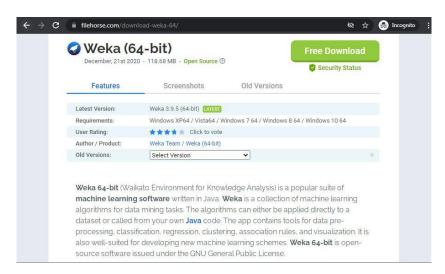
Study of WEKA tool and applying data mining techniques on following data sets in ARFF or CSV file Format.

Weka stands for Waikato Environment for Knowledge Analysis, it is software that is used in the data science field for data mining. It is free software. It is written in Java hence it can be run on any system supporting Java, so weka can be run on different operating systems like Windows, Linux, Mac, etc. Weka provides a collection of visualization tools that can be used for data analysis, cleaning, and predictive modeling. Weka can perform a number of tasks like data preprocessing, clustering, classification, regression, visualization, and feature selection.

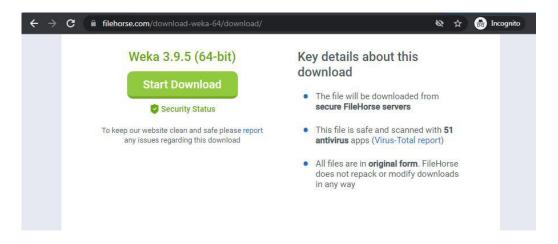
Installing Weka on Windows

Step 1: Visit this website using any web browser. Click on Free Download.

https://waikato.github.io/weka-wiki/downloading_weka/



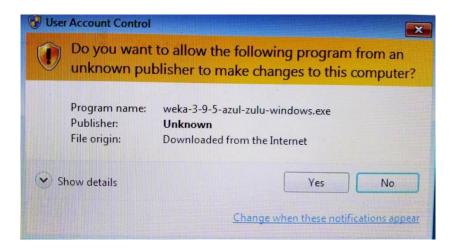
Step 2: It will redirect to a new webpage, click on Start Download. Downloading of the executable file will start shortly.



Step 3: Now check for the executable file in downloads in your system and run it.



Step 4: It will prompt confirmation to make changes to your system. Click on Yes.



Step 5: Setup screen will appear, click on Next.



Step 6: The next screen will be of License Agreement, click on I Agree.



Step 7: Next screen is of choosing components, all components are already marked so don't change anything just click on the Install button.



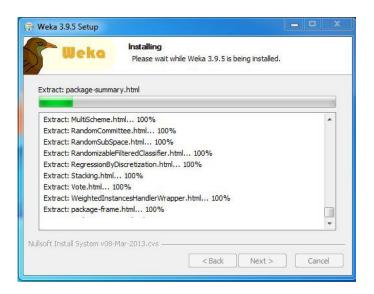
Step 8: The next screen will be of installing location so choose the drive which will have sufficient memory space for installation. It needed a memory space of 301 MB.



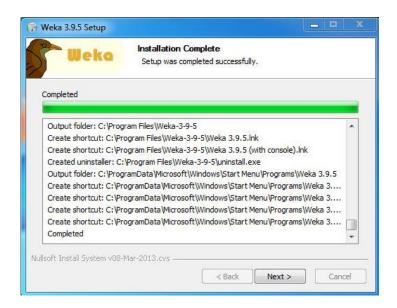
Step 9: Next screen will be of choosing the Start menu folder so don't do anything just click on Install Button.



Step 10: After this installation process will start and will hardly take a minute to complete the installation.



Step 11: Click on the Next button after the installation process is complete.



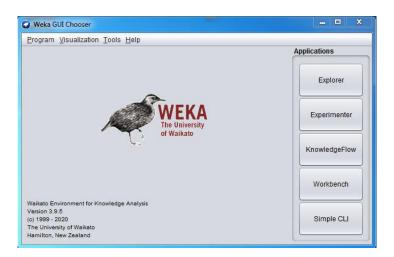
Step 12: Click on Finish to finish the installation process.



Step 13: Weka is successfully installed on the system and an icon is created on the desktop.



Step 14: Run the software and see the interface.

