Learning Open Information Extraction of Implicit Relations from Reading Comprehension Datasets

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Abstract

The relationship between two entities in a sentence is often implied by word order and common sense, rather than an explicit predicate. For example, it is evident that “Fed chair Powell indicates rate hike” implies (Powell, is a, Fed chair) and (Powell, works for, Fed). These tuples are just as significant as the explicit-predicate tuple (Powell, indicates, rate hike), but have much lower recall under traditional Open Information Extraction (OpenIE) systems. Implicit tuples are our term for this type of extraction where the relation is not present in the input sentence. There is very little OpenIE training data available relative to other NLP tasks and none focused on implicit relations. We develop an open source, parse-based tool for converting large reading comprehension datasets to OpenIE datasets and release a dataset 35x larger than previously available by sentence count. A baseline neural model trained on this data outperforms previous methods on the implicit extraction task.

1 Introduction

Open Information Extraction (OpenIE) is the NLP task of generating (subject, relation, object) tuples from unstructured text e.g. “Fed chair Powell indicates rate hike” outputs (Powell, indicates, rate hike). The modifier open is used to contrast IE research in which the relation belongs to a fixed set. OpenIE has been shown to be useful for several downstream applications such as knowledge base construction (Wities et al., 2017), textual entailment (Berant et al., 2011), and other natural language understanding tasks (Stanovsky et al., 2015). In our previous example an extraction was missing: (Powell, works for, Fed). Implicit extractions are our term for this type of tuple where the relation (“works for” in this example) is not contained in the input sentence. In both colloquial and formal language, many relations are evident without being explicitly stated. However, despite their pervasiveness, there has not been prior work targeted at implicit predicates in the general case. Implicit information extractors for some specific implicit relations such as noun-mediated relations, numerical relations, and others (Pal and Mausam, 2016; Saha et al., 2017; Saha and Mausam, 2018) have been researched. While specific extractors are important, there are a multiplicity of implicit relation types and it would be intractable to categorize and design extractors for each one.

Past general OpenIE systems have been plagued by low recall on implicit relations (Stanovsky et al., 2018). In OpenIE’s original application – web-scale knowledge base construction – this low recall is tolerable because facts are often restated in many ways (Banko et al., 2007). However, in downstream NLU applications an implied relationship may be significant and only stated once (Stanovsky et al., 2015).

The contribution of this work is twofold. In Section 4, we introduce our parse-based conversion tool and convert two large reading comprehension datasets into implicit OpenIE datasets. In Section 5 and 6, we train a simple neural model on this data and compare to previous systems on precision-recall curves using a new gold test set for implicit tuples.

2 Problem Statement

We suggest that OpenIE research focus on producing implicit relations where the predicate is not contained in the input span. Formally, we define implicit tuples as (subject, relation, object) tuples that:

1. Have a subject and object word or phrase contained in the input sentence.
2. Have a relation token(s) entailed by word order of the sentence but not contained in it.
These “implicit” or “common sense” tuples reproduce the relation explicitly, which may be important for downstream NLU applications using OpenIE as an intermediate schema. For example, in Figure 1, the input sentence tells us that the Norsemen swore fealty to Charles III under “their leader Rollo”. From this our model outputs (The Norse leader, was, Rollo) despite the relation never being contained in the input sentence. Our definition of implicit tuples corresponds to the “frequently occurring recall errors” identified in previous OpenIE systems (Stanovsky et al., 2018): noun-mediated, sentence-level inference, long sentence, nominalization, noisy informal, and PP-attachment. We use the term implicit tuple to collectively refer to all of these situations where the predicate is absent or very obfuscated.

3 Related Work

3.1 Traditional Methods

Due to space constraints, see Niklaus et al. (2018) for a survey of non-neural methods. Of these, several works have focused on pattern-based implicit information extractors for noun-mediated relations, numerical relations, and others (Pal and Mausam, 2016; Saha et al., 2017; Saha and Mausam, 2018). In this work we compare to OpenIE-4, ClausIE (Corro and Gemulla, 2013), ReVerb (Fader et al., 2011), OLLIE (Mausam et al., 2012), Stanford OpenIE (Angeli et al., 2015), and PropS (Stanovsky et al., 2016).

