# OPIEC: An Open Information Extraction Corpus

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## Abstract

Open information extraction (OIE) systems extract relations and their arguments from natural language text in an unsupervised manner. The resulting extractions are a valuable resource for downstream tasks such as knowledge base construction, open question answering, or event schema induction. In this paper, we release an OIE corpus called OPIEC extracted from the text of English Wikipedia and analyze its contents. OPIEC complements the available OIE resources: It is the largest OIE corpus publicly available to date (over 340M triples) and contains valuable metadata such as provenance information, confidence scores, linguistic annotations, and semantic annotations including spatial and temporal information. We analyze the OPIEC corpus by comparing its content with knowledge bases such as DBpedia or YAGO, which are also based on Wikipedia. We found that most of the facts between entities present in OPIEC cannot be found in DBpedia and/or YAGO, that OIE facts often differ in the level of specificity compared to knowledge base facts, and that OIE open relations are generally highly polysemous. We believe that the OPIEC corpus is a valuable resource for future research on automated knowledge base construction.

## 1. Introduction

Open information extraction (OIE) is the task of extracting relations and their arguments from natural language text in an unsupervised manner [Banko et al., 2007]. The output of such systems is usually structured in the form of (*subject*, *relation*, *object*)-triples. For example, from the sentence *"Bell is a telecommunication company, which is based in L. A.,"* an OIE system may yield the extractions *("Bell"; "is"; "telecommunication company")* and *("Bell"; "is based in"; "L. A.")*. The extractions of OIE systems from large corpora are a valuable resource for downstream tasks [Etzioni et al., 2008, Mausam, 2016] such as automated knowledge base construction [Riedel et al., 2013, Wu et al., 2018, Vashishth et al., 2018, Shi and Weninger, 2018], open question answering [Fader et al., 2013], event schema induction [Balasubramanian et al., 2013], generating inference rules [Jain et al., 2016], or for improving OIE systems themselves [Mausam et al., 2012, Yahya et al., 2014]. A number of derived resources have been produced from OIE extractions, including as entailment

rules [Jain et al., 2016], question paraphrases [Fader et al., 2013], Rel-grams [Balasubramanian et al., 2012], and OIE-based embeddings [Stanovsky et al., 2015].

In this paper, we release a new OIE corpus called *OPIEC*. The OPIEC corpus has been extracted from the full text of the English Wikipedia using the Stanford CoreNLP pipeline [Manning et al., 2014] and the state-of-the-art OIE system MinIE [Gashteovski et al., 2017]. OPIEC complements available OIE resources [Fader et al., 2011, Lin et al., 2012, Nakashole et al., 2012, Moro and Navigli, 2012, 2013, Delli Bovi et al., 2015b,a]: It is the largest OIE corpus publicly available to date (with over 340M triples) and contains valuable metadata information for each of its extractions not available in existing resources (see Tab. 1 for an overview). In particular, OPIEC provides for each triple detailed provenance information, syntactic annotations (such as POS tags, lemmas, dependency parses), semantic annotations (such as polarity, modality, attribution, space, time), entity annotations (NER types and, when available, Wikipedia links), as well as confidence scores.

We performed a detailed data profiling study of the OPIEC corpus to analyze its contents and potential usefulness for downstream applications. We observed that a substantial fraction of the OIE extractions was not self-contained (e.g., because no anaphora resolution was performed) or overly specific (e.g., because arguments are entire complex phrases). Since these extractions are more difficult to work with, we created the *OPIEC-Clean* subcorpus (104M triples), in which triples express relations between clear concepts. In particular, OPIEC-Clean contains triples in which arguments are restricted to named entities (as recognized by an NER system), match a Wikipedia page title (e.g., concepts such as *political party* or *movie*), or link directly to a Wikipedia page. Although OPIEC-Clean is substantially smaller than the full OPIEC corpus, it is nevertheless four times larger than the largest prior OIE corpus.

To gain insight into the information present in the OPIEC corpus, we compared its content with the DBpedia [Bizer et al., 2009] and YAGO [Hoffart et al., 2013] knowledge bases, which are also constructed from Wikipedia (e.g., from infoboxes). Since such an analysis is difficult to perform due to the openness and ambiguity of OIE extractions, we followed standard practice and used a simple form of distant supervision. In particular, we analyze the *OPIEC-Linked* subcorpus (5.8M triples), which contains only those triples in which both arguments are linked to Wikipedia articles, i.e., where we have golden labels for disambiguation. We found that most of the facts between entities present in OPIEC-Linked cannot be found in DBpedia and/or YAGO, that OIE facts often differ in the level of specificity compared to knowledge base facts, and that frequent OIE open relations are generally highly polysemous.

Along with the OPIEC corpus as well as the OPIEC-Clean and OPIEC-Linked subcorpora, we release the codebase used to construct the corpus as well as a number of derived resources, most notably a corpus of open relations between arguments of various entity types along with their frequencies. We believe that the OPIEC corpus is a valuable resource for future research on automated knowledge base construction.

## 2. Related OIE Corpora

Many structured information resources created from semi-structured or unstructured data have been constructed in recent years. Here we focus on large-scale OIE corpora, which do

| | # triples (millions) | # unique arguments (millions) | # unique relations (millions) | disamb. args (aut./gold) | confi-dence | prove-nance | syntactic annotat. | semantic annotat. |
|---|---|---|---|---|---|---|---|---|
| ReVerb | 14.7 | 2.2 | 0.7 | - / - | ✓ | ✓ | ✓ | - |
| ReVerb-Linked | 3.0 | 0.8 | 0.5 | ✓ / - | - | - | - | - |
| PATTY (Wiki) | 15.8 | 0.9 | 1.6 | ✓ / - | - | - | - | - |
| WiseNet 2.0 | 2.3 | 1.4 | 0.2 | - / ✓ | - | - | - | - |
| DefIE | 20.3 | 2.5 | 0.3 | ✓ / - | - | - | - | - |
| KB-Unify | 25.5 | 2.1 | 2.3 | ✓ / - | - | - | - | - |
| OPIEC | 341.0 | 104.9 | 63.9 | - / - | ✓ | ✓ | ✓ | ✓ |
| OPIEC-Clean | 104.0 | 11.1 | 22.8 | - / - | ✓ | ✓ | ✓ | ✓ |
| OPIEC-Linked | 5.8 | 2.1 | 0.9 | - / ✓ | ✓ | ✓ | ✓ | ✓ |

Table 1: Available OIE corpora and their properties. All numbers are in millions. Syntactic annotations include POS tags, lemmas, and dependency parses. Semantic annotations include attribution, polarity, modality, space, and time.

not make use of a predefined set of arguments and/or relations. OIE corpora complement more targeted resources such as knowledge bases (e.g., DBpedia, YAGO) or NELL [Mitchell et al., 2018], as well as smaller, manually crafted corpora such as the one of Stanovsky and Dagan [2016]; see also the discussion in Sec. 5. An overview of the OPIEC corpus, its subcorpora, and related OIE corpora is given in Tab. 1.

One of the first and widely-used OIE resource is the ReVerb corpus [Fader et al., 2011], which consists of the high-confidence extractions of the ReVerb OIE system from the ClueWeb09 corpus. In subsequent work, a subset of the ReVerb corpus with automatically disambiguated arguments was released [Lin et al., 2012]. The PATTY [Nakashole et al., 2012], WiseNet [Moro and Navigli, 2012], WiseNet 2.0 [Moro and Navigli, 2013], and DefIE [Delli Bovi et al., 2015b] corpora additionally organize open relations in relational synsets and then the relational synsets into taxonomies. Finally, KB-Unify [Delli Bovi et al., 2015a] integrates multiple different OIE corpora into a single resource.

The largest prior corpus is KB-Unify, which consists of 25.5M triples in roughly 4.5M distinct open relations and arguments. Both OPIEC (341M and 105M/64M, resp.) and OPIEC-Clean (104M and 11M/23M) are significantly larger than KB-Unify, both in terms of number of triples as well as in terms of distinct arguments and relations. One of the reasons for this size difference is that the MinIE extractor, which we used to create the OPIEC corpus, produces more extractions than the extractors used to create prior resources. The OPIEC corpus—but not OPIEC-Clean and OPIEC-Linked–also contains all extractions produced by MinIE unfiltered, whereas most prior corpora use filtering rules aiming to provide higher-quality extractions (e.g., frequency constraints).

