

## (An Incomplete List of) Popular LLM Evals

Human Preferences for chat

**Chatbot Arena**

LLM as a judge for chat

Alpaca Eval  
MT Bench  
**Arena Hard V1 / V2**

It's easy to improve any one of the benchmarks.

Static Benchmarks for Instruct LLM

**LivecodeBench**  
**AIME 2024 / 2025**  
GPQA  
MMLU Pro  
IFEval

It's much harder to improve **without degrading other domains.**

Function Calling & Agent

BFCL V2 / V3  
NexusBench V1 / V2  
**TauBench**  
**Toolformer**

but it can be much harder to improve some benchmark

但要提升某些基準測試表現



# Do you really need post-training?

## Use Cases

Follow a few instructions  
(do not discuss XXX)

Query real-time database or  
knowledgebase

Create a medical LLM /  
Cybersecurity LLM

Follow 20+ instructions tightly;  
Improve targeted capabilities  
("Create a strong SQL / function  
calling / reasoning model")

## Methods

Prompting

Retrieval- Augmented  
Generation (RAG) or  
Search

Continual Pre-training +  
Post-training

Post-training

## Characteristics

Simple yet brittle: models may not always  
follow all instructions

Adapt to rapidly-changing knowledgebase

Inject large-scale domain  
knowledge (>1B tokens) not seen during  
pre-training

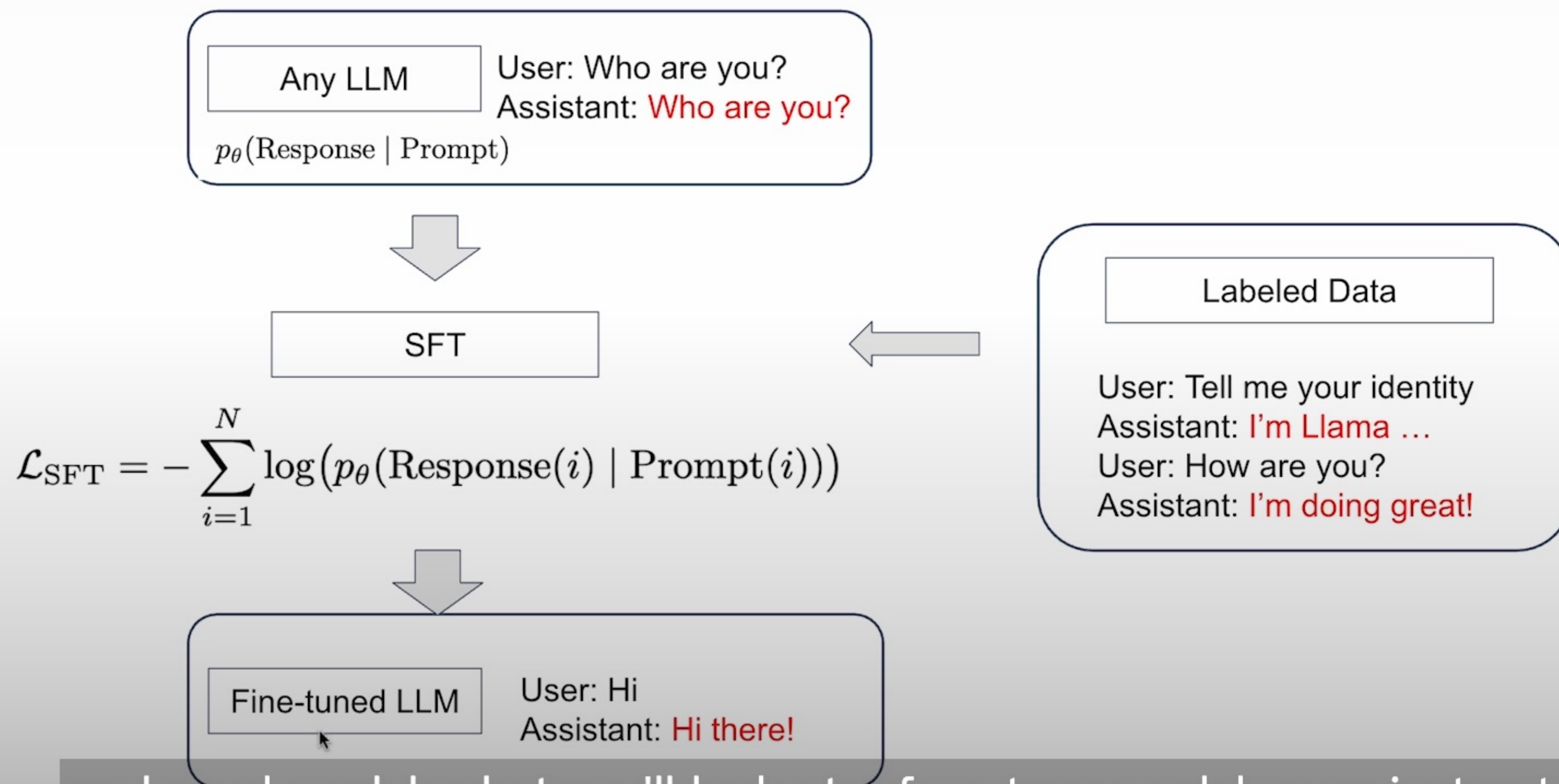
Reliably change model behavior & improve  
targeted capabilities;  
May degrade other capabilities if not done  
right

how to do post-training and when to do post-training.

