Q1 to Q15 are subjective answer type questions, Answer them briefly.

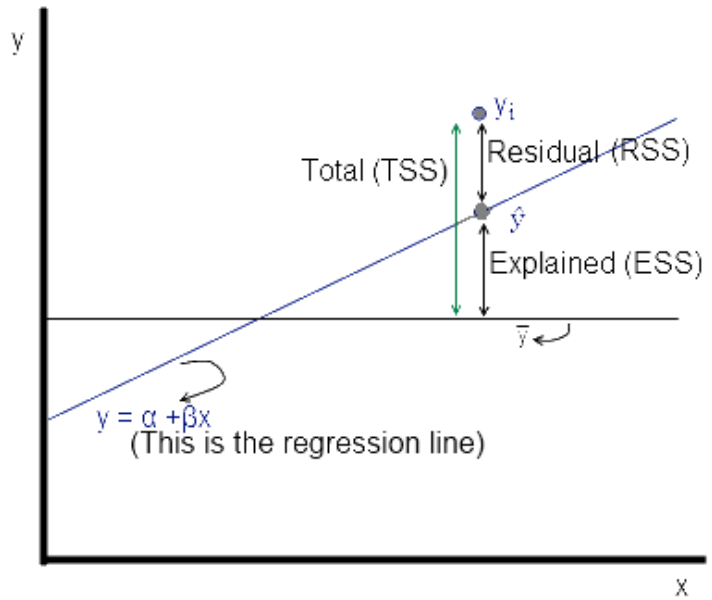
1. R-squared or Residual Sum of Squares (RSS) which one of these two is a better measure of goodness of fit model in regression and why?

Ans: The residual sum of squares (RSS) is the absolute amount of explained variation, whereas R-squared is the absolute amount of variation as a proportion of total variation. The residual sum of squares is used to help you decide if a statistical model is a good fit for your data. It measures the overall difference between your data and the values predicted by your estimation model (a "residual" is a measure of the distance from a data point to a regression line). R-Squared value or coefficient of determination is a statistical measure of how close data points are to the line of best fit (regression line). The R-Squared value is always between 0 and 1 (0% and 100%).

So, R – Squared is better than RSS.

2. What are TSS (Total Sum of Squares), ESS (Explained Sum of Squares) and RSS (Residual Sum of Squares) in regression. Also mention the equation relating these three metrics with each other.

Ans: The total sum of squares (TSS) measures how much variation there is in the observed data, while the residual sum of squares measures the variation in the error between the observed data and modeled values.



$\hat{y}$ is the predicted value of y given x, using the equation $y = \alpha + \beta x$.

y_i is the actual observed value of y

$\bar{y}$ is the mean of y.

The distances that RSS, ESS and TSS represent are shown in the diagram to the left - but remember that the actual calculations are squares of these distances.

$$TSS = \Sigma (y_i - \bar{y})^2$$

$$RSS = \Sigma (y_i - \hat{y})^2$$

$$ESS = \Sigma (\hat{y} - \bar{y})^2$$

The explained sum of squares (ESS) is the sum of the squares of the deviations of the predicted values from the mean value of a response variable, in a standard regression model.

The residual sum of squares (RSS) measures the level of variance in the error term, or residuals, of a regression model. 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.

3. What is the need of regularization in machine learning?

Ans: Regularization refers to techniques that are used to calibrate machine learning models in order to minimize the adjusted loss function and prevent overfitting or underfitting. Using Regularization, we can fit our machine learning model appropriately on a given test set and hence reduce the errors in it.

Regularization is one of the most important concepts of machine learning. It is a technique to prevent the model from overfitting by adding extra information to it.

Sometimes the machine learning model performs well with the training data but does not perform well with the test data. It means the model is not able to predict the output when deals with unseen data by introducing noise in the output, and hence the model is called overfitted. This problem can be deal with the help of a regularization technique.

This technique can be used in such a way that it will allow to maintain all variables or features in the model by reducing the magnitude of the variables. Hence, it maintains accuracy as well as a generalization of the model.

It mainly regularizes or reduces the coefficient of features toward zero. In simple words, "*In regularization technique, we reduce the magnitude of the features by keeping the same number of features.*"

4. What is Gini–impurity index?

Ans: Gini Impurity is a measurement used to build Decision Trees to determine how the features of a dataset should split nodes to form the tree. More precisely, the Gini Impurity of a dataset is a number between 0-0.5, which indicates the likelihood of new, random data being misclassified if it were given a random class label according to the class distribution in the dataset.

$$Gini(D) = 1 - \sum_{i=1}^{k} p_i^2$$

5. Are unregularized decision-trees prone to overfitting? If yes, why?

Ans: Decision trees are prone to overfitting, especially when a tree is particularly deep. This is due to the amount of specificity we look at leading to smaller sample of events that meet the previous assumptions. Overfitting refers to the condition when the model completely fits the training data but fails to generalize the testing unseen data. Overfit condition arises when the model memorizes the noise of the training data and fails to capture important patterns. A perfectly fit decision tree performs well for training data but performs poorly for unseen test data.

6. What is an ensemble technique in machine learning?

Ans: Ensemble methods is a machine learning technique that combines several base models in order to produce one optimal predictive model. There are two main reasons to use an ensemble over a single model, and they are related; they are: Performance: An ensemble can make better predictions and achieve better performance than any single contributing model. Robustness: An ensemble reduces the spread or dispersion of the predictions and model performance.

