Unsupervised Deep Keyphrase Generation

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Abstract

Keyphrase generation aims to summarize long documents with a collection of salient phrases. Deep neural models have demonstrated a remarkable success in this task, capable of predicting keyphrases that are even absent from a document. However, such abstractiveness is acquired at the expense of a substantial amount of annotated data. In this paper, we present a novel method for keyphrase generation, AutoKeyGen, without the supervision of any human annotation. Motivated by the observation that an absent keyphrase in one document can appear in other places, in whole or in part, we first construct a phrase bank by pooling all phrases in a corpus. With this phrase bank, we then draw candidate absent keyphrases for each document through a partial matching process. To rank both types of candidates, we combine their lexical- and semantic-level similarities to the input document. Moreover, we utilize these top-ranked candidates as to train a deep generative model for more absent keyphrases. Extensive experiments demonstrate that AutoKeyGen outperforms all unsupervised baselines and can even beat strong supervised method in certain cases.

1 Introduction

Keyphrase generation aims to produce a list of short phrases to summarize and characterize a long document (e.g., research papers and news articles). It has a wide spectrum of applications, to name a few, information retrieval (Jones and Staveley, 1999), text summarization (Zhang et al., 2004), and text categorization (Hulth and Megyesi, 2006).

The trade-off between the capability of generating absent keyphrases (i.e., phrases do not appear in the original document) and the reliance on document-keyphrase supervision has long existed among keyphrase generation methods.

Extracive methods (Hasan and Ng, 2010; Shang et al., 2018; Bennani-Smires et al., 2018) can only predict phrases that appear in the original document. Nevertheless, many of them do not need any direct supervision and they demonstrate great robustness across various genres of text. Some studies expand the extraction scope from the input document to its neighbor documents (Wan and Xiao, 2008; Florescu and Caragea, 2017), but they still cannot predict absent keyphrases well. Meng et al. (2017) has shown that in scientific documents, up to 50% of keyphrases are absent from the source text, yet they can be helpful for applications such as search and recommendation (Boudin and Gallina, 2021).

With the advance of deep neural networks, recent studies (Meng et al., 2017; Chen et al., 2019; Sun et al., 2019; Alzaidy et al., 2019; Yuan et al., 2018; Meng et al., 2020) are capable of generating keyphrases, according to their semantic relevance to a document, no matter they are present or not. Although these methods have achieved state-of-the-art performance, all these deep models are supervised and typically require a tremendous number of document-keyphrase pairs, which could be expensive and laborious to collect. For example, Meng et al. (2017) utilized more than 500,000 author-annotated scientific papers to train a RNN model. Similarly, Xiong et al. (2019) collected 68,000 webpages and have them annotated by professional annotators.

In this paper, we aim to alleviate this trade-off by proposing an unsupervised method that can generate both present and absent keyphrases without utilizing any human annotations. We observe that absent keyphrases of a document can be present in other documents as present keyphrases. Also, many absent keyphrases in fact appear in the original document in part as separate tokens. For example, in the Inspec dataset, one of the benchmark datasets in keyphrase generation, 99% of absent keyphrases can be found in other documents. And for 56.8% of absent keyphrases, all their tokens separately
A method of modeling virtual worlds in databases is presented. The virtual world model is conceptually divided into two parts in databases. This paper shows the importance of management when information in planning to handle a security breach is becoming necessary, if not mandatory, for organizations to perform ongoing risk analysis to protect their systems. Organizations need to realize that the theft of information is a management issue as well as a technology one. [...] It has poor coding efficiency. In this coding technique is extremely simple, simply removing a fixed number of least significant bits from each codeword. Although this source of the PCM bitstream to be reduced by pulse code modulation (PCM) with}

**Figure 1:** An overview of our proposed AutoKeyGen framework with a part of real example. The full version of the example can be found in our case study.

Inspired by these observations, we propose a novel unsupervised deep keyphrase generation method AutoKeyGen as illustrated in Figure 1. Specifically, we first follow previous works (Hasan and Ng, 2010; Shang et al., 2018; Bennani-Smires et al., 2018) to extract candidate present keyphrases from all documents and then pool them together into a phrase bank. From this present phrase bank, we can now draw candidate absent keyphrase for each document through a partial matching process, requiring each stemmed word in the candidate phrase should exist in the input document. To rank both types of keyphrases, we fuse two popular measurements in unsupervised keyphrase extraction methods, i.e., the TF-IDF score at the lexical level and embedding similarity at the semantic level. We further utilize these top-ranked present and absent candidates as “silver” data to train a deep generative model. This generative model is expected to augment absent keyphrases by a biased beam search method, which encourages the model to predict words from the input document instead of from the vocabulary.

