Towards Presenting Relevant Facts and Answers on Inconsistent and Uncertain Knowledge

Yuqing Tang, Felipe Meneguzzi, Katia Sycara
Carnegie Mellon University, USA
{yuqing.tang,meneguzz,katia}@cs.cmu.edu

Murat Sensoy, Jeff Z. Pan
University of Aberdeen, UK
{m.sensoy,jeff.z.pan}@abdn.ac.uk

Achille Fokoue and Mudhakar Srivatsa
IBM Watson Research Center, USA
{achille,msrivats}@us.ibm.com

***Abstract*—In the presence of vast amount of data and their semantic representation, it is a formidable task for a human decision-maker to effectively locate the most relevant facts, identify critical conflicts, and master a big picture of the information for high quality decision making. This paper proposes a presentation framework which applies argumentation-based reasoning to present relevant facts and answers. Knowledge retrieved from a distributed semantic KB are fed into an argumentation-based reasoning engine which re-organizes the knowledge into coherent arguments, estimates the beliefs of the arguments, and analyzes the pattern of conflicts among the arguments to preliminarily determine the acceptability of these arguments for the decision-maker to review. In order to lower the decision-maker's cognitive load, the argumentation is pruned to present only the arguments and the conflicts that most likely concern the decision-maker. This argumentation pruning algorithm can be adapted to enable a decision-maker to interact with the system and navigate through the information incrementally unfolding the argumentation constructed for the answers.**

I. Introduction

Gathering relevant information from multiple sources is a critical requirement for effective decision making during coalition operations. Such information is intended to improve the knowledge and situation awareness of military commanders to accomplish the tactical tasks at hand. The networked information systems available to modern militaries, as well as the vast array of sensors now employed in intelligence gathering allow an unprecedented amount of information to be collected and disseminated to the all decision makers. This vast amount of information creates many opportunities, but also puts the decision maker in danger of being provided too much information, so raw data is seldom directly presented to decision makers, but rather, processed, summarized and aggregated to allow a decision maker to create a mental big-picture. It is widely understood that any kind of information source (be it human or signals-based) suffers from a degree of inconsistency and uncertainty, as no sensor is perfect and human sources may suffer from various biases. Thus, in order to improve the quality of the decisions made based on such information, it is critical to understand, process, abstract and characterize the uncertainty and inconsistency while presenting the resulting information.

In this paper, we propose a presentation framework that applies argumentation-based reasoning to present relevant facts and answers linked by reasons. The knowledge are stored in distributed semantic web knowledge bases. These knowledge bases are then required via an ontological knowledge reasoner and answers are fed into an argumentation-based reasoning engine which re-organizes the knowledge into coherent arguments, estimates the beliefs of the arguments, and analyzes the pattern of conflicts among the arguments to preliminarily determine the acceptability of these arguments for a decision-maker to review (see Section V). In order to lower the decision-maker's cognitive load, the argumentation is pruned to present only the arguments and the conflicts that most likely concern the decision-maker (see Section VI). The contribution of this paper is bridging the gap between the knowledge and answers with a formal model of human argumentation so as to enable a decision-maker to review the inconsistency and uncertainty handling in a manner similar to his/her mental view.

II. A motivated scenario

This work is motivated by the following scenario. A military unit M needs to determine whether or not to pass through a bridge named Rainbow. Relevant information regarding the bridge is being gathered from both sensors and human reports. Cameras and water sensors are installed on and under the bridge. A UAV flies over the bridge. The cameras on the bridge and UAV can observe the bridge from different angles. The water sensors are programmed to detect enemy vessels passing under the bridge. All these sensors are federated into a networked information system. There are also two units, K and P, which are currently deployed to the area near the bridge. Unit K is a surveillance unit which is deployed to patrol the area. It has no capability to effectively prevent any enemy from approaching the bridge. Unit P is a well-armed force which is deployed in a critical point on a path towards the bridge. Unit P is capable to hold back the enemy to some extent. These two units write reports into the networked information system. The information provided by the sensors and human reports typically contains uncertainty and inconsistency. The decision support system needs to locate the relevant information, provide reasoning related to the decisions, estimating the beliefs out of uncertainty, preliminarily resolve the inconsistency for the decision-maker to review.

