A Survey of Belief Revision on Reputation Management

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Abstract

Reputation management is a process of tracking, reporting and reacting to an entity's actions and other entities' opinions about those actions. In practical world, as each action may have different effects, entities changing opinions towards each other is unavoidable. The belief on an entity is based on the entity's reputation. In a reputation management system, the reputation of a certain entity may change according to different events, so changes the belief. Changing of believes is called belief revision. In this paper, we will make an brief introduction about belief revision models and their implementations in reputation management area.

KEYWORDS: Reputation Management, Belief Revision, Rationality, AGM

1 Introduction

Under the rapid development of computer technologies, the traditional forms of getting cues related to trustworthiness, such as physical encounter, have been gradually replaced by computer mediated communications. Because computer mediated communications usually take place between parties who have never communicated with each other before, and without physical contact it is hard to collect solid evidence about unknown communication partners, the trustworthiness is hard to be assured. In that case, the most common method to decide whether to trust an entity or not is referring to the comments made by other entities which have communicated with the entity before.

Reputation is closely related to trust. It can be considered as a collective measure of trustworthiness based on the ratings or referrals from members in a community. Therefore, the basic idea of reputation management systems is to let entities rate each other, and generate a reputation score by using reputation computation engines (see [3]). However, when communicate with a certain entity, not every entity may share the same experience of communication, and one entity may not have the same story of communicating with it at every time. For example, Alice and Bob each bought a digital camera on eBay from Clair, Alice was satisfied, but Bob thought the service was bad. Days later, Alice bought another camera from Clair, he thought the service was not as good as before. Here come the concerns: how to change opinion of an entity according to different events? How to adjust the trust of an entity according to changes in referrals?

Belief revision [4] is the process of adapting beliefs when they are contradicted by the new coming information. It works with a knowledge base, which is a set of assumptions. When new information is found, it would be added to the knowledge base. When contradiction is detected in the knowledge base, the belief revision system will revise the knowledge base by contracting some assumptions to get rid of the contradiction. In a word, belief revision is the process of keep the consistency of believes. To my best concerned, there are two categories of belief revision algorithms, logical algorithms and probability algorithms.

In this paper, we make a survey about belief revision and its implementation on Reputation Management Systems. In section 2, we will present a logical algorithm, the AGM model of belief revision. Section 3 shows the probability algorithms of trust revision. Section 4 presents the concrete implementation of belief revision on reputation management area. The last section concludes the paper and discusses the trend of belief revision research.

2 The AGM Belief Revision Framework

The AGM belief revision framework [6][9], which defines the properties that should be satisfied in order to keep the operators being considered rational, is named after its proponents. Its rationale is that all justification of beliefs relies on coherence within a belief system, which means that not only new beliefs can be justified by coherence but old beliefs can also be adjusted according to coherence.

Before the introduction of AGM model, following logical connectives should be known (see table 1)

Connective	Meaning	Connective	Meaning
$\neg$	negation	$\wedge$	conjunction
$\vee$	disjunction	$\rightarrow$	implication
$\top$	truth	$\perp$	falsity
$\vdash$	infer	$\subseteq$	contain

Table 1: Logical Connectives

Suppose there is a consistent belief set K represented by a set of sentences in a logical language L. In K, there are three possible epistemic states towards a logical sentence P: accepted, rejected and unknown. Because only the assumption which can keep coherence in K is a truth, the truth of P depends on coherence between P and other beliefs in K. All the belief in K should meet the following requirements:

1. $\perp$ is not a logical consequence of the sentences in K. (It implies that there are no contradictions between beliefs.)

2. If K $\vdash$ q, then q $\in$ K. (It means that all sentences, which can keep consistency of belief set K, can be added into K.)

As a consequence of above requirements, a new proposition P can be accepted only under the condition that there is no doubt that P is true in K. If $\neg$ P is true in K, then P is rejected. If both P and $\neg$ P result in inconsistency in K, then P is in state unknown. So the belief set K should be logically consistent, and it is possible to predict what belief can be accepted.

2.1 Belief Changes

In coherence theory, there are three types of belief changes: expansion, contraction and revision (see [8][7]).

