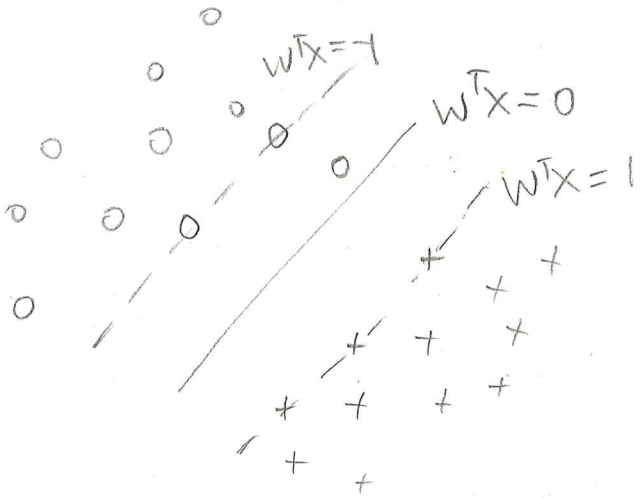
SVM - Optimization:

$$\min \|w\|^2, \quad \text{s.t.} \quad y_i(w^T x_i) \geq 1 \quad \text{for } i=1,\dots,N \qquad (1)$$

Quadratic optimization s.t. linear Constraints.

The optimization of (1) is equivalent to the unconstrained optimization problem over w:

$$\min \underbrace{\|w\|^2}_{\text{Regularization}} + \underbrace{\lambda}_{\text{hand-tuning parameter}} \sum_{i=1}^{N} \underbrace{\max(0, 1 - y_i f(x_i))}_{\text{Loss function "hinge" loss}}, \quad f(x_i) = w^T x_i$$



1. $y_i f(x_i) > 1$, points is outside margin. No Contribution to loss

2. $y_i f(x_i) = 1$, points on margin. No Contribution.

3. $y_i f(x_i) < 1$, points violates Margin Constraint. Contributes to loss