Université Abdelmalek Essaadi

Faculté des Sciences et Techniques - Tanger

Département Génie Informatique

Filière :

« Logiciels et systèmes intelligents »

LSI

TP: Suivi des Indicateurs de Performance d'une Entreprise Commerciale

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1. Experiment 1 - Creation of Dataware house

a. Creating the databases

```
mysql> SHOW DATABASES;
+--------------------+
| Database           |
+--------------------+
| HireBase           |
| information_schema |
| mysql              |
| performance_schema |
| sys                |
+--------------------+
5 rows in set (0.01 sec)
```

b. Creating Table

```
mysql> SHOW TABLES
    -> ;
+--------------------+
| Tables_in_HireBase |
+--------------------+
| Customer           |
| Hire               |
| Van                |
+--------------------+
3 rows in set (0.00 sec)

mysql>
```

i. **Verify Customer Data:**

```
mysql> SELECT * FROM Customer LIMIT 10;
+------------+--------------+-------------+--------+-------------+-----------------+--------------+
| CustomerId | CustomerName | DateOfBirth | Town   | TelephoneNo | DrivingLicenceNo | Occupation   |
+------------+--------------+-------------+--------+-------------+-----------------+--------------+
| N01        | Customer01   | 2000-01-01  | Town01 | Phone01     | Licence01       | Occupation01 |
| N02        | Customer02   | 2000-01-02  | Town02 | Phone02     | Licence02       | Occupation02 |
| N03        | Customer03   | 2000-01-03  | Town03 | Phone03     | Licence03       | Occupation03 |
| N04        | Customer04   | 2000-01-04  | Town04 | Phone04     | Licence04       | Occupation04 |
| N05        | Customer05   | 2000-01-05  | Town05 | Phone05     | Licence05       | Occupation05 |
| N06        | Customer06   | 2000-01-06  | Town06 | Phone06     | Licence06       | Occupation06 |
| N07        | Customer07   | 2000-01-07  | Town07 | Phone07     | Licence07       | Occupation07 |
| N08        | Customer08   | 2000-01-08  | Town08 | Phone08     | Licence08       | Occupation08 |
| N09        | Customer09   | 2000-01-09  | Town09 | Phone09     | Licence09       | Occupation09 |
| N10        | Customer10   | 2000-01-10  | Town10 | Phone10     | Licence10       | Occupation10 |
+------------+--------------+-------------+--------+-------------+-----------------+--------------+
10 rows in set (0.00 sec)
```

ii. **Verify Van Data:**

```
mysql> SELECT * FROM Van LIMIT 10;
+-------+--------+---------+------+--------+------+--------+
| RegNo | Make   | Model   | Year | Colour | CC   | Class  |
+-------+--------+---------+------+--------+------+--------+
| Reg1  | Make1  | Model1  | 2009 | White  | 2500 | Medium |
| Reg10 | Make10 | Model10 | 2010 | White  | 2500 | Medium |
| Reg11 | Make11 | Model11 | 2011 | White  | 3000 | Large  |
| Reg12 | Make12 | Model12 | 2008 | White  | 2000 | Small  |
| Reg13 | Make13 | Model13 | 2009 | Black  | 2500 | Medium |
| Reg14 | Make14 | Model14 | 2010 | Black  | 3000 | Large  |
| Reg15 | Make15 | Model15 | 2011 | White  | 2000 | Small  |
| Reg16 | Make16 | Model16 | 2008 | White  | 2500 | Medium |
| Reg17 | Make17 | Model17 | 2009 | White  | 3000 | Large  |
| Reg18 | Make18 | Model18 | 2010 | Black  | 2000 | Small  |
+-------+--------+---------+------+--------+------+--------+
10 rows in set (0.00 sec)
```

iii. **Verify Hire Data:**

```
mysql> SELECT * FROM Hire LIMIT 10;
+--------+------------+------------+-------+----------+---------+------------+-----------+--------------+-----------+
| HireId | HireDate   | CustomerId | RegNo | NoOfDays | VanHire | SatNavHire | Insurance | DamageWaiver | TotalBill |
+--------+------------+------------+-------+----------+---------+------------+-----------+--------------+-----------+
| H0001  | 2011-01-01 | N01        | Reg1  |        1 |  100.00 |      10.00 |     20.00 |        40.00 |    170.00 |
| H0002  | 2011-01-02 | N02        | Reg2  |        2 |  200.00 |      20.00 |     40.00 |        80.00 |    340.00 |
| H0003  | 2011-01-03 | N03        | Reg3  |        3 |  300.00 |      30.00 |     60.00 |       120.00 |    510.00 |
| H0004  | 2011-01-04 | N04        | Reg4  |        1 |  100.00 |      10.00 |     20.00 |        40.00 |    170.00 |
| H0005  | 2011-01-05 | N05        | Reg5  |        2 |  200.00 |      20.00 |     40.00 |        80.00 |    340.00 |
| H0006  | 2011-01-06 | N06        | Reg6  |        3 |  300.00 |      30.00 |     60.00 |       120.00 |    510.00 |
| H0007  | 2011-01-07 | N07        | Reg7  |        1 |  100.00 |      10.00 |     20.00 |        40.00 |    170.00 |
| H0008  | 2011-01-08 | N08        | Reg8  |        2 |  200.00 |      20.00 |     40.00 |        80.00 |    340.00 |
| H0009  | 2011-01-09 | N09        | Reg9  |        3 |  300.00 |      30.00 |     60.00 |       120.00 |    510.00 |
| H0010  | 2011-01-10 | N10        | Reg10 |        1 |  100.00 |      10.00 |     20.00 |        40.00 |    170.00 |
+--------+------------+------------+-------+----------+---------+------------+-----------+--------------+-----------+
10 rows in set (0.00 sec)
```

c. Create the Data Warehouse

```
+--------------------+
| Database           |
+--------------------+
| HireBase           |
| TopHireDW          |
| information_schema |
| mysql              |
| performance_schema |
| sys                |
+--------------------+
6 rows in set (0.00 sec)

mysql>
```

d. Creating Table

```
mysql> SHOW TABLES
    -> ;
+---------------------+
| Tables_in_TopHireDW |
+---------------------+
| DimCustomer         |
| DimDate             |
| DimVan              |
| FactHire            |
+---------------------+
4 rows in set (0.00 sec)
```

i. **Verify Date Dimension (`DimDate`):**

```
mysql> SELECT * FROM DimDate LIMIT 15;
+----------+---------+---------+------------+------------+
| DateKey  | Year    | Month   | Date       | DateString |
+----------+---------+---------+------------+------------+
|        0 | Unknown | Unknown | 0001-01-01 | Unknown    |
| 20060101 | 2006    | 2006-01 | 2006-01-01 | 2006-01-01 |
| 20060102 | 2006    | 2006-01 | 2006-01-02 | 2006-01-02 |
| 20060103 | 2006    | 2006-01 | 2006-01-03 | 2006-01-03 |
| 20060104 | 2006    | 2006-01 | 2006-01-04 | 2006-01-04 |
| 20060105 | 2006    | 2006-01 | 2006-01-05 | 2006-01-05 |
| 20060106 | 2006    | 2006-01 | 2006-01-06 | 2006-01-06 |
| 20060107 | 2006    | 2006-01 | 2006-01-07 | 2006-01-07 |
| 20060108 | 2006    | 2006-01 | 2006-01-08 | 2006-01-08 |
| 20060109 | 2006    | 2006-01 | 2006-01-09 | 2006-01-09 |
| 20060110 | 2006    | 2006-01 | 2006-01-10 | 2006-01-10 |
| 20060111 | 2006    | 2006-01 | 2006-01-11 | 2006-01-11 |
| 20060112 | 2006    | 2006-01 | 2006-01-12 | 2006-01-12 |
| 20060113 | 2006    | 2006-01 | 2006-01-13 | 2006-01-13 |
| 20060114 | 2006    | 2006-01 | 2006-01-14 | 2006-01-14 |
+----------+---------+---------+------------+------------+
15 rows in set (0.00 sec)
```

ii. **Verify Customer Dimension (`DimCustomer`):**

```
mysql> SELECT * FROM DimCustomer LIMIT 10;
+-------------+------------+--------------+-------------+--------+-------------+------------------+--------------+
| CustomerKey | CustomerId | CustomerName | DateOfBirth | Town   | TelephoneNo | DrivingLicenceNo | Occupation   |
+-------------+------------+--------------+-------------+--------+-------------+------------------+--------------+
|           1 | N01        | Customer01   | 2000-01-01  | Town01 | Phone01     | Licence01        | Occupation01 |
|           2 | N02        | Customer02   | 2000-01-02  | Town02 | Phone02     | Licence02        | Occupation02 |
|           3 | N03        | Customer03   | 2000-01-03  | Town03 | Phone03     | Licence03        | Occupation03 |
|           4 | N04        | Customer04   | 2000-01-04  | Town04 | Phone04     | Licence04        | Occupation04 |
|           5 | N05        | Customer05   | 2000-01-05  | Town05 | Phone05     | Licence05        | Occupation05 |
|           6 | N06        | Customer06   | 2000-01-06  | Town06 | Phone06     | Licence06        | Occupation06 |
|           7 | N07        | Customer07   | 2000-01-07  | Town07 | Phone07     | Licence07        | Occupation07 |
|           8 | N08        | Customer08   | 2000-01-08  | Town08 | Phone08     | Licence08        | Occupation08 |
|           9 | N09        | Customer09   | 2000-01-09  | Town09 | Phone09     | Licence09        | Occupation09 |
|          10 | N10        | Customer10   | 2000-01-10  | Town10 | Phone10     | Licence10        | Occupation10 |
+-------------+------------+--------------+-------------+--------+-------------+------------------+--------------+
10 rows in set (0.00 sec)
```

iii. **Verify Van Dimension (`DimVan`):**

```
mysql> SELECT * FROM DimVan LIMIT 10;
+--------+-------+--------+---------+------+--------+------+--------+
| VanKey | RegNo | Make   | Model   | Year | Colour | CC   | Class  |
+--------+-------+--------+---------+------+--------+------+--------+
|      1 | Reg1  | Make1  | Model1  | 2009 | White  | 2500 | Medium |
|      2 | Reg10 | Make10 | Model10 | 2010 | White  | 2500 | Medium |
|      3 | Reg11 | Make11 | Model11 | 2011 | White  | 3000 | Large  |
|      4 | Reg12 | Make12 | Model12 | 2008 | White  | 2000 | Small  |
|      5 | Reg13 | Make13 | Model13 | 2009 | Black  | 2500 | Medium |
|      6 | Reg14 | Make14 | Model14 | 2010 | Black  | 3000 | Large  |
|      7 | Reg15 | Make15 | Model15 | 2011 | White  | 2000 | Small  |
|      8 | Reg16 | Make16 | Model16 | 2008 | White  | 2500 | Medium |
|      9 | Reg17 | Make17 | Model17 | 2009 | White  | 3000 | Large  |
|     10 | Reg18 | Make18 | Model18 | 2010 | Black  | 2000 | Small  |
+--------+-------+--------+---------+------+--------+------+--------+
10 rows in set (0.00 sec)
```

iii) ETL Implementation

```
mysql> INSERT INTO FactHire (
    ->     SnapshotDateKey,
    ->     HireDateKey,
    ->     CustomerKey,
    ->     VanKey,
    ->     HireId,
    ->
    ->     -- Measures from source
    ->     NoOfDays,
    ->     VanHire,
    ->     SatNavHire,
    ->     Insurance,
    ->     DamageWaiver,
    ->     TotalBill
    -> )...
```

1. **Check Row Count**

```
mysql> SELECT COUNT(*) FROM FactHire;
+----------+
| COUNT(*) |
+----------+
|     1000 |
+----------+
1 row in set (0.00 sec)
```

2. **Inspect Sample Data:**

```
mysql> SELECT * FROM FactHire LIMIT 10;
```

SnapshotDateKey	HireDateKey	CustomerKey	VanKey	HireId	NoOfDays	VanHire	SatNavHire	Insurance	DamageWaiver	TotalBill
20110101	20110101	1	1	H0801	3	300.00	30.00	60.00	120.00	510.00
20110101	20110101	1	1	H0601	1	100.00	10.00	20.00	40.00	170.00
20110101	20110101	1	1	H0401	2	200.00	20.00	40.00	80.00	340.00
20110101	20110101	1	1	H0201	3	300.00	30.00	60.00	120.00	510.00
20110101	20110101	1	1	H0001	1	100.00	10.00	20.00	40.00	170.00
20110102	20110102	2	12	H0802	1	100.00	10.00	20.00	40.00	170.00
20110102	20110102	2	12	H0602	2	200.00	20.00	40.00	80.00	340.00
20110102	20110102	2	12	H0402	3	300.00	30.00	60.00	120.00	510.00
20110102	20110102	2	12	H0202	1	100.00	10.00	20.00	40.00	170.00
20110102	20110102	2	12	H0002	2	200.00	20.00	40.00	80.00	340.00

