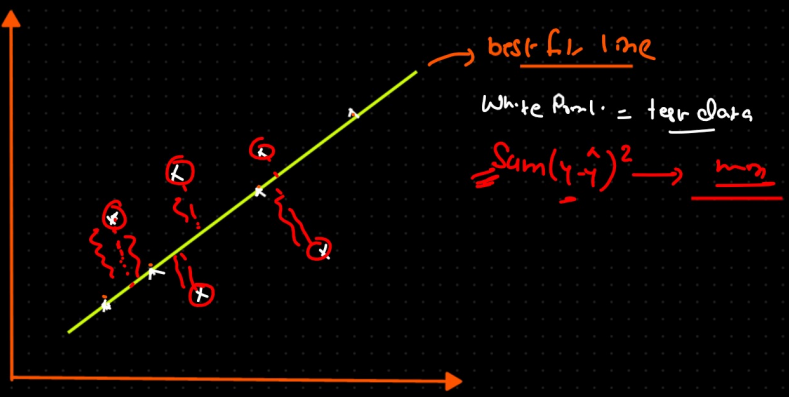
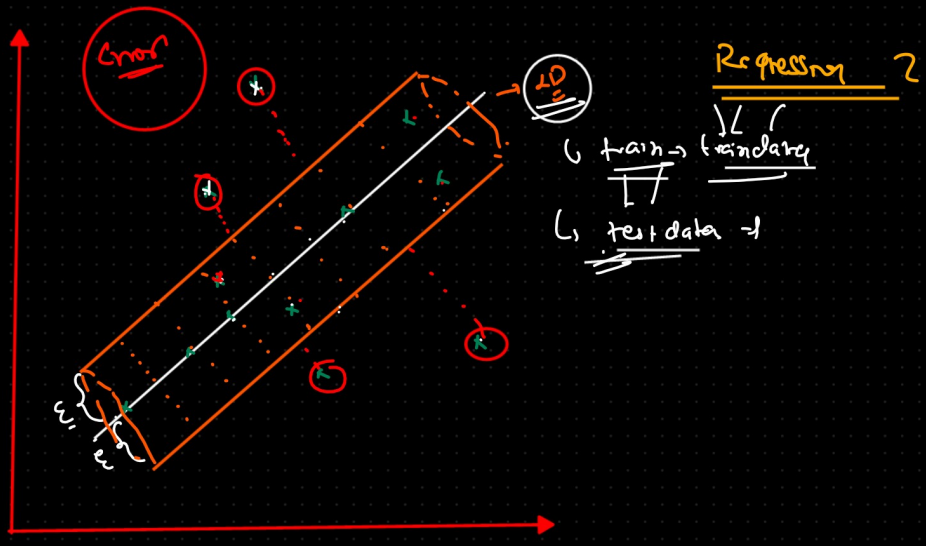
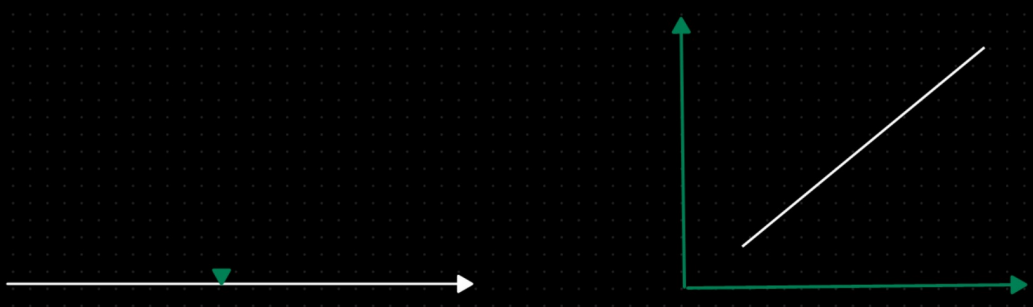
1. SVR.
2. Python implement.
3. Dt
4. hyperparameter

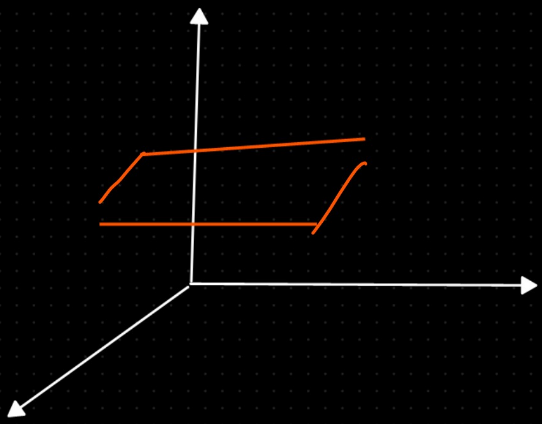
SVR ⇒

Linear reg.









