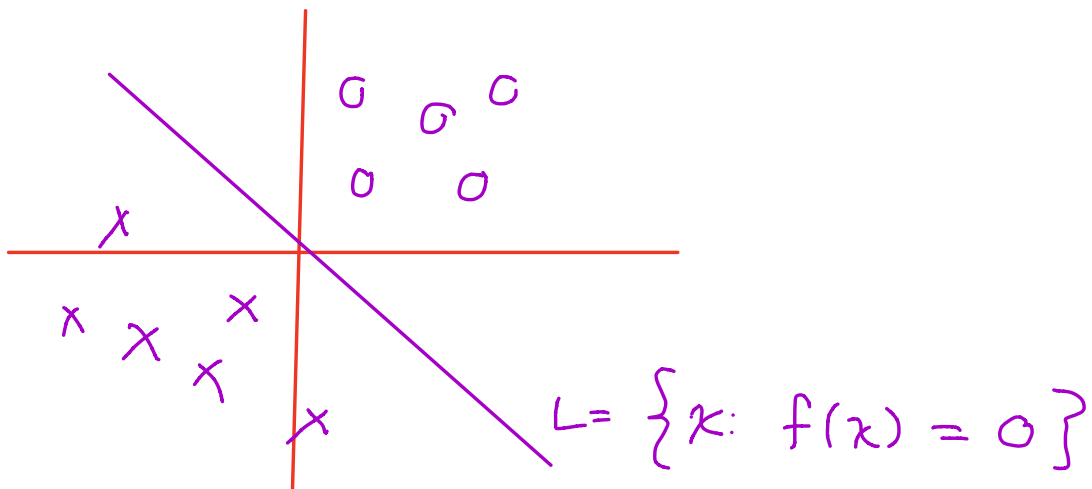


Maximum Margin Hypoplane



$$f(x) = \beta_0 + x^T \beta$$

If the data are perfectly separable
then there exists a unique function that achieves
this.

$$(\beta_0, \beta) = \arg \max \frac{1}{\|\beta\|}$$

$$\{\beta_0, \beta: y_i (x_i^T \beta + \beta_0) \geq 1\}$$

↑ only satisfied
if perfect
classification

$$= \arg \max \frac{1}{\|\beta\|}$$

$$\{\beta_0, \beta : \underbrace{y_i}_{\text{"1"}} \underbrace{\left(\frac{x_i^T \beta + \beta_0}{\|\beta\|} \right)}_{\text{"1"}} \geq \underbrace{1}_{\text{"1"}}\}$$

Goal: find the largest value s.t. the perfectly classified points are furthest from the hyperplane.

Convex Optimization

Looking to solve

$$\arg \min_{\{\beta_0, \beta : y_i(x_i^T \beta + \beta_0) \geq 1\}} \|\beta\|^2$$

Constrained optimization problem.

Using Lagrange multipliers

$$\begin{aligned} L_p = & \frac{1}{2} \|\beta\|^2 - \alpha_1 (y_1 (x_1^T \beta + \beta_0) - 1) \\ & - \alpha_2 (y_2 (x_2^T \beta + \beta_0) - 1) \\ & \vdots \\ & - \alpha_N (y_N (x_N^T \beta + \beta_0) - 1) \end{aligned}$$

+ constraints to be satisfied

$$\frac{\partial L_D}{\partial \beta} = \frac{\partial}{\partial \beta} \left\{ \frac{1}{2} \|\beta\|^2 - \sum \alpha_i (y_i (x_i^T \beta - \beta_0) - 1) \right\}$$

$$\Rightarrow \beta = \sum_{i=1}^N \alpha_i y_i x_i \quad 0 = \sum_{i=1}^N \alpha_i y_i$$

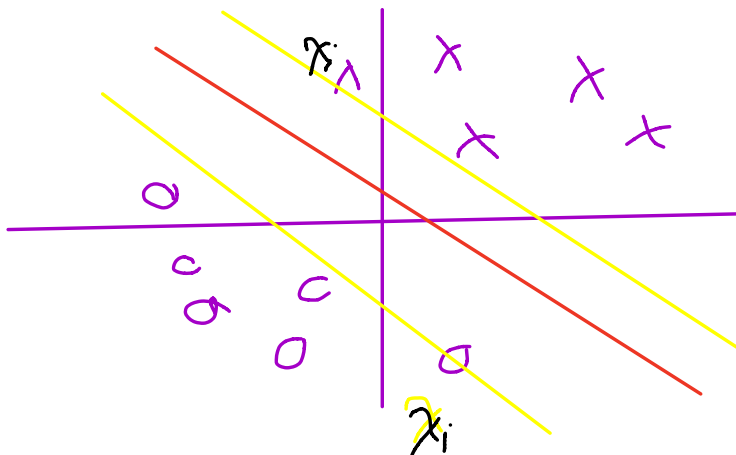
The dual Lagrangian can be written

$$L_D = \sum \alpha_i - \frac{1}{2} \sum_i \sum_k \alpha_i \alpha_k y_i y_k x_i^T x_k$$

these constraints are the KKT conditions

$$\alpha_i [y_i (x_i^T \beta + \beta_0) - 1] = 0$$

if $\alpha_i > 0$ then $y_i (x_i^T \beta + \beta_0) = 1$.



these touching points are going to be
the only contributors to $\sum \alpha_i y_i x_i$

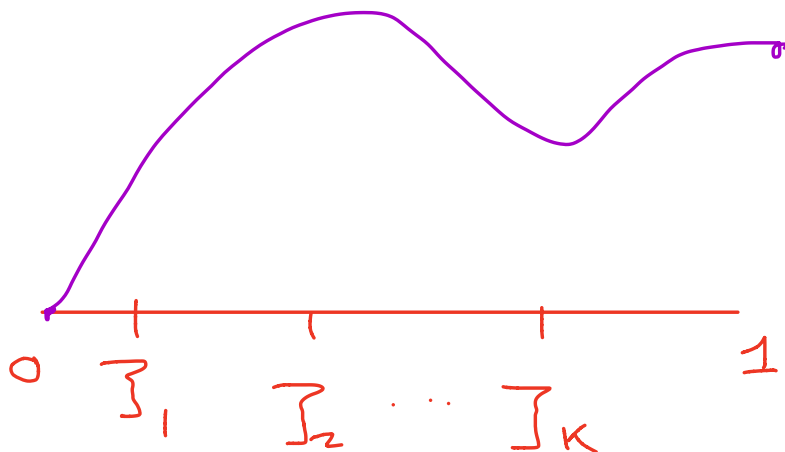
Moreover if $y_i(x_i^T \beta + \beta_0)$ is off the margin and
do not contribute to the α_i in the sum $\sum \alpha_i y_i x_i$.

Basis Expansion

$$Y = \sum_{i=1}^N \beta_i x_i + \beta_0 \quad \text{replaced with} \quad Y = \sum_{i=1}^N \beta_i f(x_i) + \beta_0$$

One good choice of functions $h(x)$ are called

splines.



Piecewise cubic polynomials on the intervals (J_i, J_{i+1})

such that $\hat{f} = \sum_{i=1}^m h_i(x_i) \in C^2$