Building a Web-Scale Dependency-Parsed Corpus from CommonCrawl

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Abstract
We present DEPCC, the largest to date linguistically analyzed corpus in English including 365 million documents, composed of 252 billion tokens and 7.5 billion of named entity occurrences in 14.3 billion sentences from a web-scale crawl of the CommonCrawl project. The sentences are processed with a dependency parser and with a named entity tagger and contain provenance information, enabling various applications ranging from training syntax-based word embeddings based on to open information extraction and question answering. We demonstrate the utility of this corpus on the verb similarity task by showing that a distributional model trained on our corpus yields better results than models trained on smaller corpora, like Wikipedia. This distributional model outperforms the state of art models of verb similarity trained on smaller corpora on the SimVerb3500 dataset.

Keywords: text corpus, Web as a corpus, common crawl, dependency parsing, verb similarity, distributional semantics

1. Introduction
Large corpora are essential for the modern data-driven approaches to natural language processing (NLP), especially for unsupervised methods, such as word embeddings (Mikolov et al., 2013) or open information extraction (Banko et al., 2007) due to the “unreasonable effectiveness of big data” (Halevy et al., 2009). However, the size of commonly used text collections in the NLP community, such as BNC or Wikipedia is in the range 0.1–3 billion tokens, which potentially limits coverage and performance of the developed models. To overcome this limitation, larger corpora are corpora can be composed of books, e.g. Goldberg and Orwant (2013) released a dataset of syntactic n-grams produced from the 345 billion token corpus of Google Books project. However, access to books is often restricted, which limits use-cases of book-derived datasets. Another source of very large amounts of texts is the Web. Multiple researchers investigated the use of the Web for construction of text corpora, producing resources, such as PUKWAC (Baroni et al., 2009) (2 billion of tokens) and ENCOW16 (Schäfer, 2015) (17 billion of tokens), yet the size of these corpora is still at least one order of magnitude smaller than the web-scale corpora, e.g. CLUEWEB and COMMONCRAWL. On the other hand, directly using the web crawl dumps is problematic for researchers as: (1) the documents are not preprocessed, containing irrelevant information, e.g. HTML markup; (2) big data infrastructure and skills are required; (3) (near) duplicates of pages; (4) documents are not linguistically analyzed, thus only shallow models can be used. The mentioned factors substantially limit the use of web-scale corpora in natural language processing research and applications. The objective of this work is to address these issues and make access to web-scale corpora a commodity by providing a web-scale corpus that is ready for NLP experiments as it is linguistically analyzed and cleansed from noisy irrelevant content. Namely, in this paper, we present a methodology for construction of linguistically analyzed corpora from the Web and release DEPCC the largest to date dependency-parsed corpus of English texts.

The CommonCrawl.org project regularly produces web-scale crawls featuring a substantial fraction of all public web pages. For instance, as of October 2017, the estimated number of pages on the Web is 47 billion while the corresponding crawl contains over 3 billion pages. To put this number into perspective, according to the same source, the indexed Web contains about 5 billion pages. Along with the raw Web ARCHive (WARC) crawls, the CommonCrawl provides preprocessed WET archives containing texts. For instance, the 29.5 Tb WARC archive (cf. Table 3) has a corresponding 4.8 Tb WET version with texts. The preprocessing used in the WET archives is limited to removal of HTML tags. After a manual check, we also noticed that in WET archives 1) some documents still contain HTML markups; 2) the archives contain duplicates of the documents; 3) documents are written in various languages making it difficult to train language-specific linguistic models. Finally, most importantly, the WET dumps are not linguistically analyzed, which significantly limits their utility for language processing applications. In this work, we address the mentioned above limitations by constructing a text corpus from CommonCrawl, which is filtered from irrelevant and duplicate documents and is linguistically analyzed. Namely, the contributions of this paper are the following:

1. We present a methodology for the creation of the text corpus from the web-scale crawls of CommonCrawl.
2. We present a software implementing the methodology in a scalable way using the MapReduce framework.
3. We present the largest to date dependency parsed corpus of English texts obtained using the developed methodology, featuring also named entity tags.
4. We show the usefulness of the web-scale corpus on the verb similarity task by outperforming the state-of-the-art on the SimVerb3500 dataset (Gerz et al., 2016).

