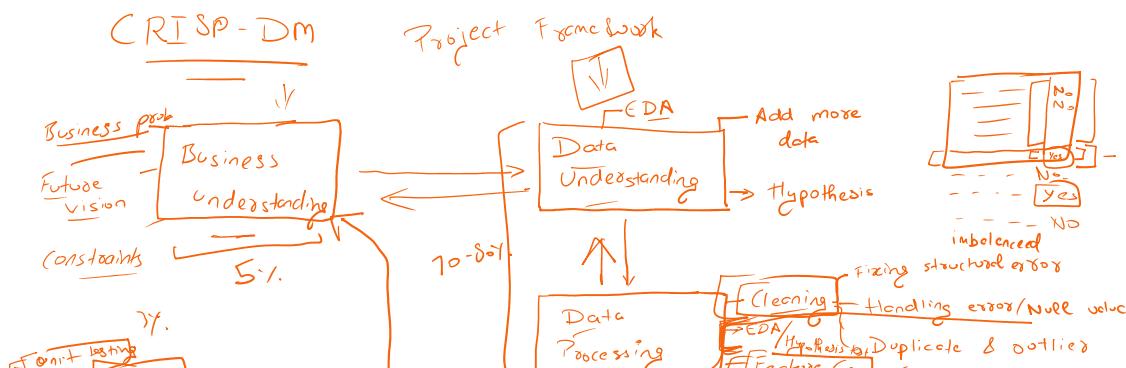
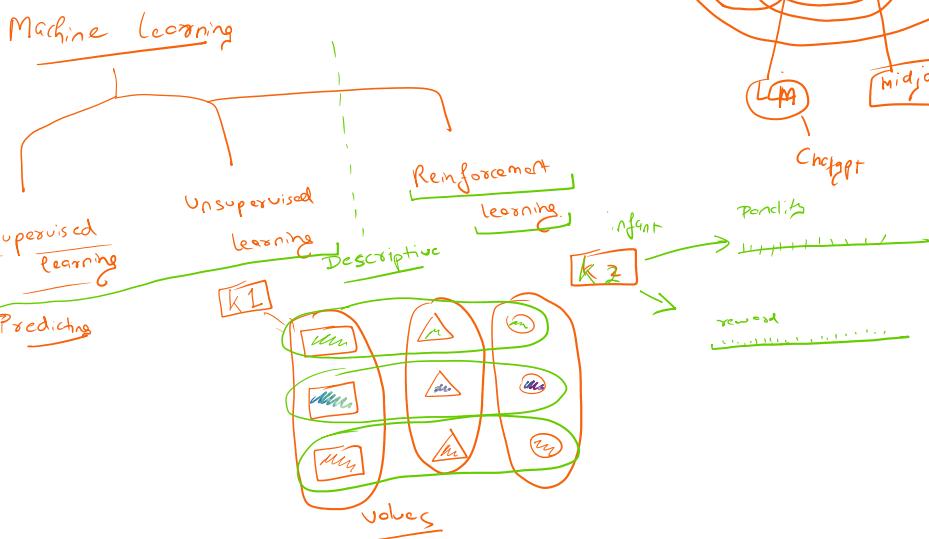
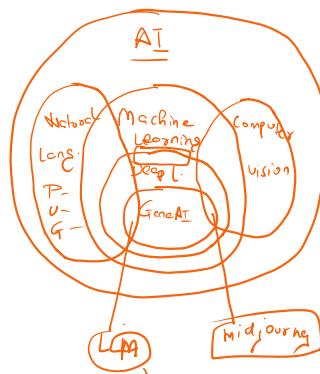
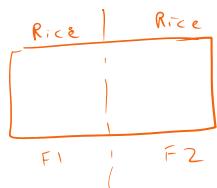
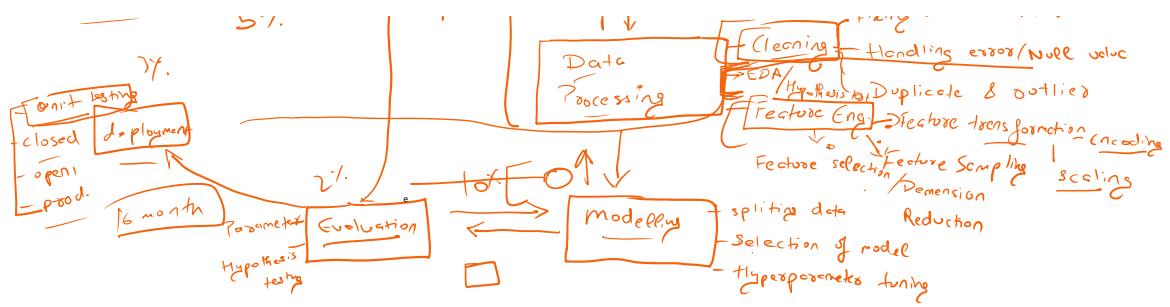
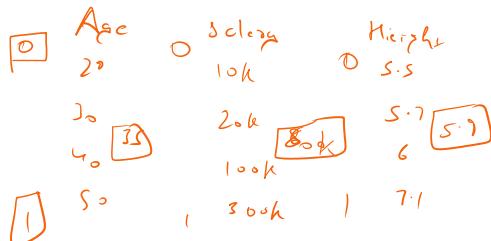


Artificial Intelligence (AI)

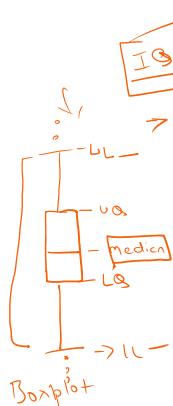
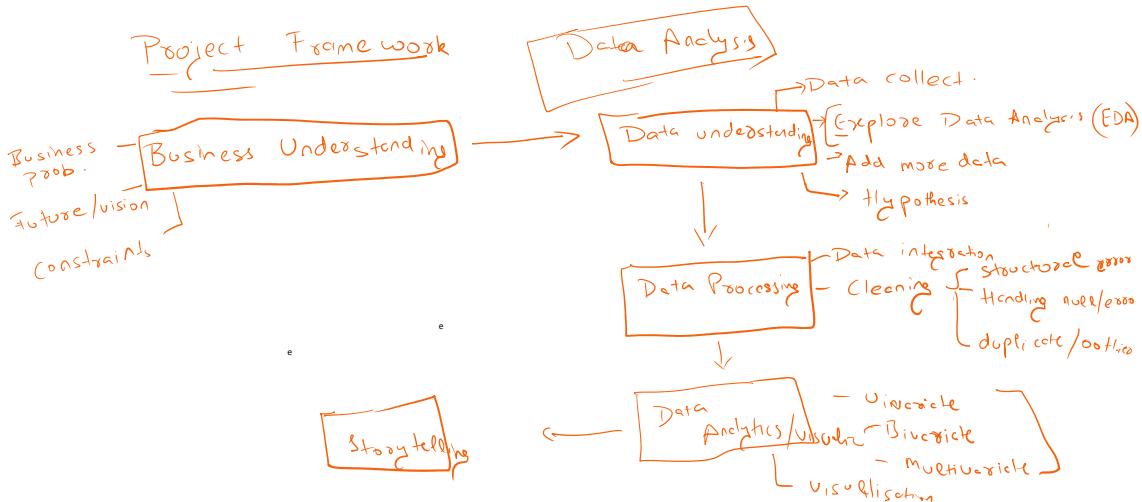




