Keyphrase Generation with Cross-Document Attention

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Abstract

Keyphrase generation aims to produce a set of phrases summarizing the essentials of a given document. Conventional methods normally apply an encoder-decoder architecture to generate the output keyphrases for an input document, where they are designed to focus on each current document so they inevitably omit crucial corpus-level information carried by other similar documents, i.e., the cross-document dependency and latent topics. In this paper, we propose CDKGEN, a Transformer-based keyphrase generator, which expands the Transformer to global attention with cross-document attention networks to incorporate available documents as references so as to generate better keyphrases with the guidance of topic information. On top of the proposed Transformer + cross-document attention architecture, we also adopt a copy mechanism to enhance our model via selecting appropriate words from documents to deal with out-of-vocabulary words in keyphrases. Experiment results on five benchmark datasets illustrate the validity and effectiveness of our model, which achieves the state-of-the-art performance on all datasets. Further analyses confirm that the proposed model is able to generate keyphrases consistent with references while keeping sufficient diversity. The code of CDKGEN is available at https://github.com/SVAIGBA/CDKGen.

1 Introduction

Keyphrases summarize the essential ideas of a document with short and informative text pieces, which are beneficial to many downstream tasks such as text summarization (Liu et al., 2009; Qazvinian et al., 2010), sentiment analysis (Wilson et al., 2005), document categorization (Hammouda et al., 2005; Hulth and Megyesi, 2006), opinion mining (Berend, 2011), and so on. Existing methods on keyphrase generation can be categorized into two types: extractive (Yang et al., 2017; Zhang et al., 2018; Sun et al., 2019) and generative methods (Meng et al., 2017; Chen et al., 2018; Yuan et al., 2018; Ye and Wang, 2018; Chan et al., 2019; Chen et al., 2019b,a). Compared to extractive methods, generative ones are more challenging since they need to produce, rather than extract, some phrases from the input document, where in most cases those phrases are absent.

Existing generative models for keyphrase generation1 mainly follow the encoder-decoder paradigm. Meng et al. (2017) firstly adopted the sequence-to-sequence (seq2seq) model for this task and many studies followed this methodology and utilized extra information (Chen et al., 2018; Ye and Wang, 2018; Chen et al., 2019a,b). However, these studies are limited in generating a fixed number of keyphrases. To alleviate this limitation, Yuan et al. (2018); Chan et al. (2019) employed a new training setup by joining all keyphrases to a delimiter-separated sequence and letting the seq2seq model decide the length of the output sequence so that it is able to produce a variable number of keyphrases for different documents. Although the aforementioned studies illustrate their effectiveness in keyphrase generation, they are expected to be enhanced in many aspects. First, in addition to the seq2seq architecture, one could use Transformer-based encoder-decoder for keyphrase generation because it has been proven useful in many similar tasks (Vaswani et al., 2017; Keskar et al., 2019; Khandelwal et al., 2019; Hoang et al., 2019; Liu and Lapata, 2019). Second, appropriately extracting and learning from external knowledge other than only the input document could provide essential help to keyphrase generation. Some

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1For simplicity, in the following paper, we use ‘keyphrase generation’ to refer to generative methods for this task, in contrast to extractive methods or keyphrase extraction.
studies proved the idea by learning extra information from titles (Chen et al., 2019b), correlations among keyphrases (Chen et al., 2018) and other keyphrases from similar documents (Chen et al., 2019a). However, there is still huge room for improvement, even with this method. This is specially true for the scenarios where there are no titles or reference keyphrases provided. In addition, the self-attention mechanism of existing Transformer architecture is at the token-level for the current document, which is not effective for cross-document dependency. Recent studies find it beneficial to incorporate knowledge by using different level of attention mechanism, such as multi-scale attention (Guo et al., 2019), n-gram attention (Diao et al., 2019), knowledge attention (Zhang et al., 2019a,b) and so on. Therefore, we propose to expand the Transformer to the corpus-level attention.

