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Recitation 8

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DS-GA 1011, Fall'25
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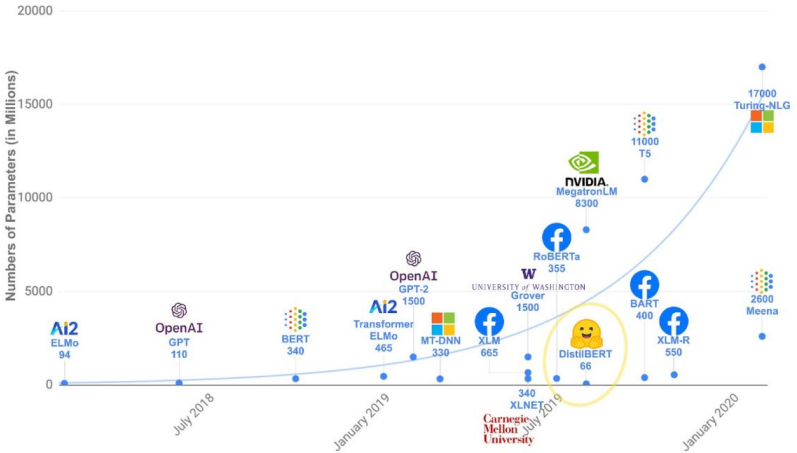
Agenda

- Efficiency Challenge
- Quantization
  - What is quantization and how to quantize?
- Pruning
  - Pruning before, during and after training?
- Knowledge Distillation
  - Distillation on outputs, weights and features

Efficiency Challenge

- What is inference? __
- Size of the model makes __



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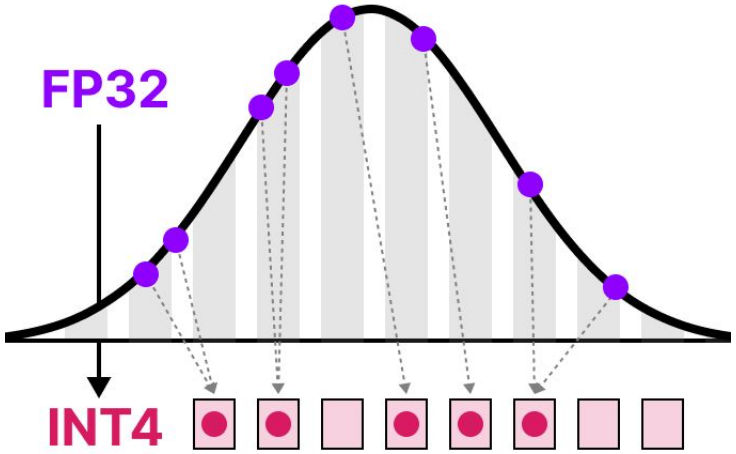
What is quantization?

- In general, it is the process of mapping a continuous or large set of values to a smaller, discrete set of values

- It is simplifying data by **rounding it to low-precision data types** while **preserving important details**



Adapted from [2]

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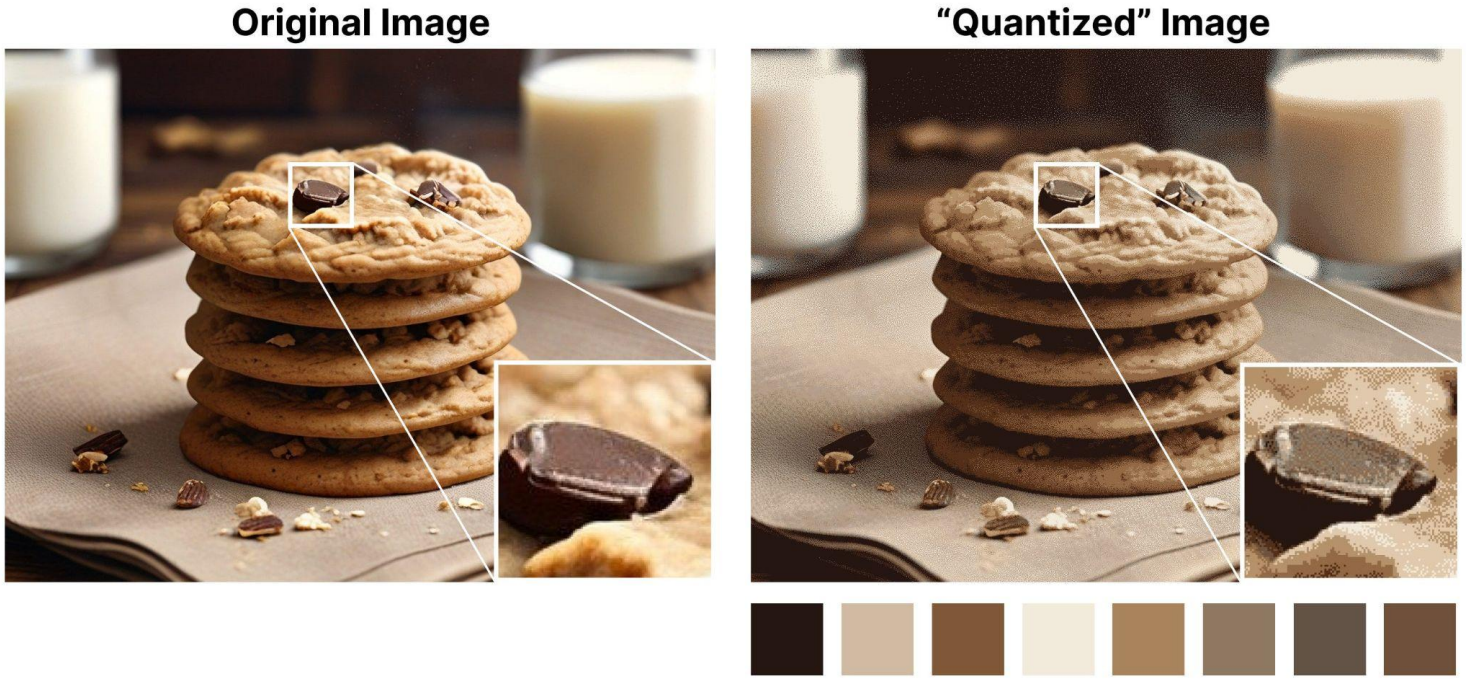
How does quantization look like in real-world?



