CSCE 689: Special Topics in Trustworthy NLP

Lecture 8: Natural Language Processing Basics (7)

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Paper Summary

- A summary of two papers is due next Monday before lecture
- Submit summary to Canvas
- Page limit: 1 page
- The summary should include
 - A brief overview of the main objectives and contributions of the paper
 - Key methodologies and approaches used in the study
 - Significant findings and results
 - Strengths and weaknesses of the paper

Paper Summary

Choose 1 paper here

- Generating Natural Language Adversarial Examples, EMNLP 2018
- BERT-ATTACK: Adversarial Attack Against BERT Using BERT, EMNLP 2020
- Universal Adversarial Triggers for Attacking and Analyzing NLP, EMNLP 2019
- Certified Robustness to Adversarial Word Substitutions, EMNLP 2019
- Towards Robustness Against Natural Language Word Substitutions, ICLR 2021
- <u>Universal and Transferable Adversarial Attacks on Aligned Language</u>
 Models, arXiv 2023

Choose 1 paper here

Course Project – Proposal

- Team: 1~2 people
- Due: 9/25
- Page limit: 2 pages
- Format: ACL style
- The proposal should include
 - The topic you choose
 - An introduction to the task
 - Evaluation metrics
 - The dataset, models, and approaches you plan to use

Invited Talk

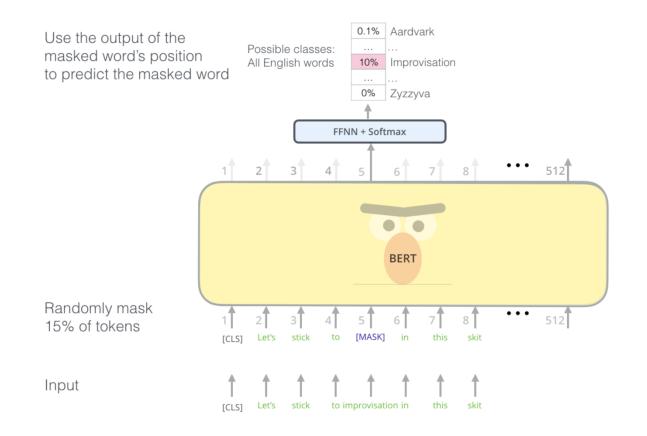
W8	10/7	Fall Break (No Class)	
	10/9	Invited Talk (Remote)	Invited Talk
	10/11	Team Project Highlights	Team Project Highlights

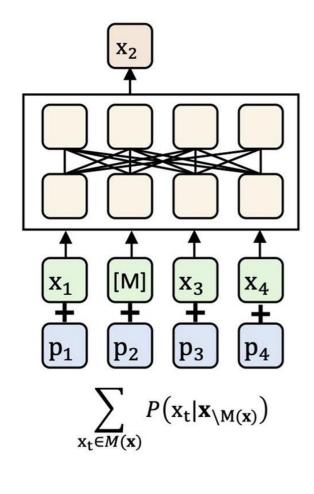
Lecture Plan

- Natural Language Processing Basics
- Large Language Models
- Prompting
- In-Context Learning
- Instruction Tuning

