LDKP: A Dataset for Identifying Keyphrases from Long Scientific Documents

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Abstract

Identifying keyphrases (KPs) from text documents is a fundamental task in natural language processing and information retrieval. Vast majority of the benchmark datasets for this task are from the scientific domain containing only the document title and abstract information. This limits keyphrase extraction (KPE) and keyphrase generation (KPG) algorithms to identify keyphrases from human-written summaries that are often very short (≈ 8 sentences). This presents three challenges for real-world applications: human-written summaries are unavailable for most documents, the documents are almost always long, and a high percentage of KPs are directly found beyond the limited context of title and abstract. Therefore, we release two extensive corpora mapping KPs of ≈ 1.3M and ≈ 100K scientific articles with their fully extracted text and additional metadata including publication venue, year, author, field of study, and citations for facilitating research on this real-world problem.

1 Introduction and Background

Identifying keyphrases (KPs) is a form of extreme summarization, where given an input document, the task is to find a set of representative phrases that can effectively summarize it. Over the last decade, we have seen an exponential increase in the velocity at which unstructured text is produced on the web, with the vast majority of them untagged or poorly tagged. KPs provide an effective way to search, summarize, tag, and manage these documents. Identifying KPs have proved to be useful as preprocessing, pre-training (Kulkarni et al., 2021), or supplementary tasks in other tasks such as search (Sanyal et al., 2019; Gutwin et al., 1999; Song et al., 2006), recommendation systems (Augenstein et al., 2017), advertising (Yih et al., 2006), summarization (Qazvinian et al., 2010), opinion mining (Berend, 2011) to name a few. This has motivated researchers to explore machine learning algorithms for automatically mapping documents to a set of keyphrases commonly referred as the keyphrase extraction (KPE) task (Kim et al., 2010; Augenstein et al., 2017).

Various algorithms have been proposed over time to solve the problem of identifying keyphrases from text documents that can primarily be categorized into supervised and unsupervised approaches (Papagiannopoulou and Tsoumakas, 2020). Majority of these approaches take an abstract (a summary) of a text document as the input and produce keyphrases as output. However, in real world industrial applications in different domains such as advertising (Hussain et al., 2017), search and indexing, finance (Gupta et al., 2020), law (Bhargava et al., 2017), and many other real-world use cases, document summaries are not readily available. Moreover, most of the documents encountered in these applications are greater than 8 sentences (the average length of abstracts in KP datasets, see Table 1). We also find that a significant percentage of keyphrases (>18%) are directly found beyond the limited context of a document’s title and abstract/summary. These constraints limit the potential of currently developed KPE and KPG algorithms to only theoretical pursuits.

Many previous studies have pointed out the constraints imposed on KPE algorithms due to...
Table 1: Characteristics of the proposed datasets compared to the existing datasets.

| Dataset                  | Size   | Long Doc | Avg # Sentences | Avg # Words | Present KPs | Absent KPs |
|--------------------------|--------|----------|-----------------|-------------|-------------|------------|
| SemEval2017 (Augenstein et al., 2017) | 0.5k   | ×        | 7.36            | 176.13      | 42.01%      | 57.69%     |
| KDD (Caragea et al., 2014)    | 0.75k  | ×        | 8.05            | 188.43      | 45.99%      | 54.01%     |
| Inspec (Hulth, 2003)            | 2k     | ×        | 5.45            | 130.57      | 55.69%      | 44.31%     |
| KP20k (Meng et al., 2017)       | 568k   | ×        | 7.42            | 188.47      | 57.4%       | 42.6%      |
| OAGKx (Çano, 2019)             | 22M    | ×        | 8.87            | 228.50      | 52.7%       | 47.3%      |
| NUS (Nguyen and Kan, 2007)     | 0.21k  | ✓        | 375.93          | 7644.43     | 67.75%      | 32.25%     |
| SemEval2010 (Kim et al., 2010) | 0.24k  | ✓        | 319.32          | 7434.52     | 42.01%      | 57.99%     |
| Krapivin (Krapivin et al., 2010)| 2.3k   | ✓        | 370.48          | 8420.76     | 44.74%      | 52.26%     |
| LDKP3K (S2ORC ← KP20K)         | 100k   | ✓        | 280.67          | 6027.10     | 76.11%      | 23.89%     |
| LDKP10K (S2ORC ← OAGKx)        | 1.3M   | ✓        | 194.76          | 4384.58     | 63.65%      | 36.35%     |

In this work, we develop two large datasets (LDKP - Long Document Keyphrase) comprising of 100K and 1.3M documents for identifying keyphrases from full-length scientific articles along with their metadata information such as venue, year of publication, author information, inbound and outbound citations, and citation contexts, among others. We achieve this by mapping the existing KP20K (Meng et al., 2017) and OAGKx (Çano, 2019) corpus for KPE and KPG to the documents available in S2ORC dataset (Lo et al., 2020). We make the dataset publicly available on Huggingace hub (Section 3) in order to facilitate research on identifying keyphrases from long documents. We hope that researchers working in this area would acknowledge the shortcomings of the popularly used datasets and methods in KPE and KPG and devise exciting new approaches for overcoming the challenges related to identifying keyphrases from long documents and contexts beyond summaries. This would make the algorithms more useful in practical real-world settings.

2 Dataset

We propose two datasets resulting from the mapping of S2ORC with KP20K and OAGKx corpus, respectively. Lo et al. (2020) released S2ORC as a huge corpus of 8.1M scientific documents. While it has full text and metadata (see Table 3) the corpus does not contain keyphrases. We took this as an opportunity to create a new corpus for identifying keyphrases from full-length scientific articles. Therefore, we took the KP20K and OAGKx scientific corpus for which keyphrases were already available and mapped them to their corresponding documents in S2ORC. This is the first time in the keyphrase community that such a large number of full-length documents with comprehensive meta-data information have been made publicly available for academic use.