To address the above aspects for enhancing keyphrase generation, we propose CDKGEN, a Transformer-based keyphrase generator with cross-document attention, where the Transformer serves as the encoder and decoder, and the cross-document attention leverages the latent topics from relevant documents so as to help the decoder generate better keyphrases. As a result, our model is able to predict topic-dependent keyphrases, especially absent ones, resembling the way that humans might give keyphrases around the same topic. On top of the Transformer + cross-document attention design, we apply the copy mechanism (See et al., 2017) to provide the ability to generate out-of-vocabulary (OOV) ² words by directly selecting words from the input document. To generate a variable number of keyphrases for different documents via an end-to-end manner, we follow Yuan et al. (2018); Chan et al. (2019) to join all keyphrases into a sequence for training CDKGEN and its baselines.

Experimental results illustrate that CDKGEN outperforms all baselines on five benchmark datasets, where the state-of-the-art performance is observed on all datasets compared to previous studies. Particularly, CDKGEN performs well on both present and absent keyphrase prediction, where the comparisons among its different baselines reveal

²OOV herein refers to words which do not appear in the keyphrases in the training data.
the capability of cross-document attention and copy mechanism, respectively. Moreover, further analyses demonstrate that CDKGEN offers an effective solution to keyphrase generation with satisfactory keyphrase number and generation diversity.

2 The Approach

Our approach, CDKGEN, follows the encoder-decoder paradigm, where Transformer is used as the backbone model for encoding and decoding. In addition, we adopt cross-document attention networks in our approach to incorporate the latent topic information from relevant documents and interact with the Transformer. A copy mechanism is applied to enhance the results to tackle the out-of-vocabulary (OOV) problem. The entire architecture of CDKGEN is illustrated in Figure 1. Formally, the overall keyphrase generation process can be described as

\[ Y = CDKGEN(d, M(d, D)) \]

where \( d = w_1w_2...w_i...w_n \) is the input document with \( w_i \) indicating its words and \( Y = kp_1kp_2...kp_j...kp_m \) the output sequence that concatenates all keyphrases \( kp_j \). \( M \) refers to the cross-document attention networks that produce latent topic embedding for CDKGEN from a collection of documents \( D \) according to \( d \). The keyphrase generation is then enhanced with the latent topics provided in \( D \). Details of the cross-document attention networks and how we integrate it with the Transformer as well as the copy mechanism applied are described in the following subsections.

2.1 Cross-Document Attention

Given the input document \( d \), relevant documents usually share similar topics, which are good references to help determine what could be the optimal keyphrases to describe \( d \). For example, for a document about ‘Travel Consultation System’, the keyphrase ‘Information Retrieval’ may be absent in the given document but appear in other relevant documents, which could provide explicit information for keyphrase generation in this scenario.

To represent and exploit the latent topics from relevant documents, we firstly aggregate all documents from a collection (i.e., the union of both training and test set) to the set \( D = \{ d_1, d_2, ..., d_k, ..., d_l \} \), and use two vector sets to represent them, i.e., key vectors \( U = \{ u_1, u_2, ..., u_k, ..., u_l \} \), and value vectors \( V = \{ v_1, v_2, ..., v_k, ..., v_l \} \) with \( u_k \) and \( v_k \) corresponding to \( d_k \). Specifically, \( u_k \) is used to compute similarity with the input document while \( v_k \) carries \( d_k \)’s encoding information for generating the final output, which acts as the latent topic embedding. Then for each input document \( d \), we represent it through its sentential encoding \( e \) and use it as the ‘query’ vector to address relevant documents. In detail, the addressing operation can be formalized as

\[ p_k = \frac{\exp(e^\top \cdot u_k)}{\sum_{k=1}^{l} \exp(e^\top \cdot u_k)}, \]

and for the entire document set \( D \), we have

\[ o = \sum_{k=1}^{l} p_k v_k, \]

where \( o \) is the output vector of the cross-document attention to represent the latent topics from relevant documents via a weighted encoding.

