

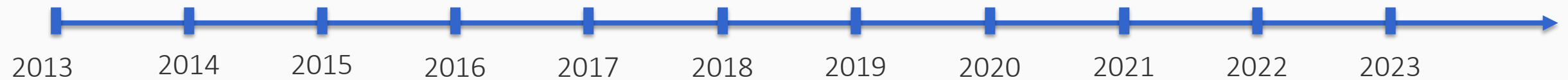
Prompting and in-context learning



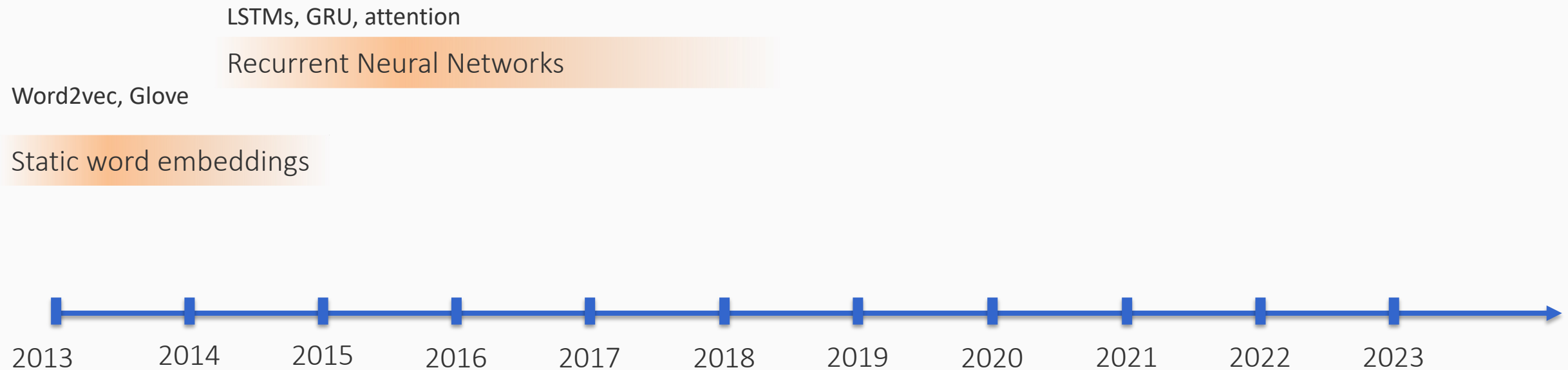
Where are we?

Word2vec, Glove

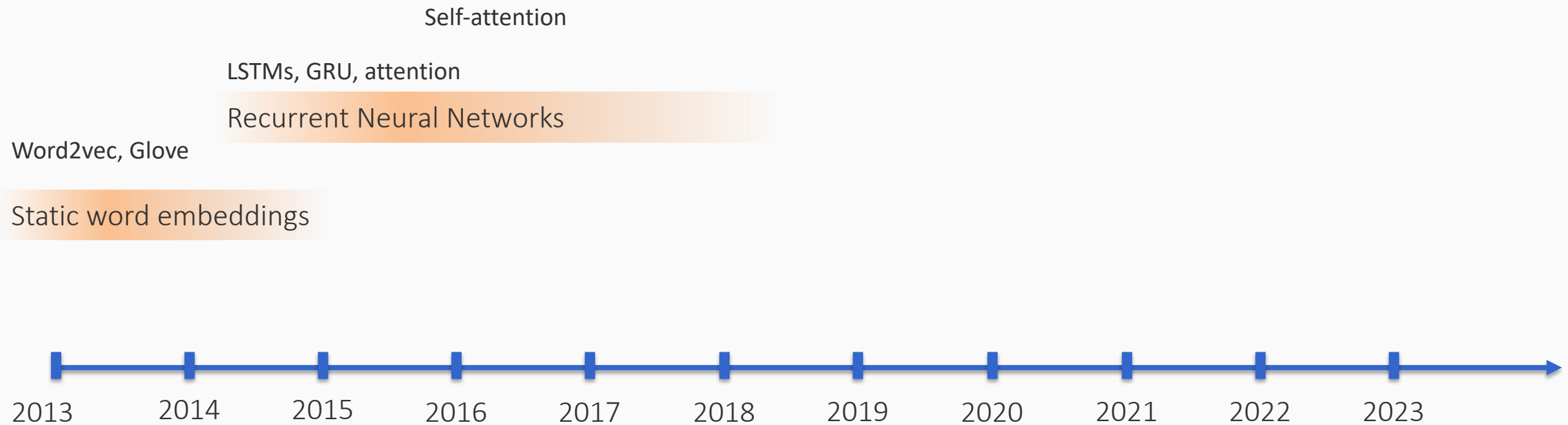
Static word embeddings



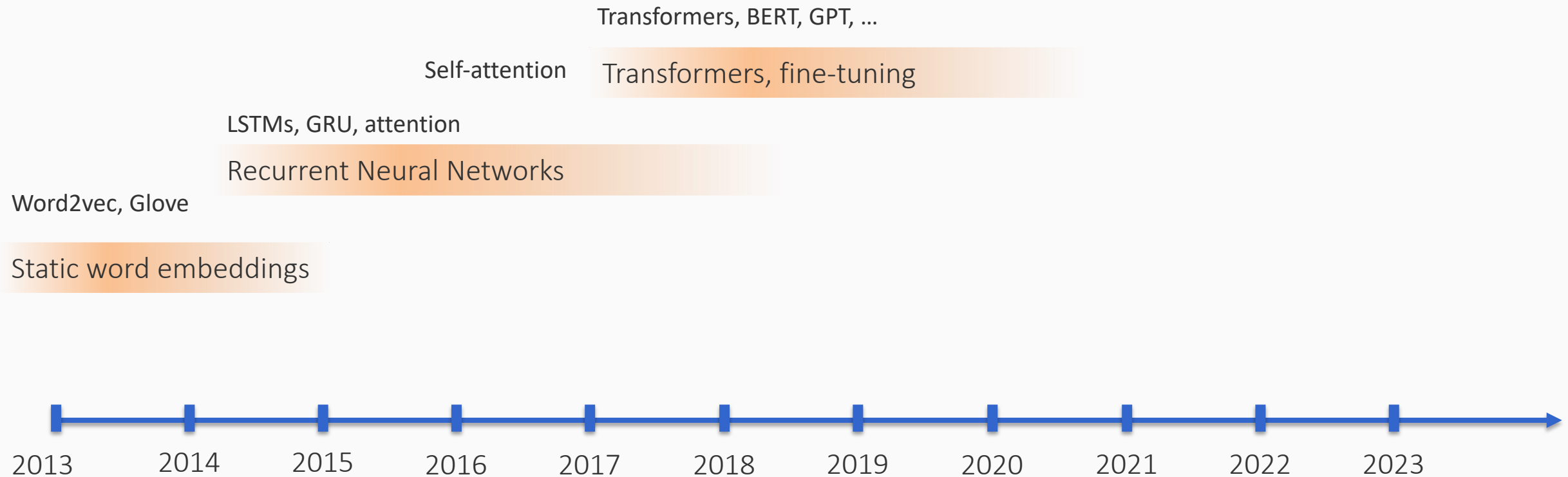
Where are we?



Where are we?



Where are we?



The BERT-flavored model: A recipe

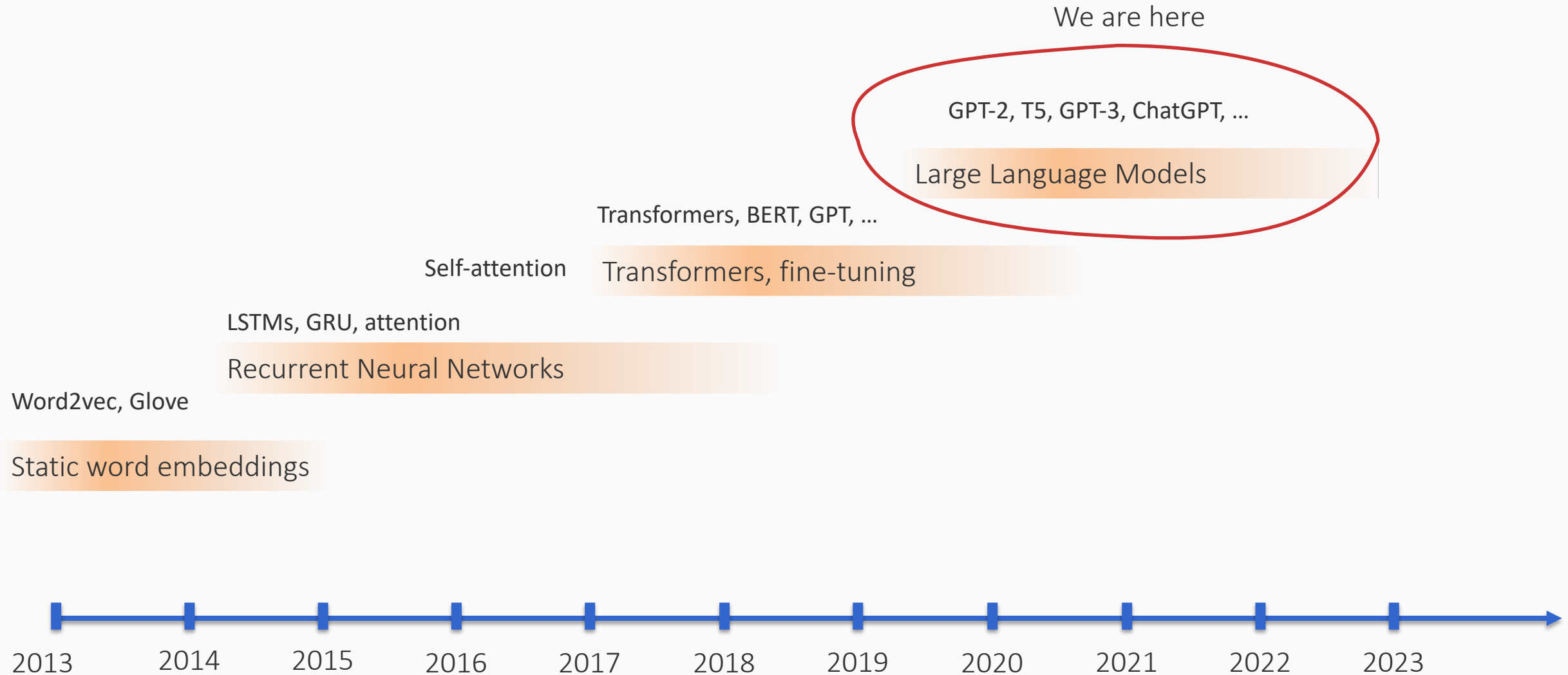
1. Start with a pre-trained transformer
2. Collect a dataset for your task
3. Fine-tune the pre-trained transformer for your model

Does this recipe always work?

