Paper Review

Prompt-Based Learning

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Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference

Schick and Schütze, 2021, EACL

It's Not Just Size That Matters: Small Language Models Are Also Few-Shot Learners

Schick and Schütze, 2021, NAACL

Outstanding Long Paper Award at 2021 NAACL

GPT Understands, Too

Liu et al., 2021, arXiv

<What Are Not Covered in This Presentation>

- **Details of Transformer**

  Vaswani et al., Attention is All You Need, NIPS, 2017

- **Details of Transformer-Based Language Models (BERT, ALBERT, GPTs, …)**

  Devlin et al., BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, NAACL, 2019

  Lan et al., ALBERT: A Lite BERT for Self-supervised Learning of Language Representations, ICLR, 2020

  Radford et al., Improving Language Understanding by Generative Pre-Training, 2018

  Radford et al., Language Models Are Unsupervised Multitask Learners, 2019

  Brown et al., Language Models Are Few-Shot Learners, NeurIPS, 2020

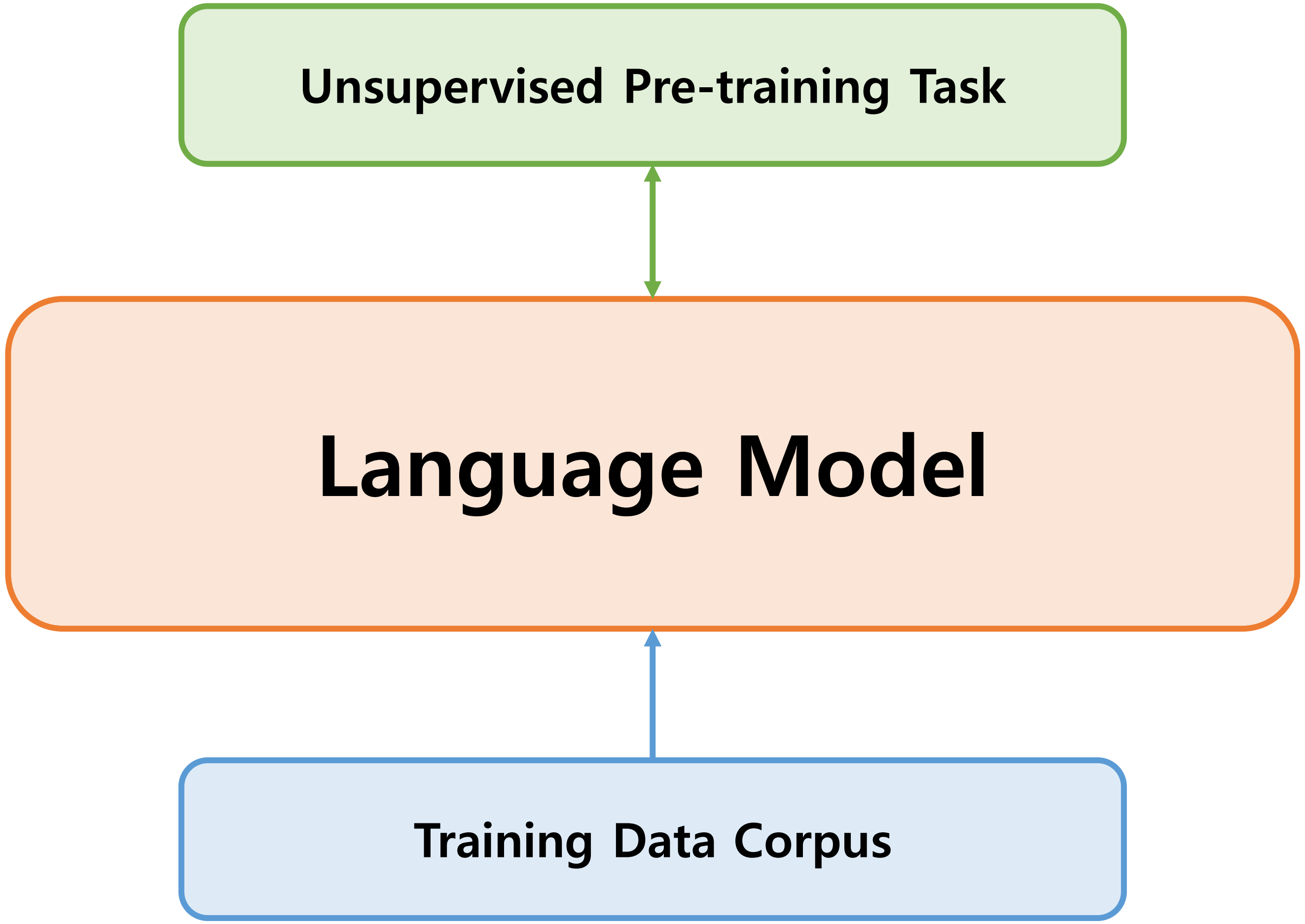
Pre-Requisites

- Hyper Scale Language Model
- Few Shot Learning for Language Model
- In-Context Learning

Introduction

-Hyper Scale Language Model

<Language Model>


Unsupervised Pre-training Task

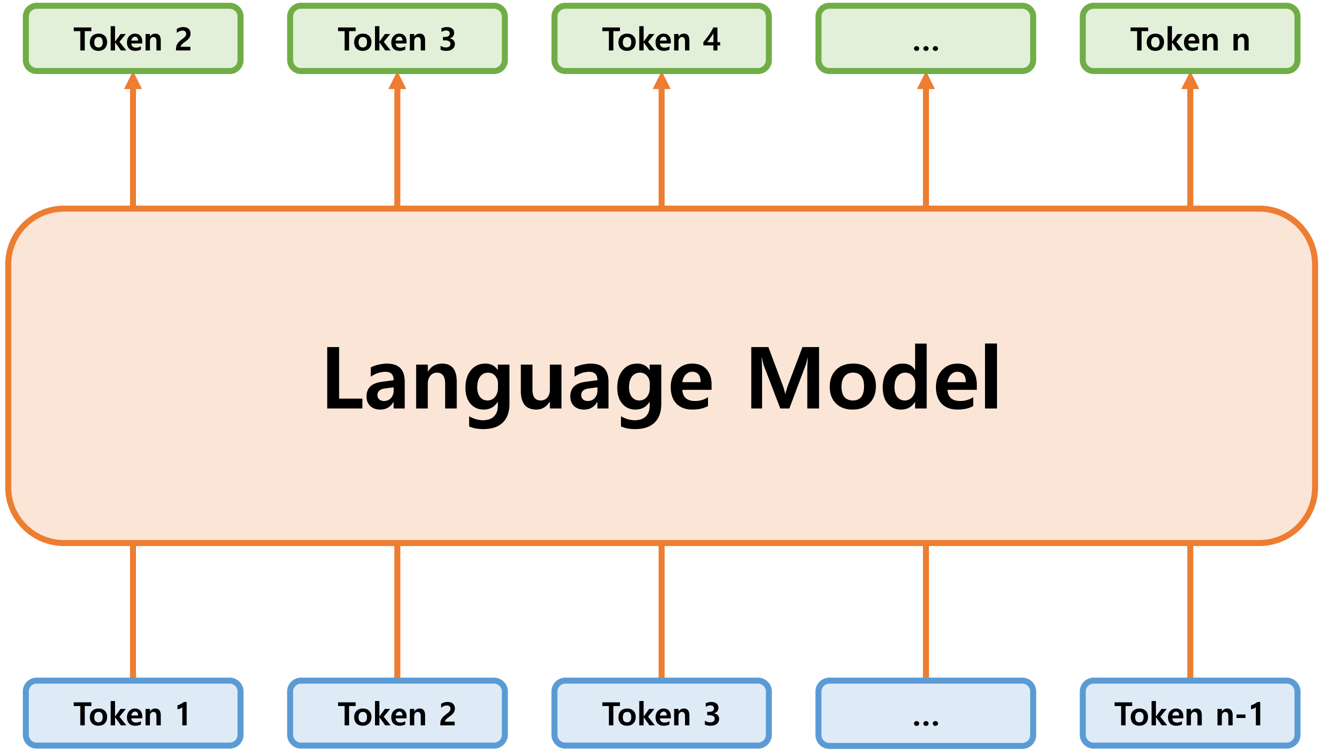
Language Model

Training Data Corpus

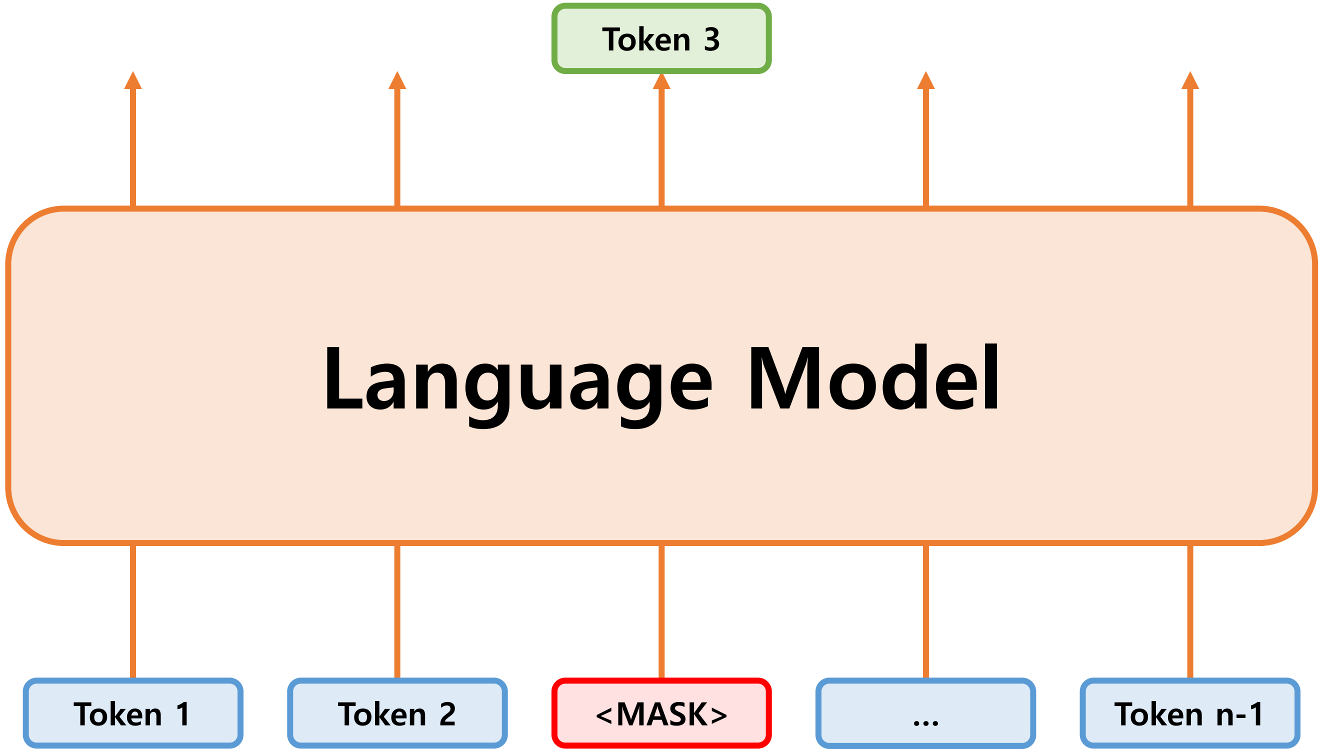
Introduction

-Hyper Scale Language Model

<Language Modeling>



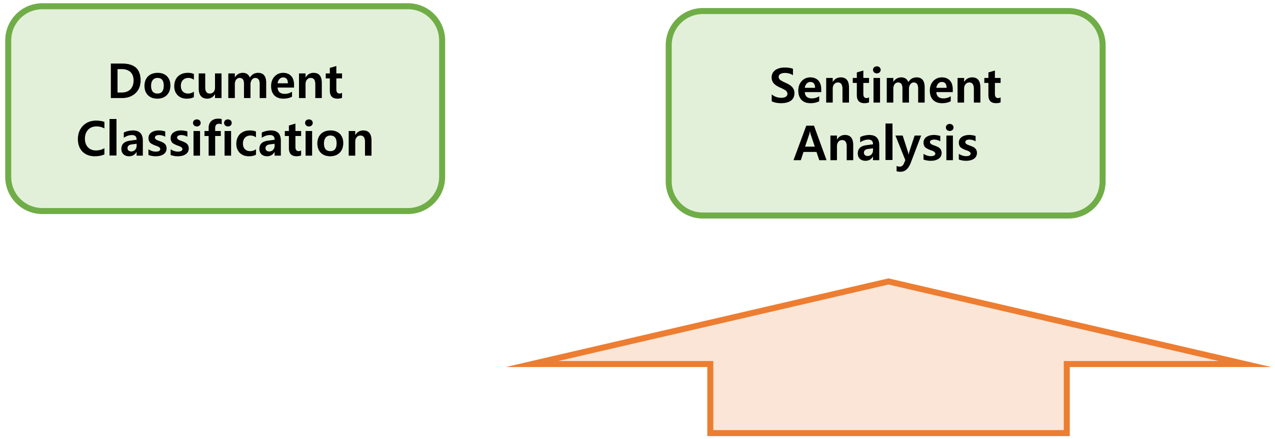
<Masked Language Modeling>


Token 3
Language Model
Token 1
Token 2
<MASK>
...
Token n-1

Introduction

-Hyper Scale Language Model

<Language Model>



Document Classification

Sentiment Analysis

...

ELMO

Embeddings from Language Model

BERT

Bidirectional Encoder Representation from Transformer

GPT

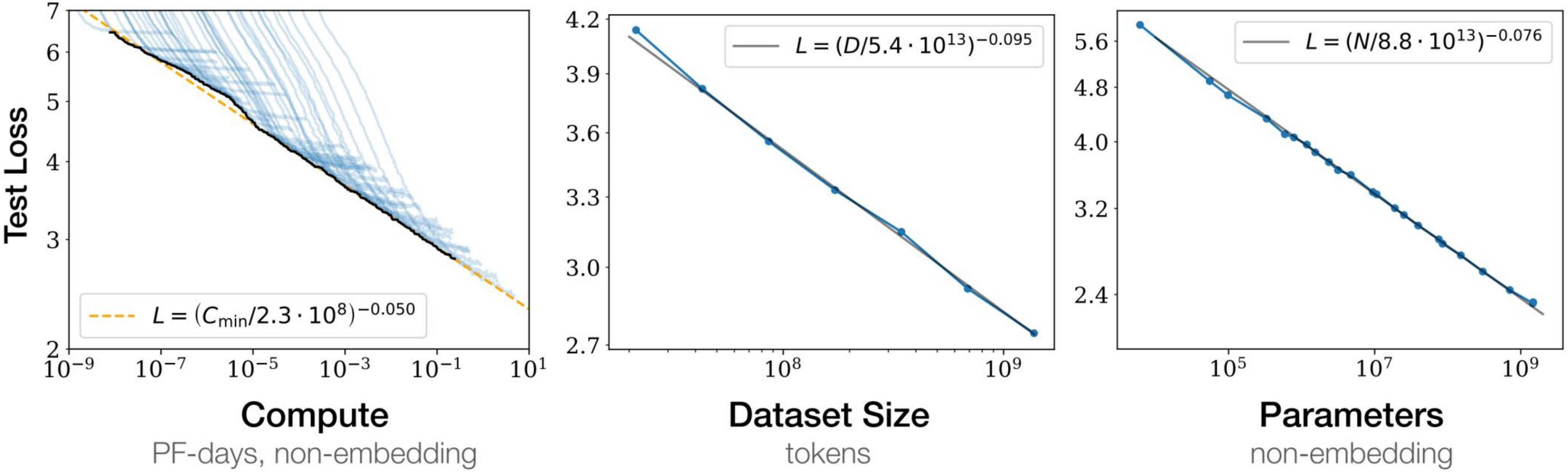
Generative Pre-trained Transformer

Kaplan et al., Scaling Laws for Neural Language Models, arXiv, 2020

Introduction

-Hyper Scale Language Model

<The Scaling Laws for LMs>

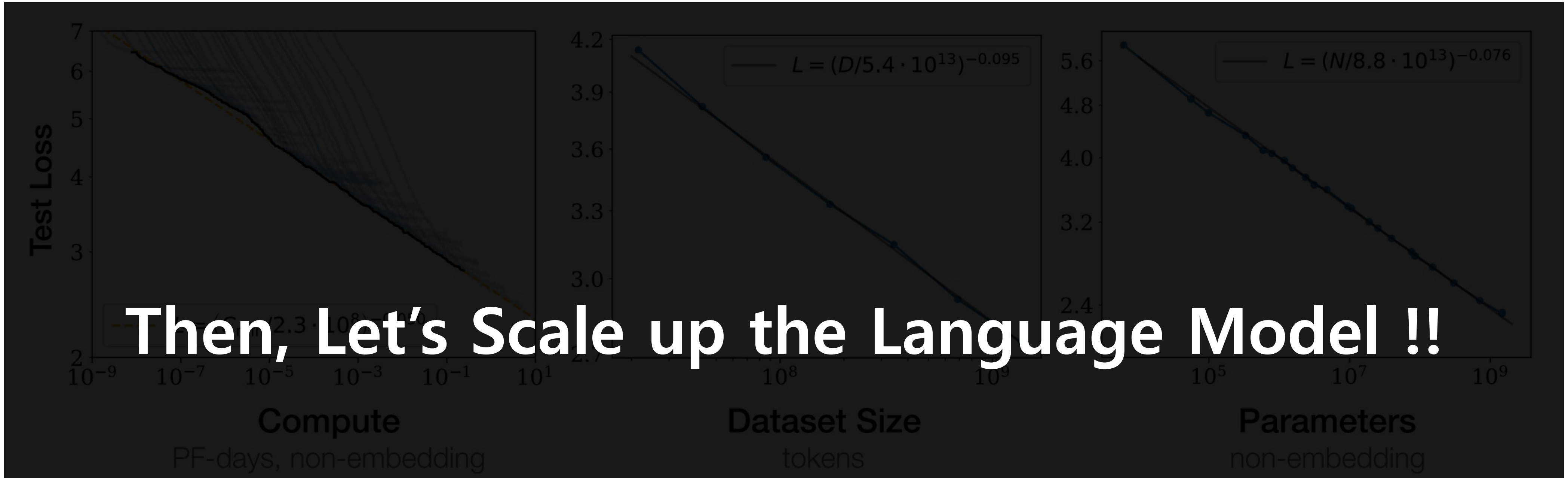


"**Language modeling performance improves** smoothly as **we increase <u>the model size</u>**, **<u>dataset size</u>**, and **<u>amount of compute</u> used for training**." (Kaplan et al., 2020)

