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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.

Extractive 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

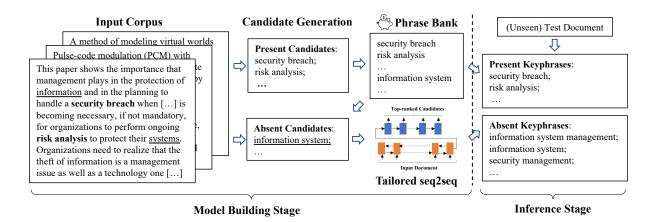


Figure 1: An overview of our proposed AutoKeyGen framework with a part of real example. The full version of the example can be found in our case study.

appear in the input document.

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 \mathcal{D} , without any keyphrase annotation. Keyphrase generation is typically formulated and evaluated as a ranking problem. Given an (unseen) input document \mathbf{x} , the goal of this task is to output a ranked list of keyprhases \mathcal{Y} . We denote the input document as a sequence of tokens, i.e., $\mathbf{x} = [x_1, \ldots, x_{|\mathbf{x}|}]$. Here, $|\mathbf{x}|$ 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 \mathcal{Y} into two ranked lists: (1) Present keyphrase ranked list, $\mathcal{Y}^P =$ $\{\mathbf{y}_1^p, \dots, \mathbf{y}_{|\mathcal{Y}^P|}^p\}$ and (2) Absent keyphrase ranked list: $\mathcal{Y}^A = \{\mathbf{y}_1^a, \dots, \mathbf{y}_{|\mathcal{Y}^A|}^a\}$. Here, $|\mathcal{Y}^P|/|\mathcal{Y}^A|$ is the number of present/absent keyphrase predictions respectively. That is, $\mathcal{Y} = \langle \mathcal{Y}^P, \mathcal{Y}^A \rangle$. Each keyphrase is also a sequence of tokens, which can contain single or multiple tokens.

Ihttps://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 $E(\mathbf{x})$ and E(c), respectively. Their semantic similarity is defined as

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

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 \mathbf{x} in corpus \mathcal{D} , the TF-IDF score of phrase c is computed as:

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

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

Fused Ranking. We observe that the embeddingbased 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.

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

The higher the RankScore(\mathbf{x}, c) is, the more likely the candidate phrase c is a keyphrase for the document \mathbf{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 $(\mathbf{h}_{enc}^1, \ldots, \mathbf{h}_{enc}^{|\mathbf{x}|})$ where $|\mathbf{x}|$ 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):

$$\begin{aligned} \mathbf{h}_{enc}^{t} &= f_{enc}(\mathbf{h}_{enc}^{t-1}, x^{t}), \\ \mathbf{c} &= q(h_{enc}^{1}, h_{enc}^{2}, ..., h_{enc}^{|\mathbf{x}|}), \\ \mathbf{h}_{dec}^{t} &= f_{dec}(\mathbf{h}_{dec}^{t-1}, o^{t-1}, \mathbf{c}) \end{aligned}$$

where \mathbf{h}_{enc}^t , and \mathbf{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 \mathbf{h}_{enc} and previously generated tokens represented as \mathbf{h}_{dec}^{t-1} :

$$p_g(y^t | y^{1,\dots,t-1}, \mathbf{x}) = f_{out}(y^{t-1}, \mathbf{h}_{dec}^t, \mathbf{c})$$

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 \mathcal{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 highquality candidate phrases. Since we only train the model with silver labels, to improve the generating

Table 1: Statistics of datasets. 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.

Dataset	Train	Valid	Test
KP20k	514,154	19,992	19,987
Inspec	-	1,500	500
Krapivin	-	1,844	460
NUS	-	-	211
SemEval	-	144	100

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 occurred in the input document. Note that, words which do not appear in the input document can still be generated so the diversity can be maintained. This also matches our observation that many absent keyprhases have all their tokens in the input document.

Relationship to Copy Mechanism. In fact, our tailored Seq2Seq model reassembles the copy mechanism proposed in (Meng et al., 2017) and can be viewed as a special version by assuming all tokens in the input documents follows a similar distribution as estimated by the encoder-decoder model.

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.

$$p_c(y^t | y^{1,\dots,t-1}, \mathbf{x}) = \frac{1}{Z} \sum_{j:x_j = y^t} exp(\psi(\mathbf{x}_j)), y^t \in \mathbf{x}$$
$$\psi(\mathbf{x}_j) = \sigma((\mathbf{h}_{dec}^j)^T W) s^t,$$

where σ 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;

Table 2: F_1 scores of present keyphrase prediction on five scientific publication datasets. ExpandRank is too slow to be evaluated on the KP20k dataset. Supervised-CopyRNN results are from its original work (Meng et al., 2017).

