[Slide credit: Iz Beltagy, Arman Cohan, Robert Logan IV, Sewon Min, Sameer Singh, and many others]

JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING

Adapting Language Models

CSCI 601-471/671 (NLP: Self-Supervised Models)

https://self-supervised.cs.jhu.edu/sp2024/

Adapting Language Models: Chapter Plan

You have a pre-trained language model that is pre-trained on massive amounts of data.

Now how to you use it to ”adapt” for your use-case?

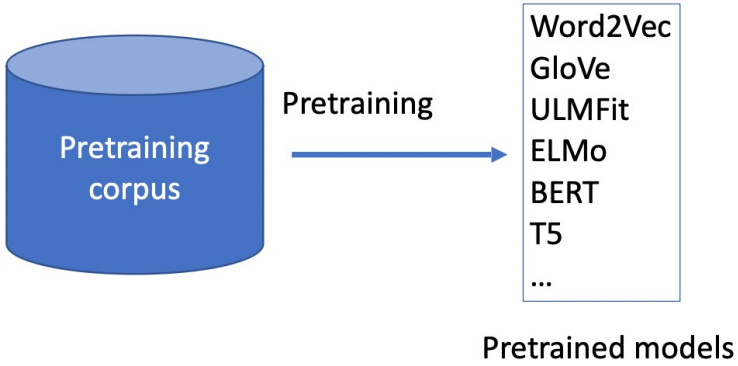
- **Prompting:** adapting model inputs (language statements)
- **Tuning:** adapting (modifying) model parameters

Adapting Language Models: Chapter Plan

1. Adaptation via Fine-tuning
2. Parameter-efficient fine-tuning
3. Adaptation via In-Context Learning
4. In-context learning of multi-step problems.

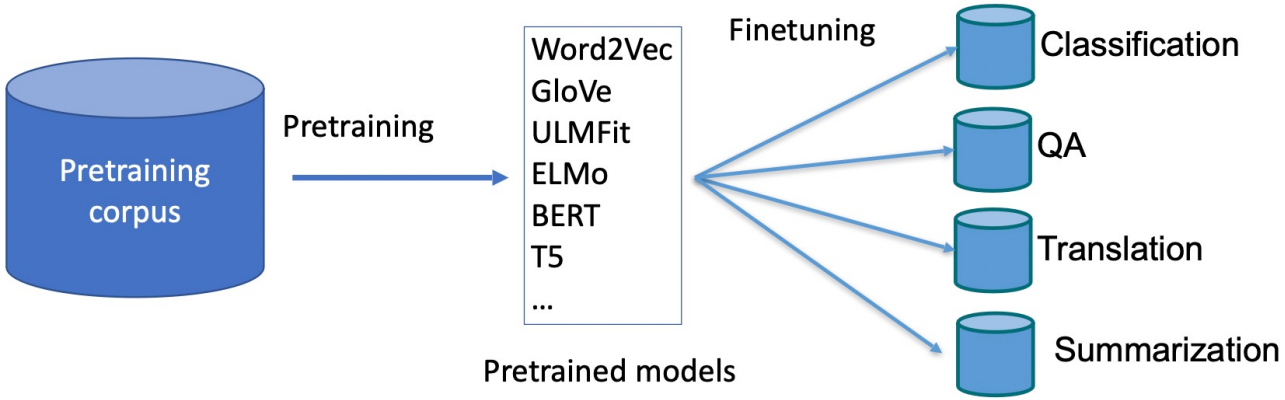
Chapter goal: Get comfortable with various forms of adapting LMs for solving your tasks!

Adaptation via Fine-Tuning

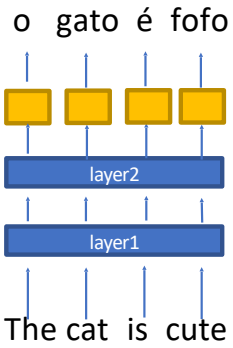


Pretrained models

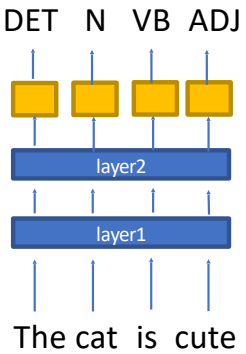
Fine-Tuning for Tasks



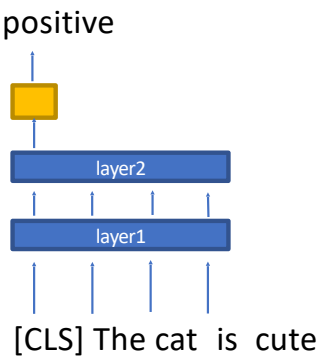
Fine-Tuning for Tasks



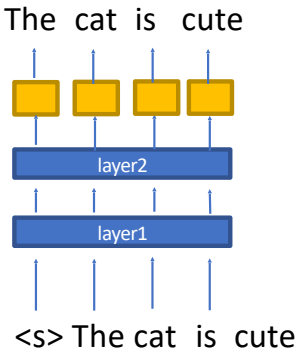
Translation



POS Tagging

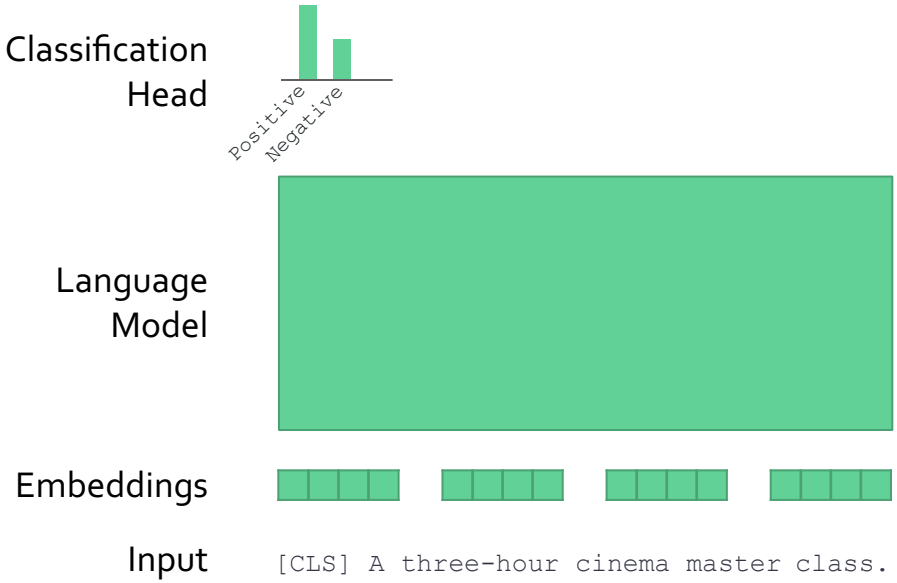


Text classification



Language modeling

Fine-tuning Pre-trained Models



- Whole model tuning:
  - Run an optimization defined on your task data that updates **all** model parameters
- Head-tuning:
  - Run an optimization defined on your task data that updates the parameters of the model "head"

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Parameter-efficient Fine-tuning

- In fine-tuning we need to updating and storing all the parameters of the LM
  - We would need to store a copy of the LM for each task

- With large models, storage management becomes difficult
  - E.g., A model of size 170B parameters requires ~340Gb of storage
  - If you fine-tune a separate model for 100 tasks:
    - 340 * 100 = 34 TB of storage!

Parameter-efficient Fine-tuning

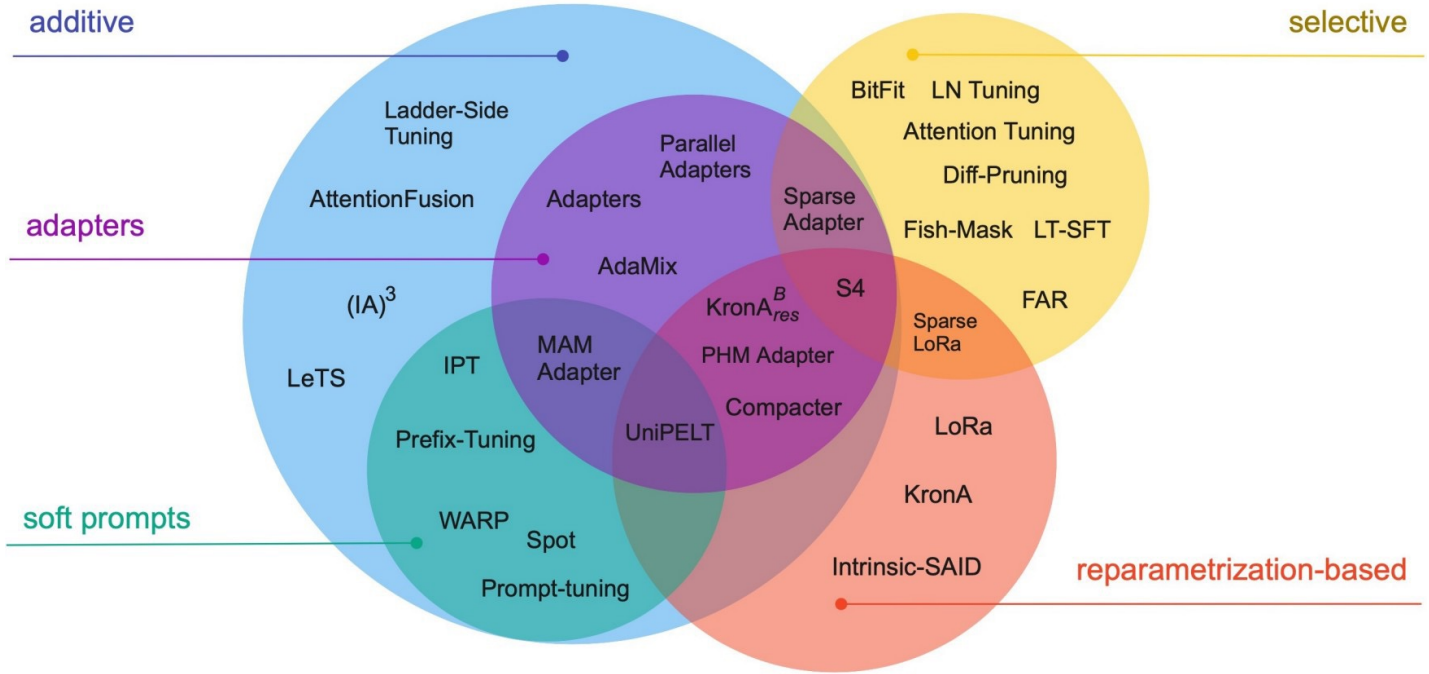
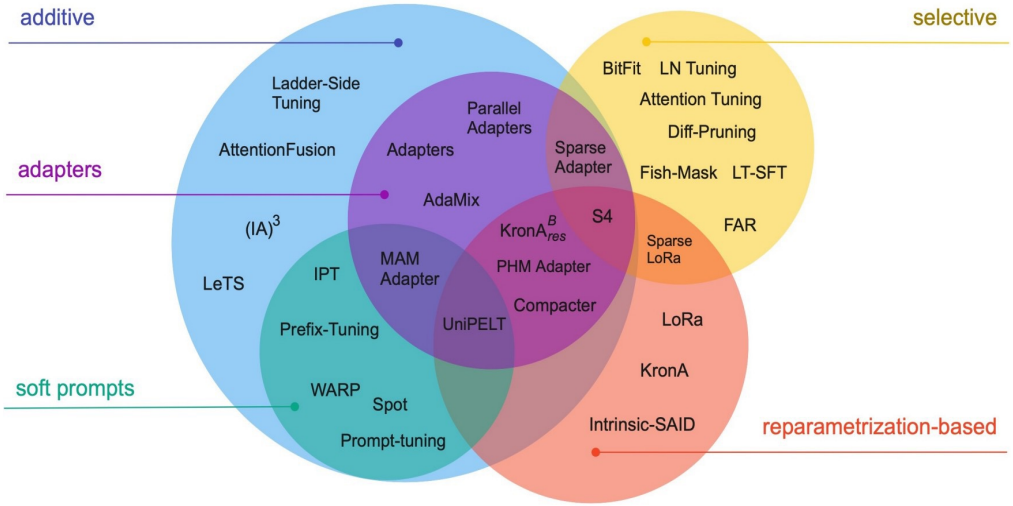


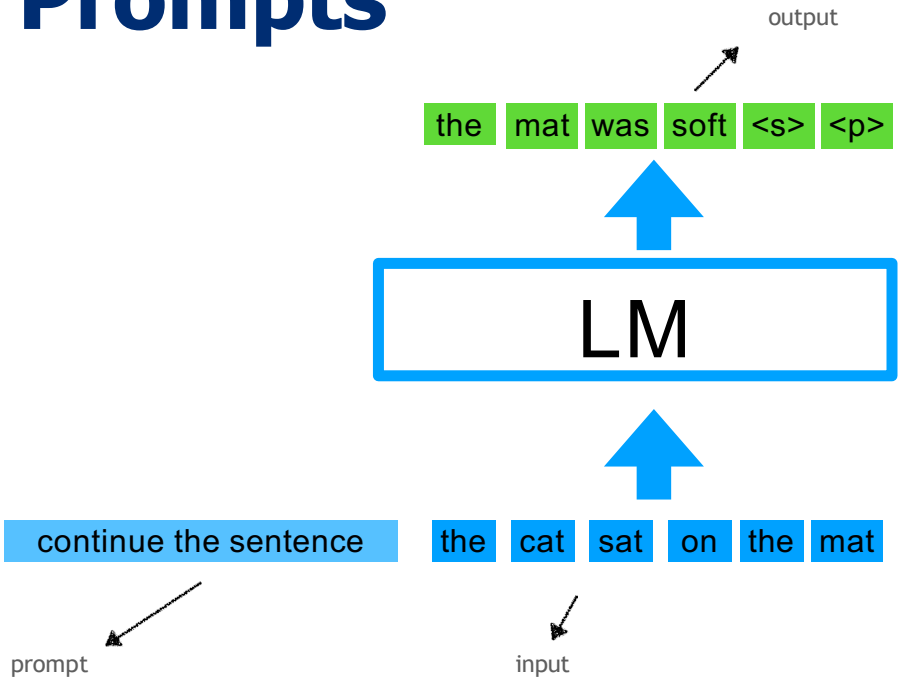
fig source https://arxiv.org/pdf/2303.15647.pdf

Parameter-efficient Fine-tuning: Adding Models

- Augmenting the existing pre-trained model with extra parameters or layers and training only the new parameters
- Two commonly used methods:
  - Soft prompts
  - Adapters

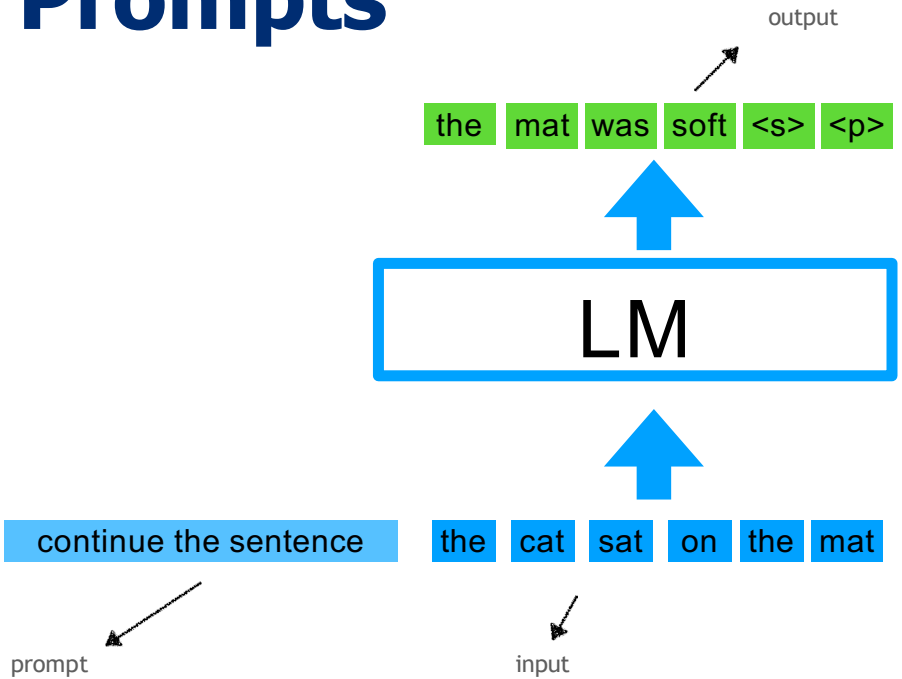


Soft Prompts



[Slide: Arman Cohan]

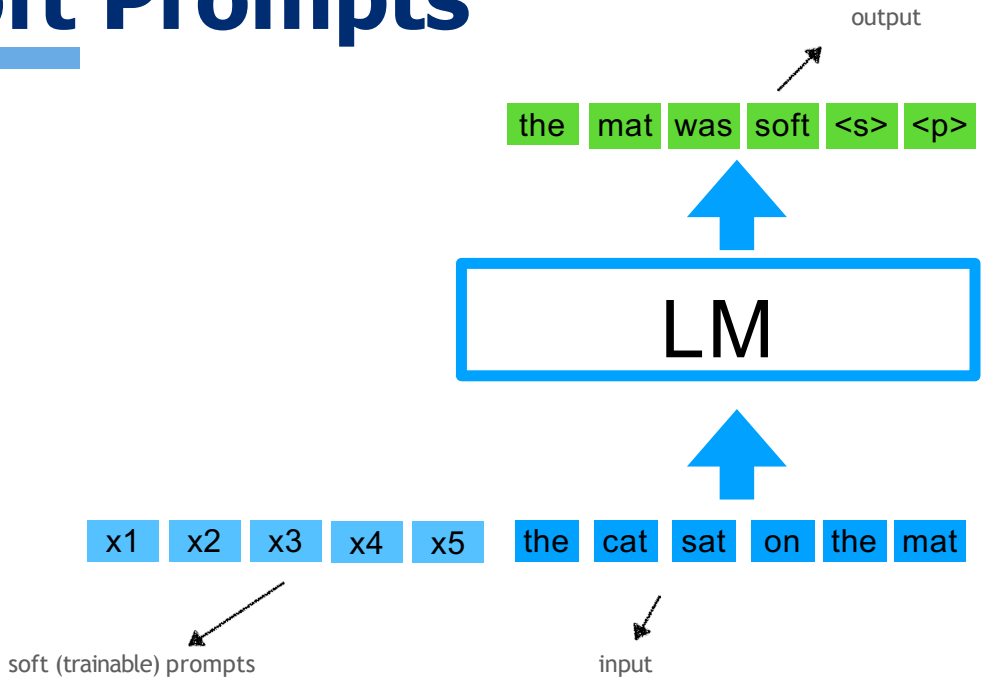
Soft Prompts



- Designing good prompts might be difficult for each task
- Maybe we can “learn” the prompts?

