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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**
- Define the problem

**Select**
- Choose model

**Adapt and align model**
- Prompt engineering
- Fine-tuning
- Align with human feedback
- Evaluate

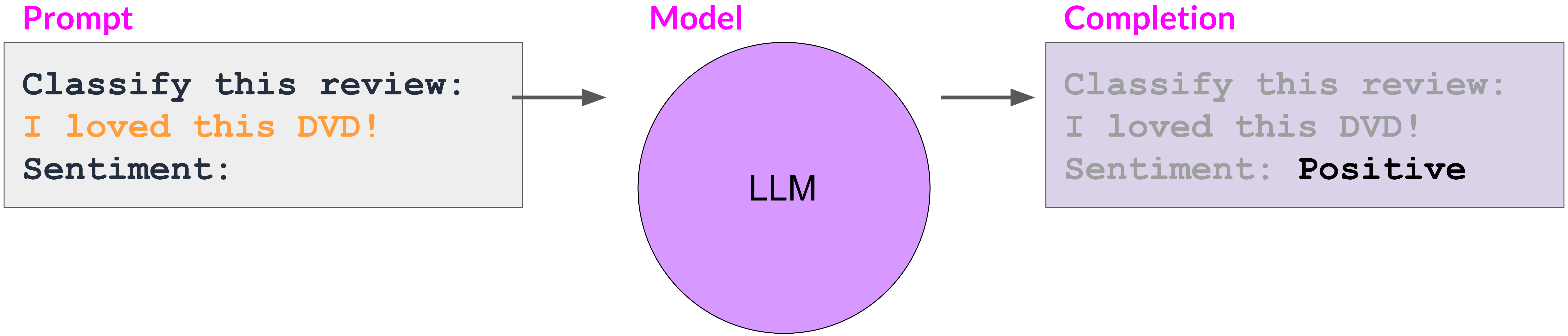
**Application integration**
- Optimize and deploy model for inference
- Augment model and build LLM-powered applications

# GenAI project lifecycle

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

# Fine-tuning an LLM with instruction prompts

# In-context learning (ICL) - zero shot inference



# 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

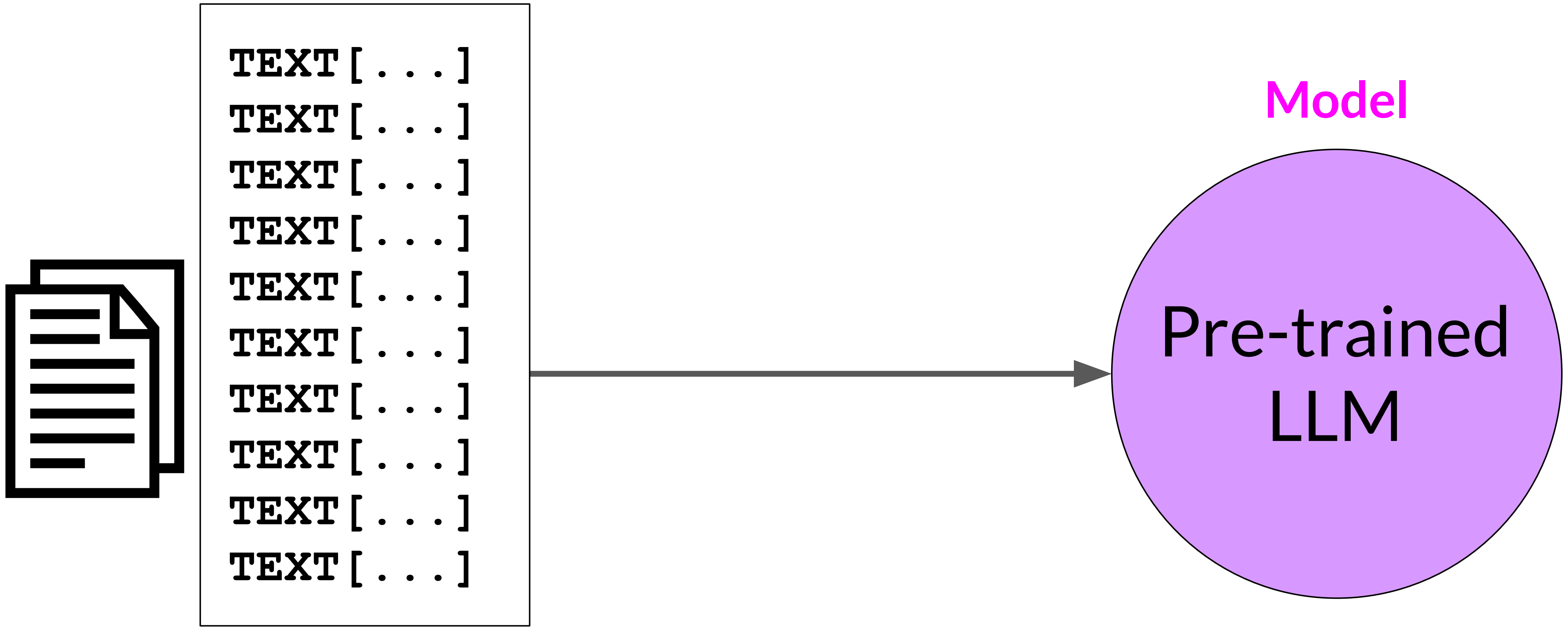
Even with multiple examples

- 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

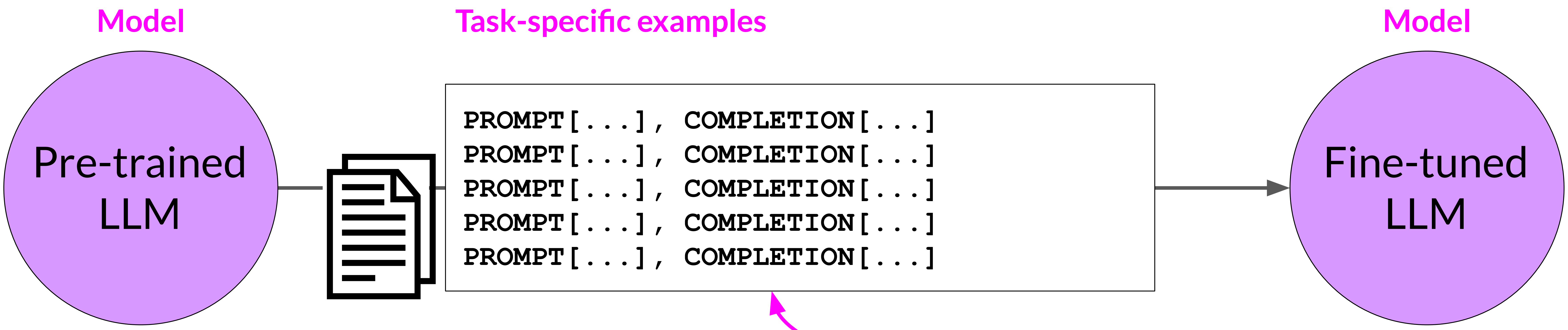
# LLM fine-tuning at a high level

## 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**



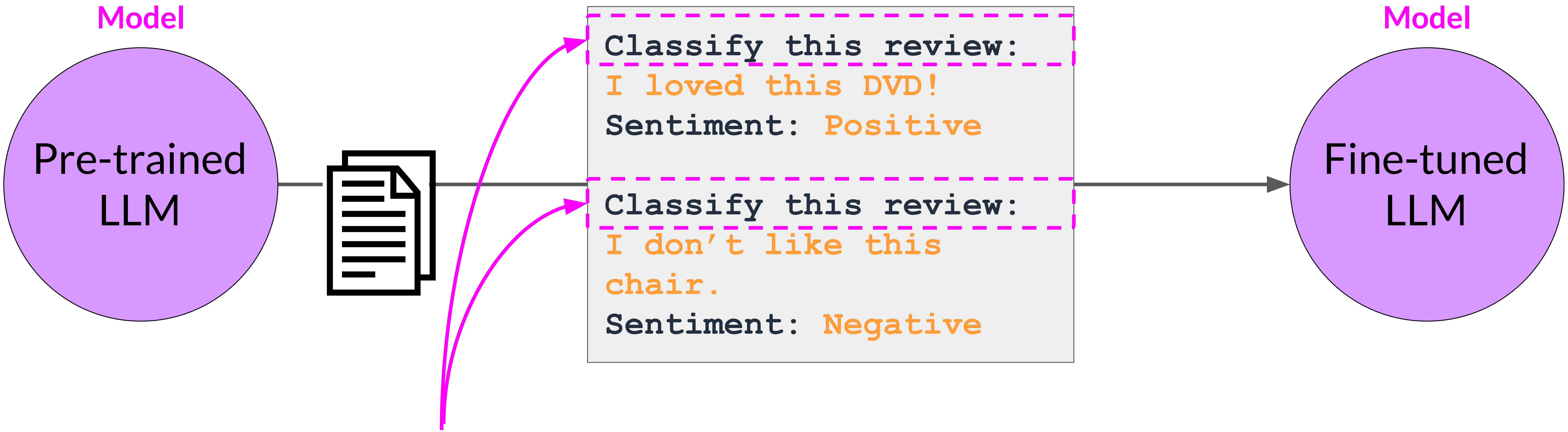

GB - TB
of labeled examples for a specific task or set of tasks

**Prompt-completion pairs**

**Improved performance**

# Using prompts to fine-tune LLMs with instruction

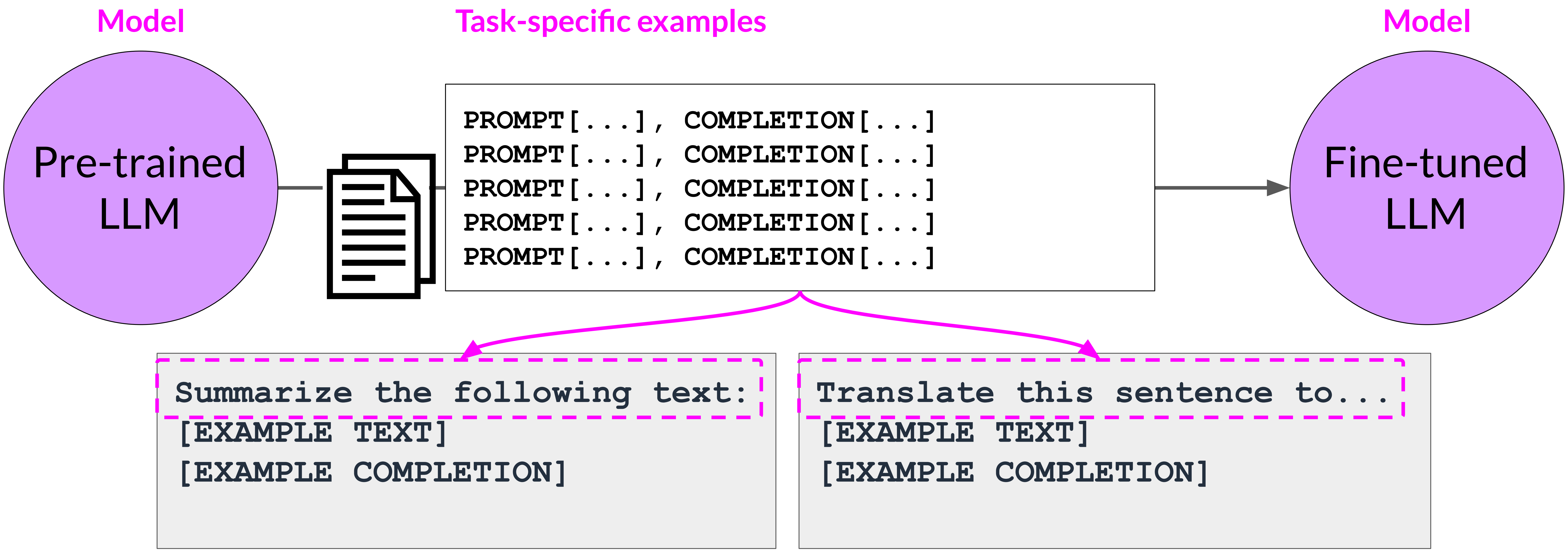
**LLM fine-tuning**




Each prompt/completion pair includes a specific "instruction" to the LLM

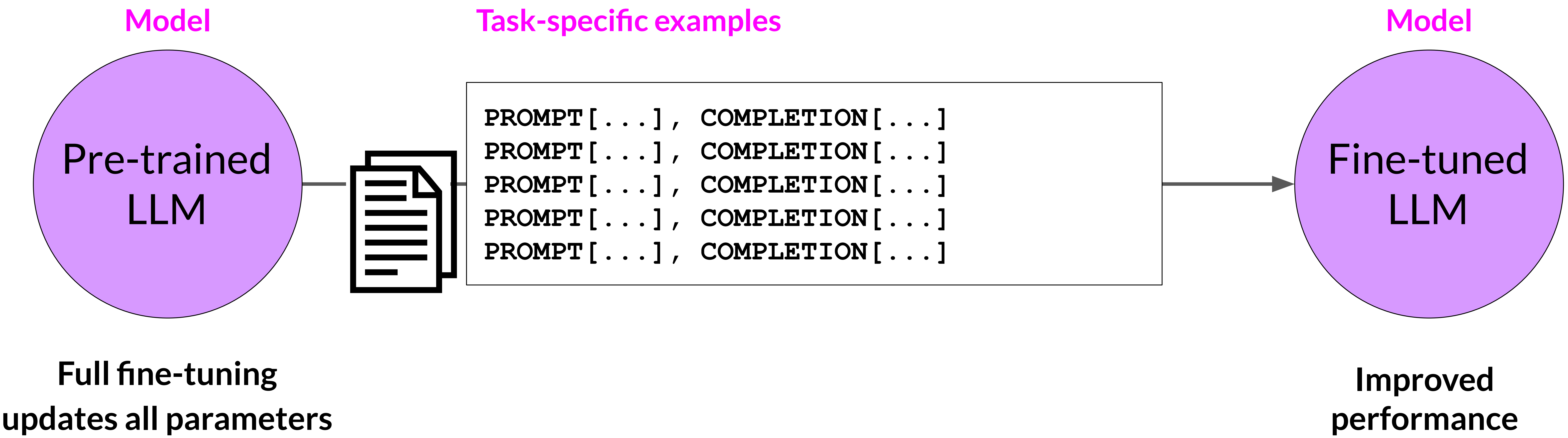
# Using prompts to fine-tune LLMs with instruction

## LLM fine-tuning



# Using prompts to fine-tune LLMs with instruction

## LLM fine-tuning



# 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

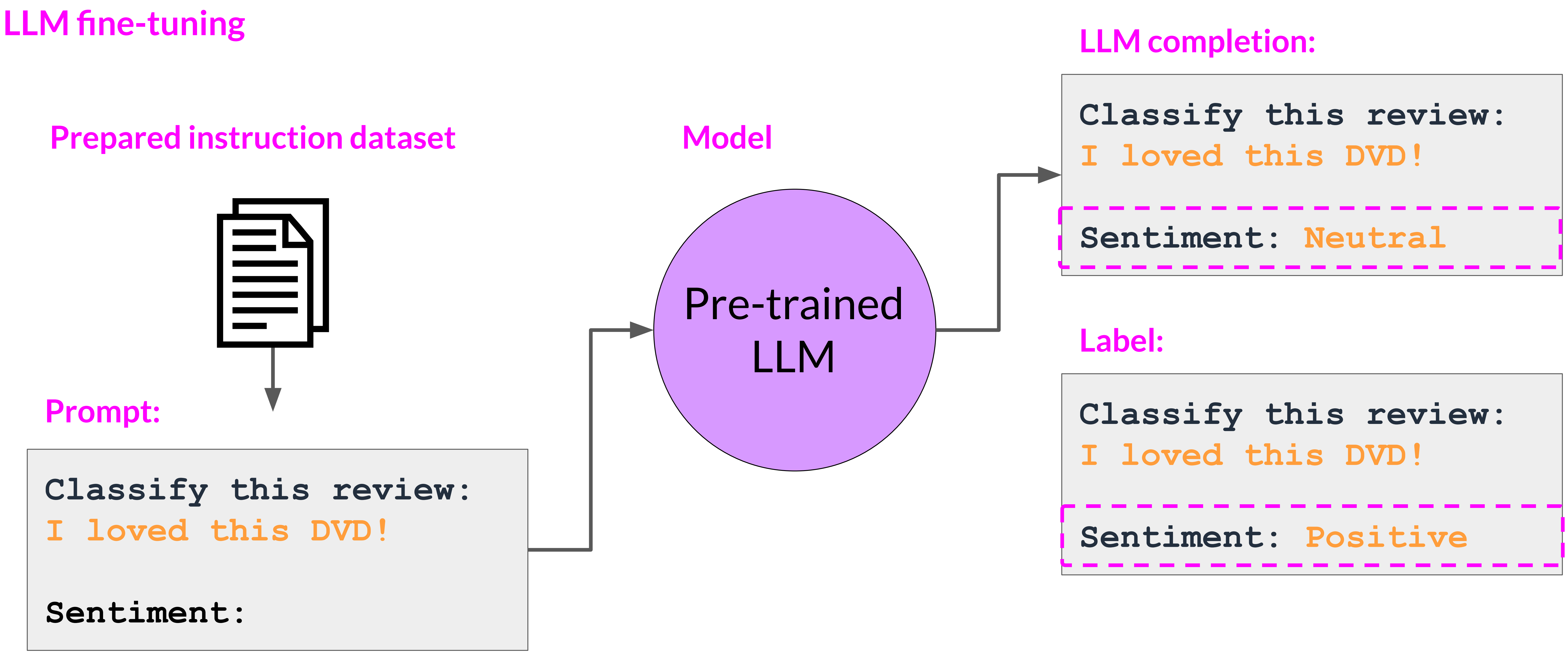
```
PROMPT[...], COMPLETION[...]
...
```

Validation

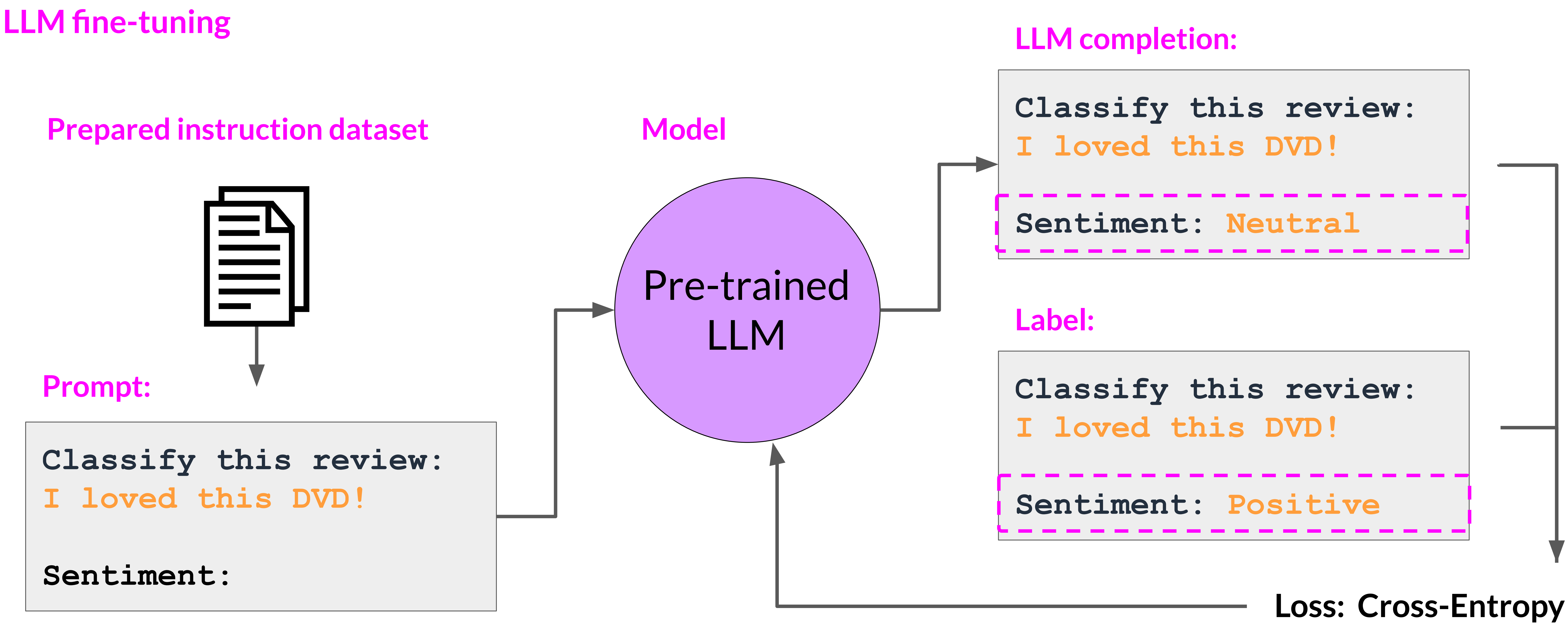
```
PROMPT[...], COMPLETION[...]
...
```

Test

# LLM fine-tuning process



# LLM fine-tuning 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

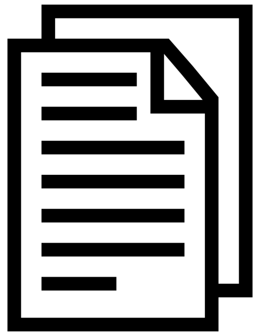
```
PROMPT[...], COMPLETION[...]
...
```

