Language Models are Few-Shot Learners

윤예준

GPT란?

- Generative Pre-trained Transformer

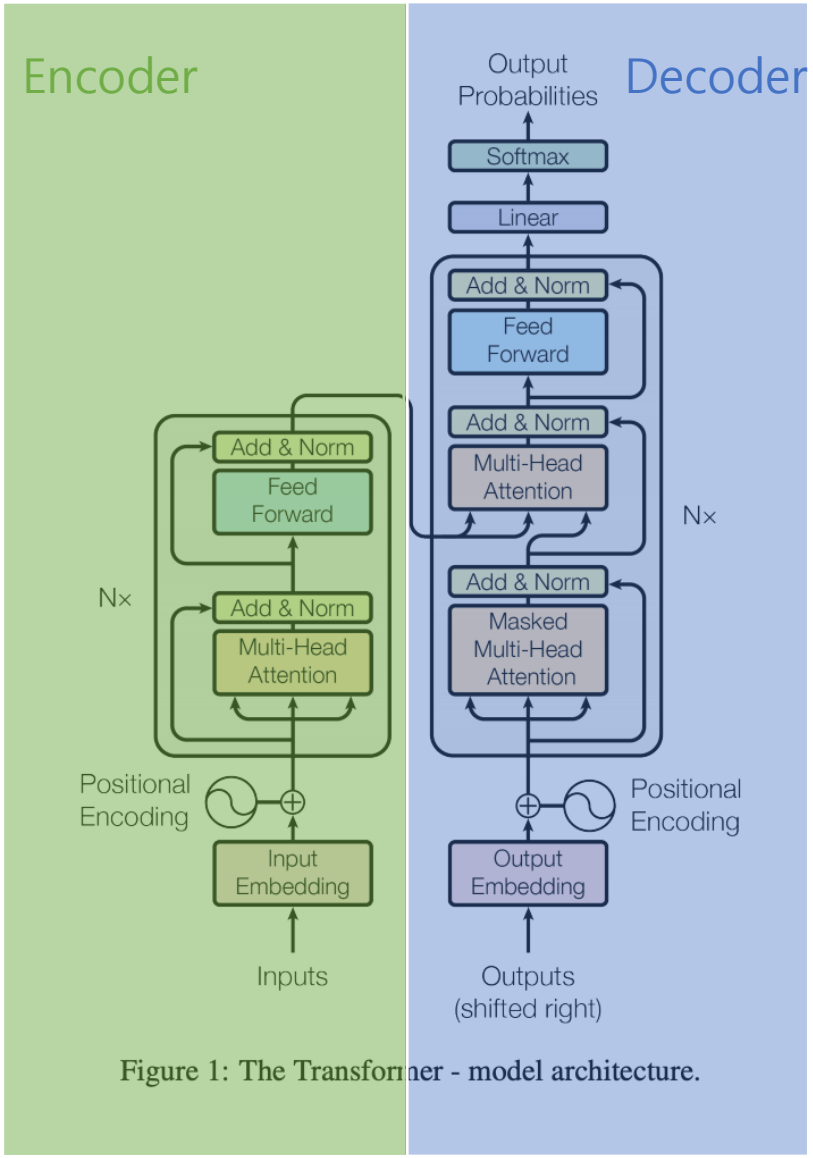
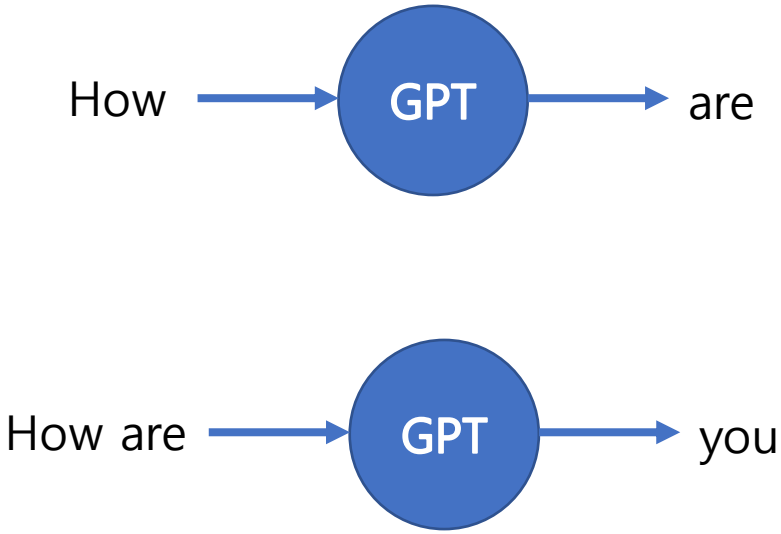