[Slide: Arman Cohan]

Soft Prompts



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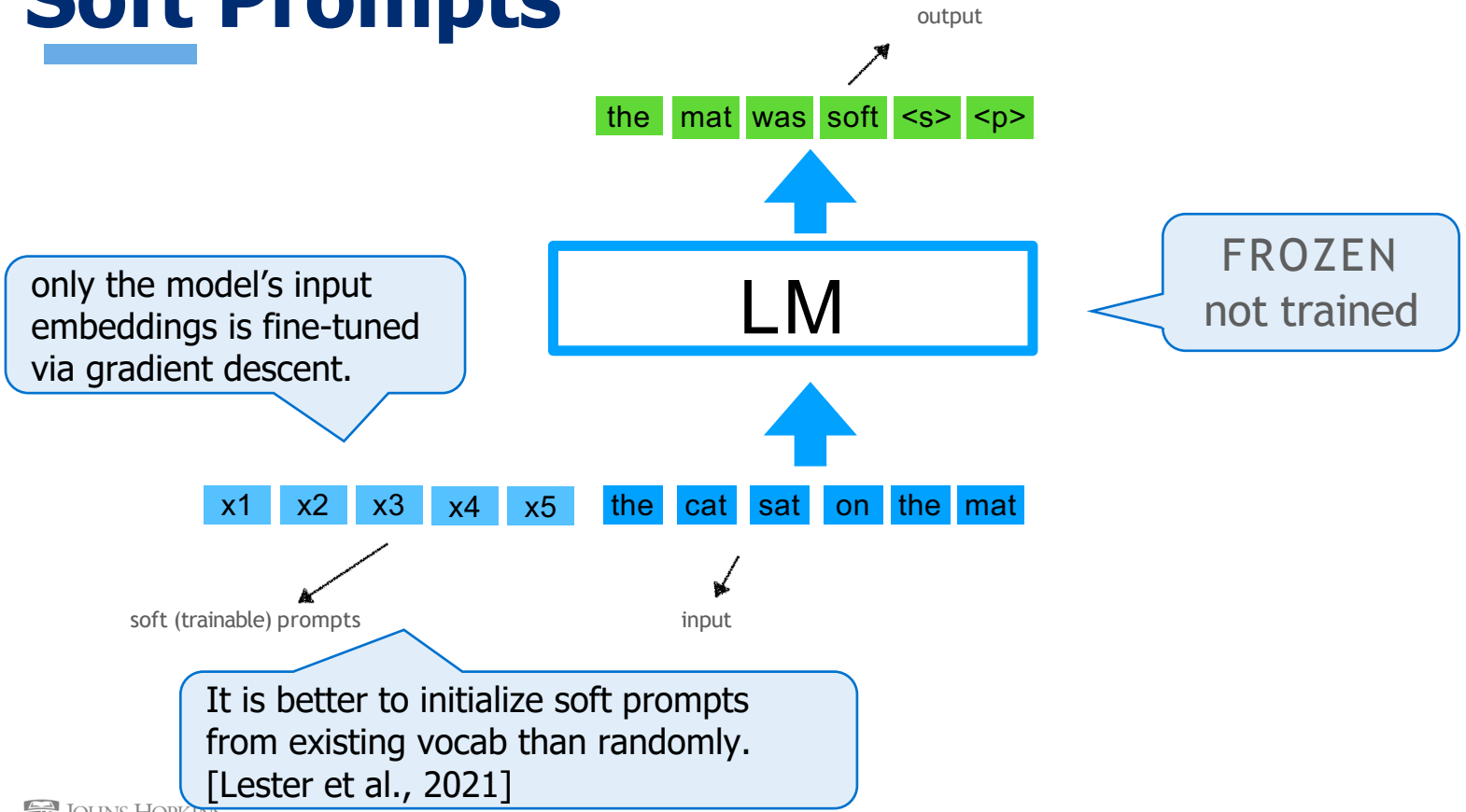
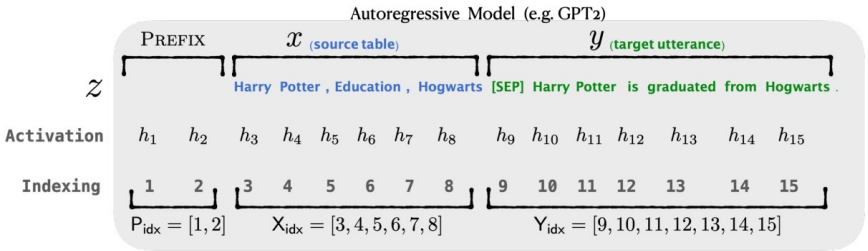
[Slide: Arman Cohan]

Soft Prompts

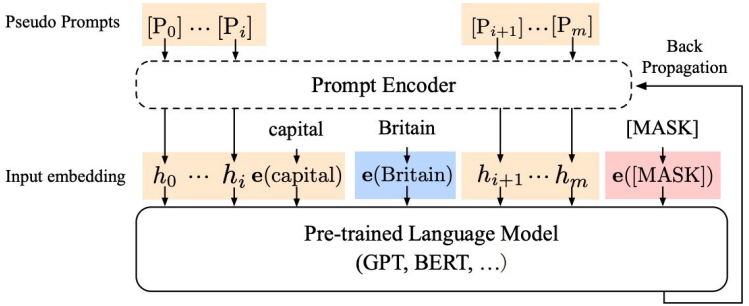


Soft Prompts

- TBD



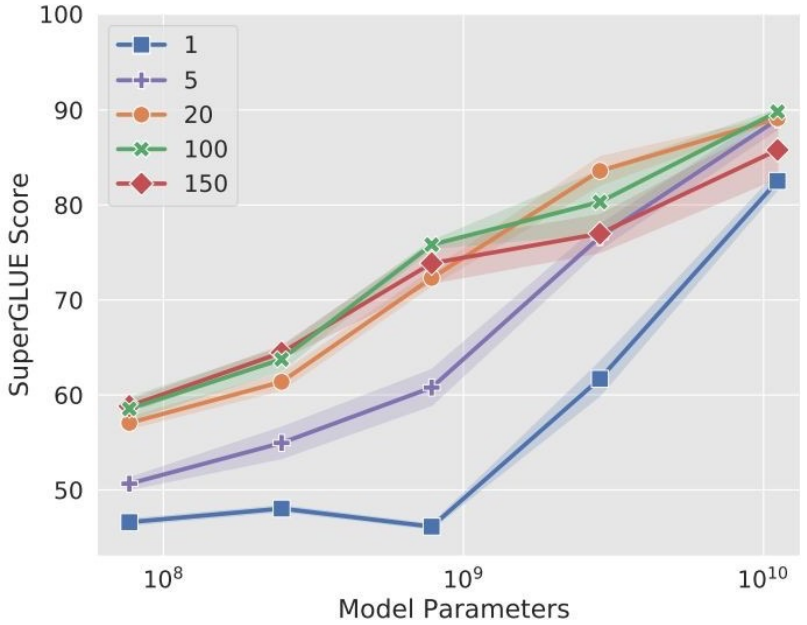
Prefix tuning - Li and Liang (2021)



Liu et al., (2021)

Prompt Tuning: Effect of Prompt Length

- The shorter the prompt, the fewer new parameters must be tuned
- Increasing prompt length is critical to achieving good performance
- The largest model still gives strong results with a single-token prompt
- Increasing beyond 20 tokens only yields marginal gains

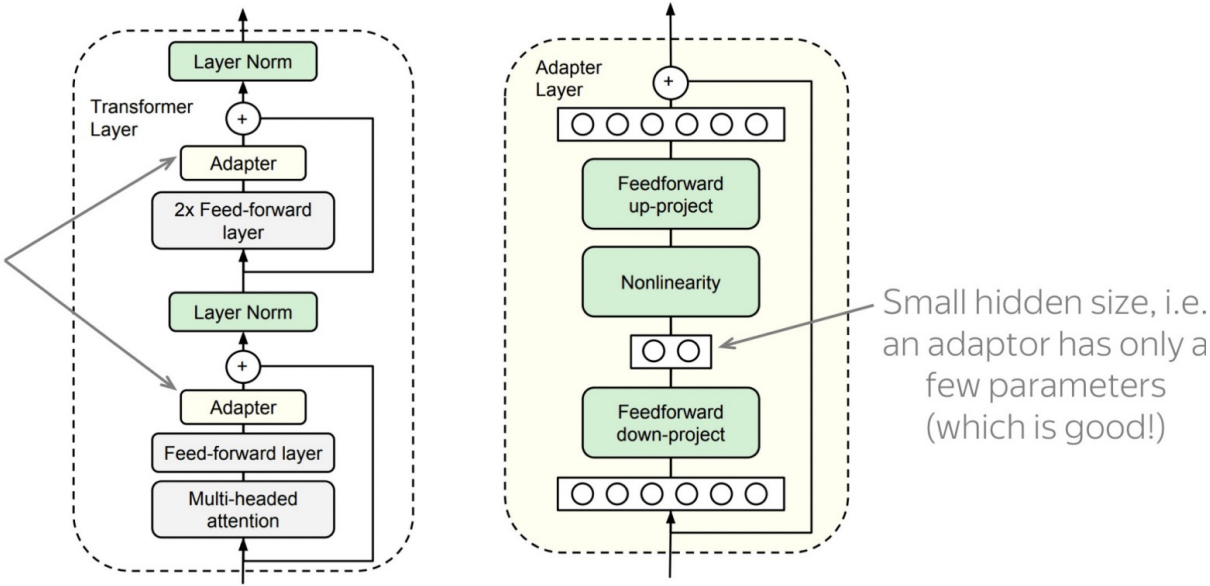


[The Power of Scale for Parameter-Efficient Prompt Tuning. Lester et al. 2021]

Adapters

- **Idea:** train small sub-networks and only tune those.
  - FF projects to a low dimensional space to reduce parameters.
- No need to store a full model for each task, only the adapter params.

Only these are trained, everything else is fixed and is the same for all tasks

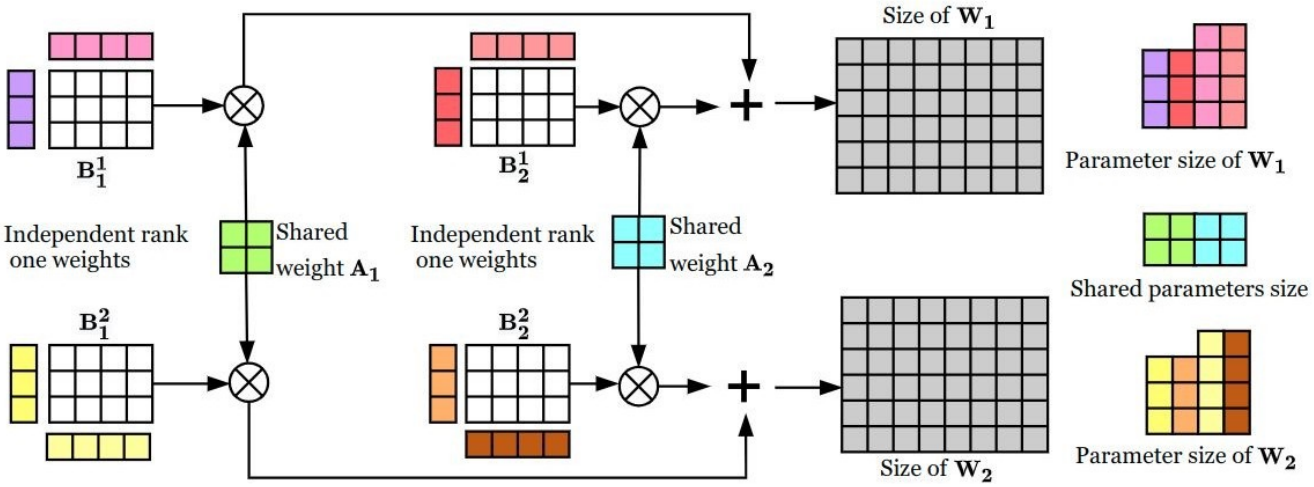


Small hidden size, i.e. an adaptor has only a few parameters (which is good!)

["Parameter-Efficient Transfer Learning for NLP" Houlsby et al., 2019.]

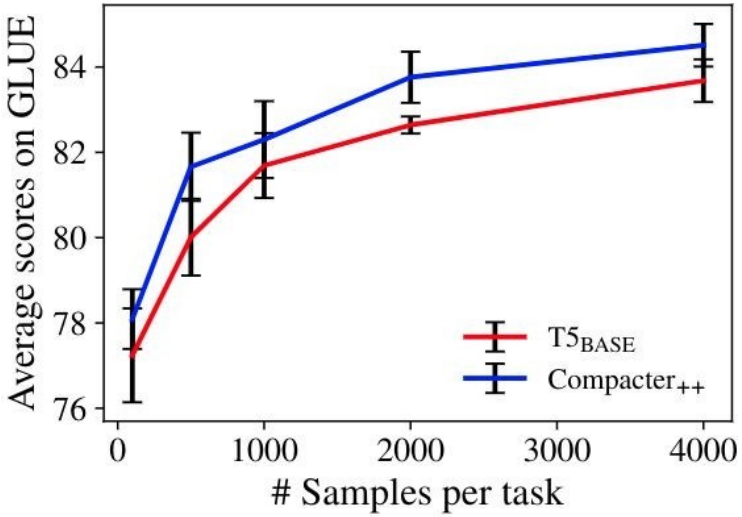
Compacter (Compact Adapter)

- Compacter layers modify Adapter layers to use low-rank parameterized of "Adapter" (i.e., parameter efficient W's).



Compacter (Compact Adapter)

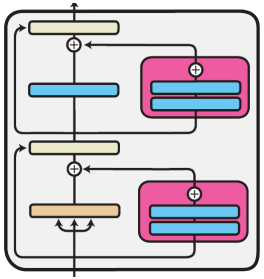
- Compacter reduces adapter parameters by a factor of 10 and achieves similar or better performance



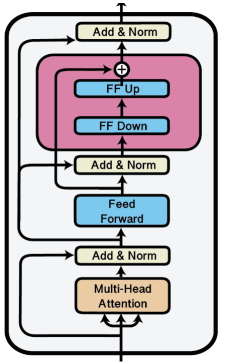
"Compacter: Efficient Low-Rank Hypercomplex Adapter Layers"

Sequential and parallel adapters

- Adapters can be routed sequentially or in parallel
- Sequential adapters are inserted between functions
  - $f_i'(\boldsymbol{x}) = f_{\phi_i}(f_{\theta_i}(\boldsymbol{x}))$
- Parallel adapters are applied in parallel:
  - $f_i'(\boldsymbol{x}) = f_{\theta_i}(\boldsymbol{x}) + f_{\phi_i}(\boldsymbol{x})$



Two parallel adapters [Stickland & Murray, 2019]



A sequential adapter [Houlsby et al., 2019]

Question:

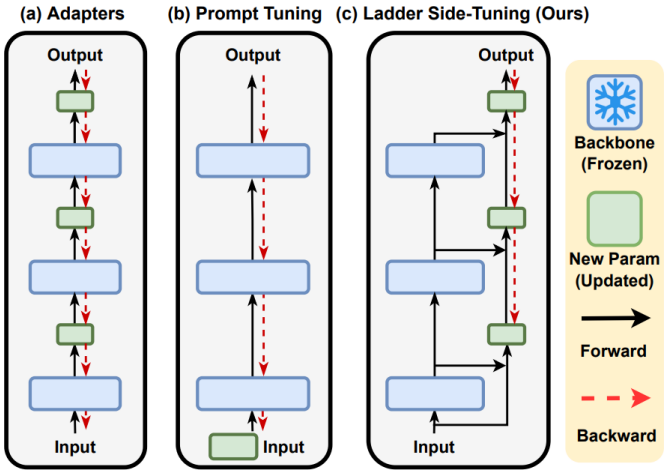
- Is optimization using PEFT and Adapters faster and more memory efficient?

Question

- Is optimization using PEFT and Adapters faster and more memory efficient?
  - It is not faster! You still need to do the entire forward and backward pass
  - It is more memory efficient
    - You only need to keep the optimizer state for parameters that you are fine-tuning and not all the parameters.
      - E.g., for Adam Optimizer, for each parameter *w* we have m_t and v_t which is the first and second order moving averages of the gradients

Ladder Side-Tuning (LST)

- Trains a small transformer network on the side of the pre-trained network
- The side network combines the hidden states of the pre-trained backbone network with its own hidden states.
- Unlike adapters/prompt-tuning that insert LST doesn't need to backprop through the large backbone model
- LST separates trainable parameters from the backbone model



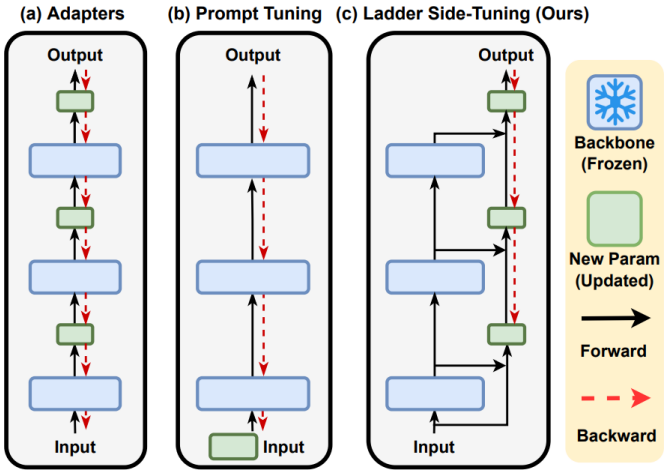
LST: Ladder Side-Tuning for Parameter and Memory Efficient Transfer Learning, Sun et al (2022)

Ladder Side-Tuning (LST)

- Their side network g is a lightweight transformer with hidden size

$$d' = \frac{1}{r} \times d \;\; ; \;\; \text{r=(2,4,8,16)}$$

- The side network g reuses frozen word embeddings and LM-Head



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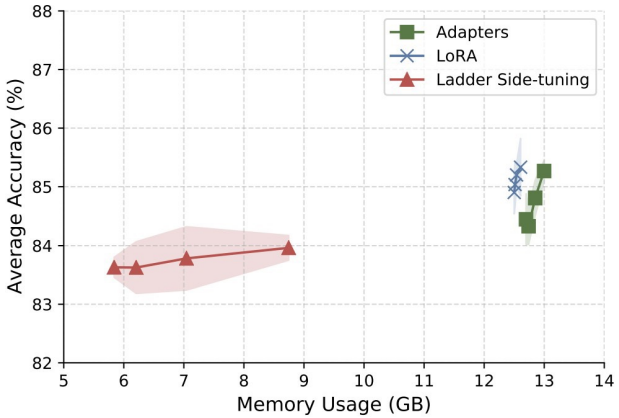


Figure 5: The accuracy-memory trade-off for Adapter, LoRA, and Ladder Side-Tuning over GLUE tasks. We vary the reduction factor in Ladder Side-Tuning, hidden dimension in Adapter, rank in LoRA to get the architectures with different training costs.

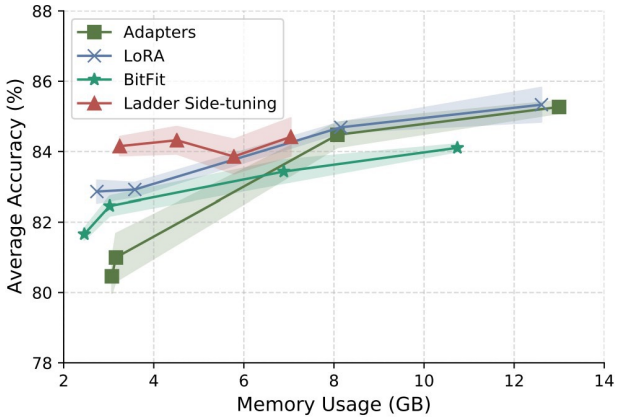
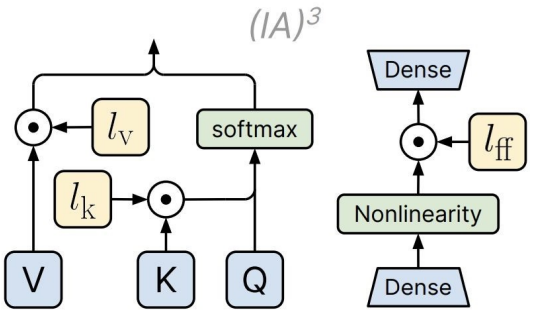
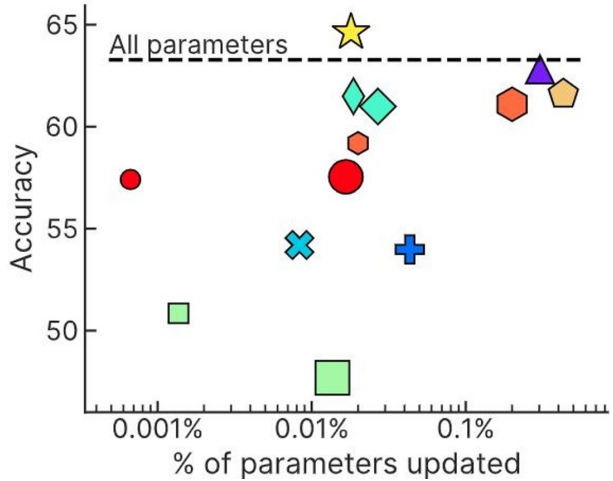


Figure 6: The accuracy-memory trade-off for Adapter, LoRA, BitFit, LST over GLUE tasks. we drop $N \in \{0, 6, 12, 18\}$ layers in an interleaving manner for LST while we gradually freeze the first $N \in \{0, 6, 12, 18\}$ layers in other methods (also remove inserted parameters in those layers).

$(IA)^3$: Infused Adapter by Inhibiting and Amplifying Inner Activations

- Element-wise rescaling of model activations with a learned vector:
  - keys and values in self-attention
  - feed-forward networks





["Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning" Liu et al., 2022.]

IA3

- Infused Adapter by Inhibiting and Amplifying Inner Activations
- A new form of parameter-efficient fine-tuning. A good param efficient finetuning method should have the following properties
  - Add/update as few params as possible
  - Strong performance after few-shot training on new tasks
  - Allow use for mixed-task batches
    - Ideally shouldn't modify the model
    - Instead directly modify the activations

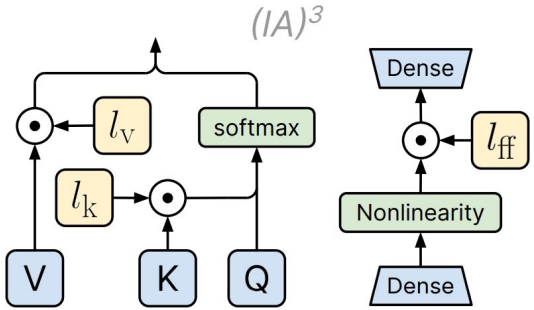
Liu et al., 2022. "Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning"

IA3

- Learns new parameters l_v, l_k, and l_{ff} which rescale the key, value, and hidden FF activations

$$\text{softmax}\left(\frac{Q(l_k \odot K^T)}{\sqrt{d_k}}\right)(l_v \odot V)$$

- Separate set of l_v, l_k, and l_{ff} for each layer



Liu et al., 2022. "Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning"

IA3

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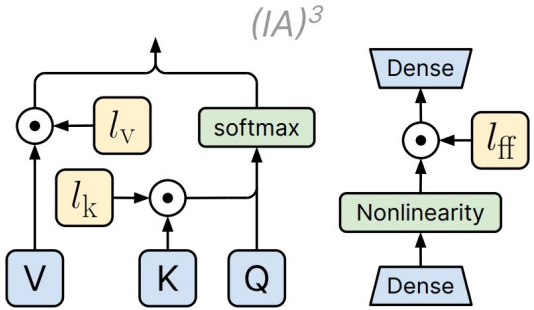
$$\text{softmax}\left(\frac{Q(l_\text{k} \odot K^T)}{\sqrt{d_k}}\right)(l_\text{v} \odot V)$$



Separate set of l_v, l_k, and l_{ff} for each layer

How many parameters does this add for an encoder-decoder network?

