



Support vector machines

Lecture 12 of “Mathematics and AI”



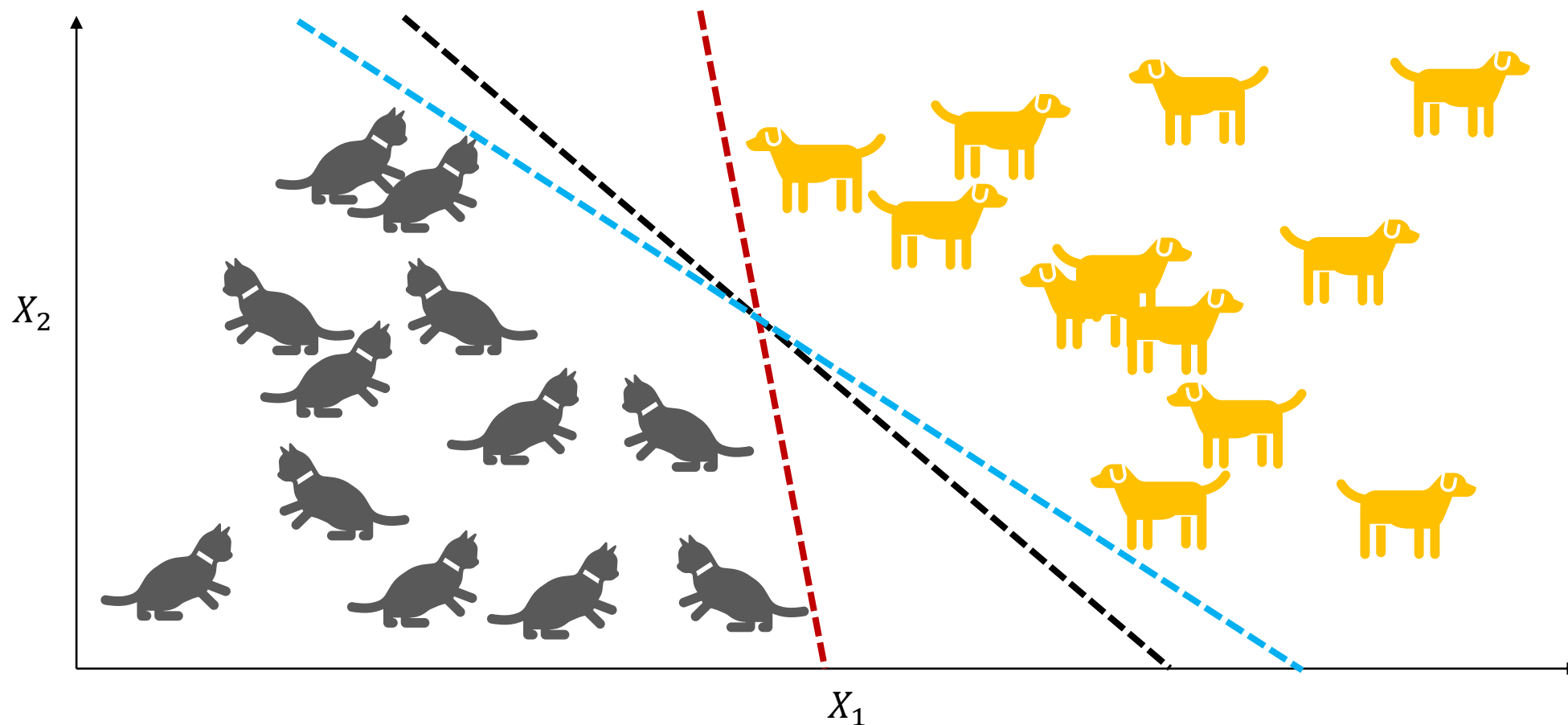
Outline

1. Maximal margin classifier
2. Support vector classifier
3. SVC and logistic regression



