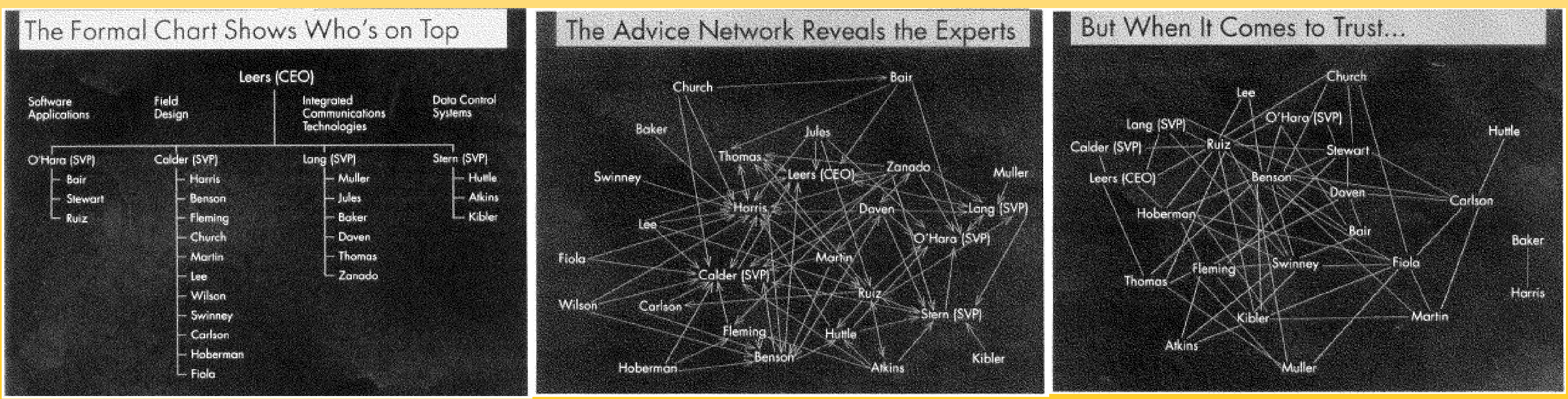
Applications (Outline)

- Organization Theory
- Semantic Web
- Viral Marketing
- Social Influence and E-Commerce
- Social Computing
- Criminal Network Analysis
- Newsgroup Message Classification
- Social Recommendation Systems
- Terrorism and Crime Related Weblog Social Network

Organization Theory

- **Krackhardt and Hanson (1993)**
  - **Informal (social) networks present in an enterprise are different from formal networks**
  - **Different patterns exist in such networks like imploded relationships, irregular communication patterns, fragile structures, holes in network and bow ties**
- **Lonier and Matthews (2004)**
  - **Survey as well as study the impact of informal networks on an enterprise**



(Source: Krackhardt and Hanson,1993)

Extracting Co-appearance Networks among Organizations

- Extracting Inter-Firm Networks from WWW (Jin et al., 2007)

Results form a search engine can be estimated in a more robust way (Matsuo et al., 2007)

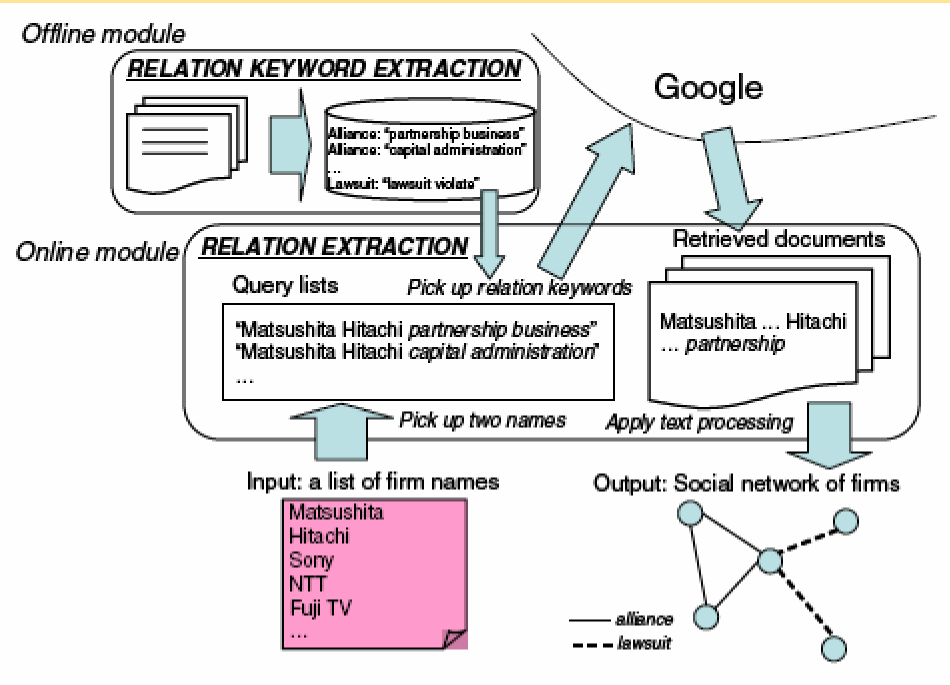
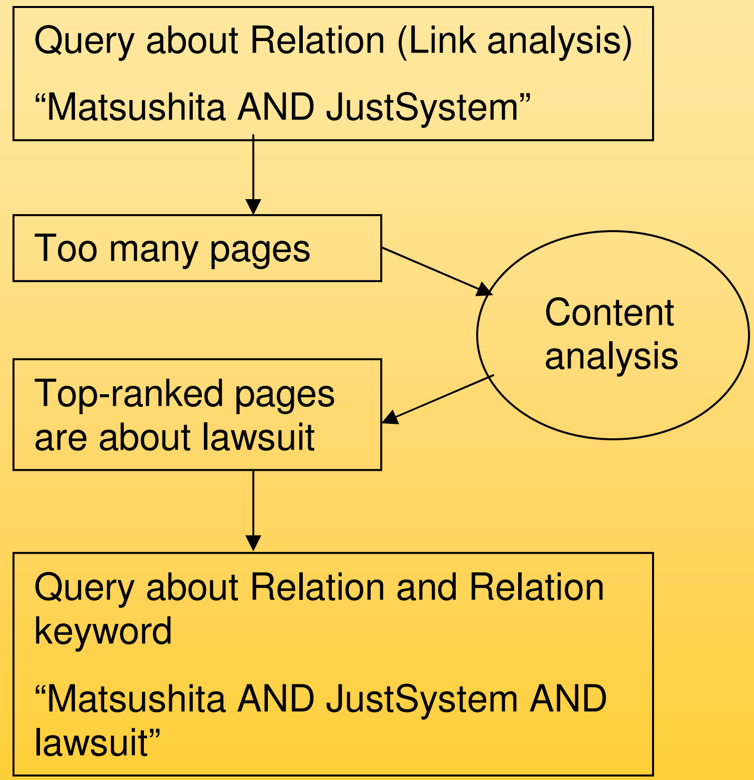


