Deep Learning

Lecture 8: GPT and Large Language Models

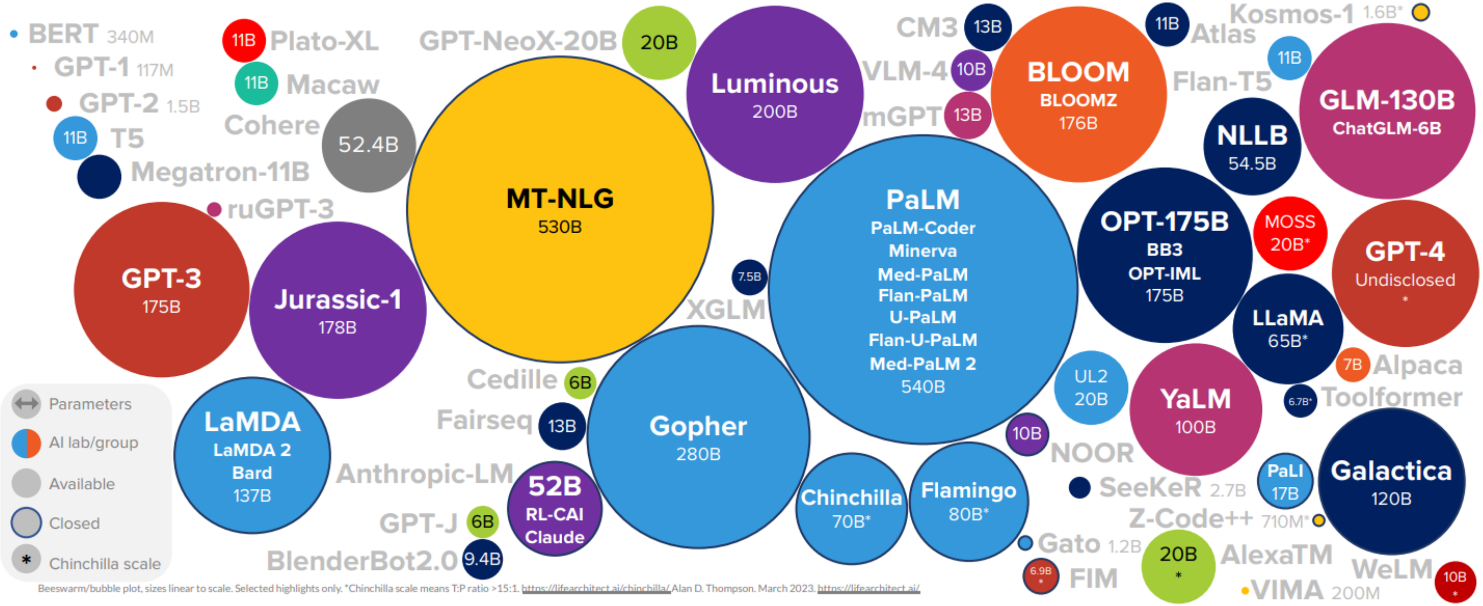
Prof. Gilles Louppe
g.louppe@uliege.be

Today

- BabyGPT
- Large language models

See `code/gpt/`.

Large language models



Beeswarm/bubble plot, sizes linear to scale. Selected highlights only. *Chinchilla scale means T:P ratio >15:1. https://lifearchitect.ai/chinchilla/ Alan D. Thompson. March 2023. https://lifearchitect.ai/

(March 2023)

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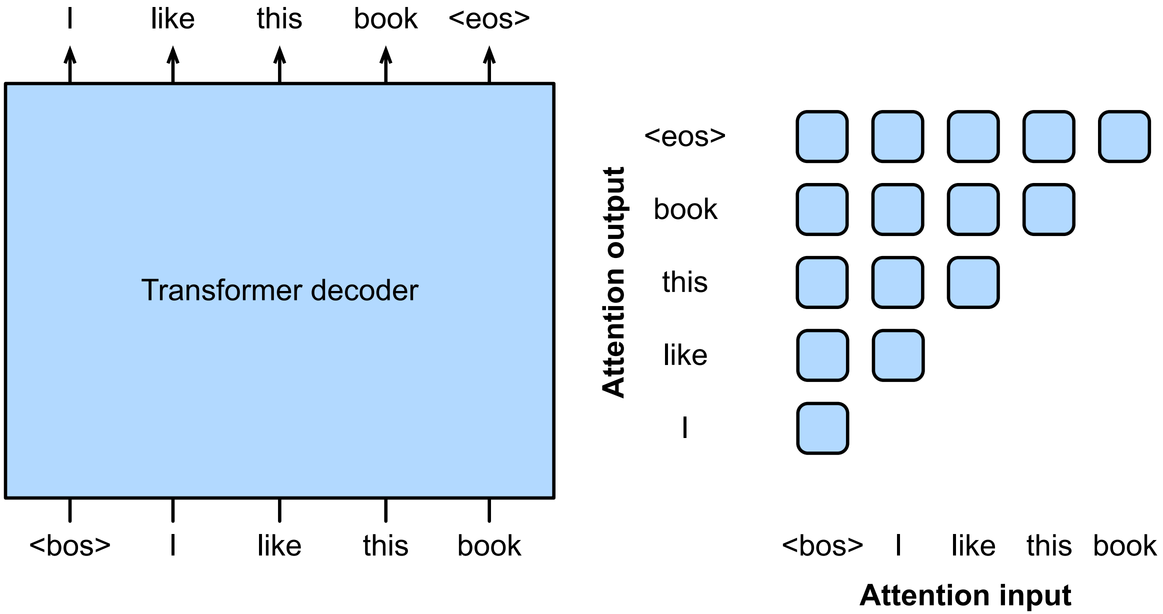
Credits: lifearchitect.ai/models, 2023.

