MACHINE LEARNING

Ans 1) A (Least Square Error)

Ans 2) A (Linear regression is sensitive to outliers)

Ans 3) B (Negative)

And 4) B (Correlation)

Ans 5) C (Low bias and high variance)

And 6) B (Predictive modal)

Ans 7) D (Regularization)

Ans 8) D (SMOTE)

Ans 9) A

Ans 10) A (True)

And 11) A & C

Ans 12) A & B

Q13 and Q15 are subjective answer type questions, Answer them briefly.

Ans 13) Regularization is a technique used in machine learning and statistics to prevent overfitting and improve the generalization of models. When a model is overfitting, it performs well on training data but fails to generalize to unseen data. Regularization helps to address this by adding a penalty term to the model's objective function, which discourages the coefficients from reaching extreme values.

Purpose of Regularization:

1. **Preventing Overfitting:** By penalizing large coefficients, regularization discourages the model from fitting the noise in the training data and helps it focus on the most important patterns.
2. **Improving Generalization:** A regularized model tends to perform better on unseen data, as it learns more robust patterns rather than memorizing the training examples.

Types of Regularization:

1. **L2 Regularization (Ridge Regression):** This adds a penalty proportional to the sum of the squares of the coefficients to the loss function. It shrinks the coefficients towards zero but does not enforce sparsity in the model.
2. **L1 Regularization (Lasso Regression):** This adds a penalty proportional to the sum of the absolute values of the coefficients to the loss function. It not only shrinks the coefficients but also performs feature selection by setting some coefficients to exactly zero.

3. **Elastic Net Regularization:** This combines both L2 and L1 penalties, balancing between Ridge and Lasso regularization. It is useful when there are correlated predictors in the data.

Implementation:

Regularization is implemented by modifying the objective function that the model optimizes during training. The regularization parameter (often denoted as lambda or alpha) controls the strength of the penalty applied to the coefficients. Tuning this parameter is crucial to achieve the right balance between fitting the training data well and generalizing to new data.

Ans 14: GPT-3.5

Searched for:

1. L1 regularization (Lasso): This algorithm adds a penalty term to the loss function based on the absolute value of the coefficients, which encourages sparsity in the model.

2. L2 regularization (Ridge): This algorithm adds a penalty term to the loss function based on the squared value of the coefficients, which prevents overfitting by shrinking large coefficients.

3. Elastic Net: This algorithm combines both L1 and L2 regularization, providing a balance between feature selection and coefficient shrinkage.

4. Dropout: This algorithm is commonly used in neural networks and randomly drops out some neurons during training to prevent overfitting.

5. Batch normalization: This algorithm normalizes input data at each layer of a neural network to prevent overfitting and stabilize training.

6. Data augmentation: This technique artificially increases the size of training data by applying transformations such as rotation, scaling, or flipping, preventing overfitting by exposing the model to more diverse examples.

7. Early stopping: This technique stops training when performance on a validation set starts to degrade, preventing overfitting by avoiding excessive model complexity.

These algorithms are commonly used for regularization in machine learning and deep learning models to prevent overfitting and improve generalization performance.

Ans 15: In linear regression, the term "error" refers to the difference between the observed value of the dependent variable and the value predicted by the linear regression model. This difference is also known as the residual.

Let's break down the components of the linear regression equation to understand where the error comes into play:

1. **Linear Regression Model**: The general form of a linear regression model with one independent variable (simple linear regression) is:

$Y = \beta 0 + \beta 1 X + \epsilon$

- Yis the dependent variable (the variable we want to predict).
- X is the independent variable (the variable used to predict Y).
- β0 is the intercept (the value of Y when X is 0).
- B1 is the slope (the change in Y for a one-unit change in X).
- ϵ represents the error term.

2. **Error Term (ϵ\epsilonϵ)**: The error term ϵ\epsilonϵ accounts for the difference between the observed values of YYY and the values predicted by the regression equation. It captures all other factors affecting YYY that are not included in the model.
   - ϵ is assumed to follow certain statistical properties in linear regression:
     - It has a mean of 0 (i.e., the errors average out to zero across the dataset).
     - It has constant variance (homoscedasticity).
     - It is independent and normally distributed.
3. **Purpose of the Error Term**: The error term ϵ\epsilonϵ acknowledges that the relationship between X and Y may not be perfectly captured by the linear model due to various factors such as measurement error, unobserved variables, or inherent variability in the data. The goal of linear regression is to minimize these errors by estimating the coefficients β0 and β1 such that the model provides the best possible fit to the data.
4. **Model Evaluation**: In practice, after fitting a linear regression model, the errors (residuals) are examined to assess how well the model fits the data. A good model will have residuals that are small and randomly distributed around zero, indicating that the model adequately explains the variation in Y based on X.

In summary, the "error" in the linear regression equation $Y = \beta 0 + \beta 1 X + \epsilon$ refers to the discrepancy between the observed values of the dependent variable and the values predicted by the linear model. It is a critical concept in understanding the reliability and accuracy of the linear regression analysis.