Abstract

Current techniques for Open Information Extraction (OIE) focus on the extraction of binary facts and suffer significant quality loss for the task of extracting higher order N-ary facts. This quality loss may not only affect the correctness, but also the completeness of an extracted fact. We present KRAKEN, an OIE system specifically designed to capture N-ary facts, as well as the results of an experimental study on extracting facts from Web text in which we examine the issue of fact completeness. Our preliminary experiments indicate that KRAKEN is a high precision OIE approach that captures more facts per sentence at greater completeness than existing OIE approaches, but is vulnerable to noisy and ungrammatical text.

1 Introduction

For the task of fact extraction from billions of Web pages the method of Open Information Extraction (OIE) (Fader et al., 2011) trains domain-independent extractors. This important characteristic enables a potential application of OIE for even very large corpora, such as the Web. Existing approaches for OIE, such as REVERB (Fader et al., 2011), WOE (Wu and Weld, 2010) or WANDERLUST (Akbik and Bross, 2009) focus on the extraction of binary facts, e.g. facts that consist of only two arguments, as well as a fact phrase which denotes the nature of the relationship between the arguments. However, a recent analysis of OIE based on Semantic Role Labeling (Christensen et al., 2011) revealed that N-ary facts (facts that connect more than two arguments) were present in 40% of surveyed English sentences. Worse, the analyses performed in (Fader et al., 2011) and (Akbik and Bross, 2009) show that incorrect handling of N-ary facts leads to extraction errors, such as incomplete, uninformative or erroneous facts. Our first example illustrates the case of a significant information loss:

a) In the 2002 film Bubba Ho-tep, Elvis lives in a nursing home.

REVERB: LivesIn(Elvis, nursing home)

In this case, the OIE system ignores the significant contextual information in the argument the 2002 film Bubba Ho-tep, which denotes the domain in which the fact LivesIn(Elvis, nursing home) is true. As a result, and by itself, the extracted fact is false. The next example shows a binary fact from a sentence that de-facto expresses an N-ary fact.

b) Elvis moved to Memphis in 1948.

REVERB: MovedTo(Elvis, Memphis)

WANDERLUST: MovedIn(Elvis, 1948)

Contrary to the previous example, the OIE systems extracted two binary facts that are not false, but incomplete, as the interaction between all three entities in this sentence can only be adequately modeled using a ternary fact. The fact MovedIn(Elvis, 1948) for example misses an important aspect, namely the location Elvis moved to in 1948. Therefore, each of these two facts is an example of important, but not crucial information loss.

Unfortunately, current OIE systems are not designed to capture the complete set of arguments for
We introduce KRAKEN, our experiments and end with conclusions. We examine intra-sentence fact correctness of unary, binary and higher order N-ary facts. Our previous system W2.1 Previous Work

Table 1: Common type-paths and the type of argument head they find.

| path                      | head of       |
|---------------------------|---------------|
| nsubj↓                    | subject       |
| nsubjpass↓                | subject (passive) |
| rcmod↑,appos↑             | subject (relative clause) |
| partmod↑,nsubj↓           | subject       |
| dobj↓                     | object        |
| prep↓,pobj↓               | object        |
| prep↓,npadvmod↓           | object        |
| advmod↓                   | context (usually modal) |
| tmod↑                     | context (temporal) |
| parataxis↓,nsubj↓         | context       |
| ccomp↓,nsubj↓             | context       |
Doublethink, a word that was coined by Orwell in the novel *1984*, describes a fictional concept.

Figure 1: Example of a sentence in Stanford typed dependency formalism. One fact phrase is *was coined*. Using the type-path `rcmod↑-appos↑`, the subject the *Doublethink* is found, the path is highlighted in dotted lines. Using `prep↓-pobj↓`, two arguments are found: *Orwell* and *the novel 1984*. One N-ary fact for this sentence is `WasCoined(Doublethink, (by) Orwell, (in) the novel 1984)`. The other is `Describes(Doublethink, fictional concept)`.

### 2. Detection of argument heads

Next, for each word of a fact phrase, KRAKEN attempts to find heads of arguments using *type-paths* as listed in Table 1. Each type-path indicates one or more links, as well as the direction of each link, to follow to find an argument head. For example, the type-path `subj↓` indicates that if one downward link of type `subj` exists, then the target of that link is an argument head. Figure 1 illustrates an example. At the end of this step, KRAKEN returns all found argument heads for the fact phrase.

### 3. Detection of full arguments

KRAKEN recursively follows all downward links from the argument head to get the full argument, excluding any links that were part of the type-path to the argument head. The combination of the detected fact phrase from step 1 and these full arguments form the fact. If a fact phrase has at least one argument, the system extracts it as a fact.