Decoder-only transformers

The decoder-only transformer has become the de facto architecture for large language models.

These models are trained with self-supervised learning, where the target sequence is the same as the input sequence, but shifted by one token to the right.



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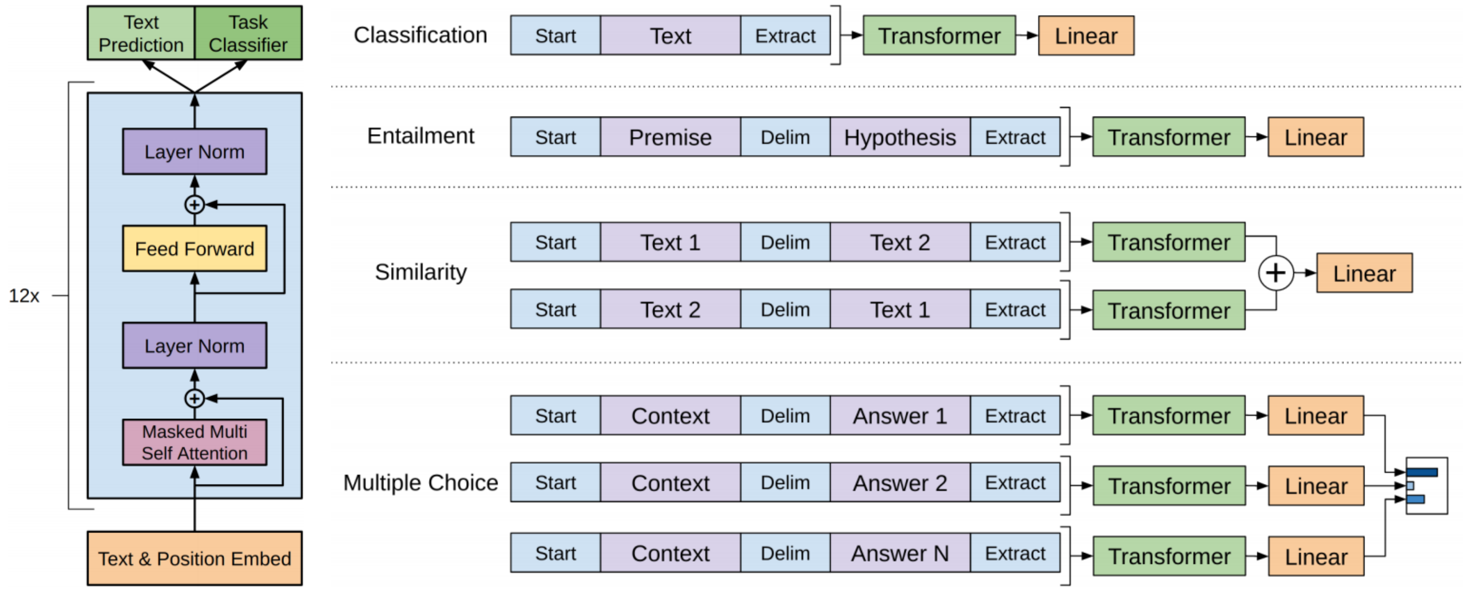
Credits: Dive Into Deep Learning, 2023.

Historically, GPT-1 was first pre-trained and then fine-tuned on downstream tasks.



