UNIT IV PREDICTING HUMAN BEHAVIOUR AND PRIVACY ISSUES

Understanding and predicting human behaviour for social communities - User data management - Inference and Distribution - Enabling new human experiences - Reality mining - Context - Awareness - Privacy in online social networks - Trust in online environment - Trust models based on subjective logic - Trust network analysis - Trust transitivity analysis - Combining trust and reputation - Trust derivation based on trust comparisons - Attack spectrum and countermeasures.

4.1 Understanding and predicting human behavior for social communities

With the rapid advance in technology, it is becoming increasingly feasible for people to take advantage of the devices and services in the surrounding environment to remain “connected” and continuously enjoy the activity they are engaged in, be it sports, entertainment, or work.

Ubiquitous computing environment will allow everyone permanent access to the Internet anytime, anywhere and anyhow.

QoE (Quality of Experience) is a consequence of a user"s internal state (e.g., predispositions, expectations, needs, motivation, mood), the characteristics of the designed system (e.g., usability, functionality, relevance) and the context (or the environment) within which the interaction occurs (e.g., social setting, meaningfulness of the activity).

4.2 User Data Management, Inference and Distribution

- User-oriented creation/execution environments lack on the capability to adapt to the heterogeneity of devices, technologies and the specificity of each individual user.
- For user flexibility and personalization requires user profile management systems which include limited information about user preferences and contexts.
- In order to apply user information across a range of services and devices, there is a need for standardization of user related data and the architecture that enables their interoperability.
- These efforts have been taken by European Telecommunications Standards Institute (ETSI), the Third Generation Partnership Project (3GPP), Open Mobile Alliance (OMA)
- Considering data requirements from a wide range of facilities the concept of Common Profile Storage (CPS) is defined by 3GPP.

  - as a framework for streamlining service-independent user data and storing it under a single logical structure in order to avoid duplications and data inconsistency

- Logically centralized data storage can be mapped to physically distributed configurations and should allow data to be accessed in a standard format
- Data storage can be grouped into three main classes: the syntactic, semantic and modeling approaches which enable interoperability of user profile data management for a Future Internet.
- To improve the degree of services personalization it is important to generate new information from the existing one.
- In this sense, social networks, user modeling and reality mining techniques can be empowered to study patterns and predict future behaviors.
- The basic motivation is the demand to exploit knowledge from various amounts of data collected, pertaining to social behavior of users in online environments.
- To handle complex situations, the concept of decomposition is applied to the situation into a hierarchy of sub-situations.
- These sub-situations can be handled autonomously with respect to sensing and reasoning. The handling of complex situations can be simplified by decomposition.
- Another similar perspective is called **layered reasoning**, where
  - the first stage involves feature extraction and grouping (i.e., resulting in low-level context),
  - the second event, state and activity recognition (i.e., originating mid-level context), while
  - the last stage is dedicated to prediction and inference of new knowledge
- Research in Social network usually focuses on
  - quantifying or qualifying the relationship between peers,
  - where algorithms such as centrality and prestige can be used to calculate the proximity, influence or importance of a node in a network,
  - while clustering and classification can be applied to similarity computation, respectively.

Combining all of pre-enunciated concepts with ontologies and semantic technologies, we present a generic framework for managing user related data, will pave the way to understanding and predicting future human behavior within social communities.

4.3 Enabling New Human Experiences

It is important to understand what are the technologies behind user data management, how to link them and what can they achieve when combined in synergy.

4.3.1. The Technologies

a. Social Networks

- Humans in all cultures at all times form complex social networks
- Social network - means ongoing relations among people that matter to those engaged in the group, either for specific reasons or for more general expressions of mutual agreement.
- Social networks among individuals who may not be related can be validated and maintained by agreement on objectives, social values, or even by choice of entertainment.
    - involve reciprocal responsibilities and roles that may be selfless or self-interest based.
- Social networks are trusted because of shared experiences and the perception of shared values and shared needs
- Behavior of individuals in online networks can be slightly different from the same individuals interacting in a more traditional social network (reality).
- It gives us invaluable approaches on the people we are communicating with, which groups are we engaged, which are our preferences, etc.

b. Reality Mining

- To overcome the differences between online and “offline” networks, reality mining techniques can be empowered to approximate both worlds, proving awareness about people actual behavior.
- It is the collection and analysis of machine sensed environmental data pertaining to human social behavior.
- It typically analyzes sensor data from mobiles, video cameras, satellites, etc

- Predictive patterns such as „honest signals" provide major factors in human decision making.
- Reality mining enables „big picture” of specific social contexts by aggregating and averaging the collected data
- It allows data/events correlation and consequently future occurrences extrapolation.

c. Context-Awareness

By assessing and analyzing visions and predictions on computing, devices, infrastructures and human interaction, it becomes clear that:

a. context is available, meaningful, and carries rich information in such environments,

b. that users" expectations and user experience is directly related to context,

c. acquiring, representing, providing, and using context becomes a crucial enabling technology for the vision of disappearing computers in everyday environments.

