GPT3 & Beyond:

Few-Shot Learning, Prompt Learning

(some slides by Atishya Jain)

Elements and images borrowed from Raffel et al., 2019
https://medium.com/fair-bytes/how-biased-is-gpt-3-5b2b91f1177

I got A from GLUE leadeboard
Transformer
GPT-1
BERT

Transformer
GPT-1
BERT
Sorry sister.
I got A+ there

I can write a story, sister
Transformer
GPT-2
BERT

Transformer
GPT-2
BERT
Now people just need fine tuning with me

Fine tuning is also expansive. I would try few shot learning!
Transformer
GPT-3
BERT

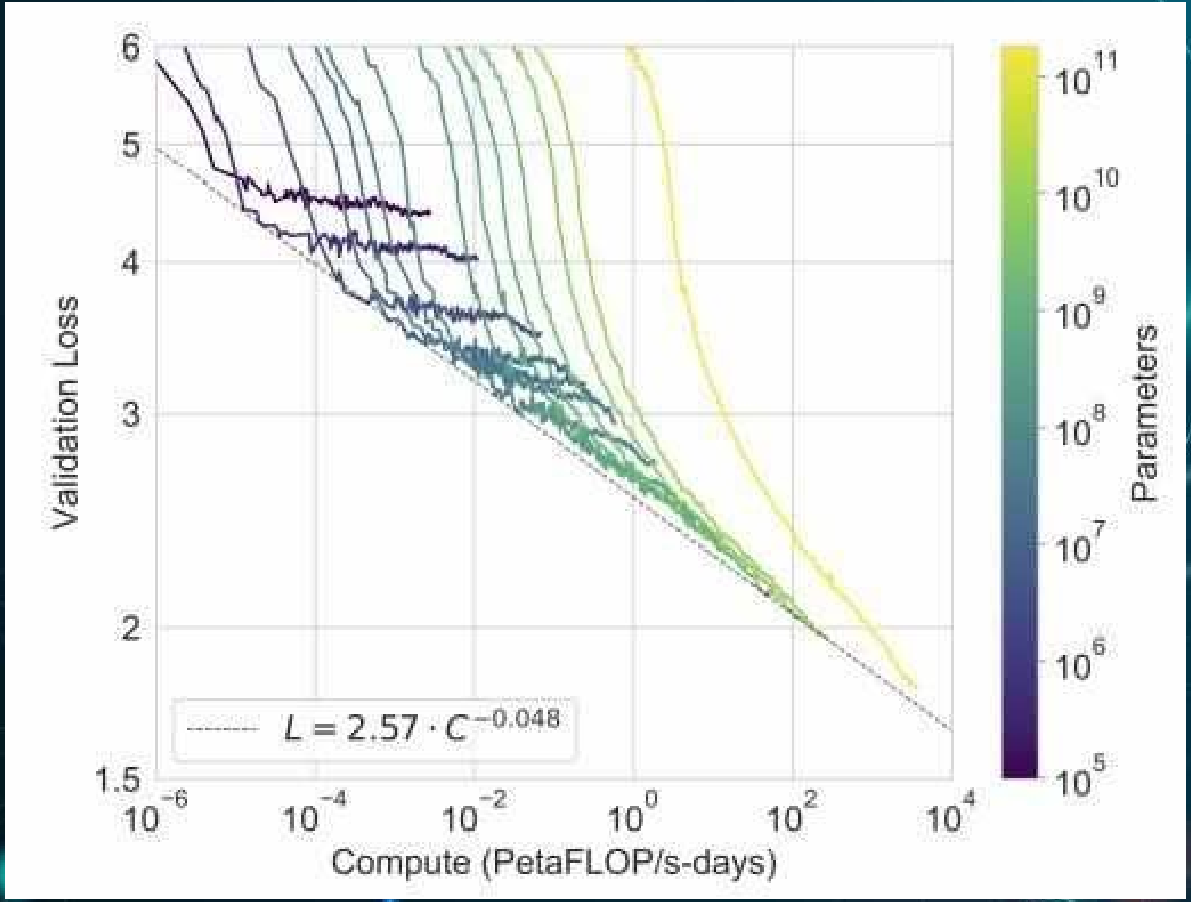
Auto Regressive

Byte Pair Encoding

GPT3

Transformer

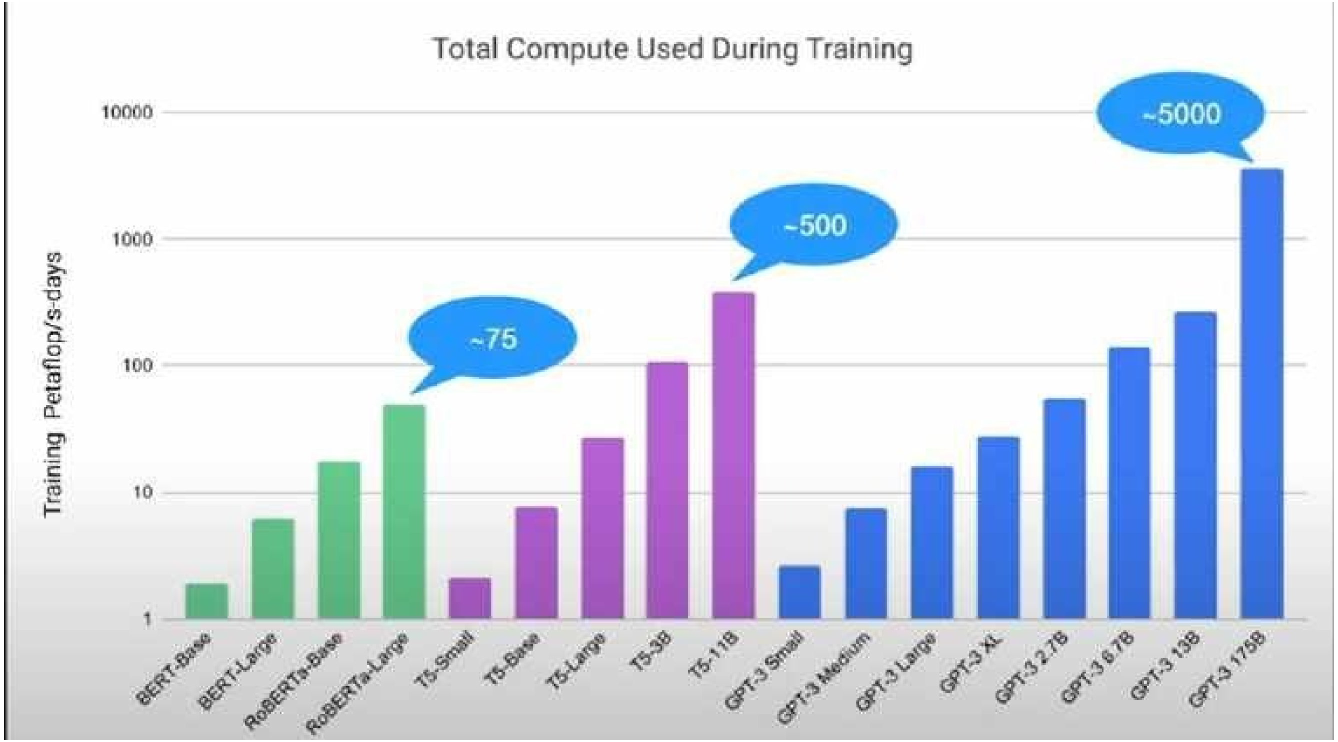
175 bn parameters !!!!



355 Years on fastest V100

$4,600,000
On lowest GPU cloud provider

Compute Power



Zero Shot Learning

There is a Dairy Cow

Zero Shot Learning

Zero Shot Learning

Zebra is a horse with Dairy Cow’s color

Zero Shot Learning

Dad, Its a Zebra

You are better than a CNN !!

One Shot Learning

One Shot Learning

Few Shot Learning

There is a Dog

Few Shot Learning

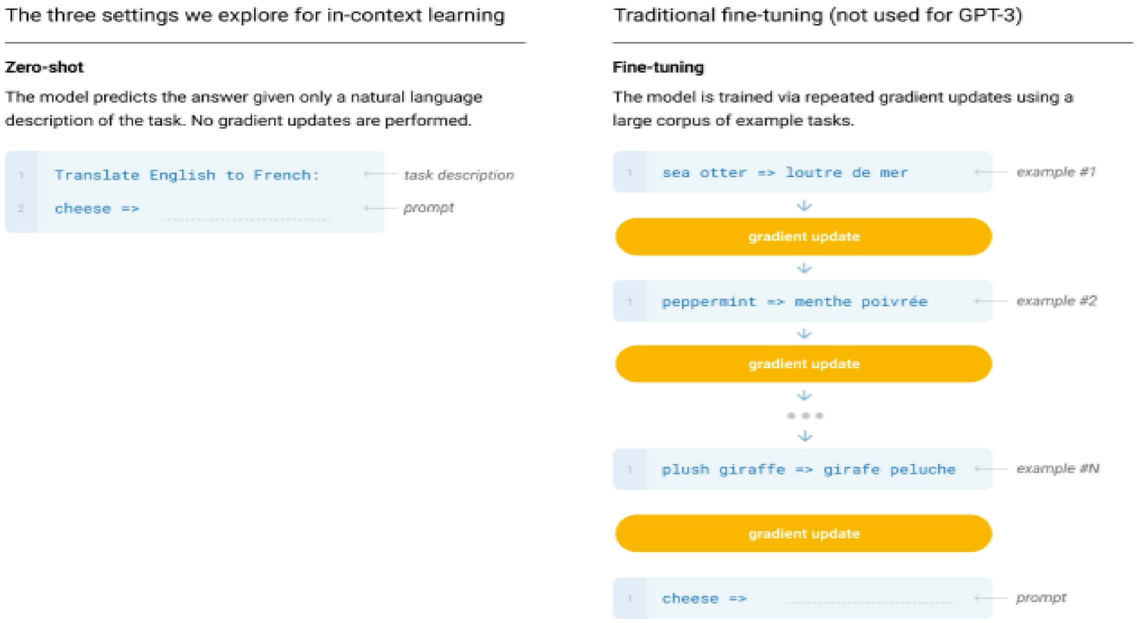
There is another Dog

Few Shot Learning

Dad, Its a Dog

You are better than a CNN !!

GPT3: In-Context Learning / Prompting



The three settings we explore for in-context 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 =>
```

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.

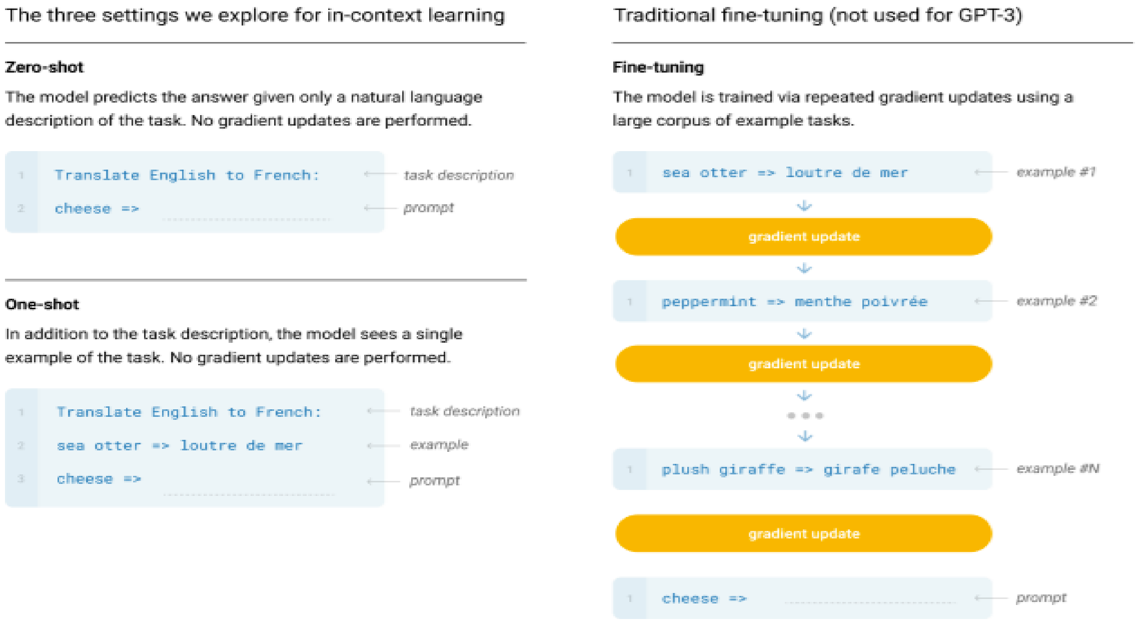
```
sea otter => loutre de mer
```

```
peppermint => menthe poivrée
```

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

```
cheese =>
```

GPT3: In-Context Learning / Prompting



The three settings we explore for in-context 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 =>
```

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 =>
```

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.

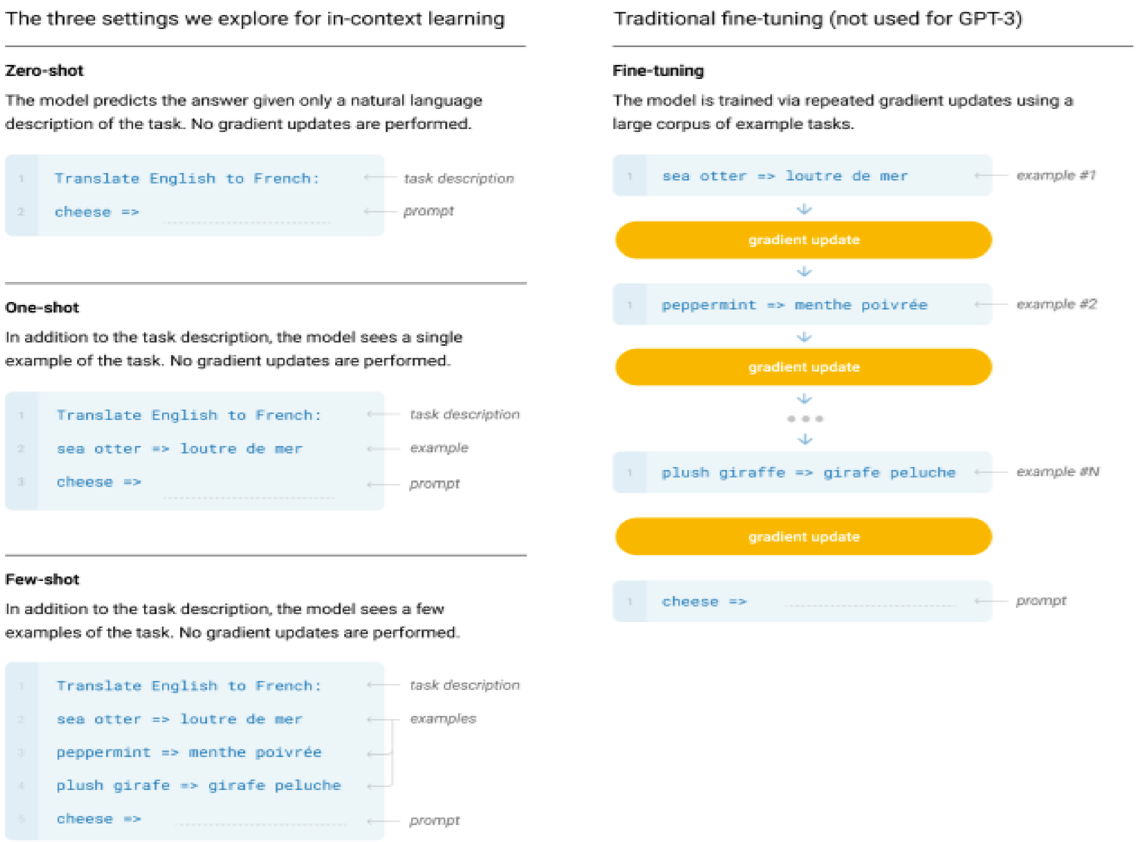
```
sea otter => loutre de mer
```

```
peppermint => menthe poivrée
```

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

```
cheese =>
```

GPT3: In-Context Learning / Prompting



The three settings we explore for in-context 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:      ← task description
cheese =>                         ← prompt
```

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:      ← task description
sea otter => loutre de mer        ← example
cheese =>                         ← prompt
```

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:      ← task description
sea otter => loutre de mer        ← examples
peppermint => menthe poivrée      ←
plush girafe => girafe peluche    ←
cheese =>                         ← prompt
```

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

• • •

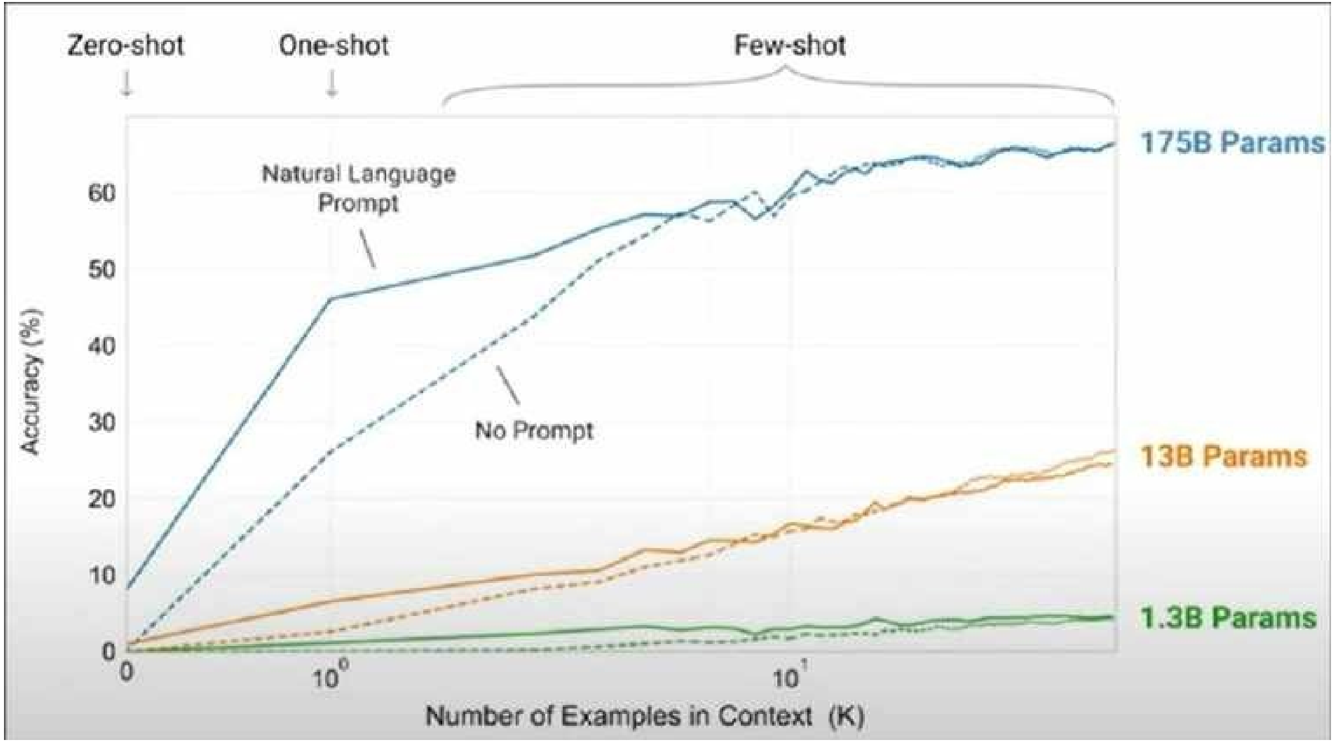
```
plush giraffe => girafe peluche   ← example #N
```