Most of the available corpora use automated methods to disambiguate entities (e.g., w.r.t. to a knowledge base). On the one hand, such links are very useful because ambiguity is restricted to open relations. On the other hand, the use of automated entity linkers may introduce errors and—perhaps more importantly—restricts the corpus to arguments that can be confidently linked. We did not perform automatic disambiguation in OPIEC, although we retained Wikipedia links when present (similar to WiseNet). Since these links are provided by humans, we consider them as golden disambiguation links. The OPIEC-

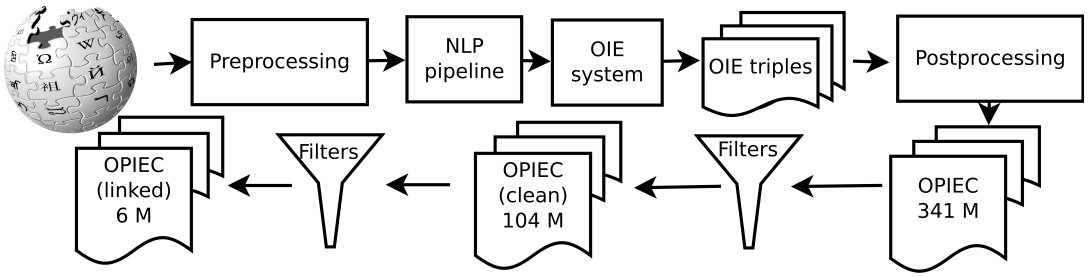



Figure 1: Corpus construction pipeline

Linked subcorpus contains almost 6M triples from OPIEC in which both arguments are disambiguated via such golden links.

A key difference between OPIEC and prior resources is in the amount of metadata provided for each triple. First, only ReVerb and OPIEC provide confidence scores for the extractions. The confidence score measures how likely it is that the triple has been extracted correctly (but not whether it is actually true). For example, given the sentence *"Bill Gates is a founder of the Microsoft."*, the extraction *("Bill Gates"; "is founder of"; "Microsoft")* is correct, whereas the extraction *("Bill Gates"; "is"; "Microsoft")* is not. Since OIE extractors are bound to make extraction errors, the extractor confidence is an important signal for downstream applications [Dong et al., 2014]. Similarly, provenance information (i.e., information about where the triple was extracted) is not provided in many prior resources.

One of the reasons why we chose MinIE to construct OPIEC is that it provides syntactic and semantics annotations for its extractions. Syntactic annotations include part-of-speech tags, lemmas, and dependency parses. Semantic annotations include attribution (source of information according to sentence), polarity (positive or negative), and modality (certainty or possibility). We also extended MinIE to additionally provide spatial and temporal annotations for its triples. The use of semantic annotations simplifies the resulting triples significantly and provides valuable contextual information; see the discussion in Section 3.

## 3. Corpus Construction

OPIEC was constructed from all the articles of the English Wikipedia dump of June 21, 2017. Fig. 1 gives an overview of the pipeline that we used. The pipeline is (apart from preprocessing) not specific to Wikipedia and thus can be used with other dataset as well. We used Apache Spark [Zaharia et al., 2016] to distribute corpus construction across a compute cluster so that large datasets can be handled. We release the entire codebase along with the actual OPIEC corpora.

### 3.1 Preprocessing

We used a modified version of WikiExtractor[1] to extract the plain text from Wikipedia pages. In particular, we modified WikiExtractor such that it retains internal Wikipedia

1. https://github.com/attardi/wikiextractor

links to other Wikipedia articles. The links are provided as additional metadata in the form of (*span*, *target page*) annotations. Custom entity linkers can be inserted into the pipeline by providing such annotations.

Wikipedia generally does not link the first phrase of an article to the article page itself; e.g., the page on New Hampshire starts with *"New Hampshire is a ..."*, where *New Hampshire* is not linked. To avoid losing this relationship, we link the first phrase that *exactly* matches the Wikipedia page name (if any) to that Wikipedia page.

### 3.2 NLP Pipeline

We ran an NLP pipeline on the preprocessed Wikipedia articles by using CoreNLP [Manning et al., 2014], version 3.8.0. We performed tokenization, sentence splitting, part-of-speech tagging, lemmatization, named entity recognition (NER) [Finkel et al., 2005], temporal tagging [Chang and Manning, 2012], and dependency parsing [Chen and Manning, 2014].

### 3.3 The MinIE-SpaTe OIE System

From each of the resulting sentences, we extract triples using the state-of-the-art OIE system MinIE [Gashteovski et al., 2017], which in turn in based on ClausIE [Del Corro and Gemulla, 2013]. MinIE *minimizes* the extractions into more compact triples by removing unnecessary words (e.g. determiners) without damaging the semantic content of the triple and by providing *semantic annotations*. The semantic annotations move auxiliary information from the triple (thereby simplifying it) to annotations. The semantic annotations include polarity, modality, attribution, and quantities. Polarity (positive or negative) indicates whether or not the triple occurred in negated form in the input sentence. *Modality* indicates whether the triple is a certainty (CT) or merely a possibility (PS) according to the input. *Attribution* refers to the supplier of the information carried within the triple, again according to the input sentence. Attributions have their own polarity and modality. Finally, quantities express specific amounts.

Consider for example the sentence: *"David Heyman said that Gilderoy Lockhart will probably not be played by Kenneth Branagh."* MinIE extracts the following triple and annotations:

("Gilderoy Lockhart"; "be played by"; "Kenneth Branagh")
*Factuality:* negative possibility
*Attribution:* "David Heyman", (positive certainty)

Many of the sentences in Wikipedia contain some sort of temporal or spatial reference (roughly 56% according to a preliminary study). Since this information is important, we modified MinIE's output to add additional semantic annotations for space and time, thereby producing SPOTL facts [Hoffart et al., 2013]. We refer to the resulting system as MinIE-SpaTe. Generally, MinIE-SpaTe makes use of syntactic information provided in the dependency parse as well as information provided by SUTime and the NER system. Details as well as a discussion on the precision of the annotations can be found in Appendix C.

We subsequently refer to a triple with any spatial or temporal annotation as a *spatial/temporal triple*. MinIE-SpaTe differentiates between three types of such spatial or tem-

poral annotations: (i) annotations on entire triples, (ii) annotations on arguments, and (iii) spatial or temporal references. In what follows, we briefly discuss these types for temporal annotations; similar distinctions apply to spatial annotations.

Temporal annotations on triples provide temporal context for the entire triple. For example, from the sentence *"Bill Gates founded Microsoft in 1975."*, MinIE–SpaTe extracts triple *("Bill Gates"; "founded"; "Microsoft")* with temporal annotation ("in", 1975). Here, "in" is a *lexicalized temporal predicate* and 1975 is the *core temporal expression*. MinIE-SpaTe outputs *temporal modifiers* when found; e.g. the temporal annotation for *"... at precisely 11:59 PM"* is *("at", "11:59 PM", premod: precisely)*). We use the TIMEX3 format [Saurı et al., 2006] for representing the temporal information about the triple.

Sometimes the arguments of a triple contain some temporal information that refers to a phrase but not to the whole triple. MinIE provides temporal annotations for arguments for this purpose. For example, from the sentence *"Isabella II opened the 17th-century Parque del Retiro."*, MinIE-SpaTe extracts *("Isabella II"; "opened"; "Parque del Retiro")* with a temporal annotation (17th-century, Parque del Retiro) for the object argument. Generally, the temporal annotation contains information on its target (e.g., object), the temporal expression (17th-Century) and the head word being modified by the temporal expression (Retiro).

Finally, some triples contain temporal references as subject or object; MinIE-SpaTe annotates such references. For example, from the input sentence *"2003 was a hot year."*, MinIE-SpaTe extracts the triple: *("2003"; "was"; "hot year")*, where the subject (*2003*) is annotated with a temporal reference.

