## Q1

Example of Prior, Posterior, and Likelihood:

Suppose you are diagnosing a medical condition based on test results.

Prior Probability (Prior): Before conducting the tests, you estimate the patient's probability of having the condition based on general statistics, say P(condition).

Likelihood Probability (Likelihood): You calculate the probability of obtaining the test results you observe if the patient has the condition, P(test results | condition), and if the patient doesn't have the condition, P(test results | ~condition).

Posterior Probability (Posterior): After receiving the test results, you use Bayes' theorem to update your estimate of the patient having the condition, P(condition | test results), based on the prior and likelihood.

## Q2

Role of Bayes' Theorem in Concept Learning: Bayes' theorem is fundamental in concept learning, particularly in probabilistic classifiers like Naïve Bayes. It allows us to update our beliefs (posterior) about a concept based on observed data (likelihood) and prior knowledge (prior). In essence, it provides a principled way to perform classification and make predictions based on evidence.

## Q3

Example of Naïve Bayes Classifier in Real Life:

Email Spam Detection: In email systems, Naïve Bayes classifiers are used to classify incoming emails as spam or not spam. It calculates the probability of an email being spam or legitimate based on the occurrence of specific words or features in the email content.

## Q4

Using Naïve Bayes for Continuous Numeric Data: Yes, Naïve Bayes can be used for continuous numeric data. To do this, you typically discretize the continuous data into intervals or use probability density functions (PDFs) to model the continuous distribution. Gaussian Naïve Bayes is a common variant that assumes a Gaussian (normal) distribution for continuous features.

## Q5

Bayesian Belief Networks (BBNs):

BBNs are probabilistic graphical models that represent and reason about uncertainty and dependencies among random variables.

They consist of nodes (random variables) and edges (conditional dependencies).

Applications include risk assessment, medical diagnosis, and fault detection in complex systems.

BBNs can resolve a wide range of issues by modeling complex probabilistic relationships and making probabilistic inferences.

## Q6

To find the chances that an alarm would be triggered when an individual is actually an intruder, we can use Bayes' theorem. We want to calculate P(I = 1 | A = 1), which is the probability of an individual being an intruder given that an alarm (A = 1) was triggered.

Prior Probability: P(I = 1) = 0.00001 (The probability of an individual being an intruder).

Likelihood Probability: P(A = 1 | I = 1) = 0.98 (The probability of an alarm given an intruder).

Likelihood Probability: P(A = 1 | I = 0) = 0.001 (The probability of an alarm given no intruder).

We use Bayes' theorem:

the chances that an alarm would be triggered when an individual is actually an intruder are approximately 0.0000097, or about 0.00097%.

## Q7

To calculate the likelihood that a person who tests positive is actually immune (random variable D), we can use Bayes' theorem. We want to find P(D = 1 | T = 1), which is the probability of being immune given a positive test result.

The probability of a false positive: P(T = 1 | D = 0) = 0.01 (1% of those who are not immune test positive).

The probability of a false negative: P(T = 0 | D = 1) = 0.05 (5% of those who are immune test negative).

The probability of being antibiotic-resistant: P(D = 1) = 0.02 (2% of those screened are immune).

We use Bayes' theorem:

the likelihood that a person who tests positive is actually immune (D = 1) is approximately 0.6597 or 65.97%. This means that there's a relatively high probability that someone who tests positive is indeed immune to the antibiotic.

## Q8

1.

To find the likelihood that the student can solve the exam problem, we need to consider the student's preparation in each category (A, B, C) and the probability of encountering a question from each category.

Probability of getting a question from A category (P(A)) = 30% = 0.30

Probability of getting a question from B category (P(B)) = 20% = 0.20

Probability of getting a question from C category (P(C)) = 50% = 0.50

using the law of total probability:

L\_solve = P(A) \* L\_solve\_given\_A + P(B) \* L\_solve\_given\_B + P(C) \* L\_solve\_given\_C

L\_solve\_given\_A = 9/10

L\_solve\_given\_B = 2/10

L\_solve\_given\_C = 6/10

L\_solve = 0.30 \* (9/10) + 0.20 \* (2/10) + 0.50 \* (6/10)

L\_solve = 0.27 + 0.04 + 0.30

L\_solve = 0.61

So, the likelihood that the student can solve the exam problem is 0.61 or 61%.

