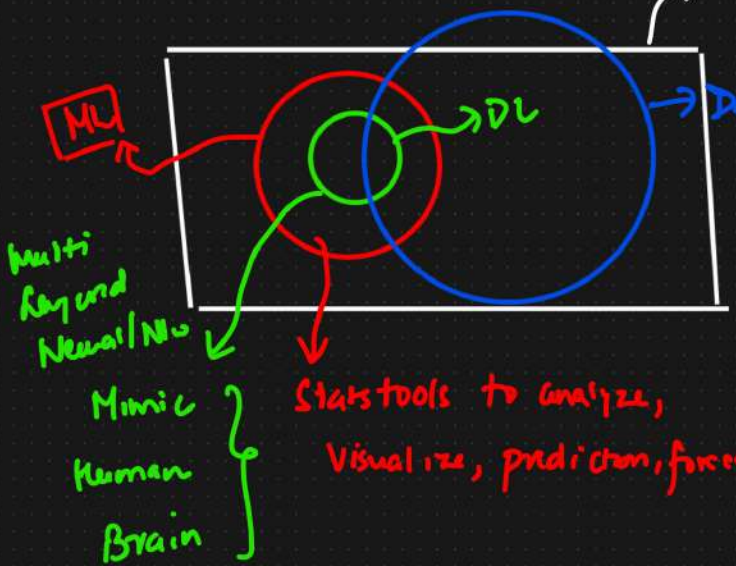
7 days Machine Learning Algorithms

Purpose : Clear the Interviews

Agenda

1. Introduction to ML (AI Vs ML Vs DL Vs DS)
2. Supervised ML and Unsupervised ML
3. Linear Regression (Maths & Geometric Intuition)
4. R^2 & Adjusted R^2
5. Ridge and Lasso Regression

① AI Vs ML Vs DL Vs DS



AI application

AI application is able to do it own task without any human intervention

Eg : Netflix → Action → Recommendation
↳ Comedy →

Amazon.in → Iphone → Headphones }

Self Driving Cars →

Machine & Deep learning

Reinforcement

- Supervised ML
  - Regression
  - CLASSIFICATION
- Unsupervised ML → CLUSTERING
  - DIMENSIONALITY REDUCTION

Supervised ML

Age	Weight
24	62
25	63
21	72
27	62

O/P

Age → hypothesis → O/P → Weight

Independent features → Age

Dependent feature → Weight

① Regression Problem

Age	Weight
24	72
23	71
25	71.5
—	—

O/P → Continuous variable → Regression Problem

② CLASSIFICATION

Binary classification
Multiclass classification

O/P

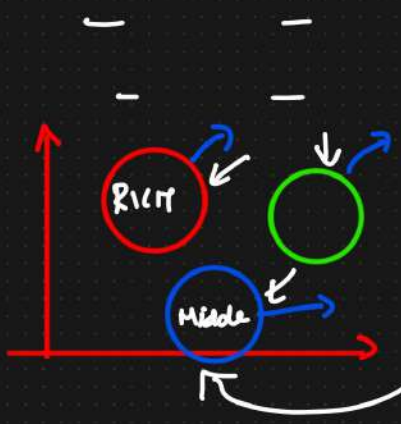
No. of hours	No. of play hours	No. of sleep	P/F
—	—	—	P
—	—	—	F
—	—	—	P
—	—	—	F

② Unsupervised ML → Clustering
→ Dimensionality Reduction

Salary	Age
—	—
—	—

{ No Dependent variable }

Clustering → Customer Segmentation



Ad marketing

GROUPING

Customer Segmentation

Eg: Product 1
↳ Rich

Product 2
↳ Middle

② Dimensionality Reduction

1000 → lower Dimension
→ 100

⇓

PCA, LDA

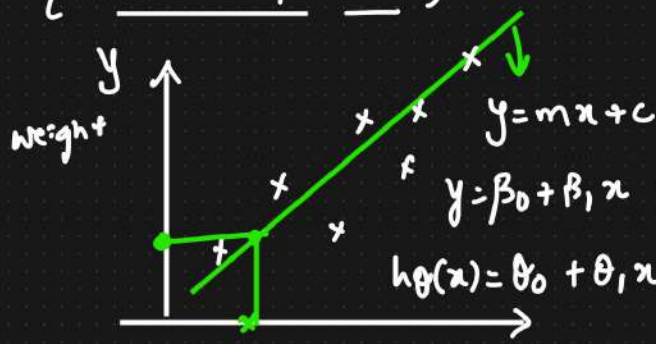
Supervised

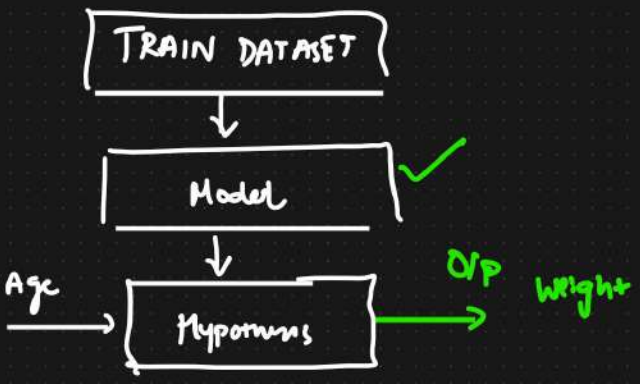
① Linear Regression
② Ridge & Lasso
③ Logistic Reg
④ Decision Tree
⑤ AdaBoost
⑥ Random Forest
⑦ Gradient Boosting
⑧ Xgboost
⑨ Naive Bayes
⑩ SVM
⑪ KNN

Unsupervised

① K means
② DBScan
③ Hierarchical
④ K Nearest Neighbor Class
⑤ PCA
⑥ LDA

① {Linear Regression}



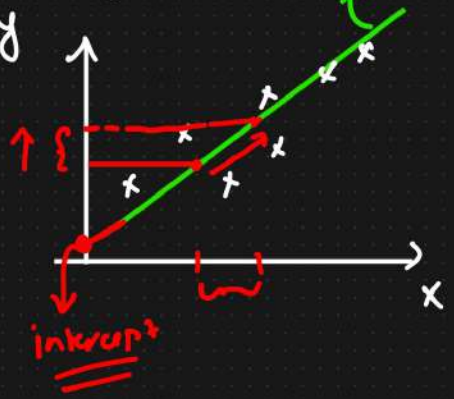


Credits : Andrew NG

y is a linear function of x

Equation of a Straight line

$h_\theta(x) = \theta_0 + \theta_1 x$



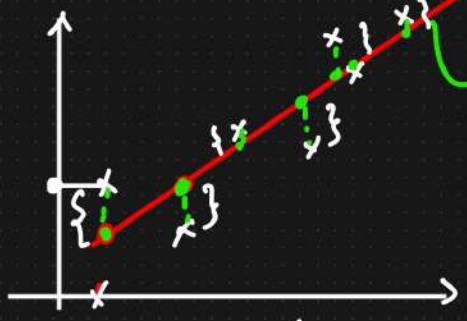
When $x = 0$

θ_0 = Intercept

θ_1 = Slope or Coefficient

x_i = data points

Linear Regression

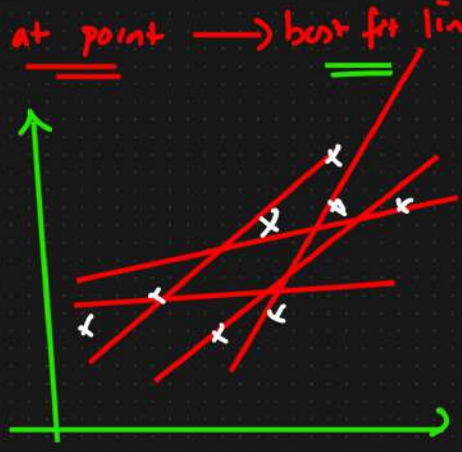


Minimal ↓↓↓↓

Best fit line

Hypothesis

$h_\theta(x) = \theta_0 + \theta_1 x$



{Derivation} → purpose

$x^n = nx^{n-1}$

$\frac{\partial (x^2)}{\partial x} = 2x$

x^2

Cost function

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

→ Cost function

↳ Squared Error Function

What we need to solve

$$\underset{\theta_0,\theta_1}{\text{minimize}} \quad \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)})-y^{(i)}\right)^2$$

$$\Downarrow$$

$$\underset{\theta_0,\theta_1}{\text{minimize}} \quad J(\theta_0,\theta_1)$$

(*) $h_\theta(x)=\theta_0+\theta_1 x$ If $\theta_0=0$

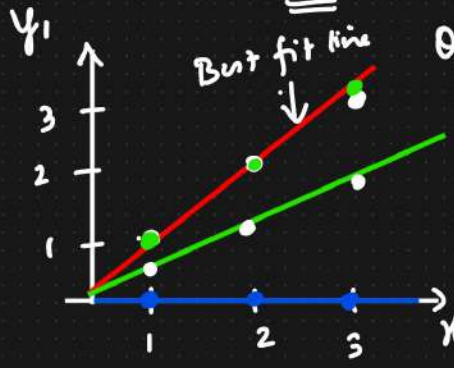
$h_\theta(x)=\theta_1 x$ → slope

$\theta_1=1$ (1, 1)

$\theta_1=0.5$ (2, 2)

(3, 3)

$\theta_1=0$



$\theta_1=2$

$\theta_1=1$

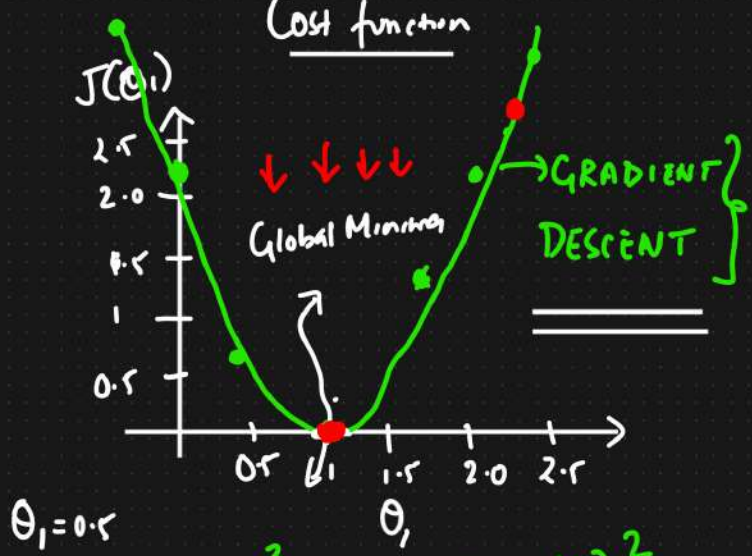
$J(\theta_1)=0$

$$J(\theta_1)=\frac{1}{2m}\sum_{i=1}^{3}\left(h_\theta(x^{(i)})-y^{(i)}\right)^2$$

$$=\frac{1}{2m}\left[(1-1)^2+(2-2)^2+(3-3)^2\right]$$

$$J(\theta_1)=0$$

Cost function



$\theta_1=0.5$

$$J(\theta_1)=\frac{1}{2m}\sum_{i=1}^{3}\left(h_\theta(x^{(i)})-y^{(i)}\right)^2$$

$$=\frac{1}{2m}\left[(0.5-1)^2+(1-2)^2+(1.5-3)^2\right]$$

$$=\frac{1}{2\times3}\left[0.25+1+2.25\right]\approx 0.58$$

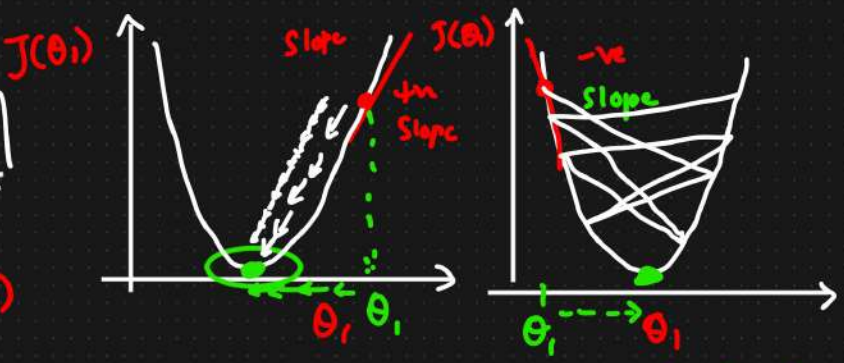
$$J(\theta_1) = \frac{1}{2m}\left[(0-1)^2 + (0-2)^2 + (0-3)^2\right]$$

$$= \frac{1}{6}\left[1+4+9\right]$$

≈ 2.3

$\alpha \Rightarrow$ Huge

$\alpha : 0.01$



Convergence Algorithm

Repeat until convergence

{

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

derivative (slope)

