CS 577: NATURAL LANGUAGE PROCESSING

Abulhair Saparov

Lecture 9: Prompting

CONSEQUENCES OF SCALING

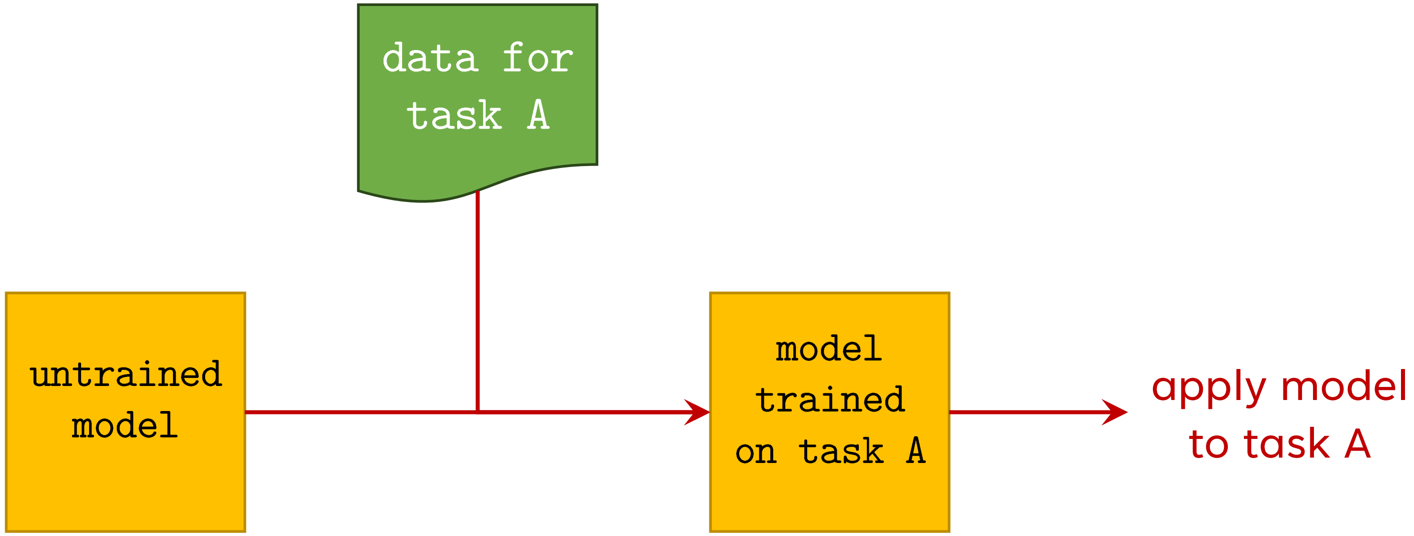
- NLP models are scaled along multiple dimensions simultaneously:
  - Model complexity (number of parameters)
  - Dataset size
  - Training time (i.e., compute)
- We observed from scaling laws that all three must be increased simultaneously.
- Otherwise, if one variable is too small, the model would not benefit from increasing values of the other two variables.
- But what are the consequences of scaling?

CONSEQUENCES OF SCALING

- As the training data size increases (e.g., for language modeling), its coverage and generality increases.
  - The data encompasses more and more diverse kinds of language, tasks, domains, etc.
- Thus, models trained on larger training sets are more likely to be able to perform a broader variety of tasks.
- This, combined with the fact that cross-entropy loss decreases with increasing scale suggests that larger models will learn to perform those tasks more accurately.

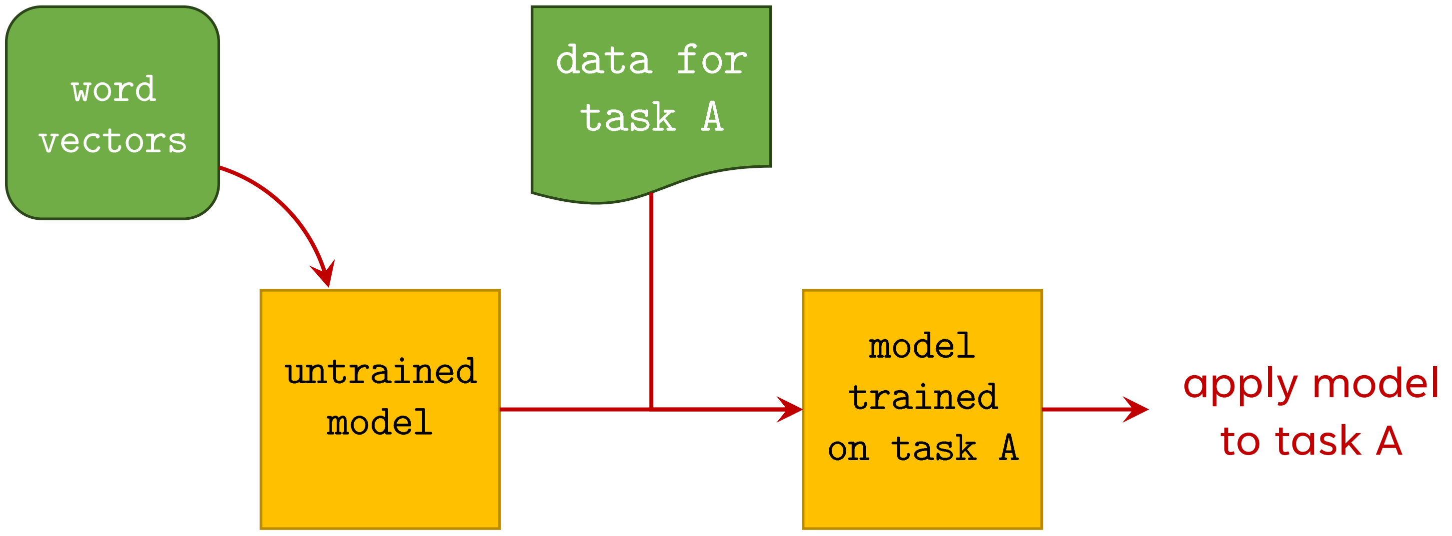
DOMAIN-SPECIFIC TRAINING

- Prior to large-scale transformer models, most NLP applications relied on domain-specific supervised training.
- Models were largely developed for specific tasks.
- Datasets were collected/annotated for these tasks.



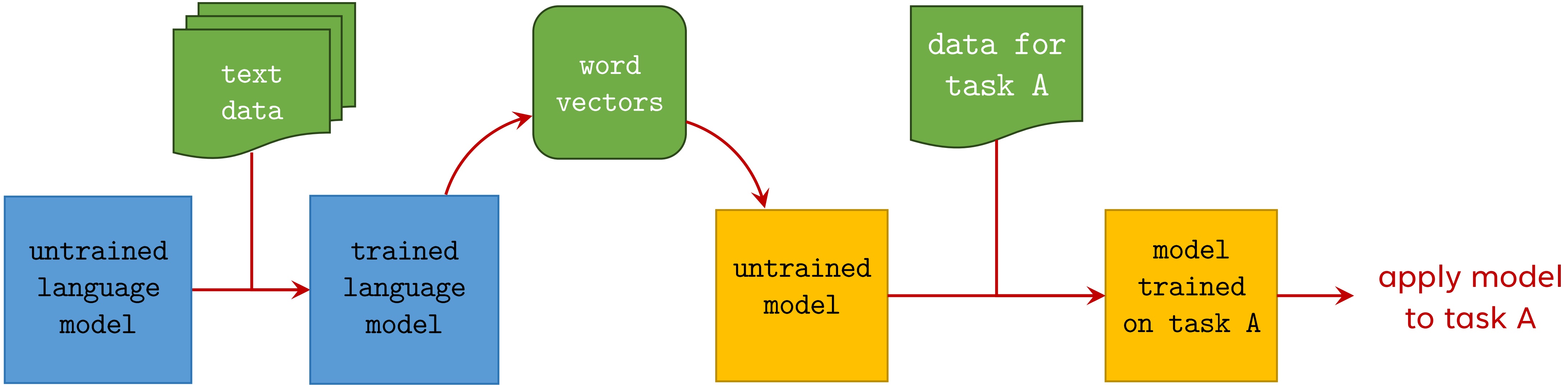
WORD VECTORS

- First learn domain-general vector representations of words.
- These word vectors can be useful as word embeddings in other models.



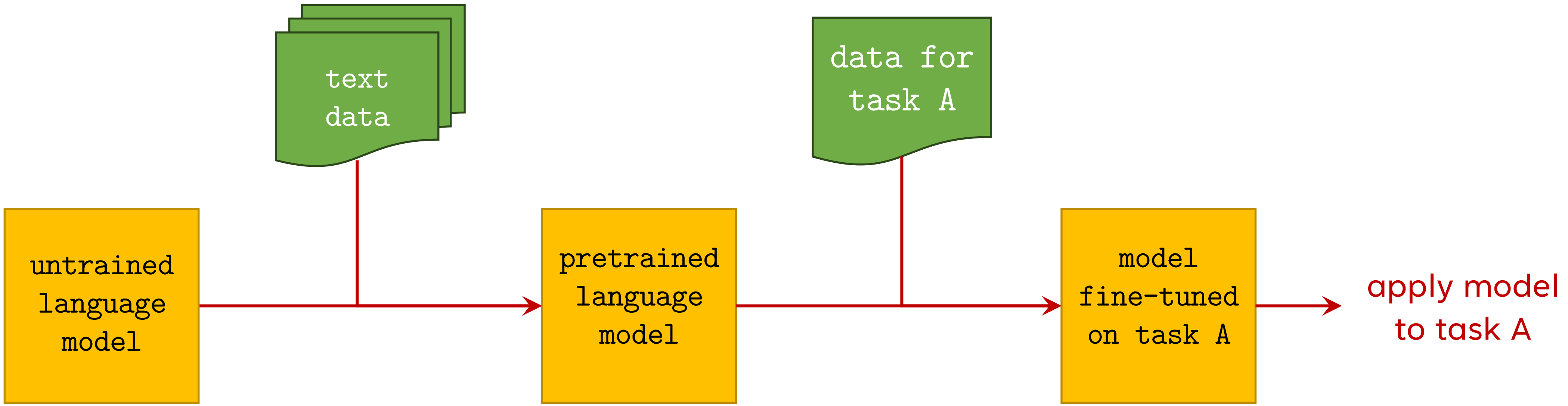
WORD VECTORS

- How to obtain word vectors?
  - One way is to train a language model on a large corpus.
  - Use the learned embeddings as word vectors.
  - There are other approaches (e.g., matrix factorization).



