One Size Does Not Fit All: Generating and Evaluating Variable Number of Keyphrases

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Abstract

Different texts shall by nature correspond to different number of keyphrases. This desideratum is largely missing from existing neural keyphrase generation models. In this study, we address this problem from both modeling and evaluation perspectives.

We first propose a recurrent-generative model that generates multiple keyphrases as delimiter-separated sequences. Generation diversity is further enhanced with two novel techniques by manipulating decoder hidden states. In contrast to previous approaches, our model is capable of generating variable number of diverse keyphrases.

We further propose two evaluation metrics tailored towards variable-number generation. We also introduce a new dataset (STACKEX) that expand beyond the only existing genre (i.e., academic writing) in keyphrase generation tasks. With both previous and new evaluation metrics, our model outperforms strong baselines on all datasets.

1   Introduction

Keyphrase generation is the task of automatically predicting keyphrases given a source text. Desired keyphrases are often multi-word units that summarize the high-level meaning and highlight certain important topics or information of the source text. Consequently, models that can successfully perform this task should be capable of not only distilling high-level information from a document, but also locating specific, important snippets therein.

To make the problem even more challenging, a keyphrase may or may not be a substring of the source text (i.e., it may be *present* or *absent*). Moreover, a given source text is usually associated with a *set* of multiple keyphrases. Thus,

Dataset	#Train	Valid	Test	Mean	Var	%(Pre)
KP20K	≈514k	≈20k	≈20k	5.3	14.2	63.3%
INSPEC	–	1500	500	9.6	22.4	78.5%
KRAPIVIN	–	1844	460	5.2	6.6	56.2%
NUS	–	169	42	11.5	64.6	51.3%
SEMEVAL	–	144	100	15.7	15.1	44.5%
STACKEX	≈298k	≈16k	≈16k	2.7	1.4	57.5%

Table 1: Statistics of datasets we use in this work. Mean and Var indicate the mean and variance of numbers of target phrases per data point, respectively.

keyphrase generation is an instance of the set generation problem, where both the size of the set and the size (i.e., the number of tokens in a phrase) of each element can vary depending on the source.

Similar to summarization, keyphrase generation is often formulated as a sequence-to-sequence (Seq2Seq) generation task in most prior studies (Meng et al., 2017; Chen et al., 2018a; Ye and Wang, 2018; Chen et al., 2018b). Conditioned on a source text, Seq2Seq models generate phrases individually or as a longer sequence jointed by delimiting tokens. Since standard Seq2Seq models generate only one sequence at a time, thus to generate multiple phrases, a common approach is to over-generate using beam search with a large beam width. Models are then evaluated by taking a *fixed* number of top predicted phrases (typically 5 or 10) and comparing them against the ground truth keyphrases.

Though this approach has achieved good empirical results, we argue that it suffers from two major limitations. Firstly, models that use beam search to generate multiple keyphrases generally lack the ability to determine the dynamic number of keyphrases needed for different source texts. Meanwhile, the parallelism in beam search also fails to model the inter-relation among the generated phrases, which can often result in diminished diversity in the output. Although certain

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existing models take output diversity into consideration during training (Chen et al., 2018a; Ye and Wang, 2018), the effort is significantly undermined during decoding due to the reliance on over-generation and phrase ranking with beam search.

Secondly, the current evaluation setup is rather problematic, since existing studies attempt to match a fixed number of outputs against a variable number of ground truth keyphrases. Empirically, the number of keyphrases can vary drastically for different source texts, depending on a plethora of factors including the length or genre of the text, the granularity of keyphrase annotation, etc. For the several commonly used keyphrase generation datasets, for example, the average number of keyphrases per data point can range from 5.3 to 15.7, with variances sometimes as large as 64.6 (Table 1). Therefore, using an arbitrary, fixed number k to evaluate entire datasets is not appropriate. In fact, under this evaluation setup, the F1 score for the oracle model on the KP20K dataset is 0.858 for $k = 5$ and 0.626 for $k = 10$, which apparently poses serious normalization issues as evaluation metrics.

To overcome these problems, we propose novel decoding strategies and evaluation metrics for the keyphrase generation task. The main contributions of this work are as follows:

1. We propose a keyphrase generation model capable of generating a **variable** number of diverse phrases. Given a source text, the model predicts the optimal number of keyphrases to generate, with the help of a *semantic coverage mechanism* and an *orthogonal regularizer*, it is able to perform more **diverse** phrase generation.

2. We **reformulate** the commonly used F_1 metric under the hypothesis of *variable-size* outputs from a model, which results in improved empirical characteristics over previous metrics based on a fixed k.

3. An additional contribution of our study is the introduction of a **new dataset** for keyphrase generation: STACKEX. With its marked difference in genre, we expect the dataset to bring added heterogeneity to keyphrase generation evaluation.