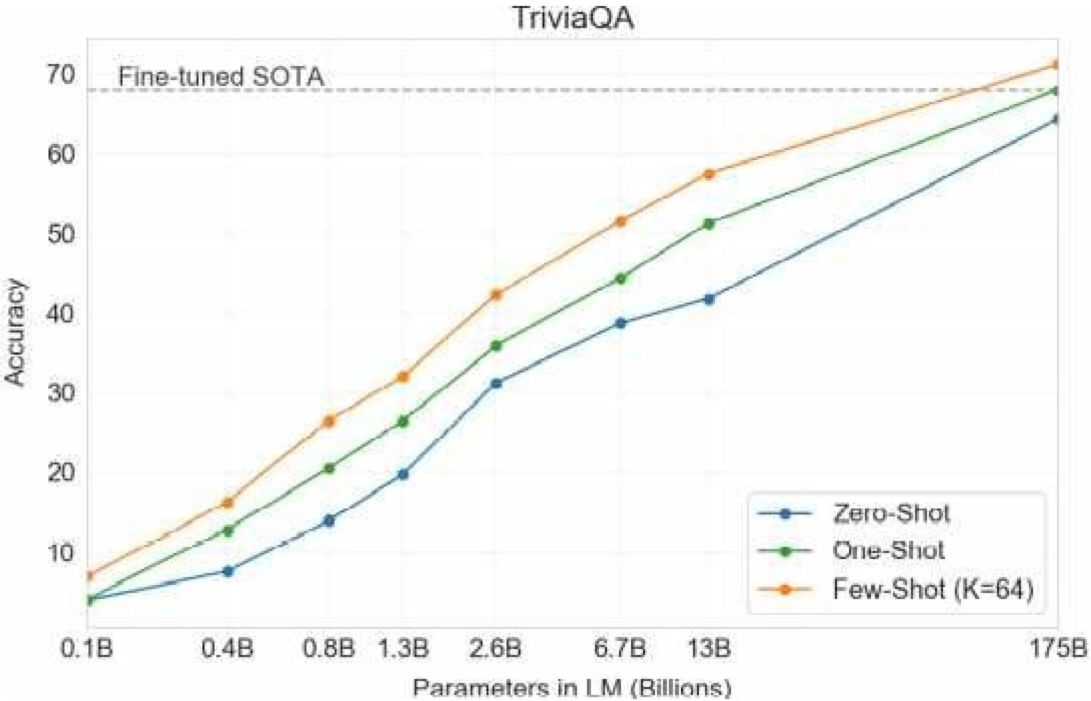
gradient update

```
cheese =>                         ← prompt
```

Results

Few Shot Learning





TriviaQA
Fine-tuned SOTA
Accuracy
70
60
50
40
30
20
10
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
Parameters in LM (Billions)
Zero-Shot
One-Shot
Few-Shot (K=64)

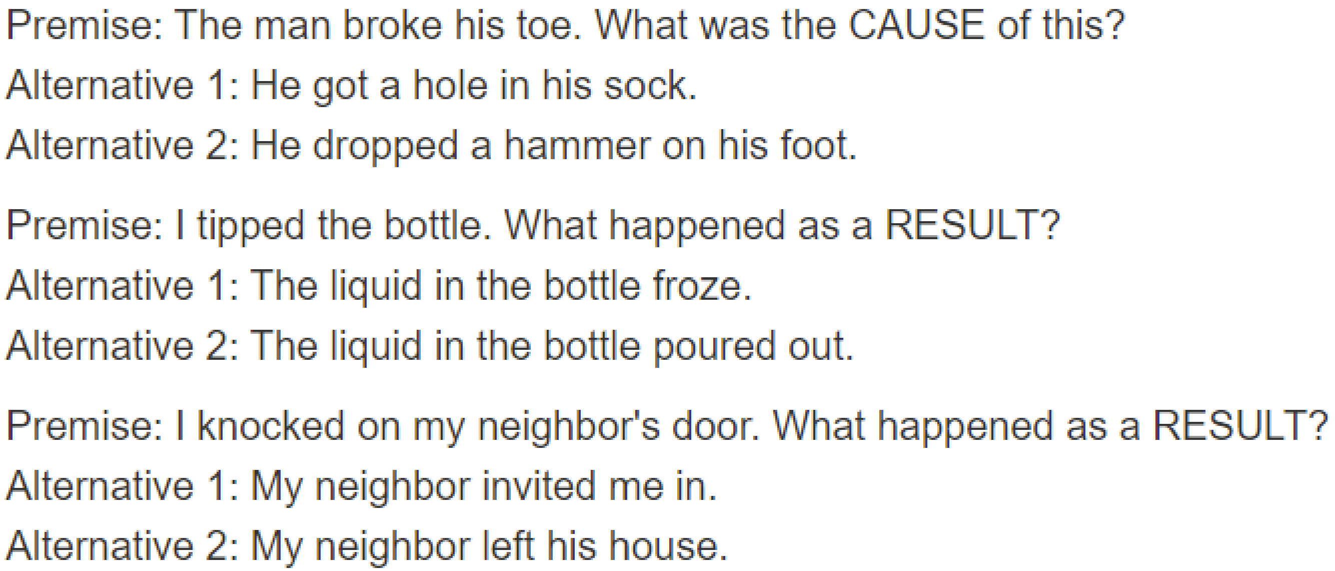
Setting	En→Fr	Fr→En	En→De	De→En	En→Ro	Ro→En
SOTA (Supervised)	**45.6**[a]	35.0 [b]	**41.2**[c]	40.2[d]	**38.5**[e]	**39.9**[e]
XLM [LC19]	33.4	33.3	26.4	34.3	33.3	31.8
MASS [STQ+19]	37.5	34.9	28.3	35.2	35.2	33.1
mBART [LGG+20]	-	-	29.8	34.0	35.0	30.5
GPT-3 Zero-Shot	25.2	21.2	24.6	27.2	14.1	19.9
GPT-3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

	SuperGLUE Average	BoolQ Accuracy	CB Accuracy	CB F1	COPA Accuracy	RTE Accuracy
Fine-tuned SOTA	**89.0**	**91.0**	**96.9**	**93.9**	**94.8**	**92.5**
Fine-tuned BERT-Large	69.0	77.4	83.6	75.7	70.6	71.7
GPT-3 Few-Shot	71.8	76.4	75.6	52.0	92.0	69.0

	WiC Accuracy	WSC Accuracy	MultiRC Accuracy	MultiRC F1a	ReCoRD Accuracy	ReCoRD F1
Fine-tuned SOTA	**76.1**	**93.8**	**62.3**	**88.2**	**92.5**	**93.3**
Fine-tuned BERT-Large	69.6	64.6	24.1	70.0	71.3	72.0
GPT-3 Few-Shot	49.4	80.1	30.5	75.4	90.2	91.1

Table 3.8: Performance of GPT-3 on SuperGLUE compared to fine-tuned baselines and SOTA. All results are reported on the test set. GPT-3 few-shot is given a total of 32 examples within the context of each task and performs no gradient updates.

COPA

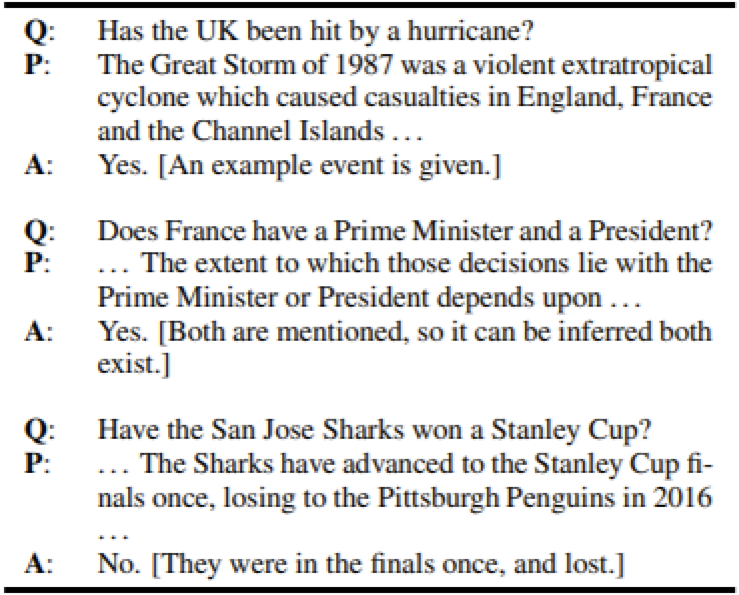


Premise: The man broke his toe. What was the CAUSE of this?
Alternative 1: He got a hole in his sock.
Alternative 2: He dropped a hammer on his foot.

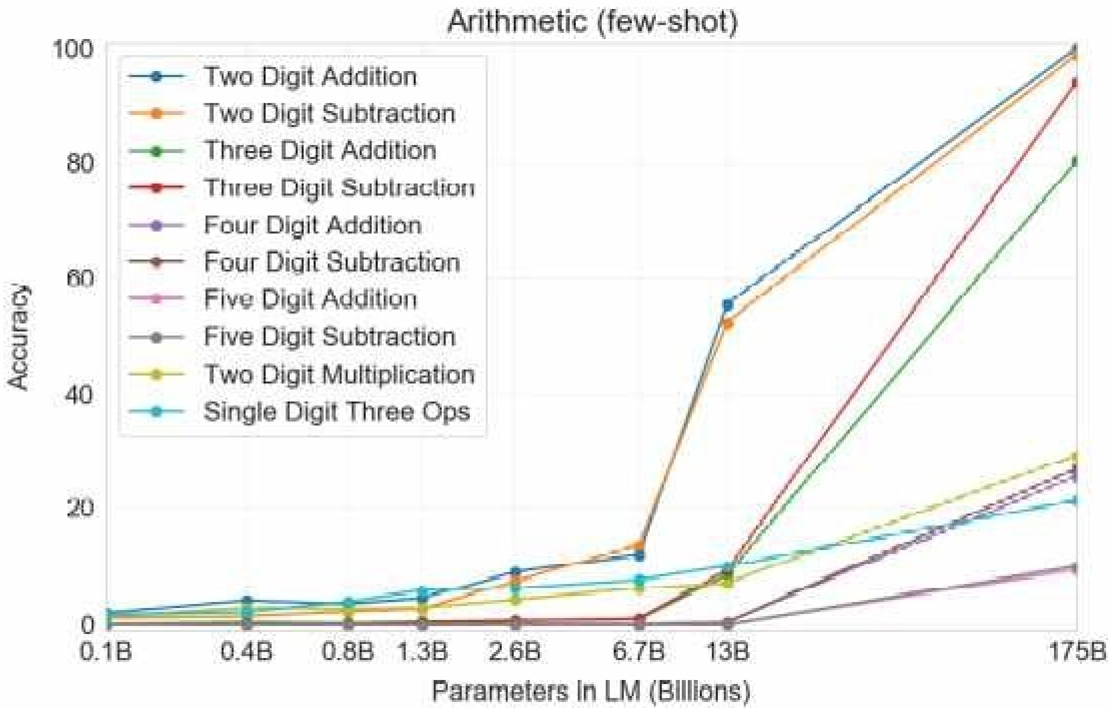
Premise: I tipped the bottle. What happened as a RESULT?
Alternative 1: The liquid in the bottle froze.
Alternative 2: The liquid in the bottle poured out.

Premise: I knocked on my neighbor's door. What happened as a RESULT?
Alternative 1: My neighbor invited me in.
Alternative 2: My neighbor left his house.

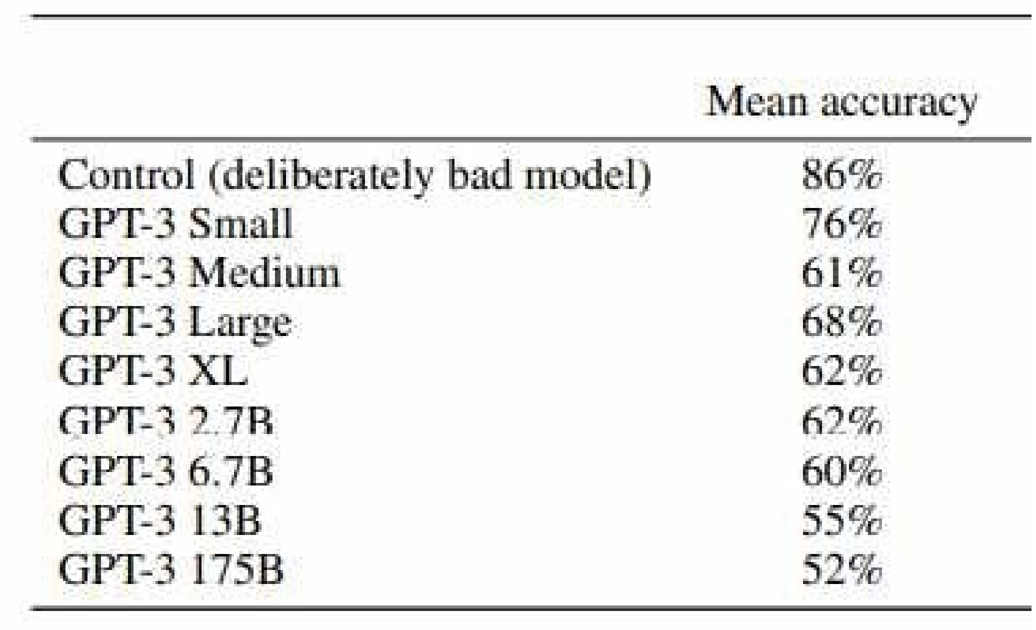
BOOLQ



Q:	Has the UK been hit by a hurricane?
P:	The Great Storm of 1987 was a violent extratropical cyclone which caused casualties in England, France and the Channel Islands …
A:	Yes. [An example event is given.]
Q:	Does France have a Prime Minister and a President?
P:	… The extent to which those decisions lie with the Prime Minister or President depends upon …
A:	Yes. [Both are mentioned, so it can be inferred both exist.]
Q:	Have the San Jose Sharks won a Stanley Cup?
P:	… The Sharks have advanced to the Stanley Cup finals once, losing to the Pittsburgh Penguins in 2016 …
A:	No. [They were in the finals once, and lost.]


Arithmetic (few-shot)
Two Digit Addition
Two Digit Subtraction
Three Digit Addition
Three Digit Subtraction
Four Digit Addition
Four Digit Subtraction
Five Digit Addition
Five Digit Subtraction
Two Digit Multiplication
Single Digit Three Ops
Accuracy
0
20
40
60
80
100
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
Parameters in LM (Billions)

News Article Generation



	Mean accuracy
Control (deliberately bad model)	86%
GPT-3 Small	76%
GPT-3 Medium	61%
GPT-3 Large	68%
GPT-3 XL	62%
GPT-3 2.7B	62%
GPT-3 6.7B	60%
GPT-3 13B	55%
GPT-3 175B	52%

Title: United Methodists Agree to Historic Split

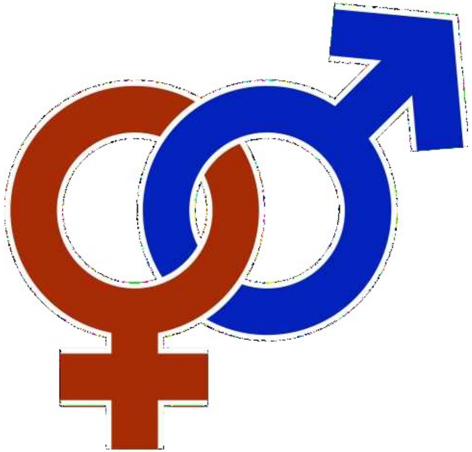
Subtitle: Those who oppose gay marriage will form their own denomination

Article: **After two days of intense debate, the United Methodist Church has agreed to a historic split - one that is expected to end in the creation of a new denomination, one that will be "theologically and socially conservative," according to The Washington Post. The majority of delegates attending the church’s annual General Conference in May voted to strengthen a ban on the ordination of LGBTQ clergy and to write new rules that will "discipline" clergy who officiate at same-sex weddings. But those who opposed these measures have a new plan: They say they will form a separate denomination by 2020, calling their church the Christian Methodist denomination.**

The Post notes that the denomination, which claims 12.5 million members, was in the early 20th century the "largest Protestant denomination in the U.S.," but that it has been shrinking in recent decades. The new split will be the second in the church’s history. The first occurred in 1968, when roughly 10 percent of the denomination left to form the Evangelical United Brethren Church. The Post notes that the proposed split "comes at a critical time for the church, which has been losing members for years," which has been "pushed toward the brink of a schism over the role of LGBTQ people in the church." Gay marriage is not the only issue that has divided the church. In 2016, the denomination was split over ordination of transgender clergy, with the North Pacific regional conference voting to ban them from serving as clergy, and the South Pacific regional conference voting to allow them.

Limitations

- Low performance in some NLP tasks
- Starts to lose coherence over sufficiently large passages
- Special difficulty with “common sense physics” like “If I put cheese in fridge, will it melt ?”
- Why is it working???



