Few-Shot Natural Language Inference Generation with PDD: Prompt and Dynamic Demonstration

Kaijian Li, Shansan Gong, Kenny Q. Zhu
School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University
2275135452@qq.com, gongshansan@sjtu.edu.cn, kzhu@cs.sjtu.edu.cn

Abstract
Natural Language Inference Generation task is to generate a text hypothesis given a text premise and a logical relation between the two. This task can be used in data augmentation and controllable text generation in practice. In this paper, we propose language models with prompt and dynamic demonstration (LM-PDD) to tackle this problem in few-shot settings. Our framework outperforms standard fine-tuned models with low resource, achieving an average 8% absolute improvement on SNLI and MNLI datasets, and the results on 13 natural language classification tasks also show that our dynamic demonstration method has good generalizability.

1 Introduction
Natural Language Inference (NLI), also known as the Recognizing Textual Entailment (RTE) is a task of determining whether a text premise $p$ can entail, contradict or be neutral with a given hypothesis $h$ (Dagan et al., 2005). This task servers as an important benchmark for testing model’s reasoning ability.

Although NLI is proposed as a classification problem, it’s also worth considering it as a generation task. Recently, several works reformulate NLI task as a generation task (Kolesnyk et al., 2016; Starc and Mladenic, 2017; Shen et al., 2018; Jafaritazehjani et al., 2019). They explore how to generate the hypothesis $h$ given a premise $p$ and a logic condition $c$ or reversely generate $p$ given $h$ and $c$. Kolesnyk et al. (2016) show that the task of generating entailed sentences can be served as a benchmark to measure the reasoning ability of sequence to sequence models. Starc and Mladenic (2017) first use it for data augmentation. They use generated hypotheses to construct a new NLI style dataset, on which a better classifier can be trained.

However, the success of these works heavily depends on the SNLI dataset (Bowman et al., 2015), which is a manually created dataset. Thus it’s a challenge to use the proposed approaches in specific domains or real-world applications which are different from the SNLI domain, and where there is not enough annotated data. In light of this, we want to explore how to improve the performance of NLI generation task in a few-shot setting.

Recently prompt-based learning has led to large improvements in NLP tasks under zero-shot or few-shot settings (Liu et al., 2021b; Petroni et al., 2019; Schick and Schütze, 2021; Shin et al., 2020). The main idea is to reformulate the downstream tasks as the pre-training task of pre-trained Language models (PLMs) using a prompt template. Brown et al. (2020) show that given a few demonstrations of inputs along with the prompt, GPT-3 achieves near state-of-the-art results in some SuperGLUE tasks. Inspired by their success, we investigate how to adapt prompts and demonstrations to NLI generation task, which is reformulated as shown in Figure 1(b).

Figure 1: The difference between how standard fine-tuning methods and prompt-based methods treat the NLI generation task. The underlined text is a demonstration. The Green words are condition-specific templates.
result on the development set less reliable, since we only use a subset of the data to measure each template. To ameliorate this, we propose a max-margin strategy to pick the template that receives a high score in its corresponding condition but low scores in all other conditions, considering the conditions in NLI task are conflicting with each other.

The second stage is to sample demonstrations. Gao et al. (2021) and Liu et al. (2021a) simply sample them by the static cosine similarity based on models trained on related datasets (this model is regarded as a retriever). This approach is suboptimal as: (1) it doesn’t make use of the training data; (2) in cases of a low-resource language, we do not have sufficient labeled data to train such a retriever. To address these issues, we propose a dynamic method that combines the probability from the generator and the probability from the retriever to help the retriever fit target tasks.

In summary, our contributions are: (1) To the best of our knowledge, we are the first to investigate NLI generation task in a few-shot setting. (2) We propose a max-margin template selection method and a dynamic demonstration selection method. Combining these two methods with PLMs, our LM-PDD model gains 8% absolute improvement over the standard fine-tuning models. (3) We test our demonstration selection method on 13 natural language classification tasks in few-shot settings, the results show our method has strong generality.

2 Problem Setup

2.1 Task Formulation

The dataset \( \mathcal{D} \) consists of premises \( \mathcal{P} \), conditions \( \mathcal{C} = \{ \text{entailment}, \text{neutral}, \text{contradiction} \} \) and hypotheses \( \mathcal{H} \). Each sample \( s_i \) is a tuple \((p^i, c^i, h^i)\), where \( p^i \in \mathcal{P}, c^i \in \mathcal{C} \) and \( h^i \in \mathcal{H} \). The NLI generation task is defined as: Given premise \( p \) and condition \( c \), predict hypothesis \( h \). This formulation is the same as Starc and Mladenic (2017) except we assume there are only \( K \) samples for per condition in training set \( \mathcal{D}_{\text{train}} \) and development set \( \mathcal{D}_{\text{dev}} \). This is following the few-shot settings in Gao et al. (2021).

