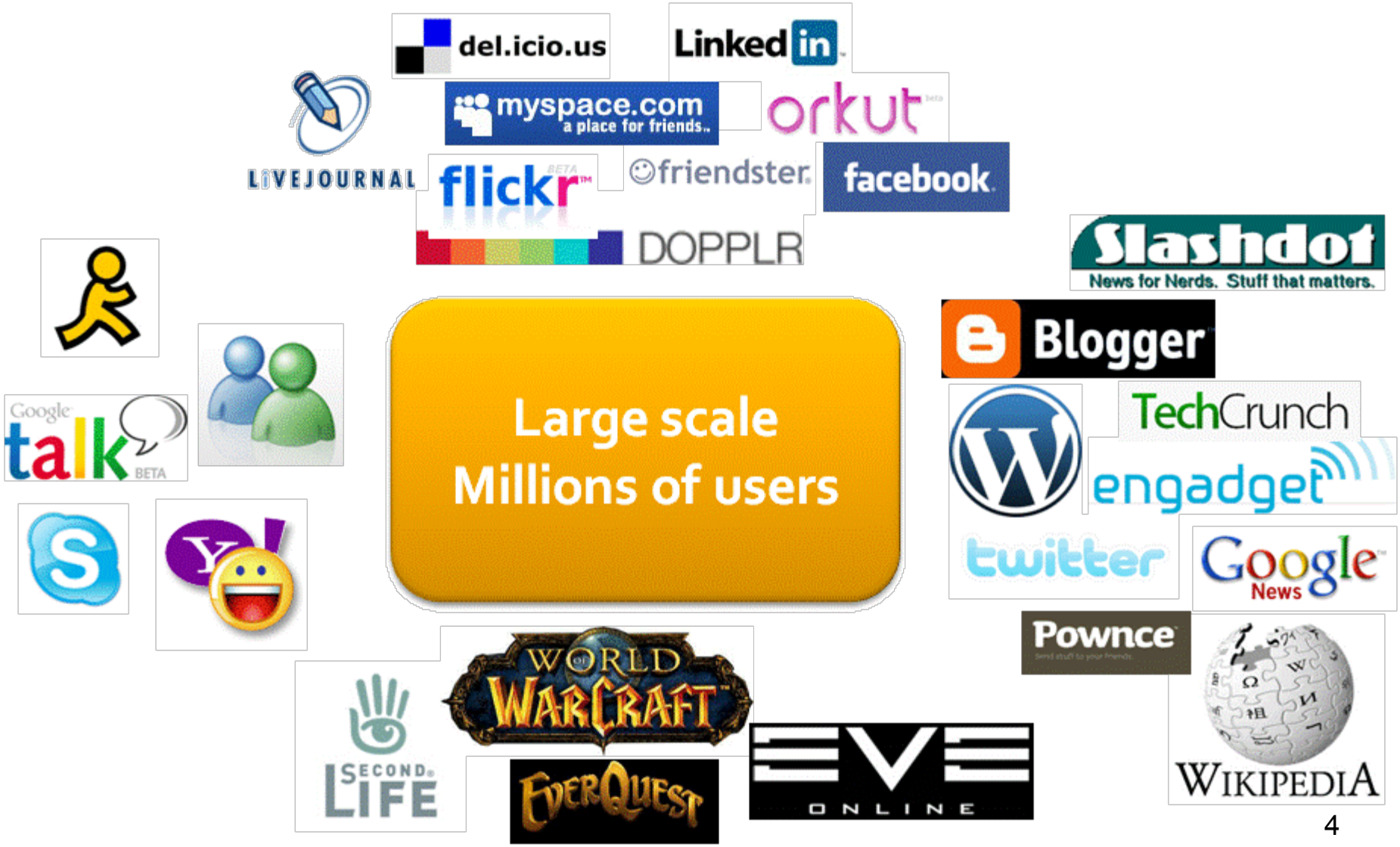
Web today


Web 1.0
blog.aysoon.com
webmaster
site web
internautes
TAG
webmaster
site web 2.0
internautes contributeurs
internautes organisés
en réseaux sociaux
Web 2.0

Web today – Diverse applications

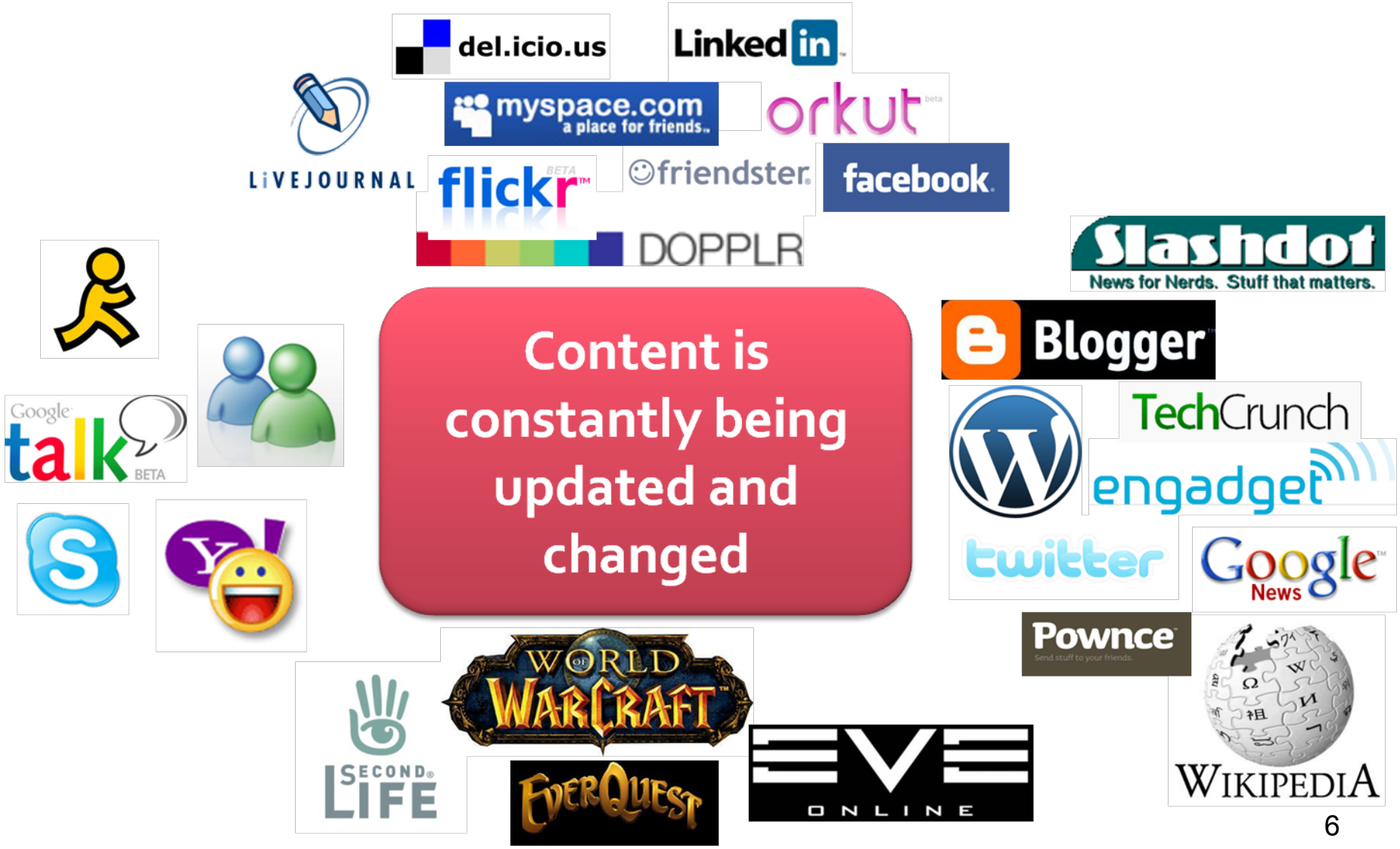
Diverse on-line computing applications

Web today – Millions of users



Web today – Rich content

Web today – Highly dynamic



Content is constantly being updated and changed

Web today – Traces of activity

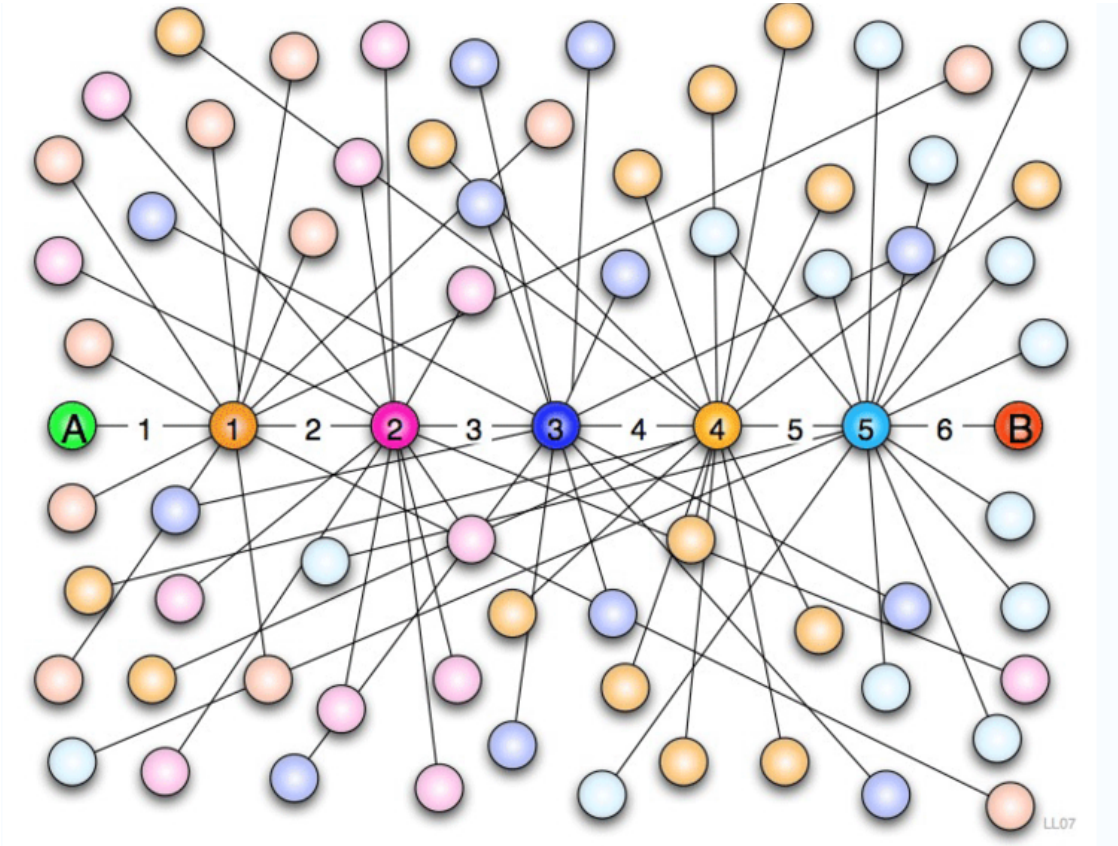
Web today – Rich interactions

Rich interactions between users and content

Web today – social networks

Six degrees of separation

We can all be connected through a series of six contacts appeals to me. It makes the world seem less brutal, and more warm and more friendly.



Why study networks?

- **Build understanding and theory:**
  - How users create content and interact with it and among themselves?
- **Build better on-line applications:**
  - How to design better services and algorithms?

