Deep Learning for Vision & Language

Natural Language Processing I: Transformers III

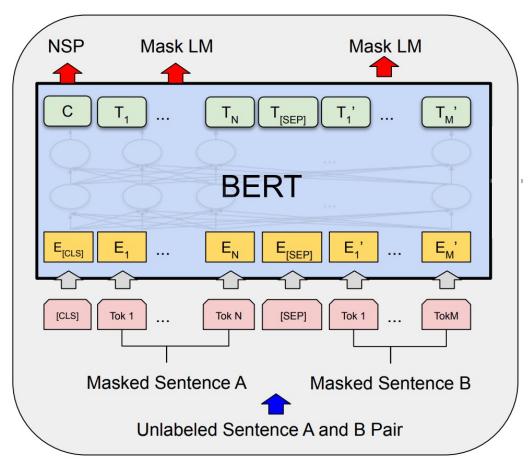


The BERT Encoder Model (October, 2018)

Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding . https://arxiv.org/abs/1810.04805

Important things to know

- No decoder
- Train the model to fill-in-the-blank by masking some of the input tokens and trying to recover the full sentence.
- The input is not one sentence but two sentences separated by a [SEP] token.
- Also try to predict whether these two input sentences are consecutive or not.

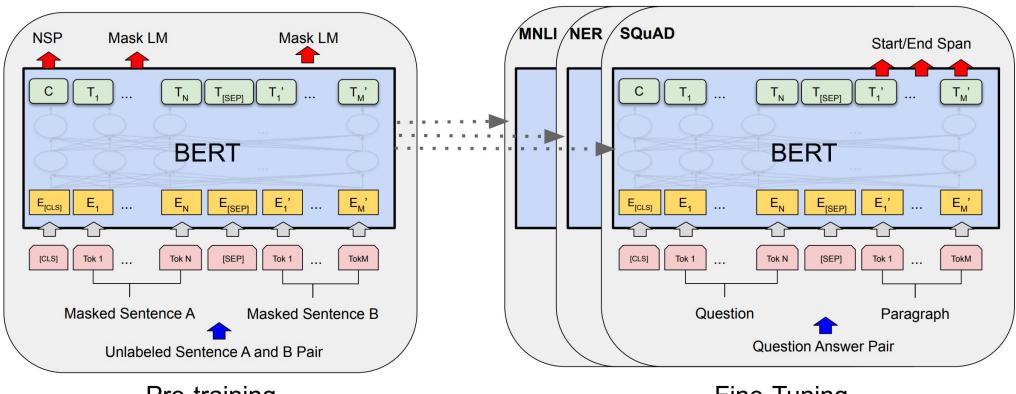


Pre-training

The BERT Encoder Model

Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language

Understanding . https://arxiv.org/abs/1810.04805

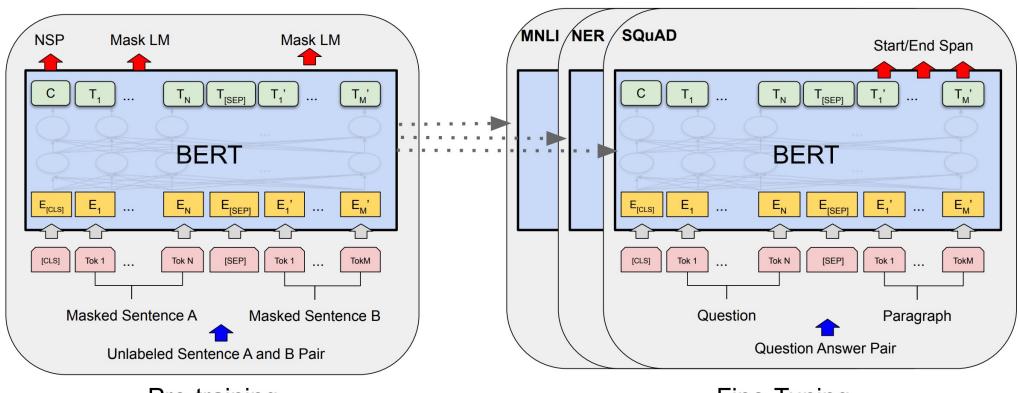


Fine-Tuning

The BERT Encoder-only Model

Devlin et al. BERT: Pre-training of Deep
Bidirectional Transformers for Language

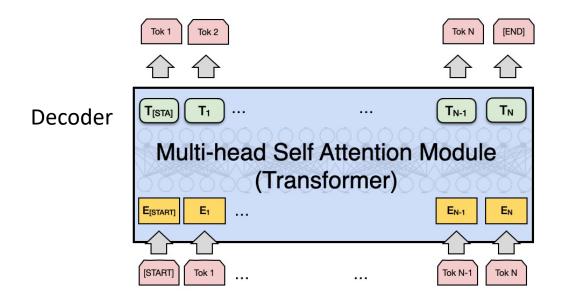
Understanding . https://arxiv.org/abs/1810.04805



