

**The Catholic University of America**

**CSC 527: Fundamental of Neural Networks**  
**Project 2 – Report**  
**The Least-Mean-Square Algorithm**

**Instructor: Dr. Hieu Bui**

**Student: Tien Pham**

## **Table of Contents**

<b>I. Introduction of Least-Mean-Square Algorithm.....</b>	<b>3</b>
<b>II. Project Report.....</b>	<b>3</b>
1. Task 1.....	3
2. Task 2.....	4
3. Task 3.....	6
4. Task 4.....	7
<b>III. References.....</b>	<b>8</b>

## I. Introduction of Least-Mean-Square Algorithm

- The least-mean-square (LMS) algorithm was developed by Widrow and Hoff (1960) and was the first linear adaptive-filtering algorithm for solving problems such as making predictions and communication-channel equalization.
- The LMS algorithm was developed based on the perceptron algorithm. Although these two algorithms have different applications, they share a common feature: Both involve the use of a *linear combiner*, therefore, the designation of “linear”.
- Some advantages of the LMS Algorithm:
  - + The LMS Algorithm’s complexity is linear
  - + The algorithm is simple to code and build
  - + The algorithm is robust with respect to external disturbances

## II. Project Report

### 1. Task 1 – Linear Prediction

- For this task, I perform the verification of the statistical learning theory of the LMS algorithm, assuming the learning rate is small.
- The learning rates used in this task are  $\eta = 0.001$ ,  $\eta = 0.002$ ,  $\eta = 0.01$ , and  $\eta = 0.02$ .
- The results are obtained as follows:

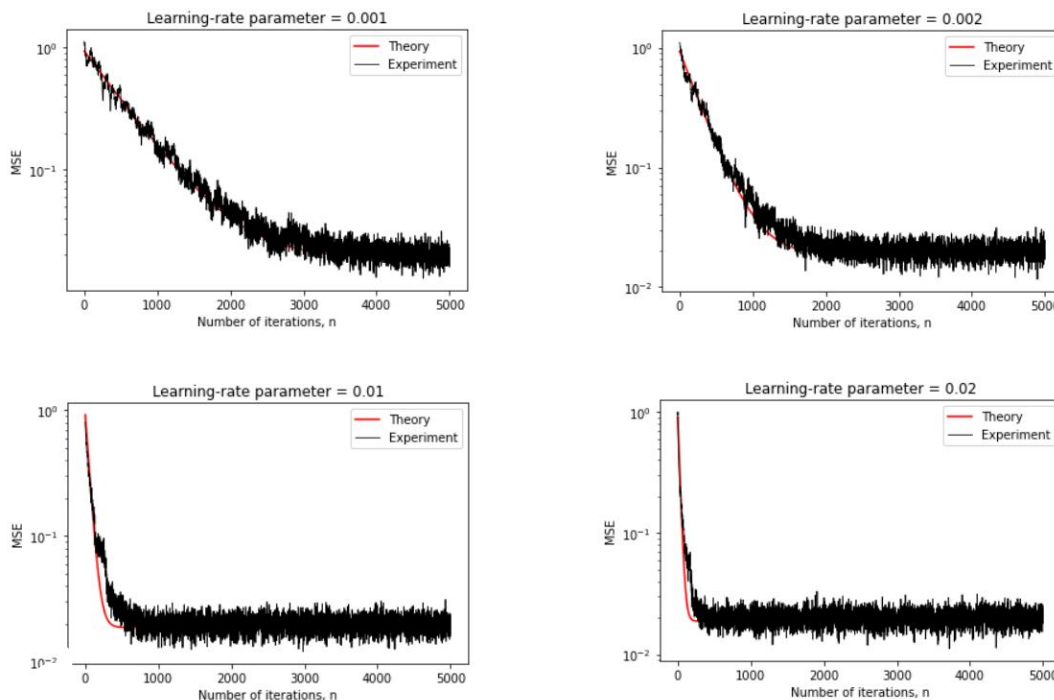


Fig 1. Experimental verification of the small-learning-rate-parameter theory of the LMS algorithm applied to an autoregressive process of order one

- The table below shows the summary of results obtained from the above plots:

Learning Rate	Number of time-steps for convergence (approx.)
0.001	3500
0.002	2200
0.01	600
0.02	400

## 2. Task 2 – Double Moon Classification

- For each distance ( $d = 1, 0, -4$ ), the program generates a training dataset and a test dataset using the given “moon” function.

