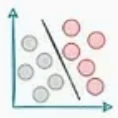
Pandas ↔ Polars ↔ SQL ↔ PySpark



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Operation	Pandas	Polars	SQL	PySpark
Import	import pandas as pd	import polars as pl	-	from pyspark.sql import SparkSession spark = SparkSession.builder.appName("ABCD")
Read CSV	df = pd.read_csv(file)	df = pl.read_csv(file)	LOAD DATA INFILE 'data.csv' INTO TABLE table FIELDS TERMINATED BY ',' LINES TERMINATED BY '\n' IGNORE 1 ROWS;	df = spark.read .csv("data.csv")
Print first 10 (or k) rows	df.head(10)	df.head(10)	SELECT * FROM table LIMIT 10;	df.show(10)
Dimensions	df.shape	df.shape	SELECT count(*) FROM table;	df.count()
			SELECT count(*) FROM INFORMATION_SCHEMA.COLUMNS where TABLE_NAME = 'table';	len(df.columns)
Datatype	df.dtypes	df.dtypes	DESCRIBE table;	df.printSchema()
Select column(s)	df[["col1", "col2"]]	df[["col1", "col2"]]	SELECT column FROM table;	df.select("col1", "col2")
Filter Data	df[df.column > 10]	df[df.column > 10]	SELECT * FROM table where column>10;	df.filter(df["column"]>10)
		df.filter(pl.col("column") > 10)		
Sort	df.sort_values("column")	df.sort("column")	SELECT * FROM table ORDER BY column;	df.orderBy("column")
Fill NaN	df.column.fillna(0)	df.column.fill_nan(0)	UPDATE table SET column=0 WHERE column IS NULL;	df.na.fill(0)
Join	pd.merge(df1, df2, on ="col", how="inner")	df1.join(df2, on="col", how="inner")	SELECT * FROM table1 JOIN table2 ON (table1.col = table2.col);	df1.join(df2, on="col", how="inner")
Concatenate	pd.concat((df1, df2))	pl.concat((df1, df2))	SELECT * FROM table1 UNION ALL table2;	df1.union(df2)
Group	df.groupby("column"). agg_col.mean()	df.groupby("column"). agg(pl.mean("agg_col"))	SELECT column, avg(agg_col) FROM table GROUP BY column;	df.groupBy("column"). agg(avg("agg_col"))
Unique values	df.column.unique()	df.column.unique()	SELECT DISTINCT column FROM table;	df.select("column"). distinct()
Rename column	df.rename(columns = {"old_name": "new_name"})	df.rename(mapping = {"old_name": "new_name"})	ALTER TABLE table RENAME COLUMN old_name TO new_name;	df.withColumnsRenamed({"old_name": "new_name"})
Delete column	df.drop(columns = ["column"])	df.drop(name = ["column"])	ALTER TABLE table DROP COLUMN column;	df.drop("col1", "col2")

Next...

4 Strategies for Multi-GPU Training

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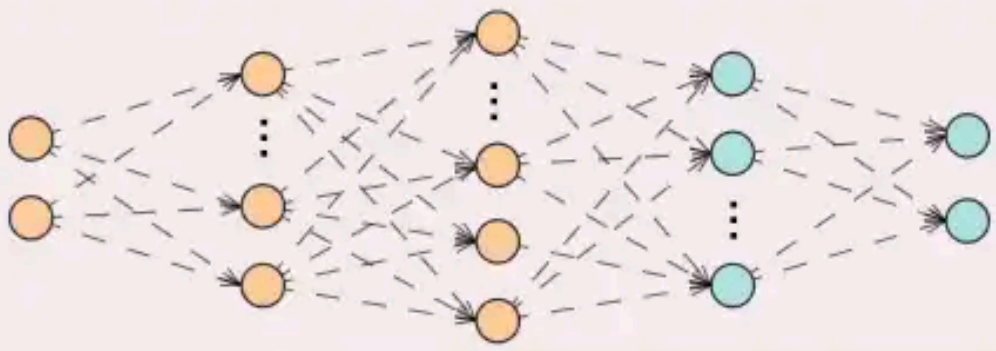
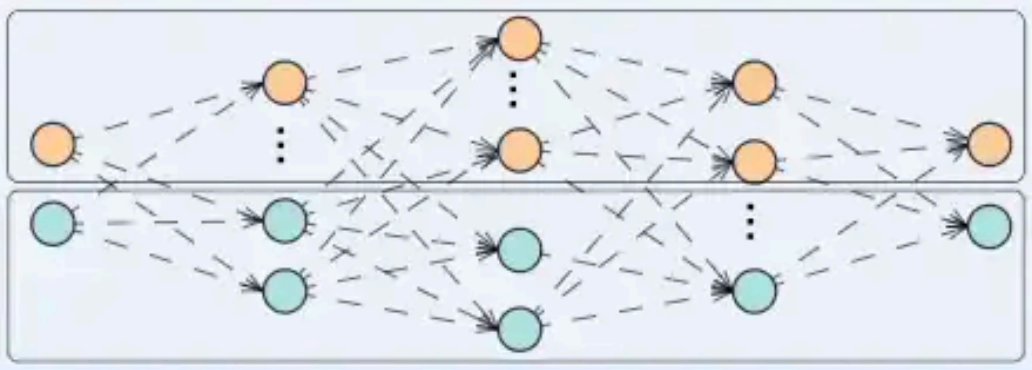
Model parallelism



Layer on 1st GPU

Layer on 2nd GPU

Tensor parallelism



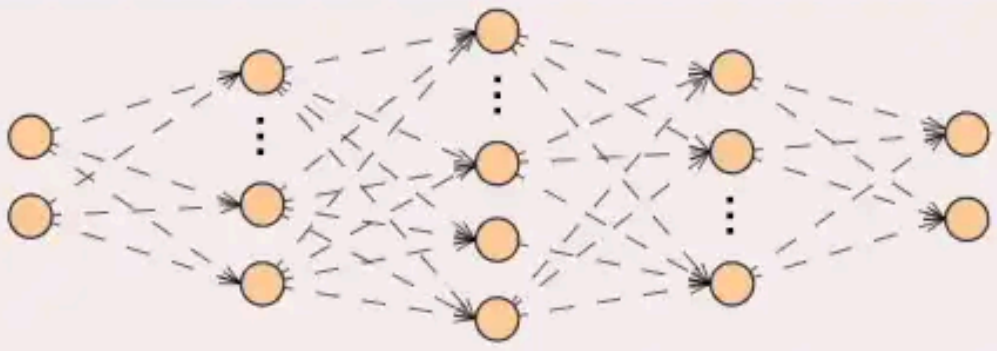
Neurons on 1st GPU

Neurons on 2nd GPU

Data parallelism

Data subset #1

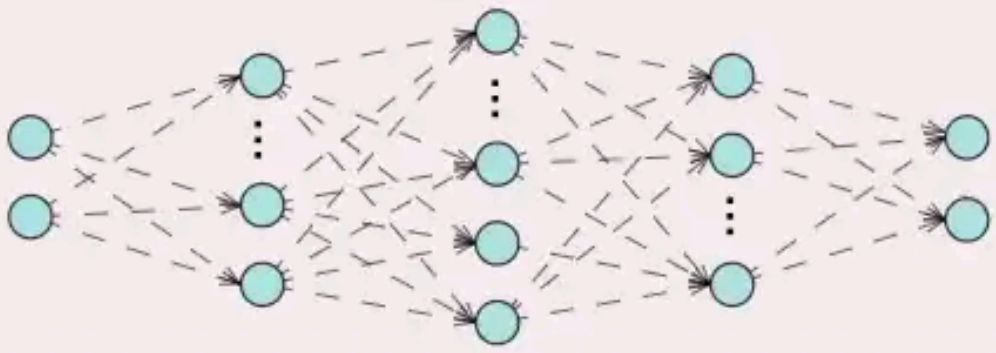
x1	x2	x3
...	...	...
...	...	...



