# Pretraining II: Decoding, Scaling, Prompting, and Beyond

CSE 5525: Foundations of Speech and Natural Language Processing

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

The Ohio State University

# Logistics

- Final Project Proposal: Due this Friday.

- Homework 3 will be released Friday night (Oct 3).
    - Topic: prompting/finetuning models for code generation (text-to-SQL)

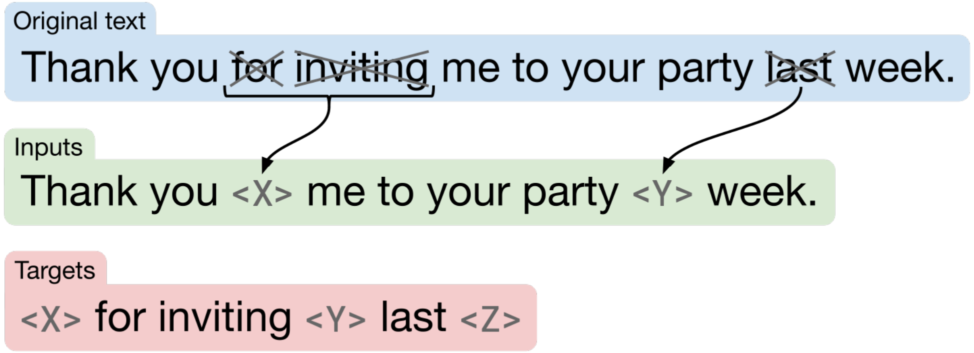
# Last Class Recap: Masked LMs

- Denoising pretraining objectives
  - BERT
  - T5
  - BART

# T5 (Text-to-Text Transfer Transformer)

**Pretraining**

- Pretraining is similar to the denoising objective of BERT:
  - Input: text with “masks” – but now spans removed (instead of just tokens)
  - Output: sequence of phrases to fill the gaps



Original text

Thank you ~~for inviting~~ me to your party ~~last~~ week.

Inputs

Thank you <X> me to your party <Y> week.

Targets

<X> for inviting <Y> last <Z>

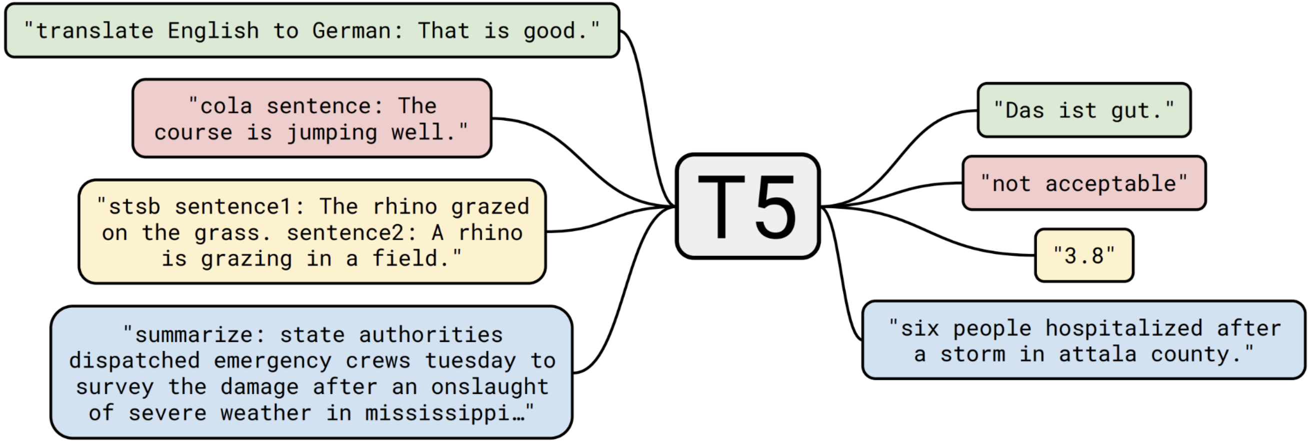
- Trained on the next token objective (only on the decoder; similar to a conditional LM)

[Raffel et al. 2019]

# T5 (Text-to-Text Transfer Transformer)

**Finetuning**

- Frame any problem as a text-to-text problem.
- Initialize with pretrained T5 and finetune every task as a text to text generation task (no new parameters required)


"translate English to German: That is good."
"cola sentence: The course is jumping well."
"stsb sentence1: The rhino grazed on the grass. sentence2: A rhino is grazing in a field."
"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"
T5
"Das ist gut."
"not acceptable"
"3.8"
"six people hospitalized after a storm in attala county."

[Raffel et al. 2019]

# Unified Language Modeling Paradigms

**UL2**

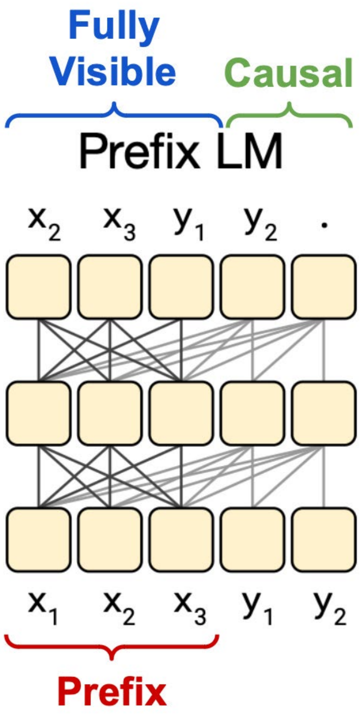
- So far, we have looked at multiple training objectives
    - Denoising
        - Masked token prediction –BERT
        - Masked span prediction – T5
        - Other denoising (shuffling, deleting, etc) – BART
    - Next token prediction (GPT)

- Can we train a model that uses all of them?
    - Can we use encoder-only architecture?
    - Can we use encoder-decoder architecture?
    - Can we use decoder only architecture?

# Do we really need a separate encoder?

**Prefix LM**

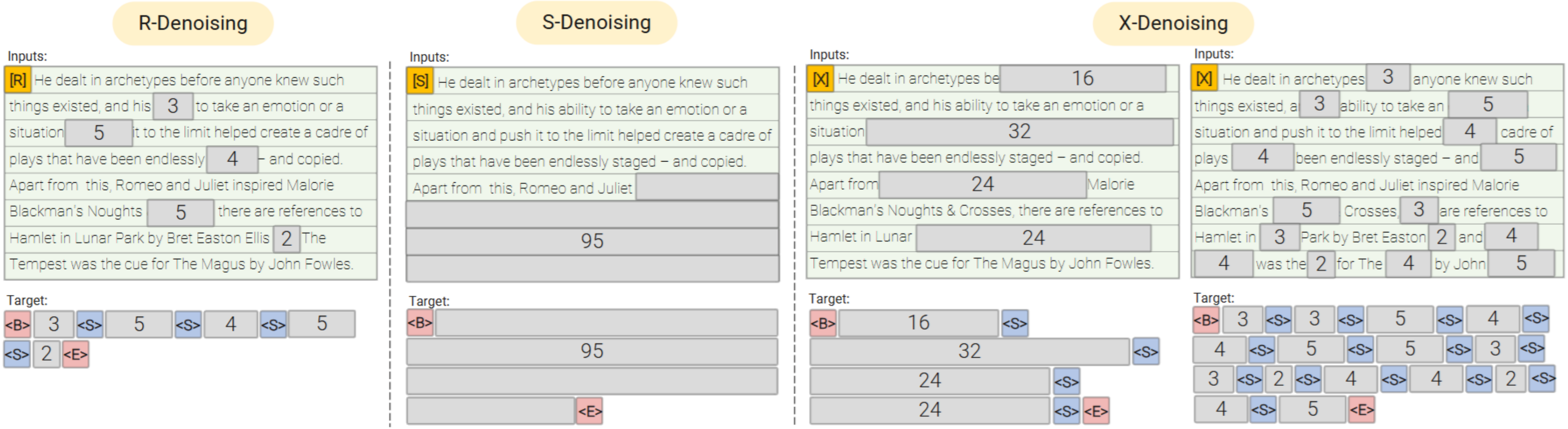
- Share the parameters of the encoder and the decoder
- Apply a bidirectional attention on the input and causal (masked) attention on the output.



# Unified Language Modeling Paradigms

## UL2

- Can use encoder-decoder or decoder-only prefix-LMs



R-Denoising
S-Denoising
X-Denoising
Inputs:
[R] He dealt in archetypes before anyone knew such things existed, and his 3 to take an emotion or a situation 5 it to the limit helped create a cadre of plays that have been endlessly 4 – and copied. Apart from this, Romeo and Juliet inspired Malorie Blackman's Noughts 5 there are references to Hamlet in Lunar Park by Bret Easton Ellis 2 The Tempest was the cue for The Magus by John Fowles.
Target:
<B> 3 <S> 5 <S> 4 <S> 5 <S> 2 <E>
Inputs:
[S] He dealt in archetypes before anyone knew such things existed, and his ability to take an emotion or a situation and push it to the limit helped create a cadre of plays that have been endlessly staged – and copied. Apart from this, Romeo and Juliet 95
Target:
<B> 95 <E>
Inputs:
[X] He dealt in archetypes be 16 things existed, and his ability to take an emotion or a situation 32 plays that have been endlessly staged – and copied. Apart from 24 Malorie Blackman's Noughts & Crosses, there are references to Hamlet in Lunar 24 Tempest was the cue for The Magus by John Fowles.
Target:
<B> 16 <S> 32 <S> 24 <S> 24 <S> <E>
Inputs:
[X] He dealt in archetypes 3 anyone knew such things existed, a 3 ability to take an 5 situation and push it to the limit helped 4 cadre of plays 4 been endlessly staged – and 5 Apart from this, Romeo and Juliet inspired Malorie Blackman's 5 Crosses, 3 are references to Hamlet in 3 Park by Bret Easton 2 and 4 4 was the 2 for The 4 by John 5
Target:
<B> 3 <S> 3 <S> 5 <S> 4 <S> 4 <S> 5 <S> 5 <S> 3 <S> 3 <S> 2 <S> 4 <S> 4 <S> 2 <S> 4 <S> 5 <E>

Figure 3: Mixture of denoisers for training UL2. Greyed out rectangles are masked tokens that are shifted to '*targets*' for prediction.