Pre-training

Fine-Tuning

The GPT-2, GPT-3 Decoder-only Model

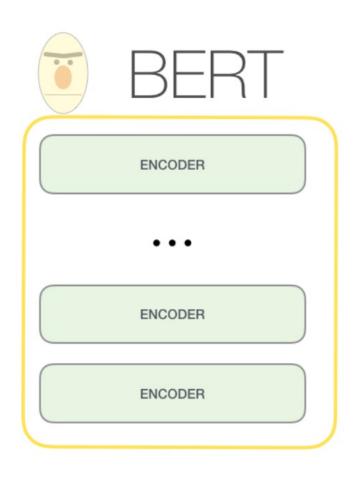


The GPT-2 Model (Feb, 2019)

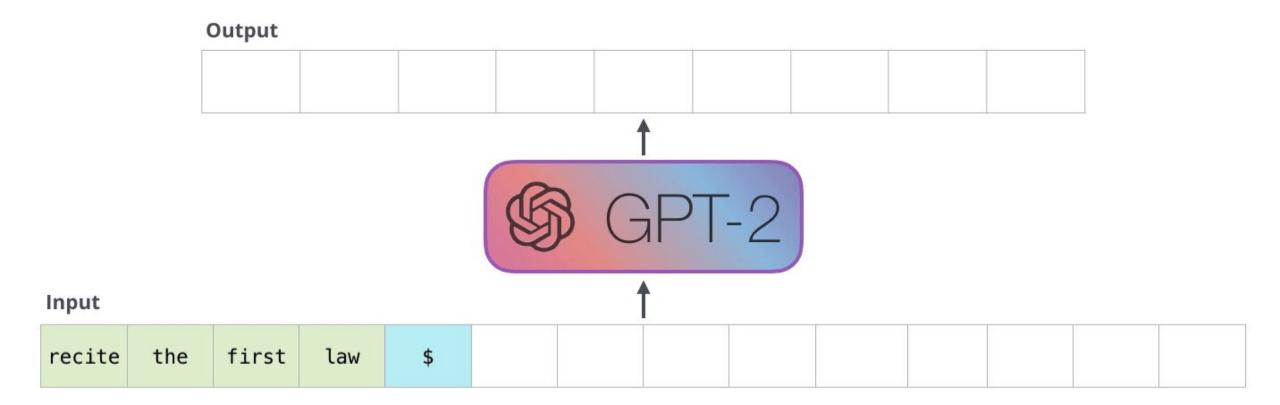
Language Models are Unsupervised Multitask Learners

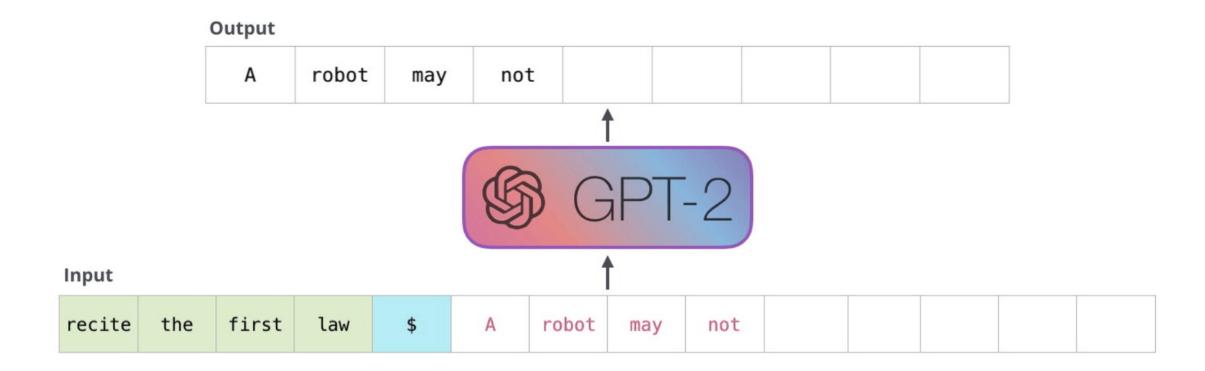
Alec Radford * 1 Jeffrey Wu * 1 Rewon Child 1 David Luan 1 Dario Amodei ** 1 Ilya Sutskever ** 1