Using only 8 colors to represent the image. Adapted from [2].
Reducing the image to use just 8 colors leads to a **loss of detail and precision**

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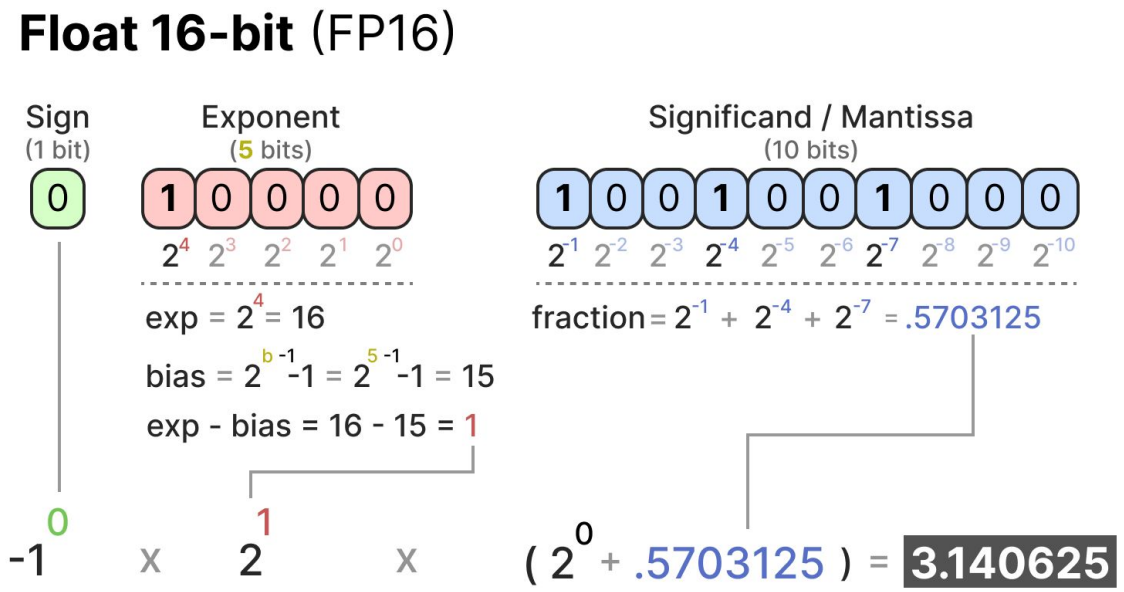
How to represent numerical values?

- Represented by “**bits**”, or binary digits
- Bits use **sign, exponent and fraction (mantissa)** to represent a value

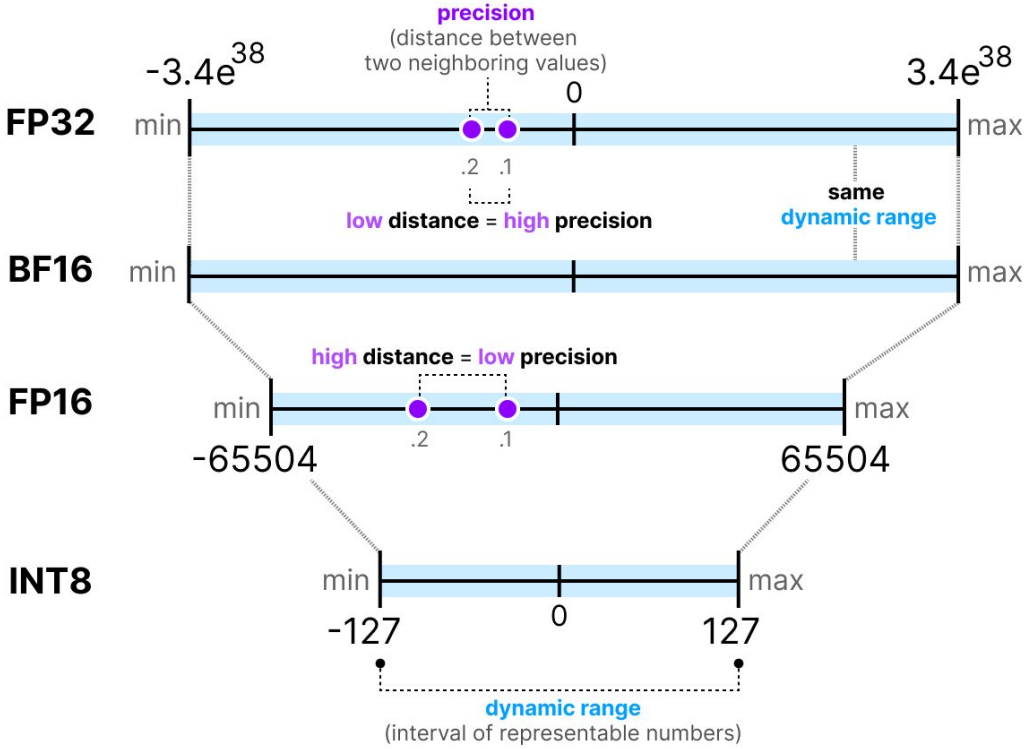


Adapted from [2]

What is precision? Common data types.. ?

- **Precision** is a measure of how precisely a number can be represented

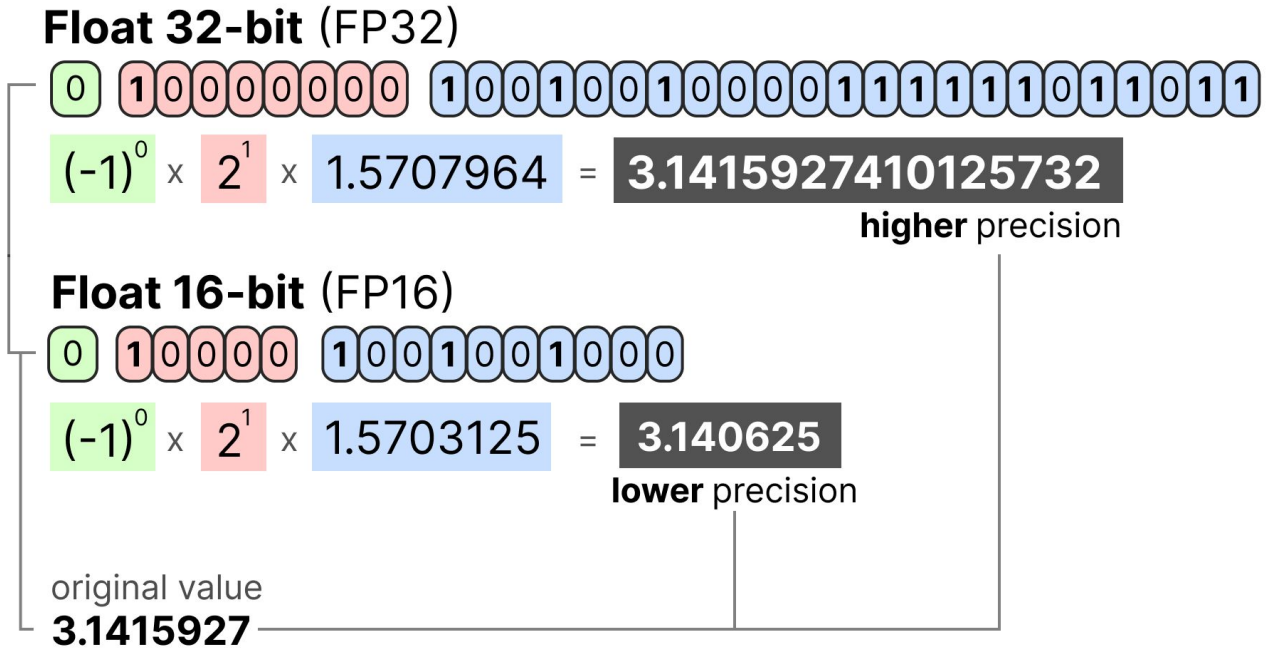
- What is the difference between BF16 and FP16?



