Fuzzy Number Approach to Trust in Coalition Environment*

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ABSTRACT

General trust management model that we present is adapted for ad-hoc coalition environment, rather than for classic client-supplier relationship. The trust representation used in the model extends the current work by using the fuzzy number approach, readily representing the trust uncertainty without sacrificing the simplicity. The model contains the trust representation part, decision-making part and a learning part. In our representation, we define the trusted agents as a type-2 fuzzy set. In a decision-making part, we use the methods from the fuzzy rule computation and fuzzy control to take trusting decision. For trust learning, we use a strictly iterative approach. We verify our model in a multi-agent simulation where the agents in the community learn to identify and refuse the defectors. Our simulation contains the environment-caused involuntary failure used as a background noise that makes the trust-learning difficult.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems

General Terms

Security

Keywords

Trust, Reputation, Fuzzy Numbers, Coalitions

1. INTRODUCTION

In our submission, we extend the current work [2] by proposing a trust model that includes an explicit uncertainty representation and is adapted to coalition environments with significant background noise. To include the uncertainty in our model, we represent trust using *fuzzy numbers*, normal convex fuzzy sets [1] on the $[0,1]$ support.

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2. FORMAL MODEL

For each agent A we define a set of agents *trusted* by A, denoted Θ_A and its membership function $\Theta_A(X)$ on the set of all agents. The set Θ_A represents the agent's A trust in other agents. Whether Θ_A is a fuzzy set or not depends on the value range and type used for trust definition. Binary trust defines a normal, crisp set - membership function takes only two values, $\Theta_A : Agents \rightarrow \{0,1\}$ - agent is either trusted completely or not at all. Use of the real value in the $[0,1]$ interval defines a standard fuzzy set, $\Theta_A : Agents \rightarrow \{[0,1]\}$. We use the fuzzy numbers to represent trust, making the set Θ_A a type-2 fuzzy set, as the membership function itself is a fuzzy set – fuzzy number. The membership function $\Theta_A(B)$ represents A's estimation of the B's trustworthiness. This formal extension allows us to represent the trust uncertainty.

Deriving Trust Observations from Coalition Cooperation Results. To obtain the trust observation, agent A evaluates the trustfulness of the coalition partners in a specific coalition C as a function of the coalition payoff. Trust observation is a single value in the $[0,1]$ interval representing the trust observation τ for each coalition member B, denoted $\tau^A_{C,B}$ or simply $\tau_{C,B}$.

To keep our algorithm domain independent, we normalize the cooperation result into $[0,1]$ interval using a subjective loss function: *subjective utility* u^A_s (or simply u_s), defined on $[u_{min}, u_{max}]$. In our experiments, the agents obtain their final *subjective utility* as $u^A_s = u^2_n$, where $u_n = \frac{u-u_{min}}{u_{max}-u_{min}}$ denotes a *success ratio* of C.

Each coalition member calculates its value u^A_s and uses this value to obtain the values $\tau^A_{C,B}$ for all coalition members. Different strategies may be used to do so, analogously to profit distribution in coalitions. The cases we consider in the scope of the current work are *equal* (flat) and a-priori trust *proportional* distribution,[1], defined as $\tau^A_{C,Agent} = \frac{defuzzy(\Theta_A(Agent))\times u_s}{Avg_{Agent_i \in C}(defuzzy(\Theta_A(Agent_i))}$.

Iterative Learning of Trust Values. In this section, we propose a precise form of the fuzzy number $\Theta_A(B)$ that represents the trust of agent A in agent B. We have opted for simple, piecewise-linear form defined by the values that can be estimated iteratively. To simplify the notation, we will denote τ^A_B or τ_B all trust observations of agent A about

[1] $defuzzy$ operation is defined as a core of the fuzzy number in our case.

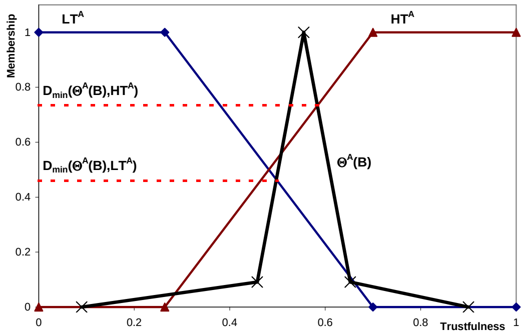

Figure 1: Example of the trust decision using the height of the $\Theta_A(B)$ intersection with LT^A and HT^A. As the incidence with the HT^A is bigger, B is trusted.

the agent B - suite of n_B real values in $[0, 1]$. Note that these values are not kept in agent's memory.

