

Announcements



Assignments

- HW6 (written + programming)
 - Due Thu 3/26, 11:59 pm
- HW7 (online)
 - Out later tonight
 - Due Tue 3/31, 11:59 pm

$$x \rightarrow \phi(x) \rightarrow \text{SVM} \rightarrow y = \pm 1$$
$$x \rightarrow \text{Net} \rightarrow x$$

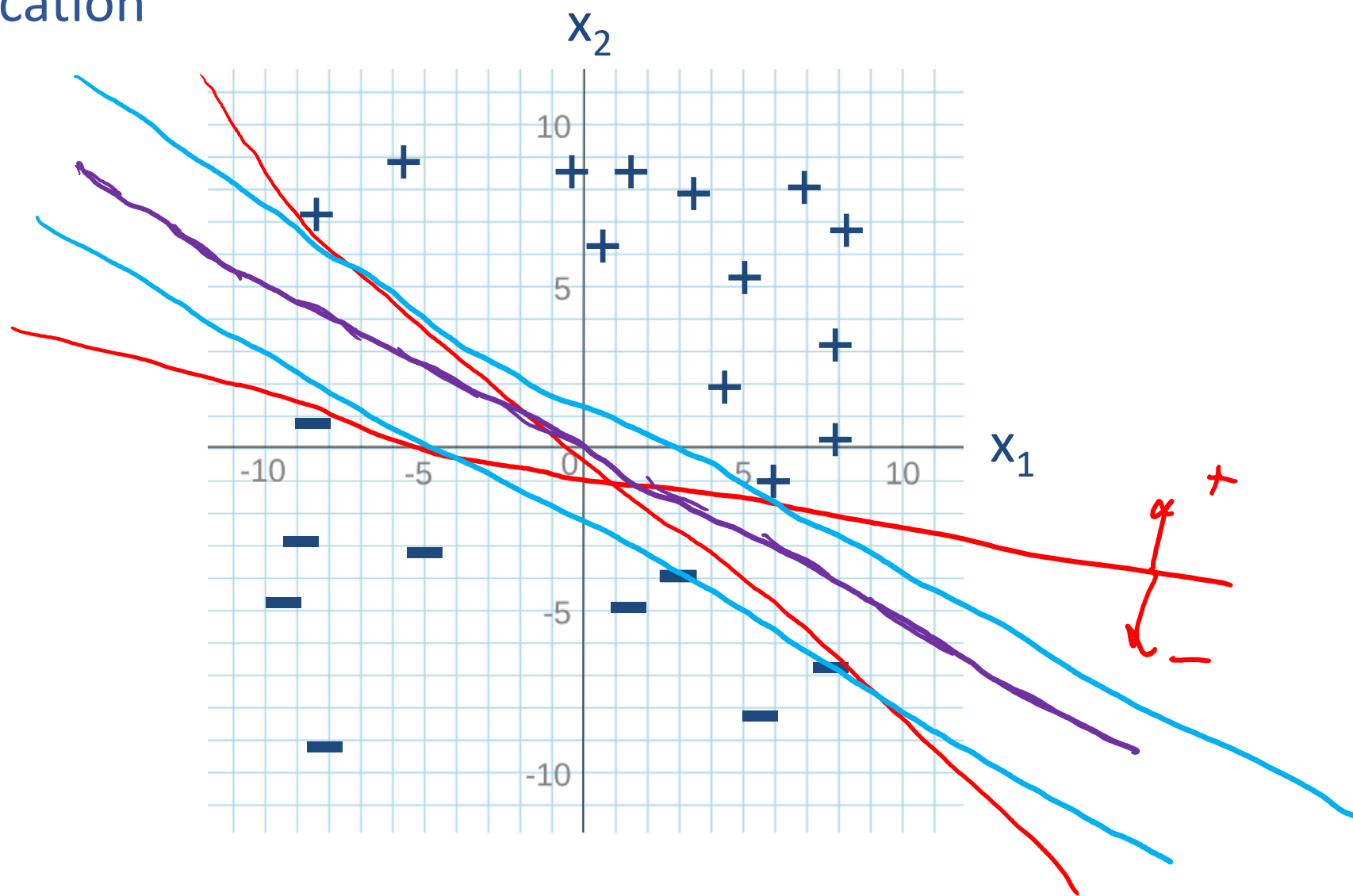
Introduction to Machine Learning

Support Vector Machines

Instructor: Pat Virtue

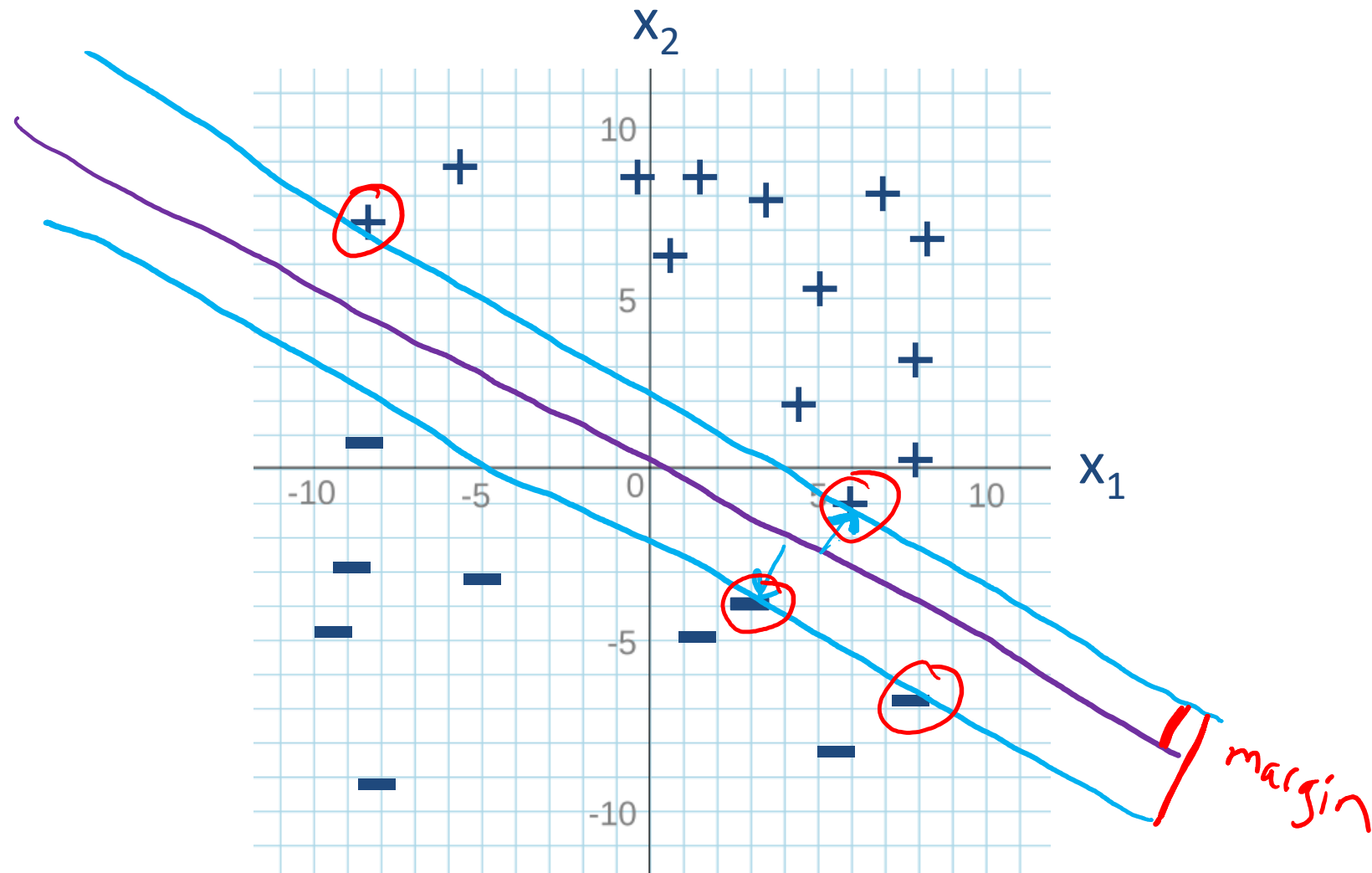
Support Vector Machines

Linear Classification



Support Vector Machines

Max Margin

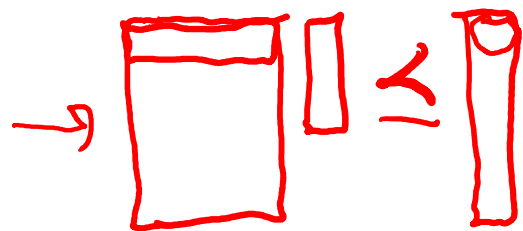


Constrained Optimization

Linear Program

$$\begin{array}{ll} \min_x & \underline{c^T x} \\ \text{s.t.} & \underline{Ax \leq b} \end{array}$$

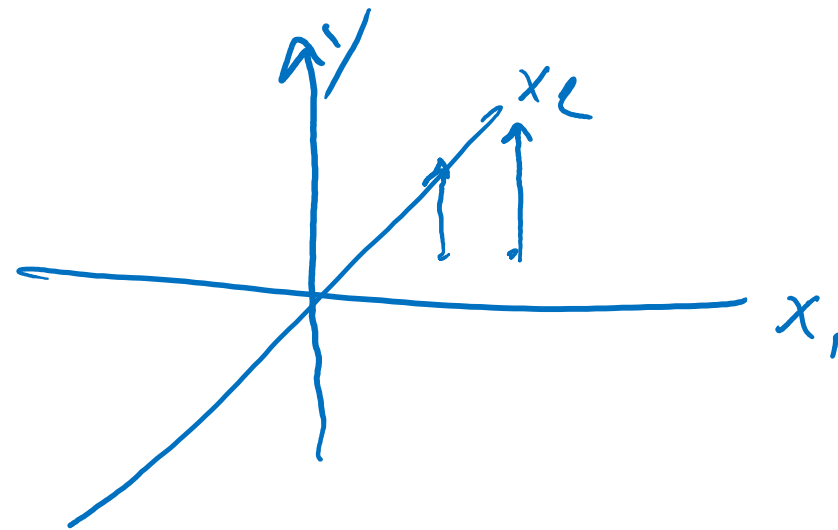
$$\underline{c_1 x_1 + c_2 x_2 = y}$$



$$\rightarrow \left[\begin{array}{l} a_{11} x_1 + a_{12} x_2 \leq b_1 \\ \vdots \end{array} \right]$$

$$\min_x f(x) \leftarrow \text{obj}$$

$$\begin{array}{l} x \in \mathbb{R}^m \\ c \in \mathbb{R}^m \\ b \in \mathbb{R}^n \\ A \in \mathbb{R}^{n \times m} \end{array}$$



