A Survey of Belief Revision on Reputation Management

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Introduction

- Reputation management is a process of tracking, reporting and reacting to an entity’s actions and other entities’ opinions about those actions.

- The basic idea of reputation management systems is to let entities rate each other, and generate a reputation score by using reputation computation engines

- The reputation is closely related to trust, the trustworthiness is hard to be assured in computer mediated communications

- 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 is the process of adapting beliefs when they are contradicted by the new coming information.
- Belief revision is the process of keep the consistency of believes

The AGM Belief Revision Framework

- The AGM belief revision framework defines the properties that should be satisfied in order to keep the operators being considered rational

Connective	Meaning	Connective	Meaning
$\neg$	negation	$\wedge$	conjunction
$\vee$	disjunction	$\rightarrow$	implication
$\top$	truth	$\bot$	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.
- There are three possible epistemic states towards a logical sentence P: accepted, rejected and unknown.
- Only the assumption which can keep coherence in K is a truth, only the truth would be kept

- All the belief in K should meet the following requirements:
- 1. $\perp$ is not a logical consequence of the sentences in K.
- 2. If $K \vdash q$, then $q \in K$.

- 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.

Expansion

- Expansion is adding a new belief without checking consistency
- 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*

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

Revision

- Revision is adding a belief while maintaining consistency of belief set
- Happens 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

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

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-*A*

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 $A \not\subseteq K$ then $K\text{-}_A = K$	K−3
Success	If $\nvdash A$, then $A \not\subseteq K\text{-}_A$	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

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

- A belief can give more valuable information than others in the belief set is epistemologically more entrenched.
- Epistemologically least entrenched sentence is removed first to keep minimal loss of information.
- In that case, when a new belief is considered by belief revision, it will be first ranked based on its entrenchment ordering.

Example

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

Example

- Eve's belief:
- A: All users in eBay are honest
- B: Claire sells digital camera in eBay
- C: Claire is a user of eBay
- D: Claire is honest

Example

- Eve's belief:
- A: All users in eBay are honest
- B: Claire sells digital camera in eBay
- C: C
- D: C

- Alice and Bob reported that they have been cheated by Claire, they paid but never got the products

Example

- Eve's belief:
- A: All users in eBay are honest
- B: Claire sells digital camera in eBay
- C: Claire is a user of eBay
- D: Claire is honest
- E: Claire is not honest

Example

- Eve's belief:
- A: All users in eBay are honest
- B: Claire sells digital camera in eBay
- C: Claire is a user of eBay
- D: Claire is honest
- E: Claire is not honest
- F: Except Alice and Bob, Clair has not cheated other person, he is honest with others

The Probability Algorithms

A Model in a Multi-agent Environment

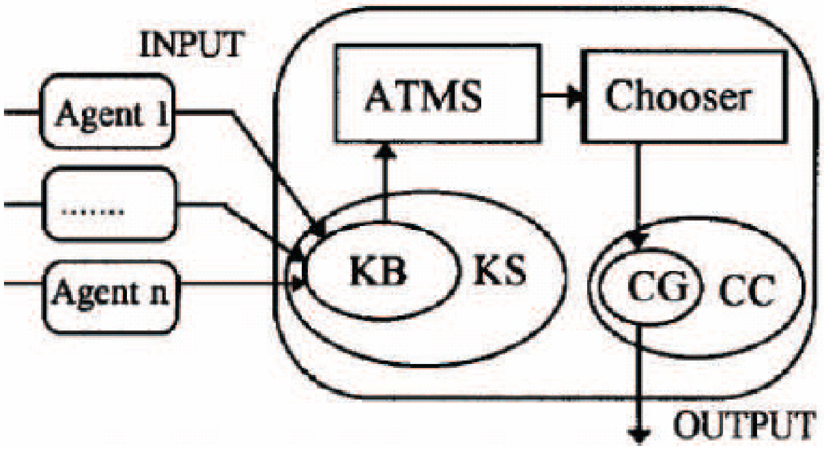

Figure 1: Architecture of the Model (in [1])

- ATM is a truth maintenance system.
- KB is knowledge base
- KS is knowledge space, which contains all nodes.
- A node represents an agent.
- OS is the origin set
- 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.

