SpeechPrompt: An Exploration of Prompt Tuning on Generative Spoken Language Model for Speech Processing Tasks

Kai-Wei Chang¹, Wei-Cheng Tseng¹, Shang-Wen Li², Hung-ye Lee¹

¹Graduate Institute of Communication Engineering, National Taiwan University, Taiwan
²Amazon AI, USA

kaiwei.chang.tw@gmail.com, r09942094@ntu.edu.tw, swdanielli@gmail.com, hungyilee@ntu.edu.tw

1. Introduction

Recently, SSL speech models [1, 2, 3, 4] can achieve state-of-the-art performance in a wide variety of speech processing tasks. The learned, highly informative representations can benefit various speech processing downstream tasks [5, 6, 7, 8]. Despite their success, adopting these models to different downstream tasks requires either (a) fine-tuning the pre-trained model [2, 3, 9] or (b) appropriately designing downstream models and loss functions [10, 11], which results in an increasing burden of human labor and memory cost [12] as the number of tasks scales [11]. Hence, there is a demand for exploring an alternative paradigm to leverage SSL speech models.

On the other hand, in the Natural Language Processing (NLP) field, prompting methods have gained researchers’ attention [13]. The methods scale up pre-trained language models (LMs) at serving multiple downstream tasks in a unified and efficient way. For each downstream task, prompting methods aim to find task-specific templates or a limited number of parameters that steer LMs to generate results for the task without modifying LM’s parameters. For example, in a sentiment classification task for movie review, we can design a prompt “[X] The movie is _”. The LM takes a sentence to be classified and fits it into the template at [X]. By generating a sentiment word from a pre-defined set of tokens (e.g. great, neutral, bad) that one-to-one mapped to classification labels, we transform the sentiment classification task into a generation problem. Alternatively, prompts are not necessary to be readable by humans. Researchers proposed prompt tuning methods that learn continuous prompts [14, 15, 16] in models’ embedding space. Studies have shown that prompt methods can reformulate most NLP tasks as generation problems and yield competitive performance [13].

The prompting paradigm is appealing as the number of downstream tasks to be served increases. Rather than requiring a specialized downstream model for each task, a generalist model can simultaneously serve many different tasks in one inference batch. Since parameters of tuned prompts are usually several orders smaller than parameters of LMs [17], the prompting paradigm significantly improves memory and computation efficiency. Furthermore, there is a unified inference process with the original pre-trained LM for all downstream tasks in the paradigm. Hence, less human labor is required in model authoring for each task. Despite the success in NLP, there is little research on the prompting paradigm in the speech community.

To bring the benefit of the prompting paradigm to the speech processing field, we propose a prompt tuning framework for multiple downstream speech processing tasks, including Keyword Spotting (KS), Intent Classification (IC), Automatic Speech Recognition (ASR), and Slot Filling (SF). The framework unifies training and inference for multiple tasks by leveraging the generation capability of the pre-trained LM. To our best knowledge, our work is the first study in the prompting paradigm that achieves competitive performance in various speech processing tasks.

We utilize Generative Spoken Language Model (GSLM) [18] as our backbone LM and apply prompting on top of it. GSLM is used, for GSLM is the first generative speech LM pre-trained on a large-scale speech dataset, and it has a large model capacity to generate meaningful output. Experiment shows that the proposed framework achieves competitive accuracy (Acc) in single-label and multi-label speech classification tasks. While the framework demonstrates the potential of prompting GSLM, we also identify the limitations when performing challenging sequence generation tasks and discuss the potential research directions in the paper. We hope by exploring and analyzing the novel prompting paradigm for speech processing, this work can...
2. Related Works

2.1. SSL Speech Representations

Learning speech representations with SSL objectives has become a vital research topic in the speech community. For example, CPC [11] learns by predicting future features in a contrastive manner. HuBERT [3] maximizes the similarity between output representations and clusters of acoustic features during pre-training. To leverage SSL representations, a common way is to build specialized downstream models on top of SSL representations and fine-tune the entire models or only the downstream ones for supervised downstream tasks. Based on this, SUPERB [10] benchmarks speech SSL techniques with a wide variety of downstream tasks. This work explores an alternative paradigm: we add a fixed, pre-trained LM on top of SSL representations and prompt the LM to generate predictions directly.