Recap: Encoder-Only Pre-Training

BERT, RoBERTa

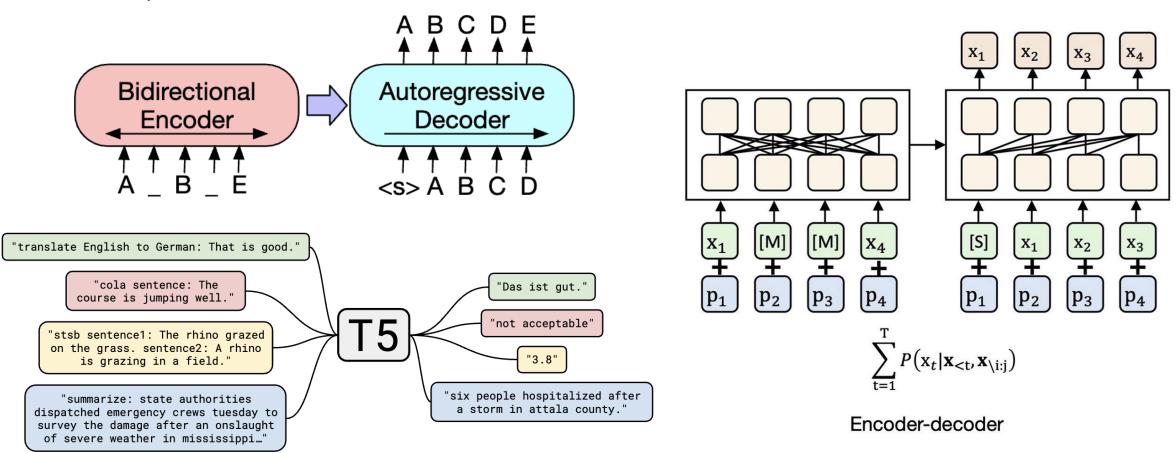




Encoder only

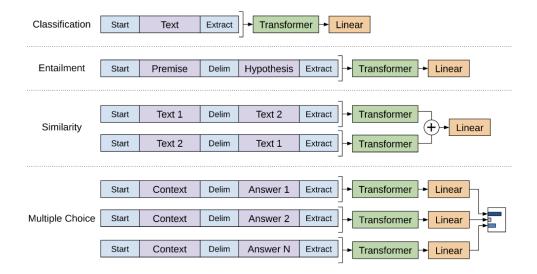
Recap: Encoder-Decoder Pre-Training

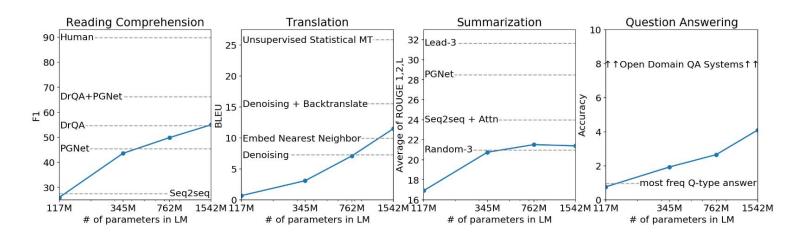
• BART, T5

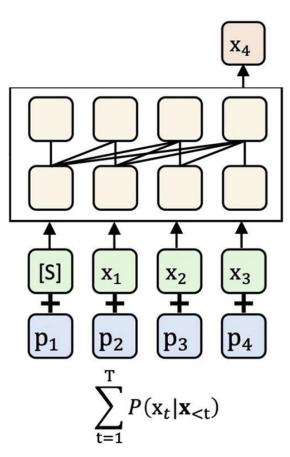


Recap: Decoder-Only Pre-Training

GPT

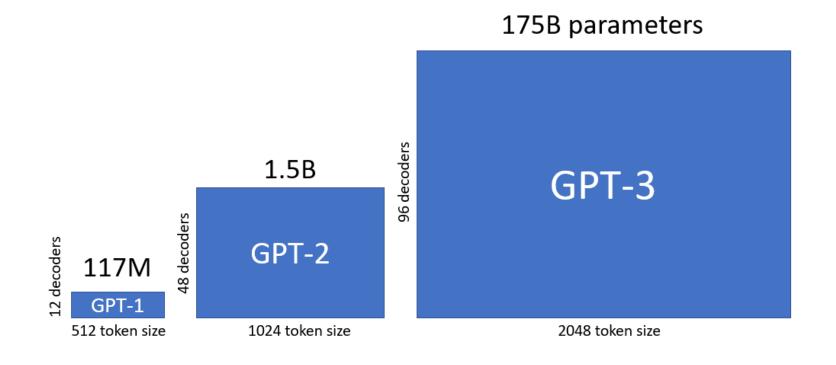






Decoder only

Scaling Is The Key



Zero-Shot Prompting

- Prompt → Completion
 - Continue writing

Prompt

This place is incredible! The lobster is the best I've ever had. The sentiment of the above sentence is

positive.

Completion

Zero-Shot Prompting

- Prompt → Completion
 - Continue writing

Prompt

Stephen Curry's clutch barrage seals another Olympic gold for USA. The topic of the above sentence is

sport.

Completion

Language Modeling

```
Binge ... on | - | and | of | is
Binge drinking ... is | and | had | in | was
Binge drinking may ... be | also | have | not | increase
Binge drinking may not ... be | have | cause | always | help
Binge drinking may not necessarily ... be | lead | cause | results | have
Binge drinking may not necessarily kill ... you | the | a | people | your
Binge drinking may not necessarily kill or ... even | injure | kill | cause | prevent
Binge drinking may not necessarily kill or even ... kill | prevent | cause | reduce | injure
Binge drinking may not necessarily kill or even damage ... your | the | a | you | someone
Binge drinking may not necessarily kill or even damage brain ... cells | functions | tissue | neurons
Binge drinking may not necessarily kill or even damage brain cells, ... some | it | the | is | long
```

