classification

— Adhoc reg & sentiment Analysis

Naive Bayes Theorem :— ML algorithm

extensively used Bayes theorem

Naive — simplistic, unsophisticated

likelihood

prior

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

evidence / marginal

posterior

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Q:- Dataset format

$$x = \{x_1\ x_2\ x_3 - \text{———} x_n\}\ \{y\} \rightarrow \text{Dep. feature}$$

Independent feature

$$\left\{ \begin{array}{l} \sum = + \\ \prod = \times \end{array} \right.$$

Bayes theorem :- $P(A/B) = \dfrac{P(B/A) * P(A)}{P(B)}$

$$P(y/x_1, x_2\ x_3 \text{———} x_n) = \frac{P(x_1/y) \cdot P(x_2/y) \cdot P(x_3/y) \text{———} P(x_n/y) * P(y)}{P(x_1) \cdot P(x_2) \cdot P(x_3) \cdot - - P(x_n)}$$

$$P(y/x_1 : x_2 x_3 - - x_n) = \frac{P(y) \prod_{i=1}^{n} P(x_i/y)}{P(x_1) P(x_2) \text{———} P(x_n)}$$

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$\therefore P(x_1)\cdot P(x_2)\cdot P(x_3)\cdot \text{———} \; P(x_n) = \text{constant}$

$$\therefore \boxed{P\left(y/x_1,x_2,x_3 \ldots x_n\right) \propto P(y)\cdot \prod_{i=1}^{n} P\left(x_i/y\right)}$$

$$y = \text{argmax}_y \, P(y) \prod_{i=1}^{n} P(x_i/y)$$

→ argmax means in $P(y)$ & $\prod_{i=1}^{n} P(x_i/y)$ which one gives us the highest probability we will consider that

Outlook

Weather	Yes	No	P(Y)	P(N)
Sunny	2	3	2/9	3/5
Overcast	4	0	4/9	0
Rainy	3	2	3/9	2/5
Total	9	5	100%	100%

Temperature

	Yes	No	P(Y)	P(N)
Hot	2	2	2/9	2/5
Mild	4	2	4/9	2/5
Cool	3	1	3/9	1/5
	9	5	100%	100%

	Play	P(Y) & P(N)
Yes	9	9/14
No	5	5/14
	14	

$P(Y/\text{Today}) =$

$$P(Y/\text{Today}) = \frac{P(\text{Sunny}/y) \cdot P(\text{Hot}/\text{yes}) \cdot P(y)}{P(\text{today})}$$

$$= \frac{2}{9} * \frac{2}{\cancel{9}} * \frac{\cancel{9}}{\cancel{14}\ 7} = \frac{2}{63}$$

$$P(N/\text{Today}) = \frac{P(\text{Sunny}/\text{Not}) * P(\text{Hot}/\text{Not}) * P(\text{No})}{P(\text{today})} = \frac{3}{5} * \frac{2}{\cancel{5}} * \frac{\cancel{5}}{\cancel{14}\ 7}$$

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

$$P(y) = \frac{\text{value of yes}}{\frac{2}{63} \times \frac{3}{35}}$$

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NLP — Sentiment Analysis

Naive Bayes

Bag of words
N-Grams
TF-IDF

OHE & LE

$$P\left(\frac{y}{S,O,R}\right) = \frac{P\left(\frac{S}{y}\right) * P\left(\frac{O}{y}\right) * P\left(\frac{R}{y}\right) * P(y)}{P(S)\cdot P(O)\cdot P(R)}$$

Google Scholar — Naive

Idv Glucose	Idv RBC	Idv BMI	I Diabetes
-	-	-	-
-	-	-	-
-	-	-	-

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

$$\boxed{P(y/Glu, RBC, BMI) = \frac{P(Glu/y) * P(RBC/y) * P(BMI/y) * P(y)}{P(Glu) \cdot P(RBC) \cdot P(BMI)}}$$