The ruleset was generated by joining the linkpaths reported in (Akbik and Bross, 2009) that contain at least one overlapping entity and one overlapping verb, and exchanging the underlying grammatical formalism with Stanford typed dependencies\(^1\), resulting in a verb-centric and human-readable ruleset.

### 3 Preliminary Experimental Study

We compare REVERB, the state-of-the-art in binary fact extraction, with KRAKEN, in order to measure the effect of using N-ary fact extraction over purely binary extractors on overall precision and completeness. Additionally, we test in how far using an IE approach based on deep syntactic parsing can be used for sentences from the Web, which have a higher chance of being ungrammatical or noisy.

| KRAKEN  | REVERB |
|---------|--------|
| sentences | 500    | 500 |
| skipped   | 155    | 0   |
| elapsed time | 319.067ms | 13.147ms |

|            | KRAKEN | REVERB |
|------------|--------|--------|
| min. confidence | -      | 0.1    |
| total facts   | 572    | 736    |
| per sentence  | 1.66   | 1.47   |
| true, complete| 308    | 166    |
| true, incomplete| 81    | 256    |
| false         | 183    | 314    |
| precision     | 0.68   | 0.61   |
| completeness  | 0.79   | 0.39   |

Table 2: The results of the comparative evaluation. KRAKEN nearly doubles the amount of recognized complete and true facts.
facts have been counted as true. We distinguish them from true and complete facts that capture all relevant arguments as given by the sentence they were extracted from. We measured an inter-annotator agreement of 87%, differently evaluated facts were discussed by the judges and resolved. Most disagreement was caused by facts with underspecified arguments, labeled as false by one judge and as true and incomplete by the other.

3.2 Evaluation Results and Discussion

KRAKEN extracts higher order N-ary facts. Table 2 show results for KRAKEN and REVERB. We measured results for REVERB with different confidence thresholds. In all measurements, we observe a significantly higher number of true and complete facts for KRAKEN, as well as both a higher overall precision and number of facts extracted per sentence. The completeness, measured as the ratio of complete facts over all true facts, is also significantly higher for KRAKEN. Figure 2 breaks down the fact arity. KRAKEN performs particularly well for binary, ternary and 4-ary facts, which are also most common. We conclude that even though our rule-set was generated on a different domain (Wikipedia text), it generalizes well to the Web domain.

Dependency parsing of Web text. One major drawback of the settings we used is our (possibly too crude) heuristic for detecting erroneous dependency parses: We set KRAKEN to extract facts from all sentences in which the dependency parse does not contain the typed dependency dep, which indicates unclear grammatical relationships. A total of 155 sentences - 31% of the overall evaluation set - were skipped as a consequence. Also, the elapsed time of the fact extraction process was more than one order of magnitude longer than REVERB, possibly limiting the ability of the system to scale to very large collections of documents.

Measurements over different sentence lengths. When limiting the maximum number of words allowed per sentence, we note modest gains in precision and losses in complete positives in both systems, see Figure 3. KRAKEN performs well even on long sentences, extracting more true and complete positives at a high precision.

Lessons learned. Based on these observations, we reach the conclusion that given the 'right portion' of sentences from a collection such as the Web, our method for N-ary OIE can be very effective, extracting more complete facts with a high precision and fact-per-sentence rate. Sentences that are well suited for our algorithm must fulfill the following desiderata: 1) They are noise free and grammatically correct, so there is a high chance for a correct parse. 2) They are fact-rich, so that processing resources are wisely used.

4 Summary and Future Work

Current OIE systems do not perform well for the task of higher order N-ary fact extraction. We presented KRAKEN, an algorithm that finds these facts with high precision, completeness, and fact-per-sentence rate. However, we also note that relying on a dependency parser comes at the cost of
speed and recall, as many sentences were skipped due to our heuristic of detecting erroneous parses.

Future work focuses on scaling the system up for use on a large Web corpus and increasing the system’s recall. To achieve this, we will work on a first step of identifying grammatical and fact-rich sentences before applying dependency parsing in a second step, filtering out all sentences that do not meet the desiderata stated in Section 3. We intend to evaluate using very fast dependency parsers, some more than two orders of magnitude faster than the Stanford parser (Cer et al., 2010), one prominent example of which is the MALTparser (Nivre et al., 2007).

Additionally, we will examine more data-driven approaches for identifying fact phrases and arguments in order to maximize the system’s recall. We intend to use such an approach to train KRaken for use on other languages such as German.

One interesting aspect of future work is the canonicalization of the fact phrases and arguments given very large collections of extracted facts. Unsupervised approaches that make use of redundancy such as (Bollegala et al., 2010) or (Yates and Etzioni, 2007) may help cluster similar fact phrases or arguments. A related possibility is the integration of facts into an existing knowledge base, using methods such as distant supervision (Mintz et al., 2009). We believe that combining OIE with a method for fact phrase canonicalization will allow us to better evaluate the system in terms of precision/recall and usefulness in the future.

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