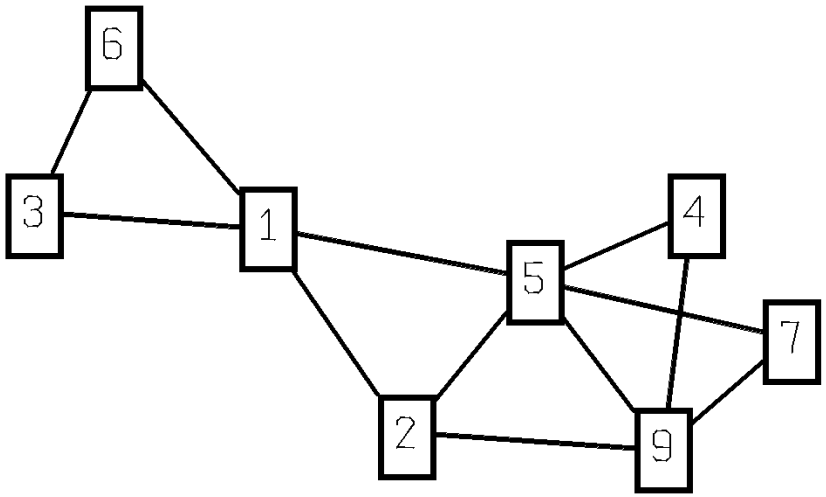
Social Networks Analysis

- A **social network** is a social structure of people, related (directly or indirectly) to each other through a common relation or interest.

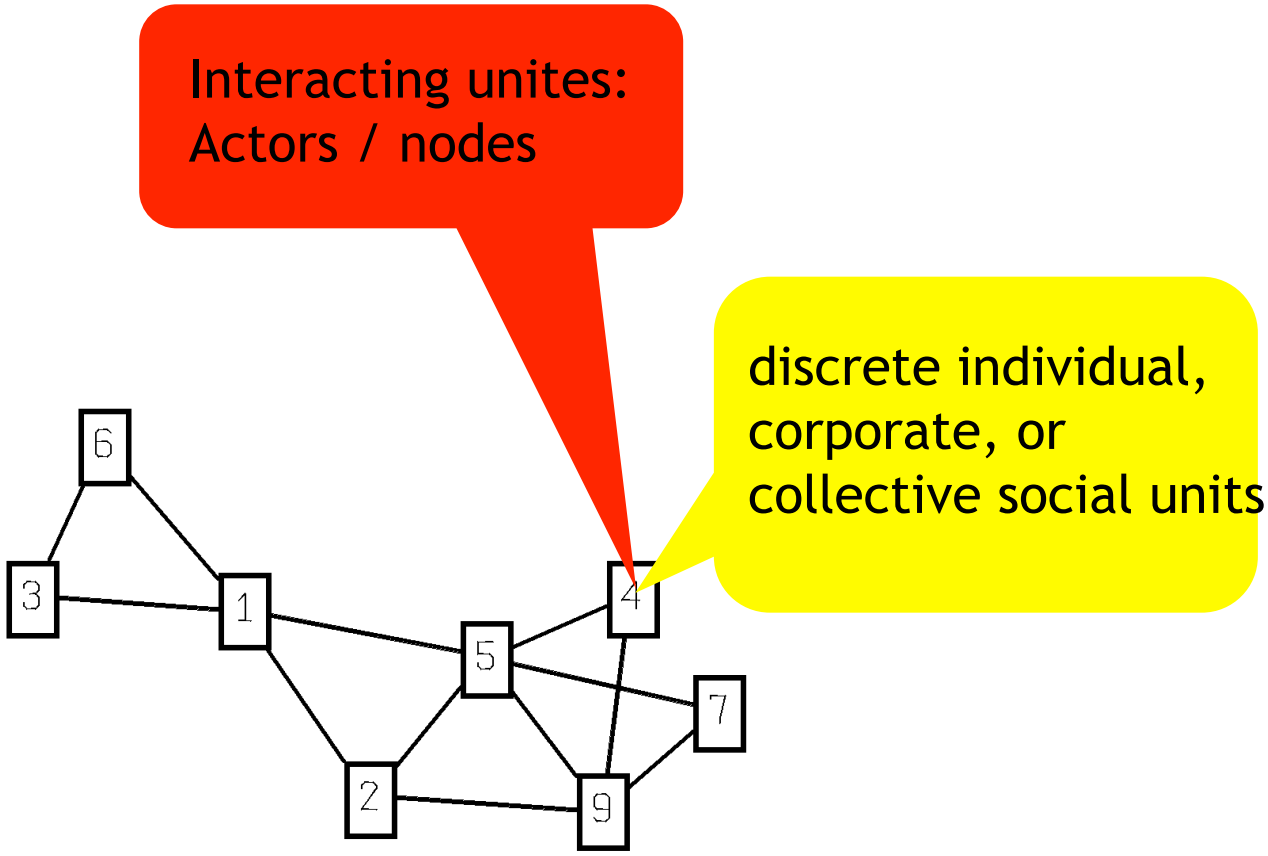
- **Social network analysis (SNA)** is the study of social networks to understand their structure and behavior.

Social Networks

- Social network: relationship among interacting units.



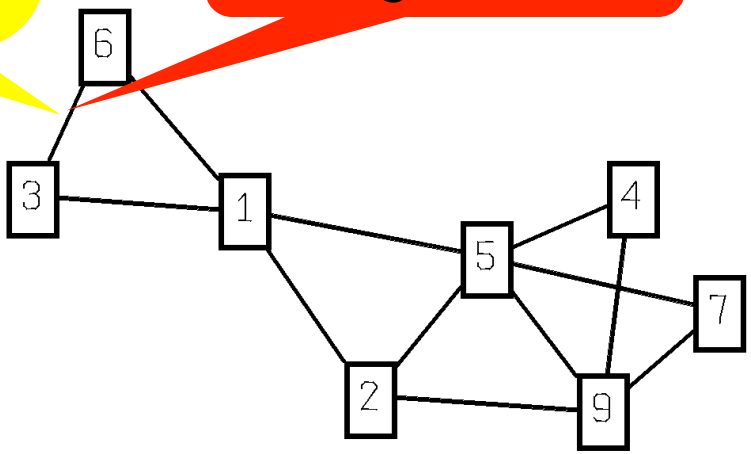
Social Networks



Social Networks

Relational ties between actors are channels to transfer, exchange or flow of resources.

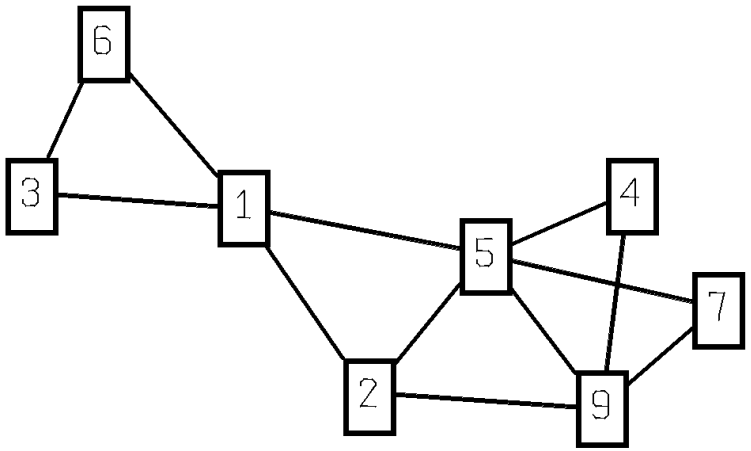
Relations, linkages or ties



Social Networks

- Social network representation
  - Adjacency matrix (socio-matrix)
  - Graph (Socio-graph)

	1	2	3	4	5	6	7	8	9
1	0	1	1	0	1	1	0	0	0
2	1	0	0	0	1	0	0	0	1
3	1	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0	1
5	1	1	0	1	0	0	1	0	1
6	1	0	1	0	0	0	0	0	0
7	0	0	0	0	1	0	0	0	1
8	0	0	0	0	0	0	0	0	0
9	0	1	0	1	1	0	1	0	0



Key Drivers for CS Research in SNA

- Computer Science has created the cyber infrastructure for
  - Social Interaction
  - Knowledge Exchange
  - Knowledge Discovery

- Ability to capture
  - different about various types of social interactions
  - at a very fine granularity
  - with practically no reporting bias

Data mining techniques can be used for building descriptive and predictive models of social interactions

SNA Techniques

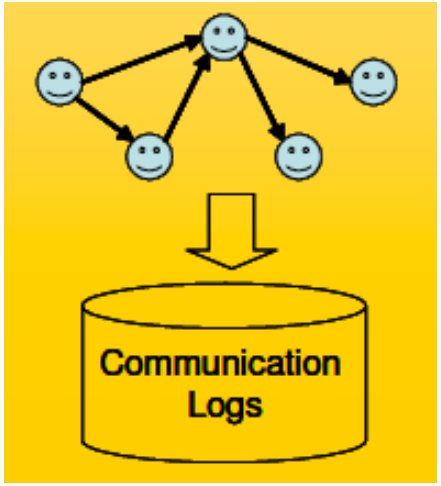
Prominent problems

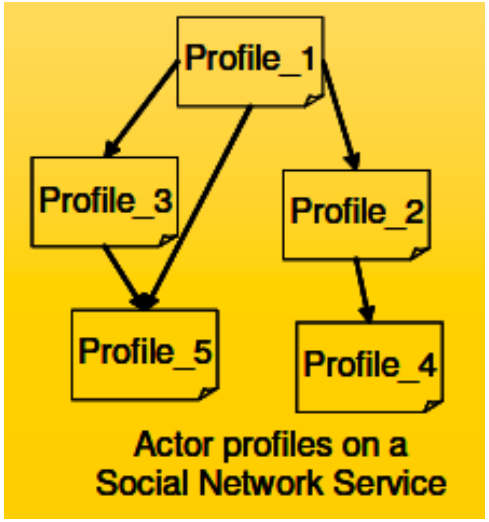
- Social network extraction/construction
- Identifying prominent/trusted/expert actors
- Identifying Spammers
- Discovering communities in social networks
- Evolution of social networks
- Link prediction
- Approximating large social networks

Social Network Extraction

- Mining a social network from data sources
- Recent research suggest that there are three sources of social network data on the web

- Content available on web pages (e.g. user homepages, message threads etc.)
- User interaction logs (e.g. email and messenger chat logs)
- Social interaction information provided by users (e.g. social network service websites such as Orkut, Friendster and MySpace)





