

# Support Vector Machines

Machine Learning  
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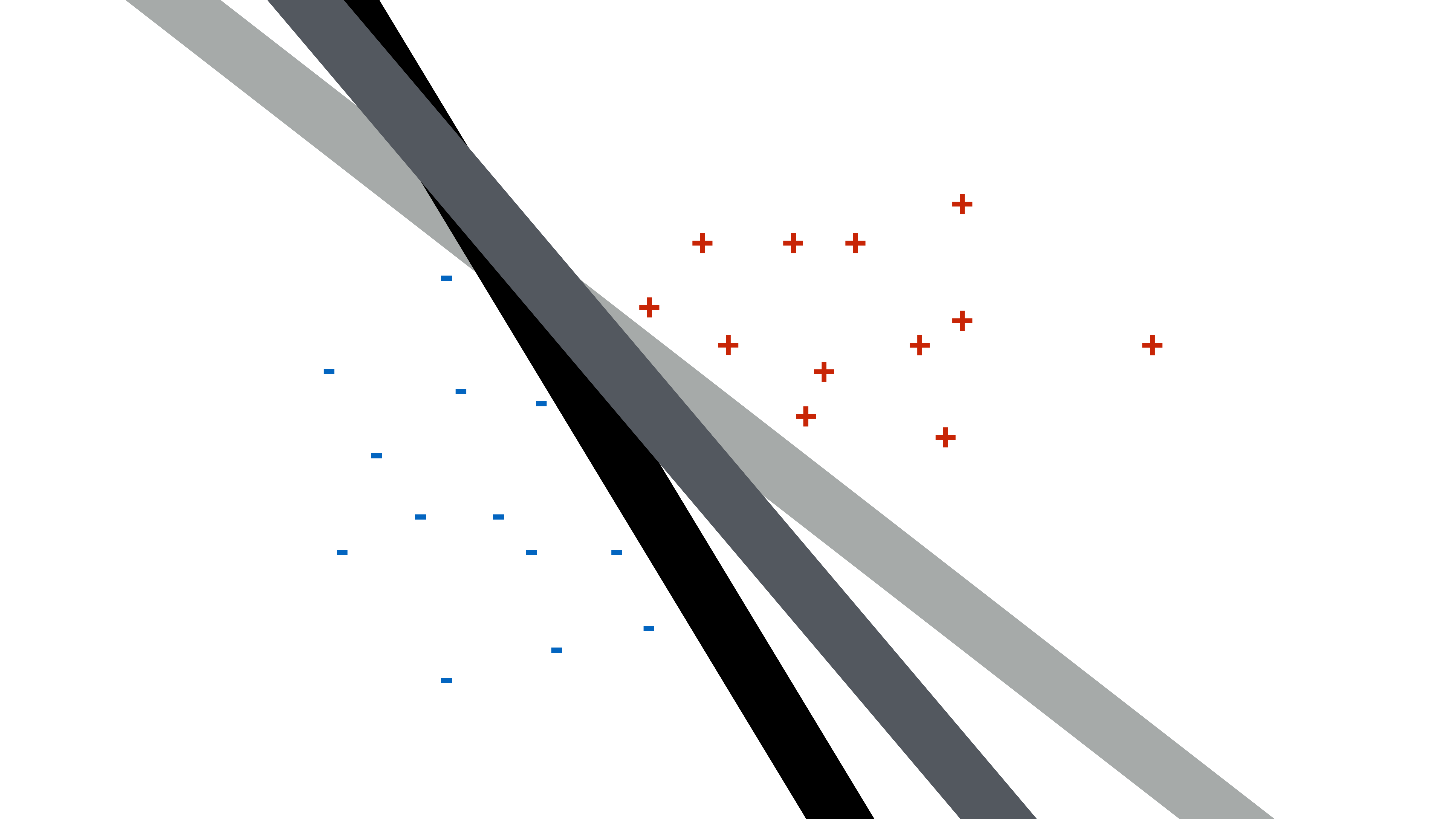
# Large-Margin Linear Classification

