

# CS229 Fall 2017, Problem Set #1: Supervised Learning

Armand Sumo – armandsumo@gmail.com

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Collaborators:

By turning in this assignment, I agree by the Stanford honor code and declare that all of this is my own work.

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## 1. Logistic regression

Average empirical loss for logistic regression:

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m \log(h_{\theta}(y^{(i)} x^{(i)}))$$

where  $y^{(i)} \in \{-1, 1\}$ ,  $h_{\theta}(x) = g(\theta^T x)$  and  $g(z) = 1/(1 + e^{-z})$

(a)

$$\begin{aligned} \nabla_{\theta} J(\theta) &= -\frac{1}{m} \sum_{i=1}^m \frac{1}{g(\theta^T y^{(i)} x^{(i)})} \nabla_{\theta} g(\theta^T y^{(i)} x^{(i)}) \\ &= -\frac{1}{m} \sum_{i=1}^m \frac{1}{g(\theta^T y^{(i)} x^{(i)})} y^{(i)} x^{(i)} g(\theta^T y^{(i)} x^{(i)}) (1 - g(\theta^T y^{(i)} x^{(i)})) \\ &= -\frac{1}{m} \sum_{i=1}^m \frac{1}{y^{(i)}} x^{(i)} (1 - g(\theta^T y^{(i)} x^{(i)})) \end{aligned}$$

$$\begin{aligned} H_{i,j} &= \frac{\partial}{\partial \theta_j} [\nabla_{\theta} J(\theta)]_i = \frac{1}{m} \sum_{i=1}^m (y^{(i)})^2 x_j^{(i)} x_i^{(i)} g(\theta^T y^{(i)} x^{(i)}) (1 - g(\theta^T y^{(i)} x^{(i)})) \\ &= \frac{\partial}{\partial \theta_j} [\nabla_{\theta} J(\theta)]_i \end{aligned} \quad \text{H is symmetric}$$

Let's show that for any vector  $z$ ,  
 $z^T H z \geq 0$

$$\sum_i \sum_j z_i x_i x_j z_j = \sum_i z_i x_i \sum_j z_j x_j = (x^T z)(x^T z) = (x^T z)^2 \geq 0$$

$$\begin{aligned} z^T H z &= \sum_i z_i^T (H z)_i = \sum_i \sum_j z_i (H_{i,j}) z_j \\ &= \sum_i \sum_j z_i \left( \frac{1}{m} \sum_{k=1}^m (y^{(k)})^2 x_j^{(k)} x_i^{(k)} g(\theta^T y^{(k)} x^{(k)}) (1 - g(\theta^T y^{(k)} x^{(k)})) \right) z_j \\ &= \frac{1}{m} \sum_{k=1}^m \sum_i \sum_j (y^{(k)})^2 z_j x_j^{(k)} z_i x_i^{(k)} g(\theta^T y^{(k)} x^{(k)}) (1 - g(\theta^T y^{(k)} x^{(k)})) \\ &= \frac{1}{m} \sum_{k=1}^m (y^{(k)})^2 g(\theta^T y^{(k)} x^{(k)}) (1 - g(\theta^T y^{(k)} x^{(k)})) ((x^{(k)})^T z)^2 \end{aligned}$$

For any vector  $z$ ,  $g(z) \in [0, 1]$ , hence  $z^T H z \geq 0$ .

This implies that  $H$  is positive semi-definite, therefore  $J$  is convex and has no local minima other than the global one.

(b) next

## Problem 2

(a)