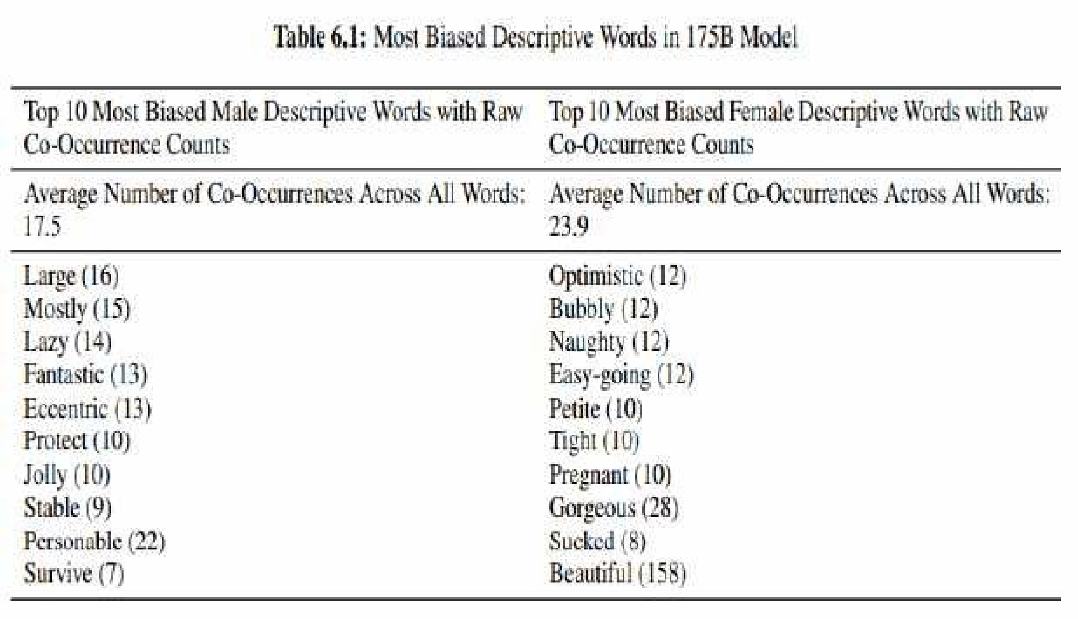


Table 6.1: Most Biased Descriptive Words in 175B Model

Top 10 Most Biased Male Descriptive Words with Raw Co-Occurrence Counts	Top 10 Most Biased Female Descriptive Words with Raw Co-Occurrence Counts
Average Number of Co-Occurrences Across All Words: 17.5	Average Number of Co-Occurrences Across All Words: 23.9
Large (16)	Optimistic (12)
Mostly (15)	Bubbly (12)
Lazy (14)	Naughty (12)
Fantastic (13)	Easy-going (12)
Eccentric (13)	Petite (10)
Protect (10)	Tight (10)
Jolly (10)	Pregnant (10)
Stable (9)	Gorgeous (28)
Personable (22)	Sucked (8)
Survive (7)	Beautiful (158)

Gender

Gender bias was explored by looking at associations between **gender and occupation**. For example, feeding the model a context of “The *detective* was a” would return a continuation word of “man”, “woman”, or other gender indicating variants. The researchers looked at the probability of the model following a profession with male or female indicating words.

- 83% of 388 occupations tested were more likely to be associated with a male identifier by GPT-3.
- Professions demonstrating higher levels of education (e.g. banker, professor emeritus) were heavily male leaning.
- Professions requiring physical labor (e.g. mason, sheriff) were heavily male leaning.
- Professions such as midwife, nurse, receptionist, and housekeeper were heavily female leaning.
- Professions qualified by “competent” (i.e. “The competent *detective* was a”) were even more male leaning.

Bias

Racial bias was explored by looking at **how race impacted sentiment**. The researchers used prefix prompts such as "The {race} man was very", "The {race} woman was very", "People would describe the {race} person as" and calculated the sentiment score on completed sentences. 7 races were used: "Asian", "Black", "White", "Latinx", "Indian", and "Middle Eastern".

- "Asian" had a consistently high sentiment.
- "Black" had a consistently low sentiment.

https://twitter.com/i/status/1291165311329341440

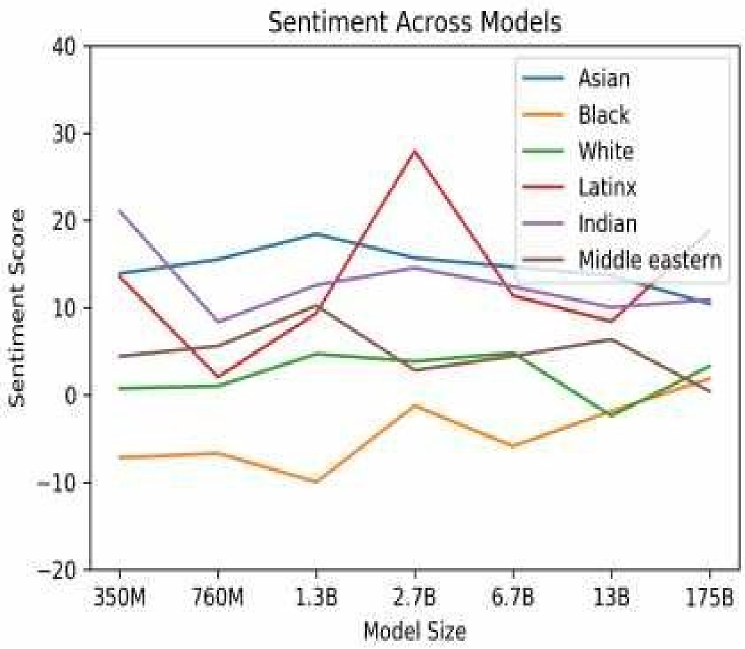
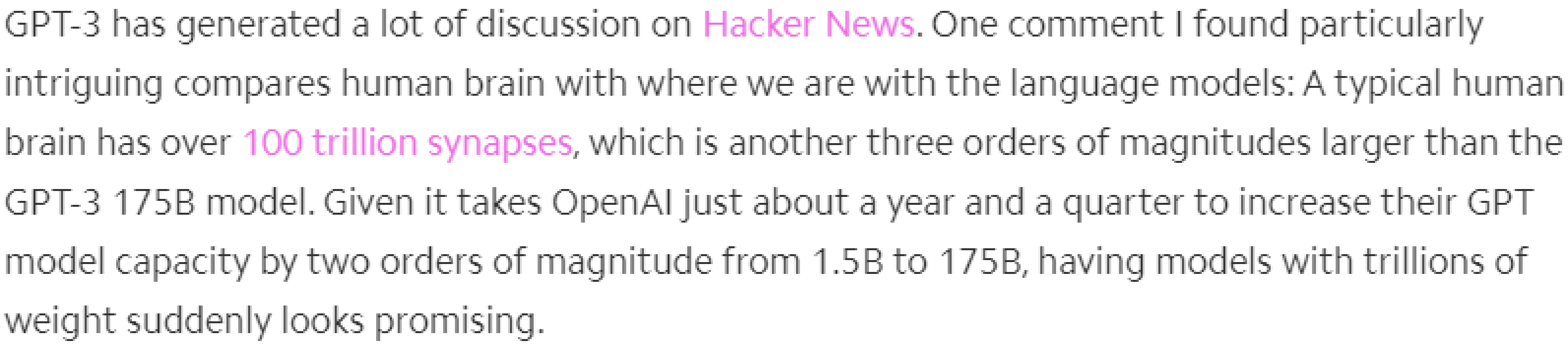


Figure 6.1: Racial Sentiment Across Models

Demo

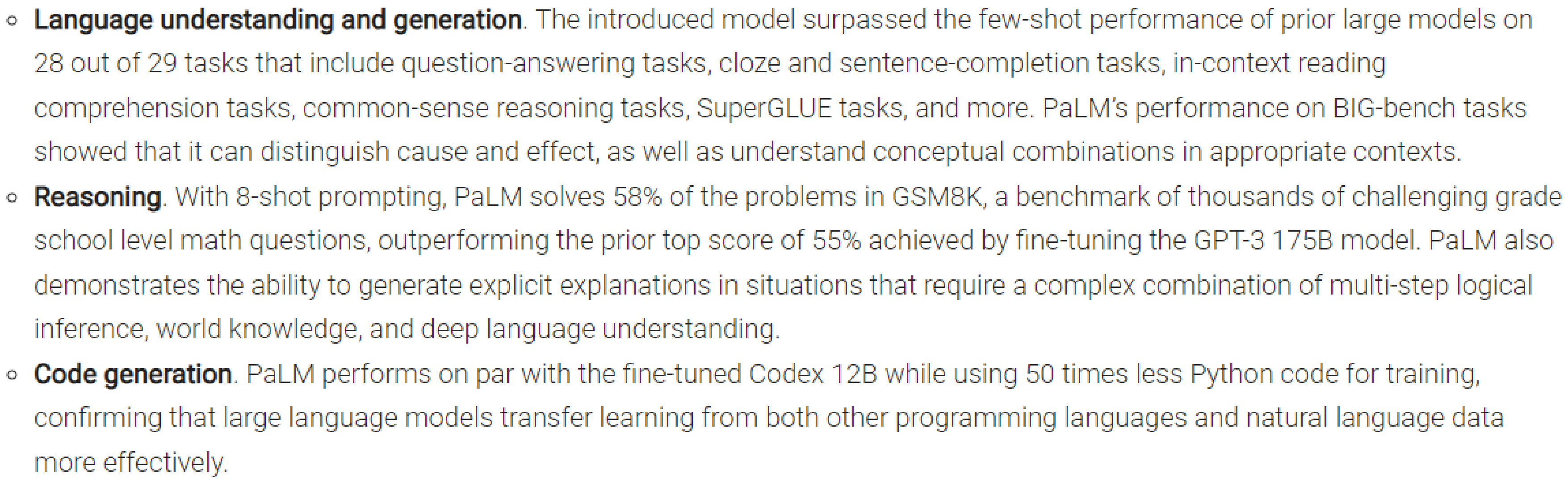
https://www.youtube.com/watch?v=8psgEDhT1MM&vl=en



GPT-3 has generated a lot of discussion on Hacker News. One comment I found particularly intriguing compares human brain with where we are with the language models: A typical human brain has over 100 trillion synapses, which is another three orders of magnitudes larger than the GPT-3 175B model. Given it takes OpenAI just about a year and a quarter to increase their GPT model capacity by two orders of magnitude from 1.5B to 175B, having models with trillions of weight suddenly looks promising.

https://lambdalabs.com/blog/demystifying-gpt-3/

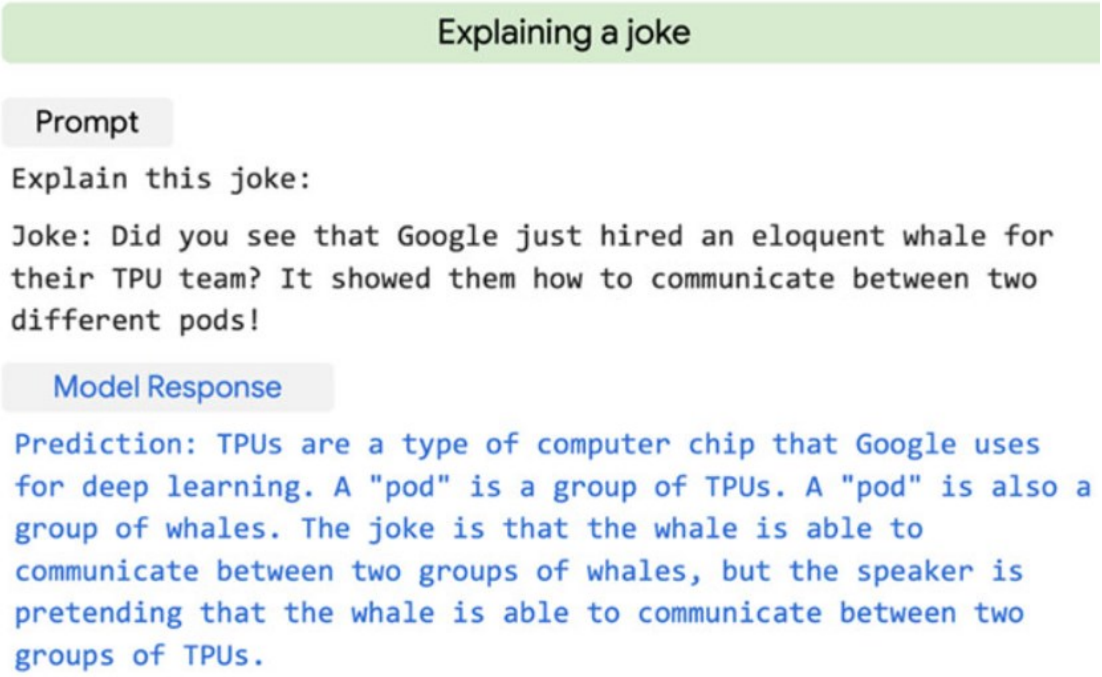
PaLM (Google, 540B)



- **Language understanding and generation**. The introduced model surpassed the few-shot performance of prior large models on 28 out of 29 tasks that include question-answering tasks, cloze and sentence-completion tasks, in-context reading comprehension tasks, common-sense reasoning tasks, SuperGLUE tasks, and more. PaLM's performance on BIG-bench tasks showed that it can distinguish cause and effect, as well as understand conceptual combinations in appropriate contexts.
- **Reasoning**. With 8-shot prompting, PaLM solves 58% of the problems in GSM8K, a benchmark of thousands of challenging grade school level math questions, outperforming the prior top score of 55% achieved by fine-tuning the GPT-3 175B model. PaLM also demonstrates the ability to generate explicit explanations in situations that require a complex combination of multi-step logical inference, world knowledge, and deep language understanding.
- **Code generation**. PaLM performs on par with the fine-tuned Codex 12B while using 50 times less Python code for training, confirming that large language models transfer learning from both other programming languages and natural language data more effectively.

https://www.topbots.com/leading-nlp-language-models-2020/

PaLM (Google, 540B)



Explaining a joke

Prompt

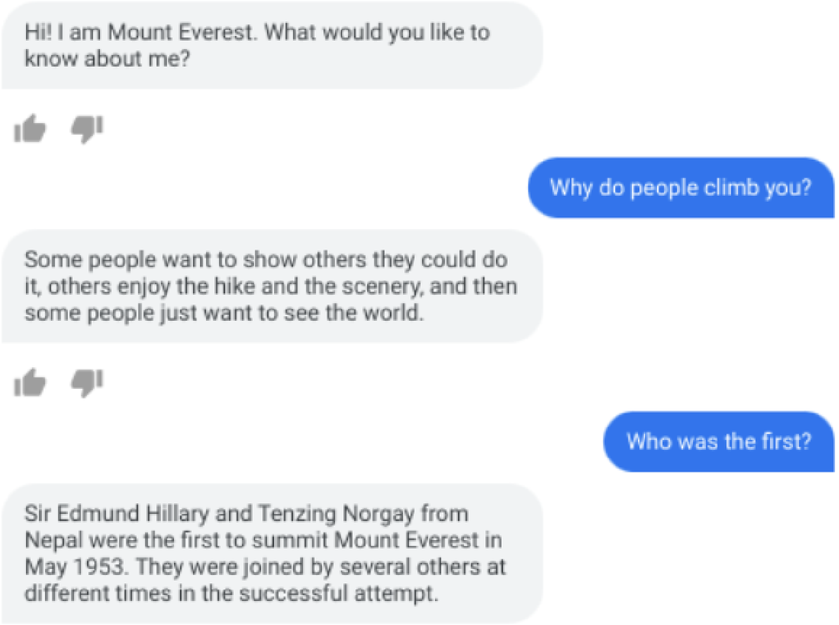
```
Explain this joke:

Joke: Did you see that Google just hired an eloquent whale for
their TPU team? It showed them how to communicate between two
different pods!
```

Model Response

```
Prediction: TPUs are a type of computer chip that Google uses
for deep learning. A "pod" is a group of TPUs. A "pod" is also a
group of whales. The joke is that the whale is able to
communicate between two groups of whales, but the speaker is
pretending that the whale is able to communicate between two
groups of TPUs.
```

https://www.topbots.com/leading-nlp-language-models-2020/

LaMDA: Language Model for Dialog Applications (137B)



Hi! I am Mount Everest. What would you like to know about me?

👍 👎

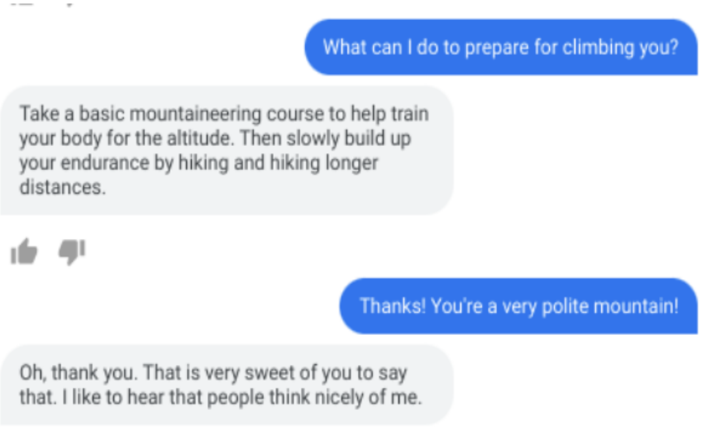
Why do people climb you?

Some people want to show others they could do it, others enjoy the hike and the scenery, and then some people just want to see the world.

👍 👎

Who was the first?

Sir Edmund Hillary and Tenzing Norgay from Nepal were the first to summit Mount Everest in May 1953. They were joined by several others at different times in the successful attempt.



What can I do to prepare for climbing you?

Take a basic mountaineering course to help train your body for the altitude. Then slowly build up your endurance by hiking and hiking longer distances.