SNA Techniques

Prominent problems

- Social network extraction/construction
- **Identifying prominent/trusted/expert actors**
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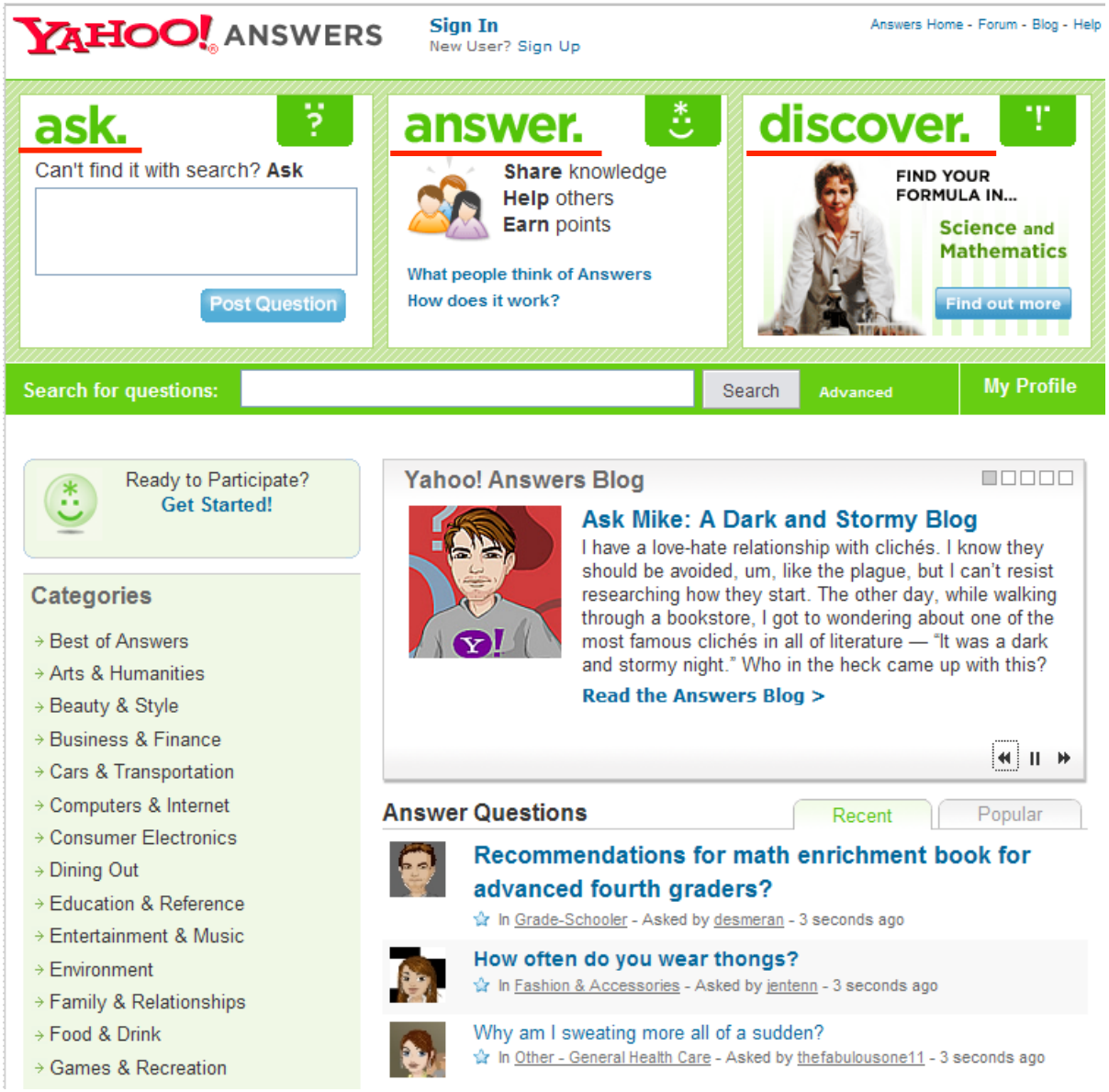
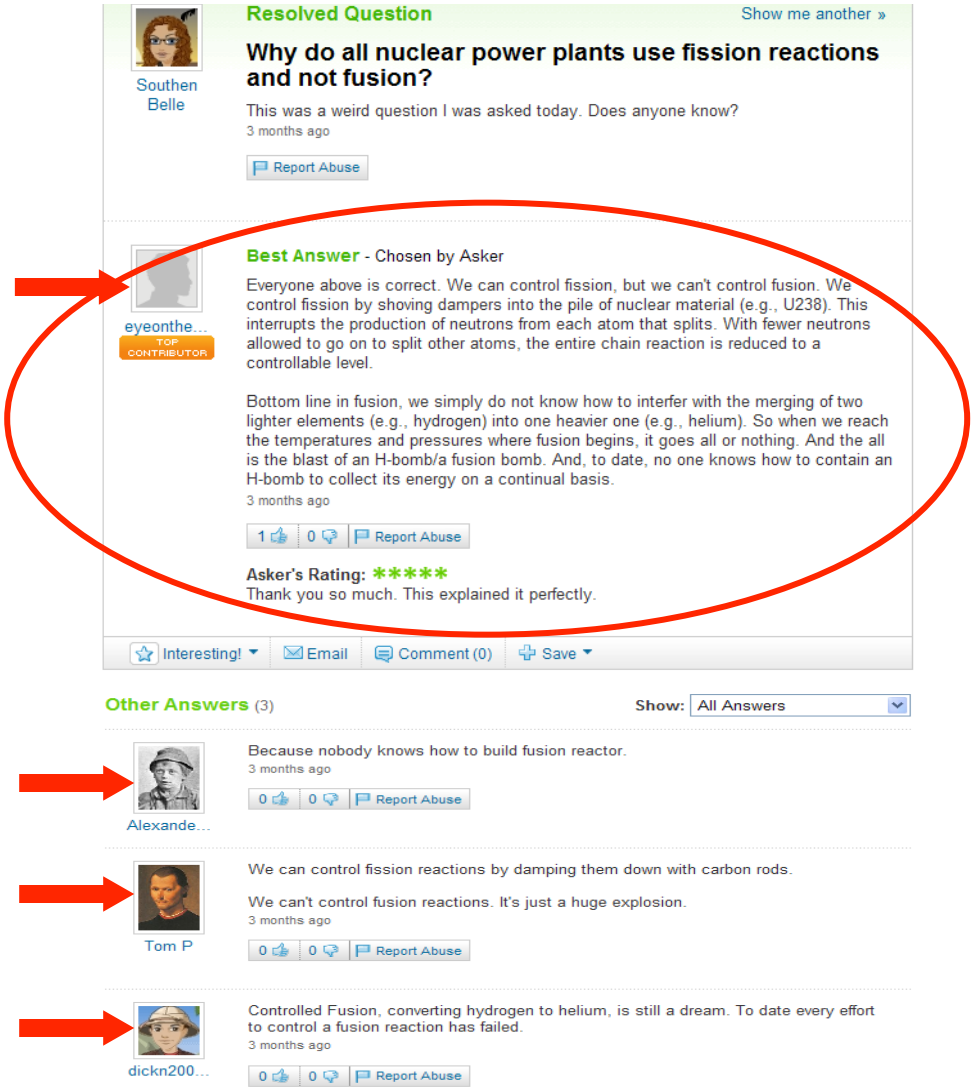
- Evolution of social networks

Yahoo! Answers

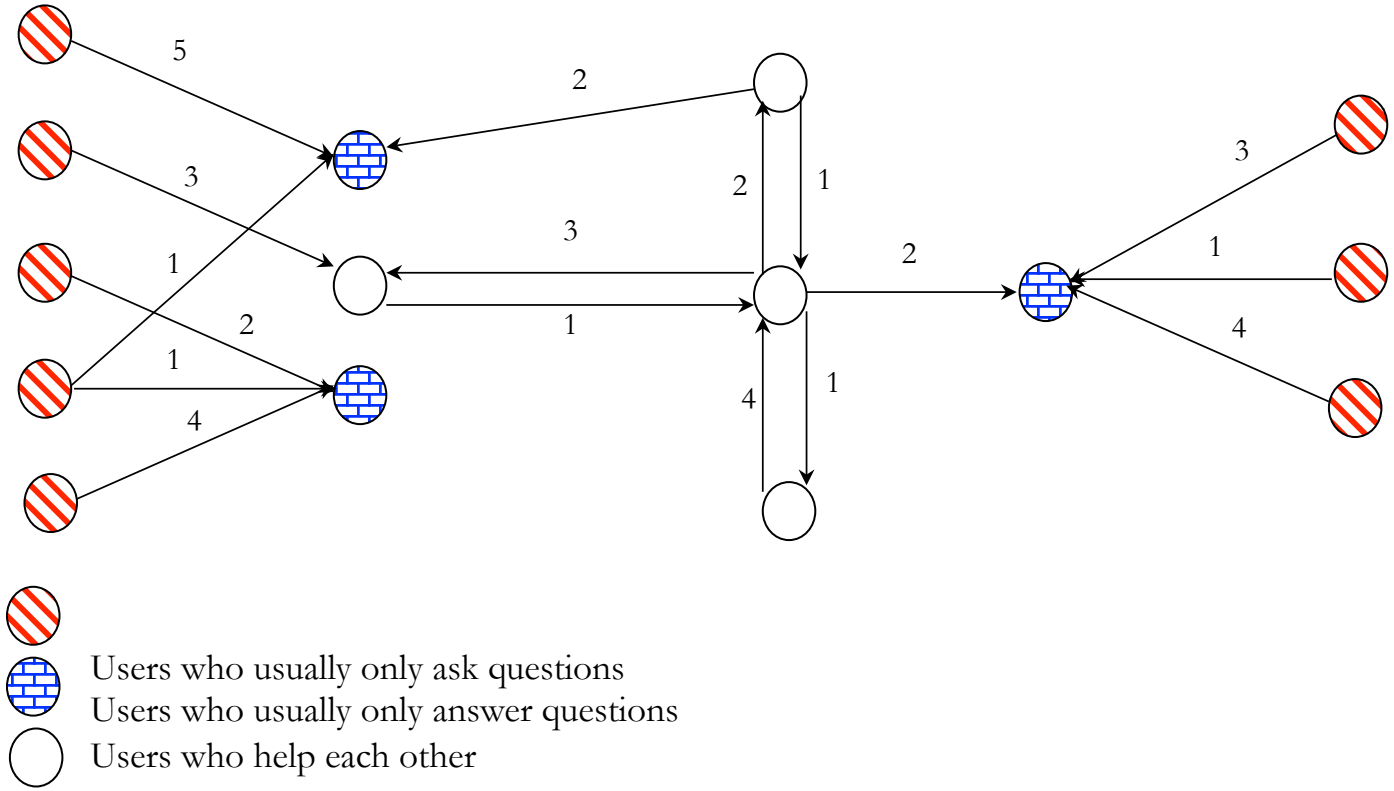


Question Life Cycle



Yahoo! Answers

Example of interactions between askers and best answerers

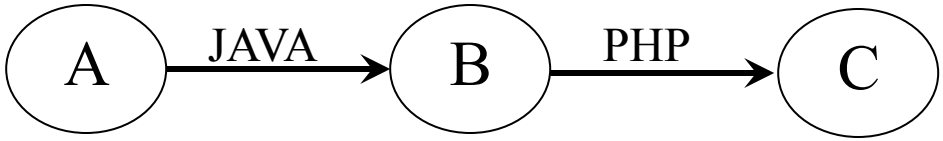


How to estimate the authority degree for each user?

PageRank?

Example: The category of "Programming"

- User *B* answers user *A*'s questions, which are about Java;
- User *C* answers *B*'s questions, which are about PHP;



➢ Is it possible to state that *C* is more expert than *B*?

- No, because: *B* and *C* have different expertise.

Proposed Approach

- The authority score of each user is simply the number of best answer of each users normalized so their square sum to 1:

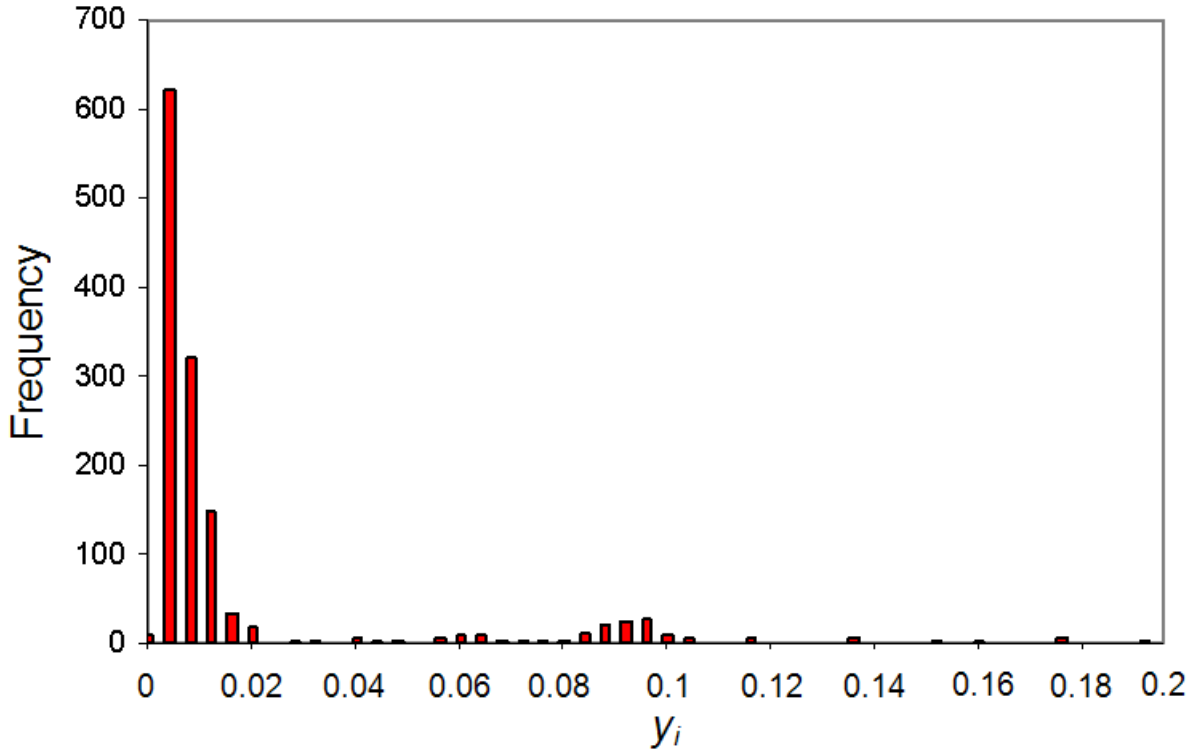
$$\sum_{i=1}^{N} (y_i)^2 = 1$$

- y_i provide a relative score of the authority of each user in each category.