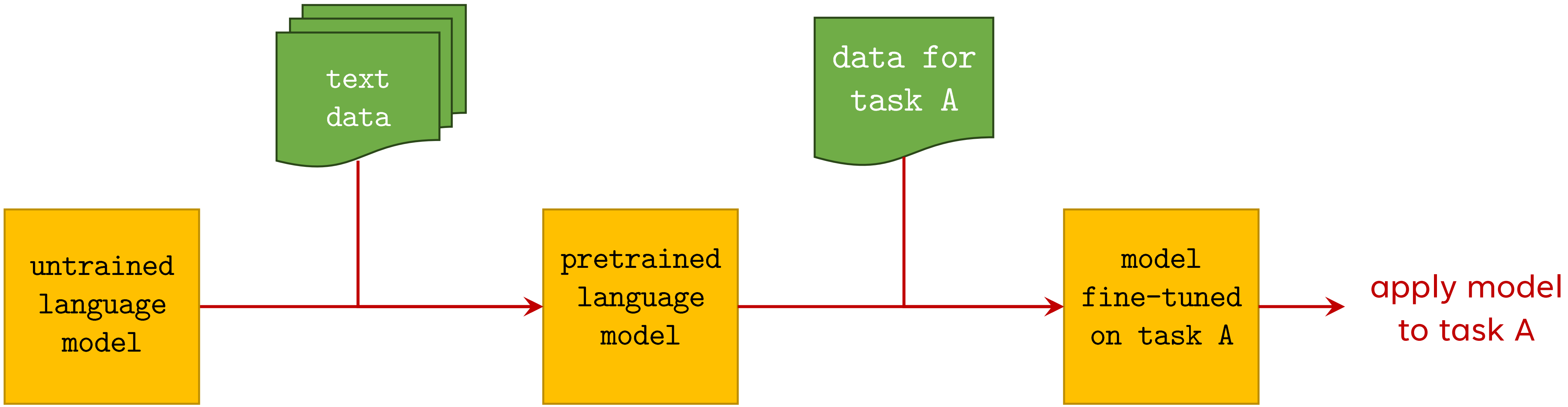
PRETRAINING

- With BERT (Devlin et al., 2018), a new paradigm became more popular:
- Pretrain BERT on large amounts of text data.
- Then fine-tune the pretrained BERT on a downstream task.



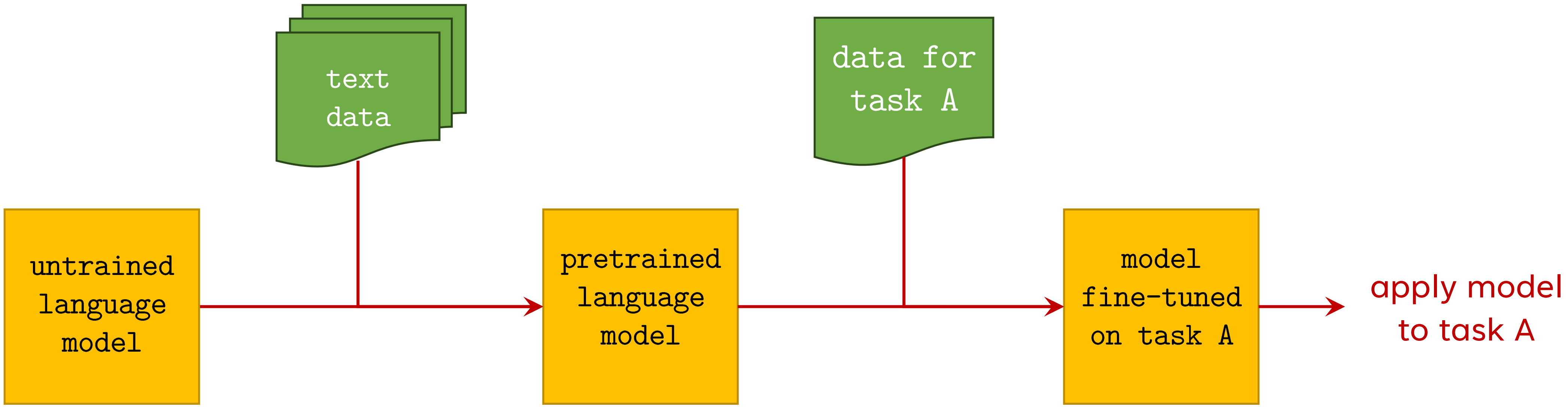
PRETRAINING

- A linear layer can be added to the last transformer layer of BERT.
- Fine-tuning can be done only on this linear layer,
- Which is much cheaper than full fine-tuning of BERT.



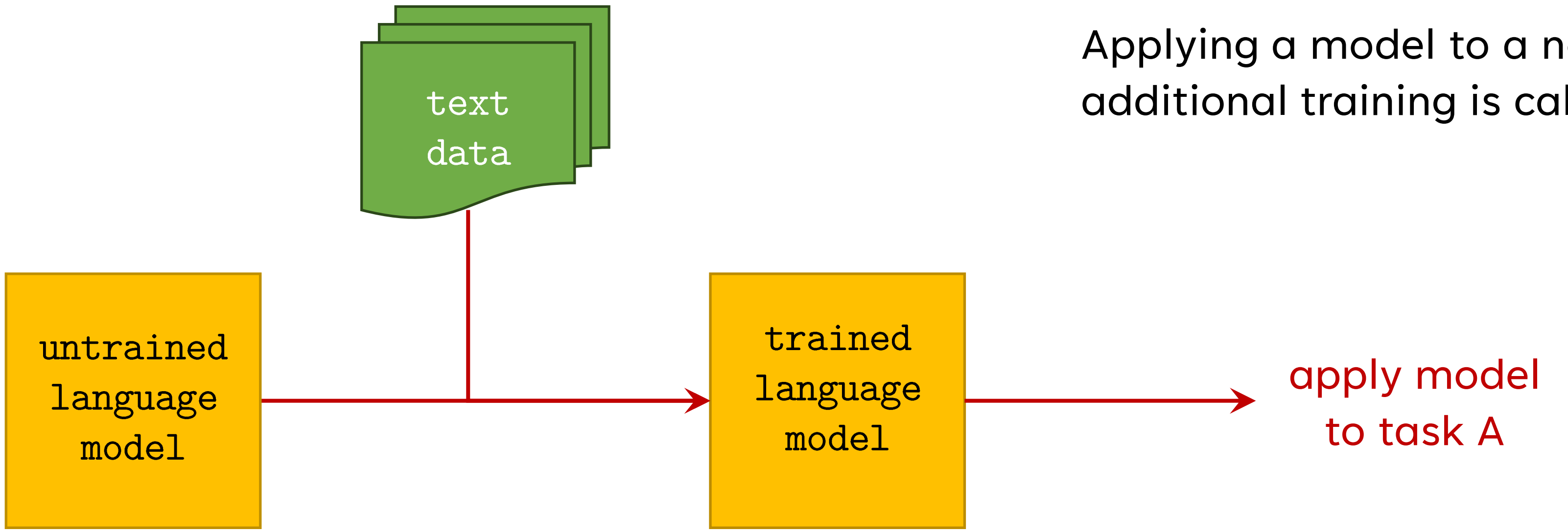
PRETRAINING

- This new paradigm only became possible thanks to the improved generality of larger language models,
- Which have been pretrained on increasingly large and broader-coverage training sets.



PRETRAINING

- With more train-time scaling, LLMs are outperforming fine-tuned models on many tasks.
- For these, tasks, we can skip fine-tuning altogether.



Applying a model to a novel example without additional training is called zero-shot learning.

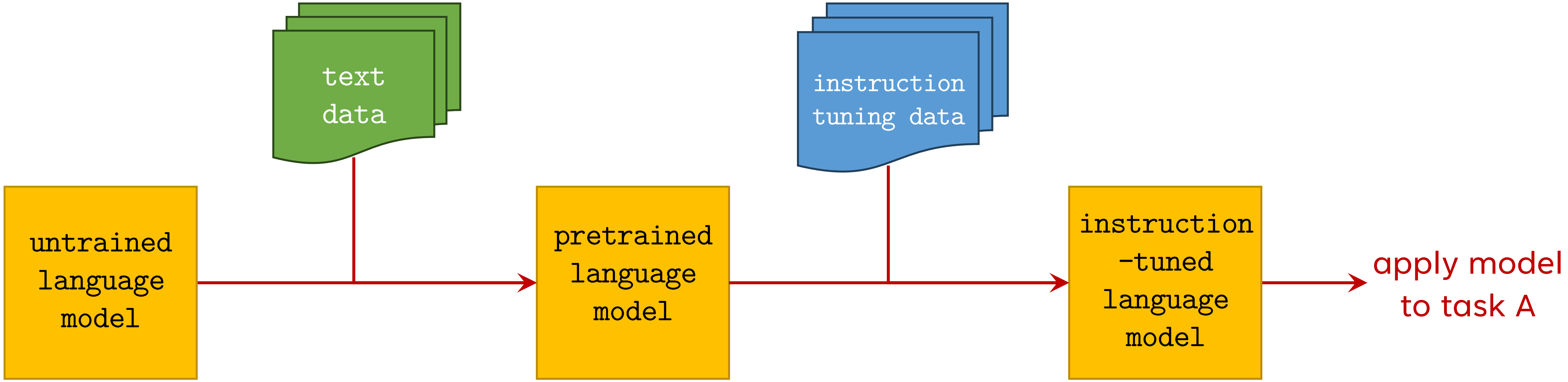
PRETRAINING

- But a model trained purely on language modeling is not necessarily very good at following instructions.
- Consider the training data:
  - It is not common to find many examples on the internet of the form

    `[task A instruction]` followed by `[task A example(s)]`
- If we want the model to be better at following instructions, we need to train it to do so further, after pretraining.

INSTRUCTION TUNING

- This additional post-training step is called instruction tuning.
- We perform supervised fine-tuning on the model on a labeled dataset:



INSTRUCTION TUNING

- This additional post-training step is called instruction tuning.
- We perform supervised fine-tuning on the model on a labeled dataset:
  - The dataset contains many examples of the form

    `[task A instruction]` followed by `[task A example(s)]`
  - For many different tasks `A`.
  - It is important that this dataset have wide coverage over a diverse set of tasks,
  - Otherwise, the model will overfit.
  - The model may be better at performing tasks in the instruction-tuning set, but its performance on other tasks will deteriorate.