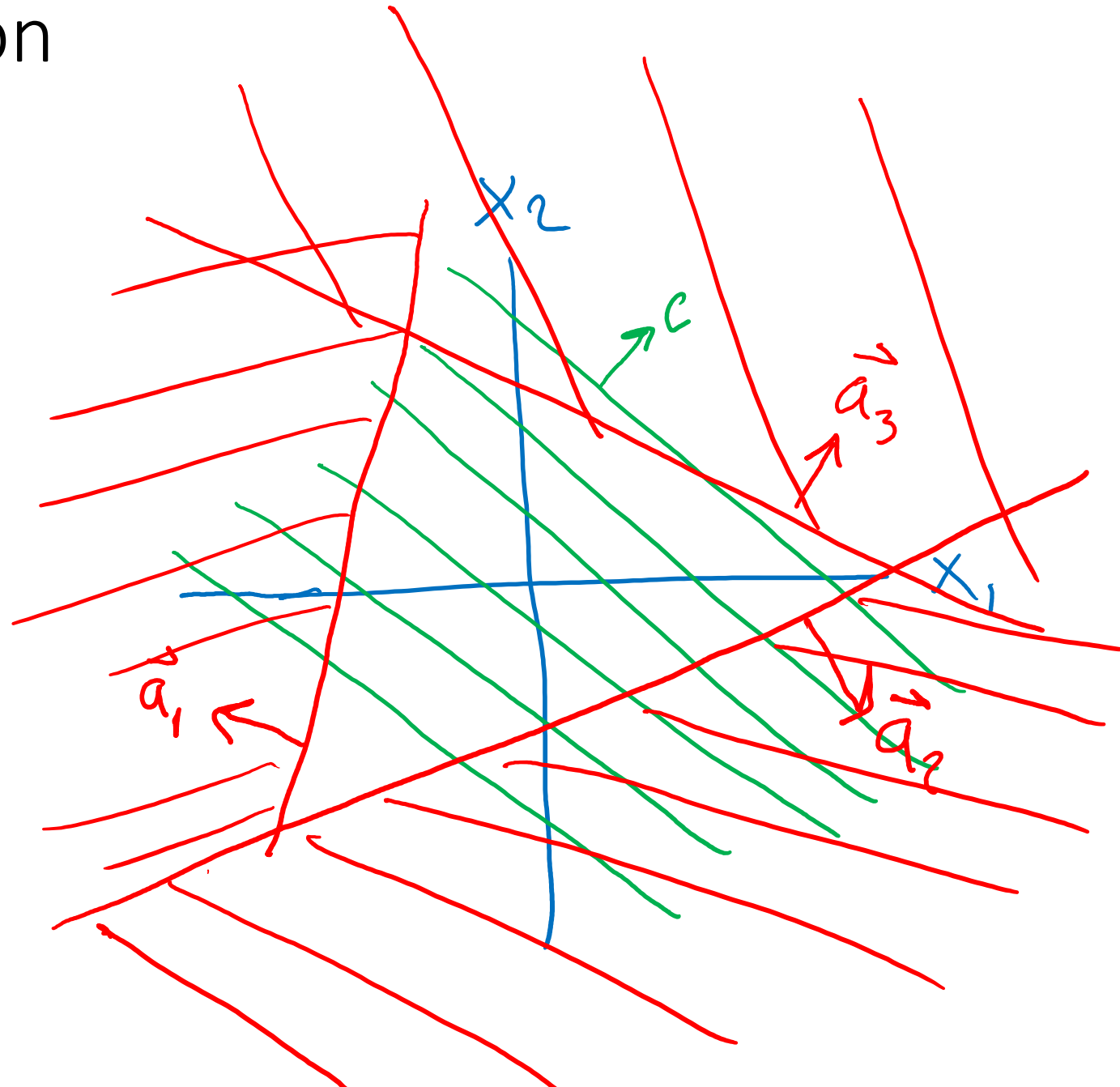
Constrained Optimization

Linear Program

$$\begin{array}{ll}\min_{\mathbf{x}} & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

$$a_{11}x_1 + a_{12}x_2 \leq b_1$$

$$a_{21}x_1 + a_{22}x_2 \leq b_2$$



Constrained Optimization

Linear Program

$$\begin{array}{ll}\min_x & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

Solvers

- Simplex
- Interior point methods

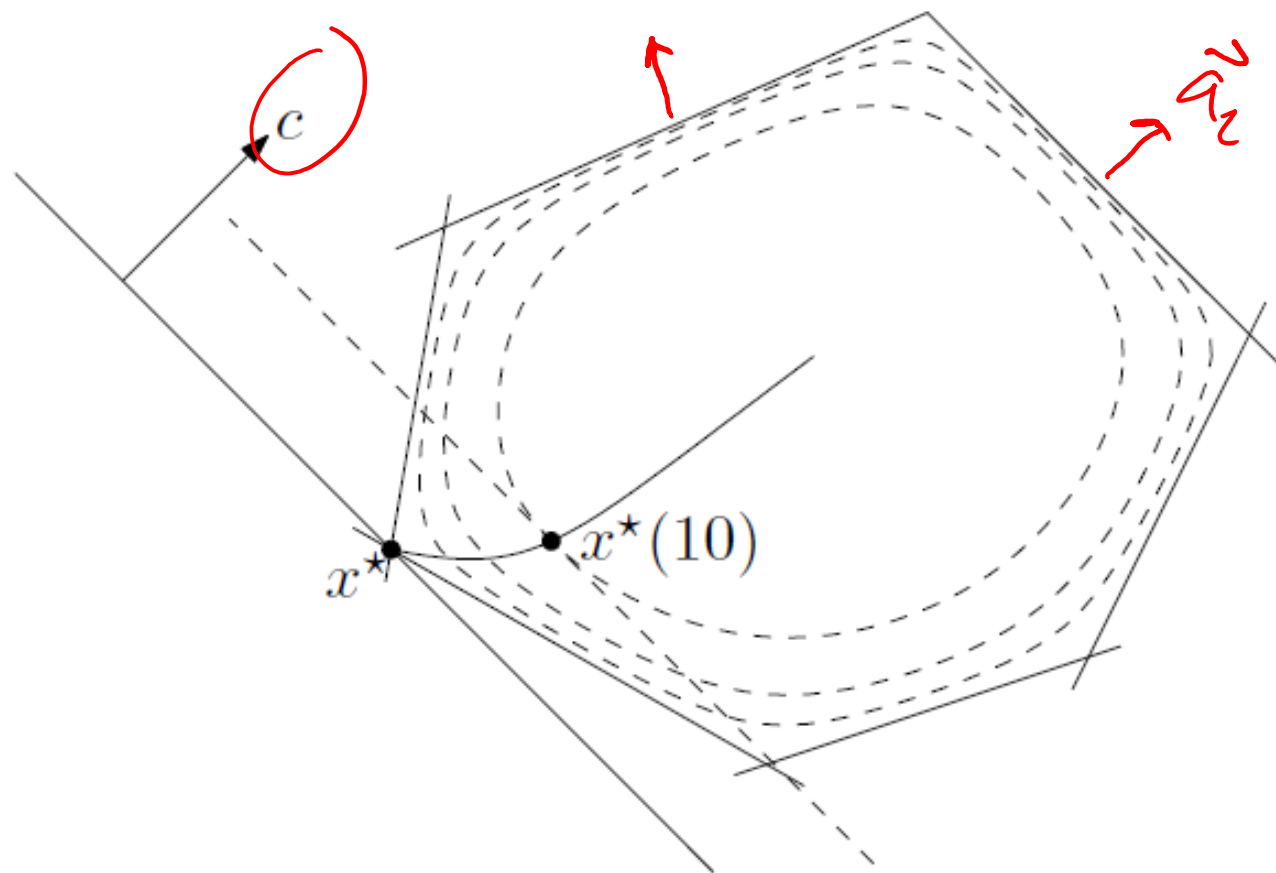


Figure: Fig 11.2 from Boyd and Vandenberghe, *Convex Optimization*

Constrained Optimization

Linear Program

$$\begin{array}{ll}\min_x & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

Solvers

- Simplex
- Interior point methods

Quadratic Program

$$\begin{array}{ll}\min_x & \underline{\mathbf{x}^T \mathbf{Q} \mathbf{x}} + \underline{\mathbf{c}^T \mathbf{x}} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

$$\mathbf{x} \in \mathbb{R}^n$$
$$\mathbf{Q} \in \mathbb{R}^{n \times n}$$

$$M=1$$

$$\|\mathbf{y} - \mathbf{X}\mathbf{w}\|_2^2$$

$$\rightarrow (\mathbf{y} - \mathbf{X}\mathbf{w})^T (\mathbf{y} - \mathbf{X}\mathbf{w})$$

$$\underline{\mathbf{w}^T \mathbf{X}^T \mathbf{X} \mathbf{w}}$$

Constrained Optimization

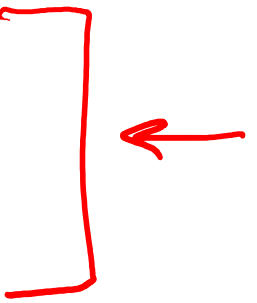
Linear Program

$$\begin{array}{ll}\min_x & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

Solvers

- Simplex
- Interior point methods

Quadratic Program

$$\begin{array}{ll}\min_x & \mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$


