Exploiting Cloze Questions for Few-Shot Text Classification and Natural Language Inference

Timo Schick  
Sulzer GmbH  
Munich, Germany  
timo.schick@sulzer.de

Hinrich Schütze  
Center for Information and Language Processing  
LMU Munich, Germany  
inquiries@cislmu.org

Abstract

Some NLP tasks can be solved in a fully unsupervised fashion by providing a pretrained language model with “task descriptions” in natural language (e.g., Radford et al., 2019). While this approach underperforms its supervised counterpart, we show in this work that the two ideas can be combined: We introduce Pattern-Exploiting Training (PET), a semi-supervised training procedure that reformulates input examples as cloze-style phrases which help the language model understand the given task. These phrases are then used to assign soft labels to a large set of unlabeled examples. Finally, regular supervised training is performed on the resulting training set. On several tasks, we show that PET outperforms both supervised training and unsupervised approaches in low-resource settings by a large margin.

1 Introduction

Learning from examples is the predominant approach for many natural language processing tasks: A model is trained on a large number of labeled examples, from which it is supposed to generalize to unseen data. Unfortunately, learning from examples alone is exceedingly difficult when there are only a few such examples. For instance, assume we are given the following pieces of text:

- $T_1 = \text{This was the best pizza I've ever had.}$
- $T_2 = \text{Pretty bad. You can get better sushi down the road for half the price.}$
- $T_3 = \text{Pizza was average. Not worth what they were asking.}$

Furthermore, imagine we are told that the labels of $T_1$ and $T_2$ are $l_1$ and $l_2$, respectively, and we are asked to infer the correct label for $T_3$. Based only on these three examples, this is impossible because plausible explanations can be found for both $l_1$ and $l_2$. However, if we know that the underlying task is to identify whether the text says anything about prices, we can easily assign $l_2$ to $T_3$. As this shows, solving a task for which we only have few examples becomes much easier when we also have a description that helps us understand the task.

With the rise of pretrained language models such as GPT (Radford et al., 2018), BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), the idea of providing task descriptions has become feasible for neural architectures: We can simply append such descriptions in natural language to an input and let the language model predict continuations that solve the task (Radford et al., 2019; Puri and Catanzaro, 2019). So far, however, this idea has only been considered in zero-shot scenarios where no training data is available at all.

In this work, we show that providing task descriptions can successfully be combined with regular supervised learning: We introduce Pattern-exploiting Training (PET), a semi-supervised training procedure that uses natural language patterns to reformulate input examples into cloze-style phrases helping a language model to identify the task to be solved. PET works in three steps: First, for each pattern a separate language model is finetuned on a small training set. The ensemble of all models is then used to annotate a large unlabeled dataset with soft labels. Finally, a regular sequence classifier is trained on the soft-labeled dataset.

On three diverse NLP tasks, we show that using PET results in large improvements over both unsupervised approaches and regular supervised training when the number of available labeled examples is limited.

2 Related Work

Providing hints in natural language for zero-shot learning was first proposed by Radford et al. (2019),
who used this idea for challenging tasks such as reading comprehension, machine translation and question answering. Recently, Puri and Catanzaro (2019) applied the same idea to text classification, providing actual task descriptions. McCann et al. (2018) also present tasks in the form of natural language sentences as part of their Natural Language Decathlon; however, their motivation is not to enable few-shot learning, but to provide a unified framework for many different types of NLP tasks.

Much recent work uses cloze-style phrases to probe the knowledge that masked language models acquire during pretraining; this is typically also done without any task-specific finetuning. Probing tasks include analyzing factual and commonsense knowledge (Petroni et al., 2019), probing the understanding of rare words (Schick and Schütze, 2019), and investigating a language model’s ability to perform symbolic reasoning (Talmor et al., 2019). Similar to our work, Jiang et al. (2019) consider the problem of finding the best description for a given task, which is a key challenge for zero-shot approaches to work. However, all of this previous work only considers the usage of patterns for probing language models and not for improving downstream task performance when labeled data are sparse.

