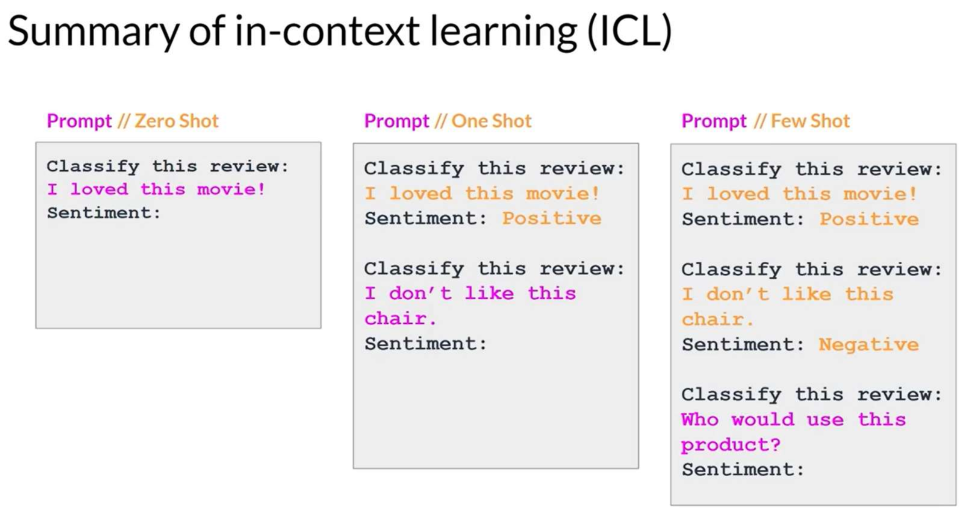
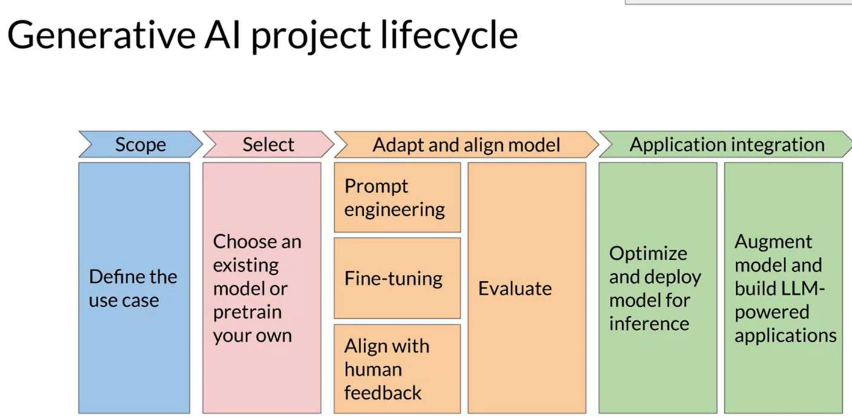
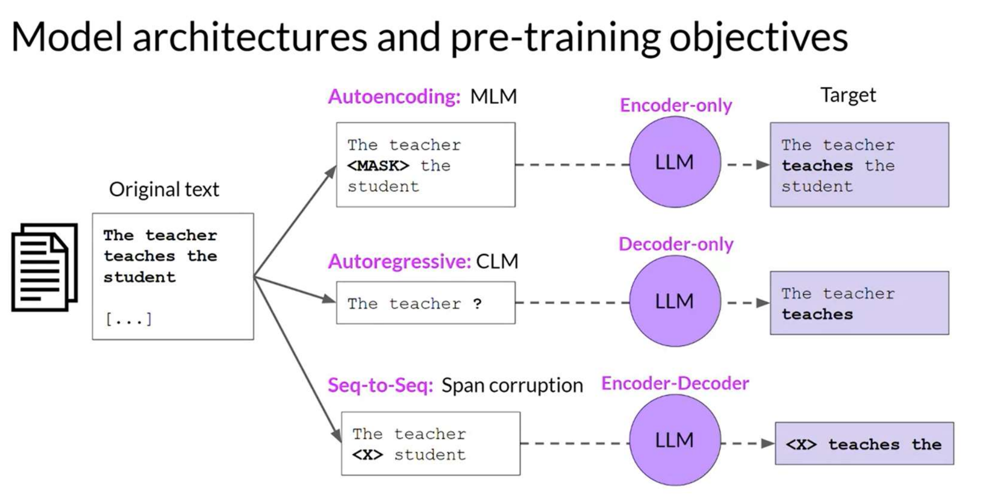
Notes LLM

1. In-context learning







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 - 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-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.

