

Homework 9

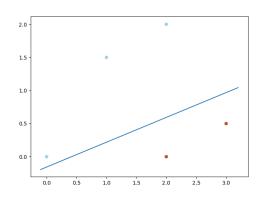
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Part I: Written Exercises

1. (a)

Answer:

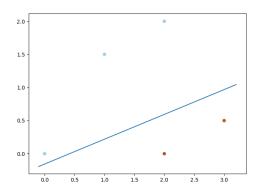
The training data and hyperplane should be as follow:



1. (b)

Answer:

The training data and hyperplane should be as follow, which will be the same as 1. (a):



1. (c)

Answer:

They are linearly separable.

1. (d)

Answer:

For
$$w^T = [6 - 16]$$
 and $w_0 = -2.5$:

The functional margin for each training example is [2.5, 22.5, 9.5, 20.5, 7.5]. And the functional margin is:



$$\gamma = \min_{i=1..n} \gamma^{(i)}$$

$$= \min_{i=1..n} y^{(i)} (w^T x^{(i)} + w_0)$$

$$= 2.5$$

The geometric margin for each training example is [0.14630143, 1.31671291, 0.55594545, 1.19967176, 0.4389043]. And the geometric margin is:

$$\gamma = \min_{i=1..n} \gamma^{(i)}$$

$$= \min_{i=1..n} y^{(i)} (w^T x^{(i)} + w_0) / ||w||_2$$

$$= 0.14630143$$

Based on functional margin, the canonical weights should be:

$$w^{(')T} = \frac{1}{2.5}w^T = [2.4 - 6.4]$$
$$w_0^{(')} = \frac{1}{2.5}w_0 = -1$$

For $100 * w^T = [100 * 12 - 100 * 32]$ and $w_0 = 100 * (-5)$:

The functional margin for each training example is [500, 4500, 1900, 4100, 1500]. And the functional margin is:

$$\gamma = \min_{i=1..n} \gamma^{(i)}$$

$$= \min_{i=1..n} y^{(i)} (w^T x^{(i)} + w_0)$$

$$= 500$$

The geometric margin for each training example is [0.14630143, 1.31671291, 0.55594545, 1.19967176, 0.4389043]. And the geometric margin is:

$$\gamma = \min_{i=1..n} \gamma^{(i)}$$

$$= \min_{i=1..n} y^{(i)} (w^T x^{(i)} + w_0) / ||w||_2$$

$$= 0.14630143$$

Based on functional margin, the canonical weights should be:

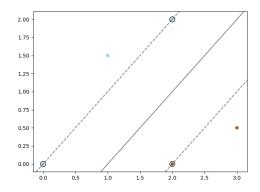
$$w^{(')T} = \frac{1}{500}w^T = [2.4 - 6.4]$$
$$w_0^{(')} = \frac{1}{500}w_0 = -1$$

1. (e)

Answer:

After I use a SVM to train my examples, I can get result as follow:





Points with a circle are support vectors, which are: $(0,0)^T$, $(2,0)^T$, $(2,2)^T$

1. (f)

Answer:

If we add point $x = (1,3)^T$, The margin and hyperplane don't change. They are:

$$margin: y = x \ and \ y = x - 2$$

$$hyperplane: y = x - 1$$

1. (g)

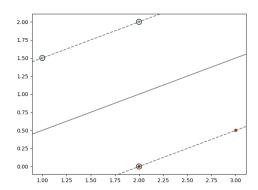
Answer:

If we remove point $x = (1, 1.5)^T$, The margin and hyperplane don't change.

1. (h)

Answer:

If we remove point $x = (0,0)^T$, The margin and hyperplane will change. They become:



1. (i)

Answer:

We can set as:

max
$$\gamma$$

subject to $y^{(i)}(w_0 + W^T x^{(i)}) >= \gamma, i = 1,..,N, ||W||_2 = 1$

2.

Answer:

The new features are:

$$\begin{split} \phi(x^{(1)}) &= [1.0, 0.6065, 0.1353, 0.0111] \\ \phi(x^{(2)}) &= [0.6065, 1.0, 0.6065, 0.1353] \\ \phi(x^{(3)}) &= [0.1353, 0.6065, 1.0, 0.6065] \\ \phi(x^{(4)}) &= [0.0111, 0.1353, 0.6065, 1.0] \end{split}$$

The coefficients are: w = [-0.656, 2.108, 2.108, -0.656], w0 = -1.900The predictions are: $y_{1.2} = -1, y_{2.5} = 1, y_{3.25} = 1$

3.

Answer:

They create the same decision boundary.

Because $||w||_2 = 1$, $\max \gamma$ equals $\max \frac{\gamma}{||w||_2}$. We also know that $\max \frac{\gamma}{||w||_2}$ equals $\max \frac{\gamma/\gamma}{||w/\gamma||_2}$. Then it becomes $\max \frac{1}{||w||_2}$, which equals $\min ||w||_2$