Introduction

-Hyper Scale Language Model

<The Scaling Laws for LMs>

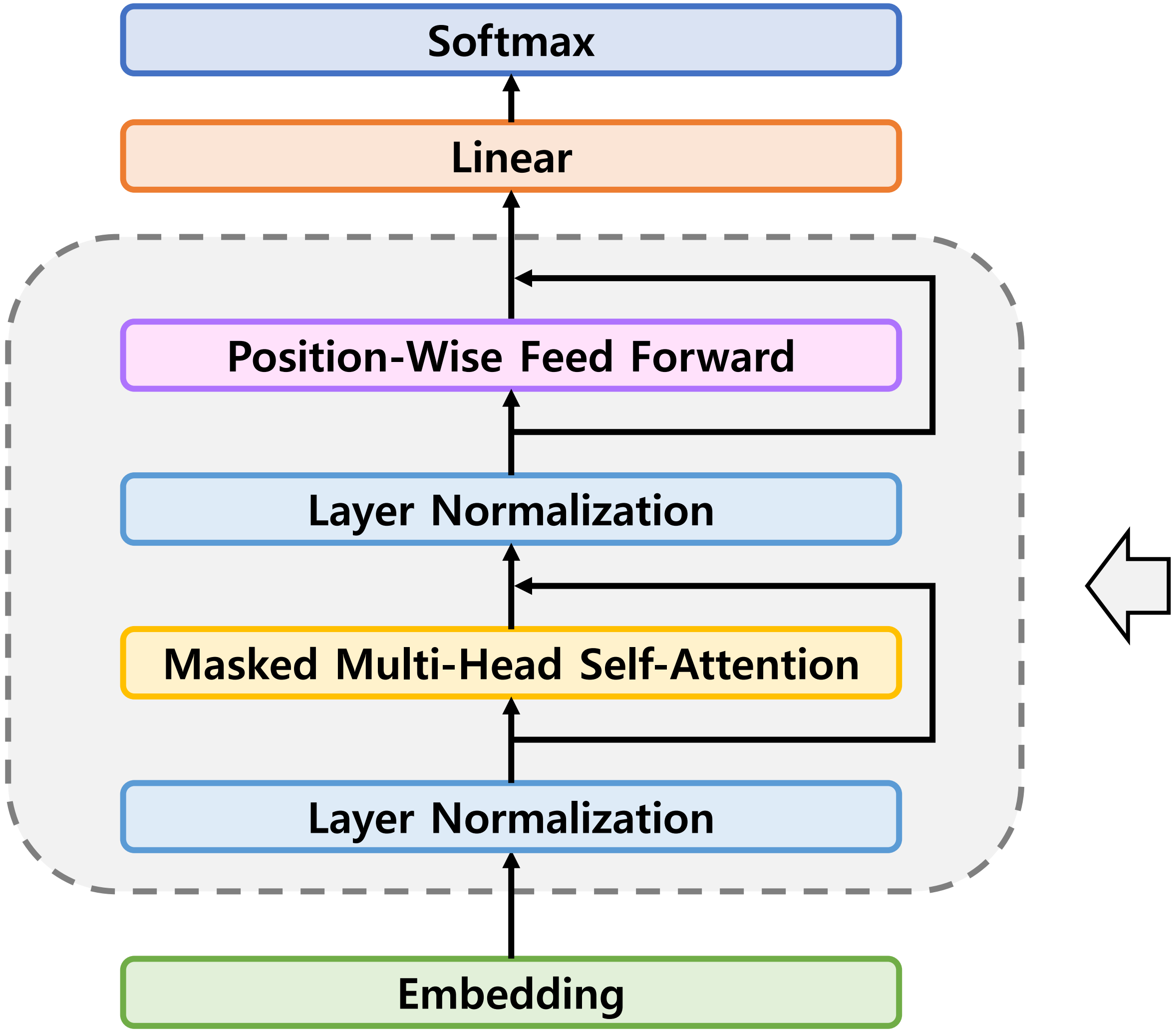


Then, Let’s Scale up the Language Model !!

“**Language modeling performance improves** smoothly as **we increase <u>the model size</u>**, **<u>dataset size</u>**, and **<u>amount of compute</u> used for training**.” (Kaplan et al., 2020)

Brown et al., Language Models Are Few-Shot Learners, NeurIPS, 2020

<Generative Pre-trained Transformer-3>



$\boldsymbol{n_{params} = 175B}$

$n_{layers} = 96$

$d_{model} = 12{,}288$

$n_{heads} = 96$

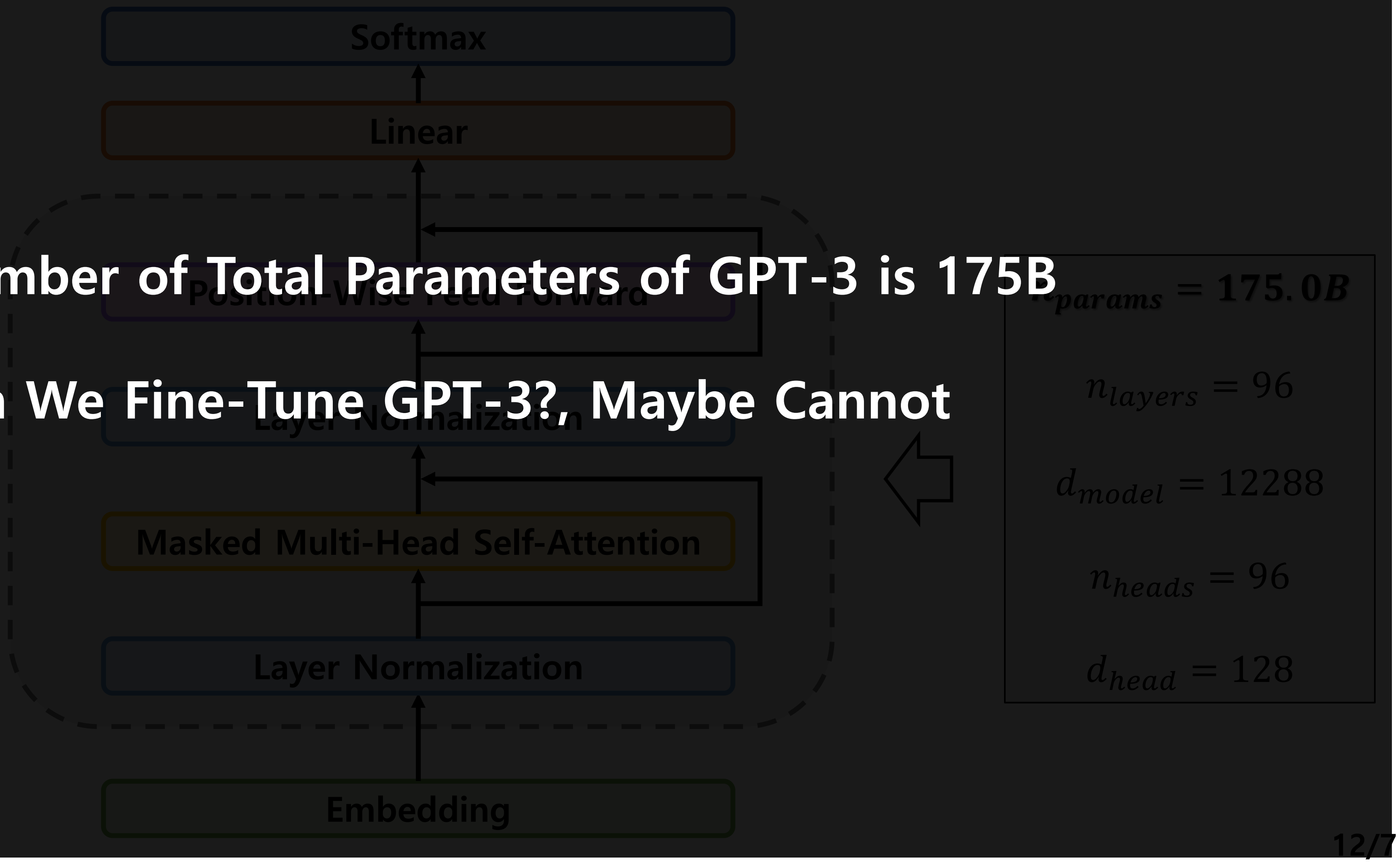
$d_{head} = 128$

Brown et al., Language Models Are Few-Shot Learners, NeurIPS, 2020

Introduction

-Hyper Scale Language Model

<Generative Pre-trained Transformer-3>



The Number of Total Parameters of GPT-3 is 175B

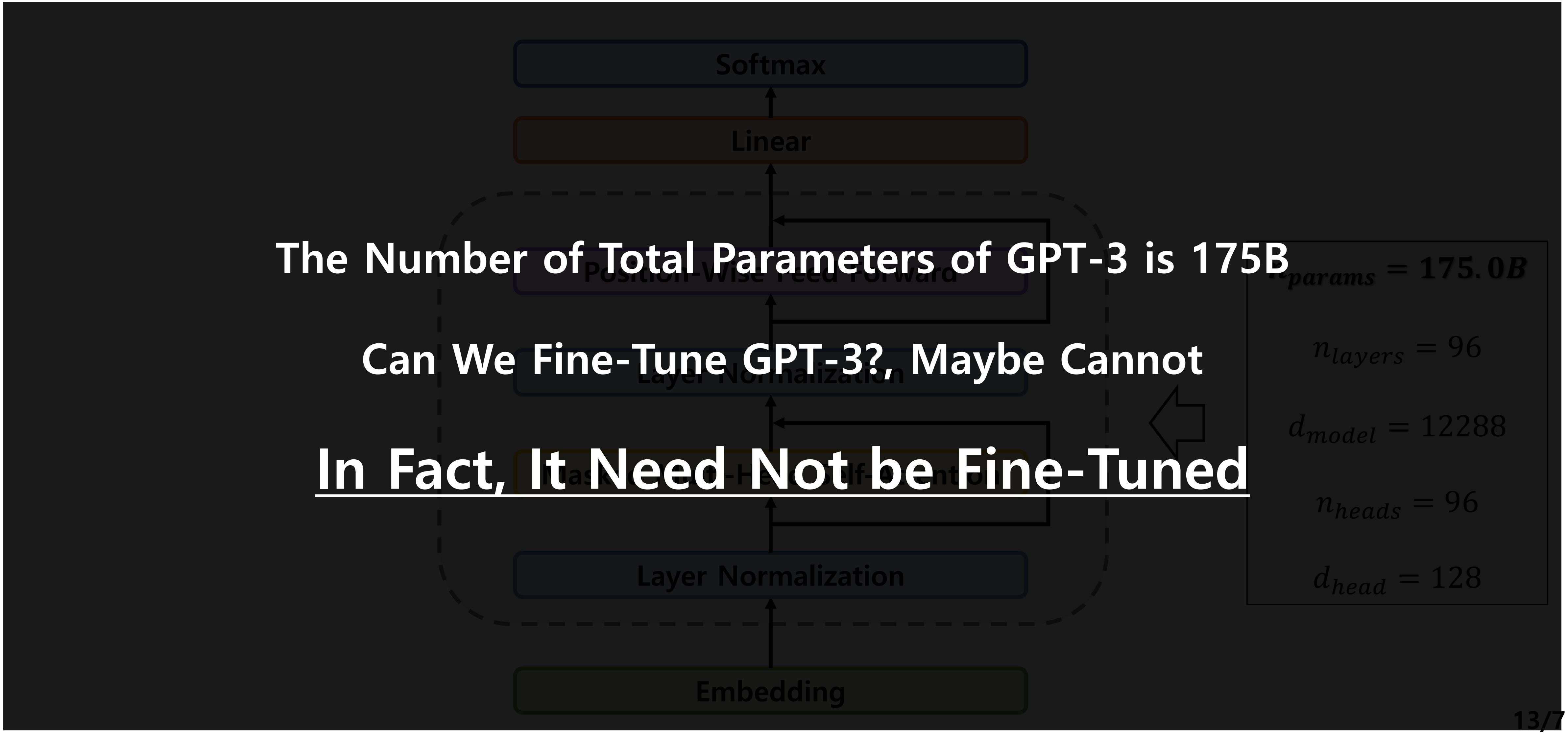
Can We Fine-Tune GPT-3?, Maybe Cannot

Brown et al., Language Models Are Few-Shot Learners, NeurIPS, 2020

Introduction

-Hyper Scale Language Model

<Generative Pre-trained Transformer-3>



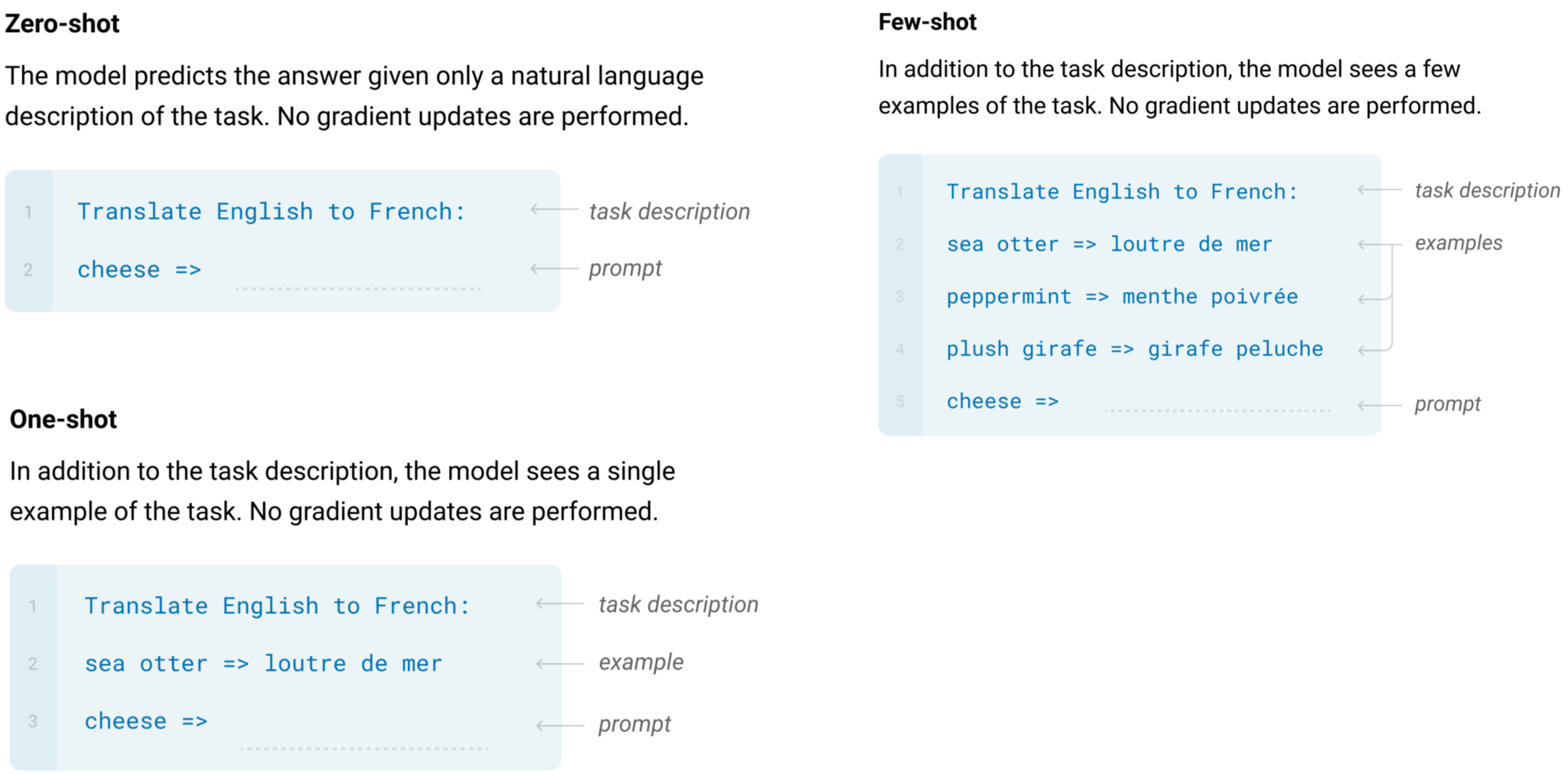
The Number of Total Parameters of GPT-3 is 175B

Can We Fine-Tune GPT-3?, Maybe Cannot

In Fact, It Need Not be Fine-Tuned

Brown et al., Language Models Are Few-Shot Learners, NeurIPS, 2020

<Few Shot Learning for LM>



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 => ..............................
```

One-shot

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

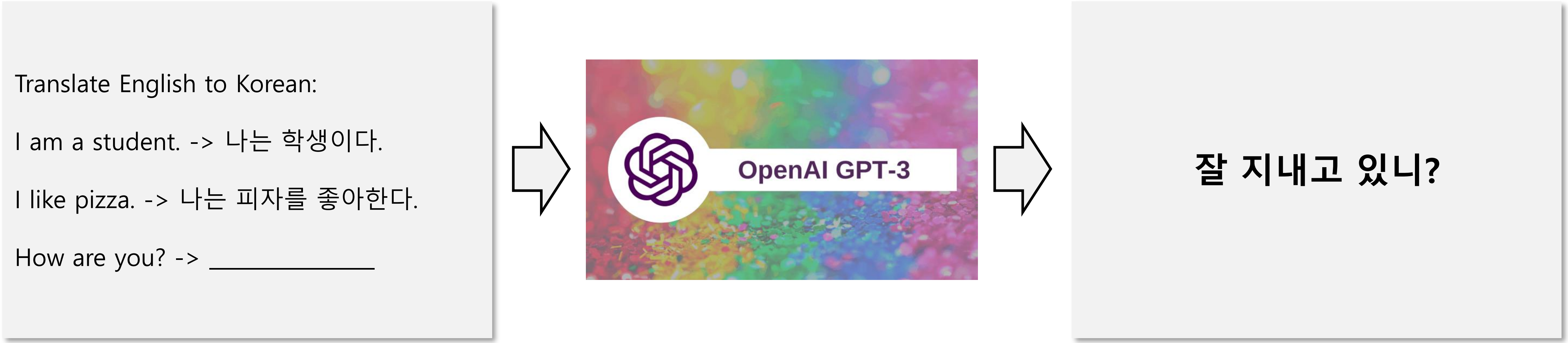
```
Translate English to French:
sea otter => loutre de mer
cheese => ..............................
```

Few-shot

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

