

Overview of Natural Language Processing

Part II & ACS L390

Lecture 11: Language Models

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Michaelmas 2024/25

The Shifts of NLP Paradigms

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Paradigms in NLP Research *before* 2017

- Rule and Symbolics
 - Focus on how to better design rules.
- Statistic and Machine Learning
 - Focus on how to design model architectures, e.g., RNN vs Transformer.

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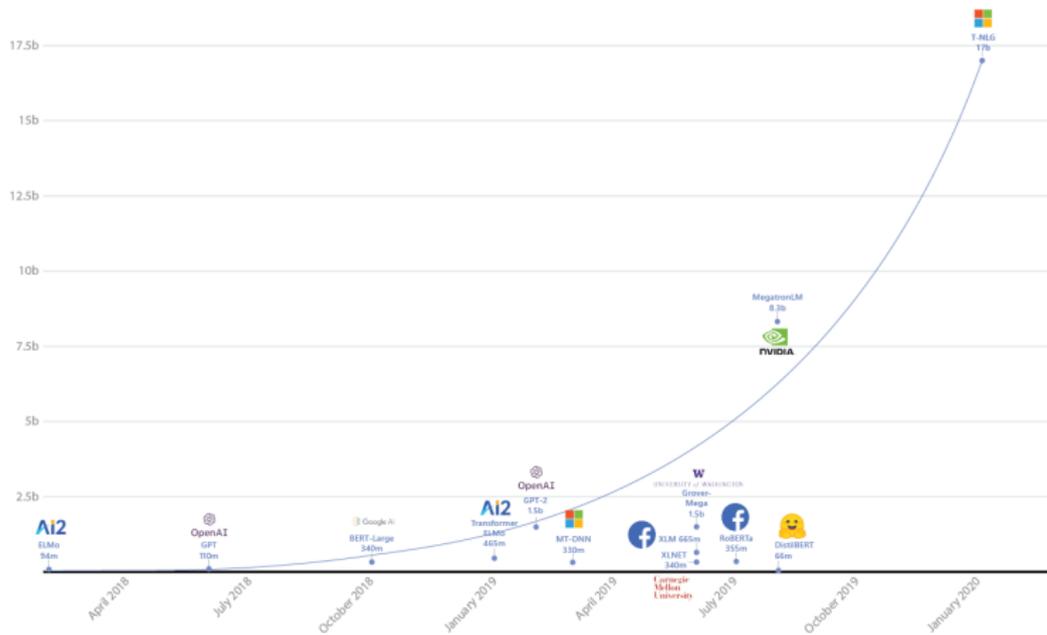
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- Prompting and Large Language Models
 - Focus on solving real-world problems (compared with traditional NLP tasks).



Lecture 11: Language Models

1. Pre-trained based NLP
2. Prompt learning and LLMs

Pre-trained based NLP

Pre-train and Fine-tune

Suppose a model is a human ...

- Pre-training can be the process of a person learning through early education stages — from infancy to high school. They learn foundational knowledge, and common sense.
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Can models learn general knowledge from raw text?

Self-supervised Learning

The main idea of self-supervised learning:

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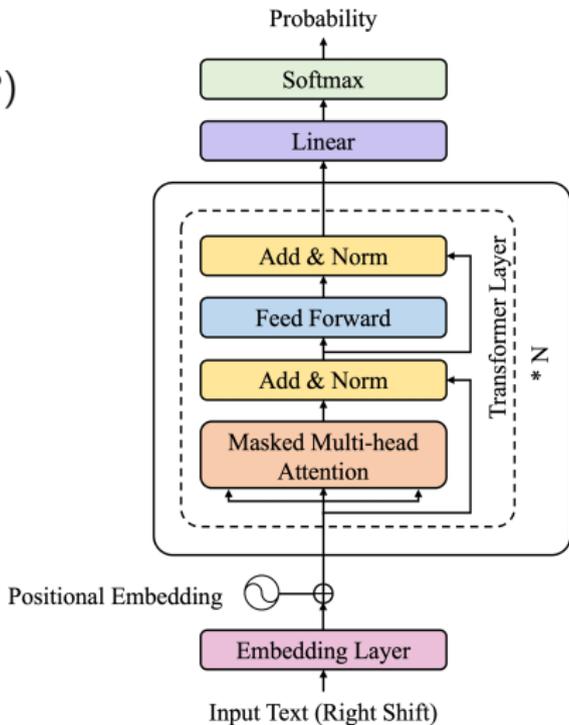
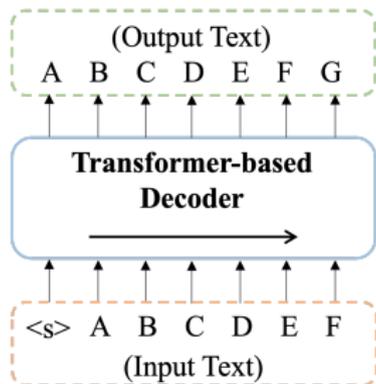
- Use the internal signal of a text as the supervising signal.

	Supervised	Self-supervised
Task	a specific task	re-construct the input
Label	human annotation	generate annotation using the data itself
Resource	limited	large

Decoder-only PLM: GPT

Improving Language Understanding by Generative Pre-Training (GPT)

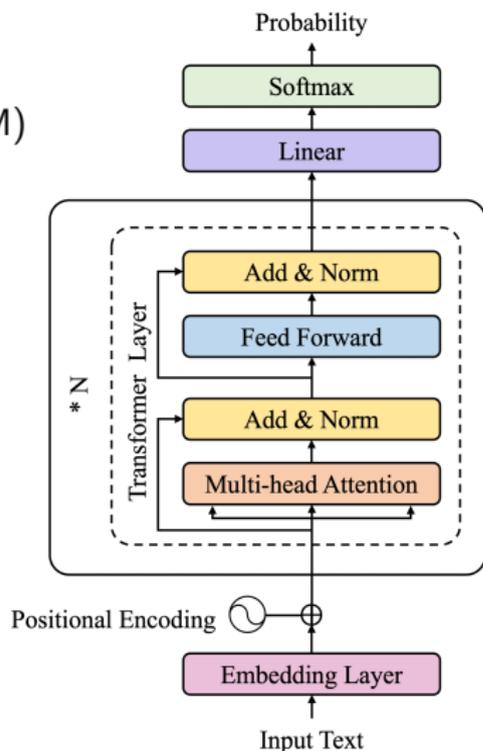
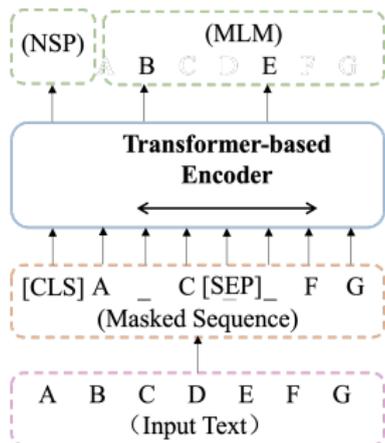
- Architecture: Transformer decoder
- Pre-training Task:
 - Next Token Prediction (NTP)
- Pre-training Data:
 - BookCorpus