III. Knowledge representation

We assume that we have a system of agents $\mathsf{AGS} = \{\mathsf{Ag}_i\}$. Each agent Ag_i models a source of data (e.g. sensors) or reports (e.g. human). An agent Ag_i has a knowledge base which is composed of a fact base Σ_i and a rule base Δ_i:

$$\mathbf{K}_i = \langle \Sigma_i, \Delta_i \rangle.$$

Both the fact base and the rule base are represented in a predicate language $\mathcal{L}$ based on a set $\mathcal{P}$ of symbols with standard connectives $\wedge$, $\vee$, $\rightarrow$, $\neg$ and standard semantics is assumed in this work. We further constrain the domain of any term of a predicate in $\mathcal{P}$ to be finite and no functional symbols are allowed for any term of a predicate in $\mathcal{P}$ to make the set of grounded predicates finite. An inference rule δ in a rule base Δ_i is of the form:

$$\delta = \frac{p_1, \ldots, p_m}{c}$$

where $p_1, .., p_m, c \in \mathcal{L}$. The $\{p_i\}$ are the set of *premises* of the rule δ, and a specific p_i is denoted by $p_i(\delta)$. c is the *conclusion* of the rule, and is denoted by $c(\delta)$. Variables are allowed in place of terms in predicates and rules with standard substitution operations.

These facts and rules are stored as reified strings in ontological knowledge bases along with their semantic information in a manner similar to the YAGO model [12]. The semantic information is concerned about the predicates used in these facts and rules, such as their identifiers and parameters. For rules, the semantic information includes the information about the rule structure such as antecedentPredicate for the predicates used in the rule premises and consequentPredicate for the predicates used in the rule conclusions. Due to the page limit, we omit the details of the RDF representation. The purpose of this RDF representation is to enable the centralized argumentation-based reasoning engine to retrieve knowledge from distributive knowledge bases through a preliminary stage of ontological reasoning using a distributive OWL-DL reasoner from our previous work [4].

IV. Estimating knowledge with uncertainty

We adopt subjective logic [5], [6], [8] to probabilistically characterize the uncertainty of facts, rules and the reasoning outcomes in terms of Dempster-Shafer theory [11]. An agent Ag_i measures the elements of $\Sigma_i \cup \Delta_i$ by a *belief measurement*

$$M_i : \Sigma_i \cup \Delta_i \mapsto B$$

which maps knowledge into a *belief space*:

$$B = \{(b, d, u) \mid b > 0, d > 0, u > 0, b + d + u = 1\}.$$

Let φ be a fact or a rule in $\Sigma_i \cup \Delta_i$. A belief measurement $M_i(\varphi) = (b, d, u)$ means that b is the probability that φ is actually true; d is the probability that φ is actually false; and u is the probability that φ is uncertain (that for example, it is not known if φ is true or not).

We enable two sources of belief measurements: probability confidence intervals and discrete evidences. Probability confidences are obtained from algorithmic processed outcomes of sensor data and human subjective estimation. Discrete evidences are obtained from past experiences of positive and negative outcomes.

A probability confidence interval is of the form:

$$CF(lp, up)$$

where lp and up are, respectively, the lower bound and upper bound of the probability. For example, a classification algorithm which processes camera video may output a confidence level $CF(0.40, 0.92)$ where 0.40 is the lower bound of the probability that the camera sees an armed force and 0.92 is the upper bound of such a probability. Following [16], a probability confidence level $CF(lp, up)$ can be translated into a belief measurement as follows: 1) $b = lp$, 2) $u = up - b$, and 3) $d = 1 - up$. For example, $CF(0.40, 0.92)$ can be translated into a belief measurement $(0.40, 0.08, 0.52)$.

