Large Language Models: Fine-tuning

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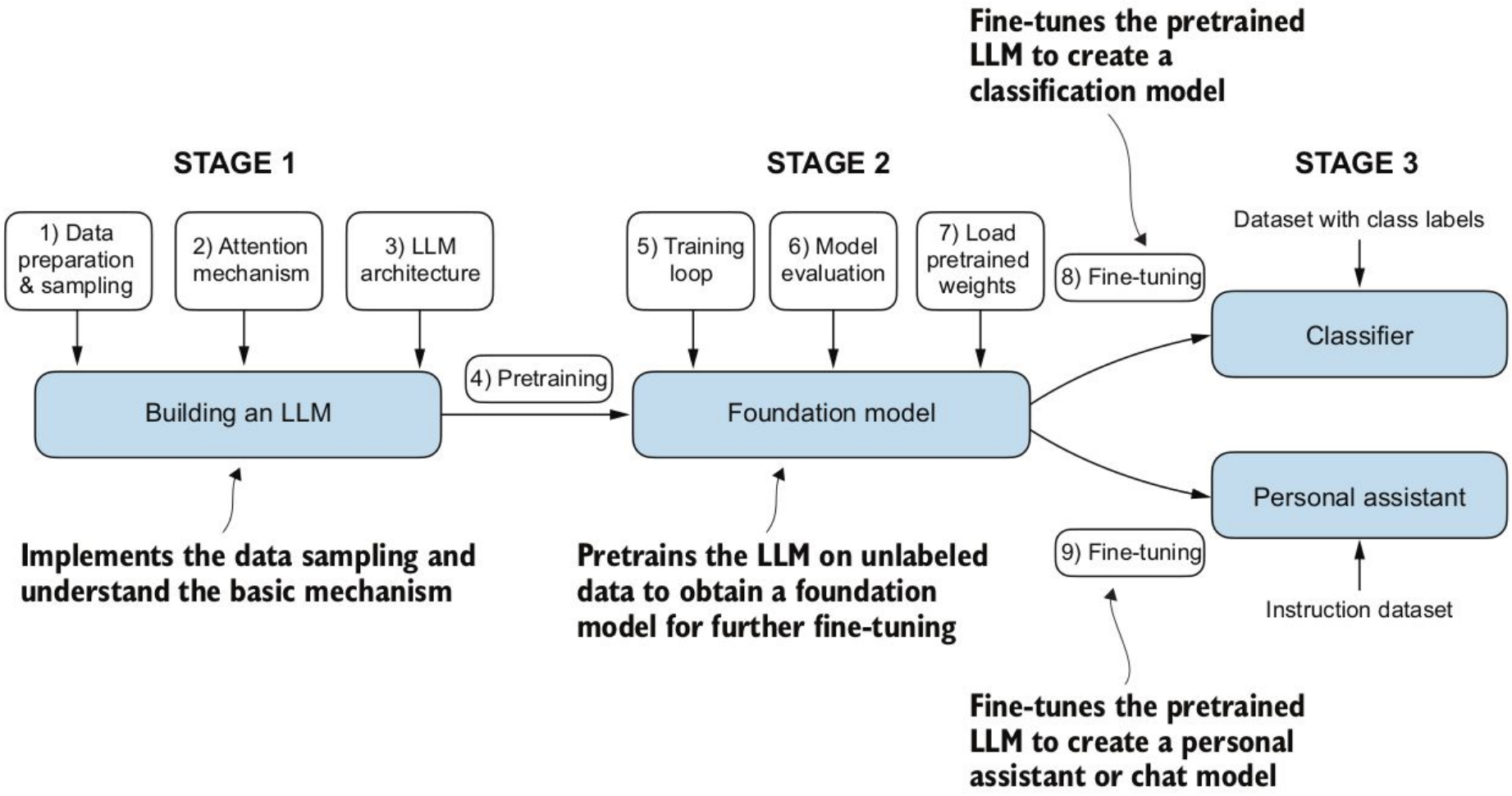
Fine-tuning

- General overview
- LoRA

FOUNDATION MODELS

Language Models are not very useful, they randomly generate texts… But this means that they somehow capture some information from natural language! They are also called *foundation models*.