2.2 Integrating Cross-Document Attention with Transformer

Although RNN based sequence-to-sequence models are widely used for keyphrase generation task, we use Transformer (Vaswani et al., 2017) as the backbone encoder-decoder framework in this paper. This has been proved to have a more effective performance than sequence-to-sequence models in many generation tasks (Vaswani et al., 2017; Keskar et al., 2019; Khandelwal et al., 2019; Hoang et al., 2019; Liu and Lapata, 2019). Once the latent topic embedding \( o \) is obtained, we combine it with the Transformer encoding-decoding process via the following steps.

First, the input document is passed through the Transformer encoder which results in a hidden state \( h_i \) for each input token \( w_i \). Then we combine \( h_i \) and \( o \) via element-wise addition \( \tilde{h}_i = h_i + o \) and send it to the decoding process through each multi-head attention layer to calculate the attention vector \( \alpha^t = \alpha^t_1 \alpha^t_2 ... \alpha^t_n \) at each decoding step \( t \). Next, \( \alpha^t \) is used to produce the context vector \( c^t \), a weighted sum of the encoding hidden states:

\[ c^t = \sum_{i=1}^{n} \alpha^t_i \tilde{h}_i. \]
where \( \sigma \) with a pointer-generator design (See et al., 2017) providing word candidates for keyphrase generation. In detail, at time step \( t \), the generation probability \( p \) is calculated by the context vector \( c^t \), the decoder output \( s^t \), and the last \((t-1)\) step prediction \( y^{t-1} \):

\[
p = \sigma(W_c c^t + W_s s^t + W_y y^{t-1}),
\]

where \( \sigma \) is the sigmoid function and \( W_c, W_s, W_y \) are trainable parameters in the sigmoid module.

Therefore, the final prediction of the entire CD-KGEN model at time step \( t \) is obtained by:

\[
y^t = \arg\max(p d_v + (1 - p) d_c),
\]

where \( d_v \) is the copy distribution (a vector with \( |V'| \) dimension) with its each element calculated by \( \sum_{\gamma: w_\gamma = w} \gamma_i \forall: 1 \leq \gamma \leq |V'| \). This provides guidance to indicate important words (to be part of keyphrases) in the input document. Note that, to align with \( d_v \), zero padding is conducted at the end of \( d_v \) to form a \( |V'|\)-dimension vector. Therefore in Eq. (7), \( p \) serves as a soft switcher to decide the preference of choosing a word from the predefined vocabulary by \( d_v \) or copy a word from input document by \( d_c \).

### 3.1 Datasets

We conduct our experiments on five benchmark datasets, which are mainly from computer science domain and described as follows.

- **INSPEC** (Hulth, 2003), which contains 2,000 journal paper abstracts with corresponding keyphrases assigned by professional indexers.
- **NUS** (Nguyen and Kan, 2007), a scientific dataset consisting of 211 full papers with their keyphrases annotated by student volunteers.
- **KRAPIVIN** (Krapivin et al., 2009), consisting of 2,304 full papers from association for computing machinery (ACM) with keyphrases provided by their authors and verified by reviewers.
- **SEMEVAL** (Kim et al., 2010), which provides 244 full papers with corresponding keyphrases collected from ACM Digital Library.
- **KP20K** (Meng et al., 2017), which contains around 568K paper abstracts collected from several online resources including ACM Digital Library, ScienceDirect, Wiley, Web of Science, etc.

\(^3\)Such vocabulary is a combination of the predefined vocabulary and words from the current input document, which ensures the model to choose from more word candidates.
The following models are used as the main base-lines in our experiments:

- **Transformer**: this is the baseline that we use as our backbone encoder-decoder only, that is, a four-layer Transformer model with 8 heads and 768 hidden units without other extensions.
- **Trans+Copy**: the Transformer model with the same architecture of the previous one and equipped with the copy mechanism, to test how it performs with consideration of OOV words.
- **Trans+CD**: the same Transformer model with cross-document attention to test how it helps in relevant documents for this task.