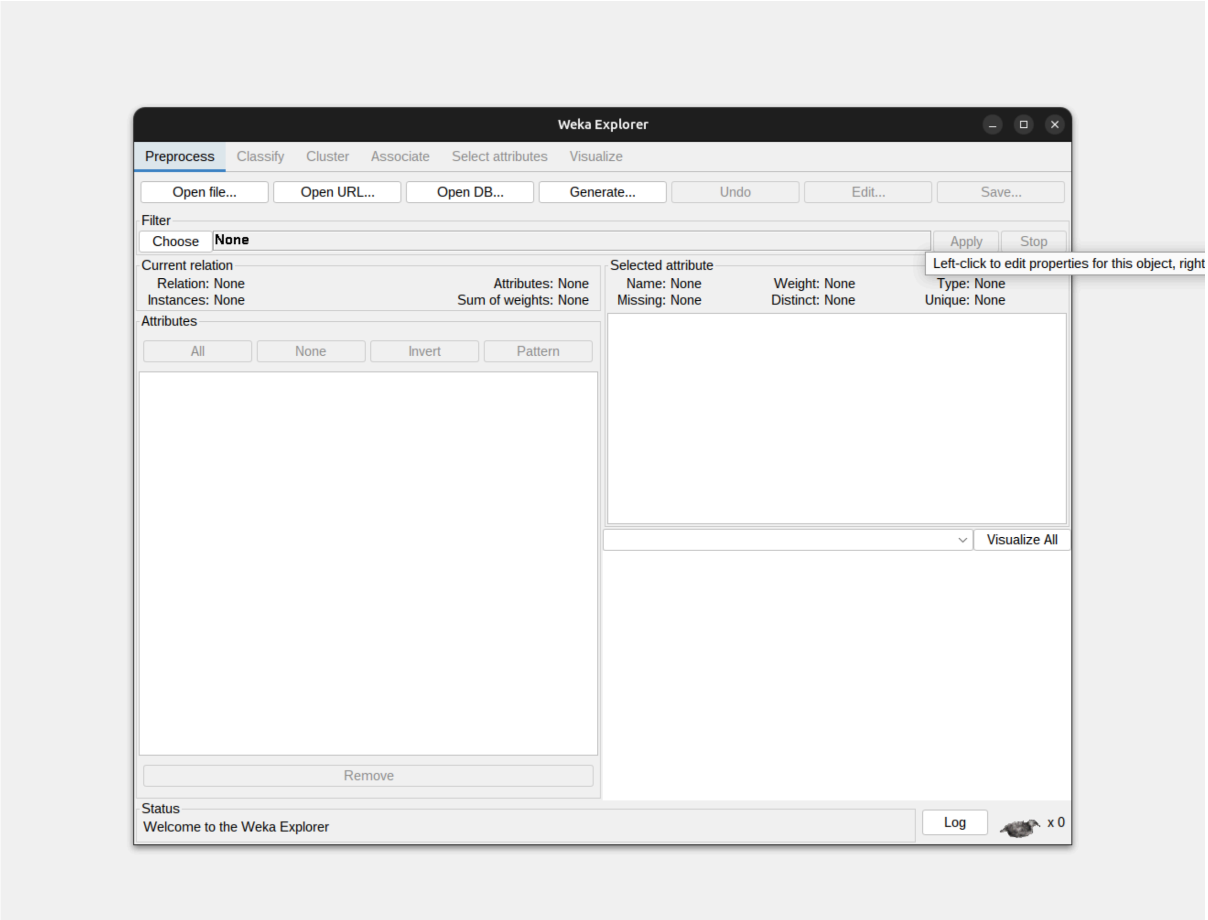
```
10 rows in set (0.00 sec)
```

2. Experiment 2 - Weka

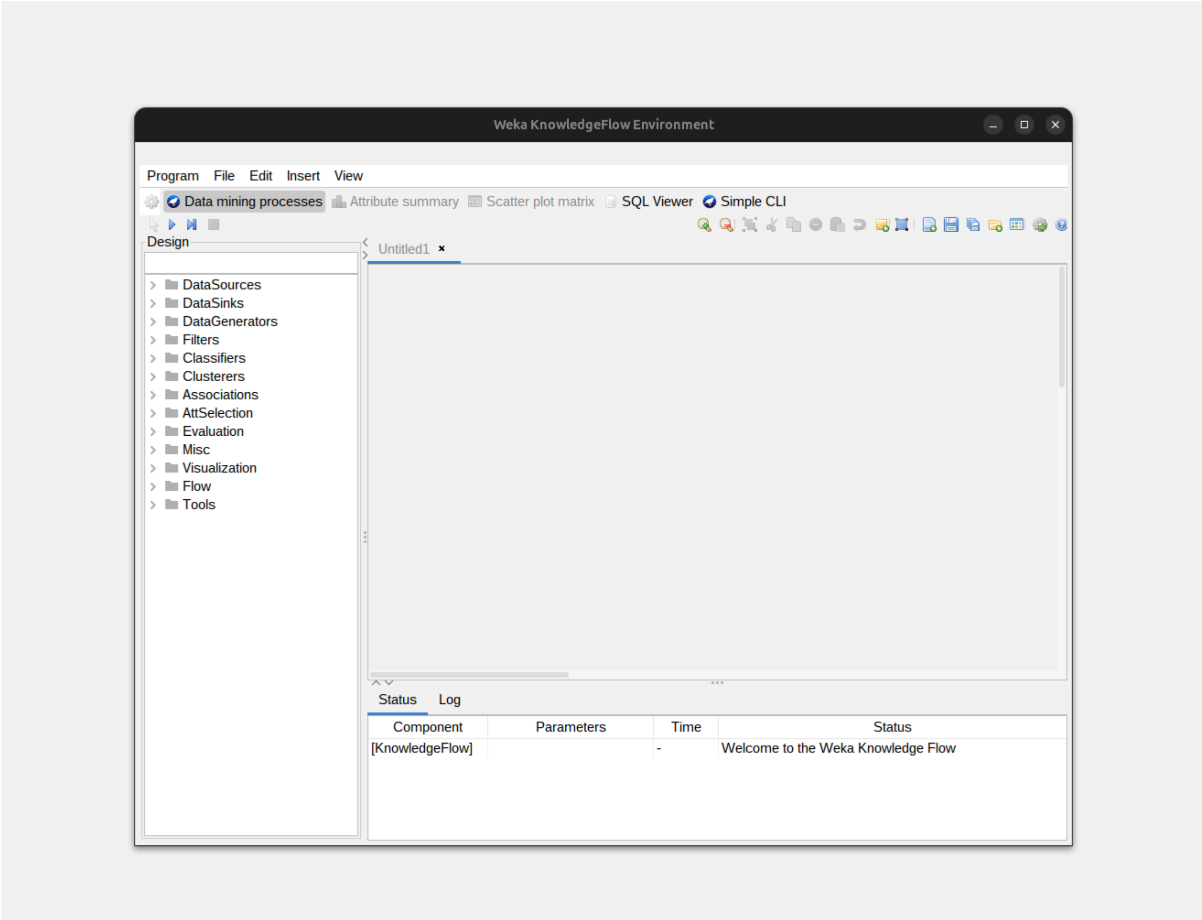
i. Installation

ii. WEKA Toolkit Features

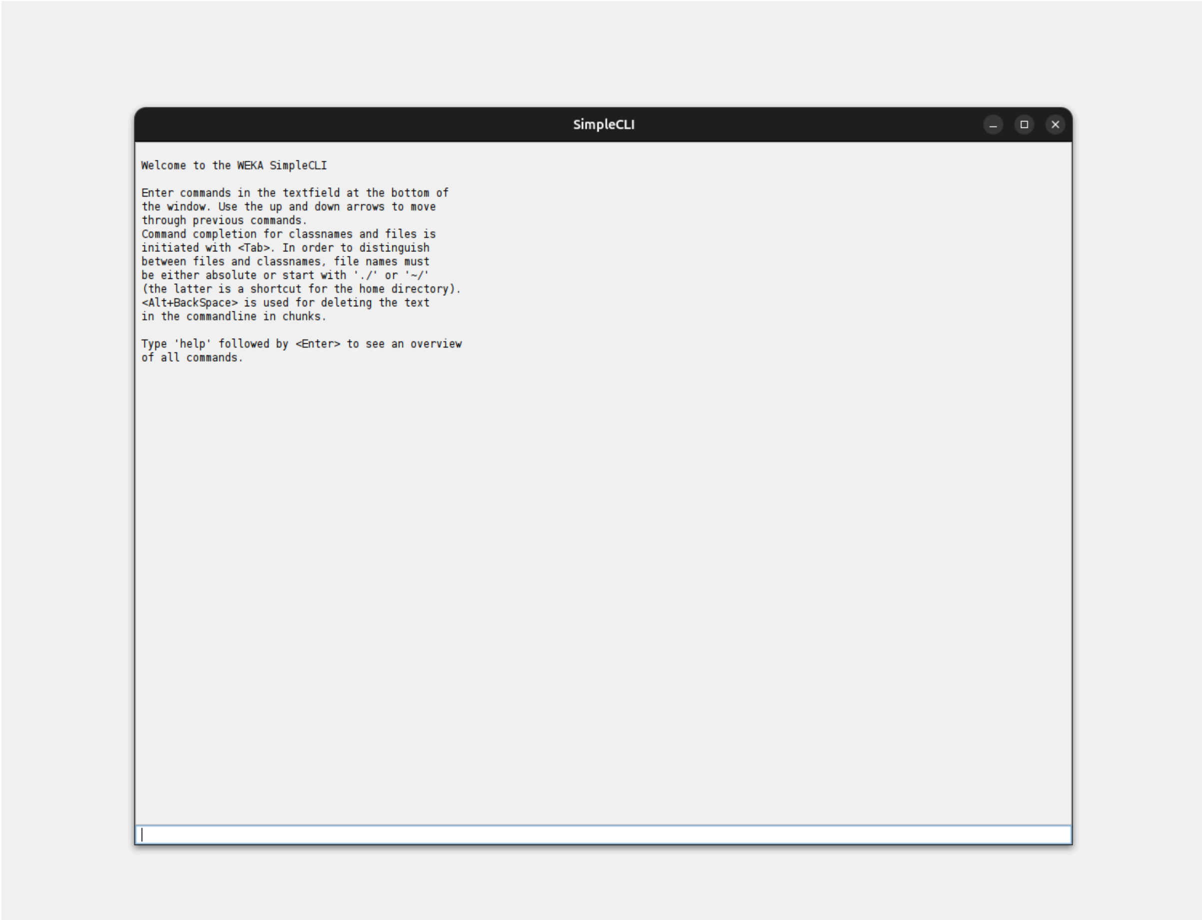
Explorer : Main interface for data preprocessing and analysis



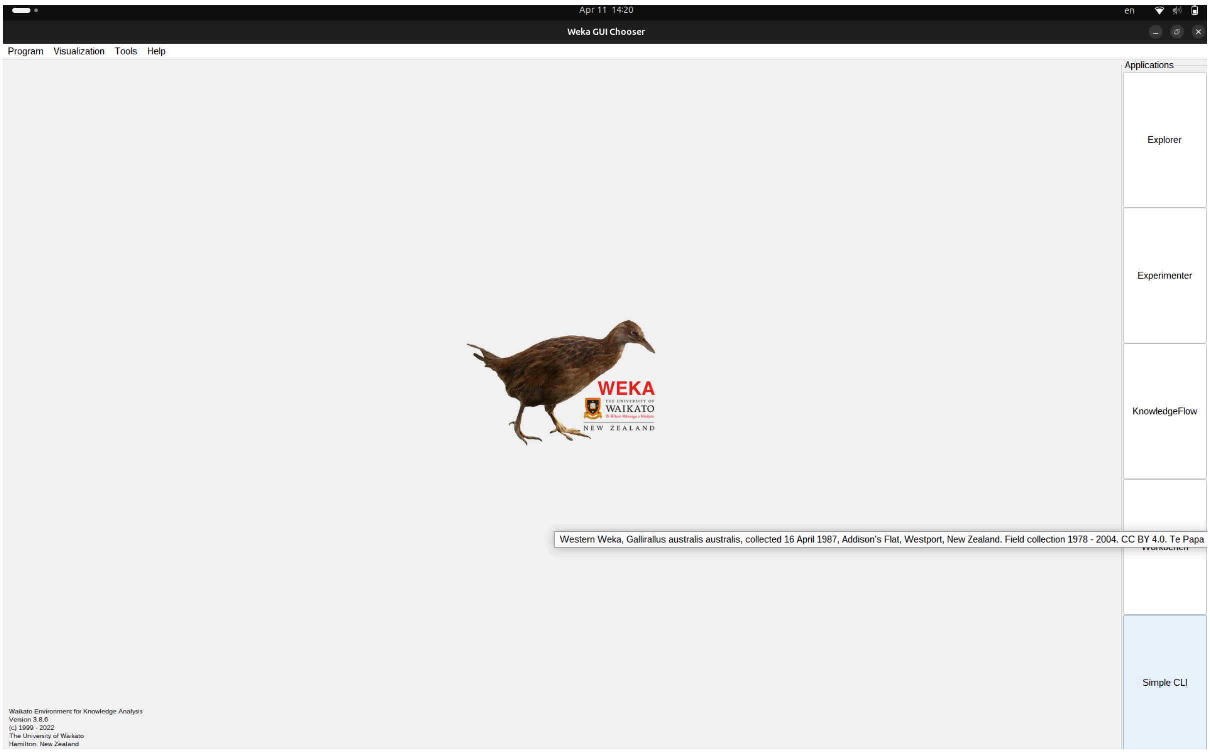
KnowledgeFlow : Drag-and-drop workflow design

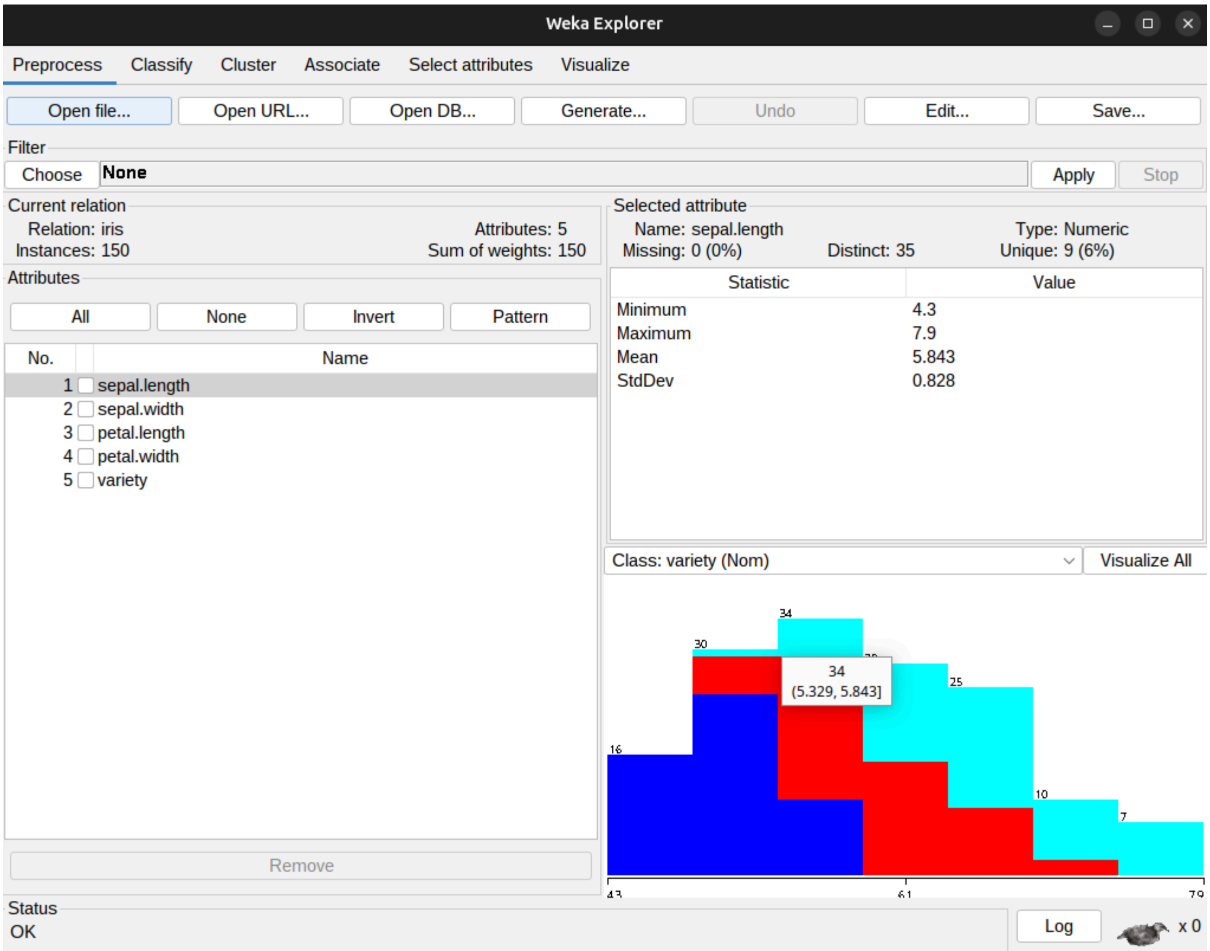


SimpleCLI : a simple command-line interface that allows direct execution of WEKA commands for operating systems that do not provide their own command line interface.

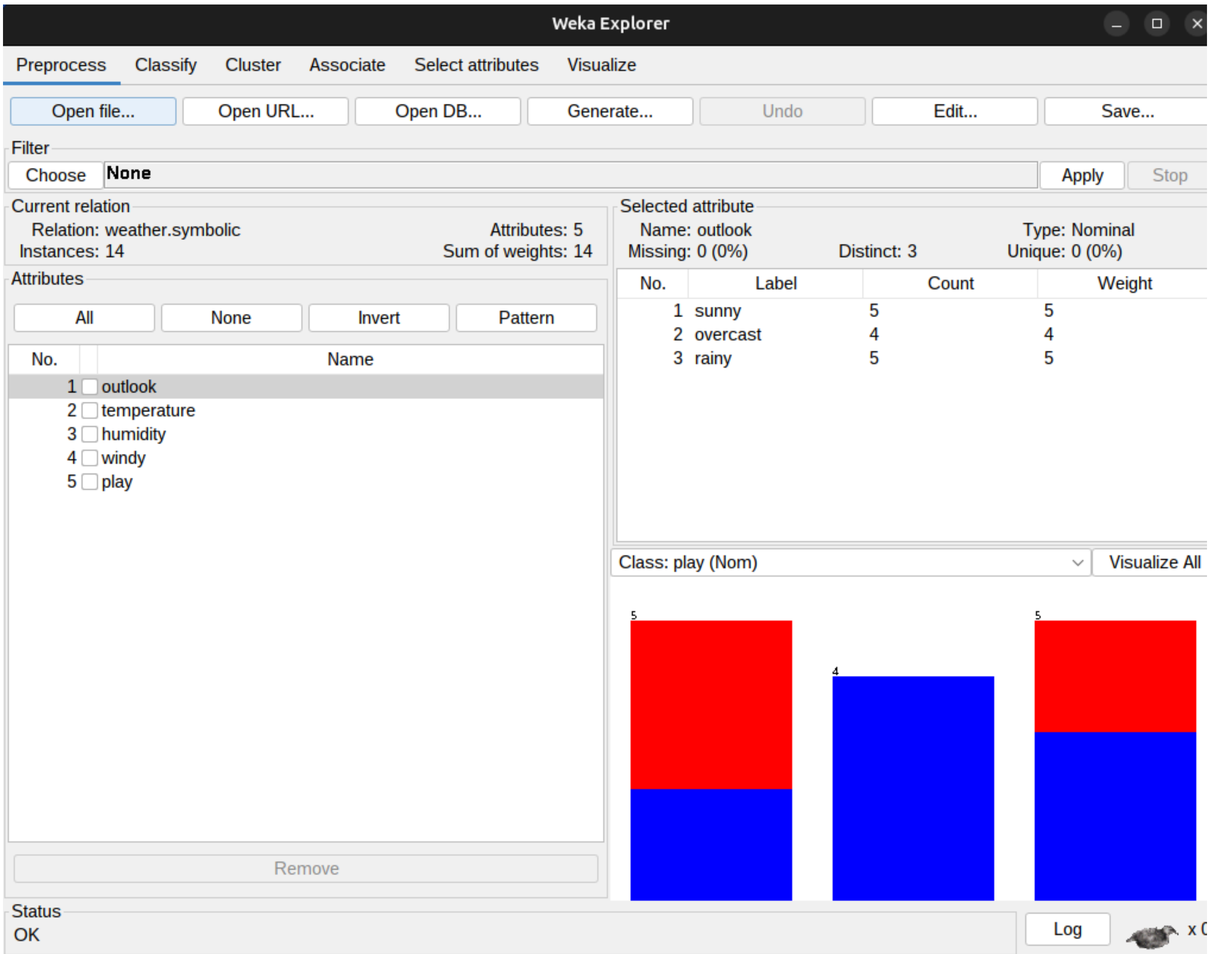


iii. Navigate the options available in the WEKA:

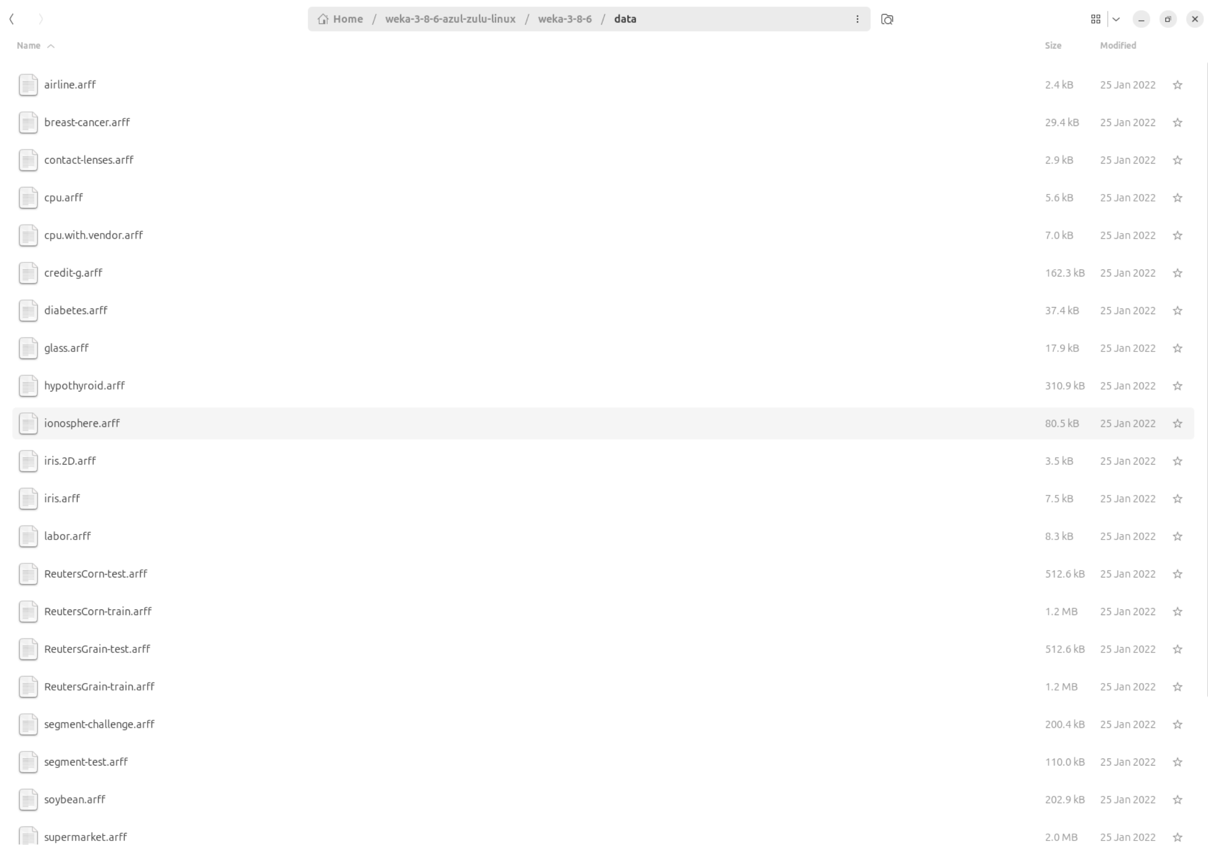




iV. Study the ARFF file format

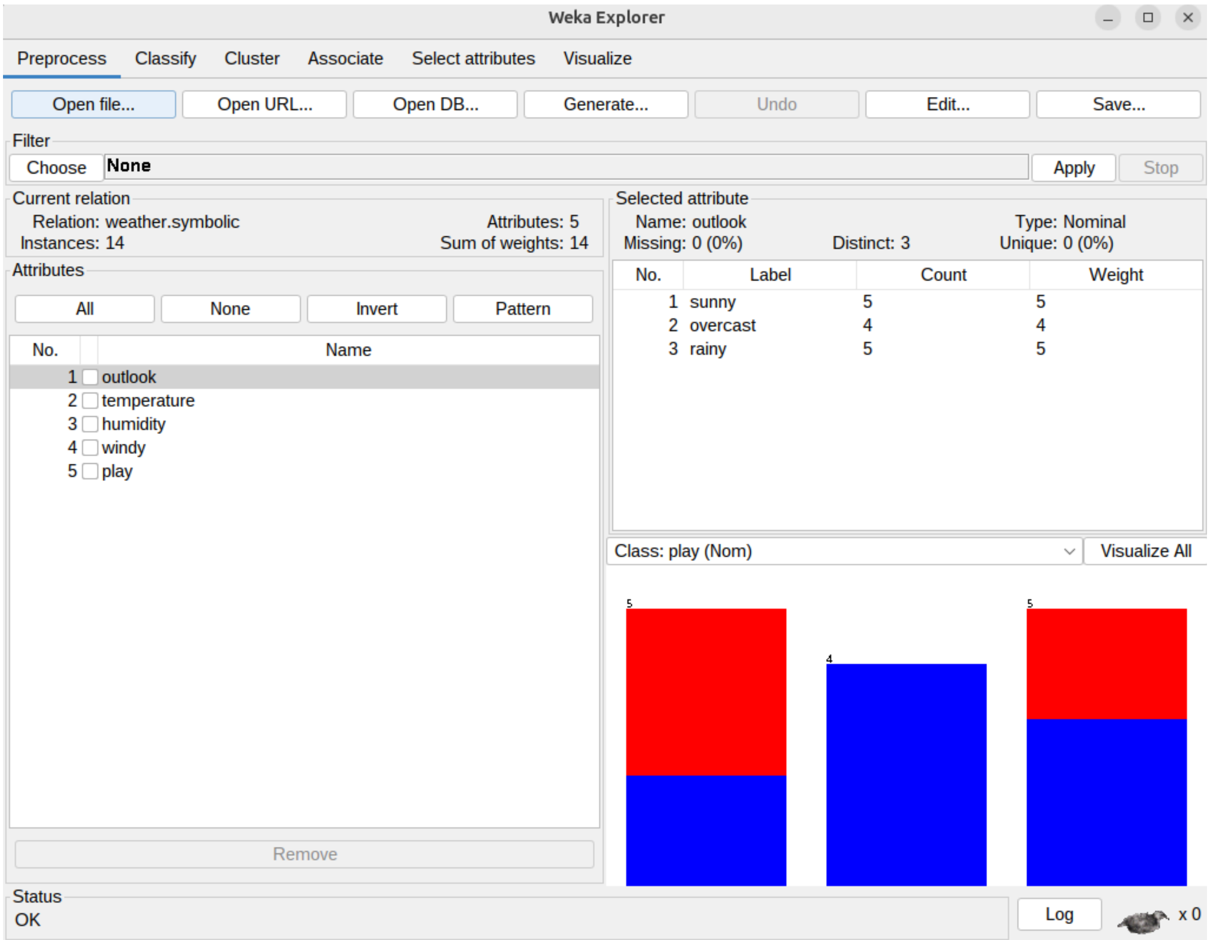


vi : Dataset Exploration

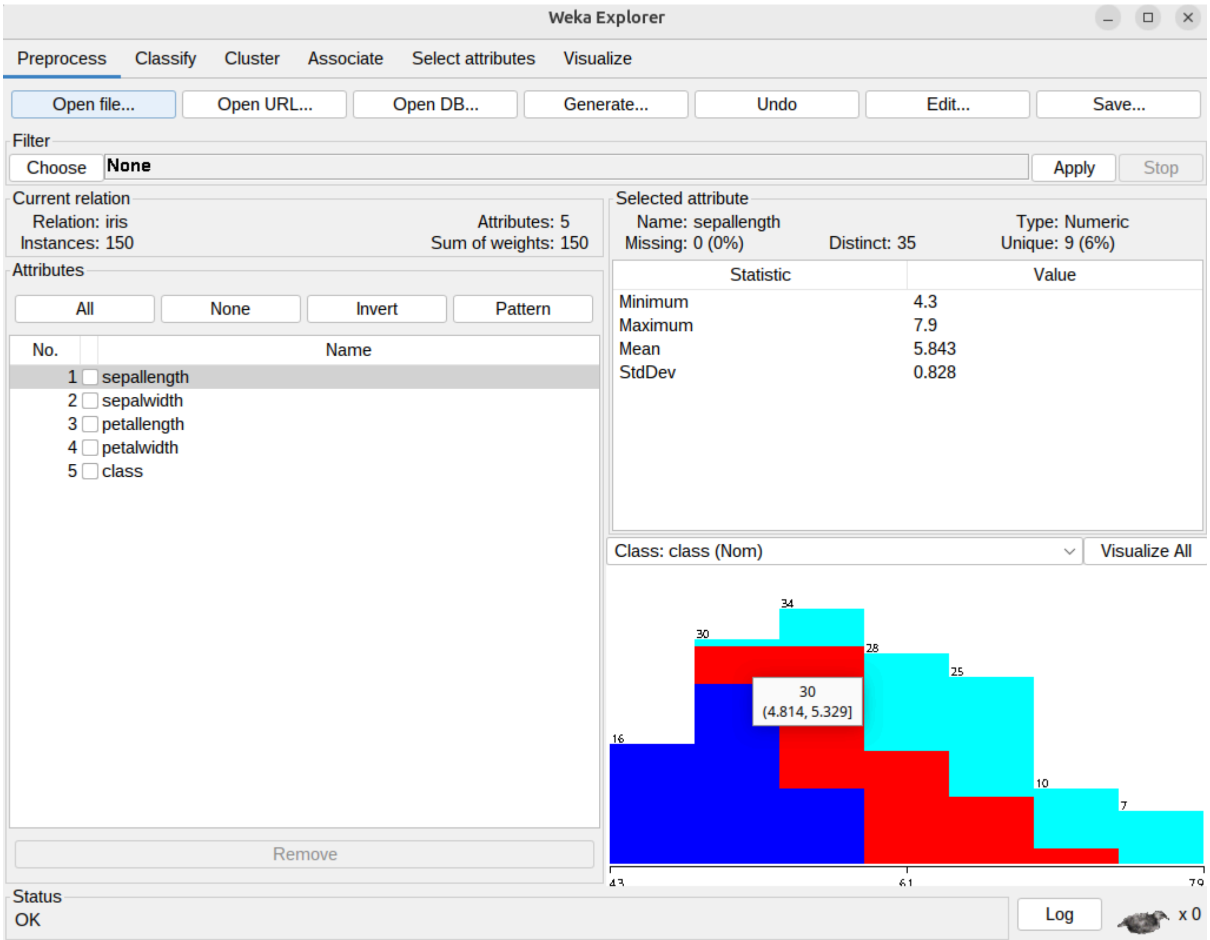


vi) Load a data set

Steps for load the Weather data set

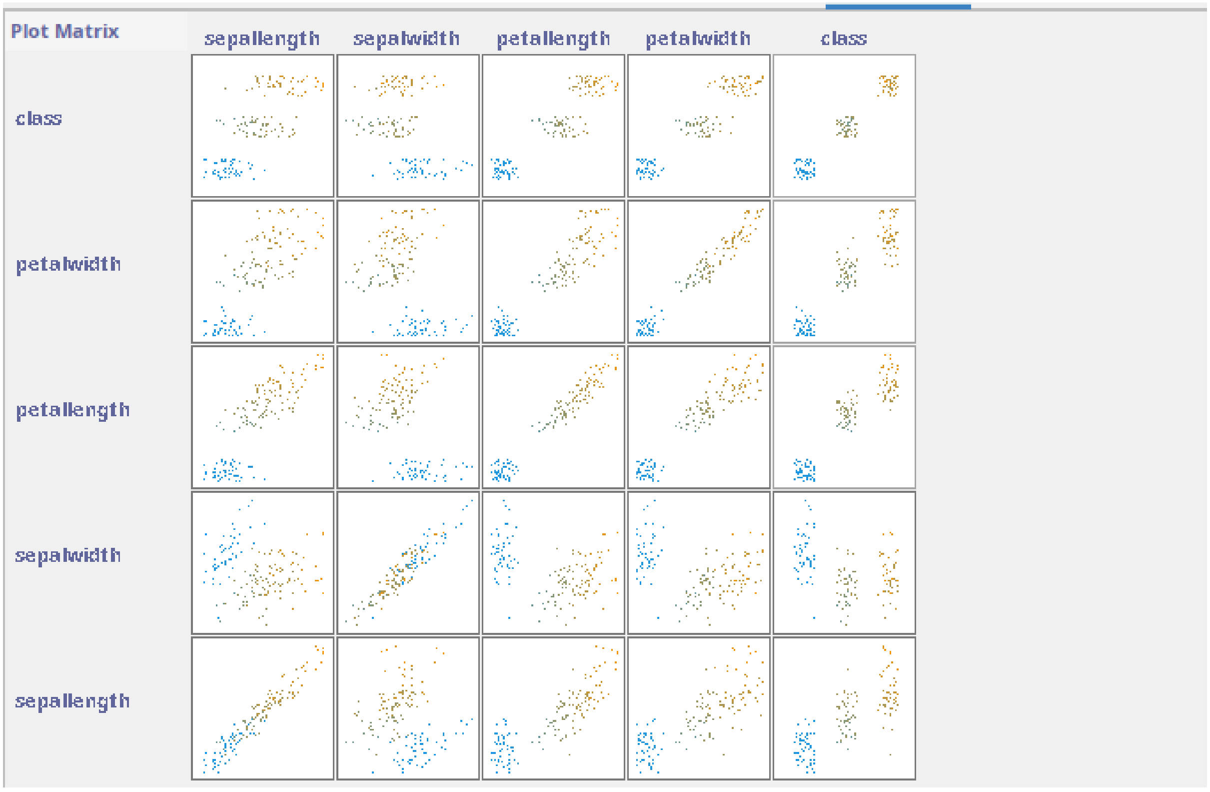


Steps for load the Iris data set.

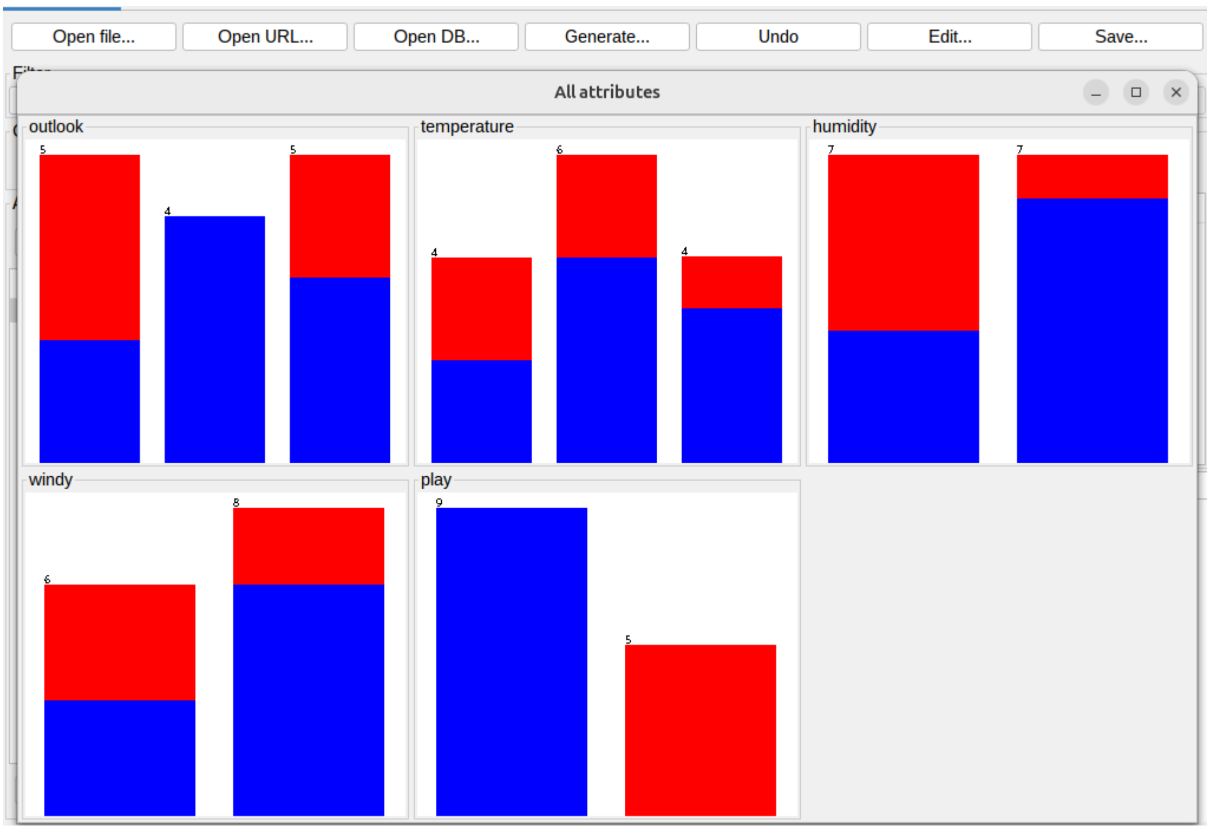


vii Load each dataset and observe the following:

vii.i Plot Histogram



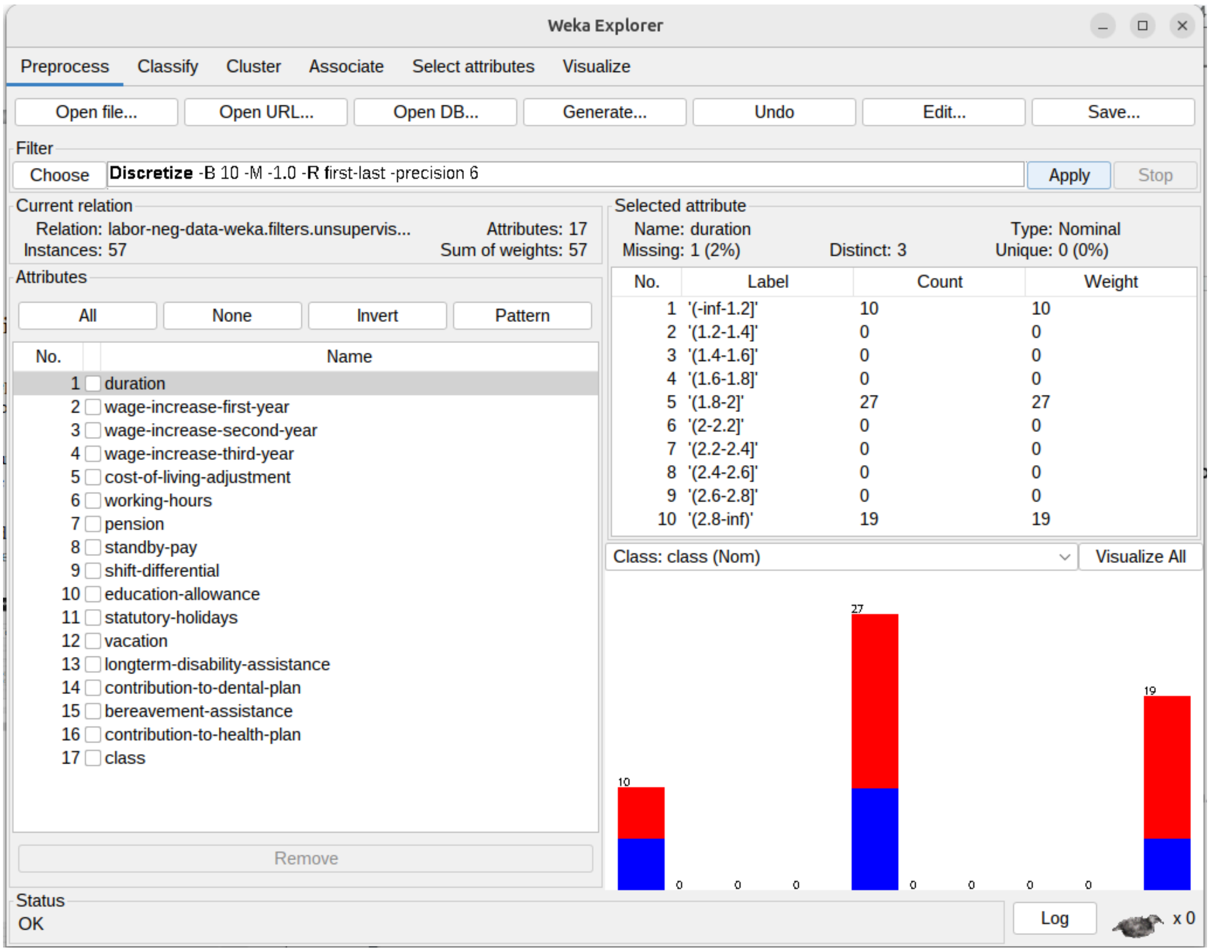
Visualize the data in various dimensions



3. **Experiment-3 : Perform data preprocessing tasks and Demonstrate performing association rule mining on data sets**

A : Data Preprocessing in Weka

1. Load Dataset :
— Open Weka → Explorer → Preprocess tab.
— Click Open File → Select labor.arff.
2. Apply Discretization :
— Choose filter : weka.filters.unsupervised.attribute.Discretize.
— Click Apply to convert numeric attributes to nominal bins.
3. Key Observations :
— Histograms show transformed distributions after discretization.
— Nominal attributes enable better association rule mining.



