# Supervised Fine-Tuning (SFT), Full Fine-Tuning, and Parameter-Efficient Fine-Tuning (PEFT)

## 1. Introduction

Large Language Models (LLMs) are first pretrained on massive amounts of text data. During pretraining, the goal is to predict the next word in a sequence. This gives the model a strong understanding of grammar, facts, and general language patterns. However, pretrained models do not follow instructions well. They tend to continue text rather than answering questions or performing tasks directly.

## 2. Supervised Fine-Tuning (SFT)

Supervised Fine-Tuning adapts a pretrained LLM to follow instructions. This is done by training the model on instruction–response pairs created by humans. Instead of predicting generic continuations, the model learns to map instructions to desired outputs.

Example:

* Instruction: What are large language models?
* Output: Large language models (LLMs) are models that generate human-like text by predicting the probability of words in a sequence.

After SFT, models are better at tasks like answering questions, summarizing text, and classifying sentiment. SFT is the first step in aligning LLMs with human needs.

## 3. Full Fine-Tuning

Full fine-tuning involves updating all parameters of the pretrained model using a smaller, labeled dataset. This process is similar to pretraining but uses supervised data instead of raw text. It is powerful because it can deeply adapt a model to domain-specific tasks.

* Key points about Full Fine-Tuning:
* • Updates all parameters of the model.
* • Uses smaller, labeled datasets (e.g., question-response pairs).
* • Great for domain-specific adaptation (e.g., medical, legal, finance).
* • Very costly in terms of compute, time, and storage.

## 4. Parameter-Efficient Fine-Tuning (PEFT)

While full fine-tuning provides maximum performance, it is resource-intensive. Parameter-Efficient Fine-Tuning (PEFT) was developed to make adaptation cheaper and faster. PEFT techniques update only a subset of model parameters or introduce small additional modules, while keeping most of the pretrained model frozen.

* Popular PEFT techniques include:
* • LoRA (Low-Rank Adaptation) – adds small matrices to attention layers.
* • Prefix-Tuning / Prompt-Tuning – learns task-specific tokens that guide the model.
* • Adapters – small trainable modules inserted into the model.
* Benefits of PEFT:
* • Much cheaper and faster training.
* • Smaller storage requirements.
* • Easy to switch between tasks/domains.

## 5. Full Fine-Tuning vs PEFT

The following table highlights the differences between Full Fine-Tuning and PEFT:

|  |  |  |
| --- | --- | --- |
| Aspect | Full Fine-Tuning | PEFT |
| Parameters Updated | All | Subset / Adapters only |
| Compute Cost | Very High | Low / Moderate |
| Training Speed | Slow | Faster |
| Storage Needs | Huge | Small |
| Performance | Best possible | Slightly lower (but close) |
| Use Cases | Domain-specific, high-stakes tasks | Cost-sensitive, multi-task adaptation |

## 6. Conclusion

Pretraining gives LLMs general language ability. Supervised Fine-Tuning teaches them to follow instructions. Full Fine-Tuning is powerful but resource-intensive, while PEFT provides an efficient alternative. Both approaches are crucial in making LLMs practical for real-world applications.