ML QUESTIONS

Category 1: Fundamentals of Machine Learning
Define machine learning. What are the main types of machine learning algorithms?
Describe the difference between supervised, unsupervised, and reinforcement learning. Provide examples of each.
What is the difference between a machine learning algorithm and a model?
Explain the concept of 'weight' in machine learning models. Why is it important?
What are the various types of data preprocessing techniques used in machine learning? Why is preprocessing essential?
Discuss the importance of normalization and standardization in data preprocessing.
What are the different types of data that can be used in machine learning models?
Explain how missing data can be handled during data preprocessing.
Describe the concept of overfitting and underfitting in machine learning. How can these issues be addressed?
List some common applications of machine learning algorithms. Provide examples for each application.
Differentiate between parametric and non-parametric machine learning algorithms. Give examples of each.
What role does the choice of algorithm play in determining the performance of a machine learning model?
Answer all this question with proper numbering and it should be in detail so that i can write in exam

1. Define Machine Learning

Machine Learning (ML) is a subset of artificial intelligence (AI) that focuses on building systems that learn from data, identify patterns, and make decisions with minimal human intervention. ML involves algorithms that improve their performance on a given task over time, based on experience or data input.

2. Main Types of Machine Learning Algorithms

The main types of machine learning algorithms are:

- **Supervised Learning**
- **Unsupervised Learning**
- **Reinforcement Learning**

3. Difference Between Supervised, Unsupervised, and Reinforcement Learning

Aspect	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Definition	Learning from labeled data to predict outcomes.	Learning from unlabeled data to find patterns or groups.	Learning through trial and error to achieve a goal.

Aspect	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Data Type	Labeled data (input-output pairs).	Unlabeled data (no output labels provided).	No explicit data; learns by interacting with the environment.
Objective	To map inputs to outputs accurately.	To identify hidden patterns or groupings in the data.	To maximize a cumulative reward by taking the right actions.
Examples	Classification (e.g., spam detection), regression (e.g., house price prediction).	Clustering (e.g., customer segmentation), dimensionality reduction (e.g., PCA).	Game playing (e.g., chess), robotics, self-driving cars.

4. Difference Between a Machine Learning Algorithm and a Model

- **Algorithm**: A step-by-step procedure or formula for solving a problem. In ML, an algorithm is the method used to train a model (e.g., decision trees, linear regression).
- **Model**: The outcome or representation created by the training process. It is the trained instance that can make predictions or classifications based on new data.

Example: A linear regression algorithm creates a linear regression model by finding the best-fit line for a given dataset.

5. Concept of 'Weight' in Machine Learning Models

Weight in a machine learning model refers to the coefficient assigned to a feature/input that determines its importance in predicting the output. In neural networks, weights connect nodes between layers and get adjusted during training to minimize the prediction error.

Importance: Weights are crucial because they control how much influence a particular feature has on the output prediction. Properly optimized weights ensure that the model learns the correct patterns from the data.

6. Types of Data Preprocessing Techniques in Machine Learning

- **Data Cleaning**: Handling missing values, removing duplicates, correcting errors.
- **Data Transformation**: Normalization, standardization, and scaling of features.
- **Feature Extraction**: Deriving new features from existing ones.
- **Encoding**: Converting categorical data into numerical format (e.g., one-hot encoding).
- **Data Integration**: Combining data from different sources into a unified dataset.
- **Data Reduction**: Reducing the number of features or samples while retaining the most important information.

Importance: Preprocessing is essential because raw data often contains noise, missing values, and inconsistencies that can negatively impact the performance of machine learning models.

7. Importance of Normalization and Standardization in Data Preprocessing

- **Normalization**: Rescales the data to a fixed range, typically [0, 1], ensuring that features have the same scale. It's essential for algorithms sensitive to feature magnitude, like k-nearest neighbors (KNN) and neural networks.
- **Standardization**: Centers the data around the mean and scales it to have unit variance. It is useful for algorithms that assume a Gaussian distribution of the data, like logistic regression and linear

discriminant analysis.

Importance: Both techniques help improve the convergence speed of gradient descent and the overall performance of models by ensuring that all features contribute equally to the result.