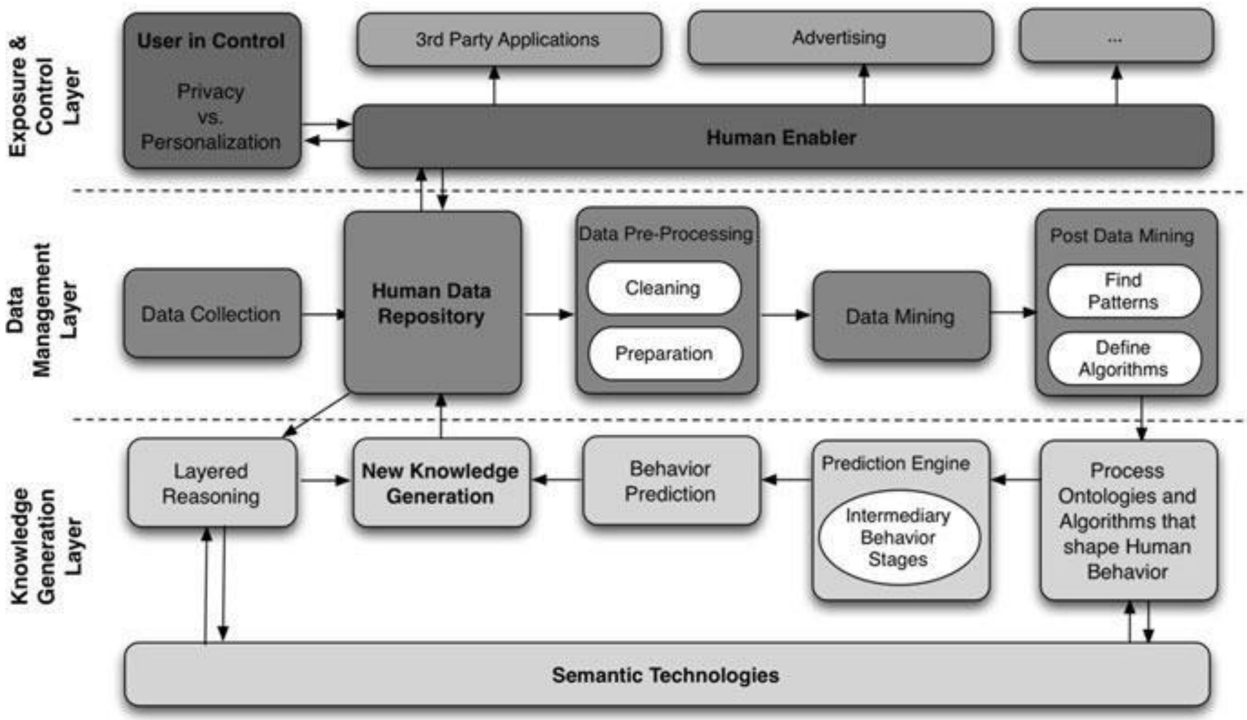
4.3.2 Architectural Framework and Methodology

To enable human behavior understanding and prediction, there are several independent but complementary steps that can be grouped into three different categories:

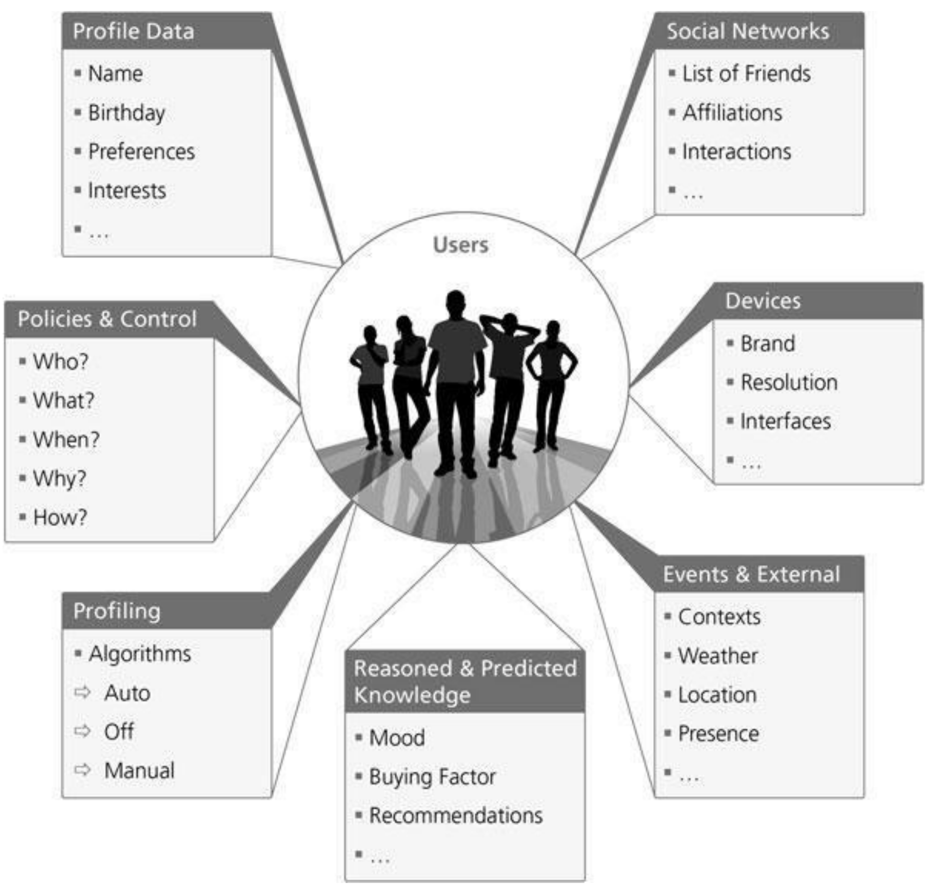
- ✓ Data Management
- ✓ New Knowledge Generation and
- ✓ Service Exposure and Control.

a. Data management

- This activity usually starts with data acquisition.
- Involves gathering of information from different information systems.
- Figure depicts these relationships as well as the sequence of activities involved.