Adapted from [2]

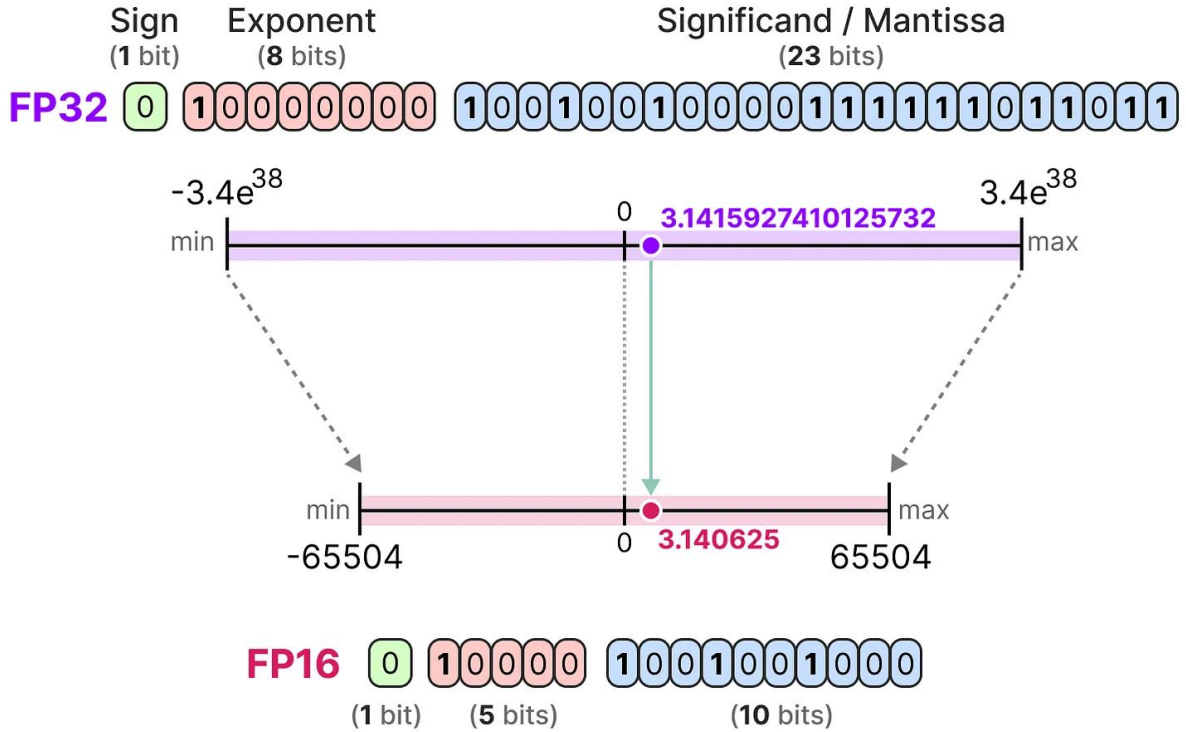
Common data types

$(-1)^{sign} \times base^{exponent} \times fraction$



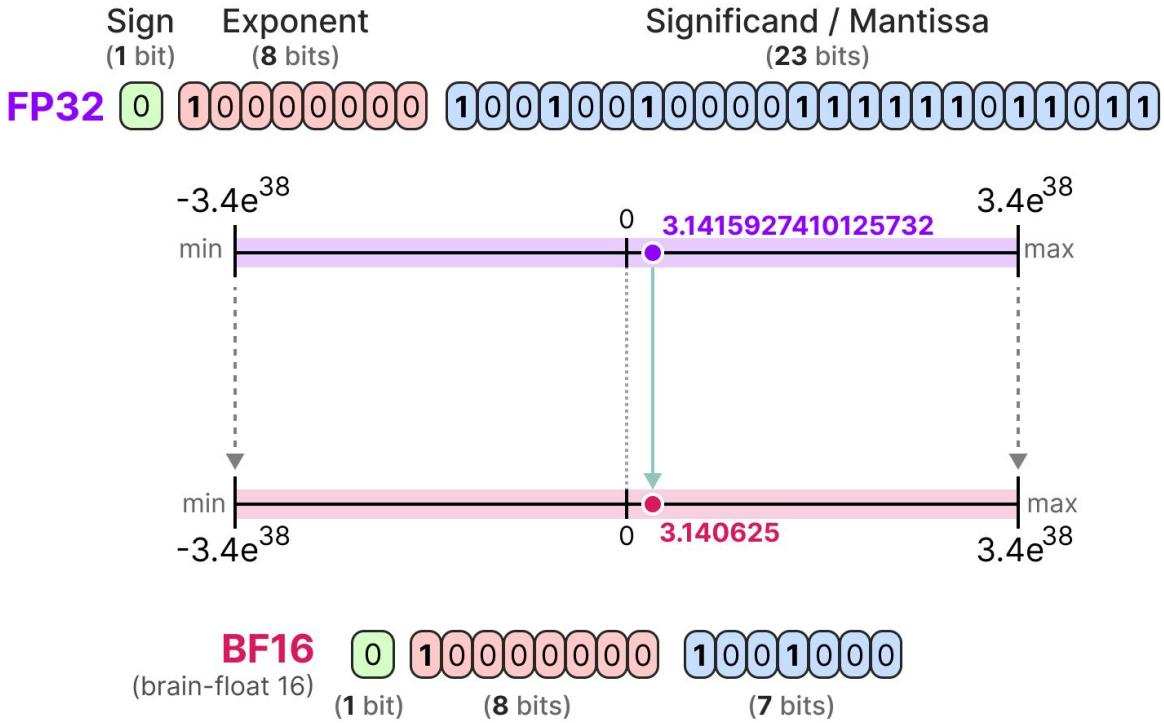
Using more bits **increases the precision** of a value. From [2]