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

- No one

Where are we?



This lecture

- Zero- and few-shot prediction
- Prompting language models a.k.a. in-context learning
- Does prompting work?

This lecture

- Zero- and few-shot prediction
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We tend to be really good at zero-shot predictions

The movie was a two hour masterclass

Positive?

Negative?

We tend to be really good at zero-shot predictions

The movie was a two hour masterclass

Positive? ✓

Negative?

We tend to be really good at zero-shot predictions

The movie was a two hour masterclass

Positive? ✓

Negative?

This movie doesn't scrape the bottom of the barrel. This movie isn't the bottom of the barrel. This movie isn't below the bottom of the barrel. This movie doesn't deserve to be mentioned in the same sentence with barrels.

Positive?

Negative?

(from Roger Ebert's review of "Freddie Got Fingered")

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Positive?

Negative? ✓

(from Roger Ebert's hilariously negative review of "Freddie Got Fingered")

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This movie doesn't scrape the bottom of the barrel. This movie isn't the bottom of the barrel. This movie isn't below the bottom of the barrel. This movie doesn't deserve to be mentioned in the same sentence with barrels.

Positive?

Negative? ✓

(from Roger Ebert's hilariously negative review of "Freddie Got Fingered")

How were you able to predict the label?

Did you have access to a labeled sentiment dataset? Did you train yourself on the data?

What can you do without large (or any) training datasets?

Answer: Few- or Zero-shot learning

Learning to perform a task with minimal task description, and perhaps a small number of examples (~10)

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Why is this interesting?

What can you do without large (or any) training datasets?

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Learning to perform a task with minimal task description, and perhaps a small number of examples (~10)

Why is this interesting?

Practically useful

- Labeling data costs money and takes expertise
- Fine-tuning models is computationally expensive

What can you do without large (or any) training datasets?

Answer: Few- or Zero-shot learning

Learning to perform a task with minimal task description, and perhaps a small number of examples (~10)

Why is this interesting?

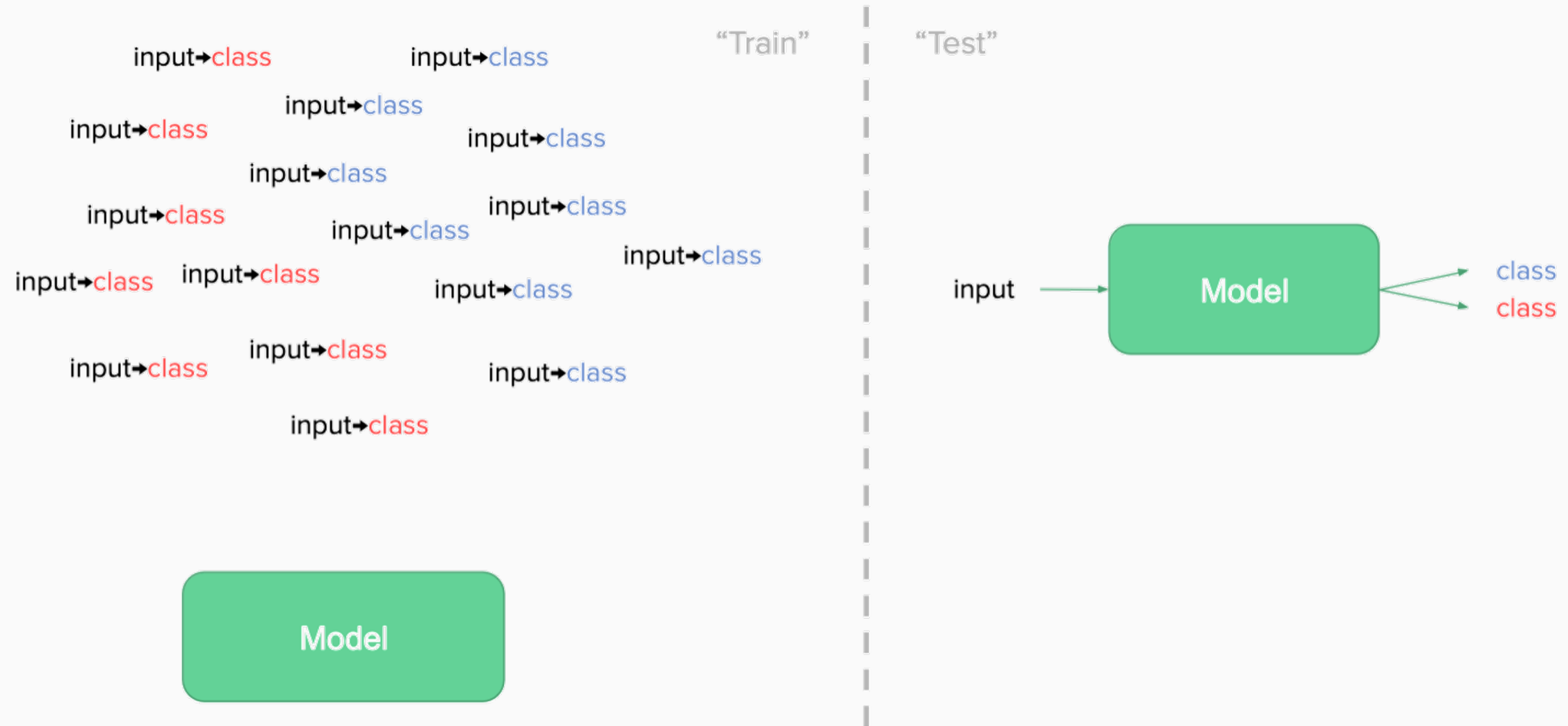
Practically useful

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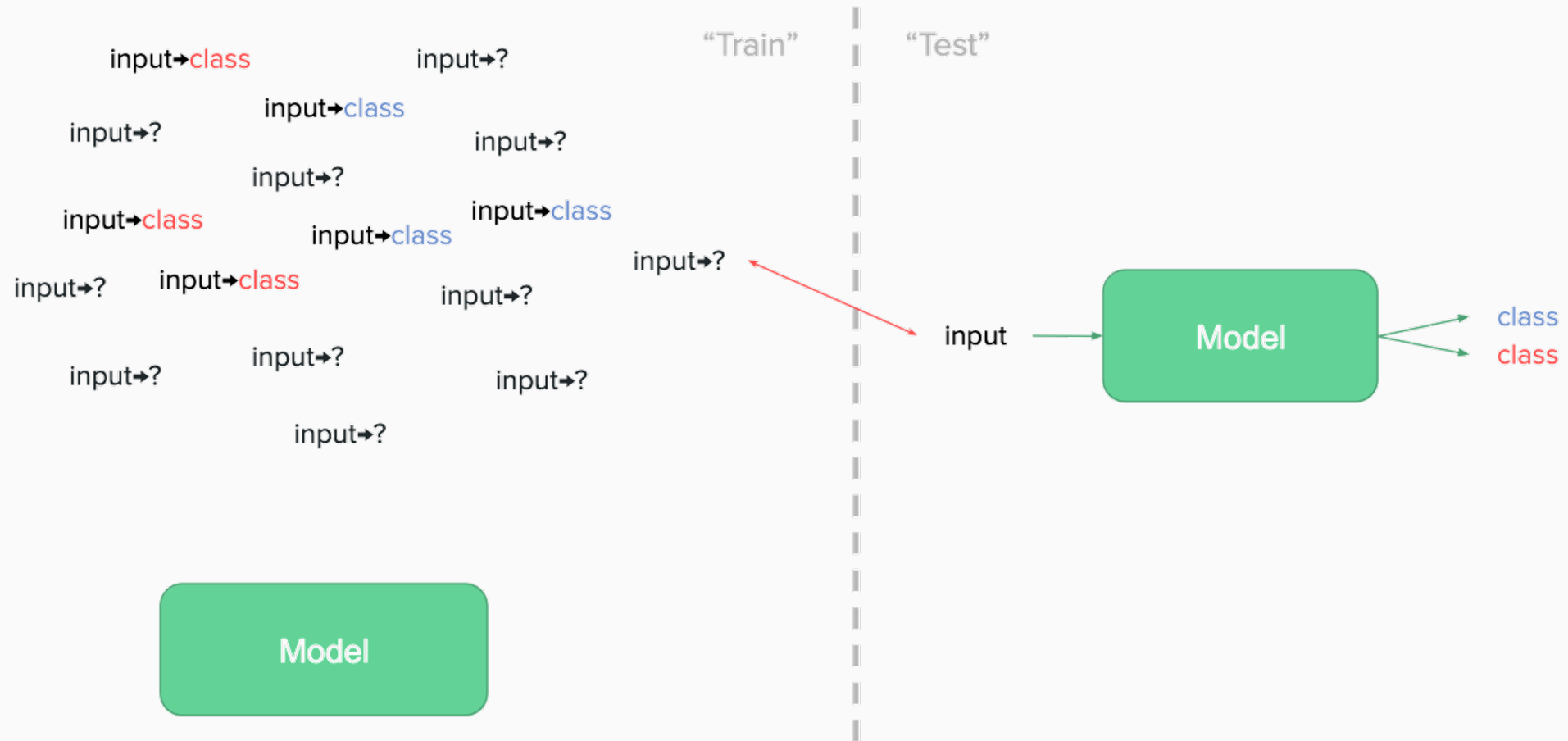
Scientifically interesting

- Generalizing correctly from a small number of examples is a good test of intelligence
- Provides insights into what models encode