A discrete evidence is of the form

$$E(r, s)$$

where r is the number of *positive outcomes* and s is *negative outcomes* for believing a fact, applying a rule, or trusting another agent. Following [15], from an evidence $E(r, s)$ we can derive a belief measurement (b, d, u) as follows: 1) $b = c(r, s)\frac{r+1}{r+s+2}$, 2) $d = c(r, s)\frac{s+1}{r+s+2}$, and 3) $u = 1 - c(r, s)$. In the computation, $c(r, s) = \frac{1}{2}\int_0^1 |f_{r,s}(x) - 1|dx$ is the *certainty level* which is computed from a probability-certainty density function $f_{r,s}(x) = \frac{x^r(1-x)^s}{\int_0^1 x^r(1-x)^s dx}$ (see [15] for more discussion). For example, seeing 10 times positive applications and 5 times negative applications of a rule, we can measure the belief of the rule with $(0.35, 0.17, 0.48)$ using the above equations.

A belief measurement over a conclusion supported by a set of facts and rules can be combined to form the belief measurements over these facts and rules. For demonstration purposes, in this paper we exemplify one operator — the discounting operator $\otimes$ (taken from [15]).

Definition 1. *Suppose $M_1 = (b_1, d_1, u_1)$ and $M_2 = (b_2, d_2, u_2)$, then $M = M_1 \otimes M_2 = (b, d, u)$ where 1) $b = b_1 b_2$, 2) $d = b_1 d_2$, and 3) $u = 1 - b_1 b_2 - b_1 d_2$.*

Depending on the applications, other operators might be introduced, such as those in [6], [15] and so on. The incorporation of other operators into this presentation framework is our future work.

V. Organizing relevant knowledge into argumentation

This section introduces a formal model of argumentation to 1) link reasons to their conclusions, 2) link the reasons and conclusions that are in conflicts, and 3) apply argumentation semantics [3] to preliminarily analyzing these conflicts in a manner analogous to human argumentation.

A. Linking information into coherent arguments

Following the argumentation framework from our previous work [13], we consider an argument to be a data structure that records a coherent view of how the facts and rules can be put together to support a conclusion. Formally, we capture this as a directed acyclic hyper-graph linking facts and rules from $\Sigma \cup \Delta$ to conclusions. In the following definitions, we take an inference rule $\delta = \frac{p_1, \ldots, p_m}{c} \in \Delta$ as a directed hyper-edge $\langle\{p_1, ..., p_m\}, \{c\}\rangle$. With respect to graph drawing, we choose to represent such a hyper-edge as a sub-graph component $G = \langle V, E\rangle$ such that $V = \{p_1, ..., p_m, c, \delta\}$ and $E = \{(p_1, \delta), ..., (p_m, \delta), (\delta, c)\}$.

Definition 2. *A* rule network $\mathcal{R}$ *is a connected directed hyper-graph $\langle V^r, E^r\rangle$ where (1) the set of vertices V^r are elements of $\mathcal{L}$; (2) the set of hyper-edges E^r are inference rules from Δ; (3) the initial vertices of an edge $e \in E^r$ are the premises of the corresponding rule δ; and (4) the terminal node of that edge is the corresponding conclusion c.*

Definition 3. *An argument from a knowledge base Σ and a rule base Δ is a pair $\langle h, H\rangle$ where 1) $H = \langle V^r, E^r\rangle$ is a rule network such that every premise of each $\delta \in E^r$ is either a member of Σ or the conclusion of some $\delta' \in E^r$, and 2) h is the only sink of E.*

In accordance with the usual terminology, $H = \langle V^r, E^r\rangle$ is the *support* of the argument, and h is the *conclusion*. $C(H)$ is the set of *intermediate conclusions* of H, the set of all the conclusions of the $\delta \in E^r$ other than h. $P(H)$ is the set of *pure premises* of H, the premises of the $\delta \in H^r$ that are not intermediate conclusions of H. $\Delta(H) \subseteq \Delta$ — the generic rules in Δ that have been instantiated into E^r through substitutions — is the set of *supporting rules* of H.

Definition 4. *The belief estimation of a conclusion h given on its supporting argument $\langle h, H\rangle$ is defined as*

$$M(h, H) = \bigotimes_{\varphi \in P(H)} M(\varphi) \otimes \bigotimes_{\delta \in \Delta(H)} M(\delta)$$

Correspondingly, the belief, disbelief and uncertainty is denoted by $b(h, H)$, $d(h, H)$ and $u(h, H)$.

With the concept of arguments and the belief estimation, we can now capture our motivated example with the following 6 arguments[1] in English.

