

Machine Learning Foundations

(機器學習基石)



Lecture 2: Learning to Answer Yes/No

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Roadmap

① When Can Machines Learn?

Lecture 1: The Learning Problem

\mathcal{A} takes \mathcal{D} and \mathcal{H} to get g

Lecture 2: Learning to Answer Yes/No

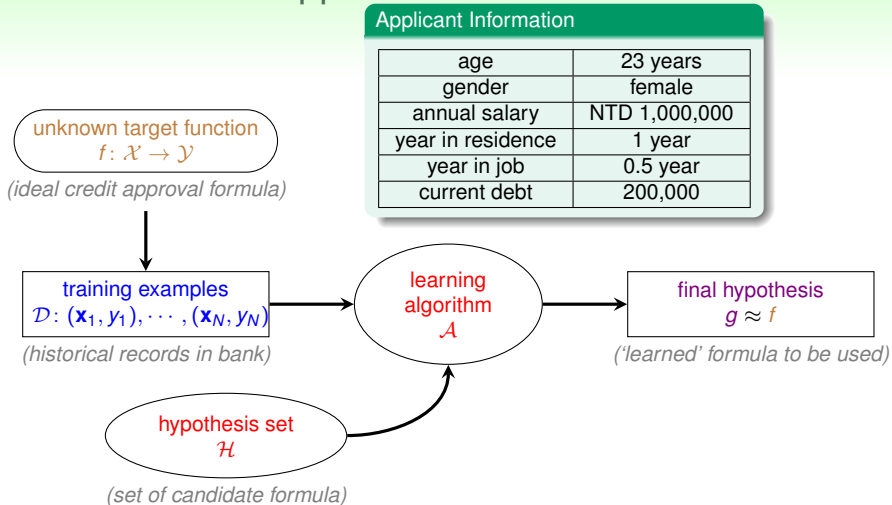
- Perceptron Hypothesis Set
- Perceptron Learning Algorithm (PLA)
- Guarantee of PLA
- Non-Separable Data

② Why Can Machines Learn?

③ How Can Machines Learn?

④ How Can Machines Learn Better?

Credit Approval Problem Revisited



what hypothesis set can we use?

A Simple Hypothesis Set: the 'Perceptron'

age	23 years
annual salary	NTD 1,000,000
year in job	0.5 year
current debt	200,000

- For $\mathbf{x} = (x_1, x_2, \dots, x_d)$ '**features of customer**', compute a weighted 'score' and

approve credit if

$$\sum_{i=1}^d w_i x_i > \text{threshold}$$

deny credit if

$$\sum_{i=1}^d w_i x_i < \text{threshold}$$

- \mathcal{Y} : **+1 (good)**, **-1 (bad)**, 0 ignored—linear formula $h \in \mathcal{H}$ are

$$h(\mathbf{x}) = \text{sign} \left(\left(\sum_{i=1}^d w_i x_i \right) - \text{threshold} \right)$$

called '**perceptron**' hypothesis historically

Vector Form of Perceptron Hypothesis

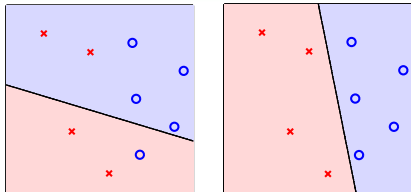
$$\begin{aligned}h(\mathbf{x}) &= \text{sign} \left(\left(\sum_{i=1}^d \mathbf{w}_i x_i \right) - \text{threshold} \right) \\&= \text{sign} \left(\left(\sum_{i=1}^d \mathbf{w}_i x_i \right) + \underbrace{(-\text{threshold})}_{\mathbf{w}_0} \cdot \underbrace{(+1)}_{x_0} \right) \\&= \text{sign} \left(\sum_{i=0}^d \mathbf{w}_i x_i \right) \\&= \text{sign} \left(\mathbf{w}^T \mathbf{x} \right)\end{aligned}$$

- each ‘tall’ \mathbf{w} represents a hypothesis h & is multiplied with ‘tall’ \mathbf{x} — **will use tall versions to simplify notation**

what do perceptrons h ‘look like’?