- Then, I apply the LMS Algorithm to train the “train dataset” (Here, number of epochs is 20 and learning rate is 0.005)

```
def Train(dataset, epochs, learningRate):
    w = np.random.rand(2)/2 - 0.25
    mseArr = []
    for epoch in range(epochs):
        mse = 0.0
        np.random.shuffle(dataset)
        for row in dataset:
            rowLabel = row[:2]
            rowLabel = np.asarray(rowLabel)
            prediction = np.dot(w, rowLabel)
            expected = row[-1]
            error = expected - prediction
            mse += error ** 2
            w = w + learningRate*error*rowLabel

        mse /= len(dataset)
        mseArr.append(mse)

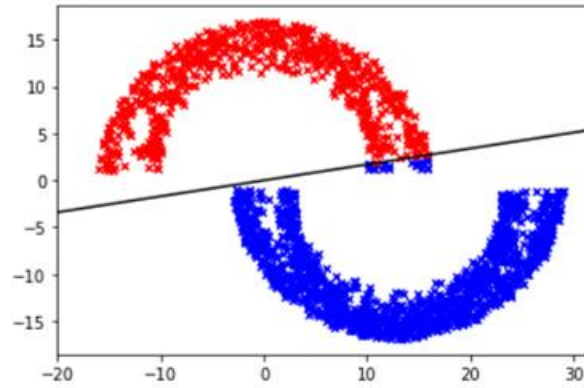
    if mse == 0:
        break

    return w, mseArr
```

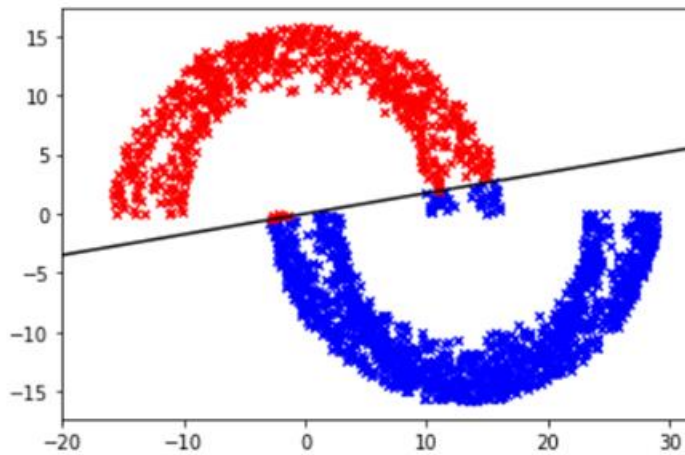
Fig 2. The LMS Algorithm for training the dataset

- Then, I use the trained result to apply on the test dataset and the results are obtained as follows:

↳ LMS Algorithm - Double Moon Classification with distance = 1 :



↳ LMS Algorithm - Double Moon Classification with distance = 0 :



↳ LMS Algorithm - Double Moon Classification with distance = -4 :

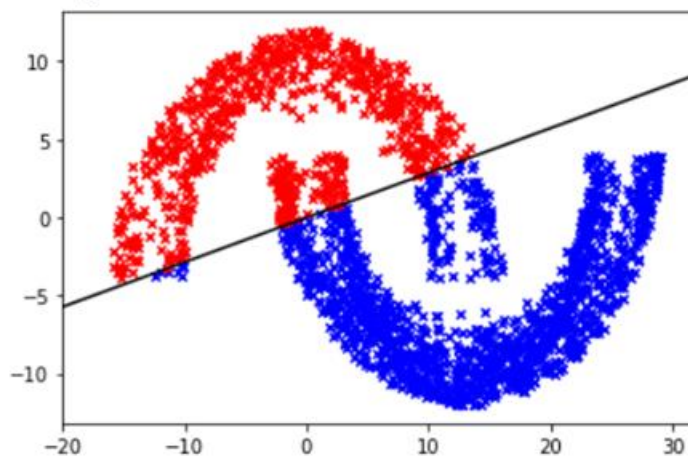


Fig 3. Double Moon Classification using LMS with distance  $d = 1$ ,  $d = 0$ , and  $d = -4$