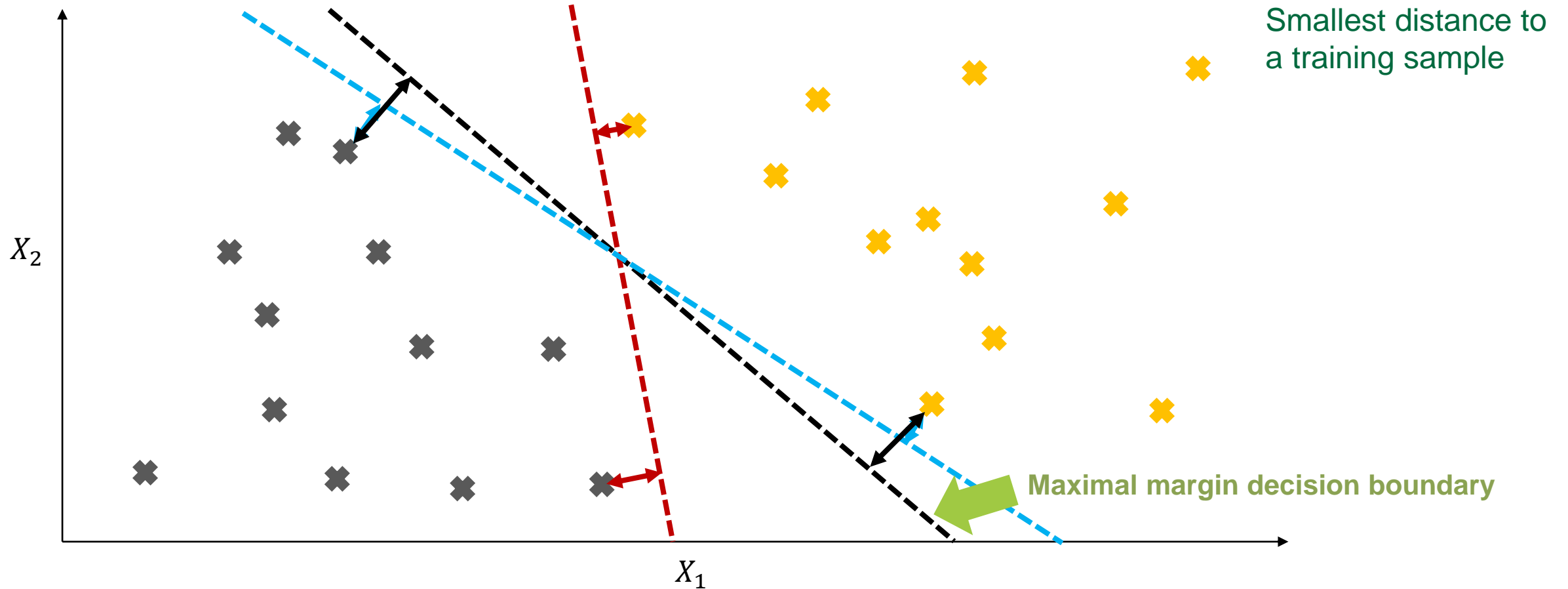
Maximal margin classifier

Linearly separable patterns



Which decision boundary is the best?

Linearly separable patterns



Hyperplanes

- Hyperplane (perpendicular to coordinate axis)