### 3.4 Postprocessing

During postprocessing, we remove clearly wrong triples, annotate the remaining triples with a confidence score, and ensure that Wikipedia links are not broken up.

In particular, MinIE retains the NER types provided during preprocessing in its extractions. We aggregated the most frequent relations per argument type and found that many of the triples were of the form *(person; "be"; organization)*, *(location; "be"; organization)*, and so on. These extractions almost always stemmed from an incorrect dependency parses obtained from sentences containing certain conjunctions. We filtered all triples with lemmatized relation *"be"* and different NER types for subject and object from MinIE-SpaTe's output.

In order to estimate whether or not a triple is correctly extracted, we followed ReVerb [Fader et al., 2011] and trained a logistic regression classifier. We used the labeled datasets provided by Gashteovski et al. [2017] as training data. Features were constructed based on an in-depth error analysis. The most important features were selected using chi-square relevance tests and include features such as the clause type, whether a coordinated conjunction has been processed, and whether or not MinIE simplified the triple. See Appendix D for a complete list of features, and Sec. 4.6 for a discussion of confidence scores and precision in our corpora.

In a final postprocessing step, we rearranged triples such that links within the triples are not split across its constituents. For example, the triple *("Peter Brooke"; "was member of"; "Parliament")* produced by MinIE splits up the linked phrase "member of Parliament",

| | OPIEC | OPIEC-Clean | OPIEC-Linked |
|---|---|---|---|
| Total triples (millions) | 341.0 | 104.0 | 5.8 |
| Triples with semantic annotations | 166.3 (49%) | 51.46 (49%) | 3.37 (58%) |
| negative polarity | 5.3 (2%) | 1.33 (1%) | 0.01 (0%) |
| possibility modality | 13.9 (4%) | 3.27 (3%) | 0.04 (1%) |
| quantities | 59.4 (17%) | 15.91 (15%) | 0.45 (8%) |
| attribution | 6.4 (2%) | 1.44 (1%) | 0.01 (0%) |
| time | 65.3 (19%) | 19.66 (19%) | 0.58 (1%) |
| space | 61.5 (18%) | 22.11 (21%) | 2.64 (45%) |
| space OR time | 111.3 (33%) | 37.22 (36%) | 3.01 (52%) |
| space AND time | 15.4 (5%) | 4.54 (4%) | 0.20 (4%) |
| Triple length in tokens ($\mu \pm \sigma$) | $7.66 \pm 4.35$ | $6.06 \pm 2.82$ | $6.45 \pm 2.65$ |
| subject ($\mu \pm \sigma$) | $2.12 \pm 2.12$ | $1.48 \pm 0.79$ | $1.92 \pm 0.94$ |
| relation ($\mu \pm \sigma$) | $3.01 \pm 2.47$ | $3.10 \pm 2.56$ | $2.77 \pm 2.14$ |
| object ($\mu \pm \sigma$) | $2.52 \pm 2.69$ | $1.48 \pm 0.79$ | $1.76 \pm 0.94$ |
| Confidence score ($\mu \pm \sigma$) | $0.53 \pm 0.23$ | $0.59 \pm 0.23$ | $0.61 \pm 0.26$ |

Table 2: Statistics for different OPIEC corpora. All frequencies are in millions. We count triples with annotations (not annotations directly). Percentages refer to the respective subcorpus.

which results an incorrect links for the object (since it does not link to *Parliament*, but to *member of parliament*). We thus rewrite such triples to *("Peter Brooke"; "was"; "member of Parliament")*.

### 3.5 Provided Metadata

All metadata collected in the pipeline are retained for each triple, including provenance information, syntactic annotations, semantic annotations, and confidence scores. A full description of the provided metadata fields can be found in Appendix B.

### 3.6 Filtering

We constructed the OPIEC-Clean and OPIEC-Linked subcorpus by filtering the OPIEC corpus. OPIEC-Clean generally only retains triples between entities or concepts, whereas OPIEC-Linked only retains triples in which both arguments are linked. The filtering rules are described in more details in the following section.

## 4. Statistics

Basic statistics such as corpus sizes, frequency of various semantic annotations, and information about the length of the extracted triples of OPIEC and its subcorpora are shown in Tab. 2. We first discuss properties of the OPIEC corpus, then describe how we constructed the OPIEC-Clean and OPIEC-Linked subcorpora, and finally provide more in-depth statistics.

### 4.1 The OPIEC Corpus

The OPIEC corpus contains all extractions produced by MinIE-SpaTe. We analyzed these extractions and found that a substantial part of the triples are more difficult to handle by downstream applications. We briefly summarize the most prevalent cases of such triples; all these triples are filtered out in OPIEC-Clean.

First of all, a large part of the triples are under-specific in that additional context information from the extraction source is required to obtain a coherent piece of information. By far the main reason for under-specificity is lack of coreference information. In particular, 22% of the arguments in OPIEC are personal pronouns, such as in the triple *("He"; "founded"; "Microsoft")*. Such triples are under-specific because provenance information is needed to resolve what "He" refers to. Similarly, about 1% of the triples have determiners as arguments (e.g. *("This"; "lead to"; "controversy")*), and 0.2% Wh-pronouns (e.g. *("what"; "are known as"; "altered states of consciousness")*). Coreference resolution in itself is a difficult problem, but the large fraction of such triples shows that coreference resolution is important to further boost the recall of OIE systems.

Another problem for OIE systems are entity mentions—most notably for works of art—that constitute clauses. For example, the musical *"Zip Goes a Million"* may be interpreted as a clause, leading to the incorrect extraction *("Zip"; "Goes"; "a Million")*. A preliminary study showed that almost 30% of all the OPIEC triples containing the same recognized named entity in both subject and object were of such a type. These cases constitute around 1% of OPIEC.

Finally, a substantial fraction of the triples in OPIEC has complicated expressions in its arguments. Consider for example the sentence *"John Smith learned a great deal of details about the U.S. Constitution."*. MinIE extracts the triple *("John Smith"; "learned"; "great deal of details about U.S. Constitution")*, which has a complicated object and is thus difficult to handle. A minimized variant such as *("John Smith"; "learned about"; "U.S. Constitution")* looses some information, but it expresses the main intent in a simpler way.

The above difficulties make the OPIEC corpus a helpful resource for research on improving or reasoning with complex OIE extractions rather than for downstream tasks.

### 4.2 The OPIEC-Clean Corpus

The OPIEC-Clean corpus is obtained from OPIEC by simply removing underspecified and complex triples. In particular, we consider a triple *clean* if the following conditions are met: (i) each argument is either linked, an entity recognized by the NER tagger, or matches a Wikipedia page title, (ii) links or recognized named entities are not split up across constituents, and (iii) the triple has a non-empty object.

Conditions (i) and (ii) rule out the complex cases mentioned in the previous section. Note that we ignore quantities (but no other modifiers) when checking condition (i). For example, the triple *("$Q_1$ electric locomotives"; "were ordered from"; "Alsthom")* with $Q_1$ = *"Three"* is considered clean; here *"electric locomotives"* holds a link to *TCDD E4000* and *"Alsthom"* holds a link to *Alsthom*.

MinIE is a clause-based OIE system and can produce extractions for so-called SV clauses: these extractions consists of only a subject and a relation, but no object. 3.5% of the triples in OPIEC are of such type. An example is the triple *("Civil War"; "have escalated"; "")*.

Although such extractions may contain useful information, we exclude them via condition (iii) to make the OPIEC-Clean corpus uniform.

Roughly 30% of the triples (104M) in OPIEC are clean according to the above constraints. Table 2 shows that clean triples are generally shorter on average and tend to have a higher confidence score than the full set of triples in OPIEC. The OPIEC-Clean corpus is easier to work with than the full OPIEC corpus; it is targeted towards both downstream applications and research in automated knowledge base construction.