Laplace Smoothing - NLP

$w_1 \; w_2 \; w_3 \; - \; — \; w_n$

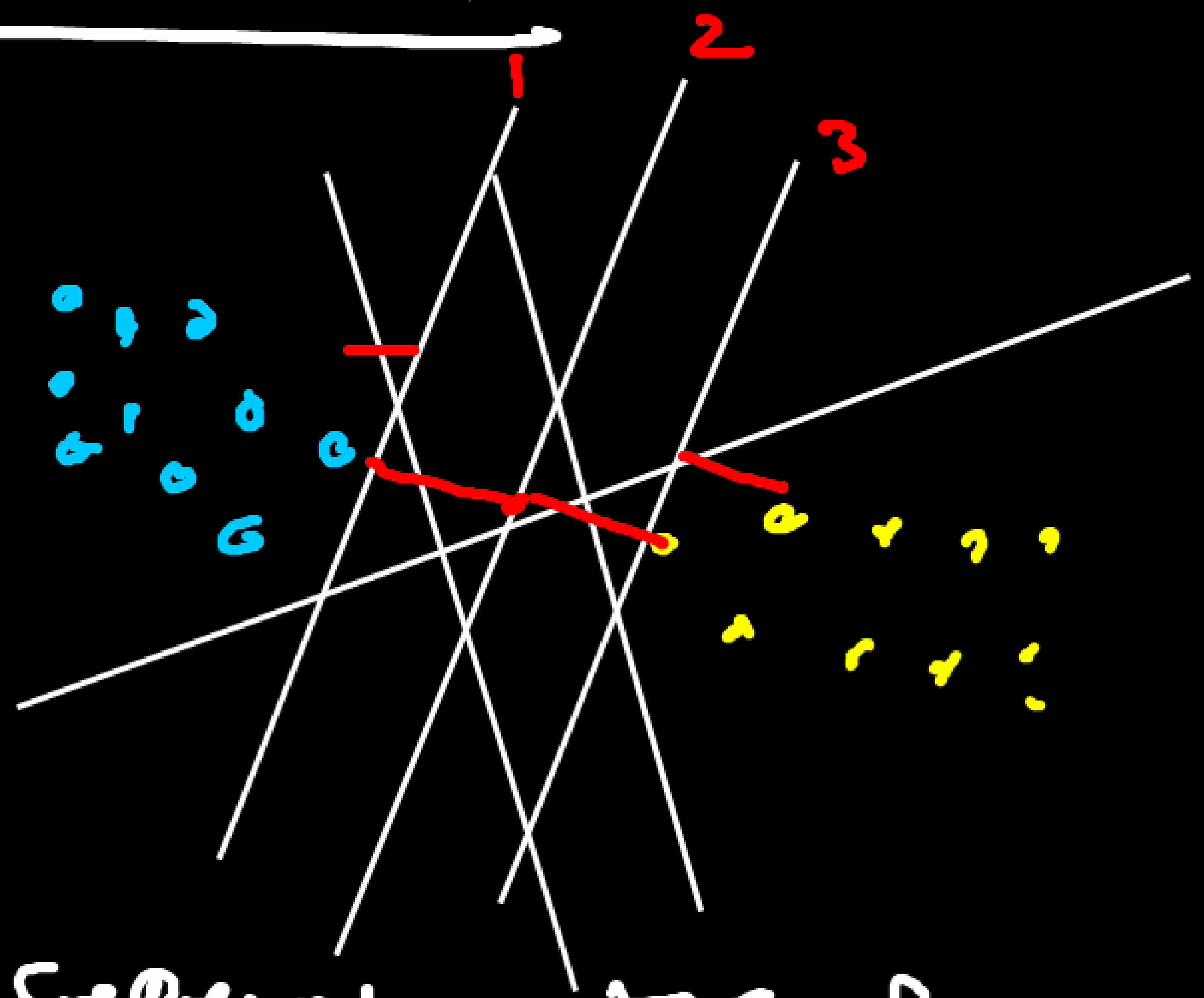
$$\boxed{P\left(w_i / y=1\right) = \frac{3}{100}}$$

Support vector Machine (SVM)

