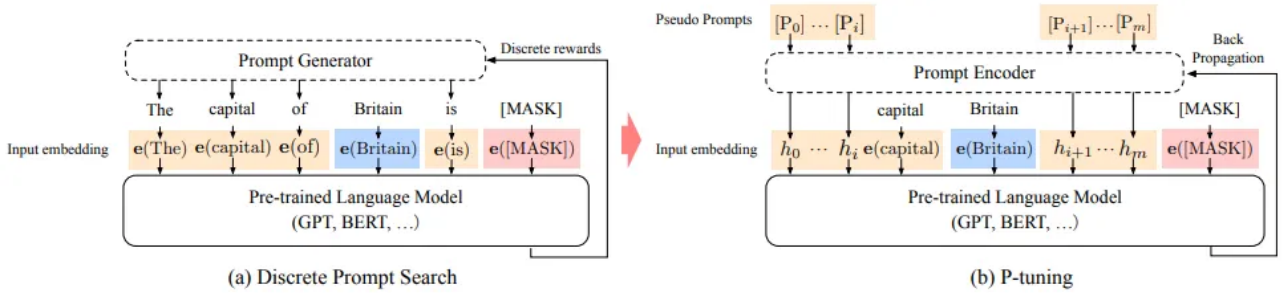
P-Tuning详解及代码实战

1. 概述

P-Tuning（论文：GPT Understands, Too），该方法**将Prompt转换为可以学习的Embedding层，并用MLP+LSTM的方式来对Prompt Embedding进行一层处理**。

2. 方法



(a) Discrete Prompt Search　　(b) P-tuning

相比Prefix Tuning，**P-Tuning加入的可微的virtual token，但仅限于输入层，没有在每一层都加**；另外，virtual token的**位置也不一定是前缀，插入的位置是可选的**。

如果**随机初始化virtual token，容易优化到局部最优值**。因此，作者通过实验发现用一个**prompt encoder来编码会收敛更快**，效果更好。即用一个**LSTM+MLP**去编码这些virtual token以后，再输入到模型。

encoder采用LSTM或者MLP：

$$
\begin{aligned}
h_i &= \mathrm{MLP}\left(\left[\overrightarrow{h_i} : \overleftarrow{h_i}\right]\right) \\
&= \mathrm{MLP}\left(\left[\mathrm{LSTM}\left(h_{0:i}\right) : \mathrm{LSTM}\left(h_{i:m}\right)\right]\right)
\end{aligned}
$$

3. 代码

https://github.com/huggingface/peft/blob/main/src/peft/tuners/p_tuning/model.py

训练 Python

```python
from transformers import AutoModelForCausalLM
from peft import (
    get_peft_config,
    get_peft_model,
    get_peft_model_state_dict,
    set_peft_model_state_dict,
    PeftType,
    TaskType,
    PromptEncoderConfig,
)

import torch
from datasets import load_dataset
import os
from transformers import AutoTokenizer
from torch.utils.data import DataLoader
from transformers import default_data_collator, get_linear_schedule_with_warmup
from tqdm import tqdm
from datasets import load_dataset


device = "cuda"

model_name_or_path = "/data/nfs/llm/model/bloomz-560m"
tokenizer_name_or_path = "/data/nfs/llm/model/bloomz-560m"

peft_config = PromptEncoderConfig(task_type=TaskType.CAUSAL_LM,
                                  num_virtual_tokens=20,
                                  encoder_hidden_size=128)

dataset_name = "twitter_complaints"
checkpoint_name = f"{dataset_name}_{model_name_or_path}_{peft_config.peft_type}_{peft_config.task_type}_v1.pt".replace("/", "_")
text_column = "Tweet text"
label_column = "text_label"
max_length = 64
lr = 3e-2
num_epochs = 10
batch_size = 8

from datasets import load_dataset

# dataset = load_dataset("ought/raft", dataset_name)

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dataset = load_dataset("/home/guodong.li/data/peft/raft/raft.py", dataset_name, cache_dir="/home/guodong.li/data/peft/data")

classes = [k.replace("_", " ") for k in dataset["train"].features["Label"].names]
print(classes)
dataset = dataset.map(
    lambda x: {"text_label": [classes[label] for label in x["Label"]]},
    batched=True,
    num_proc=1,
)
print(dataset)
dataset["train"][0]

# data preprocessing
# padding_side = "left"
# tokenizer = AutoTokenizer.from_pretrained(model_name_or_path, padding_side=padding_side)
tokenizer = AutoTokenizer.from_pretrained(model_name_or_path)
if tokenizer.pad_token_id is None:
    tokenizer.pad_token_id = tokenizer.eos_token_id
target_max_length = max([len(tokenizer(class_label)["input_ids"]) for class_label in classes])
print("target_max_length:", target_max_length)


def preprocess_function(examples):
    batch_size = len(examples[text_column])
    inputs = [f"{text_column} : {x} Label : " for x in examples[text_column]]
    targets = [str(x) for x in examples[label_column]]
    model_inputs = tokenizer(inputs)
    labels = tokenizer(targets)
    for i in range(batch_size):
        sample_input_ids = model_inputs["input_ids"][i]
        label_input_ids = labels["input_ids"][i] + [tokenizer.pad_token_id]
        # print(i, sample_input_ids, label_input_ids)
        model_inputs["input_ids"][i] = sample_input_ids + label_input_ids
        labels["input_ids"][i] = [-100] * len(sample_input_ids) + label_input_ids
        model_inputs["attention_mask"][i] = [1] * len(model_inputs["input_ids"][i])
    # print(model_inputs)
    for i in range(batch_size):
        sample_input_ids = model_inputs["input_ids"][i]
        label_input_ids = labels["input_ids"][i]
        model_inputs["input_ids"][i] = [tokenizer.pad_token_id] * (
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            max_length - len(sample_input_ids)
        ) + sample_input_ids
        model_inputs["attention_mask"][i] = [0] * (max_length - len(sample_input_ids)) + model_inputs[
            "attention_mask"
        ][i]
        labels["input_ids"][i] = [-100] * (max_length - len(sample_input_ids)) + label_input_ids
        model_inputs["input_ids"][i] = torch.tensor(model_inputs["input_ids"][i][:max_length])
        model_inputs["attention_mask"][i] = torch.tensor(model_inputs["attention_mask"][i][:max_length])
        labels["input_ids"][i] = torch.tensor(labels["input_ids"][i][:max_length])
    model_inputs["labels"] = labels["input_ids"]
    return model_inputs


processed_datasets = dataset.map(
    preprocess_function,
    batched=True,
    num_proc=1,
    remove_columns=dataset["train"].column_names,
    load_from_cache_file=False,
    desc="Running tokenizer on dataset",
)

train_dataset = processed_datasets["train"]
eval_dataset = processed_datasets["train"]


train_dataloader = DataLoader(train_dataset, shuffle=True, collate_fn=default_data_collator, batch_size=batch_size, pin_memory=True)
eval_dataloader = DataLoader(eval_dataset, collate_fn=default_data_collator, batch_size=batch_size, pin_memory=True)


def test_preprocess_function(examples):
    batch_size = len(examples[text_column])
    inputs = [f"{text_column} : {x} Label : " for x in examples[text_column]]
    model_inputs = tokenizer(inputs)
    # print(model_inputs)
    for i in range(batch_size):
        sample_input_ids = model_inputs["input_ids"][i]
        model_inputs["input_ids"][i] = [tokenizer.pad_token_id] * (max_length - len(sample_input_ids)) + sample_input_ids
```