To further demonstrate the effectiveness of our model, we compare it with existing models from previous studies, including **CopyRNN** (Meng et al., 2017), **CorrRNN** (Chen et al., 2018), **KB-KE-KR-M** (Chen et al., 2019a), **MultiTask** (Ye and Wang, 2018), **TG-Net** (Chen et al., 2019b) with their reported results on the benchmark datasets, as well as the performance of **CatSeq** and **CatSeqD** from Yuan et al. (2018) and Chan et al. (2019), **CatSeqCorr** and **CatSeqTG** from Chan et al. (2019). In addition, we also compare with the reinforcement learning implementation (Chan et al., 2019) of the aforementioned **CatSeq** models.

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### 3.3 Evaluation Metrics

Following Meng et al. (2017) and Yuan et al. (2018), we adopt macro-averaged precision, recall and F-measure ($F_1$) as evaluation metrics by comparing the top $k$ predicted keyphrases with the ground-truth keyphrases. In our experiments, $k$ is set to be 5, 10, M and O, where M and O are variable cutoffs which are equal to the number of predictions and ground-truth keyphrases, respectively. Similar to previous work (Meng et al., 2017;
Yuan et al., 2018; Chen et al., 2018, 2019b), we apply Porter Stemmer\(^3\) to obtain word stems for keyphrases to facilitate evaluation.

### 3.4 Implementation

We implement a Transformer structure similar to Vaswani et al. (2017), with 4 layers and 8 self-attention heads, 768 dimensions for hidden states, 768 for maximum input length, and random initialization. For cross-document attention, we utilize sentence-transformer (Reimers and Gurevych, 2019) to initialize key vectors \(u_k\) and value vectors \(v_k\) in order to guarantee reliable addressing as a warm start for those vectors and they are updated during the training process. Different from \(u_k\) and \(v_k\), the sentential encoding \(e\) of each input document \(d\) is represented as the average of its word representations which are randomly initialized to ensure their compatibility with the backbone Transformer’s vector space during training. In the training stage, we choose the top 50,000 frequent words to form the predefined vocabulary and set the embedding dimension to 768. We adopt Adam as the optimizer with a learning rate of 0.0001 and a dropout rate of 0.5. We use beam search to generate multiple phrases and set beam size to 50 and maximum sequence length to 40.

### 4 Experimental Results

In this section, we compare our model with baselines and existing studies on the experimental datasets. The performance comparison for present and absent keyphrase prediction, as well as with existing studies, are presented in the following three subsections, respectively.

#### 4.1 Present Keyphrase Prediction

The results on present keyphrase prediction are reported in Tables 2 and 3, with several observations.

First, CDKGEN achieves the best performance over all baselines, which indicates the advantage of incorporating cross-document attention and copy mechanism into the Transformer. For example, in both fixed and variable cut-off settings, CDKGEN outperforms TRANSFORMER with significant improvements. Second, comparisons between TRANSFORMER and TRANS+COPY, as well as TRANS+CD and CDKGEN, confirm the effectiveness of the copy mechanism, similar to that observed in Meng et al. (2017); Yuan et al. (2018); Chen et al. (2018, 2019b), where TRANS+COPY and CDKGEN show a consistent improvement over TRANSFORMER and TRANS+CD, respectively. Since generating present keyphrases mainly requires a model having stronger ‘extraction’ abilities, a copy mechanism thus provides an effective solution to fulfilling this requirement especially for those present keyphrases with their words which also appear in the input document. When comparing TRANS+COPY vs. TRANSFORMER, and CDKGEN vs. TRANS+CD, it is observed that the performance gains from copy mechanism on INSPEC and KP20k are larger than that of the other three datasets. This is because there are fewer present keyphrases in NUS, KRAPIVIN and SEMEVAL, so as their contained words; copy mechanism is not able to copy appropriate words to the output.