8. Different Types of Data Used in Machine Learning Models

- **Numerical Data**: Continuous or discrete numbers (e.g., age, salary).
- **Categorical Data**: Qualitative data representing categories (e.g., gender, color).
- **Text Data**: Unstructured data in text form (e.g., reviews, emails).
- **Image Data**: Visual information captured as pixels (e.g., photos, medical scans).
- **Audio Data**: Sound recordings or signals (e.g., speech recognition).
- **Time-Series Data**: Data points indexed in time order (e.g., stock prices, weather data).

9. Handling Missing Data in Data Preprocessing

- **Deletion**: Removing rows or columns with missing values.
- **Imputation**: Replacing missing values with mean, median, mode, or using advanced techniques like k-nearest neighbors or regression.
- **Prediction Models**: Using algorithms to predict missing values based on other features.
- **Data Augmentation**: Creating synthetic data points to fill in missing data.

Importance: Proper handling of missing data ensures the model's robustness and prevents bias in predictions.

10. Concept of Overfitting and Underfitting in Machine Learning

- **Overfitting**: Occurs when a model learns the training data too well, including its noise and outliers, leading to poor generalization to new data.
  - **Solution**: Use regularization techniques (L1/L2), cross-validation, simpler models, or more training data.
- **Underfitting**: Occurs when a model is too simple to capture the underlying patterns in the data, resulting in poor performance on both training and new data.
  - **Solution**: Use more complex models, add more features, or reduce noise in the data.

11. Common Applications of Machine Learning Algorithms

1. **Image Recognition**: Identifying objects in images (e.g., facial recognition, medical imaging).
2. **Natural Language Processing (NLP)**: Understanding human language (e.g., chatbots, sentiment analysis).
3. **Fraud Detection**: Identifying fraudulent activities (e.g., credit card fraud detection).
4. **Recommendation Systems**: Suggesting products or content (e.g., Netflix recommendations, Amazon product suggestions).
5. **Predictive Maintenance**: Predicting equipment failures in advance (e.g., in manufacturing, aviation).

12. Difference Between Parametric and Non-Parametric Machine Learning Algorithms

Aspect	Parametric Algorithms	Non-Parametric Algorithms
Definition	Assumes a fixed number of parameters for learning.	Does not assume a fixed form; model complexity grows with data.
Examples	Linear regression, logistic regression, Naive Bayes.	Decision trees, k-nearest neighbors (KNN), support vector machines (SVM).
Advantages	Simpler, faster to compute, less prone to overfitting.	Flexible, can model complex relationships, does not assume data distribution.
Disadvantages	Limited by predefined form, may underfit complex data.	Slower, may overfit if not properly tuned.

13. Role of Algorithm Choice in Determining the Performance of a Machine Learning Model

The choice of algorithm directly impacts the model's performance due to the following factors:

- **Data Size and Quality**: Some algorithms perform better with large datasets (e.g., neural networks), while others are suited for smaller datasets (e.g., decision trees).
- **Nature of the Data**: Algorithms like SVMs work well with high-dimensional data, while KNN may struggle without dimensionality reduction.
- **Computational Resources**: Complex algorithms like deep neural networks require significant computational power and memory.
- **Interpretability Requirements**: Simple algorithms like linear regression offer high interpretability, while complex models like random forests or neural networks may provide higher accuracy but less transparency.

Choosing the right algorithm requires understanding the problem domain, the nature of the data, and the desired outcome.

Category 2: Model Accuracy, Feature Selection, Dimensionality Reduction, and Probability Theory
What is model accuracy, and how is it measured in machine learning?
How does the size and quality of training data affect the accuracy of a machine learning model?
Define 'features' in the context of machine learning. Why are features important?
Explain the concept of feature selection. Why is it important in building a machine learning model?
What is high-dimensional data, and why does it pose challenges for machine learning algorithms?
Describe techniques used for dimensionality reduction. How do they help in improving model performance?
What is Principal Component Analysis (PCA)? How is it used for dimensionality reduction?
Explain the curse of dimensionality and its impact on machine learning models.
Describe the role of probability theory in machine learning. Provide examples where probability theory is applied.
What is a confusion matrix, and how is it used to evaluate the performance of a classification model?
Discuss the importance of cross-validation in assessing model accuracy.
What is regularization, and how does it help in improving the performance of machine learning models?
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1. What is Model Accuracy, and How is it Measured in Machine Learning?

Model accuracy is a metric used to evaluate the performance of a machine learning model. It is defined as the ratio of the number of correct predictions to the total number of predictions made by the model. Accuracy is primarily used for classification problems.

