Multi-Document Keyphrase Extraction: Dataset, Baselines and Review

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Abstract

Keyphrase extraction has been extensively researched within the single-document setting, with an abundance of methods, datasets and applications. 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 prior dataset exists 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 stimulate this pursuit, we present here the first dataset for the task, MK-DUC-01, which can serve as a new benchmark, and test multiple keyphrase extraction baselines on our data. In addition, we provide a brief, yet comprehensive, literature review of the task.

1 Introduction

Keyphrase extraction (KPE) is the task of selecting important and topical phrases from within a body of text (Turney, 2000). Single-document KPE has been a long standing task (Dennis, 1967) garnering 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 KPE is resourced with a multitude of datasets across several domains (e.g., scientific papers (Kim and Kan, 2009; Krapivin et al., 2009) or news (Wan and Xiao, 2008; Marujo et al., 2012)), and is frequently reviewed in survey papers to report on continual advancements of methods for solving the task (e.g. Hasan and Ng, 2014; Siddiqi and Sharan, 2015; Merroni et al., 2019; Papagiannopoulou and Tsoumakas, 2020).

Conversely, multi-document KPE (MKPE) has been sporadically researched, even though it is just as valuable for indicating the central aspects of a set of related documents. As laid out in §2, few works have explicitly targeted the task, however MKPE was also implemented within applications of information exploration. In addition, MKPE was implicitly leveraged as a medium for supporting multi-document summarization. To make matters trickier, no dataset was previously available for MKPE, consisting of sets of documents and corresponding gold lists of keyphrases. Previous works, therefore, did not evaluate with standard automatic KPE methods, or conducted extrinsic evaluations through summarization.

To stimulate a more established research line on MKPE, we first briefly review the research conducted around the task (§2), and then present our MKPE dataset,¹ which can provide a testing benchmark for the task (§3). The dataset is based on the existing DUC-2001 single-document KPE dataset (Wan and Xiao, 2008) in the news domain. We leverage the properties of the original DUC-2001 multi-document summarization dataset² to convert the single-document KPE dataset to a multi-document one using an automatic procedure followed by manual cleaning. We run several KPE algorithms on the dataset to demonstrate the current state of the task on the new benchmark (§4).

The multi-document setting poses the challenge of handling large inputs with cross-document relationships, which manifests high information redundancy along with dispersed complementing information. These issues were indeed apparent during our dataset creation process, and were treated accordingly. As for potential solutions, recent advances in multi-text processing (e.g., Caciularu et al., 2021; Mao et al., 2020) make MKPE an even more relevant and timely task to drive forward.

¹Reproducing code will be released upon publication.
²https://duc.nist.gov
2 Task Background

We outline the research conducted on MKPE. Few works have expressly tackled the task, however it has also been applied in several studies on multi-document summarization and exploration.

Works on MKPE. Redundancy is naturally a dominant characteristic to harness for consolidating information across a set of related documents. Hammouda et al. (2005) ranked word-sequences, common to all documents, with lexical features, and evaluated resulting keyphrases against the search-query used for retrieving the set of web documents. Bharti et al. (2017) also used term-frequency features, evaluating the keywords against the aggregated words in the source news articles’ headlines. Qing-sheng (2007) designed cluster-based and MMR-based (Carbonell and Goldstein, 1998) algorithms an Yangjie et al. (2008) used TF-IDF and word-level features to score words.

Another approach taken was merging keyphrase lists from individual documents in the document-set. Berend and Farkas (2013) classified candidate keyphrases using a maxent model with features of word surface-form and Wikipedia knowledge, and unified lists with an information gain metric. The final list of keyphrases was compared to a topic overview paragraph. Bayatmakou et al. (2017) applied RAKE (Rose et al., 2010) per document and word similarity for merging. Evaluation was conducted with manual satisfaction ratings. Relatedly, Wan and Xiao (2008) proposed a method for single-document KPE, that ranks a document’s keyphrases with respect to similar “collaborating” documents. That paper also introduced the single-document KPE dataset that we build upon for MKPE (§3).

As apparent, the works addressing the task employ rather simplistic methods, and, notably, evaluate inconsistently and in a non-methodological manner. We advocate revisiting the MKPE task with modern approaches, and with our dataset as a testing benchmark for comparability. While preparing training data is left for future work, extracting keyphrases from a document set may be facilitated by semi-supervised techniques. In summarization, for example, Mao et al. (2020) used reinforcement learning against reference summaries, which can be borrowed for detecting keyphrases rather than summary sentences. Lebanoff et al. (2018) capitalized on the abundant single-document summarization data and adapted it for the multi-document setting, as can be respectively applied in KPE. Additionally, it is worth exploring how to leverage multi-document word representations (Caciularu et al., 2021) for the use of phrase salience detection.

