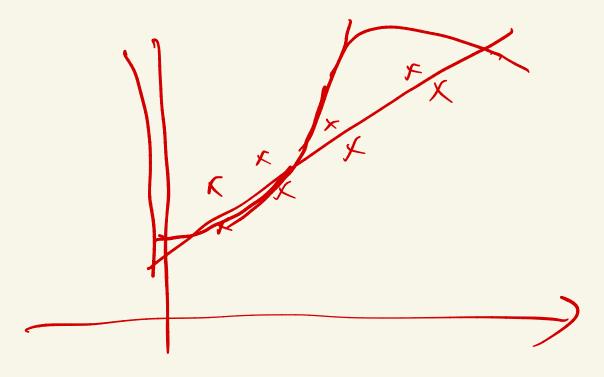
Lecture 4 Kernel Method



d. dimension of input

P: dimension of new feature

DER DERP

DE RO parameter

representation Learning

 $J = \theta^{\dagger} \varphi_{cx}$, 3-dim

× 103

1 = 0 7 0 cm p-dim

n: # Samples $\theta = \frac{2}{2} \beta_i \phi c x^{(i)}) \beta_i \in \mathbb{R}$ tim.

(D= P. pexa)

J gradiene

descene assuption. 0:= Out & E cyai) - o pexail & cxai) = £13; \$(xa))+ + 2 cy (i) -0 (pcx)) (xi) = = = (B; + & cyci) - OT & (x (1)) & (x (1))

$$\theta^{l}$$

 $\beta_i := \beta_i + d Cy^{(i)} - \sum_{j=1}^{n} \beta_j \psi C \times^{(i)} \int \varphi C \times^{(i)} \int$ l scalar R unrelated to B: multiplication # gradient steps

i, j ∈ {1, --- n} A.# dota samples

$$k = n$$

$$Q = \frac{L}{i\pi} \beta_i \psi Q x^{\alpha i}$$

 $k(x,z) = \phi \cos \phi cz$ $= (x^{7}z)^{2} \qquad O(3)$ $= (x^{7}z)^{2} \qquad \times CR^{3} \qquad d=3$ $\phi cx; \qquad \phi cx; \qquad \phi cx \in R^{9} \quad d^{2}$