Figure 2. System flow to extract a firm network.



Semantic Web Community

- Ding et al (2005)
  - Semantic web enables explicit, online representation of social information while social networks provide a new paradigm for knowledge management e.g. Friend-of-a-friend (FOAF) project (http://www.foaf-project.org)
  - Applied SNA techniques to study this FOAF data (DS-FOAF)

Preliminary analysis of DS-FOAF data (Ding et al, 2005)

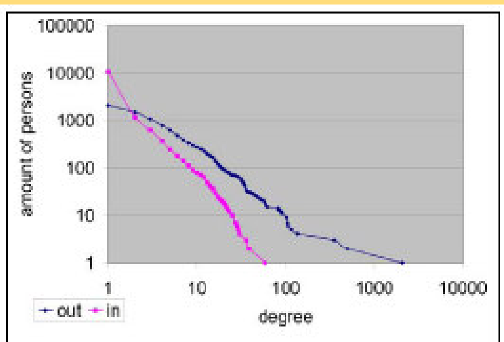


Figure 3: Cumulative distribution of in-degree and out-degree

Degree distribution

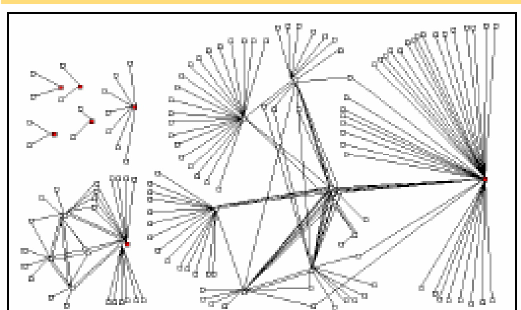
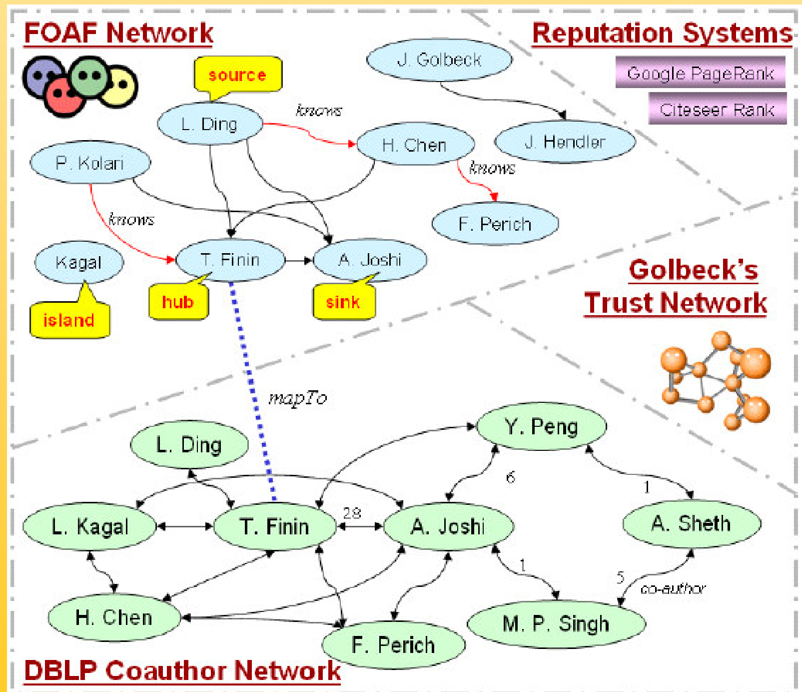


Figure 4: We found that connected components in FOAF networks followed a few simple patterns.

Connected components



Trust across multiple sources (Ding et al, 2005)