Third, the cross-document attention is proved

| Model          | INSPEC | NUS | KRAPIVIN | SEMEVAL | KP20k |
|----------------|--------|-----|----------|----------|-------|
|                | \(F_1\@M\) | \(F_1\@O\) | \(F_1\@M\) | \(F_1\@O\) | \(F_1\@M\) | \(F_1\@O\) | \(F_1\@M\) | \(F_1\@O\) | \(F_1\@M\) | \(F_1\@O\) |
| CATSEQ         | 0.262  | 0.307 | 0.397    | 0.383    | 0.354  | 0.324  | 0.283  | 0.310  | 0.367  | 0.319  |
| CATSEQ-RL      | 0.300  | -     | 0.426    | -        | 0.362  | -     | 0.327  | -     | 0.383  | -     |
| CATSEQD        | 0.263  | 0.331 | 0.394    | 0.406    | 0.349  | 0.371  | 0.274  | 0.357  | 0.363  | 0.357  |
| CATSEQD-RL     | 0.292  | -     | 0.419    | -        | 0.360  | -     | 0.316  | -     | -      | -      |
| CATSEQCORR     | 0.269  | -     | 0.390    | -        | 0.349  | -     | 0.290  | -     | 0.365  | -      |
| CATSEQCORR-RL  | 0.291  | -     | 0.414    | -        | 0.369  | -     | 0.322  | -     | 0.382  | -      |
| CATSEQTG       | 0.270  | -     | 0.393    | -        | 0.366  | -     | 0.290  | -     | 0.366  | -      |
| CATSEQTG-RL    | 0.301  | -     | 0.433    | -        | 0.369  | -     | 0.329  | -     | 0.386  | -      |
| TRANSFORMER    | 0.256  | 0.247 | 0.369    | 0.371    | 0.357  | 0.318  | 0.277  | 0.329  | 0.334  | 0.287  |
| TRANS+COPY     | 0.282  | 0.279 | 0.402    | 0.385    | 0.359  | 0.331  | 0.299  | 0.327  | 0.377  | 0.322  |
| TRANS+CD       | 0.279  | 0.301 | 0.411    | 0.409    | 0.361  | 0.352  | 0.311  | 0.338  | 0.385  | 0.337  |
| CDKGEN         | 0.305  | 0.334 | 0.435    | 0.412    | 0.372  | 0.375  | 0.329  | 0.359  | 0.398  | 0.361  |

Table 3: Present keyphrase prediction results on five benchmark datasets from previous studies and our models. \(F_1\) scores on the top M and O keyphrases are reported, where M and O are variable cut-offs, which are equal to the number of predictions and ground-truth keyphrases, respectively. Note that we do not include COPYRNN, CORRNN, KG-KE-KR-M, MULTI-TASK and TG-NET in the table since they did not conduct this evaluation.

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\(^3\)https://www.nltk.org/_modules/nltk/stem/porter.html
The ability to generate absent keyphrases is the biggest improvement. The underlying reason is that the cross-document attention helps with their support. Second, removing the copy mechanism generally does not hurt the performance. The reason is rather straightforward because the copy mechanism is only able to choose present words in the input document while those words may not be included in absent keyphrases. Third, similar to the present keyphrase generation, cross-document attention provides significant improvement for absent keyphrases. It is a direct evidence that relevant documents help the decoding process choose appropriate words to form keyphrases that do not directly correspond to the current document. These results further demonstrate the generalization capability of CDKG.