INSTRUCTION TUNING

- Many current language models provide both non-instruction-tuned and instruction-tuned variants.
- Compare performance of `Llama-3.2` vs `Llama-3.2-Instruct`.
- Evaluate on three benchmarks:
  - GSM8k: Grade-school math word problems
  - MATH: Math competition problems
  - AQUA-RAT: Algebraic word problems (GRE/GMAT level)

LLMs	gsm8k	aqua_rat	math
meta-llama/Llama-3.2-3B	0.1084	0.20008	0.0664
meta-llama/Llama-3.2-3B-Instruct	0.5155	0.3819	0.2824
meta-llama/Llama-3.1-8B	0.4147	0.3425	0.138
meta-llama/Llama-3.1-8B-Instruct	0.6831	0.4409	0.2904

[Yanan Chen, Clearance of the Confusion: LLM's base and instruct version]

INSTRUCTION TUNING

- Most modern language models are instruction-tuned as chatbots.
- Inputs to these models are more organized:
  - `System message`: The instructions for the chatbot (i.e., what is the task?).
  - `Assistant message 1`: The first message from the chatbot.
  - `User message 1`: The first message from the user.

    …
  - Assistant message n
  - User message n
- No restriction on whether the first message is an assistant or user message.
- Likewise for the last message.

INSTRUCTION TUNING

- Most modern language models are instruction-tuned as chatbots.
- Example:
  - `System message`: "Please classify movie reviews as ‘positive’ or ‘negative’."
  - `User message`: "This movie is great."

INSTRUCTION TUNING

- Behind the scenes, these chat formats are translated into text strings for the language model.
- Example Llama 2 input:

```
[INST]
<<SYS>>
Please classify movie reviews as 'positive' or 'negative'.
<</SYS>>
[/INST]

[INST]This movie is great.[/INST]
```

INSTRUCTION TUNING

- Behind the scenes, these chat formats are translated into text strings for the language model.
- Example Llama 3 input:

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|>

Please classify movie reviews as ‘positive’ or ‘negative’.
<|eot_id|>

<|start_header_id|>user<|end_header_id|>

This movie is great.<|eot_id|>
```

INSTRUCTION TUNING

- Behind the scenes, these chat formats are translated into text strings for the language model.
- Example Alpaca input:

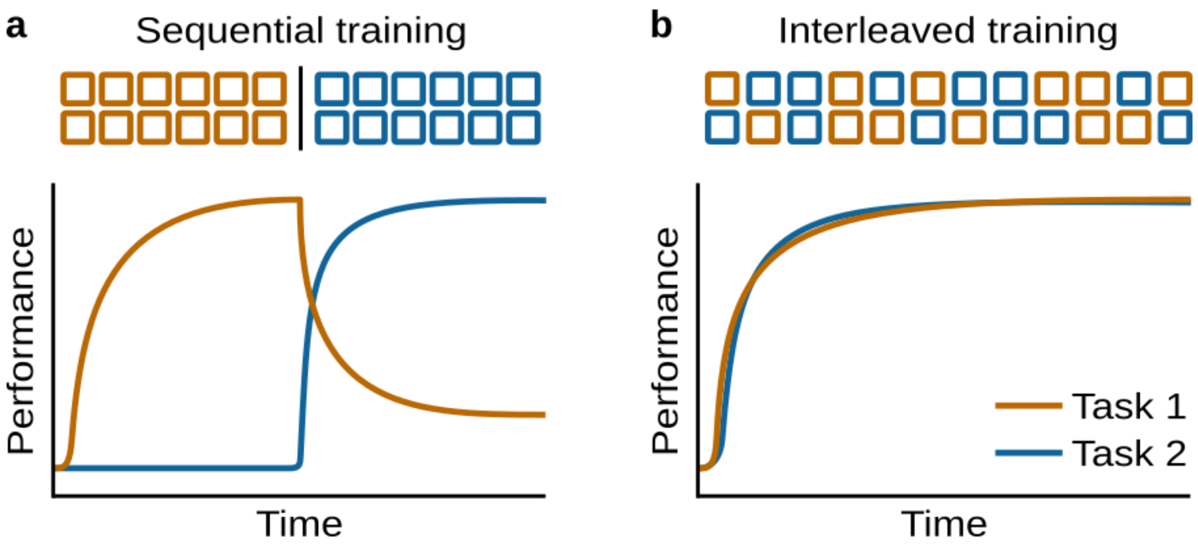
```
### Instruction:
Please classify movie reviews as ‘positive’ or ‘negative’.

### Instruction:
This movie is great.

### Response:
```

CATASTROPHIC FORGETTING

- Catastrophic forgetting is the phenomena that occurs when a model is first trained on task A, and then later trained on task B,
- As the model is trained on task B, its performance on task A deteriorates.



[van de Ven* and Soures* et al., 2024]

CATASTROPHIC FORGETTING

- Catastrophic forgetting is the phenomena that occurs when a model is first trained on task A, and then later trained on task B,
- As the model is trained on task B, its performance on task A deteriorates.
- Some mitigation techniques:
  - Mix some data from task A into that for task B during post-training.
  - Related: make sure the post-training data has wide coverage/high diversity.
    - This may require large-scale manual annotation of instruction tuning datasets.
  - Limit the post-training to fewer epochs/iterations.

LIMITATIONS OF PRETRAINING

- There are some contexts where this new paradigm may not be as successful as traditional domain-specific training.
- Extremely low-resource languages.
- Domains that are very poorly represented in the training data.
  - Tasks that require information that is newer than the training data.
- Tasks on non-text modalities.
  - E.g., video question-answering.
  - Robotics applications.
  - Sounds and music.

PROMPTING

- After pre-training and instruction tuning, there are still many ways to convert tasks into text inputs for language models.
- This is termed prompting or prompt engineering:
  - Find the best "framing" of a task to maximize model performance.
  - Example: Sentiment analysis

```
Please classify movie reviews as 'positive' or 'negative'.

Review: This movie is great.

Response:
```

PROMPTING

- After pre-training and instruction tuning, there are still many ways to convert tasks into text inputs for language models.
- This is termed prompting or prompt engineering:
  - Find the best "framing" of a task to maximize model performance.
  - Example: Sentiment analysis

```
Review: This movie is great.
This review is: (a) positive, or (b) negative.
Response:
```

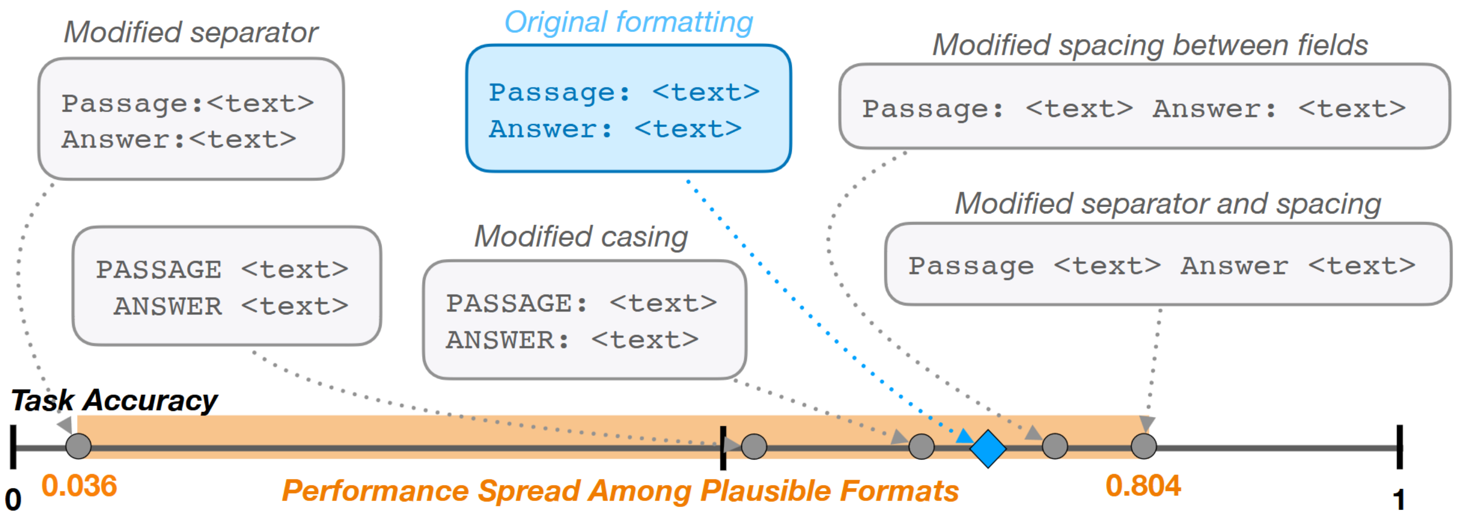
PROMPTING

- After pre-training and instruction tuning, there are still many ways to convert tasks into text inputs for language models.
- This is termed prompting or prompt engineering:
  - Find the best "framing" of a task to maximize model performance.
  - Example: Sentiment analysis

```
Review: This movie is great.
Consider this review and analyze whether it is positive or
negative. Provide an explanation of your reasoning, followed by
either "Response: positive" or "Response: negative".
```

PROMPT SENSITIVITY

- LLM behavior (and performance on tasks) is sensitive to the prompt.
- Example: `task280` from `SuperNaturalQuestions` (Wang et al., 2022)
- Given a passage, classify whether it confirms or resists stereotypes about either gender, profession, race, or religion. (Llama-2-7B)



[Sclar et al., 2024]

PROMPT SENSITIVITY

- LLM behavior (and performance on tasks) is sensitive to the prompt.
- Example: Other tasks from `SuperNaturalQuestions`
- Given a passage, classify whether it confirms or resists stereotypes about either gender, profession, race, or religion. (Llama-2-7B)

Task Id	Prompt Format 1 (p_1)	Prompt Format 2 (p_2)	Acc p_1	Acc p_2	Diff.
task280	`passage:{}\n answer:{}`	`passage {}\n answer {}`	0.043	0.826	0.783
task317	`Passage::{} Answer::{}`	`Passage:: {} Answer:: {}`	0.076	0.638	0.562
task190	`Sentence[I]- {}Sentence[II]- {} -- Answer\t{}`	`Sentence[A]- {}Sentence[B]- {} -- Answer\t{}`	0.360	0.614	0.254
task904	`input:: {} \n output:: {}`	`input::{} \n output::{}`	0.418	0.616	0.198
task320	`target - {} \n{} \nanswer - {}`	`target - {}; \n{}; \nanswer - {}`	0.361	0.476	0.115
task322	`COMMENT: {} ANSWER: {}`	`comment: {} answer: {}`	0.614	0.714	0.100
task279	`Passage : {}. Answer : {}`	`PASSAGE : {}. ANSWER : {}`	0.372	0.441	0.069

[Sclar et al., 2024]

FEW-SHOT PROMPTING

- Brown et al. (2021) show that adding few-shot examples to the prompt can improve language model performance on tasks.
  - Few-shot prompting
  - 1-shot prompt example:

```
Please classify movie reviews as ‘positive’ or ‘negative’.

