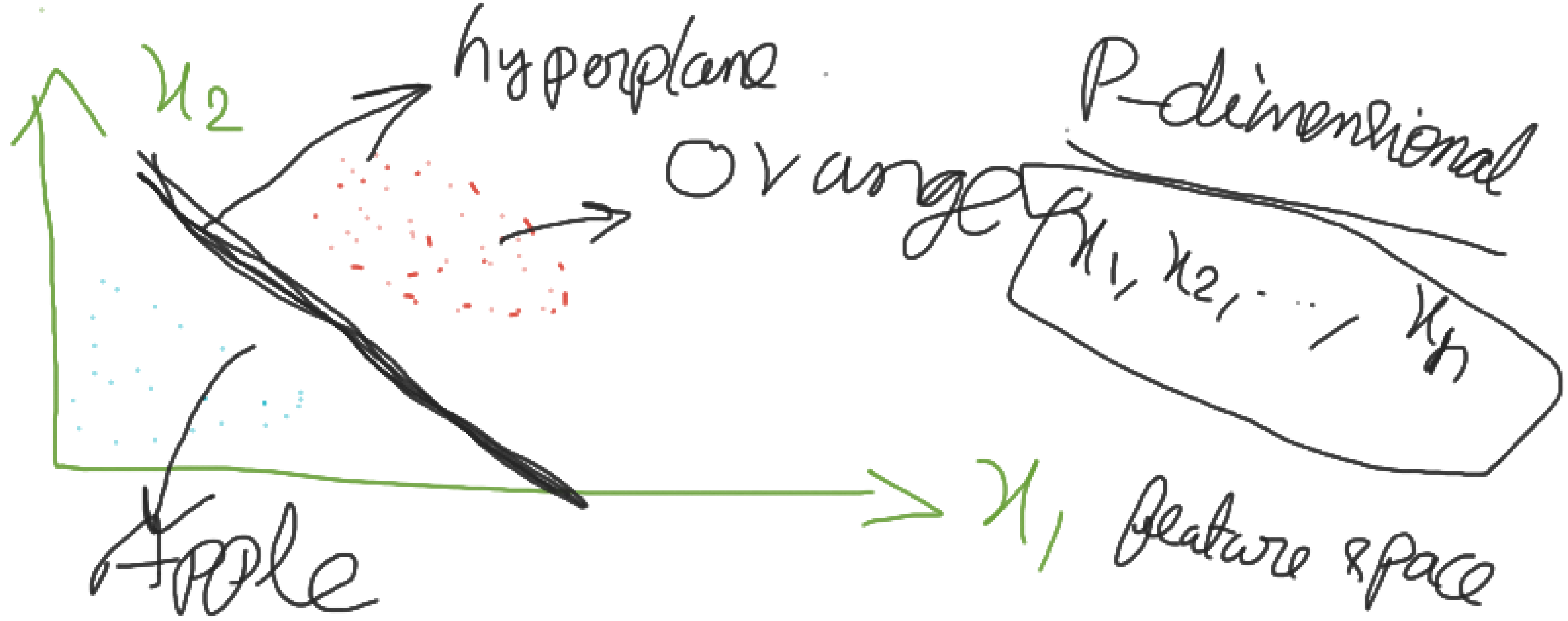
“A SMILE IS THE EASIEST WAY OUT OF A DIFFICULT SITUATION.”

1. Hyperplane
2. how to classify a data point using hyperplane
3. maximal margin hyperplane
4. maximal margin classifier
5. support vector classifier
6. support vector machines
7. applications

hyperplane

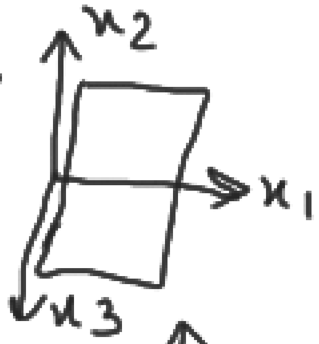
SVM

approach
classification

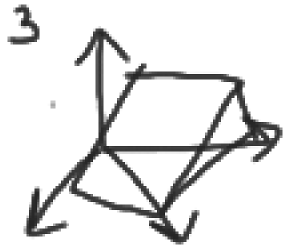

x_2
hyperplane
Orange
P-dimensional
$x_1, x_2, \dots, x_n$
Apple
x_1
feature space

I have a 2D space 

, $(P-1) \Rightarrow P = 2 = 2-1 = 1D$ sub space.