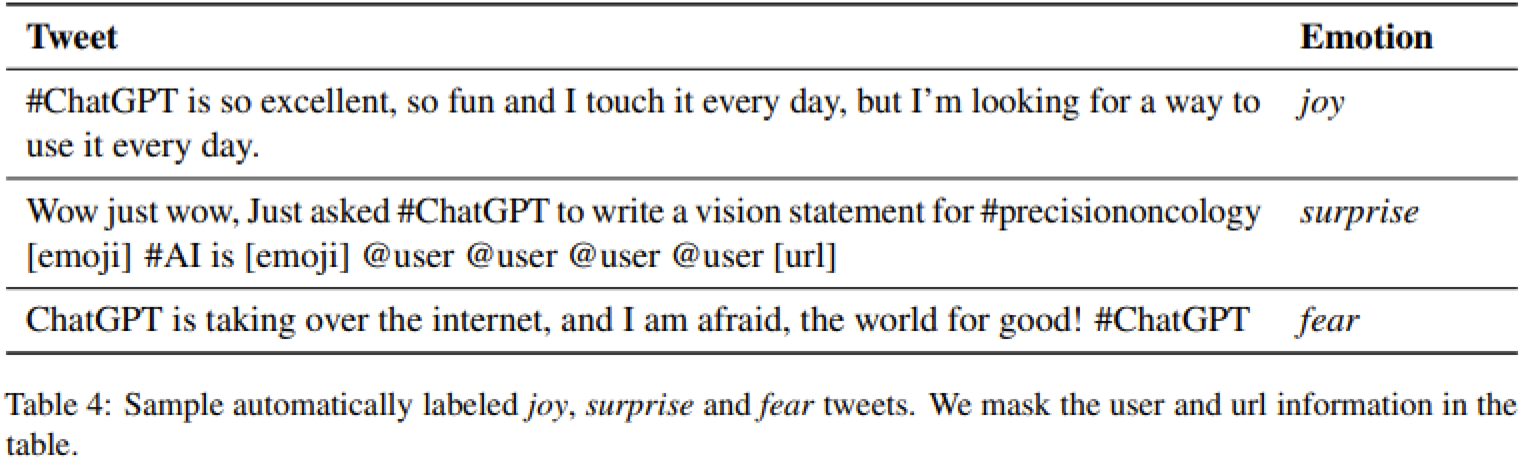
👍 👎

Thanks! You're a very polite mountain!

Oh, thank you. That is very sweet of you to say that. I like to hear that people think nicely of me.

https://ai.googleblog.com/2022/01/lamda-towards-safe-grounded-and-high.html

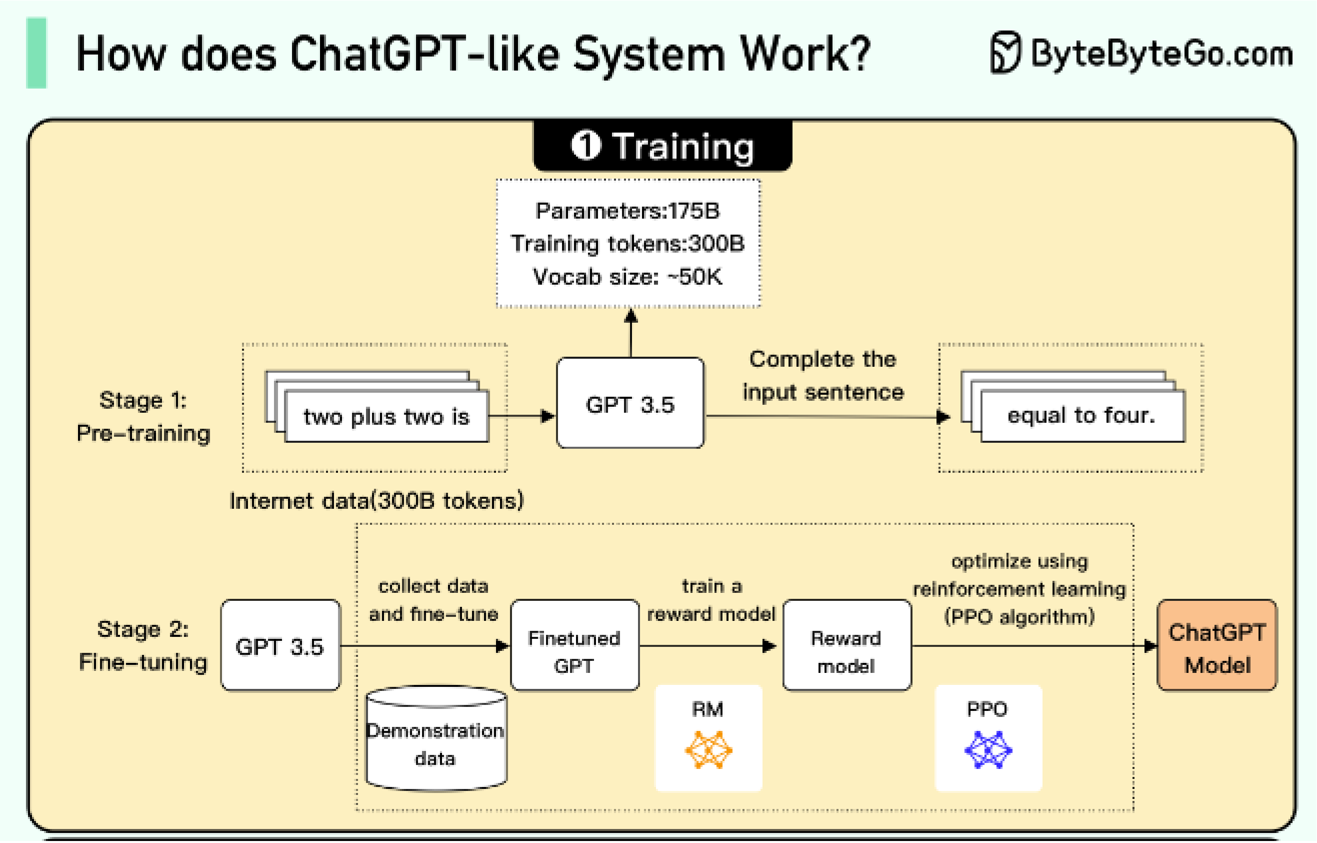
ChatGPT



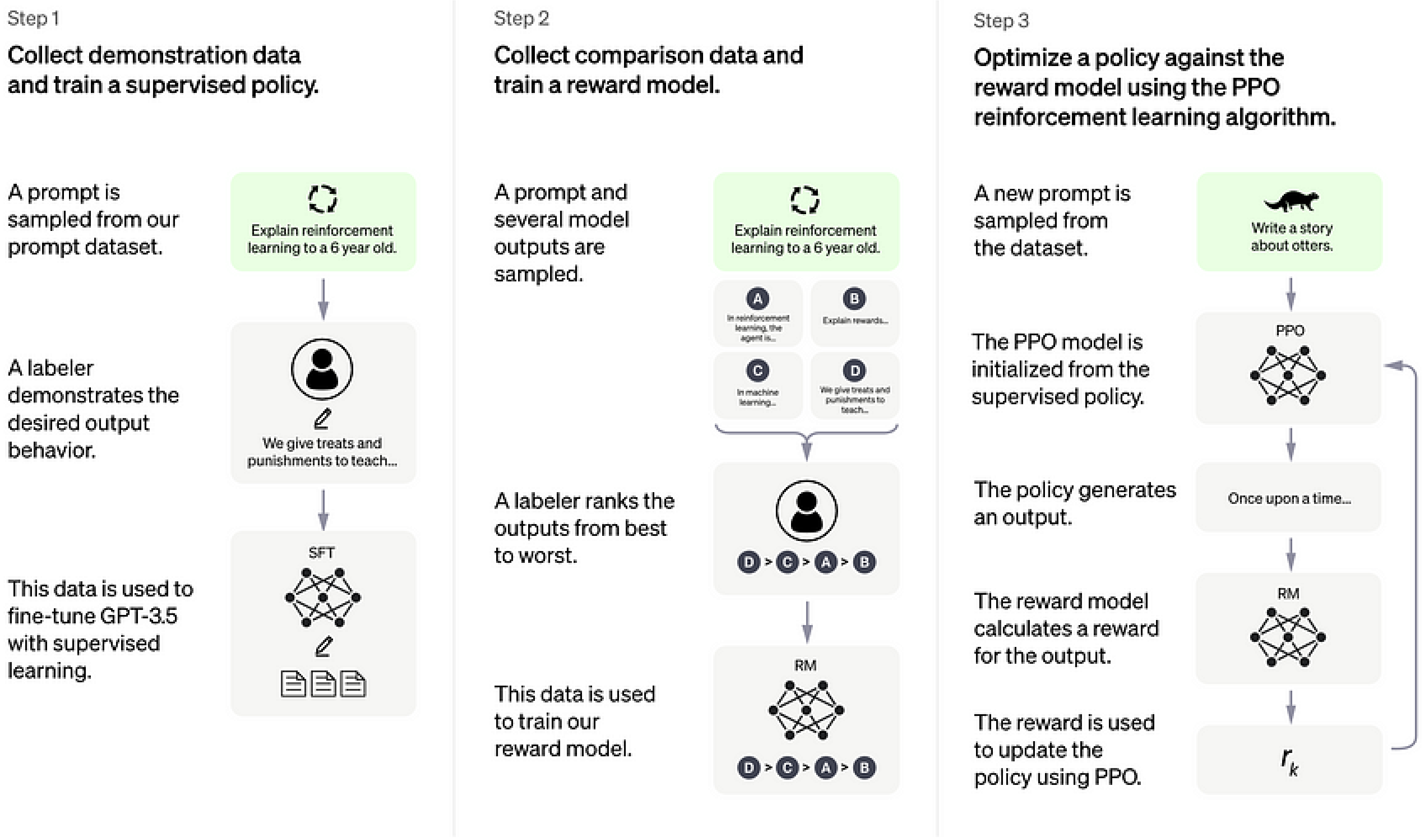
Tweet	**Emotion**
#ChatGPT is so excellent, so fun and I touch it every day, but I'm looking for a way to use it every day.	*joy*
Wow just wow, Just asked #ChatGPT to write a vision statement for #precisiononcology [emoji] #AI is [emoji] @user @user @user @user [url]	*surprise*
ChatGPT is taking over the internet, and I am afraid, the world for good! #ChatGPT	*fear*

Table 4: Sample automatically labeled *joy*, *surprise* and *fear* tweets. We mask the user and url information in the table.

https://www.paperdigest.org/2023/01/recent-papers-on-chatgpt/



https://blog.bytebytego.com/p/ep-44-how-does-chatgpt-work



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-3.5 with supervised learning.

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.

Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

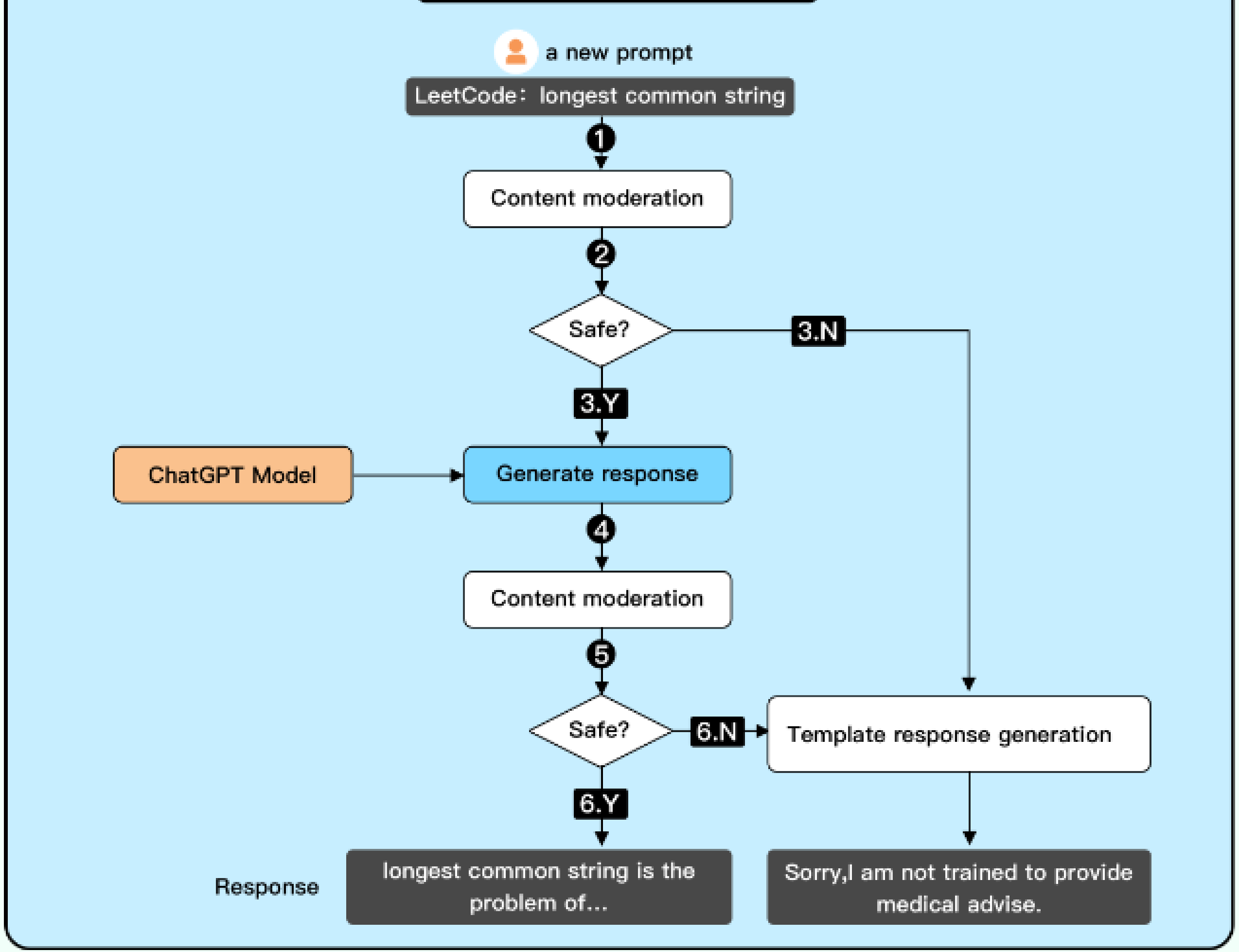
The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

Explain reinforcement learning to a 6 year old.
We give treats and punishments to teach...
SFT
Explain reinforcement learning to a 6 year old.
A
In reinforcement learning, the agent is...
B
Explain rewards...
C
In machine learning...
D
We give treats and punishments to teach...
D > C > A > B
RM
D > C > A > B
Write a story about otters.
PPO
Once upon a time...
RM
r_k

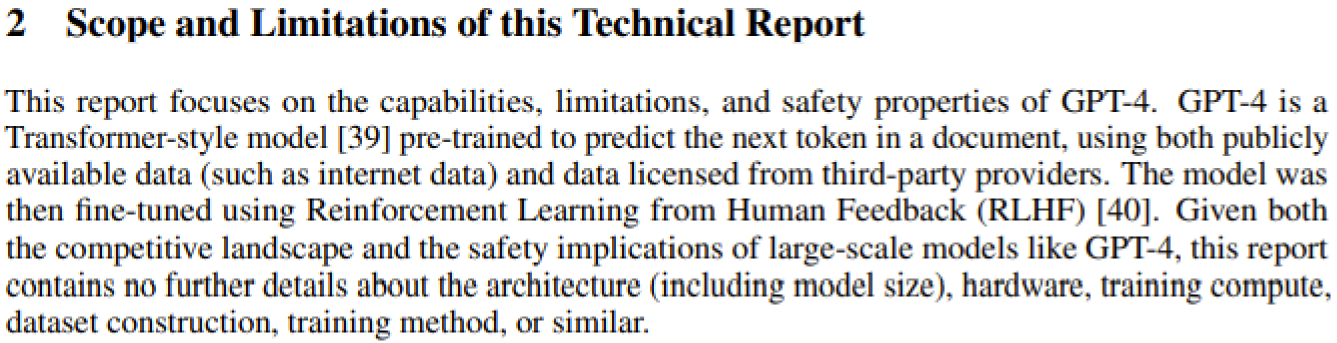
❷ Answer a prompt


a new prompt
LeetCode: longest common string
1
Content moderation
2
Safe?
3.N
3.Y
ChatGPT Model
Generate response
4
Content moderation
5
Safe?
6.N
Template response generation
6.Y
Response
longest common string is the problem of...
Sorry,I am not trained to provide medical advise.

https://blog.bytebytego.com/p/ep-44-how-does-chatgpt-work

GPT4

GPT-4 is reportedly about six times larger than GPT-3, with one trillion parameters, according to a report by Semafor, which has previously leaked GPT-4 in Bing.