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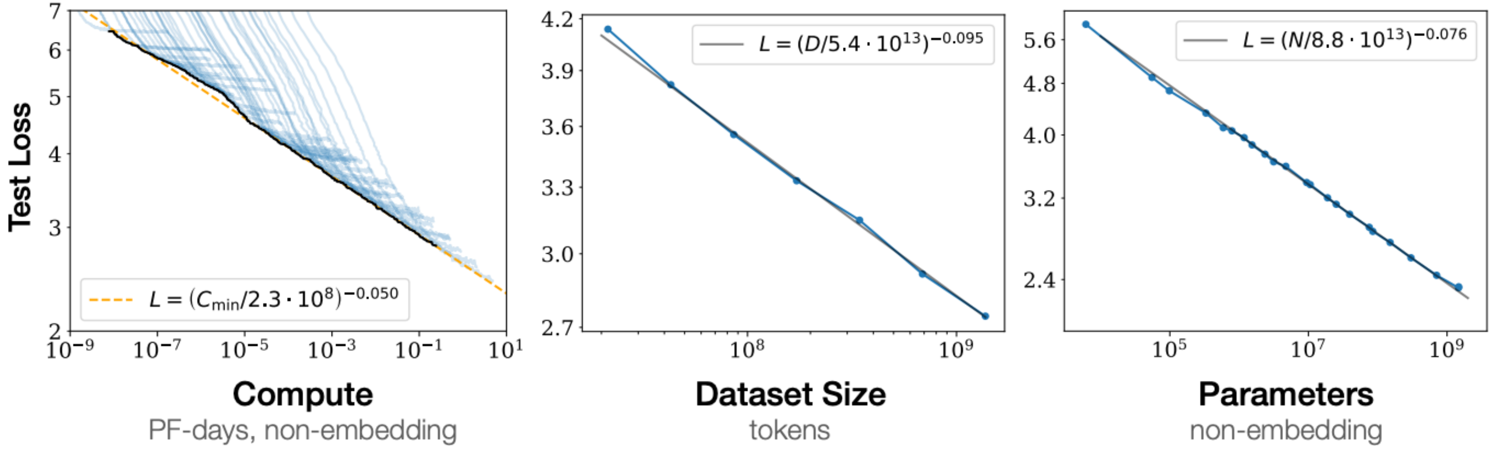
Credits: Radford et al., Improving Language Understanding by Generative Pre-Training, 2018.

Scaling laws

Transformer language model performance improves smoothly as we increase the model size, the dataset size, and amount of compute used for training.

For optimal performance, all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.



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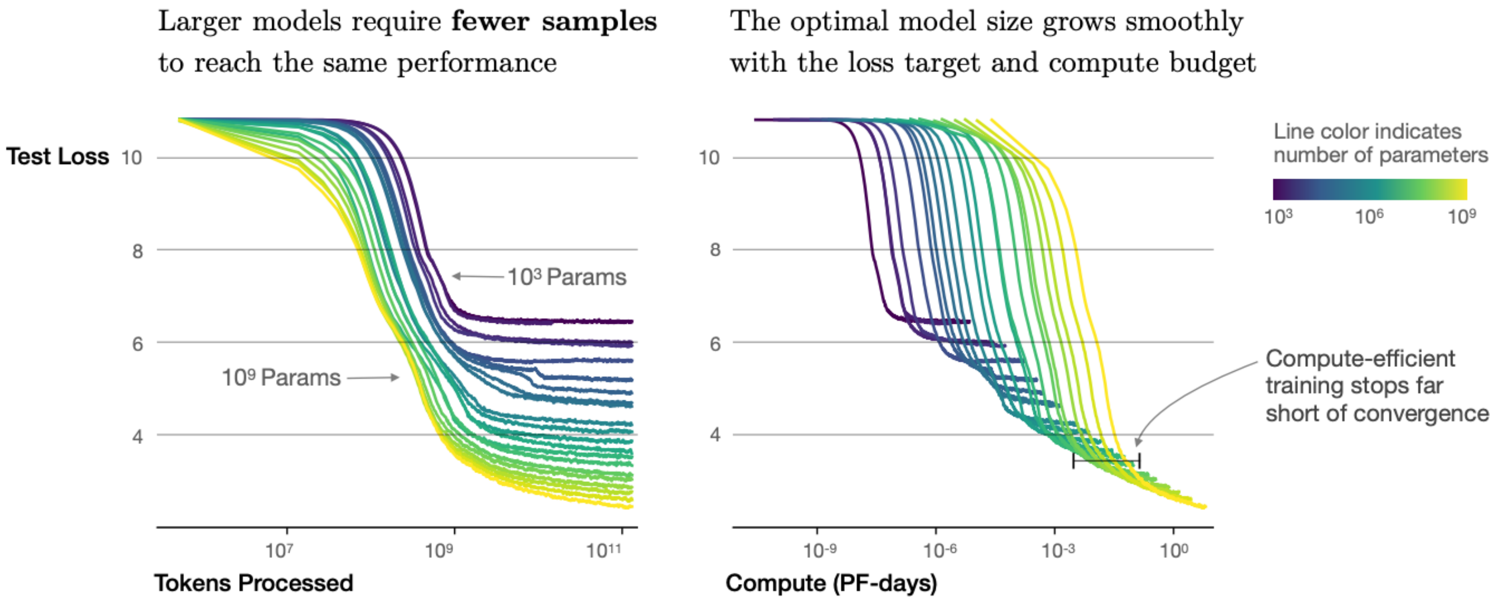
Credits: Kaplan et al, 2020.

Large models also enjoy better sample efficiency than small models.

- Larger models require less data to achieve the same performance.
- The optimal model size shows to grow smoothly with the amount of compute available for training.