Input: I really don’t like this movie.
Response: negative

Input: This movie is great!
Response:
```

[Graham Neubig, 11-711 Lecture Slides, 2024]

REAL SAMPLE FEW-SHOT PROMPT

Problem: Find the domain of the expression $\frac{\sqrt{x-2}}{\sqrt{5-x}}$.
Solution:
I need to find the domain of this expression.
This expression has two square root expressions.
I know the values under each square root must be non-negative.
So let me start by ensuring that.
I set $x - 2 \geq 0$, which simplifies to $x \geq 2$.
Then, I set $5 - x \geq 0$, which simplifies to $x \leq 5$.
But I need to make sure the denominator is not zero.
So, $5 - x$ must also be greater than zero, which gives me $x < 5$.
Therefore, the domain of the expression is $\boxed{[2, 5)}$.
Answer: $[2, 5)$.
Final Answer: The final answer is $[2, 5)$. I hope it is correct.
—
Problem: If $\det \mathbf{A} = 2$ and $\det \mathbf{B} = 12$, then find $\det(\mathbf{AB})$.
Solution:
I need to find the determinant of the product of matrices A and B.
I remember that the determinant of the product of two matrices equals the product of their determinants.
So, $\det(\mathbf{AB}) = (\det \mathbf{A})(\det \mathbf{B}) = (2)(12) = \boxed{24}$.
Answer: 24.
Final Answer: The final answer is 24. I hope it is correct.
—

[Agarwal et al., 2024]

REAL SAMPLE FEW-SHOT PROMPT

—

Problem: Terrell usually lifts two 20-pound weights 12 times. If he uses two 15-pound weights instead, how many times must Terrell lift them in order to lift the same total weight?
Solution:
Okay, so Terrell lifts a total of $2 \cdot 12 \cdot 20 = 480$ pounds of weight with the 20-pound weights.
Well, if he switches to 15-pound weights, the total weight lifted will be $2 \cdot 15 \cdot n = 30n$ pounds, where n is the number of lifts.
I want to find the number of lifts, n, for the total weight lifted to be the same.
I equate $30n$ to 480 pounds and solve for n.

$$\begin{aligned} 30n &= 480 \\ \Rightarrow \quad n &= 480/30 = \boxed{16} \end{aligned}$$

Answer: 16.
Final Answer: The final answer is 16. I hope it is correct.

—

[Agarwal et al., 2024]

REAL SAMPLE FEW-SHOT PROMPT

—

Problem: If the system of equations

$$\begin{aligned} 6x - 4y &= a, \\ 6y - 9x &= b. \end{aligned}$$

The equations are expressed in LaTeX.

has a solution (x, y) where x and y are both nonzero, find $\frac{a}{b}$, assuming b is nonzero.
Solution:
I'm given a system of two equations.
I see that if I multiply the first equation by $-\frac{3}{2}$, I'll get another equation that has the same left-hand side as the second equation, $6y - 9x$.
Let me try that

$$6y - 9x = -\frac{3}{2}a.$$

Ah, I also know that $6y - 9x = b$, so I can equate these two equations.
So,

$$-\frac{3}{2}a = b \Rightarrow \frac{a}{b} = \boxed{-\frac{2}{3}}.$$

Answer: $-\frac{2}{3}$.
Final Answer: The final answer is $-\frac{2}{3}$. I hope it is correct.
—

[Agarwal et al., 2024]

IN-CONTEXT LEARNING

- Few-shot prompting can be used to “teach” LMs tasks via in-context examples (also called in-context demonstrations).
  - This is called in-context learning.

```
start : 5
free : 4
twenty : 6
aquifer : 7
deoxyribose :
```

IN-CONTEXT LEARNING

- Few-shot prompting can be used to “teach” LMs tasks via in-context examples (also called in-context demonstrations).
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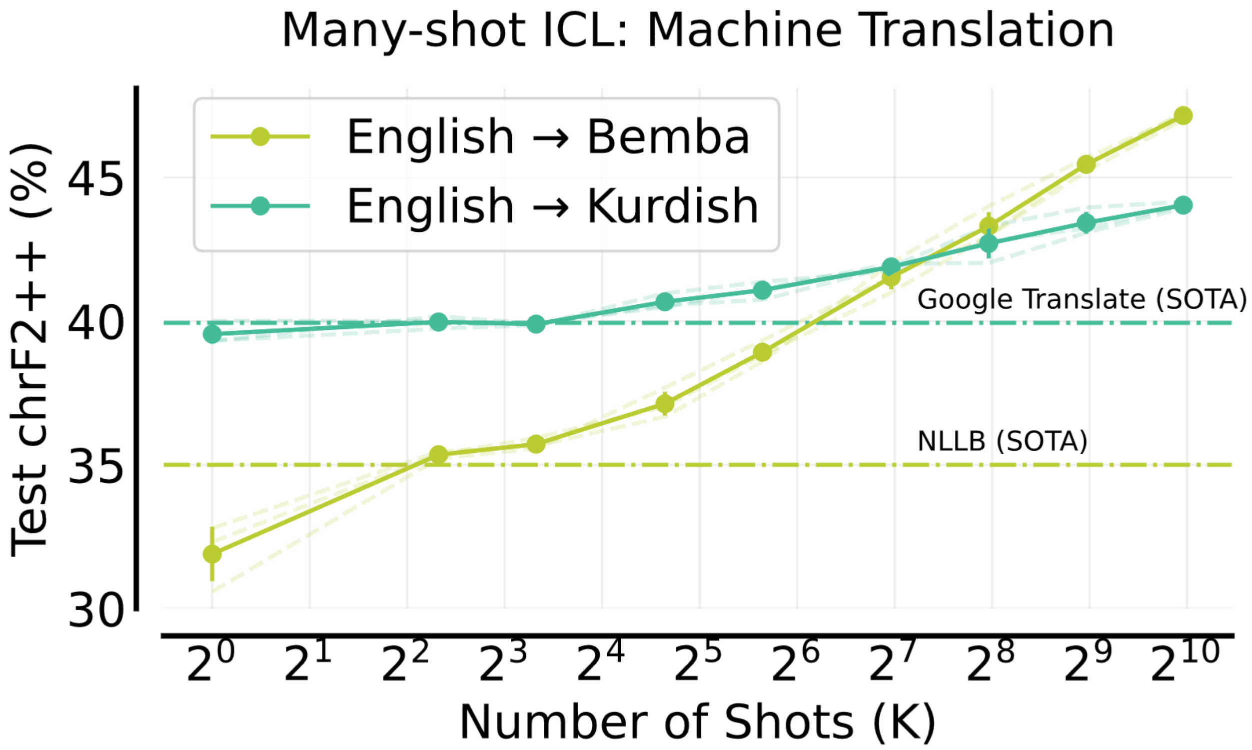
```
Input: I really don’t like this movie.
Response: positive