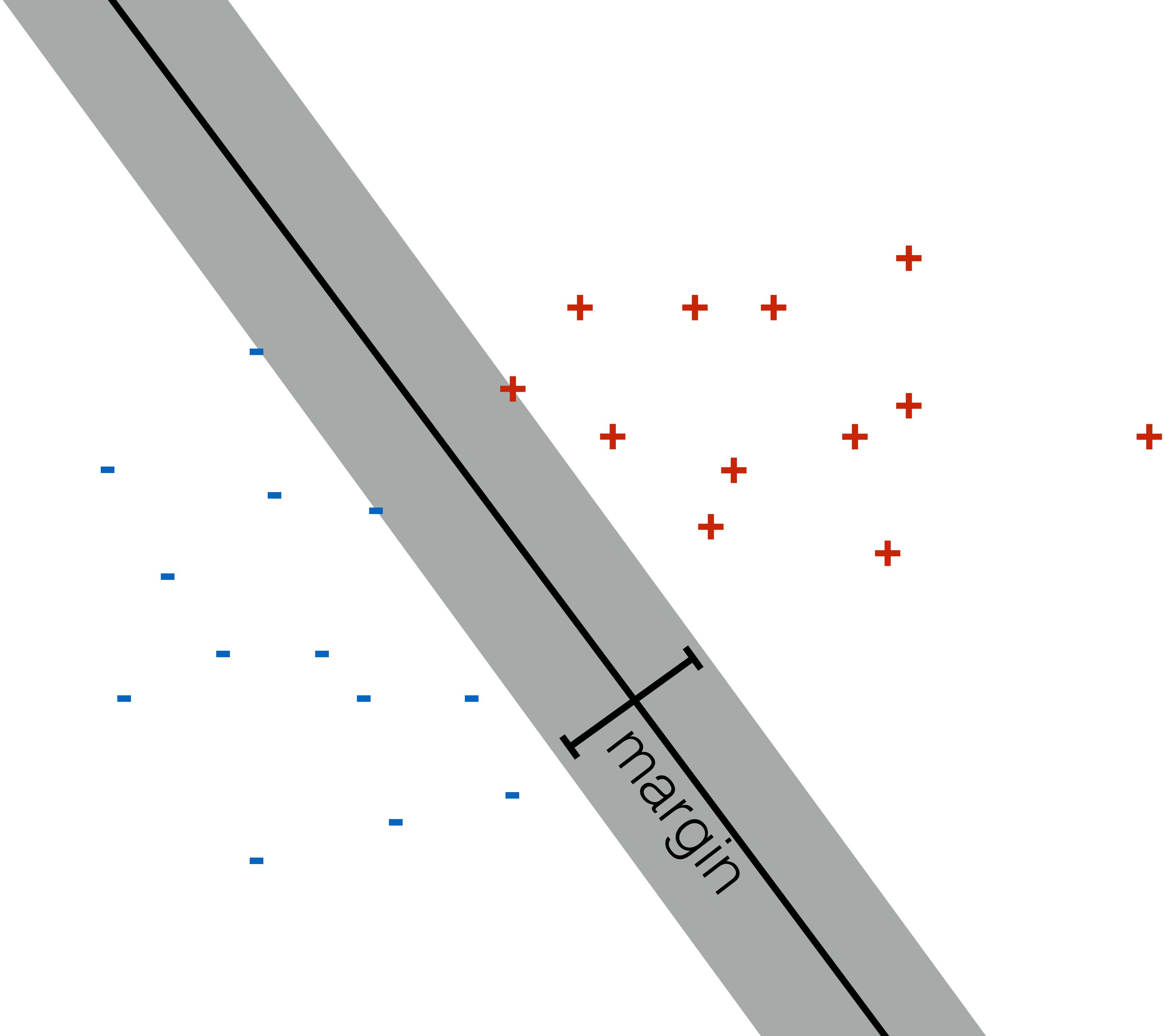
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# Outline