### 4.3 The OPIEC-Linked Corpus

The OPIEC-Linked corpus contains only those triples from OPIEC-Clean in which both arguments are linked. Although the corpus is much smaller than OPIEC-Clean (5.8M triples, i.e., roughly 5.5% of OPIEC-Clean), it is the largest corpus to date with golden disambiguation links for the arguments. We use the corpus mainly to compare OIE extractions with the information present in the DBpedia and YAGO knowledge bases; see Sec. 5.

### 4.4 Semantic Annotations

About 49% of all triples in OPIEC contain some sort of semantic annotation (cf. Tab. 2); in OPIEC-Linked, the fraction increases to 58%. Most of the semantic annotations referred to quantities, space or time; these annotations provide important context for the extractions. There is a significantly smaller amount of negative polarity and possibility modality annotations. One reason for the lack of such annotations may be in the nature of the Wikipedia articles, which aim to contain encyclopedic, factual statements and are thus more rarely negated or hedged.

The distribution of annotations is similar for OPIEC and OPIEC-Clean, but differs significantly for OPIEC-Linked. In particular, we observe a drop in quantity annotations in OPIEC-Linked because most of the linked phrases do not contain quantities. The fraction of spatial triples in OPIEC-Linked is also much higher than the rest of the corpora. The reason is because Wikipedia contains many pages for locations, which are also linked and contain factual knowledge, thus resulting in many triples with spatial reference (e.g. the triple *("Camborne School of Mines"; "was relocated to"; "Penryn")*).

### 4.5 NER Types and Frequent Relations

For OPIEC-Clean, Fig. 2 shows the fraction of arguments and argument pairs that are recognized as named entities by the NER tagger, along with the NER type distribution of the arguments.

Out of the around 210M arguments, roughly 42% are recognized named entities. The most frequent NER type is *person*, followed by *location* and *organization*. The remaining NER types are not that frequent (less than 3% each). On the other hand, 58% of the arguments are not typed. These are mostly concepts (more precisely, strings that match Wikipedia pages not referring to an entity) and are thus not recognized by the NER system. The top-10 most frequent arguments which are not typed are the words *film, population, city, village, father, song, company, town, album* and *time*, with frequencies varying between 408k and 616k.

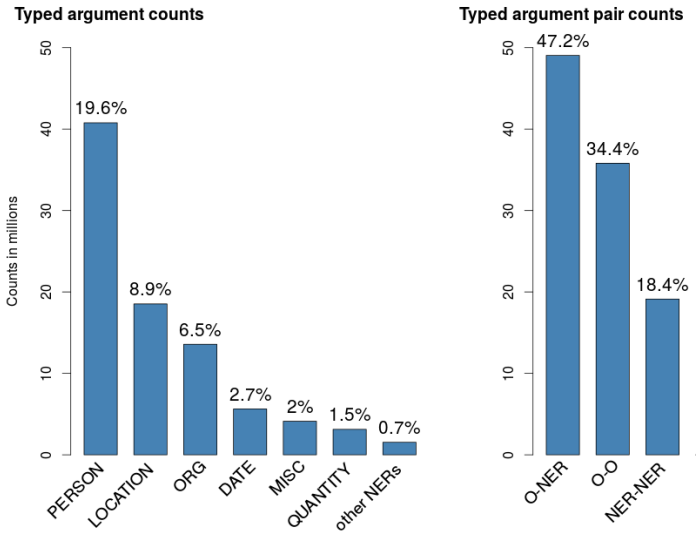


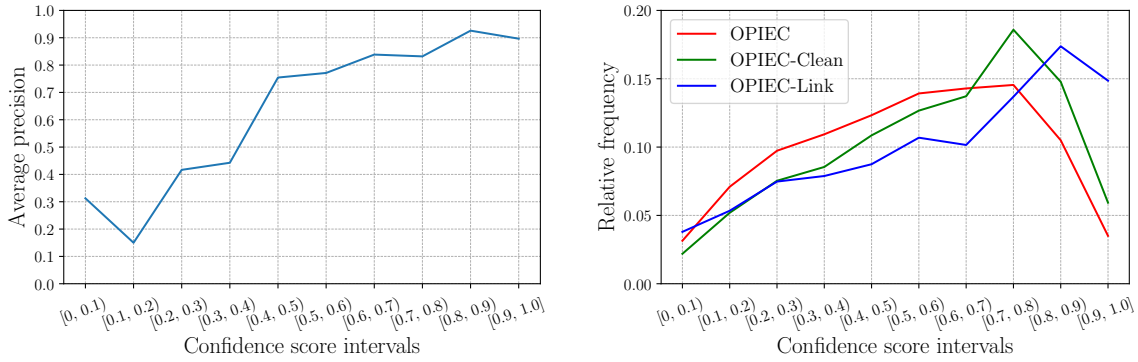

Figure 2: Distribution of NER types for arguments and argument pairs in OPIEC-Clean. Here "O" refers to arguments that are not recognized as a named entity.

| PERSON-PERSON | | LOCATION-LOCATION | | PERSON-LOCATION | |
|---|---|---|---|---|---|
| *"have"* | (130,019) | *"be in"* | (2,126,562) | *"be bear in"* | (203,091) |
| *"marry"* | (49,405) | *"have"* | (40,298) | *"die in"* | (37,952) |
| *"be son of"* | (40,265) | *"be village in administrative district of"* | (9,130) | *"return to"* | (36,702) |
| *"be daughter of"* | (37,089) | *"be north of"* | (3,816) | *"move to"* | (36,072) |
| *"be bear to"* | (29,043) | *"be suburb of"* | (3,291) | *"be in"* | (25,847) |
| *"be know as"* | (25,607) | *"be west of"* | (3,238) | *"live in"* | (22,399) |
| *"defeat"* | (22,151) | *"be part of"* | (3,188) | *"grow up in"* | (17,571) |

Table 3: Most frequent open relations between persons and locations (as recognized by the NER tagger) in OPIEC-Clean

Fig. 2 also reports the fraction of triples in which none, one, or both arguments are recognized as a named entity. We found that 18% of the triples (19M) in OPIEC-Clean have two typed arguments, and around 66% of the triples (69M) have at least one typed argument. Thus the majority of the triples involves named entities. 34% of the triples do not have recognized named entity arguments.

Tab. 3 shows the most frequent open relations between arguments recognized as persons and/or locations (which in turn are the top-3 most frequent argument type pairs). We will analyze some of the open relations in more detail in Sec. 5. For now, note that the most frequent relation between persons is *"have"*, which is highly polysemous. Other relations, such as "*marry*" and *"be son of"*, are much less ambiguous. We provide all open relations between recognized argument types as well as their frequencies with the OPIEC-Clean corpus.




(a) Precision of confidence score

(b) Distribution of confidence scores

Figure 3: Precision and distribution of confidence scores

### 4.6 Precision and Confidence Score

Each triple in the OPIEC corpora is annotated with a confidence score for correct extraction. To evaluate the accuracy of the confidence score, we created a fresh sample of triples (662 in total) and manually evaluated the correctness of the triples following the procedure of Gashteovski et al. [2017][2]. We bucketized the triples by confidence score into ten equi-width intervals and calculated the precision within each interval; see Fig. 3a. We found that the confidence score is highly correlated to precision (Pearson correlation of $r = 0.93$) and thus provides useful information.

The distribution in confidence scores across the various corpora is shown in Fig. 3b. We found that OPIEC-Clean and, in particular, OPIEC-Link contain a large fraction of high-confidence triples than the raw OPIEC corpus: these corpora are cleaner in that more potentially erroneous extractions are filtered out. Although triples with lower confidence score tend to be more inaccurate, they may still provide suitable information. We thus included these triples into our corpora; the confidence score allows downstream applications to handle these triples as appropriate.

## 5. Analysis

In this section, we compare the information present in the OIE triples in OPIEC with the information present in the DBpedia[Auer et al., 2007] and YAGO [Hoffart et al., 2013] knowledge bases. Since all resources extract information from Wikipedia— OPIEC from the text and DBpedia as well as YAGO from semi-structured parts of Wikipedia—, we wanted to understand whether and to what extent they are complementary. Generally, the disambiguation of OIE triples w.r.t. a given knowledge base is in itself a difficult problem. We avoid this problem here by (1) restricting ourselves to the OPIEC-Linked corpus (for which we have golden entity links) and (2) focusing on statistics that do not require a full disambiguation of the open relations, but are nevertheless insightful.