Input: This movie is great!
Response: negative

Input: The plot was too convoluted.
Response:
```

IN-CONTEXT LEARNING

- Few-shot prompting can be used to “teach” LMs tasks via in-context examples (also called in-context demonstrations).
  - This is called in-context learning.
- But it is not clear that the model is learning any new task from in-context learning (ICL).
- Rather, the in-context examples may just be helping to specify the task to the model, and the model is only able to perform tasks that appear in its training.
- More research is needed to better understand ICL.

HOW TO CHOOSE FEW-SHOT EXAMPLES?

- How many few-shot examples should we use?
- It depends on the task (and the specific model).



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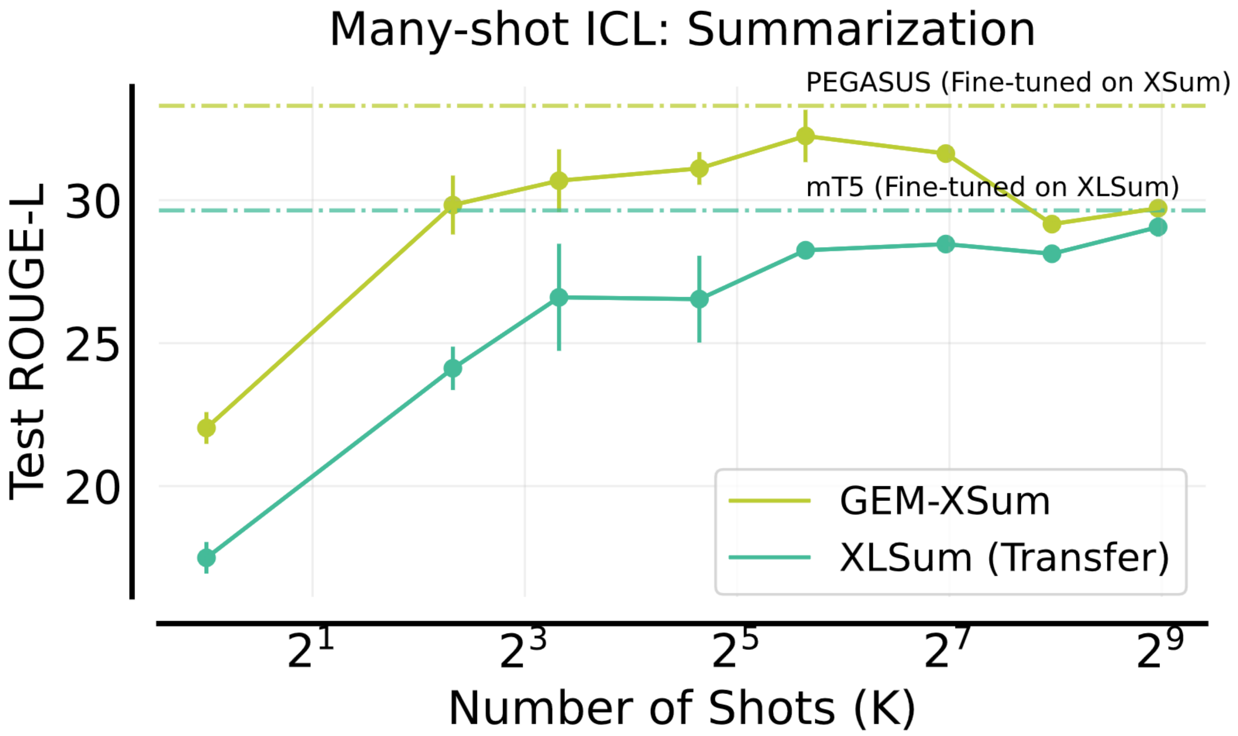
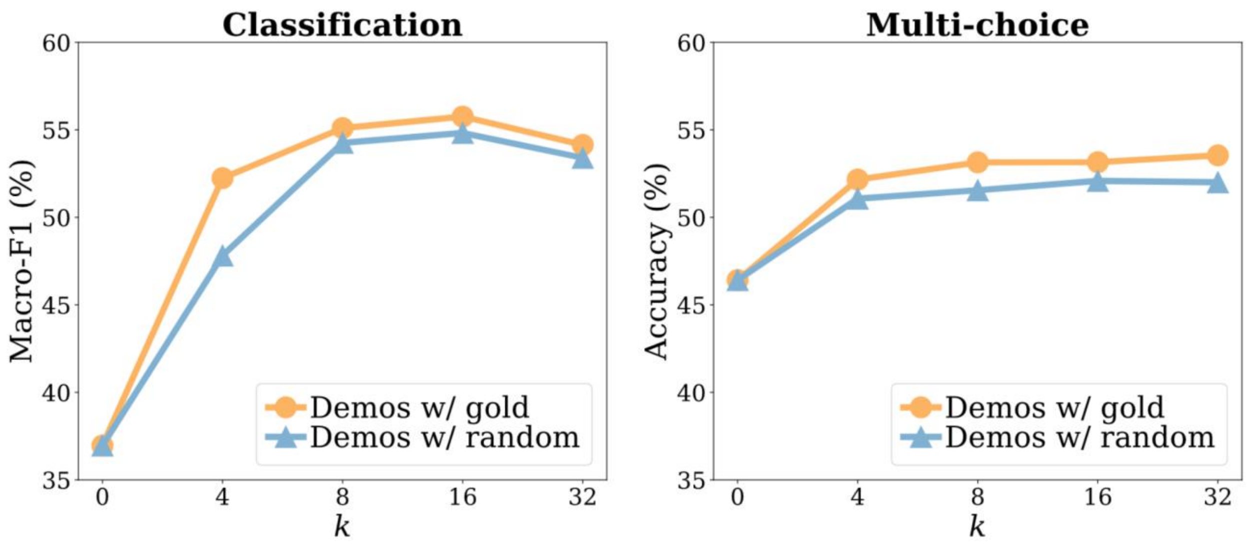


[Agarwal et al., 2024]

HOW TO CHOOSE FEW-SHOT EXAMPLES?

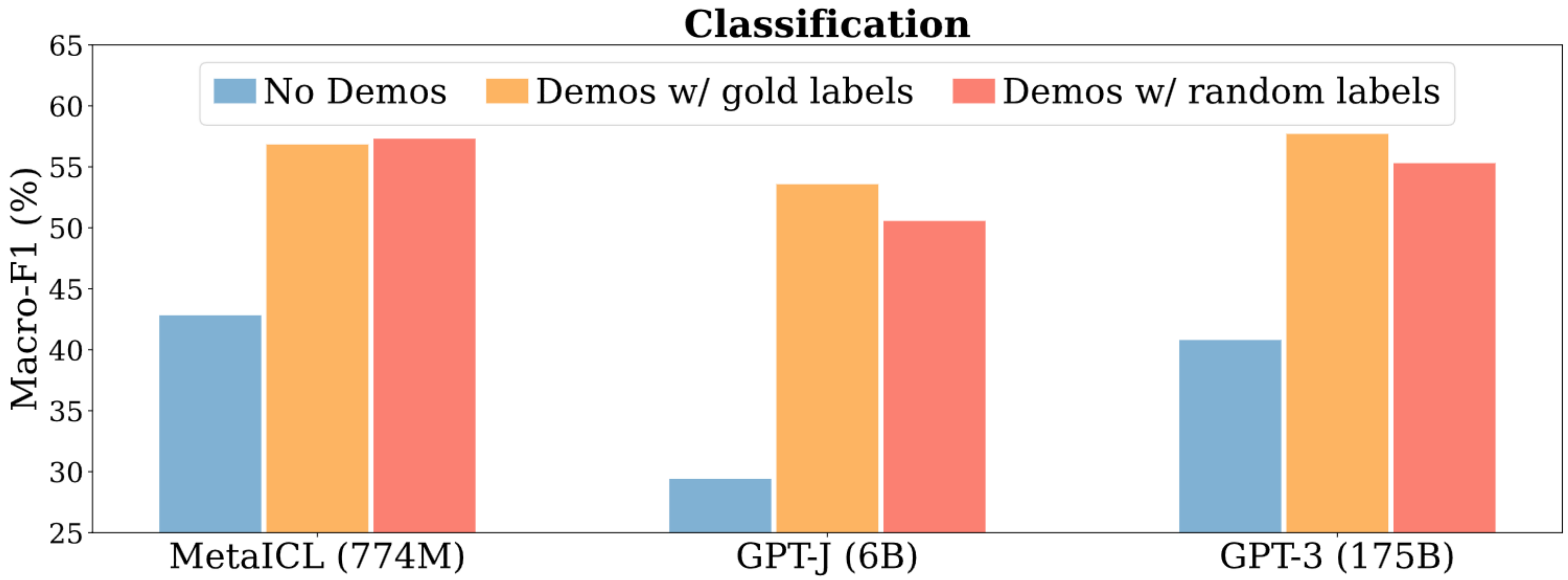
- How many few-shot examples should we use?
- For some tasks and models, too many examples can hurt performance.



[Min et al., 2022]

HOW TO CHOOSE FEW-SHOT EXAMPLES?