Learning Rate

}

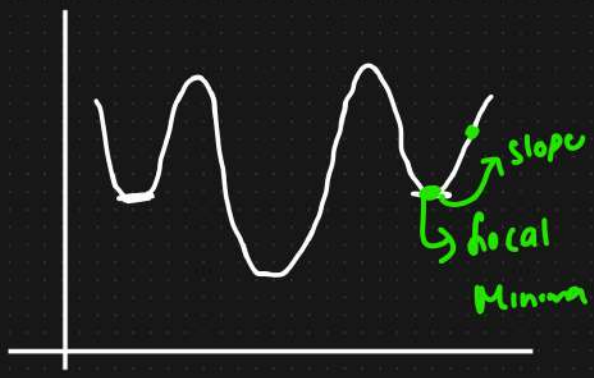
$\theta_1 := \theta_1 - \alpha(+ve)$

$\theta_1 := \theta_1 - \alpha(-ve)$

$\theta_1 := \theta_1 + \alpha(ve)$

$\theta_1 := \theta_1 - \alpha(0)$

$\theta_1 := \theta_1$



GRADIENT DESCENT Algorithm

Repeat until convergence

{

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

}

$j : 0$ and 1

$$\frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_j} \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

$\frac{1}{2m}$ x^2 ✓ $\frac{2}{2m}$ x

Convergence Algorithm:

$$h_\theta(x) = \theta_0 + \theta_1 x$$

$x^2 \Rightarrow 2x$

$$\frac{\partial}{\partial \theta_1}(\theta_1 x) = x$$

$$\begin{cases} j=0 \Rightarrow \dfrac{\partial}{\partial \theta_0} J(\theta_0, \theta_1) = \dfrac{1}{m} \displaystyle\sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right) \\ j=1 \Rightarrow \dfrac{\partial}{\partial \theta_1} J(\theta_0, \theta_1) = \dfrac{1}{m} \displaystyle\sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right) x^{(i)} \end{cases}$$

$\{\alpha = 0.001\}$ α = Learning Rate

Repeat until convergence

{

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)$$

$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right) x^{(i)}$$

}

Performance Metrics

R^2 and Adjusted R^2

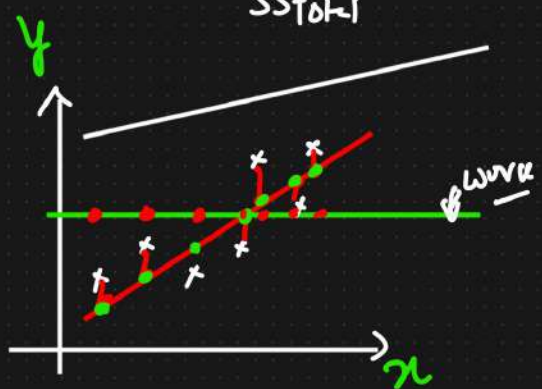
-ve ???

$h_\theta(x)$

$$R^2 = 1 - \frac{SS_{Res}}{SS_{Total}} = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} = 1 - \boxed{\frac{\text{low}}{\text{High}}}$$

Small number = Big number = 90%

Higher



$R^2 = 85\%$

2 $R^2 = 90\%$

3 $R^2 = 91\%$ ✓ → Model

Adjusted R^2

p = features or predictors

$$R^2_{adjusted} = 1 - \frac{(1-R^2)(N-1)}{N-p-1}$$

(✓ ↑ Big ✓)

$p=2 > p=3$

$N-p-1$ >> $p=3$

= N = No. of datapoint

P = No. of predictors

p >>>

		86%
$p=2$	$= R^2 = 90\%$	$R^2_{adjusted} = 86\%$ ↓↓
$p=3$	$= R^2 = 91\%$ ↑↑	$R^2_{adjusted} = 82\%$ ↓↓
	R^2 ↑↑↑	82%

Day 2 – Five Machine Learning Algorithm

Agenda

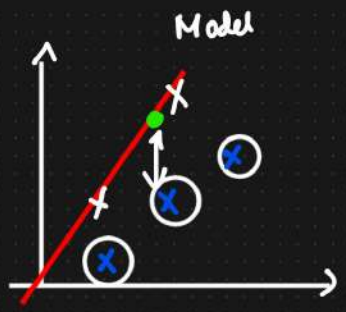
① Ridge and Lasso Regression
② Assumption of Linear Regression
③ Logistic Regression
④ Confusion Matrix
⑤ Practicals Implementation

① Ridge And Lasso Regression

$$\text{Cost function } J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^i) - y^{(i)})^2$$

$\theta_0 : 0$

$J(\theta_0, \theta_1) = 0$ ↓↓↓



{Training data}

Overfitting

✓ (Low Bias)

① Model Accuracy is bad with Training data
② Model Accuracy is also bad with Test data

Underfitting { High Bias, High Variance }

Model performs well → Training data

Fails to perform well → Test Data ✓ (High Variance)

Model 1

Traing Acc = 90%

Test Acc = 80%

⇓

{ Overfitting
Low Bias, High Variance }

Model 2

Traing Acc = 92%

Test Acc = 91%

⇓

{ Generalized Model }

{ Low Bias
Low Variance }

Model 3

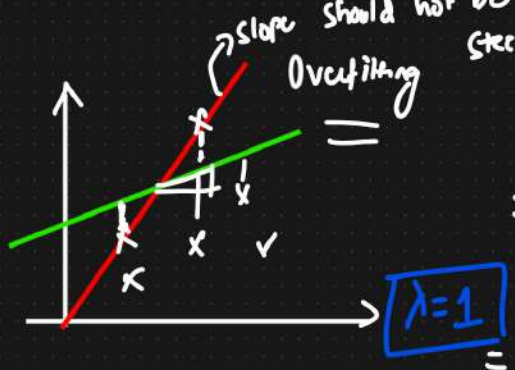
Traing Acc = 70%.

Test Acc = 65%

⇓

Underfitting

High Bias, High Variance



$h_\theta(x) = \hat{y}$ $\theta_1 = 2$ $\theta_0 = 0$

$h_\theta(x) = \theta_0 + \theta_1 x$

$h_\theta(x) = \theta_1 x$ → slope

$J(\theta_1) = 0$

$= \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$

$\lambda = 1$

$= (\hat{y}^i - y^{(i)})^2 + \lambda (\text{slope})^2$ ✓

$= 0 + 1(2)^2$

$= 4$ ⇓⇓ ↓↓

$= (\hat{y}^{(i)} - y^{(i)})^2 + \lambda (\text{slope})^2$

(Small value) $+ 1(1.5)^2$

$=$ (Small value) $+ 2.25$

≅ 3 ↓↓

Ridge (L2 Regularization)

{ Prevent Overfitting }

situations { Hyperparameter }

R^2, adjusted R^2

λ → Hyperparameter ✓

Convergence

{ }

Lasso (L1 Regularization)

→ feature selection

$= (\hat{y} - y)^2 + \lambda |\text{slope}|$

$|\theta_0 + \theta_1 + \theta_2 + \theta_3 + \theta_4 + \theta_5 \cdots + \theta_n|$

$h_\theta(x) = \hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4 + \cdots + \theta_n x_n$

① Preventing Overfitting } → { L1 Regulation }
② Feature Selection } → { L2 Regularization }

{ λ → Cross validation }

⇓

Performance metrics

⇓

Ridge Regression (L2 Norm)

Cost function = $(h_\theta(x^{(i)}) - y^{(i)})^2 + \lambda (slope)^2$

④

Purpose : Preventing Overfitting

$|\theta_0 + \theta_1 + \theta_2 + \theta_3 \dots + \theta_n|$

Lasso Regression (L1 Reg)

Cost function = $(h_\theta(x^{(i)}) - y^{(i)})^2 + \lambda |slope|$

Purpose : ① Prevent Overfitting ② Feature Selection

Assumption of Linear Regression

① Normal / Gaussian Distribution → Model will get trained well

✓ ② {Standardization {Scaling data} → Z-score $\mu = 0, \sigma = 1$}

③ Linearity

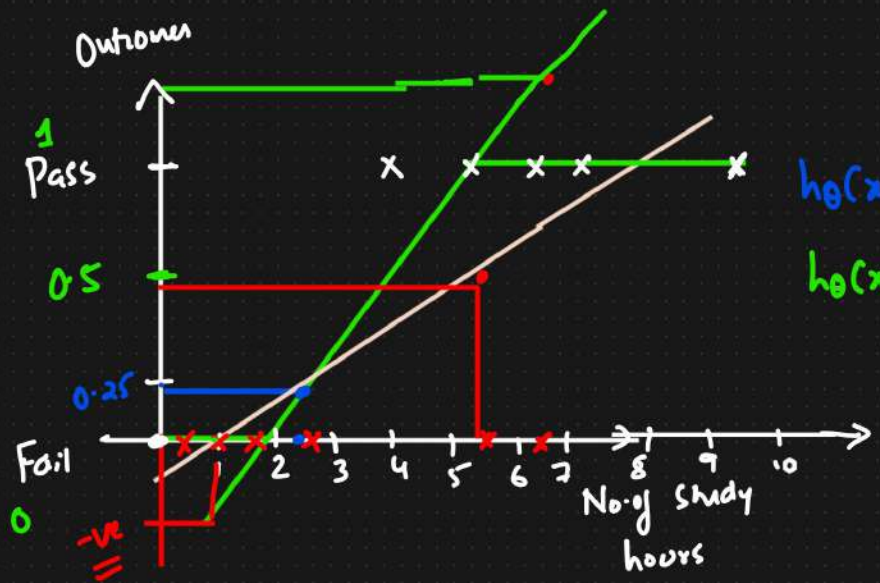
X_3 [X_1 X_2] [Y] ↗ 95%

Variation Inflation factor?