B.Load each dataset into Weka and run Aprior algorithm with different support and confidence values. Study the rules generated.

1. Load Weather Dataset :
— Load weather.symbolic via Preprocess tab.
2. Run Apriori :
— Switch to Associate tab → Select Apriori.

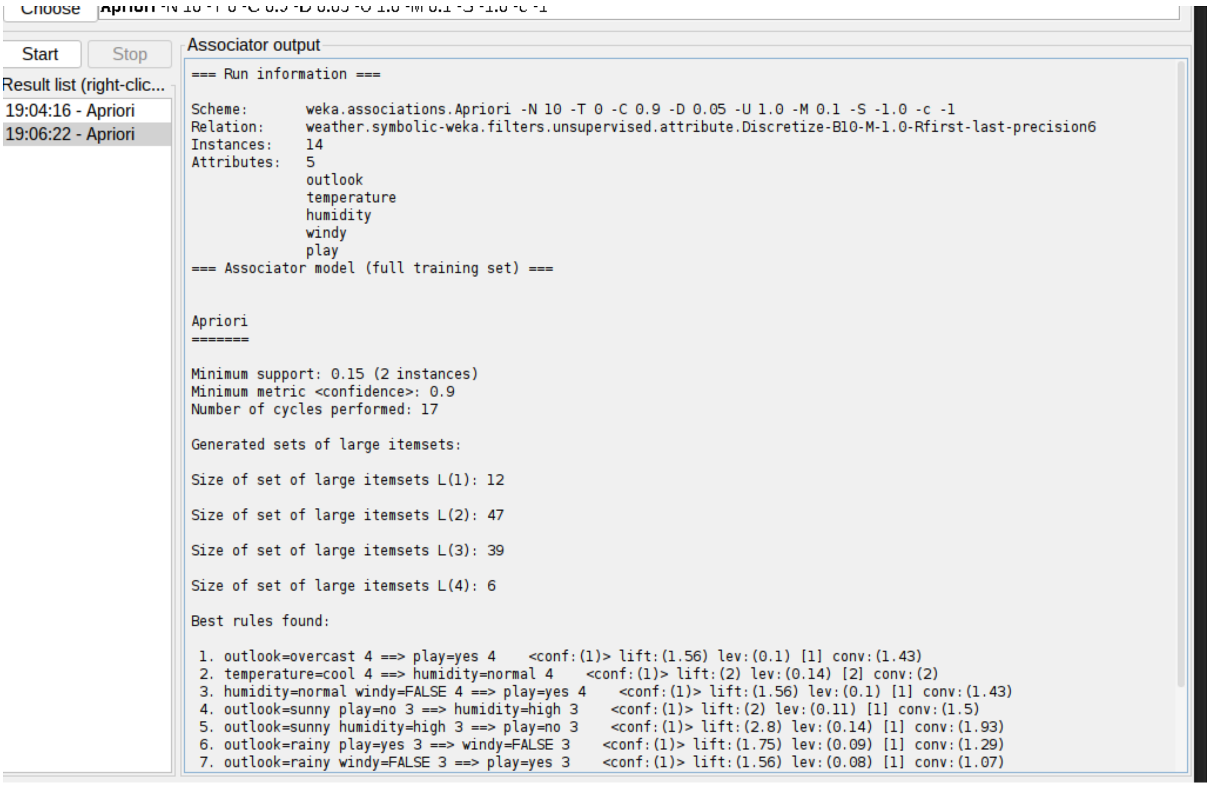
— **Parameters : Support = 0.15, Confidence = 0.9, Number of Rules = 10**

3. Key Rules :

1. outlook=overcast => play=yes (Confidence: 100%)

2. humidity=normal, windy=FALSE => play=yes (Confidence: 100%)

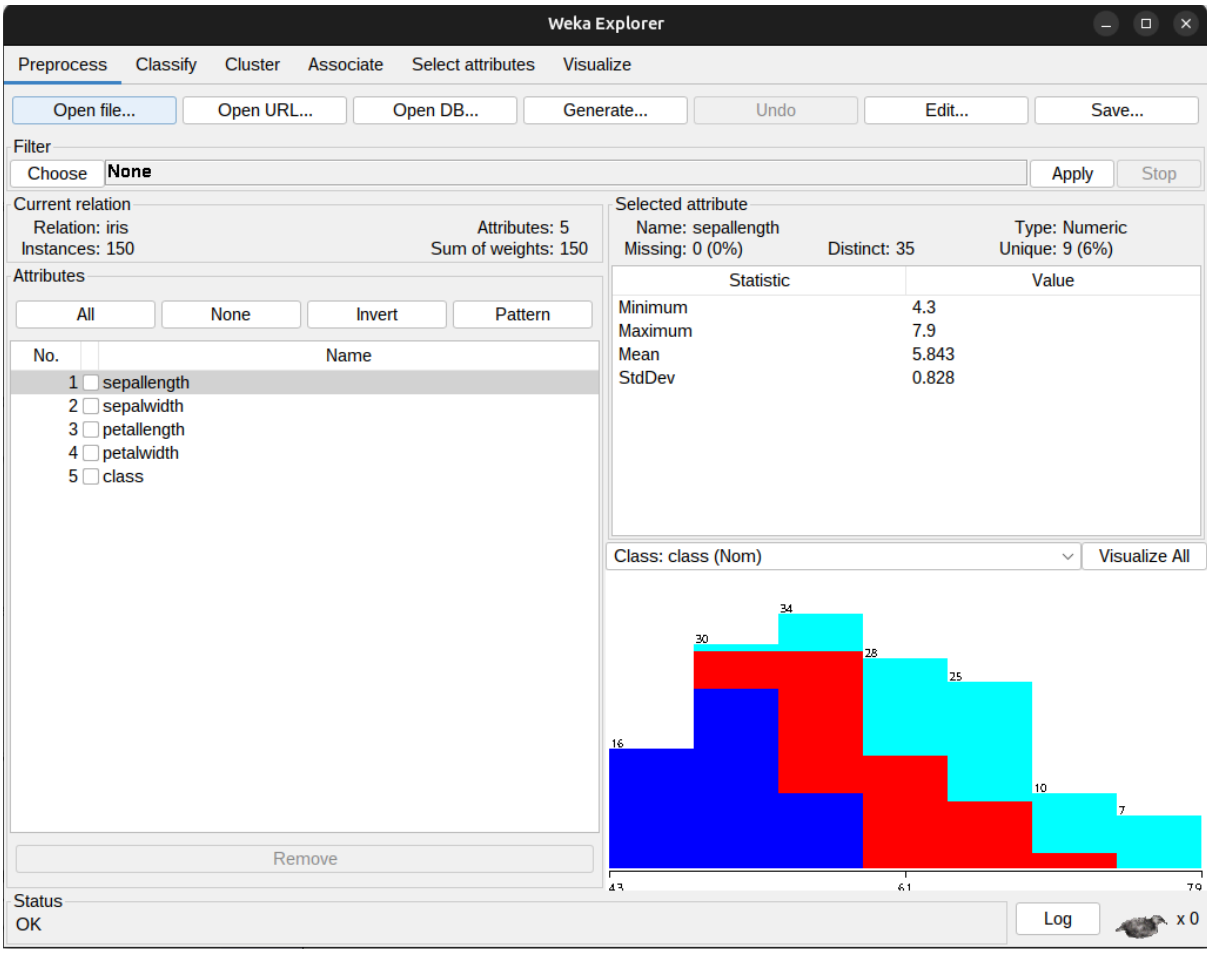
C. Apply different discretization filters on numerical attributes and run the Aprior association rule algorithm. Study the rules generated. Derive interesting insights and observe the effect of discretization in the rule generation process.



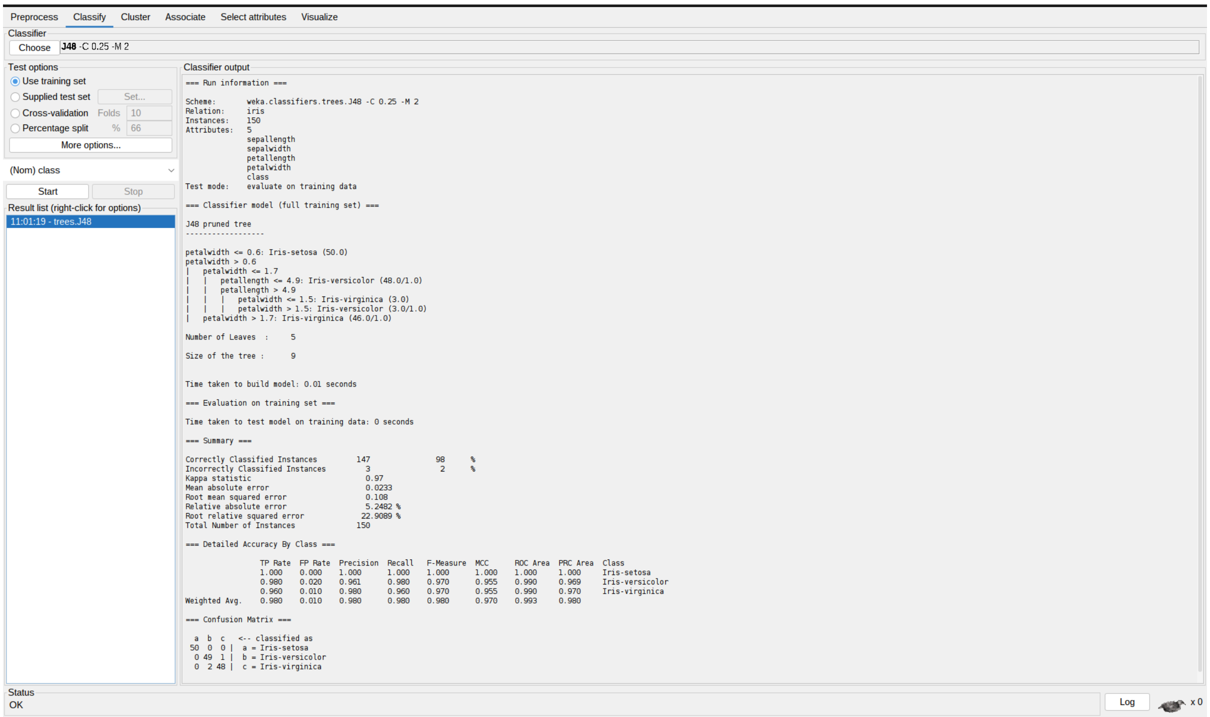

```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
Relation:     weather.symbolic-weka.filters.unsupervised.attribute.Discretize-B10-M-1.0-Rfirst-last-precision6
Instances:    14
Attributes:   5
              outlook
              temperature
              humidity
              windy
              play
=== Associator model (full training set) ===


Apriori
=======

Minimum support: 0.15 (2 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 17

Generated sets of large itemsets:

Size of set of large itemsets L(1): 12

Size of set of large itemsets L(2): 47

Size of set of large itemsets L(3): 39

Size of set of large itemsets L(4): 6

Best rules found:

 1. outlook=overcast 4 ==> play=yes 4    <conf:(1)> lift:(1.56) lev:(0.1) [1] conv:(1.43)
 2. temperature=cool 4 ==> humidity=normal 4    <conf:(1)> lift:(2) lev:(0.14) [2] conv:(2)
 3. humidity=normal windy=FALSE 4 ==> play=yes 4    <conf:(1)> lift:(1.56) lev:(0.1) [1] conv:(1.43)
 4. outlook=sunny play=no 3 ==> humidity=high 3    <conf:(1)> lift:(2) lev:(0.11) [1] conv:(1.5)
 5. outlook=sunny humidity=high 3 ==> play=no 3    <conf:(1)> lift:(2.8) lev:(0.14) [1] conv:(1.93)
 6. outlook=rainy play=yes 3 ==> windy=FALSE 3    <conf:(1)> lift:(1.75) lev:(0.09) [1] conv:(1.29)
 7. outlook=rainy windy=FALSE 3 ==> play=yes 3    <conf:(1)> lift:(1.56) lev:(0.08) [1] conv:(1.07)
```

Experiment-4: 4. Demonstrate performing classification on data sets.

Part A: Running ID3 and J48 Classifiers



J48 Classifier:



Results & Discussion (Based on provided J48 Output):

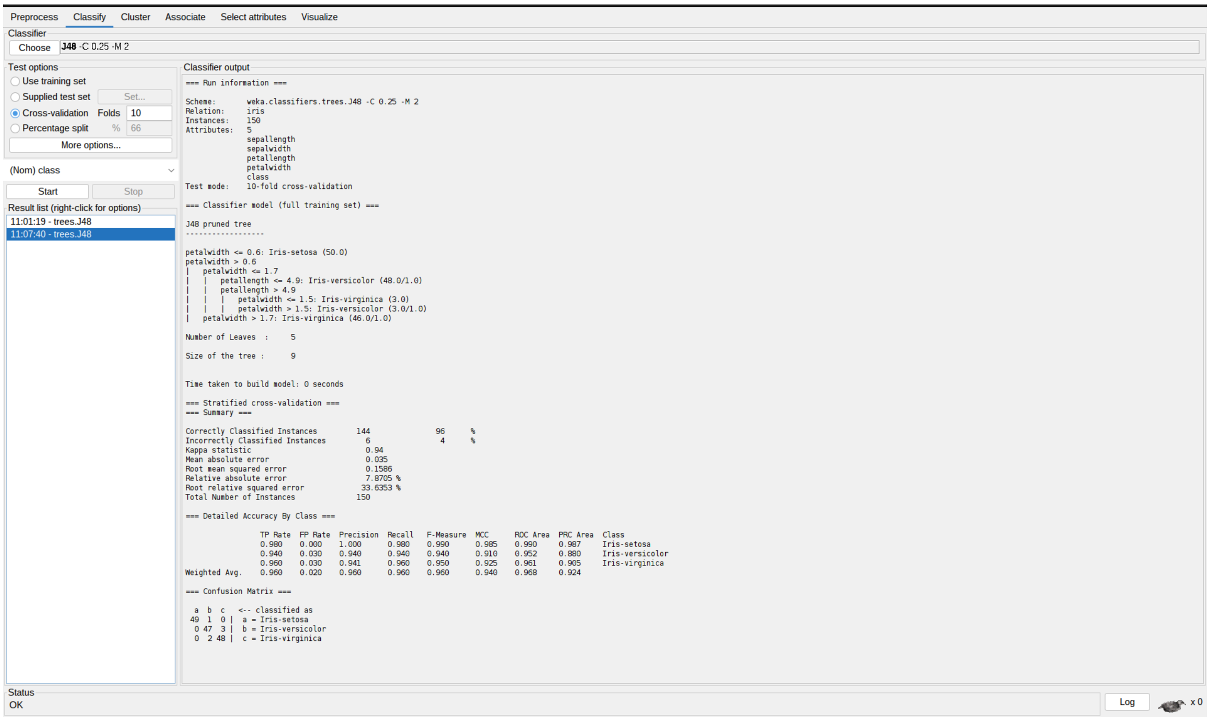
- **Classifier Model: The J48 algorithm generated a decision tree (shown in the output). The tree uses attributes like `petalwidth` and `petallength` to classify the instances.**
- **Evaluation (Training Set):**
  - **Accuracy: 147 out of 150 instances correctly classified (98%). This is very high, as expected when evaluating on the data the model was trained on.**
  - **Incorrectly Classified Instances: 3 (2%).**
  - **Kappa Statistic: 0.97. This indicates a very high level of agreement between the predicted and actual classes, significantly better than chance. A Kappa of 1 means perfect agreement.**
  - **Entropy Measures: The output shows values like "K&B Information Score" (227.8573 bits) and "Class complexity | order 0" (237.7444 bits). These relate to the information content and complexity of the class distribution and the model. Lower entropy/complexity improvement might indicate a simpler model.**

