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DeepLearning.AI

aws

Generative AI and large-language models (LLMs)

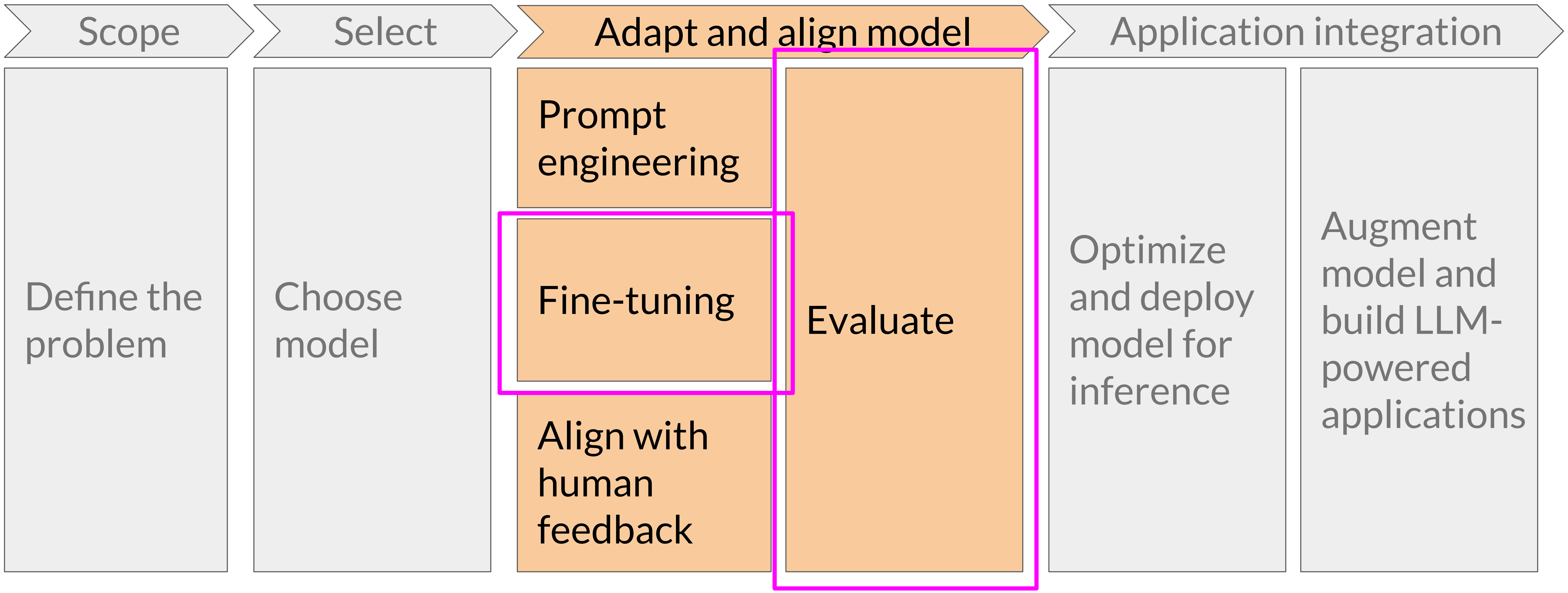
FINE-TUNING, INSTRUCTION PROMPTS, AND PARAMETER EFFICIENT FINE-TUNING

Fine-tuning with instruction prompts

GenAI project lifecycle

Scope	Select	Adapt and align model		Application integration	
Define the problem	Choose model	Prompt engineering Fine-tuning Align with human feedback	Evaluate	Optimize and deploy model for inference	Augment model and build LLM-powered applications

GenAI project lifecycle



Fine-tuning an LLM with instruction prompts

In-context learning (ICL) - zero shot inference

Prompt

```
Classify this review:
I loved this DVD!
Sentiment:
```

Model

LLM

Completion

```
Classify this review:
I loved this DVD!
Sentiment: Positive
```

In-context learning (ICL) - zero shot inference

Prompt

```
Classify this review:
I loved this DVD!
Sentiment:
```

Model

LLM

Completion

```
Classify this review:
I loved this DVD!
Sentiment: eived a
very nice book review
```

In-context learning (ICL) - one/few shot inference

Prompt

```
Classify this review:
I loved this DVD!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment:
```

Model

LLM

Completion

```
Classify this review:
I loved this DVD!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment: Negative
```

One-shot or Few-shot Inference

Limitations of in-context learning

```
Classify this review:
I loved this movie!
Sentiment: Positive

Classify this review:
I don't like this chair.
Sentiment: Negative

Classify this review:
This sofa is so ugly.
Sentiment: Negative

Classify this review:
Who would use this product?
Sentiment:
```

Context Window

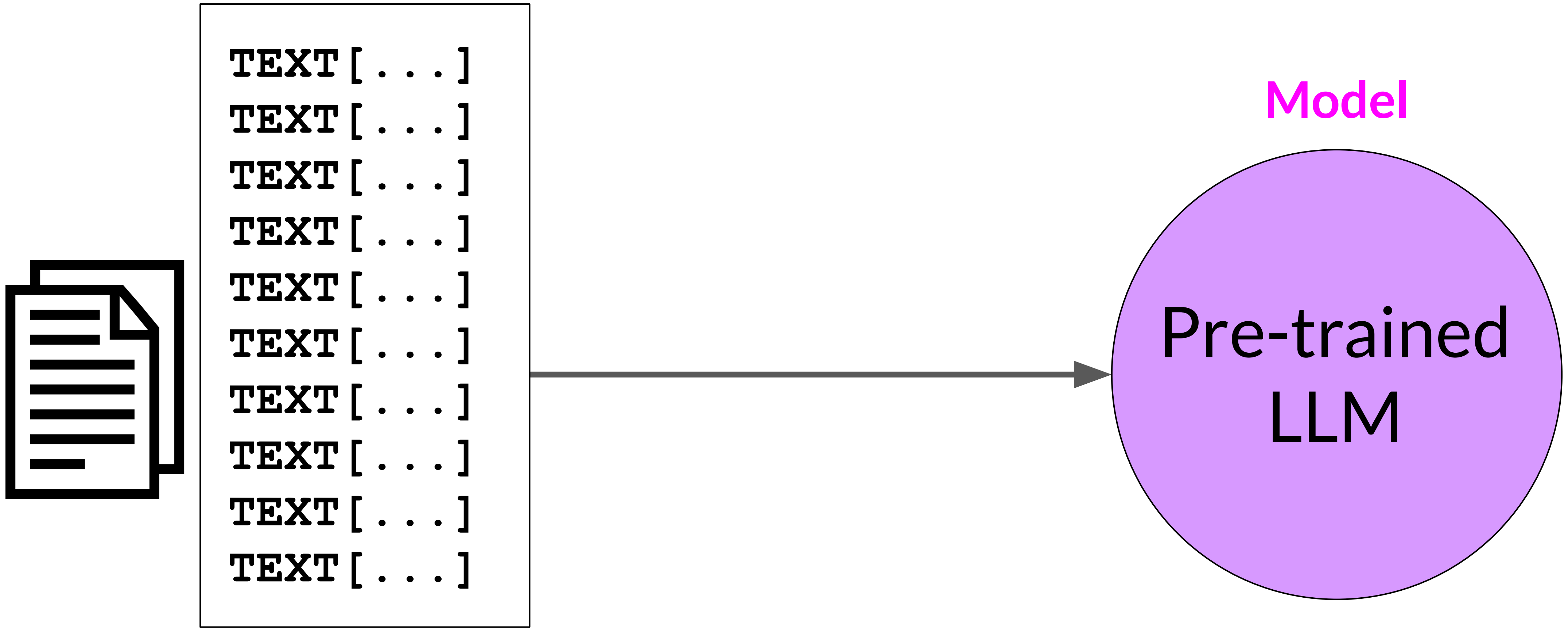
Even with multiple examples

- In-context learning may not work for smaller models LLM
- Examples take up space in the context window

Instead, try **fine-tuning** the model

LLM fine-tuning at a high level

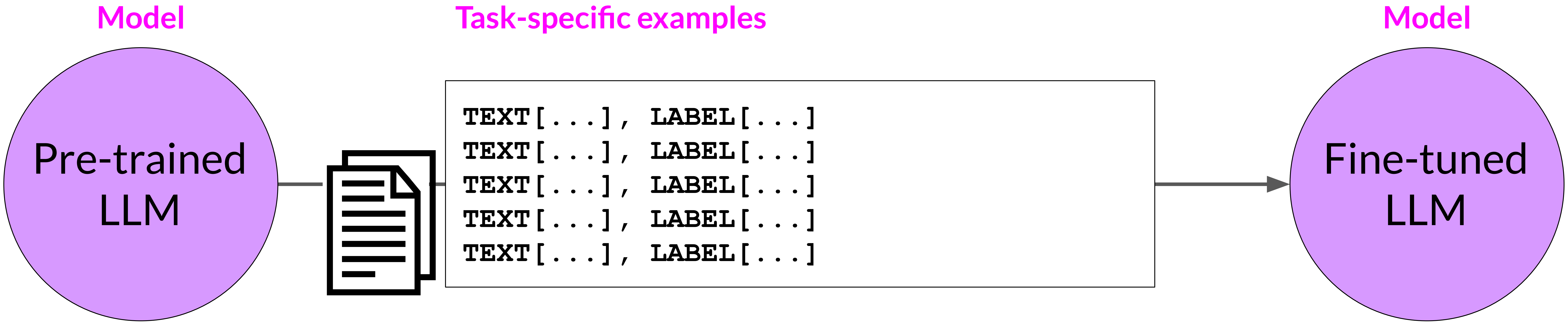
LLM pre-training



GB - TB - PB
of unstructured textual data

LLM fine-tuning at a high level

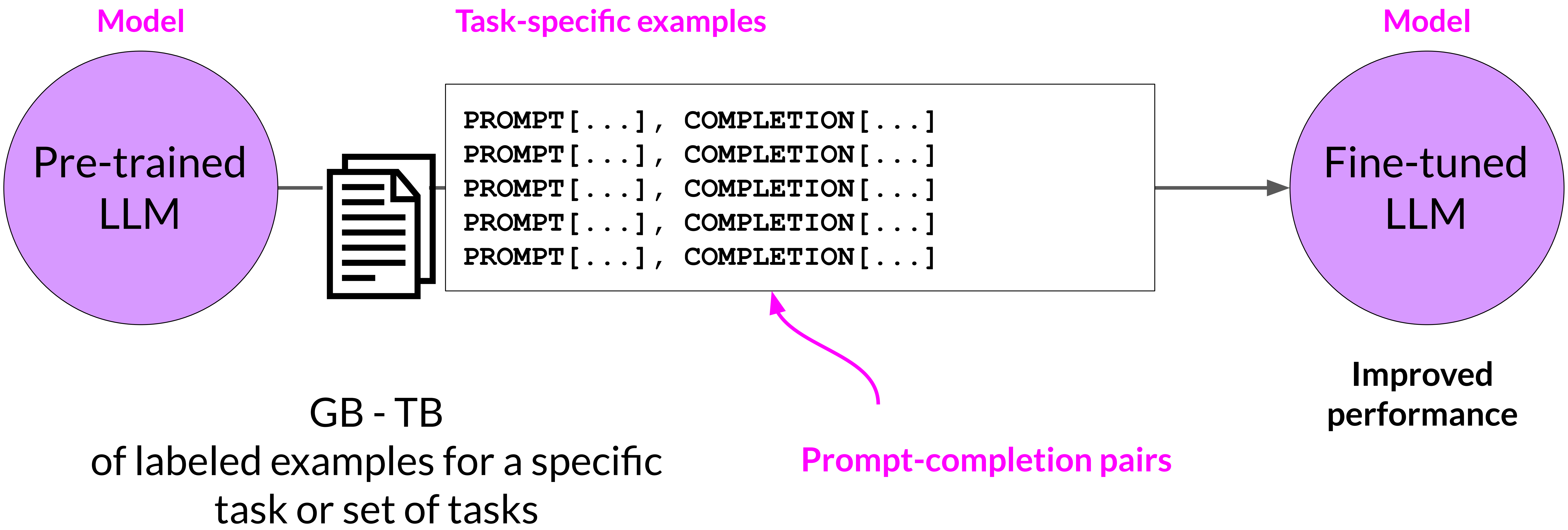
LLM fine-tuning



GB - TB
of labeled examples for a specific
task or set of tasks

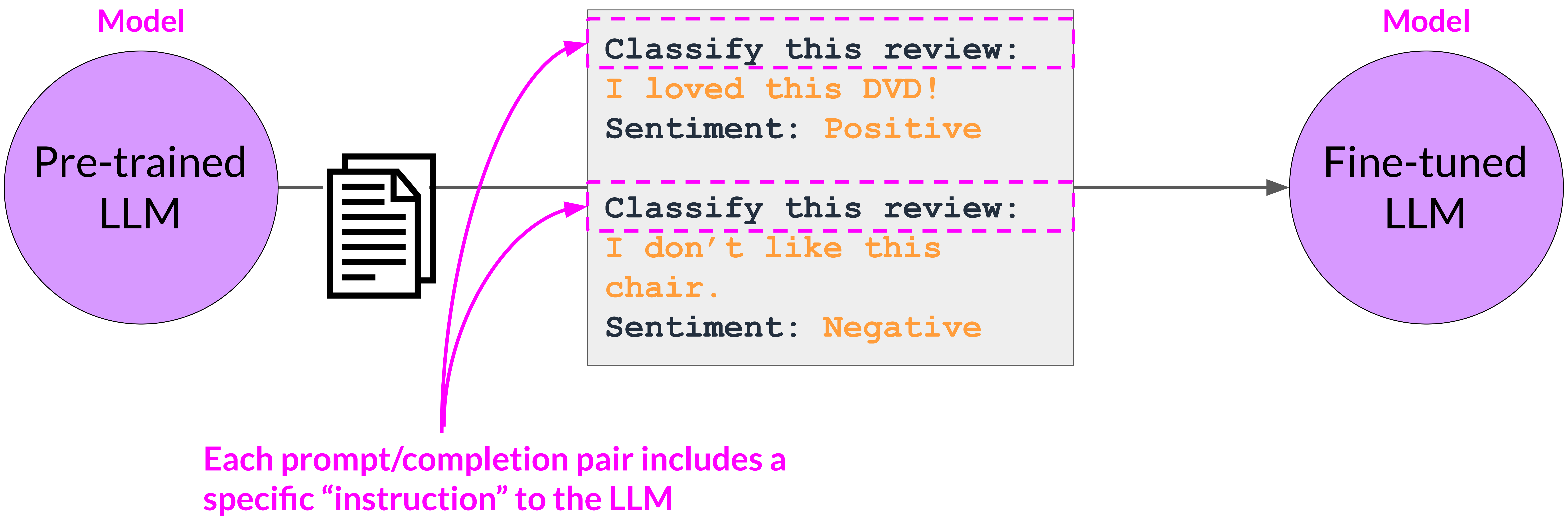
LLM fine-tuning at a high level

LLM fine-tuning



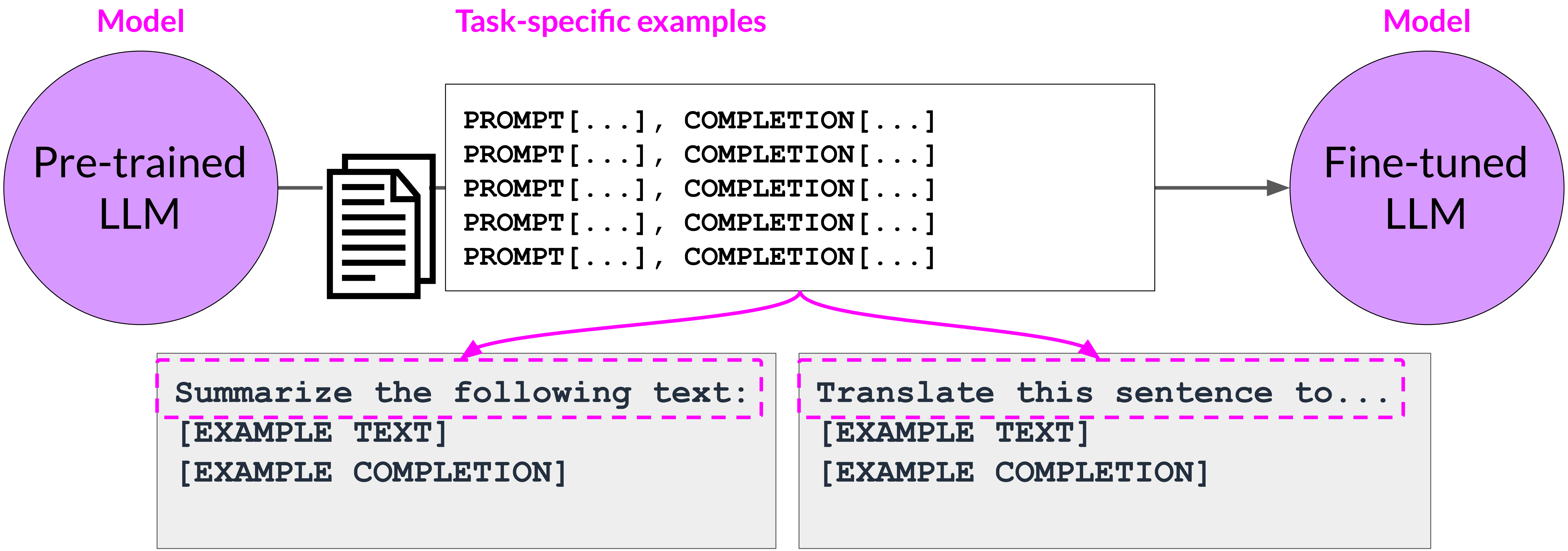
Using prompts to fine-tune LLMs with instruction

LLM fine-tuning



Using prompts to fine-tune LLMs with instruction

LLM fine-tuning



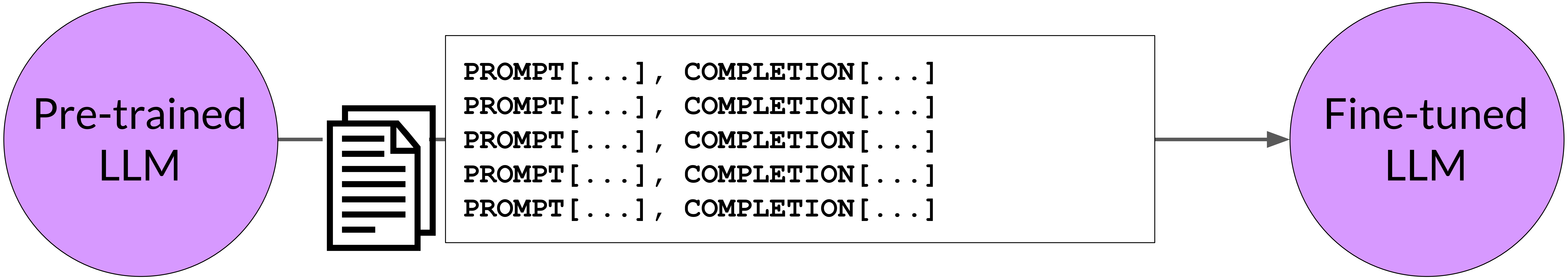
Using prompts to fine-tune LLMs with instruction

LLM fine-tuning

Model

Task-specific examples

Model



Full fine-tuning updates all parameters

Improved performance

Sample prompt instruction templates

Classification / sentiment analysis

```
jinja: "Given the following review:\n{{review_body}}\npredict the associated rating\
  \ from the following choices (1 being lowest and 5 being highest)\n- {{ answer_choices\
  \ | join('\\n- ') }} \n|||\n{{answer_choices[star_rating-1]}}"
```

Text generation

```
jinja: Generate a {{star_rating}}-star review (1 being lowest and 5 being highest)
  about this product {{product_title}}.          |||          {{review_body}}
```

Text summarization

```
jinja: "Give a short sentence describing the following product review:\n{{review_body}}\
  \ \n|||\n{{review_headline}}"
```

Source: https://github.com/bigscience-workshop/promptsource/blob/main/promptsource/templates/amazon_polarity/templates.yaml

LLM fine-tuning process

LLM fine-tuning

Prepared instruction dataset

Training splits

```
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
```

Training

```
PROMPT[...], COMPLETION[...]
...
```

Validation

```
PROMPT[...], COMPLETION[...]
...
```

Test

LLM fine-tuning process

LLM fine-tuning

Prepared instruction dataset

Prompt:

```
Classify this review:
I loved this DVD!

Sentiment:
```

Model

Pre-trained LLM

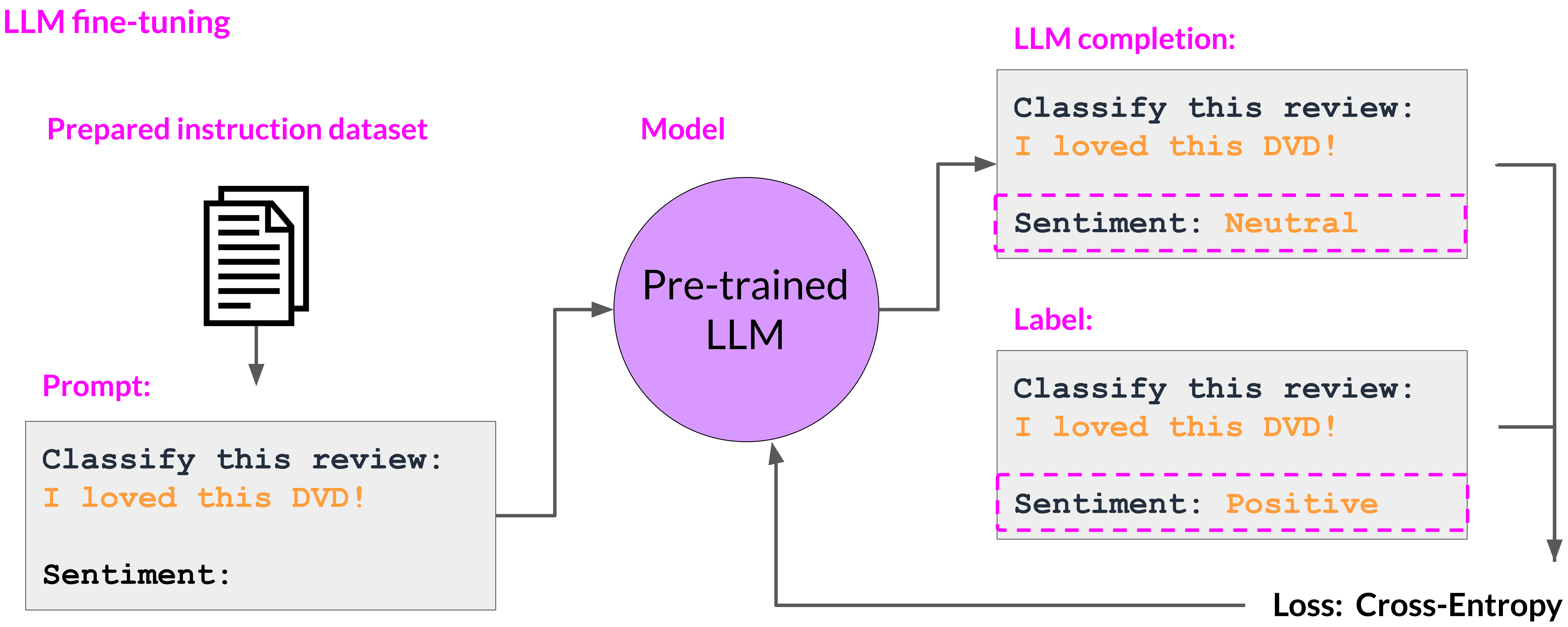
LLM completion:

```
Classify this review:
I loved this DVD!

Sentiment: Neutral
```

Label:

```
Classify this review:
I loved this DVD!

Sentiment: Positive
```

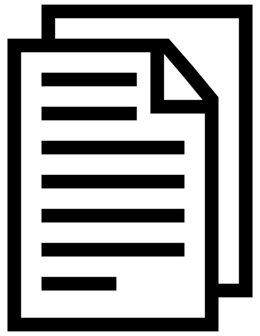
LLM fine-tuning process



LLM fine-tuning process

LLM fine-tuning

Prepared instruction dataset



Training splits

```
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
```

Training

```
PROMPT[...], COMPLETION[...]
...
```

Validation

validation_accuracy

```
PROMPT[...], COMPLETION[...]
...
```

Test

LLM fine-tuning process

LLM fine-tuning

Prepared instruction dataset

Training splits

```
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
```

Training

```
PROMPT[...], COMPLETION[...]
...
```

Validation

```
PROMPT[...], COMPLETION[...]
...
```

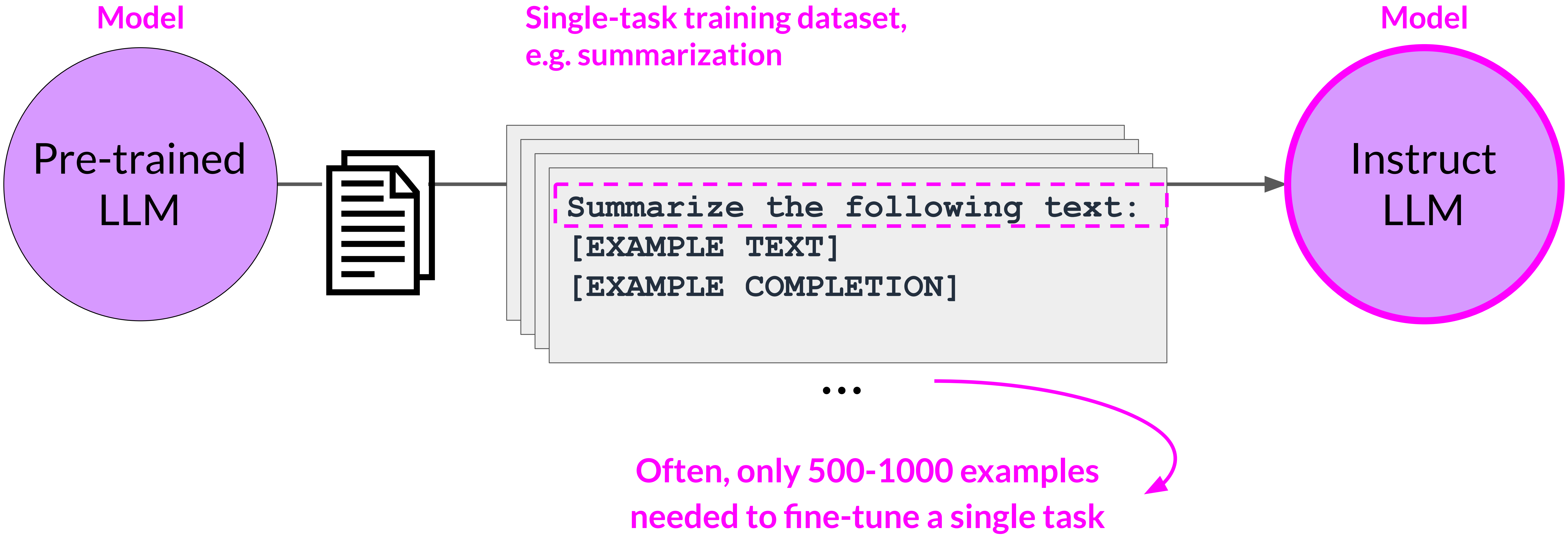
Test

test_accuracy

LLM fine-tuning process

Fine-tuning on a single task

Fine-tuning on a single task



Catastrophic forgetting

- Fine-tuning can significantly increase the performance of a model on a specific task...