Argument $A1$

Trust	Unit "M" trusts the UAV (trust experiences: 10 positive and 5 negative)
Prem	The UAV does not see any abnormal situation on the Rainbow bridge (confidence interval: $CF(0.56, 0.94)$)
Rule	If no abnormal situation is seen on a bridge, then the bridge is clear (rule validity: 30 positive experiences and 2 negative experiences)
Concl	The Rainbow bridge is clear (argument belief: $(0.40, 0.04, 0.56)$)

Argument $A2$

[1] In the arguments, we annotate a premise with "Prem", annotate a rule with "Rule", annotate a conclusion with "Concl", and annotate a premise about trust specially with "Trust".

Trust Unit “M” trusts the camera installed on the Rainbow bridge (trust experiences: 12 positive and 5 negative)

Prem The camera sees an unidentifiable armed force on the bridge (confidence interval: $CF(0.56, 0.94)$)

Rule If an unidentifiable armed force is seen on a bridge, then the bridge is not clear (rule validity: 9 positive experiences and 1 negative experiences)

Concl The Rainbow bridge is not clear (argument belief: $(0.42, 0.04, 0.54)$)

Argument $A3$

Trust Unit “M” trusts unit “K” (trust experiences: 10 positive and 1 negative)

Prem Unit “K” sees an armed force identified as “id001” at a location labeled by “l1” (confidence interval: $CF(0.48, 0.90)$)

Prem Unit “K” knows that location “l1” is a critical point to the Rainbow bridge (confidence interval: $CF(0.48, 0.90)$)

Rule If an armed force is seen at a location $LocX$ which is a critical point to another location $LocY$, then the armed force is likely moving towards location $LocY$ (rule validity: 20 positive experiences and 8 negative experiences)

Concl The armed force “id001” is moving towards the Rainbow bridge (argument belief: $(0.27, 0.05, 0.67)$)

Argument $A4$

Trust Unit “M” trusts unit “P” (trust experiences: 10 positive and 1 negative)

Trust Unit “M” trusts unit “K” (trust experiences: 10 positive and 1 negative)

Prem Unit “P” strongly holds location labeled by “l2” (confidence interval: $CF(0.72, 0.96)$)

Prem Unit “P” knows that location “l2” is a critical point between location “l1” and the Rainbow bridge (confidence interval: $CF(0.48, 0.90)$)

Prem Unit “K” knows that the armed force “id001” is an enemy force (confidence interval: $CF(0.48, 0.90)$)

Prem Unit “K” sees an armed force identified as “id001” at a location labeled by “l1” (confidence interval: $CF(0.48, 0.90)$)

Rule If an enemy force is moving from a location $LocX$ to another location $LocZ$ but an intermediate critical point $LocY$ is strongly held, then the enemy force is not able to move to $LocZ$ (rule validity: 20 positive experiences and 5 negative experiences)

Concl The armed force “id001” is not able to move to the Rainbow bridge (argument belief: $(0.39, 0.02, 0.59)$)

Argument $A5$

Trust Unit “M” trusts unit “K” (trust experiences: 10 positive and 1 negative)

Prem Unit “K” sees an armed force identified as “id001” at a location labeled by “l1” (confidence interval: $CF(0.48, 0.90)$)

Prem Unit “K” knows that the armed force “id001” is an enemy force (confidence interval: $CF(0.48, 0.90)$)

Prem Unit “K” knows that location “l1” is a critical point to the bridge Rainbow (confidence interval: $CF(0.48, 0.90)$)

Rule If an armed force is seen at a location $LocX$ which is a critical point to another location $LocY$, then the armed force is likely moving towards location $LocY$ (rule validity: 20 positive experiences and 8 negative experiences)

Rule If an enemy force is moving towards a location, then such a location is not clear (rule validity: 20 positive experiences and 2 negative experiences)

Concl The Rainbow bridge is not clear (argument belief: $(0.16, 0.03, 0.81)$)

Argument $A6$

Trust Unit “M” trusts the water sensor (trust experiences: 6 positive and 4 negative)

Prem The water sensor detect an enemy vessel passing under the Rainbow bridge (confidence interval: $CF(0.48, 0.90)$)