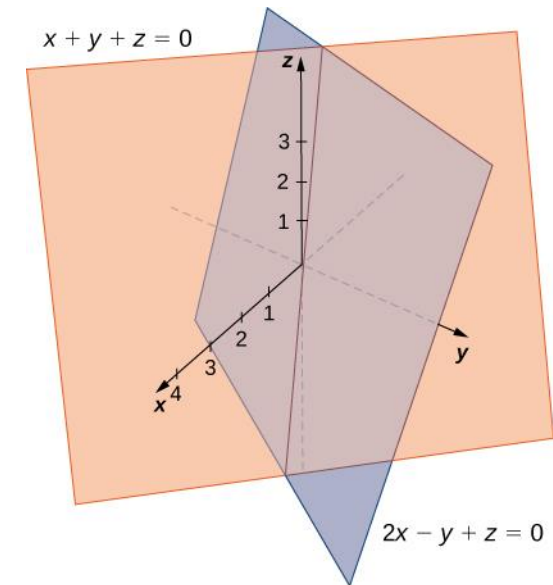
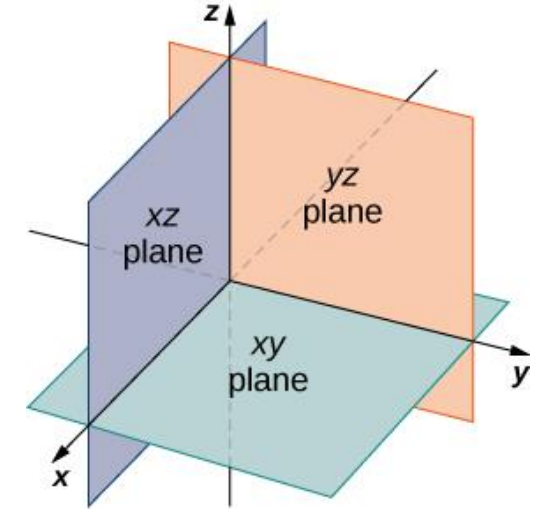
$$\beta_0 + x_j = 0$$

- Hyperplane (general case)

$$\beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \cdots + \beta_p x_{i,p} = 0$$

- Hyperplane in vector notation

$$\beta_0 + \vec{\beta} \cdot \vec{x}_i = 0$$



Hyperplanes as separators

- Hyperplane in vector notation

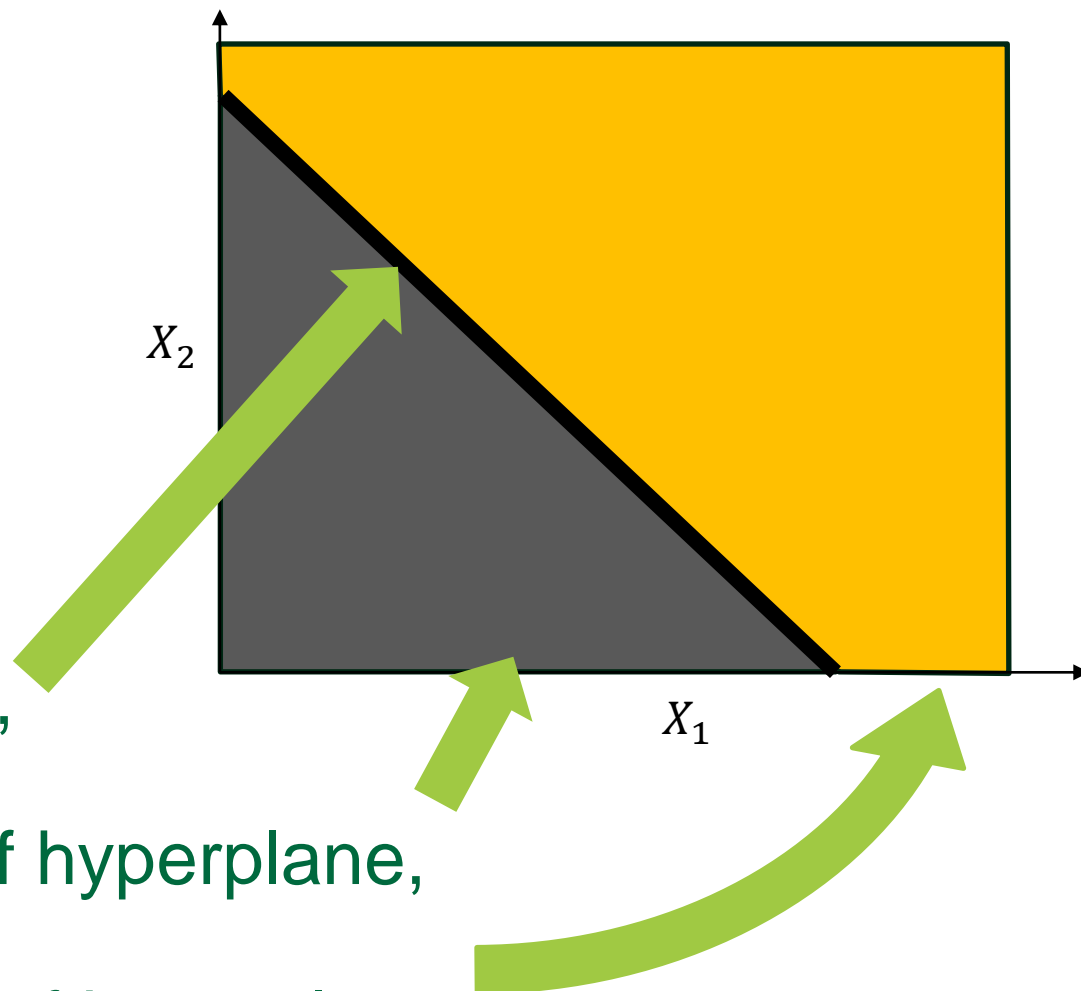
$$\beta_0 + \vec{\beta} \cdot \vec{x}_i = 0$$

