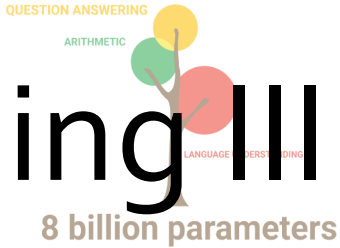


Pretraining III: Scaling, Prompting, and Beyond

CSE 5525: Foundations of Speech and Natural Language Processing

https://shocheen.github.io/courses/cse-5525-spring-2025

THE OHIO STATE UNIVERSITY

Logistics

- Final Project Proposal: Due next Wednesday.
  - I will hold office hours on Monday (12.30-2pm) at DL 581 in person.

- Homework 3 will be released early Thursday (Feb 20) morning.
  - Topic: prompting/finetuning models for code generation (text-to-SQL)

Last Class Recap: Masked LMs

- Denoising pretraining objectives
  - BERT
  - T5
  - BART
  - UL2
  - Causal LM is king → we will mostly focus on this going forward, although masked LMs have their uses

- Decoding algorithms:
  - Search: greedy, beam search
  - Sampling: Ancestral sampling, temperature, top-k sampling, top-p sampling.

Scaling Up

Next-word Prediction

- Language models do next word prediction
- At first look, next-word-completion seems like a very simple task
- Why does it make sense to focus on it so much?

Scaling Up

Why Does it Make Sense?

The woman walked across the street, checking for traffic over ___

Scaling Up

Why Does it Make Sense?

I went to the ocean to see the fish, turtles, seals, and ____

Scaling Up

Why Does it Make Sense?

Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink. The movie was _____

Scaling Up

Why Does it Make Sense?

Iroh went into the kitchen to make some tea. Standing next to Iroh, Zuko pondered his destiny. Zuko left the ____

Scaling Up

Why Does it Make Sense?

I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, _____

Scaling Up

Why Does it Make Sense?

Ohio State is located in _____

Scaling Up

Why Does it Make Sense?

- The woman walked across the street, checking for traffic over ___ [coreference]
- I went to the ocean to see the fish, turtles, seals, and ____ [lexical semantics / topics]
- 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]
- I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, _____ [reasoning]
- Ohio State is located in _____ [knowledge]

The learned representations have to account for a lot to succeed in this seemingly straightforward task

Examples from Stanford CS 224N

Some History: the GPTs

GPT [Radford et al. 2018]

- Transformer LM released in 2018 by OpenAI
- Decoder with 12 transformer blocks, 117M parameters, 768-dimensional hidden states, 3072-dimensional feed-forward hidden layers; BPE with 40k merges
- Trained on BookCorpus: over 7,000 unique books: long spans of contiguous text for learning long-distance dependencies
- Impressive results when fine-tuned on several NLP tasks: Entailment, textual similarity, multiple choice questions

Some History: the GPTs

GPT-2 [Radford et al. 2018]

- GPT-2 scaled the models to 1.5B parameters
- Increasingly convincing generations
- Impressive results on benchmarks

	LAMBADA (PPL)	LAMBADA (ACC)	CBT-CN (ACC)	CBT-NE (ACC)	WikiText2 (PPL)	PTB (PPL)	enwik8 (BPB)	text8 (BPC)	WikiText103 (PPL)	1BW (PPL)
SOTA	99.8	59.23	85.7	82.3	39.14	46.54	0.99	1.08	18.3	**21.8**
117M	**35.13**	45.99	**87.65**	**83.4**	**29.41**	65.85	1.16	1.17	37.50	75.20
345M	**15.60**	55.48	**92.35**	**87.1**	**22.76**	47.33	1.01	**1.06**	26.37	55.72
762M	**10.87**	**60.12**	**93.45**	**88.0**	**19.93**	**40.31**	**0.97**	**1.02**	22.05	44.575
1542M	**8.63**	**63.24**	**93.30**	**89.05**	**18.34**	**35.76**	**0.93**	**0.98**	**17.48**	42.16

Table 3. Zero-shot results on many datasets. No training or fine-tuning was performed for any of these results. PTB and WikiText-2 results are from (Gong et al., 2018). CBT results are from (Bajgar et al., 2016). LAMBADA accuracy result is from (Hoang et al., 2018) and LAMBADA perplexity result is from (Grave et al., 2016). Other results are from (Dai et al., 2019).

Some History: the GPTs

GPT-3 [Brown et al. 2020]

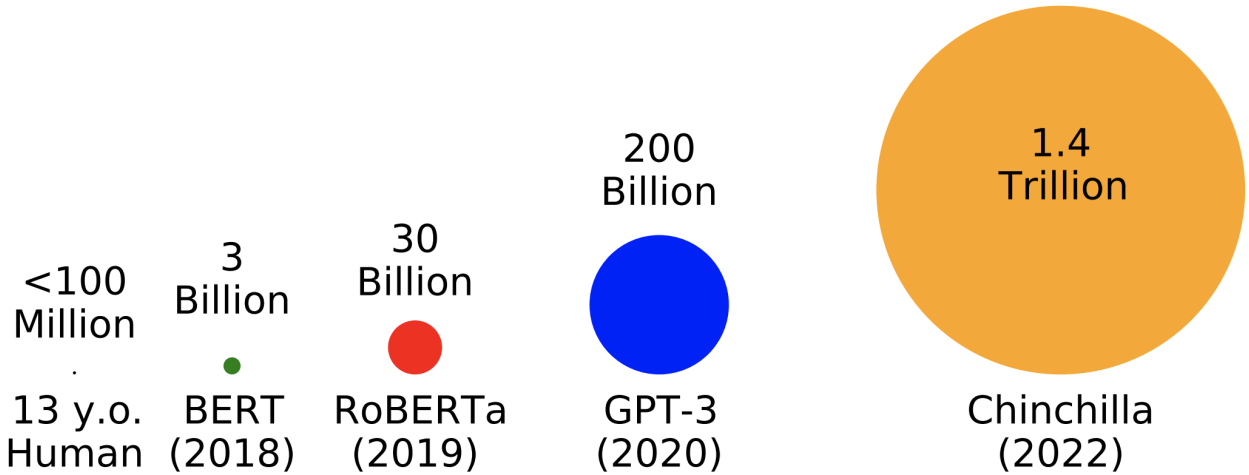
- GPT-3 scaled the model size to 175B parameters
- So far, two ways of interaction with models:
  - Sample from the distribution (generation)
  - Fine-tune on a specific task
- GPT-3 demonstrated few-shot learning **without parameter updates — In-context Learning (ICL)**
  - In-context examples seem to specify the task, allowing the model to complete it on a new input
  - More on this later on …

Scaling Up

- Two dimensions of scaling up:
  - **Data:** the number of raw tokens the learner is given
  - **Parameters:** the number of parameters in the model
- All this requires scaling up **compute**
  - Storage (memory, disk space, etc), GPUs, networking

Scaling Up

Data



https://babylm.github.io/

Scaling Up

Data

- How do we get text data at scale?
- Scrape whatever we can get from the web
  - Seed webcrawler with initial URLs
  - Identify new URLs via outlinks
  - Download HTML pages, extract raw text, postprocess text
- Done? Not really …
  - The Internet is a mess
  - What would you do next?

Data

Web Scraping: Filtering Heuristics

- Deduplication
- Remove junk — what is junk?
  - One option: text that is very unlikely according to simple n-gram model
- Remove pages that are not interesting
  - One option: few inlinks → not interesting
- Remove non-English data a language classifier
- Remove stuff your model probably is better of without: personally identifiable information, adult content, hate speech, copyrighted data, NLP benchmarks (why?)