Model copy on 1st GPU

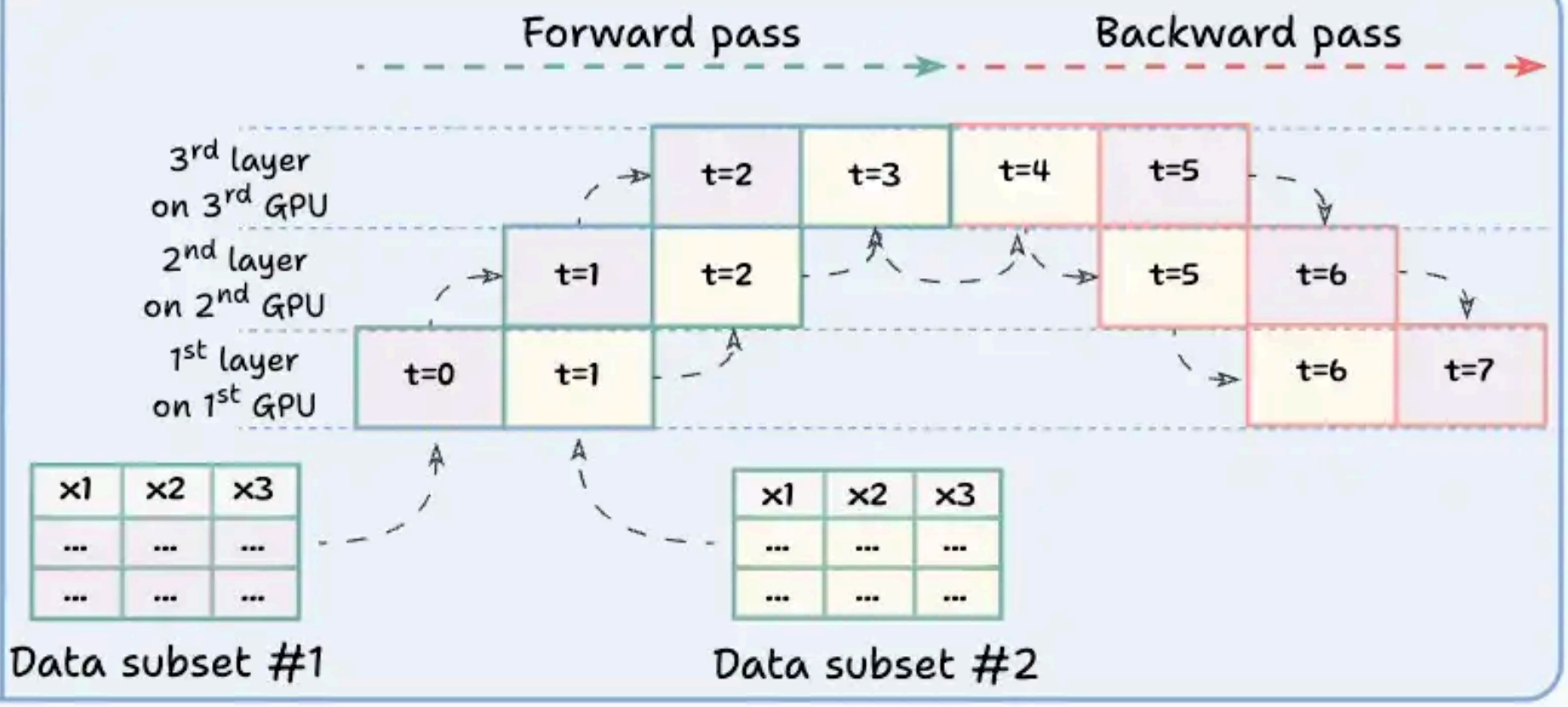
Data subset #2

x1	x2	x3
...	...	...
...	...	...



Model copy on 2nd GPU

Pipeline parallelism



Next...

4 Ways to Test ML Models in Production

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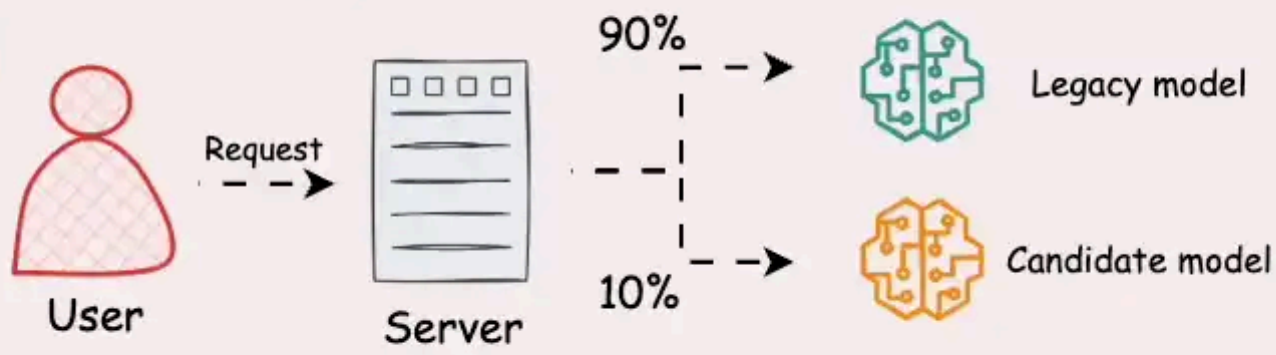
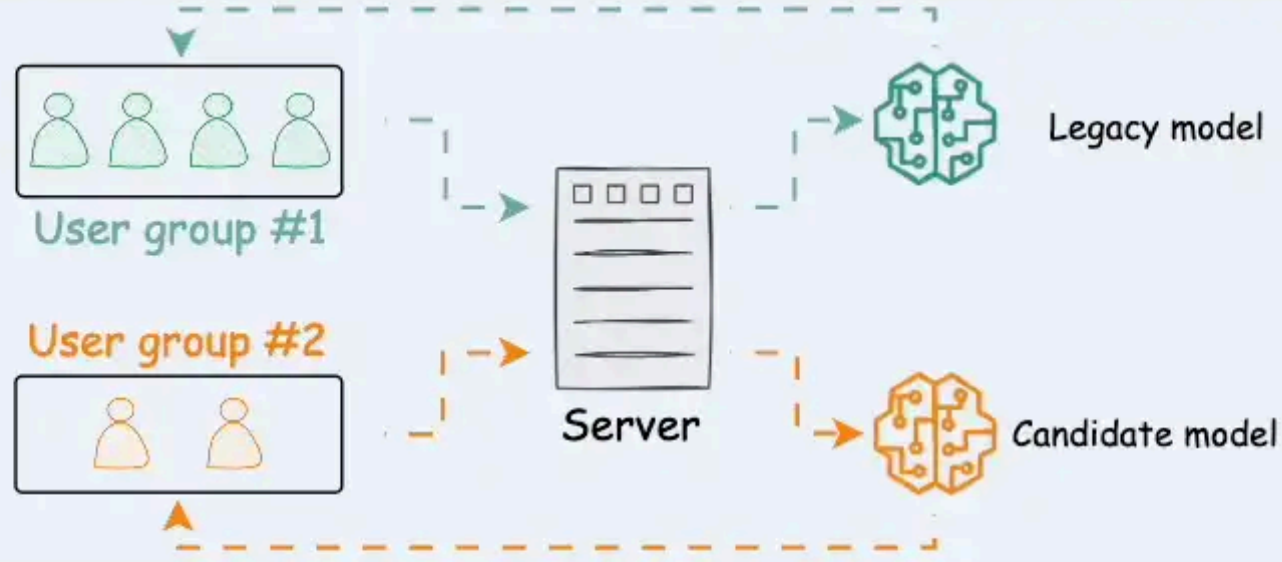
1) A/B Testing



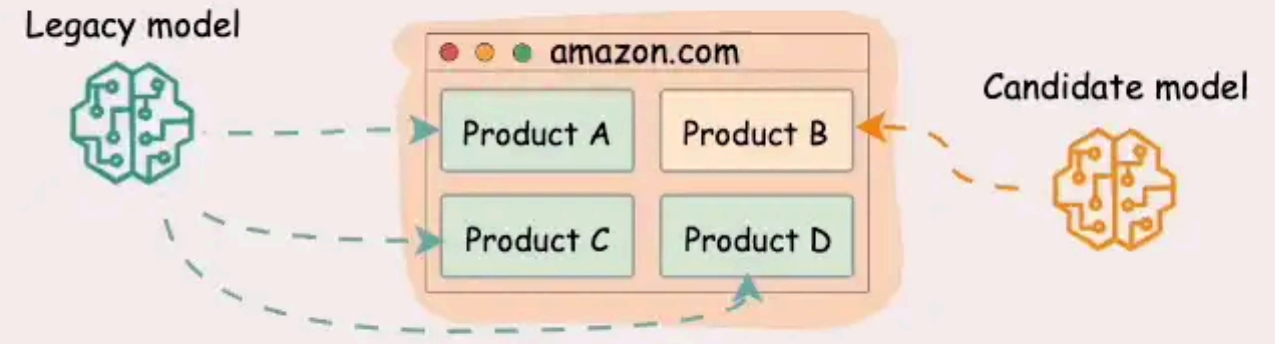
Send some requests to the candidate model.

2) Canary Testing



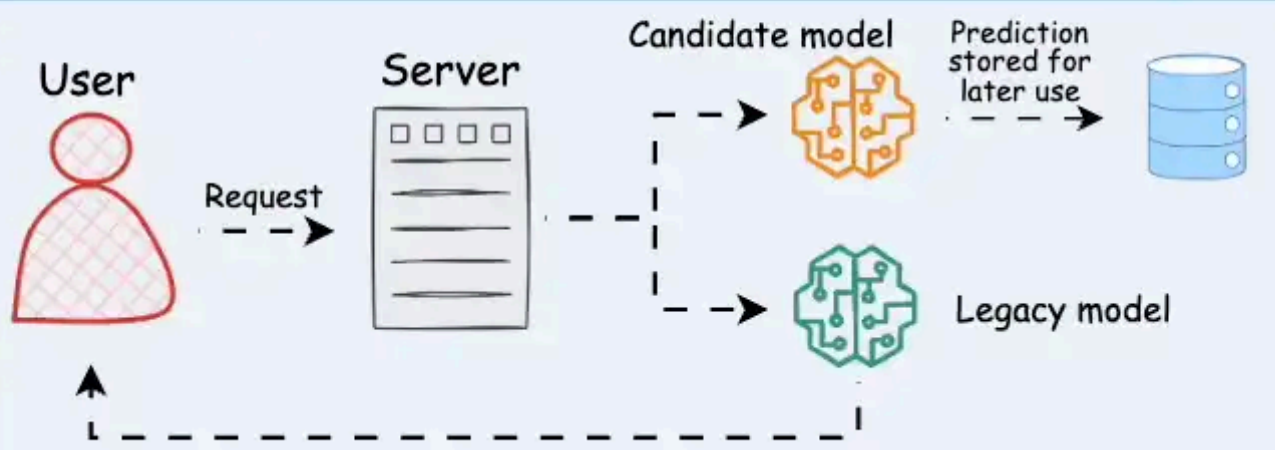
Release the candidate model only to a few users.

3) Interleaved Testing



Use both models for predictions.

4) Shadow Testing



Store the predictions from candidate model for later use/ inspection.

Next...

