Few-Shot Text Generation with Pattern-Exploiting Training

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Abstract
Providing pretrained language models with simple task descriptions or prompts in natural language yields impressive few-shot results for a wide range of text classification tasks when combined with gradient-based learning from examples. In this paper, we show that the underlying idea can also be applied to text generation tasks: We adapt Pattern-Exploiting Training (PET), a recently proposed few-shot approach, for finetuning generative language models on text generation tasks. On several text summarization and headline generation datasets, our proposed variant of PET gives consistent improvements over a strong baseline in few-shot settings.\(^1\)

1 Introduction
Pretraining large neural networks with a language modeling objective has led to significant improvements throughout NLP (Peters et al., 2018; Howard and Ruder, 2018; Radford et al., 2018; Devlin et al., 2019). Further improvements are often possible by choosing a different pretraining objective that more closely matches the downstream task of interest. Examples include casing prediction for named entity recognition (Mayhew et al., 2020), gap sentence generation for summarization (Zhang et al., 2020), and sentence unshuffling for discourse representations (Lee et al., 2020).

While such approaches often reduce the amount of training data required, they still do not perform well if only a handful of examples is available for the downstream task, which is common for real-world uses of NLP. In such few-shot settings, however, significant gains are possible by proceeding the other way around: Instead of making pretraining more similar to a downstream task, we can reformulate the task itself to make it more similar to the pretraining objective. For masked language models (e.g., Devlin et al., 2019; Lewis et al., 2020), one such reformulation technique is to convert inputs to cloze questions by adding a text snippet that contains some form of task description, often in the form of a short prompt (Radford et al., 2019; Schick and Schütze, 2020a). Besides making pretraining and finetuning more similar, this approach has the compelling benefit of enabling users to explain a task to a pretrained model, making it much easier for the model to understand the task. Examples in Figure 1 demonstrate that pretrained language models can make use of such text snippets to adapt their output for a generation task.

While this idea even works in an unsupervised setting (Radford et al., 2019) or when examples are simply provided as additional context (Brown et al., 2020), it only unfolds its full potential when combined with gradient-based training on a handful of labeled examples (Schick and Schütze, 2020b). In particular, Pattern-Exploiting Training (PET) – an approach proposed by Schick and Schütze (2020a) that combines task descriptions with learning from examples – performs strongly for various few-shot

\(^1\)Our implementation is publicly available at https://github.com/timoschick/pet.

Figure 1: Texts generated by PEGASUS-large with different patterns for input \(x = \) Dear John, Your Internet Banking accounts are now setup again for accessing. The login id is still your main account with the password being reset to the last six (6) digits of your SSN.
text classification datasets. However, it can only be applied to classification tasks and is therefore not applicable to any problems that require the generation of text sequences.

In this paper, we adapt PET to train generative models on text generation tasks. In particular, we propose several modifications that enable us to fine-tune a pretrained PEGASUS model (Zhang et al., 2020) with PET. We evaluate our approach on a diverse set of six English headline generation and text summarization tasks both in zero-shot and few-shot settings and show that PEGASUS trained with our adapted version of PET clearly outperforms regular finetuning.

In summary, our contributions are as follows:

• We describe how PET can be modified for finetuning generative language models for sequence generation tasks.

• We show that training PEGASUS with PET outperforms regular finetuning across a large set of tasks and training set sizes.

• We analyze the factors contributing to PET’s strong performance.

2 Related Work

Masked language modeling was proposed as a pre-training objective by Devlin et al. (2019). Several variants of this objective have been proposed that involve generating sequences of text, including T5 (Raffel et al., 2020), BART (Lewis et al., 2020) and PEGASUS (Zhang et al., 2020), on which our approach is based.

The idea to rephrase tasks as cloze questions is commonly used to probe the knowledge contained within masked language models (e.g., Petroni et al., 2019; Wang et al., 2019; Schick and Schütze, 2020c; Ettinger, 2020). Schick and Schütze (2020a) propose PET, which combines this idea with gradient-based learning for few-shot text classification. Jiang et al. (2020) and Schick et al. (2020) consider the problem of finding the best way to rephrase a given task as a cloze question. Closely related to our work, Schick and Schütze (2020b) propose a modification to PET that enables the generation of multiple tokens, but their approach still requires a text classification objective and does not scale to long output sequences.