Perceptrons in \mathbb{R}^2

$$h(\mathbf{x}) = \text{sign}(w_0 + w_1x_1 + w_2x_2)$$



- customer features \mathbf{x} : points on the plane (or points in \mathbb{R}^d)
- labels y : $\circ (+1)$, $\times (-1)$
- hypothesis h : **lines** (or hyperplanes in \mathbb{R}^d)
— **positive** on one side of a line, **negative** on the other side
- different line classifies customers differently

perceptrons \Leftrightarrow **linear (binary) classifiers**

Fun Time

Consider using a perceptron to detect spam messages.

Assume that each email is represented by the frequency of keyword occurrence, and output $+1$ indicates a spam. Which keywords below shall have large positive weights in a **good perceptron** for the task?

- ① coffee, tea, hamburger, steak
- ② free, drug, fantastic, deal
- ③ machine, learning, statistics, textbook
- ④ national, Taiwan, university, coursera

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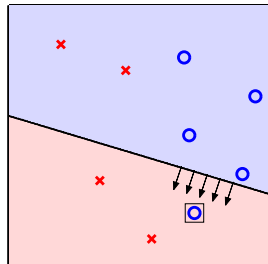
Reference Answer: ②

The occurrence of keywords with positive weights increase the 'spam score', and hence those keywords should often appear in spams.

Select g from \mathcal{H}

\mathcal{H} = all possible perceptrons, $g = ?$

- want: $g \approx f$ (hard when f unknown)
- almost necessary: $g \approx f$ on \mathcal{D} , ideally $g(\mathbf{x}_n) = f(\mathbf{x}_n) = y_n$
- difficult: \mathcal{H} is of **infinite** size
- idea: start from some g_0 , and ‘correct’ its mistakes on \mathcal{D}



will represent g_0 by its weight vector \mathbf{w}_0

Perceptron Learning Algorithm

start from some \mathbf{w}_0 (say, $\mathbf{0}$), and 'correct' its mistakes on \mathcal{D}

For $t = 0, 1, \dots$

- 1 find a **mistake** of \mathbf{w}_t called $(\mathbf{x}_{n(t)}, y_{n(t)})$

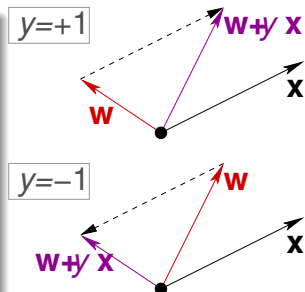
$$\text{sign}(\mathbf{w}_t^T \mathbf{x}_{n(t)}) \neq y_{n(t)}$$

- 2 (try to) correct the mistake by

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)}$$

... until **no more mistakes**

return **last \mathbf{w}** (called \mathbf{w}_{PLA}) as g



That's it!

知错能改，善莫大焉

—A fault confessed is half redressed. :-)

Practical Implementation of PLA

start from some \mathbf{w}_0 (say, $\mathbf{0}$), and 'correct' its mistakes on \mathcal{D}

Cyclic PLA

For $t = 0, 1, \dots$

- 1 find **the next** mistake of \mathbf{w}_t called $(\mathbf{x}_{n(t)}, y_{n(t)})$