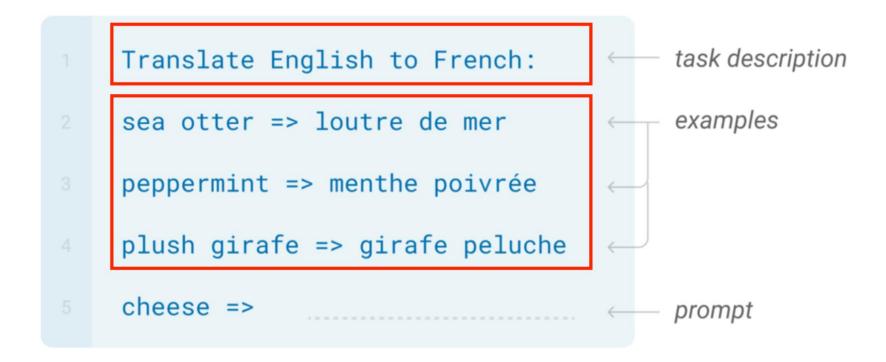
Training language models in a large scale \rightarrow Large Language Models (LLMs)

Zero-Shot Prompting

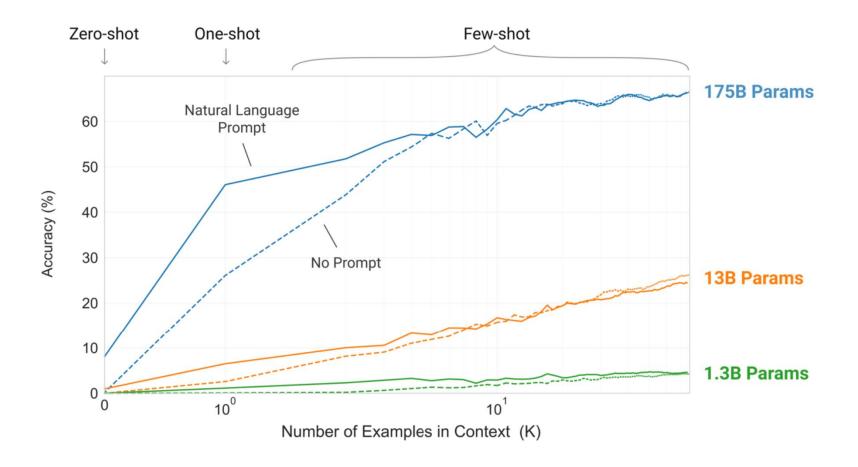
Prompt This place is incredible! The lobster is the best I've ever had. The sentiment of the above sentence is positive. Stephen Curry's clutch barrage seals another Olympic gold for USA. The topic of the above sentence is sport. Completion Completion

In-Context Learning

Few-shot prompting



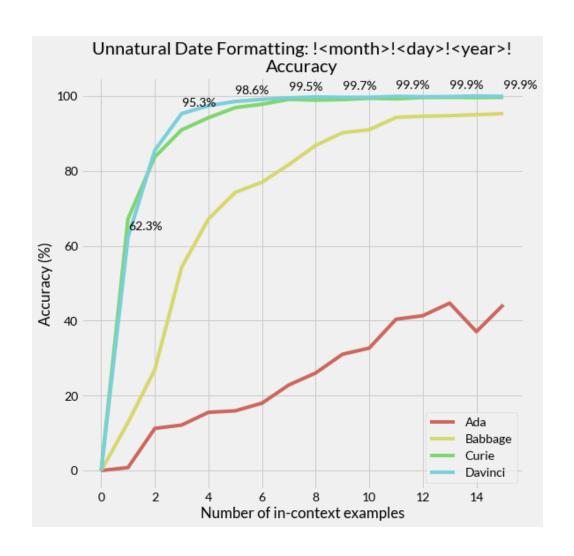
In-Context Learning



In-Context Learning

```
Input: 2014-06-01
Output: !06!01!2014!
Input: 2007-12-13
Output: !12!13!2007!
Input: 2010-09-23
Output: !09!23!2010!
Input: 2005-07-23
Output: !07!23!2005!

L - - model completion
```

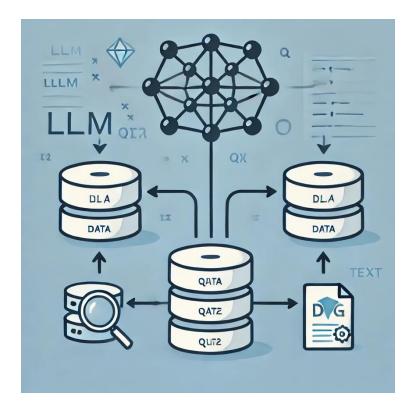


A New Way to Use NLP Models

- Task-specific features + task-specific model
- General embeddings + task-specific model
- General embeddings + general model + task-specific fine-tuning
- General embeddings + general model + task-specific prompting