Semantic Web and SNA

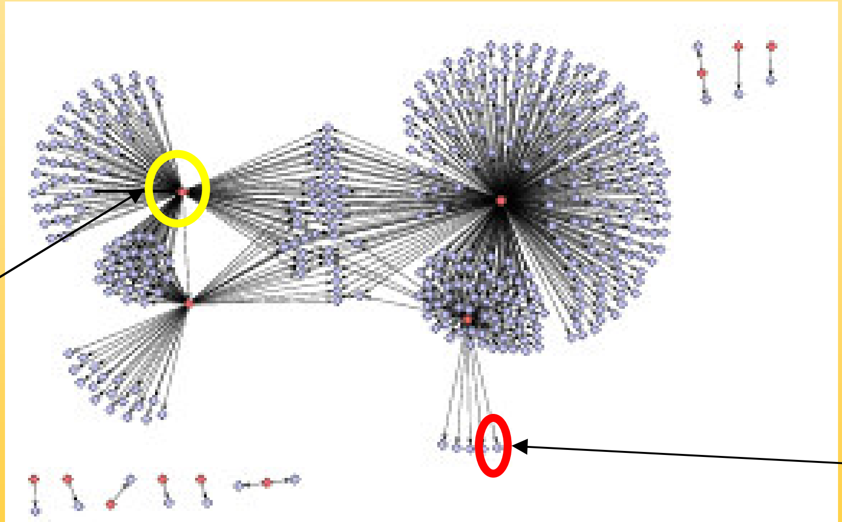
- The friend of a friend (FOAF) project has enabled collection of machine readable data on online social interactions between individuals. http://www.foaf-project.org
- Mika (2005) illustrates Flink system (http://flink.semanticweb.org/) for extraction, aggregation and visualization of online social network.

The Sun never sets under the Semantic Web: the network of semantic web researchers across globe (Mika, 2005)

Snapshot of clusters (http://flink.semanticweb.org/)

Viral Marketing

- Domingos(2005), Domingos and Richardson (2001, 2002)
  - *Network value* of a customer is the expected profit from marketing a product to a customer, accounting for the customer's influence on the buying decisions of other customers
  - Propose a greedy strategy for identifying customers with maximum network value



(Source: Leskovec et al, 2006)

- Kempe at al (2003)
  - For a general class of cascading models, the problem of identifying customers with maximum network value is NP-hard
  - A greedy strategy provides a solution within 63% of the optimal

Social Influence and E-Commerce[1]