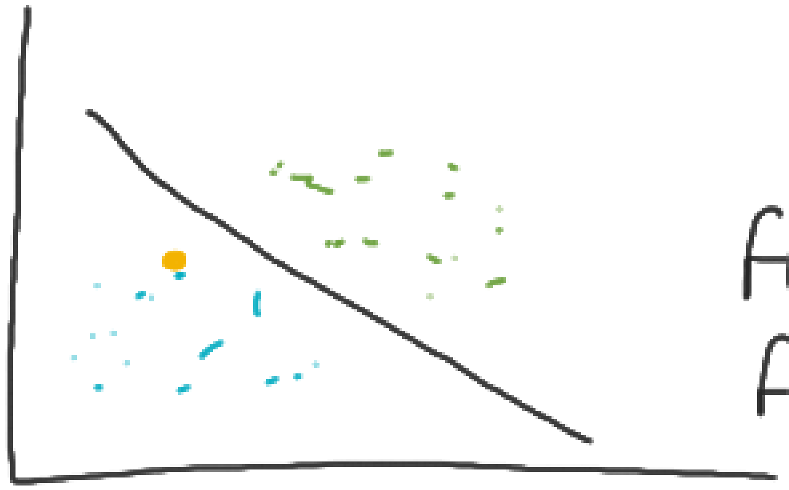
3D space, 

, $P = 3 \Rightarrow (P-1) = 3-1$
$= 2D$ subspace.

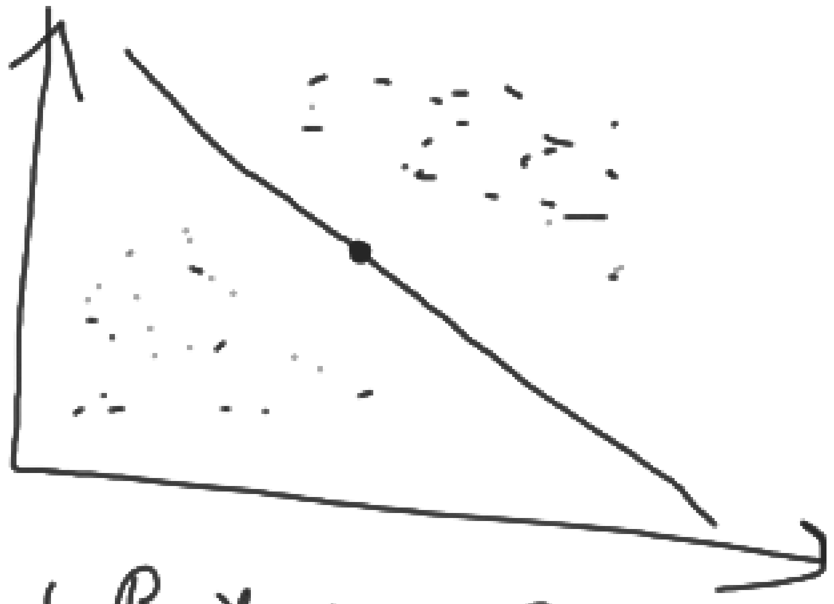
4D space, 
, $P=4$, $(P-1) = 4-1$
$= 3$ | hyperplane
3D subspace

$X = [x_1, x_2, \dots, x_p]^T$

datapoint



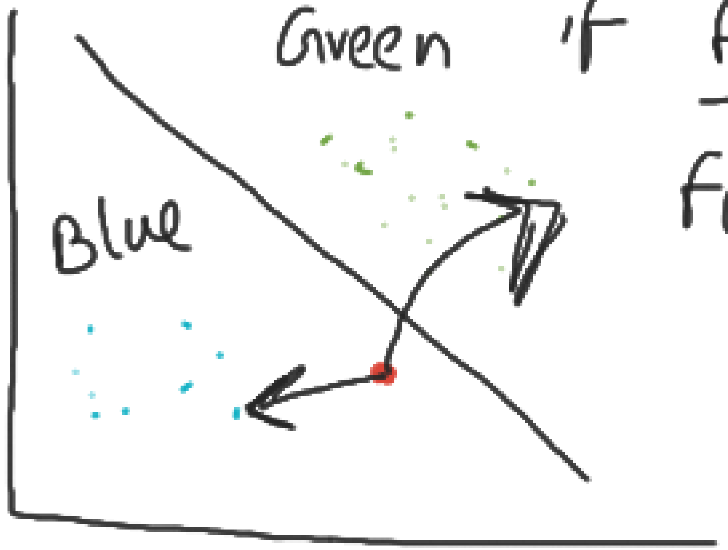
$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}$$



$f(X^*) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$

$f(x^*) =$ some value

$f(x^*) < 0$, X^* lies on one side of a hyperplane



red → Test observation

if $f(x^*) < 0$, then x^* will lie on one side of a hyperplane.

