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K.V.G COLLEGE OF ENGINEERING, SULLIA, D.K. – 574 327

(AFFILIATED TO VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELAGAVI)

DEPARTMENT COMPUTER SCIENCE AND ENGINEERING(AI&ML)

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PRACTICAL COMPONENT OF

MACHINE LEARNING II

COURSE CODE: BAI702

VII SEMESTER

Course Material Prepared by **Course Material Approved by**

LIST OF EXPERIMENTS

Sl. No.	Experiment	Page No.	Marks Awarded	Staff Signature
1	Read a dataset from the user and i. Use the Find-S algorithm to find the most specific hypothesis that is consistent with the positive examples. Ii. What is the final hypothesis after processing all the positive examples? Using the same dataset, apply the Candidate Elimination algorithm. Determine the final version space after processing all examples (both positive and negative). What are the most specific and most general hypotheses in the version space?			
2	Read a dataset and use an example-based method (such as RIPPER or CN2) to generate a set of classification rules . Apply the FOIL algorithm (First-Order Inductive Learner) to learn first-order rules for predicting.			
3	Read a supervised dataset and use bagging and boosting technique to classify the dataset. Indicate the performance of the model.			
4	Read an unsupervised dataset and group the dataset based on similarity based on k-means clustering .			
5	Read a dataset and perform unsupervised learning using SOM algorithm.			
6	Write a function to generate uniform random numbers in the interval [0, 1]. Use this function to generate 10 random samples and evaluate f(x) for each sample. What are the sampled function values? Using the samples generated in the previous step, estimate the integral I using the Monte Carlo method.			
7	Read a dataset and indicate the likelihood of an event occurring using Bayesian Networks.			
8	Refer to the dataset in question 7 and indicate inferences based on the sequence of steps .			
Average Marks Out of :				

Marks Distribution	**Max. Marks**	**Marks Awarded**
Average Marks Scaled Up		
Lab Test Marks		
Total Marks in the Practical Component of the Course		
Signature of the Staff with date		

Experiment 1: Read a dataset from the user and i. Use the Find-S algorithm to find the most specific hypothesis that is consistent with the positive examples. Ii. What is the final hypothesis after processing all the positive examples? Using the same dataset, apply the Candidate Elimination algorithm. Determine the final version space after processing all examples (both positive and negative). What are the most specific and most general hypotheses in the version space?

Code Implementation:

```
import pandas as pd


# Load dataset
df = pd.read_csv("C:/Users/CS&E/Downloads/exp1_data.csv")
X = df.iloc[:, :-1].values  # Features
y = df.iloc[:, -1].values   # Target


# ------------ FIND-S Algorithm ------------ #
def find_s(X, y):
    hypothesis = X[0].copy()
    for i in range(len(y)):
        if y[i] == "Yes":
            for j in range(len(hypothesis)):
                if X[i][j] != hypothesis[j]:
                    hypothesis[j] = "?"
    return hypothesis


final_hypothesis = find_s(X, y)
print("=== FIND-S RESULT ===")
print("Most Specific Hypothesis:", final_hypothesis)
```

```
# ------------ CANDIDATE ELIMINATION ------------ #
num_attributes = X.shape[1]
S = list(X[0])  # Most specific hypothesis
G = [['?' for _ in range(num_attributes)]]  # Most general hypothesis

# Function to check if a hypothesis matches an instance
def matches(hypothesis, instance):
    return all(h == '?' or h == val for h, val in zip(hypothesis, instance))

# Function to check consistency of a hypothesis with all examples
def is_consistent(hypothesis, X, y):
    for xi, yi in zip(X, y):
        if matches(hypothesis, xi) and yi == "No":
            return False
        if not matches(hypothesis, xi) and yi == "Yes":
            return False
    return True

# Candidate Elimination Loop
for i, instance in enumerate(X):
    if y[i] == 'Yes':  # Positive example
        for j in range(num_attributes):
            if S[j] != instance[j]:
                S[j] = '?'
        G = [g for g in G if matches(g, instance)]
    else:  # Negative example
        new_G = []
        for g in G:
```

```
        for j in range(num_attributes):
            if g[j] == '?':
                if S[j] != '?':
                    new_hypothesis = g.copy()
                    new_hypothesis[j] = S[j]
                    if is_consistent(new_hypothesis, X, y):
                        if new_hypothesis not in new_G:
                            new_G.append(new_hypothesis)
    G = new_G

print("\n=== CANDIDATE ELIMINATION RESULT ===")
print("Final Specific Hypothesis (S):", S)
print("Final General Hypotheses (G):")
for g in G:
    print(g)
```