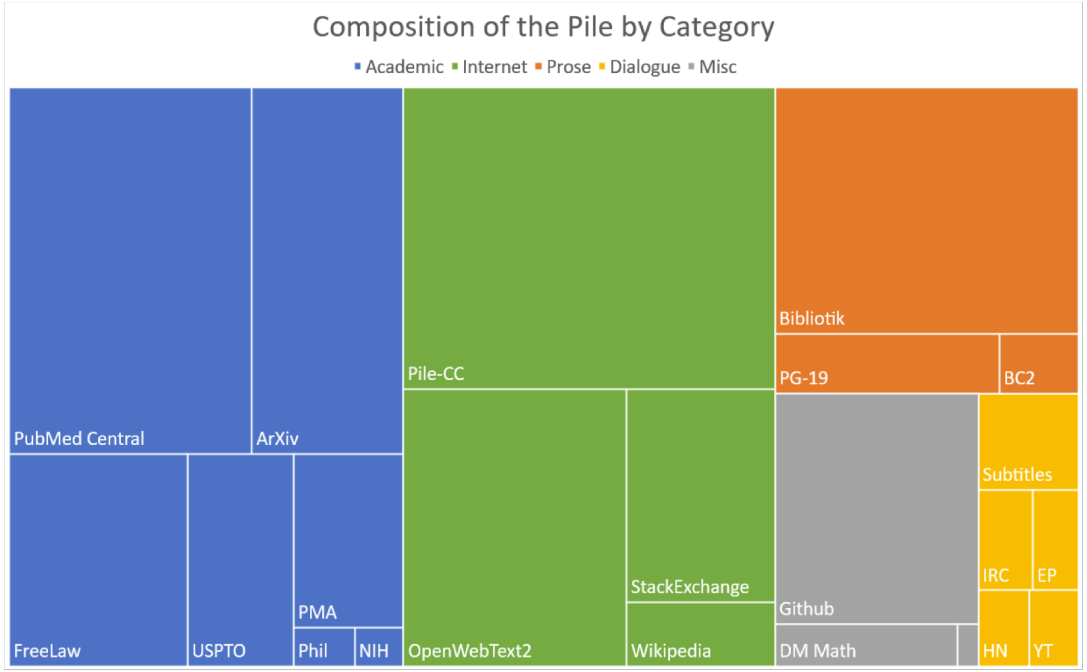
Data

Web Scraping: Filtering Tradeoffs

- Personally identifiable information
  - But what about the phone numbers of public companies?
- Adult content and hate speech
  - Very culturally dependent
- Copyrighted data
  - How to identify? Is it fair use?

Data

Composition: the Pile



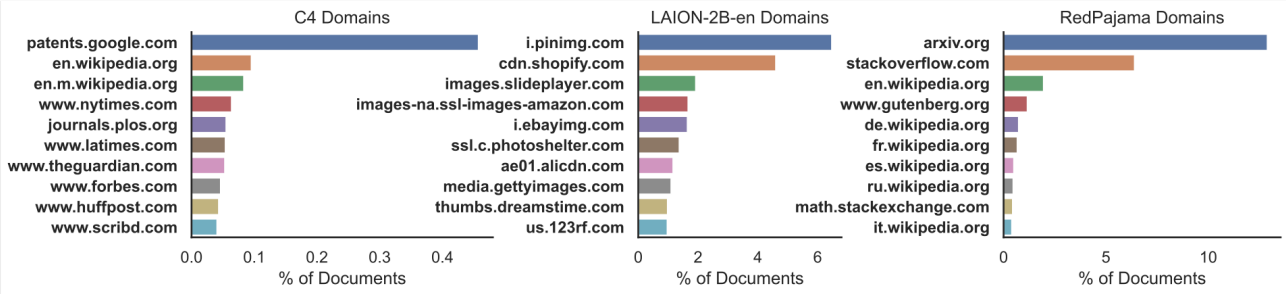
[Gao et al. 2020]

Data

Large Raw Text Corpora

WIMBD Demo

Dataset	Origin	Model	Size (GB)	# Documents	# Tokens
OpenWebText	Gokaslan & Cohen (2019)	GPT-2* (Radford et al., 2019)	41.2	8,005,939	7,767,705,349
C4	Raffel et al. (2020)	T5 (Raffel et al., 2020)	838.7	364,868,892	153,607,833,664
mC4-en	Chung et al. (2023)	umT5 (Chung et al., 2023)	14,694.0	3,928,733,374	2,703,077,876,916
OSCAR	Abadji et al. (2022)	BLOOM* (Scao et al., 2022)	3,327.3	431,584,362	475,992,028,559
The Pile	Gao et al. (2020)	GPT-J/Neo & Pythia (Biderman et al., 2023)	1,369.0	210,607,728	285,794,281,816
RedPajama	Together Computer (2023)	LLaMA* (Touvron et al., 2023)	5,602.0	930,453,833	1,023,865,191,958
S2ORC	Lo et al. (2020)	SciBERT* (Beltagy et al., 2019)	692.7	11,241,499	59,863,121,791
peS2o	Soldaini & Lo (2023)	-	504.3	8,242,162	44,024,690,229
LAION-2B-en	Schuhmann et al. (2022)	Stable Diffusion* (Rombach et al., 2022)	570.2	2,319,907,827	29,643,340,153
The Stack	Kocetkov et al. (2023)	StarCoder* (Li et al., 2023)	7,830.8	544,750,672	1,525,618,728,620



[Elazar et al. 2023]

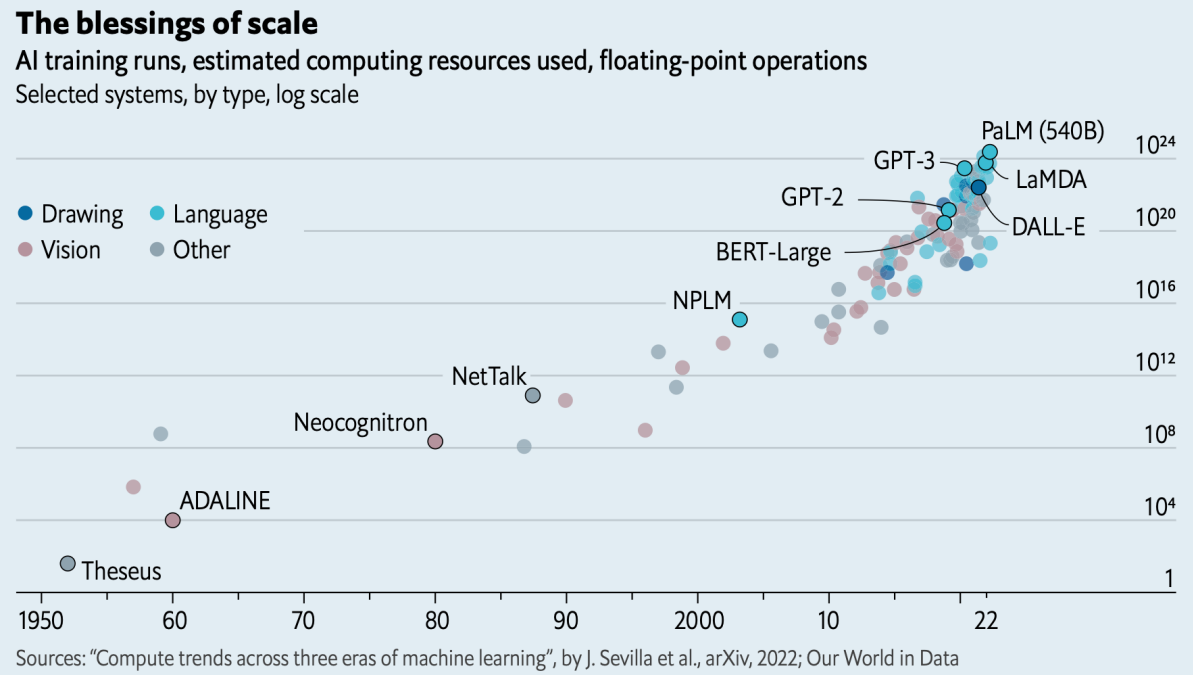
Data

What is the Web Missing?

