FREE

15 DS/ML Cheat Sheets for Data Scientists

15 SINGLE FRAME SUMMARIES

Daily Dose of Data Science

Avi Chawla
DailyDoseofDS.com

Pandas ↔ Polars ↔ SQL ↔ PySpark

blog.DailyDoseofDS.com

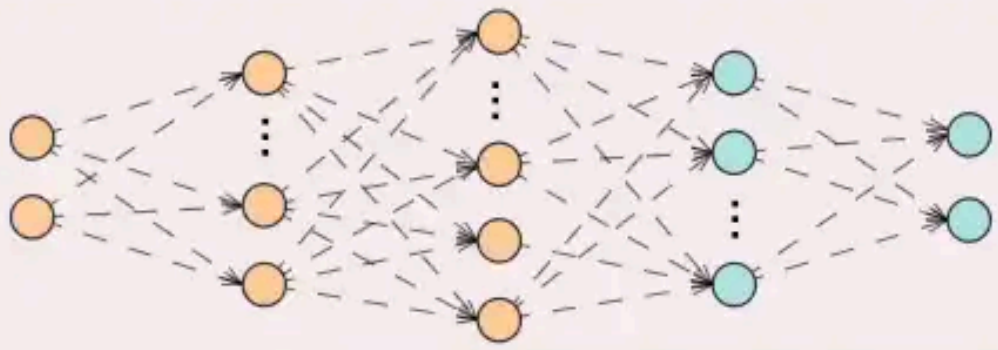
Operation	Pandas	Polars	SQL	PySpark
Import	import pandas as pd	import polars as pl	-	from pyspark.sql import SparkSession spark = SparkSession.builder.appName("ABCD")
Read CSV	df = pd.read_csv(file)	df = pl.read_csv(file)	LOAD DATA INFILE 'data.csv' INTO TABLE table FIELDS TERMINATED BY ',' LINES TERMINATED 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

blog.DailyDoseofDS.com

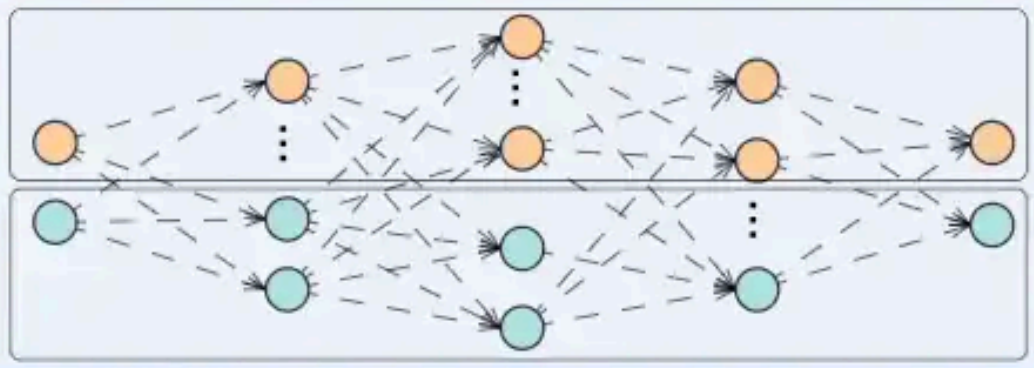
Model parallelism



Layer on 1st GPU

Layer on 2nd GPU

Tensor parallelism



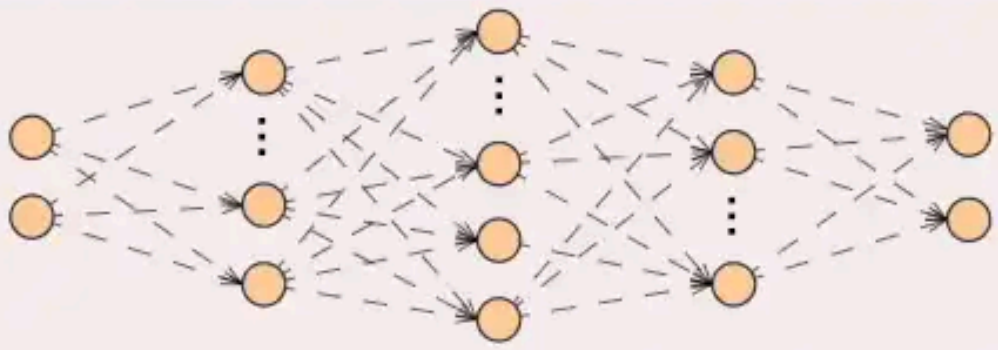
Neurons on 1st GPU

Neurons on 2nd GPU

Data parallelism

Data subset #1

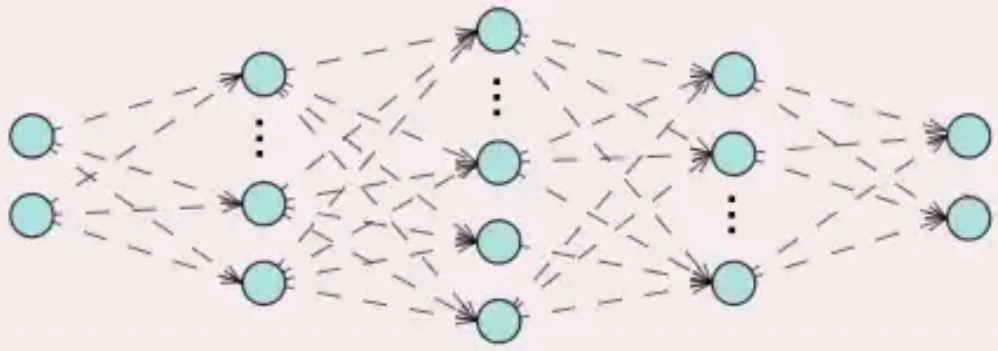
x1	x2	x3
...	...	...
...	...	...



Model copy on 1st GPU

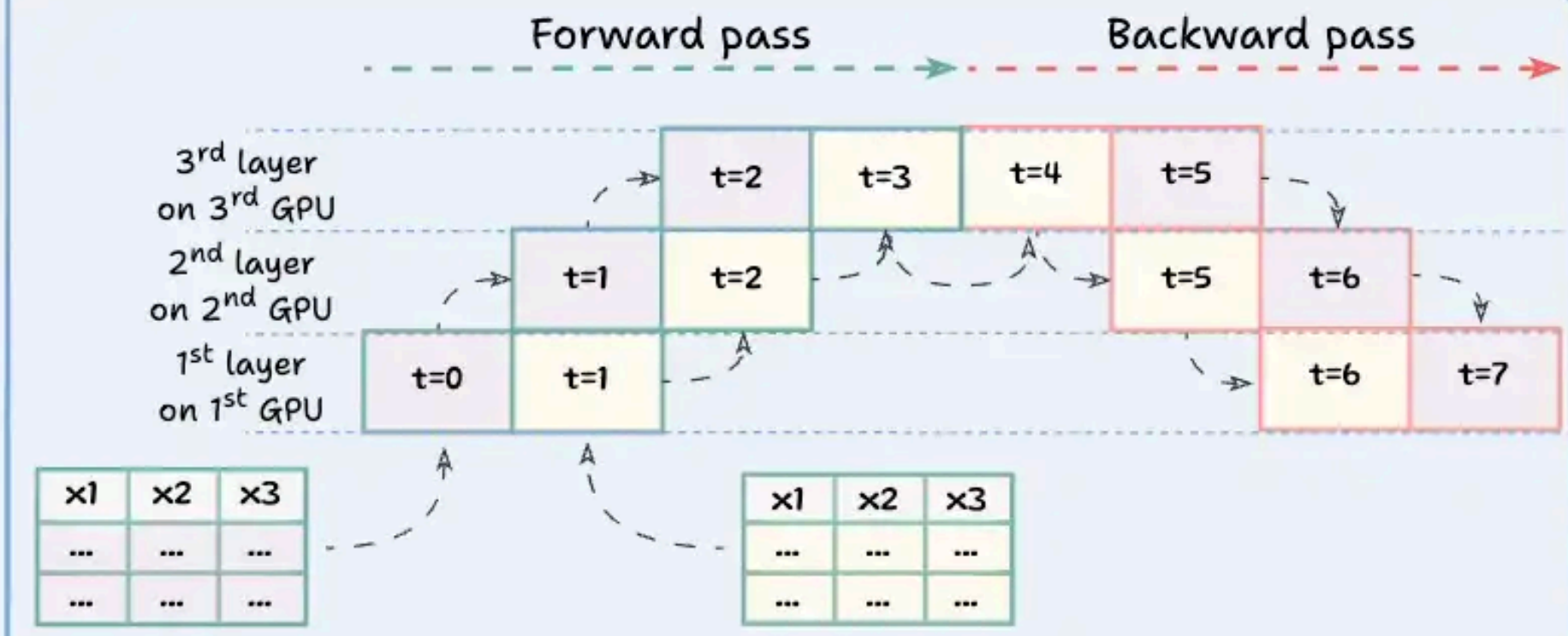
Data subset #2

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



Model copy on 2nd GPU

Pipeline parallelism

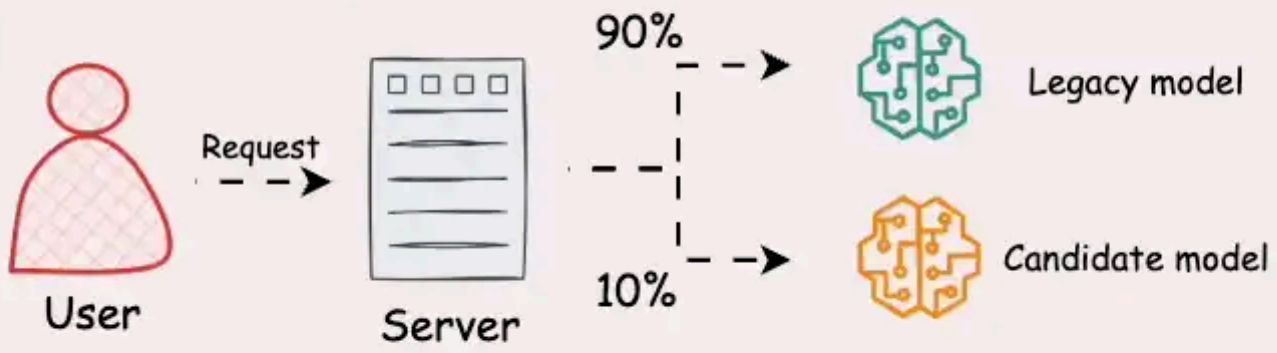


Next...