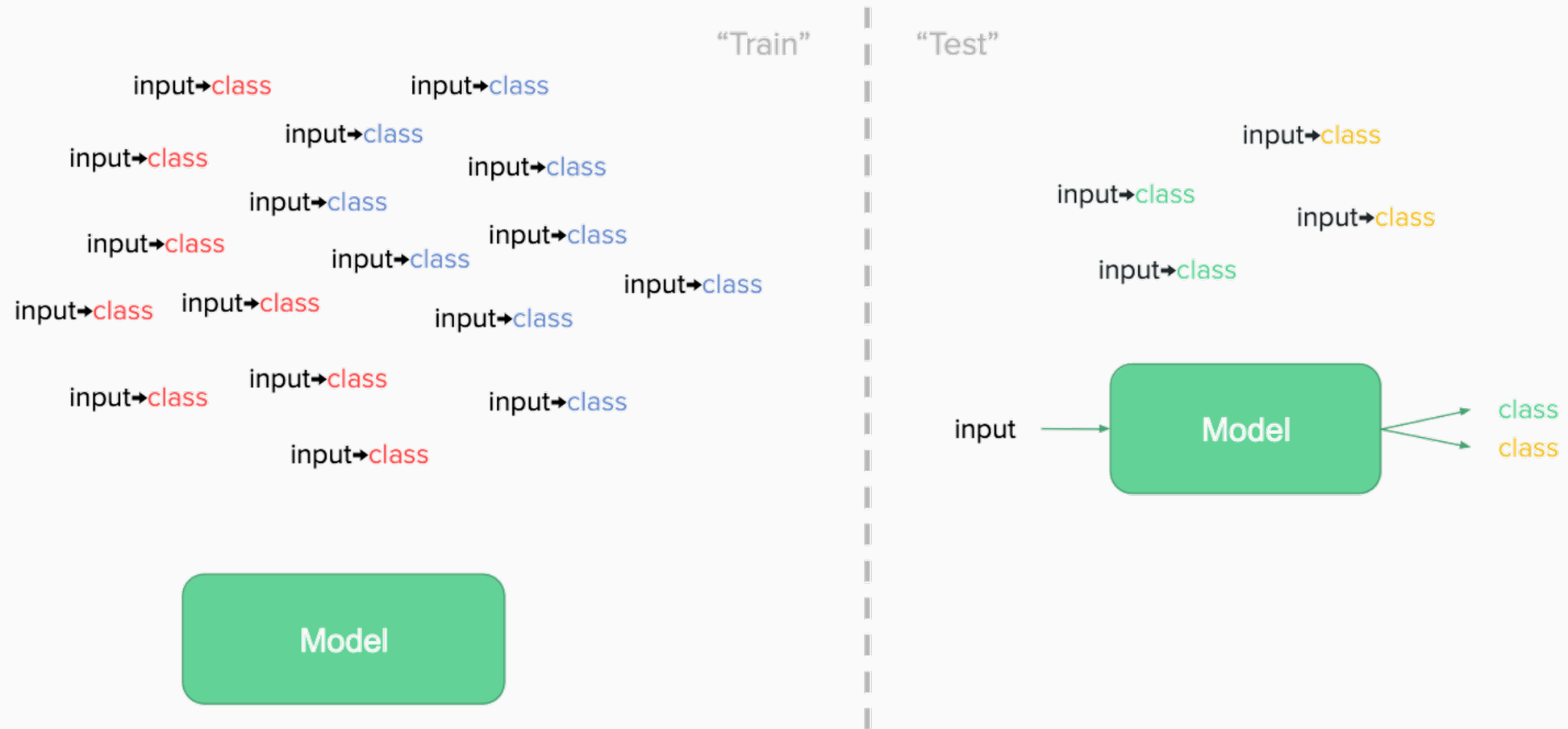
Supervised learning



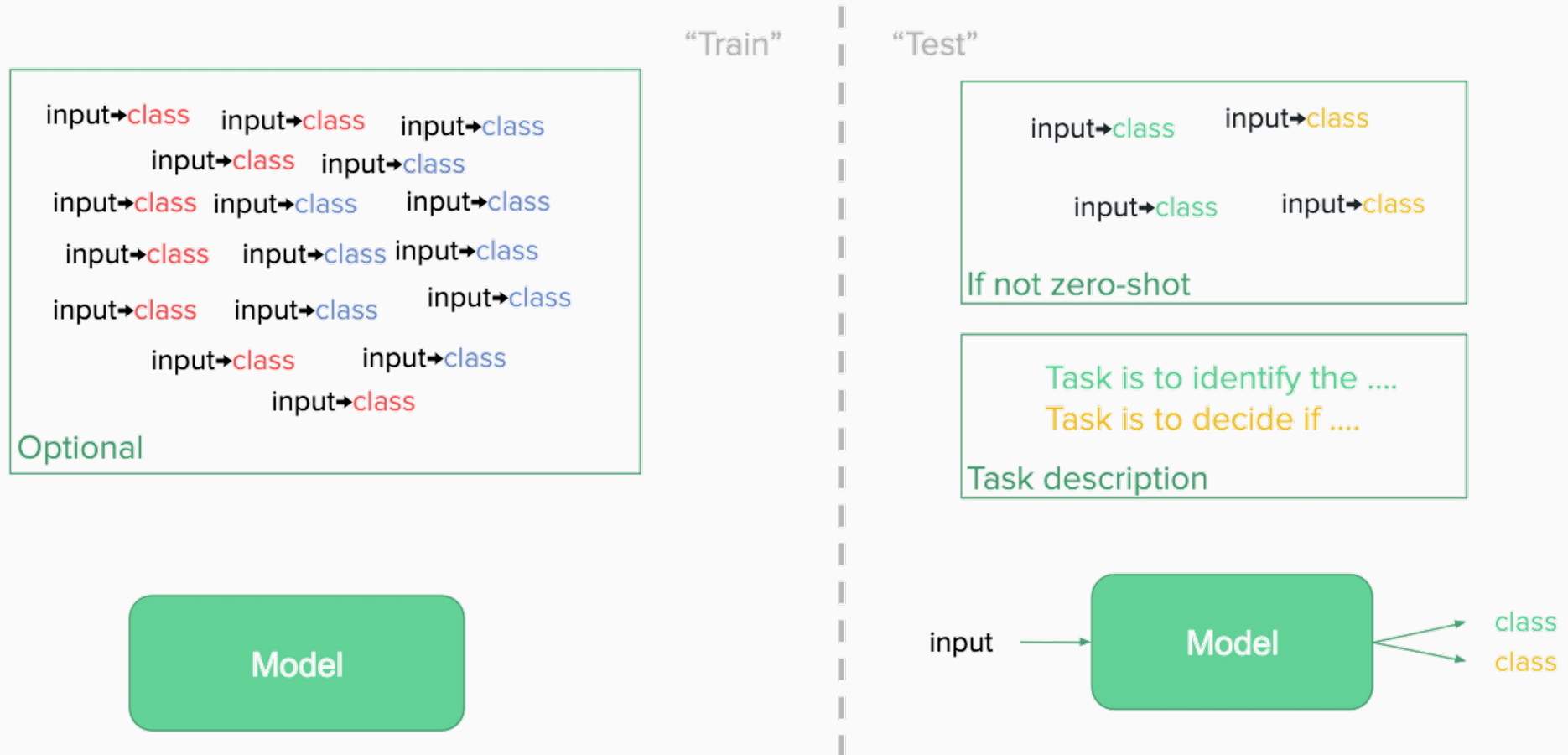
Semi-supervised learning



Few-shot learning (before LLMs)



Modern few-shot learning



This lecture

- Zero- and few-shot prediction
- Prompting language models a.k.a. in-context learning
- Does prompting work?

Zero- and Few-shot predictions with a language model

Zero-shot

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



Zero- and Few-shot predictions with a language model

Zero-shot

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



One-shot

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



Zero- and Few-shot predictions with a language model

Zero-shot

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



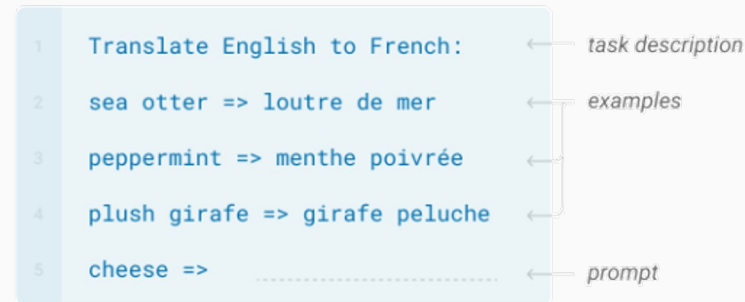
One-shot

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

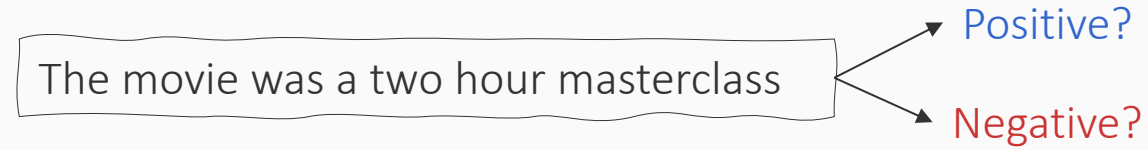


Few-shot

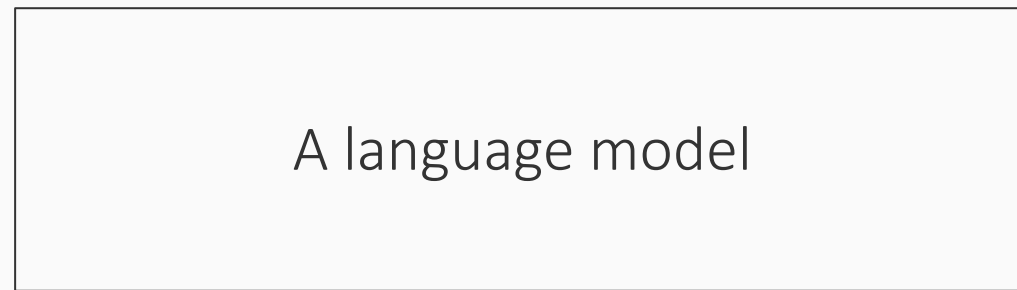
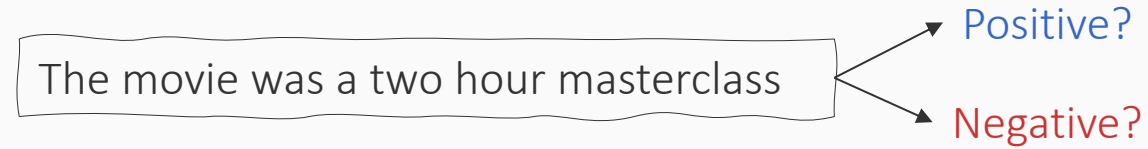
In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.