3 Pattern-Exploiting Training

Let $M$ be a masked language model with vocabulary $V$ and mask token $\_\_\_ \in V$, and let $L$ be a set of labels. We define a pattern to be a function $P$ that takes as input a sequence of phrases $x = (s_1, \ldots, s_k)$ with $s_i \in V^*$ and outputs a single phrase $P(x) \in V^*$ that contains exactly one mask token, i.e., its output can be viewed as a cloze question. Furthermore, we define a verbalizer as an injective function $v : L \rightarrow V$ that maps each label to a word from $M$’s vocabulary. We refer to $(P, v)$ as a pattern-verbalizer pair (PVP).

The underlying intuition for these definitions is as follows: Given an input $x$, we apply $P$ to obtain an input representation $P(x)$, which is then processed by $M$ to identify the $y \in L$ for which $v(y)$ is the most likely candidate at the masked position. For example, consider the task of identifying whether two sentences $a$ and $b$ contradict each other (label $y_0$) or agree with each other ($y_1$). For this task, we may choose a pattern

$$P(a, b) = (a? \_\_\_ \_\_. b).$$

combined with a verbalizer $v$ that maps $y_0$ to “Yes” and $y_1$ to “No”. Given an example input pair

$$x = (\text{Mia likes pie, Mia hates pie}),$$

the task now changes from having to assign a label without inherent meaning to answering whether the most likely choice for the masked position in

$$P(x) = \text{Mia likes pie? ___. Mia hates pie.}$$

is “Yes” or “No”.

PVP Training and Inference

Let $p = (P, v)$ be a PVP. We assume access to a small training set $T$ and a (typically much larger) set of unlabeled examples $D$. For each sequence $z \in V^*$ that contains exactly one mask token and $w \in V$, we denote with $M(w | z)$ the unnormalized score that the language model assigns to $w$ at the masked position. Given some input $x$, we define the unnormalized score for each label $y \in L$ as

$$s_p(y | x) = M(v(y) | P(x))$$

and obtain the corresponding probability distribution using standard softmax:

$$q_p(y | x) = \frac{e^{s_p(y | x)}}{\sum_{y' \in L} e^{s_p(y' | x)}}$$

We use the cross-entropy between $q_p(y | x)$ and the true (one-hot) distribution of training example $(x, y)$—summed over all $(x, y) \in T$—as loss for finetuning $M$ on $p$.

Auxiliary Language Modeling

As a model finetuned on some PVP is still a language model at its core, regular language modeling suggests itself as an auxiliary task to prevent catastrophic forgetting, especially when only a few training examples are available. With $L_{CE}$ denoting cross-entropy loss and $L_{MLM}$ denoting language modeling loss, we compute the final loss as

$$L = (1 - \alpha) \cdot L_{CE} + \alpha \cdot L_{MLM}$$

This idea was recently applied by Chronopoulou et al. (2019), who employ auxiliary language modeling in a data-rich scenario. As $L_{MLM}$ is typically much larger than $L_{CE}$, in preliminary experiments, we found a small value of $\alpha = 10^{-4}$ to consistently give good results, so we use it in all our experiments. To obtain sentences for language modeling,
we use the unlabeled set $D$. However, we do not train directly on each $x \in D$, but rather on $P(x)$, where we never ask the language model to predict anything for the masked slot.

### Combining PVPs

A key challenge for a pattern-based approach in a low-resource scenario is that in the absence of a large development set, it is hard to identify which PVPs perform well. To overcome this problem, we resort to the following strategy, which closely resembles knowledge distillation (Hinton et al., 2015). First, we define a set $P$ of patterns that intuitively make sense for a given task. We then use these patterns to automatically create a large soft-labeled dataset $T'$ as follows:

1. We finetune a separate language model $M_p$ for each $p \in P$. As we assume $T$ to contain only a few examples, this finetuning is cheap even for a large number of PVPs.