Larger models require **fewer samples** to reach the same performance

The optimal model size grows smoothly with the loss target and compute budget

Compute-efficient training stops far short of convergence

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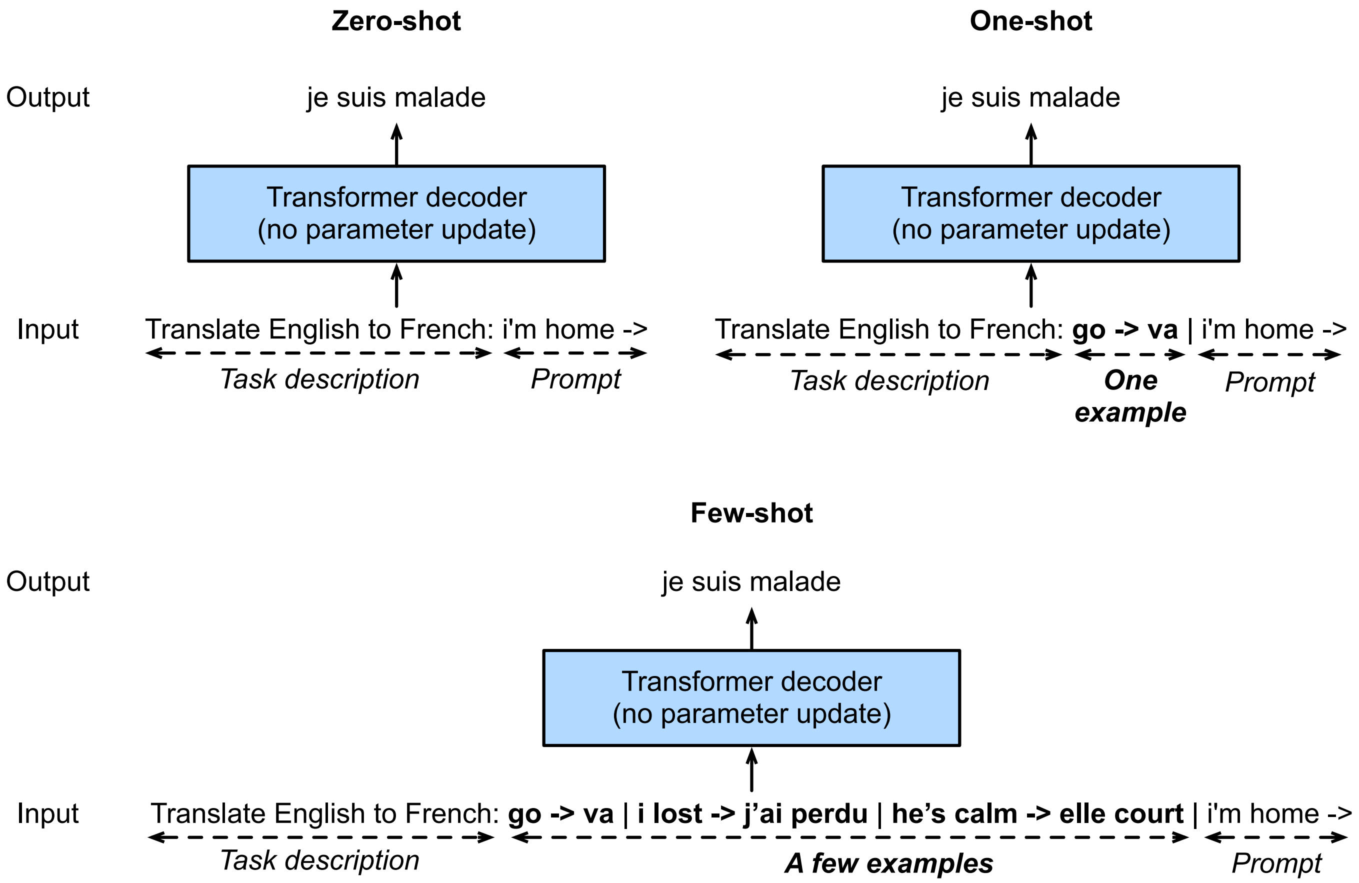
Credits: Kaplan et al, 2020.

In-context learning

GPT-2 and following models demonstrated potential of using the same language model for multiple tasks, **without updating the model weights**.

Zero-shot, one-shot and few-shot learning consist in prompting the model with a few examples of the target task and letting it learn from them. This paradigm is called in-context learning.