### 3. Task 3

- Below is the Double Moon Classification result from the Rosenblatt Perceptron method (Source: Tien Pham – csc527 – Project1 - <https://github.com/tienpham2103/csc527/tree/master/Project1>)

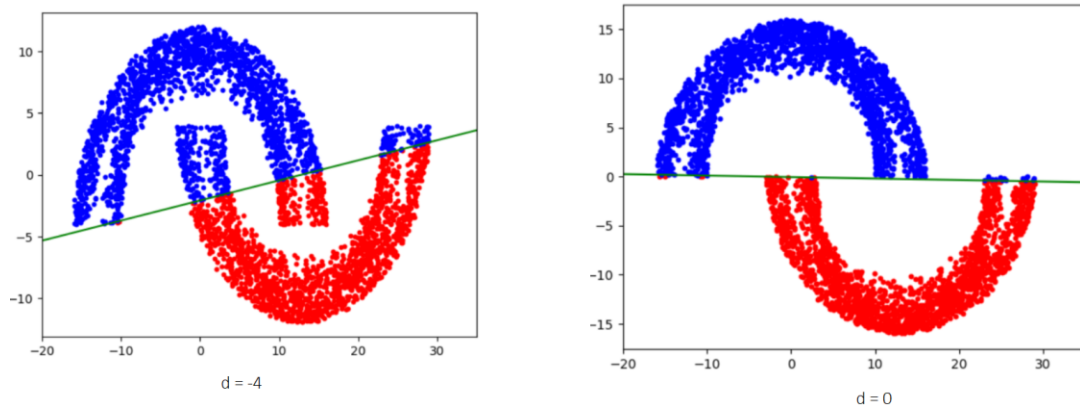


Fig 4. Double Moon Classification using Rosenblatt Perception with distance  $d = -4$  and  $d = 0$

- Below is the Double Moon Classification result from the method of Least Square (Source: Tien Pham – csc527 – Homework4 - <https://raw.githubusercontent.com/tienpham2103/csc527/master/Homework4/2%20moon%20classification.png>)