Common data types



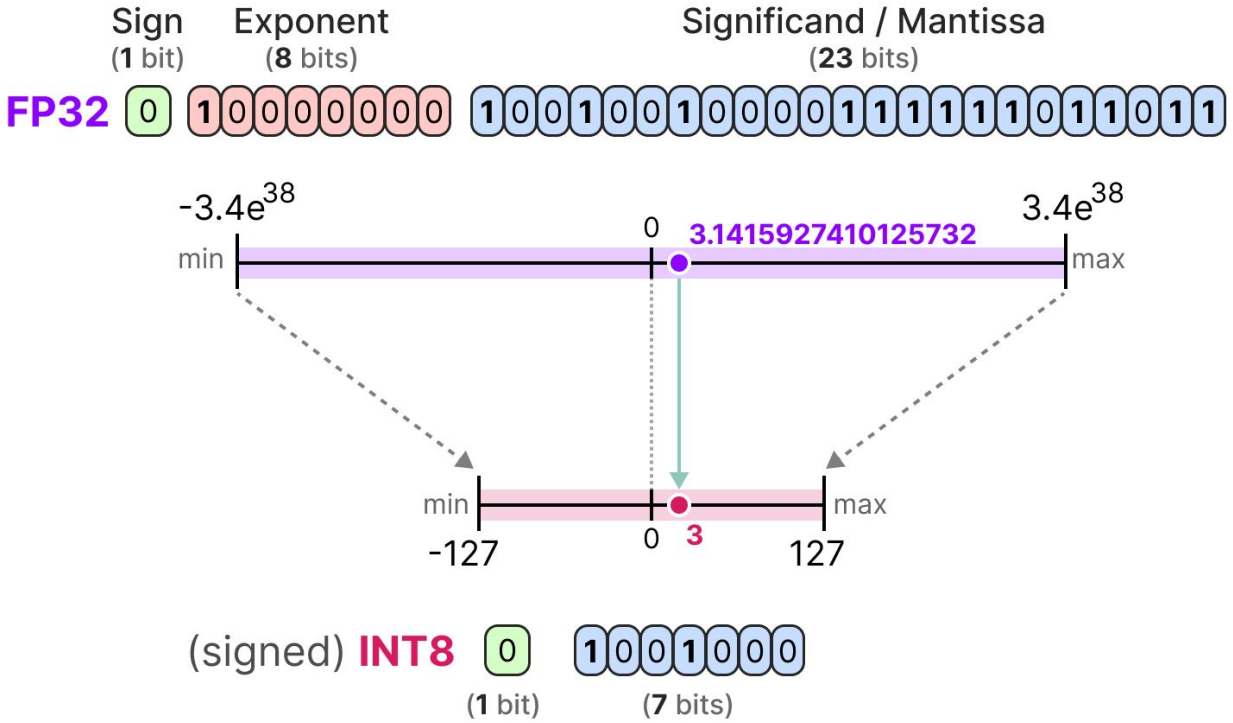
The **range of values reduces** with quantization. From [2]

Common data types



BF16 introduced to **have same range** as **FP32**. From [2]

Common data types



Can convert FP32 to 8-bit integer representations to save a lot of memory. From [2]

How much memory do we use.. ?

- **Memory = [# bits/ 8] * # params**

- Let's say you have a *Llama-3-8B*, how much memory would you need to just load the model weights?
  - **FP32** -> 32-bits = 32/8 * 8B ~ 32 GB
  - **FP16** -> 16-bits = 16/8 * 8B ~ 16 GB
  - **BF16** -> 16-bits = 16/8 * 8B ~ 16 GB
  - **INT-8** -> 8-bits = 8/8 * 8B ~ 8 GB
  - **4-bit** -> 4-bits = 4/8 * 8B ~ 4 GB

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*Actual GPU memory usage when running a model depends on several other factors such as: CUDA/runtime overhead, activation buffers, attention caches (for generation), context size etc, and if training — gradients and optimizer/momentum states (can multiply memory by 2–6x)

Absolute maximum (absmax) quantization

- How would you scale a number into the range [-127, 127] ?
  - Divide by its absolute maximum value and multiply by 127

$$\mathbf{X}_{\text{dequant}} = \frac{\max|\mathbf{X}|}{127} \cdot \mathbf{X}_{\text{quant}}$$

$$\mathbf{X}_{\text{quant}} = \text{round}\left(\frac{\mathbf{X}}{\max|\mathbf{X}|} \cdot 127\right)$$