4 Ways to Test ML Models in Production

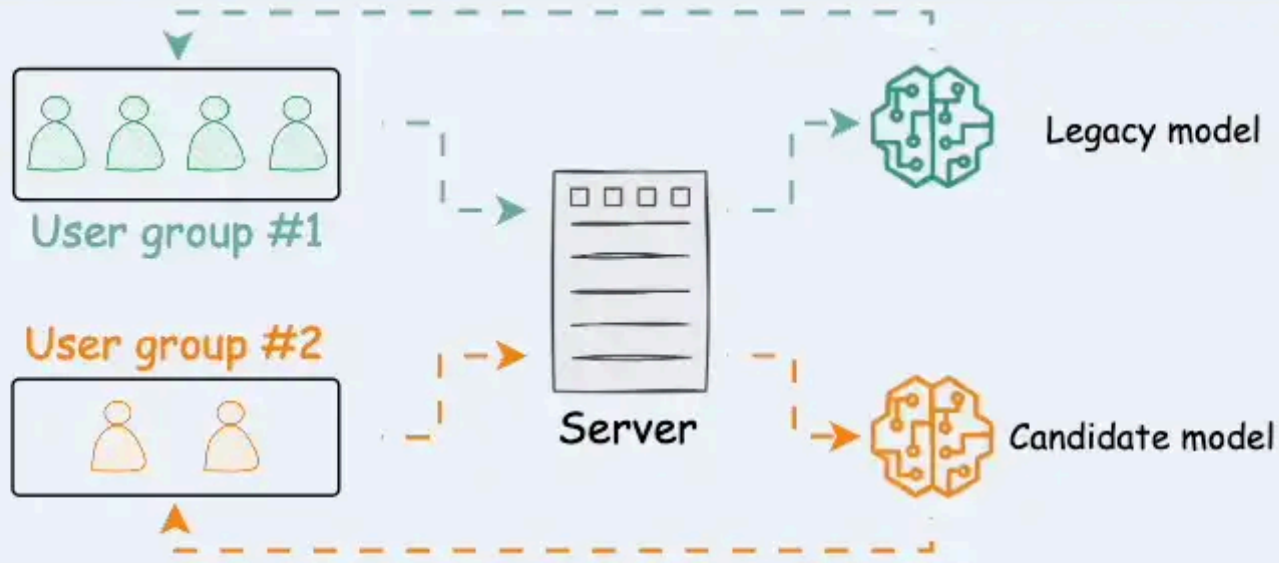
blog.DailyDoseofDS.com

1) A/B Testing



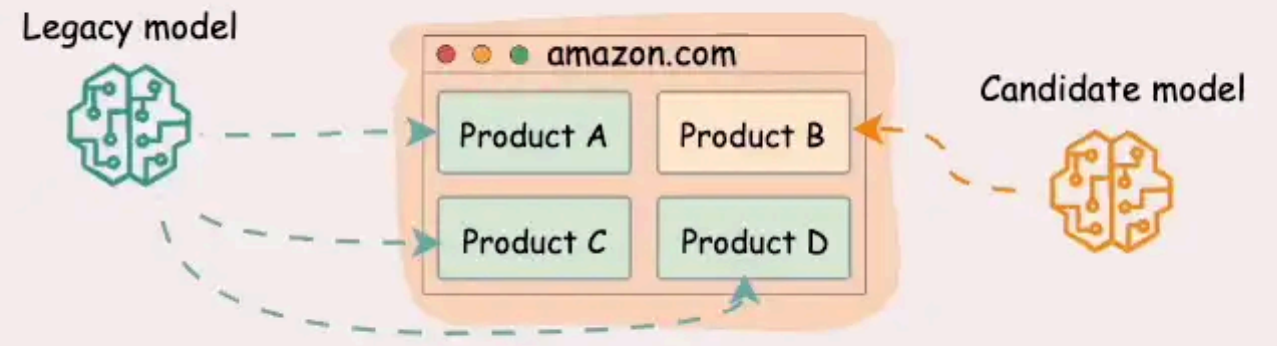
Send some requests to the candidate model.

2) Canary Testing



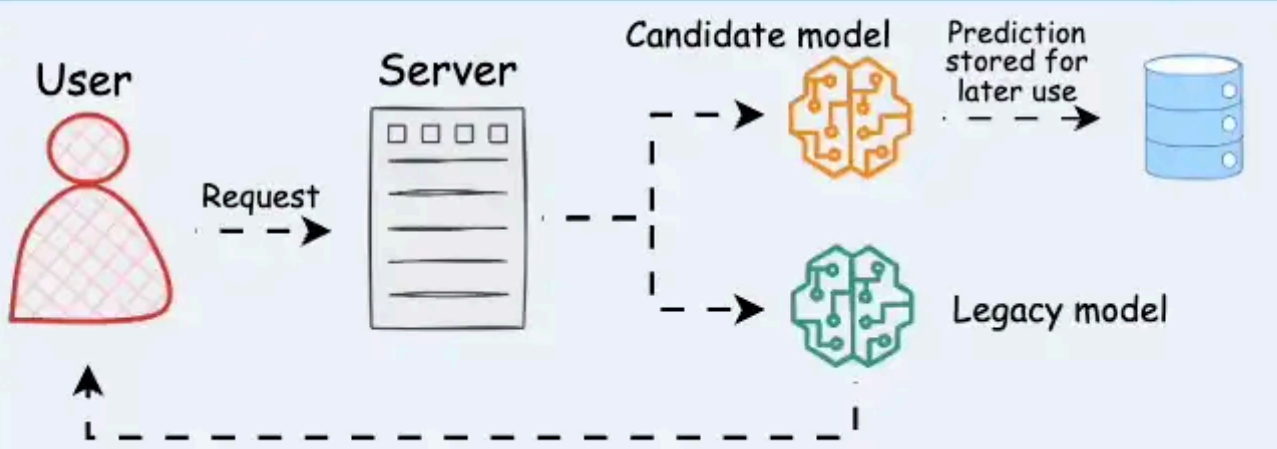
Release the candidate model only to a few users.

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

blog.DailyDoseofDS.com

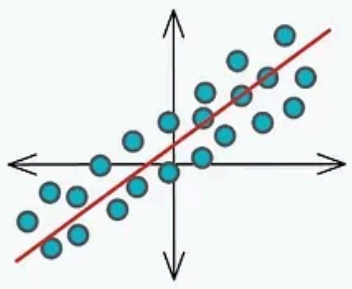
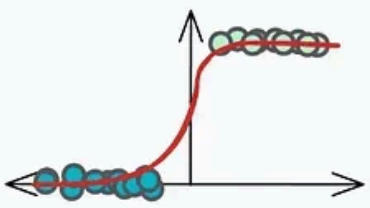
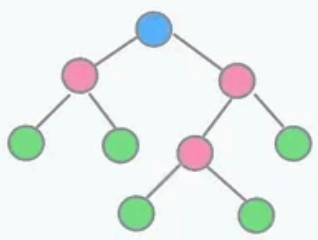
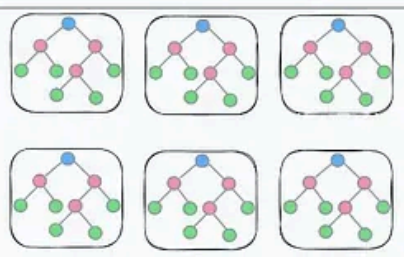
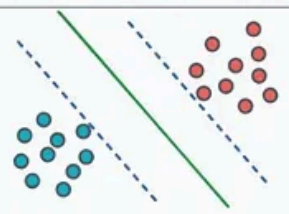
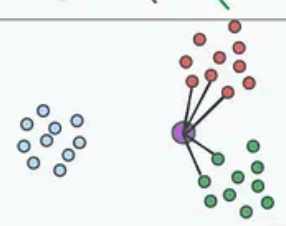
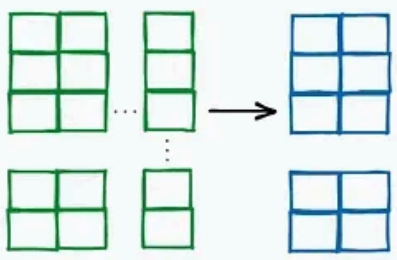
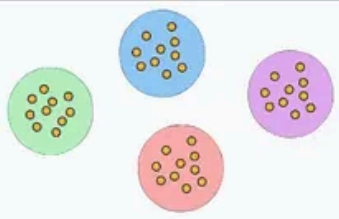
- ☑ Use efficient optimizers—AdamW, Adam, etc.
- ☑ Utilize hardware accelerators (GPUs/TPUs).
- ☑ Max out the batch size.
- ☑ Use Bayesian Optimization if hyperparameter search space is big.
- ☑ Set max_workers in the DataLoader.
- ☑ Set pin_memory in DataLoader.
- ☑ Use mixed precision training.
- ☑ 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

blog.DailyDoseofDS.com

		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	$O(iknm)$	??