2 Related Work

2.1 Keyphrase Extraction and Generation

Traditional keyphrase extraction has been studied extensively in past decades. In most existing literature, keyphrase extraction has been formulated as a two-step process. First, lexical features such as part-of-speech tags are used to determine a list of phrase candidates by heuristic methods (Witten et al., 1999; Liu et al., 2011; Wang et al., 2016; Yang et al., 2017). Second, a ranking algorithm is adopted to rank the candidate list and the top ranked candidates are selected as keyphrases. A wide variety of methods were applied for ranking, such as bagged decision trees (Medelyan et al., 2009; Lopez and Romary, 2010), Multi-Layer Perceptron, Support Vector Machine (Lopez and Romary, 2010) and PageRank (Mihalcea and Tarau, 2004; Le et al., 2016; Wan and Xiao, 2008). Recently, Zhang et al. (2016); Luan et al. (2017); Gollapalli et al. (2017) used sequence labeling models to extract keyphrases from text. Similarly, Subramanian et al. (2017) used Pointer Networks to point to the start and end positions of keyphrases in a source text.

The main drawback of keyphrase extraction is that sometimes keyphrases are absent from the source text, thus an extractive model will fail predicting those keyphrases. Meng et al. (2017) first proposed the CopyRNN, a neural generative model that both generates words from vocabulary and points to words from the source text. Recently, based on the CopyRNN architecture, Chen et al. (2018a) proposed the CorrRNN, which takes states and attention vectors from previous steps into account in both encoder and decoder to reduce duplication and improve coverage. Ye and Wang (2018) proposed semi-supervised methods by leveraging both labeled and unlabeled data for training. Chen et al. (2018b); Ye and Wang (2018) proposed to use structure information (e.g., title of source text) to improve keyphrase generation performance. Note that none of the above works are able to generate variable number of phrases, which is one of our contributions.

2.2 Sequence to Sequence Generation

Sequence to Sequence (Seq2Seq) learning was first introduced by Sutskever et al. (2014); together with the soft attention mechanism of (Bahdanau et al., 2014), it has been widely used in natural language generation tasks. Gülçehre et al. (2016);

Gu et al. (2016) used a mixture of generation and pointing to overcome the problem of large vocabulary size. Paulus et al. (2017); Zhou et al. (2017) applied Seq2Seq models on summary generation tasks, while Du et al. (2017); Yuan et al. (2017) generated questions conditioned on documents and answers from machine comprehension datasets. Seq2Seq was also applied on neural sentence simplification (Zhang and Lapata, 2017) and paraphrase generation tasks (Xu et al., 2018).

3   Model Architecture

Given a piece of source text, our objective is to generate a variable number of multi-word phrases. To this end, we opt for the sequence-to-sequence framework (Seq2Seq) as the basis of our model, combined with attention and pointer softmax mechanisms in the decoder.

Since each data example contains one source text sequence and multiple target phrase sequences (dubbed ONE2MANY, and each sequence can be of multi-word), two paradigms can be adopted for training Seq2Seq models. The first one (Meng et al., 2017) is to divide each ONE2MANY data example into multiple ONE2ONE examples, and the resulting models (e.g. CopyRNN) can generate one phrase at once and must rely on beam search technique to produce more unique phrases.

To enable models to generate multiple phrases and control the number to output, we propose the second training paradigm ONE2SEQ, in which we concatenate multiple phrases into a single sequence with a delimiter $\langle \text{SEP} \rangle$, and this concatenated sequence is then used as the target for sequence generation during training. An overview of the model's structure is shown in Figure 1.[1]

Notations

In the following subsections, we use w to denote input text tokens, x to denote token embeddings, h to denote hidden states, and y to denote output text tokens. Superscripts denote time-steps in a sequence, and subscripts e and d indicate whether a variable resides in the encoder or the decoder of the model, respectively. The absence of a superscript indicates multiplicity in the time dimension. L refers to a linear transformation and L^f refers to it followed by a non-linear activation function f. Angled brackets, $\langle \rangle$, denote concatenation.

3.1   Sequence to Sequence Generation

3.1.1   The Encoder-Decoder Model

Given a source text consisting of N words $w_e^1, \ldots, w_e^N$, the encoder converts their corresponding embeddings $x_e^1, \ldots, x_e^N$ into a set of N real-valued vectors $h_e = (h_e^1, \ldots, h_e^N)$ with a bidirectional GRU (Cho et al., 2014):

$$h_e^t = \text{GRU}_e(x_e^t, h_e^{t-1}) \qquad (1)$$

Dropout (Srivastava et al., 2014) is applied to both x_e and h_e for regularization.

The decoder is a uni-directional GRU, which generates a new state h_d^t at each time-step t from the word embedding x_d^t and the recurrent state h_d^{t-1}:

$$h_d^t = \text{GRU}_d(x_d^t, h_d^{t-1}).^2 \qquad (2)$$

The initial state h_d^0 is derived from the final encoder state h_e^N by applying a single-layer feedforward neural net (FNN): $h_d^0 = L_0^{\tanh}(h_e^N)$. Dropout is applied to both the embeddings x_d and the GRU states h_d.