Other approaches for few-shot learning in NLP commonly require large sets of examples from related tasks (Gu et al., 2018; Dou et al., 2019; Qian and Yu, 2019), parallel data for consistency training (Xie et al., 2019; Chen et al., 2020), or highly specialized methods tailored towards a specific task (Laban et al., 2020). In contrast, PET requires no additional labeled data and provides an intuitive interface to leverage task-specific human knowledge.

Finally, our proposed variant of PET is closely related to concurrent work by He et al. (2020) who use prompts and keywords for controllable text generation (but do so only in high-resource settings) and to prefix-constrained decoding (Knowles and Koehn, 2016; Wuebker et al., 2016; Keskar et al., 2019).

3 PEGASUS Pretraining

PEGASUS (Zhang et al., 2020) is a standard Transformer encoder-decoder architecture (Vaswani et al., 2017) that is pretrained using gap-sentences generation, an objective tailored to text summarization tasks. This pretraining objective requires a set of documents consisting of multiple sentences. The key idea is to preprocess each document by (i) picking a subset of sentences that are important to the document, (ii) replacing each of these sentences by a mask token, and (iii) concatenating all removed sentences into a pseudo-summary. The Transformer model is then trained to generate this pseudo-summary given the partially masked document. Similar to prior work (e.g., Raffel et al., 2020; Lewis et al., 2020), this is done by processing the entire masked document using the encoder and generating the output in an autoregressive fashion using the decoder. For picking informative sentences, the informativeness of each sentence is measured as the Rouge1 F1 score (Lin, 2004) between the sentence and the remaining document and the top- \( m \) sentences according to this measure are selected.

Zhang et al. (2020) train two variants of PEGASUS: PEGASUS-base, a 12-layer model with approximately 223M parameters, and PEGASUS-large, a 16-layer model with 568M parameters. As only the latter version is publicly available, all of our experiments are based on PEGASUS-large.

4 Pattern-Exploiting Training

We first discuss Pattern-Exploiting Training (PET) for text classification tasks, i.e., for problems where some textual input \( x \in \mathcal{X} \) must be mapped to a single output \( y \) from a finite set \( \mathcal{Y} \). Let \( M \) be a masked language model (MLM), \( T \) its set of tokens
and \( y \in T \) the mask token; we denote the set of all token sequences as \( T^* \). PET requires:

- a pattern \( P : \mathcal{X} \rightarrow T^* \) that maps inputs to cloze questions containing exactly one mask;
- a verbalizer \( v : \mathcal{Y} \rightarrow T \) that maps each output to a single token representing its meaning.

The probability of \( y \) given \( x \) is then derived from the score that \( M \) assigns to \( v(y) \) at the masked position in \( P(x) \).

As shown in (Jiang et al., 2020; Schick and Schütze, 2020a), some pairs \((P,v)\) work much better than others. However, in the absence of a large development set, pairs that work well are often hard to distinguish from those that perform poorly. PET alleviates this issue by enabling the simultaneous usage of multiple pattern-verbalizer pairs and combining them using a mechanism similar to knowledge distillation (Hinton et al., 2015):

1. For each pair \((P,v)\), a separate MLM is finetuned on all available training data.
2. The ensemble of MLMs is used to annotate a set of unlabeled examples with soft labels.
3. A single MLM with a sequence classification head is finetuned on the resulting soft-labeled dataset and serves as the final classifier.

**PET for Text Generation**

There are several differences to consider when designing a form of PET appropriate for the generative setting: First, we do not require a verbalizer as the output space already consists of natural language sentences, i.e., \( \mathcal{Y} \subseteq T^* \). Second, the encoder-decoder architecture of most generative language models supports some subtle adjustments with regard to the application of patterns. Finally, we need a novel strategy for combining multiple patterns as we cannot simply average the text sequences produced by different models in a meaningful way.