- Figure below exemplifies the type of information that can be stored in the Human Data Repository



- Data is not usually captured without errors. Therefore it is necessary to preprocess it in advance before mining.
- Otherwise it would not be possible to correlate information correctly.
- Once this is done, data is mined by using two different approaches:
    - ✓ know statistical algorithms to help pattern recognition and consequent algorithmic modeling,
    - ✓ the opposite approach, where specific algorithms are designed to identify patterns in the data (this requires previous modeling).

Combining both, allows us to address the specifics of our applications, and at the same time, automatically detect new relevant correlations that might occur after a few iterations.

b. Knowledge Generation

- New information inference is based on user related data (called as context)
- Three different categories:
    - Real-time
    - Historical data
    - Reasoned context
- In Fig. below, there are several layers of abstraction in a context-aware system and any context-aware middleware or architecture must therefore be capable of building representations and models of these abstractions.
- However, these high-level abstractions can only be made from lower level context, which requires some form of context management function (performed by a Context Broker).
- In our case, this is performed at the **Human Data Repository**.
- The main context management features are context acquisition, context aggregation & fusion, context dissemination, discovery and lookup.
- In order to manipulate context information, it must be represented in some form that is compatible with the models that will be used in the reasoning and situation recognition processes.
- These models could be object oriented, ontological, rule based, logic based, based on semantic graphs or fuzzy logic sets.
- Reasoning mechanisms allow high-level context to be deduced or situations to be recognized that is output of one process can be used as an input to another.

- Reasoning is also used to check the consistency of context and context models.
- It is very important to stress that the prediction does not necessarily anticipates the user wishes or desires, but a possible future that could be interesting for the user.

c. Service Exposure and Control

- The third layer is divided into two main capabilities.
- The **first is user-centric** and relates to the ability of the user to stay in control of the whole scenario, enabling it to specify when, what, why, who, where and how the data is or can be accessed.
- Through the Human Enabler, users are able to influence the way their behavior is predicted, by controlling how there are being profiled (automatic, off, manually personalized).
- This is essential for establishing and managing trust and for safeguarding privacy, as well as for designing and implementing business security models and policies.
- The **second set of features is associated with the capacity of exposing this information** (both raw data and inferred one) to third party service providers (such as advertising agencies), through well defined web service interfaces.
- Besides exposing user related information, the human enabler allows data to be subscribed, syndicated or updated on request.

4.3.3. Innovations

The analysis of the first results indicated the following key findings:

- It is possible to infer user behavior based on user preferences, social networks and context-aware systems, with the help of reality/data mining techniques.
- Proximity and Similarity are great weight indicators for inferring influence and can be computed or calculated analytically.
- Both online and offline social networks have influence over a person"s behavior.
- User perceived QoE is improved as the methodology delivers personalization, contextualization, interactivity, adaptation and privacy.
- Users are willing to participate in their own profiling experience and the results are positive.

Applying these techniques into different fields of computer social sciences may have significant applicability in different parts of the value chain.

Examples:

- Infer and suggest missing information in users profile according to his/her peers contextual information.
- Understand how a specific user can be influenced by another user or community and vice versa.
- Understand how similar two users are, even if they do not have friends in common.

4.4 Privacy in Online Social Networks

- There is a dramatic growth in number and popularity of online social networks. There are many networks available with more than 100 million registered users such as Facebook, MySpace, QZone, Windows Live Spaces etc.
- People may connect, discover and share by using these online social networks. The exponential growth of online communities in the area of social networks attracts the attention of the researchers about the importance of managing trust in online environment.
- Users of the online social networks may share their experiences and opinions within the networks about an item which may be a product or service.
- **Collaborative filtering system** is the most popular method in recommender system.
  - The task is to predict the utility of items to a particular user based on a database of user rates from a sample or population of other users.
- Because of the different taste of different people, they rate differently according to their subjective taste.
- If two people rate a set of items similarly, they share similar tastes. In the recommender system, this information is used to recommend items that one participant likes, to other persons in the same cluster.
- Performs poor when there is insufficient previous common rating available between users; known as cold start problem
- To overcome the cold start problem trust based approach to recommendation has emerged.

- This approach assumes a trust network among users and makes recommendations based on the ratings of the users that are directly or indirectly trusted by the target user.
- **Trust** could be used as supplementary or replacement of collaborative filtering system
- Trust and reputation systems can be used in order to assist users in predicting and selecting the best quality services
- Binomial Bayesian reputation systems normally take ratings expressed in a discrete binary form as either
    - positive (e.g. *good*) or
    - negative (e.g. *bad*).
- Multinomial Bayesian reputation systems allow the possibility of providing ratings with discrete graded levels such as e.g. *mediocre – bad –average – good – excellent*
- Trust models based on subjective logic are directly compatible with Bayesian reputation systems because a bi-jectivemapping exists between their respective trust and reputation representations.
- This provides a powerful basis for combining trust and reputation systems for assessing the quality of online services.
- Trust systems can be used to derive local and subjective measures of trust, meaning that different agents can derive different trust in the same entity.
- Reputation systems compute scores based on direct input from members in the community which is not based on transitivity
- Bayesian reputation systems are directly compatible with trust systems based on subjective logic, they can be seamlessly integrated. This provides a powerful and flexible basis for online trust and reputation management.

