Q1. Provide an example of the concepts of Prior, Posterior, and Likelihood.

Example of Prior, Posterior, and Likelihood: Let's consider a medical test for a rare disease.

Prior Probability: Before performing any test, the doctor estimates that the probability of a patient having the disease (D) is very low, say P(D) = 0.001.

Likelihood Probability: The test's likelihood is as follows:

* If a patient has the disease (D), the test will be positive (T+) with probability P(T+|D) = 0.98.
* If a patient does not have the disease (¬D), the test will be negative (T-) with probability P(T-|¬D) = 0.95.

Posterior Probability: After performing the test and obtaining a positive result (T+), the doctor calculates the probability that the patient actually has the disease: P(D|T+) = (P(T+|D) \* P(D)) / P(T+) = (0.98 \* 0.001) / P(T+).

Q2. What role does Bayes' theorem play in the concept learning principle?

Bayes' Theorem in Concept Learning: Bayes' theorem is central to the concept learning principle in machine learning. It helps update beliefs about hypotheses based on new evidence. In concept learning, Bayes' theorem plays a crucial role in calculating posterior probabilities of hypotheses given observed data. It enables the transition from prior beliefs to updated beliefs based on observed outcomes.

Q3. Offer an example of how the Nave Bayes classifier is used in real life.

Example of Naïve Bayes in Real Life: Naïve Bayes classifiers are commonly used in various real-life applications, such as spam email detection. For instance, in spam filtering, the classifier calculates the probabilities of certain words or phrases occurring in spam or non-spam emails. Based on these probabilities, it assigns a class label (spam or non-spam) to incoming emails.

Q4. Can the Nave Bayes classifier be used on continuous numeric data? If so, how can you go about doing it?

Using Naïve Bayes with Continuous Numeric Data: Naïve Bayes classifiers are traditionally designed for discrete data with categorical features. However, they can be adapted to handle continuous numeric data using techniques like kernel density estimation or discretization. Continuous data can be divided into intervals, and the likelihood probabilities can be estimated within those intervals.

Q5. What are Bayesian Belief Networks, and how do they work? What are their applications? Are they capable of resolving a wide range of issues?

Bayesian Belief Networks (BBNs): Bayesian Belief Networks (BBNs) are graphical models that represent probabilistic relationships between variables using directed acyclic graphs. Each node represents a variable, and edges represent probabilistic dependencies. BBNs are used for various applications, including medical diagnosis, risk assessment, and decision-making under uncertainty. They capture complex dependencies and can resolve a wide range of issues by modeling probabilistic relationships.

Q6. Passengers are checked in an airport screening system to see if there is an intruder. Let I be the random variable that indicates whether someone is an intruder I = 1) or not I = 0), and A be the variable that indicates alarm I = 0). If an intruder is detected with probability P(A = 1|I = 1) = 0.98 and a non-intruder is detected with probability P(A = 1|I = 0) = 0.001, an alarm will be triggered, implying the error factor. The likelihood of an intruder in the passenger population is P(I = 1) = 0.00001. What are the chances that an alarm would be triggered when an individual is actually an intruder?

Chances of Triggering an Alarm for an Intruder: P(Alarm = 1|Intruder = 1) = P(Alarm = 1 and Intruder = 1) / P(Intruder = 1) P(Alarm = 1|Intruder = 1) = 0.98 \* 0.00001 / 0.00001 = 0.98

Q7. An antibiotic resistance test (random variable T) has 1% false positives (i.e., 1% of those who are not immune to an antibiotic display a positive result in the test) and 5% false negatives (i.e., 1% of those who are not resistant to an antibiotic show a positive result in the test) (i.e. 5 percent of those actually resistant to an antibiotic test negative). Assume that 2% of those who were screened were antibiotic-resistant. Calculate the likelihood that a person who tests positive is actually immune (random variable D).

Antibiotic Resistance Test: Let T = positive test result, D = immune to antibiotic P(D = 1|T = 1) = (P(T = 1|D = 1) \* P(D = 1)) / P(T = 1) P(D = 1|T = 1) = (0.99 \* 0.02) / (0.02 \* 0.99 + 0.98 \* 0.01) ≈ 0.66

Q8. In order to prepare for the test, a student knows that there will be one question in the exam that is either form A, B, or C. The chances of getting an A, B, or C on the exam are 30 percent, 20%, and 50 percent, respectively. During the planning, the student solved 9 of 10 type A problems, 2 of 10 type B problems, and 6 of 10 type C problems.

1. What is the likelihood that the student can solve the exam problem?
2. Given the student's solution, what is the likelihood that the problem was of form A?

Likelihood of solving an exam problem: P(Solve) = P(A) \* P(B) \* P(C) = 0.30 \* 0.20 \* 0.50 = 0.03

Likelihood of problem being of form A given student solved it: P(A|Solve) = (P(Solve|A) \* P(A)) / P(Solve) P(A|Solve) = (0.9 \* 0.30) / 0.03 = 0.90

Q9. A bank installs a CCTV system to track and photograph incoming customers. Despite the constant influx of customers, we divide the timeline into 5 minute bins. There may be a customer coming into the bank with a 5% chance in each 5-minute time period, or there may be no customer (again, for simplicity, we assume that either there is 1 customer or none, not the case of multiple customers). If there is a client, the CCTV will detect them with a 99 percent probability. If there is no customer, the camera can take a false photograph with a 10% chance of detecting movement from other objects.

1. How many customers come into the bank on a daily basis (10 hours)?
2. On a daily basis, how many fake photographs (photographs taken when there is no customer) and how many missed photographs (photographs taken when there is a customer) are there?
3. Explain likelihood that there is a customer if there is a photograph?

Number of customers per day (10 hours): P(Customer) = 0.05 (in each 5-minute interval) Number of customers per day = 6 \* 10 \* 0.05 = 3

Daily fake and missed photographs: Fake photographs = 10 \* 60 \* 0.10 = 60 Missed photographs = 10 \* 60 \* 0.01 = 6

Likelihood of a customer given a photograph: P(Customer|Photo) = P(Photo|Customer) \* P(Customer) / P(Photo) P(Customer|Photo) = (0.99 \* 0.05) / (0.99 \* 0.05 + 0.01 \* 0.95) ≈ 0.99

Q10. Create the conditional probability table associated with the node Won Toss in the Bayesian Belief network to represent the conditional independence assumptions of the Nave Bayes classifier for the match winning prediction problem in Section 6.4.4.

In a Bayesian Belief Network for the match winning prediction problem, the node "Won Toss" can take values "Yes" or "No." The conditional probability table (CPT) for the "Won Toss" node in the Naïve Bayes classifier reflects the conditional independence assumptions. Here's how the CPT could look:

| **Won Toss** | **P(Won Toss)** |
| --- | --- |
| Yes | 0.5 |
| No | 0.5 |

In the context of a match winning prediction, this table represents the probabilities associated with the team winning the toss ("Yes") or not winning the toss ("No"). These probabilities are estimated based on historical data or other relevant factors. The Naïve Bayes classifier assumes conditional independence, so the probabilities are calculated independently for each outcome.