	Kp20K			Inspec			Krapivin			NUS			SemEval		
Model	@5	@10	$@\mathcal{O}$	@5	@10	$@\mathcal{O}$	@5	@10	$@\mathcal{O}$	@5	@10	$@\mathcal{O}$	@5	@10	$@\mathcal{O}$
TF-IDF	7.2	9.4	6.3	24.2	28.0	24.8	11.5	14.0	13.3	11.6	14.2	12.5	16.1	16.7	15.3
SingleRank	9.9	12.4	10.3	21.4	29.7	22.8	9.6	13.6	13.4	13.7	16.2	18.9	13.2	16.9	14.7
TextRank	18.1	15.1	14.1	26.3	27.9	26.0	14.8	13.9	13.0	18.7	19.5	19.9	16.8	18.3	18.1
ExpandRank	N/A	N/A	N/A	21.1	29.5	26.8	9.6	13.6	11.9	13.7	16.2	15.7	13.5	16.3	14.4
EmbedRank	15.5	15.6	15.8	29.5	34.4	32.8	13.1	13.8	13.9	10.3	13.4	14.7	10.8	14.5	13.9
AutoKeyGen	23.4	24.6	23.8	30.3	34.5	33.1	17.1	15.5	15.8	21.8	23.3	23.7	18.7	24.0	22.7
AutoKeyGen-OnlyBank	22.9	23.1	23.1	29.7	32.8	32.1	15.9	14.3	14.2	20.7	21.8	22.3	16.3	20.9	20.4
AutoKeyGen-OnlyEmbed	21.2	22.9	21.8	29.7	34.8	32.7	15.9	16.4	14.3	20.4	21.3	22.6	15.3	16.5	15.9
Supervised-CopyRNN	32.8	25.5	N/A	29.2	33.6	N/A	30.2	25.2	N/A	34.2	31.7	N/A	29.1	29.6	N/A

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 widelyused scientific datsets 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 datasets².

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 Emebedding 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, $\hat{\mathcal{Y}} = (\hat{\mathbf{y}}_1, \dots, \hat{\mathbf{y}}_{|\hat{\mathcal{Y}}|})$ and the corresponding groundtruth keyphrase set \mathcal{Y} , we first truncate it with a cutoff k (i.e., $\hat{\mathcal{Y}}_{:k} = (\hat{\mathbf{y}}_1, \dots, \hat{\mathbf{y}}_{\min(k, |\hat{\mathcal{Y}}|)}))$ and then evaluate its preci-

²Dataset release is from https://github.com/ memray/OpenNMT-kpg-release

	Kp20K		Inspec		Krapivin		NUS		SemEval	
Model	R@10	R@20	R@10	R@20	R@10	R@20	R@10	R@20	R@10	R@20
Other Unsupervised Methods ExpandRank AutoKeyGen	0 N/A 2.3	0 N/A 2.5	0 0.02 1.7	0 0.05 2.1	0 0.01 3.3	0 0.015 5.4	0 0.005 2.4	0 0.04 3.2	0 0 1.0	0 0.004 1.1
AutoKeyGen-OnlyBank	1.8	2.2	1.5	1.7	3.1	4.1	2.1	2.6	0.7	0.9
Supervised-CopyRNN	11.5	14.0	5.1	6.8	11.6	14.2	7.8	10.0	4.9	5.7

Table 3: Recall scores of absent keyphrase prediction on five scientific publications datasets. ExpandRank is too slow to be evaluated on the KP20k dataset.

sion and recall:

$$P@k = \frac{|\hat{\mathcal{Y}}_{:k} \cap \mathcal{Y}|}{|\hat{\mathcal{Y}}_{:k}|}, R@k = \frac{|\hat{\mathcal{Y}}_{:k} \cap \mathcal{Y}|}{|\mathcal{Y}|}$$

 $F_1@k$ is the harmonic mean of P@k and R@k. $F_1@O$ can be viewed as a special case of $F_1@k$ when $k = |\mathcal{Y}|$. In other words, we only examine the same amount of keyphrases as the number of our groundtruth keyphrases.

We apply Porter Stemmer provided by NLTK (Bird et al., 2009) to both ground-truth and predicted keyphrases to determine whether phrases appear in the original document and whether two keyphrases match or not.

4.4 Implementation Details

For all the methods that involve keyphrase extraction, we utilize the open-source toolkit pke³ for phrase candidate generation. The window size of the graph-based models SingleRank, TextRank and ExpandRank has been searched from 2 to 10, and again, the best performance is selected.

The vocabulary \mathcal{V} in the seq2seq model consists of 50,000 most frequent words. We train the model for 500,000 steps and select the last checkpoint for inference. The dimension of LSTM cell is 256, the embedding dimension is 200, and the max length of source text is 512. Models are optimized using Adagrad (Duchi et al., 2011) with initial learning rate sets to 0.001, and will be linearly decayed by 0.8 after every 5 epochs. The beam size for keyphrase generating beam search is 20.

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 $F_1@\mathcal{O}$ performances among all the unsupervised methods. EmbedRank is arguably the strongest baseline method, however,

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.

4.6 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.

³https://github.com/boudinfl/pke

This paper shows the importance that management plays in the protection of information and in the planning to handle a Input Document 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. Present Ground Truth: {security breach, risk analysis, management issue, theft of information} AutoKeyGen (ordered): security breach, risk analysis, information, security, business decisions, management issue Ground Truth: {Information security, information system, case of information theft, information security management, Absent human factor, data protection procedure, security management} AutoKeyGen (ordered): security risk, information system, information management, information security management, import concern, data mine, security management, data management

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.

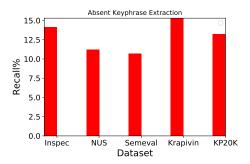


Figure 3: The recall of absent keyphrases using all the phrases in phrase bank on five datasets.

"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 bankd 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 Kerphrase 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 overgeneration erros 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

Embddings (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-ofwords 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 pointergenerator 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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