1. Provide an example of the concepts of Prior, Posterior, and Likelihood.
2. Ans: An example of the concepts of Prior, Posterior and Likelihood: 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 P(Disease). 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 likelihood probability in this example is the probability of observing the symptoms given that the individual has the disease. This probability is represented by a likelihood function P(Symptoms|Disease). The posterior probability is the updated belief about the probability of the individual having the disease after taking into account the observed symptoms, which is represented by P(Disease|Symptoms).
3. What role does Bayes' theorem play in the concept learning principle?

Ans: Bayes' theorem plays a crucial role in the concept learning principle by allowing us to update our beliefs about the probability of a hypothesis or a parameter given new data. This is a key step in the concept learning process, as it allows us to adjust our beliefs based on new information and improve the accuracy of our predictions.

1. 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 the field of sentiment analysis. Sentiment analysis is the process of using natural language processing techniques to determine the sentiment of text data, such as news articles, social media posts, or product reviews. The Naive Bayes classifier can be used to classify the sentiment of the text as positive, negative or neutral.

The classifier is trained on a dataset of labeled text data, and then used to classify new incoming text data. The features in this case are the frequency of positive or negative words in the text and the class labels are "positive", "negative" or "neutral". The algorithm uses the Bayes' theorem to make predictions based on the frequency of words in the text and the prior probability of the text being positive, negative or neutral.

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

Ans: The Naive Bayes classifier is typically used for categorical data, where the features take on discrete values, and the goal is to predict a categorical class label. However, it can also be used for continuous numeric data by making some assumptions about the underlying probability distributions of the features and the class label.

One way to use the Naive Bayes classifier on continuous numeric data is to assume that the features and the class label follow a Gaussian distribution. This is known as the Gaussian Naive Bayes classifier. In this case, the likelihood function for a feature x, given a class label y, would be modeled as a Gaussian probability density function with parameters mean and variance.

Another way to use the Naive Bayes classifier on continuous numeric data is to use a technique called binning, which involves grouping the continuous data into discrete bins or intervals. This way, the continuous data can be treated as categorical data, and the Naive Bayes classifier can be applied as usual. This can be a good choice when the data has a high dimensionality and when it's not clear what the underlying probability distribution of the data is.

1. 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, are a type of probabilistic graphical model that represents the probabilistic relationships between a set of variables. They are a graphical representation of Bayesian reasoning, which is a method for updating beliefs about the state of the world based on new evidence.

A BBN consists of a directed acyclic graph (DAG) where each node represents a random variable and each directed edge represents the conditional dependency between two variables. The BBN uses conditional probability tables to represent the conditional probability distributions of each variable given its parents in the graph.

1. 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: To find the probability that an alarm is triggered when an individual is actually an intruder, we can use Bayes' theorem:

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

where P(I=1) = 0.00001 is the prior probability of an individual being an intruder. P(A=1|I=1) = 0.98 is the likelihood of an alarm being triggered given that the individual is an intruder. P(A=1) = P(A=1|I=1) \* P(I=1) + P(A=1|I=0) \* P(I=0)

P(I=0) = 1 - P(I=1) = 0.99999 P(A=1|I=0) = 0.001 is the likelihood of an alarm being triggered given that the individual is not an intruder.

So, P(A=1) = P(A=1|I=1) \* P(I=1) + P(A=1|I=0) \* P(I=0) = 0.98 \* 0.00001 + 0.001 \* 0.99999 = 0.00098

Therefore, P(I=1|A=1) = P(A=1|I=1) \* P(I=1) / P(A=1) = (0.98 \* 0.00001) / 0.00098 = 0.0102 or 1.02%.

So, there's a 1.02% chance that an alarm would be triggered when an individual is actually an intruder.

1. 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: To calculate the likelihood that a person who tests positive is actually immune (random variable D), we can use Bayes' theorem:

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

where:

P(D=1) = 0.02 is the prior probability of a person being immune to the antibiotic P(T=1|D=1) = 1 - 5% = 0.95 is the likelihood of a person testing positive given that they are immune P(T=1) = P(T=1|D=1) \* P(D=1) + P(T=1|D=0) \* P(D=0)

P(D=0) = 1 - P(D=1) = 0.98 is the probability of a person not being immune to the antibiotic P(T=1|D=0) = 0.01 is the likelihood of a person testing positive given that they are not immune

So, P(T=1) = P(T=1|D=1) \* P(D=1) + P(T=1|D=0) \* P(D=0) = 0.95 \* 0.02 + 0.01 \* 0.98 = 0.022

Therefore, P(D=1|T=1) = P(T=1|D=1) \* P(D=1) / P(T=1) = (0.95 \* 0.02) / 0.022 = 0.8695 or 86.95%.

So, there's an 86.95% likelihood that a person who tests positive is actually immune.

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. Ans: To calculate the likelihood that the student can solve the exam problem, you would use the conditional probability of the student solving a problem of type A, B, or C, given that the problem is of type A, B, or C. In this case, the probability of the student solving a problem of type A is 9/10, the probability of the student solving a problem of type B is 2/10 and the probability of the student solving a problem of type C is 6/10. So, the overall likelihood of the student solving the exam problem is: P(solve|A)P(A) + P(solve|B)P(B) + P(solve|C)P(C) = (9/10)(30/100) + (2/10)(20/100) + (6/10)(50/100) = 0.27 or 27%.
3. Given the student's solution, what is the likelihood that the problem was of form A?
4. Ans: To calculate the likelihood that the problem was of form A given the student's solution, you would use Bayes' theorem: P(A|solve) = P(solve|A) \* P(A) / P(solve). So, P(A|solve) = (9/10) \* (30/100) / 0.27 = 0.3 or 30%.

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. Ans: If there is a customer coming into the bank with a 5% chance in each 5-minute time period, and the bank is open for 10 hours, there will be 120 5-minute bins. So, the number of customers coming into the bank daily would be 120 \* 5% = 6 customers.
3. 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?
4. Ans: On a daily basis, if the CCTV detects a customer with a 99% probability and there are 6 customers coming into the bank, the number of customers that will be correctly detected would be 6 \* 99% = 5.94 customers. If there is no customer, the camera can take a false photograph with a 10% chance, and in 120 bins, the number of fake photographs will be 120 \* 10% = 12.
5. Explain likelihood that there is a customer if there is a photograph?
6. Ans: The likelihood that there is a customer if there is a photograph is: P(customer|photograph) = P(photograph|customer) \* P(customer) / P(photograph) = (99% \* 6) / (99% \* 6 + 10% \* 120) = approximately 0.98 or 98%.

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.