Plug-Tagger: A Pluggable Sequence Labeling Framework Using Language Models

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Abstract

Plug-and-play functionality allows deep learning models to adapt well to different tasks without requiring any parameters modified. Recently, prefix-tuning was shown to be a plug-and-play method on various text generation tasks by simply inserting corresponding continuous vectors into the inputs. However, sequence labeling tasks invalidate existing plug-and-play methods since different label sets demand changes to the architecture of the model classifier. In this work, we propose the use of label word prediction instead of classification to totally reuse the architecture of pre-trained models for sequence labeling tasks. Specifically, for each task, a label word set is first constructed by selecting a high-frequency word for each class respectively, and then, task-specific vectors are inserted into the inputs and optimized to manipulate the model predictions towards the corresponding label words. As a result, by simply switching the plugin vectors on the input, a frozen pre-trained language model is allowed to perform different tasks. Experimental results on three sequence labeling tasks show that the performance of the proposed method can achieve comparable performance with standard fine-tuning with only 0.1% task-specific parameters. In addition, our method is up to 70 times faster than non-plug-and-play methods while switching different tasks under the resource-constrained scenario.

Introduction

Fine-tuning is a primary paradigm for transferring pre-trained language models (PLMs) to downstream natural language processing (NLP) tasks (Radford et al. 2019; Devlin et al. 2019). However, standard fine-tuning requires retraining the large-scale parameters of a PLM for each task. In real-world scenarios where tasks switch very frequently, retraining and redeploying (Sharma et al. 2018) the PLM can be prohibitively expensive. In addition, even storing PLMs like BERT (110M parameters) for each task can be tough. Therefore, it is necessary to find a better way to transfer PLMs towards downstream tasks with minimal cost. In the ideal case, no modification of PLM is required, and performing different tasks does not require redeployment, but is done by switching lightweight modules. This approach is known as the plug-and-play method as shown in Figure 1.

Adapter-tuning (Raffel et al. 2020; Houlsby et al. 2019) and prefix-tuning (Li and Liang 2021) are popular methods for achieving pluggability. These approaches focus on keeping parameters of the PLMs fixed and optimizing only a few parameters for each task. By inserting a task-specific adapter layer between layers of the PLM, adapter-tuning merely needs to store the parameters of one shared PLM and multiple task-specific layers to perform different tasks, rather than storing a full copy of the PLM for each task. Prefix-tuning does not modify the model architecture and instead prepends a sequence of continuous task-specific vectors to the inputs. These vectors work as a prompt for the model, manipulating it to generate outputs required by different tasks. Thus, generation tasks performed by the PLM can be switched by simply switching the prefix vectors at the inputs.

However, adapter-tuning adds additional layers to the PLM, which modifies the architecture, the inconvenience of redeploying the model when switching to new tasks remains unsolved. Prefix-tuning is only plug-and-play on text generation because the language model head can be shared between different generation tasks, but different
label sets make it impossible for classification tasks to share a classifier. Therefore, prefix-tuning cannot be directly transferred to classification tasks such as sequence labeling.

To overcome this limitation, in this paper, we propose plug-tagger, a plug-and-play framework for various sequence labeling tasks. The proposed method allows a frozen PLM to perform different tasks without modifying the model but instead by switching plugin vectors on the input. The change to the label set leads to an unavoidable modification of the model classifier, but we overcome this problem by reformulating sequence labeling to the task of predicting the label words. We take high-frequency words predicted by PLM to serve as the label words for corresponding labels. For example, the entities of person names such as “Xavier” can be recognized by predicting a common name (label word) such as “John”. Benefiting from the reuse of the entire architecture of PLMs, our method can directly utilize plugin vectors to switch tasks without making any modifications to the model, as shown on the right side of Figure 1. Our method is also useful in industrial applications, where the PLM typically requires hardware acceleration for each new task deployment (Sharma et al. 2018). A plug-and-play approach, with no modifications to the model architecture, allows us to accelerate multiple tasks with only one accelerated PLM.