$$\text{sign} \left(\mathbf{w}_t^T \mathbf{x}_{n(t)} \right) \neq y_{n(t)}$$

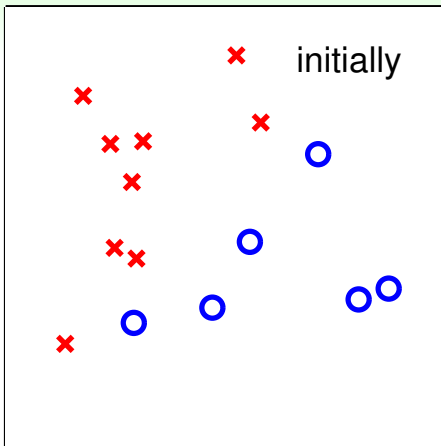
- 2 correct the mistake by

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)}$$

... until **a full cycle of not encountering mistakes**

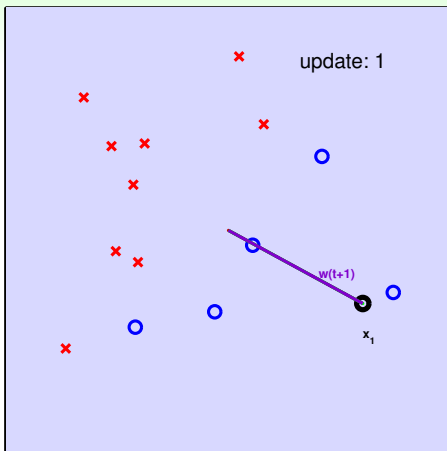
next can follow naïve cycle $(1, \dots, N)$
or **precomputed random cycle**

Seeing is Believing



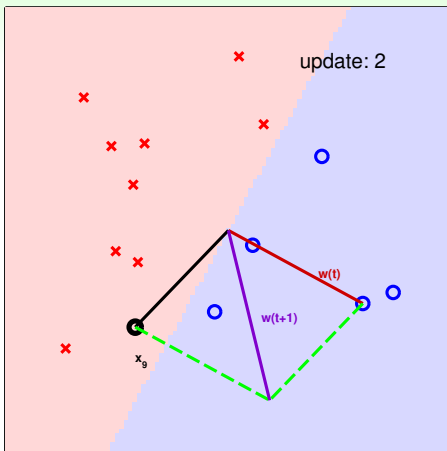
worked like a charm with < 20 lines!!
(note: made $x_i \gg x_0 = 1$ for visual purpose)