Encoder-only PLM: BERT

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

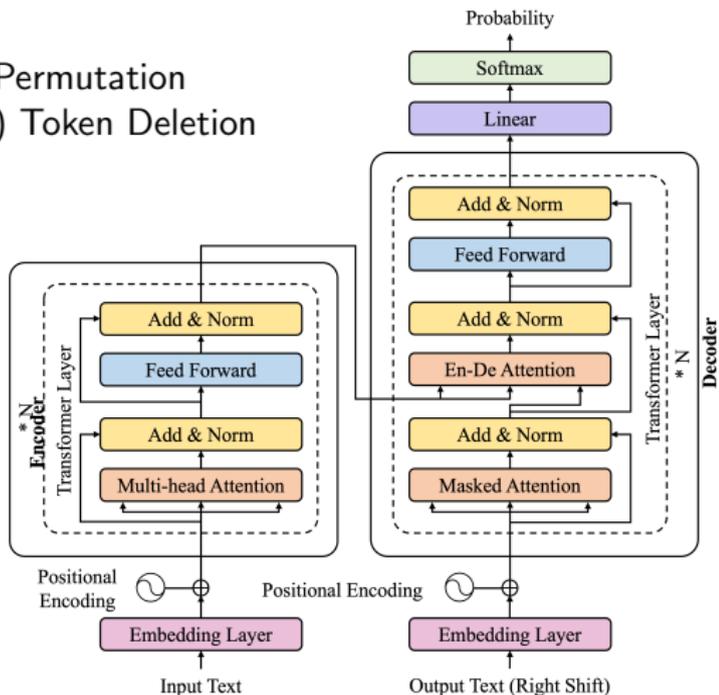
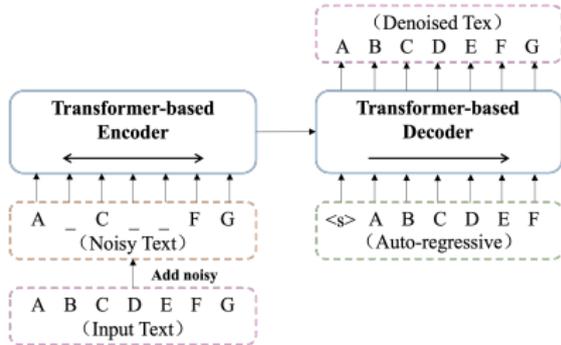
- Architecture: Transformer encoder
- Pre-training Task:
 - Masked Language Modeling (MLM)
 - Next Sentence Prediction (NSP)
- Pre-training Data:
 - BookCorpus and Wikipedia



En-De PLM: BART

BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension

- Architecture: Transformer encoder-decoder
- Pre-training Task:
 - (1) Masking (2) Sentence Permutation
 - (3) Document Rotation (4) Token Deletion
 - (5) Text Infilling
- Pre-training Data:
 - BookCorpus, Wikipedia
 - Webtext, and stories



Adapting PLMs to Downstream Tasks

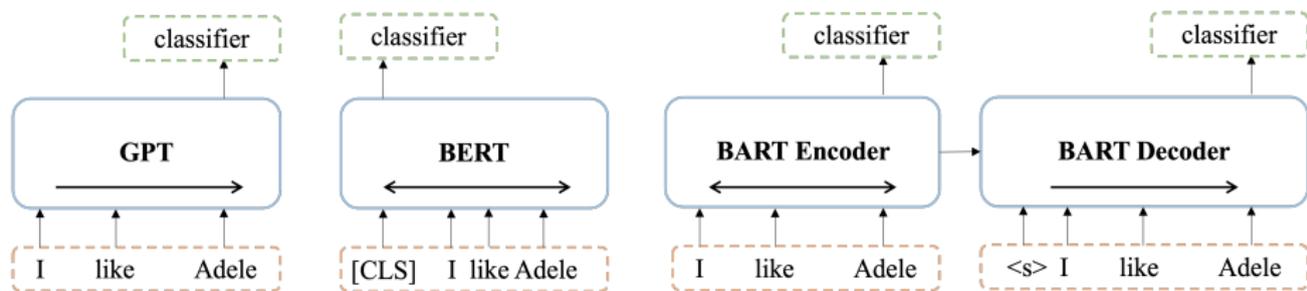
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Full Fine-tuning

- Update all parameters of a PLM on downstream tasks.
- Case 1: Sentiment Analysis

