MACHINE LEARNING

1. D
2. A
3. B
4. B
5. C
6. B
7. D
8. D
9. A
10. B
11. A
12. A, D
13. Regularization is a technique used in machine learning to prevent overfitting and improve the generalization performance of a model. It involves adding a penalty term to the loss function that the model is trying to minimize during training. The penalty term is a function of the model parameters and is designed to discourage the model from fitting the training data too closely and instead encourage it to learn simpler and more generalizable patterns. There are two commonly used regularization techniques in machine learning:

    L1 regularization (Lasso regularization): It adds a penalty term proportional to the absolute value of the model parameters. This technique promotes sparse models by driving some of the model parameters to exactly zero.

    L2 regularization (Ridge regularization): It adds a penalty term proportional to the square of the model parameters. This technique encourages models to have small and smooth parameter values, which can reduce the impact of noisy or irrelevant features.

    Both L1 and L2 regularization techniques can be applied to linear regression, logistic regression, neural networks, and other machine learning models. They can help prevent overfitting, improve model generalization, and increase model interpretability by reducing the impact of irrelevant or noisy features.

14. Regularization can be applied to a variety of machine learning algorithms, including linear regression, logistic regression, support vector machines (SVMs), and neural networks.

    For linear regression, L1 regularization (also known as Lasso regularization) and L2 regularization (also known as Ridge regularization) are commonly used.

    For logistic regression, L1 regularization and L2 regularization can also be used, but they are often referred to as L1 penalty and L2 penalty instead.

    For SVMs, L2 regularization is commonly used, and it is often referred to as C regularization or the C parameter.

15.

In linear regression, the error term represents the difference between the predicted values of the dependent variable and the actual observed values of the dependent variable. It is also known as the residual error or the unexplained error.

The linear regression equation is given as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon$$

Here, y is the dependent variable, $x_1, x_2, \ldots, x_p$ are the independent variables, $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ are the coefficients or the parameters, and ε is the error term.

The error term captures the variation in y that is not explained by the independent variables $x_1, x_2, \ldots, x_p$. It represents the random and unpredictable part of the dependent variable. In other words, it is the difference between the actual observed values of y and the predicted values of y based on the linear regression model.

The goal of linear regression is to minimize the sum of the squared errors (SSE), which is the sum of the squares of the differences between the actual observed values of y and the predicted values of y based on the linear regression model. The coefficients or the parameters of the model are estimated by minimizing the SSE using various methods such as the least squares method, maximum likelihood estimation, or gradient descent.