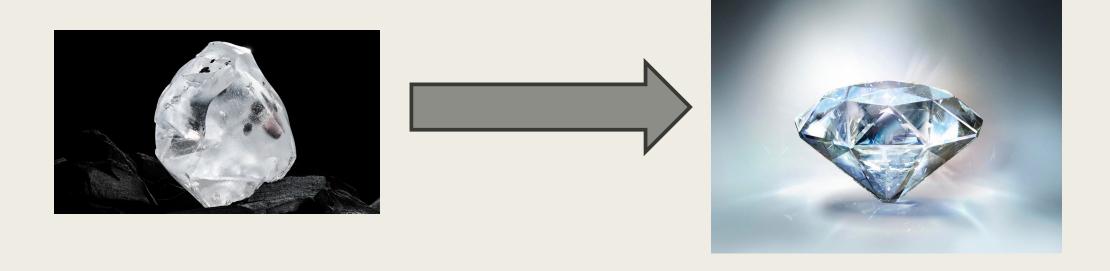
Fine-Tuning LLMs

Krish Thakker

What is Fine-Tuning?



Base Model

(davinci (GPT-3))

Prompt: Tell me how to fine-tune a model

Completion:

How can I control the complexity of a model?

How do I know when my model is done?

How do I test a model?

How do I define a task for my model?

How do I scale a model?

How do I make a probabilistic model?

How do I start using a model once it's complete?

How do I cope with missing data?

How do I make my modeling efforts sustainable?

Fine-tuned Model

(text-davinci-003)

Prompt: Tell me how to fine-tune a model

Completion:

Fine-tuning a model involves adjusting the parameters of a pre-trained model in order to make it better suited for a given task. There are generally three steps to fine-tuning a model:

- Select a base model Select a pre-trained deep learning model that has been trained on a large dataset.
- Adjust parameters Adjust parameters of the pre-trained model to better suit the desired task. This may include changing the number of layers, adjusting learning rate, adding regularization, or tweaking the optimizer.
- Train the model Train the new model on the desired dataset. The amount of data and the amount of training required will depend on the task and the model.

Terms To Know

LLM = Large Language
Model (a subset of
machine learning
models)

PEFT = Parameter-Efficient Fine-Tuning LoRA = Low-Rank Adaptation

Hugging Face = library of machine learning models and datasets

BERT = Bidirectional
Encoder Representations
from Transformers (an
LLM used for natural
language processing)

DistilBERT = smaller, faster cheaper version of BERT

High-Level Overview



Load a dataset to train LLM



Set metrics to judge accuracy



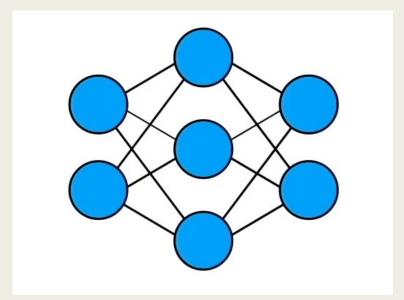
Test untrained model

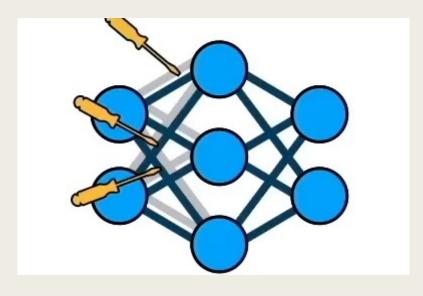


Fine-tune model with PEFT/LoRA



Test fine-tuned model



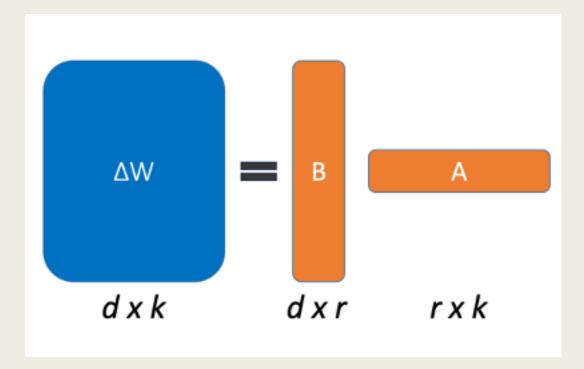


What is PEFT?

- Parameter-Efficient Fine-Tuning
- Freezes most of the parameters of a model
- Only fine-tunes a few of the parameters
- Optimizes time and cost of fine-tuning process

What is LoRA?

- Low-Rank Adaptation: A PEFT technique
- Adds new trainable parameters
- Let d = 1,000, k = 1000
- Ex: 1,000 x 1,000 parameter model = 1,000,000 parameters
- Set a low rank: r = 4.
- 4,000 + 4,000 = 8,000 < 1,000,000 parameters
- **0.8**%



Install + Import

- Evaluate
- Datasets
- PEFT
- Transformers

Install Packages

[1]: !pip install evaluate datasets peft transformers

...

