



VIVEKANANDA INSTITUTE OF PROFESSIONAL STUDIES - TECHNICAL CAMPUS

Grade A++ Accredited Institution by NAAC

NBA Accredited for MCA Programme; Recognized under Section 2(f) by UGC;
Affiliated to GGSIP University, Delhi; Recognized by Bar Council of India and AICTE
An ISO 9001:2015 Certified Institution

SCHOOL OF ENGINEERING & TECHNOLOGY

B.Tech Programme: Computer Science & Engineering

Course Title: Data Warehousing Data Mining Lab

Course Code: CIE-405P

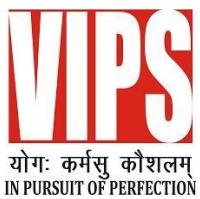
Semester: 7th

Submitted By

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Branch & Section: CSE-A (G2)



An ISO 9001:2015 Certified Institution
SCHOOL OF ENGINEERING & TECHNOLOGY

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VISION OF INSTITUTE

To be an educational institute that empowers the field of engineering to build a sustainable future by providing quality education with innovative practices that supports people, planet and profit.

MISSION OF INSTITUTE

To groom the future engineers by providing value-based education and awakening students' curiosity, nurturing creativity and building capabilities to enable them to make significant contributions to the world.



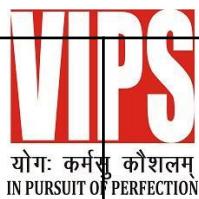
An ISO 9001:2015 Certified Institution
SCHOOL OF ENGINEERING & TECHNOLOGY

VIVEKANANDA INSTITUTE OF PROFESSIONAL STUDIES - TECHNICAL CAMPUS
Gurukulam, Kukatpally, Hyderabad, Telangana, India - 500072

Grade A++ Accredited Institution by NAAC
1st MCA Rank in India 1st Semester

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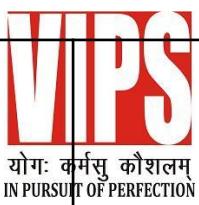
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| | | | | | | | | |

EXPERIMENT 1

Aim: Study of ETL process and its tools.

Theory: ETL Process (Extract, Transform, Load)

The ETL process is a key part of data warehousing that helps in moving and preparing data for analysis. In this process, data is first extracted from multiple sources, transformed into a clean and consistent format, and then loaded into a data warehouse. This ensures that organizations have accurate, well-structured data available for reporting, analytics, and decision-making.

- Extract: Collect data from multiple sources like databases, files, and applications.
- Transform: Clean, format, and convert data into a common structure; handle errors and missing values.
- Load: Store the processed data into a data warehouse for reporting and analysis.

Dataset:

Purpose: A small retail sales log for Jan–Jun 2025. Each row = one order.

Columns:

- order_id: Unique ID (2001–2025).
- date: Order date (DD-MM-2025).
- customer_name: Buyer's name.
- product: Item bought (Laptop, Mouse, Keyboard, Monitor, plus a few like Tablet, Printer, Desk Lamp, Office Chair).
- quantity: Units purchased (mostly 1–3).
- price: Per-unit price in the same currency.
- region: Customer/market region (North, South, East, West).

Program:

```
▶ import pandas as pd
sales_data=pd.read_csv('sales_data.csv')
print(sales_data.head())
```

| | order_id | date | customer_name | product | quantity | price | region |
|---|----------|------------|---------------|----------|----------|---------|--------|
| 0 | 1001 | 2025-01-15 | Alice Johnson | Laptop | 1.0 | 1299.99 | North |
| 1 | 1002 | 2025-01-17 | Bob Williams | Mouse | 2.0 | 24.50 | South |
| 2 | 1003 | 2025-01-20 | Charlie Brown | Keyboard | 1.0 | 75.00 | East |
| 3 | 1004 | 2025-01-22 | David Smith | Keyboard | 1.0 | NaN | East |
| 4 | 1005 | 2025-02-05 | Eva Green | Monitor | 2.0 | 300.50 | West |

```
▶ sales_data_cleaned = sales_data.fillna(0)

sales_data_cleaned['total_amount'] = sales_data_cleaned['quantity'] * sales_data_cleaned['price']

display(sales_data_cleaned['total_amount'].head(4))

display(sales_data_cleaned.head(4))
```

→ total_amount

| | |
|---|---------|
| 0 | 1299.99 |
| 1 | 49.00 |
| 2 | 75.00 |
| 3 | 0.00 |
| 4 | 601.00 |

dtype: float64

| | order_id | date | customer_name | product | quantity | price | region | total_amount |
|---|----------|------------|---------------|----------|----------|---------|--------|--------------|
| 0 | 1001 | 2025-01-15 | Alice Johnson | Laptop | 1.0 | 1299.99 | North | 1299.99 |
| 1 | 1002 | 2025-01-17 | Bob Williams | Mouse | 2.0 | 24.50 | South | 49.00 |
| 2 | 1003 | 2025-01-20 | Charlie Brown | Keyboard | 1.0 | 75.00 | East | 75.00 |
| 3 | 1004 | 2025-01-22 | David Smith | Keyboard | 1.0 | 0.00 | East | 0.00 |
| 4 | 1005 | 2025-02-05 | Eva Green | Monitor | 2.0 | 300.50 | West | 601.00 |

```
[ ] sales_data_cleaned.to_csv('sales_data_cleaned.csv', index=False)
```

```
▶ cleaned_file=pd.read_csv('sales_data_cleaned.csv')
display(cleaned_file.head())
```

→ order_id

| | order_id | date | customer_name | product | quantity | price | region | total_amount |
|---|----------|------------|---------------|----------|----------|---------|--------|--------------|
| 0 | 1001 | 2025-01-15 | Alice Johnson | Laptop | 1.0 | 1299.99 | North | 1299.99 |
| 1 | 1002 | 2025-01-17 | Bob Williams | Mouse | 2.0 | 24.50 | South | 49.00 |
| 2 | 1003 | 2025-01-20 | Charlie Brown | Keyboard | 1.0 | 75.00 | East | 75.00 |
| 3 | 1004 | 2025-01-22 | David Smith | Keyboard | 1.0 | 0.00 | East | 0.00 |
| 4 | 1005 | 2025-02-05 | Eva Green | Monitor | 2.0 | 300.50 | West | 601.00 |

Learning Outcomes:

EXPERIMENT 2

Aim: Program of Data warehouse cleansing to input names from users (inconsistent) and format them.

Theory: Data warehouse cleansing is part of the Transform stage in the ETL (Extract, Transform, Load) process. It improves data quality by making it accurate, complete, and consistent before storing it in the warehouse.

When users input names, inconsistencies like wrong case, extra spaces, or typos may occur. Cleansing ensures a uniform format, e.g., " john DOE " → "John Doe".

In Python, common string functions used for cleansing names are:

- `strip()` – Removes extra spaces from start and end.
- `title()` – Converts text to Title Case.
- `lower()` / `upper()` – Converts text to lower or upper case if needed.
- `replace()` – Replaces unwanted characters or patterns.

Clean data ensures accurate analytics and better decision-making.

Dataset:

The column `Raw_name` contains user-entered names in inconsistent formats.

It includes common formatting issues such as:

- Leading and trailing spaces
- Multiple spaces between first and last names
- Random mix of uppercase and lowercase letters
- Same names entered in different formatting styles

This dataset is intentionally kept “dirty” so that it can be used for practicing data cleansing and standardization tasks.