Seeing is Believing



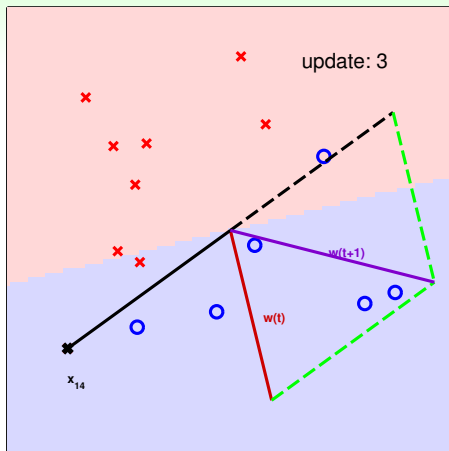
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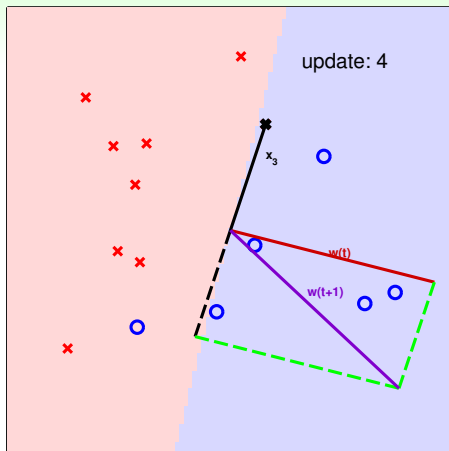
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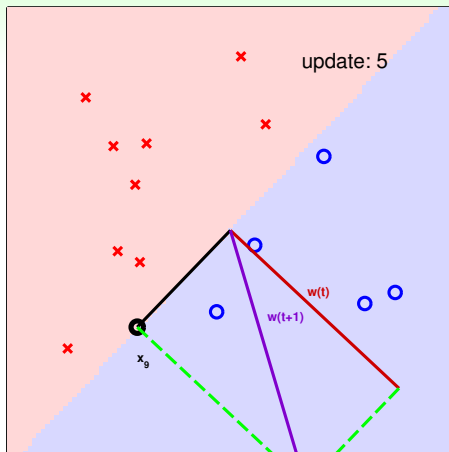
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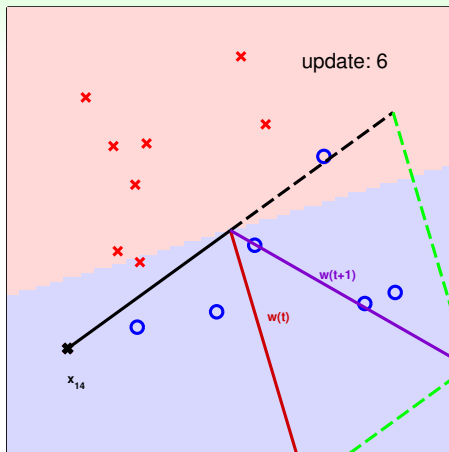
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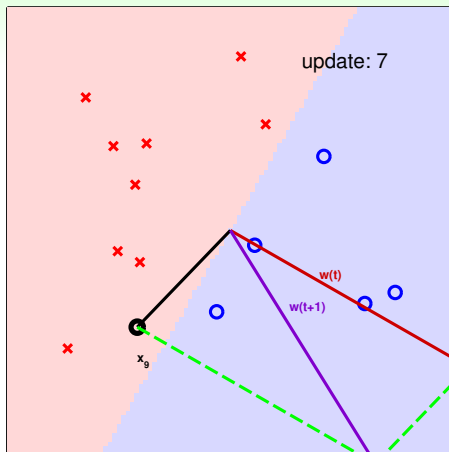
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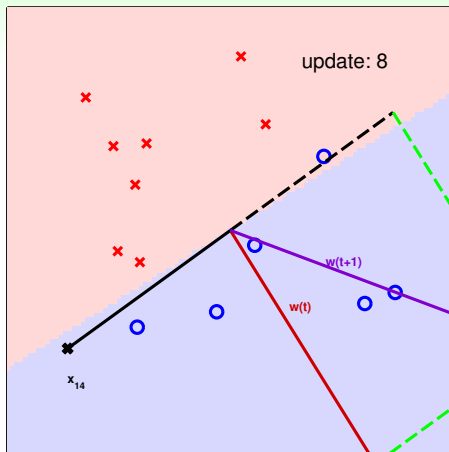
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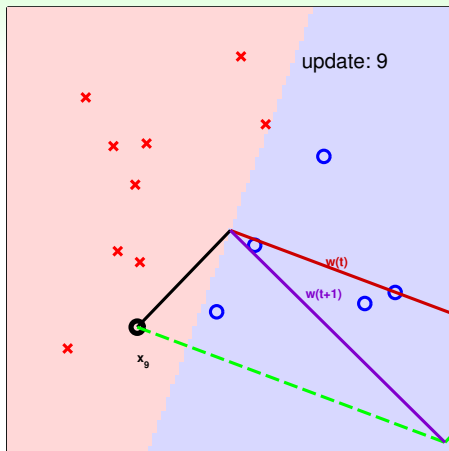
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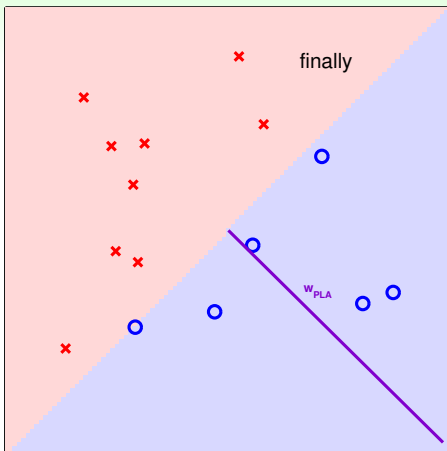
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Some Remaining Issues of PLA

‘correct’ mistakes on \mathcal{D} **until no mistakes**

Algorithmic: halt (with no mistake)?