2.2 Evaluation protocol

Previous works show the performance of models fine-tuned on the small dataset is largely affected by the data split and hyper-parameters (Dodge et al., 2020; Zhang et al., 2021a). To address this issue, we use the same evaluation protocol in Gao et al. (2021). We measure the average performance on 5 different randomly sampled \( \mathcal{D}_{\text{train}} \) and \( \mathcal{D}_{\text{dev}} \) splits. The hyper-parameters are chosen by the performance in \( \mathcal{D}_{\text{dev}} \) for each split.

3 Preliminaries

In this section, we first show how to fine-tune models with prompts and demonstrations. Then we introduce the automatic template generation method and demonstration strategy proposed in LM-BFF (Gao et al., 2021).

3.1 Prompt-based Fine-tuning with Demonstration

Starting from the GPT model (Radford et al., 2018), pre-train and fine-tune paradigm becomes the mainstream method. To solve this task, we can use an autoregressive language model \( \mathcal{L} \) (eg., GPT-2 (Radford et al., 2019), BART (Lewis et al., 2020a)). For each sample \( s_i = (p^i, c^i, h^i) \), we take input \( x^i \) as:

\[
x^i = [c^i] [\text{SEP}] [p^i]
\]

\( \mathcal{L} \) is fine-tuned to maximize the objective:

\[
P(h^i|p^i, c^i) = \prod_j P_\theta(h_j^i|x^i, h_{1:j-1}^i) \quad (1)
\]

However, this paradigm is hard to learn from a small amount of data.

Prompt is a possible solution for this problem. We can reformulate the task with a template so that the input sentences are closer to the inputs during pretraining. For a sample \( s_i = (p^i, \text{contradiction}, h^i) \), we can create a prompt as:

\[
x^i_{\text{prompt}} = [p^i] \text{ But } ___
\]

\( \mathcal{L} \) will fill in the blank based on the prefix, which is the same as the pretraining task. We use the template word “But” here, because we hope it can direct \( \mathcal{L} \) to generate the rest part with opposite meanings. As showed in 1(b), we can also add some demonstrations in the prompt \( x^i_{\text{prompt}} \) as:

\[
[p^{(1)}] \text{ But } [h^{(1)}] [\text{SEP}] ... [\text{SEP}] [r^i] \text{ But } ___
\]

These demonstrations are selected from \( \mathcal{D}_{\text{train}} \).

3.2 Automatic generation of template

Gao et al. (2021) generate templates automatically with a T5 model (Raffel et al., 2020) for classification problems.
For an input sample \( s_i = (x_i, y_i) \in \mathcal{D}_{\text{train}}' \), they build three different kinds of filled prompts \( \mathcal{T}_g(s_i) \) whose template words are replaced by a [MASK] token. Then a T5 model is used to fill in the [MASK] part. Because T5 is pre-trained to fill in the missing spans, there is no need to specific the number of [MASK] tokens here, which is more convenient than previous gradient-based prompt search methods (Wallace et al., 2019; Shin et al., 2020). The goal is to find the template \( \mathcal{T} \) which maximizes:

\[
\sum_{s_i \in \mathcal{D}_{\text{train}}'} \log P_{T5}(\mathcal{T} | \mathcal{T}_g(s_i))
\]  

During the decoding, a wide beam search (e.g., 100) is used to obtain a large set of diverse templates. The reason why they need so many templates here is that the templates are affected by the architecture and pre-training tasks of the PLMs. These templates generated by T5 may not work on the \( \mathcal{L} \) finally used. They fine-tuned each generated template on \( \mathcal{D}_{\text{train}}' \) and use \( \mathcal{D}_{\text{dev}}' \) to pick the best template \( \mathcal{T}' \):

\[
\mathcal{T}' = \arg \max_{\mathcal{T}} S_{\mathcal{L}}(\mathcal{D}_{\text{train}}', \mathcal{D}_{\text{dev}}', \mathcal{T})
\]

where \( S_{\mathcal{L}} \) is a score function to measure performance using \( \mathcal{L} \).

### 3.3 Demonstration with Similarity

To get the demonstrations, GPT-3 uses a random strategy to draw from \( \mathcal{D}_{\text{train}}' \). Gao et al. (2021) and Liu et al. (2021a) use a BERT (Devlin et al., 2019)/RoBERTa (Liu et al., 2019) based retriever to sample examples with similarity. Their experiment results show (1) controlling the examples used in prompt is crucial for the model’s performance; (2) using a model fine-tuned on task-related datasets is better than the original pre-trained model.

They use SBERT (Reimers and Gurevych, 2019), which is fine-tuned on a large and diverse dataset, to build the retriever. The same SBERT model is used to encode both input samples and candidate demonstrations:

\[
\text{emb}(s_i) = \text{SBERT}(p^i)
\]

The similarity is judged by cosine similarity:

\[
\text{Sim}(s_i, s_j) = \frac{\text{emb}(s_i) \cdot \text{emb}(s_j)}{\|\text{emb}(s_i)\|_2 \cdot \|\text{emb}(s_j)\|_2}
\]

The demonstrations examples for \( s_i \) are sampled from the top 50% instances.