- Three sets of points

$\{ \vec{x}_i \mid \beta_0 + \vec{\beta} \cdot \vec{x}_i = 0 \} \rightarrow \vec{x}_i$ in hyperplane,

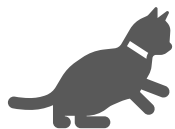
$\{ \vec{x}_i \mid \beta_0 + \vec{\beta} \cdot \vec{x}_i < 0 \} \rightarrow \vec{x}_i$ on one side of hyperplane,

$\{ \vec{x}_i \mid \beta_0 + \vec{\beta} \cdot \vec{x}_i > 0 \} \rightarrow \vec{x}_i$ on other side of hyperplane



Linear decision boundary for binary classification

$$\{\vec{x}_i \mid \beta_0 + \vec{\beta} \cdot \vec{x}_i < 0\}$$



$$\{\vec{x}_i \mid \beta_0 + \vec{\beta} \cdot \vec{x}_i > 0\}$$



➤ \vec{x}_i on one side of hyperplane

➤ (\vec{x}_i, y_i) is “cat”

➤ $y_i = -1$

➤ \vec{x}_i on other side of hyperplane

➤ (\vec{x}_i, y_i) is “dog”

➤ $y_i = +1$

For **all** training samples:



$$y_i (\beta_0 + \vec{\beta} \cdot \vec{x}_i) \geq 0$$



Replace with quantitative formulation?

Hyperplanes and normal vectors

- Hyperplane in vector notation

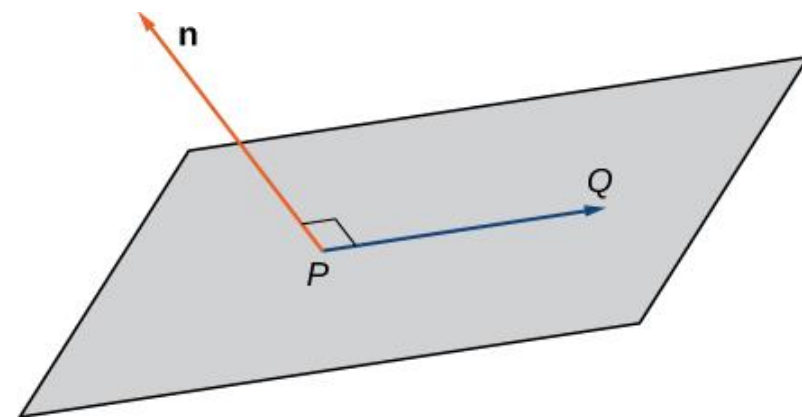
$$\beta_0 + \vec{\beta} \cdot \vec{x}_i = 0$$

- Hyperplane in normal-vector notation

$$\vec{\beta} \cdot (\vec{x}_i - \vec{P}) = 0$$

$$\text{with } \vec{P} = \left(-\frac{\beta_0}{\beta_1} \quad 0 \quad \dots \quad 0 \right)^T$$

