P-Tuning v2详解及代码实战

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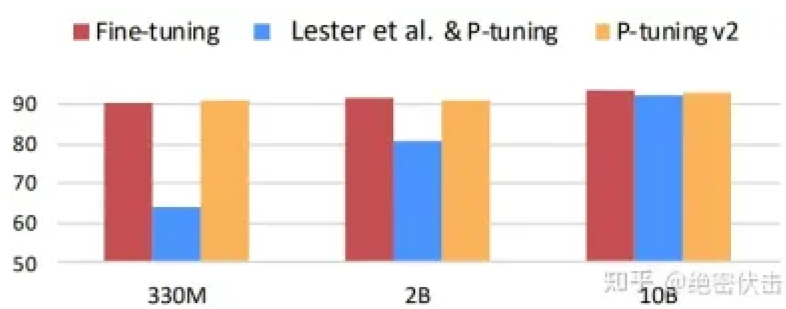
1. 背景

P–Tuning 的问题是在小参数量模型上表现差（如图所示）。



于是就有了v2版本：《P–Tuning v2: Prompt Tuning Can Be Comparable to Fine–tuning Universally Across Scales and Tasks》。P–Tuning v2 的目标就是要让 Prompt Tuning 能够在不同参数规模的预训练模型、针对不同下游任务的结果上都达到匹敌 Fine–tuning 的结果。

1.1. 主要结构

相比 Prompt Tuning 和 P–tuning 的方法， P–tuning v2 方法**在多层加入了 Prompts tokens 作为输入**，带来两个方面的好处：

a. 带来更多可学习的参数（从 P–tuning 和 Prompt Tuning 的0.1%增加到0.1%–3%），同时也足够 parameter–efficient。

b. 加入到更深层结构中的 Prompt 能给模型预测带来更直接的影响。

v1 到 v2 的可视化：蓝色部分为参数冻结，橙色部分为可训练部分。

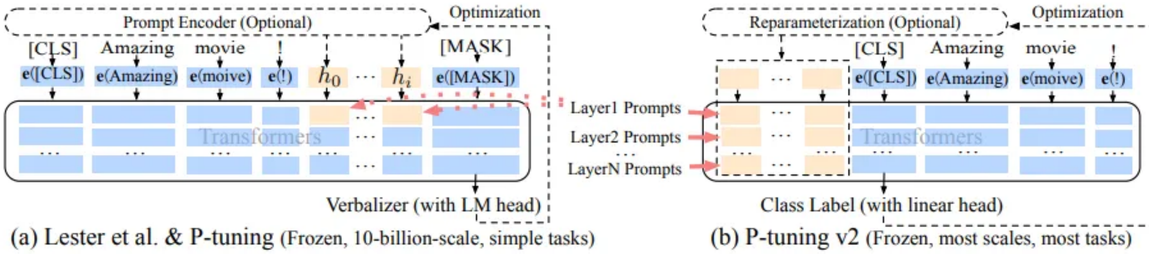
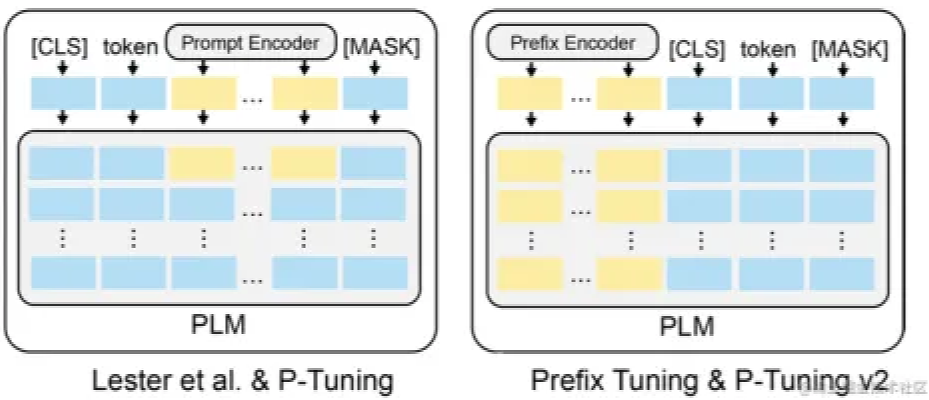


Figure 2: From Lester et al. (2021) & P-tuning to P-tuning v2. Orange blocks (i.e., $h_0, ..., h_i$) refer to trainable prompt embeddings; blue blocks are embeddings stored or computed by frozen pre-trained language models.

2. 总结

来自清华大学的团队发布的两种参数高效Prompt微调方法P-Tuning、P-Tuning v2，可以简单的将**P-Tuning认为是针对Prompt Tuning的改进，P-Tuning v2认为是针对Prefix Tuning的改进**。



3. 代码

PEFT 中 Prefix Tuning 相关的代码是基于清华开源的P-tuning-v2 进行的重构；同时，我们可以在chatglm-6b和chatglm2-6b中看到类似的代码。PEFT 中源码如下所示。

代码　　Python

```python
class PrefixEncoder(torch.nn.Module):
    def __init__(self, config):
        super().__init__()
        self.prefix_projection = config.prefix_projection
        token_dim = config.token_dim
        num_layers = config.num_layers
        encoder_hidden_size = config.encoder_hidden_size
        num_virtual_tokens = config.num_virtual_tokens
        if self.prefix_projection and not config.inference_mode:
            # Use a two-layer MLP to encode the prefix
            # 初始化重参数化的编码器
            self.embedding = torch.nn.Embedding(num_virtual_tokens, token_dim)
            self.transform = torch.nn.Sequential(
                torch.nn.Linear(token_dim, encoder_hidden_size),
                torch.nn.Tanh(),
                torch.nn.Linear(encoder_hidden_size, num_layers * 2 * token_dim),
            )
        else:
            self.embedding = torch.nn.Embedding(num_virtual_tokens, num_layers * 2 * token_dim)

    def forward(self, prefix: torch.Tensor):
        if self.prefix_projection:
            prefix_tokens = self.embedding(prefix)
            past_key_values = self.transform(prefix_tokens)
        else:
            past_key_values = self.embedding(prefix)
        return past_key_values
```

从上面的源码也可以看到 Prefix Tuning 与 P-Tuning v2 最主要的差别就是是否进行重新参数化编码。

训练

Python

```python
from transformers import AutoModelForCausalLM
from peft import get_peft_config, get_peft_model, PrefixTuningConfig, TaskType, PeftType
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 = PrefixTuningConfig(task_type=TaskType.CAUSAL_LM,
                                 num_virtual_tokens=30)

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)
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
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] * (
            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])
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        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
        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))

# creating model
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
        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)
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```
        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=}")

```

推理 Python

```python
from peft import PeftModel, PeftConfig

peft_model_id = f"{model_name_or_path}_{peft_config.peft_type}_{peft_config.task_type}"
config = PeftConfig.from_pretrained(peft_model_id)
# 加载基础模型
model = AutoModelForCausalLM.from_pretrained(config.base_model_name_or_path)
# 加载PEFT模型
model = PeftModel.from_pretrained(model, peft_model_id)

# 编码
inputs = tokenizer(f'{text_column} : {dataset["test"][i]["Tweet text"]} Label : ', return_tensors="pt")

# 模型推理
outputs = model.generate(
        input_ids=inputs["input_ids"],
        attention_mask=inputs["attention_mask"],
        max_new_tokens=10,
        eos_token_id=3
    )

# 解码
print(tokenizer.batch_decode(outputs.detach().cpu().numpy(), skip_special_tokens=True))
```