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[...]
...
```

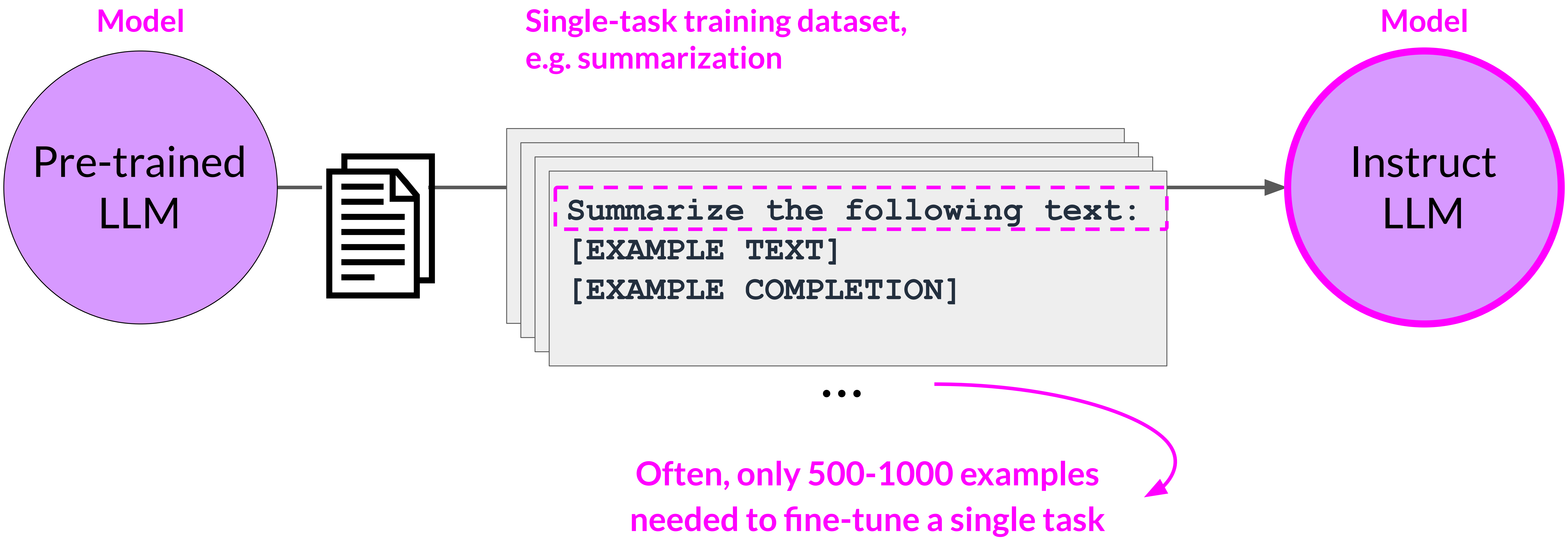
Test

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

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```
Classify this review:
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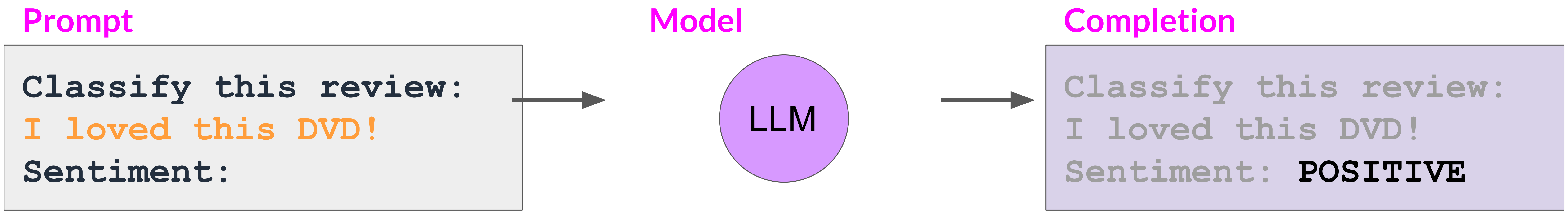
# Catastrophic forgetting

- 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**

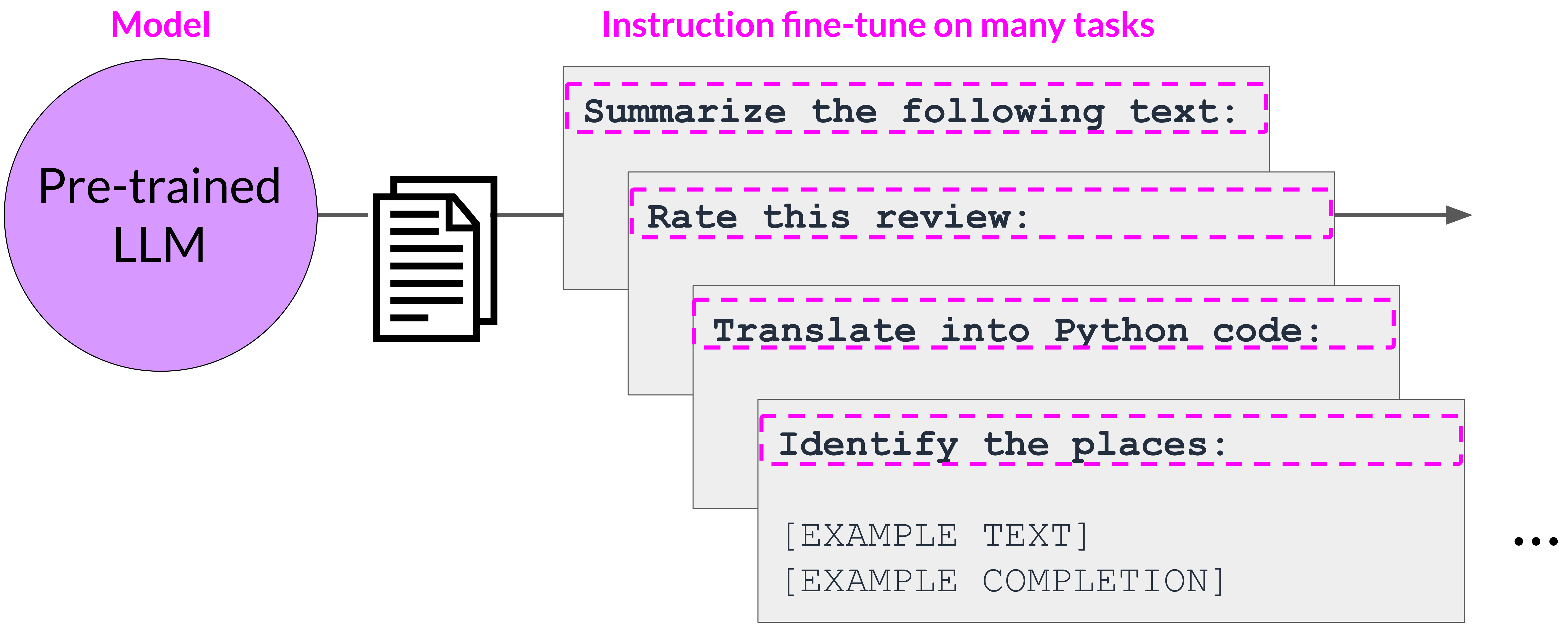
```
What is the name of
the cat?
Charlie the cat roamed
the garden at night.
The garden was
positive.
```

# How to avoid catastrophic forgetting

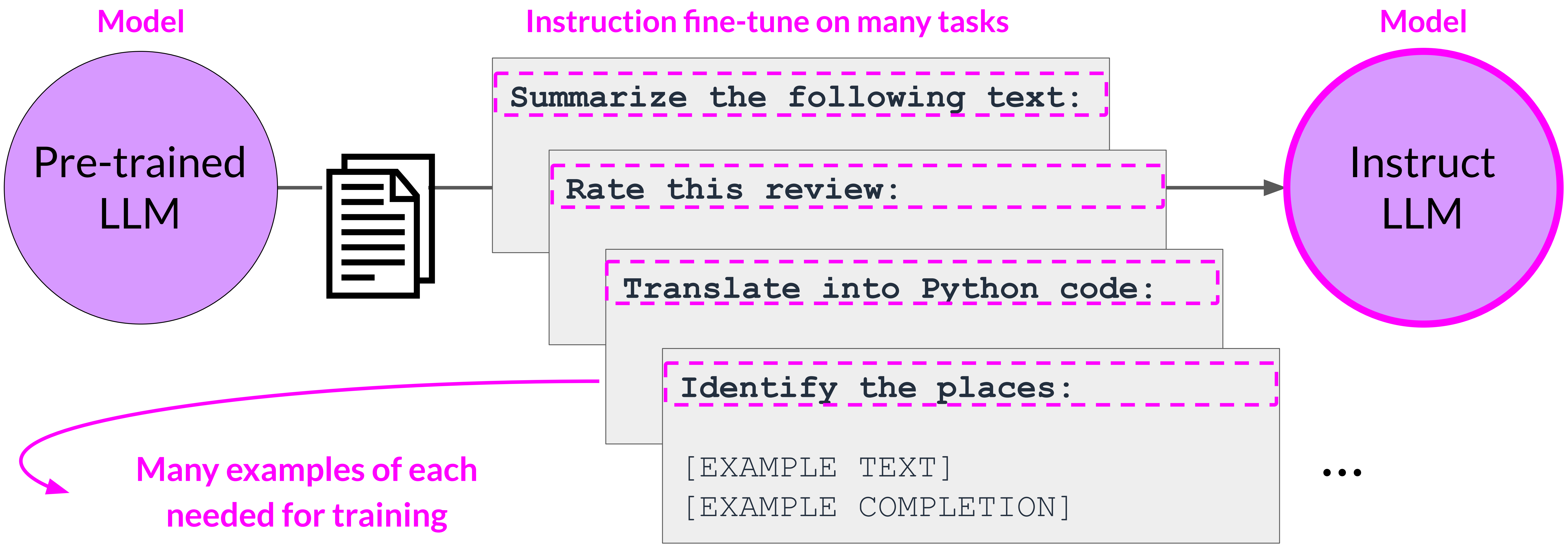
- First note that you might not have to!
- Fine-tune on **multiple tasks** at the same time
- Consider **Parameter Efficient Fine-tuning** (PEFT)

# Multi-task, instruction fine-tuning

# Multi-task, instruction fine-tuning

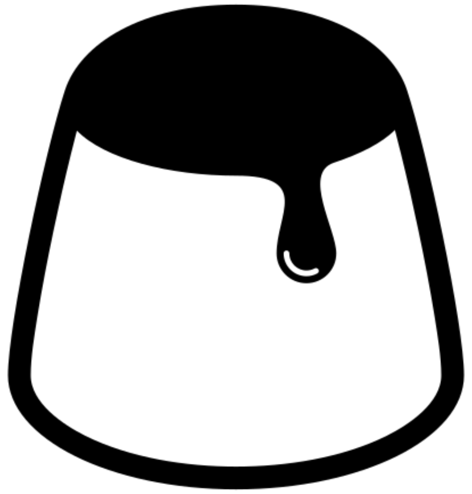


# Multi-task, instruction fine-tuning



# Instruction fine-tuning with FLAN

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

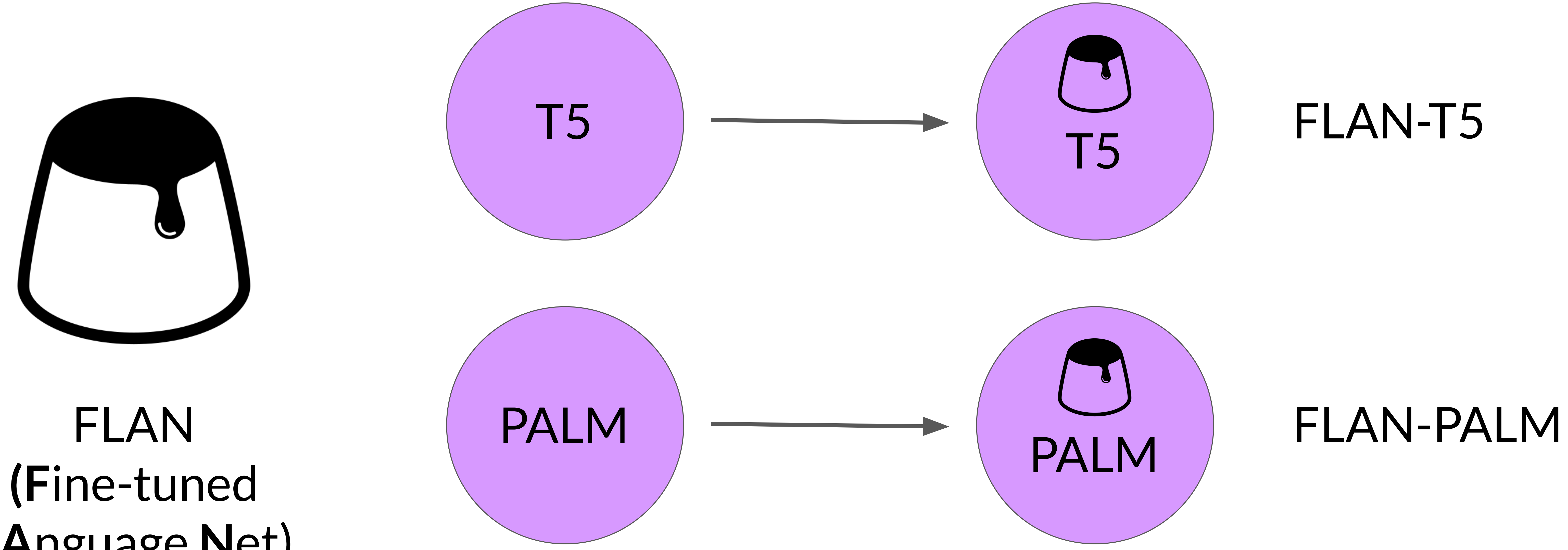


FLAN

*“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
(**F**ine-tuned
**LA**nguage **N**et)

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

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

TO-samll Fine-tuned
**T0-SF**

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

…

**55 Datasets**
**14 Categories**
**193 Tasks**

Multi-modal Few-shot Fine_tunning
**Muffin**

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

…

**69 Datasets**
**27 Categories**
**80 Tasks**

Chain of Thought Reasoning
**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

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- Natural language inference,
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# 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!",
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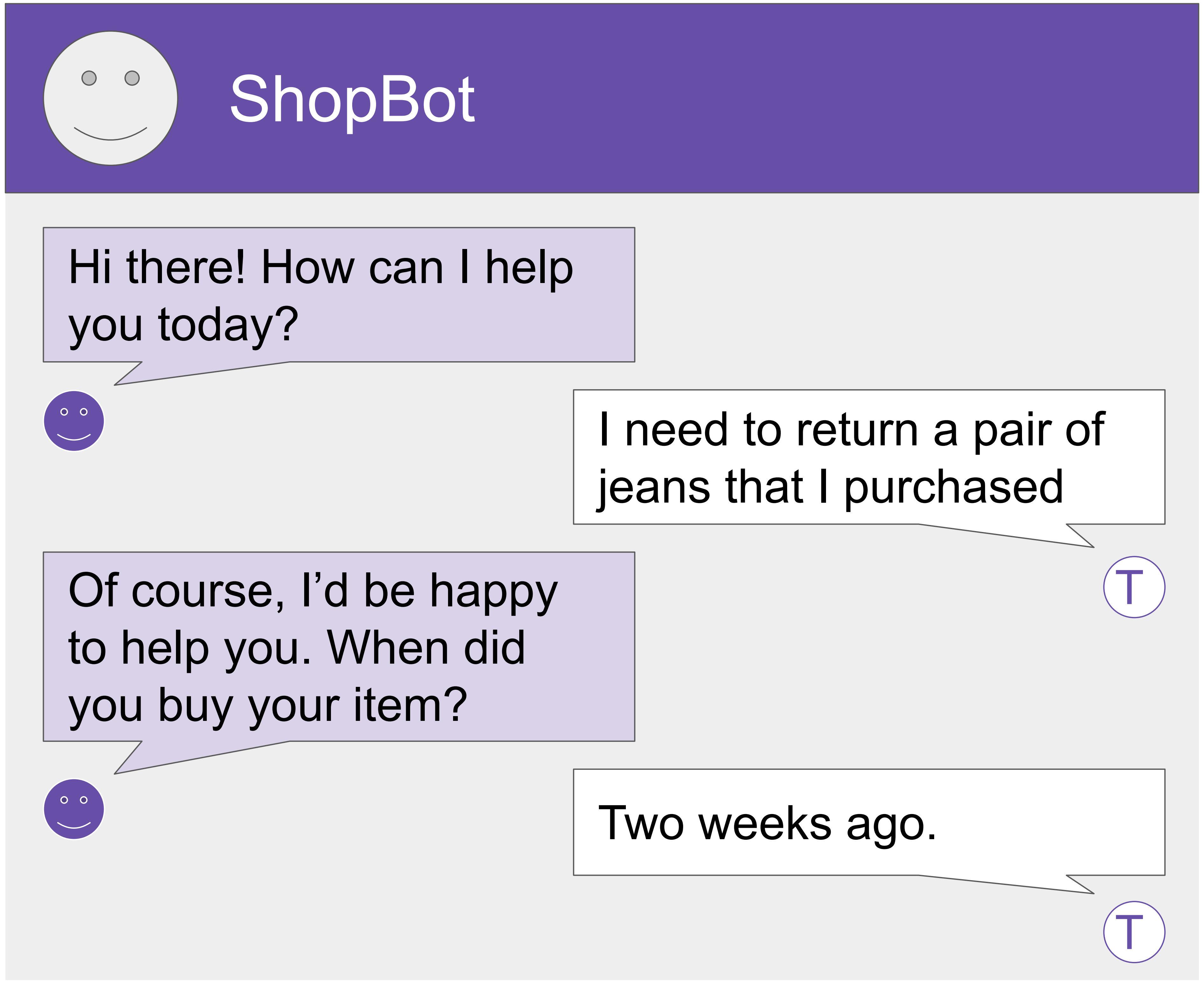
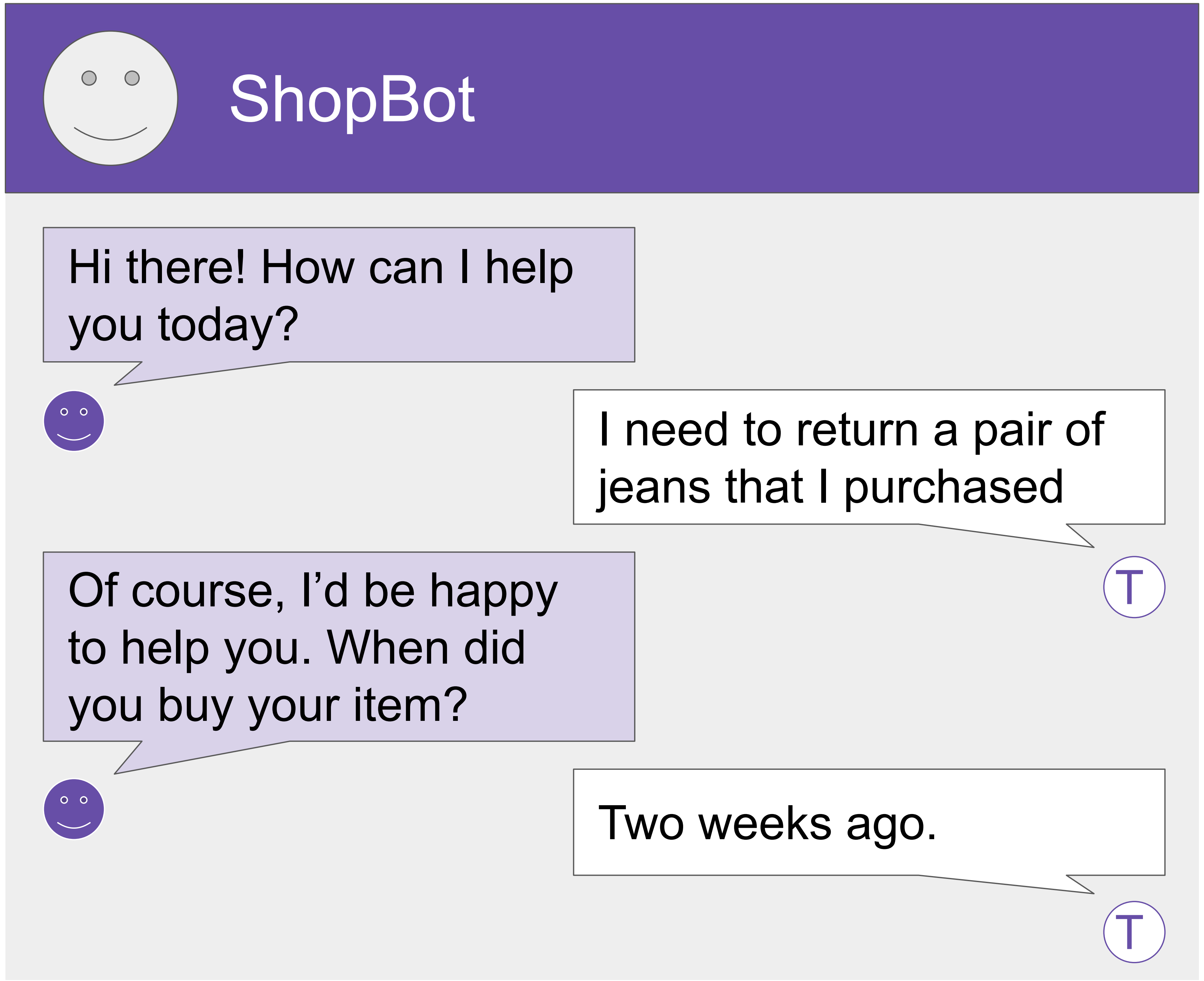
```