Output:

```
=== FIND-S RESULT ===
Most Specific Hypothesis: ['Sunny' 'Warm' '?' 'Strong' '?' '?']
=== CANDIDATE ELIMINATION RESULT ===
Final Specific Hypothesis (S): ['Sunny' 'Warm' '?' 'Strong' '?' '?']
Final General Hypotheses (G):
['Sunny', '?', '?', '?', '?', '?']
['?', 'Warm', '?', '?', '?', '?']
```

Experiment 2: Read a dataset and use an example-based method (such as RIPPER or CN2) to generate a set of classification rules . Apply the FOIL algorithm (First-Order Inductive Learner) to learn first-order rules for predicting.

Code Implementation:

```
import pandas as pd

# Load dataset

df = pd.read_csv("exp2&3_data.csv")  # CSV should have a "Fruit" column as target

# Split features and target

X = df.iloc[:, :-1].values  # Features

y = df.iloc[:, -1].values   # Target

attributes = list(df.columns[:-1])

target_class = "Apple"  # You can change this as needed

def foil(X, y, attributes, target_class):

    rules = []
```

```
    used_indices = set()

    for i in range(len(X)):
        if y[i] != target_class or i in used_indices:
            continue

        rule = []
        for j in range(len(attributes)):
            attr_val = X[i][j]
            rule.append((j, attr_val))

        # Try all subsets of conditions to form a good rule
        for k in range(len(rule), 0, -1):
            from itertools import combinations
            for conds in combinations(rule, k):
                # Check if this subset covers only positive examples
                matches_target = []
                matches_others = []
                for m in range(len(X)):
                    if all(X[m][j] == val for j, val in conds):
                        if y[m] == target_class:
                            matches_target.append(m)
                        else:
                            matches_others.append(m)
                if matches_target and not matches_others:
                    # Valid rule found
                    rule_str = " AND ".join(f"{attributes[j]} = {val}" for j, val in conds)
                    rules.append(f"IF {rule_str} THEN {target_class}")
                    used_indices.update(matches_target)
```

```
                break
            else:
                continue
            break

    return rules
def cn2_like(X, y, attributes):
    rules = []
    seen = set()
    for i in range(len(X)):
        rule = []
        for j in range(len(attributes)):
            rule.append(f"{attributes[j]} = {X[i][j]}")
        rule_str = f"IF {' AND '.join(rule)} THEN {y[i]}"
        if rule_str not in seen:
            seen.add(rule_str)
            rules.append(rule_str)
    return rules
foil_rules = foil(X, y, attributes, target_class)
cn2_rules = cn2_like(X, y, attributes)
print("\n=== CN2-like Example-based Rules ===")
for r in cn2_rules:
    print(r)
print("\n=== FOIL-style Rules to predict:", target_class, "===")
for r in foil_rules:
    print(r)
```

Output:

=== CN2-like Example-based Rules ===

IF Color = Red AND Shape = Small AND Size = Oblong THEN Apple

IF Color = Yellow AND Shape = Large AND Size = Oblong THEN Banana

IF Color = Green AND Shape = Medium AND Size = Round THEN Apple

IF Color = Red AND Shape = Medium AND Size = Oblong THEN Cherry

IF Color = Yellow AND Shape = Medium AND Size = Round THEN Banana

IF Color = Green AND Shape = Small AND Size = Oblong THEN Watermelon

IF Color = Red AND Shape = Large AND Size = Oblong THEN Cherry

IF Color = Yellow AND Shape = Large AND Size = Round THEN Banana

IF Color = Red AND Shape = Small AND Size = Round THEN Apple

IF Color = Red AND Shape = Large AND Size = Round THEN Apple

IF Color = Green AND Shape = Small AND Size = Round THEN Apple

IF Color = Green AND Shape = Large AND Size = Oblong THEN Watermelon

IF Color = Yellow AND Shape = Medium AND Size = Oblong THEN Banana

IF Color = Red AND Shape = Medium AND Size = Round THEN Cherry

IF Color = Yellow AND Shape = Small AND Size = Round THEN Banana

IF Color = Green AND Shape = Large AND Size = Round THEN Watermelon

IF Color = Green AND Shape = Medium AND Size = Oblong THEN Watermelon

=== FOIL-style Rules to predict: Apple ===

IF Color = Red AND Shape = Small AND Size = Oblong THEN Apple

IF Color = Green AND Shape = Medium AND Size = Round THEN Apple

IF Color = Red AND Shape = Small AND Size = Round THEN Apple

IF Color = Red AND Shape = Large AND Size = Round THEN Apple

IF Color = Green AND Shape = Small AND Size = Round THEN Apple

Experiment 3: Read a supervised dataset and use bagging and boosting technique to classify the dataset. Indicate the performance of the model. Code Code Implementation:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import BaggingClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
# Step 1: Load dataset
data = pd.read_csv("exp2&3_data.csv")  # Make sure your file is named 'fruit_data.csv'
# Step 2: Encode categorical features
le = LabelEncoder()
for column in data.columns:
    data[column] = le.fit_transform(data[column])
# Step 3: Split data
```

```
X = data.drop("Fruit", axis=1)  # Features: Color, Shape, Size
y = data["Fruit"]               # Target: Fruit type
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# Step 4: Bagging
bagging = BaggingClassifier(DecisionTreeClassifier(), n_estimators=10, random_state=42)
bagging.fit(X_train, y_train)
bagging_preds = bagging.predict(X_test)
bagging_acc = accuracy_score(y_test, bagging_preds)
# Step 5: Boosting (Gradient Boosting)
boosting = GradientBoostingClassifier(n_estimators=10, max_depth=3, random_state=42)
boosting.fit(X_train, y_train)
boosting_preds = boosting.predict(X_test)
boosting_acc = accuracy_score(y_test, boosting_preds)