SVR

Constraint for svm (svc) $\Rightarrow$ $\{ \hat{y} (w^T x + b) \geq 1 \}$

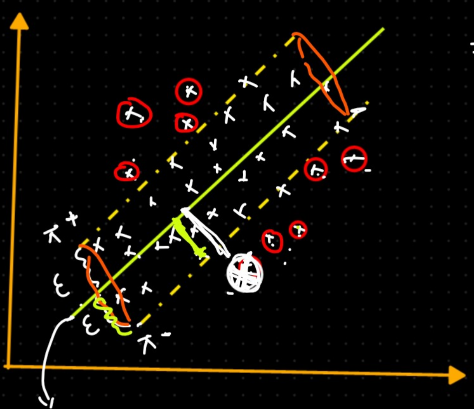
$$\text{minimise}_{(w,b)} = \frac{\|w\|}{2}$$

SVC → hard classifier
SVC → soft classifier

cost function $\Rightarrow$ $\min_{(w,b)} \frac{\|w\|}{2} + C_i \sum_{i=1} \xi_i$ → ETA

hinge loss.

Support vector Regressor



hyperplane = ε

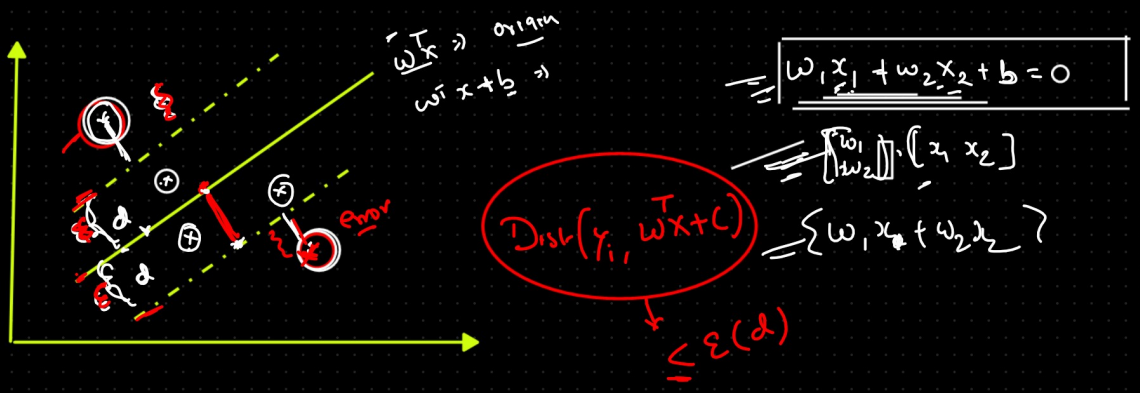
$w^T x + c$

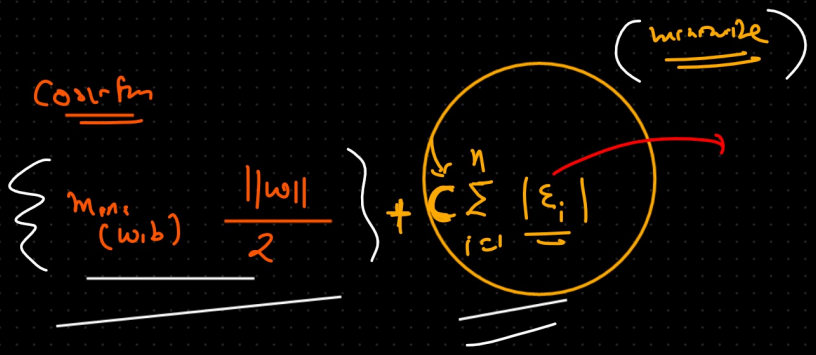
$\Rightarrow \{$ Reduce the error / minimize the error $\}$