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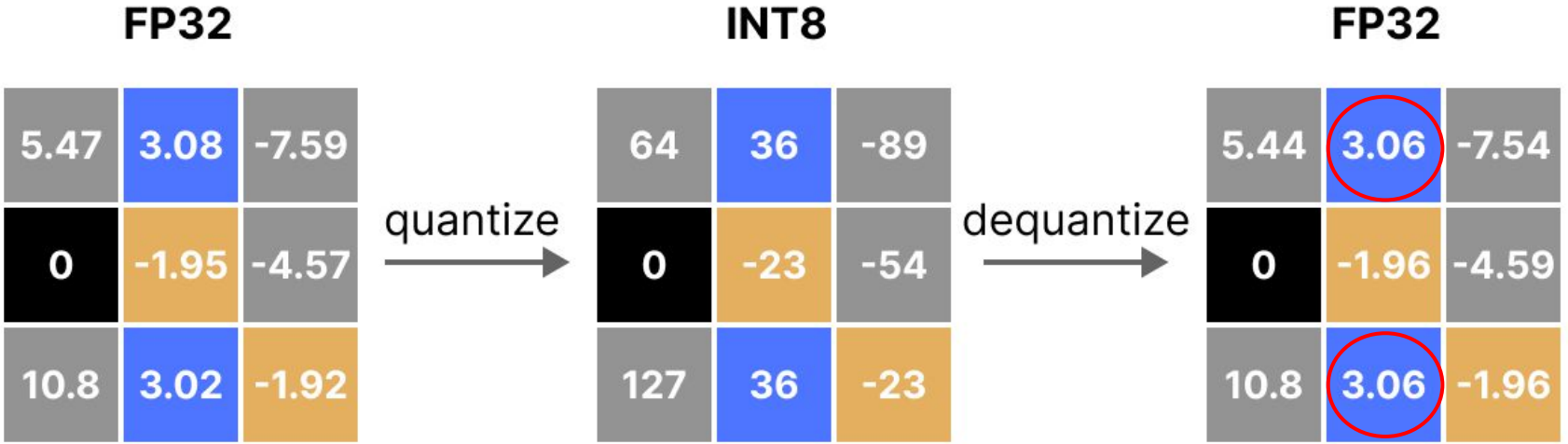
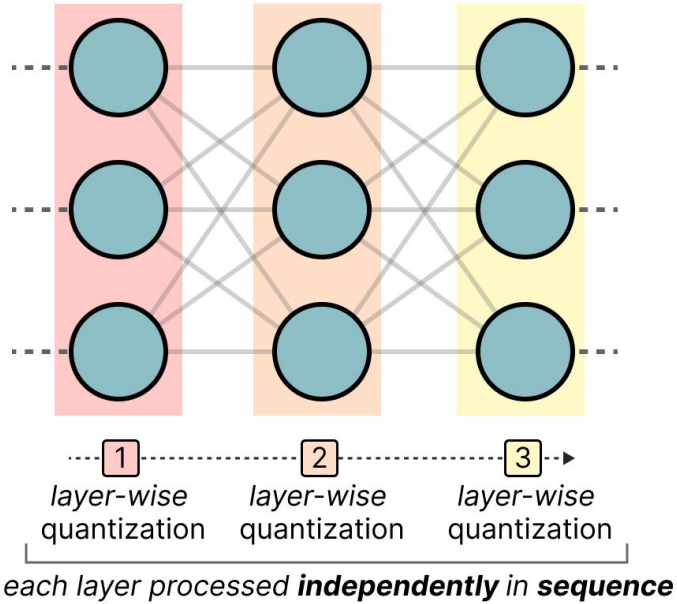
Quantization error

- Applying the quantization and then dequantization process to retrieve the original – leads to quantization error (= delta b/w original and dequantized)



GPTQ

- Each layer is quantized independently. Given a *layer l* with a weight matrix, W_l find the quantized weights $\widehat{W}_l$ **[3]**



$$\widehat{W}_l^* = \arg\min_{W_l} \|W_l X - \widehat{W}_l X\|^2$$

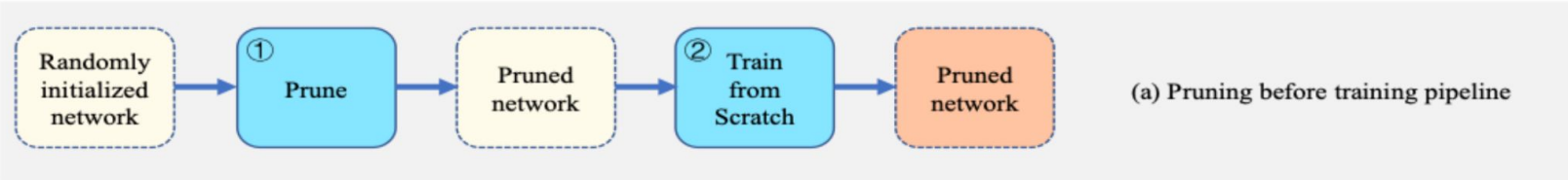
Model Pruning

- **What is model pruning?**
  - Removing parts of a neural network that contribute little to its output
  - Reduces model size and speeds up inference – without affecting output quality much

- **How is it different from quantization?**
  - Pruning reduces model size by reducing # parameters, while quantization does so by reducing precision of each parameters

Pruning before training

- **Procedure**: Prune the randomly initialized network followed by training from scratch. Reduces pre-training cost significantly
- Implementation: Weights are zeroed out using a binary mask

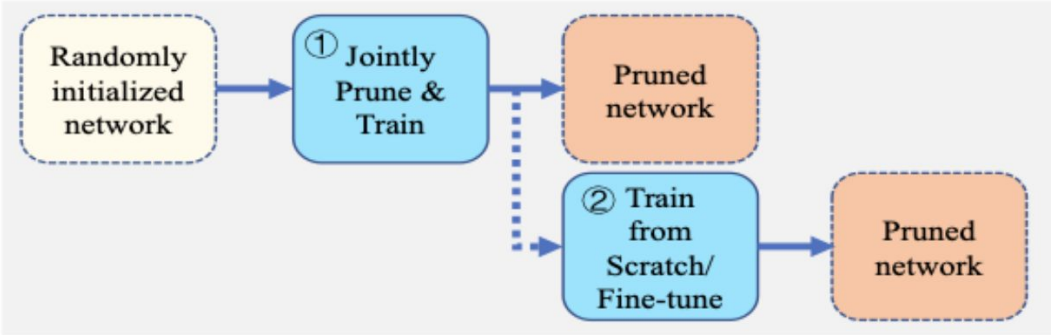


Adapted from [8]

- Examples:
  - **SNIP** [4] – one-shot pruning before training based on sensitivity
  - **GraSP** [5] – gradient-based pruning preserving training signal flow
  - **RANDOM** [6] – random pruning performs strikingly well

Pruning during training

- **Procedure**: Jointly prune and train the weights and the mask during training.

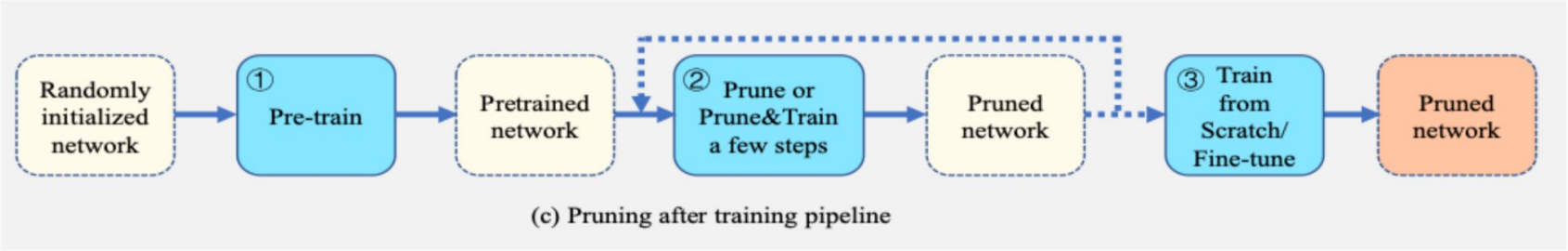


* Dashed lines indicate that subsequent operations are not required

- Examples:
  - **Sparse Regularization** - To impose a sparse constraint on the loss function, for example adding a L_1 regularization term [7]
  - **Score based methods** - Evaluate the scores of parameters during model training and directly prune parameters with low scores [8]
    - **Sheared Llama** [12] - performs structured pruning interleaved with training

Pruning after training

- **Procedure**: Jointly prune and train the weights and the mask during training
  - Follows a pretrain-prune-retrain process, as shown in the figure below.