- Vector $\vec{\beta}$ is the **normal vector** of the hyperplane



Normal vectors and margins

- Hyperplane in normal-vector notation

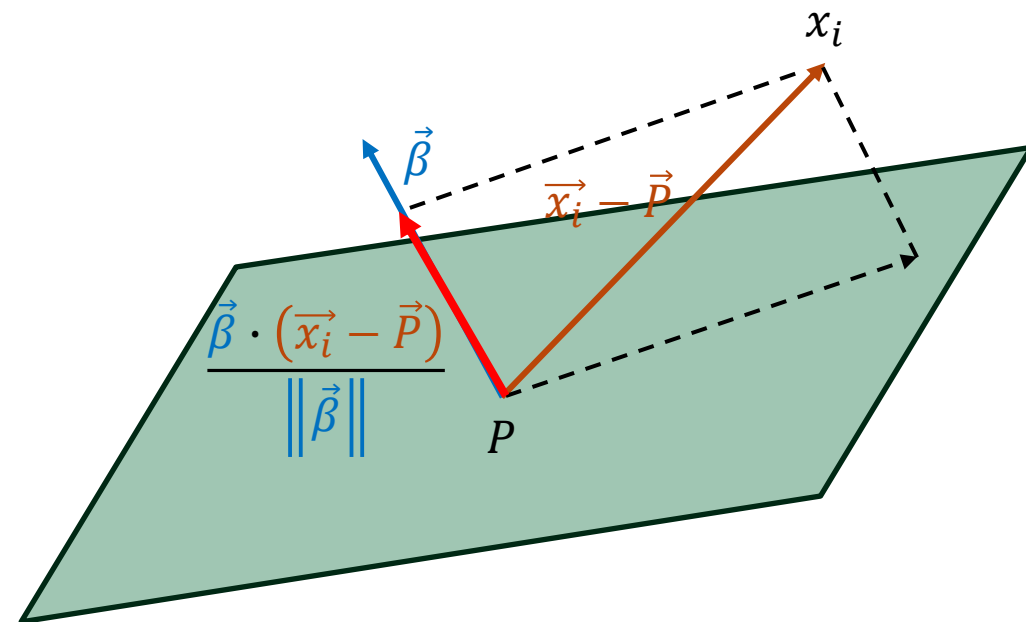
$$\vec{\beta} \cdot (\vec{x}_i - \vec{P}) = 0$$

- Distance from \vec{x}_i to hyperplane

$$d_{\vec{\beta}, \vec{x}_i} = \frac{\|\vec{\beta} \cdot (\vec{x}_i - \vec{P})\|}{\|\vec{\beta}\|}$$

- Special case when $\|\vec{\beta}\| = 1$:

$$d_{\vec{\beta}, \vec{x}_i} = \|\vec{\beta} \cdot (\vec{x}_i - \vec{P})\| = |\beta_0 + \vec{\beta} \cdot \vec{x}_i|$$



Maximal margin classifier

- Find the linear decision boundary (i.e., hyperplane) with the largest margin

For all training samples:

$$\begin{array}{ccc} \text{🐱} & y_i \left(\beta_0 + \vec{\beta} \cdot \vec{x}_i \right) > M & \text{🐶} \\ & \text{with } \left\| \vec{\beta} \right\| = 1 \end{array}$$



Maximal margin classifier: Optimization problem

$$\text{maximize}_{\beta_0, \beta_1, \dots, \beta_p, M} M$$

$$\text{subject to } \sum_{j=1}^p \beta_j^2 = 1,$$

$$y_i(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip}) \geq M \quad \forall i = 1, \dots, n$$

