Q1. What is prior probability? Give an example.

Prior probability, also known as a priori probability, refers to the probability assigned to an event or hypothesis before considering any new evidence or data. It represents the initial beliefs or assumptions about the likelihood of an event occurring based on available information. A prior probability is often used as a starting point in Bayesian inference, which is updated using new evidence to obtain a posterior probability.

Example: Consider a medical diagnosis scenario where a doctor estimates the probability of a patient having a certain disease based on general knowledge and historical data, before performing any tests on the patient.

Q2. What is posterior probability? Give an example.

Posterior probability is the updated probability of an event or hypothesis after taking into account new evidence or data. It is calculated using Bayes' theorem, which incorporates both the prior probability and the likelihood of the evidence. The posterior probability reflects the revised belief about the event's likelihood based on the available information.

Example: Continuing with the medical diagnosis scenario, after conducting tests and obtaining specific test results, the doctor calculates the probability of the patient having the disease based on both the prior probability and the new test results.

Q3. What is likelihood probability? Give an example.

Likelihood probability represents the probability of observing a particular set of evidence or data given a specific hypothesis or event. It quantifies the strength of the evidence in support of a hypothesis. Unlike prior and posterior probabilities, the likelihood probability focuses on how well the data matches a given hypothesis.

Example: In a coin-tossing experiment, the likelihood probability would be the probability of observing a specific sequence of heads and tails given a certain hypothesis about the fairness of the coin.

Q4. What is Naïve Bayes classifier? Why is it named so?

The Naïve Bayes classifier is a probabilistic machine learning algorithm based on Bayes' theorem. It is used for classification tasks, where the goal is to assign a class label to an input instance. The "naïve" aspect of the algorithm comes from the assumption that features are conditionally independent, which simplifies the calculation of the posterior probabilities.

Q5. What is optimal Bayes classifier?

The optimal Bayes classifier, also known as the Bayes optimal classifier, is a theoretical classifier that achieves the lowest possible error rate among all classifiers for a given classification problem. It's based on the Bayes decision rule, which assigns an instance to the class that has the highest posterior probability

Q6. Write any two features of Bayesian learning methods.

Features of Bayesian Learning Methods:

1. Incorporation of Prior Knowledge: Bayesian learning methods allow prior knowledge or assumptions to be incorporated into the learning process through prior probabilities. This is particularly useful when dealing with limited data.
2. Updating of Probabilities: Bayesian methods allow for the iterative updating of probabilities as new evidence becomes available. This iterative process leads to refined estimates and predictions.

Q7. Define the concept of consistent learners.

Consistent learners are machine learning algorithms that, as the sample size increases, converge to the true underlying function or distribution that generated the data. In other words, the predictions of consistent learners become increasingly accurate as more data is provided.

Q8. Write any two strengths of Bayes classifier.

1. Incorporates Prior Information: Bayes classifiers allow for the incorporation of prior knowledge or beliefs into the classification process, which can be particularly helpful in scenarios with limited training data.
2. Handles Missing Data: The probabilistic nature of the Bayes classifier allows it to handle missing data gracefully. It can still make predictions even if some features have missing values.

Q9. Write any two weaknesses of Bayes classifier.

1. Assumption of Feature Independence: The Naïve Bayes classifier assumes that features are conditionally independent given the class label. This assumption may not hold true in all real-world scenarios.
2. Sensitivity to Feature Distribution: The performance of the Bayes classifier is highly influenced by the distribution of features. If the distribution doesn't match the assumptions, the classifier may yield suboptimal results.

Q10. Explain how Naïve Bayes classifier is used for

1. Text classification
2. Spam filtering
3. Market sentiment analysis
4. Text Classification: Naïve Bayes is widely used for text classification tasks, such as spam detection, sentiment analysis, and topic categorization. It calculates the probability of a document belonging to a particular class based on the occurrence of words or features in the document.
5. Spam Filtering: In spam filtering, Naïve Bayes examines the words and patterns in an email to estimate the likelihood of it being spam or not. It calculates the posterior probability of an email being spam given its features.
6. Market Sentiment Analysis: Naïve Bayes can be used for market sentiment analysis to classify public opinions or social media posts as positive, negative, or neutral. It analyzes the occurrence of specific words or phrases associated with sentiments in the text.