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BERT and GPTs

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Contents

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- Transformer review: teacher forcing
- BERT
- GPT

Some materials are from a great course [1]

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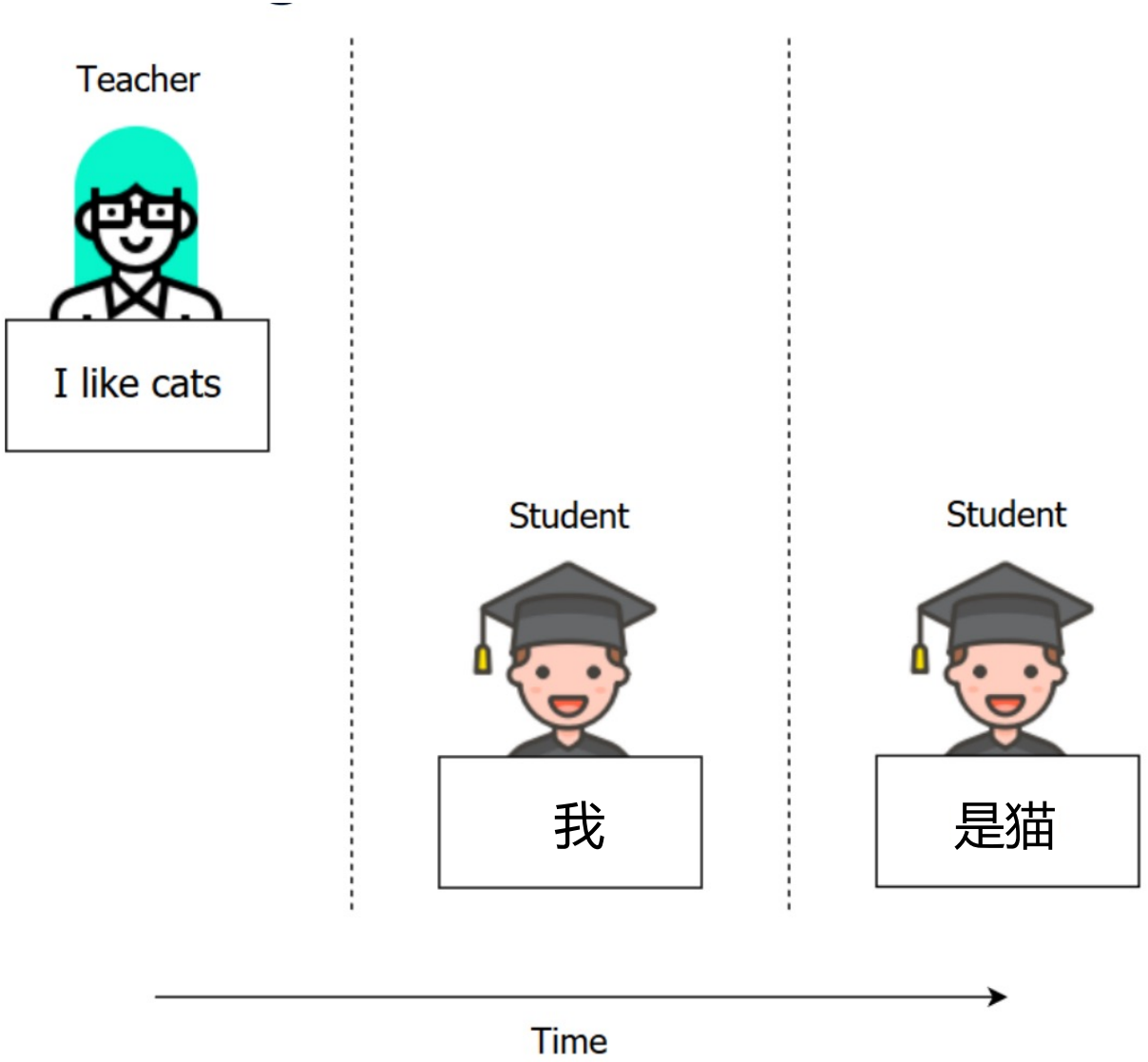
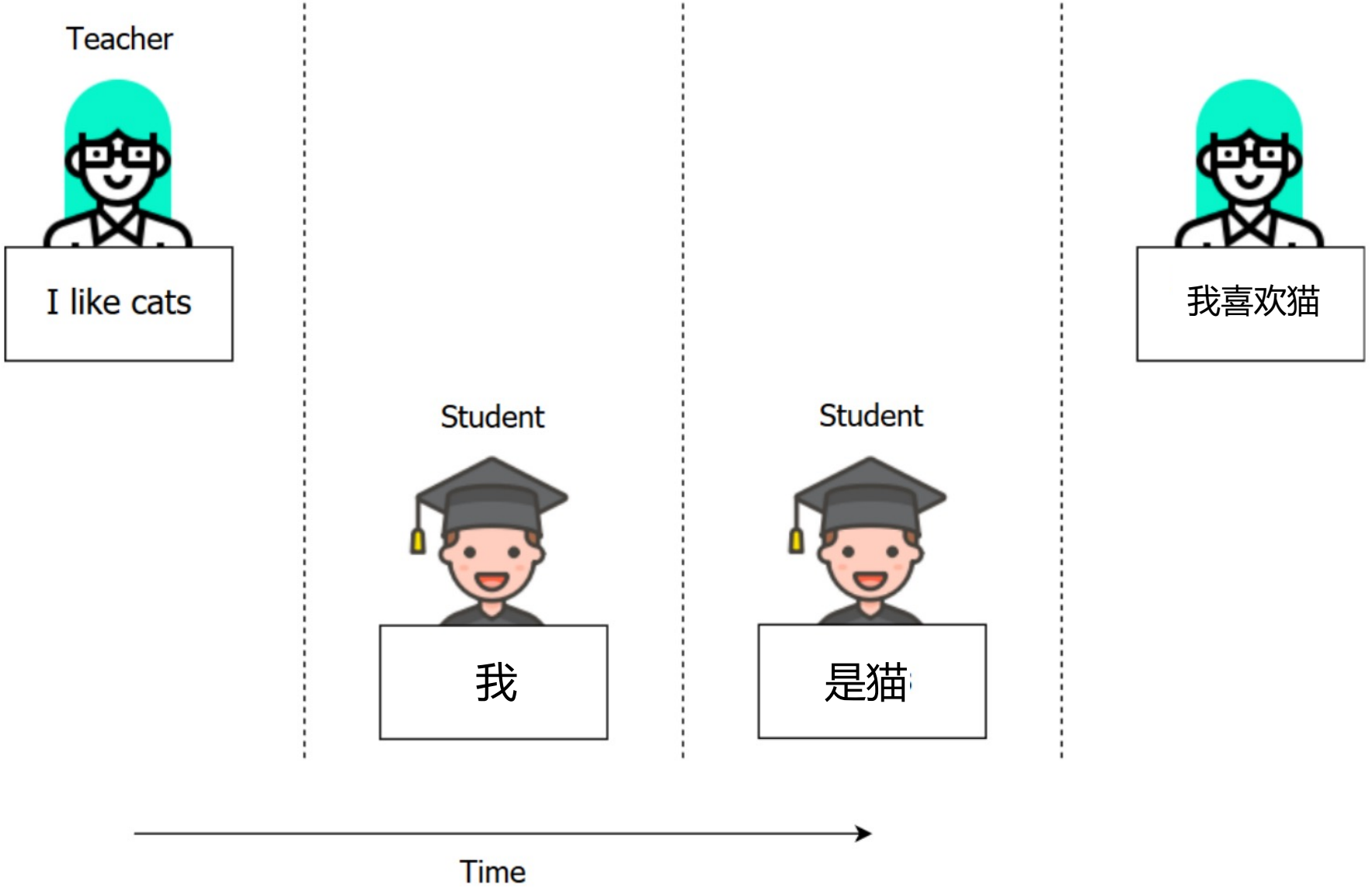
[1] Stanford CS224n: Natural Language Processing with Deep Learning

