Intro to GPT & X-shot learning

GPT & Benchmarks

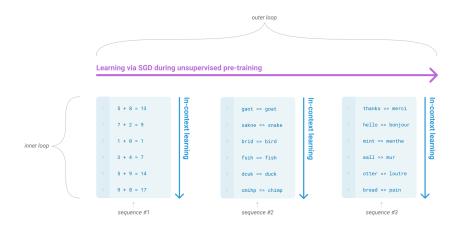
Learning goals

- Recap GPT and the ideas behind standard language modelling
- Understand the difference between fine-tuning and X-shot learning

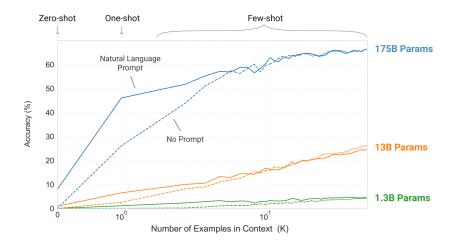
GPT

- Like BERT, GPT is a language model.
- But not MLM, but a conventional language model: it predicts the next word (or subword).
- Like BERT, GPT is trained on a huge corpus, actually an even huger corpus.
- Like BERT, GPT is a transformer architecture.
- Difference 1: GPT is a single model that aims to solve all tasks.
 - It can also switch back and forth between tasks and solve tasks within tasks, another human capability that is important in practice. "fluidity"
- Difference 2: GPT leverages task descriptions.
- Difference 3: GPT is effective at few-shot learning.

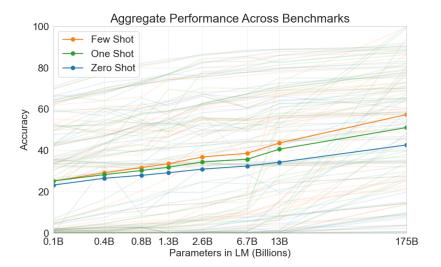
GPT: TWO TYPES OF LEARNING



GPT: EFFECTIVE IN-CONTEXT LEARNING



X-SHOT COMPARISON AND EFFECT OF LARGER CORPORA



FINE-TUNING (NOT USED BY GPT)

Traditional fine-tuning (not used for GPT-3)

Fine-tuning

The model is trained via repeated gradient updates using a large corpus of example tasks.



ZERO-SHOT (NO GRADIENT UPDATE)

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

ONE-SHOT (NO GRADIENT UPDATE)

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

FEW-SHOT (NO GRADIENT UPDATE)

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

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Translate English to French: 

sea otter => loutre de mer 

peppermint => menthe poivrée

plush girafe => girafe peluche

cheese => 

prompt
```

ARCHITECTURE

| Model Name | $n_{ m params}$ | $n_{ m layers}$ | $d_{ m model}$ | $n_{ m heads}$ | $d_{ m head}$ | Batch Size | Learning Rate |
|-----------------------|-----------------|-----------------|----------------|----------------|---------------|------------|----------------------|
| GPT-3 Small | 125M | 12 | 768 | 12 | 64 | 0.5M | 6.0×10^{-4} |
| GPT-3 Medium | 350M | 24 | 1024 | 16 | 64 | 0.5M | $3.0 	imes 10^{-4}$ |
| GPT-3 Large | 760M | 24 | 1536 | 16 | 96 | 0.5M | 2.5×10^{-4} |
| GPT-3 XL | 1.3B | 24 | 2048 | 24 | 128 | 1 M | 2.0×10^{-4} |
| GPT-3 2.7B | 2.7B | 32 | 2560 | 32 | 80 | 1 M | 1.6×10^{-4} |
| GPT-3 6.7B | 6.7B | 32 | 4096 | 32 | 128 | 2M | 1.2×10^{-4} |
| GPT-3 13B | 13.0B | 40 | 5140 | 40 | 128 | 2M | 1.0×10^{-4} |
| GPT-3 175B or "GPT-3" | 175.0B | 96 | 12288 | 96 | 128 | 3.2M | 0.6×10^{-4} |

TRAINING CORPUS

| Dataset | Quantity (tokens) | Weight in training mix | Epochs elapsed when training for 300B tokens |
|-------------------------|-------------------|------------------------|--|
| Common Crawl (filtered) | 410 billion | 60% | 0.44 |
| WebText2 | 19 billion | 22% | 2.9 |
| Books1 | 12 billion | 8% | 1.9 |
| Books2 | 55 billion | 8% | 0.43 |
| Wikipedia | 3 billion | 3% | 3.4 |

LOSS AS A FUNCTION OF COMPUTE