### 4 Methodology

The architecture of our model is depicted in Figure 2. In this section, firstly we give out the hand-crafted templates. Then we introduce our prompt selection method and dynamic demonstration strategy.

#### 4.1 Hand-crafted Templates

| Condition    | Template          |
|--------------|-------------------|
| Entailment   | [p] Then [h]      |
| Neutral      | [p] Maybe [h]     |
| Contradiction| [p] But [h]       |

Table 1: Hand-crafted templates used in our experiments

Manually defining the templates for each condition requires domain expertise knowledge. Table 1 shows our manually defined templates, which is
different from the templates defined for NLI classification task (Schick and Schütze, 2021). We design them based on our knowledge, intuition, and some simple tests on the $\mathcal{L}$ we used.

4.2 Max-margin Template Selection

First we adapt the method in section 3.2 so that it works on conditional generation problem in our task. For an input sample $s_t = (p^t, c^t, h^t) \in \mathcal{D}_{\text{train}}$, we build the filled prompt as:

$$\mathcal{T}_5(s_i) = [p^t] \text{ [MASK]} \text{ [h}^t]$$

Since we need to define a different template for each condition $m \in \mathcal{C}$, equation 2 is modified as:

$$\sum_{s_t \in \mathcal{D}_{\text{train}}, c^t = m} \log P_{\mathcal{T}_5}(\mathcal{T}_m|\mathcal{T}_5(s_i)) \quad (6)$$

where $\mathcal{T}_m$ is the template used for samples whose condition is $m$. To pick the best template $\mathcal{T}_m$, we use:

$$\mathcal{T}_m = \arg \max_{\mathcal{T}_m} S_{\mathcal{L}}(\mathcal{D}_m, \mathcal{D}_{\text{dev}}, \mathcal{T}_m) \quad (7)$$

where $\mathcal{D}_m = \{s_t|s_t \in \mathcal{D}, c^t = m\}$. We call this method as top template selection.

Experiments in Gao et al. (2021) show the size of $\mathcal{D}_{\text{dev}}$ used in equation 3 will significantly influence the quality of chosen templates, while we only use $1/|\mathcal{C}|$ samples in $\mathcal{D}_{\text{dev}}$ to measure each template in equation 7.

To address this issue, we propose our max-margin template selection method. Considering the conditions in NLI generation task conflicting with each other, we can give such assumption: A good template should not get high scores in other conditions. For example, the template $[p]$ But $[h]$ designed for “contradiction” are supposed to achieve a bad performance in “entailment” and “neutral”. Based on this, we refine function 7 as:

$$\mathcal{T}_m = \arg \max_{\mathcal{T}_m} \sum_{k \in \mathcal{C}} d_{m,k} \cdot S_{\mathcal{L}}(\mathcal{D}_k, \mathcal{D}_{\text{dev}}, \mathcal{T}_m) \quad (8)$$

where, $d_{m,k} = \begin{cases} 1, & \text{if } m = k \\ -1, & \text{otherwise} \end{cases}$

4.3 Dynamic Demonstration

For classification problem, Gao et al. (2021) sample one example for each class. In this task, we only sample one example with the same condition as the demonstration, because templates for each condition are totally different from each other, and mixing templates as an input will mislead $\mathcal{L}$.

We call the demonstration method in section 3.3 as static demonstration since the retriever is not changed in the whole experiments and the embedding for each sample is fixed. As we have mentioned in section 3.3, a model fine-tuned on task-related datasets performs better, we wonder can we train the retriever based on $\mathcal{D}_{\text{train}}$ which has no similarity labels?

One solution is to annotate the similarity score for each pair. But it’s unrealistic as: (1) It’s hard for a human to design the similarity boundary; (2) the number of desired annotations is quite large even in a few-shot setting since it’s square to $|\mathcal{D}_{\text{train}}|$.

Inspired by the document retrieve method from RAG (Lewis et al., 2020b) and prompt ensemble method from Jiang et al. (2020), we propose dynamic demonstration method by modifying the model objective $P(h^i|p^t, c^t)$ as:

$$\prod_j \sum_k P_{\theta_r}(s_k|s_i)P_{\theta_m}(h^i_j|x^{\text{prompt}}_i, s_k, h^i_{j-1}) \quad (9)$$

where, $P_{\theta_r}(s_k|s_i) = \frac{\exp(\text{Sim}(s_i, s_k))}{\sum_t \exp(\text{Sim}(s_i, s_t))}$

Here $s_k, s_t \in \mathcal{D}^{\text{dev}}$. Thus the retriever’s parameters $\theta_r$ are optimized to maximize the similarity score of the input sample $s_i$ and the sample which leads to the largest generator probability of the ground truth.

During training, calculating $P_{\theta_r}(s_k|s_i)$ over the whole $\mathcal{D}^{\text{dev}}$ is costly, so we do a top-k approximation. For each sample $s_i$: (1) First we calculate $P_{\theta_r}(s_k|s_i)$ over $\mathcal{D}_{\text{train}}$ and choose the samples with top-k probability; (2) these chosen samples make up $\mathcal{D}_i$, then we calculate equation 9, where $s_k, s_t \in \mathcal{D}_i$.