The representation we propose uses the average value to define the core $defuzzy(\Theta_A(B)) = Avg\{\tau_B\}$. Left and right boundaries are defined by $\min\{\tau_B\}$ and $\max\{\tau_B\}$, both with the membership $= 0$. With increasing number of observations, the influence of $\sigma_A\{\tau_B\}$, iteratively estimated using the relation $\sigma^2\{\tau_B\} \leq \widehat{\sigma^2\{\tau_B\}} = Avg\{\tau_B^2\} - Avg^2\{\tau_B\}$, increases, as the membership descends to the points defined as $max\{\min\{\tau_B\}, Avg\{\tau_B\} - \widehat{\sigma_A\{\tau_B\}}\}$ and $\min\{\max\{\tau_B\}, Avg\{\tau_B\} + \widehat{\sigma_A\{\tau_B\}}\}$, both with membership $\frac{1}{n_B+1}$. After sufficient number of observations, our shape (see fig. 1) is almost triangular, with emphasis on average performance rather than *min* and *max* values.

Self-Trust as a Parameter for Trusting Decisions. In our model, each agent also estimates the trust in itself: $\Theta_A(A)$. There are two principal uses for this data for such behavior: (i) detection of unreliable platform or agent component (ii) and environmental adaptation. In many cases, it is difficult or even impossible to estimate correctly what is the expected payoff of the cooperation in the given environment. In our approach, we rather integrate this information into the cooperation rules derived from the self-trust data.

We define two linguistic variables on the trust membership support ($[0, 1]$). First of them is a *low trust* domain, denoted LT^A while the other is *high-trust* domain, HT^A. The sum of their membership functions is equal to 1 on the whole interval $[0, 1]$ - they form a partitioning of unity.

First, we define that $HT^A = 1$ for all trust values higher than $HT^A(defuzzy(\Theta_A(A))) = 1$, as that agent A considers itself as trusted. From this value on, we decrease the trust linearly until we reach 0 membership for the trust $= \max\{\min\{\tau_A\}, defuzzy(\Theta_A(A)) - \widehat{\sigma_A\{\tau_A\}}\}$. LT^A is complementary to HT^A, as shown with the inference in fig. 1.

The Decision to Cooperate and Partner Selection. Θ_A with the fuzzy intervals HT^A and LT^A represent the mental state of the agent. When an agent proposes a coalition or is invited to participate in one, it needs to take a trusting decision; it has to decide which other agents are admissible as partners and order the admissible partners by trust to minimize the risk.

To establish whether an agent B is trusted, we use the Mamdani inference (with *min* t-norm) to calculate the incidence of $\Theta_A(B)$ with the intervals HT^A and LT^A: $D_{min}(\Theta_A(B), HT^A) = hgt(\Theta_A(B) \cap_{min} HT^A)$ and $D_{min}(\Theta_A(B), LT^A) = hgt(\Theta_A(B) \cap_{min} LT^A)$. Agent B is *trusted* iff $D_{min}(\Theta_A(B), HT^A) \geq D_{min}(\Theta_A(B), LT^A)$.

When an agent A needs to organize a coalition, it identifies a subset of trusted agents. Then, it calculates the *usefulness* of these agents for the coalition using the social knowledge in its acquaintance model. The usefulness of each agent is then multiplied by the trustworthiness (defuzzyfied) of this agent, to account for the *willingness* and the candidates are ordered by this value. Suitable subset of acceptable candidates is then invited to form a coalition.

When the agent A is invited to participate in a coalition, it evaluates its trust in the members of the coalition and agrees only if all members are considered to be trustful.

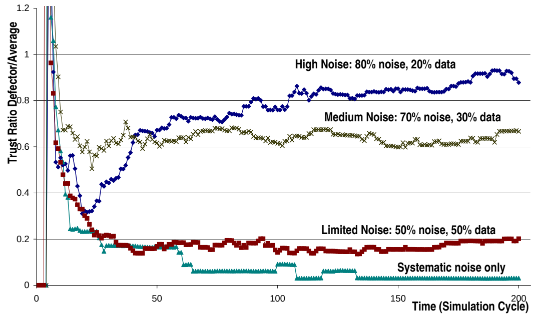

Figure 2: Experimental results for various levels of background noise.

3. EXPERIMENTS

In our experiments, we have evaluated a capacity of agents to detect a defector between the agents who form the coalitions and eliminate this agent from future collaboration. We have conducted the experiments using a fully-fledged multi-agent simulation based on a logistics management scenario. Environment is specific with high level of background noise, both systematic and stochastic. We can see (fig. 2) that in the model is still reasonably robust even if the data contains 70% of the noise and 30% of signal.

4. CONCLUSIONS AND FUTURE WORK

The mechanism we present differentiates from the current work in two aspects - by extending the trust learning and use to the coalition environment and by the use of fuzzy numbers to represent uncertainty. In all other aspects, we have kept the mechanism simple, so that it is easy to embed. The experiments show that the model we propose is robust with respect to noise and adapts itself to the environment, making it an ideal candidate for ubiquitous systems integration.

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5. REFERENCES

[1] D. Dubois and H. Prade. Fuzzy real algebra:some results. *Fuzzy Sets and Systems*, 2(4):327–348, 1979.

[2] S. Ramchurn, D. Huynh, and N. R. Jennings. Trust in multiagent systems. *The Knowledge Engineering Review*, 19(1), 2004.