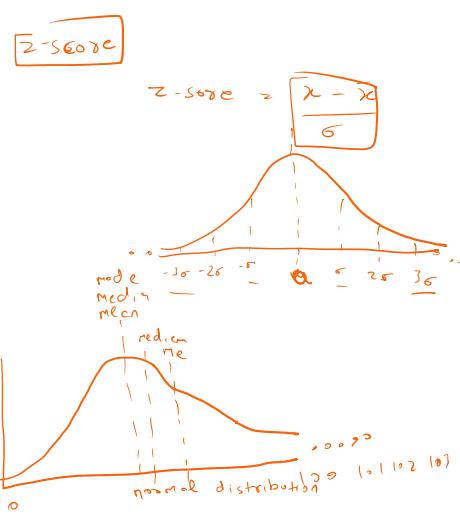
$\frac{35 - 800}{8.9} = -8.9$



- ✓ F1, F2 - no change
- ✓ F1 > F2 - Hypothesis



$$\begin{aligned} \text{IQR} &= Q_3 - Q_1 \\ Q_1 &= Q_1 + 1.5 \times \text{IQR} \\ L_1 &= Q_3 - 1.5 \times \text{IQR} \end{aligned}$$



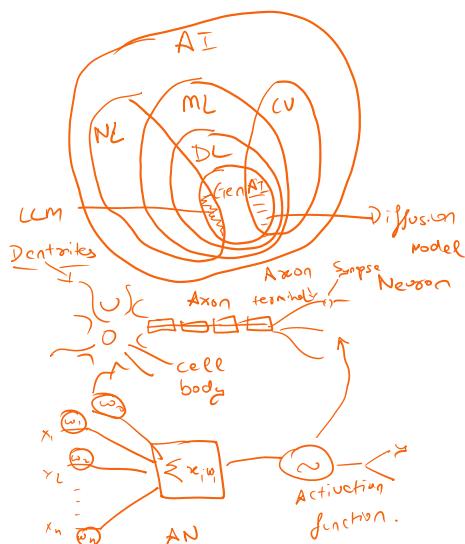
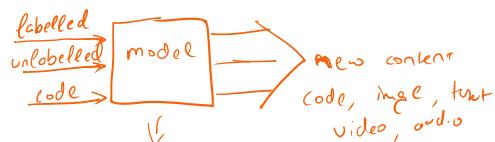
Artificial Intelligence (AI)

Artificial Intelligence (AI)

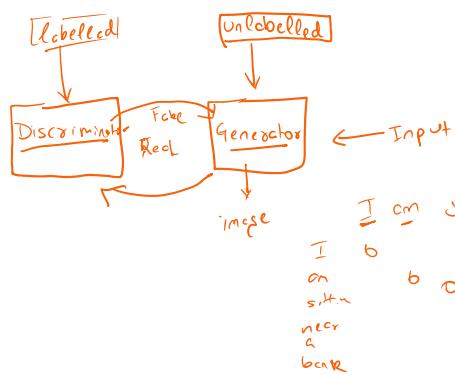
Machine learning - understanding the data

Deep learning - Processing of huge data

Generative AI - Generating new content



GAN



Large Language Model

Attention model

I cm sitting near a bank
I b
on sitn
near a
bank

Large language models

Transformers

Language translation

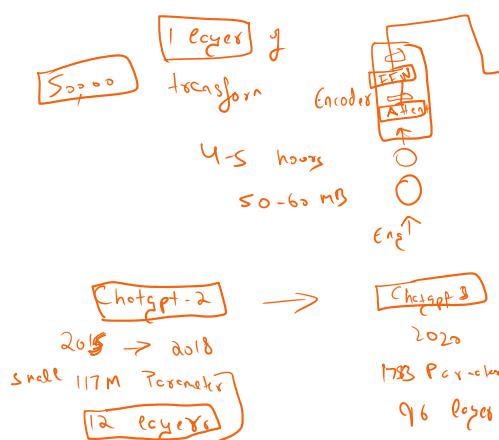
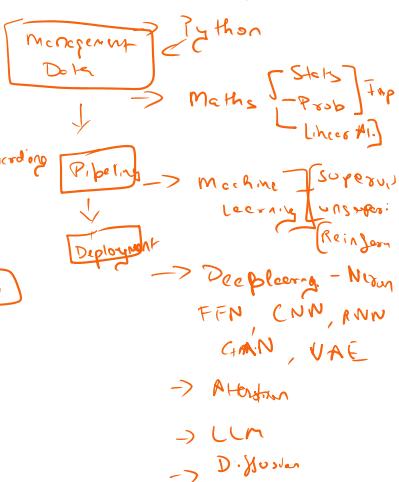


Image captioning model

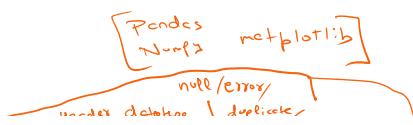
Diffusion model

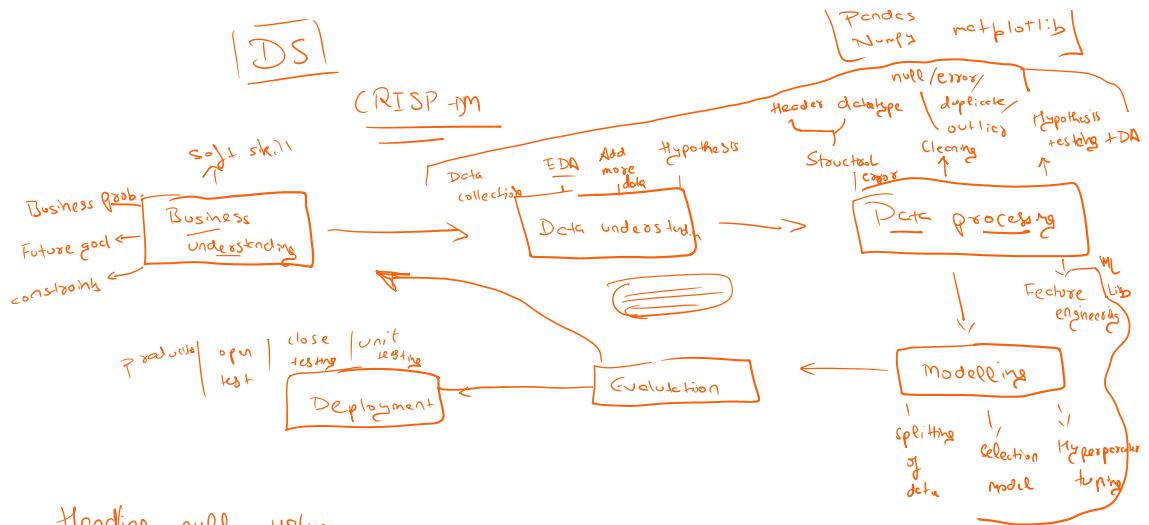
Roadmap of AI Eng.