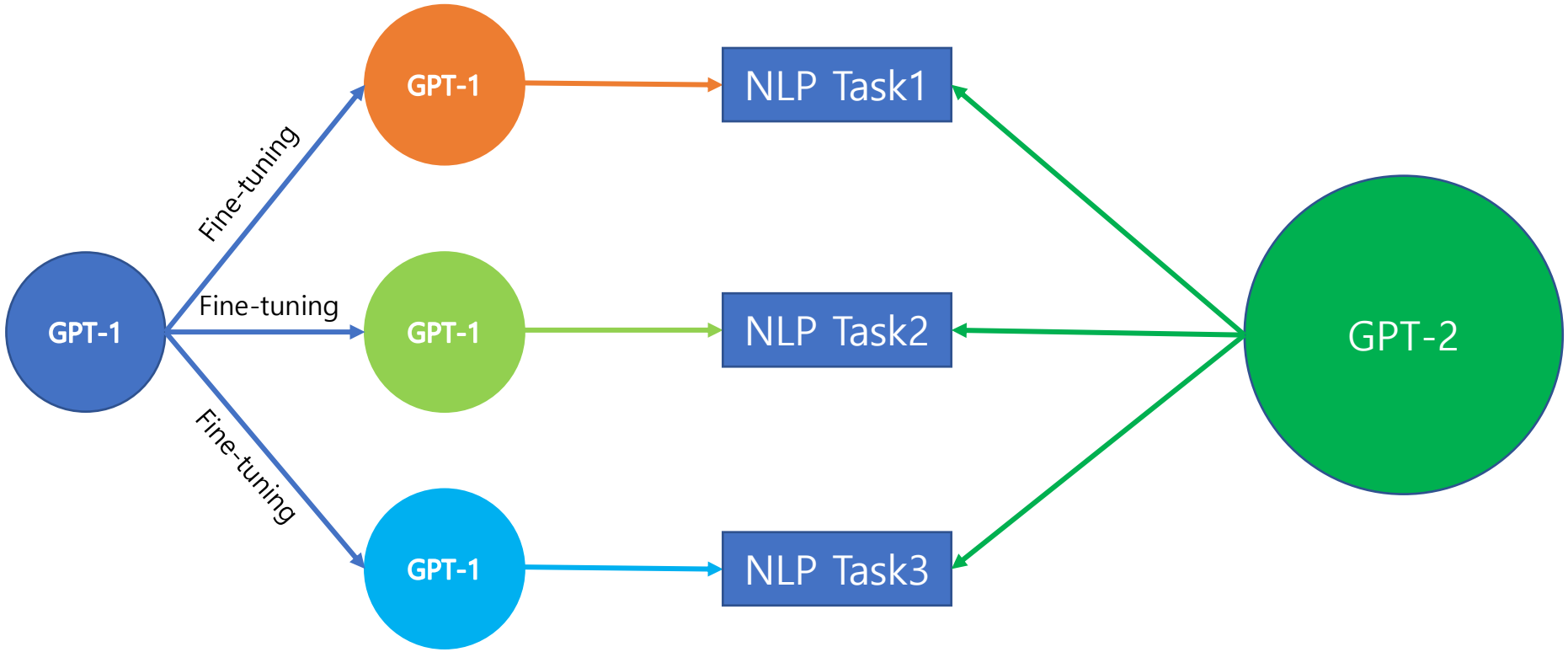
Figure 1: The Transformer - model architecture.

Autoregressive Language model

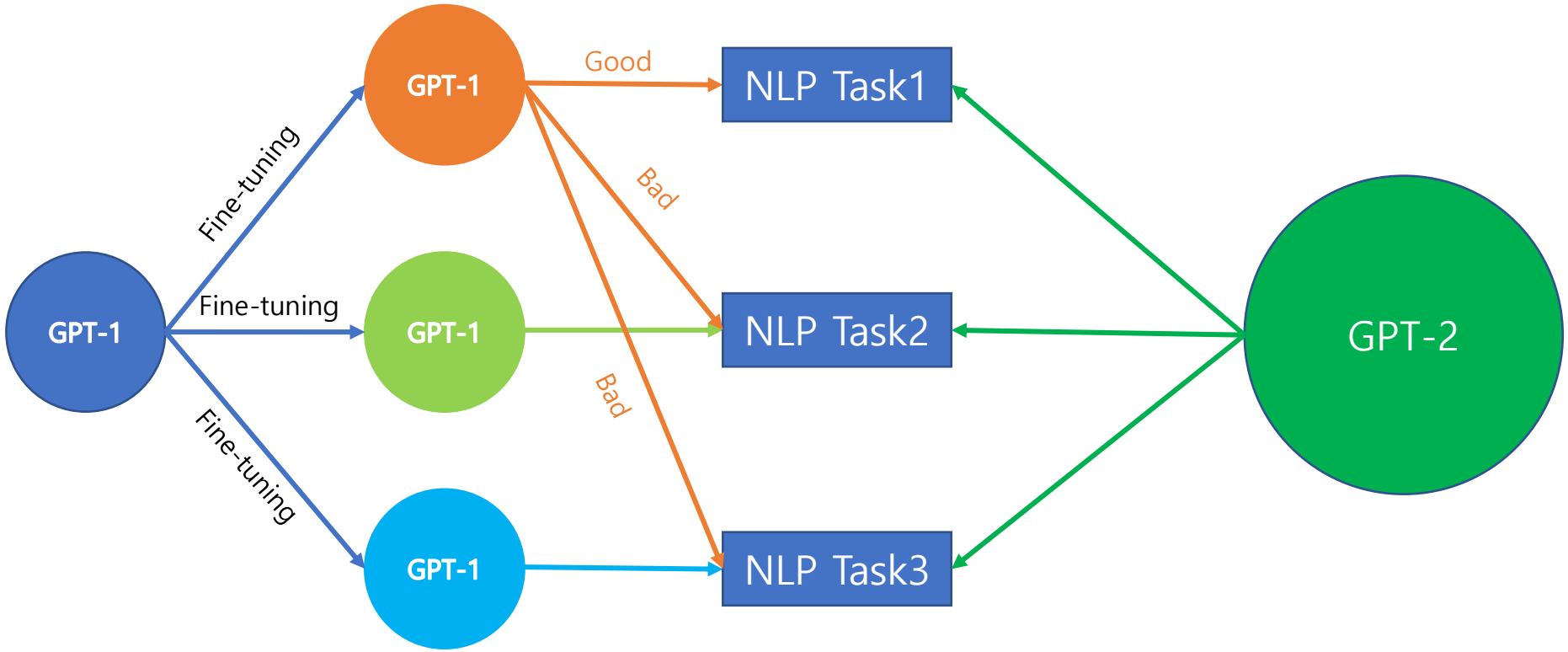
Language model's current output depends on previous output.