④ Multi Collinearity

Logistic Regression (classification) → Binary classification

No. of study	No. of play	P/F
—	—	P
—	—	F



Linear Regression ?? ✓

$h_\theta(x) < 0.5 \Rightarrow 0 \rightarrow$ Fail

$h_\theta(x) \geq 0.5 \Rightarrow 1 \rightarrow$ PASS ✓

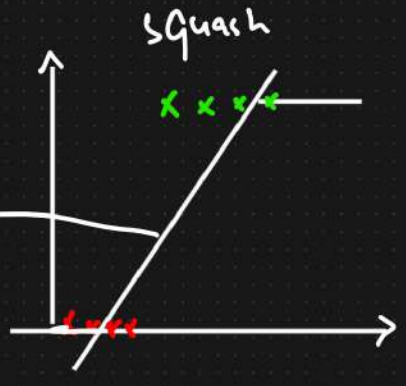
{ Sigmoid function }

0 to 1 ✓

Decision Boundary Logistic Regression

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 - \cdots + \theta_n x_n$$

$$\boxed{h_\theta(x) = \theta^T x}$$



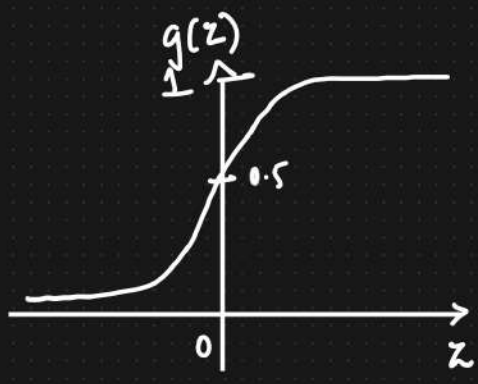
$h_\theta(x) = \theta_0 + \theta_1 x_1$

$h_\theta(x) = g(\theta_0 + \theta_1 x_1)$

Let $z = \theta_0 + \theta_1 x$

$h_\theta(x) = g(z)$

$$h_\theta(x) = \frac{1}{1+e^{-z}}$$ → Sigmoid or Logistic function



$g(z) \geq 0.5$ when $z \geq 0$ ✓

$$\boxed{h_\theta(x) = \frac{1}{1+e^{-(\theta_0+\theta_1 x)}}}$$

Training Set

$$\{(x^1, y^1), (x^2, y^2), (x^3, y^3) \dots (x^n, y^n)\}$$

$y \in \{0, 1\} \rightarrow$ 2 o/p

$$h_\theta(z) = \frac{1}{1 + e^{-z}} \qquad \boxed{z = \theta_1 x}$$

Change parameter θ_1 ?

Cost function

$$h_\theta(x) = \theta_0 + \theta_1 x$$

Linear Regression $J(\theta_1) = \frac{1}{m} \sum_{i=1}^{m} \overbrace{\frac{1}{2} (h_\theta(x^i) - y^i)^2}^{\text{Cost function}}$

Logistic Regression

$$\boxed{h_\theta(x) = \frac{1}{1 + e^{-(\theta_1 x)}}}$$

Logistic Regr Cost function $= \frac{1}{2} (h_\theta(x^{(i)}) - y^{(i)})^2$

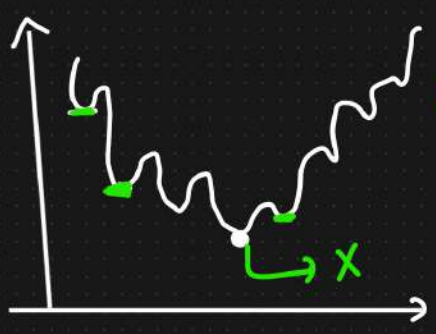
We cannot use this cost function for Logistic

$$h_\theta(x) = \frac{1}{1 + e^{-(\theta_1 x)}}$$

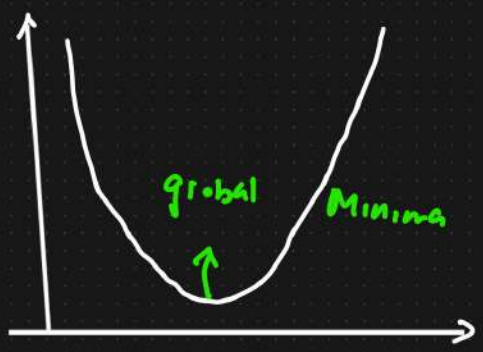
Gradient Descent

Gradient Descent

Non convex function



Convex function

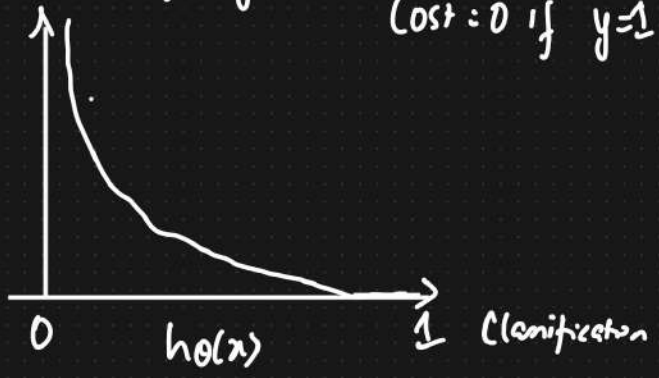


Logistic Regression Cost function

$$h_\theta(x) = \frac{1}{1+e^{-(\theta_1 x)}}$$

$$J(\theta_1) = \begin{cases} -\log(h_\theta(x^i)) & y=1 \\ -\log(1-h_\theta(x^i)) & y=0 \end{cases}$$

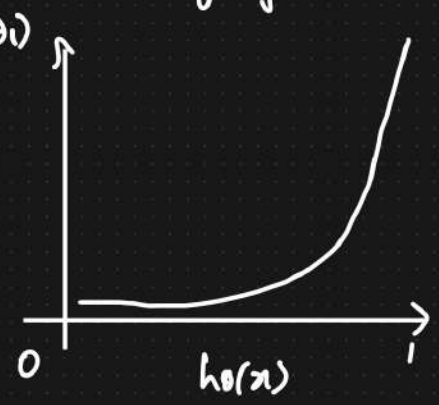
$J(\theta_1)$ if $y=1$



Cost: 0 if $y=1$, $h_\theta(x)=1$

Classification

if $y=0$



$$\text{Cost}(h_\theta(x^i), y) = \begin{cases} -\log(h_\theta(x)) & \text{if } y=1 \\ -\log(1-h_\theta(x)) & \text{if } y=0 \end{cases}$$

$$\boxed{\text{Cost}(h_\theta(x^i), y) = -y\log(h_\theta(x^i)) - (1-y)\log(1-h_\theta(x))}$$

if $y=1$

$\Downarrow$ cost function.

$$\text{Cost}(h_\theta(x^i), y)) = -\log(h_\theta(x^i))$$

if $y=0$

$$\text{Cost}(h_\theta(x^i), y) = -\log(1-h_\theta(x^i))$$

$$J(\theta_1) = -\frac{1}{2m}\sum_{i=1}^{m}\left[(y^i \log(h_\theta(x^i)) + (1-y^i)\log(1-h_\theta(x^i))\right]$$

↓ cost

$$h_\theta(x^i) = \frac{1}{1+e^{-\theta_1 x}}$$

→ Repeat until convergence

{

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j}(J(\theta_1))$$

}

Performance Metrics {Classification problem}

x_1	x_2	y (Actual)	$\hat{y}$ (O/p)
–	–	0	1
–	–	1	1
–	–	0	0
–	–	1	1
–	–	1	1
–	–	0	1
–	–	1	0

{Actual}

Pred	1	0
1	3	2
0	1	1

Prediction	1	0
1	TP	FP↓
0	FN↓	TN

Actual

→ Confusion matrix

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

② 0 → 900, 1 → 100 } Imbalanced Dataset

$$= \frac{3+1}{3+2+1+1} = \frac{4}{7}$$

$$= 0.57 = 57\%$$

0 → 600, 1 → 400 } Balanced Data

0 : 900, 1 : 100 } Biased

{ Model → 0 = $\frac{900}{1000} = 90\%$ }

. TPR, Sensitivity

① Precision

$$\frac{TP}{TP + FP}$$

② Recall

$$\left\{ \frac{TP}{TP + FN} \right\}$$

③ F-Score.

{ Tom Stock market is going to crash } → Precision

{ Spam classification } → Precision

{ HAS CANCER OR NOT } → Recall

Pred \ Actual	1	0
1	TP	FP
0	FN	TN

$$F\text{-}\beta\text{eta} = (1 + \beta^2) \frac{\text{Precision} \times \text{Recall}}{\beta^2 \times \text{Precision} + \text{Recall}}$$

$$\beta = 1 \quad = (1+1) \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1-Score

$$= \frac{2\,(\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

Harmonic mean

$$= \frac{2xy}{x+y}$$

$$\beta = 0.5 \quad (1 + (0.5)^2) \frac{P \times R}{(0.25)\,P + R}$$

F0.5 Score

$\beta = 2$ FN >> FP.

F2 Score

3rd Day → Machine Learning Algorithms

Agenda

① Practicals → Simple Examples
② Naive Bayes Intuition
③ KNN algorithms

Previous Session

① Linear Regression
② Ridge & Lasso
③ Logistic Regression

⇒ Complex

① Naive Bayes Intuition {Classification}

⇓

{BAYES THEOREM}

Rolling a Dice

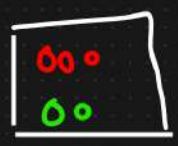
{1, 2, 3, 4, 5, 6}

$P(1) = \frac{1}{6}$ $P(3) = \frac{1}{6}$

$P(2) = \frac{1}{6}$

{Independent Events}

Dependent Event



First Event ✓

$P(R) = \frac{3}{5}$ → R ✓

Given Marble

$P(G) = \frac{2}{4} = \frac{1}{2}$ → G

Dependents

$P(G) = \frac{2}{5}$

$P(R) = \frac{3}{4}$

$P(R \text{ and } G) = P(R) * P(G/R)$ → Conditional probability

$P(A \text{ and } B) = P(A) * P(B/A)$

$\Rightarrow$ P(A and B) = P(B and A) {Yes}

$P(A) * P(B/A) = P(B) * P(A/B)$

$$P(B/A) = \frac{P(B) * P(A/B)}{P(A)}$$

→ Bayes Theorem

(RUX Naive Bayes

I/P

x_1	x_2	x_3	x_4	x_5	...	x_n	y → o/p
→ –	–	–	–	–		–	– ✓
→							
→							

$$P(y/x_1,x_2,x_3 \dots x_n) = \frac{P(y) * P(x_1,x_2 \dots x_n/y)}{P(x_1,x_2 \dots x_n)}$$

Yes or No

$$= \frac{P(y) * P(x_1/y_1) * P(x_2/y_2) * P(x_3/y_3) \dots P(x_n/y_n)}{P(x_1) * P(x_2) * P(x_3) * \dots P(x_n)}$$

DATASET

x_1	x_2	x_3	x_4	y
→				Yes ✓
				No ✓

$$P(y=Yes/x_i) = \frac{P(Yes) * P(x_1/Yes) * P(x_2/Yes) * P(x_3/Yes) * P(x_4/Yes)}{P(x_1) * P(x_2) * P(x_3) * P(x_4)}$$

Constant Ignore → # fixed

$$P(y=No/x_i) = \frac{P(No) * P(x_1/No) * P(x_2/No) * P(x_3/No) * P(x_4/No)}{P(x_1) * P(x_2) * P(x_3) * P(x_4)}$$

Constant → # fixed

x_i → Yes / No

$P(Yes|x_i) = 0.13$ $\quad P(No|x_i) = 0.05$

$\Downarrow$ $\quad \geq 0.5 \Rightarrow 1$

$< 0.5 \Rightarrow 0$

$$P(Yes|x_i) = \frac{0.13}{0.13+0.05} = 0.72 = 72\%$$

$P(No|x_i) = 1 - 0.72 = 0.28 = 28\%$

DATASET

Binary class

Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

x_1

Outlook — P(Sunny / Yes)

	Yes	No	P(Y)	P(No)
Sunny	2	3	2/9	3/5
Overcast	4	0	4/9	0/5
Rain	3	2	3/9	2/5
Total	9	5		