Online Social Networks

- A social network is a map of the relevant ties between the individuals, organizations, nations etc. being studied.
- With the evolution of digital age, Internet provides a greater scope of implementing social networks online. Online social networks have broader and easier coverage of members worldwide to share information and resources.
- The first online social networks were called UseNet Newsgroups. designed and built by Duke University graduate students Tom Truscott and Jim Ellis in 1979.

- Facebook is the largest and most popular online social network at this moment (www.insidefacebook.com).
- It had 350 million Monthly Active Users (MAU) at the beginning of January 2010. But it has been growing too fast around the world since then.
- As on 10 February 2010, roughly 23 million more people are using Facebook compared to 30 days ago, many in countries with big populations around the world. This is an interesting shift from much of Facebook‟s international growth to date.
- Once Facebook began offering the service in multiple languages it started blowing up in many countries like Canada, Iceland, Norway, South Africa, Chile, etc.
- The United States is at the top with more than five million new users; it also continues to be the single largest country on Facebook, with 108 million MAU

Table a Top ten mostly visited social networks in Jan"09– based on MAU

Rank	Site	Monthly visit
1	facebook.com	1,191,373,339
2	myspace.com	810,153,536
3	twitter.com	54,218,731
4	flixster.com	53,389,974
5	linkedin.com	42,744,438
6	tagged.com	39,630,927
7	classmates.com	35,219,210
8	myyearbook.com	33,121,821
9	livejournal.com	25,221,354
10	imeem.com	22,993,608

4.5 Trust in Online Environment

- Trust has become important topic of research in many fields including sociology, psychology, philosophy, economics, business, law and IT.
- Trust is a complex word with multiple dimensions.
- Though dozens of proposed definitions are available in the literature, a complete formal unambiguous definition of trust is rare.
- Trust is used as a word or concept with no real definition.
- Trust is such a concept that crosses disciplines and also domains. The focus of definition differs on the basis of the goal and the scope of the projects.
- Two forms

- reliability trust or evaluation trust
- decision trust

- **Evaluation trust** can be interpreted as the reliability of something or somebody. It can be defined as the subjective probability by which an individual, A, expects that another individual, B, performs a given action on which its welfare depends.
- The **decision trust** captures broader concept of trust. It can be defined as the extent to which one party is willing to depend on something or somebody in a given situation with a feeling of relative security, even though negative consequences are possible.

4.6 Trust Models Based on Subjective Logic

- Subjective logic is a type of probabilistic logic that explicitly takes uncertainty and belief ownership into account.
- Arguments in subjective logic are subjective opinions about states in a state space.
- A binomial opinion applies to a single proposition, and can be represented as a Beta distribution. A multinomial opinion applies to a collection of propositions, and can be represented as a Dirichlet distribution.
- Subjective logic defines a trust metric called *opinion* denoted by $\omega_X^A = (\vec{b}, u, \vec{a})$ which expresses the relying party A"s belief over a state space X.
  - Here $\vec{b}$ represents belief masses over the states of X, and *u* represent uncertainty mass where $\vec{b}$,u € $[0, 1]$ and $\sum \vec{b} + u = 1$.
  - The vector
    $\vec{a} \in [0,1]$
  - represents the base rates over X, and is used for computing the probability expectation value of a state x.

- Binomial opinions are expressed as $\omega_x^A = (b, d, u, a)$ where d denotes disbelief in x. When the statement x for example says "*David is honest and reliable*", then the opinion can be interpreted as reliability trust in David.
- Let us assume that Alice needs to get her car serviced, and that she asks Bob to recommend a good car mechanic. When Bob recommends David, Alice would like to get

a second opinion, so she asks Claire for her opinion about David. This situation is illustrated in Fig. 4.6 a

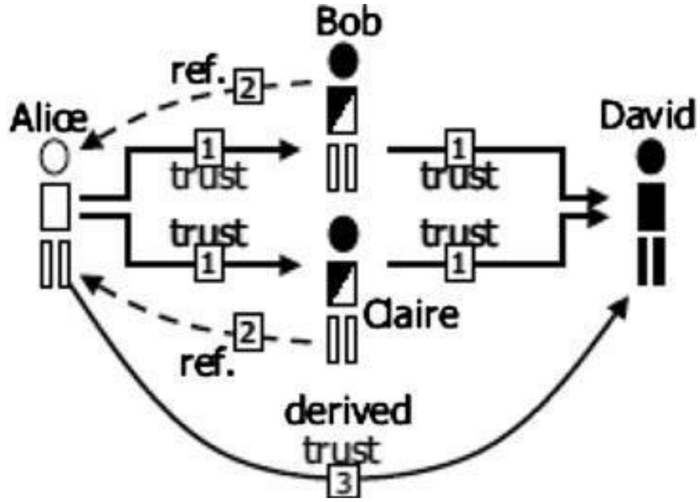


Fig. 4.6 a Deriving trust from parallel transitive chains

When trust and referrals are expressed as subjective opinions, each transitive trust path Alice →Bob→ David→ and Alice → Claire → David can be computed with the *transitivity operator*, where the idea is that the referrals from Bob and Claire are discounted as a function Alice‟s trust in Bob and Claire respectively. Finally the two paths can be combined using the cumulative or averaging fusion operator. These operators form part of *Subjective Logic and semantic constraints* must be satisfied in order for the transitive trust derivation to be meaningful.

