CS11-711 Advanced NLP

Fine-Tuning

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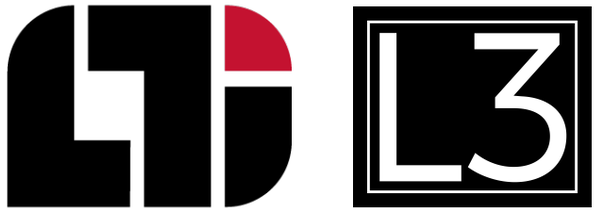


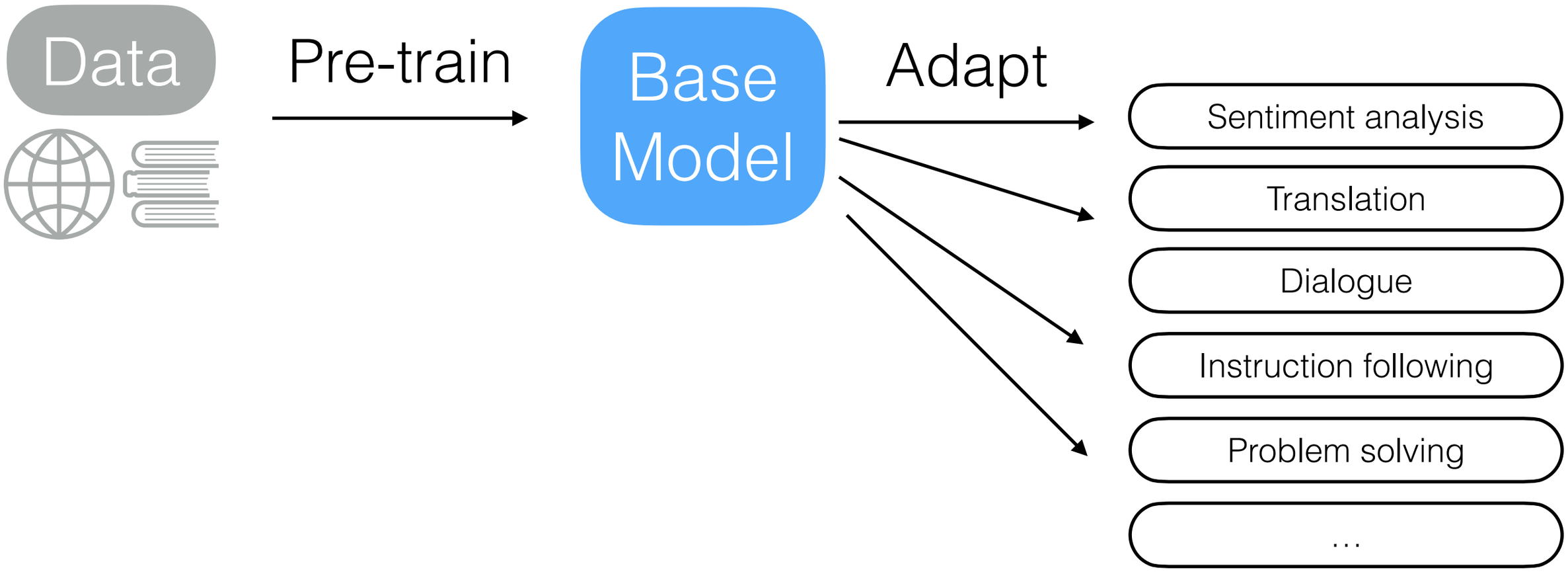
https://cmu-l3.github.io/anlp-fall2025/

https://github.com/cmu-l3/anlp-fall2025-code

Slides adapted from Graham Neubig's Fall 2024 course

Recap: Pre-training

Lecture 6



Recap: prompting

Lecture 7

Example:
“Translate this sentence into English:
この映画が嫌い”

Base Model + Prompt → Translation

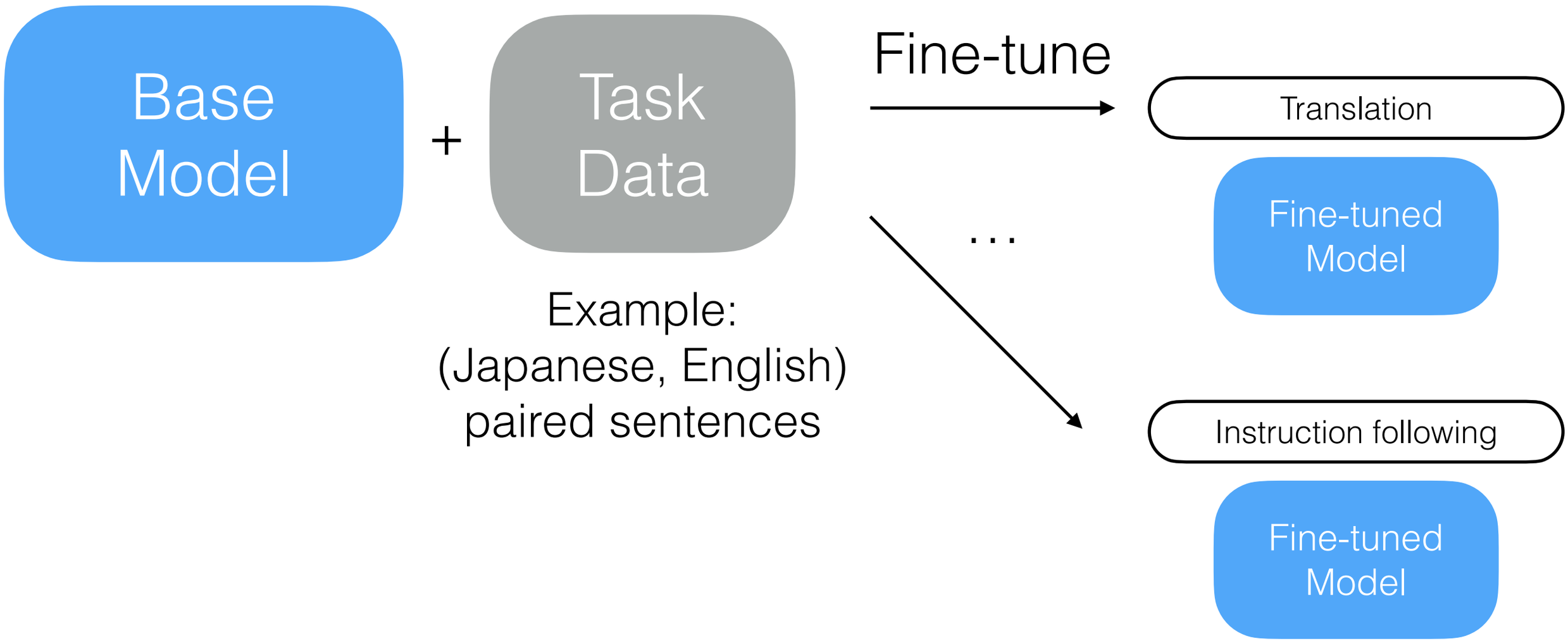
Prompt → Sentiment analysis

Prompt → Instruction following

Prompt → Problem solving

...

