Bootstrapping from Language in the Analogical Theory of Mind Model

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Abstract

Many psychologists have argued that language acquisition plays an important role in the development of Theory of Mind (ToM) reasoning in children. Several accounts of this interaction exist: some believe that language gives children the ability to express already formed ToM reasoning (e.g. He, Bolz, & Baillargeon, 2011), while others argue that learning specific grammatical structures engenders new reasoning abilities (e.g. de Villiers & Pyers, 1997). Questions remain about the mechanism by which this interaction occurs. In this paper, we show that the Analogical Theory of Mind (AToM; Rabkina et al., 2017) computational model can bootstrap aspects of ToM reasoning from sentential complement training, and that its performance matches improvement patterns of children who are trained using similar stimuli. This provides an implemented algorithmic account of bootstrapping ToM reasoning from language within a broader model of ToM development.

Keywords: analogy; cognitive modeling; false belief; sentential complements; structure-mapping; theory of mind;

Introduction

There is considerable evidence that language acquisition affects Theory of Mind (ToM) development (Milligan, Astington, & Dack, 2007). However, debate has centered on the extent of the effects: some researchers report that the ability to understand more complex language simply gives children an ability to demonstrate pre-existing ToM reasoning skills (e.g. He, Bolz, & Baillargeon, 2011). Others suggest that, as children use language more frequently in conversation, they gain a vocabulary with which to mentalize about others' belief and desire states (Harris, 1996). Yet others find that learning certain grammatical structures is a necessary prerequisite for gaining ToM reasoning abilities, and that children bootstrap ToM from these grammatical structures (de Villiers & Pyers, 1997; de Villiers & Pyers, 2002; Hale & Tager-Flusberg, 2003; Lohmann & Tomasello, 2003; see Hofmann, 2016 for a review).

Here, we investigate the latter argument and provide a mechanistic account of linguistic bootstrapping within an existing computational ToM framework, Analogical Theory of Mind (AToM; Rabkina et al., 2017). The AToM model treats ToM reasoning as analogical processing, by comparing structural representations of events to previous experiences. We argue that ToM bootstrapping from language arises from an additional analogical step during encoding: alignment of a syntactic construction and its arguments, which leads to an understanding of nested structure and the relationships between nested forms. Thus, analogical processing occurs twice in our model: once during language interpretation, and again during ToM reasoning.

In representing syntactic structure, we turn to an emerging paradigm in linguistics, called construction grammar (Goldberg, 2003), which proposes joint representations for syntax and semantics, called constructions. Using constructions to represent utterances provides clear structural links between syntactic form and semantic function that facilitate analogical transfer.

In this paper, we show that the AToM model naturally extends to model ToM bootstrapping from language. We begin by describing AToM and its theoretical and computational underpinnings. We then describe our approach to modeling linguistic bootstrapping. We summarize and model a training study in which children bootstrapped ToM reasoning from sentential complement training (Hale & Tager-Flusberg, 2003). We close with related work and future directions.

Background

Structure-Mapping and SAGE-WM

Structure-mapping Theory (SMT; Gentner, 1983) is a theory of analogy and similarity in human cognition. SMT states that structural similarity is preferred over feature-based similarity alone in everyday reasoning. This claim is supported by a wide variety of psychological and computational evidence (Forbus, 2001).

The Structure-mapping Engine (SME; Forbus et al., 2016) is a computational model of SMT. It takes two structured predicate calculus cases, called a *base* and a *target*, as inputs and calculates one or more *mappings* between them. Each mapping contains *correspondences* between statements and entities in the two cases and a *structural similarity score* that rewards deep matching structure. Statements and entities from one case that are missing in the other can be projected across as *candidate inferences*. In AToM, candidate inferences are used to predict mental states.

The Sequential Analogical Generalization Engine, Working Memory (SAGE-WM; Kandaswamy et al., 2014) is a model of analogical generalization and retrieval within working memory. SAGE-WM holds a small number of cases and *generalizations* at a time. Analogical generalizations are formed from previously-encountered cases that have been aligned via SME (Kuehne et al., 2000).

During retrieval, an incoming case, or *probe*, is first compared, via SME, to all generalizations currently in WM in reverse chronological order (i.e. starting with the most recently-seen generalization). If a generalization with a structural similarity score to the probe that is above a pre-set threshold is encountered, that generalization is retrieved. If no such generalization exists, the remaining ungeneralized cases are compared to the probe. If none of the cases are a sufficiently good match, retrieval fails. The probe is then added to WM, either by generalization with a retrieved case or as a new ungeneralized example.

