Abstract

Keyphrase extraction has been comprehensively researched within the single-document setting, with an abundance of methods and a wealth of datasets. In contrast, multi-document keyphrase extraction has been infrequently studied, despite its utility for describing sets of documents, and its use in summarization. Moreover, no dataset existed for multi-document keyphrase extraction, hindering the progress of the task. Recent advances in multi-text processing make the task an even more appealing challenge to pursue. To initiate this pursuit, we present here the first literature review and the first dataset for the task, 

1 Introduction

Keyphrase extraction (KE) is the task of selecting important and topical phrases from within a body of text (Turney, 2000). Single-document KE has garnered extensive research due to its vast practical uses. For example, keyphrases are listed on scientific or news articles, product descriptions and meeting transcripts to give the reader a hint at the matters of the source text. Additionally, these keyphrases are serviceable for downstream tasks like document categorization (Hulth and Megyesi, 2006), clustering (Jones and Mahoui, 2000), summarization (Jones et al., 2002) and search (Gutwin et al., 1999). Hence, single-document KE is resourced with a multitude of datasets across several domains (e.g. Kim and Kan (2009) and Krapivin et al. (2009) for scientific papers, or Wan and Xiao (2008) and Marujo et al. (2012) for news), and is frequently reviewed in survey papers to report on the advancements of the task (e.g. Hasan and Ng, 2014; Siddiqi and Sharan, 2015; Merrouni et al., 2019; Papagiannopoulou and Tsoumakas, 2020).

Conversely, multi-document KE (MDKE) has been sporadically researched. To the best of our knowledge, only about a handful of works have explicitly targeted the task (§2.1). This is despite it being just as valuable for gaining a high-level depiction of a set of related documents, and it being leveraged as a medium for supporting multi-document summarization (§2.2). It could additionally assist the aspect-based summarization task in extracting the aspects around which summaries are to be generated – especially useful when the texts are information-rich with high sub-topical variation (e.g Frermann and Klementiev, 2019; Gerani et al., 2019; Hayashi et al., 2021). Moreover, the multi-document setting, with its large inputs and information variability, introduces an interesting and challenging dimension of complexity that recent advances in text processing may tackle.

To initiate a more established research line on MDKE, we provide here the first literature review on the task, and propose a MDKE dataset, which can provide a benchmark for the task. The dataset is based on the existing DUC-2001 single-document KE dataset (Wan and Xiao, 2008) in the news domain. We leverage the properties of the original DUC-2001 multi-document summarization dataset to convert the single-document KE dataset to a multi-document one. We run several KE algorithms on the dataset to demonstrate the current state of the task on the new benchmark.

We start with the literature review on MDKE in §2, and describe the new dataset and its experimentation in §3.

1 github.com/OriShapira/MkDUC-01
2 https://www-nlpir.nist.gov/projects/duc/guidelines/2001.html
2 Multi-Document KE Review

We outline the research conducted explicitly and indirectly on MDKE. Few works have expressly tackled multi-document KE, however it has also been applied in several studies on multi-document summarization (MDS), as an intermediate step.

2.1 Works on Multi-Document KE

Hammouda et al. (2005) seem to be the first to have worked on the MDKE task, targeting the web-document domain. Word-sequences common to all documents are ranked based on term frequency, term position in documents, and use in titles or headlines. To evaluate, 10 sets of 30 documents are retrieved via query search. The system keyphrases are compared, by word-stem overlap, to the single corresponding document-set search query.

Berend and Farkas (2013) approach the task by merging keyphrase lists from individual documents in a document set. Within a document, n-grams, that satisfy several rules, are classified as keyphrases with a trained maxent model that uses features of word surface form and basic Wikipedia knowledge. An information gain metric ranks the unified list of keyphrases, from which the top-15 are taken out of a subset of documents. To evaluate, scientific paper sets from ACL workshops (Schäfer et al., 2012) (110 workshops with ~14 articles each) were paired with their respective “call-for-papers” (CFP) website sections. A system keyphrase list on a paper set was then compared to the CFP text via word-level cosine similarity. Also, NLP experts assessed whether keyphrase lists indeed properly characterized the corresponding workshop.

