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Reduction of ambiguity due to synonym and Homographs in Punjabi Language

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Abstract— ***We present a probabilistic generative model for learning semantic parsers from ambiguous supervision. Our approach learns from natural language sentences paired with world states consisting of multiple potential logical meaning representations. It disambiguates the meaning of each sentence while simultaneously learning a semantic parser that maps sentences into logical form. Compared to a previous generative model for semantic alignment, it also supports full semantic parsing.***

Keywords— reranking, syntactic parsing, semantic parsing, semantic role labeling , named entity recognition

1) INTRODUCTION

Grounded language acquisition involves learning to comprehend and/or generate language by simply observing its use in a naturally occurring context in which the meaning of a sentence is grounded in perception and/or action (Roy, 2002; Yu and Ballard, 2004; Gold and Scassellati, 2007; Chen et al., 2010). B¨orschinger et al. (2011) introduced an approach that reduces grounded language learning to unsupervised probabilistic context-free grammar (PCFG) induction and demonstrated its effectiveness on the task of sportscasting simulated robot soccer games. Subsequently, Kim and Mooney (2012) extended their approach to make it tractable for the more complex problem of learning to follow natural-language navigation instructions from observations of humans following such instructions in a virtual environment (Chen and Mooney, 2011). The observed sequence of actions provides very weak, ambiguous supervision for learning instructional language since there are many possible ways to describe the same execution path. Although their approach improved accuracy on the navigation task compared to the original work of Chen and Mooney (2011), it was still far from human performance. Since their system employs a generative model, discriminative reranking (Collins, 2000) could potentially improve its performance. By training a discriminative classifier that uses global features of complete parses to identify correct interpretations, a reranker can significantly improve the accuracy of a generative model. Reranking has been successfully employed to improve syntactic parsing (Collins, 2002b), semantic parsing (Lu et al., 2008; Ge and Mooney, 2006), semantic role labeling (Toutanova et al., 2005), and named entity recognition (Collins, 2002c). Standard reranking requires gold-standard interpretations (e.g. parse trees) to train the discriminative classifier. However, grounded language learning does not provide gold-standard interpretations for the training examples. Only the ambiguous perceptual context of the utterance is provided as supervision. For the navigation task, this supervision consists of the observed sequence of actions taken by a human when following an instruction. Therefore, it is impossible to directly apply conventional discriminative reranking to such problems. We show how to adapt reranking to work with such weak supervision. Instead of using gold-standard annotations to determine the correct interpretations, we simply prefer interpretations of navigation instructions that, when executed in the world, actually reach the intended destination. Additionally, we extensively revise the features typically used in parse reranking to work with the PCFG approach to grounded language learning.

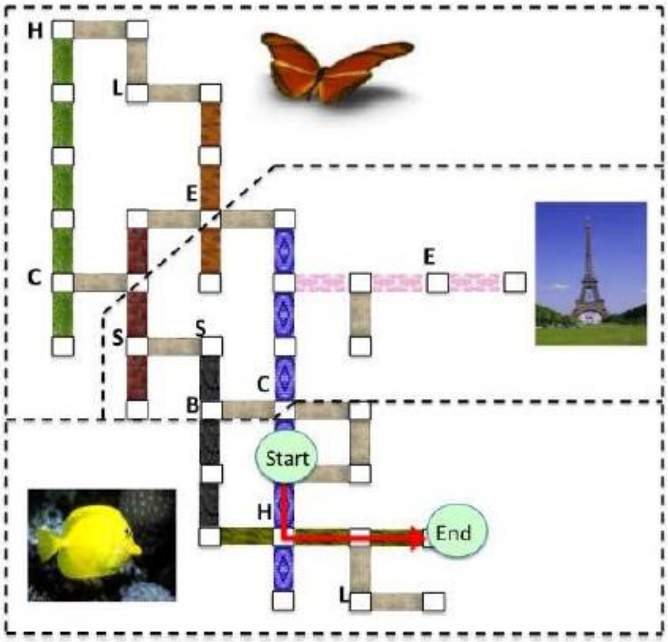

Figure 1: This is an example of a route in our virtual world. The world consists of interconnecting hallways with varying floor tiles and paintings on the wall (butterfly, fish, or Eiffel Tower.) Letters indicate objects (e.g. 'C' is a chair) at a location.

For example, in probabilistic logic, the synonymy relation between "man" and "guy" is represented by: 8x. man(x) , guy(x) | w1 and the hyponymy relation between "car" and "vehicle" is: 8x. car(x)) vehicle(x) | w2 where w1 and w1 are some certainty measure estimated from the distributional semantics. For inference, we use probabilistic logic frameworks like Markov Logic Networks (MLN) (Richardson and Domingos, 2006) and Probabilistic Soft Logic (PSL) (Kimmig et al., 2012). They are Statistical Relational Learning (SRL) techniques (Getoor and Taskar, 2007) that combine logical and statistical knowledge in one uniform framework, and provide a mechanism for coherent probabilistic inference. We implemented this semantic parser (Beltagy et al., 2013; Beltagy et al., 2014) and used it to perform two tasks that require deep semantic analysis, Recognizing Textual Entailment (RTE), and Semantic Textual Similarity (STS).