A concrete example: Sentiment classification



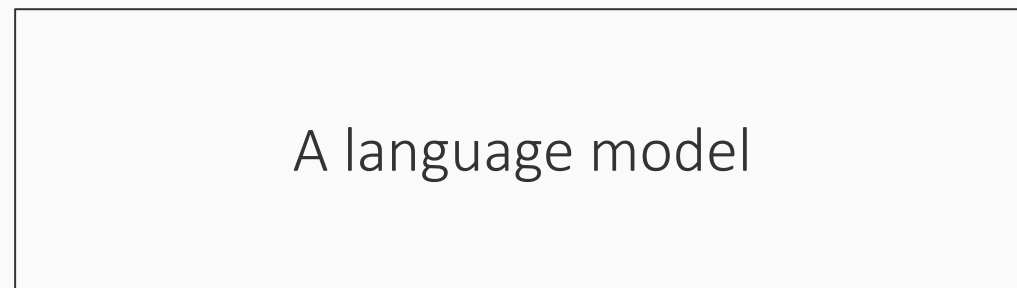
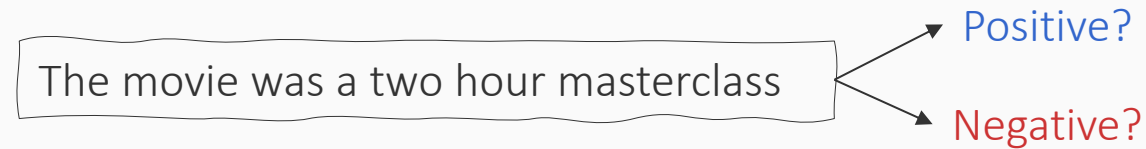
A concrete example: Sentiment classification



The movie was a two hour masterclass. It was

↑

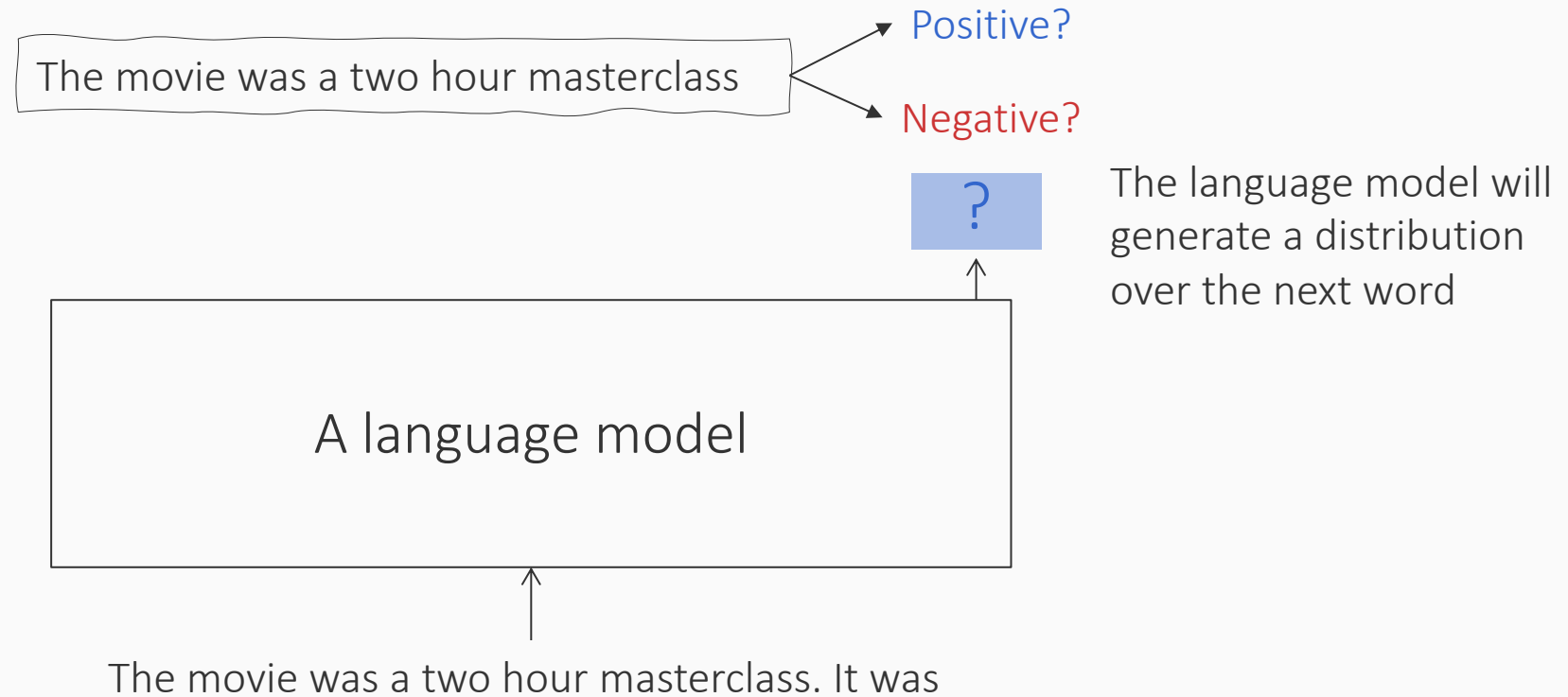
A concrete example: Sentiment classification



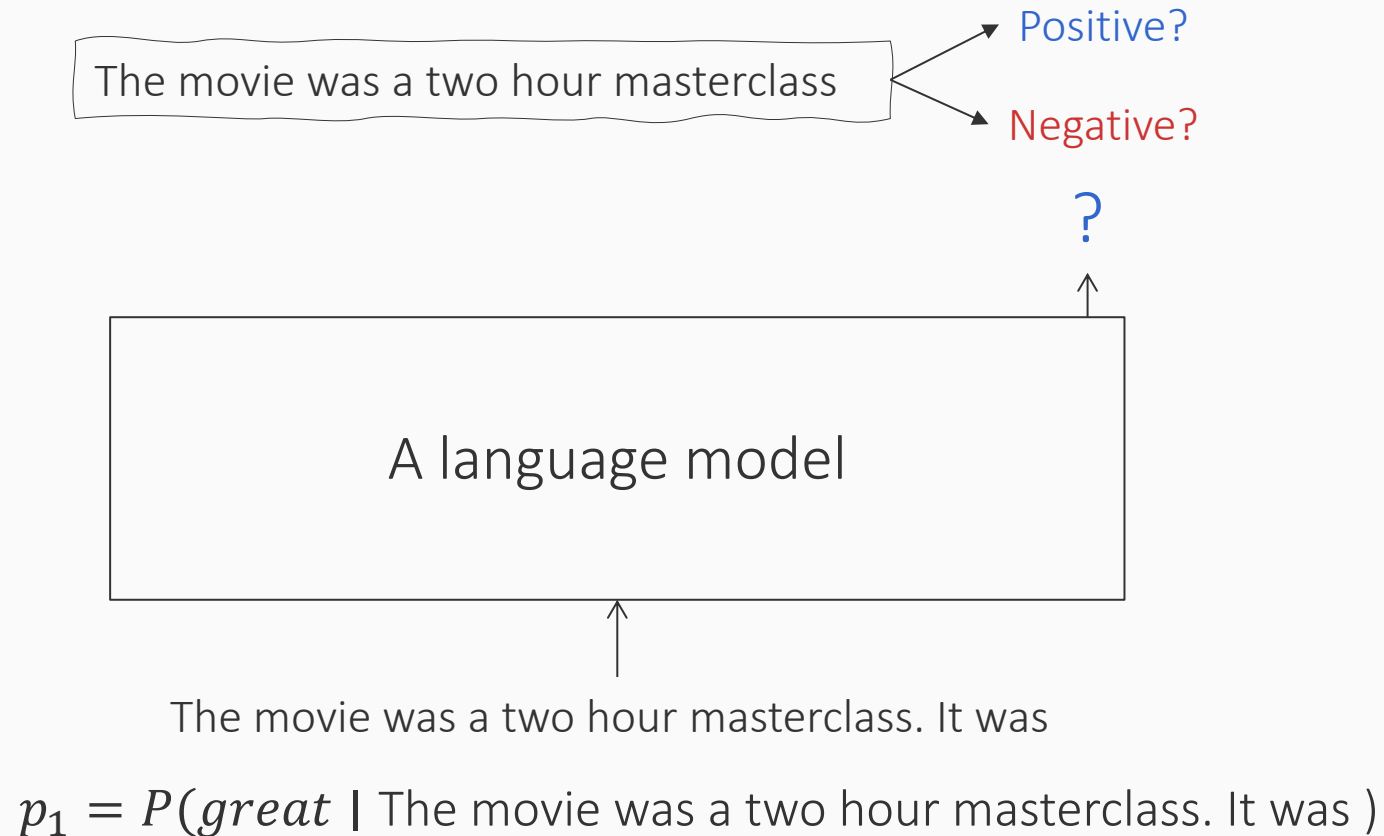
The movie was a two hour masterclass. It was

This part was not part of the original input. We add it to make the language model behave in ways that we would like.