Liu et al., 2022. "Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning"

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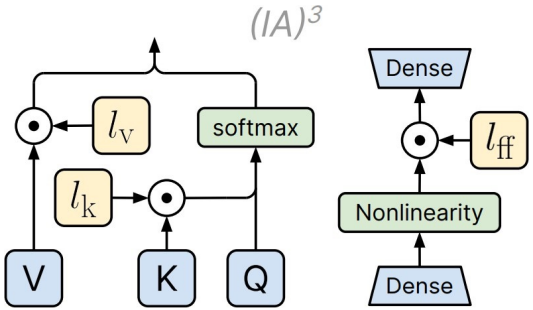


How many parameters does this add for an encoder-decoder network?

encoder: $L \times (d_v + d_k + d_{ff})$

decoder: $L \times (2d_v + 2d_k + d_{ff})$

factor of 2 is for self-attention and cross attention on decoder

Liu et al., 2022. "Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning"

Parameter-efficient fine-tuning

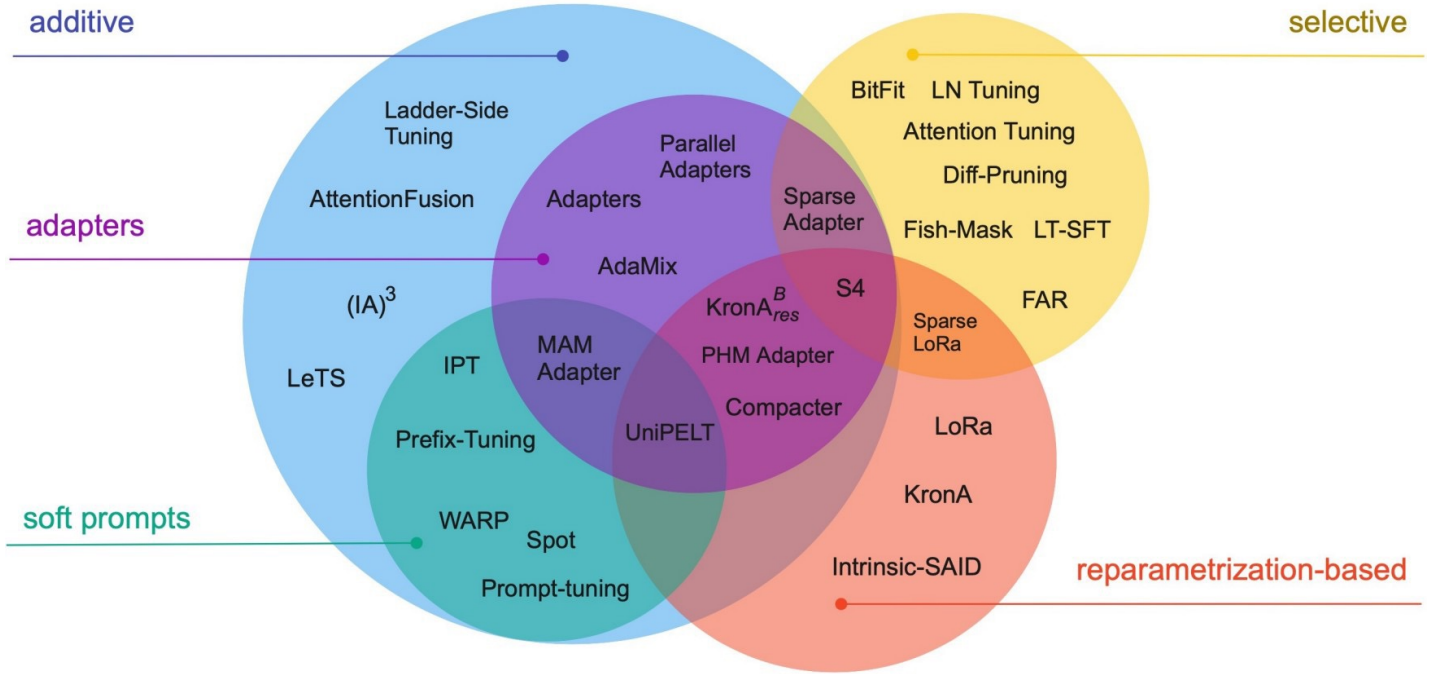


fig source https://arxiv.org/pdf/2303.15647.pdf

Selective methods

- Selective methods fine-tune a subset of the existing parameters of the model.
- It could be a layer depth-based selection, layer type-based selection, or even individual parameter selection.

Ben Zaken et al., 2021. “BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models”

BitFit

- BitFit adds bias terms in self-attention and MLP layers and tunes those.

$$\mathbf{Q}^{m,\ell}(\mathbf{x}) = \mathbf{W}_q^{m,\ell}\mathbf{x} + \mathbf{b}_q^{m,\ell}$$
$$\mathbf{K}^{m,\ell}(\mathbf{x}) = \mathbf{W}_k^{m,\ell}\mathbf{x} + \mathbf{b}_k^{m,\ell}$$
$$\mathbf{V}^{m,\ell}(\mathbf{x}) = \mathbf{W}_v^{m,\ell}\mathbf{x} + \mathbf{b}_v^{m,\ell}$$

$$\mathbf{h}_2^\ell = \text{Dropout}\left(\mathbf{W}_{m_1}^\ell \cdot \mathbf{h}_1^\ell + \mathbf{b}_{m_1}^\ell\right) \quad (1)$$
$$\mathbf{h}_3^\ell = \mathbf{g}_{LN_1}^\ell \odot \frac{(\mathbf{h}_2^\ell + \mathbf{x}) - \mu}{\sigma} + \mathbf{b}_{LN_1}^\ell \quad (2)$$
$$\mathbf{h}_4^\ell = \text{GELU}\left(\mathbf{W}_{m_2}^\ell \cdot \mathbf{h}_3^\ell + \mathbf{b}_{m_2}^\ell\right) \quad (3)$$
$$\mathbf{h}_5^\ell = \text{Dropout}\left(\mathbf{W}_{m_3}^\ell \cdot \mathbf{h}_4^\ell + \mathbf{b}_{m_3}^\ell\right) \quad (4)$$
$$\text{out}^\ell = \mathbf{g}_{LN_2}^\ell \odot \frac{(\mathbf{h}_5^\ell + \mathbf{h}_3^\ell) - \mu}{\sigma} + \mathbf{b}_{LN_2}^\ell \quad (5)$$

- BitFit only updates about 0.05% of the model parameters.

Ben Zaken et al., 2021. "BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models"

BitFit

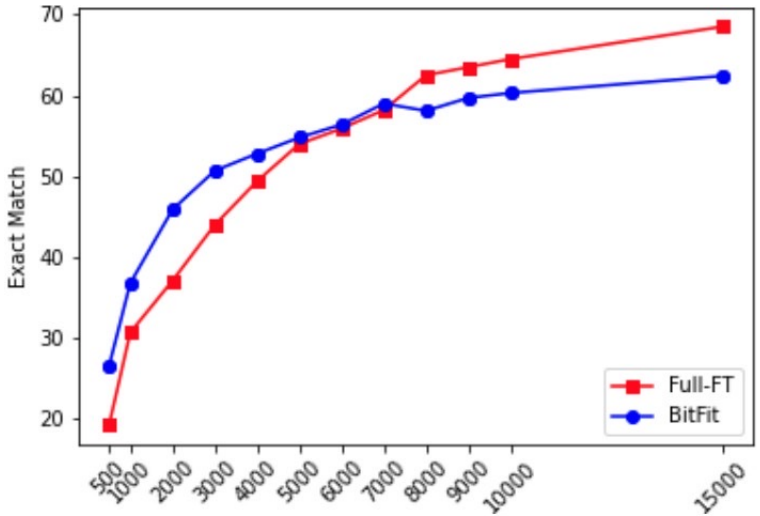


Figure 2: Comparison of BitFit and Full-FT with $\text{BERT}_{\text{BASE}}$ exact match score on SQuAD validation set.

Ben Zaken et al., 2021. "BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models"

Freeze and Reconfigure (FAR)

- selects columns of parameter matrices to prune and reconfigures linear layers into trainable and frozen
- Two stages:
  - In the first stage, the most important rows of parameter matrices are identified for updating
  - In the second stage, the network is reconfigured by splitting each parameter $W \in \mathbb{R}^{in \times h}$ into a trainable component $W_t \in \mathbb{R}^{in \times h'}$ and frozen component $W_f \in \mathbb{R}^{in \times (h-h')}$
    - h is the number of desired parameters

Efficient Fine-Tuning of Compressed Language Models with Learners, Vucetic et al (2022)

Reparametrization based methods

- Reparametrize the weights of the network using a low-rank transformation. This decreases the trainable parameter count while still allowing the method to work with high-dimensional matrices

LoRa

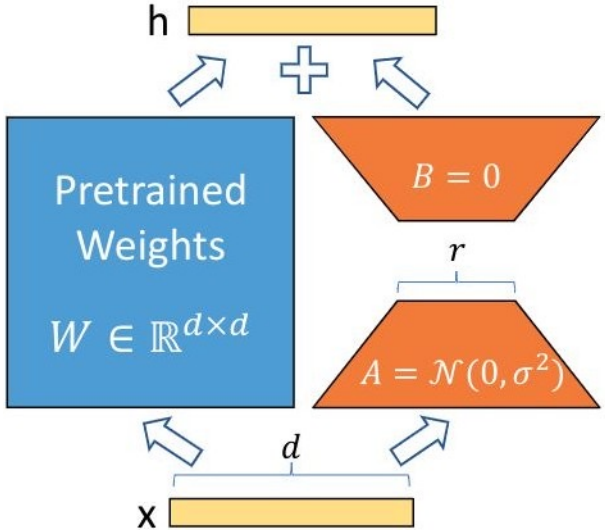
- Hypothesis: the intrinsic rank of the weight matrices in a large language model is low
- Parameter update for a weight matrix is decomposed into a product of two low-rank matrices

$$W \leftarrow W + \Delta W$$

$$\Delta W = BA$$

$$B \in \mathbb{R}^{d,r}, A \in \mathbb{R}^{r,k}, \; r \ll min(k, d)$$

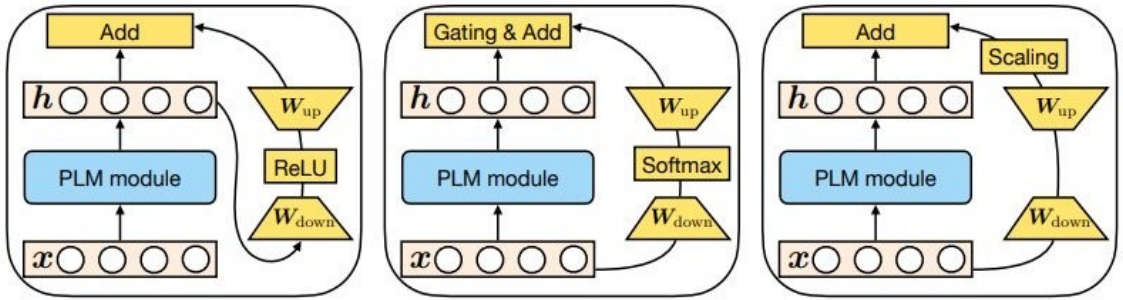
- A is initialized with random Gaussian Initialization, B is initialized to zaro



["LoRA: Low-Rank Adaptation of Large Language Models" Hu et al., 2021.]

Unified View of Parameter-Efficient Tuning

- He et al. [2022] show that LoRA, prefix tuning, and adapters can be expressed with a similar functional form
- Specifically, all methods can be expressed as modifying a model's hidden representation h



(a) Adapter (b) Prefix Tuning (c) LoRA

slide adapted from: Sebastian Ruder (2022)

Unified View of Parameter-Efficient Tuning

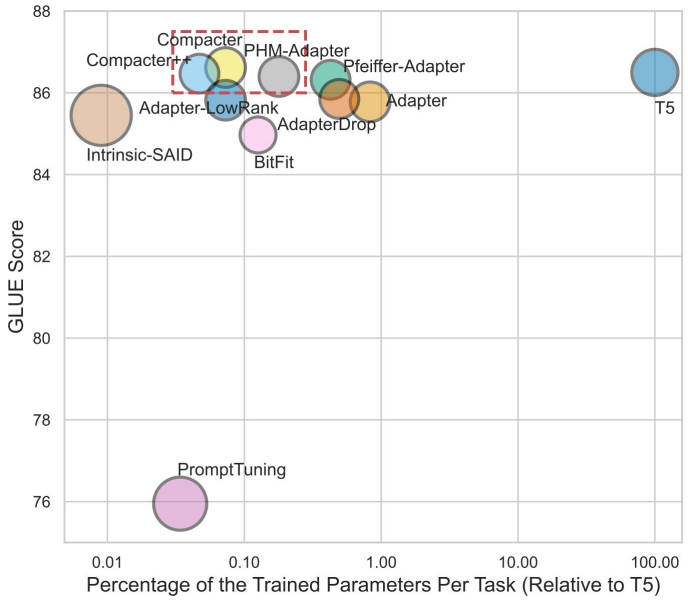
- He et al. [2022] show that LoRA, prefix tuning, and adapters can be expressed with a similar functional form
- Specifically, all methods can be expressed as modifying a model's hidden representation h

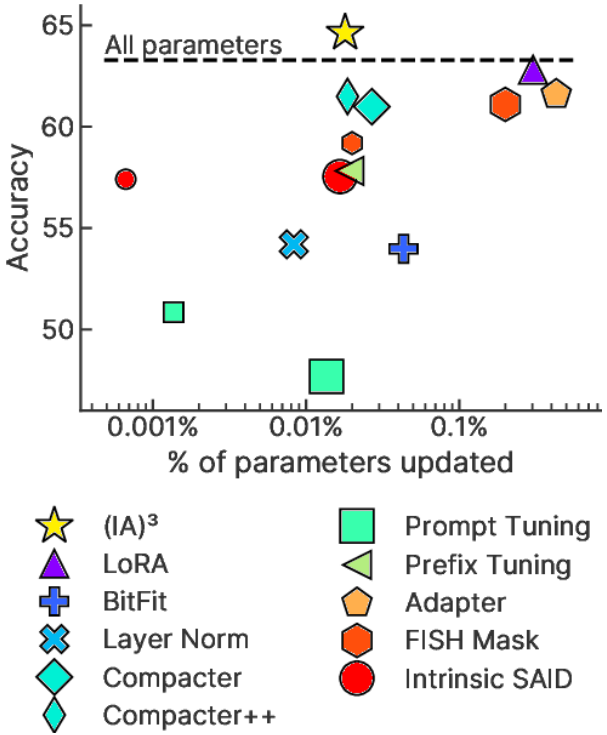
Method	$\Delta \boldsymbol{h}$ functional form	insertion form	modified representation	composition function
		Existing Methods		
Prefix Tuning	$\text{softmax}(\boldsymbol{x}\boldsymbol{W}_q\boldsymbol{P}_k^\top)\boldsymbol{P}_v$	parallel	head attn	$\boldsymbol{h} \leftarrow (1-\lambda)\boldsymbol{h} + \lambda\Delta\boldsymbol{h}$
Adapter	$\text{ReLU}(\boldsymbol{h}\boldsymbol{W}_{\text{down}})\boldsymbol{W}_{\text{up}}$	sequential	ffn/attn	$\boldsymbol{h} \leftarrow \boldsymbol{h} + \Delta\boldsymbol{h}$
LoRA	$\boldsymbol{x}\boldsymbol{W}_{\text{down}}\boldsymbol{W}_{\text{up}}$	parallel	attn key/val	$\boldsymbol{h} \leftarrow \boldsymbol{h} + s \cdot \Delta\boldsymbol{h}$

- We can express parameter and input composition methods as function composition

slide adapted from: Sebastian Ruder (2022)

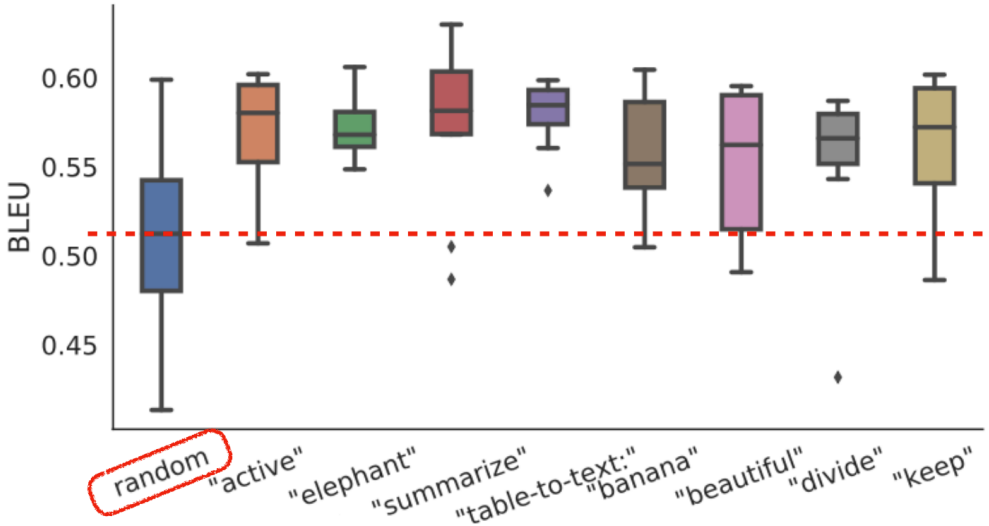
Performance/compactness comparison





Insights about soft prompt in NLP

- Initialization matters a lot (word embeddings >> random)



d Liang. Prefix-Tuning: Optimizing Continuous Prompts for Generation. 2021.

Prompt Tuning: Interpretability

- Are continuous prompts interpretable?

Opposite goal: how unfaithful can their interpretation be of what they do?

Something related to sentiment analysis? 🤔

p^*: optimized for the task

+

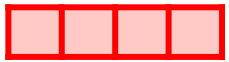
```
Sentence: That was a
great fantasy movie.
```

→ LM → `positive`

["Prompt Waywardness: The Curious Case of Discretized Interpretation of Continuous Prompts" Khashabi et al., 2022.]

nearest-neighbor
mapping of continuous prompt onto the word embeddings

$\tilde{p}$: optimized for the task + project to a given text



p^*: optimized for the task

```
Sentence: That was a
great fantasy movie.
```

positive

definition of another task:

```
Write down the conclusion you can
reach by combining the given
Fact 1 and Fact 2.
```

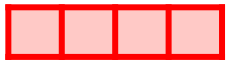
random sentence from web:

```
int clamp(int val, int min_val) {
    return std::max(min_val, val);
}
```


["Prompt Waywardness: The Curious Case of Discretized Interpretation of Continuous Prompts" Khashabi et al., 2022.]

continuous prompts that
project to any given text
with tiny drop in task accuracy!

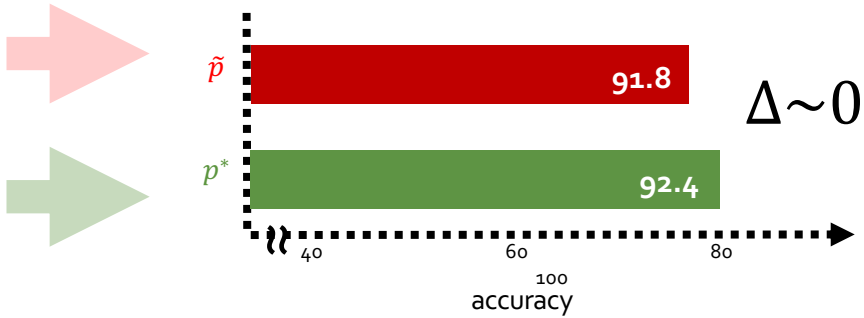
$\tilde{p}$: optimized for the task + project to a given text



p^*: optimized for the task

Sentence: That was a great fantasy movie.

positive



$\Delta \sim 0.6\%$

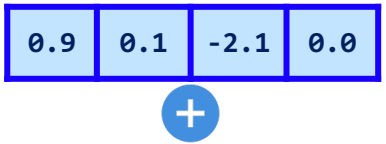
["Prompt Waywardness: The Curious Case of Discretized Interpretation of Continuous Prompts" Khashabi et al., 2022.]

What is the sentiment of the following review? (positive or negative)

+

Sentence: That was a great fantasy movie.

discrete (text) prompts:
easy to interpret, but not easy to optimize



Sentence: That was a great fantasy movie.

continuous prompts:
unclear how to interpret, but easy to optimize

["Prompt Waywardness: The Curious Case of Discretized Interpretation of Continuous Prompts" Khashabi et al., 2022.]

Open questions & future work

- Parameter efficient optimization — optimize fewer parameters than the whole model.
  - Space efficiency — fewer parameters to store
  - Computation efficiency? A bit unclear

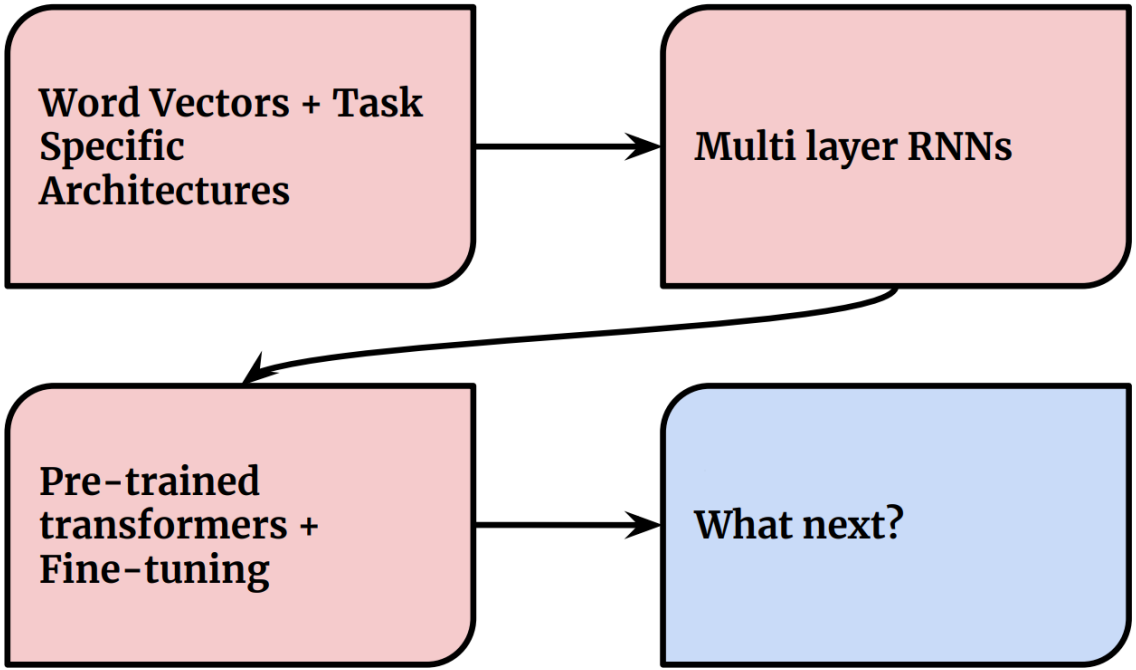
- Their interpretability is not quite clear.