Bayatmakou et al. (2017) also take a single-to-multi-document approach. A set of documents is retrieved with a search query, and individual documents’ keyphrases are extracted with RAKE (Rose et al., 2010). The keyphrases in the unified lists are re-scored according to word co-occurrence within keyphrases and term-frequency within documents, weighted by document salience (similarity to the search query). While an automatic evaluation is proposed (measuring against the query and co-occurrence of keywords and query in documents), the actual assessment is a manual satisfaction rating against the search query. Experiments were performed over a large dataset of scientific abstracts.\(^3\)

As for keyword extraction (unigrams), Bharti et al. (2017) propose several methods of term-frequency for scoring words in sets of news articles. They evaluate the resulting keyword list against the aggregated words in the articles’ headlines, with recall and precision. Qing-sheng (2007) design cluster-based and MMR-based algorithms, and test against annotated data. YangJie et al. (2008) use tf-idf and word-level features to score words. No further details are available on the latter two references, as their papers could not be retrieved.

Relating to MDKE, Wan and Xiao (2008) propose a method for single-document KE, CollabRank, that ranks a document’s keyphrases with respect to similar “collaborating” documents. To compute word saliency, they produce an affinity graph reflecting co-occurrence relationships between documents’ words. That paper also introduces the single-document KE dataset that we build upon for MDKE (§3).

2.2 KE for Multi-Document Summarization

MDS aims to generate a passage that covers the main issues of the source document-set. Keyphrases naturally point to the central aspects, and can therefore assist in marking the important information for a summary.

Some works extract keyphrases from the document-set, e.g. with conventional term-frequency methods (Alshahrani and Bikdash, 2019), by using single-document KE algorithms on the concatenated documents (Nayeem and Chali, 2017), or through query similarity for query-focused summarization (Ma et al., 2008). These keyphrases are then used to rank sentences across the documents for the potential summaries. Output summaries are standardly evaluated against reference summaries from MDS datasets. While keyphrases have also been extracted per document for the same purpose of MDS (e.g. Bhaskar, 2013; Fejer and Omar, 2015), it is difficult to assess which approach is most effective since various factors impact the resulting summaries.

Other works focus on word importance rather than keyphrase extraction. Hong and Nenkova (2014) assign importance to documents’ content words based on their appearance in reference summaries. Alternative methods include ILP frameworks for bigram selection and weighting, using syntactic and external information (Li et al., 2015), or through a joint sentence/keyword reinforcement process that converges to a high quality summary (Li and Zheng, 2020).
2.3 KE Evaluation

Most single-document KE works automatically evaluate a keyphrase list against a gold list. As seen in §2.1 above, the few works on MDKE do not conduct such evaluations due to the lack of test datasets, which we counteract with our proposed MDKE dataset (§3). They all conduct disparate assessments, and evaluate against references that are limited in informativeness or that are unrepresentative of keyphrase requisites.

The most prominent KE metric for comparing against a gold keyphrase list is the $F1@k$ metric, which considers the recall and precision of the predicted list, truncated to $k$ items, against the full gold list. Words are often stemmed to allow some reasonable variation of word forms. To allow for a broader valuation, the unigram-level $F1@k$ score is also used – where the two lists of keyphrases are each flattened out to a single list of words. Other, less exploited metrics include the Mean Reciprocal Rank (Voorhees and Tice, 2000) and Mean Average Precision, that also take list-order into account. (See a KE review paper, such as (Sun et al., 2020), for more details on the evaluation metrics.)

3 New Dataset

3.1 Dataset Formation

Our proposed MDKE dataset, which we name MK-DUC-01, builds upon the DUC-2001 single-document KE dataset introduced by Wan and Xiao (2008), for the news domain.

The DUC-2001 MDS dataset (Over, 2001) consists of 30 topics, each containing an average of 10.27 related news articles (308 in total). Experts summarized each individual article, as well as each of the document-sets, with different length summaries. Overall, there are three 100-token-long summaries per document, and three summaries per document-set, at lengths 50, 100, 200 and 400 tokens. Wan and Xiao (2008) further annotated each document with a list of keyphrases. On average, there are 8.08 keyphrases per document, with 2.09 words per keyphrase. This data is still widely used for the news-domain single-document KE task.

To restructure the single-document KE dataset for the multi-document setting, we carried out an automatic merging and reranking process, followed by a manual refinement procedure:

**Automatic merging and reranking.** For each topic $t$ with its corresponding document-set $D_t = \{d_1, d_2, ..., d_{n_t}\}$, and 400-token topic reference summaries $S_t = \{s_1, s_2, s_3\}$, we first provided a score for each stemmed word $w$ in $D_t$ as $w_{score}(w, t) = \overline{df(w, D_t)}$, $df(w, S_t)$ where $df(w, X)$ stands for $w$’s document-frequency in document-set $X$, i.e. the number of documents of $X$ in which $w$ appears.