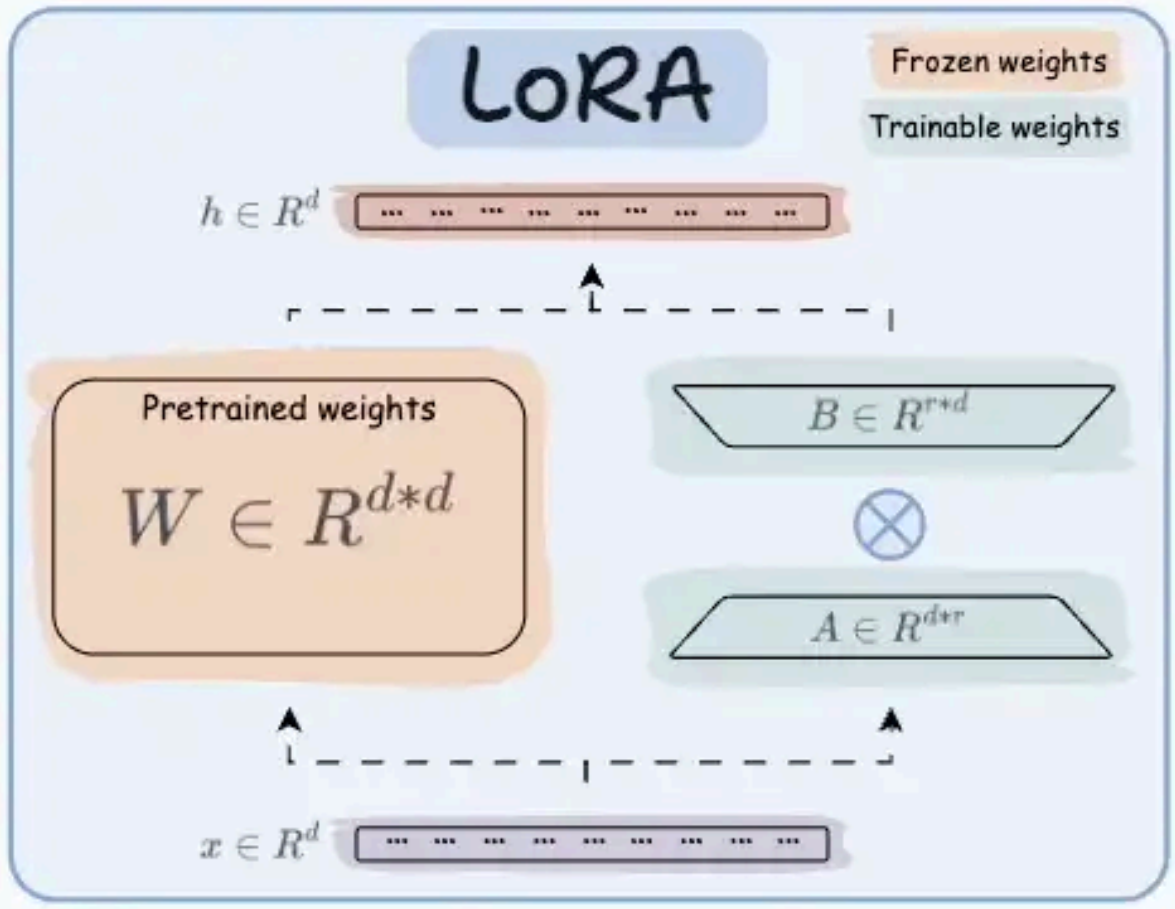
n: samples | m: dimensions | n_{epoch}: epochs | c: classes | d_{tree}: depth

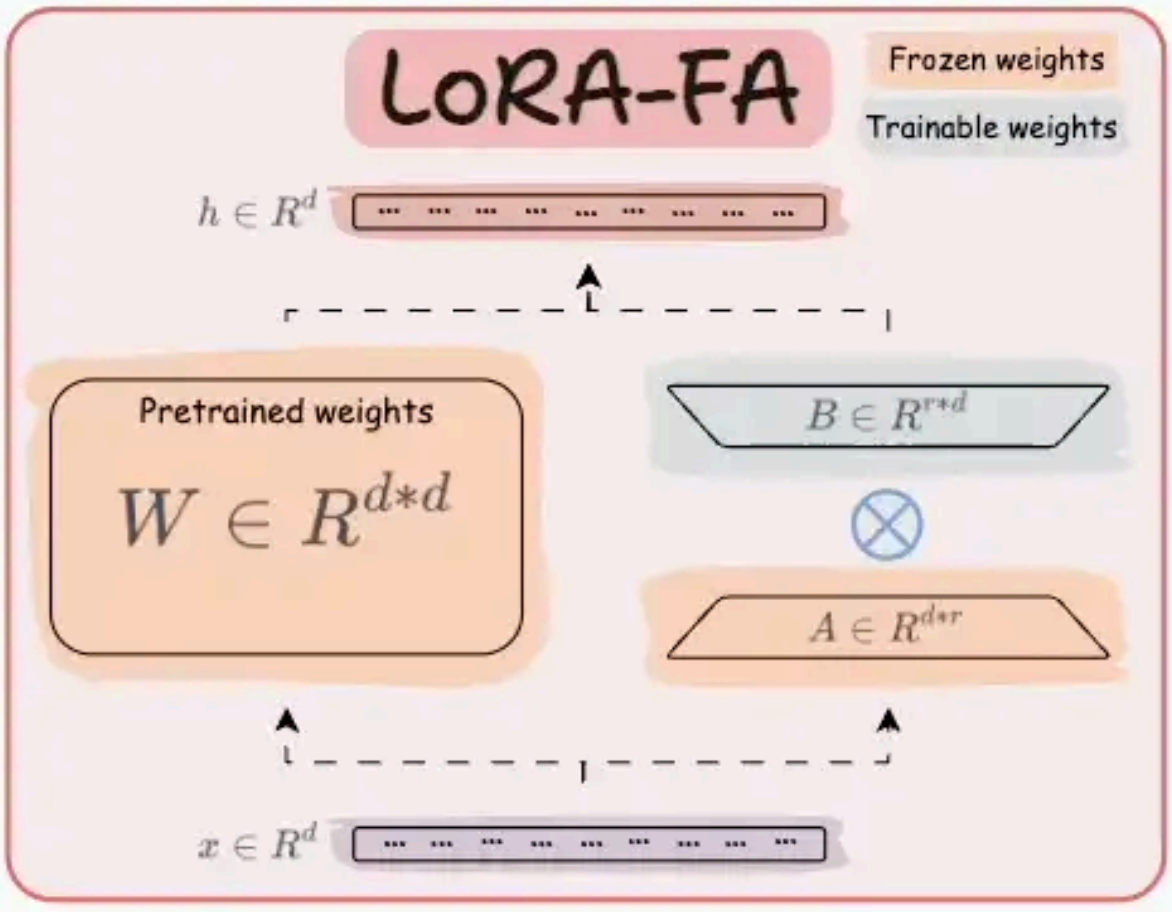
n_{SV}: Support vectors | k: clusters | i: iterations

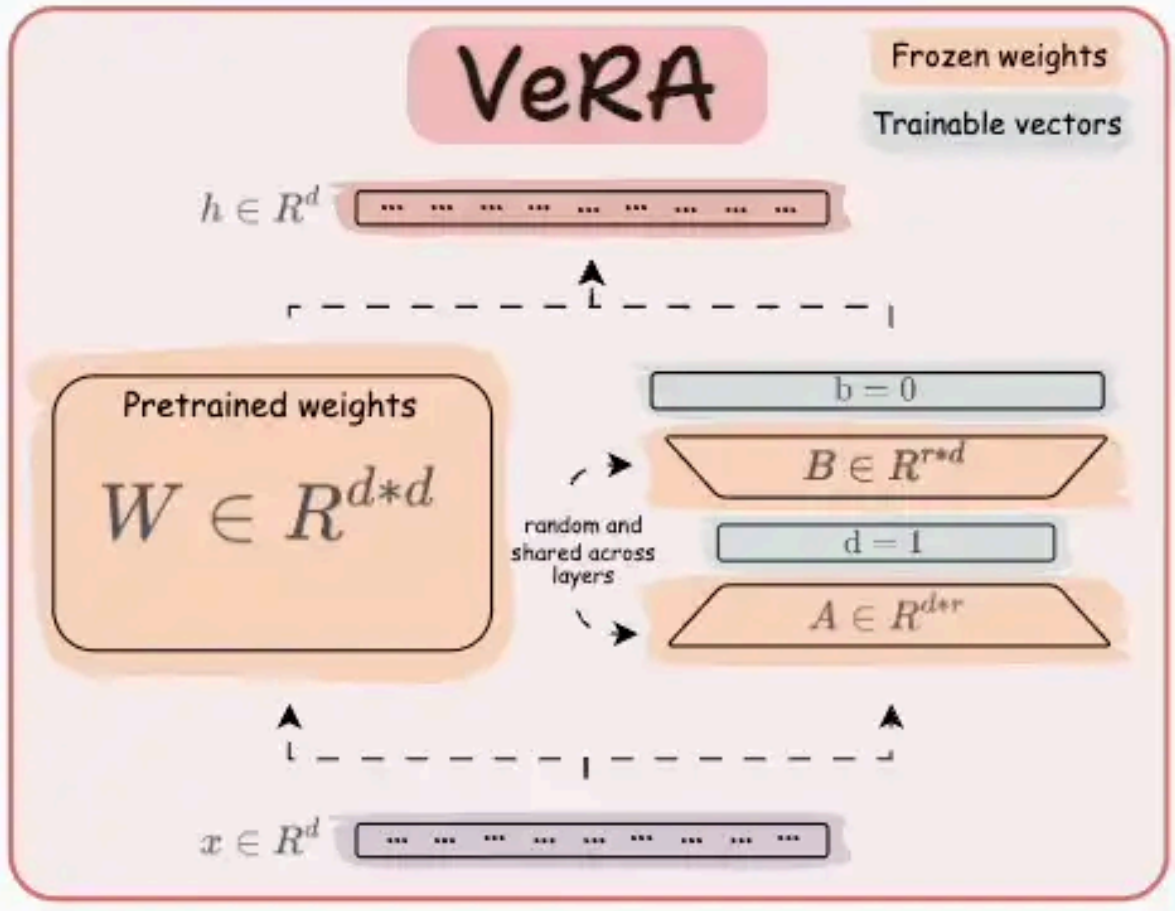
Next...