Today: fine-tuning



Today's lecture

- Fine-tuning basics
- Instruction tuning
- Knowledge distillation

Fine-tuning

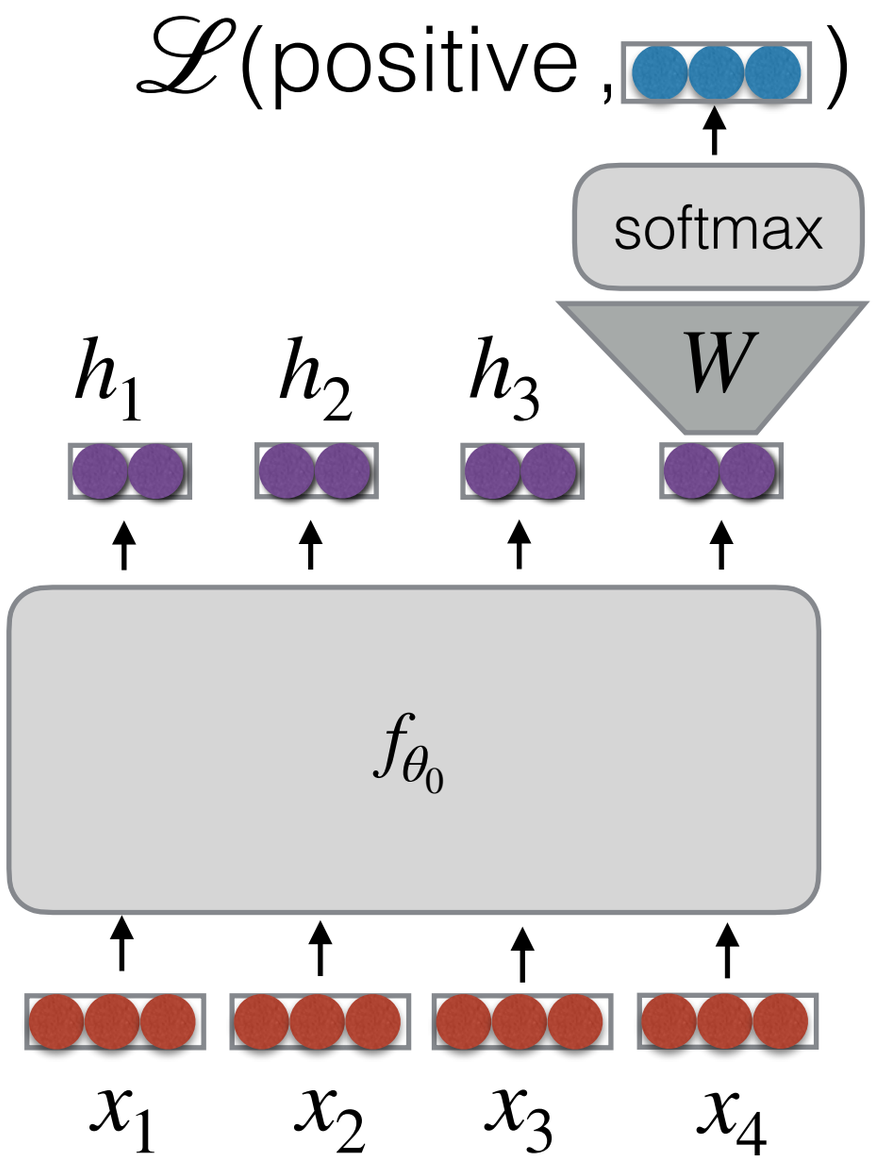
- **Fine-tuning**: continued gradient-based training of a pre-trained model
- Given pre-trained parameters θ_0 and data $D = \{(x, y)_n\}_{n=1}^{N}$, solve:

$$\theta^* = \text{argmin}_\theta \mathbb{E}_{(x,y)\sim D} \left[\mathscr{L}(f_\theta(x), y) \right]$$

+ techniques to prevent overfitting (e.g., regularization, dropout)

Example: classification

- Given: A sequence model $f_{\theta_0}(x_1, \ldots, x_T) \rightarrow h_1, \ldots, h_T$
  - θ_0: pre-trained weights
- Data $D = \{(x, y)_n\}_{n=1}^{N}$
  - x: input text
  - $y \in \{1,2,\ldots, K\}$ class label
- Add output head to last hidden state
  - $p_\theta(y \mid x) = \text{softmax}(Wh + b)$
    - $W \in \mathbb{R}^{K \times d}, h \in \mathbb{R}^d, b \in \mathbb{R}^K$
- Loss: cross-entropy loss $(-\log p_\theta(y \mid x))$
- By default, update all parameters $\theta = (\theta_0, W, b)$



Code example

This notebook shows fine-tuning a language model with a classification head.

Task: Given a name, predict how many vowels (a, e, i, o, u) it contains.

```
data = open
print(f"Tot
data[1000:1
```

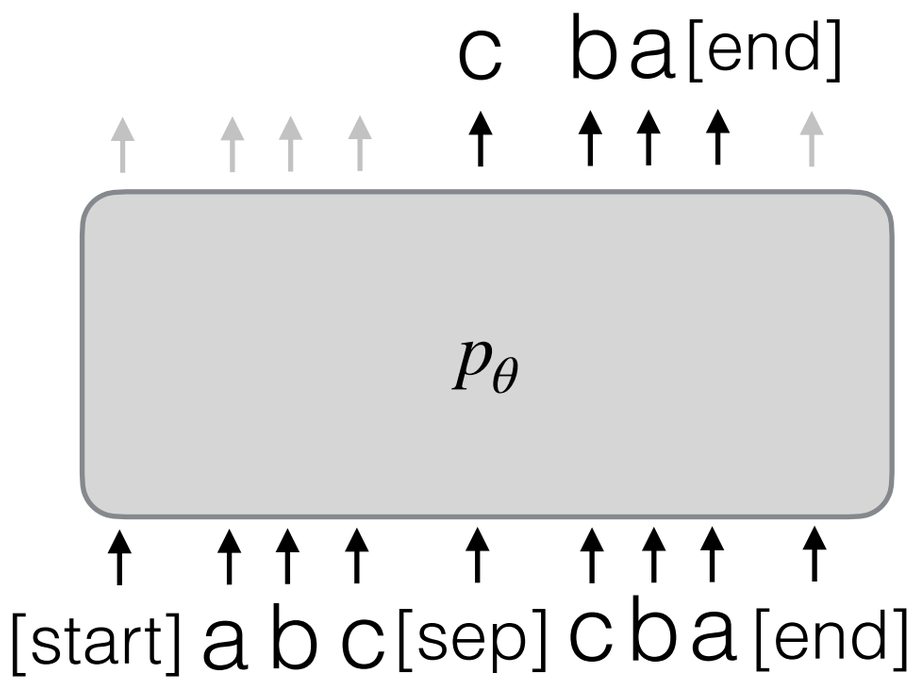
```python
class LMClassifier(nn.Module):
    def __init__(self, base_model, num_classes=11):
        super().__init__()
        self.base_model = base_model
        self.num_classes = num_classes
        self.hidden_size = base_model.config.hidden_size
        self.classifier = nn.Linear(self.hidden_size,  num_classes)

    def _last_token_hidden(self, hidden_states, attention_mask):
        # Find the position of the last non-padding token
        if attention_mask is not None:
            seq_lengths = attention_mask.sum(dim=1) - 1
            batch_size = hidden_states.size(0)
            last_hidden = hidden_states[torch.arange(batch_size), seq_lengths]
        else:
            last_hidden = hidden_states[:, -1, :]  # Last token
        return last_hidden

    def forward(self, input_ids, attention_mask=None):
        outputs = self.base_model(
            input_ids,
            attention_mask=attention_mask,
            output_hidden_states=True
        )
        hs = outputs.hidden_states[-1]  # (batch_size, seq_len, hidden_size)
        h_last = self._last_token_hidden(hs, attention_mask)
        logits = self.classifier(h_last)
        return logits
```