如何進行後訓練以及何時進行後訓練



## SFT: Imitating Example Responses



on based model, what you'll look at a fine-tune model or an instruct model,

基於基礎模型，你將會看到一個微調模型或是指令模型，



## Best Use Cases for SFT

- **Jumpstarting new model behavior**
  - Pre-trained models -> Instruct models
  - Non-reasoning models -> reasoning models
  - Let the model uses certain tools without providing tool descriptions in the prompt
- **Improving model capabilities**
  - Distilling capabilities for small models by training on high-quality synthetic data generated from larger models

synthetic data generated by a larger model.  
這些訓練資料是由較大型模型生成的合成數據



## Principles of SFT Data Curation

- **Common methods for high-quality SFT data curation:**
  - **Distillation:** Generate responses from a stronger and larger instruct model
  - **Best of K / rejection sampling:** Generate multiple responses from the original model, select the best among them
  - **Filtering:** start from larger scale SFT dataset, filter according to the quality of responses and diversity of the prompts
- **Quality > quantity for improving capabilities:**
  - 1,000 high-quality, diverse data > 1,000,000 mixed-quality data

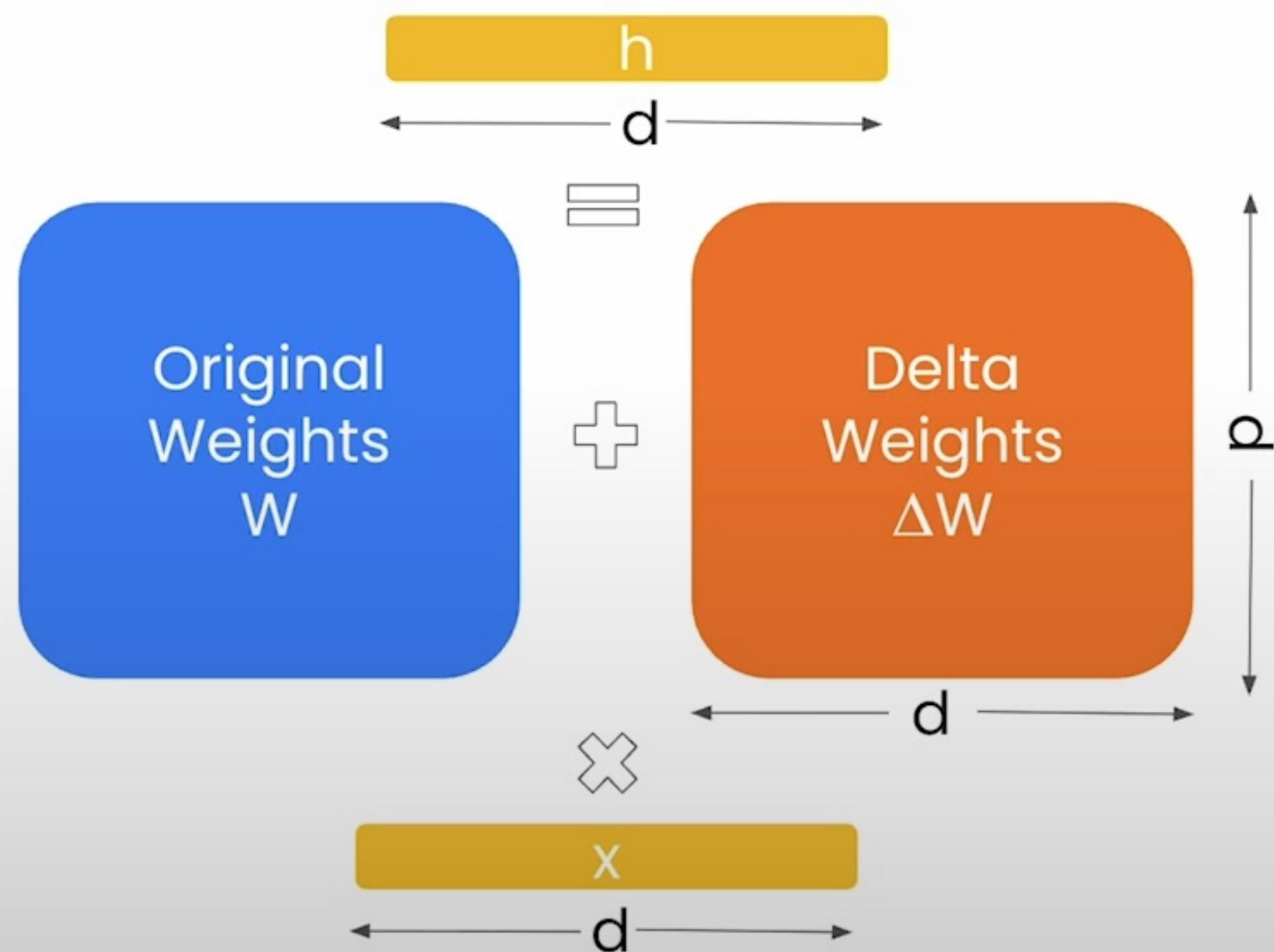
will be forced to imitate such response and thus degrading the performance.