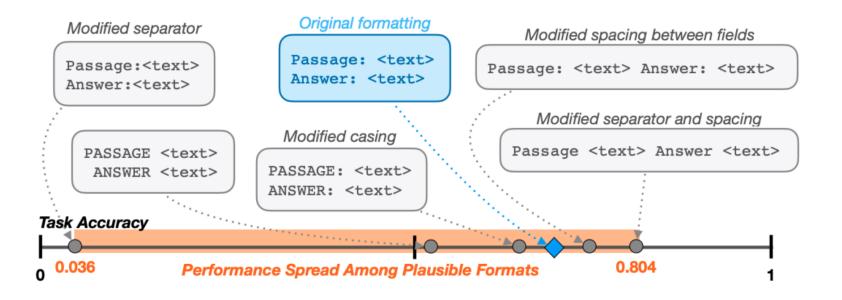
Large Language Models as Database

- Pre-training → building knowledge database from corpus
- Prompting → query database



Prompt Engineering

- LLMs are sensitive to prompts
- Prompt engineering: search for better prompts



Prompt Engineering: Chain-of-Thought

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 X

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.

Prompt Engineering: Chain-of-Thought

(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. X

(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 X

(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 $4 \cdot \checkmark$

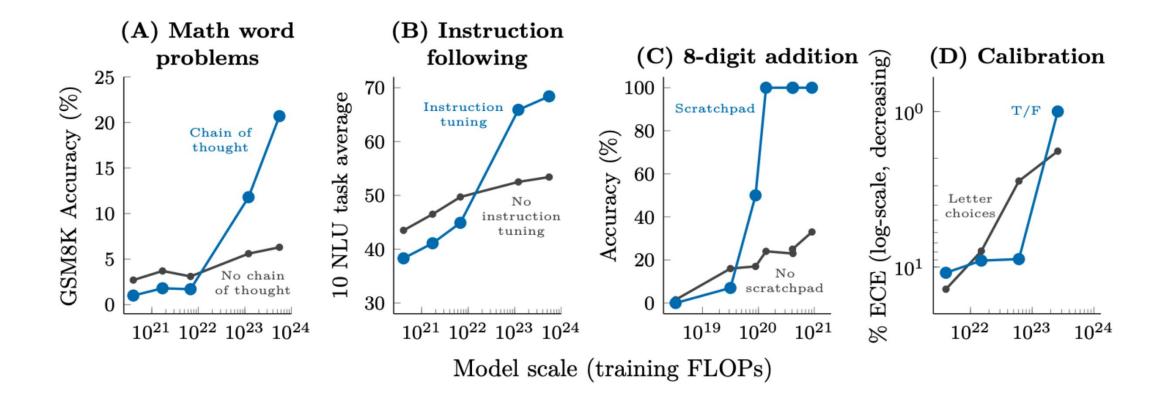
(d) Zero-shot-CoT (Ours)

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.

Scaling Is The Key



Lecture Plan

- Natural Language Processing Basics
- Large Language Models
- Prompting
- In-Context Learning
- Instruction Tuning

Instruction Tuning

Continuing writing does not always work

Prompt

This place is incredible! The lobster is the best I've ever had. The sentiment of the above sentence is

positive.

Completion

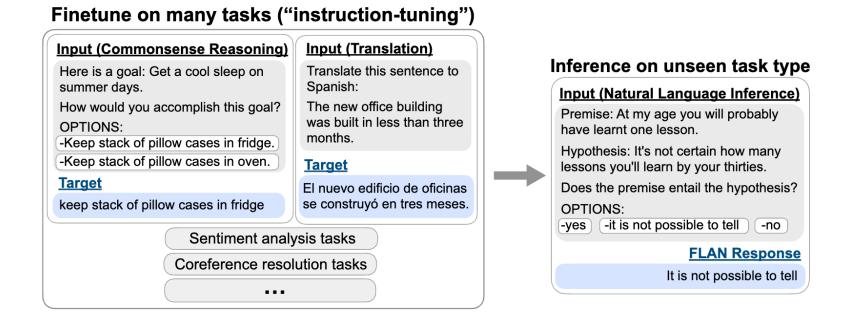
Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A: The answer (arabic numerals) is

(Output) 8 X

Instruction Tuning

Training LLMs to following human thoughts



Instruction Tuning

Training LLMs to following human thoughts

Annotated task definitions

You will be given two pieces of text... One of them is simpler ...

You are expected to output 'Text one' if the first sentence is simpler.