2) BACKGROUND

This section describes existing models and algorithms employed in the current research. Our model is built on top of the generative semantic parsing model developed by Lu et al. (2008). After learning a probabilistic alignment and parsing model, we also used the WASP and WASP −1 systems to produce additional parsing and generation results. In particular, since our current system is incapable of effectively generating NL sentences from MR logical forms, in order to demonstrate how our matching results can aid NL generation, we use WASP −1 to learn a generator. This follows the experimental scheme of Chen et al. (2010), which demonstrated that an improved NL–MR matching from Liang et al. (2009) results in better overall parsing and generation. Finally, our overall generative model uses the IGSL (Iterative Generation Strategy Learning) method of Chen and Mooney (2008) to initially estimate the prior probability of each event-type generating a natural-language comment.

3) RELATED WORK

Building systems that learn to interpret navigation instructions has recently received some attention due to its application in building mobile robots. Our work is the most similar to that of Matuszek et al. (2010). Their system learns to follow navigation instructions from example pairs of instructions and map traces with no prior linguistic knowledge. They used a general-purpose semantic parser learner WASP (Wong and Mooney 2006) to learn a semantic parser and constrain the parsing results with physical limitations imposed by the environment. However, their virtual world is relatively simple with no objects or attribute information as it is constructed from laser sensors. Similarly, Shimizu and Haas (2009) built a system that learns to parse navigation instructions. They restrict the space of possible actions to 15 labels and treat the parsing problem as a sequence labeling problem. This has the advantage that context of the surrounding instructions are taken into account. However, their formal language is very limited in that there are only 15 possible parses for an instruction. There is some recent work that explores direction following in more complex environments. Vogel and Jurafsky (2010) built a learning system for the HCRC Map Task corpus (Anderson et al. 1991) that uses reinforcement learning to learn to navigate from one landmark to another. The environment consists of named locations laid out on a map. Kollar et al. (2010) presented a system that solves the navigation problem for a real office environment. They use LIDAR and camera data collected from a robot to build a semantic map of the world and to simulate navigation. However, both of these systems were directly given object names or required other resources to learn to identify objects in the world. Moreover, both systems used lists of predefined spatial terms. In contrast, we do not assume any existing linguistic knowledge or resource. Besides navigation instructions, there has also been work on learning to interpret other kinds of instructions. Recently, there has been some interest in learning how to interpret English instructions describing how to use a particular website or perform other computer tasks (Branavan et al. 2009; Lau, Drews, and Nichols 2009). These systems learn to predict the correct computer action (pressing a button, choosing a menu item, typing into a text field, etc.) corresponding to each step in the instructions. Our work also fits into the broader area of *grounded language acquisition*, in which language is learned by simply observing its use in some naturally occurring perceptual context (see Mooney (2008) for a review). Unlike most work in statistical NLP which requires annotating large corpora with detailed syntactic and/or semanticmarkup, this approach tries to learn language without explicit supervision in a manner more analogous to how children acquire language. This approach also grounds the meaning of words and sentences in perception and action instead of arbitrary semantic tokens. One of the core issues in grounded language acquisition is solving the correspondence between language and the semantic context. Various approaches have been used including supervised training (Snyder and Barzilay 2007), iteratively retraining a semantic parser/language generator to disambiguate the context (Kate and Mooney 2007; Chen, Kim, and Mooney 2010), building a generative model of the content selection process (Liang, Jordan, and Klein 2009; Kim andMooney 2010), and using a ranking approach (Bordes, Usunier, and Weston 2010). Our work differs from these previous approaches in that we explicitly model the relationships between the semantic entities rather than treating them as individual items.

4) Approach

A semantic parser is three components, a formal language, an ontology, and an inference mechanism. This section explains the details of these components in semantic parser. It also points out the future work related to each part of the system. **Formal Language:** first-order logic Natural sentences are mapped to logical form using Boxer (Bos, 2008), which maps the input sentences into a lexically-based logical form, in which the predicates are words in the sentence. For example, the sentence "A man is driving a car" in logical form is:

$$\exists x, y, z.\ man(x) \wedge agent(y, x) \wedge drive(y) \wedge patient(y, z) \wedge car(z)$$

We call Boxer's output alone an uninterpreted logical form because predicates do not have meaning by themselves. They still need to be connected with an ontology.
Future work: While Boxer has wide coverage, additional linguistic phenomena like generalized quantifiers need to be handled.

Input: A set of training examples (e_i; y_i),
where e_i is a NL sentence and y_i =arg max$_{\text{y belongs to GEN}(e_i)}$ EXEC(y)
Output: The parameter vector W , averaged over all iterations 1:::T

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procedure PERCEPTRON
Initialize _W = 0
for t = 1….T; i = 1….n do
yi = arg maxy belongs to GEN(ei) _(ei; y) _ _W
if yi 6= yi then
W = W + (ei; yi ) != phi(ei; yi)
end if
end for
end procedure
```

5) Conclusion

We have presented a novel generative model capable of probabilistically aligning natural language sentences to their correct meaning representations given the ambiguous supervision provided by a grounded language acquisition scenario. Our model is also capable of simultaneously learning to semantically parse NL sentences into their corresponding meaning representations. Experimental results in Robocup sportscasting show that the NL–MR matchings inferred by our model are significantly more accurate than those produced by all previous methods. Our approach also learns competitive semantic parsers and improved language generators compared to previous methods. In particular, we showed that our alignments provide a better foundation for learning accurate semantic parsers and tactical generators compared to those of Liang et al. (2009), whose generative model is limited by a simple bag-of-words assumption. In the future, we plan to test our model on more complicated data with higher degrees of ambiguity as well as more complex meaning representations. One immediate direction is evaluating our approach on the datasets of weather forecasts and NFL football articles used by Liang et al. (2009). However, our current model does not support matching multiple meaning representations to the same natural-language sentence, and needs to be extended to allow multiple MRs to generate a single NL sentence.

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