Uncertain Spatiotemporal Logic for General Intelligence

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Abstract

Spatiotemporal reasoning is an important skill that an AGI is expected to have, innately or not. Much work has already been done in defining reasoning systems for space, time and spacetime, such as the Region Connection Calculus for space, Allen's Interval Algebra for time, or the Qualitative Trajectory Calculus for motion. However, these reasoning systems rarely take adequate account of uncertainty, which poses an obstacle to using them in an AGI system confronted with an uncertain reality. In this paper we show how to use PLN (Probabilistic Logic Networks) to represent spatiotemporal knowledge and reasoning, via incorporating existing spatiotemporal calculi, and considering a novel extension of standard PLN truth values inspired by $\mathcal{P}(\mathcal{Z})$-logic. This "PLN-ization" of existing spatiotemporal calculi, we suggest, constitutes an approach to spatiotemporal inference suitable for use in AGI systems that incorporate logic-based components.

Introduction

Most of the problems and situations humans confront every day involve space and time explicitly and centrally. Thus, any AGI system aspiring to even vaguely reach humanlike intelligence must have some reasonably efficient and general means to solve spatiotemporal problems. Multiple alternate or complementary methodologies may be used to achieve this, including spatiotemporal logical inference, internal simulation, or techniques like recurrent neural nets whose dynamics defy simple analytic explanation. We focus here on spatiotemporal logical inference, addressing the problem of creating a spatiotemporal logic adequate for use within an AGI system that confronts the same sort of real-world problems that humans typically do.

Should Spatiotemporal Intuition Be Preprogrammed Or Learned? In principle, one might argue, an AGI should be able to *learn* to reason about space and time just like anything else, obviating the need for spatiotemporal logic or other pre-programmed mechanisms. This would clearly be true of a highly powerful AGI system like (the purely theoretical) AIXI^{tl}. However this kind of foundational learning about space and time may be objectionably costly in practice. Also, it seems clear that some fundamental intuition for space and time is hard-coded into the human infant's brain (Joh05), which provides conceptual motivation for supplying AGI systems with some a priori spatiotemporal knowledge.

Overview A great deal of excellent work has already been done in the areas of spatial, temporal and spatiotemporal reasoning, such as the Region Connection Calculus (RCC93) for topology, the Cardinal Direction Calculus (LLR09) for direction, Allen's Interval Algebra for time, or the Qualitative Trajectory Calculus for motion. Extensions to deal with uncertainty have been introduced too. However, we believe, they do not quite provide an adequate foundation for a logic-incorporating AGI system to do spatiotemporal reasoning. For instance, according to a fuzzy extension of RCC as developed in (SDCCK08), asking how much Z is a part of X knowing how much Y is a part of X and Z is a part of Y (see Figure 1) would result in the answer $[0, 1]$ (a state of total ignorance), as Z can be either totally part of X or not at all. For that reason we consider probability distributions of fuzzy values (Yan09) rather than fuzzy values or intervals of fuzzy values.

So we will show how to represent spatiotemporal knowledge via incorporating existing spatiotemporal calculi into the PLN (GIGH08) uncertain reasoning framework, and then show how to carry out spatiotemporal logical inference using PLN inference rules.

Uncertainty with Distributional Fuzzy Values

The uncertainty extension we use is inspired by $\mathcal{P}(\mathcal{Z})$ (Yan09), an extension of fuzzy logic that considers distributions of fuzzy values rather than mere fuzzy values. For instance the connector $\neg$ (often defined as $\neg x = 1 - x$) is extended into a connector such that the resulting density function is $\mu_{\neg}(x) = \mu(1 - x)$ where μ is the probability density function of the argument.