15 Ways to Optimize Neural Network Training

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- ☑ Use efficient optimizers—AdamW, Adam, etc.
- ☑ Utilize hardware accelerators (GPUs/TPUs).
- ☑ Max out the batch size.
- ☑ Use Bayesian Optimization if hyperparameter search space is big.
- ☑ Set max_workers in the DataLoader.
- ☑ Set pin_memory in DataLoader.
- ☑ Use mixed precision training.
- ☑ Use He or Xavier initialization for faster convergence (usually helps).
- ☑ Use activation checkpointing to optimize memory (run-time will go up).
- ☑ Utilize multi-GPU training through Model/Data/Pipeline/Tensor parallelism.
- ☑ For large models, use DeepSpeed, FSDP, YaFSDP, etc.
- ☑ Normalize data after transferring to GPU (for numerical data, like pixels).
- ☑ Use gradient accumulation (may have marginal improvement at times).
- ☑ Always use DistributedDataParallel, not DataParallel.
- ☑ torch.rand(2, 2, device = ...) creates a tensors directly on the GPU.
- ☒ torch.rand(2,2).cuda() first creates on the CPU, then transfers to GPU.

Always profile your code to identify and to identify eliminate performance bottlenecks.

Next...

Time Complexity of 10 Most Popular ML Algorithms

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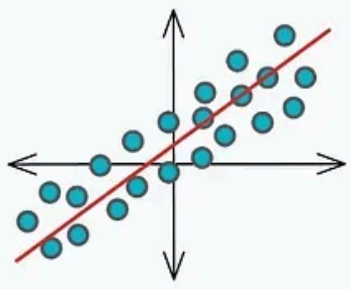
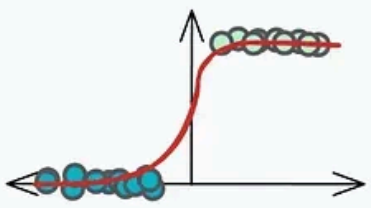
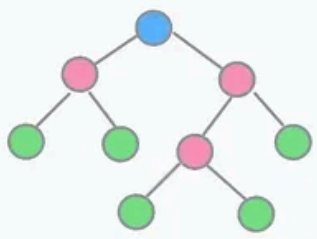
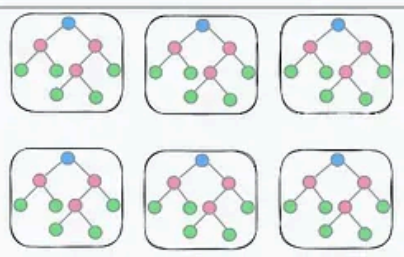
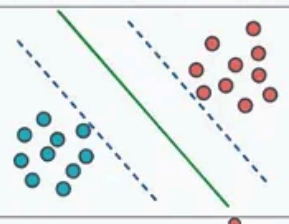
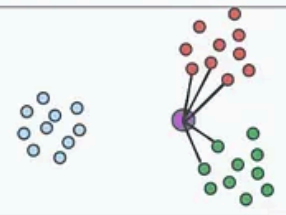
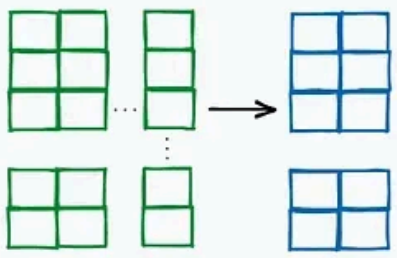
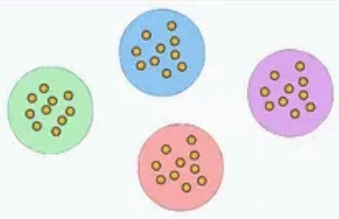
		Training	*Inference*
	Linear Regression (OLS)	$O(nm^2 + m^3)$	$O(m)$
	Linear Regression (SGD)	$O(n_{epoch}nm)$	$O(m)$
	Logistic Regression (Binary)	$O(n_{epoch}nm)$	$O(m)$
	Logistic Regression (Multiclass OvR)	$O(n_{epoch}nmc)$	$O(mc)$
	Decision Tree	$O(n \cdot log(n) \cdot m)$ $O(n^2 \cdot m)$* **Worst case**	$O(d_{tree})$
	Random Forest Classifier	$O(n_{trees} \cdot n \cdot log(n) \cdot m)$	$O(n_{trees} \cdot d_{tree})$
	Support Vector Machines (SVMs)	$O(n^2m + n^3)$	$O(m \cdot n_{SV})$
	k-Nearest Neighbors	—	$O(nm)$
$P(B\|A) = \frac{P(\mathrm{B} \cap A)}{P(A)}$	Naive Bayes	$O(nm)$	$O(mc)$
	Principal Component Analysis (PCA)	$O(nm^2 + m^3)$	—
	t-SNE	$O(n^2m)$	—
	KMeans Clustering	$O(iknm)$	??

n: samples | m: dimensions | n_{epoch}: epochs | c: classes | d_{tree}: depth

n_{SV}: Support vectors | k: clusters | i: iterations

Next...