2. We use the ensemble $\{M_p \mid p \in P\}$ of fine-tuned models to annotate examples from $D$ with soft labels. We first combine the unnormalized class scores for each example $x \in D$ as

$$s_p(y \mid x) = \frac{1}{Z} \sum_{p \in P} w(p) \cdot s_p(y \mid x)$$

where $Z = \sum_{p \in P} w(p)$ and $w(p)$ is a weighing term for each PVP. We experiment with two different realizations of this weighing term: either we simply set $w(p) = 1$ for all $p$ or we set $w(p)$ to be the accuracy obtained using $p$ on the training set before training. We refer to these two variants as uniform and weighted, respectively. An idea similar to our weighted variant was recently proposed by Jiang et al. (2019) in a zero-shot setting.

3. We transform the above scores into a probability distribution $q$ using softmax. Following Hinton et al. (2015), we use a temperature of $T = 2$ to obtain a suitably soft distribution. The pair $(x, q)$ is added to our new (soft-labeled) training set $T'$.

Finally, we finetune a pretrained language model with a regular sequence classification head on $T'$; this model then serves as our final classifier.

### 4 Experiments

#### Setup

We evaluate PET on three NLP datasets: Yelp Reviews, AG’s News (Zhang et al., 2015) and MNLI (Williams et al., 2018). For all of our experiments, we use RoBERTa large (Liu et al., 2019) as language model. Our implementation is based on the Transformers library (Wolf et al., 2019) and PyTorch (Paszke et al., 2017).

We investigate the performance of both regular supervised training and PET for training set sizes of $t = 10, 50, 100, 1000$. For each $t$, we obtain the training set $T$ by choosing $t$ examples evenly distributed across all labels. Similarly, we construct the set $D$ of unlabeled examples by selecting 10,000 examples per label and removing all labels.

As we consider a few-shot setting, we assume no access to a large development set on which hyperparameters could be optimized. Our choice of hyperparameters is thus based on choices made in previous work and practical considerations. We use a learning rate of $1 \cdot 10^{-5}$ because we found higher learning rates to often result in unstable training with no accuracy improvements even on the training set. For regular supervised training, we use a batch size of 16, a maximum sequence length of 256 and perform training for 250 steps. For PET, we subdivide each batch into 4 labeled examples from $T$ to compute $L_{CE}$ and 12 unlabeled examples from $D$ to compute $L_{MLM}$. Accordingly, we multiply the number of total training steps by 4 (i.e., 1000), so that the number of times each labeled example is seen remains constant.

For training the final PET classifier, we use the same set of hyperparameters as for the individual PVP models, but we train for 5000 steps due to the increased training set size.

#### Patterns

We now describe the patterns and verbalizers used for all tasks. We use two vertical bars ($||$) to mark boundaries between text segments.\footnote{The way different segments are handled depends on the language model being used; they may e.g. be assigned different segment embeddings (Devlin et al., 2019), be separated by special tokens (Liu et al., 2019; Yang et al., 2019) or simply be ignored. For example, $[a \parallel b]$ is given to BERT as the input “[CLS] a [SEP] b [SEP]”.

**Yelp** For the Yelp Reviews Full Star dataset (Zhang et al., 2015), the task is to estimate the rating that a customer gave to a restaurant on a 1-
We define the verbalizer \( v \) as

\[
\begin{align*}
    v(1) &= \text{terrible} & v(2) &= \text{bad} & v(3) &= \text{okay} \\
    v(4) &= \text{good} & v(5) &= \text{great}
\end{align*}
\]

resulting in a total of 4 PVPs for the Yelp dataset.

**AG’s News** AG’s News is a news classification dataset, where given a headline \( a \) and text body \( b \), news have to be classified as belonging to one of the categories World (1), Sports (2), Business (3) or Science/Tech (4). For \( x = (a, b) \), we define the following patterns:

\[
\begin{align*}
P_1(a) &= \text{It was _____ a} \\
P_2(a) &= a. \text{ All in all, it was _____} \\
P_3(a) &= \text{Just _____! || a} \\
P_4(a) &= a || \text{In summary, the restaurant is _____}
\end{align*}
\]

We define the verbalizer \( v \) as

\[
\begin{align*}
    v(1) &= \text{World} & v(2) &= \text{Sports} \\
    v(3) &= \text{Business} & v(4) &= \text{Tech}
\end{align*}
\]

which gives a total of 6 PVPs for AG’s News.

