

Cross-Situation Trust Reasoning

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Abstract

We propose an ontology-based approach for inferences linking trust information in two different situations. That reasoning process can augment the typically sparse trust information, by inferring the missing information from other situational conditions, and can better support situation-aware trust management. Our work is more comprehensive in comparison with other models and considers various aspects of the relationship between situation-awareness and trust management.

1 Introduction

As many researchers have realized, trust may be situation-specific, for instance, a person may trust her or his financial advisor about investment analysis but does not trust the same advisor in health-care. The situation in which the truster is confronted with the trust judgment problem might not be the same as the situation in which the expected valid information has been created. For example, an investor (the truster) may attempt to use some information in a situation of buying stocks that has been created by a financial expert (the trustee) in another situation of giving a financial investment seminar [12]. Therefore we need a suitable means to represent the situation for trust evaluation and a suitable method to infer trust information between different situations. Situation awareness [1] is regarded as a special kind of context-awareness, by modeling situations as sets of associated contextual information. By the word *context* we mean the same as the widely accepted definition of context [7]: “*Context is any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the interaction between a user and an application, including the user and the application themselves.*” In this paper we try

to model customization of trust information for every individual situation. Moreover, we assess implicit impact of trust information in different situations on each other (e.g. if a person is trusted in academia he will most likely be trusted in an industrial arena as well).

This paper is organized as follows. Section 2 discusses related work. In section 3 our proposed model is presented. An application example is given to demonstrate the potential use of our proposed model in Section 4. Finally, Section 5 concludes the paper and outlines some future work.

2 Related Work

From the literature we can find that extension of a trust model with context representation can reduce complexity in the management of trust relationships [15], improve the recommendation process [16], help to infer trust information in context hierarchies [11], improve performance [17], help to learn policies/norms at runtime [17, 21], and provide protection against changes of identity and first time offenders [17, 18]. Context related information has been represented as: Context-aware domains [15, 16], Intensional Programming [23], Multi-dimensional goals [10], Clustering [17], and Ontologies [21].

[19] provides a survey of different approaches to model context for ubiquitous computing. In this work numerous approaches are reviewed, classified relative to their core elements and evaluated with respect to their appropriateness for ubiquitous computing. The authors arrive at the conclusion that the most promising assets for context modeling for ubiquitous computing environments can be found in the ontology category in comparison with other approaches like key-value models, mark-up scheme models, graphical models, object-oriented models, and logic based models. This selection is based on the six requirements dominant in pervasive environments: distributed composi-

tion, partial validation, richness and quality of information, incompleteness and ambiguity, level of formality, and applicability to existing environments.

We present a state-of-the-art survey of context representation for trust management in [20]. In the rest of this section ontology-based approaches to this problem are examined in more details.

Golbeck et al. [9] propose an ontology for trust. In [8] the authors consider a model using context-specific reputation by assigning numeric ratings to different types of connections based on context of the analysis. In [21] rules to describe how certain context-sensitive information (trust factors) reduces or enhances the trust value have been specified for this trust ontology.

In [22] contextual information (context attributes) is used to adjust the output of a trust determination process. Each attribute can adjust the trust value positively or negatively according to a specified weight. As an illustration, if t is the trust value and ω is the weight of the context property then the adjusting function can be t^ω for decrease or $\sqrt[\omega]{t}$ for increase. A context ontology connects the context attributes with each other in an appropriate manner, enabling the utilization of context attributes which do not exactly match the query, but are “close enough” to it.

In [6] cases where a truster does not have enough information to produce a trust value for a given task, but she knows instead the previous partner behavior performing similar tasks are considered. This model estimates trust using the information about similar tasks. The similarity ($D(s_1, s_2)$) between two tasks s_1 and s_2 is obtained from the comparison of the task attributes.

$$D(s_1, s_2) = 1 - \frac{1}{n} \cdot \sum_{i=1}^n |s_{1i} - s_{2i}|$$

where n is the number of task attributes, s_{1i} is the i -th attribute of task s_1 , and s_{2i} is the i -th attribute of task s_2 .