5 Techniques to fine-tune LLMs

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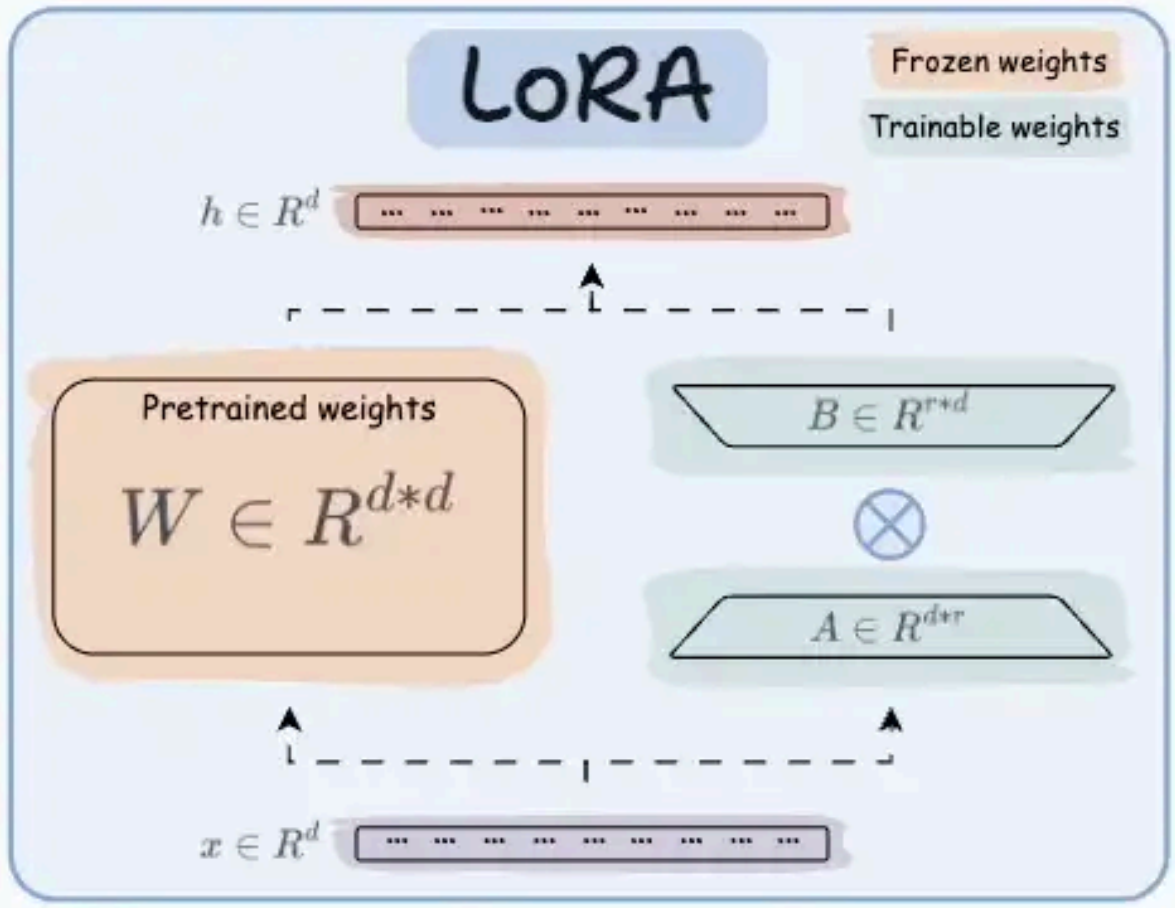
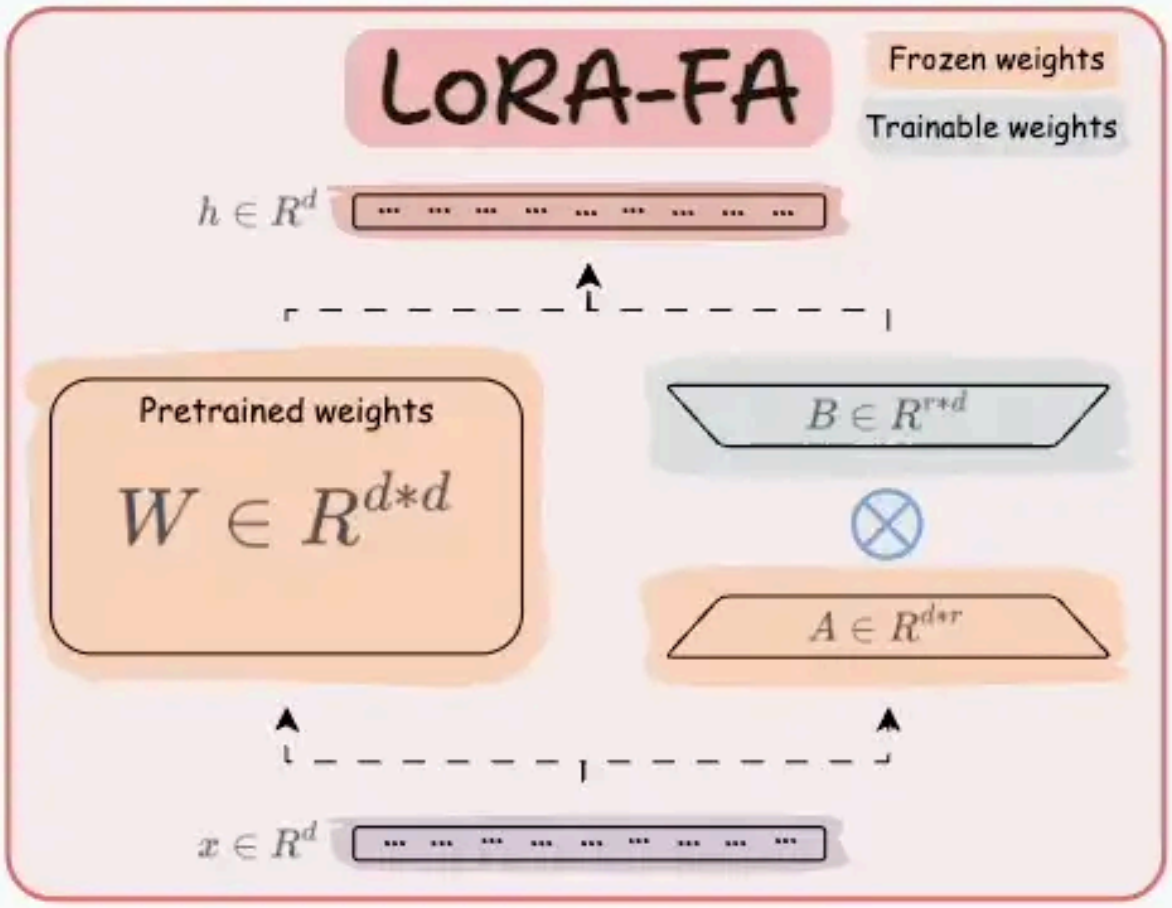
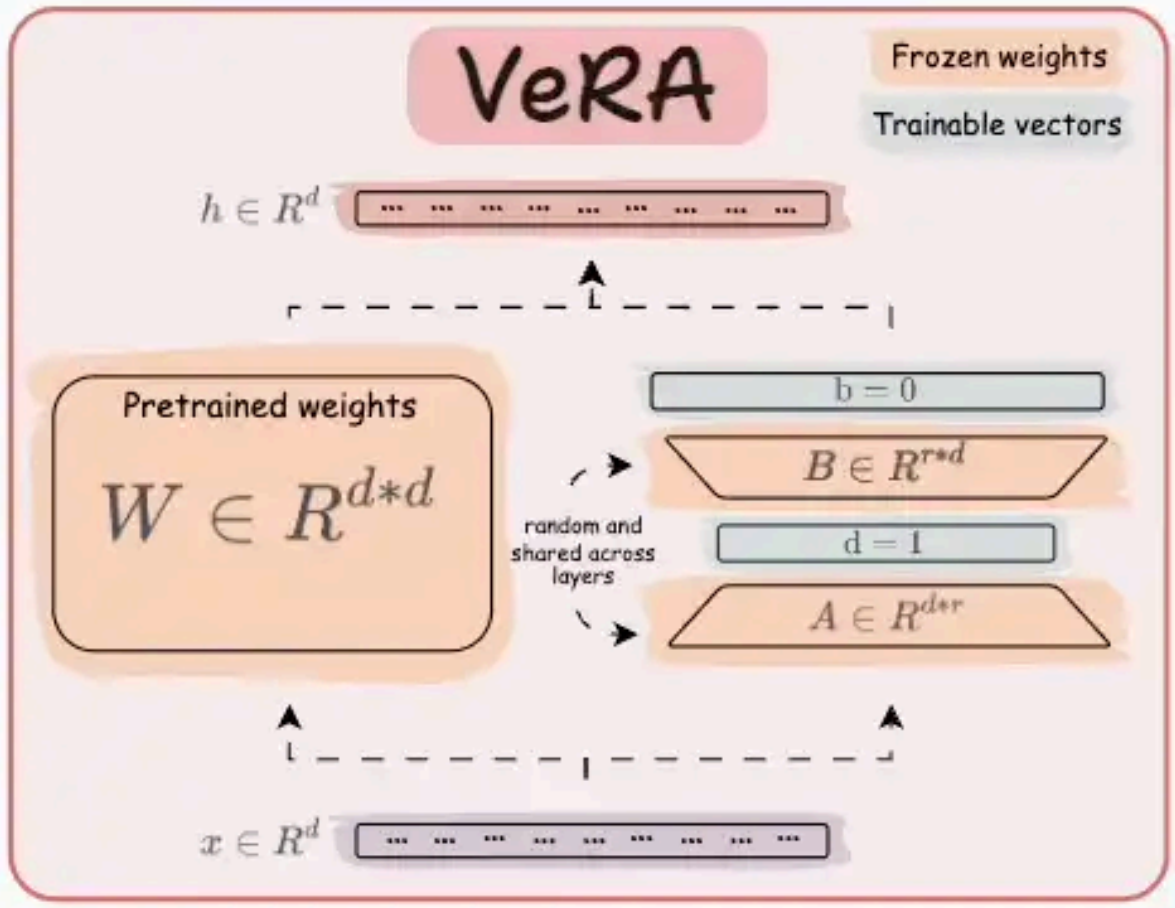
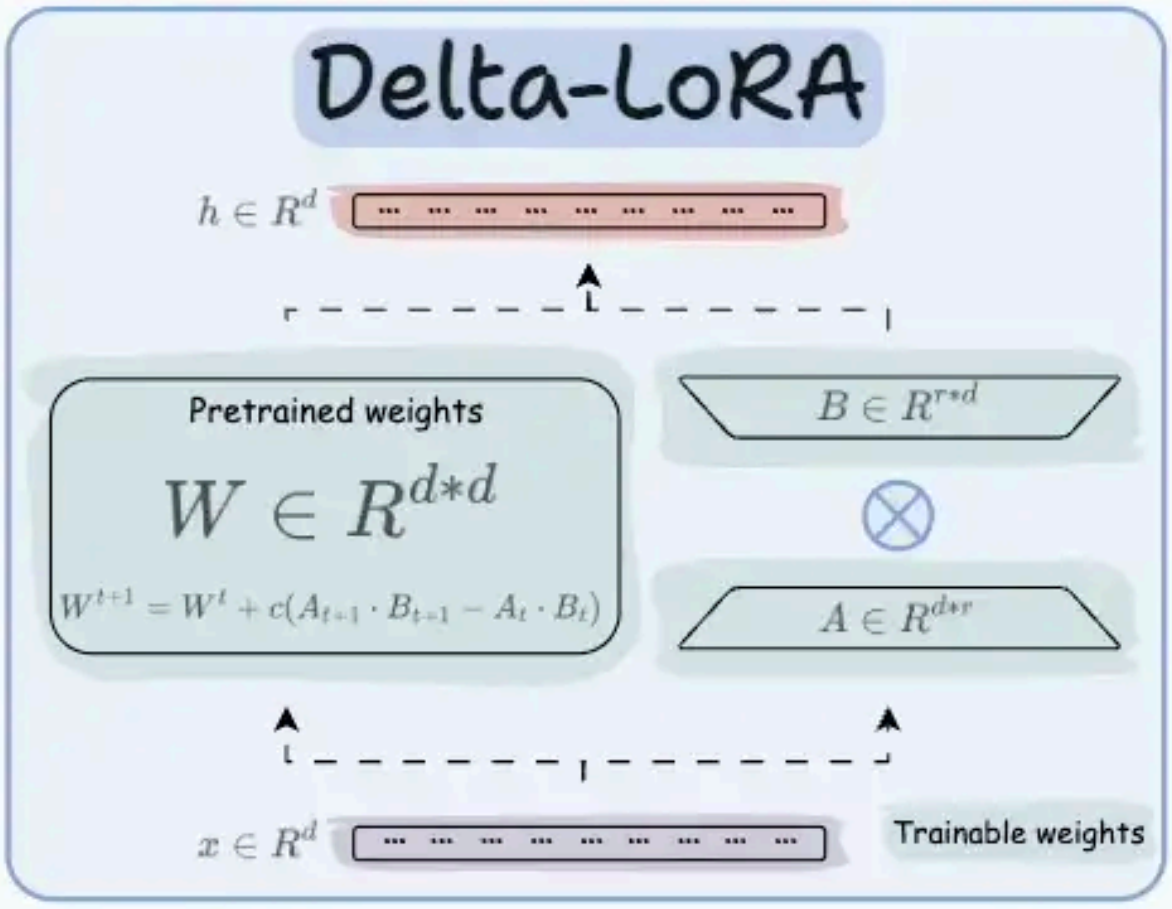
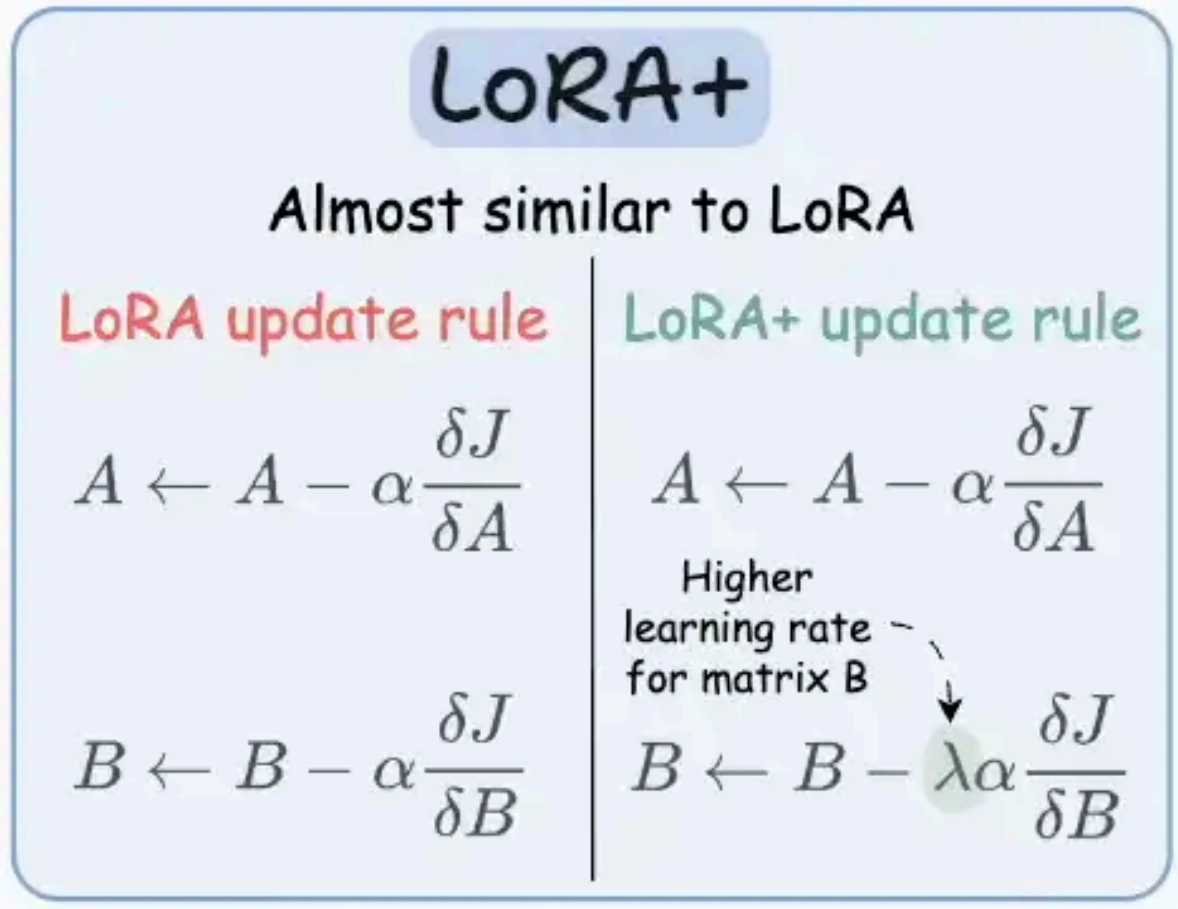




