Introduction

References

- [Nice overview (https://lightning.ai/pages/community/article/understanding-llama-adapters/#prompt-tuning-and-prefix-tuning)](https://lightning.ai/pages/community/article/understanding-llama-adapters/#prompt-tuning-and-prefix-tuning)

The goal of Transfer Learning is to adapt a Pre-Trained model for a Source task (the "base" model) to solve a new Target task.

Fine-Tuning (additional training with Source task-specific examples) is a common method of adaptation.

But *Prompt Engineering* can be used for adaptation as well

- creating a prompt that adapts the text-continuation ("predict the next") behavior of a LLM
- to produce a solution to the Target task

Large Language Model as a Universal base model

Within the context of NLP tasks

- Text to text is a [Universal API](NLP_Universal_Model.ipynb#A-Universal-API:-Text-to-text)
    - The Target task's input and output can both be re-formatted into text
- Large Language Models (LLM) can be a Universal "base" Model
    - convert all Target tasks into instances of the LM "predict the next" task
- Eliminating the need for Target task specific "head" layers to be appended to the base model

An essential part of the Universal API is converting an example of the Target task to text.

- so that the solution to the Target Task is an instance of the text-continuation ("predict the next") task

To illustrate, suppose we want our LLM base model to adapt to solving the task of Summarization.

A training example for the Summarization task might look like

```
{PREFIX} {DOC} Summary: {SUMMARY}
```

where

- `{DOC}` and `{SUMMARY}` are placeholders for the features (i.e., document) and target/label (i.e., the summary)
- `{PREFIX}` are *instructions* for the summarization task. For example
    - `Produce a one paragraph summary of the following:`

We refer to

- the text up to an including the `Summary:` as the *prompt*
    - the features of the converted example
- the remainder of the text (i.e., `{SUMMARY}`) as the *continuation*
    - the target of the converted example

The features for a test example (i.e, a request to summarize) would be the prompt without a continuation

```
{PREFIX} {DOC} Summary:
```

We would hope that the LLM's completion (continuation) of this prompt would be the target `{SUMMARY}`

This representation of the relationship between features and target for the Target task

- adapts the LLM
- by causing it to compute
  $p(\{\text{TARGET}\} \,|\, \{\text{PREFIX}\} \; \{\text{DOC}\} \;)$
- rather than the native LLM objective
  $$p(\{\text{TARGET}\} \,| \;\; \{\text{DOC}\} \;)$$

That is:

- `{PREFIX}` *conditions* the LLM to product a continuation
- that satisfies the Target Task

Prompt Design/Prompt Engineering via Tuning

A base model may be adapted to solve a Target Task *without fine-tuning*

- using Prompt Engineering
- crafting a prompt
    - that conditions the LLM text-continuation behavior
    - to produce output consistent with a Target Task

This is *parameter efficient* in that **no** existing parameters are changed, nor are any added.

The conditioning prompt usually consists of

- detailed "instructions"
- exemplars: examples of the input/output relationship for the Target task

In the above Summarization task example, we could imagine various choices for the instructions `{PREFIX}`

- `Summarize the following article: [SEP]`
- `Produce a summary of: [SEP]`
- `A "summary" has the following properties ... Create a summary of: [SEP]`
- Exemplars: a number of `{DOC}`:`{SUMMARY}` pairs

Does it matter which we choose ?

- the last two, being more specific, might be preferable
- but at the cost of using a greater fraction of the LLM model's fixed maximum Context length

Prompt engineering (*prompt design*) is the "art" of constructing prompts in order to get an LLM to solve a task.

It is an *inference time* technique

- does not modify parameters of base model
- in contrast to Fine Tuning

This has been treated more as an art ("GPT Whisperer") than a science.

- rules of thumb, without scientific validation

Hard prompt tuning

We can formalize prompt design as a formal task.

One can imagine `{PREFIX}` as a sequence of token *variables*

$$\langle \text{TOK}_1 \rangle, \ldots, \langle \text{TOK}_p \rangle$$

Prompt design can be viewed as an optimization task

- finding the optimal tokens in the `{PREFIX}`
- as measured through a Performance Metric on the Target task
- we treat each token variable $\langle \text{TOK}_t \rangle$ as a *parameter* to be solved for

The problem is that each token is a *categorical* variable

- member of the discrete set $\mathbf{V}$: the vocabulary of tokens
- we can't differentiate with respect to a discrete value
- so can't optimize by Gradient Descent