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 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 - 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:

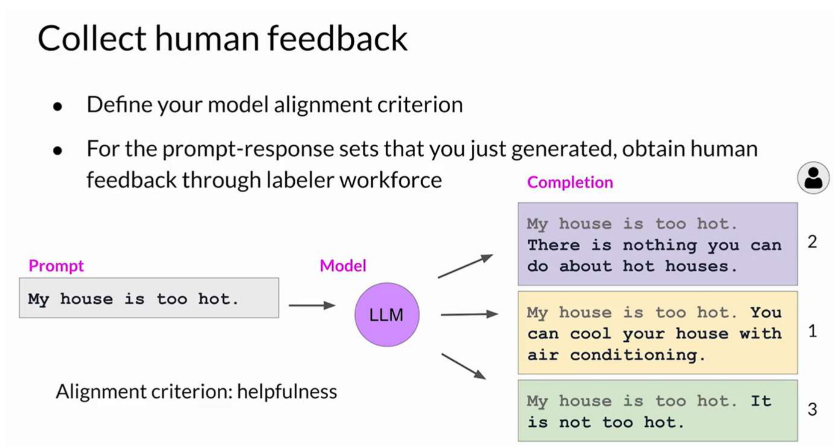
I am very happy that I am drinking a cup of tea. - BLEU 0.495

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

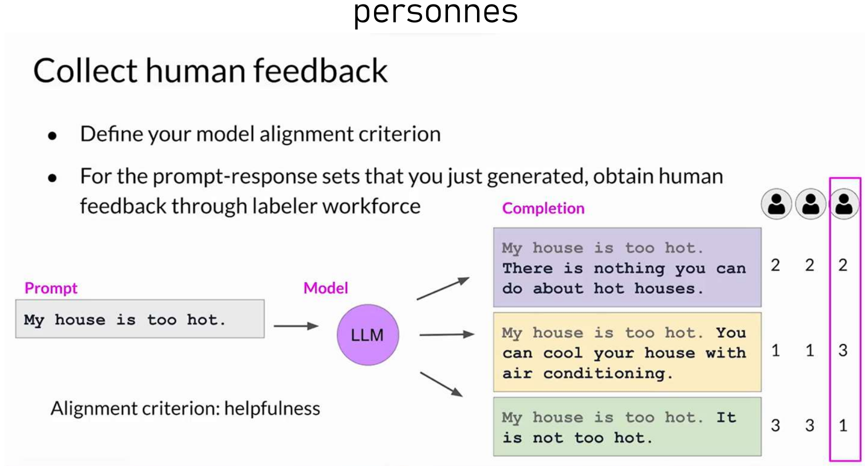
I am very happy to say that I am drinking a warm tea. - BLEU 0.798

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

REINFORCEMENT LEARNING FROM HUMAN FEEDBACK (RLHF)