| Model          | INSPEC@10 | INSPEC@50 | NUS@10 | NUS@50 | KRAPIVIN@10 | KRAPIVIN@50 | SEMEVAL@10 | SEMEVAL@50 | KP20K@10 | KP20K@50 |
|----------------|-----------|-----------|--------|--------|--------------|--------------|------------|------------|----------|----------|
| COPYRNN        | 0.051     | 0.101     | 0.078  | 0.144  | 0.116        | 0.195        | 0.049      | 0.075      | 0.115    | 0.189    |
| CORRNN         | -         | -         | 0.059  | -      | 0.108        | -            | 0.041      | -          | -        | -        |
| CATSEQ         | 0.028     | 0.029     | 0.037  | 0.031  | 0.070        | 0.074        | 0.025      | 0.025      | 0.060    | 0.062    |
| CATSEQD        | 0.052     | 0.071     | 0.084  | 0.110  | 0.120        | 0.145        | 0.046      | 0.063      | 0.117    | 0.151    |
| MULTI-TASK     | 0.022     | 0.013     | 0.015  | -      | 0.021        | 0.006        | 0.006      | -          | 0.021    | -        |
| TG-NET         | 0.063     | 0.115     | 0.075  | 0.137  | 0.146        | 0.253        | 0.045      | 0.076      | 0.156    | 0.268    |
| TRANSFORMER    | 0.044     | 0.098     | 0.067  | 0.132  | 0.077        | 0.189        | 0.044      | 0.055      | 0.109    | 0.155    |
| TRANS+COPY     | 0.053     | 0.106     | 0.081  | 0.147  | 0.082        | 0.193        | 0.051      | 0.079      | 0.121    | 0.178    |
| TRANS+CD       | 0.067     | 0.108     | 0.083  | 0.152  | 0.119        | 0.199        | 0.052      | 0.081      | 0.133    | 0.211    |
| CDKG           | 0.068     | 0.117     | 0.087  | 0.155  | 0.151        | 0.257        | 0.056      | 0.088      | 0.166    | 0.273    |

Table 4: Absent keyphrase prediction results on five benchmark datasets from previous studies and our models. Recall on the top 10 and 50 generated keyphrases are reported.

4.3 Comparison with Existing Studies

We also compare CDKG and its baselines with existing models on the same datasets, with their results reported at the upper parts of Tables 2 ~ 5. There are several comparisons drawn from different aspects. First, Transformer confirms its superiority to sequence-to-sequence structures in this task. The comparison between TRANS+COPY and COPY-RNN clearly illustrates that the encoding-decoding process implemented by Transformer has better results on both the present and absent keyphrases. This is aligned with the observations in other studies also using Transformer (Vaswani et al., 2017; Keskar et al., 2019; Khandelwal et al., 2019; Hoang et al., 2019; Liu and Lapata, 2019). Second, it is proved that directly using cross-document at-
We analyze several aspects of CDKG and its baselines regarding their generation results. The details are illustrated in this section.

## 5 Analyses

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### 5.1 Number of Generated Keyphrase

In addition to the performance evaluation by $F_1$ or recall scores, an important criterion for generative models is to investigate how many keyphrases are generated, especially when one uses keyphrase sequence as the decoding target. In doing so, we follow Chan et al. (2019) to use mean absolute error (MAE) to calculate the difference between the prediction and ground-truth (oracle) keyphrase numbers, where a lower MAE refers to better generation performance. We also list the average number of generated keyphrases to evaluate how close such a number is with respect to the oracle one. The results from different models on the KP20k validation set are shown in Table 6. In general, CDKG has the lowest MAE on both present and absent keyphrases, where it outperforms all base-

