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

#### Ans: concepts of Prior, Posterior, and Likelihood.

#### Example 1: Fair Dice Roll

A six-sided fair dice is rolled. What is the a priori probability of rolling a 2, 4, or 6, in a dice roll?

The number of desired outcomes is 3 (rolling a 2, 4, or 6), and there are 6 outcomes in total. The a priori probability for this example is calculated as follows:

A priori probability = 3 / 6 = 50%. Therefore, the a priori probability of rolling a 2, 4, or 6 is 50%.

Suppose an individual is chosen from a high school population at random.  The probability of choosing a female individual is 50%.  The probability of choosing an individual with brown hair is 40%.  The conditional probability that the individual is female and with brown hair is 20%.  If the individual extracted at random from the high school population is female, what is the conditional probability that she also has brown hair?  This is an example of posterior probability and it can be calculated using Bayes’ Formula.

* P(female) = 0.5
* P(brown hair) = 0.4
* P(female/brown hair) = 0.2

Probability(female/brown hair) = {P(brown hair/female) x P(female)} / P(brown hair)

P(female/brown hair) = (0.2 x 0.5) / (0.4).

The posterior probability of choosing a female with brown hair = 0.25 or a 1 in 4 chance.

Suppose we have a coin that is assumed to be fair. If we flip the coin one time, the probability that it will land on heads is 0.5. Now suppose we flip the coin 100 times and it only lands on heads 17 times. We would say that the likelihood that the coin is fair is quite low. If the coin was actually fair, we would expect it to land on heads much more often.

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

Ans: Bayes' theorem play important role in the concept learning principle which is as follows.

The Bayes theorem is a method for calculating a hypothesis’s probability based on its prior probability, the probabilities of observing specific data given the hypothesis, and the seen data itself. The Bayes theorem determines the posterior probability of each hypothesis. It calculates the likelihood of each conceivable hypothesis before determining which is the most likely.

It is a method to calculate the posterior probability of h from the prior probability P(h) together with P(D) and P(D|h) where D is training data and H is hypothesis space .

P(D|h) is called the likelihood of the data D given h

• If every hypothesis in H is equally probable a priori (P(hi) = P(hj) for all hi and hj

• Any hypothesis that maximizes P(D|h) is called a maximum likelihood (ML) hypothesis, hML= hargmax P(D | h) h €H

Output the hypothesis hMAP with the highest posterior probability given as:

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confidence](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RDaRXhpZgAATU0AKgAAAAgABAE7AAIAAAAFAAAISodpAAQAAAABAAAIUJydAAEAAAAKAAAQyOocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFVzZXIAAAAFkAMAAgAAABQAABCekAQAAgAAABQAABCykpEAAgAAAAMxNwAAkpIAAgAAAAMxNwAA6hwABwAACAwAAAiSAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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Given no previous information of which hypothesis is more likely, it is fair to give each hypothesis h in H the same prior probability. We should require that these prior probabilities amount to 1 because we presume the target notion is contained in H.Two cases:

Case 1: h is inconsistent with the training data D.

Case 2: Consider a case where h is consistent with D

After considering case 1 and 2 , Bayes theorem implies that the posterior probability p(h/D) under the assumed P(h) and P(D/h) is

A screenshot of a computer

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

Ans: Suppose we have a dataset of **weather conditions** and corresponding target variable "**Play**". So using this dataset we need to decide that whether we should play or not on a particular day according to the weather conditions. So to solve this problem, we need to follow the below steps:

1. Convert the given dataset into frequency tables.
2. Generate Likelihood table by finding the probabilities of given features.
3. Now, use Bayes theorem to calculate the posterior probability.
4. **Frequency table for the Weather Conditions:**

|  |  |  |  |
| --- | --- | --- | --- |
| Weather | Yes | No | |
| Overcast | 5 | 0 | |
| Rainy | 2 | 2 | |
| Sunny | 3 | 2 | |
| Total | 10 | 5 | |
| Weather | No | | Yes | Frequency |
| Overcast | 0 | | 5 | 5/14= 0.35 |
| Rainy | 2 | | 2 | 4/14=0.29 |
| Sunny | 2 | | 3 | 5/14=0.35 |
| All | 4/14=0.29 | | 10/14=0.71 |  |

