



[Unit 1 Linear Classifiers and Course](#) > [Generalizations \(2 weeks\)](#)

[Lecture 4. Linear Classification and Generalization](#)

> 5. Stochastic Gradient Descent

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5. Stochastic Gradient Descent

Stochastic Gradient Descent

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SGD and Hinge Loss

1/1 point (graded)

As we saw in the lecture above,

$$J(\theta, \theta_0) = \frac{1}{n} \sum_{i=1}^n \text{Loss}_h(y^{(i)}(\theta \cdot x^{(i)} + \theta_0)) + \frac{\lambda}{2} \|\theta\|^2 = \frac{1}{n} \sum_{i=1}^n [\text{Loss}_h(y^{(i)}(\theta \cdot x^{(i)} + \theta_0)) + \frac{\lambda}{2} \|\theta\|^2]$$

With stochastic gradient descent, we choose $i \in \{1, \dots, n\}$ at random and update θ such that

$$\theta \leftarrow \theta - \eta \nabla_{\theta} [\text{Loss}_h(y^{(i)} (\theta \cdot x^{(i)} + \theta_0)) + \frac{\lambda}{2} \|\theta\|^2]$$

What is $\nabla_{\theta} [\text{Loss}_h(y^{(i)} (\theta \cdot x^{(i)} + \theta_0))]$ if $\text{Loss}_h(y^{(i)} (\theta \cdot x^{(i)} + \theta_0)) > 0$?

☐ $y^{(i)} x^{(i)}$
☒ $-y^{(i)} x^{(i)}$
☐ 0

☐ $\lambda \theta$
☐ $-\lambda \theta$


Solution:

If $\text{Loss}_h(y^{(i)} (\theta \cdot x^{(i)} + \theta_0)) > 0$,

$$\text{Loss}_h(y^{(i)} (\theta \cdot x^{(i)} + \theta_0)) = 1 - y^{(i)} (\theta \cdot x^{(i)} + \theta_0)$$

. Thus

$$\nabla_{\theta} \text{Loss}_h(y^{(i)} (\theta \cdot x^{(i)} + \theta_0)) = -y^{(i)} x^{(i)}$$

.

You have used 1 of 3 attempts

i Answers are displayed within the problem

Comparison with Perceptron

1/1 point (graded)

Observing the update step of SGD,

$$\theta \leftarrow \theta - \eta \nabla_{\theta} [\text{Loss}_h(y^{(i)} (\theta \cdot x^{(i)} + \theta_0)) + \frac{\lambda}{2} \|\theta\|^2]$$

Which of the following is true?

- ☐ As in perceptron, θ is not updated when there is no mistake
- ☒ Differently from perceptron, θ is updated even when there is no mistake



Solution:

We can see from

$$\theta \leftarrow \begin{cases} (1 - \lambda\eta) \theta & \text{if Loss}=0 \\ (1 - \lambda\eta) \theta + \eta y^{(i)} x^{(i)} & \text{if Loss}>0 \end{cases}$$

that θ is updated even when the sum of losses is 0. This is different from perceptron.

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|--|--|----|
| | <u>Not clear the gradient of the function</u>
Hello staff, I was wondering if you could point to us more material to understand the function from which the gradient was derived, i have ... | 2 |
| | <u>The update of theta_0 would be just -y_i?</u> | 4 |
| | <u>Regularization Term Increase Margin</u> | 2 |
| | <u>random sampling</u>
What is the idea behind random sampling? The outcome is better? We sample only a fraction of the set? | 4 |
| | <u>How is θ_0 updated?</u> | 2 |
| | <u>Mistake in the video?</u>
Community TA | 8 |
| | <u>Why do we use a decreasing learning rate. ?</u>
Hi everyone, Can someone please explain clearly what professor means when he said we " use a decreasing learning rate due to stochastic... | 11 |

? What is the gradient of the Regularization component of objective formula

2

In the example we take the gradient of the loss function only, what about the regularization piece. Is it simply $\text{Lambda} * \text{Theta}$? Just intrigue...

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