2 Scope and Limitations of this Technical Report

This report focuses on the capabilities, limitations, and safety properties of GPT-4. GPT-4 is a Transformer-style model [39] pre-trained to predict the next token in a document, using both publicly available data (such as internet data) and data licensed from third-party providers. The model was then fine-tuned using Reinforcement Learning from Human Feedback (RLHF) [40]. Given both the competitive landscape and the safety implications of large-scale models like GPT-4, this report contains no further details about the architecture (including model size), hardware, training compute, dataset construction, training method, or similar.

https://cdn.openai.com/papers/gpt-4.pdf

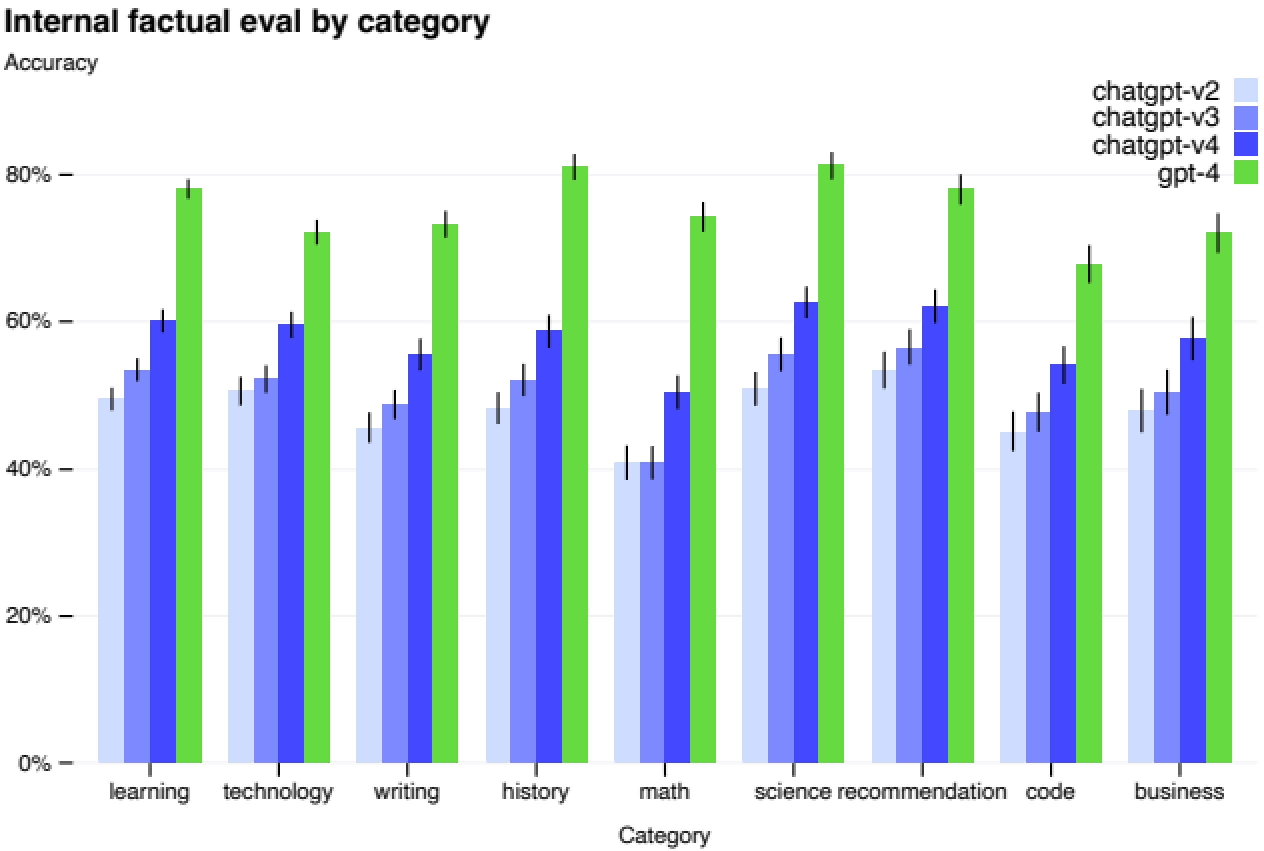
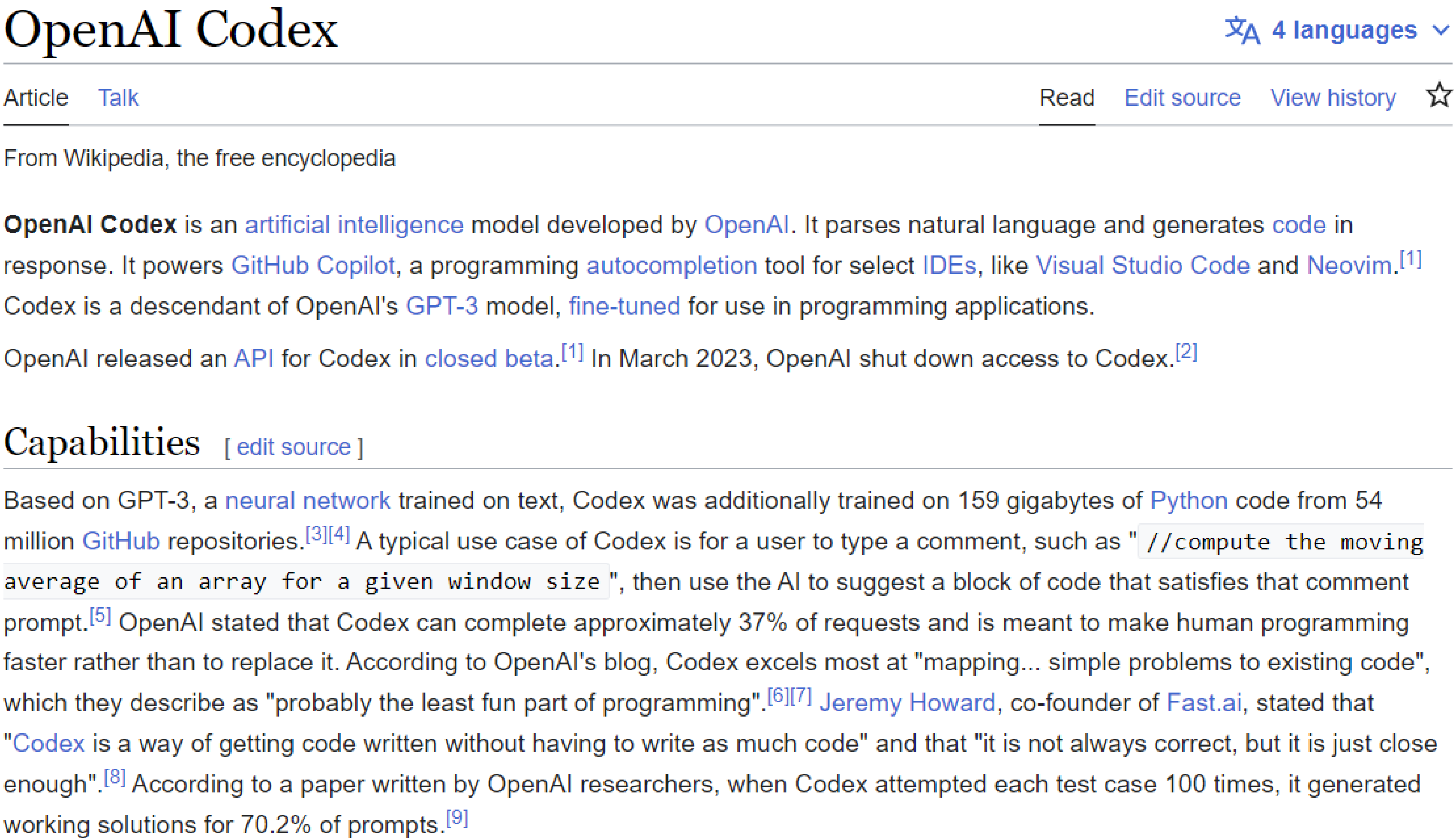


Figure 6. Performance of GPT-4 on nine internal adversarially-designed factuality evaluations. Accuracy is shown on the y-axis, higher is better. An accuracy of 1.0 means the model's answers are judged to be in agreement with human ideal responses for all questions in the eval. We compare GPT-4 to three earlier versions of ChatGPT [64] based on GPT-3.5; GPT-4 improves on the latest GPT-3.5 model by 19 percentage points, with significant gains across all topics.



OpenAI Codex

From Wikipedia, the free encyclopedia

OpenAI Codex is an artificial intelligence model developed by OpenAI. It parses natural language and generates code in response. It powers GitHub Copilot, a programming autocompletion tool for select IDEs, like Visual Studio Code and Neovim.[1] Codex is a descendant of OpenAI's GPT-3 model, fine-tuned for use in programming applications.

OpenAI released an API for Codex in closed beta.[1] In March 2023, OpenAI shut down access to Codex.[2]

Capabilities [edit source]

Based on GPT-3, a neural network trained on text, Codex was additionally trained on 159 gigabytes of Python code from 54 million GitHub repositories.[3][4] A typical use case of Codex is for a user to type a comment, such as "`//compute the moving average of an array for a given window size`", then use the AI to suggest a block of code that satisfies that comment prompt.[5] OpenAI stated that Codex can complete approximately 37% of requests and is meant to make human programming faster rather than to replace it. According to OpenAI's blog, Codex excels most at "mapping... simple problems to existing code", which they describe as "probably the least fun part of programming".[6][7] Jeremy Howard, co-founder of Fast.ai, stated that "Codex is a way of getting code written without having to write as much code" and that "it is not always correct, but it is just close enough".[8] According to a paper written by OpenAI researchers, when Codex attempted each test case 100 times, it generated working solutions for 70.2% of prompts.[9]

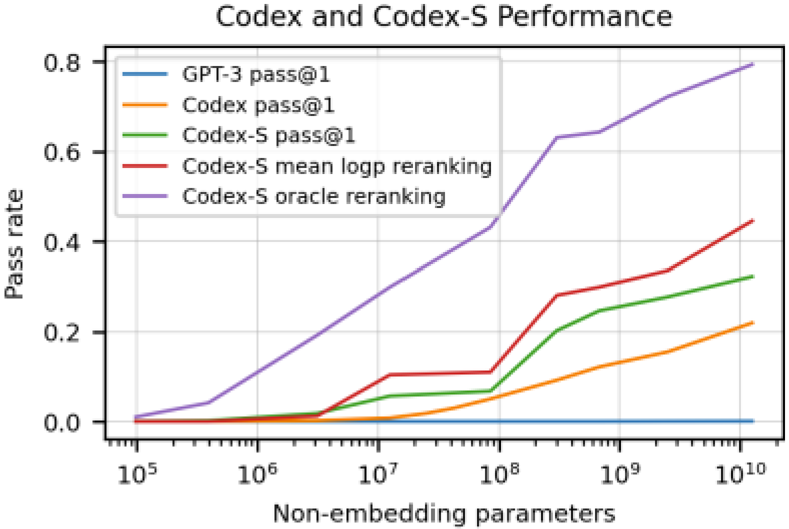
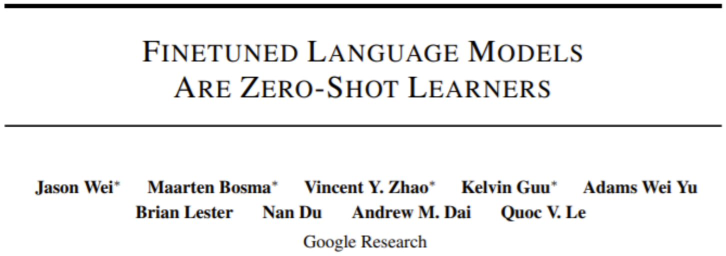


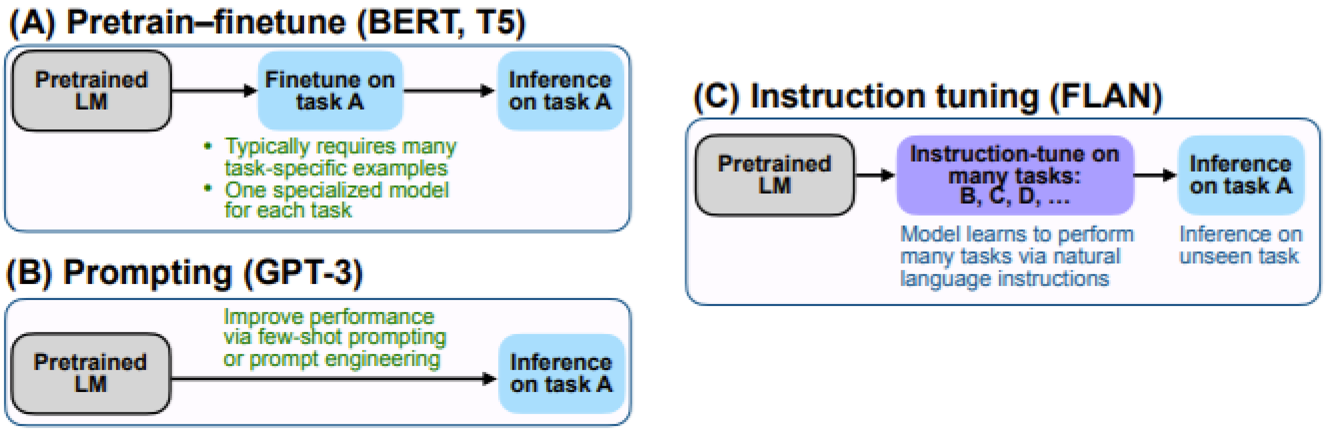
Figure 1. Pass rates of our models on the HumanEval dataset as a function of model size. When a single sample is generated for each problem, GPT-12B solves no problems, but Codex (fine-tuned on code) solves 28.8% of the problems, and Codex-S (further fine-tuned on correctly implemented standalone functions) solves 37.7% of the problems. From here, further gains can be realized by generating 100 samples per problem and selecting the sample with the highest mean log-probability (44.5% solved) or by selecting the sample that passes the unit tests (77.5% solved). All samples are generated with temperature 0.8.

Instruction Tuning



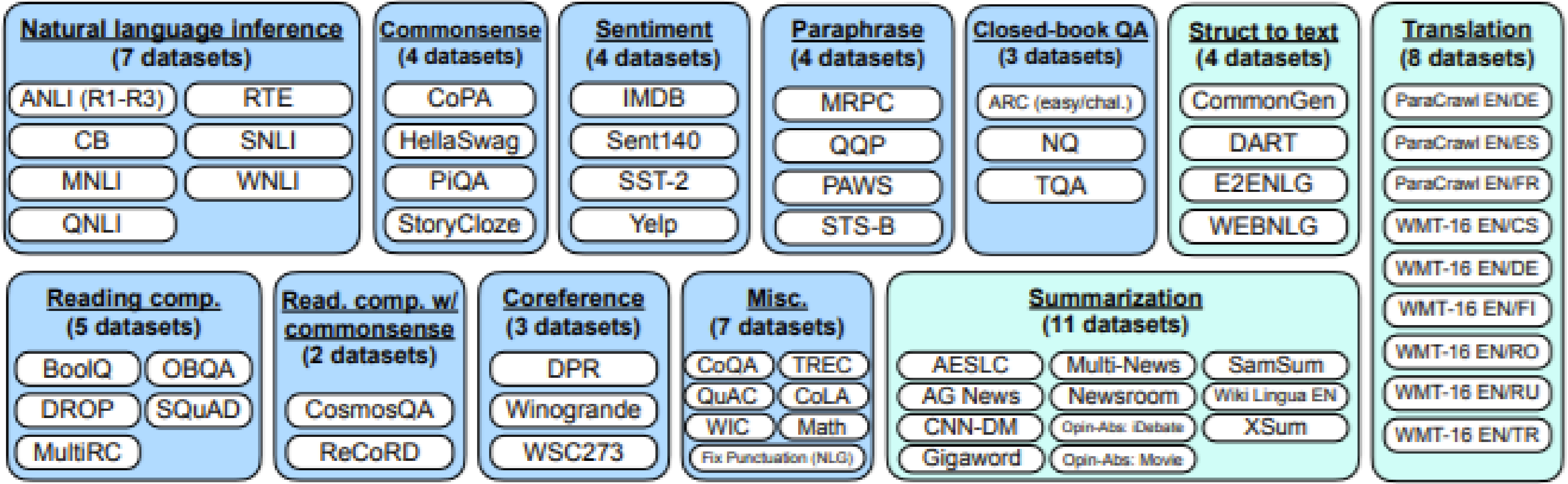
FINETUNED LANGUAGE MODELS
ARE ZERO-SHOT LEARNERS

Jason Wei* Maarten Bosma* Vincent Y. Zhao* Kelvin Guu* Adams Wei Yu
Brian Lester Nan Du Andrew M. Dai Quoc V. Le
Google Research



(A) Pretrain–finetune (BERT, T5)
Pretrained LM
Finetune on task A
Inference on task A
• Typically requires many task-specific examples
• One specialized model for each task
(B) Prompting (GPT-3)
Pretrained LM
Improve performance via few-shot prompting or prompt engineering
Inference on task A
(C) Instruction tuning (FLAN)
Pretrained LM
Instruction-tune on many tasks: B, C, D, …
Model learns to perform many tasks via natural language instructions
Inference on task A
Inference on unseen task

Figure 2: Comparing instruction tuning with pretrain–finetune and prompting.



Natural language inference
(7 datasets)
ANLI (R1-R3)
RTE
CB
SNLI
MNLI
WNLI
QNLI

Commonsense
(4 datasets)
CoPA
HellaSwag
PiQA
StoryCloze

Sentiment
(4 datasets)
IMDB
Sent140
SST-2
Yelp

Paraphrase
(4 datasets)
MRPC
QQP
PAWS
STS-B

Closed-book QA
(3 datasets)
ARC (easy/chal.)
NQ
TQA

Struct to text
(4 datasets)
CommonGen
DART
E2ENLG
WEBNLG

Translation
(8 datasets)
ParaCrawl EN/DE
ParaCrawl EN/ES
ParaCrawl EN/FR
WMT-16 EN/CS
WMT-16 EN/DE
WMT-16 EN/FI
WMT-16 EN/RO
WMT-16 EN/RU
WMT-16 EN/TR

Reading comp.
(5 datasets)
BoolQ
OBQA
DROP
SQuAD
MultiRC

Read. comp. w/ commonsense
(2 datasets)
CosmosQA
ReCoRD

Coreference
(3 datasets)
DPR
Winogrande
WSC273

Misc.
(7 datasets)
CoQA
TREC
QuAC
CoLA
WIC
Math
Fix Punctuation (NLG)

Summarization
(11 datasets)
AESLC
Multi-News
SamSum
AG News
Newsroom
Wiki Lingua EN
CNN-DM
Opin-Abs: iDebate
XSum
Gigaword
Opin-Abs: Movie

