1. Which of the following methods do we use to find the best fit line for data in Linear Regression?

A) Least Square Error

2. Which of the following statement is true about outliers in linear regression?

A) Linear regression is sensitive to outliers

3. A line falls from left to right if a slope is ______?

B) Negative

4. Which of the following will have symmetric relation between dependent variable and independent variable?

A) Regression

5. Which of the following is the reason for over fitting condition?

A) High bias and high variance

6. If output involves label then that model is called as:

C) Reinforcement learning

7. Lasso and Ridge regression techniques belong to _________?

D) Regularization

8. To overcome with imbalance dataset which technique can be used?

D) SMOTE

9. The AUC Receiver Operator Characteristic (AUCROC) curve is an evaluation metric for binary classification problems. It uses _____ to make graph?

A) TPR and FPR

10. In AUC Receiver Operator Characteristic (AUCROC) curve for the better model area under the curve should be less.

   A) True

11. Pick the feature extraction from below:

A) Construction bag of words from a email

B) Apply PCA to project high dimensional data

C) Removing stop words

D) Forward selection

12. Which of the following is true about Normal Equation used to compute the coefficient of the Linear

Regression?

C) We need to iterate.

Q13. Explain the term regularization?

This is a form of regression, that constrains/ regularizes or shrinks the coefficient estimates towards zero. In other words, this technique discourages learning a more complex or flexible model, so as to avoid the risk of overfitting.

A simple relation for linear regression looks like this. Here Y represents the learned relation and β represents the coefficient estimates for different variables or predictors(X).

$$Y \approx \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta pXp$$

The fitting procedure involves a loss function, known as residual sum of squares or RSS. The coefficients are chosen, such that they minimize this loss function.

$$\mathrm{RSS} = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 .$$

Now, this will adjust the coefficients based on your training data. If there is noise in the training data, then the estimated coefficients won't generalize well to the future data. This is where regularization comes in and shrinks or regularizes these learned estimates towards zero.

A standard least squares model tends to have some variance in it, i.e. this model won't generalize well for a data set different than its training data. Regularization, significantly reduces the variance of the model, without substantial increase in its bias. So, the tuning parameter λ, used in the regularization techniques described above, controls the impact on bias and variance. As the value of λ rises, it reduces the value of coefficients and thus reducing the variance. Till a point, this increase in λ is beneficial as it is only reducing the variance (hence avoiding overfitting), without losing any important properties in the data. But after certain value, the model starts losing important properties, giving rise to bias in the model and thus underfitting. Therefore, the value of λ should be carefully selected.

14. Which particular algorithms are used for regularization?

There are three main regularization techniques, namely:

1. Ridge Regression (L2 Norm)
2. Lasso (L1 Norm)
3. Dropout

Ridge and Lasso can be used for any algorithms involving weight parameters, including neural nets. Dropout is primarily used in any kind of neural networks e.g. ANN, DNN, CNN or RNN to moderate the learning. Let's take a closer look at each of the techniques.

Ridge Regression:

Ridge regression is also called L2 norm or regularization. When using this technique, we add the sum of weight's square to a loss function and thus create a new loss function which is denoted thus:

$$\text{Loss} = \sum_{j=1}^{m}\left(Yi - Wo - \sum_{i=1}^{n} Wi\,Xji\right)^2 + \lambda \sum_{i=1}^{n} Wi^2$$

As seen above, the original loss function is modified by adding normalized weights. Here normalized weights are in the form of squares.

You may have noticed parameters λ along with normalized weights. λ is the parameter that needs to be tuned using a cross-validation dataset. When you use λ=0, it returns the residual sum of square as loss function which you chose initially. For a very high value of λ, loss will ignore core loss function and minimize weight's square and will end up taking the parameters' value as zero.

Now the parameters are learned using a modified loss function. To minimize the above function, parameters need to be as small as possible. Thus, L2 norm prevents weights from rising too high.

Lasso Regression:

Also called lasso regression and denoted as below:

$$\text{Loss} = \sum_{j=1}^{m}\left(Yi - Wo - \sum_{i=1}^{n} Wi\,Xji\right)^2 + \lambda \sum_{i=1}^{n} |Wi|$$

This technique is different from ridge regression as it uses absolute weight values for normalization. λ is again a tuning parameter and behaves in the same as it does when using ridge regression.

As loss function only considers absolute weights, optimization algorithms penalize higher weight values.
In ridge regression, loss function along with the optimization algorithm brings parameters near to zero but not actually zero, while lasso eliminates less important features and sets respective weight values to zero. Thus, lasso also performs features selection along with regularization.

Q15. Explain the term error present in linear regression equation?

Linear regression most often uses mean-square error (MSE) to calculate the error of the model. MSE is calculated by:

1. measuring the distance of the observed y-values from the predicted y-values at each value of x;
2. squaring each of these distances;
3. calculating the mean of each of the squared distances.

Linear regression fits a line to the data by finding the regression coefficient that results in the smallest MSE.