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## 5. The Kernel Perceptron Algorithm

### Computational Efficiency



*kernel*  
**Recall perceptron**

$$\theta = 0 \quad \alpha_1 = \dots = \alpha_n = 0$$

run through  $i = 1, \dots, n$

$$\text{if } y^{(i)} \theta \cdot \phi(x^{(i)}) \leq 0$$

$$\theta \leftarrow \theta + y^{(i)} \phi(x^{(i)})$$

$$\alpha_i \leftarrow \alpha_i + 1$$



$$\theta \cdot \phi(x^{(i)}) = \sum_{j=1}^n \alpha_j y^{(j)} K(x^{(i)} x^{(j)})$$

OK?

So you can think of the kernel function here as a kind of similarity measure.

How similar the  $j$ -th example is to the  $i$ -th example.

So our predicted value here is now

how important the  $j$ -th example is.

Its label times how similar the example

we wish to make a prediction on and the  $j$ -th training example.

All right.

That is now the kernel perceptron algorithm.

▶ 7:34 / 7:34

▶ Speed 1.50x



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## How the Kernel Perceptron Algorithm Works: Initialization

1/1 point (graded)

Recall that the original Perceptron Algorithm is given as the following:

**Perceptron** $\left(\{(x^{(i)}, y^{(i)}), i = 1, \dots, n\}, T\right)$  :

```

initialize  $\theta = 0$  (vector);
for  $t = 1, \dots, T$ ,
  for  $i = 1, \dots, n$ 
    if  $y^{(i)} (\theta \cdot x^{(i)}) \leq 0$ ,
      then update  $\theta = \theta + y^{(i)} x^{(i)}$ .
```

In the lecture, it was introduced that we can always express  $\theta$  as

$$\theta = \sum_{j=1}^n \alpha_j y^{(j)} \phi(x^{(j)})$$

where values of  $\alpha_1, \dots, \alpha_n$  may vary at each step of the algorithm. In other words, we can reformulate the algorithm so that we somehow initialize and update  $\alpha_j$ 's, instead of  $\theta$ .

The reformulated algorithm, or **kernel perceptron**, can be given in the following form:

**Kernel Perceptron** $\left(\{(x^{(i)}, y^{(i)}), i = 1, \dots, n, T\}\right)$

```

Initialize  $\alpha_1, \alpha_2, \dots, \alpha_n$  to some values;
for  $t = 1, \dots, T$ 
  for  $i = 1, \dots, n$ 
    if (Mistake Condition Expressed in  $\alpha_j$ )
      Update  $\alpha_j$  appropriately
```

Look at the initialization statement of the algorithm. Which of the following is an equivalent way to initialize  $\alpha_1, \alpha_2, \dots, \alpha_n$  if we want the same result as initializing  $\theta = 0$ ?

☐  $\alpha_1 = \dots = \alpha_n = \theta$

☐  $\alpha_1 = \dots = \alpha_n = 1$

☒  $\alpha_1 = \dots = \alpha_n = 0$  ✓

☐  $\alpha_1 = \dots = \alpha_n = -1$

### Solution:

Since  $\theta = \sum_{j=1}^n \alpha_j y^{(j)} \phi(x^{(j)})$ , setting  $\alpha_j = 0$  for all  $j$  leads to  $\theta = 0$ .

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You have used 1 of 1 attempt

📘 Answers are displayed within the problem

## How the Kernel Perceptron Algorithm Works: The Update

1/1 point (graded)

As in the previous problem, our goal is to correctly reformulate the original perceptron algorithm. In other words, we want the algorithm to be about updating  $\alpha_j$ 's instead of  $\theta$ .

**Kernel Perceptron**  $\left( \{ (x^{(i)}, y^{(i)}), i = 1, \dots, n, T \} \right)$

initialize  $\alpha_1, \alpha_2, \dots, \alpha_n$  to some values;

for  $t = 1, \dots, T$

for  $i = 1, \dots, n$

if (Mistake Condition Expressed in  $\alpha_j$ )

Update  $\alpha_j$  appropriately

Now look at the line "**Update  $\alpha_j$  appropriately**" in the above algorithm. Remember that we express  $\theta$  as

$$\theta = \sum_{j=1}^n \alpha_j y^{(j)} \phi(x^{(j)})$$

Assuming that there was a mistake in classifying the  $i$ th data point i.e.

$$y^{(i)} (\theta \cdot x^{(i)}) \leq 0$$

which of the following conditions about  $\alpha_1, \dots, \alpha_n$  is equivalent to

$$\theta = \theta + y^{(i)} \phi(x^{(i)}),$$

the update condition of the original algorithm?

☒  $\alpha_i = \alpha_i + 1$  ✓

☐  $\alpha_i = \alpha_i - 1$

☐  $\alpha_j = \alpha_j + 1$  for all  $j \in 1, \dots, n$

**Solution:**

Expand  $\theta$  in the last equation and it turns out only  $\alpha_i$  gets updated:

$$\alpha_i y^{(i)} \phi(x^{(i)}) + y^{(i)} \phi(x^{(i)}) = (\alpha_i + 1) y^{(i)} \phi(x^{(i)}).$$

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You have used 1 of 1 attempt

**i** Answers are displayed within the problem

## How the Kernel Perceptron Algorithm Works: The Mistake Condition

1/1 point (graded)

**Kernel Perceptron**  $\left( \{ (x^{(i)}, y^{(i)}), i = 1, \dots, n, T \} \right)$

initialize  $\alpha_1, \alpha_2, \dots, \alpha_n$  to some values;

for  $t = 1, \dots, T$

for  $i = 1, \dots, n$   
 if (Mistake Condition Expressed in  $\alpha_j$ )  
 Update  $\alpha_j$  appropriately

Now look at the line "**Mistake Condition Expressed in  $\alpha_j$** " in the above algorithm. Remember that we express  $\theta$  as

$$\theta = \sum_{j=1}^n \alpha_j y^{(j)} \phi(x^{(j)})$$

Which of the following conditions is equivalent to  $y^{(i)} (\theta \cdot \phi(x^{(i)})) \leq 0$ ? Remember from the video lecture above that given feature vectors  $\phi(x)$  and  $\phi(x')$ , we define the Kernel function  $K$  as

$$K(x, x') = \phi(x) \phi(x').$$

☒  $y^{(i)} \sum_{j=1}^n \alpha_j y^{(j)} K(x^j, x^i) \leq 0$  ✓

☐  $y^{(i)} \sum_{j=1}^n \alpha_i y^{(j)} K(x^j, x^i) \leq 0$

☐  $y^{(i)} \sum_{j=1}^n \alpha_j y^{(i)} K(x^j, x^i) \leq 0$

☐  $y^{(i)} \sum_{j=1}^n \alpha_j y^{(j)} \phi(x^{(j)}) \leq 0$

**Solution:**

Substitute  $\theta$  with  $\sum_{j=1}^n \alpha_j y^{(j)} \phi(x^{(j)})$  in  $y^{(i)} (\theta \cdot \phi(x^{(i)})) \leq 0$ .

Submit

You have used 1 of 1 attempt

**i** Answers are displayed within the problem

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