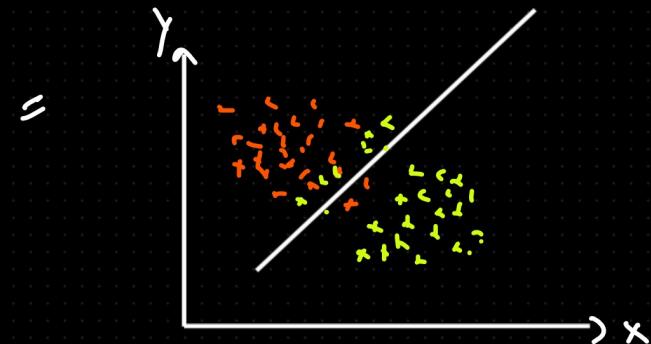


SVM kernels

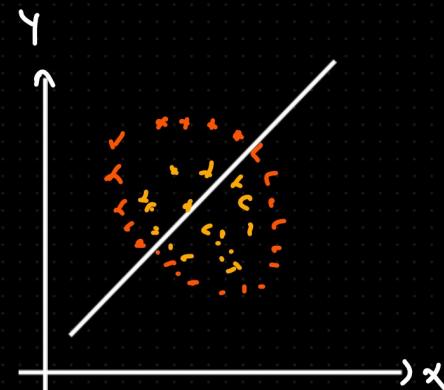
function

- ① Regression
- ② Classification

Linear Separable data



Non-linear Separable data



Transformation

- = ① Polynomial
- ② Sigmoid
- ③ RBF

} Convert data into
higher Dimension

{lower Dim → higher Dim}

$$\left\{ \begin{array}{l} 1D \rightarrow 2D \\ 2D \rightarrow 3D \\ 3D \rightarrow 4D \end{array} \right\}$$

transform this \boxed{x}

variable $\Rightarrow x^2$

$$x_1 x_2 =$$

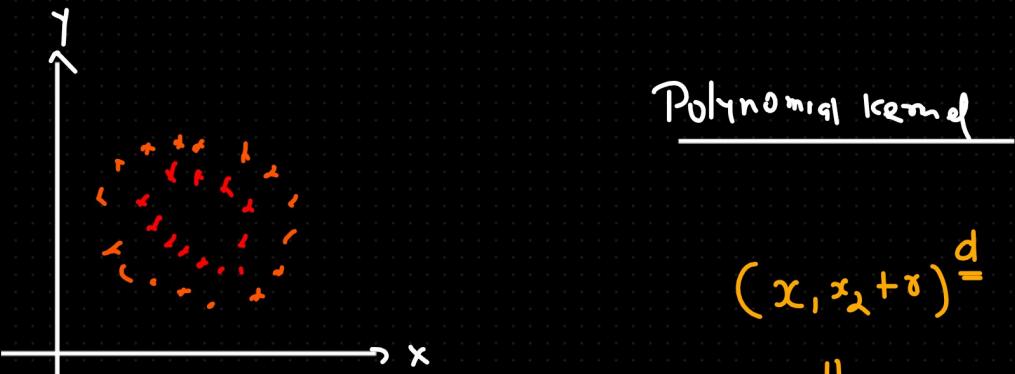
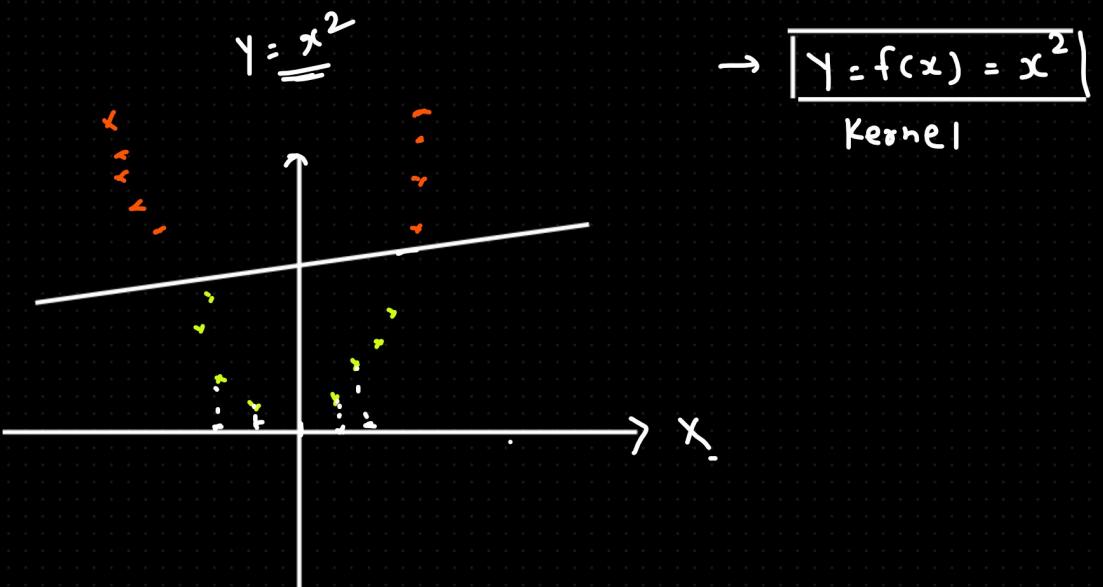
$$\boxed{xxx}$$

