# Large Language Models

CSC413 Tutorial 9

Yongchao Zhou

### Overview

- What are LLMs?
- Why LLMs?
- Emergent Capabilities
  - Few-shot In-context Learning
  - Advanced Prompt Techniques
- LLM Training
  - Architectures
  - Objectives
- LLM Finetuning
  - Instruction finetuning
  - o RLHF
  - Bootstrapping
- LLM Risks

### What are Language Models?

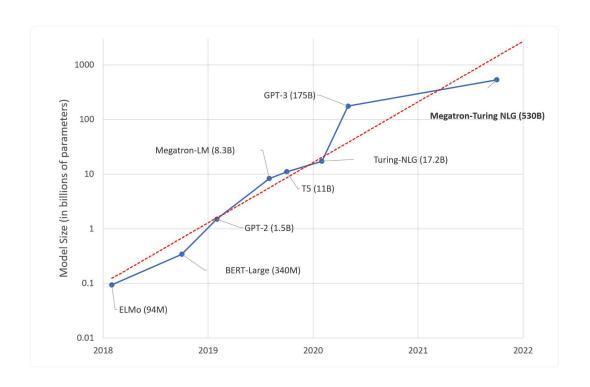
- Narrow Sense
  - A probabilistic model that assigns a probability to every finite sequence (grammatical or not)

Sentence: "the cat sat on the mat"

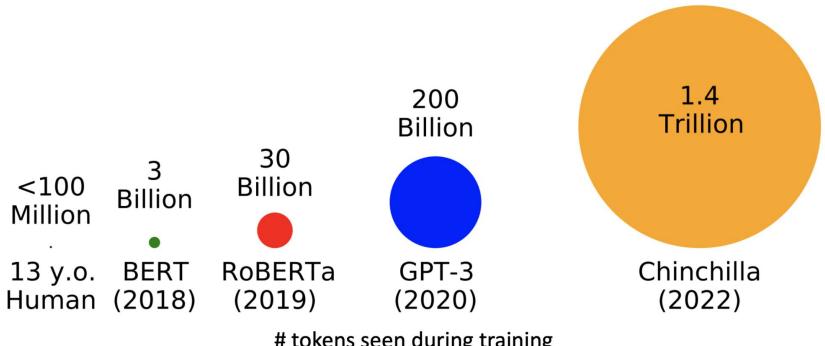
$$P(\text{the cat sat on the mat}) = P(\text{the}) * P(\text{cat}|\text{the}) * P(\text{sat}|\text{the cat})$$
 
$$*P(\text{on}|\text{the cat sat}) * P(\text{the}|\text{the cat sat on})$$
 
$$*P(\text{mat}|\text{the cat sat on the})$$
 
$$Implicit \ \text{order}$$

- Broad Sense
  - Decoder-only models (GPT-X, OPT, LLaMA, PaLM)
  - Encoder-only models (BERT, RoBERTa, ELECTRA)
  - Encoder-decoder models (T5, BART)