During the test, we only use the retriever to sample the top-1 example as the demonstration, which is different from the decoding strategy used in RAG. Because RAG retrieves context from a corpus of 21M documents, where a lot of documents with relevant information can be found, while in a few-shot setting, the size of $\mathcal{D}_{\text{train}}$ is quite small.

5 Experiments

In this section we first present our experiments setup and baseline models in Section 5.1 and Section 5.2 respectively. Then we show the different aspects of evaluation results and give a detailed
analysis from Section 5.3 to Section 5.6. According to our experiments, we want to determine these questions: First, does the maximum margin function help to automatically generate templates and does dynamic demonstration work in the few-shot setting? Second, are the sentences produced by our model reasonable? Third, how is the generalization ability of our dynamic demonstration method?

5.1 Experiments Setup

**Dataset.** We evaluate our model on two English datasets: SNLI and MNLI. Because the MNLI test set doesn’t have ground truth labels, we use the mismatched development set as the test set and matched development set as the development set. Different from Gao et al. (2021) use $K = 16$ for classification tasks, we set $K = 200$ considering the generation task is more challenging. Detailed statistics are listed in Table 2.

| Dataset | #Training | #Development | #Test |
|---------|-----------|--------------|-------|
| SNLI    | 550,152   | 10,000       | 10,000|
| MNLI    | 392,302   | 10,000       | 10,000|

Table 2: Statistics of SNLI and MNLI dataset.

**Evaluation Metrics.** We adopt the standard text generation metrics perplexity (PPL), BLEU-4 score (Papineni et al., 2002) and ROUGE-2 score (Lin, 2004) to automatically compare generated results and reference hypotheses. Since these metrics do not consider the semantic meaning of sentences, we further use a state-of-the-art NLI classifier trained on 4 datasets (Nie et al., 2020) to calculate the accuracy of predictions, which achieves 92.6% and 90.6% accuracy in SNLI and MNLI mismatched datasets respectively. Good hypotheses are supposed to be not only accurate but also diverse, and therefore we use distinct n-grams normalized by the total number of generated n-grams $\text{Div-n}$ (Li et al., 2016) to measure diversity. We also develop human evaluation in Section 5.4.

**Implement Details.** We use BART-large as the generator. For the retriever, we deploy our experiment with the BERT-base and SBERT models. We optimize models using Adam (Kingma and Ba, 2015). The hyper-parameters are chosen by $\mathcal{D}_{\text{dev}}$. The max length is set to 128 for non-demonstration methods and 170 for others. We conduct all experiments on single NVIDIA V100 16GB GPUs without half-precision. We use ROUGE-2 on the development set to choose the best models instead of the accuracy because we find the NLI classifier tends to give high accuracy even before the model is converged. More details can be found in Appendix A and B, including the generality of dynamic demonstration and generated prompts.

5.2 Baselines

We compare our model with both unsupervised and supervised methods:

- **Rule-base:** A simple rule-based method. First, we use Stanford Stanza (Qi et al., 2020) to tokenize premises and get POS tags. For entailment, we simplify the premises by removing $\text{adj}$ and $\text{adv}$ words as hypothesis. For contradiction, we randomly replace one word in each premise with its antonym. If there are no candidate words, we add negative words into the sentence (e.g. “not” and “don’t”). For neutral, we randomly replace one word in each premise with its hyponym.

- **AMD:** A RNN-based model proposed by Starc and Mladenic (2017). It learns a latent representation $z$ that represents the mapping between the premise and the label on one side, and the hypothesis on the other side.

- **BART-large:** A pre-trained language model which performances well on a range of abstractive dialogue, question answering, and summarization tasks.

5.3 Main Results & Analysis

Our main results is shown in Table 3. Overall, the full-shot finetuning of the BART-large model performs best except for diversity with overwhelming training consumption as a sacrifice, and the rule-base method outperforms methods in few-shot settings in terms of accuracy, while fails to perform well in other metrics. Despite the fair accuracy, the rigid rule leads the generated hypotheses less comprehensible, and the trivial edition would not provide much gain for data augmentation. In the few-shot setting, AMD is poor due to lack of pre-trained knowledge, and prompt-based methods take advantage over the most of metrics because the training and the predicting share the same LM objective. Generally, the B-4, R-2 and PPL are not always consistent with the accuracy result but the oscillation is slight. The increase of diversity is usually associated with the decline of B-4 and R-2, which is explainable because these metrics only consider the overlap of n-grams with one fixed reference sentence and neglect their semantic meaning. Our dynamic demonstration yields the best
Table 3: Our main results using BART-large generator. Best results in few-shot settings are marked with **bold** font. ♠ stands for **Full-shot**: fine-tune with full data; ♣ stands for **Zero-shot**: no training data; other methods are in Few-shot setting: we use K = 200 (per class) for few-shot experiments. We report mean performance over 5 different split. For accuracy metric, we also report standard deviation; man: use manually defined prompt; top: auto prompt selected by maximum score; mm: auto prompt selected by max margin; static: use static SBERT as the retriever; dynamic: train SBERT retriever with generator; ↓: lower is better.