Applications using MKPE. To alleviate the consumption of information from within document sets, there is a line of research developing interactive systems for knowledge exploration (Shapira et al., 2021). Many applications provide a form of a keyphrase list to highlight relevant sub-topics in the document set (e.g. Leuski et al., 2003; Handler and O’Connor, 2017; Shahpura et al., 2021; Hirsch et al., 2021). Here too, keyphrases were extracted using redundancy-based methods, like TF-IDF, TextRank (Mihalcea and Tarau, 2004) or cross-document coreference resolution (Cattan et al., 2021).

KPE for multi-document summarization. Multi-document summarization (MDS) aims to generate a passage covering the salient issues of the source document-set. Keyphrases naturally point to central aspects, and can therefore assist in marking the information for a summary. Some works detected salient phrases in the document-set, e.g., with conventional term-frequency methods (Alshahrani and Bikdash, 2019), by using single-document KPE algorithms on the concatenated documents (Nayeem and Chali, 2017), or through query-similarity for query-focused summarization (Ma et al., 2008). Hong and Nenkova (2014) assigned importance to documents’ content words based on their appearance in reference summaries. ILP frameworks were also employed (Li et al., 2015; Li and Zheng, 2020) for weighting phrases around which to summarize. While most of these methods, in consequence, produce keyphrases, their intention is generating summaries that are standardly evaluated against reference summaries.

KPE evaluation. Most single-document KPE works automatically evaluate a keyphrase list against a gold list, as we now enable also for MKPE with our new dataset. The most prominent metric is $F1@k$, which considers the recall and precision of the predicted list, truncated to $k$ items, against the full gold list. To allow for some reasonable lexical variation of keyphrases, words are often stemmed, and unigram-level $F1@k$ is used – where the two lists of keyphrases are each flattened out to respective lists of words.

A major disadvantage of this evaluation approach is that it penalizes synonymous keyphrases not contained in the gold list. This is potentially
further exacerbated in the multi-document setting, which contains higher paraphrasic diversity across documents. Our dataset annotation process facilitated preparation of substitute clusters within gold keyphrase lists, thus allowing for some synonymy of predicted keyphrases (§3).

### 3 New Dataset

Our MKPE dataset, named MK-DUC-01, builds upon the DUC-2001 single-document KPE dataset (Wan and Xiao, 2008), for the news domain.

The DUC-2001 MDS dataset (Over, 2001) consists of 30 topics, each containing ~10.3 related news articles (308 total). Experts summarized each individual article, as well as each of the document-sets, yielding 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 the data with lists of ~8.1 keyphrases per document, at ~2.1 words per keyphrase. This data is still widely used for the single-document KPE task.

The availability of document-level keyphrases and document clusters – unique to the DUC-2001 dataset – allows deducing multi-document-level keyphrases. The single-document KPE dataset is restructured for the multi-document setting by carrying 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 $D_t = \{d_1, ..., d_{n_t}\}$, and 400-token reference summaries $S_t = \{s_1, s_2, s_3\}$, we first scored each stemmed word $w$ in $D_t$ as $\text{word\_score}(w, t) = \text{avg}(d_f(w, D_t), d_f(w, S_t))$ where $d_f(w, X)$ stands for $w$’s document-frequency in document-set $X$, i.e. the percentage of documents of $X$ in which $w$ appears. As expressed earlier, the frequency of words in the document set are useful for indicating the importance of concepts for the topic. We additionally leverage the reference summaries for providing a strong signal for topic-level salience.

We then unified $D_t$’s $n_t$ lists of keyphrases (from the single-document KPE dataset), removing duplicates and phrases not appearing in $D_t$, to form a single list of potential keyphrases, $K_t$'. Each phrase $p \in K_t'$ was then scored as $\text{phrase\_score}(p, t) = \text{avg}_{w \in p}(\text{word\_score}(w, t))$, 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 MKPE 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 (e.g., “1990 census” and “1990 population count”) to form keyphrase substitute clusters, with the more commonly used variant as the preferred alternative; (4) produced substitute clusters for persons’ titled proper nouns, when the title is optional (e.g., a cluster for “Bill Clinton” containing “President Clinton” and “Governor Bill Clinton”), leaving the untitled version as the preferred alternative. These annotation actions emphasize the need for proper consolidation of repetitive and complementing information in the multi-document setting.