Otherwise output 'Text two'.

Given a sentence with a missing word, pick the answer option that best fills out the missing word in the sentence. Indicate each answer with its index ('a', 'b', 'c', 'd').

Given a document, generate a short title of the document. The title should convey the main idea/event/topic about which the document is being written.

Category	Description
Input Content	Primary description of the task input
Additional Input Content	Additional details on task input
Action Content	Action to perform for task
Input Mention	Mentions of input within action content
Output Content	Primary description of task output
Additional Output Content	Additional details on task output
Label List	Task output labels (classification only)
Label Definition	Task Label definitions (classification only)

Step 1 Collect demonstration data. and train a supervised policy. A prompt is sampled from our Explain the moon prompt dataset. landing to a 6 year old A labeler demonstrates the desired output behavior. Some people went to the moon... This data is used to fine-tune GPT-3 with supervised learning.

Step 2

Collect comparison data, and train a reward model.

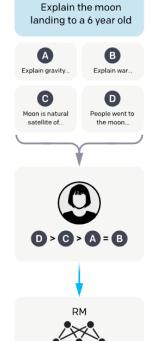
A prompt and several model outputs are sampled.

A labeler ranks

the outputs from best to worst.

This data is used

to train our reward model.



Step 3

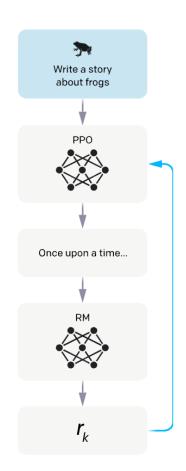
Optimize a policy against the reward model using reinforcement learning.

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.



Supervised Fine-Tuning (SFT)

Use-case	Prompt		
Brainstorming	List five ideas for how to regain enthusiasm for my career		
Generation	Write a short story where a bear goes to the beach makes friends with a seal, and then returns home		
Rewrite	This is the summary of a Broadway play:		
	{summary}		
	This is the outline of the commercial for that play:		

Use-case	(%)
Generation	45.6%
Open QA	12.4%
Brainstorming	11.2%
Chat	8.4%
Rewrite	6.6%
Summarization	4.2%
Classification	3.5%
Other	3.5%
Closed QA	2.6%
Extract	1.9%

Number of Prompts			
	SFT Data		
split	source	size	
train	labeler	11,295	
train	customer	1,430	
valid	labeler	1,550	
valid	customer	103	

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.



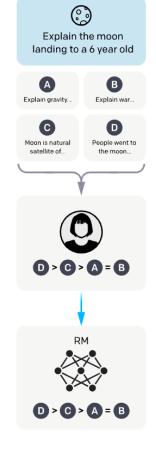
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Step 3

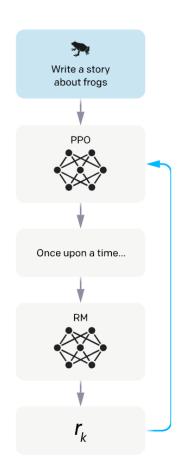
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Step 1

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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.



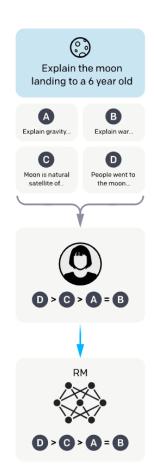
Step 2

Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

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Optimize a policy against the reward model using reinforcement learning.

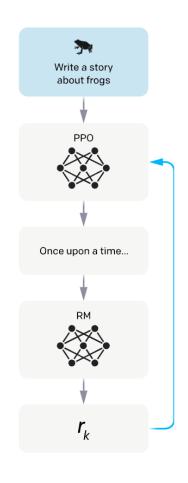
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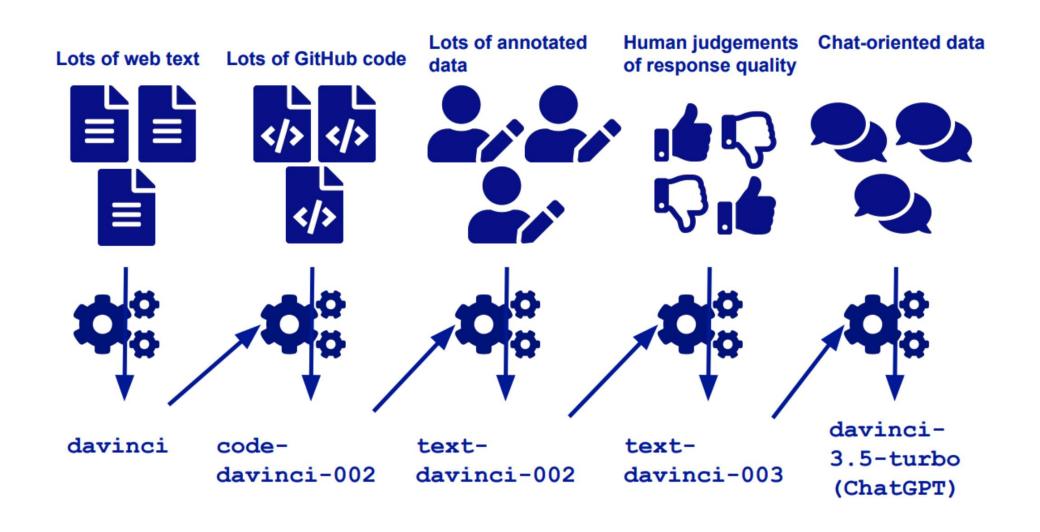
ChatGPT: InstructGPT + Dialogue Data