Solvers

- Conjugate gradient
- Ellipsoid method
- Interior point methods

Constrained Optimization

Linear Program

$$\begin{array}{ll}\min_x & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

Solvers

- Simplex
- Interior point methods

Quadratic Program

$$\begin{array}{ll}\min_x & \mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$


Special Case

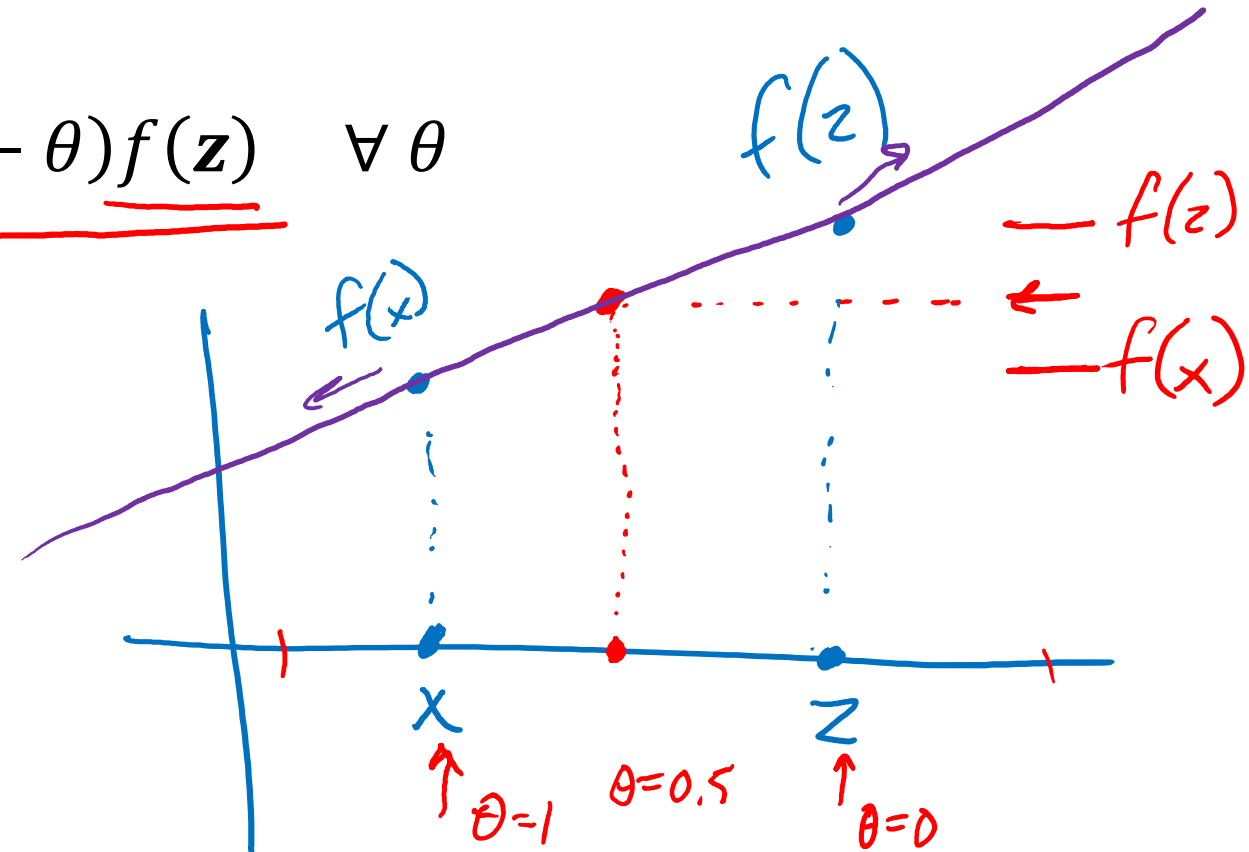
- If $\mathbf{Q}$ is **positive-definite**, the problem is **convex**
- $\mathbf{Q}$ is positive-definite if:
$$\mathbf{v}^T \mathbf{Q} \mathbf{v} > 0 \quad \forall \mathbf{v} \in \mathbb{R}^M \setminus \mathbf{0}$$

Convex Optimization

Linear function

If $f(\mathbf{x})$ is linear, then:

- $f(\mathbf{x} + \mathbf{z}) = f(\mathbf{x}) + f(\mathbf{z})$
- $f(\theta \mathbf{x}) = \theta f(\mathbf{x}) \quad \forall \theta$
- $f(\theta \mathbf{x} + (1 - \theta)\mathbf{z}) = \theta f(\mathbf{x}) + (1 - \theta)f(\mathbf{z}) \quad \forall \theta$



Convex Optimization

Convex function

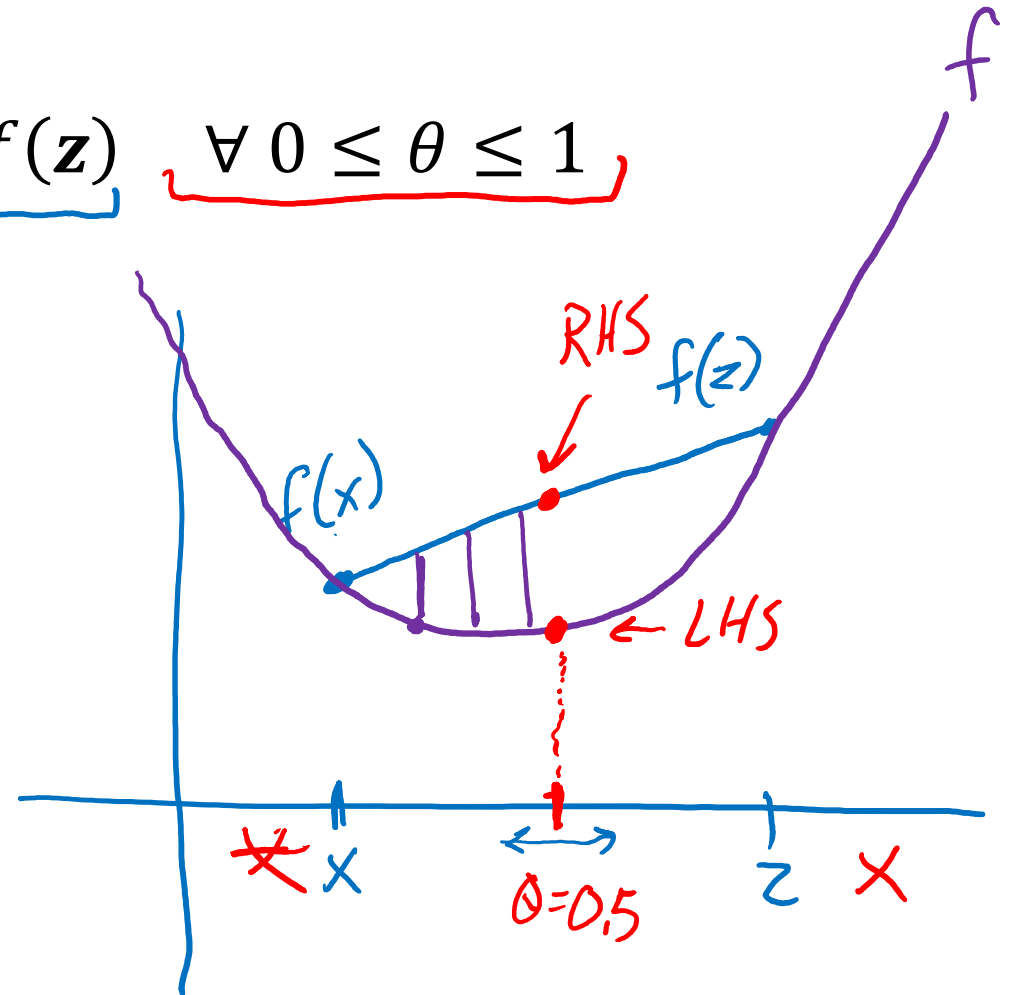
If $f(x)$ is convex, then:

- $f(\theta x + (1 - \theta)z) \leq \theta f(x) + (1 - \theta)f(z) \quad \forall 0 \leq \theta \leq 1$

Convex optimization

If $f(x)$ is convex, then:

- Every local minimum is also a global minimum 😊



Constrained Optimization

Linear Program

$$\begin{array}{ll}\min_x & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

Solvers

- Simplex
- Interior point methods

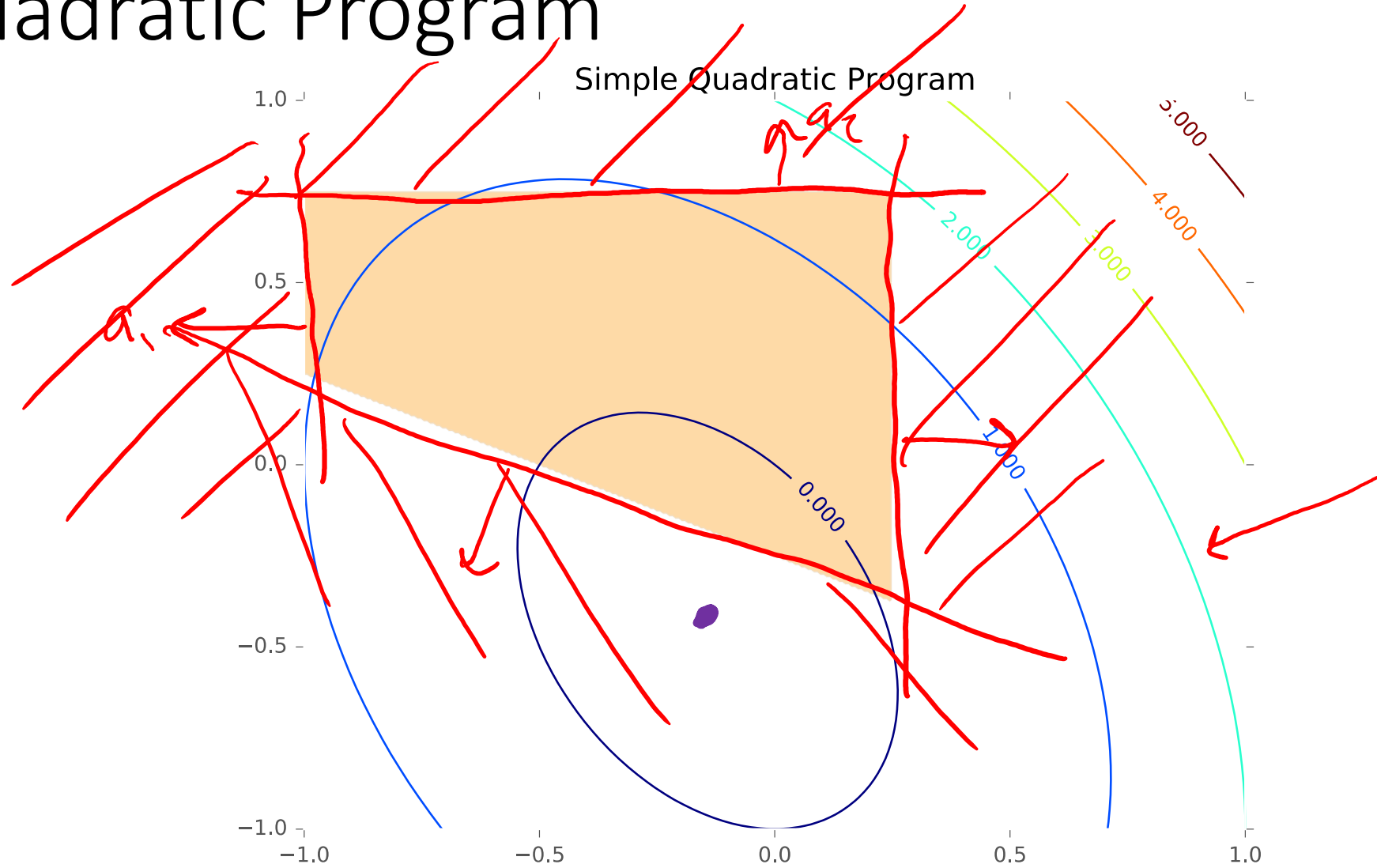
Quadratic Program

$$\begin{array}{ll}\min_x & \mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} \leq \mathbf{b}\end{array}$$

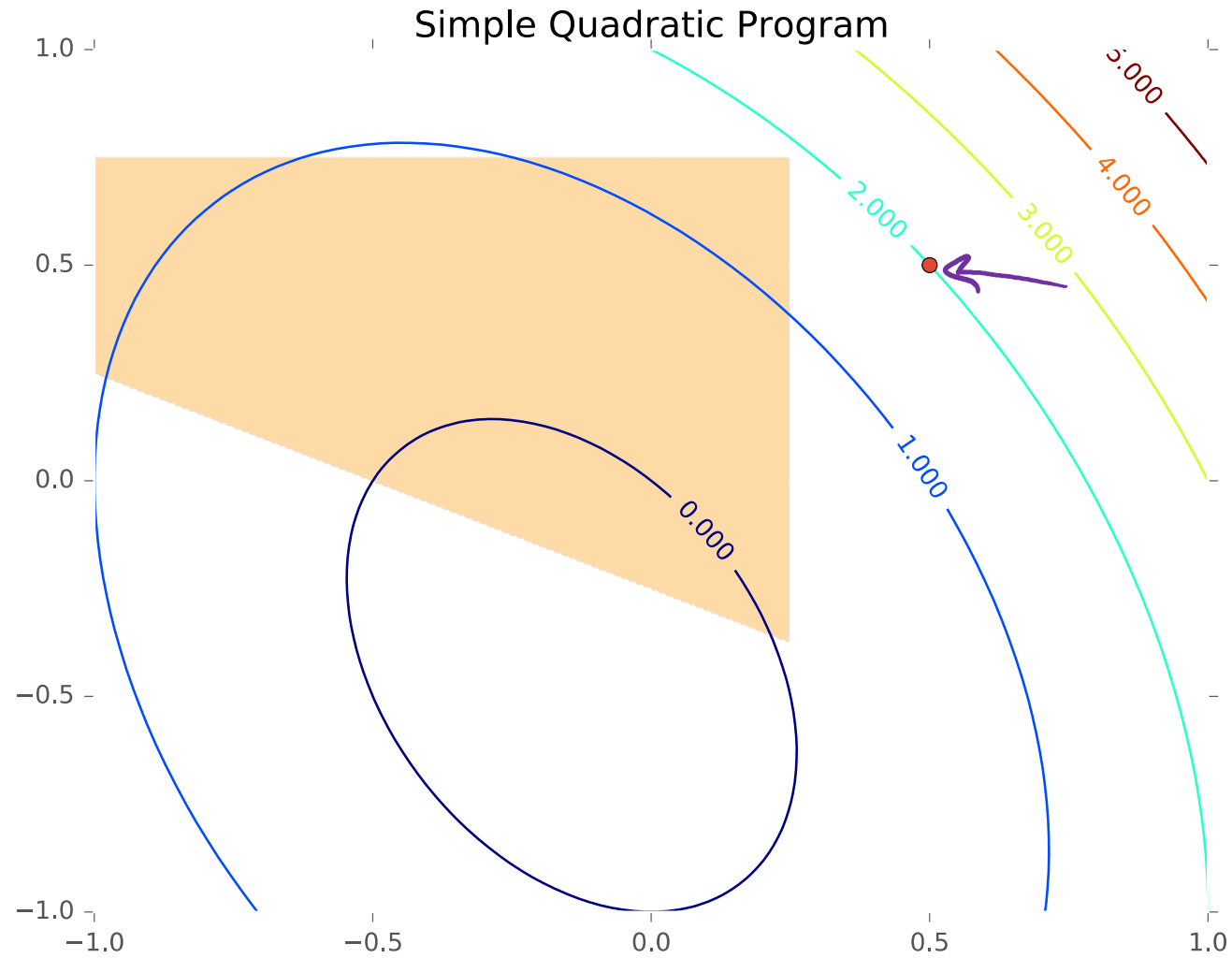

Special Case

- If $\mathbf{Q}$ is positive-definite, the problem is convex
- $\mathbf{Q}$ is positive-definite if:
$$\mathbf{v}^T \mathbf{Q} \mathbf{v} > 0 \quad \forall \mathbf{v} \in \mathbb{R}^M \setminus \mathbf{0}$$