- naïve cyclic: ??
- random cyclic: ??
- other variant: ??

Learning: $g \approx f$?

- on \mathcal{D} , if halt, yes (no mistake)
- outside \mathcal{D} : ??
- if not halting: ??

[to be shown] if (...), after ‘enough’ corrections,
any PLA variant halts

Fun Time

Let's try to think about why PLA may work.

Let $n = n(t)$, according to the rule of PLA below, which formula is true?

$$\text{sign}(\mathbf{w}_t^T \mathbf{x}_n) \neq y_n, \quad \mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_n \mathbf{x}_n$$

- ① $\mathbf{w}_{t+1}^T \mathbf{x}_n = y_n$
- ② $\text{sign}(\mathbf{w}_{t+1}^T \mathbf{x}_n) = y_n$
- ③ $y_n \mathbf{w}_{t+1}^T \mathbf{x}_n \geq y_n \mathbf{w}_t^T \mathbf{x}_n$
- ④ $y_n \mathbf{w}_{t+1}^T \mathbf{x}_n < y_n \mathbf{w}_t^T \mathbf{x}_n$

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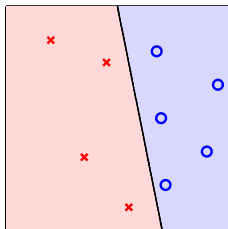
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- ④ $y_n \mathbf{w}_{t+1}^T \mathbf{x}_n < y_n \mathbf{w}_t^T \mathbf{x}_n$

Reference Answer: ③

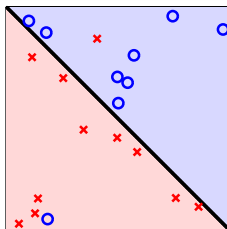
Simply multiply the second part of the rule by $y_n \mathbf{x}_n$. The result shows that **the rule somewhat 'tries to correct the mistake.'**

Linear Separability

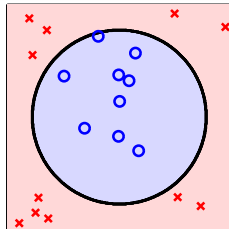
- if PLA halts (i.e. no more mistakes),
(**necessary condition**) \mathcal{D} allows some \mathbf{w} to make no mistake
- call such \mathcal{D} **linear separable**



(linear separable)



(not linear separable)



(not linear separable)

assume linear separable \mathcal{D} ,
does PLA always **halt**?

PLA Fact: \mathbf{w}_t Gets More Aligned with \mathbf{w}_f

linear separable $\mathcal{D} \Leftrightarrow$ **exists perfect \mathbf{w}_f such that $y_n = \text{sign}(\mathbf{w}_f^T \mathbf{x}_n)$**

- \mathbf{w}_f perfect hence every \mathbf{x}_n correctly away from line:

$$y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)} \geq \min_n y_n \mathbf{w}_f^T \mathbf{x}_n > 0$$

- $\mathbf{w}_f^T \mathbf{w}_t \uparrow$ by updating with any $(\mathbf{x}_{n(t)}, y_{n(t)})$

$$\begin{aligned} \mathbf{w}_f^T \mathbf{w}_{t+1} &= \mathbf{w}_f^T (\mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)}) \\ &\geq \mathbf{w}_f^T \mathbf{w}_t + \min_n y_n \mathbf{w}_f^T \mathbf{x}_n \\ &> \mathbf{w}_f^T \mathbf{w}_t + 0. \end{aligned}$$

\mathbf{w}_t appears more aligned with \mathbf{w}_f after update
(really?)