# Step 6: Show results
print("Bagging Accuracy:", round(bagging_acc * 100, 2), "%")
print("Boosting Accuracy:", round(boosting_acc * 100, 2), "%")
```

Output:

Bagging Accuracy: 71.43 %

Boosting Accuracy: 71.43 %

Experiment 4: Read an unsupervised dataset and group the dataset based on similarity based on k-means clustering .

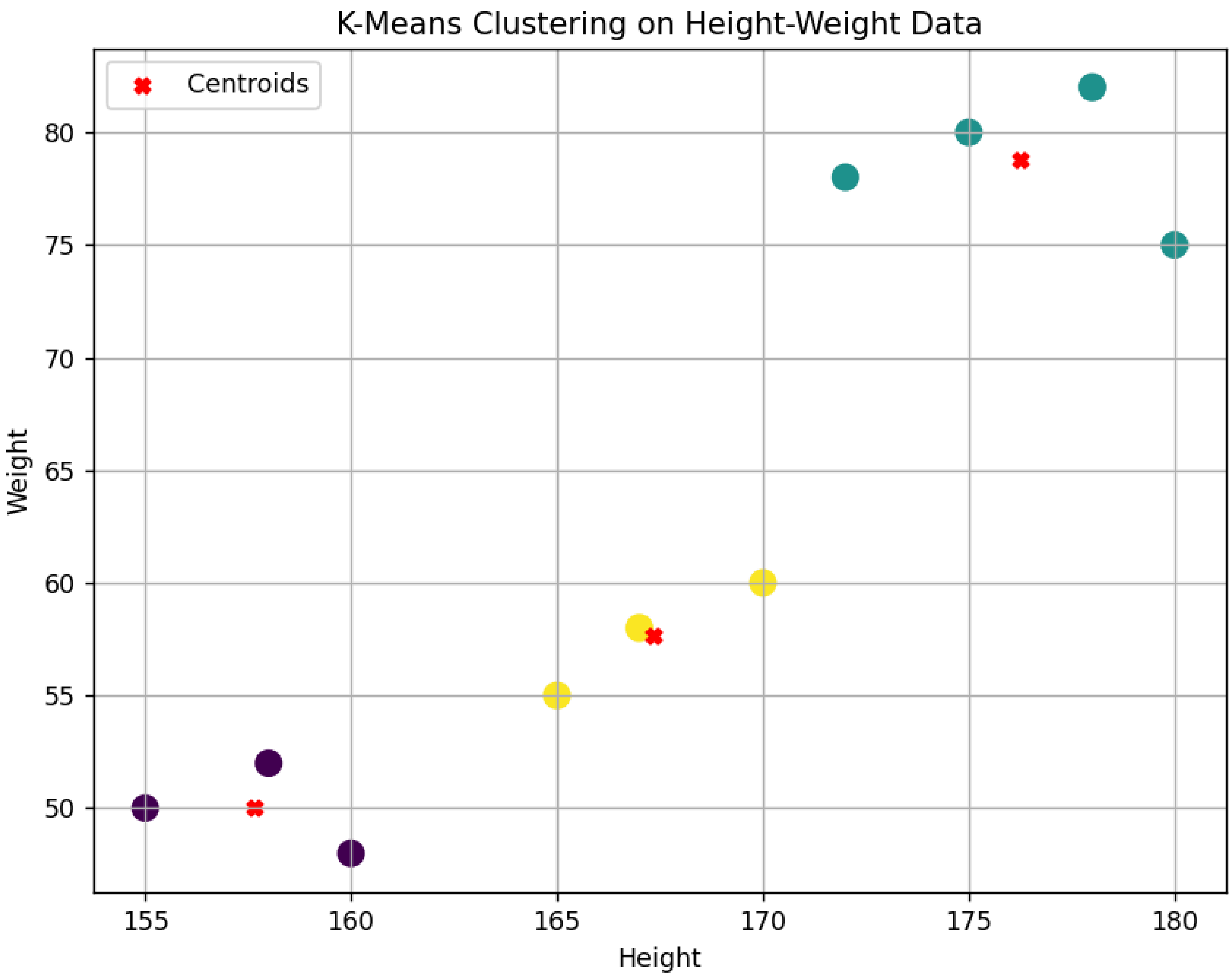
Code Implementation:

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
# Step 1: Load the dataset
data = pd.read_csv('exp4&5_data.csv')
# Step 2: Apply K-Means Clustering
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(data)
# Step 3: Add cluster labels to the dataset
data['Cluster'] = kmeans.labels_
# Step 4: Display the clustered data
print(data)
# Step 5: Visualize the clusters
```

```
plt.figure(figsize=(8,6))
plt.scatter(data['Height'], data['Weight'], c=data['Cluster'], cmap='viridis', s=100)
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], color='red',
marker='X', label='Centroids')
plt.xlabel("Height")
plt.ylabel("Weight")
plt.title("K-Means Clustering on Height-Weight Data")
plt.legend()
plt.grid(True)
plt.show()
```

Output:

```
Height  Weight  Cluster
0   170   60    2
1   165   55    2
2   180   75    1
3   155   50    0
4   160   48    0
5   175   80    1
6   172   78    1
7   178   82    1
8   158   52    0
9   167   58    2
```



