Generative Pre-Trained Transformers

GPT-3 (2020) & X-shot learning

Learning goals

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

GPT RECAP

- Like BERT, GPTs are called “language models“.
- Like BERT, GPTs are trained on huge corpora, actually on even huger (closed-source) corpora.
- Like BERT, GPTs are based on the transformer architecture.
- Unlike GPTs, BERT is *not* a language model in the conventional sense, i.e. not an ARLM
- BERT instead relies on the cloze taks, i.e. it is an MLM
- GPTs are conventional ARLMs: they are just trained on predicting the next word (or subword).

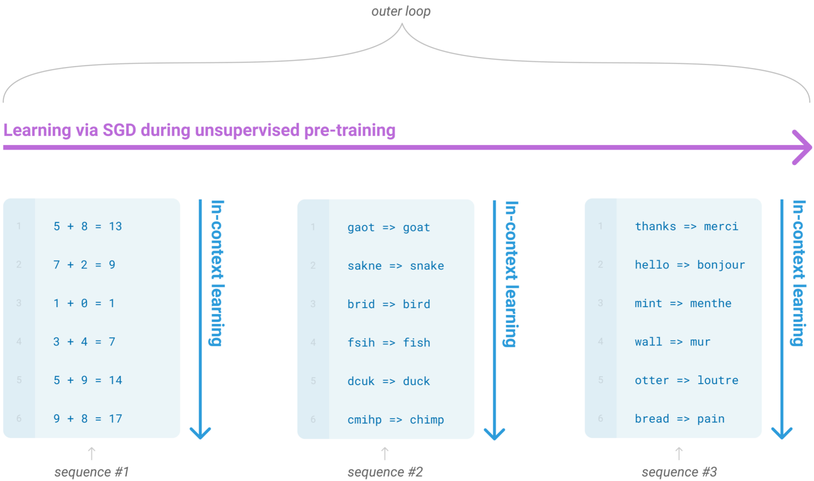
GPT RECAP

- Difference 1: GPTs rely on the transformer decoder

  → They are called “*generative*“ Large Language Models (LLM)

  → BERT relies on the encoder, hence not perfectly suited for generation
- Difference 2: 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 3: GPT leverages task descriptions.
- Difference 4: GPT is effective at few-shot learning.

IN-CONTEXT LEARNING



outer loop

Learning via SGD during unsupervised pre-training

```
5 + 8 = 13
7 + 2 = 9
1 + 0 = 1
3 + 4 = 7
5 + 9 = 14
9 + 8 = 17
```

in-context learning

sequence #1

```
gaot => goat
sakne => snake
brid => bird
fsih => fish
dcuk => duck
cmihp => chimp
```

in-context learning

sequence #2

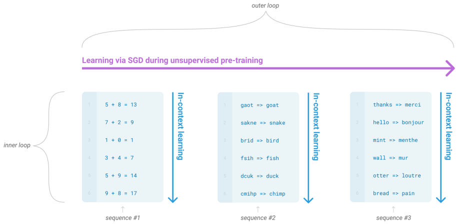
```
thanks => merci
hello => bonjour
mint => menthe
wall => mur
otter => loutre
bread => pain
```

in-context learning

sequence #3

▸ Source: Brown et al., 2020

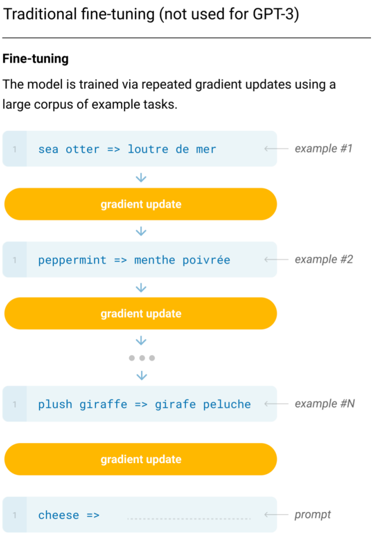
IN-CONTEXT LEARNING



▸ Source: Brown et al., 2020

- **Pre-training (Outer loop):**
  - Model develops broad set of skills and abilities
  - Trained via gradient descent
- **Inference (Inner loop):**
  - It uses these abilities to rapidly adapt to a desired task (= *in-context learning*)
  - Just a single forward pass w/o any gradient updates

LEARNING IN BERT & CO.



