RESEARCH STATEMENT: STRUCTURED REASONING

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ABSTRACT

We have been working extensively on building efficient structured models for fundamental natural language processing tasks such as named entity recognition and semantic parsing (Jie, 2020). We proposed various hypergraph structures and developed efficient dynamic-programming algorithms to perform inference. Our research efforts demonstrated that the hypergraph-based models have a strong capability and expressivity in extracting structures from text. We further developed a structured prediction framework that is able to perform efficient inference for almost all DAG-based hypergraphs. On top of that, we are focusing on developing structured models that are capable of performing reasoning over structures which lead to more explainable models and predictions. Our definition of *structure* applies to not only natural language but also other modalities such as vision and speech because of Transformer's success. While structures are expensive to annotate in natural language, we introduce a future direction towards using self-supervised learning for extracting structures.

1 STRUCTURED PREDICTION

We built structured models for the task of named entity recognition (NER) (Jie et al., 2017; 2019; Jie & Lu, 2019; Xu et al., 2021; Yang et al., 2020) and semantic parsing (Jie & Lu, 2014; 2018). We focused on these two tasks as both of them require semantic-level understanding from natural language. Motivated by the shallow semantics existing in the syntactic dependency trees, we built *dependency-guided* models for NER (Tjong Kim Sang & De Meulder, 2003) and extracted meaningful structures in semantic parsing (Zelle & Mooney, 1996). The special property that named entities often form sub-tree structures in syntactic dependencies allows us to efficiently identify the possible candidates of named entities in the graphical model design. We design a *dependency-guided model* (DGM) (Jie et al., 2017) based on the semi-Markov CRF (Lafferty et al., 2001; Sarawagi & Cohen, 2004) model with linear complexity on average while achieving comparable or better performance than the semi-Markov CRF. Furthermore, we proposed the *dependency-guided LSTM-CRF* models (Jie & Lu, 2019; Xu et al., 2021) to fully exploit the dependency structured information such as high-order dependencies and dependency labels. In semantic parsing, we proposed the *dependency-based hybrid tree* model (Jie & Lu, 2014; 2018) to learn the latent dependency trees (Zhou et al., 2021) which is able to represent the semantic structure and capture the alignment with natural language. Motivated by the Eisner's algorithm in dependency parsing (Eisner, 2000), we design a hypergraph that allows us to perform dynamic programming and efficiently extract the latent dependency-based hybrid tree from natural language. The experiments show that dependency-based hybrid trees are more robust in capturing the language-specific characteristics such as word-ordering compared to the constituency-based trees (Lu, 2014). Our research efforts demonstrate that the hypergraph-based models are expressive and capable of learning meaningful structures from natural language.

1.1 EFFICIENT HYPERGRAPH INFERENCE FRAMEWORK

In practice, we need to design efficient inference algorithms for different hypergraph structures (e.g., linear-chain or tree structures). Such algorithms often cost a significant amount of efforts to implement. In order to make the inference process more generic, we have developed and continue to

work on a structured prediction framework (Lu, 2017)[1] that is able to help us perform inference on almost all arbitrary structures. The underlying inference algorithm is a generalized version of the *inside-outside* algorithm (Baker, 1979) where we developed the extension and applied to general directed acyclic hypergraph structures. As the linear-chain CRF is the most commonly used architecture in practice, we also developed the efficient framework[2] for the research community to use. Our framework is able to improve the experimental complexity from $\mathcal{O}(N)$ to $\mathcal{O}(\log N)$ following parallel-scan algorithm (Blelloch, 1990; Rush, 2020). Along this line of work, we are interested in building more efficient algorithms for general hypergraph structures. For example, typical constituency parsing or other structured parsing tasks require efficient inference algorithm for tree-based structures. How to efficiently incorporate the inference procedure into our frameworks remains as a technical challenge. The Torch-Struct (Rush, 2020) framework implemented many architectures but the underlying codebase is specific to some particular structures. Our purpose is to allows developers or researchers to only focus on the structure design rather than the inference procedure.

2   REASONING ON STRUCTURES

W also focus on the reasoning ability of structured models (Jie et al., 2022) where we perform reasoning over the structures. Specifically, we try to answer the question that "*How can we make use of the expressiveness in graphical models to perform symbolic reasoning?*". Our goal is to build an interpretable model that gives explainable predictions under the scope of modern neural architectures. We proposed a deductive system that allows us iteratively construct partial structures and perform reasoning over these structures. We adopt the math word problem (MWP) solving as the downstream task as it essentially evaluate the reasoning ability of our proposed model. To make iterative and explainable predictions, we carefully design the "*expression chain*" structures using neural module networks (Andreas et al., 2016; Gupta et al., 2020). We then perform reasoning (such as *addition* and *subtraction*) among the mathematical quantities by forming mathematical expressions. Our experiments demonstrate that the underlying deductive system presents explainable step during the MWP solving procedure.

The underlying deductive system design can also be applied to other tasks that consider multi-step reasoning, such as HotpotQA (Yang et al., 2018). The reasoning happens between states (e.g., partial structures) where we apply differentiable actions to the previous state to become a new state (Guo et al., 2018). The resulting step-by-step process is similar to the concept of "*reasoning chain*" (Jhamtani & Clark, 2020; Saha et al., 2020) and diffusion models (Sohl-Dickstein et al., 2015; Weng, 2021). For example, we are interested in how models exploit the relations among the rationales (i.e., relevant sentences) in reading comprehension. Such relations could be latent and we need to build latent-variable models (Jie & Lu, 2018) to find such relations. Besides, we can also apply the deductive system to dependency parsing where the tree generation happens in a top-down and step-by-step manner. Similar to the diffusion models in DALL-E-2 (Ramesh et al., 2021), the deductive system is also able to sample from the intermediate state and continue to generate new states.

The same philosophy applies to the vision-language tasks such as visual question answering (VQA) (Antol et al., 2015) where we can represent each image with several discrete visual tokens (Van Den Oord et al., 2017; Razavi et al., 2019). We can learn the alignments (Wan et al., 2021) between the visual tokens and natural language to gradually locate the region that is most relevant to the question.

3   SELF-SUPERVISED LEARNING FOR STRUCTURES

The success of Transformers (Vaswani et al., 2017) architecture brings our attention to self-supervised learning. Transformer-based models with self-supervised pre-training are able to achieve state-of-the-art performance in downstream NLU tasks. In the recent remark by Meta Research[3]:

> "*We believe that self-supervised learning is one of the most promising ways to build such background knowledge and approximate a form of common sense in AI systems.*"

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[1] https://github.com/sutd-statnlp/statnlp-neural
[2] https://github.com/allanj/pytorch_neural_crf
[3] https://ai.facebook.com/blog/self-supervised-learning-the-dark-matter-of-intelligence/

A huge amount of research efforts have demonstrated that the current language models with standard random masking pre-training strategy has a strong capability in understanding the natural language as well as the linguistic structures behind it. However, the secret behind remains a mystery to us as we cannot explicitly extract or model the meaning or the linguistic structures through self-supervised learning. Such phenomena inspire us to explore the direction that extracting structures from the self-supervised perspective. For example, Hu et al. (2021) shows that we can perform grammar induction after pre-training with a parsing specific objective function. The essential idea is to design an elegant pre-training objective function to incorporate the structured prior knowledge of the downstream task, such as semantic and syntactic structures.

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