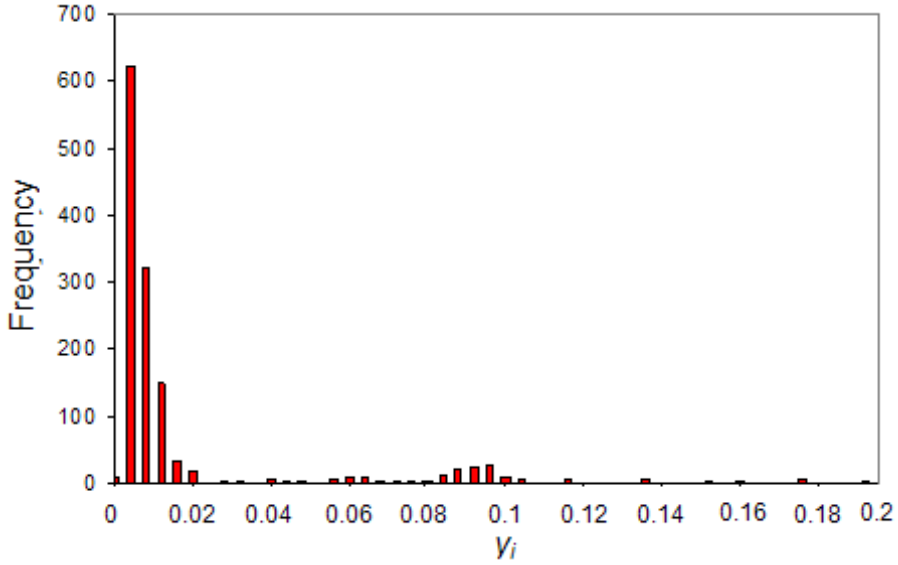
➢ We are interested in all sets of U_i having large values of y_i.

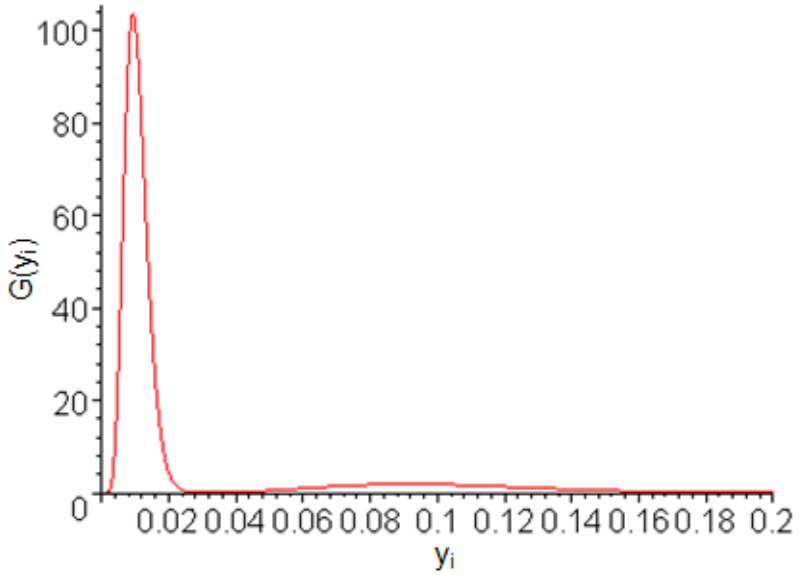
Authority Score

- Example: Category of "Engineering"



Authority Score





Automatic Identification of Authorities

Input: A set $U = \{u_1, u_2, \ldots, u_N\}$ of users
Output: A set $E = \{e_1, e_2, \ldots, e_d\}$ of authoritative users

1. For a given category, estimate the authority scores of each user;
2. Normalize y_i, where $\sum_{i=1}^{N} (y_i)^2 = 1$;
3. Estimate the *pdf* of the authority scores with $m = 2$;
   3.1. Apply FCM as initialization of the EM algorithm;
   3.2. Apply EM to estimate the parameters of the mixture;
4. Use the results of the EM algorithm in order to derive a classification decision about the membership of y_i in each component.

Experiments

We conduct experiments on datasets which represent users' activities over one full year for six categories:

Category	% users who ask only	% users who answer only	% users who ask and answer
Engineering	65%	31%	4%
Biology	60%	36%	4%
Programming	66%	29%	5%
Mathematics	64%	31%	5%
Physics	60%	34%	6%
Chemistry	63%	32%	5%

Authoritative Users

Puggy

Add to my Contacts Block User

Member since: November 22, 2006

45,478 points
Level 7

49%
Best answer

TOP CONTRIBUTOR

Mathematics

About me: Just a 28 year old Canadian guy who loves tutoring math. I might want to teach someday.

As much as I love helping people understand mathematics, please refrain from e-mailing me your question in private; it's not fair that I should give special treatment to some and not others.

While I cannot guarantee to always be correct, I can (almost) guarantee a step-by-step solution where my mistake can easily be traced. Spotting of this error alone separates those truly willing to learn from those merely wanting the answer to their homework problem.

Mathematica

Add to my Contacts Block User

Member since: January 10, 2007

40,609 points
Level 7

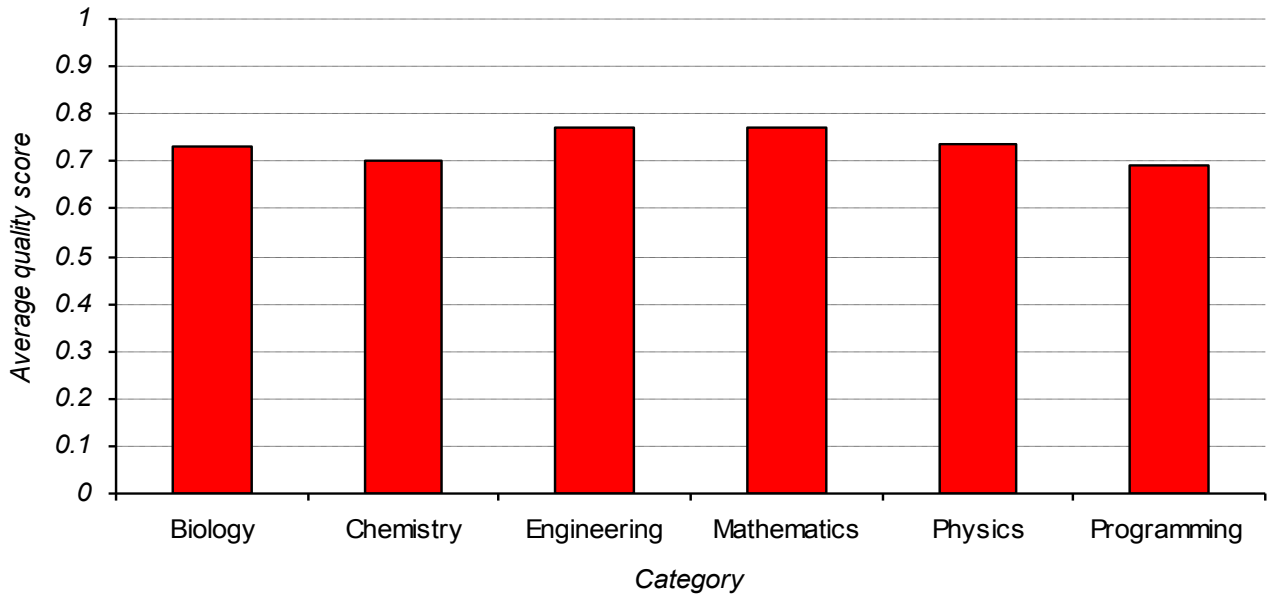
72%
Best answer

TOP CONTRIBUTOR

Mathematics

About me: I have tutored math since 1993. My specialty is high school subjects - specifically Algebra, Geometry and Trigonometry. I currently work for a large test-publishing company.

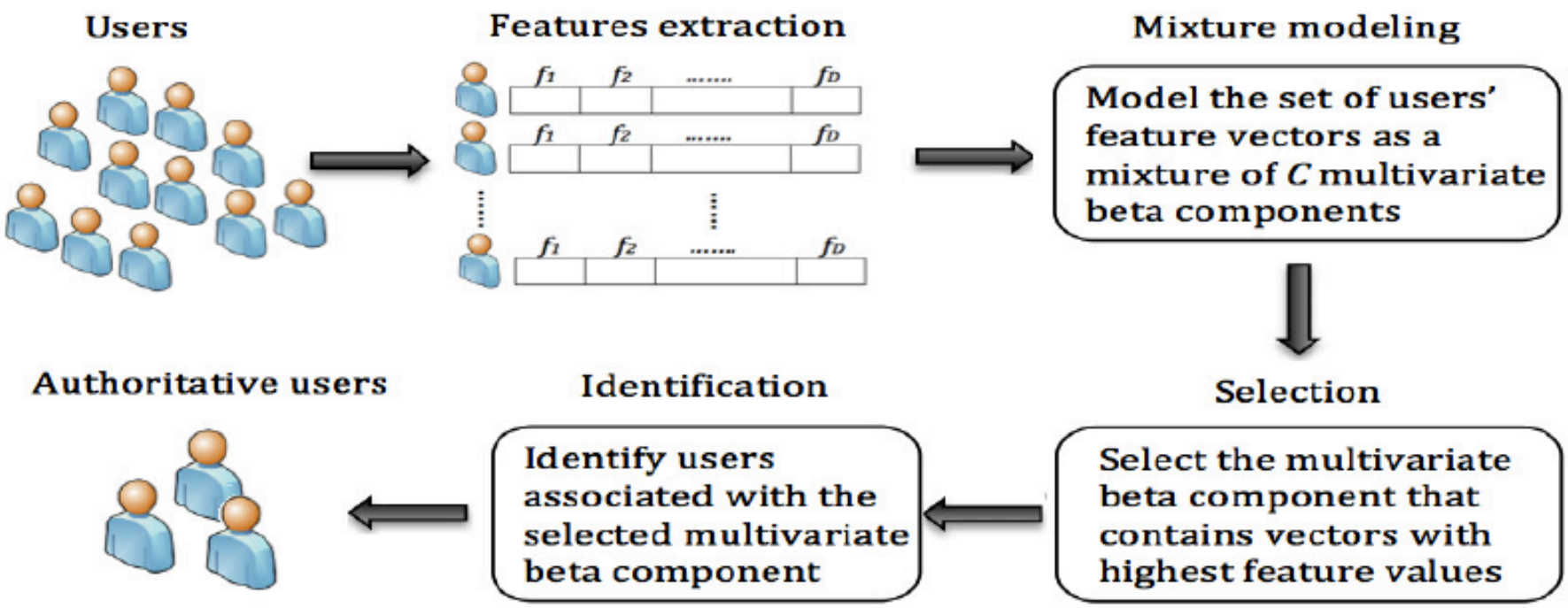
Quality of Content



- The identified authoritative users generate high-quality content in Yahoo! Answers.