- Low-resource languages
- Dialects with fewer speakers (e.g., Maghrezi Arabic)
- Non-written languages (e.g., American Sign Language)
- Language from people not on the web

All this comes to reinforce biases, which impact the technology available to people

Scaling Up
Compute



The Economist; London Vol. 443, Iss. 9300, (Jun 11, 2022): 17-20.

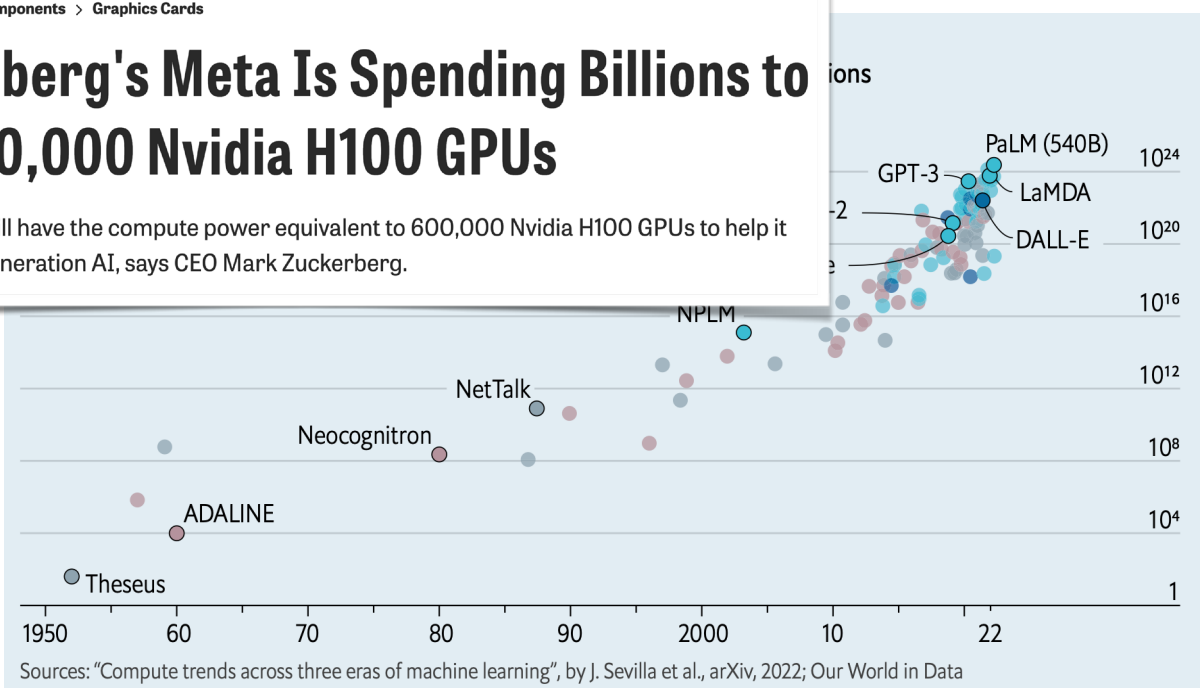
Scaling Up

Compute

Home > News > Components > Graphics Cards

Zuckerberg's Meta Is Spending Billions to Buy 350,000 Nvidia H100 GPUs

In total, Meta will have the compute power equivalent to 600,000 Nvidia H100 GPUs to help it develop next-generation AI, says CEO Mark Zuckerberg.



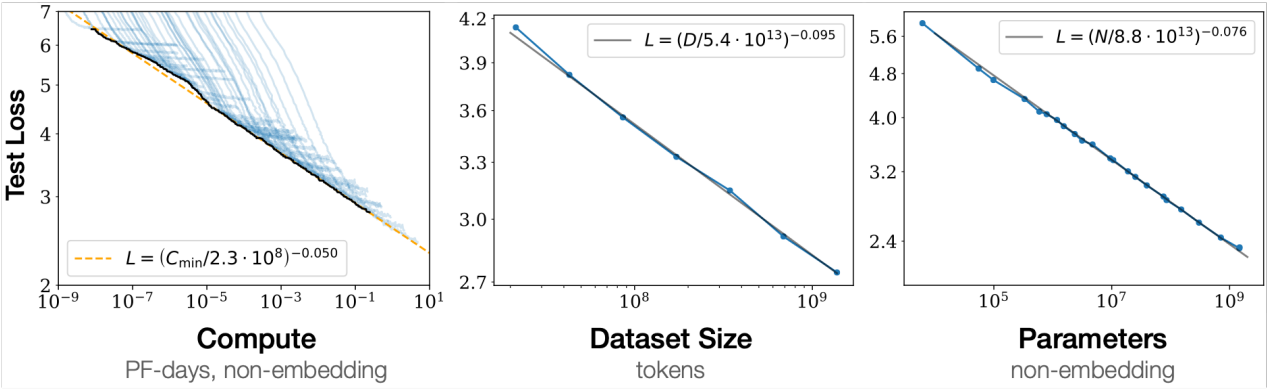
The Economist; London Vol. 443, Iss. 9300, (Jun 11, 2022): 17-20.
https://www.pcmag.com/news/zuckerbergs-meta-is-spending-billions-to-buy-350000-nvidia-h100-gpus

Scaling Up Impact

How Does Performance Improve?

- When we scale up…
  - The model size
  - The number of training examples
  - The batch size
  - The number of model updates (i.e., training longer)

Scaling Laws

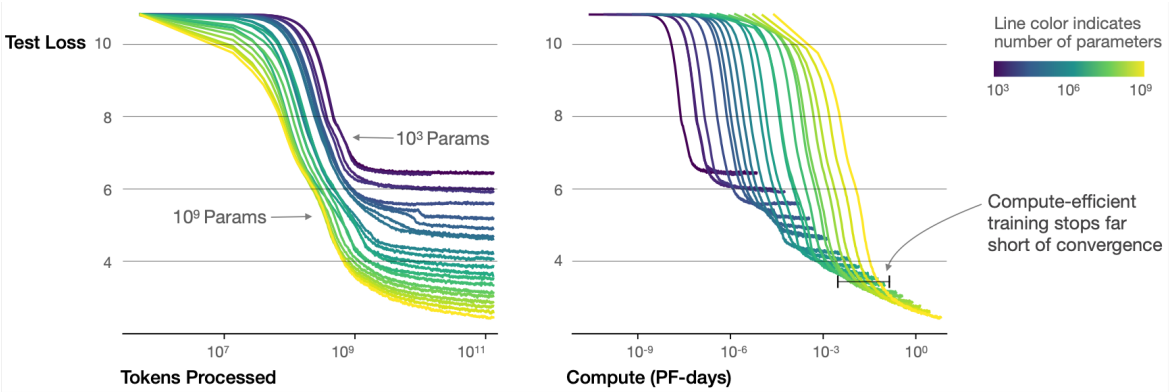


- Empirical test loss has a power law relationship with each individual factor
- Transformers scale well, and in a very predictable way

