LLMs as few-shot learners

NLP: Fall 2024

Anoop Sarkar

"Language provides a natural domain for the study of artificial intelligence, as the vast majority of reasoning tasks can be efficiently expressed and evaluated in language, and the world's text provides a wealth of data for unsupervised learning via generative modeling."

- OpenAI

Improving Language Understanding by Generative Pre-Training

GPT1

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https://openai.com/research/language-unsupervised **Jun 2018**

GPT1

Pre-training an autoregressive language model

BooksCorpus: 7K unpublished books (1B words)

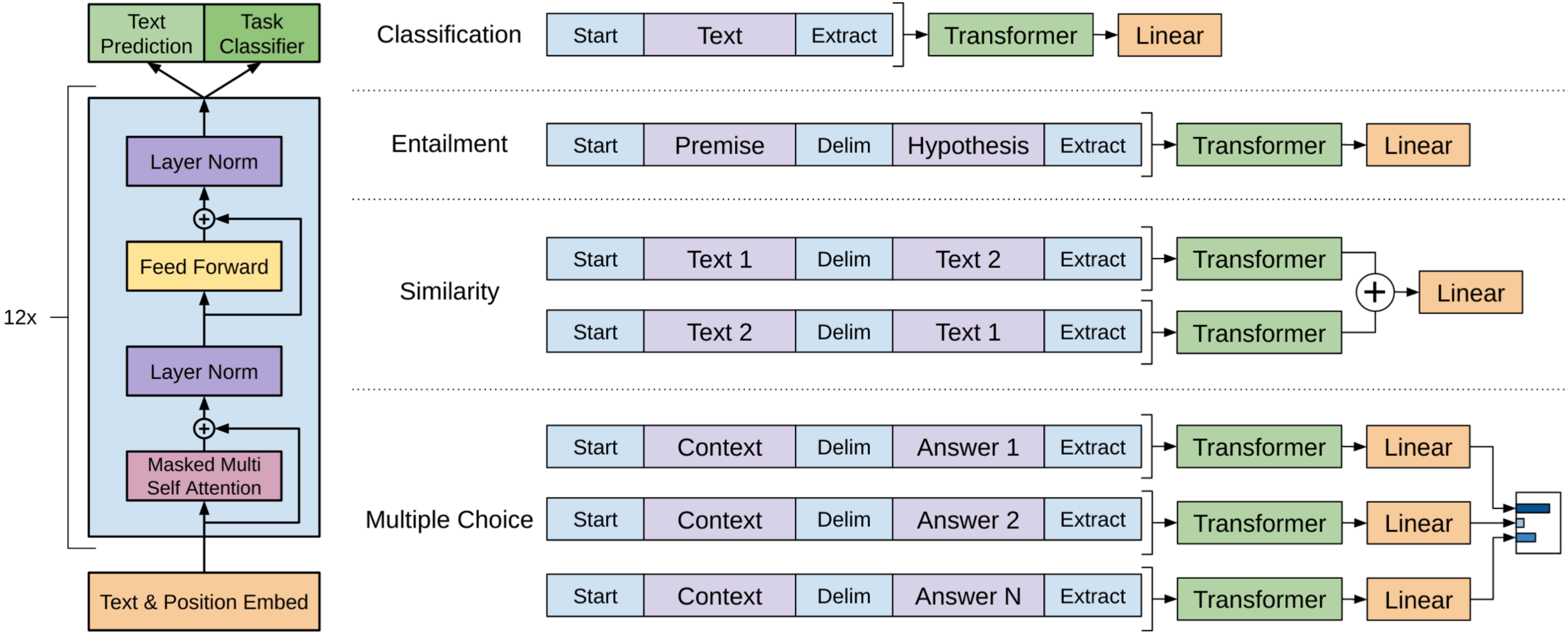
- Start with a large amount of unlabeled data $\mathscr{U} = \{u_1, \ldots, u_n\}$
- Pre-training objective: Maximize the likelihood of predicting the next token
  - $L_i(\mathscr{U}) = \sum_i \log P(u_i \mid u_{i-k}, \ldots, u_{i-1}; \Theta)$
- This is equivalent to training a Transformer decoder
  - $h_0 = U\boxed{W_e} + W_p$
  - $h_\ell = \text{transformer\_block}(h_{\ell-1}) \forall \ell \in [1,n]$
  - $P(u) = \text{softmax}(h_n \boxed{W_e^T})$
- Directionality is needed to generate a well-formed probability distribution

$U = (u_{-k}, \ldots, u_{-1})$ is the context vector of tokens

n is the number of Transformer layers

W_e is the token embedding matrix

W_p is the position embedding matrix



This setup was for fine-tuning GPT1 but also works for in-context learning in GPT2 and GPT3.

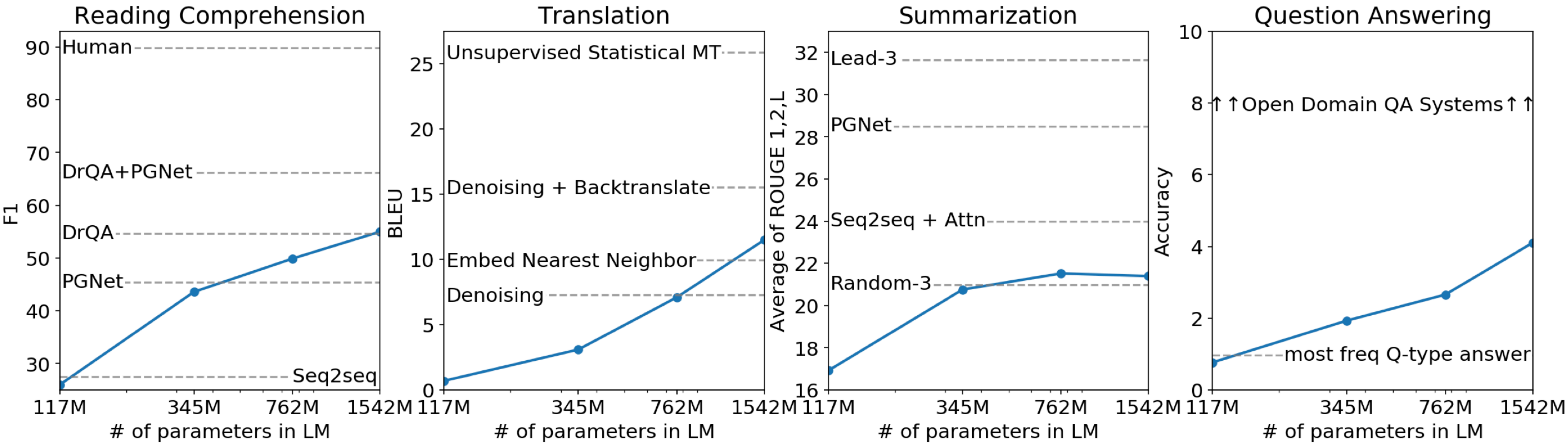
The GPT2 paper

Language Models are Unsupervised Multitask Learners

Alec Radford [* 1] **Jeffrey Wu** [* 1] **Rewon Child** [1] **David Luan** [1] **Dario Amodei** [** 1] **Ilya Sutskever** [** 1]

https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

Feb 2019



Reading Comprehension
Human
DrQA+PGNet
DrQA
PGNet
Seq2seq
F1
Translation
Unsupervised Statistical MT
Denoising + Backtranslate
Embed Nearest Neighbor
Denoising
BLEU
Summarization
Lead-3
PGNet
Seq2seq + Attn
Random-3
Average of ROUGE 1,2,L
Question Answering
↑↑Open Domain QA Systems↑↑
most freq Q-type answer
Accuracy
117M
345M
762M
1542M
# of parameters in LM

WebText corpus

- Train on web scale corpus but with more reliable data compared to the CommonCrawl.
- English-only, so language detection is used
- Outgoing links from reddit (with at least 3 karma)
- No reddit data was used, instead use the content of the web sites linked on reddit discussions
- 8M documents with 40GB of text

Language detection: https://github.com/CLD2Owners/cld2

News site scraping: https://github.com/codelucas/newspaper

”I’m not the cleverest man in the world, but like they say in French: **Je ne suis pas un imbecile [I’m not a fool].**
In a now-deleted post from Aug. 16, Soheil Eid, Tory candidate in the riding of Joliette, wrote in French: ”**Mentez mentez, il en restera toujours quelque chose**,” which translates as, ”**Lie lie and something will always remain.**”
“I hate the word ‘**perfume**,”’ Burr says. ‘It’s somewhat better in French: ‘**parfum**.’
If listened carefully at 29:55, a conversation can be heard between two guys in French: “**-Comment on fait pour aller de l’autre coté? -Quel autre coté?**”, which means “**- How do you get to the other side? - What side?**”.
If this sounds like a bit of a stretch, consider this question in French: **As-tu aller au cinéma?**, or **Did you go to the movies?**, which literally translates as Have-you to go to movies/theater?
“**Brevet Sans Garantie Du Gouvernement**”, translated to English: “**Patented without government warranty**”.

Table 1. Examples of naturally occurring demonstrations of English to French and French to English translation found throughout the WebText training set.

Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

Table 2. Architecture hyperparameters for the 4 model sizes.

