LANGUAGE TO LOGICAL FORM WITH NEURAL ATTENTION

ABSTRACT

Semantic parsing is the task of translating text to a formal meaning representation such as logical forms or structured queries. There has recently been a surge of interest in developing machine learning methods for semantic parsing.

DATA

The model under this paper was trained on four different datasets covering different domains & using different meaning representations.

JOBS - This benchmark dataset contains 640 queries to a database of job listings. Specifically, questions are paired with Prolog-style queries.

GEO - This is a standard semantic parsing benchmark which contains 880 queries to a database of U.S. geography. GEO has 880 instances split into a training set of 680 training examples and 200 test examples. We used the same meaning representation based on lambda-calculus as Kwiatkowski et al. (2011). Values for the variables city, state, country, river, and number are identified.

ATIS - This dataset has 5, 410 queries to a flight booking system. The standard split has 4, 480 training instances, 480 development instances, and 450 test instances. Sentences are paired with lambda-calculus expressions.

IFTTT - Quirk et al. (2015) created this dataset by extracting a large number of if-this-then-that recipes from the IFTTT website. Recipes are simple programs with exactly one trigger and one action which users specify on the site. Whenever the conditions of the trigger are satisfied, the action is performed. In the dataset, there are 552 trigger functions from 128 channels, and 229 action functions from 99 channels.

METHODOLOGY

This paper utilizes the general encoder-decoder paradigm to the semantic parsing task. This model learns from natural language descriptions paired with meaning representations; it encodes sentences and decodes logical forms using recurrent neural networks with long short-term memory (LSTM) units. It treats semantic parsing as a vanilla sequence transduction task. It also introduces an attention mechanism allowing the model to learn soft alignments between natural language and logical forms and present an argument identification step to handle rare mentions of entities and number.

The aim is to learn a model which maps natural language input q = x1 · · · x|q| to a logical form representation of its meaning a = y1 · · · y|a| . The conditional probability p (a|q) is decomposed as: p (a|q) = Y |a| t=1 p (yt |y<t, q). Sequence-to-Sequence Model This model regards both input q and output a as sequences. As shown in Figure 2, the encoder and

decoder are two different L-layer recurrent neural networks with long short-term memory (LSTM) units which recursively process tokens one by one.

MODEL

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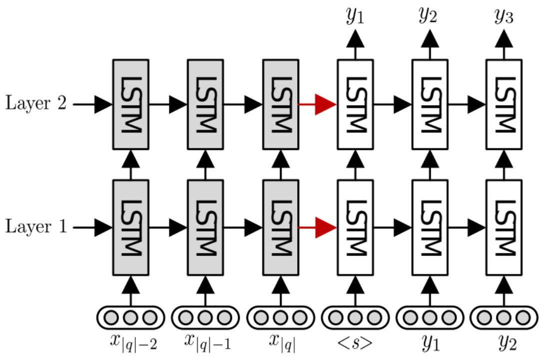

Attention Mechanism As shown in Equation (3), the hidden vectors of the input sequence are not directly used in the decoding process. However, it makes intuitively sense to consider relevant information from the input to better predict the current token. Following this idea, various techniques have been proposed to integrate encoder-side information (in the form of a context vector) at each time step of the decoder

CONCLUSION

This paper presented an encoder-decoder neural network model for mapping natural language descriptions to their meaning representations. We encode natural language utterances into vectors and generate their corresponding logical forms as sequences or trees using recurrent neural networks with long short-term memory units. Experimental results show that enhancing the model with a hierarchical tree decoder and an attention mechanism improves performance across the board.