2.1.1 Expansion

Expansion is adding a new belief without checking consistency, which occurs when learning new information. During expansion operations, sentence A which is in state unknown can be changed to the state accepted. After expanding with sentence A, belief set K is denoted as $K+_A$. The postulates of expansion is in table 2.

Name	Postulate	Denote
Closure	For any sentence A and any belief set K, $K+_A$ is a belief set	K+1
Success	$A \in K+_A$	K+2
Expansion	$K \subseteq K+_A$	K+3
Inclusion 1	If $A \in K$, then $K+_A = K$	K+4
Inclusion 2	If $K \subseteq H$, then $K+_A \subseteq H+_A$	K+5
Represen -tation	For all belief sets K and all sentences A, $K+_A$ is the smallest belief set that satisfies (K+1) – (K+5)	K+6

Table 2: Postulates of Expansion

The first postulate requires the result belief set to be consistent. The postulates K+4 and K+5 are referred as inclusion principle and the postulate K+6 requires us to ensure the resultant belief set is the smallest one.

2.1.2 Revision

Revision is adding a belief while maintaining consistency of belief set. During the process of revision, belief set need to be revised when a newly introduced concept results in contradiction with the existing concepts in the original belief set. After revising with sentence A, belief set K is denoted as $K*_A$. The postulates of revision is in table 3.

Name	Postulate	Denote
Closure	For any sentence A and any belief set K, $K*_A$ is a belief set	$K*1$
Success	$A \in K*_A$	$K*2$
Expansion1	$K*_A \subseteq K+_A$	$K*3$
Expansion2	If $\neg A \notin K$, then $K+_A \in K*_A$	$K*4$
Consistency Preservation	$K*_A = K\perp$ if and only if $\vdash \neg A$	$K*5$
Extension -ality	If $\vdash A \leftrightarrow B$, then $K*_A = K*_B$	$K*6$
Conjunct -ion1	$K*_{A\wedge B} \subseteq (K*_A)+_B$	$K*7$
Conjunct -ion2	If $\neg B \notin K*_A$, then $(K*_A)+_B \subseteq K*_{A\wedge B}$	$K*8$

Table 3: Postulates of Revision

In result set $K*_A$, criterion of informational economy should be held, which means belief should be retained as much as possible, and unnecessary loss of information should be avoided in the process of belief revision. The first six postulates in the table are similar to the ones of expansion operator. Postulates K*7 and K*8 are composite belief revisions which express a revision in a form of expansion. It is important that the result set must be consistent.

2.1.3 Contraction

Contraction is to remove a belief. It refers to deleting one or more sentences from K to ensure the result set is closed under logical consequences. After belief set K been contracted by sentence A, new belief set is denoted as $K\text{-}_A$. The postulates of contraction is in table 4.

Name	Postulate	Denote
Closure	For any sentence A and any belief set K, $K\text{-}_A$ is a belief set	K−1
Inclusion	$K\text{-}_A \subseteq K$	K−2
Vacuity	If $A \nsubseteq K$ then $K\text{-}_A = K$	K−3
Success	If $\nvdash A$, then $A \nsubseteq K\text{-}_A$	K−4
Recovery	If $A \in K$, then $K \subseteq (K\text{-}_A)+_A$	K−5
Extension -ality	If $\vdash A \leftrightarrow B$, then $K\text{-}_A = K\text{-}_B$	K−6
Conjunct -ion1	$K\text{-}_A \cap K\text{-}_B \subseteq K\text{-}_{A\wedge B}$	K−7
Conjunct -ion2	If $A \notin K\text{-}_{A\wedge B}$ then $K\text{-}_{A\wedge B} \subseteq K\text{-}_A$	K−8

Table 4: Postulates of Contraction

Eight postulates have been defined for contraction. Those postulates distinguish sentences that are inconsistent in belief set and may be removed to keep coherency. However, which sentence should be removed is depend on the degree of epistemic entrenchment, which formally represents the relative importance of a sentence in a belief set. The postulates of epistemic entrenchment is in table 5.