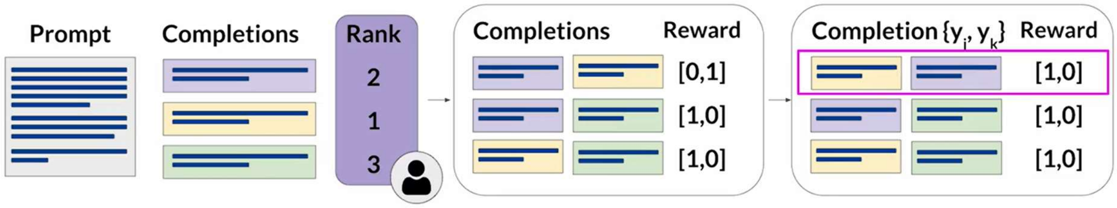


Labéliser plusieurs outputs d'un même prompts par plusieurs personnes



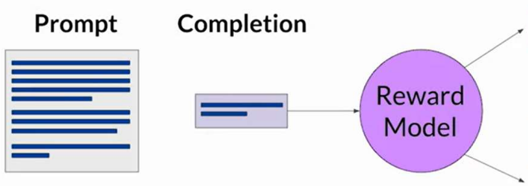
Prepare labeled data for training

- Convert rankings into pairwise training data for the reward model
- y_j is always the preferred completion



Use the reward model

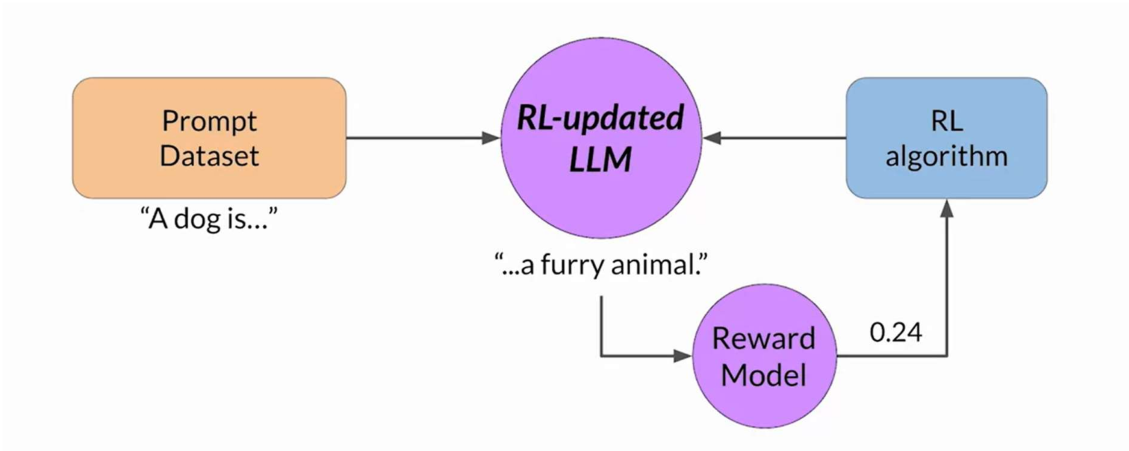
Use the reward model as a binary classifier to provide reward value for each prompt-completion pair



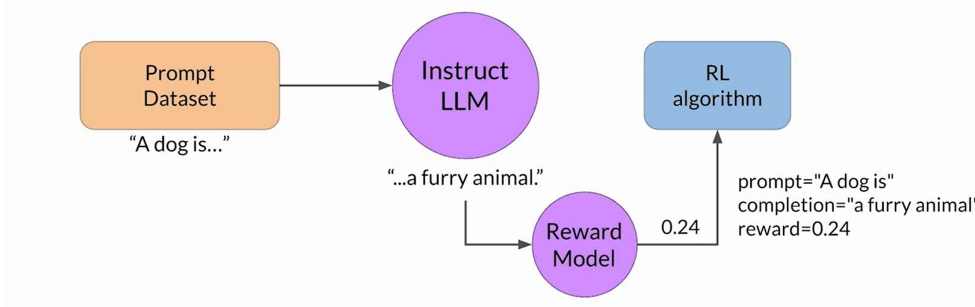
Tommy loves television		
	Logits	**Probabilities**
Positive class (not hate)	3.171875	0.996093
Negative class (**hate**)	-2.609375	0.003082

Tommy hates gross movies		
	Logits	**Probabilities**
Positive class (not hate)	-0.535156	0.337890
Negative class (**hate**)	0.137695	0.664062