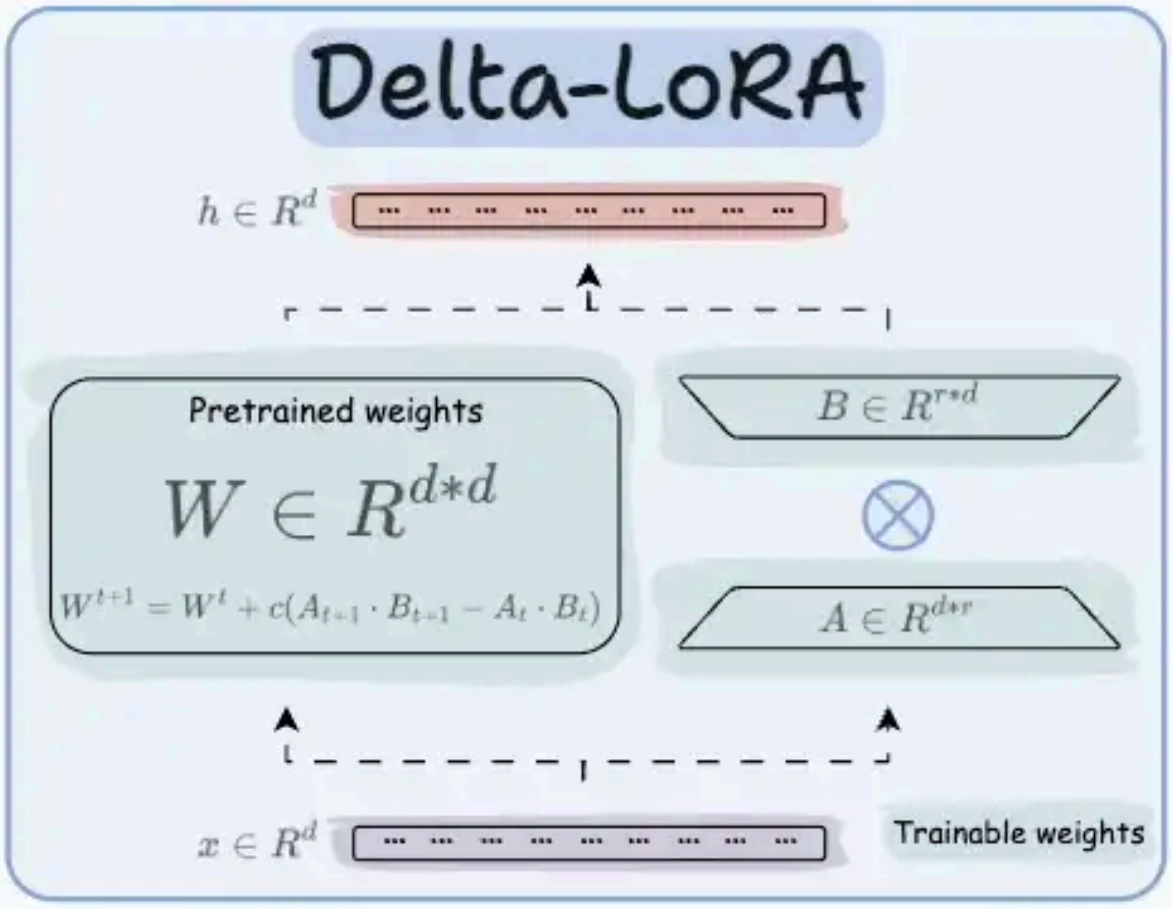
5 Techniques to fine-tune LLMs

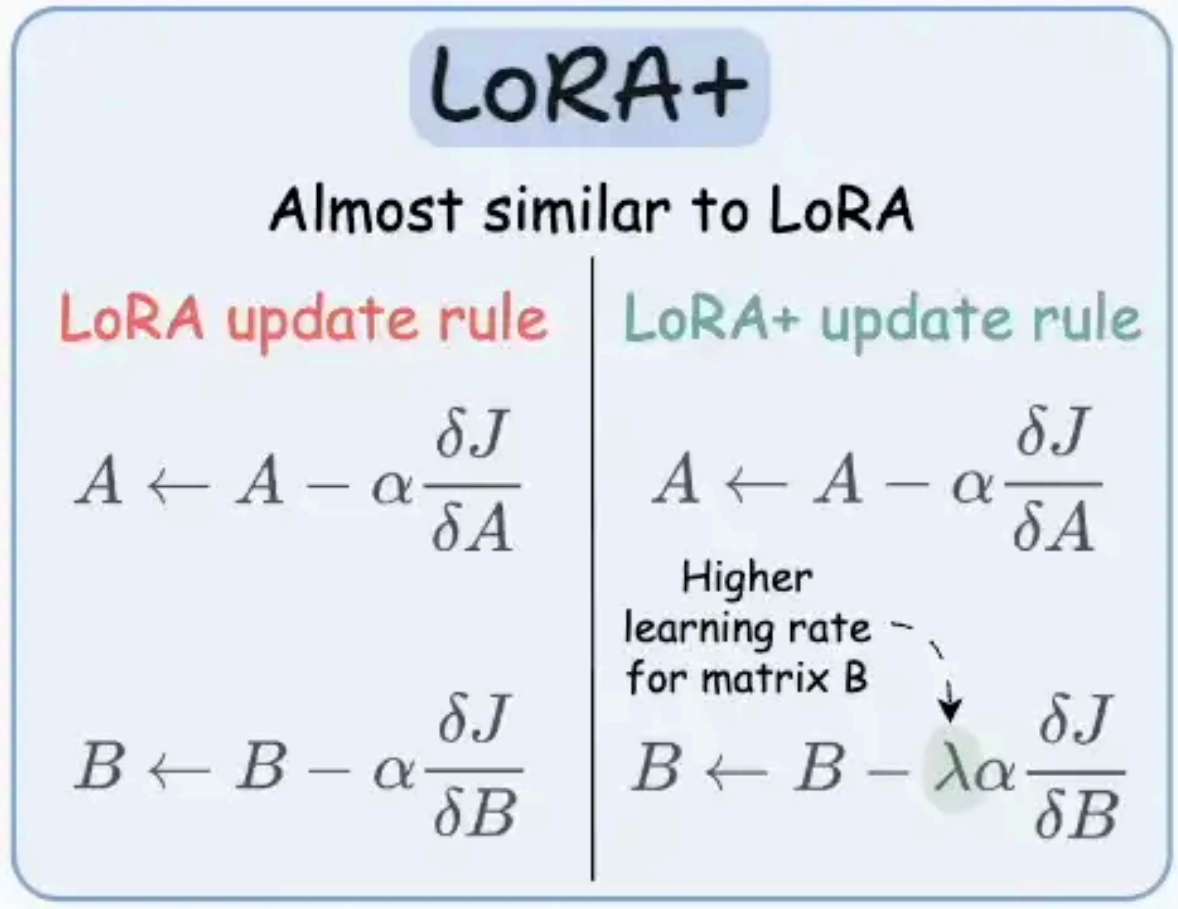
blog.DailyDoseofDS.com





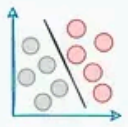






Next...

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



blog.DailyDoseofDS.com

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

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

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

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

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

Sorting Methods

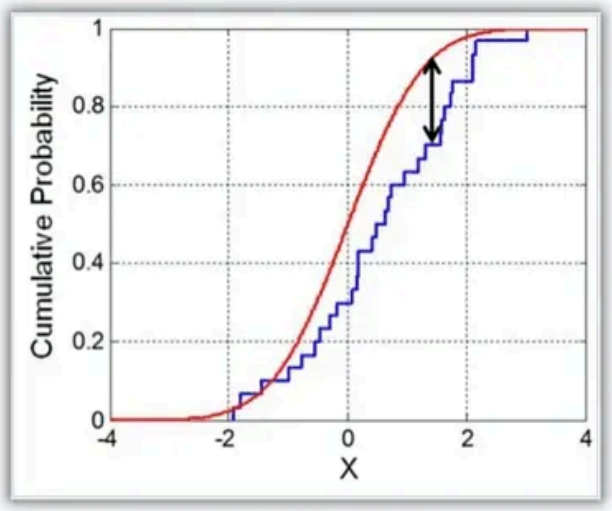
Method	Description
np.sort(<np-array>, <axis>)	Sort Array
np.argsort(<np-array>, <axis>)	Return the order of indices that sort the array

Next...