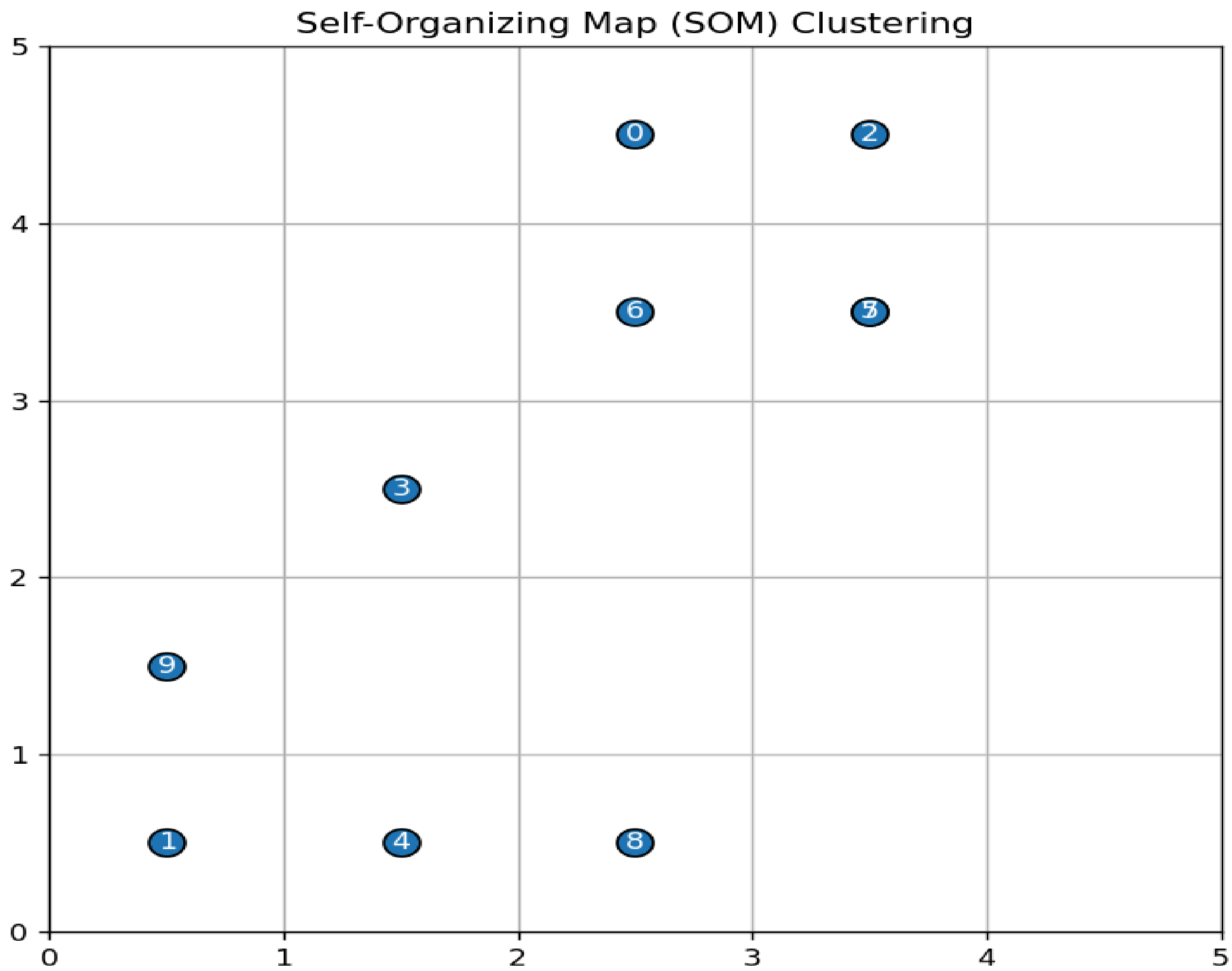
Experiment 5: Read a dataset and perform unsupervised learning using SOM algorithm.