Before fine-tuning

Prompt

```
Classify this review:
I loved this DVD!
Sentiment:
```

Model

LLM

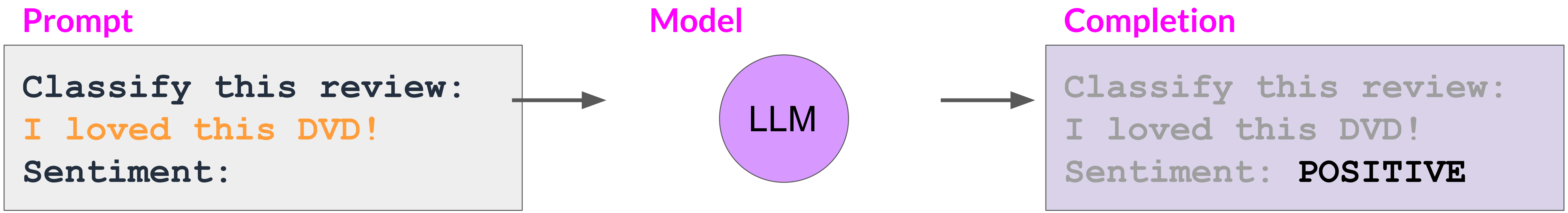
Completion

```
Classify this review:
I loved this DVD!
Sentiment: eived a
very nice book review
```

Catastrophic forgetting

- Fine-tuning can significantly increase the performance of a model on a specific task...

After fine-tuning



Catastrophic forgetting

- …but can lead to reduction in ability on other tasks

Before fine-tuning

Prompt

```
What is the name of
the cat?
Charlie the cat roamed
the garden at night.
```

Model

LLM

Completion

```
What is the name of
the cat?
Charlie the cat roamed
the garden at night.
Charlie
```

Catastrophic forgetting

- …but can lead to reduction in ability on other tasks

After fine-tuning

Prompt

```
What is the name of
the cat?
Charlie the cat roamed
the garden at night.
```

Model

LLM

Completion

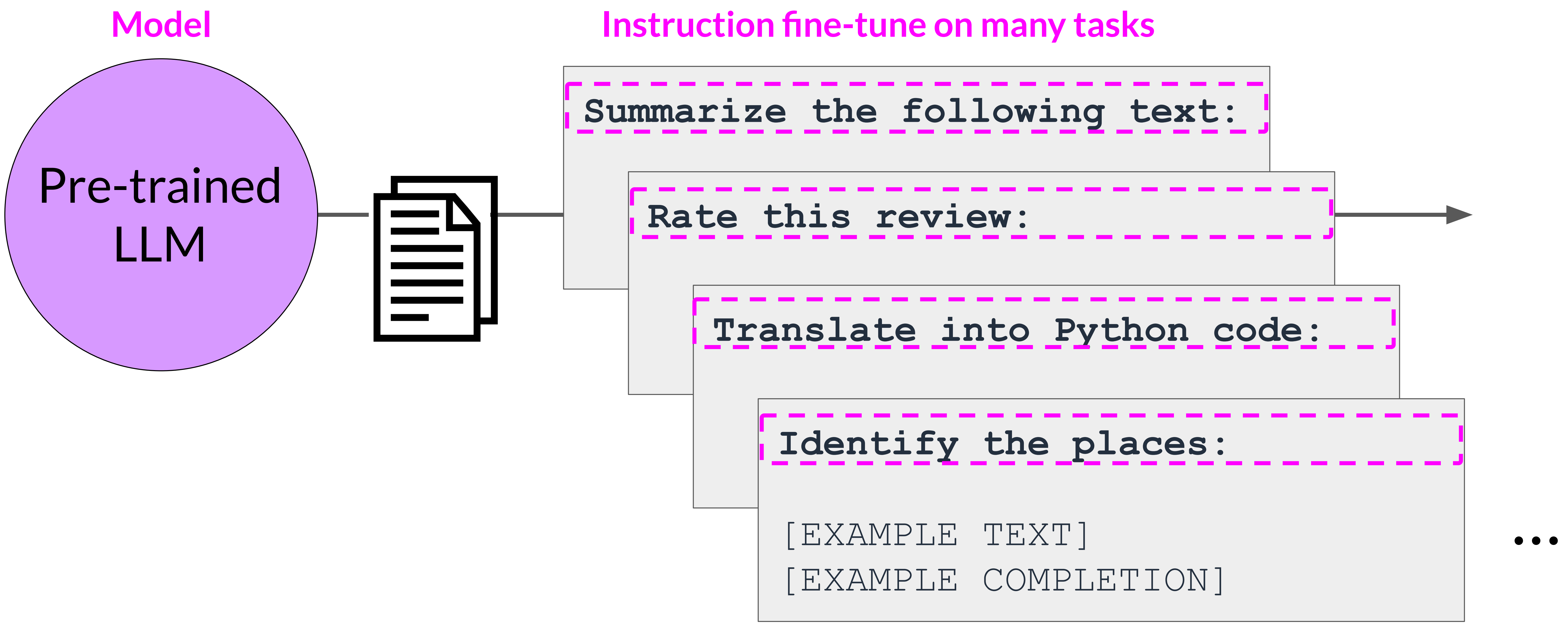
```
What is the name of
the cat?
Charlie the cat roamed
the garden at night.
The garden was
positive.
```

How to avoid catastrophic forgetting

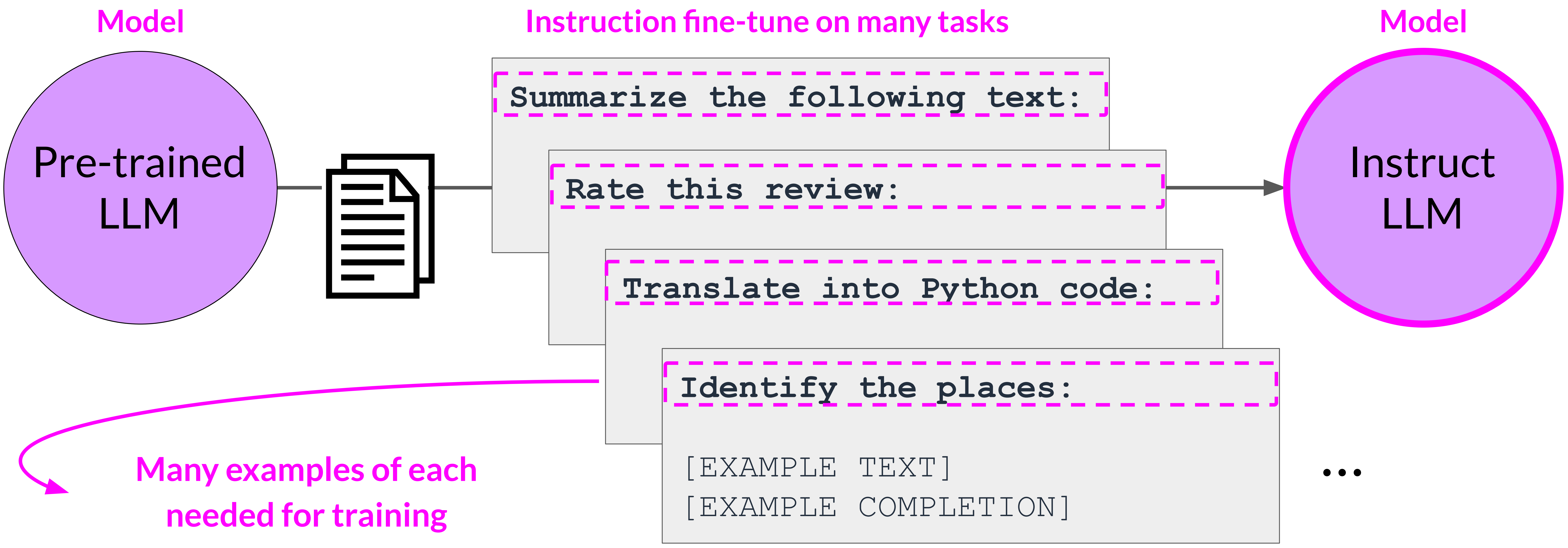
- First note that you might not have to!
- Fine-tune on **multiple tasks** at the same time
- Consider **Parameter Efficient Fine-tuning** (PEFT)

Multi-task, instruction fine-tuning

Multi-task, instruction fine-tuning

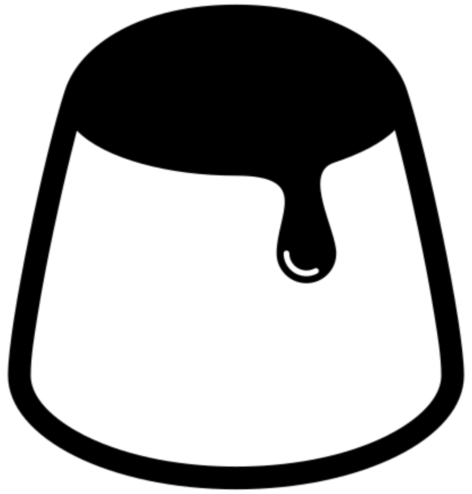


Multi-task, instruction fine-tuning



Instruction fine-tuning with FLAN

- FLAN models refer to a specific set of instructions used to perform instruction fine-tuning

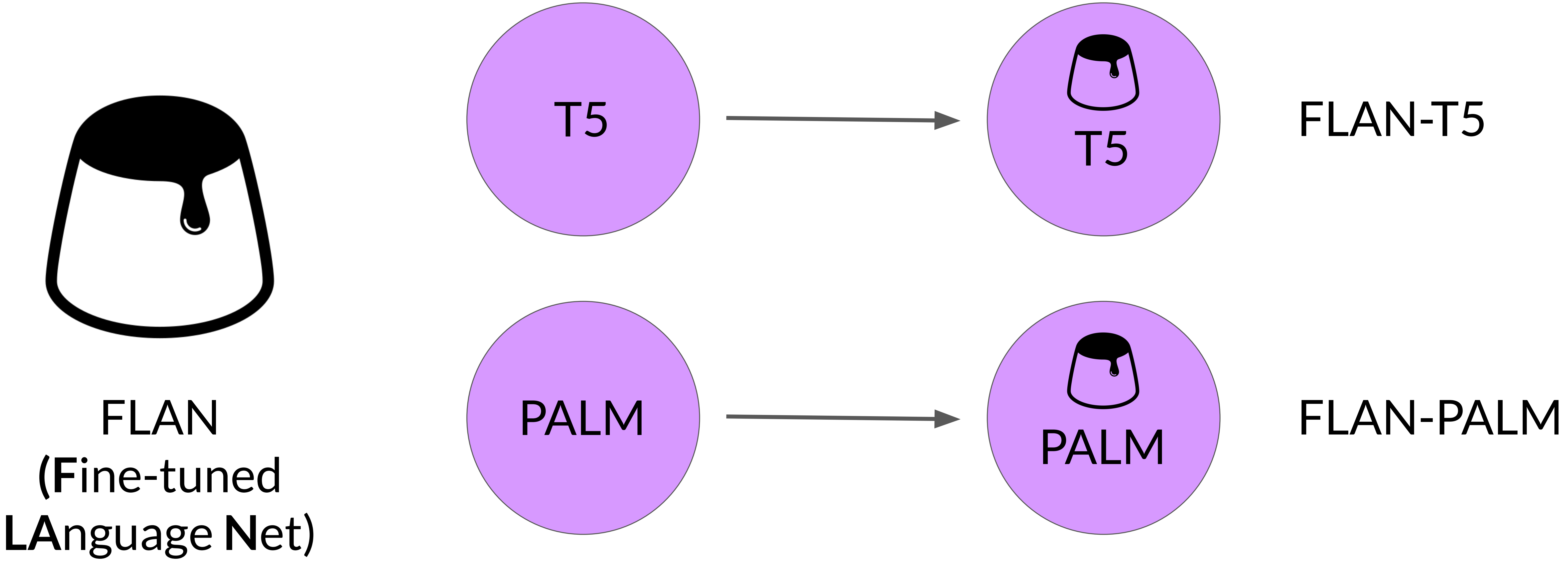


FLAN

"The metaphorical dessert to the main course of pretraining"

Instruction fine-tuning with FLAN

- FLAN models refer to a specific set of instructions used to perform instruction fine-tuning



FLAN-T5: Fine-tuned version of pre-trained T5 model

- FLAN-T5 is a great, general purpose, instruct model

T0-SF

- Commonsense Reasoning,
- Question Generation,
- Closed-book QA,
- Adversarial QA,
- Extractive QA

…

55 Datasets
14 Categories
193 Tasks

Muffin

- Natural language inference,
- Code instruction gen,
- Code repair
- Dialog context generation,
- Summarization (SAMSum)

…

69 Datasets
27 Categories
80 Tasks

CoT (reasoning)

- Arithmetic reasoning,
- Commonsense reasoning
- Explanation generation,
- Sentence composition,
- Implicit reasoning,

…

9 Datasets
1 Category
9 Tasks

Natural Instructions

- Cause effect classification,
- Commonsense reasoning,
- Named Entity Recognition,
- Toxic Language Detection,
- Question answering

…

372 Datasets
108 Categories
1554 Tasks

Source: Chung et al. 2022, “Scaling Instruction-Finetuned Language Models”

FLAN-T5: Fine-tuned version of pre-trained T5 model

- FLAN-T5 is a great, general purpose, instruct model

T0-SF

- Commonsense Reasoning,
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- Natural language inference,
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Source: Chung et al. 2022, “Scaling Instruction-Finetuned Language Models”

SAMSum: A dialogue dataset

Sample prompt training dataset (**samsum**) to fine-tune FLAN-T5 from pretrained T5

Datasets: **samsum** | Tasks: Summarization | Languages: English

dialogue (string)	summary (string)
"Amanda: I baked cookies. Do you want some? Jerry: Sure! Amanda: I'll bring you tomorrow :-)"	"Amanda baked cookies and will bring Jerry some tomorrow."
"Olivia: Who are you voting for in this election? Oliver: Liberals as always. Olivia: Me too!! Oliver: Great"	"Olivia and Olivier are voting for liberals in this election. "
"Tim: Hi, what's up? Kim: Bad mood tbh, I was going to do lots of stuff but ended up procrastinating Tim: What did…	"Kim may try the pomodoro technique recommended by Tim to get more stuff done."

Source: https://huggingface.co/datasets/samsum, https://github.com/google-research/FLAN/blob/2c79a31/flan/v2/templates.py#L3285

Sample FLAN-T5 prompt templates

```
"samsum": [
    ("{dialogue}\n\Briefly summarize that dialogue.", "{summary}"),
    ("Here is a dialogue:\n{dialogue}\n\nWrite a short summary!",
     "{summary}"),
    ("Dialogue:\n{dialogue}\n\nWhat is a summary of this dialogue?",
     "{summary}"),
    ("{dialogue}\n\nWhat was that dialogue about, in two sentences or less?",
     "{summary}"),
    ("Here is a dialogue:\n{dialogue}\n\nWhat were they talking about?",
     "{summary}"),
    ("Dialogue:\n{dialogue}\nWhat were the main points in that "
     "conversation?", "{summary}"),
    ("Dialogue:\n{dialogue}\nWhat was going on in that conversation?",
     "{summary}"),
]
```

Sample FLAN-T5 prompt templates

```
"samsum": [
       ("{dialogue}\n\Briefly summarize that dialogue.", "{summary}"),
       ("Here is a dialogue:\n{dialogue}\n\nWrite a short summary!",
        "{summary}"),
       ("Dialogue:\n{dialogue}\n\nWhat is a summary of this dialogue?",
        "{summary}"),
       ("{dialogue}\n\nWhat was that dialogue about, in two sentences or less?",
        "{summary}"),
       ("Here is a dialogue:\n{dialogue}\n\nWhat were they talking about?",
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        "conversation?", "{summary}"),
       ("Dialogue:\n{dialogue}\nWhat was going on in that conversation?",
        "{summary}"),
]
```
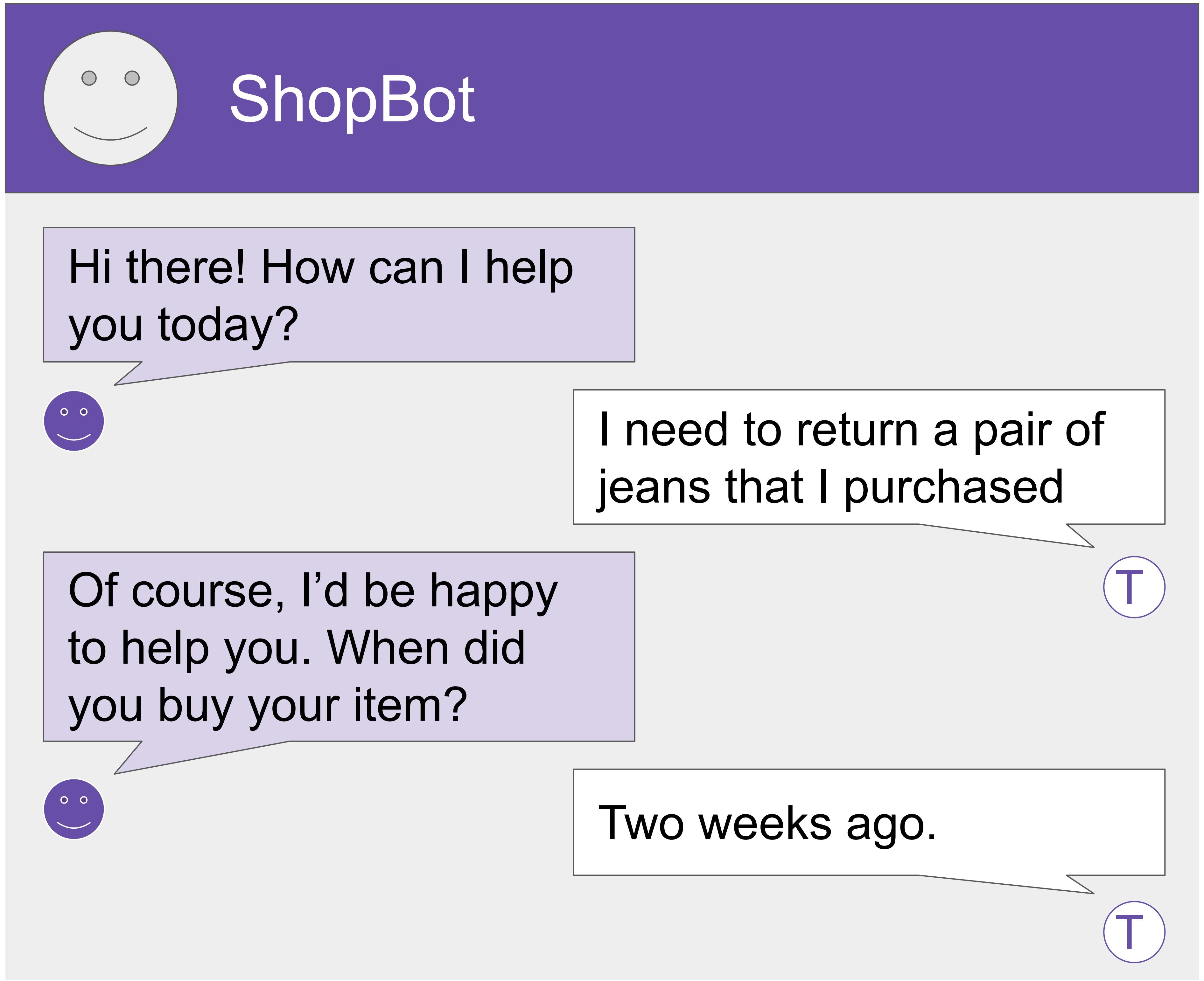
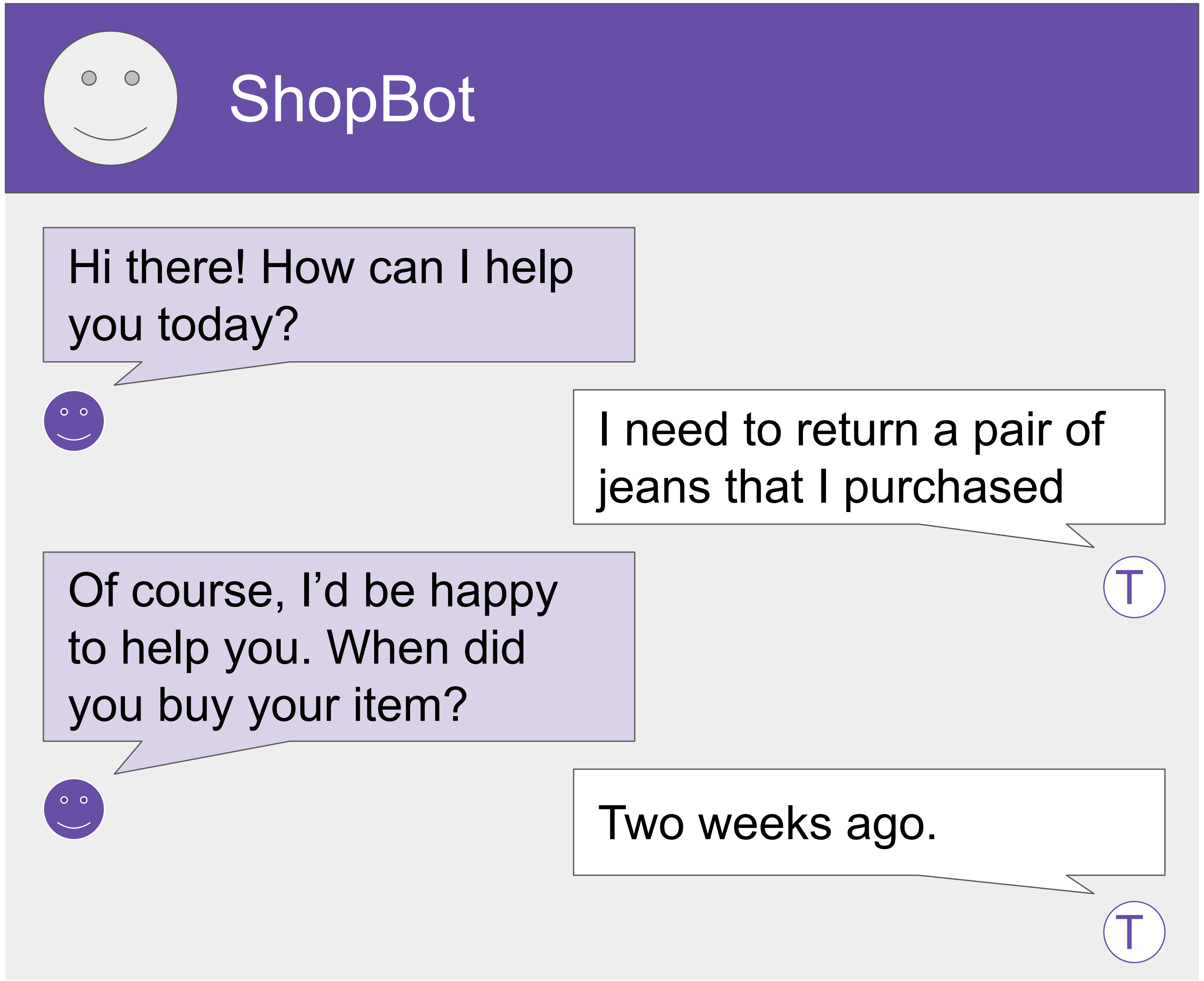

Improving FLAN-T5's summarization capabilities



Improving FLAN-T5's summarization capabilities



Goal: Summarize conversations to identify actions to take

Improving FLAN-T5's summarization capabilities

Further fine-tune FLAN-T5 with a domain-specific instruction dataset (**dialogsum**)

Datasets: knkarthick/**dialogsum** like 13

Tasks: Summarization Text2Text Generation Text Generation Languages: English Multilinguality: monolingual Size Categorie

Language Creators: expert-generated Annotations Creators: expert-generated Source Datasets: original License: mit

Dataset card Files and versions Community 4

Dataset Preview

Split

train (12.5k rows)

id (string)	dialogue (string)	summary (string)
"train_0"	"#Person1#: Hi, Mr. Smith. I'm Doctor Hawkins. Why are you here today? #Person2#: I found it would be a good…	"Mr. Smith's getting a check-up, and Doctor Hawkins advises him to have one every year. Hawkins'll give some…
"train_1"	"#Person1#: Hello Mrs. Parker, how have you been? #Person2#: Hello Dr. Peters. Just fine thank you. Ricky…	"Mrs Parker takes Ricky for his vaccines. Dr. Peters checks the record and then gives Ricky a vaccine."
"train_2"	"#Person1#: Excuse me, did you see a set of keys? #Person2#: What kind of keys? #Person1#: Five keys and a small foot ornament. #Person2#: What a shame! I didn't see them. #Person1#: Well, can you help me look for it? That's my first time here. #Person2#: Sure. It's my pleasure. I'd like to help you look for the missing keys. #Person1#: It's very kind of you. #Person2#: It's not a big deal.Hey, I found them. #Person1#: Oh, thank God! I don't know how to thank you, guys. #Person2#: You're welcome."	"#Person1#'s looking for a set of keys and asks for #Person2#'s help to find them."