# Summary of different pretraining objectives

- Denoising Objectives

- Next token prediction

- Combine them all.

- Which one should we use?
  - denoising objectives are great but pretty insufficient as a standalone objective -- less "loss exposure", also a little contrived
  - Causal LMs – high loss exposure, natural to formulate – also enables other interesting phenomenon like "few-shot learning" – with enough data and scale, Causal LMs turned out to be just as good without needing bidirectional context.

What happened to BERT & T5? On Transformer Encoders, PrefixLM and Denoising Objectives — Yi Tay

# Going forward – decoder only LMs

- We will (mostly) talk about decoder only LMs going forward as they are most commonly used now
    - Like GPTs, Claude, Llama models, Mistral, Qwen, and many more.

# Why decoder only LMs?

**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?

# Why decoder only LMs?

## Why Does it Make Sense?

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

# Why decoder only LMs?

**Why Does it Make Sense?**

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

# Why decoder only LMs?

## 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 _____

# Why decoder only LMs?

## 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 ____

# Why decoder only LMs?

**Why Does it Make Sense?**

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

# Why decoder only LMs?

## Why Does it Make Sense?

Ohio State is located in ______

# Why decoder only LMs?

## 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

# What Can We Do with LMs?

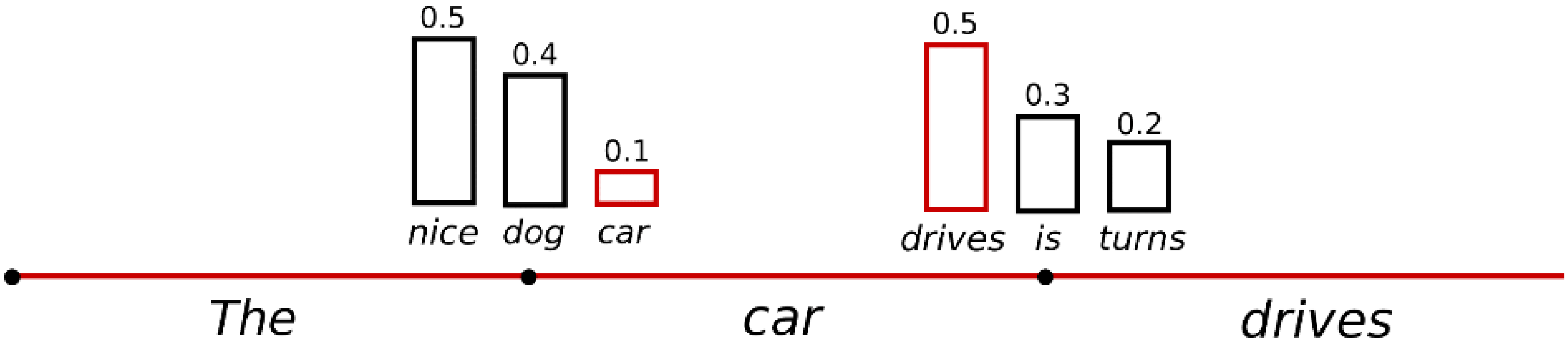
- Given a sequence $\overline{x}$ compute the probability of the sequence
  - $p(\overline{x}) = \prod_{i=1}^{N} p(x_i | x_1, \ldots, x_{i-1})$
- Given a prefix, generate a  sequence autoregressively(i.e., generating one token at a time)
  - The prefix can be empty (sort of: always includes a start token)
  - This prefix is called a **prompt**

# Decoding strategies

# Sampling

- Sampling:

$$x_i \sim p(x_i | x_1, \dots, x_{i-1}) \text{ until } x_i = \text{STOP}$$



This can often generate incoherent gibberish

Source: https://huggingface.co/blog/how-to-generate

# Greedy Decoding

- Greedy (i.e., $\arg max$):

$$x_i = \arg\underset{x_1 \in \mathcal{V}}{max}\, p(x_i | x_1, \dots, x_{i-1}) \text{ until } x_i = \mathrm{STOP}$$

- How many different strings can we generate this way?

# Adjusting Distribution **Temperature**

- Let's say we want something between sampling and greedy
  - Not fully deterministic
  - But to control how focused on the top of the distribution with high likelihood
- Add a temperature parameter to the softmax
  - Given z is the vector with logits, and $T \in \mathbb{R}$ in the temperature

$$p(y_i \mid x) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

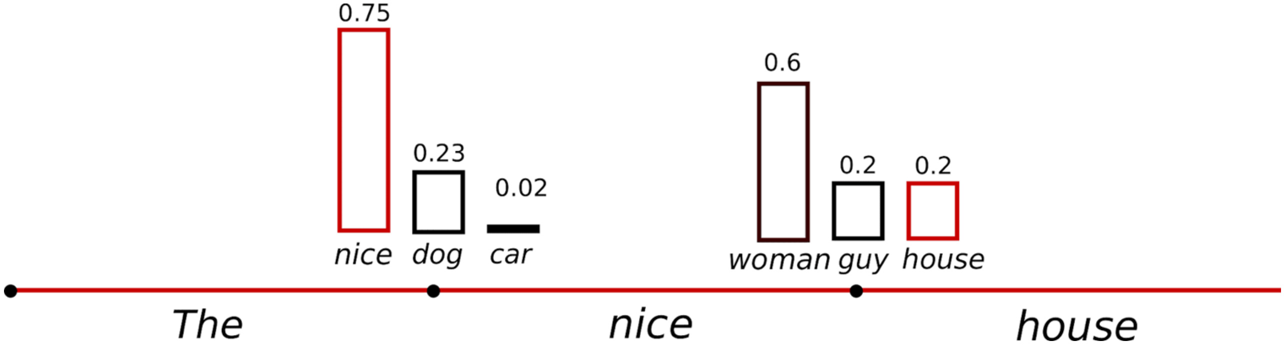
Higher T: softens probabilities.
Lower  T: sharpens probabilities.

# Adjusting Distribution **Temperature**

- Add a temperature parameter to the softmax
  - Given $z$ is the vector with logits, and $T \in \mathbb{R}$ in the temperature

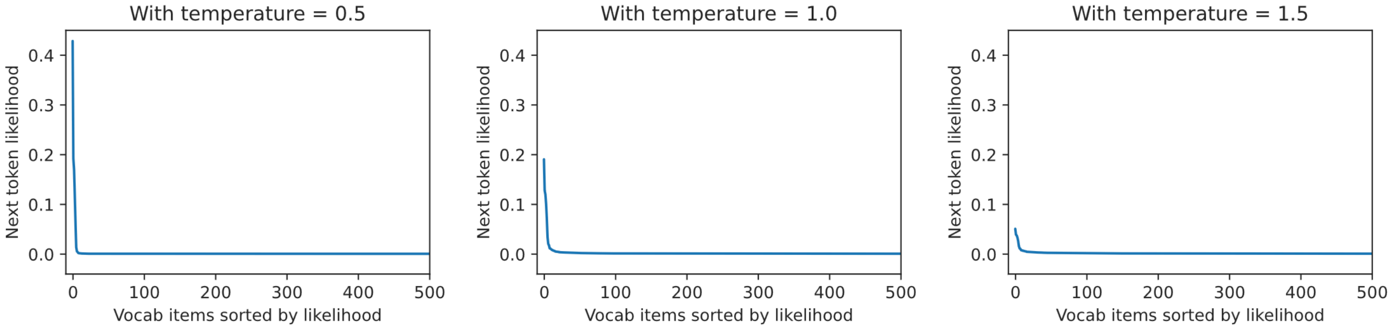
$$p(y_i \mid x) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

Higher T: softens probabilities.
Lower T: sharpens probabilities.



# Adjusting Distribution Temperature

- What happens with $T = 1$? $T = 0$ (or almost)? $T \in [0,1)$? $T > 1$?



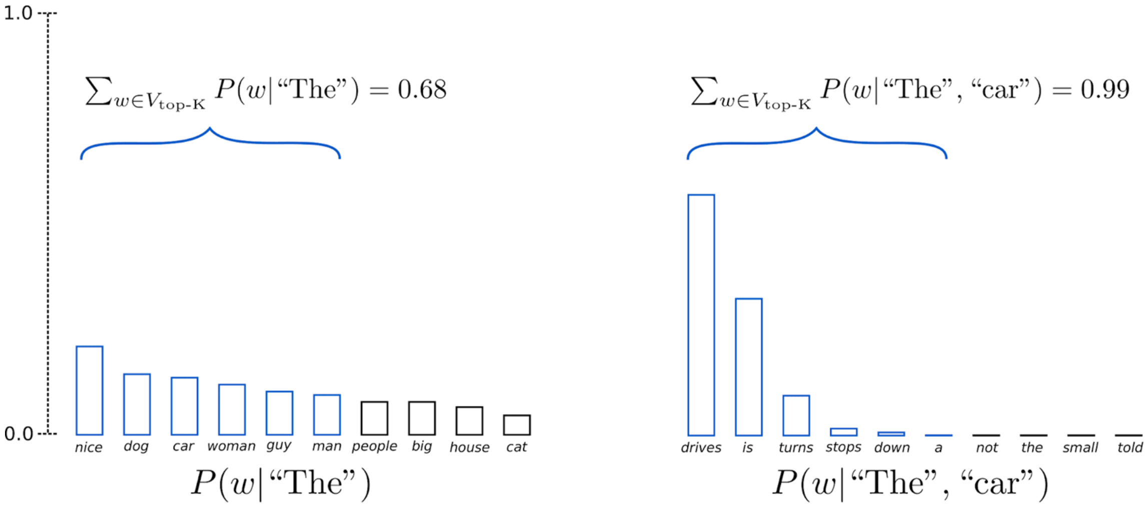
Plots from Daphne Ippolito / Chenyan Xiong, CMU LLMs course http://cmu-llms.org/