3.1.2   Attentive Decoding

When generating token y^t, in order to better incorporate information from the source text, an attention mechanism (Bahdanau et al., 2014) is employed to infer the importance $\alpha^{t,i}$ of each source word w_e^i given the current decoder state h_d^t. This importance is measured by an energy function with a 2-layer FNN:

$$\text{energy}(h_d^t, h_e^i) = L_1(L_2^{\tanh}(\langle h_d^t, h_e^i \rangle)). \qquad (3)$$

The output over all decoding steps t thus define a distribution over the source sequence:

$$\alpha^t = \text{softmax}(\text{energy}(h_d^t, h_e)). \qquad (4)$$

These attention scores are then used as weights for a refined representation of the source encodings, which is then concatenated to the decoder state h_d^t to derive a generative distribution p_a:

$$p_a(y^t) = L_3^{\text{softmax}}(L_4^{\tanh}(\langle h_d^t, \sum_i \alpha^{t,i} \cdot h_e^i \rangle)),$$

$$\qquad (5)$$

where the output size of L_3 equals to the target vocabulary size. Subscript a indicates the *abstractive* nature of p_a since it is a distribution over a prescribed vocabulary.

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[1] We plan to release the code, datasets and model outputs for reproducing our results.

[2] During training (with teacher forcing), w_d^t is the ground truth target token at previous time-step $t - 1$; during evaluation, $w_d^t = y^{t-1}$, is the prediction at the previous time-step.
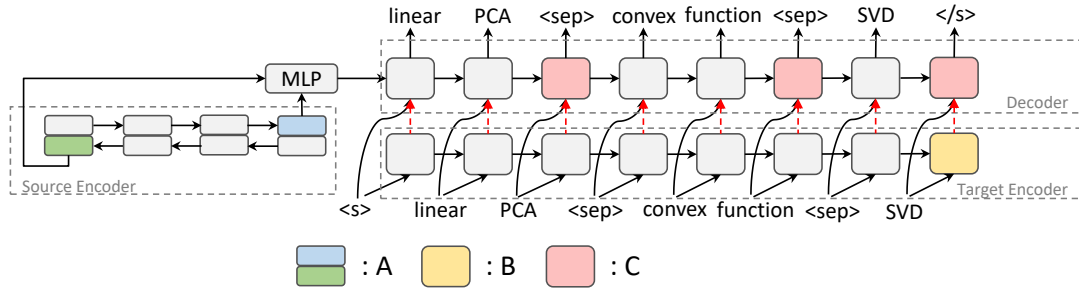
Figure 1: Improving diversity in a Seq2Seq model. A represents last states of an bi-directional source encoder; B represents last state of and target encoder; C indicates decoder states where target tokens are either delimiters or end of sentence tokens. During orthogonal regularization, all C states are used; during target encoder training, we maximize mutual information between states A with B. Red dash arrow indicates a detached path, i.e., no back-propagation through such path.

3.1.3 Pointer Softmax

We employ the pointer softmax (Gülçehre et al., 2016) mechanism to switch between generating a token y^t (from a vocabulary) and pointing (to a token in the source text). Specifically, the pointer softmax module computes a scalar switch s^t at each generation time-step and uses it to interpolate the abstractive distribution $p_a(y^t)$ over the vocabulary (see Equation 5) and the extractive distribution $p_x(y^t) = \alpha^t$ over the source text tokens:

$$p(y^t) = s^t \cdot p_a(y^t) + (1 - s^t) \cdot p_x(y^t), \quad (6)$$

where s^t is conditioned on both the attention-weighted source representation $\sum_i \alpha^{t,i} \cdot h_e^i$ and the decoder state h_d^t:

$$s^t = L_5^{\mathrm{sigmoid}}(\tanh(L_6(\sum_i \alpha^{t,i} \cdot h_e^i) + L_7(h_d^t))). \quad (7)$$

3.2 Mechanisms for Diverse Generation

There are usually multiple keyphrases for a given source text because each keyphrase represents certain aspects of the text. Therefore keyphrase diversity is desired for the keyphrase generation. Most previous keyphrase generation models generate multiple phrases by over-generation, which is highly prone to generate similar phrases due to the nature of beam search. Given our objective to generate variable numbers of keyphrases, we need to adopt new strategies for achieving better diversity in the output.

Recall that we represent variable numbers of keyphrases as delimiter-separated sequences. One particular issue we observed during error analysis is that the model tends to produce identical tokens following the delimiter token. For example, suppose a target sequence contains n delimiter tokens at time-steps $t_1, \ldots, t_n$. During training, the model is rewarded for generating the same delimiter token at these time-steps, which presumably introduces much homogeneity in the corresponding decoder states $h_d^{t_1}, \ldots, h_d^{t_n}$. When these states are subsequently used as inputs at the time-steps immediately following the delimiter, the decoder naturally produces highly similar distributions over the following tokens, resulting in identical tokens being decoded. To alleviate this problem, we propose two plug-in components for the sequential generation model.