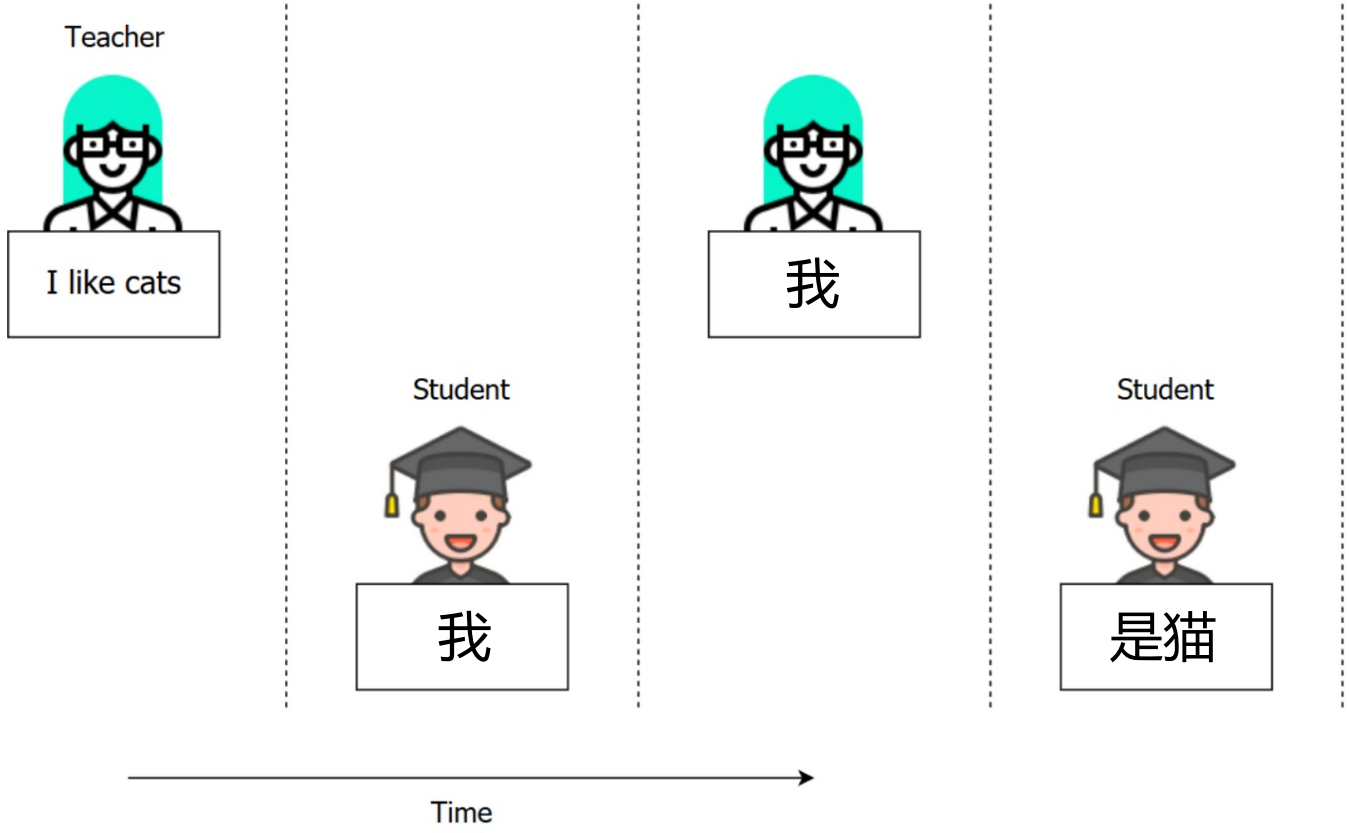
Training without teacher forcing



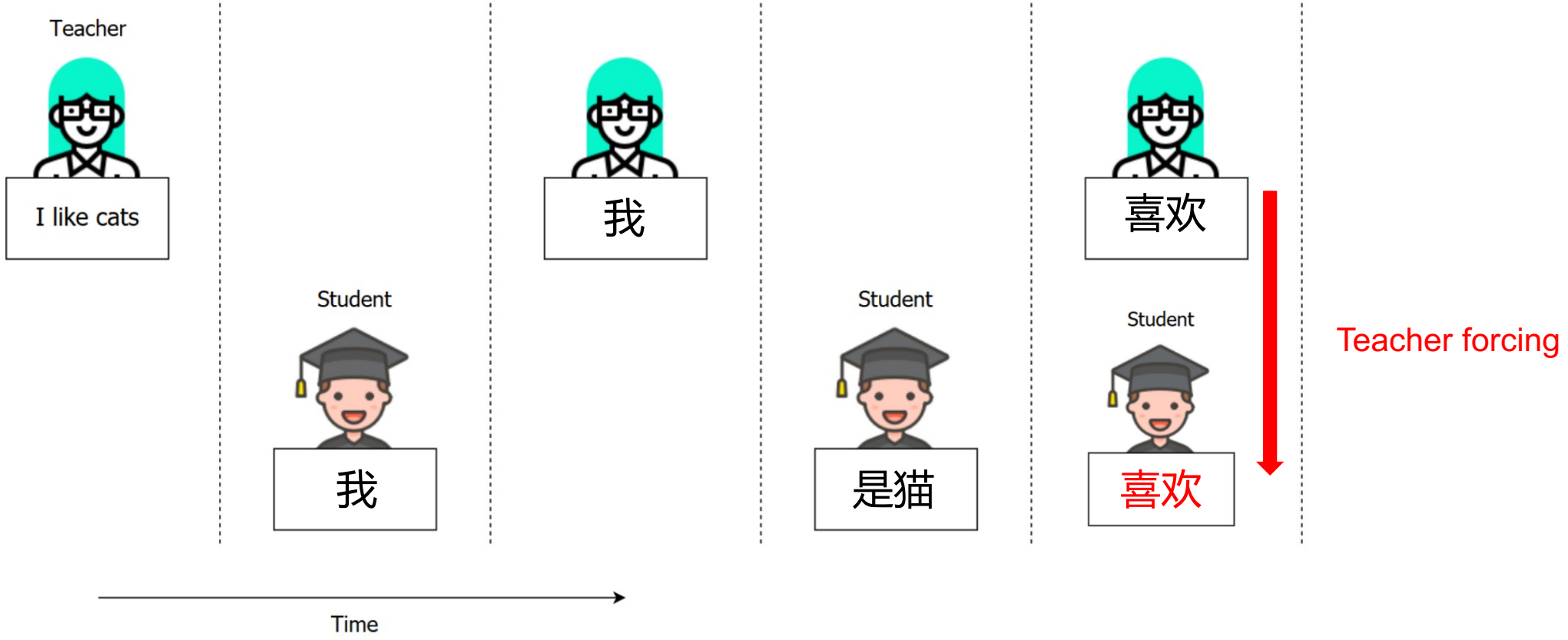
Training without teacher forcing



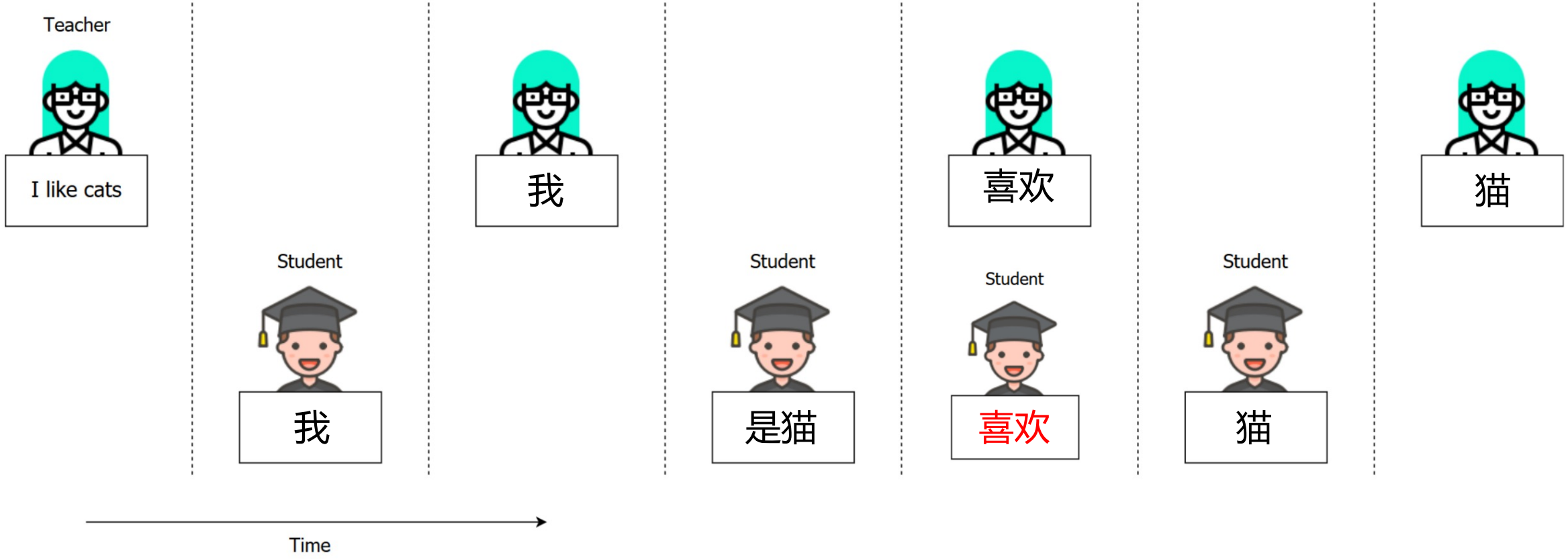
Training with teacher forcing



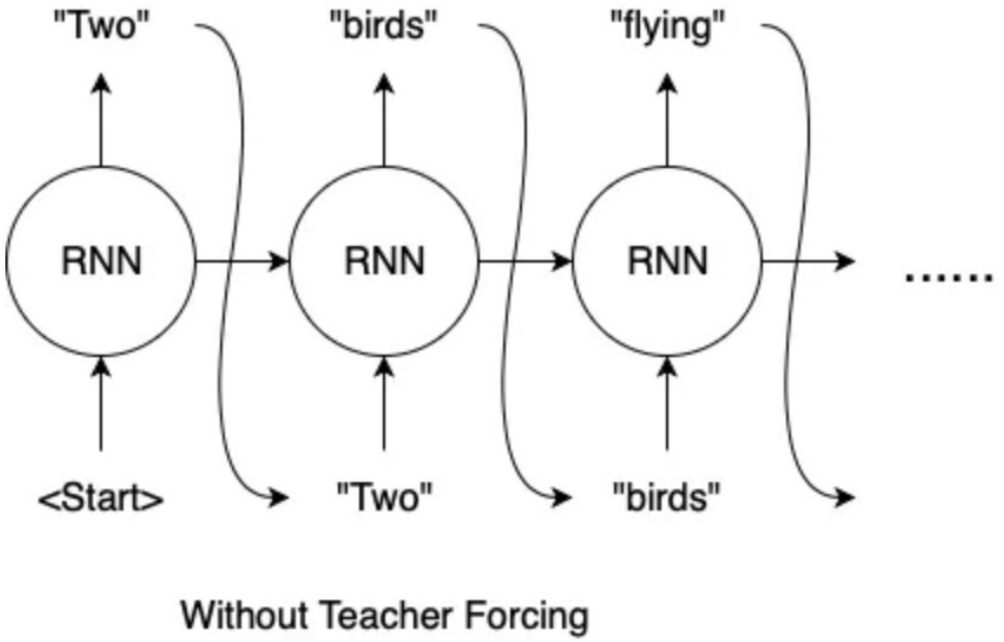
Training with teacher forcing



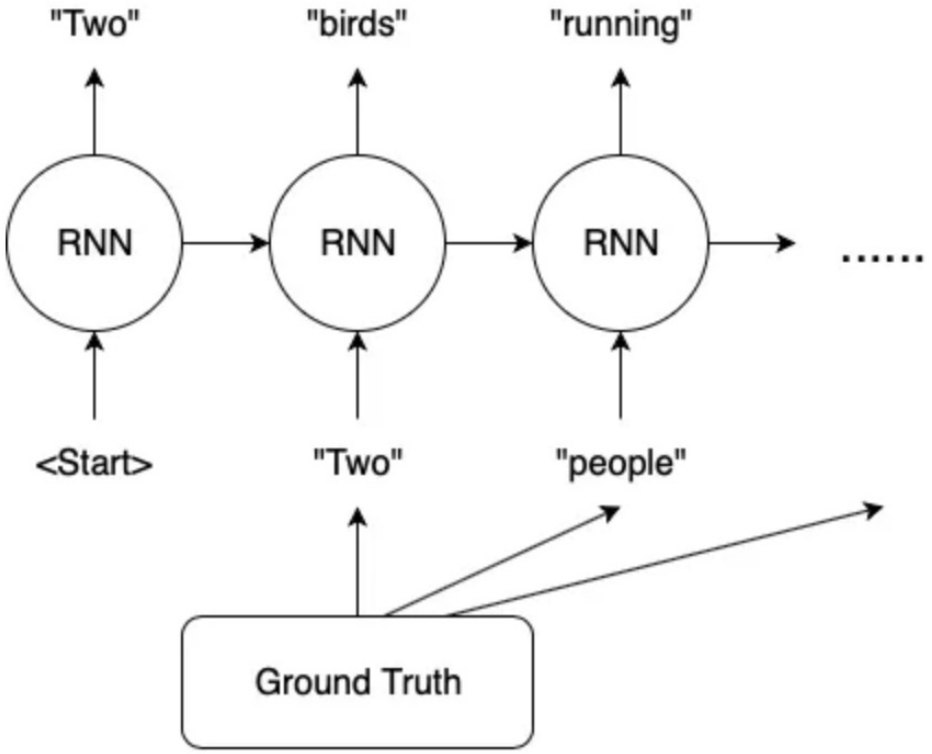
Training with teacher forcing



With and without teacher forcing



Without Teacher Forcing

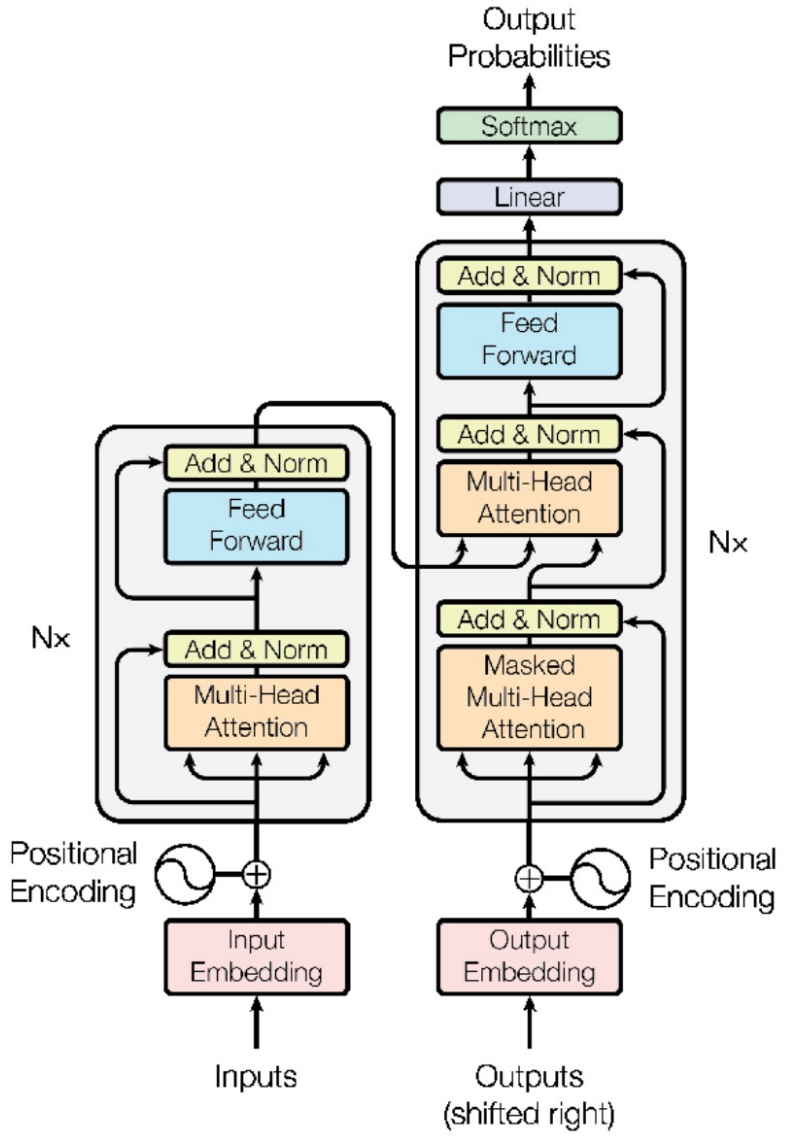


With Teacher Forcing

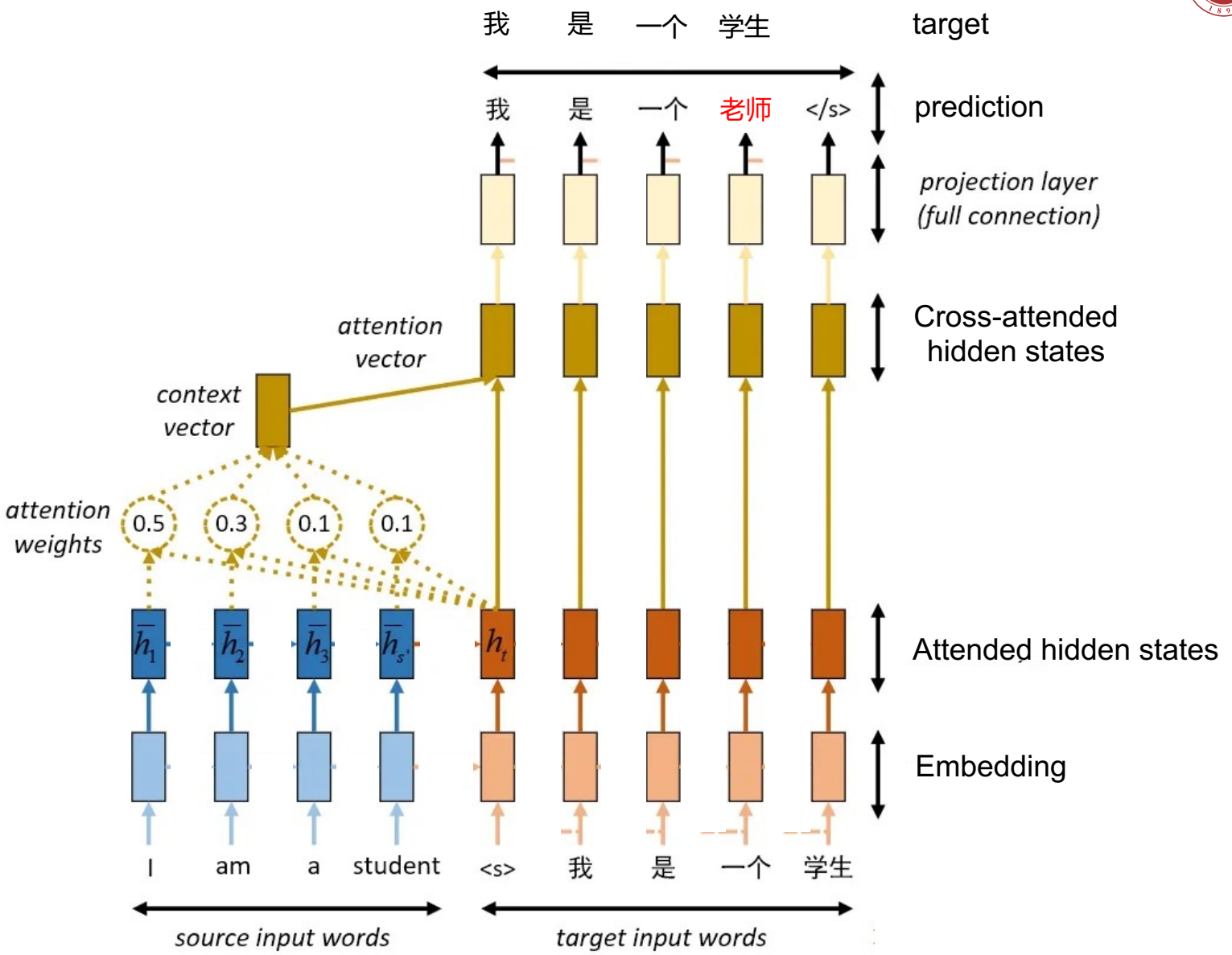
Transformer