- **Open research question:** How to bridge the gap between continuous prompts vs discrete prompts?

- https://arxiv.org/pdf/2112.07916.pdf

In-Context Learning

The Phases of Paradigms



“I have an extremely large collection of clean labeled data”

-- No one

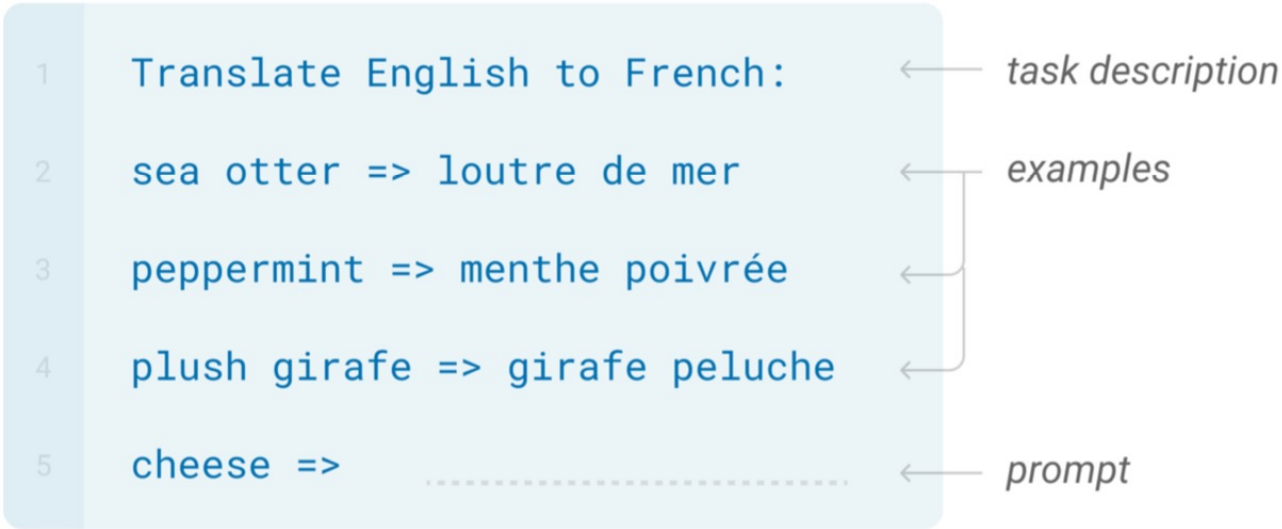
[Colin Raffel]

Limitations of Pre-training -> Fine-tuning

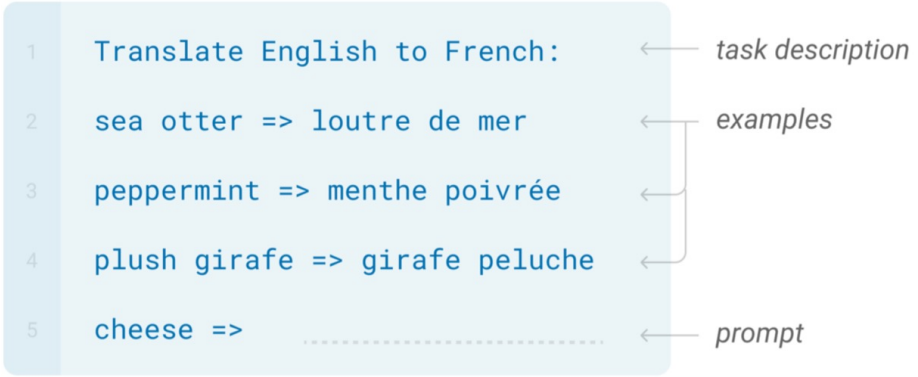
- Often you need a large labeled data
  - Though more pre-training can reduce the need for labeled data

- End up with many copies (or sub-copies) of the same model

In-context Learning



In-Context Learning



- Learns to do a downstream task by conditioning on input-output examples!

- **No weight update** — our model is not **explicitly pre-trained** to learn from examples
  - The underlying models are quite general

- Today's focus:
  - How to use effectively in practice?
  - Fundamentally, why does it work?

In-context Learning

Reverse words in a sentence

This is great
Great is this

The man on the moon
Moon the on man the

Will this really work
Work really this will

I hope this is a big achievement
Achievement big I hope this is

The king came home on a horse
Home horse king came the

https://gpt3experiments.substack.com/p/is-gpt-3-really-doing-few-shot-learning

In-context Learning

Context (passage and previous question/answer pairs)

Tom goes everywhere with Catherine Green, a 54-year-old secretary. He moves around her office at work and goes shopping with her. "Most people don't seem to mind Tom," says Catherine, who thinks he is wonderful. "He's my fourth child," she says. She may think of him and treat him that way as her son. He moves around buying his food, paying his health bills and his taxes, but in fact Tom is a dog.

Catherine and Tom live in Sweden, a country where everyone is expected to lead an orderly life according to rules laid down by the government, which also provides a high level of care for its people. This level of care costs money.

People in Sweden pay taxes on everything, so aren't surprised to find that owning a dog means more taxes. Some people are paying as much as 500 Swedish kronor in taxes a year for the right to keep their dog, which is spent by the government on dog hospitals and sometimes medical treatment for a dog that falls ill. However, most such treatment is expensive, so owners often decide to offer health and even life _ for their dog.

In Sweden dog owners must pay for any damage their dog does. A Swedish Kennel Club official explains what this means: if your dog runs out on the road and gets hit by a passing car, you, as the owner, have to pay for any damage done to the car, even if your dog has been killed in the accident.

Q: How old is Catherine?
A: 54

Q: where does she live?
A:

Model answer: Stockholm
Turker answers: Sweden, Sweden, in Sweden, Sweden

GPT3: Try it yourself!

https://beta.openai.com/playground

In-Context (Few Shot) Prompting

- Popularized by GPT-3 (but predates that model)
- Perform a task based on a few examples provided in the inference time.
- The model identifies patterns in examples and replicates it

