Enhancing Language Generation with Effective Checkpoints of Pre-trained Language Model

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Abstract

This work empirically explores effective exploiting of intermediate output from pre-trained language models (PrLMs) for language generation tasks. For this purpose, we propose an improved method to integrate public checkpoints of PrLMs for the most convenience and perform extensive experiments on 6 different kinds of PrLMs, including BERT, ELECTRA, GPT2, Multi-lingual BERT, and XLM RoBERTa. Evaluation with automatic metrics shows that our approach significantly improves the generation quality on the generation tasks, up to 1.8 BLEU points for neural machine translation (Korean-to-English, Korean-to-Chinese) and 1.8 ROUGE points improvements for text summarization.

1 Introduction

Pre-trained Language Models (PrLMs), such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and ELECTRA (Clark et al., 2020), have thoroughly changed the landscape of state-of-the-art performance on many Natural Language Understanding (NLU) tasks. Also, publicly released checkpoints of the PrLMs allow natural language processing (NLP) researchers to gain SOTA results while saving vast compute and time resources. The widely used method to exploit PrLM is fine-tuning. However, for Natural Language Generation (NLG) tasks, such methods do not get as much performance gain as in the NLU task. Several previous studies proposed methods that better use prior knowledge of the PrLM for NLG tasks (Yang et al., 2020; Zhu et al., 2020; Chen et al., 2020). Expanding the previous studies, in this paper, we propose an improved method that exploits the checkpoint of the PrLM into the Transformer models (Vaswani et al., 2017).

The existing methods for leveraging PrLM in NLG tasks can be roughly classified into two categories: Reusing the PrLM as a starting point and Integrating the intermediate output of the PrLM. The former, the widely used in various NLP tasks, denotes to initialize the part of Transformer from the PrLM for generation tasks (Clinchant et al., 2019; Edunov et al., 2019; Rothe et al., 2020) or replace the input embedding with the PrLM. The latter is an approach that first extracts the contextualized representation from a LM for an input sentence and fuses it into a neural model (Yang et al., 2020; Zhu et al., 2020; Chen et al., 2020). As our preliminary experiment shows, we expand this approach and explore in many ways towards better performance. In both of the preceding approaches, whether to freeze or fine-tune the parameter of PrLM is also an important issue. For the former (Reusing the PrLM), several works demonstrated that freezing the PrLM at training time led to a significant performance drop. Meanwhile, for the latter approach (Integrating the PrLM), prior studies adopted the whole or half-freezing instead of fine-tuning the parameters of the PrLMs. Yang et al. (2020) suggested that the reason why fine-tuning PrLM in neural machine translation (NMT) does not work as well as in other NLP tasks is due to the availability of large training data and the high capacity of baseline NMT models (i.e., Transformer), where excessive fine-tuning leads to the catastrophic forgetting phenomenon (Goodfellow et al., 2015). Also, Zhu et al. (2020) shows that freezing the BERT in NMT is better than fine-tuning with a large gap. This is in line with our experimental results. Thus in this empirical study, we freeze the parameters of the PrLMs in our experiments.

This paper focuses on finding an effective
method integrating the intermediate output into the Transformer model to improve the generation quality, unlike the widely used methods such as initializing a part of Transformer and replacing the input embedding with the PrLM. To this end, similar to Zhu et al. (2020), we insert PrLM-dedicated modules that take the intermediate output from the PrLM and make the extra flow for PrLM in Transformer layers. This allows us to integrate PrLM into the Transformer without considering the PrLM’s configuration such as modeling, dimension and vocabulary. Based on extensive empirical experiments, we finally adopt an improved method that uses the Second-to-last (i.e., penultimate) hidden state of the PrLM as the contextualized representation and proceeds, in only Source-side (Encoder), Summation of the source input flow and the PrLM flow generated through the PrLM-dedicated modules. In our proposed encoder, the PrLM representation $H_P$ is merged with the source flow to generate the output $H_S$ of $n^{th}$ encoder layer:

$$H_S^n = (\text{Flow}_P + \text{Flow}_S) + \text{Attn}_S,$$

$$\text{Flow}_P = \text{FNN}(\text{Attn}_P + H_{S,n-1}^P),$$

$$\text{Attn}_P = \text{PrLMAttn}(H_{S,n-1}^P, H_P, H_{S,n}),$$

$$\text{Flow}_S = \text{FNN}(\text{Attn}_S + H_{S,n-1}^S),$$

$$\text{Attn}_S = \text{Attn}(H_{S,n-1}^S, H_{S,n-1}^S, H_{S,n-1}^S),$$

where $\text{PrLMAttn}$ is the PrLM-dedicated attention module that takes the previous hidden state $H_{S,n-1}^P$ as a query and the PrLM representation $H_P$ as a key and a value and $\text{Attn}$ is the original one. We adopt the summation strategy for merging the two different flows, and it gains better results than previous works such as gate network (Yang et al., 2020) and dropnet (Zhu et al., 2020).

3 Experiments

To demonstrate the effectiveness of the proposed method, we perform extensive experiments on two NMT and abstractive text summarization tasks. For translation, we use BLEU (Papineni et al., 2002) for the evaluation of translation quality, and for text summarization, we report unigram and bigram overlap (ROUGE-1 and ROUGE2) to assess informativeness, and the longest common subsequence (ROUGE-L) to assess fluency with ROUGE scores (Lin, 2004). All the model training is on a single NVIDIA Tesla V100 GPU (16130MiB, Google Colab).

3.1 Datasets and Experimental Setting

We evaluate our approach on language generation tasks such as translation and text summarization. For translation tasks, we use two machine translation datasets: AIHub Ko→En \(^2\) (containing 1.6M

\(^1\)https://github.com/tmtmaj/Exploiting-PrLM-for-NLG-tasks

\(^2\)http://www.aihub.or.kr/
Table 1: Experimental results on translation tasks. Both Clinchant et al. (2019) and Zhu et al. (2020) use ELECTRA base.

| Systems                  | Ko→Ch       | Ko→En       |
|--------------------------|-------------|-------------|
| Transformer              | 30.35 (-)   | 41.19 (-)   |
| (Zhu et al., 2020)       | 31.33 (+0.9) | 41.97 (+0.7) |
| (Clinchant et al., 2019) | 31.75 (+1.4) | 41.55 (+0.4) |
| **Korean-specific PrLM** |             |             |
| +KoBERT                  | 31.20 (+0.8) | 42.17 (+0.9) |
| +HanBERT                 | 31.39 (+0.9) | 42.03 (+0.8) |
| +DistilKoBERT            | 30.94 (+0.5) | 41.91 (+0.7) |
| +ELEC. small             | 31.51 (+1.1) | 42.20 (+1.0) |
| +ELEC. base              | **32.17 (+1.8)** | **42.59 (+1.4)** |
| +KoGPT2                  | 30.38 (+0.0) | 41.74 (+0.5) |
| **Multi-language PrLM**  |             |             |
| +BERT cased              | 30.57 (+0.2) | 41.17 (-0.0) |
| +BERT uncased            | 30.78 (+0.4) | 41.22 (+0.0) |
| +RoBERTa base            | 31.09 (+0.7) | 41.85 (+0.6) |
| +RoBERTa large           | 31.64 (+1.2) | 42.01 (+0.8) |

Table 2: Experimental results on summarization task. △ denotes average improvements.

| Systems                  | R-1       | R-2       | R-L       | △      |
|--------------------------|-----------|-----------|-----------|--------|
| Transformer              | 46.32     | 29.56     | 37.88     | -      |
| Oracle                   | 57.17     | 44.00     | 44.46     | -      |
| **Korean-specific PrLM** |           |           |           |        |
| +KoBERT                  | 47.05     | 30.40     | 38.68     | +0.8   |
| +HanBERT                 | 47.49     | 31.22     | 39.51     | +1.5   |
| +DistilKoBERT            | 46.64     | 29.86     | 38.43     | +0.4   |
| +ELEC. small             | 47.10     | 30.88     | 39.01     | +1.1   |
| +ELEC. base              | **47.90** | **31.44** | **39.91** | +1.8   |
| +KoGPT2                  | 46.99     | 30.51     | 38.65     | +0.8   |
| **Multi-language PrLM**  |           |           |           |        |
| +BERT cased              | 46.44     | 29.61     | 38.11     | +0.1   |
| +BERT uncased            | 46.92     | 29.80     | 38.40     | +0.4   |
| +RoBERTa base            | 47.01     | 30.55     | 38.89     | +0.9   |
| +RoBERTa large           | 46.77     | 30.31     | 38.66     | +0.6   |