Teacher forcing is used when training transformer

- To avoid error accumulation
- To accelerate training due to parallel computing endowed by masked attention



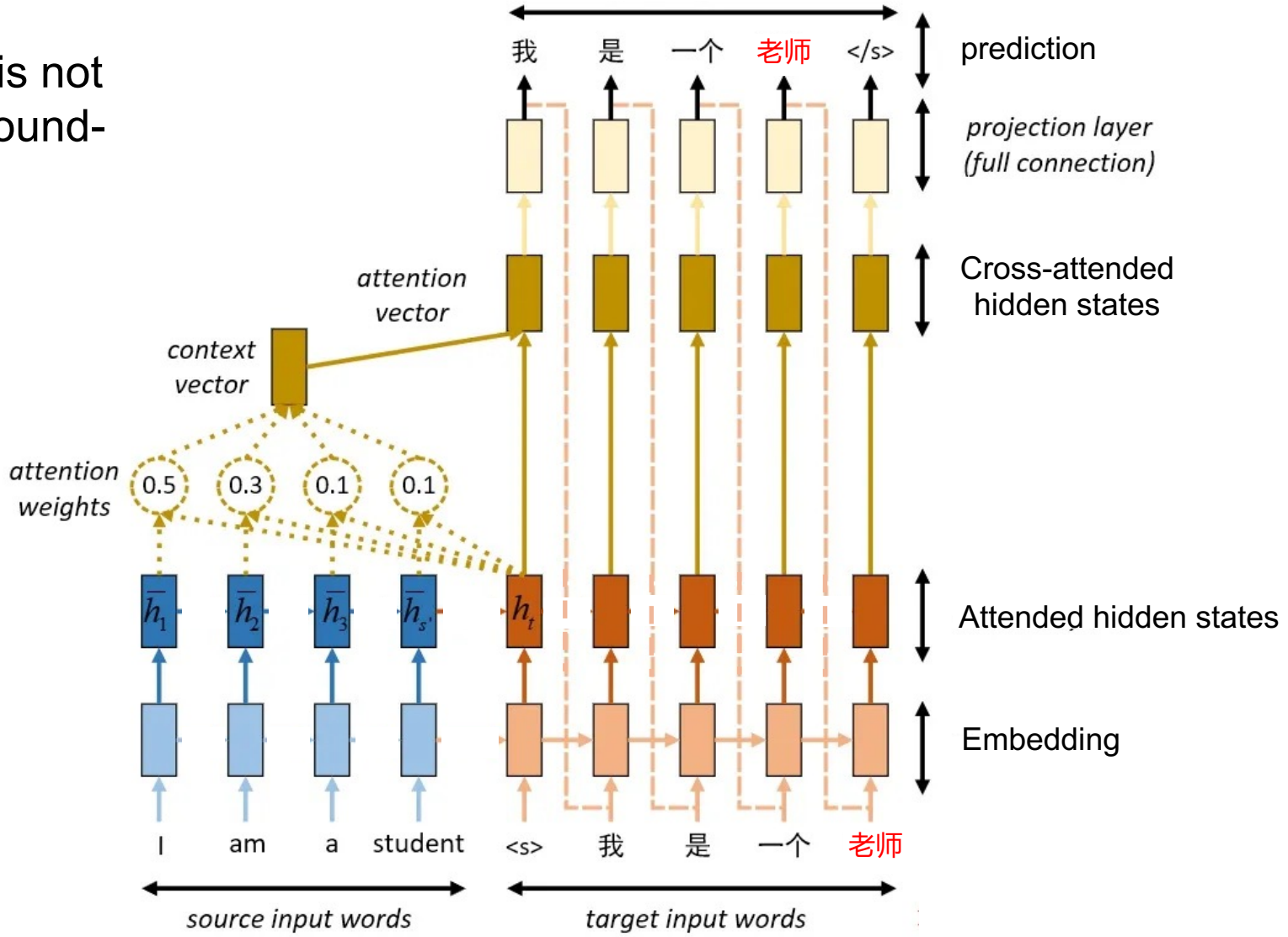
Training transformer with teacher forcing



Inference

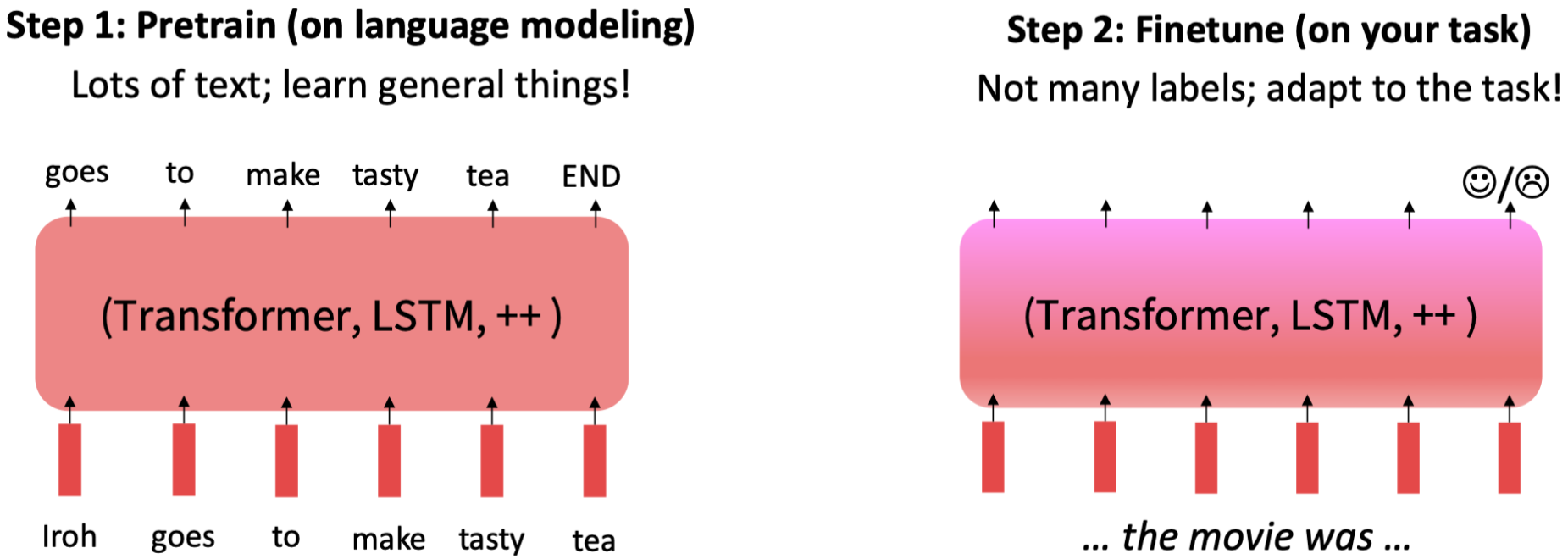
During inference, teacher forcing is not used since wo do not have the ground-truth label

- Cannot be parallel!



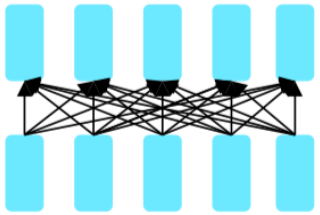
The Pretraining / Finetuning Paradigm

Pretraining can improve NLP applications by serving as parameter initialization.