Program:

```
[12] import pandas as pd
     name_data=pd.read_csv('name_raw_data.csv')
     print(name_data.head())
```

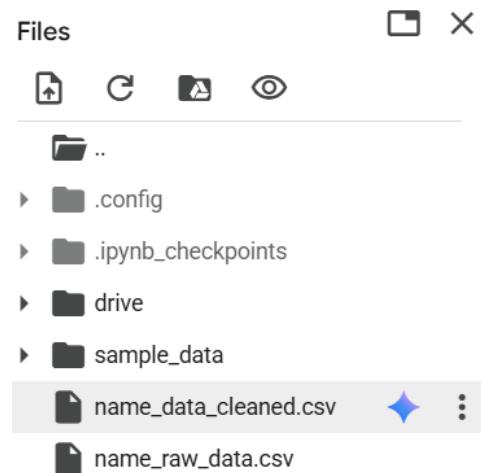
```
Raw_name
0      RaHuL ShArMa
1      rahul SHARma
2      RAHUL sharma
3      PrIyA KaPoOr
4      priya KAPOOR
```

```
▶ name_data['cleaned_name'] = name_data['Raw_name'].str.strip()  
▶ name_data['cleaned_name'] = name_data['cleaned_name'].str.title()  
▶ name_data['cleaned_name'] = name_data['cleaned_name'].apply(lambda x: ' '.join(x.split()))  
  
name_data = name_data.drop_duplicates(subset=['cleaned_name'])  
  
display(name_data.head())
```

| | Raw_name | cleaned_name | grid |
|----|--------------|--------------|------|
| 0 | RaHuL ShArMa | Rahul Sharma | grid |
| 3 | PrlyA KaPoOr | Priya Kapoor | grid |
| 6 | aMiT KuMaR | Amit Kumar | grid |
| 9 | SuNiTa slnGh | Sunita Singh | grid |
| 12 | MoHiT VeRmA | Mohit Verma | grid |

```
[17] name_data.to_csv('name_data_cleaned.csv', index=False)
```

Output:



Learning Outcomes:

EXPERIMENT 3

Aim: Program of Data warehouse cleansing to remove redundancy in data.

Theory:

Redundancy occurs when **duplicate records** or **repeated attributes** exist in data.
DW cleansing removes:

- Exact duplicates (same row)
 - Near duplicates (same name with different spellings)
 - Repeated entries due to system errors
- Redundancy increases storage cost and leads to incorrect analytics.

Techniques include:

- Primary key-based deduplication
- Hashing on rows
- Similarity-based duplicate detection (Levenshtein)
- Canonical formatting (lowercasing, trimming)

Dataset:

| customer_id | customer_name | email |
|-------------|---------------|-----------------|
| 101 | John Doe | john@gmail.com |
| 102 | john doe | john@gmail.com |
| 103 | Priya Sharma | priya@gmail.com |
| 104 | PRIYA SHARMA | priya@gmail.com |
| 105 | Rohit Verma | rohit@gmail.com |

Goal → remove duplicates & standardize names.

Program:

```
!pip install fuzzywuzzy
!pip install python-Levenshtein

→ Collecting fuzzywuzzy
  Downloading fuzzywuzzy-0.18.0-py2.py3-none-any.whl.metadata (4.9 kB)
  Downloading fuzzywuzzy-0.18.0-py2.py3-none-any.whl (18 kB)
  Installing collected packages: fuzzywuzzy
    Successfully installed fuzzywuzzy-0.18.0
  Collecting python-Levenshtein
    Downloading python_levenshtein-0.27.1-py3-none-any.whl.metadata (3.7 kB)
  Collecting Levenshtein==0.27.1 (from python-Levenshtein)
    Downloading levenshtein-0.27.1-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (3.6 kB)
  Collecting rapidfuzz<4.0.0,>=3.9.0 (from Levenshtein==0.27.1->python-Levenshtein)
    Downloading rapidfuzz-3.14.1-cp312-cp312-manylinux_2_27_x86_64.manylinux_2_28_x86_64.whl.metadata (12 kB)
  Downloading python_levenshtein-0.27.1-py3-none-any.whl (9.4 kB)
  Downloading levenshtein-0.27.1-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (159 kB)
  ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━................................................................
  159.9/159.9 kB 3.2 MB/s eta 0:00:00
  Downloading rapidfuzz-3.14.1-cp312-cp312-manylinux_2_27_x86_64.manylinux_2_28_x86_64.whl (3.2 kB)
  ━━━━━━━................................................................
  3.2/3.2 kB 39.3 MB/s eta 0:00:00
  Installing collected packages: rapidfuzz, Levenshtein, python-Levenshtein
    Successfully installed Levenshtein-0.27.1 python-Levenshtein-0.27.1 rapidfuzz-3.14.1
```

```
▶ import pandas as pd
from fuzzywuzzy import fuzz
from fuzzywuzzy import process
import matplotlib.pyplot as plt

customer_data=pd.read_csv('customer_data.csv')
print(customer_data.head())

customer_data['Name']=customer_data['Name'].str.title()
customer_data['Address']=customer_data['Name'].str.strip().str.title()

print("After Standardization\n", customer_data)
```

```
→ Customer_ID      Name      Email      Phone      Address
 0      101      John Doe  john@example.com  1234567890      123 Elm St
 1      102      Jane Smith  jane@example.com  2345678901      456 Oak St
 2      103      John Doe  john@example.com  1234567890  123 Elm Street
 3      104      Alice Brown  alice@example.com  3456789012      789 Pine St
 4      105      Bob Martin  bob@example.com  4567890123      321 Maple Ave
After Standardization
  Customer_ID      Name      Email      Phone      Address
 0      101      John Doe  john@example.com  1234567890      John Doe
 1      102      Jane Smith  jane@example.com  2345678901      Jane Smith
 2      103      John Doe  john@example.com  1234567890      John Doe
 3      104      Alice Brown  alice@example.com  3456789012      Alice Brown
 4      105      Bob Martin  bob@example.com  4567890123      Bob Martin
 5      106      Jane Smith  jane@example.com  2345678901      Jane Smith
 6      107      Jon Doe  jon@example.com  1234567890      Jon Doe
 7      108      Ally Brown  alice@example.com  3456789012      Ally Brown
```

```

▶ customer_data_wo_duplicates=customer_data.drop_duplicates(subset=['Name', 'Address'])
print("After removing duplicates\n", customer_data_wo_duplicates)

customer_data=customer_data_wo_duplicates.drop_duplicates(subset=['Email'], keep='first')
print("After removing duplicates\n", customer_data)

names=customer_data['Name'].tolist()
print('Potential Near Duplicates')

for i in range(len(names)):
    for j in range(i+1, len(names)):
        if fuzz.ratio(names[i], names[j]) >= 80:
            print(names[i], names[j], "Similarity found")

plt.figure(figsize=(8, 4))
customer_data['Name'].str.len().hist()
plt.xlabel("Name Length")
plt.ylabel("Frequency")
plt.title("Distribution of Customer Name Lengths")
plt.show()

```

Output:

After removing duplicates

| | Customer_ID | Name | Email | Phone | Address |
|---|-------------|-------------|-------------------|------------|-------------|
| 0 | 101 | John Doe | john@example.com | 1234567890 | John Doe |
| 1 | 102 | Jane Smith | jane@example.com | 2345678901 | Jane Smith |
| 3 | 104 | Alice Brown | alice@example.com | 3456789012 | Alice Brown |
| 4 | 105 | Bob Martin | bob@example.com | 4567890123 | Bob Martin |
| 6 | 107 | Jon Doe | jon@example.com | 1234567890 | Jon Doe |
| 7 | 108 | Ally Brown | alice@example.com | 3456789012 | Ally Brown |