Perplexity Results

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

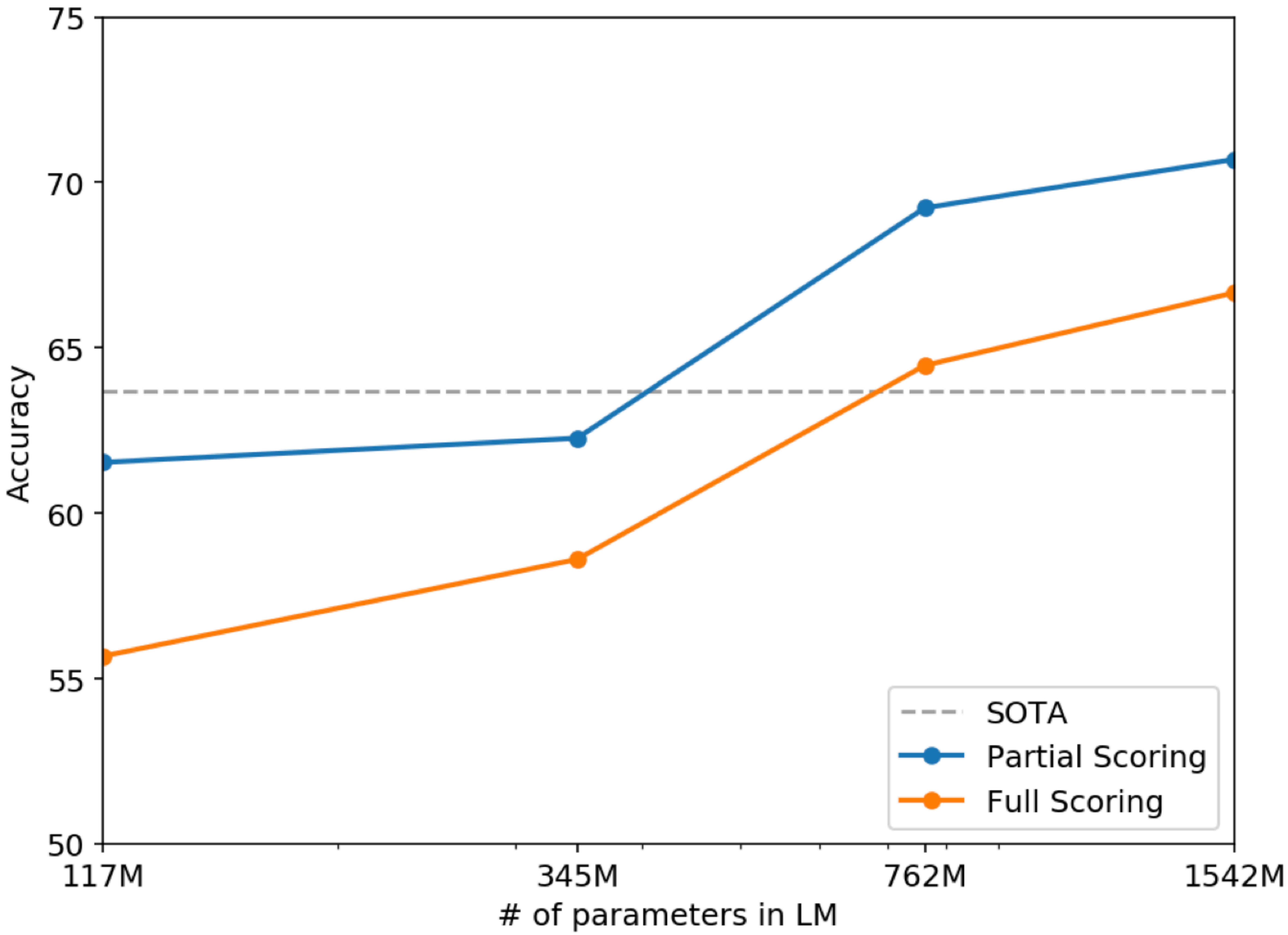


Figure 3. Performance on the Winograd Schema Challenge as a function of model capacity.

The GPT3 paper

Language Models are Few-Shot Learners

Tom B. Brown* **Benjamin Mann*** **Nick Ryder*** **Melanie Subbiah***

Jared Kaplan† **Prafulla Dhariwal** **Arvind Neelakantan** **Pranav Shyam**

Girish Sastry **Amanda Askell** **Sandhini Agarwal** **Ariel Herbert-Voss**

Gretchen Krueger **Tom Henighan** **Rewon Child** **Aditya Ramesh**

Daniel M. Ziegler **Jeffrey Wu** **Clemens Winter**

Christopher Hesse **Mark Chen** **Eric Sigler** **Mateusz Litwin** **Scott Gray**

Benjamin Chess **Jack Clark** **Christopher Berner**

Sam McCandlish **Alec Radford** **Ilya Sutskever** **Dario Amodei**

https://arxiv.org/abs/2005.14165

NeurIPS 2020, Vancouver, BC

Traditional fine-tuning (not used for GPT-3)

Fine-tuning

The model is trained via repeated gradient updates using a large corpus of example tasks.

Zero-shot

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

`Translate English to French:`	*task description*
`cheese =>`	*prompt*

One-shot

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

`Translate English to French:`	*task description*
`sea otter => loutre de mer`	*example*
`cheese =>`	*prompt*

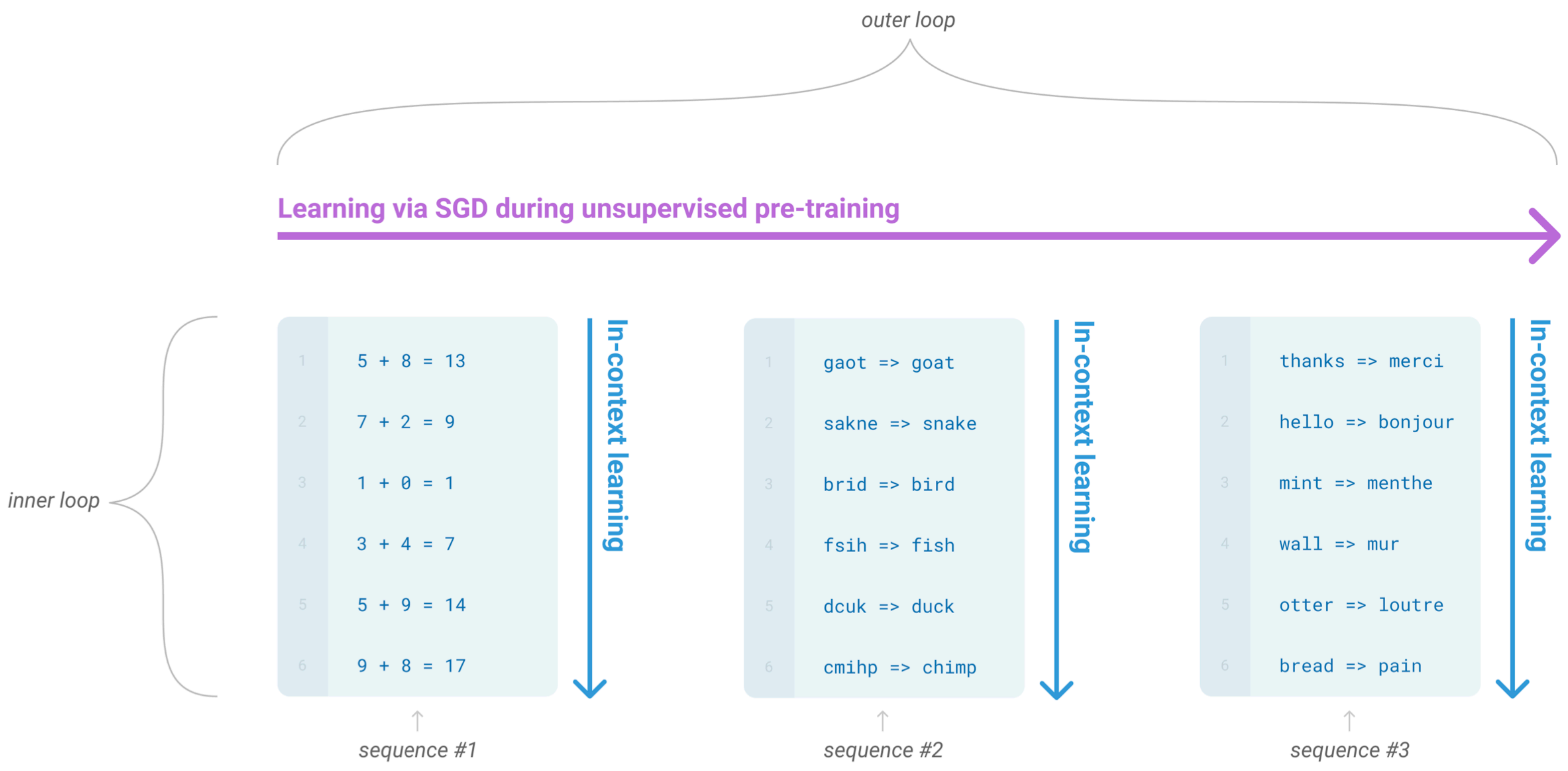
Few-shot

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

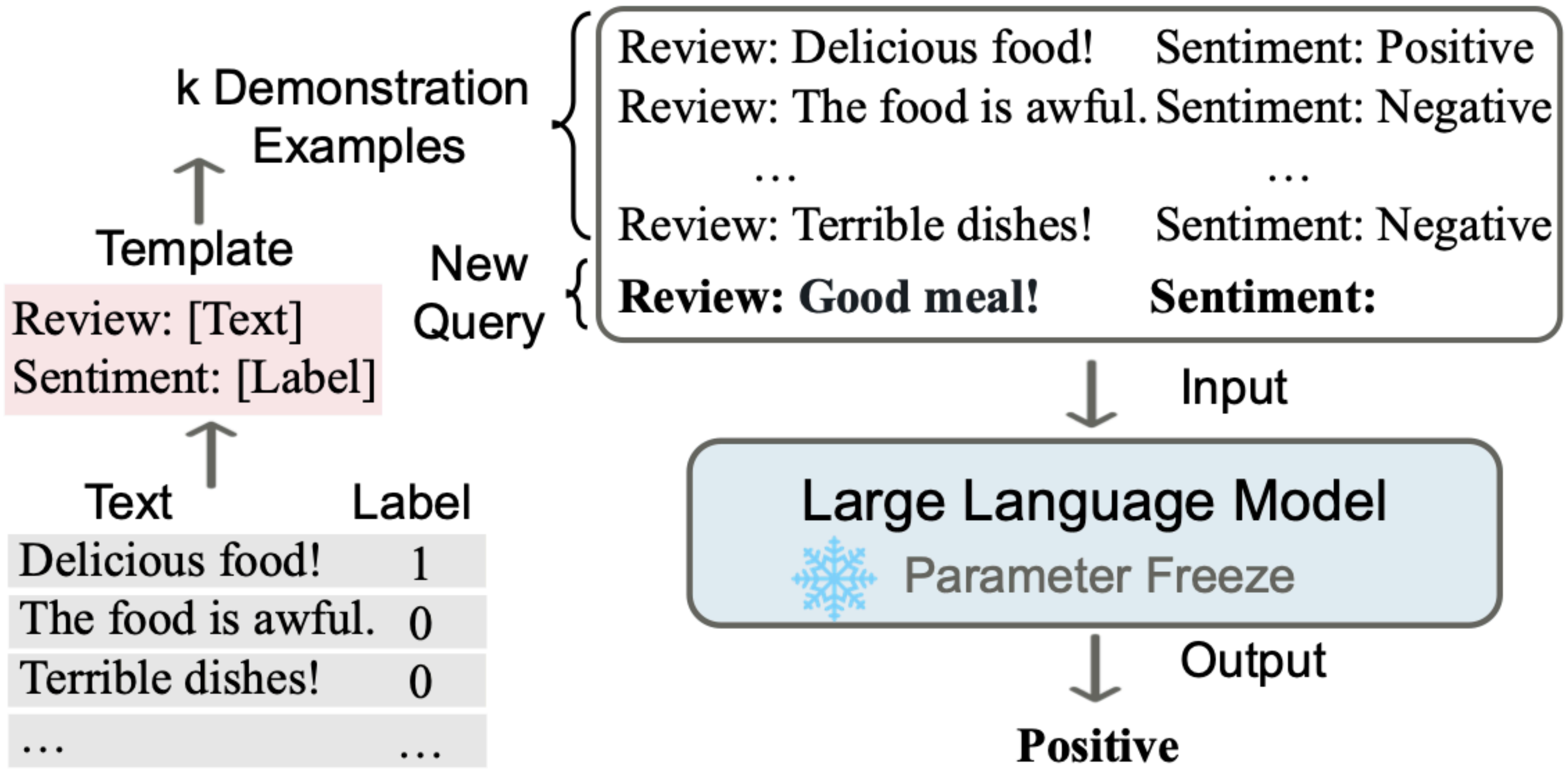
`Translate English to French:`	*task description*
`sea otter => loutre de mer`	*examples*
`peppermint => menthe poivrée`	
`plush girafe => girafe peluche`	
`cheese =>`	*prompt*