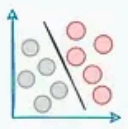






Next...

40 NumPy Methods That Data Scientists Use 95% of the Time



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NumPy Array Creation Methods

Method	Description
np.array(<list>)	NumPy array from Python list
np.array(<list-of-lists>)	NumPy array from list of lists
np.array(<pandas-series>)	NumPy array from PD Series
df.values	NumPy array from DataFrame
np.zeros(<size>)	NumPy array of all zeros
np.ones(<size>)	NumPy array of all ones
np.eye(<size>)	Identity NumPy array
np.arange(<start>,<stop>,<step>)	Equally spaced NumPy array with specific step
np.linspace(<start>,<stop>,<count>)	Equally spaced NumPy array with specific size
np.random.randint(<low>,<high>,<size>)	NumPy array of random ints
np.random.random(<size>)	NumPy array of random floats

NumPy Array Manipulation Methods

Method	Description
array.reshape(<new-shape>)	Reshape NumPy Array
array.transpose() OR array.T	Transpose NumPy Array
np.concatenate(<np-arrays>, <axis>)	Concatenate NumPy Arrays
np.flatten(<Nd-np-array>)	Flatten a NumPy Array
np.unique(<np-array>, <axis>)	Find unique elements
array.tolist()	NumPy Array to List

Search Methods

Method	Description
np.argmax(<np-array>, <axis>)	Max Element Index
np.argmin(<np-array>, <axis>)	Min Element Index
np.where(<condition>,<true-return-value>, <false-return-value>)	Conditional Search and Replacement
np.nonzero(<np-array>)	Index of non-zero elements

Mathematical Operations

Method	Description
np.sin(<np-array>)	Trigonometric Functions
np.cos(<np-array>)	
np.tan(<np-array>)	
np.floor(<np-array>)	Element-wise floor value
np.ceil(<np-array>)	Element-wise ceiling value
np.rint(<np-array>)	Round to nearest int
np.round_(<np-array>, <decimal-places>)	Round to decimal places
np.exp(<np-array>)	Element-wise exponent
np.log(<np-array>)	Element-wise logarithm
np.sqrt(<np-array>)	Element-wise square root
np.sum(<np-array>, <axis>)	Sum along an axis
np.mean(<np-array>, <axis>)	Mean along an axis
np.std(<np-array>, <axis>)	Std. dev along an axis

Matrix and Vector Operations

Method	Description
np.dot(<np-array1, np-array2>)	Dot Product
np.matmul(<np-array1, np-array2>)	Matrix Multiplication
np-array1 @ np-array2	
np.linalg.norm(<np-array>)	Vector Norm

Sorting Methods

Method	Description
np.sort(<np-array>, <axis>)	Sort Array
np.argsort(<np-array>, <axis>)	Return the order of indices that sort the array

Next...

11 Most Important Plots in Data Science

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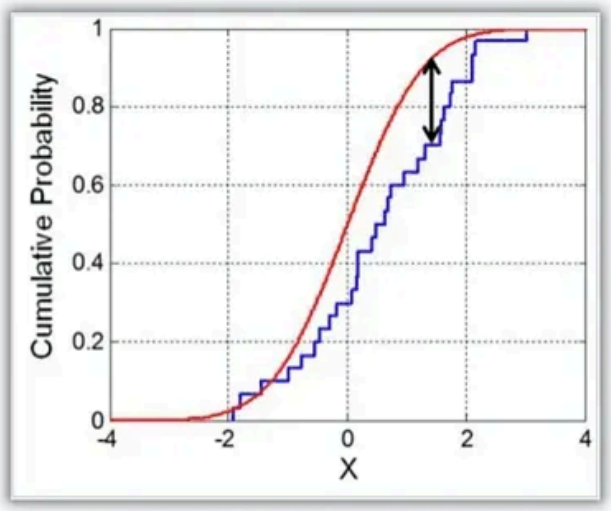
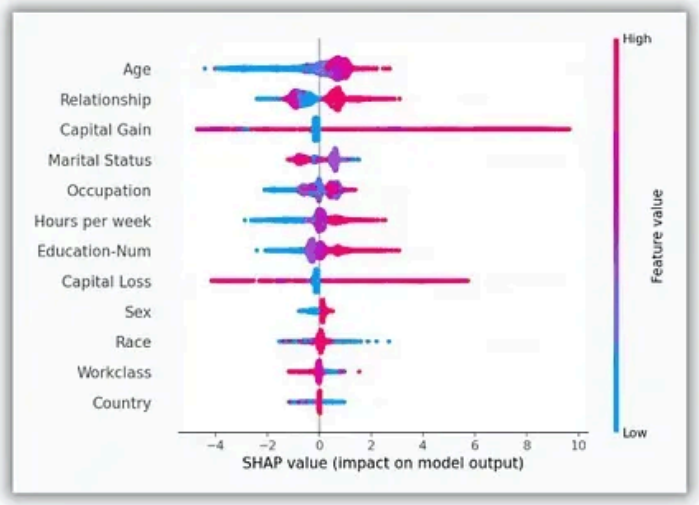
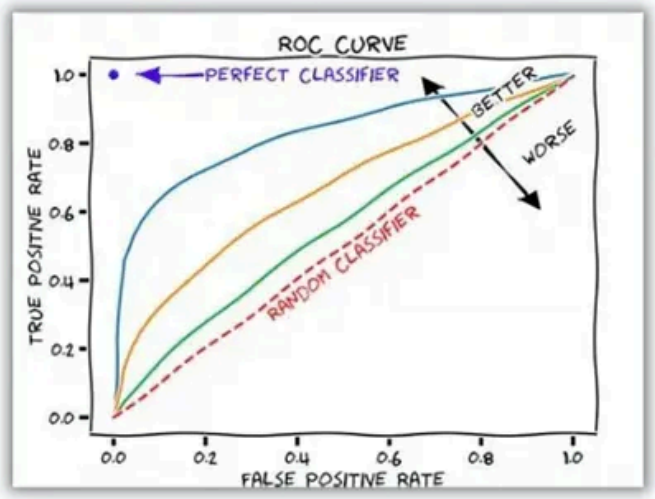
1 KS Plot