將被迫模仿此類回應，從而導致效能下降。

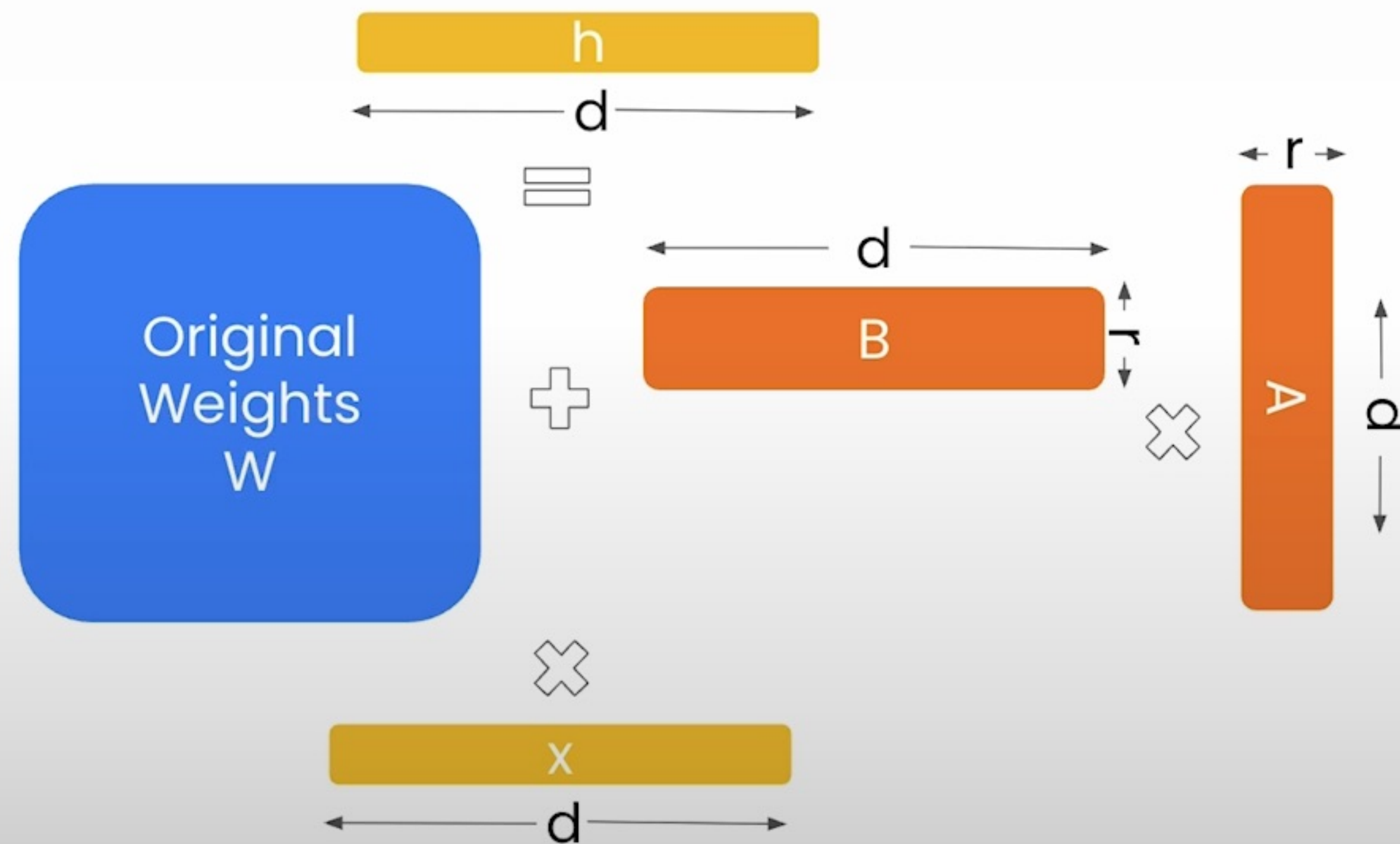


# Full Fine-tuning vs Parameter Efficient Fine-tuning (PEFT)

$$h = (W + \Delta W)x$$
$$W, \Delta W \in \mathbb{R}^{d \times d}, h, x \in \mathbb{R}^{d \times 1}$$



$$h = (W + BA)x$$
$$B \in \mathbb{R}^{d \times r}, A \in \mathbb{R}^{r \times d}$$



Both full-finetuning and PEFT can be used in any of the post-training methods.  
PEFT like Lora saves memory, learns less while forgets less [1]

[1] Biderman, Dan, Jacob Portes, Jose Javier Gonzalez Ortiz, Mansheej Paul, Philip Greengard, Connor Jennings, Daniel King et al. "Lora learns less and forgets less." *arXiv preprint arXiv:2405.09673* (2024).