**Applying Bayes'theorem:**

**P(Yes|Sunny)= P(Sunny|Yes)\*P(Yes)/P(Sunny)**

P(Sunny|Yes)= 3/10= 0.3

P(Sunny)= 0.35

P(Yes)=0.71

So P(Yes|Sunny) = 0.3\*0.71/0.35= **0.60**

**P(No|Sunny)= P(Sunny|No)\*P(No)/P(Sunny)**

P(Sunny|NO)= 2/4=0.5

P(No)= 0.29

P(Sunny)= 0.35

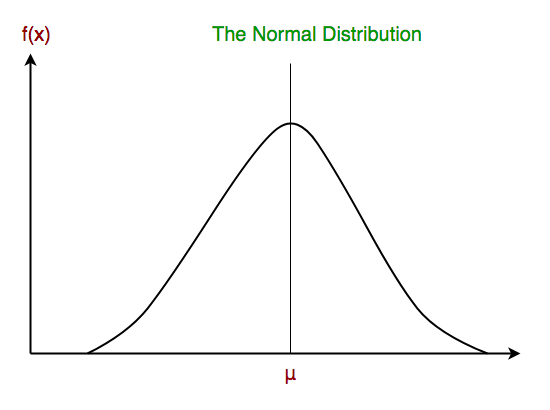
So P(No|Sunny)= 0.5\*0.29/0.35 = **0.41**

So as we can see from the above calculation that **P(Yes|Sunny)>P(No|Sunny)**

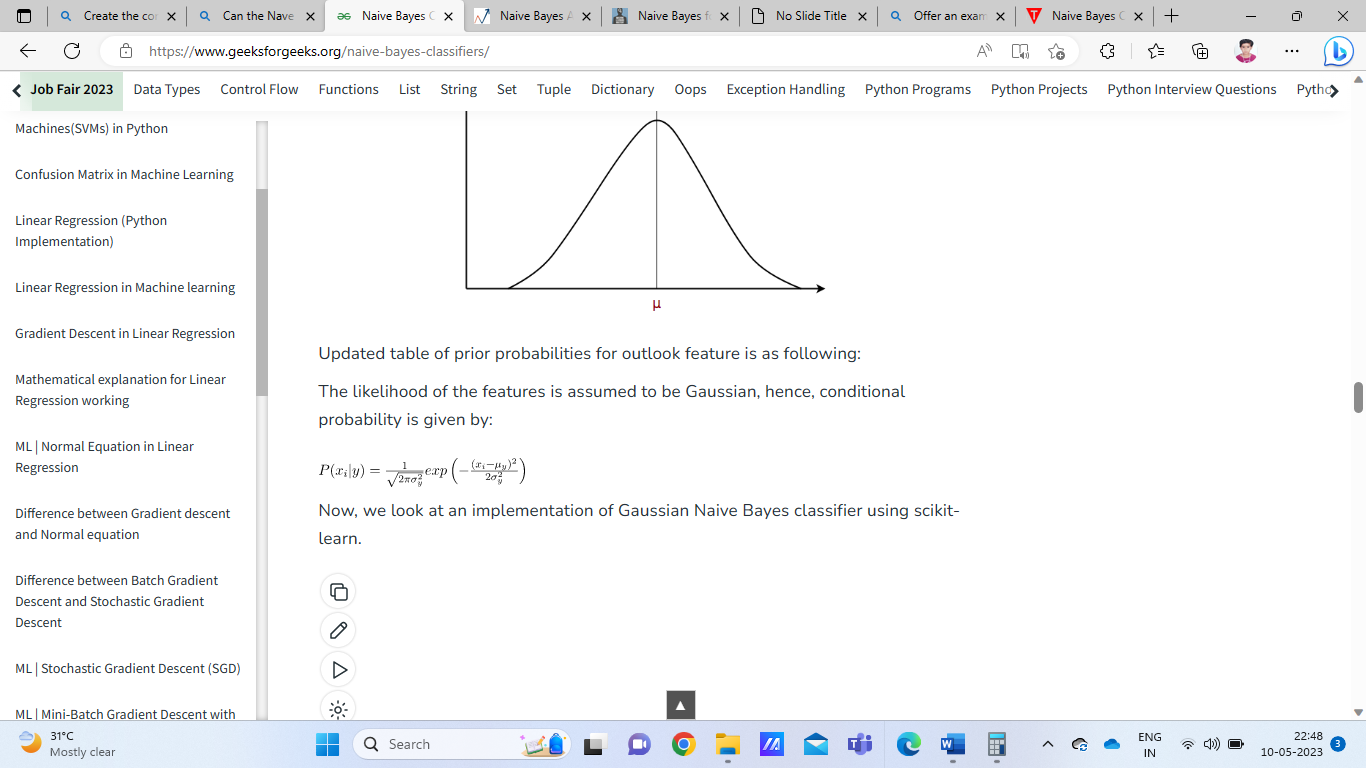
**Hence on a Sunny day, Player can play the game.**