7. What is the difference between Bagging and Boosting techniques?

Ans:

- Bagging is a method of merging the same type of predictions. Boosting is a method of merging different types of predictions.
- Bagging decreases variance, not bias, and solves over-fitting issues in a model. Boosting decreases bias, not variance.
- In Bagging, each model receives an equal weight. In Boosting, models are weighed based on their performance.
- Models are built independently in Bagging. New models are affected by a previously built model's performance in Boosting.
- In Bagging, training data subsets are drawn randomly with a replacement for the training dataset. In Boosting, every new subset comprises the elements that were misclassified by previous models.

- Bagging is usually applied where the classifier is unstable and has a high variance. Boosting is usually applied where the classifier is stable and simple and has high bias.

8. What is out-of-bag error in random forests?

Ans: The out-of-bag (OOB) error is the average error for each calculated using predictions from the trees that do not contain in their respective bootstrap sample. This allows the RandomForestClassifier to be fit and validated whilst being trained. In others words OOB error is When the data are not selected as sample of data for any decision tree remain aside internally that kind of data is called out of bad sample.

9. What is K-fold cross-validation?

Ans: K-fold Cross-Validation is when the dataset is split into a K number of folds and is used to evaluate the model's ability when given new data. K refers to the number of groups the data sample is split into. For example, if you see that the k-value is 5, we can call this a 5-fold cross-validation.

10. What is hyper parameter tuning in machine learning and why it is done?

Ans: Hyperparameter tuning consists of finding a set of optimal hyperparameter values for a learning algorithm while applying this optimized algorithm to any data set. That combination of hyperparameters maximizes the model's performance, minimizing a predefined loss function to produce better results with fewer errors.

Hyperparameter tuning takes advantage of the processing to test different hyperparameter configurations when training your model. It can give you optimized values for hyperparameters, which maximizes your model's predictive accuracy.

11. What issues can occur if we have a large learning rate in Gradient Descent?

Ans: Large learning rates puts the model at risk of overshooting the minima so it will not be able to converge: what is known as exploding gradient. A learning rate that is too large can cause the model to converge too quickly to a suboptimal solution, whereas a learning rate that is too small can cause the process to get stuck.

12. Can we use Logistic Regression for classification of Non-Linear Data? If not, why?

Ans: It can only be used to predict discrete functions. Hence, the dependent variable of Logistic Regression is bound to the discrete number set. It is very fast at classifying unknown records. Non-linear problems can't be solved with logistic regression because it has a linear decision surface. logistic regression can generate nonlinear decision boundary when the features are properly processed.

13. Differentiate between Adaboost and Gradient Boosting.

Ans:

S.No	Adaboost	Gradient Boost
1	An additive model where shortcomings of previous models are identified by high-weight data points.	An additive model where shortcomings of previous models are identified by the gradient.
2	The trees are usually grown as decision stumps.	The trees are grown to a greater depth usually ranging from 8 to 32 terminal nodes.
3	Each classifier has different weights assigned to the final prediction based on its performance.	All classifiers are weighed equally and their predictive capacity is restricted with learning rate to increase accuracy.
4	It gives weights to both classifiers and observations thus capturing maximum variance within data.	It builds trees on previous classifier’s residuals thus capturing variance in data.

14. What is bias-variance trade off in machine learning?

Ans: Bias and variance are inversely connected and It is nearly impossible practically to have an ML model with a low bias and a low variance. When we modify the ML algorithm to better fit a given data set, it will in turn lead to low bias but will increase the variance. This way, the model will fit with the data set while increasing the chances of inaccurate predictions. The same applies while creating a low variance model with a higher bias. Although it will reduce the risk of inaccurate predictions, the model will not properly match the data set.

Hence it is a delicate balance between both biases and variance. But having a higher variance does not indicate a bad ML algorithm. Machine learning algorithms should be created accordingly so that they are able to handle some variance. Underfitting occurs when a model is unable to capture the underlying pattern of the data. Such models usually present with high bias and low variance.

15. Give short description each of Linear, RBF, Polynomial kernels used in SVM.

Ans: **Linear Kernel**

It is the most basic type of kernel, usually one dimensional in nature. It proves to be the best function when there are lots of features. The linear kernel is mostly preferred for **text-classification problems** as most of these kinds of classification problems can be linearly separated.

Linear kernel functions are **faster** than other functions.

Linear Kernel Formula

$$F(x, xj) = sum(x.xj)$$

Here, **x, xj** represents the data you're trying to classify.

Polynomial Kernel

It is a more generalized representation of the linear kernel. It **is not** as preferred as other kernel functions as it is **less efficient** and accurate.

Polynomial Kernel Formula

$$F(x, xj) = (x.xj+1)^d$$

Here '.' shows the **dot product** of both the values, and **d** denotes the degree.

F(x, xj) representing the **decision boundary** to separate the given classes.

Gaussian Radial Basis Function (RBF)

It is one of the most preferred and used kernel functions in svm. It is usually chosen for non-linear data. It helps to make proper separation when there is no prior knowledge of data.

Gaussian Radial Basis Formula

$$F(x, xj) = \exp(-\text{gamma} * ||x - xj||^2)$$

The value of gamma varies from **0 to 1**. You have to manually provide the value of gamma in the code. The most preferred value for **gamma is 0.1**.