An Interactive Connectionist Model of Semantic Intensionality

RESEARCH PROPOSAL. Formal semantics has traditionally been defined in terms of intensions, or mappings from possible worlds to truth values. This permits the description of a wide number of linguistic phenomena, such as counterfactuals, conditionals, propositional attitudes, and tense. However, intensionality introduces a computational learning problem: to acquire intensional functions from possible worlds to truth values, individuals must be exposed to a rich variety of possible world representations (Partee, 1979). This poses an issue both to formal linguists who wish to model semantic acquisition, and to computationalists hoping to apply linguistic theories to the domain of natural language processing. We suggest that connectionist models may help address this problem, and propose a general-purpose framework for integrating compositional semantic theory with acquisition, processing, and interaction.

Our proposed framework models words and phrases in terms of *distributed representations*, which are dense, real-valued vectors existing in some high-dimensional space. While initially randomized, these representations will be trained via deep learning to capture complex lexical and phrasal information. Although latent and not directly interpretable, these representations have been used to model lexical similarity, semantic relationships, and linguistic shift (Kulkarni et al., 2015) at the word level. In our work, we simultaneously train a composition function $\mathbf{g}(\vec{x}, \vec{y})$, which can be applied repeatedly to obtain similar vector representations at the sentential level.

To capture meaning, these representations are trained to optimize some communicative goal. As such, we propose to represent language and interaction in terms of partially observable Markov decision processes (POMDPs), which build probability distributions over possible world states. These probability distributions, termed *belief states*, can serve as probabilistic, task-dependent analogues to intensions (Andreas, 2018). POMDPs build action policies based on their belief states and receive feedback accordingly, so that vector representations and belief state updates can be trained in an end-to-end manner, as shown in Figure 1. In this way, we have preserved the notion of intensionality, but we have "extracted" it from the compositional semantic representations.

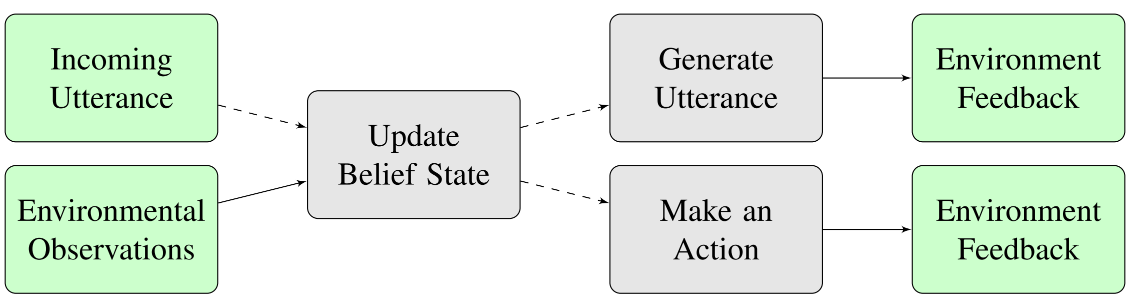

Figure 1: End-to-end training of interactive language-learning framework

We propose testing this model on a variety of situated learning tasks. Simulated tasks such as instruction-following and generation require rich world representations and complex sentence structures. Existing instruction-following datasets such as the Sequential CONtext-dependent Execution dataset, or SCONE (Long et al., 2016), are designed to test specific linguistic mechanisms such as ellipsis and anaphora (i.e., coreference resolution) and will provide a starting point for our work. We intend to build similar tasks which focus intensional aspects of language. In addition to these simulated tasks, natural language interfaces (e.g., Siri, Amazon Alexa) may give rise to similar instruction-following datasets which are grounded in an API. Collecting these kinds of real-world datasets is necessary for testing our model at scale, but this is not the proposed starting point of our work.

Rather, we suggest that meaning can be *scaffolded* via multitask learning, in which intermediate vector representations are trained to perform well on a variety of tasks. This allows us to evaluate the model on increasingly complicated tasks while benefiting from the domain-specificity of simple tasks. Further, note that our proposed learning framework does not require interactivity. A system which performs well on situated learning tasks may also be trained and tested on non-interactive tasks, such as the GLUE benchmarks (Wang et al., 2018). These benchmarks are designed to evaluate sentence representations, via tasks such as textual entailment and question-answering, with a focus on phenomena such as quantification, negation, scope ambiguity, and monotonicity.

Throughout this work, we will concentrate on testing the explanatory power of our connectionist model. Mainstream formal semantics has been shown to capture a wide variety of linguistic phenomena, and the burden of proof lies on distributional semantic models to correctly duplicate these predictions. While we have focused here on semantics and acquisition, we will also explore how this model interacts with other aspects of language processing. In many ways, the model described above is designed to be maximally integrable, and it can be easily combined with existing frameworks such as the Rational Speech Acts model of pragmatics.

INTELLECTUAL MERIT. This work is intended to contribute to both computational and theoretical linguistics. On the computational side, we hope to provide new methodologies for sentence representation learning, with a focus on interactive language learning. On the theoretical side, we hope to lay the groundwork for connectionist models of semantics and meaning representation.

BROADER IMPACTS. We hope to build models which are compatible with human constraints on language use. One key aspect of this is the amount of data needed to train the system. In the model described above, the intensionality is off-loaded to the environment representation. Along with multi-task learning, we propose this will increase data-efficiency and generalization. Computational linguistics has focused disproportionately on English due to the wealth of available data, but we hope this shift towards efficiency may lead to NLP applications for low-resource languages.

References

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