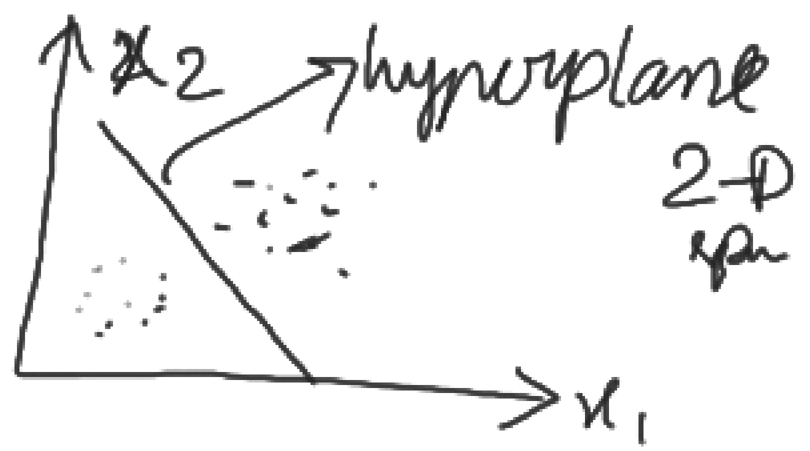
$$f(x^*) = -20$$

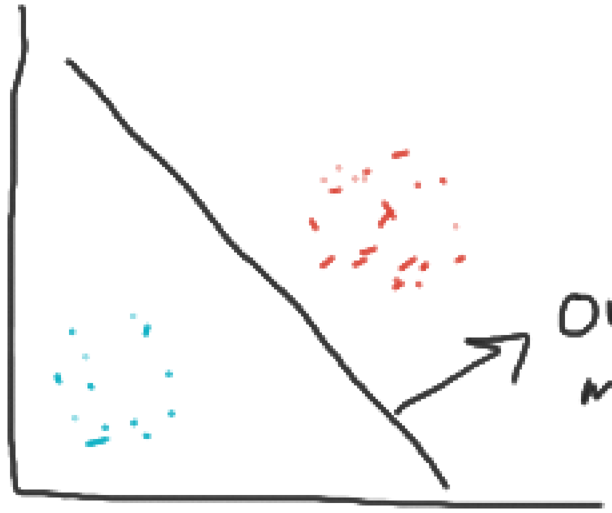
if $f(x^*) > 0$, then x^* will lie on another side of hyperplane.

$$f(x^*) = 200 > 0$$

$$\boxed{f(x^*) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p}$$

our hyperplane will divide our p-dimensional space into equal parts





one of many ways

scope of forming hyperplanes is infinite.

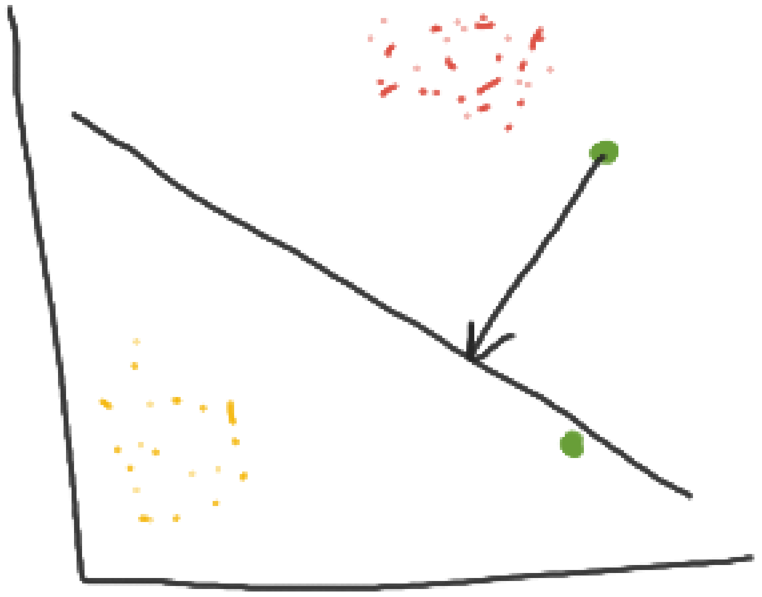
This gap → hyperplane which acts as a natural classifier

$$\boxed{f(x) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p}$$

$f(x) \to 295 > 0$ (+ve)

classifier?

$f(x) \to -50 < 0$ (-)



$f(x) = \boxed{295} > 0$

~~confidently~~ say, that (x^*) is lying in the red region

$f(x) = -\boxed{0.7} < 0$

we are not confident that this x^* belonged to any particular class.

1. hyperplane.
2. how to classify a data point using this hyperplane.

SVM → Gen form of ~~SVC~~ max margin classifier

SVC → Gen form of Max-Margin classifier → using maximal margin hyperplane, we classify a datapoint

hyperplane.