

report_2

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#Assignment 2

0.1 Compute a linear regression fromm the training data.

Using `lm()`to fit a linear regression model without intercept, we got the summary of the model as follows:

0.2 Estimate traing and test MSE

The MSE for training and test data show as follows:

0.3 Commenting on Significant Variable Contributions to the Model.

The coefficient `Jitter.Abs.`, `Shimmer.APQ5`, `Shimmer.APQ11`, `NHR`, `HNR`, `DFA`, `PPE` is highly significant, as their P-value are less than 0.001, which suggests that they have a strong and statistically reliable impact on the response variable. The coefficient `Shimmer` is statistically significant, with a P-value < 0.01 , indicating that `Shimmer` has a meaningful and reliable impact on the response variable.

0.4 Using `RidgeOpt`to compute optimal parameters when $\lambda=1, 100$ and 1000 .

The training and test MSE for different λ and the degrees of freedom shows as follows:

0.5 Comenting on which is the most appropriate penalty parameter.

Among the selected penalty parameters, $\lambda = 100$ is the most appropriate .It provides the lowest test data MSE(0.9323316). Besides, the degree of freedom for $\lambda = 100$ is 9.924887, which shows a balanced model complexity that avoids both overfitting and underfitting.

1 Assignment 4. Theory

1.1 Express the cost function of the linear regression in the matrix form.

The cost function for the linear regression in the matrix form is defined as:

$$J(\theta) = \frac{1}{n} \sum_{i=1}^n (\hat{y}(x_i; \theta) - y_i)^2 = \frac{1}{n} \|\hat{y} - y\|_2^2 = \frac{1}{n} \|X\theta - y\|_2^2 = \frac{1}{n} \|\epsilon\|_2^2$$

where: - $\hat{y} = X\theta$ is the vector of the predicted values - y is the vector of true values - $\epsilon = y - \hat{y}$ is the residuals
- $\|\cdot\|$ denotes the Euclidean norm This cost function is also referred to as the least squares cost. It can be found on page 40, formula(3.11).

1.2 Code for assignment 2