GPT-3: Language Models are Few-Shot Learners

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

One-shot

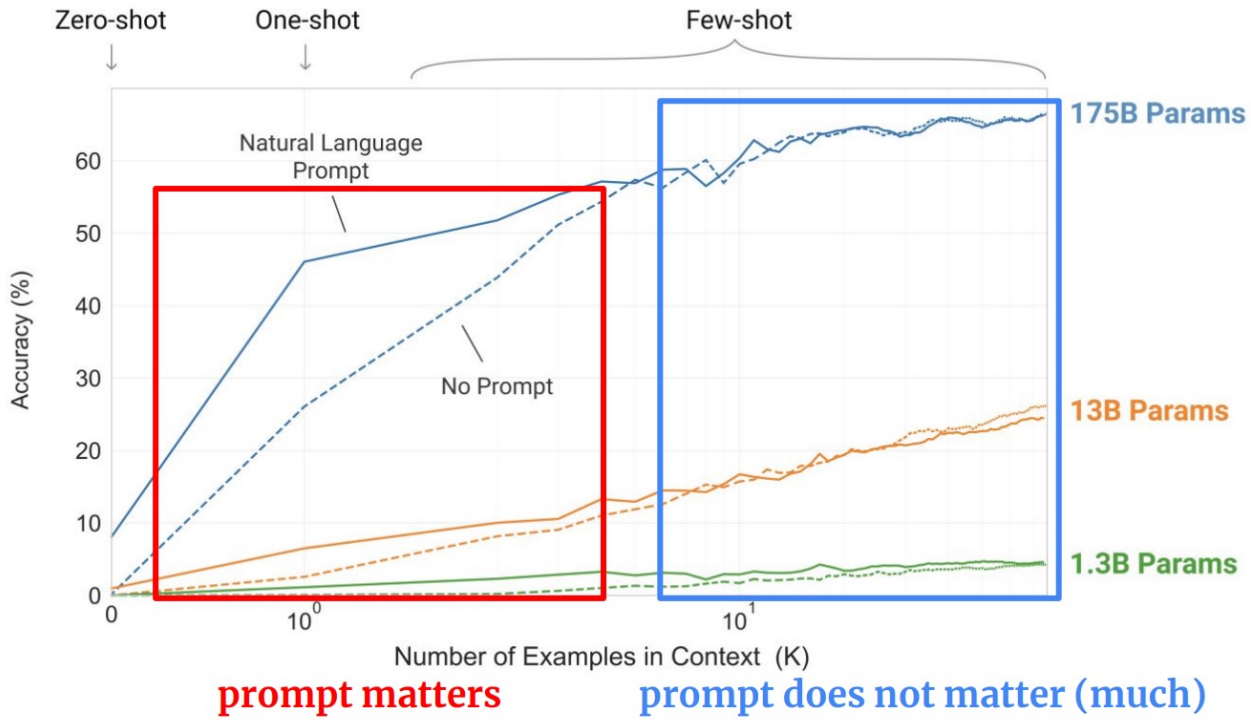
In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← example
3  cheese =>                           ← prompt
```

Few-shot

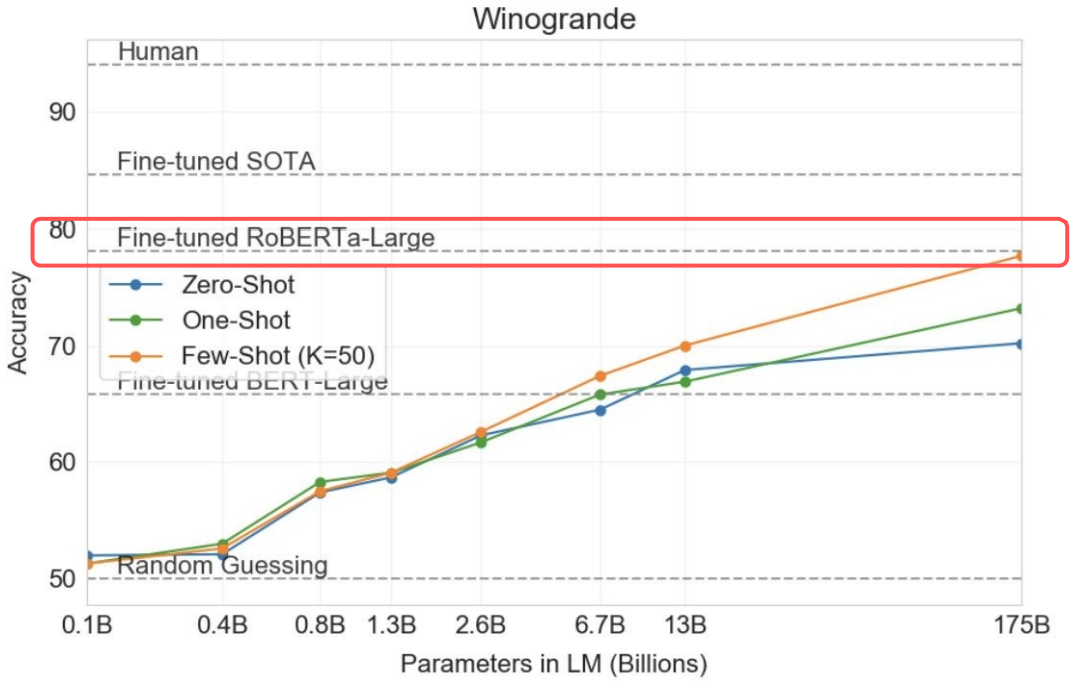
In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```



In-context learning results

Brown et al. 2020. "Language Models are Few-Shot Learners"



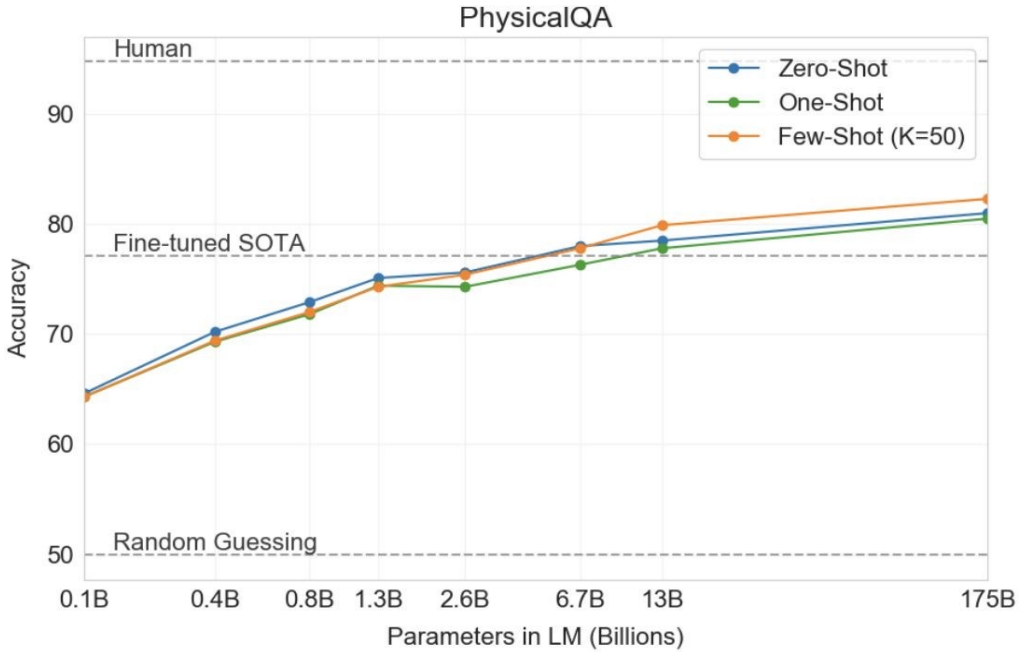
✓	Robert woke up at 9:00am while Samuel woke up at 6:00am, so **he** had *less* time to get ready for school.	**Robert** / Samuel
	Robert woke up at 9:00am while Samuel woke up at 6:00am, so **he** had *more* time to get ready for school.	Robert / **Samuel**

In-context learning results

To separate egg whites from the yolk using a water bottle, you should…

a. ***Squeeze*** the water bottle and press it against the yolk. ***Release,*** which creates suction and lifts the yolk.

b. ***Place*** the water bottle and press it against the yolk. ***Keep pushing,*** which creates suction and lifts the yolk.

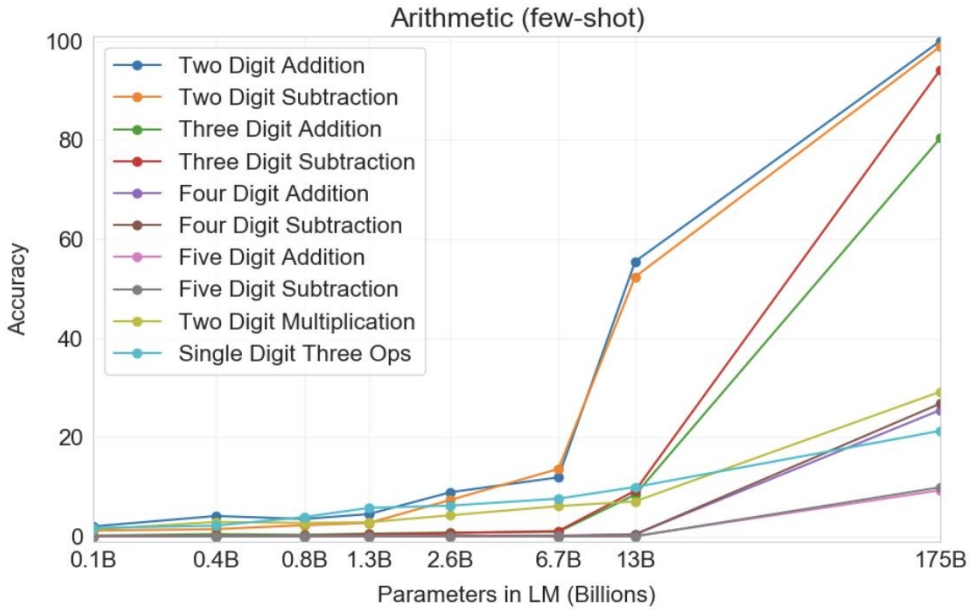


Brown et al. 2020. "Language Models are Few-Shot Learners"

In-context learning results

- Example:
  - Q: What is 48 plus 76?
  - A: 124

- Observations:
  - Scale is important
  - Number of digits correlate with their difficulty.
  - Multiplication is harder than summation!



Brown et al. 2020. "Language Models are Few-Shot Learners"

The Phases of Our Understanding

"Language modeling is a useful subtask for many NLP tasks"
– everyone, pre-2018

"Language modeling is a useful supertask for many NLP tasks"
– everyone, post-2018

Why Do We Care About Few-Shot Learning?

Practically Useful

Intellectually Intriguing

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Practically Useful

Labeling data is costly

- May require domain expertise
  - Medical, legal, financial
- Inputs may be long/complex
  - Grammaticality
- Outputs may be complex
  - Semantic parsing

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh; quote credit: Colin Raffel]

Practically Useful

Labeling data is costly

You want to do best with what you have

- You don't want to get more data
- Emergent, time-sensitive scenarios
  - Something new happened
  - Need to react quickly!

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Practically Useful

Labeling data is costly

You want to do best with what you have

Finetuning can unstable

- Training is sensitive to hyperparams
- Not enough validation data
- We don't quite understand how finetuning works

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Practically Useful

Labeling data is costly

You want to do best with what you have

Finetuning can be unstable

Finetuning large LMs is expensive

- Expensive to train, time and memory

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Intellectually Intriguing

Potential test for "Intelligent Behavior"

- Generalization from few examples
  - Fundamental piece of intelligence
  - Often used in psychology
  - Quickly adjust to environment

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Intellectually Intriguing

Potential test for "Intelligent Behavior"

"But… Deep learning is data hungry!"

- Long-standing criticism of DL
- Understand why it doesn't work here
  - Or does it?
- What are the new limitations of DL?

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Intellectually Intriguing

Potential test for "Intelligent Behavior"

"But… Deep learning is data hungry!"

Insights into Language Modeling

- What does an LLM "know"?
- What are the biases/limitations of LLMs?
- …

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Intellectually Intriguing

Potential test for "Intelligent Behavior"

"But… Deep learning is data hungry!"

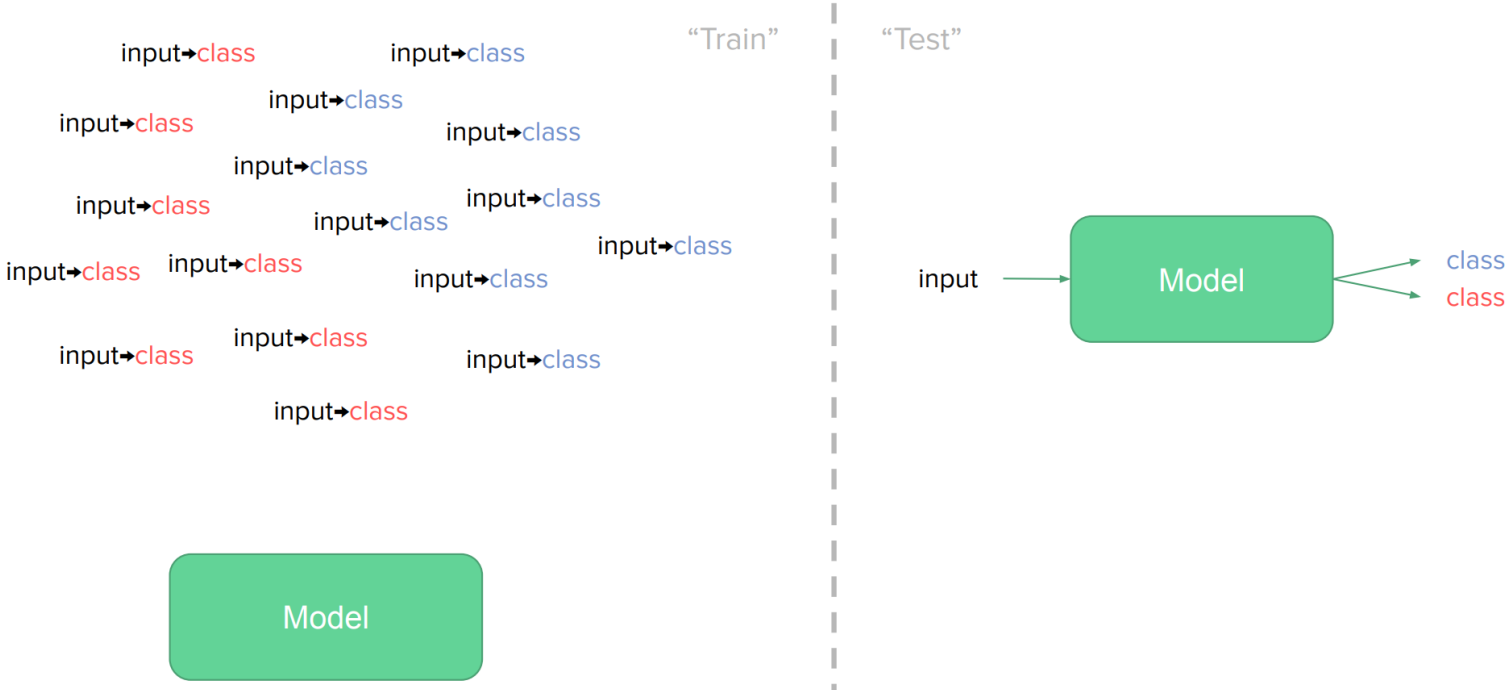
Insights into Language Modeling

Because LARGE language models

- Training/inference/access is tough
