MACHINE LEARNING

Answers:

1. **Q.1)** option- A
2. **Q.2)** option- A
3. **Q.3)** option- B
4. **Q.4)** option- C
5. **Q.5)** option- C
6. **Q.6)** option- B
7. **Q.7)** option- D
8. **Q.8)** option- D
9. **Q.9)** option- A
10. **Q.10)** option- B
11. **Q.11)** option- B
12. **Q.12)** option- A & B
13. **Q.13) Explain the term regularization?**

    Ans:
    - Regularization is a set of methods for reducing overfitting in machine learning models. Regularization helps control model complexity by preventing overfitting to training data, resulting in better generalization to new data.
    - Regularization can help balance the trade-off between model bias (underfitting) and model variance (overfitting) in machine learning, which leads to improved performance.
    - Regularization can stabilize the model by reducing coefficient sensitivity to small data changes when features are highly correlated.

14. **Q.14) Which particular algorithms are used for regularization?**

    Ans:

    Regularization is a technique used to reduce errors by fitting the function appropriately on the given training set and avoiding overfitting. The commonly used regularization technique is:
    - Ridge Regularization
    - Lasso Regularization

    Ridge Regularization:
    - Ridge regression is one of the types of linear regression in which a small amount of bias is introduced so that we can get better long-term predictions.
    - Ridge regression is a regularization technique, which is used to reduce the complexity of the model. It is also called as L2 regularization.

- In this technique, the cost function is altered by adding the penalty term to it. The amount of bias added to the model is called Ridge Regression penalty. We can calculate it by multiplying with the lambda to the squared weight of each individual feature.
- The equation for the cost function in ridge regression will be:

$$\sum_{i=1}^{M}(y_i - y'_i)^2 = \sum_{i=1}^{M}\left(y_i - \sum_{j=0}^{n}\beta_j * x_{ij}\right)^2 + \lambda\sum_{j=0}^{n}\beta_j^{\,2}$$

Here,

- ➢ In the above equation, the penalty term regularizes the coefficients of the model, and hence ridge regression reduces the amplitudes of the coefficients that decreases the complexity of the model.
- ➢ As we can see from the above equation, if the values of λ tend to zero, the equation becomes the cost function of the linear regression model. Hence, for the minimum value of λ, the model will resemble the linear regression model.
- ➢ A general linear or polynomial regression will fail if there is high collinearity between the independent variables, so to solve such problems, Ridge regression can be used.

Lasso Regularization

- Lasso regression is another regularization technique to reduce the complexity of the model. It stands for Least Absolute and Selection Operator.
- It is like the Ridge Regression except that the penalty term contains only the absolute weights instead of a square of weights.
- Since it takes absolute values, hence, it can shrink the slope to 0, whereas Ridge Regression can only shrink it near to 0.
- It is also called as L1 regularization. The equation for the cost function of Lasso regression will be:

$$\sum_{i=1}^{M}(y_i - y'_i)^2 = \sum_{i=1}^{M}\left(y_i - \sum_{j=0}^{n}\beta_j * x_{ij}\right)^2 + \lambda\sum_{j=0}^{n}|\beta_j|$$

- ➢ Some of the features in this technique are completely neglected for model evaluation.

- Hence, the Lasso regression can help us to reduce the overfitting in the model as well as the feature selection.

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

Ans:

- In a regression analysis, the error term (also known as the residual term) represents the variability in the dependent variable that is not explained by the independent variables included in the model.
- It captures all other factors that influence the dependent variable but are not explicitly accounted for in the regression model.
- The error term consists of various components, such as measurement error, omitted variables, and random variation. These factors make the observed data points deviate from the predicted values generated by the regression equation.
- The error term is assumed to be normally distributed with a mean of zero and constant variance (homoscedasticity) in classical linear regression models.