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        model_inputs["attention_mask"][i] = [0] * (max_length - len(sample_input_ids)) + model_inputs["attention_mask"][i]

        model_inputs["input_ids"][i] = torch.tensor(model_inputs["input_ids"][i][:max_length])
        model_inputs["attention_mask"][i] = torch.tensor(model_inputs["attention_mask"][i][:max_length])
    return model_inputs


test_dataset = dataset["test"].map(
    test_preprocess_function,
    batched=True,
    num_proc=1,
    remove_columns=dataset["train"].column_names,
    load_from_cache_file=False,
    desc="Running tokenizer on dataset",
)

test_dataloader = DataLoader(test_dataset, collate_fn=default_data_collator, batch_size=batch_size, pin_memory=True)
next(iter(test_dataloader))

model = AutoModelForCausalLM.from_pretrained(model_name_or_path)
model = get_peft_model(model, peft_config)
model.print_trainable_parameters()

# model
# optimizer and lr scheduler
optimizer = torch.optim.AdamW(model.parameters(), lr=lr)
lr_scheduler = get_linear_schedule_with_warmup(
    optimizer=optimizer,
    num_warmup_steps=0,
    num_training_steps=(len(train_dataloader) * num_epochs),
)

# training and evaluation
model = model.to(device)

for epoch in range(num_epochs):
    model.train()
    total_loss = 0
    for step, batch in enumerate(tqdm(train_dataloader)):
        batch = {k: v.to(device) for k, v in batch.items()}
        #         print(batch)
        #         print(batch["input_ids"].shape)
        outputs = model(**batch)
        loss = outputs.loss
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        total_loss += loss.detach().float()
        loss.backward()
        optimizer.step()
        lr_scheduler.step()
        optimizer.zero_grad()

    model.eval()
    eval_loss = 0
    eval_preds = []
    for step, batch in enumerate(tqdm(eval_dataloader)):
        batch = {k: v.to(device) for k, v in batch.items()}
        with torch.no_grad():
            outputs = model(**batch)
        loss = outputs.loss
        eval_loss += loss.detach().float()
        eval_preds.extend(
            tokenizer.batch_decode(torch.argmax(outputs.logits, -1).detach().cpu().numpy(), skip_special_tokens=True)
        )

    eval_epoch_loss = eval_loss / len(eval_dataloader)
    eval_ppl = torch.exp(eval_epoch_loss)
    train_epoch_loss = total_loss / len(train_dataloader)
    train_ppl = torch.exp(train_epoch_loss)
    print(f"{epoch=}: {train_ppl=} {train_epoch_loss=} {eval_ppl=} {eval_epoch_loss=}")
```