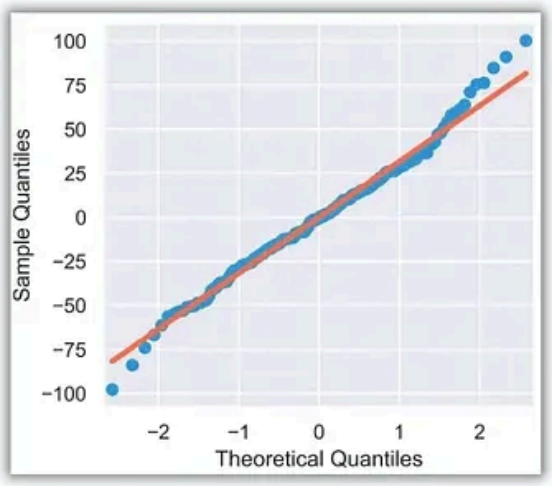
2 SHAP Plot



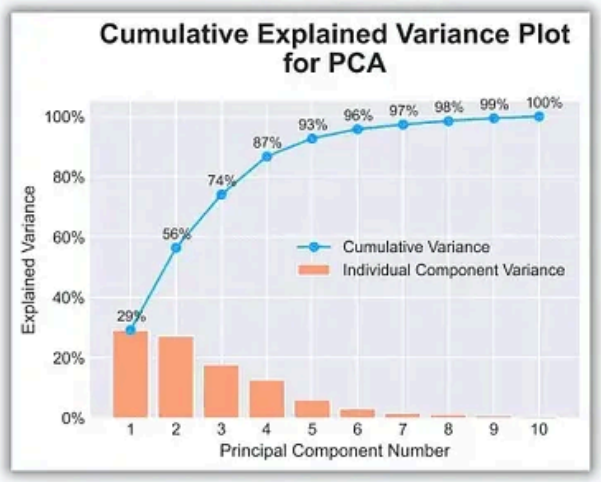
3 ROC Curve



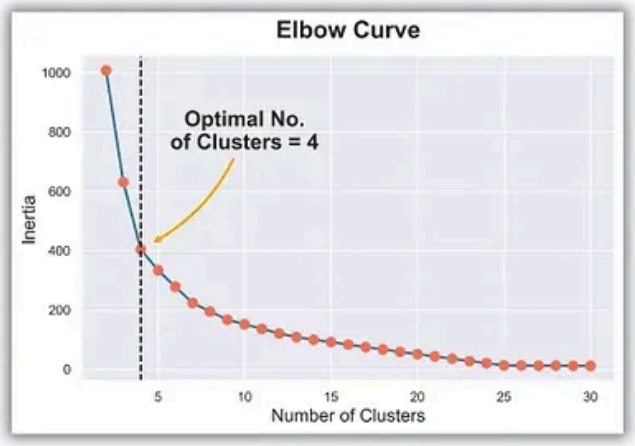
4 QQ Plot



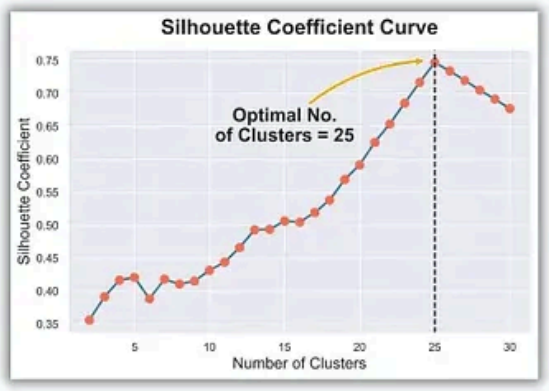
5 Cumulative Explained Variance



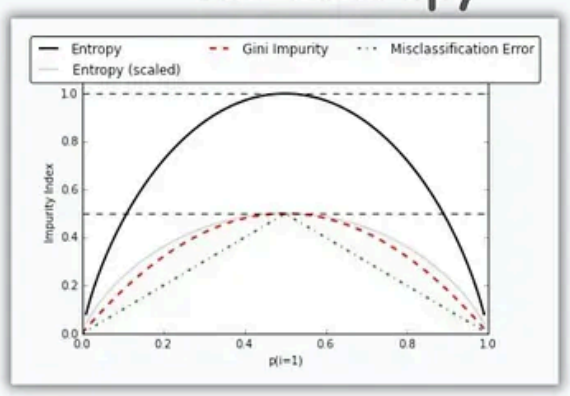
6 Elbow Curve



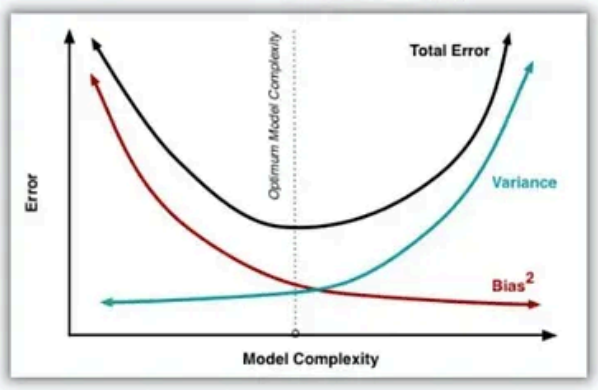
7 Silhouette Curve



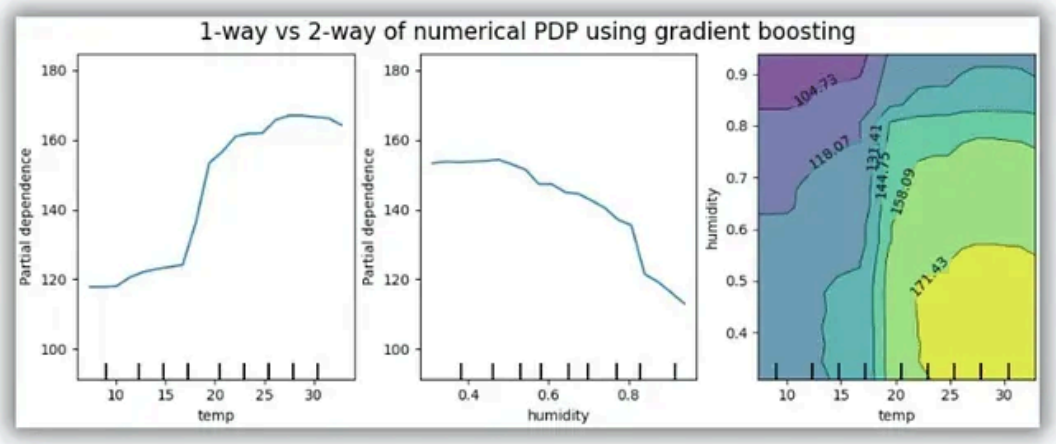
8 Gini impurity vs. Entropy



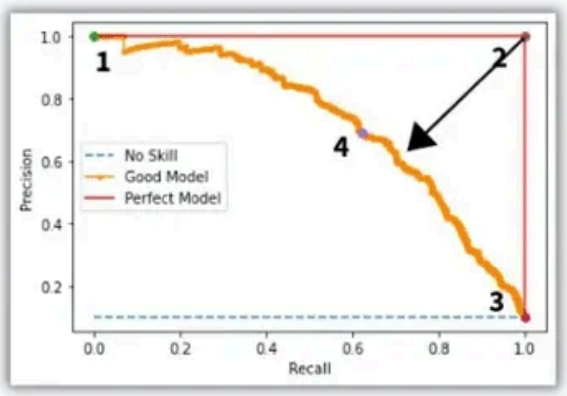
9 Bias-Variance Tradeoff



10 Partial Dependency Plot



11 Precision Recall Plot



Next...

10 Most Common Loss Functions in Machine Learning

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Loss Function Name	Description	Function
Regression Loss Functions		
Mean Bias Error	Captures average bias in prediction. But is rarely used for training.	$\mathcal{L}_{MBE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i))$
Mean Absolute Error	Measures absolute average bias in prediction. Also called L1 Loss.	$\mathcal{L}_{MAE} = \frac{1}{N}\sum_{i=1}^{N}\lvert y_i - f(x_i)\rvert$
Mean Squared Error	Average squared distance between actual and predicted. Also called L2 Loss.	$\mathcal{L}_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i))^2$
Root Mean Squared Error	Square root of MSE. Loss and dependent variable have same units.	$\mathcal{L}_{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i))^2}$
Huber Loss	A combination of MSE and MAE. It is parametric loss function.	$\mathcal{L}_{\text{Huberloss}} = \begin{cases} \frac{1}{2}(y_i - f(x_i))^2 & : \lvert y_i - f(x_i)\rvert \le \delta \\ \delta(\lvert y_i - f(x_i)\rvert - \frac{1}{2}\delta) & : otherwise \end{cases}$
Log Cosh Loss	Similar to Huber Loss + non-parametric. But computationally expensive.	$\mathcal{L}_{\text{LogCosh}} = \frac{1}{N}\sum_{i=1}^{N} log(cosh(f(x_i) - y_i))$
Classification Loss Functions (Binary + Multi-class)		
Binary Cross Entropy (BCE)	Loss function for binary classification tasks.	$\mathcal{L}_{BCE} = \frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(x_i)) + (1 - y_i) \cdot log(1 - p(x_i))$
Hinge Loss	Penalizes wrong and right (but less confident) predictions. Commonly used in SVMs.	$\mathcal{L}_{\text{Hinge}} = max(0, 1 - (f(x) \cdot y))$
Cross Entropy Loss	Extension of BCE loss to multi-class classification.	$\mathcal{L}_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}.log(f(x_{ij}))$ $N : samples; M : classes$
KL Divergence	Minimizes the divergence between predicted and true probability distribution	$\mathcal{L}_{KL} = \sum_{i=1}^{N} y_i \cdot log(\frac{y_i}{f(x_i)})$

Next...