DS

RTSP - m





Handling null values

→ removing null values

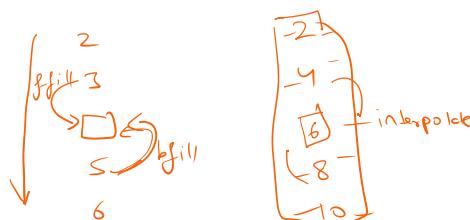
→ categorical mode
→ numeric mean / median

mean - if there are no outlier

median - if there are outlier

bfill/ffill

interpolate ↑



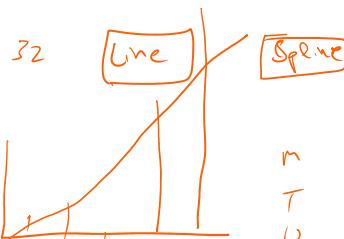
→ Cleaning of Null values

→ removing null values

→ filling null values

Quantitative
continuous discrete

Qualitative
ordinal categorical



→ mean / median

mode

m
T
U
T
F
m
T

32 - 32 -
34 - 34 -

36 -

38 -

40 -

(m)
T

Constant

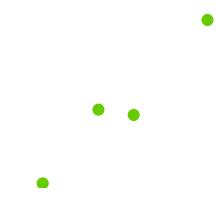
→ Supervised learning model

→ bfill / ffill

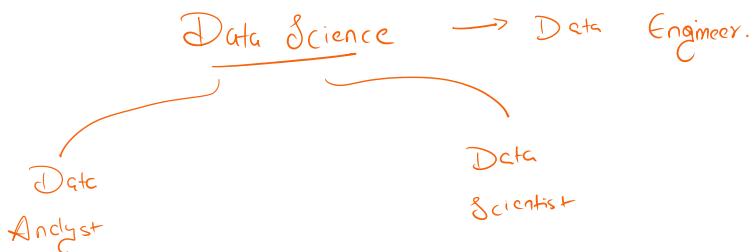
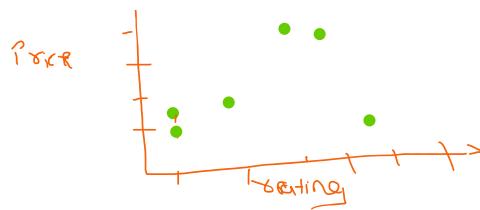
→ interpolate (T, m)

R	P
-1	25
2	30
-1	31
3	62

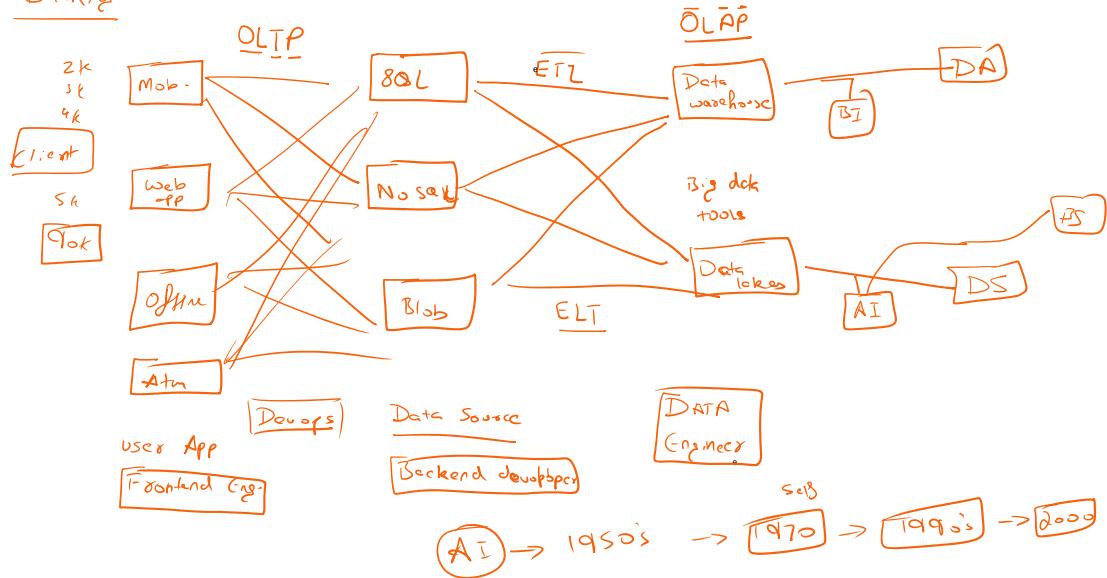
P<R



2	30
-1	31
3	62
4	40
5	25
6	60



Banking

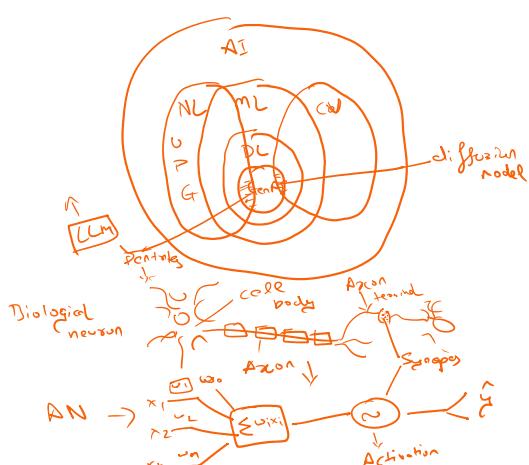


ML → machine learning → understanding

DL → Deep learning → processing

Gen AI → Generative AI → Generate

NL → Natural language → language



DE

→ SQL

→ Python

→ R

DS

→ Python

→ Clouds

→ ML

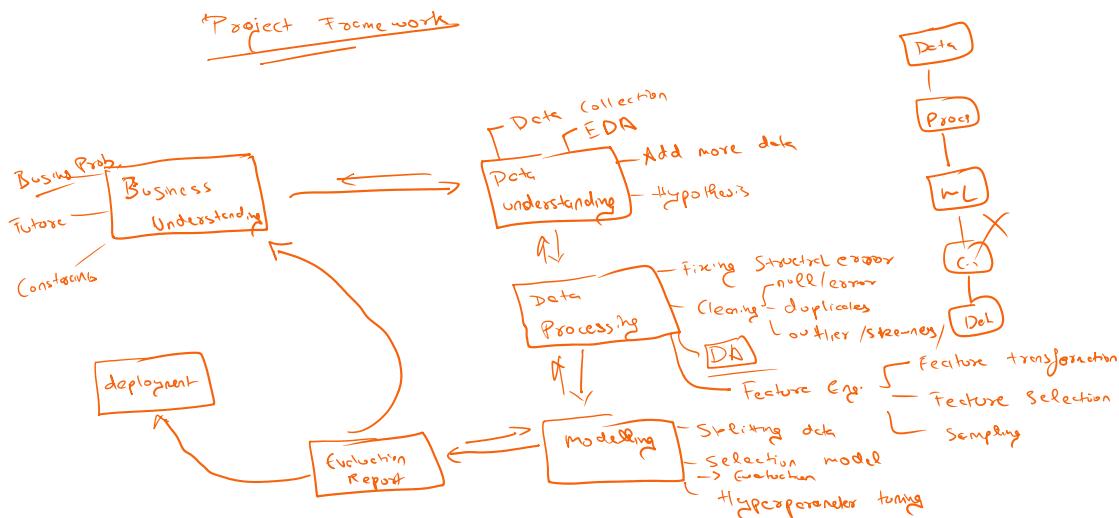
DA

→ Python

→ SQL

→ BI

→ Python	→ Cloudy	→ SQL
→ Spark	→ ML	→ BI
→ Hadoop	→ DP	→ Excel
→ Azure, GCP, AWS	→ Gen API	→ Storytelling
	→ Devops	