Rule If an enemy vessel is detected under a bridge, then the bridge is not clear (rule validity: 10 positive experiences and 5 negative experiences)

Concl The Rainbow bridge is not clear (argument belief: $(0.30, 0.06, 0.64)$)

Let information coming from the bridge camera, the UAV, the water-sensor (“W-Sensor”), unit “M” and “K” be represented in the language $\mathcal{L}$ defined in Section III, arguments $A1$—$A6$ can be automatically generated with the algorithms and implementation described in [13], [14]. The graphical representation of these arguments can be found in Figure 1 where each argument is bounded by a box. Inside each argument, information sources (e.g. camera, UAV, and etc.) are depicted as circles, the input facts and conclusions are depicted by inner boxes, and rules are depicted by ovals. For simplicity, only belief measurements on conclusions are displayed.

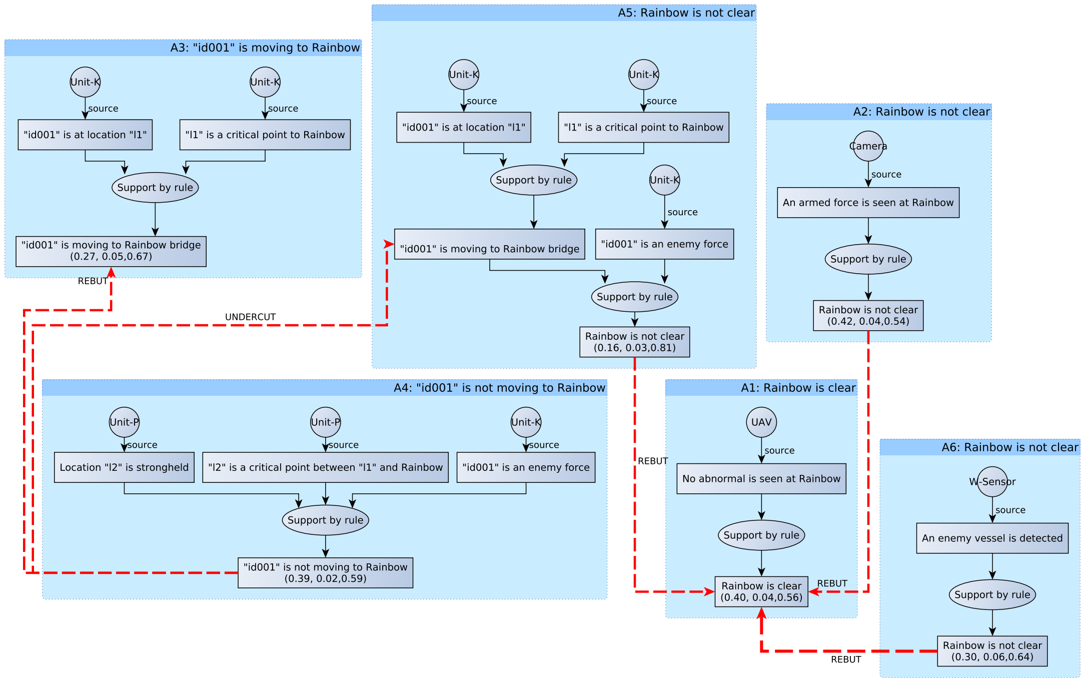

Fig. 1: An argumentation graph

B. Linking and filtering conflicting information

A key notion in argumentation is that arguments *defeat* one another — that is, one argument casts doubt on another by, for example, casting doubt on one of the premises of the second argument — and that it is possible to take a set of arguments that interact in this way and analyze their acceptability. This notion of defeat re-establishes conflicts among the information as defeat links among the arguments.