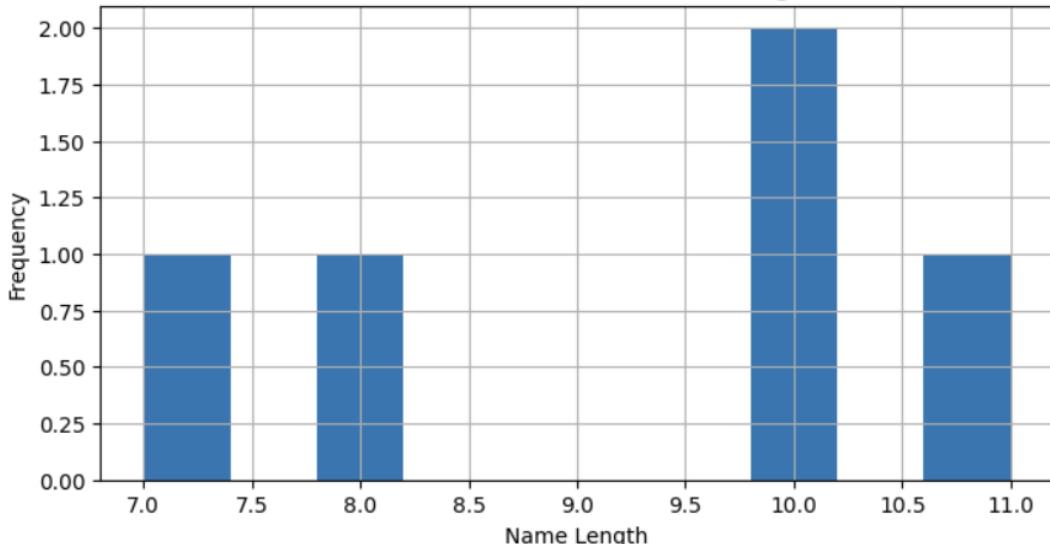
After removing duplicates

| | Customer_ID | Name | Email | Phone | Address |
|---|-------------|-------------|-------------------|------------|-------------|
| 0 | 101 | John Doe | john@example.com | 1234567890 | John Doe |
| 1 | 102 | Jane Smith | jane@example.com | 2345678901 | Jane Smith |
| 3 | 104 | Alice Brown | alice@example.com | 3456789012 | Alice Brown |
| 4 | 105 | Bob Martin | bob@example.com | 4567890123 | Bob Martin |
| 6 | 107 | Jon Doe | jon@example.com | 1234567890 | Jon Doe |

Potential Near Duplicates

John Doe Jon Doe Similarity found

Distribution of Customer Name Lengths



TIGMANSU SHAH BAHRI

CSE-B

35917702722

Learning Outcomes:

EXPERIMENT 4

Aim: Introduction to WEKA tool.

Theory:

WEKA (Waikato Environment for Knowledge Analysis) is an open-source data mining tool containing ML algorithms for **classification, clustering, association mining, visualization**.

Functions:

- Preprocessing (cleaning, normalization)
- Classification (J48, Naive Bayes, SVM)
- Clustering (K-Means, EM)
- Association (Apriori)
- Visualization (scatter plots, histograms)

Supports **ARFF, CSV** formats.

Used widely for academic ML experiments.

Dataset:

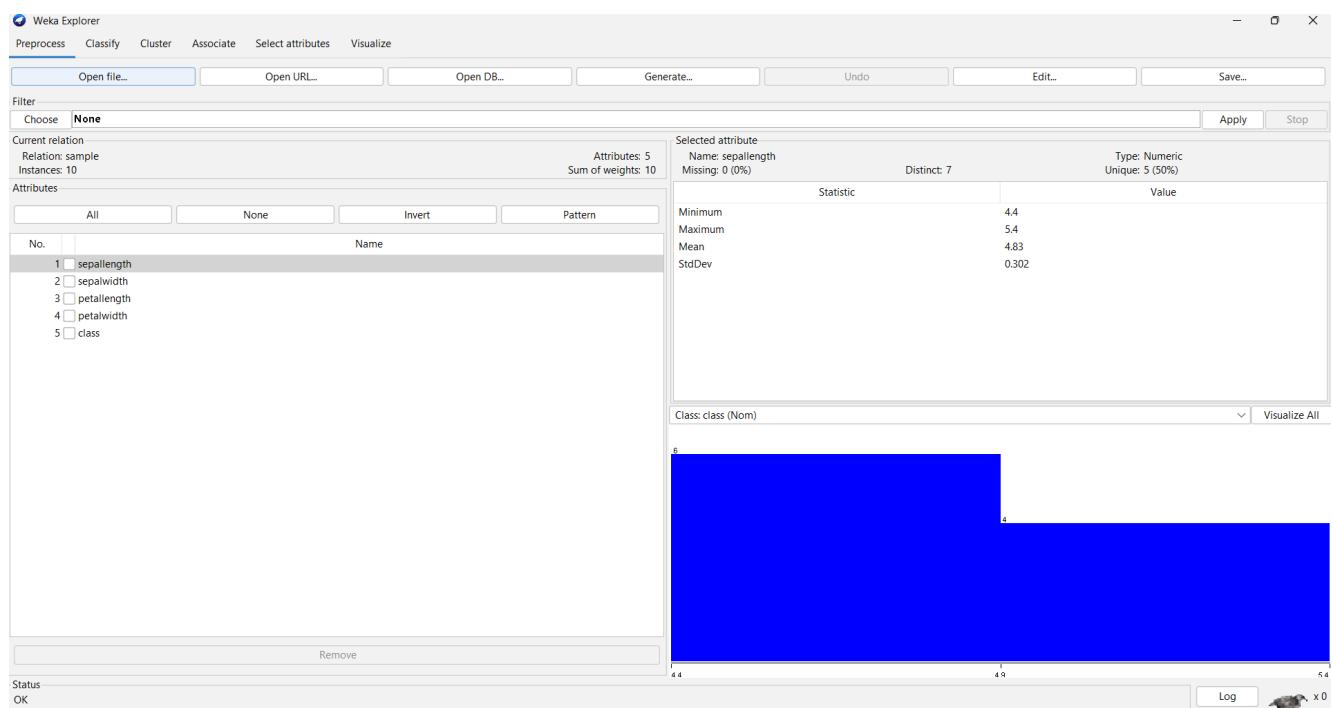
@relation weather

```
@attribute outlook {sunny, overcast, rainy}
@attribute temperature numeric
@attribute humidity numeric
@attribute windy {true, false}
@attribute play {yes, no}
```

@data

```
sunny,85,85,false,no
sunny,80,90,true,no
overcast,83,78,false,yes
rainy,70,96,false,yes
```

WEKA:



Weka Explorer

Preprocess Classify Cluster Associate Select attributes Visualize

Classifier

Choose **ZeroR**

Test options

Use training set

Supplied test set

Cross-validation Folds

Percentage split %

(Num) sepalwidth

Result list (right-click for options)

13:52:54 - rules.ZeroR

Classifier output

```
==== Run information ====
Scheme: weka.classifiers.rules.ZeroR
Relation: sample
Instances: 10
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode: 10-fold cross-validation

==== Classifier model (full training set) ====
ZeroR predicts class value: 3.319999999999994

Time taken to build model: 0 seconds

==== Cross-validation ====
==== Summary ===

Correlation coefficient -1
Mean absolute error 0.2667
Root mean squared error 0.3174
Relative absolute error 100 %
Root relative squared error 100 %
Total Number of Instances 10
```

Weka Explorer

Preprocess Classify Cluster Associate Select attributes Visualize

Classifier

Choose **ZeroR**

Test options

Use training set

Supplied test set

Cross-validation Folds

Percentage split %

(Num) sepalwidth

Result list (right-click for options)

13:52:54 - rules.ZeroR

13:53:25 - rules.ZeroR

Classifier output

```
==== Run information ====
Scheme: weka.classifiers.rules.ZeroR
Relation: sample
Instances: 10
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode: split 66.0% train, remainder test

==== Classifier model (full training set) ====
ZeroR predicts class value: 3.319999999999994

Time taken to build model: 0 seconds

==== Evaluation on test split ====
Time taken to test model on test split: 0 seconds

==== Summary ===

Correlation coefficient 0
Mean absolute error 0.3714
Root mean squared error 0.4032
Relative absolute error 100 %
Root relative squared error 100 %
Total Number of Instances 3
```

Preprocess Classify **Cluster** Associate Select attributes Visualize

Clusterer
Choose **EM** -I 100 -N 1 -X 10 -max -1 -ll-cv 1.0E-6 -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100