- Askers are very selective in choosing the best answerers

Identifying Authorities in Online Communities



Workflow of the proposed approach.

Multivariate Beta Mixture Model

$$\mathcal{F}(\vec{X}_i|\alpha,\vec{a},\vec{b}) = \sum_{c=1}^{C} \alpha_c \, \mathcal{F}_c(\vec{X}_i|\vec{a_c},\vec{b_c})$$

$$\mathcal{F}_c(\vec{X}_i|\vec{a_c},\vec{b_c}) = \prod_{d=1}^{D} f(x_{id}|a_{cd},b_{cd})$$

$$f(x_{id}|a_{cd},b_{cd}) = \frac{\Gamma(a_{cd}+b_{cd})}{\Gamma(a_{cd})\Gamma(b_{cd})} x_{id}^{a_{cd}-1}(1-x_{id})^{b_{cd}-1}$$

Algorithm

ALGORITHM 2: Authoritative users identification procedure

Input : A set $U = \{U_1, \ldots, U_N\}$ of N users
Output: A set $A = \{A_1, \ldots, A_K\}$ of K authoritative users
begin
For a given online community, estimate a feature vector $\vec{X}_i$ for each user;
Normalize $\{\vec{X}_i\}$, as discussed at the beginning of Section 3;
Apply Algorithm 1 to cluster the users into C multivariate beta components;
Use the results of the EM algorithm to decide about the membership of $\vec{X}_i$ in each component;
Select the multivariate beta component that corresponds to the highest feature values;
Identify authoritative users in U associated with the set of $\vec{X}_i$ that belong to the selected component and store them in A;
Return A;
end

Twitter data – 2012 Quebec election

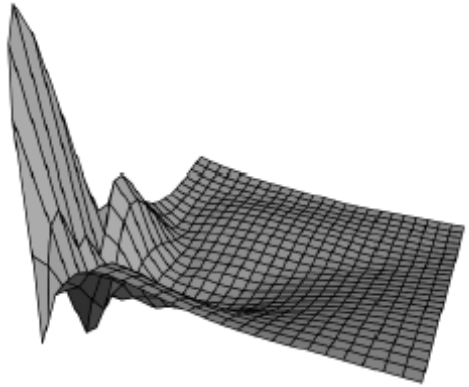
- The data set consists of tweets posted between August 18, 2012 and August 20, 2012 (three days overall during the electoral campaign, including Quebec's political party leaders' debate which took place on August 19, 2012).

- 904 users; 76 users (8.4% of the whole data set) among them were labeled as authoritative and 828 users were labelled as non-authoritative

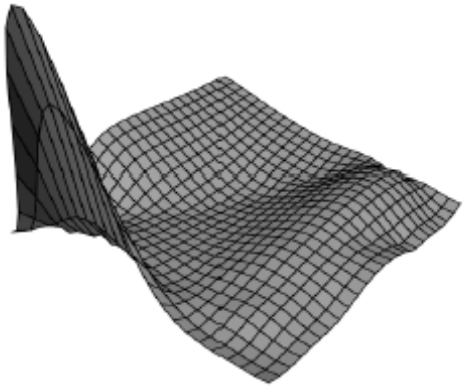
Twitter data – 2012 Quebec election

- Features
  - The number of followers of a user, which indicates the size of the audience for that user
  - The Followers to Followees ratio (F-F ratio), that is, the number of a user's followers and the number of other people that the user follows (followees).
  - The number of retweets, which measures the number of times an author's tweets were retweeted by other users
  - The number of mentions, which is measured by the number of times a user was cited or had her tweet replied to.

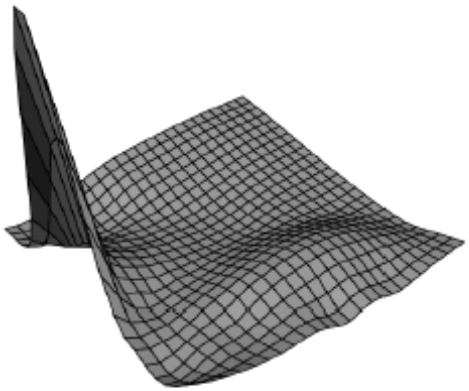
Twitter data – 2012 Quebec election



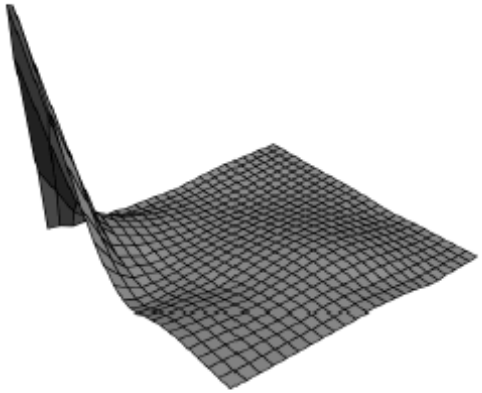
(a) Number of followers and F-F ratio.



(b) Number of followers and number of retweets.



(c) Number of followers and number of mentions.



(d) Number of retweets and number of mentions.

Density curves of several $2D$ user features combinations over Quebec Election

Twitter data – 2012 Quebec election

Input features	Accuracy	CD	FA	F-measure
# of followers and F-F ratio	95.2%	97.3%	4.9%	0.774
# of followers and # of retweets	97.3%	98.6%	2.7%	0.862
# of followers and # of mentions	98.5%	100%	1.5%	0.921
# of retweets and # of mentions	97.3%	94.7%	2.4%	0.857
# of followers, # of retweets and # of mentions	97.3%	97.3%	2.6%	0.860
# of followers, F-F ratio and # of retweets	97.4%	98.6%	2.6%	0.867
F-F ratio, # of retweets and # of mentions	97.3%	98.6%	2.7%	0.862
All features	**99.2%**	**97.3%**	**0.6%**	**0.954**

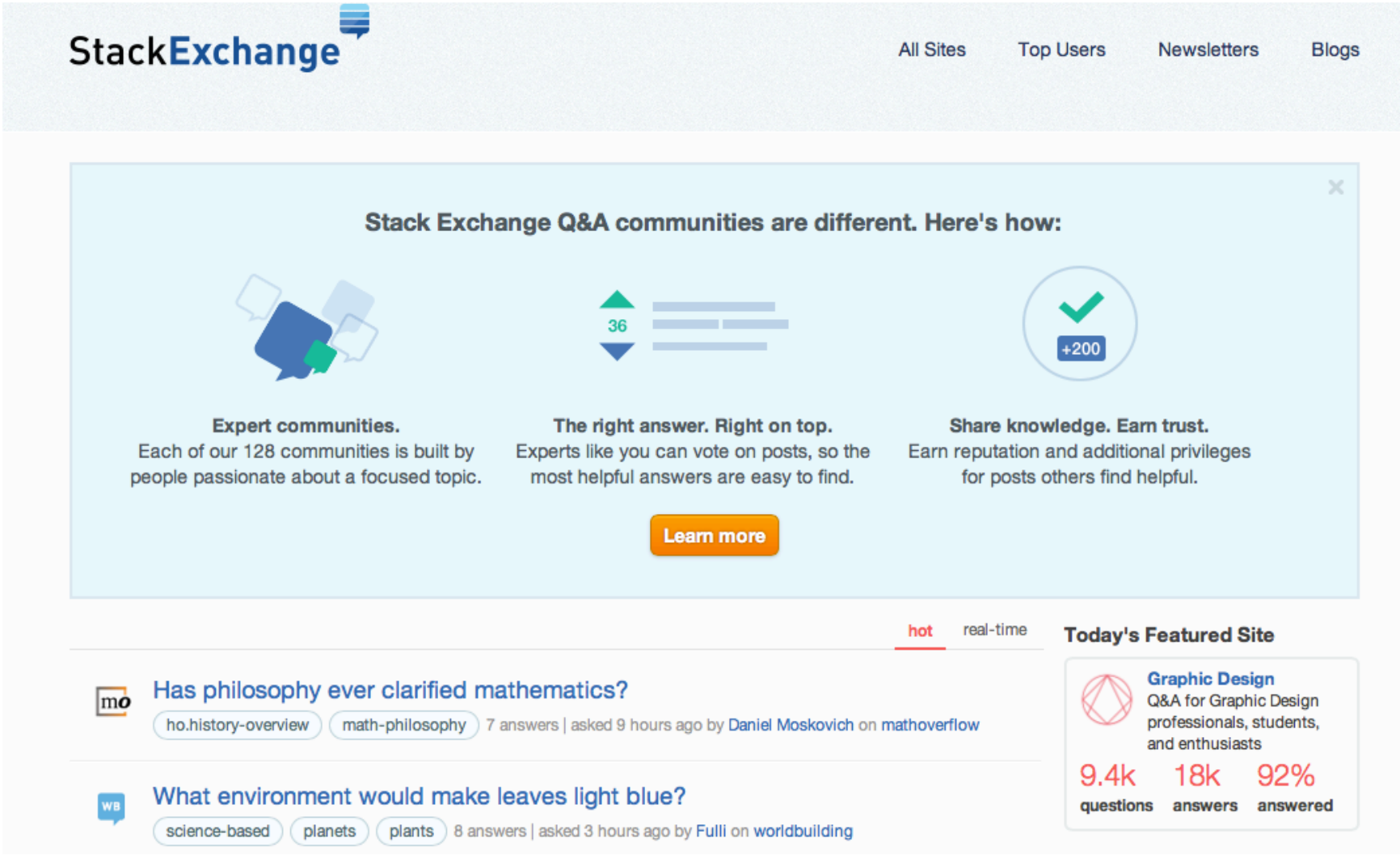
Performance results over Quebec Election data.

Twitter data – 2012 Quebec election

Algorithm	Accuracy	CD	FA	F-measure
Proposed	**99.2%**	**97.3%**	**0.6%**	**0.954**
AdaBoost	99.2%	98.7%	0.7%	0.955
Bagging	98.8%	94.7%	0.7%	0.935
Decorate	99.4%	97.4%	0.4%	0.967
LogitBoost	98.8%	94.7%	0.7%	0.935
MultiBosstAB	98.6%	94.7%	1%	0.923
ADTree	99%	96.1%	0.7%	0.942
Random Forest	99.3%	98.7%	0.6%	0.962
RBF Network	97.7%	92.1%	1.7%	0.875

Accuracies of compared algorithms on Quebec Election data.