Introducing ChatGPT

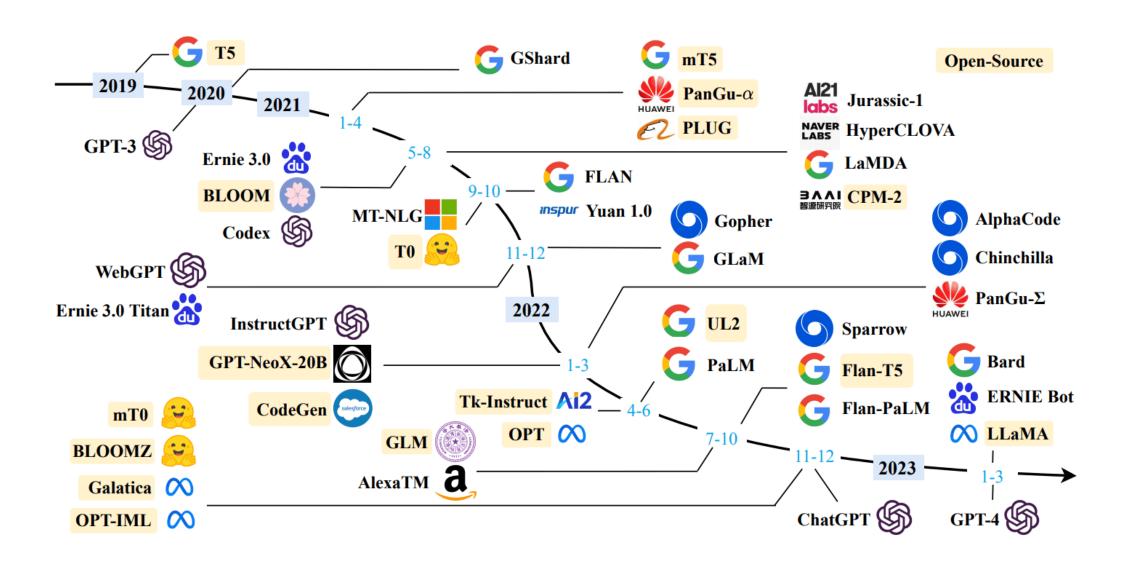
We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests.

"We trained this model using Reinforcement Learning from Human Feedback (RLHF), using the same methods as InstructGPT, but with slight differences in the data collection setup. We trained an initial model using supervised finetuning: human AI trainers provided conversations in which they played both sides—the user and an AI assistant. We gave the trainers access to model-written suggestions to help them compose their responses. We mixed this new dialogue dataset with the InstructGPT dataset, which we transformed into a dialogue format."

ChatGPT: InstructGPT + Dialogue Data

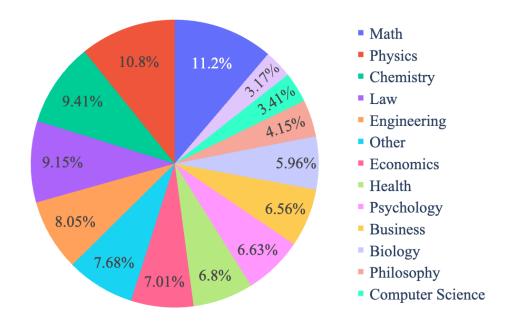


Large Language Models



Benchmark

MMLU and MMLU-pro



```
Find all c in \mathbb{Z}_3 such that \mathbb{Z}_3[x]/(x^2+c) is a field. (A) 0 (B) 1 (C) 2 (D) 3
```

Figure 14: An Abstract Algebra example.

What is the embryological origin of the hyoid bone?

