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GPT-3 and the future of language modeling

CS685 Fall 2020
Advanced Natural Language Processing

Mohit Iyyer
College of Information and Computer Sciences
University of Massachusetts Amherst

Stuff from last time

- How is the [CLS] token pretrained (e.g., how does it learn a contextualized vector during pretraining?) Is it shared across all pretraining sentences?

- We get multiple embeddings per token in ELMo and BERT (different layers), how do we choose which to use?

- Project proposal feedback by the end of the week!

- Practice exams available on Piazza

Today, an alternative to "pretrain+finetune", which involves simply getting rid of fine-tuning

"Language models are few-shot learners", Brown et al., 2020

The language model “scaling wars”!

ELMo: 93M params, 2-layer biLSTM

BERT-base: 110M params, 12-layer Transformer

BERT-large: 340M params, 24-layer Transformer

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BERT-large: 340M params, 24-layer Transformer

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or “GPT-3”	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

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The language model “scaling wars”!

ELMo: 1B training tokens

BERT: 3.3B training tokens

RoBERTa: ~30B training tokens

The language model “scaling wars”!

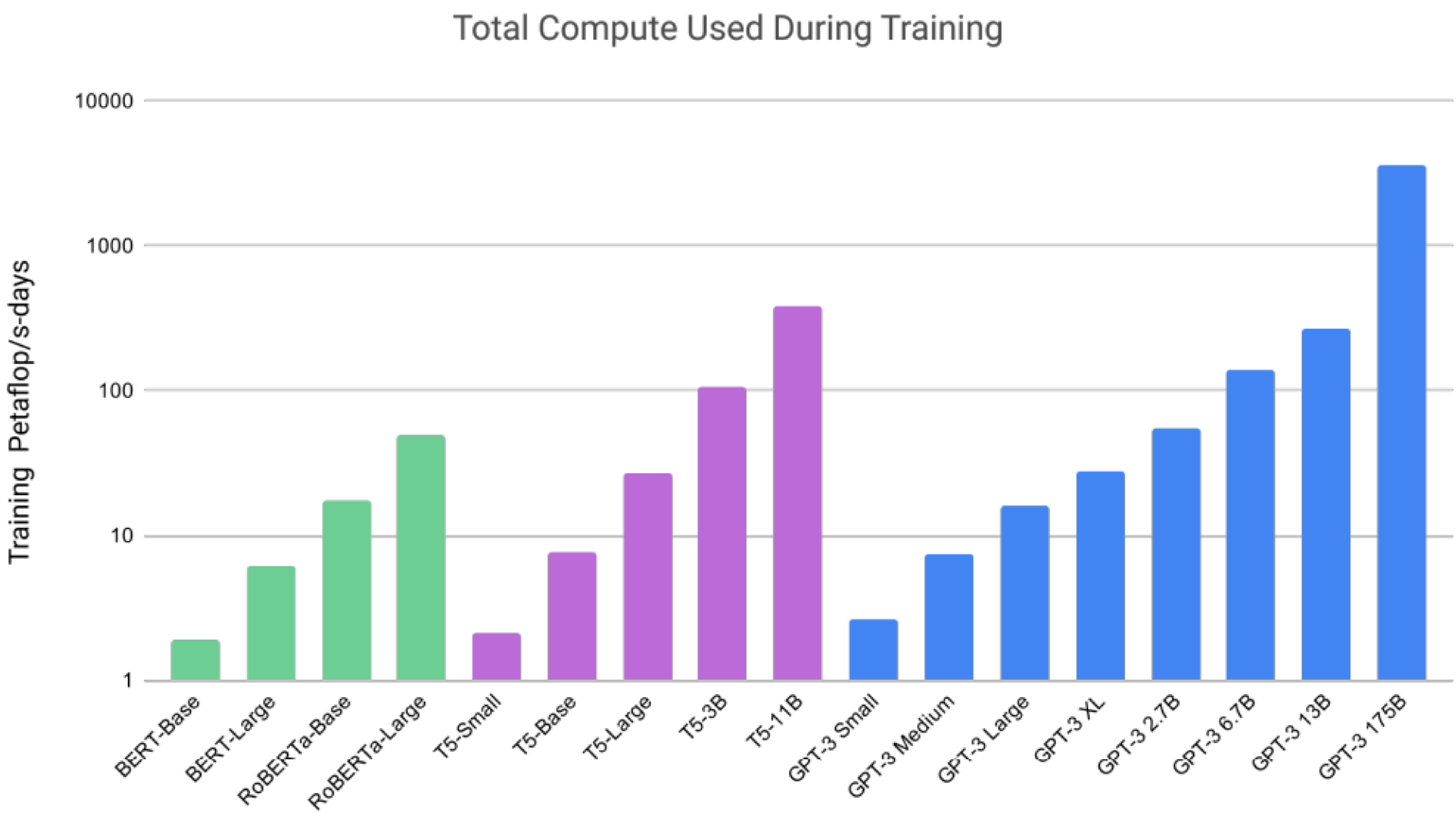
ELMo: 1B training tokens

BERT: 3.3B training tokens

RoBERTa: ~30B training tokens

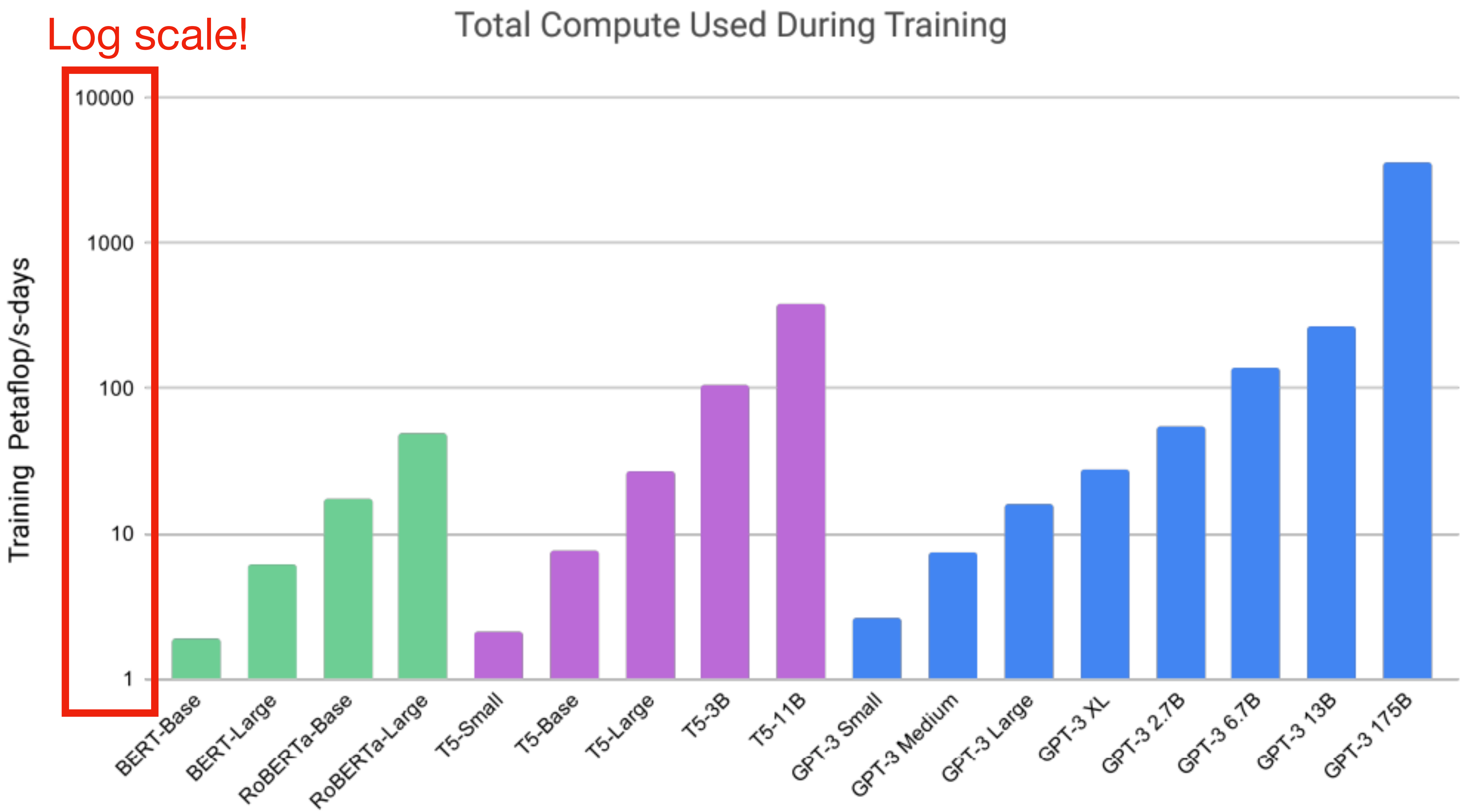
Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for $\boxed{\text{300B tokens}}$
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

The language model "scaling wars"!



The language model “scaling wars”!

Log scale!



so… what does all of this scaling buy us?

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.
sea otter => loutre de mer
example #1
gradient update
peppermint => menthe poivrée
example #2
gradient update
plush giraffe => girafe peluche
example #N
gradient update
cheese =>
prompt
Downstream training data
Downstream test data

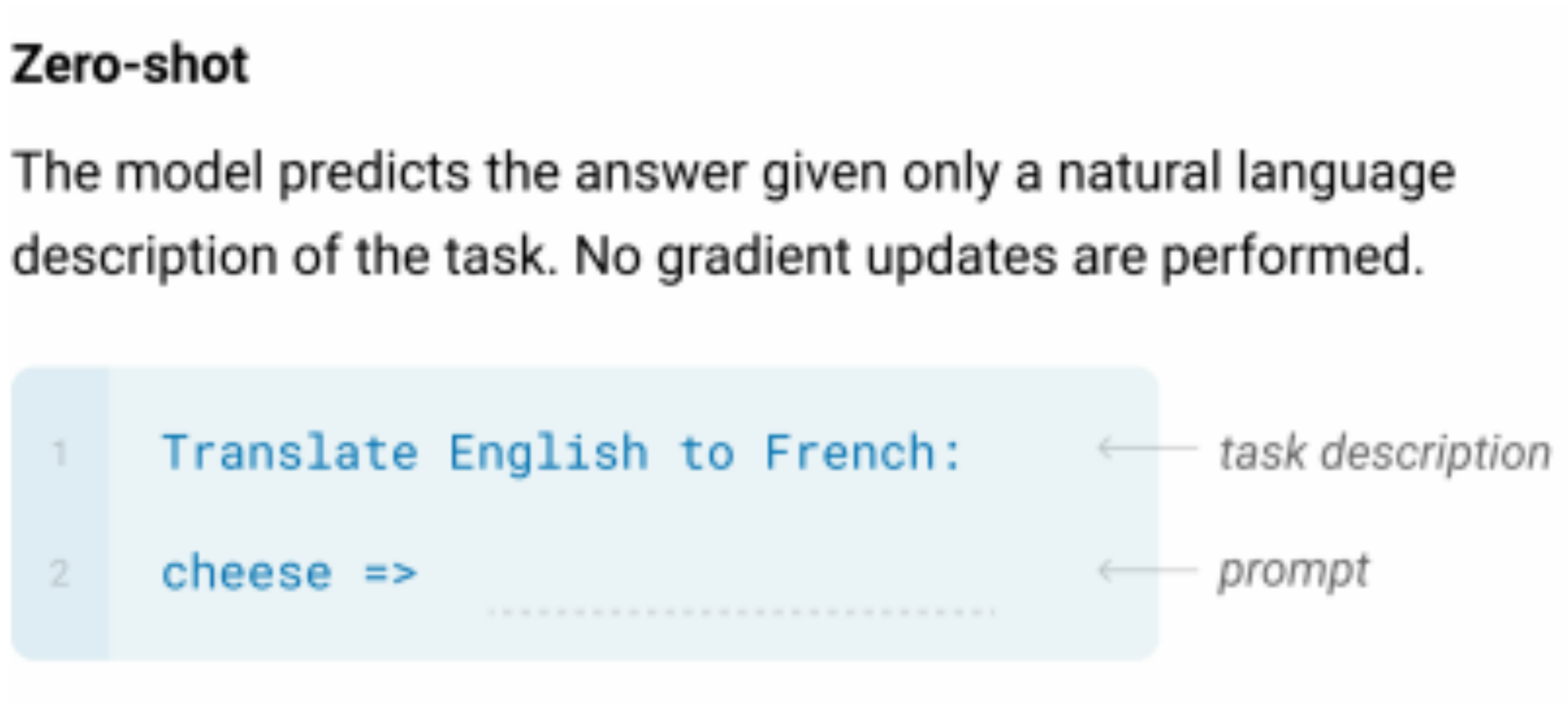
Zero-shot

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

```
Translate English to French:
cheese =>
```

task description

prompt



No fine-tuning!!! Literally just take a pretrained LM and give it the following prefix:

“Translate English to French: cheese =>”