## Large Language Models - Billions of Parameters



### Large Language Models - Hundreds of Billions of Tokens

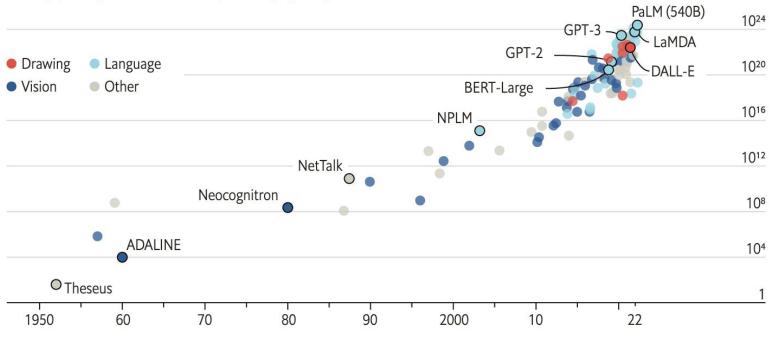


# tokens seen during training

## Large Language Models - yottaFlops of Compute

#### Al training runs, estimated computing resources used

Floating-point operations, selected systems, by type, log scale

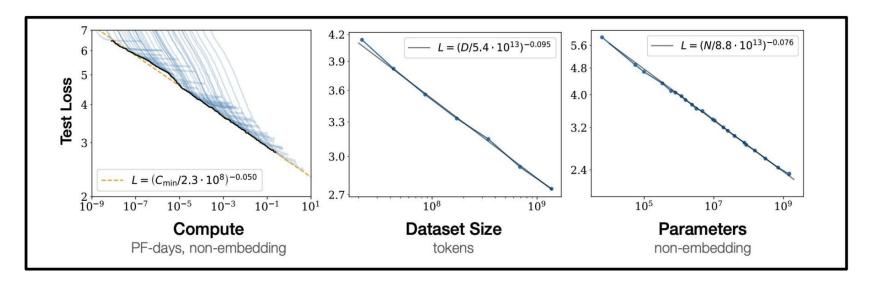


https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture11-prompting-rlhf.pdf

## Why LLMs?

### Scaling Law for Neural Language Models

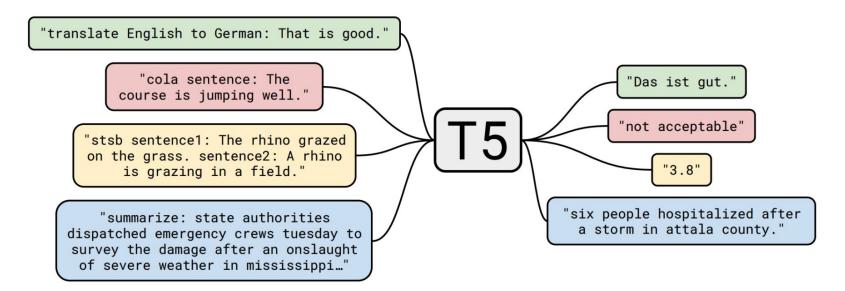
• Performance depends strongly on scale! We keep getting better performance as we scale the model, data, and compute up!



### Why LLMs?

#### Generalization

We can now use one single model to solve many NLP tasks

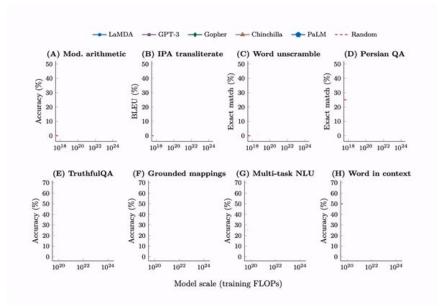


https://arxiv.org/pdf/1910.10683.pdf

## Why LLMs?

### Emergent Abilities

Some ability of LM is not present in smaller models but is present in larger models



https://docs.google.com/presentation/d/1yzbmYB5E7G8IY2-KzhmArmPYwwl7o7CUST1xRZDUu1Y/edit?resourcekey=0-6\_TnUMoK WCk FN2BiPxmbw#slide=id.g1fc34b3ac18 0 27

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.