Temperature

	Yes	No	P(Y)	P(N)
Hot	2	2	2/9	2/5
Mild	4	2	4/9	2/5
Cold	3	1	3/9	1/5
Total	9	5		

PLAY

		P(Yes)	P(N)
Yes	9	9/14	5/14
No	5		
Total	14		

→ Test (Sunny, Hot) → O/P

$$P(Yes|(Sunny, Hot)) = P(Yes) * P(Sunny/Yes) * P(Hot/Yes)$$

$P(\text{Sunny}) * P(\text{Hot})$

$= \frac{1}{14} * \frac{2}{1} * \frac{2}{9}$

$= \frac{2}{63} = 0.031$

$$P(\text{No} \mid \text{Sunny, Hot}) = \frac{P(\text{No}) * P(\text{Sunny}/\text{No}) * P(\text{Hot} \mid \text{No})}{P(\text{Sunny}) * P(\text{Hot})} \rightarrow \text{Constant}$$

$= \frac{5}{14} * \frac{3}{5} * \frac{2}{5}$

$= \frac{3}{35} = 0.085$

$P(\text{Yes} \mid \text{Sunny, Hot}) = 0.031 = 1 - 0.73 = 0.27 = 27\%$

$P(\text{No} \mid \text{Sunny, Hot}) = 0.085 = \frac{0.085}{0.031 + 0.085} = 0.73 = 73\%$

→ (Sunny, hot) ⟶ Yes or No

Answer → No ✓

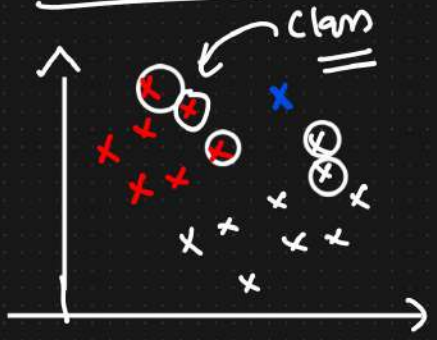
Assignment

('Overcast, Mild') ⟶ Naive Bayes ?

② KNN Algorithm {K Nearest Neighbour}

- Classification
- Regression

① Classification



K Nearest Neighbour

K = 5

Maximum No

Red = 3

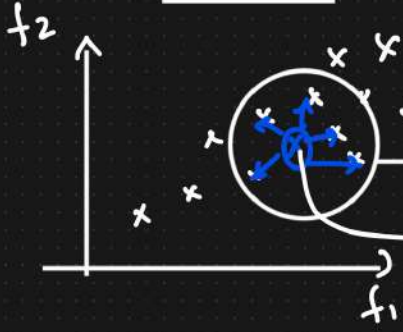
White = 2

K = 1 to 50

K = 5 → Hyperparameter

Error Rate ↑↑.

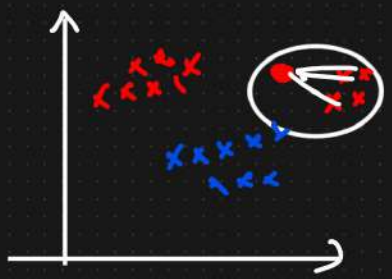
Regression



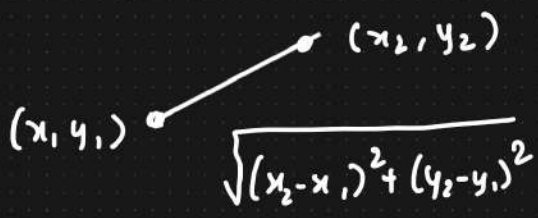
K Nearest

① Outliers

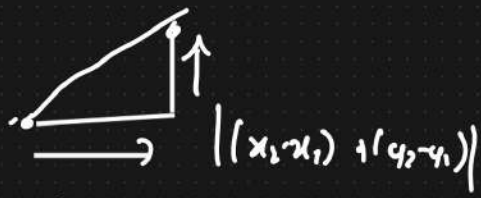
② Imbalanced



Euclidean Distance ✓



Manhattan Distance ✓



|(x2 - x1) (y2 - y1)|

Day 4 - Machine Learning Algorithms

Agenda

1. Decision Tree CLASSIFICATION
2. DECISION TREE REGRESSION
3. PRACTICAL IMPLEMENTATION
4. Ensemble Techniques

Agenda

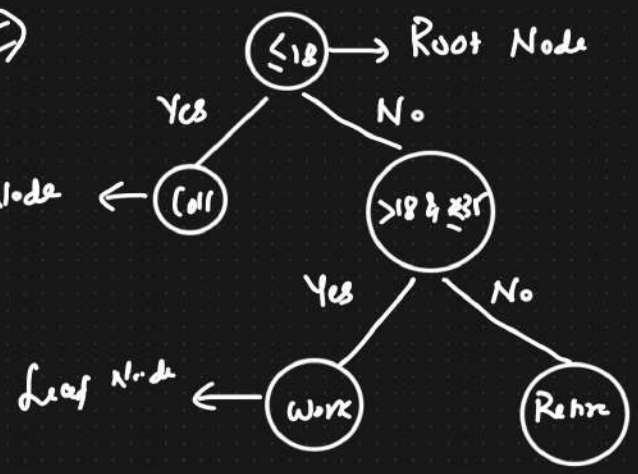
{DAY 1, DAY 2, DAY 3} ⇓ Experience

Decision Tree {Solving many usecase}

↳ Regression
↳ Classification

Regression & Classification ⇒ Decision Trees

```
if (age ≤ 18):
    Print ("College")
elif (age >18 and age ≤ 35):
    Print (Work)
else :
    Print ("Retire")
```



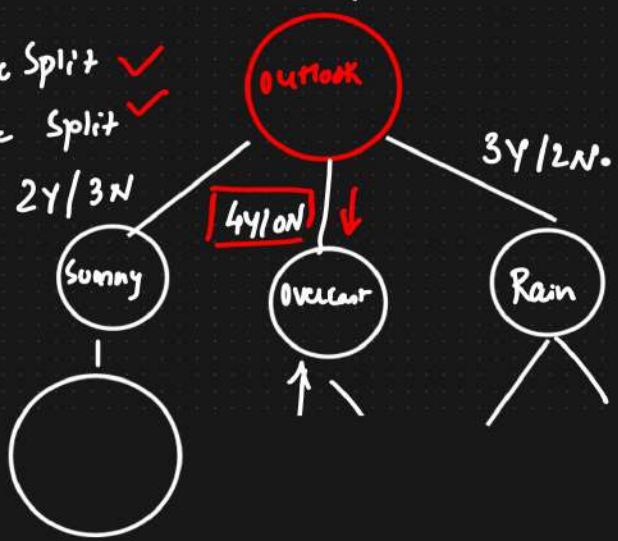
DECISION TREE

Nest if else ⇒ Decision Tree

CLASSIFICATION 9Y/5N

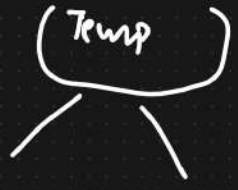
Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Pure Split
Impure Split



① Purity → Pure Split ??

↳ Entropy
↳ Gini Impurity



Pure Leaf Node

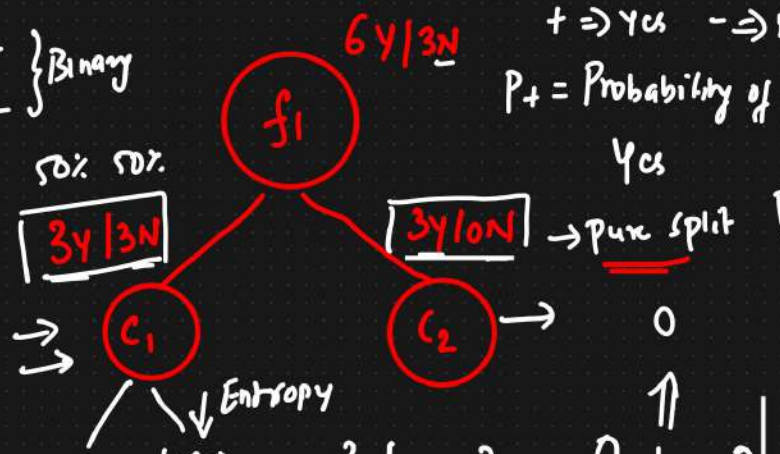
Leaf Node Pure

② How the features are selected
↳ Information Gain? }

① Entropy

$$H(S) = -P_+ \log_2 P_+ - P_- \log_2 P_-$$

+ } Binary
−



+ ⇒ Yes − ⇒ No

P_+ = Probability of Yes

→ Pure split

0

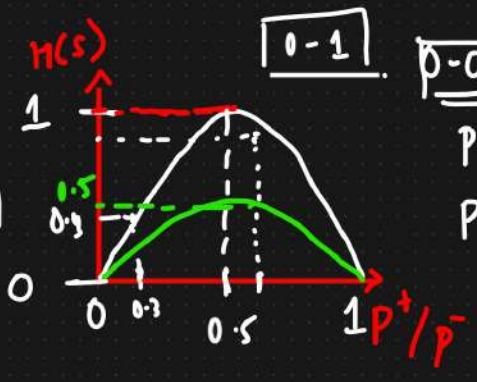
$$H(S) = -\frac{3}{3}\log_2\frac{3}{3} - \frac{0}{3}\log_2\frac{0}{3}$$

$$= -1 \log_2 1$$

$$= 0 \rightarrow \text{Pure Split}$$

① Gini Impurity

$$G.I = 1 - \sum_{i=1}^{n} (p)^2$$



$p^+ = 0.5$

$p^- = 0.5$

$p = 1-q$

$q = 1-p$

$$H(S) = -\frac{3}{6}\log_2 3/6 - \frac{3}{6}\log_2 3/6$$

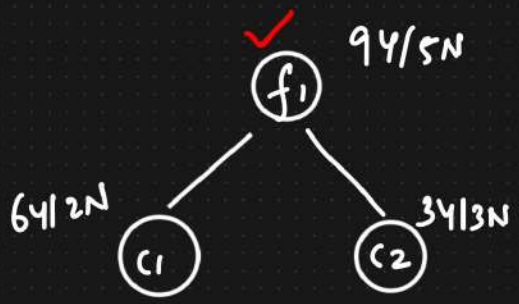
$$= 1$$

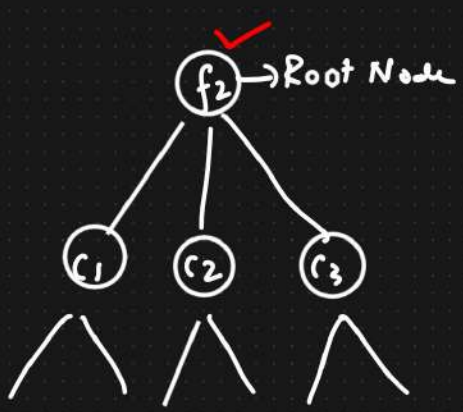
↳ Impure Split

Purity Test → Entropy

f1 f2 f3

② Which feature to take to split??

