Learning Rich Representation of Keyphrases from Text

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Abstract

In this work, we explore how to learn task-specific language models aimed towards learning rich representation of keyphrases from text documents. We experiment with different masking strategies for pre-training transformer language models (LMs) in discriminative as well as generative settings. In the discriminative setting, we introduce a new pre-training objective - **Keyphrase Boundary Infilling with Replacement (KBIR)**, showing large gains in performance (upto 9.26 points in F1) over SOTA, when LM pre-trained using KBIR is fine-tuned for the task of keyphrase extraction. In the generative setting, we introduce a new pre-training setup for BART - **KeyBART**, that reproduces the keyphrases related to the input text in the CatSeq format, instead of the denoised original input. This also led to gains in performance (upto 4.33 points in F1@M) over SOTA for keyphrase generation. Additionally, we also fine-tune the pre-trained language models on named entity recognition (NER), question answering (QA), relation extraction (RE), abstractive summarization and achieve comparable performance with that of the SOTA, showing that learning rich representation of keyphrases is indeed beneficial for many other fundamental NLP tasks.

1 Introduction and Background

Keyphrases capture the most salient topics of a document and facilitates extreme summarization. Identifying them in an automated way from a text document can be useful for several downstream tasks - classification (Hulth and Megyesi, 2006), clustering (Hammouda et al., 2005), summarization (Qazvinian et al., 2010; Zhang et al., 2004), reviewer and document recommendation (Augenstein et al., 2017), and many different information retrieval tasks such as enabling semantic and faceted search (Sanyal et al., 2019; Gutwin et al., 1999), query expansion (Song et al., 2006), and interactive document retrieval (Jones and Staveley, 1999).

Keyphrases could either be **extractive** (part of the document) or **abstractive** (not part of the document). Prior works have referred to them as present and absent keyphrases, respectively. Automatically identifying them entails the process of detecting the extractive (Hasan and Ng, 2014) and generating the abstractive keyphrases (Cano and Bojar, 2019a) from a given document. While extractive approaches have mostly dominated over the generative ones with higher accuracies (Cano and Bojar, 2019b), the task is far from solved and the performances of the present systems are worse in comparison to many other NLP tasks (Liu et al., 2010). Some of the major challenges are the varied length of the documents to be processed, their structural inconsistency and developing strategies that can perform well in different domains.

Most of the prior work on identifying keyphrases using deep learning techniques have concentrated on developing new architectures and frameworks based on different training paradigms such as seq2seq (Meng et al., 2017; Yuan et al., 2018; Zhang et al., 2017a; Chen et al., 2018; Ye and Wang, 2018; Chen et al., 2019; Ye et al., 2021), sequence tagging (Alzaidy et al., 2019), reinforcement learning (Chen et al., 2019), adversarial training (Swaminathan et al., 2020) and game theory (Saxena et al., 2020). Although, there has been tremendous progress in learning better semantic and syntactic representation of language at different levels - characters, words, phrases, sentences and documents (Liu et al., 2020b), there hasn’t been any effort in learning rich pre-trained representations of keyphrases, which is the major focus of this work.

Transformer language models when pre-trained on large corpora with different pre-training objectives (Qiu et al., 2020) have shown great success...
in various downstream tasks on fine-tuning, including the tasks of keyphrase extraction (Sahrawat et al., 2019; Martinc et al., 2020; Santosh et al., 2020) and generation (Liu et al., 2020a). However, pre-training objectives tailored towards learning better representation of keyphrases that can result in improving the performance of identifying and generating keyphrases from text have not yet been explored. This motivated us to look into this specific problem and make an attempt to answer some of the questions below:

**Q1** - Can we formulate a pre-training objective for language models that can learn better representation of keyphrases?

**Q2** - Does learning rich representation of keyphrases in a language model lead to performance gains for the tasks of keyphrase extraction and generation?

**Q3** - Do rich keyphrase representations aid other fundamental tasks in NLP such as NER, QA, RE and summarization?

Previous attempts look at training language models for learning better representation of text spans (Joshi et al., 2020), summary sentences (Zhang et al., 2020), and tokens for named entity recognition (Yamada et al., 2020). In order to effectively learn rich representation of keyphrases in a BERT like discriminative setup we propose a new pre-training objective - **Keyphrase Boundary Infilling with Replacement (KBIR)** (Section 2) which utilizes a multi-task learning setup for optimizing a combined loss of Masked Language Modeling (MLM) (Devlin et al., 2018), **Keyphrase Boundary Infilling (KBI)** (Section 2.1) and **Keyphrase Replacement Classification (KRC)** (Section 2.2). The key contributions of this work is the introduction of the KBI and KRC objectives that when combined with MLM helps to learn good representation of keyphrases validated by obtaining SOTA performance for the task of keyphrase extraction on three benchmark datasets (Section 4.2), beating the existing SOTA (Duan et al., 2021) by at most 9.26 F1 points on the SemEval 2017 corpus (Augenstein et al., 2017).