- How many few-shot examples should we use?
- Interestingly, in some cases, the labels of the few-shot examples do not even need to be correct.



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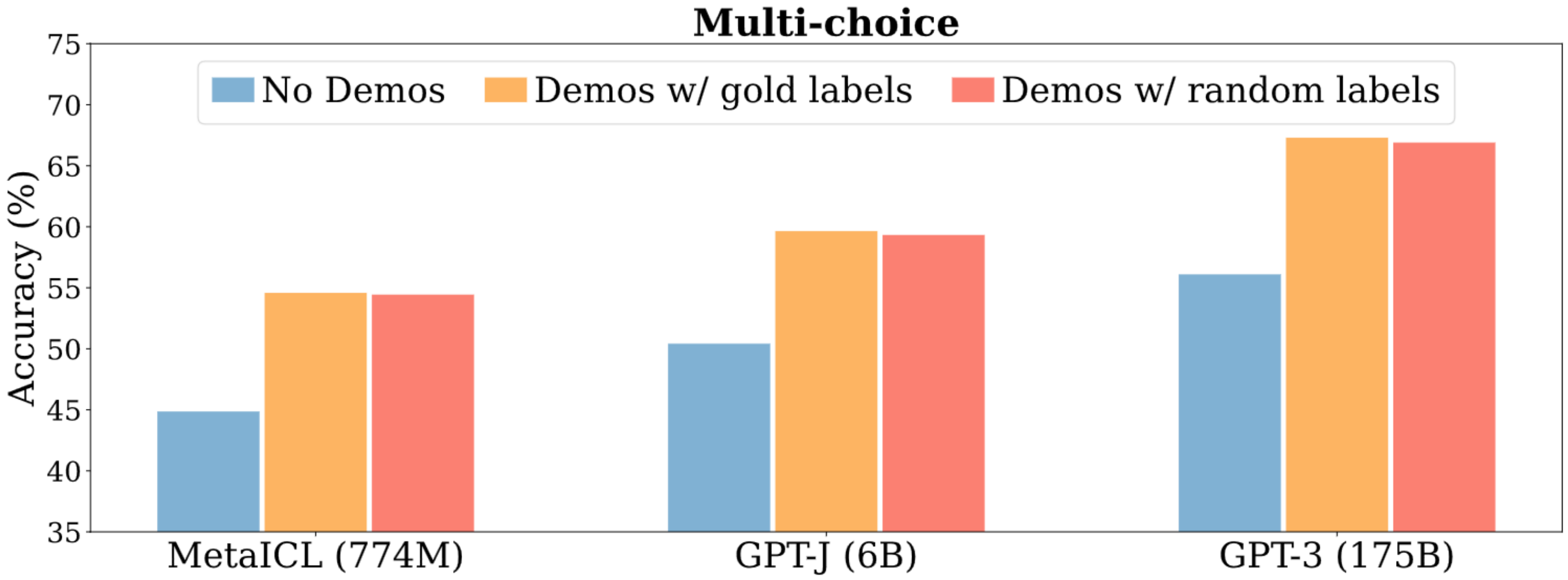
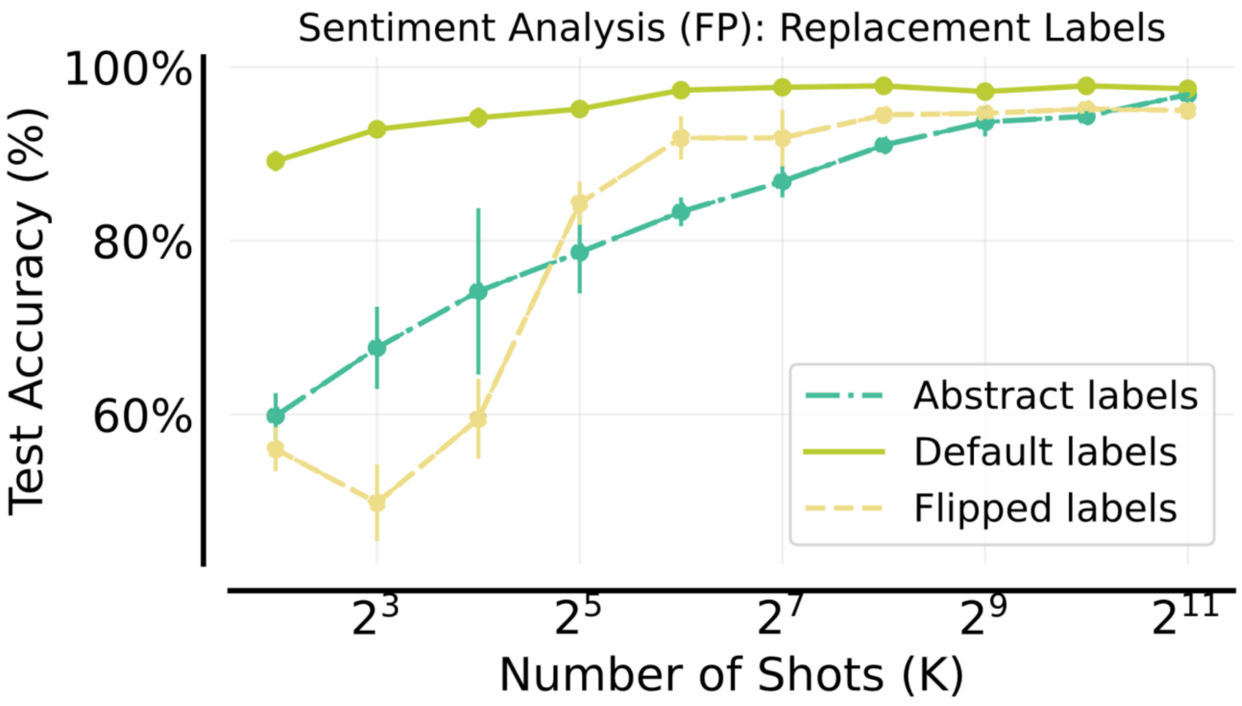


[Min et al., 2022]

HOW TO CHOOSE FEW-SHOT EXAMPLES?

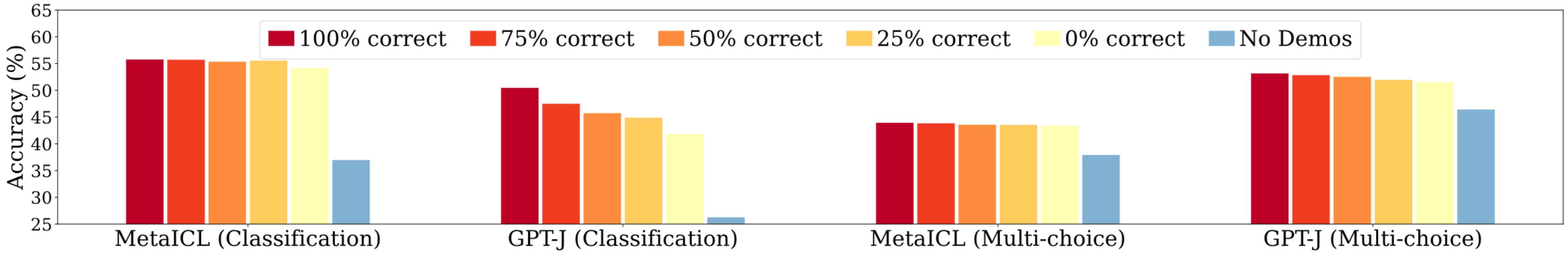
- More in-context examples helps performance when the labels are flipped ('negative', 'positive' is replaced with 'positive', 'negative'), and when labels are replaced with abstract labels ('negative', 'positive' replaced with 'A', 'B').



[Agarwal et al., 2024]

HOW TO CHOOSE FEW-SHOT EXAMPLES?

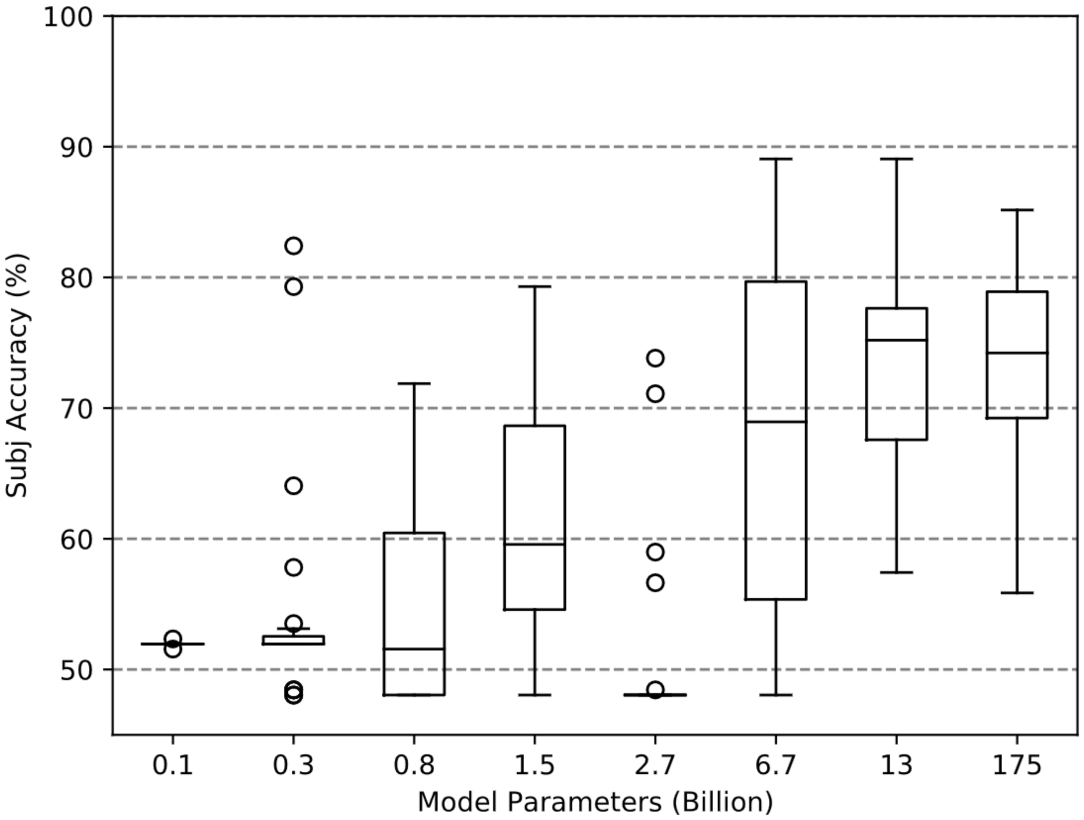
- However, best practice is to aim for 100% correct labels.



[Min et al., 2022]

HOW TO CHOOSE FEW-SHOT EXAMPLES?

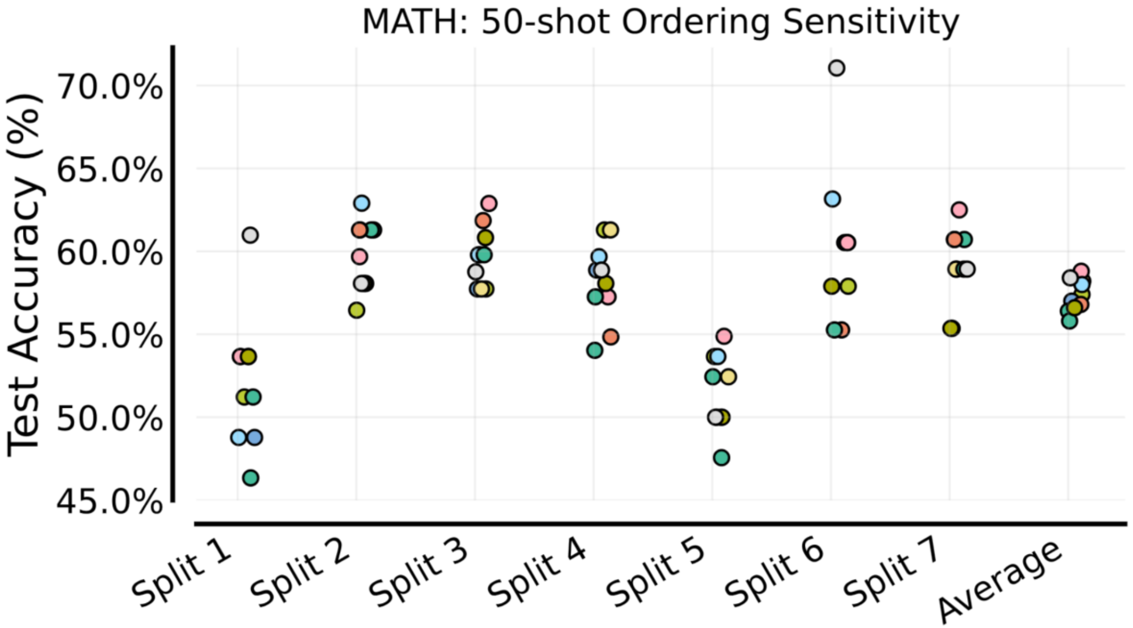
- LLM performance is sensitive to the order of few-shot examples.



[Lu et al., 2022]

HOW TO CHOOSE FEW-SHOT EXAMPLES?

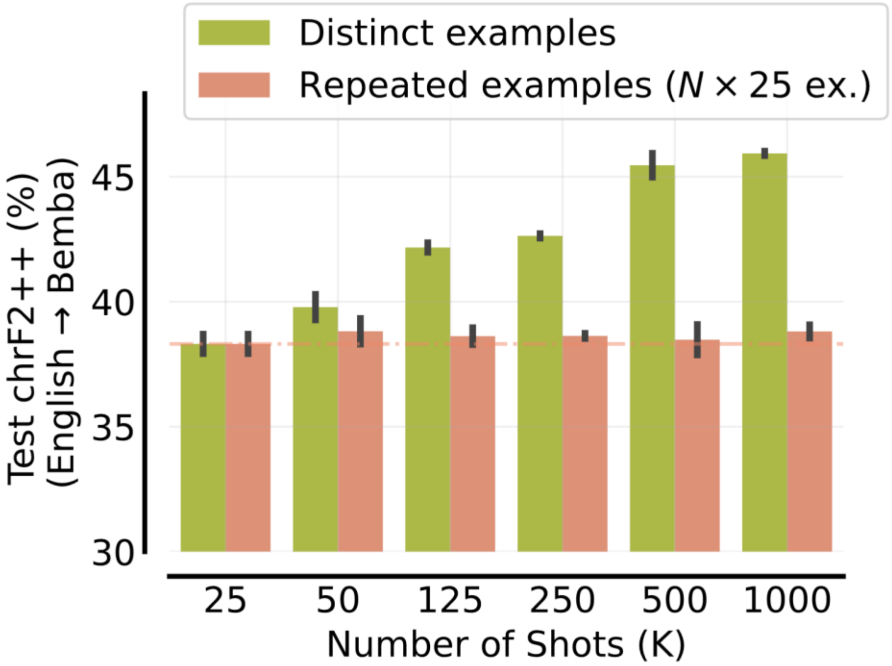
- LLM performance is sensitive to the order of few-shot examples.