[Figure is from Stanford CS224n]

BERT: Bidirectional Encoder Representations from Transformers



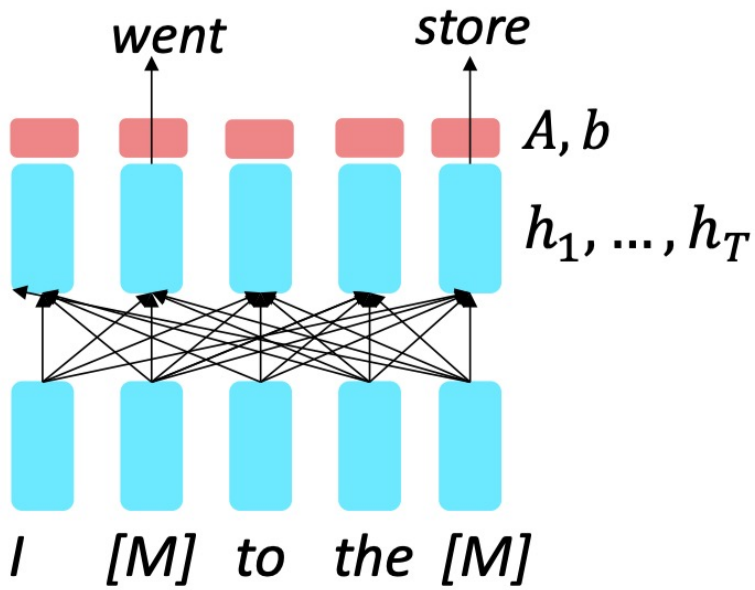
Encoders

- Gets bidirectional context – can condition on future!
- How do we train them to build strong representations?

Devlin et al., 2018 proposed the "Masked LM" objective and **released the weights of a pretrained Transformer**, a model they labeled BERT.

BERT, roughly speaking, pre-trained the encoder of the transformer.

It replace some fraction of words in the input with a special [MASK] token; predict these words.



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BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

BERT details

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Details about BERT

- Two models were released:
  - BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million params.
  - BERT-large: 24 layers, 1024-dim hidden states, 16 attention heads, 340 million params.
- Trained on:
  - BooksCorpus (800 million words)
  - English Wikipedia (2,500 million words)
- Pretraining is expensive and impractical on a single GPU.
  - BERT was pretrained with 64 TPU chips for a total of 4 days.
  - (TPUs are special tensor operation acceleration hardware)

BERT finetune

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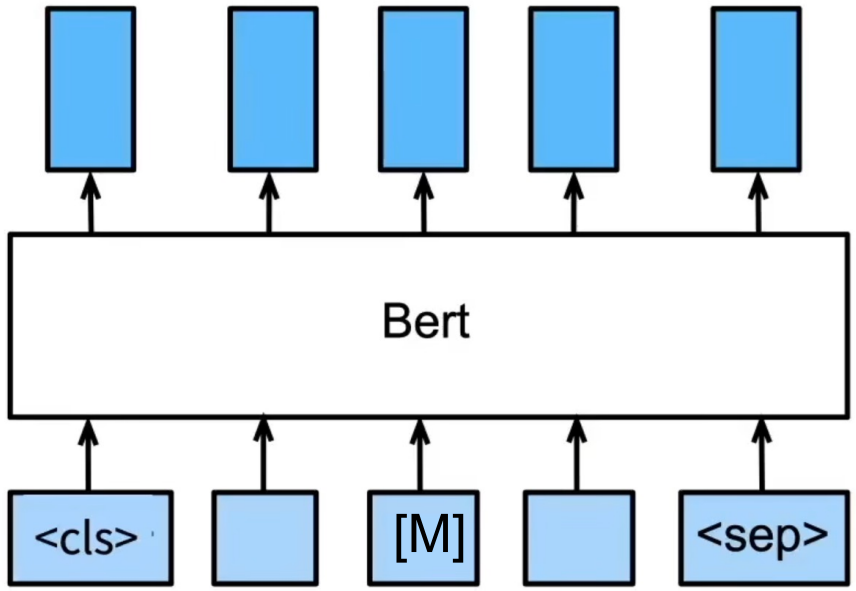
After pre-training, BERT can learn great representations for each word. We can use it as a starting point to finetune downstream tasks. In this way, BERT can perform well in that specific downstream task

To finetune BERT, we will add or change the output layer of the BERT model, and train all parameters with downstream dataset

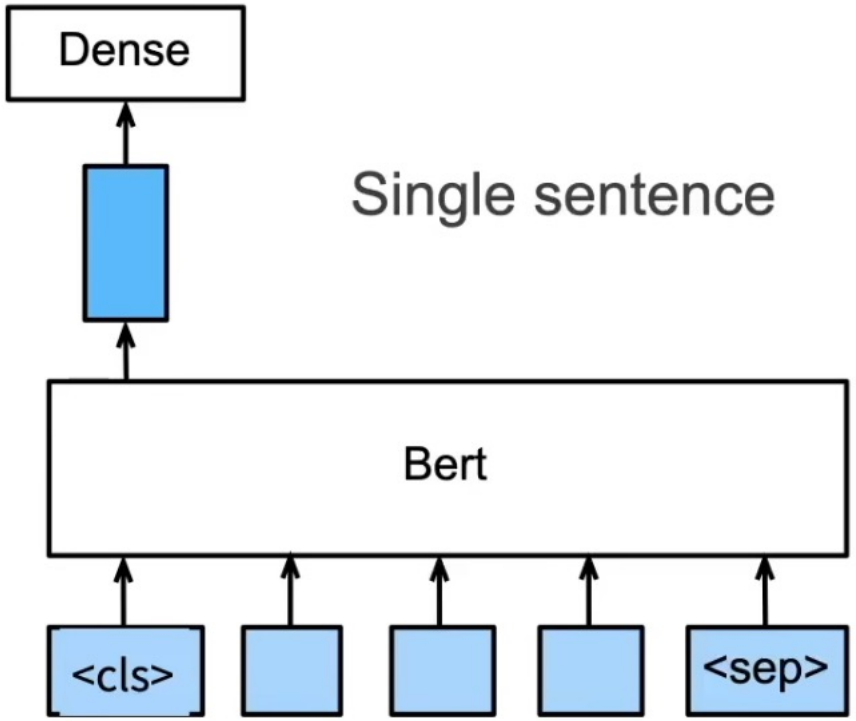
During the finetune stage, only a few downstream dataset is enough. This significantly widens the applications of natural language processing

Pretraining and finetuning become the standard practices in most AI fields (NLP, CV, etc.)

Finetune BERT to sentence classification

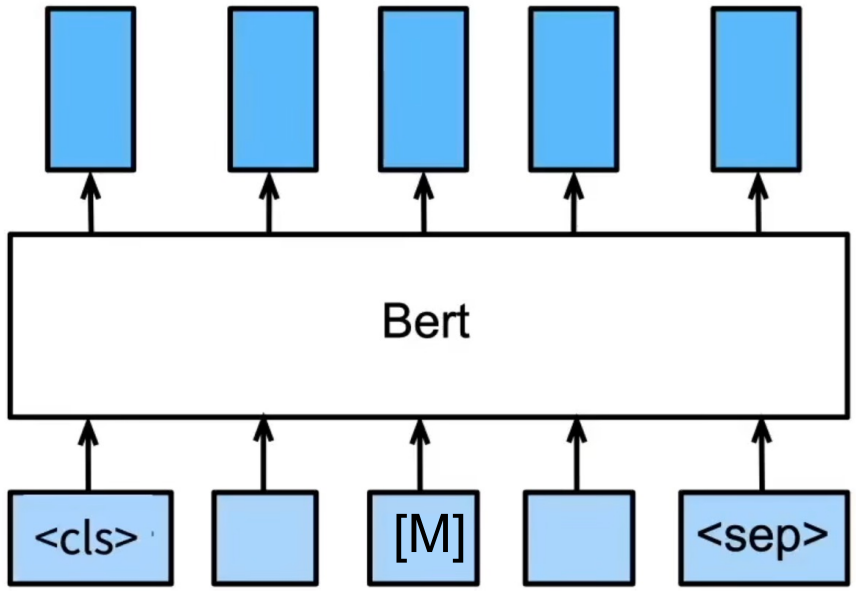


Pre-train

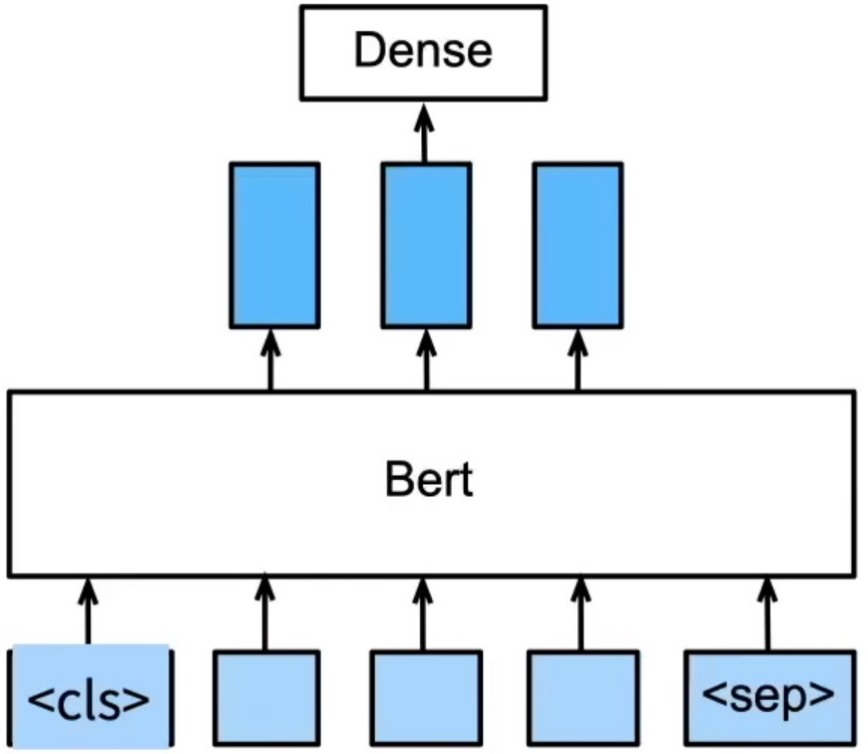


Finetune

Finetune BERT to entity recognition



Pre-train



Finetune

BERT finetune performance

BERT was massively popular and hugely versatile; finetuning BERT led to new state-of-the-art results on a broad range of tasks.

- **QQP:** Quora Question Pairs (detect paraphrase questions)
- **QNLI**: natural language inference over question answering data
- **SST-2**: sentiment analysis
- **CoLA**: corpus of linguistic acceptability (detect whether sentences are grammatical.)
- **STS-B**: semantic textual similarity
- **MRPC**: microsoft paraphrase corpus
- **RTE**: a small natural language inference corpus

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

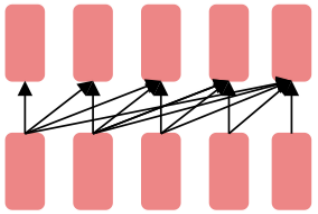
BERT limitations

Pretrain encoders such as BERT is great. It particularly suits in information extraction.

However, it is not good at text generation which cannot look into the future

If your task involves generating sequences, consider using a pretrained decoder; BERT and other pretrained encoders don't naturally lead to nice autoregressive (1-word-at-a-time) generation methods.

Pretrain decoder



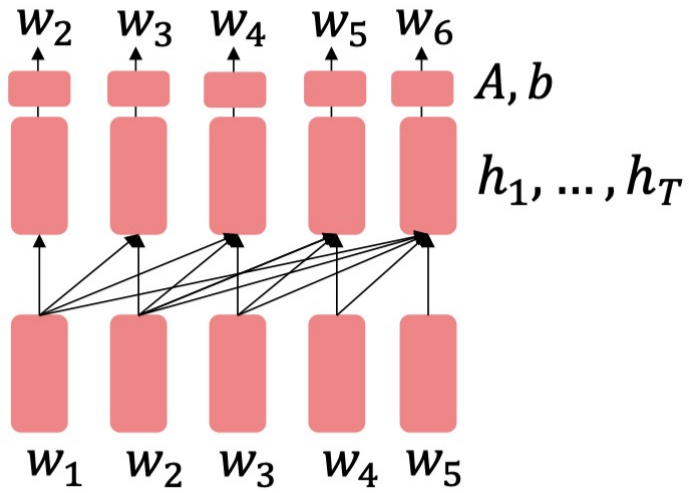
Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words
- All the biggest pretrained models are Decoders.