#### One-shot

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



#### 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 

peppermint => menthe poivrée

plush girafe => girafe peluche

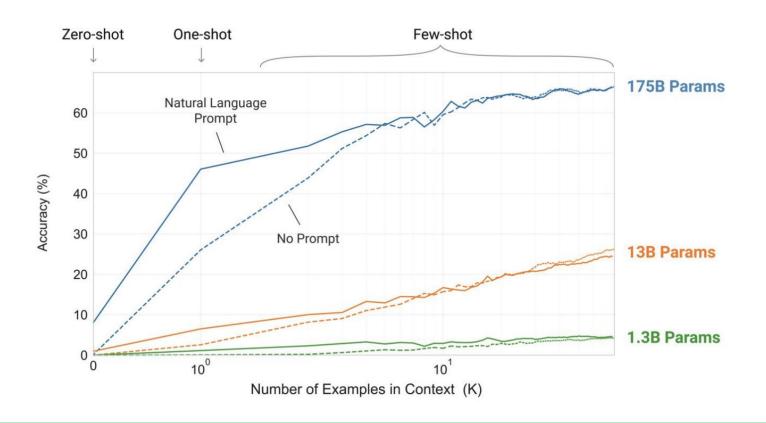
cheese => 

prompt
```

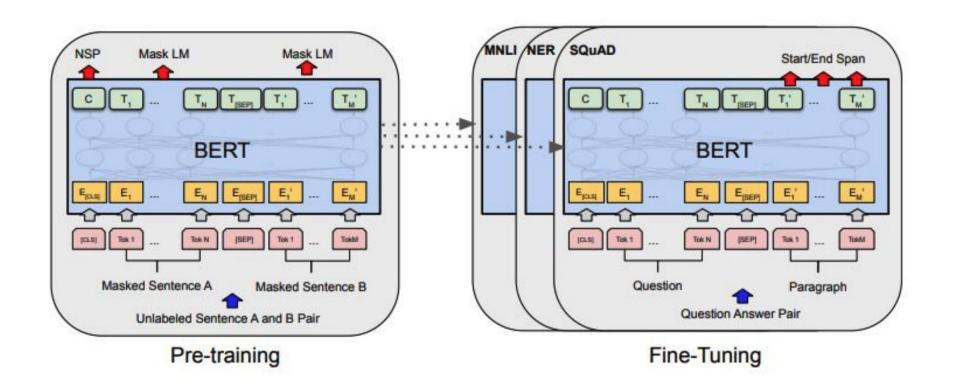
https://arxiv.org/pdf/2005.14165.pdf

	No Prompt	Prompt
Zero-shot (os)	skicts = sticks	Please unscramble the letters into a word, and write that word: skicts = sticks
1-shot (1s)	chiar = chair skicts = sticks	Please unscramble the letters into a word, and write that word: chiar = chair skicts = sticks
Few-shot (FS)	chiar = chair [] pciinc = picnic skicts = sticks	Please unscramble the letters into a word, and write that word: chiar = chair [] pciinc = picnic skicts = sticks

https://www.cs.princeton.edu/courses/archive/fall22/cos597G/lectures/lec04.pdf



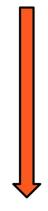
## **Pretraining + Fine-tuning** Paradigm



## **Pretraining + Prompting Paradigm**

- Fine-tuning (FT)
  - + Strongest performance
  - Need curated and labeled dataset for each new task (typically 1k-100k ex.)
  - Poor generalization, spurious feature exploitation
- Few-shot (FS)
  - + Much less task-specific data needed
  - + No spurious feature exploitation
  - Challenging
- One-shot (1S)
  - + "Most natural," e.g. giving humans instructions
  - Challenging
- Zero-shot (OS)
  - + Most convenient
  - o Challenging, can be ambiguous

Stronger task-specific performance



More convenient, general, less data

## **Emergent Capability - Chain of Thoughts Prompting**

#### **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.

## **Emergent Capability - Chain of Thoughts Prompting**

#### Math Word Problems (free response)

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.

#### StrategyQA

Q: Yes or no: Would a pear sink in water?

A: The density of a pear is about 0.6 g/cm<sup>3</sup>, which is less than water. Thus, a pear would float. So the answer is no.

