

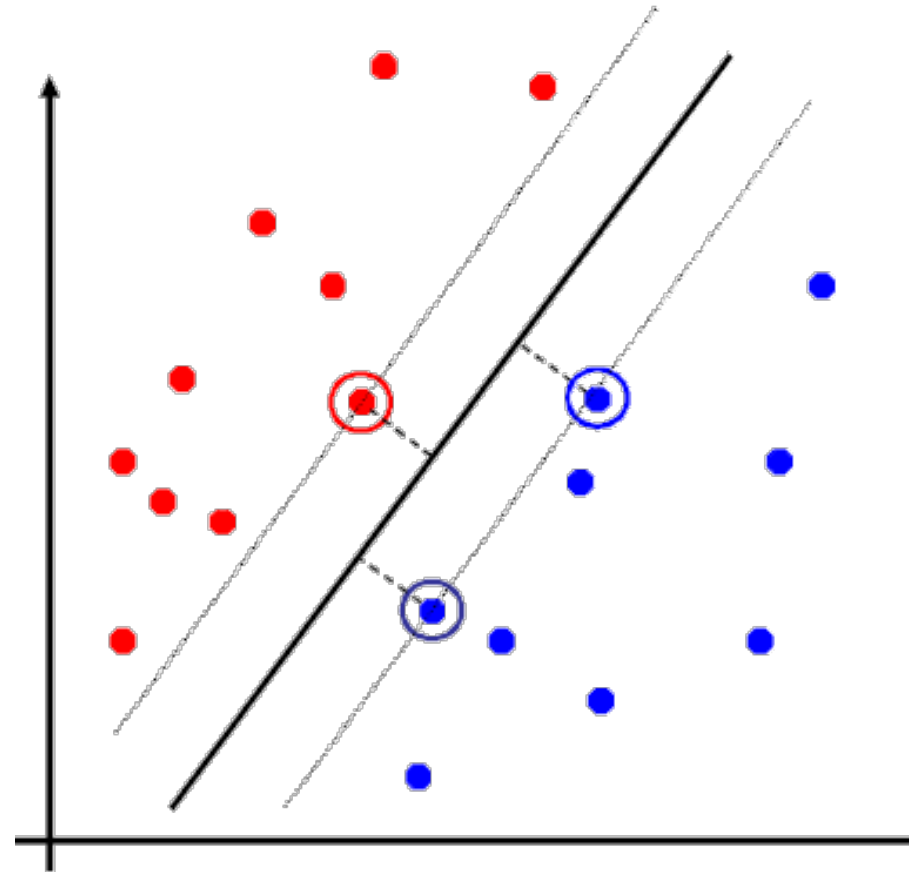
Support Vector Machines: What is the margin?

Mining of Massive Datasets
Leskovec, Rajaraman, and Ullman
Stanford University



Support Vector Machines

- Separating hyperplane is defined by the support vectors
 - Points on \pm planes from the solution
 - If you knew these points, you could ignore the rest
 - If no degeneracies, $d+1$ support vectors (for d dim. data)



Canonical Hyperplane: Problem

■ Problem:

- Let $(w \cdot x + b)y = \gamma$
then $(2w \cdot x + 2b)y = 2\gamma$

- Scaling w increases margin!

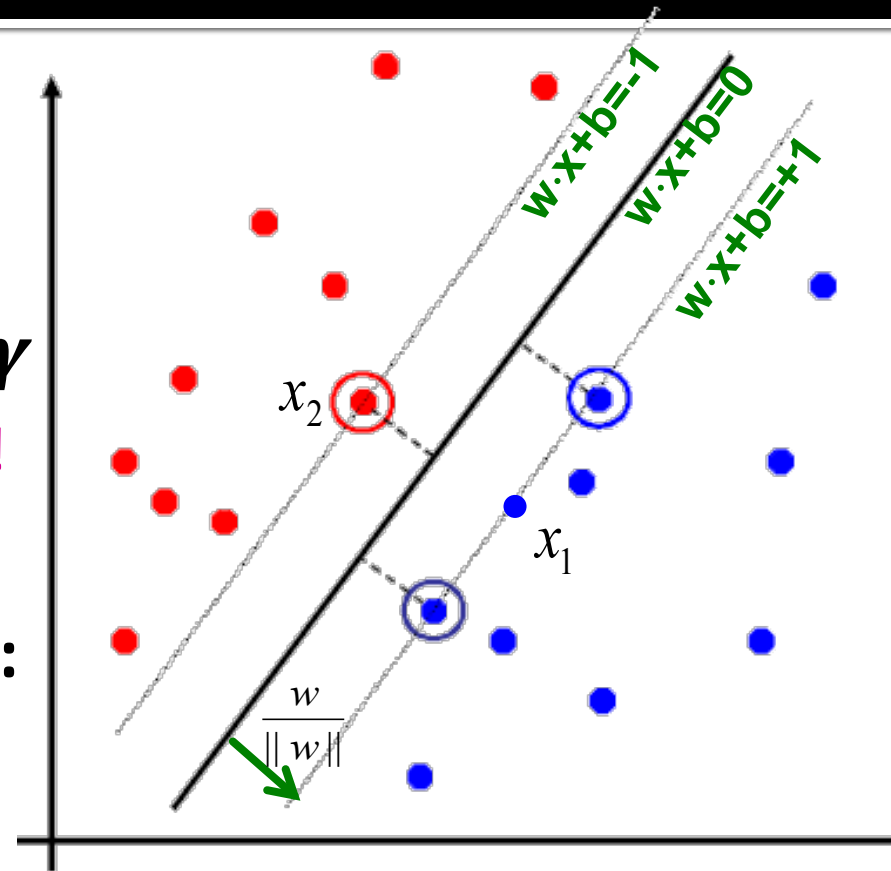
■ Solution:

- Work with normalized w :

$$\gamma = \left(\frac{w}{\|w\|} \cdot x + b \right) y$$

- Let's also require **support vectors** x_j
to be on the plane defined by:

$$w \cdot x_j + b = \pm 1$$



$$\|w\| = \sqrt{\sum_{j=1}^d (w^{(j)})^2}$$

Canonical Hyperplane: Solution

- Want to maximize margin γ !
- What is the relation between x_1 and x_2 ?

- $x_1 = x_2 + 2\gamma \frac{w}{\|w\|}$

- We also know:

- $w \cdot x_1 + b = +1$

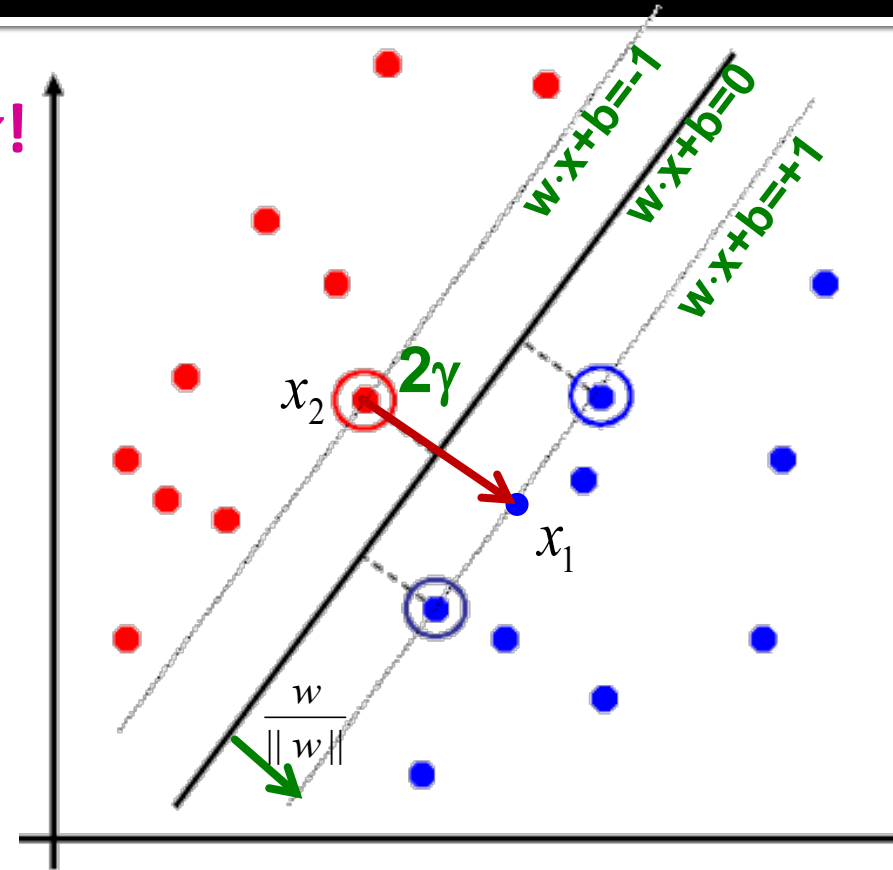
- $w \cdot x_2 + b = -1$

- So:

- $w \cdot x_1 + b = +1$

- $w \left(x_2 + 2\gamma \frac{w}{\|w\|} \right) + b = +1$

- $\underbrace{w \cdot x_2 + b}_{-1} + 2\gamma \frac{w \cdot w}{\|w\|} = +1$



$$\Rightarrow \gamma = \frac{\|w\|}{w \cdot w} = \frac{1}{\|w\|}$$

Note:

$$w \cdot w = \|w\|^2$$

Maximizing the Margin

- We started with

$$\max_{w, \gamma} \gamma$$

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq \gamma$$

But w can be arbitrarily large!

- We normalized and...

$$\max \gamma \approx \max \frac{1}{\|w\|} \approx \min \|w\| \approx \min \frac{1}{2} \|w\|^2$$

- Then:

$$\min_w \frac{1}{2} \|w\|^2$$

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq 1$$

This is called SVM with “hard” constraints