Imports

```
from datasets import load_dataset, DatasetDict, Dataset

from transformers import (
    AutoTokenizer,
    AutoConfig,
    AutoModelForSequenceClassification,
    DataCollatorWithPadding,
    TrainingArguments,
    Trainer)

from peft import PeftModel, PeftConfig, get_peft_model, LoraConfig
import evaluate
import torch
import numpy as np
```

Dataset

- Load imdb-truncated dataset
- From Hugging Face library
- Display training data

```
Dataset
[3]: # load imdb-truncated dataset
     dataset = load_dataset('shawhin/imdb-truncated')
    Downloading readme: 100%
                                                                       592/592 [00:00<00:00, 57.5kB/s]
     Downloading data: 100%
                                                                     836k/836k [00:00<00:00, 2.70MB/s]
    Downloading data: 100%
                                                                     853k/853k [00:00<00:00, 4.27MB/s]
    Generating train split: 100%
                                                                        1000/1000 [00:00<00:00, 3592.63 examples/s]
    Generating validation split: 100%
                                                                            1000/1000 [00:00<00:00, 67959.17 examples/s]
[4]: dataset
[4]: DatasetDict({
         train: Dataset({
              features: ['label', 'text'],
              num_rows: 1000
         validation: Dataset({
             features: ['label', 'text'],
             num rows: 1000
         })
     })
[5]: # display % of training data with label=1
     np.array(dataset['train']['label']).sum()/len(dataset['train']['label'])
[5]: 0.5
```



Metrics + Model

- DistilBERT is used
 - Faster model for testing purposes
- Define metric labels
- Generate model

Set Metrics and Load Model

Accuracy

- Evaluates accuracy
- Allows model to finetune effectively

Accuracy Evaluation

```
[9]: # import accuracy evaluation metric
accuracy = evaluate.load("accuracy")
# define an evaluation function to pass into trainer later
def compute metrics(p):
    predictions, labels = p
    predictions = np.argmax(predictions, axis=1)

return {"accuracy": accuracy.compute(predictions=predictions, references=labels)}
```

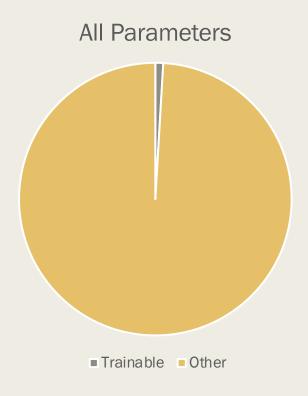
Test Untrained Model

- List of movie ratings
- Predictions for +/are unknown
- 60% accuracy

Apply Untrained Model to Text

```
• [10]: # define list of examples
      text_list = ["It was good.", "Not a fan, don't recommed.",...
                   "Better than the first one.", "This is not worth watching even once.",
                   "This one is a pass."]
      print("Untrained model predictions:")
      print("----")
      for text in text_list:
          # tokenize text
          inputs = tokenizer.encode(text, return tensors="pt")
          # compute logits
          logits = model(inputs).logits
          # convert logits to label
          predictions = torch.argmax(logits)
          print(text + " - " + id2label[predictions.tolist()])
      Untrained model predictions:
      It was good. - Negative
      Not a fan, don't recommed. - Negative
      Better than the first one. - Negative
      This is not worth watching even once. - Negative
      This one is a pass. - Negative
```

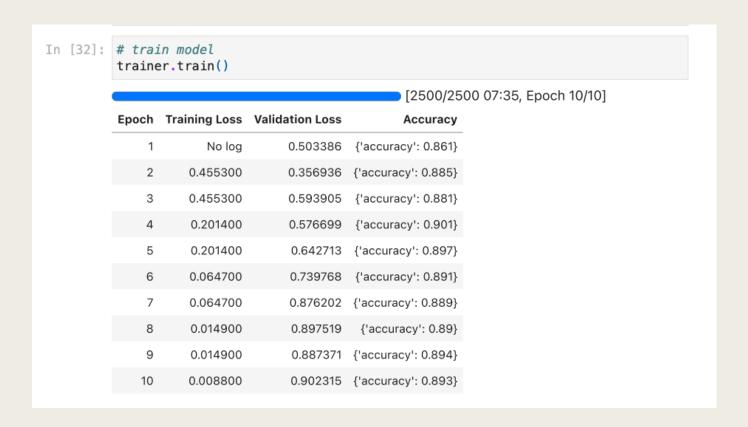
PEFT/LoRA Setup



Train Model with PEFT/LoRA

Fine-Tune

- Trains model using LoRA
- Accuracy metric is used to show progress
- Took 7:35 minutes



Test Fine-Tuned Model

- Fine-Tuned Model is used to display predictions
- 60% **■** 100% accuracy

Generate Prediction

```
In [38]: print("Trained model predictions:")
print("------")
for text in text_list:
    inputs = tokenizer.encode(text, return_tensors="pt")

logits = model(inputs).logits
    predictions = torch.max(logits,1).indices

print(text + " - " + id2label[predictions.tolist()[0]])
```

QUESTIONS?