

# Maximal Margin Classifier: The Math



The maximal margin classifier solves a constrained optimization problem:

$$\max_{\beta_0, \beta_1, \dots, \beta_p} M$$

subject to:

$$\|\beta\| = 1$$

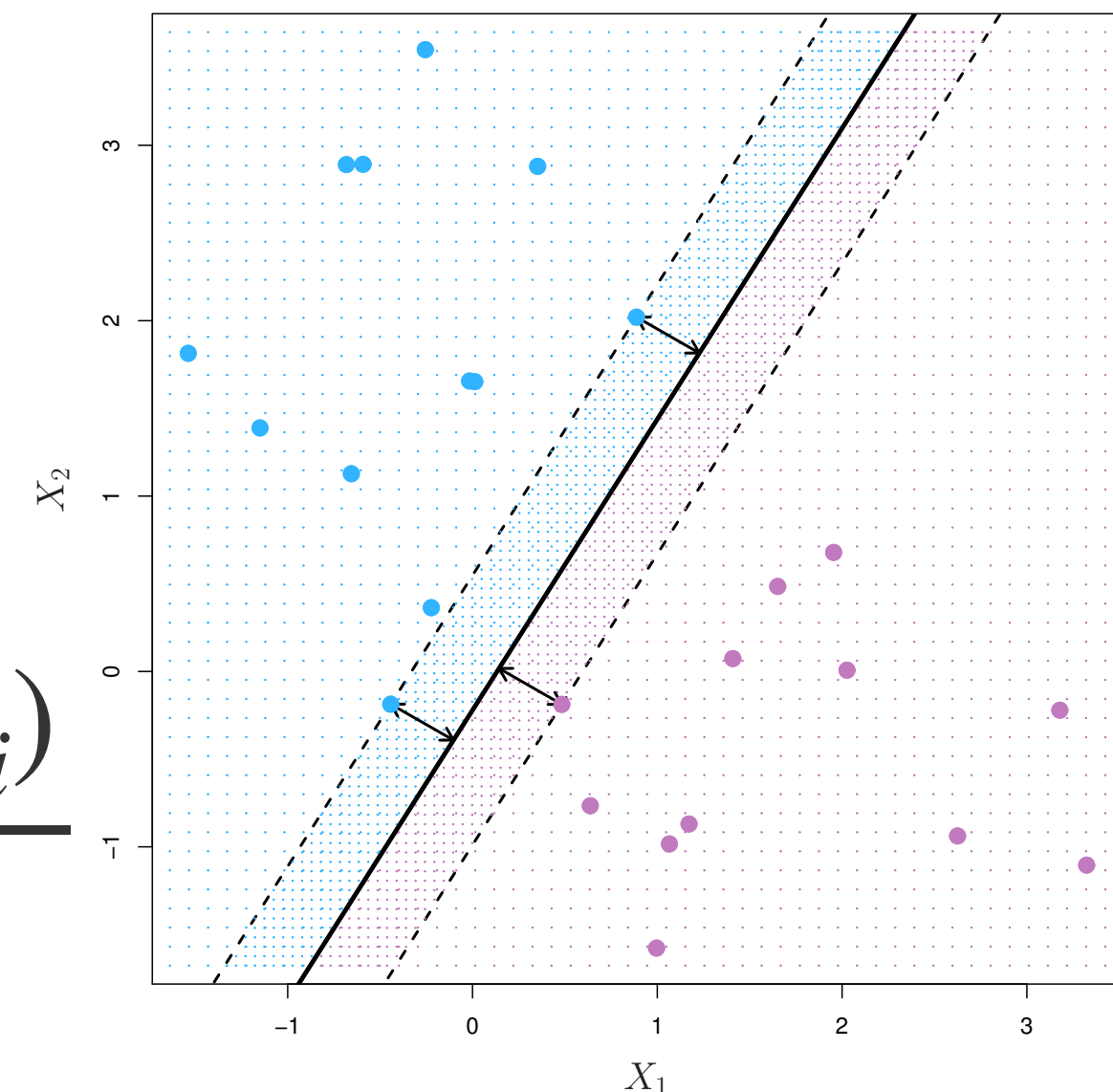
$$y_i(\beta_0 + \beta^T x_i) \geq M, \quad \forall i = 1, \dots, n$$

ensured each observation is on the correct side of the hyperplane  
and at least a distance  $M$  from the hyperplane,  
i.e.,  $M$  is the margin of the hyperplane

distance between  $x_i$  and line where

$$\|\beta\| = \sqrt{\sum_{j=1}^p \beta_j^2} \text{ is the Euclidean norm of } \beta$$

$$\left\{ \frac{y_i(\beta_0 + \beta^T x_i)}{\|\beta\|} \right\}$$



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The maximal margin classifier solves a constrained optimization problem:

$$\underbrace{\arg \max_{\beta_0, \beta} \left\{ \frac{1}{\|\beta\|} \min_i [y_i(\beta_0 + \beta^T x_i)] \right\}}_{\text{maximize the minimum distance between hyperplane and point}} \leftarrow \begin{array}{l} \text{easier to minimize} \\ \arg \min_{\beta_0, \beta} \frac{1}{2} \|\beta\|^2 \end{array}$$

maximize the minimum distance between hyperplane and point

$$\text{subject to: } y_i(\beta_0 + \beta^T x_i) \geq 1, \quad \forall i = 1, \dots, n$$

distance between  $x_i$  and line where

$$\|\beta\| = \sqrt{\sum_{j=1}^p \beta_j^2} \text{ is the Euclidean norm of } \beta$$

$$\left\{ \frac{y_i(\beta_0 + \beta^T x_i)}{\|\beta\|} \right\}$$