✓ 0.0s Python

Language model fine-tuning

- Given: A language model $p_{\theta_0}(y \mid x)$
- Data $D = \{(x, y)_n\}_{n=1}^{N}$
  - x: input text
  - y: output text
- Loss: cross-entropy loss

$$\mathscr{L}_{MLE} = -\sum_{t=1}^{T} \log p_\theta(y_t \mid x, y_{<t})$$



Code example

This notebook demonstrates fine-tuning a language model for a generation task.

Task: Given a name, generate its reverse (e.g., emma → amme)

```
data = open('names.txt').read().splitlines()
print(f"Total names: {len(data)}")
data[1000:1010]
```

12] ✓ 0.0s

```
Total names: 32033
Before fine-tuning:
==================================================
Reverse the name: emma. Answer: 0.4812529443310765.
Reverse the name: noah. Answer: it is only a person of that name
000B. Boole, 1
Reverse the name: olivia. Answer: a. The person is named Olivia.
```

```
After fine-tuning:
==================================================
emma       → amme       (expected: amme      ) ✓
noah       → haon       (expected: haon      ) ✓
olivia     → aivilo     (expected: aivilo    ) ✓
liam       → mail       (expected: mail      ) ✓
sophia     → aihpos     (expected: aihpos    ) ✓
mason      → nosam      (expected: nosam     ) ✓
isabella   → allebasi   (expected: allebasi  ) ✓
william    → luottiw    (expected: mailliw   ) ✗
mia        → aim        (expected: aim       ) ✓
james      → semaj      (expected: semaj     ) ✓
```

Library code example

```
614         for epoch in range(starting_epoch, args.num_train_epochs):
615             model.train()
616             if args.with_tracking:
617                 total_loss = 0
618             if args.resume_from_checkpoint and epoch == starting_epoch and resume_step is not None:
619                 # We skip the first `n` batches in the dataloader when resuming from a checkpoint
620                 active_dataloader = accelerator.skip_first_batches(train_dataloader, resume_step)
621             else:
622                 active_dataloader = train_dataloader
623             for step, batch in enumerate(active_dataloader):
624                 with accelerator.accumulate(model):
625                     outputs = model(**batch)
626                     loss = outputs.loss
627                     # We keep track of the loss at each epoch
628                     if args.with_tracking:
629                         total_loss += loss.detach().float()
630                     accelerator.backward(loss)
631                     optimizer.step()
632                     lr_scheduler.step()
633                     optimizer.zero_grad()
634 
635                 # Checks if the accelerator has performed an optimization step behind the scenes
636                 if accelerator.sync_gradients:
637                     progress_bar.update(1)
638                     completed_steps += 1
639 
640                 if isinstance(checkpointing_steps, int):
641                     if completed_steps % checkpointing_steps == 0 and accelerator.sync_gradients:
642                         output_dir = f"step_{completed_steps}"
643                         if args.output_dir is not None:
644                             output_dir = os.path.join(args.output_dir, output_dir)
645                         accelerator.save_state(output_dir)
646                 if completed_steps >= args.max_train_steps:
647                     break
```

https://github.com/huggingface/transformers/blob/main/examples/pytorch/language-modeling/run_clm_no_trainer.py

Should I fine-tune all parameters?

- Option 1: Update only the output head (W, b)
  - Cheap: only $K \times d + K$ parameters
  - Assumes that the pre-trained representations are good, e.g. linearly separate the labels
- Option 2: Update all parameters
  - Expensive: $|\theta|$ parameters (e.g., 1M, 1B, 100B, …)
  - Changes the representations
  - May lead to overfitting
- Option 3: Update a small number of parameters inside the model
  - Cheaper: $<< |\theta|$ parameters
  - Can change the representations
  - “Parameter-efficient fine-tuning (PEFT)” methods

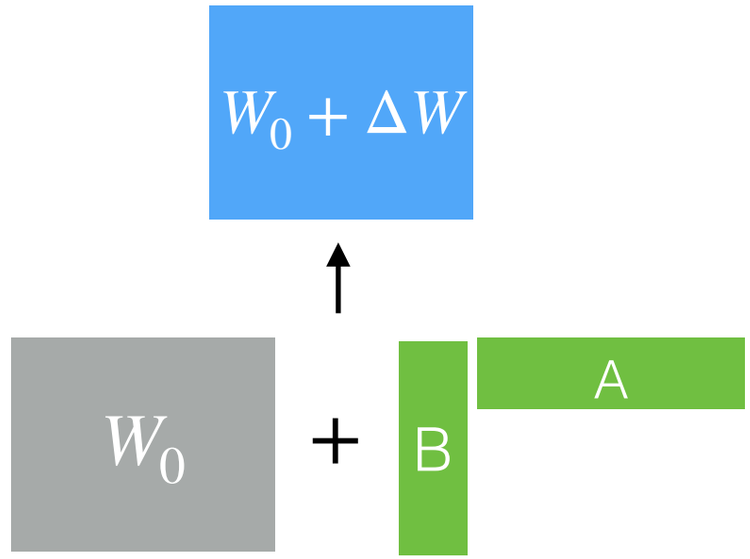
Example: Low-Rank Adaptation (LoRA)

[Hu et al 2021]

- Given weights $W_0 \in \mathbb{R}^{d \times d'}$, introduce new weights A, B:

$$W_0 + \underbrace{BA}_{\Delta W}$$

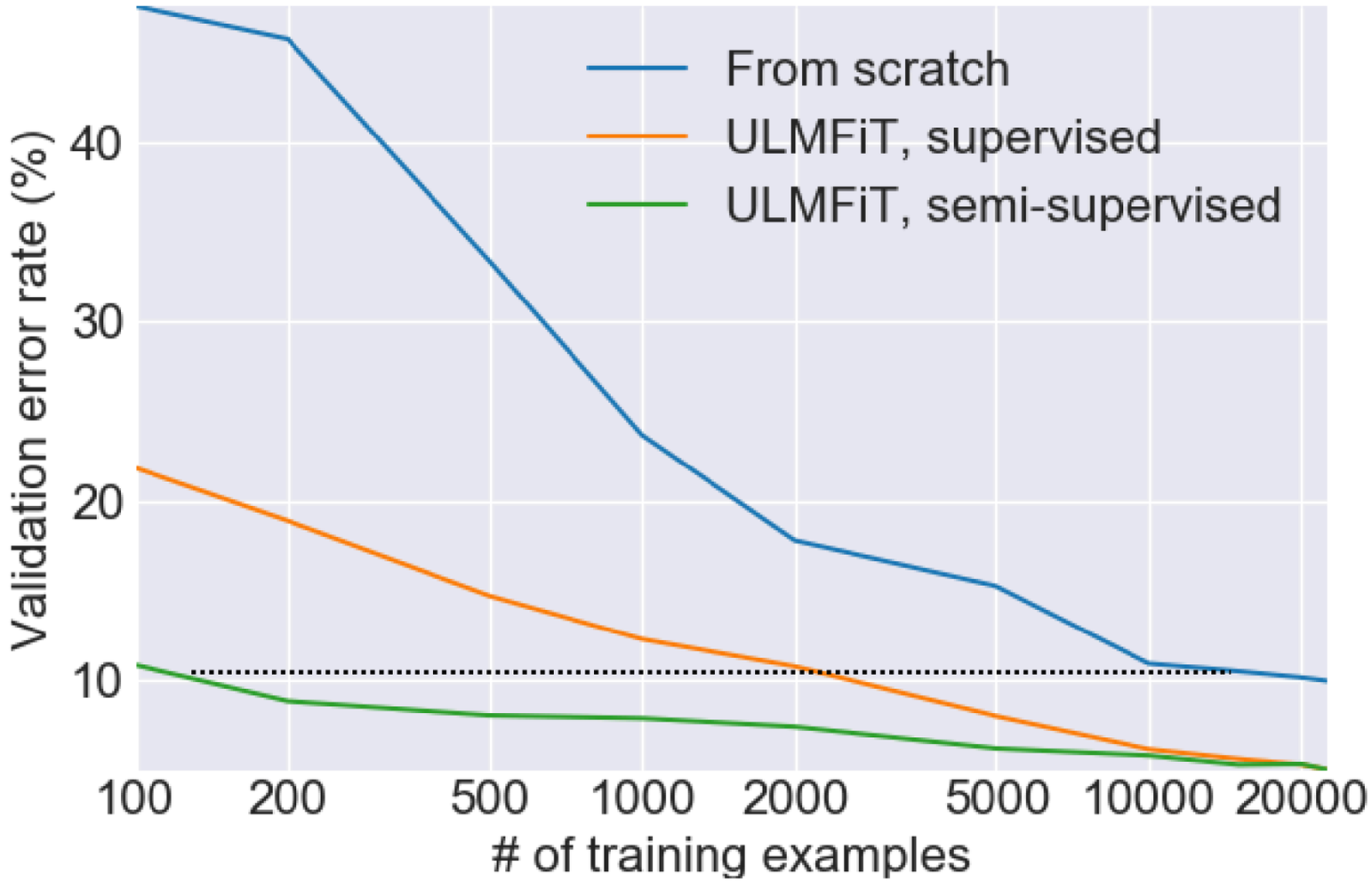
where $B \in \mathbb{R}^{d \times r}$, $A \in \mathbb{R}^{r \times d'}$, $r \ll \min(d, k)$



- *Only* update B and A during fine-tuning.
- After fine-tuning, simply use the weight matrix $W = W_0 + \Delta W$
- Scale ΔW by $\frac{\alpha}{r}$
- Apply to W_q and W_v in the attention layers

Effects of fine-tuning

- Starting from a pre-trained model is data-efficient



Howard & Ruder 2018

Effects of fine-tuning

- "Narrows" the distribution
  - Pre-training: minimize $D_{KL}(p_{data}, p_\theta)$
  - Fine-tuning: minimize $D_{KL}(p_{data\ finetune}, p_\theta; p_0)$
- Typically the pretraining data will cover a wider distribution than the fine-tuning data

Effects of fine-tuning

- Example symptoms:
  - Summarization model doesn’t work well on translation
  - Model trained with specific formatting requires the formatting
- Model can’t few-shot learn well after fine-tuning …

```
Testing different prompts for 'sophia' (expected: aihpos)
============================================================
Train     :
  Prompt: Reverse the name: sophia. Answer:...
  Output: aihpos     ✓
Variation 1:
  Prompt: Reverse: sophia =>...
  Output: aihpos     ✓
Variation 2:
  Prompt: What is sophia backwards?...
  Output:            ✗
Variation 3:
  Prompt: sophia reversed is:...
  Output: aihsopi    ✗
```

Example data

X

Y

Article (paper)

Abstract


```
{
    "abstract": "\" we have studied the leptonic decay @xmath0 , via
    "article": "\"the leptonic decays of a charged pseudoscalar meso
    "section_names": "[sec:introduction]introduction\n[sec:detector]
}
```


Training set: 300,000+ examples

https://huggingface.co/datasets/armanc/scientific_papers

Example data

X

Article (paper)
Problem

Y

Abstract
Solution

```
{'problem': 'A board game spinner is divided into three parts labele
 'level': 'Level 1',
'type': 'Counting & Probability',
'solution': 'The spinner is guaranteed to land on exactly one of th
```

Training set: 7,500 examples

https://huggingface.co/datasets/hendrycks/competition_math

Example data

X

Article (paper)
Problem
Prompt

Y

Abstract
Solution
Response

question string · *lengths*	response string · *lengths*
12↔4.07k 96.5%	0↔1.5k 92.9%
How does the sentence end?…	B). Rebecca was saddened by people's vile insults. Here's why: "Thicker skin" is a way to say that…
Write a sentence not in English.	Voici une phrase en français: "Le chat mange la souris." Explication pour un enfant de cinq ans: Cette phrase n'est pas en anglais, mais en français. Elle dit que le chat (l'animal avec des moustaches et qui dit "miaou") mange la souris (un petit animal avec une longue queue).