The main contributions of this paper can be summarized as follows:

- We proposed a pluggable component on PLMs for sequence labeling, and the proposed method can accomplish new tasks by modifying the input rather than modifying the model.
- We propose a new paradigm for sequence labeling tasks. It transforms the classification task into a label word prediction task by reusing the language model head of PLM.
- Experiments on a variety of sequence labeling tasks demonstrate the effectiveness of our approach. Besides, in experiments with limited computational resources, our method is up to 70 times faster than other methods.

**Approach**

In this work, we are looking for a plug-and-play method for sequence labeling, which aims to make a frozen model perform different sequence labeling tasks by switching task-specific lightweight modules on the input. In this section, we first introduce the key challenges of achieving pluggability on sequence labeling. Next, we propose an overview of our approach, and finally, we detail the two primary components of our approach.

**Problem Statement**

Given a sequence of words $X = [x_1, \ldots, x_n]$, the goal of sequence labeling is to predict the sequence of gold label $Y = [y_1, y_2, \ldots, y_n]$ with equal length. The predictions of a sequence labeling system can be expressed as $\hat{Y} = F(X; \Theta)$ where $\Theta$ is the parameters of the system. The traditional system based on fine-tuning and classifier can be decomposed into the following equations:

$$H = Encoder_{\phi_1}(X)$$
$$\hat{Y} = \text{argmax}(\text{Softmax}(HW + b))$$  \(1\)

where $W \in \mathbb{R}^{h \times l}$, $l$ is the size of label set, $h$ is the dimension of hidden state. $Encoder_{\phi_1}$ is a PLM without language model head. Parameters of system $\Theta$ is decomposed into $\phi_1$, $W$ and $b$.

The requirements of the plug-and-play method are lightweight and no modification of the model. There are two challenges to achieve this goal. The first challenge arises from the large-scale $\phi_1$, standard fine-tuning requires an entire new model for every task. That is, each task requires a large number of task-specific parameters when using PLM. The second one is that the dimension of $W$ cannot be frozen due to different label sets. For example, NER’s label consists of entity types such as person, location and organization, but POS’s label consists of part of speech types like adjective, noun and adverb. It’s challenging to map so many different task-specific labels onto the same label space. This prevents the model’s classifier layer from remaining frozen.

**Model Overview**

The architecture of the proposed model is shown in Figure 2. We switch the lightweight plugin vectors on the input rather than reloading large-scale parameters of PLM to perform different tasks. The label word mechanism replaces the task-specific classifier to avoid the modification of the model architecture. Under the influence of the plugin vector, the model predicts the corresponding label words of input, and the actual labels can be obtained by label word mapping. Take NER as an example, we feed the input “Olivia likes apple” with the plugin of NER into the frozen language model, the output of language model will be “John likes apple”. “John” is the label word of PER (person) in NER, after label word mapping, we get the NER label of the input: “PER O O”.

We define the label word map as $M$, $\Theta_{lm}$ is the parameters of the frozen language model, $\Theta_P$ is plugin vector. The label words predicted by plug-tagger can be describe as $\hat{Y} = F(X; \Theta_P; \Theta_{lm})$ where $\{X, \Theta_P\}$ is the inputs, and we use label word mapping to get the real labels $\hat{Y} = M(\hat{Y})$. The following two sections detail essential parts of the plug-tagger: plugin vector and label word mechanism.

**Plugin Vector**

To solve the problem of storing and reloading large-scale parameters for various tasks, we plugin vector to control the model behavior without modifying the architecture and parameters of the model. The plugin vector $\Theta_P$ consists of a few continuous vectors and is combined with input. In the following two subsections, we show two ways to combine the plugin vector with the input.

**Plugin in embedding**

The input of PLM is the text $X$ processed by embedding, which can be described as $X' = \cdots$
To alleviate problems caused by the task-specific classifier, we propose label word mechanism, which reformulates the sequence labeling to the label word prediction. Label word is the most common word for a label. For example, the uncommon name “Olivia” can be substituted with the more common name “John”.