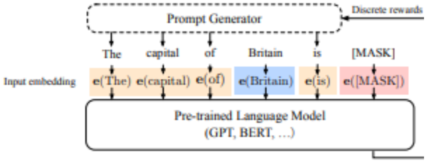
Because tokens are discrete (hard) values, we refer to this method as *Hard Prompt Fine-Tuning*

- optimizing the prompt at the *token* level

Without differentiability, hard prompt fine tuning may devolve to

- an exhaustive (but finite) search for the optimal `{PREFIX}` sequence

Discrete Prompt Search



(a) Discrete Prompt Search

Attribution: https://arxiv.org/pdf/2103.10385.pdf#page=3

Soft prompt tuning; Prefix tuning

References

- The Power of Scale for Parameter-Efficient Prompt Tuning (https://arxiv.org/pdf/2104.08691.pdf)
- Prefix-Tuning: Optimizing Continuous Prompts for Generation (https://arxiv.org/pdf/2101.00190.pdf)

We showed above that

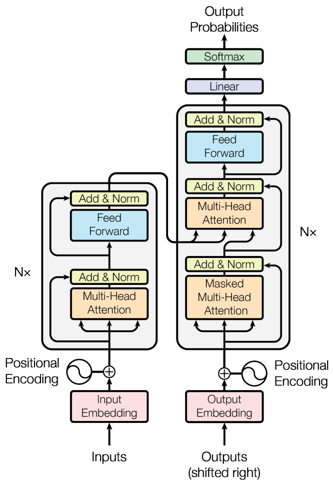
- "hard prompts" do not admit discovery by the traditional back-propagation method of Deep Learning
- due to the discrete nature of tokens.

An examination of the Transformer architecture

- reveals a relatively simple solution
- to the problem of discrete (token) values

That is: look at the values to which tokens are transformed after the *first* layer (Input embedding) of the Transformer

Transformer (Encoder/Decoder)



The Input Embedding layer

- maps a token
    - encoded as a OHE vector of length $|\mathbf{V}|$, indicting the index within Vocabulary $\mathbf{V}$
- to an "embedding" vector of length d (the internal dimension of the output of all layers in the Transformer)

These embeddings

- are continuous (not discrete) values
- that are parameters solved for by back-propagation
- Conceptually implemented as
    - a matrix multiple of the length $|V|$ OHE vector and $(|V| \times d)$ matrix of embeddings

Denoting the embedding of token $\mathbf{x}_t$ as $e(\mathbf{x}_t)$

- the Input Embedding later transforms input sequence of *discrete* token values
$$\mathbf{x}_{(0)}, \ldots, \mathbf{x}_{(\bar{T})}$$
to sequence of *continuous* embedding values
$$e(\mathbf{x}_{(0)}), \ldots, e(\mathbf{x}_{(\bar{T})})$$

The embeddings of the "pseudo tokens" in `{PREFIX}` are referred to as *soft prompts*.

- the embedding of the prefix token at position t is shown as $\mathbf{h}_t$ in the diagram below

The soft prompts *don't need to be mapped to Natural Language* tokens

- we just create placeholder tokens in the input $\mathbf{x}$

Since the embedding of pseudo tokens does not have to be human-readable

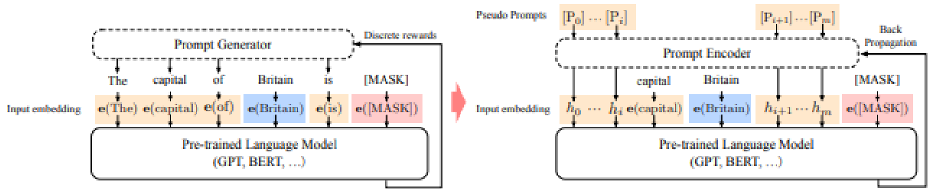
- we can use a very small number of them
- we can place them anywhere in $\mathbf{x}$, not just as a prefix
- the special case where the placeholders are restricted to a prefix of $\mathbf{x}$ is called *prefix tuning*

In effect: the embeddings of pseudo tokens

- represent instructions to perform the Target task
- written in non-human language

Discrete Prompt Search

GPT Understands, Too



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

Figure 2. An example of prompt search for "The capital of Britain is [MASK]". Given the context (blue zone, "Britain") and target (red zone, "[MASK]"), the orange zone refer to the prompt tokens. In (a), the prompt generator only receives discrete rewards; on the contrary, in (b) the pseudo prompts and prompt encoder can be optimized in a differentiable way. Sometimes, adding few task-related anchor tokens (such as "capital" in (b)) will bring further improvement.