2. The annotation guidelines are provided at http://www.uni-mannheim.de/media/Einrichtungen/dws/Files_Research/Software/MinIE/minie-labeling-guide.pdf

| location | | associatedMusicalArtist | | spouse | |
|---|---|---|---|---|---|
| *"be in"* | (35,754) | *"be"* | (5,521) | *"be wife of"* | (1,580) |
| *"have"* | (2,500) | *"have"* | (3,248) | *"be"* | (980) |
| *"be"* | (1,473) | *"be guitarist of"* | (619) | *"marry"* | (551) |
| *"be at"* | (793) | *"be drummer of"* | (433) | *"be widow of"* | (392) |
| *"be of"* | (525) | *"be feature"* | (377) | *"be marry to"* | (246) |
| *"be historic home located at"* | (520) | *"be frontman of"* | (367) | *"have"* | (244) |

Table 4: The most frequent open relations aligned to the DBpedia relations *location*, *associatedMusicalArtist*, and *spouse* in OPEIC-Linked

### 5.1 Alignment With Knowledge Bases

To align the OIE tripes from OPIEC-Linked to YAGO or DBpedia, we make use of the distant supervision assumption. For each open triple $(s, r_{\text{open}}, o)$ from OPIEC-Linked, we search the KB for any triple of form $(s, r_{\text{KB}}, o)$ or $(o, r_{\text{KB}}, s)$. Here $s$ and $o$ refer to disambiguated entities, whereas $r_{\text{open}}$ refers to an open relation and $r_{\text{KB}}$ to a KB relation. If such a triple exists, we say that triple $(s, r_{\text{open}}, o)$ has a *KB hit*, and that $r_{\text{open}}$ *is aligned with* $r_{\text{KB}}$. In fact, if $r_{\text{open}}$ (e.g., *"was born in"*) is a mention of KB relation $r_{\text{KB}}$ (e.g., *birthPlace*), and subject and object are not swapped, then both triples express the same information. Otherwise, the open triple (e.g., *"was born in"*) and the KB triple (e.g., *deathPlace*) express different information or inverse relations. We can thus think of the number of KB hits as an optimistic measure of the number of open triples that are represented in the KB (with caveats, see below): the KB contains some relation between the corresponding entities, although not necessarily the one being mentioned.

We observed that 26.9% of the OIE triples in OPIEC-Linked have a KB hit in either DBpedia or YAGO. More specifically, 23.6% of the triples have a KB hit in DBpedia, 18.2% in YAGO, and 15% in both DBpedia and YAGO. Most of these triples have exactly one hit in the corresponding KB. Consequently, 73.1% of the linked triples do not have a KB hit; we analyze these triples below.

Tab. 4 shows the most frequent open relations aligned to the DBpedia relations *location*, *associatedMusicalArtist*, and *spouse*. The frequencies correspond to the number of OIE triples that (1) have the specified open relation (e.g., *"be wife of"*) and (2) have a KB hit with the specified KB relation (e.g., *spouse*). There is clearly no 1:1 correspondence between open relations and KB relations. On the one hand, open relations can be highly ambiguous (e.g., *"be"* has hits to *location* and *associatedMusicalArtits*). On the other hand, open relations can also be more specific than KB relations (e.g., *"be guitarist of"* is more specific than *associatedMusicalArtist*) or semantically different (e.g., *"be widow of"* and *spouse*) than the KB relations they align to.

To gain more insight into the type of triples contained in OPIEC-Clean, we selected the top-100 most frequent open relations for further analysis. These relations constitute roughly 38% of the OPIEC-Clean corpus, relation frequencies are thus highly skewed. We then used OPIEC-Linked as a proxy for the number of DBpedia hits of these relations. The results are summarized in Tab. 5 as well as in Appendix A. The open relation *"have"*, for

example, is aligned to 320 distinct DBpedia relations, the most frequent ones being *author, director,* and *writer*. Generally, the fraction of KB hits (from OPIEC-Linked) is quite low, averaging at 14.7% for the top-100 relations. This indicates that there is a substantial amount of information present in OIE triples that is not present in KBs. Moreover, about 40 distinct KB relations align on average with each open relation, which again indicates that open relations should not be directly mapped to KB relations.

By far the most frequent open relations in OPIEC-Clean are *"be"* and *"have"*, which constitute 21.1% and 6.1% of all the triples, respectively. These open relations are also the most ambiguous ones in that they are aligned with 403 and 320 different DBpedia relations, respectively. Here the open relations are far more "generic" than the KB relations that they are aligned to. This is illustrated in the following examples:

| | | |
|---|---|---|
| *("Claudia Hiersche"; "be"; "actress")* | $\xrightarrow{DBpedia}$ | (Claudia_Hiersche; occupation; Actress) |
| *("Cole Porter"; "have"; "Can-Can" )* | $\xrightarrow{DBpedia}$ | (Can-Can_(musical); musicBy; Cole_Porter) |
| | $\xrightarrow{DBpedia}$ | (Can-Can_(musical); lyrics; Cole_Porter) |
| *("Oddbins"; "have"; "Wine")* | $\xrightarrow{DBpedia}$ | (Oddbins; product; Wine) |

Note that in these cases, "have" refers to the possessive (e.g., Odbbins' Wine).

### 5.2 Spatio-Temporal Facts

We also investigated to what extent the space and time annotations in OIE triples relate to corresponding space and time annotations in YAGO. In particular, YAGO provides:

- *YAGO date facts*, which have entities as subjects and dates as objects: e.g., (Keith_Joseph, wasBornOnDate, 1918-01-17).
- *YAGO meta-facts*, which are spatial or temporal information about other YAGO facts: e.g., (Steven_Lennon, playsFor, Sandnes_Ulf) has meta-fact (occursUntil, 2014).

Note that date facts roughly correspond to temporal reference annotations in OPIEC, wheres meta-facts correspond to spatial or temporal triple annotations.

To compare OPIEC with YAGO date facts, we selected all triples with (i) a disambiguated subject and (ii) an object that is annotated as date from OPIEC. There are 645,525 such triples. As before, we align these triples to YAGO using an optimistic notion of a KB hit. In particular, a *KB date hit* for an OIE date fact $(s, r_{\text{open}}, d_{\text{open}})$ is any KB fact of form $(s, r_{\text{KB}}, d_{\text{KB}})$, i.e., we require that there is temporal information but ignore whether or not it matches. We use this optimistic notion of KB date hit to avoid disambiguating the open relation or date. Even with this optimistic notion, we observed that only 32,209 (5%) of the OIE date facts have a KB date hit in the YAGO date facts.

We also compared the spatial and temporal annotations of OPIEC-Linked with the YAGO meta-facts. We found that roughly 10,974 OPIEC-Linked triples have a KB hit with a YAGO triple that also has an associated a meta-fact. Out of these linked OIE triples, 2,216 are temporal and 2,181 are spatial.