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.

```
sea otter => loutre de mer
```

example #1

gradient update

```
peppermint => menthe poivrée
```

example #2

gradient update

• • •

```
plush giraffe => girafe peluche
```

example #N

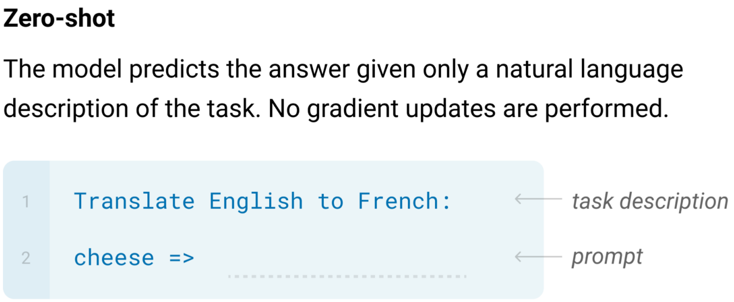
gradient update

```
cheese =>
```

prompt

▸ Source: Brown et al., 2020

ZERO-SHOT LEARNING



Zero-shot

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

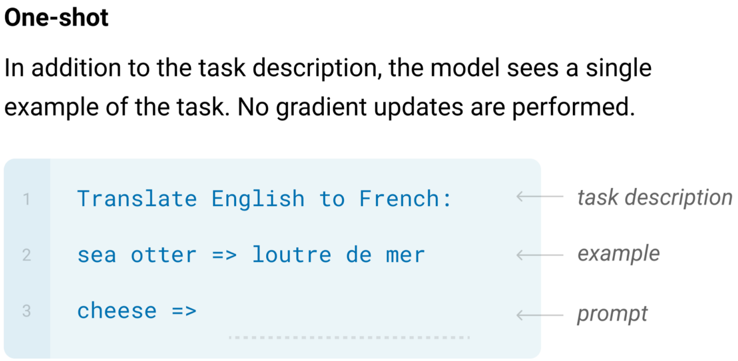
```
Translate English to French:
cheese =>
```

task description
prompt

▸ Source: Brown et al., 2020

- No gradient updates
- Learning happens “on the fly“
- Model has to “understand“ the task description

ONE-SHOT LEARNING



One-shot

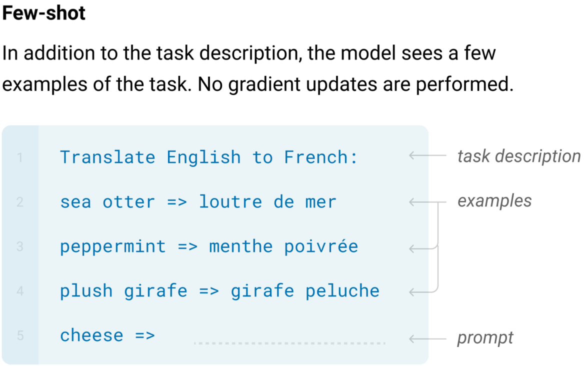
In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
Translate English to French:
sea otter => loutre de mer
cheese =>
```

Source: Brown et al., 2020

- No gradient updates
- Model has to “understand“ the task description
- Understanding supported by *one* demonstration

FEW-SHOT LEARNING



Few-shot

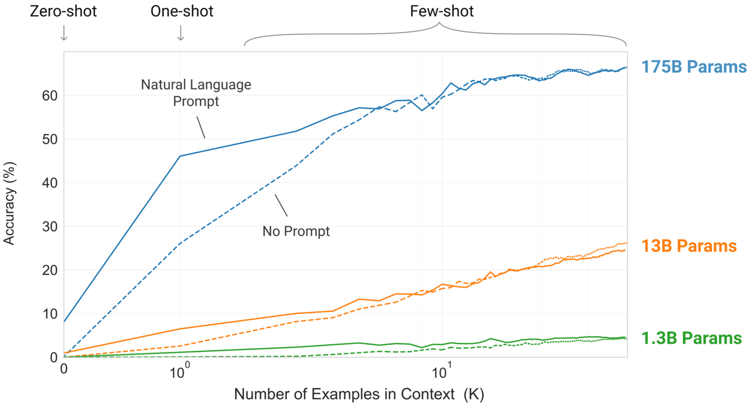
In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French:
sea otter => loutre de mer
peppermint => menthe poivrée
plush girafe => girafe peluche
cheese => ................................
```