Generative Pretrained Transformer (GPT) [Radford et al., 2018] was a big success in pretraining a decoder!

GPT, roughly speaking, pre-trained the decoder of the transformer.

GPT typically stands for "Generative Pretrained Transformer"



The very first GPT paper

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Improving Language Understanding by Generative Pre-Training

Alec Radford
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Karthik Narasimhan
OpenAI
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Tim Salimans
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OpenAI
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GPT architecture

Let $U = (u_{-k}, \ldots, u_{-1})$ be the context vector of tokens. The structure of GPT is as follows

$$
\begin{aligned}
h_0 &= UW_e + W_p \\
h_l &= \texttt{transformer\_block}(h_{l-1}) \forall i \in [1, n] \\
P(u) &= \texttt{softmax}(h_n W_e^T)
\end{aligned}
$$

which is exactly the same as the transformer decoder

Language modelling, the target of GPT, is much harder than filling in the placeholder, the target of BERT. This explains that why BERT performs better than GPT.

But language modelling has much wider applications than filling in the placeholder

GPT details

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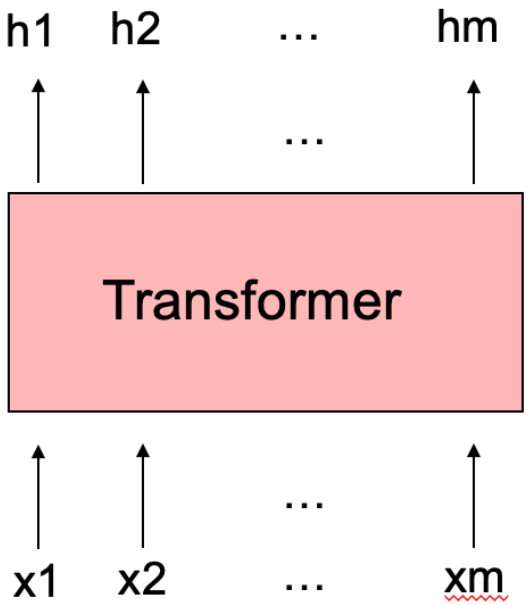
- Transformer decoder with 12 layers, 117M parameters.
- 768-dimensional hidden states, 3072-dimensional feed-forward hidden layers.
- Byte-pair encoding with 40,000 merges
- Trained on BooksCorpus: over 7000 unique books.
  - Contains long spans of contiguous text, for learning long-distance dependencies.

GPT finetune

Given a sequence of downstream tokens {x1, x2, …, xm}, and its label y



+

$$\text{softmax}(h_\ell^m W_y)$$

=

$$L_3(\mathcal{C}) = L_2(\mathcal{C}) + \lambda * L_1(\mathcal{C})$$

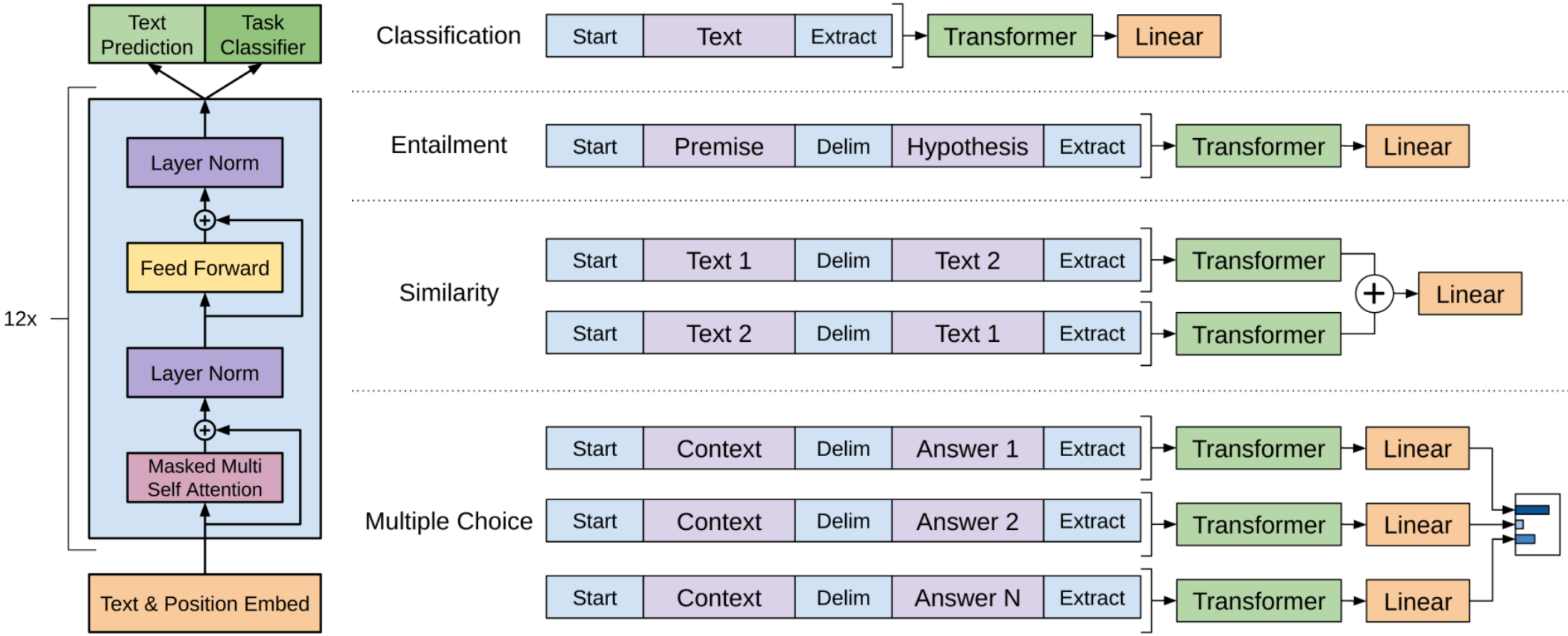
$$L_1(\mathcal{U}) = \sum_i \log P(u_i | u_{i-k}, \ldots, u_{i-1}; \Theta)$$

$$P(y|x^1, \ldots, x^m) = \texttt{softmax}(h_l^m W_y).$$

$$L_2(\mathcal{C}) = \sum_{(x,y)} \log P(y|x^1, \ldots, x^m).$$

GPT finetune

It is very natural to perform fine-tuning with GPT



GPT Performance

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Method	MNLI-m	MNLI-mm	SNLI	SciTail	QNLI	RTE
ESIM + ELMo [44] (5x)	-	-	89.3	-	-	-
CAFE [58] (5x)	80.2	79.0	89.3	-	-	-
Stochastic Answer Network [35] (3x)	80.6	80.1	-	-	-	-
CAFE [58]	78.7	77.9	88.5	83.3		
GenSen [64]	71.4	71.3	-	-	82.3	59.2
Multi-task BiLSTM + Attn [64]	72.2	72.1	-	-	82.1	**61.7**
Finetuned Transformer LM (ours)	**82.1**	**81.4**	**89.9**	**88.3**	**88.1**	56.0

GPT-1 is the first model that significantly improves performances over various tasks

However, BERT, with bidirectional information, outperforms GPT-1 by a large margin shortly

GPT-2

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GPT is based on the decoder-only architecture, and BERT is based on the encoder-only architecture

BERT has shown much stronger performance than GPT

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
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GPT-2

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How to strike back? **Increasing the data and enlarging the models!**

Language Models are Unsupervised Multitask Learners

Alec Radford [*1] **Jeffrey Wu** [*1] **Rewon Child** [1] **David Luan** [1] **Dario Amodei** [**1] **Ilya Sutskever** [**1]

GPT-2

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GPT increases to 1.5B parameters

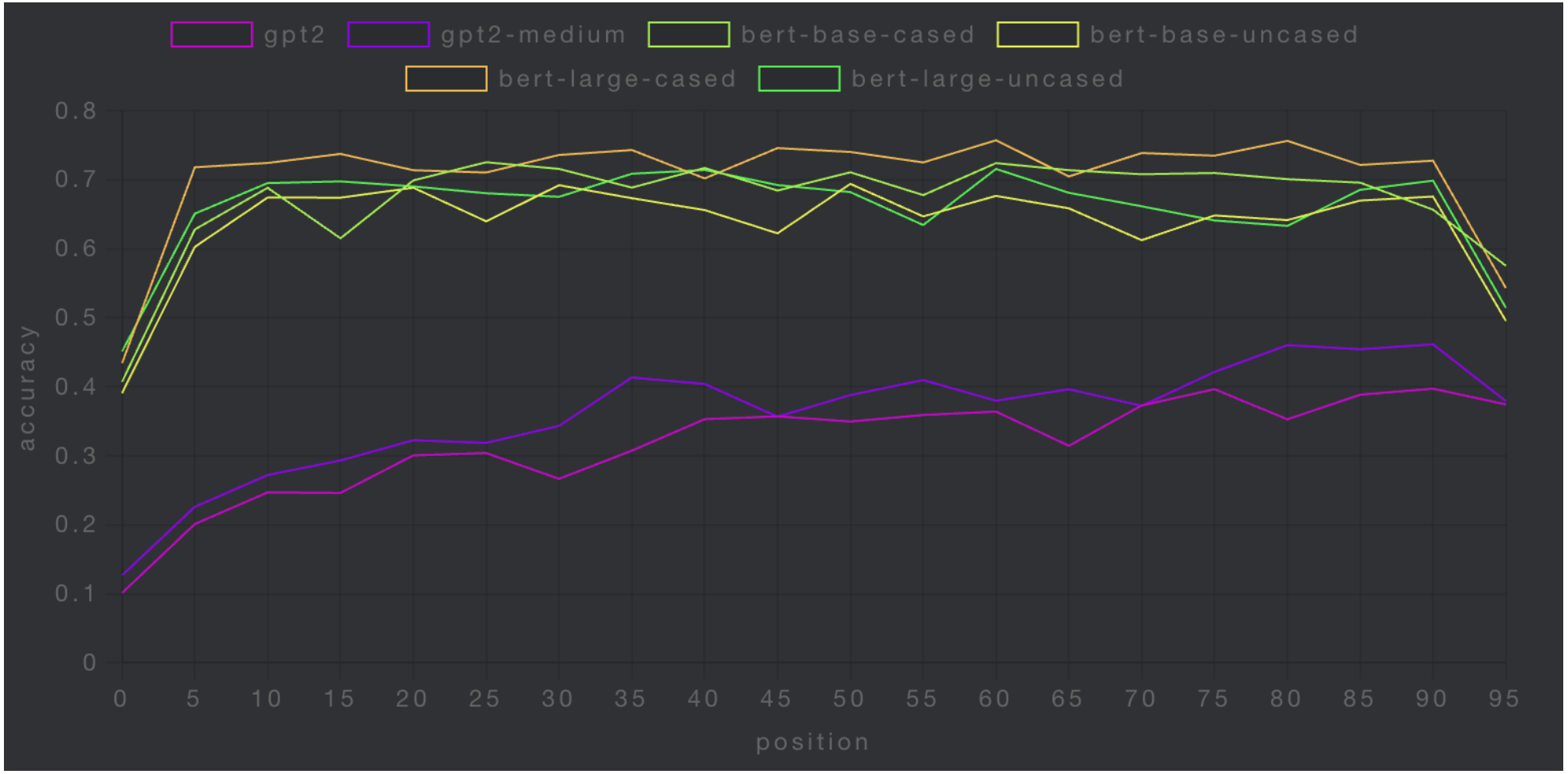
Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

BERT model size

Table 2. Architecture hyperparameters for the 4 model sizes.