https://openai.com/blog/better-language-models/



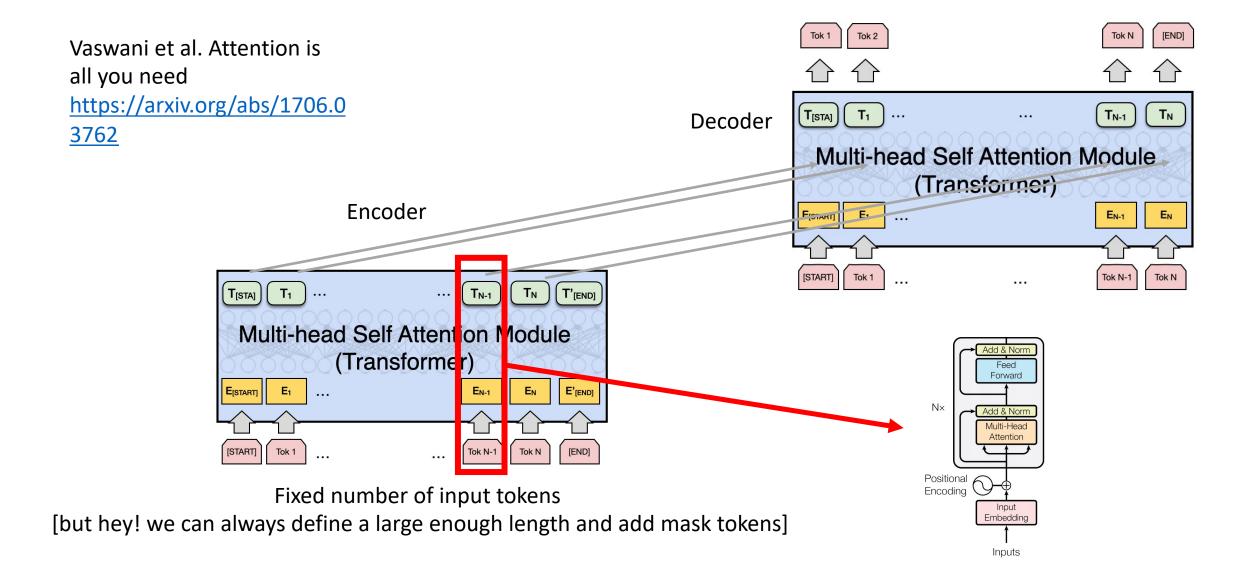




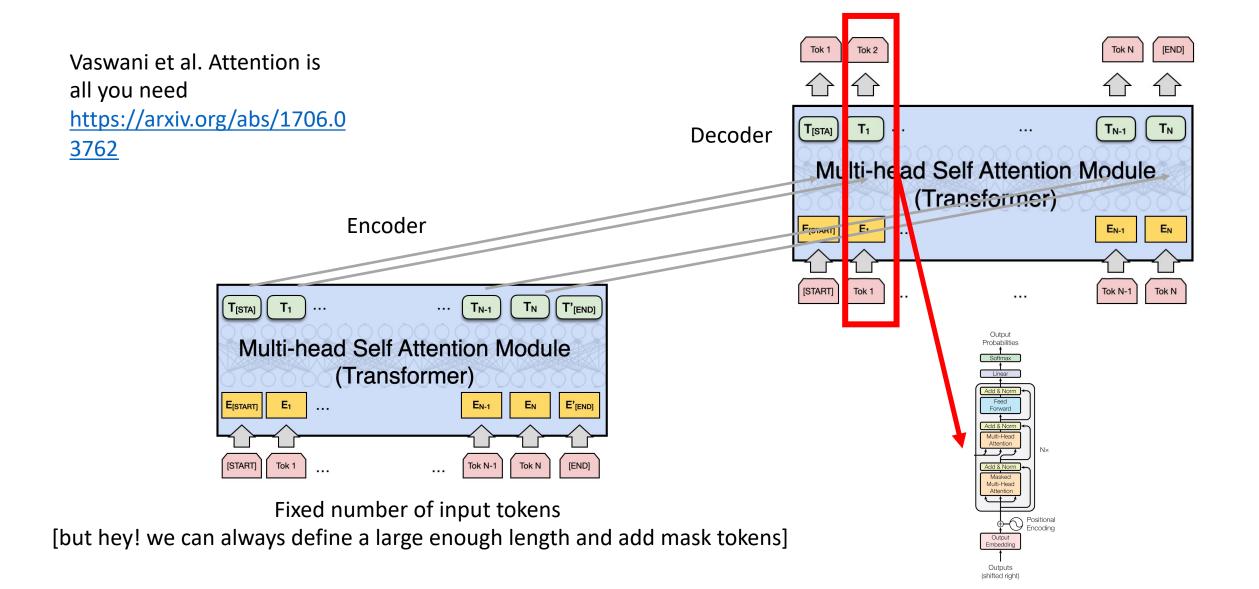


GPT BERT Self-Attention Masked Self-Attention

Attention is All you Need



Attention is All you Need



GPT BERT Self-Attention Masked Self-Attention



GPT-1 vs GPT-2 vs GPT-3

	GPT-1	GPT-2	GPT-3
Parameters	117 Million	1.5 Billion	175 Billion
Decoder Layers	12	48	96
Context Token Size	512	1024	2048
Hidden Layer	768	1600	12288
Batch Size	64	512	3.2M

GPT-3 (July, 2020)

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	3.0×10^{-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}

GPT family keeps growing

- GPT-3.5
- GPT-3.5-turbo
- GPT-4
- GPT-4-turbo

Competitors

- PaLM (Google)
- Gemini family (Gemini Pro) (Google)
- Mistral 7xMoE (Open Source by Mistral.ai)
- Llama-2 70B (Open Source by Meta AI)