Example support-dialog summarization

Prompt (created from template)

```
Summarize the following conversation.
Tommy: Hello. My name is Tommy Sandals, I have a reservation.
Mike: May I see some identification, sir, please?
Tommy: Sure. Here you go.
Mike: Thank you so much. Have you got a credit card, Mr.
Sandals?
Tommy: I sure do.
Mike: Thank you, sir. You'll be in room 507, nonsmoking,
queen bed.
Tommy: That's great, thank you!
Mike: Enjoy your stay!
```

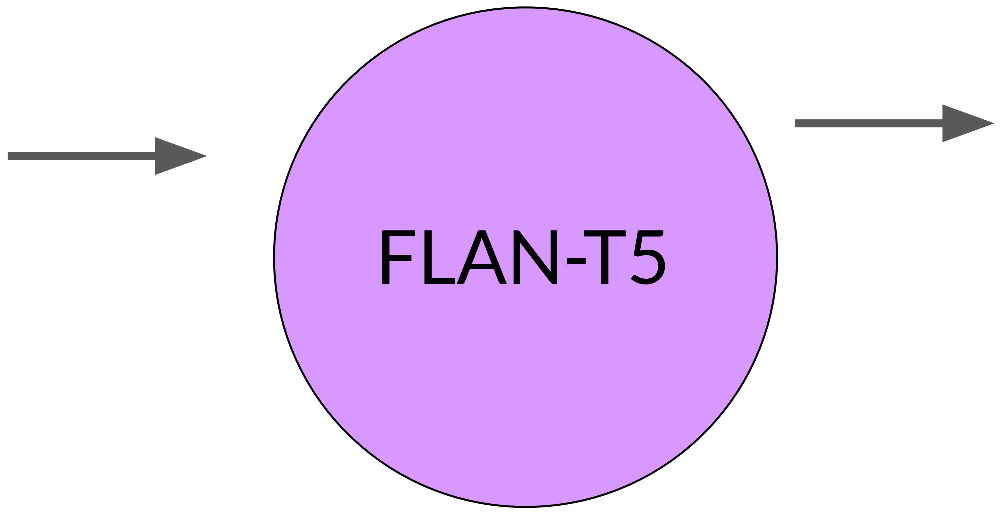
Source: https://huggingface.co/datasets/knkarthick/dialogsum/viewer/knkarthick--dialogsum/

Summary **before** fine-tuning FLAN-T5 with our dataset

Prompt (created from template)

```
Summarize the following
conversation.
Tommy: Hello. My name is
Tommy Sandals, I have a
reservation.
Mike: May I see some
...
...
...
Tommy: That's great, thank
you!
Mike: Enjoy your stay!
```

Model



Completion (Summary)

```
Tommy Sandals has a reservation
for a room at the Venetian
Hotel in Las Vegas.
```

Adequate completion, but does not match human baseline.

```
Human baseline summary:
Tommy Sandals has got a
reservation. Mike asks for his
identification and credit card
and helps his check-in.
```

Summary **before** fine-tuning FLAN-T5 with our dataset

Prompt (created from template)

```
Summarize the following
conversation.
Tommy: Hello. My name is
Tommy Sandals, I have a
reservation.
Mike: May I see some
...
...
...
Tommy: That's great, thank
you!
Mike: Enjoy your stay!
```

Model

FLAN-T5

Completion (Summary)

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Tommy Sandals has a reservation
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Prompt (created from template)

```
Summarize the following
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Mike: May I see some
...
...
...
Tommy: That's great, thank
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Mike: Enjoy your stay!
```
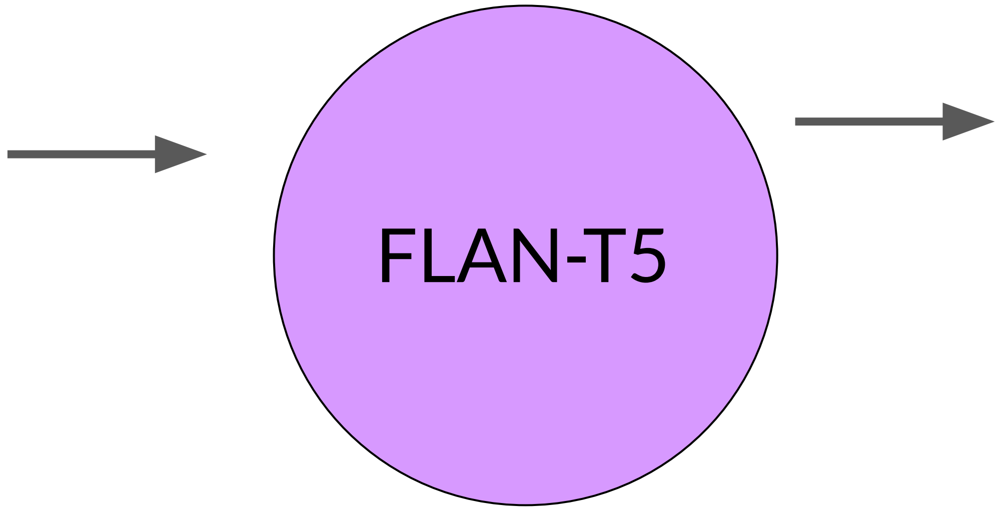

Model



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Summary **after** fine-tuning FLAN-T5 with our dataset

Prompt (created from template)

```
Summarize the following
conversation.
Tommy: Hello. My name is
Tommy Sandals, I have a
reservation.
Mike: May I see some
...
...
...
Tommy: That's great, thank
you!
Mike: Enjoy your stay!
```

Model

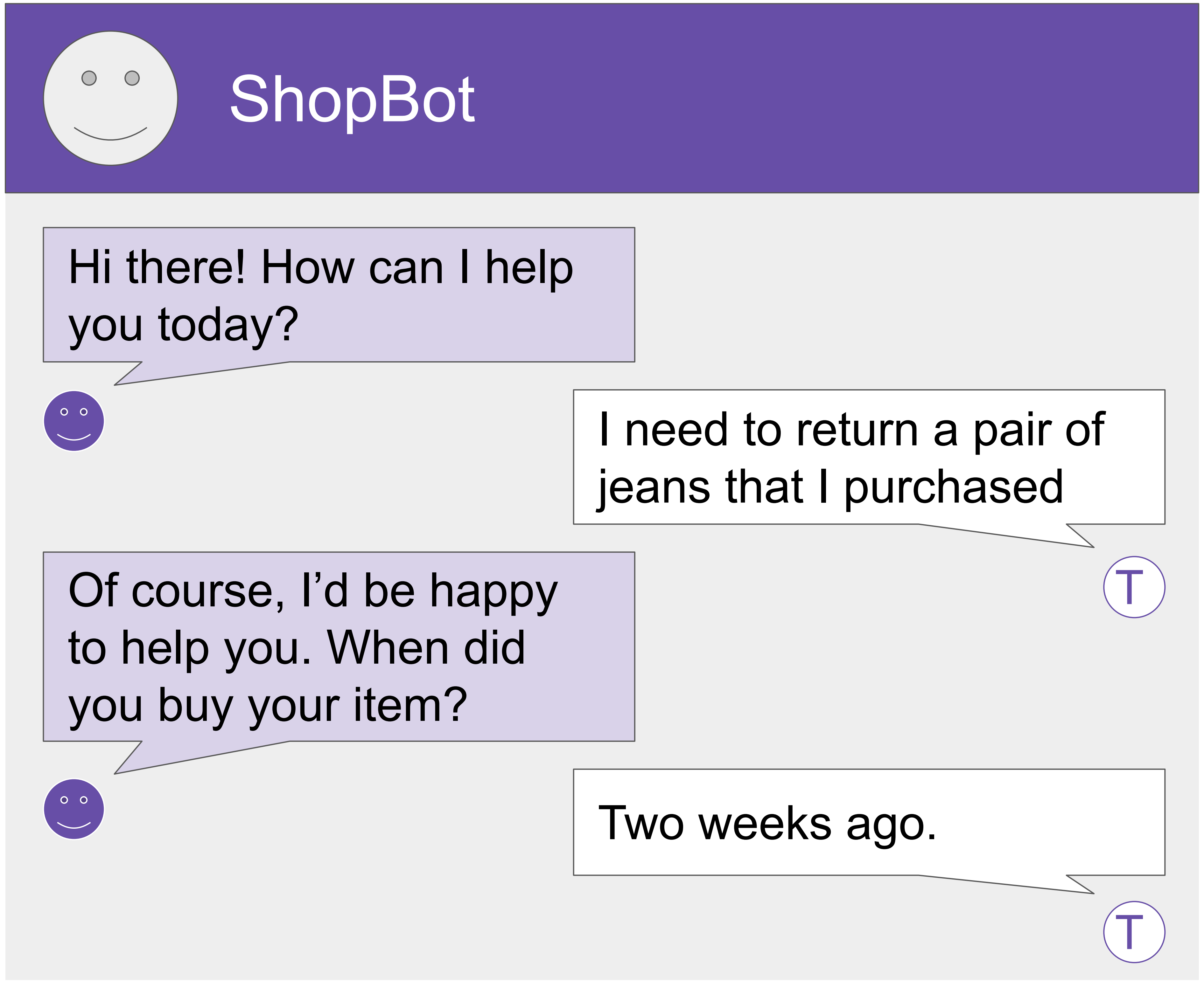
FLAN-T5
(Fine-tuned)

Completion (Summary)

```
Tommy Sandals has a
reservation and checks in
showing his ID and credit
card. Mike helps him to
check in and approves his
reservation.
```

Better summary, more-closely matches human baseline.

Fine-tuning with your own data



Model evaluation metrics

LLM Evaluation - Challenges

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

LLM Evaluation - Challenges

"Mike really loves drinking tea." ❤️ ☕	=	"Mike adores sipping tea." ❤️ ☕
"Mike does **not** drink coffee." 🤢 ☕	≠	"Mike does drink coffee." 🧐 ☕

LLM Evaluation - Metrics

ROUGE

BLEU SCORE

- Used for text summarization
- Compares a summary to one or more reference summaries

- Used for text translation
- Compares to human-generated translations

LLM Evaluation - Metrics - Terminology

n-gram

The dog lay on the rug as I sipped a cup of tea.

bigram

unigram

LLM Evaluation - Metrics - ROUGE-1

Reference (human):

It is cold outside.

Generated output:

It is very cold outside.

$$\text{ROUGE-1 Recall} = \frac{\text{unigram matches}}{\text{unigrams in reference}} = \frac{4}{4} = 1.0$$

$$\text{ROUGE-1 Precision:} = \frac{\text{unigram matches}}{\text{unigrams in output}} = \frac{4}{5} = 0.8$$

$$\text{ROUGE-1 F1:} = 2\,\frac{\text{precision x recall}}{\text{precision + recall}} = 2\,\frac{0.8}{1.8} = 0.89$$

LLM Evaluation - Metrics - ROUGE-1

Reference (human):

It is cold outside.

Generated output:

It is not cold outside.

$$\text{ROUGE-1 Recall} = \frac{\text{unigram matches}}{\text{unigrams in reference}} = \frac{4}{4} = 1.0$$

$$\text{ROUGE-1 Precision:} = \frac{\text{unigram matches}}{\text{unigrams in output}} = \frac{4}{5} = 0.8$$

$$\text{ROUGE-1 F1:} = 2\,\frac{\text{precision x recall}}{\text{precision + recall}} = 2\,\frac{0.8}{1.8} = 0.89$$

LLM Evaluation - Metrics - ROUGE-2

Reference (human):

It is cold outside.

It is	is cold	cold outside

Generated output:

It is very cold outside.

It is	is very	very cold	cold outside

LLM Evaluation - Metrics - ROUGE-2

Reference (human):

It is cold outside.

It is	is cold	cold outside

Generated output:

It is very cold outside.

It is	is very	very cold	cold outside

$$\text{ROUGE-2 Recall:} = \frac{\text{bigram matches}}{\text{bigrams in reference}} = \frac{2}{3} = 0.67$$

$$\text{ROUGE-2 Precision:} = \frac{\text{bigram matches}}{\text{bigrams in output}} = \frac{2}{4} = 0.5$$

$$\text{ROUGE-2 F1:} = 2\,\frac{\text{precision x recall}}{\text{precision + recall}} = 2\,\frac{0.335}{1.17} = 0.57$$

LLM Evaluation - Metrics - ROUGE-L

Reference (human):

It is cold outside.

Generated output:

It is very cold outside.

Longest common subsequence (LCS):

It is

cold outside

2

LLM Evaluation - Metrics - ROUGE-L

Reference (human):

It is cold outside.

Generated output:

It is very cold outside.

$$\text{ROUGE-L Recall:} = \frac{\text{LCS(Gen, Ref)}}{\text{unigrams in reference}} = \frac{2}{4} = 0.5$$

$$\text{ROUGE-L Precision:} = \frac{\text{LCS(Gen, Ref)}}{\text{unigrams in output}} = \frac{2}{5} = 0.4$$

$$\text{ROUGE-L F1:} = 2\,\frac{\text{precision x recall}}{\text{precision + recall}} = 2\,\frac{0.2}{0.9} = 0.44$$

LLM Evaluation - Metrics - ROUGE-L

Reference (human):

It is cold outside.

Generated output:

It is very cold outside.

LCS:
Longest common subsequence

$$\text{ROUGE-L Recall:} = \frac{\text{LCS(Gen, Ref)}}{\text{unigrams in reference}} = \frac{2}{4} = 0.5$$

$$\text{ROUGE-L Precision:} = \frac{\text{LCS(Gen, Ref)}}{\text{unigrams in output}} = \frac{2}{5} = 0.4$$

$$\text{ROUGE-L F1:} = 2\,\frac{\text{precision x recall}}{\text{precision + recall}} = 2\,\frac{0.2}{0.9} = 0.44$$

LLM Evaluation - Metrics - ROUGE hacking

Reference (human):

It is cold outside.

Generated output:

cold cold cold cold

LLM Evaluation - Metrics - ROUGE clipping

Reference (human):

It is cold outside.

Generated output:

cold cold cold cold

$$\text{ROUGE-1 Precision} = \frac{\text{unigram matches}}{\text{unigrams in output}} = \frac{4}{4} = 1.0$$

$$\text{Modified precision} = \frac{\text{clip(unigram matches)}}{\text{unigrams in output}} = \frac{1}{4} = 0.25$$

Generated output:

outside cold it is

$$\text{Modified precision} = \frac{\text{clip(unigram matches)}}{\text{unigrams in output}} = \frac{4}{4} = 1.0$$

LLM Evaluation - Metrics

ROUGE

- Used for text summarization
- Compares a summary to one or more reference summaries

BLEU SCORE

- Used for text translation
- Compares to human-generated translations

LLM Evaluation - Metrics - BLEU

BLEU metric = Avg(precision across range of n-gram sizes)

Reference (human):

I am very happy to say that I am drinking a warm cup of tea.

Generated output:

I am very happy that I am drinking a cup of tea. - BLEU 0.495

I am very happy that I am drinking a warm cup of tea. - BLEU 0.730

I am very happy to say that I am drinking a warm tea. - BLEU 0.798

I am very happy to say that I am drinking a warm cup of tea. - BLEU 1.000

LLM Evaluation - Metrics

ROUGE

BLEU SCORE

- Used for text summarization
- Compares a summary to one or more reference summaries

- Used for text translation
- Compares to human-generated translations

Benchmarks

Evaluation benchmarks

GLUE

SuperGLUE

HELM

MMLU (Massive Multitask Language Understanding)

BIG-bench

GLUE

GLUE

The tasks included in SuperGLUE benchmark:

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	**146**	coreference/NLI	acc.	fiction books

Source: Wang et al. 2018, "GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding"

SuperGLUE

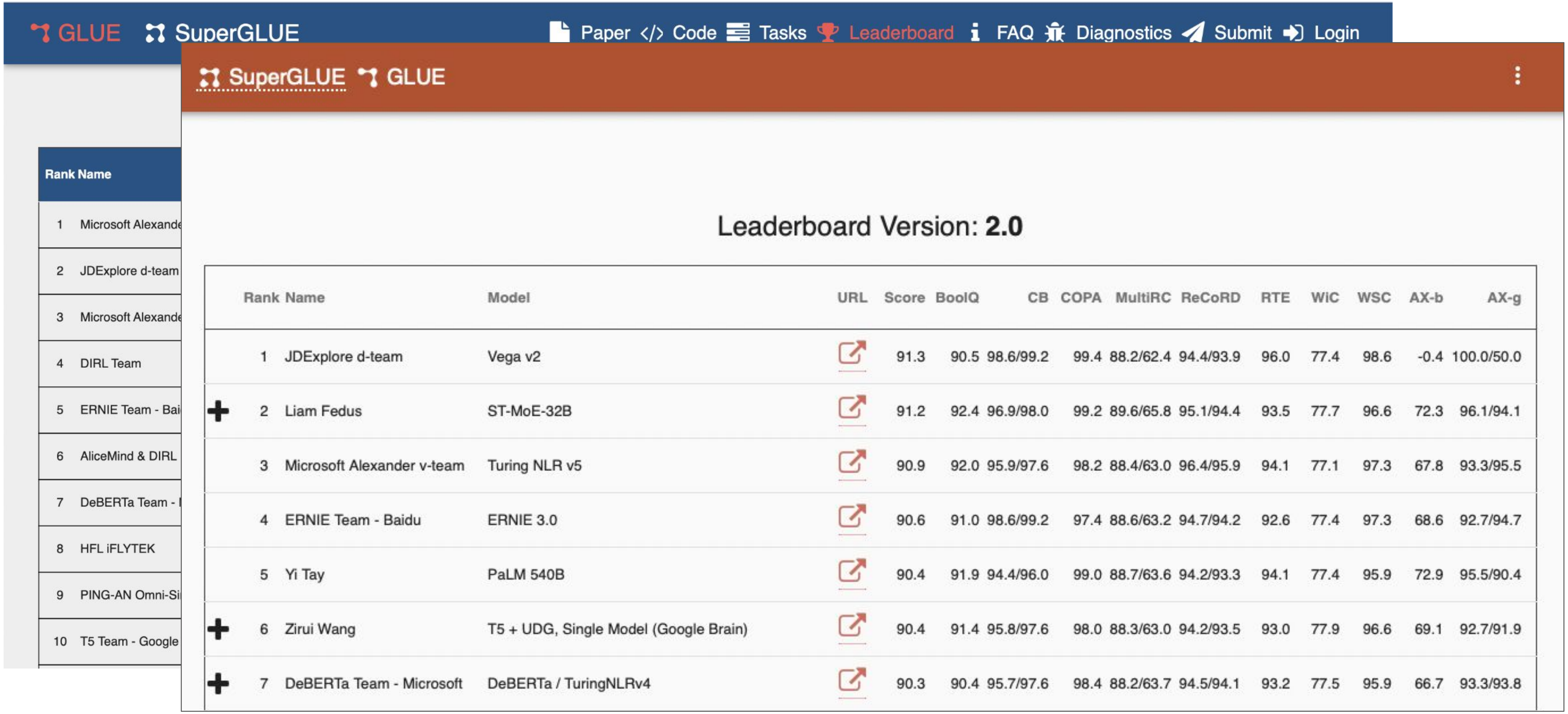
SuperGLUE

The tasks included in SuperGLUE benchmark:

Corpus	|Train|	|Dev|	|Test|	Task	Metrics	Text Sources
BoolQ	9427	3270	3245	QA	acc.	Google queries, Wikipedia
CB	250	57	250	NLI	acc./F1	various
COPA	400	100	500	QA	acc.	blogs, photography encyclopedia
MultiRC	5100	953	1800	QA	$F1_a$/EM	various
ReCoRD	101k	10k	10k	QA	F1/EM	news (CNN, Daily Mail)
RTE	2500	278	300	NLI	acc.	news, Wikipedia
WiC	6000	638	1400	WSD	acc.	WordNet, VerbNet, Wiktionary
WSC	554	104	146	coref.	acc.	fiction books

Source: Wang et al. 2019, "SuperGLUE: A Stickier Benchmark for General-Purpose Language Understanding Systems"

GLUE and SuperGLUE leaderboards



Rank	Name
1	Microsoft Alexande
2	JDExplore d-team
3	Microsoft Alexande
4	DIRL Team
5	ERNIE Team - Bai
6	AliceMind & DIRL
7	DeBERTa Team -
8	HFL iFLYTEK
9	PING-AN Omni-Si
10	T5 Team - Google

	Rank	Name	Model	URL	Score	BoolQ	CB	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-b	AX-g
	1	JDExplore d-team	Vega v2		91.3	90.5	98.6/99.2	99.4	88.2/62.4	94.4/93.9	96.0	77.4	98.6	-0.4	100.0/50.0
+	2	Liam Fedus	ST-MoE-32B		91.2	92.4	96.9/98.0	99.2	89.6/65.8	95.1/94.4	93.5	77.7	96.6	72.3	96.1/94.1
	3	Microsoft Alexander v-team	Turing NLR v5		90.9	92.0	95.9/97.6	98.2	88.4/63.0	96.4/95.9	94.1	77.1	97.3	67.8	93.3/95.5
	4	ERNIE Team - Baidu	ERNIE 3.0		90.6	91.0	98.6/99.2	97.4	88.6/63.2	94.7/94.2	92.6	77.4	97.3	68.6	92.7/94.7
	5	Yi Tay	PaLM 540B		90.4	91.9	94.4/96.0	99.0	88.7/63.6	94.2/93.3	94.1	77.4	95.9	72.9	95.5/90.4
+	6	Zirui Wang	T5 + UDG, Single Model (Google Brain)		90.4	91.4	95.8/97.6	98.0	88.3/63.0	94.2/93.5	93.0	77.9	96.6	69.1	92.7/91.9
+	7	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.3	90.4	95.7/97.6	98.4	88.2/63.7	94.5/94.1	93.2	77.5	95.9	66.7	93.3/93.8

Disclaimer: metrics may not be up-to-date. Check https://super.gluebenchmark.com and https://gluebenchmark.com/leaderboard for the latest.

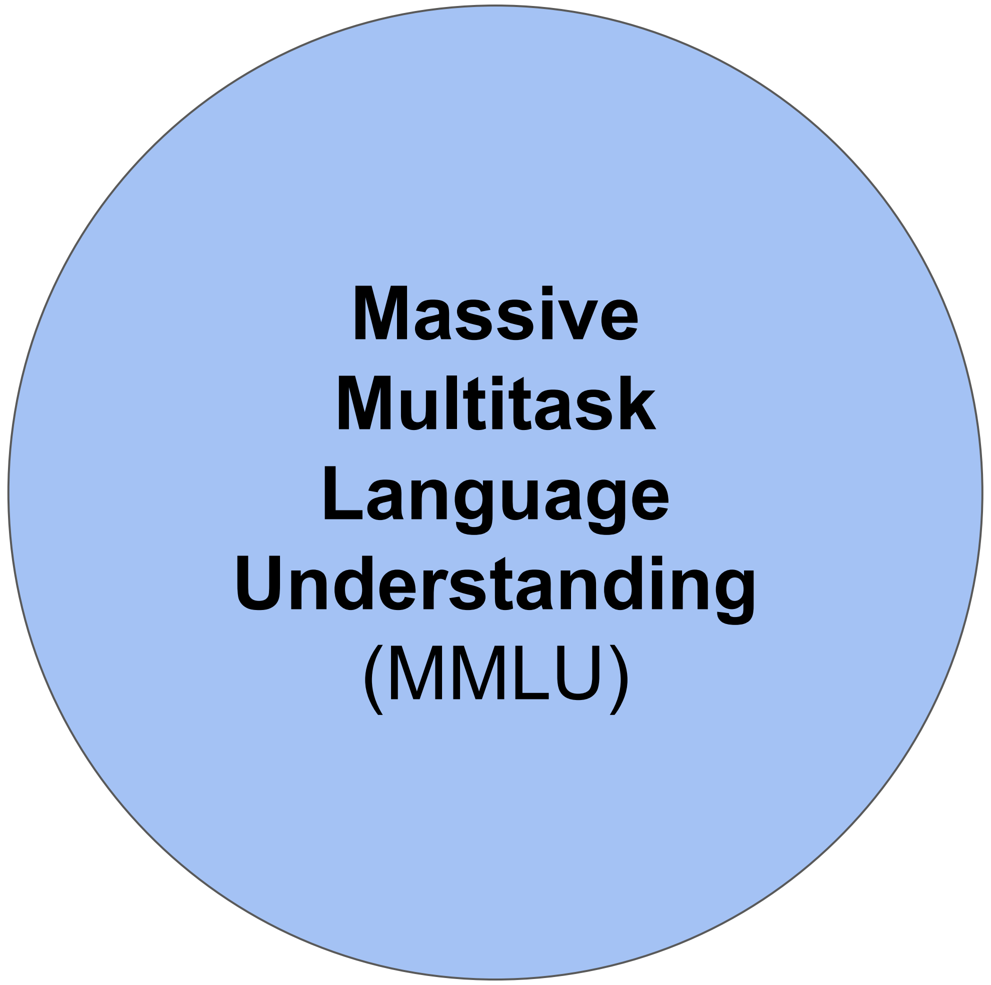
Benchmarks for massive models

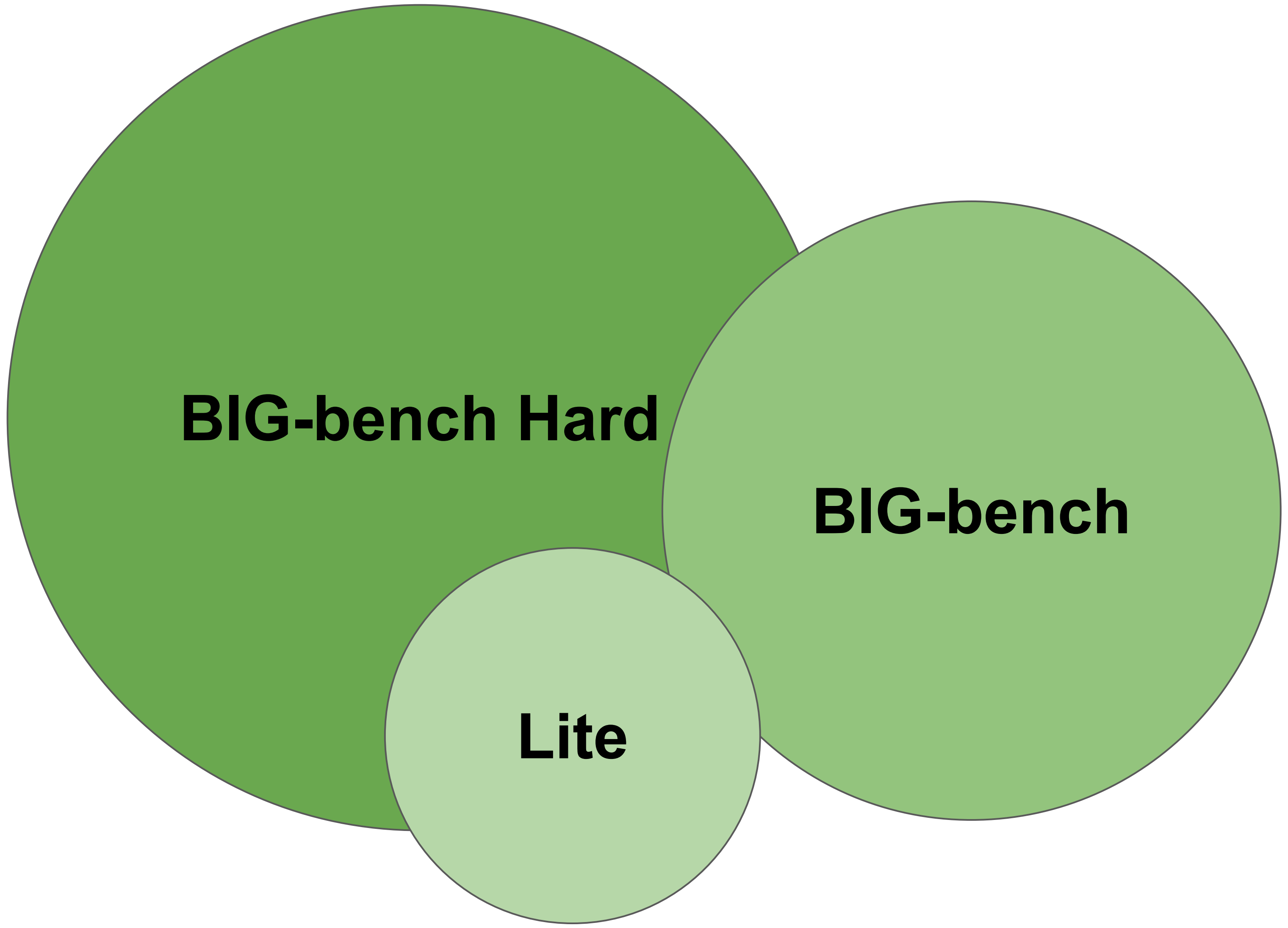
Massive Multitask Language Understanding
(MMLU)

2021

Source: Hendrycks, 2021. “Measuring Massive Multitask Language Understanding”

Benchmarks for massive models





2021

2022

Source: Hendrycks, 2021. “Measuring Massive Multitask Language Understanding”

Source: Suzgun et al. 2022. “Challenging BIG-Bench tasks and whether chain-of-thought can solve them“

Holistic Evaluation of Language Models (HELM)

HELM

Metrics:

1. Accuracy
2. Calibration
3. Robustness
4. Fairness
5. Bias
6. Toxicity
7. Efficiency

Models

Scenarios	J1-Jumbo	J1-Grande	J1-Large	Anthropic-LM	BLOOM	T0pp	Cohere XL	Cohere Large	Cohere Medium	Cohere Small	GPT-NeoX
NaturalQuestions (open)			✔	✔	✔	✔	✔	✔	✔	✔	✔
NaturalQuestions (closed)	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
BoolQ	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
NarrativeQA	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
QuAC	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
HellaSwag	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
OpenBookQA	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
TruthfulQA	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
MMLU	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
MS MARCO				✔	✔		✔	✔	✔	✔	✔
TREC				✔	✔		✔	✔	✔	✔	✔
XSUM	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
CNN/DM	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
IMDB	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
CivilComments	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
RAFT	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔

Holistic Evaluation of Language Models (HELM)

Center for Research on Foundation Models

HELM Models Scenarios Results Raw runs v0.2.2 (last updated 2023-03-19)

Core scenarios

The scenarios where we evaluate all the models.