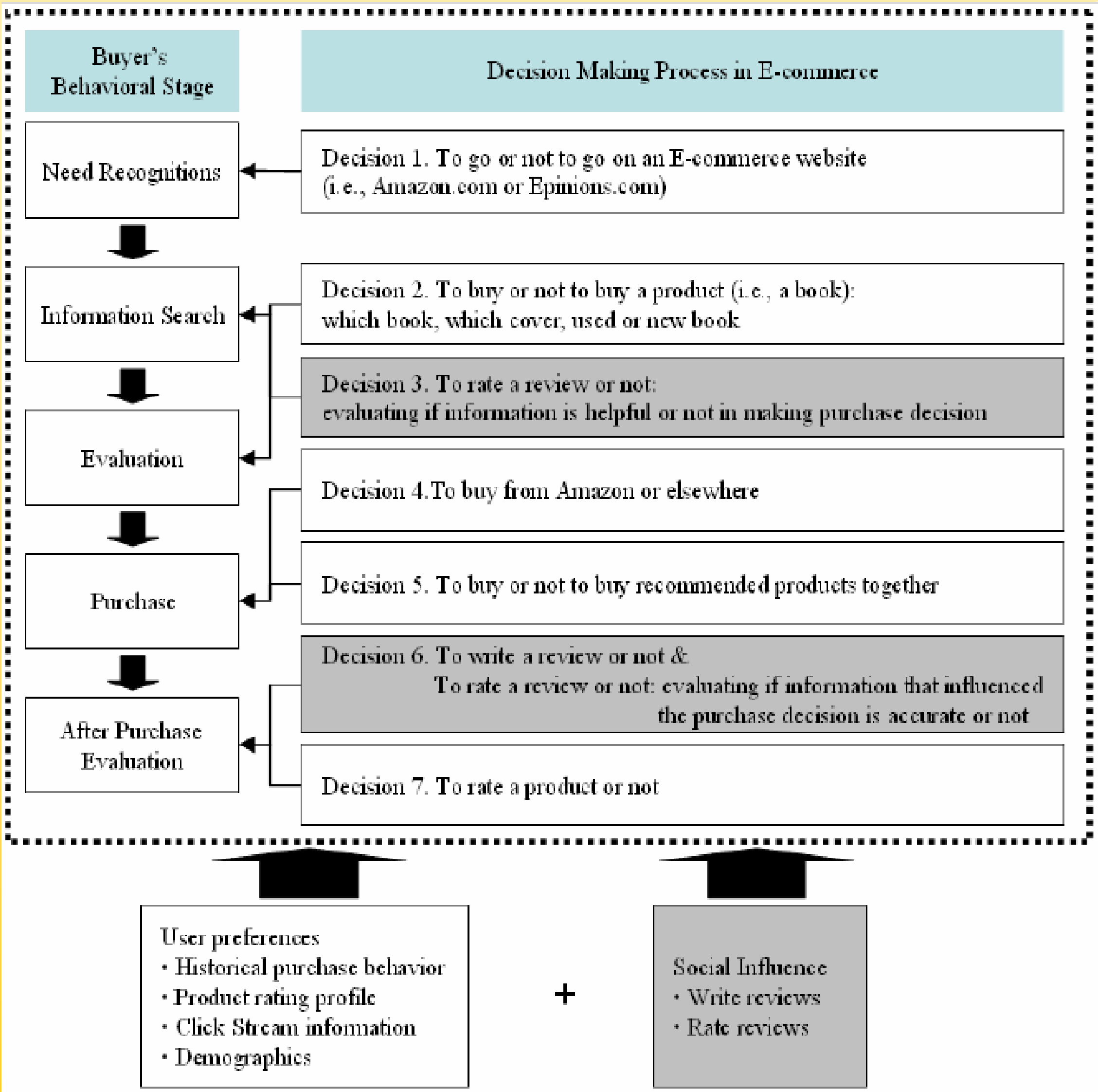


Figure. 1. A decision making process in E-commerce

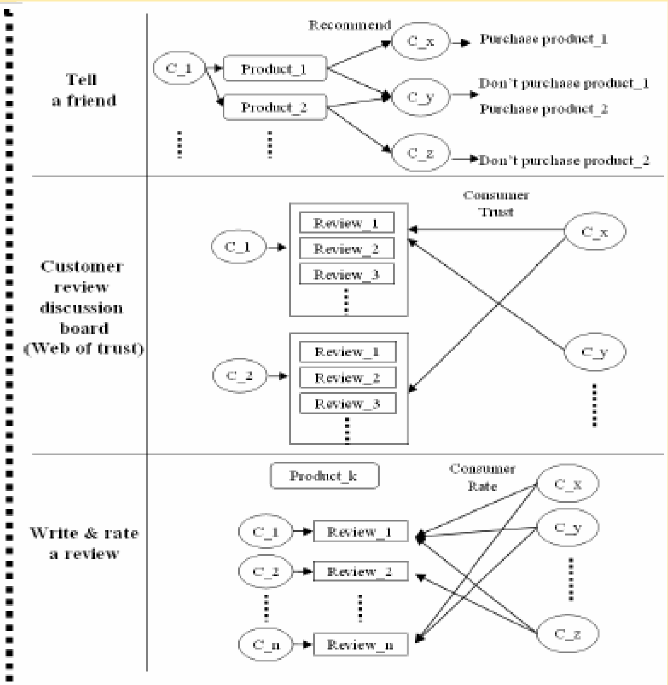


Figure 2. The data about social interaction

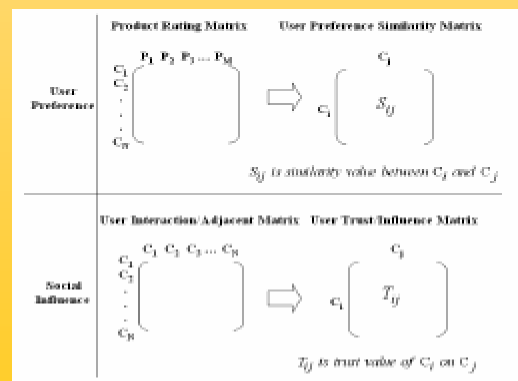


Figure 3. E-commerce information source

1. Young Ae Kim, Jaideep Srivastava: Impact of social influence in e-commerce decision making. ICEC 2007: 293-302

Social Computing

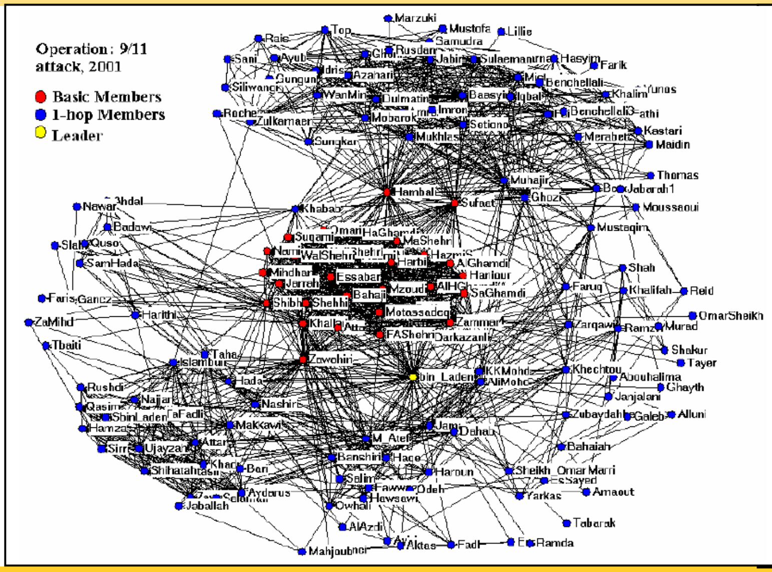
- Combining social computing and ubiquitous computing
  - iBand: A bracelet like device used for exchanging personal and relationship info.
    (Kanis et al. 2005)

Criminal Network Analysis

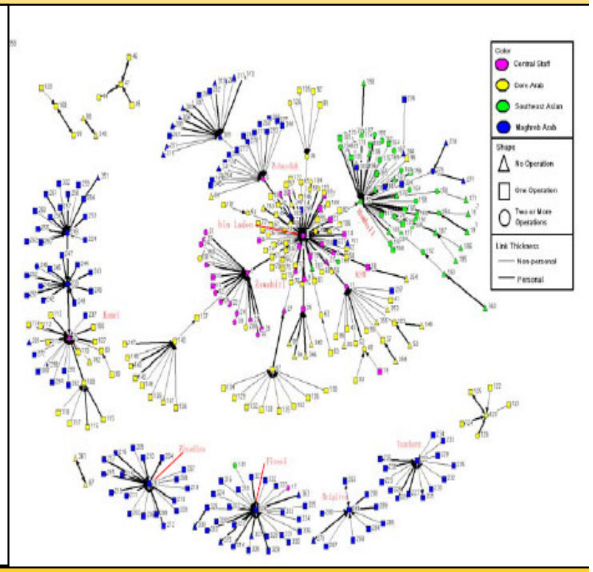
- **Example (Qin et al, 2005)**
  - **Information collected on social relations between members of Global Salafi Jihad (GSJ) network from multiple sources (e.g. reports of court proceedings)**
  - **Applied social network analysis as well as Web structural mining to this network**
  - **Authority derivation graph (ADG) captures (directed) authority in the criminal network**