Regression
classification

popular algorithm - 1990 to 2005

Geometrical intuition

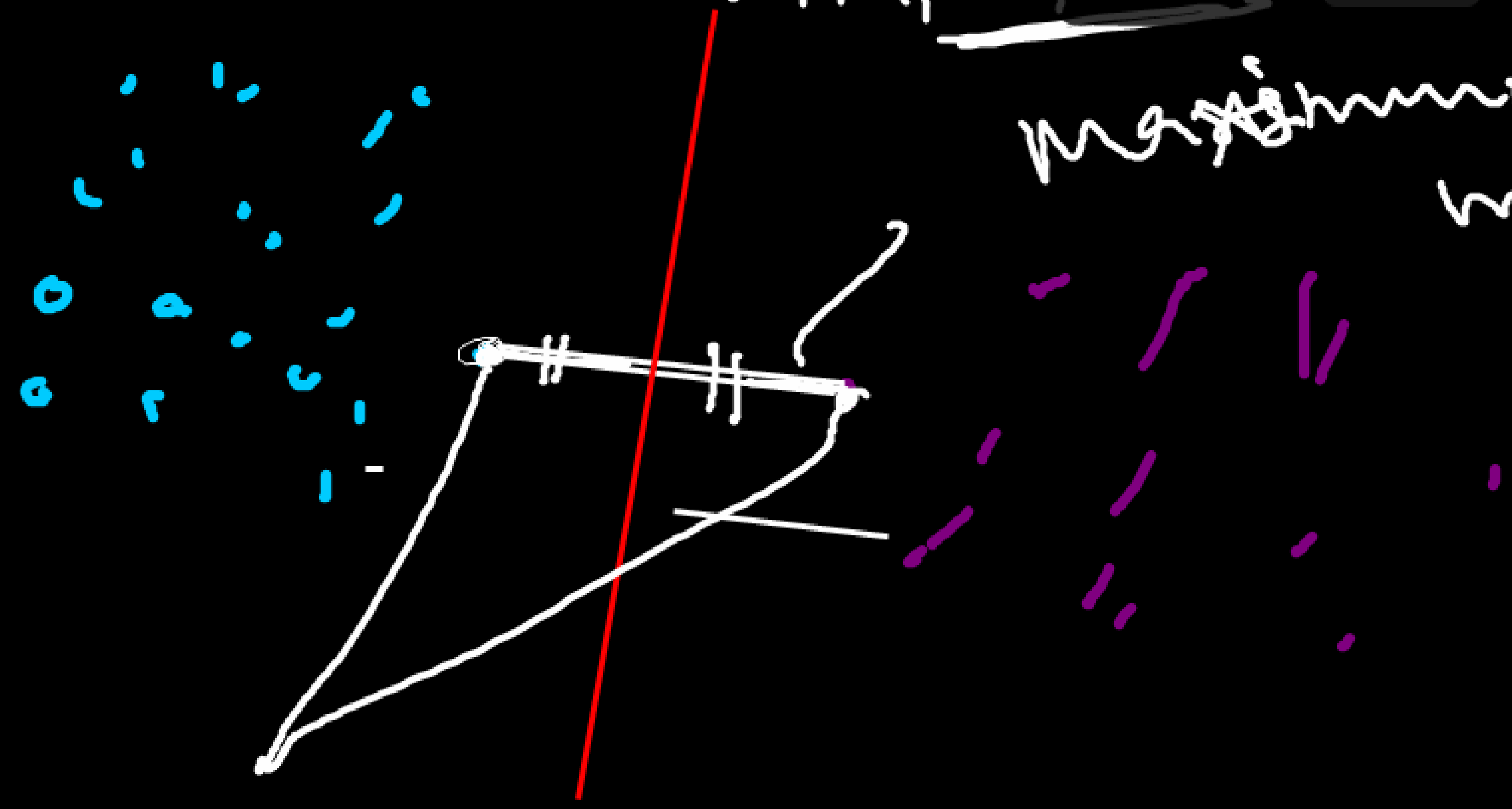


(1) Many π's that seperate the (+)ve from (−)ve

→ Key idea of SVM :- π that seperate +ve from −ve pts and "widely" as possible.