Cluster mode
 Use training set
 Supplied test set Set...
 Percentage split % 66
 Classes to clusters evaluation (Nom) class
 Store clusters for visualization
 Ignore attributes
Start Stop

Result list (right-click for options)
13:54:23 - EM
13:54:40 - EM
13:54:50 - EM

Clusterer output
Number of iterations performed: 2

| Attribute | Cluster |
|-------------|----------|
| | 0 (1) |
| ===== | |
| sepallength | |
| mean | 4.7167 |
| std. dev. | 0.2192 |
| sepalwidth | |
| mean | 3.2833 |
| std. dev. | 0.2192 |
| petallength | |
| mean | 1.4333 |
| std. dev. | 0.1247 |
| petalwidth | |
| mean | 0.2167 |
| std. dev. | 0.0687 |
| class | |
| Iris-setosa | 7 |
| [total] | 7 |

Time taken to build model (percentage split) : 0 seconds

Clustered Instances
0 4 (100%)

Log likelihood: -26.13312

Preprocess Classify Cluster Associate **Select attributes** Visualize

Attribute Evaluator
Choose **CfsSubsetEval -P 1 -E 1**

Search Method
Choose **BestFirst** -D 1 -N 5

Attribute Selection Mode
 Use full training set
 Cross-validation Folds 10 Seed 1
(Num) sepallength

Start Stop

Result list (right-click for options)
13:55:29 - BestFirst + CfsSubsetEval

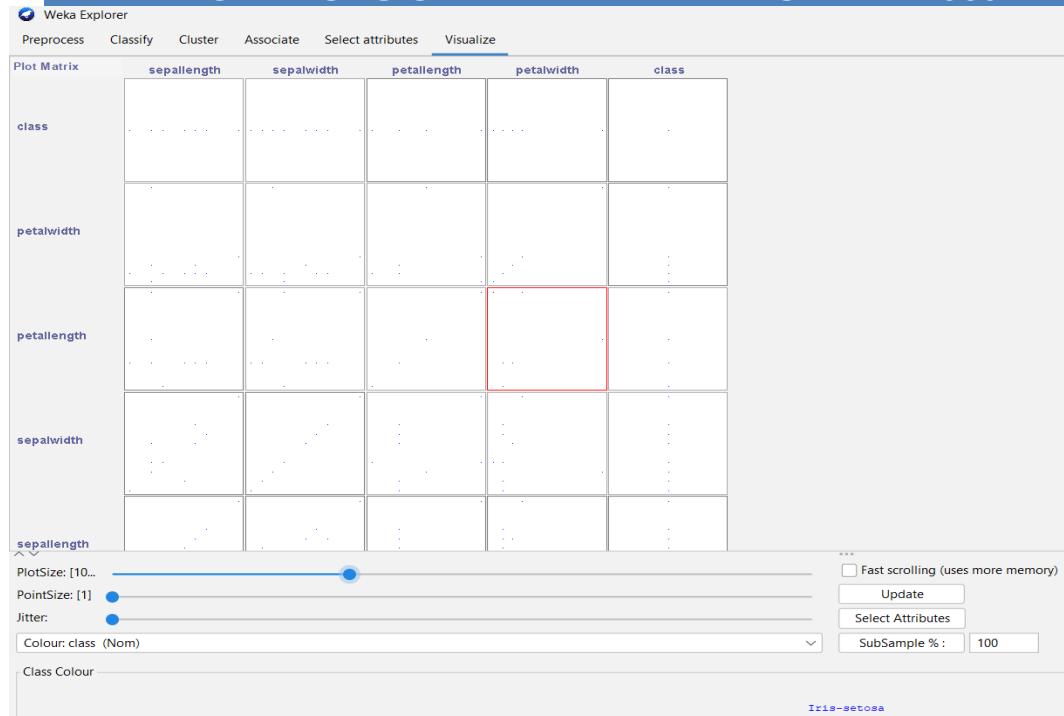
Attribute selection output
==== Run information ===

| Evaluator: | weka.attributeSelection.CfsSubsetEval -P 1 -E 1 |
|-------------|---|
| Search: | weka.attributeSelection.BestFirst -D 1 -N 5 |
| Relation: | sample |
| Instances: | 10 |
| Attributes: | 5 |
| | sepallength |
| | sepalwidth |
| | petallength |
| | petalwidth |
| | class |

Evaluation mode: 10-fold cross-validation

==== Attribute selection 10 fold cross-validation seed: 1 ===

| number of folds (%) | attribute |
|---------------------|---------------|
| 10(100 %) | 2 sepalwidth |
| 2 (20 %) | 3 petallength |
| 8 (80 %) | 4 petalwidth |
| 0 (0 %) | 5 class |



Learning Outcomes:

EXPERIMENT 5

Aim: Implementation of Classification technique on ARFF files using WEKA.

Theory:

Classification predicts a **categorical class** using supervised learning.

Algorithms used in WEKA:

- **J48 (Decision Tree)**
- **Naive Bayes**
- **Random Forest**
- **SVM (SMO)**

Process:

1. Load ARFF
2. Preprocess
3. Choose classifier
4. Train/Test split
5. Evaluate accuracy, precision, confusion matrix

Dataset:

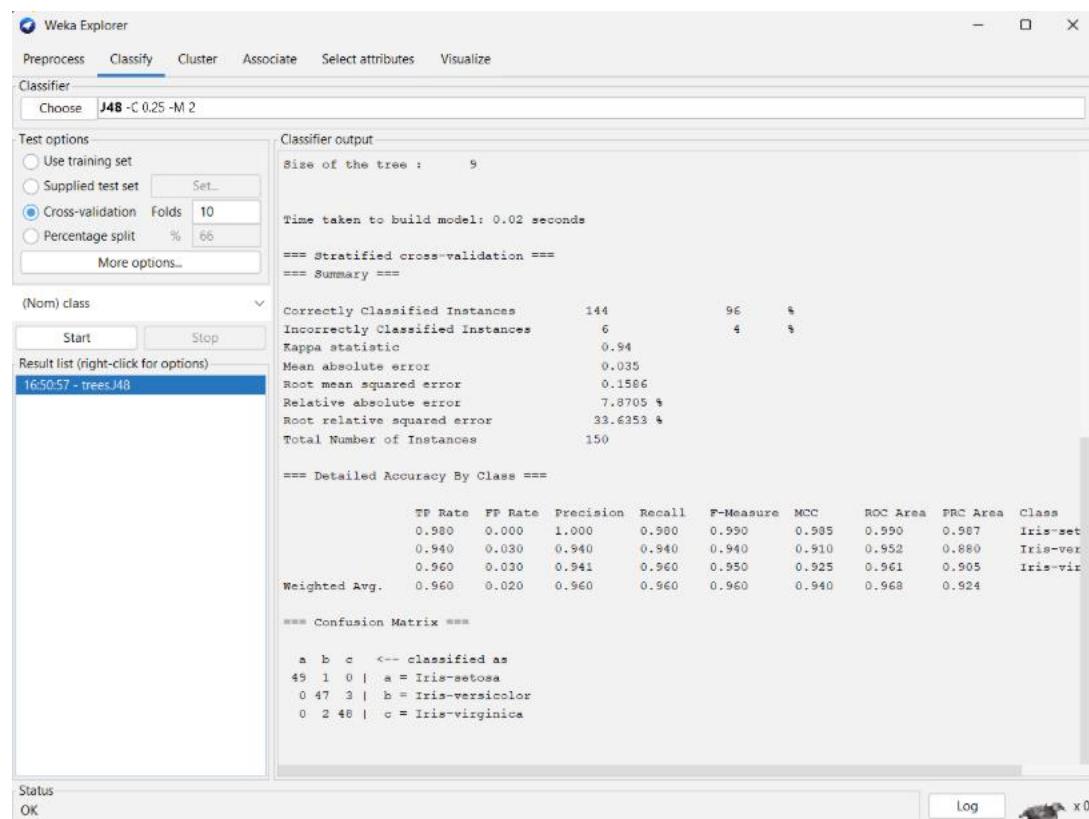
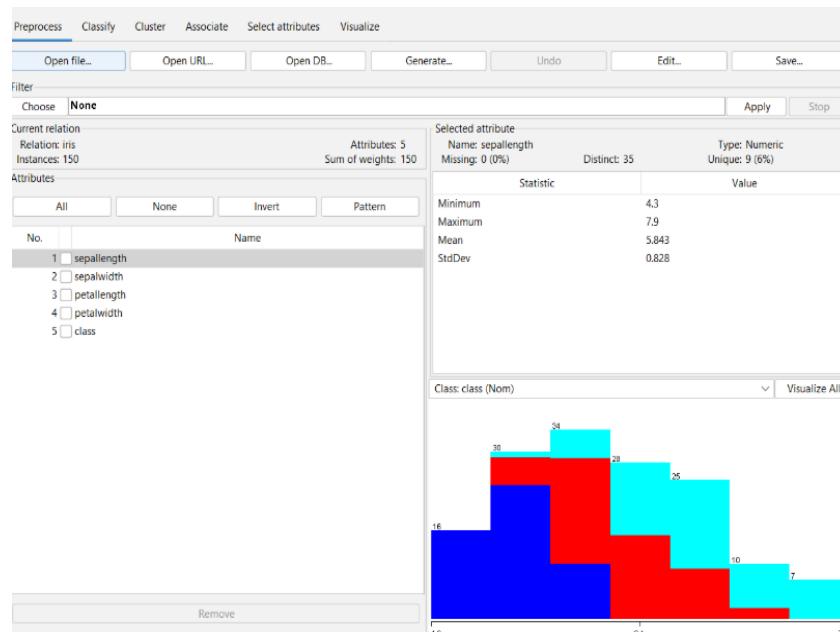
@relation iris