To provide further insight, we analyzed the spatial-temporal annotations of OPIEC more closely. We identified two major reasons why spatio-temporal information is not

| Open relation | Frequency in OPIEC-Clean | Frequency in OPIEC-Link | # KB hits | # distinct KB rel.s | Top-3 aligned DBpedia rel. and hit frequency | |
|---|---|---|---|---|---|---|
| *"be"* | 21,911,174 | 1,475,332 | 162,438 (11.0%) | 403 | type | 72,542 |
| | | | | | occupation | 12,254 |
| | | | | | isPartOf | 6,776 |
| *"have"* | 6,369,086 | 216,332 | 118,625 (54.8%) | 320 | author | 11,678 |
| | | | | | director | 9,429 |
| | | | | | writer | 8,751 |
| *"be in"* | 3,219,301 | 1,150,667 | 734,330 (63.8%) | 221 | country | 269,189 |
| | | | | | isPartOf | 200,851 |
| | | | | | state | 65,242 |
| *"include"* | 487,899 | 14,746 | 1,364 (9.2%) | 127 | type | 376 |
| | | | | | associatedBand | 75 |
| | | | | | associatedMusicalArtist | 75 |
| *"be bear in"* | 289,947 | 7,138 | 1,478 (20.7%) | 31 | birthPlace | 1,172 |
| | | | | | isPartOf | 68 |
| | | | | | deathPlace | 60 |
| *"win"* | 236,169 | 8,819 | 819 (9.3%) | 53 | award | 236 |
| | | | | | race | 235 |
| | | | | | team | 45 |
| *"be know as"* | 215,809 | 7,993 | 545 (6.8%) | 119 | associatedBand | 37 |
| | | | | | location | 37 |
| | | | | | associatedMusicalArtist | 37 |
| *"become"* | 213,807 | 5,123 | 321 (6.3%) | 76 | successor | 52 |
| | | | | | associatedBand | 28 |
| | | | | | associatedMusicalArtist | 28 |
| *"have be"* | 191,140 | 1,855 | 100 (5.4%) | 30 | type | 16 |
| | | | | | position | 9 |
| | | | | | occupation | 8 |
| *"play"* | 163,643 | 4,842 | 754 (15.6%) | 54 | portrayer | 340 |
| | | | | | author | 90 |
| | | | | | instrument | 70 |
| *"be know"* | 157,751 | 351 | 50 (14.2%) | 14 | occupation | 20 |
| | | | | | family | 11 |
| | | | | | type | 4 |
| *"die in"* | 146,681 | 638 | 117 (18.3%) | 17 | deathPlace | 66 |
| | | | | | battle | 13 |
| | | | | | commander | 9 |
| *"join"* | 134,159 | 2,656 | 811 (30.5%) | 59 | team | 264 |
| | | | | | associatedBand | 100 |
| | | | | | associatedMusicalArtist | 100 |

Table 5: The most frequent open relations in OPIEC-Clean, along with DBpedia alignment information from OPIEC-Link

found in KBs: (i) the information in missing from the KB, and (ii) the information is available only indirectly. For an example of missing information, consider the OPIEC-

Linked triple *("Iain Duncan Smith", "is leader of", "Conservative Party")* with temporal annotations *(pred="from", 2001)* and *(pred="to", 2003)*. YAGO contains the KB hit (Iain_Duncan_Smith; isAffiliatedTo; Conservative_Party_(UK)). Note that the YAGO relation is less specific than the open relation, and that no temporal information is present. As another example, consider the OIE triple *("Neue Nationalgalerie"; "be built by"; "Ludwig Mises van der Rohe")* with temporal annotation *(pred="in", 1968)*. Again, the YAGO hit (Neue_Nationalgalerie; linksTo; Ludwig_Mies_van_der_Rohe) is less specific and lacks temporal information. YAGO does contain the triple (Neue_Nationalgalerie; hasLongitude; 13.37) with temporal meta-fact 1968-01-01. Here the temporal information is present in the KB, but only indirectly and for a different relation.

Generally, the low number of KB hits indicates that a wealth of additional spatial and/or temporal information is present in OIE data, and that the spatial/temporal annotations provided in OPIEC are potentially very valuable for automated KB completion tasks.

### 5.3 Non-Aligned OIE Triples

We found that more than half of the triples in OPIEC-Linked that do not have a KB hit refer to one of the top-100 most frequent relations in OPIEC-Clean. Since OPIEC-Clean is much larger than OPIEC-Linked, this indicates that it contains many facts not present in DBpedia. Naturally, not all these facts are correct, though, and disambiguation is a major challenge. In particular, we took a random sample of 100 non-aligned triples from OPIEC-Linked and manually labeled each triple as *correctly extracted* or *incorrectly extracted*. 60% of the triples were considered to be correctly extracted. In another sample of 100 high-confidence triples (score $> 0.5$), 80% were correctly extracted. This shows clearly the potential and the challenges of harnessing the knowledge contained within the OIE triples.

## 6. Conclusions

We created OPIEC, a large open information extraction corpus extracted from Wikipedia. OPIEC consists of hundreds of millions of triples, along with rich metadata such as provenance information, syntactic annotations, semantic annotations, and confidence scores. We reported on a data profiling study of the OPIEC corpus as well as subcorpora. In particular, we analyzed to what extent OPIEC overlaps with the DBpedia and YAGO knowledge bases. Our study indicates that most open facts do not have counterparts in the KB such that OIE corpora contain complementary information. For the information that overlaps, open relation are often more specific, more generic, or simply correlated to KB relations (instead of semantically equivalent). We hope that the OPIEC corpus, its subcorpora, derived statistics, as well as the codebase used to create the corpus are a valuable resource for automated KB construction and downstream applications.

## References

Sören Auer, Christian Bizer, Georgi Kobilarov, Jens Lehmann, Richard Cyganiak, and Zachary Ives. Dbpedia: A nucleus for a web of open data. In *The semantic web*, pages 722–735. Springer, 2007.

Niranjan Balasubramanian, Stephen Soderland, Oren Etzioni, et al. Rel-grams: a probabilistic model of relations in text. In *Proceedings of the Joint Workshop on Automatic Knowledge Base Construction and Web-scale Knowledge Extraction*, pages 101–105. Association for Computational Linguistics, 2012.

Niranjan Balasubramanian, Stephen Soderland, Oren Etzioni, et al. Generating coherent event schemas at scale. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1721–1731, 2013.

Michele Banko, Michael J Cafarella, Stephen Soderland, Matthew Broadhead, and Oren Etzioni. Open information extraction from the web. In *IJCAI*, volume 7, pages 2670–2676, 2007.

Christian Bizer, Jens Lehmann, Georgi Kobilarov, Sören Auer, Christian Becker, Richard Cyganiak, and Sebastian Hellmann. Dbpedia-a crystallization point for the web of data. *Web Semantics: science, services and agents on the world wide web*, 7(3):154–165, 2009.

Angel X Chang and Christopher D Manning. Sutime: A library for recognizing and normalizing time expressions. In *Lrec*, volume 2012, pages 3735–3740, 2012.

Danqi Chen and Christopher Manning. A fast and accurate dependency parser using neural networks. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 740–750, 2014.

Luciano Del Corro and Rainer Gemulla. Clausie: clause-based open information extraction. In *Proceedings of the 22nd international conference on World Wide Web*, pages 355–366. ACM, 2013.

Claudio Delli Bovi, Luis Espinosa-Anke, and Roberto Navigli. Knowledge base unification via sense embeddings and disambiguation. In *The 2015 Conference on Empirical Methods in Natural Language; 2015 Sept 17-21; Lisbon, Portugal.[Stroudsburg]: ACL (Association for Computational Linguistics); 2015. p. 726-36.* ACL (Association for Computational Linguistics), 2015a.

Claudio Delli Bovi, Luca Telesca, and Roberto Navigli. Large-scale information extraction from textual definitions through deep syntactic and semantic analysis. *Transactions of the Association for Computational Linguistics*, 3:529–543, 2015b.

Xin Dong, Evgeniy Gabrilovich, Geremy Heitz, Wilko Horn, Ni Lao, Kevin Murphy, Thomas Strohmann, Shaohua Sun, and Wei Zhang. Knowledge vault: A web-scale approach to probabilistic knowledge fusion. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 601–610. ACM, 2014.

Oren Etzioni, Michele Banko, Stephen Soderland, and Daniel S Weld. Open information extraction from the web. *Communications of the ACM*, 51(12):68–74, 2008.

Anthony Fader, Stephen Soderland, and Oren Etzioni. Identifying relations for open information extraction. In *Proceedings of the conference on empirical methods in natural language processing*, pages 1535–1545. Association for Computational Linguistics, 2011.

Anthony Fader, Luke Zettlemoyer, and Oren Etzioni. Paraphrase-driven learning for open question answering. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, volume 1, pages 1608–1618, 2013.

Jenny Rose Finkel, Trond Grenager, and Christopher Manning. Incorporating non-local information into information extraction systems by gibbs sampling. In *Proceedings of the 43rd annual meeting on association for computational linguistics*, pages 363–370. Association for Computational Linguistics, 2005.