**Label Word Selection** Algorithm [I] represents the entire label word selection processing. For each label, a dictionary \(\text{freq}\) was built to counts its candidate label words and corresponding frequency. We traverse the training set, for each word in the sentence, we use the language model to get top-k high-probability candidate words and update dictionary \(\text{freq}\) corresponding to the word’s label \(\text{c}\). After traversing the training set, we filter some words that are not suitable for label words such as the words that frequently occur in all \(\text{freq}\). Under the condition that the label word of each label is not the same, the remaining words with the
where $N$ is the number of sentences. When combined with
\[ \begin{align*}
\text{LabelMap} & \rightarrow \text{words} \\
X & \rightarrow \text{predictions of language model} \quad \text{LM}
\end{align*} \]

we get the label map $M$ based on predictions of language model $\text{LM}(X)$;

In particular, for tasks that need to use the BIO schema, two special treatments are needed: 1) We don’t count label word $O$. It’s hard to pick a representative word for the others category. In the training and inference phase, the word with label $O$ predict itself. 2) We look for label words respectively for B and I of the same category, because the internal order of the phrases brings more information, and distinguishing BI is beneficial for tasks that require boundary information. In the experiment section, we will discuss the influence of the label word mechanism on the performance in detail.

Training objective  We reformulate sequence labeling to a special language modeling task. After selecting label words, we get the label map $M$ to map label set to words in vocabulary. For sequence $X$, the gold label $Y$ is reintroduced to $\bar{Y} = [\bar{y}_1, ... , \bar{y}_n]$ where $\bar{y}_i = M(y_i)$. The sentence-level loss can be described as follows:

\[ \text{Loss} = - \sum_{i=1}^{N} \log(P(\bar{Y}_i|X_i)), \quad (5) \]

where $N$ is the number of sentences. When combined with the plugin vectors, parameters of plugin vectors $\Theta_P$ and the embeddings of label words are the only trainable parameters.

During the inference phase, we take the prediction result of the first subword of each word and find its corresponding label according to the label map.

Experiments
In this section, we present the experimental results to show the transferability and efficiency of plug-tagger. We conducted experiments on three sequence labeling tasks to verify whether plug-tagger could adapt to different tasks. We also simulate scenarios that require redeployment to verify whether plug-tagger could ease the inconvenience caused by redeployment.

The transferability of plug-tagger

Dataset  To verify the transferability of our methods, we conduct experiments on NER, POS and chunking. CoNLL 2003 shared task (CoNLL2003) is the standard benchmark dataset which was collected from Reuters Corpus. This dataset consists of annotations for NER, POS and chunking, so we conduct three tasks on it. In addition, we selected another representative dataset for each task, including ACE 2005 (ACE05) for NER, Wall Street Journal (WSJ) (Marcus, Santorini, and Marcinkiewicz [1993]) for POS and CoNLL 2000 (Tjong Kim Sang and Buchholz [2000]) for chunking. We use the BIO2 tagging scheme for all the tasks and follow the standard dataset preprocessing and split. The CoNLL 2000 does not have an officially divided validation set, we use the test set as the validation set. The statistics of the datasets are summarized in Table 1.

| Task  | Dataset  | #Train | #Dev  | #Test | Class |
|-------|----------|--------|-------|-------|-------|
| NER   | CoNLL 2003 | 204, 567 | 51, 578 | 46, 666 | 8     |
|       | ACE 2005  | 144, 405 | 35, 461 | 30, 508 | 14    |
| POS   | CoNLL 2003 | 204, 567 | 51, 578 | 46, 666 | 45    |
|       | WSJ      | 912, 344 | 131, 768 | 129, 654 | 46    |
| Chunking | CoNLL 2003 | 204, 567 | 51, 578 | 46, 666 | 20    |
|       | CoNLL 2000 | 211, 727 | -     | 47, 377 | 22    |

Table 1: Statistics of the datasets on NER, POS and chunking. # means number of tokens in dataset.

Baseline Methods  We compare plug-tagger with three baselines:

• **FINE-TUNING** ([Devlin et al. 2019](https://catalog.ldc.upenn.edu/LDC2006T06)) optimizes the all parameters of PLM with a task-specific classifier. Standard fine-tuning can show the normal performance of a pre-trained model.