2.2. Generative Spoken Language Model

Researchers proposed Generative Spoken Language Model (GSLM) [18] to model the rich expressiveness of spoken language based on discovered units of raw audio without any text or labels. GSLM first leverages the representation learning ability of SSL speech models and encodes raw speech into a sequence of discrete units by an SSL model and the K-means clustering algorithm. A generative unit language model (uLM), the core component of GSLM, is then trained to perform speech generation on top of discrete units. The technique shows competitive performance to generate novel speech unconditionally or conditioned on a speech segment. GSLM can be considered the speech version of GPT-3 [19] and is the first generative speech LM trained on a large speech corpus. The work opens the door to applying prompt tuning methods for speech processing tasks.

2.3. Prompting and Reprogramming

Prompting refers to techniques for finding task-specific instructions or templates that steer a pre-trained LM without modifying its parameters [13]. By concatenating examples and a task description to the original sentence as the input, GPT-3 [19] performs in-context learning to directly generate labels of the sentence. Although in-context learning yields competitive results, it requires heavy hand-crafted prompt engineering, and it is difficult to scale to smaller pre-trained models [20]. To avoid hand-crafted prompt engineering, automatically generating templates [21, 22] is another research direction.

Under the premise of fixing pre-trained LMs’ parameters, researchers further explore prompt tuning, where continuous prompts are learned in the model’s embedding space. For example, [17, 15] learn continuous prompts in LMs’ input embedding space. We refer to this kind of methods as input prompt tuning. Another similar technique to input prompt tuning is model reprogramming [23], where an input transformation function is learned to reprogram a pre-trained model to perform a target task. [24, 25] have explored reprogramming acoustic models while focusing on single-label classification tasks with a supervised model. In this work, the proposed framework can perform various speech processing tasks and is not limited to input transformation. Alternatively, Prefix-Tuning [13] and P-Tuning v2 [16] performs deep prompt tuning, in which prefix prompts are further prepended at the input of model’s hidden layer. We mainly utilize deep prompt tuning in this work. Meanwhile, we also investigate applying prompts only at the input of the LM for comparing different prompting techniques.

3. Method

We propose a prompting framework to adapt GSLM to a given downstream task by conditioning the uLM on task-specific prompts. Figure 1 illustrates the framework. An utterance is first encoded into discrete units by an SSL speech model and a K-means quantizer. The uLM then takes the sequence of units as input and prepends it with task-specific prompts. We then perform conditional generation with the uLM to output units that will be mapped to task labels with a pre-defined verbalizer. In the following, we describe details in the framework, including applying prompts at uLM, controlling the output of conditional generation, and the label mapping with a verbalizer.

3.1. Prompt Tuning

A causal uLM M takes a discrete unit sequence u as input and autoregressively outputs a sequence u = M(u) until an end-of-sentence token "[EOS]" is produced.

In prompt tuning, the parameters of the pre-trained uLM M are fixed. Given M and a downstream task, a set of trainable task-specific prompt vectors P is optimized during adaptation with supervision from the task. The number of trainable parameters for each task is denoted as |P|. We adopt deep prompt tuning similar to [14, 16] in our framework. Given an utterance, the SSL model and the quantizer first encode it into a sequence of discrete units u_0 = \{u_1, u_2, \ldots, u_T\}, u_i \in U, where T is the unit sequence length, and U is the unit space of the uLM. Trainable continuous prompts are then applied to (a) the input of the uLM in its embedding space and (b) the input of the attention mechanism in each Transformer block.

