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

Ans- Let's consider an example of flipping a coin. Suppose you have a coin and you want to determine the probability that it will land on heads.

Prior: Before flipping the coin, your prior probability of getting heads is 0.5, as the coin is unbiased and has an equal chance of landing on either heads or tails.

Likelihood: The likelihood is the probability of observing the outcome given a specific parameter value. In this case, the likelihood of getting heads is 0.5, as the coin has an equal chance of landing on either heads or tails.

Posterior: After flipping the coin and observing the outcome, you can update your prior probability to obtain the posterior probability of getting heads. For example, if the coin lands on heads, the posterior probability of getting heads is:

Posterior probability = (Prior probability x Likelihood) / Evidence

where Evidence is the probability of observing the outcome, which is 0.5 in this case. So, the posterior probability of getting heads given that the coin landed on heads is:

Posterior probability = (0.5 x 0.5) / 0.5 = 0.5

This means that the probability of the coin landing on heads is still 0.5, as the observation of getting heads doesn't change the prior probability. However, if you flip the coin multiple times and get a series of heads or tails, the posterior probability will change as you update the prior probability based on the new observations.

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

Ans- Bayes' theorem is a fundamental concept in the concept learning principle, as it allows us to update our beliefs about the likelihood of an event or hypothesis based on new evidence or observations. The concept learning principle is a framework for understanding how humans and machines learn and form categories or concepts based on examples and feedback.

Bayes' theorem provides a way to update our prior beliefs (prior probability) about the likelihood of a hypothesis given new evidence (likelihood) to obtain an updated belief (posterior probability). In the context of concept learning, this means that we can use Bayes' theorem to update our belief about the probability of an object belonging to a particular category based on new examples or feedback.

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

Ans- One example of how the Naive Bayes classifier is used in real life is in spam email filtering. Email providers such as Gmail, Yahoo, and Outlook use Naive Bayes classifiers to identify whether incoming emails are spam or not.

In this application, the classifier analyses the contents of the email and assigns a probability to it being spam or not. It does this by using the Bayes theorem to calculate the probability of an email being spam given its content, as well as the probability of an email not being spam given its content.

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

Ans- Yes, Naive Bayes classifiers can be used on continuous numeric data, but it requires some additional steps to handle the continuous nature of the data.

There are two common approaches to handling continuous data in Naive Bayes classifiers: discretization and kernel density estimation.

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

Ans-Bayesian belief networks (BBNs), also known as Bayesian networks or causal probabilistic networks, are graphical models used for probabilistic reasoning and decision-making under uncertainty. BBNs represent the relationships between variables using a directed acyclic graph (DAG), where the nodes represent variables and the edges represent the probabilistic dependencies between them.

BBNs have a wide range of applications in various domains, such as medicine, finance, engineering, and social sciences. Some common applications of BBNs include, Risk analysis and decision-making and Natural language processing.

BBNs are capable of resolving a wide range of issues, but their effectiveness depends on the quality and quantity of the data and the accuracy of the model assumptions. BBNs can handle both discrete and continuous variables, and they can capture complex dependencies between variables that are difficult to model using other techniques. However, BBNs can be computationally expensive and require careful construction and validation to ensure their accuracy and reliability.

**6. 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?**

Ans-We want to calculate the probability of an alarm being triggered given that an individual is actually an intruder, i.e., P(I = 1|A = 1).

Using Bayes' theorem, we have:

P(I = 1|A = 1) = P(A = 1|I = 1) \* P(I = 1) / P(A = 1)

To calculate the denominator, we can use the law of total probability:

P(A = 1) = P(A = 1|I = 1) \* P(I = 1) + P(A = 1|I = 0) \* P(I = 0)

Substituting the given values, we get:

P(A = 1) = 0.98 \* 0.00001 + 0.001 \* (1 - 0.00001) = 0.0010198

Now, substituting this and the given values in the equation for P(I = 1|A = 1), we get,

P(I = 1|A = 1) = 0.98 \* 0.00001 / 0.0010198 = 0.0096

Therefore, the chances of an alarm being triggered when an individual is actually an intruder is 0.0096, or approximately 0.96%

**7. 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).**

Ans-We want to calculate the probability that a person who tests positive is actually immune to the antibiotic, i.e., P(D = 1|T = 1).