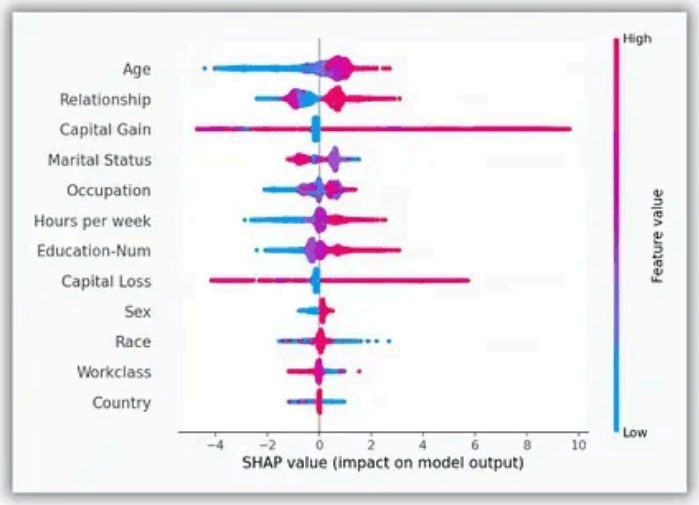
11 Most Important Plots in Data Science

blog.DailyDoseofDS.com

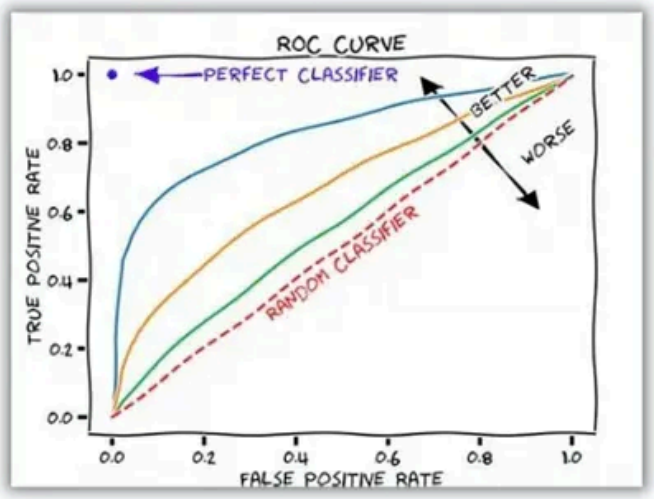
1 KS Plot



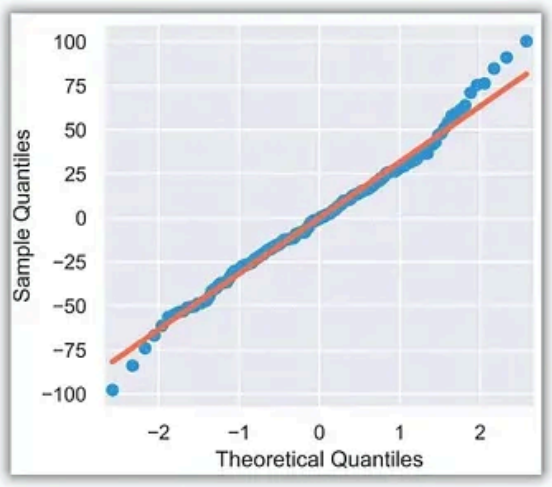
2 SHAP Plot



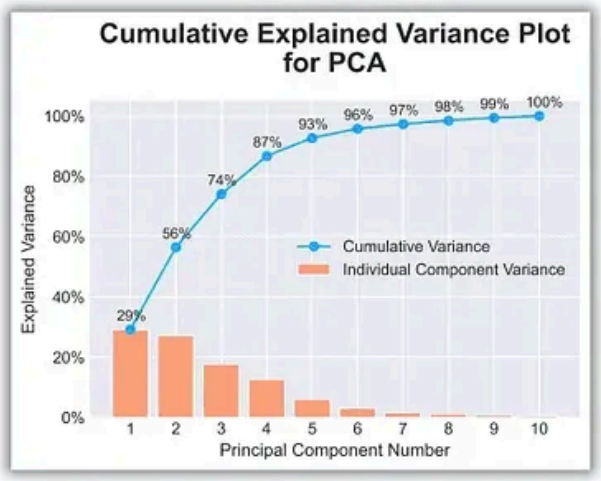
3 ROC Curve



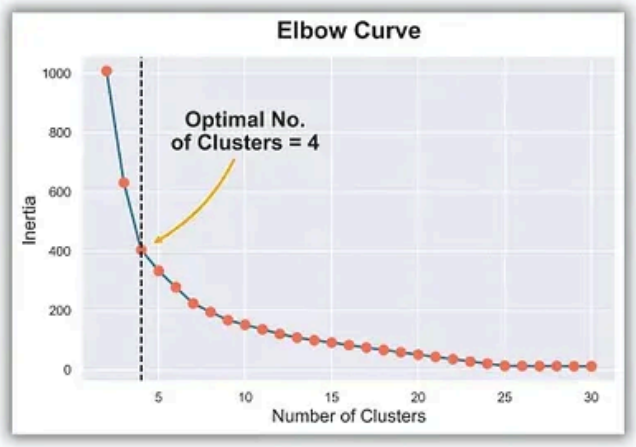
4 QQ Plot



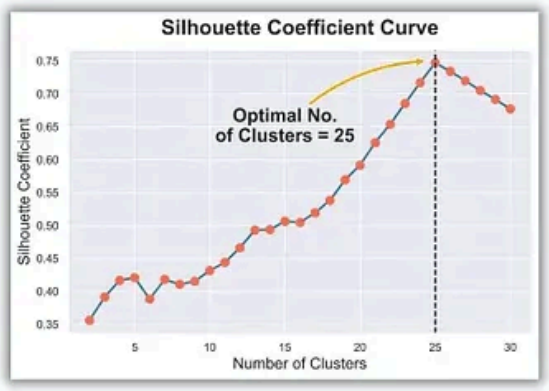
5 Cumulative Explained Variance



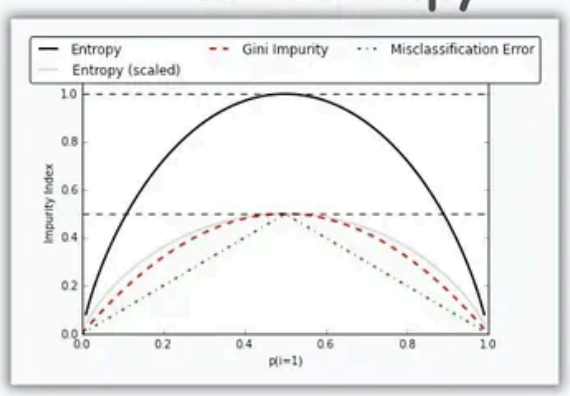
6 Elbow Curve



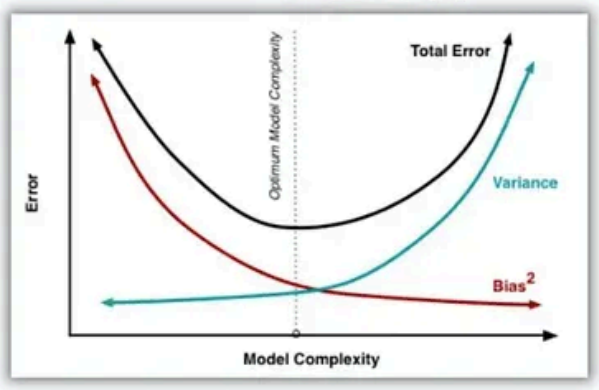
7 Silhouette Curve



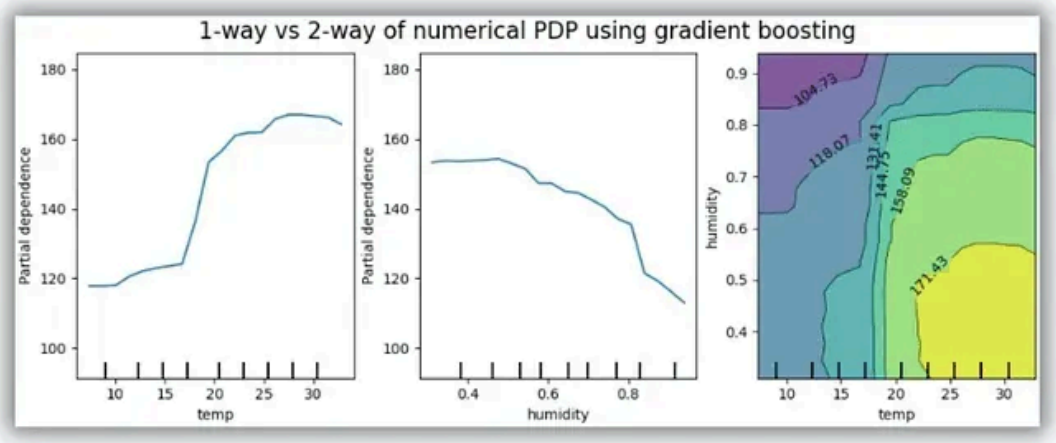
8 Gini impurity vs. Entropy



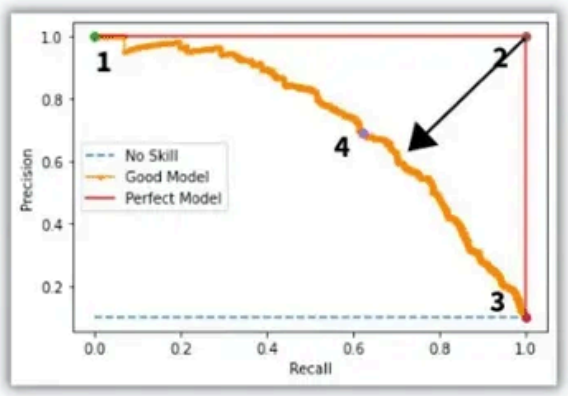
9 Bias-Variance Tradeoff



10 Partial Dependency Plot



11 Precision Recall Plot



Next...