3.2.1 Semantic Coverage

We propose a mechanism called *semantic coverage* that focuses on the semantic representations of generated phrases. Specifically, we introduce another uni-directional recurrent model $\mathrm{GRU}_{\mathrm{SC}}$ (dubbed *target encoder*) which encodes decoder-generated tokens y^τ, where $\tau \in [0, t)$, into hidden states h_{SC}^t. This state is then taken as an extra input to the decoder GRU, modifying Equation 2 to:

$$h_d^t = \mathrm{GRU}_d(\langle x_d^t, h_{\mathrm{SC}}^t \rangle, h_d^{t-1}). \quad (8)$$

If the target encoder were to be updated with the training signal from generation (i.e., backpropagating error from the decoder GRU to the target encoder), the resulting decoder is essentially a 2-layer GRU with residual connections. Instead, inspired by previous representation learning works (Logeswaran and Lee, 2018; van den Oord et al., 2018; Hjelm et al., 2018), we train the target encoder in an self-supervised fashion (Figure 1). That is, we extract target encoder's final

hidden state vector h_{SC}^M, where M is the length of target sequence, and use it as a general representation of the target phrases. We train by maximizing the mutual information between these phrase representations and the final state of the source encoder h_e^T as follows. For each phrase representation vector h_{SC}^M, we take the enocdings $H_e^T = \{h_{e,1}^T, \ldots, h_{e,N}^T\}$ of N different source texts, where $h_{e,true}^T$ is the encoder representation for the current source text, and the remaining $N - 1$ are negative samples (sampled at random) from the training data. The target encoder is trained to minimize the classification loss:

$$\mathcal{L}_{\text{SC}} = -\log \frac{g(h_{e,true}^T, h_{\text{SC}}^M)}{\sum_{i \in [1,N]} g(h_{e,i}^T, h_{\text{SC}}^M)}, \quad (9)$$
$$g(h_a, h_b) = \exp(h_a^\top B h_b)$$

where B is bi-linear transformation.

The motivation here is to constrain the overall representation of generated keyphrase to be semantically close to the overall meaning of the source text. With such representations as input to the decoder, the semantic coverage mechanism can potentially help to provide useful keyphrase information and guide generation.

3.2.2 Orthogonal Regularization

We also propose orthogonal regularization, which explicitly encourages the delimiter-generating decoder states to be different from each other. This is inspired by Bousmalis et al. (2016), who use orthogonal regularization to encourage representations across domains to be as distinct as possible. Specifically, we stack the decoder hidden states corresponding to delimiters together to form matrix $H = \langle h_d^{t_1}, \ldots, h_d^{t_n} \rangle$ and use the following equation as the orthogonal regularization loss:

$$\mathcal{L}_{\text{OR}} = \left\| H^\top H \odot (\mathbf{1} - I_n) \right\|_2, \quad (10)$$

where $H^\top$ is the matrix transpose of H, I_n is the identity matrix of rank n, $\odot$ indicates element wise multiplication, $\|M\|_2$ indicates L^2 norm of each element in a matrix M. This loss function prefers orthogonality among the hidden states $h_d^{t_1}, \ldots, h_d^{t_n}$ and thus improves diversity in the tokens following the delimiters.

3.2.3 Training Loss

We adopt the widely used negative log-likelihood loss in our sequence generation model, denoted as $\mathcal{L}_{\text{NLL}}$. The overall loss we use in our model is

$$\mathcal{L} = \mathcal{L}_{\text{NLL}} + \lambda_{\text{OR}} \cdot \mathcal{L}_{\text{OR}} + \lambda_{\text{SC}} \cdot \mathcal{L}_{\text{SC}}, \quad (11)$$

where λ_{OR} and λ_{SC} are hyper-parameters.

3.3 Decoding Strategies

According to different task requirements, various decoding methods can be applied to generate the target sequence y. Prior studies Meng et al. (2017); Yang et al. (2017) focus more on generating excessive number of phrases by leveraging beam search to proliferate the output phrases. In contrast, models trained under ONE2SEQ paradigm are capable of determining the proper number of phrases to output. In light of previous research in psychology (Van Zandt and Townsend, 1993; Forster and Bednall, 1976), we name these two decoding/search strategies as Exhaustive Decoding and Self-terminating Decoding, respectively, due to their resemblance to the way humans behave in serial memory tasks. Simply speaking, the major difference lies in whether a model is capable of controlling the number of phrases to output. We describe the detailed decoding strategies used in this study as follows:

3.3.1 Exhaustive Decoding

As traditional keyphrase tasks evaluate models with a fixed number of top-ranked predictions (say F-score @5 and @10), existing keyphrase generation studies have to over-generate phrases by means of beam search (commonly with a large beam size, e.g., 150 and 200 in (Chen et al., 2018b; Meng et al., 2017), respectively), a heuristic search algorithm that returns K approximate optimal sequences. For the ONE2ONE setting, each returned sequence is a unique phrase itself. But for ONE2SEQ, each produced sequence contains several phrases and additional processes (Ye and Wang, 2018) are needed to obtain the final unique (ordered) phrase list.

It is worth noting that the time complexity of beam search is $O(Bm)$, where B is the beam width, and m is the maximum length of generated sequences. Therefore the exhaustive decoding is generally very computationally expensive, especially for ONE2SEQ setting where m is much larger than in ONE2ONE. It is also wasteful as we observe that less than 5% of phrases generated by ONE2SEQ models are unique.

3.3.2 Self-terminating Decoding

An innate characteristic of keyphrase tasks is that the number of keyphrases varies depending on the document and dataset genre, therefore dynamically outputting a variable number of phrases is a desirable property for keyphrase generation models. Since our proposed model is trained to generate a variable number of phrases as a single sequence joined by delimiters, we can obtain multiple phrases by simply decoding a single sequence for each given source text. The resulting model thus implicitly performs the additional task of dynamically estimating the proper size of the target phrase set: once the model believes that an adequate number of phrases have been generated, it outputs a special token $\langle \text{EOS} \rangle$ to terminate the decoding process.

One notable attribute of the self-terminating decoding strategy is that, by generating a set of phrases in a single sequence, the model conditions its current generation on all previously generated phrases. Compared to the exhaustive strategy (i.e., phrases being generated independently by beam search in parallel), our model can model the dependency among its output in a more explicit fashion. Additionally, since multiple phrases are decoded as a single sequence, decoding can be performed more efficiently than exhaustive decoding by conducting greedy search or beam search on only the top-scored sequence.

4 Evaluating Keyphrase Generation

Formally, given a source text, suppose that a model predicts a list of unique keyphrases $\hat{\mathcal{Y}} = (\hat{y}_1, \ldots, \hat{y}_m)$ ordered by the quality of the predictions $\hat{y}_i$, and that the ground truth keyphrases for the given source text is the oracle set $\mathcal{Y}$. When only the top k predictions $\hat{\mathcal{Y}}_{:k} = (\hat{y}_1, \ldots, \hat{y}_{\min(k,m)})$ are used for evaluation, *precision*, *recall*, and F_1 score are consequently conditioned on k and defined as:

$$P@k = \frac{|\hat{\mathcal{Y}}_{:k} \cap \mathcal{Y}|}{|\hat{\mathcal{Y}}_{:k}|} \tag{12}$$

$$R@k = \frac{|\hat{\mathcal{Y}}_{:k} \cap \mathcal{Y}|}{|\mathcal{Y}|} \tag{13}$$

$$F_1@k = \frac{2 * P@k * R@k}{P@k + R@k} \tag{14}$$

As discussed in Section 1, the number of generated keyphrases used for evaluation can have a critical impact on the quality of the resulting evaluation metrics. Here we compare three choices of k and the implications on keyphrase evaluation for each choice:

- $\mathbf{F}_1@k$, where k is a pre-defined constant (usually 5 or 10). Due to the high variance of the number of ground truth keyphrases, it is often the case that $|\hat{\mathcal{Y}}_{:k}| \leq k < |\mathcal{Y}|$, and thus $R@k$ — and in turn $F_1@k$ — of an oracle model can be smaller than 1.0. This undesirable property is unfortunately prevalent in the evaluation metrics adopted by all existing keyphrase generation studies to our knowledge.

A simple remedy is to set k as a variable number which is specific to each data example. Here we define two new metrics:

- $\mathbf{F}_1@\mathcal{O}$: $\mathcal{O}$ denotes the number of oracle (ground truth) keyphrases. In this case, $k = |\mathcal{Y}|$, which means for each data example, the number of predicted phrases taken for evaluation is the same as the number of ground truth keyphrases.

- $\mathbf{F}_1@\mathcal{M}$: $\mathcal{M}$ denotes the number of predicted keyphrases. In this case, $k = |\hat{\mathcal{Y}}|$ and we simply take all the predicted phrases for evaluation without truncation.

By simply extending the *constant* number k to different variables accordingly, both $\mathbf{F}_1@\mathcal{O}$ and $\mathbf{F}_1@\mathcal{M}$ are capable of reflecting the nature of *variable* number of phrases for each document, and a model can achieve the maximum F_1 score of 1.0 if and only if it predicts the exact same phrases as the ground truth. Another merit of $\mathbf{F}_1@\mathcal{O}$ is that it is independent from model outputs, therefore we can use it to compare existing models.

5 Datasets and Experiments

In this section, we report our experiment results on multiple datasets and compare with existing models. We use `catSeq` to refer to the delimiter-concatenated sequence-to-sequences model described in Section 3; `catSeqD` refers to the model augmented with orthogonal regularization and semantic coverage mechanism.

To construct target sequences for training `catSeq` and `catSeqD`, ground truth keyphrases are sorted by their order of first occurrence in the

Model	Kp20K			Inspec			Krapivin			NUS			SemEval		
	F_1@5	F_1@10	F_1@$\mathcal{O}$	F_1@5	F_1@10	F_1@$\mathcal{O}$	F_1@5	F_1@10	F_1@$\mathcal{O}$	F_1@5	F_1@10	F_1@$\mathcal{O}$	F_1@5	F_1@10	F_1@$\mathcal{O}$
TfIdf	0.072	0.094	0.063	0.160	0.244	0.208	0.067	0.093	0.068	0.112	0.140	0.122	0.088	0.147	0.113
TextRank	0.181	0.151	0.184	0.286	0.339	0.335	0.185	0.160	0.211	0.230	0.216	0.238	0.217	0.226	0.229
KEA	0.046	0.044	0.051	0.022	0.022	0.022	0.018	0.017	0.017	0.073	0.071	0.081	0.068	0.065	0.066
Maui	0.005	0.005	0.004	0.035	0.046	0.039	0.005	0.007	0.006	0.004	0.006	0.006	0.011	0.014	0.011
CopyRNN	<u>0.328</u>	0.255	–	**0.292**	**0.336**	–	0.302	0.252	–	0.342	0.317	–	0.291	0.296	–
CopyRNN*	0.317	<u>0.273</u>	<u>0.335</u>	0.244	0.289	0.290	0.305	0.266	<u>0.325</u>	**0.376**	<u>0.352</u>	**0.406**	<u>0.318</u>	<u>0.318</u>	<u>0.317</u>
catSeq	0.314	<u>0.273</u>	0.319	<u>0.290</u>	0.300	<u>0.307</u>	<u>0.307</u>	<u>0.274</u>	0.324	0.359	0.349	<u>0.383</u>	0.302	0.306	0.310
catSeqD	**0.348**	**0.298**	**0.357**	0.276	<u>0.333</u>	**0.331**	**0.325**	**0.285**	**0.371**	<u>0.374</u>	**0.366**	**0.406**	**0.327**	**0.352**	**0.357**

Table 2: Performance of present keyphrase prediction on scientific publications datasets. Best/second-best performing score in each column is highlighted with bold/underline.

source text. Keyphrases that do not appear in the source text are appended to the end. This order may guide the attention mechanism to attend to source positions in a smoother way. Implementation details can be found in Appendix B.

We include four non-neural extractive models and CopyRNN (Meng et al., 2017) as baselines. We use CopyRNN to denote the model reported by Meng et al. (2017), CopyRNN* to denote our implementation of CopyRNN based on their open sourced code. To draw fair comparison with existing study, we use the same model hyperparameter setting as used in (Meng et al., 2017) and use exhaustive decoding strategy for most experiments. KEA (Witten et al., 1999) and Maui (Medelyan et al., 2009) are trained on a subset of 50,000 documents from either KP20K (Table 2) or STACKEX (Table 3) instead of all documents due to implementation limits (without fine-tuning on target dataset).

In Section 5.3, we apply the self-terminating decoding strategy. Since no existing model supports such decoding strategy, we only report results from our proposed models. They can be used for comparison in future studies.

5.1 Experiments on Scientific Publications

Our first dataset consists of a collection of scientific publication datasets, namely KP20K, INSPEC, KRAPIVIN, NUS, and SEMEVAL, that have been widely used in existing literature (Meng et al., 2017; Chen et al., 2018a; Ye and Wang, 2018; Chen et al., 2018b). KP20K, for example, was introduced by Meng et al. (2017) and comprises more than half a million scientific publications. For each article, the abstract and title are used as the source text while the author keywords are used as target. The other four datasets contain

much fewer articles, and thus used to test transferability of our model (without fine-tuning).

Model	Present			Absent	
	F_1@5	F_1@10	F_1@$\mathcal{O}$	R@10	R@50
TfIdf	0.080	0.089	0.052	-	-
TextRank	0.121	0.101	0.116	-	-
KEA	0.049	0.048	0.053	-	-
Maui	0.358	0.233	0.518	-	-
CopyRNN*	0.442	0.303	**0.662**	<u>0.488</u>	<u>0.660</u>
catSeq	**0.483**	**0.455**	0.635	0.407	0.422
catSeqD	<u>0.466</u>	<u>0.391</u>	<u>0.658</u>	**0.585**	**0.691**

Table 3: Model performance on STACKEX dataset.

We report our model's performance on the *present*-keyphrase portion of the KP20K dataset in Table 2.[3] To compare with previous works, we provide compute F_1@5 and F_1@10 scores. The new proposed $\mathbf{F_1@\mathcal{O}}$ metric indicates consistent ranking with F_1@5/10 for most cases. Due to its target number sensitivity, we find that its value is closer to F_1@5 for KP20K and KRAPIVIN where average target keyphrases is less and closer to F_1@10 for the other three datasets.

From the result we can see that the neural-based models outperform non-neural models by large margins. Our implemented CopyRNN achieves better or comparable performance against the original model, and on NUS and SemEval the advantage is more salient.

As for the proposed models, both catSeq and catSeqD yield comparable results to CopyRNN, indicating that ONE2SEQ paradigm can work well as an alternative option for the keyphrase generation. catSeqD outperforms catSeq on all metrics, suggesting the semantic coverage and orthogonal regularization help the model to generate

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[3]We show experiment results on absent data in Appendix A.

	KP20K		STACKEX	
Model	$\mathbf{F}_1@\mathcal{O}$	$\mathbf{F}_1@\mathcal{M}$	$\mathbf{F}_1@\mathcal{O}$	$\mathbf{F}_1@\mathcal{M}$
Greedy Search				
catSeq	0.331	0.324	0.592	0.563
catSeqD	**0.334**	**0.339**	**0.596**	**0.593**
Top Ranked Sequence in Beam Search				
catSeq	0.243	0.251	0.524	0.527
catSeqD	0.319	0.334	0.565	0.570

Table 4: $\mathbf{F}_1@\mathcal{O}$ and $\mathbf{F}_1@\mathcal{M}$ scores when generating variable number of keyphrases (self-terminating decoding).

higher quality keyphrases and achieve better generalizability. To our surprise, on the metric $F_1@10$ for KP20K and KRAPIVIN (average number of keyphrases is only 5), where high-recall models like CopyRNN are more favored, catSeqD is still able to outperform ONE2ONE baselines, indicating that the proposed mechanisms for diverse generation are effective.