#### SayCan (Instructing a robot)

Human: How would you bring me something that isn't a fruit?

Explanation: the user wants something to eat that isn't a fruit. An energy bar is not a fruit, so I will bring the user an energy bar.

Plan: 1. find(energy bar) 2. pick(energy bar) 3. find(user) 4. put(energy bar) 5. done().

#### Math Word Problems (multiple choice)

Q: How many keystrokes are needed to type the numbers from 1 to 500? Answer Choices: (a) 1156 (b) 1392 (c) 1480 (d) 1562 (e) 1788

A: There are 9 one-digit numbers from 1 to 9. There are 90 two-digit numbers from 10 to 99. There are 401 three-digit numbers from 100 to 500.9 + 90(2) + 401(3) = 1392. The answer is (b).

#### Date Understanding

O: The concert was scheduled to be on 06/01/1943, but was delayed by one day to today. What is the date 10 days ago in MM/DD/YYYY?

A: One day after 06/01/1943 is 06/02/1943, so today is 06/02/1943. 10 days before today is 05/23/1943. So the answer is 05/23/1943

Last Letter Concatenation

Q: Take the last letters of the words

A: The last letter of "Lady" is "v". The

Concatenating them is "ya". So the

in "Lady Gaga" and concatenate

last letter of "Gaga" is "a".

answer is va.

#### CSQA (commonsense)

Q: Sammy wanted to go to where the people were. Where might he go? Options: (a) race track (b) populated areas (c) desert (d) apartment (e) roadblock

A: The answer must be a place with a lot of people. Race tracks, desert. apartments, and roadblocks don't have a lot of people, but populated areas do. So the answer is (b).

#### Sports Understanding

Q: Is the following sentence plausible? "Joao Moutinho caught the screen pass in the NFC championship."

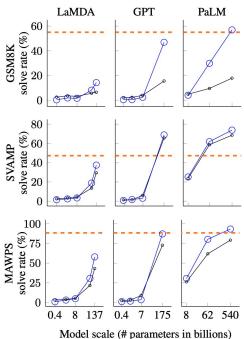
A: Joao Moutinho is a soccer player. The NFC championship is part of American football, not soccer. So the answer is no

#### Coin Flip (state tracking)

Q: A coin is heads up. Maybelle flips the coin. Shalonda does not flip the coin. Is the coin still heads up?

