

For these exercises, it will be helpful to review the notes on [Linear Classifiers](#) and the [Perceptron](#). You may also find it helpful to write some test code with a local python installation or in a [google colab notebook](#).

## 1) Classification

Consider a linear classifier through the origin in 4 dimensions, specified by

$$\theta = (1, -1, 2, -3)$$

Which of the following points  $x$  are classified as positive, i.e.  $h(x; \theta) = +1$ ?

1.  $(1, -1, 2, -3)$
2.  $(1, 2, 3, 4)$
3.  $(-1, -1, -1, -1)$
4.  $(1, 1, 1, 1)$

Enter a Python list with a subset of the numbers 1, 2, 3, 4:

100.00%

*You have infinitely many submissions remaining.*

Solution: [1, 3]

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### Explanation:

In a classification problem, a point is considered positive if  $\text{sign}(\theta \cdot x)$  is positive and otherwise negative. Note that  $\theta \cdot x$  is equal to

$$\sum_i x_i \theta_i$$

Therefore, we have that

$$\theta \cdot x_1 = (1, -1, 2, -3) \cdot (1, -1, 2, -3) = 15$$

So the first point  $x_1$  is classified positively. Similar computations show that  $x_3$  classified positively.

## 2) Classifier vs Hyperplane

Consider another parameter vector

$$\theta' = (-1, 1, -2, 3)$$

Ex2a

Does  $\theta'$  represent the same hyperplane as  $\theta$  does?

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Solution: yes

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**Explanation:**

Note that the hyperplane defined by a norm vector  $\theta$  is the set of points  $x$  such that  $\theta \cdot x = 0$ . Now,  $\theta'$  determines the same hyperplane as  $\theta$ . This is because a hyperplane  $H$  is defined as the set of points  $x$  such that  $x \cdot \theta$  is equal to 0 ( $x$  is perpendicular to  $\theta$ ) for some arbitrary  $\theta$ . For our specific  $\theta$  in this problem, note that

$$\theta \cdot x = 0 = -\theta \cdot x$$

Which shows that the set of points perpendicular to  $-\theta$  is equivalent to the points perpendicular to  $\theta$ .

Ex2b

Does  $\theta'$  represent the same classifier as  $\theta$  does?

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Solution: no

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**Explanation:**

Note that hyperplanes specified by norm vectors  $\theta'$  and  $\theta$  are the same. However, because  $\theta'$  and  $\theta$  point in opposite directions,  $\theta'$  determines a different classifier than  $\theta$  since the  $\text{sign}(\theta \cdot x)$  is different.

### 3) Linearly Separable Training

As [discussed in lecture and in the lecture notes](#), note that  $\mathcal{E}_n(\theta, \theta_0)$  refers to the training error of the linear classifier specified by  $\theta, \theta_0$ , and  $\mathcal{E}(\theta, \theta_0)$  refers to its test error. What does the fact that the training data are *linearly separable* imply?

Select "yes" or "no" for each of the following statements:

Ex3a

There must exist  $\theta, \theta_0$  such that  $\mathcal{E}(\theta, \theta_0) = 0$

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Solution: no

**Explanation:**

There doesn't necessarily exist a hyperplane such that  $\mathcal{E}(\theta, \theta_0) = 0$  since just because the training data is separable by a specific hyperplane doesn't mean the entire underlying data distribution will be separable by a hyperplane

**Ex3b**

There must exist  $\theta, \theta_0$  such that  $\mathcal{E}_n(\theta, \theta_0) = 0$

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**Ex3c**

A separator with 0 training error exists

100.00%

*You have infinitely many submissions remaining.*

### Ex3d

A separator with 0 testing error exists, for all possible test sets

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### Ex3e

The perceptron algorithm will find  $\theta, \theta_0$  such that  $\mathcal{E}_n(\theta, \theta_0) = 0$

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*You have infinitely many submissions remaining.*

Solution: yes

#### Explanation:

If the data is linearly separable, then perceptron will find a separator.

## 4) Separable Through Origin?

Provide two points,  $(x_0, x_1)$  and  $(y_0, y_1)$  in two dimensions that are linearly separable but not linearly separable through the origin. If you get stuck try drawing a picture and review the notes on [offsets](#).

Enter a Python list with two entries of the form `[[ x0, x1], label]` where label is 1 or -1. (So each entry represents a point with 2 dimensions and its label)

Submit

View Answer

100.00%

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