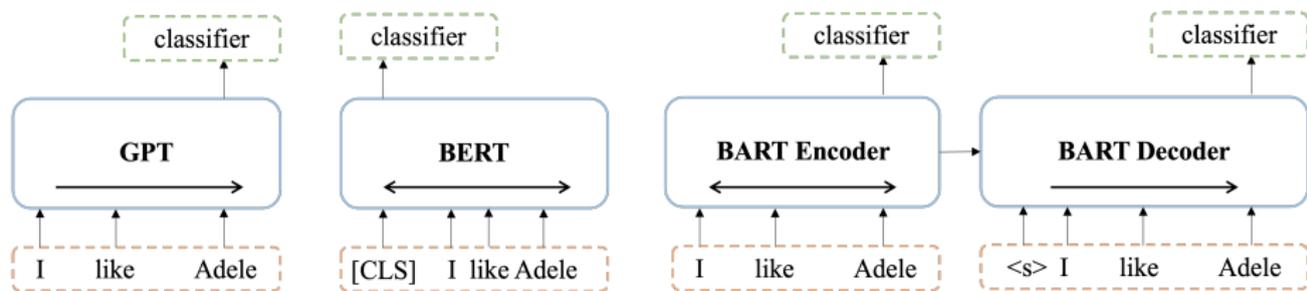


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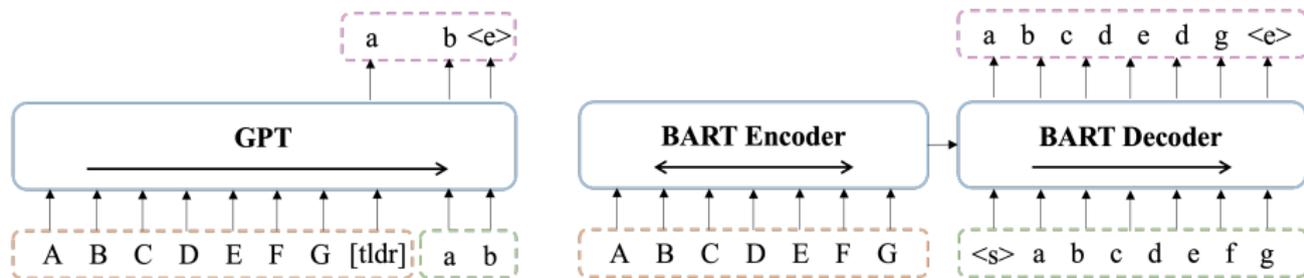
Trick: Continual pre-training (Reading).

Adapting PLMs to Downstream Tasks

After pre-training on large raw data, we fine-tune the PLM to a specific task.

Full Fine-tuning

- Update all parameters of a PLM on downstream tasks.
- Case 2: Summarisation

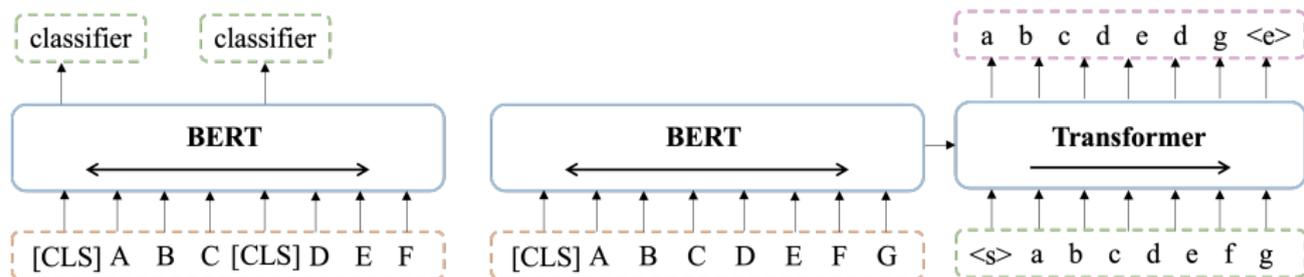


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Reading: Text Summarization with Pretrained Encoders

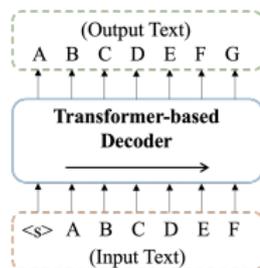
Adapting PLMs to Downstream Tasks

It is empirically considered that the Encoder models are better at NLU tasks, while Decoder and En-De models are better at NLG.