The corpus and the software tools are available online.

http://www.natcorp.ox.ac.uk

http://www.worldwidewebsize.com at 02.10.2017
https://www.inf.uni-hamburg.de/en/inst/ab/lt/resources/data/depcc.html
2. Related Work

In Table 1, we compares the DEPCC corpus to seven existing large-scale English corpora, described below. WACKYPEDIA (Baroni et al., 2009) is a parsed version of English Wikipedia as of 2009. The articles are part-of-speech tagged with the TreeTagger (Schmid, 1994) and dependency parsed with the Malt parser (Nivre et al., 2007). Similarly to our corpus, the results are presented in the CoNLL format. The 2017 version of WIKIPEDIA contains three times more tokens, compared to the version of 2009, yet the recent dumps are not linguistically analyzed. PUKWAC is a dependency parsed version of the UKWAC corpus (Baroni et al., 2009), which is processed in the same way as the WACKYPEDIA corpus. GIGAWORD (Parker et al., 2011) is a large corpus of newswire, which is not dependency parsed. The CLUEWEB12 is a corpus similar to the raw CommonCrawl corpus: it contains archives of linguistically unprocessed web pages. The authors of the GOOGLE SYNTACTIC NGRAMS corpus (Goldberg and Orwant, 2013) parsed a huge collection of books and released a dataset of syntactic dependencies. However, the source texts, due to copyright restrictions, are not shared, which limits potential use-cases of this resource. Finally, ENCODING (Schäfer, 2015) is arguably the most similar corpus to DEPCC. The authors also rely on the Malt parser and perform named entity tagging. However, the former is roughly ten times smaller as compared to DEPCC.

3. Building a Web-Scale Dependency-Parsed Corpus in English from CommonCrawl

Figure 1 shows how a linguistically analyzed corpus is built from the Web. First, web pages are downloaded by the web crawler of CommonCrawl, called CCBot. Second, preprocessing, involving elimination of duplicates and language detection, is performed using the C4Corpus tool. Finally, we perform linguistic analysis of the corpus and save the results in the CoNLL format.

3.1. Input Web Crawl: the CommonCrawl

The DEPCC corpus is based on the crawl of February 2016, containing more than 1.73 billion URLs. The original files are located in the “commoncrawl” bucket on the S3 distributed file system. As summarized in Table 1, the total size of the gzip compressed files is about 30 Tb.

3.2. Preprocessing of Texts: the C4Corpus Tool

The raw corpus was processed with the C4Corpus tool (Habernal et al., 2016) and is available on S3. The tool performs preprocessing of the raw corpus, in five phases: (1) license detection, language detection, and boilerplate removal; (2) exact match de-duplication; (3) detecting near duplicates; (4) removing near duplicates; (5) grouping the final corpus by language and license. The resulting output is a gzip compressed corpus with a total size of 0.83 Tb (cf. Table 1). For further processing, we selected only English texts with the total size of 0.68 Tb, based on the language detection in the first phase.

3.3. Linguistic Analysis of Texts

Linguistic analysis consists of four stages presented in Figure 1 and is implemented using the Apache Hadoop framework for parallelization and the Apache UIMA framework for integration of linguistic analysers via the DKPro Core library (Eckart de Castilho and Gurevych, 2014).