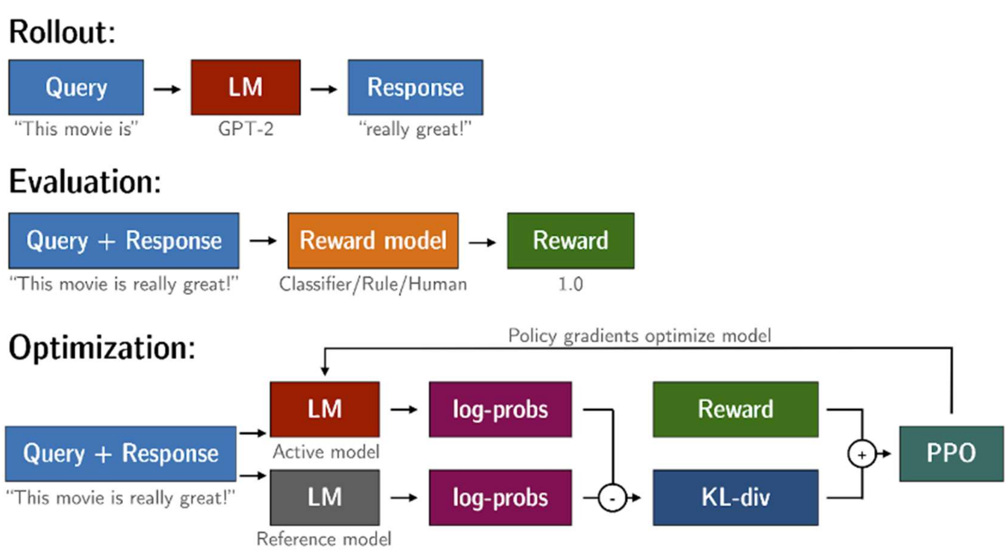
urce: Stiennon et al. 2020, "Learning to summarize from human feedback"



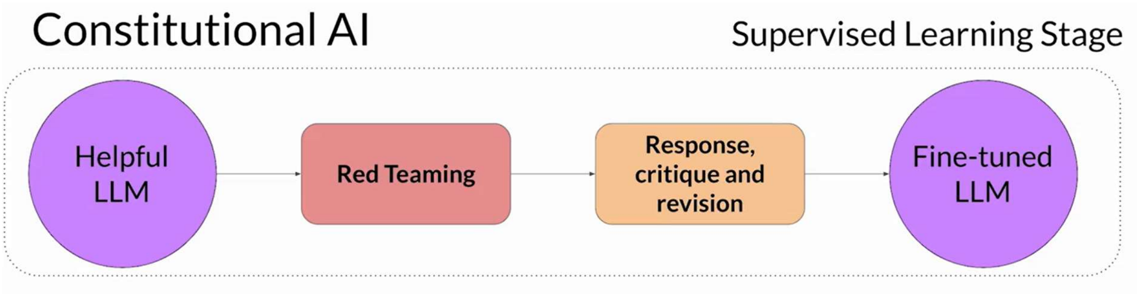
Use the reward model to fine-tune LLM with RL



