Note: For all coding problems, you will implement them in a single jupyter notebook.

Note: this is the distribution of questions:

(a) Question 1 to Question 8: Everyone has to attempt.

(b) Question 9 - Question 10: Only for Graduate Students

(c) Question 11 - Question 12: Bonus marks

Problem 1 (5 points)

What is the difference between Root Mean Squared Error (RMSE) and Mean Squared Error(MSE) . Describe the context in which they will be most useful? Which of these loss penalises larger differences between the predicted and expected results and why?

Problem 2 (5 points)

Multiple choice question: Which of the following statements is true about the relationship between features and dataset sizes? Choose one of the following and explain the chosen answer

(a) When training a model, as you add more features to the dataset, you often need to increase the dataset's size to ensure the model learns reliably.

(b) When training a model, adding more features to the dataset increases the amount of information you can extract from the dataset. This allows you to use smaller datasets to train the model and still extract good performances from the data.

(c) When training a learning algorithm, as you decrease the number of features in the dataset, you need to increase the training sample to make up the difference

(d) When training a learning algorithm, the number of features in your dataset is entirely dependent on the amount of information you can extract from the dataset.

Problem 3 (4 points)

You are building a deep learning model and after some x epochs you found that training loss is decreasing, however, your validation loss is more or less constant. What would be the most likely cause of this and suggestion to rectify it

(a) Learning rate is too high

(b) no Convergence of gradient descent

(c) Less Training data

(d) stuck in local minima

Problem 4 (4 points)

Perceptron

(a) is a linear classifier. A. True B. False

(b) and cannot be trained on linearly unseperable data. A. True B. False

Problem 5 (4 points)

Logistic Regression

(a) is a linear classifier. A. True B. False

(b) and always has a unique solution A. True B. False

Problem 6 (10 points)

Which of the following is true, given the optimal learning rate?

(a) Batch gradient descent is always guaranteed to converge to the global optimum of a loss function.

(b) Stochastic gradient descent is always guaranteed to converge to the global optimum of a loss function.

(c) For convex loss functions (i.e. with a bowl shape), batch gradient descent is guaranteed to eventually converge to the global optimum while stochastic gradient descent is not.

(d) For convex loss functions (i.e. with a bowl shape), stochastic gradient descent is guaranteed to eventually converge to the global optimum while batch gradient descent is not.

(e) For convex loss functions (i.e. with a bowl shape), both stochastic gradient descent and batch gradient descent will eventually converge to the global optimum.

(f) For convex loss functions (i.e. with a bowl shape), neither stochastic gradient ndescent nor batch gradient descent are guaranteed to converge to the global optimum.

Problem 7 (5 points)

Given the following data on a 2D plane :

x	y
-1	-2
1	-1
2	3

Fit a linear regression model to the data without the constant term: $y_i = \beta x_i + \epsilon_i$. Give an expression of the minimization problem for finding β, Show how to compute it's value and show the value

Problem 8 (20 points)

Perform a polynomial fitting compute a design matrix with

$$X_{ij} = y_i^j \tag{1}$$

You should implement this without a single for loop by using vectorization and broadcast. Here $1 \leq j \leq 50$ and $y = -20, -19.9, ..., 20$. Implement code that generates such a matrix.

Problem 9 (15 points)

You are training a logistic regression model. You initialize the parameters with 0's. Is this a good idea? Explain your answer.

Imagine you are training a Logistic Regression. There are few parameters

Problem 10 (15 points)

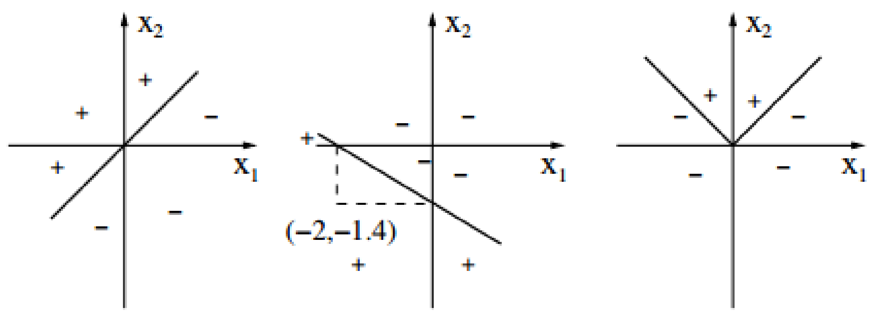
According to the class, loss of logistic regression can be simplified to the following form:

$$cost(f(x), y) = -ylog(f(x)) - (1-y)log(1-f(x)) \tag{2}$$

What will happen when $y = 1$ and $f(x) = 1$? Will this work in actual implementations?

Problem 11 (extra credit 20 points)

In these three examples, find the perceptron weights w_0, w_1, w_2 for each of them. the line that seperates the two classes is given by the decision boundary that divied into positive and negative classes. (No calculations required, you can simply note the answer.)



Problem 12 (extra credit 20 points)

Consider the evaluation of E as given below:

$$E = g(x, y, z) = \sigma(c(ax + by) + dz) \tag{3}$$

Here x, y, z are inputs and a, b, c, d are parameters. σ is logistic sigmoid function defined as:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{4}$$

Note that E is the function of a, b, c, d Compute the partial derivative of E with respect to parameters a, b, d i.e $\frac{\partial E}{\partial a}, \frac{\partial E}{\partial b}, \frac{\partial E}{\partial d}$