Ranking	Leader	Gatekeeper	Outlier
	Central Member		
1	Zawahiri	bin Laden	Khalifah
2	Makkawi	Zawahiri	SbinLaden
3	Islambuli	Khadr	Ghayth
4	bin Laden	Sirri	M Atef
5	Attar	Zubaydah	Sheikh Omar
	Core Arab		
1	Khallad	Harithi	Elbaneh
2	Shibh	Nashiri	Khadr4
3	Jarrah	Khallad	Janjalani
4	Atta	Johani	Dahab
5	Mihdhar	ZaMihd	Mehdi
	Maghreb Arab		
1	Hambali	Baasyir	Siliwangi
2	Baasyir	Hambali	Fathi
3	Mukhlas	Gungun	Naharudin
4	Iqbal	Muhajir	Yunos2
5	Azahari	Setiono	Maidin
	Southeast Asian		
1	Doha	Yarkas	Mujati
2	Benyaich2	Zaoui	Parlin
3	Fateh	Chaib	Mahdjoub
4	Chaib	DavidC	Zinedine
5	Benyaich1	Maaroufi	Ziyad

Terrorists with top centrality ranks in each clump



1-hop network of 9/11 attack

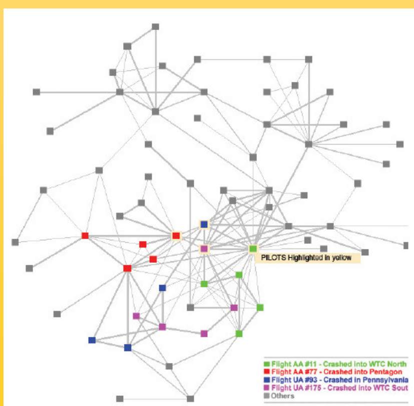


ADG of GSJ network

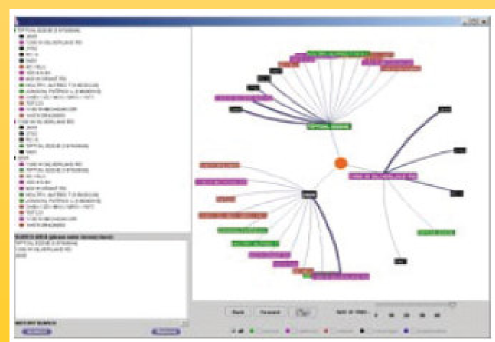
Criminal Network Analysis

- Knowledge gained by applying SNA to criminal network aids law enforcement agencies to fight crime proactively
- Criminal networks are large, dynamic and characterized by uncertainty.
- Need to integrate information from multiple sources (criminal incidents) to discover regular patterns of structure, operation and information flow (Xu and Chen, 2005)
- Computing SNA measures like centrality is NP-hard
  - **Approximation techniques (Carpenter et al 2002)**
- Visualization techniques for such criminal networks are needed

Figure: Terrorist network of 9/11 hijackers (Krebs, 2001/ Xu and Chen, 2005)



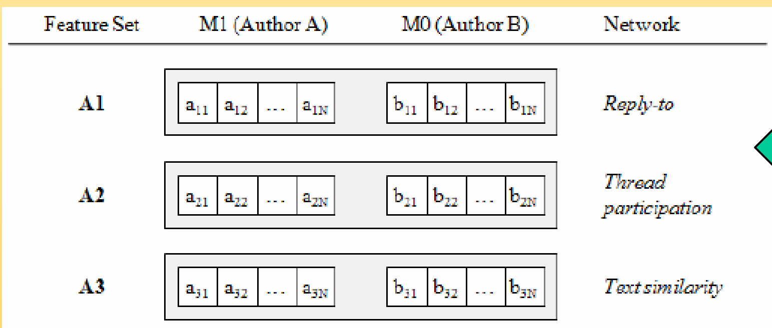
Example of 1st generation visualization tool.

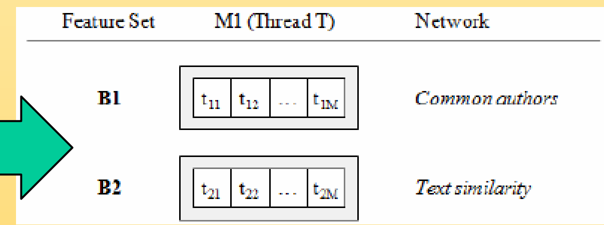


Example of 2nd generation visualization tool

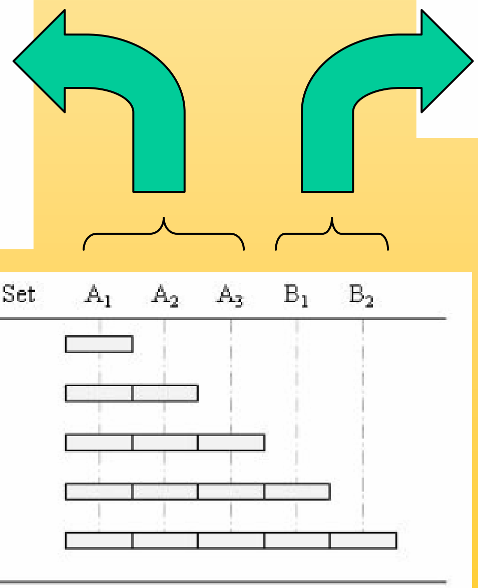
Newsgroup Message Classification

- Using SNA to help classify newsgroup messages (Fortuna et. Al, 2007)
  - SVM classifier
  - Rich feature set from “networks”





Networks where users socially interact with others through posting and replying



Networks where similarities between two nodes are determined by authors or contents

Social Recommendation Systems

- **Initial approaches**
  - **Anonymous recommendations: treat individuals preferences as independent of each other**
  - **Failure to account for influence of individual's social network on his/her preferences**
- **Kautz et al (1997)**
  - **Incorporate information of social networks into recommendation systems**
  - **Enables more focused and effective search**
- **McDonald (2003)**
  - **Analyzes the use of social networks in recommendation systems**
  - **Highlights the need to balance between purely social match vs. expert match**
  - **Aggregate social networks may not work best for individuals**
- **Palau et al, (2004)**
  - **Apply social network analysis techniques to represent & analyze collaboration in recommender systems**
- **Lam (2004)**
  - **SNACK - an automated collaborative system that incorporates social information for recommendations**
  - **Mitigates the problem of cold-start, i.e. recommending to a user who not yet specified preferences**