Attribution: https://arxiv.org/pdf/2103.10385.pdf#page=3

During Soft Prompt Tuning

- we use a small number of Target task examples
- to learn the embeddings for the pseudo tokens
- keeping the embeddings of non-pseudo tokens and all other weights of the base model frozen

Since only the embeddings of the new pseudo tokens are learned

- **all** Target task specific information from the Fine-Tuning Target training dataset
- is encoded in the new embeddings

Soft prompt tuning: refinements

Recall

- the embeddings of pseudo tokens act as a kind of "instruction" to perform the Target task
- Transformer blocks are stacked in many models
    - thus, there is an embedding in each Transformer block in the stack

Our initial description of prompt tuning created pseudo tokens only at the first block in the stack of Transformer blocks.

Different methods have been tried to add embeddings at the pseudo token positions at *other* blocks in the stack.

One reference [Prefix-Tuning: Optimizing Continuous Prompts for Generation (https://arxiv.org/pdf/2101.00190.pdf)](https://arxiv.org/pdf/2101.00190.pdf) learns embeddings corresponding to the positions of pseudo tokens

- at *every* level of the stack

Another reference ([LLaMA-Adapter (https://arxiv.org/pdf/2303.16199.pdf#page=3)](https://arxiv.org/pdf/2303.16199.pdf#page=3)) learns embeddings corresponding to the positions of pseudo tokens

- only at the *top-most* levels of the stack
- perhaps consistent with the result of removing spans of Adapters reported in the Adapter section above
    - adaptation is most influential at the *top* levels of the stack

Results: Adaptation via prompts

Space efficiency

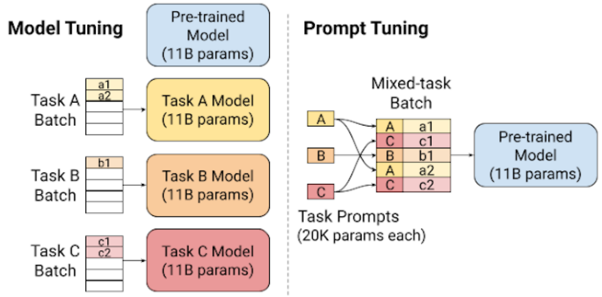
Suppose we have 3 Target tasks: A, B, C.

Fine-Tuning (*model tuning*) each results in 3 copies of the large base model.

In contrast, since the base model is shared in Prompt Tuning

- We can *separately* learn embeddings for placeholder tokens for each of the 3 tasks
- Place the embeddings for each within the Input Embedding
    - e.g., as rows of the Embedding matrix
- to solve the 3 tasks in a single instance of the base model
- by pre-pending the prefix for the appropriate task to each inference-time example

Adaptation via prompts



Left: *With model tuning, incoming data are routed to task-specific models.* ***Right***: *With prompt tuning, examples and prompts from different tasks can flow through a single frozen model in large batches, better utilizing serving resources.*

Attribution: https://arxiv.org/pdf/2104.08691.pdf#page=2

Performance of various forms of adaptation

The following table compares various forms of adaptation

- Fine-tuning (model tuning)
- Adapter (from the module on [Paramter Efficient Transfer Learning (ParameterEfficient_TransferLearning.ipynb#Adapters)](ParameterEfficient_TransferLearning.ipynb#Adapters))
- Prefix Tuning

The number in parenthesis next to the name of the adaptation is

- the size of the adapted parameters as a fraction of base model parameters.
- note that for all metrics except TER, a bigger performance number is better

We can see that Prefix Tuning (row 5 of table)

- using only a small number of adapted parameters (0.1% of base model parameters)
- performs similarly *or better* than full Fine-Tuning for many tasks
    - evaluated on base models which are the Medium and Large variants of GPT-2