1D

...



$$\underline{x} = \boxed{y = x^2}$$

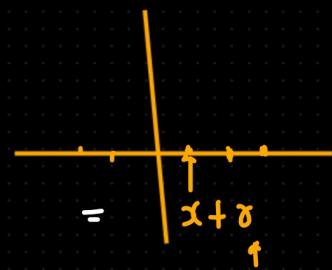


$$(x_1, x_2 + \delta)^d \quad d=1, \delta=0$$



$$(x_1, x_2 + 0)^1$$

$$\Rightarrow \underline{x^2} =$$



$$f(x_1, x_2) \Rightarrow \text{Polynomial kernel} \underset{\text{function}}{\overline{\Pi}} \Rightarrow \frac{(x_1 \cdot x_2 + \gamma)^d}{\text{_____}}$$

$x_1, x_2, Y \Rightarrow \text{Binary class}$
OVR

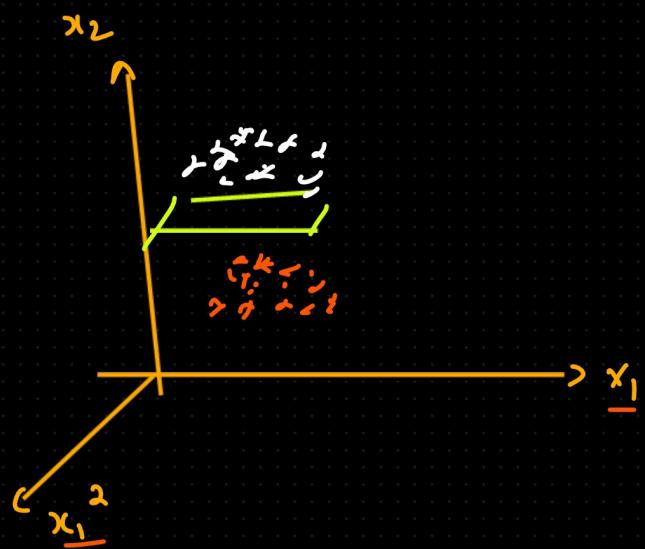
$$\text{RBF Kernel} = f(x_1, x_2) = \exp^{-\left(\frac{\|x_1 - x_2\|^2}{2\sigma^2}\right)}$$

fn =

$$\frac{(x_1 \cdot x_2 + \gamma)^d}{\text{_____}} \Rightarrow \begin{pmatrix} x_1^2 & x_1 \cdot x_2 & x_2^2 \end{pmatrix}$$

2D $\xrightarrow{x_1 \cdot x_2}$

$$x_1 \ x_2 \ Y \quad \textcircled{x_1^2} \quad \frac{x_2^2}{=} \quad x_1 x_2$$

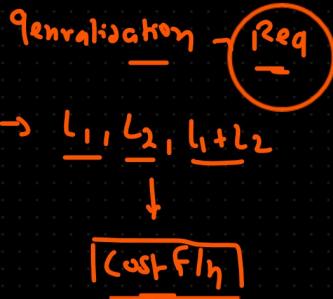


- linear reg
 - log reg
 - SVM
 - DT
- Ridge
Lasso
Elastic

Regularization

Reducing Overfitting

low bias + high variance



Ensemble technique \Rightarrow More than one model

OR

Compound technique

Bagging



Multiple model Parallel

Custom model

~~Decision tree~~ \rightarrow Random forest

Breeding

multiple model Sequentially



{ AdaBoosting
Gradient-Boosting -
XGB -

= Decision tree
(catboost)