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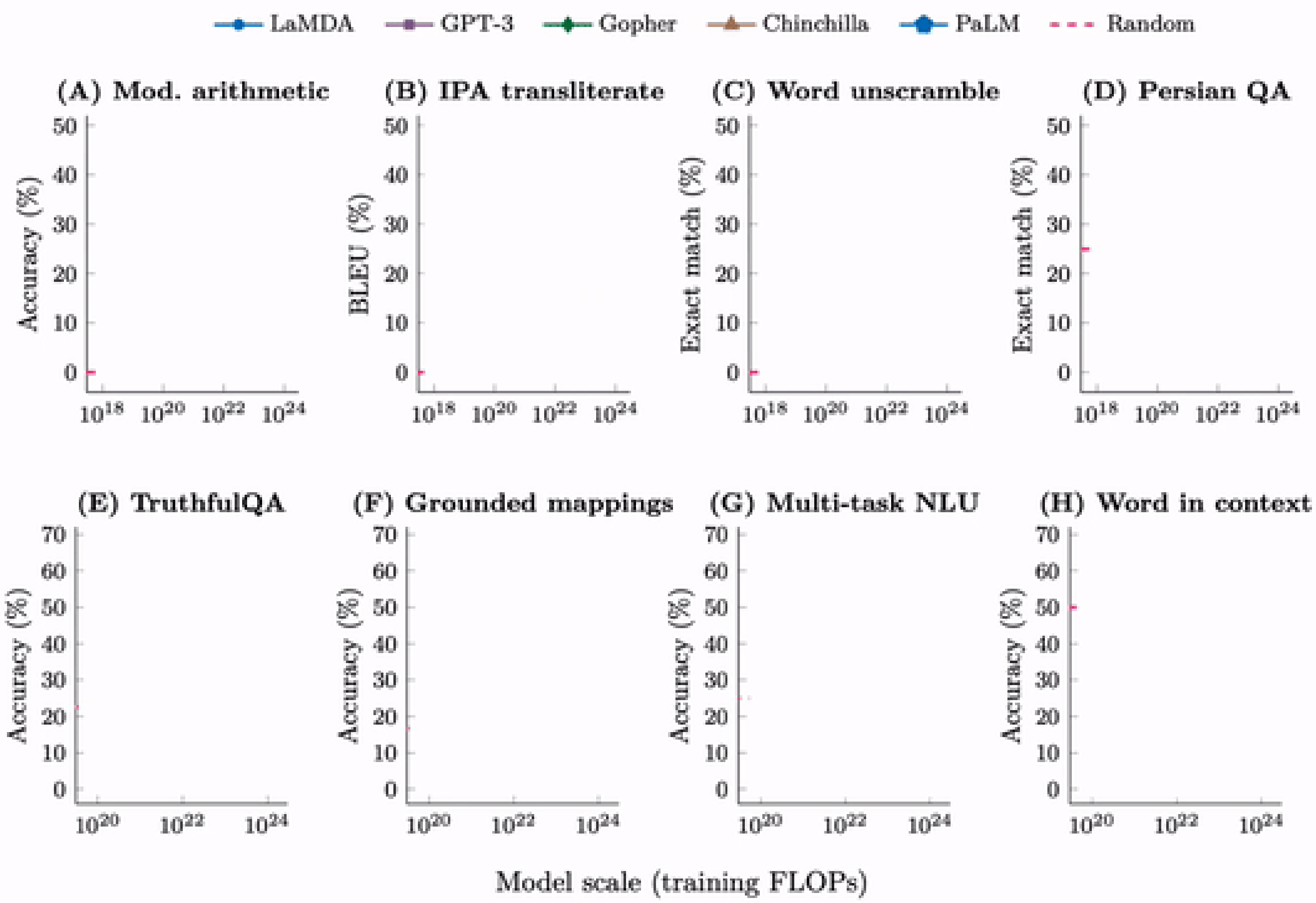
Credits: Dive Into Deep Learning, 2023.

(demo)

Emergent abilities

As language models grow in size, they start to exhibit emergent abilities that are not present in the original training data.

A (few-shot) prompted task is **emergent** if it achieves random performance for small models and then (suddenly) improves as the model size increases.