PLA Fact: \mathbf{w}_t Does Not Grow Too Fast

\mathbf{w}_t changed only when mistake

$$\Leftrightarrow \text{sign}(\mathbf{w}_t^T \mathbf{x}_{n(t)}) \neq y_{n(t)} \Leftrightarrow y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} \leq 0$$

- mistake 'limits' $\|\mathbf{w}_t\|^2$ growth, even when updating with 'longest' \mathbf{x}_n

$$\begin{aligned} \|\mathbf{w}_{t+1}\|^2 &= \|\mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)}\|^2 \\ &= \|\mathbf{w}_t\|^2 + 2y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} + \|y_{n(t)} \mathbf{x}_{n(t)}\|^2 \\ &\leq \|\mathbf{w}_t\|^2 + 0 + \|y_{n(t)} \mathbf{x}_{n(t)}\|^2 \\ &\leq \|\mathbf{w}_t\|^2 + \max_n \|y_n \mathbf{x}_n\|^2 \end{aligned}$$

start from $\mathbf{w}_0 = \mathbf{0}$, after T mistake corrections,

$$\frac{\mathbf{w}_f^T}{\|\mathbf{w}_f\|} \frac{\mathbf{w}_T}{\|\mathbf{w}_T\|} \geq \sqrt{T} \cdot \text{constant}$$

Fun Time

Let's upper-bound T , the number of mistakes that PLA 'corrects'.

$$\text{Define } R^2 = \max_n \|\mathbf{x}_n\|^2 \quad \rho = \min_n y_n \frac{\mathbf{w}_f^T \mathbf{x}_n}{\|\mathbf{w}_f\|}$$

We want to show that $T \leq \square$. Express the upper bound \square by the two terms above.

R^2 - 半径的平方，每个向量的长度，最大的是多少

ρ - 我们想要的那条线，目标线的法向量跟每个点的内积，如果是线性可分的话， ρ 一定是大于0的

- ① R/ρ
- ② R^2/ρ^2
- ③ R/ρ^2
- ④ ρ^2/R^2

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- ① R/ρ
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- ③ R/ρ^2
- ④ ρ^2/R^2

Reference Answer: ②

The maximum value of $\frac{\mathbf{w}_f^T \mathbf{w}_t}{\|\mathbf{w}_f\| \|\mathbf{w}_t\|}$ is 1. Since T mistake corrections **increase the inner product by \sqrt{T} · constant**, the maximum number of corrected mistakes is $1/\text{constant}^2$.

More about PLA

Guarantee

as long as **linear separable** and **correct by mistake**

- inner product of \mathbf{w}_f and \mathbf{w}_t grows fast; length of \mathbf{w}_t grows slowly
- PLA 'lines' are more and more aligned with $\mathbf{w}_f \Rightarrow$ halts

Pros

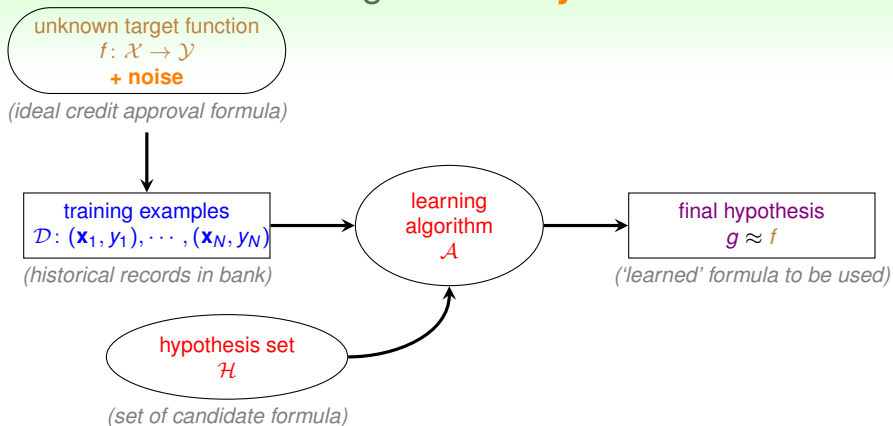
simple to implement, fast, works in any dimension d

Cons

- **'assumes' linear separable** \mathcal{D} to halt
—property unknown in advance (no need for PLA if we know \mathbf{w}_f)
- not fully sure **how long halting takes** (ρ depends on \mathbf{w}_f)
—though practically fast

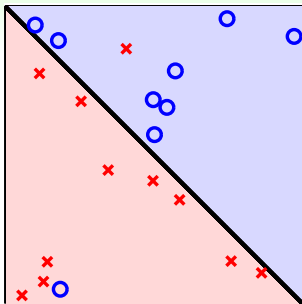
what if \mathcal{D} not linear separable?