One-shot

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

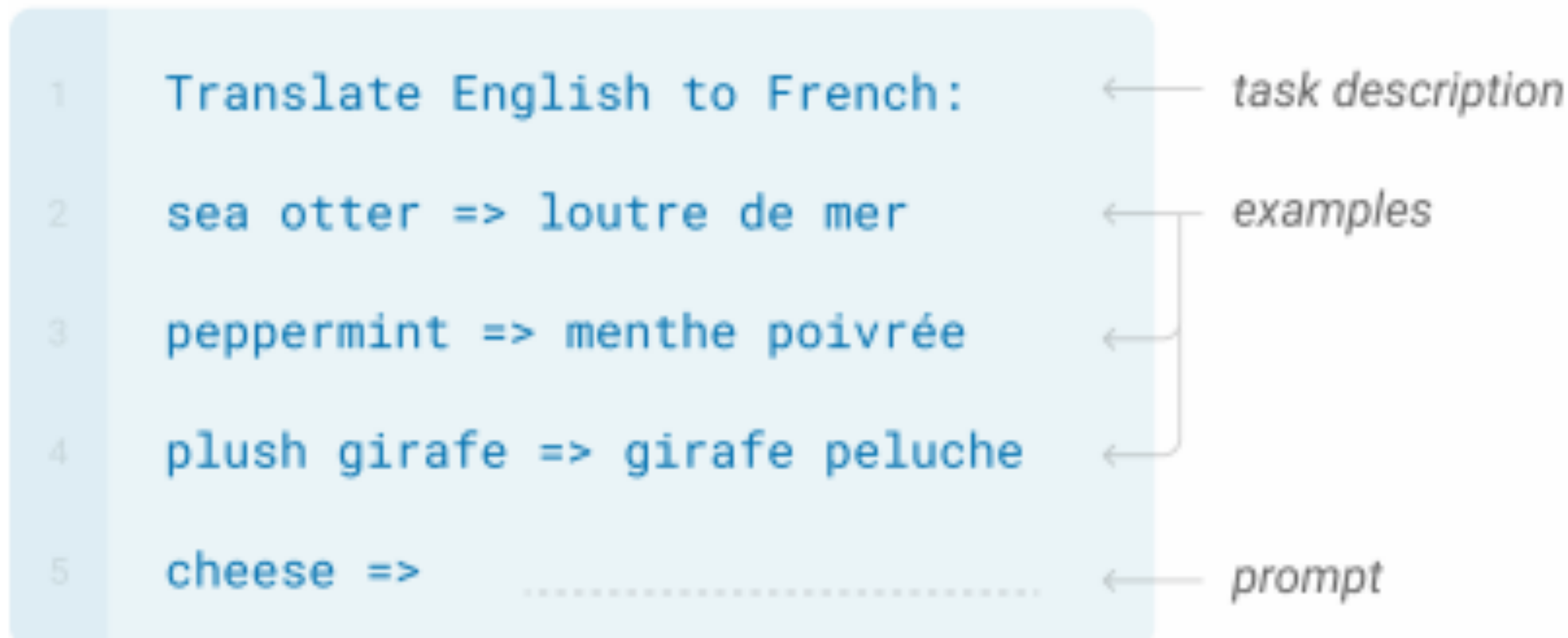
```
Translate English to French:        ← task description
sea otter => loutre de mer          ← example
cheese =>                           ← prompt
```

No fine-tuning!!! Literally just take a pretrained LM and give it the following prefix:

“Translate English to French: sea otter => loutre de mer, cheese =>”

Few-shot

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



No fine-tuning!!! Literally just take a pretrained LM and give it the following prefix:

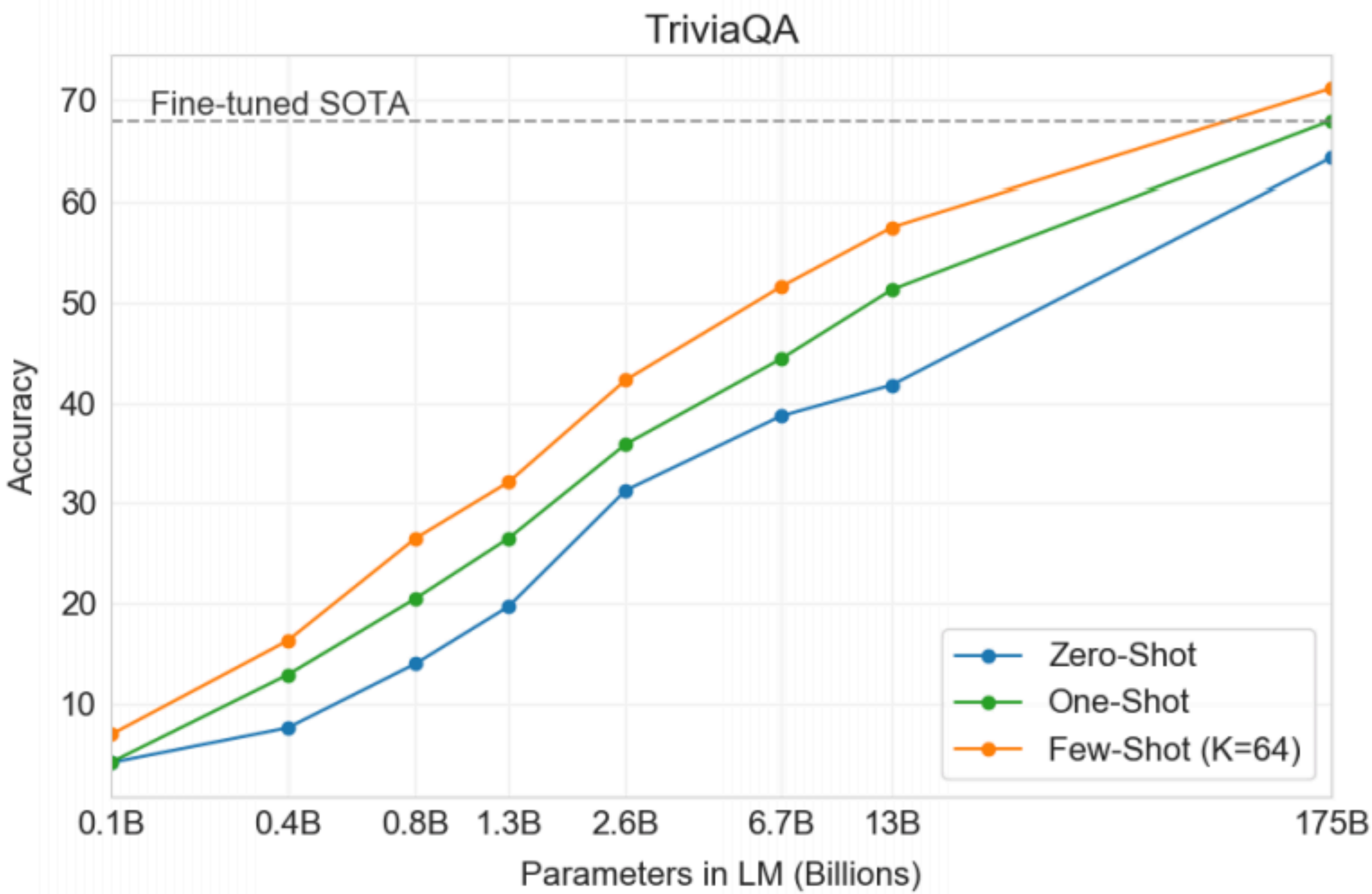
“Translate English to French: sea otter => loutre de mer, peppermint => … (few more examples), cheese =>”