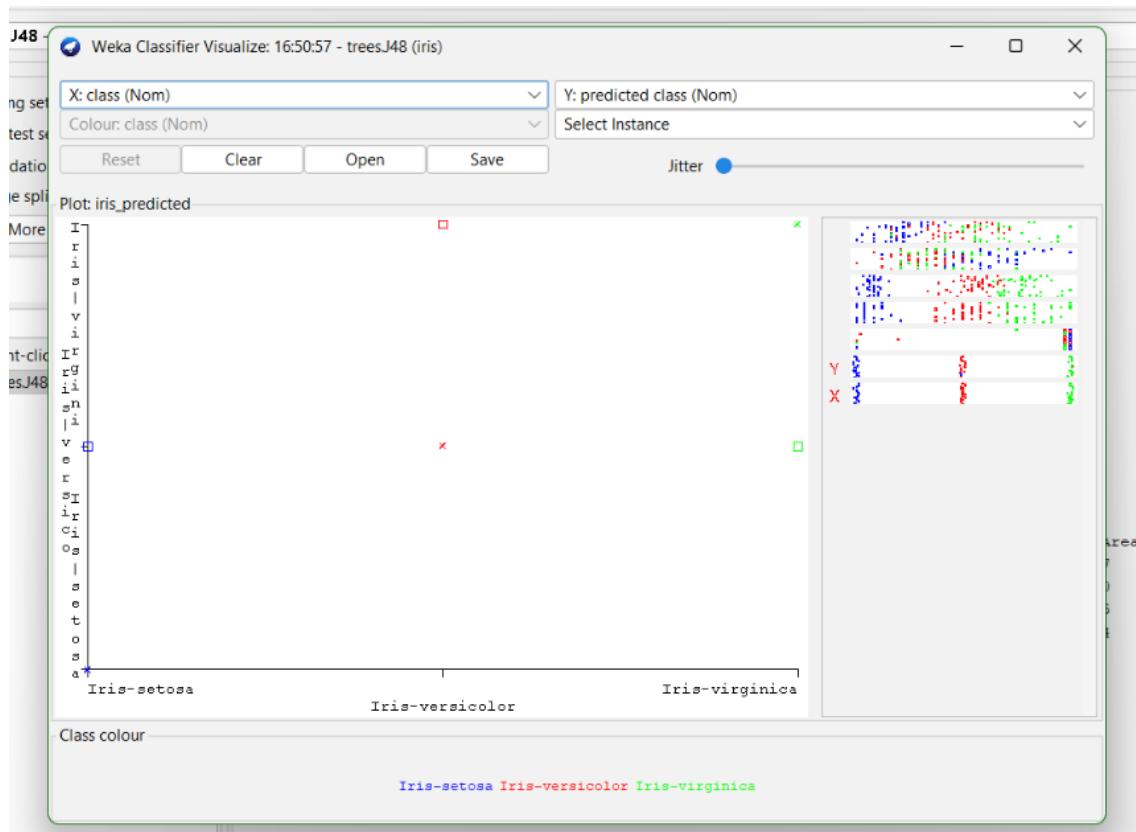
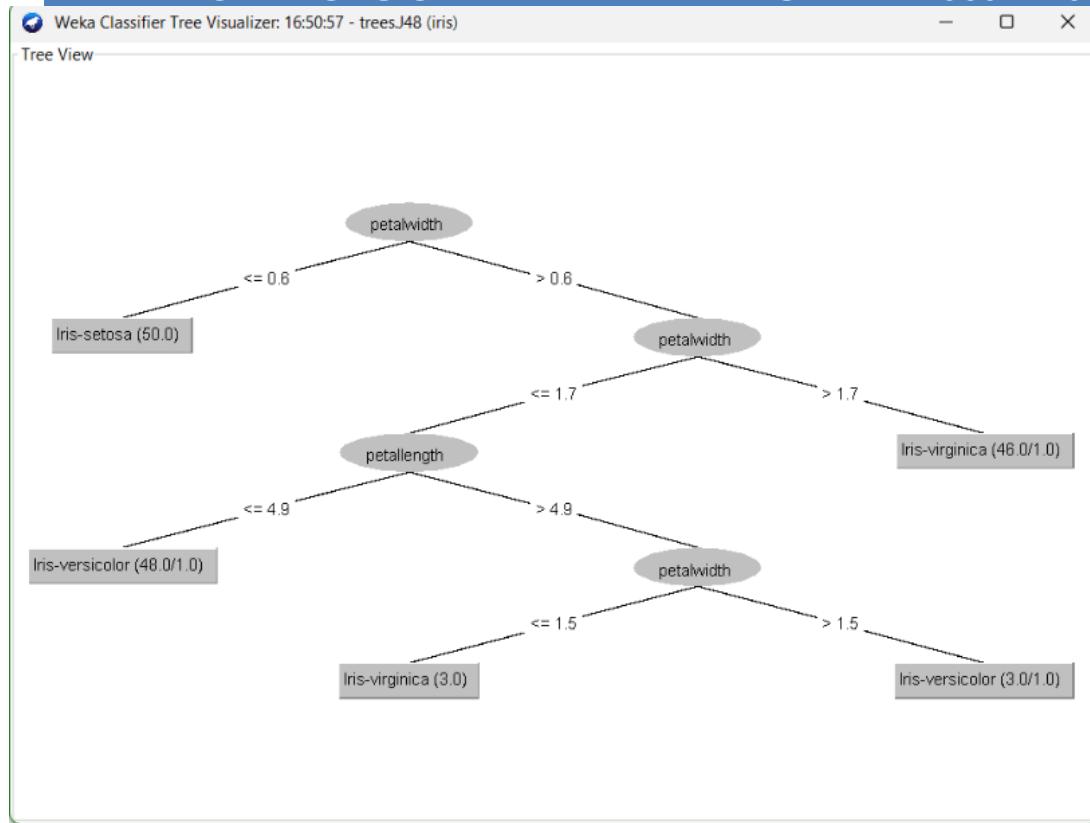
```
@attribute sepallength numeric
@attribute sepalwidth numeric
@attribute petallength numeric
@attribute petalwidth numeric
@attribute class {setosa, versicolor, virginica}
```

@data

```
5.1,3.5,1.4,0.2, setosa
6.2,2.2,4.5,1.5, versicolor
6.5,3.0,5.2,2.0, virginica
```

WEKA:





Learning Outcomes:

EXPERIMENT 6

Aim: Implementation of Clustering technique on ARFF files using WEKA.