Formula:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Measurement:
Accuracy is measured using a test dataset that the model has not seen during training. High accuracy indicates that the model's predictions closely match the actual labels in the dataset.

2. How Does the Size and Quality of Training Data Affect the Accuracy of a Machine Learning Model?

- **Size of Training Data**: A larger dataset generally provides more diverse examples, helping the model learn better patterns and generalize well to new data. A small dataset might lead to overfitting or underfitting, reducing model accuracy.
- **Quality of Training Data**: High-quality data with minimal noise, outliers, and missing values leads to better model performance. Poor-quality data can introduce bias, lead to incorrect patterns, and ultimately reduce model accuracy.

3. Define 'Features' in the Context of Machine Learning. Why Are Features Important?

Features are individual measurable properties or characteristics of the data used by a machine learning model to make predictions. They are the input variables that the model uses to understand the data.

Importance:

- Features capture the underlying patterns in the data.
- They determine the model's ability to learn and make accurate predictions.
- Good feature selection improves model accuracy and reduces computational costs.

4. Explain the Concept of Feature Selection. Why Is It Important in Building a Machine Learning Model?

Feature Selection is the process of selecting a subset of relevant features for building a machine learning model. It aims to improve the model's performance by reducing the number of input variables, which minimizes overfitting, enhances model interpretability, and reduces training time.

Importance:

- **Improves Accuracy**: By removing irrelevant or redundant features, the model focuses on the most informative data, leading to better performance.
- **Reduces Overfitting**: Reduces the risk of fitting noise and irrelevant details in the data.
- **Reduces Complexity**: Less computational power is required, making the model more efficient.

5. What is High-Dimensional Data, and Why Does It Pose Challenges for Machine Learning Algorithms?

High-Dimensional Data refers to datasets with a large number of features or variables. For example, an image dataset with millions of pixels as features is considered high-dimensional.

Challenges:

- **Curse of Dimensionality**: As the number of features increases, the volume of the feature space grows exponentially, making the data sparse and increasing the complexity of the model.
- **Overfitting**: High-dimensional data can lead to overfitting, where the model captures noise instead of patterns.
- **Computational Complexity**: Requires more time and resources for processing and training.

6. Describe Techniques Used for Dimensionality Reduction. How Do They Help in Improving Model Performance?

Dimensionality Reduction techniques reduce the number of input variables while retaining the most important information. Common techniques include:

- **Principal Component Analysis (PCA)**: Transforms the data into a lower-dimensional space by identifying the directions (principal components) that maximize variance.
- **Linear Discriminant Analysis (LDA)**: Reduces dimensionality while preserving the class separability.
- **t-Distributed Stochastic Neighbor Embedding (t-SNE)**: A non-linear technique that reduces dimensions for data visualization.

- **Autoencoders**: Neural networks that learn to compress and reconstruct data to find a lower-dimensional representation.

Benefits:

- **Improves Performance**: Reduces overfitting and the risk of the curse of dimensionality.
- **Enhances Interpretability**: Simplifies the model by focusing on fewer but more informative features.
- **Reduces Computational Costs**: Less data to process leads to faster training and inference times.

7. What is Principal Component Analysis (PCA)? How is it Used for Dimensionality Reduction?

Principal Component Analysis (PCA) is a linear dimensionality reduction technique that identifies the directions (principal components) along which the variation in the data is maximized.

How It Works:

- PCA computes the eigenvalues and eigenvectors of the covariance matrix of the data.
- The eigenvectors corresponding to the largest eigenvalues represent the directions with the most variance.
- Data is then projected onto these principal components, reducing the number of dimensions.

Usage:

- PCA is used to reduce the dimensionality of datasets while retaining most of the variability, improving the efficiency and performance of machine learning models.

8. Explain the Curse of Dimensionality and Its Impact on Machine Learning Models.

Curse of Dimensionality refers to the exponential increase in data required to maintain the same level of accuracy as the number of features increases. It makes the data sparse and the distance between points increases, reducing the effectiveness of distance-based algorithms.

Impact:

- **Increased Computation**: Requires more data and computational power.
- **Overfitting**: High-dimensional data can lead to models learning noise instead of patterns.
- **Poor Generalization**: Models may struggle to generalize well to new data.