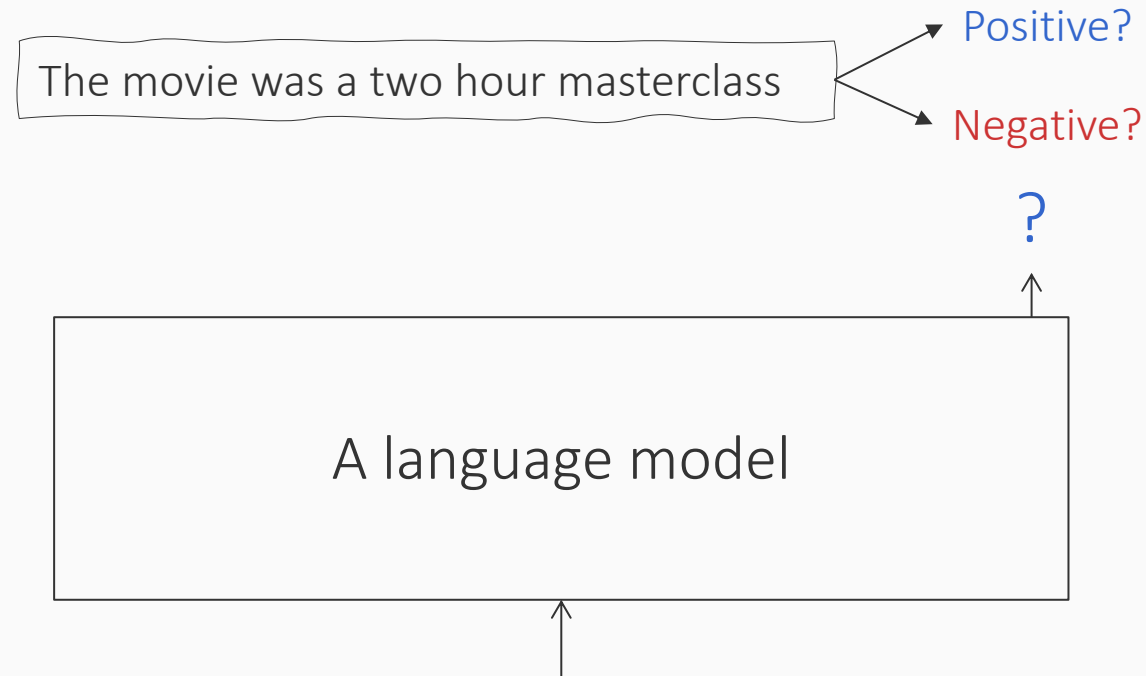
A concrete example: Sentiment classification



A concrete example: Sentiment classification



A concrete example: Sentiment classification

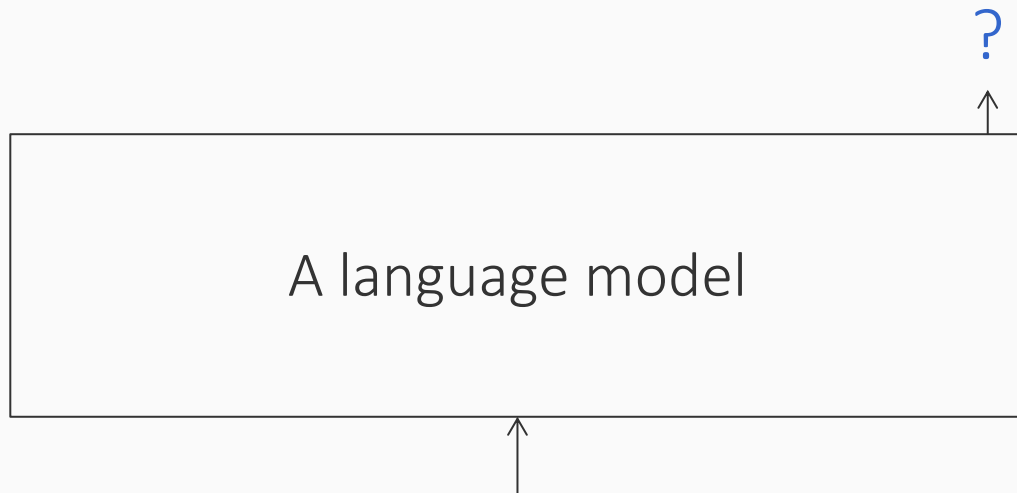
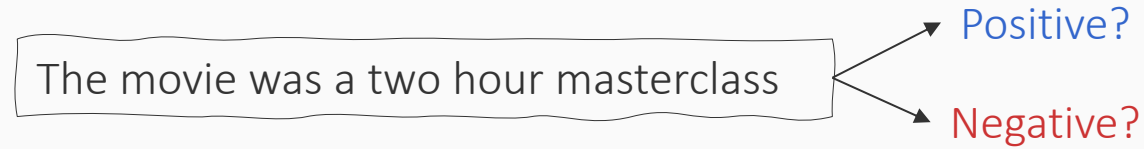


The movie was a two hour masterclass. It was

$$p_1 = P(\textit{great} \mid \text{The movie was a two hour masterclass. It was})$$

$$p_2 = P(\textit{terrible} \mid \text{The movie was a two hour masterclass. It was})$$

In the few-shot setting: Sentiment classification



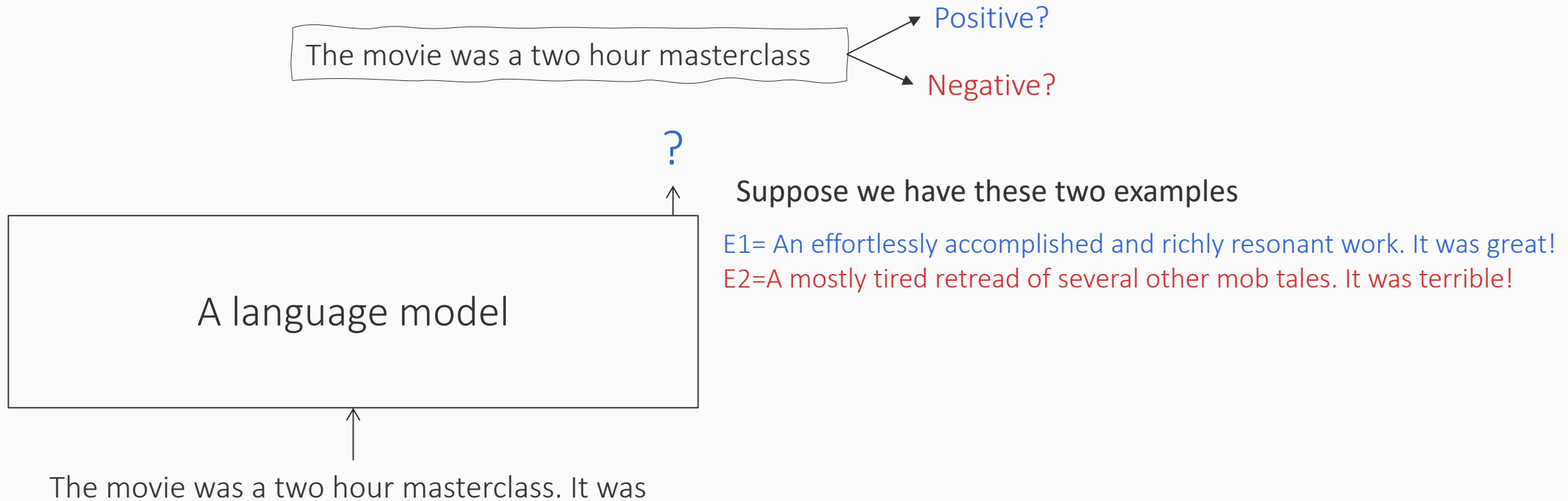
The movie was a two hour masterclass. It was

Suppose we have these two examples

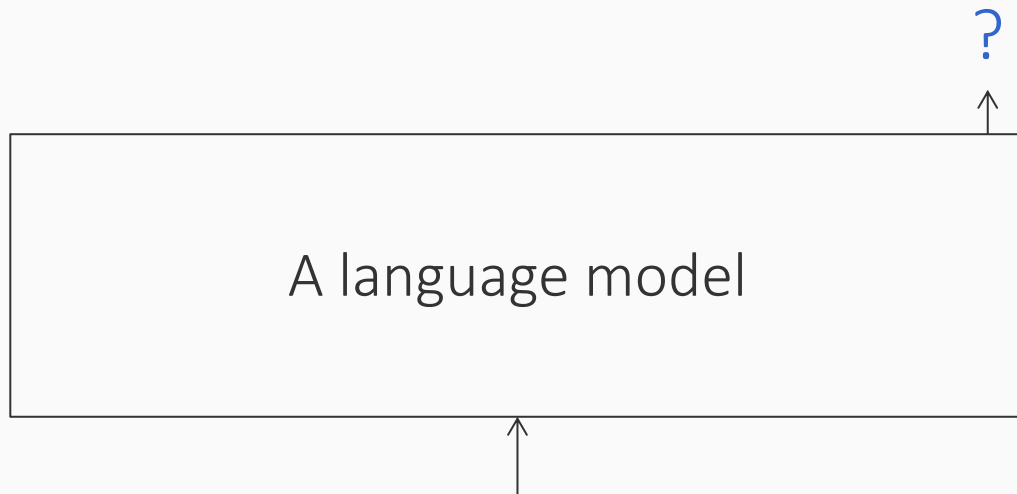
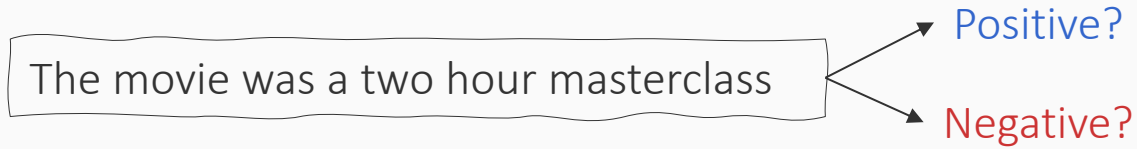
An effortlessly accomplished and richly resonant work. It was great!

A mostly tired retread of several other mob tales. It was terrible!

