# Geometric Derivation of SVMs 

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## 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 $w$



## $w^{\top} x=b$

(1) $S=\left\{x \in \mathbb{R}^{d} \mid w^{T} x=b\right\}$. What does this look like?
(2) Note that $w^{T} x=b \Longleftrightarrow \frac{w^{\top} x}{\|w\|_{2}}=\frac{b}{\|w\|_{2}}$

## Level Surfaces of $f(v)=w^{\top} v$ with $\|w\|_{2}=1$

$w^{T} v=5$

$$
w^{T} v=4
$$

$$
w^{T} v=3
$$

$$
w^{T} v=2
$$

$$
w^{T} v=1
$$

$$
w^{T} v=0
$$

$$
w^{T} v=-1
$$

$$
w^{T} v=-2
$$

$$
w^{T} v=-3
$$

$$
w^{T} v=-4
$$

## Sides of the Hyperplane $w^{\top} v=15$



## Signed Distance from $x$ to Hyperplane $w^{\top} v=b$

- "Signed" distance? Isn't distance always non-negative?
- If we have a vector $x \in \mathbb{R}^{d}$ and a hyperplane $H=\left\{v \mid w^{T} v=b\right\}$ 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 $w^{\top} x>b$ and a negative distance if $w^{\top} x<b$.


## Signed Distance from $x_{1}, x_{2}$ to Hyperplane $w^{\top} v=20$



## Question

## Question

You have been given a data set $\left(x_{i}, y_{i}\right)$ for $i=1, \ldots, n$ where $x_{i} \in \mathbb{R}^{d}$ and $y_{i} \in\{-1,1\}$. You are also given a hyper plane parameterized by $w \in \mathbb{R}^{d}$ and $b \in \mathbb{R}$. Give an algorithm to check if $w^{\top} x=b$ separates the data points correctly or in other words, if $y=+1$ and $y=-1$ fall on two different sides of the hyperplane.

## Linearly Separable

## Definition

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

## Linearly Separable Data



How many separating hyperplanes?

## Many Separating Hyperplanes Exist



How do we pick one?

## Geometric Margin

## Definition

Let $H$ be a hyperplane that separates the data $\left(x_{i}, y_{i}\right)$ for $i=1, \ldots, n$. The geometric margin of this hyperplane is

$$
\min _{i} d\left(x_{i}, H\right),
$$

the distance from the hyperplane to the closest data point.

## Maximum Margin Separating Hyperplane



## Maximizing margin

We want to:

$$
\underset{i}{\operatorname{maximize}} \min _{i} d\left(x_{i}, H\right)
$$

Remember:

$$
d\left(x_{i}, H\right)=\left|\frac{w^{\top} x_{i}-b}{\|w\|_{2}}\right|=\frac{y_{i}\left(w^{\top} x_{i}-b\right)}{\|w\|_{2}} .
$$

So:

$$
\operatorname{maximize}_{w, b} \min _{i} \frac{y_{i}\left(w^{T} x_{i}-b\right)}{\|w\|_{2}}
$$

Note, if $M=\min _{i} \frac{y_{i}\left(w^{\top} x_{i}-b\right)}{\|w\|_{2}}$, then $\frac{y_{i}\left(w^{\top} x_{i}-b\right)}{\|w\|_{2}} \geq M$ for all $i$

## Maximizing margin

We can rewrite this in a more standard form:

$$
\begin{array}{ll}
\operatorname{maximize}_{w, b, M} & M \\
\text { subject to } & \frac{y_{i}\left(w^{T} x_{i}-b\right)}{\|w\|_{2}} \geq M \quad \text { for all } i .
\end{array}
$$

fix $\|w\|_{2}=1 / M$ to obtain

$$
\begin{array}{ll}
\operatorname{maximize}_{w, b} & 1 /\|w\|_{2} \\
\text { subject to } & y_{i}\left(w^{\top} x_{i}-b\right) \geq 1 \quad \text { for all } i .
\end{array}
$$

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

$$
\begin{array}{ll}
\operatorname{minimize}_{w, b} & \|w\|_{2}^{2} \\
\text { subject to } & y_{i}\left(w^{T} x_{i}-b\right) \geq 1 \quad \text { for all } i .
\end{array}
$$

## 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

$\operatorname{minimize}_{w, b, \xi} \quad\|w\|_{2}^{2}+\frac{c}{n} \sum_{i=1}^{n} \xi_{i}$
subject to
$y_{i}\left(w^{T} x_{i}-b\right) \geq 1-\xi_{i} \quad$ for all $i$
$\xi_{i} \geq 0$ for all $i$.
(1) What does $\xi_{i}>0$ mean?
(2) What does $C$ control?
(3) Note that $\frac{y_{i}\left(w^{\top} x_{i}+a\right)}{\|w\|_{2}} \geq \frac{1-\xi_{i}}{\|w\|_{2}}$. What does $\xi_{i}=1$ and $\xi_{i}=3$ mean?

## Question

## Question

Explain geometrically what the following optimization problem computes:

$$
\begin{array}{ll}
\operatorname{minimize}_{w, a, \xi} & \frac{1}{n} \sum_{i=1}^{n} \xi_{i} \\
\text { subject to } & y_{i}\left(w^{T} x_{i}+a\right) \geq 1-\xi_{i} \quad \text { for all } i \\
& \|w\|_{2}^{2} \leq r^{2} \\
& \xi_{i} \geq 0 \text { for all } i .
\end{array}
$$

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