Name	Postulate	Denote
Transitivity	For any A, B and C,if $A \leqslant B$ and $B \leqslant C$ then $A \leqslant C$	EE1
Dominance	For any A and B, if A $\vdash$ B, then $A \leqslant B$	EE2
Conjunctive -ness	For any A and B in K, A $\leq A \wedge B$ or $B \leq A \wedge B$	EE3
Minimality	When $K \neq K_{\perp}$, $A \notin K$ iff $A \leq B$, for all B	EE4
Maximality	If $B \leq A$ for all B, then $\vdash A$	EE5

Table 5: Postulates of Epistemic Entrenchment

The degree of epistemic entrenchment depends on the importance of the information and belief. A belief can give more valuable information than others in the belief set is epistemologically more entrenched. During the contraction operation, epistemologically least entrenched sentence is removed first to keep minimal loss of information. It is obvious that sentences are epistemologically less entrenched is revised earlier. In that case, when a new belief is considered by belief revision, it will be first ranked based on its entrenchment ordering.

2.2 Example

Suppose Eve initially has the following beliefs:

- A: All users in eBay are honest
- B: Claire sells digital camera in eBay
- C: Claire is a user of eBay

Set the belief set of Eve is K. Given the above sentences, we can infer and add a new sentence:

- D: Claire is honest

In this case we say K is expanded by D. However, when Eve reading comments about Claire, she found that Alice and Bob reported that they have been cheated by Claire, they paid but never got the products. Thus D is no longer consistence in K, so we add ¬ D into K. The addition of ¬ D is an expansion operation. Let us rename ¬ D as:

- E: Claire is not honest

Hence, the resultant belief set includes A, B, C, D and E.

We can find that inconsistent sentences D and E both exist in result set. As a consequence of that, Eve needs to revise her belief set to keep K consistent. So the belief set is revised by adding new sentence to K:

- F:Except Alice and Bob, Clair has not cheated other person, he is honest with others

Now K contains sentences A, B, C, D, E and F.

However, there are still inconsistent sentences D and E exist in K. In this case, Eve need to retract one of these two sentences from K. By using the principle of epistemic entrenchment, Eve found that sentence E hold more valuable information because it contains specific information about victims, so E are epistemologically more entrenched. Hence D is removed from K, and K is consistent by containing sentences: A, B, C, E, F.

3 The Probability Algorithms

James Clerk Maxwell said "The true logic for this world is the calculus of probabilities, which takes account of the magnitude of the probability which is, or ought to be, in a reasonable man's mind."

In computational systems, compare to probability theories, a pure logic framework may be less representational to present epistemic states. By using probability, one can express that A is more or less trustworthy than B in more accurate form. In reputation management systems, this probability can also be used in further operations, such as computing reputation score or decide whether or not to revise belief set with sentences from A.

As I best concerned, several probability belief revision models of trust have been published in recent years. In the following parts, we will introduce three of them in detail.

3.1 A Model in a Multi-agent Environment

3.1.1 Introduction

A model for belief revision in a multi-agent environment is proposed in paper [1]. This model combines the assumption-based reasoning with techniques to deal with uncertainty of distinguishing credibility of information and reliability of resource. The architecture of the model is in Figure 1.

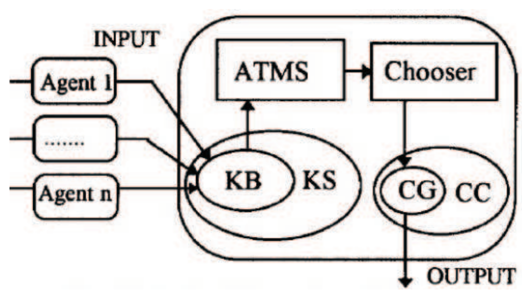

Figure 1: Architecture of the Model (in [1])

In Figure 1, ATM is a truth maintenance system. KB is knowledge base, which contains currently introduced nodes that includes a set of assumptions. KS is knowledge space, which contains all nodes. A node represents an agent. OS is the origin set, which contains nodes where the assumptions originated from. Nogood is a subset of

KB that contains inconsistent assumptions, so good is a subset of KB without inconsistency. CG is current good, which is the current preferred good set. CC is current context, which is the context of CG.