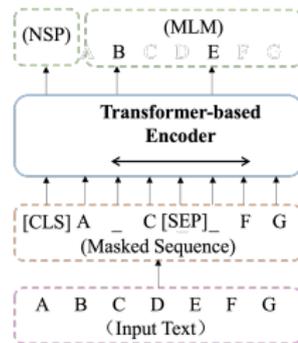
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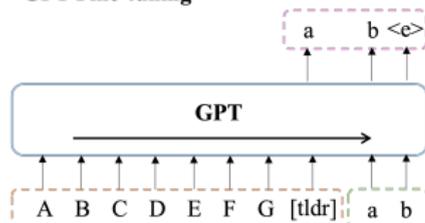
GPT Pre-training



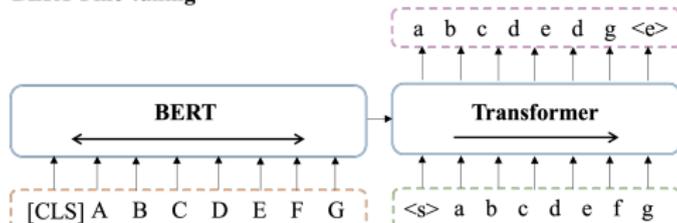
BERT Pre-training



GPT Fine-tuning



BERT Fine-tuning

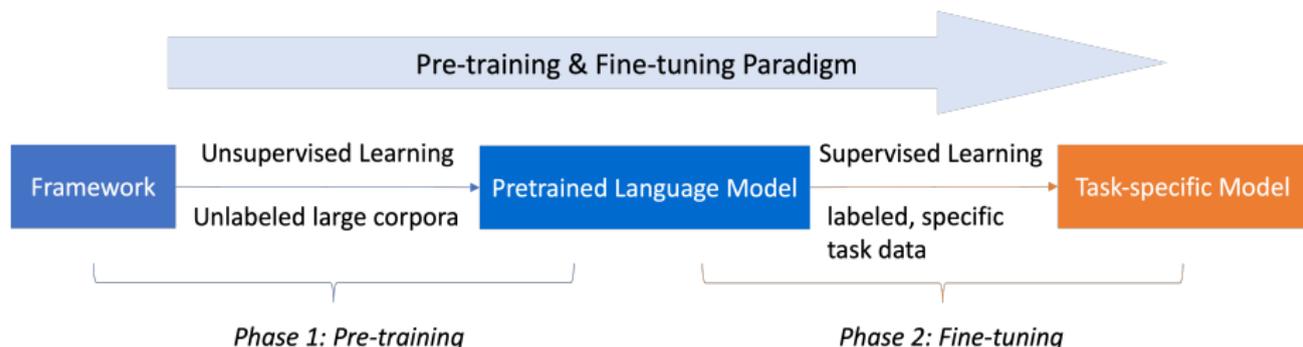


There is a gap between the language modeling task and downstream tasks.

Pre-trained based NLP

Although fine-tuning is less costly than pre-training (**data size**), it still cannot meet the increasing demand:

- Need to update all model parameters (still not cheap).
- One fine-tuned model for one specific task.
- Cannot be used for low-resource settings.



Prompt Learning and Large Language Models

Prompt Learning

Main idea of prompt learning

- Adapting a downstream task into a language modeling format.

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Take sentiment analysis (SST2) for example:

- Given a movie review \mathbf{X} as the input, e.g.:
 $\mathbf{X} =$ *“it 's about issues most adults have to face in marriage and i think that 's what i liked about it – the real issues tucked between the silly and crude storyline”*

the task asks a model to generate a binary label (positive or negative).

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the task asks a model to generate a binary label (positive or negative).