[Accuracy | Calibration | Robustness | Fairness | Efficiency | General information | Bias | Toxicity | Summarization metrics | JSON]

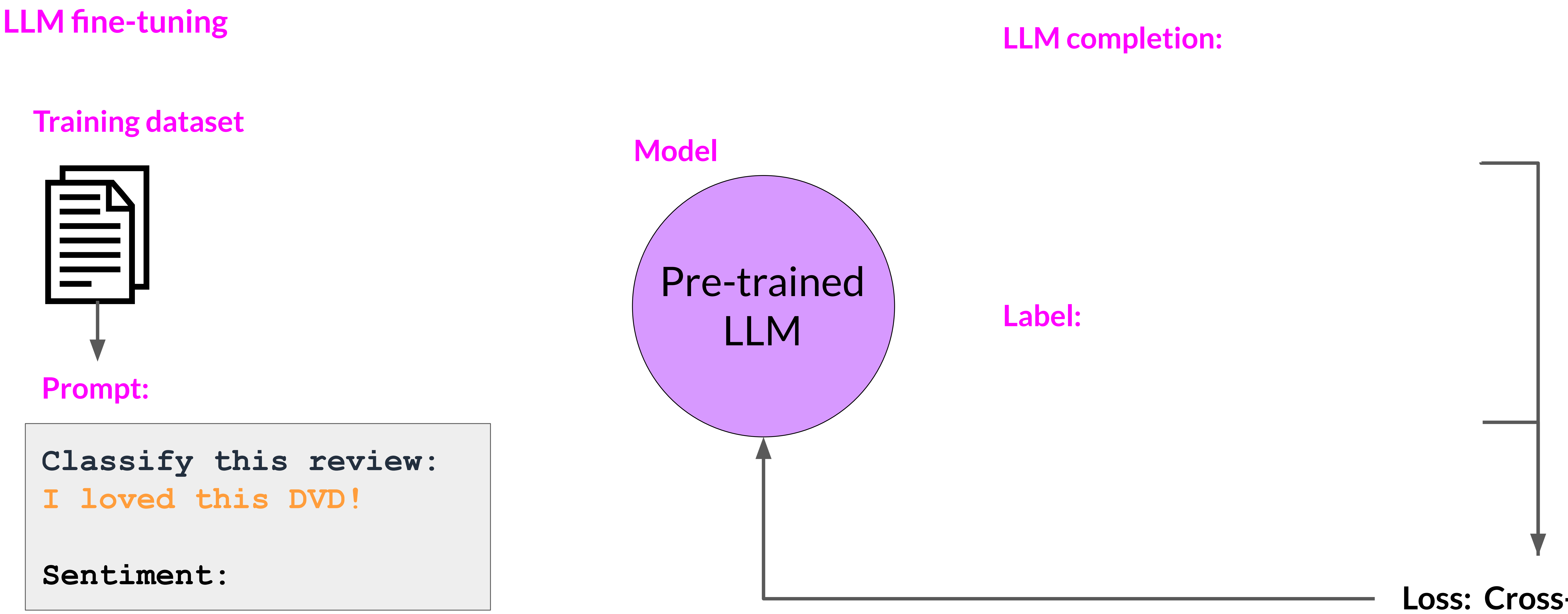
Accuracy

Model/adapter	Mean win rate ↑ [sort]	MMLU - EM ↑ [sort]	BoolQ - EM ↑ [sort]	NarrativeQA - F1 ↑ [sort]	NaturalQuestions (closed-book) - F1 ↑ [sort]	NaturalQuestions (open-book) - F1 ↑ [sort]	QuAC - F1 ↑ [sort]	HellaSwag - EM ↑ [sort]	OpenbookQA - EM ↑ [sort]	TruthfulQA - EM ↑ [sort]
Cohere Command beta (52.4B)	**0.93**	0.452	0.856	**0.752**	0.372	0.76	0.432	0.811	0.582	0.269
text-davinci-002	0.93	0.568	0.877	0.727	0.383	0.713	0.445	0.815	0.594	**0.61**
text-davinci-	0.898	**0.569**	0.881	0.727	0.406	0.77	0.525	0.822	0.646	0.593

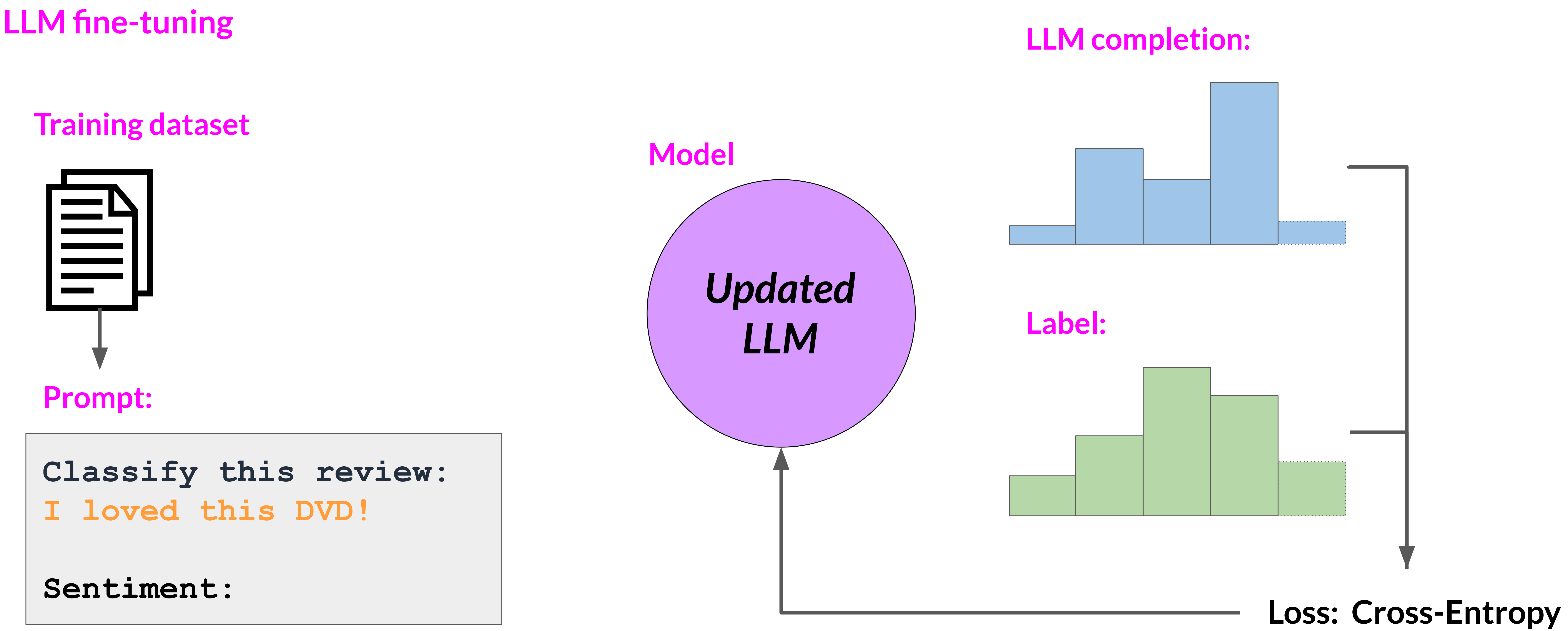
Disclaimer: metrics may not be up-to-date. Check https://crfm.stanford.edu/helm/latest for the latest.

Key takeaways

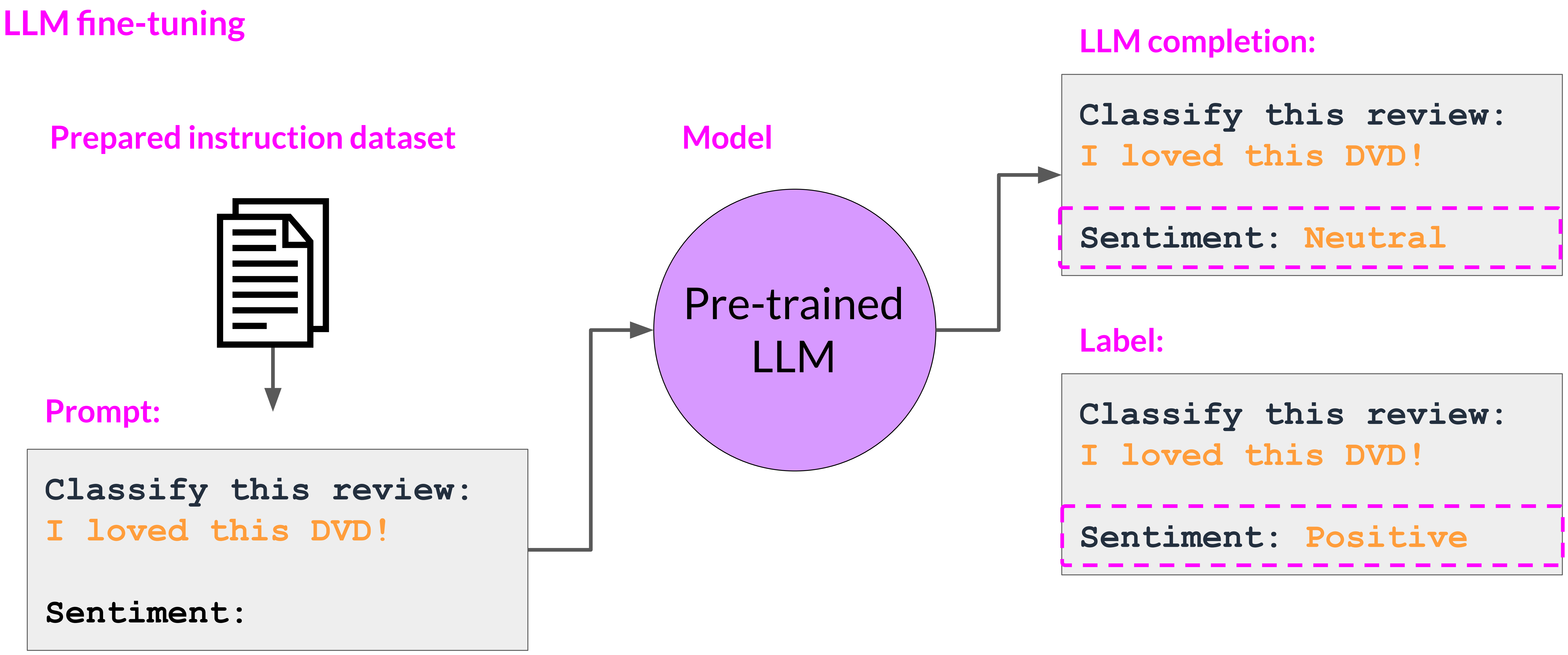
LLM fine-tuning process



LLM fine-tuning process

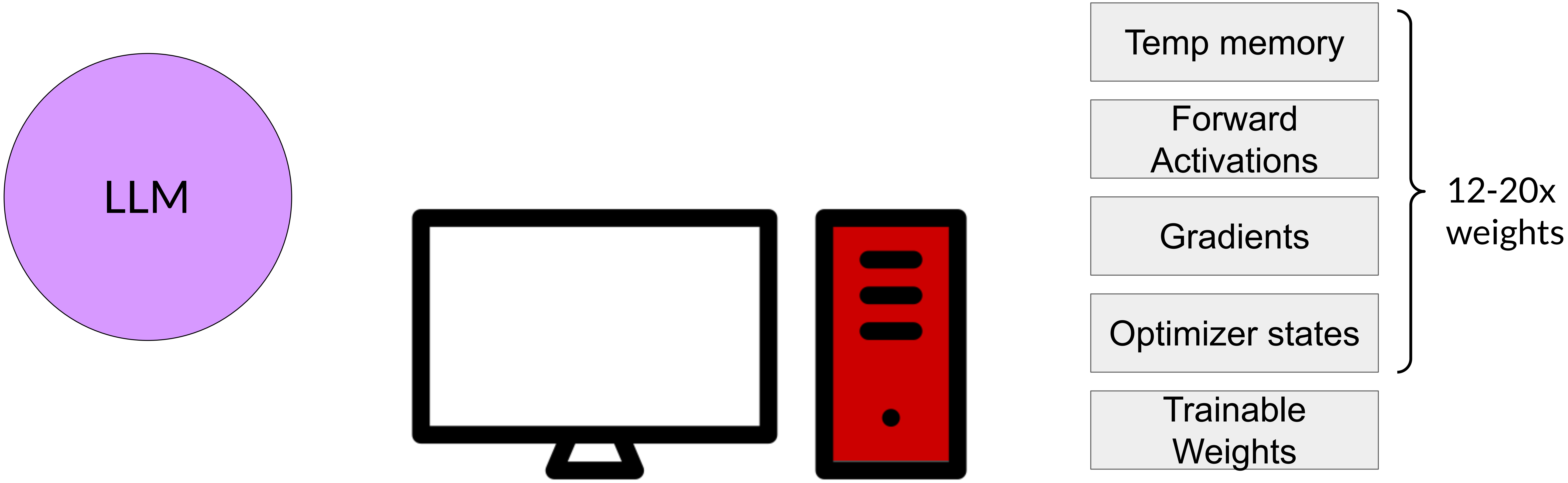


LLM fine-tuning process

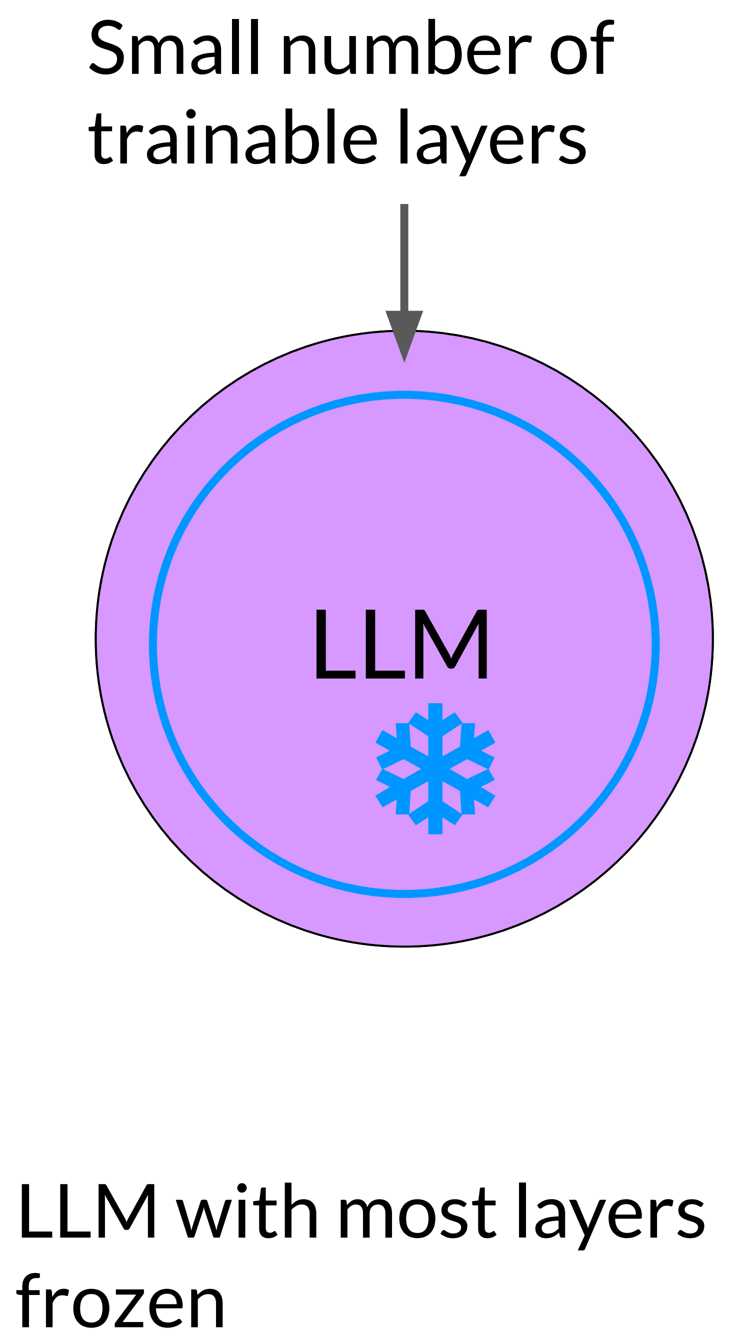


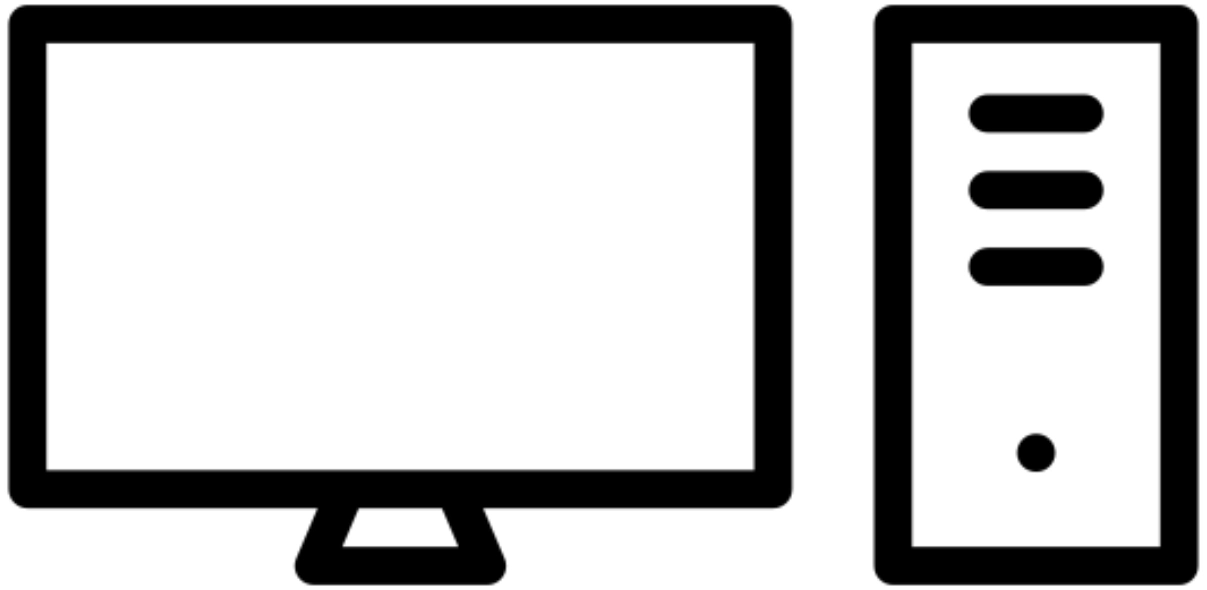
Parameter-efficient Fine-tuning (PEFT)

Full fine-tuning of large LLMs is challenging

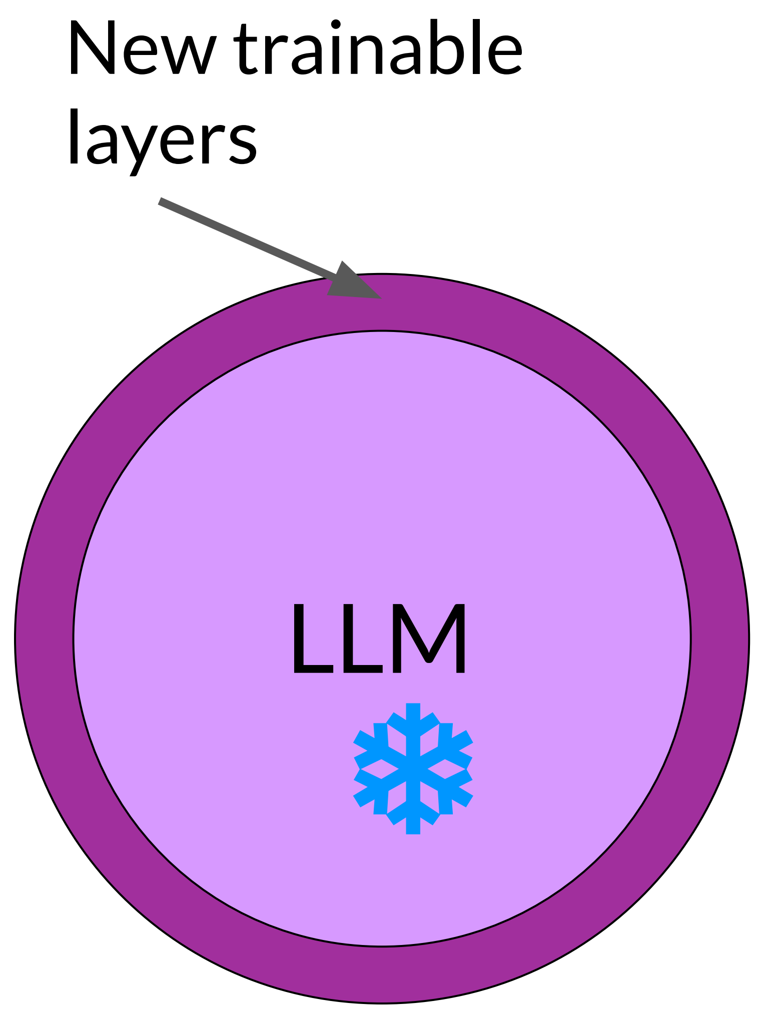


Parameter efficient fine-tuning (PEFT)

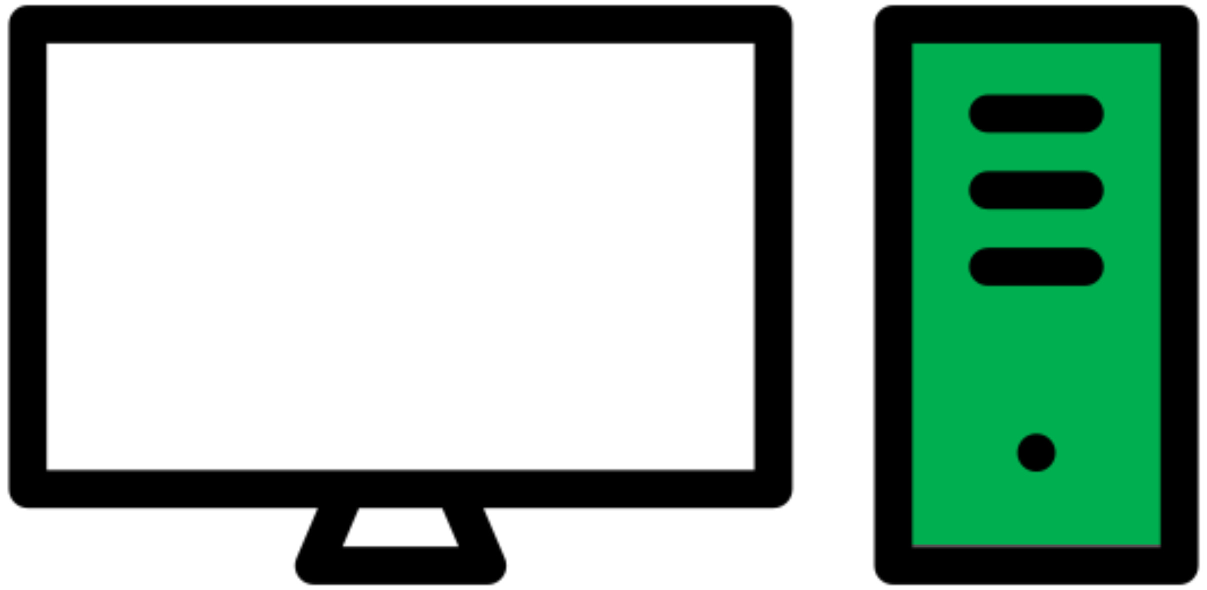




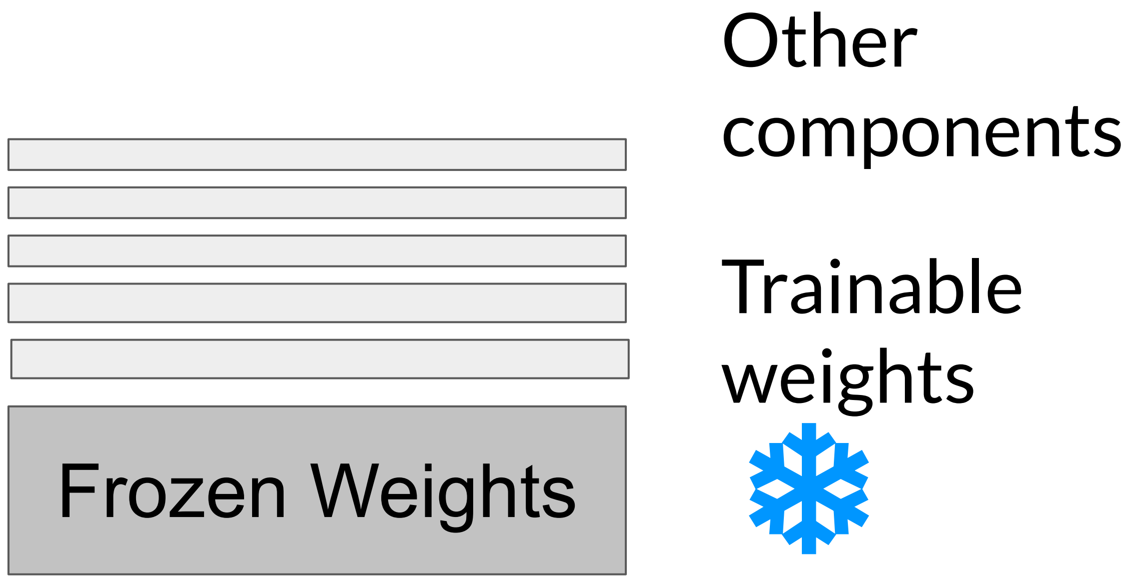
Parameter efficient fine-tuning (PEFT)