- Each color represents an ordering of examples.



[Agarwal et al., 2024]

HOW TO CHOOSE FEW-SHOT EXAMPLES?

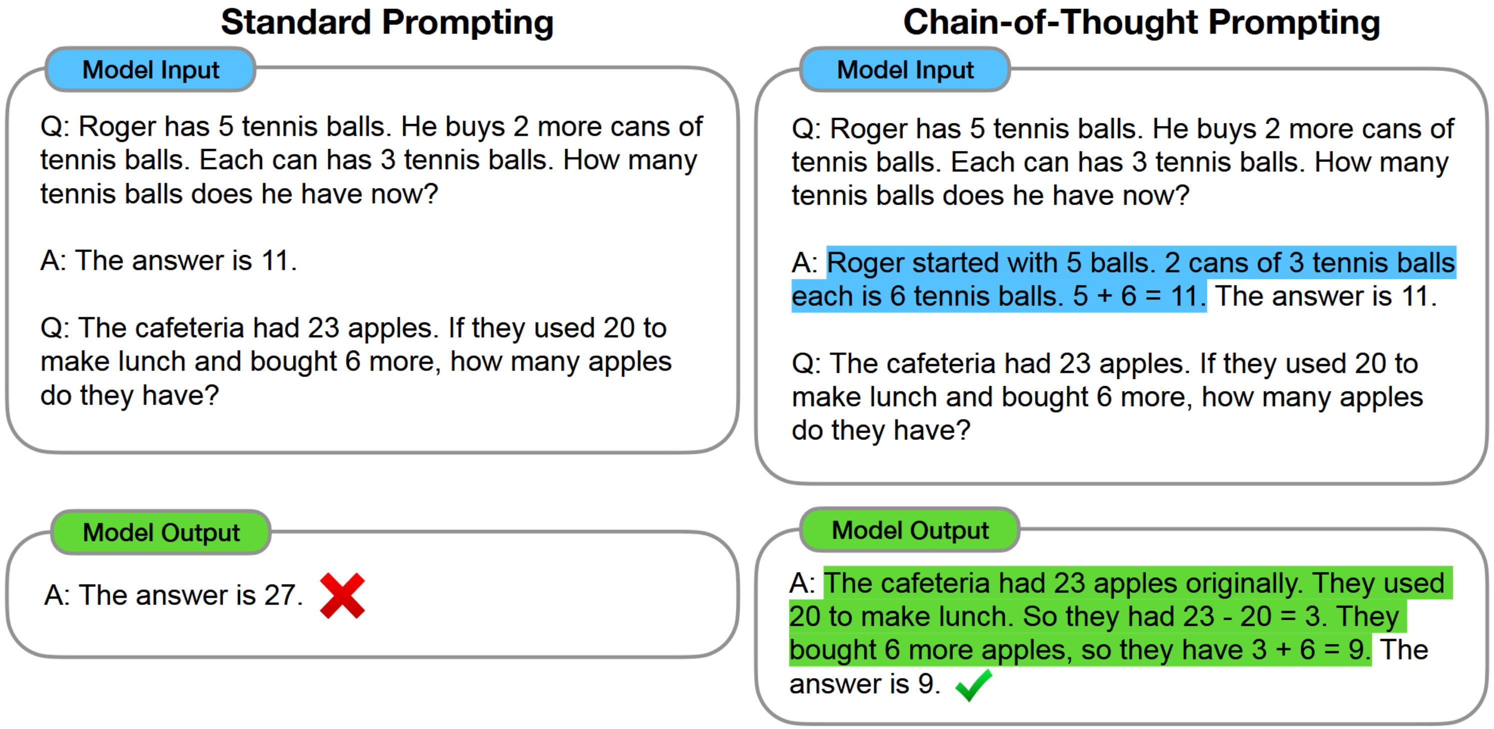
- In-context example diversity helps performance.



[Agarwal et al., 2024]

CHAIN-OF-THOUGHT PROMPTING

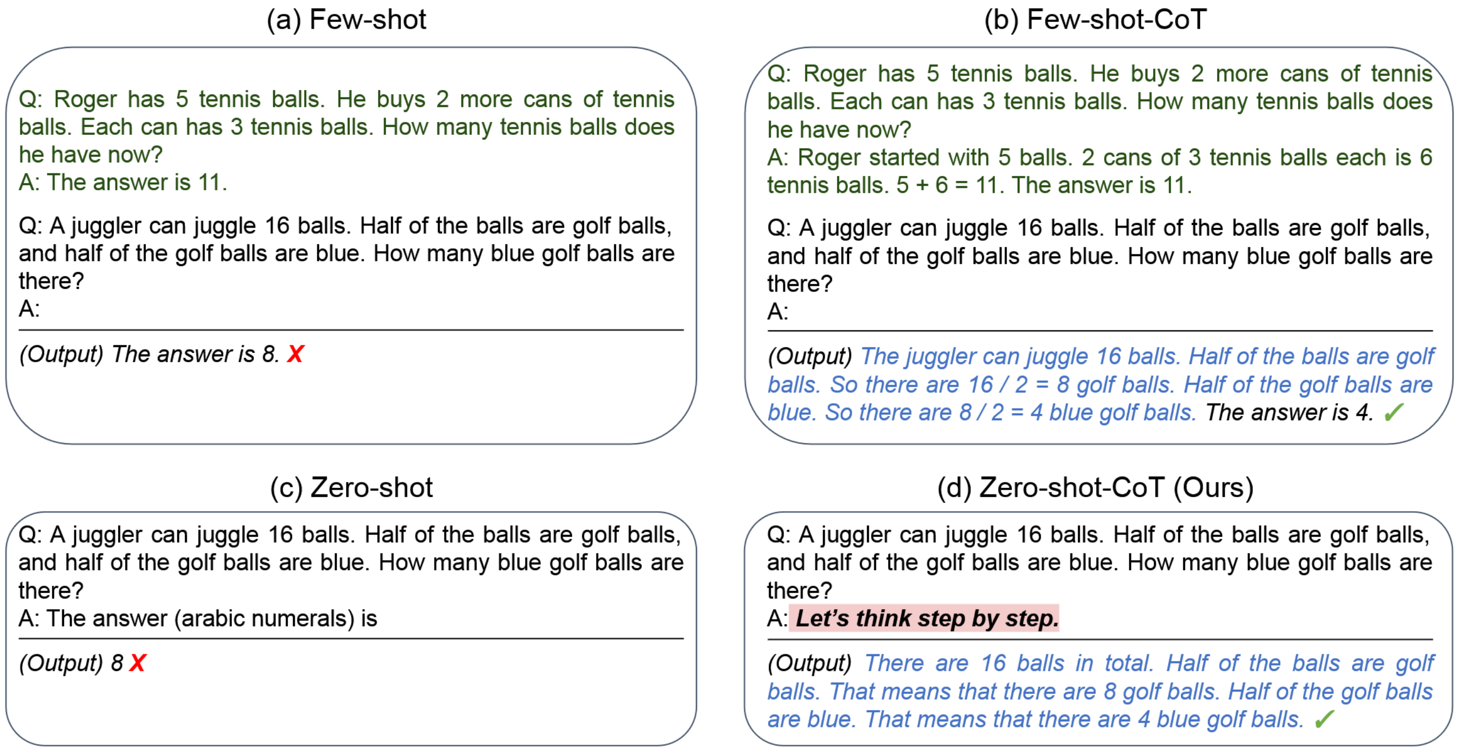
- We can design the prompt to induce the model to output its step-by-step reasoning.



[Wei et al., 2022]

CHAIN-OF-THOUGHT PROMPTING

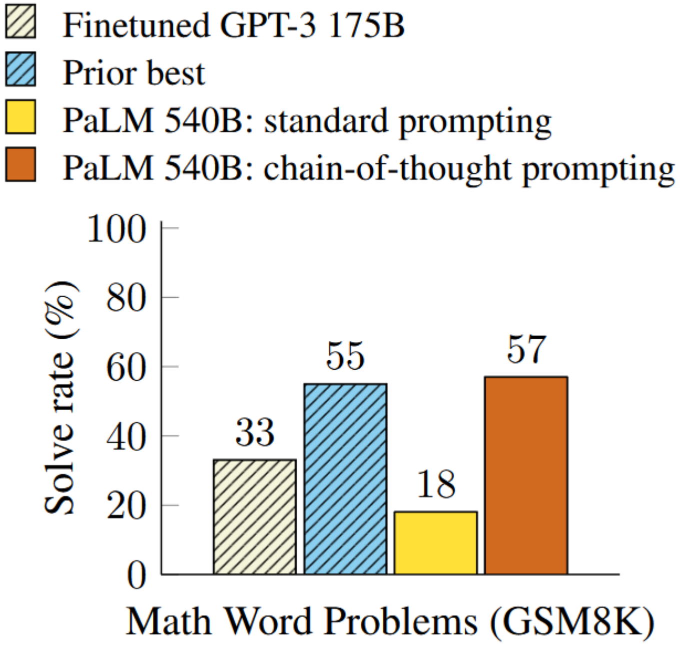
- This is called chain-of-thought (CoT) prompting.
- CoT prompting can be done zero-shot:



[Kojima et al., 2022]

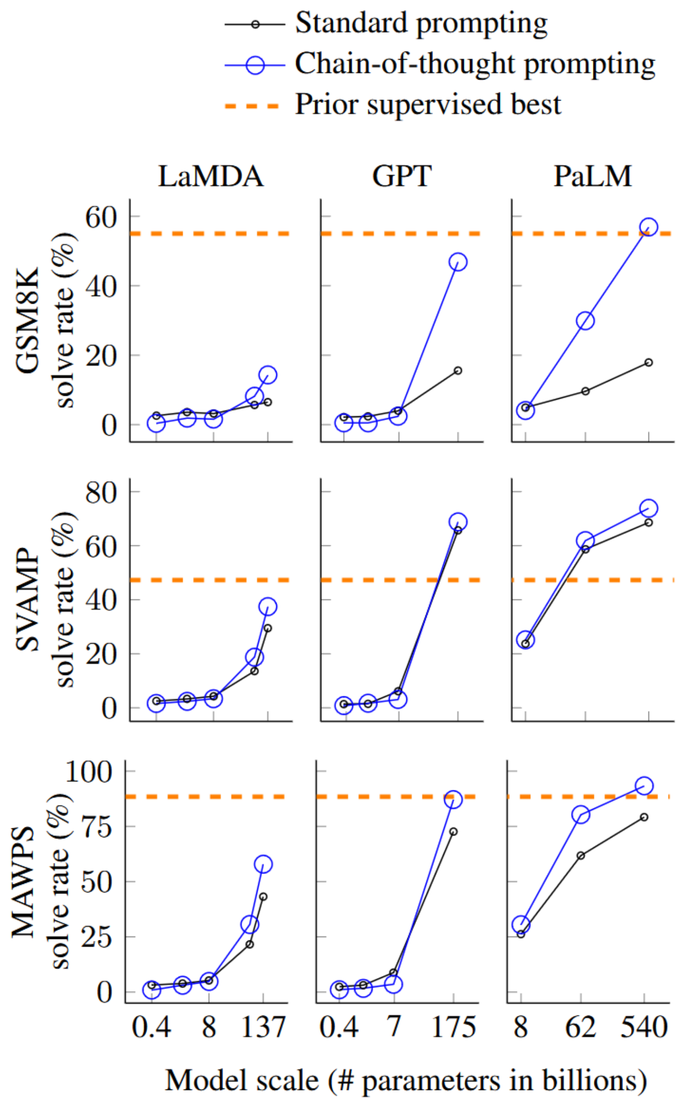
CHAIN-OF-THOUGHT PROMPTING

- CoT prompting can significantly improve performance on reasoning tasks.



[Wei et al., 2022]

CHAIN-OF-THOUGHT PROMPTING

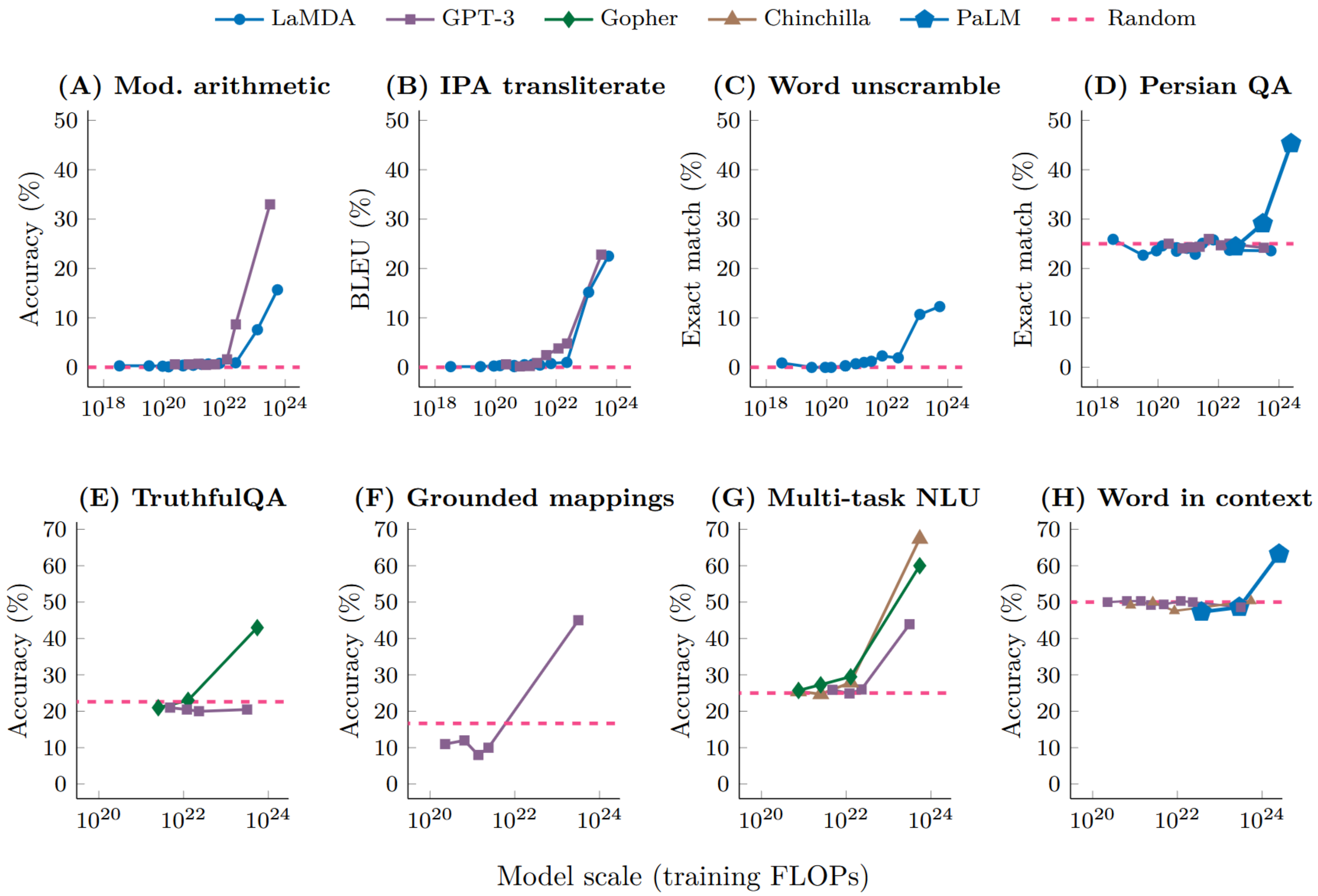


[Wei et al., 2022]

EMERGENT ABILITIES

- Only larger models seem to benefit from few-shot prompting (are capable of in-context learning) or benefit from chain-of-thought prompting.
- Is this a consequence of scaling?
- If so, shouldn't scaling laws predict this ability?