Training set: 2,910,000 examples

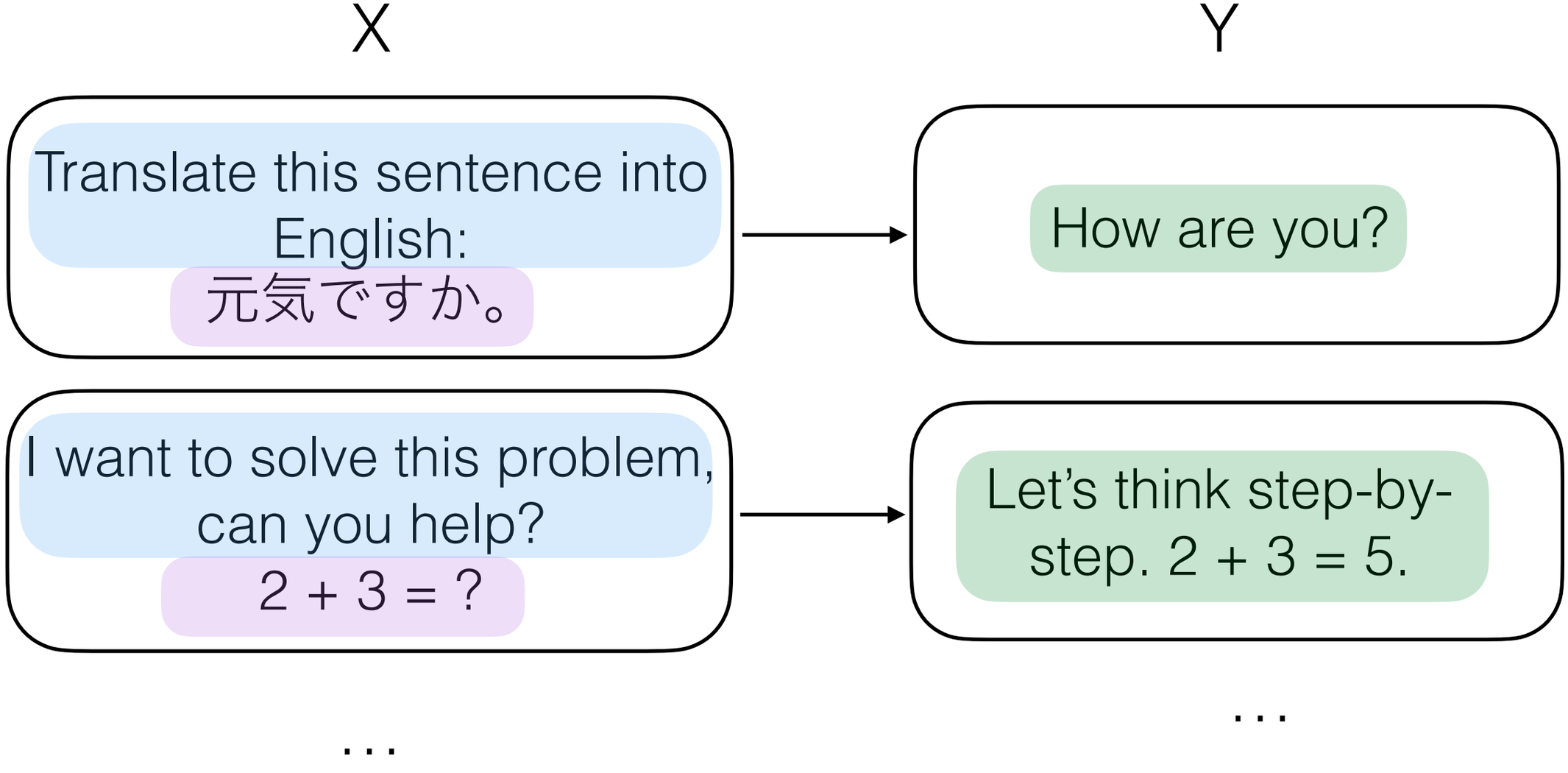
https://huggingface.co/datasets/Open-Orca/OpenOrca

Today's lecture

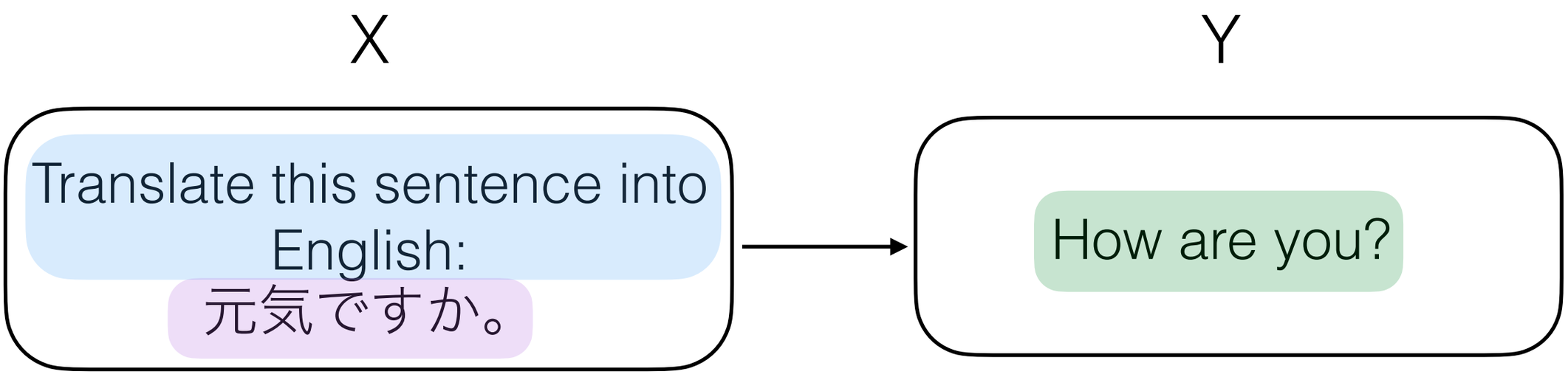
- Fine-tuning basics
- **Instruction tuning**
  - Chat tuning

Basic idea

- Fine-tune a model to perform multiple tasks
- Insight: use (instruction + input, output) data