9. Describe the Role of Probability Theory in Machine Learning. Provide Examples Where Probability Theory is Applied.

Probability Theory provides the mathematical foundation for handling uncertainty, making decisions, and predicting outcomes in machine learning. It is used in various algorithms and models to calculate likelihoods, make predictions, and assess risks.

Applications:

- **Naive Bayes Classifier**: Uses Bayes' theorem to classify data based on the probability of belonging to different classes.
- **Hidden Markov Models**: Used in speech recognition and time series analysis.
- **Expectation-Maximization Algorithm**: Used for clustering in the presence of uncertainty.
- **Regularization**: Adds a probability-based penalty to model complexity to prevent overfitting.

10. What is a Confusion Matrix, and How is It Used to Evaluate the Performance of a Classification Model?

Confusion Matrix is a table that describes the performance of a classification model by showing the actual vs. predicted classifications. It helps in evaluating accuracy and other metrics like precision, recall, and F1 score.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Usage:

- **Accuracy**: $\frac{TP+TN}{TP+TN+FP+FN}$
- **Precision**: $\frac{TP}{TP+FP}$
- **Recall**: $\frac{TP}{TP+FN}$
- **F1 Score**: $2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

11. Discuss the Importance of Cross-Validation in Assessing Model Accuracy.

Cross-Validation is a technique for assessing the accuracy and robustness of a machine learning model by partitioning the data into several subsets (folds) and training/testing the model multiple times with different subsets.

Importance:

- **Prevents Overfitting**: Ensures the model generalizes well to new data by testing on multiple subsets.
- **Provides Robust Accuracy Estimates**: Offers a more reliable estimate of model performance compared to a single train-test split.
- **Helps in Model Selection**: Assists in selecting the best model and hyperparameters by comparing performance across multiple folds.

12. What is Regularization, and How Does It Help in Improving the Performance of Machine Learning Models?

Regularization is a technique used to prevent overfitting by adding a penalty to the loss function for complex models. It constrains the model's complexity, encouraging simpler models that generalize better to new data.

Types:

- **L1 Regularization (Lasso)**: Adds an absolute value of weights penalty to the loss function, promoting sparsity (many weights are zero).
- **L2 Regularization (Ridge)**: Adds a squared value of weights penalty, discouraging large weights without making them exactly zero.

Importance:

- **Reduces Overfitting**: Prevents the model from fitting noise in the training data.
- **Improves Generalization**: Ensures the model performs well on new, unseen data.
- **Promotes Simplicity**: Encourages simpler models that are easier to interpret.

These detailed answers should provide you with a comprehensive understanding of these machine learning concepts for your exam.

Category 3: Specific Algorithms (SVM, Decision Tree, Bayes', Linear Regression, k-means Clustering)
What is Support Vector Machine (SVM), and how does it work?
Explain the difference between linear and non-linear SVM. When would you use one over the other?
Describe the working of a Decision Tree algorithm. How is it used for classification?
What is the concept of entropy in a Decision Tree? How is it used to build the tree?
Explain Bayes' theorem. How is it applied in machine learning?
What is Naive Bayes classification, and how does it differ from other types of classifiers?
Describe the linear regression algorithm. What is its purpose in machine learning?
What are the assumptions of linear regression, and why are they important?
Explain the difference between simple and multiple linear regression.
What is k-means clustering, and how does it work?
How do you determine the optimal number of clusters in k-means clustering?
Compare and contrast the use cases of SVM, Decision Trees, and Naive Bayes algorithms.
Explain the concept of kernel functions in SVM. Why are they important?
What are the advantages and disadvantages of using a Decision Tree for classification?
What are some common challenges faced when using linear regression models?
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1. What is Support Vector Machine (SVM), and How Does It Work?

Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression tasks. It works by finding the hyperplane that best separates data points of different classes in a high-dimensional space. The goal is to maximize the margin, which is the distance between the hyperplane and the nearest data points (support vectors) from each class.

How SVM Works:

- The SVM algorithm identifies the support vectors, which are the critical data points closest to the separating hyperplane.
- It then maximizes the margin between these support vectors and the hyperplane to find the optimal separating boundary.
- If the data is not linearly separable, SVM uses a kernel trick to transform the input space into a higher-dimensional space where a linear hyperplane can separate the classes.