We define a wider class of connectors that can modulate the output of the distribution. Let $F : [0, 1]^n \mapsto ([0, 1] \mapsto \mathbb{R}^+)$ be a n-ary connector that takes n fuzzy values and returns a probability density function. In that case the probability density function $\mu_F : [0, 1] \mapsto \mathbb{R}^+$ resulting from the extension of F over density functions is:
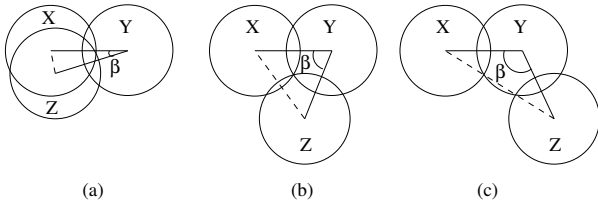
Figure 1: d_{XZ}, in dashline, for 3 different angles

$$\mu_F =$$

$$\underbrace{\int_0^1 \ldots \int_0^1}_{n} F(x_1,\ldots,x_n)\mu_1(x_1)\ldots\mu_n(x_n)dx_1\ldots dx_n$$

(1)

where μ_1, ..., μ_n are the n input arguments. Let us give an example of such a connector with a fuzzy version of the RCC relationship `PartOf` (P for short). A typical inference rule in the crisp case would be:

$$\frac{\texttt{P}(X,Y) \qquad \texttt{P}(Y,Z)}{\texttt{P}(X,Z)}$$

(2)

expressing the transitivity of P. But using a distribution of fuzzy values we would have the following rule

$$\frac{\texttt{P}(X,Y)\,\langle\mu_1\rangle \qquad \texttt{P}(Y,Z)\,\langle\mu_2\rangle}{\texttt{P}(X,Z)\,\langle\mu_{POT}\rangle}$$

(3)

POT stands for PartOf Transitivity. The definition of μ_{POT} for that particular inference rule may depend on many assumptions like the shapes and sizes of regions X, Y and Z. We have worked out the exact definition of μ_{POT} based on simplified assumptions (regions are unitary circles) in the extended version of this paper.

It should not be too hard to derive a more realistic formula based on other more complex assumptions. Though another possibility would be to let the system learn POT (as well as other connectors) based on its experience. Because it is not obvious what are the right assumptions in the first place. So the agent would initially perform spatial reasoning not too accurately, but would improve over time.

Of course the rule could also be extended to involve more premises containing information about sizes and shapes of the regions.

Simplifying Numerical Calculation Using probability density as described above is computationally expensive. To decrease computational cost, several cruder approaches are possible, such as discretizing the probability density functions with a coarse resolution, or restricting attention to beta distributions and treating only their means and variances (as in (Yan09)).

Example of Spatio-temporal Inference in PLN

We now give an example of spatiotemporal inference rules coded in PLN. This paper is too short to contain examples of real-world commonsense inferences, but we invite the author to visit the OpenCog project Wiki web page which contains a few examples [1].

Although the current implementation of PLN incorporates both fuzziness and probability it does not have a built-in truth value to represent distributional fuzzy values. However, we intend to add that extension to the PLN implementation in the near future, and for our present theoretical purposes we will just assume that such a distributional fuzzy value exists, let us call it *DF Truth Value*.

Here is an example of the inference rule expressing the transitivity for the relationship `PartOf`

```
ForAllLink $X $Y $Z
    ImplicationLink
        ANDLink
            PartOf($X, $Y) ⟨tv₁⟩
            PartOf($Y, $Z) ⟨tv₂⟩
        ANDLink
            tv₃ = μ_POT(tv₁, tv₂)
            PartOf($X, $Z) ⟨tv₃⟩
```

(4)

Conclusion

Every AGI system that aspires to humanlike intelligence must carry out spatiotemporal inference in some way. Logic is not the only way to carry out spatiotemporal inference broadly construed. But if one *is* going to use logic, we believe the most effective approach is to incorporate specific spatiotemporal calculi, extended to encompass distributional fuzzy truth values. The next step is to implement it in the OpenCog implementation of PLN, and carry out a large number of practical examples. Alongside their direct practical value, these examples will teach us a great deal about uncertain spatiotemporal logic, including issues such as the proper settings of the various parameters and the customization of inference control mechanisms.

References

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[1]http://www.opencog.org/wiki/Spatiotemporal_Inference