Social Recommendation Systems

Deriving Ratings Through Social Network Structures

(Alshabib et al 2006)

- **Motivation: Sparsity problem in recommendation systems**
- **Using social networks to aggregate ratings in a recommendation system**
- **Compare rating based at the level of product categories instead of products**
- **A user with many ratings should have more weight than a user with fewer ratings.**
- **Recommendation based on the social network built from trust and reputation.**

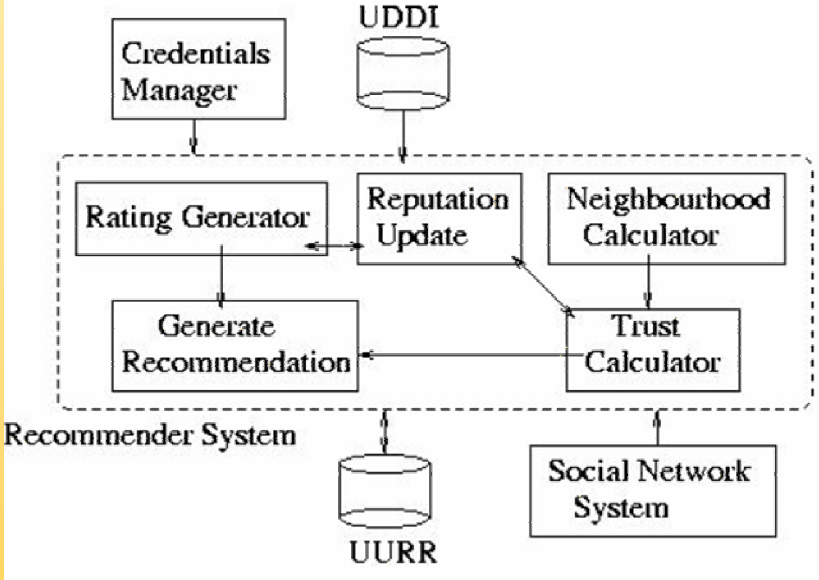


Fig. 4. Internal Architecture of the Recommender Component

Terrorism and Crime Related Weblog Social Network

- Yang and Ng, 2007

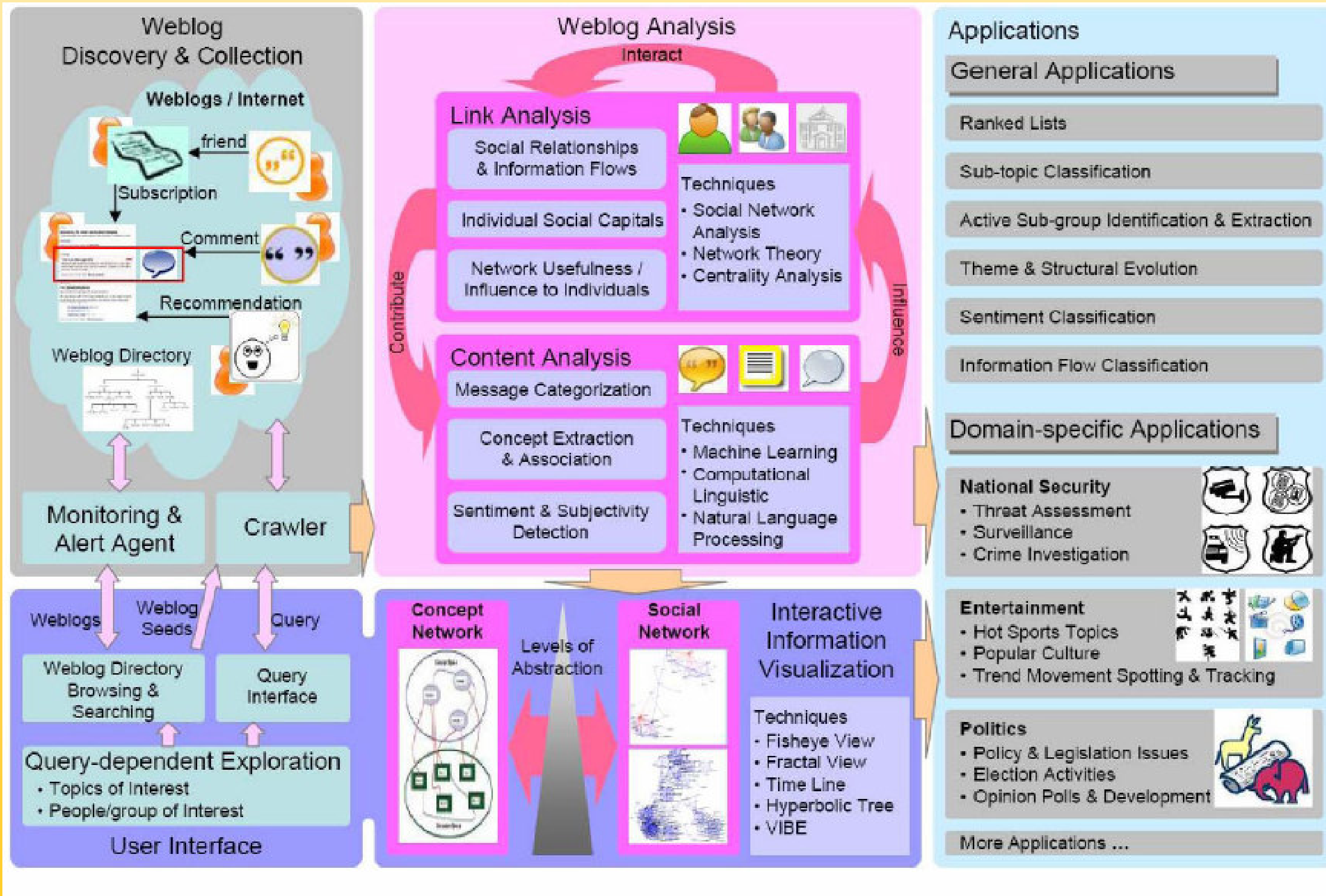
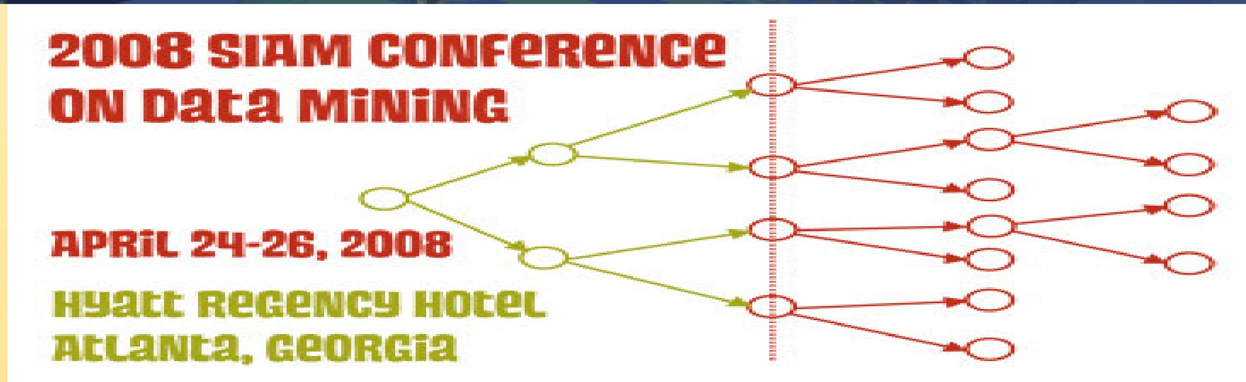