GPT-1 vs GPT-2


GPT-1
Fine-tuning
GPT-1
NLP Task1
Fine-tuning
GPT-1
NLP Task2
Fine-tuning
GPT-1
NLP Task3
GPT-2

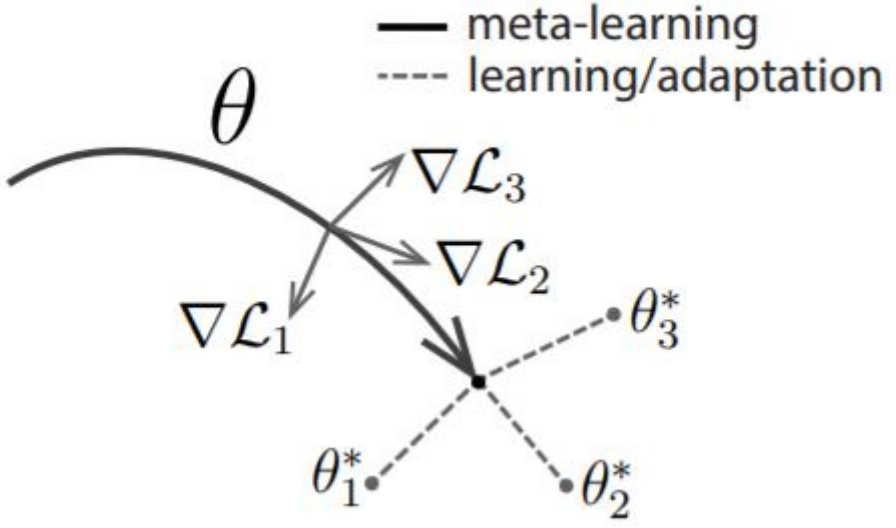
GPT-1 vs GPT-2


GPT-1
Fine-tuning
GPT-1
Good
Bad
NLP Task1
Fine-tuning
GPT-1
Bad
NLP Task2
Fine-tuning
GPT-1
NLP Task3
GPT-2

Multitask-learning vs Meta-learning

MAML (Model-Agnostic Meta-Learning)

- gradient update 과정에서 weight initialization을 재정의하는 것



MQAN (Multitask Question Answering Network)

- Translation training example
  - (translate to french, english text, french text)
- Reading comprehension training
  - (answer the question, document, question, answer)

https://arxiv.org/abs/1703.03400

https://arxiv.org/abs/1806.08730

GPT-3

Limitations

- While the architecture is task-agnostic, there is still a need for task-specific datasets and task-specific fine-tuning

Removing this limitation would be desirable because

- The need for a large dataset of labeled examples for every new task limits the applicability of language models.
- The potential to exploit spurious correlations in training data fundamentally grows with the expressiveness of the model and the narrowness of the training distribution.
- Humans do not require large supervised datasets to learn most language tasks

