Story Understanding and Inference Using Schemas

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1 Abstract

We present a system for learning generalized stereotypical patterns of events—or “schemas”—from natural language stories, and applying them to understand other stories. Our schema language supports complex event descriptions, temporal relations, arbitrary inter-relation of typed entities, and logical deduction. More complex schemas can be learned by applying simpler schemas to semantic parses of stories and combining multiple filled-in schema matches. Starting with a relatively small set of “protoschemas”, we have learned coherent schemas from children’s stories and used them to generate interesting inferences about unseen stories.

2 Background

Truly understanding a story requires a large amount of knowledge about the world, and the ability to reason about that knowledge. Schemas have a long history in cognitive science and artificial intelligence, from psychological and discourse models (Piaget, 1923; van Dijk and Kintsch, 1983) to more computational musings on their application to story understanding (Minsky, 1974; Levesque et al., 2012). The basic ideas—storing generalized patterns of events, matching small pieces of them to observations, and “filling in” the matched values to the rest of the schema—persist throughout the literature.

Accumulating a sufficient corpus of schemas for story understanding, though, is not an easy task; the breadth of even “common sense” knowledge is immense, and so such knowledge resists manual entry. Past approaches to automatic schema acquisition have largely applied statistical or neural network-based techniques to large text corpora, e.g. (Chambers and Jurafsky, 2011; Pichotta and Mooney, 2016; Yuan et al., 2018). Symbolic approaches like GENESIS (Mooney, 1990) learned specializations of known schemas, but started with very complex schemas like “police officer wanting to arrest criminals”, and were not well equipped to deal with actions they had no prior knowledge of.

3 Our Approach

We propose a system that learns schemas in the manner a two-year-old human child might: starting with a handwritten corpus of dozens to hundreds of simple “protoschemas” like “X helps Y with action A”, “X eats food F to alleviate hunger”, and other general actions a very young human child would be likely to understand, we generate schema matches from simple children’s book stories, combine these matches into more complex schemas, and save those learned schemas to continue the learning process.

Our schema formulas are represented in Episodic Logic (Hwang, 1992), a rich and expressive logical form that mirrors many features of natural language and supports efficient inference. We parse stories into the same representation, and match logical formulas from the story parse to logical formulas in our schemas, substituting bound values for their variables in the rest of the schema. We combine schemas based on heuristics like precondition/postcondition unification, goal/postcondition unification, and temporal ordering, and then generalize the constants of those learned schemas into variables for later use.

With only a small set of protoschemas, we have extracted schemas like “monkey climbs tree to get coconut to eat it” from real children’s stories, and used them to make inferences about similar stories with omitted information.

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