Theory:

Clustering is **unsupervised learning** that groups similar data points.

WEKA supports:

- **K-Means**
- **EM**
- **Hierarchical Clustering**

Steps:

1. Load ARFF
2. Remove class label (unsupervised)
3. Apply K-Means
4. Visualize cluster assignments

Dataset:

@relation customers

@attribute age numeric

@attribute annual_income numeric

@attribute spending_score numeric

@data

25,30000,39

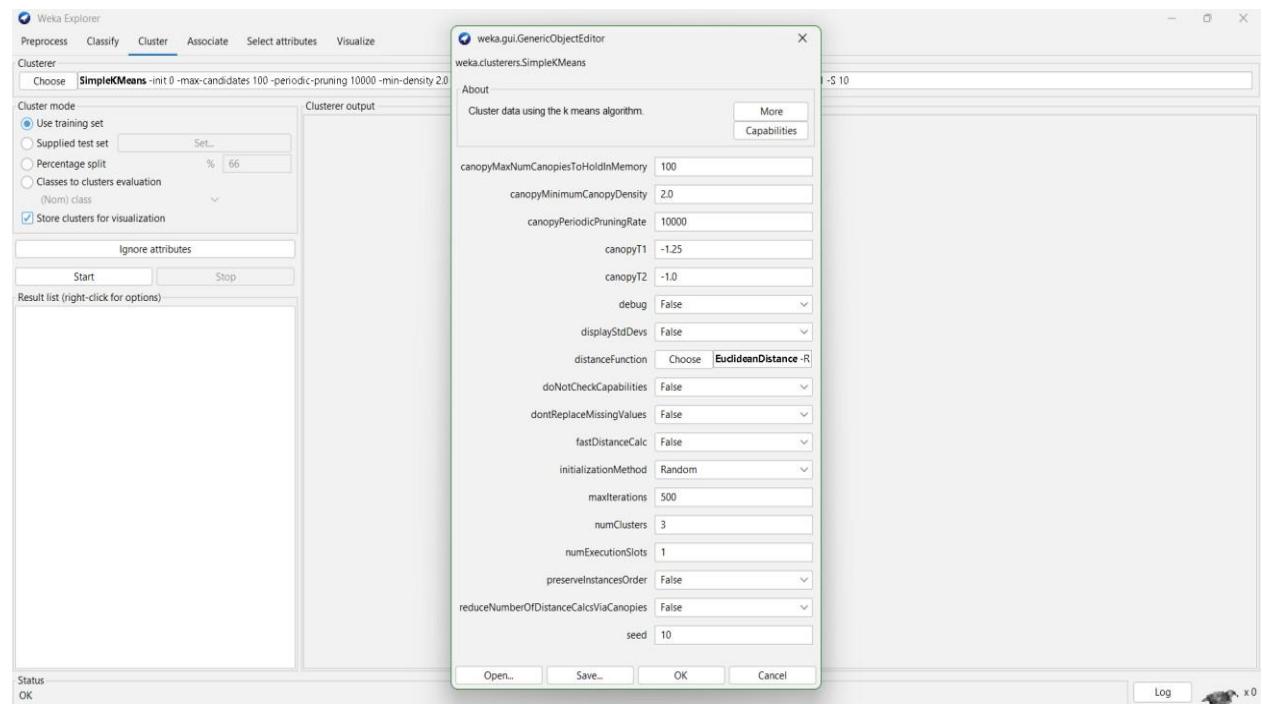
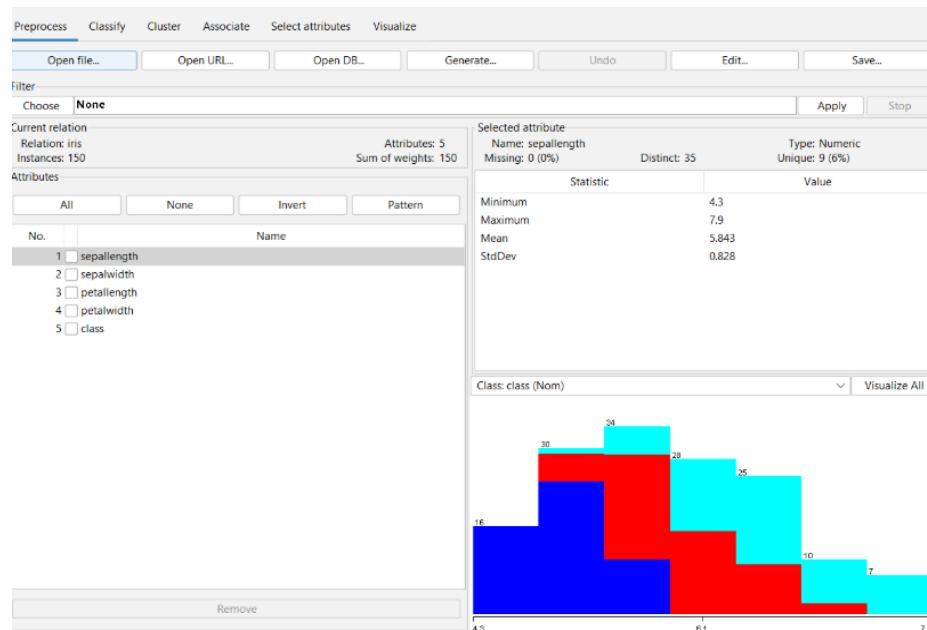
45,60000,70

20,15000,20

33,45000,55

52,80000,85

WEKA:



Weka Explorer

Preprocess Classify Cluster Associate Select attributes Visualize

Clusterer

Choose: SimpleKMeans -init 0 -max-candidates 100 -periodic-pruning 10000 -min-density 2.0 -t1 -1.25 -t2 -1.0 -N 3 -A "weka.core.EuclideanDistance" -R "first-last" -l 500 -num-slots 1 -S 10

Cluster mode

Use training set

Supplied test set Set...

Percentage split % 66

Classes to clusters evaluation (Nom) class

Store clusters for visualization

Ignore attributes

Start Stop

Result list (right-click for options): 16:08:03 - SimpleKMeans

Time taken to build model (full training data) : 0.01 seconds

== Model and evaluation on training set ==

Clustered Instances

| | |
|---|-----------|
| 0 | 61 (41%) |
| 1 | 50 (33%) |
| 2 | 39 (26%) |

Class attribute: class

Classes to Clusters:

| | | | |
|----|----|----|-------------------------|
| 0 | 1 | 2 | <-- assigned to cluster |
| 0 | 50 | 0 | Iris-setosa |
| 47 | 0 | 3 | Iris-versicolor |
| 14 | 0 | 36 | Iris-virginica |