We then unified $D_t$’s $n_t$ lists of keyphrases (from the single-document KE dataset), removing exact phrase duplicates and phrases that do not appear anywhere in $D_t$, to form a single list of potential keyphrases, $K'_t$. Each phrase $p \in K'_t$ was then scored as $phrase_{score}(p, t) = \overline{avg_{w \in p}(w_{score}(w, t))}$, i.e. the average of $p$’s stem scores. This generated a ranked list of keyphrases, $K_t$, ordered by a salience score.

Lastly, we merged pairs of phrases in $K_t$ where one was contained within the other (stemmed and disregarding word order), leaving only the longer variant or the one earlier in $K_t$, e.g., merging “routine training” / “routine train flight”. Due to the variance of keyphrases’ informativeness across documents, we found that this heuristic effectively filtered out overly generic or repetitive keyphrases.

**Manual refinement.** As we strived to generate a high-quality MDKE benchmark dataset, we further refined the keyphrase lists produced by the automatic stage above. One of the authors looked over the 30 $K_t$ lists with the relevant topic documents and reference summaries open for assistance, and carried out the following: (1) removed phrases that were particularly scarce or of low informativeness (e.g., “similar transmission” in the “Mad Cow Disease” topic); (2) removed phrases that were not synonymous with others, but were clearly implied from other phrases (e.g., “U.S. Senate” where other keyphrases mention the Senate); (3) clustered together phrases that can be used replaceably

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| # topics | Full | Trun-20 |
|----------|------|--------|
|          | 30   | 30     |
| Avg (StD) # docs per topic | 10.27 (2.24) | 10.27 (2.24) |
| Avg (StD) # KPs per topic | 43.8 (15.6) | 19.97 (0.18) |
| Avg (StD) KP word-length | 2.13 (0.66) | 2.17 (0.66) |
| # KPs with substitute cluster | 142 of 1314 | 104 of 599 |
| Avg (StD) # KPs in clusters | 2.82 (1.26) | 3.07 (1.37) |

Table 1: MK-DUC-01 stats, on the full data and when truncating the keyphrase lists to 20. (KP = keyphrase)
We demonstrate the use of MK-DUC-01 by testing ten existing single-document KE algorithms and a multi-document one. The single-document algorithms are applied in two modes: (1) Concat, where all topic documents are concatenated into a single text that is then fed to the algorithm to output a list of keyphrases per topic; (2) Merge, where for each topic, the algorithm is fed one document at a time, and the generated lists of keyphrases are merged using a similar strategy as in the automatic merging and reranking procedure in §3.1, except that \( \text{word\_score}(w, t) = df(w, D_t) \), i.e., it does not consider the reference summary set – which is naturally unavailable in the KE task. CollabRank (Wan and Xiao, 2008) uses its collaborating documents, hence only Merge is applied. The algorithm by Bayatmakou et al. (2017) was designed as a multi-document algorithm, but follows a similar approach to our Merge mode, running RAKE (Rose et al., 2010) per document, and merging keyphrase lists with a method different from ours.

For evaluation, we employ the standard stemmed \( F1@k \) and unigram-F1@k metrics for \( k \in \{1, 5, 10, 20\} \), on the MK-DUC-01 data, both in the Tranc-20 version (Table 2) and in its full version (Table 4 in the appendix). We witness a clear benefit of the Merge strategy across nearly all algorithms, and a strong significant improvement over the official MDKE algorithm.

### 4 Conclusion

We review the research conducted on multi-document KE, which is far understudied compared to its single-document counterpart. Only a few works have tackled the MDKE task head-on, all without the existence of a suitable dataset. Meanwhile, the notion of MDKE has been indirectly applied in multi-document summarization research, and can potentially assist in new trends within the summarization community, using recent advances in multi-text processing. We introduce the first MDKE dataset as a benchmark, and evaluate different KE algorithms on it, acting as baseline results for the task.
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A Further Experiment Details

**Additional baseline evaluations.** Table 4 presents the results on the full gold keyphrase lists (non-truncated). When compared to the results on the Trunc-20 truncated lists (Table 2), there is an expected degradation in all scores, since the keyphrases lower in the lists are less representative keyphrases of the respective document sets. This, and the longer absolute lengths of the lists, make it less likely for the KE algorithms to extract correct keyphrases, and hence yield considerably lower recall scores across the board (not shown here), while precision scores mostly remain the same or are slightly higher.