- This model is thus both belief-based and Bayesian.
- A trust relationship between A and B is denoted as [A:B]. The transitivity of two arcs is denoted as “:” and the fusion of two parallel paths is denoted as “◊”. The trust network of Fig. 4.6 a can then be expressed as:

  [A,D] = ([A,B]:[B,D]) ◊ ([A,C] : [C,D])
- The corresponding transitivity operator for opinions denoted as “ ” and the ⊗ corresponding fusion operator as “⊕”. The mathematical expression for combining the opinions about the trust relationships of Fig. 4.6 a is then:

$$\omega_D^A = \left(\omega_B^A \otimes \omega_D^B\right) \oplus \left(\omega_C^A \otimes \omega_D^C\right)$$

- Arbitrarily complex trust networks can be analysed with TNA-SL which consists of a network exploration method combined with trust analysis based on subjective logic.
- The method is based on simplifying complex trust networks into a directed series parallel graph (DSPG) before applying subjective logic calculus.

4.7 Trust network analysis

- Trust networks consist of transitive trust relationships between people, organizations and software agents connected through a medium for communication and interaction.
- Trust network analysis using subjective logic (TNA-SL) takes directed trust edges between pairs as input, and can be used to derive a level of trust between arbitrary parties that are interconnected through the network.
    - In case of no explicit trust paths between two parties exist; subjective logic allows a level of trust to be derived through the default vacuous opinions.
    - TNA-SL is suitable for many types of trust networks.
    - Limitation : complex trust networks must be simplified to *series-parallel* networks in order for TNA-SL to produce consistent results.
    - The simplification consisted of gradually removing the least certain trust paths until the whole network can be represented in a series-parallel form.
    - As this process removes information it is intuitively sub-optimal.

4.7.1 Operators for Deriving Trust

- Subjective logic is a belief calculus specifically developed for modeling trust relationships.
    - Beliefs are represented on binary state spaces, where each of the two possible states can consist of sub-states.
    - Belief functions on binary state spaces are called *subjective opinions*
- Expressed in the form of an ordered tuple

  $W_X^A = (b, d, u, a)$

  where b, d, and *u* represent belief, disbelief and uncertainty respectively where
  b, d, *u* ∈ [0, 1] and b+d+u = 1
- The base rate parameter a ∈ [0,1] represents the base rate probability in the absence of evidence, and is used for computing an opinion"s probability expectation value

$E(W_X^A) = b + au$

- A subjective opinion is interpreted as an agent A"s belief in the truth of statement x
- A"s opinion about x is denoted as W_X^A
- Subjective logic defines a rich set of operators for combining subjective opinions in various ways. Some operators represent generalizations of binary logic and probability calculus, whereas others are unique to belief calculus because they depend on belief ownership.

Transitivity is used to compute trust along a chain of trust edges. Assume two agents A and B where A has referral trust in B, denoted by W_B^A, for the purpose of judging the functional or referral trustworthiness of C.

In addition B has functional or referral trust in C, denoted by W_C^B. Agent A can then derive her trust in C by discounting B"s trust in C with A"s trust in B, denoted by $W_C^{A:B}$.

By using the symbol "⊗ to designate this operator, we define

$$\omega_C^{A:B} = \omega_B^A \otimes \omega_C^B \begin{cases} b_C^{A:B} = b_B^A b_C^B \\ d_C^{A:B} = b_B^A d_C^B \\ u_C^{A:B} = d_B^A + u_B^A + b_B^A u_C^B \\ a_C^{A:B} = a_C^B. \end{cases}$$

Cumulative *Fusion* is equivalent to Bayesian updating in statistics. The cumulative fusion of two possibly conflicting opinions is an opinion that reflects both opinions in a fair and equal way

Let W_C^A and W_C^B be A"s and B"s trust in C respectively. The opinion $W_C^{A\diamond B}$ is then called the fused trust between W_C^A and W_C^B, By using the symbol "⊕ to designate this operator, we define

$$\omega_C^{A\diamond B} = \omega_B^A \oplus \omega_C^B \begin{cases} b_C^{A\diamond B} = (b_C^A u_C^B + b_C^B u_C^A) / (u_C^A + u_C^B - u_C^A u_C^B) \\ d_C^{A\diamond B} = (d_C^A u_C^B + d_C^B u_C^A) / (u_C^A + u_C^B - u_C^A u_C^B) \\ u_C^{A\diamond B} = (u_C^A u_C^B) / (u_C^A + u_C^B - u_C^A u_C^B) \\ a_C^{A\diamond B} = a_C^A. \end{cases}$$

The effect of the cumulative fusion operator is to amplify belief and disbelief and reduce uncertainty

4.7.2 Trust Path Dependency and Network Simplification

- Transitive trust networks can involve many principals
- Capital letters A, B, C and D will be used to denote principals.
- A single trust relationship can be expressed as a directed edge between two nodes that represent the trust source and the trust target of that edge.
- For example the edge [A, B] means that A trusts B. The symbol ":" is used to denote the transitive connection of two consecutive trust edges to form a transitive trust path.
- The trust relationships between four principals A, B, C and D connected serially can be expressed as:

  ([A,D]) = ([A,B] : [B,C] : [C,D])
- We will use the symbol "◊" to denote the graph connector. The "◊" symbol visually resembles a simple graph of two parallel paths between a pair of agents.
- In short notation, A‟s combination of the two parallel trust paths from her to D is then expressed as:

  ([A,D]) = (([A,B] : [B,D]) ◊ ([A,C] : [C,D]))
- Trust networks can have dependent paths. This is illustrated on the left-hand side of Fig. 4.7.a. The expression for the graph on the left-hand side of Fig. 4.7.a would be:

  ([A,D]) = (([A,B] : [B,D]) ◊ ([A,C] : [C,D]) ◊ ([A,B] : [B,C] : [C,D]))
- Trust network analysis with subjective logic may produce inconsistent results when applied directly to non-canonical expressions.