In the few-shot setting: Sentiment classification



In the few-shot setting: Sentiment classification



Suppose we have these two examples

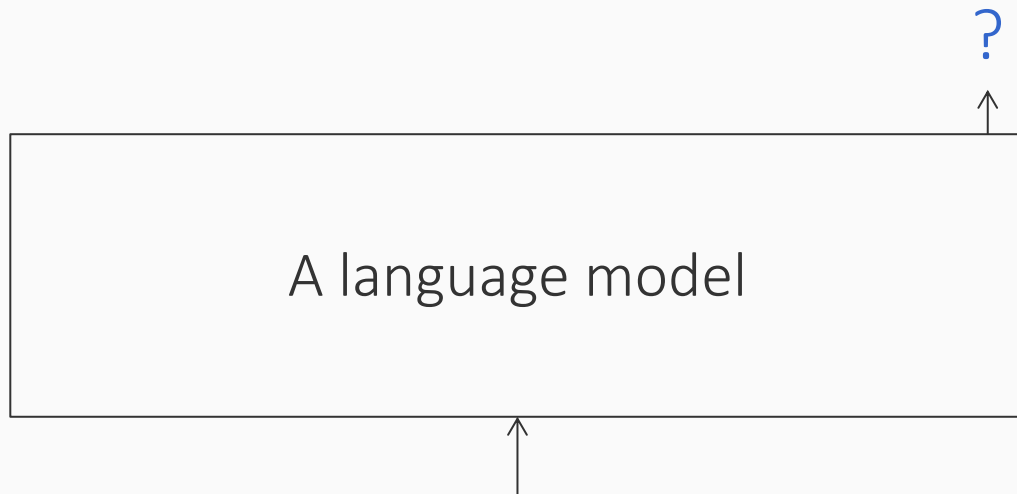
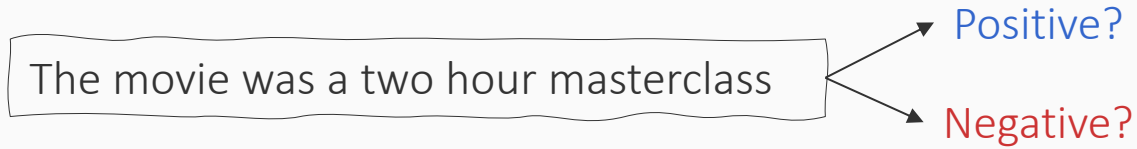
E1= An effortlessly accomplished and richly resonant work. It was great!

E2=A mostly tired retread of several other mob tales. It was terrible!

E1 [SEP] E2 [SEP] The movie was a two hour masterclass. It was

$$p_1 = P(\textit{great} \mid \text{E1 [SEP] E2 [SEP] The movie was a two hour masterclass. It was})$$

In the few-shot setting: Sentiment classification



Suppose we have these two examples

E1= An effortlessly accomplished and richly resonant work. It was great!

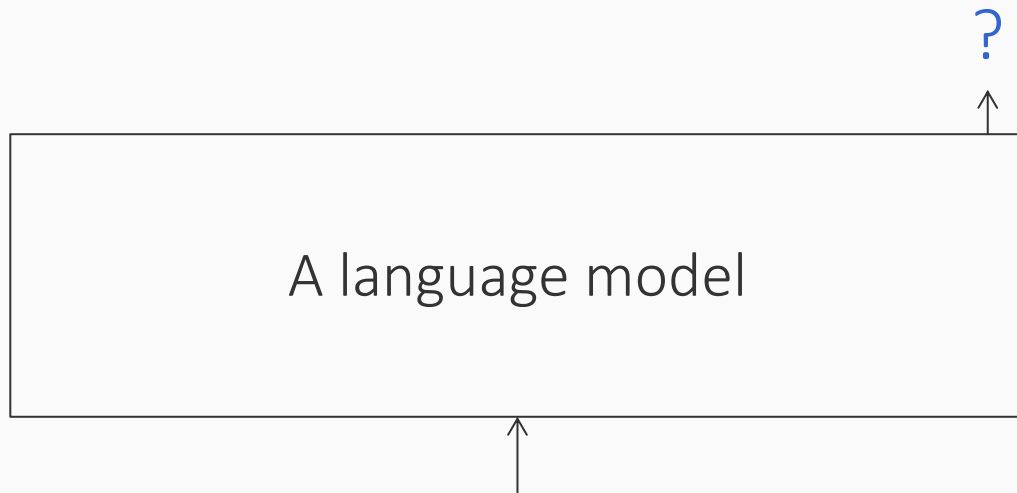
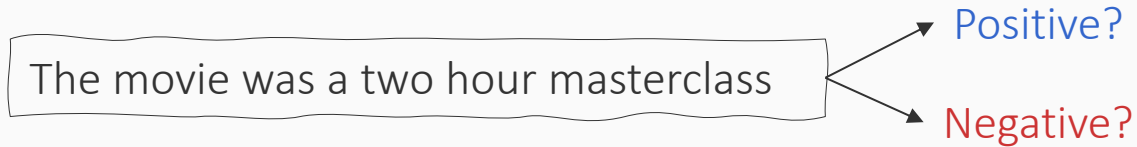
E2=A mostly tired retread of several other mob tales. It was terrible!

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$$p_1 = P(\textit{great} \mid \text{E1 [SEP] E2 [SEP] The movie was a two hour masterclass. It was})$$

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In the few-shot setting: Sentiment classification



Suppose we have these two examples

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If $p_1 > p_2$ then label = Positive otherwise label = Negative

In the few-shot setting: Sentiment classification

The movie was a two hour masterclass

Positive?

Negative?

ork. It was great!
was terrible!

Why might this idea have any hope of working?

E1 [SEP] E2 [SEP]

$p_1 =$
 $p_2 =$

If $p_1 > p_2$ then label = **Positive** otherwise label = **Negative**

This has been the subject of much research discussion

- Demonstrations do not teach a new task; instead, it is about locating an already-learned task during pretraining (Reynolds & McDonell, 2021)
- LMs do not exactly understand the meaning of their prompt (Webson & Pavlick, 2021)
- Demonstrations are about providing a latent concept so that LM generates coherent next tokens (Xie et al. 2022)
- In-context learning performance is highly correlated with term frequencies during pretraining (Razeghi et al. 2022)
- LMs do not need input-label mapping in demonstrations, instead, it uses the specification of the input & label distribution separately (Min et al. 2022)
- Data properties lead to the emergence of few-shot learning (burstiness, long-tailedness, many-to-one or one-to-many mappings, a Zipfian distribution) (Chan et al. 2022)

Prompting language models: Some terminology

An effortlessly accomplished and richly resonant work. It was great!
A mostly tired retread of several other mob tales. It was terrible!
A movie was a two hour masterclass. It was _____!

Prompting language models: Some terminology

Prompt: A conditioning text coming before the test input

Demonstrations: A special instance of prompt which is a concatenation of the k-shot training data (in in-context learning, prompt==demonstrations)

An effortlessly accomplished and richly resonant work. It was great!
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Prompting language models: Some terminology

Prompt: A conditioning text coming before the test input

Demonstrations: A special instance of prompt which is a concatenation of the k-shot training data (in in-context learning, prompt==demonstrations)

Pattern: A function that maps an input to the text (a.k.a. template)

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Prompting language models: Some terminology

Prompt: A conditioning text coming before the test input

Demonstrations: A special instance of prompt which is a concatenation of the k-shot training data (in in-context learning, prompt==demonstrations)

Pattern: A function that maps an input to the text (a.k.a. template)

Verbalizer: A function that maps a label to the text (a.k.a. label words)

An effortlessly accomplished and richly resonant work. **It was great!**

A mostly tired retread of several other mob tales. **It was terrible!**

A movie was a two hour masterclass. **It was _____!**

Examples of patterns and verbalizers

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 great!

Pattern: $f(\langle x \rangle) = \langle x \rangle$

Verbalizer: $v(\text{"positive"}) = \text{"It was great!"}$, $f(\text{"negative"}) = \text{"It was terrible!"}$

Examples of patterns and verbalizers

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 great!

Pattern: $f(\langle x \rangle) = \langle x \rangle$

Verbalizer: $v(\text{"positive"}) = \text{"It was great!"}$, $v(\text{"negative"}) = \text{"It was terrible!"}$

Review: An effortlessly accomplished and richly resonant work.	Sentiment: positive
Review: A mostly tired retread of several other mob tales.	Sentiment: negative
Review: A three-hour cinema master class.	Sentiment: positive

Pattern: $f(\langle x \rangle) = \text{"Review: } \langle x \rangle \text{"}$

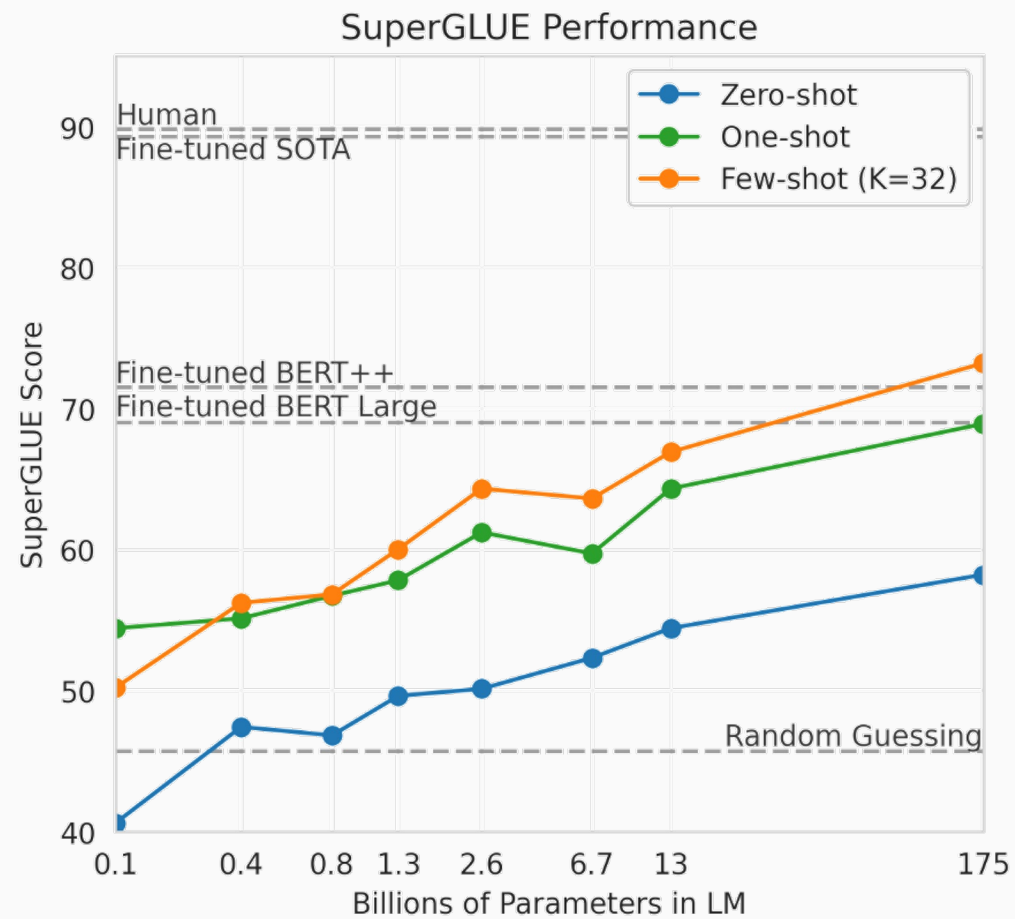
Verbalizer: $v(\langle x \rangle) = \text{"Sentiment: } \langle x \rangle \text{"}$

