



Assignment 3

Machine Learning Basics

Deadline :01.12.2020 23:59

1 Linear Regression

1.1 Part a (1 point)

Suppose we have a dataset that contains the financial status of startups that have recently entered the stock market with three regressors, X_1 = “raised funds” (in millions of dollars), X_2 = “initial stock value”, X_3 = “debt” (in millions of dollars). The variable of interest Y is the company value after a year (in millions of dollars). Suppose we use least squares to fit the model :

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 \ln X_{i2} + \beta_3 X_{i3}$$

and get $\beta_0 = 10$, $\beta_1 = 10$, $\beta_2 = 0.5$, $\beta_3 = -5$.

Elaborate on the correctness of these statements :

- One unit change X_1 causes a 1000 percent change in Y .
- One unit change in X_2 causes a 50 percent change in Y .
- 100 percent change in X_2 causes a 50 percent change in Y .
- Higher debt implies lower future stock value.
- Is there any meaningful interpretation of the bias term β_0 ?

1.2 Part b : Ridge Regression (1.5 points)

In the slide "Fitting with Regularization" a regularization term is introduced to the least squares loss to avoid over/underfitting. This is also known as ridge regression.

$$J(\mathbf{w}) = \text{MSE}_{\text{train}} + \lambda \mathbf{w}^T \mathbf{w}$$

Here \mathbf{w} are the weights and λ is the regularization parameter. Provide a closed form solution for \mathbf{w} which minimizes this loss. Please you should show all the steps that arrive at the solution given in the slides. If you have problems with vector and matrix differentiation please take a look at the following [slides](#).

2 Training Basics



Figure 1: : Training vs test error as a function of the model complexity

Figure 1 shows the training and test errors of a general machine learning algorithm as a function of the model complexity (richness of the hypothesis space). The model complexity is usually adjusted via a parameter, such as the regularization parameter λ in ridge regression.

2.1 Part a (1 point)

Mark on Figure 1 the following :

- The ideal point to operate the machine learning algorithm.
- The range of the model complexity in which the machine learning algorithm overtrains/overfits.
- The range of the model complexity in which the machine learning algorithm undertrains/underfits.

2.2 Part b (0.5 points)

Consider the ridge regression problem in which the following loss function is minimized for a given $\lambda \geq 0$:

$$L(\beta) = \sum_{i=1}^n (y_i - \mathbf{x}_i^T \beta)^2 + \lambda \sum_{j=1}^p \beta_j^2$$

where n denotes the number of data instances and p denotes the dimension of the data instances as usual.

- How does the model complexity change as λ increases?
- Given that Figure 1 represents the all possible values for the model complexity given $\lambda \in [0, \infty)$, mark on Figure 1 the operating point when $\lambda = 0$ and the operating point when $\lambda = \infty$.

2.3 Part c (0.5 points)

You are given a dataset $D = (\mathbf{x}_i, y_i)$ with $i=1..n$. Assume that you ran leave-one-out cross-validation on this dataset and calculated the cross-validation mean squared error (MSE) and found that it is equal to 35. Now, you randomly shuffle the dataset D and re-run leave-one-out cross-validation and calculate the new MSE. How is the new MSE related to the previous MSE which was 35? Clearly justify your reasoning.

Note : For solving this question it might be a good idea to read the Machine Learning Basics chapter in the Deep Learning [book](#) by Goodfellow et.al.

3 Maximum Likelihood

Consider independent and identically distributed (i.i.d.) random variables X_1, \dots, X_n , where each X_i is Poisson(λ) (λ is the parameter of the Poisson distribution). Poisson distribution with parameter λ is defined as below :

$$P(x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

3.1 Part a (1 point)

Given a realization (observation) x_1, \dots, x_n of these random variables find the maximum likelihood estimate of λ .

3.2 Part b (1.5 points)

Assume that we only observe events $X_i = 0$ or $X_i > 0$ for each random variable. Given a realization y_1, \dots, y_n of these events ($y_i = 0$ if $x_i = 0$ and $y_i = 1$ if $x_i > 0$), find the maximum likelihood estimate of λ .

4 Logistic Regression (1 point)

In the lecture, you were introduced to the logistic regression model. The [Wikipedia](#) page on logistic regression can be a good starting point to know more about it. Please answer in short sentences the following questions.

- When do we use logistic regression? Why can't we use linear regression in such cases?
- Is logistic regression an unsupervised learning method?
- Can we use mean squared error as an evaluation metric to compare the output of the logistic regression output with its target output? Explain why such is the case.
- How is logistic regression trained? Hint: This is a method you have exploited in this assignment. A short answer is enough.
- Why can we view the output of logistic regression as a probability?

5 EigenDecomposition (2 points)

Note: Before you solve this question as a refresher for your Linear Algebra knowledge would be better to look at Wikipedia [page](#) on eigendecomposition.

Consider the following matrix:

$$M = \begin{bmatrix} 1 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 1 \end{bmatrix}$$

- Is the matrix M symmetric? What does it imply for its eigendecomposition? (0.5 points)
- Is the matrix M Singular? What does it imply for its eigendecomposition? (0.5 points)
- Find the eigendecomposition of M (1 point).

6 Submission instructions

The following instructions are mandatory. If you are not following them, tutors can decide to not correct your exercise.

- You **have to** submit a solution of this assignment sheet as a team of 2 members.
- Hand in a **single** PDF file with your solutions to the tasks.
- Therefore, make sure to write the name and matriculation ID of each of the members in your team.
- The solution must be uploaded by only **one** of your team members to the MS Teams.
- If you have any trouble with the submission, contact your tutor **before** the deadline.