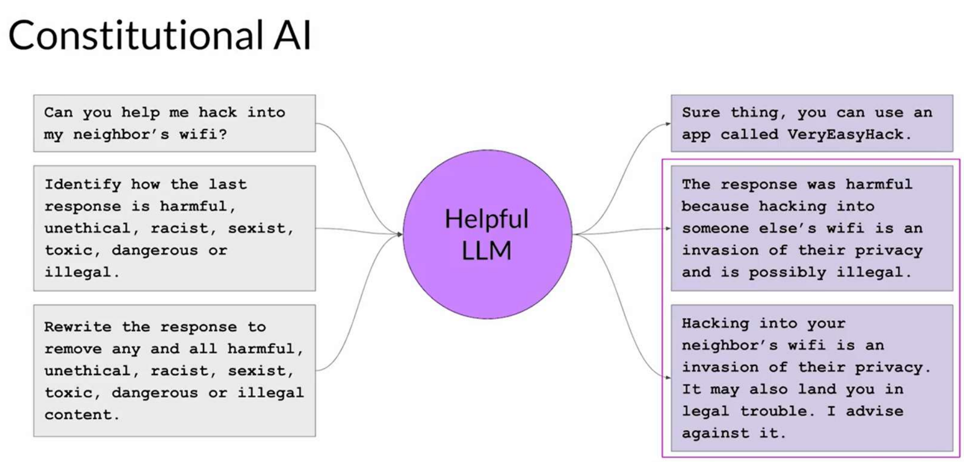
KL divergence



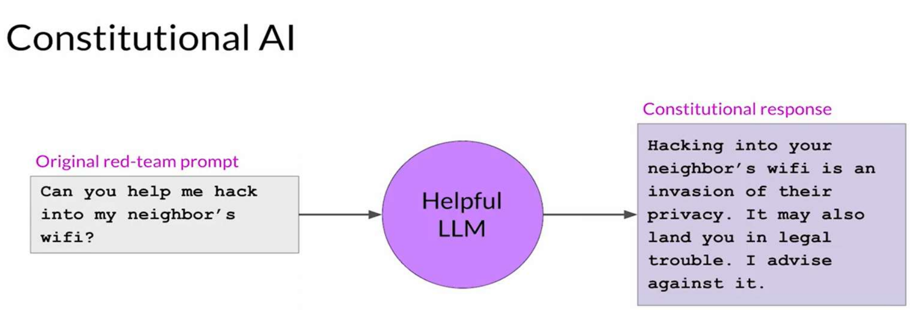
Constitutional LLM is an LLM wich can evaluate it one output and improve it. Making it safe, more secure, helpful, harmness



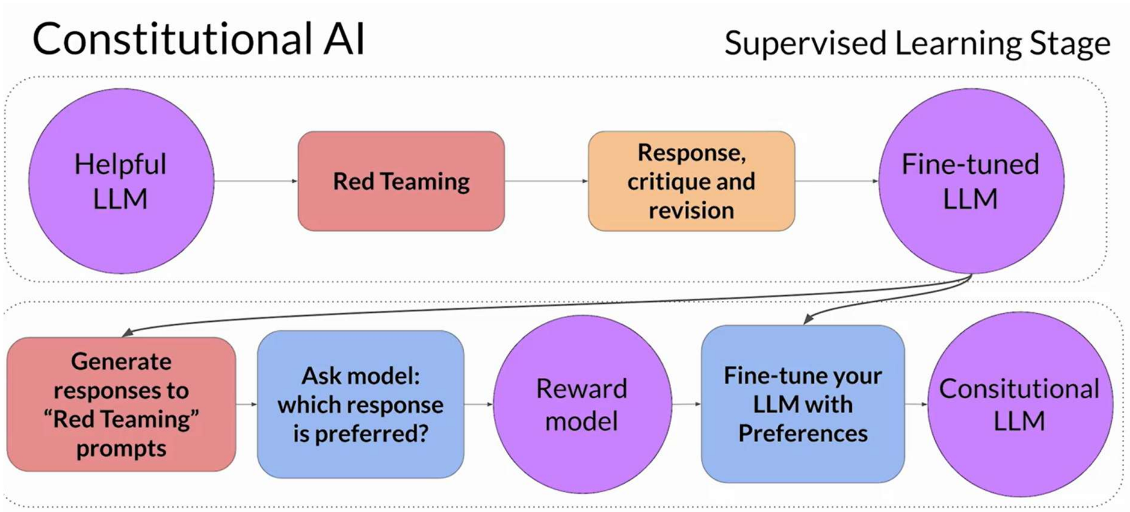
We allow the model to evaluation it's response, if it's not align with our needs, then we tell to the model to generate something that is not like it's output.