Performance, by method of adaptation

	E2E					WebNLG									DART					
	BLEU	NIST	MET	R-L	CIDEr	BLEU			MET			TER ↓			BLEU	MET	TER ↓	Mover	BERT	BLEURT
						S	U	A	S	U	A	S	U	A						
						GPT-2$_{\text{MEDIUM}}$														
FINE-TUNE	68.2	8.62	**46.2**	71.0	2.47	**64.2**	27.7	46.5	**0.45**	0.30	0.38	**0.33**	0.76	0.53	46.2	**0.39**	**0.46**	**0.50**	**0.94**	**0.39**
FT-TOP2	68.1	8.59	46.0	70.8	2.41	53.6	18.9	36.0	0.38	0.23	0.31	0.49	0.99	0.72	41.0	0.34	0.56	0.43	0.93	0.21
ADAPTER(3%)	68.9	8.71	46.1	71.3	2.47	60.4	**48.3**	54.9	0.43	**0.38**	**0.41**	0.35	**0.45**	**0.39**	45.2	0.38	**0.46**	**0.50**	**0.94**	**0.39**
ADAPTER(0.1%)	66.3	8.41	45.0	69.8	2.40	54.5	45.1	50.2	0.39	0.36	0.38	0.40	0.46	0.43	42.4	0.36	0.48	0.47	**0.94**	0.33
PREFIX(0.1%)	**69.7**	**8.81**	46.1	**71.4**	**2.49**	62.9	45.6	**55.1**	0.44	**0.38**	**0.41**	0.35	0.49	0.41	**46.4**	0.38	**0.46**	**0.50**	**0.94**	**0.39**
						GPT-2$_{\text{LARGE}}$														
FINE-TUNE	68.5	8.78	46.0	69.9	2.45	**65.3**	43.1	55.5	**0.46**	0.38	**0.42**	**0.33**	0.53	0.42	**47.0**	**0.39**	0.46	**0.51**	**0.94**	**0.40**
Prefix	**70.3**	**8.85**	**46.2**	**71.7**	**2.47**	63.4	**47.7**	**56.3**	0.45	**0.39**	**0.42**	0.34	**0.48**	**0.40**	46.7	**0.39**	**0.45**	**0.51**	**0.94**	**0.40**
SOTA	68.6	8.70	45.3	70.8	2.37	63.9	52.8	57.1	0.46	0.41	0.44	-	-	-	-	-	-	-	-	-

Table 1: Metrics (higher is better, except for TER) for table-to-text generation on E2E (left), WebNLG (middle) and DART (right). With only 0.1% parameters, Prefix-tuning outperforms other lightweight baselines and achieves a comparable performance with fine-tuning. The best score is boldfaced for both GPT-2$_{\text{MEDIUM}}$ and GPT-2$_{\text{LARGE}}$.

n.b., for the TER metric: smaller is better

Attribution: https://arxiv.org/pdf/2101.00190.pdf#page=7

Prefix length

How long does the prefix need to be ?

- how many pseudo tokens in the prompt

The results of several experiments show

- a small number (10) of pseudo tokens achieves most of the performance
- hence, the number of Target task specific parameters does not need to be large

Effect of Prefix Length on Adaptation via Prefix Tuning

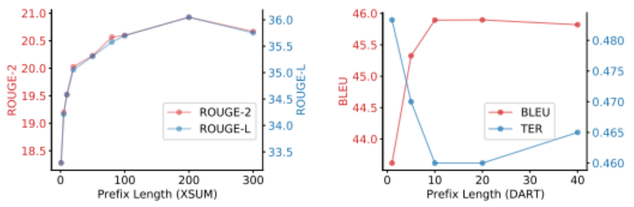


Figure 4: Prefix length vs. performance on summerization (left) and table-to-text (right). Performance increases as the prefix length increases up to a threshold (200 for summarization and 10 for table-to-text) and then a slight performance drop occurs. Each plot reports two metrics (on two vertical axes).

n.b., for the TER metric: smaller is better

Attribution: https://arxiv.org/pdf/2101.00190.pdf#page=8

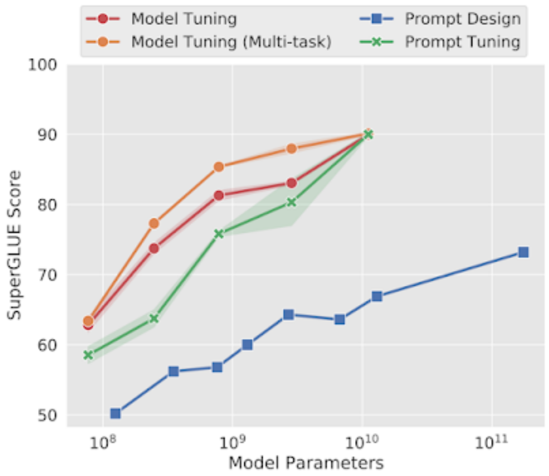
Performance as a function of base model size

The general ordering of adapted models, from best to worst is

- Fine-tuning (model tuning)
- Prompt tuning
- Prompt Design (Prompt Engineering)

However: the gap between Model Tuning and Prompt Tuning *disappears* as we use larger base models.

Adaptation by base model size



As scale increases, prompt tuning matches model tuning, despite tuning 25,000 times fewer parameters.

Attribution: https://arxiv.org/pdf/2104.08691.pdf#page=1

In [2]:

```
print("Done")
```

```
Done
```