Table 1: Comparison of existing large text corpora for English with the DEPCC corpus.

| Type          | WaCkypedia | Wikipedia | PukWaC | GigaWord | ENCOD16 | ClueWeb12 | Syn.Ngrams | DEPCC |
|---------------|------------|-----------|--------|----------|---------|-----------|------------|-------|
| Tokens (billions) | 0.80       | 2.90      | 1.91   | 1.76     | 16.82   | N/A       | 345.00     | 251.92|
| Documents (millions) | 1.10       | 5.47      | 5.69   | 4.11     | 9.22    | 733.02    | 3.50       | 364.80|
| Source texts   | Encyclop.   | Encyclop. | Web    | News     | Web     | Books     | Web        | Web   |
| Preprocessing  | Yes         | Yes       | Yes    | Yes      | Yes     | No        | Yes        | Yes   |
| NER            | No          | No        | No     | No       | Yes     | No        | No         | Yes   |
| Dependency-parsed | Yes        | No        | Yes    | No       | Yes     | Yes       | Yes        | Yes   |

Figure 1: Outline of the corpus construction approach and experiments described in the paper.
Table 2: An excerpt from an output document in the CoNLL format: a document header plus a sentence are shown. Here, “ID” is a word index, “FORM” is word form, “LEMMA” is lemma or stem of word form, “UPOSTAG” is universal part-of-speech tag, “XPOSTAG” is language-specific part-of-speech tag, “FEATS” is a list of morphological features, “HEAD” is head of the current word, which is either a value of ID or zero, “DEPREL” is universal dependency relation to the “HEAD”, “DEPS” is enhanced dependency graph in the form of head-deprel pairs, and “NER” is named entity tag.

3.3.1. POS Tagging and Lemmatization
For morphological analysis of texts, we used OpenNLP part-of-speech tagger and Stanford lemmatizer.

3.3.2. Named Entity Recognition
To detect occurrences of persons, locations, and organizations we use the Stanford NER tool [Finkel et al., 2005] 11
Overall, 7.48 billion occurrences of named entities were identified in the 251.92 billion tokens output corpus.

3.3.3. Dependency Parsing
To make possible large-scale parsing of texts possible, a parser needs to be not only reasonably accurate but also fast. Unfortunately, the most accurate parsers, such as Stanford parser based on the PCFG grammar [De Marneffe et al., 2006], according to our experiments, take up to 60 minutes to process 1 Mb of text on a single core, which was prohibitively slow for our use-case (details of the hardware configuration are available in Section 3.5.). We tested all versions of the Stanford, Malt [Hall et al., 2010], and Mate [Ballesteros and Bohnet, 2014] parsers for English available via the DKPro Core framework. To dependency-parse texts, we selected the Malt parser, due to an optimal ratio of efficiency and effectiveness (parsing of 1 Mb of text per core in 1–4 minutes). This parser was successfully used in the past for the construction of linguistically analyzed web corpora, such as PukWaC [Baroni et al., 2009] and EN-COW16 [Schafer, 2015]. While more accurate parsers exist, e.g. the Stanford parser, according to our experiments, even the neural-based version of this parser is substantially slower. On the other hand, as shown by Chen and Manning [2014], the performance of the Malt parser is only about 1.5–2.5 points below the neural-based Stanford parser. In particular, we used the stack model based on the projective transition system with the Malt. To compensate the lack of the dependency enhancement in Malt, we use the system of [Ruppert et al., 2015] to perform collapsing and enhancing of dependencies. Note that, both original and enhanced versions are saved respectively into the columns “DEPREL” and “DEPS” as illustrated in Table 2.

3.4. Format of the Output Documents
The documents are encoded in the CoNLL format as illustrated in Table 2. The corpus is released as a collection of 19,101 compressed gzip files.

3.5. Computational Resources
The linguistic analysis was performed on a Hadoop 2.6 cluster during 110 hours using 341 containers each with one Intel Xeon CPU E5-2603v4@1.70GHz and 8Gb of RAM.