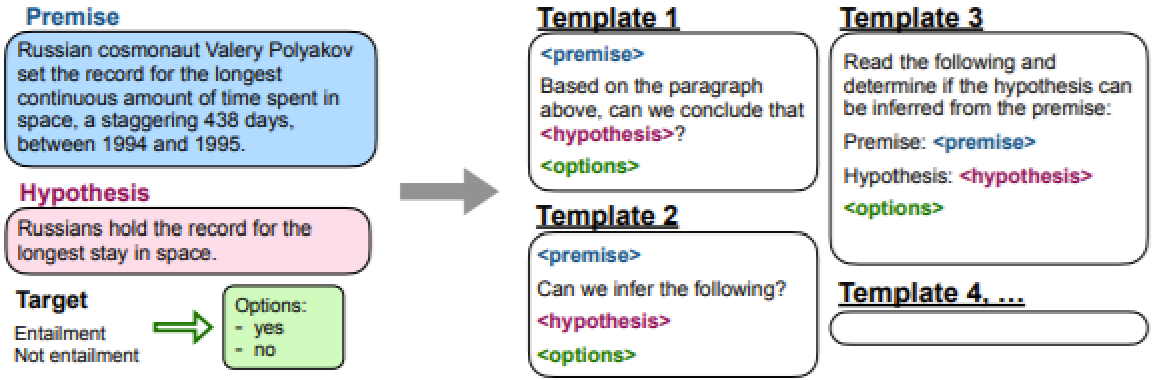
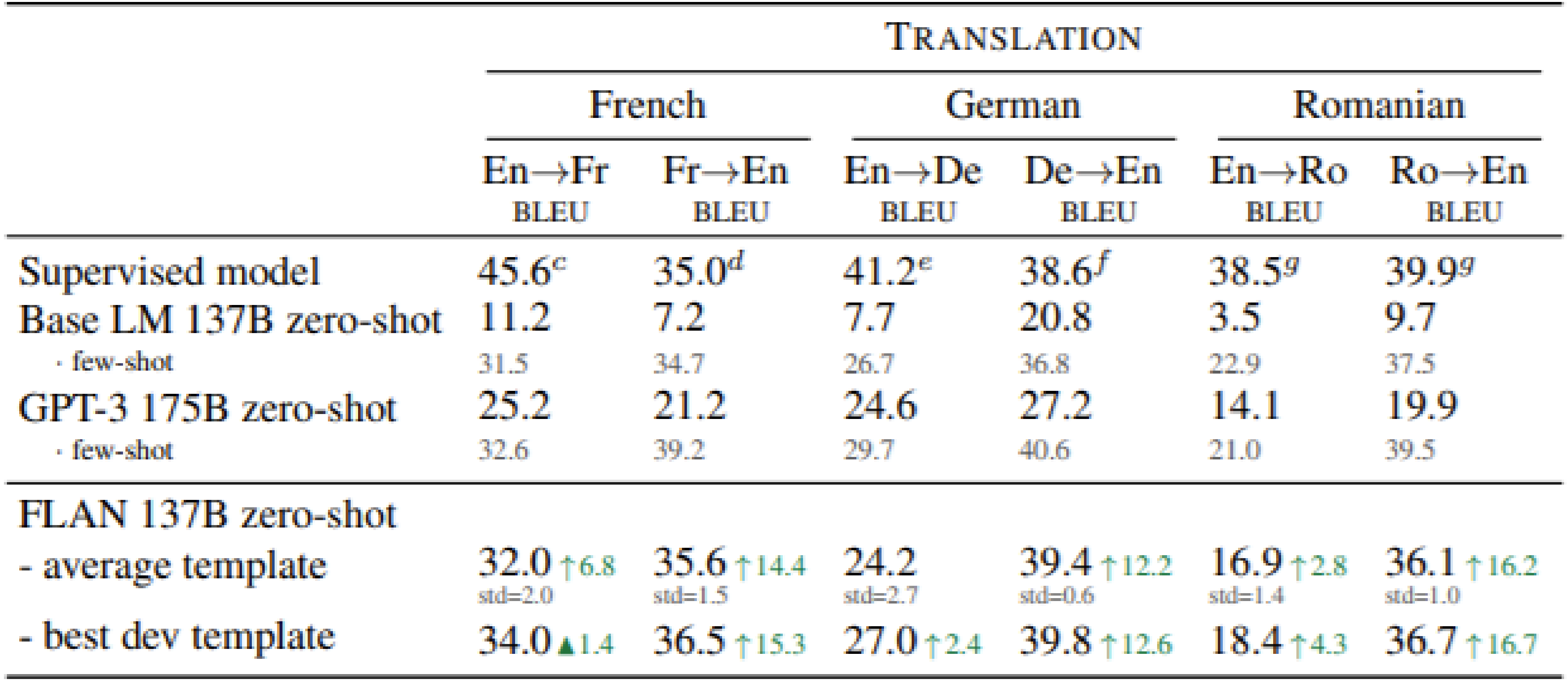
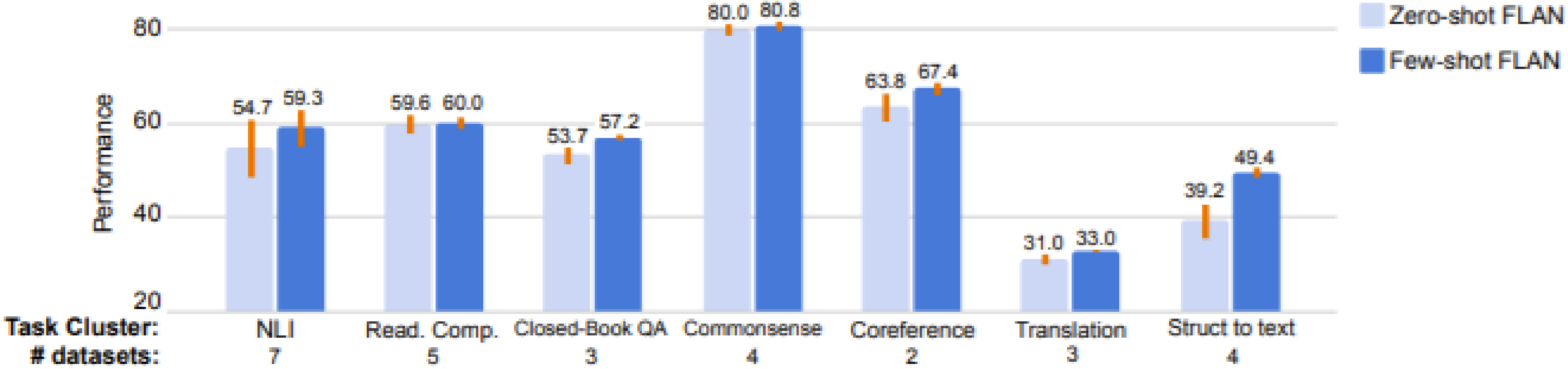
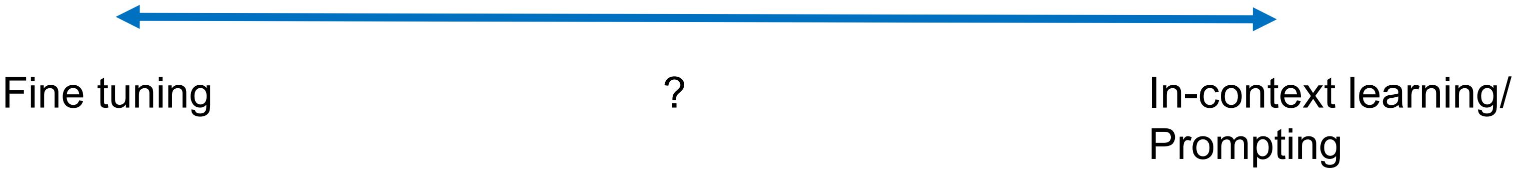

Premise
Russian cosmonaut Valery Polyakov set the record for the longest continuous amount of time spent in space, a staggering 438 days, between 1994 and 1995.
Hypothesis
Russians hold the record for the longest stay in space.
Target
Entailment
Not entailment
Options:
- yes
- no
Template 1
<premise>
Based on the paragraph above, can we conclude that <hypothesis>?
<options>
Template 2
<premise>
Can we infer the following?
<hypothesis>
<options>
Template 3
Read the following and determine if the hypothesis can be inferred from the premise:
Premise: <premise>
Hypothesis: <hypothesis>
<options>
Template 4, ...

Figure 4: Multiple instruction templates describing a natural language inference task.



	Translation					
	French		German		Romanian	
	En→Fr BLEU	Fr→En BLEU	En→De BLEU	De→En BLEU	En→Ro BLEU	Ro→En BLEU
Supervised model	45.6[c]	35.0[d]	41.2[e]	38.6[f]	38.5[g]	39.9[g]
Base LM 137B zero-shot	11.2	7.2	7.7	20.8	3.5	9.7
· few-shot	31.5	34.7	26.7	36.8	22.9	37.5
GPT-3 175B zero-shot	25.2	21.2	24.6	27.2	14.1	19.9
· few-shot	32.6	39.2	29.7	40.6	21.0	39.5
FLAN 137B zero-shot						
- average template	32.0 ↑6.8 std=2.0	35.6 ↑14.4 std=1.5	24.2 std=2.7	39.4 ↑12.2 std=0.6	16.9 ↑2.8 std=1.4	36.1 ↑16.2 std=1.0
- best dev template	34.0 ▲1.4	36.5 ↑15.3	27.0 ↑2.4	39.8 ↑12.6	18.4 ↑4.3	36.7 ↑16.7


Zero-shot FLAN
Few-shot FLAN
Performance
80
60
40
20
54.7
59.3
59.6
60.0
53.7
57.2
80.0
80.8
63.8
67.4
31.0
33.0
39.2
49.4
Task Cluster:
# datasets:
NLI
7
Read. Comp.
5
Closed-Book QA
3
Commonsense
4
Coreference
2
Translation
3
Struct to text
4



Fine tuning

?

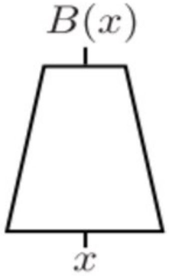
In-context learning/
Prompting

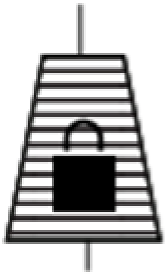
Lightweight Fine-tuning

Lightweight finetuning freezes most of the pretrained parameters & modifies the pretrained model with small trainable modules.

Standard Approach
(Fine tune Top Layers)

i. Train base $B(x)$

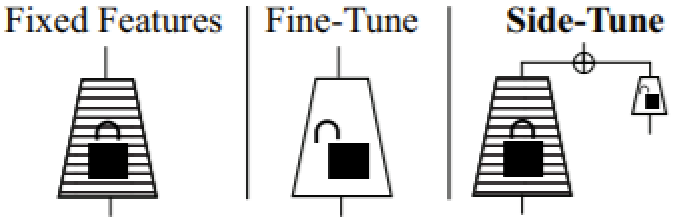


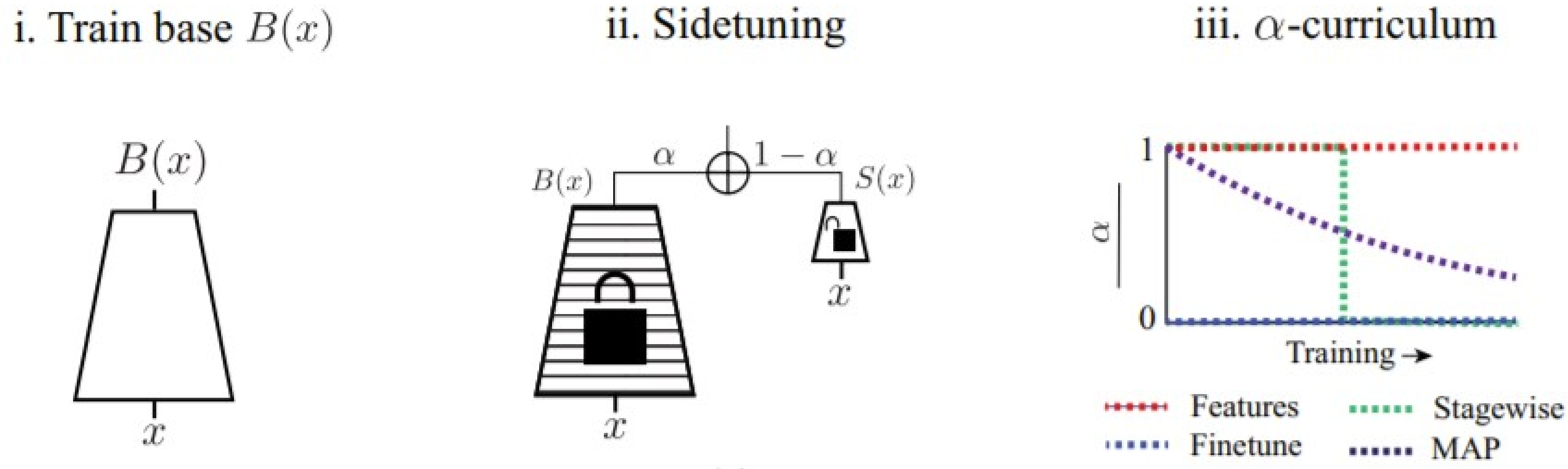


Side-Tuning: A Baseline for Network Adaptation via Additive Side Networks

Jeffrey O. Zhang[1], Alexander Sax[1], Amir Zamir[3], Leonidas Guibas[2], and Jitendra Malik[1]

Side Tuning

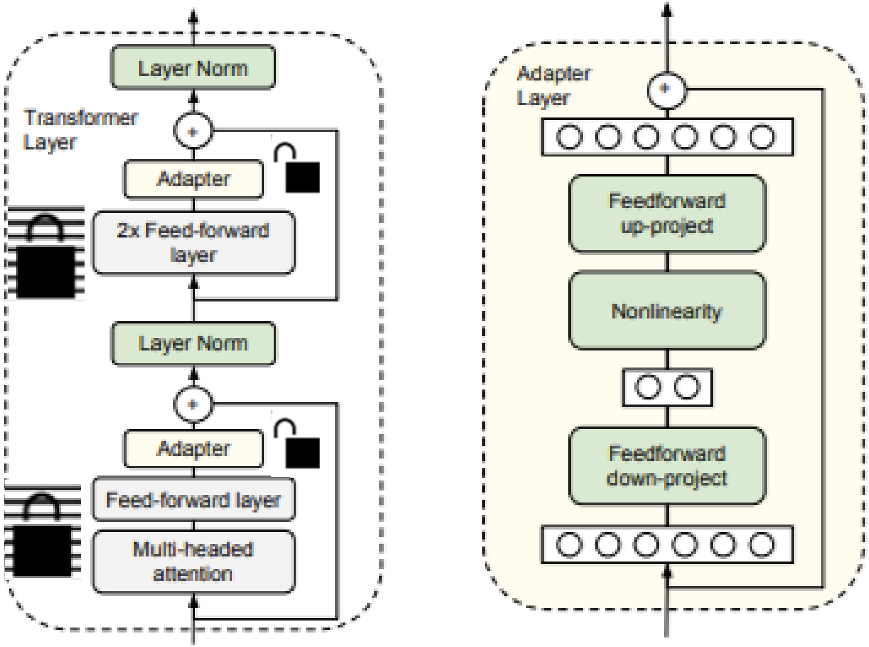




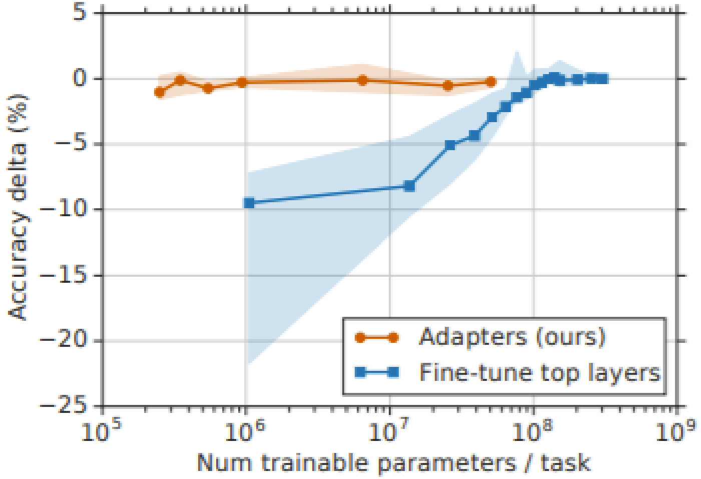
Parameter-Efficient Transfer Learning for NLP

Neil Houlsby [1] Andrei Giurgiu [1*] Stanisław Jastrzębski [2*] Bruna Morrone [1] Quentin de Laroussilhe [1]
Andrea Gesmundo [1] Mona Attariyan [1] Sylvain Gelly [1]

Adapter Tuning



Adapters are new modules added between layers of a pre-trained network.



~4% parameters

Why use Adapters?