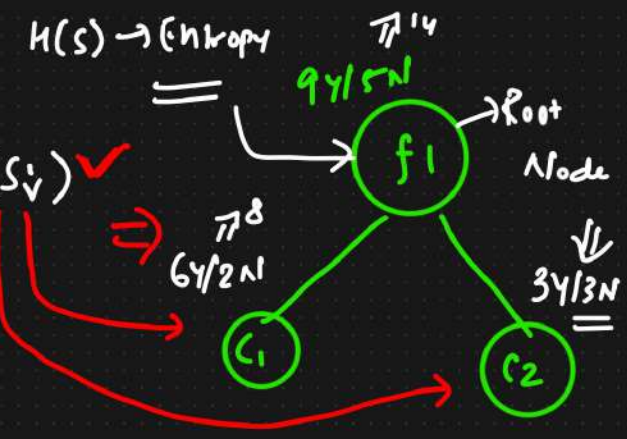




Information Gain

$$Gain(S, f_1) = H(S) - \sum_{v \in Val} \frac{|S_v|}{|S|} H(S_v)$$

(Root Node)



$$H(S) = -p_+ \log_2 p_+ - p_- \log_2 (p_-)$$

$$= -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right)$$

$$\approx = \boxed{0.94}$$

$$H(C_1) = -\frac{6}{8}\log_2\frac{6}{8} - \frac{2}{8}\log_2\frac{2}{8}$$

$$H(C_1) = 0.81 \qquad \boxed{H(C_2) = 1}$$

$$Gain(S, f_1) = 0.94 - \left[\frac{8}{14} \times 0.81 + \frac{6}{14} \times 1\right]$$

$$Gain(S, f_1) = 0.049$$

$$Gain(S, f_2) = 0.051$$

Using which feature should I start splitting first

f_2

$$Gain(S, f_2) >> Gain(S, f_1)$$

② GINI Impurity ✓

$n = 2$ output { Yes / No

$$G.I = 1 - \sum_{i=1}^{n} (p)^2 \rightarrow$$

$$= 1 - \left[(p_+)^2 + (p_-)^2\right]$$

{Entropy}

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

$$= 1 - \left[\frac{1}{2}\right] = \underline{0.5}$$

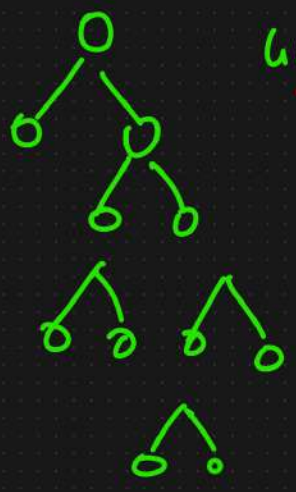
2Y/2N ⇒ Impure Split

Entropy = 1

Gini Impurity = 0.5

Entropy → fog

100



Gini Impurity → Simple Maths

Fast

Gini >> Entropy

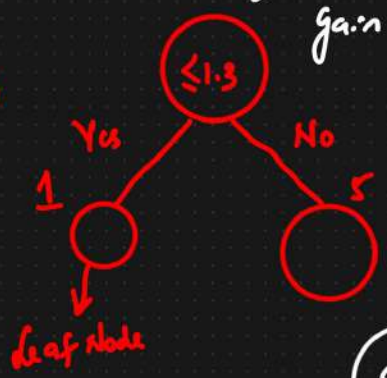
→ continuous

f1	O/P
2.3	
1.3	
4	
5	
7	
3	

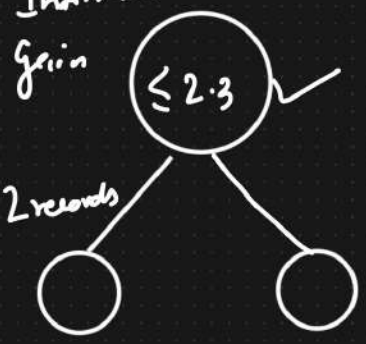
⇒

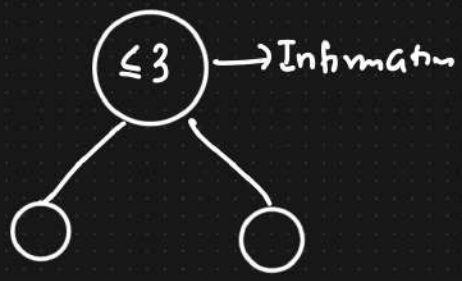
f1
1.3
2.3
3
4
5
7

O/P →



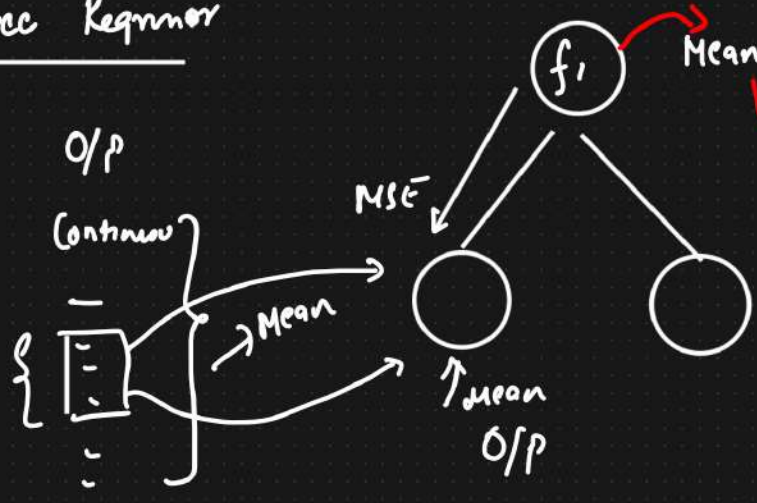
Best Info gain





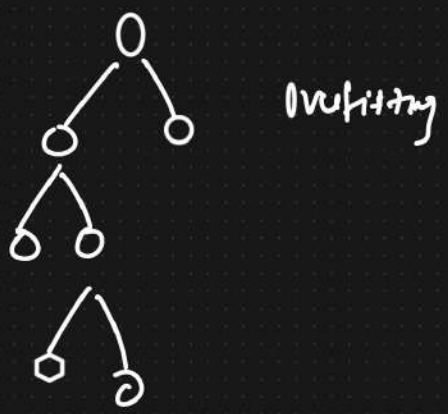
Decision Tree Regressor

f1	f2	O/P



MSE or MAE

$$\frac{1}{2m}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

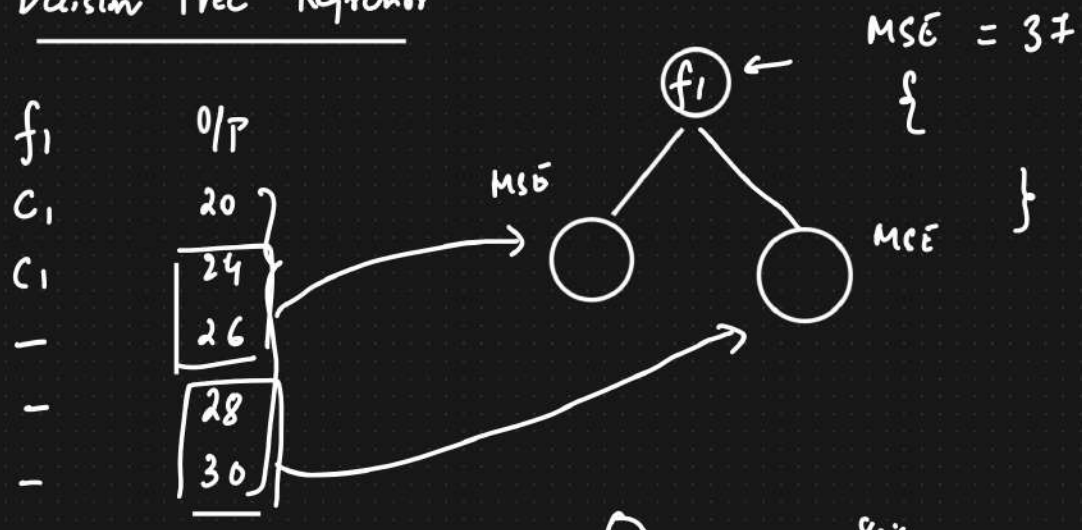


Hyperparameters

Decision → Overfitting

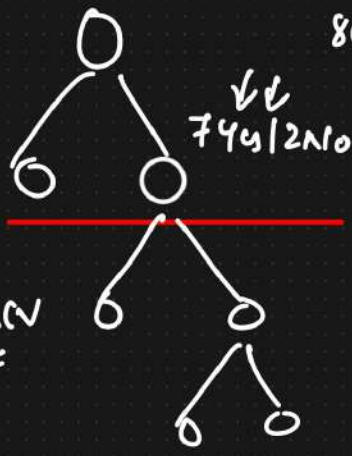
{ ① Post Pruning
② Pre Pruning }

Decision Tree Regressor



post pruning

pre pruning



Hyperparameter

GridSearchCV

max_depth, max_leaf

Day 5 — Machine Learning Algorithms

Agenda

1. Ensemble Techniques → Bagging, Boosting
2. Random Forest
3. AdaBoost
4. Xgboost → Youtube channel

{ DJANGO } FLASK EDA Deep Learning

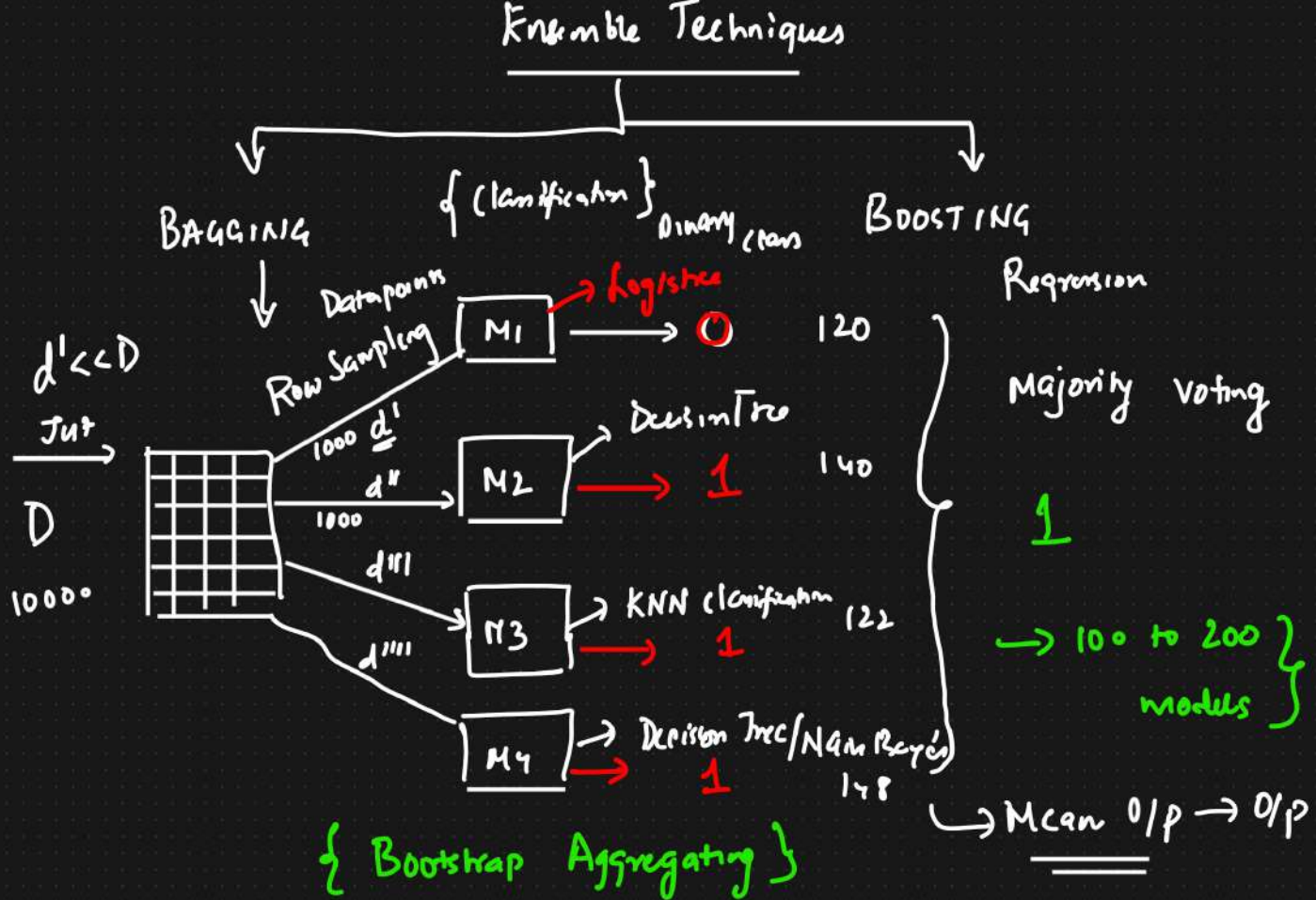
Stats ML NLP

Ensemble Techniques

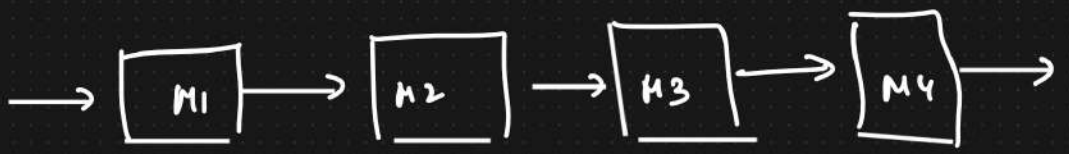
① Classification & Regression

↳ 1 Algorithm → Cl, Reg

Multiple Algorithms to Solve a problem?