```
Translate English to French:
sea otter => loutre de mer
peppermint => menthe poivrée
plush girafe => girafe peluche
cheese => ..............................
```

<Few Shot Learning for LM>



Translate English to Korean:

I am a student. -> 나는 학생이다.

I like pizza. -> 나는 피자를 좋아한다.

How are you? -> ______________

잘 지내고 있니?

Introduction

-Few Shot Learning for LM

<Few Shot Learning for LM>

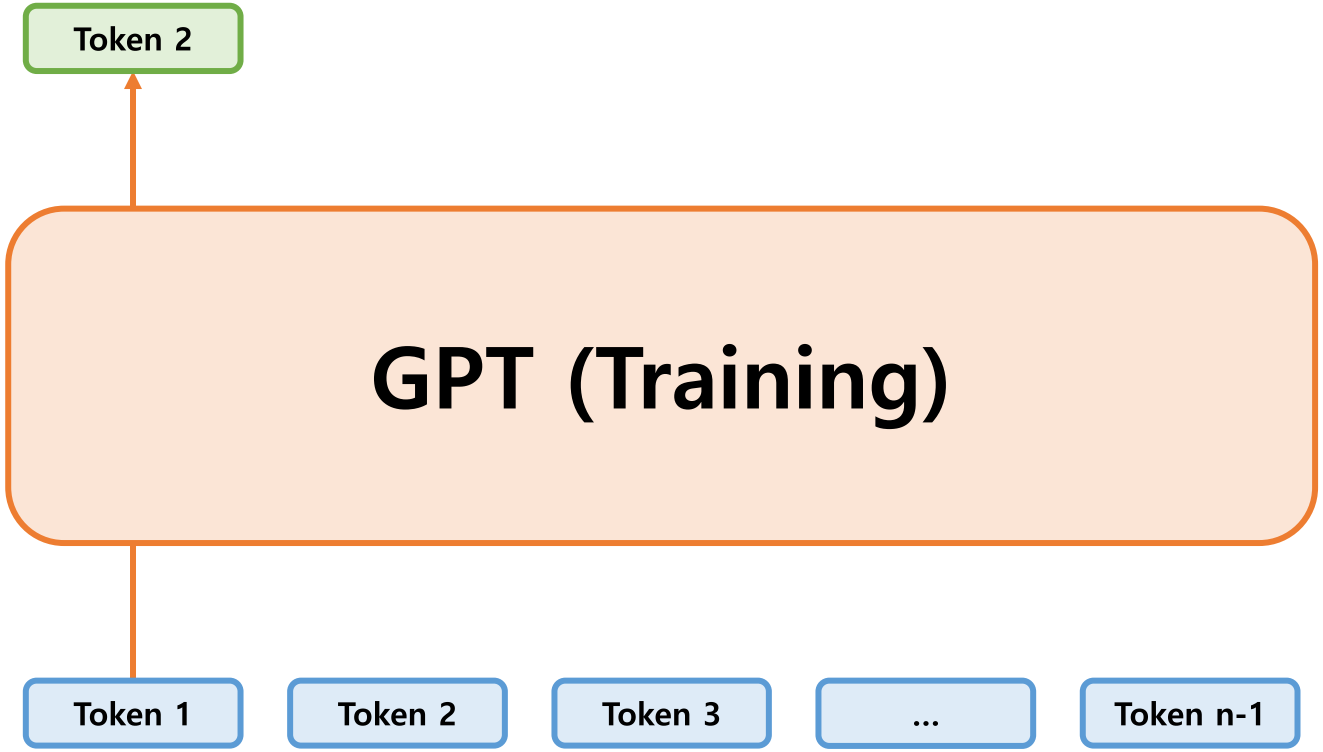
Answer the question:

Where is the capital of UK? -> London

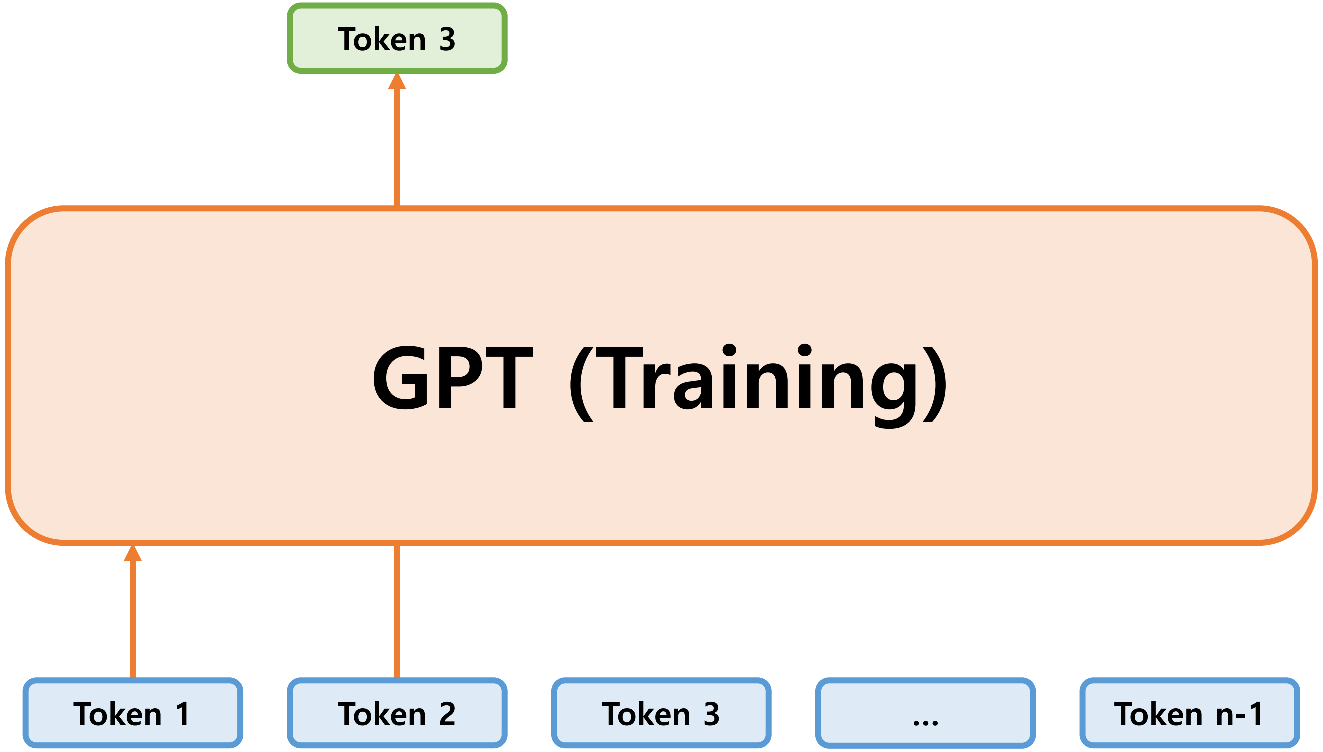
Who founded Apple? -> __________

Steve Jobs

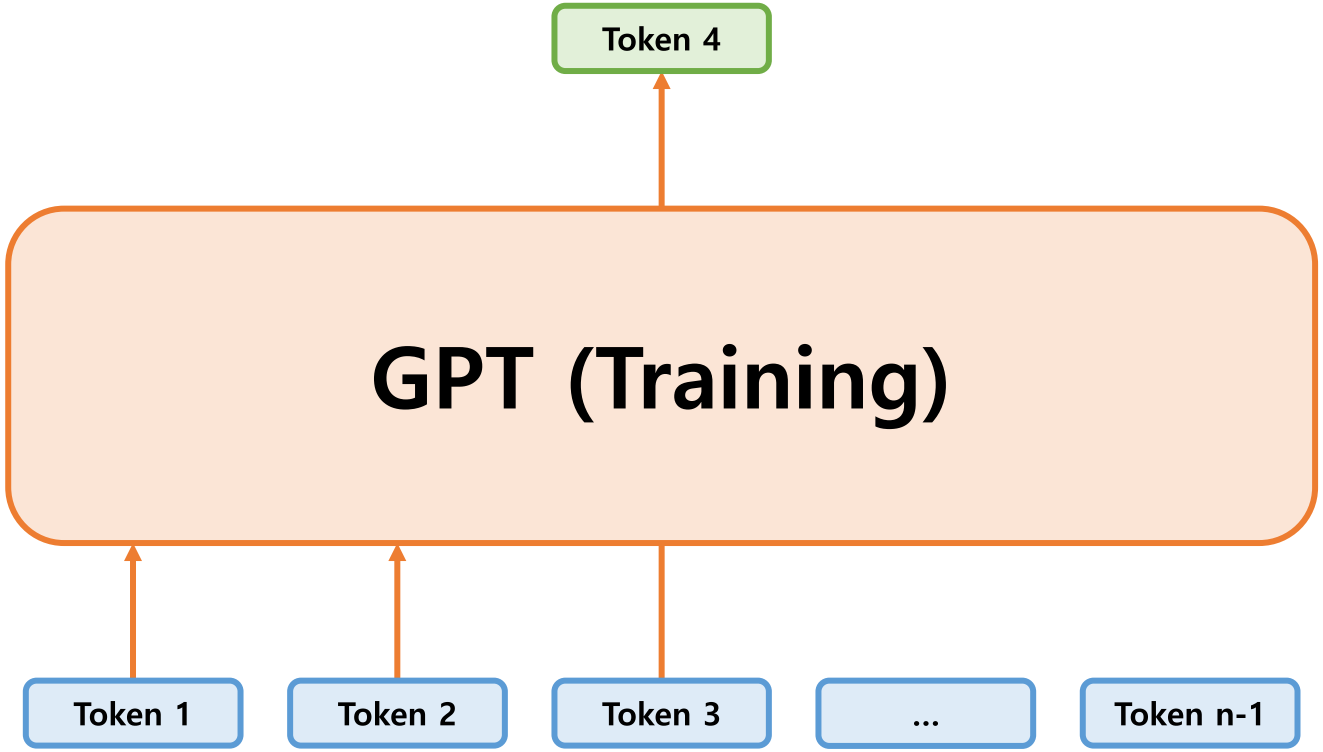
<In-Context Learning>


Token 2
GPT (Training)
Token 1
Token 2
Token 3
...
Token n-1

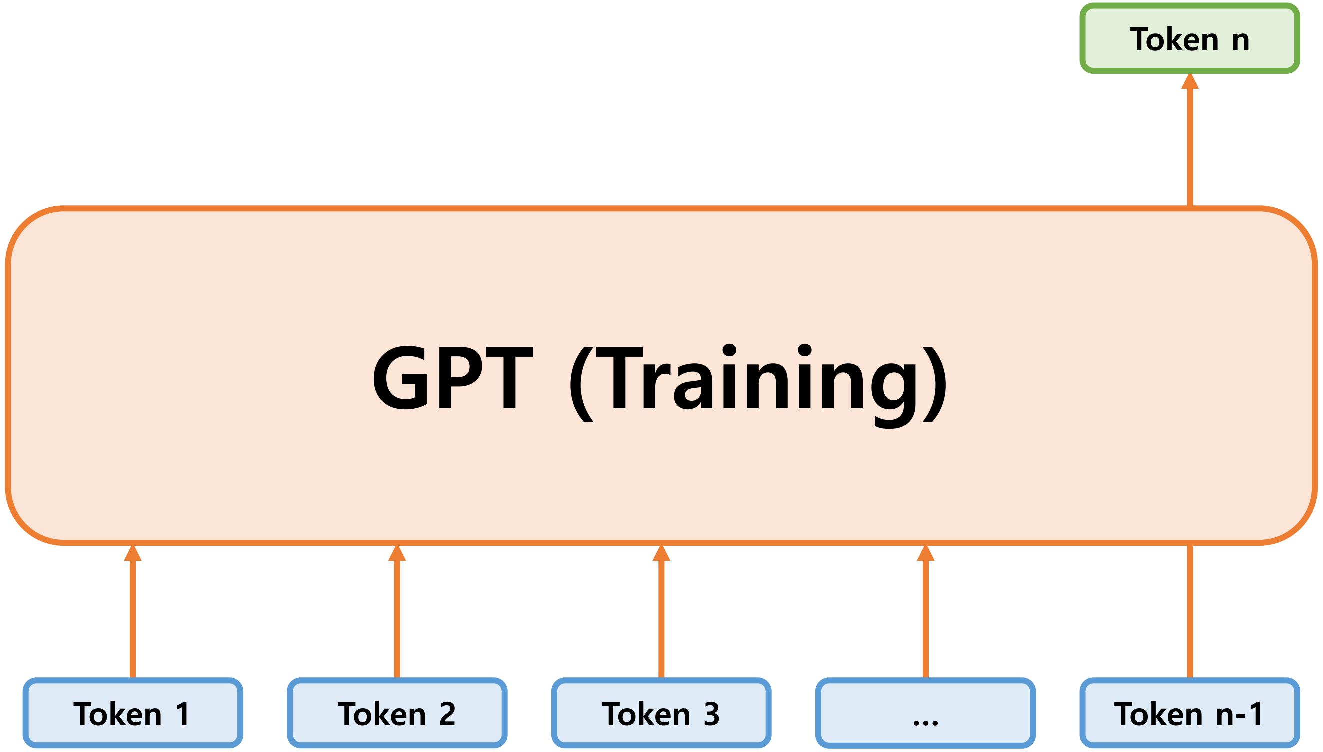
<In-Context Learning>


Token 3
GPT (Training)
Token 1
Token 2
Token 3
...
Token n-1

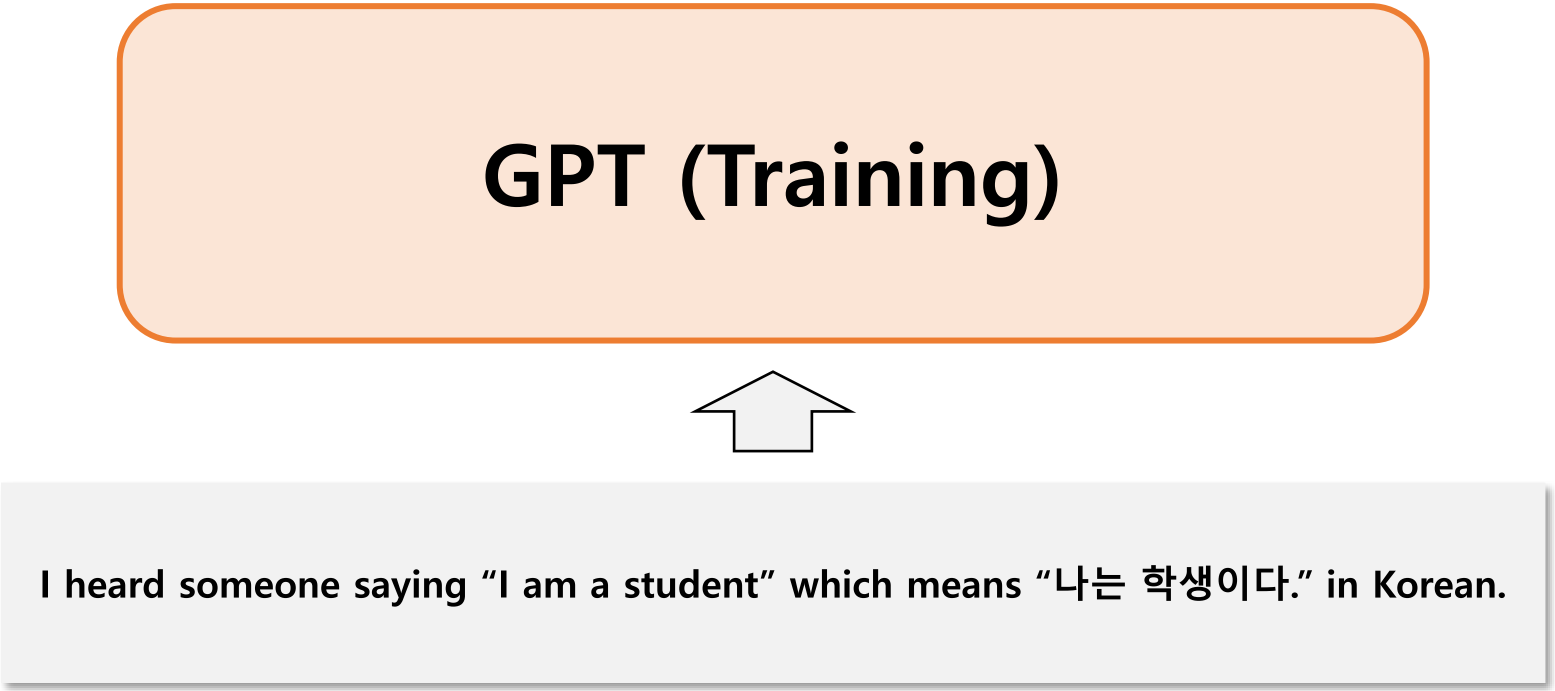
<In-Context Learning>


Token 4
GPT (Training)
Token 1
Token 2
Token 3
...
Token n-1

<In-Context Learning>


Token n
GPT (Training)
Token 1
Token 2
Token 3
...
Token n-1

<In-Context Learning>



GPT (Training)

I heard someone saying “I am a student” which means “나는 학생이다.” in Korean.

Introduction

-In-Context Learning

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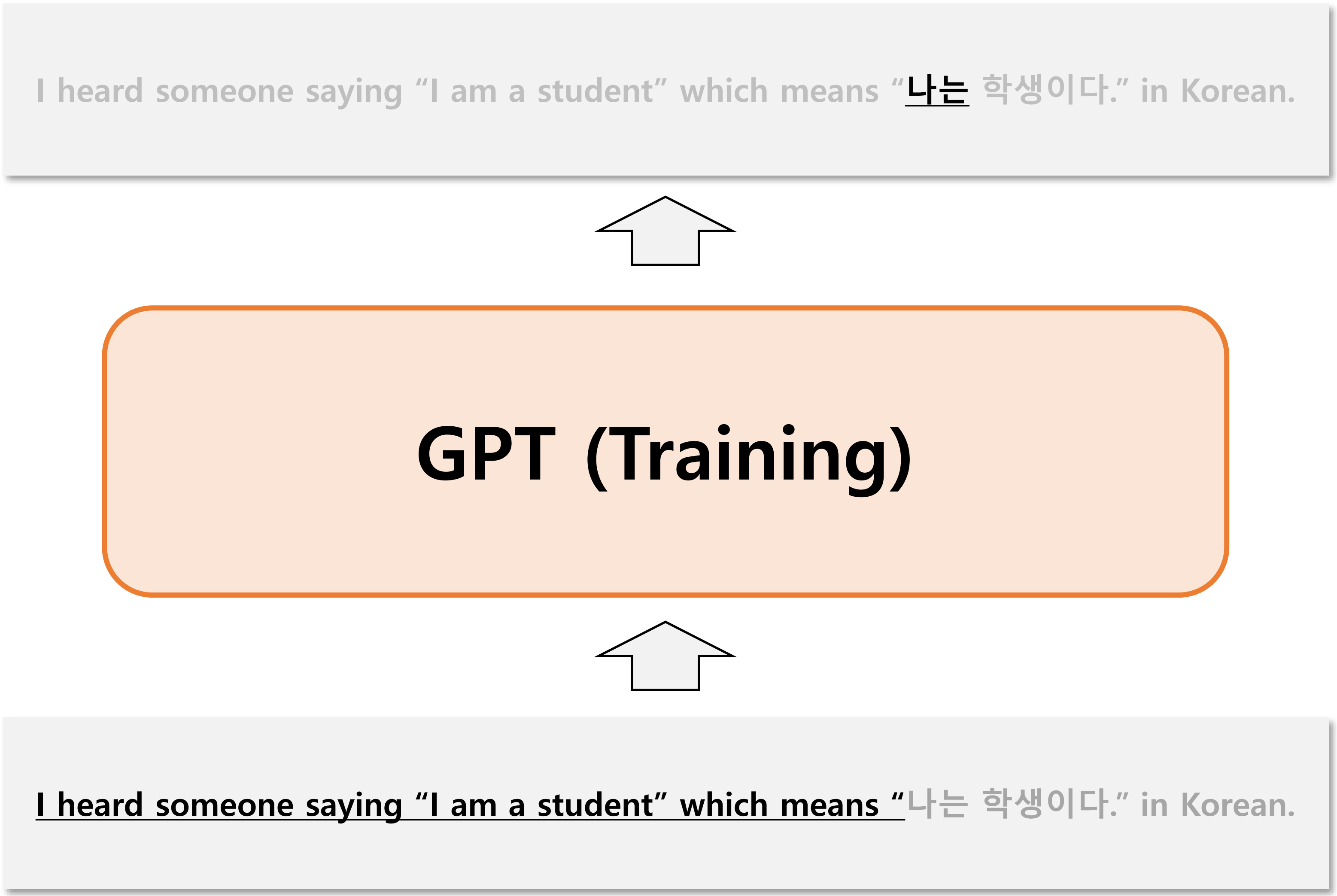

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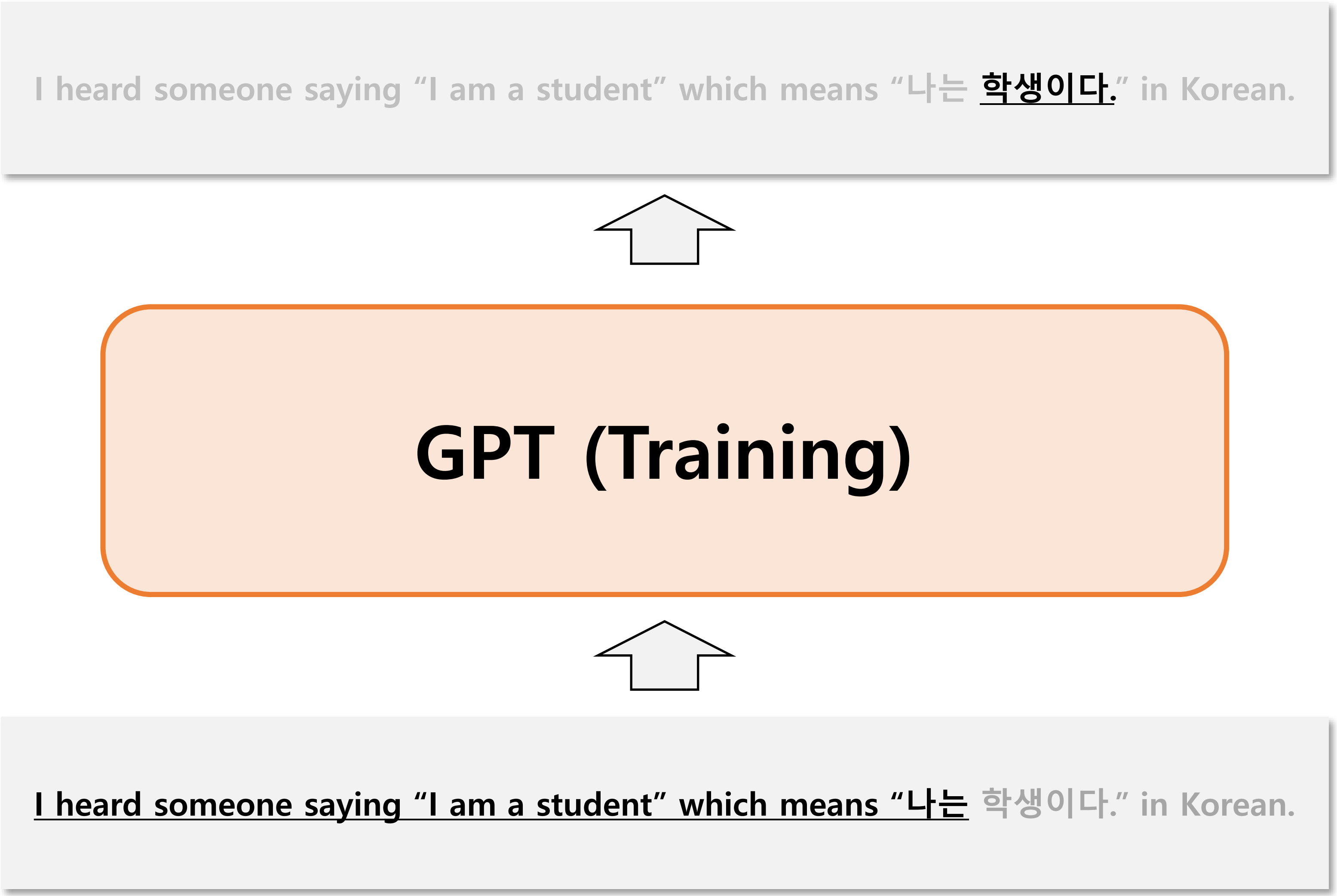

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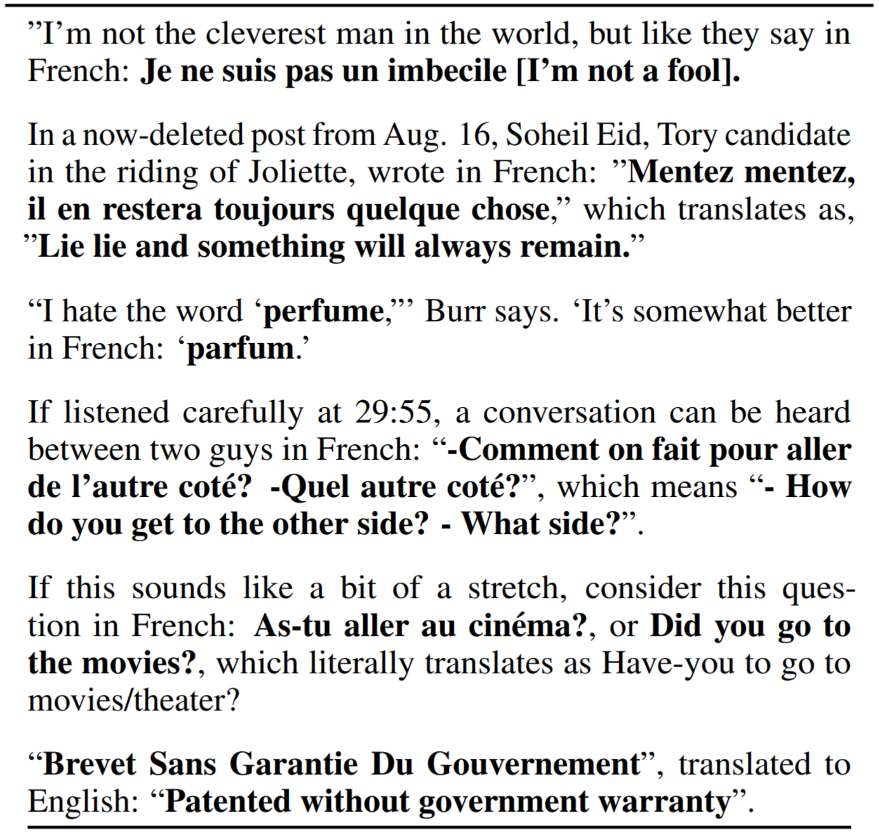


”I’m not the cleverest man in the world, but like they say in French: **Je ne suis pas un imbecile [I’m not a fool].**

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**”.

“Examples of **naturally occurring demonstrations of English to French and French to English translation** found throughout the WebText training set.” (Radford et al., 2019)

Brown et al., Language Models Are Few Shot Learners, NeurIPS, 2020

Introduction

-In-Context Learning

<In-Context Few Shot Learning>

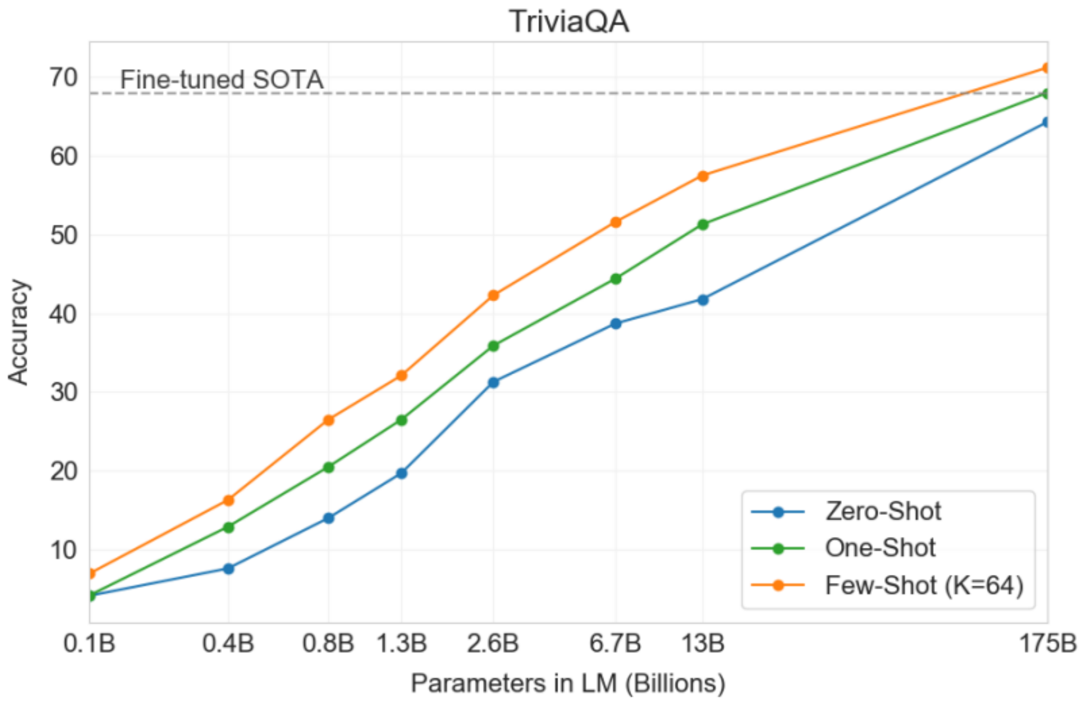


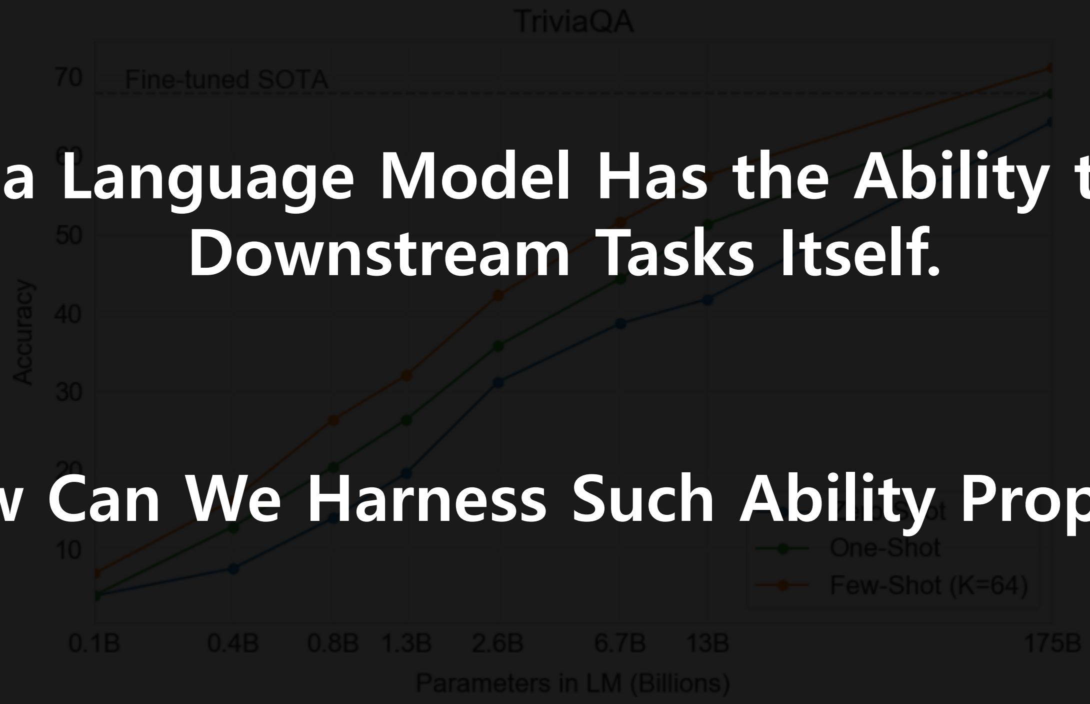
Figure 3.3: On TriviaQA GPT3's performance grows smoothly with model size, suggesting that language models continue to absorb knowledge as their capacity increases. One-shot and few-shot performance make significant gains over zero-shot behavior, matching and exceeding the performance of the SOTA fine-tuned open-domain model, RAG [LPP+20]

Introduction

-In-Context Learning

Brown et al., Language Models Are Few Shot Learners, NeurIPS, 2020

<In-Context Few Shot Learning>



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Pre-training of a Language Model Has the Ability to Perform Many Downstream Tasks Itself.

How Can We Harness Such Ability Properly?

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Outstanding Long Paper Award at 2021 NAACL

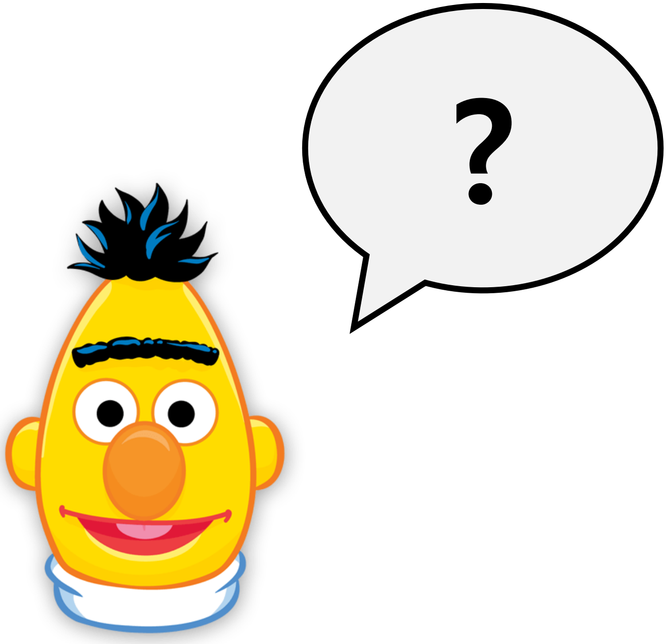
Pattern-Exploiting Training

- Pattern-Verbalizer Pair
- PVP Training and Inference
- PET with Multiple Masks

<Pattern-Verbalizer Pair>

Question Answering

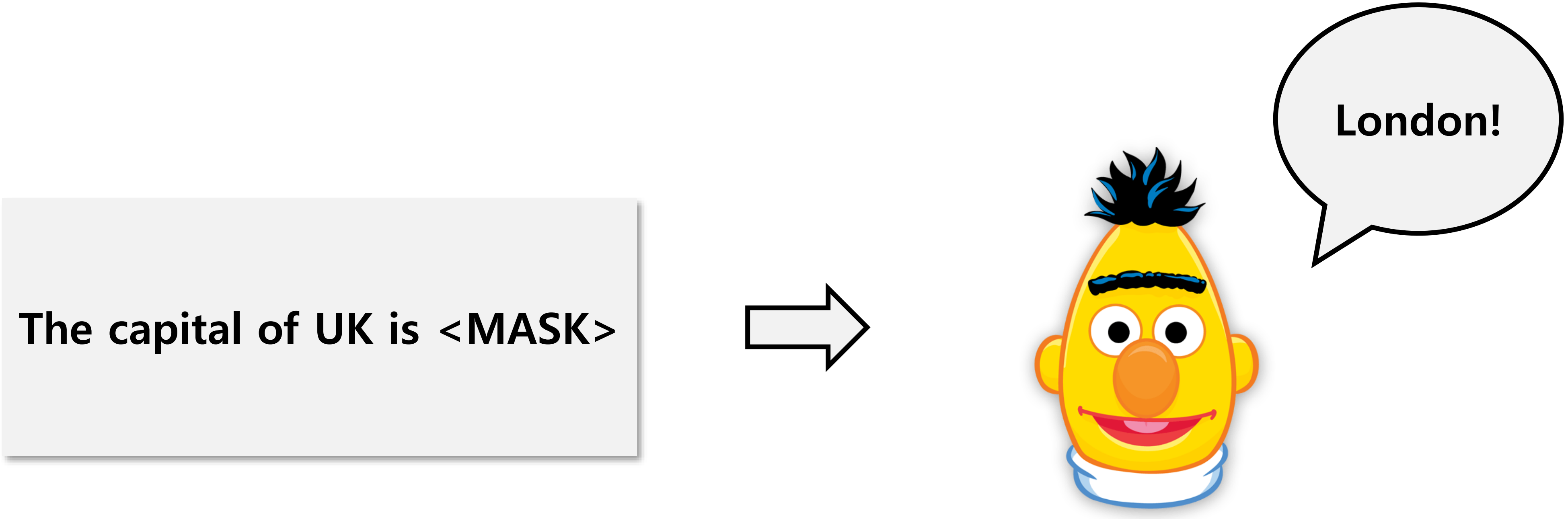
Where is the capital of UK?



Pattern-Exploiting Training

-Pattern-Verbalizer Pair

<Pattern-Verbalizer Pair>



The capital of UK is <MASK>

London!

Pattern-Exploiting Training

-Pattern-Verbalizer Pair

