# Structure and Predictions

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PERCEPTRON: SLIDES ADAPTED FROM LIANG HUANG

## How do we set the feature weights?

- Goal is to minimize errors
- Want to reward features that lead to right answers
- Penalize features that lead to wrong answers
- Problem: predictions are correlated

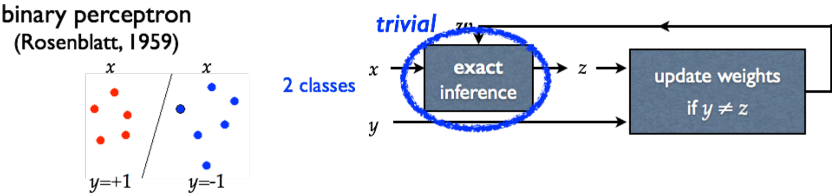
## Perceptron Algorithm

- Rather than just counting up how often we see events?
- We'll use this for intuition in 2D case

## Perceptron Algorithm

$\vec{w}_1 \leftarrow \vec{0}$
**for** $t \leftarrow 1 \dots T$ **do**
    Receive $x_t$
    $\hat{y}_t \leftarrow \text{sgn}(\vec{w}_t \cdot \vec{x}_t)$
    Receive $y_t$
    **if** $\hat{y}_t \neq y_t$ **then**
        $\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t$
    **else**
        $\vec{w}_{t+1} \leftarrow w_t$
**return** $w_{T+1}$

# Binary to Structure



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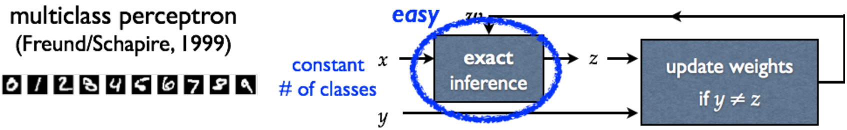
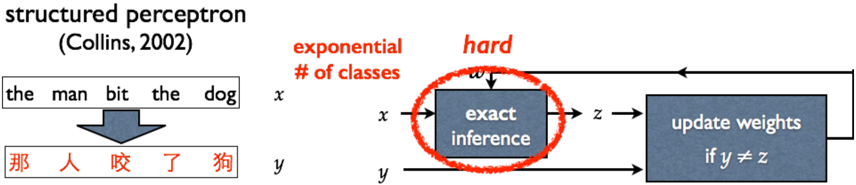


# Binary to Structure



## Generic Perceptron

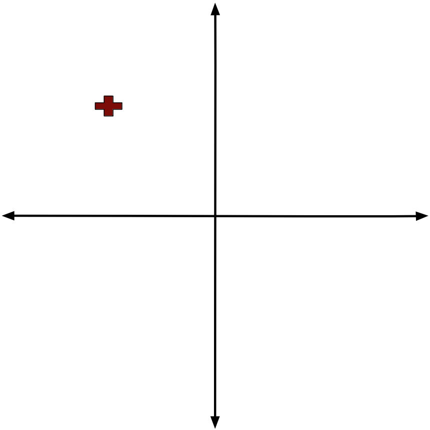
- perceptron is the simplest machine learning algorithm
- online-learning: one example at a time
- learning by doing
  - find the best output under the current weights
  - update weights at mistakes

## 2D Example

Initially, weight vector is zero:

$$\vec{w}_1 = \langle 0, 0 \rangle \tag{1}$$

## Observation 1



$$x_1 = \langle -2, 2 \rangle \quad (2)$$
$$\hat{y}_1 = 0 \quad (3)$$
$$y_1 = +1 \quad (4)$$

## Update 1

$$\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t \tag{5}$$

$$\vec{w}_2 \leftarrow \tag{6}$$

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$$\vec{w}_2 \leftarrow \langle 0, 0 \rangle + \langle -2, 2 \rangle \tag{6}$$

$$\tag{7}$$

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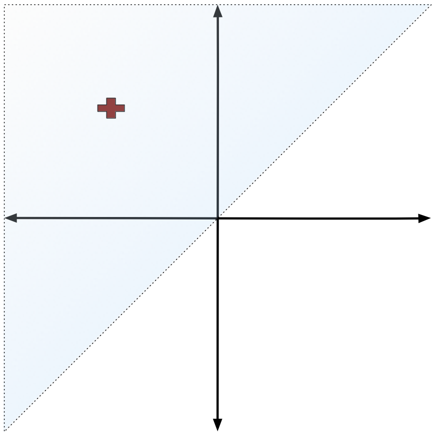
$$\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t \tag{5}$$