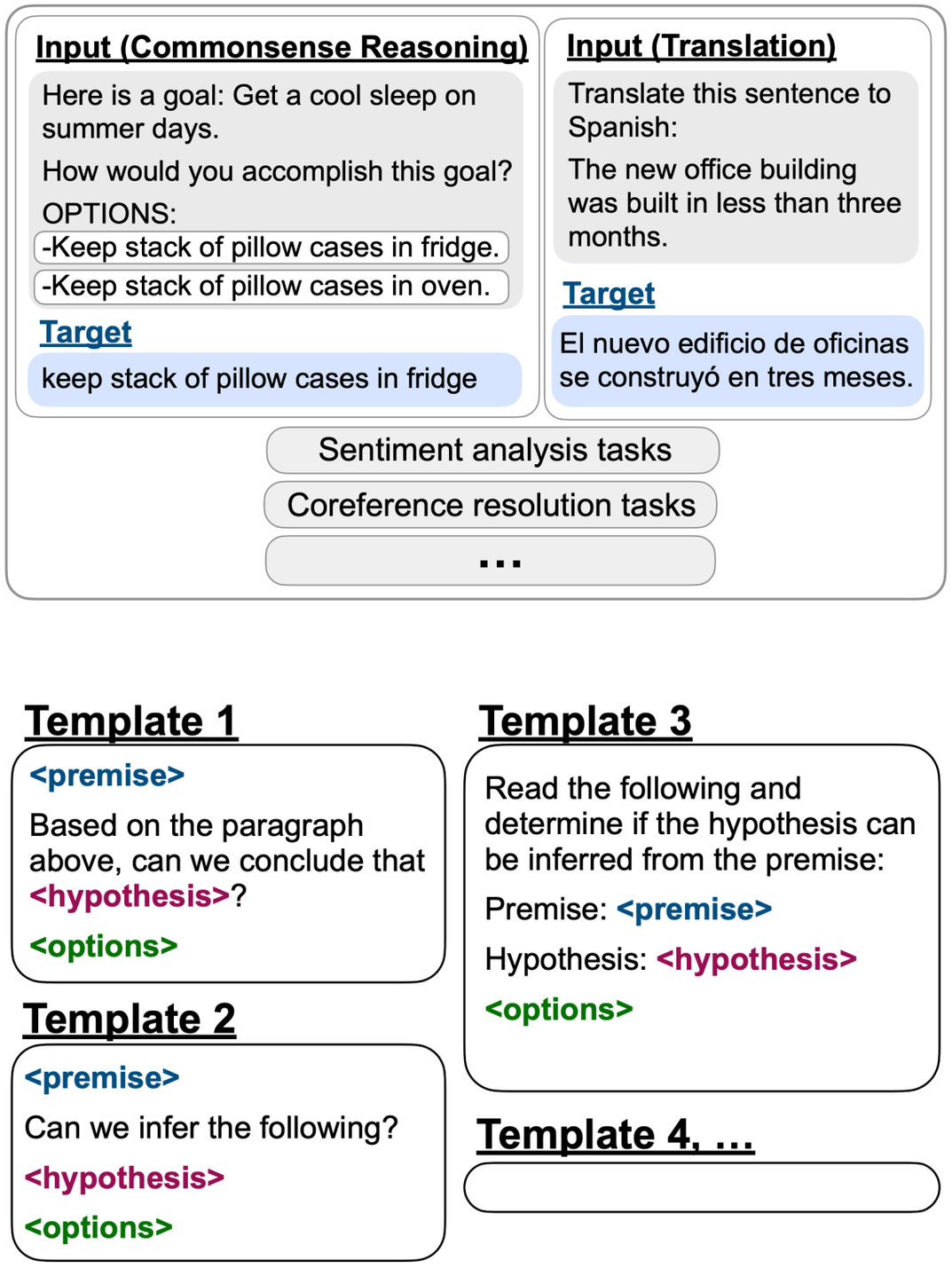
Variations



- Instructions: template, human, model-generated
- Input: dataset, human, model-generated
- Output: dataset, human, model-generated
- Domain: general, code, math, chat, …

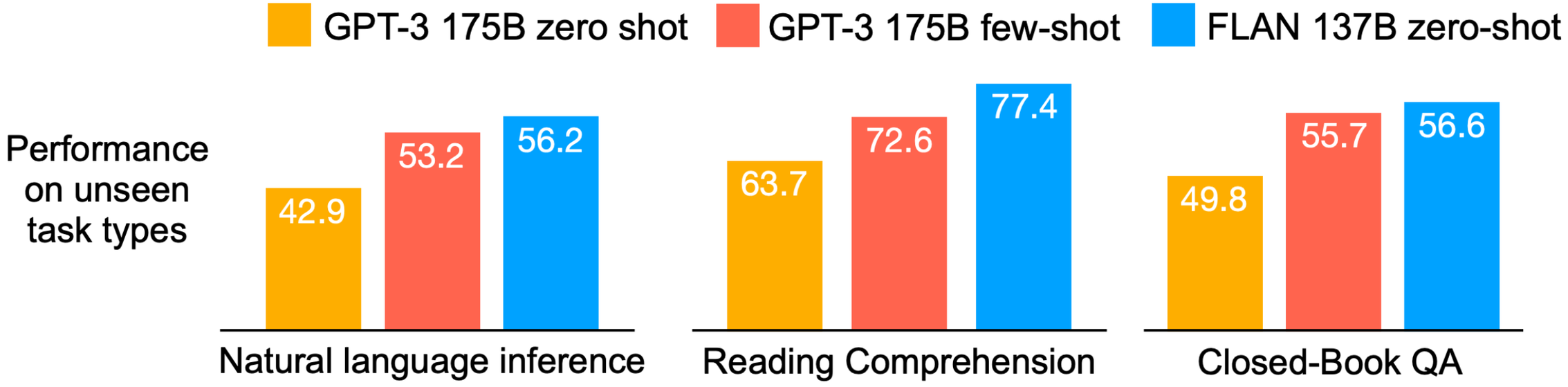
Example: FLAN [Wei et al 2021]

- 62 NLP datasets
- Instructions: templates
- Input: from dataset
- Output: from dataset



Example: FLAN [Wei et al 2021]

- Key finding: model can generalize to unseen tasks



Example: SuperNaturalInstructions

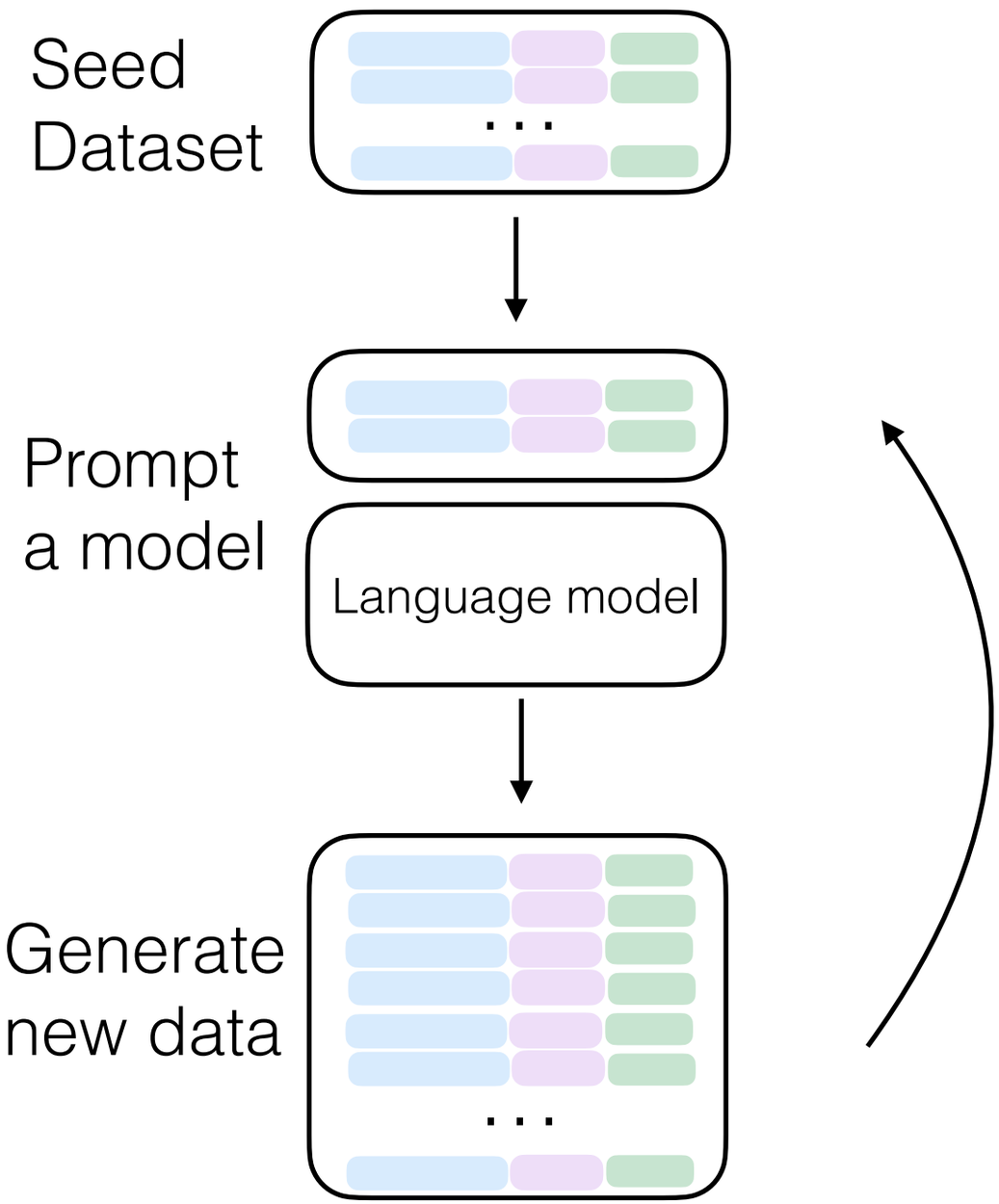
[Mishra et al 2021, Wang & Mishra et al 2022]