75 Terms That All Data Scientists Remember by Heart ❤️

By Avi Chawla

DailyDoseofDS.com

A
Accuracy
Area Under Curve (AUC)
ARIMA

B
Bias
Bayes Theorem
Binomial Distribution

C
Clustering
Confusion Matrix
Cross-validation

D
Decision Trees
Dimensionality Reduction
Discriminative Model

E
Ensemble
EDA
Entropy

F
Feature Engineering
F-score
Feature Extraction

G
Gradient Descent
Gaussian Distribution
Gradient Boosting

H
Hypothesis
Hierarchical Clustering
Heteroscedasticity

I
Information Gain
Independent Variable
Imbalance

J
Jupyter
Joint Probability
Jaccard Index

K
Kernel Density Estimation
KS Test
KMeans Clustering

L
Likelihood
Linear Regression
L1/L2 Regularization

M
Max Likelihood Estimation
Multicollinearity
Mutual Information

N
Naive Bayes
Normalisation
Null Hypothesis

O
Overfitting
Outliers
One-hot encoding

P
PCA
Precision
P-value

Q
QQ-Plot
QR decomposition

R
Random Forest
Recall
ROC Curve

S
SVM
Standardisation
Sampling

T
t-SNE
T-distribution
Type I/II Error

U
Underfitting
UMAP
Uniform Distribution

V
Variance
Validation Curve
Vanishing Gradient

W
Word Embedding
Word Cloud
Weights

X
XGBoost
XLNet

Y
YOLO
Yellowbrick

Z
Z-score
Z-test
Zero-shot learning

Next...

10 Most Common Loss Functions in Machine Learning

blog.DailyDoseofDS.com

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...

11 Types of Variables in a Dataset

blog.DailyDoseofDS.com

Independent variable

x1	x2	y
...	...	...
...	...	...
...	...	...
...	...	...

Dependent variable

x1	x2	y
...	...	...
...	...	...
...	...	...
...	...	...

Interaction variables

Population: HIGH | MED | LOW

Income: HIGH | MED | LOW

All combinations

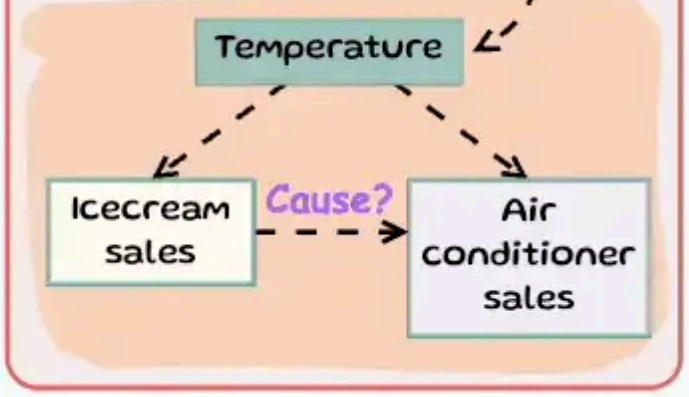
HH	HM	HL	MH	MM	ML	LH	LM	LL
...	...	...	...	...	...	...	...	...

Latent variable

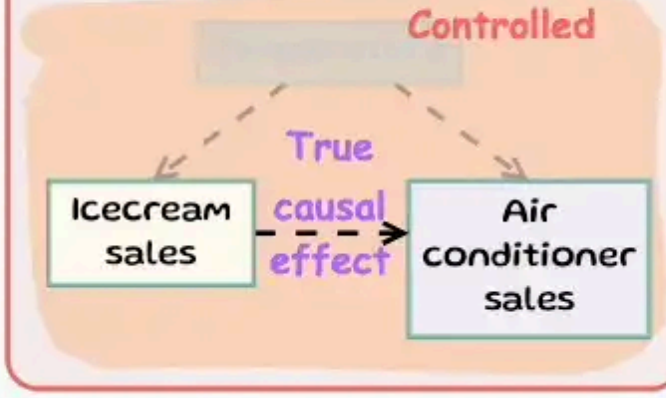
Unobserved

x1	x2	y
...	...	...
...	...	...
...	...	...
...	...	...

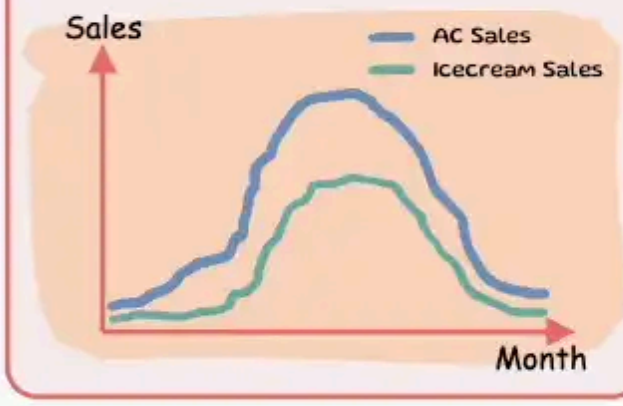
Confounding variable



Control variable



Correlated variables

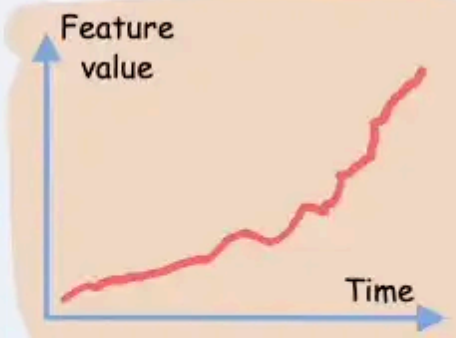


Leaky variable

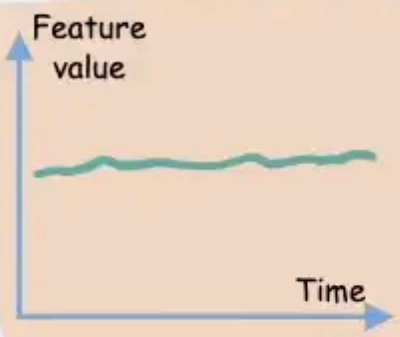
x	y
...	...
...	...
...	...
...	...

Feature value depends on outcome

Non-stationary variable



Stationary variable



Lagged variable

x1	lag_x1
a	-
b	a
c	b
d	c

Next...

7 Categorical Data Encoding Techniques

blog.DailyDoseofDS.com

1) One-hot encoding

Color
Green
Red
Black
Orange

→

Green	Red	Black	Orange
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

2) Dummy encoding

Green	Red	Black	Orange
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	0

Drop one feature randomly from one-hot encoding

3) Effect encoding

Green	Red	Black
1	0	0
0	1	0
0	0	1
−1	−1	−1

Set value of row with all zeros to -1

4) Label encoding

Color
Green
Red
Black
Green

Assign unique labels to each category →

Encoding
1
2
3
1

5) Ordinal encoding

Size
XS
S
L
M

ordered categories

Assign unique labels to each category →

Encoding
1
2
4
3

6) Count encoding

Color
Green
Red
Black
Green

Encode based on frequency →

Encoding
2
1
1
2

7) Binary encoding

Color
Green
Red
Black
Green

Assign binary labels →

Color_0	Color_1
0	0
0	1
1	0
1	1

Next...

20 Most Common Magic Methods in Python OOP

blog.DailyDoseofDS.com

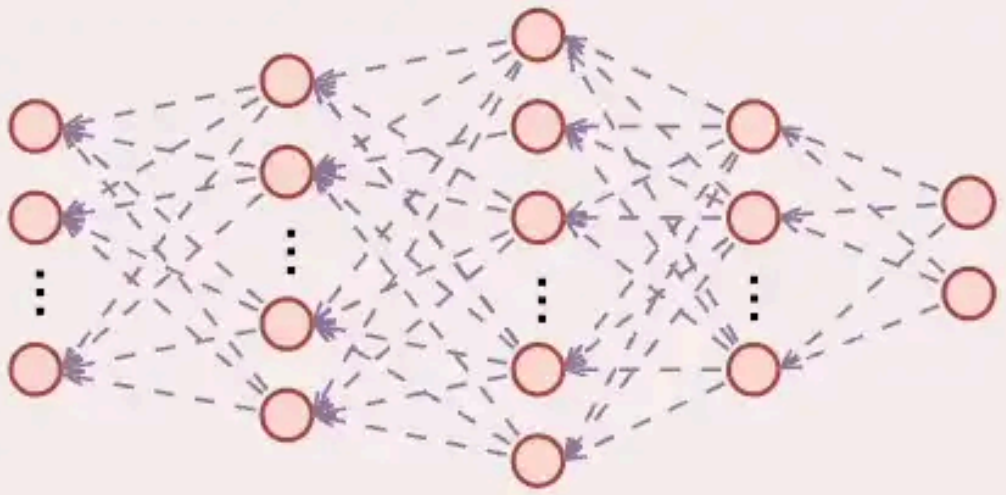
Magic Method	Syntax	Usage/Description
__new__	__new__(cls, *args, **kwags):	Invoked before __init__ to allocate memory to object
__init__	__init__(self, *args, **kwags):	Invoked after __new__ to initialise the object
__str__	__str__(self):	Invoked when str(obj) or print(obj) is used
__int__	__int__(self):	Invoked when int(obj) is used
__len__	__len__(self):	Invoked when len(obj) is used
__call__	__call__(self, *args, **kwags):	Invoked when class object is called as a function: obj()
__getitem__	__getitem__(self, key):	Invoked when object is indexed: obj[key]
__setitem__	__setitem__(self, key, value):	Invoked when object is indexed and value is set: obj[key]=value
__delitem__	__delitem__(self, key):	Invoked when object's index is deleted: del obj[key]
__contains__	__contains__(self, item):	Invoked when the in operator is used: item in obj
__bool__	__bool__(self):	Invoked when object is used in boolean context: if obj or bool(obj)
__iter__	__iter__(self):	Invoked when object is iterated: for x in obj
__eq__	__eq__(self, other):	Invoked when == operator is used to compare two objects: obj1 == obj2
__ne__	__ne__(self, other):	Invoked when != operator is used to compare two objects: obj1 != obj2
__gt__	__gt__(self, other):	Invoked when > operator is used to compare two objects: obj1 > obj2
__add__	__add__(self, other):	Invoked when two objects are added: obj1 + obj2
__mul__	__mul__(self, other):	Invoked when two objects are multiplied: obj1 * obj2
__abs__	__abs__(self):	Invoked to compute absolute value of object: abs(obj)
__neg__	__neg__(self):	Invoked when unary operator - is used on an object: -obj
__invert__	__invert__(self):	Invoked when ~(tilde) operator is used to invert an object: ~obj

Next...