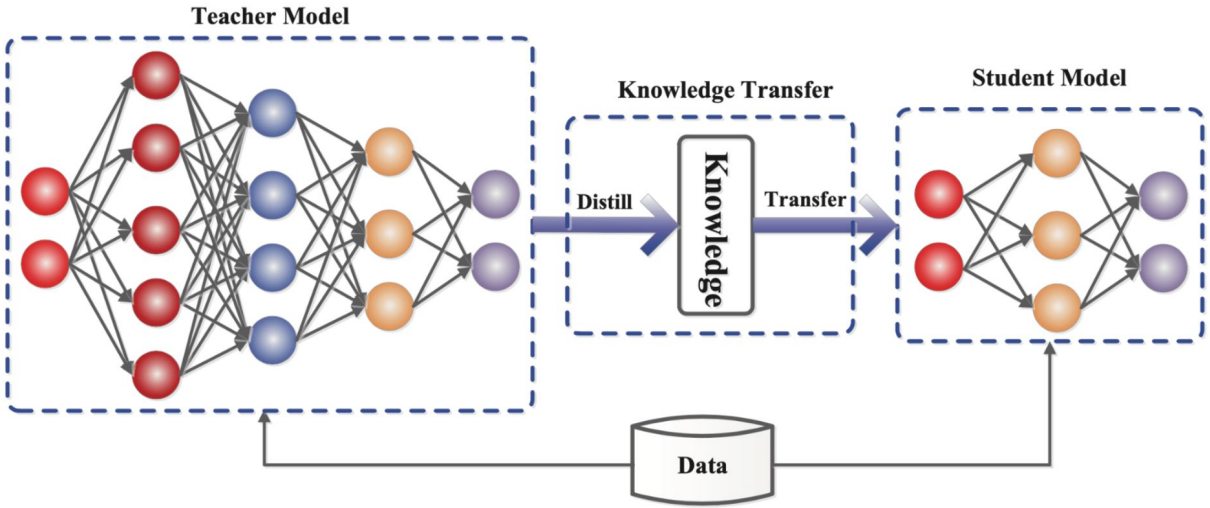
(c) Pruning after training pipeline

* Dashed lines indicate that subsequent operations are not required

- Examples:
  - **Lottery Ticket Hypothesis [9]**: Every overparameterized network has a smaller winning subnet that can perform just as well when trained independently
  - **Sparse GPT [10]:** LLMs can be pruned to 50% sparsity in one-shot, without any retraining
  - **Early BERT [11]:** Identifies structured winning tickets in the early stage of BERT

Knowledge Distillation

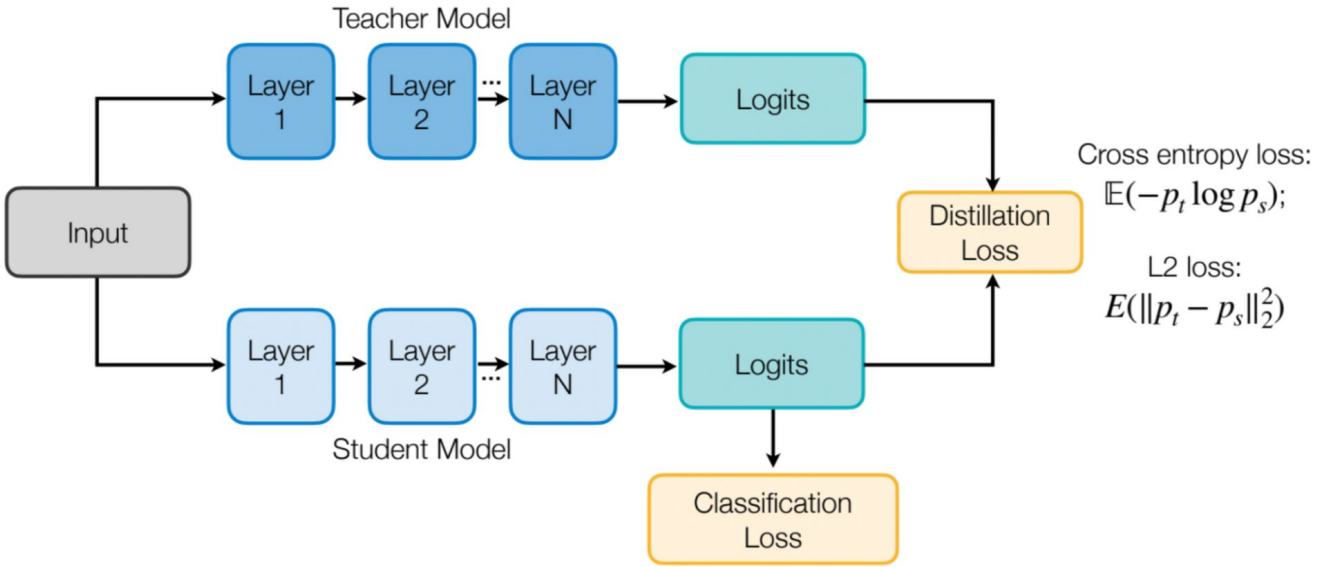
- **Goal**: To **transfer knowledge** from a **larger model** to a **student model**



- Why not train a student model **from scratch** instead?