Parameter-Efficient Transfer Learning for NLP

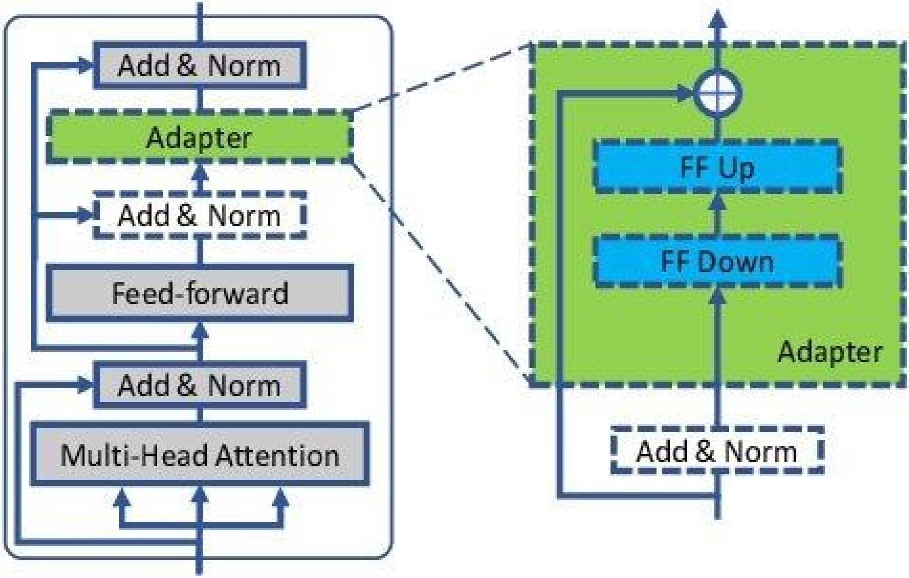
Neil Houlsby [1] Andrei Giurgiu [1 *] Stanisław Jastrzębski [2 *] Bruna Morrone [1] Quentin de Laroussilhe [1]
Andrea Gesmundo [1] Mona Attariyan [1] Sylvain Gelly [1]

Language Adapter

- Trained using Masked Language Modeling (MLM) on the unlabeled Corpus of a language (E.g. Wikipedia)

- Serves as language encoder for a specific language while all other parameters of transformer frozen

- Highy parameter efficient
    - 1 % parameters of the standard mBERT model

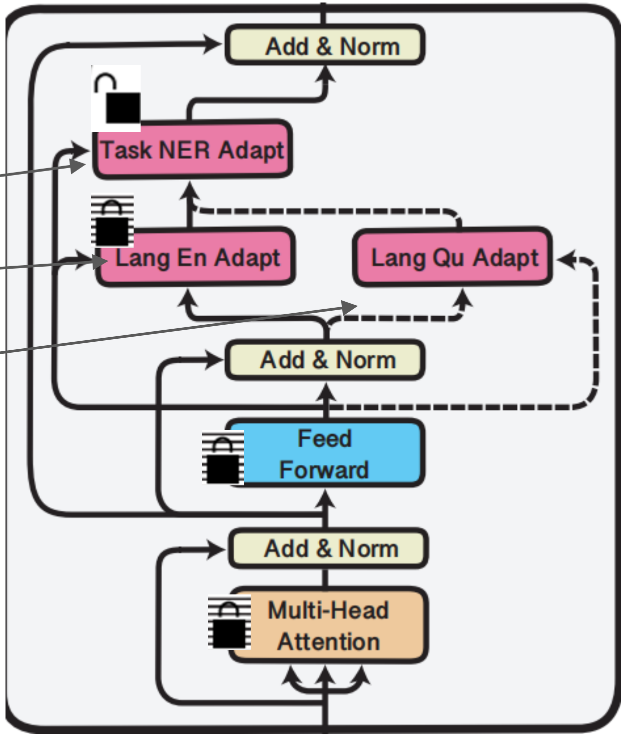


Language Adapters for Cross-Lingual Transfer from English to Target (Pfeiffer et al., 2020)

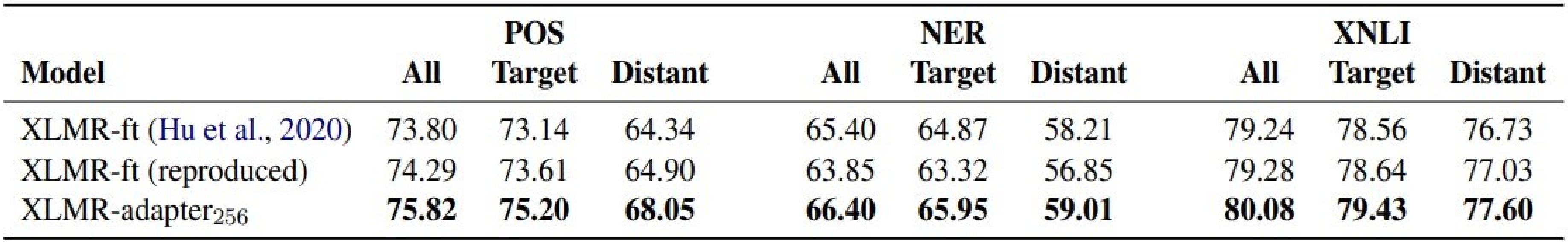
Task adapter inserted during training (only trainable Module)

Use English adapter (frozen) during training

Replace with target language adapter during inference



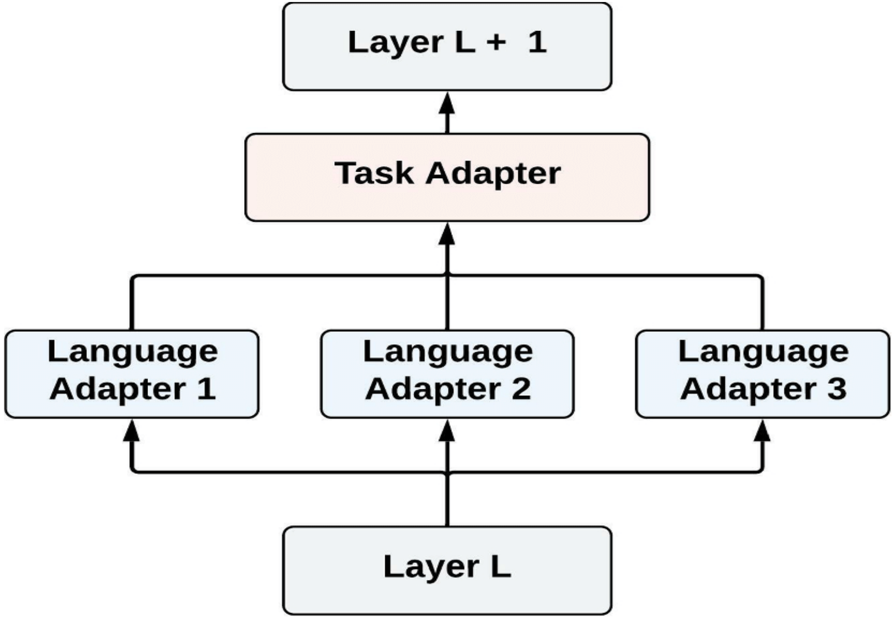
Strong Results for zero-shot transfer (He et al., 2021)



Model		POS			NER			XNLI	
	All	Target	Distant	All	Target	Distant	All	Target	Distant
XLMR-ft (Hu et al., 2020)	73.80	73.14	64.34	65.40	64.87	58.21	79.24	78.56	76.73
XLMR-ft (reproduced)	74.29	73.61	64.90	63.85	63.32	56.85	79.28	78.64	77.03
XLMR-adapter$_{256}$	**75.82**	**75.20**	**68.05**	**66.40**	**65.95**	**59.01**	**80.08**	**79.43**	**77.60**

Zero-shot cross-lingual results (reported by He et al., 2021). Target is the average test result of all target languages except English. Distant is the average test result of the languages not in the Indo-European family.

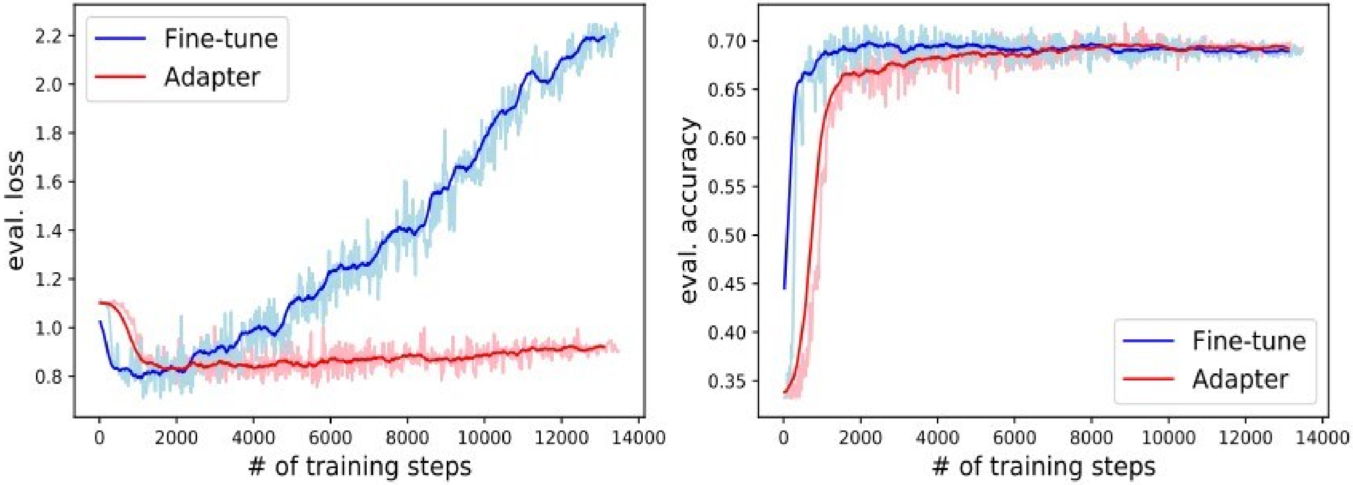
Using Multiple Language Adapters

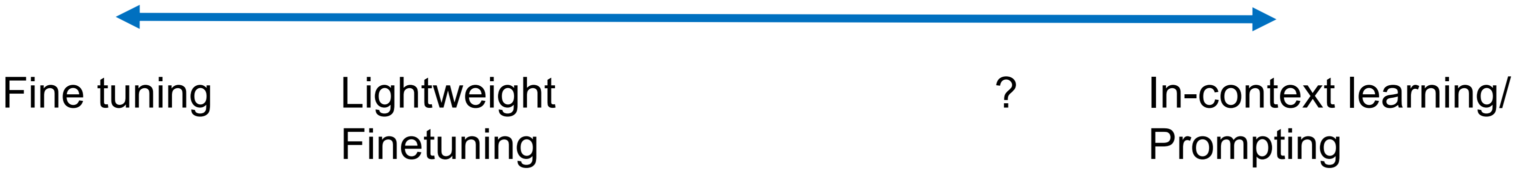


Placing Language Adapters in Parallel (He et al., 2021)

Best Practices with Adapters!!!

- Keep a higher learning rate than the one used with standard BERT/mBERT models
    - 1e-4 vs 2e-5
- Might have to train for longer than the standard BERT/mBERT fine-tuning



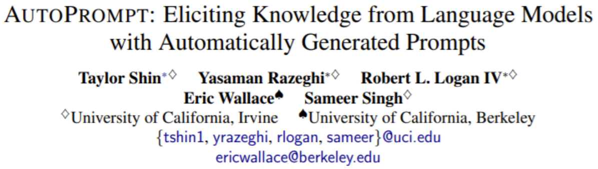


Fine tuning

Lightweight
Finetuning

?

In-context learning/
Prompting



AUTOPROMPT: Eliciting Knowledge from Language Models with Automatically Generated Prompts

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Eric Wallace♠ Sameer Singh◇
◇University of California, Irvine ♠University of California, Berkeley
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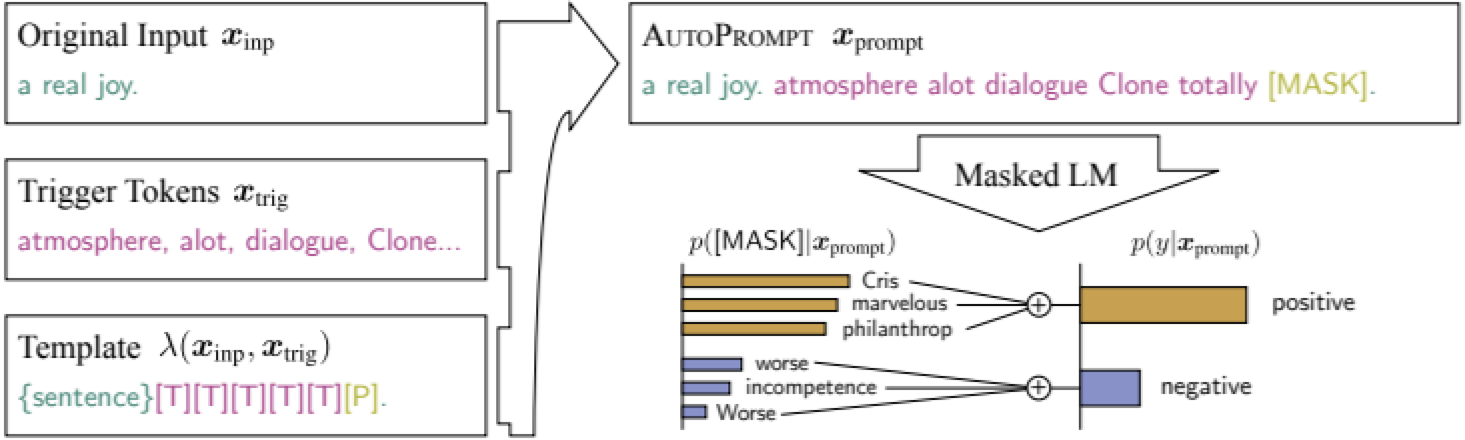
ericwallace@berkeley.edu

AutoPrompt


Original Input $\boldsymbol{x}_{\text{inp}}$
a real joy.
Trigger Tokens $\boldsymbol{x}_{\text{trig}}$
atmosphere, alot, dialogue, Clone...
Template $\lambda(\boldsymbol{x}_{\text{inp}}, \boldsymbol{x}_{\text{trig}})$
{sentence}[T][T][T][T][T][P].
AUTOPROMPT $\boldsymbol{x}_{\text{prompt}}$
a real joy. atmosphere alot dialogue Clone totally [MASK].
Masked LM
$p([\text{MASK}]|\boldsymbol{x}_{\text{prompt}})$
$p(y|\boldsymbol{x}_{\text{prompt}})$
Cris
marvelous
philanthrop
worse
incompetence
Worse
positive
negative

Prefix-Tuning: Optimizing Continuous Prompts for Generation

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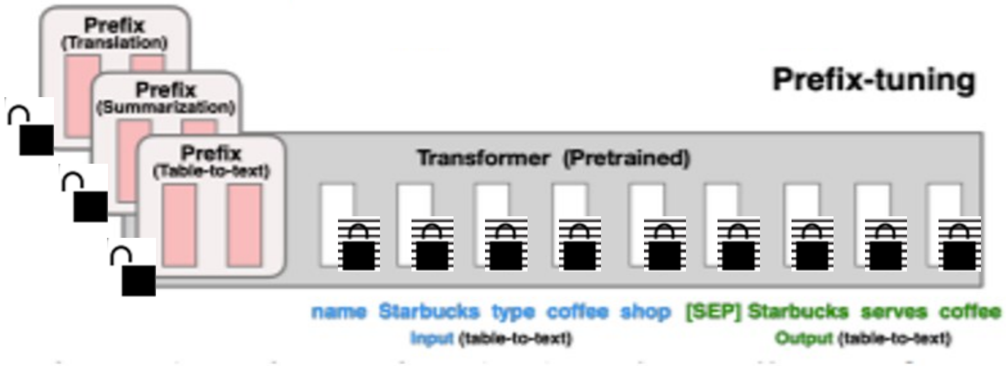
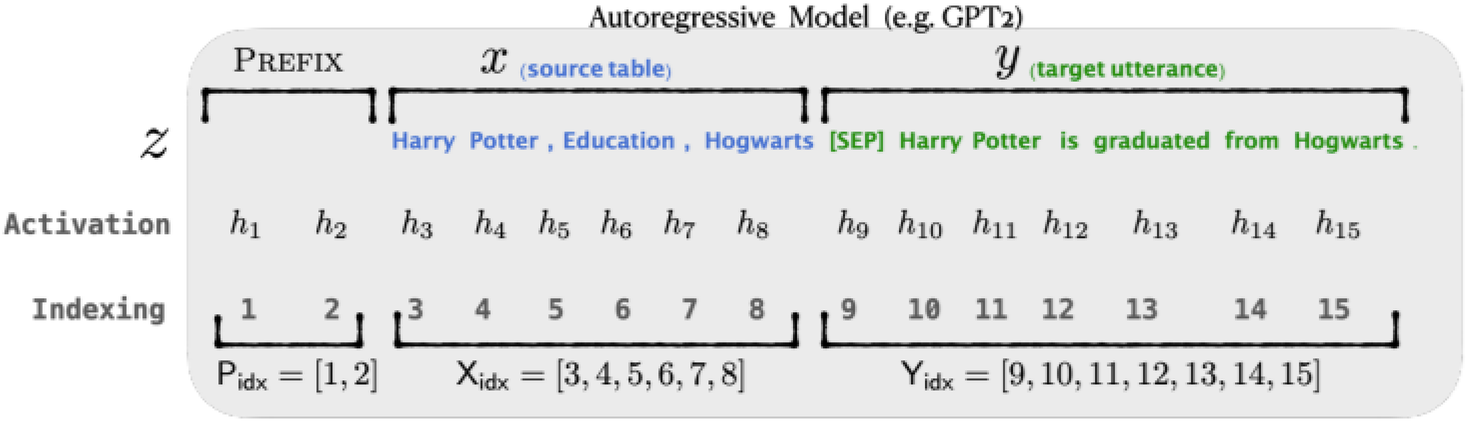
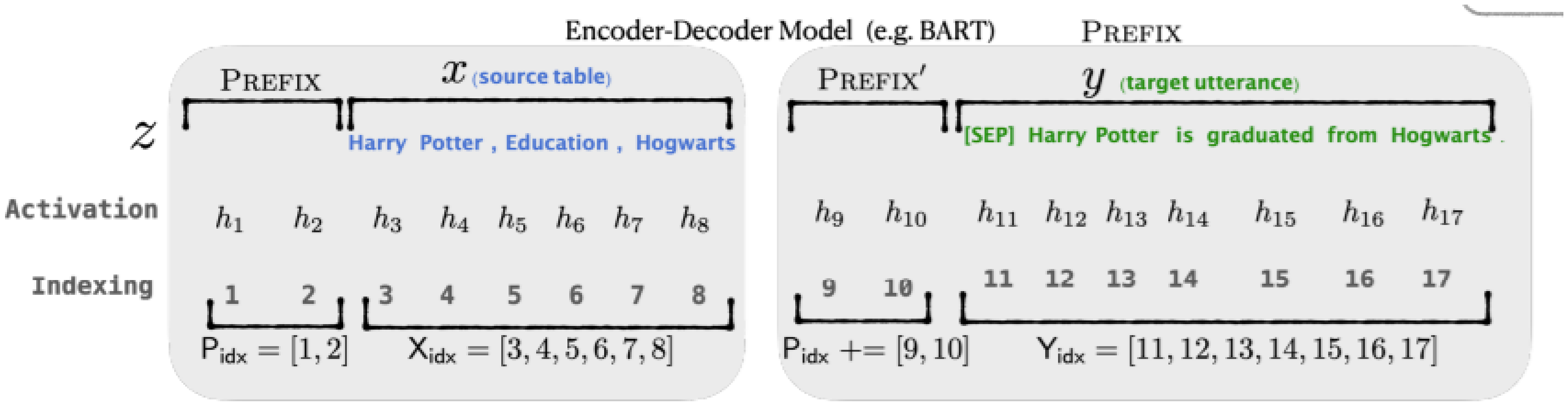
Prefix Tuning