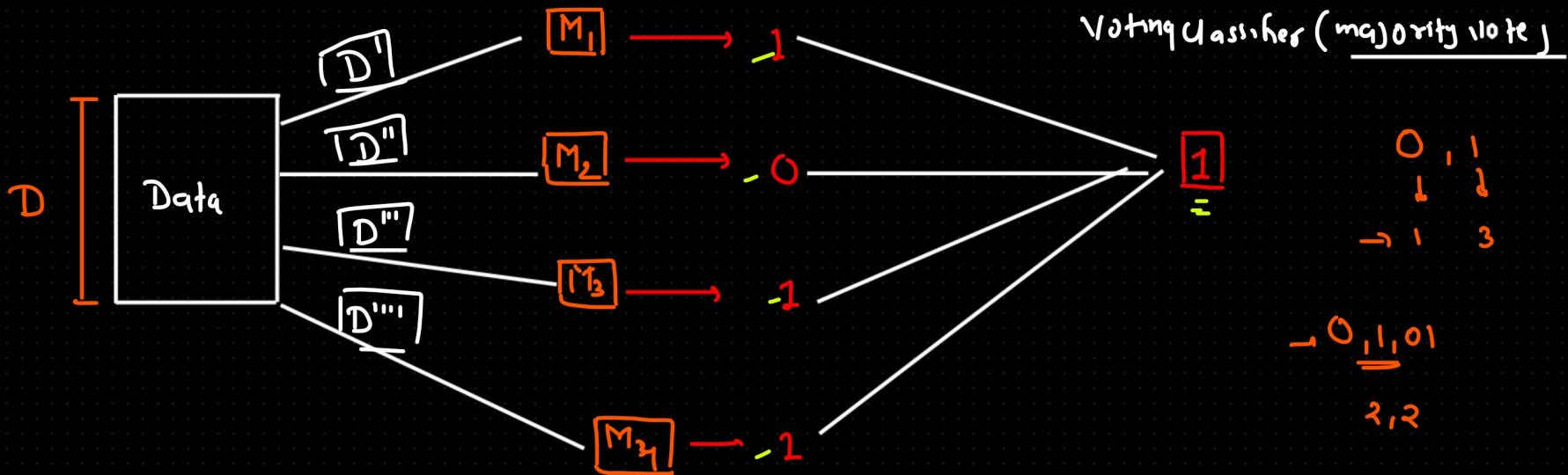
Stacking

multiple model in 2 stages

SVC, DT, Unreq

Bagging

Decision tree | Naive Bayes | Logreg | SVM



Bootstrap Aggregating

Aggregation

Bagging \Rightarrow Bootstrap + Aggregation

Sample

majority vote

Regression \rightarrow Avg of all the output

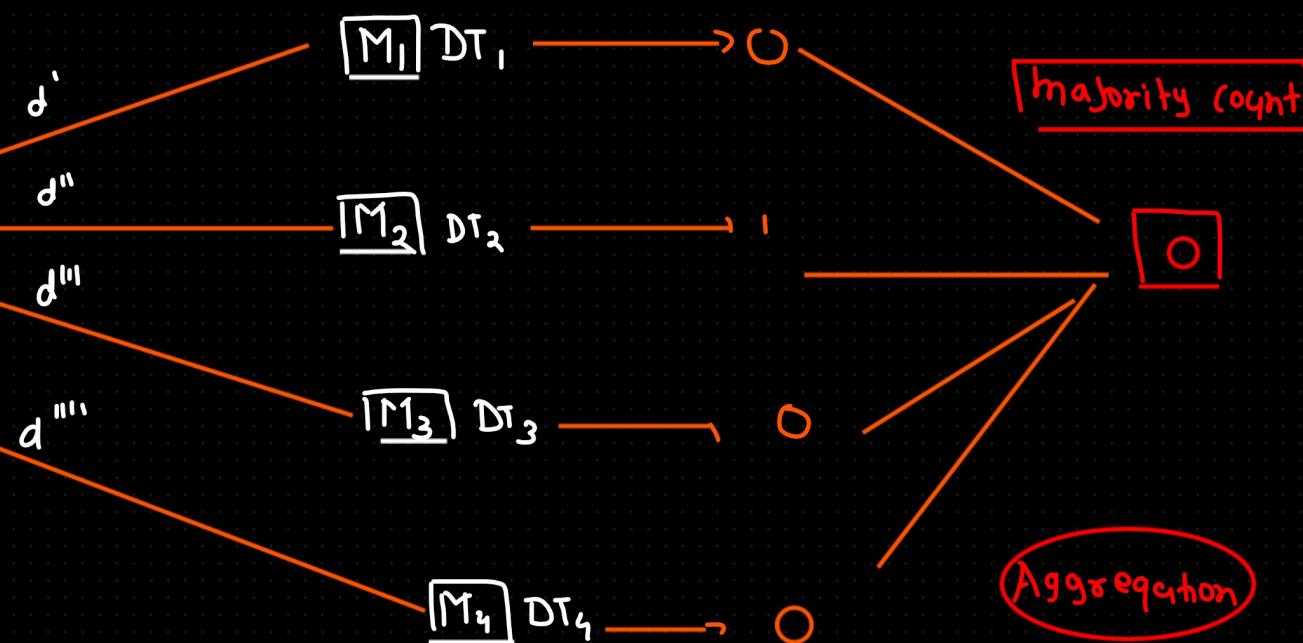
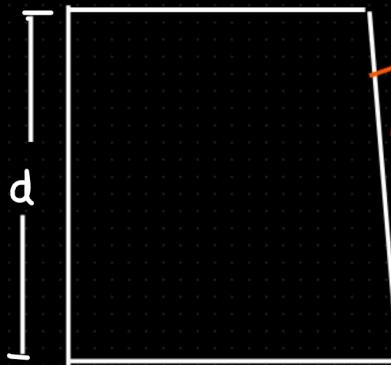
Random forest \Rightarrow the base learner will be Decision tree.

$d' \times d$

$d'' \times d$

$d''' \times d$

$d'''' \times d$



Bootstrap

$d' | d'' | d''' | d'''' \Rightarrow$ Subset of the data \Rightarrow Random Sample

(Row Sample) + (Column Sample)
=

= Bootstrap Data

	D	
1	x_1, x_2, x_3, x_4, x_5	1
2	5	12