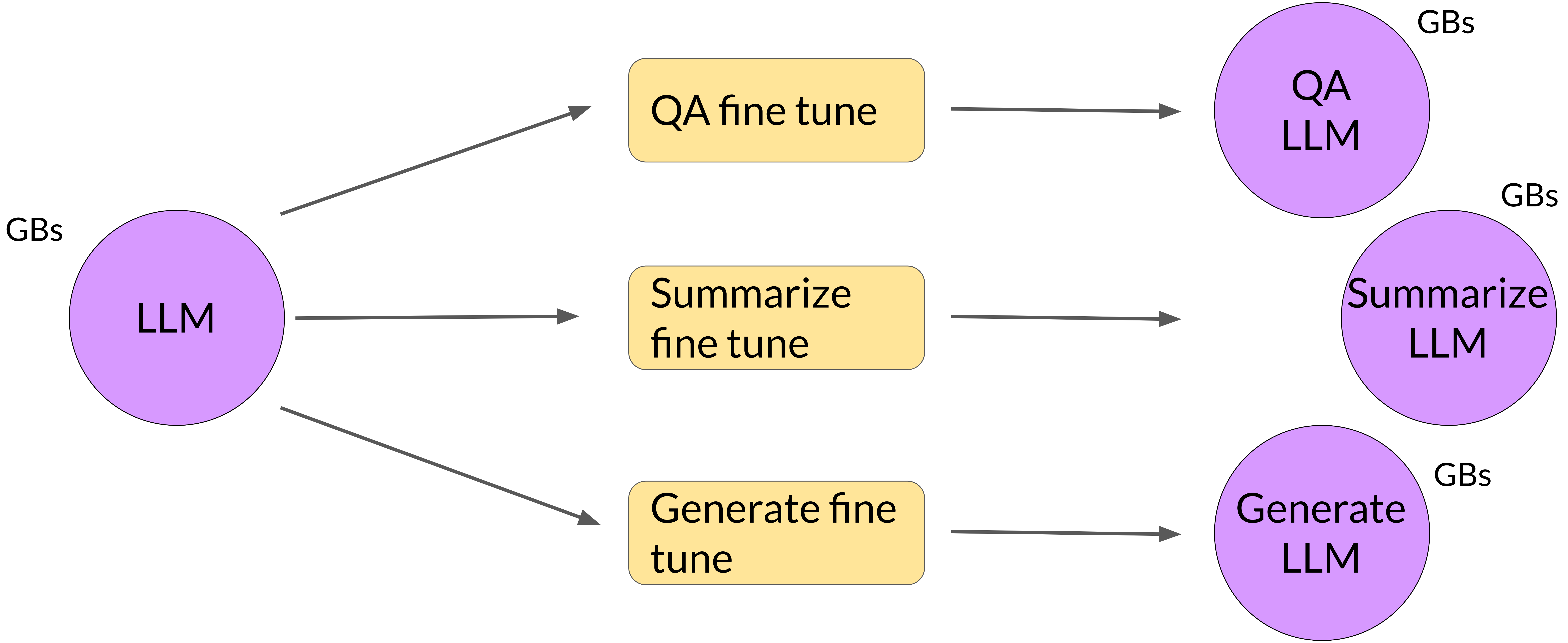
LLM with additional layers for PEFT



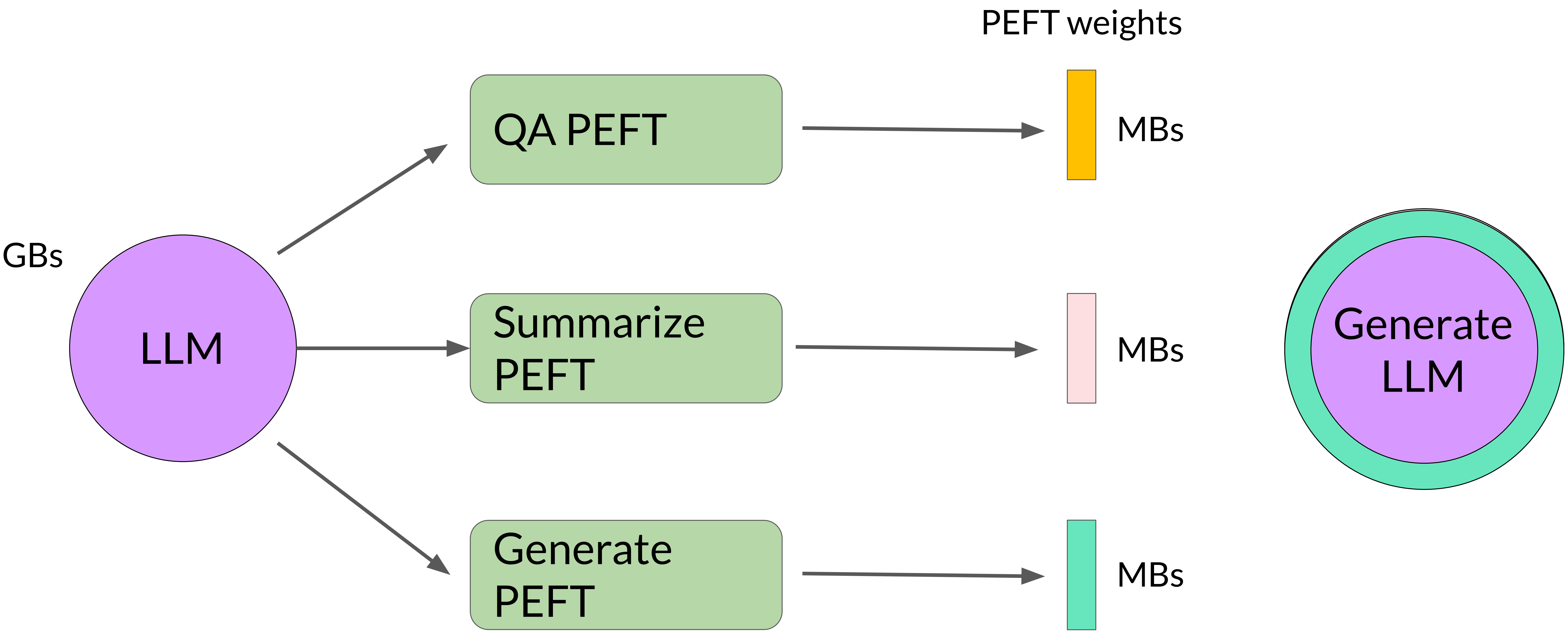
Less prone to catastrophic forgetting



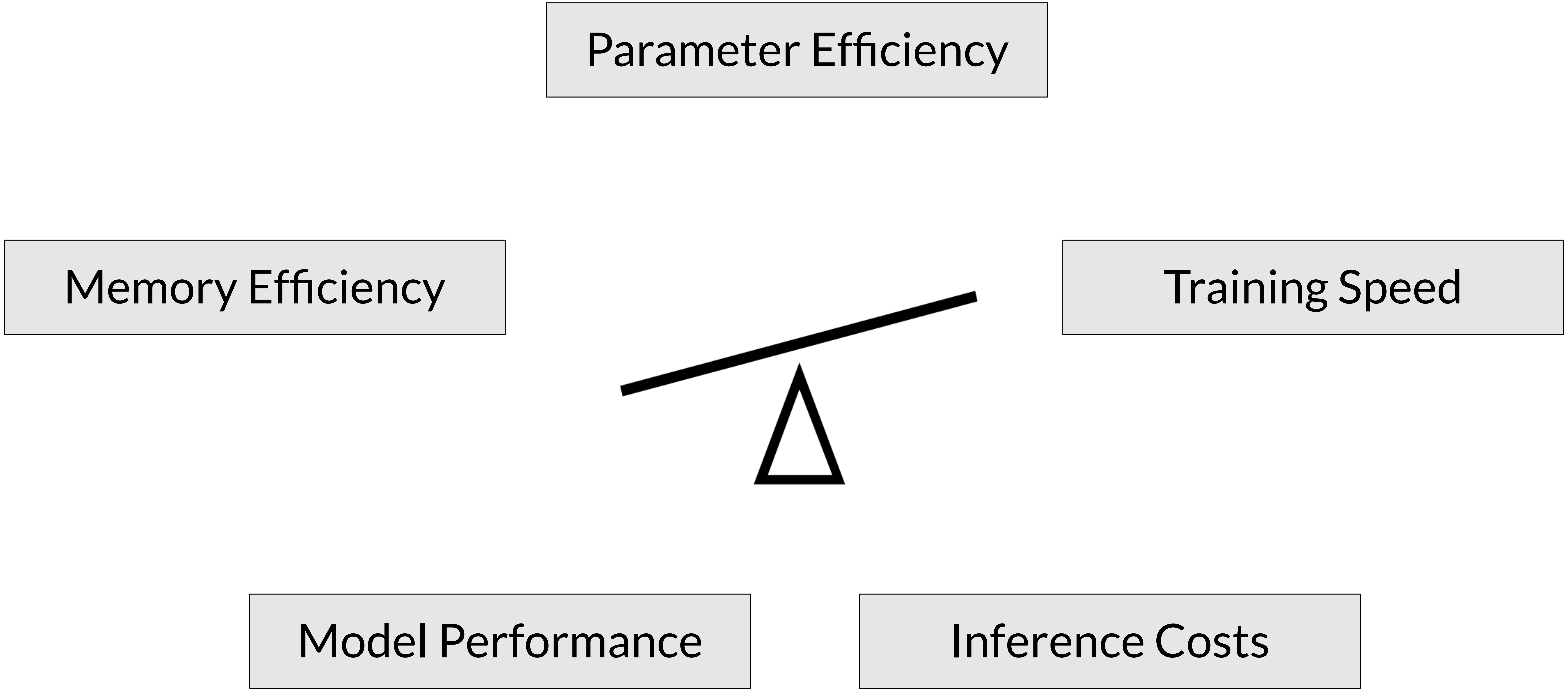
Full fine-tuning creates full copy of original LLM per task



PEFT fine-tuning saves space and is flexible



PEFT Trade-offs



PEFT methods

Selective

Select subset of initial LLM parameters to fine-tune

Reparameterization

Reparameterize model weights using a low-rank representation

Source: Lialin et al. 2023, "Scaling Down to Scale Up: A Guide to Parameter-Efficient Fine-Tuning",

PEFT methods

Selective

Select subset of initial LLM parameters to fine-tune

Reparameterization

Reparameterize model weights using a low-rank representation

LoRA

Additive

Add trainable layers or parameters to model

Adapters

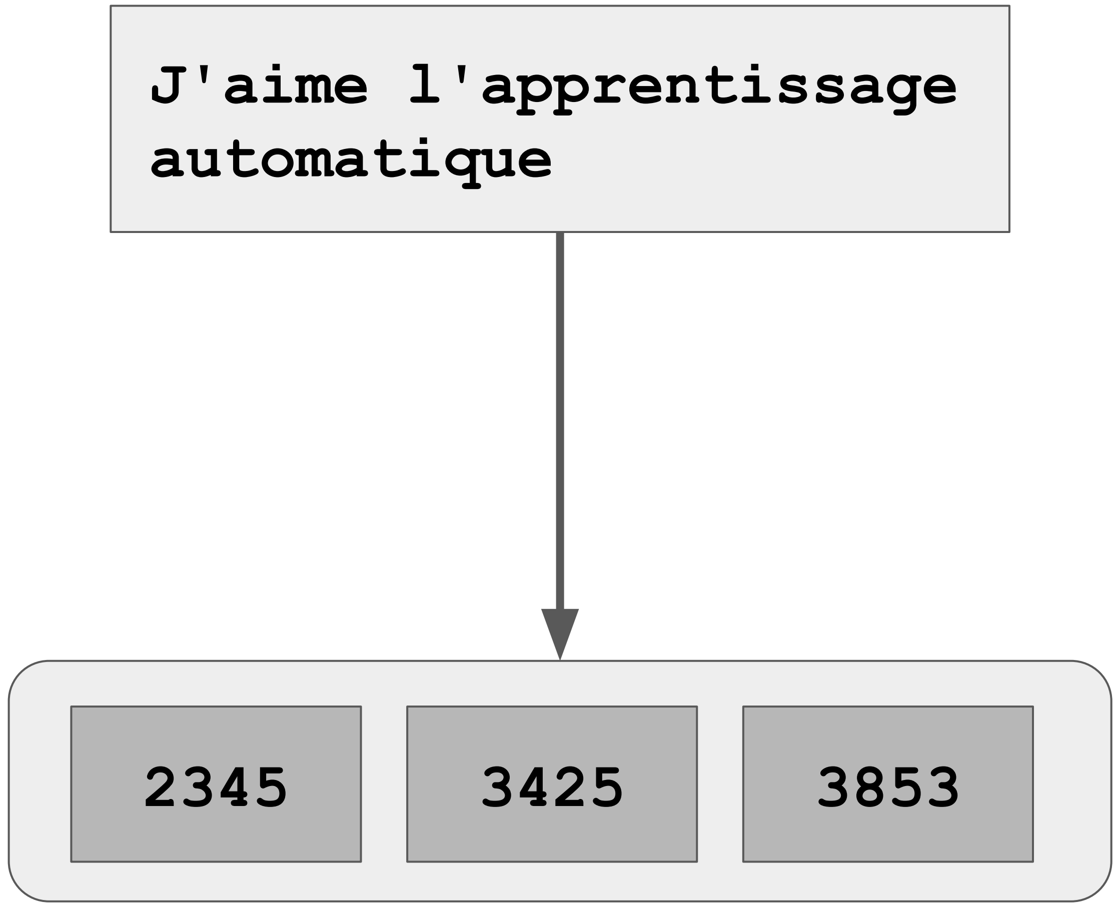
Soft Prompts

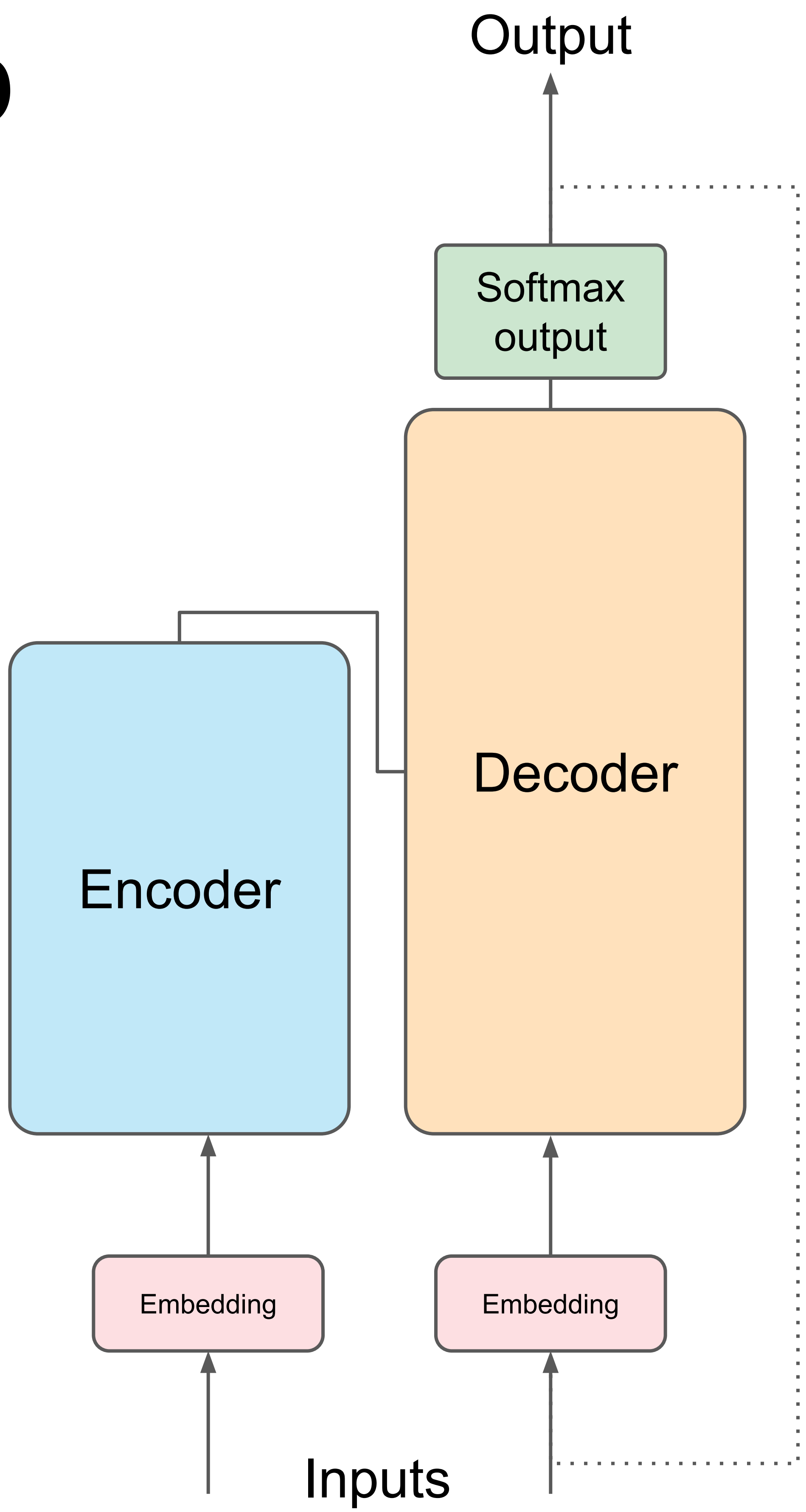
Prompt Tuning

Source: Lialin et al. 2023, "Scaling Down to Scale Up: A Guide to Parameter-Efficient Fine-Tuning",

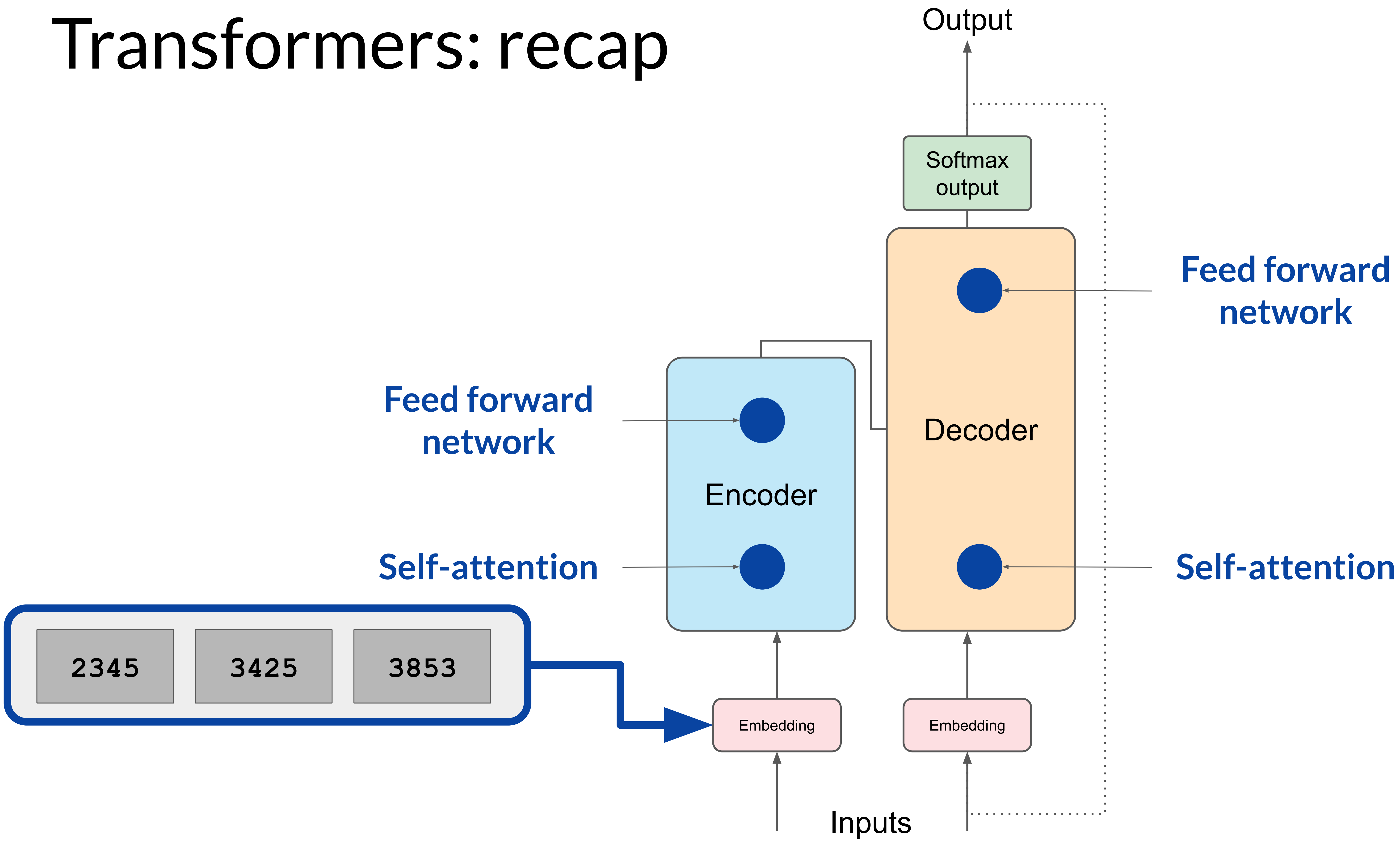
Low-Rank Adaptation of Large Language Models (LoRA)