- 1,600 tasks
- Instructions: crowdsourced
- Input: crowdsourced
- Output: crowdsourced

Example: Self-Instruct

[Mishra et al 2021, Wang & Mishra et al 2022]

- 50,000+ instructions
- Instructions: model
- Input: model
- Output: model



Example: Self-Instruct

[Mishra et al 2021, Wang & Mishra et al 2022]

- 50,000+ instructions
- Instructions: model
- Input: model
- Output: model

Instruction: Given an address and city, come up with the zip code.
Input:
Address: 123 Main Street, City: San Francisco
Output: 94105

Instruction: I am looking for a job and I need to fill out an application form. Can you please help me complete it?
Input:
Application Form:
Name:_____ Age:_____ Sex:_____
Phone Number:_____ Email Address:_____
Education:_____ ...
Output:
Name: John Doe Age: 25 Sex: Male
Phone Number: ...

Instruction: How to write a code for converting degrees fahrenheit to celsius.
Input: Null
Output:

```
def convert_fahrenheit_to_celsius(fahr):
    celsius = (fahr - 32) * 5 / 9
    return celsius
```

Recap: instruction tuning

- Finetune on (instruction, input, output) examples
  - Get data from humans or model generations
- Resulting model can perform many tasks
- Lots of followup work on instruction-tuning data for certain domains: general, code, math, **chat**, …

Chat tuning

- Ultimately, format a chat as a sequence of tokens
  - System prompt
  - [user, assistant, user, assistant, …]
- “Instruction+input” are implicitly in the conversation

System

User

Assistant

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|>

You are a helpful AI assistant for travel tips and
recommendations<|eot_id|>
<|start_header_id|>user<|end_header_id|>

