# Multi-Layer Perceptron (MLP) for Wine Quality Classification

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## 1 Introduction

This project focuses on building a basic Multi-Layer Perceptron (MLP) from scratch using NumPy to classify wine quality based on physicochemical properties. The dataset used for this classification contains characteristics such as acidity, pH, and alcohol content, as well as the quality rating of the wines. The project includes both theoretical and practical tasks, including data preprocessing, model implementation, and evaluation using various learning rates.

## 2 Dataset Description

The dataset used in this project is the Wine Quality Dataset, which includes both red and white wines. For the purpose of this assignment, we focus on the red wine dataset. The dataset contains the following features:

- Fixed acidity
- Volatile acidity
- Citric acid
- Residual sugar
- Chlorides

- Free sulfur dioxide
- Total sulfur dioxide
- Density
- pH
- Sulphates
- Alcohol
- Quality (score between 0 and 10)

# 3 Methodology

## 3.1 Data Preprocessing

The red wine dataset was loaded using NumPy and preprocessed by normalizing and standardizing the features. The dataset was then split into training and testing sets with an 80% to 20% ratio, respectively.

## 3.2 Model Architecture

We implemented a basic MLP from scratch, starting with a simple architecture containing one hidden layer. The number of input nodes corresponds to the features of the wine, while the output node corresponds to the quality rating.

## 3.3 Training Process

The model was trained using the backpropagation algorithm, with a learning rate range from $1 \times 10^{-8}$ to 10. We evaluated the loss reduction over training iterations for each learning rate.

# 4 Results

## 4.1 Loss Reduction with Different Learning Rates

The following plots show the loss reduction across 10,000 iterations for different learning rates:

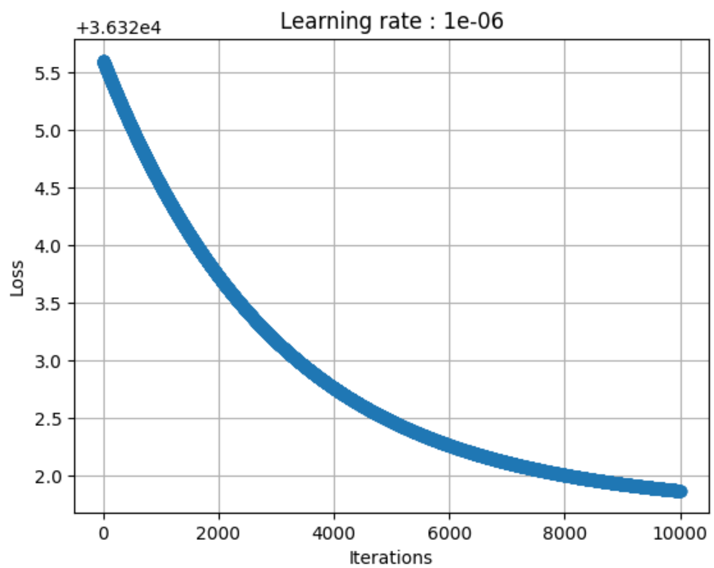


Figure 1: Learning rate: 1e-06

## 4.2 Model Performance

The model's performance was evaluated based on several metrics, including accuracy, precision, recall, and F1-score. These metrics helped assess how well the model generalizes to unseen data.

# 5 Analysis

The results from training with different learning rates demonstrate how the learning rate impacts convergence. Higher learning rates tend to cause unstable training, while lower rates lead to slower convergence. By observing