<u>Code Implementation</u>:

```
import pandas as pd
import numpy as np
from minisom import MiniSom
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
# Load data
data = pd.read_csv('exp4&5_data.csv')
X = data.values
# Normalize data
scaler = MinMaxScaler()
```

```
X_scaled = scaler.fit_transform(X)
# Initialize and train SOM
som = MiniSom(x=5, y=5, input_len=2, sigma=1.0, learning_rate=0.5, random_seed=0)
som.train_random(X_scaled, 100)
# Plot the SOM with markers
plt.figure(figsize=(7, 7))
for i, x in enumerate(X_scaled):
    w = som.winner(x)
    plt.plot(w[0] + 0.5, w[1] + 0.5, 'o', markerfacecolor='C0',
             markeredgecolor='k', markersize=12)
    plt.text(w[0] + 0.5, w[1] + 0.5, str(i), color='white', ha='center', va='center')
plt.xlim(0, 5)
plt.ylim(0, 5)
plt.title('Self-Organizing Map (SOM) Clustering')
plt.grid(True)
plt.show()
```

Output:



Experiment 6: Write a function to generate uniform random numbers in the interval [0, 1]. Use this function to generate 10 random samples and evaluate f(x) for each sample. What are the sampled function values? Using the

samples generated in the previous step, estimate the integral I using the Monte Carlo method.

Code Implementation:

```
import random
# 1. Generate a uniform random number in [0, 1]
def generate_uniform():
    return random.random()
# 2. Define the function f(x) = x^2 (you can change this)
def f(x):
    return x ** 2
# 3. Generate 10 random samples and evaluate f(x), More samples → Better approximation.
samples = [generate_uniform() for _ in range(10)]
function_values = [f(x) for x in samples]
print("Generated Samples:")
for i, x in enumerate(samples):
    print(f"x[{i+1}] = {x:.4f}, f(x) = {function_values[i]:.4f}")
# 4. Monte Carlo Integration over [0,1]
monte_carlo_estimate = sum(function_values) / len(samples)
print(f"\nEstimated Integral (Monte Carlo): {monte_carlo_estimate:.4f}")
```

Output:

```
Generated Samples:
x[1] = 0.1661, f(x) = 0.0276
x[2] = 0.6421, f(x) = 0.4123
x[3] = 0.7312, f(x) = 0.5347
x[4] = 0.7810, f(x) = 0.6100
x[5] = 0.2966, f(x) = 0.0880
x[6] = 0.7893, f(x) = 0.6229
x[7] = 0.9423, f(x) = 0.8880
x[8] = 0.4592, f(x) = 0.2109
```

x[9] = 0.2868, f(x) = 0.0823

x[10] = 0.0209, f(x) = 0.0004

Experiment 7: Read a dataset and indicate the likelihood of an event occurring using Bayesian Networks.

<u>Code Implementation</u>:

```
import pandas as pd
from pgmpy.models import DiscreteBayesianNetwork
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.inference import VariableElimination
# Step 1: Load the dataset
data = pd.read_csv('exp7&8_data.csv')
# Step 2: Define the Bayesian Network structure
model = DiscreteBayesianNetwork([
    ('Difficulty', 'Grade'),
    ('Intelligence', 'Grade')
])
# Step 3: Train the model using Maximum Likelihood Estimation
model.fit(data, estimator=MaximumLikelihoodEstimator)
# Step 4: Inference
inference = VariableElimination(model)
# Step 5: Query probabilities
print("P(Grade):")
print(inference.query(variables=['Grade']))
print("\nP(Grade | Intelligence=High):")
print(inference.query(variables=['Grade'], evidence={'Intelligence': 'High'}))
```

Output:

INFO:pgmpy: Datatype (N=numerical, C=Categorical Unordered, O=Categorical Ordered) inferred from data:

```
{'Difficulty': 'C', 'Intelligence': 'C', 'Grade': 'C'}

P(Grade):
+----------+--------------+
| Grade    |   phi(Grade) |
+==========+==============+
| Grade(A) |       0.2500 |
+----------+--------------+
| Grade(B) |       0.5000 |
+----------+--------------+
| Grade(C) |       0.2500 |
+----------+--------------+

P(Grade | Intelligence=High):
+----------+--------------+
| Grade    |   phi(Grade) |
+==========+==============+
| Grade(A) |       0.5000 |
+----------+--------------+
| Grade(B) |       0.5000 |
+----------+--------------+
| Grade(C) |       0.0000 |
+----------+--------------+
```

Experiment 8: Refer to the dataset in question 7 and indicate inferences based on the sequence of steps .