Meta-learning

Few-Shot Learning

Zero-shot

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

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

One-shot

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

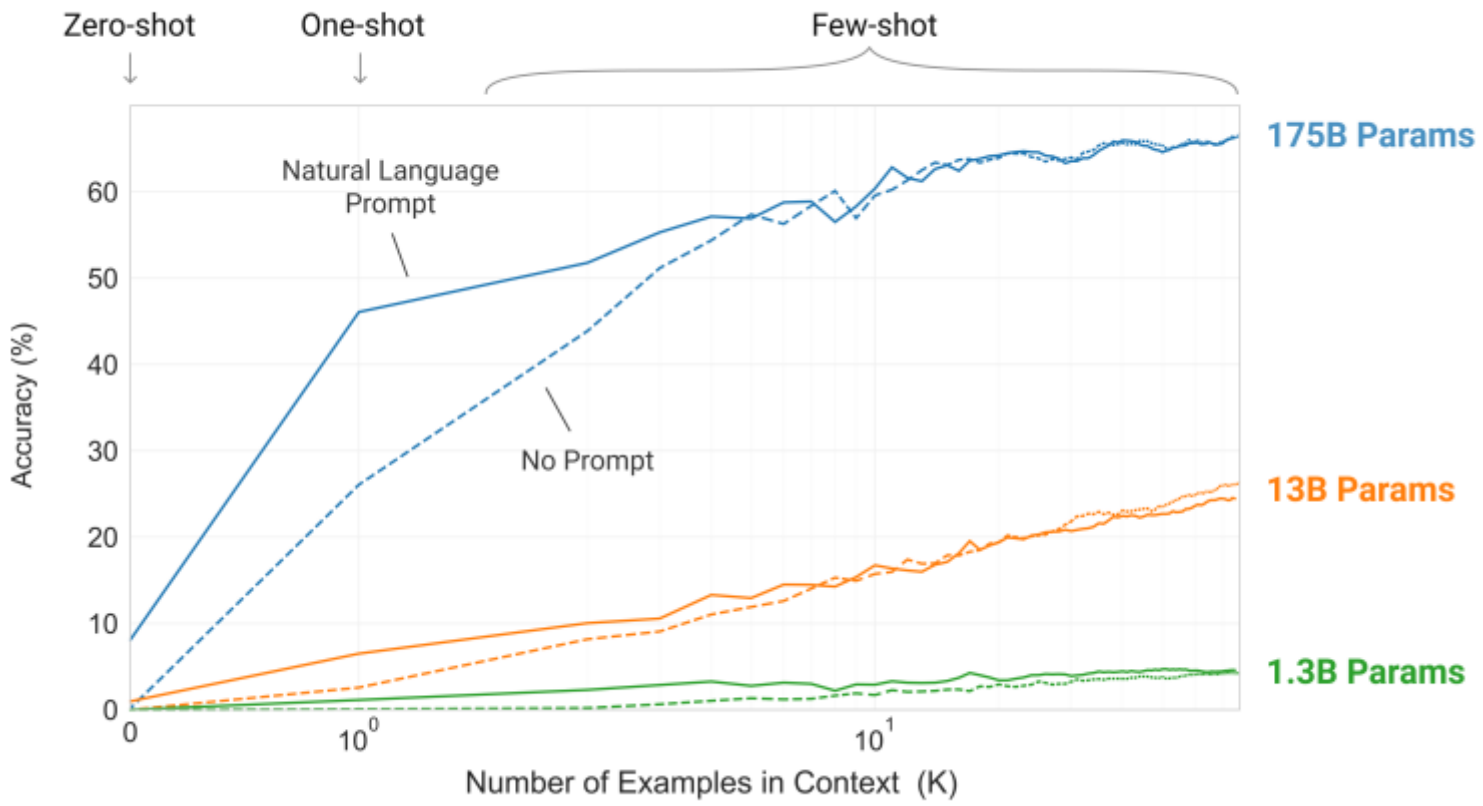
```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← example
3  cheese =>                           ← prompt
```

Few-shot

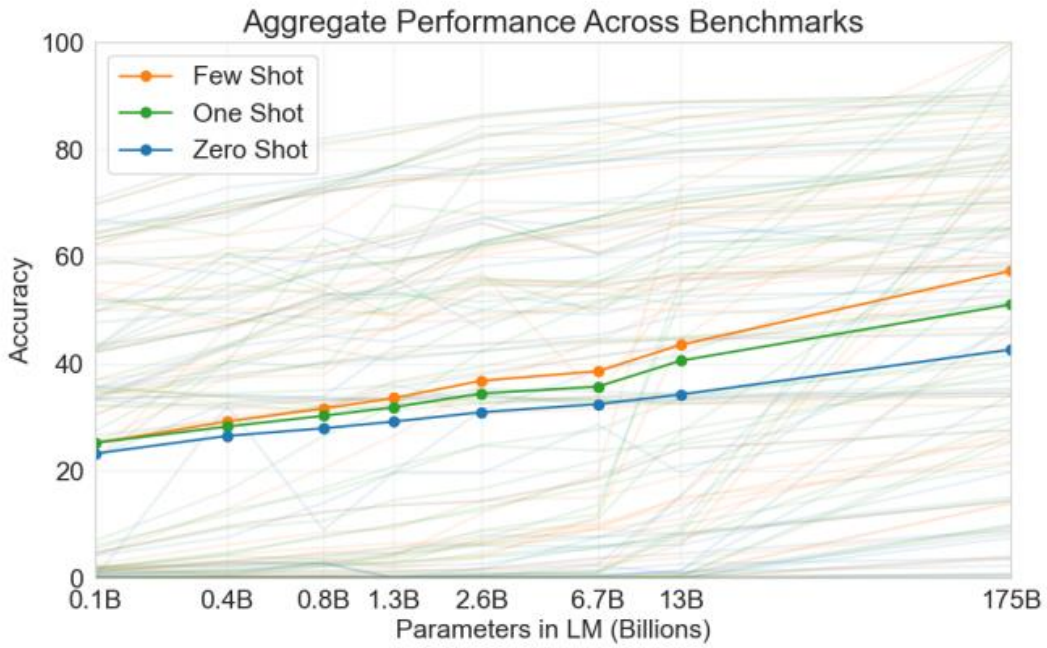
In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

GPT-3


Zero-shot
One-shot
Few-shot
Natural Language Prompt
No Prompt
175B Params
13B Params
1.3B Params
Accuracy (%)
0
10
20
30
40
50
60
0
10^0
10^1
Number of Examples in Context (K)