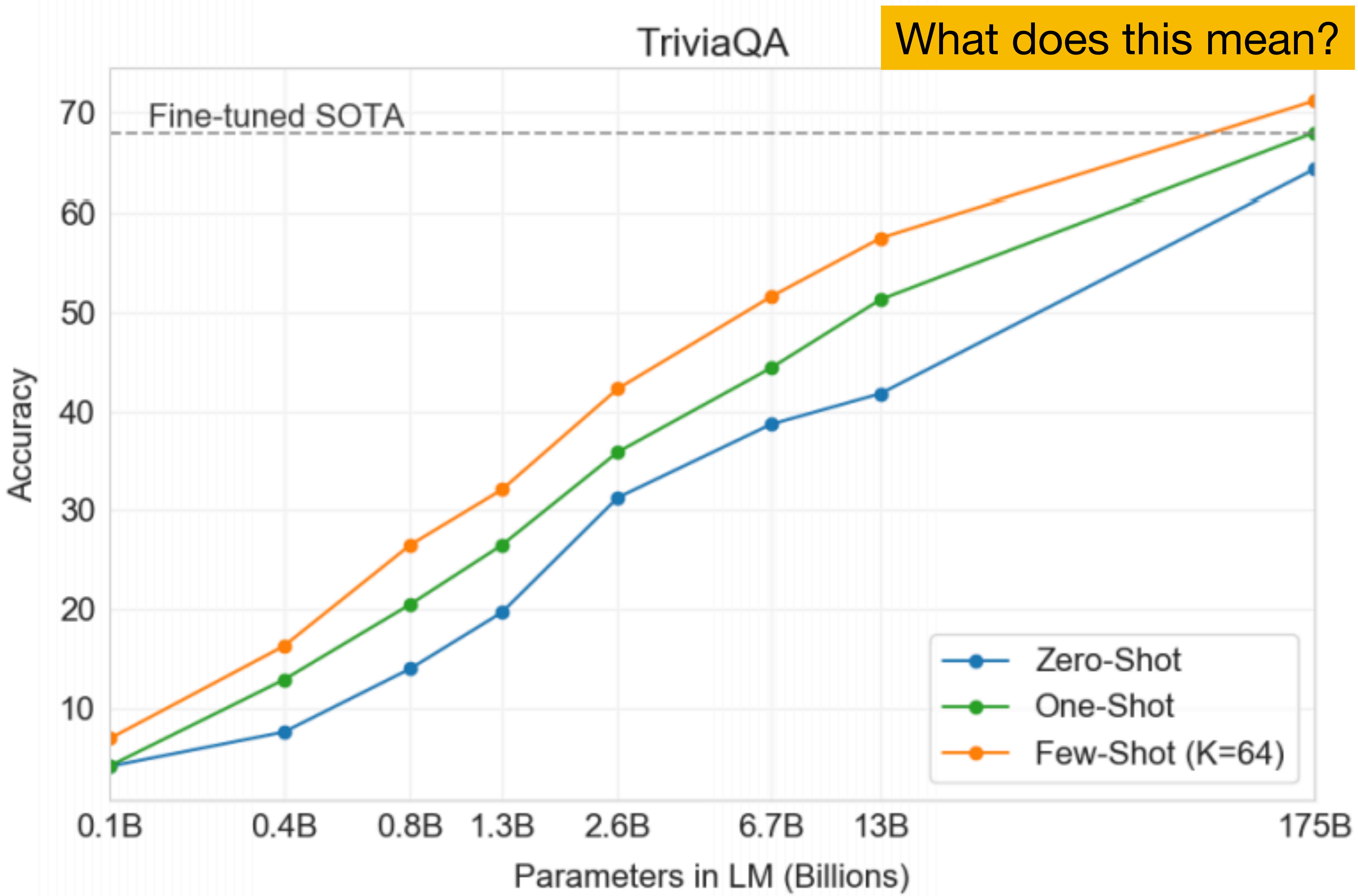
Max of 100 examples fed into the prefix in this way

How does this new paradigm compare to “pretrain + finetune”?

TriviaQA

Question
Miami Beach in Florida borders which ocean?
What was the occupation of Lovely Rita according to the song by the Beatles
Who was Poopdeck Pappys most famous son?
The Nazi regime was Germany's Third Reich; which was the first Reich?
At which English racecourse did two horses collapse and die in the parade ring due to electrocution, in February 2011?
Which type of hat takes its name from an 1894 novel by George Du Maurier where the title character has the surname O'Ferrall ?
What was the Elephant Man's real name?


TriviaQA
Fine-tuned SOTA
Accuracy
70
60
50
40
30
20
10
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
Parameters in LM (Billions)
Zero-Shot
One-Shot
Few-Shot (K=64)