Code Implementation:

```
import pandas as pd
```

```
from pgmpy.models import DiscreteBayesianNetwork
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.inference import VariableElimination
# Step 1: Load the dataset
data = pd.read_csv('exp7&8_data.csv')
# Step 2: Define the Bayesian Network structure
model = DiscreteBayesianNetwork([
    ('Difficulty', 'Grade'),
    ('Intelligence', 'Grade')
])
# Step 3: Train the model using MLE
model.fit(data, estimator=MaximumLikelihoodEstimator)
# Step 4: Perform inference
inference = VariableElimination(model)
# Step 5: Inference - Marginal probability of Grade
grade_dist = inference.query(variables=['Grade'])
print("\n📊 P(Grade):\n", grade_dist)
print("\n🧠 Inference 1:")
print("- Grade B is most common.")
print("- A and C are equally less frequent.")
# Step 6: Inference - P(Grade | Intelligence=High)
grade_given_intel = inference.query(variables=['Grade'], evidence={'Intelligence': 'High'})
print("\n📊 P(Grade | Intelligence=High):\n", grade_given_intel)
print("\n🧠 Inference 2:")
print("- High intelligence increases chances of Grade A or B.")
print("- Grade C becomes unlikely.")
# Step 7: Inference - P(Grade | Difficulty=Hard)
grade_given_difficulty = inference.query(variables=['Grade'], evidence={'Difficulty':
'Hard'})
```

```
print("\n📊 P(Grade | Difficulty=Hard):\n", grade_given_difficulty)
# Manually verify actual counts from dataset for Difficulty = Hard
print("\n📊 Actual frequencies from data (Difficulty=Hard):")
hard_df = data[data['Difficulty'] == 'Hard']
print(hard_df['Grade'].value_counts(normalize=True))
print("\n🧠 Inference 3:")
print("- From data: 60% C, 40% B for hard subjects.")
print("- If model shows 50-50, it might be due to inference smoothing or CPT grouping.")
print("- Grade A does not occur under Hard difficulty in data.")
```

Output:

```
INFO:pgmpy: Datatype (N=numerical, C=Categorical Unordered, O=Categorical Ordered) inferred from data:
 {'Difficulty': 'C', 'Intelligence': 'C', 'Grade': 'C'}
📊 P(Grade):
 +----------+--------------+
| Grade    |   phi(Grade) |
+==========+==============+
| Grade(A) |       0.2500 |
+----------+--------------+
| Grade(B) |       0.5000 |
+----------+--------------+
| Grade(C) |       0.2500 |
+----------+--------------+
🧠 Inference 1:
- Grade B is most common.
- A and C are equally less frequent.

📊 P(Grade | Intelligence=High):
 +----------+--------------+
```

```
| Grade    |   phi(Grade) |
+==========+==============+
| Grade(A) |       0.5000 |
+----------+--------------+
| Grade(B) |       0.5000 |
+----------+--------------+
| Grade(C) |       0.0000 |
+----------+--------------+
```

🧠 Inference 2:

- High intelligence increases chances of Grade A or B.

- Grade C becomes unlikely.

📊 P(Grade | Difficulty=Hard):

```
+----------+--------------+
| Grade    |   phi(Grade) |
+==========+==============+
| Grade(A) |       0.0000 |
+----------+--------------+
| Grade(B) |       0.5000 |
+----------+--------------+
| Grade(C) |       0.5000 |
+----------+--------------+
```

📊 Actual frequencies from data (Difficulty=Hard):

Grade

C   0.6

B   0.4

Name: proportion, dtype: float64

🧠 Inference 3:

- From data: 60% C, 40% B for hard subjects.

- If model shows 50-50, it might be due to inference smoothing or CPT grouping.

- Grade A does not occur under Hard difficulty in data.