Rank 🔺	Model	😭 Arena Elo 🔺	1 95% CI ▲	♦ Votes ▲	Organization A	License
1	GPT-4-0125-preview	1253	+10/-11	3922	OpenAI	Proprietary
2	GPT-4-1106-preview	1252	+5/-6	35385	OpenAI	Proprietary
3	Bard (Gemini Pro)	1224	+9/-9	9081	Google	Proprietary
4	GPT-4-0314	1190	+5/-6	18945	OpenAI	Proprietary
5	GPT-4-0613	1162	+4/-5	29950	OpenAI	Proprietary
6	Mistral Medium	1150	+6/-7	15447	Mistral	Proprietary
7	Claude-1	1149	+6/-6	18189	Anthropic	Proprietary
8	Claude-2.0	1132	+6/-7	12131	Anthropic	Proprietary
9	Gemini Pro (Dev API)	1120	+7/-7	7616	Google	Proprietary
10	Claude-2.1	1119	+5/-6	25494	Anthropic	Proprietary
11	GPT-3.5-Turbo-0613	1118	+5/-5	33617	OpenAI	Proprietary
12	Mixtral-8x7b-Instruct-v0.1	1118	+5/-7	15705	Mistral	Apache 2.0
13	Yi-34B-Chat	1115	+7/-8	6710	01 AI	Yi License
14	Gemini Pro	1114	+7/-8	6969	Google	Proprietary
15	Claude-Instant-1	1109	+4/-7	18689	Anthropic	Proprietary
16	WizardLM-70B-v1.0	1105	+6/-7	8483	Microsoft	Llama 2 Community
17	GPT-3.5-Turbo-0314	1105	+10/-9	5960	OpenAI	Proprietary

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27 <u>GPT-3.5-Turbo-1106</u> 1071 +4/-5 15711 OpenAI Proprietary		
------------------------------------------------------------------	--	--

41	Llama-2-7b-chat	1024	+8/-9	7722	Meta	Llama 2 Community
43	Mistral-7B-Instruct-v0.1	1006	+8/-7	7919	Mistral	Apache 2.0

Prompt Engineering

```
Poor English input: I eated the purple berries.

Good English output: I ate the purple berries.

Poor English input: Thank you for picking me as your designer. I'd appreciate it.

Good English output: Thank you for choosing me as your designer. I appreciate it.

Poor English input: The mentioned changes have done. or I did the alteration that you requested. or I changed things you wanted and did the modifications.

Good English output: The requested changes have been made. or I made the alteration that you requested. or I changed things you wanted and made the modifications.

Poor English input: I'd be more than happy to work with you in another project.

Good English output: I'd be more than happy to work with you on another project.
```

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

Prompt Engineering

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

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

Prompt Engineer

Prompt engineering

文A 12 languages ~

Article Talk

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From Wikipedia, the free encyclopedia

Prompt engineering is a concept in artificial intelligence (AI), particularly natural language processing (NLP). In prompt engineering, the description of the task that the AI is supposed to accomplish is embedded in the input, e.g., as a question, instead of it being implicitly given. Prompt engineering typically works by converting one or more tasks to a prompt-based dataset and training a language model with what has been called "prompt-based learning" or just "prompt learning".[1][2]

History [edit]

The GPT-2 and GPT-3 language models^[3] were important steps in prompt engineering. In 2021, multitask^[jargon] prompt engineering using multiple NLP datasets showed good performance on new tasks.^[4] In a method called chain-of-thought (CoT) prompting, few-shot examples of a task are given to the language model which improves its ability to reason.^[5] CoT prompting can also be a zero-shot learning task by prepending text to the prompt that encourages a chain of thought (e.g. "Let's think step by step"), which may also improve the performance of a language model in multi-step reasoning problems.^[6] The broad accessibility of these tools were driven by the publication of several open-source notebooks and community-led projects for image synthesis.^[7]

A description for handling prompts reported that over 2,000 public prompts for around 170 datasets were available in February 2022.[8]

How would you come up with a solution for this problem?

The kid is throwing rocks at the window



The <subject>kid</subject> is throwing <object>rocks</object> at the <destination>window</destination>

Prompt Engineering

Input: The cat is throwing the ball into the ground

Output: The <subject>cat</subject> is throwing the <object>ball</object> into the

<destination>ground</ground>

Input: The snake is being attacked by the wolf

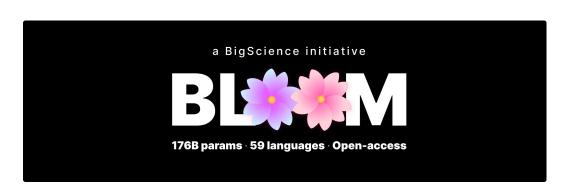
Output: The <object>snake</object> is being attacked by the <actor>wolf</actor>

Input: The kid is throwing rocks at the window

Output:

Prompt Engineering

- Any Large Language Model (LLM) such as GPT-3 can be turned into a general purpose problem solver in this way.
- Obviously, it is not going to work well for every use case.
- Other Large Language Models trained at the scale of GPT-3 that are actually publicly available:
- BLOOM-176B and OPT-175B:



Democratizing access to large-scale language models with OPT-175B

However these are still limited

- Predicting the next word can lead to intelligent behavior such as the one exemplified earlier however this still limited
- What makes some of the new LLMs special? ChatGPT (GPT-3.5, 3.5 Turbo, 4, 4-turbo), FLAN-T5, OPT-IML

Instruction Tuning (e.g. FLAN-T5 by Google)

Language

model

Instruction finetuning

Please answer the following question. What is the boiling point of Nitrogen?

Chain-of-thought finetuning

Answer the following question by reasoning step-by-step.