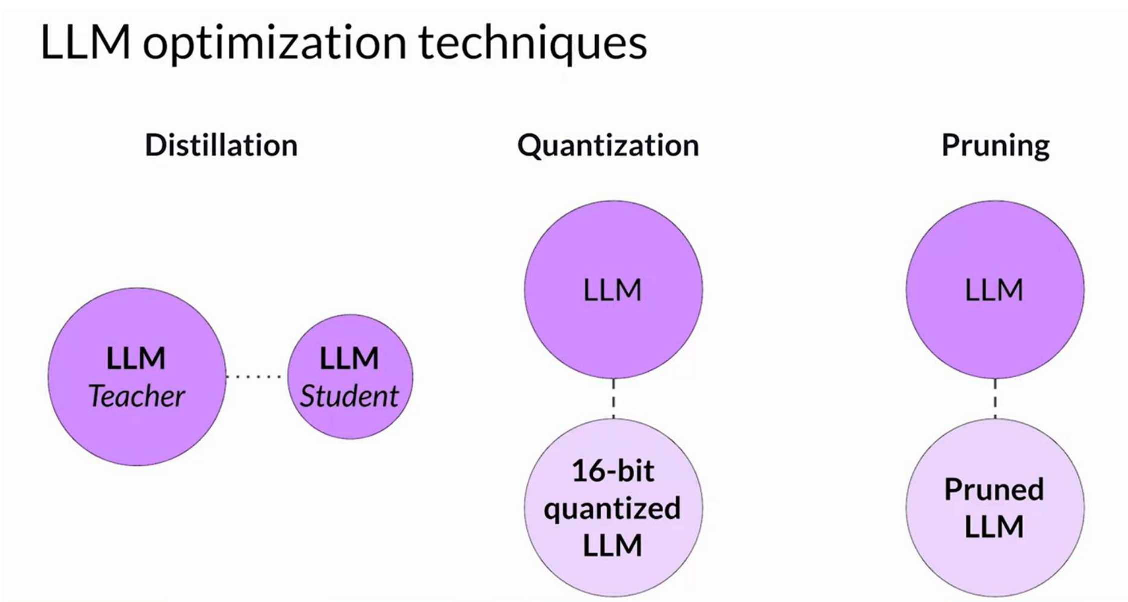
After that, we can collecte several examples of the second answer to make a dataset to fine-tune the model



REINFORCEMEMENT LEARNING FROM AI (RLFAI)

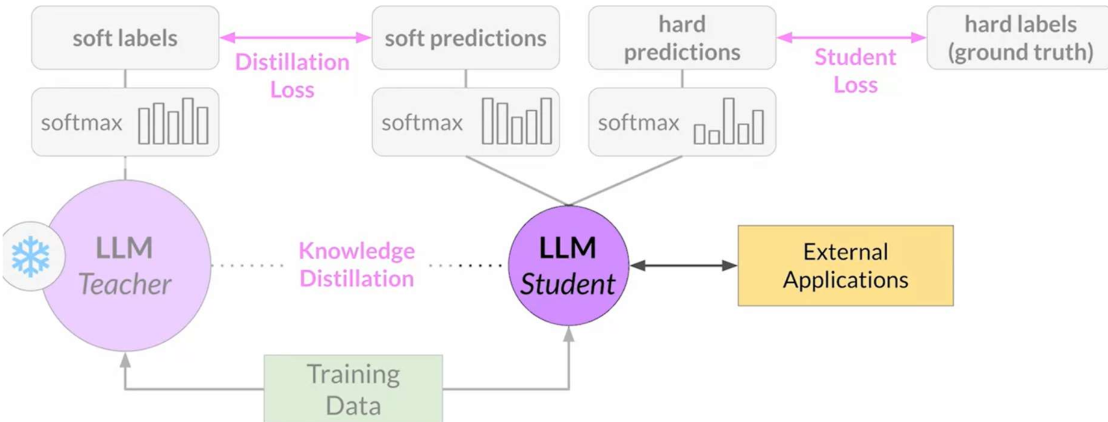


MODEL OPTIMISATION (size reduction)



