Towards a Spatio-Temporal Agent-Based Recommender System

(Extended Abstract)

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ABSTRACT

Agent-based recommender systems have been widely employed in the last years to provide informative suggestions to users, showing the advantage of exploiting components like beliefs, goals and trust in the recommendation computation. However, many real-world recommendation scenarios, like the traffic or the health ones, require to represent and reason about spatial and temporal knowledge, considering also their inner incomplete and vague connotation. This paper tackles this challenge, and introduces STARS, an agent-based recommender system based on the Belief-Desire-Intention (BDI) architecture. Our approach extends the BDI model with spatial and temporal reasoning to represent and reason about fuzzy beliefs and desires dynamics.

1. INTRODUCTION

Agent-based recommender systems [9, 4, 5, 6, 7, 2, 12] have been proposed in the last years in different scenarios, e.g., the tourism, health-care and traffic ones, to provide suggestions to support users in the achievement of their goals. The advantage of such a kind of recommender systems is that of encoding in the system users' beliefs and goals to return a recommendation as close as possible to their needs, with the possibility to take in also additional information like the confidence in the source. These application scenarios require in addition to formalize the knowledge about the time and the location in which the action is taking place. This information often needs to be processed at the same time, as in the case of the traffic scenario where a traffic jam is identified by its location and the time it is occurring during the day, and requires to encode a certain degree of vagueness. In this paper, we answer the following research question: *how to represent and reason about fuzzy spatial-temporal knowledge to provide useful recommendations?* To answer this question, we introduce STARS, a Spatio-temporal Cognitive Agent-based Recommender System. Based on the extension principle of fuzzy set theory [18], we define fuzzy Allen's intervals [1] to model temporal knowledge, while fuzzy topological relations are defined in terms of region connection calculus [13], where regions are represented as fuzzy sets. These two components, namely spatial and temporal information, are combined together based on the assumption that the degree to which a spatio-temporal belief is true is the *minimum* between the confidence degrees of the spatial belief and temporal one, respectively. Spatio-temporal knowledge is then exploited by agents to update their beliefs following the other agents' recommendations, with the aim to reach their goals. Up to our knowledge, STARS is the first agent-based recommender system taking into account at the some time spatial and temporal knowledge, and the vagueness and incompleteness typical of these components. Related work, e.g., [8], considers either spatial or temporal knowledge, and does not consider the fuzzy connotation of spatio-temporal knowledge, e.g., [16, 3].

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2. SPATIO-TEMPORAL BELIEF REPRESENTATION AND REASONING

This work is an extension of the recommender system based on the BDI model we presented in [12, 11], where a spatio-temporal representation of beliefs and desires is proposed. A spatio-temporal belief is an event defined as a spatial relation holding in a temporal interval. A spatio-temporal belief consists then of a sequence of snapshots of an entity taken at specific time points: b_1 at t_1, b_2 at t_2,..., b_n at t_n where $t_1, t_2, ..., t_n \in T$ and $b_1, b_2, ..., b_n$ are spatio-temporal beliefs concerning a moving spatial object (e.g., a car, a moving person, ...).

2.1 Fuzzy Allen's intervals

The 12 relations defined by Allen for simple time intervals [1] are generalized for modeling fuzzy time relations. Each basic relation can be defined in terms of endpoint relations as in [10]. Using the extension principle, a fuzzy temporal relation is defined. For example, the fuzzy relation d_f is introduced for the temporal relation d (during), and it is defined as follows:

$$X d_f Y \Leftrightarrow (X^- >_f Y^-) \wedge (X^+ <_f Y^+)$$

Table 1: **Fuzzy RCC definitions**

Name	Definition	Fuzzy Definition
$DC(x,y)$	$\neg C(x,y)$	$1 - C(x,y)$
$P(x,y)$	$\forall z \in U, C(z,x) \to C(z,y)$	$\inf_{z\in U} I_W(C(z,x), C(z,y))$
$PP(x,y)$	$P(x,y) \wedge \neg P(y,x)$	$\min(P(x,y), 1 - P(y,x))$
$EQ(x,y)$	$P(x,y) \wedge P(y,x)$	$\min((P(x,y), P(y,x))$
$O(x,y)$	$\exists z \in U, P(z,x) \wedge P(z,y)$	$\sup_{z\in C} T_W(P(z,x), P(z,y))$
$DR(x,y)$	$\neg O(x,y)$	$1 - O(x,y)$
$PO(x,y)$	$O(x,y) \wedge \neg P(x,y) \wedge \neg P(y,x)$	$\min(O(x,y), 1 - P(x,y), 1 - P(y,x)))$
$EC(x,y)$	$C(x,y) \wedge \neg O(x,y)$	$\min(C(x,y), 1 - O(x,y))$
$NTP(x,y)$	$\forall z \in U, C(z,x) \to O(z,y)$	$\inf_{t\in U} I_W(C(z,x), O(z,y))$
$TPP(x,y)$	$PP(x,y) \wedge \neg NTP(x,y)$	$\min(PP(x,y), 1 - NTP(x,y))$
$NTPP(x,y)$	$PP(x,y) \wedge NTP(x,y)$	$\min(1 - P(x,y), NTP(x,y))$