Fine-tuning fails at scale

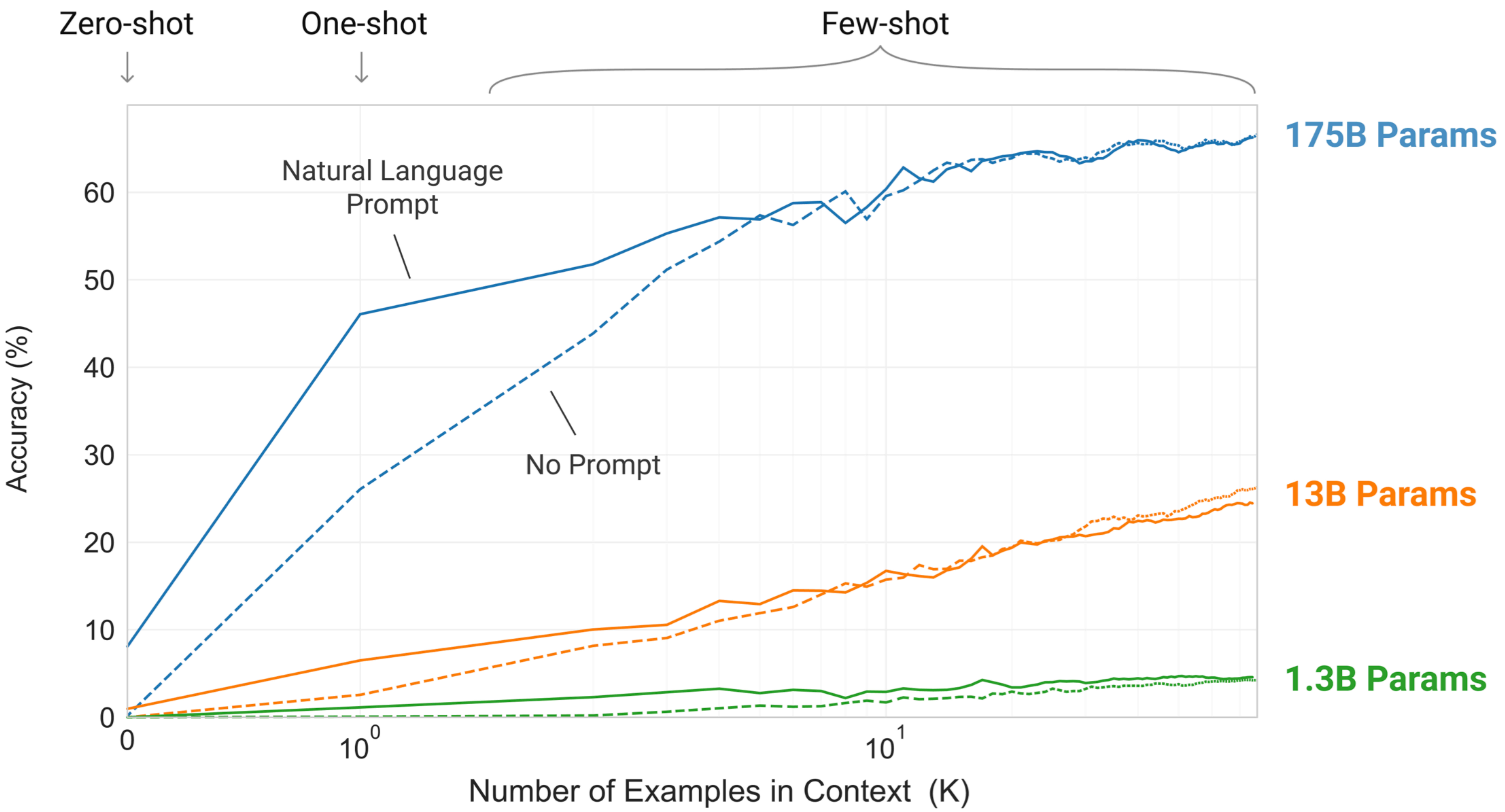
- LLMs >10B parameters are very difficult to fine-tune and requires a big compute budget
- So in-context learning using a long prompt or prefix is needed to coax the answer from a "predict the next token" approach to solving multiple tasks
- Pre-training on web-scale text can observe many different tasks in-context during training in the inner loop (per batch)
- Gradient descent improves the model representations based on next token prediction over many batch updates in the outer loop

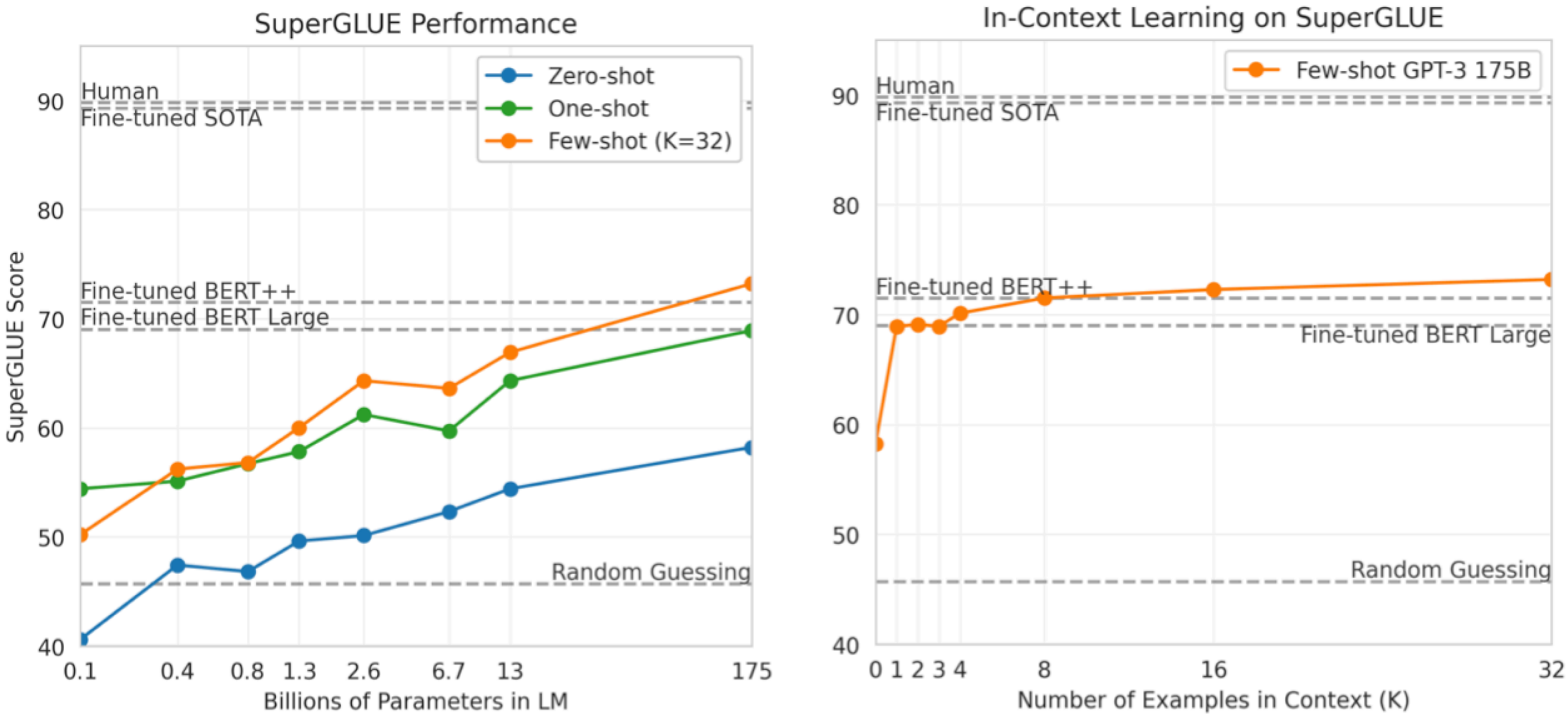

outer loop
Learning via SGD during unsupervised pre-training
inner loop
5 + 8 = 13
7 + 2 = 9
1 + 0 = 1
3 + 4 = 7
5 + 9 = 14
9 + 8 = 17
In-context learning
sequence #1
gaot => goat
sakne => snake
brid => bird
fsih => fish
dcuk => duck
cmihp => chimp
In-context learning
sequence #2
thanks => merci
hello => bonjour
mint => menthe
wall => mur
otter => loutre
bread => pain
In-context learning
sequence #3

Inference time



https://arxiv.org/abs/2301.00234


Zero-shot
One-shot
Few-shot
175B Params
13B Params
1.3B Params
Natural Language Prompt
No Prompt
Accuracy (%)
60
50
40
30
20
10
0
0
10^0
10^1
Number of Examples in Context (K)



Performance on SuperGLUE increases with number of examples in context. We find the difference in performance between the BERT-Large and BERT++ to be roughly equivalent to the difference between GPT-3 with one example per context versus eight examples per context.