# 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)

$\boxed{\texttt{Summarize the following conversation.}}$

```
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**

FLAN-T5

**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)**

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Summarize the following
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Tommy: Hello. My name is
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Mike: May I see some
...
...
...
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FLAN-T5

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**Model**

FLAN-T5

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**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)

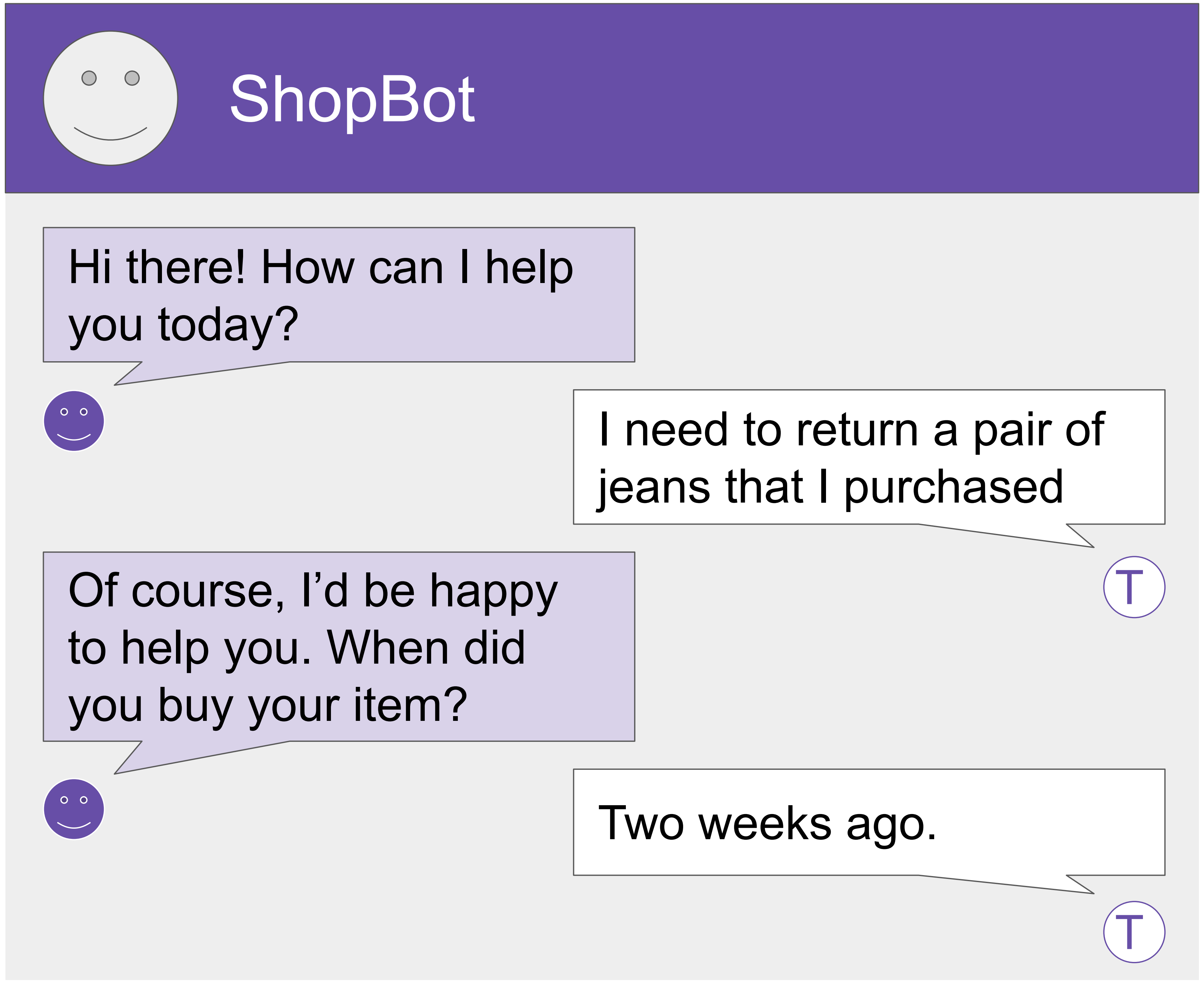
→

**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

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

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

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

# 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

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

BLEU SCORE

- 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

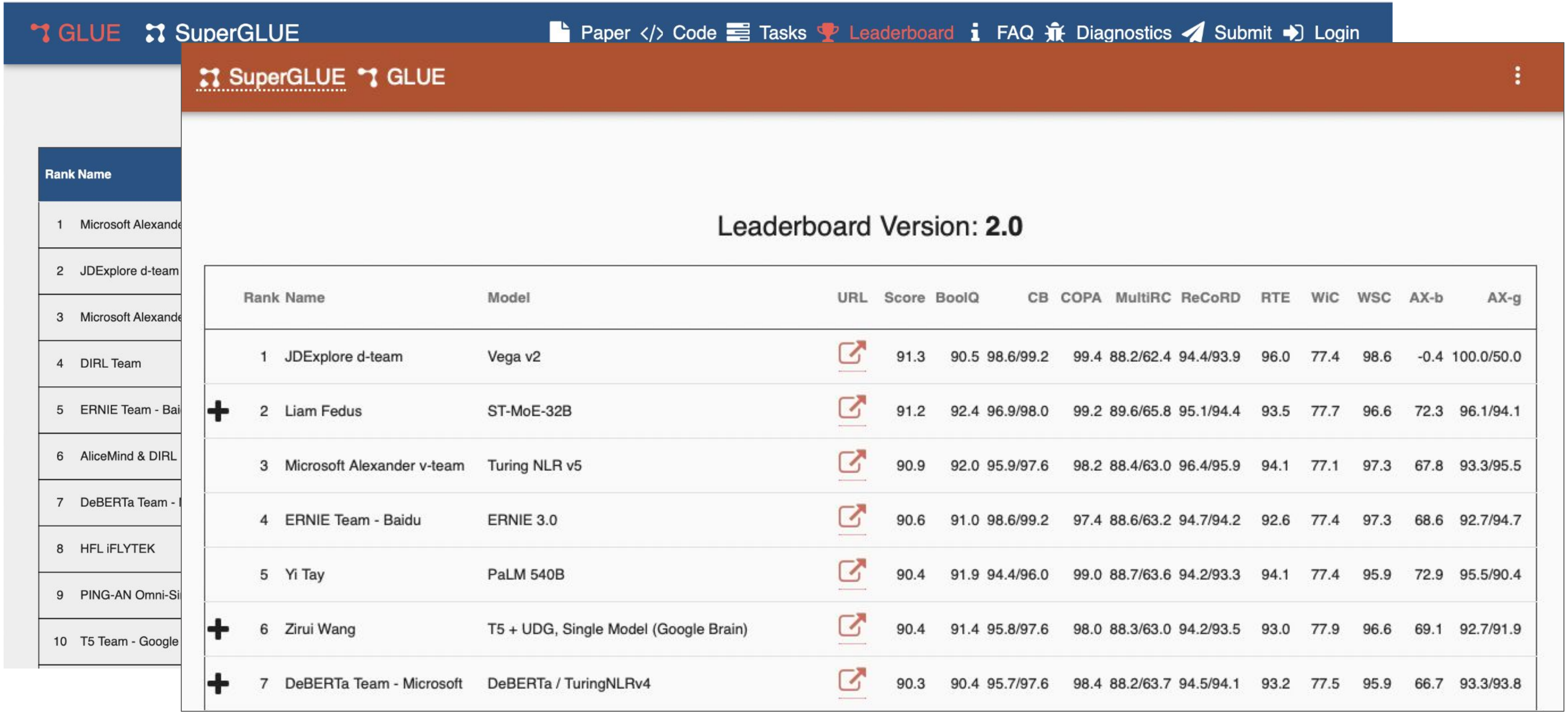
SuperGLUE

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



GLUE SuperGLUE Paper Code Tasks Leaderboard FAQ Diagnostics Submit Login

| 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 - I |
| 8 | HFL iFLYTEK |
| 9 | PING-AN Omni-Si |
| 10 | T5 Team - Google |

SuperGLUE GLUE

Leaderboard Version: **2.0**

| | 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.

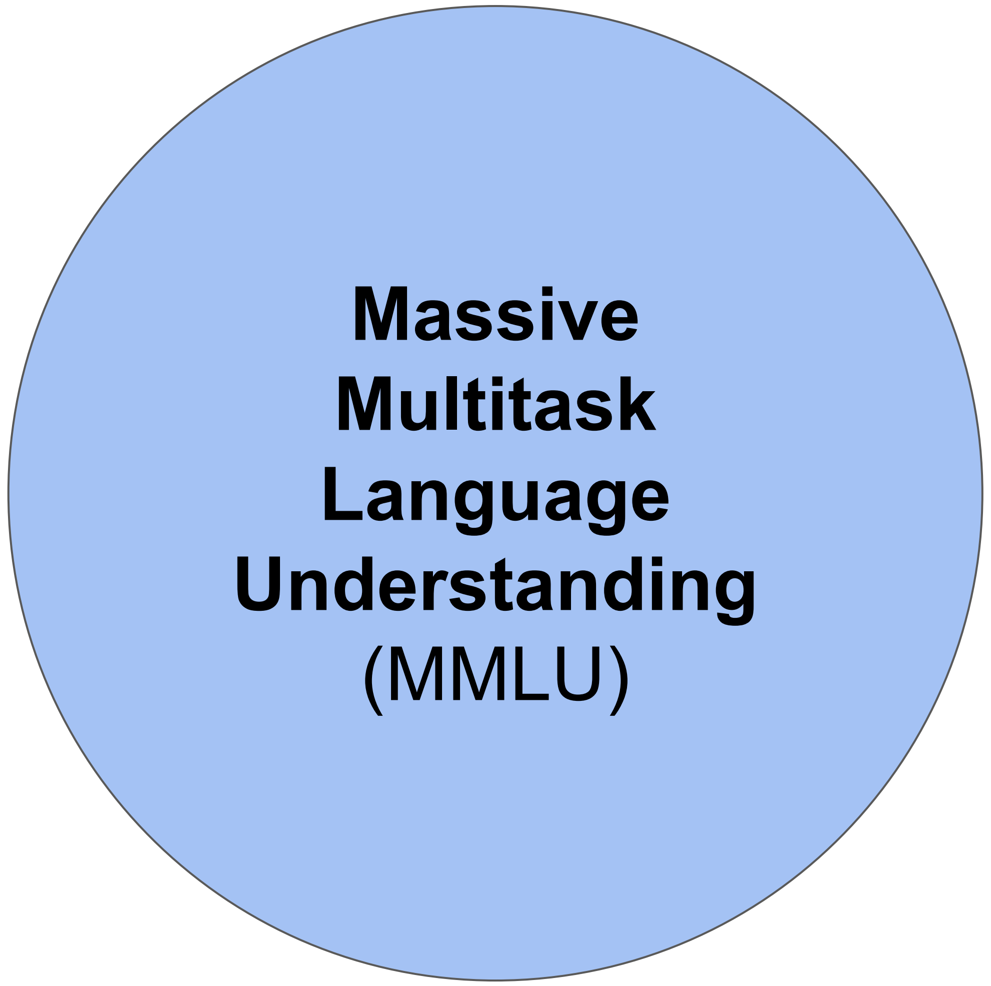
# Benchmarks for massive models

**Massive Multitask Language Understanding** (MMLU)

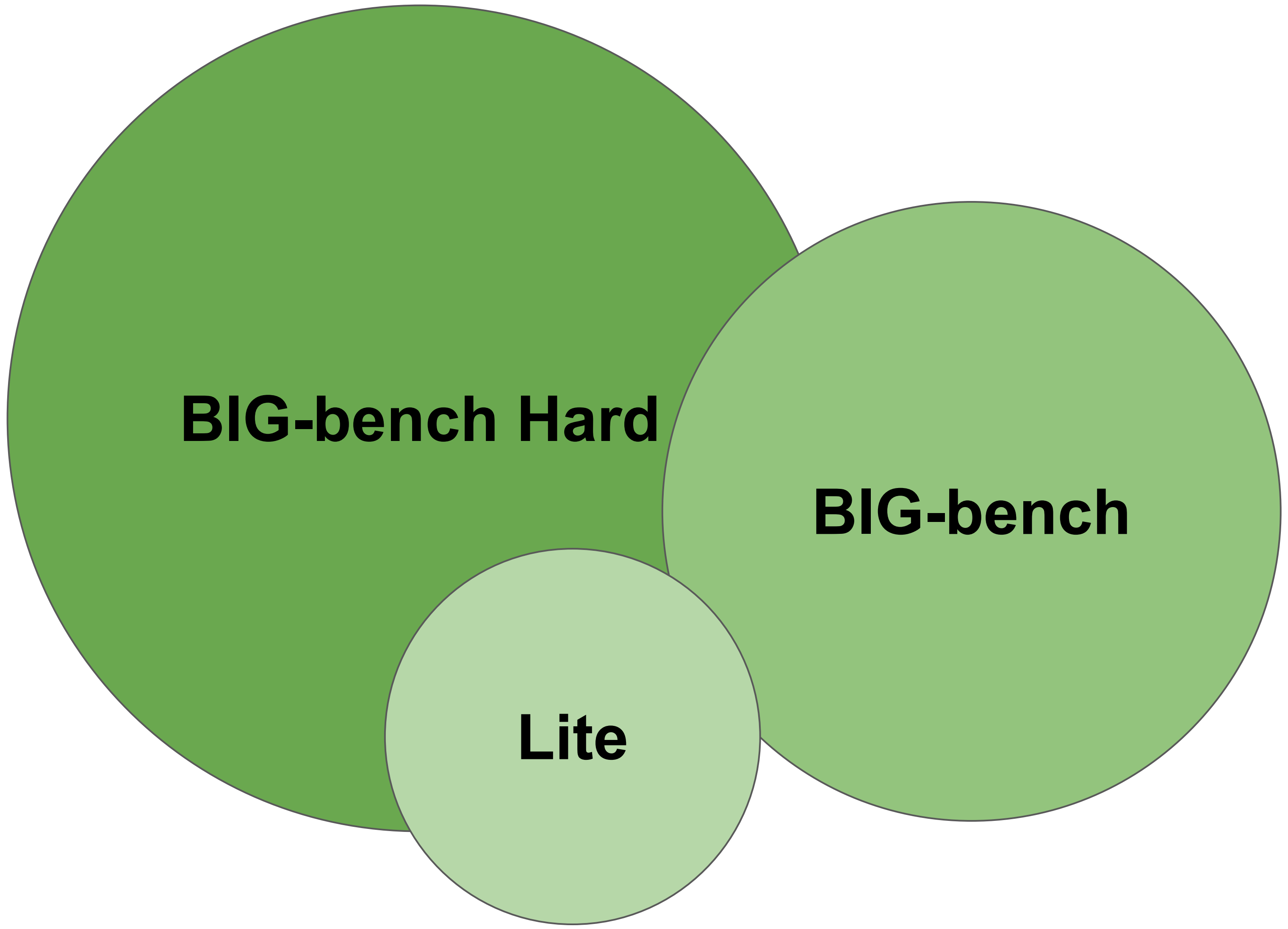
2021

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**

**LLM completion:**

**Training dataset**

**Model**

Pre-trained LLM

**Label:**

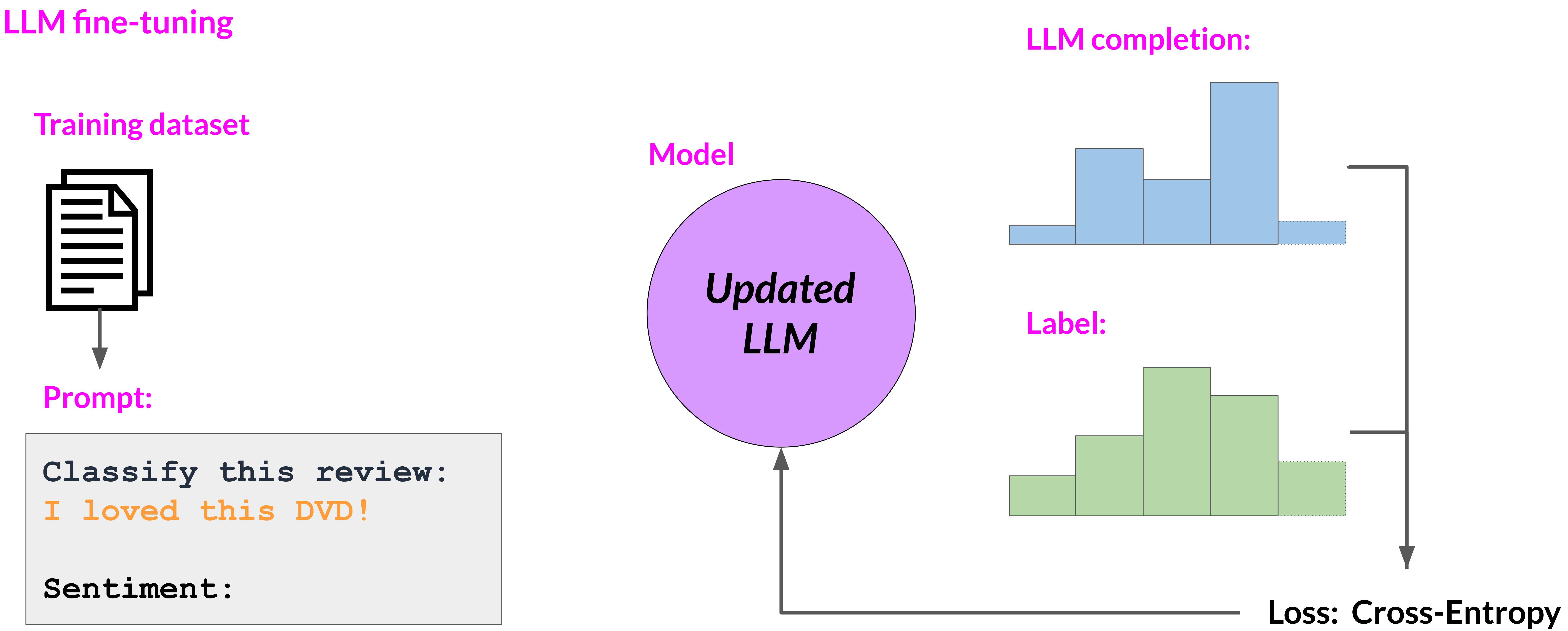
**Prompt:**

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

Sentiment:
```