Stack Exchange data




Stack Overflow
Server Fault
Super User
Meta Stack Exchange
Web Applications
Webmasters
Arqade
Seasoned Advice
Game Development
Photography
Cross Validated
Home Improvement
Geographic Information Systems
Mathematics
TeX - LaTeX
Ask Ubuntu
Personal Finance & Money
English Language & Usage
Stack Apps
User Experience
Unix & Linux
WordPress Development
Theoretical Computer Science
Role-playing Games
Ask Different
Q&A for power users of Apple hardware and software
questions 45k
answers 71k
answered 74%
users 69k
"How do I recompile Bash to avoid Shellshock (the remote exploit CVE-2014-6271 and CVE-2014-7169)?" – asked Sep 24 at 18:35
Visit Site
Bicycles
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Electrical Engineering
Android Enthusiasts
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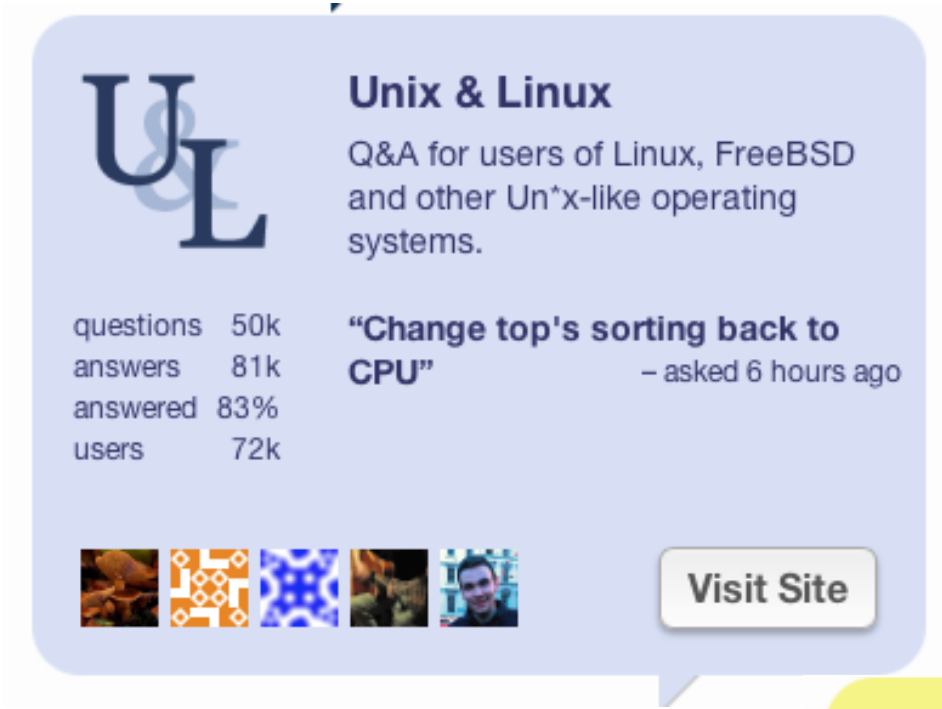
Quantitative Finance
Project Management
Skeptics


Unix & Linux
Q&A for users of Linux, FreeBSD and other Un*x-like operating systems.
questions 50k
answers 81k
answered 83%
users 72k
"Change top's sorting back to CPU"
– asked 6 hours ago
Visit Site


Game Development
Q&A for professional and independent game developers
questions 22k
answers 41k
answered 92%
users 41k
"Why is it bad to hard-code content?"
– asked 19 hours ago
Visit Site

Input features	Accuracy	CD	FA	F-measure
# of answers and # of best answers	97.6%	76.6%	0.0%	0.868
# of best answers and Z-score	95.7%	58.2%	0.0%	0.736
# of best answers and # of votes received	90.7%	89.3%	9.1%	0.664
# of answers and Z-score	95.3%	100%	5.2%	0.814
# of answers, # of best answers and Z-score	97.7%	78.6%	0.1%	0.875
# of answers, # of best answers and # of votes received	92.9%	100%	7.9%	0.743
# of best answers, # of votes received and Z-score	92.1%	100%	9.8%	0.700
All features	**99.1%**	**97.0%**	**0.6%**	**0.956**

(a)

Input features	Accuracy	CD	FA	F-measure
# of answers and # of best answers	97.6%	100%	2.6%	0.890
# of best answers and Z-score	92.7%	94.8%	7.5%	0.718
# of best answers and # of votes received	93.6%	92.8%	6.3%	0.739
# of answers and Z-score	89.1%	96.9%	11.7%	0.635
# of answers, # of best answers and Z-score	98.4%	94.8%	1.2%	0.920
# of answers, # of best answers and # of votes received	98.9%	93.9%	0.5%	0.943
# of best answers, # of votes received and Z-score	96.6%	92.8%	2.9%	0.842
All features	**99.2%**	**95.9%**	**0.4%**	**0.959**

(b)

Performance results of the proposed approach over : (a) Game Development data, (b) Unix & Linux data.

Algorithm	Accuracy	CD	FA	F-measure
Proposed	**99.1%**	**97%**	**0.6%**	**0.956**
AdaBoost	99.1%	96.1%	0.6%	0.956
Bagging	99%	96.1%	0.7%	0.952
Decorate	98.4%	92.2%	0.9%	0.922
LogitBoost	99%	96.1%	0.7%	0.952
MultiBoostAB	98.9%	97%	0.9%	0.948
ADTree	99.1%	97%	0.6%	0.956
Random Forest	98.9%	96.1%	0.8%	0.947
RBF Network	98.3%	94.2%	1.2%	0.919
SVM	98.9%	95.1%	0.8%	0.942

(a)

Algorithm	Accuracy	CD	FA	F-measure
Proposed	**98.9%**	**93.9%**	**0.5%**	**0.943**
AdaBoost	98.9%	96.1%	0.7%	0.951
Bagging	97.9%	92.2%	1.3%	0.904
Decorate	98.3%	96.1%	1.3%	0.925
LogitBoost	98.7%	96.1%	0.9%	0.942
MultiBoostAB	97.7%	94.1%	1.8%	0.897
ADTree	98.7%	94.1%	0.7%	0.941
Random Forest	98.3%	96.1%	1.3%	0.925
RBF Network	98.1%	96.1%	1.6%	0.916
SVM	98.7%	96.1%	0.9%	0.942

(b)

Accuracies of compared algorithms on: (a) Game Development data, (b) Unix & Linux data.

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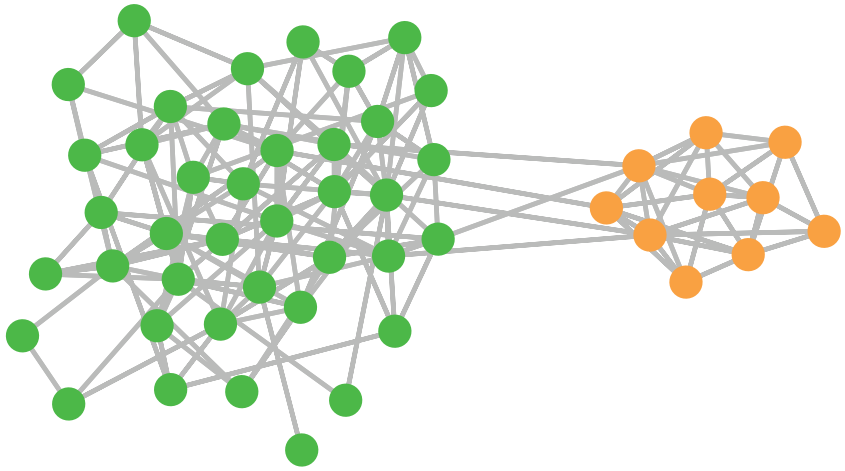
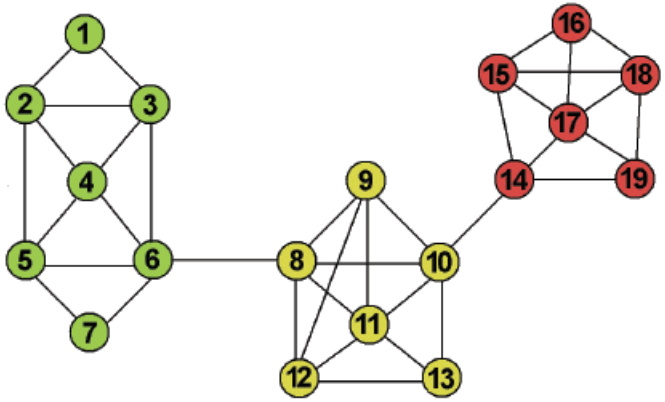
- Evolution of social networks

Community Structure in Social Network



Graph Clustering



0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	1	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	1	0	1	1	0	0	0	0
0	0	0	0	0	0	0	1	1	1	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	1	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0

Algorithms based on Czekanovski-Dice Distance

Distance between two nodes

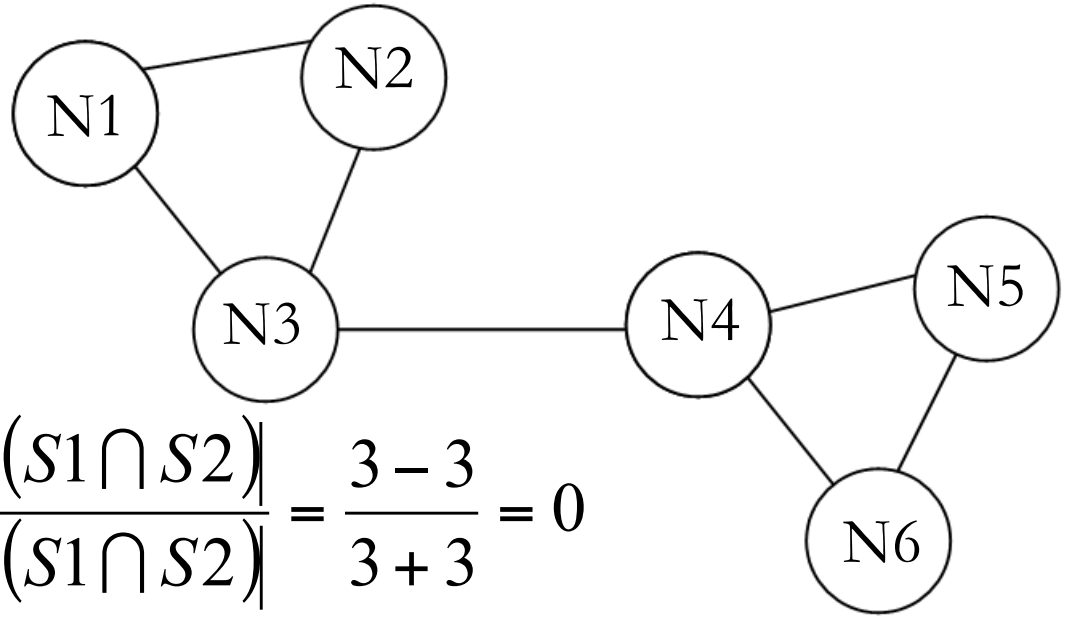
$$dist(N1, N2) = \frac{|(S1 \cup S2)| - |(S1 \cap S2)|}{|(S1 \cup S2)| + |(S1 \cap S2)|}$$

S1: number of nodes connected to N1 (including N1)
S2: number of nodes connected to N2 (including N2)

Small distance ➔ High similarity

Czekanovski-Dice Distance

- **Exemple**



- dist(N1, N2) = ?

S1 = {N1, N2, N3}
S2 = {N2, N1, N3}

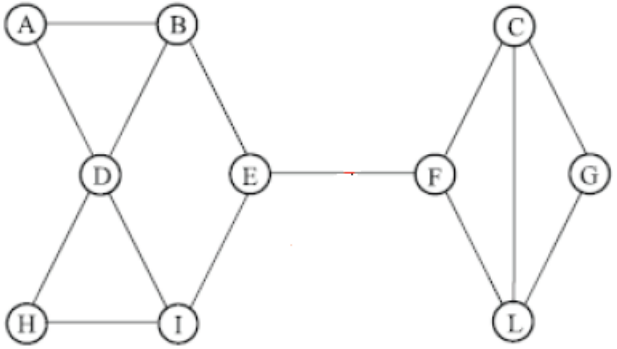
$$dist(N1,N2) = \frac{\left|(S1 \cup S2)\right| - \left|(S1 \cap S2)\right|}{\left|(S1 \cup S2)\right| + \left|(S1 \cap S2)\right|} = \frac{3-3}{3+3} = 0$$

- dist(N3, N4) = ?