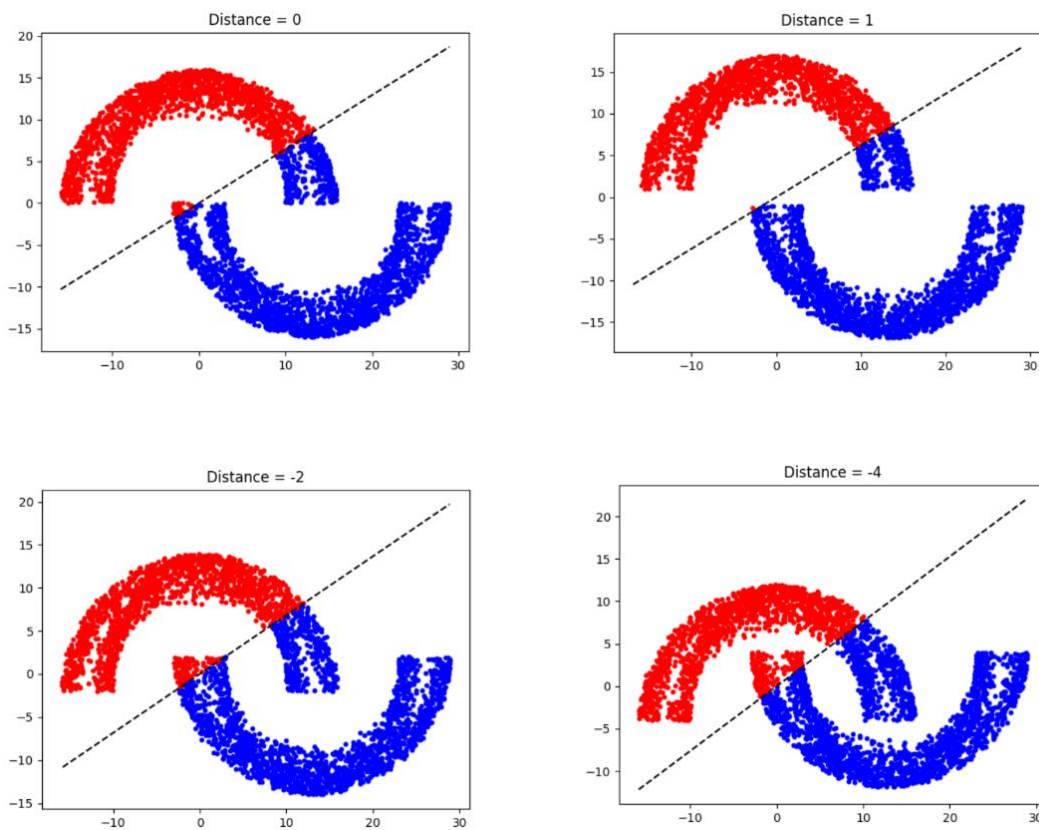


Fig 5. Double Moon Classification using Least Squares method with distance  $d = 0$ ,  $d = 1$ ,  $d = -2$ , and  $d = -4$

- In order to make better comparison, let us check the Mean Square Error of each method/algorithm:

Distance (d)	Average Mean Square Error		
	Rosenblatt Perceptron	Least Squares	Least Mean Square
1	N/A	0.36	0.28
0	0.015	0.42	0.32
-4	0.7	0.72	0.48

- It can be seen that the LMS algorithm always performs better than the Least Squares method, that the LMS algorithm performs better than the Rosenblatt Perceptron method for  $d = 0$  (and presumably,  $d = 1$  as well), which means the problem is linearly classifiable, and that the LMS algorithm performs worse than the Rosenblatt Perceptron method for  $d = -4$ , which means the problem is non-linearly classifiable.

#### 4. Task 4

- Below is the learning curves of the LMS algorithm applied to the Double Moon Classification for different values of distance:

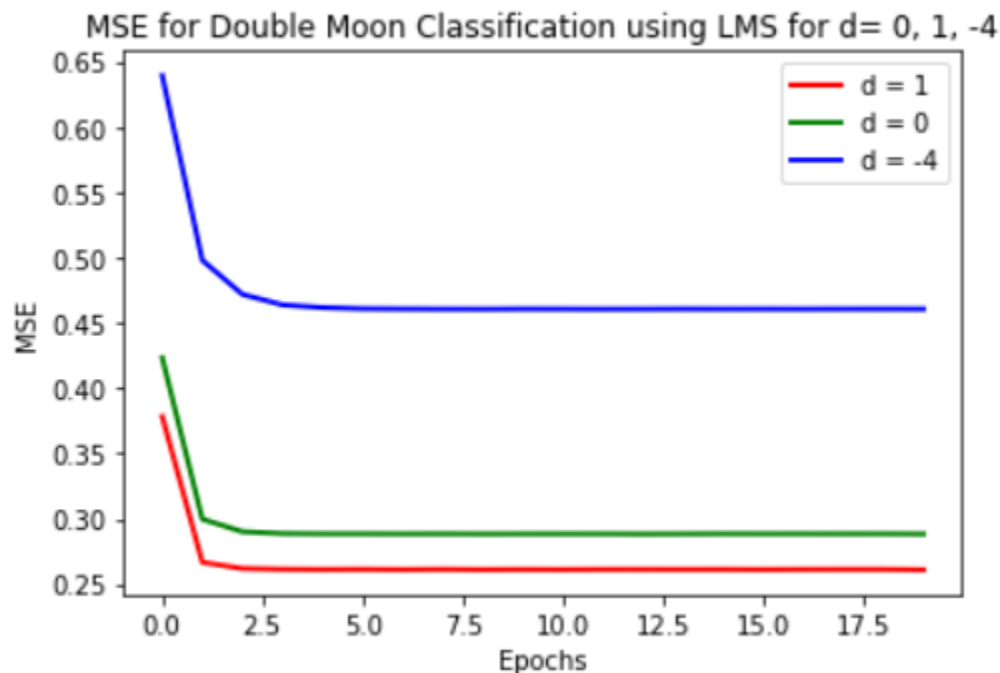


Fig 6. Learning curves for different values of distance

- On the verge of linear separability ( $d = 0$ ), the mean square error of LMS algorithm is approximately 0.32 and the mean square error of Rosenblatt Perceptron is 0.015.

### **III. References**

1. Simon, H. (2009). Neural Network and Learning Machine (3<sup>rd</sup> Edition)
2. Least-Mean-Squares Python. Retrieved from:  
<https://matousc89.github.io/padasip/sources/filters/lms.html>

The codes for this project can be found at my GitHub

(<https://github.com/tienpham2103/csc527/tree/master/Project%202>)