Full Fine Tuning, LoRA and RAG

blog.DailyDoseofDS.com

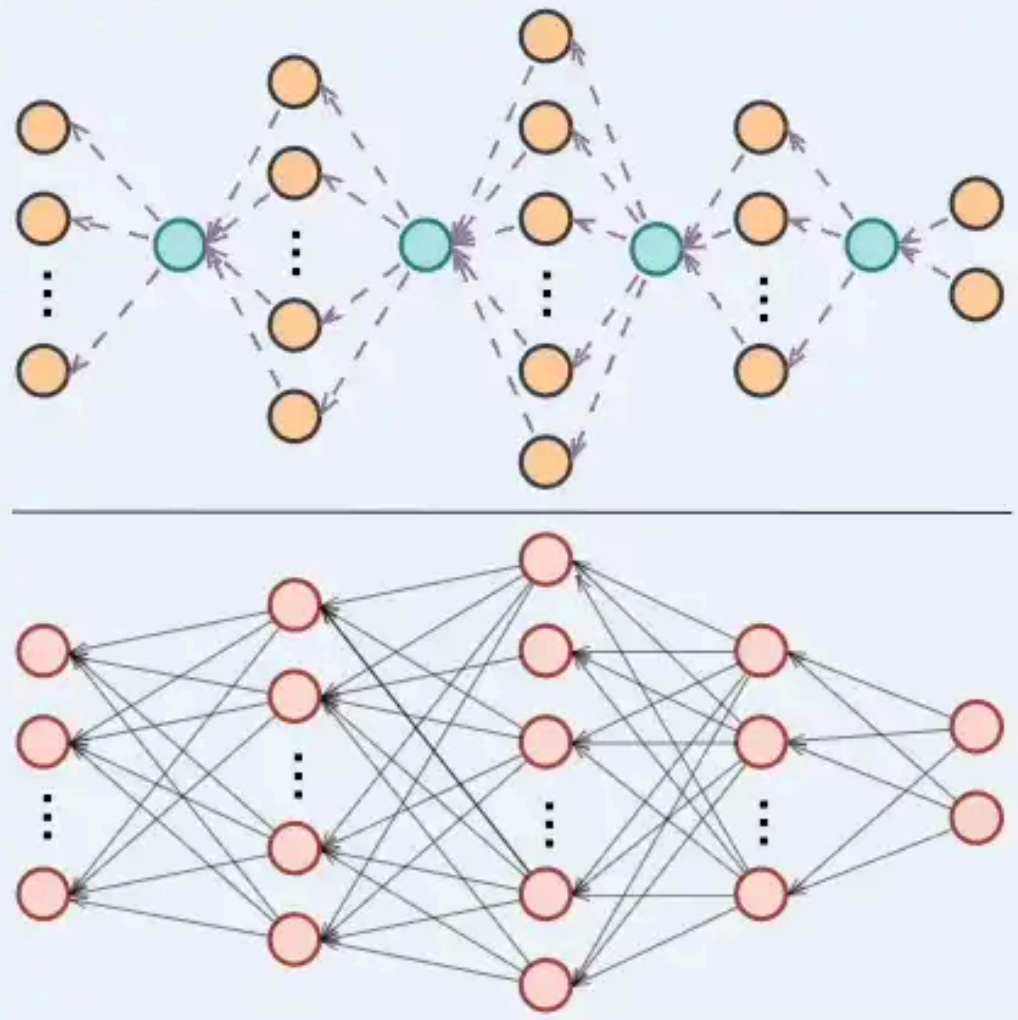
Full Fine Tuning



Gradient flow

Full pre-trained network

LoRA Fine Tuning



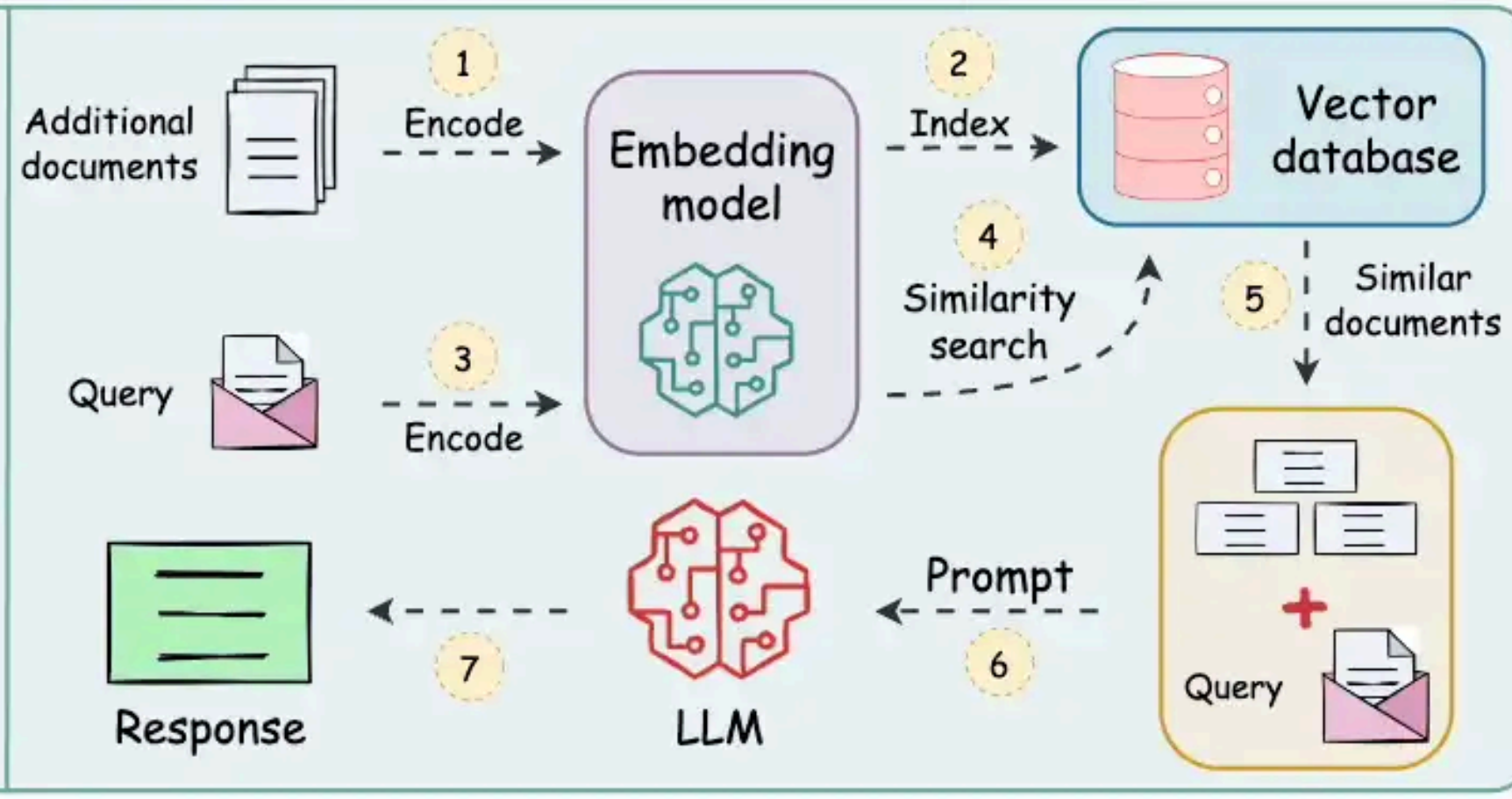
Gradient flow

Additional LoRA layers

No gradient flow

Full pre-trained network

RAG

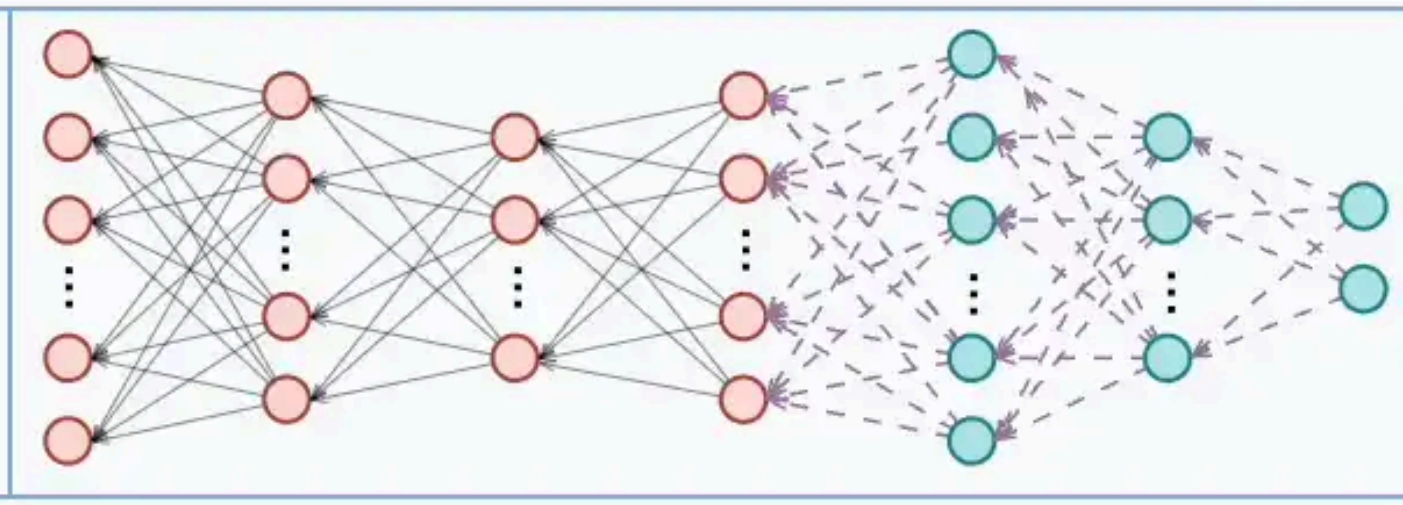


Next...

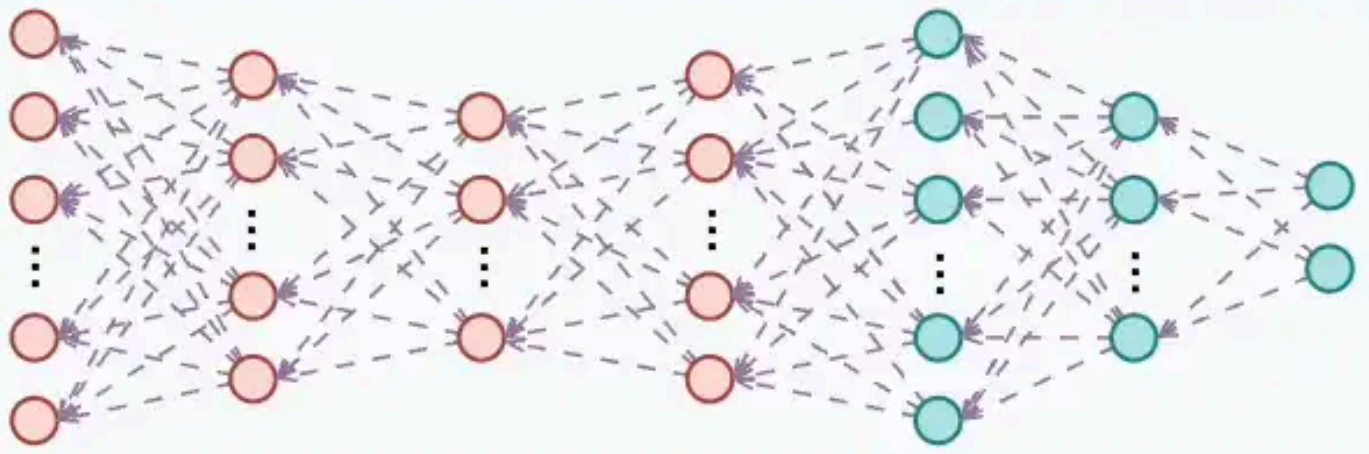