Fig. 4.7.a Network simplification by removing weakest path

It is therefore desirable to express graphs in a form where an arc only appears once. A canonical expression can be defined as an expression of a trust graph in structured notation where every edge only appears once.

Assuming that the path ([A,B]:[B,C]:[C,D]) is the weakest path in the graph on the left-hand side of Fig. 4.7.a, network simplification of the dependent graph would be to remove the edge [B,C] from the graph, as illustrated on the right-hand side of Fig. 4.7.a.

4.8 Trust Transitivity Analysis

Assume two agents A and B where A trusts B, and B believes that proposition x is true. Then by transitivity, agent A will also believe that proposition x is true. This assumes that B recommends x to A. In our approach, trust and belief are formally expressed as opinions. The transitive linking of these two opinions consists of discounting B"s opinion about x by A"s opinion about B, in order to derive A"s opinion about x. This principle is illustrated in Fig. 4.8.a below

Fig. 4.8.a Principle of trust transitivity

solid arrows - initial direct trust

dotted arrow - derived indirect trust

4.8.1 Uncertainty Favoring Trust Transitivity

A"s disbelief in the recommending agent B means that A thinks that B ignores the truth value of x. As a result A also ignores the truth value of x.

Uncertainty Favoring Discounting

Let A and B be two agents

where A"s opinion about B"s recommendations is expressed as

$$w_B^A = \{ b_B^A, d_B^A, u_B^A, a_B^A\}$$

let x be a proposition where B"s opinion about x is recommended to A with the opinion

$$w_x^B = \{ b_x^B, d_x^B, u_x^B, a_x^B\}$$

Let

$$w_x^{A:B} = \{ b_x^{A:B}, d_x^{A:B}, u_x^{A:B}, a_x^{A:B}\}$$

$$\begin{cases} b_x^{A:B} = b_B^A b_x^B \\ d_x^{A:B} = d_B^A d_x^B \\ u_x^{A:B} = d_B^A + u_B^A + b_B^A u_x^B \\ a_x^{A:B} = a_x^B \end{cases}$$

$w_x^{A:B}$ - the uncertainty favoring discounted opinion of A.

By using the symbol $\otimes$

$w_x^{A:B} = w_B^A \otimes w_x^B$

This operator is associative but not commutative. This means that the combination of opinions can start in either end of the path, and that the order in which opinions are combined is significant.

Figure below 4.8.b illustrates an example of applying the discounting operator for independent opinions, where

$w_B^A = \{0.1, 0.8, 0.1\}$ discounts $w_x^B = \{0.8, 0.1, 0.1\}$ to produce $w_x^{A:B} = \{\ 0.08, 0.01, 0.91\}$

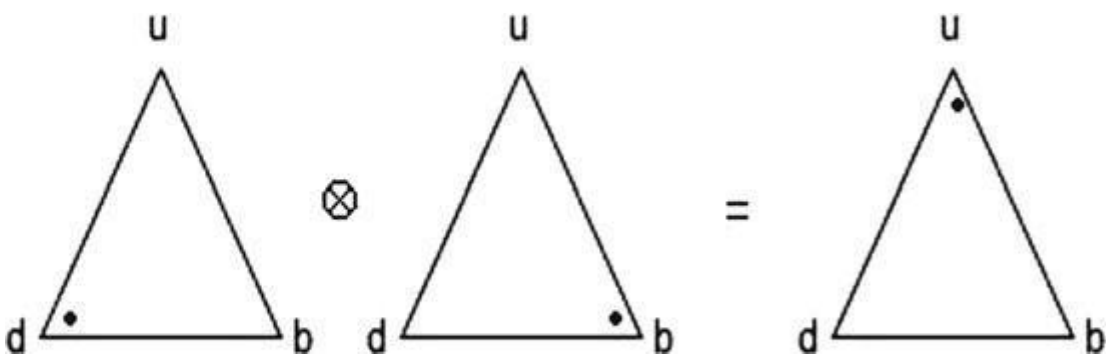


Fig. 4.8.b Example of applying the discounting operator for independent opinions

4.8.2 Opposite Belief Favoring

A"s disbelief in the recommending agent B. A not only disbelieves in x to the degree that B recommends belief, but she also believes in x to the degree that B recommends disbelief in x, because the combination of two disbeliefs results in belief in this case.

Opposite Belief Favoring Discounting

Let A and B be two agents where A"s opinion about B"s recommendations is expressed as

$w_B^A = \{ b_B^A, d_B^A, u_B^A, a_B^A \}$

let x be a proposition where B"s opinion about x is recommended to A with the opinion

$w_x^B = \{ b_x^B, d_x^B, u_x^B, a_x^B \}$

Let

$w_x^{A:B} = \{ b_x^{A:B}, d_x^{A:B}, u_x^{A:B}, a_x^{A:B} \}$

$$\begin{cases} b_x^{A:B} = b_B^A b_x^B + d_B^A d_x^B \\ d_x^{A:B} = b_B^A d_x^B + b_B^A d_x^B \\ u_x^{A:B} = u_B^A + (b_B^A + d_B^A) u_x^B \\ a_x^{A:B} = a_x^B \end{cases}$$

$w_x^{A:B}$ - opposite belief favoring discounted recommendation from B to A

By using the symbol $\otimes$

$w_x^{A:B} = w_B^A \otimes w_x^B$

This operator models the principle that "*your enemy's enemy is your friend*". It is doubtful whether it is meaningful to model more than two arcs in a transitive path with this principle. In other words, it is doubtful whether the enemy of your enemy"s enemy necessarily is your enemy too.