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

Multi-task instruction finetuning (1.8K tasks)

Inference: generalization to unseen tasks

Q: Can Geoffrey Hinton have a conversation with George Washington?

Give the rationale before answering.

-320.4F

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.

Geoffrey Hinton is a British-Canadian computer scientist born in 1947. George Washington died in 1799. Thus, they could not have had a conversation together. So the answer is "no".

FLAN-T5

Model input (Disambiguation QA)

Q: In the following sentences, explain the antecedent of the pronoun (which thing the pronoun refers to), or state that it is ambiguous.

Sentence: The reporter and the chef will discuss their favorite dishes.

Options:

- (A) They will discuss the reporter's favorite dishes
- (B) They will discuss the chef's favorite dishes
- (C) Ambiguous

A: Let's think step by step.

Before instruction finetuning

The reporter and the chef will discuss their favorite dishes.

The reporter and the chef will discuss the reporter's favorite dishes.

The reporter and the chef will discuss the chef's favorite dishes.

The reporter and the chef will discuss the reporter's and the chef's favorite dishes.



FLAN-T5

Model input (Disambiguation QA)

Q: In the following sentences, explain the antecedent of the pronoun (which thing the pronoun refers to), or state that it is ambiguous.

Sentence: The reporter and the chef will discuss their favorite dishes.

Options:

- (A) They will discuss the reporter's favorite dishes
- (B) They will discuss the chef's favorite dishes
- (C) Ambiguous

A: Let's think step by step.

After instruction finetuning

The reporter and the chef will discuss their favorite dishes does not indicate whose favorite dishes they will discuss. So, the answer is (C).

InstructGPT (ChatGPT)

Step 1

Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3 with supervised learning.



Some people went

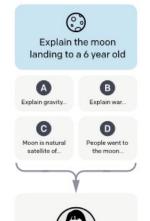
Explain the moon

landing to a 6 year old

Step 2

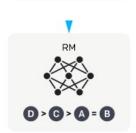
Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



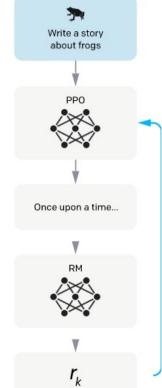
D > G > A = B

Step 3

Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

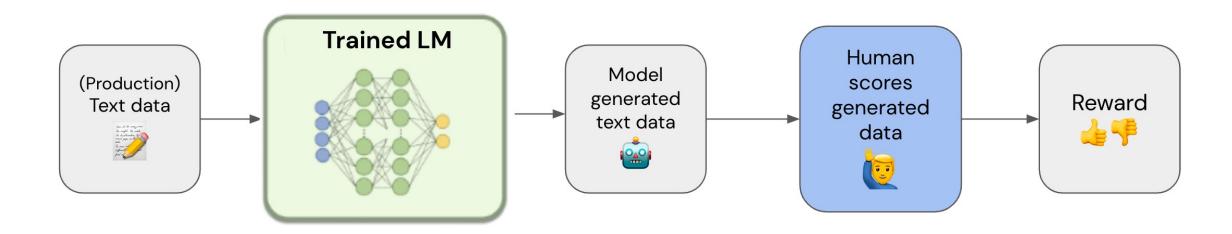
The policy generates an output.



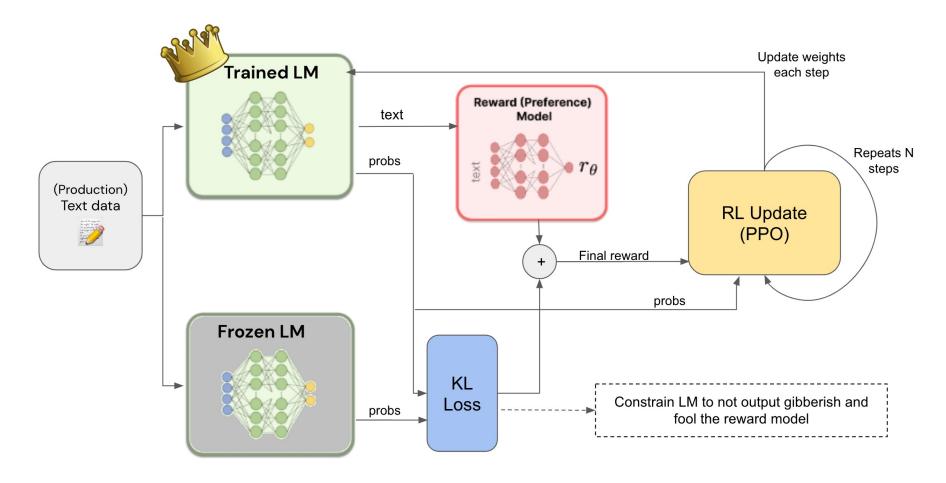
The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

Step by Step: Train a Reward Model that learns from Human Ratings e.g. from 1 to 5



Step by Step: Train the LM to generate text that gets high reward but still produces stuff that makes sense