Korean-specific PrLMs leads to better performance than using multi-language PrLMs.

4. Explorations for leveraging PrLM

Our proposed method for leveraging PrLM is to use the Second-to-last hidden state of the PrLM as the contextualized representation and proceeds, in only Source-side (Encoder). Summation of the source input flow and the PrLM flow after the FNN. In this subsection, the setting is the default, and we change only the target part of each experiment. We conducted the following four analyses on the Korean-Chinese and Korean-English datasets.

4.1 Which hidden state of the PrLM to extract?

We evaluated the impact on how to extract the contextualized representation from the PrLM. As shown in Table 3a, using the second-to-last (i.e., penultimate) hidden state of the PrLM performs the best. It has also been demonstrated in Yang et al. (2020). Moreover, as another attempt, we dynamically extracted the hidden state of each layer based on sentence embedding of $n^{th}$ layer, which can be gained by averaging the PrLM layer (known as PrLM embeddings, Dyn. [Aver] in Table 3a) or using the output of the first token (the [CLS] token, Dyn. [CLS]). However, they did not get a big performance boost.
4.2 How to merge the PrLM representation with the source input flow?

We compared the impact of different merging strategies for the contextualized representation of PrLM. There are directly using the PrLM as the input embedding (Direct in Table 3b) and four merging strategies such as Summation, Average, using Gate Network (Yang et al., 2020), and using Dropnet (Zhu et al., 2020). As shown in Table 3b, the summation of the PrLM flow and the source input flow got the better improvement over others, so we adopted the Summation strategy in our experiments.

4.3 Where do the PrLM merge with the source input flow?

In the Table 3c, we analyzed where in the encoder layer of Transformer it would be better to merge the PrLM and source flows. There are four positions in a Transformer-encoder layer: after Attn, after $1^{st}$ Add&Norm, after FFN, and after $2^{nd}$ Add&Norm. It is interesting to find that merging after FFN can get the best performance. Another observation is that merging the contextualized representation of the PrLM before the Add&Norm (i.e., after Attn or FFN) works better.

4.4 Where do the PrLM flow add?

We evaluated where to add the PrLM: source-side, target-side, and both sides. As shown in the Table 3d, report the results. Among them, adding the PrLM to only source-side (i.e., encoder) gained the best result. Intuitively, since contextual representation from the fixed PrLM contains universal information, not information for generation tasks, combining it directly with the target context may adversely affect performance improvement.

5 More analyses

5.1 Leveraging Multi-PrLMs

We assumed that because PrLMs were trained with different datasets (size, domain) and diverse configurations, they would contain specific prior knowledge. So, we tried to integrate two or more PrLMs simultaneously (Multi-PrLMs) by adding more extra modules in each encoder layer. Contrary to our expectations, as shown in Table 4, using Multi-PrLMs cannot get a significant performance boost over using single-PrLM.

5.2 Fine-tuning v.s. Freezing

We compared the impact of fine-tuning and freezing the parameters of PrLM when using our method. Table 5 shows the results. We can see that freeze-
Table 5: Fine-tuning v.s. Freezing

| Systems                  | Ko→Ch | Ko→En |
|-------------------------|-------|-------|
| Transformer             | 30.35 (-) | 41.19 (-) |
| **Freezing PrLM (Ours)**|       |       |
| +ELEC. small            | 31.51 (+1.1) | 42.20 (+1.0) |
| +ELEC. base             | 32.17 (+1.8) | 42.59 (+1.4) |
| **Fine-tuning PrLM**    |       |       |
| +ELEC. small            | 31.52 (+1.1) | 41.98 (+0.8) |
| +ELEC. base             | 29.89 (-0.4) | 38.92 (-2.3) |