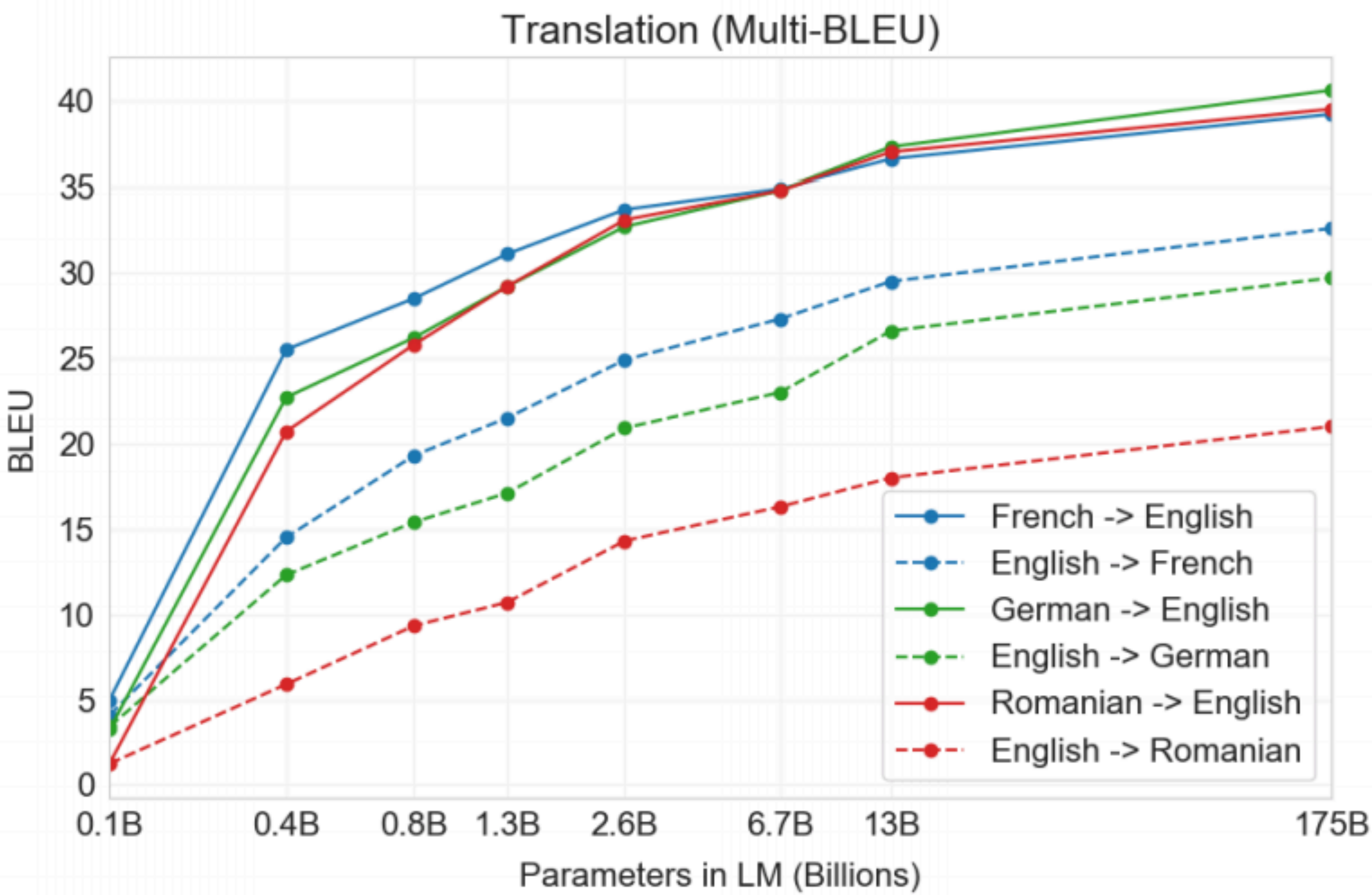


TriviaQA
What does this mean?
Fine-tuned SOTA
70
60
50
40
30
20
10
Accuracy
0.1B
0.4B
0.8B
1.3B
2.6B
6.7B
13B
175B
Parameters in LM (Billions)
Zero-Shot
One-Shot
Few-Shot (K=64)

What about translation? (7% of GPT3's training data is in languages other than English)

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>

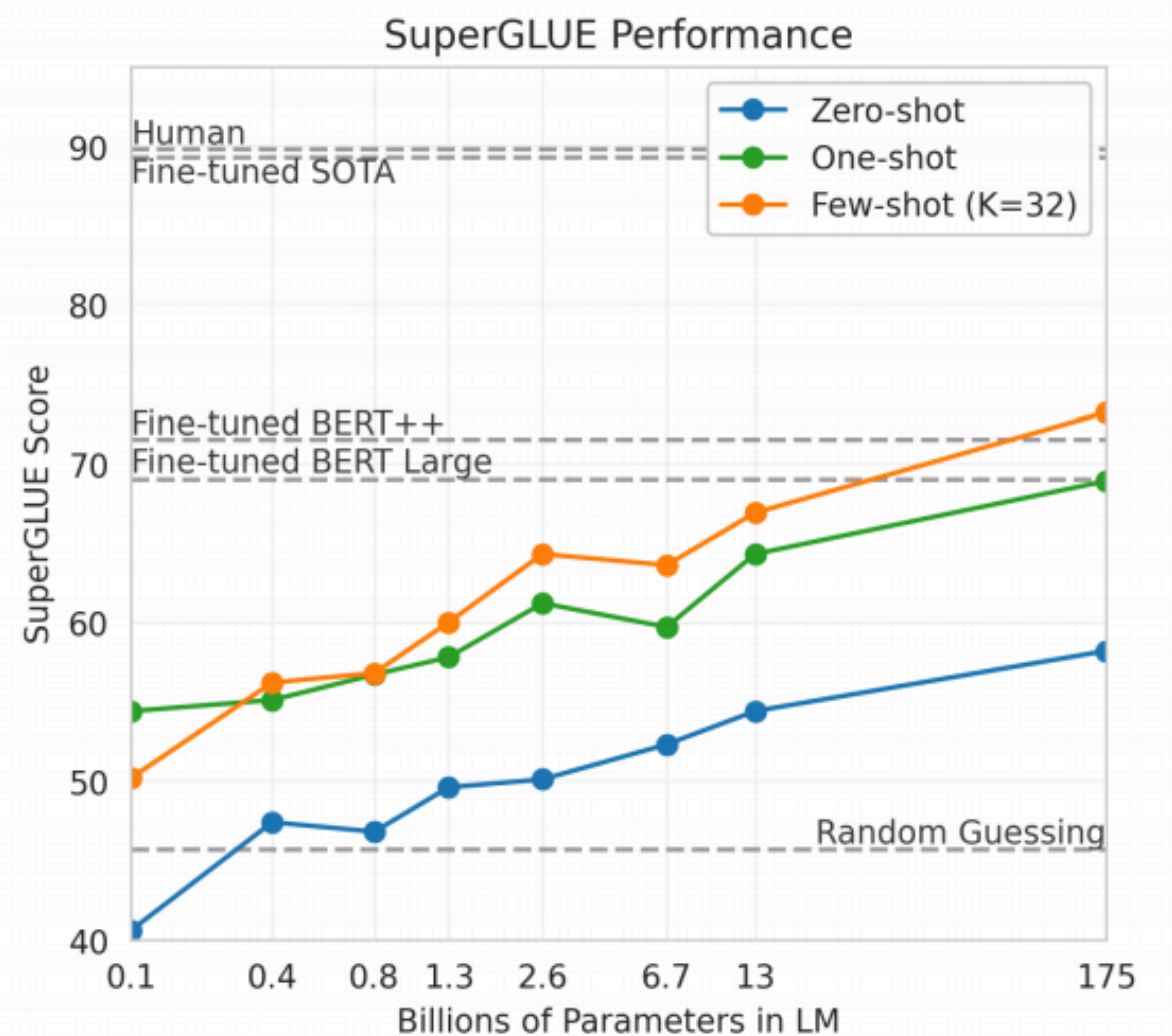
Improvements haven't plateaued!



What about reading comprehension QA?