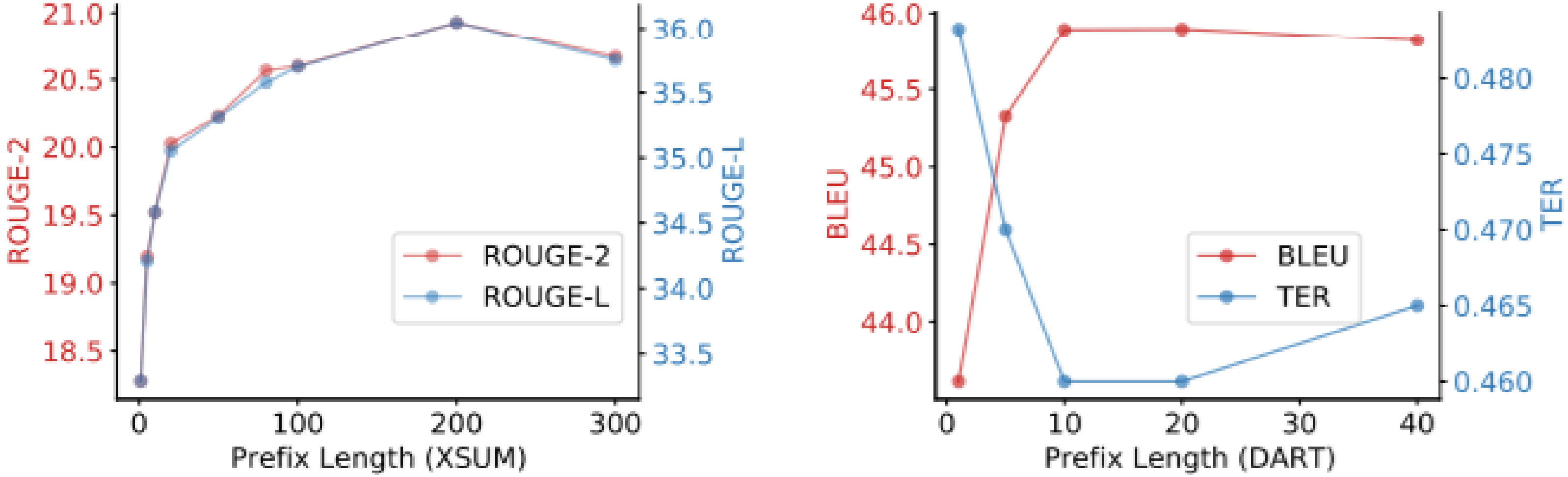


0.1% parameters

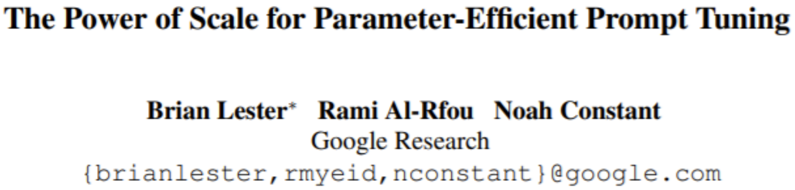


Autoregressive Model (e.g. GPT2)
PREFIX
x (source table)
y (target utterance)
z
Harry Potter , Education , Hogwarts [SEP] Harry Potter is graduated from Hogwarts .
Activation
h_1 h_2 h_3 h_4 h_5 h_6 h_7 h_8 h_9 h_{10} h_{11} h_{12} h_{13} h_{14} h_{15}
Indexing
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
$\mathsf{P}_{\mathsf{idx}} = [1, 2]$
$\mathsf{X}_{\mathsf{idx}} = [3, 4, 5, 6, 7, 8]$
$\mathsf{Y}_{\mathsf{idx}} = [9, 10, 11, 12, 13, 14, 15]$


Encoder-Decoder Model (e.g. BART)
PREFIX
PREFIX
x (source table)
z
Harry Potter , Education , Hogwarts
PREFIX′
y (target utterance)
[SEP] Harry Potter is graduated from Hogwarts .
Activation
h_1 h_2 h_3 h_4 h_5 h_6 h_7 h_8
h_9 h_{10} h_{11} h_{12} h_{13} h_{14} h_{15} h_{16} h_{17}
Indexing
1 2 3 4 5 6 7 8
9 10 11 12 13 14 15 16 17
$\mathsf{P}_{\mathsf{idx}} = [1, 2]$
$\mathsf{X}_{\mathsf{idx}} = [3, 4, 5, 6, 7, 8]$
$\mathsf{P}_{\mathsf{idx}} += [9, 10]$
$\mathsf{Y}_{\mathsf{idx}} = [11, 12, 13, 14, 15, 16, 17]$


ROUGE-2
ROUGE-L
21.0
20.5
20.0
19.5
19.0
18.5
36.0
35.5
35.0
34.5
34.0
33.5
0
100
200
300
Prefix Length (XSUM)
ROUGE-2
ROUGE-L
BLEU
TER
46.0
45.5
45.0
44.5
44.0
0.480
0.475
0.470
0.465
0.460
0
10
20
30
40
Prefix Length (DART)
BLEU
TER

Prompt Tuning



The Power of Scale for Parameter-Efficient Prompt Tuning

Brian Lester* **Rami Al-Rfou** **Noah Constant**
Google Research
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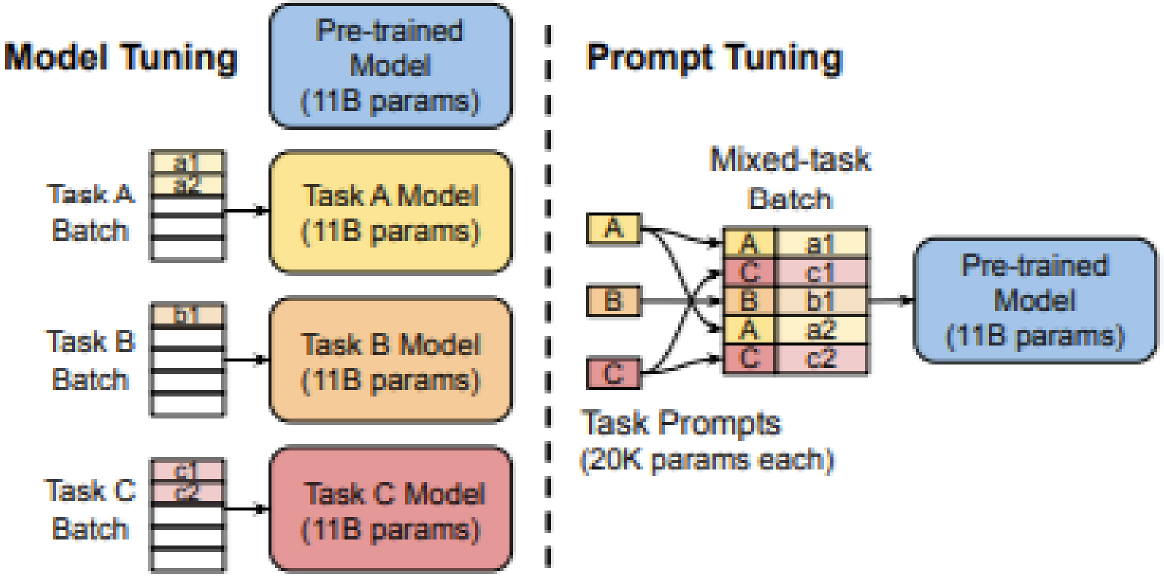

Model Tuning
Pre-trained Model (11B params)
Task A Batch
a1
a2
Task A Model (11B params)
Task B Batch
b1
Task B Model (11B params)
Task C Batch
c1
c2
Task C Model (11B params)
Prompt Tuning
Mixed-task Batch
A
B
C
A a1
C c1
B b1
A a2
C c2
Pre-trained Model (11B params)
Task Prompts (20K params each)

Design Decisions

Initialization

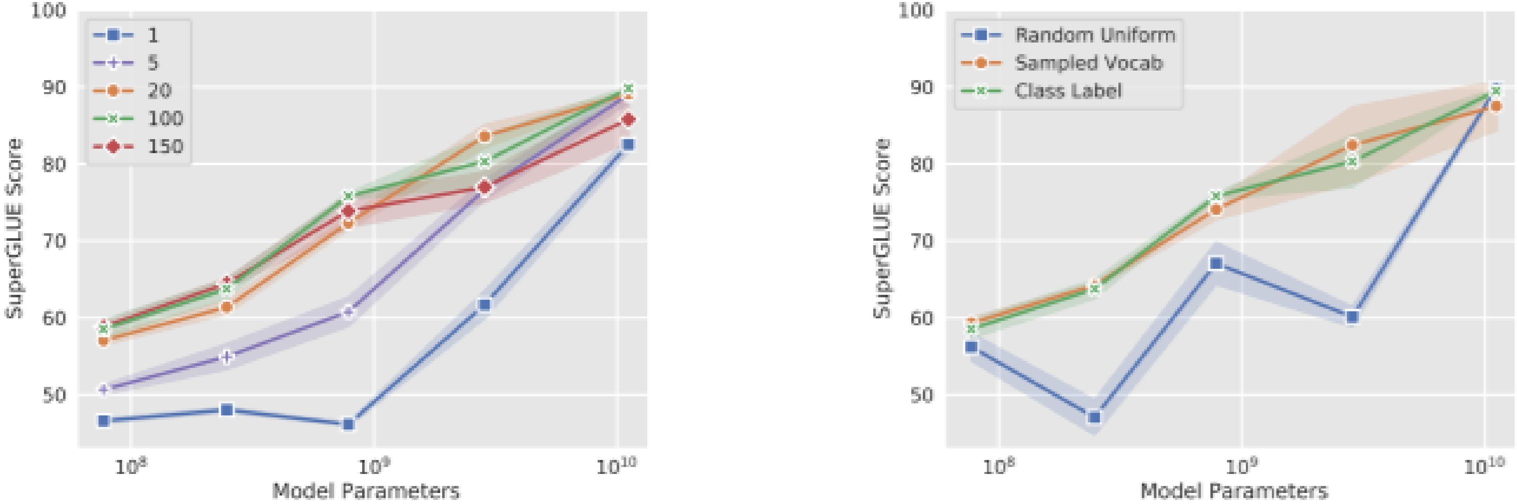
- The simplest is to train from scratch, using random initialization.

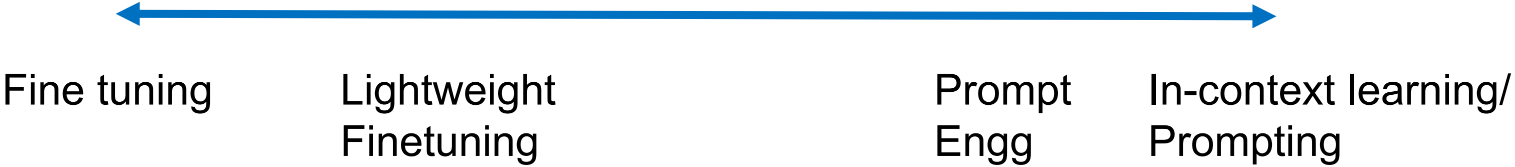
- Initialize each prompt token to an embedding drawn from the model’s vocabulary

- For classification tasks, a third option is to initialize the prompt with embeddings that enumerate the output classes

Length of Prompt

- The parameter cost is EP, where E is the token embedding dimension and P is the prompt length.


100
90
80
70
60
50
SuperGLUE Score
10^8
10^9
10^{10}
Model Parameters
1
5
20
100
150
100
90
80
70
60
50
SuperGLUE Score
10^8
10^9
10^{10}
Model Parameters
Random Uniform
Sampled Vocab
Class Label



Fine tuning

Lightweight Finetuning

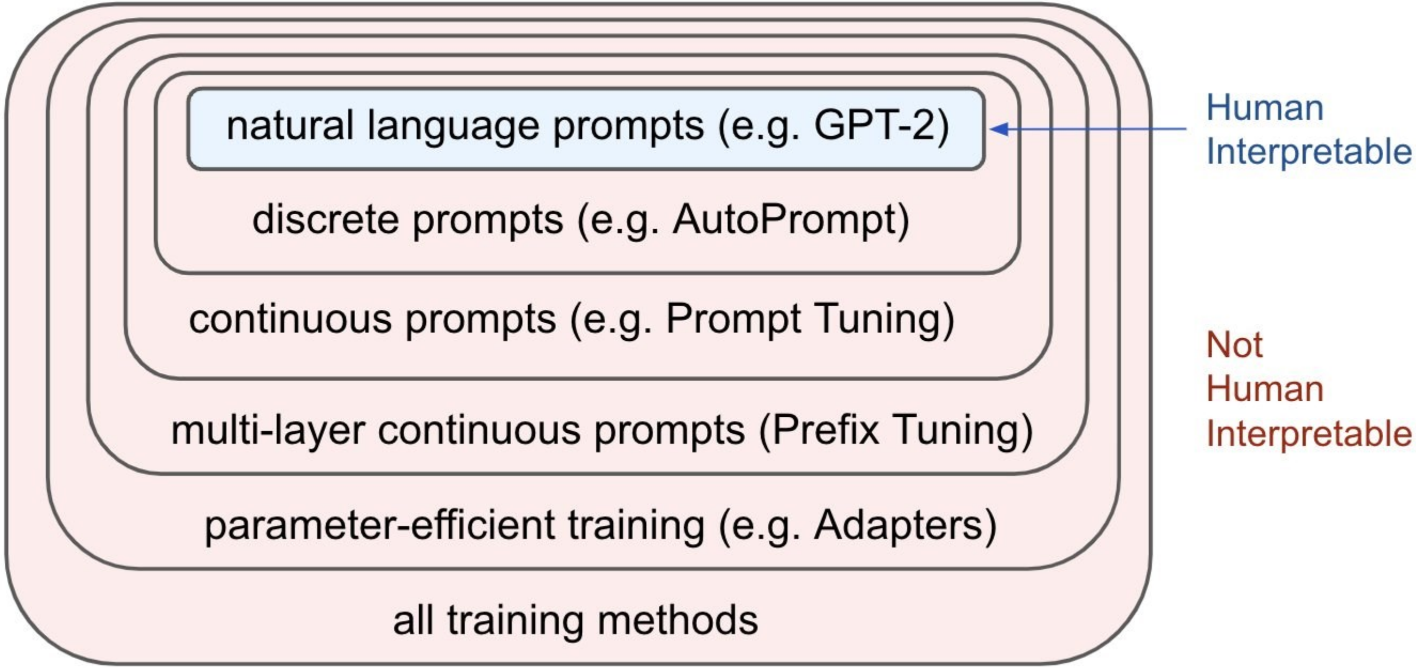
Prompt Engg

In-context learning/ Prompting

A Taxonomy of Prompting Methods

By Graham Neubig (10/15/2022)

See CMU ANLP Prompting Lecture, A Unified View of Parameter-Efficient Transfer Learning



natural language prompts (e.g. GPT-2)

discrete prompts (e.g. AutoPrompt)

continuous prompts (e.g. Prompt Tuning)

multi-layer continuous prompts (Prefix Tuning)

parameter-efficient training (e.g. Adapters)

all training methods

Human Interpretable

Not Human Interpretable

GPT-2: https://openai.com/blog/better-language-models/

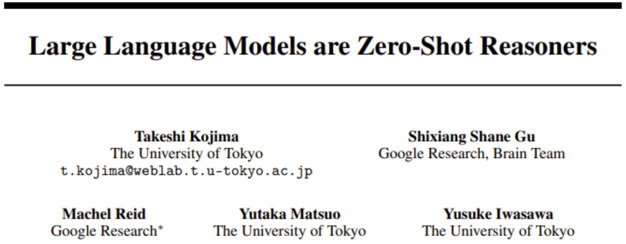
AutoPrompt: https://arxiv.org/abs/2010.15980

Prompt Tuning: https://arxiv.org/abs/2104.08691

Prefix Tuning: https://arxiv.org/abs/2101.00190

Adapters: https://arxiv.org/abs/2010.15980

Chain of Thought Prompting



Large Language Models are Zero-Shot Reasoners

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Shixiang Shane Gu
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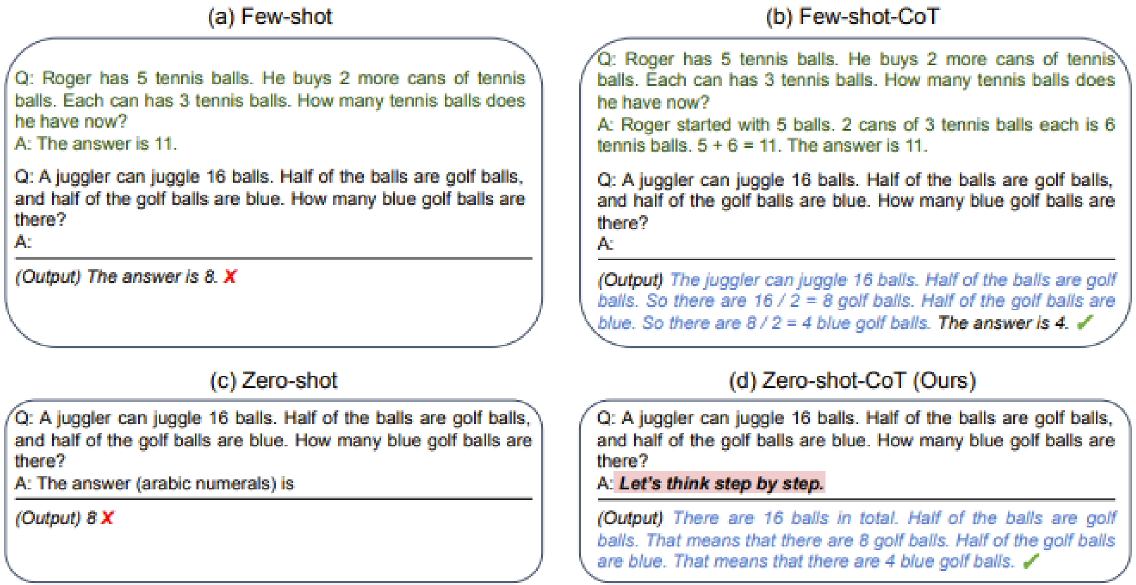
Machel Reid
Google Research*

Yutaka Matsuo
The University of Tokyo

Yusuke Iwasawa
The University of Tokyo

Simply adding “Let’s think step by step” before each answer increases the accuracy on MultiArith from 17.7% to 78.7% and GSM8K from 10.4% to 40.7% with GPT-3. https://t.co/ebvxSbac1K pic.twitter.com/lpZwDTf06m



(a) Few-shot

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: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The answer is 8. ✗

(b) Few-shot-CoT

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: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The juggler can juggle 16 balls. Half of the balls are golf balls. So there are 16 / 2 = 8 golf balls. Half of the golf balls are blue. So there are 8 / 2 = 4 blue golf balls. The answer is 4. ✓

(c) Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: The answer (arabic numerals) is

(Output) 8 ✗

(d) Zero-shot-CoT (Ours)

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: ***Let’s think step by step.***

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls. ✓

http://new-savanna.blogspot.com/2022/05/lets-think-step-by-step-is-all-you-need.html