Table 6: Inference Speed on Ko→En NMT task

| Systems        | sentences/s | tokens/s |
|----------------|-------------|----------|
| Transformer    | 164.20 (-)  | 4.56k (-) |
| **Our Systems**|             |          |
| +ELEC. small   | 155.59 (-5%) | 4.35k (-5%) |
| +ELEC. base    | 139.81 (-17%) | 3.92k (-16%) |

Previous studies rely on the structural compatibility of Transformer and PrLM. For example, Clinchant et al. (2019) presented initializing the encoder of Transformer from BERT (fine-tuned or fixed) and observed that freezing the PrLM causes a considerable performance drop. Conneau and Lample (2019) verified that initialization methods with CLM or MLM trained on multi-lingual corpora and showed such initialization are useful on MT. Rothe et al. (2020) used the publicly available PrLM checkpoints to initialize Transformer. While the initialization method is useful to some extent, there is a prerequisite for matching vocabulary and model size/hyper-parameters to them of PrLM.

Zhu et al. (2020) proposed a new method that extracts the last hidden state of BERT for an input sentence and fuses it into the encoder and decoder of the Transformer through an extra attention module, and evaluated the effectiveness of their method on supervised, semi-supervised and unsupervised NMT. Yang et al. (2020) introduced a concerted training framework with three techniques for fusing PrLM and NMT model. Although they also extract the hidden state of PrLM and integrate it into NMT model, the NMT model must follow the PrLM model’s configurations such as word segmentation rule and vocabulary.

Our work is related to both Zhu et al. (2020) and Yang et al. (2020) in the sense that we all aim to extract the intermediate output of the PrLM and integrate it into a neural model for better generation quality. As an extension of Zhu et al. (2020), we propose an upgraded method adopted through extensive empirical experiments. Our work differs from Yang et al. (2020) in that we use the publicly available checkpoints that have various configurations and fix the PrLM at training time.

7 Conclusion

While most of the previous works on PrLM address the integration of PrLMs with fine-tuning, we propose an alternative in which a modified Transformer-encoder takes the intermediate output from PrLM to exploit its prior knowledge effectively in a straightforward way. Our method does not have to consider the PrLM’s configuration, such as its model size, model dimension, and vocabulary. Correspondingly, our approach and reported empirical settings can be smoothly applied to any languages using any checkpoints of PrLMs.
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A Experimental Settings

A.1 Model Setting

In our experiment, we use Transformer (Vaswani et al., 2017) as the baseline model for NMT and abstractive text summarization tasks. Additionally, for NMT tasks, we compare our approach to the following baselines:

- (Zhu et al., 2020): A method that inserts the last-hidden state of fixed PrLM through PrLM-dedicated attention module in Transformer-encoder and decoder.
- (Clinchant et al., 2019) (Direct* in Table 1): A method that replaces the input embedding with the PrLM that is fine-tuned in training time. They all use ELECTRA base as the PrLM.

For the Transformer model, we use a base Transformer configuration (Vaswani et al., 2017) with an embedding size of 512, 6 encoder and decoder layers, 8 attention heads, shared source and target embedding, the standard relu activation function, and sinusoidal positional embedding. We train with a batch size of 3500 tokens and optimize the model parameters using Adam optimizer with a learning rate $7 \times 10^{-4}$, learning rate warm-up over the first 4000 steps. Additionally, we apply label smoothing with a factor of 0.1. We average over the last 5 checkpoints and run inference with a beam size of 5. All models are trained for 50 epochs using the Torch-based toolkit, Fairseq(-py) (Ott et al., 2019). For the text summarization task, we reduce the number of encoder and decoder layers to 4 and use Trigram Blocking (Paulus et al., 2018) to reduce redundancy during inference time. Other settings are the same as above.