- Large-margin and model complexity
- Formalizing large margin
- Quadratic program form
- Soft-margin





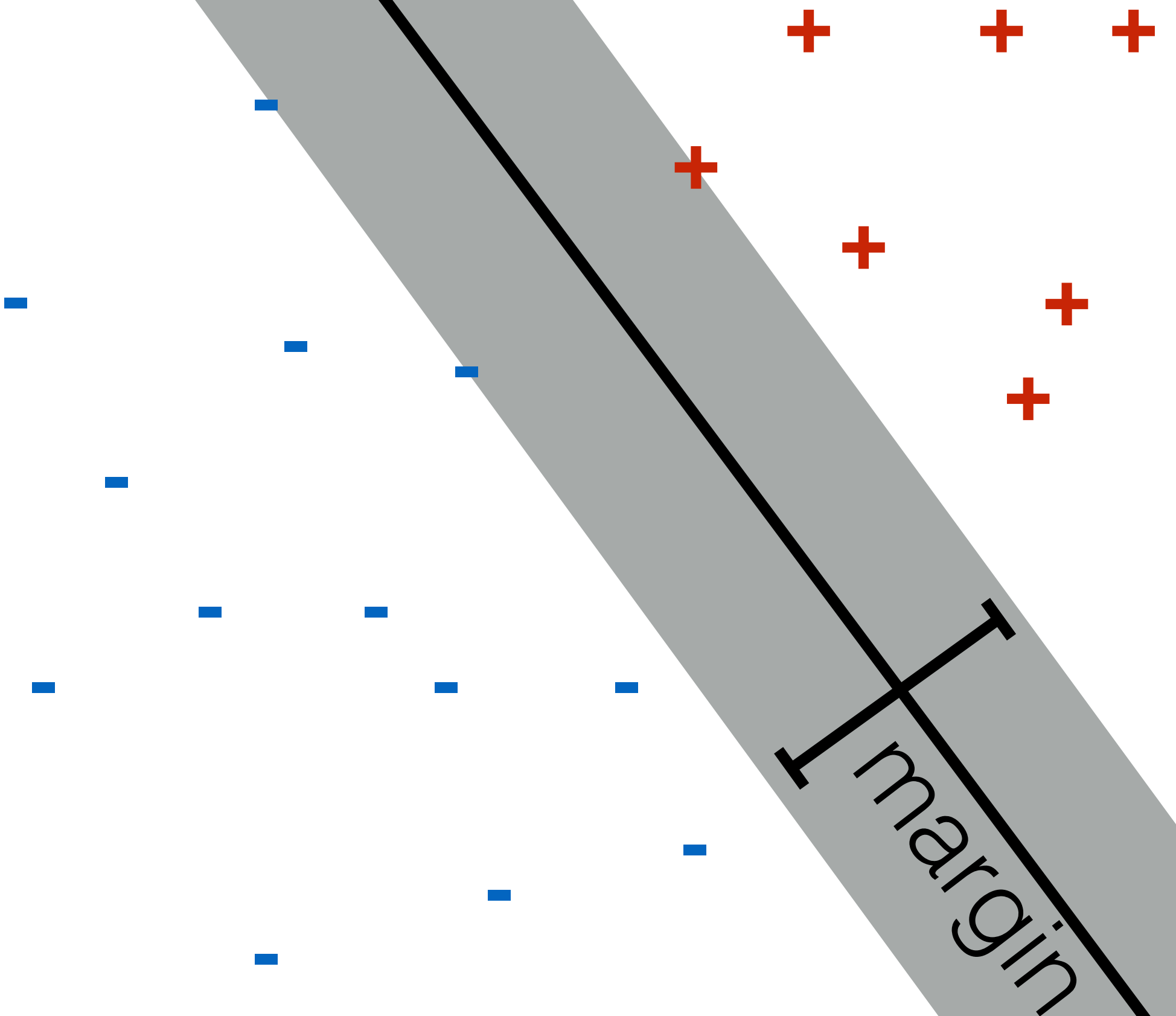


# Quantifying the Margin

$$D = \{(x_1, y_1), \dots, (x_n, y_n)\} \quad x_i \in \mathbb{R}^d \quad y_i \in \{-1, +1\}$$