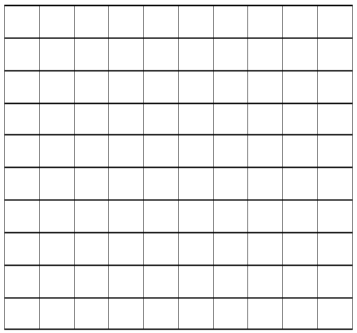
S3 = {N3, N1, N2, N4}
S4 = {N4, N3, N5, N6}

$$dist(N3,N4) = \frac{\left|(S3 \cup S4)\right| - \left|(S3 \cap S4)\right|}{\left|(S3 \cup S4)\right| + \left|(S3 \cap S4)\right|} = \frac{6-2}{6+2} = 0.5$$

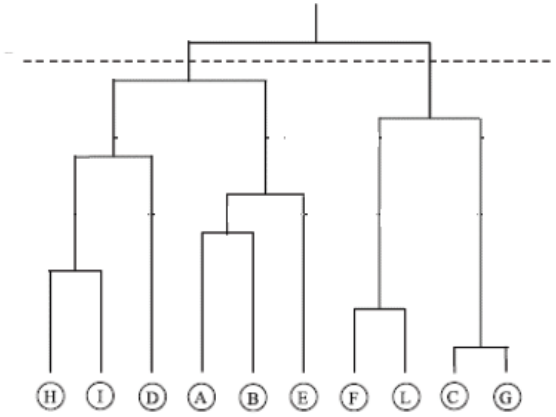
Czekanovski-Dice Distance



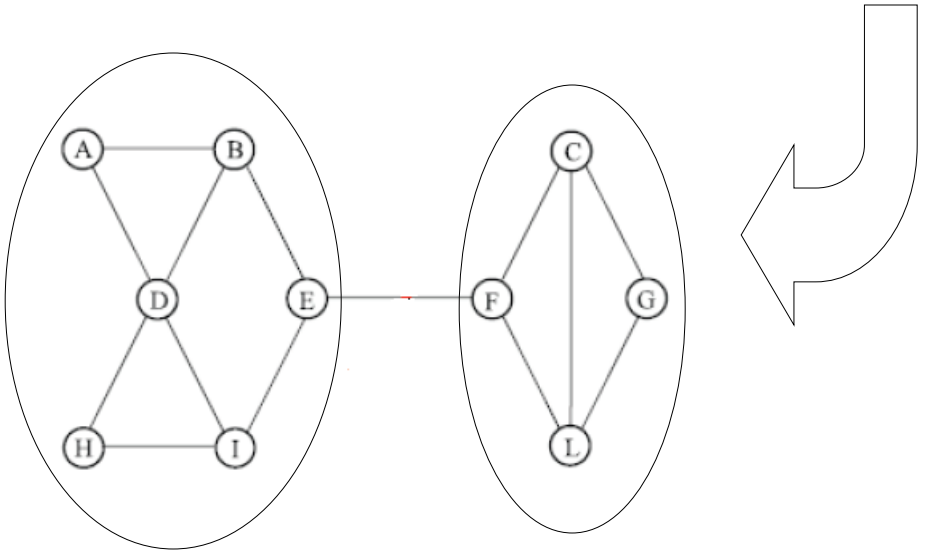
(a) Graph



(b) Smilarity Matrix



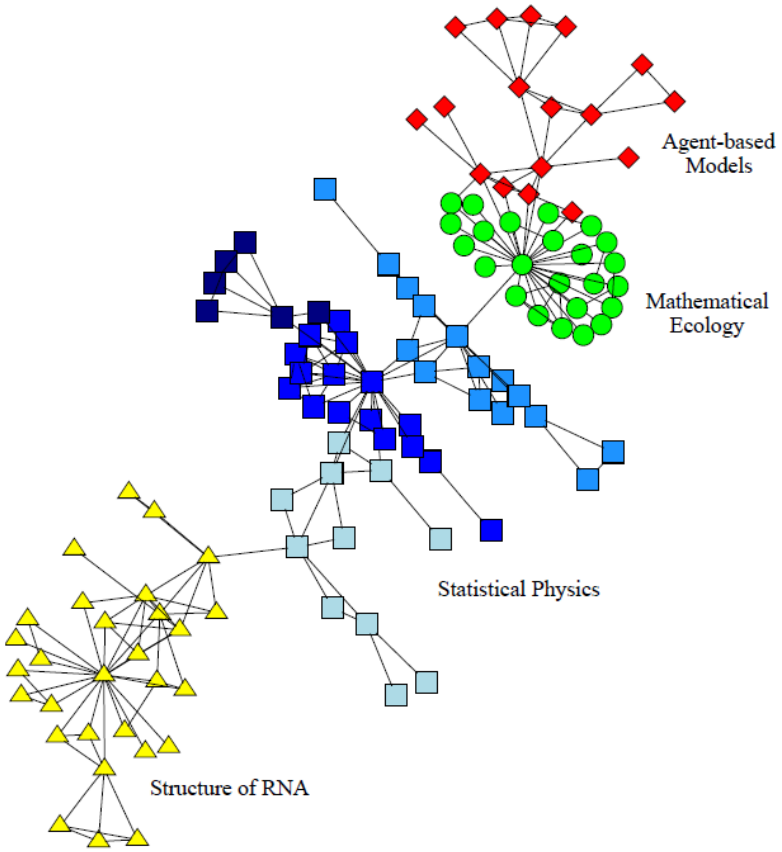
(c) Dendogramme



(d) Clustering

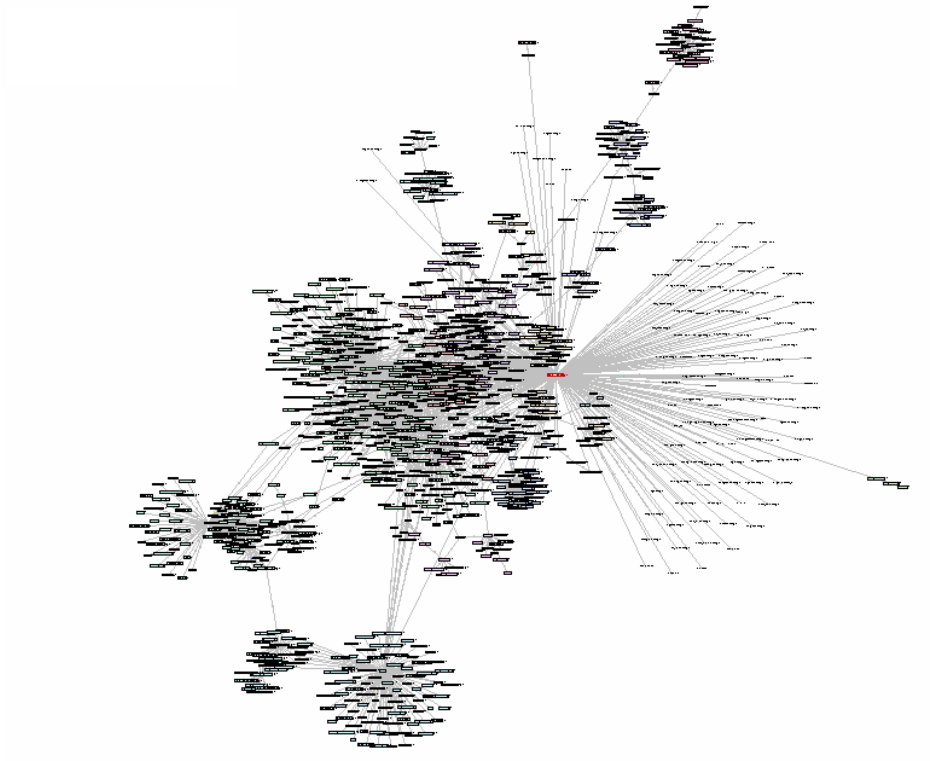
Application

The Santa Fe Institute collaboration network



Application

Enron email network



Discovering Knowledge-Sharing Communities in Question-Answering Forums

Knowledge-Sharing Community

1. A knowledge-sharing community is defined by a set of askers and authoritative users.
2. Within each community, askers exhibit more homogenous behavior in terms of their interactions with authoritative users than elsewhere.
3. Authoritative users may belong to more than one community.

Knowledge-Sharing Community

Existing graph-based community detection methods are not appropriate for our study.