▸ Source: Brown et al., 2020

- No gradient updates
- Model has to “understand“ the task description
- Understanding supported by *few* demonstrations

EFFECTIVE IN-CONTEXT LEARNING*



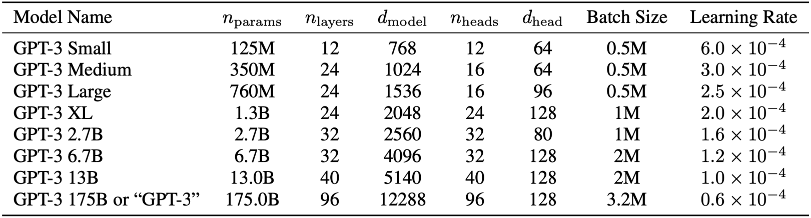
▸ Source: Brown et al., 2020

- Number/Selection of demonstrations = Hyperparameter
- Larger model → Better in-context learning capabilities

*on an artificial, simple word scrambling/manipulation task

ARCHITECTURE

- Various sizes released; GPT-3 usually refers to largest one
- Both width (d_{model}) and depth (n_{layers}) are scaled
- Number of heads adjusted to d_{model}

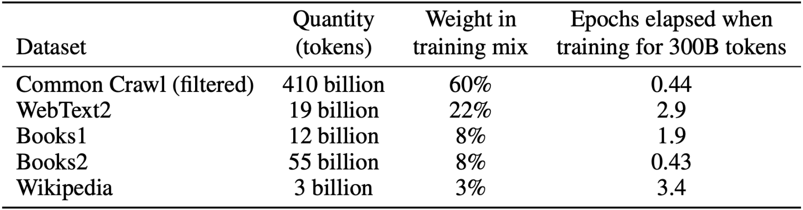


Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	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}

▸ Source: Brown et al., 2020

TRAINING CORPUS

- BERT: 3.3B words (rougly 4B – 6B tokens)
- GPT-3: 499B tokens
- Increased by two orders of magnitude within < 2yrs
- Content: Mostly the internet (incl. test sets of popular benchmarks)

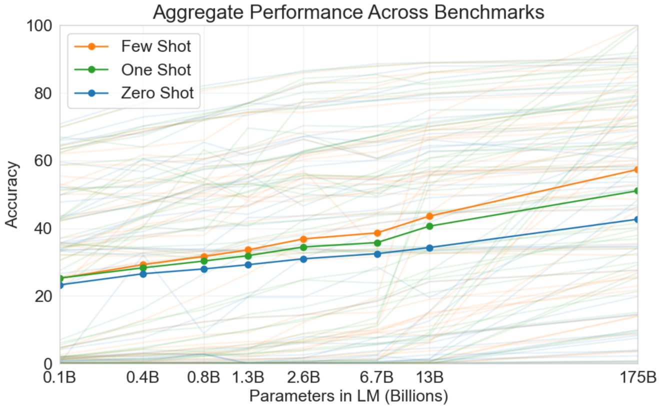


Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

▸ Source: Brown et al., 2020

X-SHOT COMPARISON

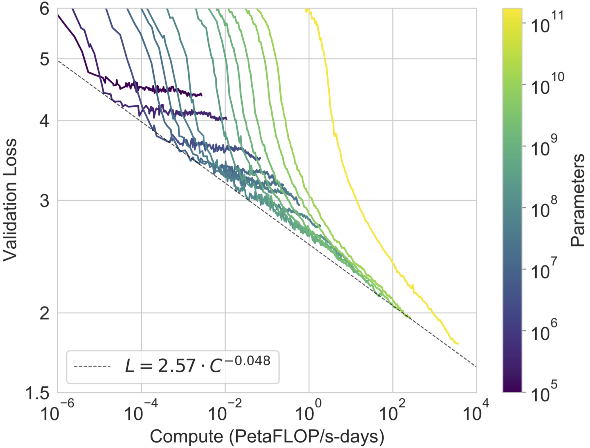
- 42 accuracy-denominated benchmarks
- Few-shot performance increases faster than zero-shot



▸ Source: Brown et al., 2020

LOSS AS A FUNCTION OF COMPUTE

Power-law trend



▸ Source: Brown et al., 2020