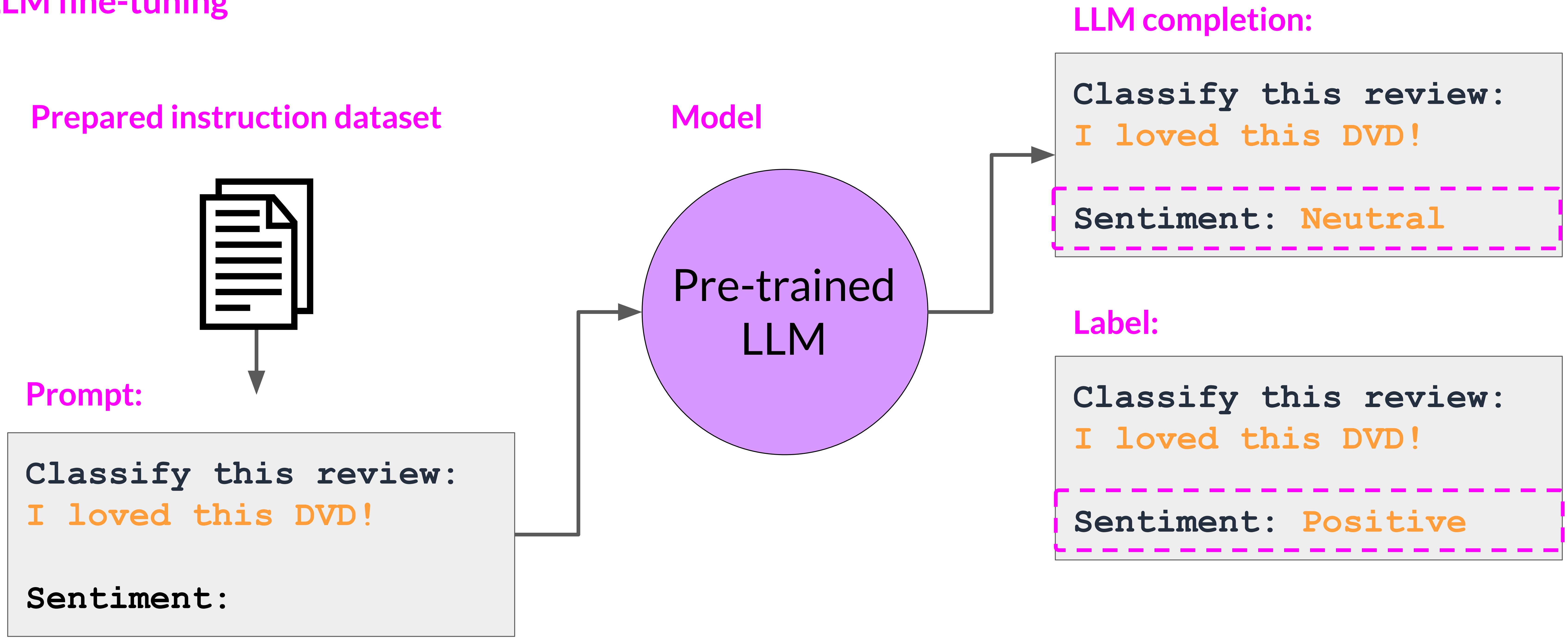
Loss: Cross-

# LLM fine-tuning process



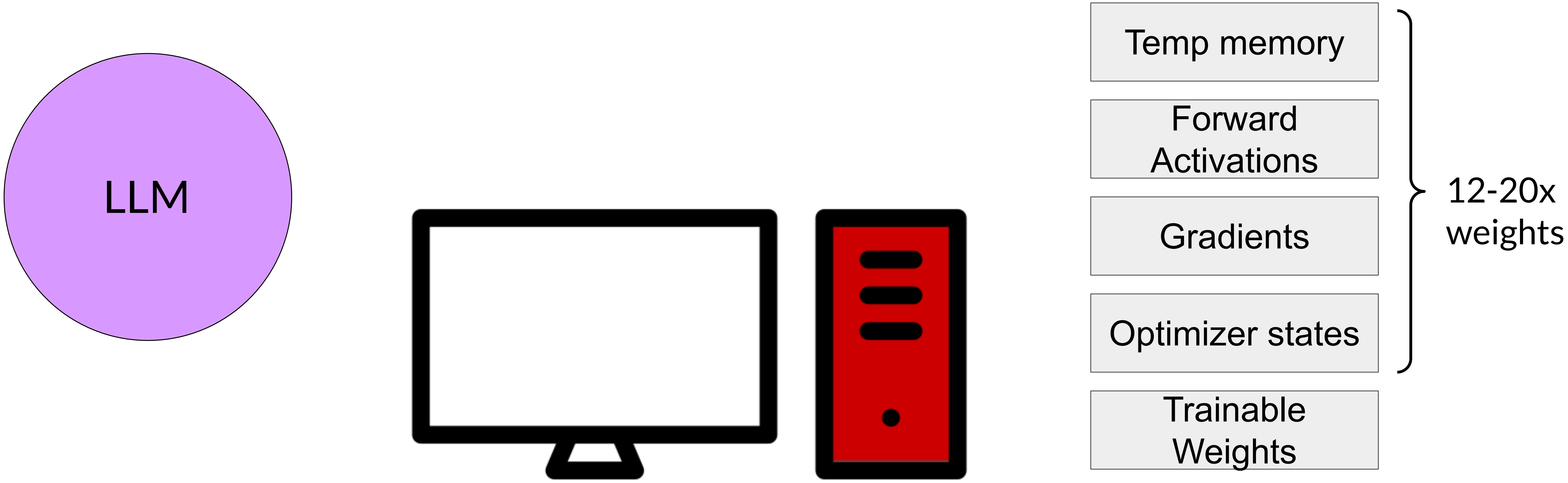
# LLM fine-tuning process

## LLM fine-tuning

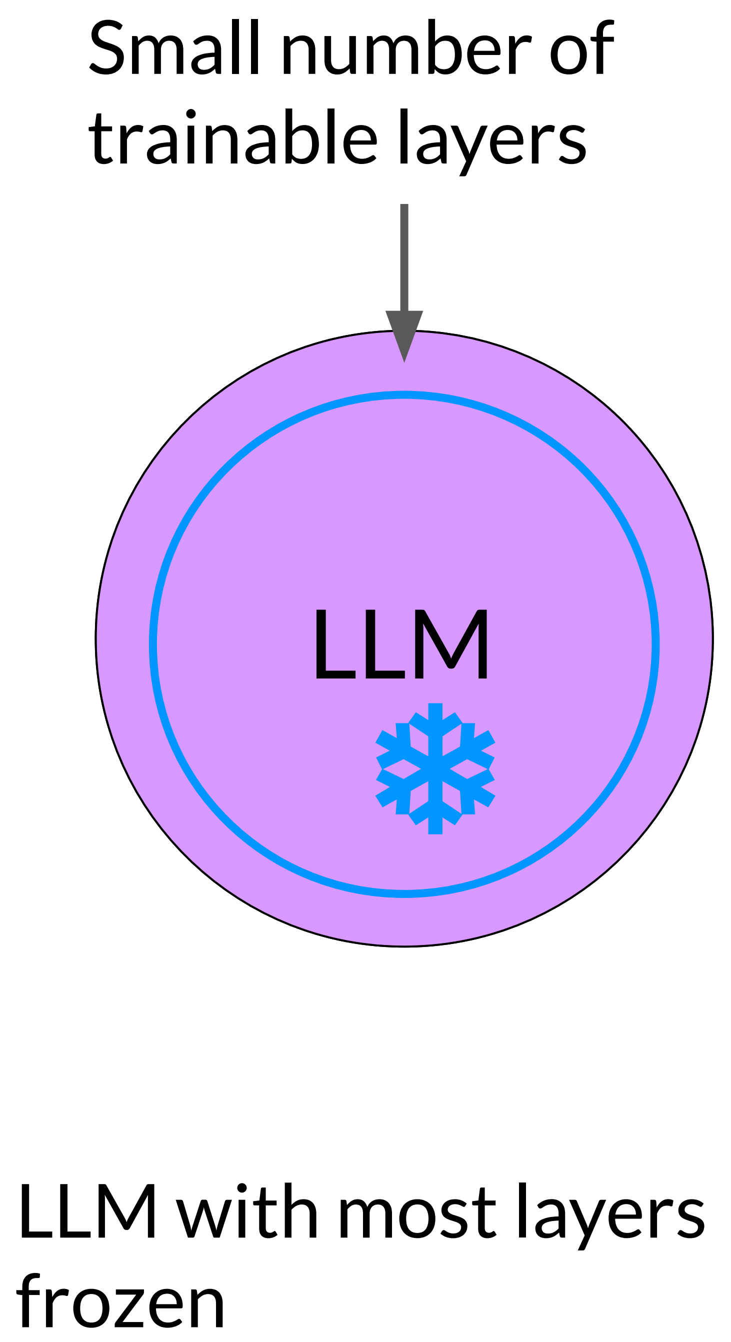


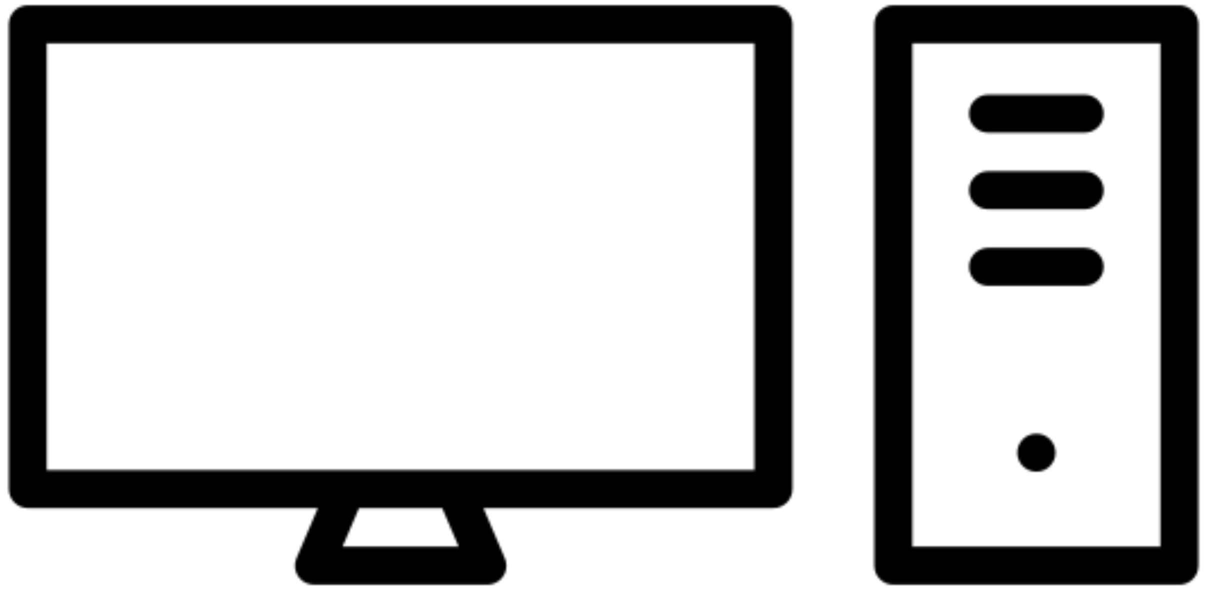
# Parameter-efficient Fine-tuning (PEFT)

# Full fine-tuning of large LLMs is challenging



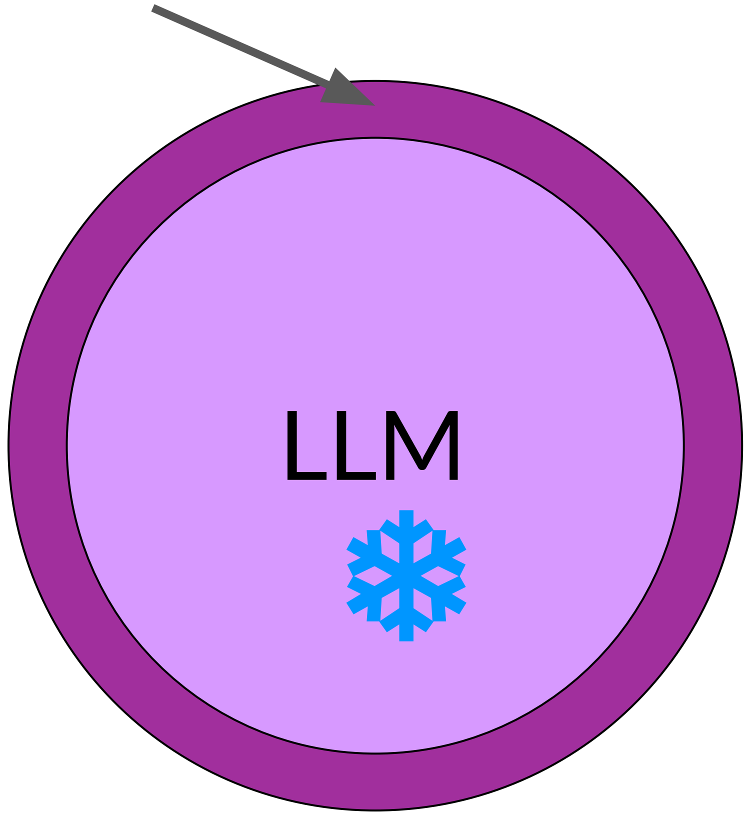
# Parameter efficient fine-tuning (PEFT)



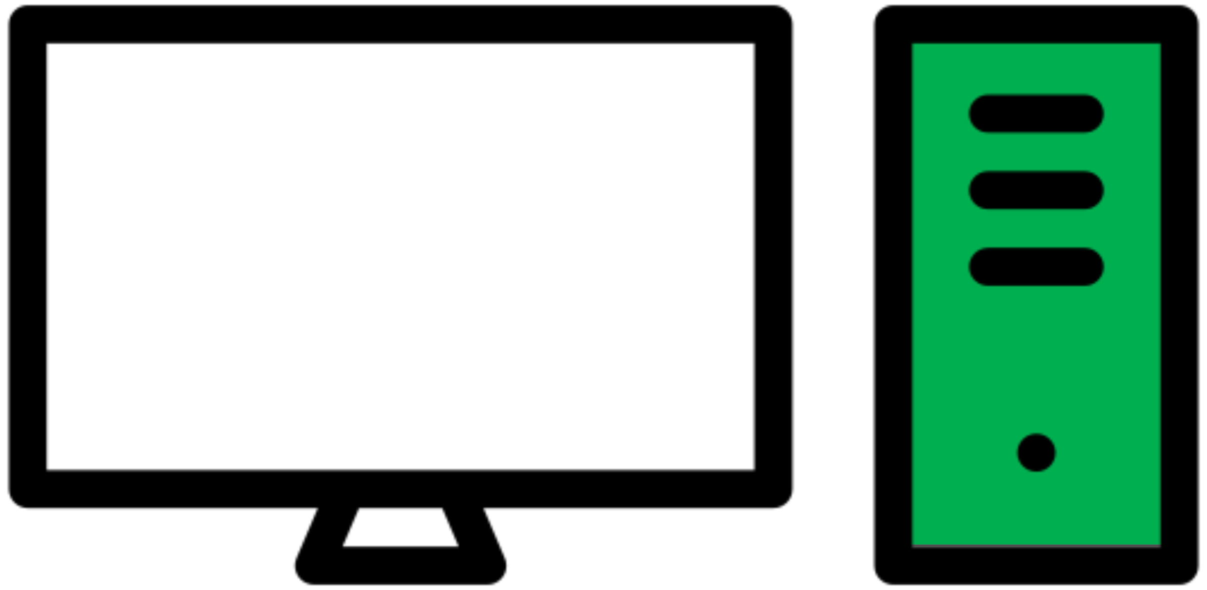
# Parameter efficient fine-tuning (PEFT)