Boosting



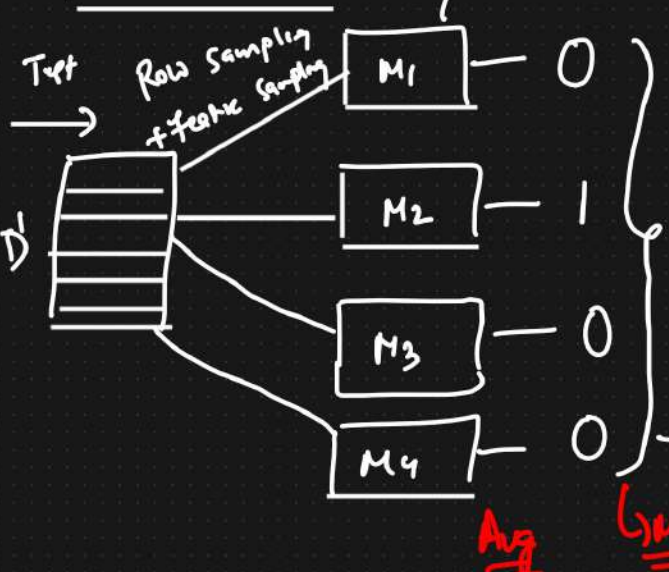
Weak learner = Weak learner = weak learner = weak learner → {STRONG LEARNER}

BAGGING → ① RANDOM FOREST CLASSIFIER ② Random Forest Regression

BOOSTING → ① Adaboost ② Gradient ③ Xgboost

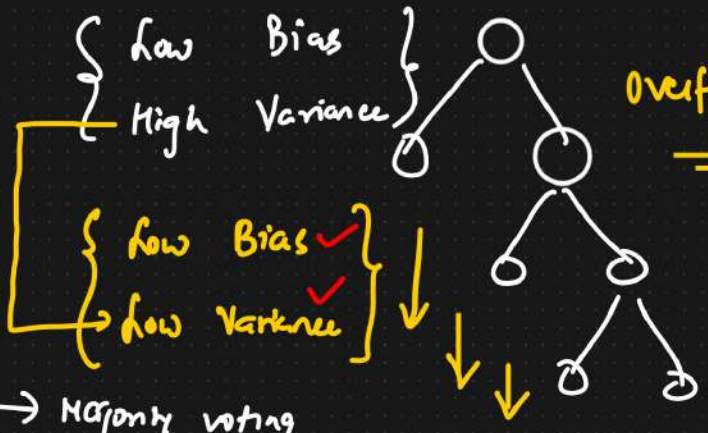
① Random Forest classifier and Regressor

Random Forest → Decision Trees



f_1 f_2 f_3 f_4

What is the main problem of DT?



Overfitting??

① Normalization ?!

Or Decision Tree

⇓

No.

② KNN { Standardization } ??

1. ⇓ Yes

↓ Impacted by Outlier??

Yes

{ Euclidean , Manhattan }

③ Random Forest → Outliers ⇒ NO → { check it google }

Bagging = Random Forest

Custom Bagging

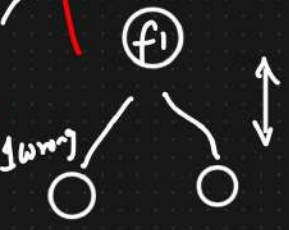
② Boosting

i) Adaboost → Decision Tree

Overall = 1

f_1	f_2	f_3	f_4	O/p	Weight	
–	–	–	–	Yes ✓	1/7	0.05
–	–	–	–	No ✓	1/7	0.05
–	–	–	–	– ✓	1/7	0.05
X –	–	–	–	–	1/7	↑0.349
–	–	–	–	– ✓	1/7	0.05
–	–	–	–	– ✓	1/7	0.05
–	–	–	–	– ✓	1/7	0.05

STUMPS



information gain & entropy

f2 f3

① { weak learner }

Total Error (TE) = 1/7

② Performance of Stump

$= \frac{1}{2}\log_e\left(\frac{1-TE}{TE}\right)$

$= \frac{1}{2}\log_e\left(\frac{1-1/7}{1/7}\right)$

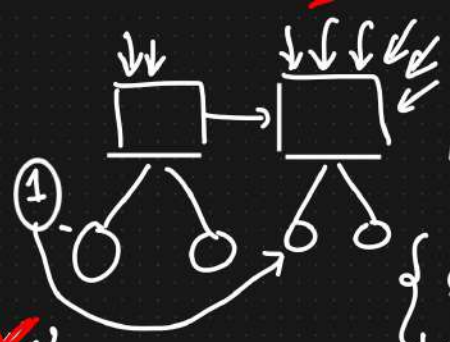
$= 0.895$

③ New Sample Weight = Weight * e^{-Ps} = $\frac{1}{7} \times e^{-0.895}$ = 0.05

Correct Records

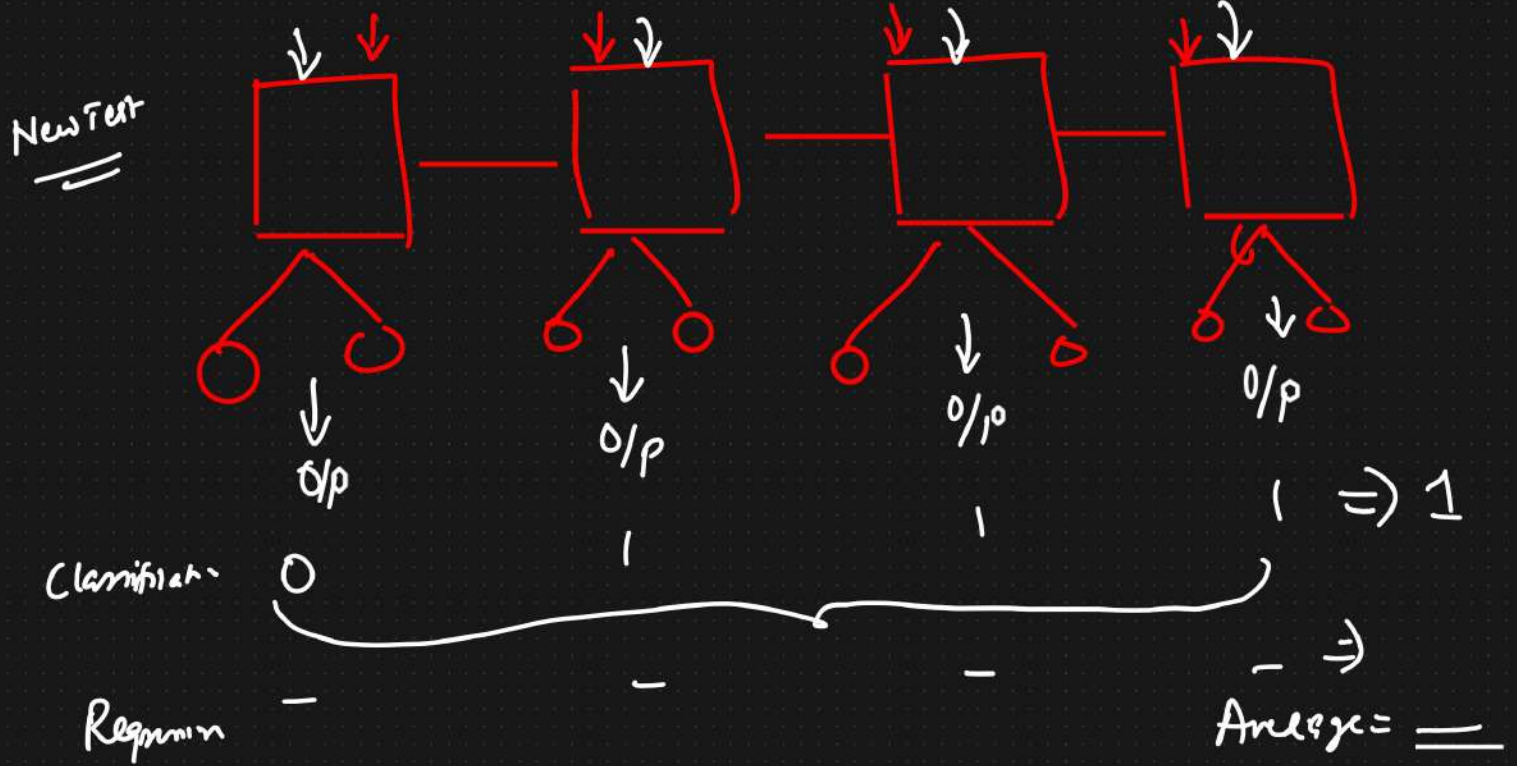
Incorrect record = Weight * e^{Ps} = $1/7 \times e^{0.895}$ = 0.349

New weight	Is it 1 ? Normalized weight	Buckets
0.05 ÷ 0.649	0.07	[0 - 0.07]
0.05 ÷ 0.649	0.07	[0.07 - 0.14]
0.05 ÷ 0.649	0.07	[0.14 - 0.21]
→ 0.349	0.537	{ [0.21 - 0.747] ✓ }
0.05	0.07	[0.747 - 0.751]
0.05	0.07	[—]
0.05	0.07	[—]
0.649	≈ 1	



Randomly . Creat { some number between [0-1]