Fine-tuning is about making Language Models solve concrete tasks, like classification, question answering, name entity recognition…


Fine-tunes the pretrained LLM to create a classification model
STAGE 1
STAGE 2
STAGE 3
1) Data preparation & sampling
2) Attention mechanism
3) LLM architecture
5) Training loop
6) Model evaluation
7) Load pretrained weights
8) Fine-tuning
Dataset with class labels
Classifier
Building an LLM
4) Pretraining
Foundation model
Personal assistant
9) Fine-tuning
Instruction dataset
Implements the data sampling and understand the basic mechanism
Pretrains the LLM on unlabeled data to obtain a foundation model for further fine-tuning
Fine-tunes the pretrained LLM to create a personal assistant or chat model

Training is expensive

We often cannot afford updating the ***whole*** model!

Most of us will not train foundation models… Rather fine-tune existing ones.

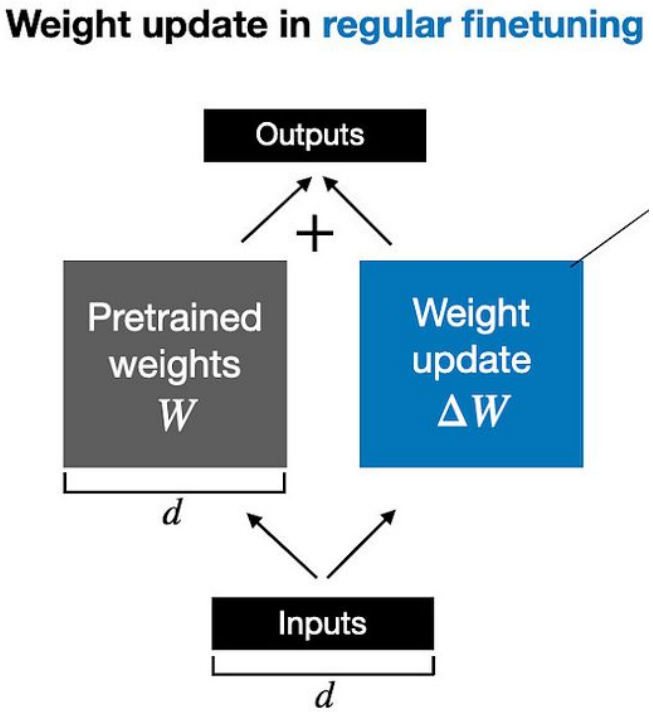
Low-rank Adaptation (LoRA)

Two key ideas:

(1) We only store the changes, not a new model
(2) We only update a small number of parameters

Idea: storing weight updates

Say we consider a linear layer with matrix W. We keep the matrix W fixed and store ΔW

