Machine learning solution

1-D

2-A

3-B

4-C

5-C

6-B

7-D

8-D

9-A

10-B

11-B

12-A

13. Explain the term regularization?

Answer:-- Regularization is a technique used in machine learning to prevent overfitting and improve the generalization performance of a model. Overfitting occurs when a model learns the training data too well, capturing noise and fluctuations in the data rather than the underlying pattern. Regularization introduces a penalty term to the model's objective function, discouraging overly complex models with large coefficients.Two types are:--1. **L1** Regularization (Lasso) 2. L2 Regularization (Ridge)

14. Which particular algorithms are used for regularization?

Answer:-- Regularization techniques can be applied to various machine learning algorithms. Some of the commonly used algorithms with regularization are:---

1. **Linear Regression with Ridge (L2) and Lasso (L1):** Regularized versions of linear regression that help prevent overfitting by adding penalty terms to the coefficients.
2. **Logistic Regression with Ridge (L2) and Lasso (L1):** Similar to linear regression, logistic regression can be regularized using L2 and L1 regularization.
3. **Support Vector Machines (SVM):** SVMs can be regularized using L2 regularization. The regularization parameter in SVM is often denoted as C.

4. **Neural Networks:** Regularization techniques like L2 regularization (weight decay) can be applied to the weights of neural network models to prevent overfitting.
5. **Decision Trees and Random Forests:** While decision trees themselves are not typically regularized, random forests can be seen as an ensemble of decision trees and can benefit from regularization through techniques like limiting the maximum depth of trees.

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

Answer:-- the term "error" refers to the difference between the predicted values of the model and the actual values observed in the data. It represents the deviation or residual between what the model predicts and what is actually observed. Mathematically, the error (ε) for each data point i in a linear regression model is given $\varepsilon_i = y_i - \hat{y}_i$

Where:

- y_i is the actual observed value for the i-th data point.
- $\hat{y}_i$ is the predicted value for the i-th data point based on the linear regression model.

The objective in linear regression is to minimize these errors across all data points. The most common method to achieve this is by minimizing the sum of squared errors (SSE), often referred to as the residual sum of squares (RSS), which is defined as:

$$SSE = \sum_{i=1}^{n} \varepsilon_i^2$$

where n is the number of data points.