4.8.3 Base Rate Sensitive Transitivity

Imagine a stranger coming to a town which is known for its citizens being honest. The stranger is looking for a car mechanic, and asks the first person he meets to direct him to a good car mechanic. The stranger receives the reply that there are two car mechanics in town, David and Eric, where David is cheap but does not always do quality work, and Eric might be a bit more expensive, but he always does a perfect job.

Translated into the formalism of subjective logic, the stranger has no other info about the person he asks than the base rate that the citizens in the town are honest. The stranger is thus ignorant, but the expectation value of a good advice is still very high.

Without taking a_B^A into account, the result of the definitions above would be that the stranger is completely ignorant about which of the mechanics is the best. An intuitive approach would then be to let the expectation value of the stranger"s trust in the recommender be the discounting factor for the recommended (b_x^B, d_x^B) parameters.

Base Rate Sensitive Discounting

The base rate sensitive discounting of a belief

$w_x^B = \{ b_x^B, d_x^B, u_x^B, a_x^B \}$

by a belief

$w_B^A = \{ b_B^A, d_B^A, u_B^A, a_B^A \}$

Produces the transitive belief $w_x^{A:B} = \{ b_x^{A:B}, d_x^{A:B}, u_x^{A:B}, a_x^{A:B} \}$

$$\begin{cases} b_x^{A:B} = E\left(\omega_B^A\right) b_x^B \\ d_x^{A:B} = E\left(\omega_B^A\right) d_x^B \\ u_x^{A:B} = 1 - E\left(\omega_B^A\right)\left(b_x^B + d_x^B\right) \\ a_x^{A:B} = a_x^B \end{cases}$$

probability expectation value E

$w_B^A = \{ b_B^A + \ a_B^A \ u_B^A \}$

A safety principle could therefore be to only apply the base rate sensitive discounting to the last transitive link.

4.8.4 Mass Hysteria

Consider how mass hysteria can be caused by people not being aware of dependence between opinions. Let"s take for example; person A recommend an opinion about a particular statement x to a group of other persons. Without being aware of the fact that the opinion came from the same origin, these persons can recommend their opinions to each other as illustrated in Fig. 4.8.c

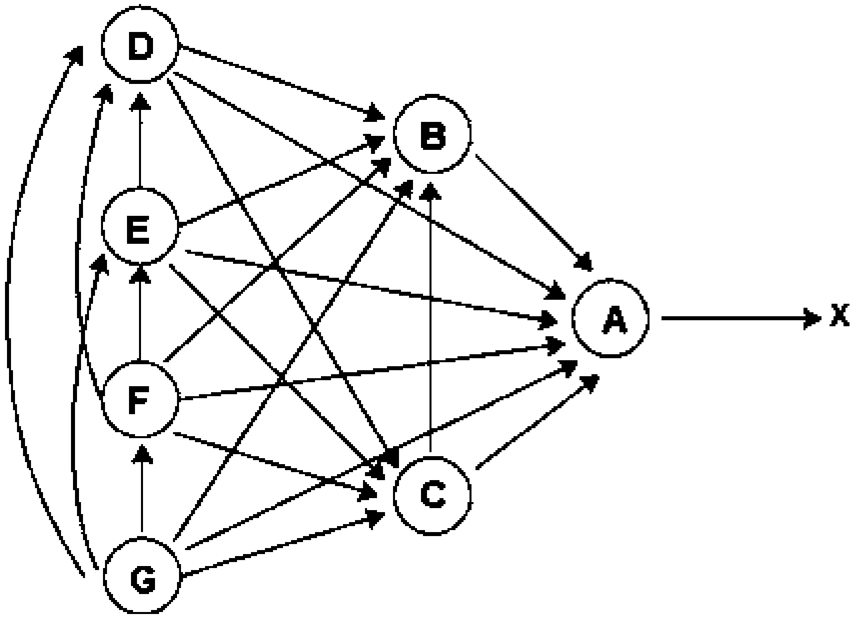


Fig. 4.8.c The effects of unknown dependence

The arrows represent trust so that for example B ->A can be interpreted as saying that B trusts A to recommend an opinion about statement x. The actual recommendation goes, of course, in the opposite direction to the arrows in Fig. 4.8.c.

If G assumes the recommended opinions to be independent and takes the consensus between them, his opinion can become abnormally strong and in fact even stronger than A‟s opinion.

In order to reduce the size of the notation, the transitivity symbol ":" will simply be omitted, and the cumulative fusion symbol ◊ will simply be written as ",". Analyzing the whole graph of dependent paths, as if they were independent, will then produce:

$$\omega_X^{\left(\begin{array}{l}\mathrm{GA, GBA, GCA, GCBA, GDA, GDBA, GDCA, GDCBA, GEA, GEBA, GECA,}\\ \mathrm{GECBA, GEDA, GEDBA, GEDCA, GEDCBA, GFA, GFBA, GFCA, GFCBA,}\\ \mathrm{GFDA, GFDBA, GFDCA, GFDCBA, GFEA, GFEBA, GFECA, GFECBA,}\\ \mathrm{GFEDA, GFEDBA, GFEDCA, GFEDCBA}\end{array}\right)} = (0.76, 0.11, 0.13, a)$$

When this process continues, an environment of self amplifying opinions, and thereby mass hysteria, is created.

