Applied Deep Learning

Prompt-Based Learning

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Slides credited from Mohit Lyyer (Umass) and Hung-Yi Lee

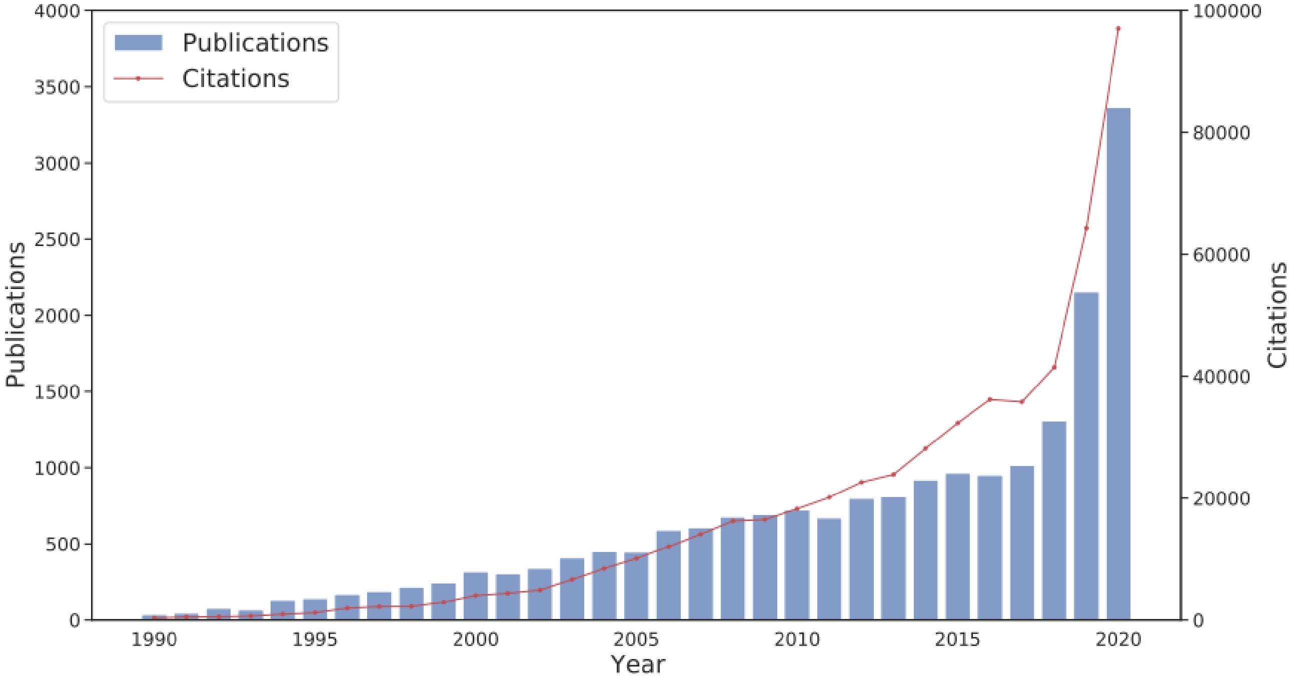
Fine-Tuning on Pretrained LMs

- (Standard) fine-tuning: use the pre-trained LMs for initialization and tuning the parameters for a **downstream** task

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Wide Usage of PLMs (Han et al., 2021)

- Increasing usage of PLMs



Issue 1: Data Scarcity

- Downstream annotated data may not be large

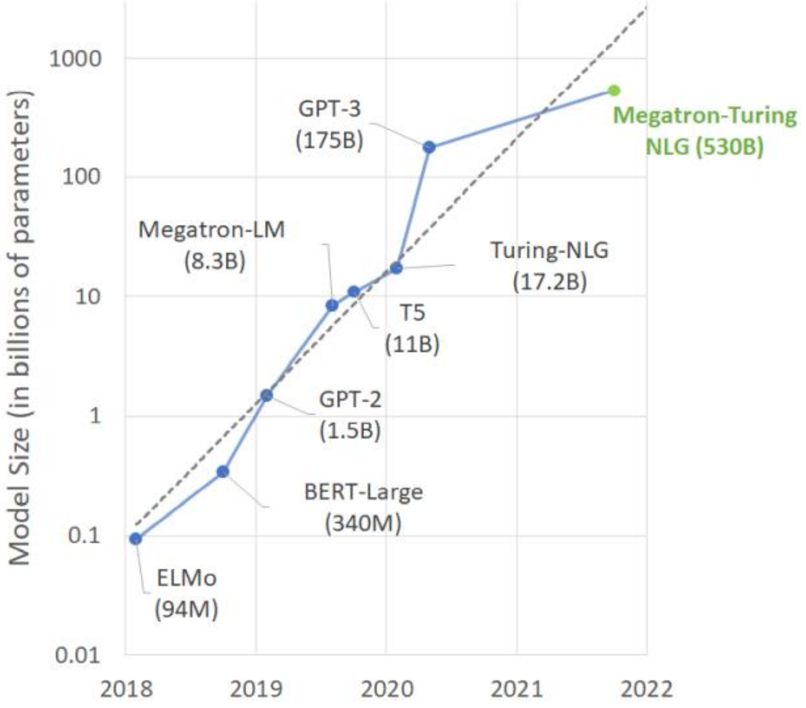
Task	MNLI	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE
Size	391K	363K	108K	67K	8.5K	5.7K	3.5K	2.5K

→ More practical cases are few-shot, one-shot or even zero-shot settings

Issue 2: Large-Scale PLMs

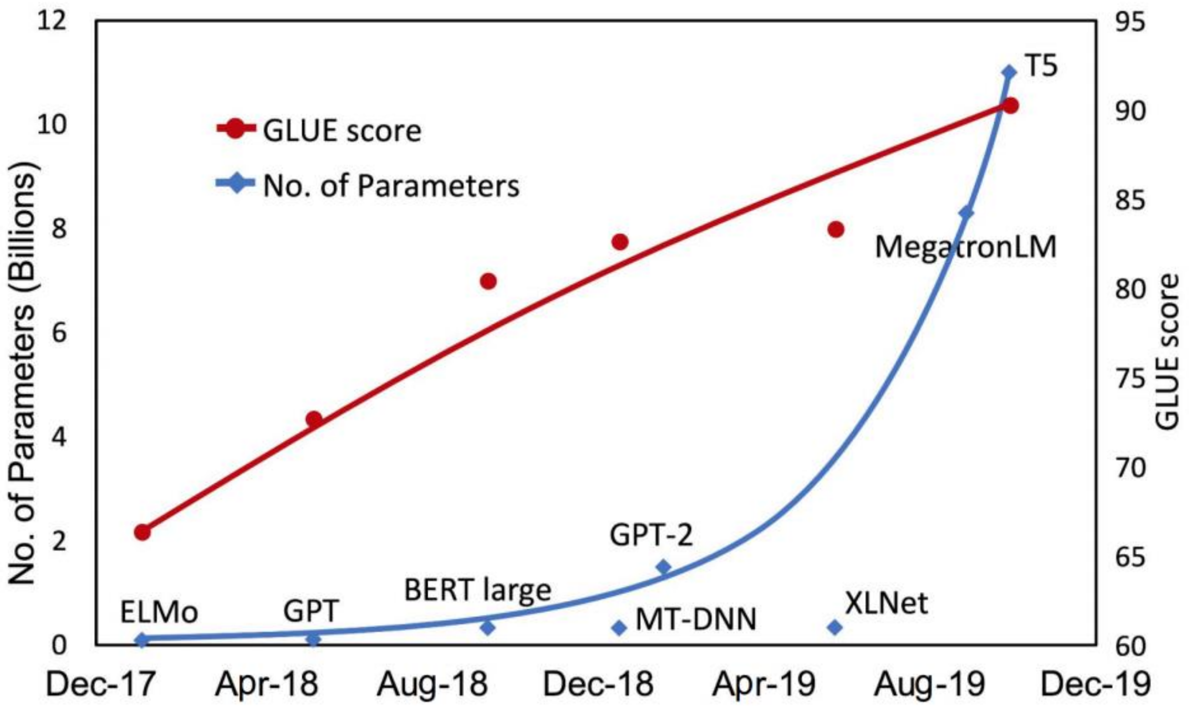
- PLMs are larger and larger

Model	#Params	#Layers
ELMo	93M	2 (BiLSTM)
BERT Base	110M	12
BERT Large	340M	24
GPT-3 Small	125M	12
GPT-3 Medium	350M	24
GPT-3 Large	760M	24
GPT-3 XL	1.3B	24
GPT-3 2.7B	2.7B	32
GPT-3 6.7B	6.7B	32
GPT-3 13B	13B	40
GPT-3 175B ("GPT-3")	175.0B	96



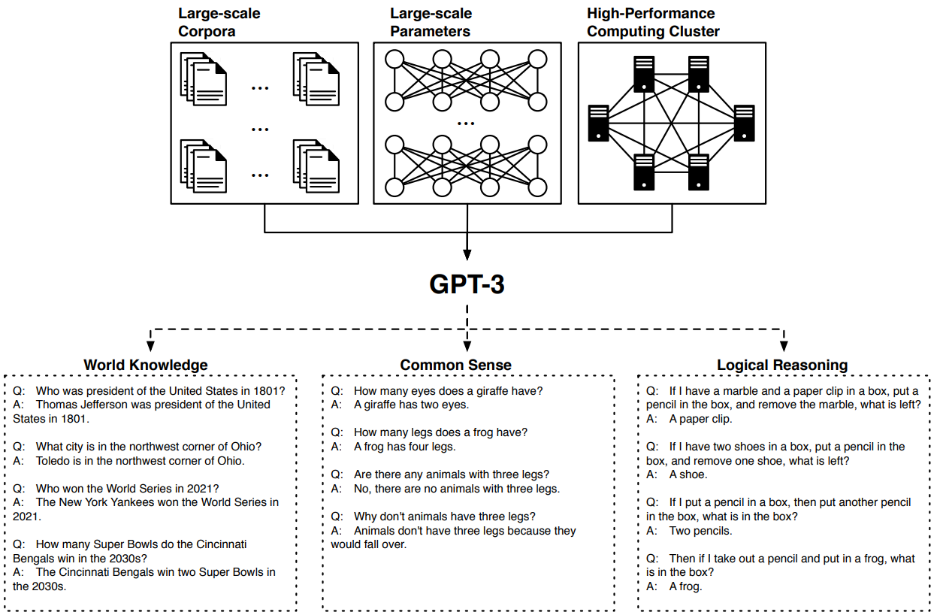
Better Performance from Larger Models

- Language understanding performance (Ahmet & Abdullah, 2021)



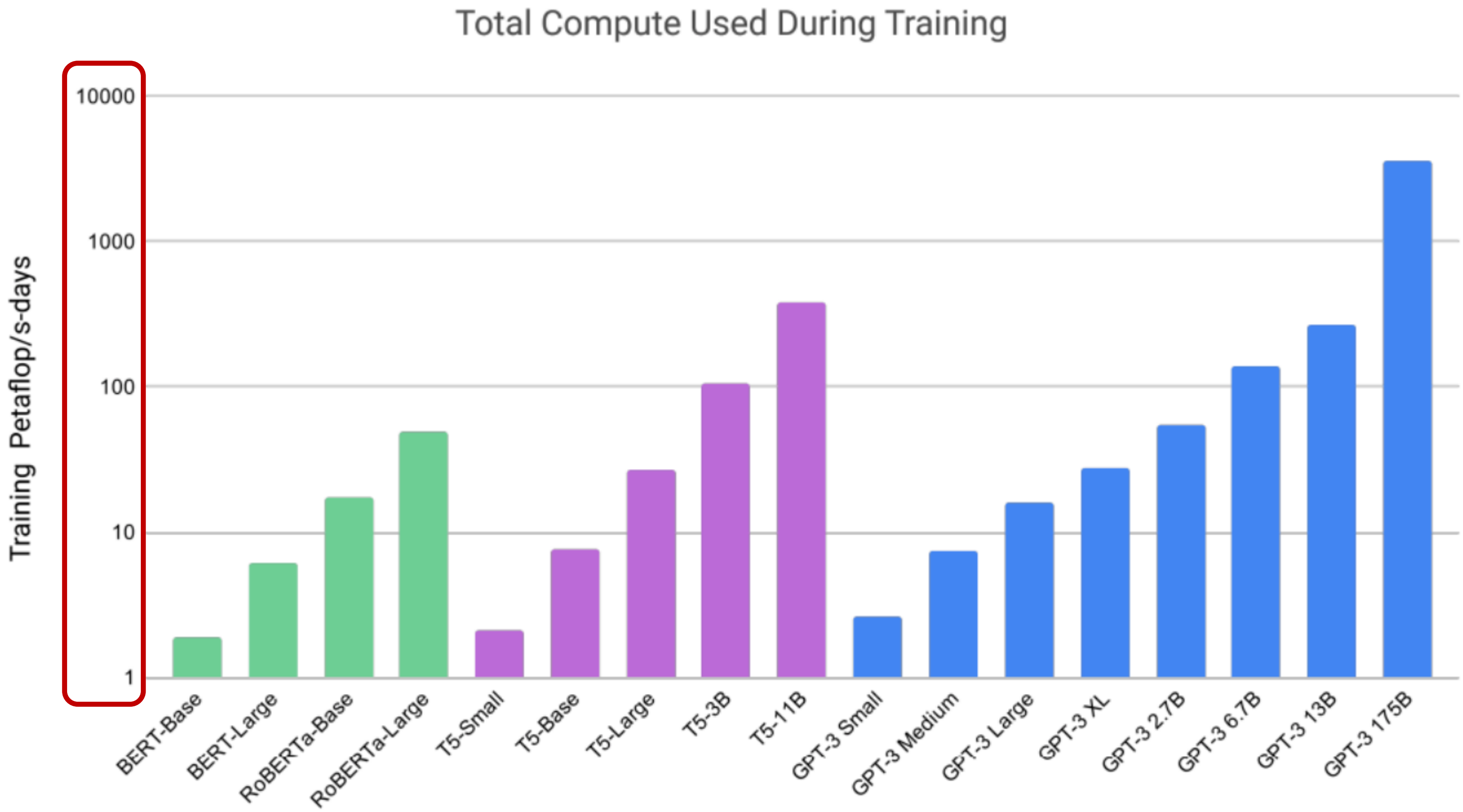
Better Performance from Large Models

- More types of data for pre-training → diverse capability



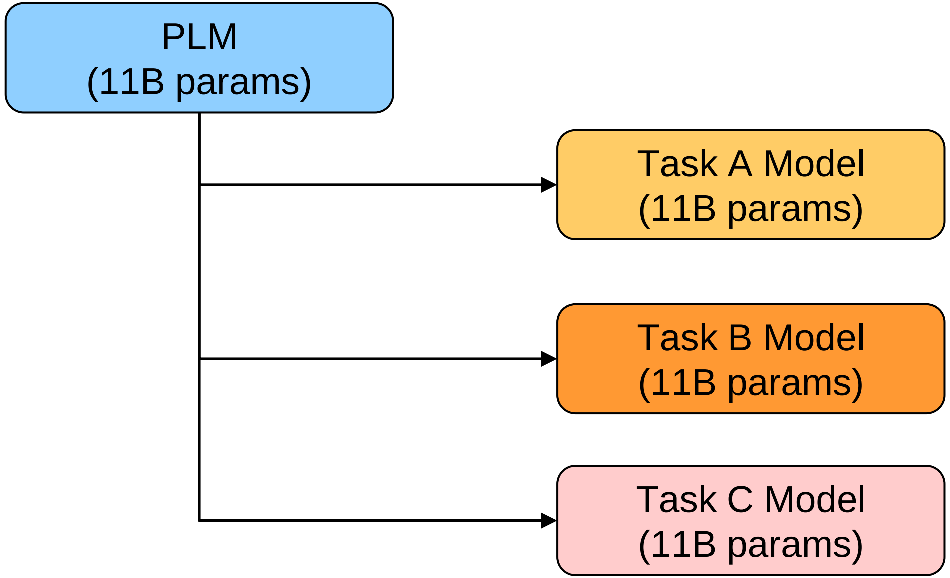
What is the problem of large PLMs?

Computing Cost of Large PLMs



Large Space Requirement

- Each task requires a copy of a large model



Practical Issues of PLMs

1) Data scarcity
2) Large PLMs
   - Higher training cost
   - Larger space requirement

→ **Solution: Prompt-Based Learning**

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Prompt-Based Learning

Leveraging big pre-trained models

GPT-3 “In-Context” Learning

- **Zero-Shot**

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

prompt (提示)

- **One-Shot**

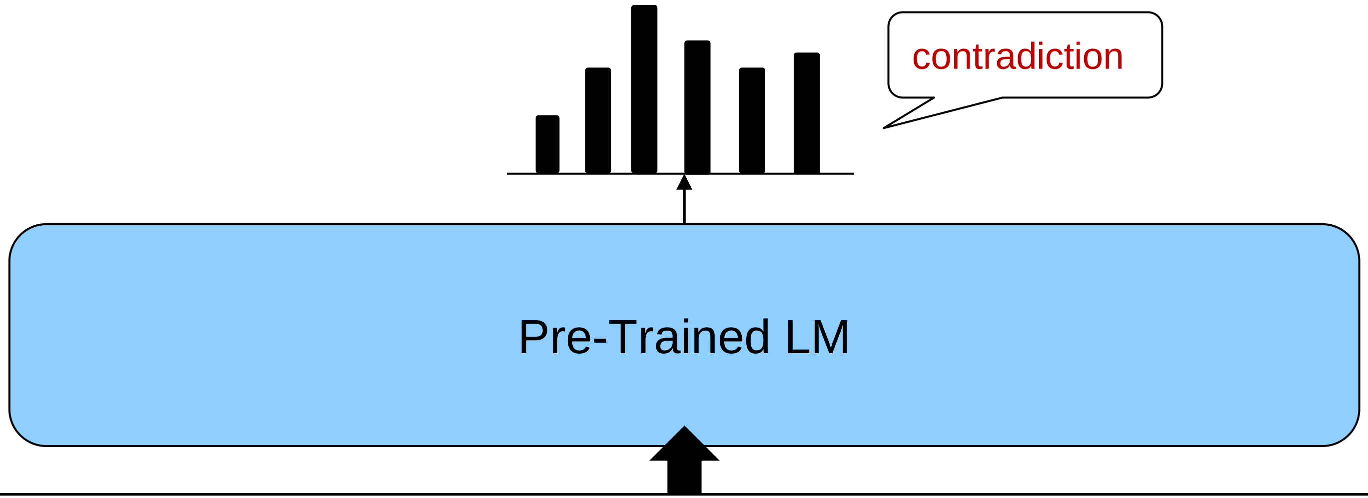
```
Translate English to French:   ← task description
sea otter => loutre de mer     ← example
cheese =>                      ← prompt
```

natural language instruction and/or a few task demonstrations

- **Few-Shot**

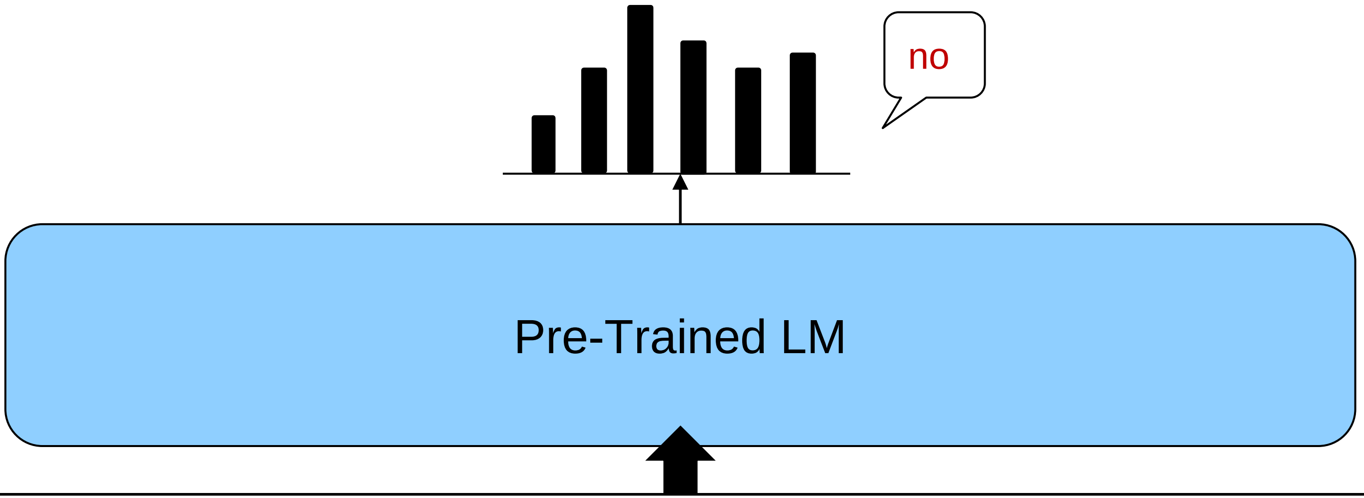
```
Translate English to French:          ← task description
sea otter => loutre de mer            ← examples
peppermint => menthe poivrée
plush girafe => girafe peluche
cheese =>                             ← prompt
```

Prompt-Tuning



[CLS] Vivian likes dancing. [SEP] Vivian loves singing. [SEP] >>> neutral
[CLS] The vacation is coming soon. [SEP] The vacation was over. [SEP] >>> contradiction
[CLS] I am going to have dinner. [SEP] I am going to eat something. [SEP] >>> entailment
……
[CLS] I like strawberries. [SEP] I hate strawberries. [SEP] >>>

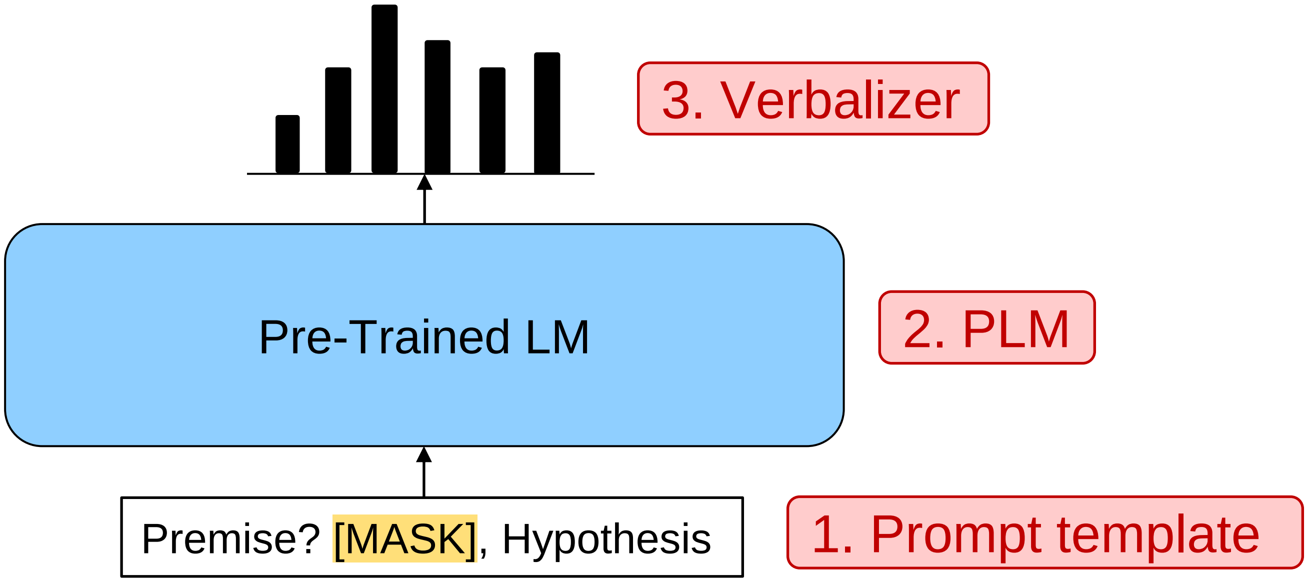
Prompt-Tuning



[CLS] Vivian likes dancing. Is it true that Vivian loves singing? [SEP] >>> maybe
[CLS] The vacation is coming soon. Is it true that the vacation was over? [SEP] >>> no
[CLS] I am going to have dinner. Is it true that I am going to eat something? [SEP] >>> yes
……
[CLS] I like strawberries. Is it true that I hate strawberries? [SEP] >>>

Prompt-Tuning

- Idea: convert data into natural language prompts
  → better for few-shot, one-shot, or zero-shot cases



Prompt-Tuning

1. Prompt template: manually designed natural language input for a task

NLI sample datapoint

Premise	Vivian is Jolin’s fans
Hypothesis	Vivian loves Jolin.
Label	0

0: “entailment”
1: “neutral”
2: “contradiction”

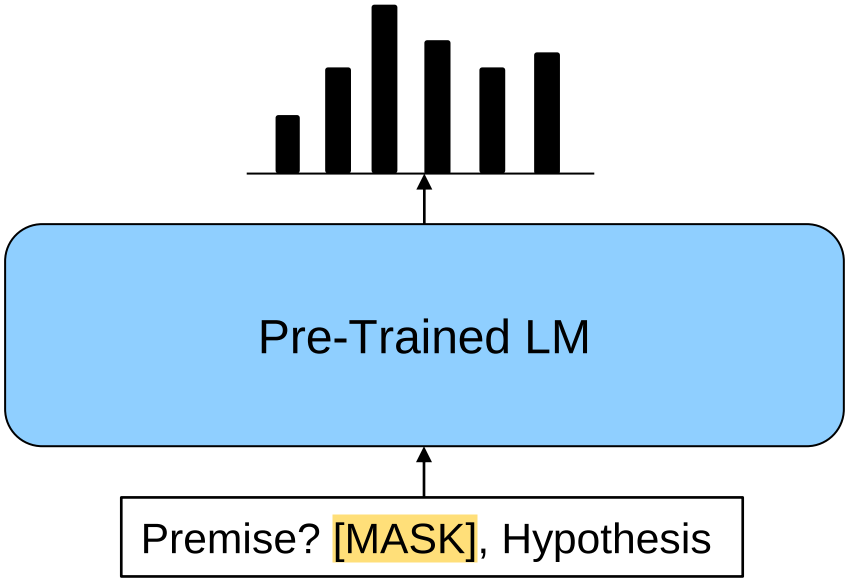
[CLS] Vivian is Jolin’s fans? [MASK], Vivian loves Jolin.

Premise? [MASK], Hypothesis

prompt template

Prompt-Tuning

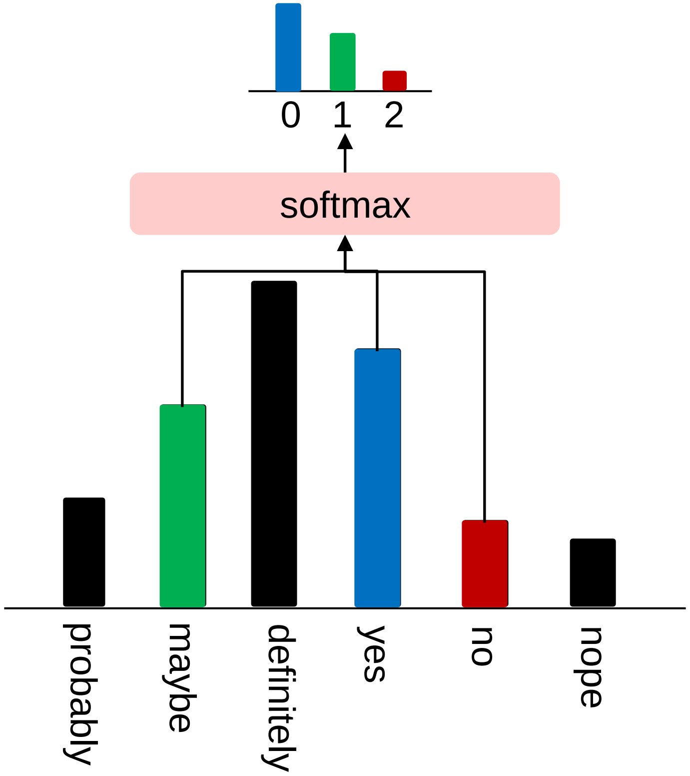
2. PLM: perform language modeling (masked LM or auto-regressive LM)



Prompt-Tuning

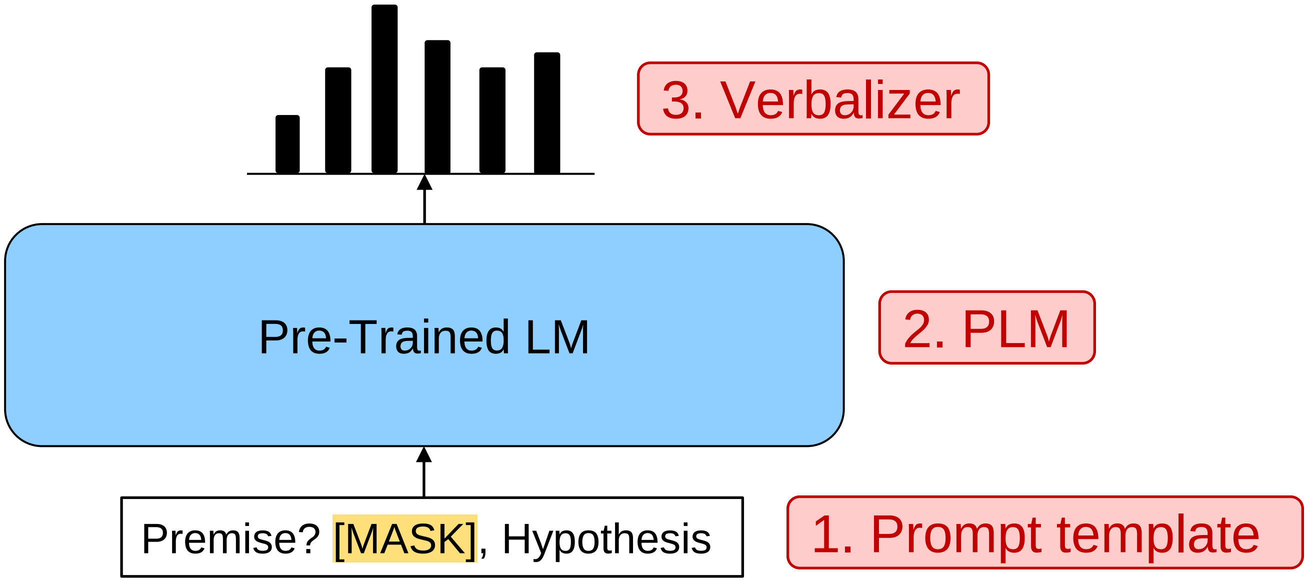
3. Verbalizer: mapping from the vocabulary to labels

0: “entailment” → yes
1: “neutral” → maybe
2: “contradiction” → no



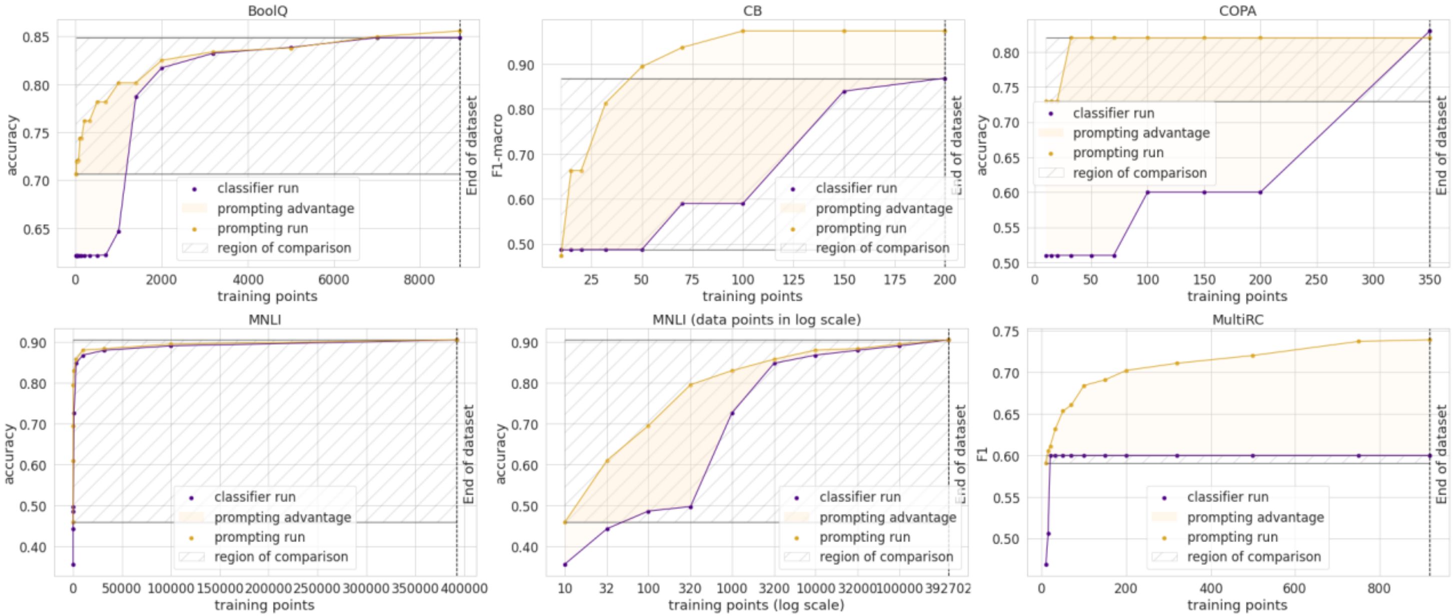
Prompt-Tuning

- Fine-tuning PLMs based on few annotated data samples
  - No parameter tuning when zero-shot settings



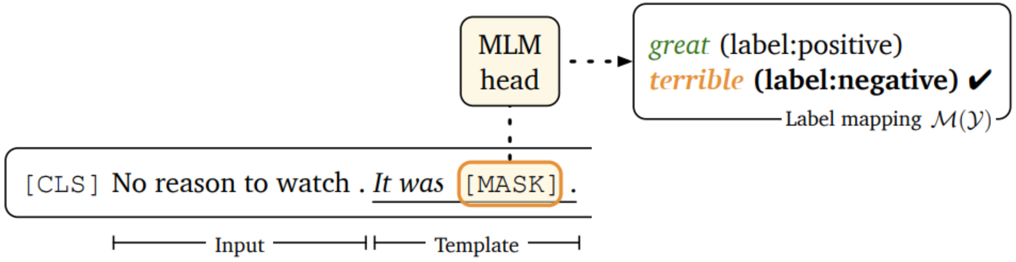
Prompt-Tuning

- Prompt-tuning is better under data scarcity (Le and Rush, 2021) due to
  - It better leverages pre-trained knowledge
  - Pre-trained knowledge can be kept

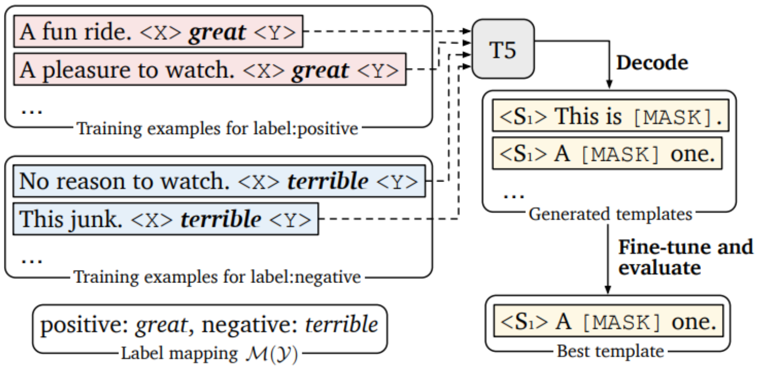


LM-BFF: Better Few-shot Fine-tuning of Language Models (Gao et al., 2021)

- Idea: prompt + demonstration for few-shot learning



- template generation



LM-BFF: Better Few-shot Fine-tuning of Language Models (Gao et al., 2021)

- Performance with RoBERTa-Large

	SST-2 (acc)	**SST-5** (acc)	**MR** (acc)	**CR** (acc)	**MPQA** (acc)	**Subj** (acc)	**TREC** (acc)	**CoLA** (Matt.)
Majority†	*50.9*	*23.1*	*50.0*	*50.0*	*50.0*	*50.0*	*18.8*	*0.0*
Prompt-based zero-shot‡	83.6	35.0	80.8	79.5	67.6	51.4	32.0	2.0
"GPT-3" in-context learning	84.8 (1.3)	30.6 (0.9)	80.5 (1.7)	87.4 (0.8)	63.8 (2.1)	53.6 (1.0)	26.2 (2.4)	-1.5 (2.4)
Fine-tuning	81.4 (3.8)	43.9 (2.0)	76.9 (5.9)	75.8 (3.2)	72.0 (3.8)	90.8 (1.8)	88.8 (2.1)	**33.9** (14.3)
Prompt-based FT (man)	92.7 (0.9)	47.4 (2.5)	87.0 (1.2)	90.3 (1.0)	84.7 (2.2)	91.2 (1.1)	84.8 (5.1)	9.3 (7.3)
+ demonstrations	92.6 (0.5)	**50.6** (1.4)	86.6 (2.2)	90.2 (1.2)	**87.0** (1.1)	**92.3** (0.8)	87.5 (3.2)	18.7 (8.8)
Prompt-based FT (auto)	92.3 (1.0)	49.2 (1.6)	85.5 (2.8)	89.0 (1.4)	85.8 (1.9)	91.2 (1.1)	88.2 (2.0)	14.0 (14.1)
+ demonstrations	**93.0** (0.6)	49.5 (1.7)	**87.7** (1.4)	**91.0** (0.9)	86.5 (2.6)	91.4 (1.8)	**89.4** (1.7)	21.8 (15.9)
Fine-tuning (full)†	*95.0*	*58.7*	*90.8*	*89.4*	*87.8*	*97.0*	*97.4*	*62.6*

	MNLI (acc)	**MNLI-mm** (acc)	**SNLI** (acc)	**QNLI** (acc)	**RTE** (acc)	**MRPC** (F1)	**QQP** (F1)	**STS-B** (Pear.)
Majority†	*32.7*	*33.0*	*33.8*	*49.5*	*52.7*	*81.2*	*0.0*	-
Prompt-based zero-shot‡	50.8	51.7	49.5	50.8	51.3	61.9	49.7	-3.2
"GPT-3" in-context learning	52.0 (0.7)	53.4 (0.6)	47.1 (0.6)	53.8 (0.4)	60.4 (1.4)	45.7 (6.0)	36.1 (5.2)	14.3 (2.8)
Fine-tuning	45.8 (6.4)	47.8 (6.8)	48.4 (4.8)	60.2 (6.5)	54.4 (3.9)	76.6 (2.5)	60.7 (4.3)	53.5 (8.5)
Prompt-based FT (man)	68.3 (2.3)	70.5 (1.9)	77.2 (3.7)	64.5 (4.2)	69.1 (3.6)	74.5 (5.3)	65.5 (5.3)	71.0 (7.0)
+ demonstrations	**70.7** (1.3)	**72.0** (1.2)	**79.7** (1.5)	**69.2** (1.9)	68.7 (2.3)	77.8 (2.0)	**69.8** (1.8)	73.5 (5.1)
Prompt-based FT (auto)	68.3 (2.5)	70.1 (2.6)	77.1 (2.1)	68.3 (7.4)	**73.9** (2.2)	76.2 (2.3)	67.0 (3.0)	75.0 (3.3)
+ demonstrations	70.0 (3.6)	**72.0** (3.1)	77.5 (3.5)	68.5 (5.4)	71.1 (5.3)	**78.1** (3.4)	67.7 (5.8)	**76.4** (6.2)
Fine-tuning (full)†	*89.8*	*89.5*	*92.6*	*93.3*	*80.9*	*91.4*	*81.7*	*91.9*

Issues of Discrete/Hard Prompts

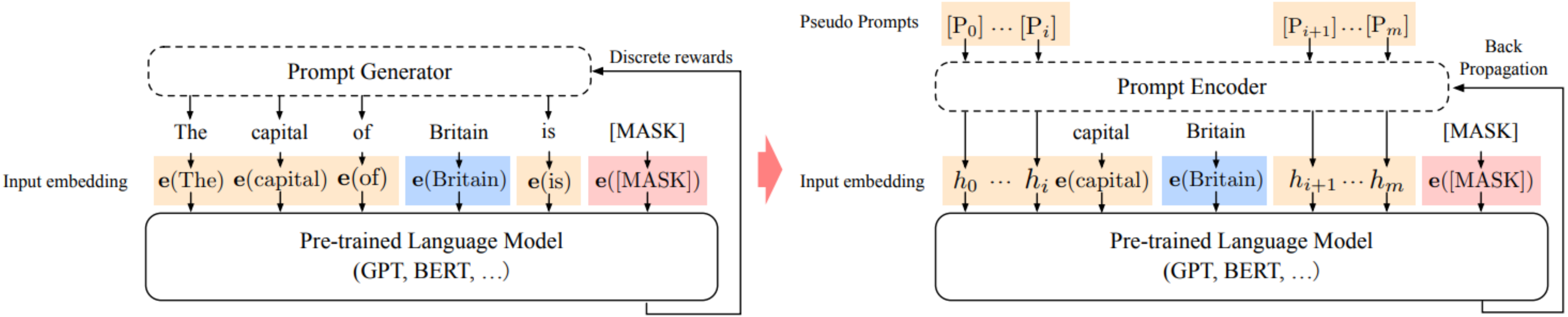
- Difficulty of manually designing prompts
  - Prompts that humans consider reasonable is not necessarily effective for LMs (Liu et al., 2021)
  - Pre-trained LMs are sensitive to the choice of prompts (Zhao et al., 2021)

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

P-Tuning (Liu et al., 2021)

- Idea: direct optimize the embeddings instead of prompt tokens

prompt search for "The capital of Britain is [MASK]".

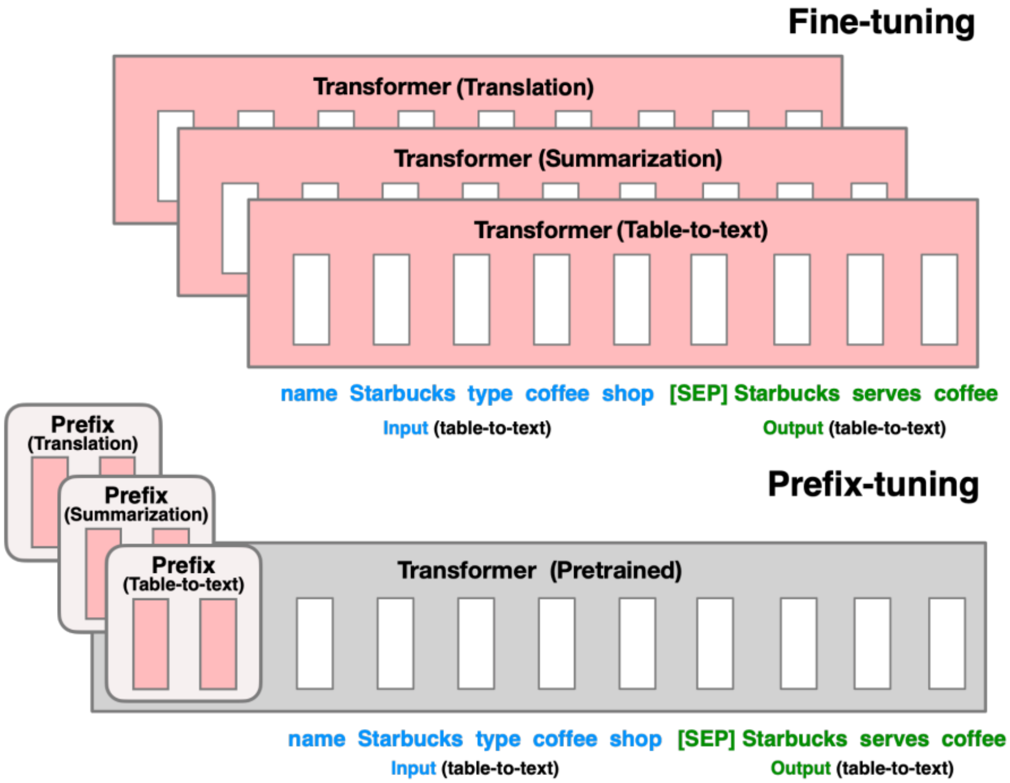


(a) Discrete Prompt Search (b) P-tuning

Prompt	$\mathcal{D}_{dev}$ Acc.	$\mathcal{D}_{dev32}$ Acc.
Does [PRE] agree with [HYP]? [MASK].	57.16	53.12
Does [HYP] agree with [PRE]? [MASK].	51.38	50.00
Premise: [PRE] Hypothesis: [HYP] Answer: [MASK].	68.59	55.20
[PRE] question: [HYP]. true or false? answer: [MASK].	70.15	53.12
P-tuning	76.45	56.25

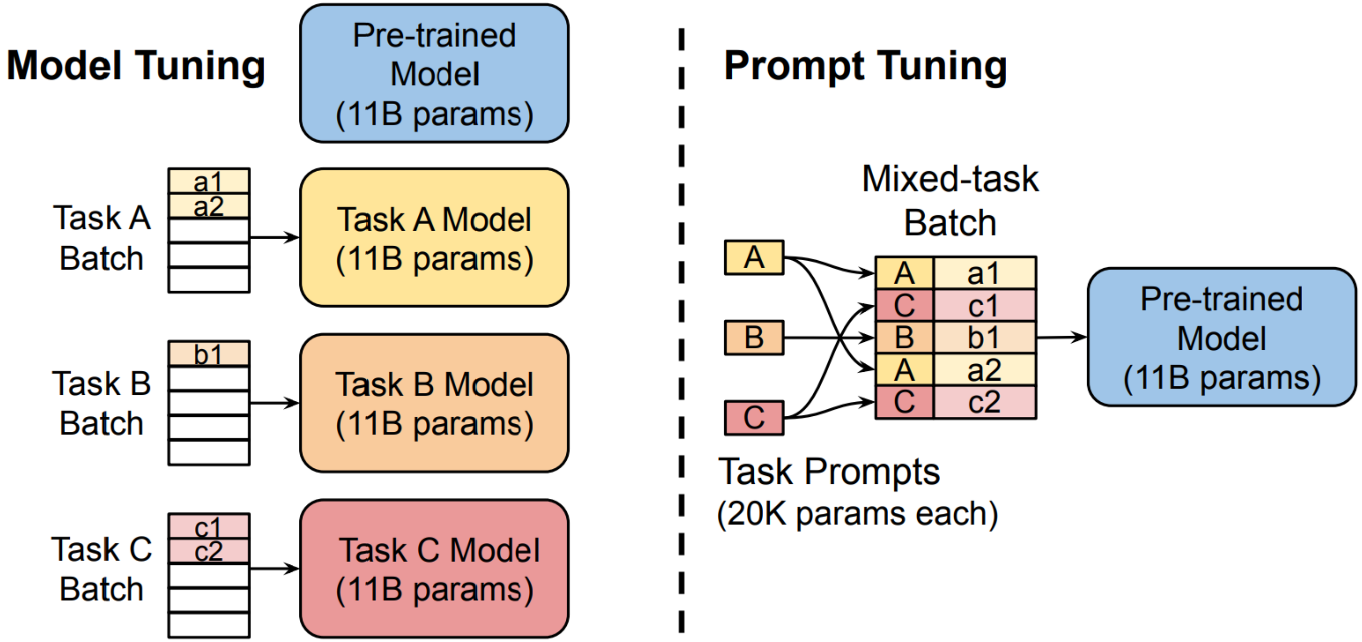
Prefix-Tuning (Li and Liang, 2021)

- Idea: only optimize the <u>prefix embeddings (all layers)</u> for efficiency



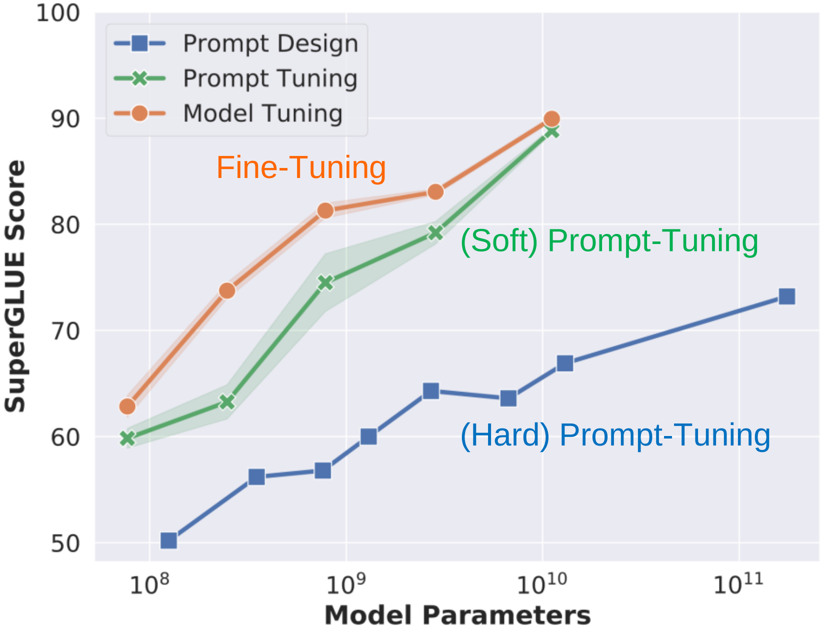
(Soft) Prompt-Tuning (Lester et al., 2021)

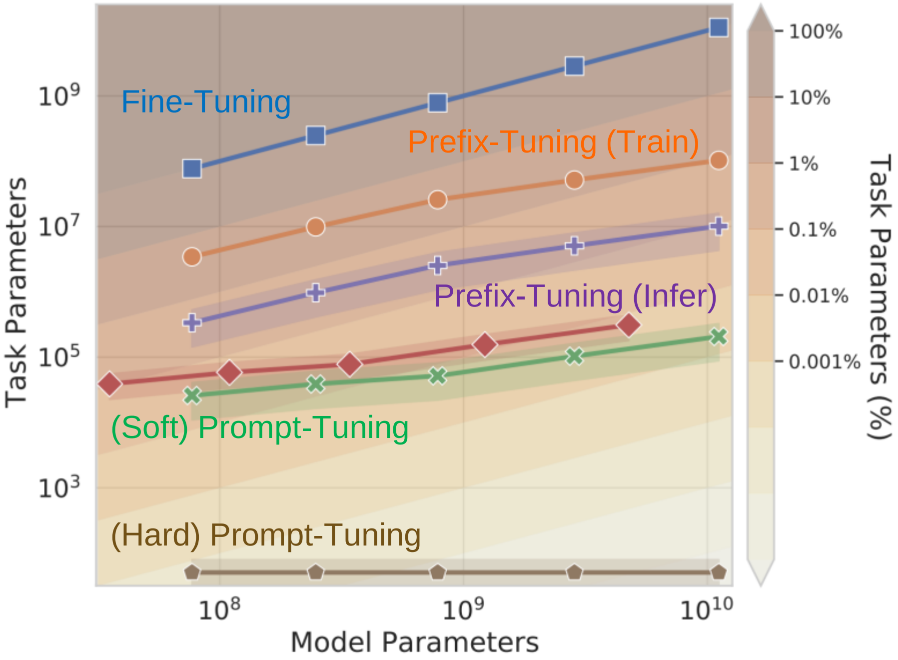
- Idea: only require storing a small task-specific prompt (one layer) for each task and enables mixed-task inference using the original PLMs



(Soft) Prompt-Tuning (Lester et al., 2021)

- Competitive performance and better space efficiency





Instruction Tuning (Wei et al., 2022)

- Idea: improve model's capability of understanding the task description

LM for sentence completion

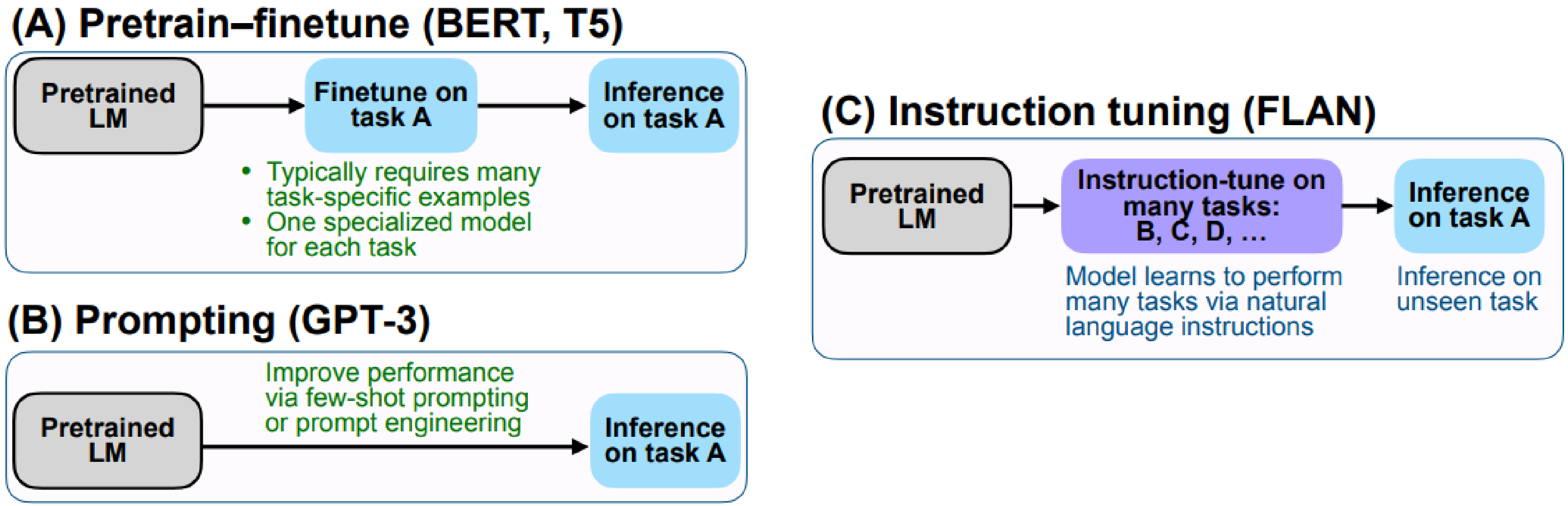
I went to Jolin's concert last night. I really loved her songs and dancing. It was ________

Detailed task instruction for LM generation

Decide the sentiment of the following sentences:
I went to Jolin's concert last night. I really loved her songs and dancing.
OPTIONS: - positive – negative - neutral

FLAN: Finetuned LANguage Models (Wei et al., 2022)

- Idea: fine-tune LM to better understand task descriptions via <u>other</u> tasks



Prompt v.s. Instruction Tuning (Wei et al., 2022)

- Prompt
- Instruction tuning

Training

Input (Commonsense Reasoning)

Here is a goal: Get a cool sleep on summer days.
How would you accomplish this goal?
OPTIONS:
-Keep stack of pillow cases in fridge.
-Keep stack of pillow cases in oven.

Target

keep stack of pillow cases in fridge

LM Fine-tuning

Inference

Prompt:

Input (Translation)

Translate this sentence to Spanish: The new office building was built in less than three months.

Target

El nuevo edificio de oficinas se construyó en tres meses.

Instruction tuning:

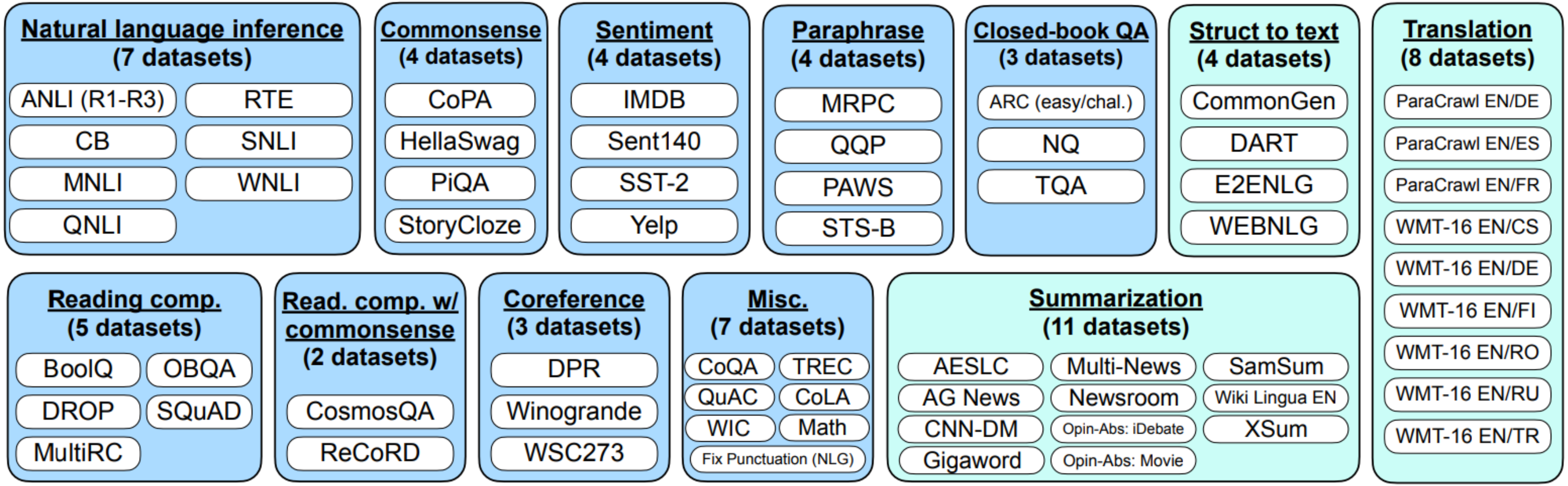
Input (Translation)

Translate this sentence to Spanish: The new office building was built in less than three months.

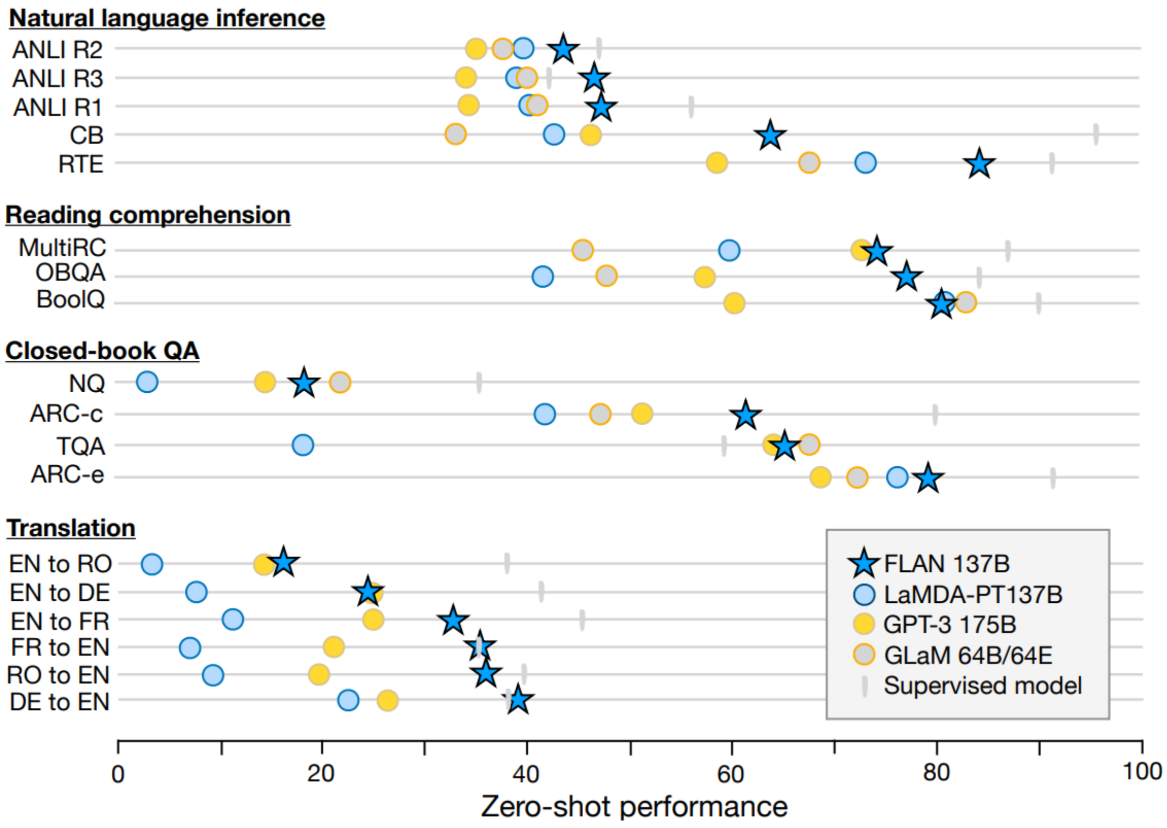
Target

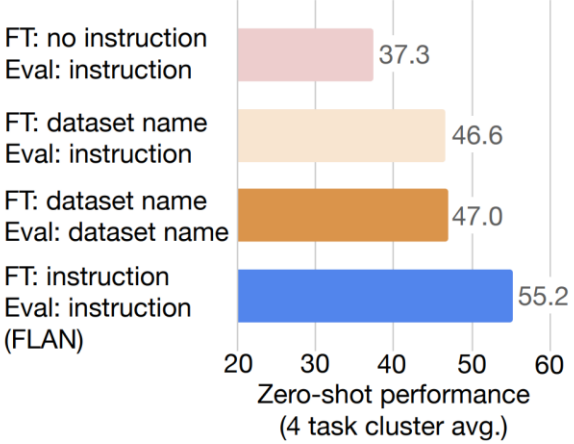
El nuevo edificio de oficinas se construyó en tres meses.

Task Clusters (Wei et al., 2022)



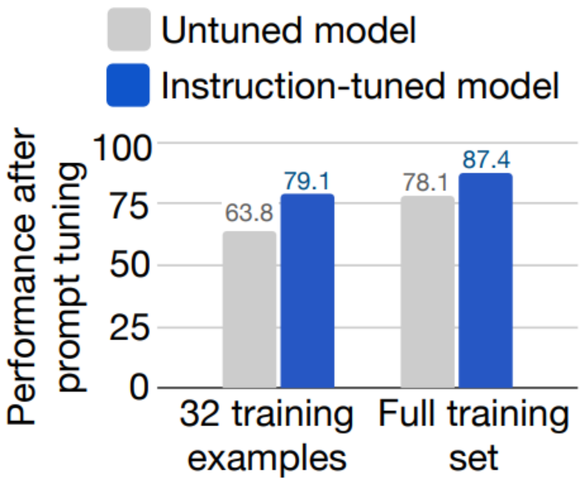
Zero-Shot Performance of FLAN

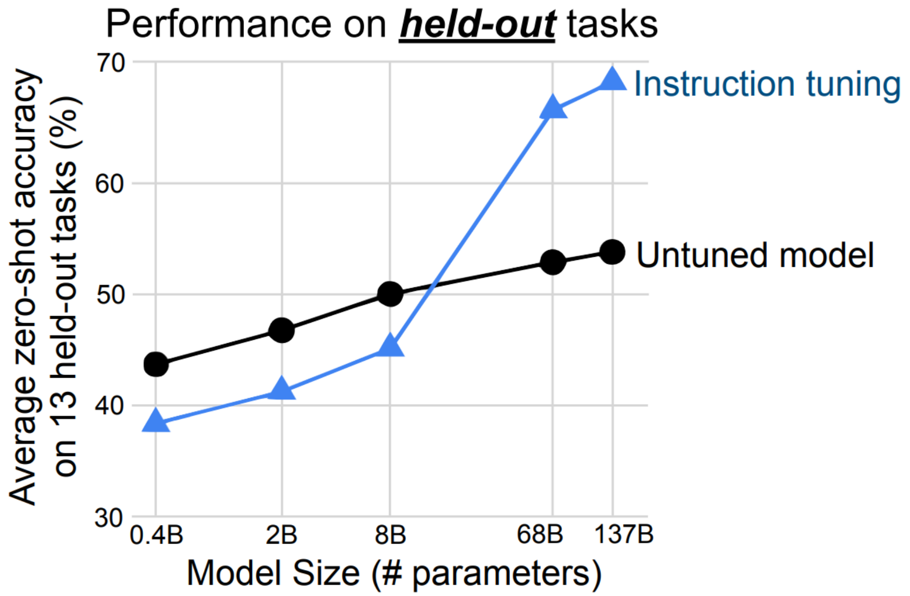




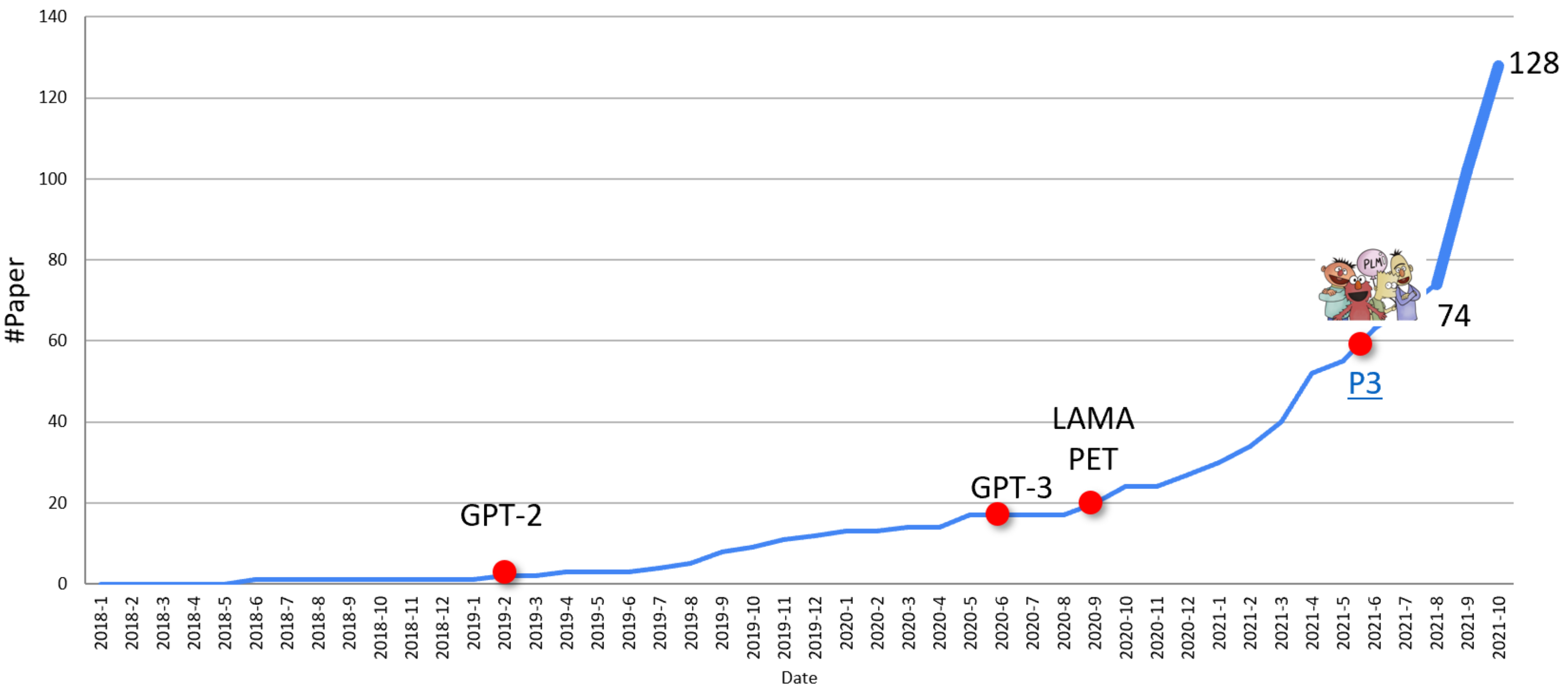
Zero-Shot Performance of FLAN

- Combine with prompt-tuning
- Model size requirement



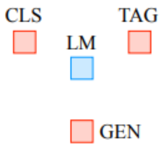
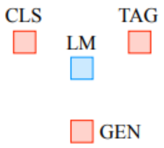
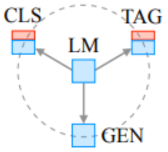
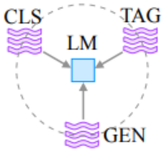


Trend of Prompt-Based Research



http://pretrain.nlpedia.ai/

Prompting Paradigm (Liu et al., 2021)

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	

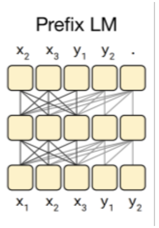
: unsupervised

: supervised

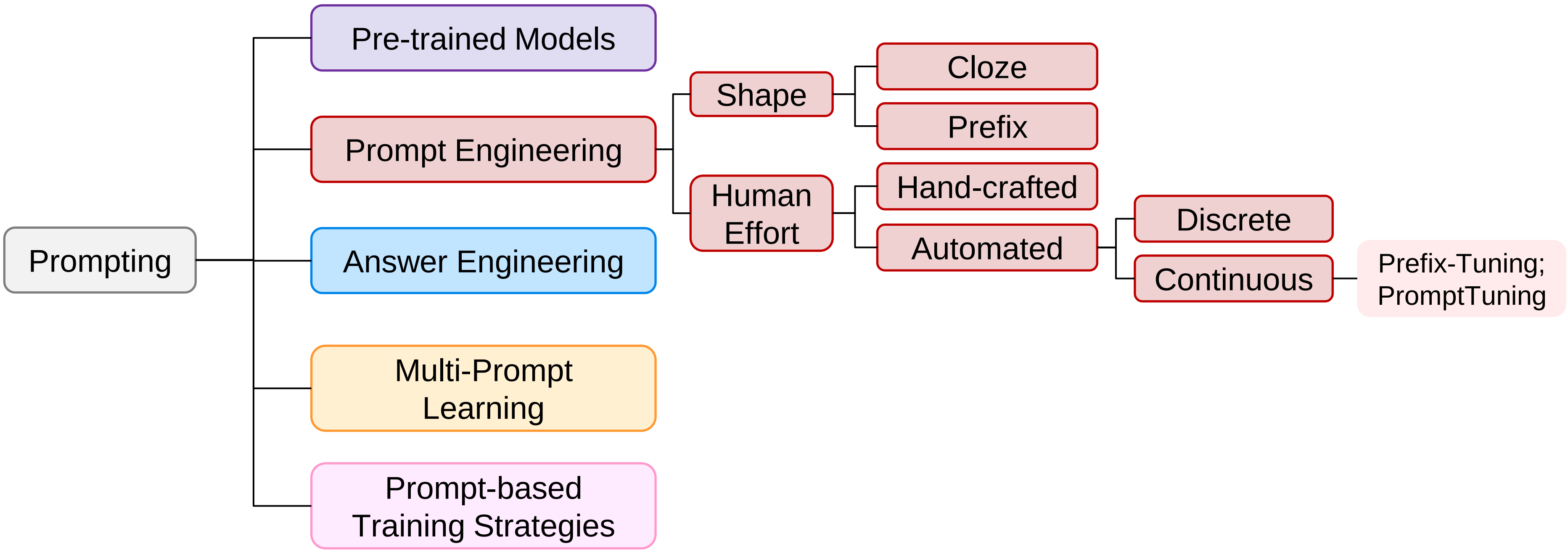
: textual prompt

Prompting Typology (Liu et al., 2021)

- Prompting
  - Pre-trained Models
    - Left-to-Right LM — GPT; GPT-2; GPT-3
    - Masked LM — BERT; RoBERTa
    - Prefix LM — UniLM
    - Encoder-Decoder — T5; BART
  - Prompt Engineering
  - Answer Engineering
  - Multi-Prompt Learning
  - Prompt-based Training Strategies



Prompting Typology (Liu et al., 2021)



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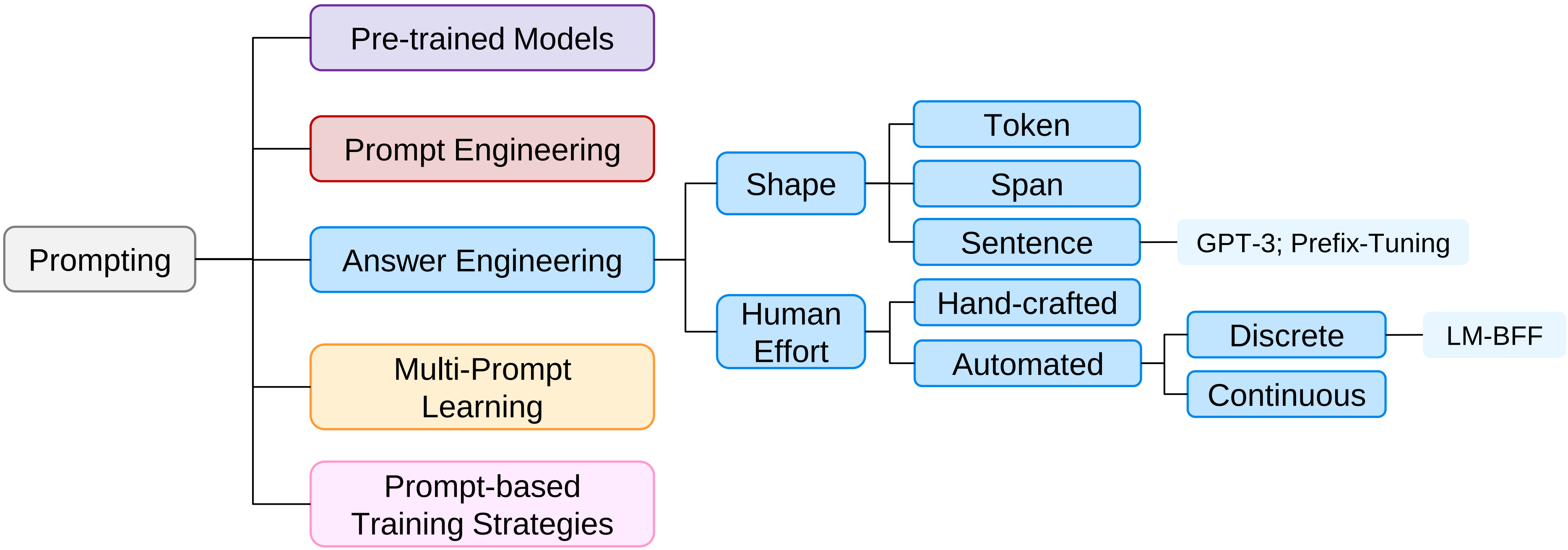

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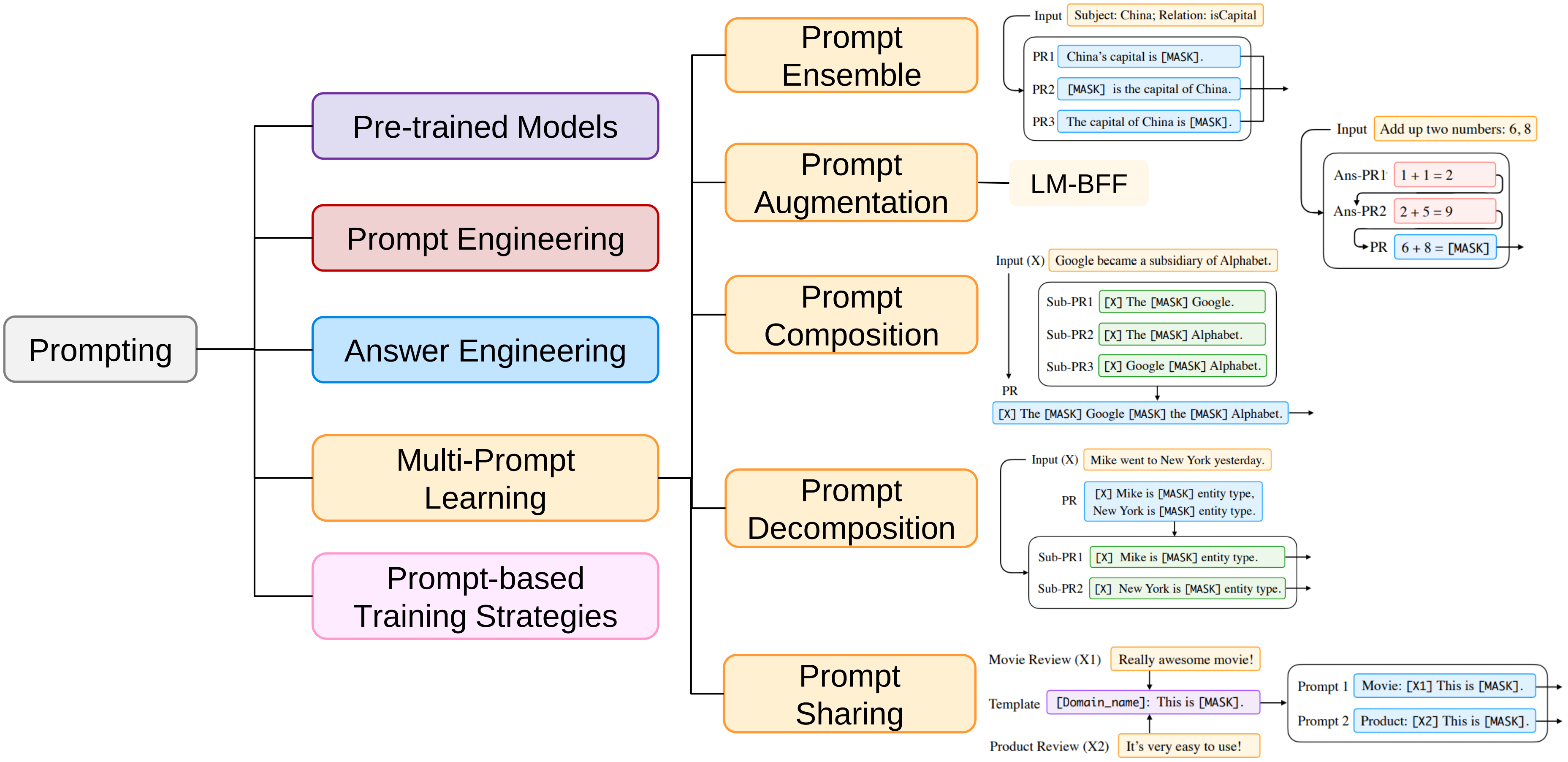

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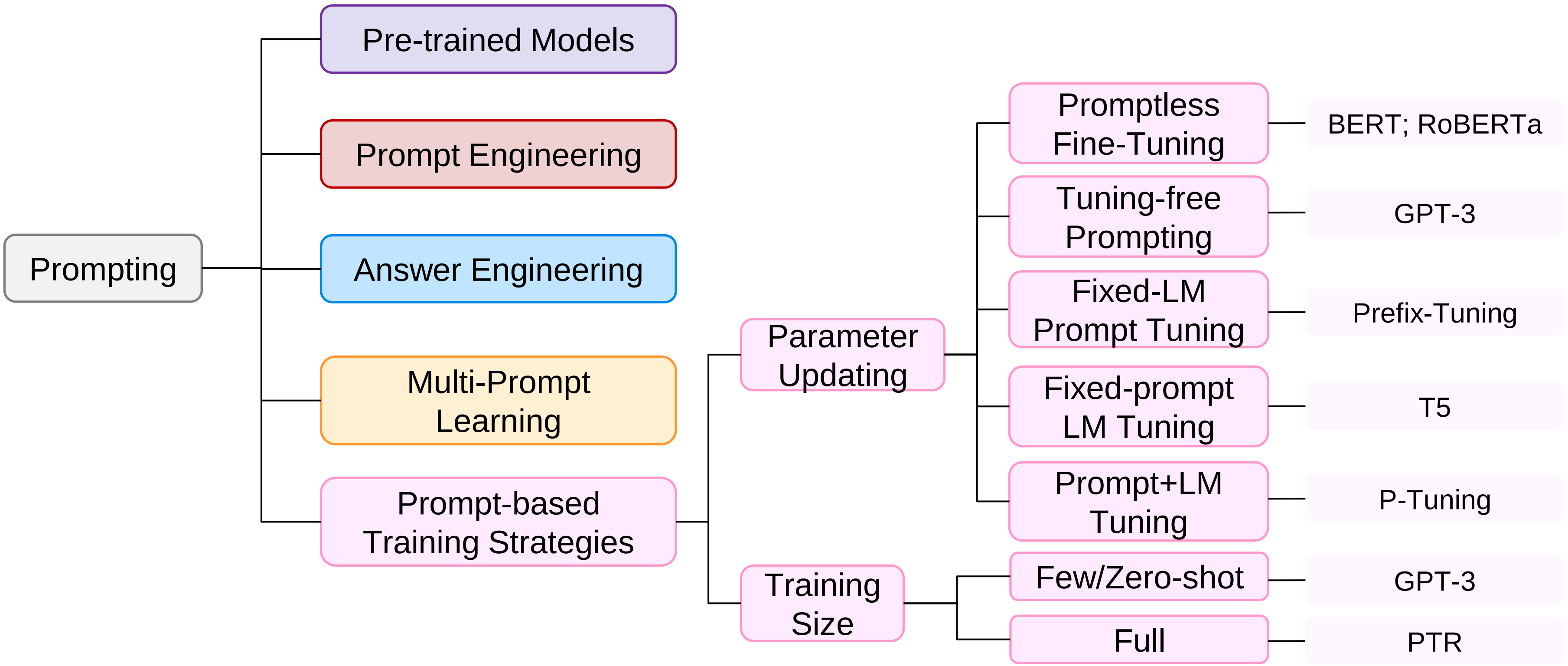
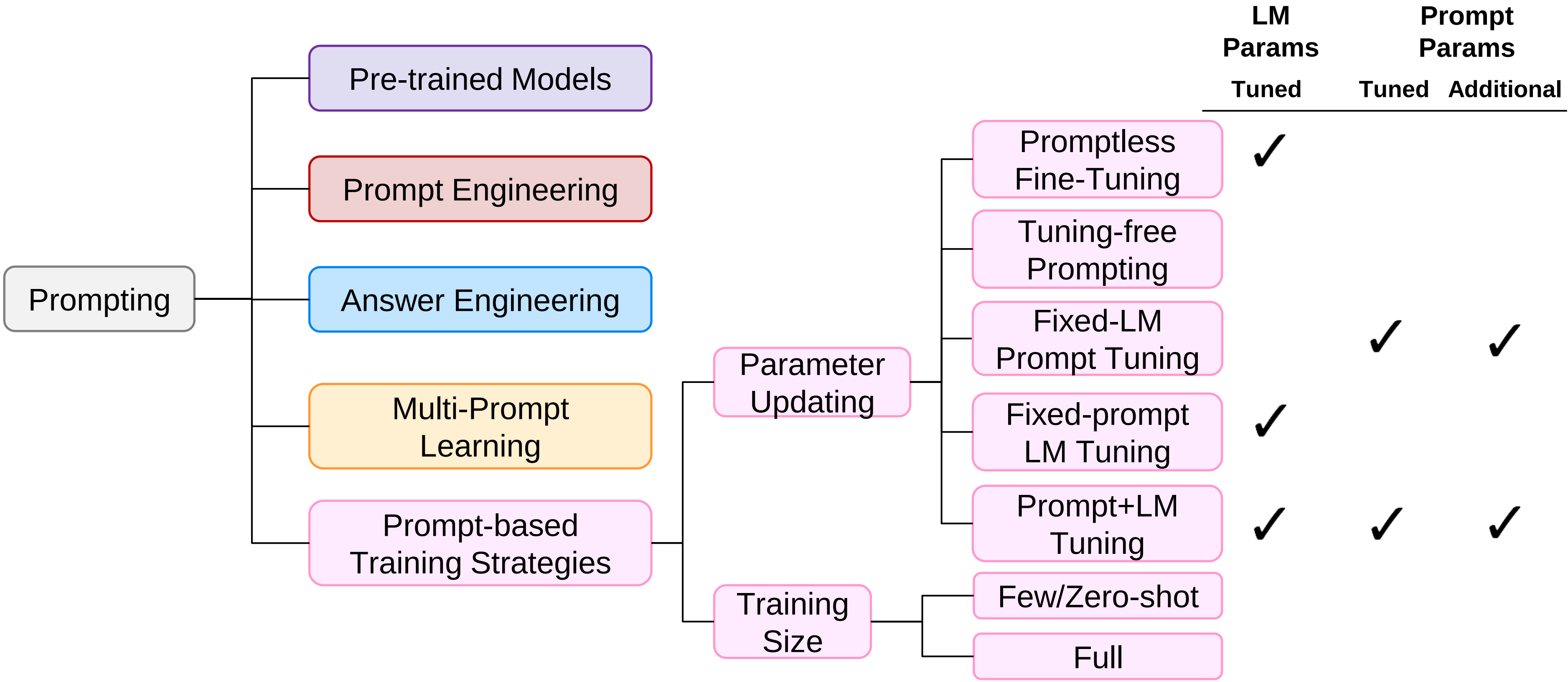


Prompting Typology (Liu et al., 2021)



Concluding Remarks

- **Prompt-Tuning**: manually designed natural language prompts
  - Human-understandable prompts
  - Sensitive to choices of prompts
  - Also work for one-shot/zero-shot settings
- **LM-BFF**: prompt-tuning + demonstration + template generation
  - Better performance
- **P-Tuning**: tuning the input (prompt) embeddings
  - Better performance via soft prompts
- **Prefix-Tuning**: only optimize the prefix embeddings (all layers)
  - Better training time/space efficiency
- **(Soft) Prompt-Tuning**: store task prompt and mixed-task learning
  - Updating less parameters
  - Better robustness
- **Instruction Tuning**: tuning LMs for understanding task instructions
  - Better zero-shot performance