We also propose a new setup for pre-training BART (Lewis et al., 2019) - **KeyBART** (Section 3), focused towards learning better representation of keyphrases in a generative setting. Instead of reproducing the denoised input text as proposed in the original setup, we produce the keyphrases associated with the input document in the Catseq (Meng et al., 2017) format from a corrupted input. We evaluated the KeyBART approach across 5 benchmark datasets for the task of keyphrase generation and obtained SOTA performances for both present and absent keyphrases (Section 4.3). Our best model surpassed the SOTA ONE2SEQ model (Ye et al., 2021) by 4.33 F1@M points and 0.98 F1@M points on Inspec (Hulth, 2003a) for present and absent keyphrases, respectively.

Additionally, we also propose a keyphrase replacement strategy motivated by (Xiong et al., 2019) that plays a key role in learning keyphrase representation in the KBIR objective as well as KeyBART. Through rigorous experiments (Section 4) we perform ablation studies on the effectiveness of various settings of our proposed framework. We also evaluated the performance of the KBIR LM across multiple span-based NLP tasks (Section 4.4) such as NER, RE and QA. We obtained better performance than RoBERTa and also comparable performance to that of the SOTA with our best model falling behind by 1.33 F1 points for NER (Section 4.4.1), 0.25 F1 points for QA (Section 4.4.3) and 1.2 F1 points for RE (Section 4.4.2). The KeyBART LM was also fine-tuned on the CNN/DailyMail dataset for the task of abstractive summarization (Section 4.4.4) giving performance better than BART by 0.17 points in ROUGE-1.

It is to be noted, although we trained our models on a large corpus of 23 million scientific articles, we find it to be performing reasonably well when fine-tuned on datasets that do not belong to the scientific domain for different NLP tasks as shown in Sections 4.4.1, 4.4.2, 4.4.3, 4.4.4. This also suggests that identifying keyphrases in the context of an input text is a fundamental NLP task and a language model trained to learn optimal representation of keyphrases can aid many other tasks.

The main contributions that we make in this work are:

- We make the first attempt to train task-specific language models in discriminative as well as generative settings geared towards learning rich representation of keyphrases from text.
- We introduce a novel pre-training objective **Keyphrase Boundary Infilling with Replacement (KBIR)** and train a new language model that achieves SOTA performance for the task of keyphrase extraction.
- We propose a new setup - **KeyBART** for pre-
training a generative language model for learning better representation of keyphrases and achieve SOTA performance on the task of keyphrase generation.

- We also empirically show how learning rich keyphrase representations from text is also useful for other NLP tasks like NER, RE, QA and summarization by achieving near SOTA performances in all of them using our language models trained using KBIR objective and KeyBART settings.

We have made our models\(^1\) publicly available (Kulkarni et al., 2021). Next, we give a detailed description of the methods that we propose in this work.

## 2 Keyphrase Boundary Infilling with Replacement (KBIR)

In the previous section, we mentioned various methods that aim at learning representations of text spans. Unlike LMs like SpanBERT (Joshi et al., 2020) and PEGASUS (Zhang et al., 2020) whose primary objective is to learn representations of random or heuristically chosen spans of text, the intuition behind learning good keyphrase representation is to provide the LM the ability to learn both spans as well as to identify important phrases (in this case keyphrases) in the context of an input text. This motivated us to devise a framework that can optimize both these objectives. Towards this effort we propose a new pre-training objective *Keyphrase Boundary Infilling with Replacement (KBIR)* which is composed of two individual tasks - *Keyphrase Boundary Infilling (KBI)* and *Keyphrase Replacement Classification (KRC)* jointly learnt in a multi-task learning setup as shown in Figure 1. We build our framework on top of RoBERTa which implements Masked Language Modeling (MLM), therefore making our LM essentially optimize MLM along with KBI and KRC objectives. Next, we describe the individual components of our framework.

### 2.1 Keyphrase Boundary Infilling (KBI)

In order to effectively learn span representations of keyphrases we propose a new pre-training objective that builds upon the span boundary objective (SBO) from (Joshi et al., 2020) and the text infilling setup from (Lewis et al., 2019). Unlike SpanBERT which replaces each of the individual tokens of a span with a [MASK] token providing a notion of how many tokens exist in the span, we replace the entire span, in this case a keyphrase, with

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\(^1\)https://zenodo.org/record/5784384
a [MASK] token as shown in Figure 2 similar to (Lewis et al., 2019). This is a more challenging task than SpanBERT’s objective since all of the original tokens in the span must be predicted through a single masked token. We predict the original tokens of the masked keyphrase by using positional embeddings in the text in conjunction with the boundary tokens. However, we limit the maximum number of tokens that can be produced, since unlike SBO we do not know the actual number of tokens. Text infilling to the best of our knowledge has not been explored in a discriminative setup as done in this work.