We release two datasets LDKP3K and LDKP10K corresponding to KP20K and OAGKx, respectively. The first corpus consists of ≈100K keyphrase tagged long documents obtained by mapping KP20K to S2ORC. The KP20K corpus mainly contains title, abstract and keyphrases for the short inputs and artificial nature of available datasets (Nguyen and Luong, 2010; Hasan and Ng, 2014; Cano and Bojar, 2019; Gallina et al., 2020; Kontoulis et al., 2021). In particular, Cano and Bojar (2019) while explaining the limitations of their proposed algorithms, note that the title and the abstract may not carry sufficient topical information about the article, even when joined together. While most datasets in the domain of KPE consist of titles and abstracts (Çano, 2019), there have been some attempts at providing long document KP datasets as well (Table 1). Krapivin et al. (2010) released 2,000 full-length scientific papers from the computer science domain. Kim et al. (2010) in a SemEval-2010 challenge released a dataset containing 244 full scientific articles along with their author and reader assigned keyphrases. Nguyen and Kan (2007) released 211 full-length scientific documents with multiple annotated keyphrases. All of these datasets were released more than a decade ago and were more suitable for machine-learning models available back then. With today’s deep learning paradigms like un/semi-supervised learning requiring Wikipedia sized corpora (>6M articles), it becomes imperative to update the KPE and KPG tasks with similar sized corpus.
computer science research articles from online digital libraries like ACM Digital Library, ScienceDirect, and Wiley. Using S2ORC documents, we increase the average length of the documents in KP20K from 7.42 sentences to 280.67 sentences, thereby also increasing the percentage of present keyphrases in the input text by 18.7%.

The second corpus corresponding to OAGKx consists of 1.3M full scientific articles from various domains with their corresponding keyphrases collected from academic graph (Sinha et al., 2015; Tang et al., 2008). The resulting corpus contains 194.7 sentences (up from 8.87 sentences) on an average with 63.65% present keyphrases (up from 52.7%). Since both datasets consist of a large number of documents, we present three versions of each dataset with the training data split into small, medium and large sizes, as given in Table 2. This was done in order to provide an opportunity even to researchers and practitioners with scarcity of computing resources to evaluate the performance of their methods on a smaller dataset that can be trained in free platforms like Google Colab1.

We also found out that some of the keyphrases in OAGKx and KP20K datasets were parsed incorrectly. Keyphrases that contain delimiters such as comma (which is also used as a separator for keyphrase list) have been broken down into two or more keyphrases, e.g., the keyphrase ‘2,4-dichlorophenoxyacetic acid’ has been broken down into ‘2’, ‘4- dichlorophenoxyacetic acid’. In some cases, the publication year, page number, DOI, e.g., 1999:14:555-558, were inaccurately added to the list of keyphrases. To solve this, we filtered out all the keyphrases that did not have any alphabetical characters in them.

Next, in order to facilitate the usage of particular sections in KPE algorithms, we standardized the section names across all the papers. The section names varied across different papers in the S2ORC dataset. For example, some papers have a section named “Introduction” while others have it as “1.Introduction”, “I. Introduction”, “I Introduction” etc. To deal with this problem, we replaced the unique section names with a common generic section name, like “introduction”, across all the papers. We did this for common sections including introduction, related work, conclusion, methodology, results, and analysis.

The proposed dataset LDKP3k and LDKP10k are further divided into train, test and validation splits as shown in Table-2. For LDKP3k, these splits are based on the splits that was present in the original KP20k dataset. For LDKP10k, we resorted to random sampling method to create these splits since OAGKX, the keyphrase dataset corresponding to LDKP10k, wasn’t originally divided into train, test and validation. Figures 1 and 2 show that the splits for both LDKP3k and LDKP10k are

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1https://colab.research.google.com/
Table 2: LDKP datasets with their train, validation and test dataset distributions.

| Dataset | LDKP3K | LDKP10K |
|---------|--------|---------|
| **Train** | | |
| Small | 20,000 | 20,000 |
| Medium | 50,000 | 50,000 |
| Large | 90,019 | 1,296,613 |
| **Test** | | |
| | 3,413 | 10,000 |
| **Validation** | | |
| | 3,339 | 10,000 |

Table 3: Information available in the metadata of each scientific paper in LDKP corpus.

| Paper details | Paper Identifier | Citations and References |
|---------------|------------------|--------------------------|
| Paper ID | ArXiv ID | Outbound Citations |
| Title | ACL ID | Inbound Citations |
| Authors | PMC ID | Bibliography |
| Year | PubMed ID | References |
| Venue | MAG ID | |
| Journal | DOI | |
| Field of Study | S2 URL | |

of adequate quality because there is a good distribution of papers in terms of field of study across all the splits.

3 Dataset Usage

Please refer to the Huggingface hub pages for LDKP3k and LDKP10k for a detailed information about downloading and using the dataset.

1. LDKP3K - https://huggingface.co/datasets/midas/ldkp3k
2. LDKP10K - https://huggingface.co/datasets/midas/ldkp10k

4 Conclusion

In this work, we identified the shortage of corpus comprising of long documents for training and evaluating keyphrase extraction and generation models. We created two very large corpus - LDKP3K and LDKP10K comprising of ≈ 100K and ≈ 1.3M documents and make it publicly available. We hope this would encourage the researchers to innovate and propose new models capable of identifying high quality keyphrases from long multi-page documents.

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