Part B: Rule Extraction, Metrics Derivation, and Cross-Validation

Steps & Results:

1. **IF-THEN Rule Extraction (from J48 model in Part A output):**
    - **Each path from the root to a leaf in the J48 tree corresponds to a rule:**
        - `IF petalwidth <= 0.6 THEN class = Iris-setosa`
        - `IF petalwidth > 0.6 AND petalwidth <= 1.7 AND petallength <= 4.9 THEN class = Iris-versicolor`
        - `IF petalwidth > 0.6 AND petalwidth <= 1.7 AND petallength > 4.9 AND petalwidth <= 1.5 THEN class = Iris-virginica`
        - `IF petalwidth > 0.6 AND petalwidth <= 1.7 AND petallength > 4.9 AND petalwidth > 1.5 THEN class = Iris-versicolor`
        - `IF petalwidth > 0.6 AND petalwidth > 1.7 THEN class = Iris-virginica`
    -
    - **These rules represent the logic learned by the J48 classifier.**
2.
3. **Deriving Metrics from Confusion Matrix (J48 - Training Set):**
    - **Let's focus on the class** `b = Iris-versicolor`**.**
        - **TP (True Positives): Correctly classified as versicolor = 49**
        - **FP (False Positives): Incorrectly classified as versicolor (but were virginica) = 2**
        - **FN (False Negatives): Were versicolor but classified as virginica = 1**
        - **TN (True Negatives): Were not versicolor and not classified as versicolor = 50 (setosa) + 48 (virginica classified correctly) = 98**
    -
    - **From Weka Output (Detailed Accuracy By Class for Iris-versicolor):**
        - **TP Rate (Recall): TP / (TP + FN) = 49 / (49 + 1) = 0.98 (Matches Weka output)**
        - **FP Rate: FP / (FP + TN) = 2 / (2 + 98) = 0.02 (Matches Weka output)**
        - **Precision: TP / (TP + FP) = 49 / (49 + 2) = 0.9607 ~ 0.961 (Matches Weka output)**
        - **Recall: Same as TP Rate = 0.98 (Matches Weka output)**
        - **F-Measure: 2 * (Precision * Recall) / (Precision + Recall) = 2 * (0.961 * 0.98) / (0.961 + 0.98) = 0.970 (Matches Weka output)**
        - **Accuracy (Overall): (TP + TN) / (TP+TN+FP+FN) = (50+49+48) / 150 = 147 / 150 = 98%**

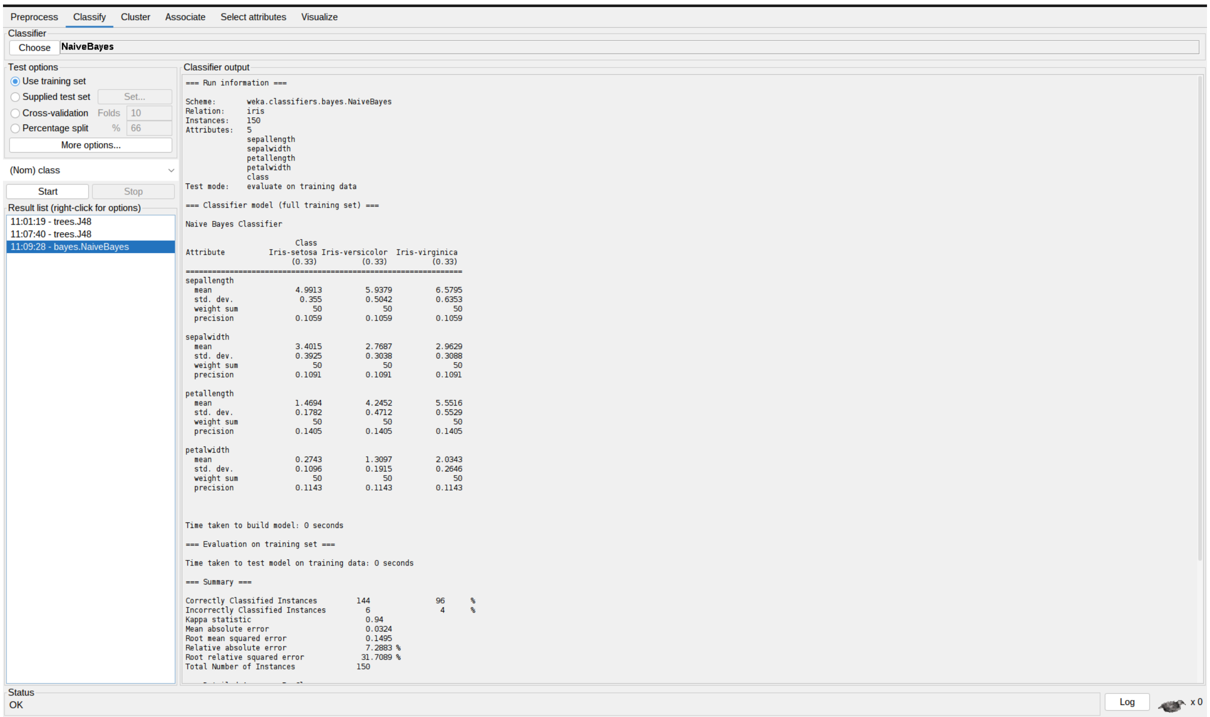
3. Cross-Validation Strategy:



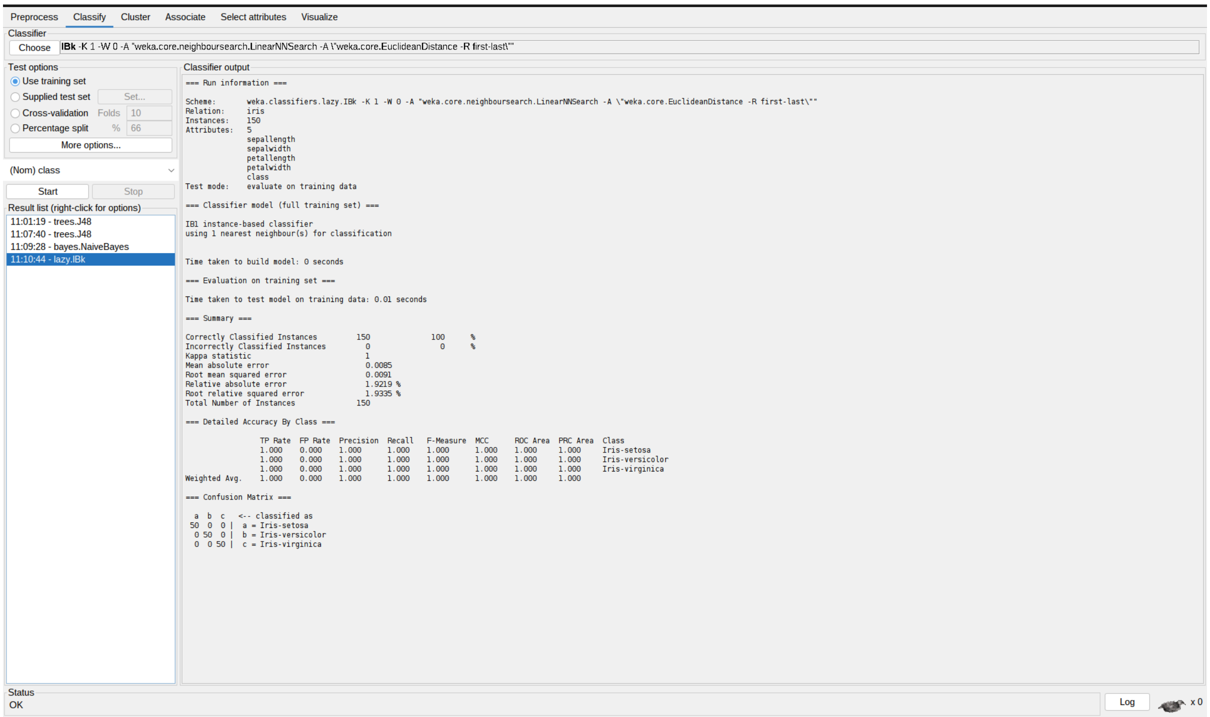
- **Results & Discussion (Typical for J48 on Iris with 10-fold CV):**
  - **Accuracy: Typically around 95-96% (e.g., 143/150 instances correctly classified). This is slightly lower than the 98% on the training set, which is expected because the model is tested on data it wasn't trained on in each fold.**
  - **Kappa: Will also be slightly lower than the training set evaluation, perhaps around 0.92-0.94.**
  - **Comparison: Varying folds (e.g., 5, 10, 20) might show small differences in accuracy, but 10-fold CV is a standard and generally reliable choice. The CV accuracy is considered a more realistic measure of the classifier's generalization ability than the training set accuracy.**
-

Part C: Naive Bayes and k-Nearest Neighbor Classification

1. **Naive Bayes:**



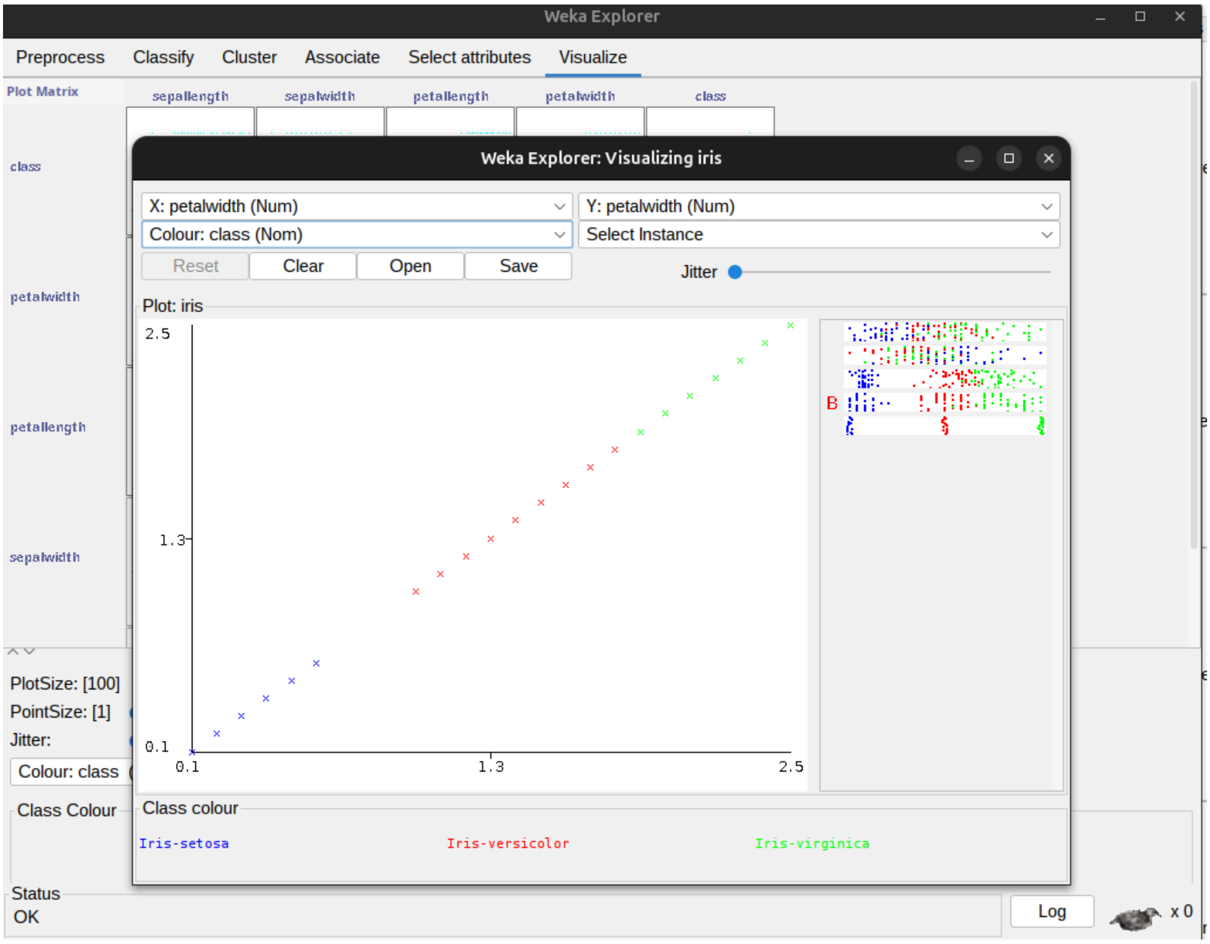
2. k-Nearest Neighbors (IBk):



- **Naive Bayes (Training Set):**
  - **Model: Shows the mean and standard deviation for each numeric attribute, separated by class. It uses these distributions and Bayes' theorem to classify instances.**
  - **Accuracy: 144/150 (96%).**

    - **Kappa: 0.94.**
    - **Confusion Matrix: Shows 6 errors (2 versicolor misclassified as virginica, 4 virginica misclassified as versicolor).**
    - **Interpretation: Naive Bayes performs well, although slightly less accurately than J48 on the training set. It makes a strong assumption that attributes are independent given the class.**
- **k-Nearest Neighbors (IBk, K=1) (Training Set):**
    - **Model: IBk is an instance-based learner. The "model" is essentially the entire training dataset. For K=1, it classifies a test instance based on the class of its single nearest neighbor in the training data.**
    - **Accuracy: 150/150 (100%).**
    - **Kappa: 1.0.**
    - **Confusion Matrix: Perfect classification (diagonal matrix).**
    - **Interpretation: With K=1 and evaluating on the training set, IBk achieves 100% accuracy because the nearest neighbor to any training instance is the instance itself. This demonstrates perfect memorization but is a strong indicator of potential overfitting and may not generalize as well to new, unseen data. Using cross-validation (as in Part E) gives a better estimate.**