We denote the output of the transformer encoder for each token in the sequence by \( x_1, \ldots, x_n \). However, since the entire span of tokens \( (x_s, \ldots, x_e) \) of a keyphrase \( (y_i) \) is masked, it is represented with a single \( x_m \), where \((s, e)\) indicates its start and end positions and \( m \) represents the index of the masked keyphrase spans. We set a maximum possible number of tokens corresponding to a keyphrase span, \( T_{\text{max}} \) such that \( i \in (1, T_{\text{max}}) \). We then expand potential tokens present in \( x_m \) using the output encodings of the external boundary tokens \( x_{s-1} \) and \( x_{e+1} \), as well as the position embedding of the target token \( p_{i-s+1} \) as shown in Equation 1.

\[
y_i = f(x_{s-1}, x_{e+1}, p_{i-s+1}) \tag{1}
\]

where, positional embeddings \( p_1, p_2, \ldots \) mark relative positions of the masked tokens with respect to the left boundary token \( x_{s-1} \). We use the Layer Normalization (Ba et al., 2016) and GeLU (Hendrycks and Gimpel, 2016) activation functions to represent \( f(\Delta) \). We then use the vector representation \( y_i \) to predict the potential token \( x_i \) from the unmasked \( x_m \) and compute the cumulative cross-entropy loss for each \( i \) present within the unmasked \( x_m \) as shown in Equation 2.

\[
\mathcal{L}_{\text{Infill}}(\theta) = \sum_{i=1}^{T_{\text{max}}} \log p(x_i \mid y_i) \tag{2}
\]

In addition to predicting the actual tokens, we use a classification head to predict the expected number of tokens corresponding to the [MASK] in the anticipation of providing a stronger learning signal. Each possible length of the [MASK] is represented as a class up to the maximum number of tokens possible \( (T_{\text{max}}) \). The architecture used for classifying the number of tokens is a single linear layer which is trained with cross-entropy loss \( \mathcal{L}_{\text{LP}}(x_m, z_m) \) along with the filled masked token \( x_m \) and the corresponding actual length of the span class \( z_m \).

The Keyphrase Boundary Infilling (KBI) objective is formally represented as:

\[
\mathcal{L}_{\text{KBI}}(\theta) = \alpha \mathcal{L}_{\text{MLM}}(\theta) + \gamma \mathcal{L}_{\text{Infill}}(\theta) + \sigma \mathcal{L}_{\text{LP}}(\theta) \tag{3}
\]

where \( \alpha \), \( \gamma \) and \( \sigma \) are co-efficients applied to each loss and are primarily used to normalize the losses across the tasks.

We propose this pre-training objective to be used with keyphrases, however the objective is generic enough to be applied to any spans of text, these could be keyphrases, entities or even random spans.

### 2.2 Keyphrase Replacement Classification (KRC)

Apart from learning representations of keyphrase spans we wanted our framework to have the ability to spot them within the context of a text input. Motivated by WKLM (Xiong et al., 2019) that explores pre-training a language model through weak supervision by replacing entities with random entities of the same type that were a part of a knowledge base, we adapt it to replace keyphrases by randomly choosing another keyphrase of variable length from the universe of keyphrases identified in a tagged corpus. The KRC task is then modeled as a binary classification task to determine whether a keyphrase is replaced or retained.

To implement this strategy, we construct a keyphrase universe by identifying the set of unique keyphrases tagged across the entire dataset. We then randomly shuffle this keyphrase universe and restrict it to 500,000 keyphrases for handling increasing computational complexity. We use the concatenated representation of boundary tokens of a keyphrase \( x_{s-1} \) and \( x_{e+1} \) as input to a linear classifier as shown in Figure 1. Given the label \( y_k \) representing whether a keyphrase was replaced or not, the objective here is to minimize the binary cross-entropy loss \( \mathcal{L}_{\text{KRC}}((x_{s-1} + x_{e+1}), y_k) \).

Finally, in order to train a LM with an objective of learning good keyphrase representations we use the KBI pre-training strategy in which we jointly optimize the KBI loss with the KRC loss along with the MLM loss \( \mathcal{L}_{\text{MLM}}(\theta) \). This is formally shown in Equation 4.

\[
\mathcal{L}_{\text{KBI-KRC}}(\theta) = \alpha \mathcal{L}_{\text{MLM}}(\theta) + \gamma \mathcal{L}_{\text{Infill}}(\theta) + \sigma \mathcal{L}_{\text{LP}}(\theta) + \delta \mathcal{L}_{\text{KRC}}(\theta) \tag{4}
\]
3 KeyBART

We also explored learning a generative LM for the text generation tasks such as keyphrase generation and abstractive summarization. Our hypothesis behind the proposed setup is that masking and replacing task-specific spans, in this case keyphrases, that need to be re-generated should allow the generative model to develop a better representation of surrounding tokens and also the spans themselves.

