1

A) Least Square Error

2

A) Linear regression is sensitive to outliers.

3

B) Negative

4

C) Both of them

5
C) Low bias and high variance

6

A) Descriptive model

7

D) Regularization

8

D) SMOTE

9

A) TPR and FPR

10

B) False

11
B) Apply PCA to project high-dimensional data

12

A) We don’t have to choose the learning rate.

13

Regularization is a technique used in machine learning and statistics to prevent overfitting and improve the generalization of a model. Overfitting occurs when a model learns the training data too well, capturing noise or random fluctuations and performing poorly on new, unseen data.

Regularization introduces a penalty term to the model's objective function, discouraging the model from becoming too complex by imposing constraints on the weights or parameters. The goal is to find a balance between fitting the training data well and avoiding overly complex models that might not generalize well.

Two common types of regularization used in linear regression are L1 regularization (Lasso) and L2 regularization (Ridge):

1. **L1 Regularization (Lasso):** In L1 regularization, a penalty is added to the absolute values of the coefficients. It has a tendency to shrink some coefficients all the way to zero, effectively performing feature selection by eliminating some features.
2. **L2 Regularization (Ridge):** In L2 regularization, a penalty is added to the sum of squared values of the coefficients. It tends to shrink all coefficients but does not usually eliminate them entirely. Ridge regression is particularly useful when there is multicollinearity among the features.

Regularization helps improve model robustness and performance on unseen data by preventing the model from fitting the noise in the training data. The strength of the regularization is controlled by a hyperparameter, which needs to be tuned to find the optimal balance between bias and variance in the model.

14)

Regularization techniques can be applied to various machine learning algorithms, but they are commonly associated with linear models. Here are some specific algorithms where regularization is often used:

1. **Linear Regression with Lasso (L1) and Ridge (L2) Regression:**
    - **Lasso Regression (L1):** It adds a penalty term based on the absolute values of the coefficients.
    - **Ridge Regression (L2):** It adds a penalty term based on the squared values of the coefficients.
2. **Logistic Regression with Lasso (L1) and Ridge (L2) Regularization:**
    - Similar to linear regression, logistic regression can also be regularized using L1 and L2 regularization.
3. **Support Vector Machines (SVM):**
    - SVMs can be regularized using the C parameter, where a smaller C value leads to a more regularized model.
4. **Neural Networks:**
    - In neural networks, regularization techniques like dropout, L1, and L2 regularization can be employed to prevent overfitting.
5. **Elastic Net:**
    - Elastic Net is a combination of L1 and L2 regularization, adding both penalty terms to the loss function.
6. **Decision Trees and Random Forests:**
    - While decision trees themselves are not typically regularized, techniques like pruning can be considered a form of regularization. Random Forests, which consist of multiple decision trees, are less prone to overfitting but do not explicitly use regularization.

It's important to note that the specific regularization techniques and parameters might vary across implementations and libraries. The choice of regularization method and the hyperparameter values often depends on the characteristics of the dataset and the problem at hand.

15)

In the context of linear regression, the term "error" refers to the difference between the observed (actual) values and the values predicted by the linear regression model. These differences are also known as residuals. Mathematically, for each data point i, the error (e_i) is given by:

$e_i = y_i - \hat{y}_i$.