Learning with Noisy Data



how to at least get $g \approx f$ on **noisy** \mathcal{D} ?

Line with Noise Tolerance



- assume ‘little’ noise: $y_n = f(\mathbf{x}_n)$ **usually**
- if so, $g \approx f$ on $\mathcal{D} \Leftrightarrow y_n = g(\mathbf{x}_n)$ **usually**
- how about

$$\mathbf{w}_g \leftarrow \operatorname{argmin}_{\mathbf{w}} \sum_{n=1}^N \mathbb{I}[y_n \neq \operatorname{sign}(\mathbf{w}^T \mathbf{x}_n)]$$

总共犯了多少错误

—**NP-hard to solve, unfortunately**

can we **modify PLA** to get
an ‘approximately good’ g ?

在所有犯错误里面选择一个最小的当作 \mathbf{w}_g

Pocket Algorithm

modify PLA algorithm (black lines) by **keeping best weights in pocket**

initialize pocket weights $\hat{\mathbf{w}}$

For $t = 0, 1, \dots$

- 1 find a (random) mistake of \mathbf{w}_t called $(\mathbf{x}_{n(t)}, y_{n(t)})$
- 2 (try to) correct the mistake by

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)}$$

- 3 if \mathbf{w}_{t+1} makes fewer mistakes than $\hat{\mathbf{w}}$, replace $\hat{\mathbf{w}}$ by \mathbf{w}_{t+1}

...until **enough iterations**

return **$\hat{\mathbf{w}}$ (called $\mathbf{w}_{\text{POCKET}}$) as \mathbf{g}**

a simple modification of PLA to find
(somewhat) 'best' weights

Fun Time

我们拿到一个资料

Should we use pocket or PLA?

Since we do not know whether \mathcal{D} is linear separable in advance, we may decide to just go with pocket instead of PLA. If \mathcal{D} is actually linear separable, what's the difference between the two?

- ① pocket on \mathcal{D} is slower than PLA
- ② pocket on \mathcal{D} is faster than PLA
- ③ pocket on \mathcal{D} returns a better g in approximating f than PLA
- ④ pocket on \mathcal{D} returns a worse g in approximating f than PLA

Fun Time

Should we use pocket or PLA?

Since we do not know whether \mathcal{D} is linear separable in advance, we may decide to just go with pocket instead of PLA. If \mathcal{D} is actually linear separable, what's the difference between the two?

- 1 pocket on \mathcal{D} is slower than PLA
- 2 pocket on \mathcal{D} is faster than PLA
- 3 pocket on \mathcal{D} returns a better g in approximating f than PLA
- 4 pocket on \mathcal{D} returns a worse g in approximating f than PLA

Reference Answer: ①

Because pocket need to check whether \mathbf{w}_{t+1} is better than $\hat{\mathbf{w}}$ in each iteration, it is slower than PLA. On linear separable \mathcal{D} , $\mathbf{w}_{\text{POCKET}}$ is the same as \mathbf{w}_{PLA} , both making no mistakes.

Summary

1 When Can Machines Learn?

Lecture 1: The Learning Problem

Lecture 2: Learning to Answer Yes/No

- Perceptron Hypothesis Set
hyperplanes/linear classifiers in \mathbb{R}^d
- Perceptron Learning Algorithm (PLA)
correct mistakes and improve iteratively
- Guarantee of PLA
no mistake eventually if linear separable
- Non-Separable Data
hold somewhat 'best' weights in pocket

• **next: the zoo of learning problems**

2 Why Can Machines Learn?

3 How Can Machines Learn?

4 How Can Machines Learn Better?