Throughout this section, let \( P \) be a pattern, \( x \in \mathcal{X} \), \( y \in \mathcal{Y} \), and \( P(x) = z \) for some \( z \in T^* \). Furthermore, let \( y = y_1 \ldots y_n \), \( z = z_1 \ldots z_m \) and let the single mask token in \( z \) be at some position \( h \leq m \). We denote the concatenation of \( y \) and \( z \) by \( yz \) and the subsequence \( y_1 \ldots y_j \) by \( y_{1:j} \). We consider an encoder-decoder model \( M \) pretrained using a masked language modeling objective. That is, the model must be able to compute a probability \( p_M(y | z) \) that measures to what extent \( y \) is a plausible substitute for the mask in \( z \). We further assume that this is done by decomposing the joint probability of \( y \) as follows:

\[
p_M(y | z) = \prod_{i=1}^{n} p_M(y_i | z; y_{1:i-1})
\]

where \( p_M(y_i | z; y_{1:i-1}) \) is obtained from \( M \) by processing \( z \) using the encoder and \( y_{1:i-1} \) using the decoder. If we happen to already know some prefix \( y_{1:k-1} \) of \( y \), the probability of the remaining sequence \( y_{k:n} \) can be expressed as

\[
p_M(y_{k:n} | z; y_{1:k-1}) = \prod_{i=k}^{n} p_M(y_i | z; y_{1:i-1})
\]

As \( M \) is an encoder-decoder language model, we have several options of how to compute the probability of \( y \) given \( x \) using pattern \( P \): We may process the entire sequence \( P(x) = z \) with the encoder as above, but we may also choose some index \( j < h \) and process \( z_1:j-1z_{k:n} \) using the encoder and \( z_{j:h-1} \) using the decoder. For example, if \( z = \text{Summary: __ Text: x} \), we can process the prefix “Summary:” using the encoder or the decoder; that is, we may either compute \( p_1 = p_M(y | z) \) or \( p_2 = p_M(y | \text{__ Text: x; Summary: }) \).

In preliminary experiments, we found tokens that belong to the partially generated output sequence (i.e., tokens that are processed using the decoder) to have a stronger impact on the model’s predictions than regular input tokens. This applies all the more to PEGASUS, which is pretrained to always generate full sentences: If some part of the used pattern is supposed to be a prefix of the sentence to be generated (e.g., a short prompt), PEGASUS tends to simply ignore this part when it is processed using the encoder.

Based on this observation, we supplement each pattern \( P \) with a decoder prefix \( d \in T^* \) that is given to the model as part of the generated sequence rather than the observed input. Accordingly, we define the probability of \( y \) given \( x \) as

\[
p_{(P,d)}(y | x) = p_M(y | P(x); d)
\]

In the example discussed above, \( p_1 \) corresponds to using \( P(x) = \text{Summary: __ Text: x} \) with an empty

\[\text{2} \text{There are several recent architectures that fulfill this requirement, including BART (Lewis et al., 2020), T5 (Raffel et al., 2020) and PEGASUS (Zhang et al., 2020).} \]
decoder prefix \( \mathbf{d} \), whereas \( p_2 \) corresponds to using the pattern \( P(x) = \cdot \) with a decoder prefix \( \mathbf{d} = \) Summary.

We finetune \( M \) on a set of training examples \( (x, y) \) simply by minimizing the cross-entropy between \( p_{(P,\mathbf{d})}(y | x) \) and \( y \) using teacher forcing.

**Combining Patterns**  If we have multiple pairs \((P_1, \mathbf{d}_1), \ldots, (P_k, \mathbf{d}_k)\) of patterns and decoder prefixes, we first finetune an individual model \( M_i \) for each \((P_i, \mathbf{d}_i)\) as in regular PET. To combine their knowledge and distill it into a single model \( \tilde{M} \), we again require a set of unlabeled examples \( \mathcal{U} \). However, we need a different strategy than Schick and Schütze (2020a) for assigning target sequences \( y \in \mathcal{Y} \) to each unlabeled example \( x \in \mathcal{U} \) because we cannot simply average all sequences generated by the individual models. Computing a single output sequence that is most likely according to all models is also infeasible as doing so efficiently would require us to keep \( k \) models in memory at the same time.