A feature of this model is the introduction of a criterion to choose the best context among the outcome of ATMS to reason. In stead of selecting a belief to contract to keep consistency of belief set, the task of Chooser is choosing a newly preferred good set among good sets in KB. The criteria of selecting choose a more plausible context by comparing the credibility of their good sets.

In order to choose CG, the reliability of source and credibility of information should be evaluated at the same time. Hence, three dynamically related parameters are introduced:

1. r_s : is the reliability of source s estimated by receiving agent.

2. c_a : is the credibility of assumption a estimated by receiving agent.

3. $c_{a,s}$: is the source credibility of assumption a estimated by the source s.

All parameters range from -1 to 1, where 1 means absolutely reliable or credible, 0 means unreliable or incredible and -1 means absolutely mendacious. The current reliability of sources and sources' credibility of assumptions are collected and saved in tables separately.

The new values of these three parameters are computed by using the following equations:

$$c_a = r_s * c_{a,s} + \mid r - r_s \mid * g * c_{a,s}$$

where r is the auto-reliability of the agent, g is the percentage of information received from source s that already belongs to CG of receiving agent within the same credibility sign. The more unreliable the resource is, the more uncertainty the assumptions would be.

c'_a is the credibility of assumption a after the discovery of the nogood.

$$c'_a = c_a - \frac{p * c_\neg a}{\mid c_a \mid + \mid c_\neg a \mid}$$

$$p = \frac{N_c}{N_c + N_n c}$$

where N_c is the number of assumptions of the biggest CC which contains assumption a, N_{nc} is the number of the biggest nogood set which contains assumption a.

As the sources' reliability should decrease with the distance between the assumption's credibility and the source's credibility on this assumption

$$r_s = 1 - \mid c_a - c_{a,s} \mid$$

Given the set R of all assumptions came from one source, the current reliability of that source is the average of all reliability for each assumption. In that case

$$r_s = \frac{\sum_{a \in R} 1 - \mid c_a - c_{a,s} \mid}{\mid R \mid}$$

Auto-reliability of agent itself is:

$$r' = \frac{r + r_s}{2}$$

However, this model can not assure convergency when many agents are unreliable.

3.1.2 Example

Suppose Jack wants to buy digital camera from Clair on eBay, he read the comments and made his temporal belief. After that, he find a new comment, his belief revision goes as following:

Eve and Frank are already in KB, and they both think Clair is honest. A positive comment from Gabriel is found, $r_s = 0.8$, $c_{a,s} = 0.9$, $g = 1$, r of Jack is 0.9, and only one assumption is get from Gabriel. Suppose there is no nogood set, so we can compute:

$$c_a = 0.8 * 0.9 + \mid 0.9 - 0.8 \mid * 1 * 0.9 = 0.81$$

$$r_s = 1 - \mid 0.81 - 0.9 \mid = 0.91$$

$$r' = \frac{0.9 + 0.91}{2} = 0.905$$

So the new credibility of "Clair is honest" is 0.81, reliability of Gabriel changes to 0.91, new auto-reliability of Jack is 0.905 now.

If there is a no good set with $C_{\neg a} = 0.28$, and it affects the credibility of assumption a as:

$$c'_a = 0.81 - \frac{\frac{3}{3+4} * 0.28}{\mid 0.81 \mid + \mid 0.28 \mid} = 0.7$$

$$r_s = 1 - \mid 0.7 - 0.9 \mid = 0.8$$

$$r' = \frac{0.9 + 0.8}{2} = 0.85$$

So after checking the consistency of all assumptions in KB, the credibility of "Clair is honest" turns to 0.7, the reliability turns to 0.8, and auto-reliability of Jack is 0.85.

3.2 Computational Quantification of Trust Updates

3.2.1 Introduction

A model handles arbitrary sequences of experience inputs is proposed in paper [5]. This model is set upon a condition that entity can only form a credible impression about trustworthiness of other parties from the past actions of those parties. It is suppose that each report of experience plays the role as a world, and it decides the probability of the corresponding worlds. Including a new report may lead to the expansion or contraction of the current set of worlds.

