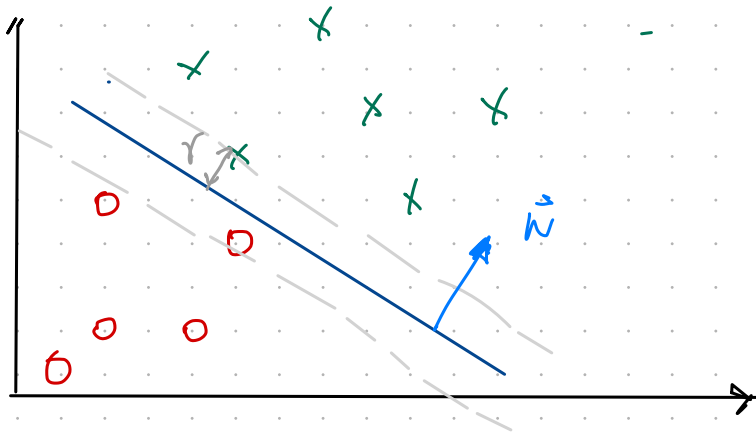


Support Vector Machine (SVM)

- Idea: Find the maximum margin hyperplane



- The SVM's optimization problem: The objective is

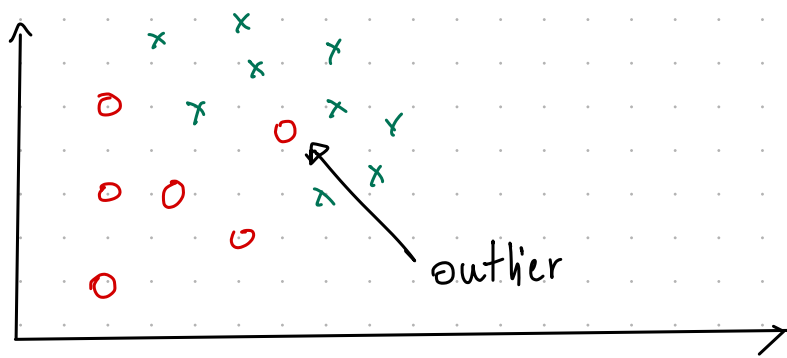
$$\min_{\vec{w}, b} \quad \vec{w}^T \vec{w} \quad \text{s.t.} \quad \forall i \quad y_i (\vec{w}^T \vec{x}_i + b) \geq 1$$

quadratic objective function
linear constraints

To find \vec{w}, b that minimize the objective, we can use quadratic programming solver (QCP).

Nice interpretation: Find us the simplest solution such that all points lie at least 1 unit away from the hyperplane on the correct side. The vector \vec{w} (and b) supports the closest points to the hyperplane where $y_i (\vec{w}^T \vec{x}_i + b) = 1$.

- Let's consider the case where data is not linearly separable.



- In this case, no separating hyperplane exists, and that's bad.
- What we would do instead is that we can sacrifice some outlier(s) in order to place the hyperplane.

SVM with Soft Constraints:

- Fix: We allow the constraints to be softened slightly with the introduction of slack (wob) variable $\xi_i \geq 0, \forall i$.

$$\min_{\vec{w}, b, \xi} \quad \underbrace{W^T W + C \sum_{i=1}^n \xi_i}_{\text{objective function}} \quad \text{s.t.} \quad \forall i \quad y_i (\vec{w}^T \vec{x}_i + b) \geq 1 - \xi_i$$

$$\forall i \quad \xi_i \geq 0$$

linear constraints

- The slack variable ξ_i allow \vec{x}_i to be closer to the hyperplane (or even be on the wrong side) but there is a penalty in the objective function for such slack.

Penalty: $C \rightarrow +\infty$, SVM will try to make all the points to be on the right side

$C \rightarrow 0$, SVM may sacrifice some points to obtain a simpler hyperplane.

- Unconstrained formulation: We set ξ_i as followed

$$\xi_i = \begin{cases} 1 - y_i(\vec{w}^T \vec{x}_i + b) & \text{if } y_i(\vec{w}^T \vec{x}_i + b) < 1 \\ 0 & \text{if } y_i(\vec{w}^T \vec{x}_i + b) \geq 1 \end{cases}$$

\Leftrightarrow

$$\xi_i = \max(1 - y_i(\vec{w}^T \vec{x}_i + b), 0)$$

- The SVM with soft constraints optimization problem:

$$\min_{\vec{w}, b} \vec{w}^T \vec{w} + C \sum_{i=1}^n \max(1 - y_i(\vec{w}^T \vec{x}_i + b), 0)$$