A: The coin was flipped by Maybelle. So the coin was flipped 1 time, which is an odd number. The coin started heads up, so after an odd number of flips, it will be tails up. So the answer is no.

- → Standard prompting
- --- Chain-of-thought prompting
- --- Prior supervised best



## Emergent Capability - Zero Shot CoT Prompting

#### (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. ✓

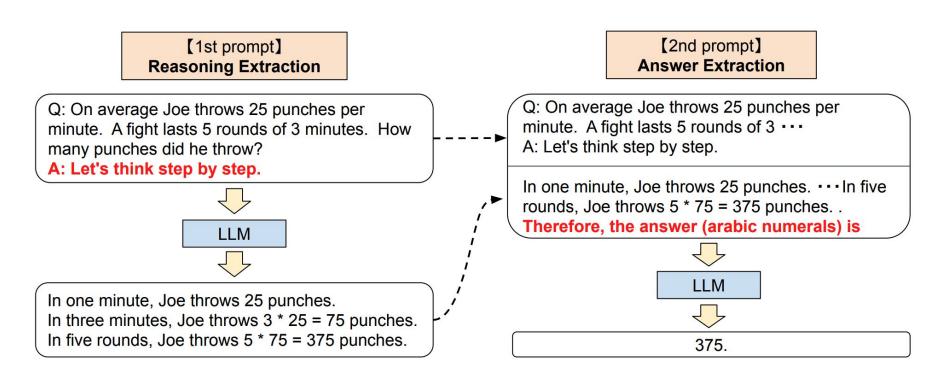
#### (d) Zero-shot-CoT (Ours)

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?

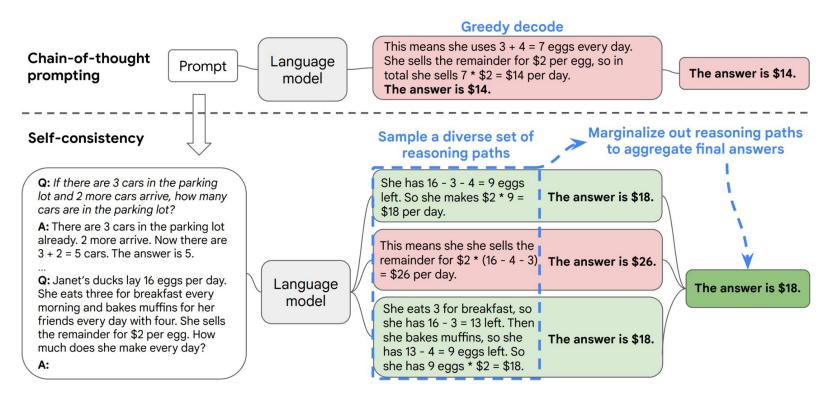
A: Let's think step by step.

(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.

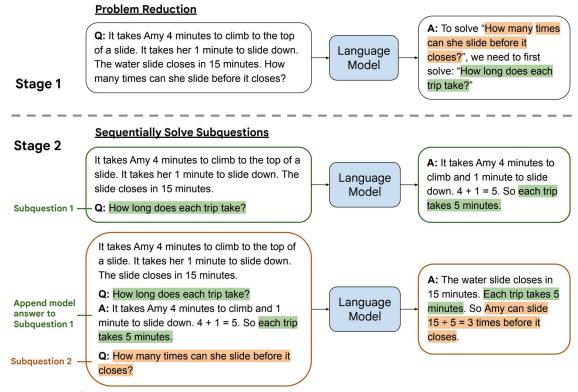
## **Emergent Capability - Zero Shot CoT Prompting**



## **Emergent Capability - Self-Consistency Prompting**



## **Emergent Capability - Least-to-Most Prompting**



https://arxiv.org/pdf/2205.10625.pdf

### Emergent Capability - Augmented Prompting Abilities

### **Advanced Prompting Techniques**

- Zero-shot CoT Prompting
- Self-Consistency
- Divide-and-Conquer

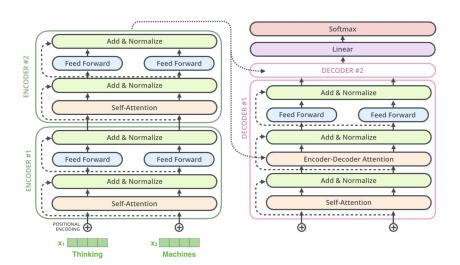
#### Ask a human to

- Explain the rationale
- Double check the answer
- Decompose to easy subproblems

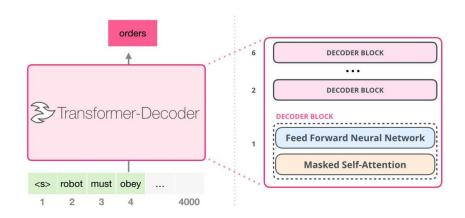
Large Language Models demonstrate some human-like behaviors!

## Training Architectures

#### **Encoder-decoder models (T5, BART)**

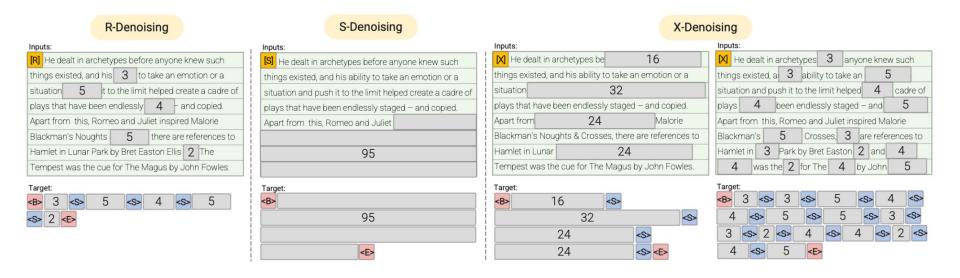


### Decoder-only models (GPT-X, PaLM)



http://jalammar.github.io/illustrated-transformer/

## Training Objectives - UL2



### What kinds of things does pretraining learn?

- Stanford University is located in \_\_\_\_\_\_, California. [Trivia]
- I put \_\_\_\_ fork down on the table. [syntax]
- The woman walked across the street, checking for traffic over \_\_\_\_ shoulder. [coreference]
- I went to the ocean to see the fish, turtles, seals, and \_\_\_\_\_\_. [lexical semantics/topic]
- Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink. The movie was \_\_\_\_. [sentiment]