Suppose X is a finite collection of possible worlds, A_X is a subset of X where A holds, Q and P are the distribution of possibility of A_X and X. During expansion, we need to find a Q on X, where $Q(A_X) = 1$. This Q should be as close as the probability of the given P on X, which can be represented as:

$$\arg \min_{Q:Q(A_X)=1} D(Q \parallel P)$$

Where "$D(Q \parallel P)$" is the mutual information between Q and P. The solution is equal to the solution of conditional distribution, which can be solved by using entropy.

Jeffrey formula is that suppose an agent has n beliefs denoted as B_i, where $1 \leqslant i \leqslant n$, for all B_i, $P(B_i) > 0$. Let $E_1 to E2_n$ be the set of propositions of the form $C_1 to C_n$, where each $C_j is B_j or \neg B_j$, so

$$(\forall A)(P(A) = \sum_m P(A|E_i)P(Ei))$$

In this model, Jeffrey formula is used to present an expansion under the condition that $P_A+(A) = a$, where 0<a<1, so $P_A+(\neg A) = 1 - a$, so the Jeffrey equations are:

$$P_A^{+J}(x_i) = p_i/a, if A(x_i)$$

$$P_A^{+J}(x_i) = p_i/(1-a), if \neg A(x_i)$$

As we can not compute the entropy of P^+ while $P^+(A) \neq 1$, but we can compute P^- under the same condition. So assume that there are m elements outside A_X, we need to find distribution Q with maximum entropy:

$$\arg \max_{Q:Q_A^+=P} D(Q \parallel P)$$

So the answer is:

$$P_A^-(x) = \frac{1}{m + 2^{H(P)}}, x \notin A_x$$

$$P_A^-(A) = \frac{2^{H(P)}}{m + 2^{H(P)}}, m = 2^{logm}$$

According to inverse Jeffrey rule:

$$P^{-J}(A) = \frac{2^{H(P_A^+)}}{2^{H(P_A^+)} + 2^{H(P_{\neg A}^+)}}$$

$$P^{-J}(\neg A) = \frac{2^{H(P_{\neg A}^+)}}{2^{H(P_A^+)} + 2^{H(P_{\neg A}^+)}}$$

In the model, each report is formed in the pair<ai,bi>, where bi is $\neg ai$, and possibility of this pair is (ei,di). As supposed, change the sequence of reports does not change the result, so the result of sequentially input k-1 reports equals to input k reports and remove the last one, so we can get equation:

$$T_{k-1} = \frac{\sum_{i=1}^{k-1} q^k(a_i)}{\sum_{i=1}^{k-1} q^k(a_i) + \sum_{i=1}^{k-1} q^k(b_i)}$$

As inclusion is the inverse operation of removal, so we can use inverse Jeffrey condition to compute:

$$q^{k+1}(\{a1, ..., bk\}) = \frac{2^{H(T_k)}}{2^{H(T_k)+2^{H(E_{k+1})}}}$$

where

$$H(T_k) = H(q(a_1), q(b_1), ..., q(b_k))$$

$$H(E_{k+1}) = H(e_{k+1}, d_{k+1})$$

and

$$q_{k+1}(\{a_{k+1}, b_{k+1}\}) = \frac{2^{H(E_{k+1})}}{2^{H(T_k)+2^{H(E_{k+1})}}}$$

Because any combination of inverse conditioning steps and conditioning steps is consistent, this model is suitable to be implemented in any conceivable scenarios of experience reports.

3.2.2 Example

Suppose Jack believes that an assumption "Clair is honest"'s possibility is 0.5, we denote it as $t_0 = d_0 = 0.5$. After that, he find a new report as "Clair is honest"'s possibility is $\frac{2}{3}$, we denote this situation as E1 = $(\frac{2}{3}, \frac{1}{3})$.

