**Machine Learning Assignment 13**

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

Ans-) Assume we are interested in finding out the likelihood of a person having a certain disease. Let D represent the event of having the disease and + represent the event of testing positive for the disease. The prior probability P(D) is the initial probability of a person having the disease, let's say it's 0.1. The posterior probability P(D|+) is the probability of a person having the disease given that they tested positive. The likelihood P(+|D) is the probability of testing positive given that the person has the disease.

2. What role does Bayes’; theorem play in the concept learning principle?

Ans-) Bayes' theorem plays a crucial role in the concept learning principle as it allows us to update our prior beliefs with new evidence. In machine learning, this principle is used to update the prior probability of a hypothesis based on new data, allowing the model to learn and make predictions.

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

Ans-) Example of using Naive Bayes classifier in real life:

One of the most common uses of Naive Bayes classifier is for spam filtering in email services. The classifier analyzes the content of an incoming email and assigns a probability of it being a spam or not. If the probability of it being spam is high, it gets filtered into a separate folder, and if not, it goes to the inbox.

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

doing it?

Ans-) Yes, the Naive Bayes classifier can be used on continuous numeric data by discretizing it into intervals or by using probability density functions.

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) are graphical models that use probabilistic relationships between variables to represent complex systems. BBNs work by representing variables as nodes in a graph and conditional probabilities as edges. They have a wide range of applications in fields such as finance, medicine, and engineering. They can be used for decision-making, risk analysis, and prediction.

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 need to calculate the posterior probability of I given A, i.e., P(I = 1|A = 1), using Bayes' theorem:

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

We can calculate P(A = 1) using the law of total probability:

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

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

P(A = 1) = 0.0010098

Now we can substitute these values into the Bayes' theorem equation:

P(I = 1|A = 1) = 0.98 \* 0.00001 / 0.0010098

P(I = 1|A = 1) = 0.0097

Therefore, the probability of an alarm being triggered when an individual is actually an intruder is 0.0097 or approximately 0.97%.

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-)To calculate the likelihood that a person who tests positive is actually immune (D = 1), we need to use Bayes' theorem:

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

We are given:

P(T=1|D=1) = 0.95 (i.e., 5% false negatives)

P(T=1|D=0) = 0.01 (i.e., 1% false positives)

P(D=1) = 0.02 (i.e., 2% of those who were screened were antibiotic-resistant)

To calculate P(T=1), we need to 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) = 0.95 \* 0.02 + 0.01 \* 0.98 = 0.0291

Now we can substitute into Bayes' theorem:

P(D=1|T=1) = 0.95 \* 0.02 / 0.0291 = 0.6505

Therefore, the likelihood that a person who tests positive is actually immune (D = 1) is 65.05%.

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?

Ans-)Let's calculate the probability that the student can solve the exam problem. We can use Bayes' theorem:

P(can solve problem) = P(A) \* P(can solve problem | A) + P(B) \* P(can solve problem | B) + P(C) \* P(can solve problem | C)

where: P(A) = 0.3, P(B) = 0.2, P(C) = 0.5 P(can solve problem | A) = 9/10 = 0.9 (the student solved 9 out of 10 type A problems) P(can solve problem | B) = 2/10 = 0.2 (the student solved 2 out of 10 type B problems) P(can solve problem | C) = 6/10 = 0.6 (the student solved 6 out of 10 type C problems)

Therefore: P(can solve problem) = 0.3 \* 0.9 + 0.2 \* 0.2 + 0.5 \* 0.6 = 0.63

So, the likelihood that the student can solve the exam problem is 0.63 or 63%.

2. Given the student’s solution, what is the likelihood that the problem was of form A?

Ans-)Now let's calculate the likelihood that the problem was of form A given that the student solved it. We can use Bayes' theorem again:

P(A | can solve problem) = P(A) \* P(can solve problem | A) / P(can solve problem)

where: P(A) = 0.3 (the probability that the exam problem is of form A) P(can solve problem | A) = 9/10 = 0.9 (the probability that the student can solve a type A problem) P(can solve problem) = 0.63 (calculated in part 1)

Therefore: P(A | can solve problem) = 0.3 \* 0.9 / 0.63 = 0.4286 or 42.86%

So, the likelihood that the problem was of form A given that the student solved it is 0.4286 or 42.86%.

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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)?

Ans-)There are 6 sets of 5-minute intervals in an hour, and 60 sets in 10 hours, so the probability of a customer entering during any one 5-minute interval is 5% or 0.05. Therefore, the expected number of customers coming in during one 5-minute interval is 0.05 x 1 = 0.05. Over a 10-hour period, the expected number of customers entering the bank would be:

0.05 x 6 x 60 = 18 customers

So, on average, 18 customers are expected to come into the bank on a daily basis.

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?

Ans-)The probability of a false photograph being taken when there is no customer is 10% or 0.1. Therefore, the expected number of false photographs taken during one 5-minute interval is:

0.1 x 1 = 0.1

And over 10 hours, the expected number of false photographs taken would be:

0.1 x 6 x 60 = 36 photographs

The probability of a missed photograph being taken when there is a customer is 1% or 0.01. Therefore, the expected number of missed photographs taken during one 5-minute interval is:

0.01 x 1 = 0.01

And over 10 hours, the expected number of missed photographs taken would be:

0.01 x 6 x 60 = 3.6 photographs

So, on average, 36 false photographs and 3.6 missed photographs are expected to be taken on a daily basis.

3. Explain likelihood that there is a customer if there is a photograph?

Ans-)If there is a photograph, the probability that there is a customer can be calculated using Bayes' theorem:

P(customer|photograph) = P(photograph|customer) x P(customer) / P(photograph)

where:

P(customer|photograph) is the probability of a customer given a photograph P(photograph|customer) is the probability of a photograph given a customer, which is 0.99 P(customer) is the probability of a customer, which is 0.05 P(photograph) is the probability of a photograph, which can be calculated using the law of total probability:

P(photograph) = P(photograph|customer) x P(customer) + P(photograph|no customer) x P(no customer) = 0.99 x 0.05 + 0.1 x 0.95 = 0.1045

Therefore,

P(customer|photograph) = 0.99 x 0.05 / 0.1045 = 0.474

So, if there is a photograph, the likelihood that there is a customer is 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-)Assuming that the features used in the Naive Bayes classifier for the match winning prediction problem are "Home Team", "Away Team", "Venue", and "Toss Winner", the conditional probability table for the node "Won Toss" would be:

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

This table represents the assumption that the outcome of the toss is independent of all other features, and that the probability of winning the toss is equal for both teams.