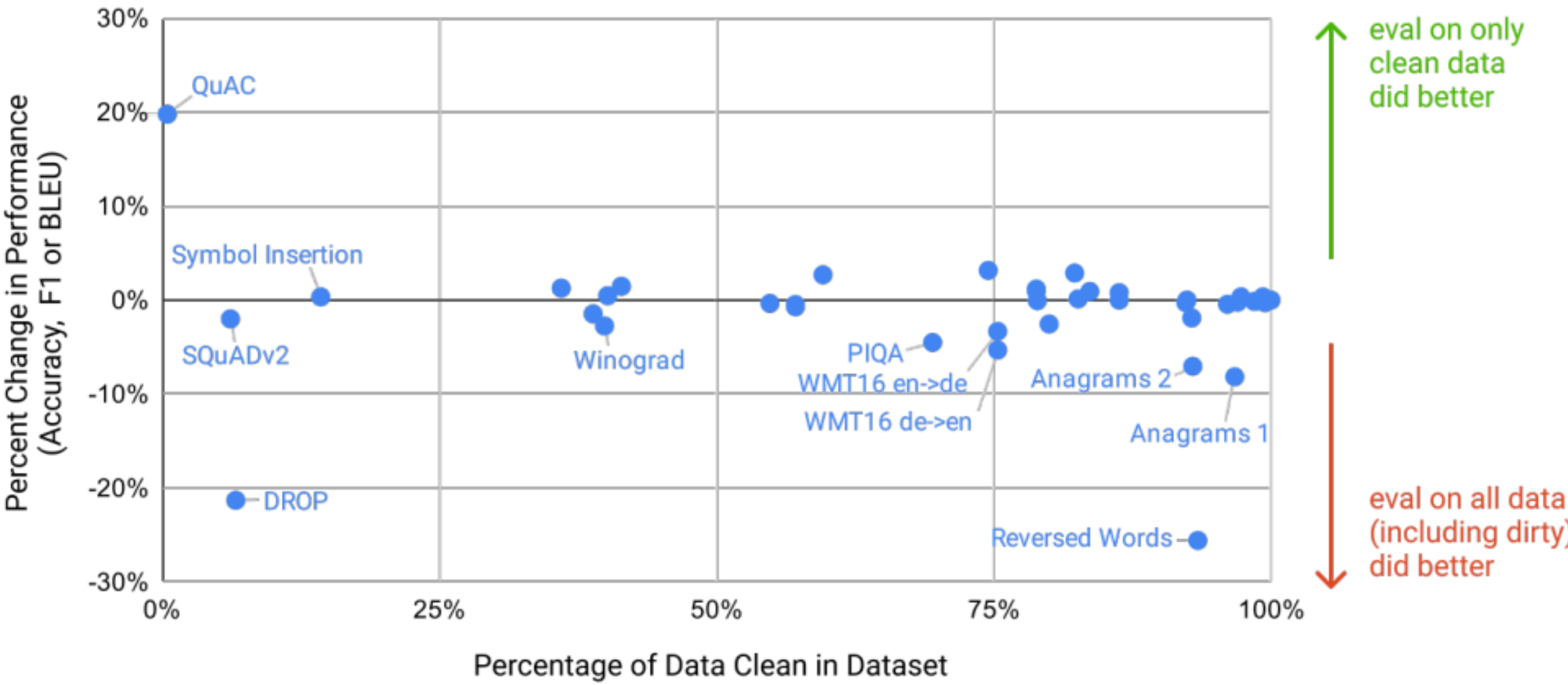
Setting	CoQA	DROP	QuAC	SQuADv2	RACE-h	RACE-m
Fine-tuned SOTA	**90.7**[a]	**89.1**[b]	**74.4**[c]	**93.0**[d]	**90.0**[e]	**93.1**[e]
GPT-3 Zero-Shot	81.5	23.6	41.5	59.5	45.5	58.4
GPT-3 One-Shot	84.0	34.3	43.3	65.4	45.9	57.4
GPT-3 Few-Shot	85.0	36.5	44.3	69.8	46.8	58.1

Struggles on “harder” datasets



SuperGLUE Performance
Zero-shot
One-shot
Few-shot (K=32)
Human
Fine-tuned SOTA
Fine-tuned BERT++
Fine-tuned BERT Large
Random Guessing
SuperGLUE Score
90
80
70
60
50
40
0.1
0.4
0.8
1.3
2.6
6.7
13
175
Billions of Parameters in LM

Data contamination



- **2 digit addition (2D+)** – The model is asked to add two integers sampled uniformly from $[0, 100)$, phrased in the form of a question, e.g. "Q: What is 48 plus 76? A: 124."
- **2 digit subtraction (2D-)** – The model is asked to subtract two integers sampled uniformly from $[0, 100)$; the answer may be negative. Example: "Q: What is 34 minus 53? A: -19".
- **3 digit addition (3D+)** – Same as 2 digit addition, except numbers are uniformly sampled from $[0, 1000)$.
- **3 digit subtraction (3D-)** – Same as 2 digit subtraction, except numbers are uniformly sampled from $[0, 1000)$.
- **4 digit addition (4D+)** – Same as 3 digit addition, except uniformly sampled from $[0, 10000)$.
- **4 digit subtraction (4D-)** – Same as 3 digit subtraction, except uniformly sampled from $[0, 10000)$.
- **5 digit addition (5D+)** – Same as 3 digit addition, except uniformly sampled from $[0, 100000)$.
- **5 digit subtraction (5D-)** – Same as 3 digit subtraction, except uniformly sampled from $[0, 100000)$.
- **2 digit multiplication (2Dx)** – The model is asked to multiply two integers sampled uniformly from $[0, 100)$, e.g. "Q: What is 24 times 42? A: 1008".
- **One-digit composite (1DC)** – The model is asked to perform a composite operation on three 1 digit numbers, with parentheses around the last two. For example, "Q: What is 6+(4*8)? A: 38". The three 1 digit numbers are selected uniformly on $[0, 10)$ and the operations are selected uniformly from {+,-,*}.

Setting	2D+	2D-	3D+	3D-	4D+	4D-	5D+	5D-	2Dx	1DC
GPT-3 Zero-shot	76.9	58.0	34.2	48.3	4.0	7.5	0.7	0.8	19.8	9.8
GPT-3 One-shot	99.6	86.4	65.5	78.7	14.0	14.0	3.5	3.8	27.4	14.3
GPT-3 Few-shot	100.0	98.9	80.4	94.2	25.5	26.8	9.3	9.9	29.2	21.3

A "whatpu" is a small, furry animal native to Tanzania. An example of a sentence that uses the word whatpu is:
We were traveling in Africa and we saw these very cute whatpus.

To do a "farduddle" means to jump up and down really fast. An example of a sentence that uses the word farduddle is:
One day when I was playing tag with my little sister, she got really excited and she started doing these crazy farduddles.
A "yalubalu" is a type of vegetable that looks like a big pumpkin. An example of a sentence that uses the word yalubalu is:
I was on a trip to Africa and I tried this yalubalu vegetable that was grown in a garden there. It was delicious.

A "Burringo" is a car with very fast acceleration. An example of a sentence that uses the word Burringo is:
In our garage we have a Burringo that my father drives to work every day.

A "Gigamuru" is a type of Japanese musical instrument. An example of a sentence that uses the word Gigamuru is:
I have a Gigamuru that my uncle gave me as a gift. I love to play it at home.

To "screeg" something is to swing a sword at it. An example of a sentence that uses the word screeg is:
We screeghed at each other for several minutes and then we went outside and ate ice cream.

So… should we drop everything and focus all of our efforts on training bigger and bigger LMs?