By using the entropy-based inverse conditioning mentioned above, we can get:

$$t_0^{(1)} + d_0^{(1)} = \frac{2^{H(\frac{1}{2},\frac{1}{2})}}{2^{H(\frac{1}{2},\frac{1}{2})} + 2^{H(\frac{2}{3},\frac{1}{3})}} = \frac{2}{2 + 1.5 * 2^{\frac{2}{3}}}$$

$$t_1^{(1)} + d_1^{(1)} = \frac{2^{H(\frac{2}{3},\frac{1}{3})}}{2^{H(\frac{1}{2},\frac{1}{2})} + 2^{H(\frac{2}{3},\frac{1}{3})}} = \frac{1.5 * 2^{\frac{2}{3}}}{2 + 1.5 * 2^{\frac{2}{3}}}$$

Because $t_0 = d_0, t_1 = 2d_1$, then $t_0^{(1)} = d_0^{(1)}, t_1^{(1)} = 2d_1^{(1)}$, we can get:

$$T_1 = t_0^{(1)} + t_1^{(1)} = \frac{1 + 2^{\frac{2}{3}}}{2 + 1.5 * 2^{\frac{2}{3}}} = \frac{18}{31}$$

$$D_1 = d_0^{(1)} + d_1^{(1)} = \frac{1 + 0.5 * 2^{\frac{2}{3}}}{2 + 1.5 * 2^{\frac{2}{3}}} = \frac{13}{31}$$

Hence, the new belief of Jack is that the possibility of "Clair is honest" is $\frac{18}{31}$.

3.3 Algorithm Using Reputation of Information Sources

3.3.1 Introduction

A multi-agent belief revision algorithm based on belief networks is proposed in paper [2]. In this model, each agent maintains two types of belief bases: a background knowledge base (KB), which contains knowledge the agent accumulated; a working knowledge base (K), which is the working memory used by agents to made decisions. K is a maximally consistent set derived KB.

There are six steps in the algorithm:

1. Acquire knowledge q with certainty values, and save it in KB
2. Build inference polytrees for q
3. Revise certainty of sentences in KB
4. Generate K
5. Find counter evidence and revise reputations
6. Report conflicts to information sources

Suppose agent X get information q from n sources S_1, S_2,..., S_n, and their certainty of q are a_1, a_2,..., a_n, the current belief q has been generated. Now, m more information sources named S_{n+1}, S_{n+2},..., S_{n+m} assert q. Then we can generate a polytree as Figure 2 According to the tree, we can compute the certainty X on q, denotes P(q = true) by calculate propagating probabilities in the tree as:

$$\pi(q^i) = C_{l\in 1,2} \prod_{m=1}^{k} P(q^i \mid s_m^l)\pi(s_m^l)$$

$$\pi(s_m^l) = P(s_m^l)$$

$$\pi(s_m^2) = 1 - \pi(s_m^l)$$

The first equation has 2^k terms where $q^1 \equiv (q = true)$, $q^2 \equiv (q = false)$, $s^1 \equiv (s = reliable)$ and $s^2 \equiv (s =$

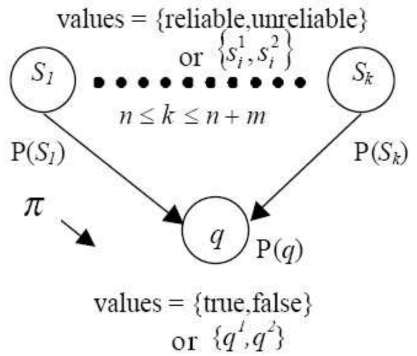

Figure 2: Polytree of the Model3 (in [2])

unreliable). So the result is a 2-tuple of downward message, $\pi(q) = (\pi(q^1), \pi(q^2))$. The revised certainty value for q is

$$P^{`}(q^1) = \xi\pi(q^1)$$

where ξ is a number to adjust the result that it meet the requirement as $P^{`}(q^1)+P^{`}(q^2) = 1$. Then tuple $< q, P^{`}(q_1) >$ enters into K. If there exist inconsistency in KB, the information with highest certainty enters into K.