[Kaplan et al. 2020]

Scaling Laws

- Larger models require fewer samples to reach the same performance
- The optimal model size grows smoothly with the loss target and compute budget



[Kaplan et al. 2020]

Scaling Laws

- Scaling laws allow us to predict the loss:
  - Given a compute budget, how should we scale the data and number of parameters to get the best model?
- Scaling laws were identified by Kaplan et al. 2020, and later refined by Hoffmann et al. 2022
- The papers also provide exact formulas with coefficients for the Transformer architectures they used

Security and Privacy Risks

- Extracting memorized training data
  - Personally identifiable information
  - Memorized storylines with real names (even if turned out to be wrong!)
- Poisoning the training data
  - LLMs ingest data at scale that enables no monitoring
- Stealing models
- Prompt stealing and "jailbreaking"

Societal Impact

- Legal issues
  - Copyright violations, liability questions, regulation
- Political issues
  - Mis/disinformation, monitoring, and censorship
- Economic issues
  - LLMs replacing human labor
- Environmental costs

WGA MBA

5. Artificial Intelligence

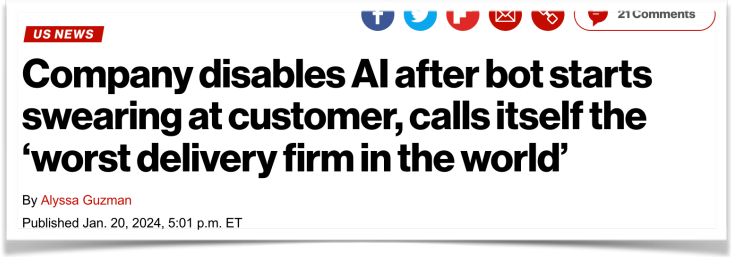
We have established regulations for the use of artificial intelligence ("AI") on MBA-covered projects in the following ways:

- AI can't write or rewrite literary material, and AI-generated material will not be considered source material under the MBA, meaning that AI-generated material can't be used to undermine a writer's credit or separated rights.
- A writer can choose to use AI when performing writing services, if the company consents and provided that the writer follows applicable company policies, but the company can't require the writer to use AI software (e.g., ChatGPT) when performing writing services.
- The Company must disclose to the writer if any materials given to the writer have been generated by AI or incorporate AI-generated material.
- The WGA reserves the right to assert that exploitation of writers' material to train AI is prohibited by MBA or other law.

https://www.wgacontract2023.org/the-campaign/summary-of-the-2023-wga-mba

Societal Implications

- Many open questions about liability and risk
- Critical for companies
- Even more critical in some domains (e.g., medical)



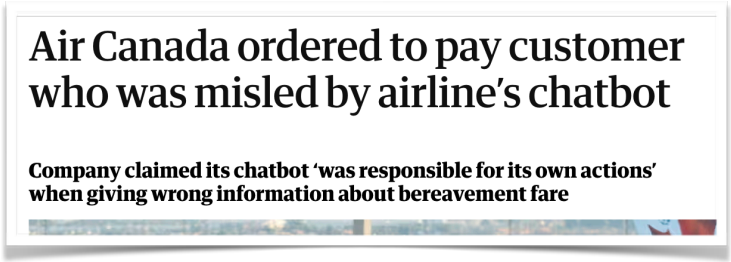
US NEWS

21 Comments

Company disables AI after bot starts swearing at customer, calls itself the 'worst delivery firm in the world'

By Alyssa Guzman

Published Jan. 20, 2024, 5:01 p.m. ET



Air Canada ordered to pay customer who was misled by airline's chatbot

Company claimed its chatbot 'was responsible for its own actions' when giving wrong information about bereavement fare

https://nypost.com/2024/01/20/news/company-disables-ai-after-bot-starts-swearing-at-customer/

https://www.theguardian.com/world/2024/feb/16/air-canada-chatbot-lawsuit

Scaling Up

What Do We Get?

- I put ____ form 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 / topics]
- 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]
- I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, _____ [reasoning]
- Cornell Tech is located in _____, New York [knowledge]

The learned representations have to account for a lot to succeed in this seemingly straightforward task

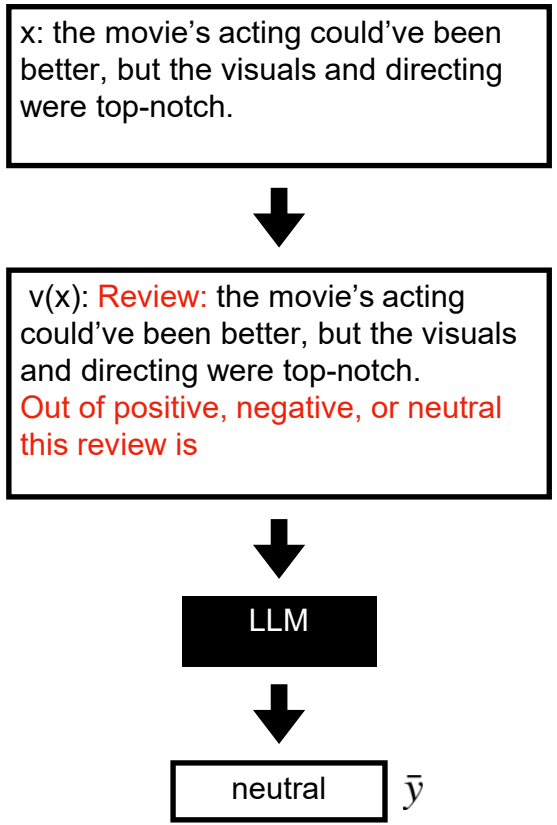
- We get really expressive representations
- Very impressive generations
- But how useful are these models?
  - Not that useful, yet
  - But: we can fine-tune them to be very useful
    - This is often called **alignment**
    - We will get back to this very soon

Working with LLMs

- A simple way to turn LLMs into task-specific models is through fine-tuning
  - Identical to what we saw with BERT and others: fine-tune with annotated data
  - You benefit from the rich representations of the LLM
- LLMs offer a completely new mode of operation that does not require any change to their parameters: **prompting**
  - With or without annotated examples: ***zero-shot*** or ***in-context learning*** (few-shot)
  - With or without intermediate reasoning steps: ***chain-of-thought*** prompting

Zero-shot Prompting

- Input: single unlabeled example x
- Output: the label y
- The task (and output) can be any text-to-text task: classification, summarization, translation
- Pre-processing: wrap x with a template using a ***verbalizer*** v(x)
- The template controls the output



Zero-shot Prompting

Constrained Output

- We generate from the model to get the output
  - What if the model output does not fit the intended format, even if it is semantically correct?
    - "… how many stars on a scale of four? 4" vs. [SEP]"… how many stars on a scale of four? four stars"
  - Or maybe not even semantically correct, but just irrelevant?

Zero-shot Prompting

Constrained Output

- We generate from the model to get the output
  - What if the model output does not fit the intended format, even if it is semantically correct?
    - "… how many stars on a scale of four? 4" vs. [SEP] "… how many stars on a scale of four? four stars"
- Generate with constraints:
  - Compare the probabilities of all possible outputs according to your format

$$\arg\max_{\bar{y}\in\{1,2,3,4\}} p(\bar{y} \mid v(\bar{x}))$$

Zero-shot Prompting

Constrained Output

- Generate with constraints:
  - Compare the probabilities of all possible outputs according to your format
  - If the label is a single token, just compare next token probabilities over labels
  - Otherwise?

