

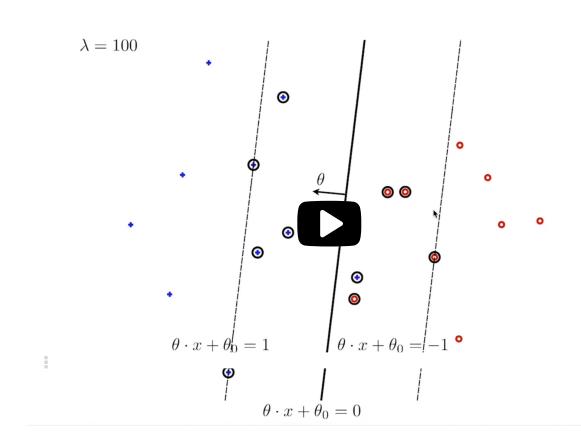
Unit 1 Linear Classifiers and Course > Generalizations (2 weeks)

Lecture 4. Linear Classification and

- > Generalization
 - > parameter

2. Review and the Lambda

2. Review and the Lambda parameter **Introduction and Review**



so some of the margin constraints are violated.

So I will incur losses on some of those points already here.

As I start increasing the value of the regularization parameter

lambda, the solution starts changing as before,

being guided more by where the bulk of the points

are similar to before.

5:57 / 5:57

▶ 1.25x

X CC

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Distance from a line to a point in terms of components

1/1 point (graded)

In a 2 dimensional space, a line L is given by L:ax+by+c=0, and a point P is given by $P=(x_0,y_0)$. What is d, the shortest distance between L and P? Express d in terms of a, b, c, x_0, y_0 .

 $abs(a*x_0+b*y_0+c)/sqrt$

✓ Answer: $abs(a*x_0 + b*y_0 +c) / sqrt(a^2 + b^2)$

STANDARD NOTATION

Solution:

Use the projection equation. Here θ is [a,b], θ_0 is c and the point is $[x_0,y_0]$.

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You have used 1 of 3 attempts

1 Answers are displayed within the problem

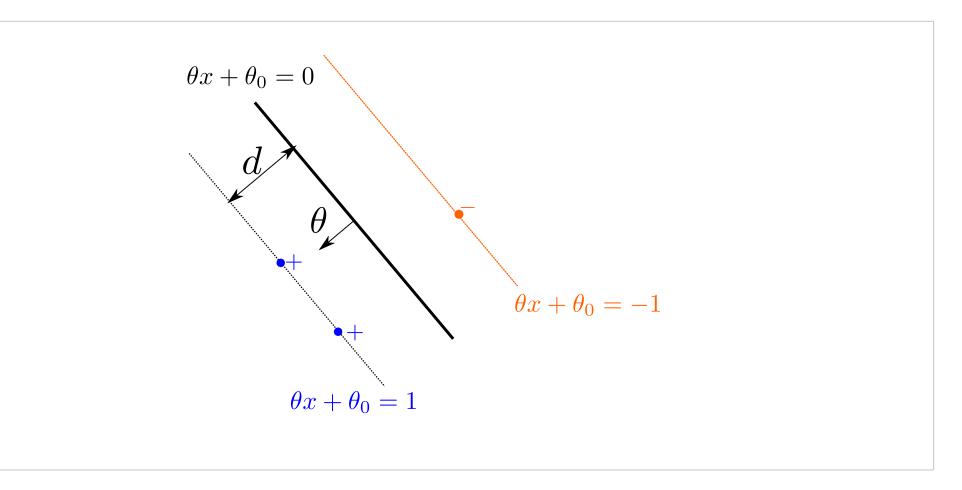
Varying Lambda in the Geometric Sense

1/1 point (graded)

Remember that the objective

$$J\left(heta, heta_{0}
ight)=rac{1}{n}\sum_{i=1}^{n}\operatorname{Loss}_{h}\left(y^{\left(i
ight)}\left(heta\cdot x^{\left(i
ight)}+ heta_{0}
ight)
ight)+rac{\lambda}{2}\left|\left|
ho
ight.|^{2}.$$

In the picture below, what happens to d, the distance between the decision boundary and the margin boundary, as we increase λ ?



- \circ d decreases
- ullet d increases \checkmark
- igcup d converges to λ

Hint: You can answer with your intuition in this question. To see whether d converges to λ , think of a simple setting where we are working in 1 dimension with just two points with labels $x_1=-1, x_2=2, y_1=-1, y_2=1$ and assume that λ is large enough where it dominates the loss function and pushes θ close enough to 0 where all points are margin violators.

Solution:

Increasing λ means we put more weight on maximizing the margin. Thus d increases.

It is not true that d always converges to λ as λ increases. Here is a counter example:

Consider a simple setting where we are working in 1 dimension with just two points with labels $x_1 = -1, x_2 = 2, y_1 = -1, y_2 = 1$ and assume that λ is large enough where it dominates the loss function and pushes θ close enough to 0 where all points are margin violators.

$$egin{array}{ll} J &=& rac{1}{2}[(1- heta+ heta_0)+(1-2 heta- heta_0)]+rac{\lambda}{2} heta^2 \ &=& rac{2-3 heta}{2}+rac{\lambda}{2} heta^2. \end{array}$$

Solve this explicitly by taking $\frac{\partial J}{\partial \theta}=0$:

$$\frac{-3}{2} + \lambda \theta = 0$$

$$\theta = \frac{3}{2\lambda}$$

$$d = \frac{1}{\theta} = \frac{2}{3}\lambda.$$

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You have used 1 of 2 attempts