Recommended Slide Deck

Natural Language Processing with Deep Learning CS224N/Ling284

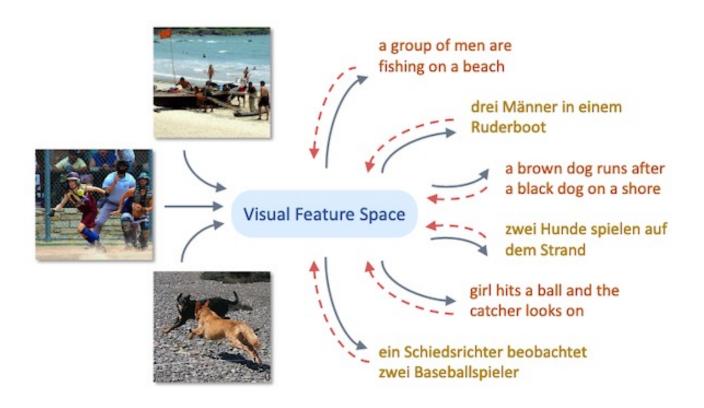


Jesse Mu

Lecture 11: Prompting, Instruction Finetuning, and RLHF

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Next Step: Multimodality



Multimodal Few-Shot Learning with Frozen Language Models

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S. M. Ali Eslami

DeepMind aeslami@deepmind.com

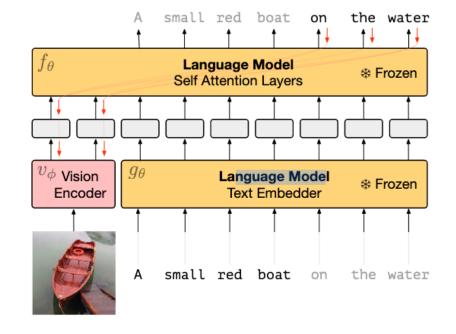
Oriol Vinyals

DeepMind vinyals@deepmind.com

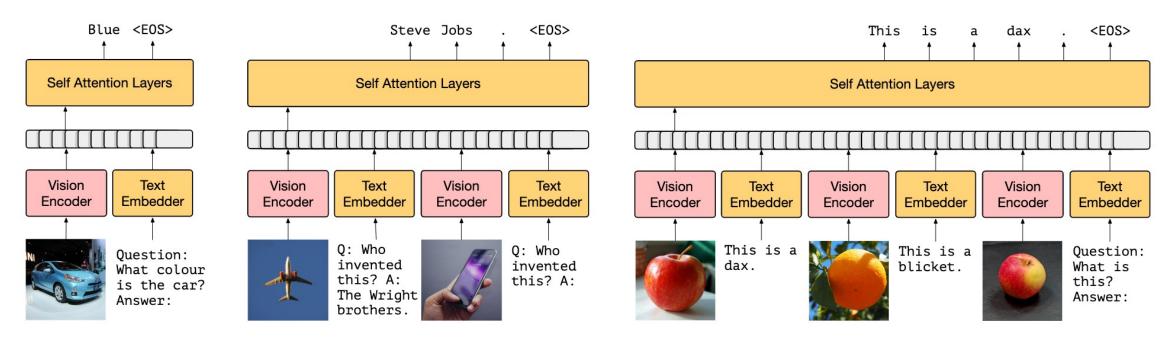
Felix Hill

DeepMind felixhill@deepmind.com

NeurIPS 2021



Training:



(a) 0-shot VQA

(b) 1-shot outside-knowledge VQA

(c) Few-shot image classification

Flamingo

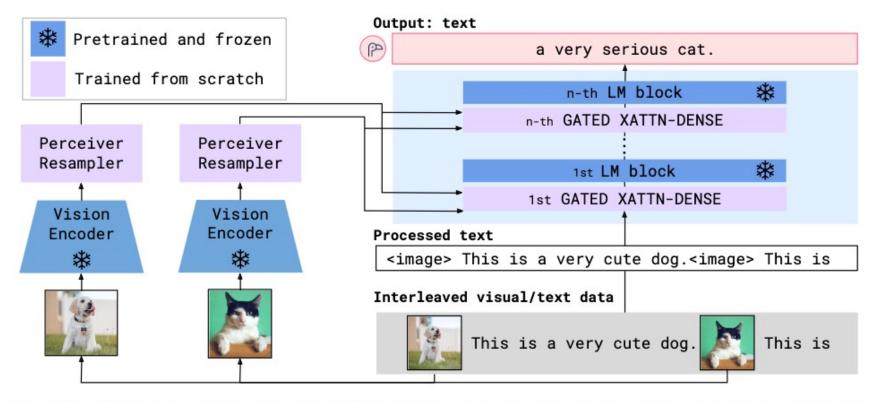
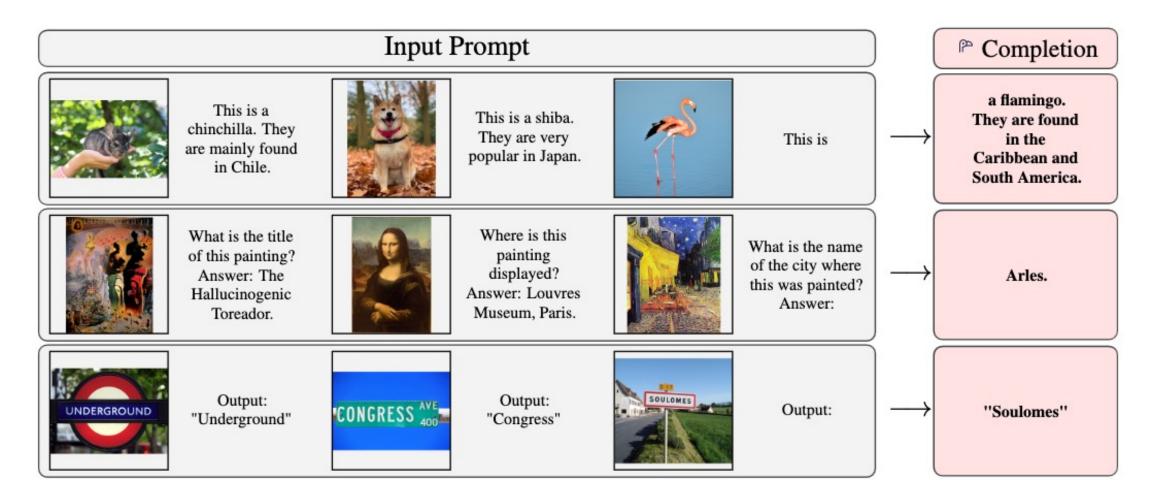
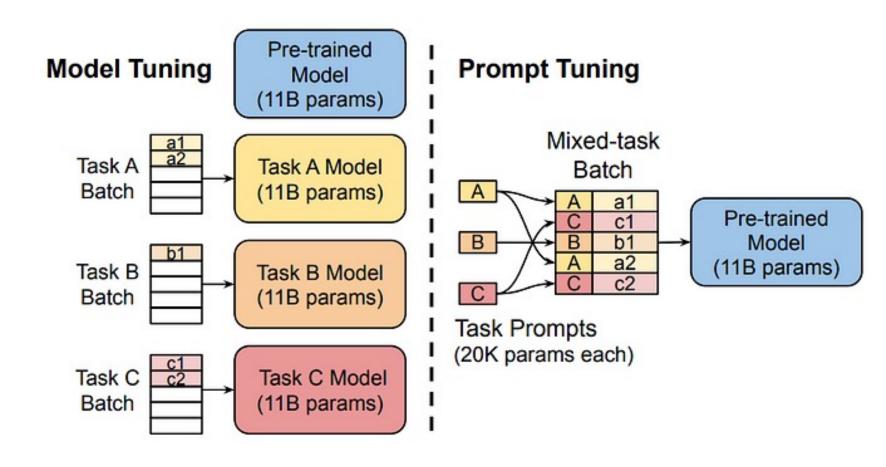


Figure 3: **Flamingo architecture overview.** Flamingo is a family of visual language models (VLMs) that take as input visual data interleaved with text and produce free-form text as output.

Flamingo

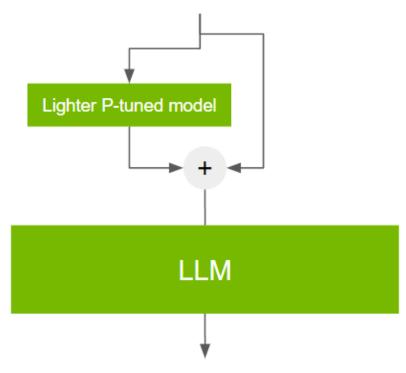


• Prompt Tuning



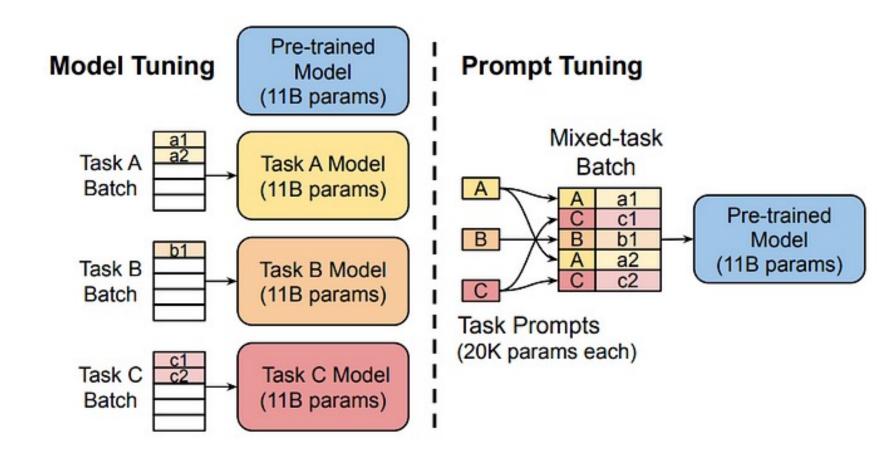
Prompt Tuning

How do I bake a cake?