- Iroh went into the kitchen to make some tea. Standing next to Iroh, Zuko pondered his destiny. Zuko left the \_\_\_\_\_. [some reasoning – this is harder]
- I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, \_\_\_\_ [some basic arithmetic; they don't learn the Fibonnaci sequence]

#### 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

Language

model

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 cafeteria had 23 apples

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".

https://arxiv.org/pdf/2210.11416.pdf

### Finetuning tasks

#### TO-SF

Commonsense reasoning
Question generation
Closed-book QA
Adversarial QA
Extractive QA
Title/context generation
Topic classification
Struct-to-text

55 Datasets, 14 Categories, 193 Tasks

#### Muffin

Natural language inference Closed-book QA
Code instruction gen. Conversational QA
Program synthesis Code repair
Dialog context generation ...

69 Datasets, 27 Categories, 80 Tasks

#### **CoT (Reasoning)**

Arithmetic reasoning Explanation generation
Commonsense Reasoning Sentence composition
Implicit reasoning ...

9 Datasets, 1 Category, 9 Tasks

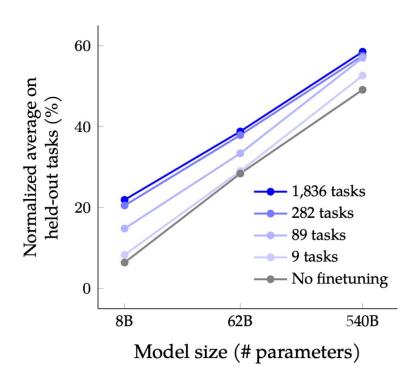
#### Natural Instructions v2

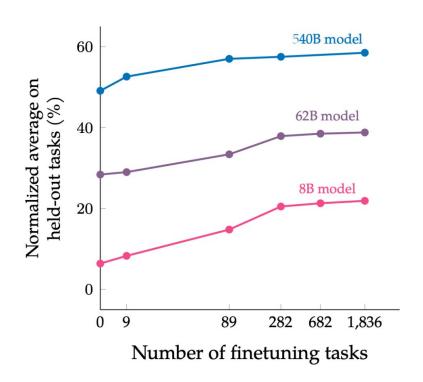
Cause effect classification
Commonsense reasoning
Named entity recognition
Toxic language detection
Question answering
Question generation
Program execution
Text categorization

372 Datasets, 108 Categories, 1554 Tasks

- ❖ A <u>Dataset</u> is an original data source (e.g. SQuAD).
- A <u>Task Category</u> is unique task setup (e.g. the SQuAD dataset is configurable for multiple task categories such as extractive question answering, query generation, and context generation).
- ❖ A <u>Task</u> is a unique <dataset, task category> pair, with any number of templates which preserve the task category (e.g. query generation on the SQuAD dataset.)