We instead resort to the following approach: For each \( x \in \mathcal{U} \), we first generate one output sequence \( y^{(P_i, \mathbf{d}_i)} \) per \((P_i, \mathbf{d}_i)\) using greedy decoding as in Zhang et al. (2020), resulting in a set of candidate outputs \( \mathcal{C}_x = \{ y^{(P_i, \mathbf{d}_i)} \mid 1 \leq i \leq k \} \). We then assign a score to each candidate \( y \in \mathcal{C}_x \). To this end, we first compute the normalized log-likelihood of \( y \) for each \((P_i, \mathbf{d}_i)\) as

\[
s_i(y \mid x) = \frac{1}{|y|} \cdot \log p_{(P_i, \mathbf{d}_i)}(y \mid x)
\]

where we divide by the length of \( y \) to correct for length bias (Boulanger-Lewandowski et al., 2013; Jean et al., 2015). We obtain the total score of \( y \) from the average of its scores according to individual patterns as \( s(y \mid x) = \exp \frac{1}{k} \sum_{i=1}^{k} s_i(y \mid x) \). The final model \( \tilde{M} \) is then trained on pairs \((x, y)\) where \( x \in \mathcal{U} \) and \( y \) is drawn from \( \mathcal{C}_x \) with probability proportional to \( s(y \mid x) \).

While we could train the final model to simply maximize \( p_{\tilde{M}}(y \mid x) \), we note that this creates a strong discrepancy between pretraining and finetuning: During pretraining, PEGASUS only processes sequences that contain at least one mask token. In the spirit of our intention to make pretraining and finetuning as similar as possible, we therefore train \( \tilde{M} \) using a trivial pattern \( P(x) = \cdot \) that just prepends a single mask token to the input and use an empty decoder prefix.

### 5 Experiments

**Tasks**  We evaluate PEGASUS with and without PET on a subset of the tasks used by Zhang et al. (2020). As we have limited compute available, we only choose those tasks for which the maximum output length in (Zhang et al., 2020) is at most 128 tokens. Specifically, we consider the following datasets:

- **AESLC** (Zhang and Tetreault, 2019): Given an email body, the title of the email must be predicted.
- **Gigaword** (Rush et al., 2015): Given the first sentence of a news article, its headline has to be generated.
- **XSum** (Narayan et al., 2018): Articles spanning a wide range of different topics have to be summarized.
- **Reddit TIFU** (Kim et al., 2019): Summaries have to be generated for posts from the TIFU community in Reddit.
- **NEWSROOM** (Grusky et al., 2018): Summaries must be generated for articles from various major publications.
- **CNN/DailyMail** (Hermann et al., 2015): For articles from CNN and the Daily Mail, a list of highlights has to be generated.

For each task, we use the entire test set for evaluation.\(^3\) We create two types of training sets containing either 10 or 100 training examples; in addition, we provide 1,000 unlabeled examples per task. Both unlabeled and training examples are randomly sampled from the original training set.\(^4\)

\(^3\)The only exception to this is NEWSROOM, which contains more than 100,000 examples. To enable a more resource-efficient evaluation, we only consider a random subset of 10,000 examples for this dataset.

\(^4\)We do not use the same few-shot datasets as Zhang et al. (2020) as they did not use a fixed random seed and thus their exact training data is not recoverable.
As previous work (Schick and Schütze, 2020b) has shown that the particular set of training examples can have a huge impact on a model’s performance, we create three distinct training sets per size (10 and 100) and task using different random seeds. Scores reported in this section are always average scores across all three sets of training examples.

Patterns We use the same set of patterns across all tasks, but we combine them with different decoder prefixes. The patterns we use are:

\[
P_1(x) = \__ x \quad P_2(x) = \text{Text: } x
\]

All decoder prefixes are shown in Table 1. We combine each pattern with each decoder prefix, resulting in four pairs \((P_1, d_1), (P_1, d_2), (P_2, d_1)\) and \((P_2, d_2)\) per task.

Setup For all of our experiments with PET, we use PEGASUS-large (Zhang et al., 2020) as underlying language model; our implementation is based on the Transformers library (Wolf et al., 2020). Unless stated differently, all experiments are performed using the same setup as Schick and Schütze (2020a) using a single GPU.

For optimizing hyperparameters, much previous work uses development sets that are larger than the training sets by multiple orders of magnitude (e.g., Xie et al., 2019; Zhang et al., 2020; Chen et al., 2020); however, assuming the existence of such large development sets is highly inconsistent with real-world few-shot settings. In contrast, Schick and Schütze (2020a) assume no development data at all and determine hyperparameters solely based on previous work and practical considerations. We choose a middle way and create a small development set of 100 examples for only one of the six tasks, XSum. We use this development set in combination with a single training set containing 10 examples to determine hyperparameters for all tasks and training sets. We do so only for hyperparameters for which no consistent value can be derived from previous work.