3.2 Neural Network Methods

Stanovsky et al. (2018) frame OpenIE as a BIO-tagging problem and train an LSTM to tag an input sentence. Tuples can be derived from the tagger, input, and BIO CFG parser. This method outperforms traditional systems, though the tagging scheme inherently constrains the relations to be part of the input sentence, prohibiting implicit relation extraction. Cui et al. (2018) bootstrap (sentence, tuple) pairs from OpenIE-4 and train a standard seq2seq with attention model using OpenNMT-py (Klein et al., 2017). The system is inhibited by its synthetic training data which is bootstrapped from a rule-based system.

3.3 Dataset Conversion Methods

Due to the lack of large datasets for OpenIE, previous works have focused on generating datasets from other tasks. These have included QA-SRL datasets (Stanovsky and Dagan, 2016) and QAMR datasets (Stanovsky et al., 2018). These methods are limited by the size of the source training data which are an order of magnitude smaller than existing reading comprehension datasets.

4 Dataset Conversion Method

Span-based Question-Answer datasets are a type of reading comprehension dataset where each entry consists of a short passage, a question about the passage, and an answer contained in the passage. The datasets used in this work are the Stanford Question Answering Dataset (SQuADv1.1) (Rajpurkar et al., 2016) and NewsQA (Trischler et al., 2017). These QA datasets were built to require reasoning beyond simple pattern-recognition, which is exactly what we desire for implicit OpenIE. Our goal is to convert the QA schema to OpenIE, as was successfully done for NLI (Demszky et al., 2018). The repository of software and converted datasets is available at http://toAppear.

4.1 QA Pairs to OpenIE Tuples

We started by examining SQuAD and noticing that each answer, $A$, corresponds to either the subject, relation, or object in an implicit extraction. The corresponding question, $Q$, contains the other two parts, i.e. either the (1) subject and relation, (2) subject and object, or (3) relation and object. Which two pieces the question contains depends on the type of question. For example, “who was... factoid” type questions contain the relation (“was”) and object (the factoid), which means that the answer is the subject. In Figure 1, “Who was Rollo” is recognized as a who was question and caught by the whoParse() parser. Similarly, a question in the form of “When did person do action” expresses a subject and a relation, with the answer containing the object. For example, “When did Einstein emigrate to the US“ and answer 1933, would convert to (Einstein, when did emigrate to the US, 1933). In cases like these the relation might not be grammatically ideal, but nevertheless captures the meaning of the input sentence.

In order to identify generic patterns, we build our parse-based tool on top of a dependency parser (Honnibal and Johnson, 2015). It uses fifteen rules, with the proper rule being identified and run

1https://github.com/knowitall/openie
based on the question type. The rule then uses its pre-specified pattern to parse the input QA pair and output a tuple. These fifteen rules are certainly not exhaustive, but cover around eighty percent of the inputs. The tool ignores questions greater than 60 characters and complex questions it cannot parse, leaving a dataset smaller than the original (see Table 1).

Each rule is on average forty lines of code that traverses a dependency parse tree according to its pre-specified pattern, extracting the matching spans at each step. A master function parse() determines which rule to apply based on the question type which is categorized by nsubj presence, and the type of question (who/what/etc.). Most questions contain an nsubj which makes the parse task easier, as this will also be the subject of the tuple. We allow the master parse() method try multiple rules. It first tries very specific rules (e.g. a parser for how questions where no subject is identified), then falls down to more generic rules. If no output is returned after all the methods are tried we throw the QA pair out. Otherwise, we find the appropriate sentence in the passage based on the index.

| Source Data | Sentences | Train Tuples | Validation Tuples |
|-------------|-----------|--------------|-------------------|
| NewsQA      | 50880     | 56646        | -                 |
| SQuAD       | 38773     | 51949        | -                 |
| Total       | 89653     | 107595       | 1000              |

Table 1: Dataset statistics.