Extensive experiments show that AutoKeyGen outperforms all unsupervised baselines consistently, and even the strong supervised baseline in certain cases.

Our contributions are summarized as follows:

- We make two important observations about absent keyphrases, illuminating the feasibility of training abstractive keyphrase models in an unsupervised manner.
- We propose a novel unsupervised deep keyphrase generation method AutoKeyGen that can perform well on predicting both present and absent keyphrases.
- We conduct extensive experiments on five benchmark datasets and demonstrate the superiority of our method AutoKeyGen over unsupervised baselines. On some datasets, AutoKeyGen even yields better results than state-of-the-art supervised methods.

**Reproducibility.** We release our codes and datasets on GitHub.\(^1\)

### 2 Problem Formulation

In this work, we aim to build a keyphrase generation model solely based on a collection of documents \(D\), without any keyphrase annotation. Keyphrase generation is typically formulated and evaluated as a ranking problem. Given an (unseen) input document \(x\), the goal of this task is to output a ranked list of keyphrases \(Y\). We denote the input document as a sequence of tokens, i.e., \(x = [x_1, \ldots, x_{|x|}]\). Here, \(|x|\) is the total number of tokens in this document.

Depending on whether a keyphrase appears in the input document or not as a whole unit, one can categorize the keyphrases in \(Y\) into two ranked lists: (1) Present keyphrase ranked list, \(Y^P = \{y_1^P, \ldots, y_n^P\}\) and (2) Absent keyphrase ranked list: \(Y^A = \{y_1^A, \ldots, y_n^A\}\). Here, \(|Y^P|/|Y^A|\) is the number of present/absent keyphrase predictions respectively. That is, \(Y = \langle Y^P, Y^A \rangle\). Each keyphrase is also a sequence of tokens, which can contain single or multiple tokens.

\(^{1}\)https://github.com/Jayshen0/Unsupervised-Deep-Keyphrase-Generation
3 Our AutoKeyGen Method

Overview. As shown in Figure 1, the training process of AutoKeyGen consists of three steps: (1) pool the candidate present keyphrases from all documents together as a phrase bank and then draw candidate absent keyphrases for each document; (2) rank all these candidates based on TF-IDF information and embedding similarity between document and candidate phrase; (3) train a Seq2Seq generative model using the silver labels derived from the second step to generate more candidate phrases that might be absent in the document or missed in the previous steps.

When it comes to the inference for new documents, AutoKeyGen will extract candidates following the phrase bank and generate candidates using the Seq2Seq model, and then, rank these candidates together following the same ranking module as (2).

3.1 Phrase Bank for Absent Keyphrases

Phrase Bank Construction. As aforementioned, absent keyphrases in one document often appear in other documents. For example, in the Inspec dataset, one of the benchmark datasets in keyphrase generation, 99% absent keyphrases are present keyphrases in some other documents; Therefore, we first construct a phrase bank by pooling together the present candidates extracted from every document in the raw document collection $\mathcal{D}$. Specifically, we follow the literature (Hasan and Ng, 2010; Shang et al., 2018; Bennani-Smires et al., 2018) to extract candidate present keyphrases from all documents. The details can be found in the implementation details in the experiments section.

Absent Candidate Generation. In many cases, tokens of an absent keyphrase can in fact be found in the source document but not in a verbatim manner. For example, in the Inspec dataset, 56.8% absent keyphrases have all their tokens separately appeared in the input document. This inspires us to conduct a partial match as follows. Given an input document $x$, one can iterate all phrases in the phrase bank and take as candidates the phrases that all tokens appear in $x$ (after stemming). We enforce the strict requirement of all tokens as the phrase bank is huge and there would be too many candidates that can partially appear in $x$. For the sake of efficiency, we implement this process via an inverted index mapping document tokens to the phrase bank, so practically we do not have to scan the entire phrase bank for each document.

3.2 Ranking Module

The keyphrase generation aims to provide a ranked list of phrases, so we need to rank the obtained candidates. From the literature, we notice that both lexical and semantic level similarities are important and effective in keyphrase ranking. In this paper, we combine both types of similarities.