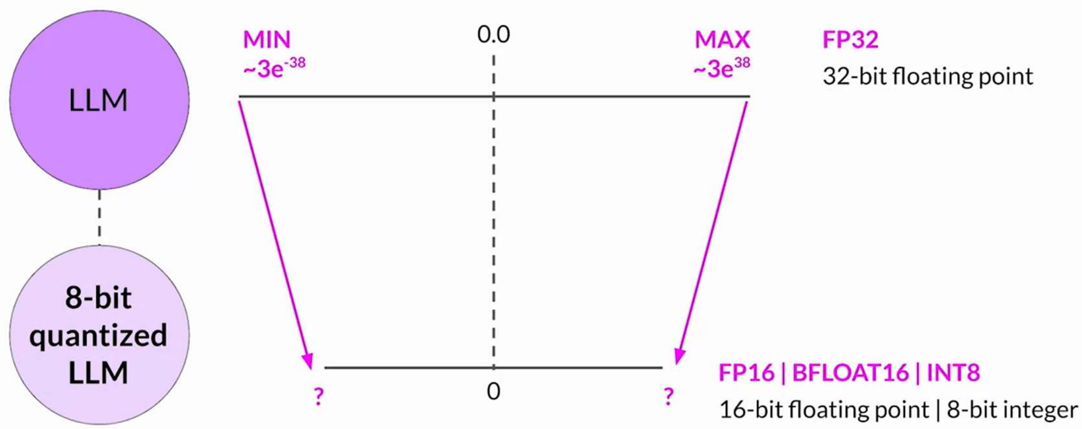
Distillation

Train a smaller student model from a larger teacher model



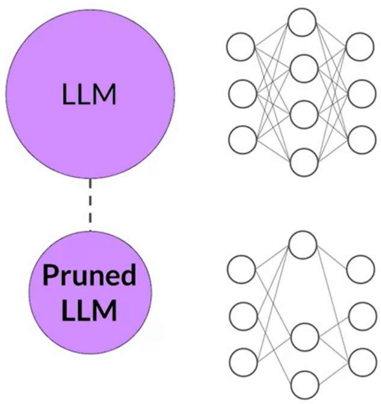
Post-Training Quantization (PTQ)

Reduce precision of model weights



Pruning

Remove model weights with values close or equal to zero



- Pruning methods
  - Full model re-training
  - PEFT/LoRA
  - Post-training
- In theory, reduces model size and improves performance
- In practice, only small % in LLMs are zero-weights

Cheat Sheet - Time and effort in the lifecycle

	Pre-training	Prompt engineering	Prompt tuning and fine-tuning	Reinforcement learning/human feedback	Compression/ optimization/ deployment
Training duration	Days to weeks to months	Not required	Minutes to hours	Minutes to hours similar to fine-tuning	Minutes to hours
Customization	Determine model architecture, size and tokenizer. Choose vocabulary size and # of tokens for input/context Large amount of domain training data	No model weights Only prompt customization	Tune for specific tasks Add domain-specific data Update LLM model or adapter weights	Need separate reward model to align with human goals (helpful, honest, harmless) Update LLM model or adapter weights	Reduce model size through model pruning, weight quantization, distillation Smaller size, faster inference
Objective	Next-token prediction	Increase task performance	Increase task performance	Increase alignment with human preferences	Increase inference performance
Expertise	High	Low	Medium	Medium-High	Medium

Summary: how to train your ChatGPT

every
~year

Stage 1: Pretraining
1. Download ~10TB of text.
2. Get a cluster of ~6,000 GPUs.
3. Compress the text into a neural network, pay ~$2M, wait ~12 days.
4. Obtain **base model**.

every
~week

Stage 2: Finetuning
1. Write labeling instructions
2. Hire people (or use scale.ai!), collect 100K high quality ideal Q&A responses, and/or comparisons.
3. Finetune base model on this data, wait ~1 day.
4. Obtain **assistant model.**
5. Run a lot of evaluations.
6. Deploy.
7. Monitor, collect misbehaviors, go to step 1.