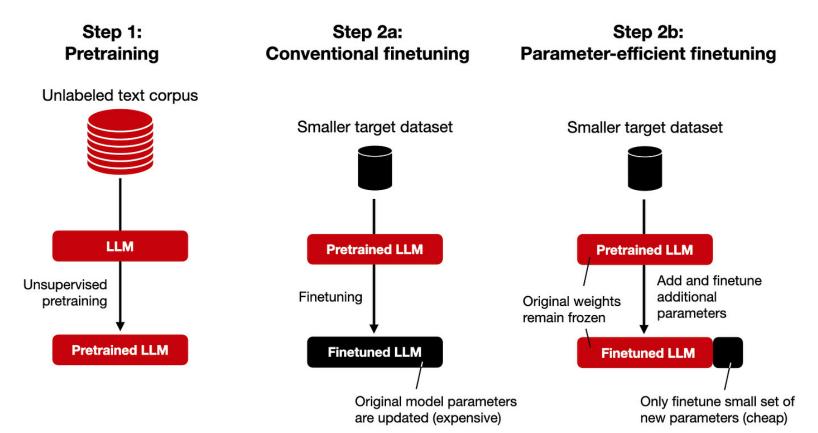
For baking a cake follow this recipe:.....

Prompt Tuning



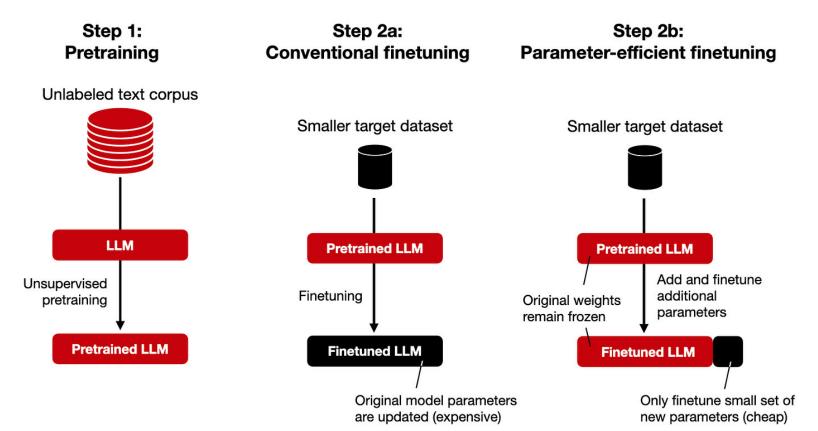
- Prompt Tuning
- Parameter Efficient Finetuning (PEFT)

https://github.com/huggingface/peft

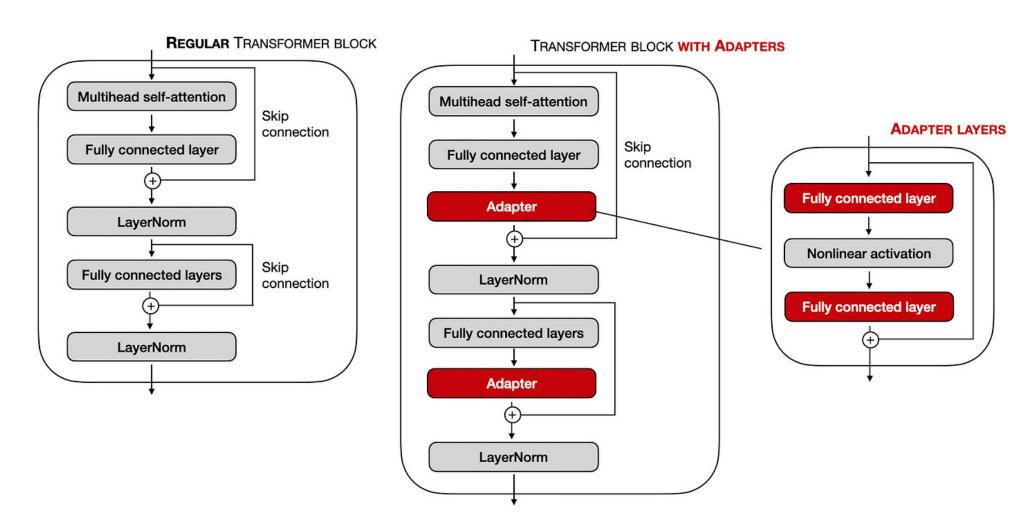


- Prompt Tuning
- Parameter Efficient Finetuning (PEFT)

https://github.com/huggingface/peft



LLM Efficient Model Finetuning: Adapters

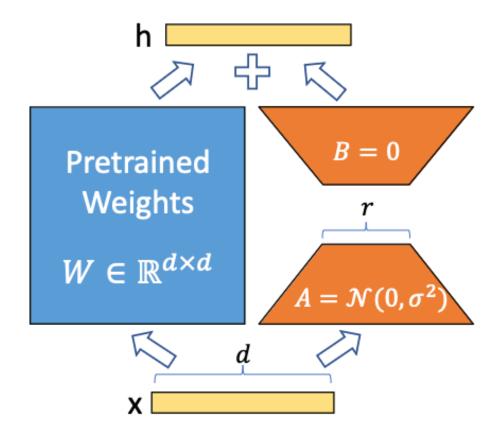


https://magazine.sebastianraschka.com/p/finetuning-llms-with-adapters

https://github.com/huggingface/peft

LoRA: Low Rank Adaptation

$$h = W_0 x + \Delta W x = W_0 x + BAx$$



LoRA: Low-Rank Adaptation of Large Language Models

Questions?