- (A) The first pharyngeal arch
- (B) The first and second pharyngeal arches
- (C) The second pharyngeal arch
- (D) The second and third pharyngeal arches

Figure 15: An Anatomy example.

Why isn't there a planet where the asteroid belt is located?

- (A) A planet once formed here but it was broken apart by a catastrophic collision.
- (B) There was not enough material in this part of the solar nebula to form a planet.
- (C) There was too much rocky material to form a terrestrial planet but not enough gaseous material to form a jovian planet.
- (D) Resonance with Jupiter prevented material from collecting together to form a planet.

Figure 16: An Astronomy example.

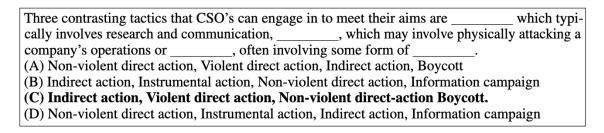


Figure 17: A Business Ethics example.

Benchmark

BIG-Bench Hard

Model Input (Navigate)

<Few shot chain-of-thought exemplars omitted for brevity>

Q: If you follow these instructions, do you return to the starting point? Turn left. Turn right. Take 5 steps. Take 4 steps. Turn around. Take 9 steps.

Options:

- Yes
- No

A: Let's think step by step.

Model Output

We start at the origin (0, 0), facing the positive y-axis.

- (1) Turn left: (0, 0), facing the negative x-axis.
- (2) Turn right: (0, 0), facing the positive y-axis.
- (3) Take 5 steps: (0, 5), facing the positive y-axis.
- (4) Take 4 steps: (0, 9), facing the positive y-axis.
- (5) Turn around: (0, 9), facing the negative y-axis.
- (6) Take 9 steps: (0, 0), facing the negative y-axis.

Since (0, 0) is (0, 0), we are indeed where we started. So the answer is **Yes**.

Model Input (Word Sorting)

<Few shot chain-of-thought exemplars omitted for brevity>

Q: Sort the following words alphabetically: List: burley bela arapaho bacteria bock

A: Let's think step by step.

Model Output

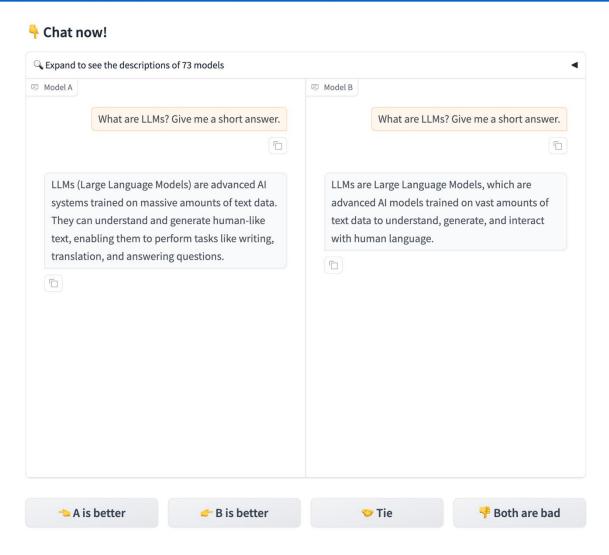
The first letter: "burley": "b" (2). "bela": "b" (2). "arapaho": "a" (1). "bacteria": "b" (2). "bock": "b" (2).

We now have: (1) "arapaho" < (2) ["burley"? "bela"? "bacteria"? "bock"]. Now let's sort this subpart ["burley"? "bela"? "bacteria"? "bock"] by looking at their second letters.

The second letter: "burley": "u" (21). "bela": "e" (5). "bacteria": "a" (1). "bock": "o" (15). We now have: (1) "bacteria" < (5) "bela" < (15) "bock" < (21) "burley". Hence, we have "arapaho" < ["bacteria" < "bela" < "bock" < "burley"]. So the answer is **arapaho bacteria bela bock burley**.