In [5] the same authors obtain the similarity ($D(s_1, s_2)$) from the comparison of the task attributes in the ontology using formula below:

$$\frac{|S_1 \cap S_2|}{|S_1 \cap S_2| + \alpha(s_1, s_2) |S_1 \setminus S_2| + (1 - \alpha(s_1, s_2)) |S_2 \setminus S_1|}$$

where $0 < \alpha < 1$; S_1 and S_2 are the set of properties of concepts s_1 and s_2 , respectively. Function α takes into account the depth of compared concepts in the ontology hierarchy.

3 The Proposed Model

We present a universal mechanism that can be combined with existing trust models to extend their ca-

pabilities towards efficient modeling of the situation-aware trust. We adopt the ontology approach to model situation, and consider our work as a complementary solution in comparison with [22] and [5]. In [22] nothing is said about how many nodes are included or what other context dependent parameters should be included in the calculation. This work does not mention how to find similar or relevant nodes. The main drawback of [5] is that does not say anything about how to find similar or relevant contexts.

3.1 The Ontology Model

We base our model on the context-specific trust ontology proposed in [9, 8] which is based on OWL [14]. In our model, the situation as concept consists of *parts* that are called *local contexts*. Such *contexts* maintain the appropriate contextual information in order to describe any situation. Axioms, supported by the Description Logics (DLs) [3], provide enhanced semantics in conceptual modeling. We use disjoint and closure axioms. The former denotes that two concepts, A and B , are by definition disjoint if $A \subseteq \neg B$. As a case in point, the situations *internal partners meeting* and *sleeping* are disjoint. The latter defines whether existential $\exists$ and universal $\forall$ restrictions are applied over a relation/property. For example, *Internal partners meeting* is a *meeting* that contains at least ($\exists$ restriction) and only ($\forall$ restriction) internal partners (restricted type of Person) and takes place only in a meeting room (restricted type of Indoor).

3.2 Situational Inference

We consider two approaches for the inference task among situations: *rule-based inference* and *similarity-based reasoning*. In [21], rules that express how the value of trust is adjusted by the underlying situation are defined for this ontology. In addition, we define the reasoning rules that reflect the relations between various situational aspects. For instance, rule-based inference can be done by abstraction rules deriving knowledge about more generic situations from more specific ones by discarding some situational information (usage of hierarchies). Consider a rule:

$$\text{context.location} \text{AND} \text{context.time} \Rightarrow \text{context.location}$$

As such, abstraction rules define the factors that are more important for the situation-awareness and help to deal with general situations, such as *context.time = afternoon*. Another type of reasoning rules exploits knowledge about the relations between the values of certain situational aspects. For example,

consider a situation S :

$context.location = Trondheim \text{ AND } context.time = 4PM$

and the rule: $4PM \Rightarrow afternoon$ allow inferring information also for the new situation S [4].

Another alternative approach for the inference task is a reasoning process to infer knowledge about quite *similar* situations. We consider that similarity between situations is a weighted sum of the similarity of their *local contexts* as parts. Furthermore, similarity of *local contexts*, described as concepts that contain even *more specific local contexts*, can be calculated in the same way recursively.

We consider several aspects (structural, relational and description) in similarity measurement of the *most specific local contexts* (as the base case of the recursion) in spite of other models that just considered the structural similarity in the ontology.

3.2.1 Structural similarity

This kind of similarity is based on the ontology structure. Structural similarity (SS) is calculated according to (2). However, if two concepts are disjoint, then it is inappropriate to measure their structural similarity. Thus, SS should be revised (SS_D) as follows:

$$SS_D(c, d) = SS(c, d) - |SS(c, d) - SS(c_F, d_F)|$$

where c_F and d_F are the nearest indirect super-concepts that are disjoint with those of the c and d , respectively [1].