4.2 Sentence Alignment

Following QA to tuple conversion, the tuple must be aligned with a sentence in the input passage. We segment the passage into sentences using periods as delimiters. The sentence containing the answer is taken as the input sentence for the tuple. Outputted sentences predominantly align with their tuple, but some exhibit partial misalignment in the case of some multi-sentence reasoning questions. 13.6% of questions require multi-sentence reasoning, so this is an upper bound on the number of partially misaligned tuples/sentences (Rajpurkar et al., 2016). While there may be heuristics that can be used to check alignment, we didn’t find a significant number of these misalignments and so left them in the corpus. Figure 1 demonstrates the conversion process.

4.3 Tuple Examination

Examining a random subset of one hundred generated tuples in the combined dataset we find 12 noun-mediated, 33 sentence-level inference, 11 long sentence, 7 nominalization, 0 noisy informal, 3 pp-attachment, 24 explicit, and 10 partially misaligned. With 66% implicit relations, this dataset shows promise in improving OpenIE’s recall on implicit relations.

5 Our model

Our implicit OpenIE extractor is implemented as a sequence to sequence model with attention (Bahdanau et al., 2014). We use a 2-Layer LSTM Encoder/Decoder with 500 parameters, general attention, SGD optimizer with adaptive learning rate, and 0.33 dropout (Hochreiter and Schmidhuber, 1997). The training objective is to maximize the likelihood of the output tuple given the input sentence. In the case of a sentence having multiple extractions, it appears in the dataset once for each output tuple. At test time, beam search is used for decoding to produce the top-10 outputs and an associated log likelihood value for each tuple (used to generate the precision-recall curves in Section 7).
6 Evaluation

We make use of the evaluation tool developed by Stanovsky and Dagan (2016) to test the precision and recall of our model against previous methods. We make two changes to the tool as described below.

6.1 Creating a Gold Dataset

The test corpus contained no implicit data, so we re-annotate 300 tuples from the CoNLL-2009 English training data to use as gold data. Both authors worked on different sentence sets then pruned the other set to ensure only implicit relations remained. We note that this is a different dataset than our training data so should be a good test of generalizability; the training data consists of Wikipedia and news articles, while the test data resembles corporate press release headlines.

6.2 Matching function for implicit tuples

We implement a new matching function (i.e. the function that decides if a generated tuple matches a gold tuple). The included matching functions used BoW overlap or BLEU, which aren’t appropriate for implicit relations; our goal is to assess whether the meaning of the predicted tuple matches the gold, not the only tokens. For example, the if the gold relation is “is employed by” we want to accept “works for”. Thus, we instead compute the cosine similarity of the subject, relation, and object embeddings to our gold tuple. All three must be above a threshold to evaluate as a match. The sequence embeddings are computed by taking the average of the GloVe embeddings of each word (i.e. BoW embedding) (Pennington et al., 2014).

7 Results

The results on our implicit corpus are shown in Figure 2 (our method in blue). For continuity with prior work, we also compare our model on the original corpus but using our new matching function in Figure 3.

Our model outperforms at every point in the implicit-tuples PR curve, accomplishing our goal of increasing recall on implicit relations. Our system performs poorly on explicit tuples, as we would expect considering our training data. We tried creating a multi-task model, but found the model either learned to produce implicit or explicit tuples. Creating a multi-task network would be ideal, though it is sufficient for production systems to use both systems in tandem.

8 Conclusion

We created a large training corpus for implicit OpenIE extractors based on SQuAD and NewsQA, trained a baseline on this dataset, and presented promising results on implicit extraction. We see this as part of a larger body of work in text-representation schemes which aim to represent meaning in a more structured form than free text. Implicit information extraction goes further than traditional OpenIE to elicit relations not contained in the original free text. This allows maximally-shortened tuples where common sense relations are made explicit. Our model should improve further as more QA datasets are released and converted to OpenIE data using our conversion tool.
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