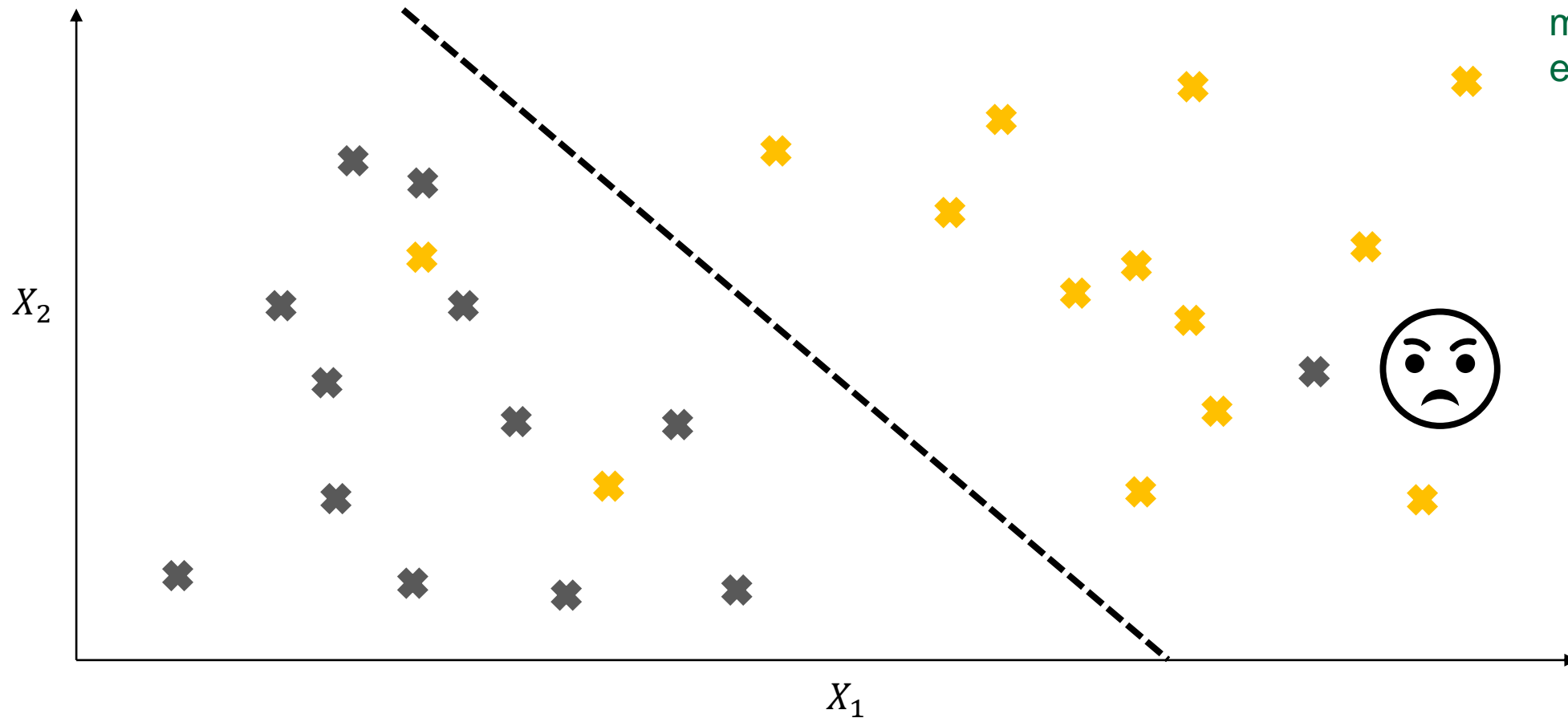


Alternative optimization problem



Support vector classifier

Data without a linear separator



Intrinsic variability,
measurement errors,
etc.