<Pattern-Verbalizer Pair>

Question Answering

Where is the capital of UK? → The capital of UK is <MASK>

Sentiment Classification

My phone doesn't work → My phone doesn't work.
So, I feel <MASK>

Pattern-Exploiting Training

-Pattern-Verbalizer Pair

<Pattern-Verbalizer Pair>

<Notation>

$M: Masked\ Language\ Model$

$V: Vocabulary$

$\_\_\_\_ \in V\ :\ Mask\ Token$

$\mathcal{L}, A: Labels, Target\ Classification\ Task$

$\mathbf{x} = (s_1, \ldots, s_k):\ Input\ for\ Task\ A$

$s_i \in V^*: Phrase$

$\boldsymbol{P}: \boldsymbol{Pattern}, where\ P(\mathbf{x}) \in V^*$

$\boldsymbol{v}: \boldsymbol{Verbalizer}, \mathcal{L} \rightarrow V$

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Task: RTE **(Recognizing Textual Entailment)**

Sen1: Oil prices rise.

Sen2: Oil prices fall back.

Label: Not Entailed

Pattern-Exploiting Training

-Pattern-Verbalizer Pair

<Pattern-Verbalizer Pair>

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Task: RTE **(Recognizing Textual Entailment)**

Sen1: **Oil prices rise.**

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Label: Not Entailed -> No

Entailed -> Yes

Pattern-Exploiting Training

-Pattern-Verbalizer Pair

<Pattern-Verbalizer Pair>

<Notation>

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$\underline{\qquad} \in V : Mask\ Token$

$\boldsymbol{\mathcal{L}}, A: \boldsymbol{Labels}, \boldsymbol{Target\ Classification\ Task}$

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Task: RTE (Recognizing Textual Entailment)

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Sen2: Oil prices fall back.

Label: Not Entailed -> No

Entailed -> Yes

$\boldsymbol{P}(\mathbf{x})$:

Oil prices rise? ____, Oil prices fall back.

<Pattern-Verbalizer Pair>

<Notation>

M: *Masked Language Model*

$\boldsymbol{V}$: ***Vocabulary***

$\_\_\_ \in V$: *Mask Token*

$\boldsymbol{\mathcal{L}}, \boldsymbol{A}$: ***Labels***, ***Target Classification Task***

$\mathbf{x} = (\boldsymbol{s_1}, \ldots, \boldsymbol{s_k})$: *Input for* ***Task A***

$\boldsymbol{s_i} \in \boldsymbol{V}^*$: ***Phrase***

$\boldsymbol{P}$: ***Pattern***, *where* $\boldsymbol{P}(\mathbf{x}) \in \boldsymbol{V}^*$

$\boldsymbol{v}$: ***Verbalizer***, $\boldsymbol{\mathcal{L}} \rightarrow \boldsymbol{V}$

$(\boldsymbol{P}, \boldsymbol{v})$: ***Pattern - Verbalizer Pair*** (PVP)

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Entailed -> Yes

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Pattern-Exploiting Training

-Pattern-Verbalizer Pair

<Pattern-Verbalizer Pair>

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$$\boldsymbol{v}: \boldsymbol{Verbalizer}, \mathcal{L} \rightarrow V: \boldsymbol{v}(\boldsymbol{y}) \in \boldsymbol{V}$$

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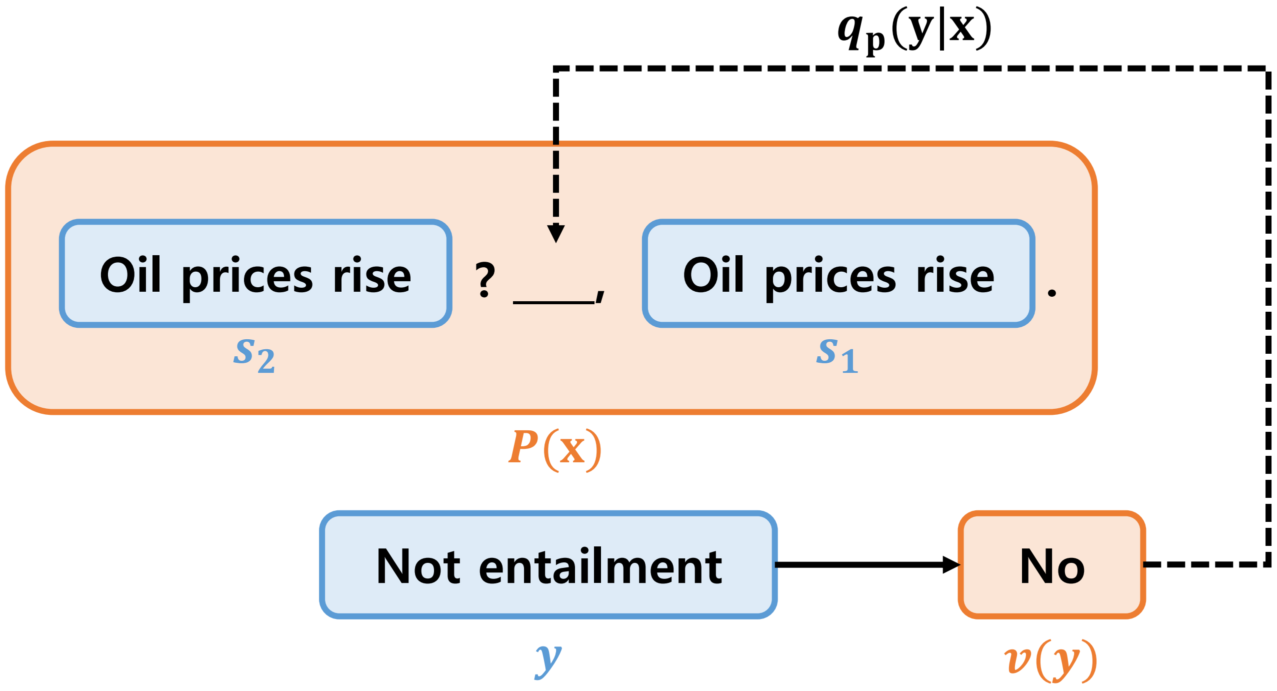
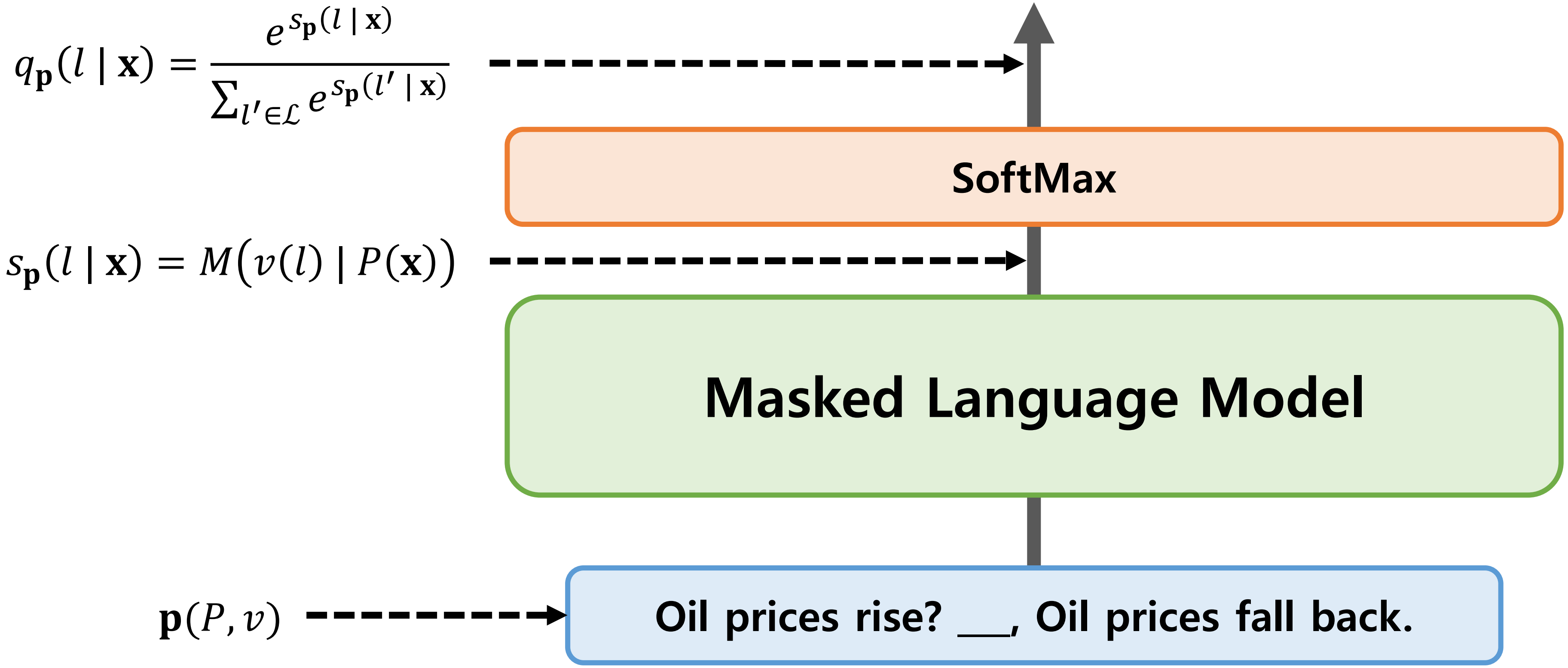


$\boldsymbol{q}_{\mathbf{p}}(\mathbf{y}|\mathbf{x})$
Oil prices rise
? ____,
Oil prices rise
.
$\boldsymbol{s}_2$
$\boldsymbol{s}_1$
$\boldsymbol{P}(\mathbf{x})$
Not entailment
No
$\boldsymbol{y}$
$\boldsymbol{v}(\boldsymbol{y})$

<PVP Training and Inference>

$$\mathbf{p} = (P, v)\text{: PVP}, \qquad s_{\mathbf{p}}(l \mid \mathbf{x}) = M\big(v(l) \mid P(\mathbf{x})\big)$$