- What else can we do? ;)

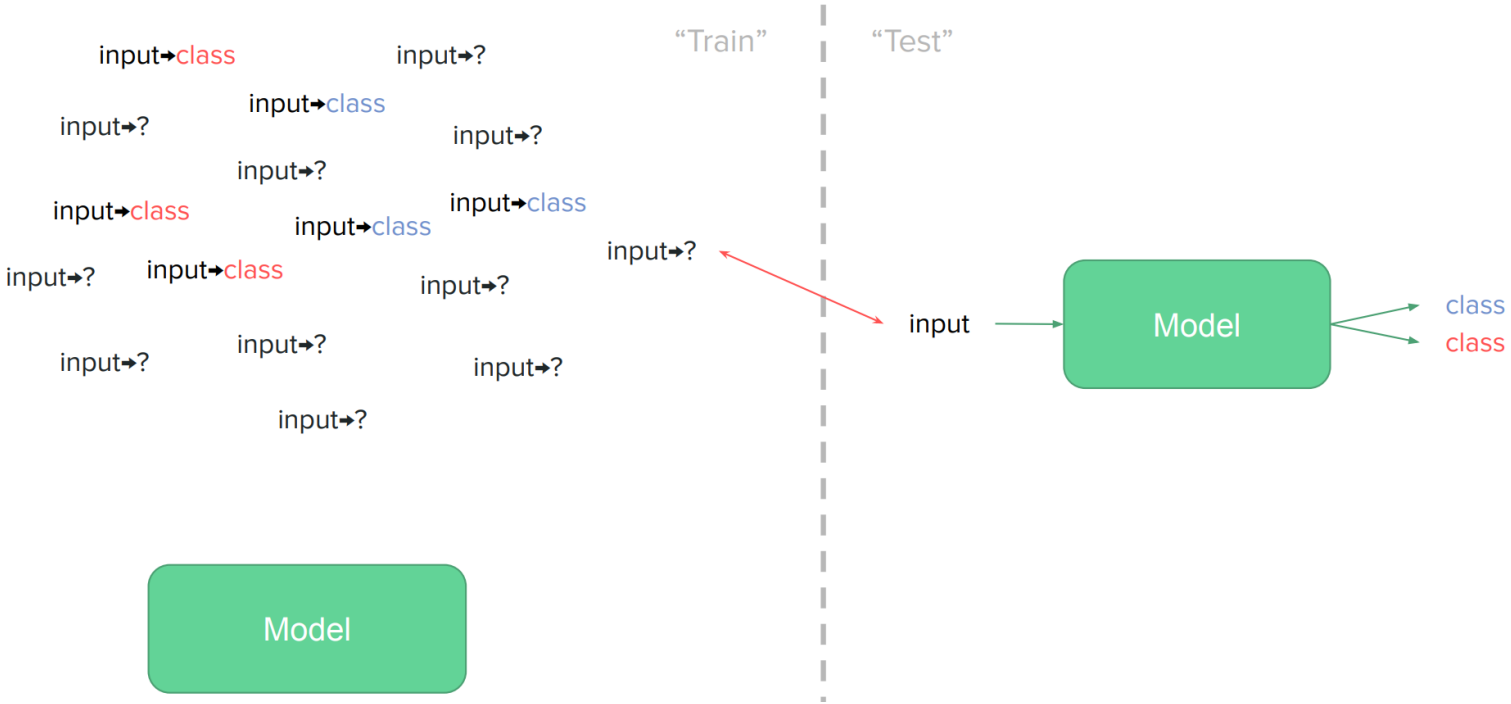
[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

The Broader Context: Supervised Learning



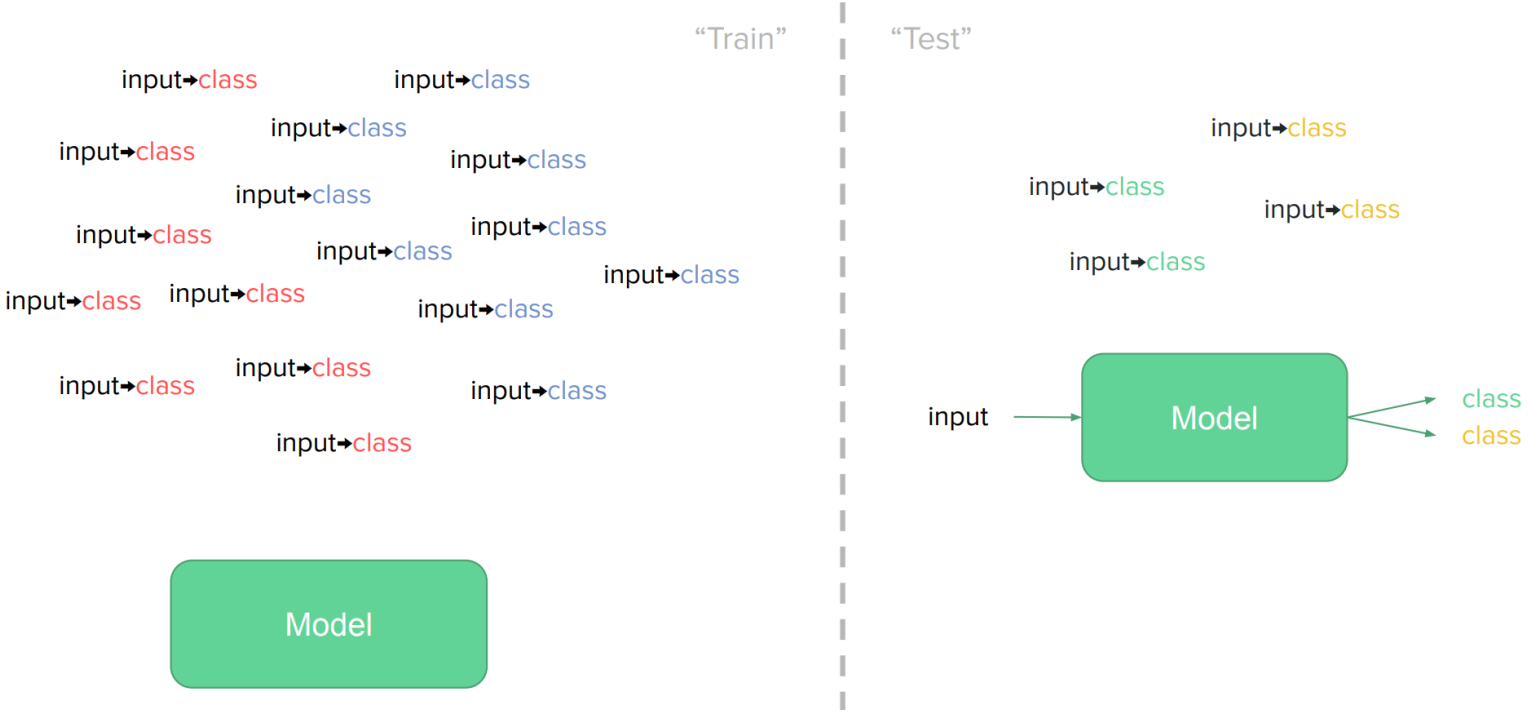
[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

The Broader Context: Semi-Supervised Learning



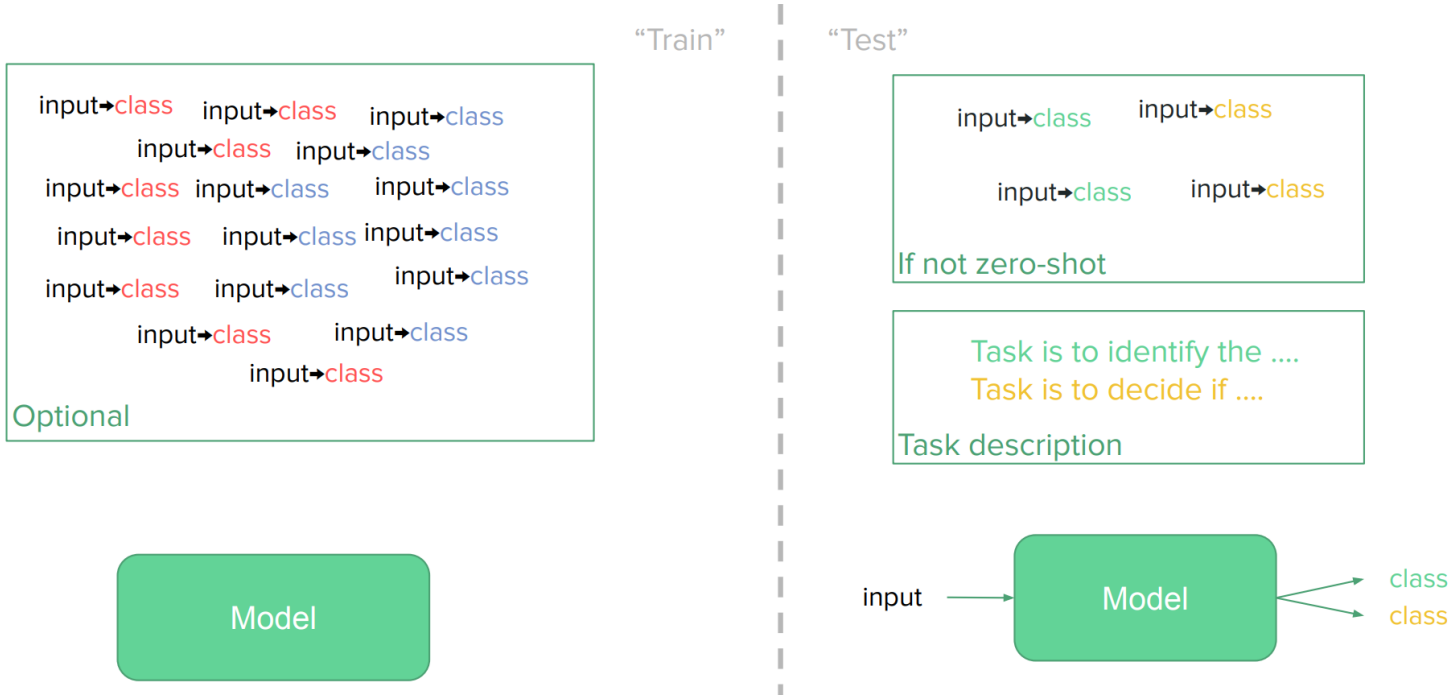
[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

The Broader Context: [Traditional] Few-shot Learning



[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

The Broader Context: [Modern] Few-shot Learning



[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

In-Context Prompting

Movie review dataset

Input: An effortlessly accomplished and richly resonant work.
Label: positive

Input: A mostly tired retread of several other mob tales.
Label: negative

An effortlessly accomplished and richly resonant work. It was great! A mostly tired retread of several other mob tales. It was terrible!

A three-hour cinema master class. It was _____

Language Model

p1 = P(It was great! | 1st train input+output \n 2nd train input+output \n A three-hour cinema master class.)

p2 = P(It was terrible! | 1st train input+output \n 2nd train input+output \n A three-hour cinema master class.)

p1>p2 "positive"

p1<p2 "negative"

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

LM Prompting: Choices of Encoding

Prompt

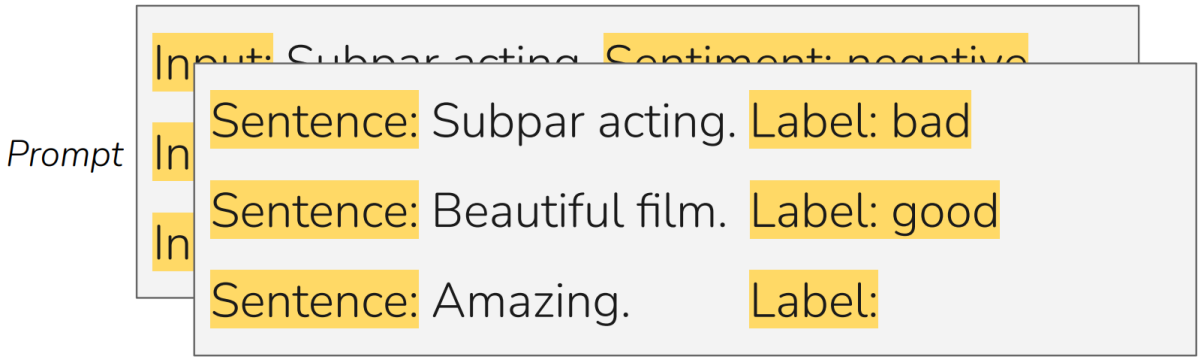
Input: Subpar acting. Sentiment: negative

Input: Beautiful film. Sentiment: positive

Input: Amazing. Sentiment:

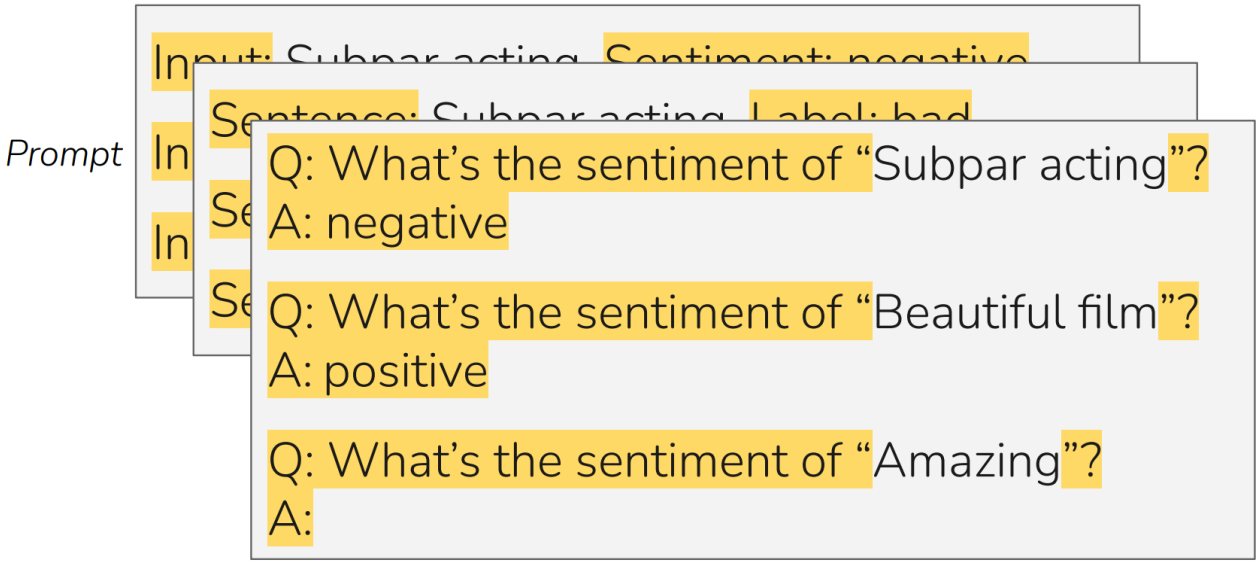
[Slide credit: Eric Wallace]

LM Prompting: Choices of Encoding



[Slide credit: Eric Wallace]

LM Prompting: Choices of Encoding



[Slide credit: Eric Wallace]

LM Prompting: Choices of Encoding

- **Pattern:** A function that encodes the inputs.
- **Verbalizer:** A function that encodes the output.

Pattern: f(<x>) = "Input: <x>"
Verbalizer: v(<x>)) = "Label: <x>)"

Input: Subpar acting. Sentiment: negative

Input: Beautiful film. Sentiment: positive

Input: Amazing. Sentiment:

Pattern: f(<x>) = "Q: What is the sentiment of <x>"
Verbalizer: v(<x>) = "A: <x>"

Q: What's the sentiment of "Subpar acting"?
A: negative

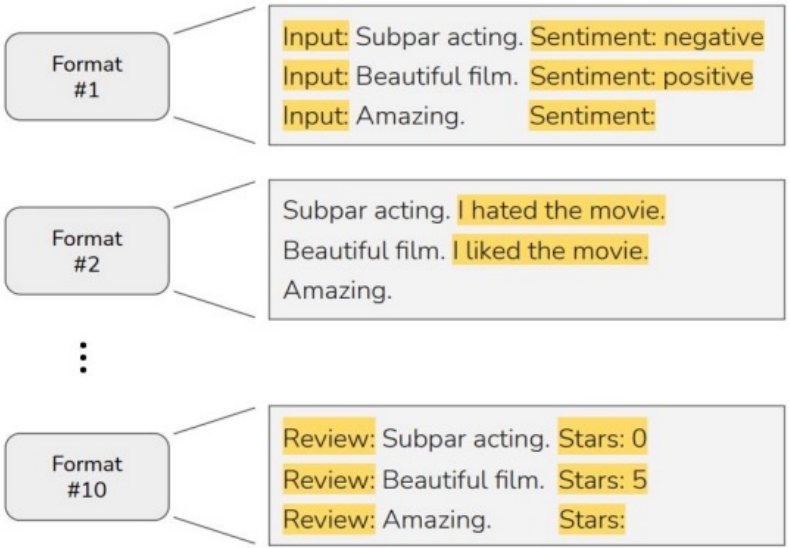
Q: What's the sentiment of "Beautiful film"?
A: positive

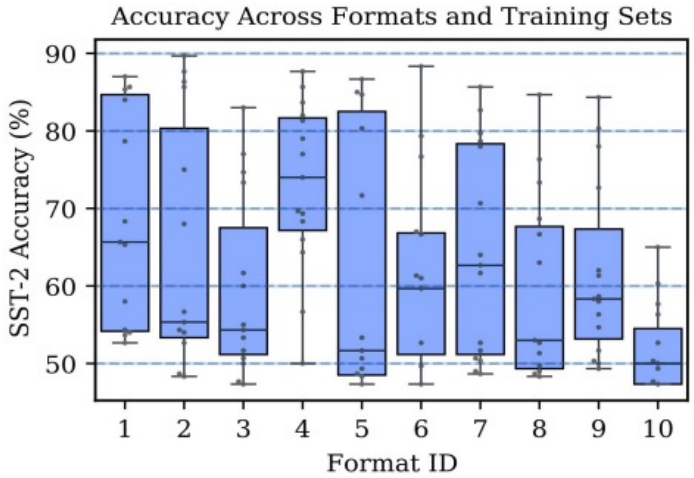
Q: What's the sentiment of "Amazing"?
A:

[Slide credit: Eric Wallace]

[Slide credit: Eric Wallace]

In-Context Learning: Sensitivity to Encoding





In-context learning is highly sensitive to prompt format (training sets and patterns/verbalizers)

[Calibrate Before Use: Improving Few-Shot Performance of Language Models." Zhao et al. 2021]

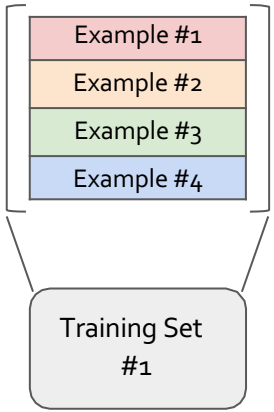
[Slide credit: Eric Wallace]

In-Context Learning: Sensitivity to Demo. Permutations

Training Set
#1

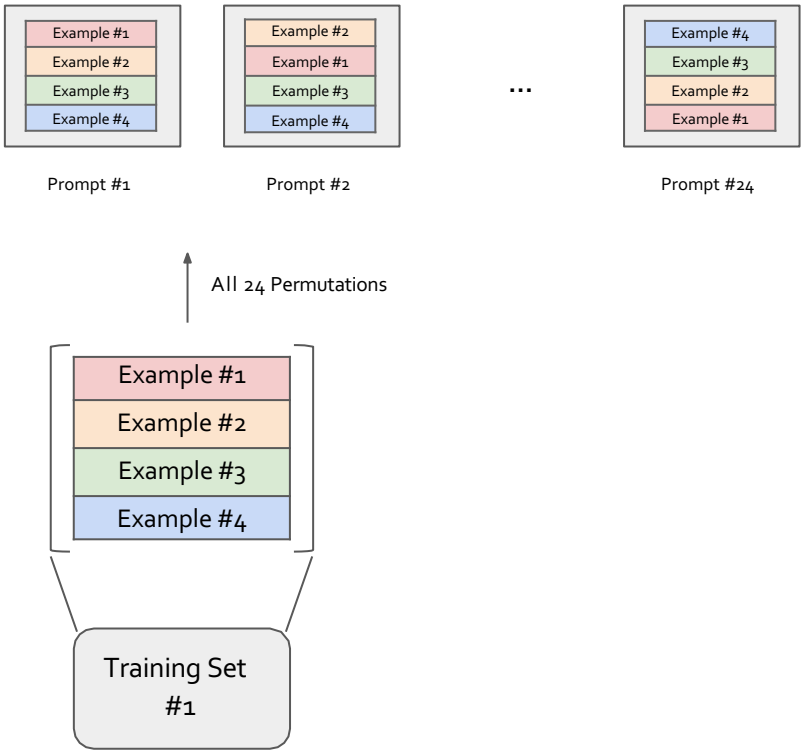
[Slide credit: Eric Wallace]

In-Context Learning: Sensitivity to Demo. Permutations



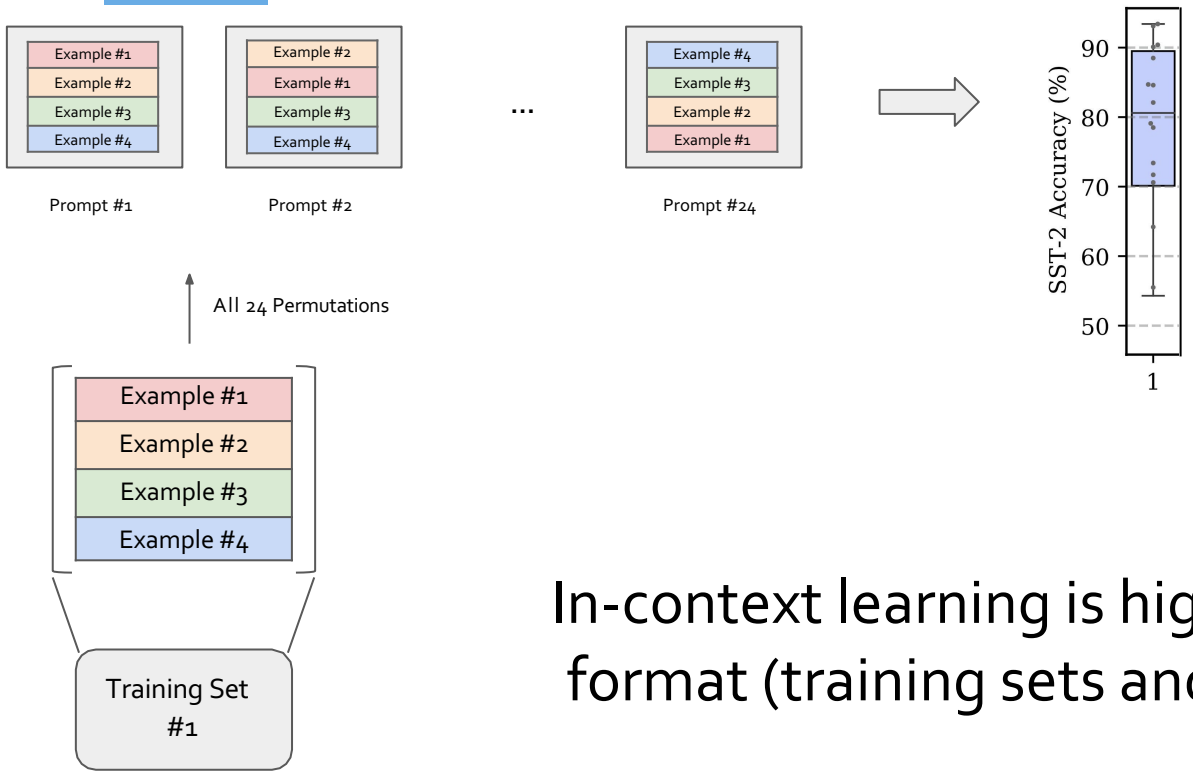
[Slide credit: Eric Wallace]

In-Context Learning: Sensitivity to Demo. Permutations



[Slide credit: Eric Wallace]

In-Context Learning: Sensitivity to Demo. Permutations

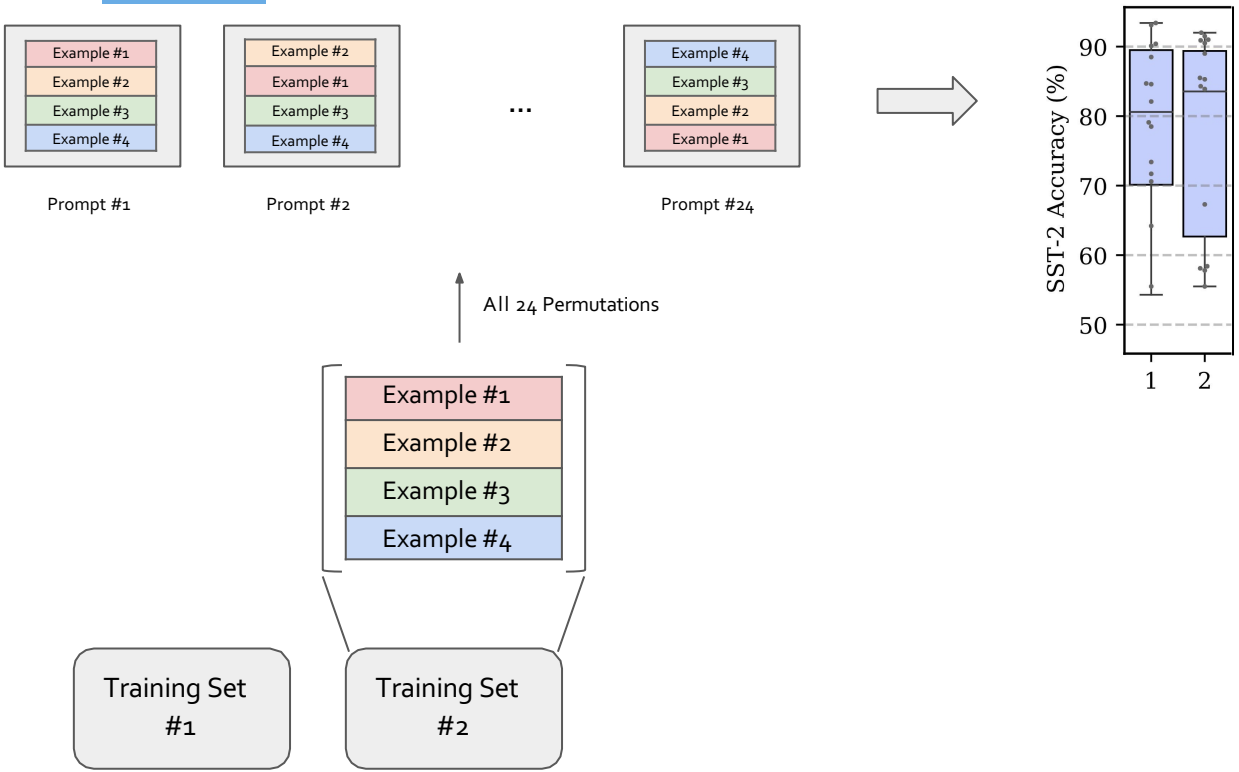


In-context learning is highly sensitive to prompt format (training sets and patterns/verbalizers)

[Calibrate Before Use: Improving Few-Shot Performance of Language Models." Zhao et al. 2021]

[Slide credit: Eric Wallace]

In-Context Learning: Sensitivity to Demo. Permutations



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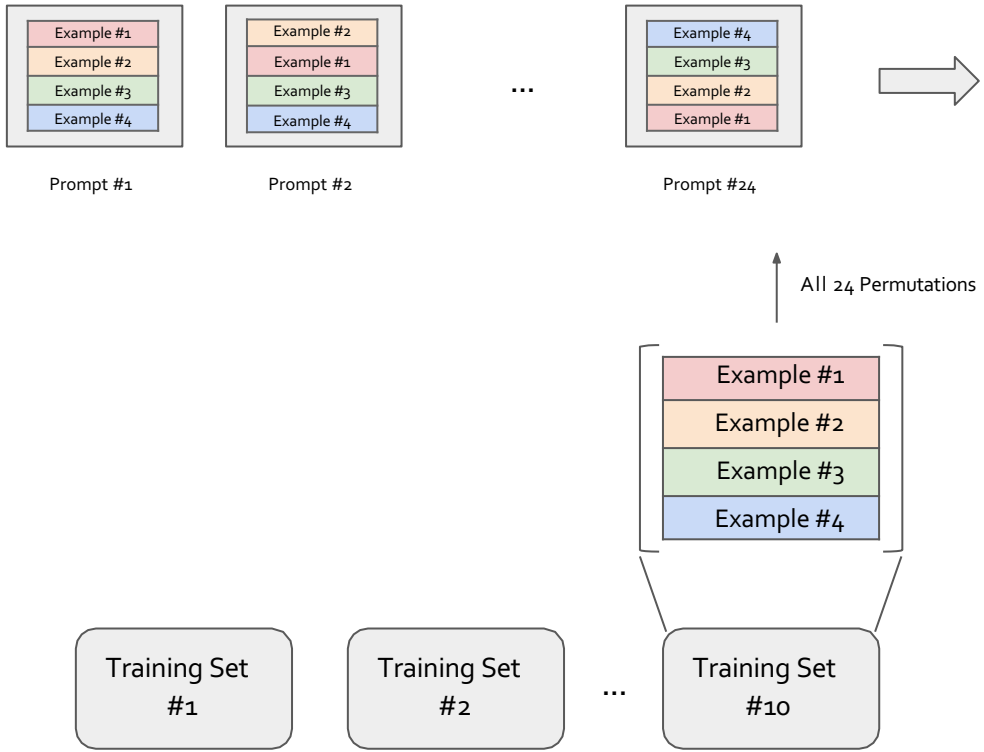
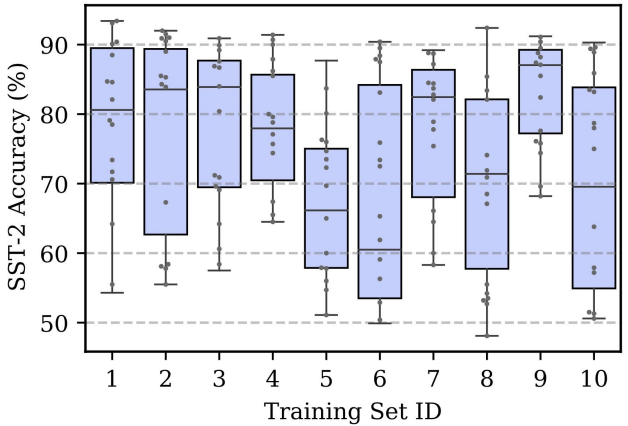
In-Context Learning: Sensitivity to Demo. Permutations





The choice of demonstrations and their order is quite important.

[Calibrate Before Use: Improving Few-Shot Performance of Language Models." Zhao et al. 2021]

Sensitivity to Wording (Framing) of Prompts

- Framing of prompts matters a lot.