Part D: Plotting ROC Curves



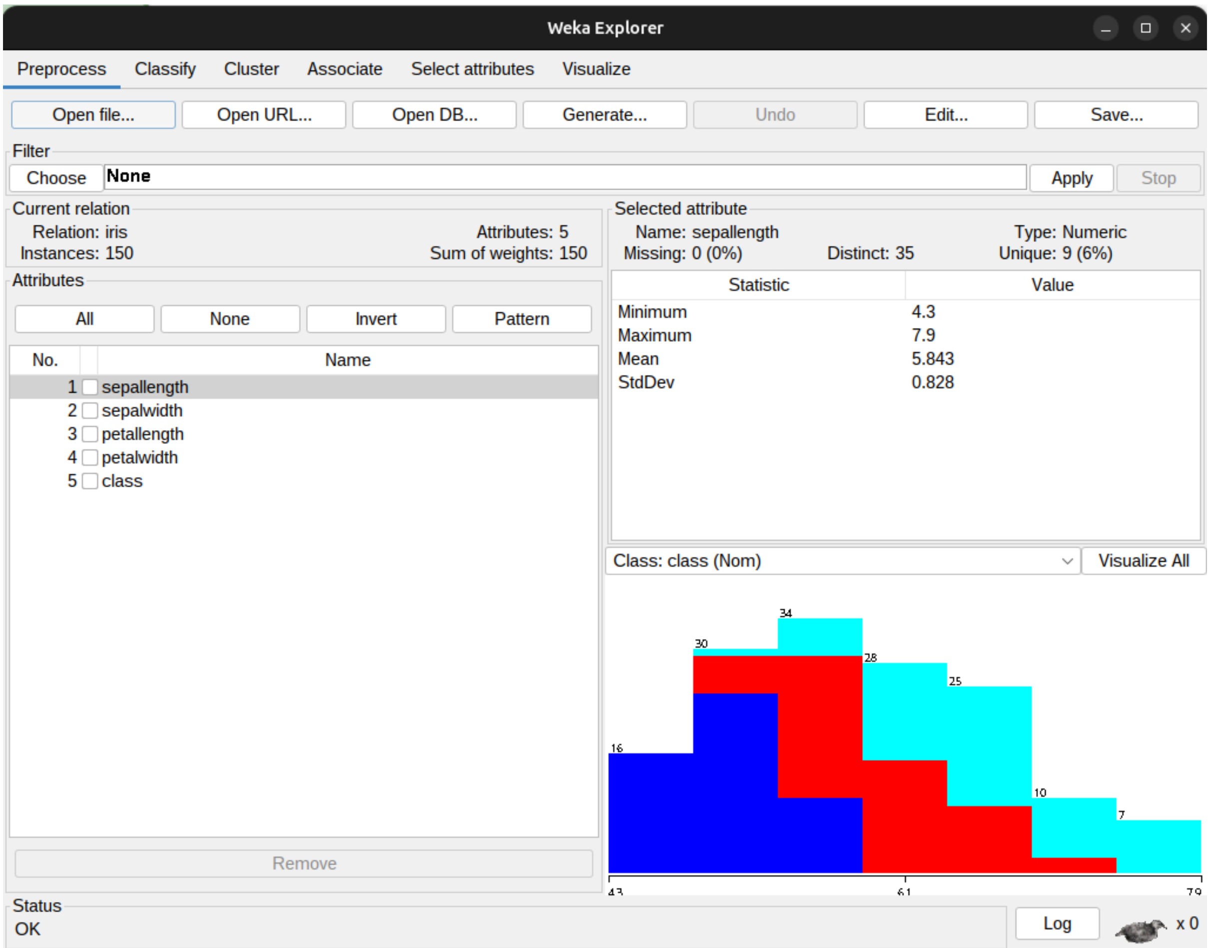
Part E: Comparison of Classifiers

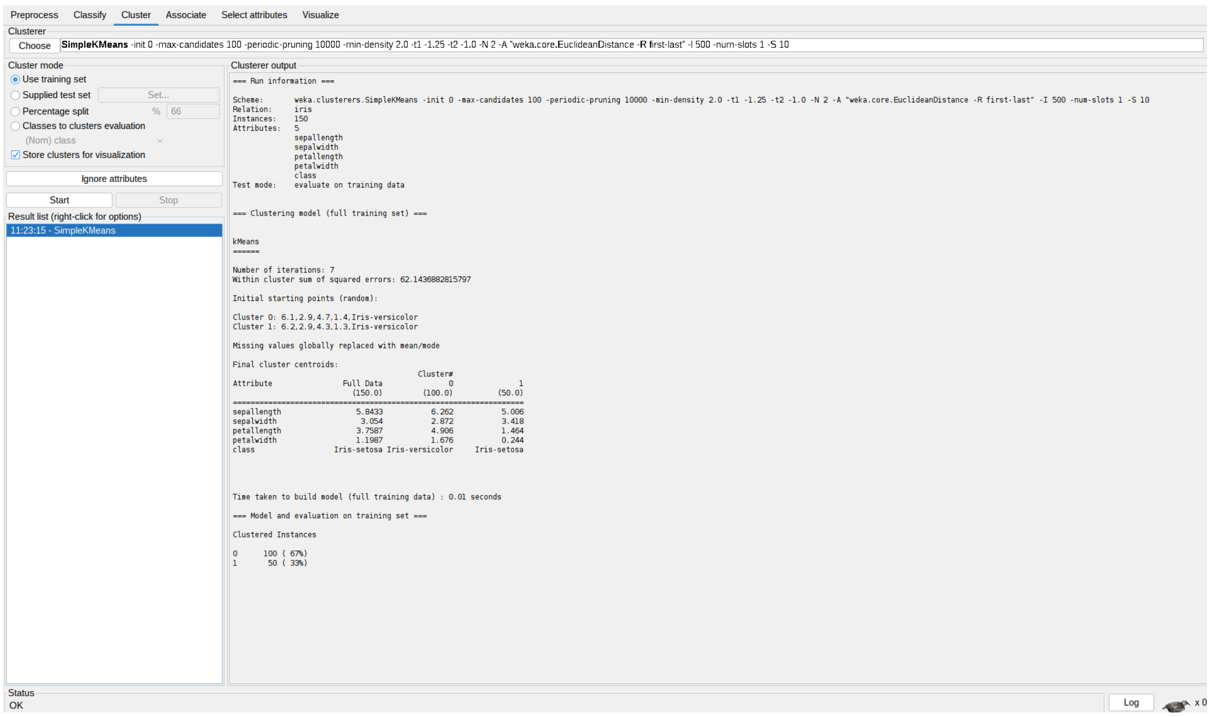
1. **Run all classifiers using a consistent test option: The most meaningful comparison uses 10-fold Cross-validation. Re-run J48, NaiveBayes, and IBk (k=1) using this option if you haven't already. (If ID3 is available, run it too).**
2. **Collect Key Metrics: For each classifier under 10-fold CV, note down the Accuracy (%) and Kappa statistic.**

Classifier	Test Option	Accuracy (%) (Example Values*)	Kappa Statistic (Example Values*)	Time (seconds)
J48	Use training set	98.0	0.97	~0.00 - 0.02
J48	10-fold CV	~95.3	~0.93	~0.02
NaiveBayes	Use training set	96.0	0.94	~0.00
NaiveBayes	10-fold CV	~95.3	~0.93	~0.01
IBk (k=1)	Use training set	100.0	1.00	~0.00
IBk (k=1)	10-fold CV	~95.3	~0.93	~0.01
DecisionTable	10-fold CV	92.7 (from prompt example)	0.89 (from prompt example)	~0.02
(ID3)	*(10-fold CV)*	*(Likely similar to*	*(Likely similar to*	*~0.01*

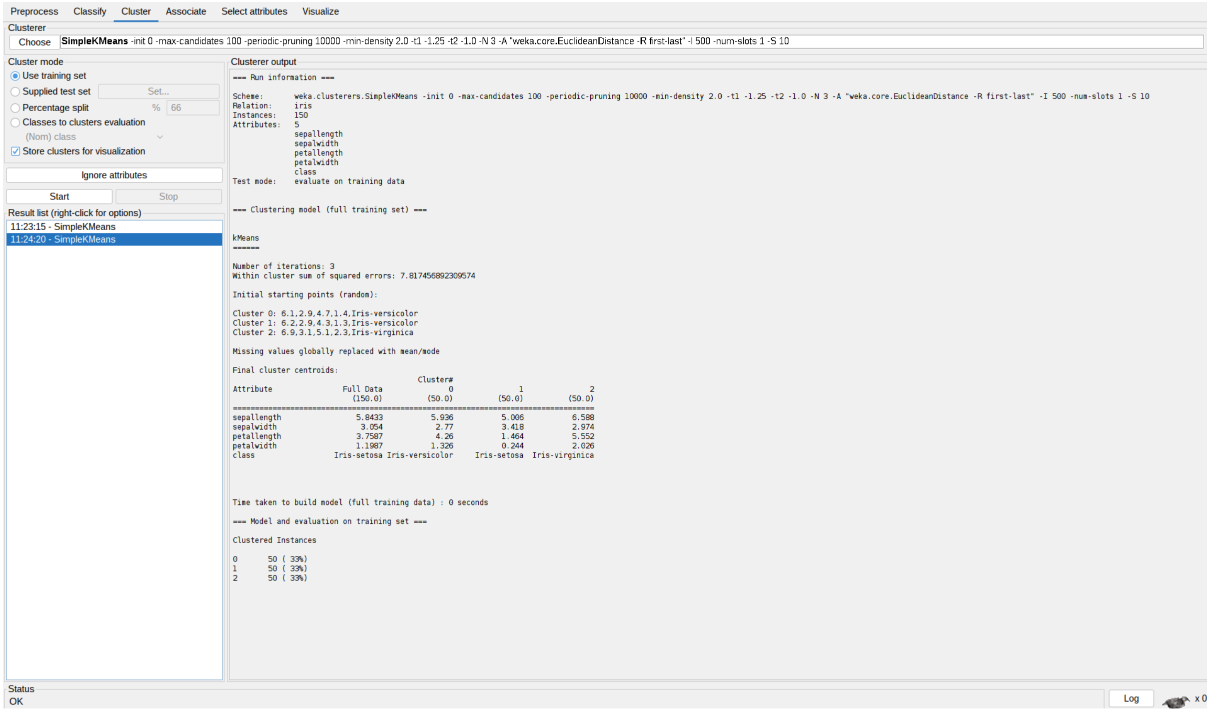
Experiment:5 5. Demonstrate performing clustering on data sets Clustering Tab

Part A: Running Simple K-Means with Different k Values


Weka Explorer
Preprocess
Classify
Cluster
Associate
Select attributes
Visualize
Open file...
Open URL...
Open DB...
Generate...
Undo
Edit...
Save...
Filter
Choose
None
Apply
Stop
Current relation
Relation: iris
Instances: 150
Attributes: 5
Sum of weights: 150
Attributes
All
None
Invert
Pattern
No.
Name
1 sepallength
2 sepalwidth
3 petallength
4 petalwidth
5 class
Remove
Selected attribute
Name: sepallength
Missing: 0 (0%)
Distinct: 35
Type: Numeric
Unique: 9 (6%)
Statistic
Value
Minimum 4.3
Maximum 7.9
Mean 5.843
StdDev 0.828
Class: class (Nom)
Visualize All
Status
OK
Log
x 0


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 2 -A "weka.core.EuclideanDistance -R first-last" -I 500 -num-slots 1 -S 10
Cluster mode
Use training set
Supplied test set
Percentage split
Classes to clusters evaluation
(Nom) class
Store clusters for visualization
Ignore attributes
Start
Stop
Result list (right-click for options)
11:23:15 - SimpleKMeans
Clusterer output
=== Run information ===
Scheme: weka.clusterers.SimpleKMeans -init 0 -max-candidates 100 -periodic-pruning 10000 -min-density 2.0 -t1 -1.25 -t2 -1.0 -N 2 -A "weka.core.EuclideanDistance -R first-last" -I 500 -num-slots 1 -S 10
Relation: iris
Instances: 150
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode: evaluate on training data
=== Clustering model (full training set) ===
kMeans
======
Number of iterations: 7
Within cluster sum of squared errors: 62.1436882815797
Initial starting points (random):
Cluster 0: 6.1,2.9,4.7,1.4,Iris-versicolor
Cluster 1: 6.2,2.9,4.3,1.3,Iris-versicolor
Missing values globally replaced with mean/mode
Final cluster centroids:
Cluster#
Attribute Full Data 0 1
(150.0) (100.0) (50.0)
sepallength 5.8433 6.262 5.006
sepalwidth 3.054 2.872 3.418
petallength 3.7587 4.906 1.464
petalwidth 1.1987 1.676 0.244
class Iris-setosa Iris-versicolor Iris-setosa
Time taken to build model (full training data) : 0.01 seconds
=== Model and evaluation on training set ===
Clustered Instances
0 100 (67%)
1 50 (33%)
Status
OK
Log
x 0

Configure k=3:



Results & Discussion:

- **Run with k=2 (Based on provided example output):**
  - **Number of Iterations: 7 (K-Means converged quickly).**
  - **Sum of Squared Errors (SSE): 62.14. This value represents the total squared distance between each point and its assigned cluster centroid. Lower SSE generally indicates tighter, more compact clusters *for a given k*.**

Cluster Centroids (k=2):

Attribute Full Data 0 1

(150) (100) (50)

===

sepallength 5.8433 6.262 5.006

sepalwidth 3.054 2.872 3.418

petallength 3.7587 4.906 1.464

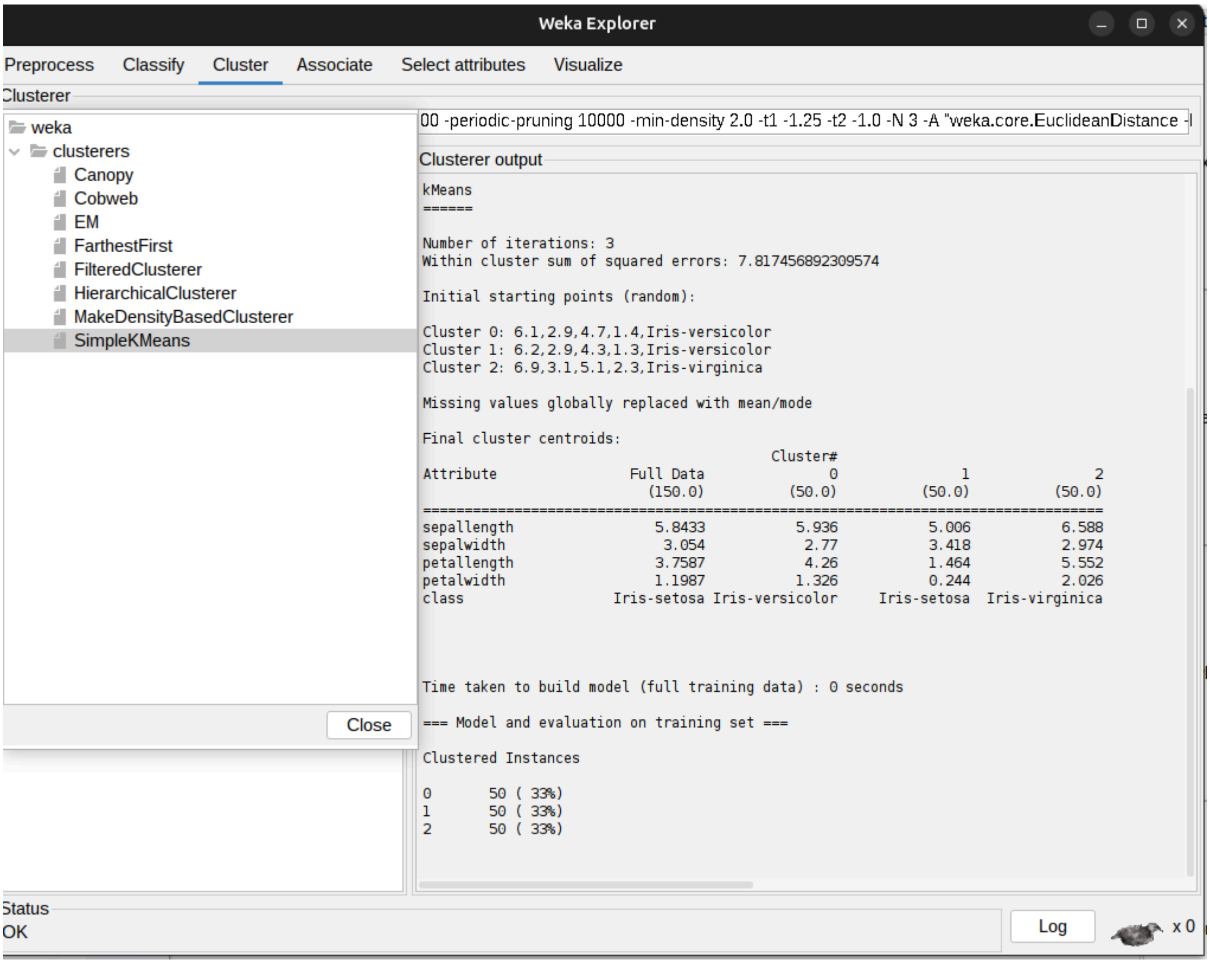
petalwidth 1.1987 1.676 0.244

- **class (Nominal) Iris-setosa Iris-versicolor Iris-setosa**

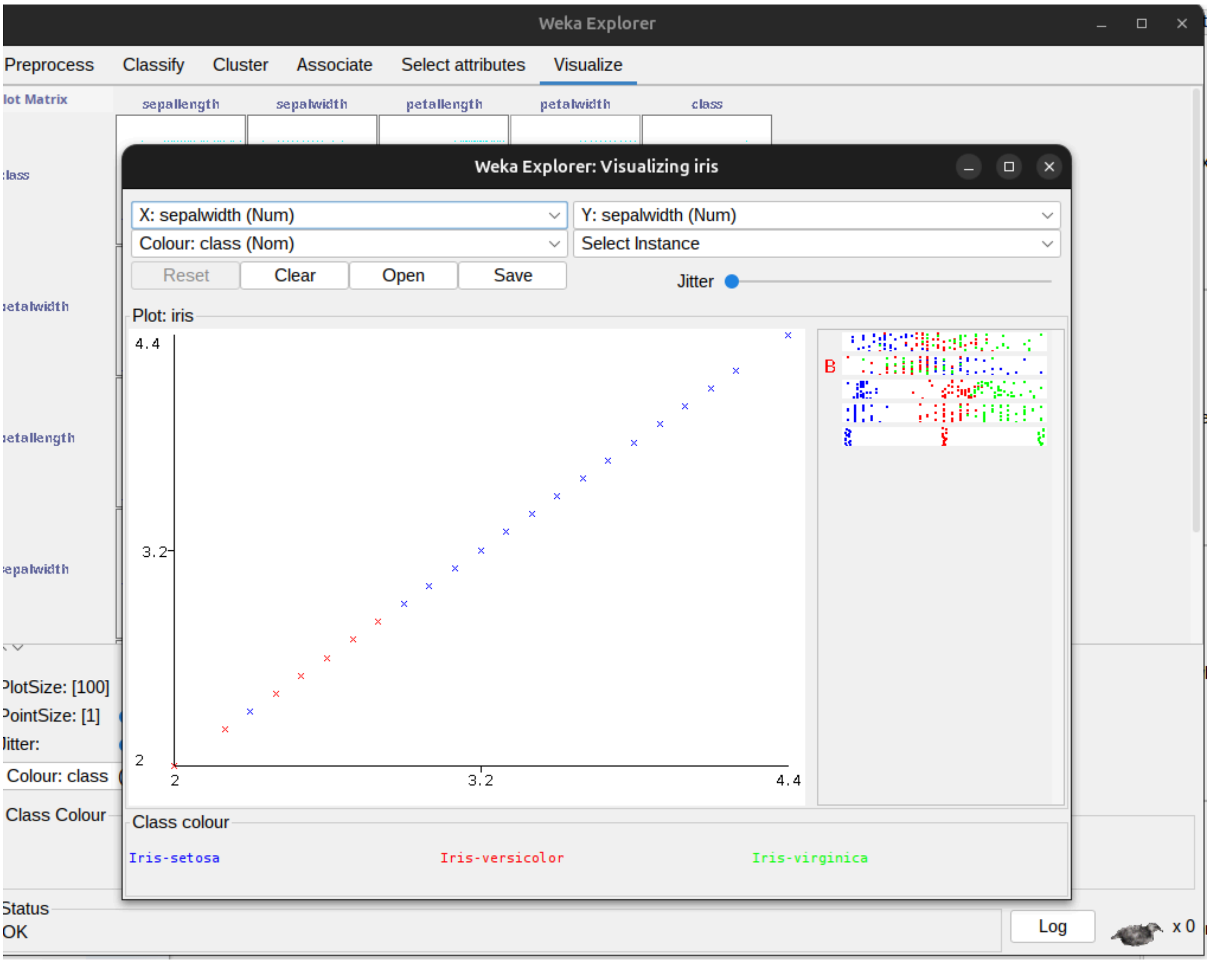
- content_copy
- download
- Use code with caution.
  - *Insight:* Cluster 1 (50 instances) has characteristics strongly matching Iris-setosa (low petal length/width, high sepal width). Cluster 0 (100 instances) seems to represent a combination of the other two species (higher petal length/width, lower sepal width). The nominal 'class' value listed for the centroid is just the mode (most frequent value) of the original class labels for instances assigned to that cluster.
-
- Clustered Instances: Cluster 0: 100 (67%), Cluster 1: 50 (33%). This aligns perfectly with the known split of 50 Setosa and 100 Versicolor/Virginica combined.