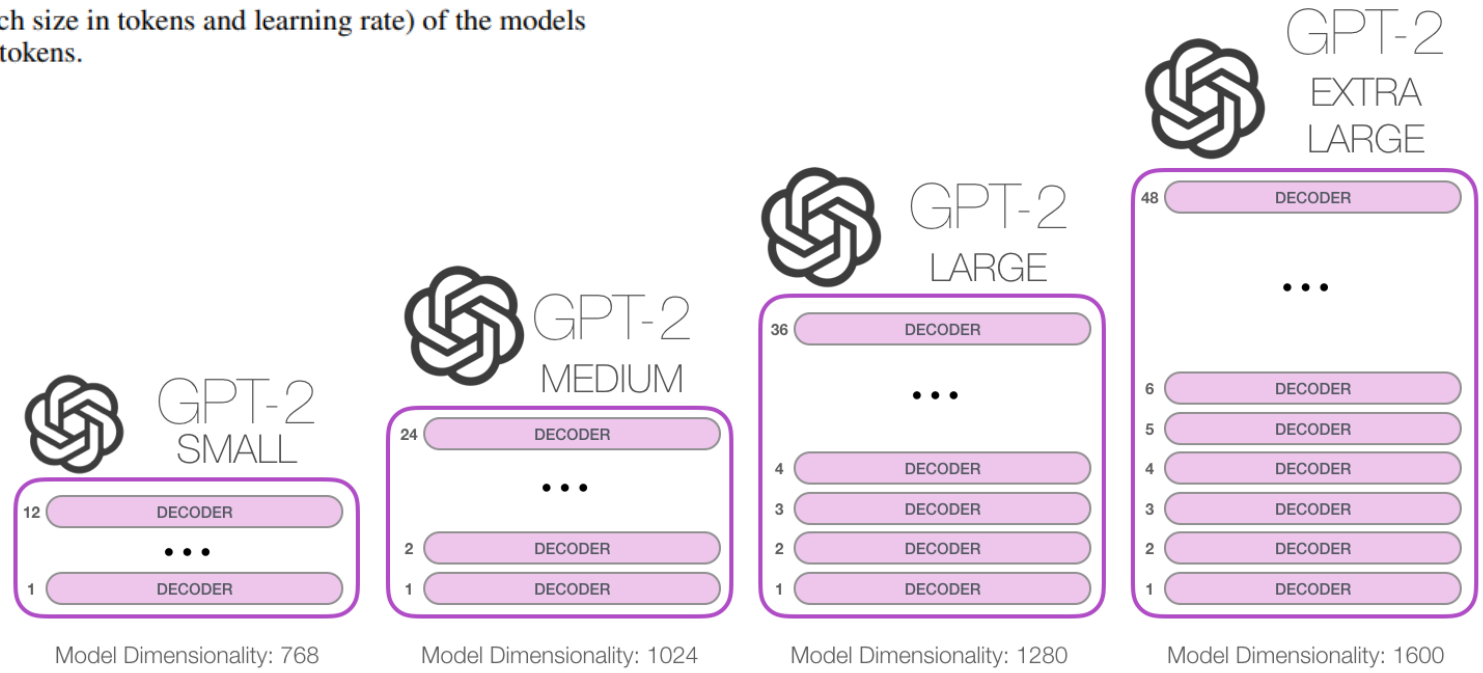
GPT-3


Aggregate Performance Across Benchmarks
Few Shot
One Shot
Zero Shot
Accuracy
100
80
60
40
20
0
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
Parameters in LM (Billions)

모델 구조

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}

Table 2.1: Sizes, architectures, and learning hyper-parameters (batch size in tokens and learning rate) of the models which we trained. All models were trained for a total of 300 billion tokens.



모델 구조

Model Name	n_p
GPT-3 Small	1
GPT-3 Medium	3
GPT-3 Large	7
GPT-3 XL	1
GPT-3 2.7B	2
GPT-3 6.7B	6
GPT-3 13B	1
GPT-3 175B or "GPT-3"	17