Example

$a_1 : e_1, e_2$

$a_2 : e_1, e_2$

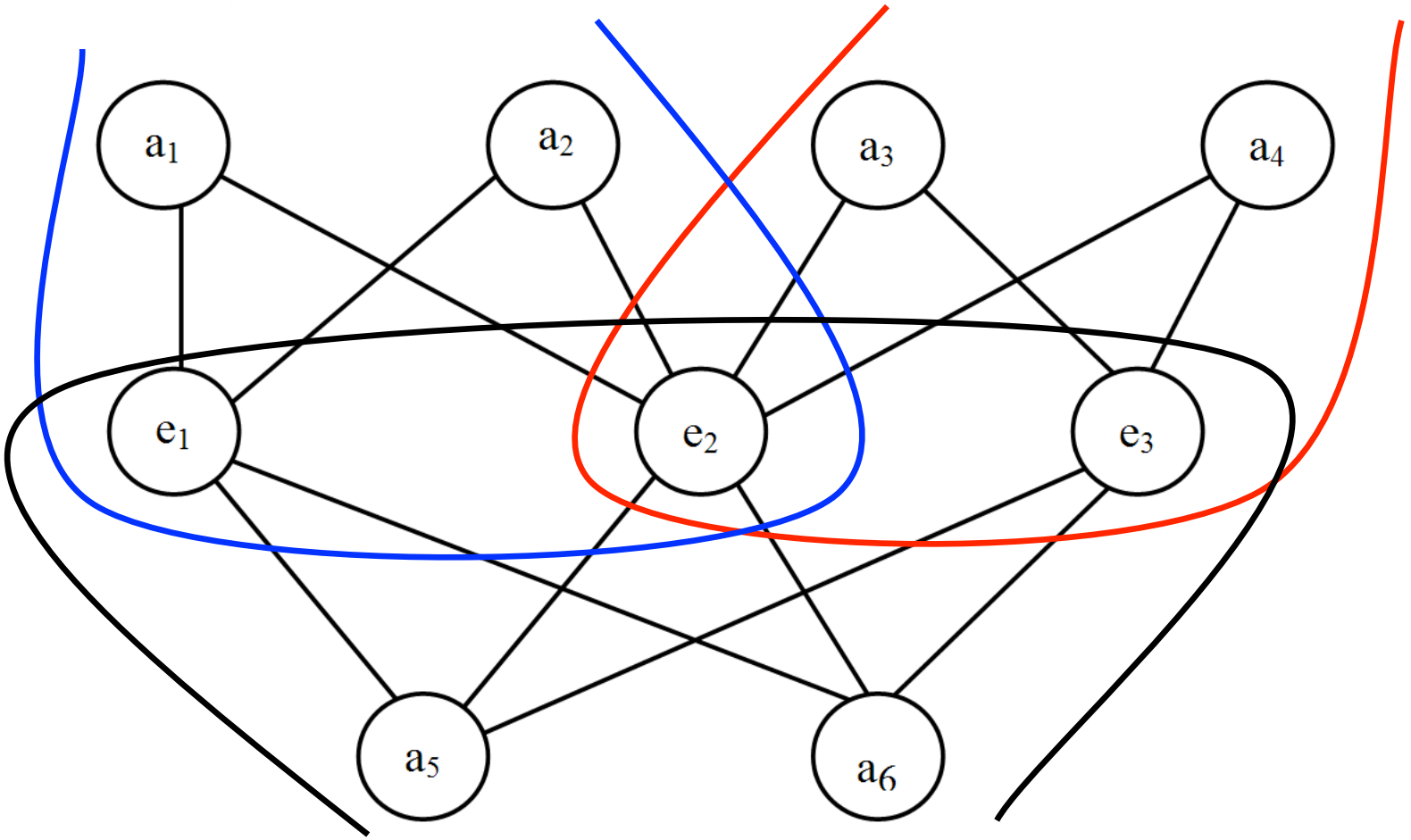
$a_3 : e_2, e_3$

$a_4 : e_2, e_3$

$a_5 : e_1, e_2, e_3$

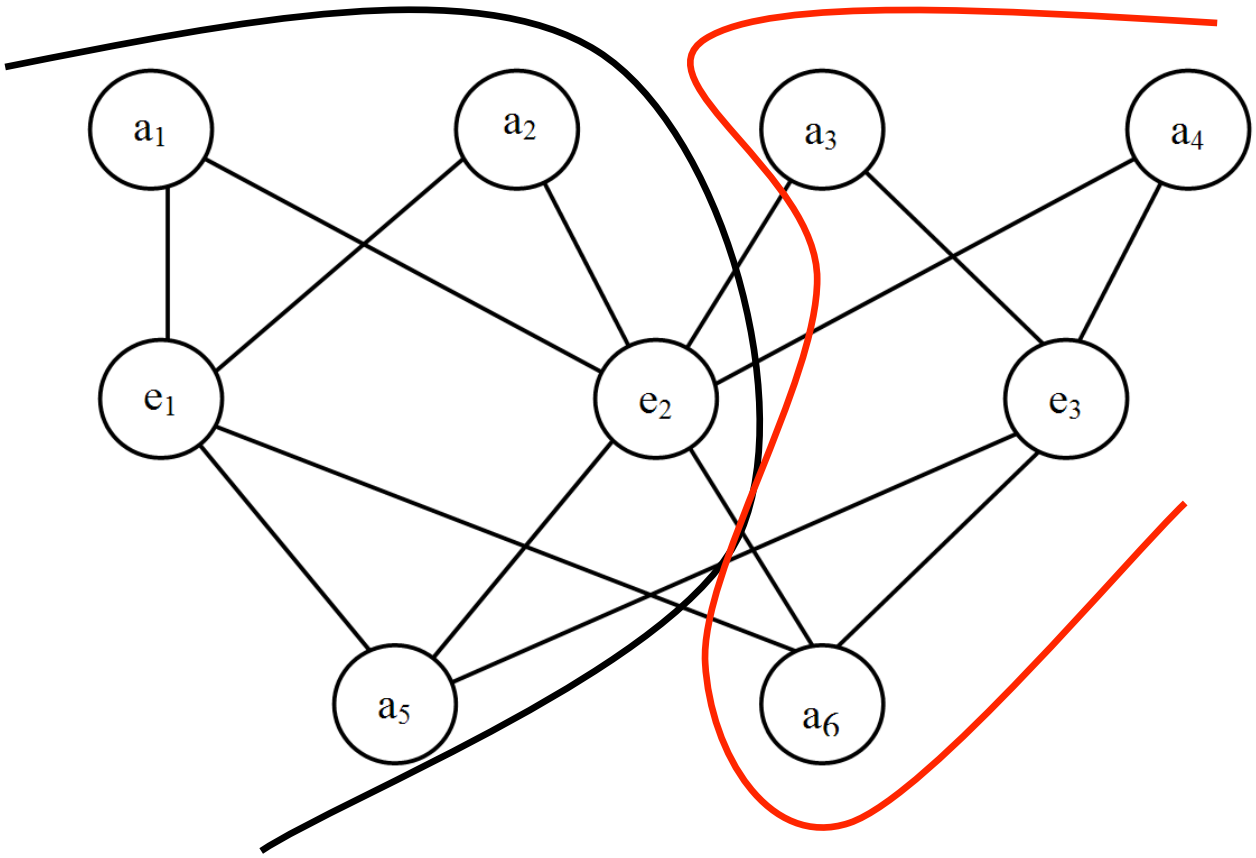
$a_6 : e_1, e_2, e_3$

Example



Modeling users interactions as a graph

The GRACLUS Algorithm



Modeling Interactions Between Users

➢ We use a transactional data model to represent the interactions between askers and authoritative users.

$$T_1 = \{e_1, e_2\}$$
$$T_2 = \{e_1, e_2, e_3\}$$
$$T_3 = \{e_1, e_2, e_3\}$$
$$T_4 = \{e_2, e_3\}$$
$$T_5 = \{e_3, e_4, e_5, e_6\}$$
$$T_6 = \{e_3, e_4, e_5\}$$
$$T_7 = \{e_3, e_4, e_5, e_6\}$$
$$T_8 = \{e_4, e_5, e_6\}$$

- The first community is defined by *T1, T2, T3* et *T4*
- The second community is defined by *T5, T6, T7* et *T8*

Illustration

	e_1	e_2	e_3	e_4	e_5	e_6
a_1	1	1	0	0	0	0
a_2	1	1	1	0	0	0
a_3	1	1	1	0	0	0
a_4	0	1	1	0	0	0
a_5	0	0	1	1	1	1
a_6	0	0	1	1	1	0
a_7	0	0	1	1	1	1
a_8	0	0	0	1	1	1

Boolean representation of the interaction between askers and authoritative users.

The TRANCLUS Algorithm

- $A = \{a_1, a_2, \ldots, a_n\}$ a set of n askers
- $E = \{e_1, e_2, \ldots, e_d\}$ a set of d authoritative users
- $TD = \{T_1, T_2, \ldots, T_n\}$ a collection of n transactions that summarizes the interactions of all askers a_i with the identified authoritative users.

Problem Definition

Given the set *A* of askers and the set *E* of authoritative users,

- Construct the set *TD*.
- Partition *TD* into a set of disjoint clusters

  $C = \{C_1, C_2, \ldots, C_{nC}\}$

➢ The identified clusters represent the communities we want to discover.

Criterion Function

$$CF(C) = \frac{1}{n^2} \sum_{s=1}^{nc} \left[\frac{1}{n_s} \sum_{e \in C_s} \left((occ(e, C_s))^3 \times Z(e) \right) \right]$$

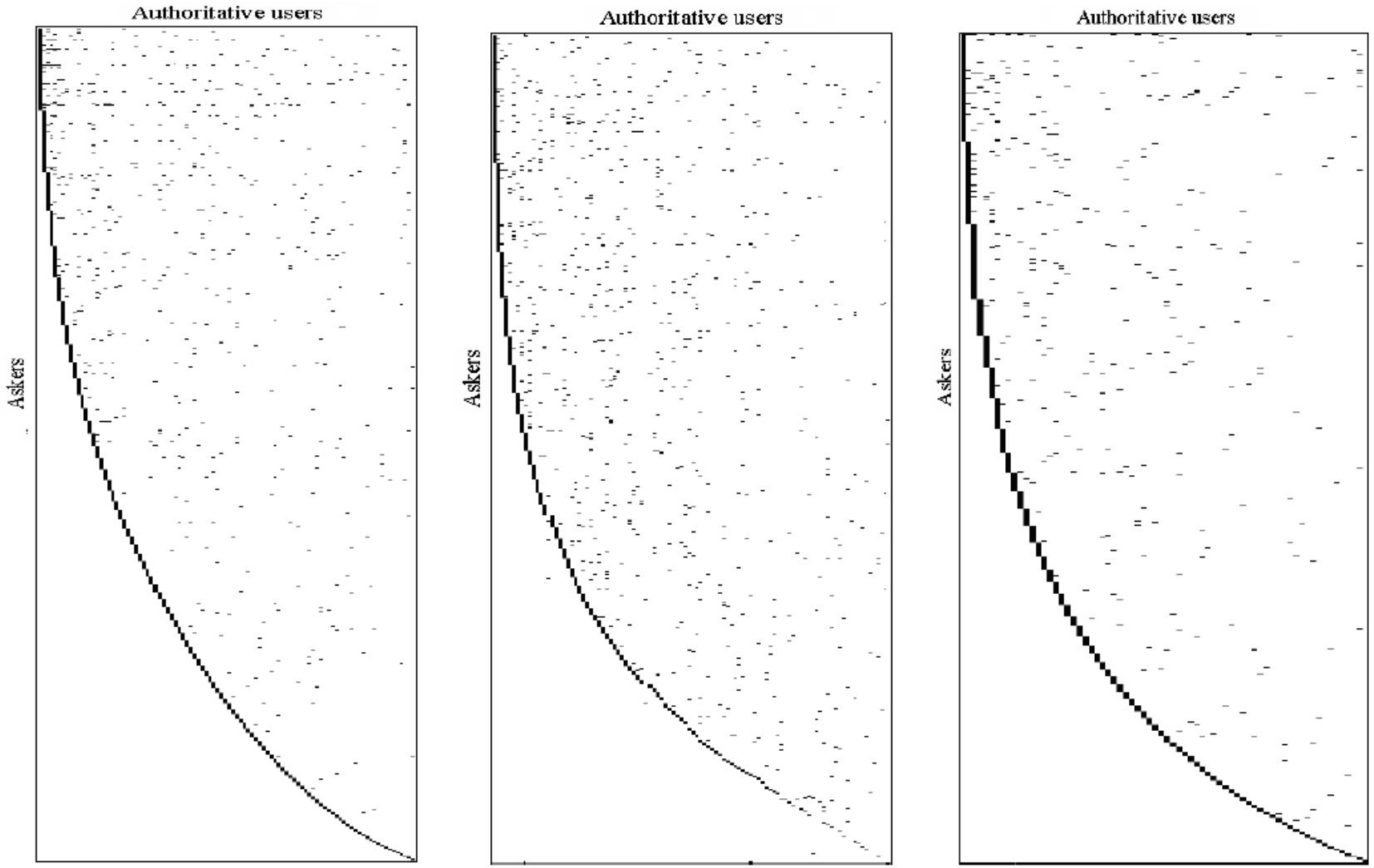
$$Z(e) = \left(n - occ(e, TD) + 1 \right)$$

The TRANCLUS Scheme

Input : A set $TD = \{T_1, T_2, \ldots, T_n\}$ of n transactions
Output: A partition $C = \{C_1, C_2, \ldots, C_{nc}\}$ of nc clusters

```
1  begin
2      for each item e in TD compute the component Z(e) = (n − occ(e, TD) + 1) ;
       // Initialization phase
3      while not end of the dataset file TD do
4          Read the next transaction < T_i, unknown >;
5          Assign T_i to an existing or new cluster C_l to maximize CF(C);
6          Write < T_i, C_l > back to TD;
       // Refinement phase
7      while move == true do
8          move = false ;
9          while not end of the dataset file TD do
10             Read the next transaction < T_i, C_l >;
11             move T_i to an existing or new cluster C_t to maximize CF(C);
12             if C_l ≠ C_t then
13                 Write < T_i, C_t > back to TD;
14                 move = true;
15 end
```

Application to Yahoo! Answers



(a) Biology. (b) Chemistry. (c) Engineering.

Content Analysis

Cluster 1	{PHP, Website, HTML, JavaScript, Ajax, Java}
Cluster 2	{C++, net, games, Windows, Java, Microsoft}

(a) Programming.

Cluster 1	{electricity, circuit, transistor, capacitor, battery, resistor, signal, amplifier }
Cluster 2	{mechanic, engine, motor, design, piping, fluid, machine }

(b) Engineering.

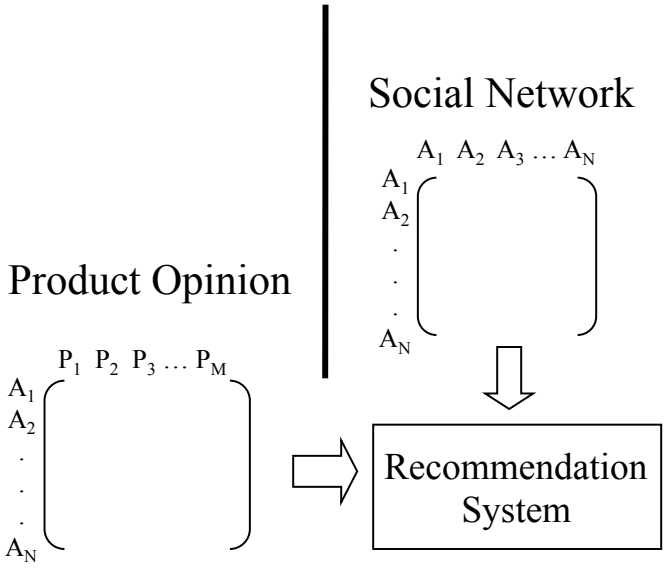
Cluster 1	{cell, dna, blood, human, chromosome, gene, virus }
Cluster 2	{animal, mitosis, meiosis ,cell, bacteria, chromosome, genetic}

(c) Biology.

- The clustered askers tend to post questions on closed related topics

Emerging Application

Influence of Social Networks on Product Recommendations



- Understanding the impact of social networks on market behavior
- Improved recommendation systems