Practical notes

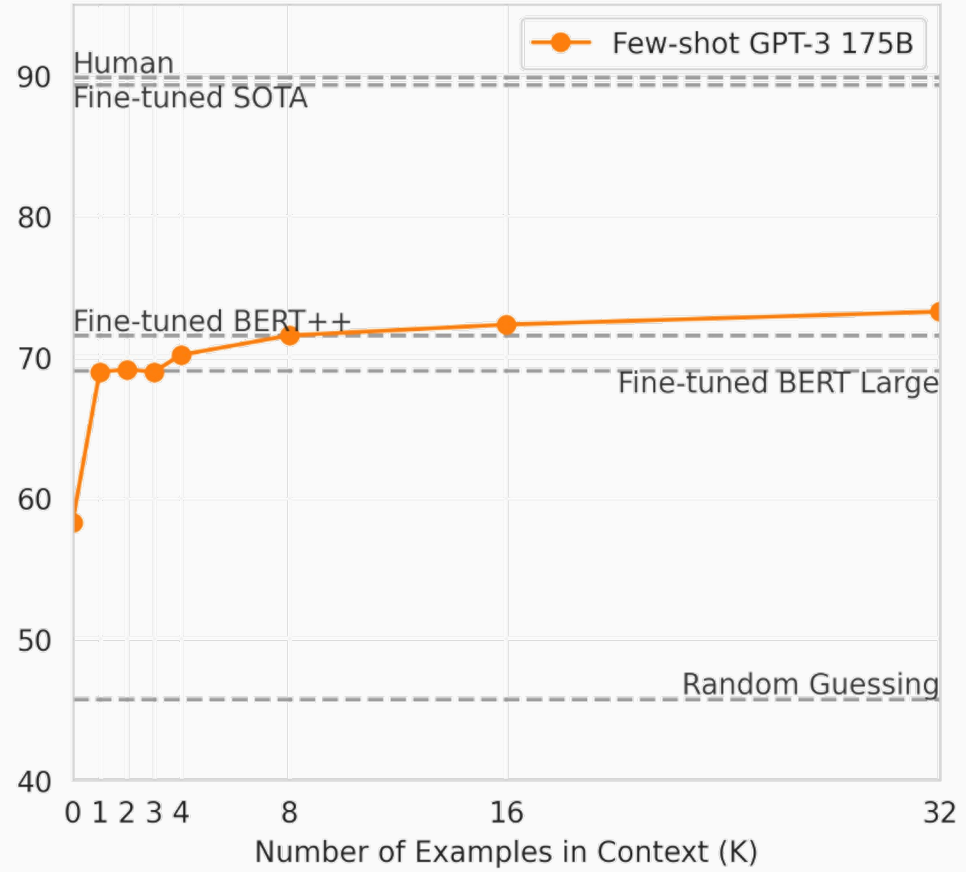
- There are many different possible patterns/verbalizers even for the same task.
- In practice, it is better to use patterns/verbalizers that makes the sequence closer to language modeling, i.e. closer to the text that the model might have seen during pretraining.
- It turns out there is huge variance in performance based on the choice of patterns/verbalizers (more in the next slide).
- You should not choose patterns/verbalizers based on the test data

This lecture

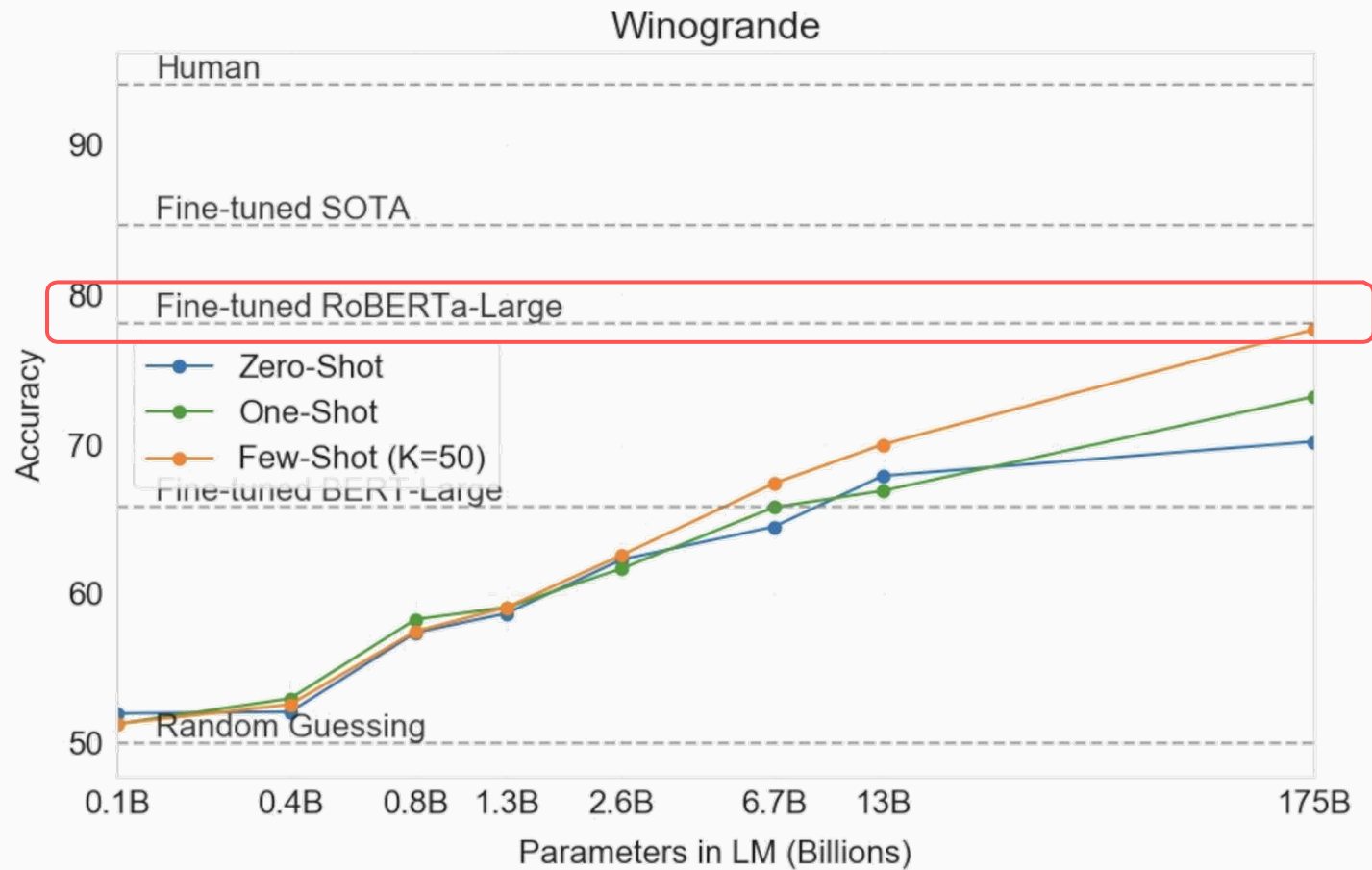
- Zero- and few-shot prediction
- Prompting language models a.k.a. in-context learning
- Does prompting work?



In-Context Learning on SuperGLUE



In-context learning results



✓ 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**

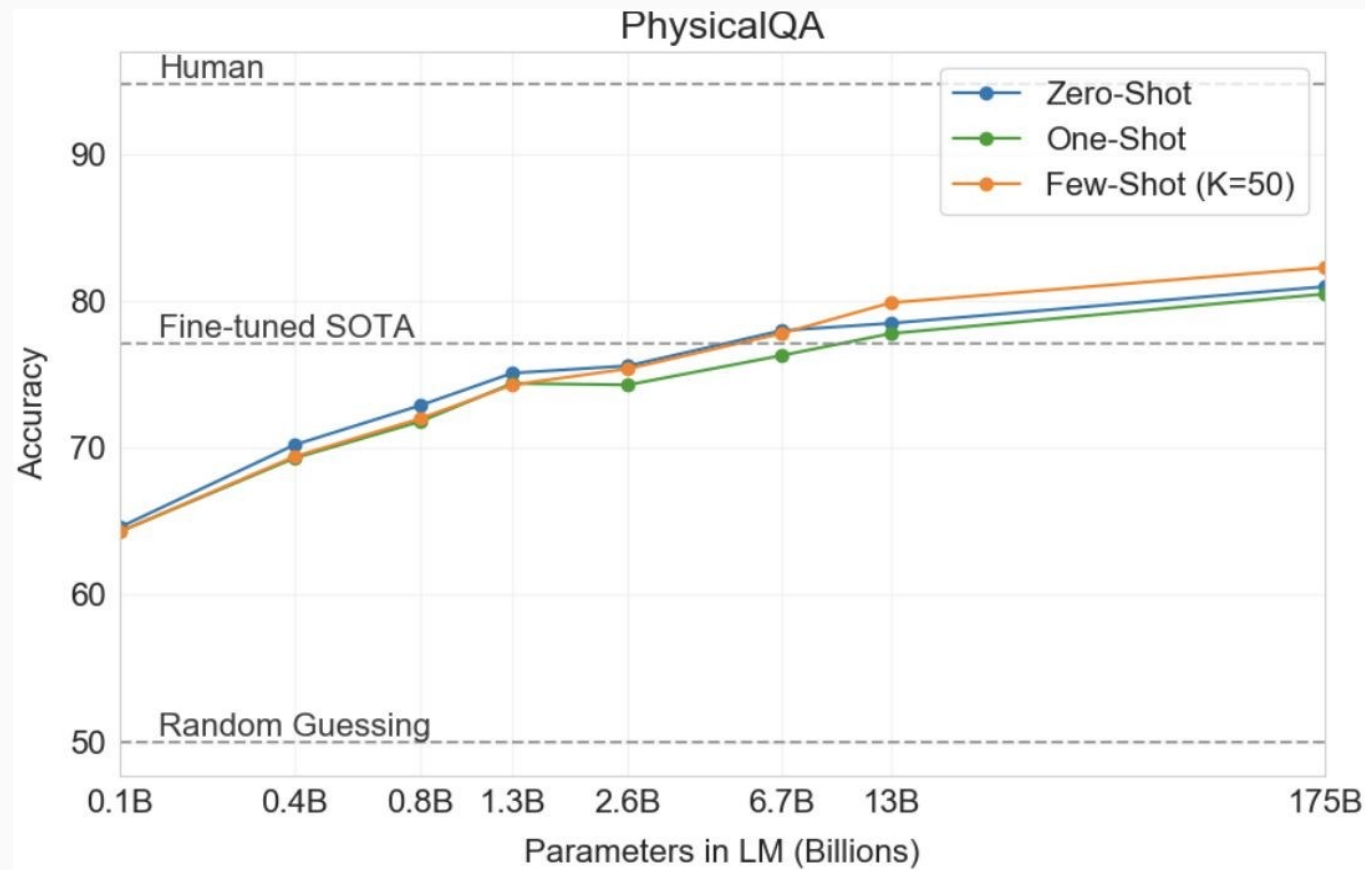
In-context learning results



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.