Table 2.1: Sizes, architectures, and l
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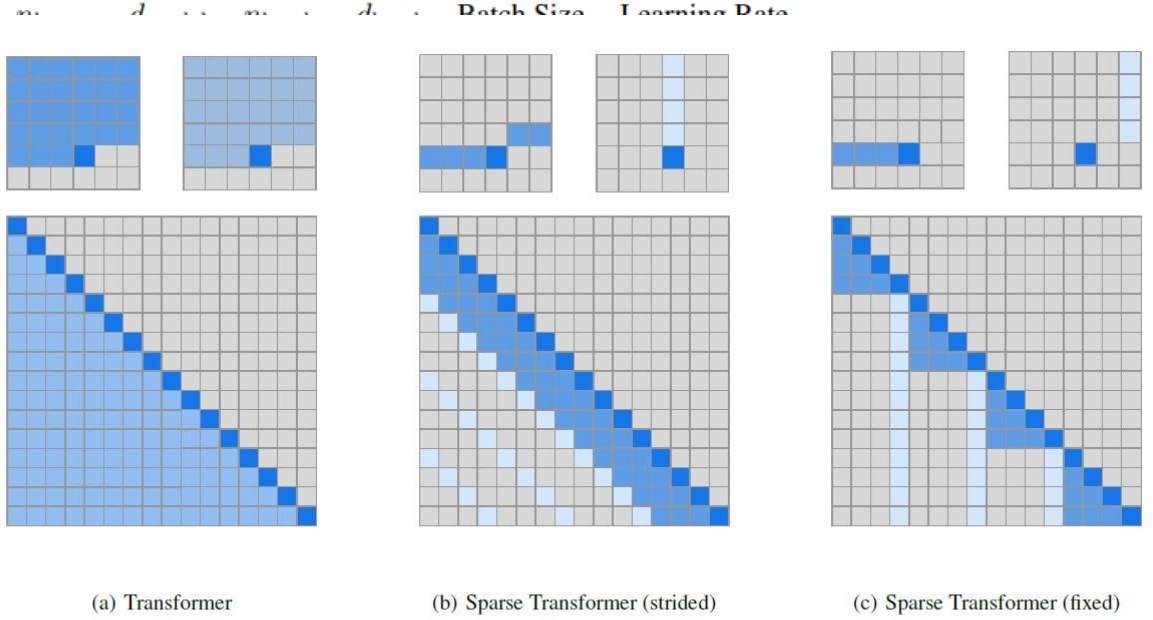
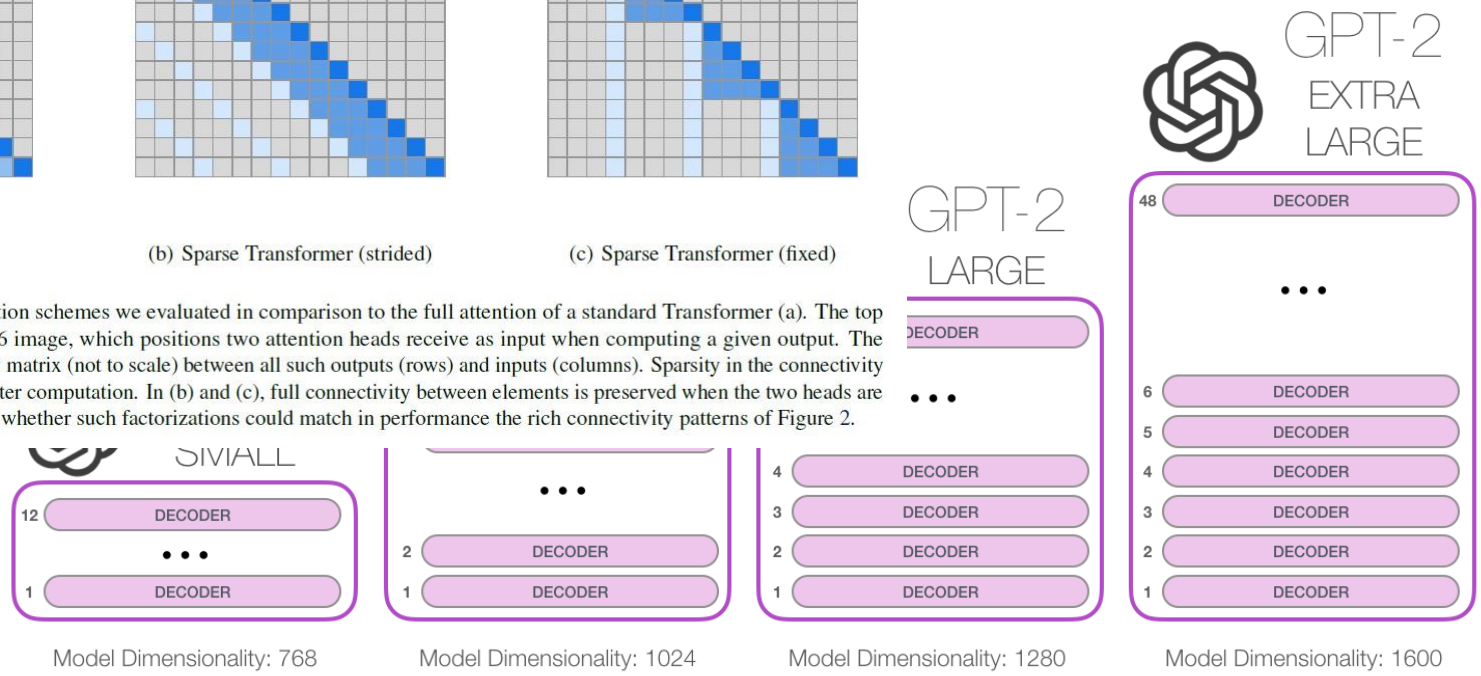


(a) Transformer (b) Sparse Transformer (strided) (c) Sparse Transformer (fixed)

Figure 3. Two 2d factorized attention schemes we evaluated in comparison to the full attention of a standard Transformer (a). The top row indicates, for an example 6x6 image, which positions two attention heads receive as input when computing a given output. The bottom row shows the connectivity matrix (not to scale) between all such outputs (rows) and inputs (columns). Sparsity in the connectivity matrix can lead to significantly faster computation. In (b) and (c), full connectivity between elements is preserved when the two heads are computed sequentially. We tested whether such factorizations could match in performance the rich connectivity patterns of Figure 2.