Definition 5. *An argument $\langle h_1, H_1\rangle$* defeats *an argument $\langle h_2, H_2\rangle$ if it rebuts, premise-undercuts, or intermediate-undercuts, where: (1) $\langle h_1, H_1\rangle$* rebuts *argument $\langle h_2, H_2\rangle$ iff $h_1 \equiv \neg h_2$; (2) $\langle h_1, H_1\rangle$* premise-undercuts *$\langle h_2, H_2\rangle$ iff there is a premise $p \in P(H_2)$ such that $h_1 \equiv \neg p$; and (3) $\langle h_1, H_1\rangle$* intermediate-undercuts *$\langle h_2, H_2\rangle$ iff there is an intermediate conclusion $c \in C(H_2)$ such that $c \neq h_2$ and $h_1 \equiv \neg c$.*

In any case in which $\langle h_1, H_1\rangle$ defeats $\langle h_2, H_2\rangle$, $\langle h_1, H_1\rangle$ is said to be a *defeater* of $\langle h_2, H_2\rangle$, and $\langle h_2, H_2\rangle$ is said to be the *defeatee*. The relation DFT collects all pairs $(\langle h_1, H_1\rangle, \langle h_2, H_2\rangle)$ such that $\langle h_1, H_1\rangle$ defeats $\langle h_2, H_2\rangle$.

To arbitrate two arguments that defeat each other, a preference relation PREF over arguments can be derived from their belief measurements to capture relative strength of the arguments.

Definition 6. *Given two arguments $A_1 = \langle h_1, H_1\rangle$ and $A_2 = \langle h_2, H_2\rangle$ with belief measurements computed, we can define a preference PREF: $(A_1, A_2) \in \mathsf{PREF}$ iff (1) $b(h_1, H_1) > b(h_2, H_2)$, or (2) $b(h_1, H_1) = b(h_2, H_2)$ and $u(h_1, H_1) > u(h_2, H_2)$.*

This is essentially comparing the two probability confidence intervals of the two arguments.

Definition 7. *Let PREF be a preference relation and DFT be a defeat relation on a set of arguments ARG. A* preference-refined defeat relation *PDFT can be defined for any two arguments A_1 and A_2 in ARG as: $(A_1, A_2) \in \mathsf{PDFT}$ iff $(A_1, A_2) \in \mathsf{DFT}$ but $(A_2, A_1) \notin \mathsf{PREF}$.*

With a preference-refined defeat relation PDFT, we obtain an abstract preference-based argumentation framework

$$\mathsf{AFD} = \langle \mathsf{ARG}, \mathsf{PDFT}\rangle$$

which is in essence by discarding defeat relations where the defeatee is preferred to the defeater. Now with preference derived from belief measurement, our running scenario becomes Figure 2.

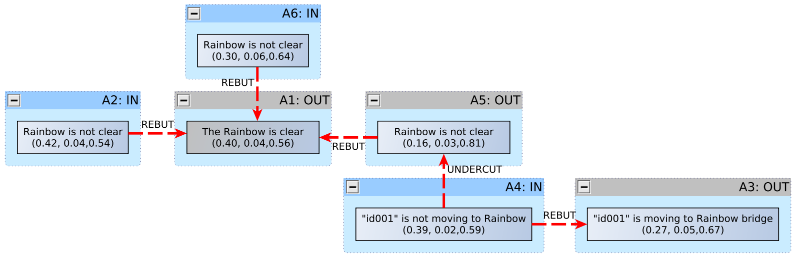

Fig. 2: Abstract argumentation modified by belief measurements

C. Analyzing acceptability

With a preference-based argumentation framework $\mathsf{AFD} = \langle \mathsf{ARG}, \mathsf{PDFT} \rangle$, the acceptability of an argument A can be characterized by the following intuitive principles modeling human argumentation:

1) A is *accepted* (labeled as "IN") if it has no defeaters, or all its defeaters are rejected.
2) A is *rejected* (labeled as "OUT") if it has at least one accepted defeater.
3) Otherwise, the acceptability of A is *undecided* (labeled as "UNDEC").

Formally, we define a *legal labeling* function L_{acc} for argumentation

$$L_{acc} : \mathsf{ARG} \mapsto \{\text{IN, OUT, UNDEC}\}$$

if it satisfies the above three principles. Note that it is impossible to have two or more arguments with conflicting conclusions to be accepted at the same time (by the 2nd principle). This guarantees that the set of conclusions of the accepted arguments is consistent. However, it is possible to have two or more arguments with conflicting conclusions to be rejected at the same time. Discussions on on argumentation semantics and labeling are out of the scope of this paper. References can be found in [1]–[3], [9].

