

# Part of Speech Tagging

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#### 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**

1:  $\vec{w}_1 \leftarrow \vec{0}$ 2: for  $t \leftarrow 1 \dots T$  do 3: Receive  $x_t$ 4:  $\hat{y}_t \leftarrow \operatorname{sgn}(\vec{w}_t \cdot \vec{x}_t)$ 5: Receive  $y_t$ 6: if  $\hat{y}_t \neq y_t$  then 7:  $\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t$ 8: else 9:  $\vec{w}_{t+1} \leftarrow w_t$ return  $w_{T+1}$ 

#### **Binary to Structure**



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#### **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:

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





$$\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t$$
 (5)  
 $\vec{w}_2 \leftarrow$  (6)

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

$$\vec{w}_2 \leftarrow \langle 0, 0 \rangle + \langle -2, 2 \rangle$$
(6)  
(7)

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

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

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





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

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

$$y_2 = -1$$
 (10)

$$\vec{w}_{t+1} \leftarrow \vec{w}_t \tag{11}$$
$$\vec{w}_2 \leftarrow \tag{12}$$

$$\vec{w}_{t+1} \leftarrow \vec{w}_t \tag{11}$$
$$\vec{w}_2 \leftarrow \langle -2, 2 \rangle \tag{12}$$
$$\tag{13}$$

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

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

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





$$x_3 = \langle 2, -1 \rangle \tag{14}$$

$$\hat{y}_3 = -4 + -2 = -6$$
 (15)

$$y_3 = +1$$
 (16)

$$\vec{w}_{t+1} \leftarrow \vec{w}_t + y_t \vec{x}_t \tag{17}$$
$$\vec{w}_3 \leftarrow \tag{18}$$

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

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

(19)

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

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

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





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

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

$$y_4 = -1$$
 (22)



(23)

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

(24)

$$\vec{w}_4 \leftarrow \vec{w}_3$$
 (23)  
 $\vec{w}_4 = \langle 0, 1 \rangle$  (24)





$$y_5 = +1$$
 (27)



(28)

$$\vec{w}_5 \leftarrow \vec{w}_4$$
 (28)

(29)

$$\vec{w}_5 \leftarrow \vec{w}_4$$
 (28)  
 $\vec{w}_5 = \langle 0, 1 \rangle$  (29)





$$y_6 = +1$$
 (32)



(33)

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

(34)

$$\vec{w}_6 \leftarrow \vec{w}_5$$
 (33)  
 $\vec{w}_6 = \langle 0, 1 \rangle$  (34)

#### **Structured Perceptron**



### **Perceptron Algorithm**

Inputs:	Training set $(x_i, y_i)$ for $i = 1 \dots n$
Initialization:	$\mathbf{W} = 0$
Define:	$F(x) = \operatorname{argmax}_{y \in \mathbf{GEN}(x)} \Phi(x, y) \cdot \mathbf{W}$
Algorithm:	For $t = 1 \dots T$ , $i = 1 \dots n$ $z_i = F(x_i)$ If $(z_i \neq y_i)$ W $\leftarrow$ W + $\Phi(x_i, y_i) - \Phi(x_i, z_i)$
Output:	Parameters W

#### **POS Example**



• weights --: (NN, NN) (NN, DT) (NN $\rightarrow$ bit)