Embedding Similarity. According to Bennani-Smires et al. (2018), modern embedding methods, such as Doc2Vec (Lau and Baldwin, 2016), are able to encode phrases and documents into a shared latent space, then the semantic relatedness can be measured by the cosine similarity in this space. We follow this work and use the Doc2Vec model pretrained on the large English Wikipedia corpus to generate 300-dimension vectors for both the input document and its candidate phrases. Specifically, we denote the embedding of the document $x$ and the candidate phrase $c$ as $E(x)$ and $E(c)$, respectively. Their semantic similarity is defined as

$$\text{Semantic}(x, c) = \frac{||E(x) \cdot E(c)||}{||E(x)|| \cdot ||E(c)||}$$

TF-IDF Information. TF-IDF, measuring the lexical-level similarity, has been observed as a simple yet strong baseline in literature (Meng et al., 2017; Campos et al., 2018). Specifically, for a document $x$ in corpus $\mathcal{D}$, the TF-IDF score of phrase $c$ is computed as:

$$\text{Lexical}(x, c) = \frac{\text{TF}(c, x)}{|x|} \log \frac{|\mathcal{D}|}{\text{DF}(c, \mathcal{D})}$$

where $|x|$ is the number of word in document $x$, TF($c$, $x$) is the term frequency of $c$ in $x$, DF($c$, $\mathcal{D}$) is the document frequency of $c$ in $\mathcal{D}$.

Fused Ranking. We observe that the embedding-based similarity and TF-IDF have different behaviors when the documents are of different lengths. Semantic representation learning such as Doc2Vec is reliable for both short and relatively longer documents (Lau and Baldwin, 2016). TF-IDF works more stable when the document is sufficiently long. Therefore, it is intuitive to unify these two heuristics for present keyphrases. We propose to combine them using a geometric mean as follows.

$$\text{RankScore}(x, c) = \sqrt{\text{Semantic}(x, c) \cdot \text{Lexical}(x, c)}$$

The higher the RankScore($x$, $c$) is, the more likely the candidate phrase $c$ is a keyphrase for the document $x$. 

3.3 Generation Module

Using our phrase bank, we can cover more than 90% of present keyphrases, however, less than 30% of absent keyphrases are included. To bring more absent candidates, we train a Seq2Seq generative model using the highest scored document-keyphrase pairs from the ranking module’s results. Specifically, we pair each document with the top-5 present candidates and top-5 absent candidates, and use these pairs as silver labels for training.

**Classical Encoder-Decoder Model.** The encoder is implemented with BiLSTM (Gers and Schmidhuber, 2001) and the decoder is implemented LSTM. The encoder maps a sequence of tokens in $x$ to a sequence of continuous hidden representations $(h_{enc}^1, \ldots, h_{enc}^{|x|})$ where $|x|$ is length of the document, an RNN decoder then generates the target keyphrase $(y^1, y^2, \ldots, y^{|y|})$ token-by-token in an auto-regressive manner ($|y|$ denotes the number of tokens in the keyphrase):

$$h_{enc}^t = f_{enc}(h_{enc}^{t-1}, x^t),$$
$$c = q(h_{enc}^1, h_{enc}^2, \ldots, h_{enc}^{|x|}),$$
$$h_{dec}^t = f_{dec}(h_{dec}^{t-1}, o^{t-1}, c)$$

where $h_{enc}^t$ and $h_{dec}^t$ are hidden states at time $t$ for encoder and decoder respectively; $f_{enc}$ and $f_{dec}$ are auto-regressive functions implemented by LSTM cells; $o^{t-1}$ is the predicted output of decoder at time $t - 1$; and $c$ is the context vector derived from all the hidden states of encoder though a non-linear function $q$.

At timestep $t$, the prediction of $y^t$ is determined based on a distribution over a fixed vocabulary, conditioned on the source representations $h_{enc}$ and previously generated tokens represented as $h_{dec}^{t-1}$:

$$p_g(y^t | y^1, \ldots, y^{t-1}, x) = f_{out}(y^t, h_{dec}^{t-1}, c)$$

where $f_{out}$ is a non-linear function, typically a softmax classifier with an attention mechanism, that outputs the probabilities over all the words in a preset vocabulary $V$.

**Our Tailored Seq2Seq Generative Model.** We use guided beam search to generate diverse keyphrases for each document. Previous work (Meng et al., 2017) has shown that even when the gold labels are available, a vanilla Seq2Seq model would collapse and fail to generate high-quality candidate phrases. Since we only train the model with silver labels, to improve the generating quality, we encourage the decoder model to generate words that appear in the input document $x$. More specifically, we double the probabilities of the words which do not appear in the input document.