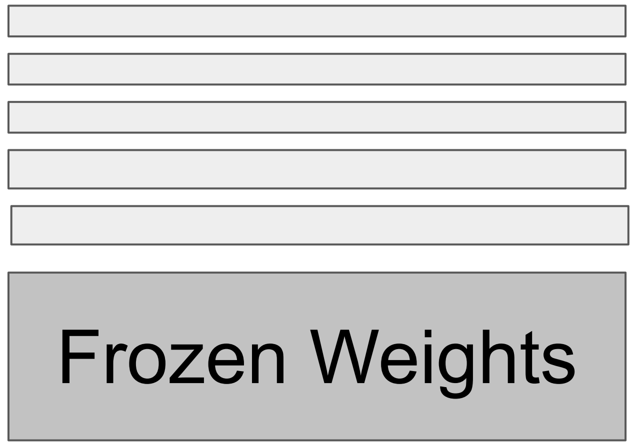
New trainable layers




LLM with additional layers for PEFT

Less prone to catastrophic forgetting

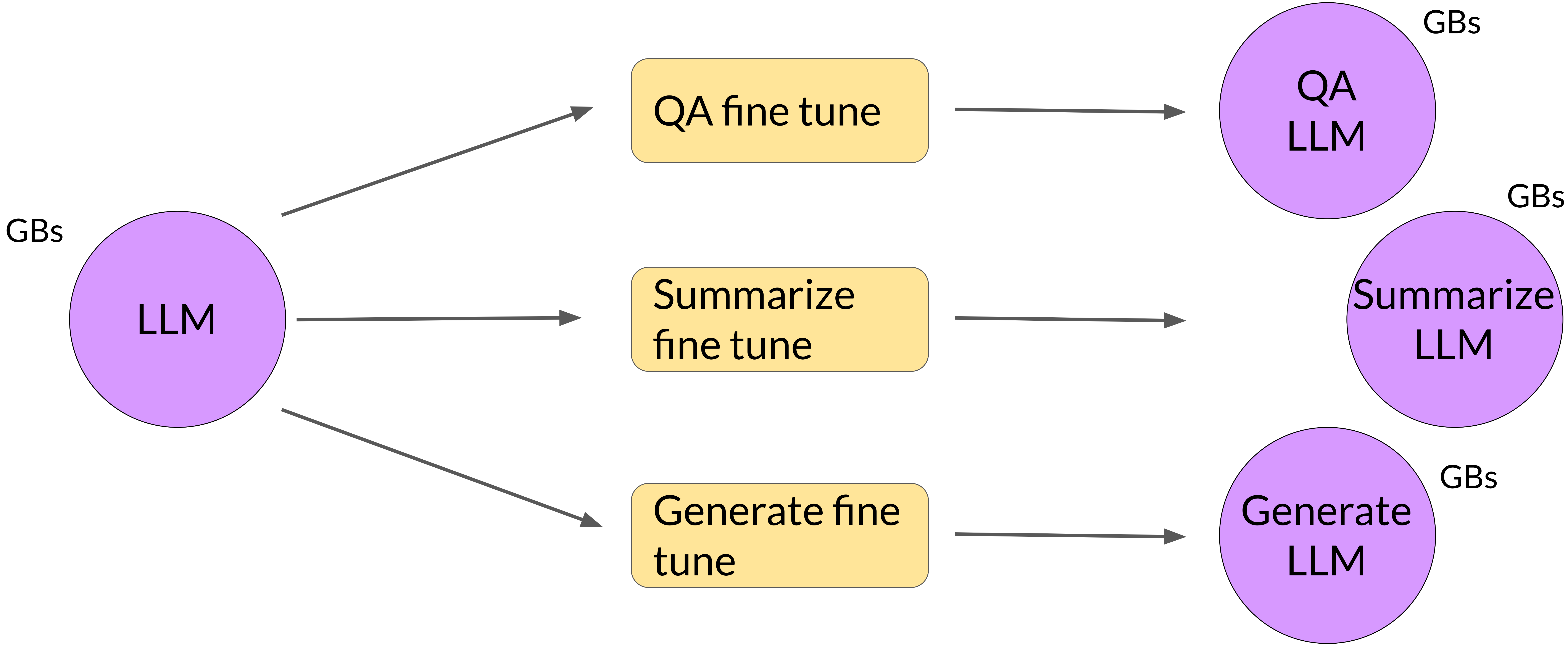




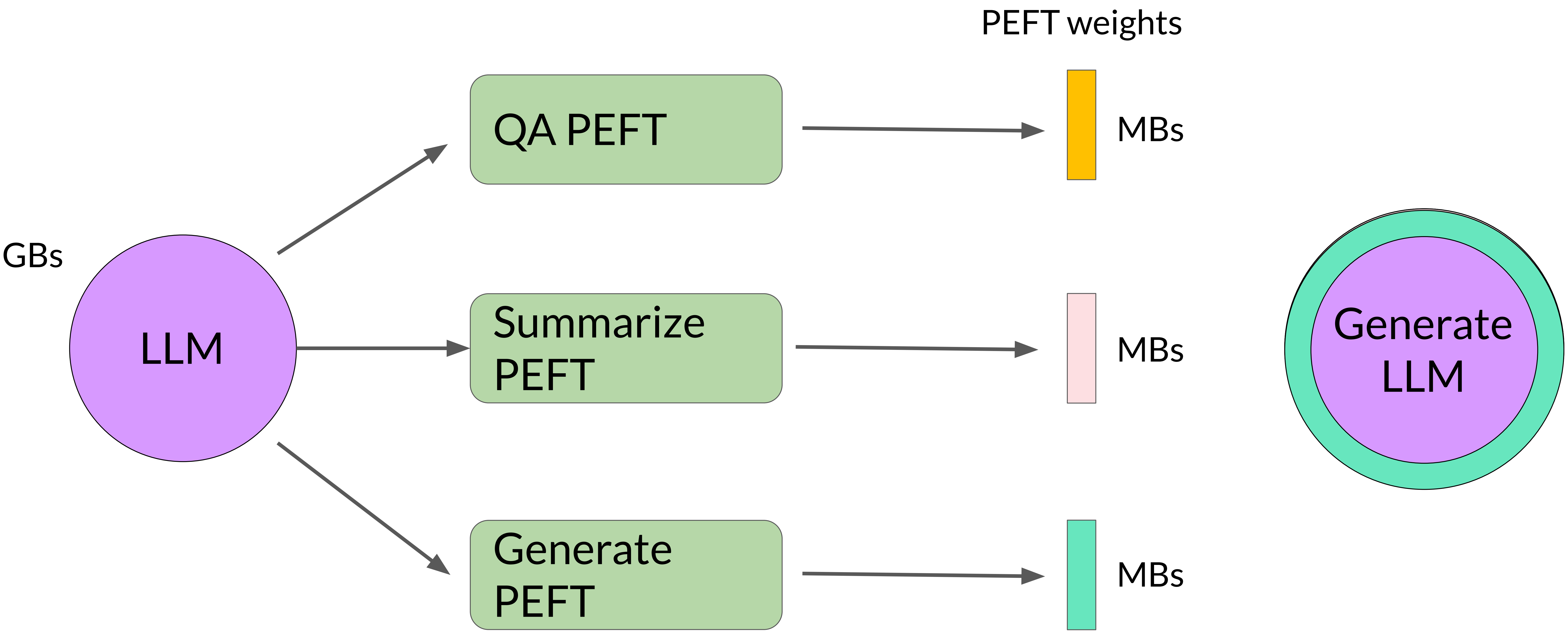

Other components

Trainable weights

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



# PEFT fine-tuning saves space and is flexible

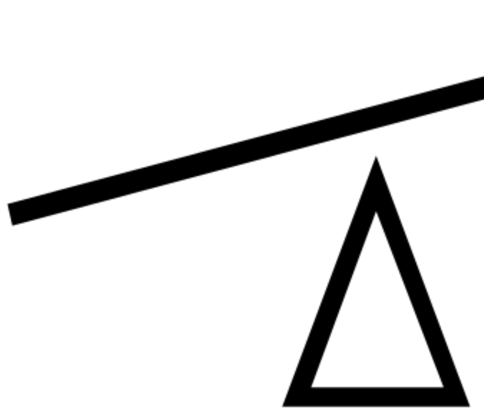


# PEFT Trade-offs

Parameter Efficiency

Memory Efficiency

Training Speed



Model Performance

Inference Costs

# 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

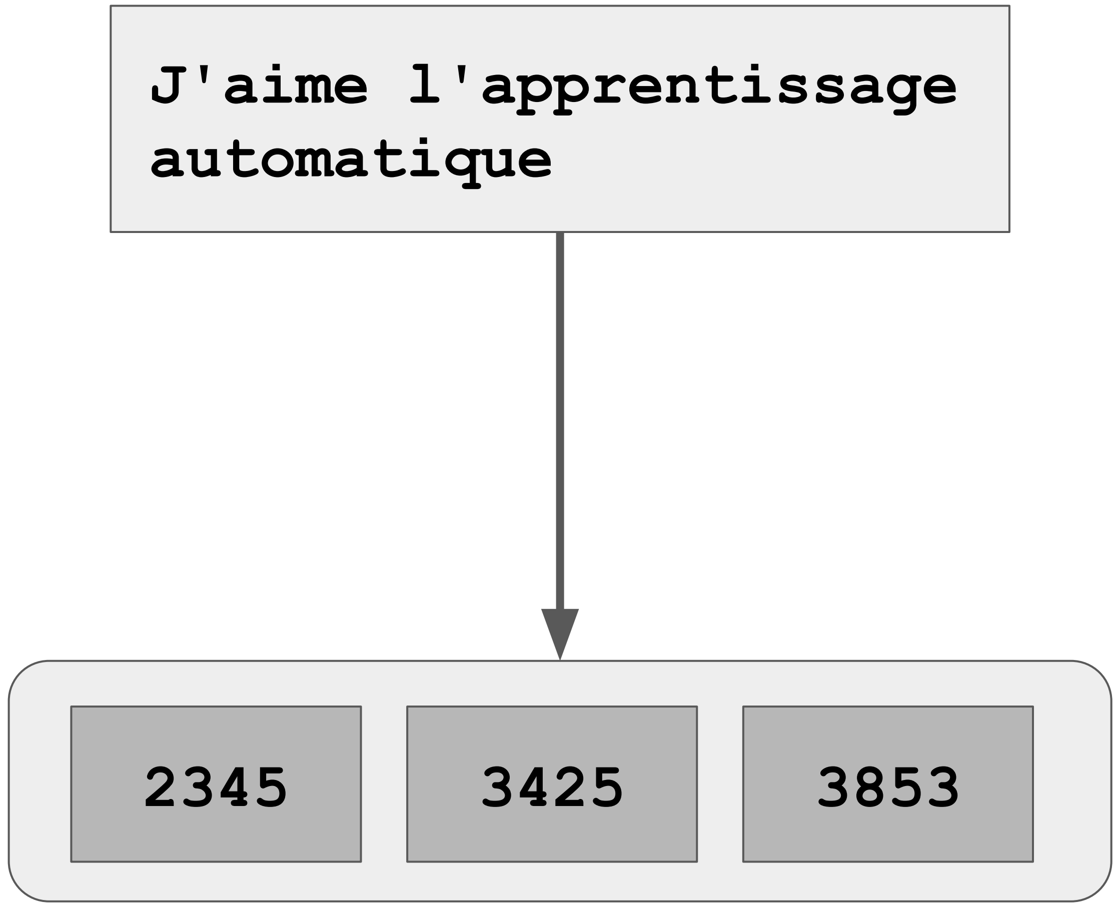
Soft Prompts

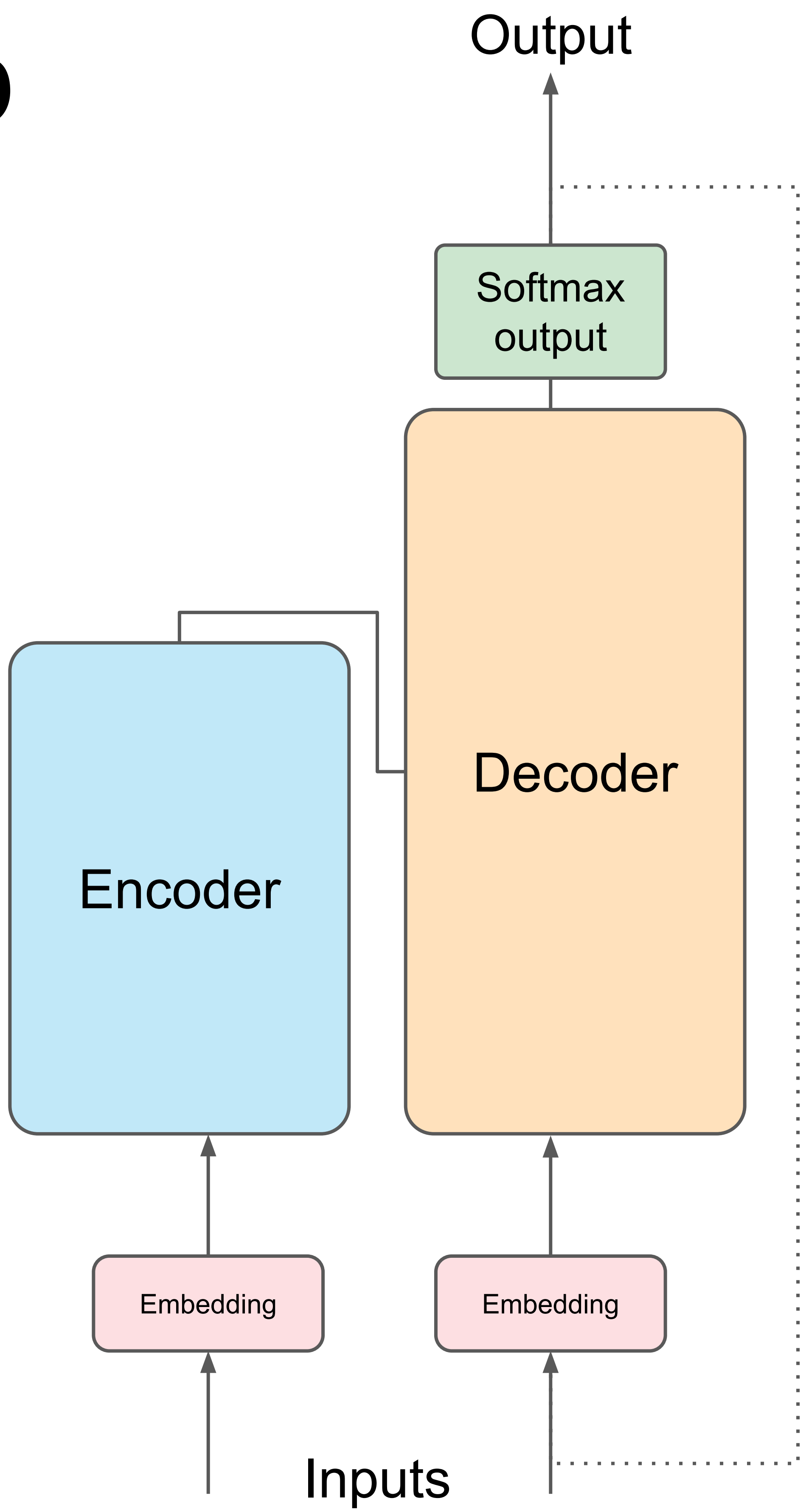
**Prompt Tuning**

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

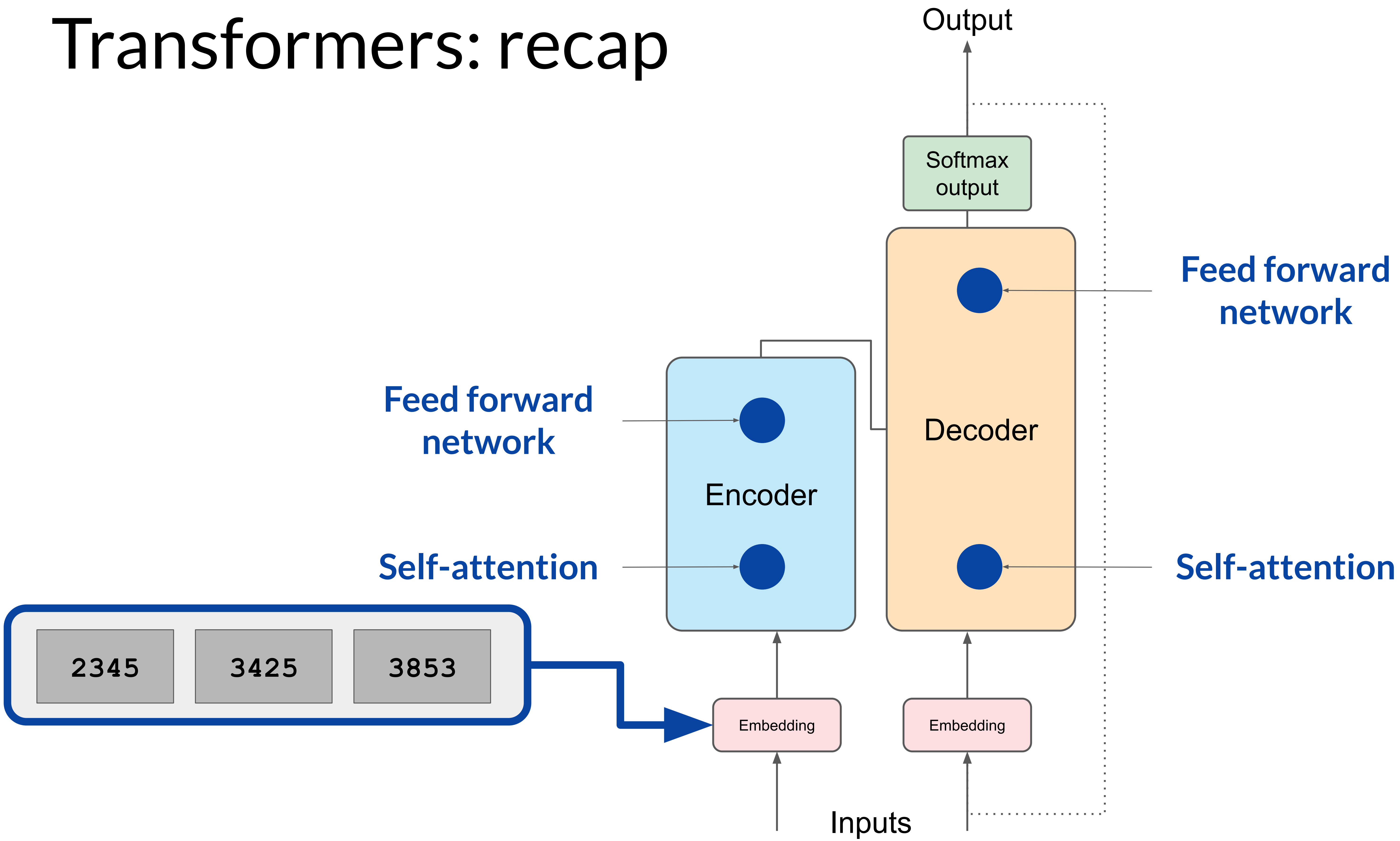
# Low-Rank Adaptation of Large Language Models (LoRA)

# Transformers: recap

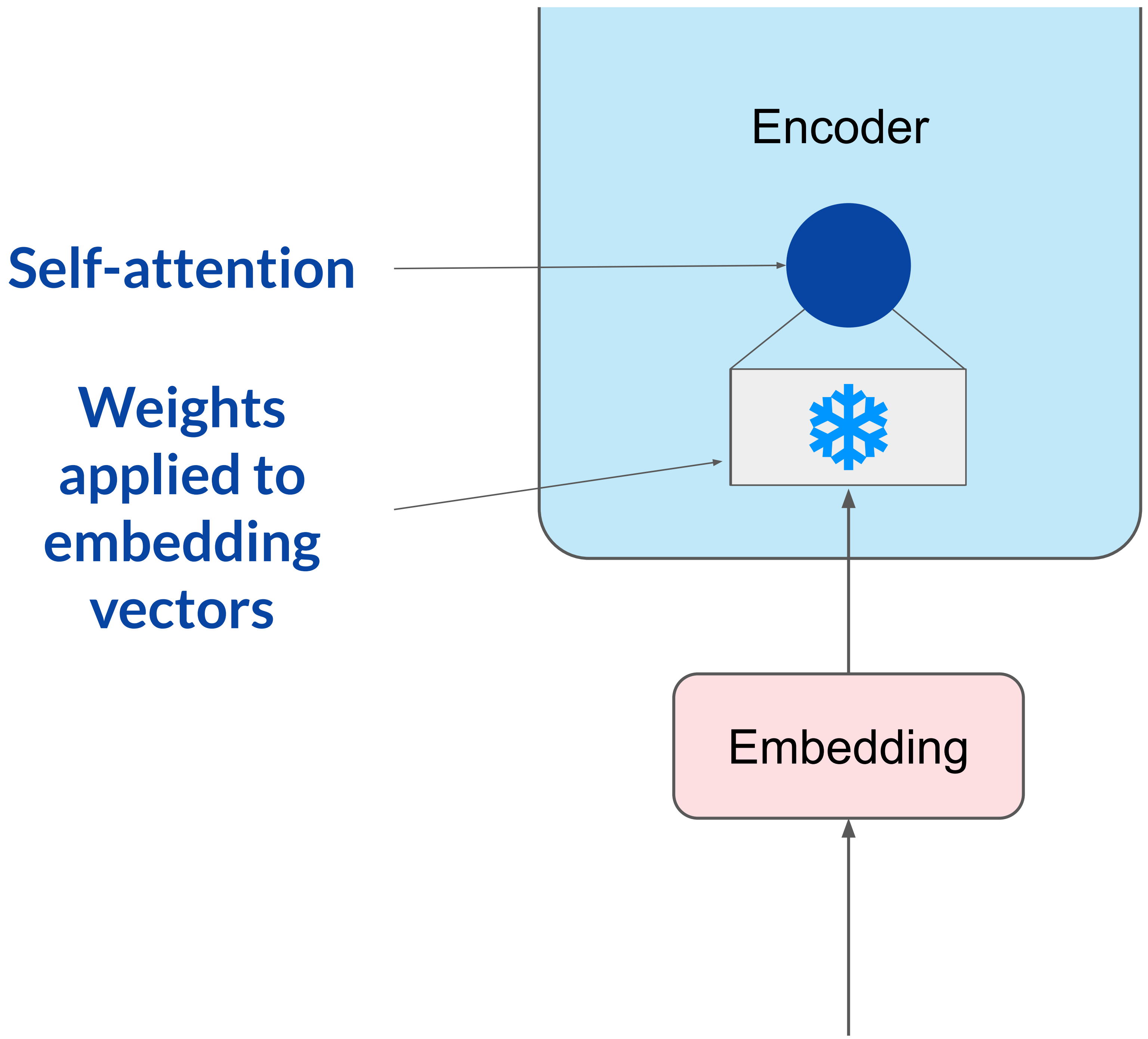


# Transformers: recap

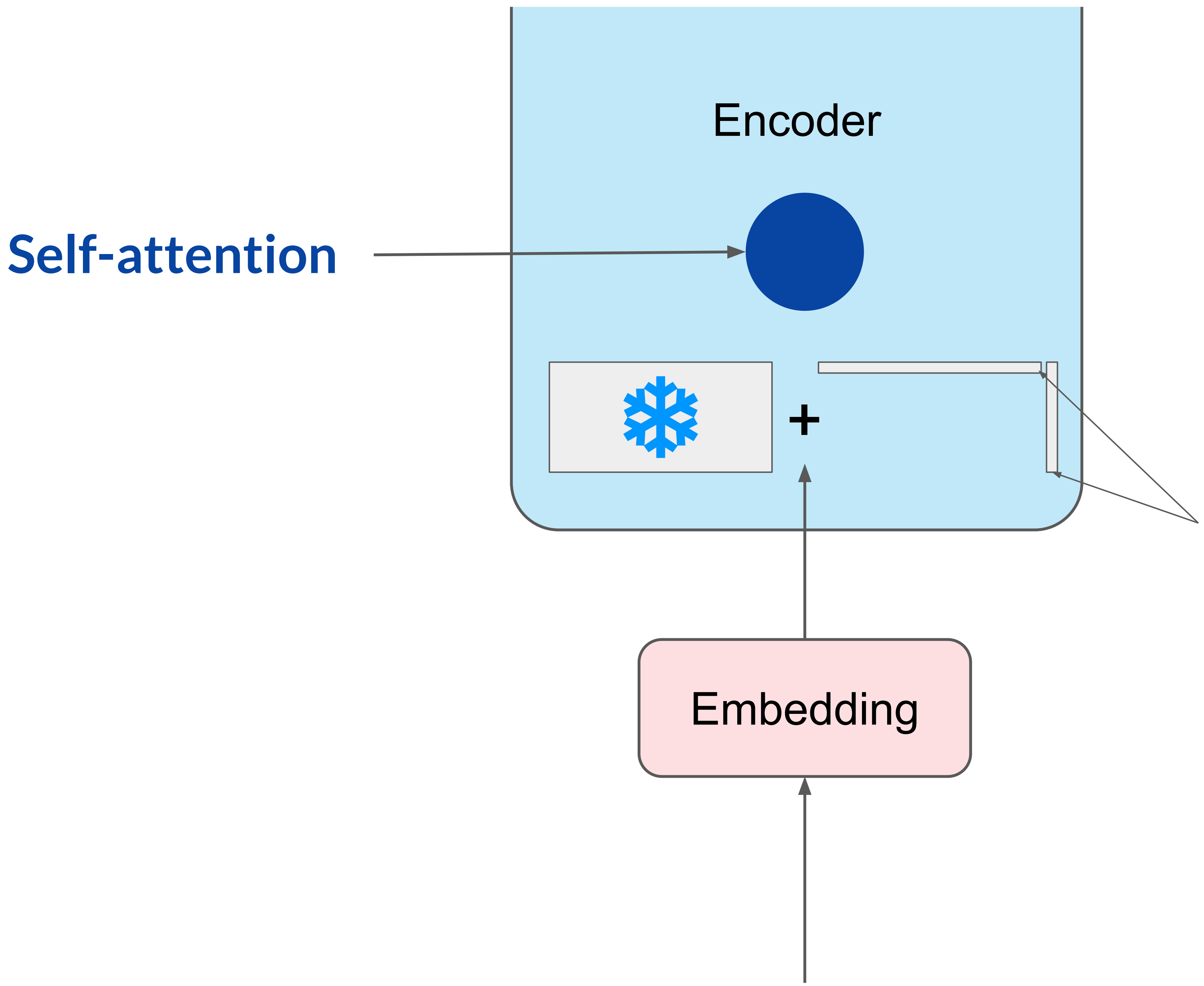


# LoRA: Low Rank Adaption of LLMs




1. Freeze most of the original LLM weights.

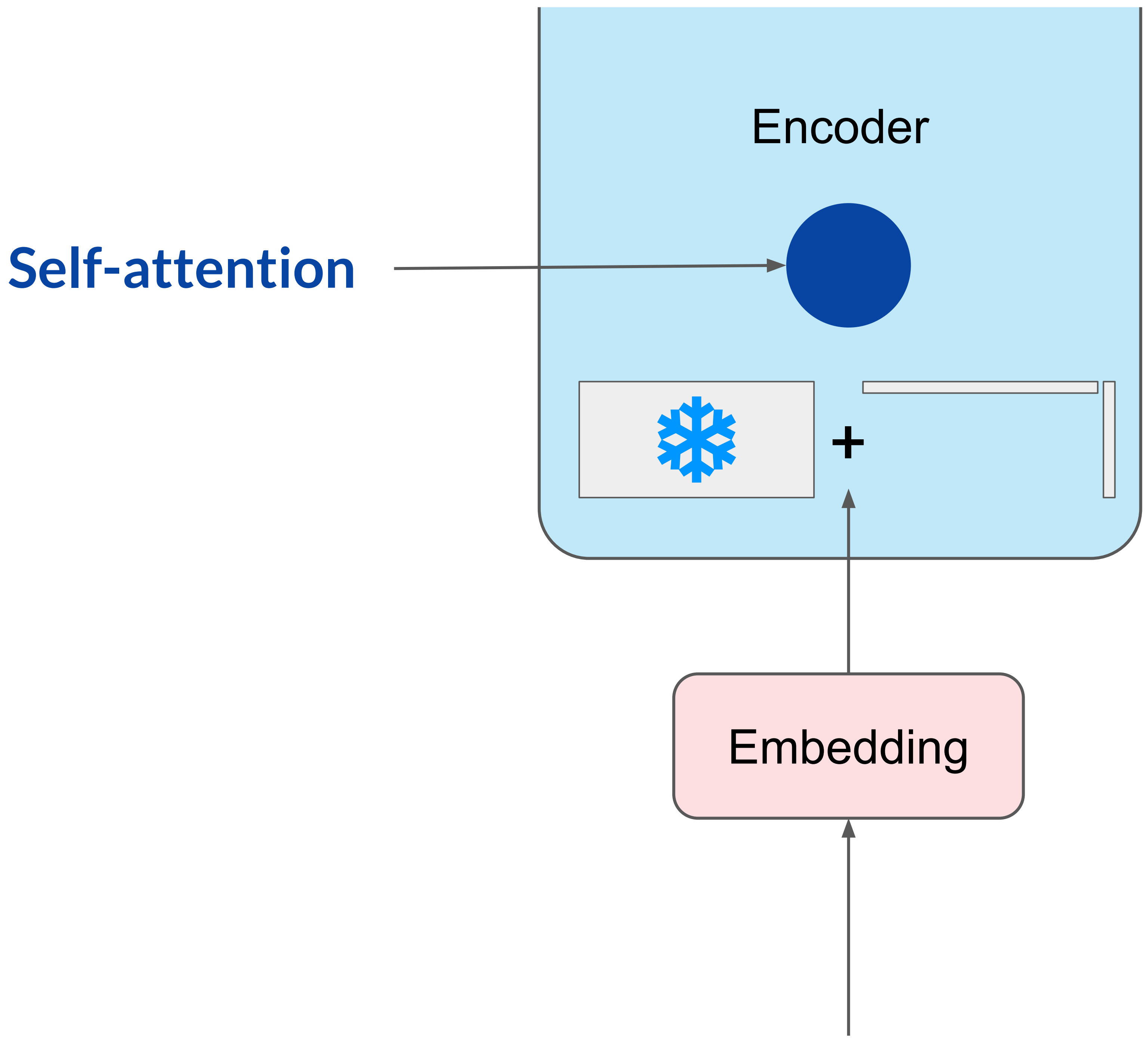
# LoRA: Low Rank Adaption of LLMs




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

Rank *r* is small dimension, typically 4, 8 … 64

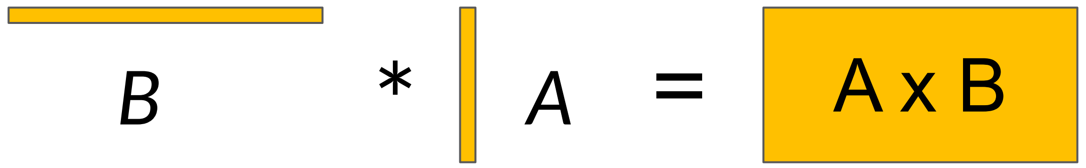
# LoRA: Low Rank Adaption of LLMs



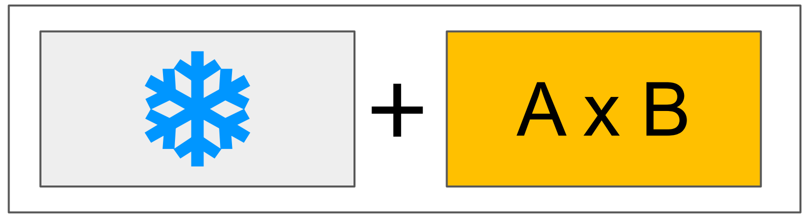

1. Freeze most of the original LLM weights.
2. Inject 2 **rank decomposition matrices**
3. Train the weights of the smaller matrices

Steps to update model for inference

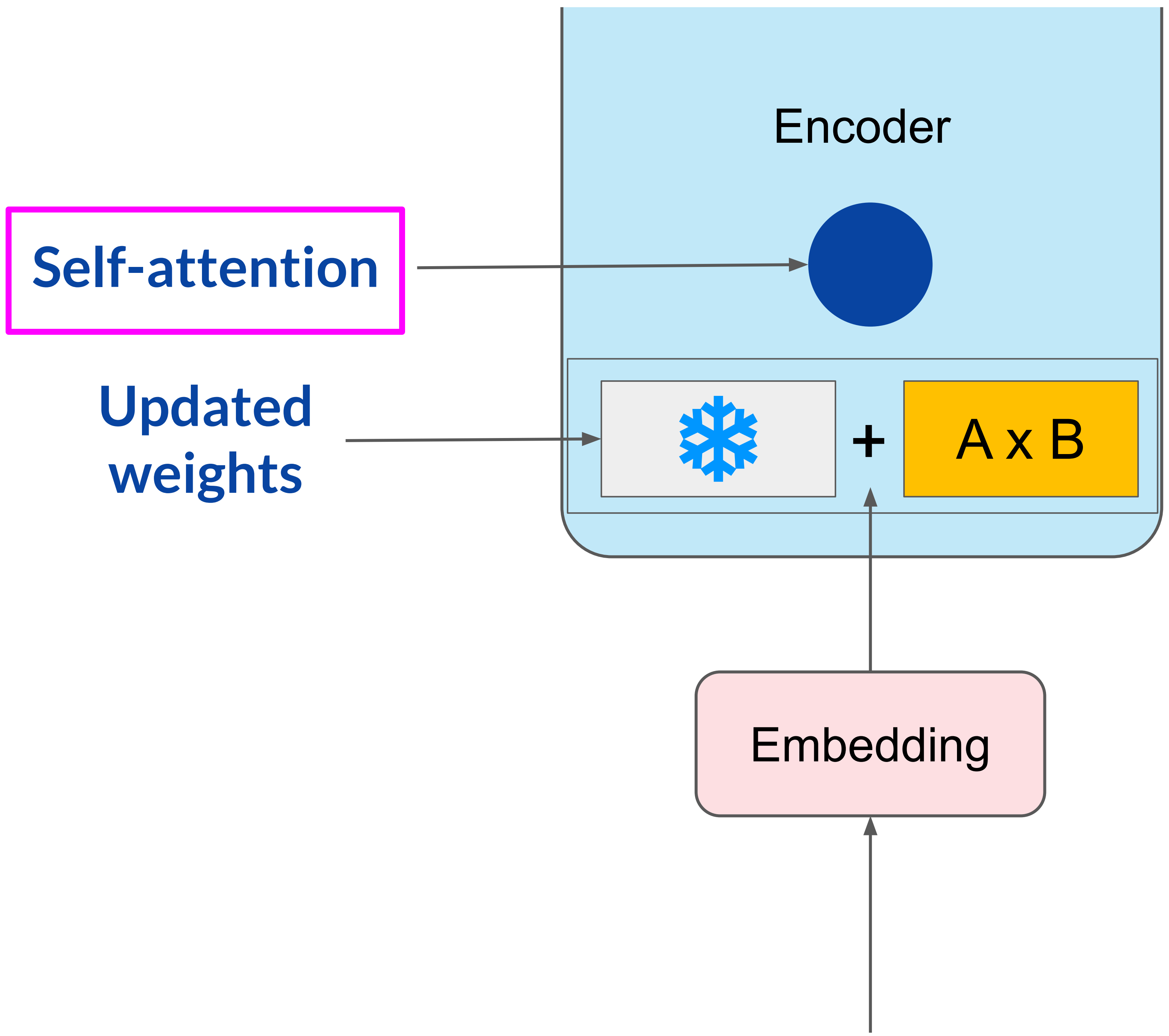
1. Matrix multiply the low rank matrices