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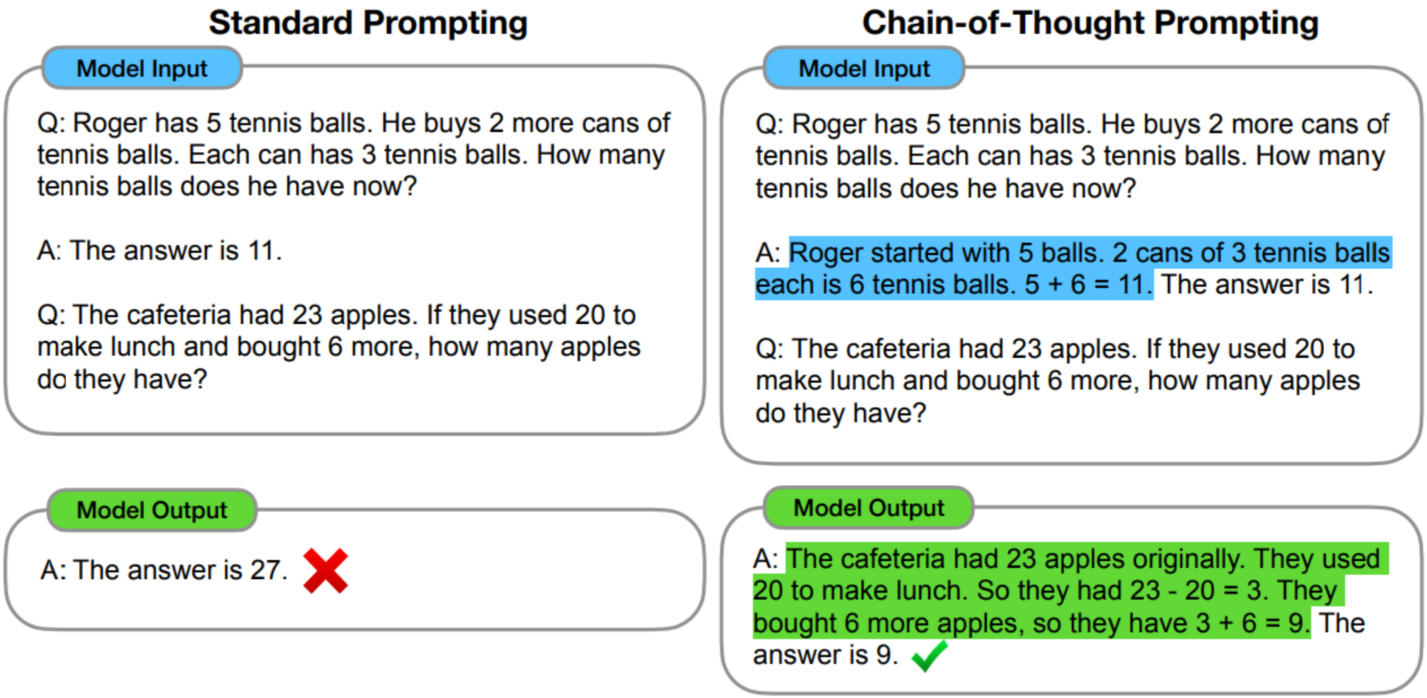
Credits: Wei et al, 2022.

Notably, chain-of-thought reasoning is an emergent ability of large language models. It improves performance on a wide range of arithmetica, commonsense, and symbolic reasoning tasks.



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. ✓

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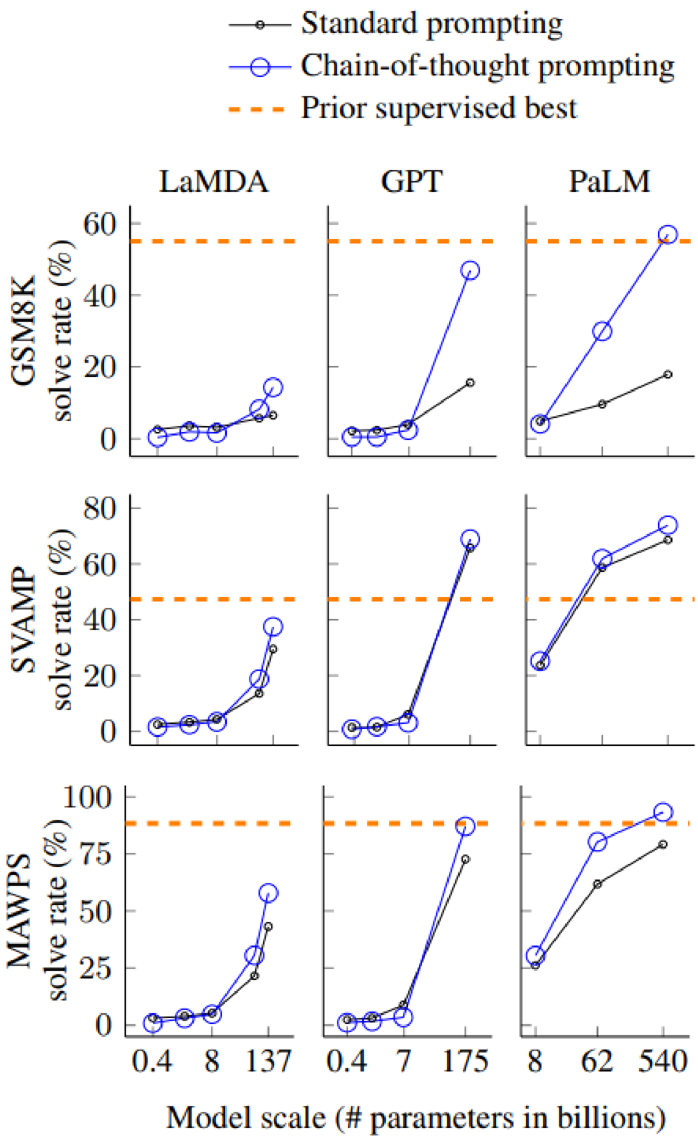
Credits: Wei et al, 2022b.