| **Table 5:** Absent keyphrase prediction results on five benchmark datasets from previous studies and our models. $F_1$ scores on the top 5 and M keyphrases are reported, where M is a variable cut-off equal to the number of predictions. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| **Model**       | **INSPEC**      | **NUS**         | **KRAPIVIN**    | **SEM_EVAL**    | **KP20k**       |
|                 | $F_1@5$  | $F_1@M$ | $F_1@5$  | $F_1@M$ | $F_1@5$  | $F_1@M$ | $F_1@5$  | $F_1@M$ |
| catseq          | 0.004  | 0.008  | 0.016  | 0.028  | 0.018  | 0.036  | 0.020  | 0.028  | 0.015  | 0.032  |
| catseq-rl       | 0.009  | 0.017  | 0.019  | 0.031  | 0.018  | 0.046  | 0.018  | 0.027  | 0.024  | 0.047  |
| catseq          | 0.007  | 0.011  | 0.014  | 0.024  | 0.018  | 0.037  | 0.016  | 0.024  | 0.015  | 0.031  |
| catseq-d-rl     | 0.010  | 0.021  | 0.022  | 0.037  | 0.026  | 0.048  | 0.021  | 0.030  | 0.023  | 0.046  |
| catseq-cor      | 0.005  | 0.009  | 0.014  | 0.024  | 0.020  | 0.038  | 0.018  | 0.026  | 0.015  | 0.032  |
| catseq-cor-r-rl | 0.010  | 0.020  | 0.022  | 0.037  | 0.022  | 0.040  | 0.021  | 0.031  | 0.022  | 0.045  |
| catseq-tg       | 0.005  | 0.011  | 0.011  | 0.018  | 0.018  | 0.034  | 0.019  | 0.027  | 0.015  | 0.032  |
| catseq-tg-rl    | 0.012  | 0.021  | 0.019  | 0.031  | 0.030  | 0.053  | 0.021  | 0.030  | 0.027  | 0.050  |
| transformer     | 0.002  | 0.007  | 0.018  | 0.022  | 0.019  | 0.033  | 0.021  | 0.021  | 0.011  | 0.035  |
| trans+copy      | 0.005  | 0.010  | 0.019  | 0.029  | 0.022  | 0.037  | 0.022  | 0.025  | 0.018  | 0.037  |
| trans+cd        | 0.007  | 0.015  | 0.024  | 0.037  | 0.023  | 0.039  | 0.022  | 0.030  | 0.021  | 0.044  |
| CDKG EN          | **0.015** | **0.022** | **0.024** | **0.038** | **0.033** | **0.057** | **0.024** | **0.033** | **0.031** | **0.052** |

| **Model** | **PRESENT** | **ABSENT** |
|-----------|-------------|------------|
|           | **MAE** | **Avg.#** | **MAE** | **Avg.#** |
| oracle    | 0.000  | 2.837  | 0.000  | 2.432  |
| catseq    | 2.271  | 3.781  | 1.943  | 0.659  |
| catseq-rl | 2.225  | 3.694  | 1.961  | 0.629  |
| catseq-d-rl | 2.292  | 3.790  | 1.914  | 0.703  |
| catseq-tg | 2.276  | 3.780  | 1.956  | 0.638  |
| catseq-cor | 2.118  | 3.733  | 1.494  | 1.574  |
| catseq-cor-rl | 2.087  | 3.666  | 1.541  | 1.455  |
| catseq-tg-rl | 2.107  | 3.696  | 1.557  | 1.409  |
| transformer | 2.204  | 3.865  | 1.961  | 0.629  |
| trans+copy | 2.477  | 3.766  | 1.798  | 1.125  |
| trans+cd   | 2.335  | 3.696  | 1.667  | 1.247  |
| CDKG EN     | **2.004** | **3.655** | **1.411** | **1.797** |

Table 6: Evaluations of predicting the correct number of keyphrases on the KP20k validation set. MAE denotes the mean absolute error and Avg. # the average number of generated keyphrases. For both MAE and Avg. #, the closer a model is to ORACLE the better it performs.
| Model         | INS | NUS | KR  | SE   | KP  |
|--------------|-----|-----|-----|------|-----|
| TRANSFORMER  | 10.11 | 12.10 | 12.44 | 14.33 | 10.10 |
| TRANS+COPY   | 12.49 | 13.11 | 13.40 | 15.22 | 12.33 |
| TRANS+CD     | 25.82 | 26.75 | 22.88 | 26.71 | 19.22 |
| CDKGEN       | 32.74 | 33.48 | 26.48 | 29.09 | 23.94 |

Table 7: The average unique predictions from different models on all datasets. INS, KR, SE and KP denote INSPEC, KRAPIVIN, SEMEVAL and KP20K, respectively.

line models as well as the previous best models (i.e. CATSEQD-RL and CATSEQTG-RL). As for the average number, CDKGEN also shows the closest number to the oracle one, especially on absent keyphrases where models with cross-document attention show significantly better results and are comparative to the reinforcement learning methods, which are designed particularly to encourage the model to generate the correct number of diversified keyphrases. Compared to such methods, our model is much more efficient without requiring a complex training procedure.

5.2 Generation Diversity

Another important criterion to evaluate generative models is the diversity of generated keyphrases. To assess with respect to such criterion, we follow Yuan et al. (2018) to calculate the average unique predictions and visualize the decoding states from different models on all experimental datasets.