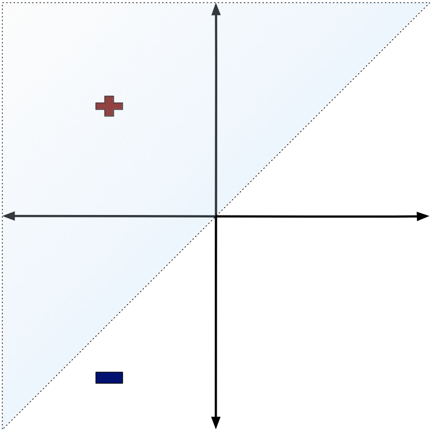
$$\vec{w}_2 \leftarrow \langle 0, 0 \rangle + \langle -2, 2 \rangle \tag{6}$$

$$\vec{w}_2 = \langle -2, 2 \rangle \tag{7}$$

## Observation 2



## Observation 2



$$x_2 = \langle -2, -3 \rangle \tag{8}$$

$$\hat{y}_2 = +4 + -6 = -2 \tag{9}$$

$$y_2 = -1 \tag{10}$$

## Update 2

$$\vec{w}_{t+1} \leftarrow \vec{w}_t \tag{11}$$

$$\vec{w}_2 \leftarrow \tag{12}$$

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$$\vec{w}_{t+1} \leftarrow \vec{w}_t \tag{11}$$

$$\vec{w}_2 \leftarrow \langle -2, 2 \rangle \tag{12}$$

$$\tag{13}$$

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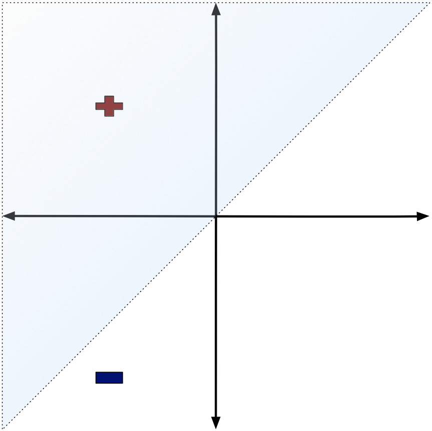
$$\vec{w}_{t+1} \leftarrow \vec{w}_t \tag{11}$$

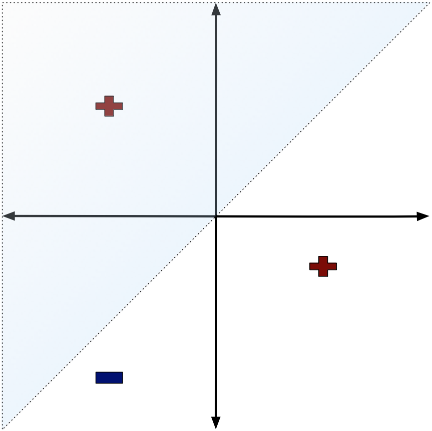
$$\vec{w}_2 \leftarrow \langle -2, 2 \rangle \tag{12}$$

$$\vec{w}_2 = \langle -2, 2 \rangle \tag{13}$$

## Observation 3



## Observation 3



$$x_3 = \langle 2, -1 \rangle \quad (14)$$
$$\hat{y}_3 = -4 + -2 = -6 \quad (15)$$
$$y_3 = +1 \quad (16)$$

## Update 3

$$\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t \tag{17}$$

$$\vec{w}_3 \leftarrow \tag{18}$$

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$$\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t \tag{17}$$

$$\vec{w}_3 \leftarrow \langle -2, 2 \rangle + \langle 2, -1 \rangle \tag{18}$$

$$\tag{19}$$

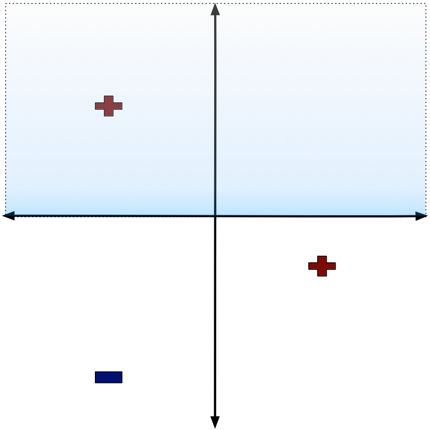
## Update 3

$$\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t \tag{17}$$

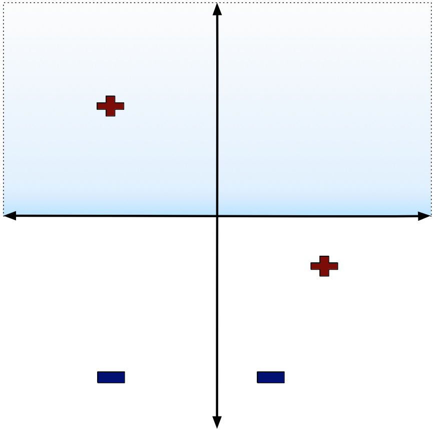
$$\vec{w}_3 \leftarrow \langle -2, 2 \rangle + \langle 2, -1 \rangle \tag{18}$$

$$\vec{w}_3 = \langle 0, 1 \rangle \tag{19}$$

## Observation 4



## Observation 4



$$x_4 = \langle 1, -4 \rangle \quad (20)$$

$$\hat{y}_4 = -4 \quad (21)$$

$$y_4 = -1 \quad (22)$$

## Update 4

$$\vec{w}_4 \leftarrow \tag{23}$$

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$$\vec{w}_4 \leftarrow \vec{w}_3 \tag{23}$$