Kiril Gashteovski, Rainer Gemulla, and Luciano Del Corro. Minie: minimizing facts in open information extraction. In *EMNLP*, pages 2630–2640, 2017.

Johannes Hoffart, Fabian M Suchanek, Klaus Berberich, and Gerhard Weikum. Yago2: A spatially and temporally enhanced knowledge base from wikipedia. *Artificial Intelligence*, 194:28–61, 2013.

Prachi Jain et al. Knowledge-guided linguistic rewrites for inference rule verification. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 86–92, 2016.

Thomas Lin, Oren Etzioni, et al. Entity linking at web scale. In *Proceedings of the Joint Workshop on Automatic Knowledge Base Construction and Web-scale Knowledge Extraction*, pages 84–88. Association for Computational Linguistics, 2012.

Christopher Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven Bethard, and David McClosky. The stanford corenlp natural language processing toolkit. In *Proceedings of 52nd annual meeting of the association for computational linguistics: system demonstrations*, pages 55–60, 2014.

Mausam, Michael Schmitz, Robert Bart, Stephen Soderland, Oren Etzioni, et al. Open language learning for information extraction. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 523–534. Association for Computational Linguistics, 2012.

Mausam Mausam. Open information extraction systems and downstream applications. In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence*, pages 4074–4077. AAAI Press, 2016.

Tom Mitchell, William Cohen, Estevam Hruschka, Partha Talukdar, Bo Yang, Justin Betteridge, Andrew Carlson, B Dalvi, Matt Gardner, Bryan Kisiel, et al. Never-ending learning. *Communications of the ACM*, 61(5):103–115, 2018.

Andrea Moro and Roberto Navigli. Wisenet: Building a wikipedia-based semantic network with ontologized relations. In *Proceedings of the 21st ACM international conference on Information and knowledge management*, pages 1672–1676. ACM, 2012.

Andrea Moro and Roberto Navigli. Integrating syntactic and semantic analysis into the open information extraction paradigm. In *IJCAI*, pages 2148–2154, 2013.

Ndapandula Nakashole, Gerhard Weikum, and Fabian Suchanek. Patty: a taxonomy of relational patterns with semantic types. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 1135–1145. Association for Computational Linguistics, 2012.

Sebastian Riedel, Limin Yao, Andrew McCallum, and Benjamin M Marlin. Relation extraction with matrix factorization and universal schemas. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 74–84, 2013.

Roser Saurı, Jessica Littman, Bob Knippen, Robert Gaizauskas, Andrea Setzer, and James Pustejovsky. Timeml annotation guidelines version 1.2. 1, 2006.

Baoxu Shi and Tim Weninger. Open-world knowledge graph completion. In *AAAI*, 2018.

Gabriel Stanovsky and Ido Dagan. Creating a large benchmark for open information extraction. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2300–2305, 2016.

Gabriel Stanovsky, Ido Dagan, et al. Open ie as an intermediate structure for semantic tasks. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, volume 2, pages 303–308, 2015.

Shikhar Vashishth, Prince Jain, and Partha Talukdar. Cesi: Canonicalizing open knowledge bases using embeddings and side information. In *Proceedings of the 2018 World Wide Web Conference on World Wide Web*, pages 1317–1327. International World Wide Web Conferences Steering Committee, 2018.

Tien-Hsuan Wu, Zhiyong Wu, Ben Kao, and Pengcheng Yin. Towards practical open knowledge base canonicalization. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pages 883–892. ACM, 2018.

Mohamed Yahya, Steven Whang, Rahul Gupta, and Alon Halevy. Renoun: Fact extraction for nominal attributes. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 325–335, 2014.

Matei Zaharia, Reynold S Xin, Patrick Wendell, Tathagata Das, Michael Armbrust, Ankur Dave, Xiangrui Meng, Josh Rosen, Shivaram Venkataraman, Michael J Franklin, et al. Apache spark: a unified engine for big data processing. *Communications of the ACM*, 59 (11):56–65, 2016.

## Appendix A. KB hits with DBpedia

| Open relation | Frequency in OPIEC-Clean | Frequency in OPIEC-Link | # KB hits | # distinct KB rels. | Top-3 aligned DBpedia rel. and hit frequency | |
|---|---|---|---|---|---|---|
| *"leave"* | 130,515 | 1,356 | 323 (23.8%) | 46 | associatedBand | 70 |
| | | | | | associatedMusicalArtist | 70 |
| | | | | | formerBandMember | 35 |
| *"take"* | 127,757 | 660 | 46 (7.0%) | 25 | writer | 4 |
| | | | | | previousWork | 4 |
| | | | | | artist | 3 |
| *"use"* | 127,537 | 2,951 | 111 (3.8%) | 50 | currency | 8 |
| | | | | | affiliation | 7 |
| | | | | | timeZone | 7 |
| *"receive"* | 118,429 | 2,133 | 220 (10.3%) | 16 | award | 193 |
| | | | | | debutTeam | 5 |
| | | | | | formerTeam | 3 |
| *"make"* | 116,688 | 1,063 | 122 (11.5%) | 36 | director | 35 |
| | | | | | writer | 24 |
| | | | | | producer | 11 |
| *"be member of"* | 104,680 | 11,480 | 3,002 (26.1%) | 71 | associatedBand | 656 |
| | | | | | associatedMusicalArtist | 656 |
| | | | | | party | 542 |
| *"return to"* | 104,392 | 482 | 102 (21.2%) | 35 | team | 43 |
| | | | | | league | 6 |
| | | | | | deathPlace | 5 |
| *"be at"* | 102,844 | 20,328 | 6,629 (32.6%) | 74 | ground | 1,599 |
| | | | | | city | 1,451 |
| | | | | | owner | 925 |
| *"be species of"* | 101,846 | 54,269 | 13,694 (25.2%) | 8 | order | 5,179 |
| | | | | | family | 4,290 |
| | | | | | kingdom | 2,824 |
| *"move to"* | 100,226 | 1,409 | 264 (18.7%) | 34 | team | 113 |
| | | | | | managerClub | 31 |
| | | | | | ground | 15 |
| *"be write by"* | 96,790 | 6,340 | 1,750 (27.6%) | 50 | author | 460 |
| | | | | | writer | 415 |
| | | | | | notableWork | 112 |
| *"be found in"* | 95,163 | 836 | 100 (12.0)% | 16 | location | 20 |
| | | | | | city | 16 |
| | | | | | headquarter | 16 |

## Appendix B. Complete List of Meta-Data Fields

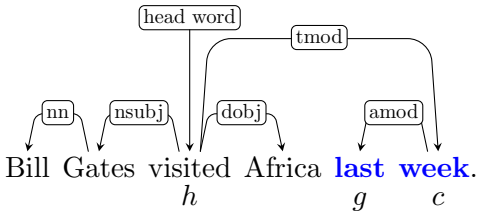
| Data field | Value |
|---|---|
| Article ID | Wikipedia article ID where the triple was extracted from. |
| Sentence | Provenance sentence where the triple was extracted from. The sentence itself is a linguistic object containing many linguistic annotations:<br>1) *Sentence ID* – each sentence has a unique ID in the corpus, containing of 2 parts: Wikipedia article ID and the order in which it appeared in the article;<br>2) *Dependency parse* – the dependency parse tree of the sentence<br>3) *Tokens* – the sentence is represented as a list of tokens. Each token contains information for: POS tag, NER type, span, the original word as found in the sentence, lemma, the index of the token within the sentence and the WikiLink object (contains offset begin/end index of the link within the article, the original phrase of the link and the link itself).<br>4) *Span* – the span of the sentence within the text document. |
| Sentence number | The position of the sentence within the Wikipedia article |
| Polarity | The polarity of the triple (either *positive* or *negative*). |
| Negative words | In case the polarity is *negative*, the negative words indicating the negation are stored here. |
| Modality | The modality of the triple (either *possibility (PS)* or *certainty (CT)*) |
| CT/PS words | If the modality of the triple is *certainty/possibility*, the words indicating the appropriate modality are stored here. |
| Attribution | Attribution of the triple if found. The annotation contains the attribution phrase, predicate, factuality, space and time |
| Quantities | Quantities of the triple (if found). |
| Subj/Rel/Obj | Lists of tokens with linguistic annotations for subject/relation/object of the triple |
| Dropped words for subj/rel/obj | To minimize the triple and make it more compact, MinIE sometimes drops words considered to be semantically redundant words (e.g. determiners). If such dropped words occur, they are stored here. |
| Time Meta-Data | Temporal annotations, containing information about TIMEX3 type, TIMEX3 xml, disambiguated temporal expression, original core words of the temporal expression, pre-modifiers/post-modifiers of the core words and temporal predicate. |
| Space Meta-Data | Spatial annotations, containing information about the original spatial words, the pre/post-modifiers and the spatial predicate. |
| Time/Space for Subj/Rel/Obj | Information about the temporal annotation on phrases. This annotation contains:<br>1) modified word – the head word of the constituent being modified;<br>2) time/space: the time/space words modifying it |
| Confidence score | The confidence score of the triple. |