- We can define a pattern function for NTP PLM (e.g., GPT):

$$P(\mathbf{X}) = \mathbf{X}. \text{ In summary, this movie is} \quad (1)$$

Prompt Learning

Take sentiment analysis (SST2) for example:

- The input is converted as:

$P(\mathbf{X}) =$ "it 's about issues most adults have to face in marriage and i think that 's what i liked about it – the real issues tucked between the silly and crude storyline. In summary, this movie is"

- Then, we define a verbalizer function:

$$V(\text{"good"}) = \text{pos} \quad (2)$$

$$V(\text{"bad"}) = \text{neg} \quad (3)$$

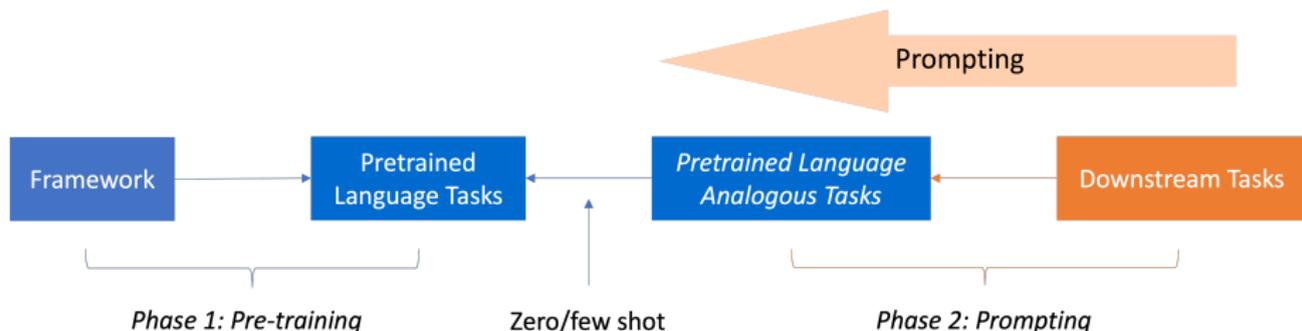
- Finally, we can ask GPT (θ) to directly perform NTP:

$$p(\text{pos}|\mathbf{X}) = \theta(y = \text{"good"}|P(\mathbf{X})) \quad (4)$$

$$p(\text{neg}|\mathbf{X}) = \theta(y = \text{"bad"}|P(\mathbf{X})) \quad (5)$$

Prompt Learning

- Make better use of PLM's pre-training knowledge.
- Zero-shot/few-shot Performance.
- One model for multiple NLP tasks (one PLM with multiple prompts).
- Unify NLP tasks in an NLG manner.



Reading: Language Models are Few-Shot Learners and Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference

Scaling from PLMs to LLMs

Intuitively:

- Model of larger parameters has better performance.
- Model trained on more data has better performance.

Scaling from PLMs to LLMs

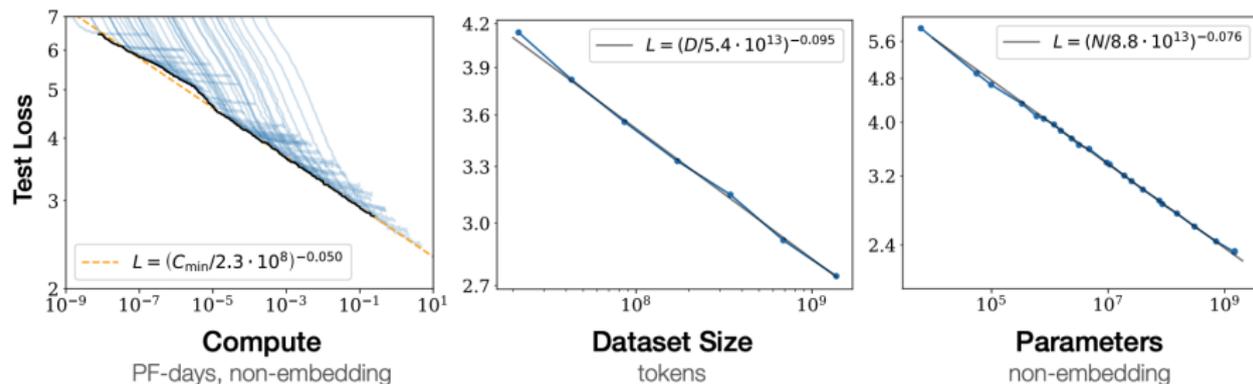
Intuitively:

- Model of larger parameters has better performance.
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But in practical:

- But training large models on small data can be **overfitting**, and training small models on large data can be **underfitting**. How can we find the balance?
- Training budgets are **limited**. How can we make the best use of training time to maximize performance?

Scaling from PLMs to LLMs



Main findings:

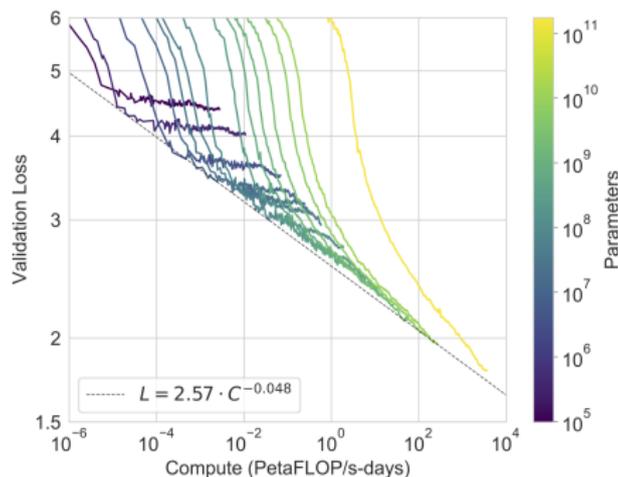
- Model performance L depends the most on amount of compute (C), size of datasets (D) and parameters (N), and each has a power-law relationship with L .
- Efficiency on the ratio of $N^{0.74}/D$.
- When C is fixed, increase large N with small D .

Reading: Scaling Laws for Neural Language Models

Scaling from PLMs to LLMs

From GPT-1 to GPT-3:

	GPT-1	GPT-2	GPT-3
Model	Transformer	Transformer	Transformer
Parameter	120M	1.5B	175B
Data Size	1.3B	10B	300B
Emergent	No	No	ICL

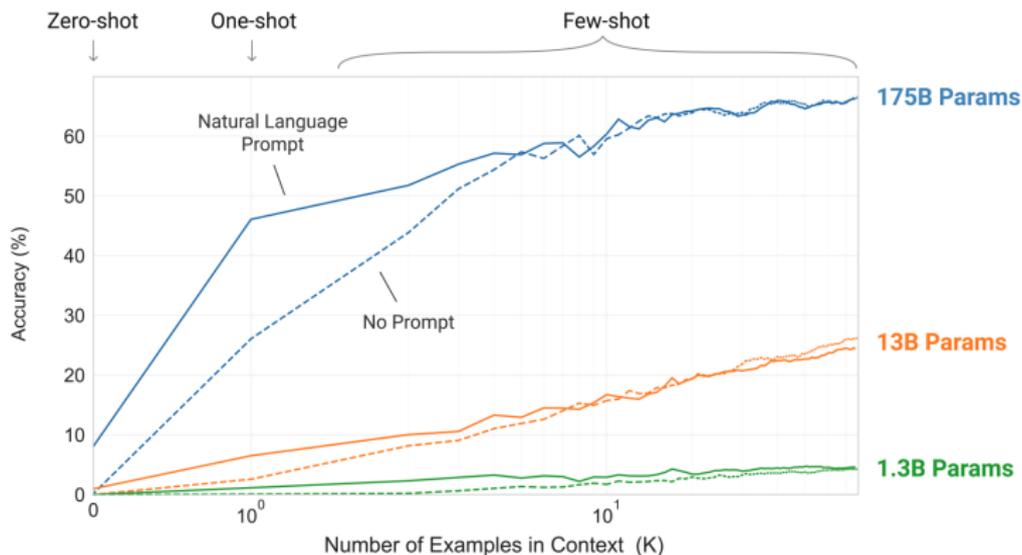


Large Language Models

In-Context Learning (ICL) in GPT-3

The ICL is regarded as an **emergent ability** of GPT-3.