Analogical Theory of Mind (AToM)

AToM is a computational cognitive model of ToM reasoning and development. It is inspired by Bach's (2011) proposal that ToM reasoning and development occur via analogical reasoning, as well as by Hoyos, Horton and Gentner's (2015) findings that structural similarity aids ToM development. We have previously shown that AToM successfully replicates Hoyos et al.'s experimental results (Rabkina et al., 2017).

AToM assumes that most ToM reasoning occurs in working memory. Given a structured case that represents the situation being reasoned about, an analogous case is retrieved via SAGE-WM, and reasoning proceeds via analogical inference. In specific training situations, such as the training study modeled here, comparison cases are assumed to already be in working memory. In real-world reasoning situations, comparison cases are assumed to be retrieved from long term memory (LTM). However, due to the nearly impossible task of representing the contents of a full LTM, AToM does not explicitly model this process.

Cases are represented via predicate calculus. Representations are generated semi-automatically using a semantic parser, EA-NLU (Tomai & Forbus, 2009). In the current experiment, information from visual stimuli (e.g. actions of toys, as acted out by experimenters while stories are told) is added manually. In representing novel training utterances, we take an approach inspired by construction grammar.

Construction Grammar

Construction grammar is an emerging paradigm in linguistics that proposes the fundamental unit of language to be pairings of form and meaning called *constructions*. Constructions are hierarchical and compositional, including morphemes, phrases and even fully grounded idioms (Goldberg, 2003). Under this approach, meaning arises not from a strict combination of words (lexical semantics) but rather from a unification of semantics provided by constructions at every level of interpretation.

It has been suggested that children acquire constructions by analogically aligning and generalizing over individual pairings of syntax and lexical semantics (Tomasello, 2003). Here we specifically focus on argument structure constructions which define how phrases and clauses combine as arguments to form a sentence. McFate and Forbus (2016) previously modeled construction acquisition using SME.

It has been argued that interpretation involves integrating the semantics associated with argument structure with the semantics of its arguments (e.g. verbal semantics) (Goldberg, 1995). Following McFate and Forbus (2016), in the present work we model this integration as structural alignment (see McFate (in press) for more detail). As a result, the nesting and implied semantics of a construction that combines clauses is applied to its arguments (i.e. the clauses themselves). This leads to bootstrapping ToM.

Bootstrapping ToM from Language

To show that AToM can bootstrap ToM reasoning from language, we model a training study by Hale and Tager-Flusberg (2003), in which children improved their performance on false belief reasoning tasks after hearing stories with a sentential complement construction. A sentence contains a sentential complement if a verb in the sentence takes a full clause as its argument (e.g. "The boy said, 'I kissed Big Bird.'").

Bootstrapping in AToM

We propose that bootstrapping from language occurs by analogy. Specifically, it arises from structural alignment between the nested argument structure representation of a contradicted sentential complement and its previously un-nested arguments (see Figure 1).

The resulting candidate inferences are combined into a new learned case (*aligned semantics*), and passed to AToM as a probe. Using SAGE-WM, a similar case is retrieved and generalized. Through the process of generalization, the meaning added by the construction is abstracted away from the specific wording of the cases that have been encountered. In the sentential complement construction, the inferred aligned semantics is a conflict between the semantics of a nested clause and the semantics of an un-nested clause within the same sentence (i.e. what was said vs. what really happened) (de Villiers & Pyers, 1997; 2002).

During subsequent ToM reasoning, the generalization can be retrieved and applied (by analogy) to recognize a conflict between a nested belief state and un-nested external events. We contextualize both the belief and external events within a global reality (de Villiers & Pyers, 2002).

Modeling Task

We model a training study by Hale and Tager-Flusberg (2003), which showed that 4-year-old children who were given training on sentential complements (SC) also improved in their false belief reasoning. Children who were only given false belief (FB) training[1] did not improve in SC performance, and children who were trained on another grammatical structure, relative clauses (RC), only improved their understanding of RC. We model the SC and RC

[1] No mental state language or sentential complement structure was used during FB training.