Full Fine Tuning, LoRA and RAG

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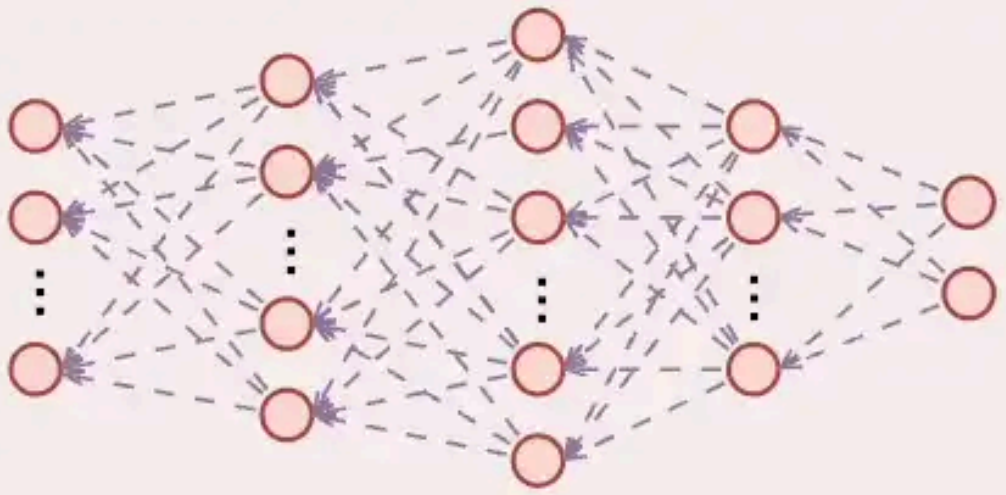
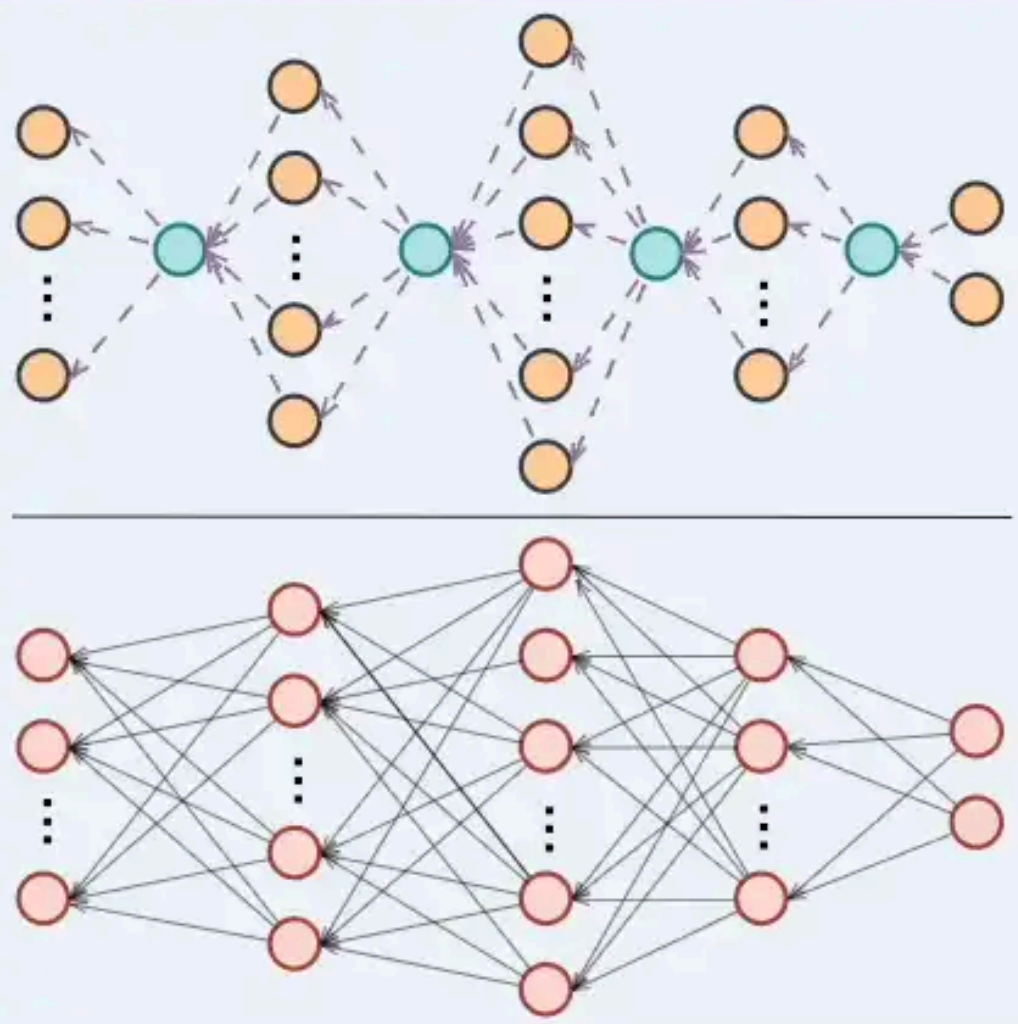
Full Fine Tuning



Gradient flow

Full pre-trained network

LoRA Fine Tuning



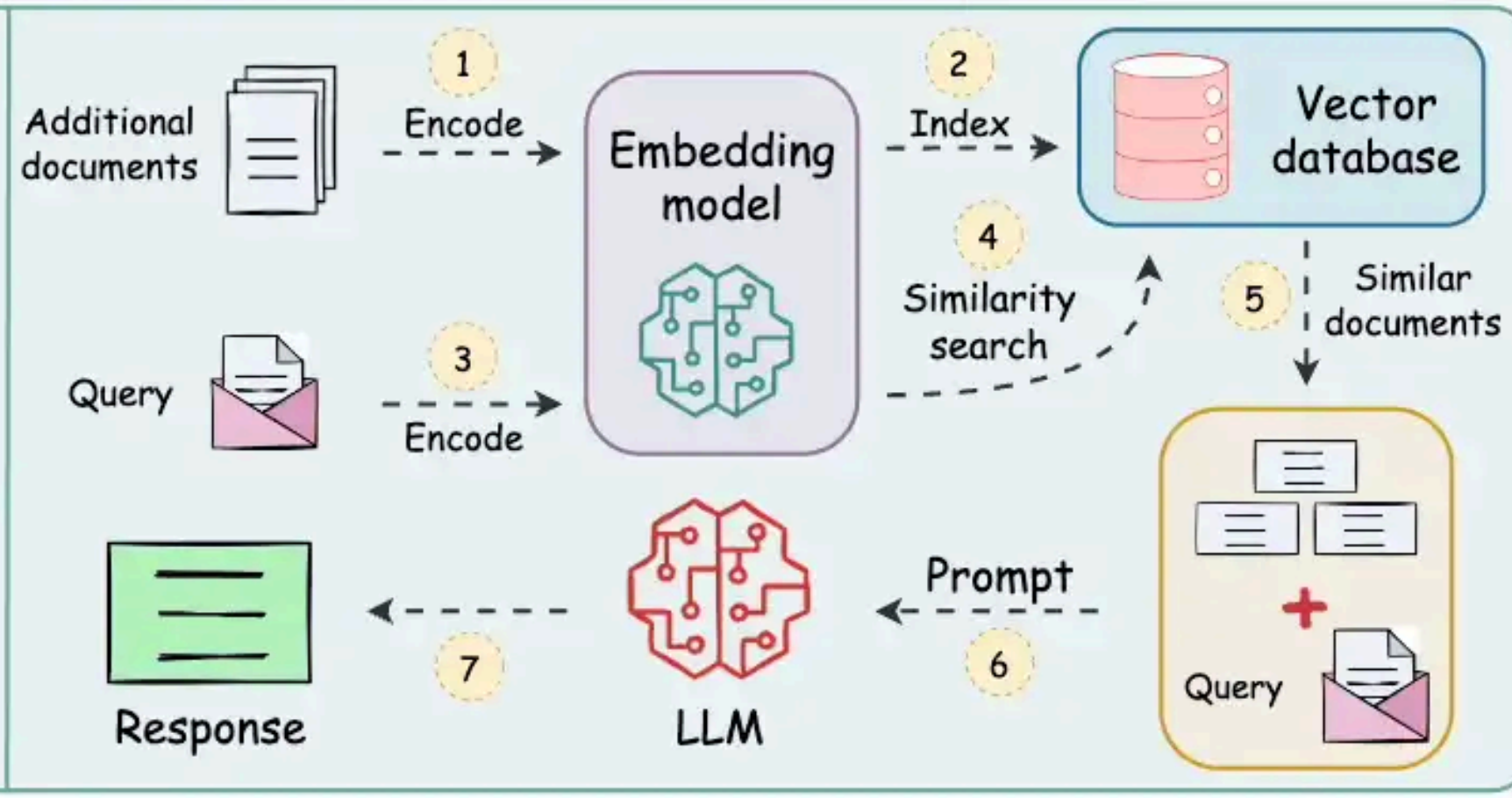
Gradient flow

Additional LoRA layers

No gradient flow

Full pre-trained network

RAG



Next...