# Top-k sampling [Fan et al., 2018]

Filter k most likely next tokens and redistributed the probability mass among only those k tokens, then sample from the new distribution

**Problem:** It doesn't dynamically adapt the number of words that are filtered from the next word probability distribution

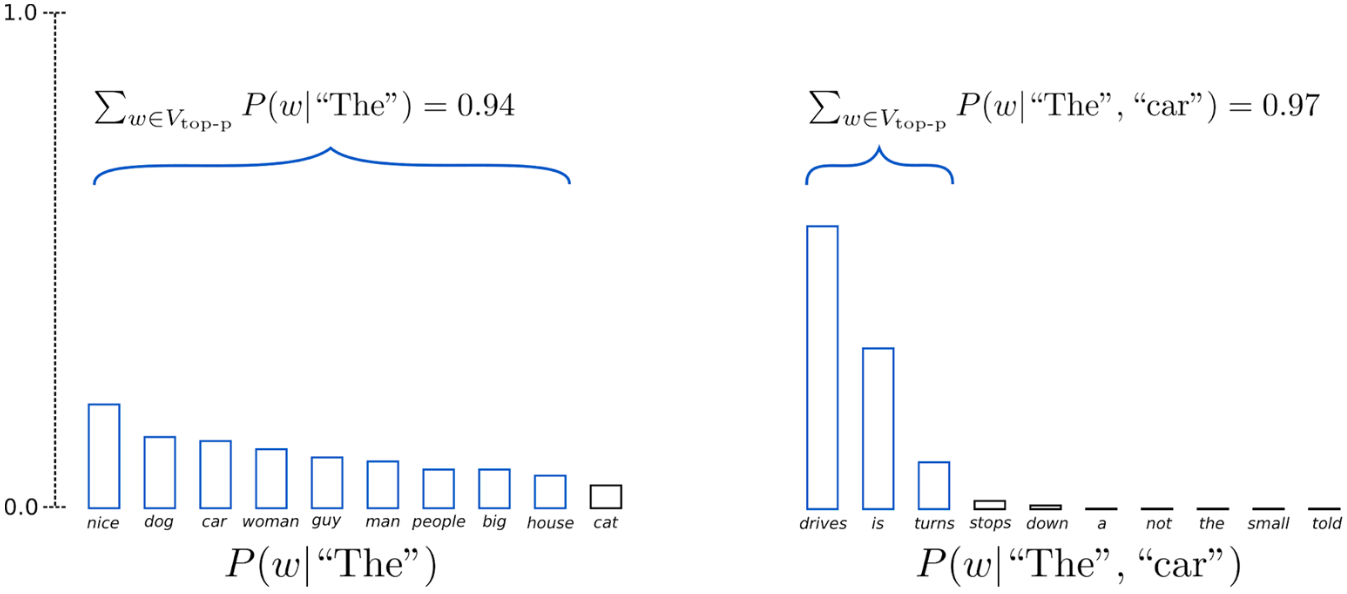
Reasonable candidates (left fig) are eliminated, and ill-fitted (right fig) are not



Source: https://huggingface.co/blog/how-to-generate

# Top-p (nucleus) sampling [Holtzman et al., 2020]

Sample from the smallest possible set of tokens whose cumulative probability exceeds the probability p



Source: https://huggingface.co/blog/how-to-generate

# Decoding

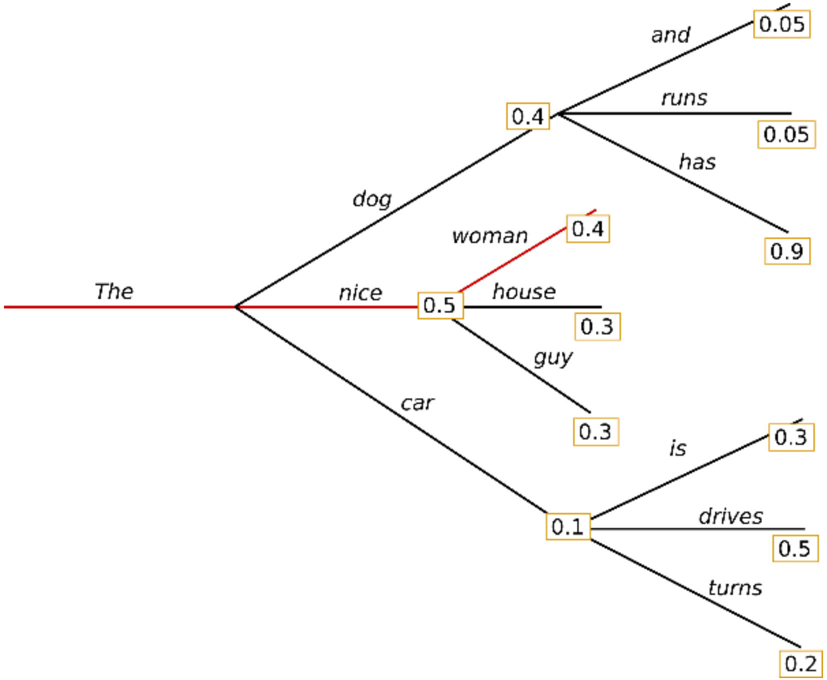
- Various decoding techniques: greedy, sampling, temperature-based, top-k, nucleus
- Most common: temperature-based
- Which are guaranteed to give you the **optimal** output? Will $\arg max$ give you the optimal output?

# Decoding

- Various decoding techniques: greedy, sampling, temperature-based, top-k, nucleus
- Most common: temperature-based
- Which are guaranteed to give you the optimal output? Will $\mathrm{arg}max$ give you the optimal output?

| | | | |
|---|---|---|---|
| | 0,2 | 0,5 | 0,1 |
| **Output 1** | I | love | Lucy |
| | 0,2 | 0,1 | 0,99 |
| **Output 2** | I | hate | Lucy |

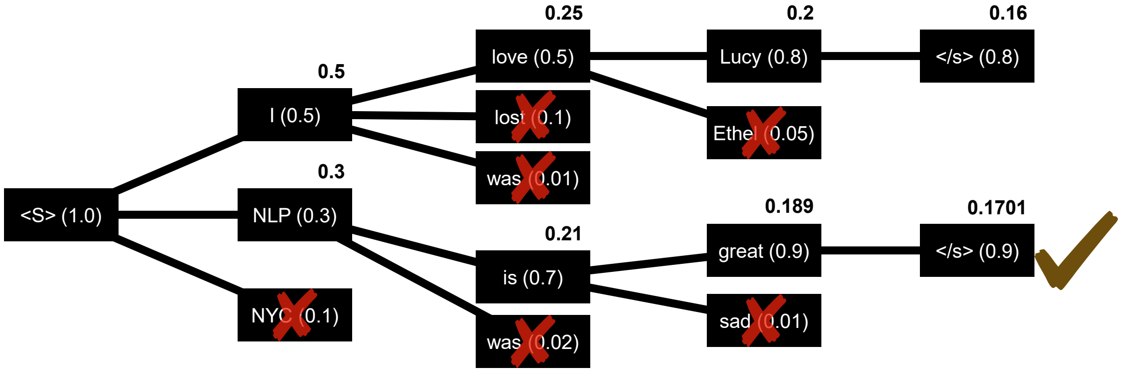
# Greedy decoding/search

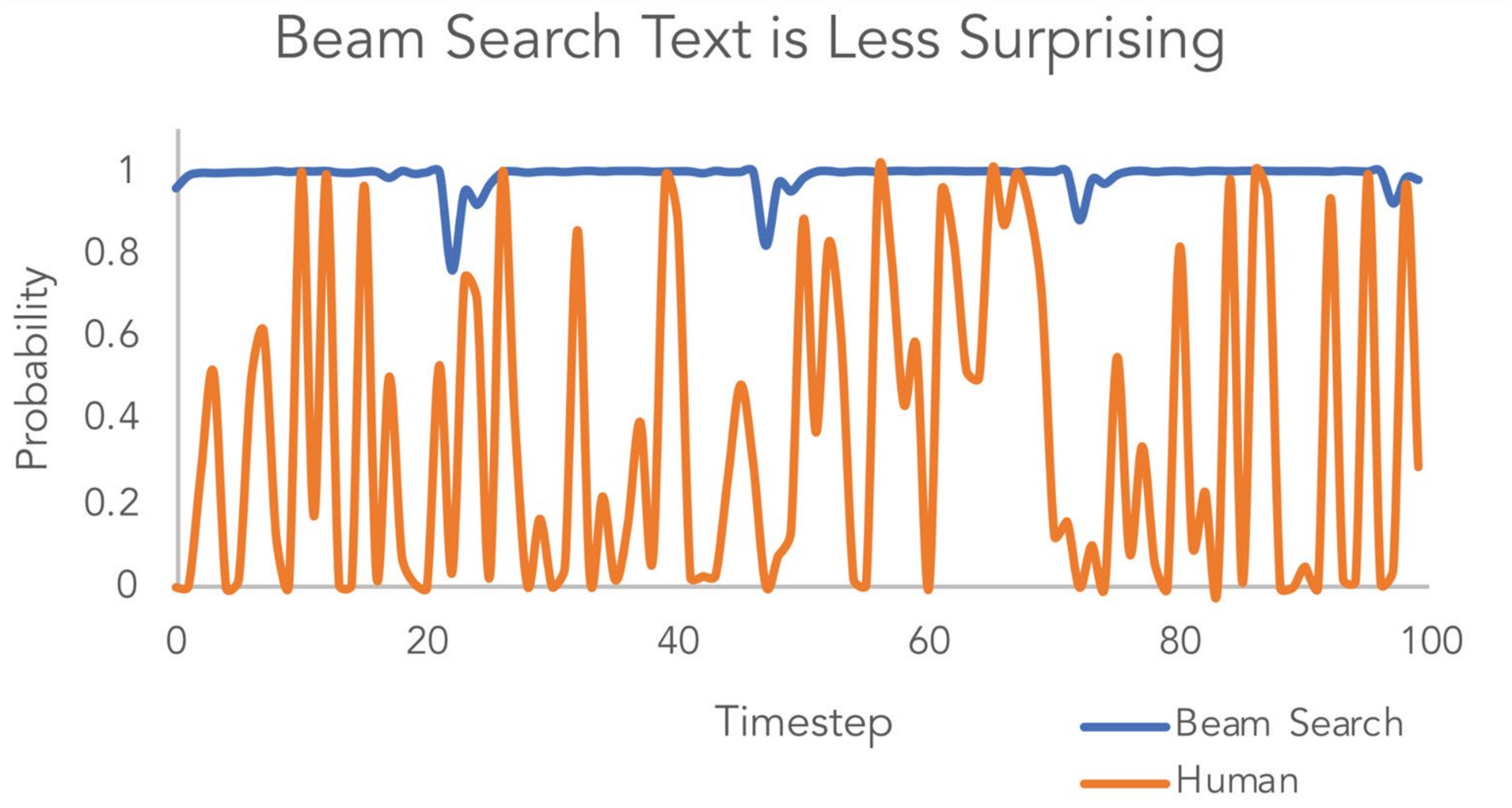


Source: https://huggingface.co/blog/how-to-generate

# Beam Search

- Sampling techniques are not optimal
  - Following a single hypothesis is just not sufficient, but enumerating all is intractable
- **Beam search** is middle ground
  - Follow a set of hypothesis, always keeping the top ones
  - The size of the set $B$ is a hyperparameter