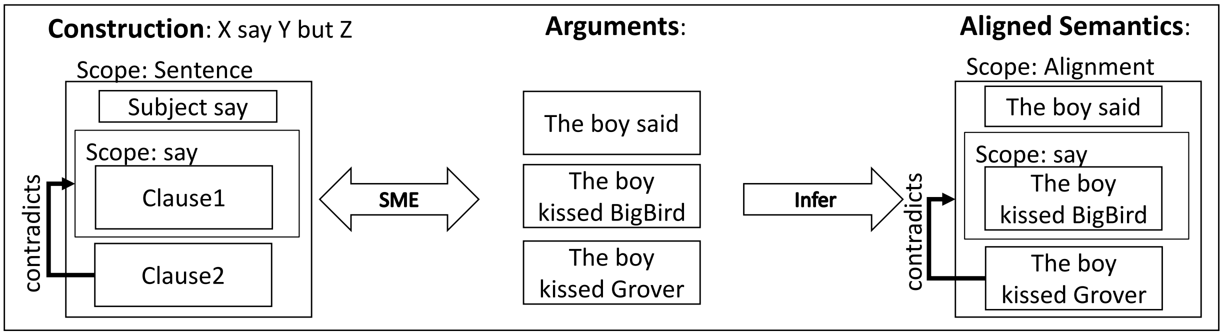

Figure 1: Example representations from a sentential complement training case, in which a boy said that he kissed Big Bird, but really he kissed Grover. The construction consists of the nesting of the first kiss verb phrase inside the say verb phrase, the un-nested second kiss verb phrase, and the contradiction between them. The arguments to the construction contain the semantics of the initial verb phrase and the two clauses. The aligned semantics (i.e. the candidate inference) state that the arguments to the un-nested verb phrase contradict the arguments to the inner, nested verb phrase.

training conditions, which show that linguistic bootstrapping for ToM reasoning is possible with some grammatical constructions (i.e. sentential complements), but not others (i.e. relative clauses). We describe these experiments below.

Sentential Complements Training During each of two training sessions, a child in the SC condition heard four stories about a boy's interaction with a *Sesame Street* character. Each story contained a sentential complement structure (e.g. "The boy said, 'I kissed Grover.'") which differed from reality (e.g. The boy kissing Big Bird). The child was then asked, "What did the boy say?" Regardless of whether the child answered correctly or not, the experimenter emphasized the difference between the contents of the embedded clause and reality, (e.g. "That's right/incorrect. The boy said, 'I kissed Grover,' but he really kissed Big Bird.")

Relative Clause Training Children in the RC condition were told stories using the relative clause structure (e.g. "Bert hugged the girl who jumped up and down.") After each story, the child was asked about the contents of the clause (e.g. "Who did Bert hug?"). The child was expected to use the relative clause structure in her answer, and the structure was emphasized in the experimenter's response (e.g. "That's right. Bert hugged the girl who jumped up and down.")

False Belief Tests During the testing session, each child was given three false belief post-tests, each of which avoided the use of mental state language and SC structures. The first was Location Change. Children were told a story about a boy named Daniel and his mom. Daniel helped his mom put a cup in the dishwasher, then went outside. While Daniel was out, his mom put the dishes away. The children were then asked whether Daniel knows where the cup is, and where he will look for it.

The second test was an Appearance-Reality test. The children were shown a sponge that looked like a rock, and asked what it looks like. They were then told to feel the object, and encouraged to say that it feels like a sponge. Children were then asked what the object is, "really and truly." They were also asked, once again, what the object looks like.

The third false belief test was an Unexpected Contents test. Children were shown a Band-Aid box and asked what they thought was in the box. They were then shown that there was actually a doll in the box. Test questions asked what the child had thought was in the box prior to looking inside, and what the child's friend would think was inside the box if the closed box was shown to the friend.

Scores on the post-test were calculated out of 6 points (2 per test; 1 per question). On average, children in the SC condition answered approximately 4.5 questions correctly[2]. Children in the RC condition averaged approximately 1 correct answer total.

Experiment

We use the implemented AToM model described in Rabkina et al. (2017). In this model, ToM reasoning and development occurs via analogical retrieval and comparison. It takes in structured, predicate calculus cases. Each case is compared to the contents of WM using SAGE-WM (Kandaswamy et al., 2014). When a case is retrieved, AToM asks for feedback about the appropriateness of the retrieval, consistent with feedback typical of ToM training experiments. If feedback is positive, the probe is generalized with the retrieved case. When surprise occurs, such as due to a shift from true belief stories to a highly alignable false belief scenario (Hoyos et al., 2015), AToM accesses LTM for a potential explanation. Note that, because no surprise occurred in the present study, LTM is never accessed.