Figure 1. Framework of the proposed Terrorism and Crime Related Weblog Social Network project



Emerging Applications in SNA

Example of E-mail Communication

- A sends an e-mail to B
  - With Cc to C
  - And Bcc to D
- C forwards this e-mail to E
- From analyzing the header, we can infer
  - A and D know that A, B, C and D know about this e-mail
  - B and C know that A, B and C know about this e-mail
  - C also knows that E knows about this e-mail
  - D also knows that B and C do not know that it knows about this e-mail; and that A knows this fact
  - E knows that A, B and C exchanged this e-mail; and that neither A nor B know that it knows about it
  - and so on and so forth …

Modeling Pair-wise Communication

- **Modeling pair-wise communication between actors**
  - **Consider the pair of actors *(A_x,A_y)***
  - **Communication *from A_x to A_y* is modeled using the Bernoulli distribution *L(x,y)=[p,1-p]***
  - **Where,**
    - ***p* = (# of emails from A_x with A_y as recipient)/(total # of emails exchanged in the network)**
- **For *N* actors there are *N(N-1)* such pairs and therefore *N(N-1)* Bernoulli distributions**
- **Every email is a Bernoulli trial where success for *L(x,y)* is realized if A_x is the sender and A_y is a recipient**

Modeling an agent's belief about global communication

- **Based on its observations, each actor entertains certain beliefs about the communication strength between all actors in the network**
- **A belief about the communication expressed by *L(x,y)* is modeled as the Beta distribution, *J(x,y)*, over the parameter of *L(x,y)***
- **Thus, belief is a probability distribution over all possible communication strengths for a given ordered pair of actors *(A_x,A_y)***

Measures for Perceptual Closeness

- We analyze the following aspects
  - Closeness between an actor's belief and reality, i.e. "true knowledge" of an actor
  - Closeness between the beliefs of two actors, i.e. the "agreement" between two actors
- We define two measures, *r-closeness* and *a-closeness* for measuring the closeness to reality and closeness in the belief states of two actors respectively

Perceptual Closeness Measures

- The a-closeness measure is defined as the level of agreement between two given actors A_x and A_y with belief states $B_{x,t}$ and $B_{y,t}$ respectively, at a given time t and is given by,

$$a-closeness(B_{x,t}, B_{y,t}) = \frac{1}{1 + div(B_{x,t}, B_{y,t}) + div(B_{y,t}, B_{x,t})} \ldots(6)$$

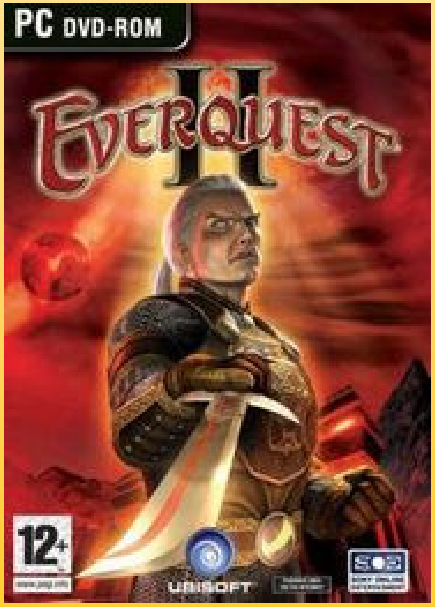
- The r-closeness measure is defined as the closeness of the given actor A_k's belief state $B_{k,t}$ to reality at a given time t and it is given by,