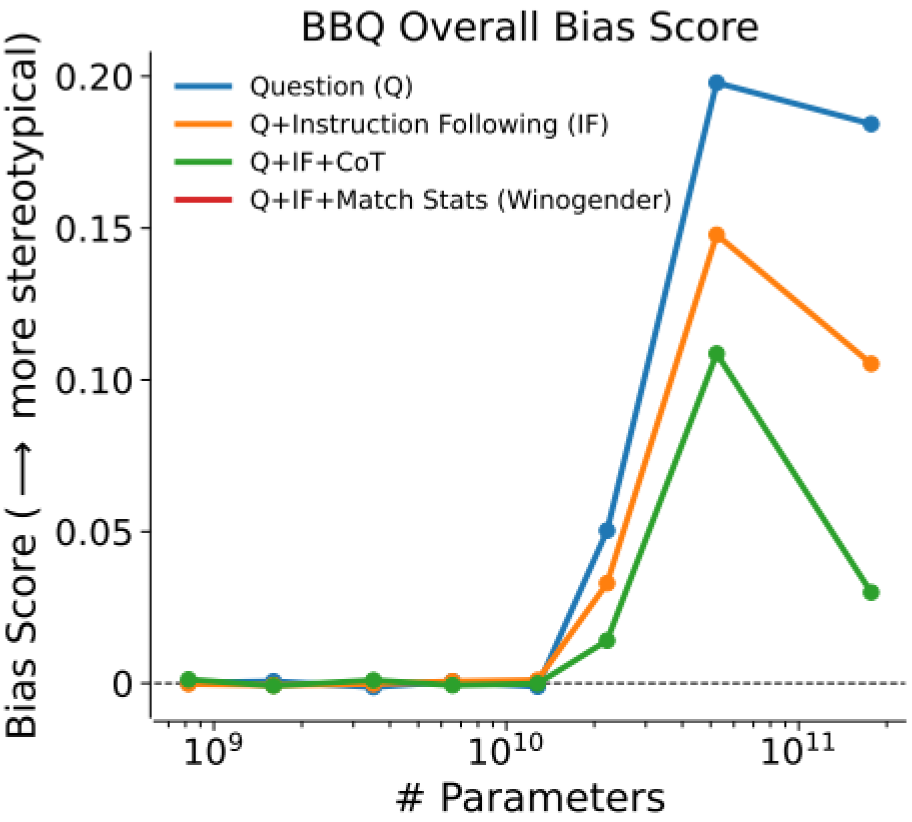


Credits: Wei et al, 2022b.

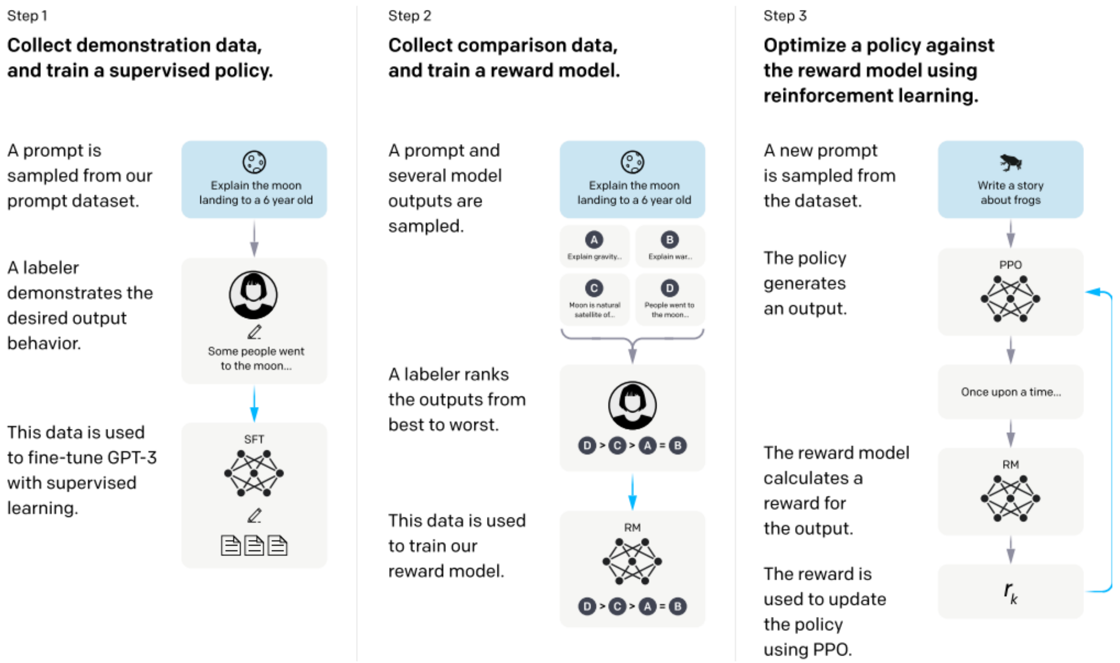
Alignment

Increasing the model size does not inherently makes models follow a user's intent better, despite emerging abilities.

Worse, scaling up the model may increase the likelihood of undesirable behaviors, including those that are harmful, unethical, or biased.



Human feedback can be used for better aligning language models with human intent, as shown by InstructGPT.