What can you help me with?<|eot_id|>
<|start_header_id|>assistant<|end_header_id|>
```

Lecture 7

Chat tuning | system prompts

- Example: OpenOrca

System Instruction: You are an AI assistant. User will you give you a task. Your goal is to complete the task as faithfully as you can. While performing the task think step-by-step and justify your steps.

User Instruction: Use the given data to calculate the median.

Input: [7, 3, 8, 2, 10]

Output: To calculate the median, I will follow these steps:
Step 1: Arrange the data in ascending order [2, 3, 7, 8, 10]
Step 2: Determine if the data set has an odd or even number of values
The data set has 5 values, which is an odd number.
Step 3: Find the middle value

Since the data set has an odd number of values, the median is the middle value in the ordered list. The middle value in the list [2, 3, 7, 8, 10] is 7.

System Instruction: You are an AI assistant. Provide a detailed answer so user don't need to search outside to understand the answer.

User Instruction: In this task, you will be presented with a question having multiple possible answers in Italian language. And you should choose a most suitable option out of "A", "B", "C", "D", and "E" based on your commonsense knowledge.

Input: Solve this question: Dove non riusciresti a vedere la luce?
Options: A scrivania B frigorifero C sole D universo E attico

Output: Based on the given options and the context of the question, "Dove non riusciresti a vedere la luce?" (Where would you not be able to see light?), the most suitable answer would be: B frigorifero (refrigerator).

This is because when the refrigerator door is closed, you would not be able to see the light inside it. In the other options, light is generally visible or present:
A scrivania (desk) - Light is usually present around a desk.
C sole (sun) - The sun is the primary source of light in our solar system.
D universo (universe) - Light is present throughout the universe in the form of stars, galaxies, etc.
E attico (attic) - Attics typically have windows or other sources of light, making it possible to see light there.

System messages: 16 hand-written

Outputs: from GPT-4

https://huggingface.co/datasets/Open-Orca/OpenOrca

Chat tuning | multi-turn

- Example: LMSys-1M

Data source: online LLM service hosted by Berkeley/Stanford

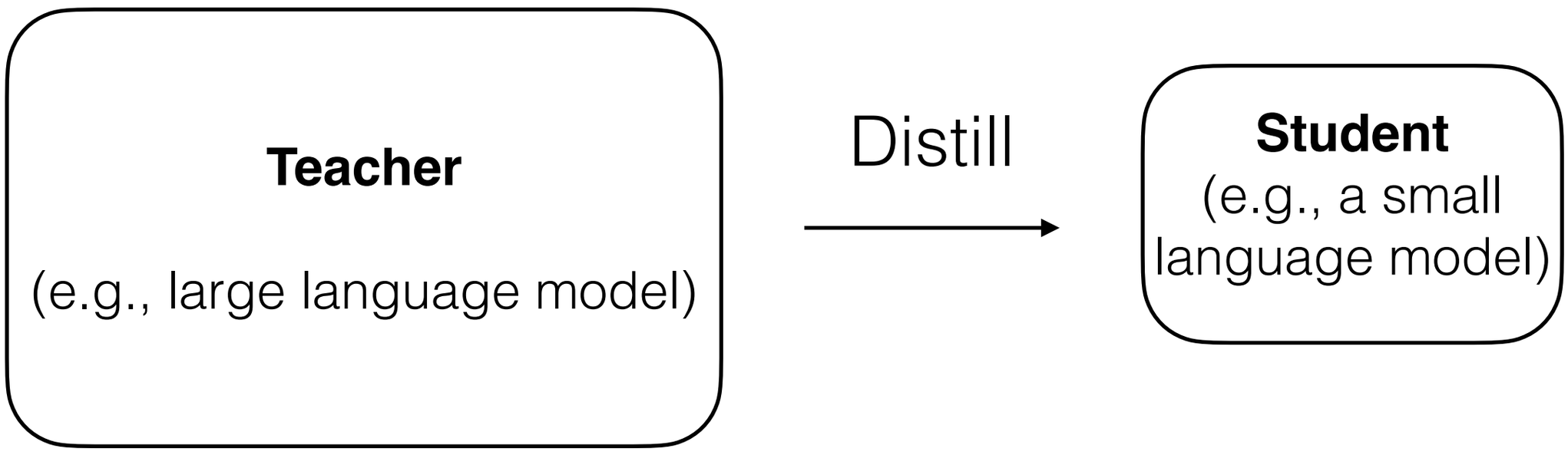
https://huggingface.co/datasets/lmsys/lmsys-chat-1m

Today's lecture

- Fine-tuning basics
- Instruction tuning
- **Knowledge distillation**

Knowledge distillation

- Several methods we discussed use a good model (e.g., GPT-4) to generate data for another model
- Instance of *knowledge distillation* [Hinton et al 2015]

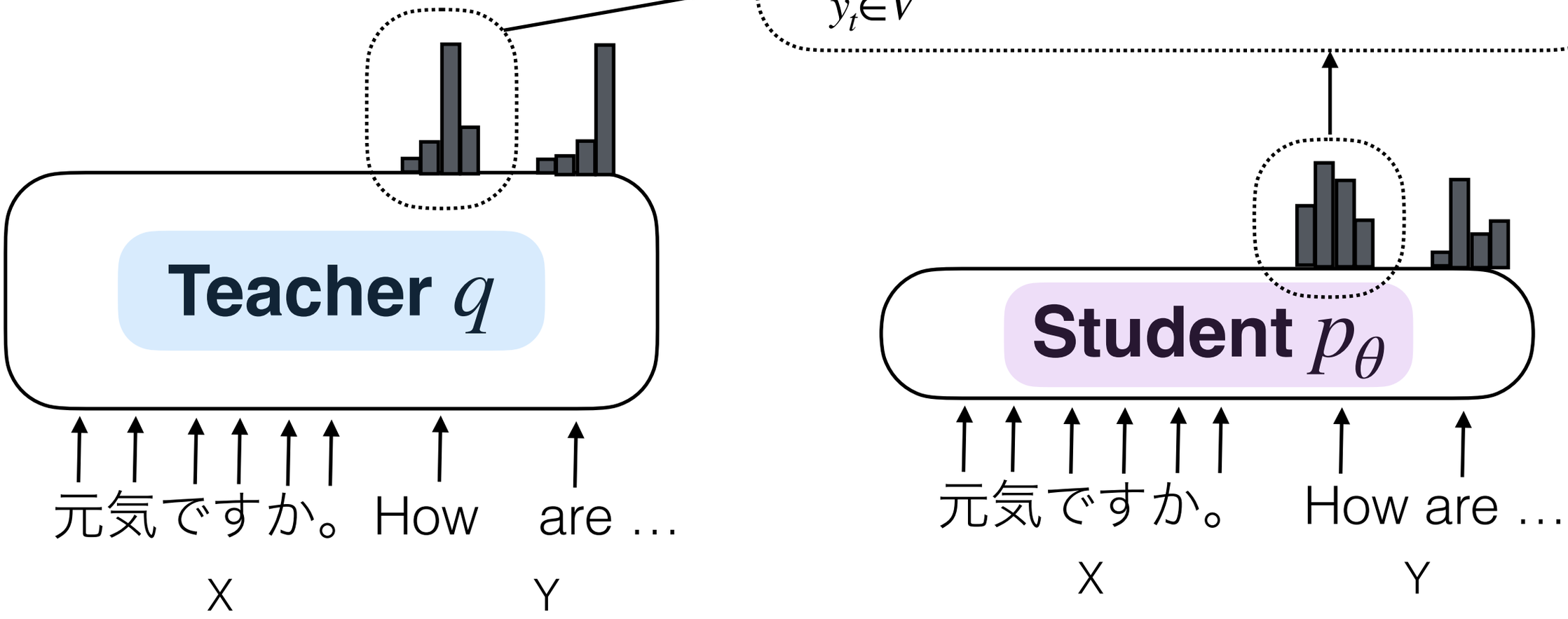


Token-level knowledge distillation
[Hinton et al 2015]

- Train student to mimic teacher's token distributions

Distillation loss
(cross entropy)

$$-\sum_{y_t \in V} q(y_t \mid y_{<t}, x) \log p_\theta(y_t \mid y_{<t}, x)$$



Token-level knowledge distillation
[Hinton et al 2015]

- Minimizes KL between teacher and student:

$$\min_{\theta} KL\left(q(y \mid x) \| p_\theta(y \mid x)\right)$$

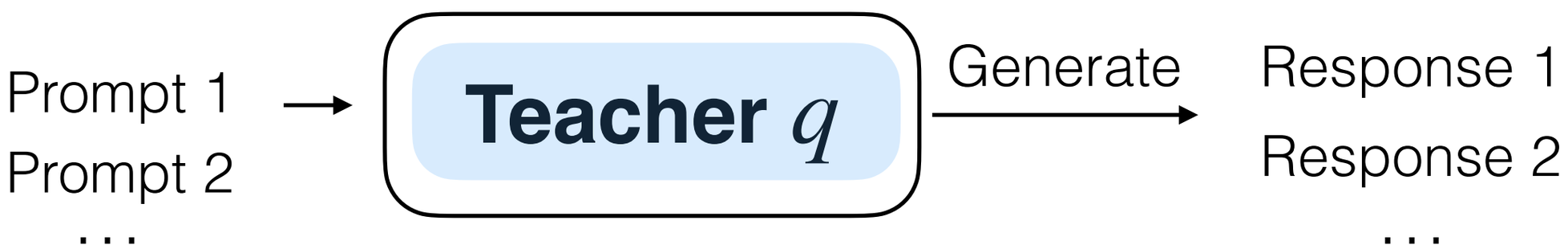
$$\equiv \min_{\theta} \mathbb{E}_{y \sim q(y|x)} \left[\sum_{t} \sum_{y_t \in V} -q(y_t \mid y_{<t}, x) \log p_\theta(y_t \mid y_{<t}, x) \right]$$

"Soft labels"

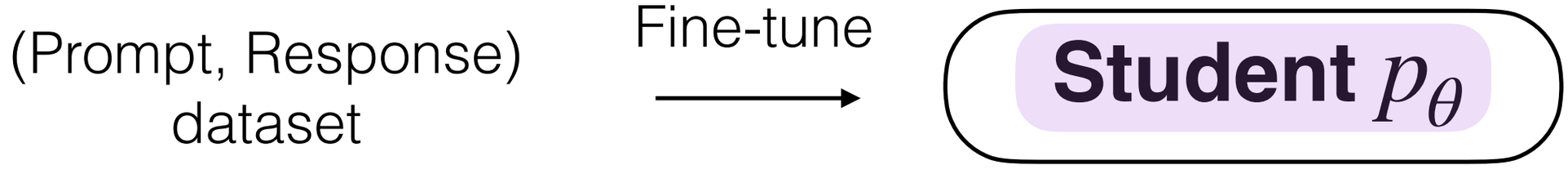
Sequence-level knowledge distillation

[Kim & Rush 2016]

- Generate with a teacher model



- Student model fine-tunes on the generated data



Example: DeepSeek-R1-Distill-Qwen-7B

Sequence-level knowledge distillation
[Kim & Rush 2016]

- Also minimizes KL between teacher and student:

$$\min_{\theta} KL\left(q(y \mid x) \| p_{\theta}(y \mid x)\right)$$

$$\equiv \min_{\theta} \mathbb{E}_{y \sim q(y|x)}\left[-\log p_{\theta}(y \mid x)\right]$$

Teacher generations

Sequence-level knowledge distillation

- [West et al 2022]: the teacher can be an "augmented" language model, e.g.

$$q \propto p_{LLM}(y \mid x) \cdot A(x, y)$$

E.g. a classifier, verifier

- In principle, if the augmented teacher is better than p_{LLM}, then the student can become better than p_{LLM} through distillation

Recap

- Fine-tuning basics
  - Adjust a model's parameters using data
  - PEFT: only update a small number of parameters
- Instruction tuning
  - Format data so that a model learns to do multiple tasks
- Knowledge distillation
  - Data can come from various teachers (human, model)

Thank you