With the implementation in our previous work [13], [14], an argumentation semantic labeling can be computed for our running scenario. The result is shown in Figure 2 where accepted ("IN") arguments are in blue color, and rejected ("OUT") arguments are in gray color. In Figure 2, we have 3 accepted arguments —$A2$, $A4$ and $A6$ — of which two support that the Rainbow bridge is not clear, and one supports that "id001" is not moving to the bridge. We have another 3 rejected arguments — $A1$, $A3$ and $A5$ — of which one supports that the Rainbow bridge is clear, one supports that the Rainbow bridge is not clear, and another one supports that "id001" is moving to the bridge. Looking at the details, $A4$ concludes that the enemy is not moving to Rainbow because the enemy will be held back by unit P. $A4$ has no defeaters, so $A4$ is "IN". As a result, $A5$ which is effectively undercut by $A4$ is "OUT". Zooming into the details, $A4$ defeats $A5$ by defeating a sub-argument $A3$ of $A5$ — $A3$ is "OUT". Both $A2$ and $A6$ have no defeaters, therefore they are both "IN". Now the preliminary analysis of the argumentation acceptability is completed. At this point, the decision-maker might want to manually modify the status of some arguments (e.g. from "IN" to "OUT", "UNDEC" to "IN", and etc.) if he/she has external reasons (e.g based on the information which is not captured in the automatic system) to do so. After the decision-maker manually modified the argument status, the automatic system applies the 3 principles iteratively to update the other arguments accordingly enabling the decision-maker to see how his/her external reasoning can be propagated to other arguments. We will evaluate the utility of this approach with a user study in our future research.

VI. Presenting Argumentation

The argumentation, belief measurement and the acceptability analysis established in the previous sections capture a logical structure over the facts, the answers and their conflicts. The logical structure is readily understood by a decision-maker. However, in bigger networked information systems and real word scenarios, the argumentation graph easily become formidable large. Algorithm 1 provides a basic presentation framework to take into account the end user's need to display only a subgraph of the argumentation that the end user is concerned about. Algorithm 1 takes as parameters an ontology $\mathcal{O}$ composed of the predicates which the end users would be interested in, an argumentation graph G which is established during the reasoning stage, and a node X in G which corresponds to a conclusion with respect to a query. Overall, Algorithm 1 enables us to achieve the follows:

Interactive exploration: Starting with the conclusion of an argument which is "IN" and has the highest belief measurement, then the user clicks on a conclusion node to expand the argument of the conclusion. From this expanded argument, the user can continue clicking on the premises, the intermediate conclusions and the rules which have defeaters to expand into a deeper investigation related to the answers. This can be achieved by incrementally enlarge the set of predicates in $\mathcal{O}$.

Presenting alternative answers: We first retrieve the relevant concepts on trust and the query from the meta-information ontology knowledge base: $\mathcal{O}_{QT} \equiv \{clear\} \sqcup \{trust\}$. Then we invoke Algorithm 1 with $\mathcal{O}_{QT}$. For example, applying these two steps on the argumentation graph of Figure 1, we can obtain Figure 3. The decision-maker now can focus on alternative answers along with their acceptability, their belief measurements and the information sources.

Exploring defeat links: We first retrieve the relevant concepts on trusts, the query, and the defeating points from the meta-information ontology knowledge base: $\mathcal{O}_{QTD} \equiv \mathcal{O}_{QT} \sqcup \mathcal{O}^{+1}(\mathsf{DFT})$ where $\mathcal{O}^{+1}(\mathsf{DFT})$ is the concepts which is with distance 1 to the defeating points in the argumentation graph. It can be obtained by investigating the argumentation graph near the defeating points: $\mathcal{O}^{+1}(\mathsf{DFT}) = \{movingTo, seeArmedForce, enemy\}$. The result is in Figure 4 where the defeating reasoning from unit "P" is highlighted.

Proactive presentation for the underlying tasks: Through modeling the underlying tasks along with their information plans [7], we can learn what are the concepts related to the next steps in the underlying tasks and then carry out the argumentation-based reasoning and bring up the most relevant subgraph of the argumentation to the users. This is one of our future direction.