Source: [Holtzman et al., 2020]

# Beam Search

- Sampling techniques are not optimal
  - Following a single hypothesis is just not sufficient, but enumerating all is intractable
- Beam search is middle ground
  - Follow a set of hypothesis, always keeping the top ones
  - The size of the set $B$ is a hyperparameter
  - It's an approximation method
  - What happens with $B = 1$? $B = \infty$?
  - What is the cost of beam search compared to the sampling techniques we saw?
  - Can you combine sampling techniques with beam search?

# Scaling

# Some History: the GPTs

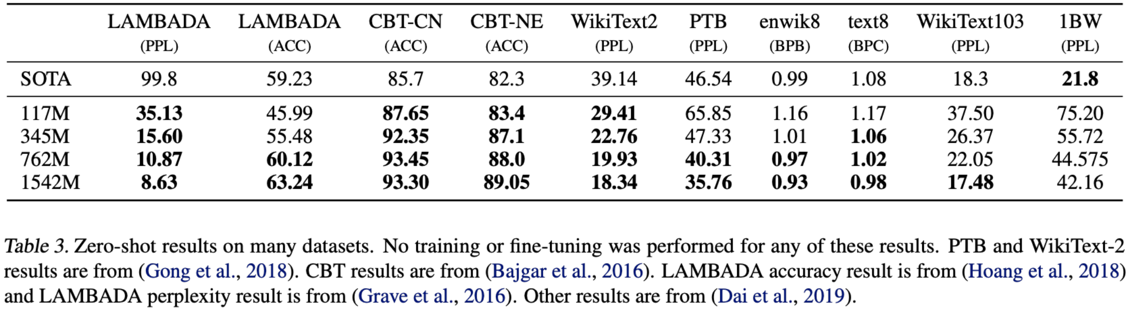
**GPT [Radford et al. 2018]**

- 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<br>(PPL) | LAMBADA<br>(ACC) | CBT-CN<br>(ACC) | CBT-NE<br>(ACC) | WikiText2<br>(PPL) | PTB<br>(PPL) | enwik8<br>(BPB) | text8<br>(BPC) | WikiText103<br>(PPL) | 1BW<br>(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]**

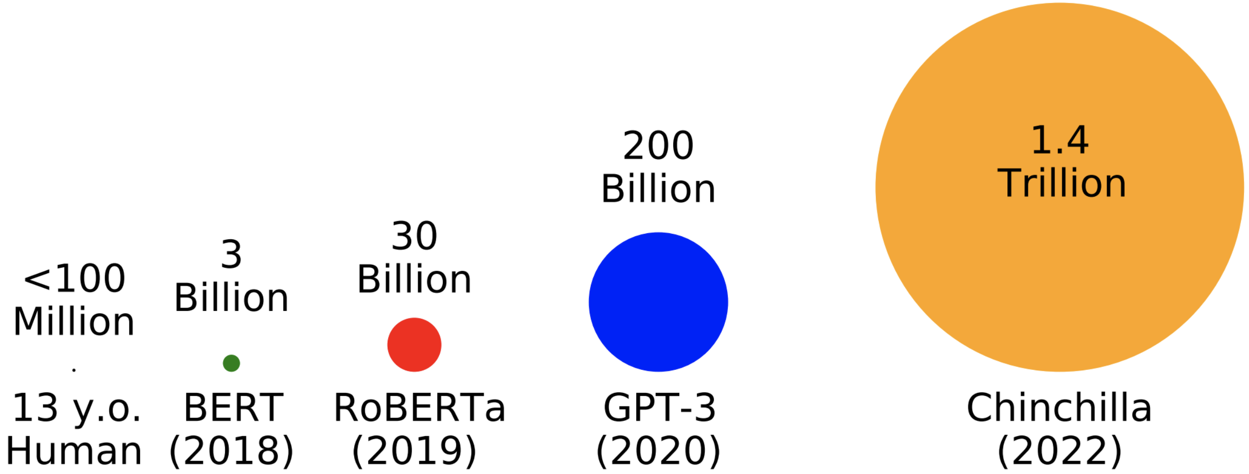
- GPT-3 scaled the model size to 175B parameters
- So far, two ways of interaction with models:
  - Sample from the distribution (generation)
  - Fine-tune on a specific task
- GPT-3 demonstrated few-shot learning **without parameter updates — In-context Learning (ICL)**
  - In-context examples seem 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 off without: personally identifiable information, adult content, hate speech, copyrighted data, NLP benchmarks (why?)

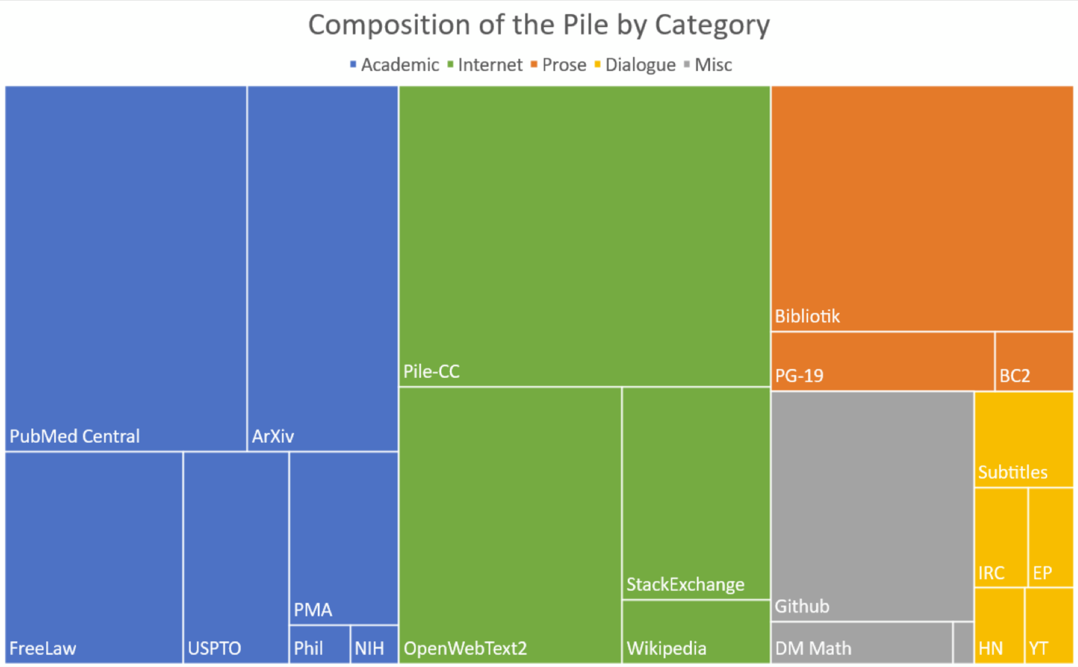
# Data

## 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

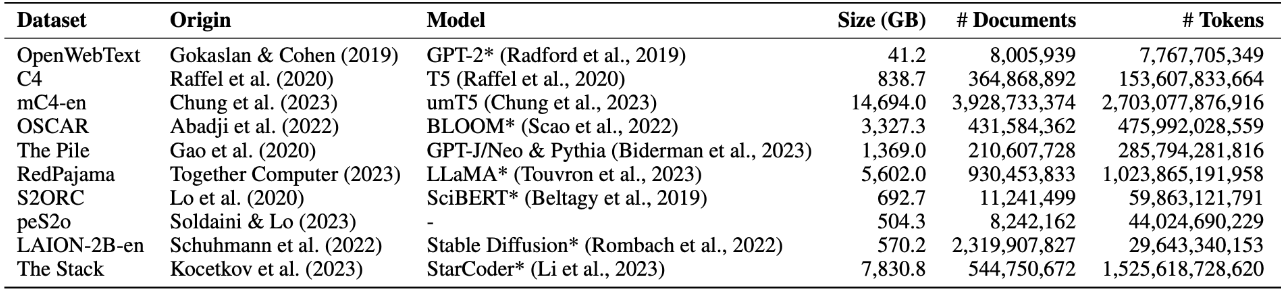


[Gao et al. 2020]