3	6	10
4	7	11
5	8	13
6	9	14
7	10	15
8	11	16
9	12	17
10	13	18

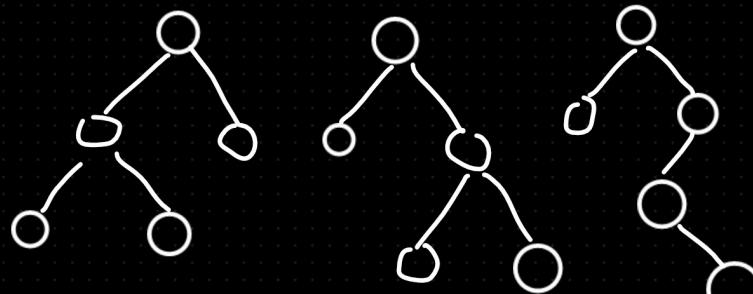
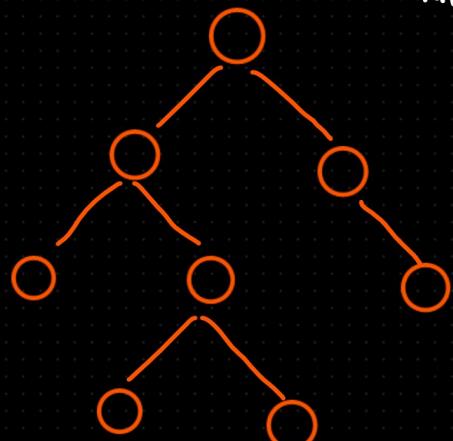
$$d' = [x_1, x_4, x_3, x_5]$$

$$d'' = [x_1, x_2, x_3, x_5]$$

!

Why we should Random forest instead of Decision tree?

multipletree



(Generalized model)

fill complete depth → Overfitting ⇒ $\begin{cases} \text{training Acc } \uparrow \uparrow \uparrow \\ \text{testing Acc } \downarrow \downarrow \downarrow \end{cases}$ } $\begin{cases} \text{low bias} \\ \text{high variance} \end{cases}$ ⇒ $\begin{cases} \text{low bias} \\ \text{low variance} \end{cases}$

- ① Reduce the Overfitting
- ② Better performance
- ③ Robustness
- ④ feature importance