| Methods     | acc (%) | B-4  | R-2  | PPL↓ | Div-2 | Div-3 | acc (%) | B-4  | R-2  | PPL↓ | Div-2 | Div-3 |
|-------------|---------|------|------|------|-------|-------|---------|------|------|------|-------|-------|
| BART-large♠ | 94.17   | 8.75 | 17.63| 41.91| 0.214 | 0.407 | 89.42   | 10.55| 19.25| 39.74| 0.365 | 0.570 |
| Rule-base♣  | 75.30   | 5.13 | 12.83| 114.34| 0.213 | 0.402 | 69.07   | 6.44 | 16.45| 107.18| 0.289 | 0.467 |

| Prompt      | acc (%) | B-4  | R-2  | PPL↓ | Div-2 | Div-3 | acc (%) | B-4  | R-2  | PPL↓ | Div-2 | Div-3 |
|-------------|---------|------|------|------|-------|-------|---------|------|------|------|-------|-------|
| Prompt_{top} | 67.41(5.63) | 8.63 | 15.58| 67.49| 0.176 | 0.343 | 58.62(3.01) | 9.66 | 16.57| 47.46| 0.424 | 0.649 |
| +static     | 71.13(9.44) | 10.15| 19.03| 63.95| 0.176 | 0.342 | 59.82(5.66) | 9.90 | 16.58| 47.47| 0.426 | 0.650 |
| +dynamic    | 74.01(7.89) | 11.15| 18.93| 71.36| 0.188 | 0.362 | 63.33(1.97) | 9.35 | 16.00| 48.87| 0.442 | 0.674 |
| Prompt_{mm}  | 68.04(10.01) | 8.50 | 15.38| 67.79| 0.176 | 0.344 | 59.20(9.81) | 9.64 | 16.45| 47.64| 0.425 | 0.653 |
| +static     | 66.79(12.23) | 8.04 | 14.71| 63.57| 0.174 | 0.336 | 59.39(5.34) | 9.96 | 16.71| 46.39| 0.426 | 0.649 |
| +dynamic    | 73.69(4.16) | 8.10 | 14.49| 68.72| 0.191 | 0.367 | 62.57(4.30) | 9.54 | 16.29| 47.42| 0.434 | 0.662 |
| Prompt_{mm}  | 69.33(6.82) | 8.51 | 15.53| 67.79| 0.176 | 0.345 | 59.53(4.20) | 9.75 | 16.71| 47.64| 0.423 | 0.647 |
| +static     | 71.81(6.17) | 8.71 | 15.49| 65.39| 0.177 | 0.342 | 59.78(4.33) | 9.69 | 16.36| 46.60| 0.424 | 0.647 |
| +dynamic    | 74.44(4.74) | 7.97 | 14.22| 70.28| 0.192 | 0.370 | 62.57(2.13) | 9.38 | 16.04| 47.45| 0.440 | 0.670 |

5.4 Human evaluation

In order to check the quality of the generated hypotheses, we carry out human evaluation. We recruit 5 students who are proficient in English to score the generation result of six models, with 50 samples in each condition and each dataset, and each sample is labeled by at least 3 evaluators. We examine two aspects of the quality: (1) Is the hypothesis in the right condition with the premise? (0 or 1) (2) Is the sentence reasonable grammatically? (0, 1 or 2, the higher the better). The main result is illustrated in the first two subfigures in Figure 3. For accuracy, the max-margin strategy is helpful in static demonstration, but in SNLI's dynamic demonstration things are different, maybe the power of dynamic demonstration hides the advantage of max-margin. The improvement of dynamic demonstration is always eye catching, which is consistent with auto-metric in Table 3. For grammaticality, the rule-based method is inferior to other methods, indicating that the rule-based method owns poor readability despite the accuracy.
To further investigate the power of dynamic demonstration in different conditions, we can find that the advantage is not obvious under the scenario where these methods already obtain high accuracy, like entailment. Instead, it is more facilitative under those difficult conditions.

5.5 Case study

The case study result is shown in Table 4. For the static method, it finds the simple connection between “family” and “child” while fails to recognize the semantic relation between the demonstration and the premise. For the dynamic method, in addition to finding the connection between “ocean” and “beach”, it also excavates the deeper pattern, which helps the PLM to generate the correct corresponding hypothesis. The case shows our dynamic demonstration method can find a more similar example as a demonstration to guide the generation than the static method.

5.6 Generality test

In order to evaluate the generality of our dynamic demonstration method, we implement it based on state-of-the-art few-shot approach: LM-BFF and develop experiments on 13 NLP classification tasks. We use $K = 10$ for all the tasks. The LM-BFF implemented by ourselves uses the same setting in the original paper. In few-shot settings, the performance of model suffers from instability, and our implementing results are quite different from theirs\(^2\), so we only compare with our implementing results. As shown in table 6, our dynamic demonstration method outperforms the static method on 10 out of 13 tasks, which suggests its strong generality.