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.

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.

Explain the moon landing to a 6 year old
Some people went to the moon...
SFT
Explain the moon landing to a 6 year old
A
Explain gravity...
B
Explain war...
C
Moon is natural satellite of...
D
People went to the moon...
D > C > A = B
RM
D > C > A = B
Write a story about frogs
PPO
Once upon a time...
RM
r_k

Figure 2: A diagram illustrating the three steps of our method: (1) supervised fine-tuning (SFT), (2) reward model (RM) training, and (3) reinforcement learning via proximal policy optimization (PPO) on this reward model. Blue arrows indicate that this data is used to train one of our models. In Step 2, boxes A-D are samples from our models that get ranked by labelers. See Section 3 for more details on our method.

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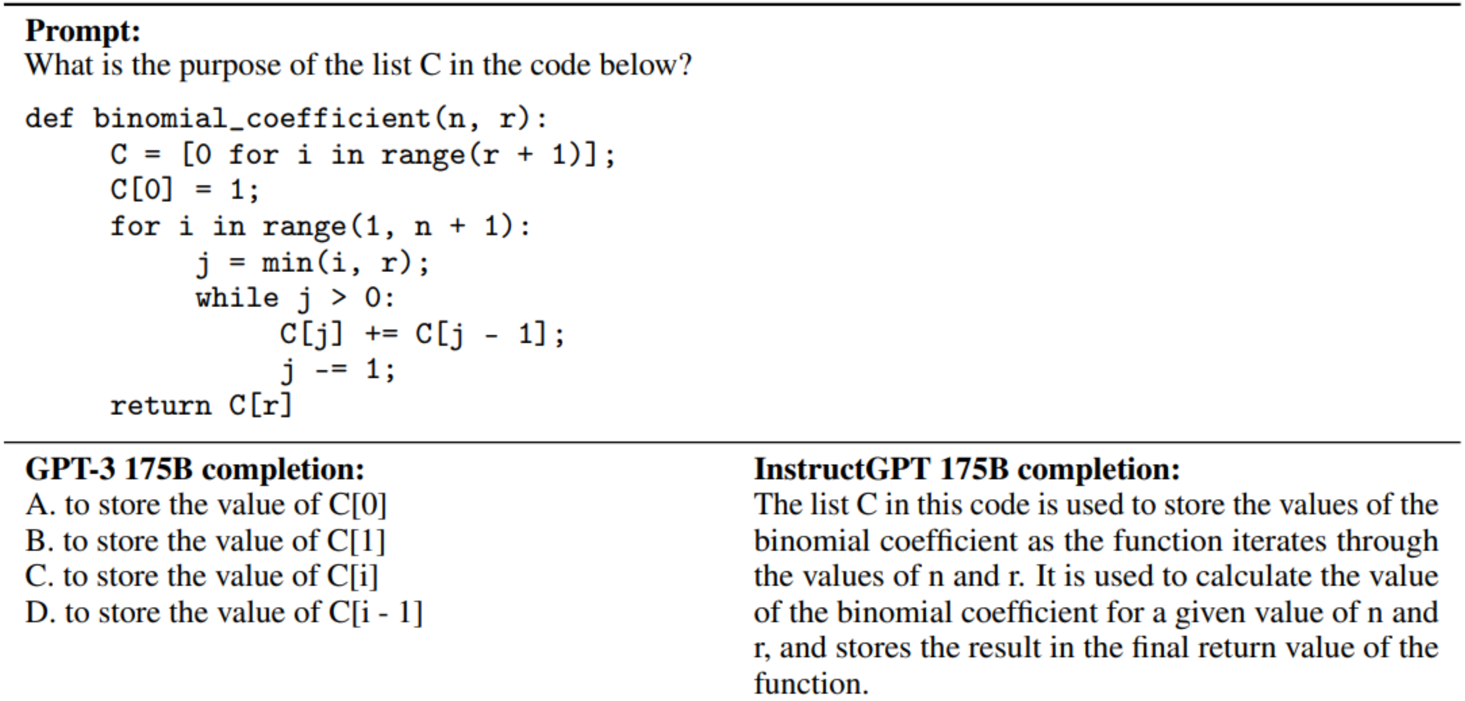
Credits: Ouyang et al, 2022.



Prompt:
What is the purpose of the list C in the code below?

```
def binomial_coefficient(n, r):
     C = [0 for i in range(r + 1)];
     C[0] = 1;
     for i in range(1, n + 1):
          j = min(i, r);
          while j > 0:
               C[j] += C[j - 1];
               j -= 1;
     return C[r]
```

GPT-3 175B completion:
A. to store the value of C[0]
B. to store the value of C[1]
C. to store the value of C[i]
D. to store the value of C[i - 1]

InstructGPT 175B completion:
The list C in this code is used to store the values of the binomial coefficient as the function iterates through the values of n and r. It is used to calculate the value of the binomial coefficient for a given value of n and r, and stores the result in the final return value of the function.

The end.