1. What is prior probability? Give an example.

Ans: Prior probability, also known as prior, is a probability distribution that represents our initial belief or knowledge about an event or a parameter before we observe any data. It is used in Bayesian statistics, which is a branch of statistics that uses probability theory to update our beliefs about an event or a parameter based on new data.

For example, let's say we are trying to predict the probability of an individual having a certain disease. Before we observe any data, we may have some prior knowledge about the prevalence of the disease in the population. For example, we know that the disease affects 1% of the population. This prior probability can be represented by a probability distribution, such as a beta distribution with parameters alpha = 1 and beta = 100.

As we collect data and observe the symptoms of the individual, we can use Bayes' theorem to update our belief about the probability of the individual having the disease. The prior probability and the new data are used to calculate the posterior probability, which represents our updated belief about the event or parameter.

1. What is posterior probability? Give an example.

Ans: Posterior probability, also known as posterior, is a probability distribution that represents our updated belief or knowledge about an event or a parameter after we observe some data. It is used in Bayesian statistics, which is a branch of statistics that uses probability theory to update our beliefs about an event or a parameter based on new data.

For example, let's say we are trying to predict the probability of an individual having a certain disease. Before we observe any data, we have some prior knowledge about the prevalence of the disease in the population, which is represented by a prior probability distribution. After we observe the symptoms of the individual, we can use Bayes' theorem to update our belief about the probability of the individual having the disease. The prior probability and the new data are used to calculate the posterior probability, which represents our updated belief about the event or parameter.

1. What is likelihood probability? Give an example.

Ans: Likelihood probability, also known as likelihood, is a probability distribution that represents the probability of observing certain data given a certain set of parameters or hypotheses. It is used in Bayesian statistics, which is a branch of statistics that uses probability theory to update our beliefs about an event or a parameter based on new data.

1. What is Naïve Bayes classifier? Why is it named so?

Ans:

Naive Bayes classifier is a probabilistic machine learning algorithm based on Bayes' Theorem, which is used for classification tasks. The name "Naive" in the Naive Bayes classifier comes from the assumption that the features in the dataset are independent of each other given the class label. This assumption simplifies the computation and allows for efficient training and prediction, but it may not always hold true in real-world data.

1. What is optimal Bayes classifier?

Ans: The optimal Bayes classifier, also known as the Bayes optimal classifier or the Bayes classifier, is a theoretical classifier that makes the best possible predictions given the underlying probability distributions of the data. It is based on the Bayes' theorem, which is a fundamental rule in probability theory that relates the prior probability of an event to the likelihood of the event and the evidence.

1. Write any two features of Bayesian learning methods.
2. Ans: Incorporation of prior knowledge: Bayesian learning methods incorporate prior knowledge or beliefs about the parameters or hypotheses of the model into the learning process. This allows the model to make more informed decisions and can lead to improved performance in certain situations.
3. Handling of uncertainty: Bayesian learning methods provide a natural way to handle uncertainty by representing it as probability distributions. This allows the model to express its uncertainty about its predictions and make more robust decisions. Additionally, Bayesian methods provide a framework for updating beliefs about the parameters or hypotheses as new data is observed, allowing the model to adapt and improve over time.
4. Define the concept of consistent learners.

Ans: Consistent learners are machine learning algorithms that are able to correctly classify new examples from the same underlying distribution as the examples used for training. In other words, a consistent learner is a learning algorithm that is able to generalize well from the training data to new, unseen data.

1. Write any two strengths of Bayes classifier.
2. Ans: Incorporation of prior knowledge: Bayesian learning methods incorporate prior knowledge or beliefs about the parameters or hypotheses of the model into the learning process. This allows the model to make more informed decisions and can lead to improved performance in certain situations.
3. Handling of uncertainty: Bayesian learning methods provide a natural way to handle uncertainty by representing it as probability distributions. This allows the model to express its uncertainty about its predictions and make more robust decisions. Additionally, Bayesian methods provide a framework for updating beliefs about the parameters or hypotheses as new data is observed, allowing the model to adapt and improve over time.
4. Write any two weaknesses of Bayes classifier.
5. Ans: Assumptions: One weakness of the Bayes classifier is that it relies on strong assumptions about the underlying probability distributions of the data. If these assumptions do not hold true in the real-world data, the classifier may not perform well. For example, the naive Bayes classifier assumes that the features are independent given the class label, which may not always hold true in real-world data.
6. Computational complexity: Another weakness of the Bayes classifier is that it can be computationally expensive to calculate the posterior probability for high-dimensional data or for complex models. This can be a limitation for large-scale applications or for real-time decision making. Additionally, the computation of the marginal likelihood can be intractable for certain models, which makes it difficult to perform model selection.

10. Explain how Naïve Bayes classifier is used for

1. Text classification

2. Spam filtering

1. Market sentiment analysis
2. Ans: Text classification: Naive Bayes classifier is commonly used for text classification tasks such as document classification, sentiment analysis, and spam detection. The basic idea is to convert the text into numerical features, such as the frequency of words or n-grams, and then use the Naive Bayes classifier to predict the class label of the text based on these features. The Multinomial Naive Bayes classifier is typically used for text classification as it assumes that the features (e.g. the frequency of words) follow a multinomial distribution.
3. Spam filtering: Naive Bayes classifier is also widely used for spam filtering, which is the task of automatically identifying and blocking unwanted emails. In this application, the features are typically the presence or absence of specific words or phrases in the email, and the class labels are "spam" or "not spam". The Bernoulli Naive Bayes classifier is typically used for this task as it assumes that the features (e.g. the presence or absence of specific words) follow a Bernoulli distribution.
4. Market sentiment analysis: Naive Bayes classifier is also used in market sentiment analysis, which is the process of using natural language processing techniques to determine the sentiment of news articles, social media posts, or other text data related to a company or market. The features are typically the frequency of positive or negative words, and the class labels are "positive", "negative" or "neutral". The Multinomial Naive Bayes classifier is typically used for this task as it assumes that the features (e.g. the frequency of positive or negative words) follow a multinomial distribution.

Top of Form