5.2 Experiments on The STACKEX Dataset

Inspired by the StackLite tag recommendation task on Kaggle, we build a new benchmark based on the public StackExchange data[4]. We use questions with titles as source, and user-assigned tags as target keyphrases.

Since oftentimes the questions on StackExchange contain less information than in scientific publications, there are fewer keyphrases per data point in STACKEX. Furthermore, StackExchange uses a tag recommendation system that suggests topic-relevant tags to users while submitting questions; therefore, we are more likely to see general terminology such as **Linux** and **Java**. This characteristic challenges models with respect to their ability to distill major topics of a question rather than selecting specific snippets from the text.

We report our models' performance on STACKEX in Table 3. Results show catSeqD performs the best; on the *absent*-keyphrase generation tasks, it outperforms catSeq by a large margin.

5.3 Generating Variable Number Keyphrases

One key advantage of our proposed model is the capability of predicting the number of keyphrases conditioned on the given source text. We thus conduct a set of experiments on KP20K and

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[4]https://archive.org/details/stackexchange, we choose 19 computer science related topics from Oct. 2017 dump.

Model	KP20K	Inspec	Krapivin	NUS	SemEval
catSeq	0.319	0.307	0.323	0.383	0.310
catSeq + Orth. Reg.	0.311	0.293	0.310	0.365	0.295
catSeq + Sem. Cov.	0.329	0.321	0.345	0.402	0.329
catSeqD	**0.357**	**0.331**	**0.371**	**0.406**	**0.357**

Table 5: Ablation study with $\mathbf{F}_1@\mathcal{O}$ scores on five scientific publication datasets.

STACKEX present keyphrase generation tasks, as shown in Table 4, to study such behavior. We adopt the self-terminating decoding strategy (Section 3.3), and use both $\mathbf{F}_1@\mathcal{O}$ and $\mathbf{F}_1@\mathcal{M}$ (Section 4) to evaluate.

In these experiments, we use beam search as in most Natural Language Generation (NLG) tasks, i.e., only use the top ranked prediction sequence as output. We compare the results with greedy search. Since no existing model is capable of generating variable number of keyphrases, in this subsection we only report performance on such setting from catSeq and catSeqD.

From Table 4 we observe that in the variable number generation setting, greedy search outperforms beam search consistently. This may because beam search tends to generate short and similar sequences. We can also see the resulting $\mathbf{F}_1@\mathcal{O}$ scores are generally lower than results reported in previous subsections, this suggests an over-generation decoding strategy may still benefit from achieving higher recall.

6 Analysis and Discussion

6.1 Ablation Study

We conduct an ablation experiment to study the effects of orthogonal regularization and semantic coverage mechanism on catSeq. As shown in Table 5, semantic coverage provides significant boost to catSeq's performance on all datasets. Orthogonal regularization hurts performance when is solely applied to catSeq model. Interestingly, when both components are enabled (catSeqD), the model outperforms catSeq by a noticeable margin on all datasets, this suggests the two components help keyphrase generation in a synergetic way. One future direction is to apply orthogonal regularization directly on target encoder, since the regularizer can potentially diversify target representations at phrase level, which may further encourage diverse keyphrase generation in decoder.
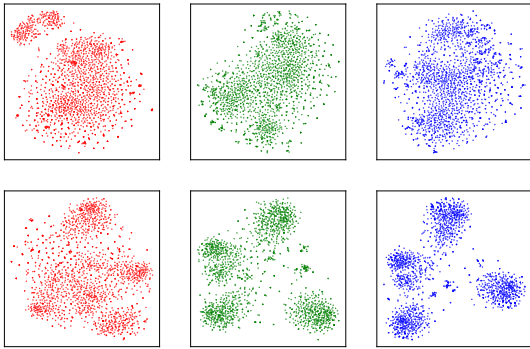
Figure 2: t-SNE results on decoder hidden states. Upper row: `catSeq`; lower row: `catSeqD`; column k shows hidden states sampled from tokens at k steps following a delimiter.

6.2 Visualizing Diversified Generation

To verify our assumption that target encoding and orthogonal regularization help to boost the diversity of generated sequences, we use two metrics, one quantitative and one qualitative, to measure diversity of generation.

First, we simply calculate the average unique predictions produced by both `catSeq` and `catSeqD` in experiments shown in Section 5.1. The resulting numbers are 20.38 and 89.70 for `catSeq` and `catSeqD` respectively. Second, from the model running on the `KP20K` validation set, we randomly sample 2000 decoder hidden states at k steps following a delimiter ($k = 1, 2, 3$) and apply an unsupervised clustering method (t-SNE (van der Maaten and Hinton, 2008)) on them. From the Figure 2 we can see that hidden states sampled from `catSeqD` are easier to cluster while hidden states sampled from `catSeq` yield one mass of vectors with no obvious distinct clusters. Results on both metrics suggest target encoding and orthogonal regularization indeed help diversifying generation of our model.