4.9 Combining trust and reputation

4.9.1 The Dirichlet Reputation System

Reputation systems collect ratings about users or service providers from members in a community.

The reputation centre is then able to compute and publish reputation scores about those users and services.

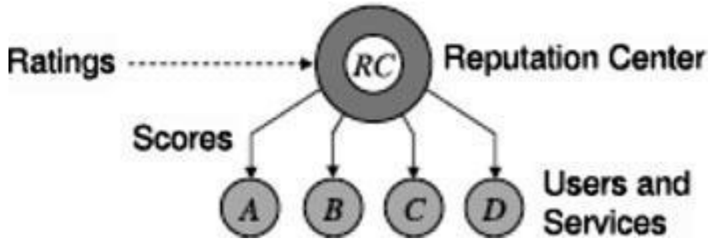


Figure 4.9.a Simple reputation system

Multinomial Bayesian systems are based on computing reputation scores by statistical updating of Dirichlet Probability Density Functions (PDF)

A posteriori (i.e. the updated) reputation score is computed by combining a priori (i.e. previous) reputation score with new ratings.

Agents are allowed to rate others agents or services with any level from a set of predefined rating levels

Reputation scores are not static but will gradually change

Let there be k different discrete rating levels. Let the rating level be indexed by i. The aggregate ratings for a particular agent can be expressed as

as: $\vec{R} = (\vec{R}(L_i)|i = 1 \ldots k).\psi\psi$

This vector can be computed recursively and can take factors such as longevity and community base rate into account.

$\vec{R}_y(L_i)\psi$ - aggregate rating of a particular level i for agent y

Before any ratings about a particular agent y have been received, its reputation is defined by common base rate

Ratings about particular agent are collected, the aggregate ratings can be computed recursively and derived scores will change accordingly.

The vector S is defined by

$$\vec{S}_y : \left(\vec{S}_y(L_i) = \frac{\vec{R}_y(L_i) + C\vec{a}(L_i)}{C + \sum_{j=1}^{k} \vec{R}_y(L_j)}; |i = 1 \ldots k\right).$$

The reputation score S is defined by

$$\sum_{i=1}^{k} \vec{S}(L_i) = 1\psi.$$

To express reputation score as a single value in some predefined interval. This can be done by assigning a point value to each rating level L :

$$\sigma = \sum_{i=1}^{k} v(L_i)\vec{S}(L_i).$$

A bijective mapping can be defined between multinomial reputation scores and opinions, which makes it possible to interpret these two mathematical representations as equivalent. The mapping can symbolically be expressed as:

$$\omega \leftrightarrow \vec{R}$$

Theorem: Equivalence Between Opinions and Reputations

Let w=(b,u,a) be an opinion, and R be a reputation, both over the same state space X so that the base rate „a" also applies to the reputation. Then the following equivalence

For $u \neq 0$*:*

$$\begin{cases} \vec{b}(x_i) = \dfrac{\vec{R}(x_i)}{C+\sum_{i=1}^{k}\vec{R}(x_i)} \\ u = \dfrac{C}{C+\sum_{i=1}^{k}\vec{R}(x_i)} \end{cases} \Longleftrightarrow \begin{cases} \vec{R}(x_i) = \dfrac{C\vec{b}(x_i)}{u} \\ u + \sum\limits_{i=1}^{k} \vec{b}(x_i) = 1 \end{cases}$$

For $u = 0$*:*

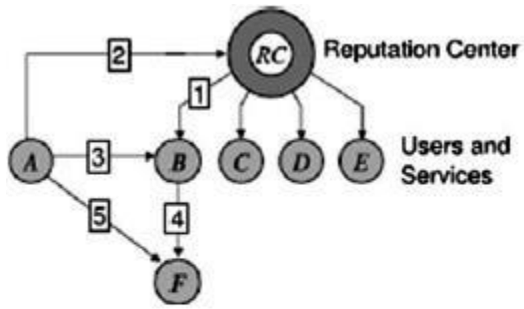
$$\begin{cases} \vec{b}(x_i) = \eta(x_i) \\ u = 0 \end{cases} \Longleftrightarrow \begin{cases} \vec{R}(x_i) = \eta(x_i) \sum\limits_{i=1}^{k} \vec{R}(x_i) = \eta(x_i)\infty \\ \sum\limits_{i=1}^{k} m(x_i) = 1 \end{cases}$$

Multinomial aggregate ratings can be used to derive binomial trust in the form of an opinion. This is done by first converting the multinomial ratings to binomial ratings according to equation below and then apply to the above theorem.

The derived converted binomial rating parameters (r,s) are given by:

$$\begin{cases} r = \sigma \sum_{i=1}^{k} \vec{R}_y(x_i) \\ s = \sum_{i=1}^{k} \vec{R}_y(x_i) - r \end{cases}$$

Figure 4.9.b illustrates a scenario where agent A needs to derive a measure of trust in agent F .



Agent B has reputation score $\vec{R}_B^{RC}$ (arrow 1), and agent A has trust w_{RC}^{A}

RC in the Reputation Centre (arrow 2), so that A can derive a measure of trust in B (arrow 3). Agent B"s trust in F (arrow 4) can be recommended to A so that A can derive a measure of trust in F (arrow 5). Mathematically this can be expressed as:

$$\omega_F^A = \omega_{RC}^A \otimes \vec{R}_B^{RC} \otimes \omega_F^B$$

The compatibility between Bayesian reputation systems and subjective logic makes this a very flexible framework for analysing trust in a network consisting of both reputation scores and private trust values.