## Q1

Prior Probability: Prior probability refers to the probability of an event occurring before considering any new evidence or information. It represents our initial belief or knowledge about the likelihood of an event happening. For example, in medical diagnosis, the prior probability of a person having a certain disease might be based on historical data or general population statistics.

## Q2

Posterior Probability: Posterior probability is the updated probability of an event occurring after taking into account new evidence or information. It is calculated using Bayes' theorem. For example, in the context of medical diagnosis, after conducting specific medical tests on a patient, the posterior probability of them having a disease is updated based on the test results.

## Q3

Likelihood Probability: Likelihood probability represents the probability of observing certain evidence or data given that a particular hypothesis or event is true. It describes how well the data supports a specific hypothesis. For example, in a coin toss experiment, the likelihood probability of getting heads given that the coin is fair is 0.5.

## Q4

Naïve Bayes Classifier: The Naïve Bayes classifier is a probabilistic machine learning algorithm used for classification tasks. It's named "naïve" because it makes a simplifying assumption that the features used to describe data are conditionally independent, which might not hold true in all real-world scenarios. Despite this simplification, Naïve Bayes can perform well in various text and categorical data classification tasks.

## Q5

Optimal Bayes Classifier: The Optimal Bayes Classifier is a theoretical classifier that can achieve the best possible classification accuracy. It calculates the posterior probability for each class and assigns the observation to the class with the highest posterior probability. However, it requires knowledge of the true underlying probability distributions, which are often unknown in practice.

## Q6

Features of Bayesian Learning Methods:

Bayesian methods provide a principled framework for incorporating prior knowledge and updating it with new evidence.

They offer a probabilistic interpretation of model predictions, which can be useful for uncertainty estimation.

## Q7

Consistent Learners: Consistent learners are machine learning algorithms that, given an infinite amount of data, will eventually converge to the correct model or hypothesis. In other words, as more data becomes available, consistent learners will consistently improve and approach the true underlying model.

## Q8

Strengths of Bayes Classifier:

It can handle both binary and multiclass classification problems.

It's particularly useful for text classification tasks, spam filtering, and situations with limited training data.

## Q9

Weaknesses of Bayes Classifier:

The Naïve Bayes assumption of feature independence may not hold in some cases, leading to suboptimal results.

It can be sensitive to the presence of irrelevant features or noisy data.

## Q10

Using Naïve Bayes Classifier:

Text Classification: Naïve Bayes is commonly used for text classification tasks, such as sentiment analysis, spam detection, and topic categorization, based on the frequency of words in documents.

Spam Filtering: In spam filtering, Naïve Bayes can classify emails as spam or not spam based on the likelihood of certain words or patterns occurring in spam emails.

Market Sentiment Analysis: Naïve Bayes can be applied to sentiment analysis of financial news or social media data to predict market sentiment (e.g., bullish or bearish) based on the sentiment expressed in textual content.