# Towards Understanding Natural Language: Semantic Parsing, Commonsense Knowledge Acquisition and Applications

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## 1 Introduction

There are various aspects of making computers understand natural language. Semantic parsing and reasoning on commonsense knowledge are the two important ones. Many NLU tasks such as question answering and co-reference resolution require semantic parsing of text and reasoning with different kinds of commonsense knowledge. In this work we present our progress towards these milestones of NLU. We demonstrate the steps we took towards the goal and the tools/techniques we developed, such as a semantic parser and a novel algorithm to automatically acquire commonsense knowledge from text. We also show the usefulness of the developed tools by applying them to solve tasks such as hard co-reference resolution. This is an ongoing research and in this paper we present our current progress and the future plans to reach the goal of developing a fully autonomous natural language understanding framework.

## 2 Completed Work

Our goal in this work is to develop an automated system that makes computers understand natural language. There are three main aspects that helped us advance a step towards that goal. Each of those aspects and the progress we made to achieve them is explained briefly in the sections below.

### 2.1 Semantic Parsing: The Knowledge Parser (K-Parser)

K-Parser is a semantic parsing and knowledge augmentation system that translates an input English text into directed acyclic graph. The nodes in the graph represent the actual words in the text and the conceptual classes of those words. The edges represent the semantic relations between the nodes. Examples of K-Parser output and an online GUI for the parser are available at www.kparser.org. Details about the parser implementation and system algorithm are also present in the "About" section on the K-Parser website.

The basic unit in the output of K-Parser is an event mention. K-Parser identifies various kinds of event mentions in the text [Sharma *et al.*, 2015b]. Each event mention in the K-Parser output is rooted at a verb. Event mentions also contain the entities participating in the event mention, and the properties of those entities. The output of K-Parser also contains semantic relations between the event mentions. These relations are driven by the causality and the occurrence of different events.

Another aspect of the K-Parser output is its ability to augment knowledge that is not explicitly mentioned in the input text. One such knowledge is added in the form of conceptual classes of nodes. For example, *"John"* is a *"person"*.

Other features of K-Parser output include the limited but useful quantification of entities, and semantic roles of some entities. A list of all such features, along with an on-line interface for trying out K-Parser is available at *www.kparser.org*. We encourage readers to try out the system and send us their feedback to help improve any aspect of the parser.

### 2.2 The Commonsense Knowledge Database

In this work, we automatically extracted a different kind of commonsense knowledge and created a knowledge base. This type of knowledge is proved helpful in solving a subset of the Winograd Schema Challenge (WSC) [Sharma *et al.*, 2015a], which is a hard co-reference resolution challenge. Let us take an example inspired from WSC to better understand the knowledge. **Sentence:** *John was bullying Tom so we rescued him.* **Question:** *Who did we rescue ?* The Commonsense knowledge required to answer the question is:
**IF** A *bullying* B *causes* T *rescued* Z **THEN** (possibly) Z = B. This knowledge is based on the events (or actions) and their participants. Hence, we call it an Event-based Conditional Commonsense (ECC).

We extracted this knowledge from a large text repository by using the K-Parser (as mentioned above). We used an logic programming (Answer Set Programming[1]) based reasoning agent to extract the knowledge from the K-Parser output. More details on the extraction process are present in [Sharma and Baral, 2016]. A demo of the kind of knowledge extracted is also present on http://bioai8core.fulton.asu.edu/knet.

### 2.3 Applications in NLU

The above two sections briefly explain the semantic parsing and commonsense knowledge database. The semantic parsing and knowledge acquisition is useless if they could not be used in a real world NLU application. So, we used our semantic parser and the kind of knowledge mentioned above to solve a subset of hard coreference resolution problem i.e. The Winograd Schema Challenge (WSC) [Sharma *et al.*, 2015c].

[1] http://potassco.sourceforge.net/teaching.html

We also used our semantic parser in an initial phase of another application to determine if a patient is suffering from Alzheimer's disease [Altshuler *et al.*, ].

## 3 Related Works

There are three different aspects of this work. Firstly, the semantic parsing framework. There are many semantic parsers available today, such as the TRIPS system [Allen *et al.*, 2007] . Despite their many advantages, these systems fails to represent the event-event and event-entity relations in the text. Many other systems such as [Vanderwende *et al.*, 2015] translate text into Abstract Meaning Representation (AMR) [Banarescu *et al.*, 2013]. Similar to K-Parser output, AMR captures various aspects of language such as concepts and relations between those concepts. There are a some things that are not addressed in AMR such as tenses and entities' quantification. K-Parser tackles these as well. Furthermore, AMR uses PropBank frame arguments for each verb, labeled arg0 to arg5. These labels are same for each verb but their interpretation is different i.e. for some verb arg1 is *recipient* whereas for other it is *object*. This makes the downstream reasoning process somewhat harder. In contrast, K-Parser uses a set of relations from KM ontology.

Secondly, there are many commonsense knowledge bases available today. These include WordNet [Miller, 1995], ConceptNet [Liu and Singh, 2004] and Freebase[2]. They are good sources of knowledge but they do not contain the type of knowledge that we extracted in this work. Narrative Chains [Chambers and Jurafsky, 2008] contain lists of partially ordered set of events that are centered around a common actor. The ordering of the events is temporal which causes them to not capture the other event-event relationships such as causality.

Thirdly, there are some works which attempted to solve the WSC. All of them are mentioned along with their comparison to our approach in [Sharma *et al.*, 2015c].

## 4 Conclusion & Future Work

With the vision of NLU, we have taken initial steps. We have developed a semantic parser that has an output representation which demonstrates many features of an ideal, machine executable formal representation. We have also used the semantic parser to identify and automatically extract a specific kind of commonsense knowledge that has not been identified before. Furthermore, we used our parser and the commonsense knowledge in solving a subset of a natural language understanding task.

As part of future work we are enhancing the K-Parser by improving the underlying systems such as the preposition sense disambiguation. We are also working on translating K-Parser output to the AMR so that it can be evaluated on the expert annotated, standard ALR corpora. We are also working on identifying the other types to commonsense knowledge needed to really understand the natural language. We will use our current framework for extracting the knowledge to extract the new knowledge. We are currently also working on developing an action language framework so that the knowledge can be used efficiently in NLU applications.

[2]http://www.freebase.com/

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