- Few-shot prompting, ICL, and CoT seem to "emerge" suddenly in sufficiently large models.
- Cross-entropy still seems to be decreasing following a power law.
  - There is no sudden/unexpected "drop" in the loss function.

EMERGENT ABILITIES

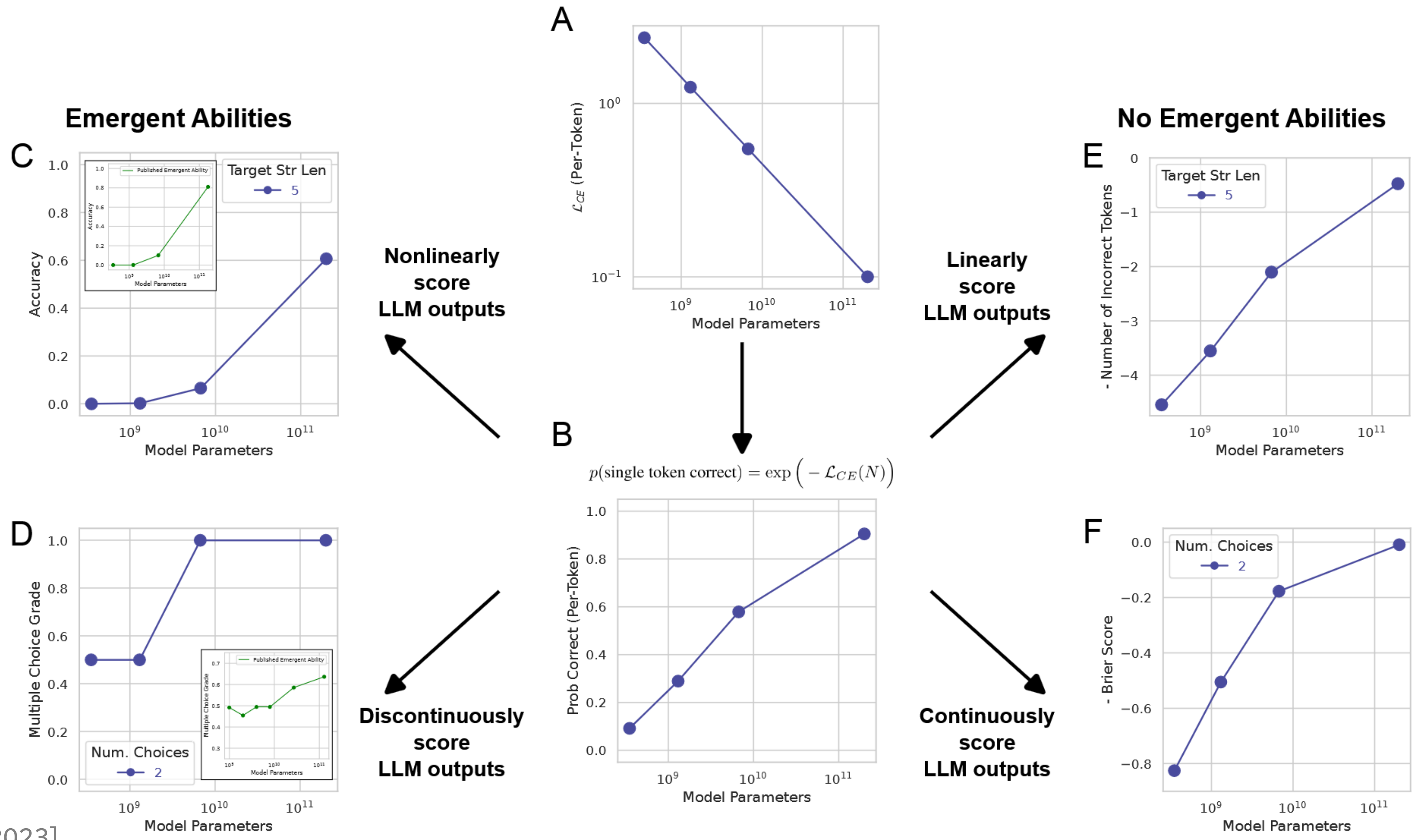


[Wei et al., 2023]

EMERGENT ABILITIES?

- Schaeffer et al. (2023) showed that if you change the performance metric, the “sudden” increase in performance becomes much smoother/linear.

EMERGENT ABILITIES?



[Schaeffer et al., 2023]

EMERGENT ABILITIES?

- Schaeffer et al. (2023) showed that if you change the performance metric, the “sudden” increase in performance becomes much smoother/linear.
- “Emergent abilities” become predictable when using a different metric.
- For example, consider a task that requires performing 10 reasoning steps.
- Suppose the model’s probability of correctly performing 1 step increases linearly with scale.
- Then the probability that the model will perform all 10 steps correctly will increase exponentially.
- So overall accuracy will seem sudden/emergent, even if per-step accuracy improves predictably.

QUESTIONS?