~~$$y_i(w^\top x_i + b) \geq 0$$~~

$$y_i(w^\top x_i + b) \geq 1 \quad \forall i \in \{1, \dots, n\}$$



$$w^T x + b \leq -1$$

$$w^T x + b \geq 1$$

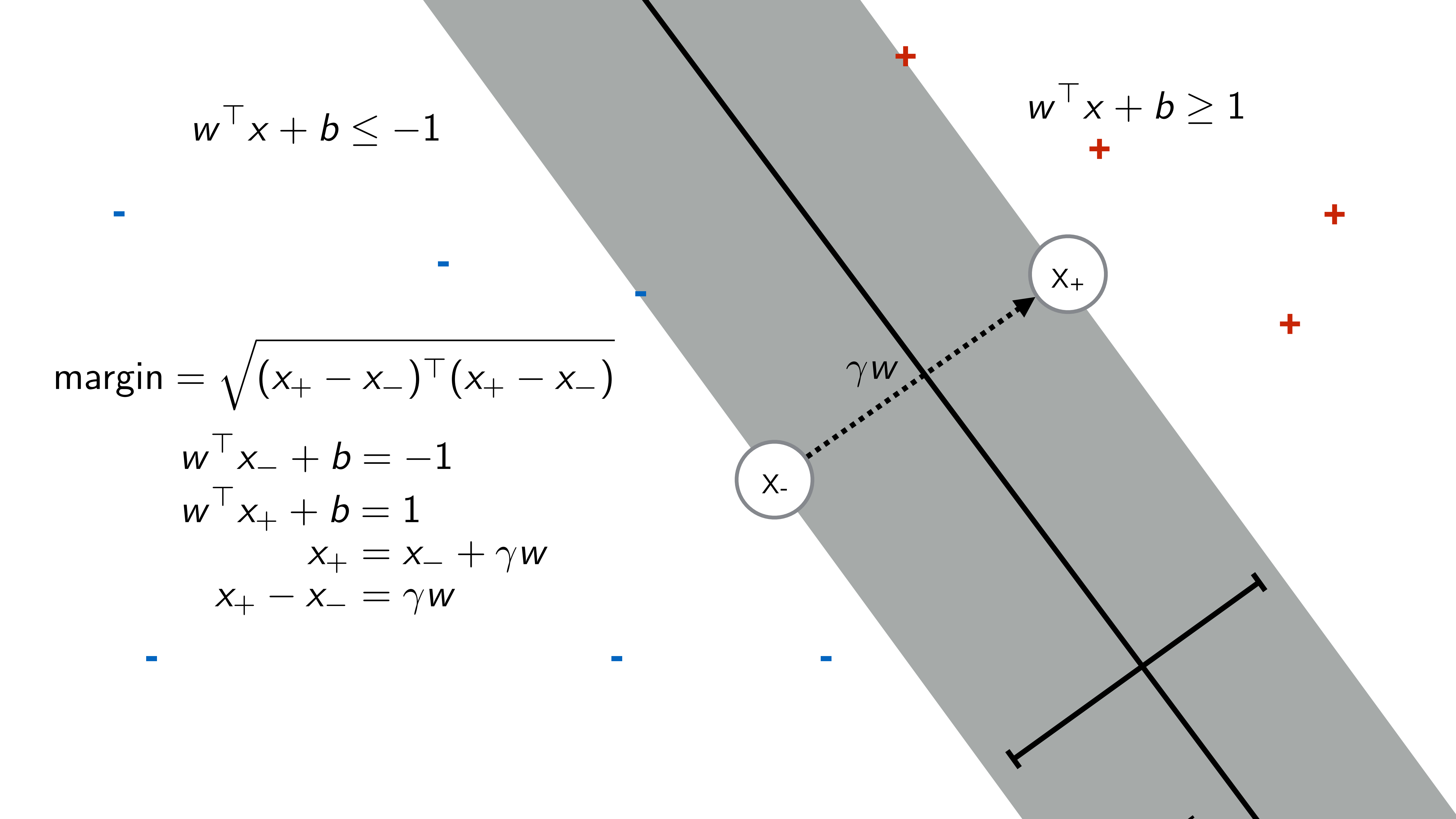
$$\text{margin} = \sqrt{(x_+ - x_-)^T (x_+ - x_-)}$$