Algorithm 1: Prune reasoning using ontology: PruneReasoning$(\mathcal{O}, G, X)$:

```
Input: (1) O: A set of relevant concepts; (2)
       G = ⟨V, E⟩: An argumentation graph; (3)
       X: A node in the argumentation graph
if X has be investigated before then
  | return {Node(X)} ;
if X ∈ O then
  | Create a node u = Node(X) for X;
  | for each (u, v) ∈ E do
  |   | S ← PruneReasoning(O, G, v);
  |   | for each w ∈ S do
  |   |   | Add (u, w) to E ;
  |   |
  | return {u};
else
  | D ← ∅;
  | for each v such that (X, v) ∈ E do
  |   | S ← PruneReasoning(O, G, v);
  |   | D ← D ∪ S;
  | if X is a conclusion and D contains no
  | elements of the argument concluded on X then
  |   | return ∅;
  | return D;
```

VII. CONCLUSIONS

In this paper, we propose a presentation framework that applies argumentation-based reasoning to present relevant facts and answers linked by reasons. An argumentation-based reasoning engine re-organizes the knowledge into coherent arguments, estimates the beliefs of the arguments, and analyzes the pattern of conflicts among the arguments to preliminarily determine the acceptability of these arguments for a decision-maker to review. The resulting argumentation is pruned to present only the arguments and the conflicts that most likely concern the decision-maker. This presentation is based on a formal model of human argumentation making the presentation approximate a human decision-maker's mental model of the information.

Future work concerns the integration of inconsistency and uncertainty handling with the distributed reasoner from our previous work [4] for scalability and efficiency. Another direction is to adapt the presentation to the human user's mental model. This can be achieved through accommodating human user's mental ontology profile in the ontological knowledge bases and reason about the concepts to be used in the presentation. To link facts to conclusions, a large collection of rules are needed. This requires efforts. One possible remedy is to automatically learn inference rules (possibly in a restricted form to limit the computational complexity) from free text reports or knowledge bases of the human user's using the approaches such as [10]. As we enable inconsistency and uncertainty handling, the requirement for correctness and accuracy of the rule learning can be relaxed to some extent. Finally, we need to develop evaluation model to study the effectiveness of the presentation.

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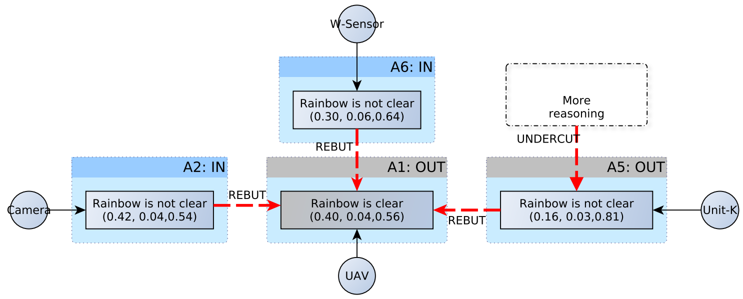

Fig. 3: Presentation focusing on trusts and the final concerns

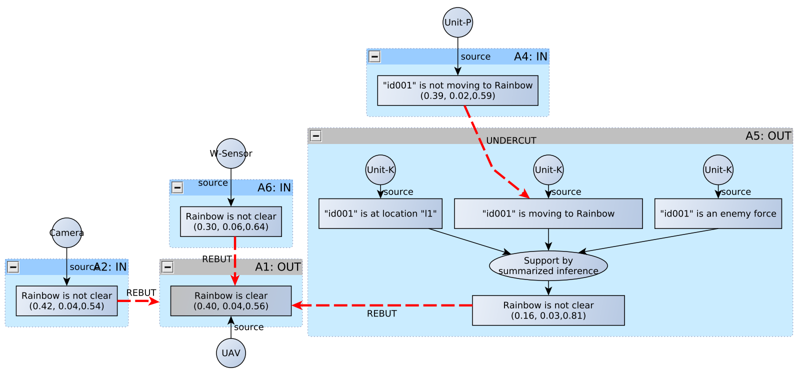

Fig. 4: Presentation focusing on trusts, the final concerns, and the relevant conflicts

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