• **FT-Sub** only optimizes sub-layer of PLM, which is the most straightforward lightweight method. We use FT-Sub show the performance of lightweight PLM without additional layers and parameters. To limit task-specific parameters to the same scale as plug-tagger.
Table 2: Experimental results for all datasets on the three tasks. The Params represent the percentage of task-specific parameters required by the method. The number after each result means the difference between this result and FINE-TUNING. Bold terms mean the best result in the same scale of parameters.

| Params       | Method      | NER (F1) | CoNLL2003 | ACE2005 | Chunking (F1) | CoNLL2003 | CoNLL2000 | POS (Acc.) | CoNLL2003 | WSJ       |
|--------------|-------------|----------|------------|---------|---------------|------------|------------|------------|------------|-----------|
| 100%         | FINE-TUNING | 91.45    | 89.02      |         | 91.41         | 97.05      |            | 95.64      | 97.69      |           |
| 0.01% - 0.1% | FT-Sub      | 84.27−7.18 | 77.37−11.65 |         | 79.94−11.47 | 83.13−13.92 |            | 88.97−6.67 | 94.94−2.75 |           |
|               | Plug-Tagger | 87.68−3.77 | 79.98−0.04  |         | 84.99−6.42   | 92.02−5.03  |            | 93.28−2.36 | 96.73−0.96 |           |
| 0.1%-1%      | Adapters    | 88.89−2.56 | 88.03−0.99  |         | 88.52−2.89   | 94.63−2.42  |            | 93.51−2.13 | 97.51−0.18 |           |
|               | Plug-Tagger | 91.58+0.13 | 87.68−1.34  |         | 90.50−0.91   | 96.48−0.57  |            | 95.01−0.63 | 97.60−0.09 |           |

- **Adapters** ([Houlsby et al. 2019](https://github.com/Adapter-Hub/adapter-transformers)) is a well-known parameter-efficient method which optimizes the parameters of additional layers inserted in PLM. We control the scale of the Adapters’ parameters by varying the number of adapter layers and the dimension of the middle layer.

**Experiment Details** We employ Roberta-Base ([Liu et al. 2019](https://huggingface.co/)) as our base model. Plug-tagger and all baselines are based on Roberta-base. The parameters and architecture are reloaded directly from HuggingFace\(^3\). For adapter-tuning, we use the Adapter-Hub\(^4\) that combines adapter-tuning and Transformers released by (Pfeiffer et al. 2020). We keep the default optimizer and scheduler settings, AdamW, and linear scheduler are used for all datasets. The maximum length of the tokenizer is 128. The default epoch is set to 10, and the batch size is 16. We find that a large learning rate often results in better performance when optimizing vectors on the input. So the default learning rate was set to 1e-3 for plug-tagger and prefix-classifier and 1e-5 for others. The hyperparameters used by each method on all data sets are given in the appendix.

For plugin vector, we additionally tune the length of plugin vectors. All experiments were conducted under the same random seed. The results are based on the hyperparameters, which are selected based on the performance on the validation set.

As for label words, We use the language model to obtain the high-frequency words of a label on the training set, and according to the combination of high-frequency words of different labels, we can select a variety of label words. The results reported in this paper are based on the set of label words with the best performance on the validation set.

To compare different methods at the same parameter scale, we limit the number of layers and size of FT-Sub and Adapters, the details are presented in the appendix.

**Main Results** Table 2 presents the results of all methods on the test set under different parameter scales. With only 0.1% task-specific parameters, plug-tagger almost outperform all other lightweight methods at the same parameter scale and achieve a comparable performance with FINE-TUNING. Under the setting of 0.01% parameters, our method performs worse than than FINE-TUNING, but still better than other methods. Next, we analyze the experimental results in detail according to the task.

**NER** is the most difficult task in our experiments. We find that our method outperform FINE-TUNING on CoNLL2003 and has the largest performance drop of all data set in ACE2005, we believe this is due to the more complex scenario of ACE2005, and less data in ACE2005 makes it more difficult to find the appropriate label words.

**Chunking**'s label has the widest range of label word candidates, which brings challenges for finding suitable label words. But we see only a small drop in chunking’s two datasets comparing to FINE-TUNING, suggesting that the plug-tagger can handle this situation. **POS** has the largest number of labels. The good performance in CoNLL2003 and WSJ proves that plug-tagger can adapt to many label words.