Cluster 0 <-- Iris-versicolor

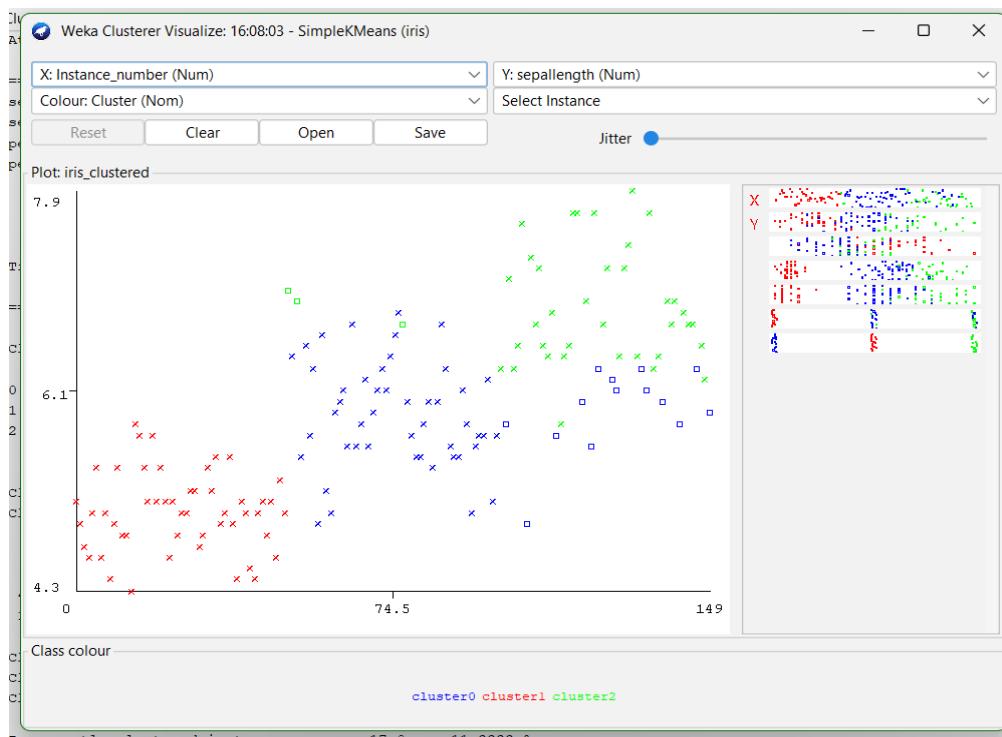
Cluster 1 <-- Iris-setosa

Cluster 2 <-- Iris-virginica

Incorrectly clustered instances : 17.0 11.3333 %

Status OK

Log x0



Learning Outcomes:

EXPERIMENT 7

Aim: Implementation of Association Rule technique on ARFF files using WEKA.

Theory:

Association mining finds **co-occurring patterns** like “bread → butter”.

Apriori algorithm steps:

1. Generate frequent itemsets using minimum support
2. Generate rules using minimum confidence
3. Output rules like:
 - {Milk} → {Bread}
 - {Laptop, Mouse} → {Bag}

Used in market basket analysis.

Dataset:

@relation market

@attribute items string

@data

"Milk,Bread"

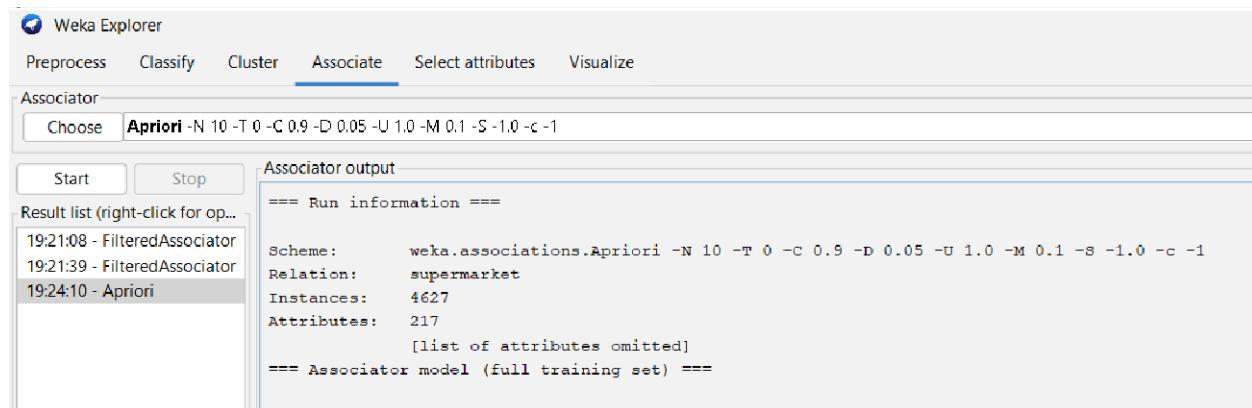
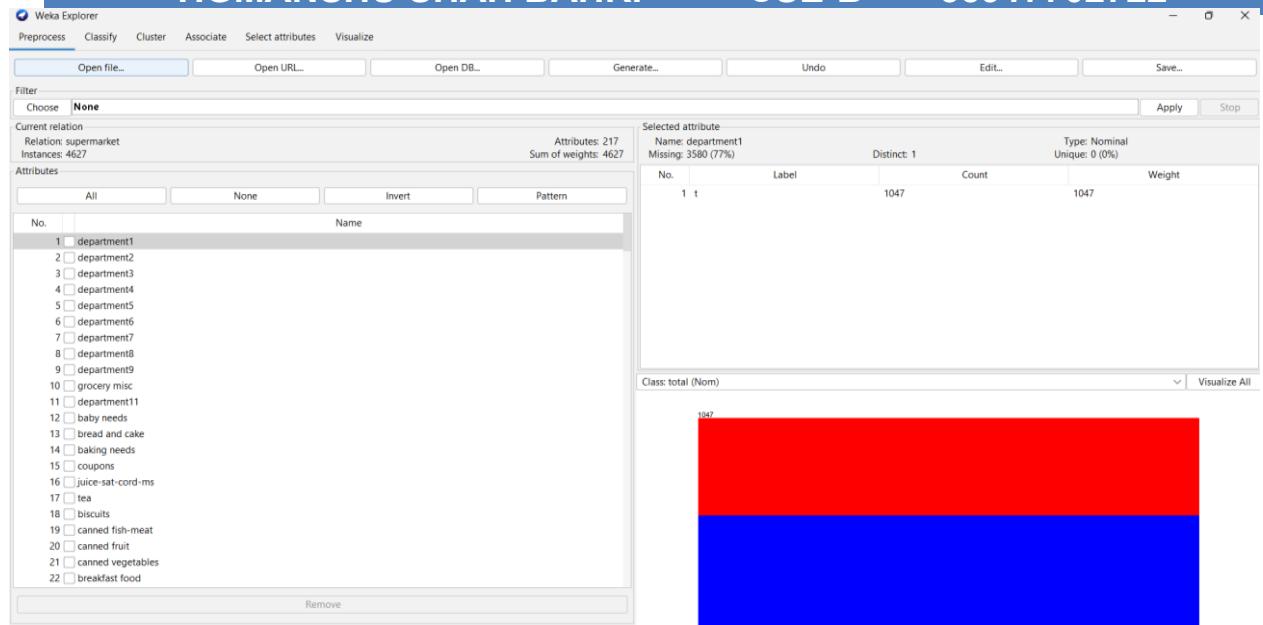
"Bread,Butter"

"Milk,Butter,Biscuits"

"Biscuits,Chips"

"Laptop,Mouse"

WEKA:



```
Apriori
=====

Minimum support: 0.15 (694 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 17

Generated sets of large itemsets:

Size of set of large itemsets L(1): 44
Size of set of large itemsets L(2): 380
Size of set of large itemsets L(3): 910
Size of set of large itemsets L(4): 633
Size of set of large itemsets L(5): 105
Size of set of large itemsets L(6): 1

Best rules found:

1. biscuits=t frozen foods=t fruit=t total=high 788 ==> bread and cake=t 723 <conf:(0.92)> lift:(1.27) lev:(0.03) [155] conv:(3.35)
2. baking needs=t biscuits=t fruit=t total=high 760 ==> bread and cake=t 696 <conf:(0.92)> lift:(1.27) lev:(0.03) [149] conv:(3.28)
3. baking needs=t frozen foods=t fruit=t total=high 770 ==> bread and cake=t 705 <conf:(0.92)> lift:(1.27) lev:(0.03) [150] conv:(3.26)
4. biscuits=t fruit=t vegetables=t total=high 815 ==> bread and cake=t 746 <conf:(0.92)> lift:(1.27) lev:(0.03) [159] conv:(3.27)
5. party snack foods=t fruit=t total=high 854 ==> bread and cake=t 779 <conf:(0.91)> lift:(1.27) lev:(0.04) [164] conv:(3.15)
6. biscuits=t frozen foods=t vegetables=t total=high 797 ==> bread and cake=t 725 <conf:(0.91)> lift:(1.26) lev:(0.03) [151] conv:(3.06)
7. baking needs=t biscuits=t vegetables=t total=high 772 ==> bread and cake=t 701 <conf:(0.91)> lift:(1.26) lev:(0.03) [145] conv:(3.01)
8. biscuits=t fruit=t total=high 954 ==> bread and cake=t 866 <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(3)
9. frozen foods=t fruit=t vegetables=t total=high 834 ==> bread and cake=t 757 <conf:(0.91)> lift:(1.26) lev:(0.03) [156] conv:(3)
10. frozen foods=t fruit=t total=high 969 ==> bread and cake=t 877 <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(2.92)
```

EXPERIMENT 8

Aim: Implementation of Visualization technique on ARFF files using WEKA.