2. Add to original weights



# LoRA: Low Rank Adaption of LLMs

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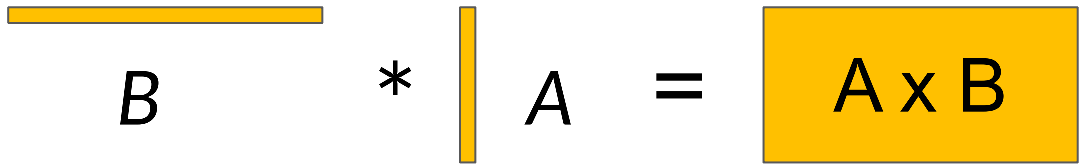


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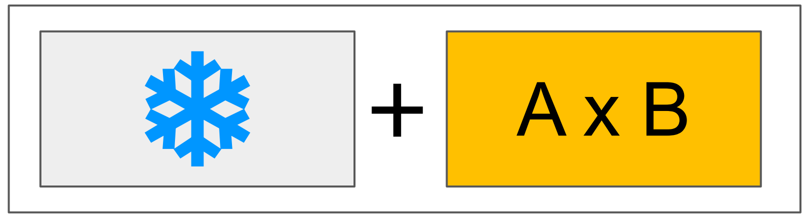
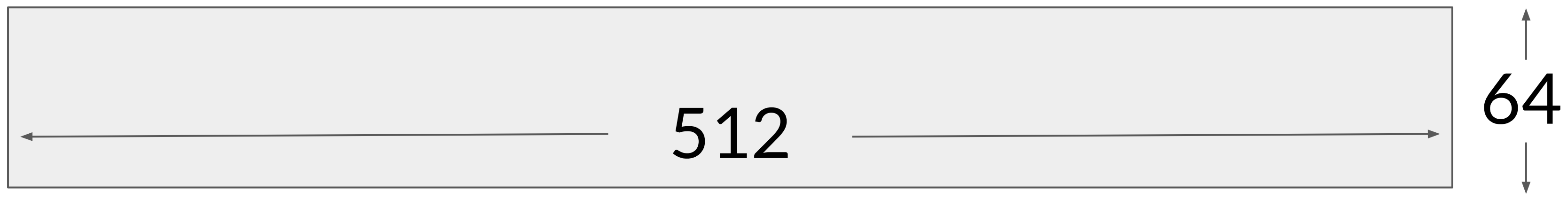


# Concrete example using base Transformer as reference

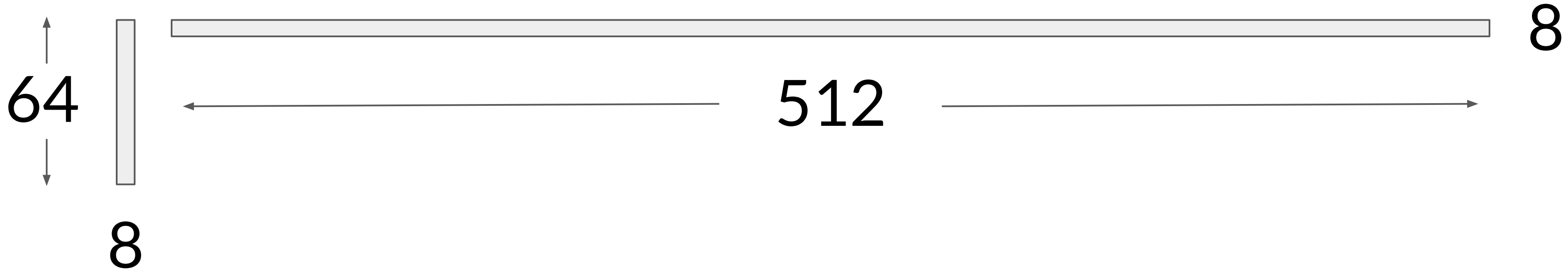
Use the base Transformer model presented by Vaswani et al. 2017:

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



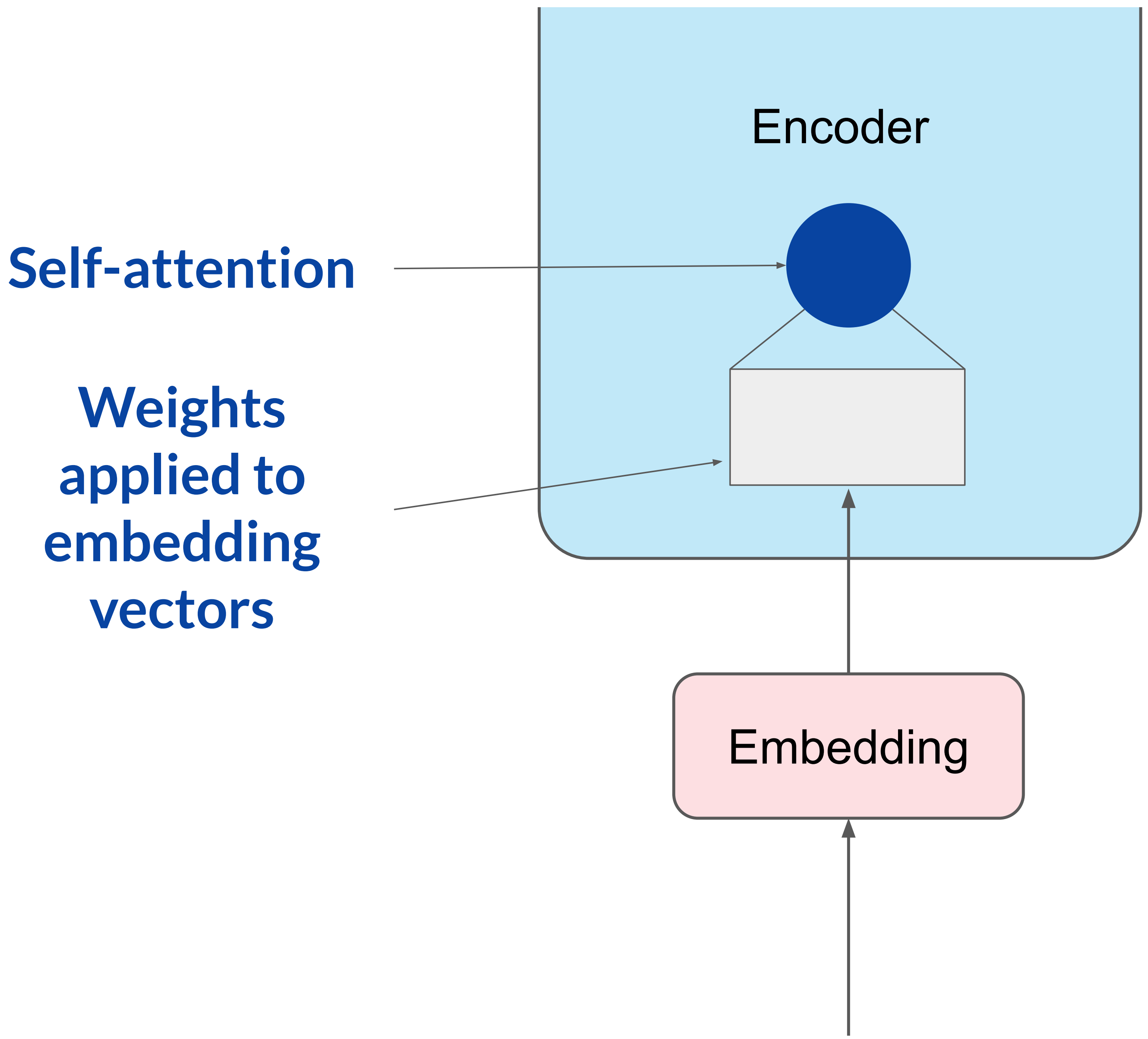

In LoRA with rank $r$ = 8:

- $A$ has dimensions $r$ x $k$ = 8 x 64 = 512 parameters
- B has dimension $d$ x $r$ = 512 x 8 = 4,096 trainable parameters

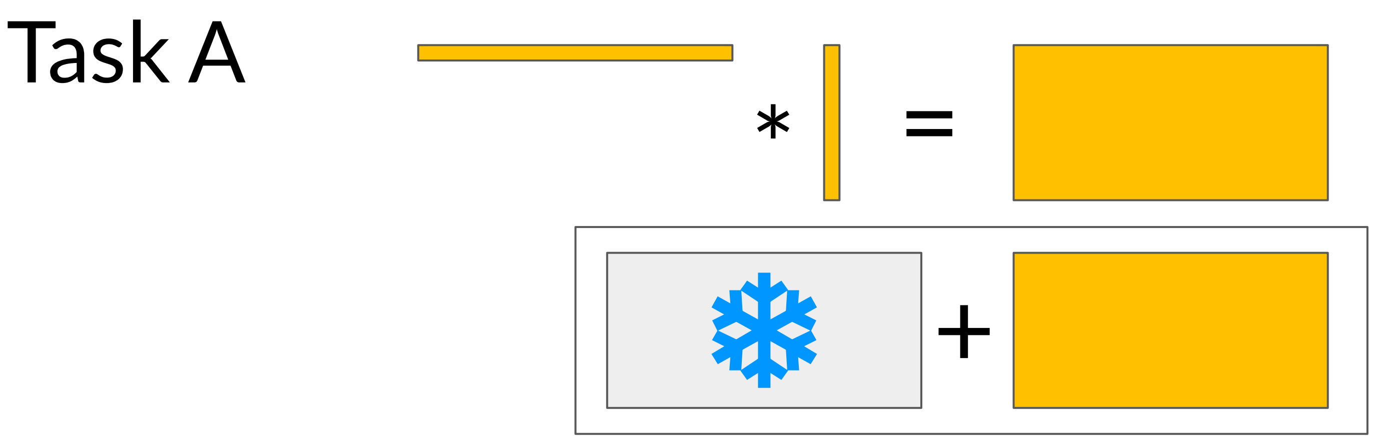



**86% reduction in parameters to train!**

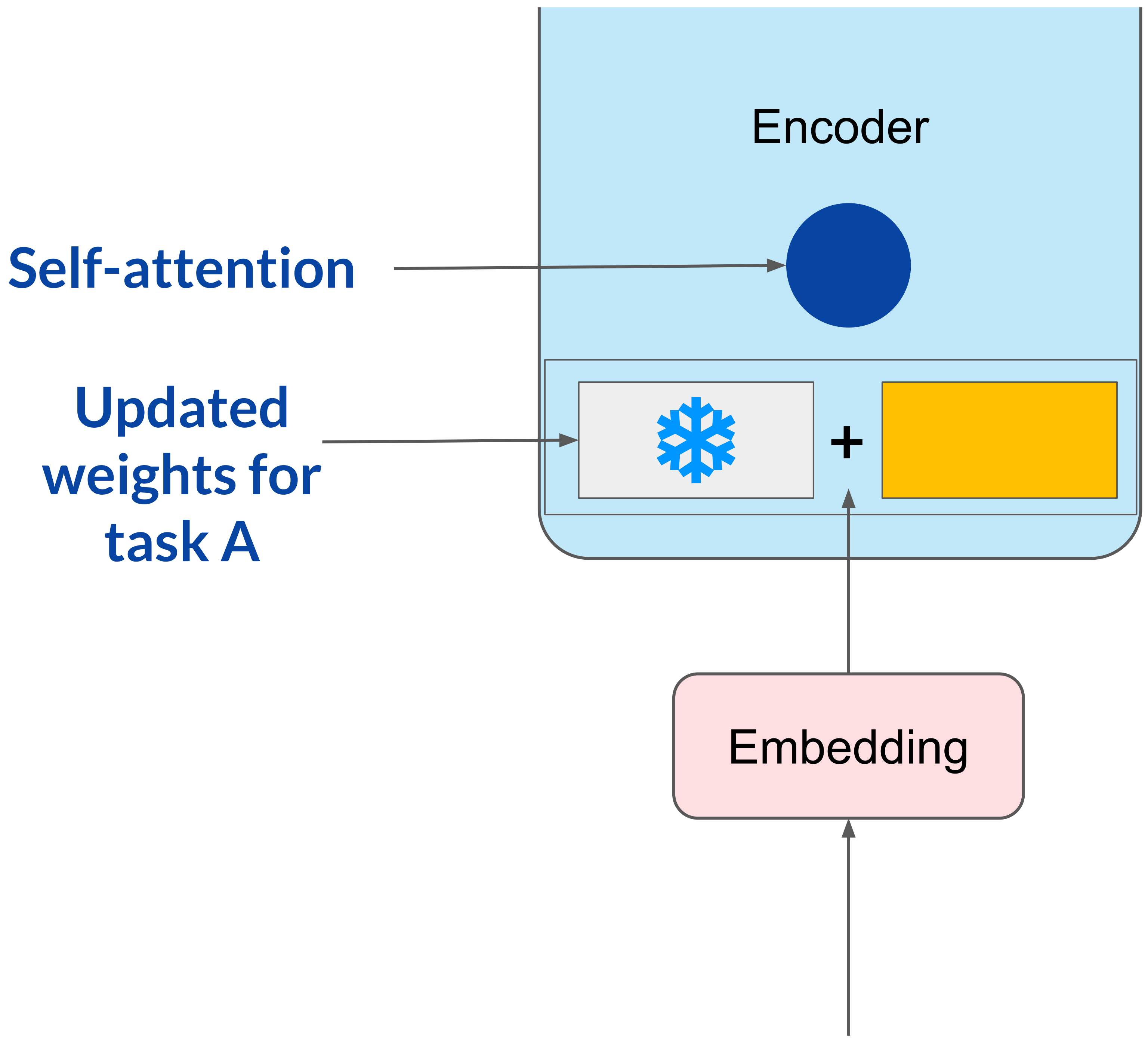
# LoRA: Low Rank Adaption of LLMs




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



# LoRA: Low Rank Adaption of LLMs

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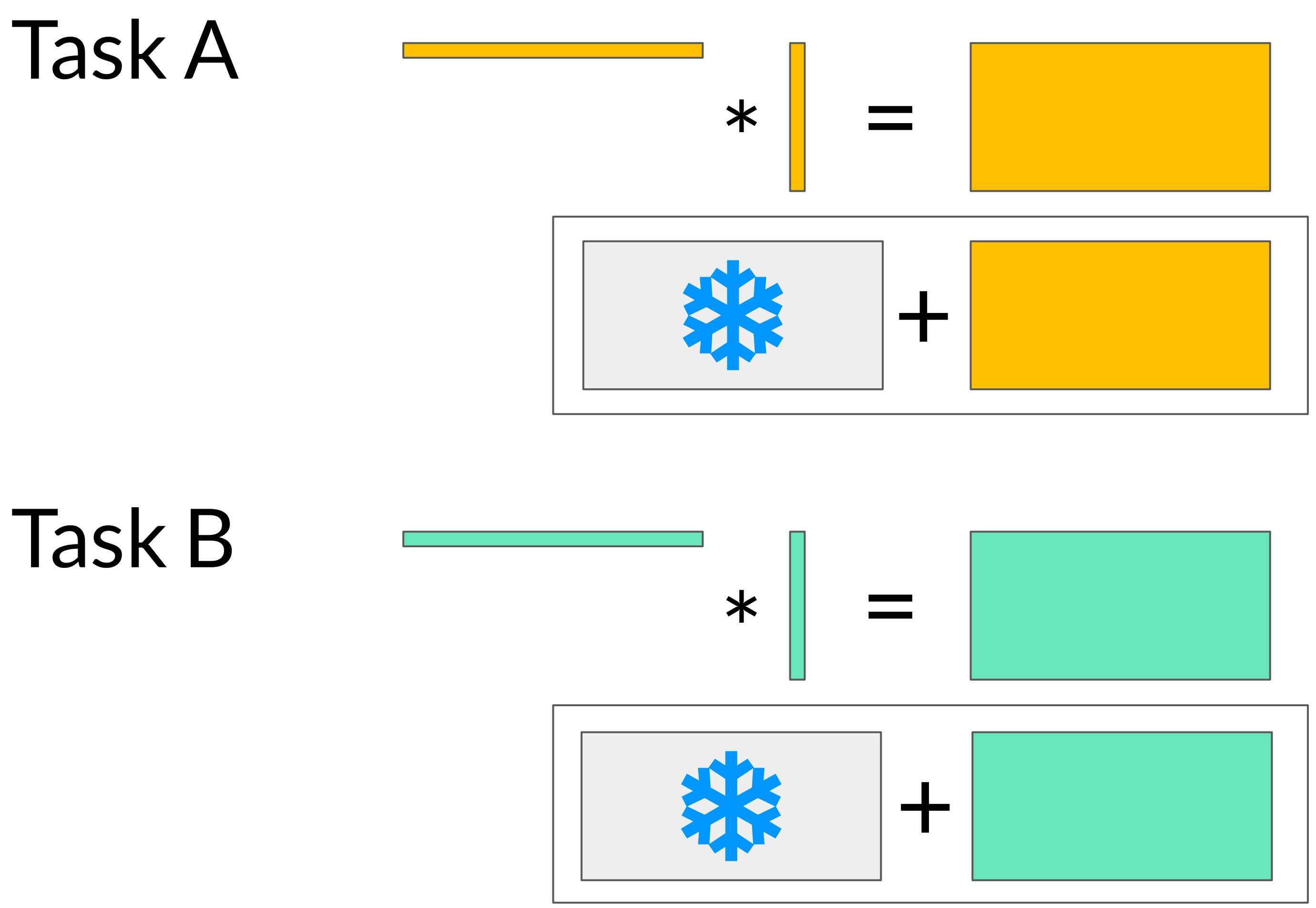
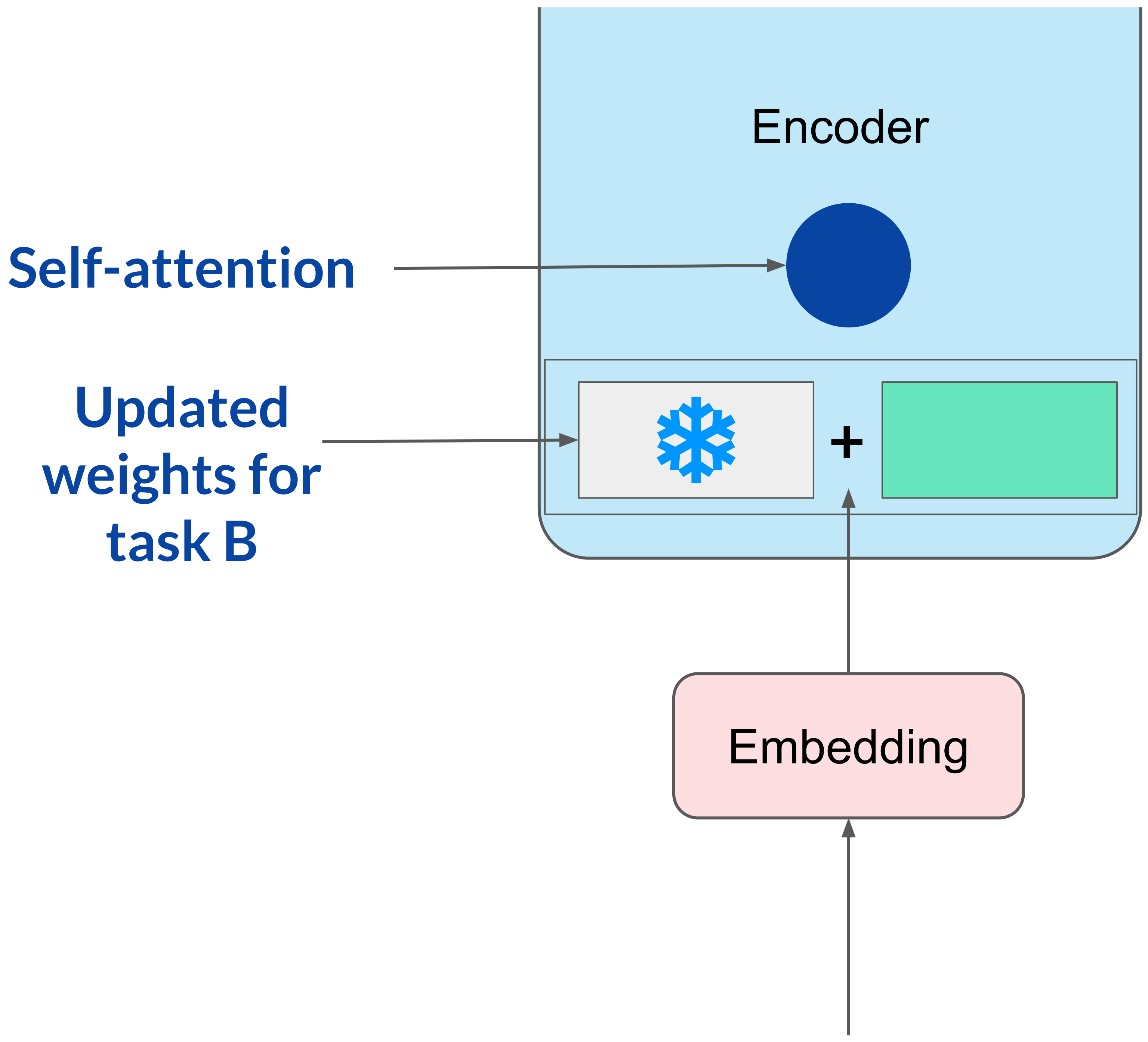
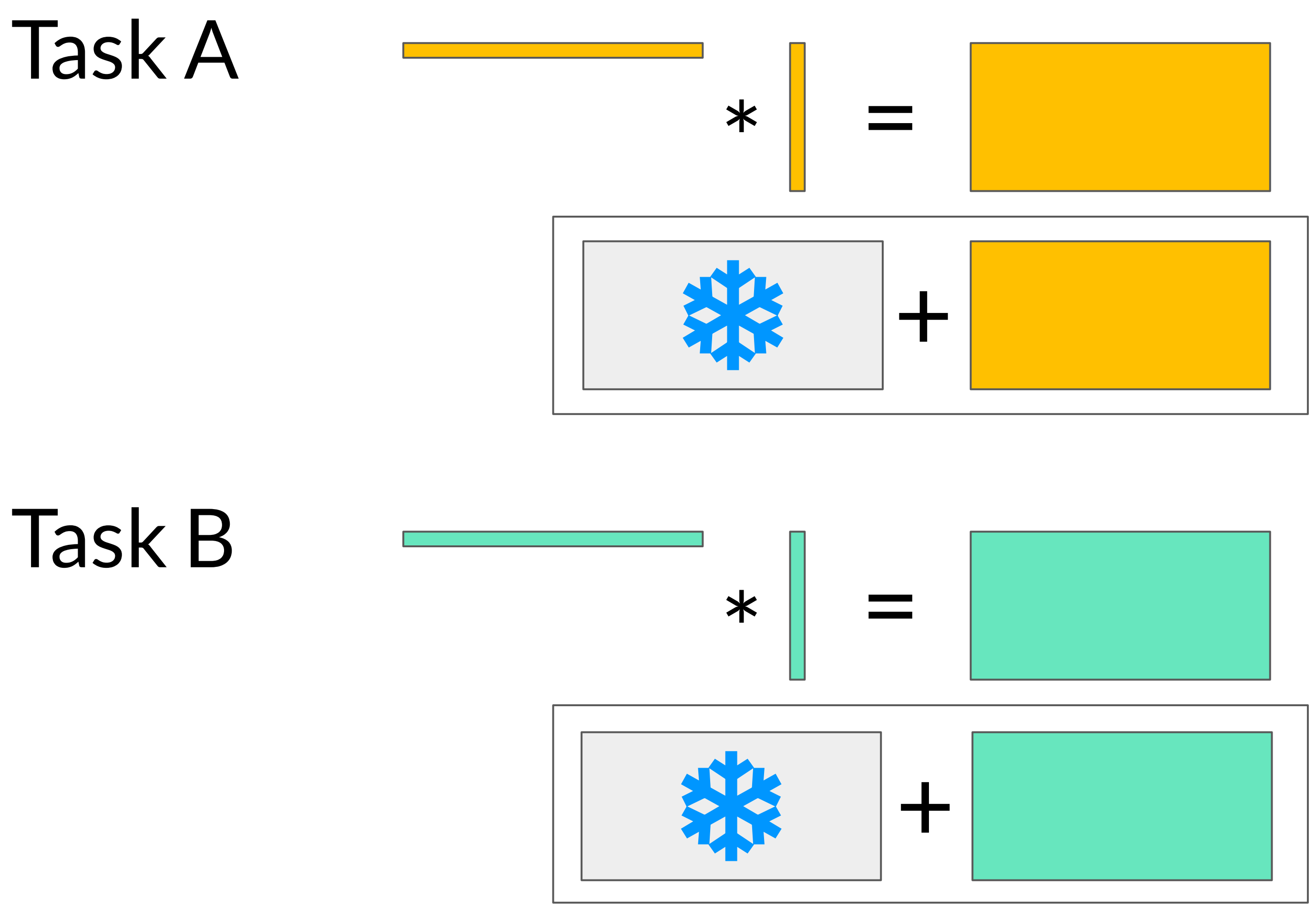