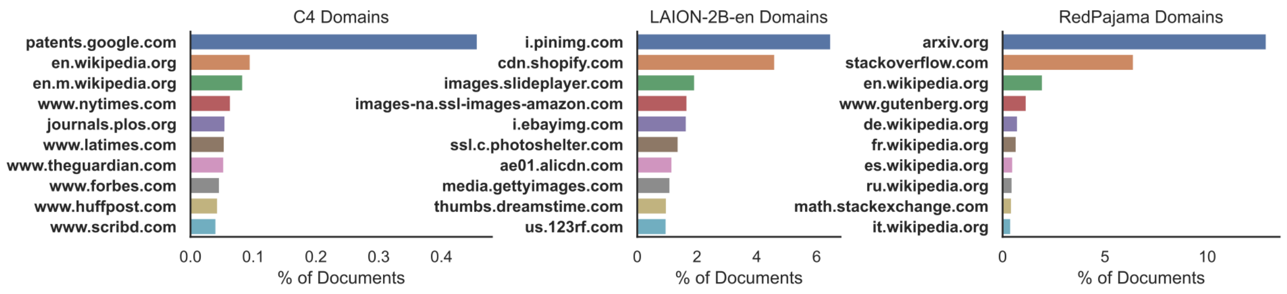
# Data

## 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

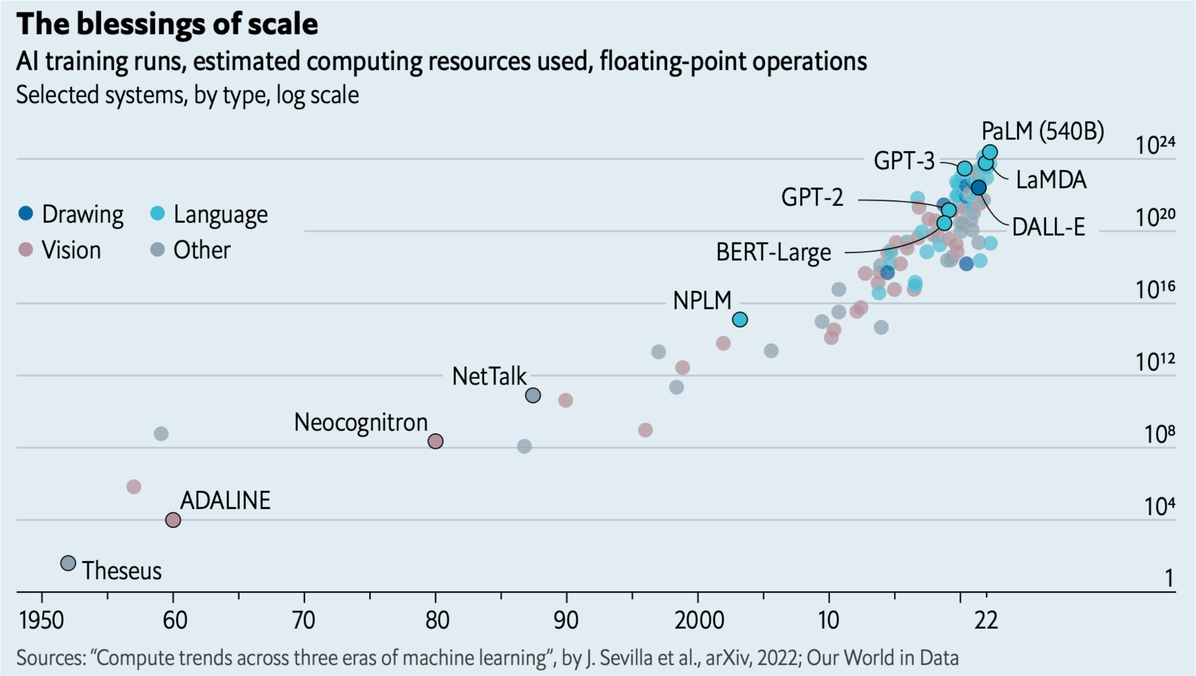
**What is the Web Missing?**

- Many non-English languages are very limited
- 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

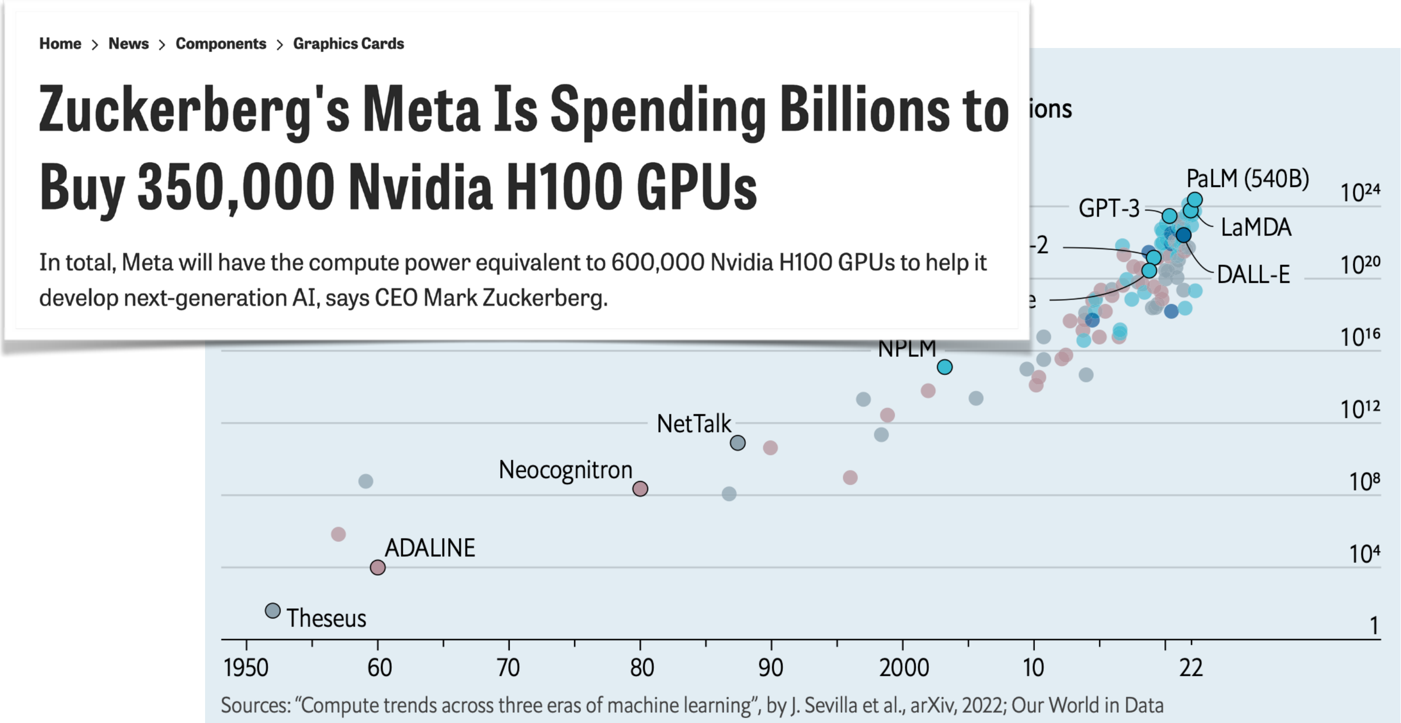
## Compute



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.

Sources: "Compute trends across three eras of machine learning", by J. Sevilla et al., arXiv, 2022; Our World in Data

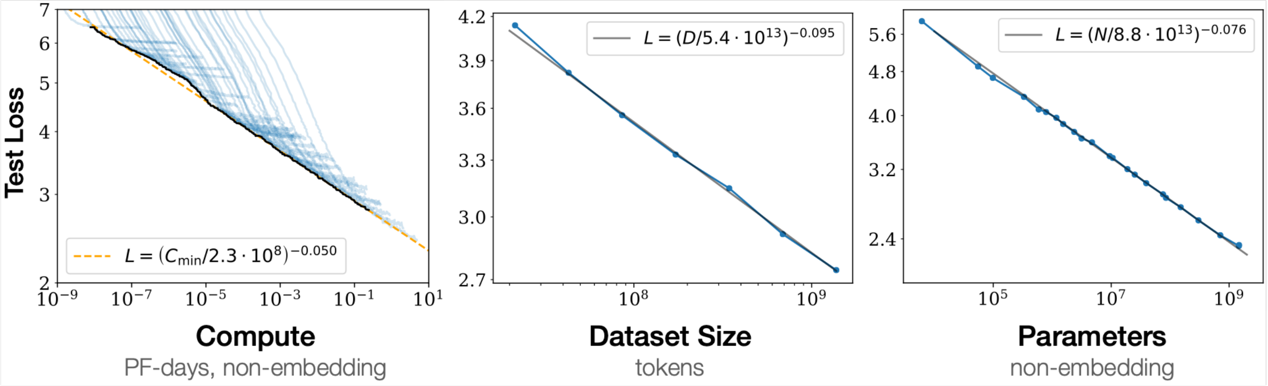
The Economist; London Vol. 443, Iss. 9300, (Jun 11, 2022): 17-20.
https://www.pcmag.com/news/zuckerbergs-meta-is-spending-billions-to-buy-350000-nvidia-h100-gpus

# 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

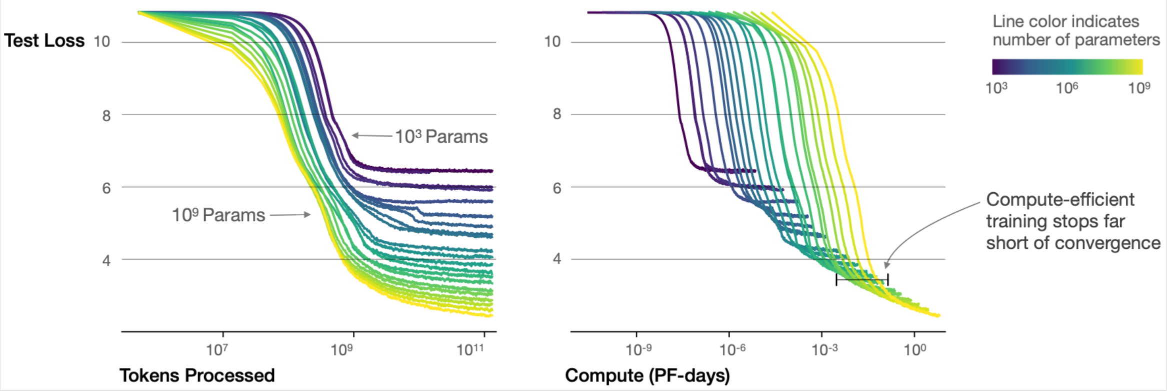


- Empirical test loss has a power law relationship with each individual factor
- Transformers scale well, and in a very predictable way