However, GPT-2, even with much larger model, cannot compete with BERT and its variant

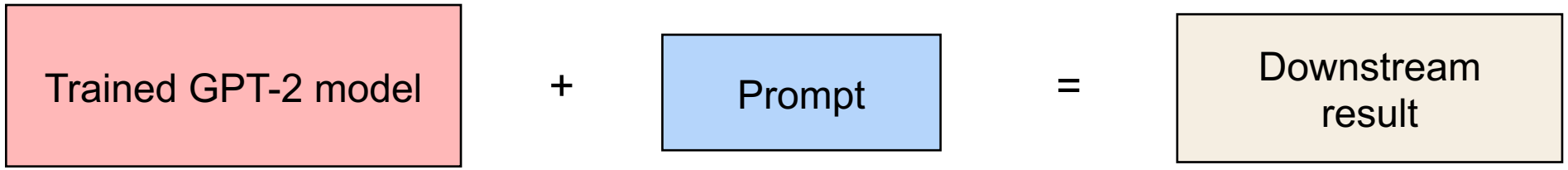
GPT-2 vs BERT



[Figure is from lukesalamone.github.io/posts/bert-vs-gpt2/]

However, GPT-2 is a zero-short learner

No need of any downstream dataset. No need to fine-tune. **Prompt** is enough!



English reference

This re-release, titled The Next Day Extra, was presented in the form of three disks: the original album, unpublished studio sessions and remixes, plus a DVD containing the four clips that have already been unveiled.

(translate to French)

GPT-2 French translation

Les nouvelles re-releases, tout en premier disc, nécessaire de l'album, un studio session et remixes, plus une DVD de l'écran de quelques clips qui ont été déjà échappés.

In contrast, BERT and its variants do not show similar capabilities

GPT-2 is a zero-short learner

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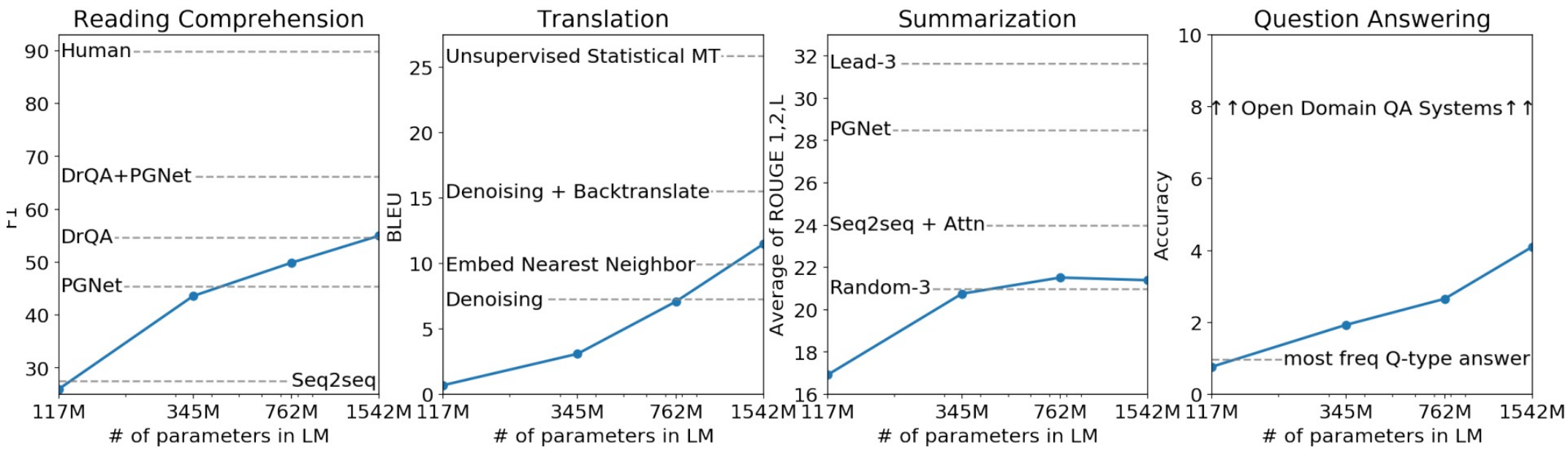
On some tasks, GPT-2 achieves SOTA results

	LAMBADA (PPL)	LAMBADA (ACC)	CBT-CN (ACC)	CBT-NE (ACC)	WikiText2 (PPL)	PTB (PPL)	enwik8 (BPB)	text8 (BPC)	WikiText103 (PPL)	1BW (PPL)
SOTA	99.8	59.23	85.7	82.3	39.14	46.54	0.99	1.08	18.3	**21.8**
117M	**35.13**	45.99	**87.65**	**83.4**	**29.41**	65.85	1.16	1.17	37.50	75.20
345M	**15.60**	55.48	**92.35**	**87.1**	**22.76**	47.33	1.01	**1.06**	26.37	55.72
762M	**10.87**	**60.12**	**93.45**	**88.0**	**19.93**	**40.31**	**0.97**	**1.02**	22.05	44.575
1542M	**8.63**	**63.24**	**93.30**	**89.05**	**18.34**	**35.76**	**0.93**	**0.98**	**17.48**	42.16

Zero-shot results on many datasets. No training or fine-tuning was performed for any of these results.

GPT-2 is still far away from SOTA in some tasks



But it shows an important trend: **Larger Model, Better Performance!**

GPT-3

The zero-shot learning capability in GPT-2 model is quite novel!

In academia, the influence of one work can be determined by the formula

$$\text{Influence} = \text{Novelty} \times \text{Effectiveness}$$

GPT-2 is novel, but not very effective. GPT-3 comes up to show strong effectiveness

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Language Models are Few-Shot Learners

Tom B. Brown* **Benjamin Mann*** **Nick Ryder*** **Melanie Subbiah***

Jared Kaplan† **Prafulla Dhariwal** **Arvind Neelakantan** **Pranav Shyam** **Girish Sastry**

Amanda Askell **Sandhini Agarwal** **Ariel Herbert-Voss** **Gretchen Krueger** **Tom Henighan**

Rewon Child **Aditya Ramesh** **Daniel M. Ziegler** **Jeffrey Wu** **Clemens Winter**

Christopher Hesse **Mark Chen** **Eric Sigler** **Mateusz Litwin** **Scott Gray**

Benjamin Chess **Jack Clark** **Christopher Berner**

Sam McCandlish **Alec Radford** **Ilya Sutskever** **Dario Amodei**

OpenAI

GPT-3

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GPT-3 gets extremely large. GPT-2 has 1.5B parameters, while GPT-3 has 175B parameters

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}

GPT-3

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GPT-2 uses zero-shots, while GPT-3 uses few-shots

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
```

GPT-3

GPT-2 uses zero-shots but GPT-3 uses few-shots

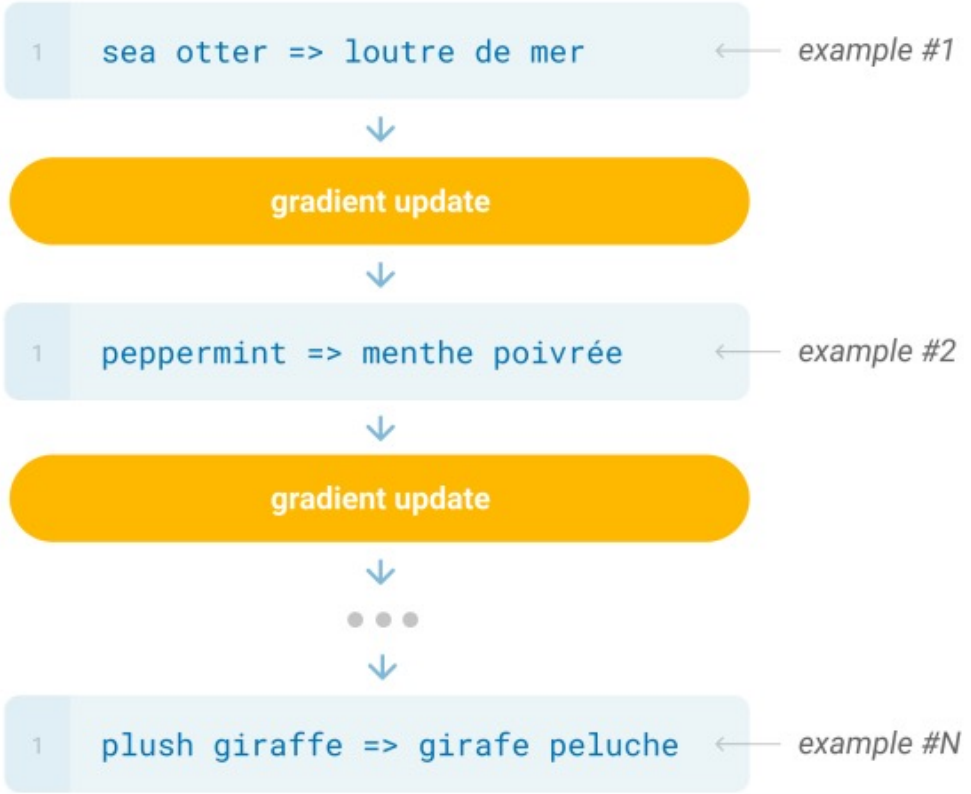
Few-shot

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

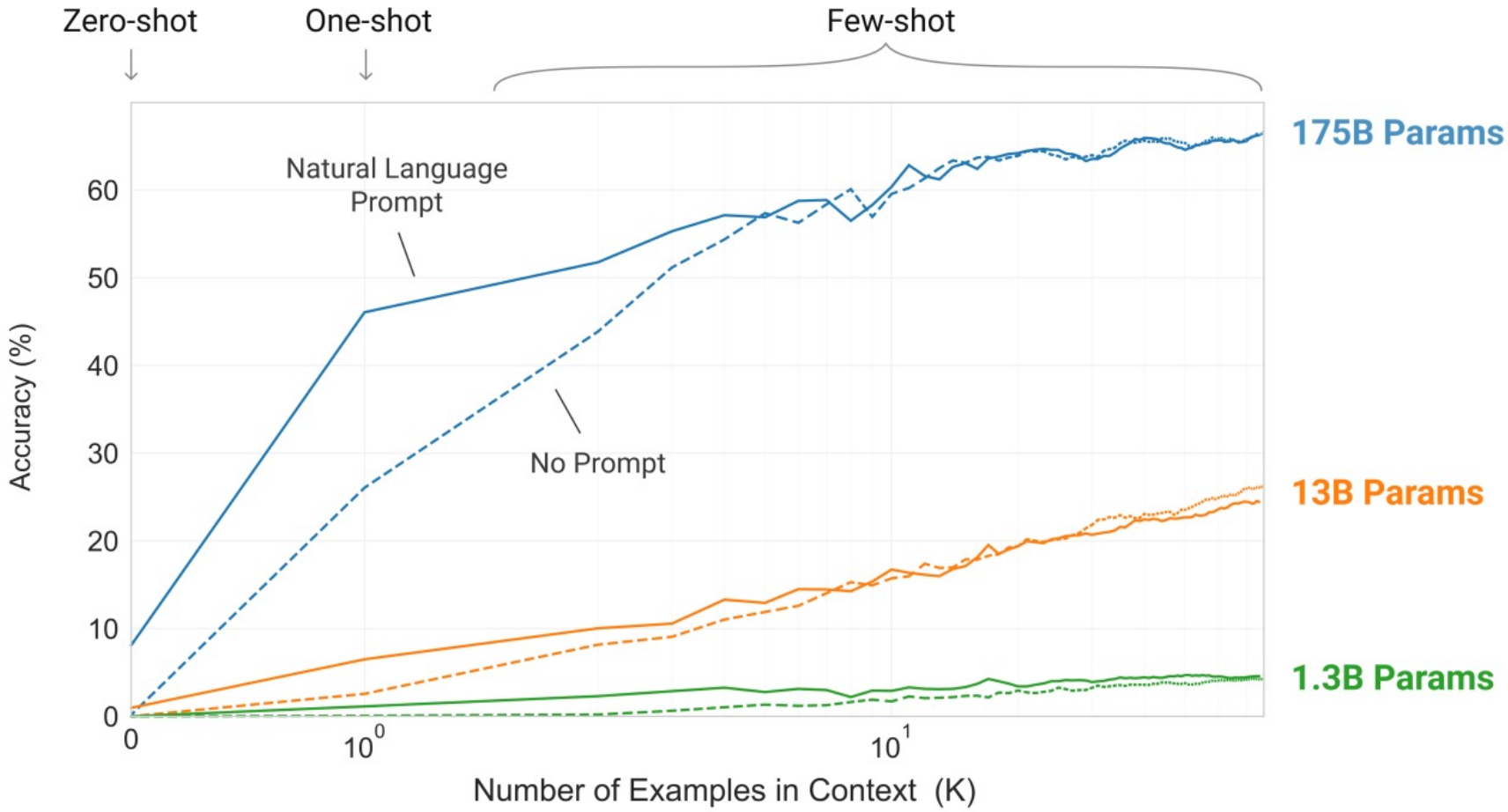
```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