(a) Prompts at the input of the uLM

Given an unit sequence u, as the original input, the input embedding layer of the uLM \( e(\cdot) : \mathbb{R} \rightarrow \mathbb{R}^d \) first transforms it into a sequence of embedding vectors: \( e(u) = [e(u_1), e(u_2), \ldots, e(u_T)] \). The sequence is then prepended with continuous prompts and fed into the uLM:

\[
[p^1_1, p^2_1, \ldots, p^i_1, e(u)]
\]

where \( p^i_1 \) are trainable vectors in \( \mathcal{P} \), and \( i \) is the prompt length.

(b) Prompts at the input of the attention mechanism

Solely applying prompts to the input embedding may not be powerful enough to steer a pre-trained LM [16]. Therefore, we also apply prompts to the input of the self-attention mechanism [26] in every Transformer block of the uLM. Given a Transformer block that takes the embedding \( x = [x_1, x_2, \ldots, x_T] \) as input, we manipulate the key K and value V in the attention function

\[
K = \text{Concat}(p^K, x_{t+1:T})W^K
\]

\[
V = \text{Concat}(p^V, x_{t+1:T})W^V
\]

where \( p^K \) and \( p^V \) are trainable vectors in \( \mathcal{P} \). That is, we replace the first I vectors of \( x \) with the trainable prompt vectors.

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1Following GSLM [18], unit deduplication is also applied universally. (e.g., the unit sequence 71 11 63 63 63 becomes 71 11 63.)
3.2. Conditional Generation and Verbalizer

To leverage the generation capability of the uLM for inference in downstream tasks, we reformulate all tasks into conditional generation problems. The uLM generates an output sequence $u_y$ conditioned on the input unit sequence $u_x$ and task-specific prompts $P$. Let $y = (y_1, ..., y_n)$, $y \in \mathcal{Y}$, be a sequence of $n$ task labels and $\mathcal{Y}$ is the label space of a task. The task label length $|y|$ is flexible depending on the task. For example, in classification tasks, $y$ can be a single label or multiple labels. In recognition tasks, $y$ can be a character sequence. To connect the LM’s output with the labels of downstream tasks, a verbalizer $v$ is introduced in the paradigm of prompting LMs. The verbalizer is a one-to-one mapping $v : \mathcal{Y} \rightarrow \mathcal{U}$ that maps from the task label space to vocabulary of the language model. In the case of the uLM, the vocabulary is the units $\mathcal{U}$. With the help of the verbalizer, the output units can be mapped back to task labels. For example, in Intent Classification, the output units $u_y = [4, 40, 27]$ can be interpreted as intent labels [“Active”, “Lights”, “Bedroom”].

The trainable prompts are then optimized with a loss function $\mathcal{L}$, which is cross-entropy for every task in the work:

$$P = \arg\min_{P} \mathcal{L}(\mathcal{M}(P, u_x), v(y))$$

4. Experiment Setup

4.1. Tasks and Datasets

We evaluate the proposed framework on various speech processing tasks, including speech classification tasks: Keyword Spotting (KS) and Intent Classification (IC); sequence generation tasks: ASR and Slot Filling (SF). Table 1 gives a brief summary for each task. We follow the same dataset and data splits as in SUPERB [10]. Due to space limitations, please refer to SUPERB for more detailed descriptions.

4.2. Implementation Details

uLM We use the checkpoints of the pre-trained uLMs corresponding to HuBERT and CPC representation with 100 clusters on fairseq [31]. The uLM is a causal LM consisting of 12 Transformer decoder layers with 151M parameters. All the parameters are fixed during prompt tuning.

Verbalizer We utilize a simple frequency-based algorithm to implement the verbalizer, in which no model estimation [27, 32] is involved to simplify the pipeline. For $N$ classes in the task (c.f. Table 1), we map those $N$ classes into $N$ unique units by the following steps: (1) Find and sort top-$N$ frequent units in the input of the training data, denoted as $[u_1, u_2, ..., u_N]$. (2) Find and sort top-$N$ frequent classes in the ground truth of the training data, denoted as $[c_1, c_2, ..., c_N]$. (3) Define the verbalizer $v$ as an one-to-one function: $v(c_i) = u_i$. We find that applying the frequency-based verbalizer improves the performance by a small margin compared to random assignment. We do not show the experiment result of random assignment due to space limitations.