Besides, during the test, LM-BFF samples demonstration sets from $D_{\text{train}}$ and ensemble the predictions across all sets, while for our dynamic demonstration, we abandon it because our dynamic demonstration method has the ability to tune hidden vectors on $D_{\text{train}}$ during training, and the model is expected to have the best result with the top-1 example, so there is no need to ensemble model to make the results more stable.

| Training | Inference |
|----------|-----------|
| LM-BFF   | 10x       |
| LM-BFF+dynamic | 1x |
|          | 16x      |

Table 5: Training and inference speed comparison

Table 5 is a comparison of training and inference speed. We can see our dynamic method takes more time to train dynamic demonstration while it takes less time to do inference. The training speed for dynamic demonstration directly depends on the hyper parameter $K$, and under the few-shot setting, a small $K$ guarantees the training speed would not be too slow.

6 Related Work

NLI Generation  Kolesnyk et al. (2016) first proposed to serve NLI task as a generation task, while

\(^2\)We directly run their released code from: https://github.com/princeton-nlp/LM-BFF
they only concentrated on entailment condition. Later Starc and Mladenic (2017) added two other conditions into this task to make it a conditional generation task. Our task definition follows many of their concepts except that we pay attention to few-shot settings. The previous works are all based on RNN architecture with attention mechanism, while in our work we use a stronger pre-trained language model as a baseline. There are some works exploring the inversion style of NLI generation task, which is to predict the premise based on the hypothesis and the condition. Kolesnyk et al. (2016) focused on entailment inversion style. They found that the model is learned to add more detailed information to the premise. Shen et al. (2018) used all three conditions to learn the conditional latent space over the representations of a logical antecedent of the given statement.

Prompt in Natural Language Generation
Prompt-based methods is usually applied to NLG tasks by using prefix prompts together with autoregressive pre-trained LMs. Radford et al. (2019) demonstrated with prompts such as “translate to french, [x], [z]” or “TL;DR”, and found that pre-trained LMs have impressive ability on generation tasks such as machine translation and summarization in the zero-shot setting. Further, Brown et al. (2020) showed that prompts also performed well in few-shot settings. Schick and Schütze (2020); Zhang et al. (2021b); Li and Liang (2021); Chen et al. (2021) explored how to adapt prompts for few-shot text summarization, machine translation, data-to-text and code generation tasks.

Automatic prompt search
The automatically selected prompts consist of discrete prompts and continuous prompts (also called soft prompts). For the discrete prompts: Jiang et al. (2020) used a text corpus to mine templates based on given training samples. Given a seed prompt, various paraphrasing methods can be exploited for generating more candidate prompts (Yuan et al., 2021; Haviv et al., 2021). Wallace et al. (2019) first proposed to search prompts automatically based on gradient. Gao et al. (2021) and Ben-David et al. (2021) explored how to use pre-trained T5 model to generate templates, which is more convenient compared with previous methods since it doesn’t need extra corpus or modification of the model. For the continuous prompts: Li and Liang (2021) first proposed to use trainable continuous task-specific hidden representation vectors as prompts. There are some works making use of discrete prompts, like initializing continuous prompts with discrete prompts and hybrid prompts (Zhong et al., 2021; Qin and Eisner, 2021; Liu et al., 2021c).

Demonstration learning
Demonstration learning is one of the methods to combine multi prompts. This method is first used by GPT series (Radford et al., 2019; Brown et al., 2020). While in GPT models the demonstrations are selected randomly, researchers found that the selection with similarity would significantly improve the final performance (Gao et al., 2021; Liu et al., 2021a). Liu et al. (2021a) and Kumar and Talukdar (2021) also discovered that the order of prompts provided to the model has a great influence on the performance of the model. However, the above methods fail to select demonstrations dynamically.

7 Conclusion
In this paper, we investigate how to solve the natural language inference generation task in a few-shot setting. We propose LM-PDD to combine a PLM with prompts and demonstrations, including a novel template selection method, which leverages the development set for conditional generation tasks, and a dynamic demonstration method. Our methods outperform previous prompt selection and demonstration methods, achieving average 8% accuracy over the vanilla fine-tuning method.

|                  | SST-2    | SST-5    | MR     | CR     | MPQA   | Subj  | TREC  |
|------------------|----------|----------|--------|--------|--------|-------|-------|
| LM-BFF (In paper)| 93.0(0.6)| 49.5(1.7)| 87.7(1.4)| 91.0(0.9)| 86.5(2.6)| 91.4(1.8)| 89.4(1.7)|
| LM-BFF (Our implement) | 93.0(0.5) | 50.4(1.2) | 87.3(1.9) | 90.7(1.1) | 86.2(1.8) | 90.4(2.3) | 86.2(3.9) |
| LM-BFF + dynamic | 91.8(0.9) | 50.6(1.3) | 88.0(1.1) | 91.2(0.8) | 86.7(1.7) | 91.2(1.7) | 87.3(3.0) |