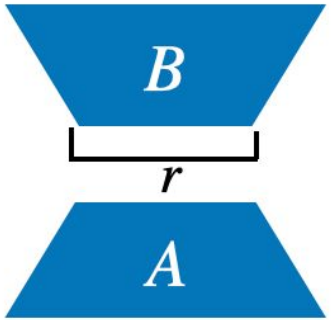


Rank approximations

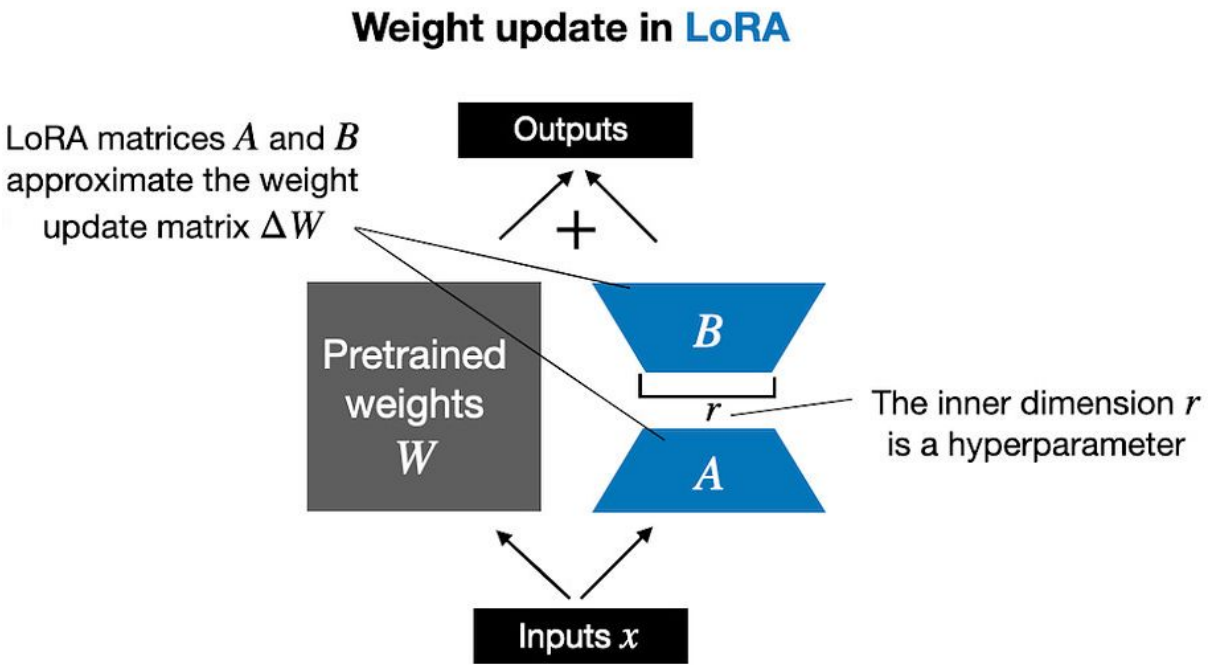
A matrix W of dimension dxd contains dxd parameters. It can be ***rank-r approximated*** by two matrices AxB with:

- A of dimension dxr
- B of dimension rxd

Instead of dxd parameters we now have 2xdxr parameters.



Weight update



LoRA Layer

```python
import math

class LoRALayer(torch.nn.Module):
    def __init__(self, in_dim, out_dim, rank, alpha):
        super().__init__()
        std_dev = 1 / torch.sqrt(torch.tensor(rank).float())
        self.A = nn.Parameter(torch.randn(in_dim, rank) * std_dev)
        self.B = nn.Parameter(torch.zeros(rank, out_dim))
        self.alpha = alpha

    def forward(self, x):
        x = self.alpha * (x @ self.A @ self.B)
        return x
```

Adding the LoRA layer

```
class LinearWithLoRA(torch.nn.Module):
    def __init__(self, linear, rank, alpha):
        super().__init__()
        self.linear = linear
        self.lora = LoRALayer(
            linear.in_features, linear.out_features, rank, alpha
        )

    def forward(self, x):
        return self.linear(x) + self.lora(x)
```

```python
def replace_linear_with_lora(model, rank, alpha):
    for name, module in model.named_children():
        if isinstance(module, torch.nn.Linear):
            # Replace the Linear layer with LinearWithLoRA
            setattr(model, name, LinearWithLoRA(module, rank, alpha))
        else:
            # Recursively apply the same function to child modules
            replace_linear_with_lora(module, rank, alpha)
```

- We then freeze the original model parameter and use the `replace_linear_with_lora` to replace the said `Linear` layers using the code below
- This will replace the `Linear` layers in the LLM with `LinearWithLoRA` layers

```python
total_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f"Total trainable parameters before: {total_params:,}")

for param in model.parameters():
    param.requires_grad = False

total_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f"Total trainable parameters after: {total_params:,}")
```

```
Total trainable parameters before: 124,441,346
Total trainable parameters after: 0
```

```python
replace_linear_with_lora(model, rank=16, alpha=16)

total_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f"Total trainable LoRA parameters: {total_params:,}")
```

```
Total trainable LoRA parameters: 2,666,528
```

```
print(model)
```

```
GPTModel(
  (tok_emb): Embedding(50257, 768)
  (pos_emb): Embedding(1024, 768)
  (drop_emb): Dropout(p=0.0, inplace=False)
  (trf_blocks): Sequential(
    (0): TransformerBlock(
      (att): MultiHeadAttention(
        (W_query): LinearWithLoRA(
          (linear): Linear(in_features=768, out_features=768, bias=True)
          (lora): LoRALayer()
        )
        (W_key): LinearWithLoRA(
          (linear): Linear(in_features=768, out_features=768, bias=True)
          (lora): LoRALayer()
        )
        (W_value): LinearWithLoRA(
          (linear): Linear(in_features=768, out_features=768, bias=True)
          (lora): LoRALayer()
        )
```