# LoRA: Low Rank Adaption of LLMs




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



# 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

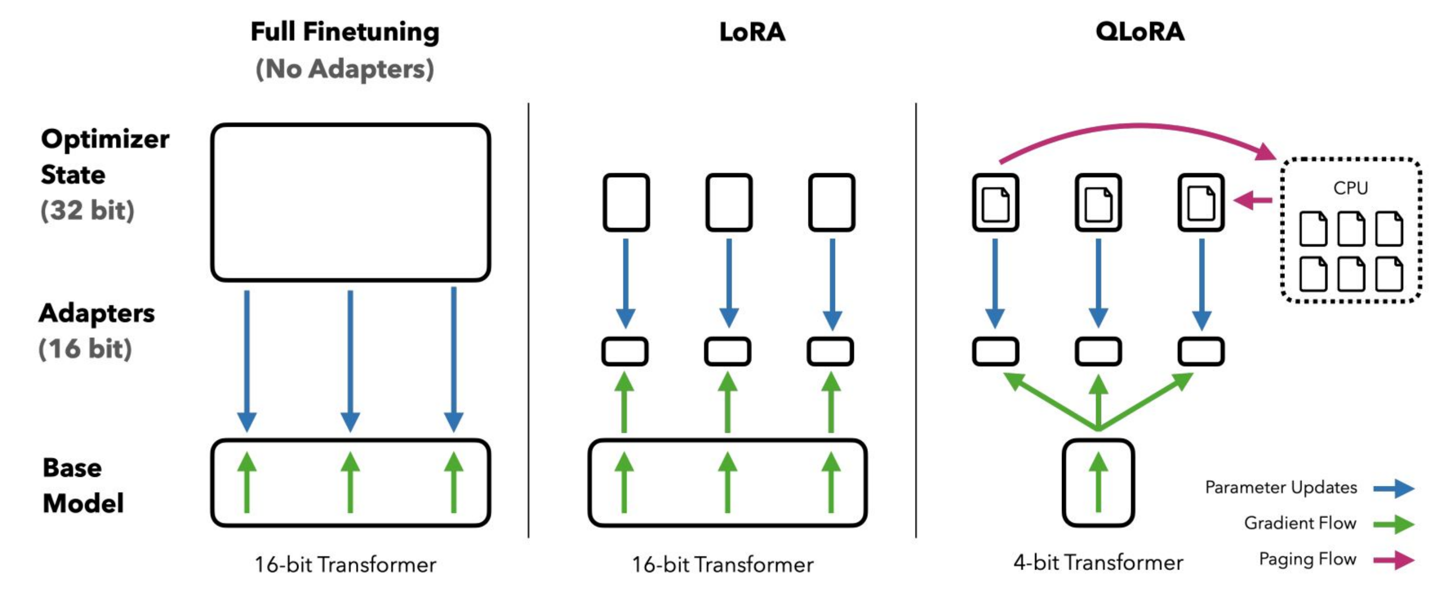
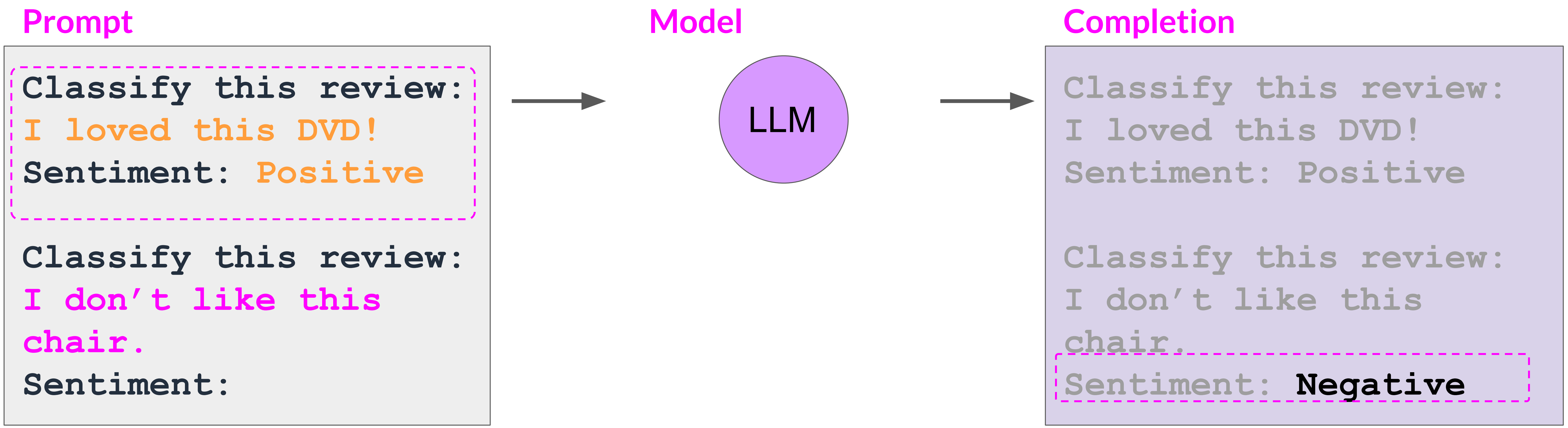



**Figure 1:** Different finetuning methods and their memory requirements. QLoRA improves over LoRA by quantizing the transformer model to 4-bit precision and using paged optimizers to handle memory spikes.