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

### Ans: Gaussian Naive Bayes is used when variables are continuous in nature. It assumes that all the variables have a normal distribution. So if not ,then transform them to the features having distribution normal. In Gaussian Naive Bayes, continuous values associated with each feature are assumed to be distributed according to a Gaussian distribution. A Gaussian distribution is also called [Normal distribution](https://en.wikipedia.org/wiki/Normal_distribution). When plotted, it gives a bell shaped curve which is symmetric about the mean of the feature values as shown below:



The likelihood of the features is assumed to be Gaussian, hence, conditional probability is given by:

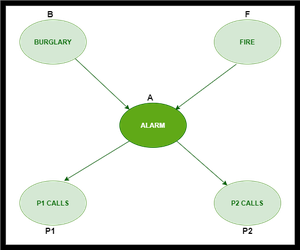


Follow training and predict steps

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 Networks, also known as Belief Networks or Bayes Nets, are a powerful probabilistic graphical model used for reasoning under uncertainty. They have been successfully applied to a wide range of tasks, including diagnostics, decision support systems, and natural language processing. **Bayesian Belief Network**is a graphical representation of different probabilistic relationships among random variables in a particular set. It is a classifier with no dependency on attributes i.e it is condition independent. Due to its feature of joint probability, the probability in Bayesian Belief Network is derived, based on a condition — P(attribute/parent) i.e probability of an attribute, true over parent attribute.

* Consider this example:



* In the above figure, we have an alarm ‘A’ – a node, say installed in a house of a person ‘gfg’, which rings upon two probabilities i.e burglary ‘B’ and fire ‘F’, which are – parent nodes of the alarm node. The alarm is the parent node of two probabilities P1 calls  ‘P1’ & P2 calls ‘P2’ person nodes.
* Upon the instance of burglary and fire, ‘P1’ and ‘P2’ call person ‘gfg’, respectively. But, there are few drawbacks in this case, as sometimes ‘P1’ may forget to call the person ‘gfg’, even after hearing the alarm, as he has a tendency to forget things, quick.  Similarly, ‘P2’, sometimes fails to call the person ‘gfg’, as he is only able to hear the alarm, from a certain distance.

Find the probability that ‘P1’ is true (P1 has called ‘gfg’), ‘P2’ is true (P2 has called ‘gfg’) when the alarm ‘A’ rang, but no burglary ‘B’ and fire ‘F’ has occurred.  P ( P1, P2, A, ~B, ~F) [ where- P1, P2 & A are ‘true’ events and ‘~B’ & ‘~F’ are ‘false’ events]

Bayesian Networks can be used for various tasks, including:

Prediction: Estimating the probability of a variable's value given the values of other variables.

Diagnosis: Identifying the most likely cause of an observed outcome.

Decision making: Evaluating the expected utility of different actions and choosing the optimal action.  
  