$$q_{\mathbf{p}}(l \mid \mathbf{x}) = \frac{e^{s_{\mathbf{p}}(l \mid \mathbf{x})}}{\sum_{l' \in \mathcal{L}} e^{s_{\mathbf{p}}(l' \mid \mathbf{x})}}$$



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$$s_{\mathbf{p}}(l \mid \mathbf{x}) = M\big(v(l) \mid P(\mathbf{x})\big)$$

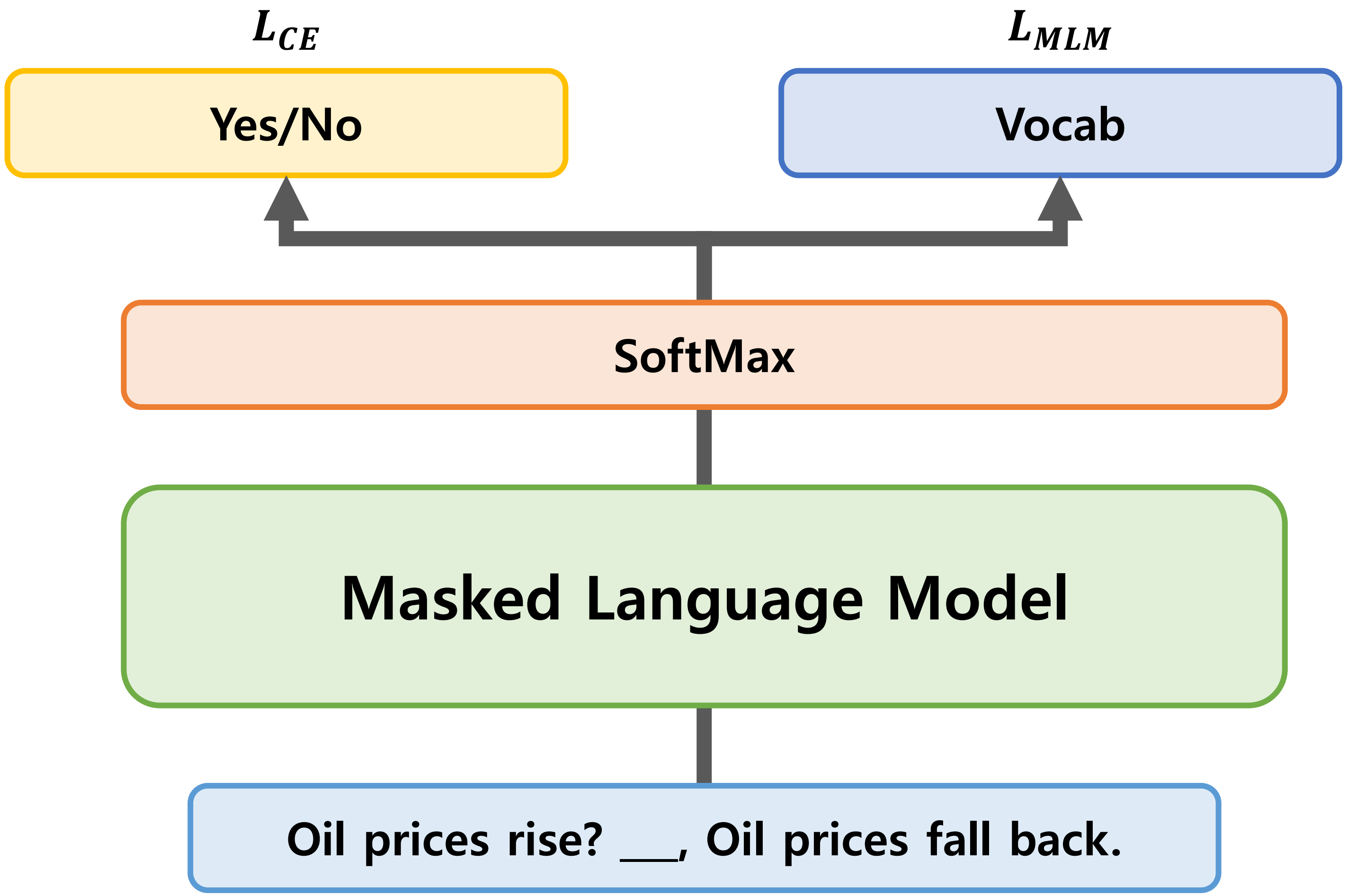
$$\mathbf{p}(P, v)$$

Pattern-Exploiting Training

-PVP Training and Inference

<Auxiliary Language Modeling>

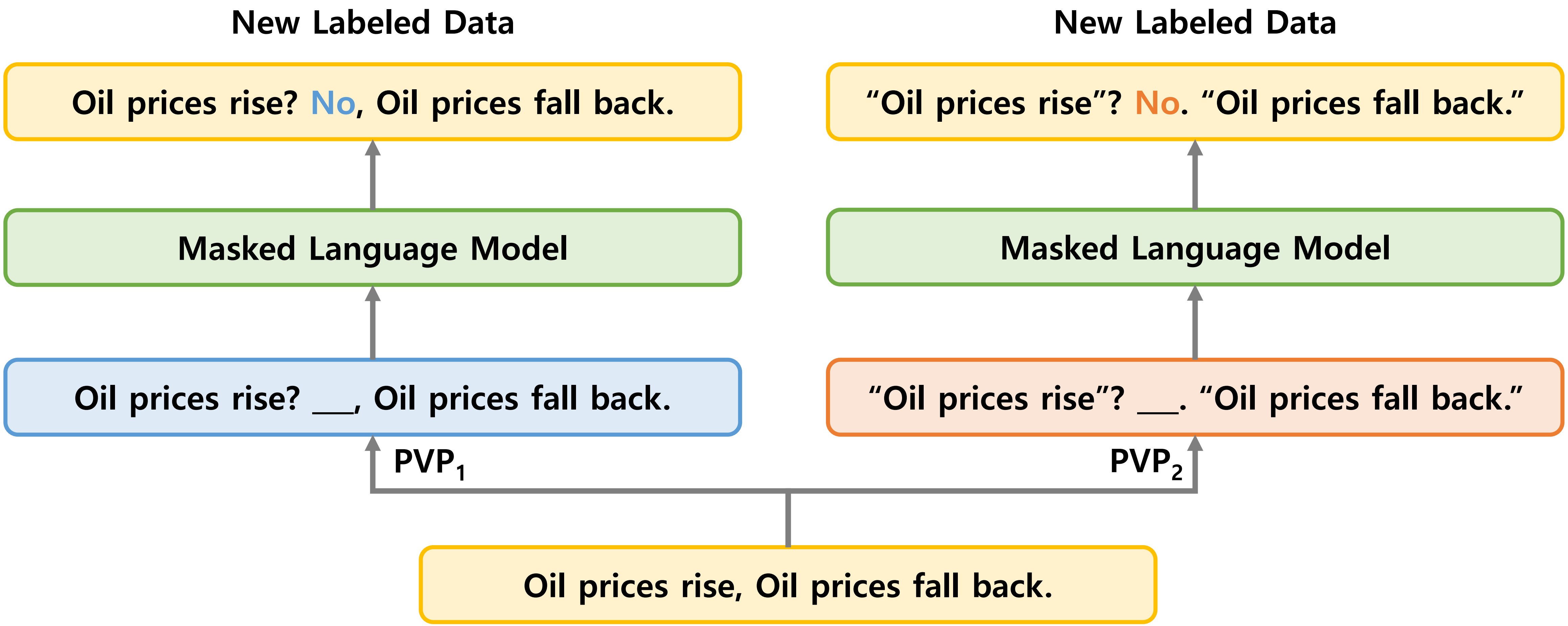
$$L = (1 - \alpha) \cdot L_{CE} + \alpha \cdot L_{MLM}$$



Pattern-Exploiting Training

-PVP Training and Inference

<Combining PVPs>


New Labeled Data
Oil prices rise? No, Oil prices fall back.
Masked Language Model
Oil prices rise? ___, Oil prices fall back.
PVP₁
New Labeled Data
"Oil prices rise"? No. "Oil prices fall back."
Masked Language Model
"Oil prices rise"? ___. "Oil prices fall back."
PVP₂
Oil prices rise, Oil prices fall back.

Pattern-Exploiting Training

-PVP Training and Inference

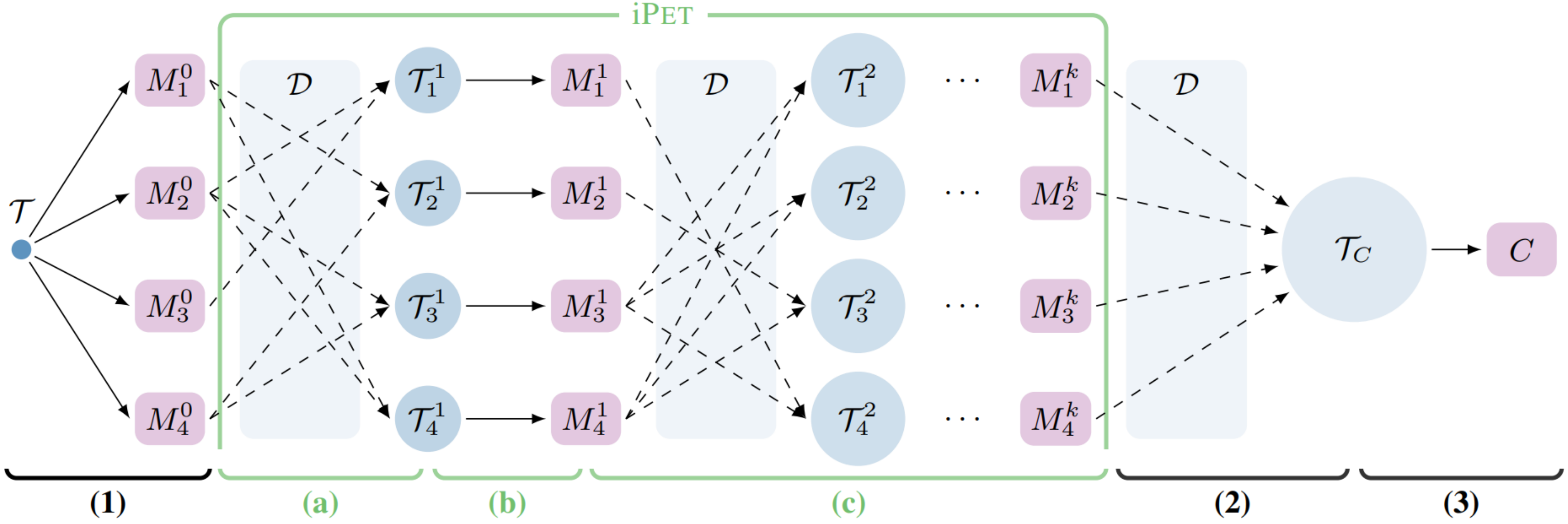
<Combining PVPs>

$\mathcal{T}$: *Training Dataset*, $\mathcal{D}$: *Unlabeled Data*

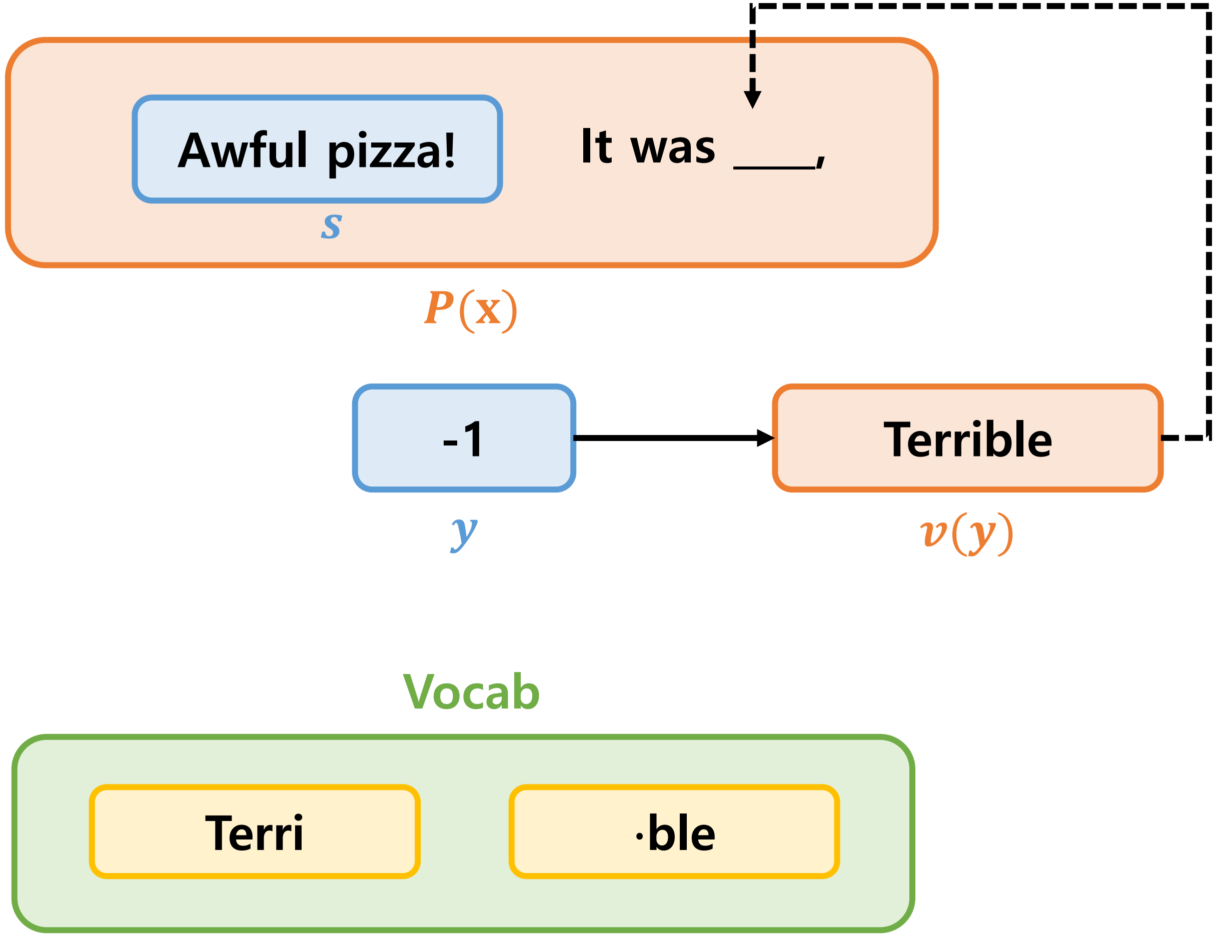
$\mathcal{M} = \{M_{\mathbf{p}} \mid \mathbf{p} \in \mathcal{P}\}$: *Ensemble of Fine-tuned Model*

$$s_{\mathcal{M}}(l \mid \mathbf{x}) = \frac{1}{Z} \sum_{\mathbf{p} \in \mathcal{P}} w(\mathbf{p}) \cdot s_{\mathbf{p}}(l \mid \mathbf{x})$$

$Z = \sum_{\mathbf{p} \in \mathcal{P}} w(\mathbf{p})$, $w(\mathbf{p})$: *Weight (1 or Accuracy before Training)*



<PET with Multiple Tasks>


Awful pizza!
It was ____,
s
$P(\mathbf{x})$
-1
Terrible
y
$v(y)$
Vocab
Terri
·ble

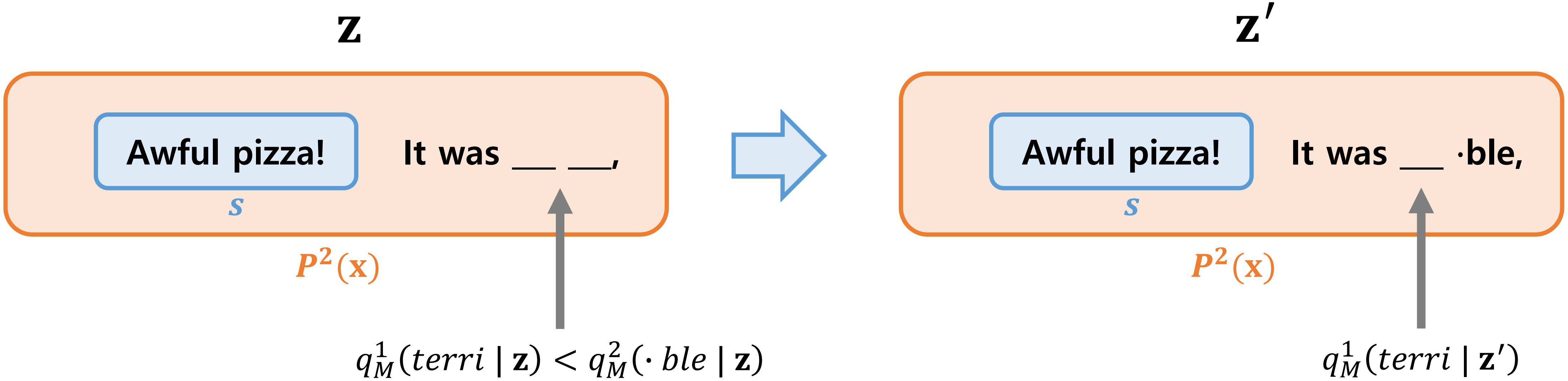
Pattern-Exploiting Training

-PVP Training and Inference

<Combining PVPs>

$$q_{\mathbf{p}}(y \mid x) = q\left(v(y) \mid P^{k}(x)\right)$$

$$q(t_1 \dots t_k \mid \mathbf{z}) = \begin{cases} 1 & if\ k = 0 \\ q_M^{j}(t_j \mid \mathbf{z}) \cdot q(t' \mid \mathbf{z}') & if\ k \geq 1 \end{cases}$$



$\mathbf{z}$

Awful pizza! It was ___ ___,

s

$P^2(\mathbf{x})$

$q_M^1(terri \mid \mathbf{z}) < q_M^2(\cdot\, ble \mid \mathbf{z})$

$\mathbf{z}'$

Awful pizza! It was ___ ·ble,

s

$P^2(\mathbf{x})$

$q_M^1(terri \mid \mathbf{z}')$

Experiments

- Tasks and Patterns

- Results

<Examples of Tasks and Patterns>

Task: WiC (Word in Context)

W: bed

S1: There's a log of trash on the bed of the river

S2: I keep a glass of water next to my bed

Label: Similar

Pattern

"s1" / "s2". Similar sense of "w"? ___. // yes, no

s1 s2 Does w have the same meaning in both sentences? ___ // yes, no

w. Sense (1) (a) "s1" (___) "s2". // b, 2

Task: COPA (Choice of Plausible Alternatives)

P: The man broke his toe. What was the cause of this?

C1: He got a hole in his sock.

C2: He dropped a hammer on his foot

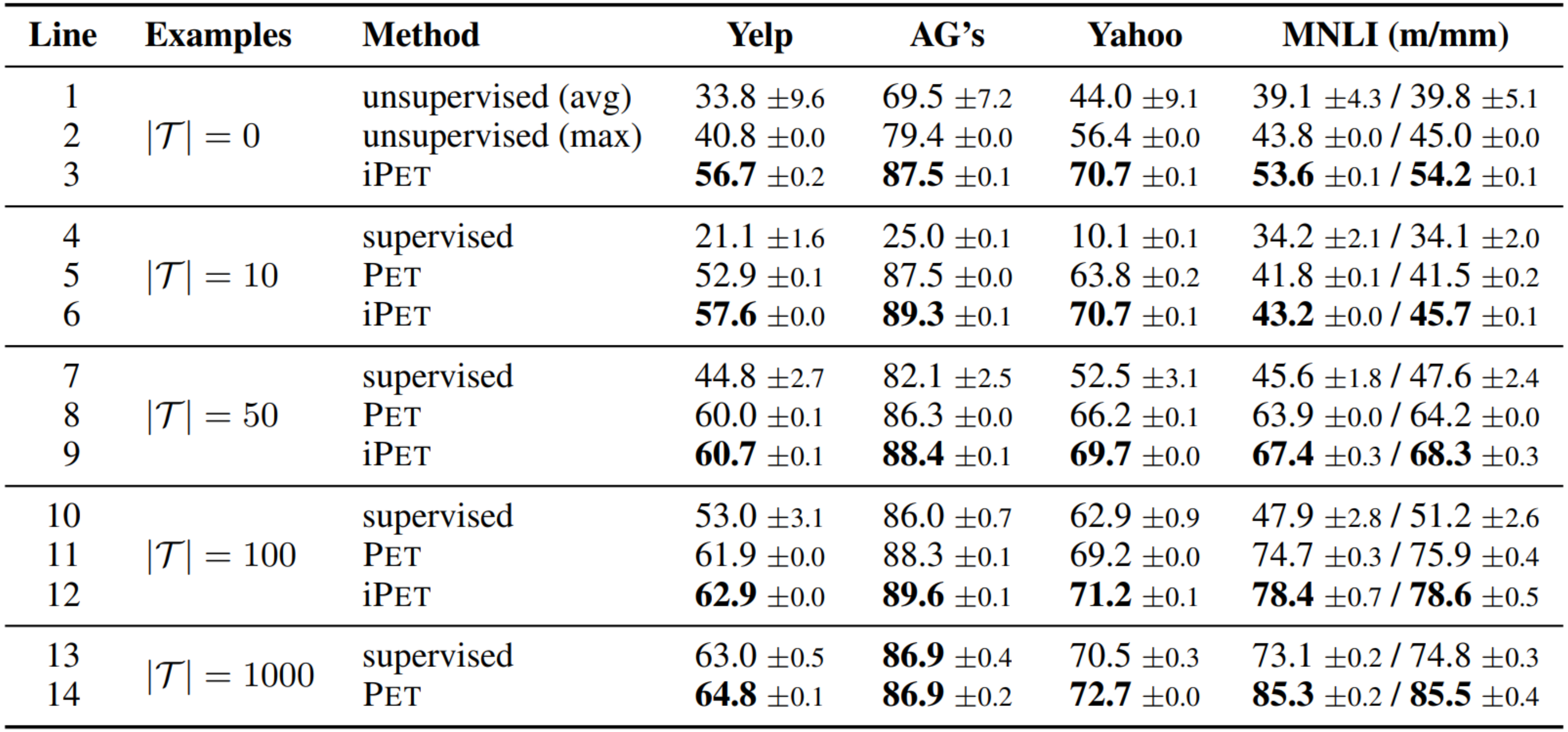
Label: C2

Pattern

"C1" or "C2"? p, so ___. // C1, C2

C1 or C2? p, so ___. // C1, C2

<Results>



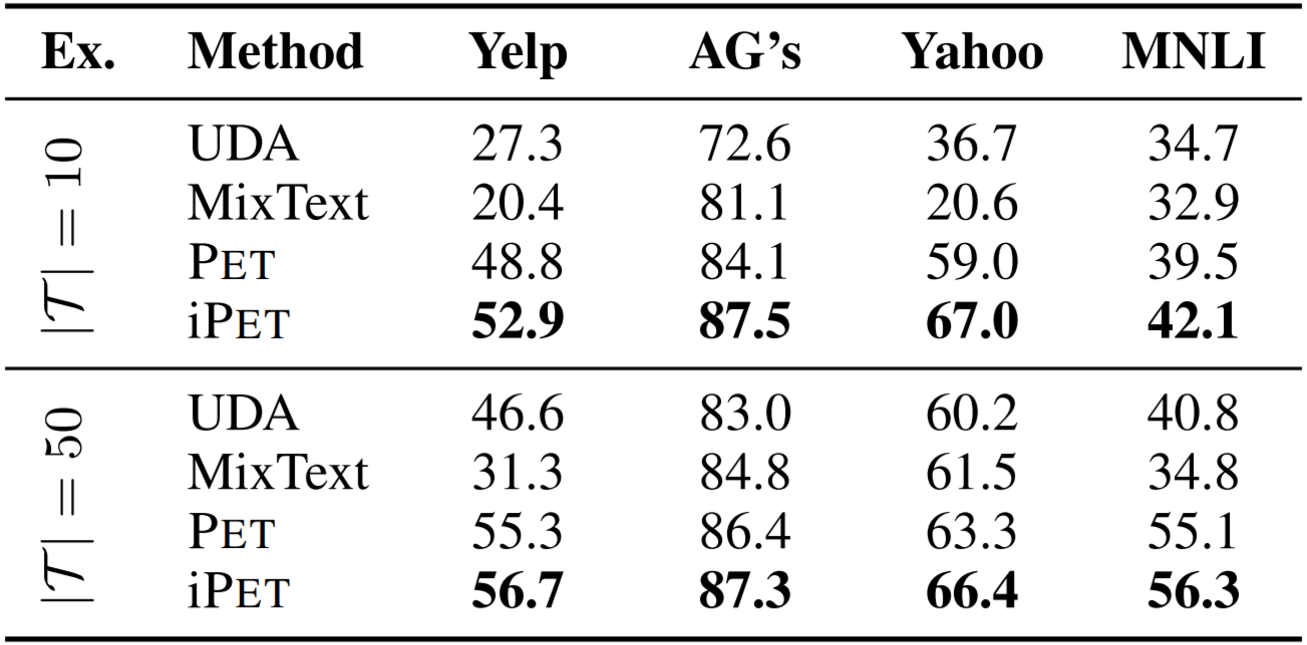
Line	Examples	Method	Yelp	AG's	Yahoo	MNLI (m/mm)
1	$\lvert\mathcal{T}\rvert = 0$	unsupervised (avg)	33.8 ±9.6	69.5 ±7.2	44.0 ±9.1	39.1 ±4.3 / 39.8 ±5.1
2		unsupervised (max)	40.8 ±0.0	79.4 ±0.0	56.4 ±0.0	43.8 ±0.0 / 45.0 ±0.0
3		iPET	**56.7** ±0.2	**87.5** ±0.1	**70.7** ±0.1	**53.6** ±0.1 / **54.2** ±0.1
4	$\lvert\mathcal{T}\rvert = 10$	supervised	21.1 ±1.6	25.0 ±0.1	10.1 ±0.1	34.2 ±2.1 / 34.1 ±2.0