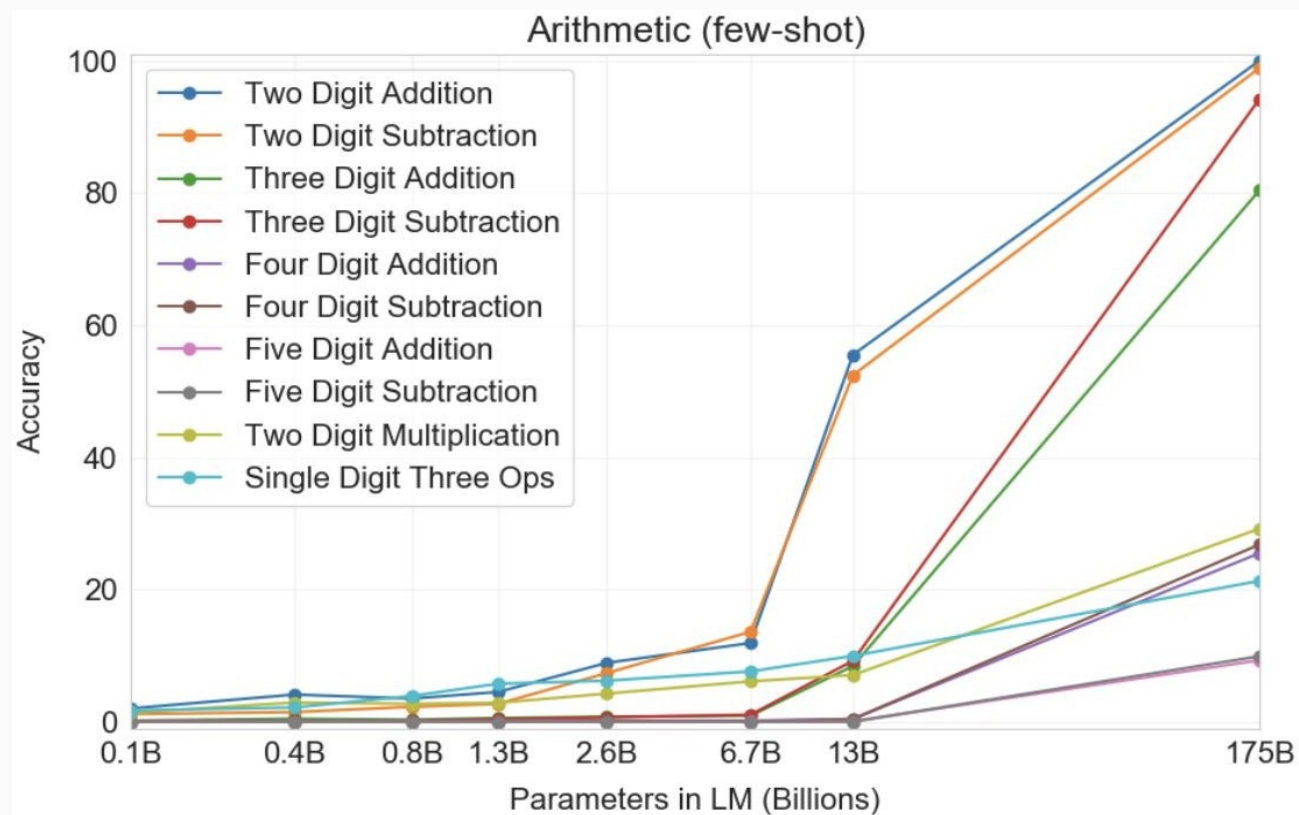
In-context learning results

Example:

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

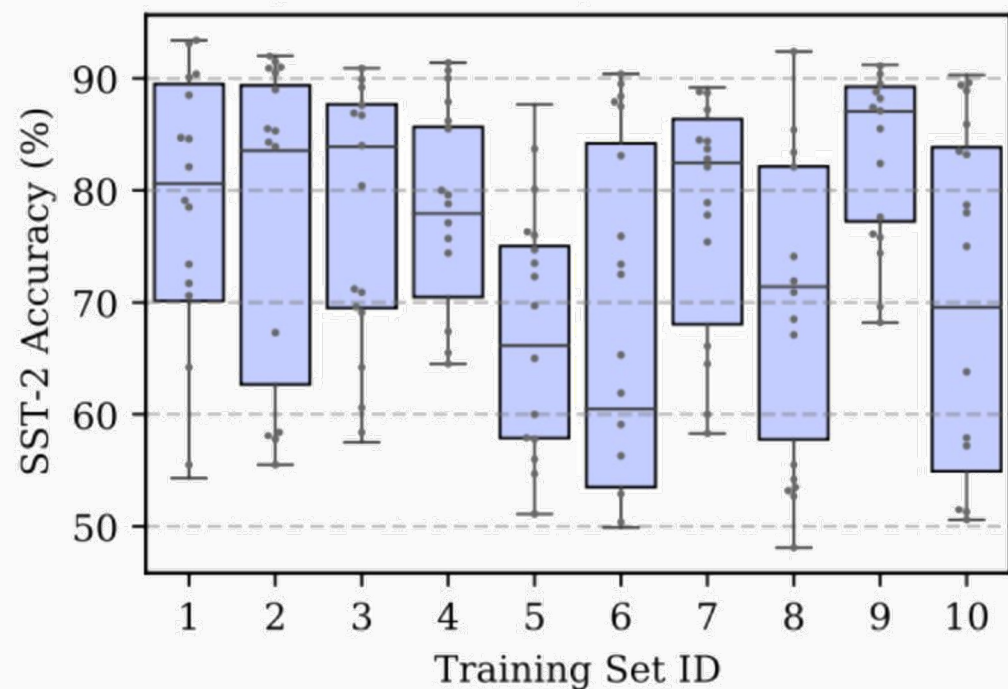
Observations:

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

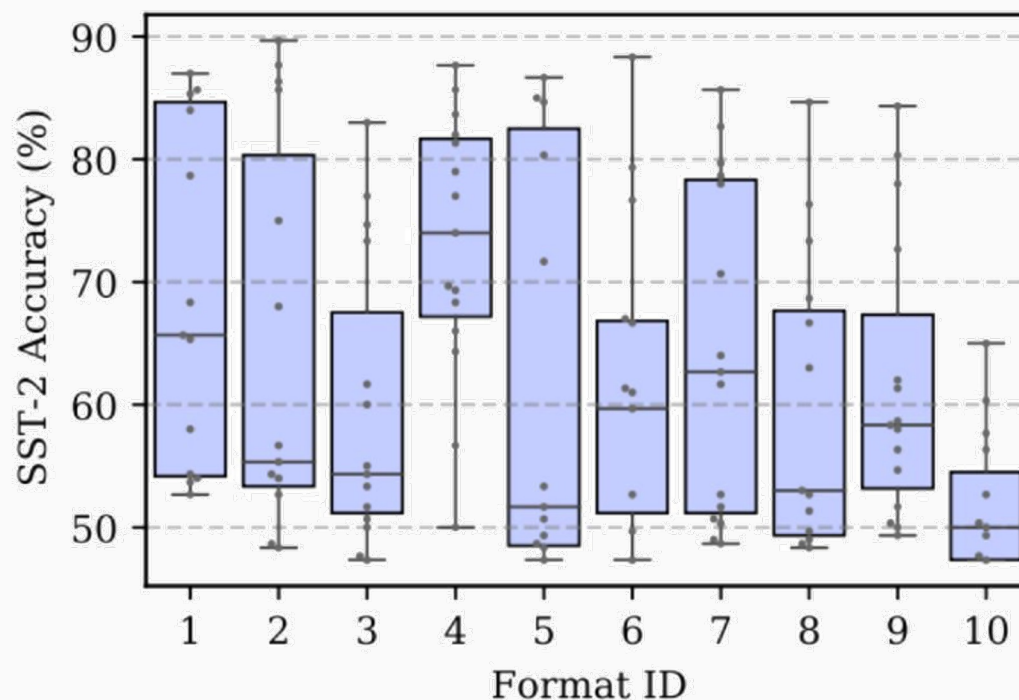


Variance across design choices

Across different training sets and permutations



Across different training sets and patterns/verbalizers



The Phases of Our Understanding

“Language modeling is a useful **subtask** for many NLP tasks”
– pre-2018

“Language modeling is a useful **supertask** for many NLP tasks”
– post-2018

Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing

Pengfei Liu

Carnegie Mellon University
pliu3@cs.cmu.edu

Weizhe Yuan

Carnegie Mellon University
weizhey@cs.cmu.edu

Jinlan Fu

National University of Singapore
jinlanjonna@gmail.com

Zhengbao Jiang

Carnegie Mellon University
zhengbaj@cs.cmu.edu

Hiroaki Hayashi

Carnegie Mellon University
hiroakih@cs.cmu.edu

Graham Neubig

Carnegie Mellon University
gneubig@cs.cmu.edu

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