6.3 Qualitative Analysis

To illustrate the difference of predictions between our proposed models, we show an example chosen from the `KP20K` validation set in Appendix C. In this example there are 29 ground truth phrases. Neither of the models is able to generate all of the keyphrases, but it is obvious that the predictions from `catSeq` all start with "test", while predictions from `catSeqD` are diverse. This to some extent verifies our assumption that without the target encoder and orthogonal regularization, decoder states following delimiters are less diverse.

7 Conclusion and Future Work

We propose a recurrent generative model that sequentially generates multiple keyphrases, with two extra modules that enhance generation diversity. We propose new metrics to evaluate keyphrase generation. Our model shows competitive performance on a set of keyphrase generation datasets, including one introduced in this work. In future work, we plan to investigate how target phrase order affects the generation behavior, and further explore set generation in an order invariant fashion.

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A Experiment Results on KP20K Absent Subset

Generating *absent* keyphrases on scientific publication datasets is a rather challenging problem. Existing studies often achieve seemingly good performance by measuring recall on tens and sometimes hundreds of keyphrases produced by exhaustive decoding with a large beam size — thus completely ignoring precision.

We report the models' R@10/50 scores on the *absent* portion of five scientific paper datasets in Table 6 to be in line with previous studies.

The absent keyphrase prediction highly prefers recall-oriented models, therefore CopyRNN with beam size of 200 is innately proper for this task setting. Howerer, from the results we observe that with the help of exhaustive decoding and diverse mechanisms, catSeqD is able to perform comparably to CopyRNN model, and it generally works better for top predictions. Even though the trend of models' performance somewhat matches what we observe on the *present* data, we argue that it is hard to compare different models' performance on such scale. We argue that STACKEX is better testbeds for *absent* keyphrase generation.

B Implementation Details

Implemntation details of our proposed models are as follows. In all experiments, the word embeddings are initialized with 100-dimensional random matrices. The number of hidden units in both the encoder and decoder GRU are 150. The number of hidden units in target encoder GRU is 150. The size of vocabulary is 50,000.

The numbers of hidden units in MLPs described in Section 3 are as follows. During negative sampling, we randomly sample 16 samples from the same batch, thus target encoding loss in Equation 9 is a 17-way classification loss. In catSeqD, we set both the λ_{OR} and λ_{SC} in Equation 11 to be 0.3. In all experiments, we use a dropout rate of 0.1.

We use *Adam* (Kingma and Ba, 2014) as the step rule for optimization. The learning rate is $1e^{-3}$. The model is implemented using *PyTorch* (Paszke et al., 2017) and OpenNMT (Klein et al., 2017).

For exhaustive decoding, we use a beam size of 50 and a maximum sequence length of 40.

Following Meng et al. (2017), lowercase and stemming are performed on both the ground truth and generated keyphrases during evaluation.

We leave out 2,000 data examples as validation set for both KP20K and STACKEX and use them to identify optimal checkpoints for testing. And all the scores reported in this paper are from checkpoints with best performances ($\mathbf{F}_1@\mathcal{O}$) on validation set.

C Example Output

See Table 7.

Model	Kp20K		Inspec		Krapivin		NUS		SemEval	
	R@10	**R@50**	**R@10**	**R@50**	**R@10**	**R@50**	**R@10**	**R@50**	**R@10**	**R@50**
CopyRNN	<u>0.115</u>	**0.189**	<u>0.051</u>	**0.101**	<u>0.116</u>	**0.195**	<u>0.078</u>	**0.144**	**0.049**	**0.075**
CopyRNN*	0.033	0.087	0.040	0.083	0.040	0.081	0.024	0.081	0.005	0.026
catSeq	0.060	0.062	0.028	0.029	0.070	0.074	0.037	0.031	0.025	0.025
catSeqD	**0.117**	<u>0.151</u>	**0.052**	<u>0.071</u>	**0.120**	<u>0.145</u>	**0.084**	<u>0.110</u>	<u>0.046</u>	<u>0.063</u>

Table 6: Performance of absent keyphrase prediction on scientific publications datasets. Best/second-best performing score in each column is highlighted with bold/underline.

Source	a visual test development environment for gui systems We have implemented an experimental test development environment (TDE) intended to raise the effectiveness of tests produced for GUI systems, and raise the productivity of the GUI system tester.The environment links a test designer, a test design library, and a test generation engine with a standard commercial capture/replay tool. These components provide a human tester the capabilities to capture sequences of interactions with the system under test (SUT), to visually manipulate and modify the sequences, and to create test designs that represent multiple individual test sequences. Test development is done using a high-level model of the SUT's GUI, and graphical representations of test designs. TDE performs certain test maintenance tasks automatically, permitting previously written test scripts to run on a revised version of the SUT.
catSeq	test development ; test development environment ; test ; test generation
catSeqD	test generation ; gui ; tool ; version ; capabilities ; systems ; design ; test ; human ; generation
Ground Truth	engine ; developer ; design ; human ; standardization ; tool ; links ; graphics ; model ; libraries ; replay ; component ; interaction ; product ; development environment ; script ; visualization ; capabilities ; systems ; experimentation ; test designer ; environments ; test generation ; testing ; maintenance ; test maintenance ; version ; effect ; sequence

Table 7: Example from KP20K validation set, predictions generated by catSeq and catSeqD models.
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