[2] This was not significantly different from the children in the FB training condition.

Representations

The first story in each training condition was semi-automatically encoded from the examples in Appendix B of Hale and Tager-Flusberg (2003). Because the text of the remaining stories was not available, we wrote new stories, including feedback, consistent with the examples provided in the original paper. Testing cases were also semi-automatically encoded from the examples provided in Appendix C of Hale and Tager-Flusberg (2003). Semi-automatic encoding involved using the EA-NLU semantic parser (Tomai & Forbus, 2009) to generate initial lexical semantics which we then manually contextualized.

In the SC training condition, the key construction was of the form "X said Y, but really Z". We represent this using a nested phrase structure representation: when an argument contains a finite clause, we maintain the verb's scope over the clause (e.g. say "…"; Figure 1, left). Otherwise, the argument is collapsed into a phrase. The sentential complement construction takes as arguments a noun phrase subject (X), the verb, and two clauses (Y and Z). When unified by analogy, the first clause becomes nested within the *say* verb phrase while the second remains at the same syntactic level. Both are within the scope of the completed clause. The construction combines the arguments, and, critically, it implies that the nested clause is contradicted by the external clause ("but really Z").

In the RC training condition, the feedback contained a relative clause "X verb the Y that Z." We use the same representation for this construction as for the SC condition (Figure 2). Because the relative clause modifies the noun, not the verb, there is no internal nesting structure. The construction takes a subject and a VP with a direct object, which in this case is a relative clause.

In each condition, we also represent the semantics of the arguments to the construction. The second element in Figure 1 shows the arguments to the construction in the SC training condition. Note that there are separate elements for each argument to the construction.

Following McFate & Forbus (2016), the construction and its arguments are unified by analogy. This results in the candidate inference shown on the right of Figure 1. What was *said* is now nested inside a separate context which is contained within the scope of the clause. Furthermore, the contents of the internal context are inferred to be contradictory from the external context. These inferences,

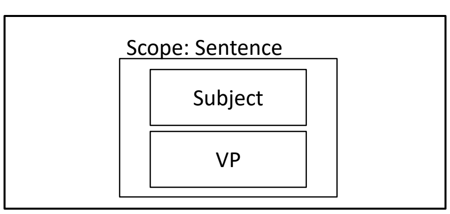

Figure 2: An example of the syntactic case of an RC training example. In this example, Bert hugs the girl who jumped.

called *aligned semantics*, are stored in AToM's working memory.

Because the language in the FB test cases did not involve sentential complements or relative clauses, we do not model interpretation of the grammatical forms used. Instead, we assume that an appropriate representation can be extracted from the language, and used EA-NLU to semi-automatically do so. We explicitly represent reality as a global scope. We also represent a belief held either by the child, or a character in the story, nested inside reality. While this presupposes that children understand that people have beliefs, it does not assume that they understand that these beliefs can differ between people or from reality. This is consistent with most verbal ToM tests, which often ask questions of the form, "What will X think?"

Figure 3 shows an example of an encoded test, Unexpected Contents. Here, the opinion that bandage boxes typically contain bandages is scoped inside reality. The belief is held by the child, and in reality, it is the case that the box contains a doll.

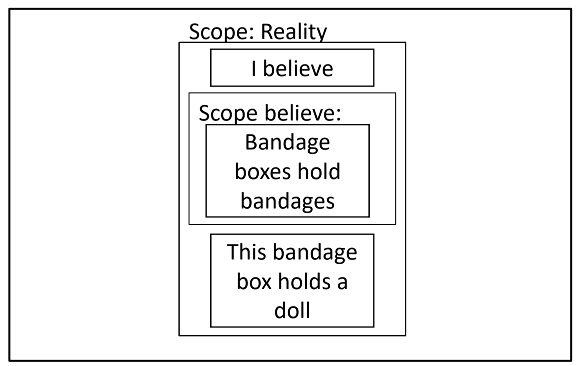

Figure 3: An example of a FB test case, Unexpected Contents.

Experiment

In each condition (SC and RC), AToM was trained on 8 stories, as in the original study. Training and testing cases were encoded as described above.

For each incoming training example, our model obtained the inferred semantics by analogy and passed them to AToM's working memory for retrieval and generalization using SAGE-WM. If a similar enough case was retrieved, the cases were generalized. Otherwise, the new case was added to the contents of WM ungeneralized. The generalization threshold was set to 0.01, consistent with Rabkina et al. (2017).