The whole dataset formation procedure yielded the final MK-DUC-01 dataset, with basic statistics appearing in Table 1. We suggest a version of the dataset where the keyphrase lists are truncated at 20 items, denoted here Trunc-20. This establishes a more representational task-setting since

|                  | Full | Trunc-20 |
|------------------|------|----------|
| # topics         | 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) |
| Avg (StD) % unique stems in cluster | 0.72 (0.06) | 0.71 (0.07) |

Table 1: MK-DUC-01 stats, on the full data and when truncating the keyphrase lists to 20. (KP = keyphrase)
Table 2: Precision results on various KPE algorithms tested with the Trunc-20 version of 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 heuristically merged and reranked. The bottom two algorithms are multi-document based KPE algorithms, and work in Merge mode only. BERT-KPE is limited in input size and hence cannot be run in Concat mode. This table corresponds to Table 3, which presents F1 scores.

Note that the variability of contextually similar keyphrases across documents enabled the formation of clusters of substitute keyphrases, which is a novel conception in KPE datasets. This assists in the evaluation process when a system outputs a keyphrase that is worded differently in the gold list of keyphrases, as seen in Table 6 (appendix). On average over all baselines, ~15% of output keyphrases are synonymous with others, with respect to the available substitute clusters. We may hence infer that improving detection of phrase redundancy in context, may improve overall results. We also observe that keyphrase token-length (Table 6) influences unigram-level scores: shorter keyphrases, likely more informationally generic, tend to yield higher precision and lower recall scores.

Table 2 shows Precision@k results, with stemming, on the Trunc-20 version of MK-DUC-01 and using the substitute clusters (evaluation procedure, F1 scores and scores on the full data in appendix). Overall, we witness the benefit of the Merge strategy, which explicitly considers redundancy across documents during the merging step. Meanwhile, some baselines tend to output many synonymous keyphrases, as seen in Table 6 (appendix). On average over all baselines, ~15% of output keyphrases are synonymous with others, with respect to the available substitute clusters. We may hence infer that improving detection of phrase redundancy in context, may improve overall results. We also observe that keyphrase token-length (Table 6) influences unigram-level scores: shorter keyphrases, likely more informationally generic, tend to yield higher precision and lower recall scores.

4 Baseline Results

We demonstrate the use of MK-DUC-01 by testing 11 existing single-document KPE algorithms and a multi-document one. 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, except that \( \text{word\_score}(w, t) = df(w, D_t) \), i.e., it does not consider the reference summary set – which is unavailable in the KPE task. BERT-KPE (Sun et al., 2021), a RoBERTa (Liu et al., 2019) model trained on the single-document OpenKP (Xiong et al., 2019) dataset, has a strict input size limit, and cannot work in Concat mode. CollabRank (Wan and Xiao, 2008) uses its collaborating documents, hence only Merge is applied. The MKPE algorithm by Bayatmakou et al. (2017) uses a merge approach different from ours.

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5 Conclusion

We review the multi-document KPE task, which is far understudied compared to its single-document counterpart. While few works have tackled the MKPE task head-on, without the existence of a suitable dataset, MKPE has also been applied for document-set summarization and exploration. We introduce the first MKPE dataset as a benchmark, and test various KPE baselines on it. Alongside recent progress in multi-text processing, we hope our dataset spurs the advancement of the MKPE task.
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A Further Experiment Details

Additional baseline evaluations. Table 3 presents the F1 scores on the Trunc-20 version of the dataset, corresponding to Table 2 in §4. Tables 4 and 5 present the results on the full gold keyphrase lists (non-truncated). When compared to the results on the Trunc-20 truncated lists (Tables 2 and 3), 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 KPE baselines to extract correct keyphrases, and hence yield considerably lower recall scores across the board (not shown here).

Evaluation details. For computing F1@k, the top-k predicted keyphrases and all gold keyphrases are stemmed, duplicates are removed from the predicted list, and stemmed keyphrases are lexically matched. If a predicted keyphrase is found in a gold keyphrase substitute cluster, then that gold keyphrase cluster cannot be matched with another predicted keyphrase. This mimics the removal of duplicates from the predicted list, just with synonymous keyphrases. Notice that this means that repeated/synonymous keyphrases are marked as appearing only once, which affects precision unfavourably.