BART (Lewis et al., 2019) generates sequences of different lengths from the input perturbed with [MASK] tokens along with token addition and deletion. On similar lines we propose learning rich keyphrase representations by attempting to generate the original present keyphrases in the Catseq format as proposed in (Meng et al., 2017) from an input perturbed with token masking, keyphrase masking and keyphrase replacement as shown in Figure 2. We call this strategy KeyBART. We maintain the order of occurrence of the keyphrases in the original document and remove duplicate occurrences. We also use the same strategy for finding keyphrase replacements as used in KRC (Section 2.2). We don’t explicitly try to model the keyphrase replacement through a replacement classification head, but rather rely on learning this implicitly as part of the generation task. Similar to BART we use a reconstruction loss objective during training which is a cross-entropy loss between the output and set of expected keyphrases.

Additionally, we train a setup called KeyBART-DOC to serve as an ablation study, with the same input text perturbations however the main objective is to generate the original input text, similar to BART’s original pre-training objective. Next, we present a detailed account of the experiments and evaluations conducted in this work.

4 Experiments and Results

4.1 Language Modeling

4.1.1 Dataset

We use the OAGKX (Cano and Bojar, 2020) dataset which consists of 23 million scientific documents across multiple domains sampled from the Open Academic Graph with keyphrases tagged by the authors of the articles. The OAGKX contains keyphrases that appear in the abstract and also those which don’t appear in the abstract, making it similar to the keyphrase generation setting with present and absent keyphrases. To the best of our knowledge we are the first to explore OAGKX dataset for pre-training a large language model. During LM pre-training we restricted the length of the input text for each sample to 512 tokens.

Note that we do not explicitly tag the keyphrases and use the readily available author tagged keyphrases associated with each document, which is a common practice in the scientific domain. This setup is analogous to how the Wikipedia corpus is used to perform entity specific pre-training in
Table 1: Hyperparameters for our pre-training strategies, all models were trained across 8 Tesla V100 GPUs with a learning rate of 1e-5 using the Adam (Kingma and Ba, 2015) optimizer. Difference in number of steps is to account for changes in batch size. MLM, Keyphrase Infilling (KI) and Keyphrase Replacement (KR) show the probability of this perturbation occurring in the original text. MLM probability is reduced for KBIR in line with (Xiong et al., 2019). Maximum Infill Span Length (MISL) and Maximum Keyphrase Replacements (MKR), are based on averages from OAGKX and computational reasons. The coefficients for the loss are used to normalize the magnitude of loss across the different tasks.

LUKE (Yamada et al., 2020) and WKLM (Xiong et al., 2019) among others. Wikipedia already contains tagged entities/concepts and these works just focus on leveraging this. We too attempt to leverage the large OAGKX corpus that provides pre-identified keyphrases. While our proposed methods are explored on a dataset specific to keyphrases, these could also be applied to entities with the Wikipedia corpus or noun phrases with the BookCorpus or any span of text.

4.1.2 Pre-training Strategies and Settings
We train LMs in different settings and hyperparameters as listed in Table 1.

Discriminative Setting - We pre-train three language models in the discriminative setting as described below. All of them use the pre-trained weights of RoBERTa-large\(^2\) as the initial weights and are trained by continuing the learning of the parameters on the OAGKX dataset using our pre-training strategies.

- **RoBERTa-extended** - Previous work (Gururangan et al., 2020) has shown that adding more data to pre-training a language model typically results in better downstream performance. To verify that our performance gains stem from modeling improvements and the new pre-training objectives proposed by us rather than addition of data, we extend the training of RoBERTa-large on the OAGKX corpus. We call this model RoBERTa-extended. This also ensures fair comparison of the LMs trained by us using our pre-training objectives with that of RoBERTa.

- **KBI** - During the pre-training of the LM with the KBI objective, we employ both token masking and keyphrase masking strategies as shown in Figure 2 and explained in Section 2.1. We randomly mask 15% of the tokens that are not included in keyphrase spans. We additionally mask 20% of the keyphrase spans with a single [MASK] token. We restrict the maximum number of tokens for a keyphrase mask span to 10, based on the average keyphrase length reported in (Çano and Bojar, 2020).

- **KBIR** - While pre-training the LM with the KBIR objective we employ 5% token masking, in line with the findings reported in (Xiong et al., 2019) and 20% of keyphrases are masked through keyphrase masking, with a maximum possible span size of 10 as in the KBI LM. Additionally, we replace 40% of the non-masked keyphrases with randomly sampled keyphrases from the keyphrase universe as explained in Section 2.2. We restrict the maximum number of keyphrases to be replaced to no more than 20, restricted by the computational complexity of the problem. Figure 1 shows the final architecture, with a multi-task learning objective trained with a weighted combined loss.

Generative Setting - In the generative setting we pre-train two language models as described below. In both the models we continue the training of the weights of BART-large\(^3\) on our corpus using our pre-training strategies.

- **KeyBART** - We perform token masking, keyphrase masking and keyphrase replacement with same masking hyperparameters as

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| Model            | Batch | Steps | Warmup | $\alpha$ | $\gamma$ | $\sigma$ | $\delta$ | MLM  | KI  | KR  | MISL | MKR |
|------------------|-------|-------|--------|---------|---------|---------|---------|------|-----|-----|------|-----|
| RoBERTa-extended | 4     | 130k  | 2.5k   | 1.0     | 0.0     | 0.0     | 0.0     | 0.15 | 0.0 | 0.0 | -    | -   |
| KBI              | 4     | 130k  | 2.5k   | 1.0     | 0.33    | 1.0     | 0.0     | 0.15 | 0.2 | 0.0 | 10   | -   |
| KBIR             | 2     | 260k  | 5k     | 1.0     | 0.33    | 1.0     | 2.0     | 0.05 | 0.2 | 0.4 | 10   | 20  |
| KeyBART          | 4     | 130k  | 2.5k   | -       | -       | -       | -       | 0.05 | 0.2 | 0.4 | 10   | 20  |
| KeyBART-DOC      | 2     | 260k  | 5k     | -       | -       | -       | -       | 0.05 | 0.2 | 0.4 | 10   | 20  |

\(^2\)https://huggingface.co/roberta-large

\(^3\)https://huggingface.co/facebook/bart-large
KBIR on the input text and pre-train the model to predict the original keyphrases in Catseq format following the setup explained in Section 3.

- **KeyBART-DOC** - This setup uses the same input denoising settings as KeyBART, with the only difference in the output, where KeyBART generates the keyphrases associated with the document in Catseq format, whereas KeyBART-DOC similar to BART generates the original denoised input.

We use the exact same data in all the pre-training setups as explained above. We increase the number of steps while decreasing the batch size such that all the models see the data the same number of times i.e 2 epochs. The batch size is only reduced to accommodate increases in memory usage in the model pre-training. Experiments were conducted using a private infrastructure, which has a carbon efficiency of 0.432 kgCO₂eq/kWh. A cumulative of 6,144 hours of computation was performed on hardware of type Tesla V100-SXM2-32GB (TDP of 300W). We calculate that the combined cost of training all these models is 796.26 KGs of CO₂ eq.

### Table 2: F1 scores for keyphrase extraction on Inspec, SE10 and SE17 datasets (* LMs trained by us).

| Model                  | Inspec | SE10 | SE17 |
|------------------------|--------|------|------|
| RoBERTa+BiLSTM-CRF     | 59.5   | 27.8 | 50.8 |
| RoBERTa+TG-CRF         | 60.4   | 29.7 | 52.1 |
| SciBERT+Hypernet-CRF   | 62.1   | 36.7 | 54.4 |
| RoBERTa+Hypernet-CRF   | 62.3   | 34.8 | 53.3 |
| RoBERTa-extended-CRF*  | 62.09  | 40.61| 52.32|
| KBI-CRF*               | 62.61  | 40.81| 59.7 |
| KBIR-CRF*              | **62.72** | **40.15** | **62.56** |

Results - Results on our pre-trained LMs outperform SOTA by significant margins across all three datasets despite having fewer parameters. While RoBERTa-extended, show gains over RoBERTa+BiLSTM-CRF, this is expected since the domain of the continued pre-training data is more in line for KE evaluation. However, the models that explicitly learn keyphrase representations such as KBI and KBIR significantly outperform RoBERTa-extended. We believe the slight gain for SemEval-2010 is because of the small size of the dataset (130 - train, 100 - test). Our models also outperformed SciBERT+Hypernet-CRF which is trained on the same scientific domain.

### 4.3 Keyphrase Generation

#### Setup
- We evaluate keyphrase generation (KG) performance on Inspec (Hulth, 2003b), NUS (Nguyen and Kan, 2007), Krapivin (Krapivin et al., 2009), SemEval (Kim et al., 2010) and KP20K (Meng et al., 2017). The task is to generate the CatSeq output of the present and absent keyphrases for a given concatenated title and abstract, as done in previous works (Meng et al., 2017; Chen et al., 2019; Yuan et al., 2018). We use the PresAbs ordering of the keyphrases as that was shown to be the most effective representation in (Meng et al., 2021). Further, we only train a single model by fine-tuning on the KP20K dataset, for 300k steps with a batch size of 32 across 4 GPUs with a learning rate of 5e-5, and perform inference on all the test datasets. Similar to (Meng et al., 2021) we use a beam width of 50 for beam search and restrict our maximum generated sequence length to 40 tokens. We also use KeyBART directly for generating the keyphrases without fine-tuning. We do this in order to see the effectiveness of pre-training the model to generate the outputs in Catseq format. This is also

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4https://github.com/midas-research/keyphrase-extraction-as-sequence-labeling-data
Table 3: Keyphrase generation for present keyphrases. SOTA is marked in Bold and our best performing models as Bold-Italicized (* LMs trained by us).

| Model                      | Inspec F1@5 | Inspec F1@M | NUS F1@5 | NUS F1@M | Krapivin F1@5 | Krapivin F1@M | SemEval F1@5 | SemEval F1@M | KP20k F1@5 | KP20k F1@M |
|---------------------------|-------------|-------------|----------|----------|---------------|---------------|--------------|--------------|------------|------------|
| catSeq (Yuan et al., 2018)| 22.5        | 26.2        | 32.3     | 39.7     | 26.9          | 35.4          | 24.2         | 28.3        | 29.1       | 36.7       |
| catSeqTG (Chen et al., 2019) | 22.9        | 27          | 32.5     | 39.3     | 28.2          | 36.6          | 24.6         | 29.0        | 29.2       | 36.6       |
| catSeqTG-2RF1 (Chen et al., 2019) | 25.3        | 30.1        | 37.5     | 43.3     | 30            | 36.9          | 28.7         | 32.9        | 32.1       | 38.6       |
| GANMR (Swaminathan et al., 2020) | 25.8        | 29.9        | 34.8     | 41.7     | 28.8          | 36.9          | -            | -           | 30.3       | 37.8       |
| ExHiRD-h (Chen et al., 2020) | 25.3        | 29.1        | -        | -        | 28.6          | 34.7          | 28.4         | 33.5        | 31.1       | 37.4       |
| Transformer (Ye et al., 2021) | 28.15       | 32.56       | 37.07    | 41.91    | 31.58         | 36.55         | 28.71        | 32.52       | 33.21      | 37.71      |
| BART*                     | 23.59        | 28.46       | 35.00    | 42.65    | 26.91         | 35.37         | 26.72        | 31.91       | 29.25      | 37.51      |
| KeyBART-DOC*              | 24.42        | 29.57       | 31.37    | 39.24    | 24.21         | 32.60         | 24.69        | 30.50       | 28.82      | 37.59      |
| KeyBART*                  | 24.49        | 29.69       | 34.77    | 43.57    | 29.24         | 38.62         | 27.47        | 33.54       | 30.71      | 39.76      |
| KeyBART* (no finetune)    | 30.72        | 36.89       | 18.86    | 21.67    | 18.35         | 20.46         | 20.25        | 25.82       | 12.57      | 15.41      |

Table 4: Keyphrase generation for absent keyphrases. SOTA is marked in Bold and our best performing models as Bold-Italicized (* LMs trained by us).

| Model                      | Inspec F1@5 | Inspec F1@M | NUS F1@5 | NUS F1@M | Krapivin F1@5 | Krapivin F1@M | SemEval F1@5 | SemEval F1@M | KP20k F1@5 | KP20k F1@M |
|---------------------------|-------------|-------------|----------|----------|---------------|---------------|--------------|--------------|------------|------------|
| catSeq (Yuan et al., 2018)| 0.4         | 0.8         | 1.6      | 2.8      | 1.8           | 3.6           | 1.6          | 2.8          | 1.5        | 3.2        |
| catSeqTG (Chen et al., 2019) | 0.5         | 1.1         | 1.1      | 1.8      | 1.8           | 3.4           | 1.1          | 1.8          | 1.5        | 3.2        |
| catSeqTG-2RF1 (Chen et al., 2019) | 1.2         | 2.1         | 1.9      | 3.1      | 3.0           | 5.3           | 2.1          | 3.0          | 2.7        | 5.0        |
| GANMR (Swaminathan et al., 2020) | 1.3         | 1.9         | 2.6      | 3.8      | 4.2           | 5.7           | -            | -            | 3.2        | 4.5        |
| ExHiRD-h (Chen et al., 2020) | 1.1         | 2.2         | 2.2      | 4.3      | 1.7           | 2.5           | 1.6          | 3.2          | -          | -          |
| Transformer (Ye et al., 2021) | 1.02        | 1.94        | 2.82     | 4.82     | 2.31          | 6.04          | 2.05         | 2.33         | 2.31       | 4.61       |
| BART*                     | 1.08        | 1.96        | 1.89     | 2.75     | 2.59          | 4.91          | 1.34         | 1.75         | 1.79       | 3.56       |
| KeyBART-DOC*              | 0.99        | 2.03        | 1.39     | 2.74     | 2.40          | 4.58          | 1.07         | 1.39         | 1.69       | 3.38       |
| KeyBART*                  | 0.95        | 1.81        | 1.23     | 1.90     | 3.09          | 6.08          | 1.96         | 2.65         | 2.03       | 4.26       |
| KeyBART* (no finetune)    | 1.83        | 2.92        | 1.46     | 2.19     | 1.29          | 2.09          | 1.12         | 1.45         | 0.70       | 1.14       |

equivalent to a zero-shot learning setup.

For our evaluation we use macro-averaged F1@5 and F1@M as in (Chan et al., 2019) and (Chen et al., 2020) for both present and absent keyphrase generation. F1@M evaluates all the keyphrases predicted by the model with the ground-truth keyphrases. F1@5, as the name suggests evaluates only the first 5 keyphrases, however when there are fewer than five keyphrases, random incorrect keyphrases are appended till it reaches five predictions. (Chan et al., 2019) show that without this appending F1@M is the same as F1@5, when predictions are fewer than five. (Ye et al., 2021) also present a ONE2SET training paradigm and for a fair comparison we compare to their Transformer (ONE2SEQ) results, since we also train in the ONE2SEQ paradigm and not ONE2SET.

Results - In Table 3 and Table 4 we see that KeyBART is the most effective pre-training method achieving SOTA on most datasets for F1@M in present and absent KG. We believe our choice of perturbation of the input during the pre-training setup makes this model robust and helps it to identify and generate keyphrases more effectively. We also observe that our results for F1@5 aren’t as competitive as F1@M and we believe this is because our model tends to favor predicting fewer than 5 keyphrases and thus tends to suffer from the random addition of keyphrases for F1@5. More concretely, the average predicted keyphrases per document for SemEval is 2.51, NUS is 2.86, Krapivin is 2.86, Inspec is 3.09 and KP20k is 2.73. In the zero-shot setting the KeyBART model did not do as well as the fine-tuned model with the exception of the results on the Inspec dataset where the non-finetuned model performs significantly better.

4.4 Other NLP Tasks

4.4.1 Named Entity Recognition

Setup - We report the performance of different models for the task of NER by conducting experiments on CoNLL-2003 dataset (Sang and De Meulder, 2003). We have used the sequence tagging token classification architecture implemented by (Wolf et al., 2020) in order to fine-tune different pre-trained models for the NER task. The architecture predicts token class types based on the output features generated by the model. For fine-tuning, we have used a learning rate of 1e-5 and the model is trained for 5 epochs on 1 GPU with a batch size of 8.
Results - Table 5 demonstrate that KBI and KBIR results in performance gains over RoBERTa on CoNLL-2003. With RoBERTa-extended, we see that only continued pre-training with the MLM objective results in minor gains. However, when we inspect the results for KBI and KBIR, we see consistent jumps in performance showing how both these architectures contribute in learning richer representations that directly impact NER performance. We hypothesize that KBIR is more effective at NER than KBI because the additional keyphrase replacement classification task builds richer boundary token representations making entity identification potentially easier. The results are also fairly competitive with SOTA NER literature despite we did not attempt in modeling entities explicitly like the SOTA (Yamada et al., 2020).

4.4.2 Relation Extraction

Setup - The relation extraction (RE) task predicts relations among pairs of entity mentions in a text. We fine-tuned our models for the sentence-level relation extraction task using the popular TACRED benchmark dataset (Zhang et al., 2017b). TACRED contains more than 100,000 sentences with entities that belong to 23 different fine-grained semantic types and with 42 different relations among entities. To fine-tune our models, we modified the input sequences to mark the start and end of the subject entity with @ and the object entity with #. We use the final layer representation of the [CLS] token as the input to a multi-class classifier.

Results - The results in the top half of Table 6 are reported from the respective papers that use various input formatting strategy. Similar to (Zhou and Chen, 2021), we also observe that a model’s performance depends heavily on the formatting of the input sequence. All models in the bottom half of the table are trained with the same input format mentioned above. We found a batch size of 32 and a learning rate between 2e-5 and 4e-5 to be optimal. We observe that our KBIR model performs slightly worse than the original RoBERTa model. We also observe similar trends for KBI and RoBERTa-extended models. We conjecture that the domain shift of the pre-training corpus is responsible for the slight performance degradation.

4.4.3 Question Answering

Setup - The relation between question answering (QA) and KE has been explored in some capacity in (Subramanian et al., 2018), which leverages keyphrase extraction for question generation. Motivated by this we evaluate our models on SQuAD v1.1 (Rajpurkar et al., 2016) dataset for the extractive question answering task. For all the models,
Table 8: Summarization results on CNN/DailyMail dataset. Our best performing models are marked as **Bold-Italicized**.

| Model                | R1   | R2   | RL   |
|----------------------|------|------|------|
| BART (Lewis et al., 2019) | 44.16| 21.28| 40.9 |
| BART*                | 42.93| 20.12| 39.72|
| KeyBART-DOC*         | 42.92| 20.07| 39.69|
| KeyBART*             | **43.10** | **20.26** | **39.90** |

we use a maximum sequence length of 512 with a sliding window of size 128. The model is fine-tuned with a learning rate of 3e-5 and batch size of 48 for 2 epochs. In order to achieve better reproducibility of results, we have used implementation by (Wolf et al., 2020) for fine-tuning the models.

**Results** - Table 5 reports the F1 and Exact Match (EM) scores achieved by different model architectures on the DEV set. We once again see improved performance with KB1 and KBIR as compared to RoBERTa. We have a curious finding where RoBERTa-extended actually performs worse than RoBERTa and we think this is because of the domain shift in the pre-training data which comprises of scientific articles. On the other hand, the models trained with keyphrase pre-training objectives are fairly competitive with the SOTA models, confirming that the learnt keyphrase representations do aid the QA task. We explicitly include LUKE w/o entity attention since that removes the entity-aware attention module, making it slightly more comparable to our results. We see that KBIR outperforms it by a slim margin on F1, however is slightly lower on the EM scores. We also highlight that our model’s performance doesn’t scale the same for EM as it does for F1 when compared to SOTA, potentially explained by the model being more likely to identify keyphrases as answers.

### 4.4.4 Summarization

**Setup** - We fine-tune BART (Lewis et al., 2019), KeyBART-DOC and KeyBART on the CNN DailyMail (Hermann et al., 2015) summarization dataset. Keyphrase Generation is also considered as an extreme form of summarization therefore we expected to see gains in performance for the summarization task. We were unable to reproduce the original BART scores for R1, R2 and RLSum, so we used the reported hyperparameters to reproduce the results to best of our ability accounting for slight implementation differences in framework versions. We hope this provides a more fair comparison with our model results.

**Results** - We do not claim SOTA for summarization models, rather want to demonstrate that there are potential performance gains by training on a keyphrase specific objective. This is exemplified in Table 8 where we see that the standard denoising autoencoder setup results in marginal losses, however training with the keyphrase generation objective actually improves the ROUGE scores across the board when compared with BART trained on the same dataset.

### 5 Qualitative Analysis

We perform a qualitative analysis on the SemEval-2010 dataset as it is the only common dataset between KE and KG tasks by leveraging predictions from the best performing models. We present three examples in Table 9 which captures the ground truth, with extracted and generated keyphrases. We observe that when the model tends to generate more keyphrases, it typically relies on the copy mechanism and hence most of the generated keyphrases are present in the text itself (Example 1). We also observe that when absent keyphrases are generated accompanied by a large number of generated keyphrases, they are usually a combination of 2 or more words directly present in the text such as ‘user study’ (Example 3). The example discusses how the authors study user behavior, potentially making ‘user study’ a fair prediction, however the ground truth would penalize the model if this was in the training phase.

Finally, we observe more generated keyphrases when the model isn’t able to identify keyphrases in text and doesn’t rely as heavily on the copy mechanism but rather on it’s understanding of the text. This results in keyphrases such as ‘natural language processing’ (Example 2). Although the predictions is not in the ground-truth, it aligns with the mentions of ‘question answering’ and ‘linguistics’. This demonstrates that the model is indeed able to generate meaningful absent keyphrases. However, we observe that the model is not able to learn or infer world knowledge required to produce the absent keyphrases in the ground-truth. For keyphrase extraction, we see that the model tends to tag phrases more frequently than previous models, improving recall. This we hypothesize is due to the model having a better understanding of keyphrases in a document, because of the keyphrase masking perturbation and also the KRC task.
We also attempted to use a combination of the Wikipedia (English) dump and S2ORC (Lo et al., 2019) corpora for pre-training our models. In order to obtain keyphrase tags for data at a large scale, we employed TextRank (Mihalcea and Tarau, 2004) on each document in the corpora. We set the maximum number of keyphrases to 10 for the TextRank algorithm and considered all keyphrases tagged by TextRank. We created random splits for our dataset to generate a train and development (dev) set. However, we found that keyphrases tagged in this manner added a lot of noise to the dataset and resulted in only marginal overall gains.

In order to train a keyphrase specific language model we also used a combined generative and discriminative approach as introduced in ELECTRA (Clark et al., 2020). The generative approach made...
the model predict the masked tokens that are part of a keyphrase. In the discriminative approach the original sequence was converted by replacing the tokens of a keyphrase with another semantically unrelated keyphrase. We were unable to stabilize the training for such a setup and didn’t get promising results.

7 Conclusion and Future Work

For the first time we explored LMs capable of learning rich keyphrase representations that achieve SOTA performance across multiple datasets for keyphrase extraction and generation tasks. Towards this effort we proposed a new pre-training objective KBIR and a new training setup KeyBART. The trained LMs clearly shows their effectiveness by achieving SOTA or near SOTA performance for various NLP tasks on datasets spanning across multiple domains. As a next step, we would like to probe our LMs to understand them more and also gauge their effectiveness for the tasks of cross-domain keyphrase extraction and generation. We really hope that our work enables researchers to develop better keyphrase extraction and generation models and push the envelope further in this area.

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