3.3.2 Example

Suppose Jack asks Alice and Bob about if Clair is honest. Alice, who with reputation as 0.8, replies he think the possibility of Clair is honest is 0.9; Bob, who with reputation as 0.7, think the possibility is 0.6. We denote as:

$$\pi(s_A^1) = p(s_A^1) = 0.8, s = \pi(s_A^2) = 1 - 0.8 = 0.2$$

$$\pi(s_B^1) = p(s_B^1) = 0.7, s = \pi(s_B^2) = 1 - 0.7 = 0.3$$

So we can compute:

$$\pi(q^1) = p(q^1 \mid s_A^1)\pi(s_A^1)p(q^1 \mid s_B^1)\pi(s_B^1) + p(q^1 \mid s_A^1)\pi(s_A^1)$$

$$p(q^1 \mid s_B^2)\pi(s_B^2) + p(q^1 \mid s_A^2)\pi(s_A^2)p(q^1 \mid s_B^1)\pi(s_B^1)$$

$$+p(q^1 \mid s_A^2)\pi(s_A^2)p(q^1 \mid s_B^2)\pi(s_B^2)$$

$$= 0.72 * 0.8 * 0.42 * 0.7 + 0.72 * 0.8 * 0.18 * 0.3$$

$$+0.18 * 0.2 * 0.42 * 0.7 + 0.18 * 0.2 * 0.18 * 0.3$$

$$= 0.212976$$

By using the same algorithm, we can get $\pi(q^2) = 0.015968$

As $\xi(\pi(q^1) + \pi(q^2)) = 1$, $\xi = 4.37$

So the new belief would be the possibility of Clair is honest is $\pi(q^1) * \xi = 0.93$

4 Implementation in Reputation Management System

There are several reputation management systems, which implements different reputation algorithms. In this section, we will make a comparison of the belief revision implementations on the most well known online reputation systems. The comparison result is in table 6. The content in "Belief Revision" section represents the complexity of belief revision algorithm, where "1" means very complex, "-1" means very simple. The content in "Result" section represents the accuracy of result, where "1" means very accurate, "-1" means very inaccurate.

Categ -ory	Name	Reputation Computat -ion Engine	Belief Revis -ion	Result
E-Comm -erce	eBay's Feedback Forum	Average of ratings	-1	-0.9
Expert Sites	AllExperts	Average of ratings	-0.5	-0.5
Product Reviewer	Epinion	Simple summation	0	0
Product Reviewer	Amazon	verage of ratings	-1	-1
Search Engines	Google's Web Page Ranking System	Flow Model	0.7	0.8

Table 6: Comparison of Belief Revision Implementations

In eBay's Feedback Forum, after each transaction, buyers can rate sellers in positive, negative or neutral values or give seller a comment in words. The reputation of sellers is calculated by adding all positive and negative ratings from unique user's most recent feedbacks. However, this simple revision of reputation when rating of buyers' change of belief is not accurate. As a seller with 10 positive 3 and 1 negative 3 has the same score as a seller with 9 positive 3, it is hard for a potent buyer to distinguish which seller is more trustworthy when they have the same reputation scores.

Users of AllExperts give rating on positive numbers in four aspects, such as Knowledgeable, Clarity of Responce, Timeliness and Politeness. However, in each aspect it uses average of ratings, which leads to inaccurate results.

Epinions is a commercial shop review site, which give comments on merchants. The site members can also rate works of other numbers. The reputation of a member is represented by its status as advisor, top reviewer or category lead. The status is entitled according to the sum of ratings. However, it is hard to distinguish trustworthiness of members in same status.

In Amazon's reputation scheme, the rating of books and reviewers are average of all their ratings. As both members and non-members can rate, the average ratings some times are biased. Without identification, it is hard to decide the reliability of resources. In that case, a user can rate infinite times and rate arbitrarily.

In Google's web page ranking system, the new rank value is based on initial ranks. The algorithm applies the principle of trust transitivity to extreme. Because rank values can flow through looped or arbitrarily long hyperlink chains, which means the result can be deceitful.

5 Conclusion

In this paper, we introduced belief revision and its implementation in reputation management systems in detail. Taking rationality as object, belief revision in AGM paradigm has became one of the standard frameworks for modeling changes of information sets. Under the construction of reputation systems, many models of revising trust have been proposed.

As I mentioned above, although there are a lot of good models, majority of most well know online reputation systems are still using simple summation or average of ratings reputation computation algorithm. The simplicity of this algorithm limits even decreases the accuracy of results. In that case, how to efficiently uniting complex belief revision model with online reputation system would be a promising research topic.

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