The results of the average unique predictions are reported in Table 7. In general cross-document attention helps to generate more diversified keyphrases so that TRANS+CD has more unique predictions than TRANSFORMER and TRANS+COPY, which is not surprising because cross-document attention enlarges the reference by relevant documents. Of all models, CDKGEN has the most unique predictions, which is a further diversified decoding process via combining cross-document attention and copy mechanism.

The visualization for CDKGEN and its baseline models are presented in Figure 2. Following Yuan et al. (2018), we randomly sample 2,000 input documents in the KP20k validation set and run different models on them. We then use t-SNE (Maaten and Hinton, 2008) to produce the 2D plots of the decoding states (vectors) from the last layer of the decoder at the first, second and third steps. It is clearly shown that the states from TRANS+CD and CDKGEN tends to be clustered into several groups while there is no obvious cluster for that from TRANSFORMER and TRANS+COPY. This suggests that cross-document attention provides useful information to diversify the decoding process so as to generate different keyphrases.

5.3 Case Study

To further analyze how keyphrases are generated, we perform a case study on an example document about ‘travel consultation system’. Figure 3 shows the input document, the most relevant documents (according to $p_k$ from the cross-document attention), target the present and absent keyphrases for the input document and the predictions from different models. It is observed that the relevant documents contain the target keyphrases (i.e. ‘language processing’ and ‘information retrieval’) which are highly related to the topic. Models with cross-document attention are able to generate them and others cannot. For present keyphrases, CDKGEN can generate more targets than others, which shows its ability to capture the right keyphrases on the same topic (i.e. information processing) with the help of cross-document attention. Specifically, for TRANSFORMER and TRANS+COPY, their predictions on both present and absent keyphrases are not satisfactory. This illustrates that only using Transformer and the input document is not enough for effective keyphrase generation.
6 Related Work

Keyphrase generation mainly consists of two methodology streams, extractive and generative approaches. There is a large body of research focusing on extracting keyphrases from documents (Hulth, 2003; Mihalcea and Tarau, 2004; Witten et al., 2005; Wu et al., 2005; Nguyen and Kan, 2007; Medelyan et al., 2008, 2009; Wan and Xiao, 2008; Grineva et al., 2009; Liu et al., 2011; Wang et al., 2016; Le et al., 2016; Zhang et al., 2016; Luan et al., 2017). Compared to extractive approaches, generative ones have attracted more attention in recent years for their ability to predict absent keyphrases for an input document. For example, Meng et al. (2017) proposed CopyRNN, which is an early study with attention and copy mechanism. Chen et al. (2018) took correlation among multiple keyphrases into consideration to eliminate duplicate keyphrases. To further enhance keyphrase generation, other studies tried to utilize extra information: Ye and Wang (2018) proposed to assign synthetic keyphrases to unlabeled documents and then use them to enlarge the training data; Chen et al. (2019a) retrieved similar documents from the training data for the input document and encoded their keyphrases as external knowledge, while Chen et al. (2019b) leveraged title information for this task. To increase the diversity of keyphrases, a reinforcement learning approach is introduced by Chan et al. (2019) to encourage their model to generate the correct number of keyphrases with an adaptive reward. Although existing models are capable of predicting both present and absent keyphrases, there is still potential to facilitate keyphrase generation with unlabeled data such as relevant documents. In doing so, CDKGEN offers a more effective and efficient solution.

7 Conclusion

In this paper, we proposed CDKGEN, a keyphrase generator based on the Transformer with cross-document attention and the copy mechanism, and compared it to several baselines on different benchmark datasets. The main contributions are as follows. First, we proposed cross-document attention to learn from relevant documents to enhance keyphrase generation. Second, we designed CDKGEN to integrate the proposed cross-document attention with the Transformer and the copy mechanism. CDKGEN achieved the state-of-the-art performance on five widely used benchmark datasets, which demonstrates its strong capability to generate highly accurate and diversified keyphrases.
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