Training Dataset

- Common Crawl dataset (constituting nearly a trillion words)

- 3 steps to improve the average quality of our datasets

(1) Filtered a version of CommonCrawl based on similarity to a range of high-quality reference corpora

(2) Performed fuzzy deduplication at the document level, within and across datasets, to prevent redundancy and preserve the integrity of our held-out validation set as an accurate measure of overfitting

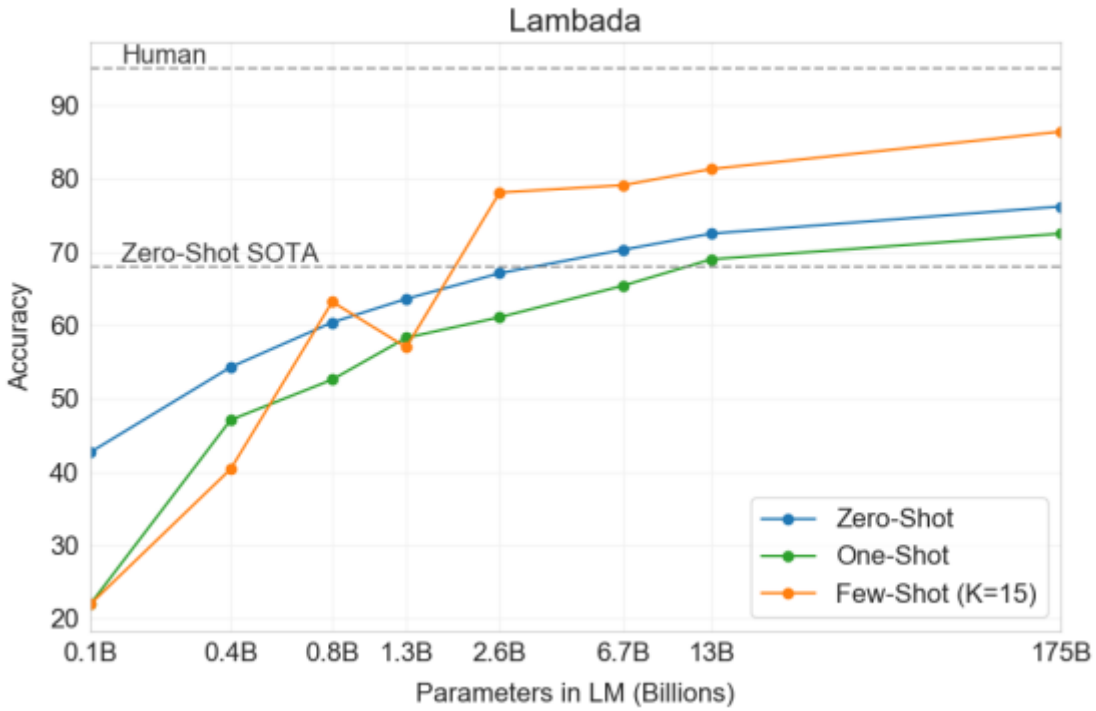
(3) Added known high-quality reference corpora to the training mix to augment CommonCrawl

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

성능 평가

Language modeling

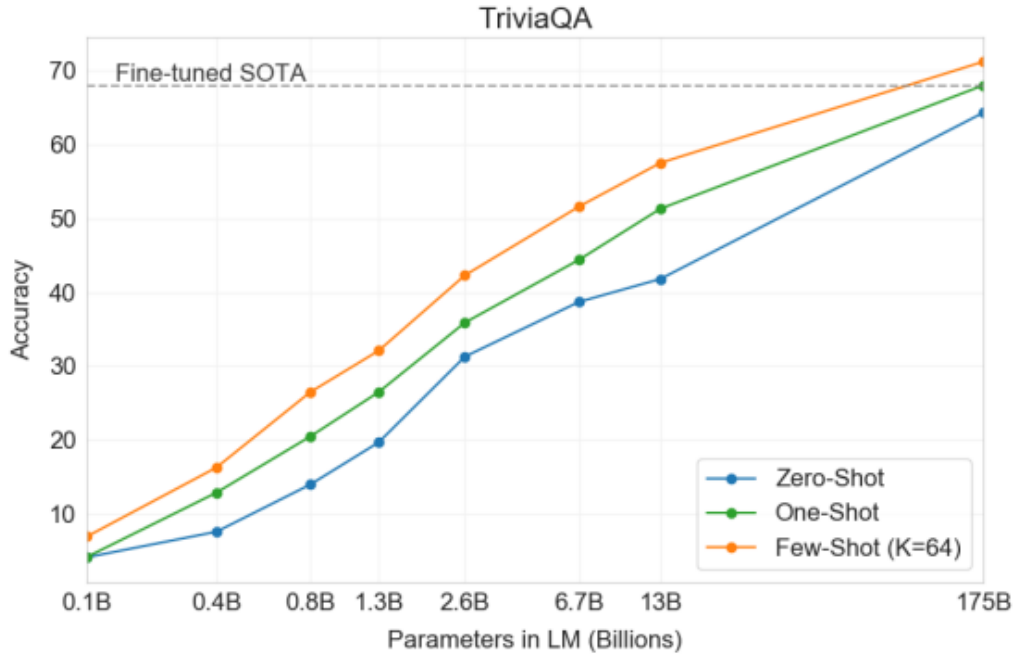
Setting	LAMBADA (acc)	LAMBADA (ppl)	StoryCloze (acc)	HellaSwag (acc)
SOTA	68.0[a]	8.63[b]	**91.8**[c]	**85.6**[d]
GPT-3 Zero-Shot	**76.2**	**3.00**	83.2	78.9
GPT-3 One-Shot	**72.5**	**3.35**	84.7	78.1
GPT-3 Few-Shot	**86.4**	**1.92**	87.7	79.3