Using Bayes' theorem, we have:

P(D = 1|T = 1) = P(T = 1|D = 1) \* P(D = 1) / P(T = 1)

To calculate the denominator, we can use the law of total probability:

P(T = 1) = P(T = 1|D = 1) \* P(D = 1) + P(T = 1|D = 0) \* P(D = 0)

Substituting the given values, we get:

P(T = 1) = 0.95 \* 0.02 + 0.01 \* (1 - 0.02)

= 0.0286

Now, substituting this and the given values in the equation for P(D = 1|T = 1), we get,

P(D = 1|T = 1) = 0.95 \* 0.02 / 0.0286

= 0.6643

Therefore, the likelihood that a person who tests positive is actually immune to the antibiotic is 0.6643, or approximately 66.43%.

**8. 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?**

Ans-1.To calculate the likelihood that the student can solve the exam problem, we need to use the law of total probability. Let S be the event that the student can solve the problem, and let F be the event that the problem is of form A, B, or C.

Then, we have:

P(S) = P(S|F=A) \* P(F=A) + P(S|F=B) \* P(F=B) + P(S|F=C) \* P(F=C)

Substituting the given values, we get:

P(S) = 0.9 \* 0.3 + 0.2 \* 0.2 + 0.6 \* 0.5

= 0.48

Therefore, the likelihood that the student can solve the exam problem is 0.48, or 48%.

2.To calculate the likelihood that the problem was of form A given the student's solution, we need to use Bayes' theorem. Let A be the event that the problem is of form A, and let S be the event that the student solved the problem.

Then, we have:

P(A|S) = P(S|A) \* P(A) / P(S)

To calculate the numerator, we can use the law of total probability:

P(S|A) = number of type A problems solved / total number of type A problems

= 9/10

Substituting the given values, we get

P(A|S) = (9/10) \* 0.3 / 0.48

= 0.5625

Therefore, the likelihood that the problem was of form A given the student's solution is 0.5625, or approximately 56.25%.

**9. 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?**

Ans-1. There are 12 \* 60 / 5 = 144 bins in a 10-hour day, and the probability of a customer coming in each bin is 5%, or 0.05. Therefore, the expected number of customers per day is:

144 \* 0.05 = 7.2

So, on average, 7-8 customers come into the bank on a daily basis.

2.To calculate the number of false and missed photographs, we need to consider each 5-minute bin separately. Let F be the event that a false photograph is taken, and let M be the event that a customer is missed. Let C be the event that a customer comes into the bank in a given bin.

If there is no customer in the bin, the probability of a false photograph is 10%, or 0.1. If there is a customer in the bin, the probability of a missed photograph is 1% (1 - 0.99).

Using these probabilities, we can calculate the expected number of false and missed photographs per day:

Expected number of false photographs = 144 \* 0.1 = 14.4

Expected number of missed photographs = 7.2 \* 0.01 = 0.072

So, on average, there are about 14-15 false photographs per day, and less than one missed photograph per day.

3.To calculate the likelihood that there is a customer if there is a photograph, we need to use Bayes' theorem. Let P be the event that there is a customer in a given bin, and let D be the event that a photograph is taken in the bin.

Then, we have:

P(P|D) = P(D|P) \* P(P) / P(D)

To calculate the numerator, we can use the law of total probability:

P(D|P) = probability of detecting the customer = 0.99

P(D|~P) = probability of taking a false photograph = 0.1

Using these values, we can calculate the denominator as:

P(D) = P(D|P) \* P(P) + P(D|~P) \* P(~P) = 0.99 \* 0.05 + 0.1 \* 0.95 = 0.1045

Substituting these values into Bayes' theorem, we get:

P(P|D) = 0.99 \* 0.05 / 0.1045 = 0.474

Therefore, the likelihood that there is a customer if there is a photograph is approximately 47.4%.

**10. 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.**

Ans-In the Bayesian Belief network for the match winning prediction problem in Section 6.4.4, the node Won Toss represents whether or not a team won the toss. The conditional probability table for this node can be constructed as follows,

Won Toss P(Won Toss)

Yes 0.5

No 0.5

This table indicates that there is a 50-50 chance of a team winning or losing the toss. The probabilities of other nodes in the network (such as the node representing the weather condition) will depend on whether or not the team won the toss, according to the Nave Bayes classifier assumptions.