For all datasets, we first tokenize sentences using language-specific tokenizer such as KoNLPy\(^5\) for Korean, jieba\(^6\) for Chinese, and Moses (Koehn et al., 2007) for English and then apply Byte-Pair Encoding (Sennrich et al., 2016) to the tokenized sentences with 32K merge-operations. Besides, most of PrLMs have a limit for input sequence length (e.g., 512), so we cut out the middle of some long text for text summarization dataset as proposed in Sun et al. (2019).

A.2 Pre-trained Language Model Setting

In our experiments, we use 6 types of different PrLMs including BERT (Devlin et al., 2019), DistilBERT (Sanh et al., 2019), ELECTRA (Clark et al., 2020), GPT2 (Radford et al., 2018), multi-lingual BERT, and XLM-RoBERTa (Conneau and Lample, 2019; Liu et al., 2019). Specifically, we use 10 different pre-trained checkpoints depending on the model size, training data set, and training level:

1. KoBERT: a BERT with 768-hidden, 12-layer, 12-heads, 8002-vocab, Korean dataset (4GB), 92M parameters; https://github.com/SKTBrain/KoBERT.git.
2. HanBERT: a BERT with 768-hidden, 12-layer, 12-heads, 54000-vocab, Korean dataset (70GB), 127M parameters; https://github.com/tbai2019/HanBert-54k-N.git.
3. DistilKoBERT: a DistilBERT with 768-hidden, 3-layer, 12-heads, 8002-vocab, Korean dataset (10GB), 28M parameters; https://huggingface.co/monologg/distilkobert.
4. ELECTRA small: a ELECTRA with 256-hidden, 12-layer, 4-heads, 35000-vocab, Korean dataset (34GB), 14M parameters; https://huggingface.co/monologg/koelectra-small-v3-discriminator.
5. ELECTRA base: a ELECTRA with 768-hidden, 12-layer, 12-heads, 35000-vocab, Korean dataset (34GB), 112M parameters; https://huggingface.co/monologg/koelectra-base-v3-discriminator.
6. KoGPT2: a GPT2 with 768-hidden, 12-layer, 12-heads, 50000-vocab, Korean dataset (20GB), 125M parameters; https://github.com/SKT-AI/KoGPT2.git.
7. Multi-lingual BERT cased: a BERT with 768-hidden, 12-layer, 12-heads, 119547-vocab, 104 languages, 177M parameters; https://huggingface.co/bert-base-multilingual-cased.
8. Multi-lingual BERT uncased: a BERT with 768-hidden, 12-layer, 12-heads, 105879-vocab, 102 languages, 167M parameters; https://huggingface.co/bert-base-multilingual-uncased.
9. XLM RoBERTa base: a BERT with 768-hidden, 12-layer, 12-heads, 250002-vocab, 100 languages (2.5TB), 277M parameters; https://huggingface.co/xlm-roberta-base.
B Details of the Notations

Let $\text{Attn}$ denote a multi-head attention module, which takes three matrices containing a query matrix $Q$, a key matrix $K$, and a value matrix $V$ and product an output matrix as follows:

$$\text{Attn}(Q, K, V) = \text{concat}(\text{head}_1, \ldots, \text{head}_i)W^o,$$

$$\text{head}_i = \text{attn}(Q_i, K_i, V_i),$$

$$\text{attn}(q, k, v) = \text{softmax}(\frac{qW^qkW^k}{\sqrt{d_{\text{model}}}})vW^v,$$  

where $\text{concat}$ denotes a concatenation operation, $\text{softmax}$ denotes a softmax function, $d_{\text{model}}$ is the dimension of the model, and $W^o, W^q, W^k, W^v$ are parameter matrices. $\text{FFN}$ consists of two fully-connected layers with a $\text{relu}$ activation in between.

$$\text{FFN} = \max(0, xW^1 + b^1)W^2 + b^2,$$  

where $\max(0, x)$ is $\text{relu}$ activation function, and $W^1, b^1, W^2, b^2$ are parameter matrices. Finally, $\text{Attn}$ and $\text{FFN}$ are connected with $\text{Add} \& \text{Norm}$, which denotes a combination module containing a residual connection (He et al., 2016) and a layer normalization (Ba et al., 2016).