# Introduction to Machine Learning (CSCI-UA.473): Homework 1

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## **Submission Instructions**

You must typeset the answers using  $\LaTeX$  and compile them into a single PDF file. Name the pdf file as:  $\langle \text{Your-NetID} \rangle$ \_hw1.pdf. For the programming part of the assignment, complete the Jupyter notebook named HW1.ipynb. Create a ZIP file containing both the PDF file and the completed Jupyter notebook. Name it  $\langle \text{Your-NetID} \rangle$  hw1.zip. Submit the ZIP file on Brightspace. The due date is **September 27**<sup>th</sup>, **2021**, **11:59 PM**.

## Theory

## Question T1: Empirical vs. Expected Cost (10 points)

We approximate the true cost function with the empirical cost function defined by:

$$\mathbb{E}_{x}\left[E(g(x), f(x))\right] = \frac{1}{N} \sum_{i=1}^{N} E(g(x^{i}), y^{i}), \tag{1}$$

where N is the number of training samples, f is the unknown function, g is the learnable function,  $y^i$  is the label associated with the input  $x^i$ . In the above equation is it okay to give an equal weight to the cost associated with each training example? Given that we established that not every data x is equally likely, is taking the sum of all per-example costs and dividing by N reasonable? Should we weigh each per-example cost differently, depending on how likely each x is? Justify your answer.

## Question T2: Perceptron Learning Algorithm (10 points)

The weight update rule of the Perceptron Learning Algorithm (PLA) is given by:

$$w(t+1) \leftarrow w(t) + y(t)x(t). \tag{2}$$

Prove the following statements:

- 1. Show that  $y(t)w^{T}(t)x(t) < 0$  (2 points)
- 2. Show that  $y(t)w^T(t+1)x(t) > y(t)w^T(t)x(t)$  (4 points)
- 3. Argue that the move from w(t) to w(t+1) is the right move as far as classifying x(t) is concerned. (4 points)

### Question T3: Gradient of Logistic Regression (10 points)

The logistic regression loss for a single sample (x, y) can be written as

$$\mathcal{L}_w(x,y) = -\left[y \cdot \log \sigma(wx) + (1-y) \cdot \log(1 - \sigma(wx))\right],\tag{3}$$

where  $\sigma(s)$  is the logistic function and w are the parameters of the model. Compute the gradient of the above loss function with respect to the parameter vector w. Show all the steps of the derivation.

#### Practicum

See the accompanying Python notebook.

Question P1: Linear Regression (20 points)

Question P2: Gradient Descent (10 points)

Question P3: Logistic Regression (40 points)