Transfer Learning vs. Fine Tuning vs. Multitask Learning vs. Federated Learning

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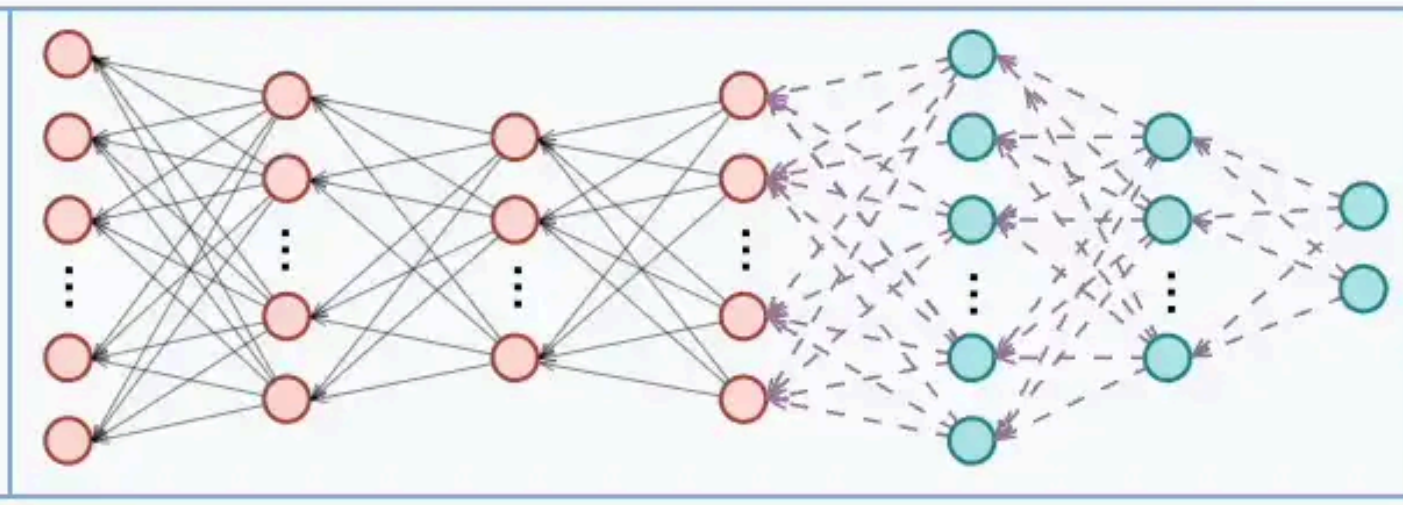
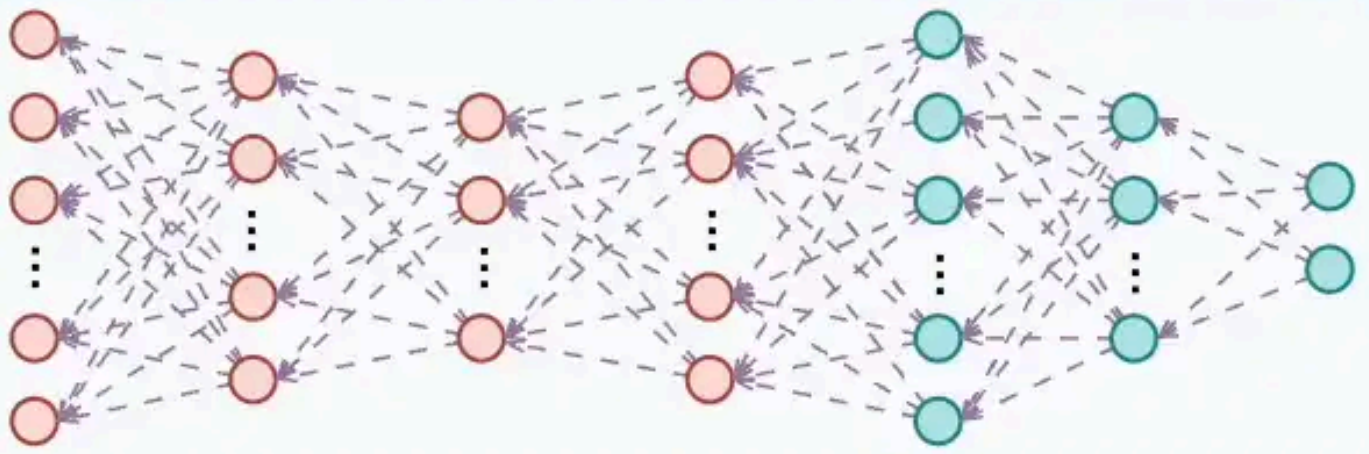
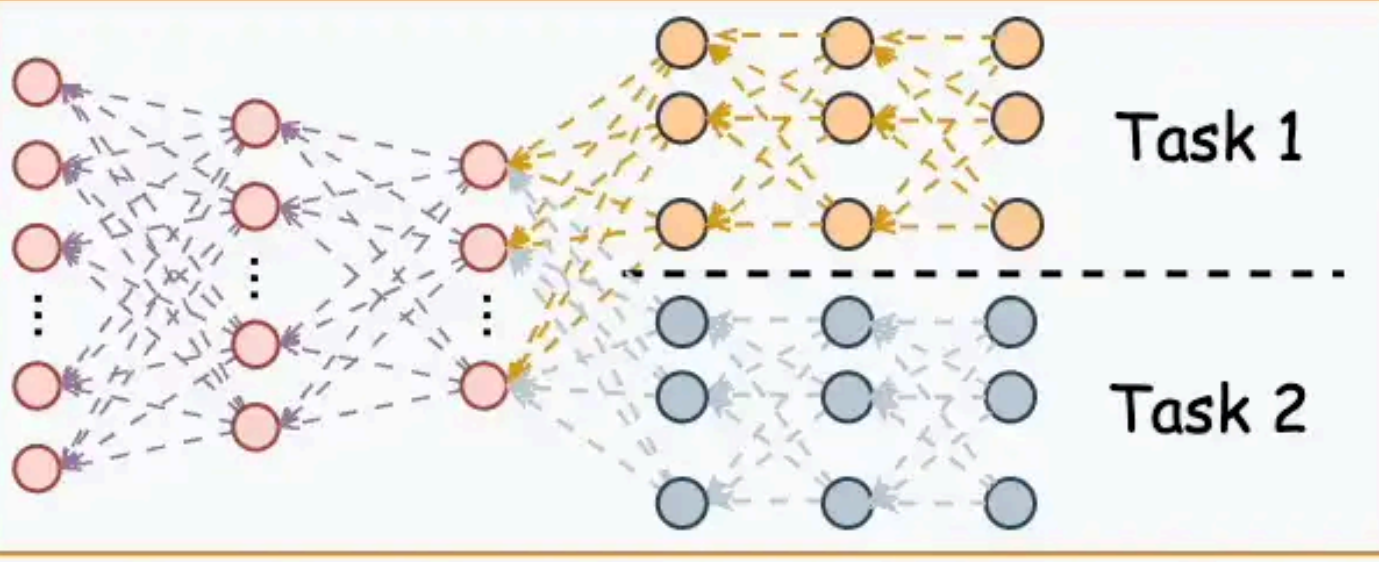
Transfer Learning



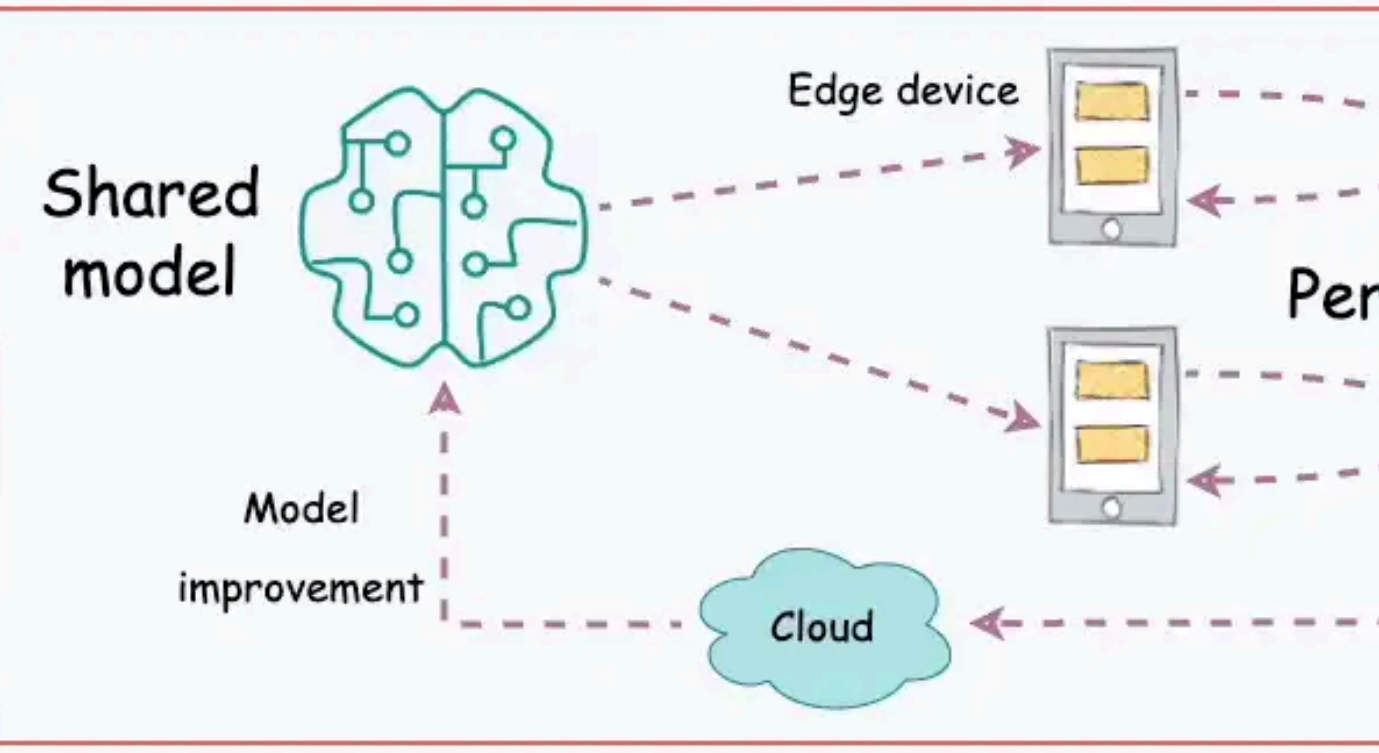
Fine Tuning



Multitask Learning



Federated Learning



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