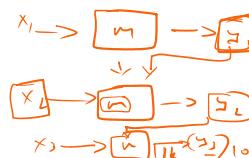
Today's topic

Prep. → Machine learning

→ Fully connected neural network

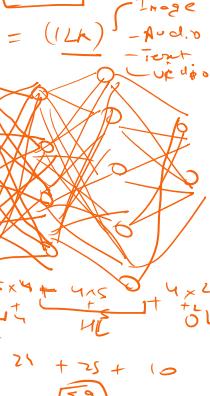
↓
Unidirection

- High dimension
- Series data



Deep learning

FFN



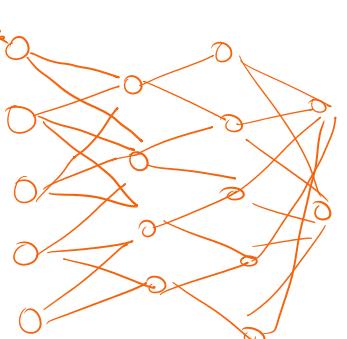
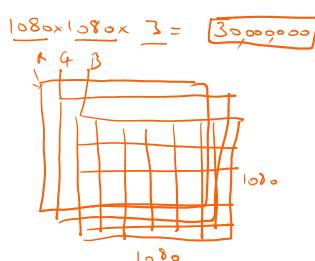
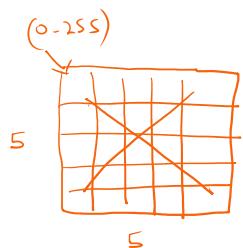
CNN - model

Convolutional Neural Network

RNN - model

Recurrent Neural Network

Convolutional Neural Network



[CONV] → Activation → Pooling (Relu)

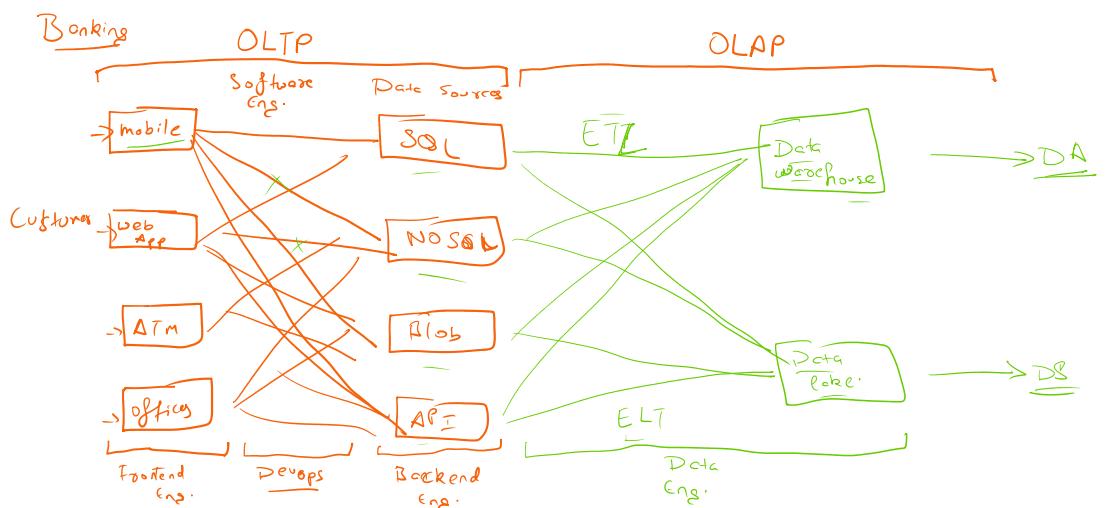
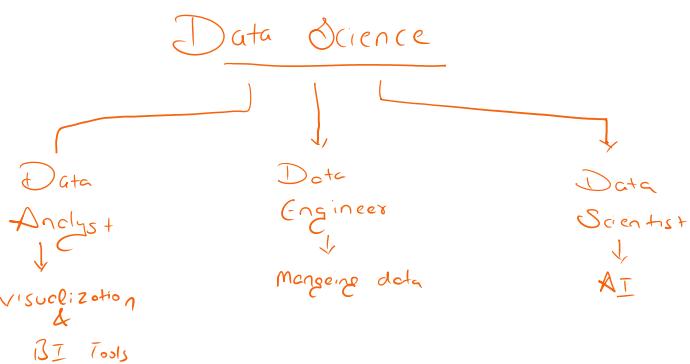
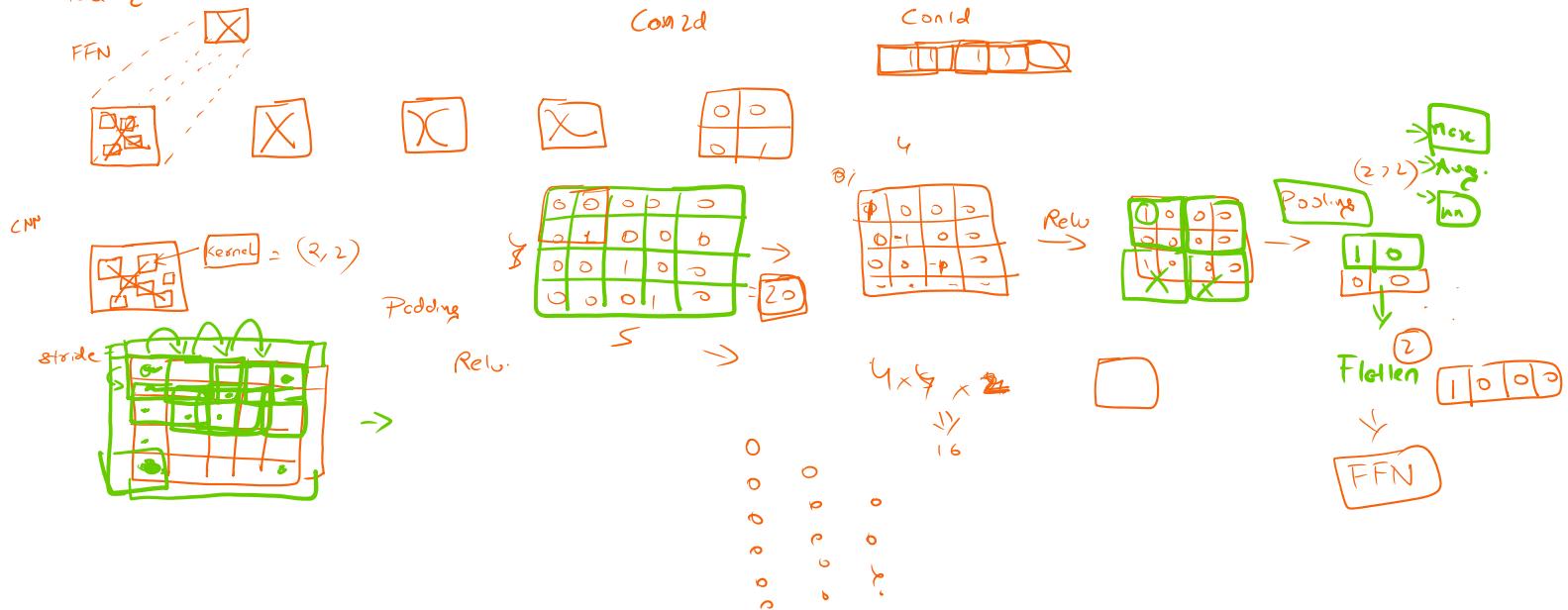
- Kernels
- strides
- Padding

ReLU

ReLU

ReLU

- strides
- Padding



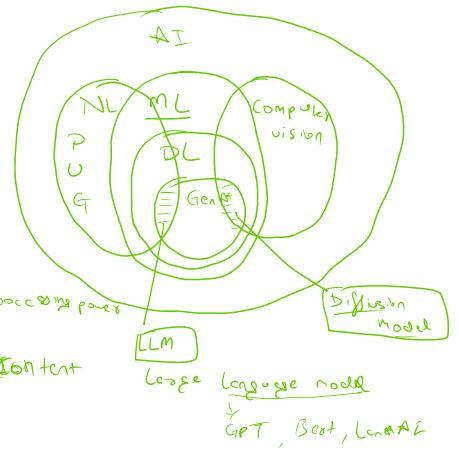
Data Science

AI → Artificial Intelligence

ML → Machine learning → understand

[DL] → Deep learning → Advance processing

Gen AI → Generative AI →
NL → Natural language

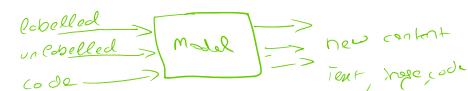


Generative AI

focns for net

Diffusion model

Prompt Eng.