With chain-of-thought Without chain-of-thought Answer the following A haiku is a japanese Answer the following yes/no question yes/no question. three-line poem. Instruction by reasoning step-by-step. That is short enough yes without Can you write a whole to fit in 280 exemplars Can vou write a whole Haiku in a Haiku in a single tweet? characters. The single tweet? answer is ves. Q: Answer the following Q: Answer the following yes/no question by yes/no question. reasoning step-by-step. Could a dandelion suffer Could a dandelion suffer from hepatitis? from hepatitis? Instruction A haiku is a japanese A: Hepatitis only affects organisms with livers. A: no three-line poem. with exemplars Dandelions don't have a liver. The answer is no. ves That is short enough Q: Answer the following Q: Answer the following yes/no question by to fit in 280 yes/no question. reasoning step-by-step. characters. The Can you write a whole Haiku Can you write a whole Haiku in a single tweet? answer is yes. in a single tweet? A: A:





### Finetune - RLHF

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.



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.



Explain war...

0

People went to

A

Explain gravity...

C

Moon is natural

satellite of...

d



Step 3

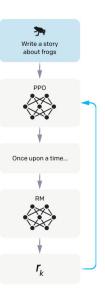
Optimize a policy against the reward model using reinforcement learning.

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.



### Application - ChatGPT

### **ChatGPT**



#### Examples

"Explain quantum computing in simple terms" →

"Got any creative ideas for a 10 year old's birthday?" →

"How do I make an HTTP request in Javascript?" →



#### Capabilities

Remembers what user said earlier in the conversation

Allows user to provide followup corrections

Trained to decline inappropriate requests



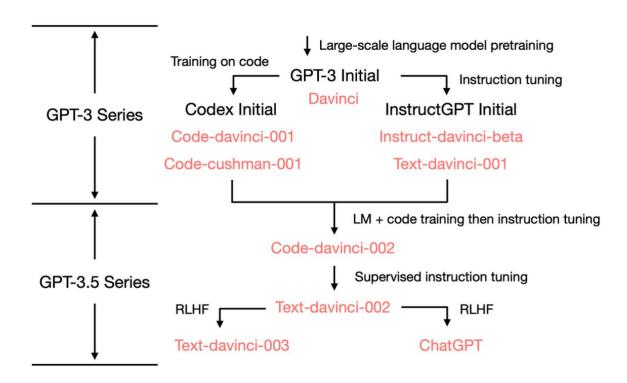
#### Limitations

May occasionally generate incorrect information

May occasionally produce harmful instructions or biased content

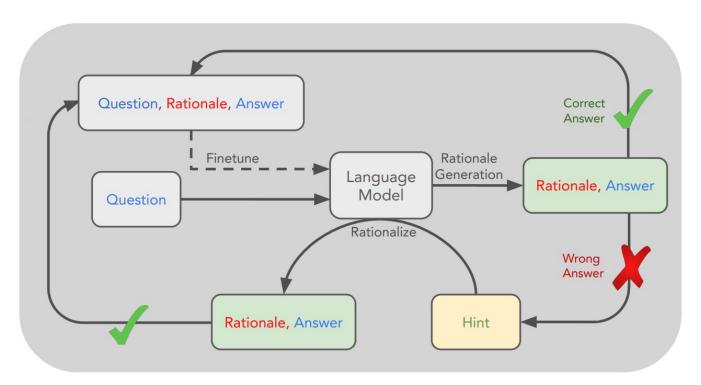
Limited knowledge of world and events after 2021

### Application - ChatGPT



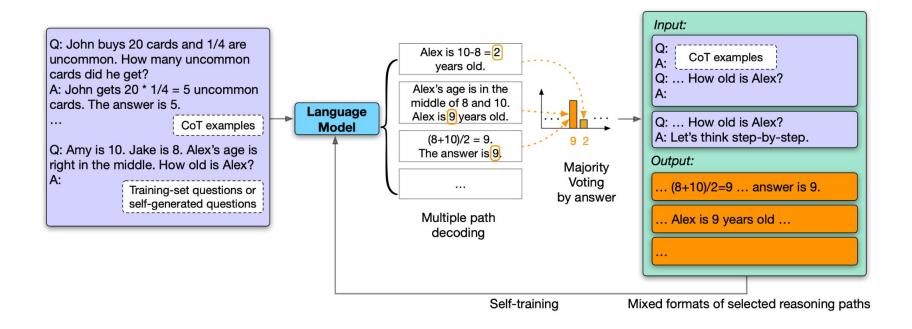