"Climbing towards NLU…", Bender & Koller, ACL 2020

Distinction between “form” and “meaning”

- Form: characters / words making up some text (or sounds etc for spoken language)
- Meaning: How the form of a given text relates to something outside of language (e.g., grounded in some world)

Distinction between “form” and “meaning”

- Thought experiment (from Emily Bender):
  - **Training data:** All well-formed Java code on GitHub, but only the text of the code; no output; no understanding of what unit tests mean
  - **Test input:** A single Java program, possibly even from the training data
  - **Expected output:** Result of executing that program

Distinction between "form" and "meaning"

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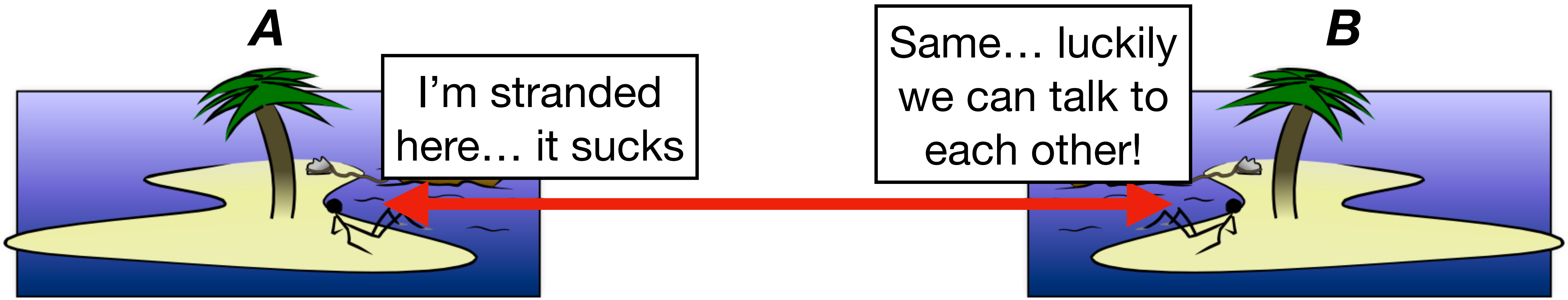
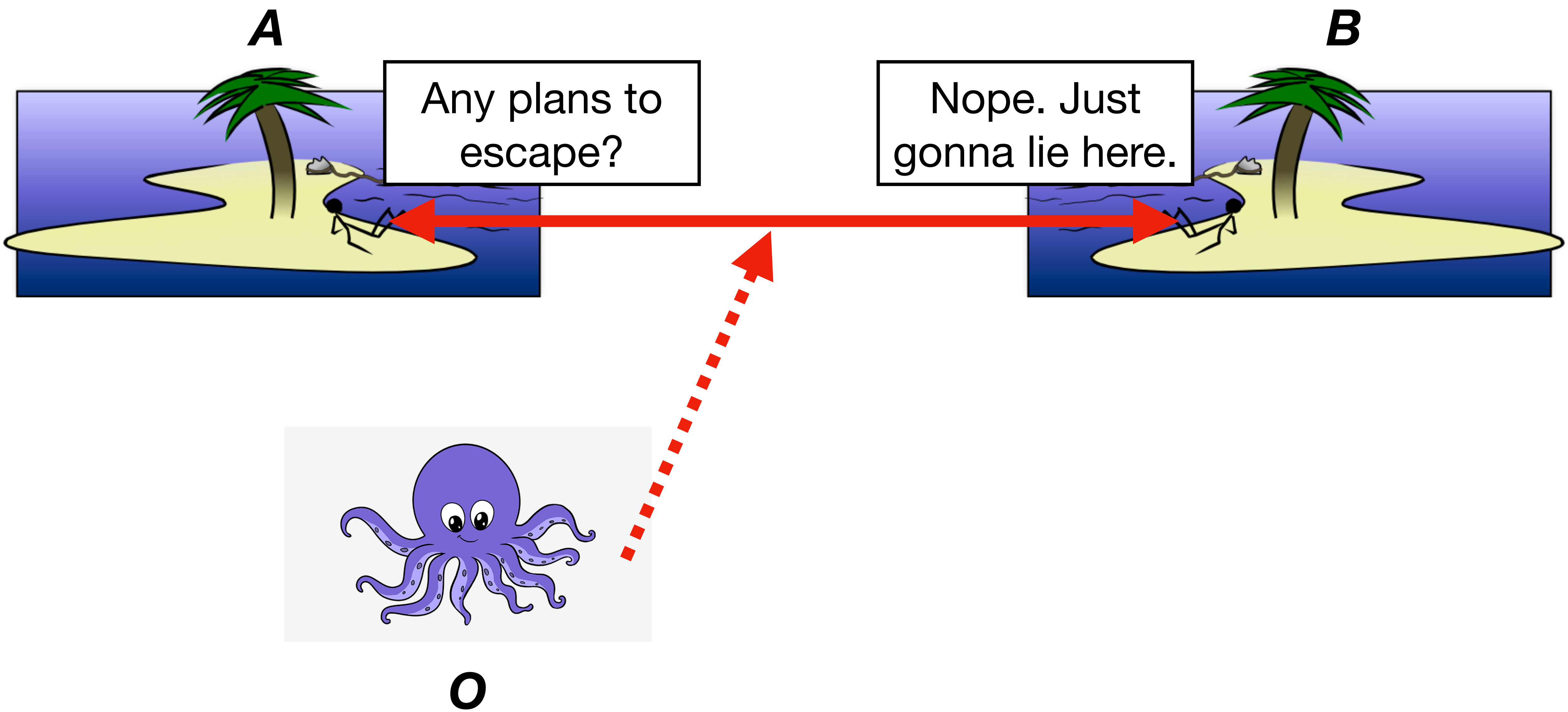
  - **Test input**: A single Java program, possibly even from the training data
  - **Expected output**: Result of executing that program

What's missing is the *meaning*… what is the program supposed to do, given just the form (code)?