0.537
0.21
0.747



Black modes VS White box Models

ANN → Black Box

→ Linear Regression → White box

Random Forest → Black box

Decision Tree → White box

Day 6 – Machine Learning Algorithms

Unsupervised ML

1. K Means Clustering
2. Hicrarichal clustering
3. Silhoutte Score
4. DBScan Clustering

Agenda

1. Svm & svR
2. Xgboost
3. PCA

Unsupervised ML

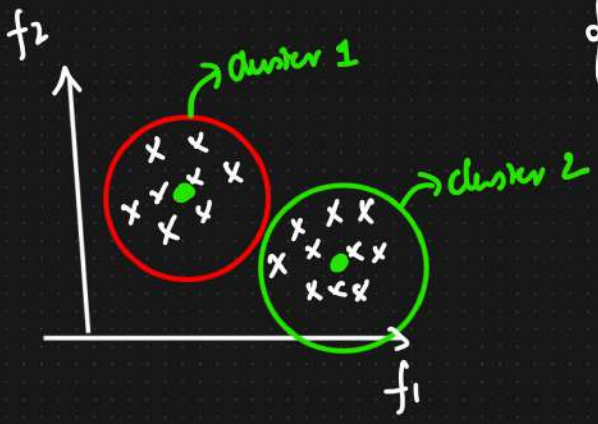
O/p

Clusters

{ Similar kind of data }

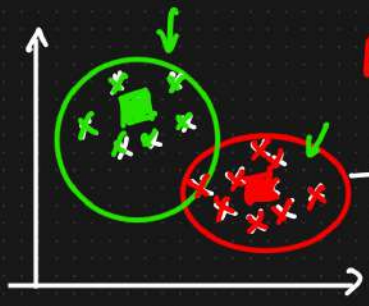
f_1	f_2
–	–
–	–
–	–
–	–

K Means Clustering



Custom Ensemble Technique

K Means → K = centroids



K=2

High dimension

K=2

centroids

① We try K values ⇒ suitable K=2

② Initialize K number of centroids ✓

③ Compute the avg to update centroids ✓

Validating

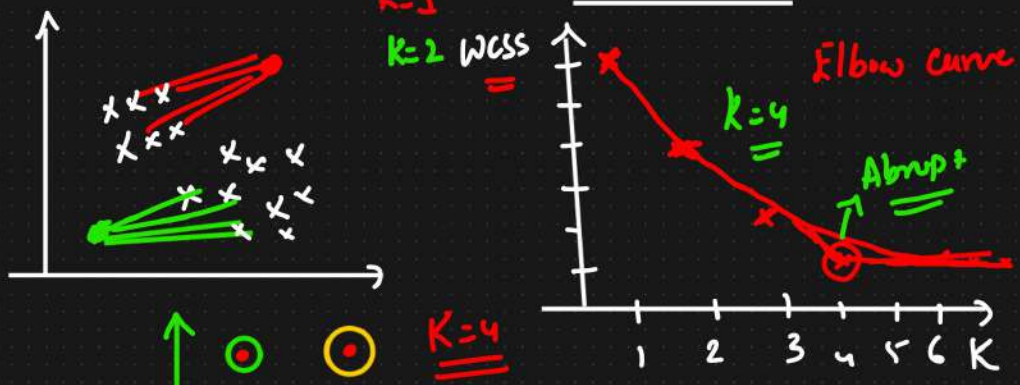
Within cluster sum of square

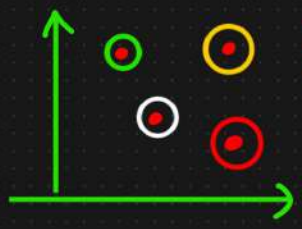
Elbow method (K value)

K=1

K=2 WCSS

for i=1,10



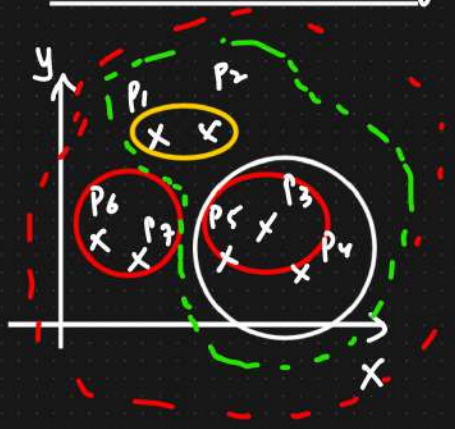


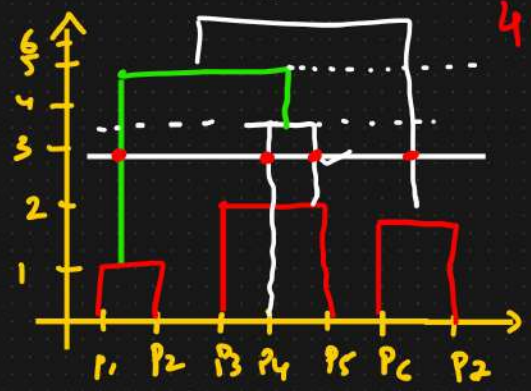
K=4

② Hierarchical Clustering

You need find the longest vertical line that has no horizontal line passed through it.

Dendrogram





4 clusters

Dataset is small

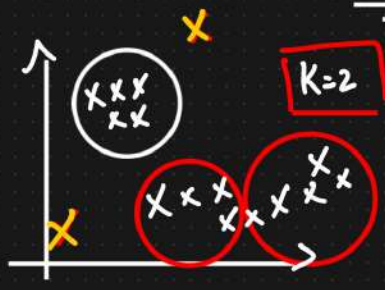
Dataset is large

Kmeans

Max Time is taken by KMeans or

Hierarchal clustering ??

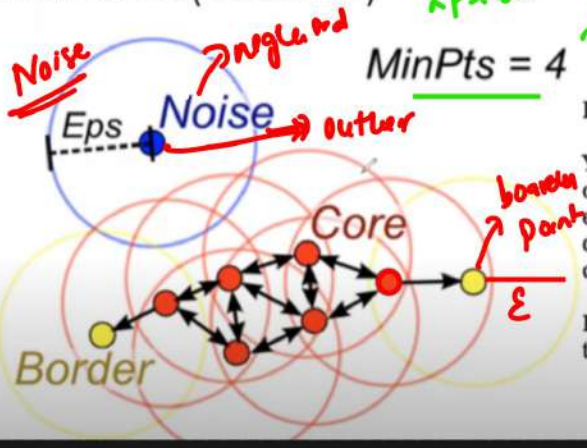
↳ Max Time



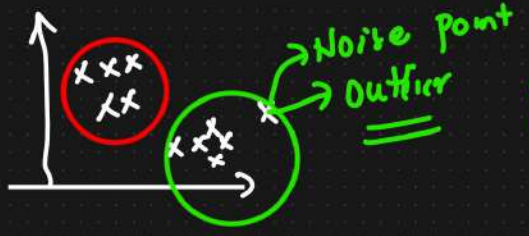
Validate Clustering Models

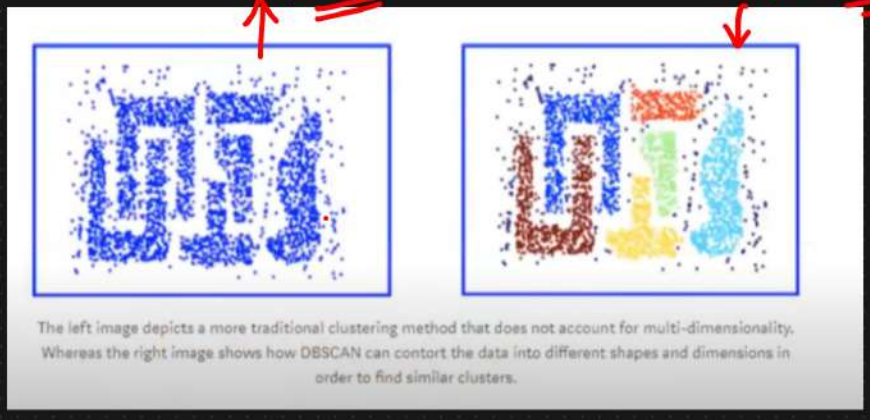
DBScan Clustering

Density-Based Spatial Clustering of Applications with Noise(DBSCAN)



① Epsilon
② Min pts
③ Core points
④ Border points
⑤ Noise point

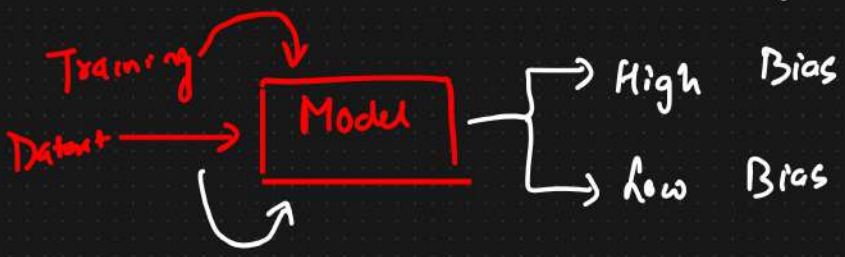




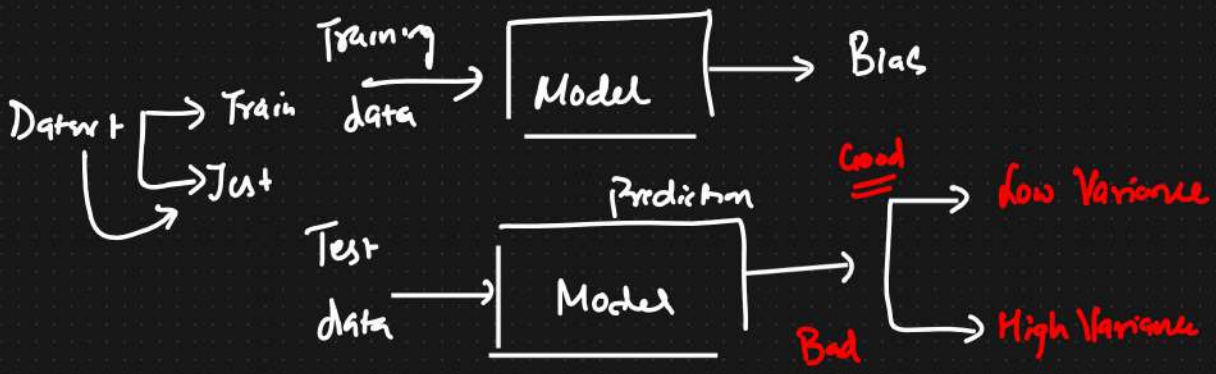
Defn of Bias And Variance

Training Dataset = 90%
Test Dataset = 70%
} ⇒ Overfitting
⇓
{ low Bias ✓ }
{ High Variance ✓ }

Bias : It is a phenomenon that skews the result of an algorithm in favor or against an idea.
↳ Training dataset



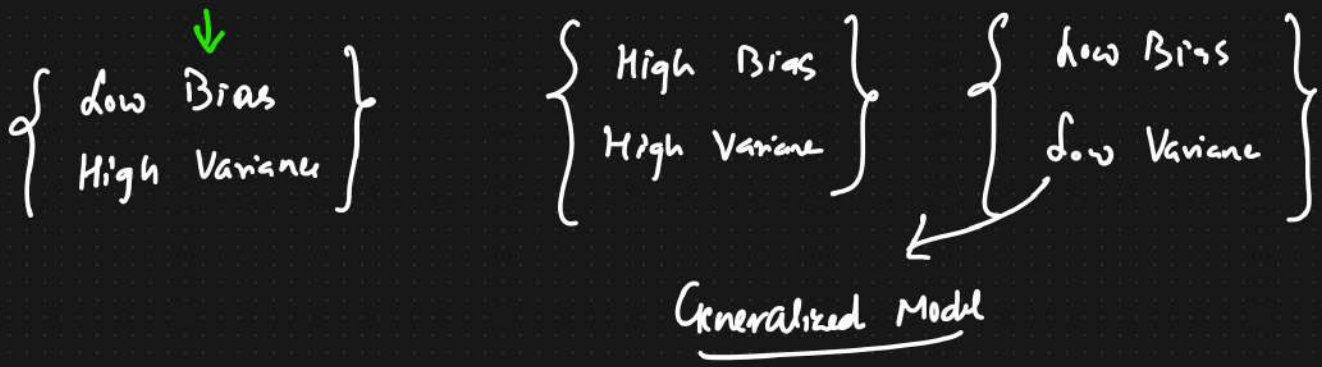
Variance : Variance refers to the changes in the model when using different portions of the training or test data



Model 1
Training Acc = 90%
Test Acc = 75%

Model 2
Train Acc = 60%
Test Acc = 55%

Model 3
Train Acc = 90%
Test = 92%


Low Bias
High Variance
High Bias
High Variance
Low Bias
Low Variance
Generalized Model