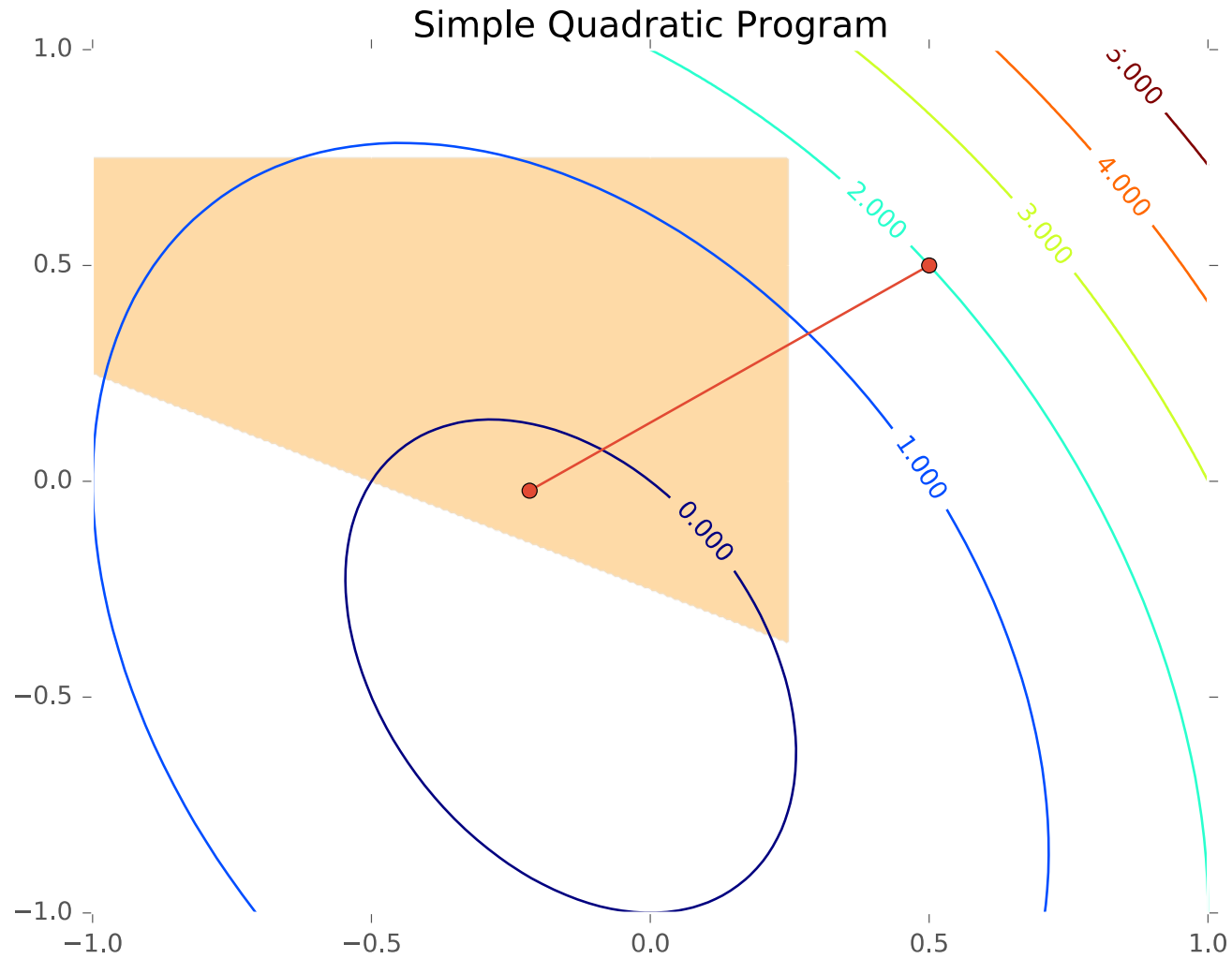
Quadratic Program



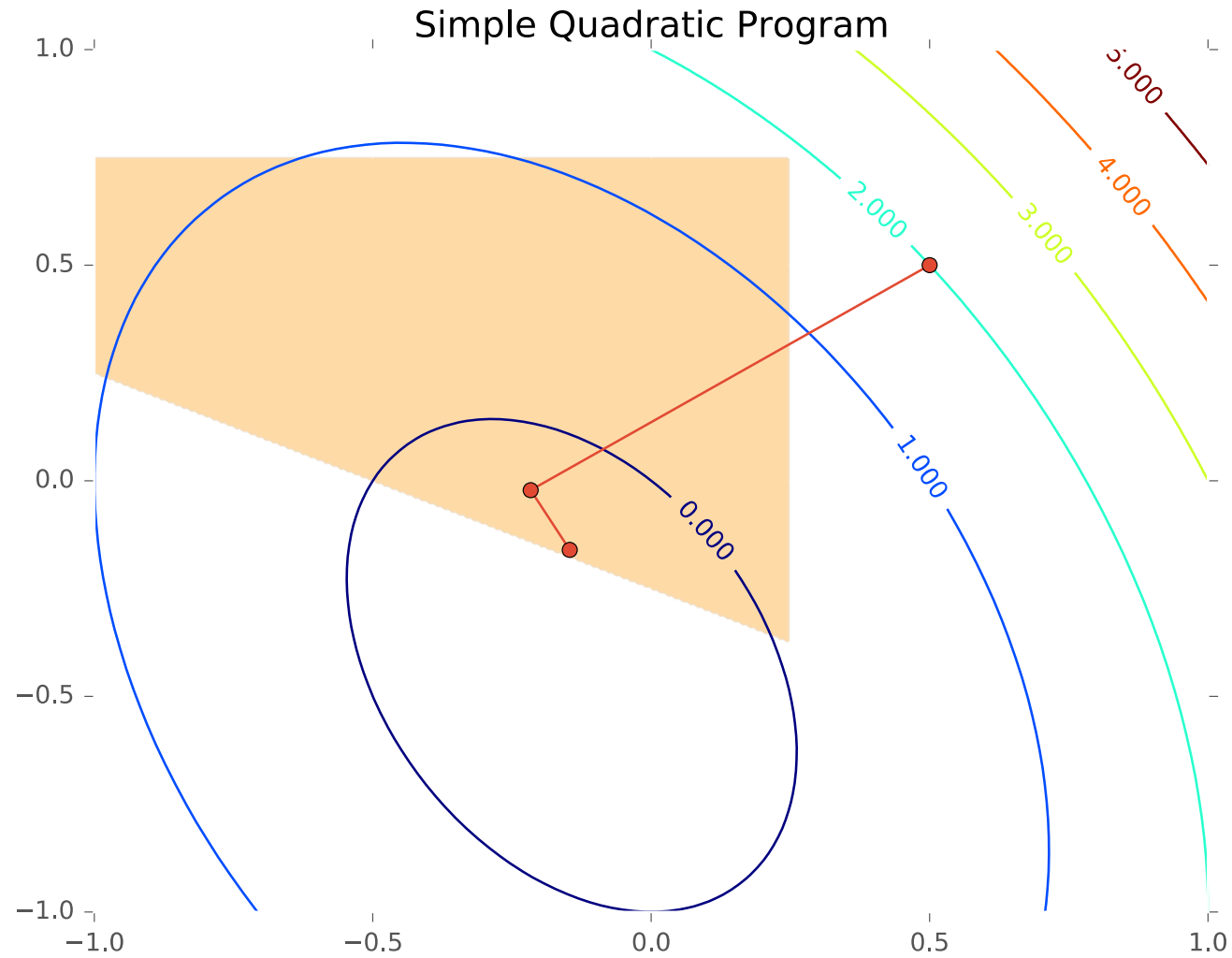
Quadratic Program



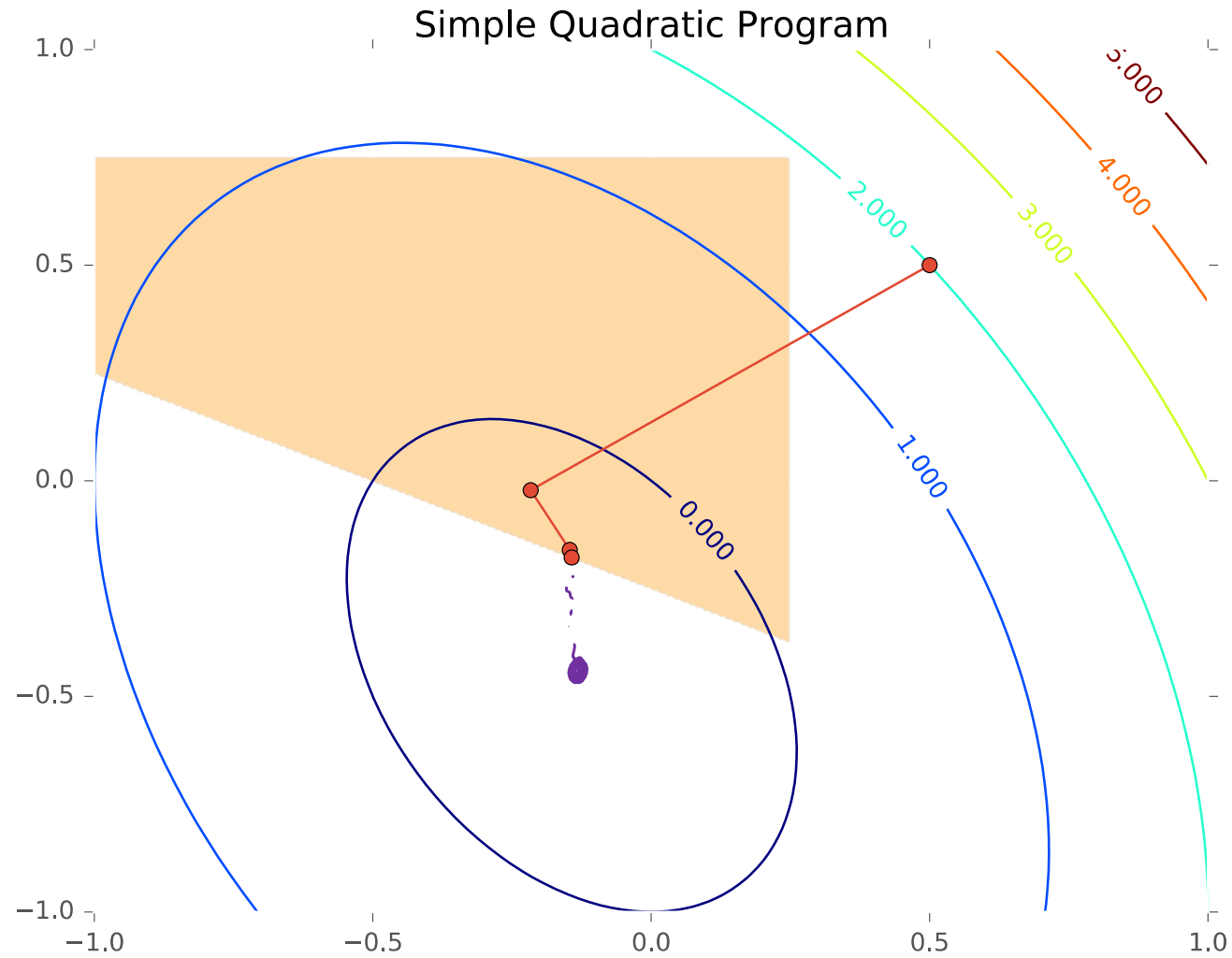
Quadratic Program



Quadratic Program

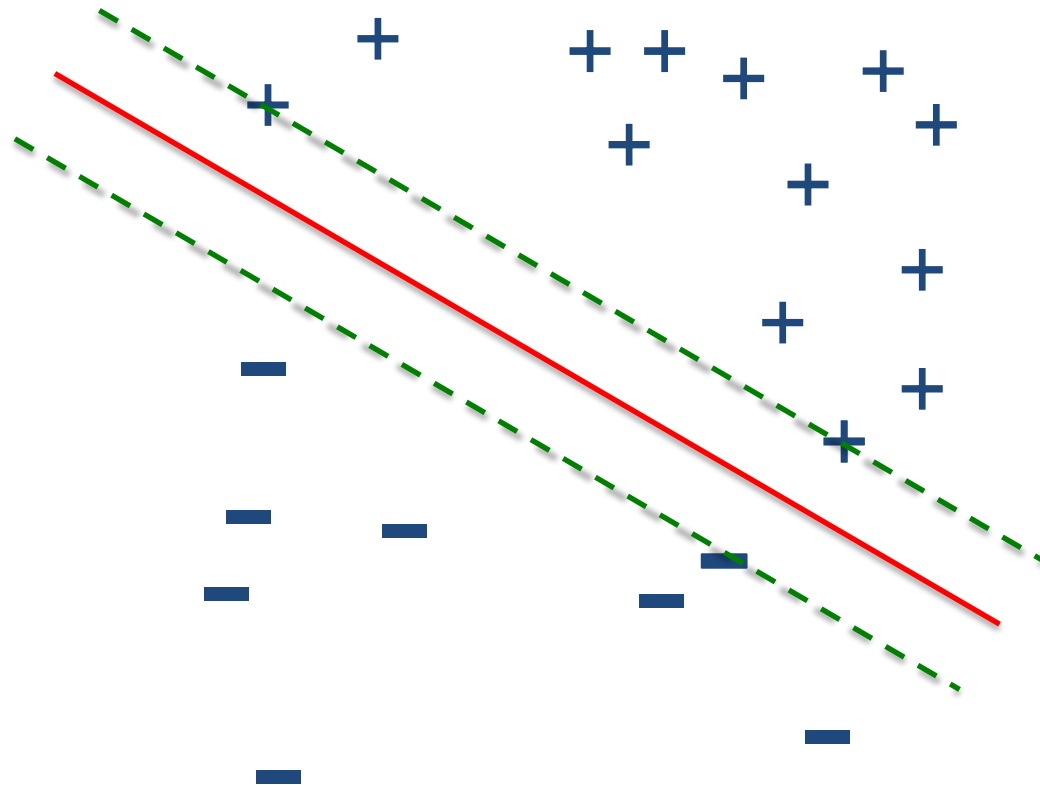


Quadratic Program



Support Vector Machines

Find linear separator with maximum margin



$$\hat{y} = h(x)$$
$$\hat{y} = [\vec{w}^T \vec{x} + b]$$

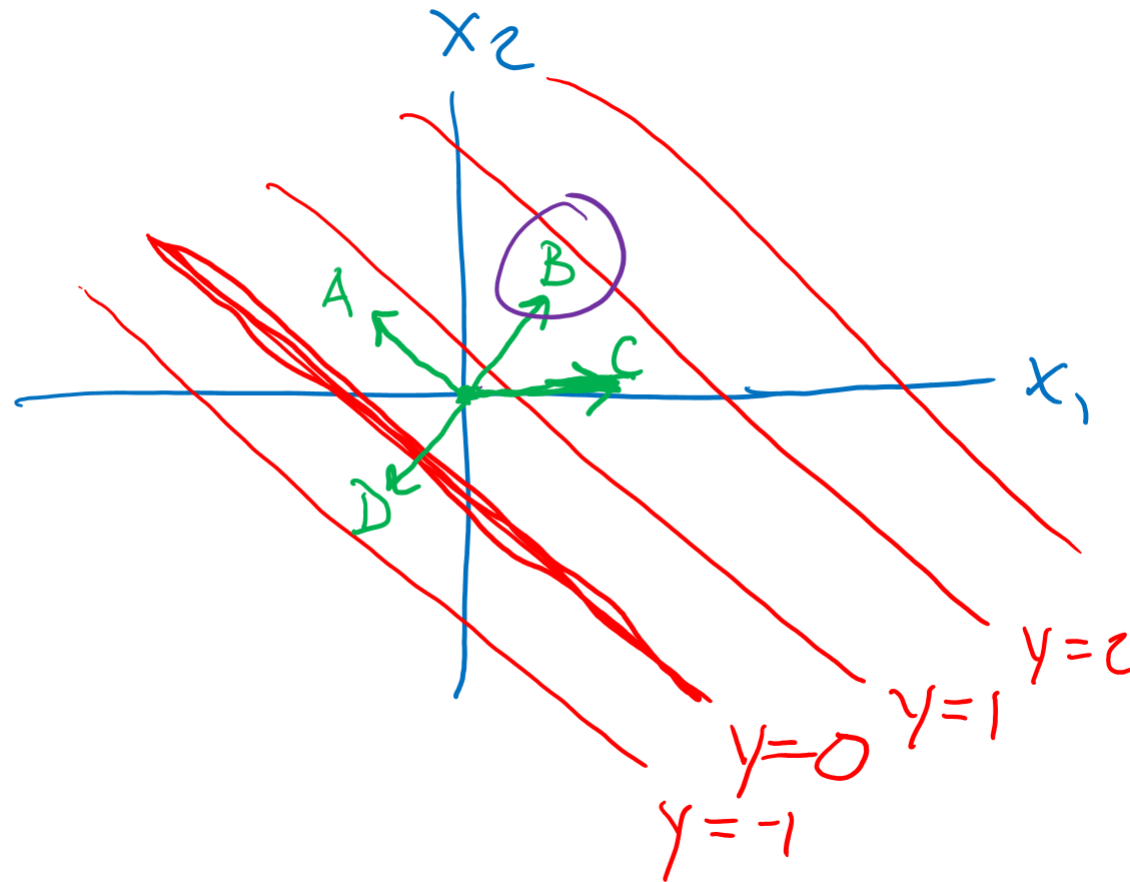
w, b

(Lecture 5) Poll

Which vector is the correct $\mathbf{w}$?

$$y = \mathbf{w}^T \mathbf{x} + b$$

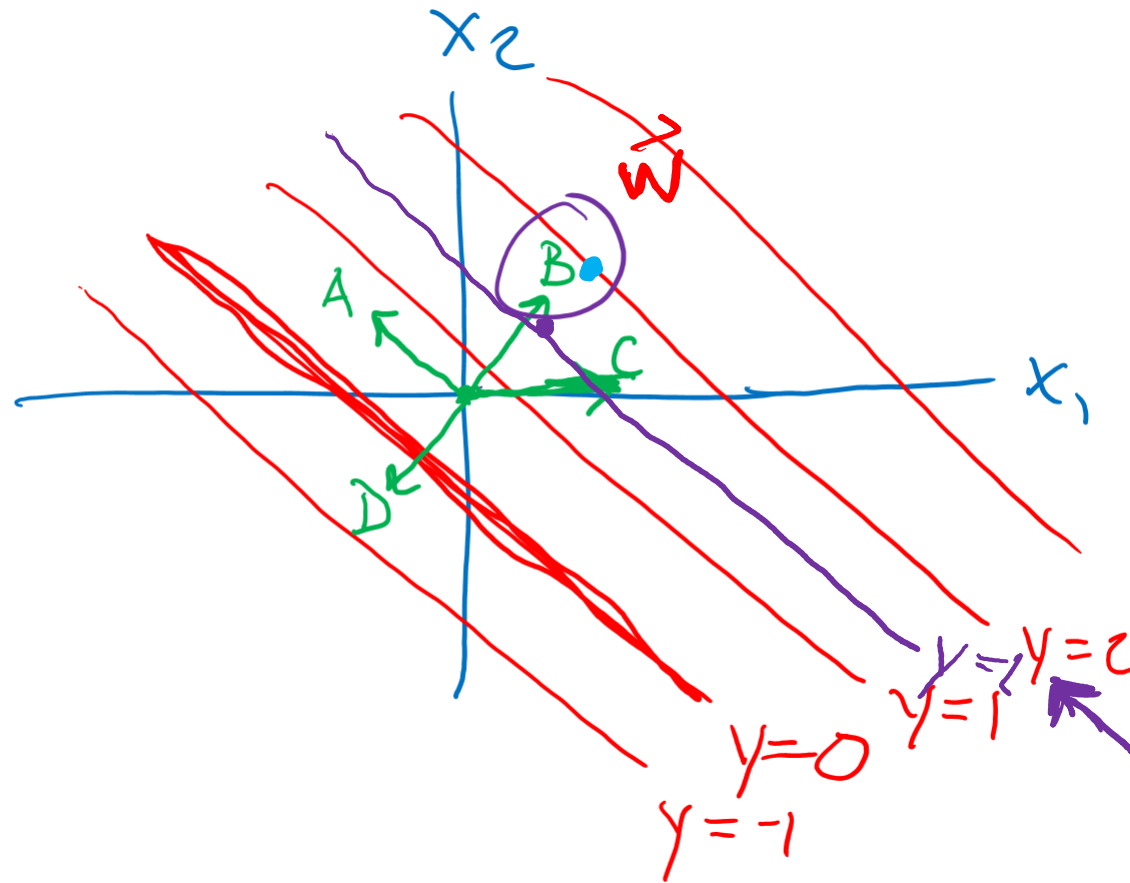
$$\vec{w} = \vec{B}$$



Piazza Poll 1

As the magnitude of w increases, will the distance between the contour lines of $y = \mathbf{w}^T \mathbf{x} + b$ increase or decrease?

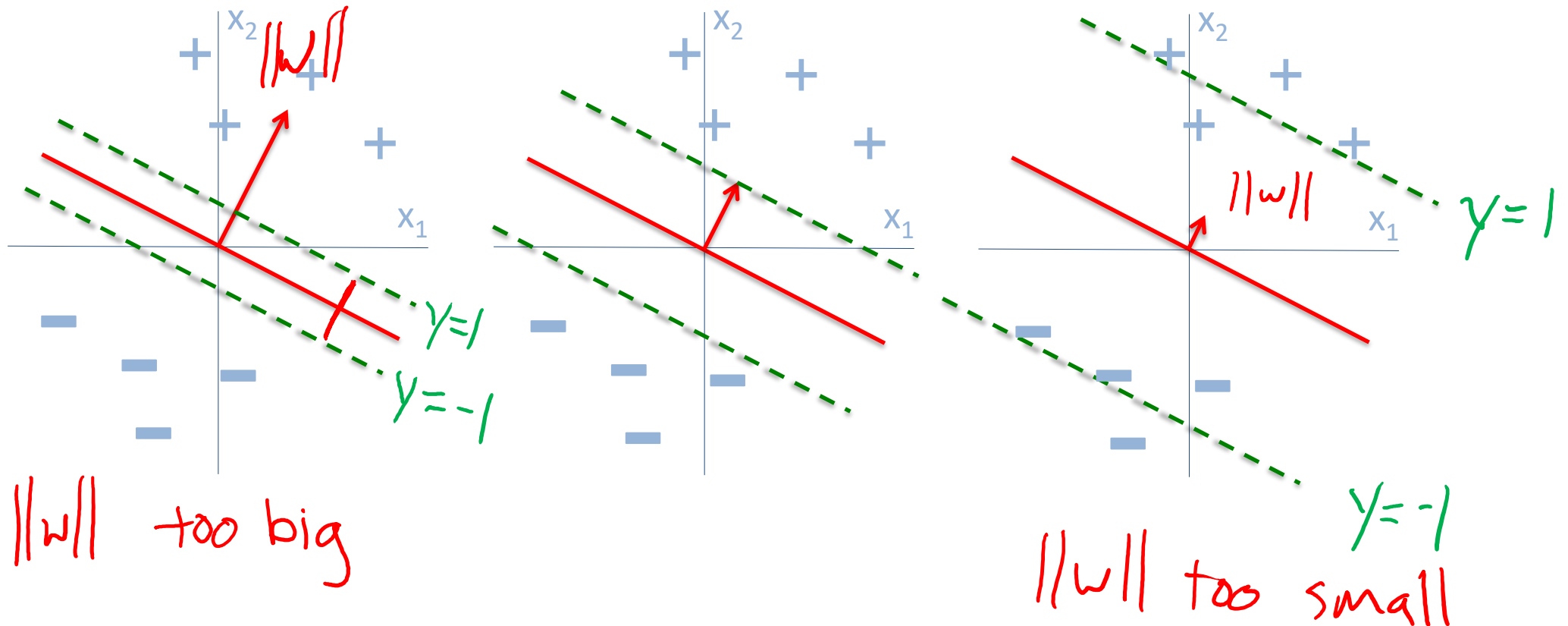
- A) Increase
- B) Decrease
- ~~C) Calamity~~



$$\begin{aligned} \mathbf{x} &= [1, 1]^T \\ \mathbf{w}_1 &= [1, 1] \\ y &= 2 \\ \mathbf{w}_2 &= [2, 2] \\ \mathbf{x} &= [\tfrac{1}{2}, \tfrac{1}{2}] \\ y &= 2 \end{aligned}$$

Support Vector Machines

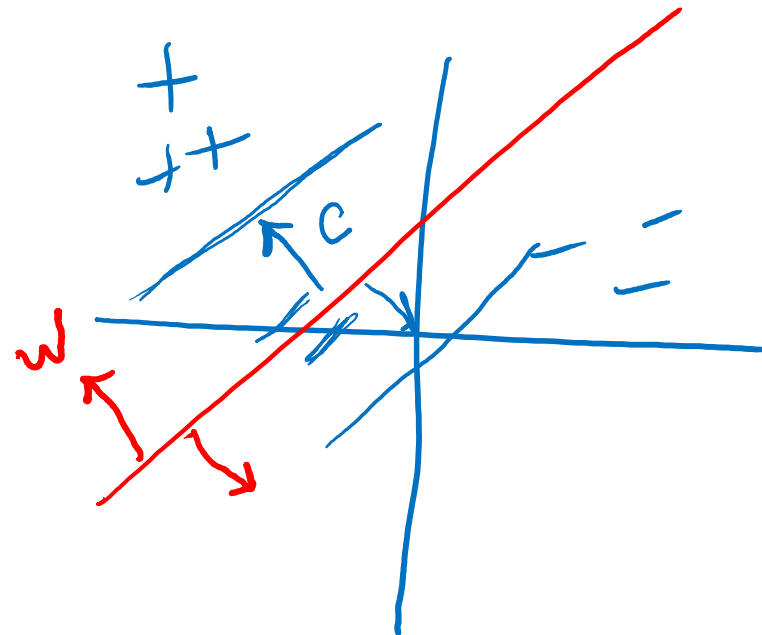
Find linear separator with maximum margin



Linear Separability

Data

$$\mathcal{D} = \{\mathbf{x}^{(i)}, y^{(i)}\}_{i=1}^N \quad \mathbf{x} \in \mathbb{R}^M, \quad y \in \{-1, +1\}$$



Linearly separable iff:

$$\begin{aligned} \exists \mathbf{w}, b \quad s.t. \quad & \mathbf{w}^T \mathbf{x}^{(i)} + b > 0 \quad \text{if } \underline{y^{(i)} = +1} \quad \text{and} \\ & \mathbf{w}^T \mathbf{x}^{(i)} + b < 0 \quad \text{if } \underline{y^{(i)} = -1} \end{aligned}$$

$$\Leftrightarrow \exists \mathbf{w}, b \quad s.t. \quad y^i (\mathbf{w}^T \mathbf{x}^i + b) > 0$$

$$\Leftrightarrow \exists \mathbf{w}, b, c \quad s.t. \quad y^i (\mathbf{w}^T \mathbf{x}^i + b) \geq c \quad \text{and } c > 0$$

$$\Leftrightarrow \exists \mathbf{w}, b \quad s.t. \quad y^i (\mathbf{w}^T \mathbf{x}^i + b) \geq 1$$

Linear Separability

Data

$$\mathcal{D} = \{\mathbf{x}^{(i)}, y^{(i)}\}_{i=1}^N \quad \mathbf{x} \in \mathbb{R}^M, \quad y \in \{-1, +1\}$$

Linearly separable iff:

$$\begin{aligned} \exists \mathbf{w}, b \quad s.t. \quad & \mathbf{w}^T \mathbf{x}^{(i)} + b > 0 \quad \text{if } y^{(i)} = +1 \quad \text{and} \\ & \mathbf{w}^T \mathbf{x}^{(i)} + b < 0 \quad \text{if } y^{(i)} = -1 \end{aligned}$$

$$\Leftrightarrow \exists \mathbf{w}, b \quad s.t. \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) > 0$$

$$\Leftrightarrow \exists \mathbf{w}, b, \mathbf{c} \quad s.t. \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq \mathbf{c} \quad \text{and} \quad \mathbf{c} > 0$$

$$\Leftrightarrow \exists \mathbf{w}, b \quad s.t. \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq 1$$

Piazza Poll 2

Are these two statements equivalent?

$$\exists \mathbf{w}, b, c \text{ s.t. } y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq c \text{ and } c > 0$$

$$\exists \mathbf{w}, b \text{ s.t. } y^{(i)}(\tilde{\mathbf{w}}^T \mathbf{x}^{(i)} + \tilde{b}) \geq 1$$

- A) Yes
- B) No
- C) Calamity

y_i

min w, b width
s.t. _____

$$\tilde{w} = \frac{w}{c}$$
$$\tilde{b} = \frac{b}{c}$$

Linear Separability

Data

$$\mathcal{D} = \{\mathbf{x}^{(i)}, y^{(i)}\}_{i=1}^N \quad \mathbf{x} \in \mathbb{R}^M, \quad y \in \{-1, +1\}$$

Linearly separable iff:

$$\begin{aligned} \exists \mathbf{w}, b \quad s.t. \quad & \mathbf{w}^T \mathbf{x}^{(i)} + b > 0 \quad \text{if } y^{(i)} = +1 \quad \text{and} \\ & \mathbf{w}^T \mathbf{x}^{(i)} + b < 0 \quad \text{if } y^{(i)} = -1 \end{aligned}$$

$$\Leftrightarrow \exists \mathbf{w}, b \quad s.t. \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) > 0$$

$$\Leftrightarrow \exists \mathbf{w}, b, c \quad s.t. \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq c \quad \text{and} \quad c > 0$$

$$\Leftrightarrow \exists \mathbf{w}, b \quad s.t. \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq 1 \quad \leftarrow$$

Support Vector Machines

Find linear separator with maximum margin

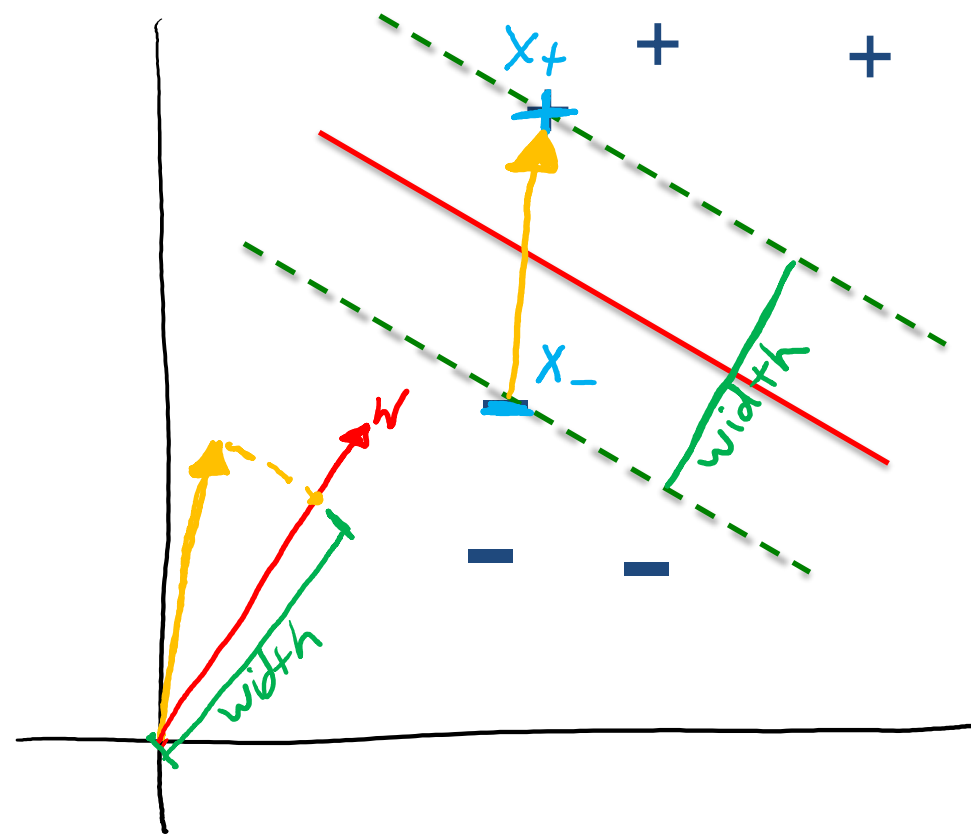
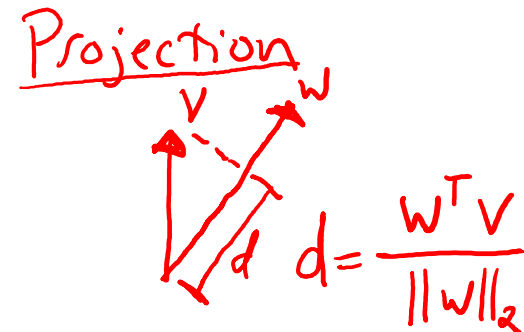
Let $\mathbf{x}_+$ and $\mathbf{x}_-$ be hypothetical points on the +/- margin from the decision boundary

$$\exists \mathbf{w}, b \quad s.t. \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq 1$$

$$\Leftrightarrow \exists \mathbf{w}, b \quad s.t. \quad \mathbf{w}^T \mathbf{x}_+ + b \geq +1 \quad \text{and} \\ \mathbf{w}^T \mathbf{x}_- + b \leq -1$$

Consider the vector from $\mathbf{x}_-$ to $\mathbf{x}_+$ and its projection onto the vector $\mathbf{w}$:

$$\text{width} = \frac{\mathbf{w}^T}{\|\mathbf{w}\|_2} (\mathbf{x}_+ - \mathbf{x}_-)$$



Support Vector Machines

Find linear separator with maximum margin

$$\max_{\mathbf{w}, b} \quad \text{"width"}$$

$$\text{s.t.} \quad y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq 1 \quad \forall i$$

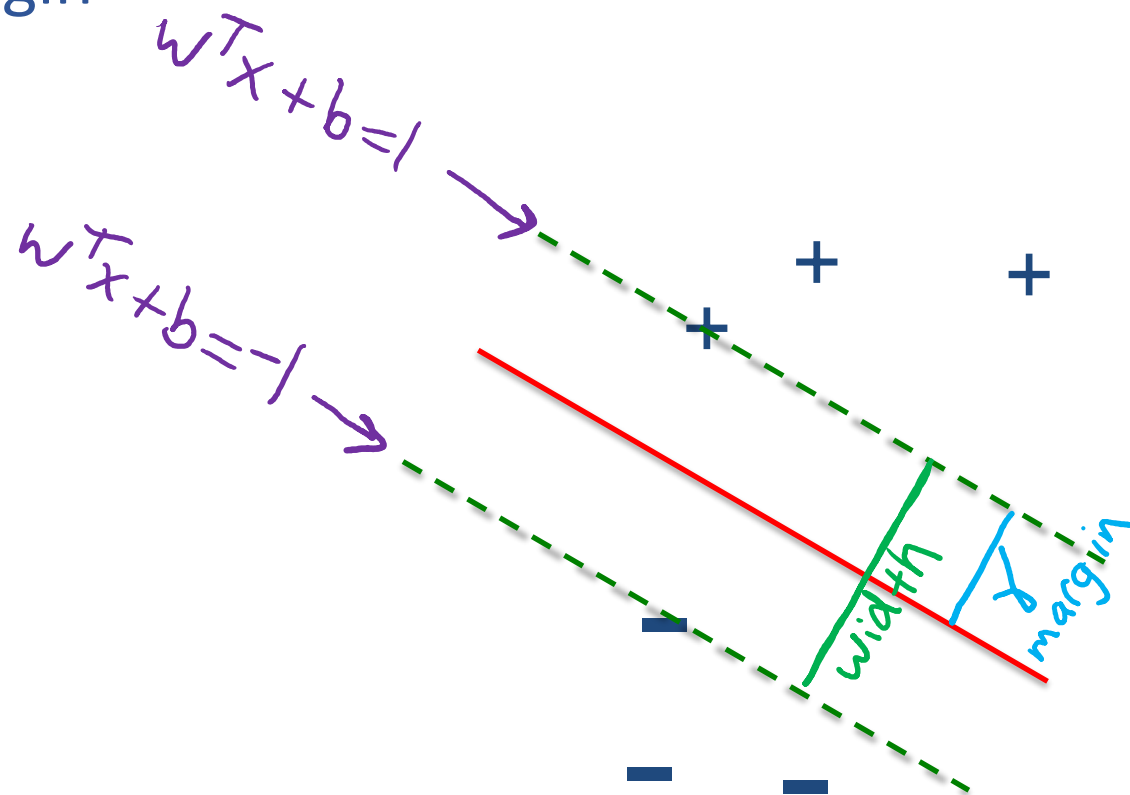
$$\text{width} = \frac{\mathbf{w}^T}{\|\mathbf{w}\|_2} (\mathbf{x}_+ - \mathbf{x}_-)$$

$$= \frac{1}{\|\mathbf{w}\|_2} (\mathbf{w}^T \mathbf{x}_+ - \mathbf{w}^T \mathbf{x}_-)$$

$$= \frac{1}{\|\mathbf{w}\|_2} ((1-b) - (-1-b))$$

$$= \frac{2}{\|\mathbf{w}\|_2}$$

$$\text{width} = \frac{\mathbf{w}^T}{\|\mathbf{w}\|_2} (\mathbf{x}_+ - \mathbf{x}_-)$$



$$\mathbf{w}^T \mathbf{x}_+ + b = 1$$

$$\mathbf{w}^T \mathbf{x}_+ = 1 - b$$

$$\mathbf{w}^T \mathbf{x}_- + b = -1$$

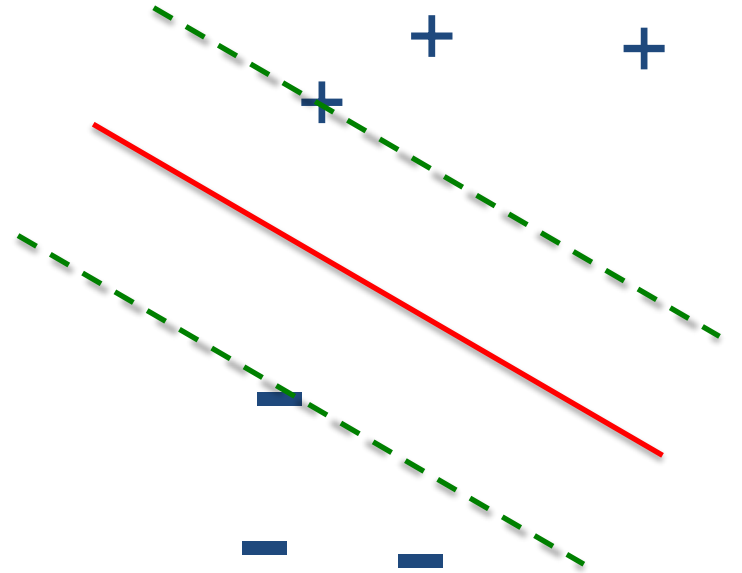
$$\mathbf{w}^T \mathbf{x}_- = -1 - b$$

Support Vector Machines

Find linear separator with maximum margin

$$\operatorname{argmax}_{w,b} \quad \text{width}$$

$$\text{width} = \frac{2}{\|w\|_2}$$



Support Vector Machines

Find linear separator with maximum margin

$$\text{width} = \frac{2}{\|\mathbf{w}\|_2}$$

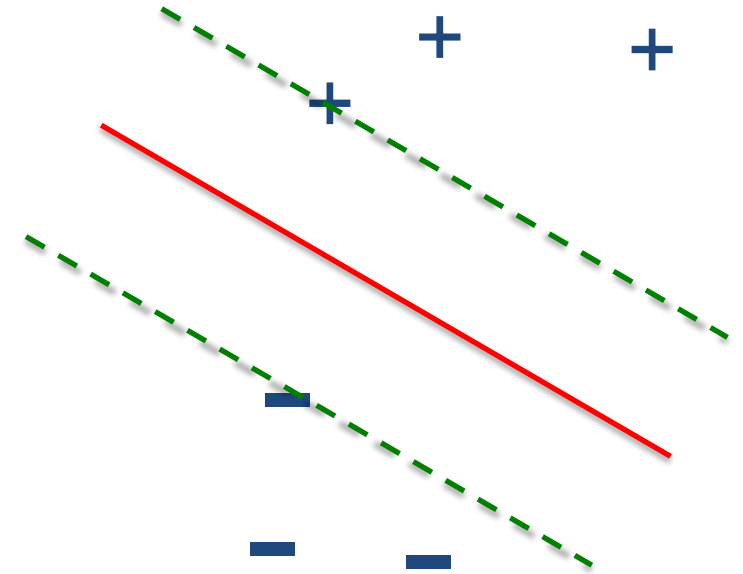
$$\operatorname{argmax}_{\mathbf{w}, b} \quad \text{width}$$

$$\Leftrightarrow \operatorname{argmax}_{\mathbf{w}, b} \quad \frac{2}{\|\mathbf{w}\|_2}$$

$$\Leftrightarrow \operatorname{argmin}_{\mathbf{w}, b} \quad \frac{1}{2} \|\mathbf{w}\|_2$$

$$\Leftrightarrow \operatorname{argmin}_{\mathbf{w}, b} \quad \frac{1}{2} \|\mathbf{w}\|_2^2$$

$$\Leftrightarrow \operatorname{argmin}_{\mathbf{w}, b} \quad \frac{1}{2} \mathbf{w}^T \mathbf{w}$$



SVM Optimization

Quadratic program!

$$\begin{array}{ll} \min_{\mathbf{w}, b} & \frac{1}{2} \mathbf{w}^T \mathbf{w} \\ \text{s.t.} & y^{(i)} (\mathbf{w}^T \mathbf{x}^{(i)} + b) \geq 1 \quad \forall i \end{array}$$

Quadratic Program

$$\begin{array}{ll} \min_x & \mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{A} \mathbf{x} \leq \mathbf{b} \end{array}$$