```
Craft a question that requires
commonsense to be answered. Based on the
given context, craft a common-sense
question, especially those that are LONG,
INTERESTING, and COMPLEX. The goal is to
write questions that are easy for humans
and hard for AI machines! To create such
questions, here are some suggestions: A.
What may (or may not) be the plausible
reason for an event? B. What may (or may
not) happen before (or after, or during)
an event?  ...
```

```
Generate questions such that you use
 - ‘what may happen’,
 - ‘will ...?’,
 - ‘why might’,
 - ‘what may have caused’,
 - ‘what may be true about’,
 - ‘what is probably true about’,
 - ‘what must’
and similar phrases in your question
based on the input context.
```


[“Reframing Instructional Prompts to GPTk's Language.” Mishra et al. 2021.]

Sensitivity to Wording (Framing) of Prompts

- Prompts can often be phrased in a language that are easier to be understood by language models.
- Generally, it is easier for LMs to follow shorter, crisp, itemized prompts.

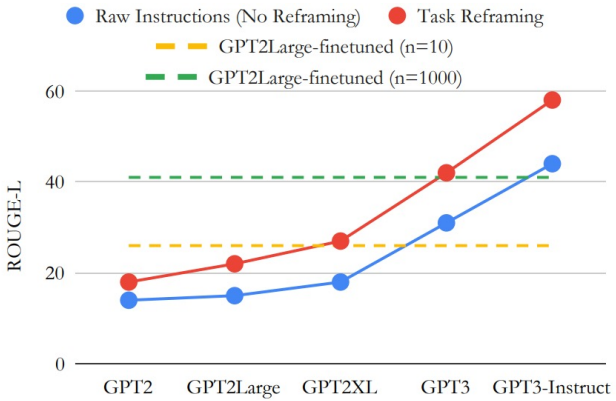


Figure 2: Across a variety of model sizes, reframed prompts consistently show considerable performance gain over raw task instructions (no reframing) in a few-shot learning setup. Since fine-tuning GPT3 is prohibitively expensive, we show the performance of fine-tuning smaller models (horizontal lines). This results indicates that *evaluating* reframed prompts on a large model like GPT3-instruct (red line) might be more effective that *fine-tuning* a smaller model like GPT2Large (green line) with 200× more data. Details of the experiments in §4.

["Reframing Instructional Prompts to GPTk's Language." Mishra et al. 2021.]

Summary Thus Far

- There are many possible ways to encode in-context examples of a fixed task
  - Many possible patterns/verbalizers
  - The choice of demonstrations
  - Ordering of the examples
  - ….

- It turns out there is a huge variance in performance depending on the encoding.
  - You can treat them as hyper-parameters
  - You should **not** choose these encodings based on the test data.

- Generally, it is better to use encoding that makes the sequence closer to language modeling — closer to what is observed during pretraining.

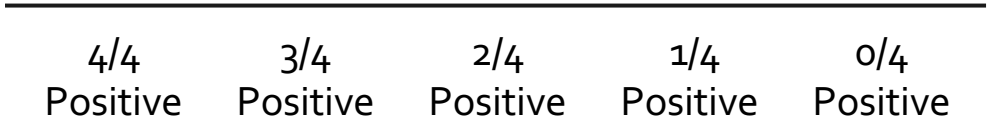
What Causes These Variances?

- Here we will provide several justifications …

Majority Label Bias

Majority Label Bias

Frequency of Positive Predictions



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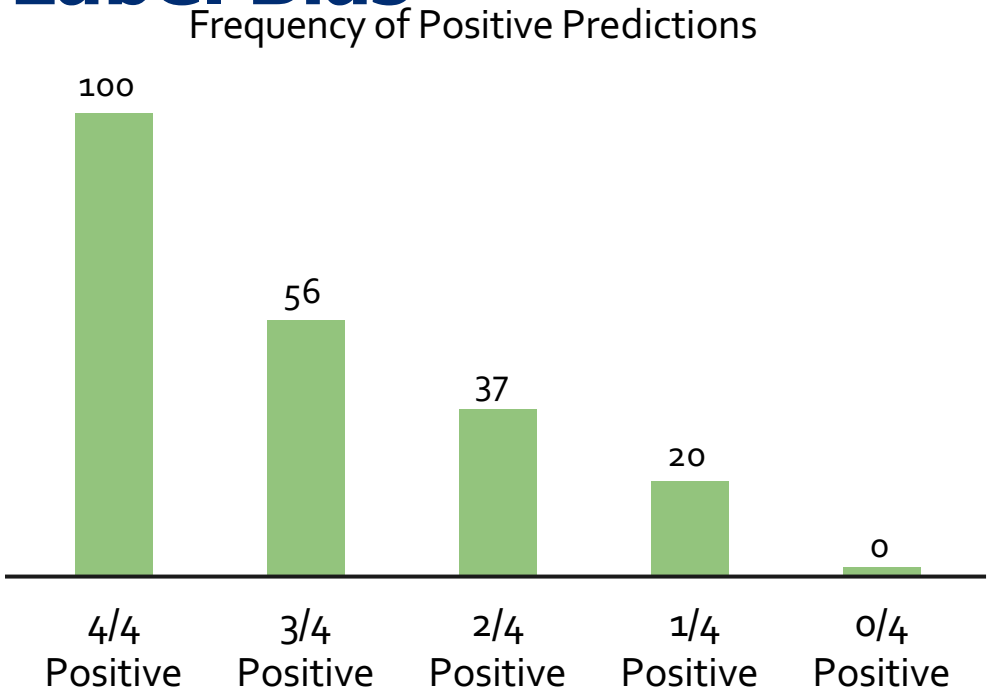

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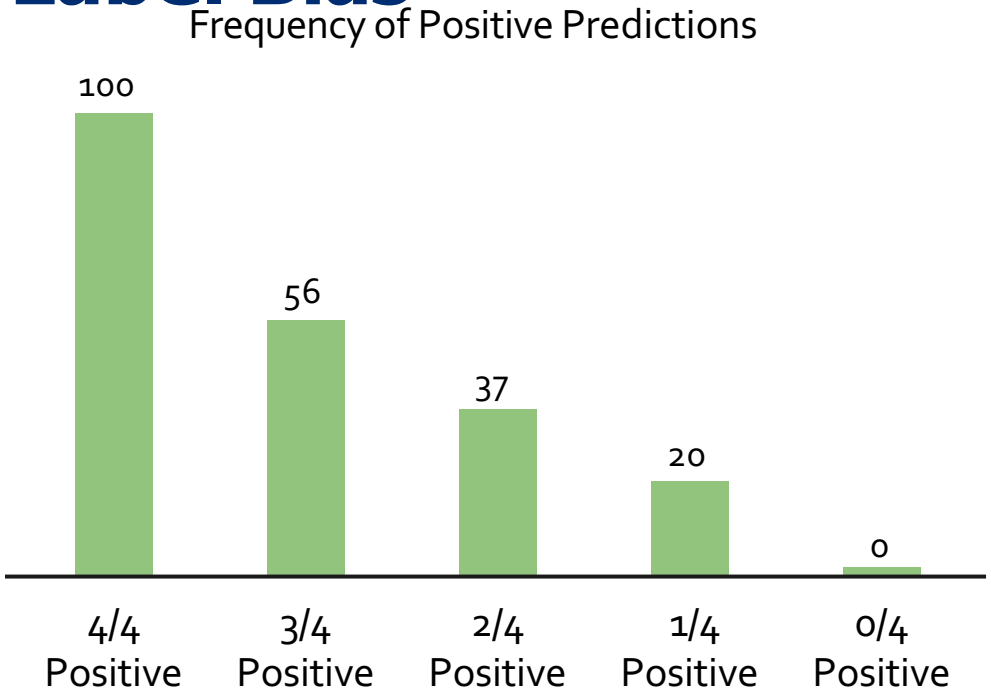


Majority label bias: frequent training answers dominate predictions
Explain some of the variances across example selections

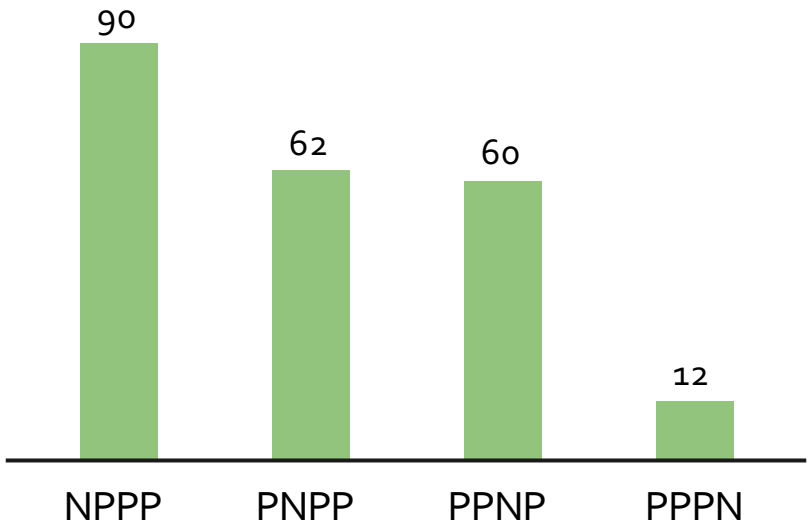
Recency Bias

Recency Bias

Frequency of Positive Predictions

Recency Bias

Frequency of Positive Predictions



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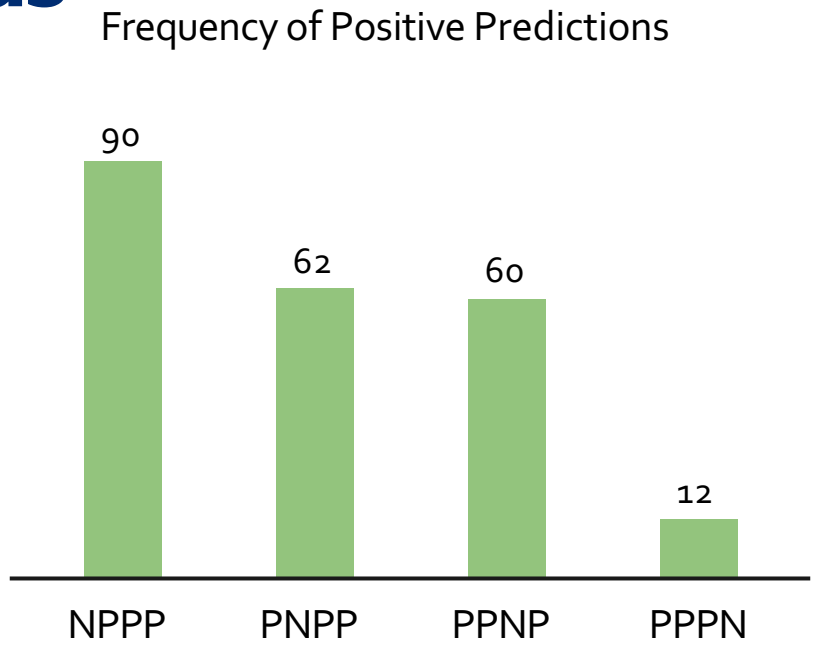
Recency Bias

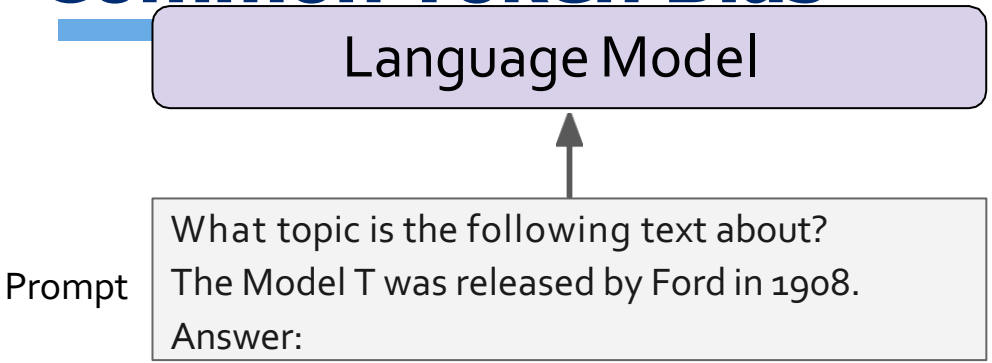


Recency bias: examples near end of prompt dominate predictions

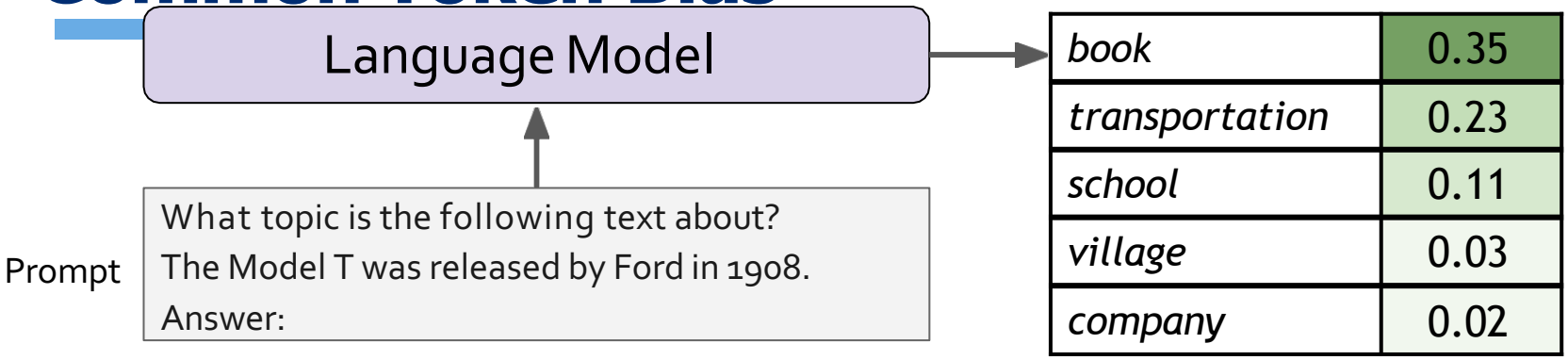
- Explains variance across example permutations

Common Token Bias

Common Token Bias



Common Token Bias

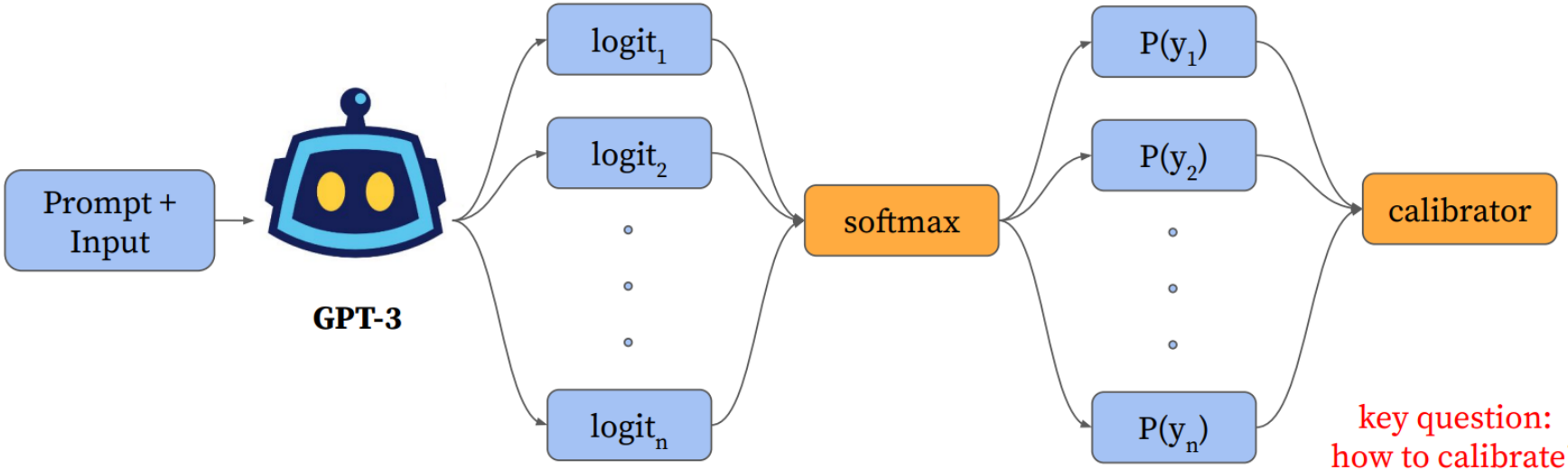


Model is biased towards predicting the incorrect frequent token "book" even when both "book" and "transportation" are equally likely labels in the dataset

	Token	Web (%)	Label (%)	Prediction (%)
❌	*book*	0.026	9	29
✅	*transportation*	0.0000006	9	4

- Common token bias: common n-grams dominate predictions
  - helps explain variance across prompt formats

Calibrating LM Probabilities



[Slide credit: Howard Yen, Vishvak Murahari]

Calibrating LM Probabilities

Step 1: Estimate the bias

Calibrating LM Probabilities

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Insert "content-free" test input into prompt