- Different from task prompt (task descriptions) & Can be combined together with prompts.
- New few-shot learning paradigm (pattern recognition at inference time).



Large Language Models

Although GPT-3 is very strong at standard NLP tasks (e.g., text classification), it shows poor performance on **complex tasks**.

Pre-training on Code.

- Code-trained model shows better performance on other tasks (in particular the mathematical and logical reasoning tasks). Why?
- Many assume that *Step-by-step* reasoning (Chain-of-Thoughts, CoT) is an emergent ability from code training.

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ❌

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. $5 + 6 = 11$. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had $23 - 20 = 3$. They bought 6 more apples, so they have $3 + 6 = 9$. The answer is 9. ✓

Reading: Evaluating Large Language Models Trained on Code and Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

Large Language Models

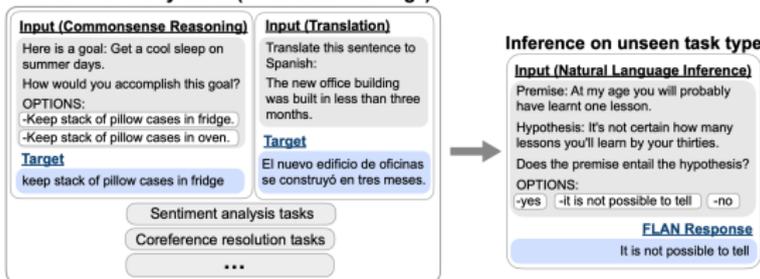
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- Standard prompting on GPT-3.
 - GPT-3 may not understand the prompt well.
 - GPT-3 cannot perform complex task.

Tuning with Instructions.

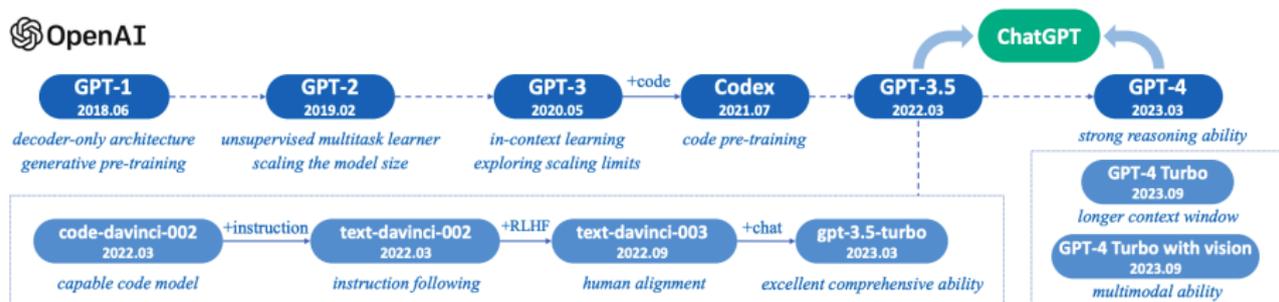
- Explicit describe the goal of tasks in natural language:
 - *“Is the sentiment of this movie review positive or negative?”*
 - *“Translate ‘how are you’ into Chinese.”*

Finetune on many tasks (“instruction-tuning”)



Reading: Finetuned Language Models Are Zero-Shot Learners

Large Language Models



More interesting topics

- Multi-modal LLMs
- LLMs as Agents (with Tools)
- Retrieval-Augmented Generation
- Hallucination in LLMs
- etc

Reading

- Chapter 3: *N*-gram Language Models. D Jurafsky and J Martin.
Speech and Language Processing
Other reading papers are embedded with hyperlinks in the previous slides of this lecture.