Day 7 : Xgboost CLASSIFIER AND REGRESSOR

Agenda

1. Xgboost classifier
2. Xgboost Regressor
3. SVM
4. SVR

$$\log\left(\frac{p}{1-p}\right) = \log\left(\frac{0.5}{0.5}\right) = 0$$

1. Xgboost Classifier

Extreme Gradient Boosting

{ Dataset }

Salary	Credit	Approval
<=50	B	0
<=50	G	1
<=50	G	1
>50	B	0
>50	G	1
>50K	N	1
<=50K	N	0

Base model → pr = 0.5

Residual: -0.5, 0.5, 0.5, -0.5, 0.5, 0.5, -0.5

Sim: 0.94

Binary DT

Salary: <=50 → [-0.5, 0.5, 0.5, -0.5], Sim = 0

Salary: >50 → [-0.5, 0.5, 0.5], Sim = 0.33

Credit: B → [-0.5], Sim = 1

Credit: G, N → [0.5, 0.5, -0.5], Sim = 0.33

$\lambda = 0$ λ ??

$$\text{Sim} = \frac{0.25}{0.5(1-0.5)} = \frac{0.25}{0.25} = 1$$

$$\frac{0.25}{0.75}$$

$$1 + 0.33 - 0 = 1.33$$

$\alpha = 0.01$ (learning)

$$\sigma[0 + \alpha(1)]$$

Sigmoid

$$\Downarrow$$

0 to 1 ✓

1. Create a Binary Decision Tree using the feature
2. Calculate Similarity weight

$$= \frac{\Sigma (\text{Residual})^2}{\Sigma(Pr(1-Pr)) + \lambda}$$

③ Information gain

New Reward → O/P

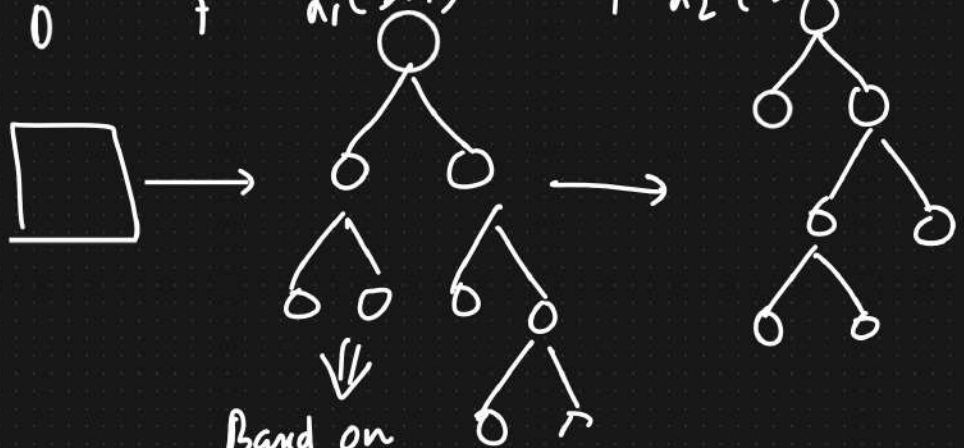
$$\sigma\left[0 + \alpha_1(DT_1) + \alpha_2(DT_2) + \alpha_3(DT_3) + \alpha_4(DT_4) + \cdots \alpha_n(DT_n)\right]$$

Xgboost → BLACK BOX Model

Pre pruning

$\lambda \rightarrow$ cross validation

$$0 + \alpha_1(DT_1) + \alpha_2(DT_2) + \alpha_3(DT_3) + \cdots + \alpha_n(DT_n)$$



Based on independent features

$$\frac{(-11-9+1+9+11)^2}{5+1} = \frac{1}{6} =$$

Base Model → 51

Sim = 76

[-11K, -9, 1, 9, 11]

② Xgboost Regressor

Exp	Gap	Salary	Res
2	Yes	40K	-11K
2.5	Yes	42K	-9K
3	No	52K	1K
4	No	60K	9K
4.5	Yes	62K	11K

O/P

$\lambda = 1$

EXP

≤ 2 | > 2

Sim = 65.5 | 28.8

[-11] | [-9, 1, 9, 11]

$\frac{121}{1+1} = 60.5$

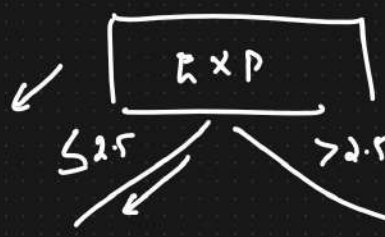
$\frac{(-9+1+9+11)^2}{4+1}$

$= \frac{144}{5} = 28.8$

$$\text{Similarity weight} = \frac{\sum(\text{Residuals})^2}{\text{No. of Resi} + \lambda}$$

Information

$= 60.5 + 28.8 - \frac{1}{6} = 89.13$



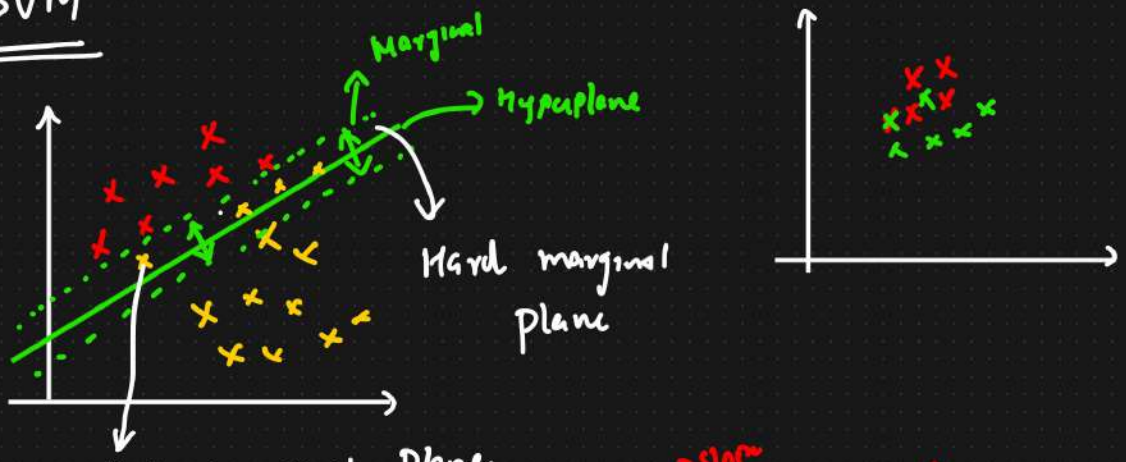
$\frac{-11-9}{2} = -10$ ✓

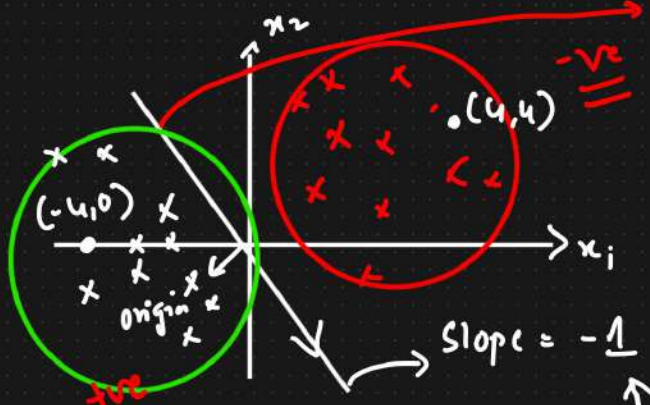
$\Rightarrow \frac{1+9+11}{3} = \frac{21}{3} = 7$

$$O/p = 51 + \alpha_1(-10) + \alpha_2(DT_2) + \alpha_3(DT_3) - \cdots + \alpha_n(DT_n)$$

① {EDA & Feature Engineering} ✓

③ SVM





$y = mx + c$ → slope, intercept

$\Downarrow \Uparrow$ → Equation of a straight line

$ax + by + c = 0$

$y = \frac{-c}{b} - \frac{ax}{b}$

$m = -a/b \quad c = \frac{-c}{b}$

$y = mx + c$

$y = w_1 x + w_2 x_2 + \cdots + b$

$b = 0$ ↑

$w \to -1$

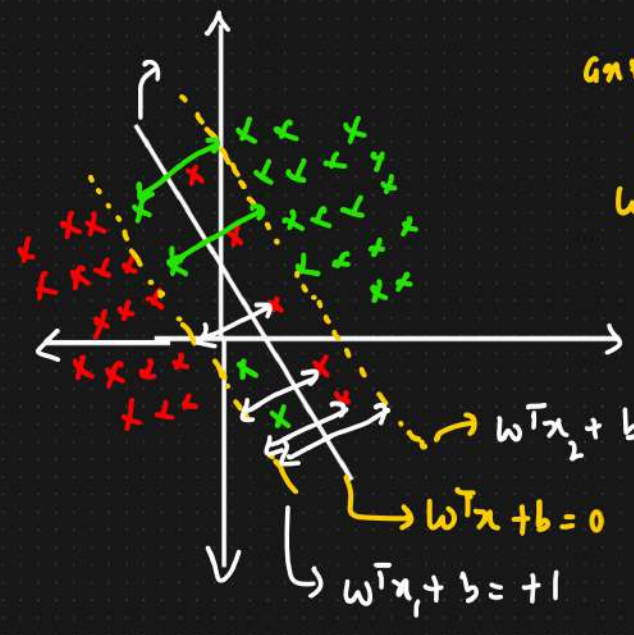
$\rightarrow \boxed{y = w^T x + b}$

$y = \begin{bmatrix} -1 \\ 0 \end{bmatrix} [-4 \;\; 0]$

$= 4 \Rightarrow$ +ve value

$y = \begin{bmatrix} -1 \\ 0 \end{bmatrix} [4, 4]$

$= -4 + 0 = -4$



$ax + by + c = 0$ ⇓ $w^T x + b = 0$

$\vec{w}$ Vectors + magnitude

$w^T x_1 + b = 1$

$w^T x_2 + b = -1$

$w^T (x_1 - x_2) = 2$

$\frac{w^T (x_1 - x_2)}{|w|} = \frac{2}{|w|}$

Maximize $_{(w,b)}$ $\frac{2}{||w||}$ ⇒ Marginal

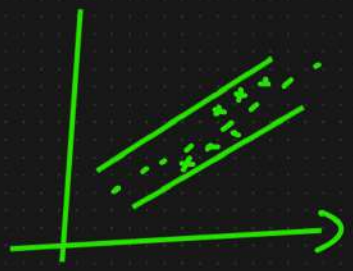
Such that $y_i \begin{cases} +1 & w^T x + b \geq 1 \\ -1 & w^T x + b \leq -1 \end{cases}$

Major Aim $y_i * (w^T x_i + b) \geq 1$

for correct point

Maximize $_{(w,b)}$ $\frac{2}{||w||}$ ⇔ Min $_{(w,b)}$ $\frac{||w||}{2}$

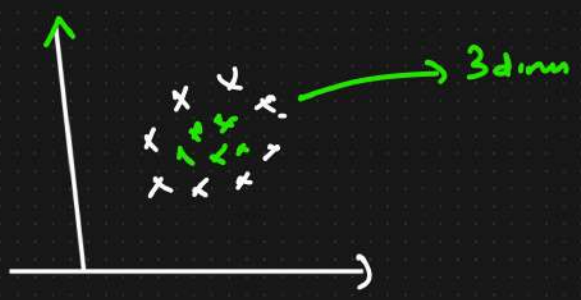
Min $_{(w,b)}$ $\frac{||w||}{2} + C_i \sum_{i=1}^{n} \xi_i$ → Summation of the distance of the wrong datapoints



{6} How many Errors we can have

SVR = Explore

SVM Kernel



Practically =