1.
   A) Least Square Error
2.
   A) Linear regression is sensitive to outliers
3.
   B) Negative
4.
   B) Correlation
5.
   C) Low bias and high variance
6.
   B) Predictive modal
7.
   D) Regularization
8.
   D) SMOTE
9.
   A) TPR and FPR
10.
   B) False
11.
   B) Apply PCA to project high dimensional data
12.
   B) It becomes slow when the number of features is very large.

13.

Ans. Regularization is a technique used in machine learning to prevent overfitting and improve the generalization of a model. Overfitting occurs when a model fits the training data too closely, capturing noise and random fluctuations in the data rather than the underlying patterns. Regularization introduces a penalty term to the model's cost function, discouraging the model from fitting the training data too closely.

6

14.
Ans. Regularization techniques can be applied to various machine learning algorithms to prevent overfitting. Some of the commonly used algorithms that incorporate regularization are:

1. **Linear Regression with Ridge Regression (L2 Regularization):**
   - Ridge regression adds the L2 regularization term to the linear regression cost function, helping to prevent overfitting by penalizing large coefficients.

2. **Linear Regression with Lasso (L1 Regularization):**
   - Lasso regression incorporates the L1 regularization term into linear regression, promoting sparsity in the coefficient values and often leading to feature selection.
3. **Logistic Regression with Ridge (L2) or Lasso (L1) Regularization:**
   - Similar to linear regression, logistic regression can use either L2 or L1 regularization to prevent overfitting and improve generalization.
4. **Elastic Net Regression:**
   - Elastic Net is a combination of L2 (Ridge) and L1 (Lasso) regularization. It includes both penalty terms in the cost function, providing a balance between the strengths of Ridge and Lasso regression.
5. **Support Vector Machines (SVM) with Regularization:**
   - SVMs can be regularized using techniques like L2 regularization, which helps control the trade-off between achieving a low training error and a low model complexity.
6. **Neural Networks with Weight Decay:**
   - Weight decay is a form of regularization used in neural networks. It involves adding a penalty term to the neural network's cost function based on the magnitude of the weights. This helps prevent overfitting in deep learning models.
7. **Decision Trees with Pruning:**
   - Pruning is a regularization technique for decision trees. It involves removing branches or nodes that do not contribute significantly to the model's predictive performance, reducing the complexity of the tree.
8. **K-Nearest Neighbors (KNN) with Ridge Regularization:**
   - Regularization can be applied to KNN by introducing a penalty term based on the distances between neighbors, helping to avoid overfitting in situations with noisy or irrelevant features.

15.

In the context of linear regression, the term "error" refers to the difference between the predicted values (obtained from the linear regression equation) and the actual observed values in the dataset. These differences represent the residuals or errors in the model.

Let's break down the linear regression equation to understand the components:

The linear regression equation for a simple linear regression model is often represented as:

$Y=b0+b1\cdot X+\varepsilon Y=b0+b1\cdot X+\varepsilon$

where:

- YY is the dependent variable (the variable we are trying to predict).
- XX is the independent variable (the input or predictor variable).

- b0b0 is the y-intercept (the value of YY when XX is 0).
- b1b1 is the slope of the line (the change in YY for a unit change in XX).
- εε represents the error term.

The error term εε captures the variability in YY that is not explained by the linear relationship with XX. In other words, it accounts for the discrepancies between the predicted values (based on the linear equation) and the actual observed values of YY. Mathematically, the error term is the difference between the observed values (YY) and the predicted values (b0+b1·Xb0+b1·X):

ε=Y−(b0+b1·X)ε=Y−(b0+b1·X)

The goal of linear regression is to find the values of b0b0 and b1b1 that minimize the sum of the squared errors (least squares method), resulting in the best-fitting line through the data points.

Understanding and analyzing the error term is crucial in evaluating the performance of a linear regression model. Common techniques involve assessing the distribution of residuals, checking for patterns or trends in residual plots, and examining summary statistics such as the mean squared error. These analyses help ensure that the assumptions of the linear regression model are met and provide insights into the model's predictive accuracy.