Zero-shot Prompting

Sensitivity and Variability

- Prompting simplifies some aspects of adapting LLMs for tasks
  - No need to do expensive parameter estimate
  - You need much less data: no training data with zero-shot prompting
- However: many sources of unexpected variability
  - There are many way to write a prompt for the same task
  - Can we expect all of them to simply function the same?

Zero-shot Prompting

Sensitivity and Variability

- Prompts create a natural language input
- So the model ability to reason about that language influences task performance
  - How “natural” it is?
  - How does it “align” with the training data?

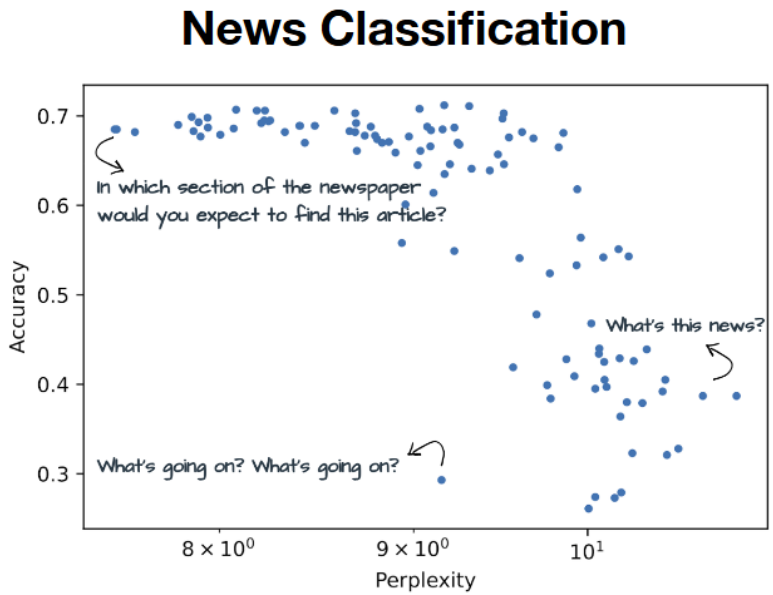


Figure 1: Accuracy vs. perplexity for the AG News dataset with OPT 175B. The x axis is in log scale. Each point stands for a different prompt.

[Gonen et al. 2022]

Zero-shot Prompting

Sensitivity and Variability

- Minor changes that should have no impact, can have dramatic effect
- For example: asking for answer in quotations

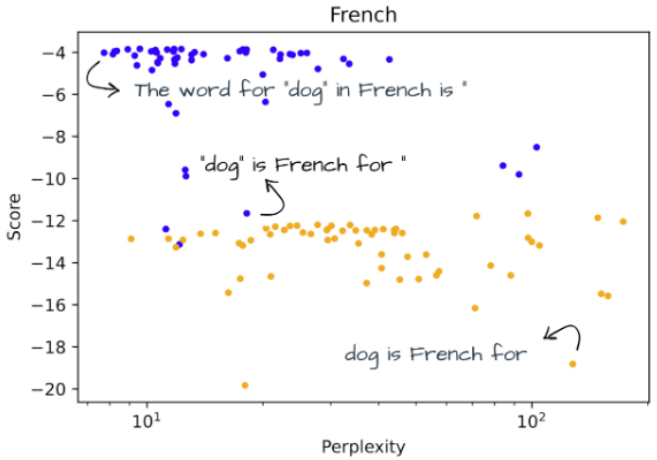


Figure 2: Score of correct label vs. perplexity for the word-level translation task in French with OPT 175B. The x axis is in log scale. The blue points stand for prompts with quotation marks for the words, while the yellow points are of prompts without quotation marks.

[Gonen et al. 2022]

Zero-shot Prompting

Sensitivity and Variability

- Prompts can even be sensitive to minor cosmetic changes
- Can influence performance in unexpected ways
- Can think of them as (very complex) hyper-parameters

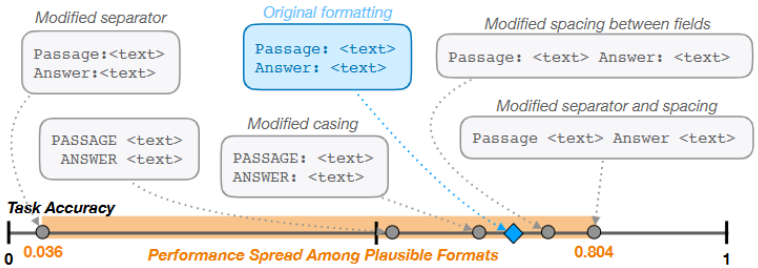


Figure 1: Slight modifications in prompt format templating may lead to significantly different model performance for a given task. Each `<text>` represents a different variable-length placeholder to be replaced with actual data samples. Example shown corresponds to 1-shot LLaMA-2-7B performances for task280 from SuperNaturalInstructions (Wang et al., 2022). This StereoSet-inspired task (Nadeem et al., 2021) requires the model to, given a short passage, classify it into one of four types of stereotype or anti-stereotype (gender, profession, race, and religion).

https://arxiv.org/abs/2310.11324

[Sc

Zero-shot Prompting

Surface Form Competition

- Given a closed set of answers, humans can explicitly restrict their choice
- Even if you constrain a model, the entire vocabulary is competing
- A very similar answer might get suck probability from the right one, but still be considered wrong

Figure 1: While humans select from given options, language models implicitly assign probability to every possible string. This creates surface form competition between different strings that represent the same concept. Example from CommonsenseQA (Talmor et al., 2019).

[Holtzman et al. 2021]

[Holtzman et al. 2021]

Zero-shot Prompting

Prompt Optimization

- Just like hyper-parameters, can think of optimizing prompts
- There are methods for searching over prompts (either using gradients or black-box optimization)
- Most do not lead to dramatically better results compared to manual engineering/hill-climbing (and are computationally intensive)
- Most important: the choice of prompt is very important for zero-shot settings

In-context Learning (ICL)

- LLMs have the ability to “learn” to complete tasks through training in the prompt
- The recipe is simple:
  - Take a small number of annotated training example
  - Convert them using verbalizer templates
  - Concatenate them and follow with the target input
  - The completion will be the label of the input

In-context Learning (ICL)

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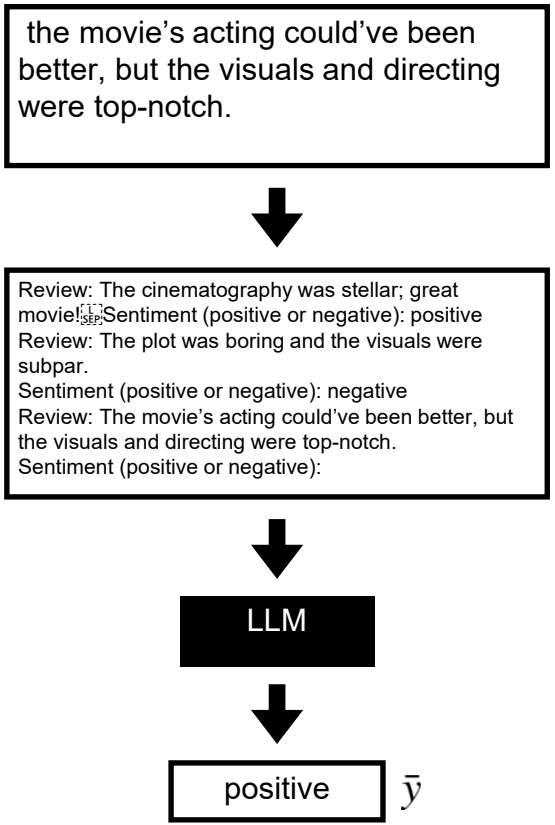