Project Framework

```

graph TD
    A[Business Prob.] --> B[Business understanding]
    B --> C[Future]
    D[understanding] --> B
    E[constraints] --> B
  
```

A hand-drawn diagram consisting of a green rectangular box containing the word "deployment". A green curved arrow originates from the bottom right corner of this box and points towards a small, empty green square located at the bottom right of the frame.

CRISP-DM

```

graph TD
    A[Data collection] --> B[EDA]
    B --> C[Data understanding]
    C --> D[Hypothesis]
    D --> E[Add more data]
    E --> A

```

The diagram illustrates an iterative machine learning workflow. It starts with 'Data collection' at the top left, which leads to 'EDA' (Exploratory Data Analysis) at the top right. This is followed by 'Data understanding' in a box at the bottom left, which leads to 'Hypothesis' at the bottom right. Finally, 'Add more data' is shown at the bottom center, which loops back to 'Data collection' at the top left.

```

graph TD
    A[Data processing] --> B[Structure]
    A --> C["Cleaning - normalization"]
    C --> D[Visualisation]
    D --> E[Feature Engineering]
    E --> F[Modeling]
    D --> A
    F --> A
  
```

```

graph TD
    ML[Machine Learning] --> Supervised[Supervised]
    ML --> Unsupervised[Unsupervised]
    Supervised --> Classification[Classification]
    Supervised --> Regression[Regression]
    Classification --> NB[Naive Bayes]
    Classification --> DT[Decision Tree]
    Classification --> RF[Random Forest]
    Classification --> SVM[SVM]
    Classification --> LR[Logistic Regression]
    Classification --> KNN[KNN]
    Unsupervised --> Clustering[Clustering]
    Unsupervised --> DR[Dimensionality Reduction]
    Clustering --> KM[K-Means]
    Clustering --> DBSCAN[DBSCAN]
    Clustering --> HC[Hierarchical Clustering]
    DR --> PCA[PCA]
    DR --> ICA[ICA]
    DR --> LDA[LDA]
    FeatureSelection[Feature Selection] --> PCA
    FeatureSelection --> ICA
    FeatureSelection --> LDA
  
```

Feature transformation → Scaling

One-hot Encoding	
Label	Encoding
a	0 0 1 0 0 0 0
b	0 1 0 0 0 0 0
c	0 0 1 0 0 0 0
d	0 0 0 1 0 0 0
e	0 0 0 0 1 0 0
f	0 0 0 0 0 1 0
g	0 0 0 0 0 0 1
h	0 0 0 0 0 0 1

String index

$$\boxed{8 +}$$

Social Simple

	<u>EE</u>	
M	0	.
F	1	
n	0	
F	1	
x	0	
o	2	

Scaling

$$\Rightarrow \text{Standardization} = Z = \frac{x - \bar{x}}{\sigma}$$

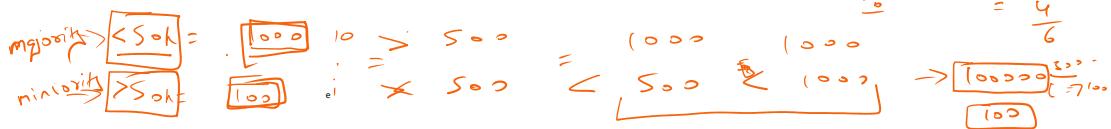
Solve Right

Standardization

$$\Rightarrow \text{Standardization} = z = \frac{x - \bar{x}}{\sigma}$$

$$\Rightarrow \text{Normalisation} = z = \frac{x_{\max} - x}{x_{\max} - x_{\min}}$$

Feature balancing



undersampling

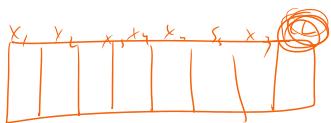
Random undersampler

GMM

Oversampling

Random oversampler

SMOTE



$$IG(x_1) = 0.4$$

Root Feature Selection

Entropy

Delta

Age

Workclass

Married

Income

Pred

$$\begin{aligned} IG(x_1) &= 0.4 \\ &\vdots \\ &IG(x_4) = 0.6 \\ &= 0.01 \\ &= 0.45 \\ &= 0.1 \end{aligned}$$

Correlation

Mutual Info

Chi-Sq

F-Score

13+

Pyramidal

42
44
51
58

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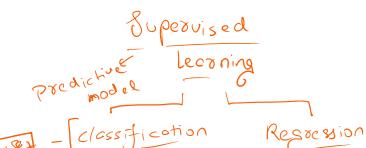
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Artificial Intelligence

Machine Learning :-

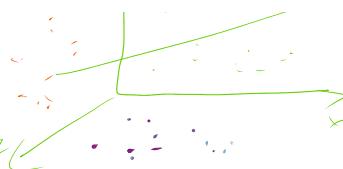


- fund.
- Naive Bayes - Prob.
 - Decision tree - Stats
 - Logistic Regression - Log.
 - KNN - Coordinate.
 - SVM - "

Independent variables					Dependent variable
Type	Wind	Temp	Hum	W/N	
D	H	H	L	Y	
R	L	L	H	Y	
C	L	L	H	N	
S	H	L	L	N	

features / columns
attribute

target label class



Ensemble Technique

Random forest

GBM

Ada boost



Day	Temp	Hum	Wind	W/N
S	Y	N		
R	N	Y	L	

Temp	Y	N
H	1/4	3/4
N	3/4	1/4

Humid

Humid	Y	N
H	3/4	1/4
L	1/4	3/4

$$P(Y) = P(Y|SNHW) = \frac{P(B|A) \cdot P(A)}{P(B)} = 0.005$$

$$P(N) = P(N|D) = \frac{P(B|N) \cdot P(N)}{P(B)} = 0.0016$$

Normalisation :-

$$\frac{P(Y)}{P(Y) + P(N)}$$

$$\begin{aligned} P(Y) &= P(Y|SNHW) = \frac{P(B|A) \cdot P(A)}{P(B)} = 0.005 \\ P(N) &= P(N|SNHW) = \frac{P(B|N) \cdot P(N)}{P(B)} = 0.0016 \\ \text{Occurrence of Event} &= \frac{\text{Total Event}}{\text{Total Event}} \\ P(HH) &= 1 \\ P(HT) &= 2/4 = 1/2 \\ P(TH) &= 1/4 \\ P(TT) &= 0 \\ P(S) &= 1/2 \\ P(N) &= 1/2 \\ P(H) &= 1/2 \\ P(L) &= 1/2 \\ P(Y) &= 3/4 \\ P(N) &= 1/4 \\ P(H) &= 1/2 \\ P(L) &= 1/2 \\ P(Y|SNHW) &= \frac{P(S|Y) \cdot P(N|Y) \cdot P(H|Y) \cdot P(L|Y) \cdot P(Y)}{P(S) \cdot P(N) \cdot P(H) \cdot P(L)} = \frac{(3/4) \cdot (1/2) \cdot (1/2) \cdot (1/2) \cdot (3/4)}{(1/2) \cdot (1/2) \cdot (1/2) \cdot (1/2)} = 0.005 \\ P(N|SNHW) &= 0 \\ P(Y|SNHW) &= 0.005 \\ P(N|SNHW) &= 0 \\ \text{Laplace Smoothening} &= 0.005 \\ \text{Zero case scenario.} &= 0.005 \end{aligned}$$

