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Both measures are important and beneficial to consider both when evaluating regressing model. But they serve different purposes. R-squared is a useful measure to assess the overall fit of the model while RSS is useful to identify the degree of the error in the model predictions. R-squared value and a low RSS value, indicating that it explains a large proportion of the variation in the dependent variable and has a low degree of error in its predictions.

2.

These are three key components used to understand the variance in the dependent variable (Y). The equation relating these three metrics is:

$$\text{total sum of squares (TSS)} = \text{explained sum of squares (ESS)} + \text{residual sum of squares (RSS)}.$$

TSS – It represents the total variability in the dependent variable (Y) before the regression model is fitted and calculated as the sum of the squared differences between each observed dependent variable value (Y) and the mean of Y.

ESS – It measures the variability in the dependent variable (Y) that is explained by the regression model and calculated as the sum of the squared differences between the predicted values (\hat{y}) and the mean of Y.

RSS – It is calculated as the sum of the squared differences between each observed value of Y and the corresponding predicted value (\hat{y}).

The RSS of squares tells you how much of the dependent variable variation your model didn't explain. It is the sum of the squared differences between the actual Y and the predicted Y.

The smaller the residual sum of squares, the better your model fits your data. The greater the residual sum of squares, the poorer your model fits your data. A value of zero means your model is a perfect fit.

3.

Regularization is one of the most important concepts of ML. While training a ML model, a model can be overfitted or underfitted. Regularization is used in ML to reduce the chance of overfitting and it is easier to interpret and deploy in real-world applications.

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Gini Impurity is a metric and it is a measurement used to build decision trees to determine how the features of a dataset should split nodes to form the tree.

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An ensemble technique in machine learning is a method that combines the predictions of multiple individual models to produce a final prediction. We can use ensemble learning technique when we want to improve the performance of ML MODELS.

ensemble classifiers are:

Stacking.

Blending.

Bagging.

Boosting

bagging (Bootstrap Aggregating) and Boosting are both ensemble techniques used in machine learning to improve the performance of base learning algorithms

Bagging is a homogeneous weak learners' model that learns from each other independently in parallel and combines them for determining the model average.

Whereas **Boosting** is also a homogeneous weak learners' model but works differently from Bagging. In this model, learners learn

sequentially and adaptively to improve model predictions of a learning algorithm.

8.

Out-of-bag Error is also known as OOB and in ML out-of-bag Error is one of these methods for validating the ML model

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K fold cross validation is a technique used to evaluate the performance of a LM models by dividing the dataset. There are commonly used variations on cross-validation, such as stratified and repeated.

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hyperparameter tuning is a crucial step in the machine learning pipeline to build models that achieve the best possible performance on the task at hand. Hyperparameter tuning allows data scientist to tweak model performance for optimal results. This process is an important part of ML and choosing hyperparameter values is crucial for success.

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It determines how quickly or slowly our model learns. It plays an important role in controlling both convergence and divergence of the algorithm when the learning rate is too large gradient descent can suffer from divergence

12

while logistic regression is a powerful and interpretable method for linear classification tasks, it may not be suitable for accurately modeling non-linear data. In such cases, it's advisable to explore other machine learning techniques that are better suited for capturing non-linear relationships in the data.

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AdaBoost (Adaptive Boosting) and Gradient Boosting are both ensemble learning methods that combine multiple weak learners (base models) to create a strong learner. Gradient Boosting, particularly implementations like XGBoost and LightGBM, is often preferred over AdaBoost due to its flexibility, scalability, and typically superior performance on a wide range of tasks

14

Bias-variance tradeoff is a fundamental concept in ML including linear models. Understanding and managing the bias-variance tradeoff is essential for building accurate and robust linear models that generalize well to new data. It describes the relationship between a model's complexity, the accuracy of its predictions, and how it can make predictions on previously unseen data that were not used to train the model

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Linear Kernel =

The linear kernel is the simplest kernel used in SVMs.

It computes the dot product between the feature vectors in the original feature space. The linear kernel is suitable for linearly separable data or when the decision boundary is expected to be close to linear.

Radial Basis Function (RBF) Kernel=

The RBF kernel, also known as the Gaussian kernel, is a popular choice for SVMs. It measures the similarity (or distance) between feature vectors in the input feature space. The RBF kernel has two hyperparameters: gamma (γ), which controls the width of the kernel, and C, which controls the regularization strength.

Polynomial Kernel =

The polynomial kernel computes the similarity between feature vectors using polynomial functions. It maps the input feature space into a higher-dimensional space using polynomial transformations. The polynomial kernel can capture non-linear relationships in the data, similar to the RBF kernel.