MACHINE LEARNING ANSWERS:

Q1]

D) Both A and B

Q2]

A) Linear regression is sensitive to outliers**.**

Q3]

A) Positive.

Q4]

B) Correlation

Q5]

C) Low bias and high variance

Q6]

A) Descriptive model.

Q7]

D) Regularization.

Q8]

D) SMOTE

Q9]

A) TPR and FPR

Q10]

B) False

Q11]

A) Construction bag of words from a email
B) Apply PCA to project high dimensional data
C) Removing stop words

Q12]

A) We don't have to choose the learning rate.
B) It becomes slow when number of features is very large.
C) We need to iterate.

Q13]

Regularization is a technique used in machine learning to prevent overfitting. Overfitting occurs when a model is too complex and fits the training data too closely, resulting in poor performance on new, unseen data.

Regularization works by adding a penalty term to the loss function used to train the model. This penalty term discourages the model from learning overly complex patterns in the training data that may not generalize well to new data.

There are two common types of regularization: L1 regularization and L2 regularization.

L1 regularization, also known as Lasso regularization, adds a penalty term equal to the absolute value of the magnitude of the coefficients to the loss function. This has the effect of shrinking some of the coefficients to zero, effectively removing the corresponding features from the model. This can be useful for feature selection, as it can help to identify the most important features.

L2 regularization, also known as Ridge regularization, adds a penalty term equal to the square of the magnitude of the coefficients to the loss function. This has the effect of shrinking all of the coefficients towards zero, but none of them will be set to exactly zero. This can help to improve the generalization performance of the model by reducing the complexity of the model.

Regularization can be applied to a wide variety of machine learning models, including linear regression, logistic regression, and neural networks.

Q14]

There are several algorithms used for regularization in machine learning, including:

1. Lasso Regression: This algorithm uses L1 regularization, which adds the absolute value of the magnitude of the coefficients to the loss function. This can help to shrink some of the coefficients to zero, effectively removing the corresponding features from the model.

2. Ridge Regression: This algorithm uses L2 regularization, which adds the square of the magnitude of the coefficients to the loss function. This can help to shrink all of the coefficients towards zero, but none of them will be set to exactly zero.
3. Elastic Net Regression: This algorithm is a combination of L1 and L2 regularization. It uses a hyperparameter to control the ratio of L1 and L2 regularization, allowing for a balance between feature selection and coefficient shrinkage.

These algorithms are used to prevent overfitting in machine learning models by adding a penalty term to the loss function. This penalty term discourages the model from assigning too much importance to individual features or coefficients, helping to control model complexity and improve generalization to new data.

Q15]

In the context of a linear regression equation, the term "error" refers to the difference between the actual value of the target variable and the predicted value of the target variable.

The linear regression equation takes the following form:

y = b0 + b1*x1 + b2*x2 + ... + bn*xn

where y is the predicted value of the target variable, x1, x2, ..., xn are the values of the input features, and b0, b1, b2, ..., bn are the coefficients of the model.

The actual value of the target variable is denoted as y_actual. The error, or residual, is then calculated as the difference between the actual value and the predicted value:

error = y_actual - y

The goal of linear regression is to find the values of the coefficients that minimize the sum of the squared errors over all of the training data. This is known as the least squares criterion.