As shown in Meng et al. (2017), the copy mechanism is useful for generating keyword extraction because it gives high probabilities to the words that exist in the input document. This is achieved by an extra probability term.

$$p_c(y^t | y^1, \ldots, y^{t-1}, x) = \frac{1}{Z} \sum_{y_j \neq y^t} \exp(\psi(x_j)), y^t \in x$$

$$\psi(x_j) = \sigma(h_{dec}^{T} W s^t),$$

where $\sigma$ is a non-linear function, $W$ is a learned parameter matrix, and $Z$ is the sum of the scores used for normalization. For CopyRNN, the probability of generating $y^t$ is the sum of $p_g$ and $p_c$.

4 Experiments

In this section, we first introduce datasets used in this study, followed by baselines, evaluation metrics, and details of implementation. Then, we present and discuss the experiment results of present keyphrase and absent keyphrase generation.

4.1 Datasets

We follow previous keyphrase generation studies (Meng et al., 2017; Ye and Wang, 2018;
Meng et al., 2019; Chen et al., 2019) and adopt five scientific publication datasets for evaluation. KP20k is the largest dataset in scientific keyphrase studies thus far. There are four other widely-used scientific datasets for comparing different models: Inspec (Tomokiyo and Hurst, 2003), Krapivin (Krapivin et al., 2009), NUS (Nguyen and Kan, 2007), and SemEval-2010 (Kim et al., 2010). Table 1 presents the details of all datasets.

All the models in our experiments are built on the KP20k training set. Only the supervised model CopyRNN uses document-keyphrase labels and the validation set. All other methods use raw documents from the KP20k training set as input. Once the model is built, it will be applied to all the five test sets for evaluations.

### 4.2 Compared Methods

We compare AutoKeyGen with five other unsupervised methods.

- **TF-IDF** (Jones, 1972) ranks the extracted noun phrase candidates by term frequency and inverse document frequency in the given documents.
- **TextRank** (Mihalcea and Tarau, 2004) simulates the word as web page, then uses the PageRank algorithm to find the keyphrases.
- **ExpandRank** (Florescu and Caragea, 2017) is an extension of TextRank utilizing Embedding similarity to get neighbouring documents to set a better edge weight in the PageRank (Page et al., 1999) algorithm.
- **EmbedRank** (Bennani-Smires et al., 2018) directly uses embedding similarity to rank the present candidate keyphrase and uses Maximal Marginal Relevance (MMR) (Carbinell and Goldstein, 2017) to increase the diversity of extracted keyphrases.

For ablation studies, we compare some variants of our **AutoKeyGen** method as follows.

- **AutoKeyGen-OnlyBank** only uses the partial match between the phrase bank and the input document to extract keyphrase candidates without any seq2seq model.
- **AutoKeyGen-OnlyEmbed** ranks the candidate phrases with only the embedding similarity without the TF-IDF information.

We also present **Supervised-CopyRNN** (Meng et al., 2017), which trains CopyRNN on the labeled KP20K dataset to generate keyphrases. Since it is trained based on gold labels, we regard it as an upper bound of all other unsupervised methods.

### 4.3 Evaluation Metrics

Following the literature, we evaluate the model performance on generating present and absent keyphrases separately. If some models generate the two types of keyphrases in a unified ranked list, we split them into two ranked lists by checking whether or not the phrases appear in the input document. The relative ranking between the phrases of the same type is therefore preserved.

We use $R@k$, $F_1@k$, and $F_1@O$ (Yuan et al., 2018) as main evaluation metrics. Specifically, $F_1@5$, $F_1@10$, and $F_1@O$ are utilized for evaluating present keyphrases and $R@10$ and $R@20$ for absent keyphrases. We report the macro-average scores over all documents in each test set.

Specifically, given a ranked list of keyphrases, either present or absent, $\hat{Y} = (\hat{y}_1, \ldots, \hat{y}_{|Y|})$ and the corresponding groundtruth keyphrase set $Y$, we first truncate it with a cutoff $k$ (i.e., $\hat{y}_{k} = (\hat{y}_1, \ldots, \hat{y}_{\min(k,|Y|)})$) and then evaluate its preci-
Table 3: Recall scores of absent keyphrase prediction on five scientific publications datasets. ExpandRank is too slow to be evaluated on the KP20k dataset.

|                | Kp20K | Inspec | Krapivin | NUS  | SemEval |
|----------------|-------|--------|----------|------|---------|
| **Model**      | R@10  | R@20   | R@10     | R@20 | R@10    | R@20   |
| Other Unsupervised Methods | 0     | 0      | 0        | 0    | 0       | 0      |
| ExpandRank     | N/A   | N/A    | 0.02     | 0.05 | 0.01    | 0.015  |
| AutoKeyGen     | 2.3   | 2.5    | 1.7      | 2.1  | 3.3     | 5.4    |
| AutoKeyGen-OnlyBank | 1.8   | 2.2    | 1.5      | 1.7  | 3.1     | 4.1    |
| Supervised-CopyRNN | 11.5  | 14.0   | 5.1      | 6.8  | 11.6    | 14.2   |

AutoKeyGen outperforms it on many datasets with a significant margin.