2. Explain the Difference Between Linear and Non-Linear SVM. When Would You Use One Over the Other?

Aspect	Linear SVM	Non-Linear SVM
Definition	Uses a linear hyperplane to separate data points into classes.	Uses kernel functions to transform data into a higher-dimensional space where it can be linearly separated.
Use Case	Best for linearly separable data or when the relationship between features is linear.	Best for non-linearly separable data or when the relationship between features is complex.
Kernel	No kernel function required; data is separated as-is.	Requires a kernel function (e.g., polynomial, radial basis function) to map data to a higher dimension.

Aspect	Linear SVM	Non-Linear SVM
Example	Sentiment analysis with linearly separable text data.	Image recognition where data points may not be linearly separable.

When to Use:

- **Linear SVM**: When the data is linearly separable or when computational efficiency is a priority.
- **Non-Linear SVM**: When the data has complex relationships or is not linearly separable.

3. Describe the Working of a Decision Tree Algorithm. How Is It Used for Classification?

A **Decision Tree** is a supervised learning algorithm used for both classification and regression tasks. It works by recursively splitting the dataset into subsets based on feature values, creating a tree-like model of decisions.

Working:

- The root node represents the entire dataset, and each internal node represents a feature or attribute.
- At each node, the dataset is split into two or more homogeneous sets based on the most significant attribute, as determined by a metric like entropy or Gini index.
- This process continues until the stopping criteria are met (e.g., maximum depth or minimum samples per leaf).
- The leaf nodes represent the final decision or classification outcome.

Usage:

- For classification, the decision tree assigns a class label based on the majority class of the data points reaching a particular leaf node.

4. What is the Concept of Entropy in a Decision Tree? How Is It Used to Build the Tree?

Entropy is a measure of the impurity or randomness in a dataset. In the context of decision trees, entropy quantifies the disorder or uncertainty in the data and helps determine the best way to split the data.

Formula:

$$\text{Entropy (H)} = -\sum(p_i \cdot \log_2(p_i))$$

Where p_i is the proportion of data points belonging to class i.

Usage in Building the Tree:

- Decision trees use entropy to find the attribute that provides the most information gain (the reduction in entropy) when splitting the data.
- The attribute with the highest information gain is selected as the decision node, ensuring that each split results in the most significant reduction in uncertainty.

5. Explain Bayes' Theorem. How Is It Applied in Machine Learning?

Bayes' Theorem describes the probability of an event, based on prior knowledge of conditions that might be related to the event. It calculates the posterior probability of a hypothesis given observed evidence.

Formula:

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)}$$

Where:

- $P(H|E)$ = Posterior probability: Probability of hypothesis H given evidence E.
- $P(E|H)$ = Likelihood: Probability of evidence E given hypothesis H.
- $P(H)$ = Prior probability: Initial probability of hypothesis H.
- $P(E)$ = Marginal probability: Total probability of evidence E.

Application in Machine Learning:

- Used in **Naive Bayes classifiers** to compute the probability of different class labels based on input features.
- Applied in spam detection, text classification, and sentiment analysis, where it determines the most probable class for a given document or text.

6. What is Naive Bayes Classification, and How Does It Differ from Other Types of Classifiers?

Naive Bayes Classification is a probabilistic classifier based on Bayes' theorem with the assumption that all features are independent given the class label (the "naive" assumption).

How It Differs:

- **Assumption of Independence**: Unlike other classifiers (e.g., Decision Trees, SVM), Naive Bayes assumes that all input features are independent of each other, which simplifies computation.
- **Speed and Efficiency**: Naive Bayes is fast, requires less training data, and works well with high-dimensional datasets, unlike more complex algorithms that may require feature selection or dimensionality reduction.
- **Use Cases**: Naive Bayes is effective for text classification tasks like spam detection and sentiment analysis.

7. Describe the Linear Regression Algorithm. What Is Its Purpose in Machine Learning?

Linear Regression is a supervised learning algorithm used to predict a continuous outcome based on one or more input features. It models the relationship between the dependent variable (target) and one or more independent variables (features) by fitting a linear equation to the observed data.

Formula:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon$$

Where:

- y = Dependent variable (target).

- β_0 = Intercept.
- $\beta_1, \beta_2, \ldots, \beta_n$ = Coefficients for each feature.
- $x_1, x_2, \ldots, x_n$ = Independent variables (features).
- ϵ = Error term (residual).

Purpose:

- To predict a numeric value based on input data.
- Used in applications like predicting house prices, sales forecasting, and analyzing relationships between variables.