	SuperGLUE Average	BoolQ Accuracy	CB Accuracy	CB F1	COPA Accuracy	RTE Accuracy
Fine-tuned SOTA	**89.0**	**91.0**	**96.9**	**93.9**	**94.8**	**92.5**
Fine-tuned BERT-Large	69.0	77.4	83.6	75.7	70.6	71.7
GPT-3 Few-Shot	71.8	76.4	75.6	52.0	92.0	69.0

	WiC Accuracy	WSC Accuracy	MultiRC Accuracy	MultiRC F1a	ReCoRD Accuracy	ReCoRD F1
Fine-tuned SOTA	**76.1**	**93.8**	**62.3**	**88.2**	**92.5**	**93.3**
Fine-tuned BERT-Large	69.6	64.6	24.1	70.0	71.3	72.0
GPT-3 Few-Shot	49.4	80.1	30.5	75.4	90.2	91.1

Table 3.5: Performance of GPT-3 on SuperGLUE compared to fine-tuned baselines and SOTA. All results are reported on the test set. GPT-3 few-shot is given a total of 32 examples within the context of each task and performs no gradient updates.

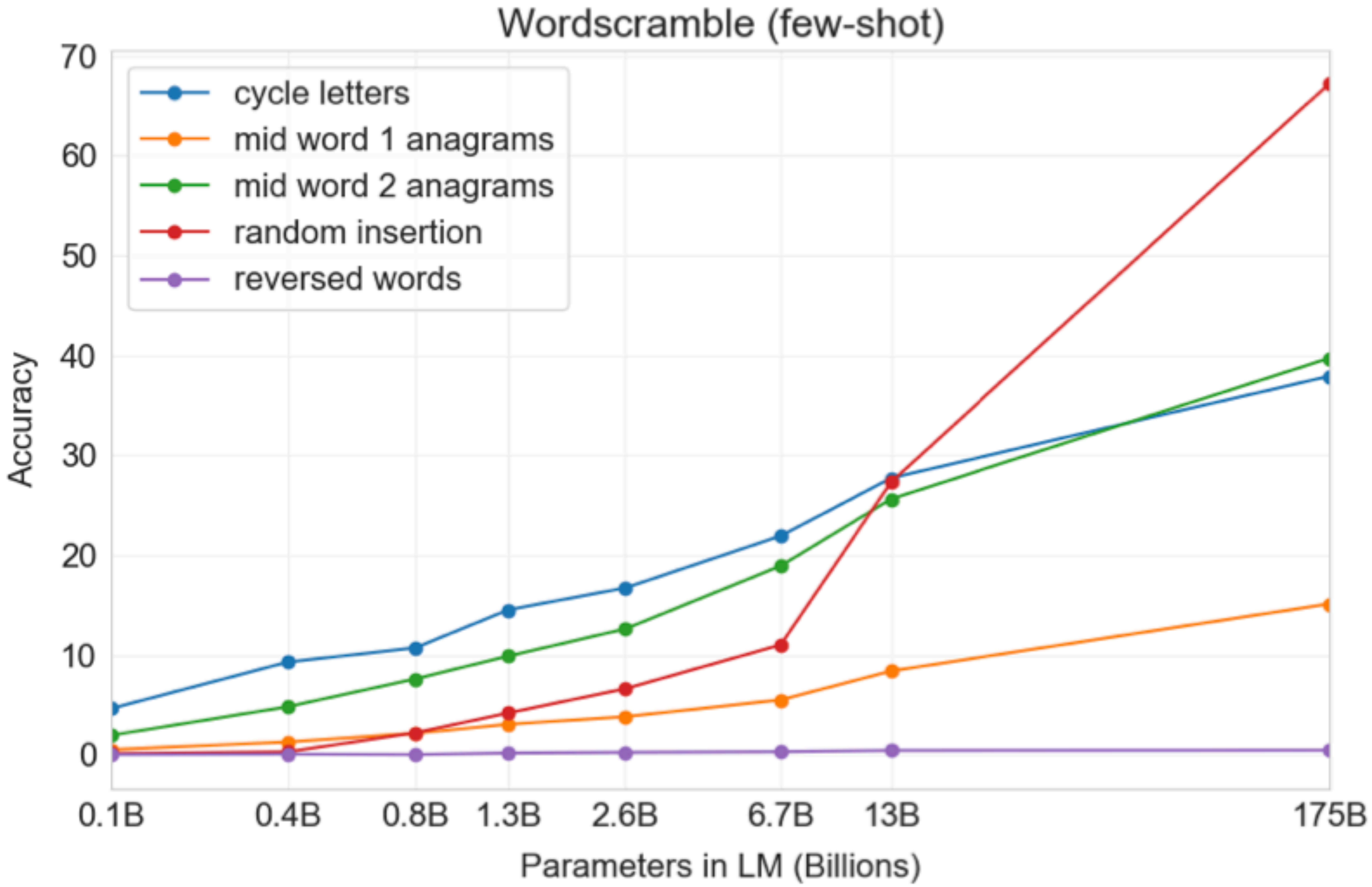
Setting	LAMBADA (acc)	LAMBADA (ppl)	StoryCloze (acc)	HellaSwag (acc)
SOTA	68.0[a]	8.63[b]	**91.8**[c]	**85.6**[d]
GPT-3 Zero-Shot	**76.2**	**3.00**	83.2	78.9
GPT-3 One-Shot	**72.5**	**3.35**	84.7	78.1
GPT-3 Few-Shot	**86.4**	**1.92**	87.7	79.3

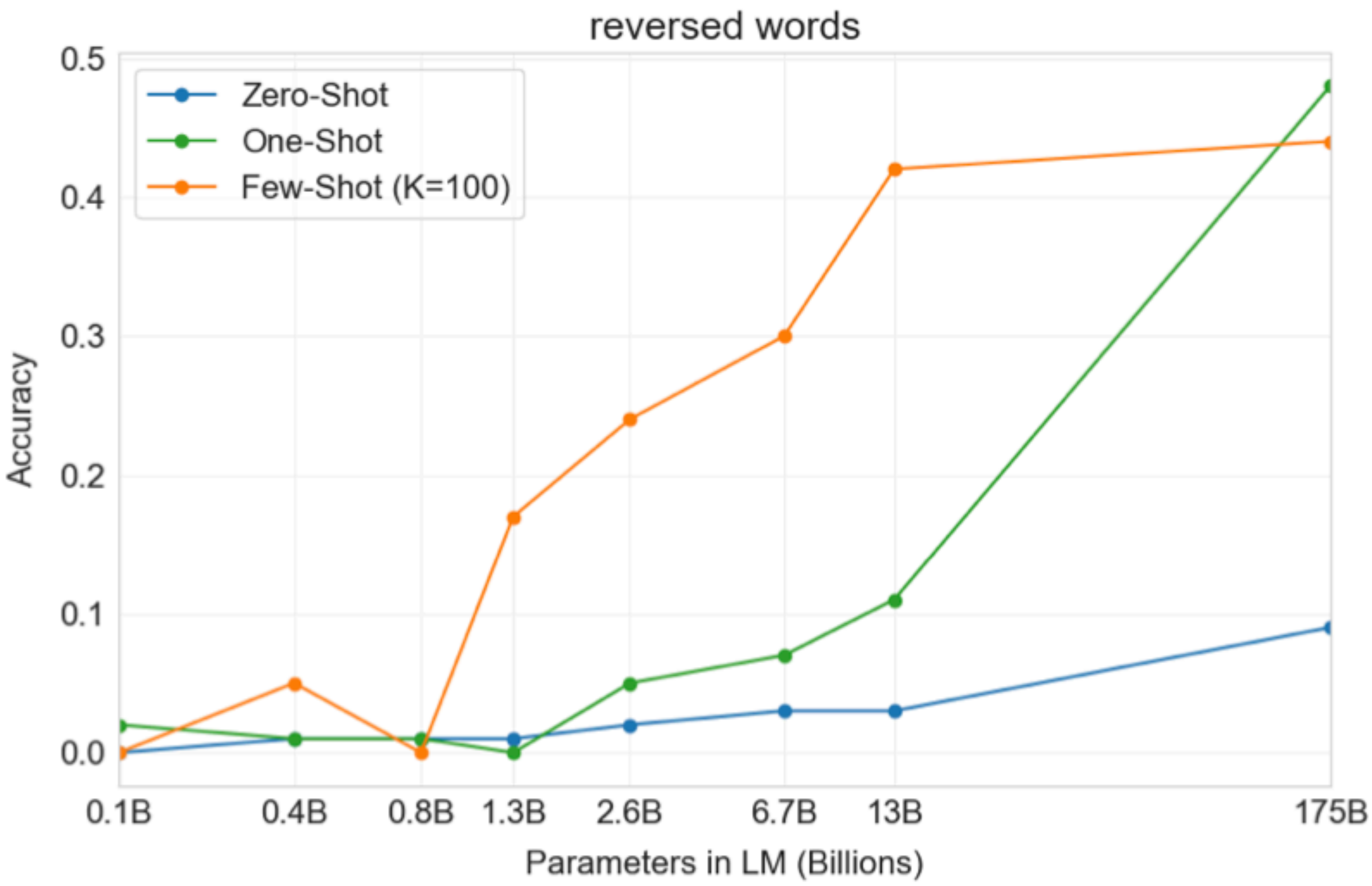
Setting	NaturalQS	WebQS	TriviaQA
RAG (Fine-tuned, Open-Domain) [LPP+20]	**44.5**	**45.5**	**68.0**
T5-11B+SSM (Fine-tuned, Closed-Book) [RRS20]	36.6	44.7	60.5
T5-11B (Fine-tuned, Closed-Book)	34.5	37.4	50.1
GPT-3 Zero-Shot	14.6	14.4	64.3
GPT-3 One-Shot	23.0	25.3	**68.0**
GPT-3 Few-Shot	29.9	41.5	**71.2**

