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Unit 1 Linear Classifiers and Course > Generalizations (2 weeks)

> Homework 2 > 1. Linear Support Vector Machines

# 1. Linear Support Vector Machines

In this problem, we will investigate minimizing the training objective for a Support Vector Machine (with margin loss).

The training objective for the Support Vector Machine (with margin loss) can be seen as optimizing a balance between the average hinge loss over the examples and a regularization term that tries to keep the parameters small (increase the margin). This balance is set by the regularization parameter  $\lambda > 0$ . Here we only consider the case without the offset parameter  $\theta_0$ (setting it to zero) so that the training objective is given by

$$\left[\frac{1}{n}\sum_{i=1}^{n}Loss_{h}\left(y^{(i)}\ \theta\cdot x^{(i)}\right)\right] + \frac{\lambda}{2}\|\theta\|^{2} = \frac{1}{n}\sum_{i=1}^{n}\left[Loss_{h}\left(y^{(i)}\ \theta\cdot x^{(i)}\right) + \frac{\lambda}{2}\|\theta\|^{2}\right] \tag{3.3}$$

where the hinge loss is given by

X

$$\operatorname{Loss}_{h}(y(\theta \cdot x)) = \max\{0, 1 - y(\theta \cdot x)\}\$$

$$\hat{\theta} = \operatorname{Argmin}_{\theta} \left[ \operatorname{Loss}_{h} \left( y \, \theta \cdot x \, \right) + \frac{\lambda}{2} \|\theta\|^{2} \right] \tag{3.4}$$

**Note:** For all of the exercises on this page, assume that n=1 where n is the number of training examples and  $x=x^{(1)}$  and  $y=y^{(1)}.$ 

## Minimizing Loss - Case 1

1/1 point (graded)

In this question, suppose that  $\mathrm{Loss}_h\left(y(\hat{ heta}\cdot x)\right)>0$ . Under this hypothesis, solve for optimisation problem and express  $\hat{ heta}$  in terms of x, y and  $\lambda$ 

y\*x/lambda

✓ Answer: x\*y/lambda

STANDARD NOTATION

**Solution:** 

$$\hat{ heta} = \operatorname{Argmin}_{ heta} \left[ \operatorname{Loss}_h \left( y \, heta \cdot x \, 
ight) + rac{\lambda}{2} \| heta \|^2 
ight]$$

The above loss can be minimized by solving for the following equation

$$0 = 
abla_{ heta} \left[ \operatorname{Loss}_h \left( y \left( heta \cdot x 
ight) 
ight) 
ight] + 
abla_{ heta} \left[ rac{\lambda}{2} \| heta \|^2 
ight]$$

Given that

$$egin{array}{lll} \operatorname{Loss}_h\left(y(\hat{ heta}\cdot x)
ight) &> 0 \ &\operatorname{Loss}_h\left(y(\hat{ heta}\cdot x)
ight) &= \max\{0,1-y( heta\cdot x)\} \ &\operatorname{Loss}_h\left(y(\hat{ heta}\cdot x)
ight) &= 1-y( heta\cdot x) \ &
abla_{ heta}\left[\operatorname{Loss}_h\left(y( heta\cdot x)
ight)
ight] &= -yx \end{array}$$

Plugging this back in the previous equation, we get:

$$0=\lambda\hat{ heta}-yx$$

$$\hat{ heta} = rac{1}{\lambda} y x$$

Submit

You have used 1 of 3 attempts

• Answers are displayed within the problem

## Minimizing Loss - Numerical Example (1)

2/2 points (graded)

Consider minimizing the above objective fuction for the following numerical example:

$$\lambda=0.5, y=1, x=\left[egin{array}{c}1\0\end{array}
ight]$$

Note that this is a classification problem where points lie on a two dimensional space. Hence  $\hat{ heta}$  would be a two dimensional vector.

Let  $\hat{ heta}=[\hat{ heta_1},\hat{ heta_2}]$  , where  $\hat{ heta_1},\hat{ heta_2}$  are the first and second components of  $\hat{ heta}$  respectively.

Solve for  $\hat{\theta_1}, \hat{\theta_2}$ .

**Hint:** For the above example, show that  $\operatorname{Loss}_h\left(y\left(\hat{ heta}\cdot x
ight)
ight)\leq 0$ 

$$\hat{ heta_1} =$$

**✓ Answer:** 1.0

$$\hat{\theta_2} =$$

**✓ Answer:** 0.0 0

#### **Solution:**

First note that for this example  $Loss_h(y(\theta \cdot x)) \leq 0$ .

To show this we use proof by contradiction.