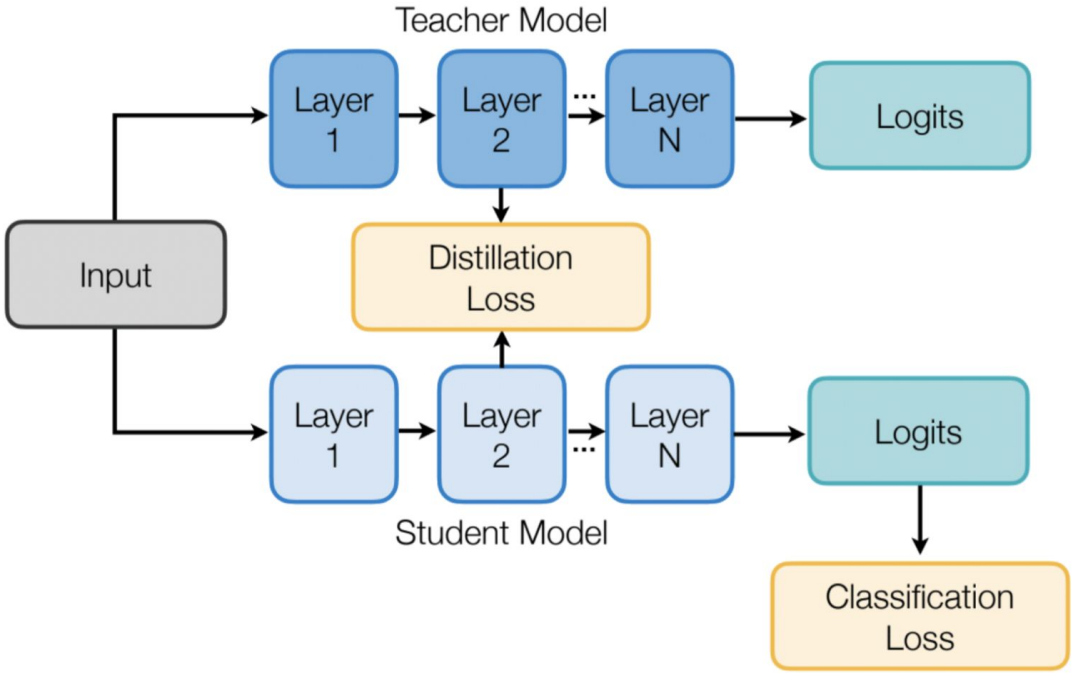
Knowledge Distillation

- Simplest way is to **match the outputs** using a **distance metric**



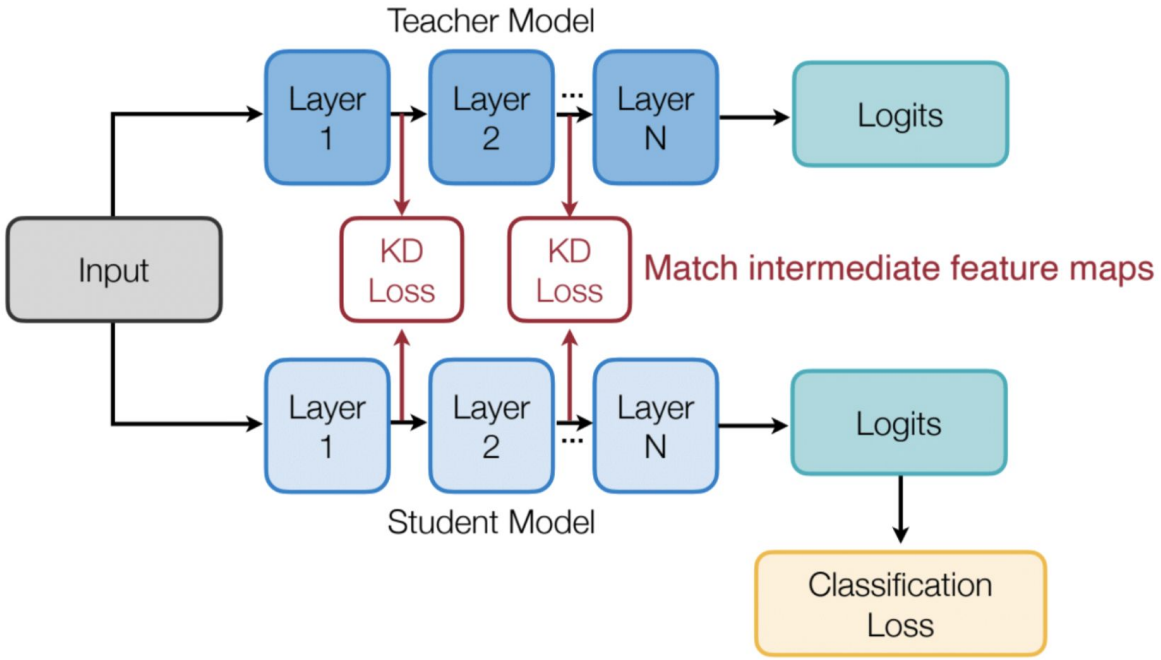
Knowledge Distillation

- Match the **weights in intermediate layers** using a **distance metric**



Knowledge Distillation

- Match the **intermediate feature maps** using a distance metric. Ex. DistilBERT