Promt Length We find that the optimal prompt length varies between tasks. For speech classification tasks, we used as fewer prompts as possible while keeping the performance competitive. Regarding sequence generation tasks, we use prompt length $l = 180$, where 4.5M parameters, which equals 3% parameters of the uLM, are trainable.

5. Results

5.1. Speech Classification Tasks

Table 2 shows the result of the proposed prompt tuning (PT) framework in multiple tasks. For comparison, we also list the performance of fine-tuning the uLM (FT-LM), where the same framework is adopted but with the entire uLM trainable. We also list the performance of fine-tuning the specialized downstream models (FT-DM) as in SUPERB [10] as a strong baseline. SUPERB utilizes linear models as downstream models for KS and IC, and 2-layer Bi-LSTMs for ASR and SF. As shown in Table 2, in speech classification tasks, prompt tuning outperforms fine-tuning the entire uLM or downstream models. The advantage might be that a sequence generation model is

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Table 1: Summary of downstream tasks used in the work. SLU denotes Spoken Language Understanding. CLS: Classification. SG: Sequence Generation. [7]: average label length in the task.

| Task   | Type       | $N_{class}$ | $|y|$ | Dataset |
|--------|------------|-------------|------|---------|
| KS     | Detection  | CLS         | 12   | 1 [28]  |
| IC     | SLU        | CLS         | 24   | 3 [29]  |
| ASR    | Recognition| SG          | 29   | 173 [30]|
| SF     | Recognition + SLU | SG | 69 | 54 | [7] |

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Figure 1: (a) The overview of the proposed framework. Task-specific prompts are applied to the unit language model (uLM) to generate predictions. (b) The uLM performs generation conditioned on the discrete unit sequence and the task prompts.
suitable for learning the correlation between labels [33].

Table 2: Performance of prompt tuning in various speech processing tasks. Fine-tuning baselines are listed for comparison. PT: Prompt Tuning. FT-LM: Fine-Tuning the pre-trained uLM. FT-DM: Fine-Tuning the Downstream Model as in SUPERB. #: Number of trainable parameters.

(a) Performance on speech classification tasks.

| Scenarios   | KS | IC |
|-------------|----|----|
| HuBERT-PT   | 95.16 | 0.08M | 98.40 | 0.15M |
| FT-LM       | 94.03 | 151M  | 97.63 | 151M  |
| FT-DM       | 96.30 | 0.2M  | 98.34 | 0.2M  |
| CPC-PT      | 93.54 | 0.05M | 97.57 | 0.05M |
| FT-LM       | 93.48 | 151M  | 95.62 | 151M  |
| FT-DM       | 91.88 | 0.07M | 64.09 | 0.07M |

(b) Performance on sequence generation tasks.

| Scenarios   | ASR | SP |
|-------------|-----|----|
| HuBERT-PT   | 34.17 | 26.14 | 66.90 | 59.47 |
| FT-LM       | 26.19 | 16.80 | 80.58 | 40.15 |
| FT-DM       | 6.42  | 1.48  | 88.53 | 25.20 |
| CPC-PT      | 59.31 | 37.12 | 65.25 | 60.84 |
| FT-LM       | 35.61 | 17.90 | 79.34 | 42.64 |
| FT-DM       | 20.18 | 5.25  | 71.19 | 49.91 |

5.2. Sequence Generation and Curse of Long Sequences

We further push the limit of the prompting paradigm to perform challenging sequence generation tasks: ASR and SF. As shown in Table 2, we find that even fine-tuning the uLM (FT-LM) is not comparable to the performance of fine-tuning the specialized downstream models (FT-DM), where CTC loss and Bi-LSTMs are adopted. To better understand the gap and possible mitigations of promoted prompt tuning, we study the correlation between the label length \(|y|\) (i.e., sequence to be generated) and the character error rates (CERs) of HuBERT-PT and HuBERT-FT-LM in ASR. Figure 3 shows that the performance drops significantly when it comes to long sequences.