3.2.2 Relational similarity

Relational similarity (RS) is based on the relations between concepts. For this kind of similarity we use a general similarity measurement algorithm of objects, called SimRank, applicable in any domain with object-to-object relationships [13]. In [13] the authors have proposed a general similarity measurement algorithm of objects, called SimRank, applicable in any domain with object-to-object relationships. Such domains are naturally modeled as graphs, with nodes representing objects and edges representing relationships. The intuition behind this algorithm is that in many domains, *similar* objects are related to *similar* objects. More precisely, objects a and b are similar if they are related to objects c and d , respectively, and c and d are themselves similar. The base case is that objects are similar to themselves. If we call the graph of objects and their relations G , then we can form a node-pair graph G^2 in which each node represents an ordered pair of nodes of G . A node (a, b) of G^2 points to a node (c, d) if, in

G , a points to c and b points to d . Similarity scores are symmetric, so for clarity we draw (a, b) and (b, a) as a single node a, b (with the union of their associated edges).

SimRank is an iterative fixed-point algorithm on G^2 to compute similarity scores for node-pairs in G^2 . The similarity score for a node v of G^2 gives a measure of similarity between the two nodes of G represented by v . Scores can be thought of as flowing from a node to its neighbors. Each iteration propagates scores one step forward along the direction of the edges, until the system stabilizes (i.e., scores converge). Since nodes of G^2 represents pairs in G , similarity is propagated from pair to pair. Under this computation, two objects are *similar* if they are referenced by *similar* objects. Below, the recursive equation for $RS(c, d)$ is given. If $c = d$ then $RS(c, d)$ is defined to be 1. Otherwise,

$$RS(c, d) = \frac{C}{|I(c)| |I(d)|} \sum_{i=1}^{|I(c)|} \sum_{j=1}^{|I(d)|} RS(I_i(c), I_j(d))$$

where C is a constant between 0 and 1. can be thought of either as confidence levels or decay factors. Consider a simple scenario where concept x has two relations with concepts m and n , so we conclude some similarity between m and n . The similarity of x with itself is 1, but we probably do not want to conclude that $RS(m, n) = RS(x, x) = 1$. Rather, we let $RS(m, n) = C \cdot RS(x, x)$ meaning that we are less confident about the similarity between m and n than we are between x and itself. $I(c)$ and $I(d)$ are set of in-neighbors of c and d respectively.

3.2.3 Description Similarity

The description similarity (DS) of two descriptions c and d is measured by comparing their distances from their common closure concept. Closure concept (cl) is the concept that restricts all its relations with both $\exists$ and $\forall$ restrictions. We consider the closure concept as the origin and calculate the Euclidean distance (d_x) of each description from it. Then we can compare these Euclidean distances with each other.

$$d_x(c, cl) = \min_{r|t \supseteq r} \sqrt{\{SS(r, t) \cdot SS_D(A(c, r), A(cl, t))\}}$$

$$DS(c, d) = 1 - \sqrt{\sum_{x \in \{\forall, \exists\}} (d_x(c, cl) - d_x(d, cl))^2}$$

$A(c, r)$ is the set of associated concepts of c through relation r and relation t subsumes each relation r [1].