Hyperplane

maximum margin



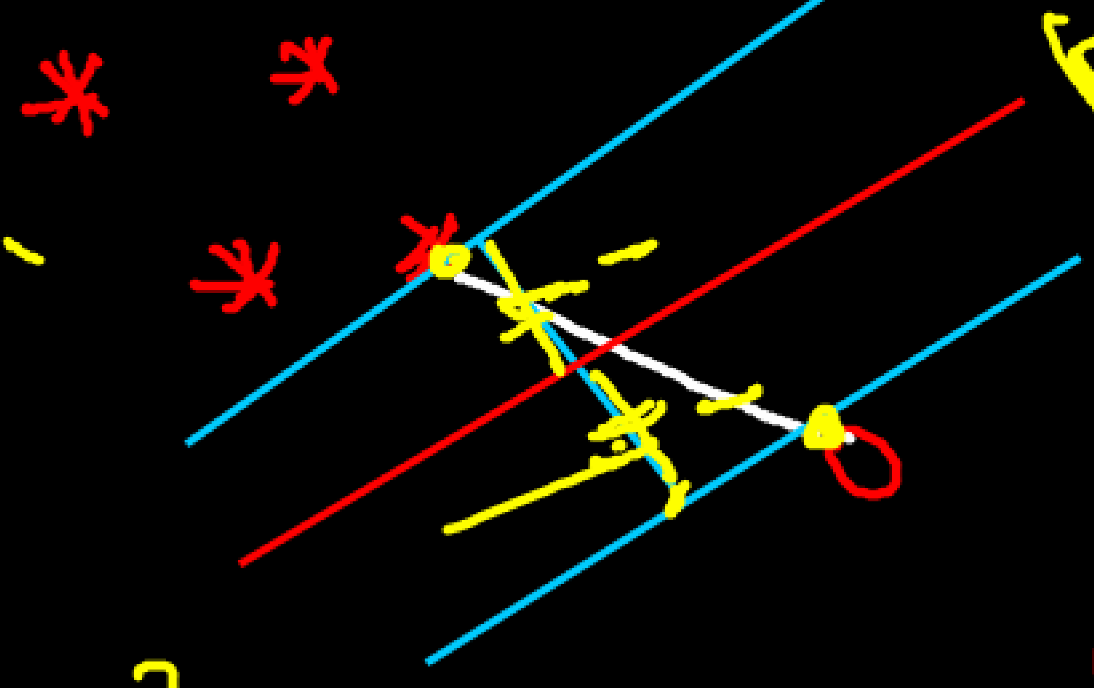
π_+ is $\parallel$ π_-

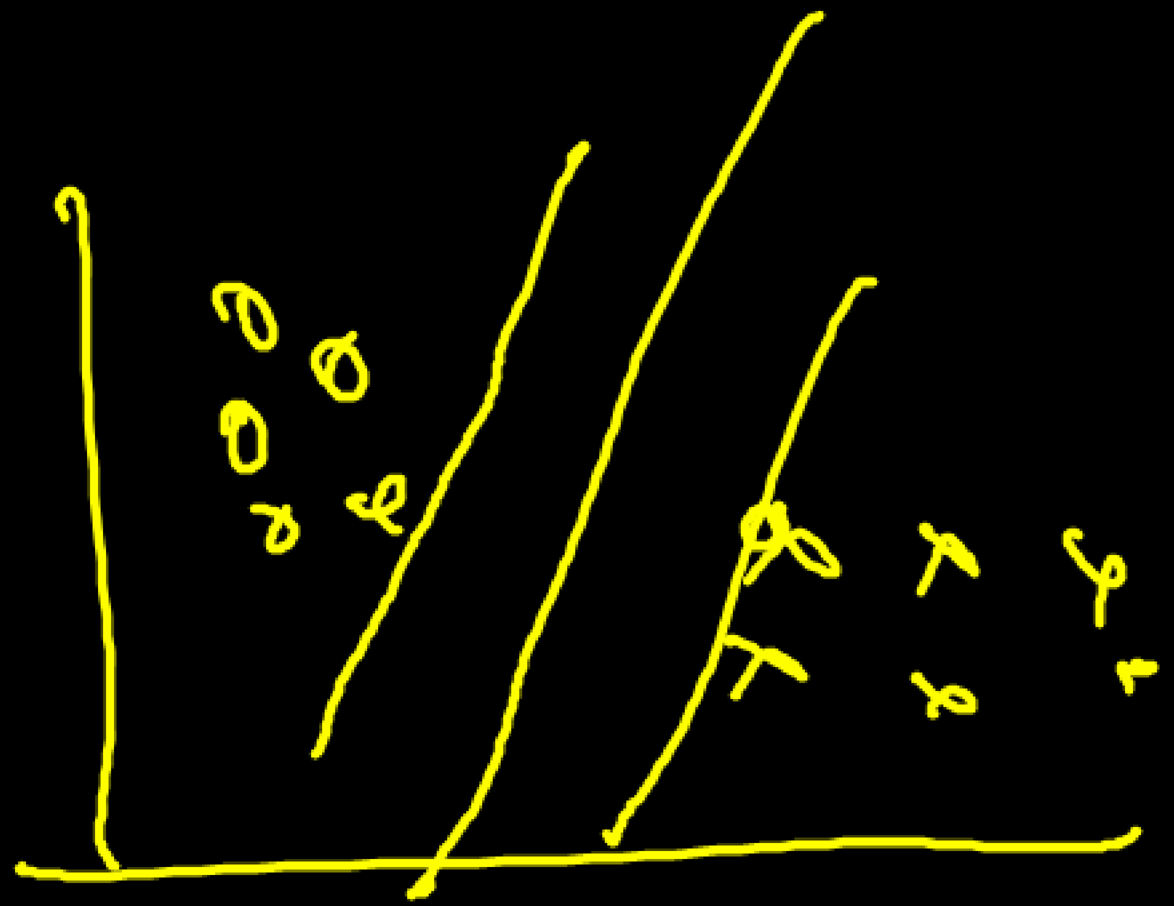
π_- is $\parallel$ π_+

Support vector

hyper.plane

+ve





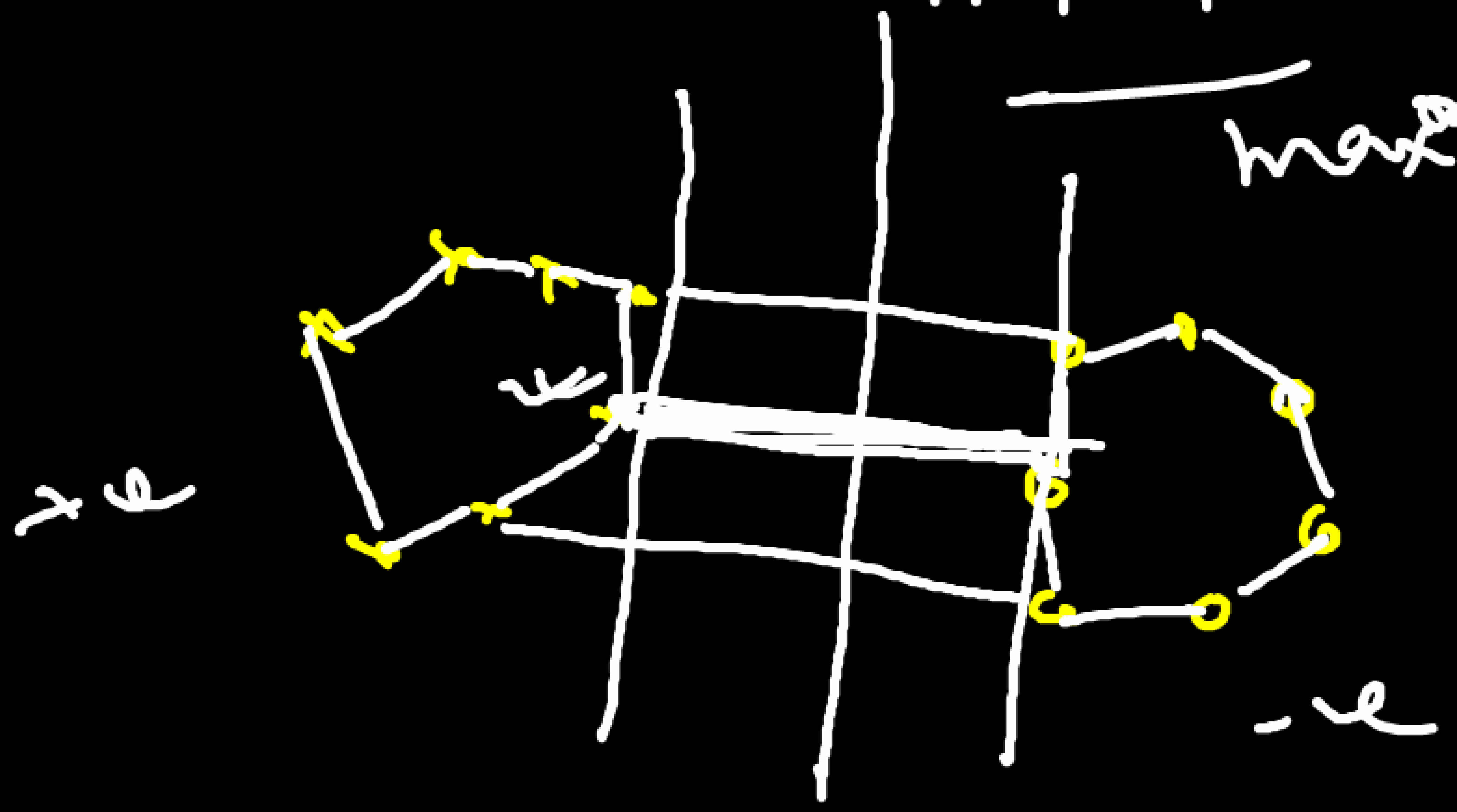
max. margin 2

Support vector

-ve

Hyperplane

max-margin hyperplane



convex hull

1. convex-hull for +ve & -ve points seperately
2. find the shortest line connecting these hulls
3. Bisect the line