Suppose  $Loss_h(y(\theta \cdot x)) > 0$ :

From the previous problem, we know that under this condition,  $\hat{ heta}=rac{yx}{\lambda}$ 

For this example,  $\hat{ heta} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$  .

For this value of  $\hat{ heta}$  , we see that  $1-(y( heta\cdot x))=1-2=-1<0$  contradicting our original assumption.

Hence,  $\operatorname{Loss}_h(y(\theta \cdot x)) \leq 0$ , which implies that  $y(\theta \cdot x) \geq 1$ .

We are left with minimizing  $\frac{\lambda}{2}\|\theta\|^2$  under the constraint  $y(\theta \cdot x) \geq 1$ .

The geometry of the problem implies that in fact,  $y\left( heta\cdot x
ight) =1.$ 

That is,  $1-(\hat{\theta_1}*1+\hat{\theta_2}*0)=0$  implying that  $\hat{\theta_1}=1$ .

Then, to minize  $\| heta\|$ ,  $\hat{ heta_2}=0$ .

Therefore 
$$\hat{ heta} = egin{bmatrix} 1 \\ 0 \end{bmatrix}$$
 .

In fact, we can show that  $\hat{theta} = \frac{x}{y\|(\|x\|^2)}$ . Looking back at the previous question, the solution of the optimization is then necessarily of the form  $\hat{ heta}=\eta yx$  for some real  $\eta>0$ .

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You have used 2 of 3 attempts

• Answers are displayed within the problem

# Minimizing Loss - Numerical Example (2)

1.0/1 point (graded)

Now, let  $\hat{ heta} = \hat{ heta} \, (\lambda)$  be the solution as a function of  $\lambda$ .

For what value of  $\|x\|^2$ , the training example (x,y) will be misclassified by  $\hat{\theta}$   $(\lambda)$ ?

$$\|x\|^2 = \boxed{0}$$
 Answer: 0

#### **Solution:**

For a point to be considered misclassified

$$y\hat{ heta}\cdot x\leq 0$$

The above condition implies that the hinge loss is greater than zero. From above problems, we know that under this condition,

$$\hat{ heta} = rac{yx}{\lambda}$$

$$y\hat{ heta}\cdot x=rac{y^2\|x\|^2}{\lambda}{\le}0$$

All terms of the product are non-negative, making it impossible to be < 0. But if  $\|x\|=0$ , the product can be 0.

Hence 
$$\|x\|^2=0$$

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You have used 1 of 3 attempts

• Answers are displayed within the problem

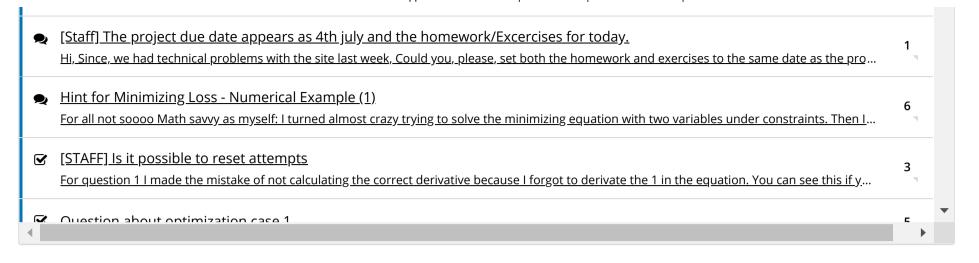
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[STAFF] More explanation needed for answer to 2nd question  Particularly: "In fact, we can show that theta^=xy  (  x)2 . Looking back at the previous question, the solution of the optimization is then necessaril	4
[Staff] Bad typing in Numerical Example (1).	2
So the takeaway is?  Lgot all the green ticks for section 1 in homework 2. However, I don't know what I should have learned from this exercise of mathematical deduc	8
<ul> <li>[Staff] Minimizing Loss - Numerical Example (2) - Curious wording</li> <li>Community TA</li> </ul>	11
Minimizing Loss - Case 1; Question about model solution	2
Overall impression about this course is bad, so far. Almost all the problems require further clarification from the TAs and reading through the discussion board. Frustrating and time consuming ex	9
Minimizing Loss - Case 1 Hey, I have tried to submit this answer many times but it doesn't submit. Where is the problem? (x* y) / - λ	2
✓ <u>Minimizing Loss - Numerical Example (1)</u> 4 new	ı_ 18
Are there more solutions to Minimizing Loss - Numerical Example (2)?  I got the green tick but the wording of the problem leads me to believe my solution might be lacking something. Is the wording misleading?	6
✓ Minimizing Loss - Numerical Example (1) Hint: how Loss could be negative?	21



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