성능 평가

Closed Book Question Answering

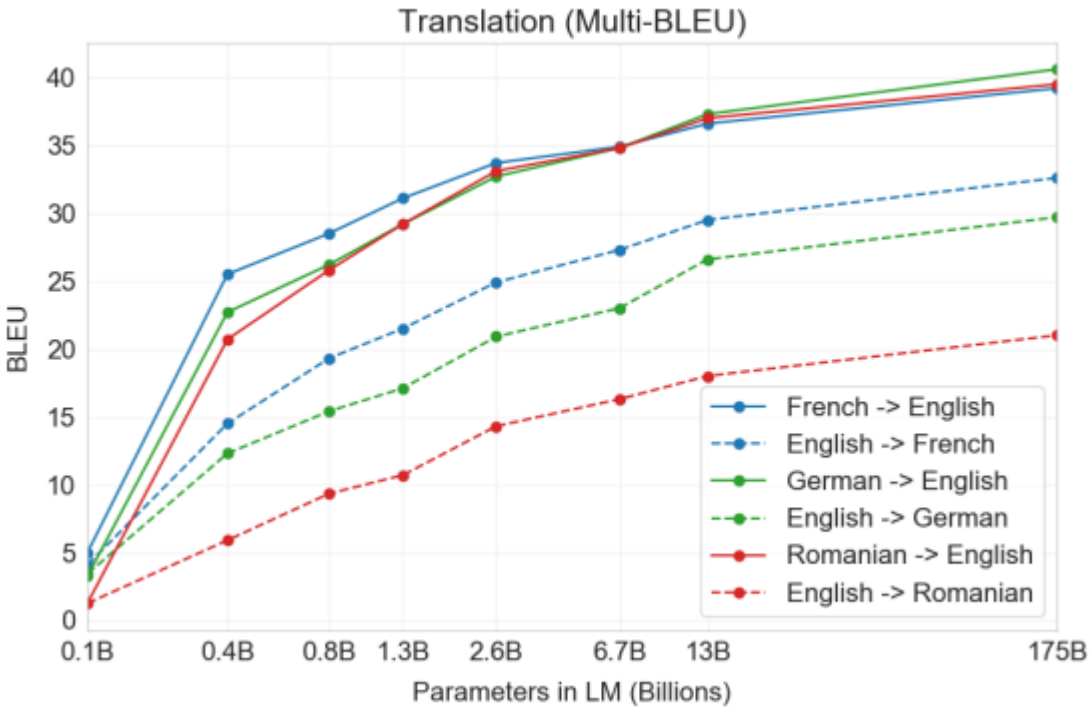
Setting	NaturalQS	WebQS	TriviaQA
RAG (Fine-tuned, Open-Domain) [LPP+20]	**44.5**	**45.5**	**68.0**
T5-11B+SSM (Fine-tuned, Closed-Book) [RRS20]	36.6	44.7	60.5
T5-11B (Fine-tuned, Closed-Book)	34.5	37.4	50.1
GPT-3 Zero-Shot	14.6	14.4	64.3
GPT-3 One-Shot	23.0	25.3	**68.0**
GPT-3 Few-Shot	29.9	41.5	**71.2**



성능 평가

Machine translation

Setting	En→Fr	Fr→En	En→De	De→En	En→Ro	Ro→En
SOTA (Supervised)	**45.6**[a]	35.0 [b]	**41.2**[c]	40.2[d]	**38.5**[e]	**39.9**[e]
XLM [LC19]	33.4	33.3	26.4	34.3	33.3	31.8
MASS [STQ+19]	37.5	34.9	28.3	35.2	35.2	33.1
mBART [LGG+20]	-	-	29.8	34.0	35.0	30.5
GPT-3 Zero-Shot	25.2	21.2	24.6	27.2	14.1	19.9
GPT-3 One-Shot	28.3	33.7	26.2	30.4	20.6	38.6
GPT-3 Few-Shot	32.6	39.2	29.7	40.6	21.0	39.5



성능 평가

News Article Generation

	Mean accuracy	95% Confidence Interval (low, hi)	t compared to control (p-value)	"I don't know" assignments
Control (deliberately bad model)	86%	83%–90%	-	3.6 %
GPT-3 Small	76%	72%–80%	3.9 (2e-4)	4.9%
GPT-3 Medium	61%	58%–65%	10.3 (7e-21)	6.0%
GPT-3 Large	68%	64%–72%	7.3 (3e-11)	8.7%
GPT-3 XL	62%	59%–65%	10.7 (1e-19)	7.5%
GPT-3 2.7B	62%	58%–65%	10.4 (5e-19)	7.1%
GPT-3 6.7B	60%	56%–63%	11.2 (3e-21)	6.2%
GPT-3 13B	55%	52%–58%	15.3 (1e-32)	7.1%
GPT-3 175B	52%	49%–54%	16.9 (1e-34)	7.8%

GPT-3

- Limitations
  - Weakeness in text synthesis and several NLP tasks
    - repeat themselves semantically at the document level, start to lose coherence over sufficiently long passages, contradict themselves, and occasionally contain non-sequitur sentences or paragraphs.

- Structural and algorithmic limitation
  - Auto-regressive
  - Pretraining objective weights every token equally