Q1 The coefficient of determination, or R2 , is a measure that provides information about the goodness of fit of a model. In the context of regression it is a statistical measure of how well the regression line approximates the actual data.R-Squared (R^2 or the coefficient of determination) is a statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable. In other words, r-squared shows how well the data fit the regression model (the goodness of fit).

Q2 Adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model. The adjusted R-squared increases when the new term improves the model more than would be expected by chance. It decreases when a predictor improves the model by less than expected. The difference between R squared and adjusted R squared value is that R squared value assumes that all the independent variables considered affect the result of the model, whereas the adjusted R squared value considers only those independent variables which actually have an effect on the performance of the model

Q3 Clearly, it is better to use Adjusted R-squared when there are multiple variables in the regression model. This would allow us to compare models with differing numbers of independent variables. Using adjusted R-squared over R-squared may be favored because of its ability to make a more accurate view of the correlation between one variable and another. Adjusted R-squared does this by taking into account how many independent variables are added to a particular model against which the stock index is measured.

Q4 Mean Squared Error(MSE) and Root Mean Square Error penalizes the large prediction errors vi-a-vis Mean Absolute Error (MAE). However, RMSE is widely used than MSE to evaluate the performance of the regression model with other random models as it has the same units as the dependent variable (Y-axis).RMSE is the square root of MSE. MSE is measured in units that are the square of the target variable, while RMSE is measured in the same units as the target variable. Due to its formulation, MSE, just like the squared loss function that it derives from, effectively penalizes larger errors more severely.

Q5 Advamtages and Disadvantages:- RMSE is widely used than MSE to evaluate the performance of the regression model with other random models as it has the same units as the dependent variable (Y-axis). MSE is a differentiable function that makes it easy to perform mathematical operations in comparison to a non-differentiable function like MAE. MSE Advantages:- It is an easy to calculate evaluation metric. All the errors are weighted on the same scale since absolute values are taken. It is useful if the training data has outliers as MAE does not penalize high errors caused by outliers. It provides an even measure of how well the model is performing. MSE Disadvantages:- One of the advantages of MSE becomes a disadvantage when there is a bad prediction. The sensitivity to outliers magnifies the high errors by squaring them. MSE will have the same effect for a single large error as too many smaller errors. But mostly we will be looking for a model which performs well enough on an overall level. MSE is scale-dependent as its scale depends on the scale of the data. This makes it highly undesirable for comparing different measures. RMSE Advantages:- RMSE is easy to understand. It serves as a heuristic for training models. It is computationally simple and easily differentiable which many optimization algorithms desire. RMSE does not penalize the errors as much as MSE does due to the square root. RMSE disadvantages:- Like MSE, RMSE is dependent on the scale of the data. It increases in magnitude if the scale of the error increases. One major drawback of RMSE is its sensitivity to outliers and the outliers have to be removed for it to function properly. RMSE increases with an increase in the size of the test sample. This is an issue when we calculate the results on different test samples.

Q6

Lasso regression, commonly referred to as L1 regularization, is a method for stopping overfitting in linear regression models by including a penalty term in the cost function. In contrast to Ridge regression, it adds the total of the absolute values of the coefficients rather than the sum of the squared coefficients. Ridge Regression is best used if the data do not have many predictor variables, whereas LASSO Regression is good if the data has many predictor variables, because it will simplify the interpretation of the model. Ridge Regularization (L2 Regularization): Ridge regularization is another variation for LASSO as the term added to the cost function is as shown below. Cost Function of Ridge Regression Model. In Ridge regularization, the penalty term can approach zero but will not be zero as it squares the coefficient (slope).

Q7 L2 regularization, also known as Ridge Regression, adds a penalty term proportional to the square of the model's parameters. This encourages the model to use all of the parameters but to reduce their values, resulting in a model that is less complex and less prone to overfitting.In an overfit model, the coefficients are generally inflated. Thus, Regularization adds penalties to the parameters and avoids them weigh heavily. The coefficients are added to the cost function of the linear equation. Thus, if the coefficient inflates, the cost function will increase.n short, Regularization in machine learning is the process of regularizing the parameters that constrain, regularizes, or shrinks the coefficient estimates towards zero. In other words, this technique discourages learning a more complex or flexible model, avoiding the risk of Overfitting.

Q8

Linear regression has some drawbacks that can limit its accuracy and applicability for certain data sets. It is sensitive to multicollinearity, meaning that if some of the independent variables are highly correlated with each other, it can affect the stability and precision of the coefficients. 1.They include all the predictors in the final model. 2.They are unable to perform feature selection. 3.They shrink the coefficients towards zero. 4.They trade the variance for bias.

Q9 If model A has RMSE of 10 and Model B has,MAE of 8 ,we choose MAE of Model B Because some of the limitations. In certain situations, accuracy score can be deceptive since it may display a high score even if the model is unable to recognise the unusual class. Therefore, it's crucial to employ metrics that account for the quantity of genuine positives and true negatives, such as precision, recall, or F1 score. This metric is the basis one. It indicates the number of correctly classified items compared to the total number of items. Keep in mind that accuracy metric has some limitations: it doesn't work well with unbalanced classes that can have many items of the same class and few other classes.

Q10 Model A uses Ridge regularization with a regularization parameter of 0.1, while Model B uses Lasso regularization with a regularization parameter of 0.5.So,We choose the model B regularization parameter Because lasso regression (L1) does both variable selection and parameter shrinkage, whereas Ridge regression only does parameter shrinkage and end up including all the coefficients in the model. In presence of correlated variables, ridge regression might be the preferred choice.

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