Normalisation =

$$\frac{P(Y)}{P(Y) + P(N)}$$

$$\frac{0.005}{0.0066} = 0.755$$

$$\frac{0.016}{0.0066} = 2.42$$

$$\frac{(N)}{P(Y) + P(N)}$$

→ maths

→ Assumptions

→ Limitation

→ Use case

→ Types
When to apply

→ Whenever you limited data

→ Fast & Simple

→ Binary data, Multiclass classification

→

Naive

Assumptions

- All feature should independent in nature
- All feature should contribute equally in pred.

Limitation

- Assumption
- Zero case scenario
- Inability to handle missing values

Use Case

- Text Data
- Medical Diagnose
- Recommendation

Types of Naive Bayes:

- Gaussian Naive Bayes - Normally distributed data & most of feature are continuous in nature
- Multinomial Naive Bayes - when most features are discrete / freq based
- Bernoulli NB - Binary data
- Complement NB - Imbalanced data
- Categorical NB - Categorical data
- Out of core NB - Big data

KNN - K-Nearest Neighbours

Step-1 - Plot all data point

$$\text{Step-2 } \boxed{K=3} - \boxed{K=4} = \boxed{K=3} = S$$

Step-3 Calculate dist

◦ Euclidean distance

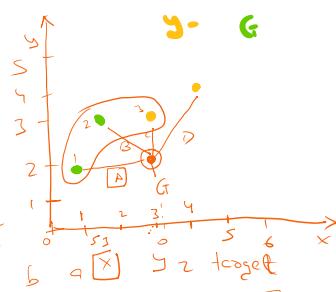
$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

$$A = \sqrt{(1-3)^2 + (2-2)^2} = \sqrt{\sum (x_i - y_i)^2}$$

$$B = \sqrt{(2-3)^2 + (3-2)^2} = \sqrt{2+1} = \sqrt{3}$$

$$C = \sqrt{(1-2)^2 + (2-1)^2} = \sqrt{1+1} = \sqrt{2}$$

$$D = \sqrt{(2-3)^2 + (1-1)^2} = \sqrt{1+0} = 1$$



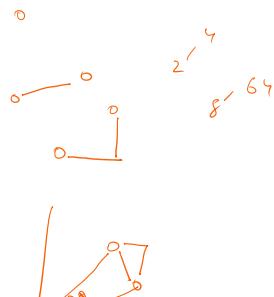
$$\begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{bmatrix} - \begin{bmatrix} 3 \\ 2 \\ 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 1-3 \\ 2-2 \\ 3-1 \\ 4-2 \\ 5-3 \end{bmatrix} = \begin{bmatrix} -2 \\ 0 \\ 2 \\ 2 \\ 2 \end{bmatrix}$$

$$\begin{bmatrix} -2 \\ 0 \\ 2 \\ 2 \\ 2 \end{bmatrix} \cdot \begin{bmatrix} -2 \\ 0 \\ 2 \\ 2 \\ 2 \end{bmatrix} = 4 + 0 + 4 + 4 + 4 = 16$$

$$\sqrt{16} = 4$$

Distance Metrics:

- Euclidean dist + Continuous data
- Manhattan dist + $\sum |x_i - y_i|$ Categorical data
- Minkowski dist + $\sqrt[p]{(x_i - y_i)^p}$ Outliers
Outliers
 $p = 2 \Rightarrow$
- Cosine similarity +



Lazy learner

Assumption:

- KNN assumes that similar data points are close to each other.

- Normalization

Limitation:

- Computationally complex

- Curse of Dimensionality

- Choice of K value

When to Apply:

- Non-linear

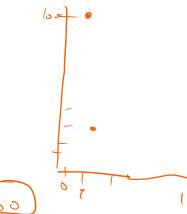
- Small-medium data

- don't need fast model



df.shape

(X [])



Use Cases

- Recommendation

- Anomaly detection

- Customer segmentation

complexity higher
computationally
expensive

Lossing on Inform

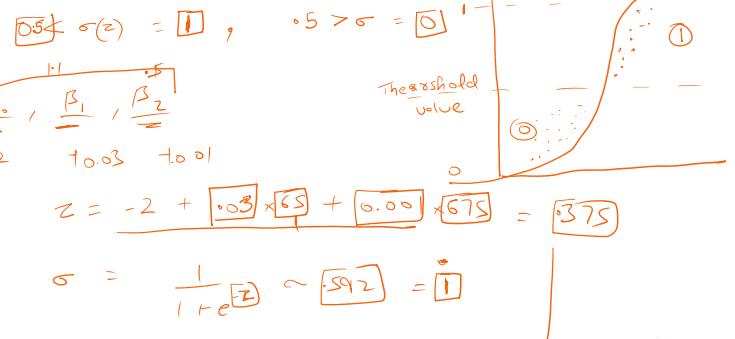
Logistic Regression

Binary Classification

$$\text{Sigmoid} - \sigma(z) = \frac{1}{1+e^{-z}} = [0, 1] \quad \bar{z} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots$$

Gradient Descent

P	x	$\sigma(z)$	P
1	50K	0.5	0.5
2	650	0.5	1
3	700	0.5	1
4	70K	0.5	1
5	800	0.5	1
6	720	0.5	1
7	65K	0.5	1
8	675	0.5	1



Assumptions:

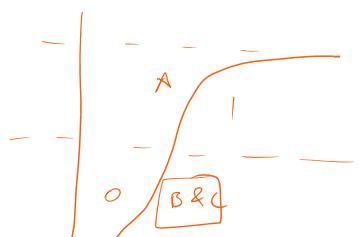
- Linear data
- Independence
- Large datasets

Limitations

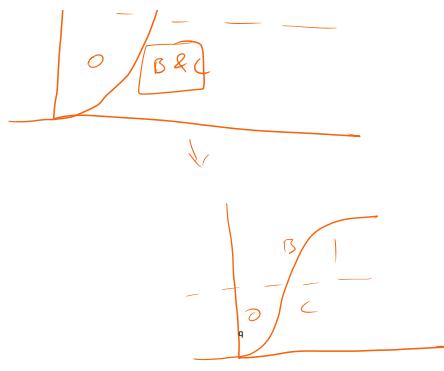
- Linearity
- Sensitive to outliers
- Scaling, selection

When to Apply:

- Binary classification
- Linearity data
- Large dataset availability



A
B
C
A
B



A
B
C
C
D
D

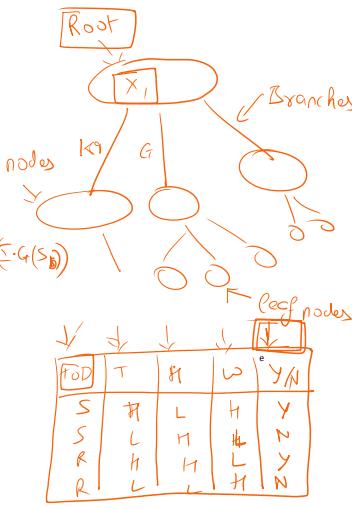
Decision Tree Model:

$$\rightarrow \text{Entropy} : H(S) = -P_1 \log_2(P_1) - P_2 \log_2(P_2)$$

Information Gain

$$= I(G) = H(S) - \sum \frac{|S_i|}{|S|} (H(S_i))$$

	Y	N	T	W
S	1	1	1	1
R	1	1	1	1



$$T(S) = \left[-\frac{1}{2} \log_2\left(\frac{1}{2}\right) - \frac{1}{2} \log_2\left(\frac{1}{2}\right) \right] = 1 \times \frac{2}{4} = 1$$

$$T(R) = \left[-\frac{1}{2} \log_2\left(\frac{1}{2}\right) - \frac{1}{2} \log_2\left(\frac{1}{2}\right) \right] = 1 \times \frac{2}{4} = 1$$

Y = 5

N = 5

$$I.G = \frac{Y}{Y+N} \log_2\left(\frac{Y}{Y+N}\right) + \frac{N}{Y+N} \log_2\left(\frac{N}{Y+N}\right)$$

$$= \frac{1}{2} \log_2\frac{1}{2} + \frac{1}{2} \log_2\left(\frac{1}{2}\right) = 1 = 1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2$$

$$E(S) = -\frac{1}{3} \log_2\left(\frac{1}{3}\right) - \frac{2}{3} \log_2\left(\frac{2}{3}\right) = a$$

S	1	2
C	3	0
R	1	3

$$\Rightarrow I.G = (a) \times \frac{3}{10} = 0.2797$$

$$I.G(C) = -\frac{3}{3} \log_2\left(\frac{1}{3}\right) - \frac{0}{3} \log_2\left(\frac{0}{3}\right) \times \frac{3}{10} =$$

$$I.G(R) = \left[-\frac{1}{4} \log_2\left(\frac{1}{4}\right) - \frac{3}{4} \log_2\left(\frac{3}{4}\right) \right] \times \frac{7}{10} = 0.0754$$

$$E(T) = -0.117$$

$$TOD = 0.89$$

$$(I.G)(1 - 0.117) = 0.89 = TOD$$

$$Temp = 51$$

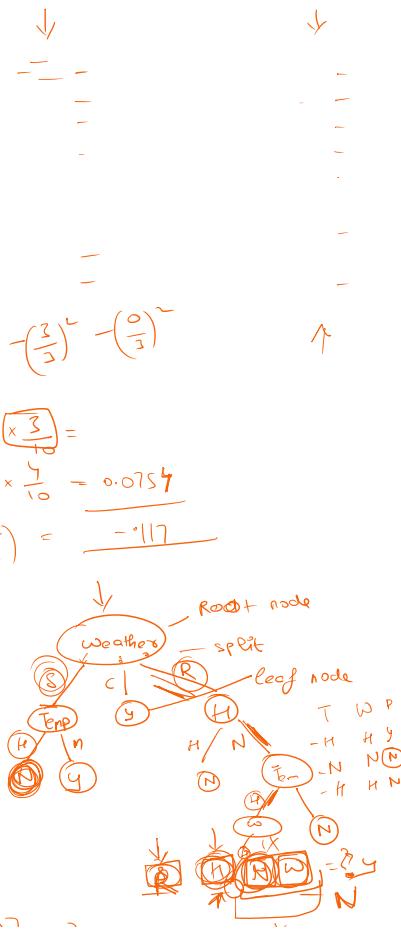
$$Hum = 37$$

$$Wind = 21$$

Binary, Multi

	Temp	Hum	Wind	Play?
	H	M	W	Y
1	H	M	W	N
2	H	M	W	Y
3	M	N	S	Y
4	M	N	S	N
5	M	N	S	N
6	M	N	S	N

Day	Weather	Temperature	Humidity	Wind	Play?
1	Sunny	Hot	High	Weak	No
2	Cloudy	Hot	High	Weak	Yes
3	Sunny	Mild	Normal	Strong	Yes
4	Cloudy	Mild	High	Strong	Yes



2	Cloudy	Hot	High	Weak	
3	Sunny	Mild	Normal	Strong	
4	Cloudy	Mild	High	Strong	
5	Rainy	Mild	High	Strong	No
6	Rainy	Cool	Normal	Strong	No
7	Rainy	Mild	High	Weak	Yes
8	Sunny	Hot	High	Strong	No
9	Cloudy	Hot	Normal	Weak	Yes
10	Rainy	Mild	High	Strong	No

$$H = -\sum p_i \log_2 p_i$$

$$H(S) = -\sum p_i \log_2 p_i$$

$$H(M) = -\sum p_i \log_2 p_i$$

$$H(L) = -\sum p_i \log_2 p_i$$



$$H = H(M) + H(N)$$

$$H = 0.92$$

$$Gini = 1 - \sum p_i^2 = \text{Multiclass classification}$$

Entropy = Binary class

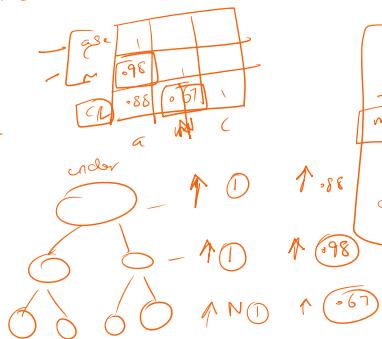
Assumptions

- Independent feature
- Hierarchical model - it's assume data can be splitted in hierarchy.

Limitations:

- Overfitting

overfit



Limitation

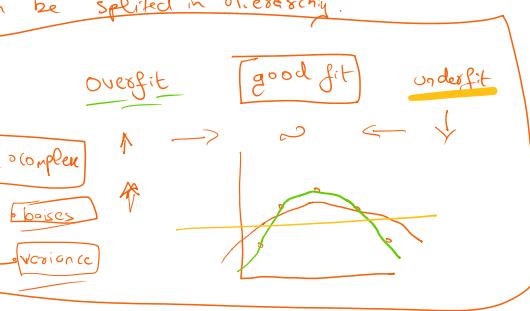
- Overfitting
- Biases
- Instability

Use Cases

- Marketing campaing
- Credit Scoring
- Customer segmentation

When to Apply

- Missing values, outliers
- interpretable model
- mix continuous & categorical



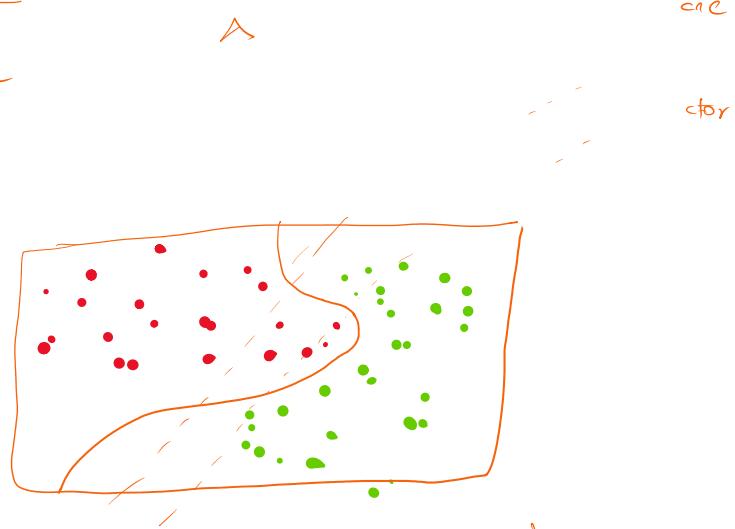
3 VM - Support Vector Machine

$$\hat{y} = mx + c$$

$$\min \frac{1}{2} \|w\|^2$$

$$\text{hyperplane} = n-1$$

- Linear Kernel
- Polynomial Kernel
- Radial Kernel



Assumptions:

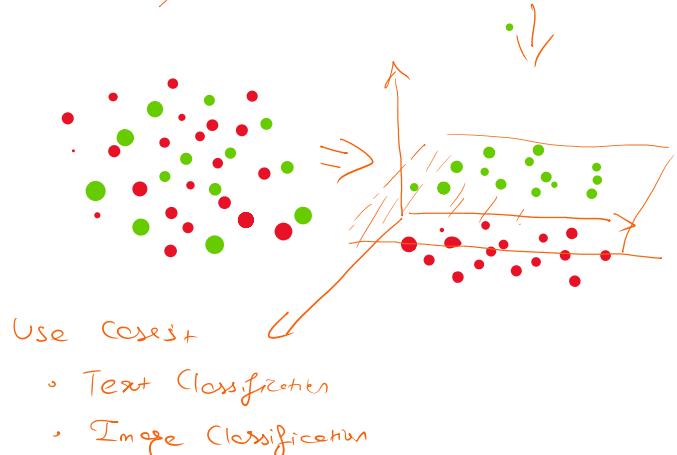
- Data linearly separable
- Classes are well separated
- Sensitive to outliers.

Limitations

- High computation & memory usage
-

When to Apply

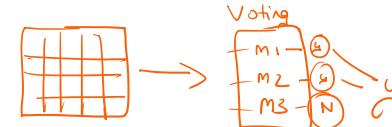
- High dimension
- Less instance
- noise free data.



Ensemble Models

Voting

Voting -

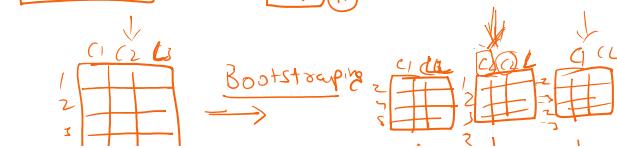


Stacking

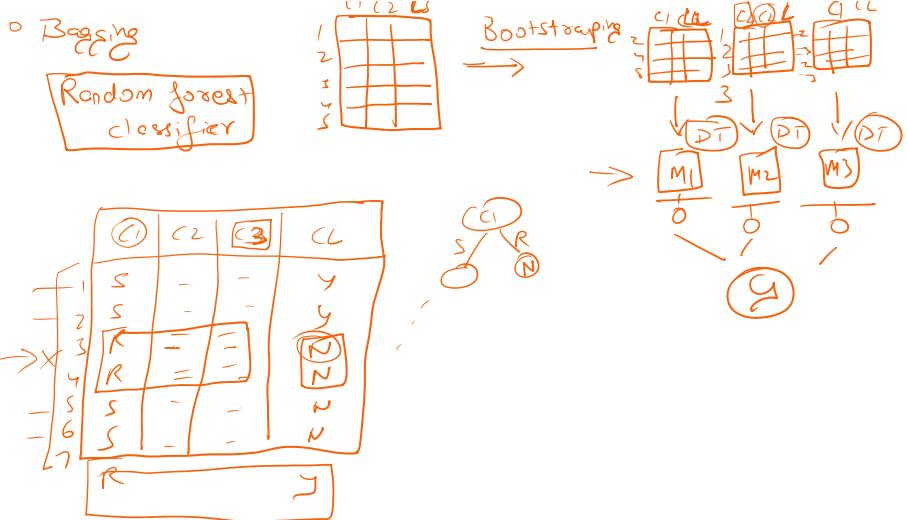
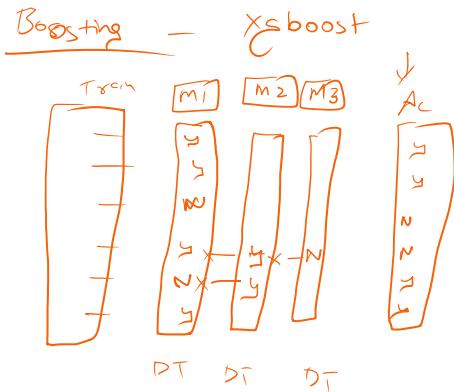


Bagging

Random Forest



Boosting - Xgboost



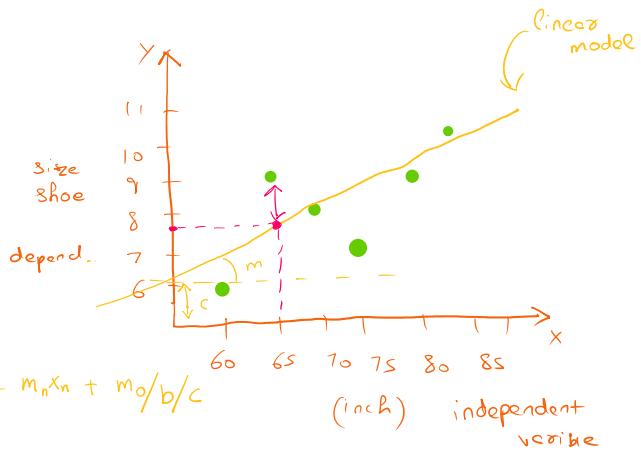
Regression Models

Linear Regression

Simple Linear regression - $\hat{y} = mx + c$

Multi-Linear Regression model - $\hat{y} = m_1x_1 + m_2x_2 + m_3x_3 \dots m_nx_n + m_0/b/c$

m = importance of feature
 m_0 = helper value to find best fit line



P1 - 65 ? 7.8

P	Area	Loci	Ame	Price
80	1000	PM	P	100
220	1000	A	M	200
80	1000	A	H	500

$y = mx + c$

Error - $(y_{act.} - \hat{y})$

Loss function

L_1 error individual

$$E = \frac{1}{n} \sum |y_{act.} - \hat{y}|$$

L_2 error =

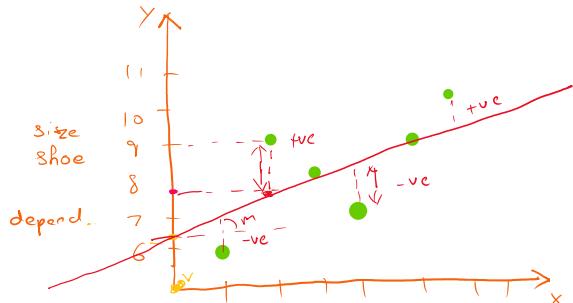
Cost function

Entire data
 Gradient descent

$$J(m, b) = \frac{1}{2n} \sum_i^n (y_i - \hat{y}_i)^2$$

$$= \frac{1}{2n} \sum_i^n (y_i - (mx_i + b))^2$$

$$m \quad b \quad E$$



APPA