In-context Learning (ICL)

Performance

- Providing ICL examples almost always leads to significant improvements

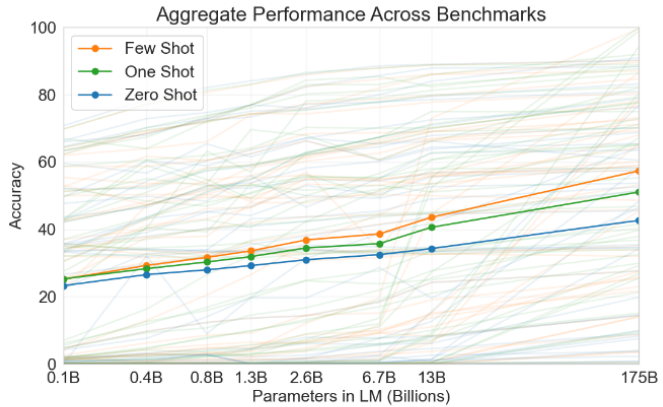

Figure 1.3: Aggregate performance for all 42 accuracy-denominated benchmarks While zero-shot performance improves steadily with model size, few-shot performance increases more rapidly, demonstrating that larger models are more proficient at in-context learning. See Figure 3.8 for a more detailed analysis on SuperGLUE, a standard NLP benchmark suite.

[Brown et al. 2020]

In-context Learning (ICL)

Performance

- Providing ICL examples almost always leads to significant improvements
- Benefits tend to diminish with more examples

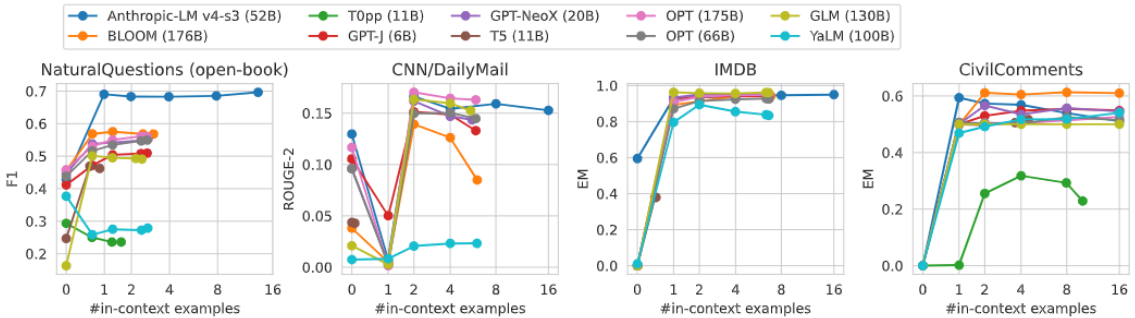

Figure 32: **Number of in-context examples.** For each model, we set the maximum number of in-context examples to [0, 1, 2, 4, 8, 16] and fit as many in-context examples as possible within the context window. We plot performance as a function of the average number of in-context examples actually used.

[Liang et al. 2022]

In-context Learning

Performance

- Model scale is important
- More examples have diminishing return
- What is the cost of more examples?

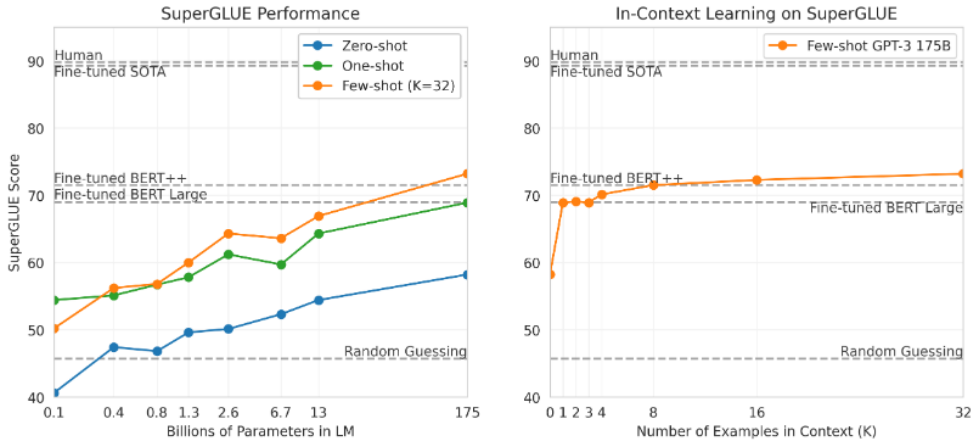

Figure 3.8: Performance on SuperGLUE increases with model size and number of examples in context. A value of $K = 32$ means that our model was shown 32 examples per task, for 256 examples total divided across the 8 tasks in SuperGLUE. We report GPT-3 values on the dev set, so our numbers are not directly comparable to the dotted reference lines (our test set results are in Table 3.8). The BERT-Large reference model was fine-tuned on the SuperGLUE training set (125K examples), whereas BERT++ was first fine-tuned on MultiNLI (392K examples) and SWAG (113K examples) before further fine-tuning on the SuperGLUE training set (for a total of 630K fine-tuning examples). We find the difference in performance between the BERT-Large and BERT++ to be roughly equivalent to the difference between GPT-3 with one example per context versus eight examples per context.

[Brown et al. 2020]

In-context Learning (ICL)

Sensitivity

- ICL can be highly sensitive to the choice of examples, their ordering, and the format of the prompt

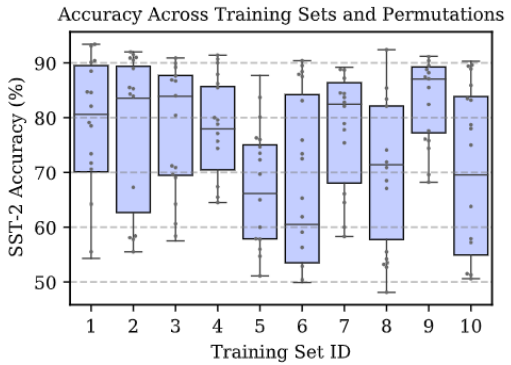

Figure 2. There is high variance in GPT-3's accuracy as we change the prompt's **training examples**, as well as the **permutation** of the examples. Here, we select ten different sets of four SST-2 training examples. For each set of examples, we vary their permutation and plot GPT-3 2.7B's accuracy for each permutation (and its quartiles).

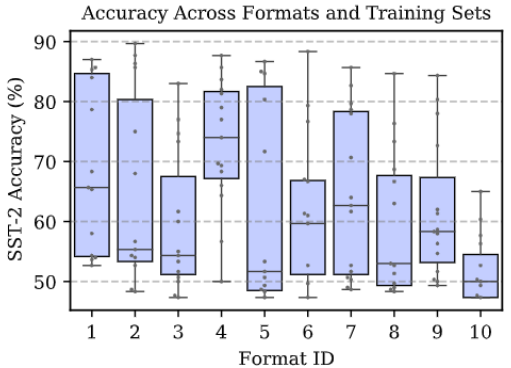

Figure 3. There is high variance in GPT-3's accuracy as we change the **prompt format**. In this figure, we use ten different prompt formats for SST-2. For each format, we plot GPT-3 2.7B's accuracy for different sets of four training examples, along with the quartiles.