Bayesian Networks can be used for various tasks, including: Prediction: Estimating the probability of a variable's value given the values of other variables. Diagnosis: Identifying the most likely cause of an observed outcome. Decision making: Evaluating the expected utility of different actions and choosing the optimal action.  
Bayesian Networks offer a powerful and flexible approach to reasoning under uncertainty, with applications spanning various fields. Their ability to model complex probabilistic relationships and make reliable inferences, even with limited data, make them a valuable tool in the realm of artificial intelligence.

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:Using Bayesian theorem.

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

= P(A = 1|I= 1)P(I = 1)/ P(A = 1|I = 1)P(I= 1) + P(A = 1|I= 0)P(I = 0)

= 0.98 × 0.00001 / 0.98 × 0.00001 + 0.001 × (1 − 0.00001)

= 0.0097

≈ 0.00001 /0.001 = 0.01

It is interesting that even though for any passenger it can be decided with high reliability (98% and 99.9%) whether (s)he is a intruder t or not, if somebody gets arrested as a intruder, (s)he is still most likely not a intruder (with a probability of 99%).

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:

T = p means Test positive,

T = n means Test negative,

D = p means person immmue (takes drug),

D = n means person does not immmue(not taken drugs)

We know:

P(T = p|D = n) = 0.01 (false positives)

(false negatives) P(T = n|D = p) = 0.05 =⇒ P(T = p|D = p) = 0.95 (true positives)

P(D = p) = 0.02 =⇒ P(D = n) = 0.98

We want to know the probability that somebody who tests positive is actually taking drugs:

P(D = p|T = p) = P(T = p|D = p)P(D = p)/ P(T = p) (Bayes theorem)

We do not know P(T = p): P(T = p) = P(T = p|D = p)P(D = p) + P(T = p|D = n)P(D = n)

We get: P(D = p|T = p) = P(T = p|D = p)P(D = p) P(T = p) (7) = P(T = p|D = p)P(D = p) P(T = p|D = p)P(D = p) + P(T = p|D = n)P(D = n)

= 0.95 · 0.02 0.95 · 0.02 + 0.01 · 0.98

= 0.019/0.0288 ≈ 0.66

There is a chance of only two thirds that someone with a positive test is actually taking drugs.

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: Solution: The probability to solve the problem of the exam is the probability of getting a problem of a certain type times the probability of solving such a problem, summed over all types. This is known as the total probability.

P(solved) = P(solved|A)P(A) + P(solved|B)P(B) + P(solved|C)P(C) (1)

= 9/10 · 30% + 2/10 · 20% + 6/10 · 50% (2)

= 27/100 + 4/100 + 30/100 = 61/100 = 0.61 (3)

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

Solution: For this to answer we need Bayes theorem.

P(A|solved) = P(solved|A)P(A) P(solved) (4)

= 9/10 · 30% 61/100 = 27/100 61/100 = 27 61 = 0.442... . (5)

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 10x12 = 120 five-minute periods per day. In each period there is a probability of 5% for an customerbeing present. Thus the average number of customers is 120×5% = 120×0.05 = 6.

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: On average there is no customer in 120− 6 of the five-minute periods. This times the probability of 10% per period for a false alarm yields (120-6) × 10% = 114 × 0.1 = 11.4 false alarms. On average there are 6 customers, each of which has a probability of 1% of getting missed. Thus the number of false photographs is 6× 1% = 0.06

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

Ans:P(customer|photograph) = P(photograph|customer)P(customer)/ P(photograh) (1)

P(photograh) =P(photograph | customer)P(customer) + P(photograph |no customer)P(no customer) (3)

P(photograh) = 0.99 \*0.05 + 0.1 \* (1 − 0.05) =0.15

Substituting (3) in (1)

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

=0.99\*0.05/0.15

= 0.342

It might be somewhat surprising that the probability of customer being present given photograph is only 34% even though the detection of customer is so reliable (99%). The reason is that customers are not so frequent (only 5%) and the probability for photograph given no airplane is relatively high (10%).

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:section 6.4.4 not mentioned