One can easily see that AutoKeyGen outperforms on all the datasets than AutoKeyGen-OnlyEmbed. It shows that the TF-IDF information adds values to the embedding-based ranking heuristic. The AutoKeyGen-OnlyEmbed model performs about the same as AutoKeyGen on the Inspec dataset, because the length of document in the Inspec dataset is the shortest among all other dataset. As we discussed earlier, TF-IDF is more stable when the documents are sufficiently long.

The obvious advantage of AutoKeyGen over AutoKeyGen-OnlyBank demonstrates that our generation module does generate some “novel” present phrases beyond the scope of the extractor.

It is worth mentioning that on the Inspec dataset, AutoKeyGen is even better than the Supervised-CopyRNN method.

4.5 Present Keyphrase Evaluation

The results of present keyphrase generation are listed in Table 2. Overall, AutoKeyGen achieves the best $F_1$@5, $F_1$@10 and $F_1$@O performances among all the unsupervised methods. EmbedRank is arguably the strongest baseline method, however,

4.6 Absent Keyphrase Evaluation

Table 3 presents the model comparison on absent keyphrase generation. Following (Meng et al., 2017), only recall score is reported as comparison. Since all unsupervised baseline methods except ExpandRank are not capable of generating any absent keyphrases, we refer to them together as “Other Unsupervised Methods”. Among all unsupervised models, AutoKeyGen has the best recall on all the datasets. Therefore, we argue that AutoKeyGen unleashes the potential to derive high-quality absent keyphrases under the unsupervised setting.

Comparing AutoKeyGen with AutoKeyGen-OnlyBank, one can tell that the generation module does help improve the performance.

4.7 Case Studies

Figure 2 presents a case study from the NUS test set. Parts of this case study have been presented in the overview of AutoKeyGen, i.e., Figure 1.
This paper shows the importance that management plays in the protection of information and in the planning to handle a security breach when a theft of information happens. Recent thefts of information that have hit major companies have caused concern. These thefts were caused by companies’ inability to determine risks associated with the protection of their data and these companies lack of planning to properly manage a security breach when it occurs. It is becoming necessary, if not mandatory, for organizations to perform ongoing risk analysis to protect their systems. Organizations need to realize that the theft of information is a management issue as well as a technology one, and that these recent security breaches were mainly caused by business decisions by management and not a lack of technology.

Figure 2: A case study of AutoKeyGen from the NUS test set. Present keyphrases are marked bold in the input document. Tokens in the input document related to absent keyphrases are underlined. Correctly predicted keyphrases are highlighted in red. The green one is a correct phrase predicted by our generating module, which is omitted by noun phrase extraction method.

Figure 3: The recall of absent keyphrases using all the phrases in phrase bank on five datasets.

“Recent security breach” is extracted as a keyphrase by the conventional noun phrase extractor, but our method successfully removes the “recent” and generates the phrase candidate “security branch” which is a groundtruth present keyphrase. This is mainly benefited from our tailored extractor.

As for the absent keyphrase, our method successfully generated “information system” and “information security management” from the phrase bank. That is, these two phrases were extract from other documents. Since all their tokens appear in this document, they are added as absent candidates.

Our method can not only obtain absent keyphrases from the phrase bank, but also generate keyphrases from the tailored seq2seq generative model. In this case, “security risk”, “information management”, and “security management” are all generated by the generation module. Although some of them are not perfectly matched with absent ground truth keyphrases, they contain similar meanings. Therefore, we believe our generative model does have a potential to produce reliable absent keyphrases.

4.8 Candidate Absent Keyphrase Quality

Figure 3 presents the intersection between the phrase bank and the groundtruth absent keyphrase. It serves as an upper bound of the recall of the absent keyphrases for the extractive part of AutoKeyGen. However, such upper bounds are very loose, as the number of generated absent candidates from the phrase bank is too big. However, this does suggest that there is a great potential of the deep unsupervised keyphrase generation, if one can come up with a better ranking module for absent keyphrases.

5 Related Work

In this section, we mainly review the literature related to the following three areas, (1) keyphrase generation, (2) word and document embeddings, and (3) encoder-decoder models.

5.1 Keyphrase Generation

Most of the existing algorithms have addressed the task of keyphrase extraction through two steps (Liu et al., 2009; Tomokiyo and Hurst, 2003). The first step is to acquire a list of keyphrase candidates. Previous studies use n-grams or noun phrases with certain part-of-speech patterns to identify potential candidates (Hulth, 2003; Le et al., 2016; Wang...
et al., 2016). AutoPhrase (Shang et al., 2018) serves as another option to extract high-quality candidates, using a distant supervised phrase mining method leveraging open-domain knowledge, such as Wikipedia. The second step is to rank candidates on their importance to the document using either supervised or unsupervised approaches with manually-defined features (Kelleher and Luz, 2005; Florescu and Caragea, 2017). Florescu and Caragea (2017) tries to score the candidate phrases as the aggregation of its words score, but over-generation errors will happen. Saxena et al. (2020) transforms keyphrase extraction into classification problem using evolutionary game theory.

The major common drawback of these keyphrase extraction methods is that they can only extract keyphrases that already appear in the source text and thus they fail to predict keyphrases in a different word order or some synonymous keyphrases.

To address this issue, keyphrase generation methods have been proposed such as CopyRNN (Meng et al., 2017) and CopyCNN (Zhang et al., 2017). These methods utilize an encoder-decoder architecture, treating the title and main text body as the source information and keyphrases as the target to predict. However, those approaches ignore the leading role of the title in the document structure. To fully leverage the title information, Ye and Wang (2018) proposed a semi-supervised learning approach that generates more training pairs and Chen et al. (2019) proposed to take title features as a query to guide the decoding process. Swaminathan et al. (2020) firstly applies GAN to keyphrase extraction problem, and it presents a new promising direction for keyphrase extraction problem.

Our work is fully unsupervised, thus being significantly different from these existing generation methods that rely on human annotations.

5.2 Word and Document Embeddings

Embeddings (Mikolov et al., 2013) represents words as vectors in a continuous vector space. It’s widely used in many NLP problems, since embeddings methods take advantages over the classic bag-of-words representation considering it can capture semantic relatedness with acceptable dimensions. The state-of-the-art embeddings methods such as (Lau and Baldwin, 2016) is able to infer a vector of a document via a embedding network. In this way, the embeddings of a short phrase and a long document can be represented in a shared vector space, which make it feasible to derive their semantic relatedness directly with the embedding similarity.

5.3 Encoder-Decoder Model

The RNN-based encoder-decoder architecture was first introduced by Cho et al. (2014) and Sutskever et al. (2014) for machine translation problems. It has also achieved great successes in many other NLP tasks (Serban et al., 2016; Liu et al., 2019). Encoder-decoder model is also used for keyphrase extraction problem. Some work (Chen et al., 2020; Allamanis et al., 2016) tried to copy certain parts of source text when generating the output. See et al. (2017) enhanced this architecture with a pointer-generator network, which allows models to copy words from the source text. Celikyilmaz et al. (2018) proposed an abstractive system where multiple encoders represent the document together with a hierarchical attention mechanism for decoding.

6 Conclusions and Future Work

In this paper we propose an unsupervised deep keyphrase generation method to derive present keyphrases and absent keyphrases from the document itself. Our design is inspired by two intuitive observations. Extensive experiments demonstrate the superiority of our method against existing unsupervised models in terms of both present and absent keyphrases.

In the future, we plan to enhance the silver label quality for the deep generative model, so the absent keyphrase generation could be further improved. One possible way is to filter the candidate phrases according to the keyphrases correlations. Another promising direction is to leverage the intrinsic article structure, such as title-body relations, for a self-supervised learning.

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References

Mikiadis Allamanis, Hao Peng, and Charles Sutton. 2016. A convolutional attention network for extreme summarization of source code. CoRR, abs/1602.03001.

Rabah Alzaidy, Cornelia Caragea, and C Lee Giles. 2019. Bi-lstm-crf sequence labeling for keyphrase extraction from scholarly documents. In The world wide web conference, pages 2551–2557.

Kamil Bennani-Smires, Claudiu Musat, Andreea Hossman, Michael Baieriswyl, and Martin Jaggi. 2018. Simple unsupervised keyphrase extraction using sentence embeddings. In Proceedings of the 22nd Conference on Computational Natural Language Learning, CoNLL 2018, Brussels, Belgium, October 31 - November 1, 2018, pages 221–229. Association for Computational Linguistics.

Steven Bird, Ewan Klein, and Edward Loper. 2009. Natural language processing with Python: analyzing text with the natural language toolkit. " O’Reilly Media, Inc.”.

Florian Boudin and Ygor Gallina. 2021. Redefining absent keyphrases and their effect on retrieval effectiveness. arXiv preprint arXiv:2103.12440.

Ricardo Campos, Vítor Mangaravite, Arian Pasquali, Alípio Mário Jorge, Célia Nunes, and Adam Jatowt. 2018. A text feature based automatic keyphrase extraction method for single documents. In Advances in Information Retrieval - 40th European Conference on IR Research, ECIR 2018, Grenoble, France, March 26-29, 2018. Proceedings, volume 10772 of Lecture Notes in Computer Science, pages 684–691. Springer.

Jaime Carbinell and Jade Goldstein. 2017. The use of mmr, diversity-based reranking for reordering documents and producing summaries. SIGIR Forum, 51(2):209–210.

Asli Celikyilmaz, Antoine Bosselut, Xiaodong He, and Yejin Choi. 2018. Deep communicating agents for abstractive summarization. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1662–1675, New Orleans, Louisiana. Association for Computational Linguistics.

Wang Chen, Hou Pong Chan, Piji Li, and Irwin King. 2020. Exclusive hierarchical decoding for deep keyphrase generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020, pages 1095–1105. Association for Computational Linguistics.

Wang Chen, Yifan Gao, Jiani Zhang, Irwin King, and Michael R Lyu. 2019. Title-guided encoding for keyphrase generation. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 6268–6275.

Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1724–1734, Doha, Qatar. Association for Computational Linguistics.

John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive subgradient methods for online learning and stochastic optimization. Journal of machine learning research, 12(Jul):2121–2159.

Corina Florescu and Cornelia Caragea. 2017. Position-Rank: An unsupervised approach to keyphrase extraction from scholarly documents. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1105–1115, Vancouver, Canada. Association for Computational Linguistics.

F. A. Gers and E. Schmidhuber. 2001. Lstm recurrent networks learn simple context-free and context-sensitive languages. IEEE Transactions on Neural Networks, 12(6):1333–1340.

Kazi Saidul Hasan and Vincent Ng. 2010. Conundrums in unsupervised keyphrase extraction: making sense of the state-of-the-art. In Proceedings of the 23rd International Conference on Computational Linguistics: Posters, pages 365–373. Association for Computational Linguistics.

Anette Hulth. 2003. Improved automatic keyword extraction given more linguistic knowledge. In Proceedings of the 2003 Conference on Empirical Methods in Natural Language Processing, EMNLP ’03, page 216–223, USA. Association for Computational Linguistics.

Anette Hulth and Beáta B. Megyesi. 2006. A study on automatically extracted keywords in text categorization. In Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics, pages 537–544, Sydney, Australia. Association for Computational Linguistics.

Karen Spärck Jones. 1972. A statistical interpretation of term specificity and its application in retrieval. Journal of Documentation, 28:11–21.

Steve Jones and Mark S. Staveley. 1999. Phrasier: a system for interactive document retrieval using keyphrases. In SIGIR ’99.

Daniel Kelleher and Saturnino Luz. 2005. Automatic hypertext keyphrase detection. In Proceedings of the 19th International Joint Conference on Artificial Intelligence, IJCAI’05, page 1608–1609, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.
Su Nam Kim, Olena Medelyan, Min-Yen Kan, and Timothy Baldwin. 2010. Semeval-2010 task 5: Automatic keyphrase extraction from scientific articles. In Proceedings of the 5th International Workshop on Semantic Evaluation, pages 21–26.

Mikalai Krapivin, Aliaksandr Autaeu, and Maurizio Marchese. 2009. Large dataset for keyphrases extraction.

Jey Han Lau and Timothy Baldwin. 2016. An empirical evaluation of doc2vec with practical insights into document embedding generation. In Proceedings of the 1st Workshop on Representation Learning for NLP, Rep4NLP@ACL 2016, Berlin, Germany, August 11, 2016, pages 78–86. Association for Computational Linguistics.

Tho Thi Ngoc Le, Minh Le Nguyen, and Akira Shimazu. 2016. Unsupervised keyphrase extraction: introducing new kinds of words to keyphrases. 29th Australasian Joint Conference, Hobart, TAS, Australia, December 5-8, 2016.

Chenchen Liu, Sarah Sands-Meyer, and Jacques Audran. 2019. The effectiveness of the student response system (SRS) in English grammar learning in a flipped English as a foreign language (EFL) class. Interact. Learn. Environ., 27(8):1178–1191.