8. What Are the Assumptions of Linear Regression, and Why Are They Important?

Assumptions of Linear Regression:

1. **Linearity**: The relationship between the independent and dependent variables should be linear.
2. **Independence**: The residuals (errors) should be independent (no correlation between residuals).
3. **Homoscedasticity**: The variance of the residuals should be constant across all levels of the independent variables.
4. **Normality**: The residuals should be normally distributed.

Importance:

- Ensuring these assumptions hold helps guarantee the validity, reliability, and interpretability of the linear regression model.
- Violations of these assumptions can lead to biased or incorrect estimates, reducing the model's predictive accuracy.

9. Explain the Difference Between Simple and Multiple Linear Regression.

Aspect	Simple Linear Regression	Multiple Linear Regression
Definition	Involves one dependent variable and one independent variable.	Involves one dependent variable and two or more independent variables.
Equation	$y = \beta_0 + \beta_1 x + \epsilon$	$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon$
Use Case	Used when the relationship is expected to be linear between two variables.	Used when multiple variables affect the dependent variable simultaneously.

10. What is K-Means Clustering, and How Does It Work?

K-Means Clustering is an unsupervised learning algorithm used to partition data into k clusters, where each data point belongs to the cluster with the nearest mean.

How It Works:

1. **Initialize**: Select k initial cluster centroids randomly.
2. **Assignment Step**: Assign each data point to the nearest cluster centroid.
3. **Update Step**: Recalculate the centroids by taking the mean of all points assigned to each cluster.
4. **Repeat**: Continue steps 2 and 3 until the centroids no longer change or a maximum number of iterations is reached.

11. How Do You Determine the Optimal Number of Clusters in K-Means Clustering?

- **Elbow Method**: Plot the sum of squared distances from each point to its assigned cluster centroid against the number of clusters. The "elbow" point, where the rate of decrease sharply slows, suggests the optimal number of clusters.
- **Silhouette Score**: Measures how similar a point is to its own cluster compared to other clusters. A higher silhouette score indicates a better-defined cluster.
- **Gap Statistic**: Compares the total within-cluster variation for different numbers of clusters with their expected values under null reference distribution.

12. Compare and Contrast the Use Cases of SVM, Decision Trees, and Naive Bayes Algorithms.

Aspect	SVM	Decision Trees	Naive Bayes
Use Case	High-dimensional data, binary or multi-class classification.	Suitable for both regression and classification, handles non-linear data.	Effective for text classification tasks like spam detection.
Strengths	Works well with complex boundaries, robust to overfitting with kernel trick.	Easy to interpret, handles both numerical and categorical data.	Simple, fast, and performs well with small datasets.
Weaknesses	Can be slow with large datasets, sensitive to outliers.	Prone to overfitting if not pruned properly.	Assumes feature independence, which may not hold in practice.

13. Explain the Concept of Kernel Functions in SVM. Why Are They Important?

Kernel Functions are mathematical functions that transform input data into a higher-dimensional space, enabling SVM to find a linear separating hyperplane for non-linearly separable data.

Importance:

- Allows SVM to handle complex relationships in the data by using different types of kernels (e.g., polynomial, Gaussian radial basis function).
- Increases the flexibility of SVM to solve a wider range of problems beyond linear separability.

14. What Are the Advantages and Disadvantages of Using a Decision Tree for Classification?

Advantages:

- Easy to understand and interpret.
- Handles both numerical and categorical data.
- Requires little data preprocessing.
- Can handle multi-output problems.

Disadvantages:

- Prone to overfitting, especially with small datasets.
- Can be biased towards features with more levels.
- Unstable, as small changes in the data can lead to a completely different tree structure.

15. What Are Some Common Challenges Faced When Using Linear Regression Models?

- **Violation of Assumptions**: Assumptions such as linearity, independence, homoscedasticity, and normality must hold true; otherwise, the model's validity can be compromised.
- **Multicollinearity**: High correlation between independent variables can lead to unreliable coefficient estimates.
- **Outliers and Leverage Points**: Outliers can disproportionately affect the model's coefficients and predictions.
- **Overfitting**: Including too many features can cause the model to capture noise rather than the underlying pattern, leading to poor generalization.

These detailed explanations cover the key aspects of each algorithm and concept, which should help you prepare effectively for your exam.