```
Input: Subpar acting. Sentiment: negative
Input: Beautiful film.  Sentiment: positive
Input:                  Sentiment:
```

Calibrating LM Probabilities

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Input: Subpar acting. Sentiment: negative
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Input: Sentiment:

Get model's prediction

positive	0.65
negative	0.35

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Calibrating LM Probabilities

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Step 2: Counter the bias ("Platt Scaling")

"Calibrate" predictions with affine transformation

$$\hat{\mathbf{q}} = \text{softmax}(\mathbf{W}\hat{\mathbf{p}} + \mathbf{b})$$

[Calibrate Before Use: Improving Few-Shot Performance of Language Models." Zhao et al. 2021]

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Calibrated probs — Original probs

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Calibrating LM Probabilities

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$$\hat{\mathbf{q}} = \text{softmax}(\mathbf{W}\hat{\mathbf{p}} + \mathbf{b})$$

$\hat{\mathbf{q}}$: Calibrated probs; $\hat{\mathbf{p}}$: Original probs

Fit $\mathbf{W}$ and $\mathbf{b}$ to so that outputs for the content-free input are uniform

[Calibrate Before Use: Improving Few-Shot Performance of Language Models." Zhao et al. 2021]

Calibrating LM Probabilities

Step 1: Estimate the bias

Note, this calibration does **not** require any labeled data.

- **Classification tasks:** normalized scores of labels
- **Generation tasks:** probabilities of the first token of the generation over the entire vocabulary

Get model's prediction

positive	0.65
negative	0.35

Step 2: Counter the bias ("Platt Scaling")

"Calibrate" predictions with affine transformation

$$\hat{\mathbf{q}} = \text{softmax}(\mathbf{W}\hat{\mathbf{p}} + \mathbf{b})$$

Calibrated probs — Original probs

Fit $\mathbf{W}$ and $\mathbf{b}$ to so that outputs for the content-free input are uniform

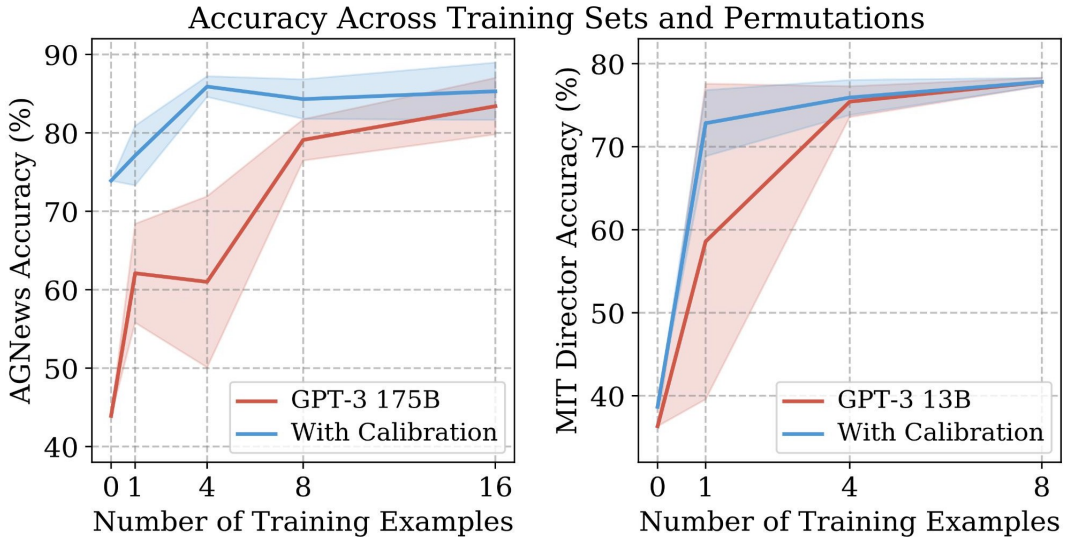
$$\mathbf{W} = \begin{pmatrix} \frac{1}{0.65} & 0 \\ 0 & \frac{1}{0.35} \end{pmatrix} \quad \mathbf{b} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

W: diagonal matrix
b: bias set to zeros

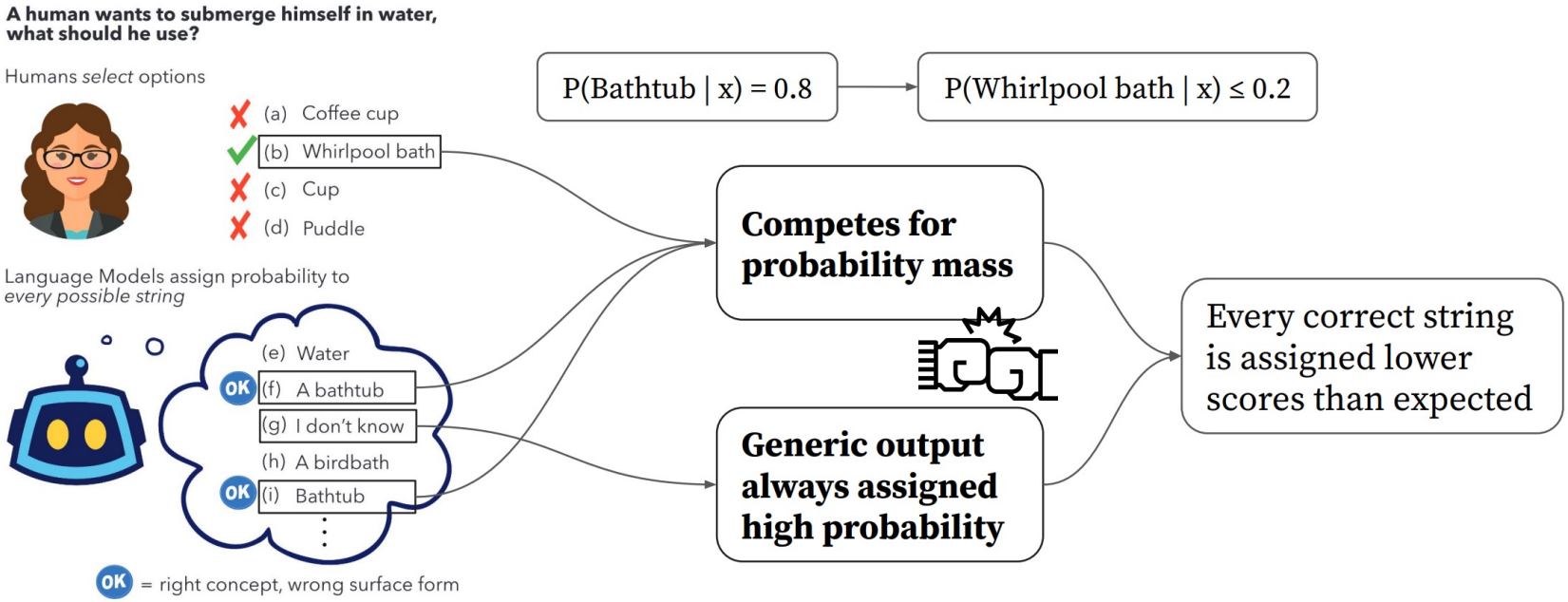
[Calibrate Before Use: Improving Few-Shot Performance of Language Models." Zhao et al. 2021]

Effect of Calibration

- Improves mean and worst-case accuracy
- Reduces variance across training sets and permutations



Surface Form Competition



Surface forms are competing for probability mass — skew the probabilities.
There are some ideas on how to calibrate for these issues (see Holtzman et al 2021).

[Slide credit: Howard Yen, Vishvak Murahari]

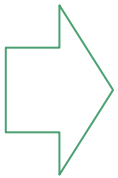
Summary Thus Far

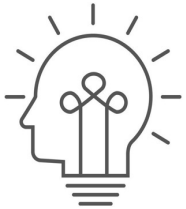
- LM prompting & In-context learning show promising results, but their performance is highly unstable/brittle.
- Better scoring: Calibration
- Other factors:
  - Better formation of demonstrations
  - Better choice of demonstrative examples
  - Better ordering of demonstrative examples

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

How/Why does In-context Learning Work?

Any arbitrary task





Language Model

A few-shot learner

How/Why does In-context Learning Work?

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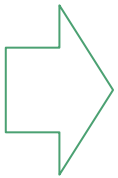
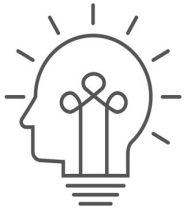




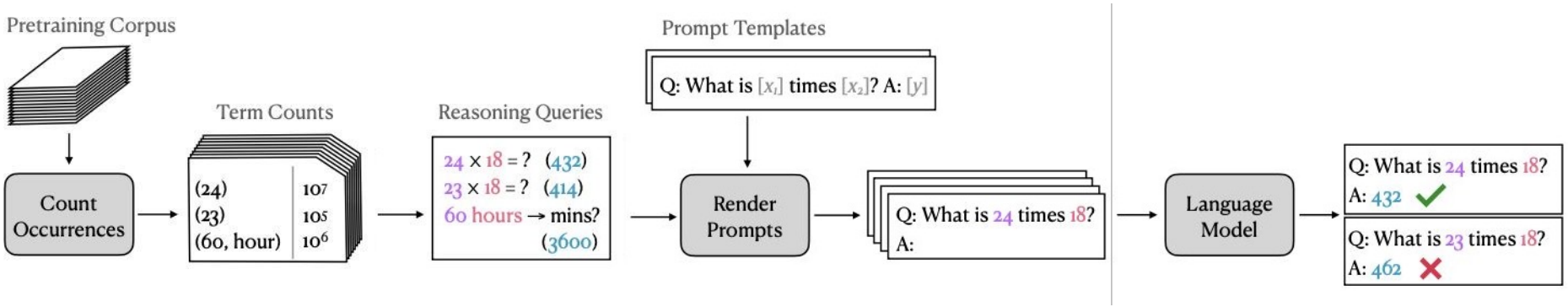
Language Model

A few-shot learner

[ACL 2022 Tutorial Beltagy, Cohan, Logan IV, Min and Singh]

Impact of Pretraining Term Frequencies

- For each task, identify relevant terms from each instance—numbers and units
- Count co-occurrences of these terms in the pretraining data (term pairs or triples within a fixed window)



["Impact of Pretraining Term Frequencies on Few-Shot Reasoning" Razeghi et al. 2022.]

Impact of Pretraining Term Frequencies

This may also indicate that, demonstrations do not teach a new task; instead, it is about locating an already-learned task during pretraining (Reynolds & McDonell, 2021)

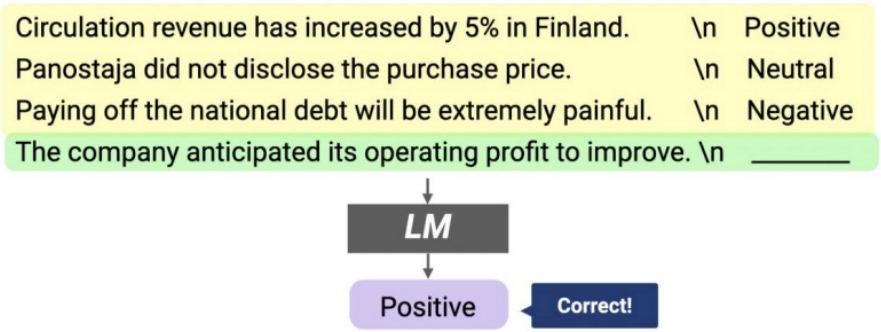
But that brings up the question of how much LMs **actually** reason when solving these tasks.🤔 Overlooking the impact of pretraining data can be misleading in evaluation!

In-context learning performance is highly correlated with term frequencies during pretraining

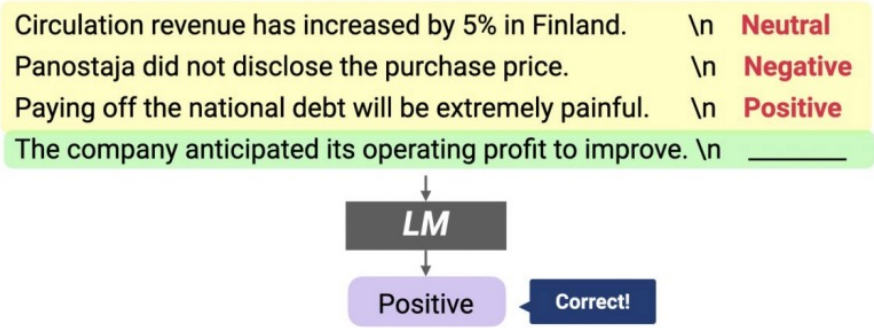
["Impact of Pretraining Term Frequencies on Few-Shot Reasoning" Razeghi et al. 2022.]

Impact of Input-Output Mapping

- Study the effect of randomizing labels in demonstrations.
  - Randomly sample a label from the correct label space



Prompt with true labels

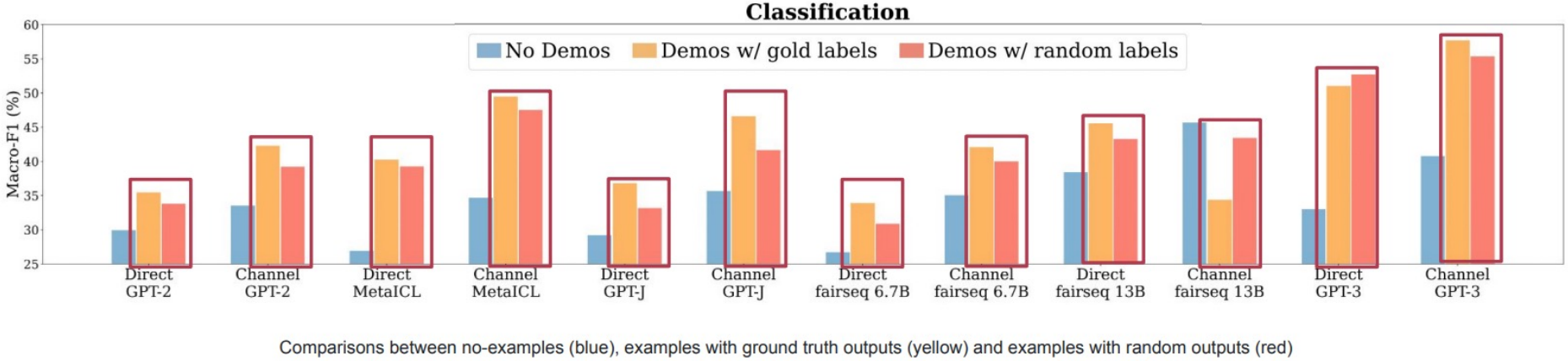


Prompt with random labels

["Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?" Min et al. 2022.]

Impact of Input-Output Mapping

- Models see a small performance drop (0–5% absolute) with random labels



Comparisons between no-examples (blue), examples with ground truth outputs (yellow) and examples with random outputs (red)

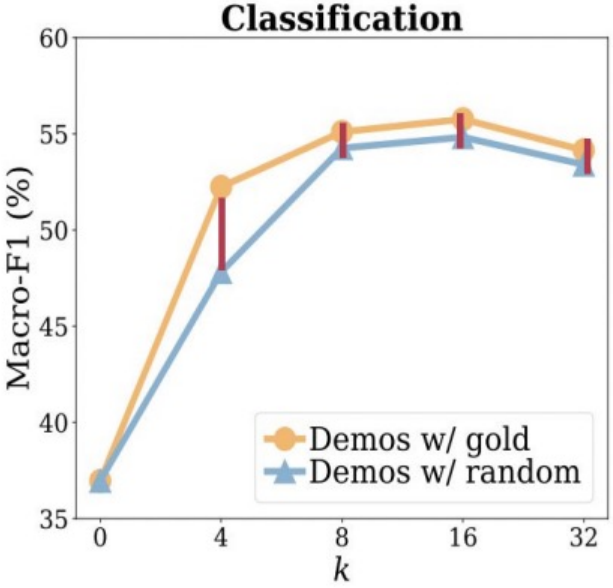
- **Takeaway:** ground truth input-label mapping in the prompt is not as important as we thought

["Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?" Min et al. 2022.]

Impact of Input-Output Ma

- Vary number of demonstrations

- **Takeaway:**
  - Performance drop from using gold labels to u
    consistently small across varying k, ranging f
  - Using small number of examples with randor
    examples



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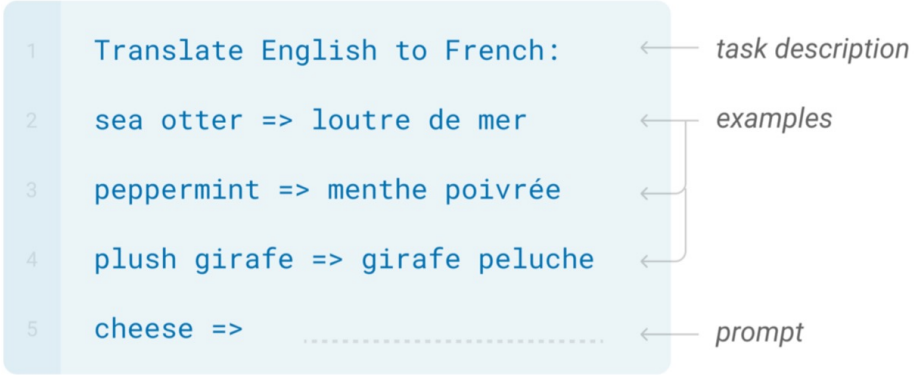
In-context Learning

CSCI 601 471/671
NLP: Self-Supervised Models

https://self-supervised.cs.jhu.edu/sp2023/

[Slide credit: Iz Beltagy, Arman Cohan, Robert Logan IV, Sewon Min, Sameer Singh, and many others]

In-Context Learning



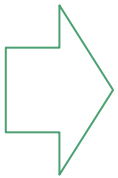
- Learns to do a downstream task by conditioning on input-output examples!

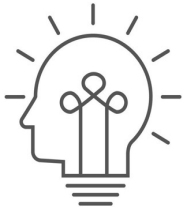
- **No weight update** — our model is not **explicitly pre-trained** to learn from examples
  - The underlying models are quite general

- Today's focus:
  - How to use effectively in practice?
  - Fundamentally, why does it work?

How/Why does In-context Learning Work?

Any arbitrary task





Language Model

A few-shot learner

In-context Learning as Bayesian Inference

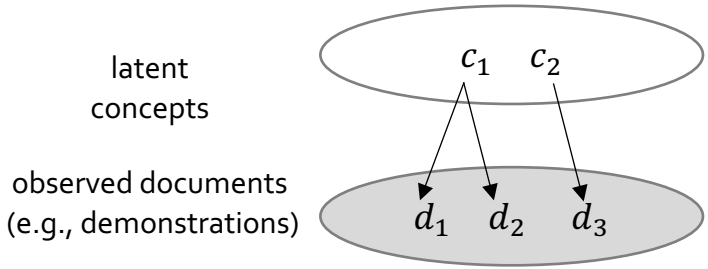
- (Xie et al., 2022) try to explain ICL as an implicit Bayesian inference.

Idea:

- (Pre-trained LM learn to represent "concepts", i.e. the ideas described by words.
- ICL enables LMs to "locate" the learned concepts.

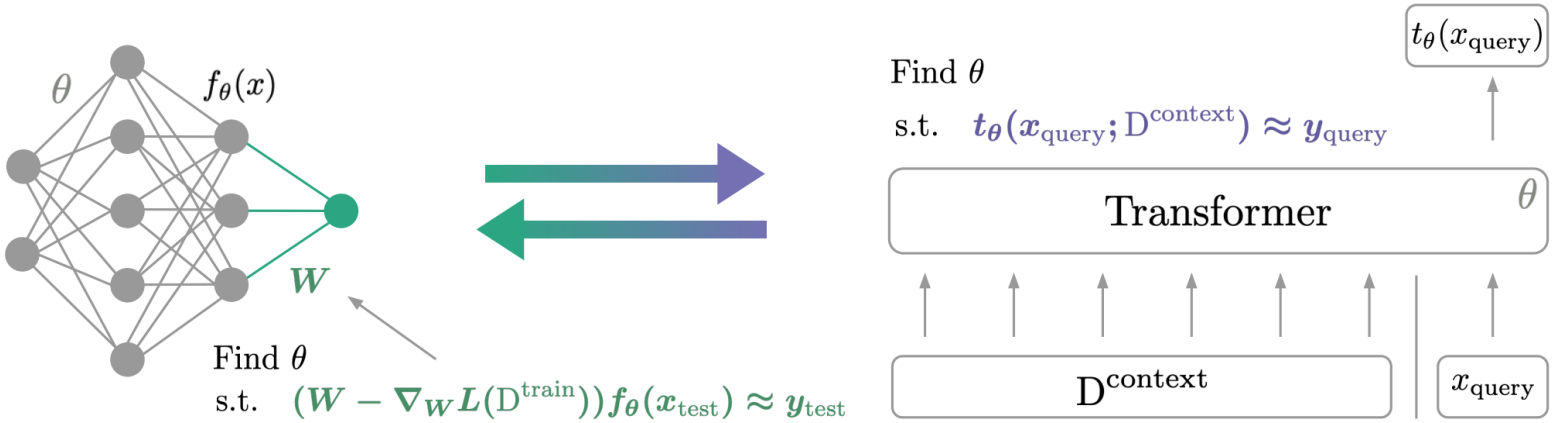
- Can formulate this intuition as a Bayesian inference
  - Prior over latent "concepts"
  - Likelihood describes connection between text and concepts
  - Given an incomplete doc, use Bayes formula to infer what concept is likely it is generated from and then complete the document.

- Does not explain everything.
  - GPT-3 can handle "unseen" concepts



In-context Learning as Gradience Descent

- ICL is implicitly equivalent to SGD on in-context demonstrations



[von Oswald et al. 2022; Akyurek et al. 2022; Dai et al. 2022, ...]

Summary & Open questions

- In-context learning has been a promising few-shot learning approach
  - No need for gradient updates → Much easier to use large models!

- Better calibration, better scoring of model outputs, and better formation of demonstrations lead to great improvements
  - How to make it less sensitive?
  - How to scale it (longer context, more training examples, wider range of tasks)?

- Still in progress …
  - Understanding how/why it works,
  - Disentangling looking up task location vs learning a new task
  - Can we predict whether in-context learning would work on a given task or not?

Prompting for Multi-Step Reasoning

- Useful slides: ACL 2023 Tutorial: Complex Reasoning in Natural Language (wenting-zhao.github.io)
- Teach-LLMs-to-Reason-7-2023 (dennyzhou.github.io)

Some Problems Involve Reasoning

Q: If there are 3 cars in the parking lot and 2 more cars arrive, how many cars are in the parking lot?

A: The answer is **5**

Arithmetic Reasoning (AR)
(+ −×÷…)

Q: Take the last letters of the words in "Elon Musk" and concatenate them

A: The answer is **nk.**

Symbolic Reasoning (SR)

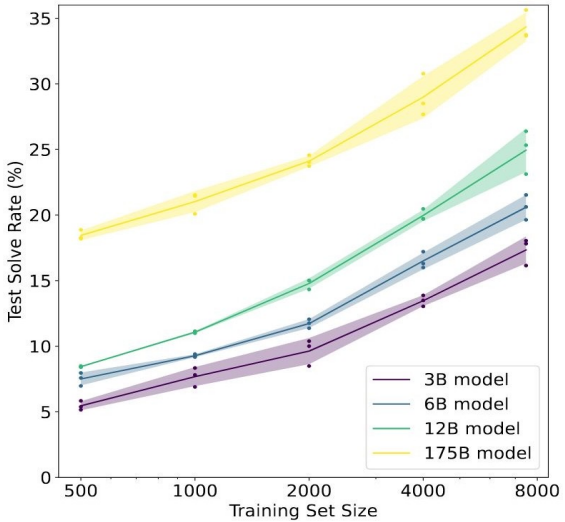
Q: What home entertainment equipment requires cable? Answer Choices: (a) radio shack (b) substation (c) television (d) cabinet

A: The answer is **(c).**

Commonsense Reasoning (CR)

Reasoning Problems

(Cobbe et al. 2021)



- Fine-tune LMs on GSM8K (arithmetic reasoning)
- One may conjecture that, to achieve >80%, one needs 100x more training data for 175B model
- Another option is to increase model sizes, which is expensive.
- Other than these, how else can we improve the model performance on tasks that require multi-step reasoning?

Reasoning Problems via Multi-Step Prompting

- **Basic idea:** Rather than showing input-output pairs, prompting the model such that it shows its proof steps.

- **Note:** ideas around models that are capable of multi-step reasoning go way back.
  - Aristotle (deduction),
  - Hume (induction),
  - Peirce (abduction)
  - Lots of other works in pre-LM era
  - Namely, my Ph.D. thesis ☺ on multi-step reasoni in semantic representations of language

[Reasoning-Driven Question-Answering for Natural Language Understanding]

- **Deduction**
  - All beans in that bag are white.
  - These beans are from that bag.
  - Therefore, these beans are white.
- **Induction**
  - These beans are from that bag.
  - These beans are white.
  - Therefore, all beans in that bag are white.
- **Abduction**
  - These beans are white.
  - All beans in that bag are white.
  - Therefore, these beans are from that bag.

Reasoning Problems via Multi-Step Prompting

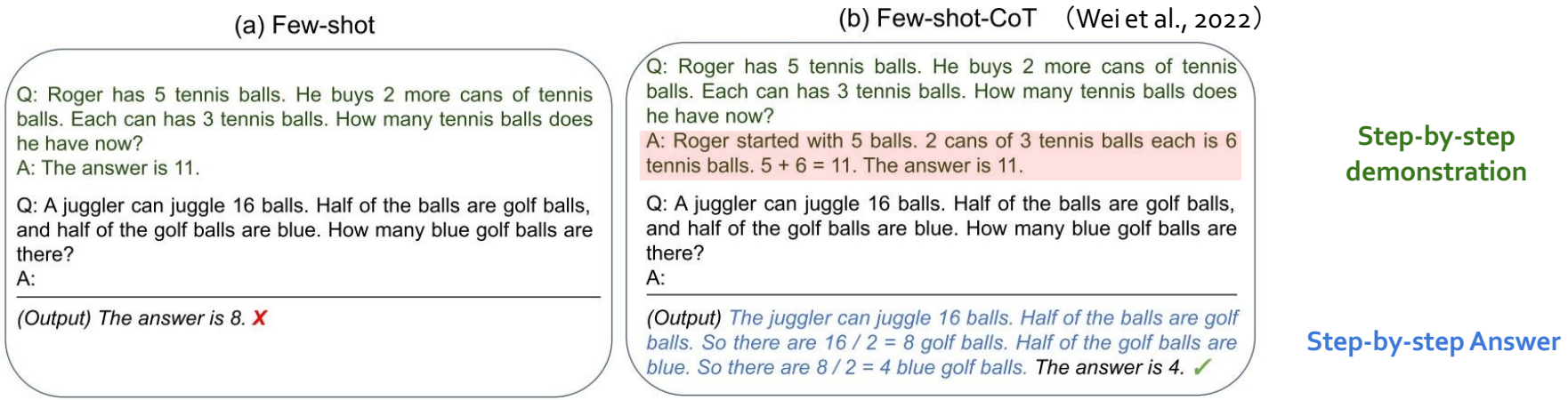
(a) Few-shot

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. ✗

Reasoning Problems via Multi-Step Prompting



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A:

(Output) The answer is 8. ✗

(b) Few-shot-CoT （Wei et al., 2022）

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. ✓

Step-by-step demonstration

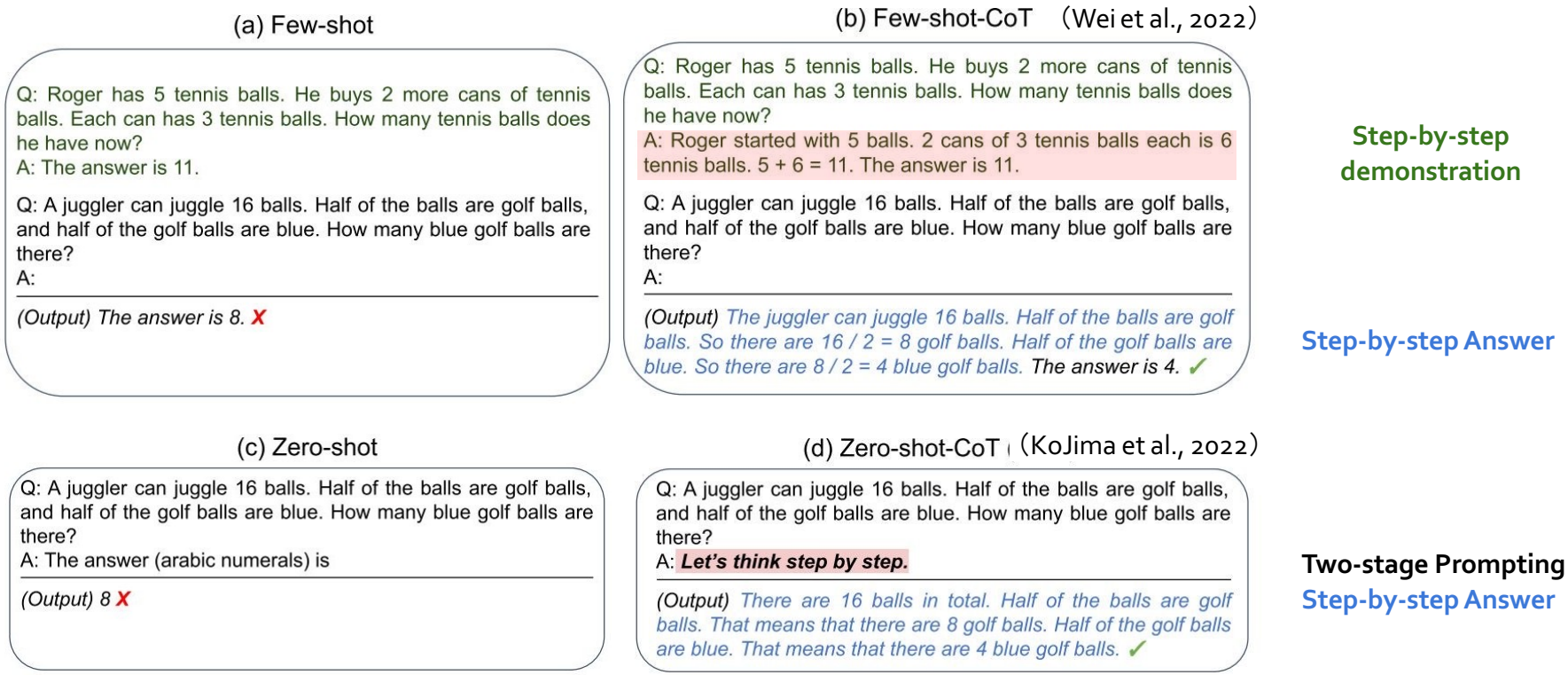
Step-by-step Answer

(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

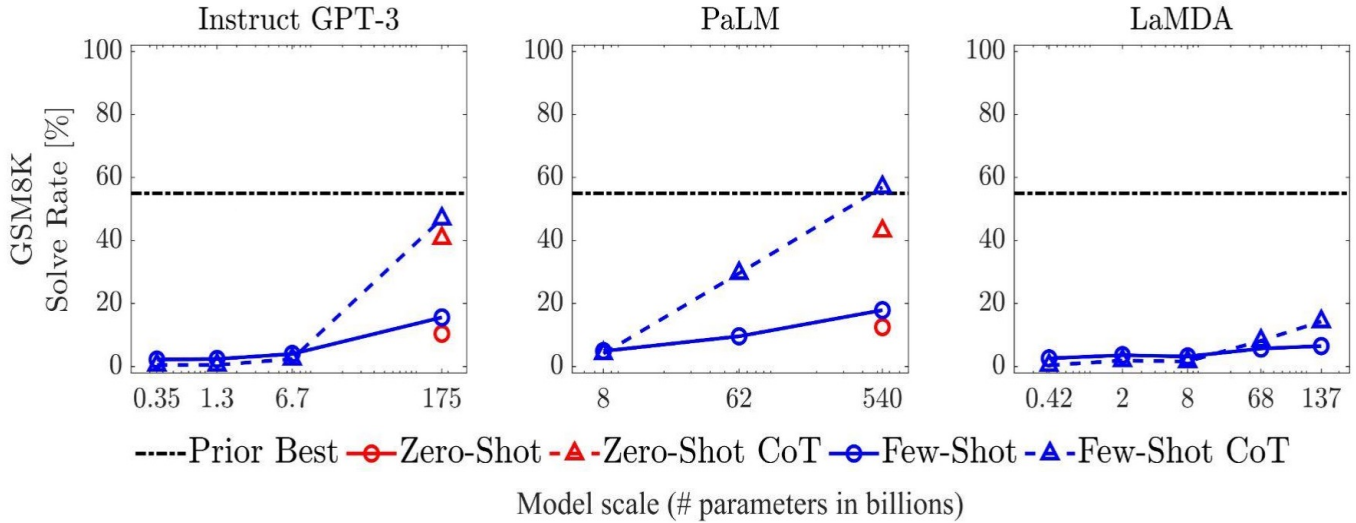
(Output) 8 ✗

Reasoning Problems via Multi-Step Prompting



Multi-Step Prompting: Empirical Results

- **Setup:** show demonstrations that contain the decompositions
- The gains of multi-step prompting increases with scale.
- Prompting achieves better perf than [smaller] models that are fine-tuned on a lot



["Chain of thought prompting elicits reasoning in large language models", Wei et al. 2022]

Multi-Step Prompting: Empirical Results

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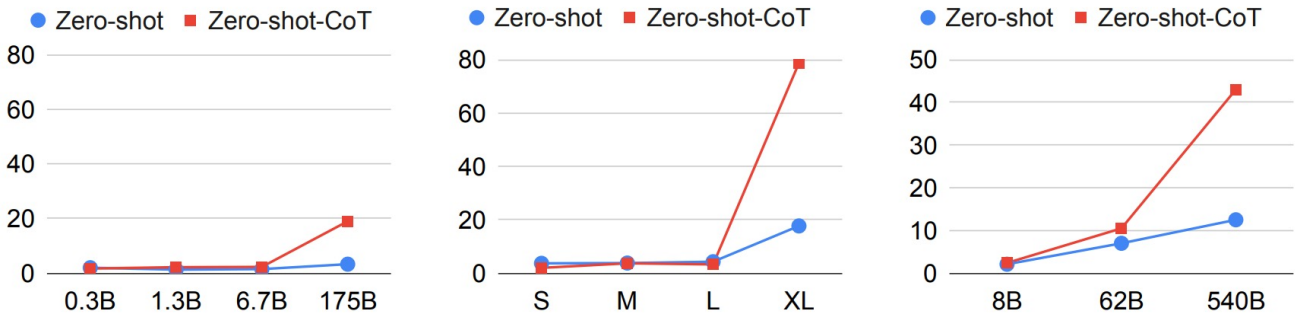


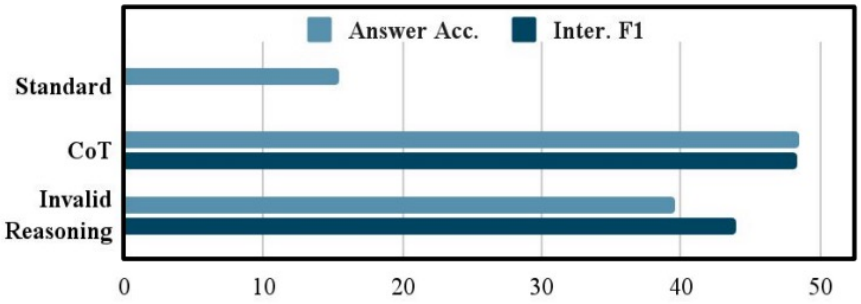
(a) MultiArith on Original GPT-3 (b) MultiArith on Instruct GPT-3 (c) GMS8K on PaLM

Figure 3: Model scale study with various types of models. S: text-ada-001, M: text-babbage-001, L: text-curie-001, XL: text-davinci-002. See Appendix A.3 and E for the detail.

["Large Language Models are Zero-Shot Reasoners", Kojima et al. 2022]

Multi-Step Prompting: Steps Don't Have to Be Correct!

- It is possible even with invalid demonstrations
- Prompting with invalid reasoning steps can ac with correct reasoning steps.



	In-context Demonstration	Inference by LLM
Query	Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?	Julie is reading a 120-page book. Yesterday, she was able to read 12 pages and today, she read twice as many pages as yesterday. If she wants to read half of the remaining pages tomorrow, how many pages should she read?
Standard	The answer is 39.	The answer is 18. ✗
CoT	Originally, Leah had 32 chocolates and her sister had 42. So in total they had 32 + 42 = 74. After eating 35, they had 74 - 35 = 39 pieces left in total. The answer is 39.	Julie is reading a 120-page book. Yesterday, she read 12 pages and today, she read 24 pages. So she read a total of 12 + 24 = 36 pages. Now she has 120 - 36 = 84 pages left. Since she wants to read half of the remaining pages, she should read 84 / 2 = 42 pages. The answer is 42. ✓
Invalid Reasoning	Originally, Leah had 32 chocolates and her sister had 42. So her sister had 42 - 32 = 10 chocolates more than Leah has. After eating 35, since 10 + 35 = 45, they had 45 - 6 = 39 pieces left in total. The answer is 39.	Yesterday, Julie read 12 pages. Today, she read 12 * 2 = 24 pages. So she read a total of 12 + 24 = 36 pages. Now she needs to read 120 - 36 = 84 more pages. She wants to read half of the remaining pages tomorrow, so she needs to read 84 / 2 = 42 pages tomorrow. The answer is 42. ✓

["Towards Understanding Chain-of-Thought Prompting", Wang et al. 2022]

Multi-Step Prompting: Parting Comments

- Prompting LMs to explain their reasoning improves their performance.
- However, their steps aren't always correct.
  - A useful repository of annotation: https://github.com/OpenBioLink/ThoughtSource

- There is much to research on here:
  - When do LMs over-reason or under-reason?
  - How do adjust the granularity of step?
  - How to use use given references in the proofs?
  - How do use external "tools" (e.g., logic, calculator, Python) in forming proofs?

Summary

- Prompting language models is a powerful way to adapt them to our desired tasks.
- They also serve as a gateway to understand the underlying dynamics inside models.
- Lots of activity in this area and room for a lot of research progress.

AI 'prompt engineer' jobs can pay up to $375,000 a year and don't always require a background in tech

Britney Nguyen May 1, 2023, 11:34 PM GMT+8

Read in app

The rise of generative AI tools like ChatGPT is creating a hot market for "prompt engineers" who test and improve chatbot answers. Getty Images