**Evaluation details.** When computing $F_1@k$, the system-keyphrase and the gold-keyphrase are compared using stemmed exact match.

When computing unigram-$F_1@k$: (1) the top-$k$ items in the system keyphrase list are retrieved; (2) those keyphrases are flattened out to a single list of stems; (3) the gold-list is also flattened to a list of stems; (4) the former is evaluated against the latter with $F_1@k$.

The average of the F1 scores over all instances is the final score presented.

**Keyphrase sizes.** Table 3 presents the average token length as produced overall by each algorithm, when using the Concat and Merge generation modes. The keyphrase sizes in Concat are representative of the corresponding algorithms’ output sizes, while the sizes in Merge go through an additional process, hence slightly altering the natural output sizes of the algorithms.

| Algorithm/Mode       | Concat | Merge |
|----------------------|--------|-------|
| TfIdf                | 1.30   | 2.22  |
| KPMiner              | 1.42   | 1.39  |
| YAKE                 | 1.99   | 2.58  |
| TextRank             | 3.64   | 2.68  |
| SingleRank           | 3.24   | 2.57  |
| TopicRank            | 1.51   | 2.08  |
| TopicalPageRank      | 3.14   | 2.52  |
| PositionRank         | 2.52   | 2.32  |
| MultipartiteRank     | 1.51   | 2.12  |
| CollabRank           | -      | 2.54  |
| (Bayatmakou et al., 2017) | - | 3.00 |

Table 3: Average number of words per keyphrase produced by the different algorithms, using the two generation modes (Concat and Merge) on MK-DUC-01.

**Single-document KE results.** We ran the relevant algorithms from Tables 2 and 4 on the single-document DUC-2001 KE dataset (308 documents and 8.08 keyphrases per document), to get a sense of their comparable quality in the single and multiple document settings. Results are presented in Table 5. There are 7 documents that were not processed in the KPMiner algorithm due to processing errors.

Overall, we see that the algorithm rankings are quite similar in the two settings, across $k$ values and in both metrics.

**Algorithm implementations.** We used the PKE Python toolkit package (Boudin, 2016) for all KE algorithms except for (Bayatmakou et al., 2017), which we implemented ourselves. The Bayatmakou et al. (2017) algorithm uses RAKE (Rose et al., 2010) as its underlying single-document KE component, for which we used the nltk-rake library. As RAKE outputted very long keyphrases yielding low scores, we used only those up to 3 words. For CollabRank, we considered all other documents in its original topic document-set as “collaborating” documents, and computed their similarity scores using spaCy (Honnibal et al., 2020) text similarity.

**Execution resources.** All algorithms and automatic methods used for annotation and experimentation were run on a standard laptop, and no special hardware was required.

Run times were up to about a second per keyphrase extraction instance, except for CollabRank which required about 15-20 seconds per document. Running the Merge mode on the document-sets required tens of seconds for some algorithms as the process iterates over all documents separately. The Concat mode, which requires a single run per document-set, was substantially faster overall.

B Dataset Example

Table 6 presents an example list of keyphrases from our MK-DUC-01 dataset. The top 20 keyphrases are used in the Trunc-20 dataset version, while the full list is used in the full dataset version. Some keyphrases have multiple wording variations, acting as the substitute clusters. The first item in a cluster is used in the standard evaluation when a flat list of keyphrases is required.

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5https://pypi.org/project/rake-nltk
Table 4: Results on various KE algorithms tested with our MK-DUC-01 dataset. In Concat mode all topic documents are concatenated as a single text input, and in Merge mode algorithms are run on individual documents after which keyphrase lists are merged and reranked. The bottom two algorithms are multi-document based KE algorithms, and work in Merge mode only.