**The efficiency of plug-tagger**

| Method    | Performance | Parameter | Architecture | NoRedeploy |
|-----------|-------------|-----------|--------------|------------|
| Fine-tuning | ✓           | ×         | ×            | ✓          |
| Classifier | ×           | ×         | ×            | ✓          |
| Adapter   | ✓           | ✓         | ×            | ✓          |
| Plug-Tagger | ✓          | ✓         | ✓            | ✓          |

Table 3: Comparison of the degree of modification of the model by different methods when switching tasks. Performance means the method can achieve a comparable performance. Parameter&Architecture means that the model does not need to modify the model parameter&Architecture. NoRedeploy means the method can perform different tasks without redeployment.

In many edge devices, computational resources are minimal ([Liu, Li, and Cheng 2021](https://github.com/Adapter-Hub/adapter-transformers)). It is not easy to run two large parameter models simultaneously, which leads to the necessity of releasing the resources of the old model to reload the new model when switching tasks, a process we...
call redeployment. Redeployment takes much time, and since it is unknown what tasks users need to complete in real scenarios, the frequency of switching tasks can be very high, which makes the disadvantages of redeployment even more apparent. As shown in Table 3, since plug-tagger switches tasks via the plugin vector on the input instead of changing the model’s architecture and parameters, there is no need to redeploy the model when switching tasks. To demonstrate the impact of redeployment, we designed an experiment that approximates a real scenario. For the real scenario where the task type is unknown, we sampled data from NER, POS, and chunking, mixing and disrupting the sampled results. To simulate the case of unknown task types, we set the batch size to 1 to make the model predict only the current sample. To simulate the resource-constrained case, if the current task is different from the previous one, the model releases its parameters of the previous task and then reloads the new task-specific parameters. We count the time it takes to complete the tasks for all sampled samples in order. The data for each task is sampled from CoNLL2003. We call the method that requires the model to be redeployed Model-Switch, and the method of simply loading the plugin vector without modifying the model is called Plugin-Switch. All experiments are conducted in the same NVIDIA GeForce RTX 3090.

We find that model-switch method fails miserably in this setting. It takes 367 seconds to process 100 samples per task. To reflect that gap, we calculate how many times faster the plugin-switch method is than the Model-switch method, as shown in Figure 3. The plugin-switch method is always much stronger than the model-switch method as the sample size increases. As can be observed in the figure, the inference speed ratio of the Plugin-switch method drops as the number of samples increases. We believe this is because increasing the sample size increases the probability of consecutive identical tasks, reducing the frequency of task switching. Despite this, our method is at least 50 times faster than the model-Switch method. This proves that the plug-and-play approach works better in resource-constrained scenarios than model-switch methods.

### Impact of label word mechanism

In this section, we explore the impact of the label word mechanism on downstream tasks, and discuss the reason of the results.

| Task | Dataset   | Plug-Classifier | Plug-Tagger |
|------|-----------|-----------------|-------------|
| NER  | CoNLL2003 | 89.52           | 91.58       |
|      | ACE2005   | 85.49           | 87.68       |
| Chunking | CoNLL2003 | 88.8            | 90.5        |
|      | CoNLL2000 | 94.39           | 96.48       |
| POS  | CoNLL2003 | 92.45           | 95.01       |
|      | WSJ       | 96.05           | 97.6        |

Table 4: Performance of Plug-Tagger and Plug-Classifier under the same setting. Plug-Classifier is the combination of plug vectors and classifier. Plug-Tagger is the combination of plug vectors and the language model head.

### Comparison of language model head and classifier

Plugin vectors can be adapted to the classifier directly, exploring this method in the main experiment makes no sense because it is not a plug-and-play method. In this subsection, we discuss whether the label word mechanism has a negative effect on downstream tasks compared to the classifier. We write the combination of plugin vector and classifier as plug-classifier. For a fair comparison, we evaluate the performance of the plug-classifier on all datasets with the same hyperparameters as the plug-tagger. The experimental results are shown in Table 4. We found that the label word mechanism is much better than the classifier on all datasets. We believe the performance benefits from 1) The task of predicting words is similar to the tasks of pre-training. 2) The label word mechanism uses more pre-training parameters because of the reusing of the language model head. These two reasons make the label word mechanism more suitable for prompt-based methods. Therefore, plug vector is better suited to be combined with the label word mechanism.