|                  | CoLA  | SNLI   | QNLI   | RTE   | MRPC  | QQP   |
|------------------|-------|--------|--------|-------|-------|-------|
| LM-BFF (In paper)| 21.8(15.9)| 77.5(3.5)| 68.5(5.4)| 71.1(5.3)| 78.1(3.4)| 67.7(5.8)|
| LM-BFF (Our implement) | 20.4(14.4) | 80.5(1.7) | 70.5(4.8) | 69.0(3.3) | 75.0(4.5) | 58.6(6.4) | - |
| LM-BFF + dynamic | 17.7(17.5)| 78.9(2.4)| 71.9(3.7)| 72.5(3.7)| 77.4(3.8)| 66.4(7.4)| - |

Table 6: Test dynamic demonstration method on 13 NLP classification tasks.
References

Eyal Ben-David, Nadav Oved, and Roi Reichart. 2021. PADA: A prompt-based autoregressive approach for adaptation to unseen domains. CoRR, abs/2102.12206.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015, pages 632–642. The Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harrison Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummins, Matthias Plappert, Fitos Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paine, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Joshua Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating large language models trained on code. CoRR, abs/2107.03374.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2005. The PASCAL recognising textual entailment challenge. In Machine Learning Challenges, Evaluating Predictive Uncertainty, Visual Object Classification and Recognizing Textual Entailment, First PASCAL Machine Learning Challenges Workshop, MLCW 2005, Southampton, UK, April 11-13, 2005, Revised Selected Papers, volume 3944 of Lecture Notes in Computer Science, pages 177–190. Springer.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics.

Jesse Dodge, Gabriel Ilharco, Roy Schwartz, Ali Farhadi, Hannaneh Hajishirzi, and Noah A. Smith. 2020. Fine-tuning pretrained language models: Weight initializations, data orders, and early stopping. CoRR, abs/2002.06305.

Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making pre-trained language models better few-shot learners. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021, pages 3816–3830. Association for Computational Linguistics.

Adi Haviv, Jonathan Berant, and Amir Globerson. 2021. Bertese: Learning to speak to BERT. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, EACL 2021, Online, April 19 - 23, 2021, pages 3618–3623. Association for Computational Linguistics.

Somayeh Jafaritazehjani, Albert Gatt, and Marc Tanti. 2019. Visually grounded generation of entailments from premises. CoRR, abs/1909.09788.

Zhenghao Jiang, Frank F. Xu, Jun Araki, and Graham Neubig. 2020. How can we know what language models know. Trans. Assoc. Comput. Linguistics, 8:423–438.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Vladyslav Kolesnyk, Tim Rocktäschel, and Sebastian Riedel. 2016. Generating natural language inference chains. CoRR, abs/1606.01404.

Sawan Kumar and Partha P. Talukdar. 2021. Reordering examples helps during priming-based few-shot learning. In Findings of the Association for Computational Linguistics: ACL/IJCNLP 2021, Online Event, August 1–6, 2021, volume ACL/IJCNLP 2021 of Findings of ACL, pages 4507–4518. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer.
2020a. BART: denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020, pages 7871–7880. Association for Computational Linguistics.

Patrick S. H. Lewis, Ethan Perez, Aleksandra Pik tus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020b. Retrieval-augmented generation for knowledge-intensive NLP tasks. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 110–119, San Diego, California. Association for Computational Linguistics.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021, pages 4582–4597. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. 2021a. What makes good in-context examples for gpt-3? CoRR, abs/2101.06804.

Pengfei Liu, Weizhe Yuan, Jnlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021b. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. arXiv preprint arXiv:2107.13586.

Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhihun Yang, and Jie Tang. 2021c. GPT understands, too. CoRR, abs/2103.10385.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692.

Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2020. Adversarial NLI: A new benchmark for natural language understanding. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pages 311–318.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick S. H. Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander H. Miller. 2019. Language models as knowledge bases! In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 2463–2473. Association for Computational Linguistics.

Peng Qi, Yuhao Zhang, Yuhui Zhang, Jason Bolton, and Christopher D. Manning. 2020. Stanza: A Python natural language processing toolkit for many human languages. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations.

Guanghui Qin and Jason Eisner. 2021. Learning how to ask: Querying lms with mixtures of soft prompts. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021, pages 5203–5212. Association for Computational Linguistics.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. J. Mach. Learn. Res., 21:140:1–140:67.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics.

Timo Schick and Hinrich Schütze. 2020. Few-shot text generation with pattern-exploiting training. CoRR, abs/2012.11926.
Timo Schick and Hinrich Schütze. 2021. Exploiting cloze-questions for few-shot text classification and natural language inference. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, EACL 2021, Online, April 19 - 23, 2021, pages 255–269. Association for Computational Linguistics.

Yikang Shen, Shawn Tan, Chin-Wei Huang, and Aaron C. Courville. 2018. Generating contradictory, neutral, and entailing sentences. CoRR, abs/1803.02710.