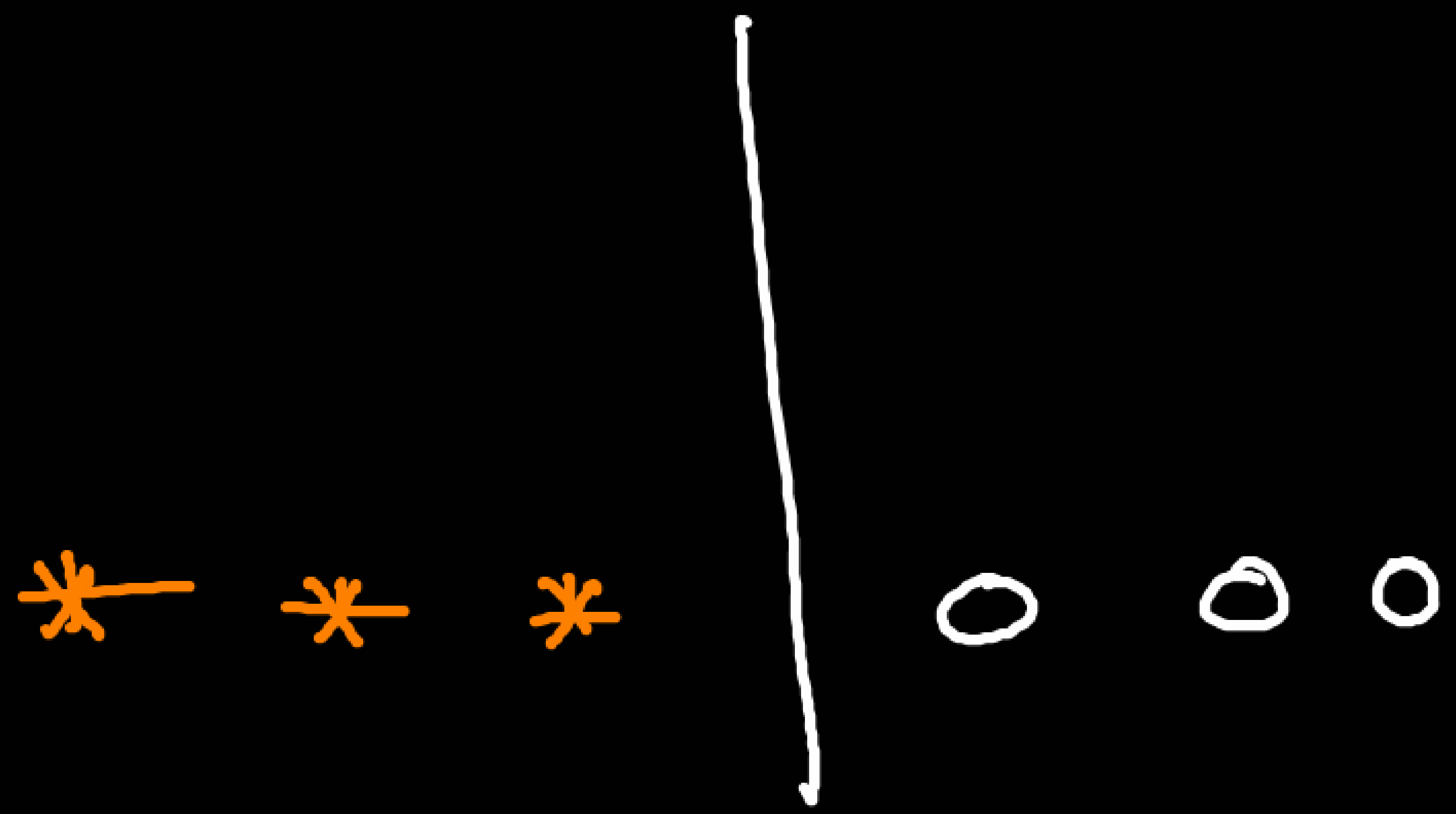
Kernal

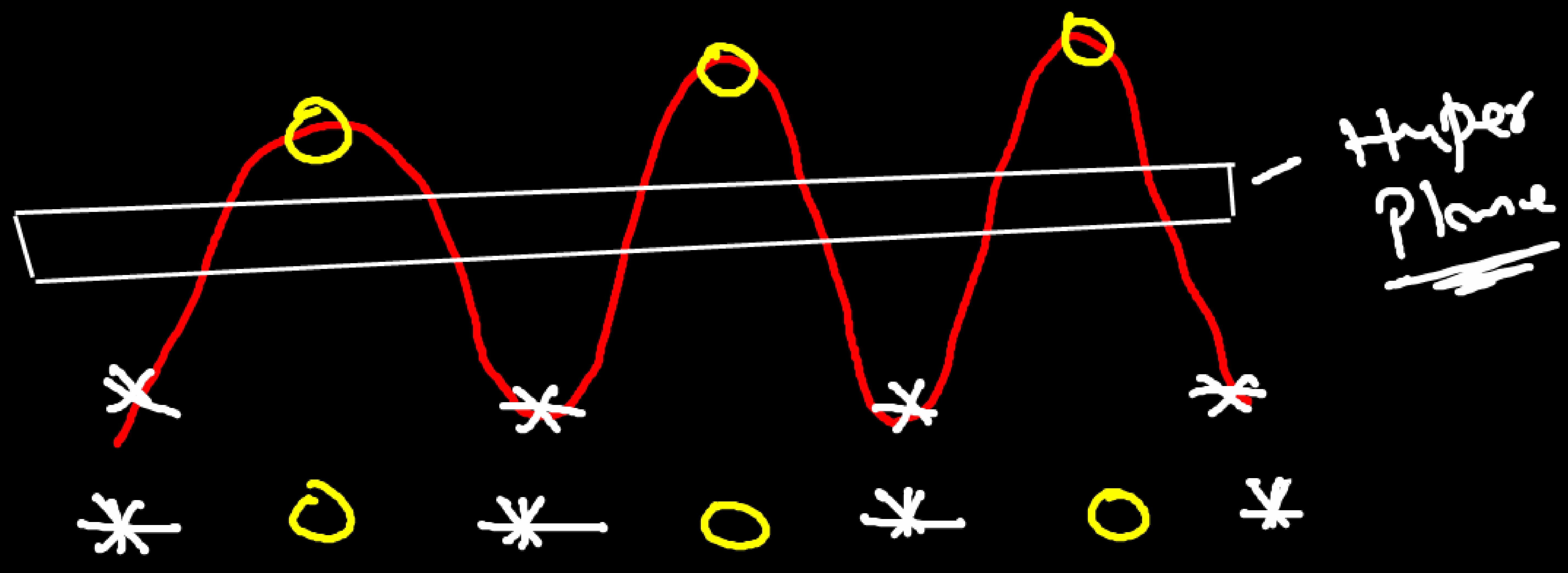
1. linear
2. sigmoid
3. polynomial
4. Rbf

Radial
Based
Func

By default

Sklern SVM





Kernel = poly

Webinar Chat

ankit to Everyone
like sin theta?

