Task 1 – Accident prediction with Naïve Bayes
Instance: X = (Weather = Rain, Road = Good, Traffic = Normal, Engine = No)

1. Priors
   P(Accident = Yes) = 5/10 = 0.5
   P(Accident = No) = 5/10 = 0.5

2. Likelihoods for Accident = Yes
   P(Rain | Yes) = 1/5
   P(Good | Yes) = 1/5
   P(Normal | Yes) = 1/5
   P(Engine = No | Yes) = 2/5

P(X | Yes) = (1/5) × (1/5) × (1/5) × (2/5) = 2/625
P(Yes | X) ∝ 0.5 × 2/625 = 1/625

3. Likelihoods for Accident = No
   P(Rain | No) = 2/5
   P(Good | No) = 3/5
   P(Normal | No) = 2/5
   P(Engine = No | No) = 4/5

P(X | No) = (2/5) × (3/5) × (2/5) × (4/5) = 48/625
P(No | X) ∝ 0.5 × 48/625 = 24/625

4. Normalised posterior probabilities
   P(Yes | X) = (1/625) / (1/625 + 24/625) = 1/25 = 0.04
   P(No | X) = (24/625) / (1/625 + 24/625) = 24/25 = 0.96

Decision: Since 0.96 > 0.04, the Bayes classifier predicts
Accident = No for X = (Rain, Good, Normal, No).

Task 2 – Weather-Based Game Prediction (Naïve Bayes, no smoothing)

Dataset size: 14
Play = yes : 9 → P(Yes) = 9/14
Play = no : 5 → P(No) = 5/14

Question 1

X = (sunny, hot, high, false)

Given Play = Yes (9 rows)

- P(outlook=sunny | Yes) = 2/9
- P(temp=hot | Yes) = 2/9
- P(humidity=high | Yes) = 3/9
- P(windy=false | Yes) = 6/9

P(X | Yes) = (2/9)(2/9)(3/9)(6/9) = 8/729

$P(Yes \mid X) \propto P(Yes)P(X|Yes) = (9/14)(8/729) = 12/1701$

Given Play = No (5 rows)

- $P(outlook=sunny \mid No) = 3/5$
- $P(temp=hot \mid No) = 2/5$
- $P(humidity=high \mid No) = 4/5$
- $P(windy=false \mid No) = 2/5$

$P(X \mid No) = (3/5)(2/5)(4/5)(2/5) = 48/625$

$P(No \mid X) \propto P(No)P(X|No) = (5/14)(48/625) = 24/875$

Normalising:

- $P(Yes \mid X) \approx 0.20$
- $P(No \mid X) \approx 0.80$

Bayes classifier decision for X: play = no.

Question 2

In Table 1, the row (sunny, hot, high, false) has play = no.
So yes, the Bayes classifier agrees with the table.

Question 3

X' = (overcast, cool, high, true)

Given Play = Yes

- $P(outlook=overcast \mid Yes) = 4/9$
- $P(temp=cool \mid Yes) = 3/9$
- $P(humidity=high \mid Yes) = 3/9$
- $P(windy=true \mid Yes) = 3/9$

$P(X' \mid Yes) = (4/9)(3/9)(3/9)(3/9) = 4/243$

$P(Yes \mid X') \propto (9/14)(4/243) = 6/567$

Given Play = No

No “overcast” cases in the 5 “no” rows, so
$P(outlook=overcast \mid No) = 0 \rightarrow P(X' \mid No) = 0 \rightarrow P(No \mid X') = 0$

Therefore the Bayes classifier chooses:

play = yes for X' = (overcast, cool, high, true).

Task 3 – Loan Approval (Naïve Bayes)

Dataset

- 5 records
- LoanApproved = Yes → 3 times
- LoanApproved = No → 2 times

P(Yes) = 3/5
P(No) = 2/5

1. Applicant: Employed, Good, Medium

Given “Yes” rows:

(Employed, Good, High)
(Employed, Good, Medium)
(Unemployed, Good, Low)

- P(Employed | Yes) = 2/3
- P(Good | Yes) = 3/3
- P(Medium | Yes) = 1/3

P(X | Yes) = (2/3)(1)(1/3) = 2/9
P(Yes | X) ∝ (3/5)(2/9)

Given “No” rows:

(Unemployed, Bad, Low)
(Employed, Bad, Medium)

- P(Good | No) = 0 → probability becomes 0

Prediction:

LoanApproved = YES

2. Applicant: Unemployed, Bad, Low

Given “No” rows:

Unemployed, Bad, Low
Employed, Bad, Medium

- P(Unemployed | No) = 1/2
- P(Bad | No) = 2/2
- P(Low | No) = 1/2

$P(X \mid No) = (1/2)(1)(1/2) = 1/4$
$P(No \mid X) \propto (2/5)(1/4)$

Given "Yes" rows:

No "Bad credit" → probability = 0

Prediction:

LoanApproved = NO

3. Effect of Scoring System

If the bank assigns scores (e.g., Employed = 3, Unemployed = 1), then:

- Naïve Bayes will treat features like numbers instead of categories.
- Bigger scores → higher probability for approval.
- It changes how probabilities are calculated but the idea is the same.

Task 4 – Disease Diagnosis

Dataset counts:
Positive = 3
Negative = 2

$P(Pos) = 3/5$
$P(Neg) = 2/5$

1. X = (Fever=Yes, Cough=No, Fatigue=Yes, Travel=No)

Positive rows: 3

- Fever Yes = 3/3
- Cough No = 2/3
- Fatigue Yes = 3/3
- Travel No = 2/3

$P(X \mid Pos) = (1)(2/3)(1)(2/3)$
Negative has Fever=Yes = 0 → $P(X \mid Neg) = 0$

Prediction: Positive

2. X = (Fever=No, Cough=Yes, Fatigue=No, Travel=No)

Negative rows: 2

- Fever No = 2/2

- Cough Yes = 2/2
- Fatigue No = 2/2
- Travel No = 1/2

P(X | Neg) = (1)(1)(1)(1/2)
Positive has Fever=No = 0 → P(X | Pos) = 0

Prediction: Negative

3. Effect of travel weighting

If travel doubles the probability:

- TravelHistory contributes more to P(X | Class)
- A patient with recent travel becomes more likely to be classified Positive

Conclusion: Weighted travel increases Positive prediction.