Approaches for Semantic Parsing in Machine Learning: A survey

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ABSTRACT

In the context of natural language processing, parsing may be defined as the method of converting structural descriptions to sequences of words in a natural language (or to sequences of symbols derived from word sequences). It has a rich ontology of type, properties, and relations. It supports automatic analysis or execution .Semantic parsing maps textual data to formal meaning Representations. This contrasts to semantic role labeling (Carreras and Marquez, 2004) and other forms of shallow semantic processing parsing It is important in computational linguistics and related areas of application like simple phrase finding, full semantic analysis of text, machine translation. This paper reviews different approaches for semantic parsing.
Keywords-Semantic Role labeling, Parsing

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1. INTRODUCTION

Semantic Parsing is mapping a natural-language sentence to a detailed representation of its complete meaning in a completely formal language. Depending on structural description assigned and the *grammar* - a description language plus set of structural constraints - according to which the parser attempts to analyse the symbol sequences presented to it. Parser accepts as input a sequence of words (or their surrogates) in some language and an abstract description of likely structural relations that may hold between words or sequences of words in the language, and produces as output zero or more structural descriptions of the input as acceptable by the structural rule set. There will be zero descriptions if either the input sequence cannot be analyzed by the grammar, or if the parser is *incomplete*, i.e. fails to find all of the structure the grammar permits. There will be more than one description if the input is *ambiguous* with respect to the grammar, i.e. if the grammar generates more than one analysis of the input.

Semantic parsers which can be constructed manually are too expensive and weak. In this paper various approaches for semantic parsing are studied and compared. Machine learning approaches (Zettlemoyer and Collins, 2005; Mooney, 2007)are supervised, and providing the target logical form for each sentence is costly and difficult to do constantly and with high quality.
Unsupervised approaches have been applied to shallow semantic tasks (e.g., paraphrasing (Lin and Pantel, 2001), information extraction (Banko et al., 2007)), but unsupervised approach to semantic parsing, uses Markov logic (Richardson and Domingos, 2006).
The USP system starts by making clusters of tokens of the same type, and then recursively clusters expressions whose subexpressions belong to the same clusters. Experiments on a biomedical corpus proven that this approach is able to successfully translate syntactic variations into a logical representation of their common meaning (e.g., USP learns to map active and passive voice to the same logical form, etc.).
This in turn allows it to correctly answer many more questions than systems based on TextRunner
(Banko et al., 2007) and DIRT (Lin and Pantel, 2001).

2. LITERATURE SURVEY

2.1 SUPERVISED APPROACH

In the past, unsupervised approaches have been applied to a few semantic tasks, but not to semantic
parsing. For example, DIRT (Lin and Pantel, 2001) learns paraphrases of binary relations based on distributional similarity of their arguments; TextRunner (Banko et al., 2007) automatically extracts relational triples in open

domains using a self-trained extractor; SNE applies relational clustering to generate a semantic network from TextRunner triples (Kok and Domingos, 2008). While these systems illustrate the unsupervised methods, the semantic content they extract is nevertheless shallow and does not compose the complete formal meaning that can be obtained by a semantic parser.

Another issue is that existing approaches to semantic parsing learn to parse syntax and semantics together. The drawback is that the complexity in syntactic processing is coupled with semantic parsing and makes the latter even harder. For example, when applying their approach to a different domain with somewhat less rigid syntax, Zettlemoyer and Collins (2007) need to introduce new combinators and new forms of candidate lexical entries. Preferably, it should leverage the enormous progress made in syntactic parsing and generate semantic parses directly from syntactic analysis.

2.2 UNSUPERVISED SEMANTIC PARSING WITH MARKOV LOGIC

Unsupervised semantic parsing (**USP**) rests on three key ideas.

First, the target predicate and object constants, which are pre-specified in supervised semantic parsing, can be viewed as clusters of syntactic variations of the same meaning, and can be learned from data. For example, borders represents the next-to relation, and can be viewed as the cluster of different forms for expressing this relation, such as “borders”, “is next to”, “share the border with”; Utah represents the state of Utah, and can be viewed as the cluster of “Utah”, “the beehive state”, etc.

Second, the recognition and clustering of candidate forms are integrated with the learning for meaning composition, where forms that are used in composition with the same forms are encouraged to cluster together, and so are forms that are composed of the same sub-forms. This amounts to a novel form of relational clustering, where clustering is done not just on fixed elements in relational tuples, but on random forms that are built up recursively.

Third, while most existing approaches (manual or supervised learning) learn to parse both syntax and semantics, unsupervised semantic parsing starts directly from syntactic analyses and focuses solely on translating them to semantic content.This enables us to control advanced syntactic parsers and (indirectly) the available rich resources for them. More importantly, it separates the complexity in syntactic analysis from the semantic one, and makes the latter much easier to perform. In particular, meaning composition does not require domain-specific procedures for generating candidate lexicons, as is often needed by supervised methods. The input to USP system consists of dependency trees of training sentences. Compared to phrase-structure syntax, dependency trees are the more appropriate starting point for semantic processing; as they already exhibit much of the relation-argument structure at the lexical level.USP first uses a deterministic procedure to convert dependency trees into quasi-logical forms (QLFs). The QLFs and their sub-formulas have natural lambda forms.

2.2.1 UNSUPERVISED LEARNING TASKS

It involves learning autoencodersfrom monolingual corpora, which has recently been applied to sequence to sequence learning (Dai & Le, 2015). However, in Dai & Le (2015)’s work, the authors only experiment with pretraining and then finetuning, but not joint training which can be viewed as a form of multi-task learning (MTL). As such, It is interested in knowing whether the same trend extends to the MTL settings. Additionally, we investigate the use of the skip-thought vectors (Kiros et al., 2015) in the context of our MTL framework. Skip-thought vectors are trained by training sequence to sequence models on pairs of consecutive sentences, which makes the skip-thought objective a natural seq2seq learning candidate. A minor technical difficulty with skip-thought objective is that the training data must consist of ordered sentences, e.g., paragraphs. Unfortunately, in many applications that include machine translation, which only have sentence-level data where the sentences are unordered. To address that, split each sentence into two halves; then use one half to predict the other half.

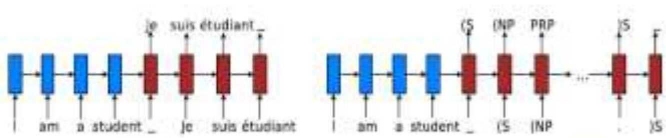

Figure 1: **Sequence to sequence learning examples** – (left) machine translation (Sutskever et al., 2014) and (*right*) constituent parsing (Vinyals et al., 2015a).

2.3 SUPERVISED SEMANTIC PARSING

A major challenge to semantic parsing is syntactic variations of the same meaning, which abound in natural languages. For example, the sentence “Utah borders Idaho” can be rephrased as“Utah is next to Idaho,”“Utah shares a border with Idaho,” etc. Manually encoding all these variations into the grammar is tedious and error-prone. Supervised semantic parsing addresses this issue by learning to construct the grammar automatically from sample meaning observations (Mooney, 2007). Existing approaches differ in the meaning representation languages they use and the amount of annotation required. In the approach of Zettlemoyer and Collins (2005), the training data consists of sentences paired with their meanings in lambda form.The major limitation of supervised approaches is that they require meaning observations for example sentences. Even in a restricted domain, doing this consistently and with high quality requires nontrivial effort. For unrestricted text, the complexity and subjectivity of annotation render it basically infeasible; even pre-specifying the target predicates and objects is very complex. Therefore, to apply semantic parsing beyond limited domains, it is crucial to develop unsupervised methods that do not rely on labeled meanings.

2.4 AN ATTENTION-ENHANCED ENCODER-DECODER MODEL

Semantic parsing aims at mapping natural language to machine interpretable meaning representations. Traditional approaches rely on high-quality lexicons, manually-built templates, and linguistic features which are either domain or representation-specific. An attention-enhanced encoder-decoder model encodes input utterances into vector representations, and produce their logical forms by conditioning the output sequences or trees on the encoding vectors. Experimental results on four datasets shown this approach performs competitively without using hand-engineered features and is easy to adapt across domains and meaning representations.
This model learns from natural language descriptions paired with meaning representations. Most previous systems rely on high-quality lexicons, manually-built templates, and features which are either domain- or representation specific. This method suggests that It can be easily customized to different domains and meaning representations.
It works on more well-defined meaning representations (such as Prolog and lambda calculus) and is conceptually simpler; it does not utilize bidirectionality or multi-level alignments.

Grefenstette et al. (2014) propose a different architecture for semantic parsing based on the combination of two neural network models. The first model learns shared representations from pairs of questions and their translations into knowledge base queries, whereas the second model generates the queries conditioned on the learned representations. However, they do not report empirical evaluation results. This encoder-decoder framework based on neural networks which has been recently repurposed for various NLP tasks such as syntactic parsing (Vinyals et al., 2015a), machine translation (Kalchbrenner and Blunsom, 2013; Cho et al., 2014; Sutskever et al., 2014), image description generation (Karpathy and Fei-Fei, 2015; Vinyals et al., 2015b), question answering (Hermann et al., 2015), and summarization (Rush et al., 2015). Mei et al. (2016) use a sequence-to-sequence model to map navigational instructions to actions.

2.4 QUESTION ANSWERING MODEL

This model applies to both images and structured knowledge bases. The model uses natural language strings to automatically assemble neural networks from a collection of compositional modules. Parameters for these modules are learned jointly with network-assembly parameters via reinforcement learning, with only (world, question, answer) triples as supervision.
It is compositional, attention model for answering questions about a variety of world representations, including images and structured knowledge bases. The model translates from questions to animatedly assembled neural networks, then applies these networks to world representations (images or knowledge bases) to produce answers. It takes advantage of two largely independent lines of work: on one hand, an extensive literature on answering questions by mapping from strings to logical representations of meaning; on the other, a series of recent successes in deep neural models for image recognition and captioning. By constructing neural networks instead of logical forms, this model leverages the best aspects of both linguistic compositionality and continuous representations.

This model has two components, trained jointly :

First, a collection of neural “modules” that can be freely composed.
Second, a network layout predictor that assembles modules into complete deep networks tailored to each question .
Previous approaches has used manually-specified modular structures for visual learning (Andreas et al., 2016).This model learn a network structure predictor jointly with module parameters and extend visual primitives from previous work to reason over structured world representations .Training data consists of (world, question, answer) triples: This approach requires no supervision of network layouts. Results shows state-of-the-art performance on two markedly different question answering tasks: one with questions about natural images, and another with more compositional questions about United States geography. It gives benchmark datasets in both visual and structured domains.

3. CONCLUSIONS

USP system is based on Markov logic, and recursively clusters expressions to abstract away syntactic variations of the same meaning. It can be applied USP to extracting a knowledge base from biomedical text and answering questions based on it.

Encoder decoder model with a hierarchical tree decoder and an attention mechanism improves performance across the board.
Question answering model achieves considerable gains in speed and sample efficiency, even with very little training data. These observations are not limited to the question answering domain, and they can be applied similarly to tasks like instruction following, game playing, and language generation.

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