Imran Azimuddin Saiyad to Everyone
yes

Yushma Premchand to Everyone
yes

Shreya Mankar to Everyone
yes

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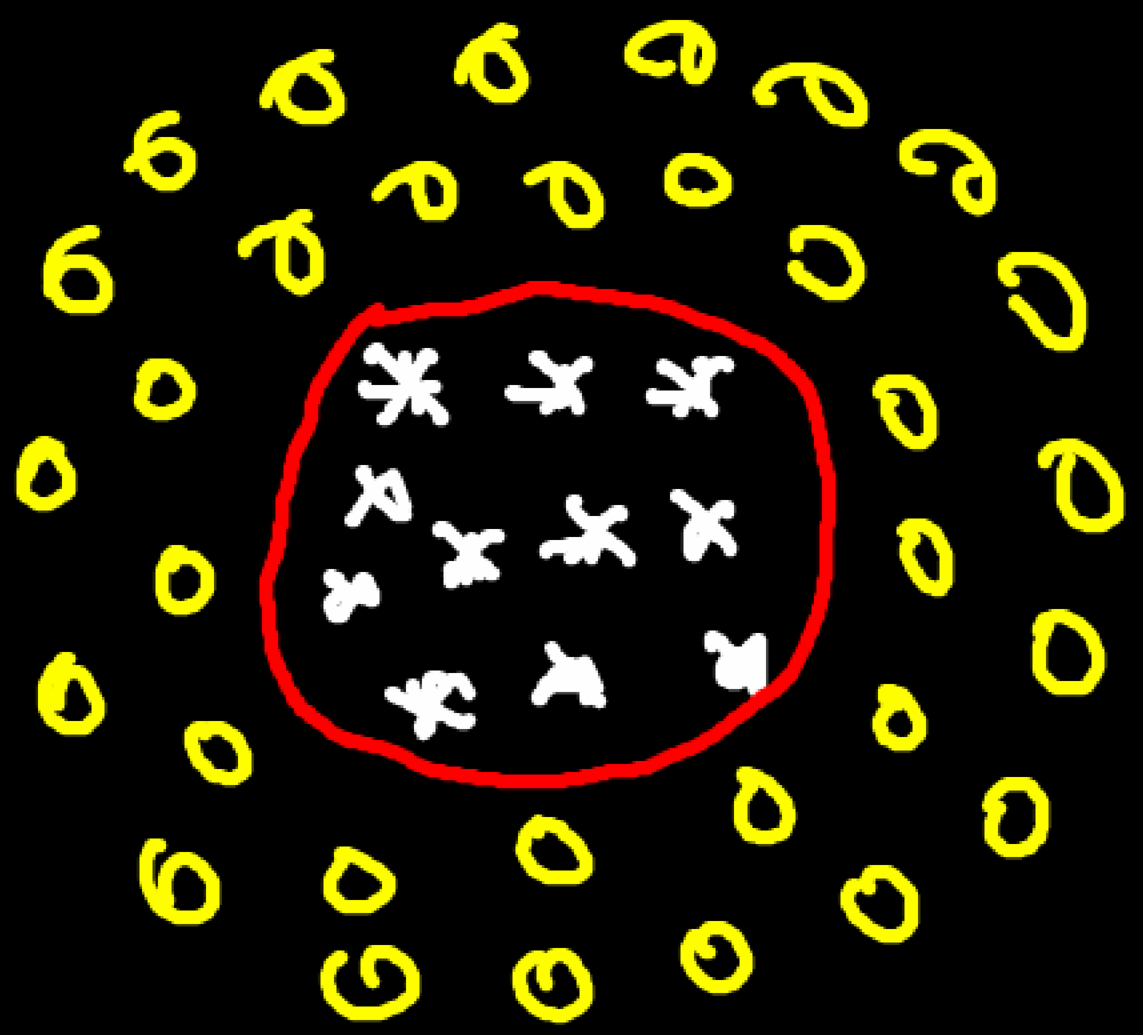

rbf

Kernel = approach

Kernel = "rbf"

= linear

= sigmoid

= poly