Fine-tuning

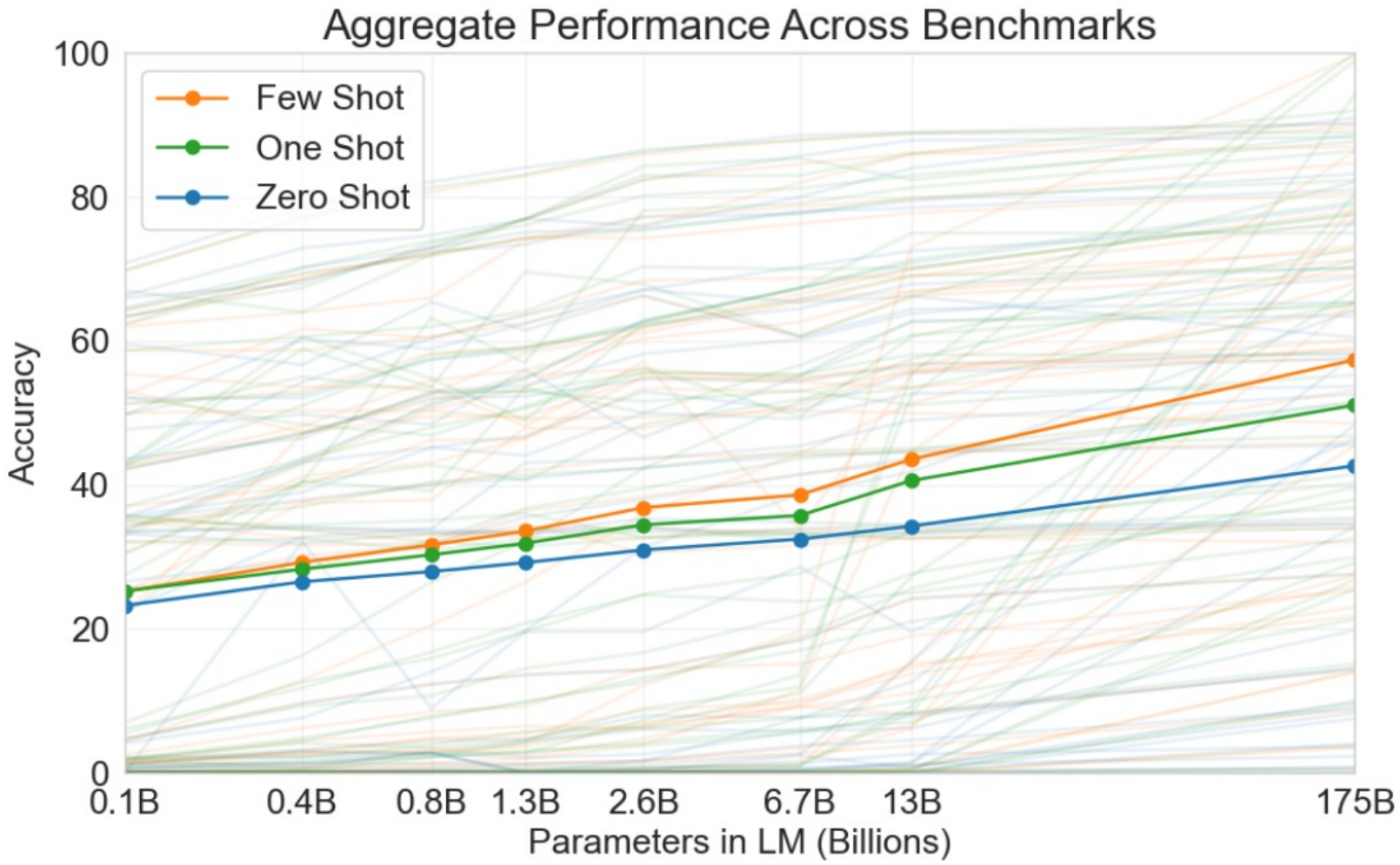
The model is trained via repeated gradient updates using a large corpus of example tasks.



Large model and few-shots are very useful

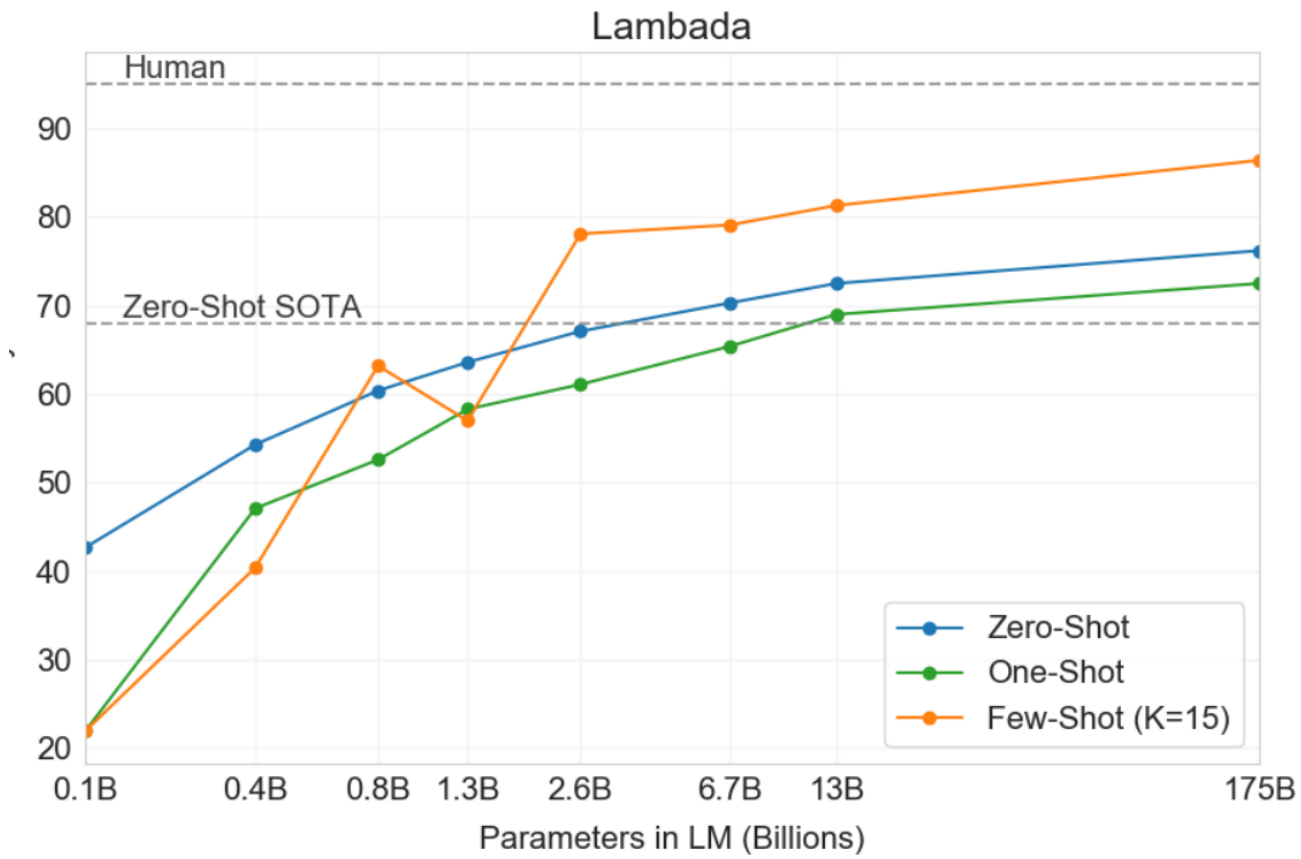


Large model and few-shots are very useful

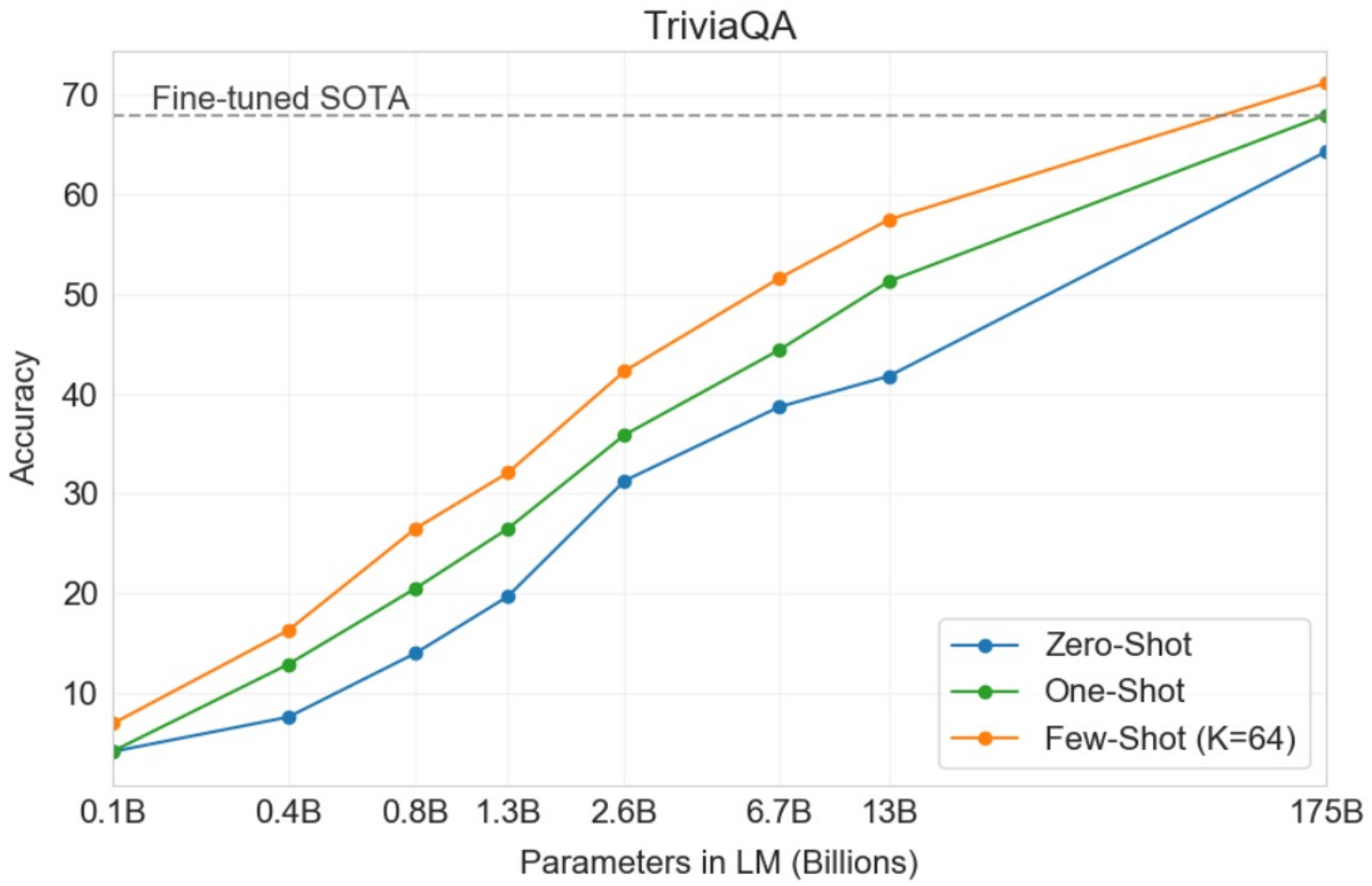


GPT-3 shows strong performance

Setting	LAMBADA (acc)	LAMBADA (ppl)
SOTA	68.0[a]	8.63[b]
GPT-3 Zero-Shot	**76.2**	**3.00**
GPT-3 One-Shot	**72.5**	**3.35**
GPT-3 Few-Shot	**86.4**	**1.92**