$$w^T x_- + b = -1$$

$$w^T x_+ + b = 1$$

$$x_+ = x_- + \gamma w$$

$$x_+ - x_- = \gamma w$$





$$\text{margin} = \sqrt{(x_+ - x_-)^\top (x_+ - x_-)}$$

$$w^\top x_- + b = -1$$

$$w^\top x_+ + b = 1$$

$$x_+ = x_- + \gamma w$$

$$x_+ - x_- = \gamma w$$

$$x_+ - x_- = \frac{2w}{w^\top w}$$

$$w^\top (x_- + \gamma w) + b = 1$$

$$w^\top x_- + b + \gamma w^\top w = 1$$

$$-1 + \gamma w^\top w = 1$$

$$\gamma = \frac{2}{w^\top w}$$

$$\text{margin} = \sqrt{\frac{4w^\top w}{w^\top w \times w^\top w}} = \frac{2}{\sqrt{w^\top w}}$$

# Large-Margin Linear Classification

$$\begin{aligned} \max_{w \in \mathbb{R}^d} \quad & \frac{2}{\sqrt{w^\top w}} \\ \text{s.t.} \quad & y_i(w^\top x_i + b) \geq 1 \quad \forall i \in \{1, \dots, n\} \end{aligned}$$

# Large-Margin Linear Classification

$$\begin{aligned} \min_{w \in \mathbb{R}^d} \quad & \frac{1}{2} w^\top w \\ \text{s.t.} \quad & y_i(w^\top x_i + b) \geq 1 \quad \forall i \in \{1, \dots, n\} \end{aligned}$$

# Quadratic Programming

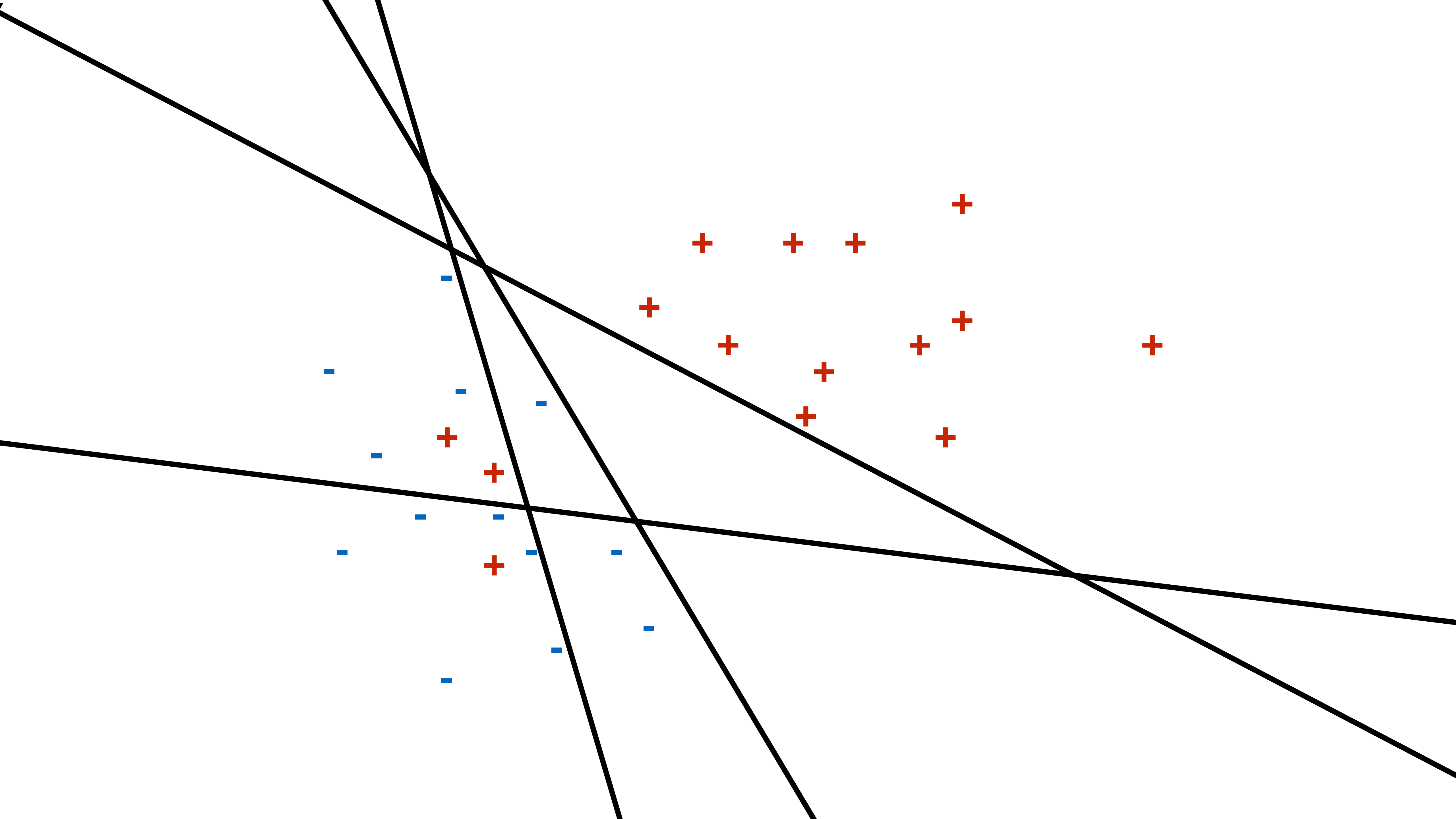
$$\min_x \quad \frac{1}{2} x^\top H x + f^\top x \quad \text{quadratic objective}$$

$$\text{s.t.} \quad A_{\text{ineq}} x \leq b_{\text{ineq}} \quad \text{linear inequality constraints}$$

$$A_{\text{eq}} x = b_{\text{eq}} \quad \text{linear equality constraints}$$

$$\min_{w \in \mathbb{R}^d} \quad \frac{1}{2} w^\top w$$

$$\text{s.t.} \quad y_i (w^\top x_i + b) \geq 1 \quad \forall i \in \{1, \dots, n\}$$



# Soft-Margin Form

$$\begin{aligned} \min_{w \in \mathbb{R}^d} \quad & \frac{1}{2} w^\top w \\ \text{s.t.} \quad & y_i(w^\top x_i + b) \geq 1 \quad \forall i \in \{1, \dots, n\} \end{aligned}$$

# Soft-Margin Form

slack penalty

$$\min_{\substack{w \in \mathbb{R}^d \\ \xi \geq 0}} \frac{1}{2} w^\top w + C \sum_{i=1}^n \xi_i$$

$$\text{s.t.} \quad y_i(w^\top x_i + b) \geq 1 - \xi_i \quad \forall i \in \{1, \dots, n\}$$

slack variables

# Summary

- Large-margin and model complexity
- Formalizing large margin
- Quadratic program form
- Soft-margin



# Optimization

- “Off-the-shelf” quadratic programming solvers
  - (usually interior-point methods with barrier functions)
- Gradient approaches using hinge-loss interpretation of slack penalty
- Dual form optimization
  - Leads to **kernel trick**, sequential minimal optimization (SMO)