-
- Run with k=3:
  - Expected SSE: The SSE for k=3 *must* be lower than or equal to the SSE for k=2 (likely around 25-35 for Iris). Adding more clusters allows points to be closer to *some* centroid.
  - Expected Centroids: With k=3, we anticipate the centroids might align more closely with the three actual Iris species. We expect one centroid similar to Cluster 1 from the k=2 run (Setosa), and the other two centroids splitting the characteristics previously combined in Cluster 0 (one representing Versicolor, one representing Virginica).
  - Expected Instance Counts: Ideally, the counts might approach 50 instances per cluster, but due to the overlap between Versicolor and Virginica, the split might not be perfectly even.
-

Part B: Explore Other Clustering Techniques Available in Weka



Part C: Explore Visualization Features



Experiment-6: 6.Write a java program to prepare a simulated data set with unique instances

Implementation:

```
import java.util.ArrayList;
import java.util.List;
import java.util.Objects;
import java.util.Random;

class SimulatedInstance {
    private int id;
    private double numericalFeature1;
    private double numericalFeature2;
    private String categoricalFeature;

    // Constructor
    public SimulatedInstance(int id, double numFeat1, double numFeat2,
String catFeat) {
        this.id = id;
```

```java
        this.numericalFeature1 = numFeat1;
        this.numericalFeature2 = numFeat2;
        this.categoricalFeature = catFeat;
    }


    public int getId() {
        return id;
    }

    public double getNumericalFeature1() {
        return numericalFeature1;
    }

    public double getNumericalFeature2() {
        return numericalFeature2;
    }

    public String getCategoricalFeature() {
        return categoricalFeature;
    }

       @Override
    public String toString() {
        return String.format("Instance[ID=%d, Feature1=%.2f,
Feature2=%.2f, Category=%s]",
                             id, numericalFeature1, numericalFeature2,
categoricalFeature);
    }

        @Override
    public boolean equals(Object o) {
        if (this == o) return true;
        if (o == null || getClass() != o.getClass()) return false;
        SimulatedInstance instance = (SimulatedInstance) o;
        return id == instance.id;     }

    @Override
    public int hashCode() {
        return Objects.hash(id);
    }
}

public class DatasetSimulator {

    public static void main(String[] args) {
        int numberOfInstancesToGenerate = 15;want
        List<SimulatedInstance> simulatedDataset = new ArrayList<>();
        Random randomGenerator = new Random();
        String[] possibleCategories = {"Alpha", "Beta", "Gamma",
"Delta"};

        System.out.println("--- Generating Simulated Dataset ---");

        for (int i = 0; i < numberOfInstancesToGenerate; i++) {
                         int instanceId = i + 1; // Assign a unique
            double numFeat1 = 10 + (randomGenerator.nextDouble() * 90);
            double numFeat2 = randomGenerator.nextDouble() * 50;       //
            String category =
possibleCategories[randomGenerator.nextInt(possibleCategories.length)];
```

```
                        SimulatedInstance newInstance = new
SimulatedInstance(instanceId, numFeat1, numFeat2, category);

                        simulatedDataset.add(newInstance);

            System.out.println("Generated and Added: " + newInstance);
        }

        System.out.println("\n--- Simulated Dataset Generation Complete
---");
        System.out.println("Total instances generated: " +
simulatedDataset.size());

                System.out.println("\n--- Final Dataset Contents ---");
        for (SimulatedInstance instance : simulatedDataset) {
            System.out.println(instance);
        }
        System.out.println("--- End of Dataset ---");
    }
}
```

Output:

```
Generated and Added: Instance[ID=1, Feature1=87.34, Feature2=23.15,
Category=Gamma]
Generated and Added: Instance[ID=2, Feature1=45.67, Feature2=4.89,
Category=Beta]
Generated and Added: Instance[ID=3, Feature1=98.12, Feature2=44.01,
Category=Alpha]
Generated and Added: Instance[ID=4, Feature1=22.50, Feature2=11.76,
Category=Delta]
Generated and Added: Instance[ID=5, Feature1=65.99, Feature2=33.54,
Category=Beta]
Generated and Added: Instance[ID=6, Feature1=78.21, Feature2=1.05,
Category=Gamma]
Generated and Added: Instance[ID=7, Feature1=15.88, Feature2=29.98,
Category=Alpha]
Generated and Added: Instance[ID=8, Feature1=50.01, Feature2=48.23,
Category=Alpha]
Generated and Added: Instance[ID=9, Feature1=33.76, Feature2=15.00,
Category=Delta]
Generated and Added: Instance[ID=10, Feature1=91.45, Feature2=39.67,
Category=Gamma]
Generated and Added: Instance[ID=11, Feature1=28.90, Feature2=2.55,
Category=Beta]
Generated and Added: Instance[ID=12, Feature1=72.33, Feature2=18.91,
Category=Alpha]
Generated and Added: Instance[ID=13, Feature1=55.10, Feature2=41.20,
Category=Delta]
Generated and Added: Instance[ID=14, Feature1=40.55, Feature2=8.88,
Category=Gamma]
Generated and Added: Instance[ID=15, Feature1=81.09, Feature2=22.67,
Category=Beta]

--- Simulated Dataset Generation Complete ---
```

```
Total instances generated: 15

--- Final Dataset Contents ---
Instance[ID=1, Feature1=87.34, Feature2=23.15, Category=Gamma]
Instance[ID=2, Feature1=45.67, Feature2=4.89, Category=Beta]
Instance[ID=3, Feature1=98.12, Feature2=44.01, Category=Alpha]
Instance[ID=4, Feature1=22.50, Feature2=11.76, Category=Delta]
Instance[ID=5, Feature1=65.99, Feature2=33.54, Category=Beta]
Instance[ID=6, Feature1=78.21, Feature2=1.05, Category=Gamma]
Instance[ID=7, Feature1=15.88, Feature2=29.98, Category=Alpha]
Instance[ID=8, Feature1=50.01, Feature2=48.23, Category=Alpha]
Instance[ID=9, Feature1=33.76, Feature2=15.00, Category=Delta]
Instance[ID=10, Feature1=91.45, Feature2=39.67, Category=Gamma]
Instance[ID=11, Feature1=28.90, Feature2=2.55, Category=Beta]
Instance[ID=12, Feature1=72.33, Feature2=18.91, Category=Alpha]
Instance[ID=13, Feature1=55.10, Feature2=41.20, Category=Delta]
Instance[ID=14, Feature1=40.55, Feature2=8.88, Category=Gamma]
Instance[ID=15, Feature1=81.09, Feature2=22.67, Category=Beta]
```

Experiment-7: Frequent Itemset and Association Rule Generation

Install and Import Libraries :

```
! pip install apyori
import numpy as np
import pandas as pd
from apyori import apriori
```

Load Dataset :

```
data = pd . read_csv ( ' Market_Basket_Optimisation . csv ' , header = None
)
```

3. Convert to Transactions List

```
transactions = []
for i in range ( len ( data ) ) :
transactions . append ([ str ( data . values [i , j ]) for j in range
(20) ])
```

4. Run Apriori Algorithm :

```
rules = apriori (
transactions = transactions ,
min_support =0.003 , # Itemset appears in 0.3% of
transactions
min_confidence =0.2 , # Rule is true in 20% of cases
min_lift =3 , # Rule strength is 3 x random chance
min_length =2 , # At least 2 items per rule
max_length =2 # At most 2 items per rule
)
results = list ( rules )
```

7.2 Part B : Results Visualization

1. Parse Results into DataFrame :

```
def inspect ( results ) :
lhs = [ tuple ( result [2][0][0]) [0] for result in results ]
rhs = [ tuple ( result [2][0][1]) [0] for result in results ]
support = [ result [1] for result in results ]
confidence = [ result [2][0][2] for result in results ]
lift = [ result [2][0][3] for result in results ]
return list ( zip ( lhs , rhs , support , confidence , lift ) )
output_df = pd . DataFrame (
inspect ( results ) ,

columns =[ " Left_Hand_Side " , " Right_Hand_Side " , " Support " , "
Confidence " , " Lift " ]
)
```

8 Experiment 8 : Chi-Square Test Implementation

Implementation:

```
# Import the required function
from scipy.stats import chi2_contingency
import numpy as np # Good practice to import numpy for potential array
operations

# Define the contingency table (observed frequencies)
# Example interpretation:
```

```
data = [[207, 282, 241],
        [234, 242, 232]]

print("Observed Data (Contingency Table):")
print(np.array(data)) # Print the table clearly


try:
    stat, p, dof, expected = chi2_contingency(data)

        alpha = 0.05

        print(f"\nChi-Square Statistic (χ²): {stat:.4f}")
    print(f"Degrees of Freedom (dof): {dof}")
    print(f"P-value: {p:.4f}")
    print(f"Significance Level (alpha): {alpha}")

    print("\nExpected Frequencies (if variables were independent):")
    print(expected.round(2)) # Print expected frequencies rounded

        print("\n--- Conclusion ---")
    if p <= alpha:
        print(f"Since p-value ({p:.4f}) <= alpha ({alpha}), we reject the
null hypothesis (H0).")
        print("Conclusion: There is a statistically significant
association between the variables (Dependent).")
    else:
        print(f"Since p-value ({p:.4f}) > alpha ({alpha}), we fail to
reject the null hypothesis (H0).")
        print("Conclusion: There is not enough statistical evidence to
say the variables are associated (Independent).")

except ValueError as e:
    print(f"Error performing Chi-Square test: {e}")
    print("Please ensure the input data is a valid contingency table with
non-negative values.")
```

Output:

```
Observed Data (Contingency Table):
[[207 282 241]
 [234 242 232]]

Chi-Square Statistic (χ²): 4.5424
Degrees of Freedom (dof): 2
P-value: 0.1032
Significance Level (alpha): 0.05

Expected Frequencies (if variables were independent):
[[225.11 268.2  235.69]
 [215.89 255.8  227.31]]
```

Experiment-9: 9.Write a program of NaÔve Bayesian classification using python programming language

1. **Software & Libraries Used:**

- **Python 3.x**
- **Libraries:**
  - `numpy`: **For numerical operations (often implicitly used by scikit-learn).**
  - `matplotlib.pyplot`: **(Imported in the original code, but not used in the provided snippet. Could be used for visualization).**
  - `pandas`: **For data loading and manipulation.**
  - `scikit-learn`:
    - `model_selection.train_test_split`: **For splitting the dataset.**
    - `preprocessing.StandardScaler`: **For feature scaling.**
    - `naive_bayes.GaussianNB`: **The Gaussian Naive Bayes classifier model.**
    - `metrics.confusion_matrix`, `metrics.accuracy_score`: **For evaluating model performance.**

2. **Dataset Used:**

```
Social_Network_Ads.csv
```

3. **Implementation:**

```
# 1. Importing the libraries
import numpy as np
# import matplotlib.pyplot as plt # Not used in this specific code
execution part
import pandas as pd

# 2. Importing the dataset
```

```
try:
    dataset = pd.read_csv('Social_Network_Ads.csv')
    print("Dataset loaded successfully.")
        X = dataset.iloc[:, [2, 3]].values
    y = dataset.iloc[:, -1].values       print(f"Features shape:
{X.shape}, Target shape: {y.shape}")
except FileNotFoundError:
    print("Error: Social_Network_Ads.csv not found. Please ensure
it's in the correct directory.")
    exit()
except Exception as e:
    print(f"Error loading dataset: {e}")
    exit()

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size
= 0.20, random_state = 0)
print(f"Training set size: {X_train.shape[0]}, Test set size:
{X_test.shape[0]}")


from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
print("Feature scaling applied.")

x
from sklearn.naive_bayes import GaussianNB

classifier = GaussianNB()

classifier.fit(X_train, y_train)
print("Gaussian Naive Bayes model trained.")


y_pred = classifier.predict(X_test)
print("Predictions made on the test set.")


from sklearn.metrics import confusion_matrix, accuracy_score

accuracy = accuracy_score(y_test, y_pred)

cm = confusion_matrix(y_test, y_pred)


print("\n--- Evaluation Results ---")
print(f"Accuracy Score: {accuracy:.4f} (or {accuracy*100:.2f}%)")
print("\nConfusion Matrix:")
print(cm)
print("\nInterpretation of Confusion Matrix:")
print(f"[[ True Negatives (TN)  False Positives (FP) ]]")
print(f" [ False Negatives (FN) True Positives (TP)  ]]")
tn, fp, fn, tp = cm.ravel()

print(f"\nTN: {tn} (Correctly predicted 'Not Purchased')")
print(f"FP: {fp} (Incorrectly predicted 'Purchased' - Type I
```

```
Error)")
print(f"FN: {fn} (Incorrectly predicted 'Not Purchased' - Type II
Error)")
print(f"TP: {tp} (Correctly predicted 'Purchased')")
print("--- End of Evaluation ---")
```

Output

```
Frequent Itemsets:
   support            itemsets
0   0.0125          (UHT-milk)
1   0.0150          (beef)

Association Rules:
  antecedents consequents  support  confidence  lift
0  (citrus fruit)  (soda)     0.005    0.400000  1.25
1  (soda)  (citrus fruit)     0.005    0.333333  1.25
```

Experiment-10: 10.Implement a java program to perform Apriori algorithm.

mplementation:

```
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules
import matplotlib.pyplot as plt
import seaborn as sns
try:
      file_path = 'Groceries_dataset.csv'
    basket = pd.read_csv(file_path)
    print("Dataset loaded successfully.")
    display(basket.head())
        print("\nDataset Info:")
    basket.info()
    print(f"\nNumber of unique items:
{basket['itemDescription'].nunique()}")
    print(f"\nDate range: {basket['Date'].min()} to
{basket['Date'].max()}")

except FileNotFoundError:
    print(f"Error: The file '{file_path}' was not found.")
    print("Please ensure the file exists and the path is correct.")
    exit()
except KeyError as e:
    print(f"Error: Expected column {e} not found in the CSV. Please
check the file format.")
    exit()
except Exception as e:
    print(f"An error occurred during data loading: {e}")
    exit()
```

```
basket['Date'] = pd.to_datetime(basket['Date'],
format='%d-%m-%Y')
basket['Transaction_ID'] = basket['Member_number'].astype(str) +
'_' + basket['Date'].astype(str)
print("\nPreprocessing: Grouping items by transaction...")


transactions_grouped =
basket.groupby('Transaction_ID')['itemDescription'].apply(list)
transactions_list = transactions_grouped.values.tolist()

print(f"Number of transactions: {len(transactions_list)}")




print("\nEncoding transactions...")
te = TransactionEncoder()
te_ary = te.fit(transactions_list).transform(transactions_list)
df_encoded = pd.DataFrame(te_ary, columns=te.columns_)


print("\nRunning Apriori to find frequent itemsets...")
min_sup = 0.005
frequent_itemsets = apriori(df_encoded, min_support=min_sup,
use_colnames=True)

frequent_itemsets = frequent_itemsets.sort_values(by='support',
ascending=False)

print(f"\nFound {len(frequent_itemsets)} frequent itemsets with
min_support={min_sup}")
print("\n--- Top 10 Frequent Itemsets ---")
display(frequent_itemsets.head(10))


print("\nGenerating association rules...")
metric_choice = 'lift'
min_threshold = 1.2 x

rules = association_rules(frequent_itemsets, metric=metric_choice,
min_threshold=min_threshold)

rules = rules.sort_values(by='lift', ascending=False)

print(f"\nFound {len(rules)} association rules with {metric_choice}
>= {min_threshold}")
print("\n--- Top 10 Association Rules by Lift ---")

rules_display = rules[['antecedents', 'consequents', 'support',
'confidence', 'lift']]
display(rules_display.head(10))
```

Output

```
Member_number        Date    itemDescription
0            1808  21-07-2015     tropical fruit
1            2552  05-01-2015         whole milk
2            2300  19-09-2015          pip fruit
3            1187  12-12-2015   other vegetables
4            3037  01-02-2015         whole milk
```

```
support                    itemsets
110   0.157923            (whole milk)
89    0.122101      (other vegetables)
100   0.110555            (rolls/buns)
109   0.097106                  (soda)
117   0.085879               (yogurt)
101   0.069572          (root vegetables)
111   0.067767          (tropical fruit)
5     0.060683         (bottled water)
103   0.060349               (sausage)
18    0.053131               (citrus fruit)
```