During testing, each case entered AToM's working memory and a similar case was retrieved via SAGE-WM. When a case was retrieved, any candidate inferences that came out of the best mapping were examined. A test was considered correct if a candidate inference implied that the true belief condition contradicted the false belief condition. For example, in the Unexpected Contents test (Figure 2), the fact that there was a doll in the box should contradict the fact that bandage boxes usually contain bandages.

Results

As described above, in each of the training trials, the inferred semantics from the construction alignment entered SAGE-WM. The first case entered ungeneralized, and formed a generalization with subsequent examples. After SC training, because the training examples are all alignable, the working memory contained a single generalization. During testing, AToM had the generalization in working memory. AToM compared each test scenario to the contents of working memory. The nested structure within each false belief scenario aligned with the nested structure of the generalization and produced a single candidate inference. In each case, this candidate inference contained a contradiction between the true belief (e.g. there is a doll inside the bandage box) and the expected false belief (e.g. the box contains bandages). These candidate inferences predicted correct responses to all of the false belief questions.

During RC training, a similar pattern emerged: the inferred semantics from each RC case were accumulated into a single generalization within WM. However, during testing, AToM was unable to align the learned generalization with the false belief stimuli. Therefore it generated no correct inferences, ergo no correct responses.

These results are consistent with the finding and Hale and Tager-Flusberg (2003): that sentential complement training bootstraps ToM, but relative clause training does not.

Discussion

In this paper, we have shown that the AToM model can explain bootstrapping from language in children's ToM development, when using representations that are inspired by construction grammar. We have modeled an empirical study by Hale and Tager-Flusberg (2003), which demonstrated that children's ToM reasoning abilities improve with sentential complement training.

One criticism of the original study is that the contents of the sentential complement are false (Lohmann & Tomasello, 2003). That is, the boy tells a lie. Our model's results suggest that this is important—the contradiction between the contents of the `say` and the `really` drives the subsequent inference that belief/observation and reality may differ. We view this as a feature, not a bug—after all, learning that beliefs may be inconsistent or incorrect is an important aspect of ToM development (de Villiers, Hobbs, & Hollebrandse, 2014).

It is important to note, however, that the contradiction is not the only aspect of the SC training that leads to improved ToM reasoning in our model. The phrasal nesting structure of SC sentences allows for structural alignment between the learned construction and the test cases (e.g. I believe X, but really Y). It is this alignment that leads to a candidate inference about a potential contradiction. Without the sentential complement, this inference would not be made.

Yet, without the contradiction, it is not clear what would be learned from the alignment. Lohmann and Tomasello (2003) report that children can improve in ToM reasoning abilities by bootstrapping from sentential complements that do not contain such a contradiction. Their SC training, however, included mental state verbs. Others (e.g. Peskin & Astingon, 2004) have shown that children with more advanced mental state language tend to have more advanced ToM reasoning abilities. The question of how sentential complements might drive ToM development on their own deserves further research.

Related Work

To the best of our knowledge, no other implemented computational model of bootstrapping ToM from language exists. However, there are several other computational cognitive models of ToM development. We describe these models here.

Hiatt and Trafton (2010; 2015) propose an ACT-R based reinforcement learning model whose pattern of learning closely matches the learning curve predicted by experimental data for first- and second-order ToM reasoning. Arslan, Taatgen, and Verbugge (2017) also model second order ToM learning in ACT-R, and find that an instance based model better predicts the mistakes made by children than does a reinforcement learning model.

Bello and Cassimatis (2006) modeled the difference in ToM reasoning between 3-year-olds and 4-year-olds as an update to a Polyscheme rule. Similarly, Goodman et al. (2006) modeled development of false belief reasoning as the transition between two Bayesian networks—one that made predictions based on a naïve understanding of ToM, and another that had a more adult-like understanding. With training, their model began to prefer the adult version of ToM reasoning.

Future Directions

The current implementation of AToM is exclusive to working memory (WM), and assumes that representations do not change between WM and LTM. However, ToM development takes place over the course of years (Wellman & Liu, 2004), and likely continues throughout the lifetime (e.g. Bach, 2011; Hess, 2006). Furthermore, evidence suggests that WM and LTM representations do differ (e.g. Cowan, 1998). A complete model of ToM reasoning and development must, then, account for consolidation to LTM. We plan to extend AToM to address this in future work.

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