Theory:

WEKA provides multiple visualization tools:

- Scatter Plots
- Attribute Histograms
- Class Color Visualization
- Cluster Visualization
- Decision Tree Visualizer

Visualization helps understand data distributions, class separability, and find outliers.

Dataset:

@relation students

@attribute hours_studied numeric

@attribute attendance numeric

@attribute marks numeric

@data

2,60,45

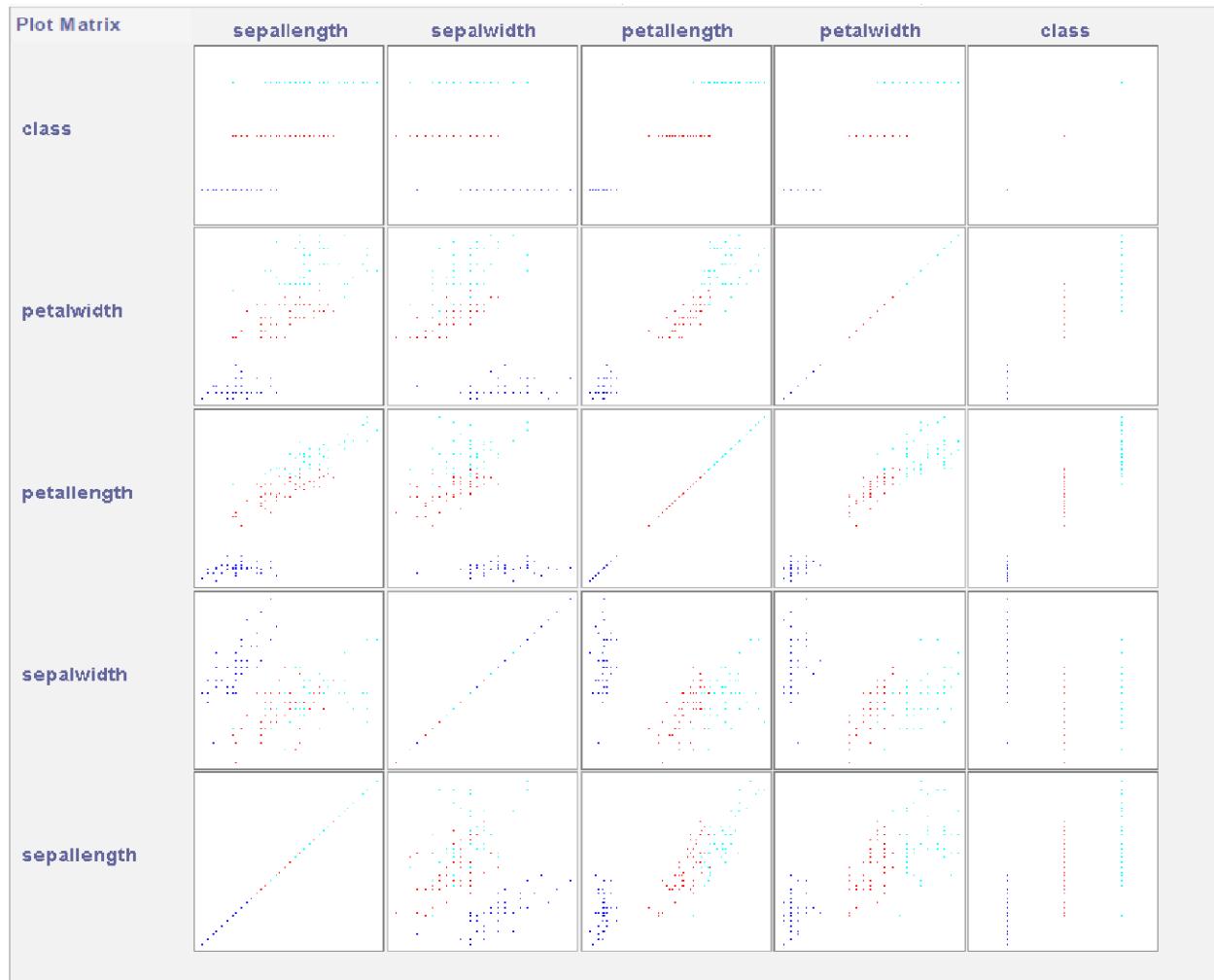
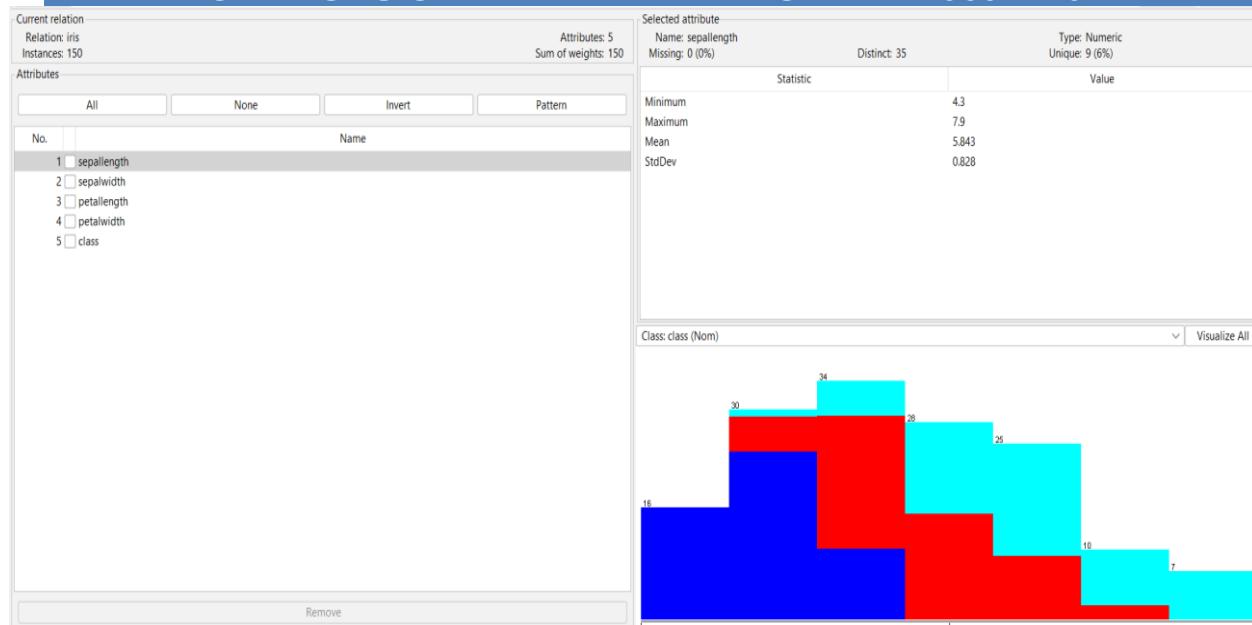
5,75,65

8,85,80

3,70,50

6,90,78

WEKA:



Learning Outcomes: