

Geometric Derivation of SVMs

Slides borrowed from David Rosenberg's 2019 course

12 Feb 2026

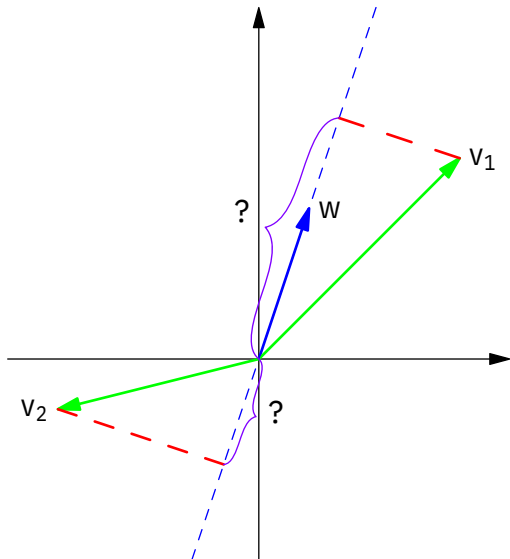
Intro Question

Question

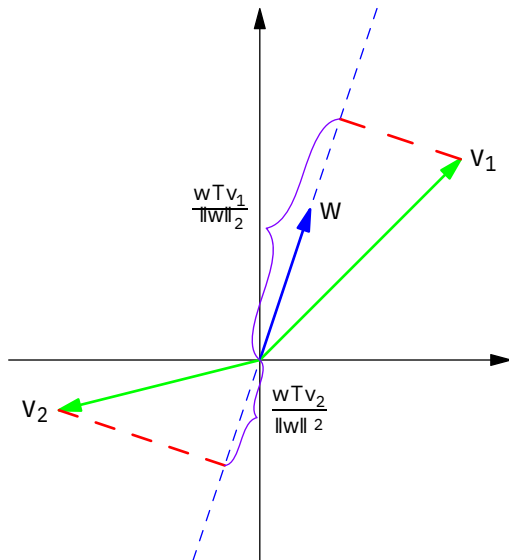
For any $w \in \mathbb{R}^d$ and $a \in \mathbb{R}$, $w^T x - b = 0$ represents the equation of a hyperplane in \mathbb{R}^d . A hyperplane divides the space \mathbb{R}^d into two parts. We are given two points $x_1, x_2 \in \mathbb{R}^d$.

- 1 For $d = 2$, consider $w = (2, 3)^T$ and $b = 6$. Does $x_1 = (0, 0)^T$ and $x_2 = (4, 3)^T$ fall on the same side of the hyper plane?
- 2 How can we write a computer program to determine this for a generic w, a, x_i and d ?

Component of v_1, v_2 in the direction w



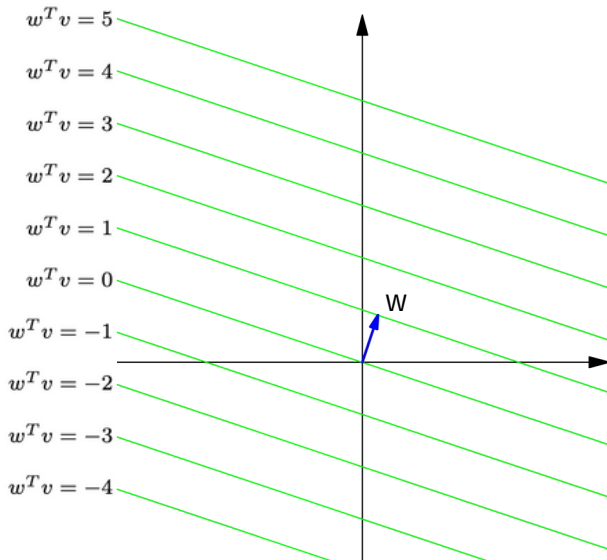
Component of v_1, v_2 in the direction w



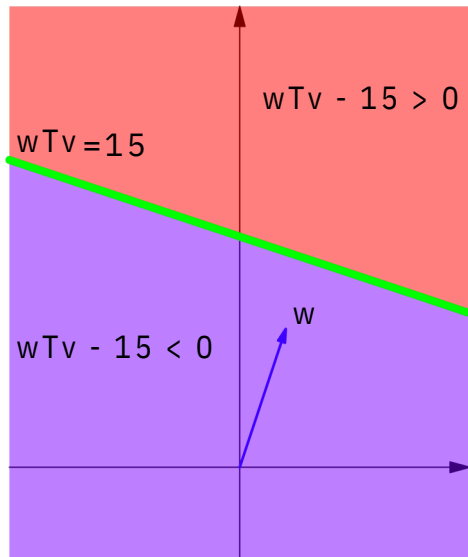
$$w^T x = b$$

- ① $S = \{x \in \mathbb{R}^d \mid w^T x = b\}$. What does this look like?
- ② Note that $w^T x = b \iff \frac{w^T x}{\|w\|_2} = \frac{b}{\|w\|_2}$

Level Surfaces of $f(v) = w^T v$ with $\|w\|_2 = 1$



Sides of the Hyperplane $w^T v = 15$



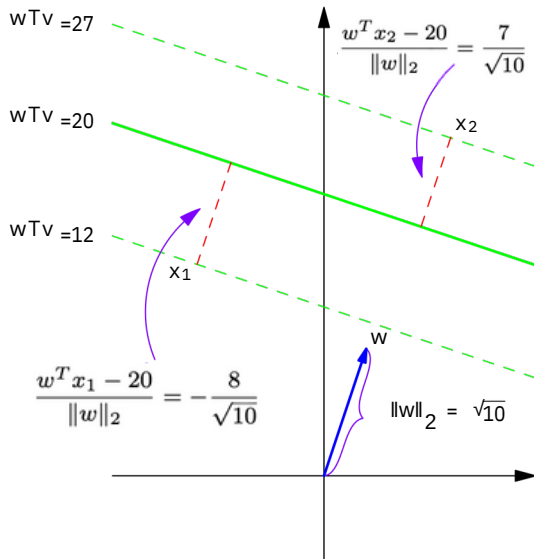
Signed Distance from x to Hyperplane $w^T v = b$

- "Signed" distance? Isn't distance always non-negative?
- If we have a vector $x \in \mathbb{R}^d$ and a hyperplane $H = \{v \mid w^T v = b\}$ we can measure the distance from x to H by

$$d(x, H) = \left| \frac{w^T x - b}{\|w\|_2} \right|.$$

- Without the absolute values we get the *signed distance*: a positive distance if $w^T x > b$ and a negative distance if $w^T x < b$.

Signed Distance from x_1, x_2 to Hyperplane $w^T v = 20$

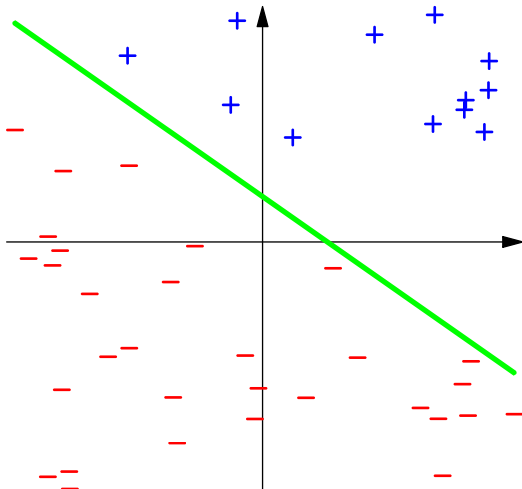


Linearly Separable

Definition

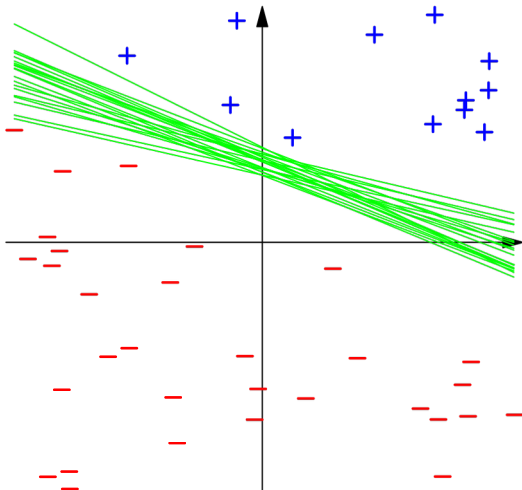
We say (x_i, y_i) for $i = 1, \dots, n$ are *linearly separable* if there is a $w \in \mathbb{R}^d$ and $b \in \mathbb{R}$ such that $y_i(w^T x_i - b) > 0$ for all i . The set $\{v \in \mathbb{R}^d \mid w^T v - b = 0\}$ is called a *separating hyperplane*.

Linearly Separable Data



How many separating hyperplanes?

Many Separating Hyperplanes Exist



How do we pick one?

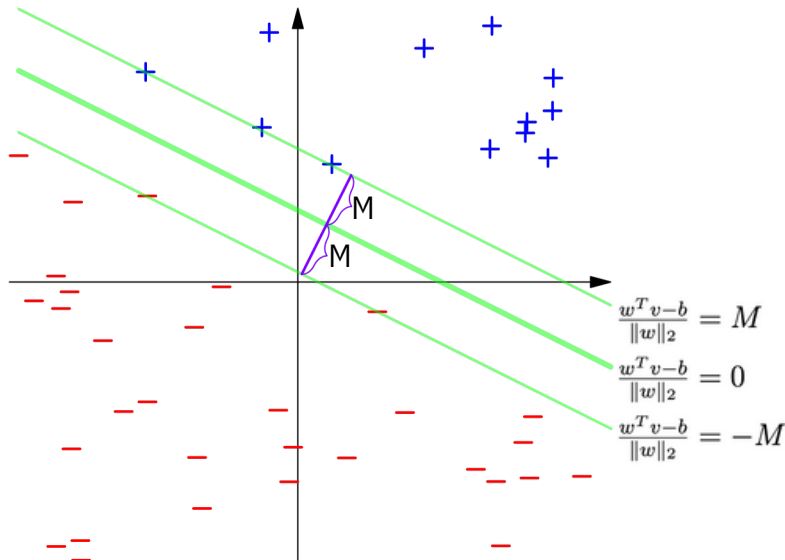
Definition

Let H be a hyperplane that separates the data (x_i, y_i) for $i = 1, \dots, n$. The geometric margin of this hyperplane is

$$\min_i d(x_i, H),$$

the distance from the hyperplane to the closest data point.

Maximum Margin Separating Hyperplane



Maximizing margin

We want to:

$$\text{maximize}_w \min_i d(x_i, H)$$

Remember:

$$d(x_i, H) = \left| \frac{w^T x_i - b}{\|w\|_2} \right| = \frac{y_i(w^T x_i - b)}{\|w\|_2}.$$

So:

$$\text{maximize}_{w,b} \min_i \frac{y_i(w^T x_i - b)}{\|w\|_2}.$$

Note, if $M = \min_i \frac{y_i(w^T x_i - b)}{\|w\|_2}$, then $\frac{y_i(w^T x_i - b)}{\|w\|_2} \geq M$ for all i

Maximizing margin

We can rewrite this in a more standard form:

$$\begin{array}{ll}\text{maximize}_{w,b,M} & M \\ \text{subject to} & \frac{y_i(w^T x_i - b)}{\|w\|_2} \geq M \quad \text{for all } i.\end{array}$$

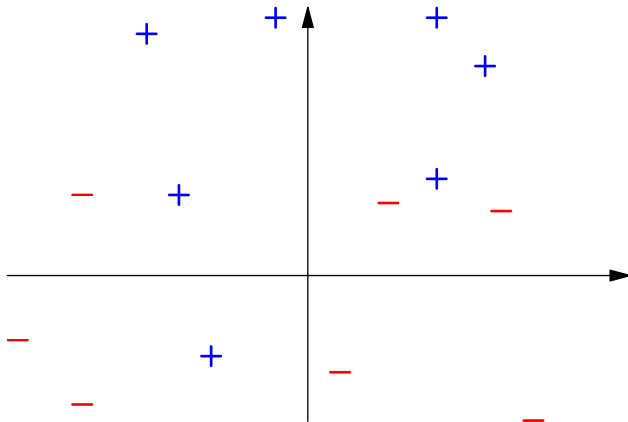
fix $\|w\|_2 = 1/M$ to obtain

$$\begin{array}{ll}\text{maximize}_{w,b} & 1/\|w\|_2 \\ \text{subject to} & y_i(w^T x_i - b) \geq 1 \quad \text{for all } i.\end{array}$$

To find the optimal w, a we can instead solve the minimization problem

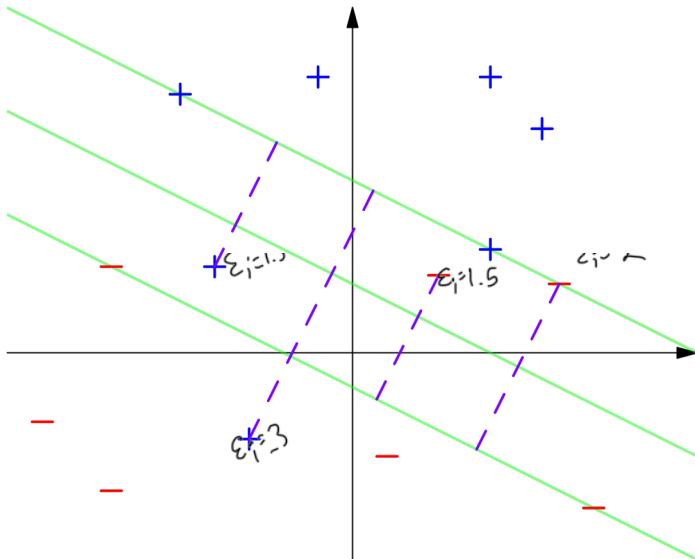
$$\begin{array}{ll}\text{minimize}_{w,b} & \|w\|_2^2 \\ \text{subject to} & y_i(w^T x_i - b) \geq 1 \quad \text{for all } i.\end{array}$$

Linearly Non-Separable



What should we do if the data isn't linearly separable?

Soft Margin SVM (unlabeled points have $\xi_i = 0$)



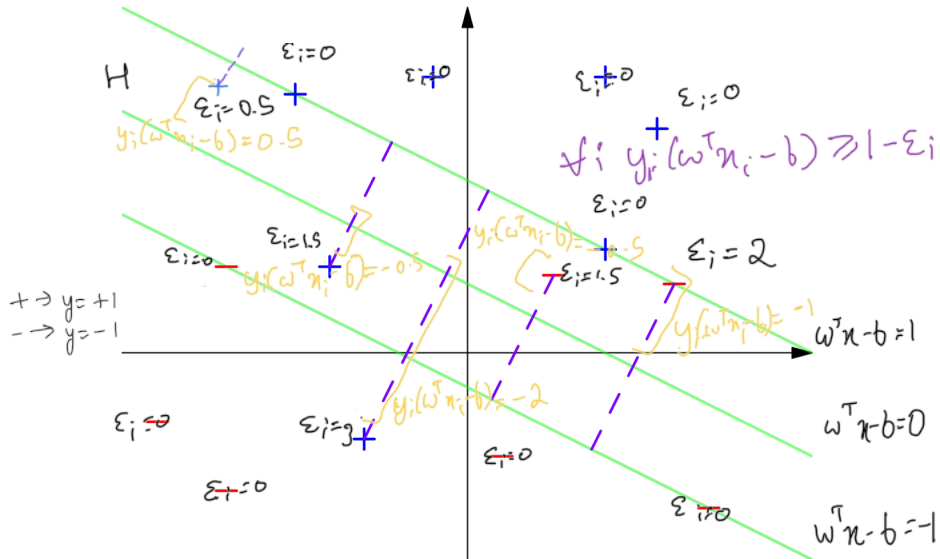
Soft Margin SVM (introduce slack)

Questions

$$\begin{aligned} &\text{minimize}_{w,b,\xi} \quad \|w\|_2^2 + \frac{C}{n} \sum_{i=1}^n \xi_i \\ &\text{subject to} \quad y_i(w^T x_i - b) \geq 1 - \xi_i \quad \text{for all } i \\ &\quad \quad \quad \xi_i \geq 0 \quad \text{for all } i. \end{aligned}$$

- 1 What does $\xi_i > 0$ mean?
- 2 What does C control?
- 3 Note that $\frac{y_i(w^T x_i + a)}{\|w\|_2} \geq \frac{1 - \xi_i}{\|w\|_2}$. What does $\xi_i = 1$ and $\xi_i = 3$ mean?

Geometric Meaning of Slack Variables



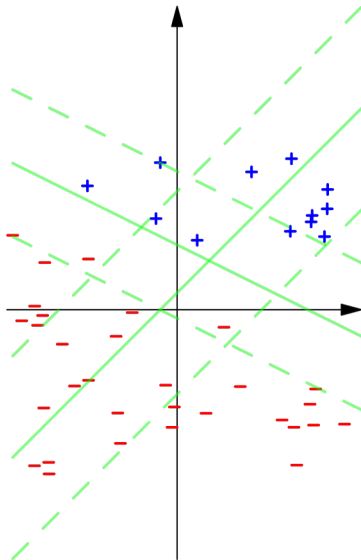
Question

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Explain geometrically what the following optimization problem computes:

$$\begin{aligned} & \text{minimize}_{w,a,\xi} && \frac{1}{n} \sum_{i=1}^n \xi_i \\ & \text{subject to} && y_i(w^T x_i + a) \geq 1 - \xi_i \quad \text{for all } i \\ & && \|w\|_2^2 \leq r^2 \\ & && \xi_i \geq 0 \quad \text{for all } i. \end{aligned}$$

Optimize Over Cases Where Margin Is At Least $1/r$



Question

Question

If your data is linearly separable, which SVM (hard margin or soft margin) would you use?

Hard margin v/s Soft margin