2.

To find the likelihood that the problem was of form A given the student's solution, we use Bayes' theorem:

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

P(A | Solve) = (0.27 \* 0.30) / 0.61

Calculate P(A | Solve):

P(A | Solve) ≈ 0.133

So, given the student's solution, the likelihood that the problem was of form A is approximately 0.133 or 13.3%.

## Q9

**1.**

In each 5-minute bin, there is a 5% chance of a customer coming in. Since there are 12 of these bins in an hour (60 minutes / 5 minutes), the probability of a customer coming in during an hour is:

Probability of customer in an hour (P\_customer) = 5% = 0.05

In 10 hours, the probability of a customer coming in is:

P\_customer\_10\_hours = 10 hours \* P\_customer

Calculate P\_customer\_10\_hours:

P\_customer\_10\_hours = 10 \* 0.05 = 0.5

So, on average, 0.5 customers come into the bank in 10 hours.

**2.**

In each 5-minute bin, there is a 5% chance of a customer coming in and a 95% chance of no customer. Let's calculate the probabilities for different scenarios:

Probability of a customer coming in (P\_customer) = 5% = 0.05

Probability of no customer coming in (P\_no\_customer) = 95% = 0.95

Now, let's consider the probabilities of different outcomes:

Probability of a customer coming in and being detected (P\_detected\_customer) = P\_customer \* 0.99

Probability of a customer coming in but not being detected (P\_missed\_customer) = P\_customer \* (1 - 0.99)

Probability of no customer coming in and a false photograph being taken (P\_false\_photograph) = P\_no\_customer \* 0.10

Number of fake photographs = P\_false\_photograph \* 120

Number of missed photographs = P\_missed\_customer \* 120

Number of fake photographs = 0.95 \* 0.10 \* 120

Number of missed photographs = 0.05 \* (1 - 0.99) \* 120

Number of fake photographs ≈ 11.4

Number of missed photographs ≈ 0.6

So, on a daily basis, there are approximately 11.4 fake photographs and about 0.6 missed photographs.

**3.**

To find the likelihood that there is a customer if there is a photograph (P(customer | photograph)), we can use Bayes' theorem:

P(customer | photograph) = (P(photograph | customer) \* P(customer)) / P(photograph)

P(customer | photograph) = (0.99 \* 0.05) / P(photograph)

Calculate P(customer | photograph):

P(customer | photograph) ≈ (0.99 \* 0.05) / (0.95 \* 0.10 + 0.05 \* (1 - 0.99))

P(customer | photograph) ≈ 0.341

So, the likelihood that there is a customer if there is a photograph is approximately 0.341 or 34.1%.

## Q10

To create a conditional probability table (CPT) for the "Won Toss" node in a Bayesian Belief Network (BBN) for the match winning prediction problem. In a Naive Bayes classifier, we assume conditional independence, which means that the outcome (winning or losing) of a match depends only on whether the team has won the toss.

Let's assume the "Won Toss" node has two states: "Yes" and "No," indicating whether the team has won the toss or not. And let's assume the "Match Win" node has two states: "Win" and "Lose," indicating whether the team wins or loses the match.

| Won Toss | P(Match Win = Win | Won Toss) | P(Match Win = Lose | Won Toss) |

| | | |

| Yes | P(Win | Yes) | P(Lose | Yes) |

| No | P(Win | No) | P(Lose | No) |

In this table:

"P(Match Win = Win | Won Toss)" represents the probability of winning the match given that the team has won the toss.

"P(Match Win = Lose | Won Toss)" represents the probability of losing the match given that the team has won the toss.