[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



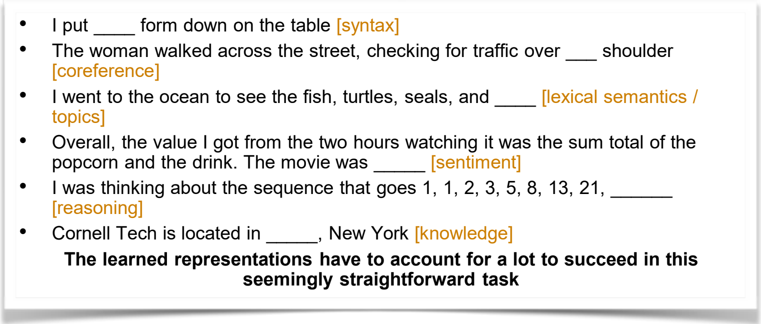
[Kaplan et al. 2020]

# 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
- There have been papers since then refining these laws.

# 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**

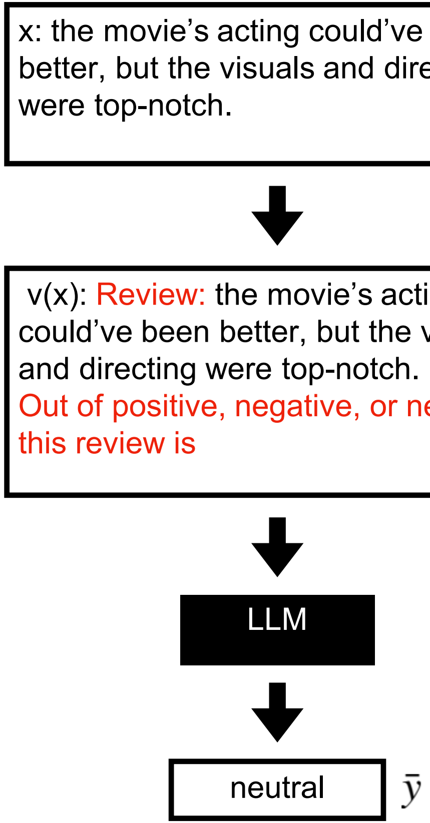
- We get really expressive representations
- Very impressive generations
- But how useful are these models?
  - Not that useful, yet
  - But: we can fine-tune them to be very useful
    - This is often called **alignment**
    - We will get back to this very soon

# 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



x: the movie’s acting could’ve been better, but the visuals and directing were top-notch.

v(x): Review: the movie’s acting could’ve been better, but the visuals and directing were top-notch. Out of positive, negative, or neutral this review is

# 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.   “… 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. "… 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?

### News Classification

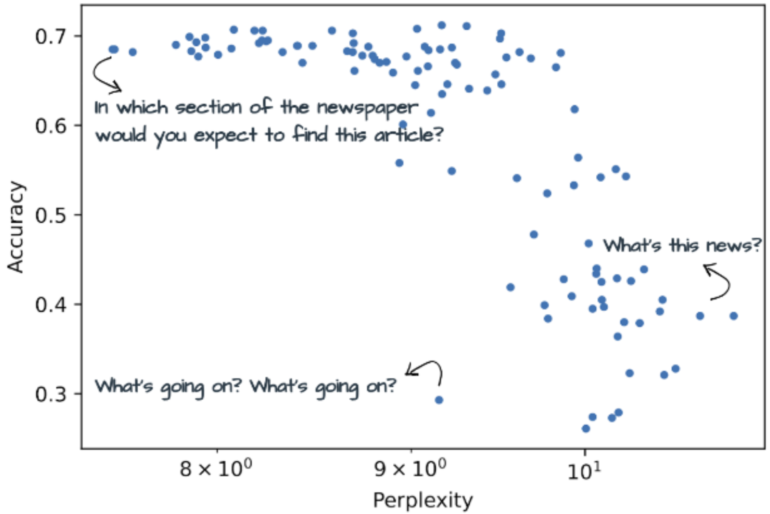


Figure 1: Accuracy vs. perplexity for the AG News dataset with OPT 175B. The $x$ axis is in log scale. Each point stands for a different prompt.

[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

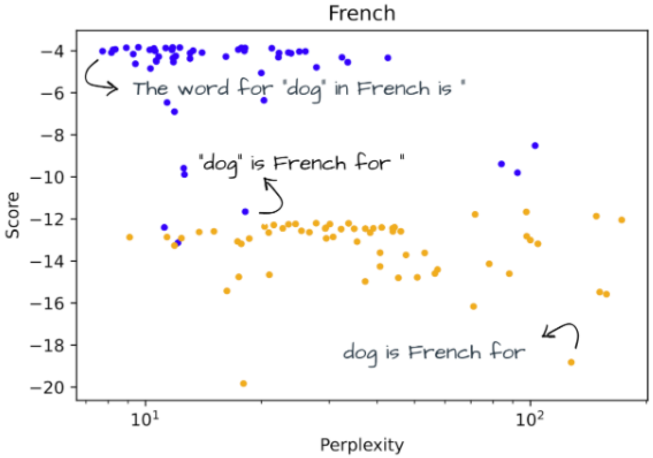


Figure 2: Score of correct label vs. perplexity for the word-level translation task in French with OPT 175B. The $x$ axis is in log scale. The blue points stand for prompts with quotation marks for the words, while the yellow points are of prompts without quotation marks.

[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

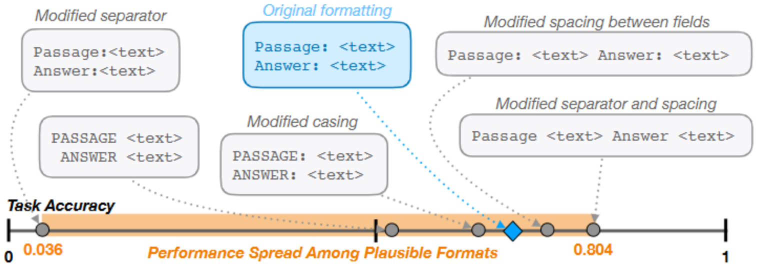


Figure 1: Slight modifications in prompt format templating may lead to significantly different model performance for a given task. Each <text> represents a different variable-length placeholder to be replaced with actual data samples. Example shown corresponds to 1-shot LLaMA-2-7B performances for task280 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).

14

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

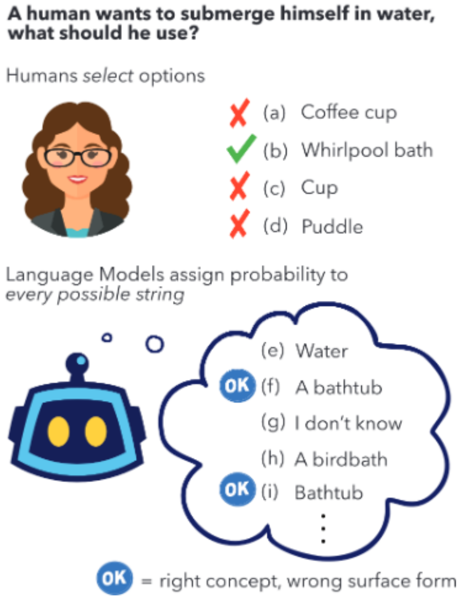

A human wants to submerge himself in water, what should he use?
Humans *select* options
✗ (a) Coffee cup
✓ (b) Whirlpool bath
✗ (c) Cup
✗ (d) Puddle
Language Models assign probability to *every possible string*
(e) Water
OK (f) A bathtub
(g) I don't know
(h) A birdbath
OK (i) Bathtub
⋮
OK = right concept, wrong surface form

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

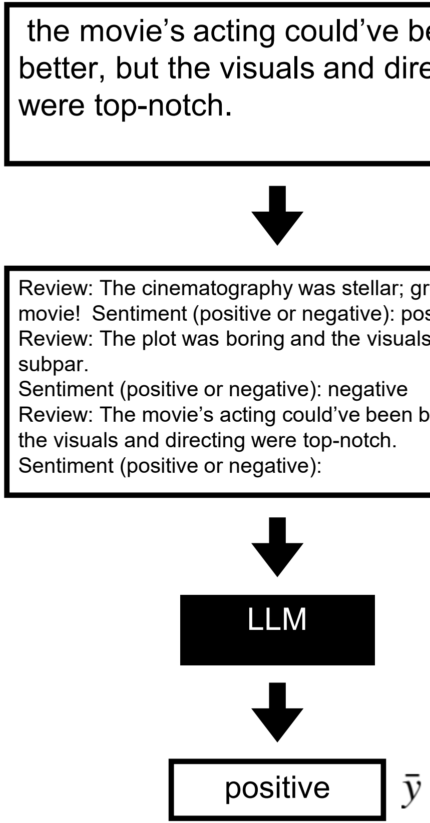
- Just like hyper-parameters, can think of optimizing prompts
- There are methods for searching over prompts (either using gradients or black-box optimization)
- Most do not lead to dramatically better results compared to manual engineering/hill-climbing (and are computationally intensive)
- Most important: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

- 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



the movie’s acting could’ve been better, but the visuals and directing were top-notch.