- The task of Chooser is choosing a newly preferred good set among good sets in KB.

- Three dynamically related parameters:
- r_s : is the reliability of source s estimated by receiving agent.
- c_a : is the credibility of assumption a estimated by receiving agent.
- $c_{a,\ s}$: is the source credibility of assumption a estimated by the source s.

- Formula to compute these three parameters are :

- $$ca = rs * ca,s + | r - rs | *g * ca,s$$

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.

- *C'a* is the credibility of assumption a after the discovery of the nogood:

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

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

- Nc is the number of assumptions of the biggest CC which contains assumption a, Nnc is the number of the biggest nogood set which contains assumption a.

- 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.

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

- Auto-reliability of agent itself is:

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

Example

- rs = 0.8, ca,s = 0.9, g = 1, r = 0.9
- If no nogood is found:

$$c_a = 0.8 * 0.9 + |0.9 - 0.8| * 1 * 0.9 = 0.81$$

$$r_s = 1 - |0.81 - 0.9| = 0.91$$

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

- If there is a nogood set:

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

$$r_s = 1 - |0.7 - 0.9| = 0.8$$

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

Computational Quantification of Trust Updates

- This is a model handles arbitrary sequences of experience inputs
- It uses Jeffrey Formula, in which suppose an agent has n beliefs denoted as *Bi*, where 1 <= *i* <= *n*, for all *Bi*, *P*(*Bi*) > 0. Let *E*1to *E*2*n* be the set of propositions of the form *C*1*to Cn*, where each *Cj is Bj or* ¬*Bj*, 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 *PA*+(*A*) = *a*, where 0<a<1, so *PA*+(¯*A*) = 1 – *a*, so the Jeffrey equations are:

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

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

- However, we can not compute the entropy of P+ while P+(A) !=1, but we can compute P– under the same condition
- Assume that there are m elements outside *AX*, 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 ￢*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:

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

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

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

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 2/3, we denote this situation as E1 = (2/3, 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 $t^{(1)}{}_0 = d^{(1)}{}_0$, $t^{(1)}{}_1 = 2d^{(1)}{}_1$,we can get:

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

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

- So the possibility of “Clair is honest” is 18/31

Algorithm Using Reputation of Information Sources

- This is a multi-agent belief revision algorithm based on belief networks

- 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

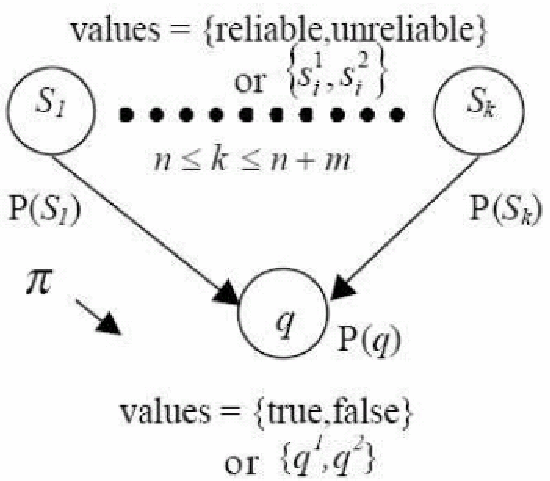

Figure 2: Polytree of the Model3 (in [2])

- 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,..., *an*, the current belief q has been generated. Now, m more information sources named *S n*+1, *S n*+2,..., *S n*+*m* assert q.

- Suppose *q*1 ≡ (*q* = *true*), *q*2 ≡ (*q* = *false*), *s*1 ≡ (*s* = *reliable*) and *s*2 ≡ (*s* = *unreliable*), so:

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

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

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

- So the result is a 2-tuple of downward message, π (*q*) = (π (*q*1), π (*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) > is the final result

Implementation in Reputation Management System

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

Conclusion

- 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.
- How to efficiently uniting complex belief revision model with online reputation system would be a promising research topic

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Thank you!

Questions?