= Constraint

$$|Y_i - (w^T x + c)| \leq \varepsilon$$

$$Y_i - (w^T x + c) \leq \varepsilon$$





Decision tree ⇒ Tree which take the Decision based on a condition

- It is based on a Condition

Sunny = 27

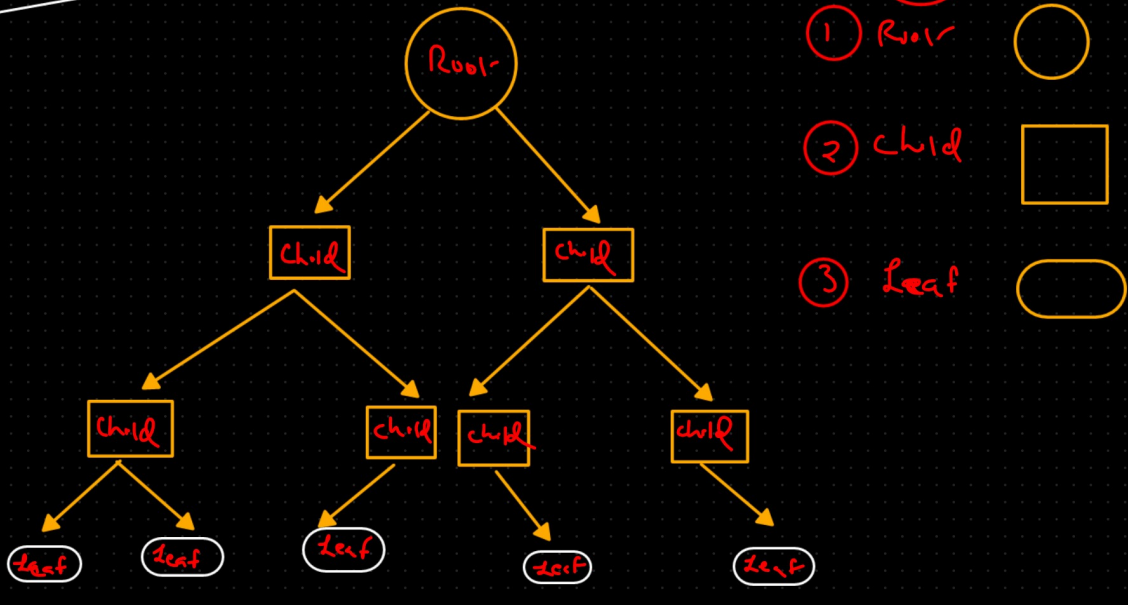
- if age ≤ 15 :-
  Print ("School")
- if age > 15 & age ≤ 25 :
  Print ("College")
- if age > 25 :
  Print ("working")

Decision tree

Tree

Diff ⇒ Node

1. Root
2. Child
3. Leaf



Decision tree algo →
1. ID3 algo
2. CART

ID3 algo → Iterative Dichotomiser
CART → classification & Reg tree

C4.5 + Updated version of ID3

ID3

1. Iterative Dichotomiser
2. Entropy ⇒ information gain
3. it will split the Data in multiclass
4. it only work with the classification
   - C4.5
   - Reg return

CART

1. classification & Reg. tree
2. Gini impurity (Gini Coef, Gini index)
3. it will split the data into Binary class
4. it works for the Reg & class.

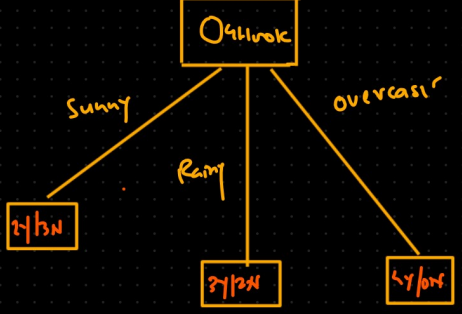
Decision tree → Regression, classification

ID3

CART

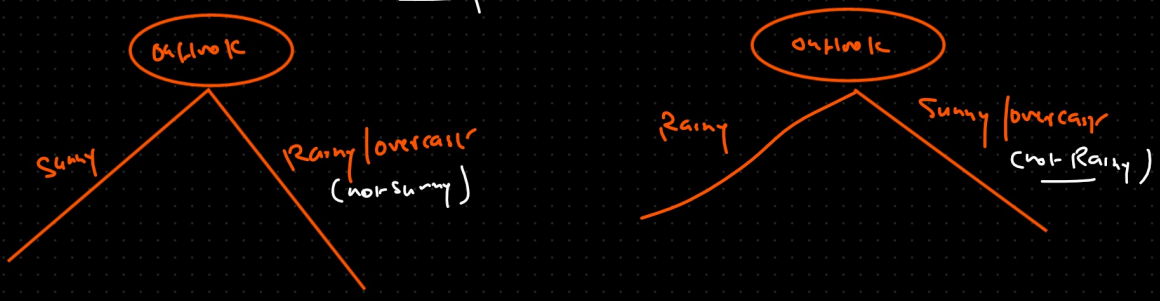
Outlook ⇒ 3

[9|5N]



Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No

CART ⇒ Binary split



Split ⇒ (1) ID3 ⇒ entropy → information gain
(2) CART ⇒ Gini impurity

Entropy ⇒ measure of Randomness

Def: (we have to find out best Root Node which is having a minimum entropy ⇒ Randomness)

Entropy → Range [0-1]

thermodynamics { if near to zero = less Randomness
if near to one = more Randomness }

{ Entropy = 0 } ⇒ No Randomness

$$\text{Entropy} = -\sum_{i=1}^{N} P_i \log(P_i)$$

2 class ⇒ (Y | N)

$$\text{Entropy} = -P_Y \log_2(P_Y) - P_N \log_2(P_N)$$

=

f = 3

$$-P_{c_1} \log_2(P_{c_1}) - P_{c_2} \log_2(P_{c_2}) - P_{c_3} \log_2(P_{c_3})$$

N ⇒ class

Dummy data

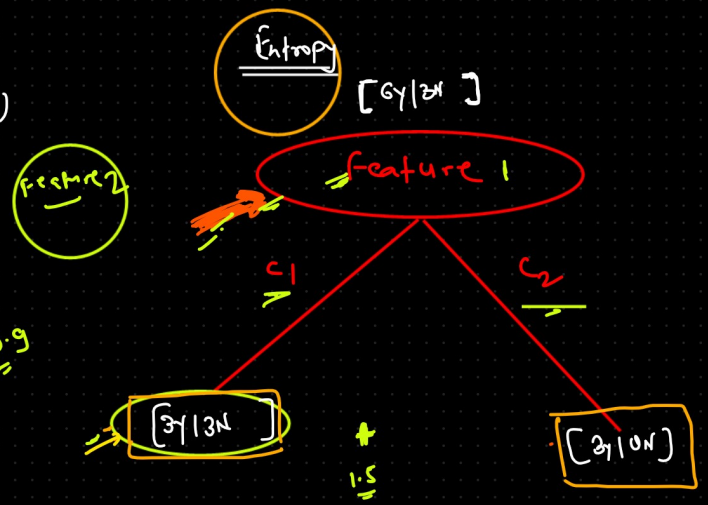
feature (C_1, C_2)	target (Y/N)
C_1	Y
C_2	Y
C_1	Y
C_2	Y
C_1	Y
C_1	N
C_2	Y
C_1	N
C_1	N

$P(Y) = \frac{3}{6} = \frac{1}{2}$

$P(N) = \frac{3}{6} = \frac{1}{2}$

$\log(m/n) = \log m - \log n$

$\log_n n = 1$



feature (C_1, C_2)

$\Rightarrow -P_Y \log_2(P_Y) - P_N \log_2 P(N)$

$\Rightarrow -\frac{3}{6}\log_2(\frac{3}{6}) - \frac{3}{6}\log_2(\frac{3}{6})$

$= -\frac{1}{2}\log_2(\frac{1}{2}) - \frac{1}{2}\log_2(\frac{1}{2})$

$= -\frac{1}{2}[\log_2(1) - \log_2(2)] - \frac{1}{2}[\log_2(1) - \log_2(2)]$

$= -\frac{1}{2}[0-1] - \frac{1}{2}[0-1]$

$= \frac{1}{2} + \frac{1}{2} = 1$

(3Y|0N) ⇒ 0

Range = [0-1]

1 = high entropy

high randomness

3Y|0N

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

$= -1(0) - 0$

$= 0 - 0 = 0$

- Y|N

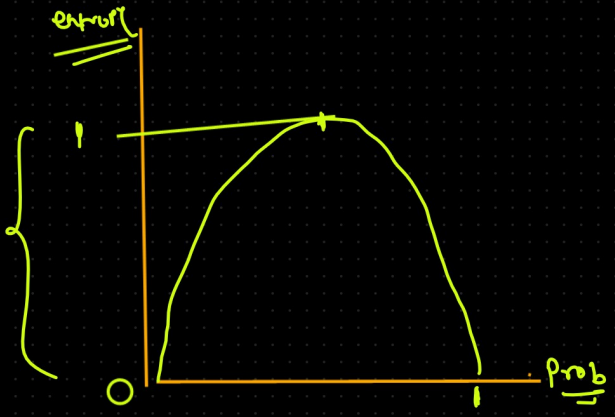
(6) - 3Y|3N ⇒ Y|N ⇒ (1)

4Y|2N ⇒ yes (Random)

<1

5Y|1N <<1

6Y|0N = 0



$(2y/3x) = ?$

Gms

r.g.

ch.f

D+R

$\Rightarrow$ practical