Transfer Learning vs. Fine Tuning vs. Multitask Learning vs. Federated Learning

blog.DailyDoseofDS.com

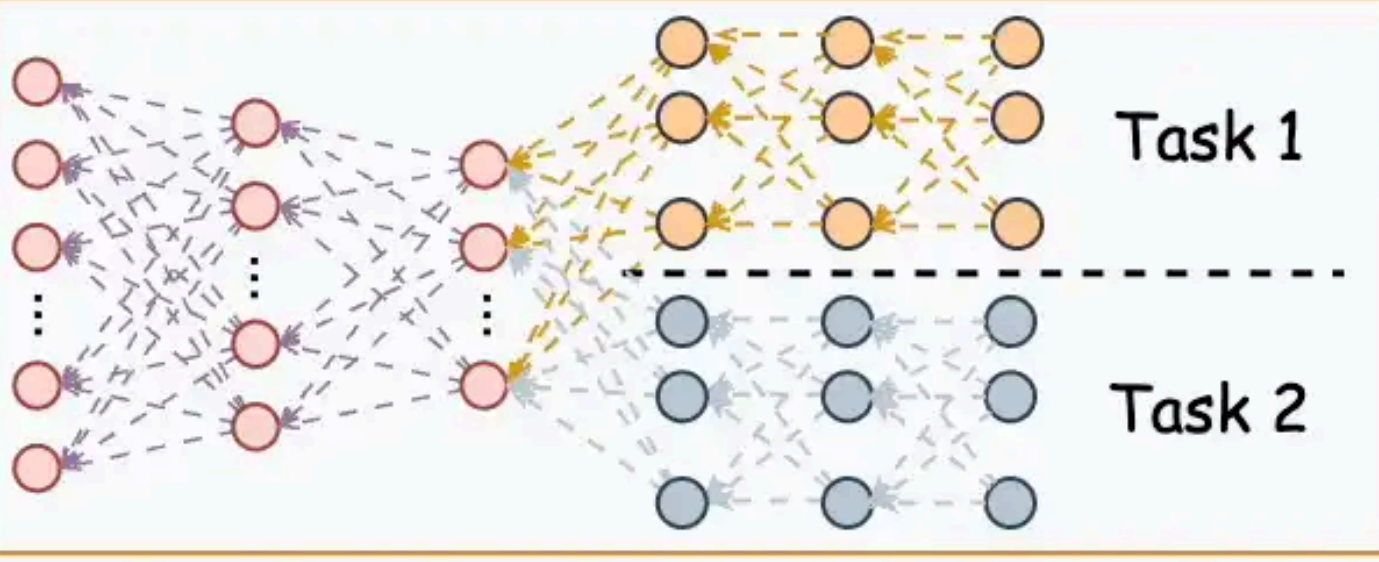
Transfer Learning



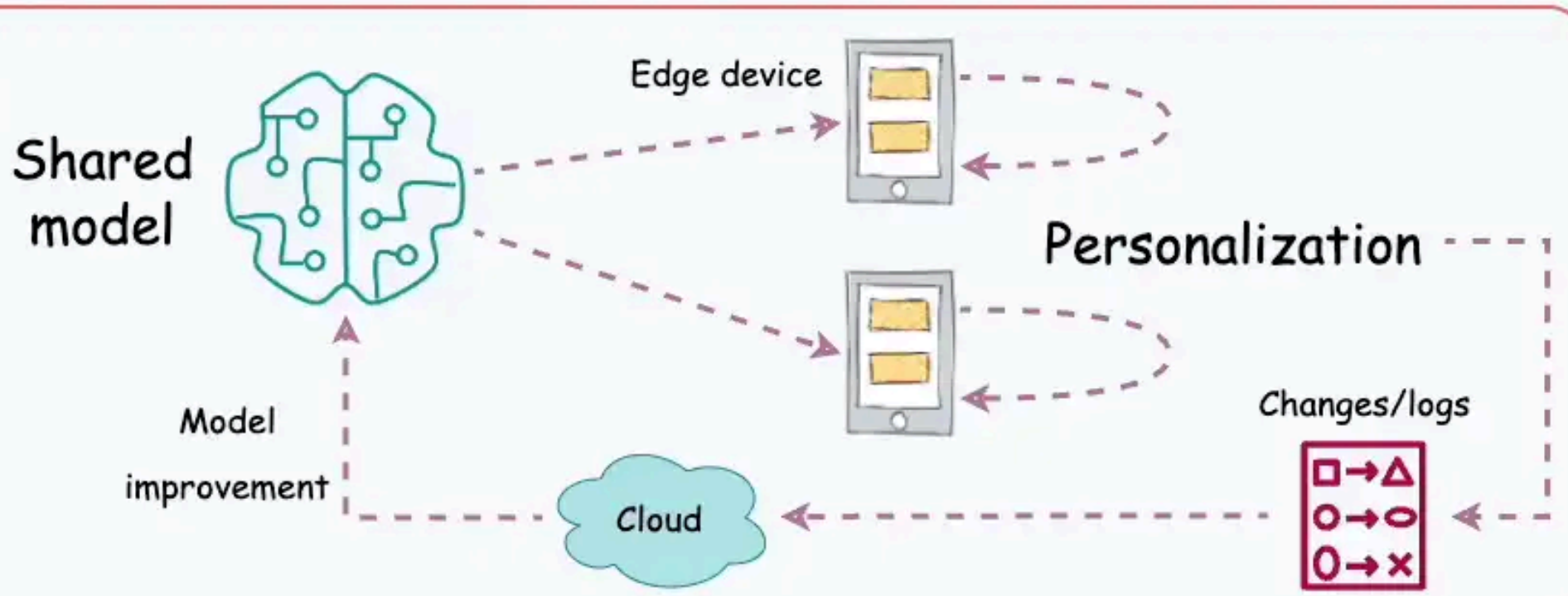
Fine Tuning



Multitask Learning



Federated Learning



Next...

Hope that was useful

Join 100k data professionals below and we'll send you a free data science PDF (530+ pages):

blog.DailyDoseofDS.com