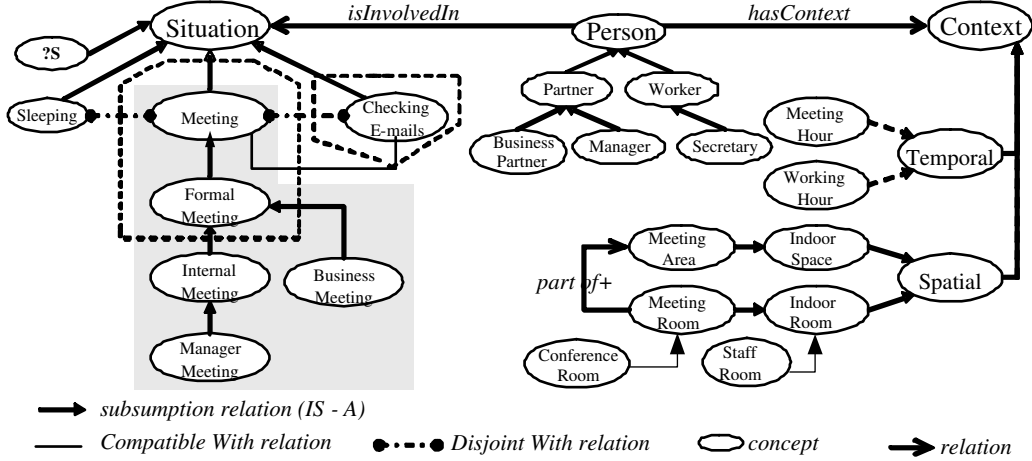


Figure 1. Semantics in the example situations ontology [2].

3.2.4 Total Similarity

The total similarity (TS) of two concepts is decided based on their *absolute similarity* and *description similarity*. Absolute similarity (AS), which is only based on semantics that concepts inherit within taxonomies, is calculated from the weighted average of *structural* and *relational* similarities. These weights are related to the importance of these two measurements and are decided for each application. TS is concluded based on the following fuzzy rules:

Rule 1: (AS is “very high”) $\vee$ (AS is “somewhat high” and DS is “high”) $\rightarrow$ (AS is a necessary condition to conclude TS)

Rule 2: (AS is “medium” $\wedge$ DS is “high”) $\rightarrow$ (both AS and DS are equally necessary conditions to conclude TS)

Rule 3: (AS is “low” $\wedge$ DS is “high”) $\rightarrow$ (DS is necessary but not sufficient to conclude TS)

Whenever two situations have very similar descriptions (DS is high), it does not strongly imply that they refer to rather similar contexts. On the other hand, whenever they are at least similar with respect to the absolute similarity, then there is a rather strong belief that they are similar, not only as closed descriptions, but also, as situations referring to equivalent contexts.

4 Example Scenario

Suppose that A and B are both *internal partners*. A trusts B to tell him secret information about their

company when they attend an *internal partner meeting* (which is scheduled during *meeting hour* in *meeting room*) as depicted in Fig1. Assume that the trust model (one of available trust estimation models) returns the trust value of “very trustworthy” among the five possible trust values of “very untrustworthy”, “untrustworthy”, “moderate”, “trustworthy”, and “very trustworthy” (equivalent to +2 out of -2, -1, 0, +1, +2) based on available information. Consider the current situation as A and B are located in an internal space (e.g., possibly not a meeting room), and are alone in that place. This situation is denoted by the uninstantiated / unclassified situation variable ?S in the figure.

The reasoning process leads us to a more specific taxonomy of situation which is, that of the *meeting* (the shaded area covering the *meeting* taxonomy), pruning the taxonomies related to other situations. Besides, this situation is *believed* to be an *internal partners meeting* situation because the *closure* axiom that both A and B are *internal partners*, holds in such a situation. On the contrary, their situation cannot be regarded as being a *business meeting* situation due to the lack the *closure* axiom that they are *business partners*. Based on the proposed model we can infer *internal partners meeting* as the most similar situation in the *meeting* taxonomy with *total similarity* value of 0.74 and consider an initial trust value of “trustworthy” ($+2 \times 0.74 = 1.48 \approx +1$) for this situation.

5 Conclusion and Future work

To sum up, we propose a model that clearly depicts how trust information in one situation can affect trust

information in other situations. This model also provides suitable mechanisms to anticipate a proper initial reputation value for a trustee within situations that he has not been present in before. We consider two approaches for the inference task among situations: *rule-based inference* and *similarity-based reasoning*. Related literature consider only the structural similarity of concepts, while we consider several dimensions (structural, relational, description) in measuring of similarity and propose an algorithm for relational similarity based on SimRank algorithm.

In the future we plan to do simulations using data from a real system to examine how well it works. Moreover, we are going to take into account the context itself when evaluating the similarity between contexts, as the similarity of two context models is in itself context dependent.

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