**MNLI** The MNLI dataset (Williams et al., 2018) consists of text pairs \( x = (a, b) \). The task is to find out whether \( a \) implies \( b \) (0), \( a \) and \( b \) contradict each other (1) or neither (2). For this task, we define two simple patterns

\[
\begin{align*}
P_1(x) &= \text{“a” ? || “b”} \\
P_2(x) &= a ? || b
\end{align*}
\]

and consider two different verbalizers \( v_1 \) and \( v_2 \) that are defined as follows:

\[
\begin{align*}
v_1(0) &= \text{Wrong} & v_1(1) &= \text{Right} & v_1(2) &= \text{Maybe} \\
v_2(0) &= \text{No} & v_2(1) &= \text{Yes} & v_2(2) &= \text{Maybe}
\end{align*}
\]

Combining the two patterns with the two verbalizers results in a total of 4 PVPs.

**Results**

We perform training for each task and training set size three times using different random seeds and report mean accuracy and standard deviation across the three runs; Table 1 shows results.\(^2\) The top rows show performance using all PVPs in a fully unsupervised setting, where both average results across all patterns (avg) and results using the best pattern (max) are reported. Importantly, finding the best pattern would require access to the test set; accordingly, this row serves only as an upper bound of fully unsupervised performance. The large difference between both rows highlights the importance of finding a strategy to cope with the

\[^2\text{Due to the limit of 2 submissions per 14 hours for the official MNLI test set, we treat the dev set as our test set.}\]
fact that we have no means of evaluating which patterns perform well.

With just 10 training examples, regular supervised learning does not perform above chance. In contrast, PET already performs much better than both the fully unsupervised approach and regular supervised training. For example, PET trained on just 10 AG’s News examples even outperforms a regular supervised model trained on 1000 examples. As we increase the training set size, the performance gains of PET become smaller, but for both 50 and 100 examples, PET continues to considerably outperform regular supervised training. With 1000 training examples, PET has no or only a small advantage on Yelp and AG’s News, but for MNLI, there is still a large gap between PET and supervised training.

5 Analysis

Combining PVPs We investigate whether PET is able to cope with situations were some of the given PVPs perform much worse than others. Table 2 compares the performance of both the best and worst performing pattern to the performance of PET (for $|T| = 10$). We see that even after fine-tuning the gap between the best and worst pattern is large, especially for Yelp. However, PET is not only able to compensate for this, but even improves accuracies over using only the best-performing pattern across all tasks. We find no clear difference between the uniform and weighted variant of PET.

Auxiliary Language Modeling We analyze the influence of the auxiliary language modeling task on PET’s performance. Figure 1 shows performance improvements from adding the language modeling task for all considered training set sizes and tasks. As can be seen, the auxiliary task is extremely valuable when training on just 10 examples. With more data, it becomes less important, some-

|          | Yelp | AG’s News | MNLI |
|----------|------|-----------|------|
| avg      | 46.8 | 83.5      | 37.9 |
| min      | 39.6 | 82.1      | 36.4 |
| max      | 52.4 | 85.0      | 40.2 |
| PET uniform | 52.7 | 87.3      | 42.0 |
| PET weighted | 52.9 | 87.5      | 41.8 |

Table 2: Average (avg), minimum (min) and maximum (max) accuracy of models based on individual patterns as well as PET after training on 10 examples

Figure 1: Accuracy improvements from adding $L_{MLM}$ during training for all tasks

times even leading to worse performance. Only for MNLI, we find language modeling to consistently help for all training set sizes considered.

6 Conclusion

We have shown that providing task descriptions to pretrained language models can be combined with regular supervised training. Our proposed method, PET, consists of defining pairs of cloze question patterns and verbalizers that help leverage the knowledge contained within pretrained language models for downstream tasks. We finetune models for all pattern-verbalizer pairs and use them to create large annotated datasets on which regular classifiers can be trained. When the initial amount of training data is limited, PET gives large improvements over regular supervised training.

Similar to Jiang et al. (2019), future work could look into automatic identification of suitable patterns and verbalizers. Furthermore, it would be interesting to see whether the idea of PET can also be transferred to other task types, e.g., token classification or question answering.

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