5		PET	52.9 ±0.1	87.5 ±0.0	63.8 ±0.2	41.8 ±0.1 / 41.5 ±0.2
6		iPET	**57.6** ±0.0	**89.3** ±0.1	**70.7** ±0.1	**43.2** ±0.0 / **45.7** ±0.1
7	$\lvert\mathcal{T}\rvert = 50$	supervised	44.8 ±2.7	82.1 ±2.5	52.5 ±3.1	45.6 ±1.8 / 47.6 ±2.4
8		PET	60.0 ±0.1	86.3 ±0.0	66.2 ±0.1	63.9 ±0.0 / 64.2 ±0.0
9		iPET	**60.7** ±0.1	**88.4** ±0.1	**69.7** ±0.0	**67.4** ±0.3 / **68.3** ±0.3
10	$\lvert\mathcal{T}\rvert = 100$	supervised	53.0 ±3.1	86.0 ±0.7	62.9 ±0.9	47.9 ±2.8 / 51.2 ±2.6
11		PET	61.9 ±0.0	88.3 ±0.1	69.2 ±0.0	74.7 ±0.3 / 75.9 ±0.4
12		iPET	**62.9** ±0.0	**89.6** ±0.1	**71.2** ±0.1	**78.4** ±0.7 / **78.6** ±0.5
13	$\lvert\mathcal{T}\rvert = 1000$	supervised	63.0 ±0.5	**86.9** ±0.4	70.5 ±0.3	73.1 ±0.2 / 74.8 ±0.3
14		PET	**64.8** ±0.1	**86.9** ±0.2	**72.7** ±0.0	**85.3** ±0.2 / **85.5** ±0.4

<Average accuracy and standard deviation for RoBERTa (large)>

Experiments

- Results

<Results>



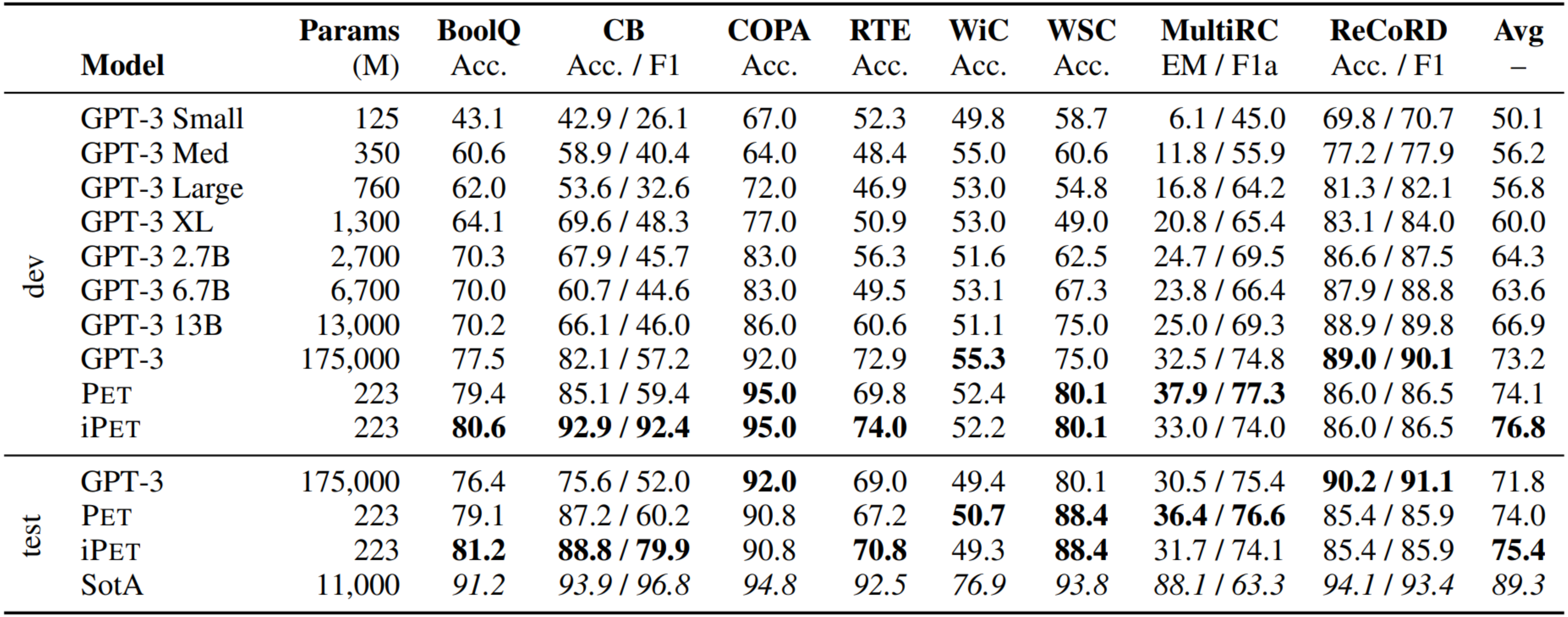
Ex.	Method	Yelp	AG's	Yahoo	MNLI
$\|\mathcal{T}\| = 10$	UDA	27.3	72.6	36.7	34.7
	MixText	20.4	81.1	20.6	32.9
	PET	48.8	84.1	59.0	39.5
	iPET	**52.9**	**87.5**	**67.0**	**42.1**
$\|\mathcal{T}\| = 50$	UDA	46.6	83.0	60.2	40.8
	MixText	31.3	84.8	61.5	34.8
	PET	55.3	86.4	63.3	55.1
	iPET	**56.7**	**87.3**	**66.4**	**56.3**

<Comparison of PET with two state-of-the-art semi-supervised method using RoBERTa (base)>

Experiments

- Results

<Results>



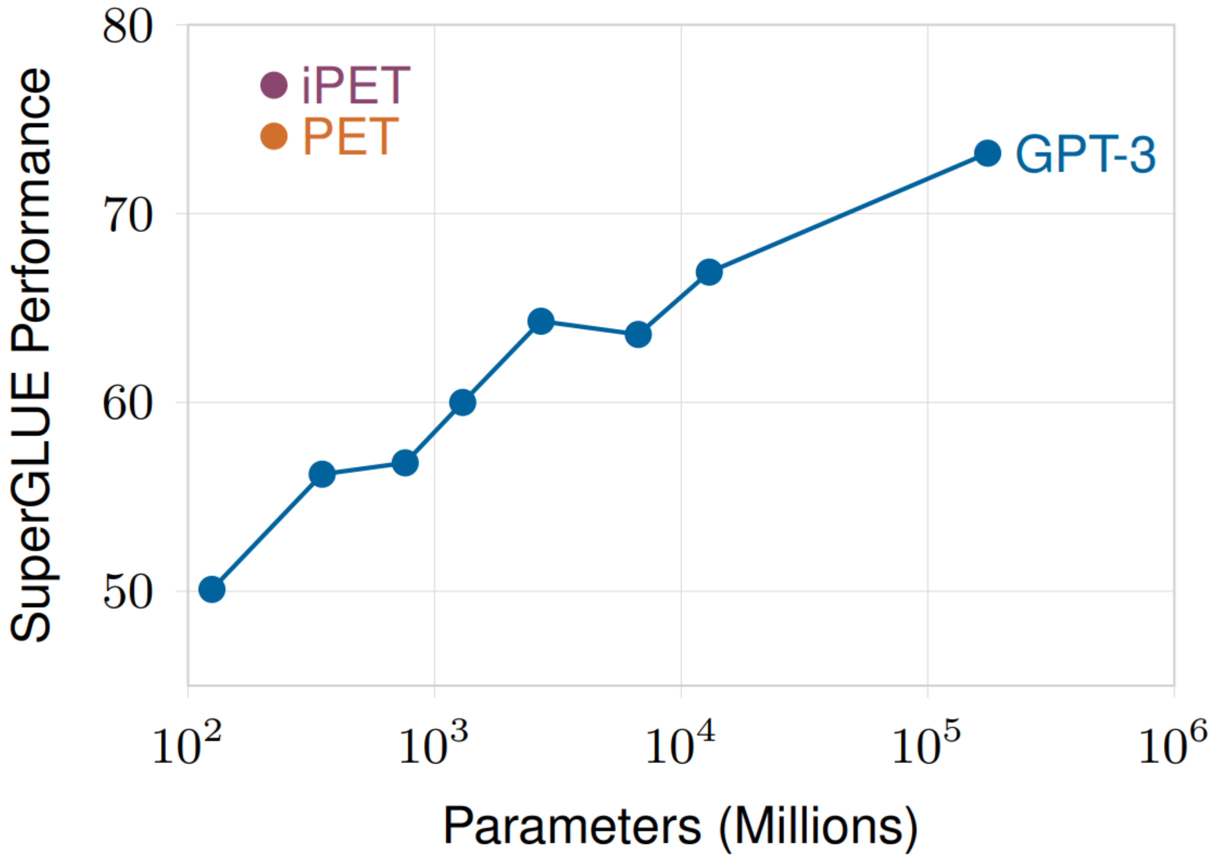
		Params	BoolQ	CB	COPA	RTE	WiC	WSC	MultiRC	ReCoRD	Avg
	Model	(M)	Acc.	Acc. / F1	Acc.	Acc.	Acc.	Acc.	EM / F1a	Acc. / F1	–
dev	GPT-3 Small	125	43.1	42.9 / 26.1	67.0	52.3	49.8	58.7	6.1 / 45.0	69.8 / 70.7	50.1
	GPT-3 Med	350	60.6	58.9 / 40.4	64.0	48.4	55.0	60.6	11.8 / 55.9	77.2 / 77.9	56.2
	GPT-3 Large	760	62.0	53.6 / 32.6	72.0	46.9	53.0	54.8	16.8 / 64.2	81.3 / 82.1	56.8
	GPT-3 XL	1,300	64.1	69.6 / 48.3	77.0	50.9	53.0	49.0	20.8 / 65.4	83.1 / 84.0	60.0
	GPT-3 2.7B	2,700	70.3	67.9 / 45.7	83.0	56.3	51.6	62.5	24.7 / 69.5	86.6 / 87.5	64.3
	GPT-3 6.7B	6,700	70.0	60.7 / 44.6	83.0	49.5	53.1	67.3	23.8 / 66.4	87.9 / 88.8	63.6
	GPT-3 13B	13,000	70.2	66.1 / 46.0	86.0	60.6	51.1	75.0	25.0 / 69.3	88.9 / 89.8	66.9
	GPT-3	175,000	77.5	82.1 / 57.2	92.0	72.9	**55.3**	75.0	32.5 / 74.8	**89.0 / 90.1**	73.2
	PET	223	79.4	85.1 / 59.4	**95.0**	69.8	52.4	**80.1**	**37.9 / 77.3**	86.0 / 86.5	74.1
	iPET	223	**80.6**	**92.9 / 92.4**	**95.0**	**74.0**	52.2	**80.1**	33.0 / 74.0	86.0 / 86.5	**76.8**
test	GPT-3	175,000	76.4	75.6 / 52.0	**92.0**	69.0	49.4	80.1	30.5 / 75.4	**90.2 / 91.1**	71.8
	PET	223	79.1	87.2 / 60.2	90.8	67.2	**50.7**	**88.4**	**36.4 / 76.6**	85.4 / 85.9	74.0
	iPET	223	**81.2**	**88.8 / 79.9**	90.8	**70.8**	49.3	**88.4**	31.7 / 74.1	85.4 / 85.9	**75.4**
	SotA	11,000	*91.2*	*93.9 / 96.8*	*94.8*	*92.5*	*76.9*	*93.8*	*88.1 / 63.3*	*94.1 / 93.4*	*89.3*

<Results on SuperGLUE for GPT-3 primed with 32 examples and for PET/iPET with ALBERT-xxlarge-v2>

Experiments

- Results

<Results>



<Performance on SuperGLUE with 32 training examples>

Conclusion

<Conclusion>

- Proposed Pattern-Exploiting Training that consists of defining pairs of cloze question patterns and verbalizers that help leverage the knowledge contained within pretrained language models for downstream tasks.

