

FoDA LZ7

# Classification (Non-Linear) SVMs & Kernels

Dec 1, 2022

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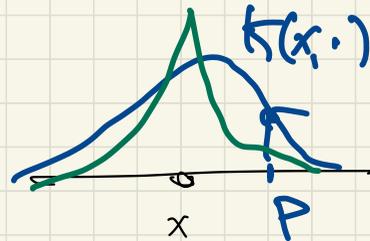
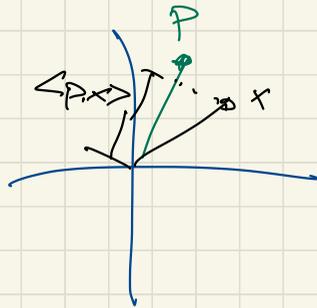


# Linear Models

dot product

$$p, x \in \mathbb{R}^d$$
$$\langle p, x \rangle = \sum_{i=1}^d p_i \cdot x_i$$

similarity function



## Kernel

- Gaussian Kernel  $K(x, p) = \exp\left(-\frac{\|x-p\|^2}{\sigma^2}\right)$
- Laplace Kernel  $K(x, p) = \exp\left(-\frac{\|x-p\|}{\sigma}\right)$
- Polynomial Kernel  $K(x, p) = (\langle x, p \rangle + c)^r$

Perceptron Also  $\text{Sign}(g_w(x)) = \langle w, x \rangle$   $T = \left(\frac{1}{\gamma^*}\right)^2$

$w = y_i x_i$   $\alpha = (1, 0, 0, \dots, 0)$

$w = \sum_{i=1}^s \alpha_i y_i x_i$

$\alpha_i = \#$  times found mistakes w/  $(x_i, y_i)$

repeat

find some  $(x_i, y_i)$  s.t.

$g_w(x_i) \neq y_i$   
mistake

$w \leftarrow w + y_i x_i$   
 $\alpha \leftarrow \alpha + (0, \dots, 0, 1, 0, \dots, 0)$

new point  $p \in \mathbb{R}^d$

$g(p) = \langle w, p \rangle = \left\langle \sum_{i=1}^s \alpha_i y_i x_i, p \right\rangle = \sum_{i=1}^s \alpha_i y_i \langle x_i, p \rangle$

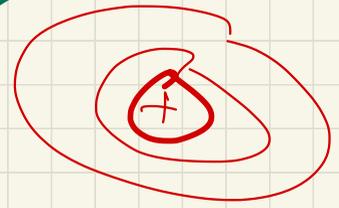
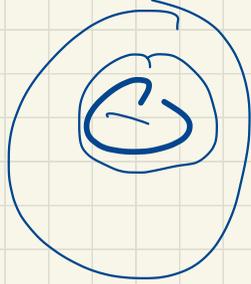
$x \in \mathbb{R}^n$   
 $\alpha = (\alpha_1, \dots, \alpha_n)$

$G_\alpha(p) = \sum_{i=1}^s \alpha_i y_i \langle x_i, p \rangle$

$\langle x_i, p \rangle$

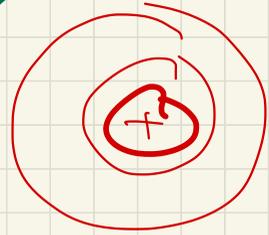
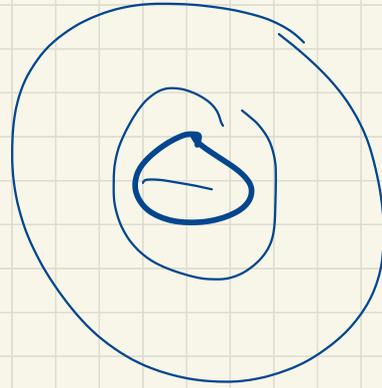
$\sum_{i=1}^s \alpha_i \langle x_i, p \rangle$