We surmise that the performance drop results from that the uLM is a causal, decoder-only model, which may be unsuitable for recognizing long sequences. Similar phenomena have also been observed in the NLP field. Due to the limitation of the unidirectional attention mechanism, generative models need more parameters and pre-trained data to work on Natural Language Understanding (NLU) tasks [14]. In a more complex task, text summarization, GPT-2 is also suffered from long sequences [14]. Although GPT-3 [19] shows competitive performance by performing NLU tasks as a generation problem, a much larger model (175B parameters) is also required. The uLM has only 151M parameters and therefore falls behind the fine-tuning of specialized downstream models in challenging sequence generation tasks, where label lengths are way longer than those in [14] (c.f. Table 1). We will continue the discussion of the limitations of existing pre-trained generative models and possible research directions in Section 6.

5.3. Prompt Length

We vary the prompt length \(l\) in HuBERT-PT to study the effect of the number of trainable parameters. In Figure 2, the result shows that as the prompt length increases, there is a trend of increasing performance. It is worth noting that it still achieves a reasonable accuracy with prompt length only equal to 2, where 52K trainable parameters are introduced.

5.4. Input Prompt tuning

When the inner parameters of pre-trained LMs are not accessible, only input prompt tuning can be applied. Thus, we further study the IC and KS performance of our approach when prompts are only used at the input of the uLM. Figure 3 shows that although deep prompt tuning (i.e., applying prompts further at LMs’ hidden layer described in section 3.1(b)) consistently outperforms input prompt tuning, the latter can also achieve competitive performance with sufficient trainable parameters.

6. Discussion and Future Works

Unlike prompt tuning in NLP, the meaning of the uLM’s vocabulary is not obvious. In NLP, it is usually simple to identify how to define the verbalizer [27], and often the verbalizer is even an identity function when the prediction target is the vocabulary itself [22]. This paper leverages a heuristic, frequency-based approach to define the verbalizer. How to better identify the mapping between discovered units and task labels is critical for performance and remains unsolved.

Although the experiments show that the proposed framework achieves competitive results in speech classification tasks, we are restricted by the nature of the uLM when performing challenging sequence generation tasks. In NLP, prompting on text classification tasks has also achieved remarkable results [15, 20, 27, 35]. However, to solve more difficult text generation tasks (e.g., summarization, translation), larger and more powerful pre-trained LMs including Prefix LMs (e.g. UniLMs [46, 27]), and Encoder-Decoder LMs (e.g. T5 [22], BART [38]) are often introduced [13, 14, 16, 39]. For speech processing
tasks, the problems might be even more difficult since the model is expected to perform recognition (KS, ASR), understanding (IC), or both at the same time (SF), while there are few LMs is expected to perform recognition (KS, ASR), understanding tasks, the problems might be even more difficult since the model can motivate the speech research communities to explore the limitation of the framework on challenging sequence generation tasks. This paper is the first exploration of prompt tuning fine-tuning the entire downstream models. We also investigate the framework achieves competitive performance compared to processing tasks. The experiment results shows that the language

7. Conclusions
In this work, we propose a prompt tuning framework based on Generative Spoken Language Model (GSLM) for speech processing tasks. The experiment results shows that the language model can be guided to directly generate the answers by tuning a limited number of task-specific vectors. In classification tasks, the framework achieves competitive performance compared to fine-tuning the entire downstream models. We also investigate the limitation of the framework on challenging sequence generation tasks. This paper is the first exploration of prompt tuning paradigm for speech processing tasks. We believe this study can motivate the speech research communities to explore the prompting paradigm more.

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