| Algorithm             | F1@k |       |       |       |       | F1@k |       |       |       |       |
|-----------------------|------|-------|-------|-------|-------|------|-------|-------|-------|-------|
|                       | 1    | 5     | 10    | 20    |       | 1    | 5     | 10    | 20    |       |
| Tf-Idf                | 0.11 | 1.22  | 2.91  | 4.27  | 2.62  | 9.31 | 16.71 | 24.53 | 0.54  | 1.21  |
| KPMiner (El-Beltagy and Rafea, 2009) | 0.95 | 3.03  | 4.90  | 7.26  | 3.26  | 12.40 | 19.25 | 25.36 | 1.06  | 3.29  |
| YAKE (Campos et al., 2020) | 1.58 | 4.56  | 7.18  | 9.42  | 3.66  | 15.28 | 22.34 | 27.10 | 1.54  | 3.37  |
| TextRank (Mihalcea and Tarau, 2004) | 0.45 | 2.76  | 3.19  | 6.24  | 6.55  | 20.28 | 25.41 | 28.91 | 1.42  | 5.53  |
| SingleRank (Wan and Xiao, 2008) | 0.42 | 3.37  | 4.74  | 8.94  | 7.82  | 20.46 | 25.23 | 28.28 | 1.56  | 4.91  |
| TopicRank (Bouguin et al., 2013) | 1.08 | 4.13  | 5.91  | 8.76  | 3.52  | 11.84 | 18.75 | 28.15 | 2.32  | 6.45  |
| TopicalPageRank (Stenicka et al., 2015) | 0.73 | 3.71  | 5.44  | 9.94  | 7.72  | 20.61 | 25.79 | 28.48 | 1.62  | 5.10  |
| PositionRank (Florescu and Caragea, 2017) | 1.28 | 5.51  | 8.14  | 12.48 | 6.24  | 18.10 | 23.75 | 28.61 | 1.76  | 4.61  |
| MultitopicRank (Boudin, 2018) | 0.93 | 3.66  | 6.70  | 9.63  | 3.75  | 12.46 | 20.21 | 29.41 | 2.45  | 6.90  |
| CollabRank (Wan and Xiao, 2008) | -    | -     | -     | -     | -     | -    | -     | -     | -     | -     |
| (Bayatmakou et al., 2017) [multi-doc] | -    | -     | -     | -     | -     | -    | -     | -     | -     | -     |

Table 5: The results of various single-document KE algorithms on the single-document DUC-2001 KE dataset, for reference as a comparison to algorithms’ results in the multi-document setting (Tables 2, 4 and 3). The average number of KPs in each document’s gold list in the dataset is 8.08, and all keyphrases are used in the evaluation. CollabRank is a single-document KE algorithm that uses related documents (within the same topic) in its operation.
| # | Keyphrase                                                                 |
|---|--------------------------------------------------------------------------|
| 1 | drug testing                                                             |
| 2 | illegal steroid use
   drug use
   illegal performance-enhancing drugs |
| 3 | Olympics gold medal                                                      |
| 4 | Seoul Olympics                                                           |
| 5 | banned steroid
   illegal anabolic steroid |
| 6 | Ben Johnson
   Canadian Ben Johnson
   Sprinter Ben Johnson
   Canadian Olympic sprinter |
| 7 | world record                                                             |
| 8 | anabolic steroid stanozolol
   illegal steroid stanzolol |
| 9 | world championships                                                      |
| 10| Charlie Francis
   Canadian coach Charlie Francis
   Canadian national sprint coach |
| 11| 100-meter dash
   100-metre sprint |
| 12| stanozolol use                                                           |
| 13| Carl Lewis
   American Carl Lewis
   U.S. sprinter Carl Lewis |
| 14| urine sample                                                             |
| 15| steroid furazabol                                                        |
| 16| Jamie Astaphan                                                           |
| 17| steroid combination                                                      |
| 18| Toronto                                                                  |
| 19| personal physician                                                       |
| 20| disgraced Olympic sprinter                                               |
| 21| Canadian inquiry
   federal inquiry |
| 22| drug scandal                                                             |
| 23| Angella Issajenko                                                        |
| 24| Johnson scandal                                                          |
| 25| stripping                                                                |
| 26| controlled substance                                                    |
| 27| world record-holder                                                     |
| 28| Hamilton spectator indoor games                                          |
| 29| disappointed nation                                                     |
| 30| record crowd                                                            |
| 31| world-class sprinter                                                    |
| 32| two-year suspension                                                     |
| 33| news conference                                                          |
| 34| first race                                                               |
| 35| second-place finish                                                     |
| 36| Lynda Huey                                                               |
| 37| first indoor loss                                                       |
| 38| slow start                                                              |
| 39| Daron Council                                                            |
| 40| homecoming                                                               |
| 41| expectation                                                              |

Table 6: The keyphrases in our MK-DUC-01 dataset for topic d31 about the Ben Johnson steroid scandal, containing 13 documents. Keyphrases with multiple items represent substitute clusters, where the first item in the cluster is the marked preferred keyphrase wording when using standard KE evaluation using a flat list of gold keyphrases. The top 20 keyphrases are used in the Trunc-20 dataset version.