Zhiyuan Liu, Peng Li, Yabin Zheng, and Maosong Sun. 2009. Clustering to find exemplar terms for keyphrase extraction. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing, pages 257–266, Singapore. Association for Computational Linguistics.

Rui Meng, Xingdi Yuan, Tong Wang, Peter Brusilovsky, Adam Trischler, and Daqing He. 2019. Does order matter? an empirical study on generating multiple keyphrases as a sequence.

Rui Meng, Xingdi Yuan, Tong Wang, Sanqiang Zhao, Adam Trischler, and Daqing He. 2020. An empirical study on neural keyphrase generation. arXiv preprint arXiv:2009.10229.

Rui Meng, Sanqiang Zhao, Shuguang Han, Daqing He, Peter Brusilovsky, and Yu Chi. 2017. Deep keyphrase generation. Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers).

Rada Mihalcea and Paul Tarau. 2004. Textrank: Bringing order into text. In Proceedings of the 2004 conference on empirical methods in natural language processing, pages 404–411.

Tomas Mikolov, Kai Chen, Greg S. Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space.

Thuy Dung Nguyen and Min-Yen Kan. 2007. Keyphrase extraction in scientific publications. In International conference on Asian digital libraries, pages 317–326. Springer.

Lawrence Page, Sergey Brin, Rajeev Motwani, and Terry Winograd. 1999. The pagerank citation ranking: Bringing order to the web. Technical report, Stanford InfoLab.

Arnav Saxena, Mudit Mangal, and Goonjan Jain. 2020. Keygames: A game theoretic approach to automatic keyphrase extraction. In Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020, pages 2037–2048. International Committee on Computational Linguistics.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get to the point: Summarization with pointer-generator networks. Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers).

Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C. Courville, and Joelle Pineau. 2016. Building end-to-end dialogue systems using generative hierarchical neural network models. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, February 12-17, 2016, Phoenix, Arizona, USA, pages 3776–3784. AAAI Press.

Jingbo Shang, Jialu Liu, Meng Jiang, Xiang Ren, Clare R. Voss, and Jiawei Han. 2018. Automated phrase mining from massive text corpora. IEEE Transactions on Knowledge and Data Engineering, 30(10):1825–1837.

Zhiqing Sun, Jian Tang, Pan Du, Zhi-Hong Deng, and Jian-Yun Nie. 2019. Divgraphpointer: A graph pointer network for extracting diverse keyphrases. arXiv preprint arXiv:1905.07689.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. In NIPS.

Avinash Swaminathan, Haimin Zhang, Debanjan Mahata, Rakesh Gosangi, Rajiv Ratn Shah, and Amanda Stent. 2020. A preliminary exploration of gans for keyphrase generation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020, pages 8021–8030. Association for Computational Linguistics.

Takashi Tomokiyo and Matthew Hurst. 2003. A language model approach to keyphrase extraction. In Proceedings of the ACL 2003 workshop on Multiword expressions: analysis, acquisition and treatment, pages 33–40.

Xiaojun Wan and Jianguo Xiao. 2008. Single document keyphrase extraction using neighborhood knowledge. In Proceedings of the Twenty-Third AAAI Conference on Artificial Intelligence, AAAI 2008, Chicago, Illinois, USA, July 13-17, 2008, pages 855–860. AAAI Press.
Minmei Wang, Bo Zhao, and Yihua Huang. 2016. PtR: Phrase-based topical ranking for automatic keyphrase extraction in scientific publications. *ICONIP 2016*.

Lee Xiong, Chuan Hu, Chenyan Xiong, Daniel Campos, and Arnold Overwijk. 2019. Open domain web keyphrase extraction beyond language modeling. *arXiv preprint arXiv:1911.02671*.

Hai Ye and Lu Wang. 2018. Semi-supervised learning for neural keyphrase generation. In *EMNLP*, pages 4142–4153. Association for Computational Linguistics.

Xingdi Yuan, Tong Wang, Rui Meng, Khushboo Thaker, Peter Brusilovsky, Daqing He, and Adam Trischler. 2018. One size does not fit all: Generating and evaluating variable number of keyphrases.

Y. Zhang, Y. Fang, and X. Weidong. 2017. Deep keyphrase generation with a convolutional sequence to sequence model. In *2017 4th International Conference on Systems and Informatics (ICSAI)*, pages 1477–1485.

Yongzheng Zhang, Nur Zincir-Heywood, and Evangelos Milios. 2004. World wide web site summarization. *Web Intell. and Agent Sys.*, 2(1):39–53.