Chatbot Arena

https://huggingface.co/spaces/Imsys/chatbot-arena-leaderboard



Chatbot Arena

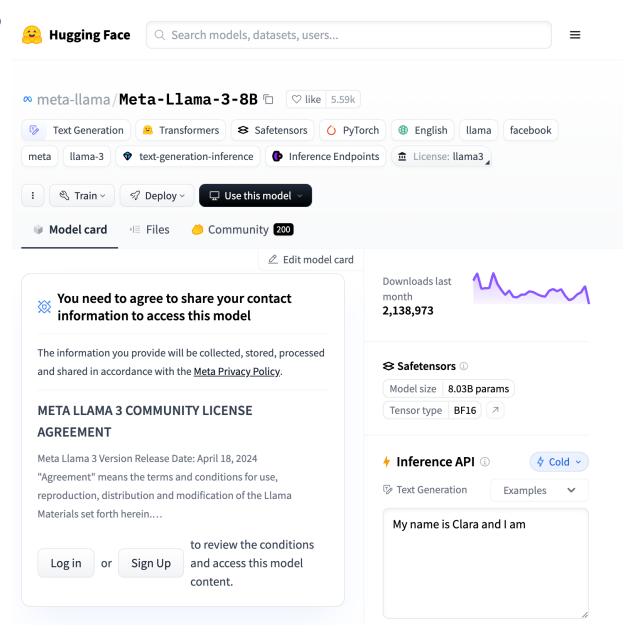
Rank* (UB)	Model	Arena Score	95% CI 🔺	Votes	Organization A	License	Knowledge Cutoff
1	ChatGPT-40-latest (2024-08-08)	1316	+4/-3	31148	OpenAI	Proprietary	2023/10
2	Gemini-1.5-Pro-Exp-0827	1300	+4/-4	22844	Google	Proprietary	2023/11
2	Gemini-1.5-Pro-Exp-0801	1298	+4/-4	26110	Google	Proprietary	2023/11
2	Grok-2-08-13	1294	+4/-4	16215	xAI	Proprietary	2024/3
5	GPT-40-2024-05-13	1285	+3/-2	86306	OpenAI	Proprietary	2023/10
6	GPT-4o-mini-2024-07-18	1274	+4/-4	26088	OpenAI	Proprietary	2023/10
6	Claude 3.5 Sonnet	1270	+3/-3	56674	Anthropic	Proprietary	2024/4
6	Gemini-1.5-Flash-Exp-0827	1268	+5/-4	16780	Google	Proprietary	2023/11
6	Grok-2-Mini-08-13	1267	+4/-4	16731	xAI	Proprietary	2024/3
6	Meta-Llama-3.1-405b-Instruct	1266	+4/-4	27397	Meta	Llama 3.1 Community	2023/12
7	Gemini Advanced App (2024-05-14)	1266	+3/-3	52236	Google	Proprietary	Online
7	GPT-40-2024-08-06	1263	+4/-4	18093	OpenAI	Proprietary	2023/10
12	Gemini-1.5-Pro-001	1259	+2/-2	76952	Google	Proprietary	2023/11
12	Gemini-1.5-Pro-Preview-0409	1257	+4/-4	55597	Google	Proprietary	2023/11
12	GPT-4-Turbo-2024-04-09	1257	+2/-3	90149	OpenAI	Proprietary	2023/12

Common None-Open-Source LLMs

- Not public but strong performance
 - ChatGPT-4o (OpenAI)
 - Gemini (Google DeepMind)
 - Grok (xAI)
 - Claude (Anthropic)
- Most of them have APIs

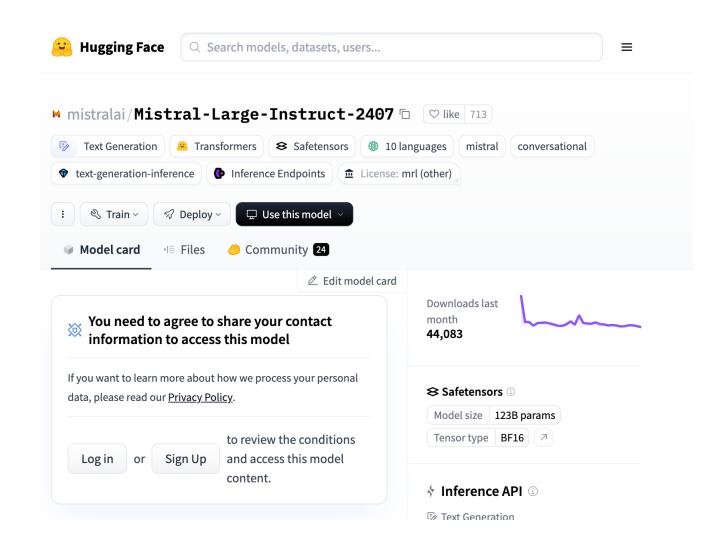
Common Open-Source LLMs

- LLaMA 3 (Meta)
 - Meta-Llama-3-8B
 - Meta-Llama-3.1-8B-Instruct
 - Meta-Llama-3-70B
 - Meta-Llama-3.1-70B-Instruct



Open-Source LLMs

- Mistral (Mistral AI)
 - Mistral-Large-Instruct-2407



Next Lecture

Adversarial Attacks and Defenses