## Appendix C. Spatio-temporal annotations of OIE triples

### C.1 Temporal Annotations on Entire Triples

As input, we have: the input sentence, its corresponding dependency parse tree, the n-ary extraction by ClausIE [Del Corro and Gemulla, 2013], and the triple generated by MinIE [Gashteovski et al., 2017]. First, we use temporal tagger (SUTime [Chang and Manning, 2012]) to get a list of temporal expressions from the input sentence. Next, we look at the head word of the triple's relation ($h$) and its descendants.

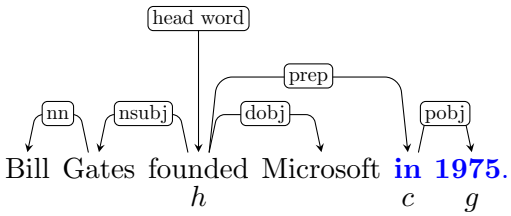
If $h$ has children ($c$) in the dependency parse graph with typed dependency `tmod` or `advmod`, then we check for each $c$ if it is contained in the list of temporal expressions. If so, we create a temporal annotation for the triple with $c$ and all the descendents of $c$ (dubbed $g$) in the dependency parse[3] (Figure 4).




n-ary extraction: ("Bill Gates"; "visited"; "Africa" "last week")
final extraction: ("Bill Gates"; "visited"; "Africa") **T: (last week)**

Figure 4: Example of temporal annotation on triple with `tmod`

If $c$ is modified by the head word of the relation $h$ with a typed dependency `prep`, then we check if the child of $c$ is a temporal expression. If so, we note the temporal annotation of the triple with $g$ and its descendants, and $c$ becomes the *lexicalized temporal predicate* (Figure 5).

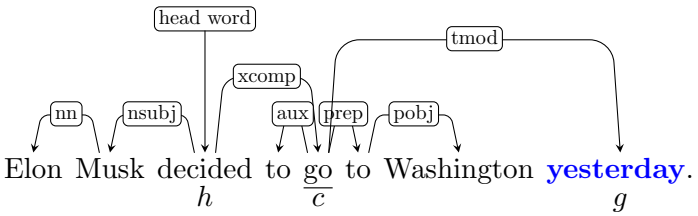



n-ary extraction: ("Bill Gates"; "founded"; "Microsoft **in 1975**")
final extraction: ("Bill Gates"; "founded"; "Microsoft") **T: (pred=in, t=1975)**

Figure 5: Example of temporal annotation on triple with `prep`

If $c$ is modified by the head word $h$ with `xcomp`, then we check for temporal annotations the same way as for `tmod` and `advmod`. However, we also treat $g$ as though is the relation

3. we exclude all the descendents containing the typed dependencies `rcmod, punct, appos, dep, cc, conj` and `vmod`, because they might yield bad temporal modifiers




n-ary extraction: ("Elon Musk"; "decided"; "to go to Washington **yesterday**")
final extraction: ("Elon Musk"; "decided to go to"; "Washington") **T: (yesterday)**

Figure 6: Example of temporal annotation on triple with `xcomp`

head word itself, so we also check if $g$'s children obey the same rules as for `tmod, advmod, prep` (Fig. 6).

Finally, MinIE-SpaTe tries to reason about how to construct the triples in a more compact manner. First, we utilize ClausIE's n-ary extractions, and then see if $n > 3$. If so, we check if the whole temporal extraction is one phrase, and if it is, then we drop it from the original triple, and proceed with the triples' structuring algorithm in MinIE (Figure 4).

### C.2 Temporal Annotations on Arguments

Sometimes the arguments themselves contain some temporal information that is about the phrase itself, but not for the whole triple. Consider the sentence: *"Isabella II opened the 17th-century Parque del Retiro in 1868."*. MinIE would extract the following triple: *("Isabella II"; "opened the **17th-century** Parc del Retiro **in**"; "**1868**")*. This triple contains two pieces of temporal information: *"1868"* and *"17th-century"*. MinIE-SpaTe rewrites this as: *("Isabella II"; "opened"; "Parque del Retiro") T: (in, 1868); Object → T: 17th-century*

Distinguishing these types of temporal information is important, because the correct temporal information should be attached to the correct place. In this example, we wouldn't want to attach *"17th century"* as a temporal annotation to the whole triple (because the park was not opened in 17th century by Isabella II), but just to the object (the park itself is from 17th century).

The way we do this is by searching for a noun or an adjective in a phrase (word $w$), and look if it has one of the following dependencies modifying it: `amod, acmop, advmod, nn, num, number, tmod`. Then, we get the children of $w$. If a child of $w$ is a temporal word, we include it in the temporal annotation and drop it from the triple[4].

### C.3 Spatial Annotations

For spatial annotations, we follow the same logic as the one for the temporal annotations. The method for spatial annotations on the entire triple is similar to the one for annotating time. The main differences are 1) instead of getting a list of annotated temporal expressions, we get a list of locations by using Stanford's NER system [Finkel et al., 2005]; 2) we use the same rules as for temporal annotations with `prep`, but not with `xcomp,tmod` and `advmod`.

4. we ignore the children derived from the following dependencies: `rcmod, punct, appos, cc, conj`

### C.4 Precision of Space-Time Annotations

In [Gashteovski et al., 2017], the authors released a dataset of a sample of 10k random sentences drawn from the New York Times corpus and their corresponding extractions with MinIE. We annotated two sets of extractions that were labeled as *correctly extracted* and that also contained space/time information respectively. For the temporal annotations on the triple, 91/100 extractions were labeled as *correctly extracted* and for the temporal annotations on the arguments 80/100 were *correctly extracted*. Similar precision was measured for the spatial annotations: 91/100 on the spatial annotations on the triples were labeled as *correctly extracted*, and 82/100 of the spatial annotations on the arguments were labeled as *correctly extracted*. An error analysis showed that common errors include wrong temporal/spatial tags (e.g. the argument *"Summer Olympics"* gets reduced to *"Olympics"* with temporal annotation *"Summer"*) and wrong dependency parse which messes up the spatio/temporal information represented in the triple annotations (e.g. two temporal annotations on a triple: *"in 1947"* and *"in 1914"*, where only one of them is correct).

## Appendix D. Confidence Score Features

| Feature | Value |
|---:|---:|
| Length (sentence / extraction) | int / int |
| Clause type | SVA, SVO, ... |
| Dropped all optional adverbials / prep. | bool / bool |
| Relation as whole string in sentence | bool |
| Comparison of POS Tags of conjunction words in subject | bool |
| Contains possessive relation / gerund | bool / bool |
| Contains infinitive verb in subj / rel | bool / bool |
| Order of words in the extraction | bool |
| Extraction contains `dep` | bool |
| Processed conjunction subj/rel/obj | bool / bool / bool |
| Object before subject in sentence | bool |
| Triple occurs in MinIE-D / MinIE-A | bool / bool |
| Is the relation frequent?[5] | bool |
| Extracts quantity / time / space | bool / bool / bool |

5. minimum support: 100 K