In-context Learning (ICL)

Sensitivity

- Ordering and choice of examples can lead to strong label bias

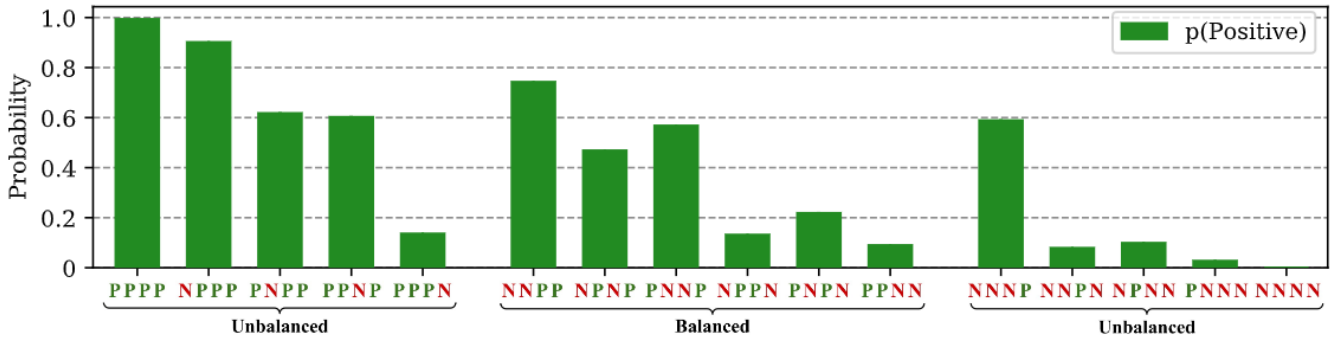

Figure 4. **Majority label and recency biases** cause GPT-3 to become biased towards certain answers and help to explain the high variance across different examples and orderings. Above, we use 4-shot SST-2 with prompts that have different class balances and permutations, e.g., [P P N N] indicates two positive training examples and then two negative. We plot how often GPT-3 2.7B predicts Positive on the balanced validation set. When the prompt is unbalanced, the predictions are unbalanced (*majority label bias*). In addition, balanced prompts that have one class repeated near the end, e.g., end with two Negative examples, will have a bias towards that class (*recency bias*).

[Zhao et al. 2021]

In-context Learning (ICL)

Sensitivity

- Particularly sensitive with fewer examples
  - Why using few examples is critical?
- There are methods that help, for examples see this tutorial

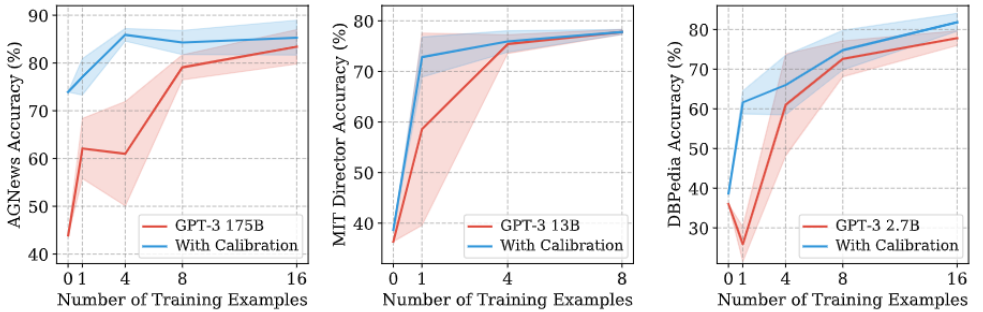

Figure 1. Few-shot learning can be highly unstable across different choices of the prompt. Above, we plot the mean accuracy (± one standard deviation) across different choices of the training examples for three different datasets and model sizes. We show that our method, *contextual calibration*, improves accuracy, reduces variance, and overall makes tools like GPT-3 more effective for end users.

[Zhao et al. 2021]

In-context Learning (ICL)

Analysis

- In some cases, the label correctness actually matters little
- But demonstrations still important
- What's happening? Demonstration are much about domain and form

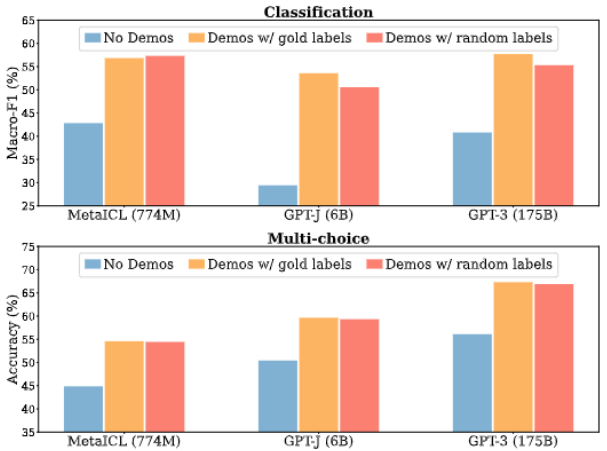

Figure 1: Results in classification (top) and multi-choice tasks (bottom), using three LMs with varying size. Reported on six datasets on which GPT-3 is evaluated; the channel method is used. See Section 4 for the full results. In-context learning performance drops only marginally when labels in the demonstrations are replaced by random labels.

[Min et al. 2022]

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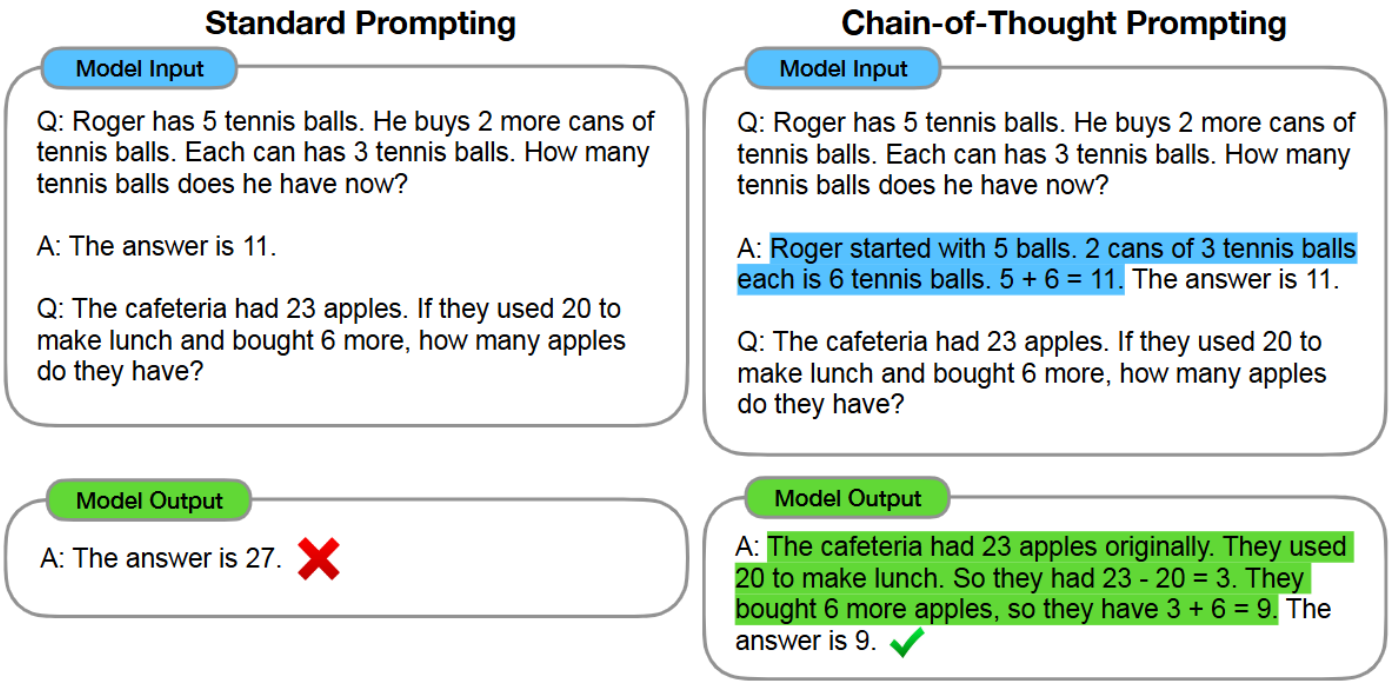
Chain-of-thought (COT) Prompting

- Some tasks require multiple reasoning steps
- Directly generating the answer requires the model internally do the reasoning steps (or shortcut somehow)
- It is empirically useful to:
  - Show the model examples of the reasoning steps through ICL
  - And then have it explicitly generate the reasoning steps

Chain-of-thought (COT) Prompting



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Chain-of-thought (COT) Prompting

Step-by-step

- COT requires ICL examples explicitly enumerating the reasoning steps
- Turn out reasoning steps can often be elicited without ICL examples
- Main idea: just “tell” the model to reason in steps

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Chain-of-thought (COT) Prompting

Step-by-step

(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. ✓

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Chain-of-thought (COT) Prompting

Step-by-step

- COT requires ICL examples explicitly enumerating the reasoning steps
- Turn out reasoning steps can often be elicited without ICL examples
- Main idea: just “tell” the model to reason in steps
- Challenge: the answer is often entangled in the reasoning text — how to extract it?

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. ✓

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Chain-of-thought (COT) Prompting

Step-by-step

- Main idea: just “tell” the model to reason in steps
- Challenge: the answer is often entangled in the reasoning text — how to extract it? → just use an LLM 😀

Chain-of-thought (COT) Prompting

Step-by-step

- Main idea: just “tell” the model to reason in steps
- Can significantly outperform zero-shot prompting with very large models
- But requires no ICL examples

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Chain-of-thought (COT) Prompting

Step-by-step

- There is no one magical prompt
- Empirically, the is a set of instructive prompts that are roughly equivalent

Table 4: Robustness study against template measured on the MultiArith dataset with text-davinci-002. (*1) This template is used in Ahn et al. [2022] where a language model is prompted to generate step-by-step actions given a high-level instruction for controlling robotic actions. (*2) This template is used in Reynolds and McDonell [2021] but is not quantitatively evaluated.

No.	Category	Template	Accuracy
1	instructive	Let's think step by step.	**78.7**
2		First, (*1)	77.3
3		Let's think about this logically.	74.5
4		Let's solve this problem by splitting it into steps. (*2)	72.2
5		Let's be realistic and think step by step.	70.8
6		Let's think like a detective step by step.	70.3
7		Let's think	57.5
8		Before we dive into the answer,	55.7
9		The answer is after the proof.	45.7
10	misleading	Don't think. Just feel.	18.8
11		Let's think step by step but reach an incorrect answer.	18.7
12		Let's count the number of "a" in the question.	16.7
13		By using the fact that the earth is round,	9.3
14	irrelevant	By the way, I found a good restaurant nearby.	17.5
15		Abrakadabra!	15.5
16		It's a beautiful day.	13.1
–		(Zero-shot)	17.7

Table 5: Robustness study of Few-shot-CoT against examples. When the examples are from entirely different tasks, the performance generally becomes worse, but when the answer formats are matched (i.e. CommonsenseQA to AQUA-RAT, multiple-choice), the performance loss is less severe. †CommonsenseQA samples are used in this variation

	Zero-shot	Few-shot-CoT †	Zero-shot-CoT	Few-shot-CoT
AQUA-RAT	22.4	31.9	33.5	39.0
MultiArith	17.7	27.0	78.7	88.2

reasoning (MultiArith), Zero-shot-CoT and Few-shot-CoT show substantial differences regarding the error patterns. First, Zero-shot-CoT tends to output unnecessary steps of reasoning after getting the correct prediction, which results in changing the prediction to incorrect one. Zero-shot-CoT also sometimes does not start reasoning, just rephrasing the input question. In contrast, Few-shot-CoT tend to fail when generated chain of thought include ternary operation, e.g. $(3 + 2) * 4$.

How does prompt selection affect Zero-shot-CoT? We validate the robustness of Zero-shot-CoT against input prompts. Table 4 summarizes performance using 16 different templates with three categories: instructive (encouraging CoT reasoning), misleading (encouraging CoT reasoning but in a wrong way), and irrelevant (nothing to do with reasoning). The results indicate that the performance is improved if the text is written in a way that encourages chain of thought reasoning, i.e., the templates are within "instructive" category. However, the difference in accuracy is significant depending on the sentence. In this experiment, "Let's think step by step." achieves the best results. Interestingly, it is found that different templates encourage the model to express reasoning quite differently (see Appendix B for sample outputs by each template). In contrast, when we use misleading or irrelevant templates, the performance does not improve. It remains an open question how to automatically create better templates for Zero-shot-CoT.

How does prompt selection affect Few-shot-CoT? Table 5 shows the performance of Few-shot-CoT when using examples from different datasets: CommonsenseQA to AQUA-RAT and CommonsenseQA to MultiArith. The domains are different in both cases, but the answer format

Chain-of-thought (COT) Prompting

Fine-tuning

- COT can also be used for fine-tuning
- And can increase zero-shot step-by-step performance

zero-shot CoT on PaLM without finetuning were only shown for math word problems, which differ substantially from the types of problems in BBH.

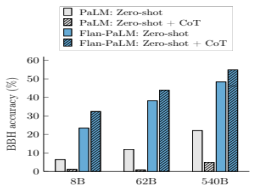

Figure 6: Zero-shot performance of PaLM and Flan-PaLM on a set of 23 challenging BIG-Bench tasks (BBH). Flan-PaLM benefits from chain-of-thought (CoT) generation activated via "let's think step-by-step."

5. Putting it all together

Given the prior results on scaling the number of tasks and including chain-of-thought data, we now show the generality of instruction finetuning by applying it to several models of different sizes, architectures, and training objectives. In addition to the PaLM family of models, we instruction-finetune **T5** models which have an encoder-decoder architecture, as opposed to PaLM's decoder-only architecture. As an extended version of the PaLM 62B model, we instruction-finetune **cont-PaLM**, which is a 62B PaLM-model initialized from PaLM-62B and then pretrained for 500B more tokens (Chowdhery et al., 2022). Finally, we instruction-finetune **U-PaLM**, which is a 540B PaLM model initialized from PaLM-540B and then pretrained with an UL2 objective for 20k additional steps (Tay et al., 2022a,b).

These evaluation results are shown in Table 5. Instruction finetuning improves normalized average performance by a large margin for all model types. For T5 models without instruction finetuning, we use LM-adapted models, which were produced by training T5 on 100B additional tokens from C4 on a standard language modeling objective (Lester et al., 2021). Given the difficulty of our evaluation benchmarks and the fact that T5 is not multilingual, T5 models benefited the most from instruction finetuning compared with their non-finetuned models. These results were quite strong for some benchmarks—for example, Flan-T5-XL is only 3B parameters and achieves a MMLU score of 52.4%, surpassing GPT-3 175B's score of 43.9%. As another highlight, the strongest overall model we achieve in this paper combines instruction finetuning with UL2 continued pre-training that was used in the U-

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