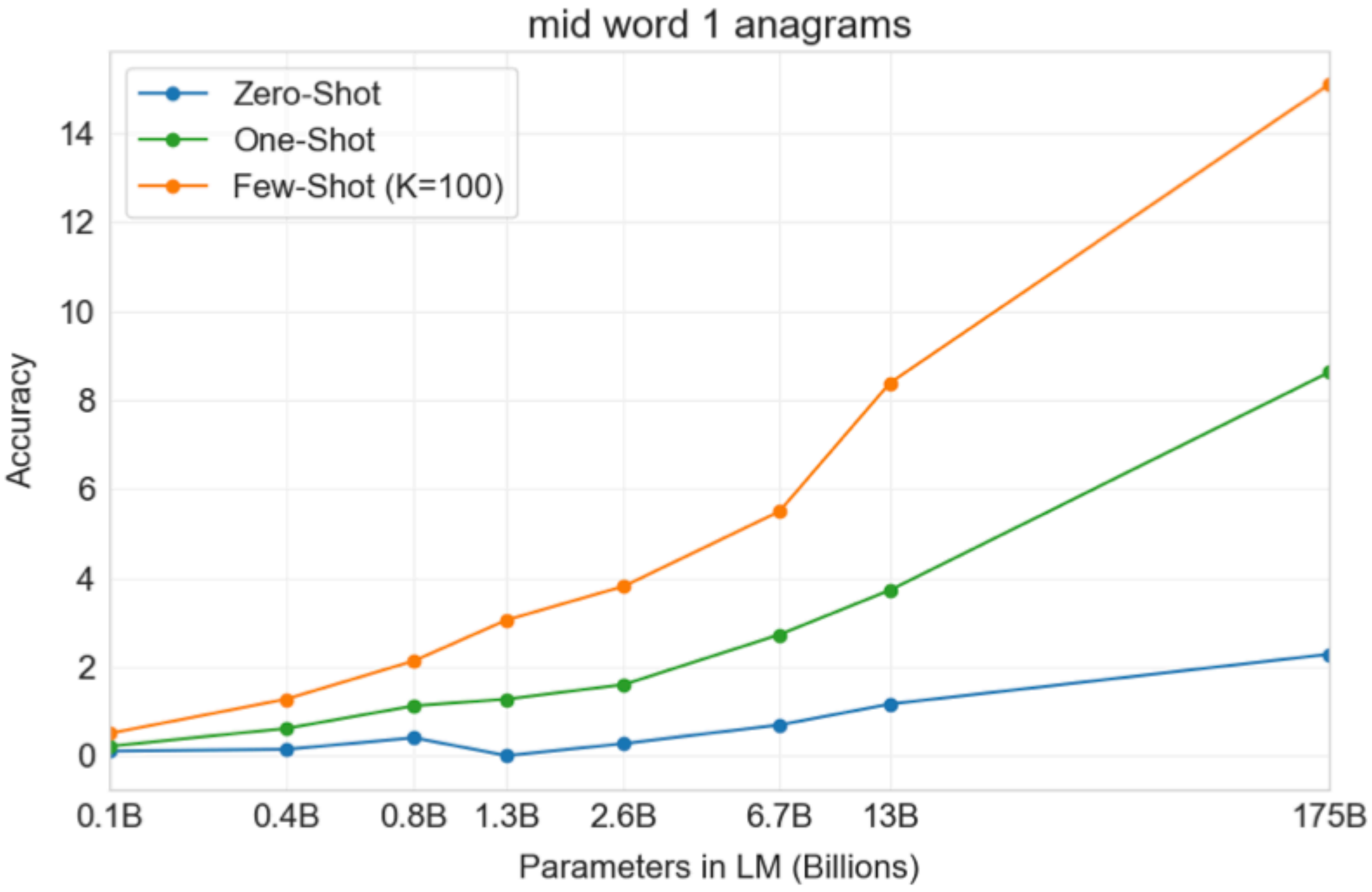
Setting	ARC (Easy)	ARC (Challenge)	CoQA	DROP
Fine-tuned SOTA	**92.0**[a]	**78.5**[b]	**90.7**[c]	**89.1**[d]
GPT-3 Zero-Shot	68.8	51.4	81.5	23.6
GPT-3 One-Shot	71.2	53.2	84.0	34.3
GPT-3 Few-Shot	70.1	51.5	85.0	36.5

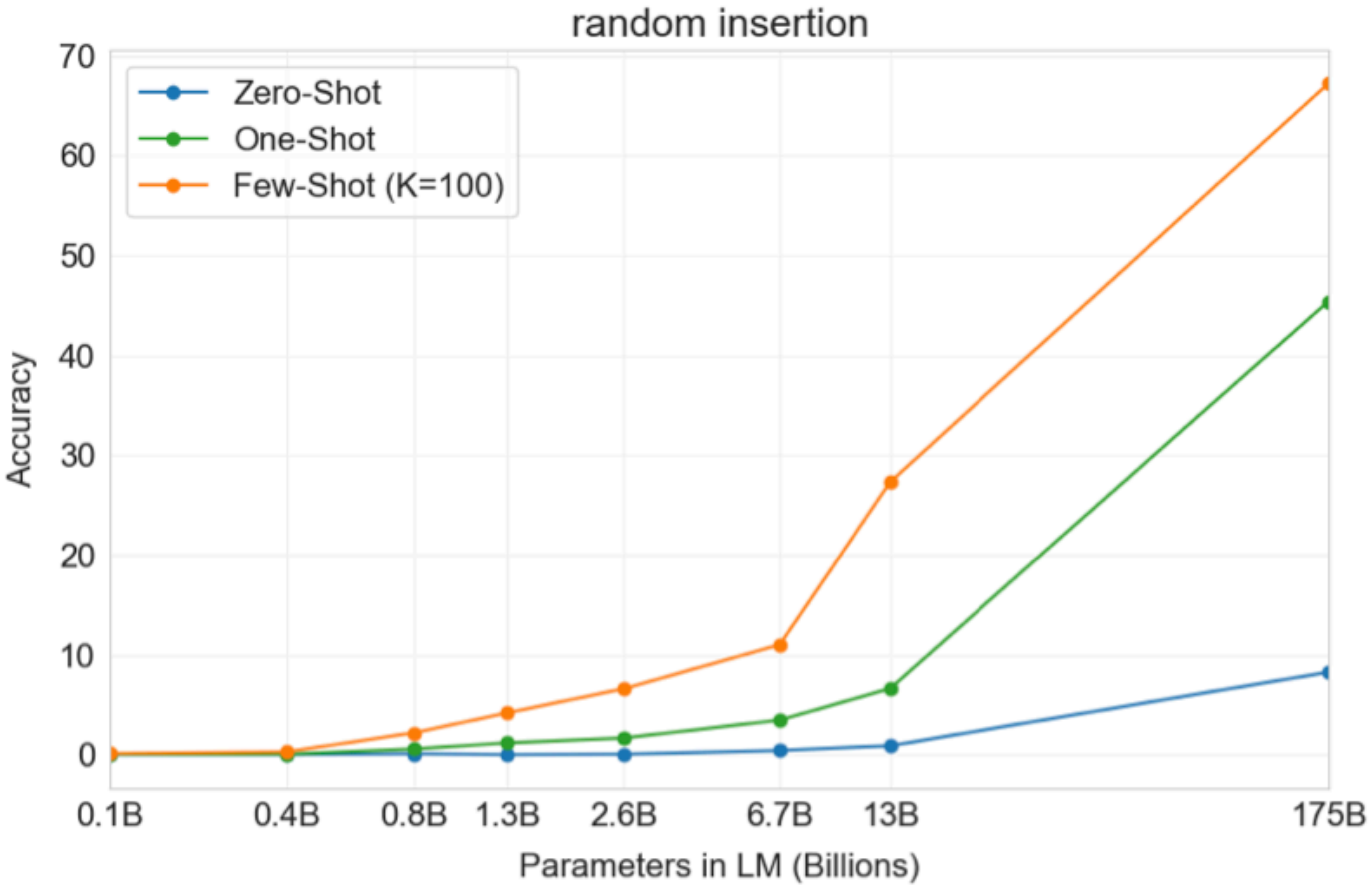
WMT 2014

Setting	En→Fr	Fr→En	En→De	De→En	En→Ro	Ro→En
SOTA (Supervised)	**45.6**[a]	35.0 [b]	**41.2**[c]	40.2[d]	**38.5**[e]	**39.9**[e]
XLM [LC19]	33.4	33.3	26.4	34.3	33.3	31.8
MASS [STQ+19]	<u>37.5</u>	34.9	28.3	35.2	<u>35.2</u>	33.1
mBART [LGG+20]	-	-	<u>29.8</u>	34.0	35.0	30.5
GPT-3 Zero-Shot	25.2	21.2	24.6	27.2	14.1	19.9
GPT-3 One-Shot	28.3	33.7	26.2	30.4	20.6	38.6
GPT-3 Few-Shot	32.6	<u>39.2</u>	29.7	<u>40.6</u>	21.0	<u>39.5</u>


Wordscramble (few-shot)
cycle letters
mid word 1 anagrams
mid word 2 anagrams
random insertion
reversed words
Accuracy
0
10
20
30
40
50
60
70
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
Parameters in LM (Billions)


reversed words
Zero-Shot
One-Shot
Few-Shot (K=100)
Accuracy
0.0
0.1
0.2
0.3
0.4
0.5
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
Parameters in LM (Billions)