Taylor Shin, Yasaman Razeghi, Robert L. Logan IV, Eric Wallace, and Sameer Singh. 2020. Autoprompt: Eliciting knowledge from language models with automatically generated prompts. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020, pages 4222–4235. Association for Computational Linguistics.

Janez Starc and Dunja Mladenic. 2017. Constructing a natural language inference dataset using generative neural networks. Comput. Speech Lang., 46:94–112.

Eric Wallace, Shi Feng, Nikhil Kandpal, Matt Gardner, and Sameer Singh. 2019. Universal adversarial triggers for attacking and analyzing NLP. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 2153–2162. Association for Computational Linguistics.

Weizhe Yuan, Graham Neubig, and Pengfei Liu. 2021. Bartscore: Evaluating generated text as text generation. CoRR, abs/2106.11520.

Tianyi Zhang, Felix Wu, Arzoo Katiyar, Kilian Q. Weinberger, and Yoav Artzi. 2021a. Revisiting few-sample BERT fine-tuning. In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021. OpenReview.net.

Zhengyan Zhang, Yuxian Gu, Xu Han, Shengqi Chen, Chaojun Xiao, Zhenbo Sun, Yuan Yao, Fanchao Qi, Jian Guan, Pei Ke, Yanzheng Cai, Guoyang Zeng, Zhixing Tan, Zhiyuan Liu, Minlie Huang, Wentao Han, Yang Liu, Xiaoyan Zhu, and Maosong Sun. 2021b. CPM-2: large-scale cost-effective pre-trained language models. CoRR, abs/2106.10715.

Zexuan Zhong, Dan Friedman, and Danqi Chen. 2021. Factual probing is [MASK]: learning vs. learning to recall. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021, pages 5017–5033. Association for Computational Linguistics.
A Implement details

We take two group of hyper-parameters: learning rate=5e-5, batch size=32 and learning rate=1e-5, batch size=16. We use $D_{dev}$ to chose the best one. warm-up steps are set as 10. For each model, we train it for 30 epochs in total. We evaluate it for each epoch starting from epoch 10.

B Analysis of the choice of retrievers

| Retriever Type | SNLI(acc) | MNLI(acc) |
|----------------|----------|-----------|
|                | top      | mm        | top      | mm        |
| random         | 68.49    | 69.35     | 59.02    | 57.37     |
| SBERT + static | 66.79    | 71.81     | 59.39    | 59.78     |
| BERT-base + dynamic | 72.43    | 72.80             | 61.96    | **62.88** |
| SBERT + dynamic | **73.69** | **74.44** | **62.57** | 62.57     |

Table 7: Impact of the choice of the retriever. random: randomly sample demonstrations.

We also investigate the effect of the choice of the retriever on the performance. As showed in Table 7, random retriever performs worst and dynamic SBERT retriever performs best. We also find dynamic pre-trained BERT-base outperforms static BERT, where BERT-base has similar model size with SBERT but it is not fine-tuned with extra dataset to learn a better sentence embedding. This indicates that with dynamic demonstration, the retriever can learn a better sentence embedding with training samples, so a small size of training set is enough to train a retriever well, which makes dynamic demonstration more useful in a low-resource domain.

C Generated prompts

We show the prompt selected by top method and our max-margin method on SNLI and MNLI dataset in Table 8, Table 9, Table 10 and Table 11.
### Table 8: Generated templates of top method in SNLI dataset

| seed | contradiction | neutral | entailment |
|------|---------------|---------|------------|
| 13   | Now           | Here    | Close up of |
| 21   | In the background | Then, | A photo of |
| 42   | At the same time, | At the end of the day, | A black and white photograph of |
| 87   | The back of   | In this video, | Description: |
| 100  | In the distance, | And | A photo of |

### Table 9: Generated templates of max-margin method in SNLI dataset

| seed | contradiction | neutral | entailment |
|------|---------------|---------|------------|
| 13   | As            | Later,  | Close up of |
| 21   | At the same time | In this photograph, | One of |
| 42   | At the same time, | On the right | A black and white photograph of |
| 87   | A close up of | A woman and | A black and white photo of |
| 100  | Then,         | Here    | The photo shows |

### Table 10: Generated templates of top method in MNLI dataset

| seed | contradiction | neutral | entailment |
|------|---------------|---------|------------|
| 13   | Though        | Although | The |
| 21   | At the end of the day | For the most part, | At the same time |
| 42   | Now           | At the end of the day, | That |
| 87   | Although       | Even    | For example, |
| 100  | Yet           | For the most part | Again, |

### Table 11: Generated templates of max-margin method in MNLI dataset

| seed | contradiction | neutral | entailment |
|------|---------------|---------|------------|
| 13   | For some reason | So | In the meantime, |
| 21   | For some reason | However, | As you can see |
| 42   | Even though   | The    | At least |
| 87   | It’s not that | Even   | Finally, |
| 100  | But in the end, | In fact | , |

Table 10: Generated templates of top method in MNLI dataset

Table 11: Generated templates of max-margin method in MNLI dataset