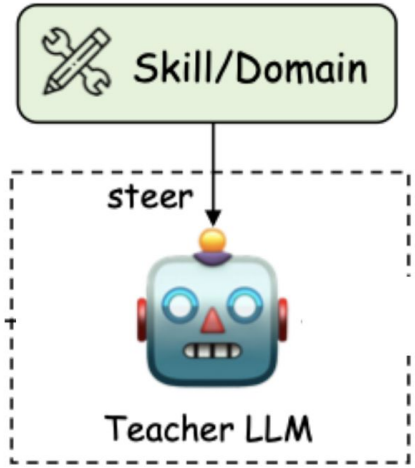


Knowledge Distillation in LLM Era

- **Inaccessible parameters**, but we still want to transfer knowledge from LLMs

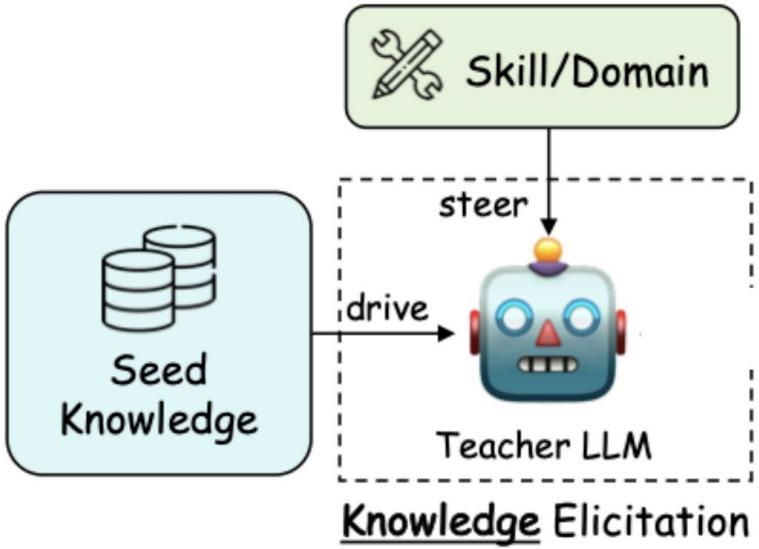
Knowledge Distillation in LLM Era

- **Steer the LLM** for a target skill or domain



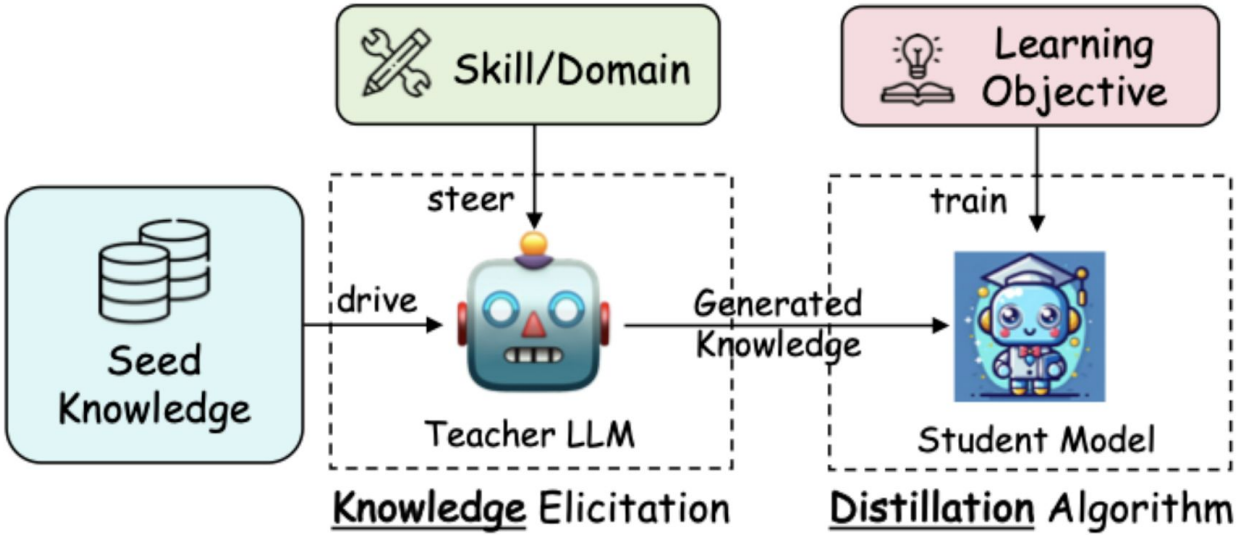
Knowledge Distillation in LLM Era

- **Feed the LLM** with a small dataset as seed knowledge



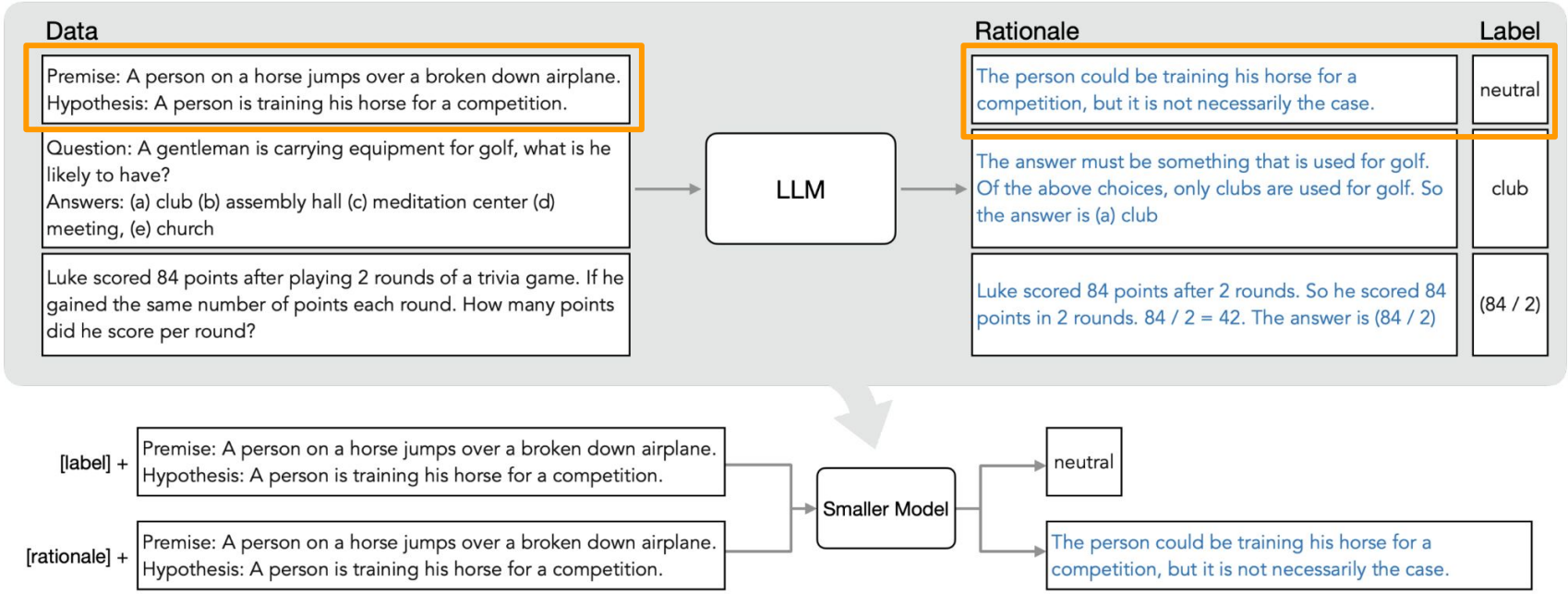
Knowledge Distillation in LLM Era

- **Generate knowledge** from the LLM with a small dataset as seed knowledge



Knowledge Distillation in LLM Era

- Can also distill on reasoning steps (rationales) extracted from LLMs



Adapted from C.-Y. Hsieh, et. al., "Distilling step-by-step! Outperforming larger language models with less training data and smaller model sizes," ACL, 2023.

Key Takeaways

- **Efficient inference** is important to **deploy models for resource-constrained devices**
- **Quantization** aims to simplify data by **rounding it to low-precision data types** while preserving information
- **Pruning** aims to **remove redundancy** in networks before, during or after training
- **Knowledge distillation** distills knowledge from a **teacher to student network**

References

1. Adapted from NYU DSGA-1011 (Fall'24) section material by Divyam Madaan
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