https://yaofu.notion.site/How-does-GPT-Obtain-its-Ability-Tracing-Emergent-Abilities-of-Language-Models-to-their-Sources-b9a57ac0fcf74f30a1ab9e3e36fa1dc1

### Finetune - Bootstrapping



- Q: What can be used to carry a small dog? Answer Choices:
- (a) swimming pool
- (b) basket
- (c) dog show
- (d) backyard
- (e) own home
- A: The answer must be something that can be used to carry a small dog. Baskets are designed to hold things. Therefore, the answer is basket (b).

### Finetune - Bootstrapping



### Large Language models Risks

- LLMs make mistakes
   (falsehoods, hallucinations)
- LLMs can be misused (misinformation, spam)
- LLMs can cause harms
   (toxicity, biases, stereotypes)
- LLMs can be attacked
   (adversarial examples, poisoning, prompt injection)
- LLMs can be useful as defenses (content moderation, explanations)



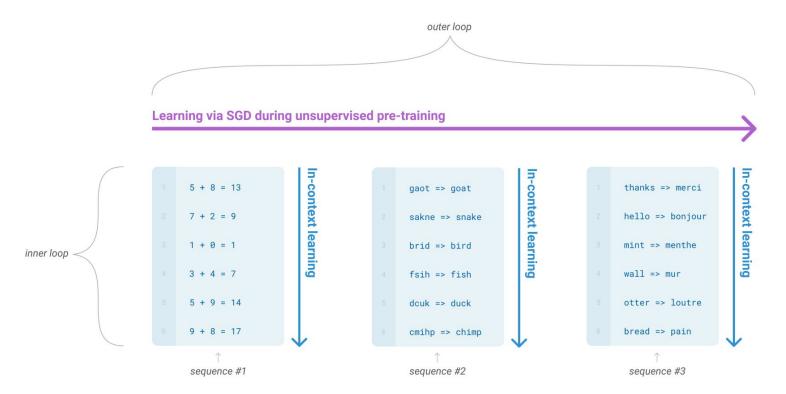
## Large language models associate Muslims with violence

<u>Abubakar Abid</u>, <u>Maheen Farooqi</u> & <u>James Zou</u> ⊠

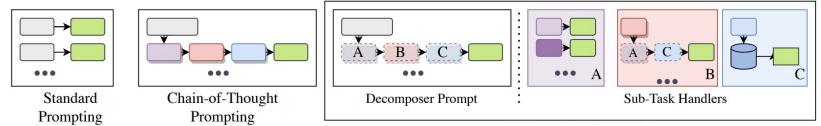
Nature Machine Intelligence 3, 461–463 (2021) | Cite this article

### Resources for further reading

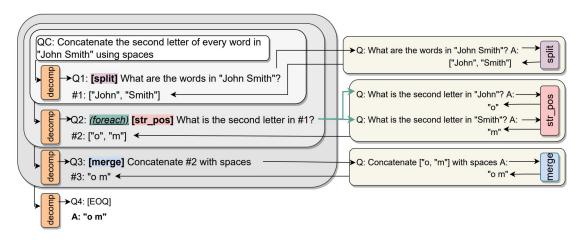
- https://web.stanford.edu/class/cs224n/
- https://stanford-cs324.github.io/winter2022/
- https://stanford-cs324.github.io/winter2023/
- https://www.cs.princeton.edu/courses/archive/fall22/cos597G/
- https://rycolab.io/classes/llm-s23/
- https://yaofu.notion.site/How-does-GPT-Obtain-its-Ability-Tracing-Emergent-Abilities-of-Language-Models-to-their-Sources-b9a57ac0fcf74f30a1ab9e3e36fa1dc1
- https://www.jasonwei.net/blog/emergence



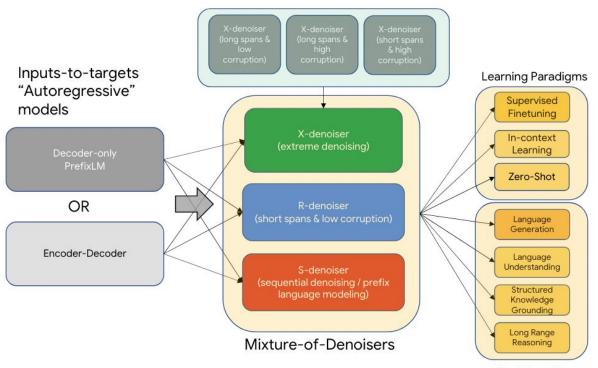
## **Emergent Capability - Decomposed Prompting**



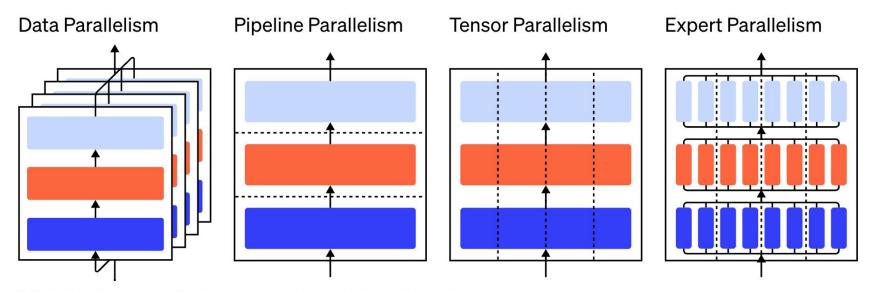
**Decomposed Prompting** 



## Training Objectives - UL2



## Training Techniques - Parallelism



An illustration of various parallelism strategies on a three-layer model. Each color refers to one layer and dashed lines separate different GPUs.

## Training Techniques - Parallelism