For computing unigram-F1@k: (1) the top-k items in the system keyphrase list are retrieved; (2) unique keyphrases from that sub-list are flattened out to a single list of stems; (3) each substitute cluster in the gold list is flattened out to a list of unique stems; (4) all gold clusters – including those with one element – are pooled together to one list of stems; (5) the predicted stems are evaluated against gold stems with recall and precision.

The average precision and average F1 scores over all instances are the final scores presented.

Concat mode implementation. When inputting one long concatenation of documents to a single-document KPE algorithm, the order of the documents may have an effect on the results. Therefore, for each of the 30 test topics, we shuffled the documents, and kept that order for all baselines.

Keyphrase sizes. Table 6, on the left side, presents the average token-length of the 20 keyphrases output by each baseline, over all topics, 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. As mentioned in §4, the keyphrase token-length has an influence on the unigram-level precision and recall scores. When a keyphrase is shorter, it has less of a chance of containing words not in the gold keyphrases, allowing for higher precision. On the other hand, it also has less opportunity to catch those gold words, leading to lower recall.

KP synonymity in outputs. For each baseline used, Table 6, on the right side, presents the average (over 20 keyphrases per topic, and over all topics) percent of keyphrases that are synonymous with others, with respect to the substitute clusters in the test dataset (i.e., this does not take into account synonymous keyphrases that do not appear in the gold list). Notably, we see that about 1 of every 4 keyphrases in TopicalPageRank outputs are synonymous with others. Nevertheless, this baseline is still one of the superior tested methods.

Single-document KPE results. We ran the algorithms from Tables 2, 3, 4 and 5 on the single-document DUC-2001 KPE 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 7. 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 the k values and in both metrics.

Algorithm implementations. We used the PKE Python toolkit package (Boudin, 2016) for most KPE algorithms. We adapted the code available for BERT-KPE4 (Sun et al., 2021) for the DUC-2001 data, and used the available trained model (RoBERTa (Liu et al., 2019) on OpenKP data (Xiong et al., 2019)). We implemented the algorithm by Bayatmakou et al. (2017) ourselves, which uses RAKE (Rose et al., 2010) as its underlying single-document KPE component (we used the nltk-rake library5). As RAKE outputted very long keyphrases yielding low scores, we used only those up to 3 words. For CollabRank, we considered all

4https://github.com/thunlp/BERT-KPE
5https://pypi.org/project/rake-nltk
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 (except for BERT-KPE) and automatic methods used for annotation and experimentation were run on a standard laptop, and no special hardware was required. BERT-KPE was run (only inference was needed) on a NVIDIA GeForce GTX 1080 Ti GPU with 11GB memory, and used less than 1GB memory during inference.

Run times were up to about a second per keyphrase extraction instance, except for ColabRank which required about 15-20 seconds per document. Running the Merge mode on the document-sets required tens of seconds for some baselines 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

Distribution of data. For our work, the DUC-2001 MDS dataset was obtained according to NIST instructions, and the DUC-2001 keyphrases were taken from github.com/boudinfl/duc-2001-pre. Since the documents from the DUC-2001 dataset cannot be freely re-distributed, we make available a script for one-click MK-DUC-01 dataset re-construction using the properly acquired DUC-2001 MDS dataset from NIST.

Example. Table 8 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 can be used in the standard evaluation when a flat list of keyphrases is required.

C Previous MKPE Evaluation Methods

As discussed in §2, the previous works explicitly solving the MKPE task did not have a proper dataset to test their resulting keyphrases. Consequently, each work tested their results differently, described as follows:

Hammouda et al. (2005) targeted the web-document domain. To evaluate, 10 sets of 30 documents were retrieved via query search by submitting a short query (2 to 3 words) into a search engine for each such set (about 30 documents per set with 500 words per document). The system keyphrases were compared, by word-stem overlap, to the single corresponding document-set search query, as an indicator for keyphrase-salience.

Berend and Farkas (2013) work on the scientific paper domain. Sets of papers from ACL workshops (Schäfer et al., 2012) focusing on a clearly distinguishable scientific area (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) retrieved common documents with a search query. While an automatic evaluation was proposed (measuring against the search query, and co-occurrence of keywords and query in documents), the actual assessment was a manual satisfaction rating against the search query. Experiments were performed over a large dataset of 13,870 scientific abstracts (https://www.webofknowledge.com).

Bharti et al. (2017) evaluated the resulting keyword list against the aggregated words in the news articles’ headlines, with recall and precision.