Slack variables ϵ_i

$$\text{maximize}_{\beta_0, \beta_1, \dots, \beta_p, \epsilon_1, \dots, \epsilon_n, M} M$$

$$\text{subject to } \sum_{j=1}^p \beta_j^2 = 1,$$

$$y_i(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip}) \geq M(1 - \epsilon_i),$$

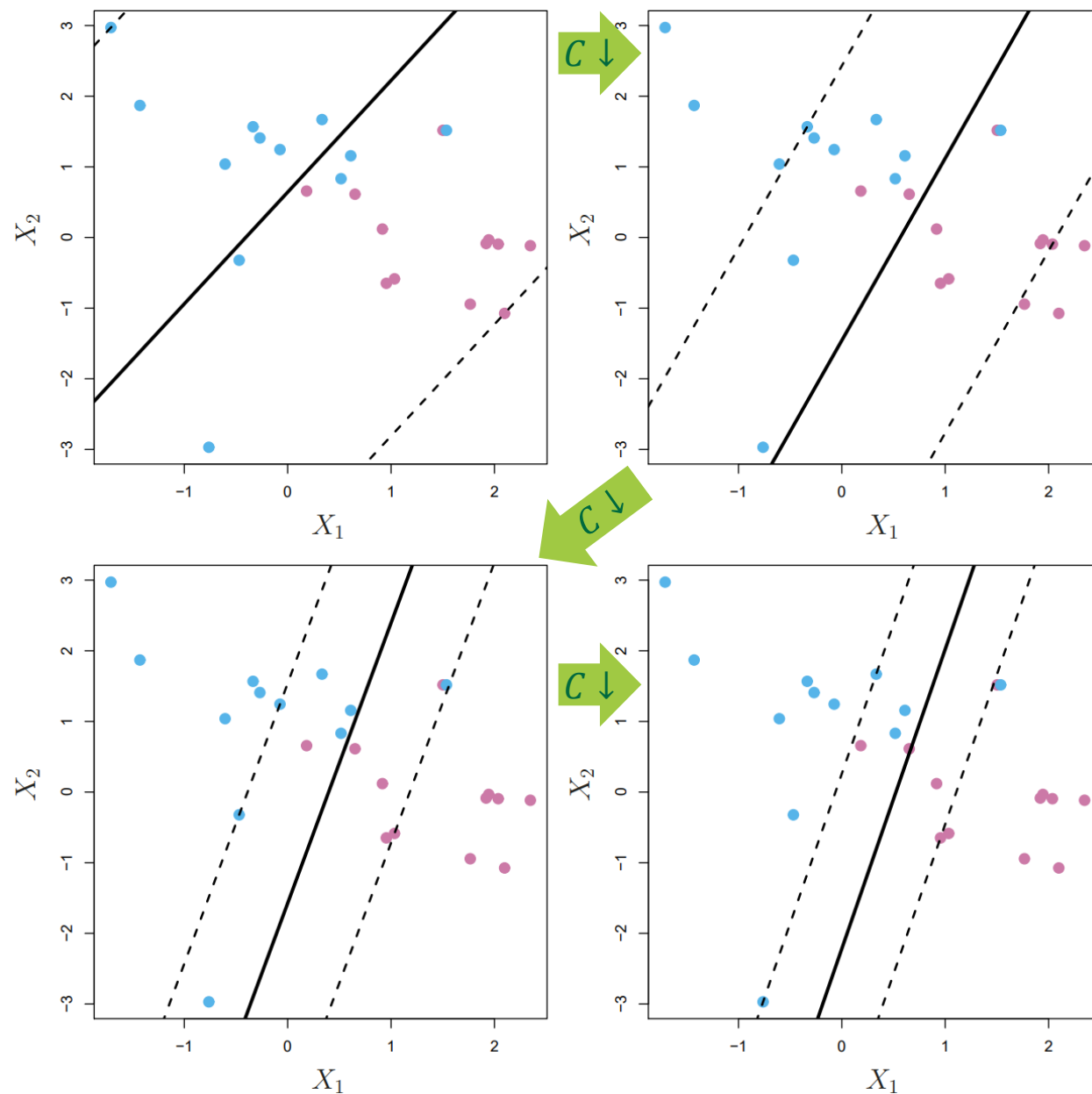
Slack variable

$$\epsilon_i \geq 0, \quad \sum_{i=1}^n \epsilon_i \leq C$$

Tuning parameter /
hyperparameter



Examples





SVC & logistic regression



Alternative optimization problem for SVC

Loss functions for SVC and linear regression