3.6. Index of the Corpus
A full-text search of all 14.3 billion sentences and their dependency relations of the DEPCC corpus will be made available.
Table 4 presents results of the experiments. The first part of the table lists five top systems in various categories (Gerz et al., 2016), representing the current state of art result on this dataset. In the original paper, two corpora were used: the “SB” is the corpus produced by the word2vec script, consisting of 8 billion tokens from various sources (Mikolov et al., 2013) and the “PolyglotWikipedia” is the English Polyglot Wikipedia corpus (Al-Rfou et al., 2015). The second part of the table presents the distributional model described in Section 4.2 trained on the corpora of various sizes. Note, that the preprocessing steps for each corpus are exactly the same as for the DepCC corpus. We observe that the smallest corpus (Wikipedia) yields the worst results. While the scores go up on the larger corpus, which is a combination of Wikipedia with two other corpora, we can reach the even better result by training the model (with exactly the same parameters) on the dependency-based features extracted from the full DepCC corpus. This model substantially outperforms also the prior state of the art models (Baroni et al., 2014; Gerz et al., 2016) on the SimVerb dataset, through the sheer size of the input corpus, as previously shown, e.g. (Banko and Brill, 2001) inter alia.

5. Conclusion

In this paper, we introduced a new web-scale corpus of English texts extracted from the CommonCrawl, the largest openly available linguistically analyzed corpus to date, according to the best of our knowledge. The documents were de-duplicated and linguistically processed with part-of-speech and named entity taggers, and a dependency parser making it possible to easily start large-scale experiments with syntax-aware models without the need in long and resource-intensive preprocessing. In our experiments on the verb similarity task, a distributional model trained on the new corpus outperformed models trained on the smaller corpora, like Wikipedia, reaching the new state of the art on the verb similarity task, a distributional model trained on exactly the same parameters) on the dependency-based features extracted from the full DepCC corpus. We observe that the smallest corpus (Wikipedia) yields the worst results. While the scores go up on the larger corpus, which is a combination of Wikipedia with two other corpora, we can reach the even better result by training the model (with exactly the same parameters) on the dependency-based features extracted from the full DepCC corpus. This model substantially outperforms also the prior state of the art models (Baroni et al., 2014; Gerz et al., 2016) on the SimVerb dataset, through the sheer size of the input corpus, as previously shown, e.g. (Banko and Brill, 2001) inter alia.

4. Evaluation: Verb Similarity Task

As an example of potential use-case, we demonstrate the utility of the corpus and the overall methodology on a verb similarity task. We chose this task since verb meaning is largely defined by the meaning of its arguments (Fillmore, 1982), therefore dependency-based features seem promising for building distributional representations of verbs.

4.1. Datasets

Recently a new challenging dataset for verb relatedness was introduced, called SimVerb3500 (Gerz et al., 2016). We use it as a benchmark in our experiments, but also test the performance of verb similarity on the SimLex222, which is the verb part of SimLex999 dataset (Hill et al., 2015).

4.2. A Distributional Model for Verb Similarity

We compute a sparse count-based representations of words using the JoBiMText framework (Biemann and Riedl, 2013). The sparse vectors are weighted using the LMI schema and converted to unit length. In our experiments, we varied also the maximum number of salient features per word (\(fpw\)) and words per feature (\(wpf\)). Conceptually, each row and column of the sparse term-feature matrix is pruned in such a way, that at most \(wpf\) non-zero elements in a row and \(fpw\) elements in a column are retained.

4.3. Discussion of Results

Table 4 presents results of the experiments. The first part of the table lists five top systems in various categories (Gerz et al., 2016), representing the current state of art result on this dataset. In the original paper, two corpora were used: the “SB” is the corpus produced by the word2vec script, consisting of 8 billion tokens from various sources (Mikolov et al., 2013) and the “PolyglotWikipedia” is the English Polyglot Wikipedia corpus (Al-Rfou et al., 2015). The second part of the table presents the distributional model described in Section 4.2 trained on the corpora of various sizes. Note, that the preprocessing steps for each corpus are exactly the same as for the DepCC corpus. We observe that the smallest corpus (Wikipedia) yields the worst results. While the scores go up on the larger corpus, which is a combination of Wikipedia with two other corpora, we can reach the even better result by training the model (with exactly the same parameters) on the dependency-based features extracted from the full DepCC corpus. This model substantially outperforms also the prior state of the art models (Baroni et al., 2014; Gerz et al., 2016) on the SimVerb dataset, through the sheer size of the input corpus, as previously shown, e.g. (Banko and Brill, 2001) inter alia.

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