1



+

1



+

+

2

+

$$= g_{\alpha}(\rho) = 0$$

# Polynomial Kernel

$$K(x, p) = (\langle x, p \rangle + c)^r$$

represent  
all polynomials  
of  $x, p$  of  
power at most  
 $r$

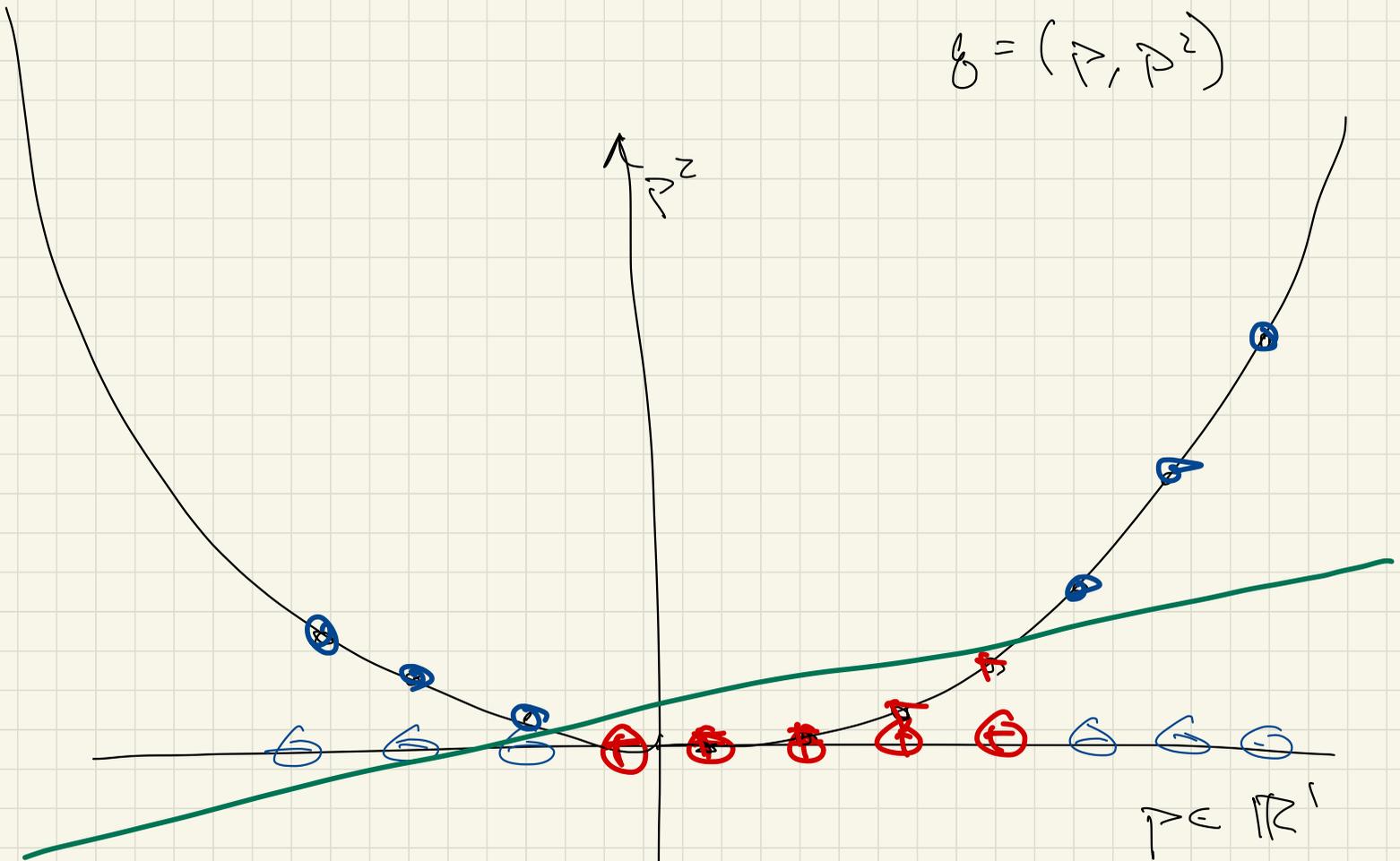
$p \rightarrow$  polynomial expansion

$$p \in \mathbb{R}^1 \quad v \in \mathbb{R}^{r+1} \quad v = (1, p, p^2, \dots, p^r)$$

$$p = (p_1, p_2) \in \mathbb{R}^2 \rightarrow g = (1, p_x, p_x^2, p_y, p_y^2, p_x \cdot p_y) \in \mathbb{R}^6$$

$$g = (p^1, p^2)$$

$\vec{p}^2$



$\vec{p}^1 \in \mathbb{R}^1$

# Polynomial Classification via Lifting

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1.  $\forall x_i \in X$  map to  $g_i \in \mathbb{R}^{(dr)}$  ex.  $(1, x_i, x_i^2, \dots)$

2. Build Linear Classifier on  $(Q, g)$   
 $g: \mathbb{R}^{(dr)} \rightarrow \mathbb{R}$

3. Apply to new  $p \in \mathbb{R}^d$   
3a. map  $p \rightarrow \mathbb{R}^{(dr)} \rightarrow g_p$

3b.  $\text{sign}(g(g_p))$

# Support Vector Machines (SVMs)

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Goal  $g_{\alpha}(P) = \sum_{i=1}^n \alpha_i K(x_i, P)$

learn  $\alpha \in \mathbb{R}^n$

how misclassified

$$z_j = y_j g_{\alpha}(x_j) = y_j$$

$$\sum_{i=1}^n \alpha_i K(x_i, x_j)$$

$$\min_{\alpha} \sum_{j=1}^n l(z_j)$$

subset

$$|S| = k$$

$$S \subset X$$

$\mathbb{1}$  support vectors

$$g_{\alpha}(P) = \sum_{x_i \in S} \alpha_i K(x_i, P)$$

$$K(x_i, x_j) \in \mathbb{R}^{n \times n}$$