- Proposed modified PET enabling to be used for tasks that require predicting multiple tokens.

- Shown that using PET, it is possible to achieve few-shot text classification performance similar to GPT-3 on SuperGLUE with LMs that have much fewer parameters.

<Conclusion>

- Proposed Pattern-Exploiting Training that consists of defining pairs of cloze question patterns and verbalizers that help leverage the knowledge contained within pretrained language models for downstream tasks.
- Proposed modified PET enabling to be used for tasks that require predicting multiple tokens.
- Shown that using PET, it is possible to achieve few-shot text classification performance similar to GPT-3 on SuperGLUE with LMs that have much fewer parameters.

PET has achieved remarkable performance, but it requires thousands of unlabeled data, and hand-crafted patterns.

Additionally, since discrete prompts are used, the results may be sub-optimal to continuous neural network.

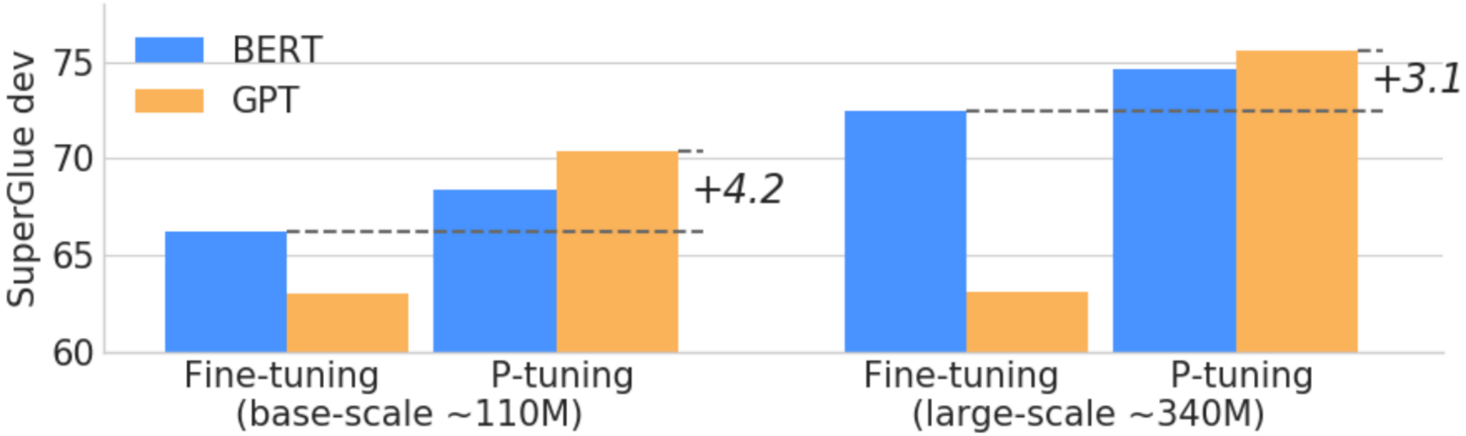
How can PET be further improved?

GPT Understands, Too

Liu et al., 2021, arXiv

P-Tuning

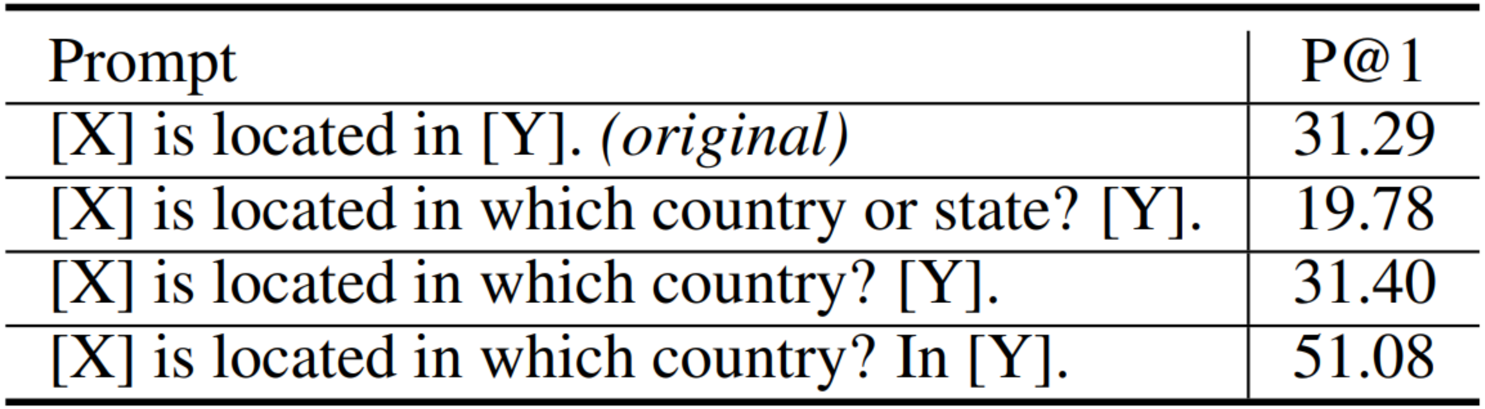
<Overview>



<Average scores on 7 dev datasets of SuperGLUE>

“GPTs can be better than similar-sized BERTs on NLU with P-tuning.”

<Overview>

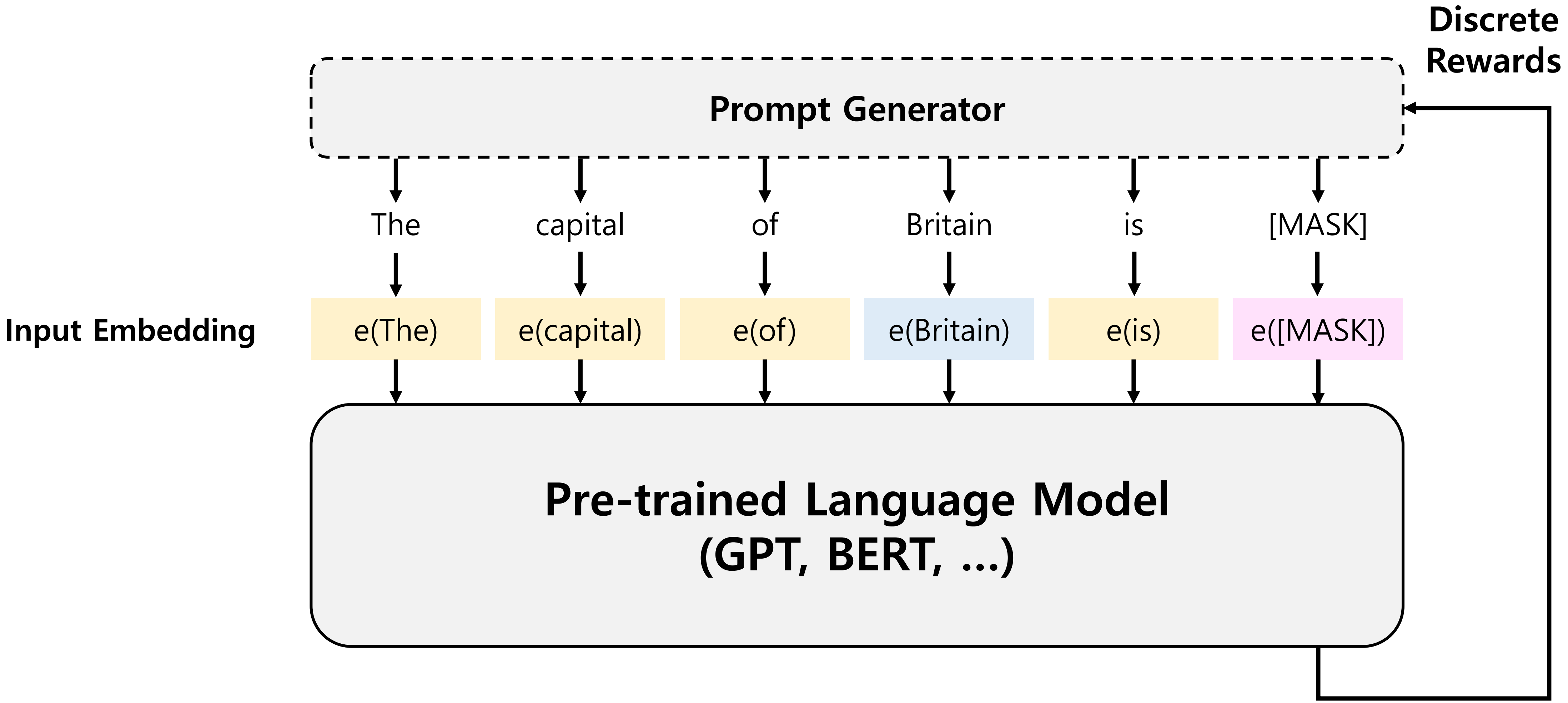


Prompt	P@1
[X] is located in [Y]. *(original)*	31.29
[X] is located in which country or state? [Y].	19.78
[X] is located in which country? [Y].	31.40
[X] is located in which country? In [Y].	51.08

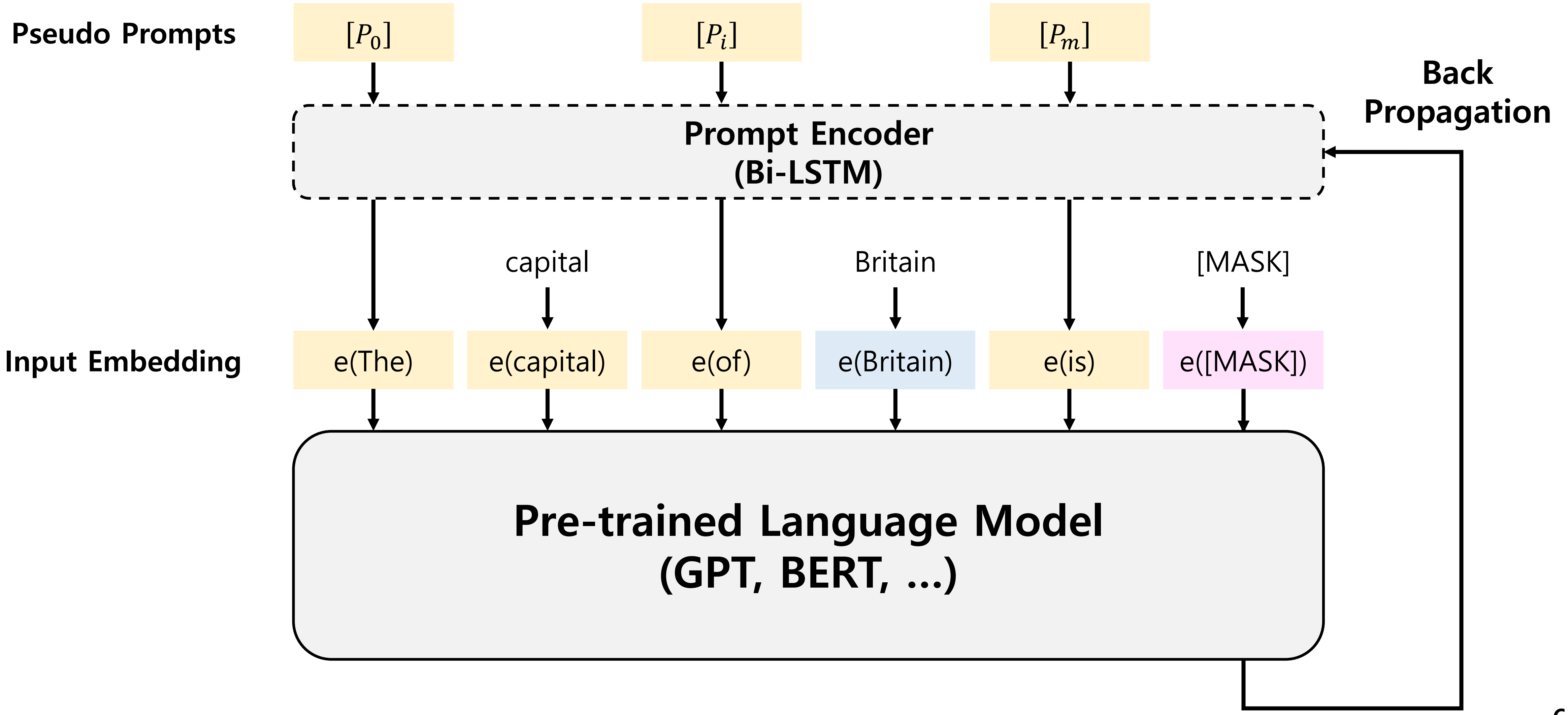
<Case study on LAMA-TREx P17 with bert-base-cased>

“A single-word change in prompts could yield a drastic difference.”

<Discrete Prompt Search>

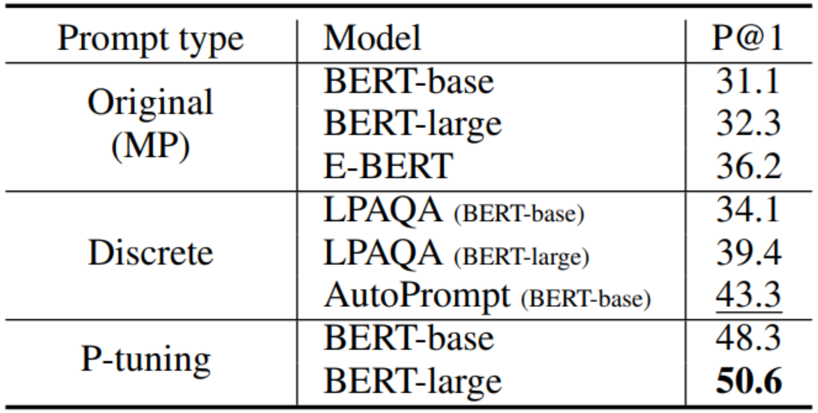

Discrete
Rewards
Prompt Generator
The
capital
of
Britain
is
[MASK]
Input Embedding
e(The)
e(capital)
e(of)
e(Britain)
e(is)
e([MASK])
Pre-trained Language Model
(GPT, BERT, …)

<P-Tuning>

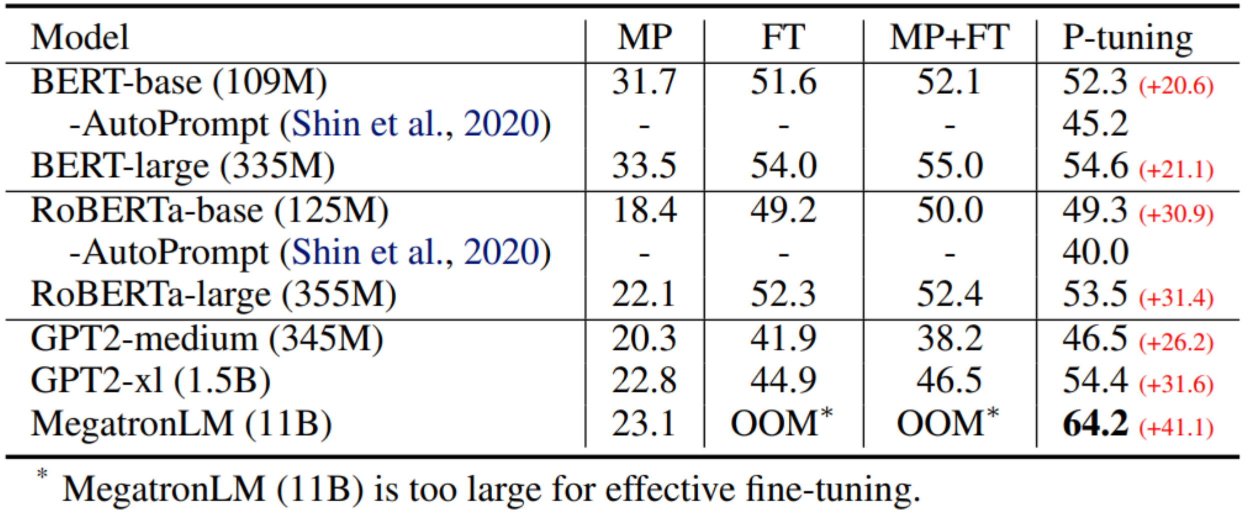

Pseudo Prompts
$[P_0]$
$[P_i]$
$[P_m]$
Back Propagation
Prompt Encoder (Bi-LSTM)
capital
Britain
[MASK]
Input Embedding
e(The)
e(capital)
e(of)
e(Britain)
e(is)
e([MASK])
Pre-trained Language Model (GPT, BERT, …)

Experiments

<Results>



Prompt type	Model	P@1
Original (MP)	BERT-base	31.1
	BERT-large	32.3
	E-BERT	36.2
Discrete	LPAQA (BERT-base)	34.1
	LPAQA (BERT-large)	39.4
	AutoPrompt (BERT-base)	43.3
P-tuning	BERT-base	48.3
	BERT-large	**50.6**



Model	MP	FT	MP+FT	P-tuning
BERT-base (109M)	31.7	51.6	52.1	52.3 (+20.6)
-AutoPrompt (Shin et al., 2020)	-	-	-	45.2
BERT-large (335M)	33.5	54.0	55.0	54.6 (+21.1)
RoBERTa-base (125M)	18.4	49.2	50.0	49.3 (+30.9)
-AutoPrompt (Shin et al., 2020)	-	-	-	40.0
RoBERTa-large (355M)	22.1	52.3	52.4	53.5 (+31.4)
GPT2-medium (345M)	20.3	41.9	38.2	46.5 (+26.2)
GPT2-xl (1.5B)	22.8	44.9	46.5	54.4 (+31.6)
MegatronLM (11B)	23.1	OOM*	OOM*	**64.2** (+41.1)

* MegatronLM (11B) is too large for effective fine-tuning.

<Knowledge probing Precision@1 on LAMA-34k (left) and LAMA-29k (right)>

"P-tuning outperforms all the discrete prompt searching baseline"

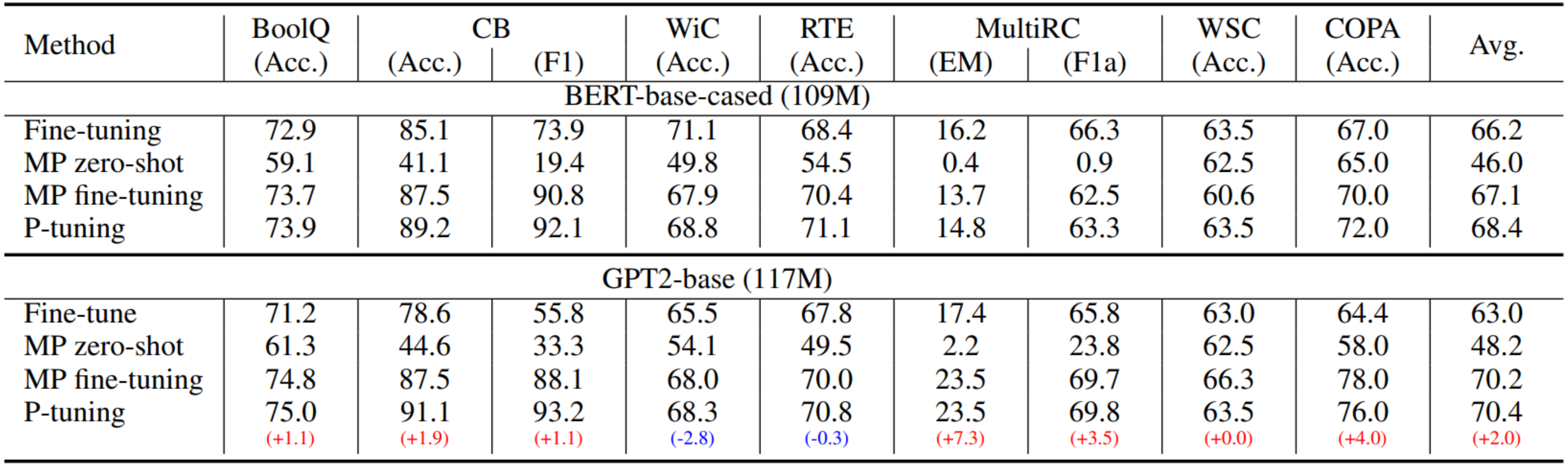
"Despite fixed pre-trained model parameters, P-tuning overwhelms the fine-tuning GPTs"

(MP: Manual Prompt, FT: Fine-tuning, MP+FT: Manual Prompt Augmented Fine-tuning, PT: P-tuning)