Transformers: recap

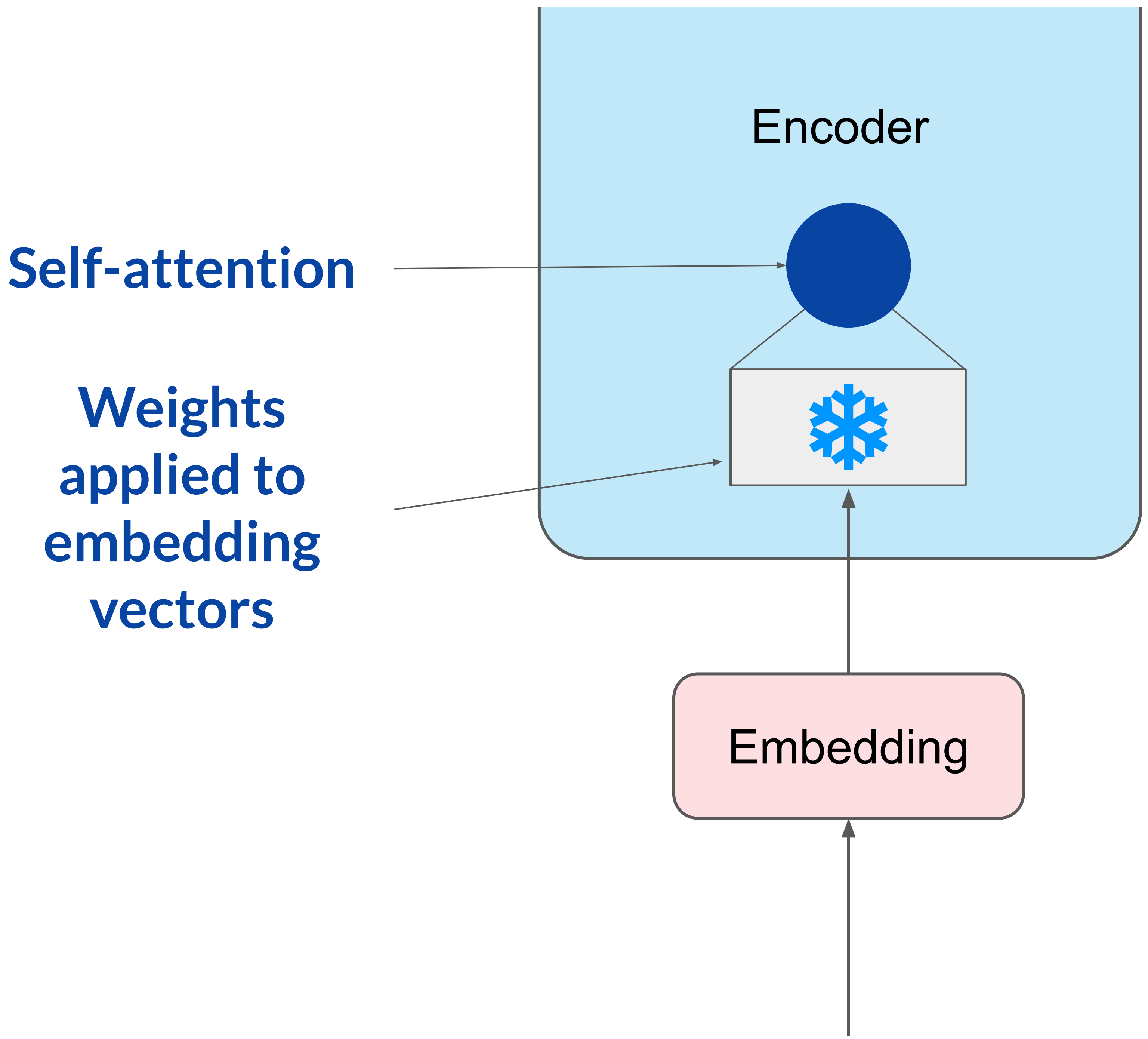




Transformers: recap

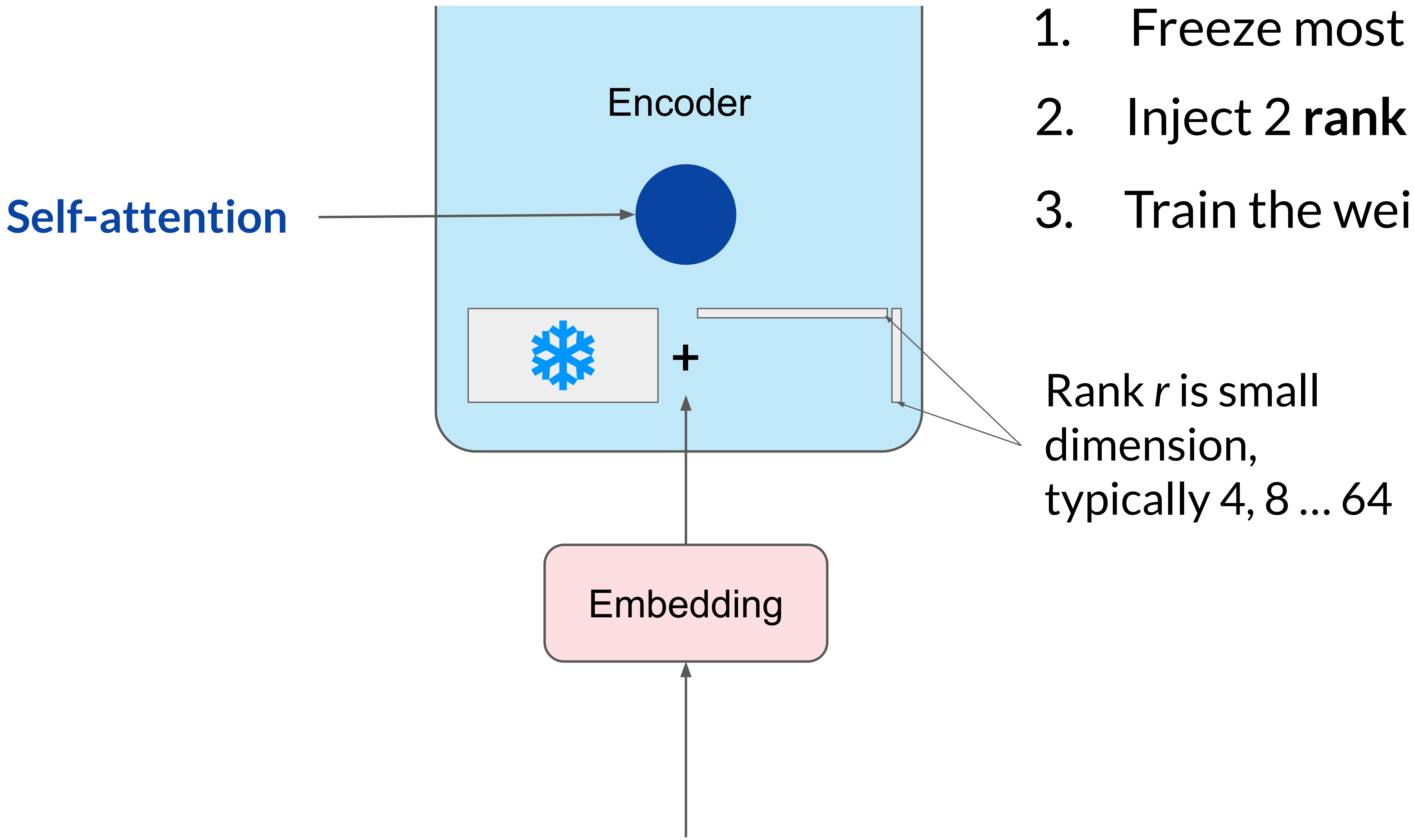


LoRA: Low Rank Adaption of LLMs



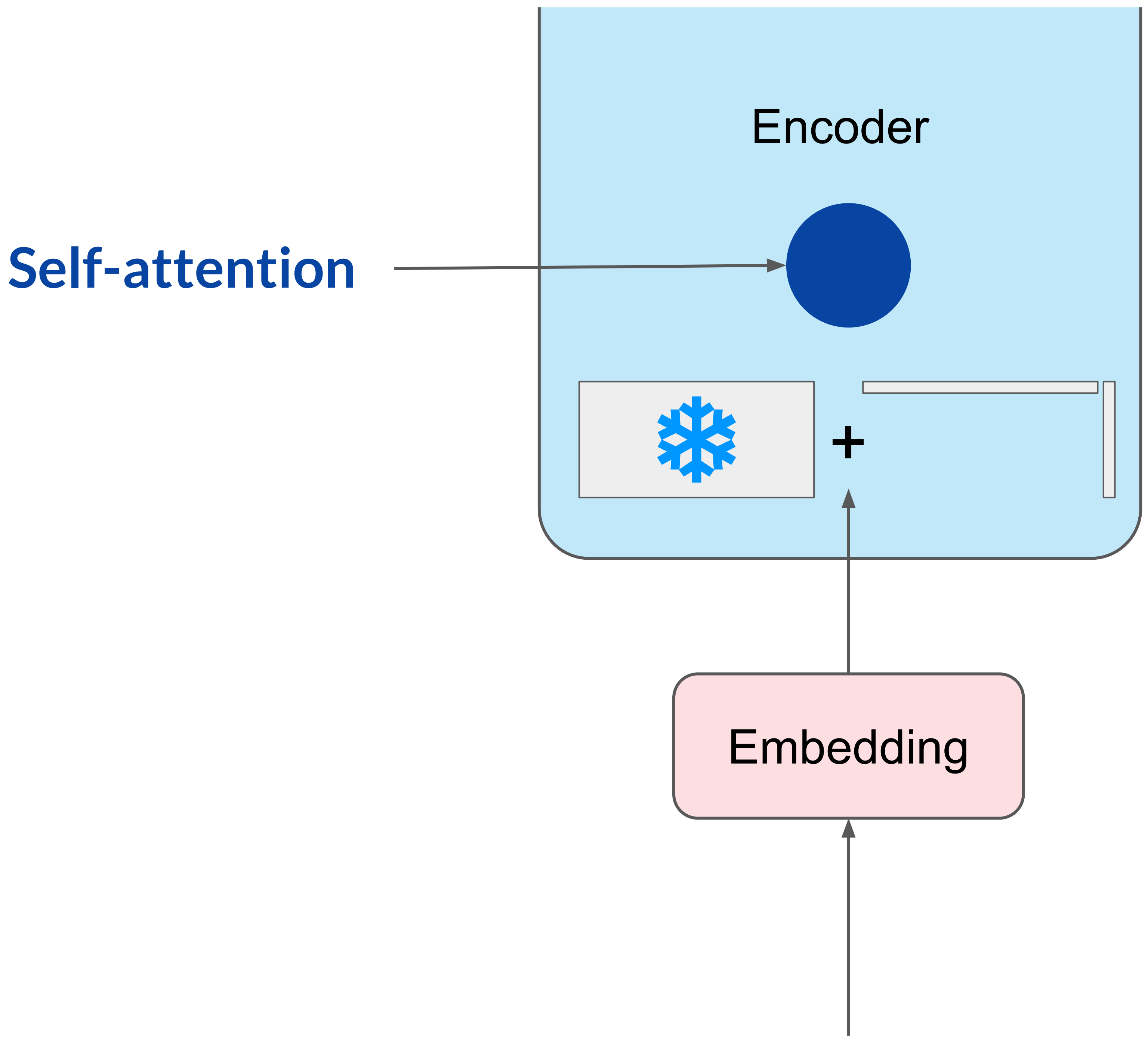
1. Freeze most of the original LLM weights.

LoRA: Low Rank Adaption of LLMs



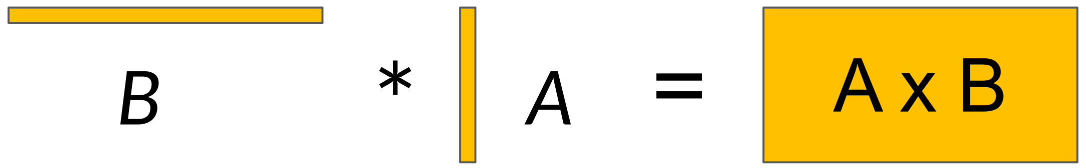
1. Freeze most of the original LLM weights.
2. Inject 2 **rank decomposition matrices**
3. Train the weights of the smaller matrices

LoRA: Low Rank Adaption of LLMs

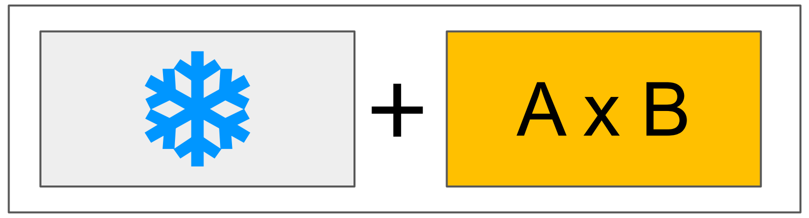


1. Freeze most of the original LLM weights.
2. Inject 2 **rank decomposition matrices**
3. Train the weights of the smaller matrices

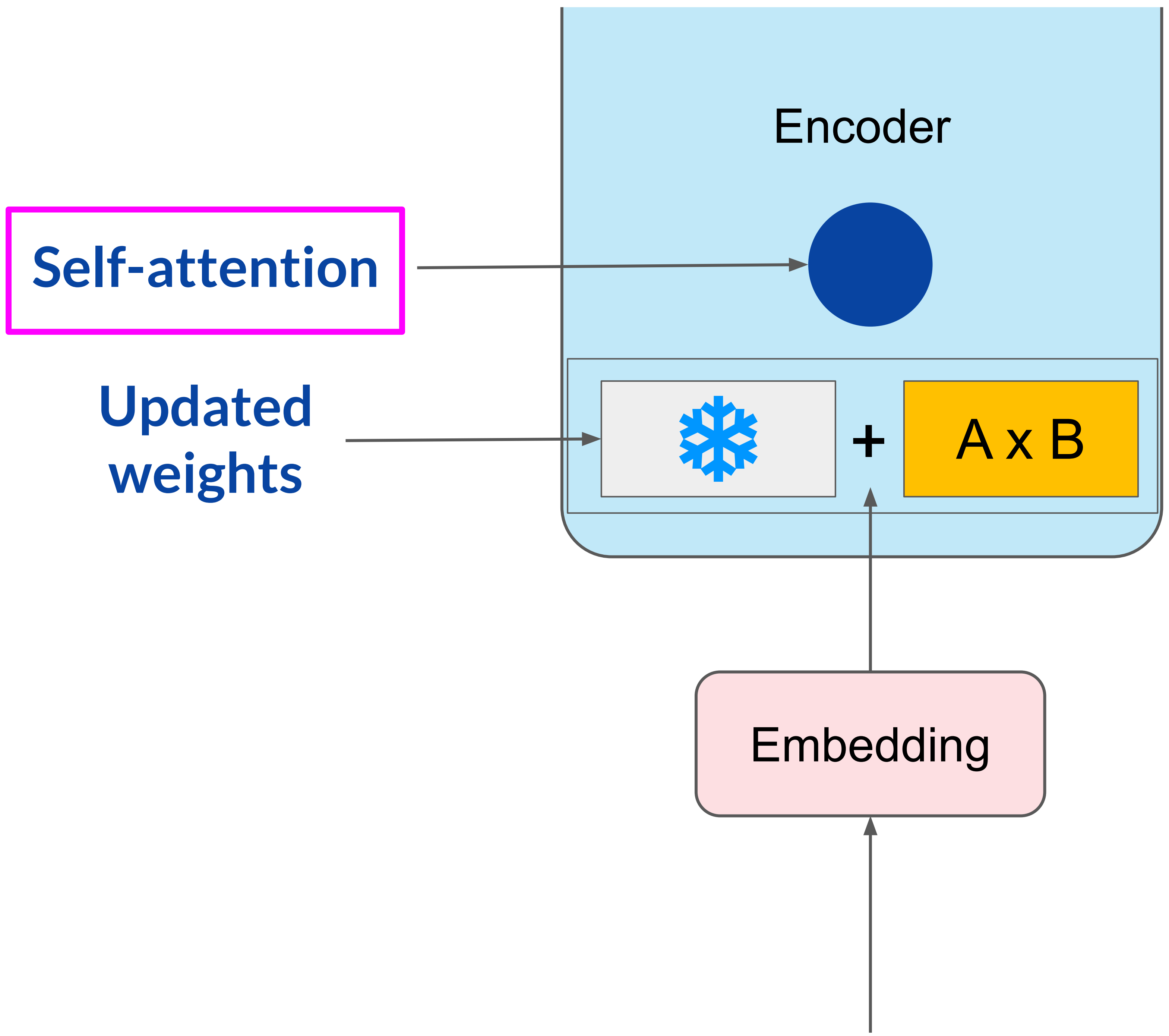
Steps to update model for inference
1. Matrix multiply the low rank matrices



2. Add to original weights



LoRA: Low Rank Adaption of LLMs



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Steps to update model for inference:
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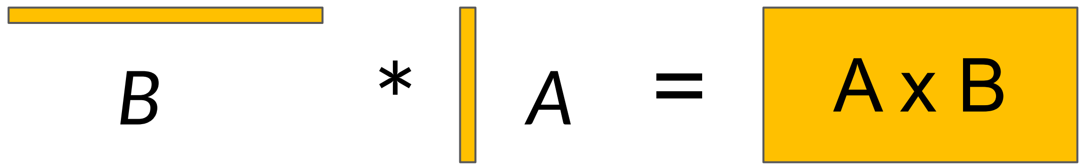

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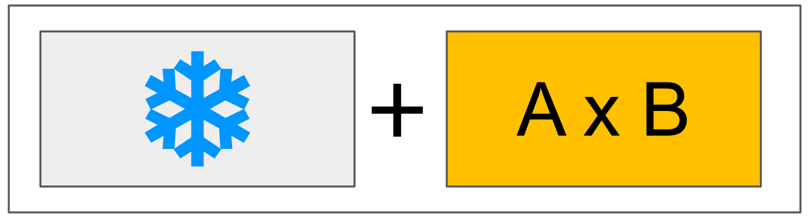
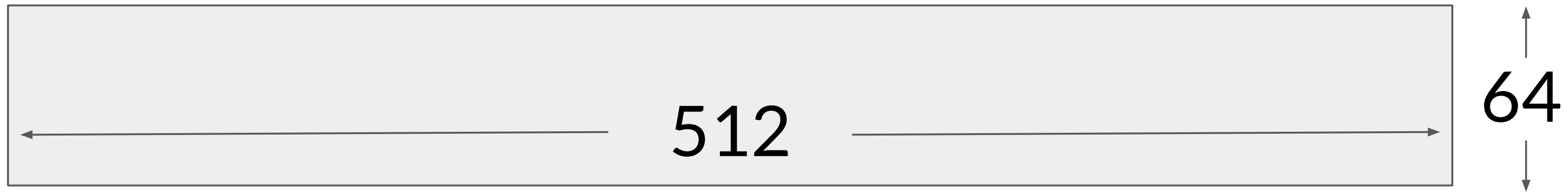


Concrete example using base Transformer as reference

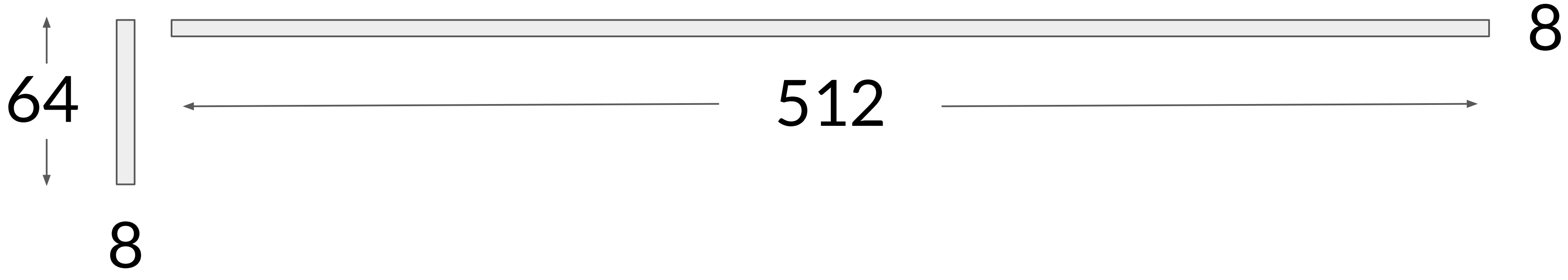
Use the base Transformer model presented by Vaswani et al. 2017:

- Transformer weights have dimensions $d \times k = 512 \times 64$
- So 512 x 64 = 32,768 trainable parameters



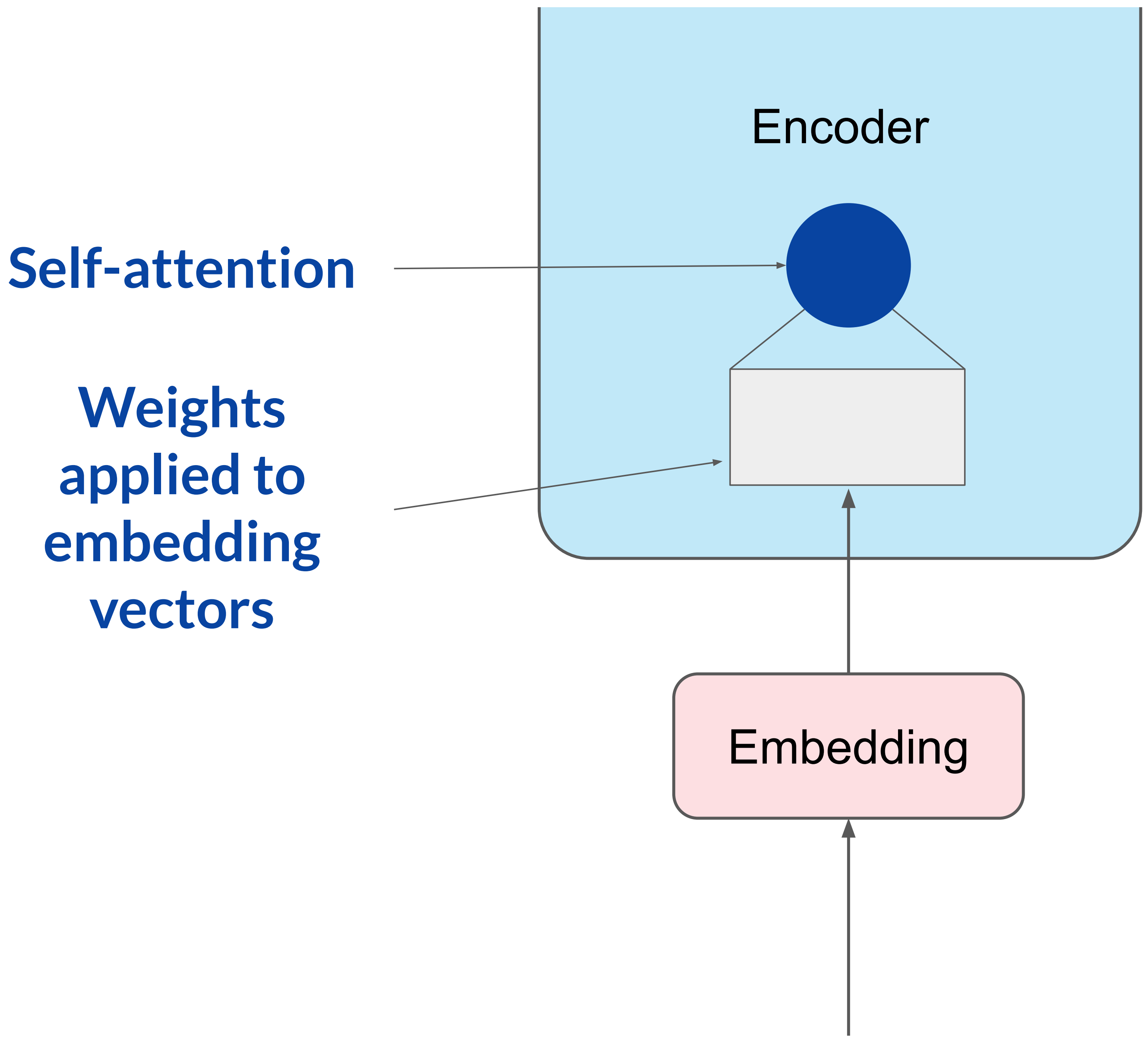
In LoRA with rank $r = 8$:

- A has dimensions $r \times k = 8 \times 64 = 512$ parameters
- B has dimension $d \times r = 512 \times 8 = 4{,}096$ trainable parameters



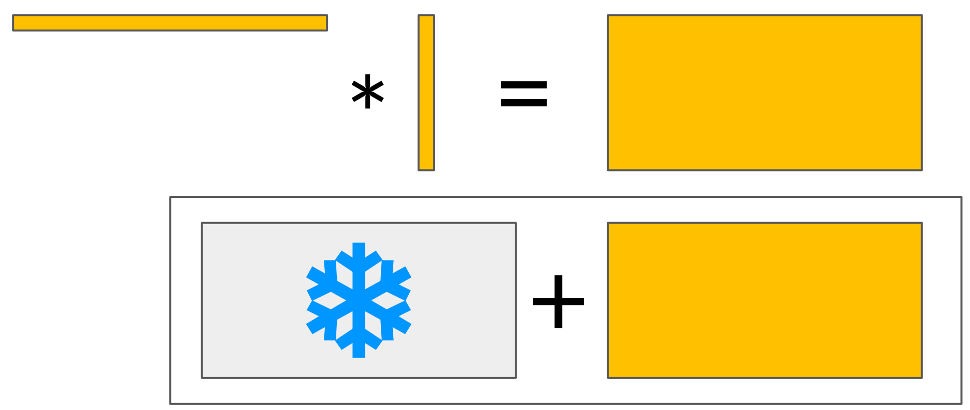
86% reduction in parameters to train!

