

● 1. SUPPORT VECTOR MACHINE (SVM)

1 Problem Formulation

Input space:

$$\mathcal{X} \subseteq \mathbb{R}^d$$

Output space:

Binary classification:

$$\mathcal{Y} = \{-1, +1\}$$

Data distribution:

$$(x_i, y_i) \sim \mathcal{D}$$

Learning Objective (Expected Risk Minimization):

$$R(f) = \mathbb{E}_{(x,y) \sim \mathcal{D}}[\ell(y, f(x))]$$

2 Model Specification

Support Vector Machine (SVM)

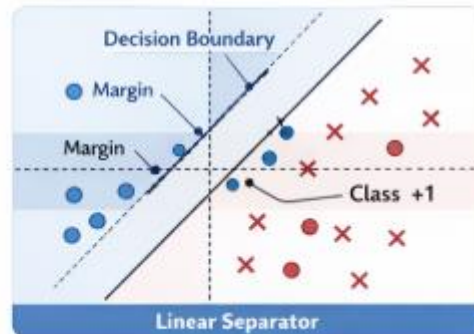
Model Specification

Hypothesis Function:

$$f(x) = w \cdot x + b$$

Hypothesis Function:

$$f(x) = \text{Piecewise Constant}$$



Hypothesis Function

Linear SVM:

$$f(x) = w^T x + b$$

Kernel SVM:

$$f(x) = \sum_{i=1}^n \alpha_i y_i K(x_i, x) + b$$

Parameter Space

$$w \in \mathbb{R}^d, \quad b \in \mathbb{R}$$

Structural Assumptions

- Linear separability (hard margin)
 - Non-linear separability via kernel trick
 - Large margin principle
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3 Loss Function

Hinge Loss

$$\ell(u, f(x)) = \max(0, 1 - u f(x))$$

Why Hinge Loss?

- Upper bound on 0–1 loss
- Encourages margin maximization

Convexity

- Convex but non-differentiable
 - Global optimum guaranteed
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4 Objective Function

Empirical Risk

$$\frac{1}{n} \sum_{i=1}^n \max(0, 1 - y_i(w^T x_i + b))$$

Regularized Form

$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \max(0, 1 - y_i f(x_i))$$

5 Optimization Method

- Quadratic Programming (QP)
- SMO algorithm (iterative)

Gradient (Subgradient)

If margin violated:

$$\nabla_w = -y_i x_i$$

Convergence

- Convex optimization \rightarrow global optimum
 - Complexity: $O(n^3)$ worst case (QP)
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6 Statistical Interpretation

- Equivalent to L2-regularized hinge risk minimization
 - Can be interpreted as MAP under specific priors
 - Output is margin distance (not probability)
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7 Regularization & Generalization

- Controlled by CCC
 - Large margin \rightarrow lower VC dimension
 - Bias-variance tradeoff via margin width
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8 Theoretical Properties

- Convex optimization
- Unique global minimum
- Consistent under separability

9 Computational Complexity

Aspect	Complexity
Training	$O(n^3)$
Inference	$O(sv)$
Memory	$O(n^2)$

(sv = number of support vectors)

10 Limitations

- Not scalable for very large datasets
 - No probabilistic output (unless calibrated)
 - Sensitive to kernel choice
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11 SVM Margin Visualization

A diagram illustrating the margin of a linear SVM. It shows a horizontal dashed line labeled "Decision boundary" on the right. Above the line are three '+' signs, and below the line are three '-' signs. A vertical line segment connects the middle '+' sign to the middle '-' sign, passing through the dashed line. This segment is labeled "Margin" with vertical bars at each end.