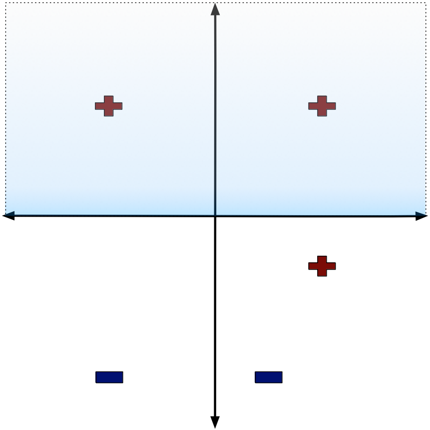
$$\tag{24}$$

## Update 4

$$\vec{w}_4 \leftarrow \vec{w}_3 \tag{23}$$

$$\vec{w}_4 = \langle 0, 1 \rangle \tag{24}$$

## Observation 5



$$x_5 = \langle 2, 2 \rangle \quad (25)$$
$$\hat{y}_5 = 2 \quad (26)$$
$$y_5 = +1 \quad (27)$$

## Update 5

$$\vec{w}_5 \longleftarrow \tag{28}$$

## Update 5

$$\vec{w}_5 \longleftarrow \vec{w}_4 \tag{28}$$

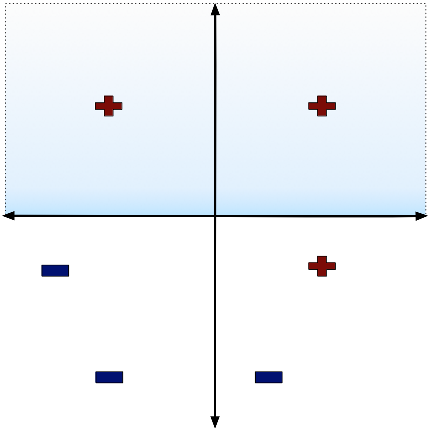
$$\tag{29}$$

## Update 5

$$\vec{w}_5 \leftarrow \vec{w}_4 \tag{28}$$

$$\vec{w}_5 = \langle 0, 1 \rangle \tag{29}$$

## Observation 6



$$x_6 = \langle 2, 2 \rangle \quad (30)$$

$$\hat{y}_6 = 2 \quad (31)$$

$$y_6 = +1 \quad (32)$$

## Update 6

$$\vec{w}_6 \leftarrow \tag{33}$$

## Update 6

$$\vec{w}_6 \longleftarrow \vec{w}_5 \tag{33}$$

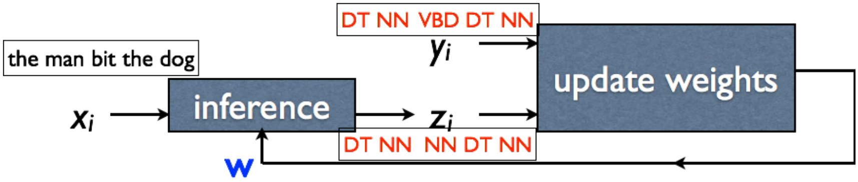
$$\tag{34}$$

## Update 6

$$\vec{w}_6 \leftarrow \vec{w}_5 \tag{33}$$

$$\vec{w}_6 = \langle 0, 1 \rangle \tag{34}$$

## Structured Perceptron



## Perceptron Algorithm

**Inputs:** Training set $(x_i, y_i)$ for $i = 1 \dots n$

**Initialization:** $\mathbf{W} = 0$

**Define:** $F(x) = \operatorname{argmax}_{y \in \mathbf{GEN}(x)} \mathbf{\Phi}(x, y) \cdot \mathbf{W}$

**Algorithm:** For $t = 1 \dots T, i = 1 \dots n$

$z_i = F(x_i)$

If $(z_i \neq y_i)$ $\quad \mathbf{W} \longleftarrow \mathbf{W} + \mathbf{\Phi}(x_i, y_i) - \mathbf{\Phi}(x_i, z_i)$

**Output:** Parameters $\mathbf{W}$

## POS Example

- gold-standard: DT NN VBD DT NN $y$
  - the man bit the dog $x$

$\Phi(x, y)$

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- current output: DT NN NN DT NN $z$
  - the man bit the dog $x$

$\Phi(x, z)$

- assume only two feature classes
  - tag bigrams $t_{i-1}$ $t_i$
  - word/tag pairs $w_i$
- weights ++: (NN,VBD) (VBD, DT) (VBD → bit)
- weights −−: (NN, NN) (NN, DT) (NN → bit)