1. What is Gradient Boosting?

Gradient Boosting is a machine learning technique used for regression and classification tasks. It builds an ensemble of weak learners, typically decision trees, and optimizes the model by minimizing a loss function using gradient descent.

2. How does Gradient Boosting work?

- 1. Initialize the model with a constant value, often the mean of the target variable.
- 2. Fit a weak learner (e.g., a decision tree) to the residuals of the current model.
- 3. Update the model by adding the predictions of the weak learner, scaled by a learning rate.
- 4. Repeat steps 2 and 3 for a predefined number of iterations or until the loss converges.

3. What are weak learners?

Weak learners are simple models that perform slightly better than random guessing. In Gradient Boosting, decision stumps or shallow decision trees are commonly used as weak learners.

4. What is the role of the learning rate in Gradient Boosting?

The learning rate controls how much each weak learner contributes to the final model. A smaller learning rate requires more iterations but often results in better performance.

5. What are the advantages of Gradient Boosting?

- 1. Handles non-linear relationships well.
- 2. High accuracy for both regression and classification tasks.
- 3. Robust to overfitting when parameters are tuned properly.

6. What are the limitations of Gradient Boosting?

- 1. Computationally intensive for large datasets.
- 2. Sensitive to outliers and noisy data.
- 3. Requires careful tuning of hyperparameters like learning rate, number of iterations, and tree depth.

7. What is overfitting in Gradient Boosting, and how is it handled?

Overfitting occurs when the model learns noise in the training data. It can be handled by:

- 1. Using regularization techniques like limiting tree depth.
- 2. Decreasing the learning rate.
- 3. Applying early stopping.

8. What is the difference between Gradient Boosting and Random Forest?

- Gradient Boosting builds trees sequentially, focusing on reducing residual errors, while Random Forest builds trees independently.
- 2. Gradient Boosting often provides higher accuracy but is more prone to overfitting.
- 3. Random Forest is faster and easier to tune.

9. What is the importance of loss functions in Gradient Boosting?

The loss function measures the difference between predicted and actual values. Gradient Boosting minimizes this loss function using gradient descent. Common loss functions include mean squared error for regression and log-loss for classification.

10. How does Gradient Boosting handle imbalanced datasets?

Gradient Boosting can handle imbalanced datasets by:

- 1. Using a custom loss function that accounts for class imbalance.
- 2. Adjusting the sample weights for underrepresented classes.

11. What is the role of regularization in Gradient Boosting?

Regularization prevents overfitting by:

- 1. Limiting tree depth.
- 2. Using subsampling techniques (row or column sampling).
- 3. Penalizing complex models.

12. What are some popular implementations of Gradient Boosting?

- 1. XGBoost: Optimized for speed and performance.
- 2. LightGBM: Efficient for large datasets.
- 3. CatBoost: Handles categorical features well.

13. What is early stopping in Gradient Boosting?

Early stopping monitors the validation error during training and stops the process if the error does not improve for a specified number of iterations.

14. How do you evaluate the performance of a Gradient Boosting model?

You can evaluate the model using metrics like:

- 1. Accuracy, Precision, Recall, F1-Score for classification.
- 2. Mean Squared Error (MSE) or R-squared for regression.

15. How does Gradient Boosting differ from AdaBoost?

- 1. Gradient Boosting minimizes a loss function using gradient descent, while AdaBoost adjusts weights of misclassified points.
- 2. Gradient Boosting is more flexible with custom loss functions, while AdaBoost primarily uses exponential loss.

16. Can Gradient Boosting handle missing data?

Yes, many implementations like XGBoost and LightGBM can handle missing data by learning optimal splits for missing values during training.