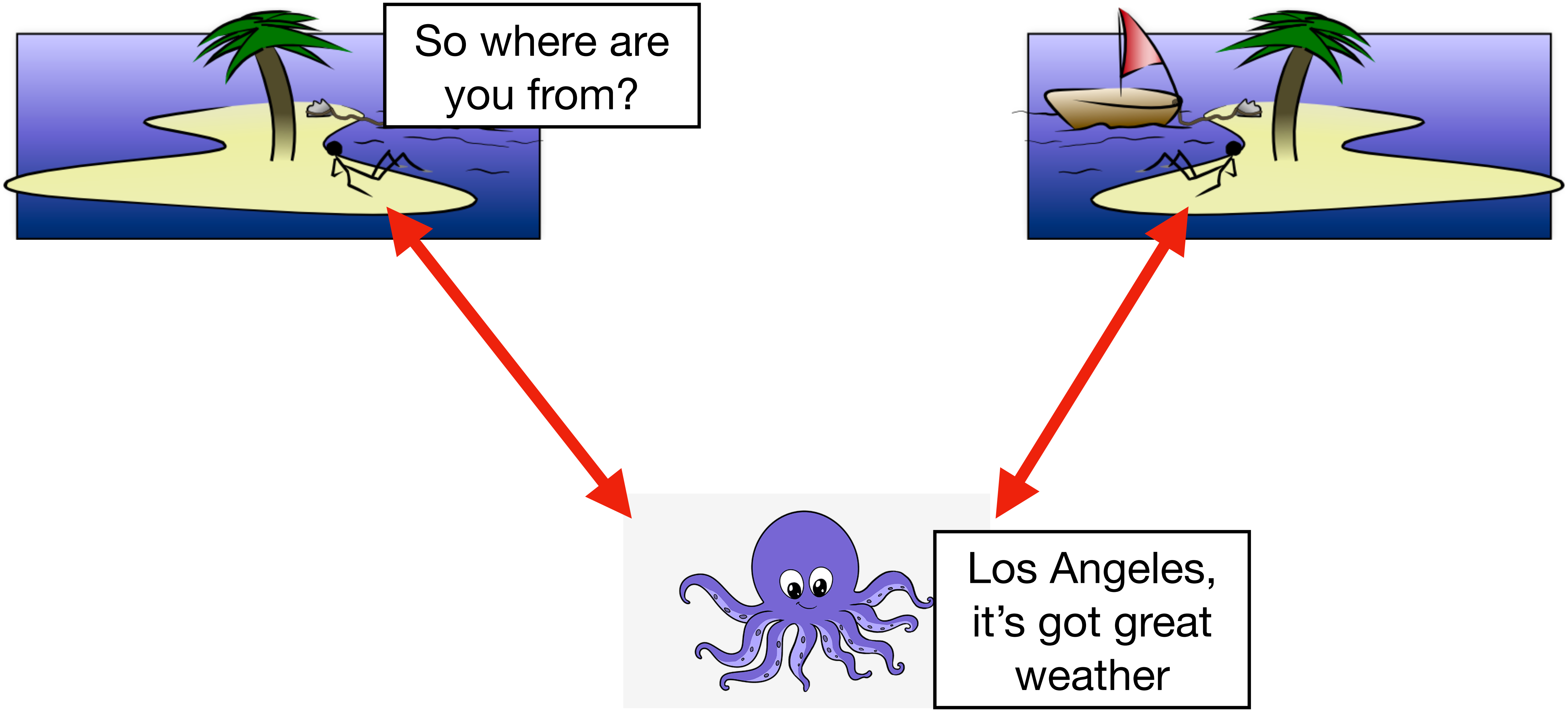
The octopus test



The octopus test



The octopus test



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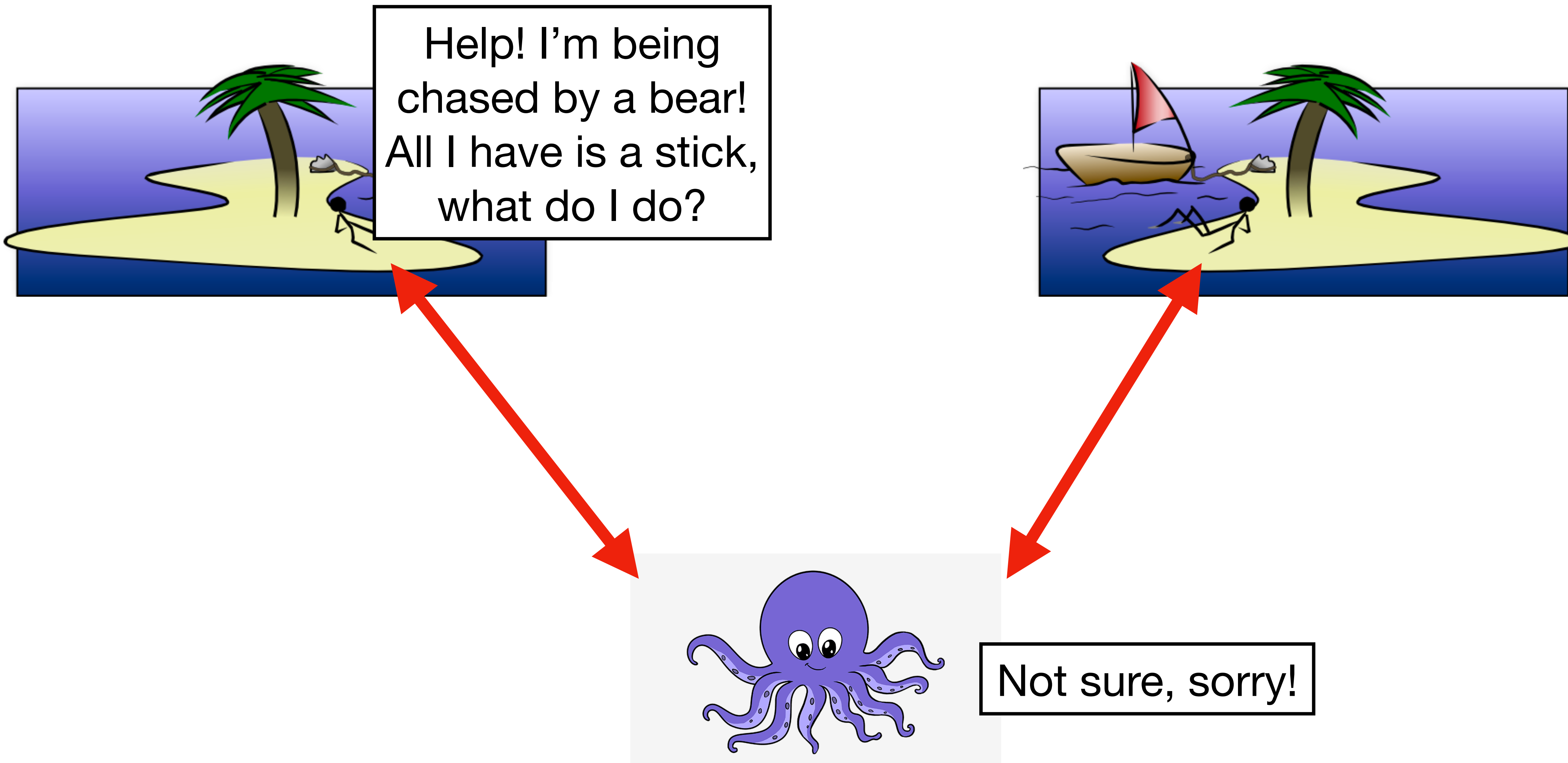

(No idea what a bear or stick is…)

O did not learn “meaning”

- **O** only observed form, without any grounding in the world on these islands
- **A** could find meaning from **O**’s utterances, even though **O** did not “understand” what it was saying
- What if **B** didn’t know what a bear was either? They might respond similarly to **O**. However, **B** can ground their responses in their own world/experience, and as such are formulating their response totally differently from **O**

So what now?

- We need more datasets that are grounded in different modalities and ways of interaction!

- We need ways to test a model's ability to generalize or adapt to new tasks

- Take some inspiration from human language learning: children do not learn from *form* alone, why should we force our machines to do so?

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