GPT-3 shows strong performance

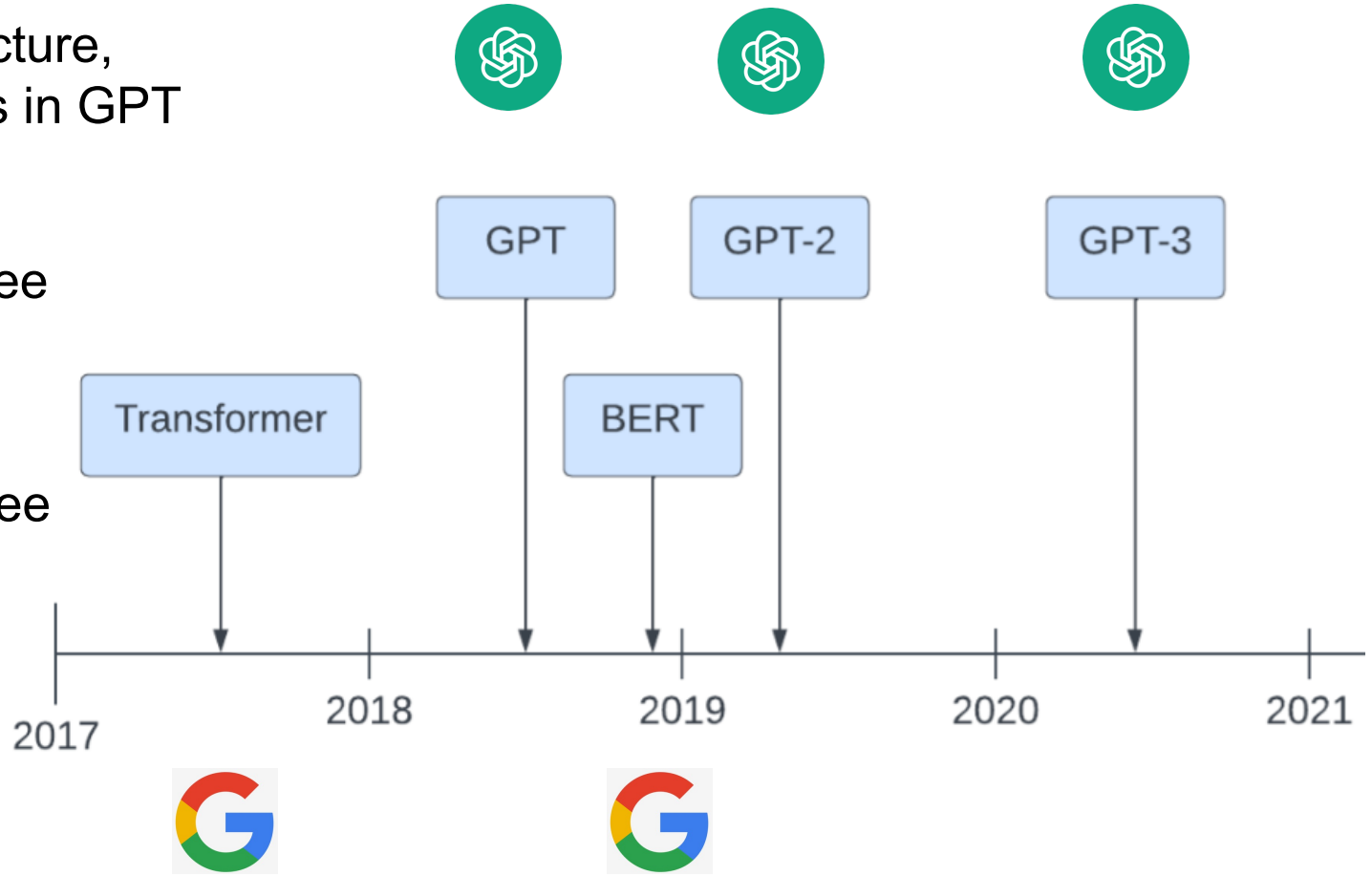


Google v.s. OpenAI

By insisting on decoder-only architecture, OpenAI achieves significant success in GPT

Who will be the final winner? We'll see

Any Chinese tech company? We'll see



Chinese Company comes!

大模型的发展历史


关键进展
准备期
ChatGPT发布，全球范围内迅速形成大模型共识。
GPT4发布，进一步掀起大模型研发热潮。
国内快速跟进大模型研发。文心一言1.0、通义千问、讯飞星火、360智脑、ChatGLM等首批模型相继发布。
跃进期
Llama2开源，极大助力全球大模型开发者生态。
GPT-4 Turbo、Gemini等海外大模型发布，继续提升模型性能。
Midjourney发布5.2
Stable Diffusion XL发布
国内闭源大模型快速发展。豆包、混元、商量3.0、盘古3.0、AndesGPT、BlueLM、星火3.0、Kimi Chat等陆续发布。
国内开源生态爆发。Baichuan、Qwen、InternLM、ChatGLM3、Yi-34B等系列模型引领开源热潮。
繁荣期
OpenAI发布Sora，极大拓展了AI在视频领域的想象力。
GPT-4o、Claude3.5、Gemini1.5、Llama3发布，海外进入“一超多强”的竞争格局。
国内多模态领域进展迅速，在部分领域领先海外。视频生成模型可灵AI、海螺视频、Vidu、PixVerse等模型陆续发布，并在海外取得较大应用进展。
国内通用模型持续提升。Qwen2.5、文心4.0、GLM4、商量5.5等通用模型陆续更新。
深化期
OpenAI发布o1，强化学习新范式，实现推理等复杂能力上的重大突破。
Claude3.5-Sonnet发布，在代码和Agent能力上掀起效率革命。
ChatGPT上线实时视频能力，深入语音视觉实时多模态应用场景。
国内推理模型迅速跟进。DeepSeek-R1、QwQ-32B-Preview、Kimi-k1.5、GLM-Zero、Skywork-o1、Step R-mini、讯飞星火X1等模型密集发布。
国内模型性能持续提升。DeepSeek-V3、Qwen2.5、豆包-Pro、混元-Turbo与GLM-4-Plus等系列模型综合能力上持续提升。
2022.12
2023.06
2023.12
2024.06
2025.01
时间

DeepSeek大模型

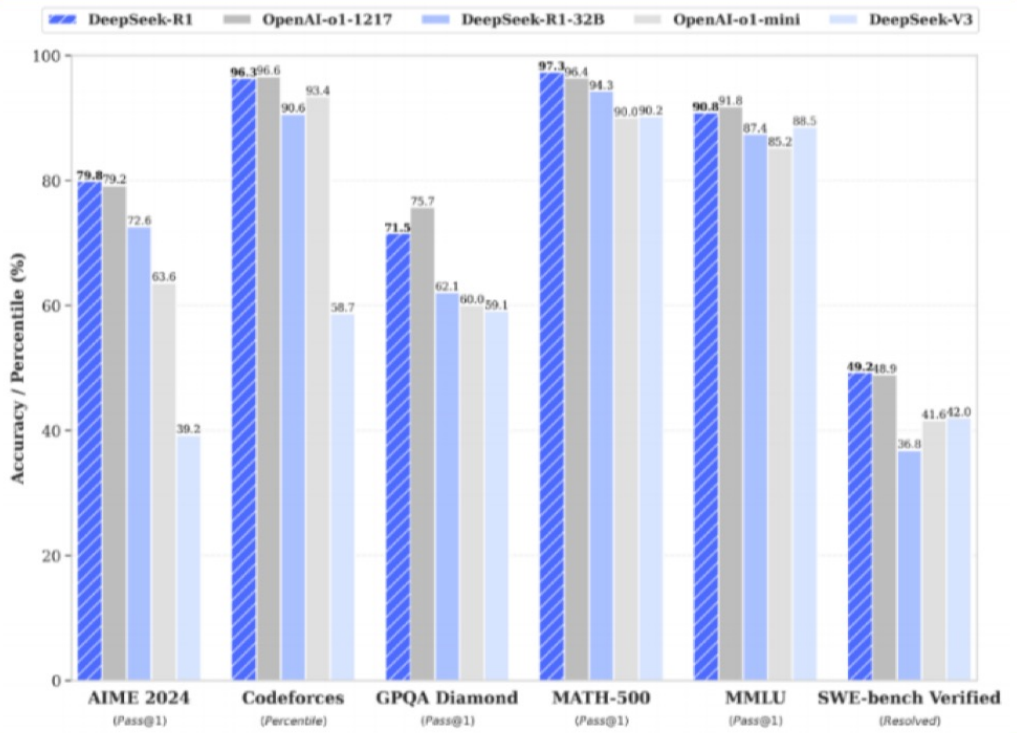
北京大学 PEKING UNIVERSITY

	DeepSeek V3	DeepSeek R1
模型定位	大语言基座模型，适合日常对话、内容生成	推理模型。侧重于**复杂逻辑能力**，擅长数学、编程和自然语言推理任务，适合高难度问题求解和专业领域应用
应用场景	适合广泛通用任务，如对话、内容生成、翻译	适合需要高精度推理和逻辑分析的专业任务，如数学竞赛、编程问题和科学研究

DeepSeek爆火的原因

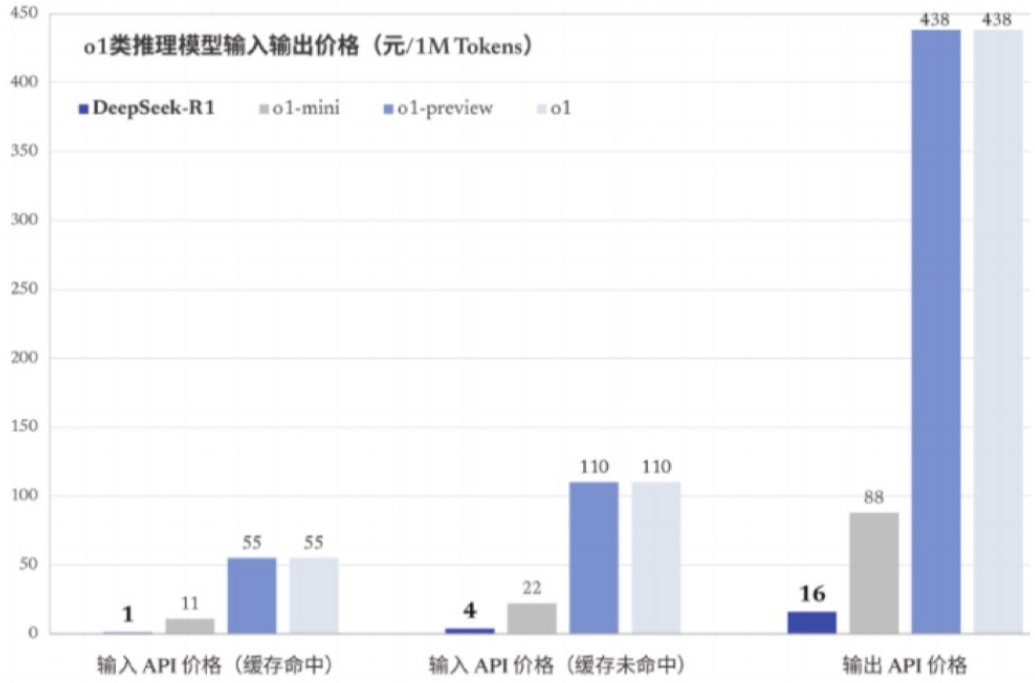
北京大学 PEKING UNIVERSITY

图2：DeepSeek 性能对齐 OpenAI-o1 正式版



资料来源：DeepSeek 官网，中国银河证券研究院

图3：推理成本低至每百万 Token 0.14 美元



资料来源：DeepSeek 官网，中国银河证券研究院

- DeepSeek-R1的推理能力进入了第一梯队，开源，打破OpenAI的技术壁垒
- DeepSeek-V3训练和推理成本低，打破了硅谷传统的“堆算力、拼资本”的大模型发展路径