Experiments

- Results

<Results>



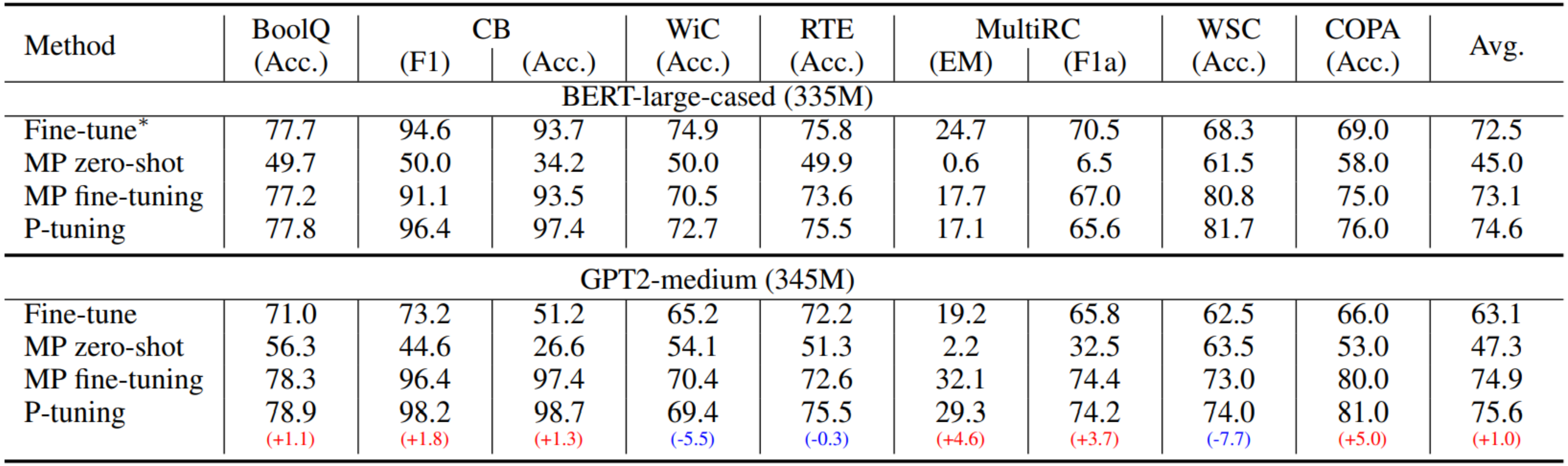
Method	BoolQ	CB		WiC	RTE	MultiRC		WSC	COPA	Avg.
	(Acc.)	(Acc.)	(F1)	(Acc.)	(Acc.)	(EM)	(F1a)	(Acc.)	(Acc.)	
BERT-base-cased (109M)										
Fine-tuning	72.9	85.1	73.9	71.1	68.4	16.2	66.3	63.5	67.0	66.2
MP zero-shot	59.1	41.1	19.4	49.8	54.5	0.4	0.9	62.5	65.0	46.0
MP fine-tuning	73.7	87.5	90.8	67.9	70.4	13.7	62.5	60.6	70.0	67.1
P-tuning	73.9	89.2	92.1	68.8	71.1	14.8	63.3	63.5	72.0	68.4
GPT2-base (117M)										
Fine-tune	71.2	78.6	55.8	65.5	67.8	17.4	65.8	63.0	64.4	63.0
MP zero-shot	61.3	44.6	33.3	54.1	49.5	2.2	23.8	62.5	58.0	48.2
MP fine-tuning	74.8	87.5	88.1	68.0	70.0	23.5	69.7	66.3	78.0	70.2
P-tuning	75.0 (+1.1)	91.1 (+1.9)	93.2 (+1.1)	68.3 (-2.8)	70.8 (-0.3)	23.5 (+7.3)	69.8 (+3.5)	63.5 (+0.0)	76.0 (+4.0)	70.4 (+2.0)

<Fully-supervised learning on SuperGLUE dev with base-scale models>

Experiments

- Results

<Results>



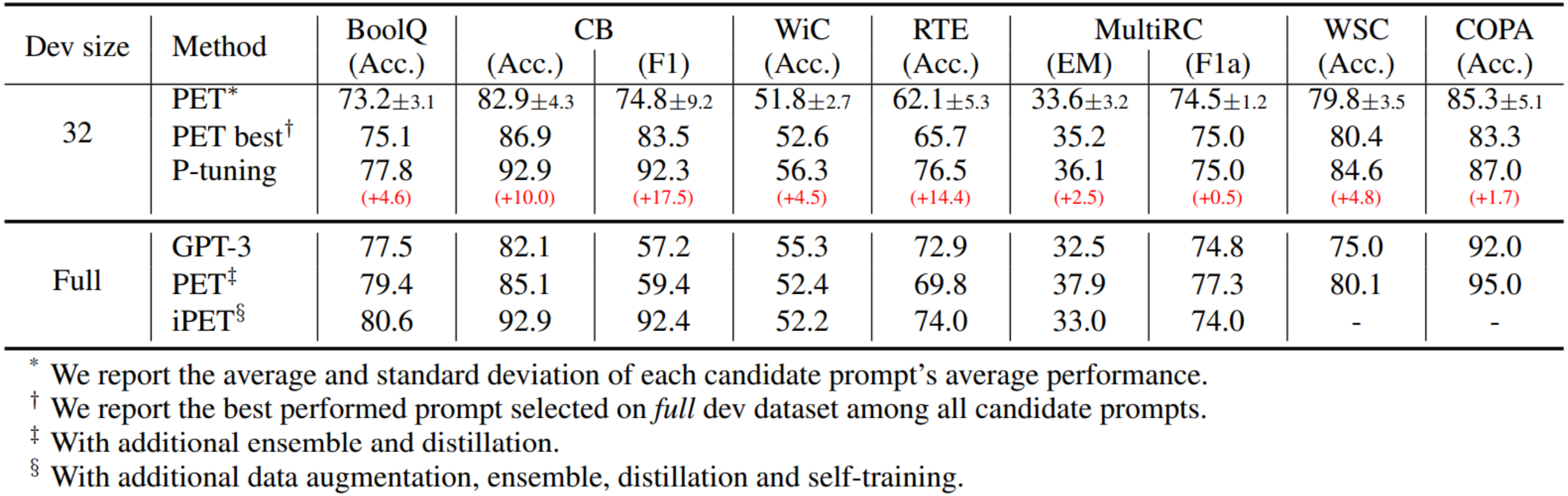
Method	BoolQ	CB		WiC	RTE	MultiRC		WSC	COPA	Avg.
	(Acc.)	(F1)	(Acc.)	(Acc.)	(Acc.)	(EM)	(F1a)	(Acc.)	(Acc.)	
BERT-large-cased (335M)										
Fine-tune*	77.7	94.6	93.7	74.9	75.8	24.7	70.5	68.3	69.0	72.5
MP zero-shot	49.7	50.0	34.2	50.0	49.9	0.6	6.5	61.5	58.0	45.0
MP fine-tuning	77.2	91.1	93.5	70.5	73.6	17.7	67.0	80.8	75.0	73.1
P-tuning	77.8	96.4	97.4	72.7	75.5	17.1	65.6	81.7	76.0	74.6
GPT2-medium (345M)										
Fine-tune	71.0	73.2	51.2	65.2	72.2	19.2	65.8	62.5	66.0	63.1
MP zero-shot	56.3	44.6	26.6	54.1	51.3	2.2	32.5	63.5	53.0	47.3
MP fine-tuning	78.3	96.4	97.4	70.4	72.6	32.1	74.4	73.0	80.0	74.9
P-tuning	78.9 (+1.1)	98.2 (+1.8)	98.7 (+1.3)	69.4 (-5.5)	75.5 (-0.3)	29.3 (+4.6)	74.2 (+3.7)	74.0 (-7.7)	81.0 (+5.0)	75.6 (+1.0)

<Fully-supervised learning on SuperGLUE dev with large-scale models>

Experiments

- Results

<Results>



Dev size	Method	BoolQ	CB		WiC	RTE	MultiRC		WSC	COPA
		(Acc.)	(Acc.)	(F1)	(Acc.)	(Acc.)	(EM)	(F1a)	(Acc.)	(Acc.)
32	PET*	73.2±3.1	82.9±4.3	74.8±9.2	51.8±2.7	62.1±5.3	33.6±3.2	74.5±1.2	79.8±3.5	85.3±5.1
	PET best†	75.1	86.9	83.5	52.6	65.7	35.2	75.0	80.4	83.3
	P-tuning	77.8 (+4.6)	92.9 (+10.0)	92.3 (+17.5)	56.3 (+4.5)	76.5 (+14.4)	36.1 (+2.5)	75.0 (+0.5)	84.6 (+4.8)	87.0 (+1.7)
Full	GPT-3	77.5	82.1	57.2	55.3	72.9	32.5	74.8	75.0	92.0
	PET‡	79.4	85.1	59.4	52.4	69.8	37.9	77.3	80.1	95.0
	iPET§	80.6	92.9	92.4	52.2	74.0	33.0	74.0	-	-

* We report the average and standard deviation of each candidate prompt's average performance.

† We report the best performed prompt selected on *full* dev dataset among all candidate prompts.

‡ With additional ensemble and distillation.

§ With additional data augmentation, ensemble, distillation and self-training.

<Few-shot learning (32 train samples) on SuperGLUE dev>

Conclusion

<Conclusion>

- Proposed P-tuning which augments pre-trained model’s ability in natural language understanding by automatically searching better prompts in the continuous space.
- On the SuperGLUE benchmark, P-tuning endows GPT-style models to show competitive performance with similar-size BERTs in natural language understanding, which is assumed impossible in the past.
- P-tuning also helps on bidirectional models and consequently outperforms state-of-the-art methods in the few-shot SuperGLUE benchmark.

Any Questions?

Thank You