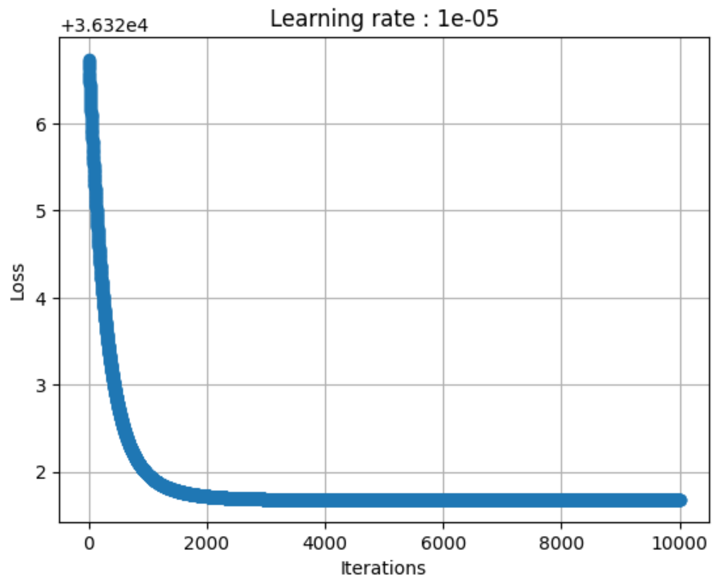


Figure 2: Learning rate: 1e-05

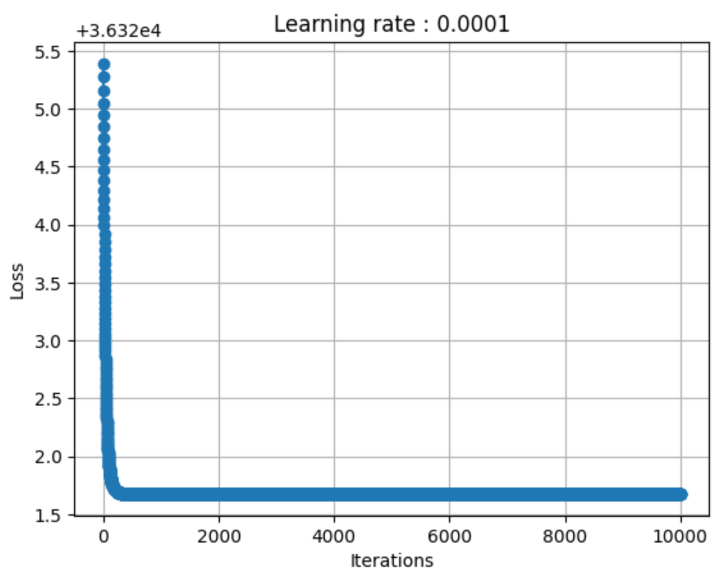


Figure 3: Learning rate: 0.0001

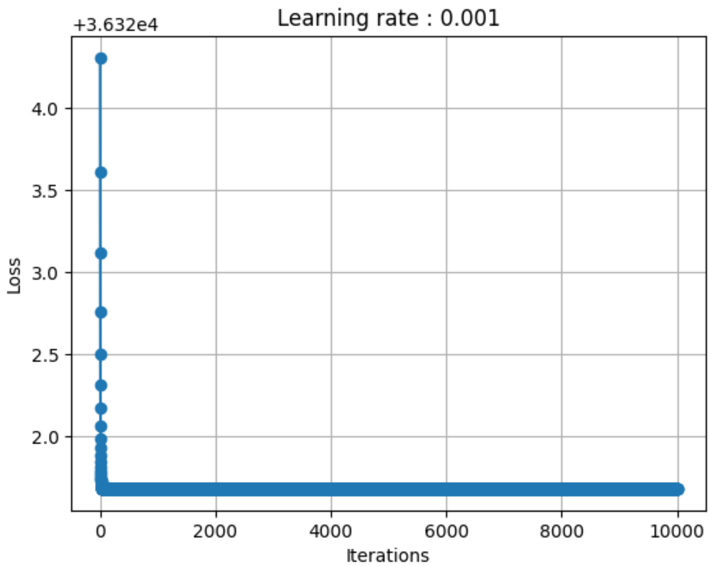


Figure 4: Learning rate: 0.001

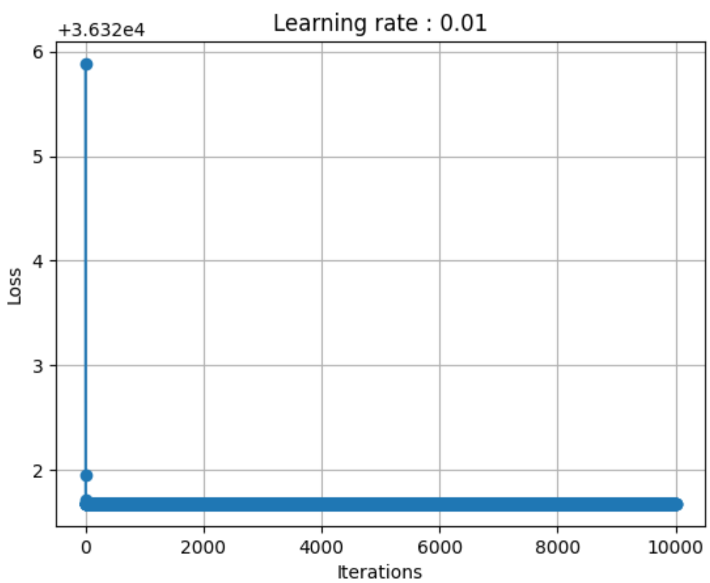


Figure 5: Learning rate: 0.01

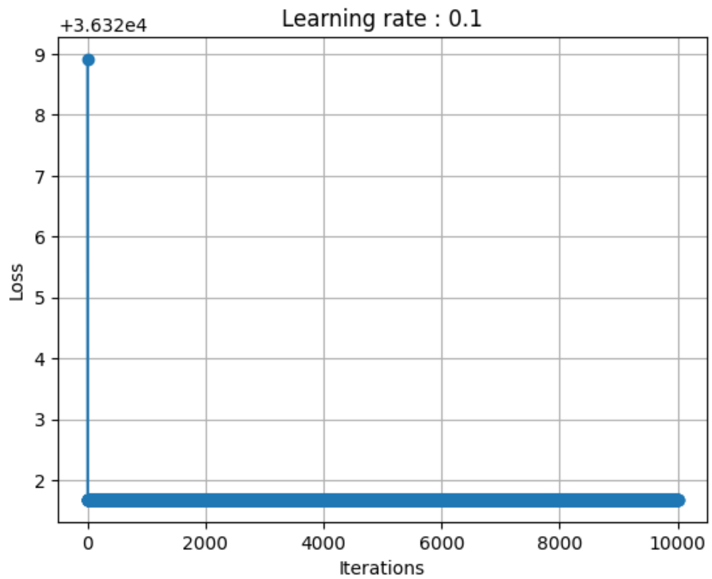


Figure 6: Learning rate: 0.1

the loss curves, we can conclude the optimal learning rate for this specific task.

# 6 Conclusion

In this project, we successfully implemented an MLP to classify wine quality using the red wine dataset. We observed the effects of different learning rates on model performance, and the results highlighted the importance of choosing the appropriate learning rate for optimal convergence.

# 7 References


- Wine Quality Dataset: https://www.kaggle.com/datasets/yasserh/wine-quality-dataset