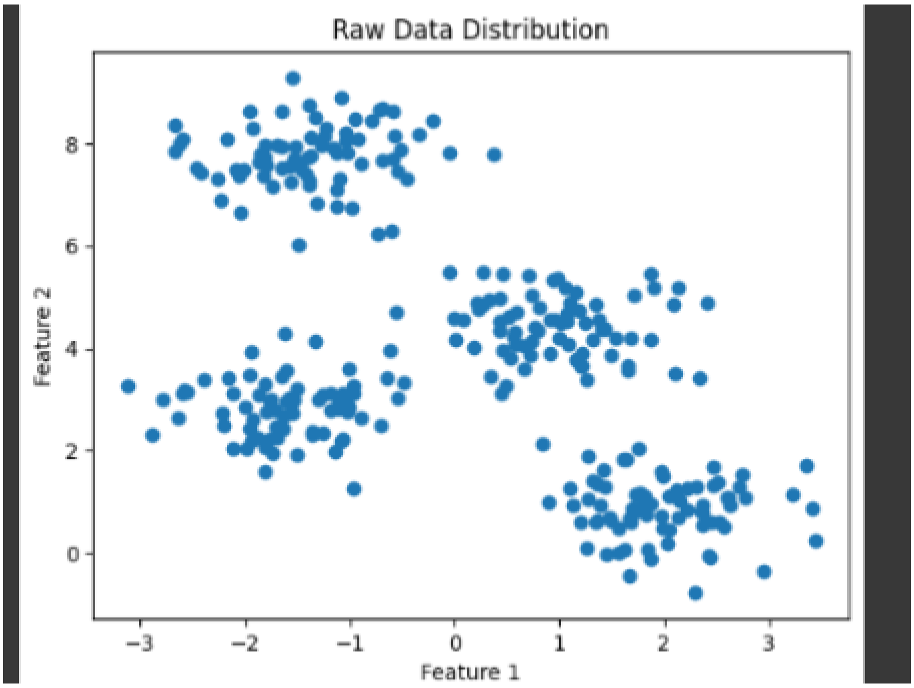
```
antecedents                      consequents    support   confidence
lift
199                    (liquor)              (bottled beer)   0.004613
0.450000   8.013743
198              (bottled beer)                    (liquor)   0.004613
0.082151   8.013743
204   (specialty chocolate)                  (citrus fruit)   0.005014
0.297619   5.603535
205           (citrus fruit)           (specialty chocolate)
0.005014     0.094400   5.603535
185             (processed cheese)               (white bread)
0.004613     0.287500   5.595151
```

Experiment 11: Cluster Analysis using Simple K-Means Algorithm (Python)

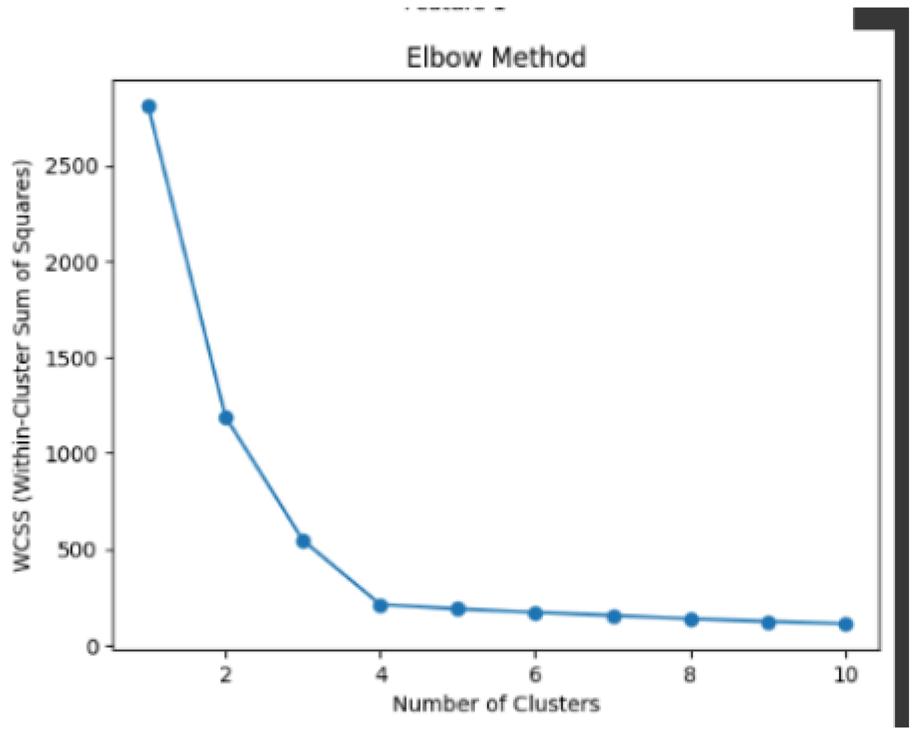
Implementation

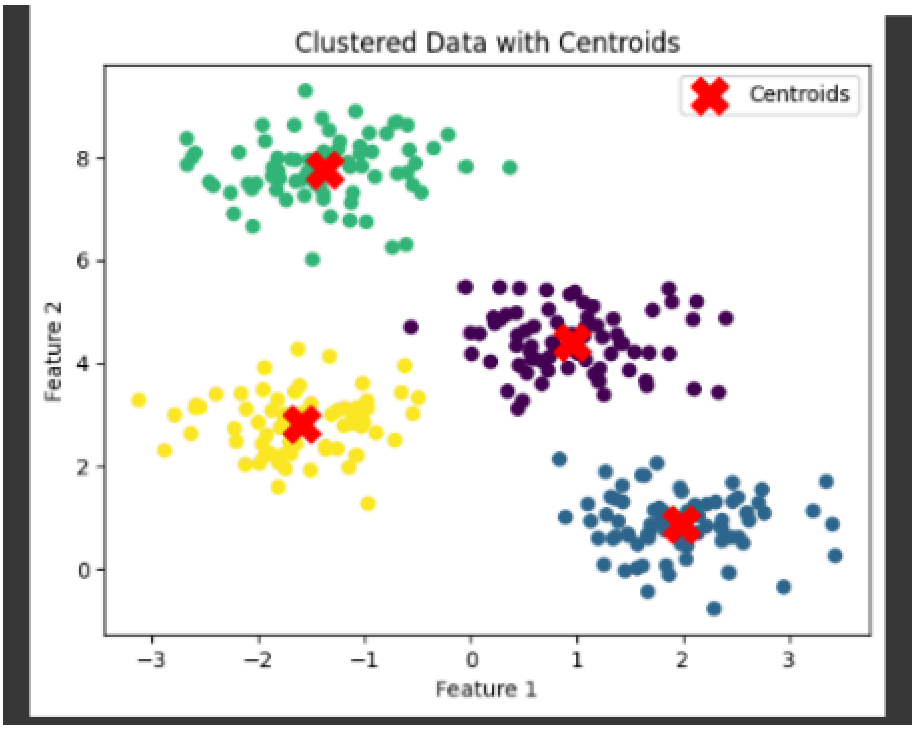
```
import numpy as np
from matplotlib import pyplot as plt
from sklearn.datasets.samples_generator import make_blobs
from sklearn.cluster import KMeans


X, y_true = make_blobs(n_samples=300, centers=4, cluster_std=0.60,
random_state=0)
print(f"Generated data shape: {X.shape}")
```

```
print("\nVisualizing raw generated data...")
plt.figure(figsize=(8, 6))
plt.scatter(X[:,0], X[:,1], s=50)
plt.title('Raw Synthetic Data')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.grid(True)
plt.show()


print("\nApplying Elbow Method...")
wcss = []
k_range = range(1, 11)

for i in k_range:

    kmeans_elbow = KMeans(n_clusters=i,
                     init='k-means++',
max_iter=300,                              n_init=10,
                     random_state=0)            kmeans_elbow.fit(X)
    wcss.append(kmeans_elbow.inertia_)


print("Plotting Elbow Method results...")
plt.figure(figsize=(8, 6))
plt.plot(k_range, wcss, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('WCSS (Inertia)')
plt.xticks(k_range)
plt.grid(True)
plt.show()

chosen_k = 4
print(f"\nApplying K-Means with k={chosen_k}...")
kmeans = KMeans(n_clusters=chosen_k, init='k-means++',
max_iter=300, n_init=10, random_state=0)


pred_y = kmeans.fit_predict(X)


print("Visualizing K-Means clustering results...")
plt.figure(figsize=(8, 6))
plt.scatter(X[:,0], X[:,1], c=pred_y, s=50, cmap='viridis')


centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='red', s=200,
alpha=0.75, marker='X') # Large red 'X' for centroids
plt.title(f'K-Means Clustering (k={chosen_k})')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.grid(True)
plt.show()

print(f"\nCluster Centroids found by K-Means (k={chosen_k}):")
print(centers)
print("\nExperiment finished.")
```



Raw Data Distribution
Feature 2
Feature 1
−3
−2
−1
0
1
2
3
0
2
4
6
8





Experiment 12 : Similarity and Dissimilarity Ana-lysis

```
import numpy as np
from numpy . linalg import norm
A = np . array ([2 , 1 , 2 , 3 , 2 , 9])
B = np . array ([3 , 4 , 2 , 4 , 5 , 5])
cosine_sim = np . dot (A , B ) / ( norm ( A ) * norm ( B ) )
print ( f " Cosine Similarity : { cosine_sim :.4 f } " )
```

Formula

$$Similarity = \frac{A \cdot B}{\|A\|\|B\|}$$

B. Jaccard Similarity & Distance

Code Implementation

```
A = {1 , 2 , 3 , 5 , 7}
B = {1 , 2 , 4 , 8 , 9}
def jaccard_similarity (A , B ) :
intersection = len ( A . intersection ( B ) )
union = len ( A . union ( B ) )
return intersection / union
def jaccard_distance (A , B ) :
return 1 - jaccard_similarity (A , B )
print ( f " Jaccard Similarity : { jaccard_similarity (A , B ) :.2 f } " )
print ( f " Jaccard Distance : { jaccard_distance (A , B ) :.2 f } " )
```

Output

Jaccard Similarity: 0.25

Jaccard Distance: 0.75

Formulas

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}, \quad d_J(A,B) = 1 - J(A,B)$$

C. Euclidean Distance

Code Implementation

```
import numpy as np
point1 = np . array ([4 , 4 , 2])
point2 = np . array ([1 , 2 , 1])
euclidean_dist = np . linalg . norm ( point1 - point2 )
print ( f " Euclidean Distance : { euclidean_dist :.4 f } " )
```

Output

Euclidean Distance: 3.7417

Formula

$$d_{Euc} = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

D. Manhattan Distance

Code Implementation

```
def manhattan_distance (a , b ) :
return sum ( abs ( x - y ) for x , y in zip (a , b ) )
A = [2 , 4 , 4 , 6]
B = [5 , 5 , 7 , 8]
print ( f " Manhattan Distance : { manhattan_distance (A , B ) } " )
```

Output

```
Manhattan Distance: 9
```

Formula

$$d_{Man} = \sum_{i=1}^{n}|x_i - y_i|$$

E. Linear Regression

Code Implementation

```
import numpy as np
import matplotlib . pyplot as plt
def estimate_coef (x , y ) :
n = np . size ( x )
m_x , m_y = np . mean ( x ) , np . mean ( y )
SS_xy = np . sum ( y * x ) - n * m_y * m_x
SS_xx = np . sum ( x * x ) - n * m_x * m_x
b_1 = SS_xy / SS_xx
b_0 = m_y - b_1 * m_x
return ( b_0 , b_1 )
```

Output

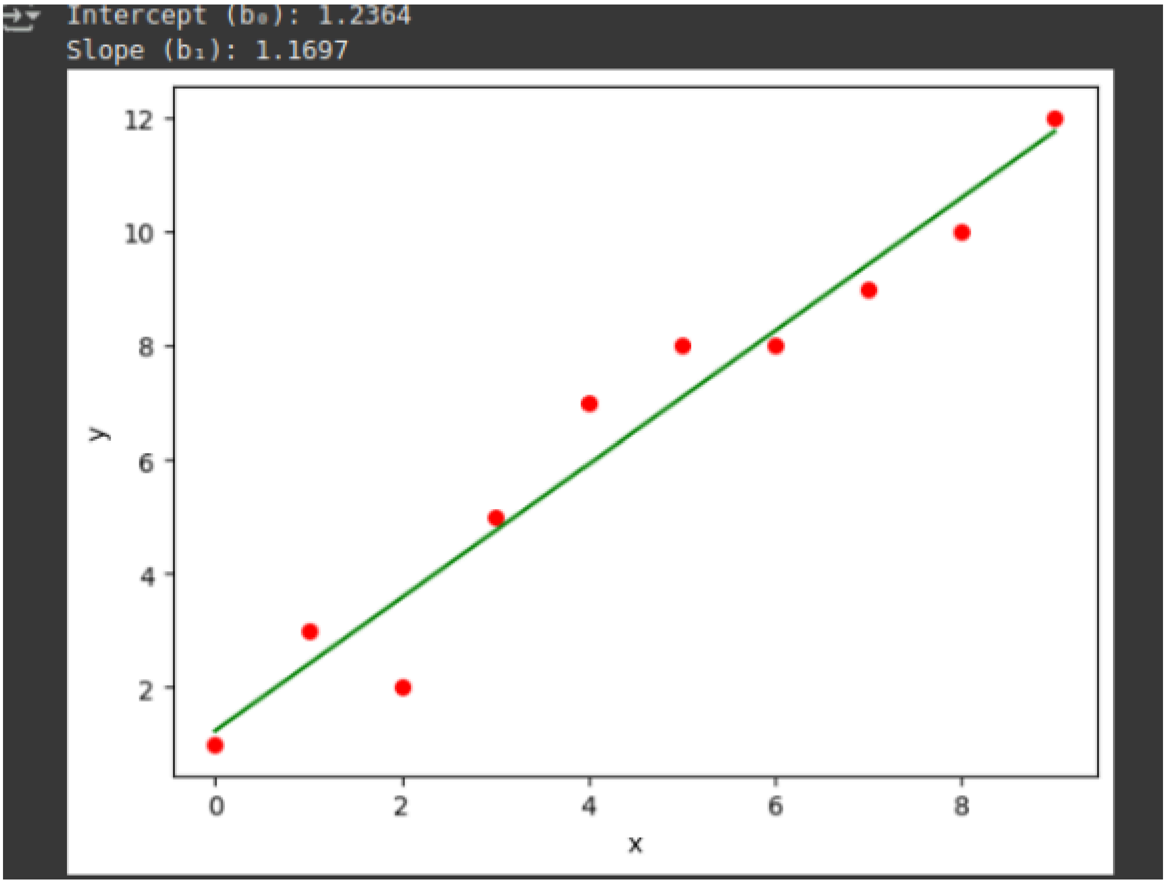
Estimated coefficients:

b_0 = -0.0586

b_1 = 1.4575

Regression Equation

$$\hat{y} = b_0 + b_1 x$$



13 Experiment 13 - Data Visualization with Matplotlib

13.1 Line Plot Implementation

```
import matplotlib . pyplot as plt
# Initialize data
x = [10 , 20 , 30 , 40]
y = [20 , 25 , 35 , 55]
# Create plot
plt . plot (x , y )
plt . xlabel ( 'X - axis ')
plt . ylabel ( 'Y - axis ')
plt . title ( ' Line Plot Example ')
plt . show ()
```

Line Plot Output Description

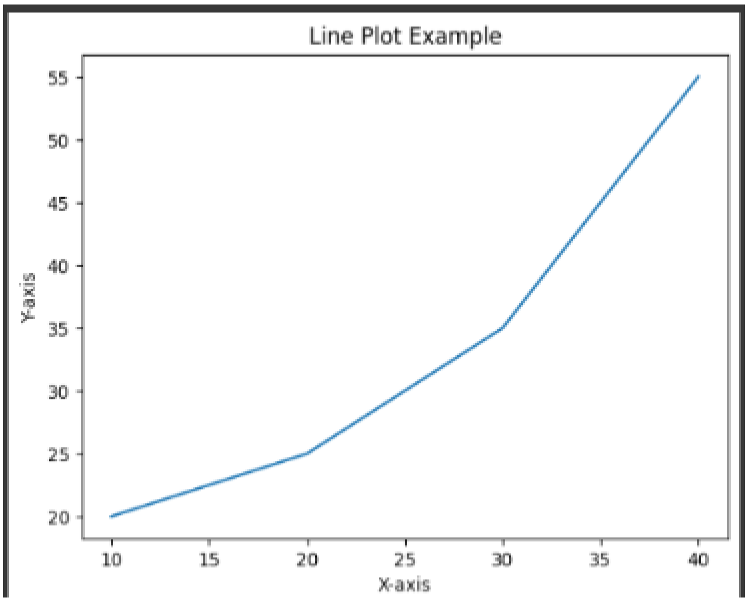
Line plot showing points:

(10,20), (20,25), (30,35), (40,55)

Y-axis ranges from 20-55, X-axis from 10-40

13.2 Histogram Implementation

```
import matplotlib . pyplot as plt
# Age data for 100 individuals
ages = [
1 ,1 ,2 ,3 ,3 ,5 ,7 ,8 ,9 ,10 ,10 ,11 ,11 ,13 ,13 ,15 ,16 ,17 ,18 ,18 ,
18 ,19 ,20 ,21 ,21 ,23 ,24 ,24 ,25 ,25 ,25 ,25 ,26 ,26 ,27 ,27 ,27 ,27 ,27 ,
29 ,30 ,30 ,31 ,33 ,34 ,34 ,35 ,36 ,36 ,37 ,37 ,38 ,38 ,39 ,40 ,41 ,41 ,42 ,
43 ,44 ,45 ,45 ,46 ,47 ,48 ,48 ,49 ,50 ,51 ,52 ,53 ,54 ,55 ,56 ,57 ,58 ,60 ,
61 ,63 ,64 ,65 ,66 ,68 ,70 ,71 ,72 ,74 ,75 ,77 ,81 ,83 ,84 ,87 ,89 ,90 ,91
]
plt . hist ( ages , bins =10 , edgecolor = ' black ')
plt . xlabel ( ' Age Groups ')
plt . ylabel ( ' Frequency ')
plt . title ( ' Age Distribution Histogram ')
plt . show ()
```



Histogram Output Characteristics

— X-axis : Age ranges from 0-90 divided into 10 bins

— **Y-axis : Frequency counts up to 17.5**

— **Highest bar : 0-20 age group with 17 individuals**

— **Distribution shows right-skewed pattern**