Qing-sheng (2007) tested against proprietary expert-annotated data.
Table 3: F1 results on various KPE algorithms tested with the Trec-20 version of 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 heuristically merged and reranked. The bottom two algorithms are multi-document based KPE algorithms, and work in Merge mode only. BERT-KPE is limited in input size and hence cannot be run in Concat mode. This table corresponds to Table 2, which presents precision scores.

| Algorithm                          | Precision/K | 1 | 5 | 10 | 20 | 1 | 5 | 10 | 20 |
|-----------------------------------|-------------|---|---|----|----|---|---|----|----|
| TF-IDF                            | 1.87        | 5.83 | 8.34 | 10.56 | 12.78 | 5.83 | 8.34 | 10.56 | 12.78 |
| KPMiner [El-Beltagy and Rafea, 2009] | 1.27        | 5.32 | 7.94 | 10.56 | 12.78 | 5.32 | 7.94 | 10.56 | 12.78 |
| YAKE [Campos et al., 2020]        | 4.50        | 16.26 | 20.82 | 25.40 | 30.00 | 16.26 | 20.82 | 25.40 | 30.00 |
| TextRank [Mihalcea and Tarau, 2004] | 4.75        | 16.62 | 21.28 | 26.24 | 31.00 | 16.62 | 21.28 | 26.24 | 31.00 |
| SingleRank [Wan and Xiao, 2008]   | 5.12        | 17.00 | 21.62 | 26.24 | 31.00 | 17.00 | 21.62 | 26.24 | 31.00 |
| TopRank [Boudin et al., 2015]     | 5.60        | 17.50 | 22.12 | 26.74 | 32.00 | 17.50 | 22.12 | 26.74 | 32.00 |
| TopicalPageRank [Sterckx et al., 2015] | 5.61    | 17.50 | 22.12 | 26.74 | 32.00 | 17.50 | 22.12 | 26.74 | 32.00 |
| PositionRank [Florescu and Caragea, 2017] | 5.60    | 17.50 | 22.12 | 26.74 | 32.00 | 17.50 | 22.12 | 26.74 | 32.00 |
| MultipartiteRank [Boudin, 2018]   | 6.10        | 18.00 | 22.62 | 27.24 | 32.50 | 18.00 | 22.62 | 27.24 | 32.50 |
| BERT-KPE [Sun et al., 2021]      | 6.86        | 18.00 | 22.62 | 27.24 | 32.50 | 18.00 | 22.62 | 27.24 | 32.50 |
| CollabRank [Wan and Xiao, 2008]   | 7.17        | 18.50 | 23.12 | 27.74 | 33.00 | 18.50 | 23.12 | 27.74 | 33.00 |
| (Baymakou et al., 2017) [multi-doc] | 7.17        | 18.50 | 23.12 | 27.74 | 33.00 | 18.50 | 23.12 | 27.74 | 33.00 |

Table 4: Precision results on various KPE algorithms tested with our full 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 heuristically merged and reranked. The bottom two algorithms are multi-document based KPE algorithms, and work in Merge mode only. BERT-KPE is limited in input size and hence cannot be run in Concat mode. This table corresponds to Table 5, which presents F1 scores.

| Algorithm                          | Precision| 1 | 5 | 10 | 20 | 1 | 5 | 10 | 20 |
|-----------------------------------|----------|---|---|----|----|---|---|----|----|
| TF-IDF                            | 1.87 | 5.83 | 8.34 | 10.56 | 12.78 | 5.83 | 8.34 | 10.56 | 12.78 |
| KPMiner [El-Beltagy and Rafea, 2009] | 1.27 | 5.32 | 7.94 | 10.56 | 12.78 | 5.32 | 7.94 | 10.56 | 12.78 |
| YAKE [Campos et al., 2020]        | 4.50 | 16.26 | 20.82 | 25.40 | 30.00 | 16.26 | 20.82 | 25.40 | 30.00 |
| TextRank [Mihalcea and Tarau, 2004] | 4.75 | 16.62 | 21.28 | 26.24 | 31.00 | 16.62 | 21.28 | 26.24 | 31.00 |
| SingleRank [Wan and Xiao, 2008]   | 5.12 | 17.00 | 21.62 | 26.24 | 31.00 | 17.00 | 21.62 | 26.24 | 31.00 |
| TopRank [Boudin et al., 2015]     | 5.60 | 17.50 | 22.12 | 26.74 | 32.00 | 17.50 | 22.12 | 26.74 | 32.00 |
| TopicalPageRank [Sterckx et al., 2015] | 5.61 | 17.50 | 22.12 | 26.74 | 32.00 | 17.50 | 22.12 | 26.74 | 32.00 |
| PositionRank [Florescu and Caragea, 2017] | 5.60 | 17.50 | 22.12 | 26.74 | 32.00 | 17.50 | 22.12 | 26.74 | 32.00 |
| MultipartiteRank [Boudin, 2018]   | 6.10 | 18.00 | 22.62 | 27.24 | 32.50 | 18.00 | 22.62 | 27.24 | 32.50 |
| BERT-KPE [Sun et al., 2021]      | 6.86 | 18.00 | 22.62 | 27.24 | 32.50 | 18.00 | 22.62 | 27.24 | 32.50 |
| CollabRank [Wan and Xiao, 2008]   | 7.17 | 18.50 | 23.12 | 27.74 | 33.00 | 18.50 | 23.12 | 27.74 | 33.00 |
| (Baymakou et al., 2017) [multi-doc] | 7.17 | 18.50 | 23.12 | 27.74 | 33.00 | 18.50 | 23.12 | 27.74 | 33.00 |