Review: The cinematography was stellar; great movie!  Sentiment (positive or negative): positive
Review: The plot was boring and the visuals were subpar.
Sentiment (positive or negative): negative
Review: The movie’s acting could’ve been better, but the visuals and directing were top-notch.
Sentiment (positive or negative):

LLM

positive $\bar{y}$

# In-context Learning (ICL)

## Performance

- Providing ICL examples almost always leads to significant improvements

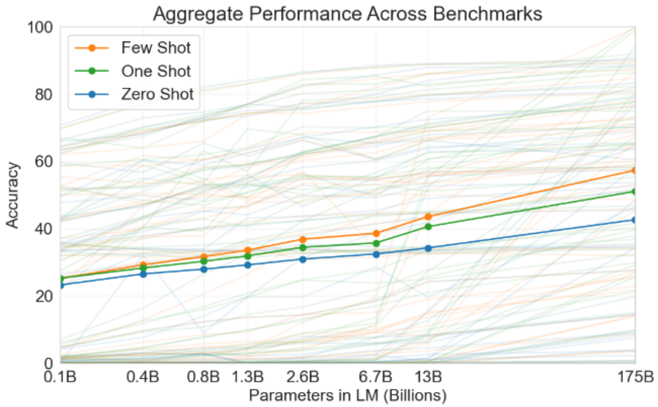


**Figure 1.3: Aggregate performance for all 42 accuracy-denominated benchmarks** While zero-shot performance improves steadily with model size, few-shot performance increases more rapidly, demonstrating that larger models are more proficient at in-context learning. See Figure 3.8 for a more detailed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

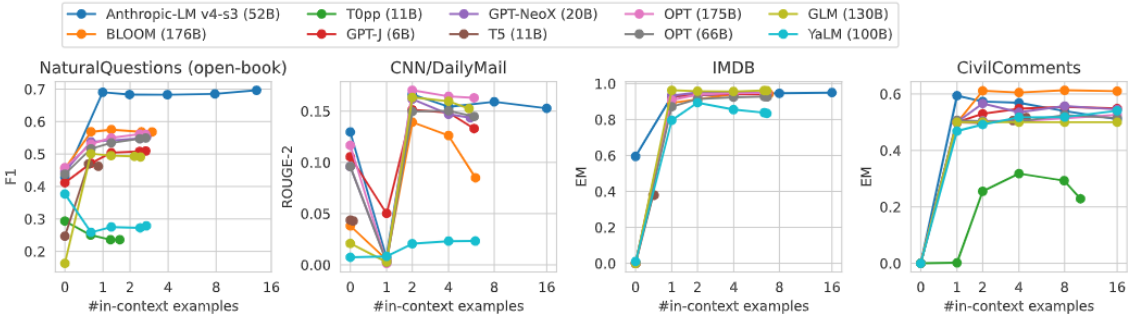


Figure 32: **Number of in-context examples.** For each model, we set the maximum number of in-context examples to [0, 1, 2, 4, 8, 16] and fit as many in-context examples as possible within the context window. We plot performance as a function of the average number of in-context examples actually used.

[Liang et al. 2022]

# In-context Learning

## Performance

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

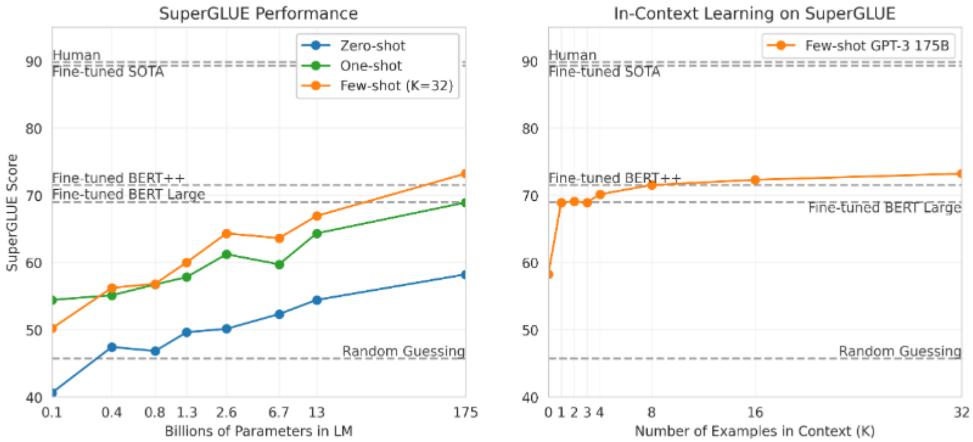


**Figure 3.8: Performance on SuperGLUE increases with model size and number of examples in context.** A value of $K = 32$ means that our model was shown 32 examples per task, for 256 examples total divided across the 8 tasks in SuperGLUE. We report GPT-3 values on the dev set, so our numbers are not 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

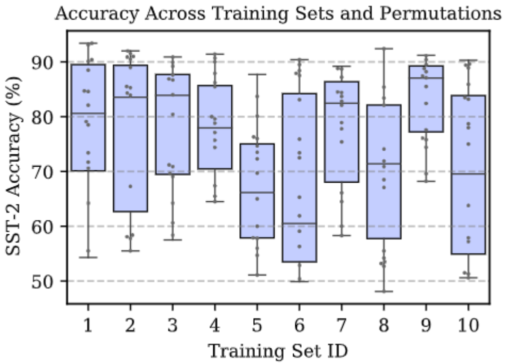


*Figure 2.* There is high variance in GPT-3's accuracy as we change the prompt's **training examples**, as well as the **permutation** of the examples. Here, we select ten different sets of four SST-2 training examples. For each set of examples, we vary their permutation and plot GPT-3 2.7B's accuracy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

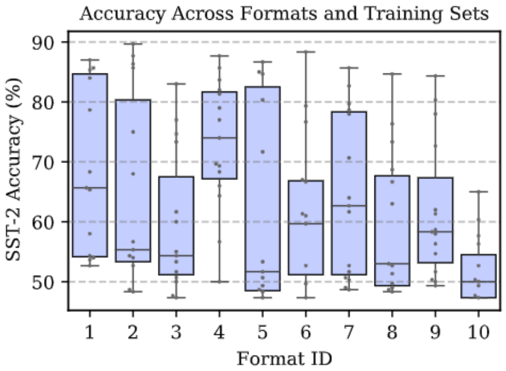


*Figure 3.* There is high variance in GPT-3's accuracy as we change the **prompt format**. In this figure, we use ten different prompt formats for SST-2. For each format, we plot GPT-3 2.7B's accuracy for different sets of four training examples, along with the quartiles.

[Z

# In-context Learning (ICL)

## Sensitivity

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

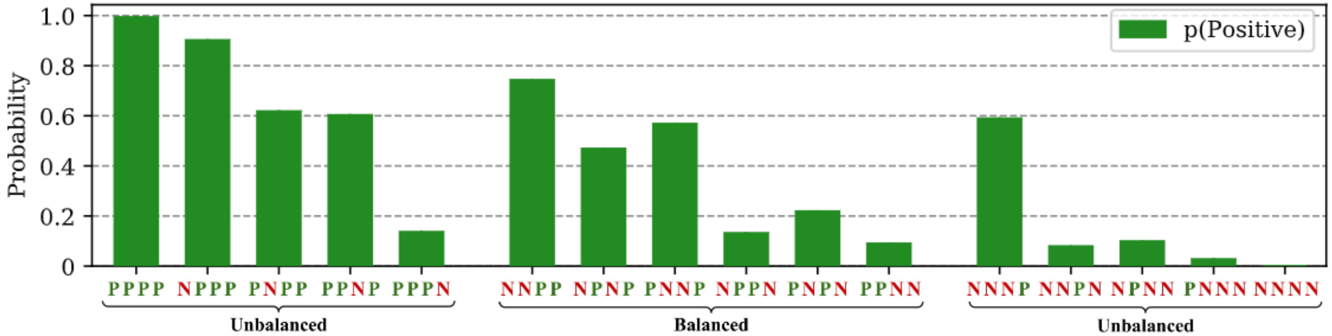


*Figure 4.* **Majority label and recency biases** cause GPT-3 to become biased towards certain answers and help to explain the high variance across different examples and orderings. Above, we use 4-shot SST-2 with prompts that have different class balances and permutations, e.g., [P P N N] indicates 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

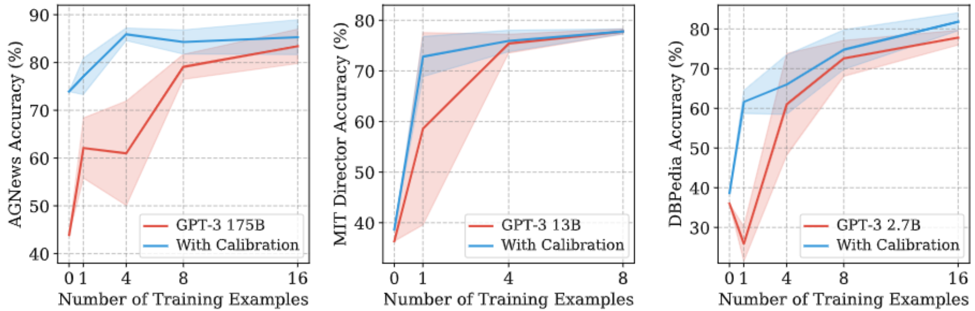


*Figure 1.* Few-shot learning can be highly unstable across different choices of the prompt. Above, we plot the mean accuracy (± one standard deviation) across different choices of the training examples for three different datasets and model sizes. We show that our method, *contextual calibration*, improves 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

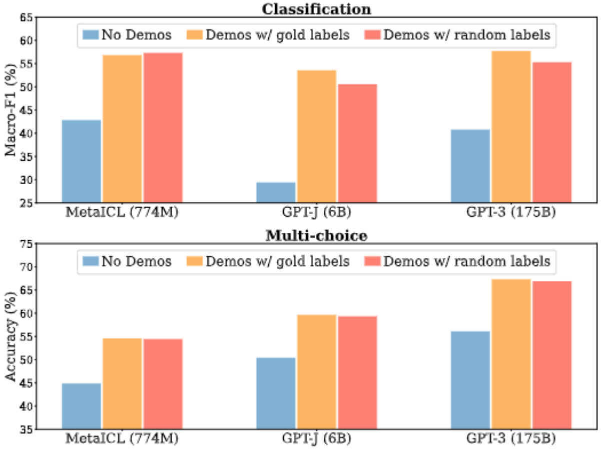


Figure 1: Results in classification (top) and multi-choice tasks (bottom), using three LMs with varying size. Reported on six datasets on which GPT-3 is evaluated; the channel method is used. See Section 4 for the full results. In-context learning performance drops only marginally when labels in the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

[Min et al. 2022]

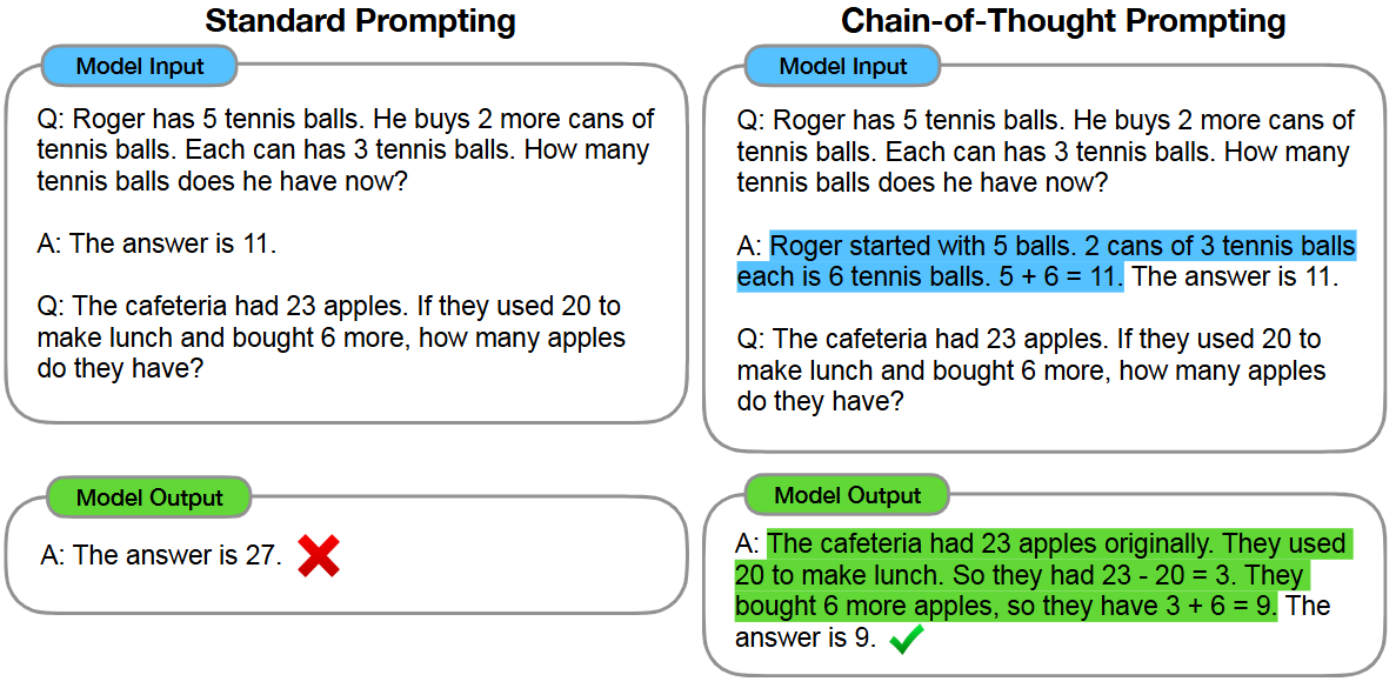
[Mi

# 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

[Wei et al. 2022]

# Chain-of-thought (COT) 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. ✓

[Wei et al. 2022]

# Chain-of-thought (COT) Prompting

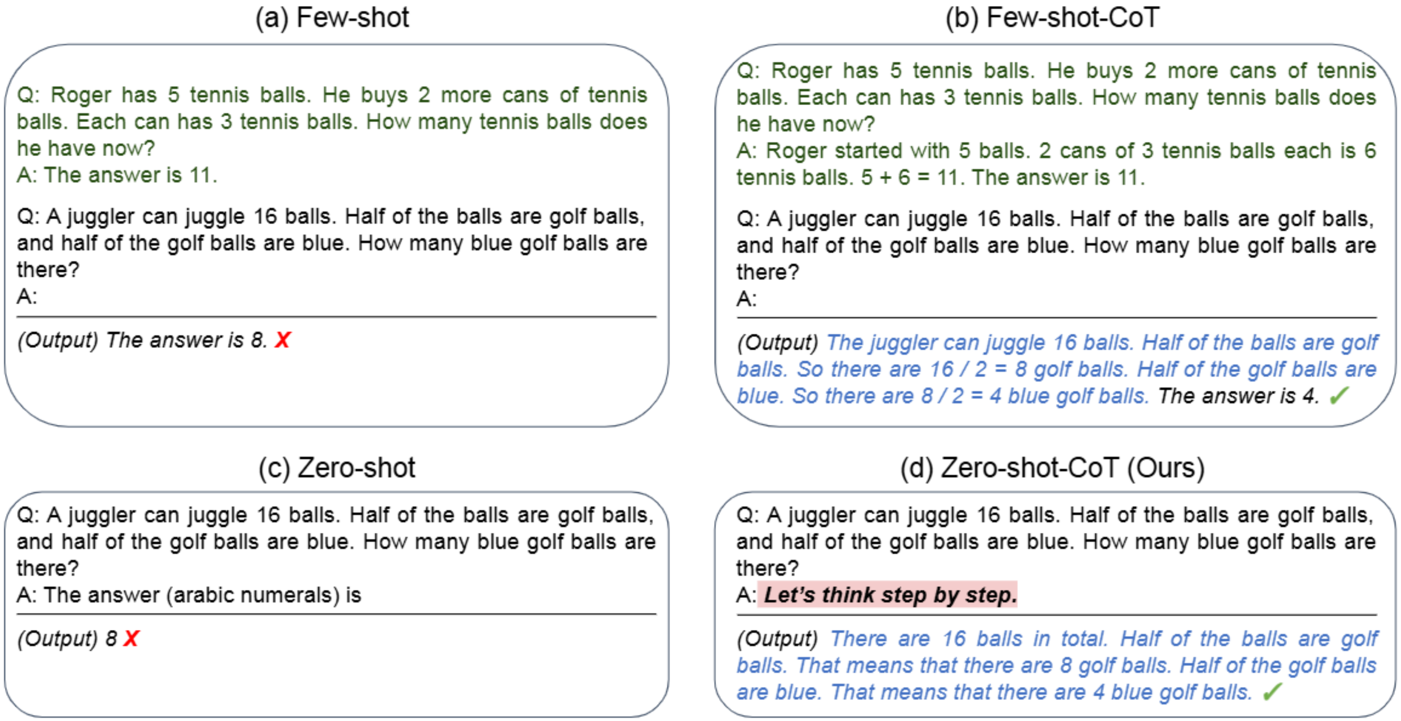
## Step-by-step

- 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

[K

# 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.***

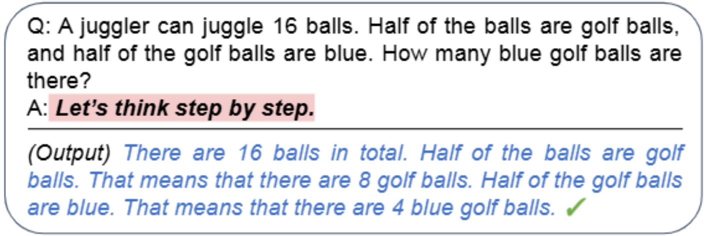
*(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.* ✓

[K

# 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.* ✓

[K

# Chain-of-thought (COT) Prompting

## Step-by-step

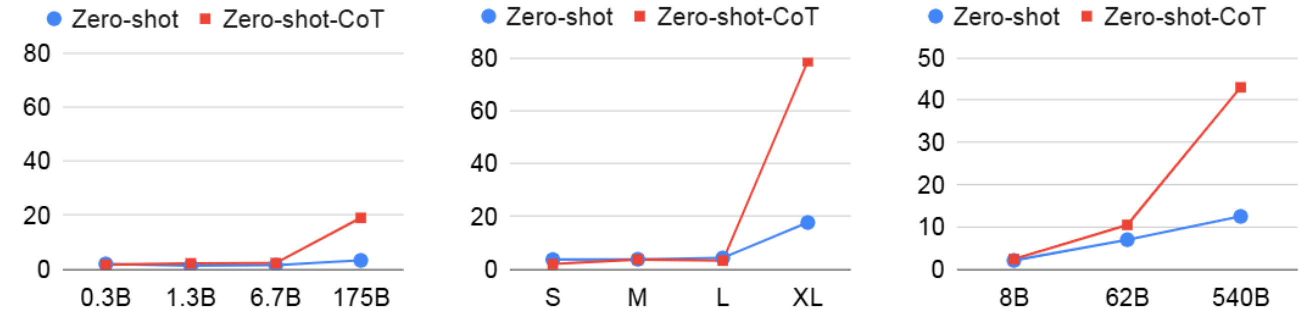
- Main idea: just “tell” the model to reason in steps
- Challenge: the answer is often entangled in the reasoning text — how to extract it? → just use an LLM 😀

[K

# 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



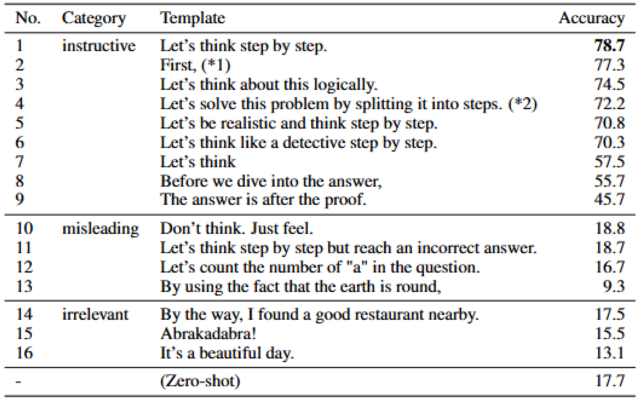
(a) MultiArith on Original GPT-3 (b) MultiArith on Instruct GPT-3 (c) GMS8K on PaLM

[Kojima et al. 2022]

# 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



| 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

[K