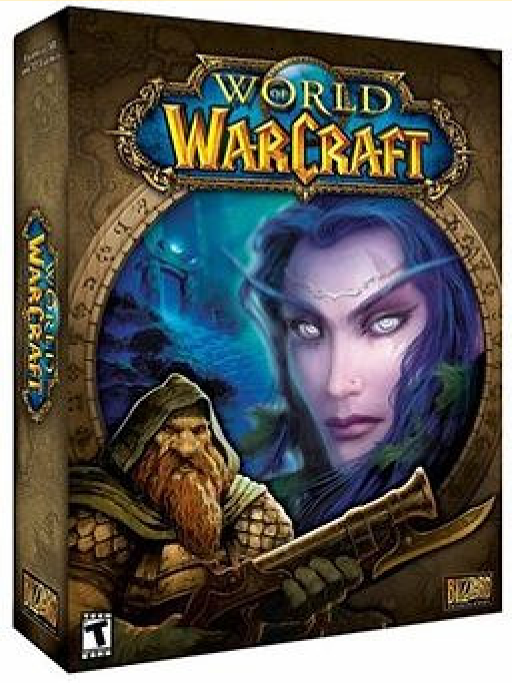
$$r-closeness(A_k) = \frac{1}{1 + div(B_{S,t}, B_{k,t})} \ldots(7)$$

Where $B_{S,t}$ is the belief state of the super-actor A_S at time t

Online Games

- Massively Multiplayer Online Role Playing Games (MMORPG) are computer games that allow hundreds to thousands of players to interact and play together in a persistent online world





SECOND LIFE

Popular MMO Games- Everquest 2, World of Warcraft and Second Life

MMORPG – Everquest 2

- MMORPGs (MMO Role Playing Games) are the most popular of MMO Games
  - Examples: World of Warcraft by Blizzard and Everquest 2 by Sony Online Entertainment
- Various logs of players' behavior are maintained
- Player activity in the environment as well his/her chat is recorded at regular time instances, each such record carries a time stamp and a location ID
- Some of the logs capture different aspects of player behavior
  - Guild membership history (member of, kicked out of, joined, left)
  - Achievements (Quests completed, experience gained)
  - Items exchanged and sold/bought between players
  - Economy (Items/properties possessed/sold/bought, banking activity, looting, items found/crafted)
  - Faction membership (faction affiliation, record of actions affecting faction affiliation)

Impact on Social Science

- Interactions in MMO Gaming environments are real
- MMO Games provide sociologists with a unique source of data allowing them to observe real interactions in the context of a complete environment on a very fine granularity
- Gets around the serious issue of unbiased complete data collection
- Analysis of such data presents novel computational challenges
  - The scale of data is much larger than normally encountered in traditional social network analysis
  - The number of environment variables captured is greater
  - Player interaction data is captured at a much finer granularity
- MMORPG data requires models capable of handling large amounts of data as well as accounting for the many environment variables impacting the social structure

Social Science Research with Everquest 2 Data

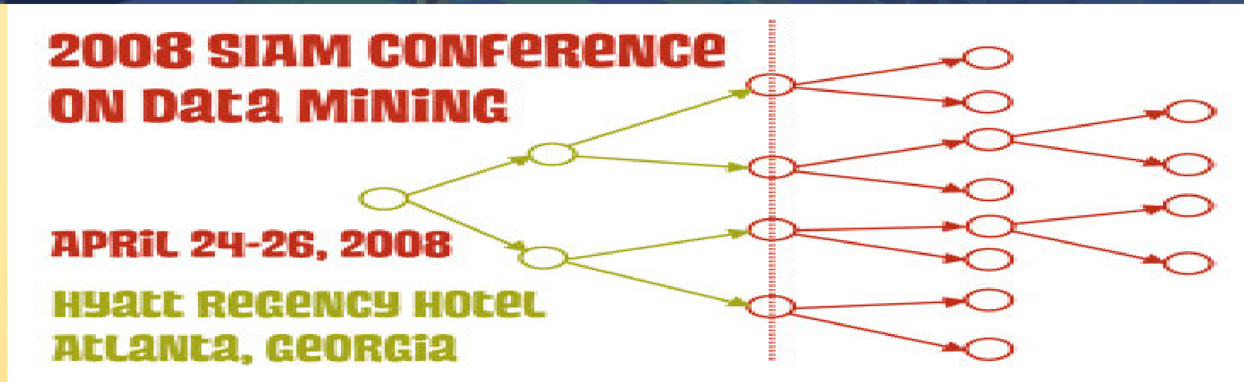
- Objective of our research from a social science point of view is to improve understanding of the dynamics of group behavior
- Traditional analysis of dynamics of group behavior works with a *fixed* and *isolated* set of individuals
- MMORPG data enables us to look at dynamics of groups in a new way
  - Multiple groups are part of a large social network
  - Individuals from the social network can join or leave groups
  - Groups are not isolated and some of them can be related i.e. they may be geared towards specific objectives, each of which works towards a larger goal (e.g. different teams working towards disaster recovery)
  - The emergence, destruction as well as dynamic memberships of the groups depend on the underlying social network as well as the environment

DM Challenges for Social Science Research with Everquest 2 Data

- Inferring player relationships and group memberships from game logs
  - Basic elements of the underlying social network such player-player and layer-group relationships need to be extracted from the game logs
- Developing measures for studying player and group characteristics
  - Novel measures need to be developed that measure individual and group relationships for dynamic groups
  - Novel metrics must also be developed for quantifying relationships between the groups themselves, the groups and the underlying social network as well as the groups and the environment
- Efficient computational models for analyzing group behavior
  - Extend existing group analysis techniques from the social science domain to handle large datasets
  - Develop novel group analysis techniques that account for the dynamic multiple group scenario as well as the data scale

Conclusion

- Computers have provided the ideal infrastructure for
  - Fostering social interaction
  - Capture it at a very fine granularity
  - Practically no reporting bias
- ➔ **Fertile research area for data mining research**
- The emerging field of computational social science has the potential to revolutionize social sciences much as
  - Gene Sequencing revolutionized study of genetics
  - The electron microscope revolutionized chemistry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