Following Zhang et al. (2020), we use a maximum input length of 512 tokens, the Adafactor optimizer (Shazeer and Stern, 2018) with square root learning rate decay, a dropout rate of 0.1 and label smoothing setting \(\epsilon = 0.1\) (Szegedy et al., 2016); we also adopt Zhang et al. (2020)’s maximum output lengths for each task. As recommended by Schick and Schütze (2020a), we train all models for 250 steps using a batch size of 8. We also tried training for 500 and 1,000 steps on our development set but found no major differences in performance. For the learning rate, we tried values of \(\alpha \cdot 10^{-5}\) with \(\alpha \in \{1, 10, 50\}\) as Schick and Schütze (2020a) use \(\alpha = 1\) and Zhang et al. (2020) use \(\alpha = 50\); we found \(\alpha = 10\) to perform best for all models.

For evaluation, we follow Zhang et al. (2020) and report Rouge1, Rouge2 and RougeL (R1/R2/RL) F1 scores (Lin, 2004) after stemming using the Porter algorithm (Porter, 1997).

Results On all six tasks, we compare the following three approaches for finetuning a pretrained PEGASUS model:

- **PEGASUS**: The regular finetuning procedure described in (Zhang et al., 2020).
- **PEGASUS-M**: Finetuning with a single trivial pattern that inserts a mask token before the first word.
- **PEGASUS-PET**: Finetuning using PET with all patterns described above.

Table 2 shows results both for zero-shot learning and for few-shot learning with 10 and 100 training examples. In the few-shot settings, PET consistently outperforms both baselines across all tasks,
resulting in an average improvement in R1 over PEGASUS of 6.31 (30.68 vs 24.37) and 2.65 (34.44 vs 31.79). While PEGASUS-M gives consistent improvements over regular finetuning, it still performs clearly worse than PET, demonstrating that the PET model is indeed able to make use of the task descriptions provided. In the zero-shot setting, PET also outperforms both baselines on average, but falls short on individual tasks.

**Analysis** We now look at the factors contributing to PET’s performance in detail. To this end, Table 3 compares the performance of the best (“best only”) and the worst (“worst only”) performing pattern and decoder prefix to that of PET in a setting with 10 training examples. We see some difference in performance between using only the best and worst patterns, but this difference is not as pronounced as in previous work (Schick and Schütze, 2020a,b). Notably, our simple strategy for combining patterns performs even better than using just the best pattern across all tasks and metrics. Table 3 also shows results for using no decoder prefix (“no dec. prefix”) and instead processing the entire input using the encoder. That is, given \((P, d)\) with \(P(x) = z_1 \ldots z_n\) and \(z_h = \_\), we compute \(p_M(y | z_1 \ldots z_{h-1} d z_h \ldots z_n)\) rather than \(p_M(y | z_1 \ldots z_n; d)\). While this variant overall performs better than PEGASUS-M, results clearly show that PEGASUS makes less use of task descriptions if they are processed using the encoder.

Finally, we look at the performance of PET as a function of the maximum output length \(\ell\). We hypothesize that the influence of the decoder prefix on generated tokens may decrease with distance. This would mean that diminishing gains are to be expected from PET for tasks that require longer text sequences to be generated. To investigate this assumption, Table 4 shows the performance of both PEGASUS and PEGASUS-PET for three tasks using maximum output lengths of \(\ell = 32\) and 128.

For both values of \(\ell\), we compute the gains \(g_{\ell}\) from using PET as the difference in performance between PEGASUS-PET and PEGASUS. On average, increasing \(\ell\) to 128 tokens reduces the gains from PET over regular finetuning by just \(g_{32} - g_{128} = 0.24\) points R1. This shows that task descriptions provided using PET have a strong impact on generated tokens even if there are dozens of other tokens in between and, accordingly, our proposed approach is also beneficial for generating long text sequences.

### 6 Conclusion

We have shown how Pattern-Exploiting Training (PET) can be transferred to text generation tasks by (i) introducing the concept of decoder prefixes and (ii) combining patterns through knowledge distillation where target sequences are generated from randomly chosen patterns. With these modifications, a pretrained PEGASUS model finetuned with PET clearly outperforms regular finetuning in few-shot settings. For future work, it would be interesting to see whether it is also possible to make pretrained language models understand more complex task descriptions than the simple prompts we have used, especially as some concurrent work (Weller et al., 2020; Efrat and Levy, 2020) suggests this might not be the case.

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