The corresponding degree of confidence, using the extension principle, can be expressed as:

$$\mu_{X d_f Y} = \min(\mu_{X^- >_f Y^-}, \mu_{X^+ <_f Y^+})$$

All the X and Y values can be generalized to fuzzy values and represented by fuzzy triangular numbers. Based on the extension principle, we define first the confidence degrees of the fuzzy relations $\geq_f$ and $\leq_f$ in order to deduce respectively those of $>_f$, $<_f$ and $=_f$. Suppose we have two fuzzy intervals A and B defined by triangular fuzzy functions as follows: $A = (a_1, a_2, a_3)$ and $B = (b_1, b_2, b_3)$. By applying the extension principle, we obtain the following fuzzy relations:

$$\mu_{A \leq_f B} = \begin{cases} 0 & \text{if} \quad a_1 > b_3 \\ \frac{b_3 - a_1}{b_3 - a_1 + a_2 - b_2} & \text{if} \quad a_1 \leq b_3, b_2 < a_2 \\ 1 & \text{if} \quad a_2 \leq b_2 \end{cases} \tag{1}$$

$$\mu_{A \geq_f B} = \begin{cases} 0 & \text{if} \quad b_1 > a_3 \\ \frac{a_3 - b_1}{a_3 - b_1 + b_2 - a_2} & \text{if} \quad b_1 \leq a_3, b_2 > a_2 \\ 1 & \text{if} \quad b_2 \leq a_2 \end{cases} \tag{2}$$

From Equations 1 and 2, we obtain the confidence degree of relations $>_f$, $<_f$ and $=_f$ as follows:

$$\begin{aligned} A <_f B &= A \leq_f B \wedge \neg(A =_f B), \\ A >_f B &= A \geq_f B \wedge \neg(A =_f B), \\ A =_f B &= A \leq_f B \wedge A \geq_f B. \end{aligned}$$

2.2 Fuzzy topological relations

The eight binary topological predicates for simple regions presented in Randell *et al.* [13] are generalized for modeling fuzzy topological relations. Based on the approach proposed by Schockaert *et al.* [15] and the definition of the RCC relations in [13], we present an approach for modelling imprecise spatial information when regions are represented as fuzzy sets. Let U be a nonempty set (representing regions) and $\mathbf{C}$ be a reflexive and symmetric binary fuzzy relation on it modeling connection. Several other topological relations can be defined based on this relation. They include the RCC8 basic relations DC, EC, PO, EQ, TPP, NTPP, and the converses of TPP and NTPP (see Table 1 for their definitions). Note that we adopt, following [14], the Łukasiewicz t-norm T_w and its corresponding implicator I_{T_w} to generalize standard logical conjunction and implication. The rationale for this choice for RCC-8 is discussed in [14]. In addition, we chose this logic for its convenience, especially in the implication function. The implicator corresponding to the Łukasiewicz t-norm is defined as: $I_{T_W} = \min(1, 1 - x + y)$. In fact, the minimum operator does not introduce any new arbitrary values, which is better suited to a qualitative treatment of uncertainty.

2.3 Fuzzy spatio-temporal belief representation and reasoning

In order to represent an imprecise spatio-temporal belief or desire such as "An accident occurred around 8 PM between road A and road B" or "I want to be at work before 9 am" we combine the RCC spatial relations with Allen's temporal relations. The degree to which this spatio-temporal belief is true is computed using the minimum between the degrees of confidence of the spatial belief and temporal one, respectively. For representing a spatio-temporal belief, we annotate spatial formulae with temporal information. This means that a spatial formula is true during a time interval or at a specific time point. In other words, it can be written as follows:

$$X \ DC_I \ Y, Y \ PO_J \ Z$$

where X and Y represent two different regions or moving objects, and I and J are time intervals. This means that X is disconnected from Y during time interval I. Similarly, Y is part of Z during time interval J. An empirical evaluation of the proposed model in the traffic domain has been addressed using the NetLogo platform [17]. For more details, we refer the reader to `http://modelingcommons.org/browse/one_model/4832#model_tabs_browse_info`.

3. CONCLUSIONS

In this paper, we have introduced the STARS agent-based recommender system where fuzzy spatio-temporal beliefs are formally represented and updated. Answering the need to represent vague spatio-temporal information to provide recommendations in the traffic scenario, we define spatio-temporal knowledge annotating spatial formulae (formalized through fuzzy region connection calculus) with temporal information (formalized through fuzzy Allen's time intervals).

Several open challenges have to be tackled as future research. For instance, further qualitative relations about directions should be introduced concerning spatial reasoning to allow the representation of a more realistic model. Moreover, introducing new metrics to further reduce the processing time is also part of our future research.

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