LoRA: Low Rank Adaption of LLMs

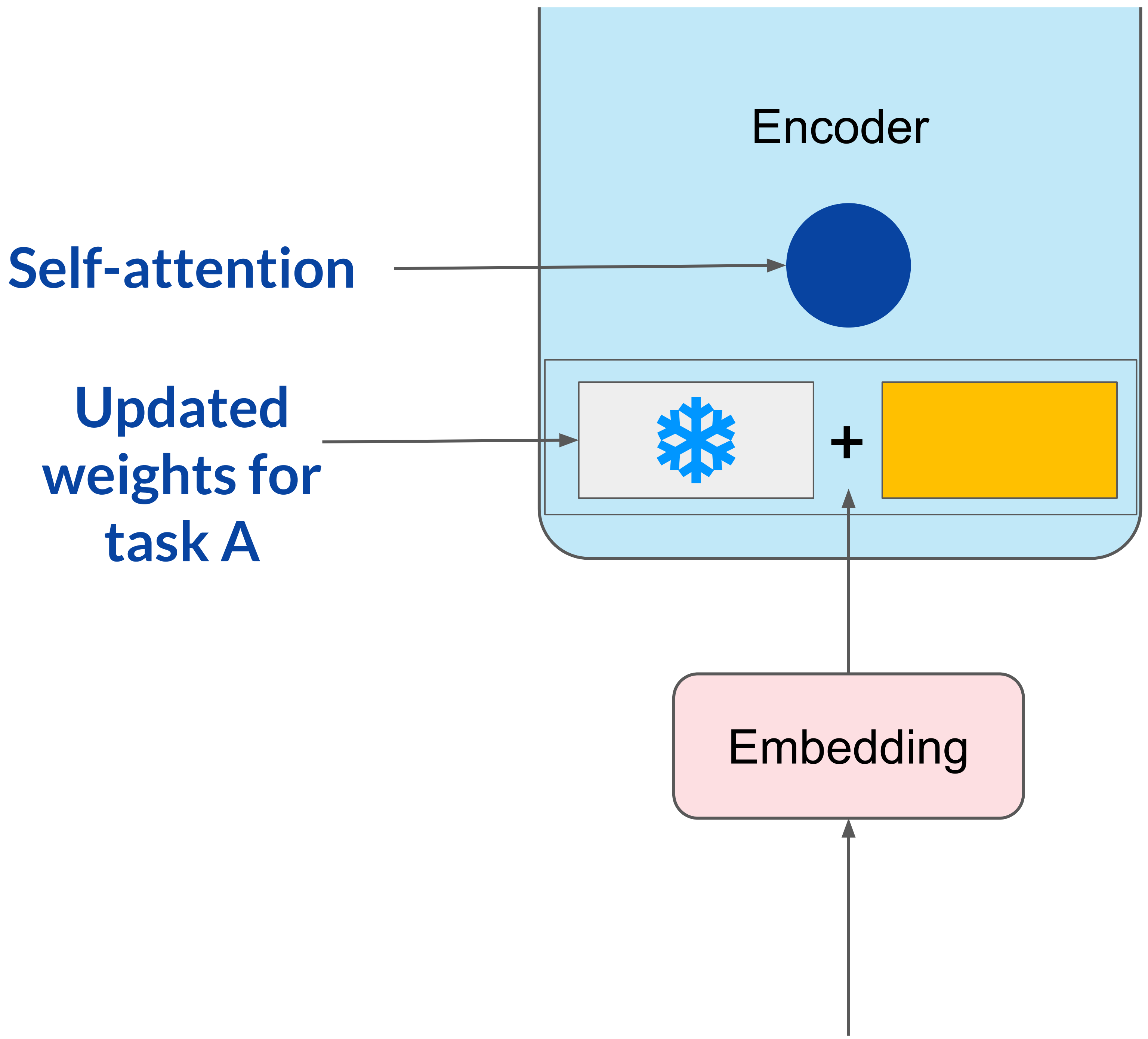


1. Train different rank decomposition matrices for different tasks
2. Update weights before inference

Task A



LoRA: Low Rank Adaption of LLMs



1. Train different rank decomposition matrices for different tasks
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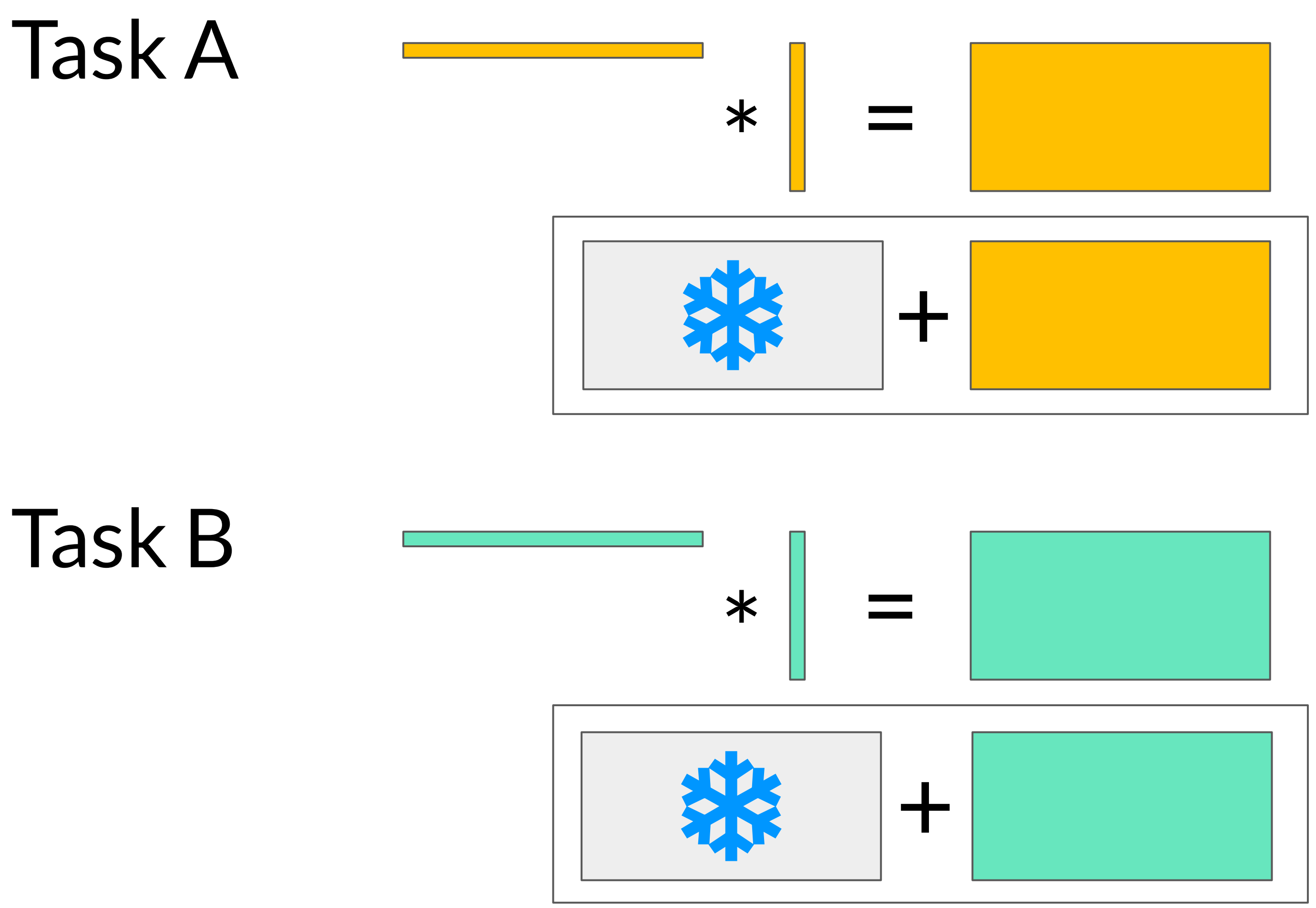
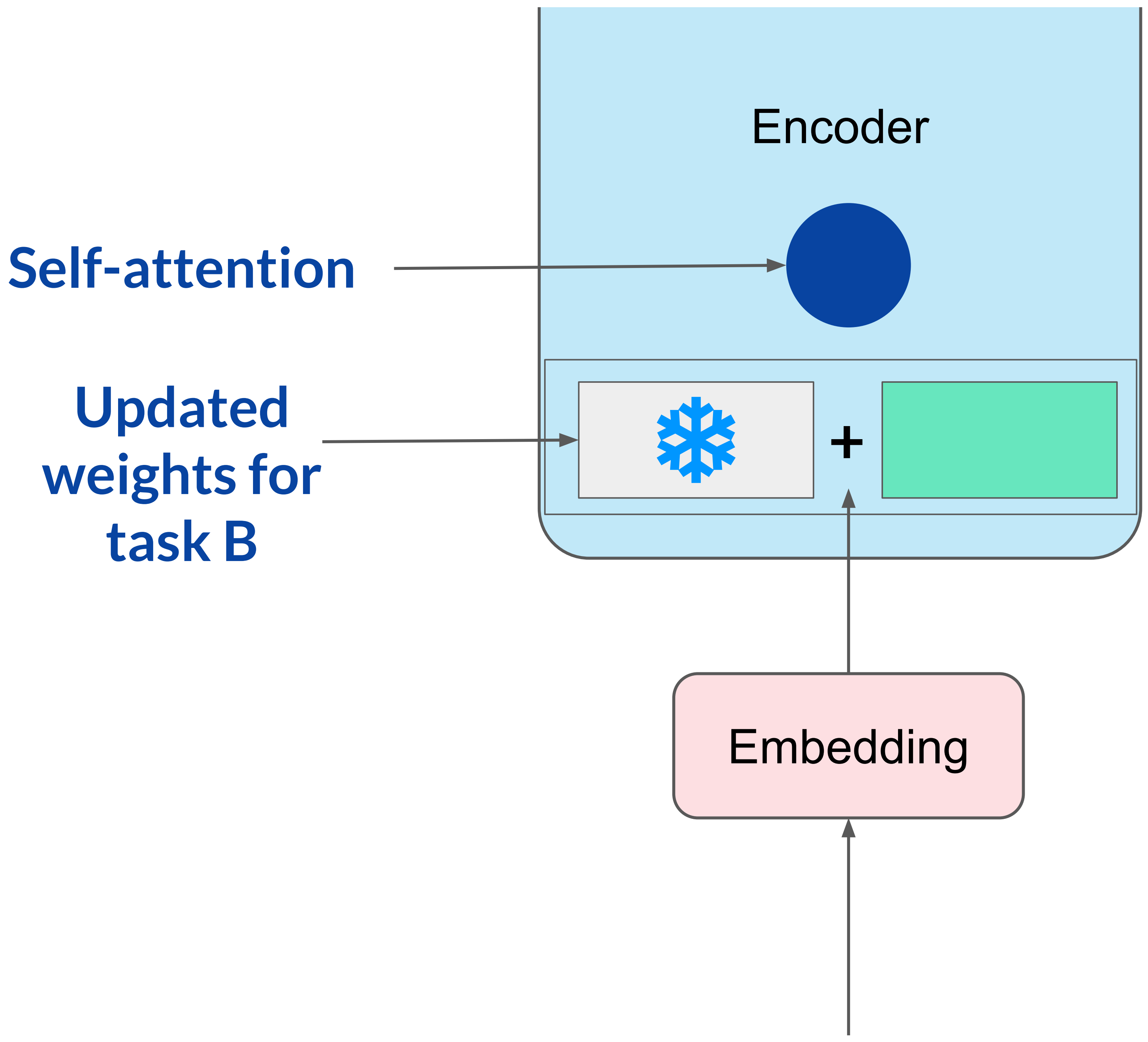


LoRA: Low Rank Adaption of LLMs



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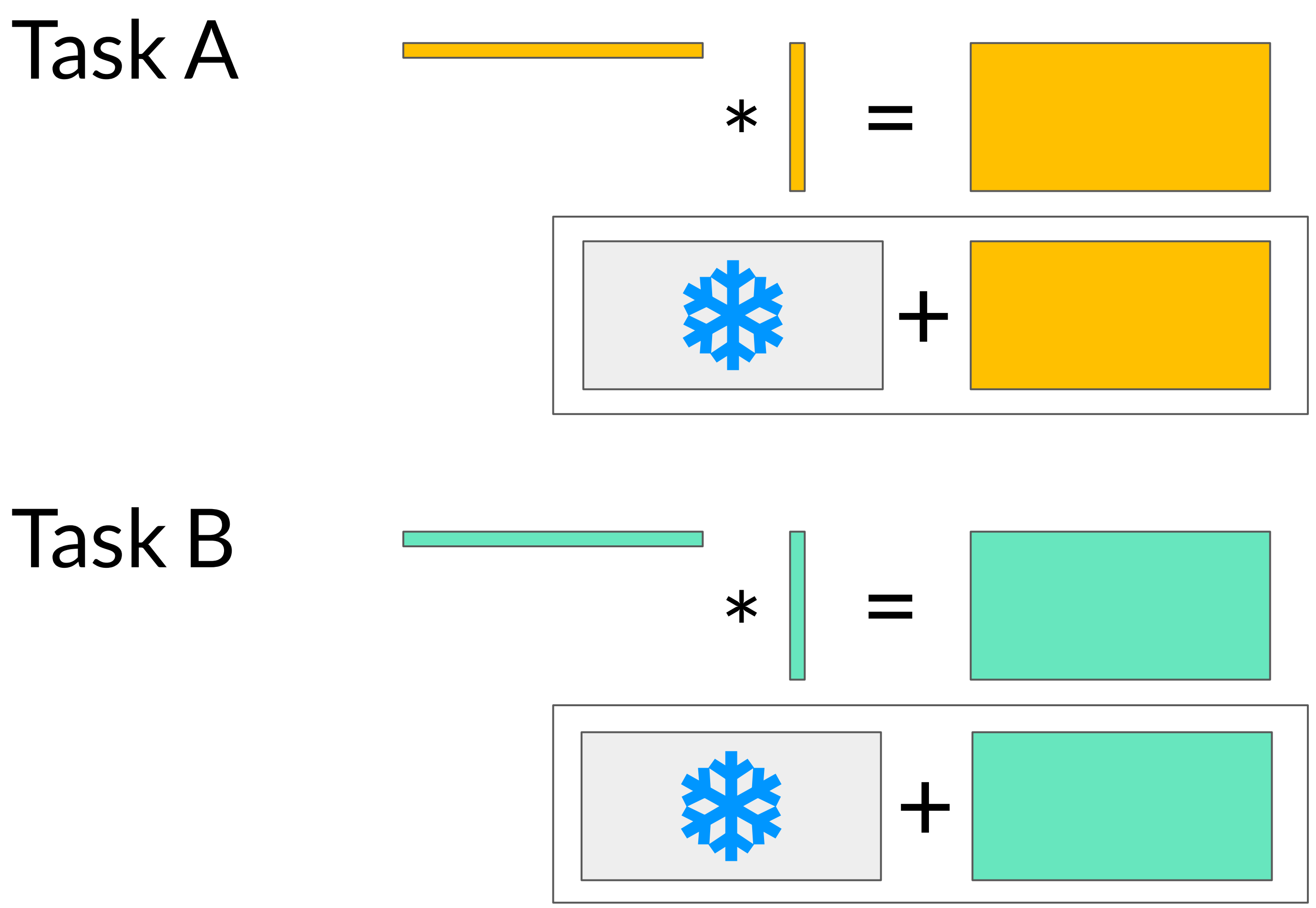


Sample ROUGE metrics for full vs. LoRA fine-tuning

Base model ROUGE

Full fine-tune ROUGE

FLAN-T5

Dialog summarization

```
flan_t5_base
{'rouge1': 0.2334,
 'rouge2': 0.0760,
 'rougeL': 0.2014,
 'rougeLsum': 0.2015}
```

Baseline score

Sample ROUGE metrics for full vs. LoRA fine-tuning

FLAN-T5

Dialog summarization

Base model ROUGE

```
flan_t5_base
{'rouge1': 0.2334,
 'rouge2': 0.0760,
 'rougeL': 0.2014,
 'rougeLsum': 0.2015}
```

Baseline score

+80.63%

Full fine-tune ROUGE

```
flan_t5_base_instruct_full
{'rouge1': 0.4216,
 'rouge2': 0.1804,
 'rougeL': 0.3384,
 'rougeLsum': 0.3384}
```

-3.20%

LoRA fine tune ROUGE

```
flan_t5_base_instruct_lora
{'rouge1': 0.4081,
 'rouge2': 0.1633,
 'rougeL': 0.3251,
 'rougeLsum': 0.3249}
```

Choosing the LoRA rank

Rank r	val_loss	BLEU	NIST	METEOR	ROUGE_L	CIDEr
1	1.23	68.72	8.7215	0.4565	0.7052	2.4329
2	1.21	69.17	8.7413	0.4590	0.7052	2.4639
4	1.18	**70.38**	**8.8439**	**0.4689**	0.7186	**2.5349**
8	1.17	69.57	8.7457	0.4636	**0.7196**	2.5196
16	**1.16**	69.61	8.7483	0.4629	0.7177	2.4985
32	**1.16**	69.33	8.7736	0.4642	0.7105	2.5255
64	**1.16**	69.24	8.7174	0.4651	0.7180	2.5070
128	**1.16**	68.73	8.6718	0.4628	0.7127	2.5030
256	**1.16**	68.92	8.6982	0.4629	0.7128	2.5012
512	**1.16**	68.78	8.6857	0.4637	0.7128	2.5025
1024	1.17	69.37	8.7495	0.4659	0.7149	2.5090

- Effectiveness of higher rank appears to plateau
- Relationship between rank and dataset size needs more empirical data

Source: Hu et al. 2021, "LoRA: Low-Rank Adaptation of Large Language Models"

QLoRA: Quantized LoRA

- Introduces 4-bit NormalFloat (nf4) data type for 4-bit quantization
- Supports double-quantization to reduce memory ~0.4 bits per parameter (~3 GB for a 65B model)
- Unified GPU-CPU memory management reduces GPU memory usage
- LoRA adapters at every layer - not just attention layers
- Minimizes accuracy trade-off

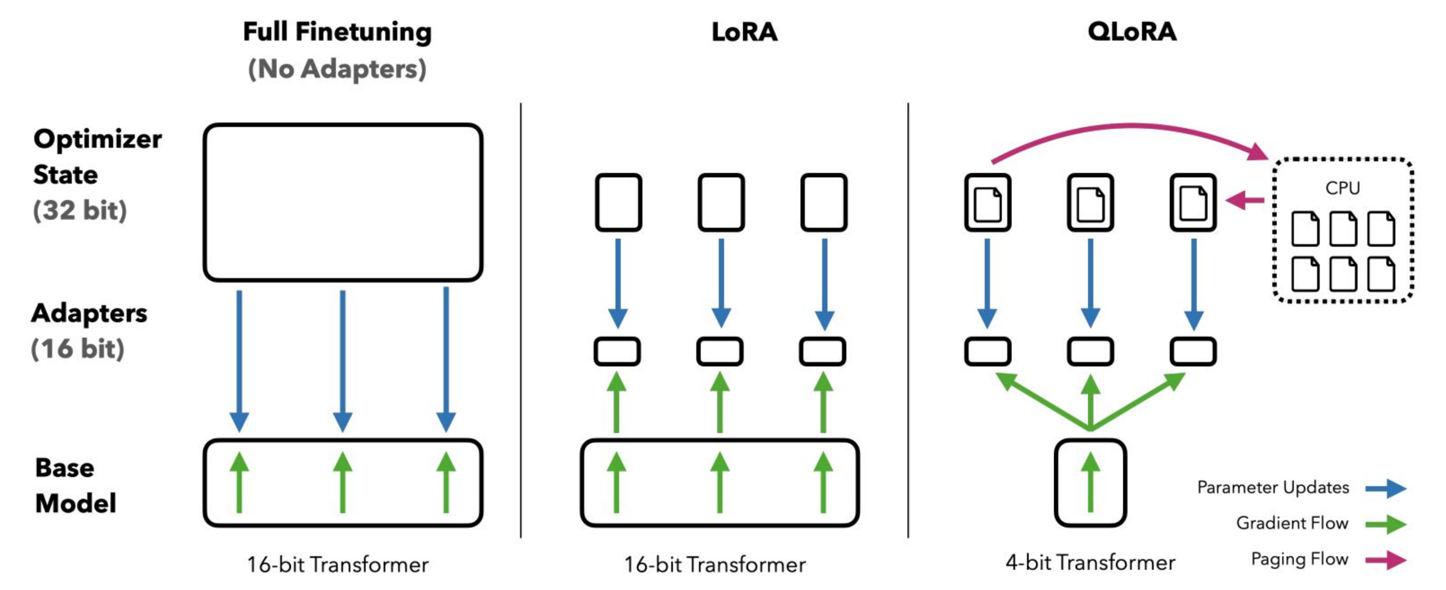


Figure 1: Different finetuning methods and their memory requirements. QLoRA improves over LoRA by quantizing the transformer model to 4-bit precision and using paged optimizers to handle memory spikes.

Source: Dettmers et al. 2023, "QLoRA: Efficient Finetuning of Quantized LLMs"

Prompt tuning with soft prompts

Prompt tuning is **not** prompt engineering!

Prompt

```
Classify this review:
I loved this DVD!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment:
```

Model

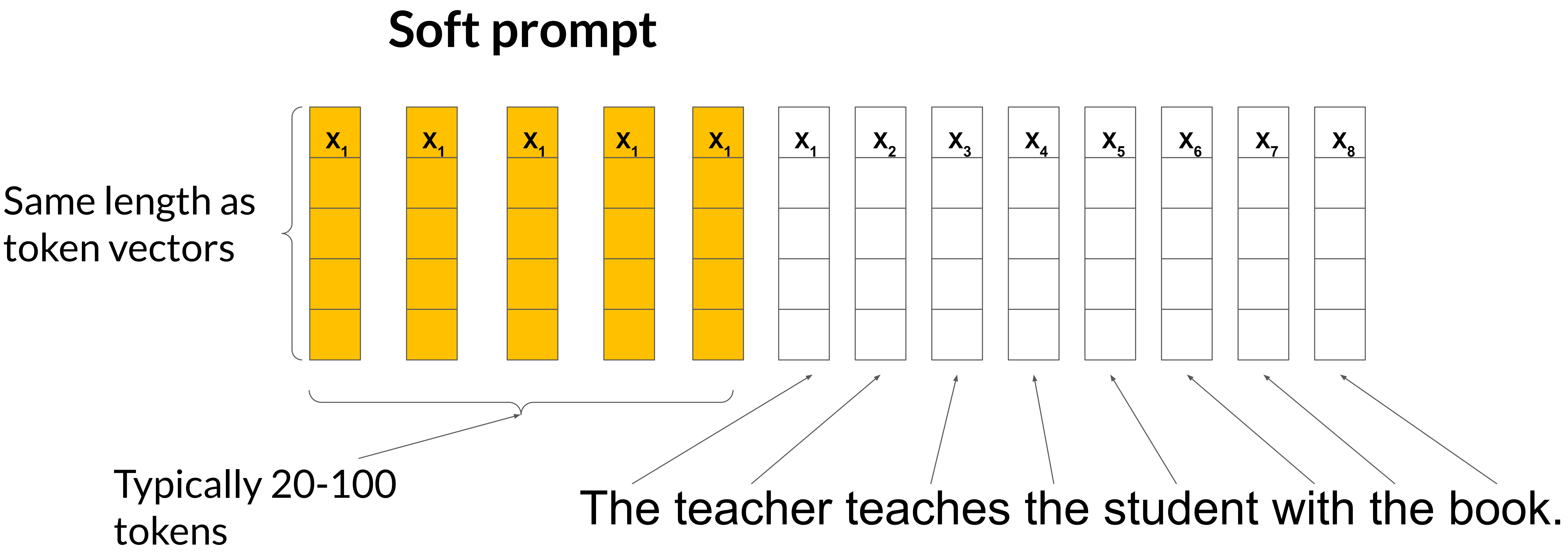
LLM

Completion

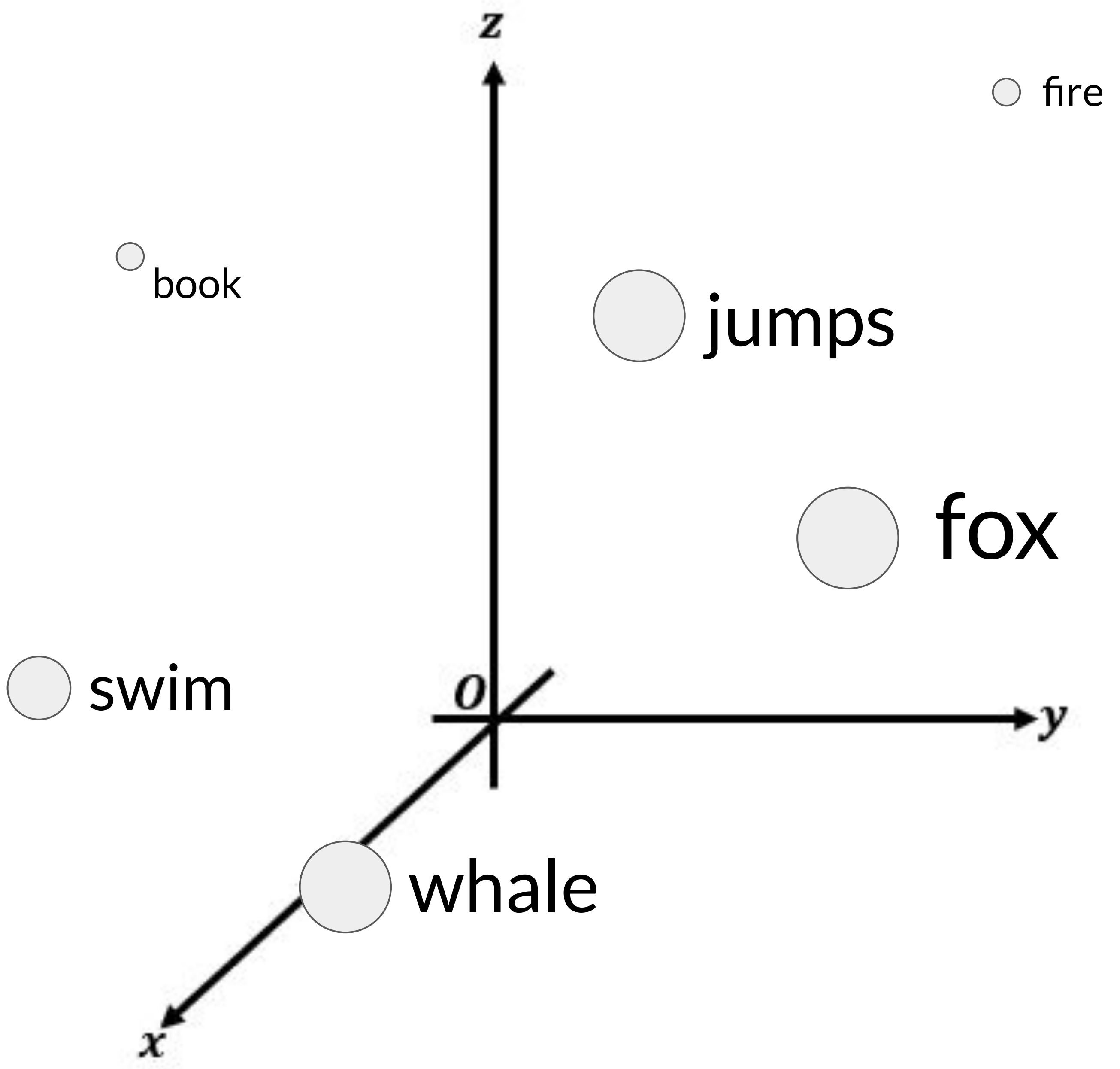
```
Classify this review:
I loved this DVD!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment: Negative
```

One-shot or Few-shot Inference

Prompt tuning adds trainable "soft prompt" to inputs

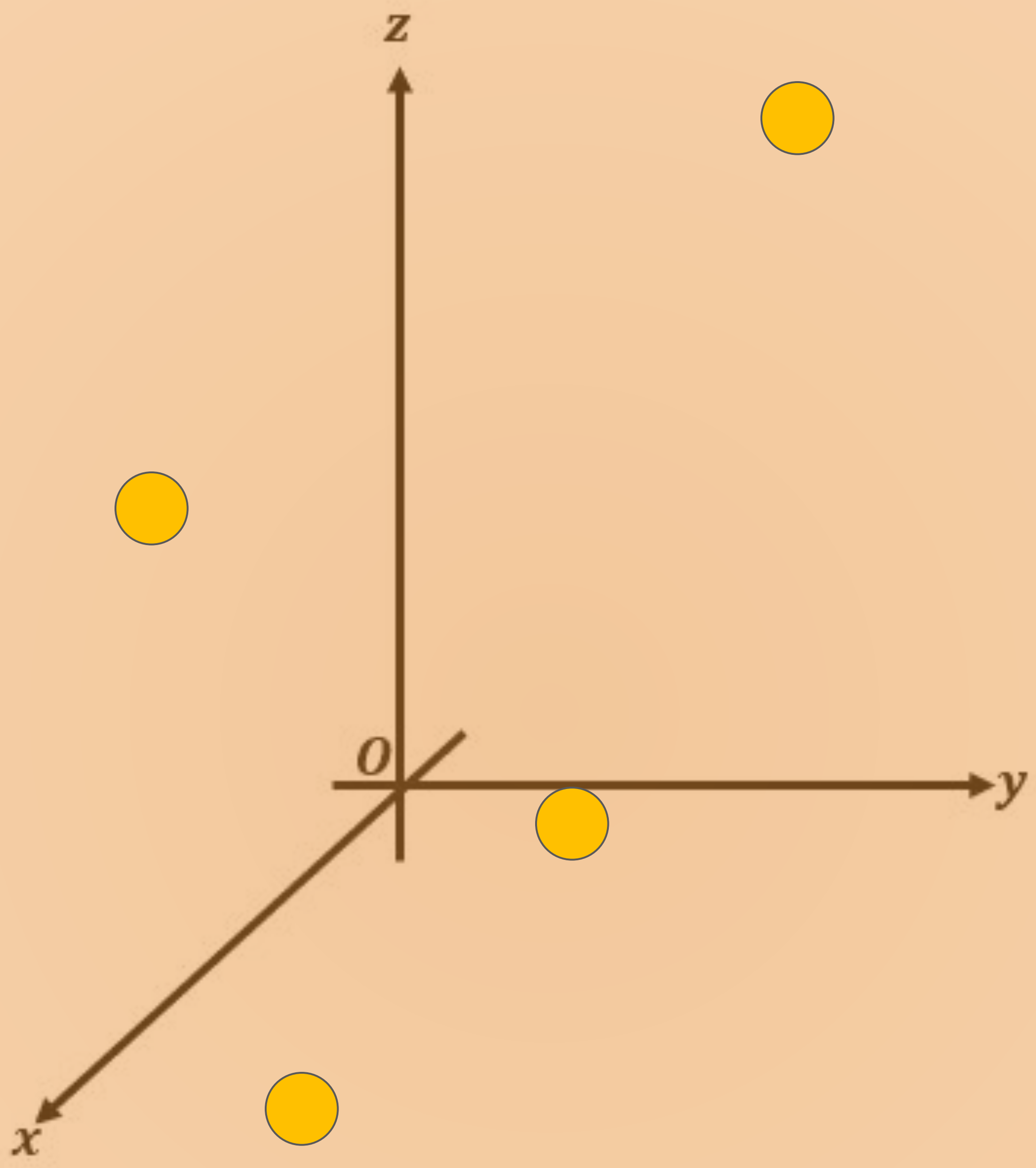


Soft prompts



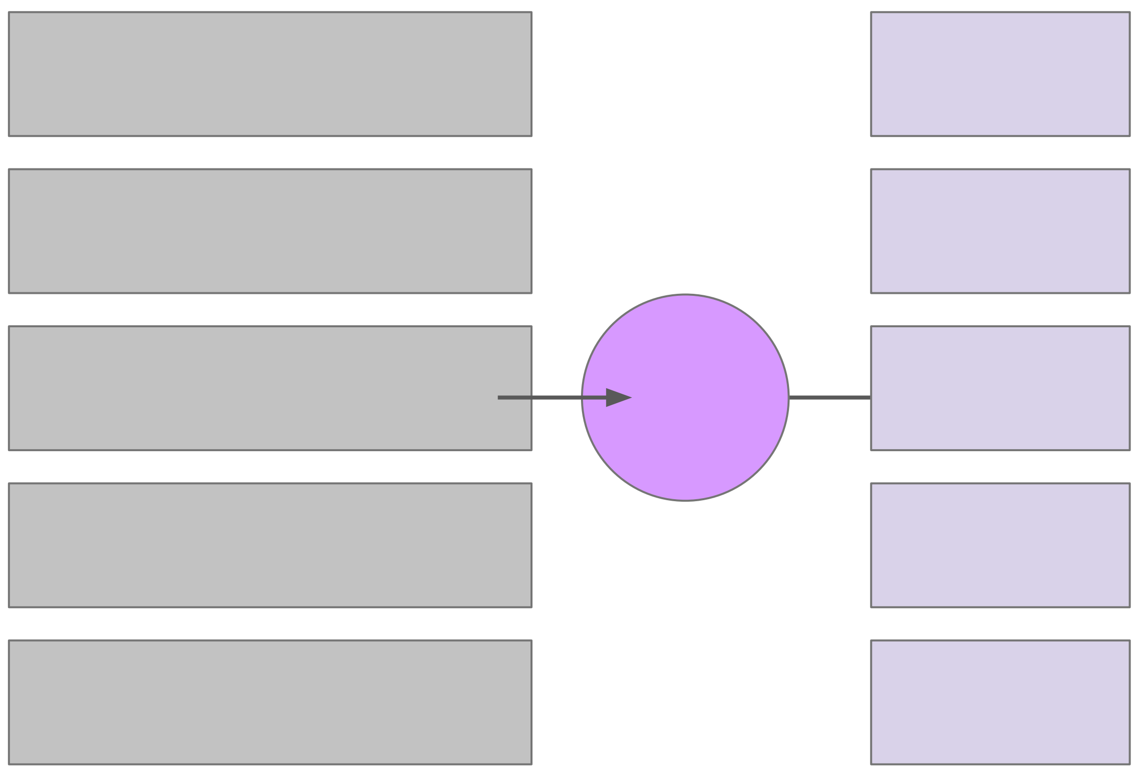
Embeddings of each token exist at unique point in multi-dimensional space

Soft prompts



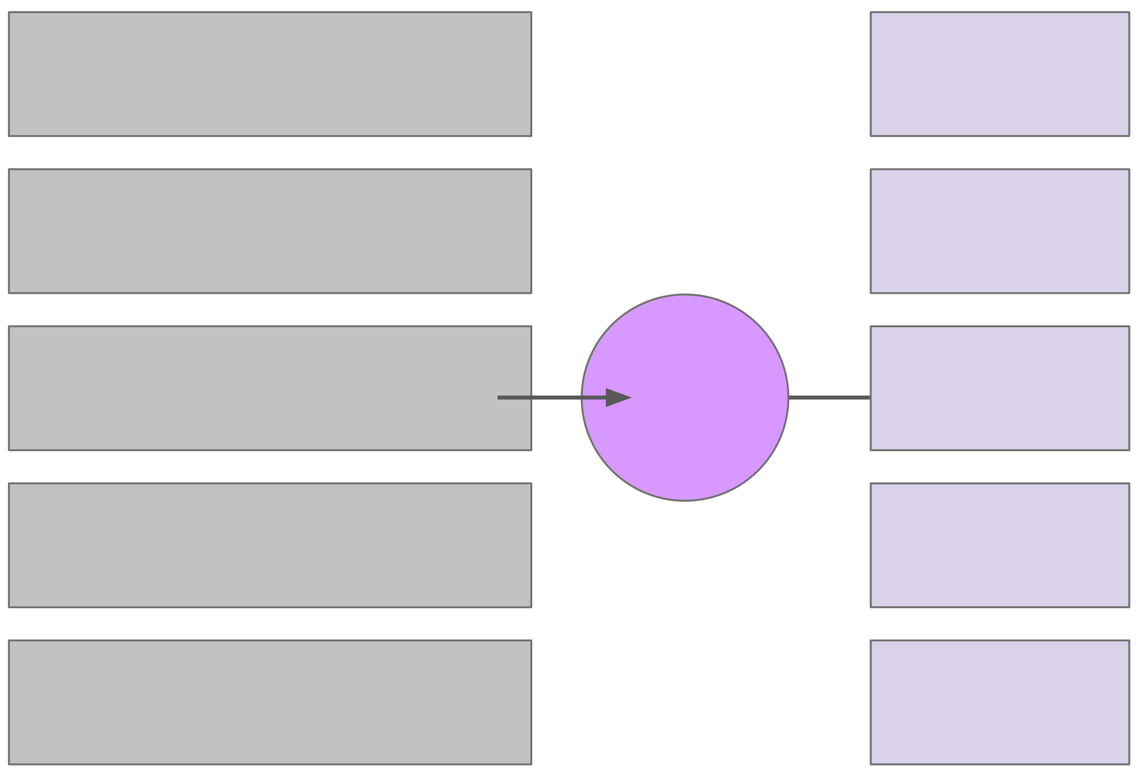
Full Fine-tuning vs prompt tuning

Weights of model updated
during training



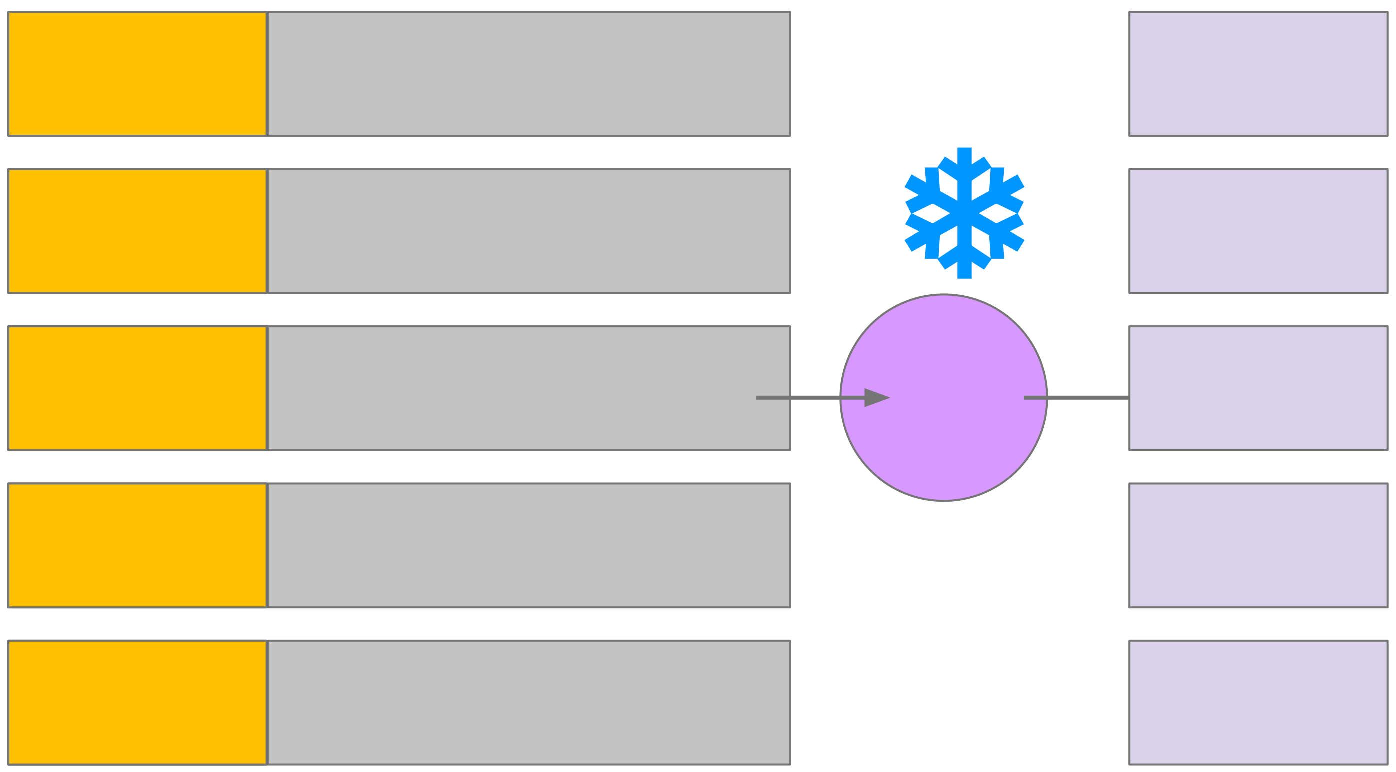
Full Fine-tuning vs prompt tuning

Weights of model updated during training



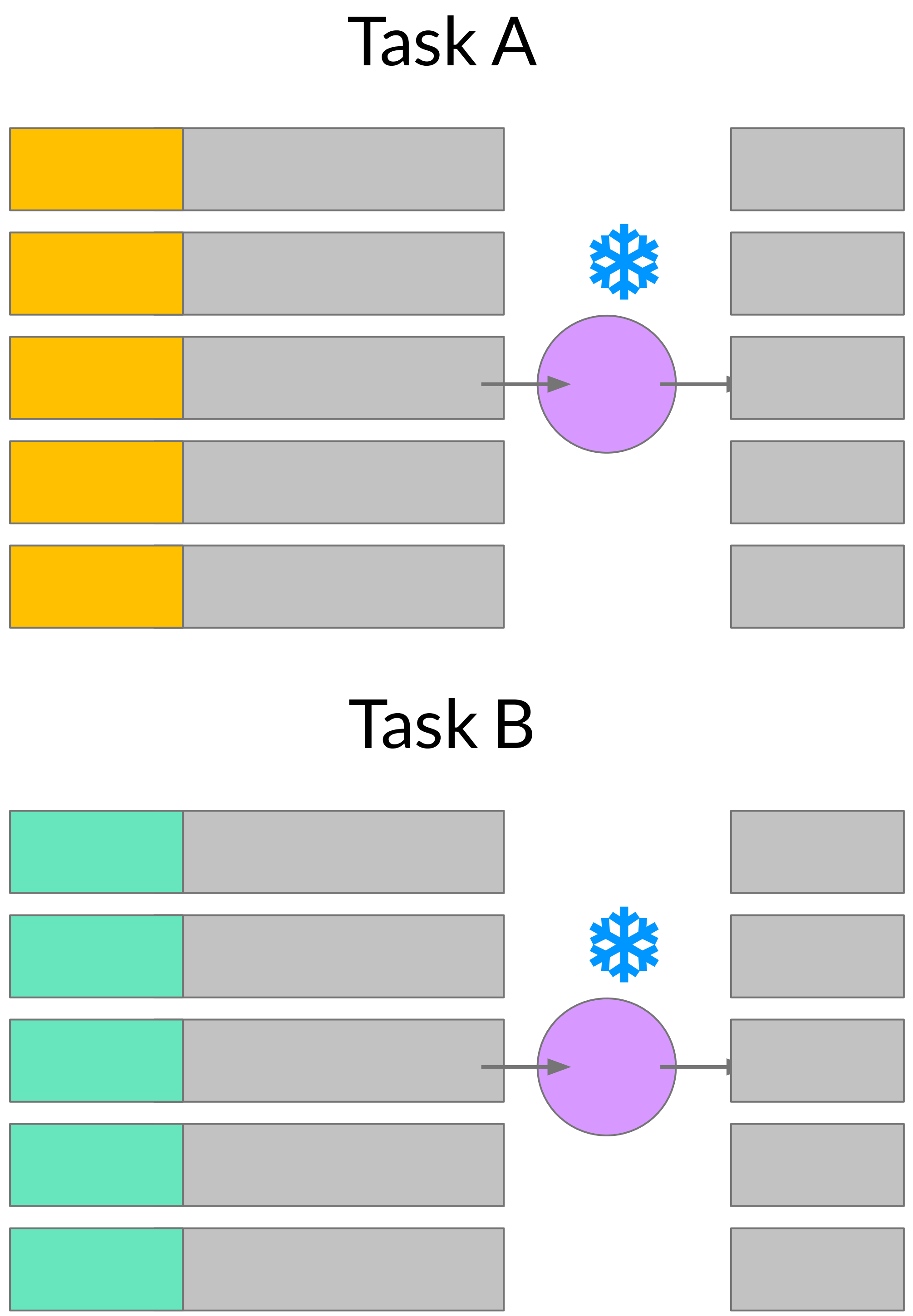
Millions to Billions of parameter updated

Weights of model frozen and soft prompt trained

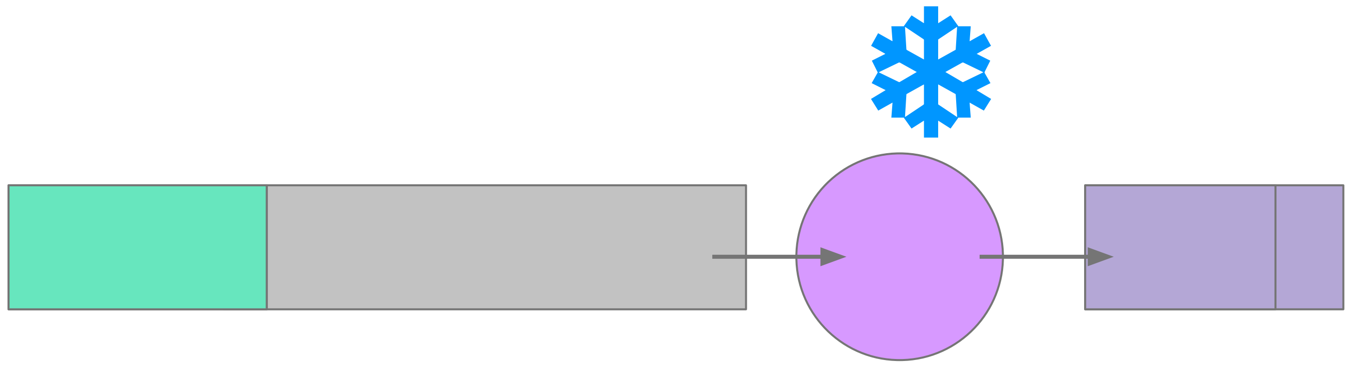


10K - 100K of parameters updated

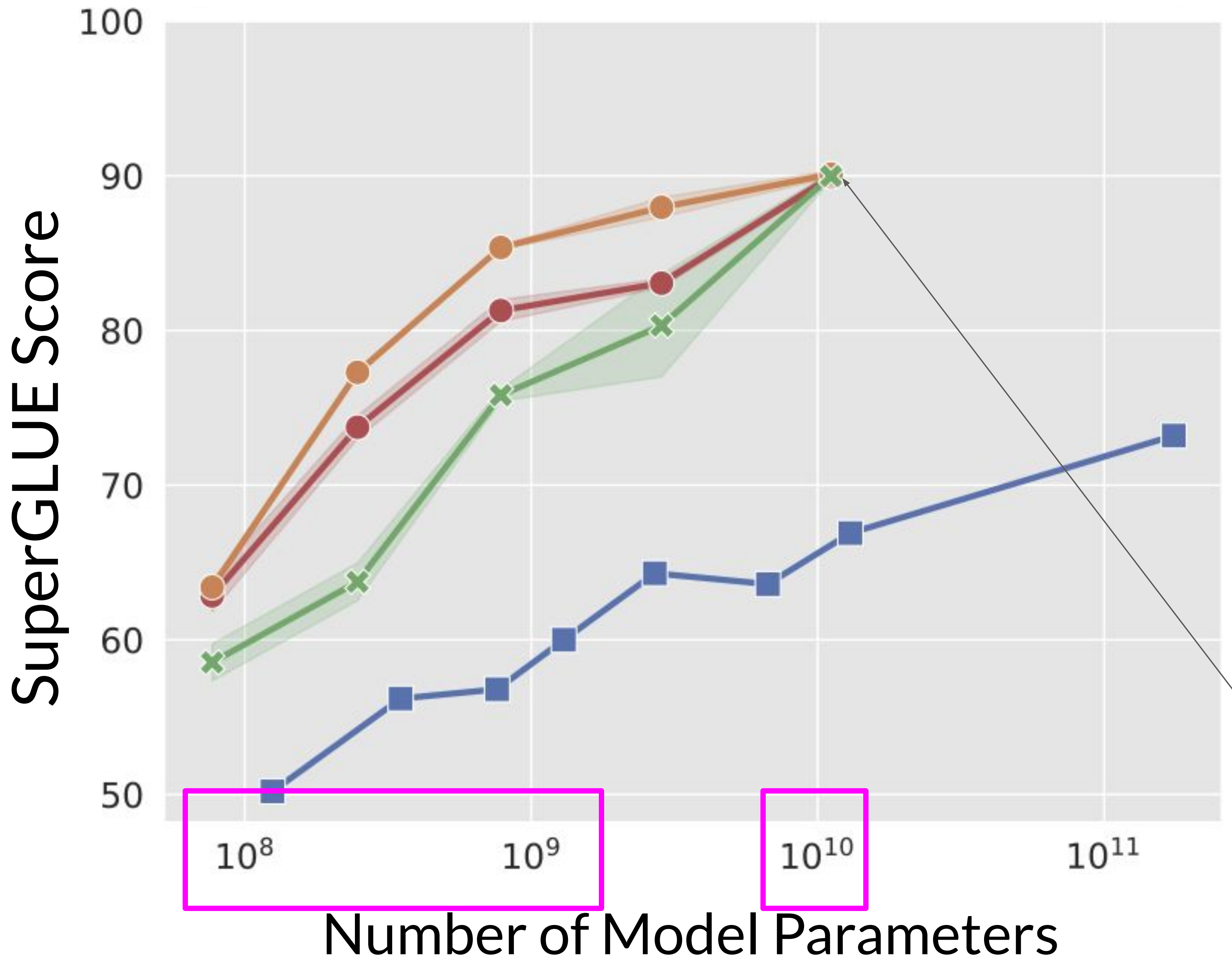
Prompt tuning for multiple tasks



Switch out soft prompt at inference time to change task!



Performance of prompt tuning

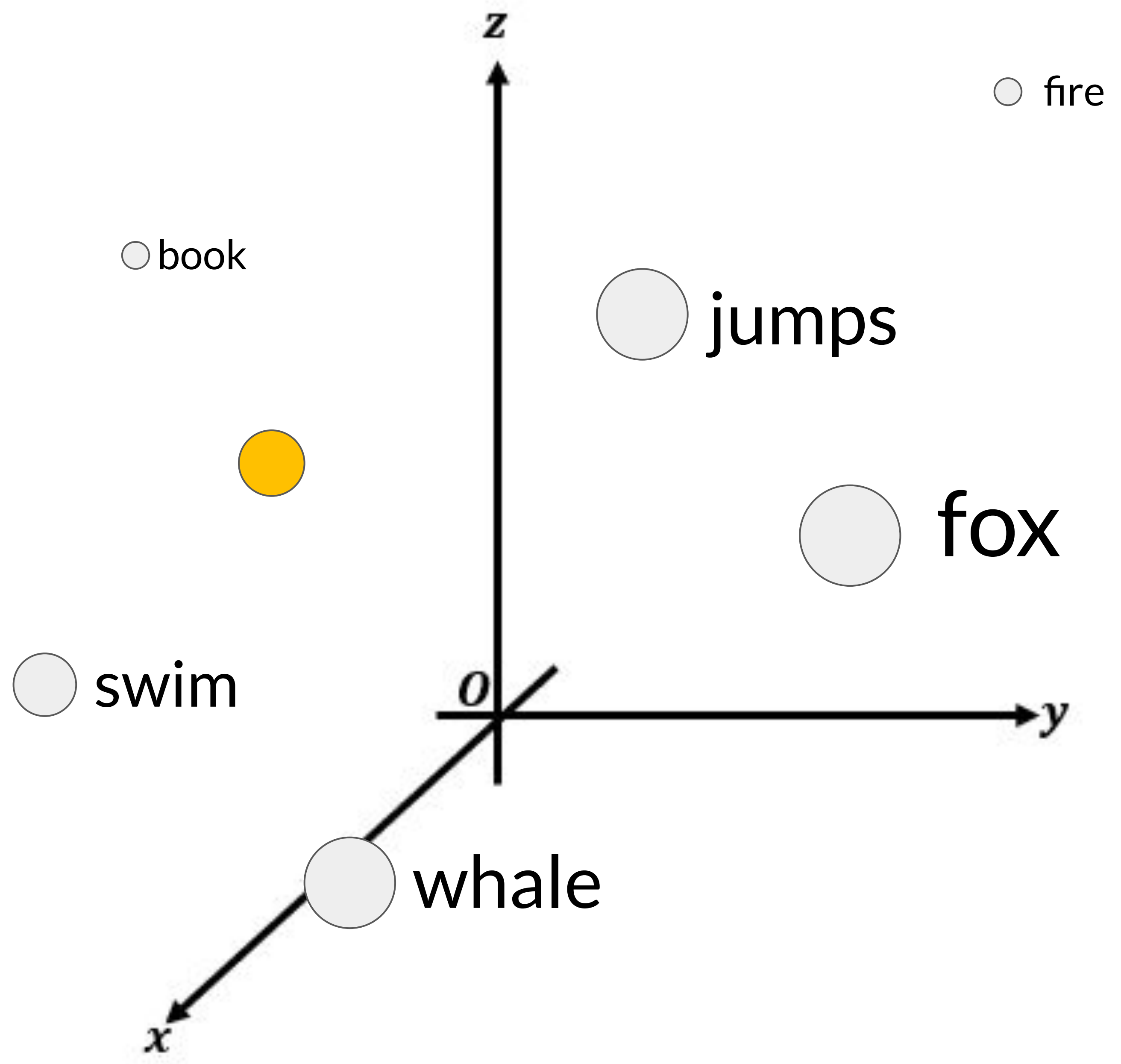


- Full Fine-tuning
- Multi-task Fine-tuning
- Prompt tuning
- Prompt engineering

Prompt tuning can be as effective as full Fine-tuning for larger models!

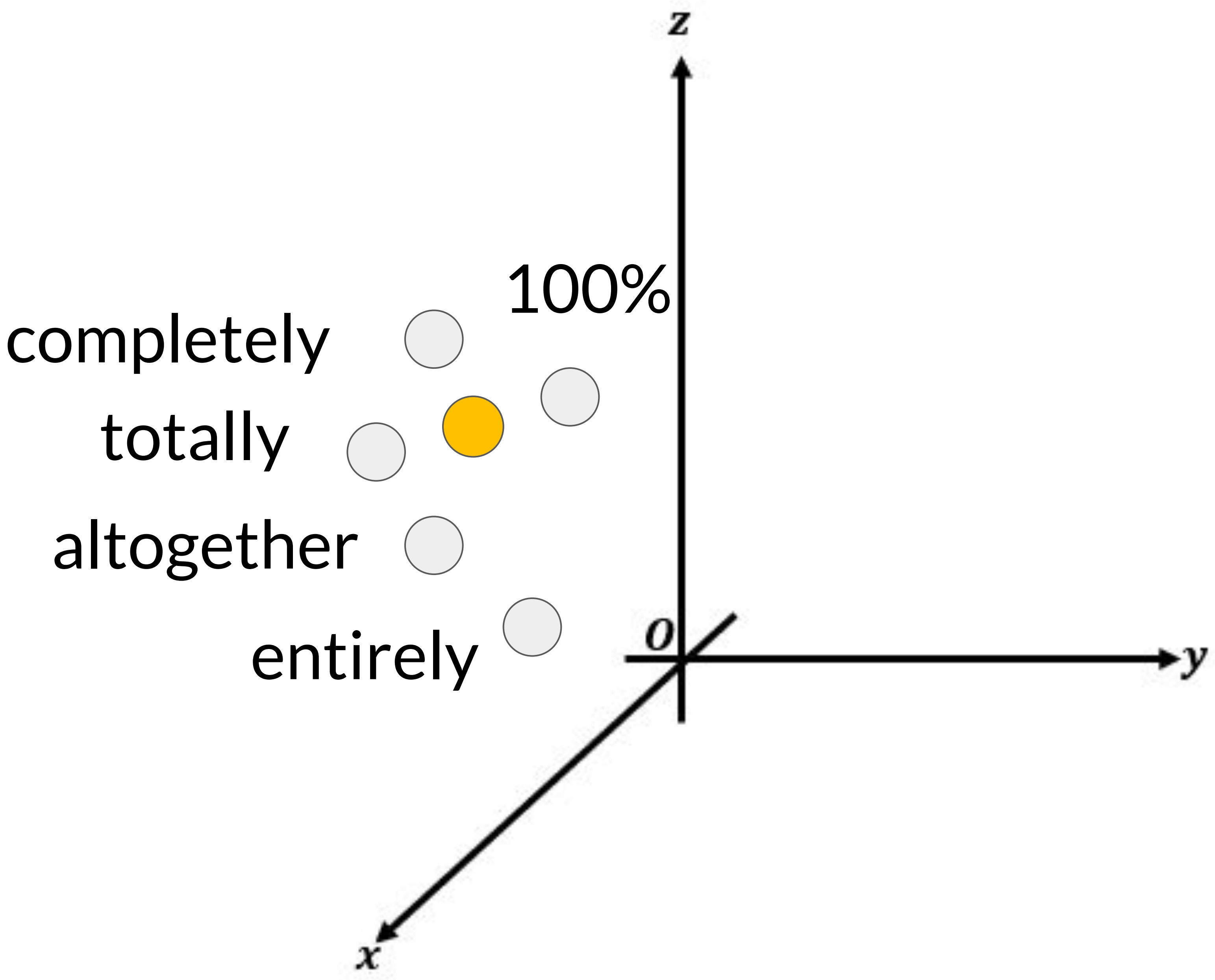
Source: Lester et al. 2021, “The Power of Scale for Parameter-Efficient Prompt Tuning”

Interpretability of soft prompts



Trained soft-prompt embedding does not correspond to a known token…

Interpretability of soft prompts



...but nearest neighbors form a semantic group with similar meanings.

PEFT methods summary

Selective

Select subset of initial LLM parameters to fine-tune

Reparameterization

Reparameterize model weights using a low-rank representation

LoRA

Additive

Add trainable layers or parameters to model

Adapters

Soft Prompts

Prompt Tuning