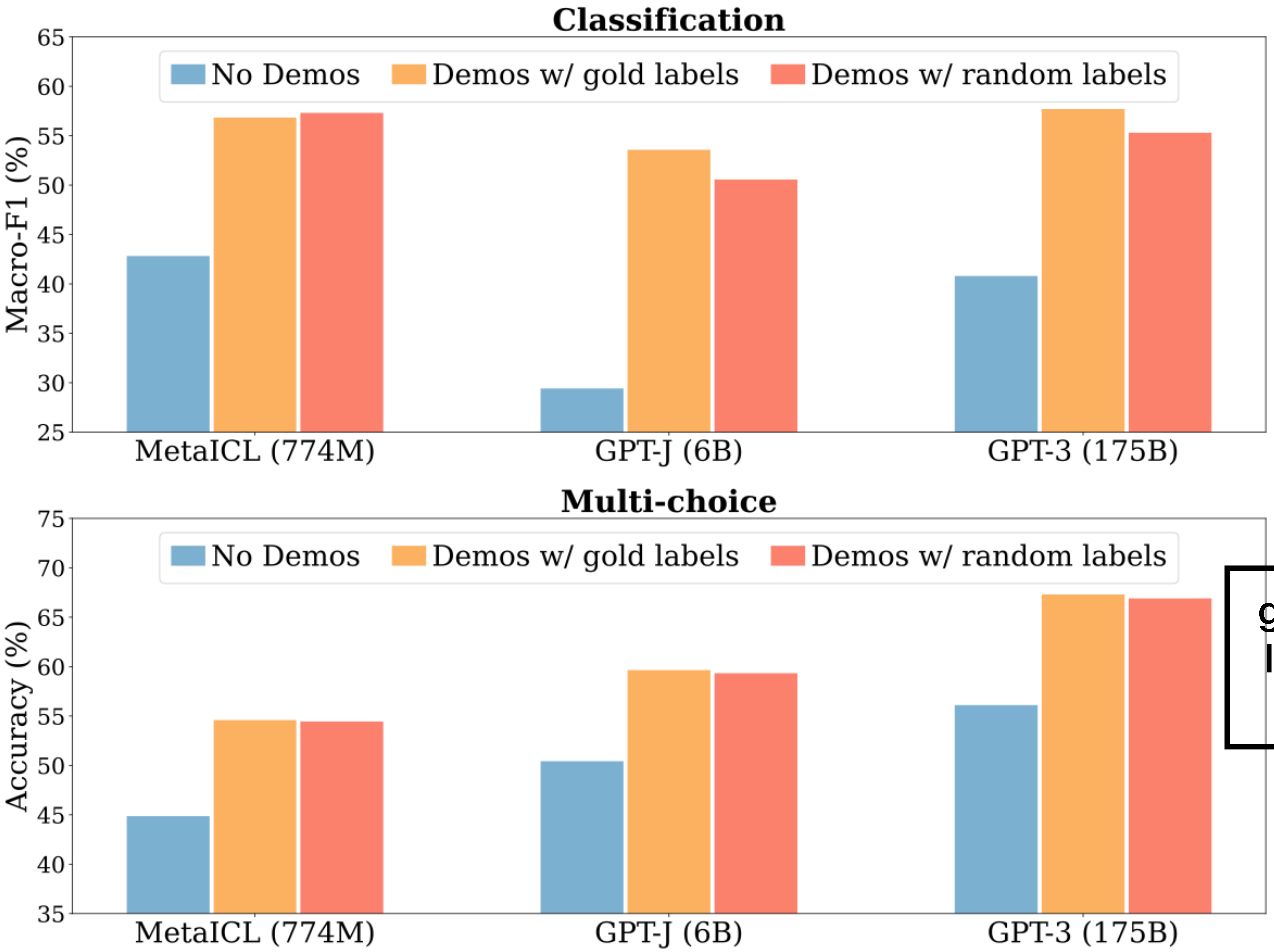

mid word 1 anagrams
Zero-Shot
One-Shot
Few-Shot (K=100)
Accuracy
Parameters in LM (Billions)
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
0
2
4
6
8
10
12
14


random insertion
Zero-Shot
One-Shot
Few-Shot (K=100)
Accuracy
Parameters in LM (Billions)
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
0
10
20
30
40
50
60
70

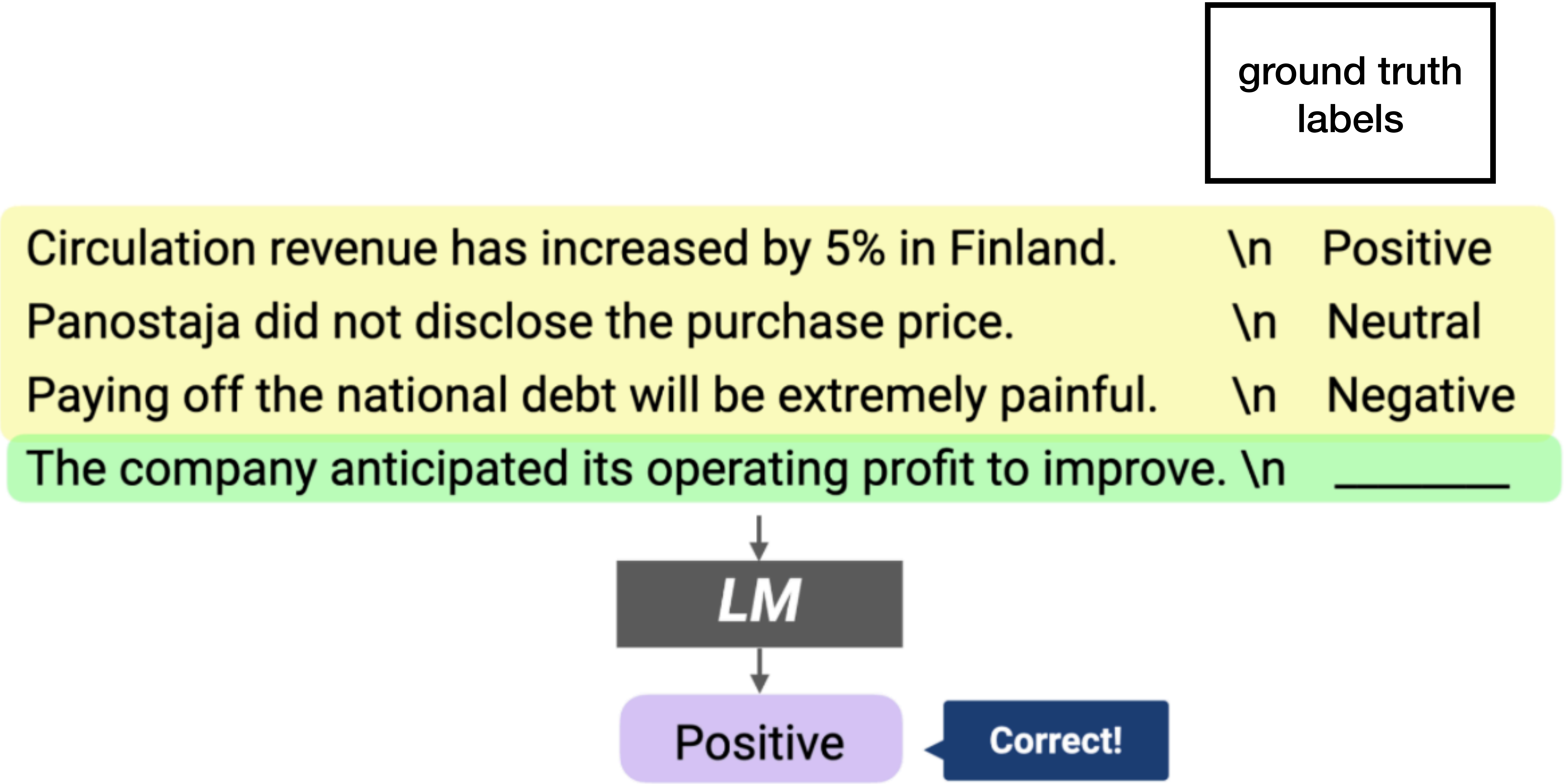
Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?

Sewon Min[1,2] **Xinxi Lyu**[1] **Ari Holtzman**[1] **Mikel Artetxe**[2]
Mike Lewis[2] **Hannaneh Hajishirzi**[1,3] **Luke Zettlemoyer**[1,2]
[1]University of Washington [2]Meta AI [3]Allen Institute for AI

https://arxiv.org/abs/2202.12837

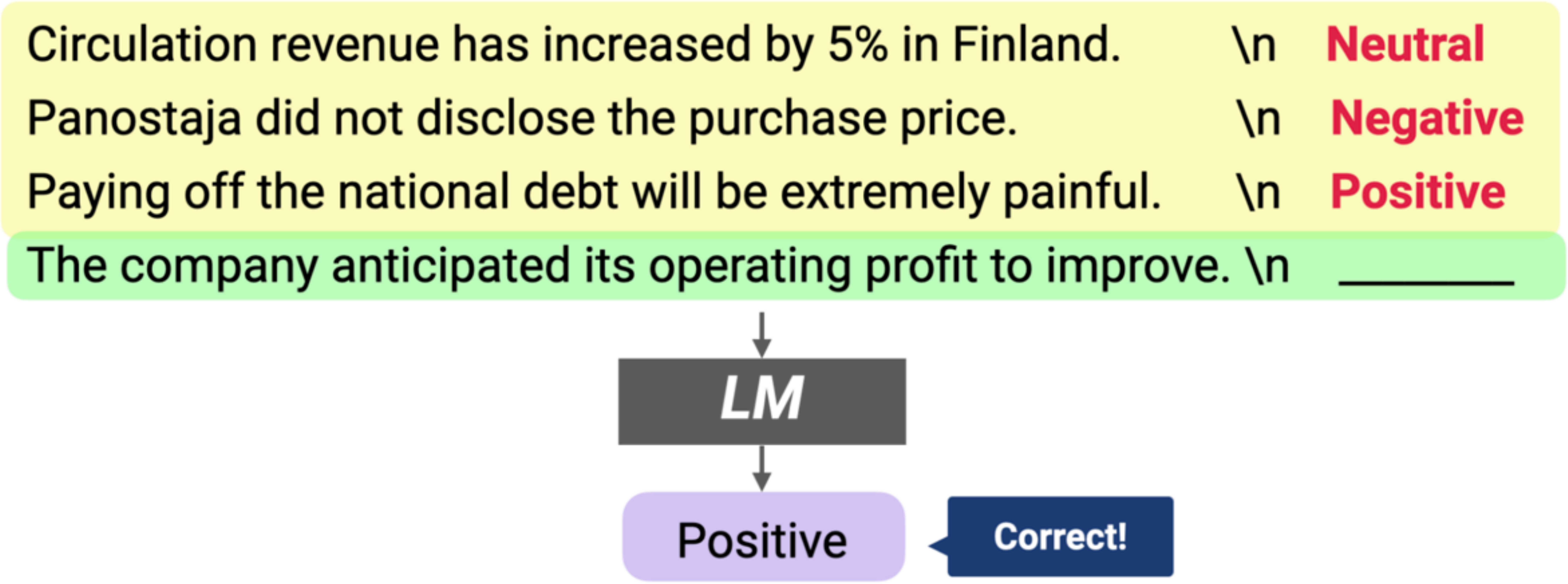


ground truth labels don't matter!



ground truth labels
Circulation revenue has increased by 5% in Finland. \n Positive
Panostaja did not disclose the purchase price. \n Neutral
Paying off the national debt will be extremely painful. \n Negative
The company anticipated its operating profit to improve. \n ______
LM
Positive
Correct!

replace true labels with random labels



Why does in-context learning work?

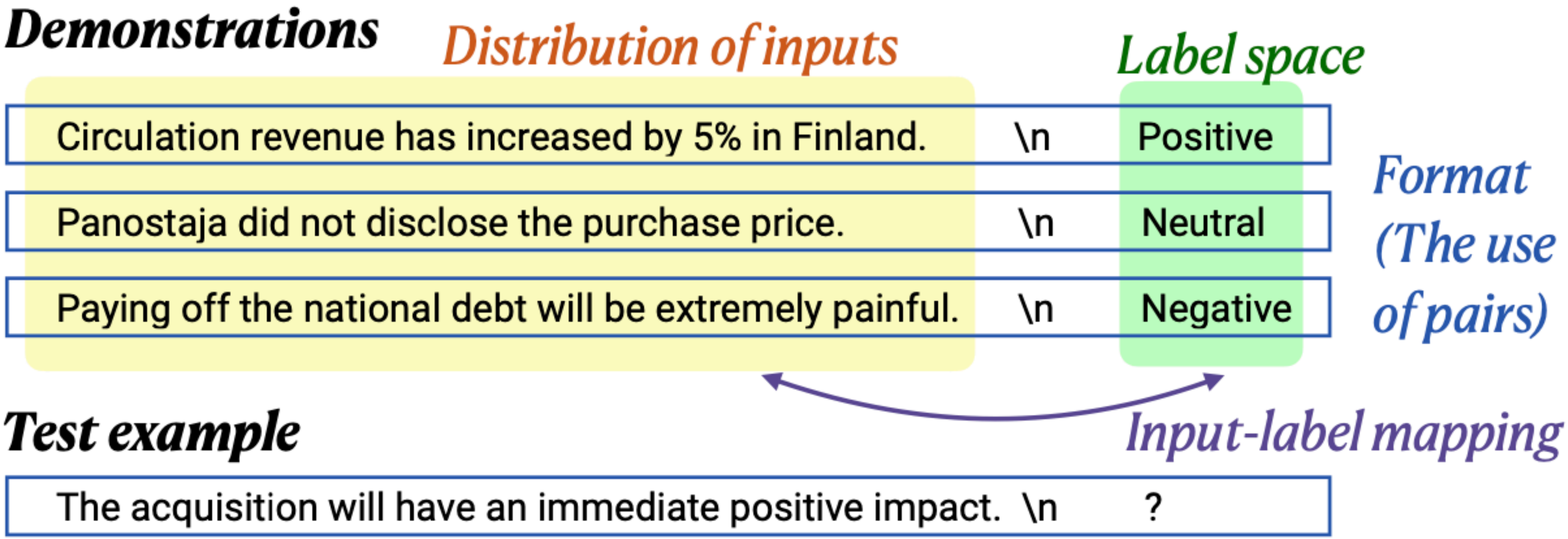
Four hypotheses

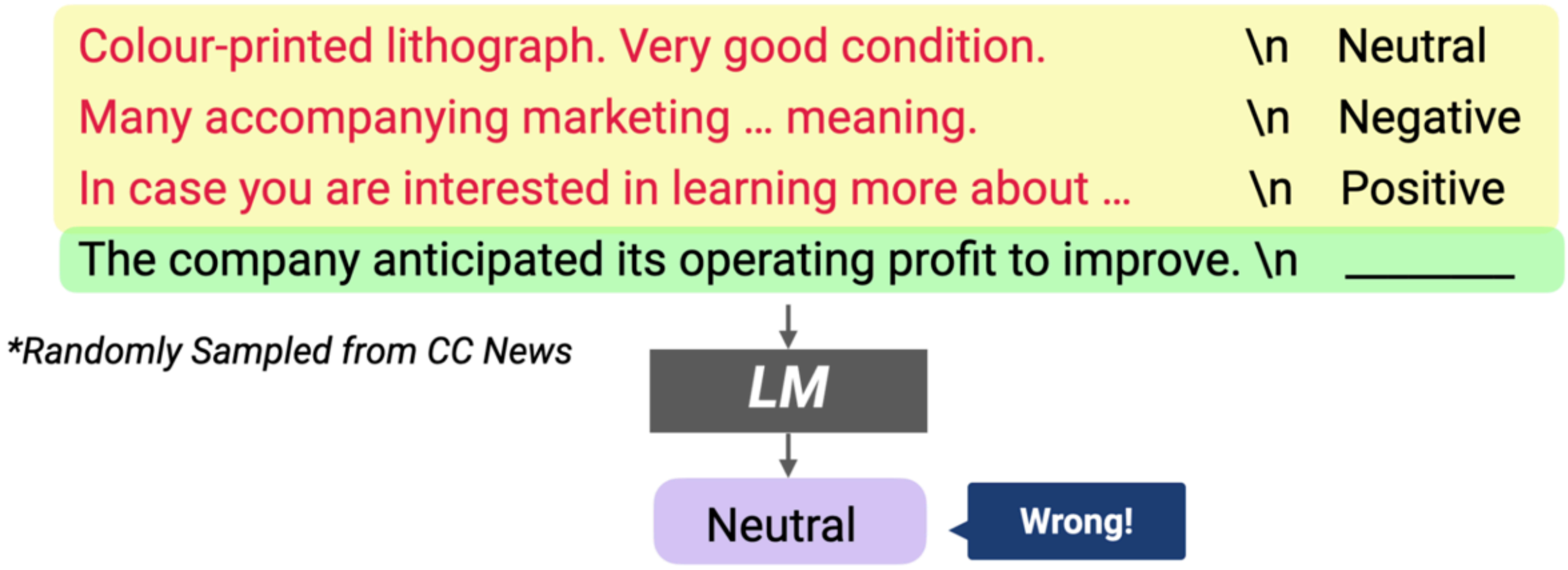
1. The input-label mapping, whether each input x_i is paired with the correct label y_i (not true)

2. The distribution that the input $x_1, \ldots, x_k$ are from (is it from a sports article, or business news?)

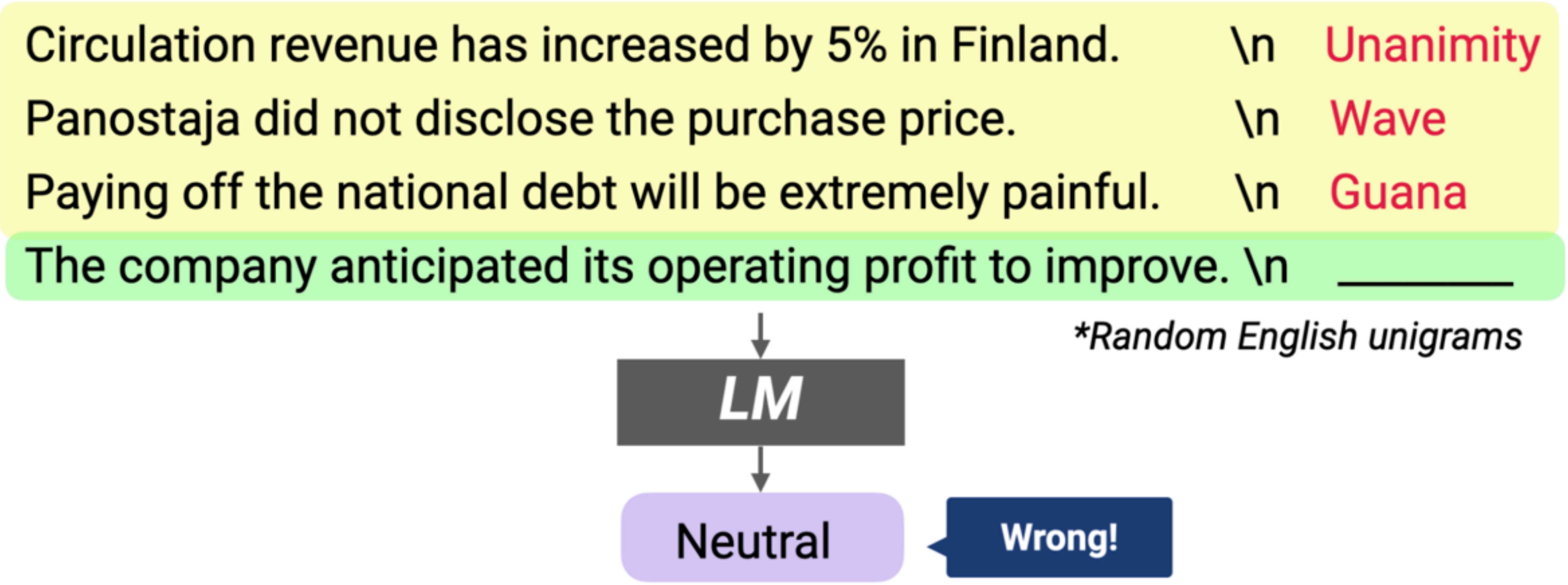
3. The output label space $y_1, \ldots, y_k$

4. The format of the demonstration, e.g. `x // y`; `Input: x Output: y`; etc.

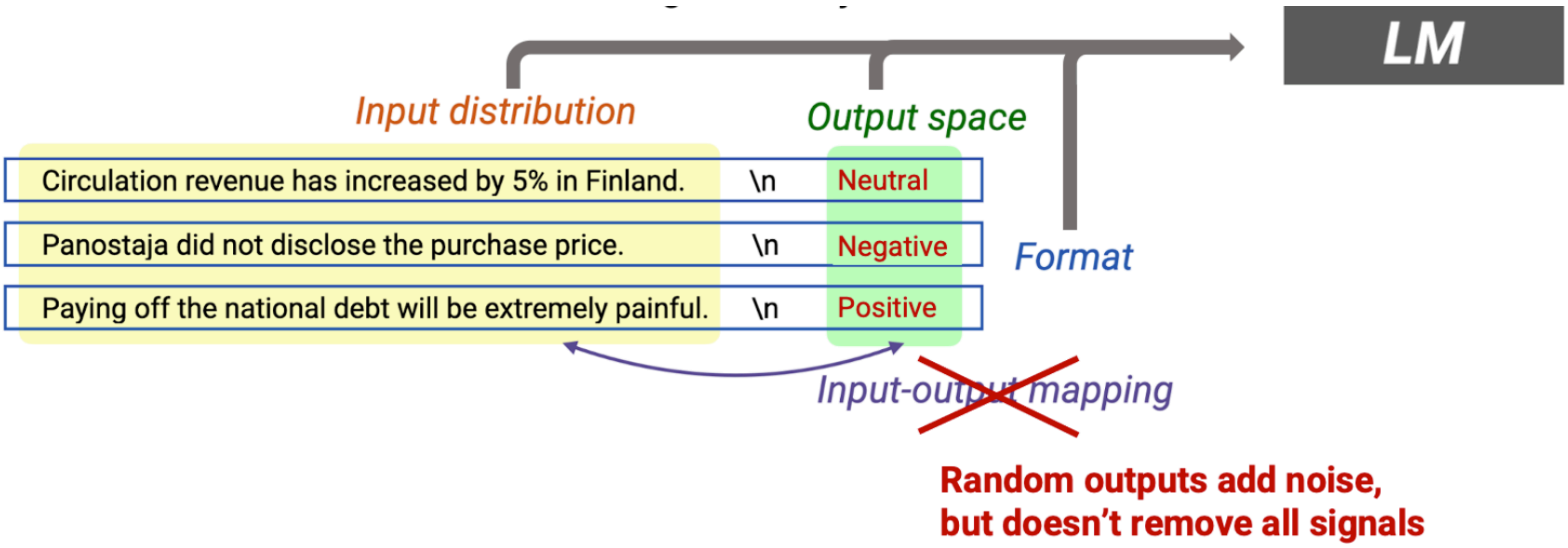

Demonstrations
Distribution of inputs
Label space
Circulation revenue has increased by 5% in Finland. \n Positive
Panostaja did not disclose the purchase price. \n Neutral
Paying off the national debt will be extremely painful. \n Negative
Format (The use of pairs)
Test example
Input-label mapping
The acquisition will have an immediate positive impact. \n ?



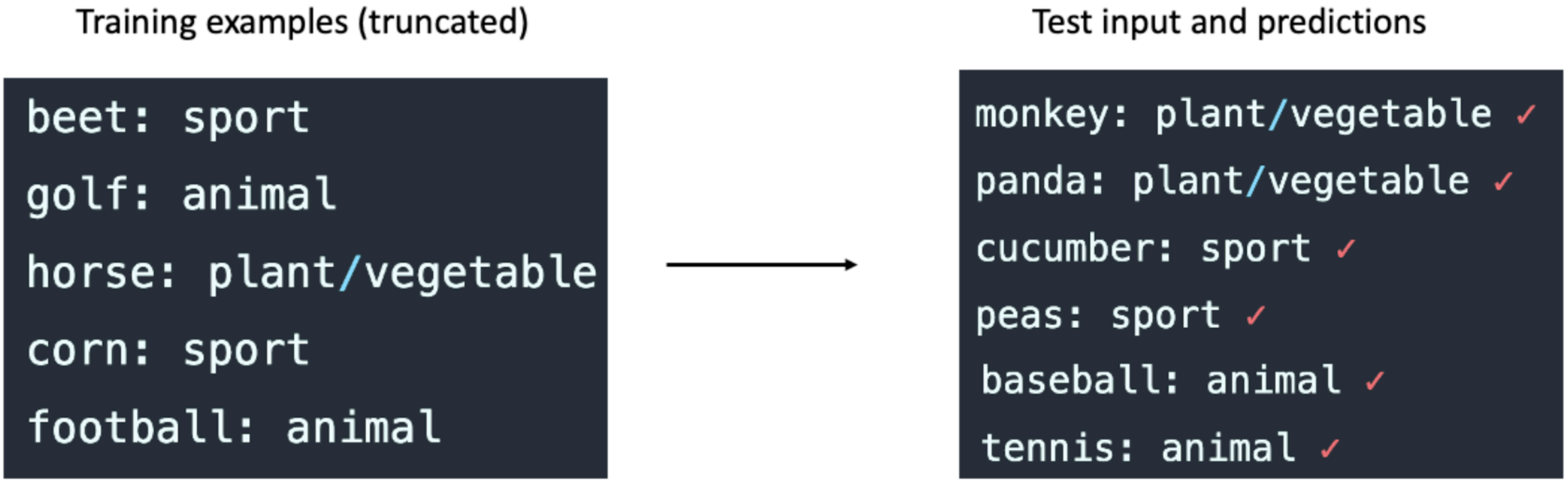
The input distribution matters: using inputs from an out of domain corpus causes a large performance drop



The output distribution matters: using labels that are random English unigrams causes a large performance drop



LM
Input distribution
Output space
Circulation revenue has increased by 5% in Finland.
\n
Neutral
Panostaja did not disclose the purchase price.
\n
Negative
Paying off the national debt will be extremely painful.
\n
Positive
Format
Input-output mapping
Random outputs add noise,
but doesn't remove all signals



An example synthetic task with unusual semantics that GPT-3 can successfully learn. A modified figure from Rong.

Efficient few-shot learning

Prompt tuning: few-shot with smaller LMs

iPet: better pre-training for each task improves accuracy for small LMs

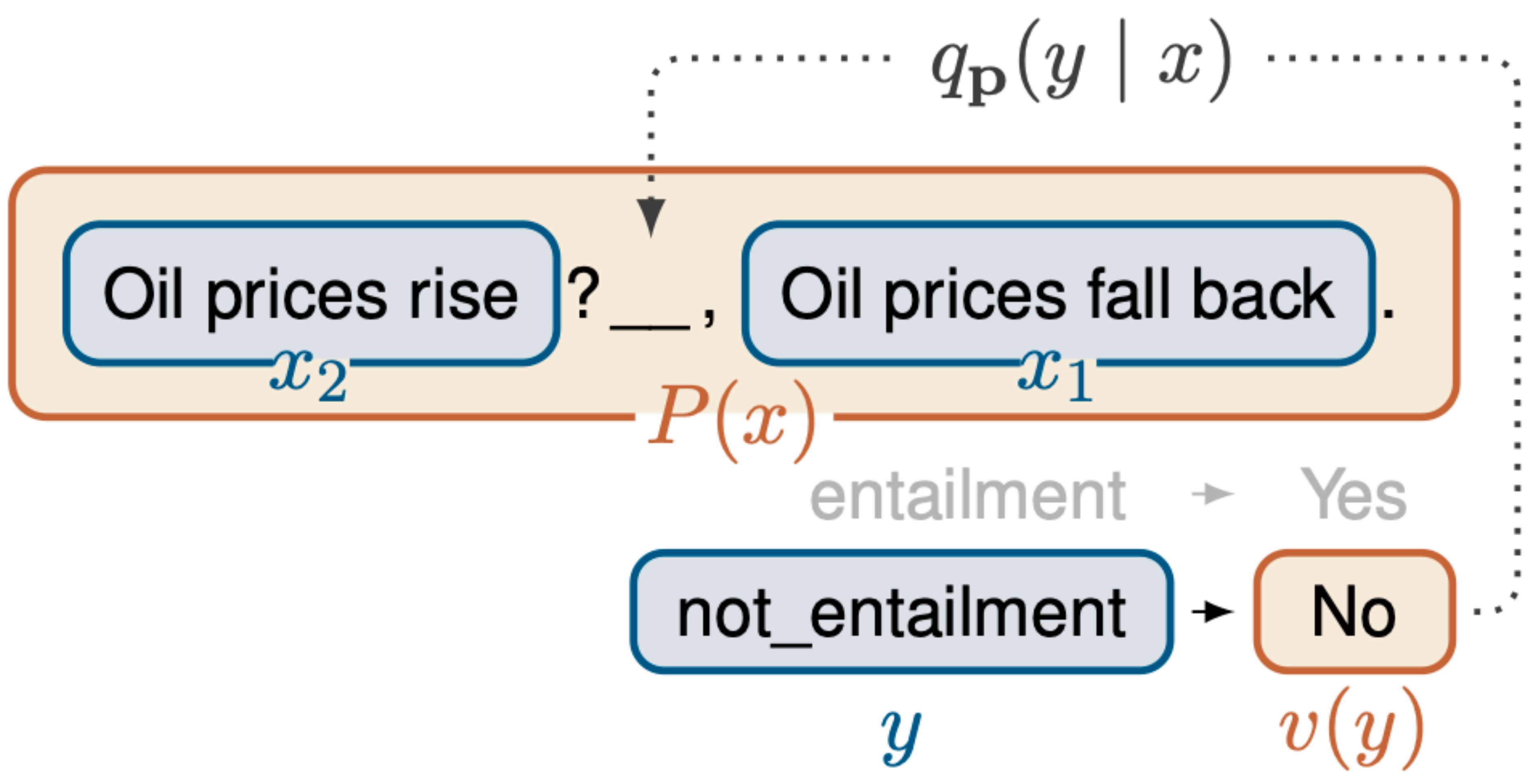


Figure 2: Application of a PVP $\mathbf{p} = (P, v)$ for recognizing textual entailment: An input $x = (x_1, x_2)$ is converted into a cloze question $P(x)$; $q_{\mathbf{p}}(y \mid x)$ for each y is derived from the probability of $v(y)$ being a plausible choice for the masked position.

test	GPT-3	175,000	71.8	prompt
	PET	223	74.0	prompt FT
	iPET	223	**75.4**	prompt FT
	SotA	11,000	*89.3*	full FT

https://arxiv.org/abs/2001.07676

Summary

Few-shot Prompting

https://arxiv.org/abs/2102.09690

- Sensitivity to prompts (Zhao et al 2021):
  - *Majority label bias* — if label distribution is not balanced
  - *Recency bias* — label at the end may be repeated.
  - *Example ordering*