### Comparison of label word option

Recall in section Approach, we discuss the option of selecting label words. We compare two ways to select a label word for the BIO schema. One is to select a label word for B label, and I label respectively. When performing label Word mapping, label words can be matched directly, so this option is called ExactMatch. The other is that select a label word to represent both the B label and I label. During the inference phase, adjacent and identical label words are combined, the first
Related Work

Sequence labeling

Sequence labeling, such as named entity recognition (NER), part-of-speech (POS) tagging and chunking, is one of the fundamental tasks of natural language processing (Ma and Hovy 2016). Early work for sequence labeling focused on feature engineering for graphical models like conditional random fields (CRFs) and Hidden Markov Models (HMM) (Lafferty, McCallum, and Pereira 2001; Passos, Kumar, and McCallum 2014; Cuong et al. 2014). Recently neural network models achieve competitive performances (Chiu and Nichols 2016; Dos Santos and Zadrozny 2014; Luo, Xiao, and Zhao 2020), and fine-tuning the pre-trained language models (Devlin et al. 2019; Liu et al. 2019; Yang et al. 2020) have been shown to achieve state-of-the-art results on sequence labeling (Bell, Yannakoudakis, and Rei 2019). The above approach basically treats sequence labeling as token-level classification and requires a task-specific classifier, works of (Athiwaratkun et al. 2020; Yan et al. 2021) convert sequence labeling into a generation task, avoiding classifier by using the sequence-to-sequence framework (Sutskever, Vinyals, and Le 2014; Cho et al. 2014; Vaswani et al. 2017; Lewis et al. 2020). But this work still needs to modify the model architecture, the inability to use native PLM and the inefficiencies of sequence-to-sequence limit its transferability and efficiency, which is not suitable for achieving our goals.

Pre-trained language model

Self-supervised representation models (Radford et al. 2018; 2019; Yang et al. 2019; Peters et al. 2018; Devlin et al. 2019) have shown substantial advances in natural language understanding after being pre-trained on large-scaled text corpora. Given an NLP task, the mainstream paradigm to use PLM is fine-tuning, which stacks a linear layer on top of the pretrained language model and then updates all parameters of model. Recently, prompt-tuning was received much attention. To get the better use of knowledge in pre-trained models, (Han et al. 2021; Schick and Schütze 2021; Cui et al. 2021; Wang et al. 2021; Chen et al. 2021; Liu et al. 2021) reformulate the paradigm of downstream tasks into new task that similar to pre-training. The standard fine-tuning relies on classifiers, prompt-tuning lacks an efficient approach to for sequence labeling. None of these paradigm suits our needs.

Lightweight deep learning

Lightweight fine-tuning method aims to using small trainable parameters to leverage the ability of PLMs (Houlsby et al. 2019). Some studies argue that redundant parameters in the model should be deleted or masked (Zaken, Ravfogel, and Goldberg 2021; Sanh, Wolf, and Rush 2020; Zhao et al. 2020; Frankie and Carbin 2019), while others argue that additional structures should be added to the model (Zhang et al. 2020; Houlsby et al. 2019; Guo, Rush, and Kim 2021). For example, adapter-tuning insert some additional layer between each layers of PLMs. Plug-and-play method controls model behavior without making any modifications to the model parameters (Madotto et al. 2020), which is also a lightweight method. (Li and Liang 2021) and (Hambardzumyan, Khachatrian, and May 2021) is a plug-and-play and lightweight method. It inserts continuous vectors into the input to allow a fixed PLM perform different tasks. But these works can not adapted to sequence labeling directly.

Conclusion

In this work, we propose plug-tagger, a plug-and-play framework for sequence labeling. The proposed framework can accomplish different tasks using vectors inserted into the input and a fixed PLM without modifying the model parameters and architecture. It achieves competitive performance on the sequence annotation tasks with only a small number of parameters and is 70 times faster than other methods in real-world scenarios requiring model redeployment.
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