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

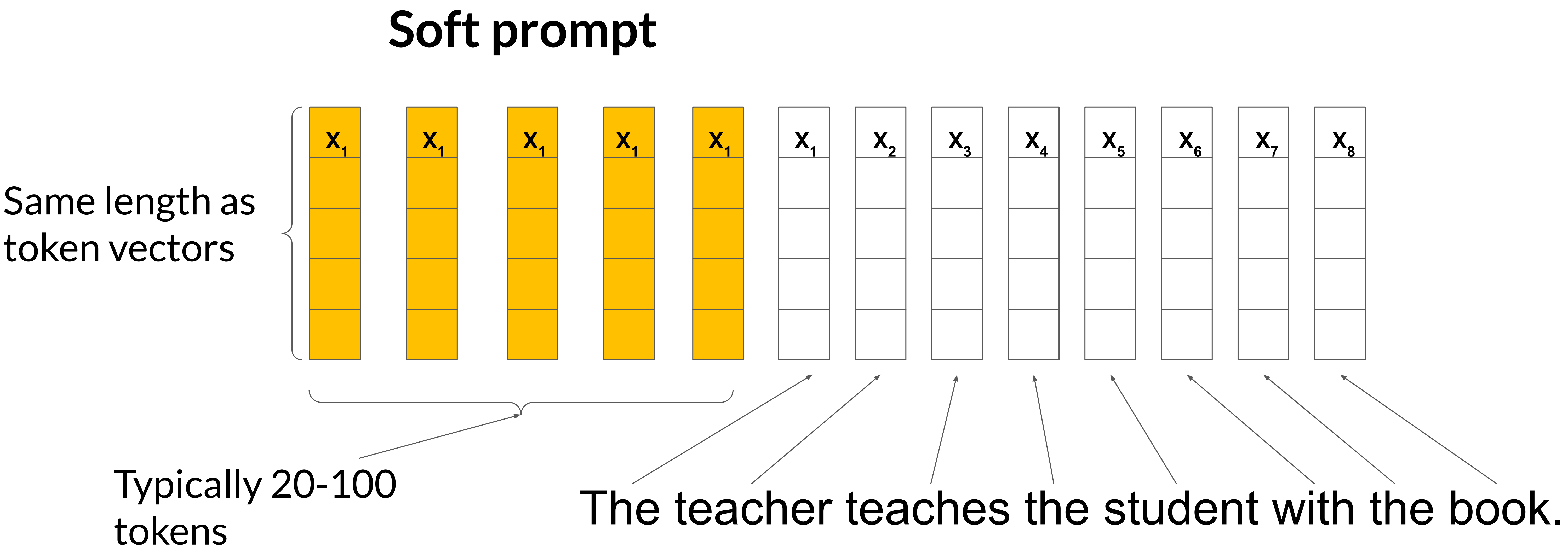
# Prompt tuning with soft prompts

# Prompt tuning is **not** prompt engineering!

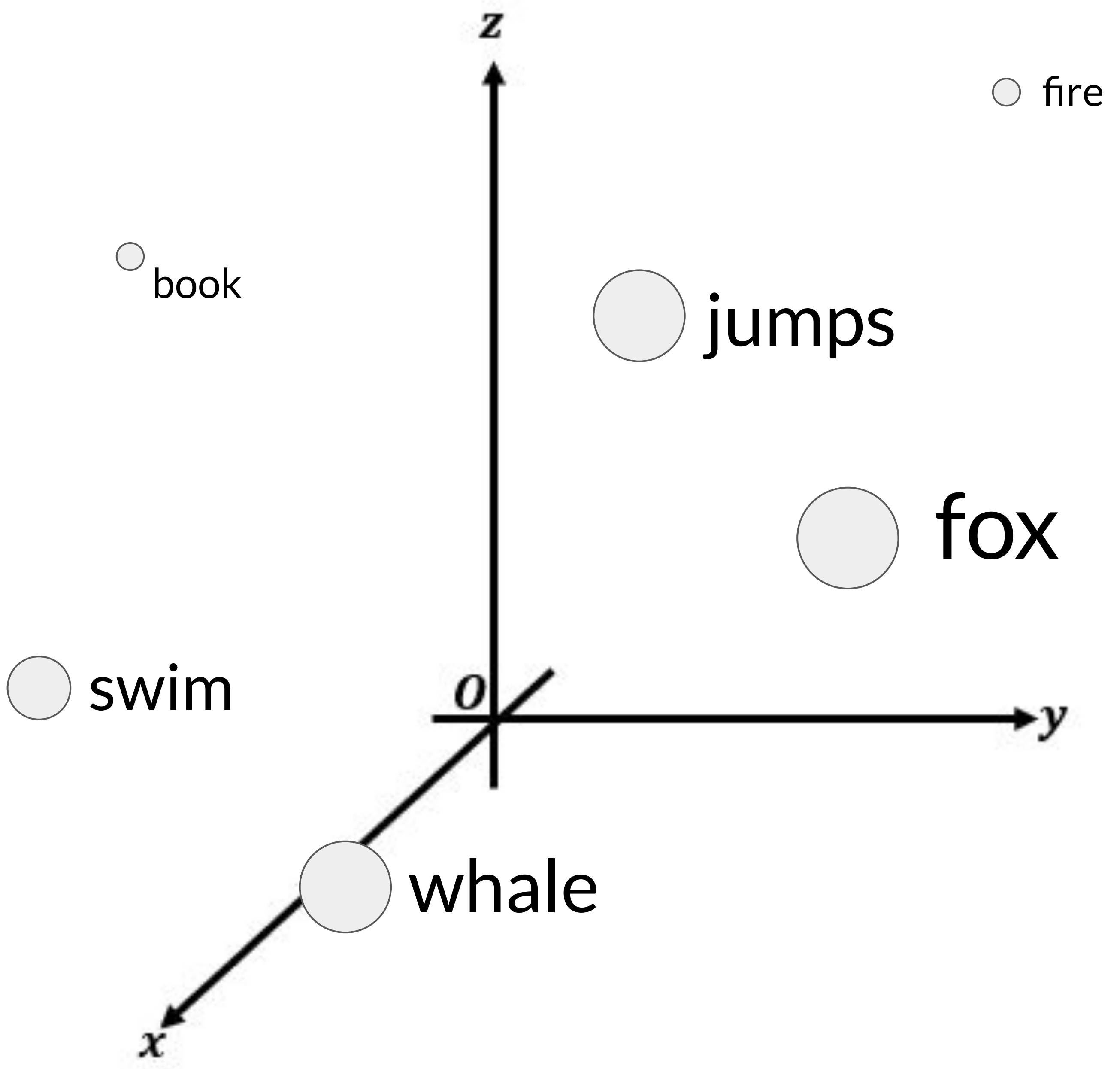



One-shot or Few-shot Inference

# Prompt tuning adds trainable “soft prompt” to inputs

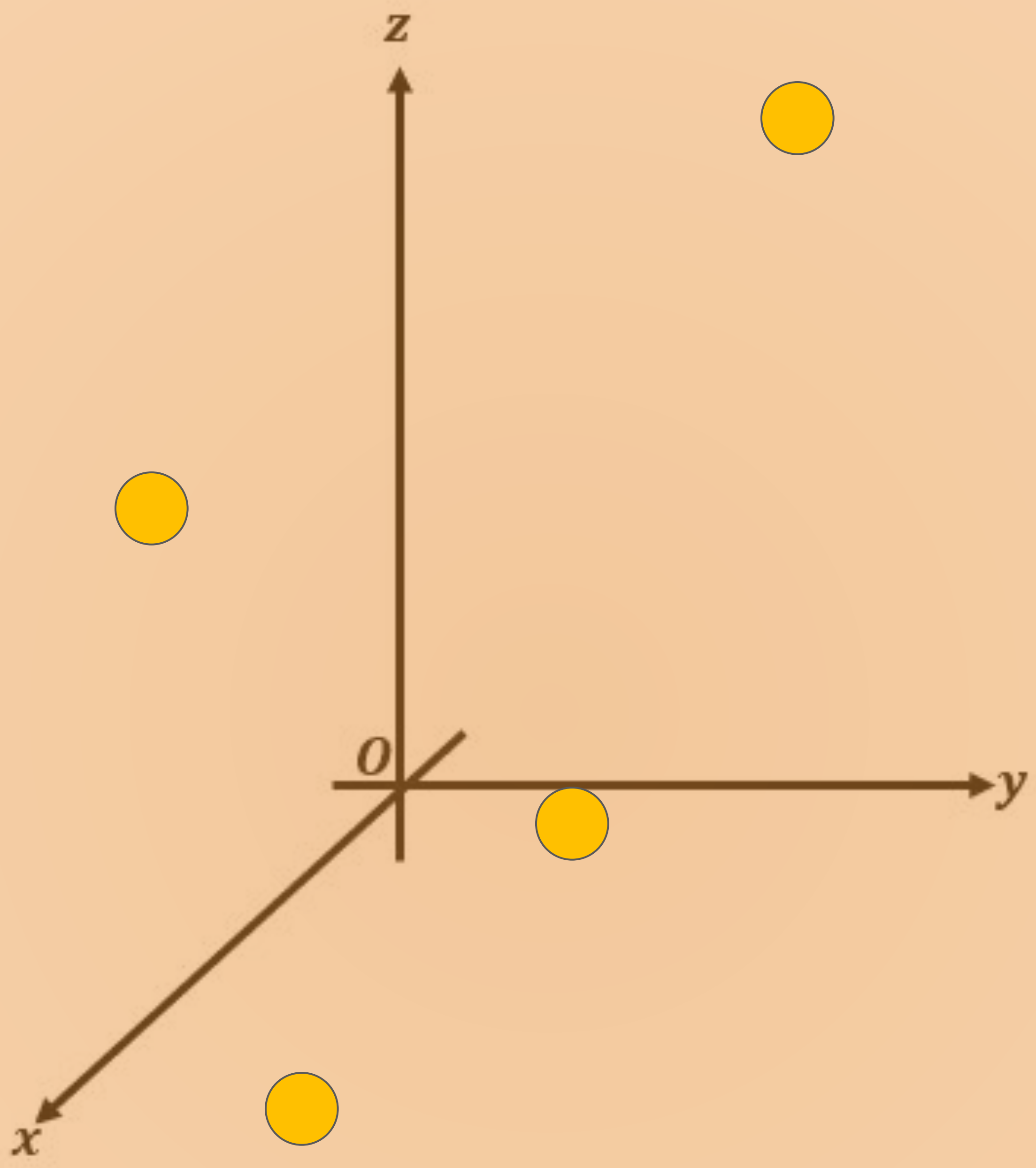


# Soft prompts



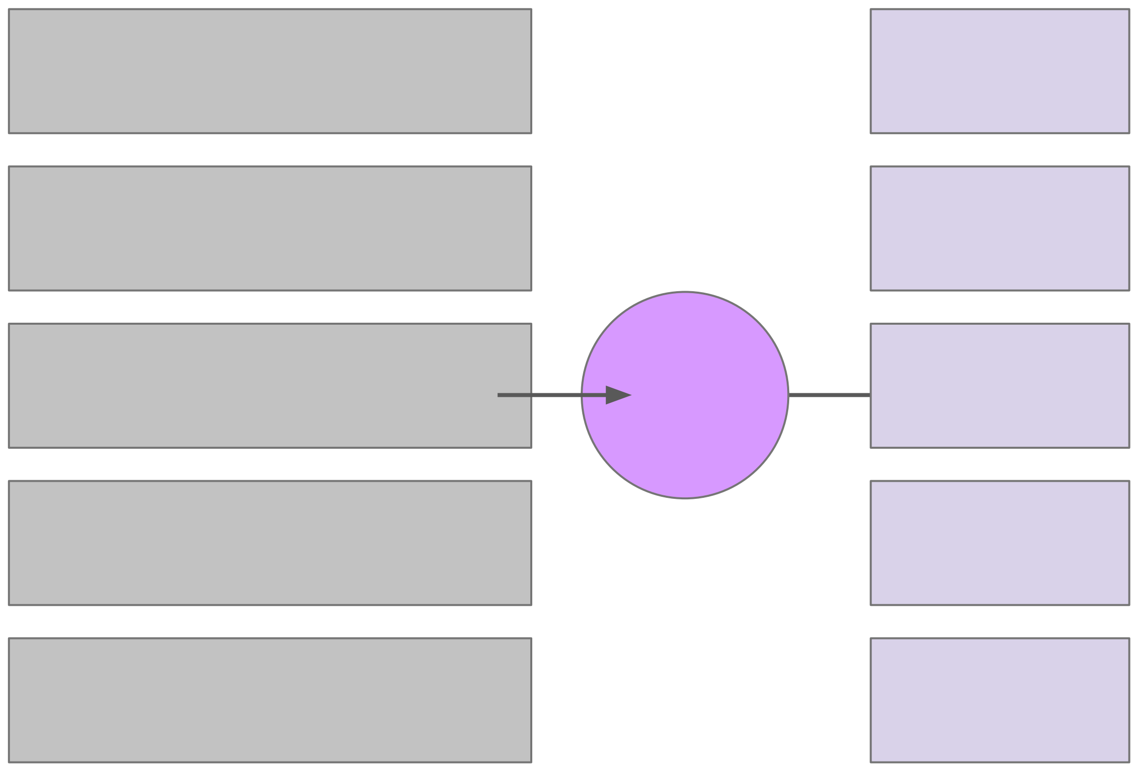

Embeddings of each token exist at unique point in multi-dimensional space

# Soft prompts



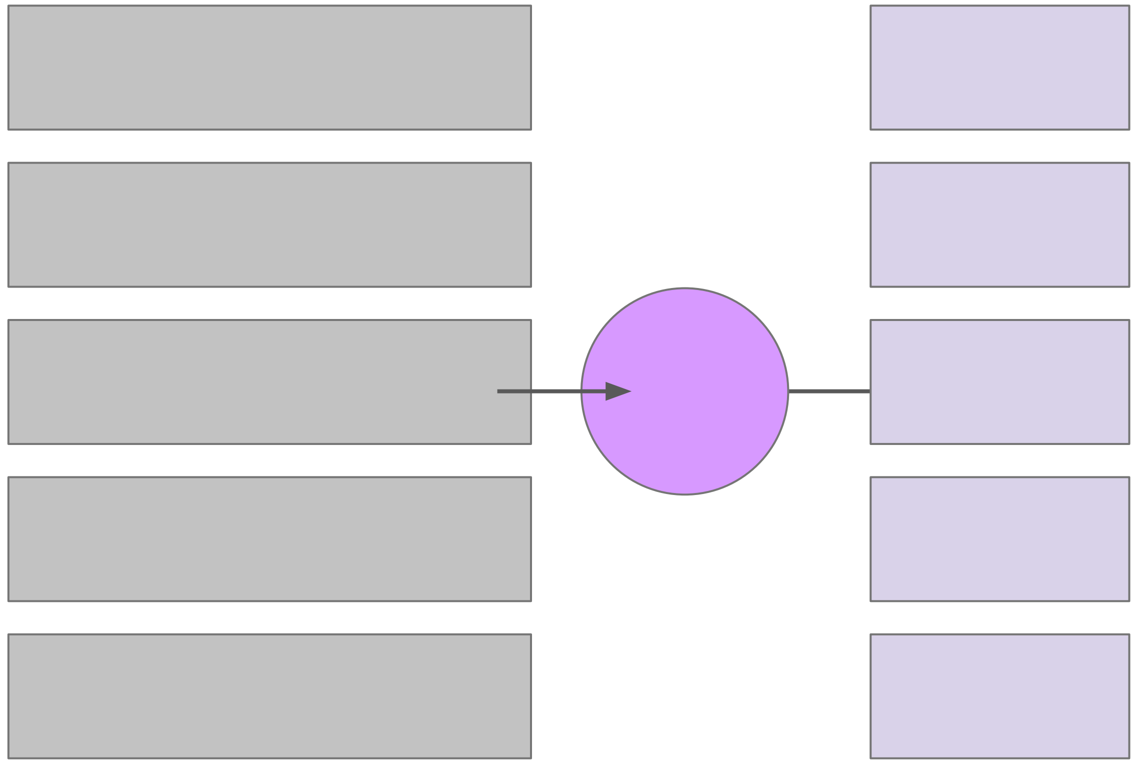
# Full Fine-tuning vs prompt tuning

Weights of model updated
during training



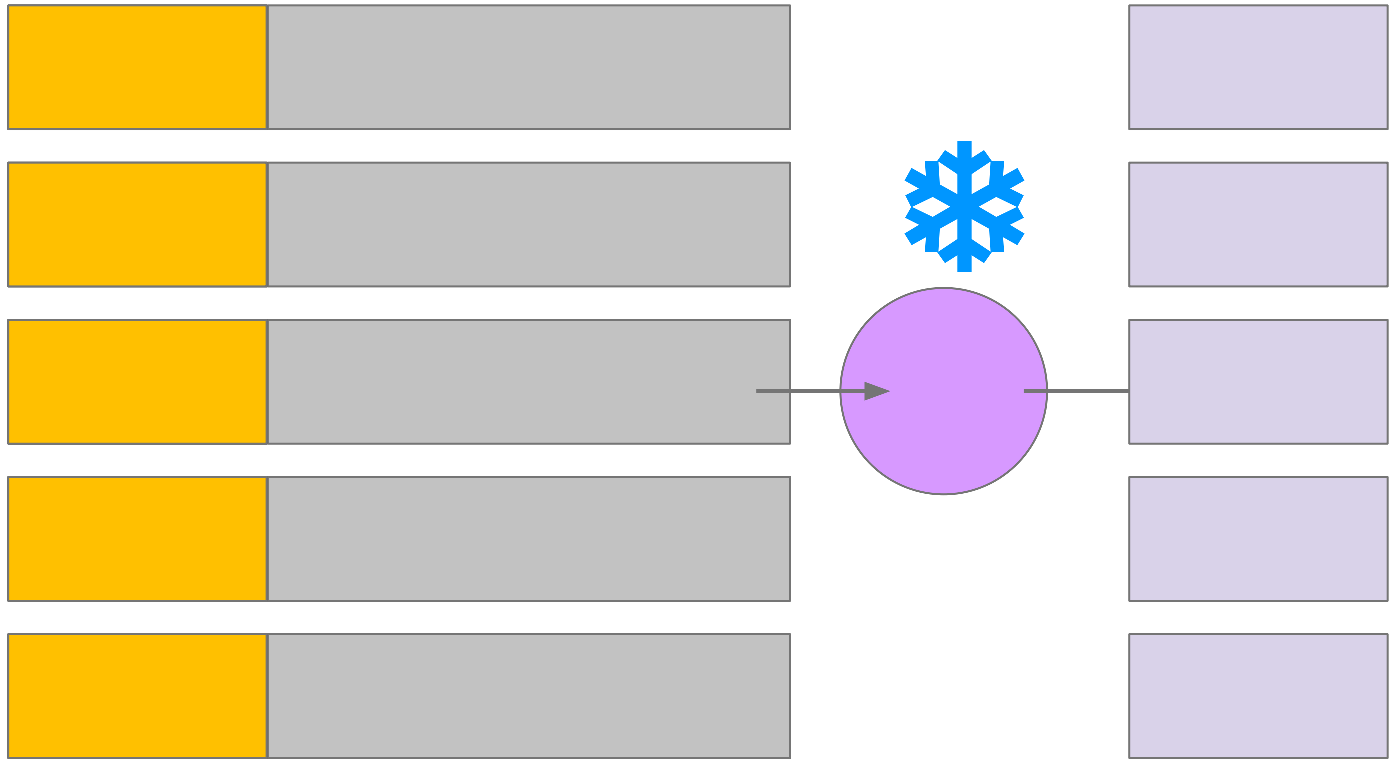
# Full Fine-tuning vs prompt tuning

Weights of model updated during training



Millions to Billions of parameter updated

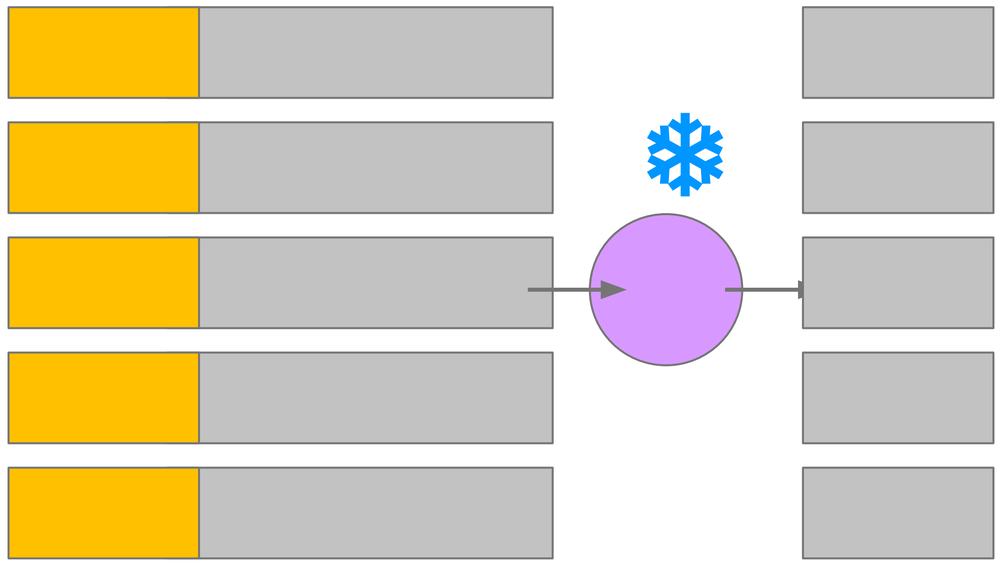
Weights of model frozen and soft prompt trained



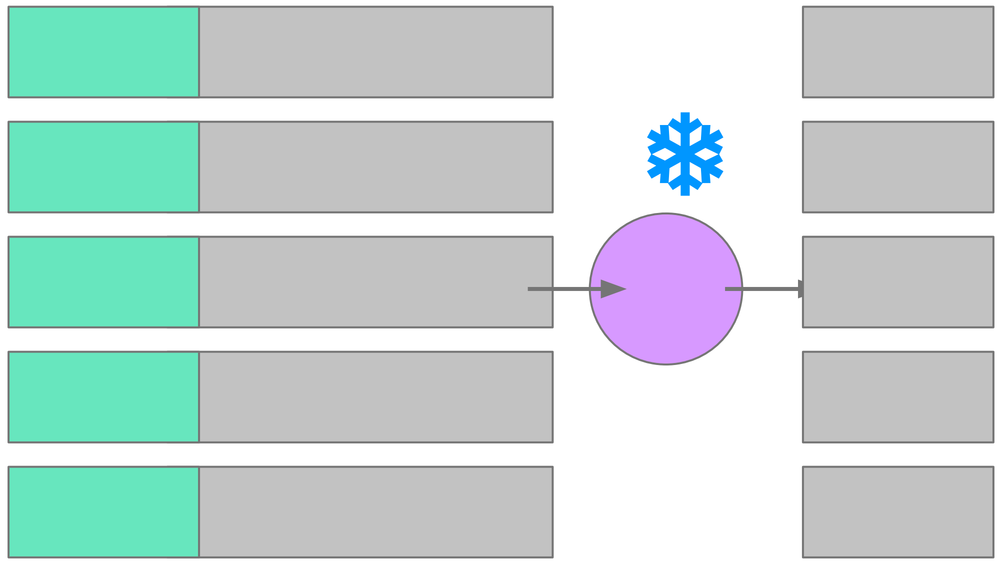
10K - 100K of parameters updated

# Prompt tuning for multiple tasks

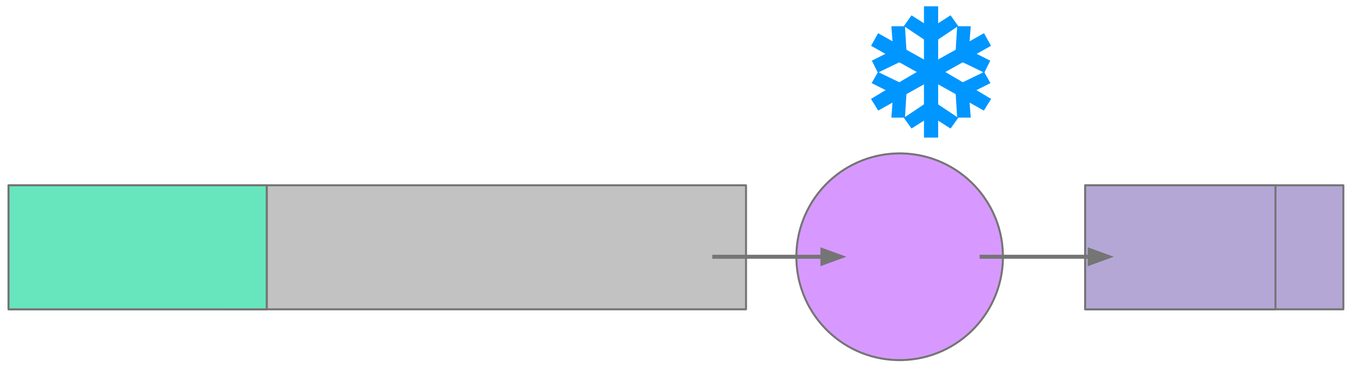
Task A



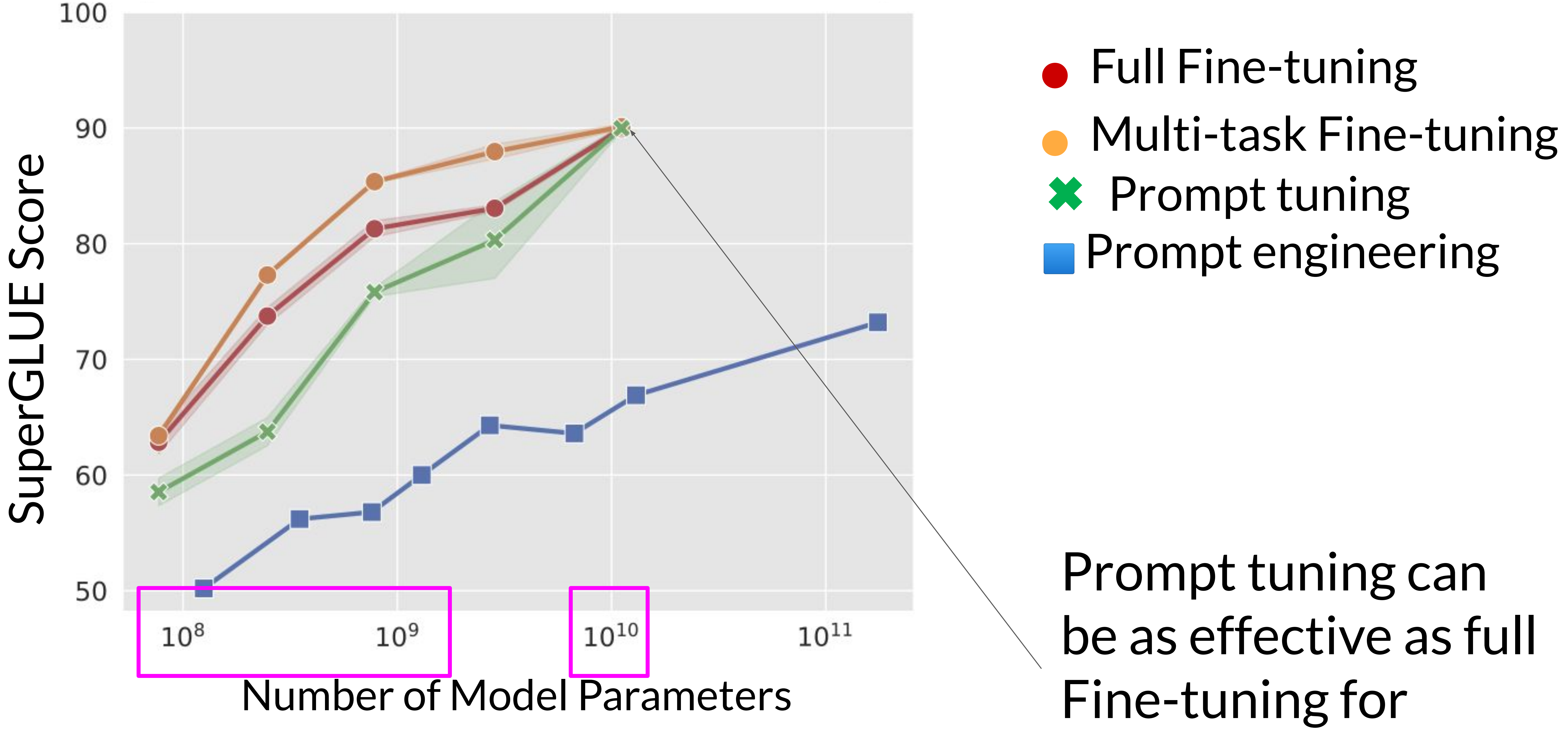
Task B



Switch out soft prompt at inference time to change task!



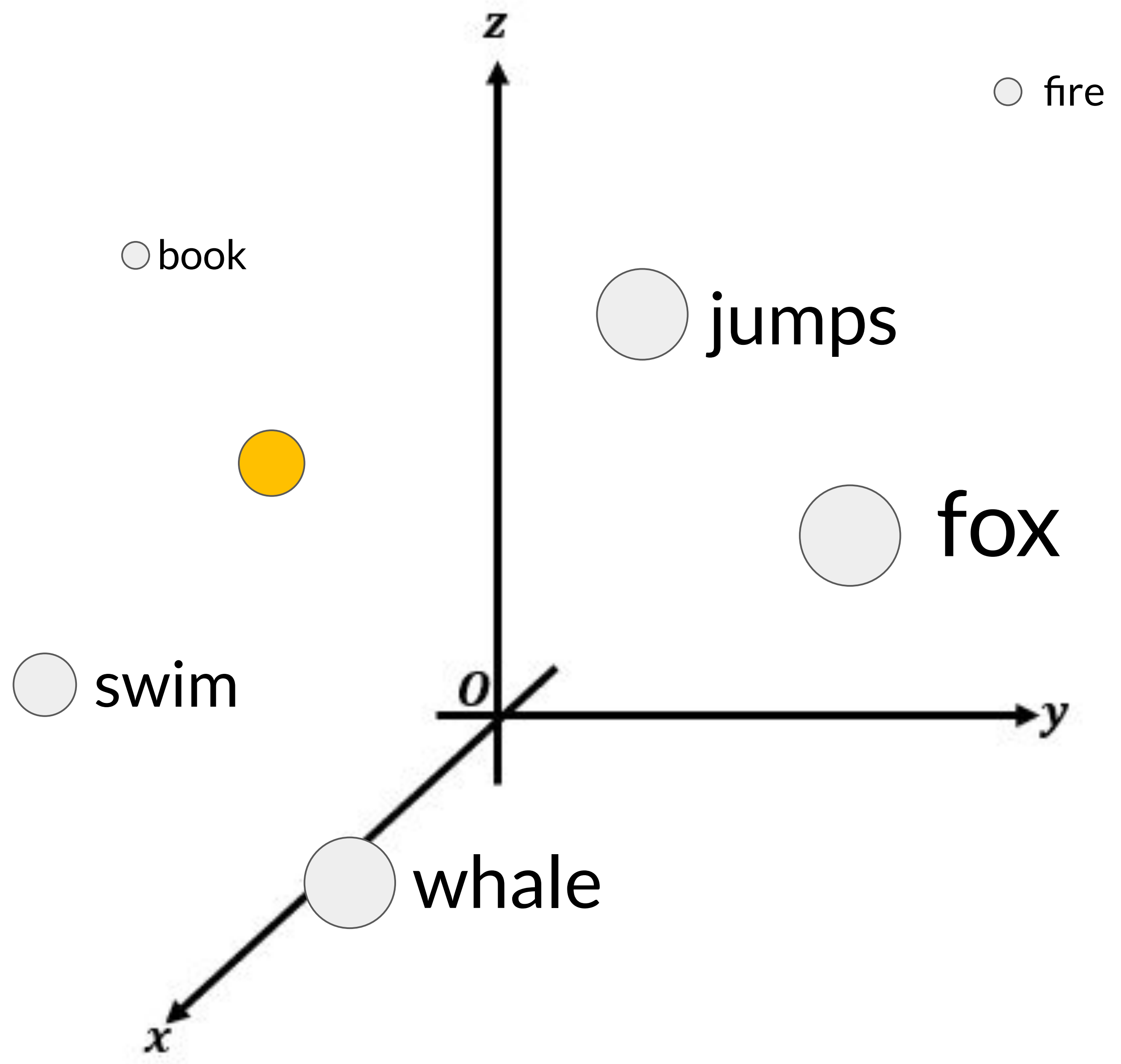
# Performance of prompt tuning




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

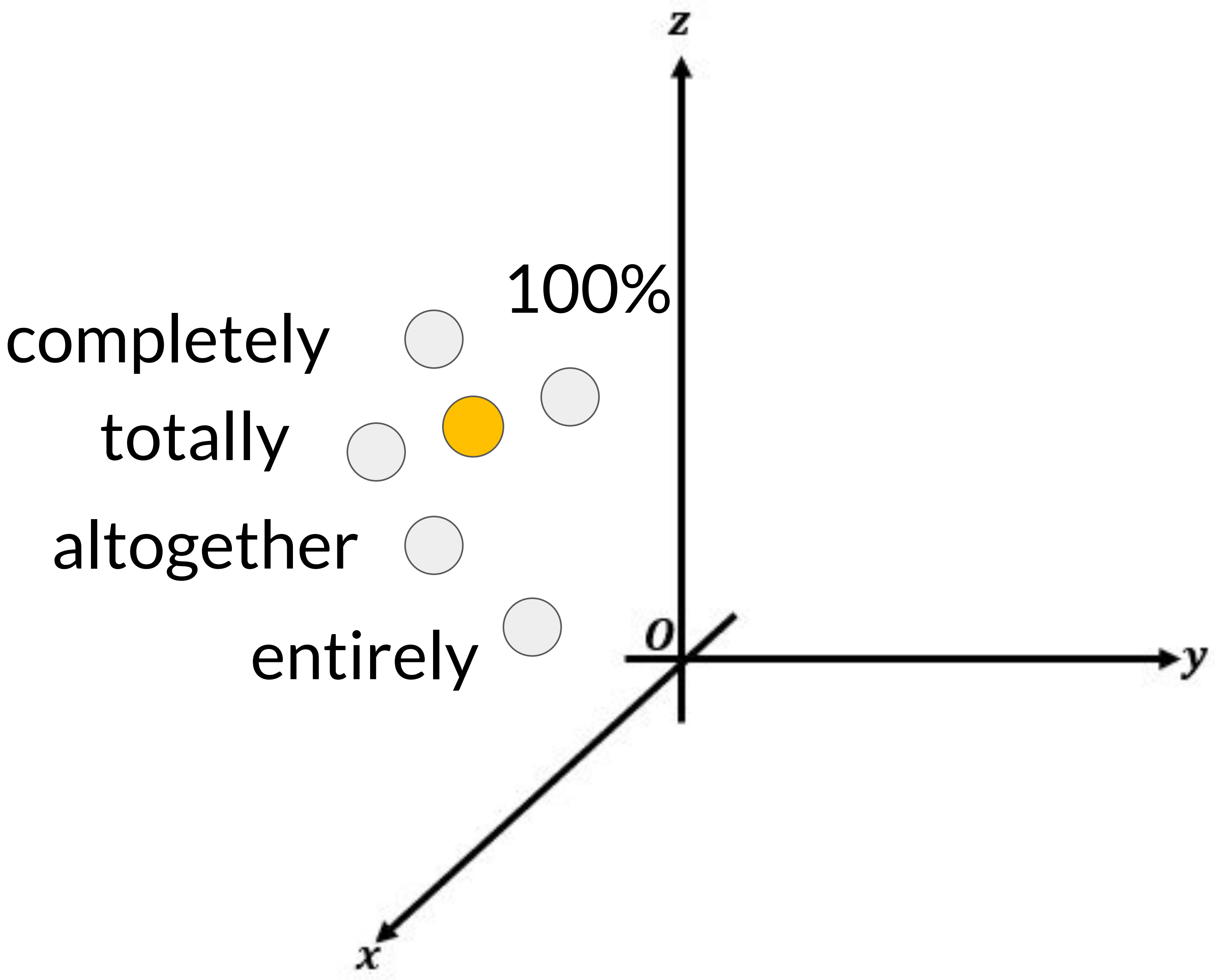
Source: Lester et al. 2021, "The Power of Scale for Parameter-Efficient Prompt Tuning"

# 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**