Table 5: F1 results on various KPE algorithms tested with our full 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 heuristically merged and reranked. The bottom two algorithms are multi-document based KPE algorithms, and work in Merge mode only. BERT-KPE is limited in input size and hence cannot be run in Concat mode. This table corresponds to Table 4, which presents precision scores.
Table 6: The average (over all topics) number of tokens per keyphrase produced by the different algorithms, and the average (over all topics) percent of keyphrases in a topic that are “synonymous”, i.e., share substitute clusters with others, in the Trunc-20 dataset version. Results are shown for the two generation modes (Concat and Merge), on the 20 output keyphrases of each baselines.

| Algorithm      | Avg. KP Word Count | Avg. % Synon. KPs |
|----------------|--------------------|-------------------|
|                | Concat             | Merge             |
|                |                    |                   |
| Tf-Idf         | 1.30               | 2.22              | 2 | 7 |
| KPMiner        | 1.42               | 1.39              | 4 | 1 |
| YAKE           | 1.99               | 2.58              | 9 | 17 |
| TextRank       | 3.64               | 2.68              | 18 | 21 |
| SingleRank     | 3.24               | 2.57              | 22 | 23 |
| TopicRank      | 1.51               | 2.08              | 4 | 13 |
| TopicalPageRank| 3.14               | 2.52              | 27 | 26 |
| PositionRank   | 2.52               | 2.32              | 26 | 25 |
| MultipartiteRank| 1.51              | 2.12              | 5 | 14 |
| BERT-KPE       | -                  | 2.81              | - | 19 |
| CollabRank     | -                  | 2.54              | - | 23 |
| (Bayatmakou et al., 2017) | - | 3.00 | - | 0 |

Table 7: The results of various single-document KPE algorithms on the single-document DUC-2001 KPE dataset (Wan and Xiao, 2008), for reference as a comparison to algorithms’ results in the multi-document setting (Tables 2, 3, 4, 5 and 6). The average number of KPs in each document’s gold list in the dataset is 8.08, and all KPs are used in the evaluation. CollabRank is a single-document KPE algorithm that uses related documents (within the same topic) in its operation.

| Algorithm      | unigram-Precision/F1@k |
|----------------|------------------------|
|                | 1          | 5          | 10         | 20         | Avg. KP Length |
| Tf-Idf         | 14.61      | 3.45       | 11.75      | 9.28       | 9.17          |
| KPMiner        | 27.24      | 6.43       | 18.18      | 14.31      | 12.53         |
| YAKE           | 18.83      | 4.43       | 15.84      | 12.44      | 12.44         |
| TextRank       | 12.99      | 3.16       | 14.81      | 11.47      | 15.88         |
| SingleRank     | 29.55      | 7.04       | 25.72      | 20.06      | 21.33         |
| TopicRank      | 35.39      | 8.36       | 25.01      | 19.51      | 19.41         |
| TopicalPageRank| 32.14      | 7.59       | 26.89      | 20.98      | 22.26         |
| PositionRank   | 38.04      | 8.22       | 29.65      | 22.97      | 25.19         |
| BERT-KPE       | 41.56      | 9.66       | 29.55      | 23.14      | 22.66         |
| CollabRank     | 37.99      | 8.94       | 29.23      | 22.88      | 24.29         |
| #  | 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 8: 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 KPE evaluation using a flat list of gold keyphrases. The top 20 keyphrases are used in the Trunc-20 dataset version.