

# **RIDGE REGRESSION MODEL – TRAINING & EVALUATION DOCUMENTATION**

## **1. INTRODUCTION**

The purpose of this project is to develop a Ridge Regression model to handle multicollinearity in input features and improve model generalization. Ridge Regression introduces L2 regularization to reduce model variance and prevent overfitting.

## **2. OBJECTIVE**

- Train a Ridge Regression model
- Tune the alpha parameter to find the optimal regularization strength
- Evaluate performance using MAE, MSE, RMSE, and R<sup>2</sup>
- Save the final trained model
- Analyze bias–variance behaviour
- Visualize performance across different alpha values

## **3. DATASET**

The dataset was split into:

- **Training set (X\_train, y\_train)**
- **Testing set (X\_test, y\_test)**

Standardization was applied before model training.

## **4. METHODOLOGY**

### **4.1 RIDGE REGRESSION TRAINING**

Ridge Regression formula:

$$\beta = (X^T X + \alpha I)^{-1} X^T y$$

- Alpha values tested:  
[0.01, 0.1, 1, 10, 100, 200, 500]
- Model trained using scikit-learn's Ridge().

### **4.2 METRICS USED**

| Metric | Explanation                                     |
|--------|---|
| MSE    | Measures squared error (penalizes large errors) |
| RMSE   | Square root of MSE – more interpretable         |

| Metric               | Explanation                      |
|----------------------|----------------------------------|
| MAE                  | Average absolute difference      |
| R <sup>2</sup> Score | Proportion of variance explained |

## 5. HYPERPARAMETER TUNING

For each alpha, the following were recorded:

- Train MSE
- Train RMSE
- Train MAE

Plots were generated:

1. **Train MSE vs Alpha (log scale)**
2. **Train RMSE vs Alpha**
3. **Train MAE vs Alpha**

These graphs show how regularization affects model complexity.

## 6. UNDERFITTING & OVERFITTING ANALYSIS

| Condition                    | Meaning      |
|------------------------------|--------------|
| High train + high test error | Underfitting |
| Low train + high test error  | Overfitting  |
| Balanced train & test error  | Good model   |

Using these metrics, the best alpha was selected.

## 7. MODEL SAVING

The final optimized Ridge model was saved as:

ridge.pkl

Using pickle:

```
import pickle
```

```
pickle.dump(model, open("ridge.pkl", "wb"))
```

## **8. RESULTS**

- Ridge Regression improved stability in presence of multicollinearity
- Optimal alpha selected based on evaluation metrics
- Performance visualizations validated bias–variance tradeoff
- Final model can be reused anytime using pickle

## **9. CONCLUSION**

Ridge Regression successfully addressed overfitting and improved prediction reliability. Hyperparameter tuning using alpha, combined with evaluation metrics and visualization, ensured an optimized and well-generalized model.