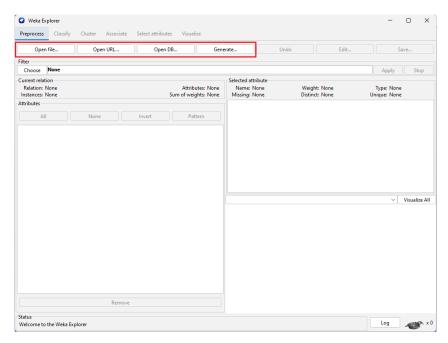


2. Implementation / Usage of WEKA for classification of datasets such as customer's data, weather forecasting data, agricultural data etc.

In order to utilize Weka Explorer, it is essential to start by loading the data into the application. Multiple sources are available for data loading within Weka Explorer. Those are,

- 1. Local file system
- 2. Web
- 3. Database
- 4. Generate Artificial Data

The diagram presented below provides a concise summary of the offerings provided by WEKA.



Various File Formats supported by WEKA:

In order to work with Weka Explorer, it is essential to **load the data** into the application. The data may in different formats such as CSV, Text, JSON and so on. WEKA supports a **wide** range of file formats to load the data.

The following is the complete list of file formats

- ➤ Arff data files(*.arff)
- > Arff data files(*arff.gz)
- > C4.5 data files(*.names)
- > C4.5 data files(*.data)
- > CSV data files(*.csv)
- ➤ JSON instance files(*.json)
- ➤ JSON instance files(*.json.gz)

- ➤ libsvm data files(*.libsvm)
- ➤ Matlab ASCII files(*.m)
- > sym light data files(*.dat)
- ➤ Binary Serialized instances(*.bsi)
- > XRFF data files(*.xrff)
- > XRFF data files(*.xrff.gz)

As we see the WEKA supports various formats of data to load, among those formats the most commonly used data formats are **Arff data files(*.arff)** and **CSV data files(*.csv)**.

NOTE: The default data format of WEKA is **Arff data files** (*.arff).

the ARFF file format:

An ARFF (Attribute-Relation File Format) file is an ASCII text file that describes a list of instances sharing a set of attributes. The ARFF file format has mainly **two sections**, those are

- Header section
- Data section

Header section:

The Header section of the ARFF file contains the **name of the relation**, a **list of the attributes** and their **types**.

@RELATION Declaration

The relation name is defined as the first line in the ARFF file.

format:

@RELATION <relation-name> - where <relation-name> is a string. The relation name must be quoted if the name includes spaces.

@ATTRIBUTE Declaration

The attribute specifies name of the attribute along with type.

format:

@ATTRIBUTE <attribute-name> <datatype> - where the <attribute-name> must start with an alphabet. The attribute name must be quoted if the name includes spaces.

Weka supports the following four datatypes:

1. Numeric attributes:

Numeric attributes can be real or integer numbers.

2. Nominal attributes:

Nominal values are defined by providing the possible values: { nominal-value1, nominal-value2, nominal-value3,... }

3. String attributes:

String attributes allow us to define attributes holding textual values.

4. Date attributes:

Date attribute defined as follows @ATTRIBUTE <name> date [<date-format>] - where <name> is the name for the attribute and <date-format> is an optional string. The default date-format string is yyyy-MM-dd'T'HH:mm:ss.

Example of Header Section:

% Title: Weather Dataset

@relation weather

@attribute Outlook {Sunny,Overcast,Rain}

@attribute Temperature numeric

@attribute Humidity numeric

@attribute Windy {True,False}

@attribute Play {Yes,No}

In the above example, The line which start with % are treated as comments.

@RELATION specifies the name of the relation.

@ATTRIBUTE specifies name of the attribute along with type and possible values.

Data section:

The Data section of the ARFF file contains the **list of data values (instance data)** separated by comma.

@data

Sunny,85,85,False,No

Sunny, 80, 90, True, No

Overcast,83,86,False,Yes

Rain,70,96,False,Yes

Rain,68,80,False,Yes

Rain,65,70,True,No

Overcast,?,65,True,Yes

Sunny,72,95,False,No

Sunny,69,70,False,Yes

Rain,75,?,False,Yes

Sunny,75,70,True,Yes

Overcast,?,90,True,Yes

Overcast,81,75,False,Yes

Rain,71,91,True,No

In the above, the symbol? indicates missing values.

3. Experiment to summarize and visualization of various datasets.

Step 1: Launch WEKA

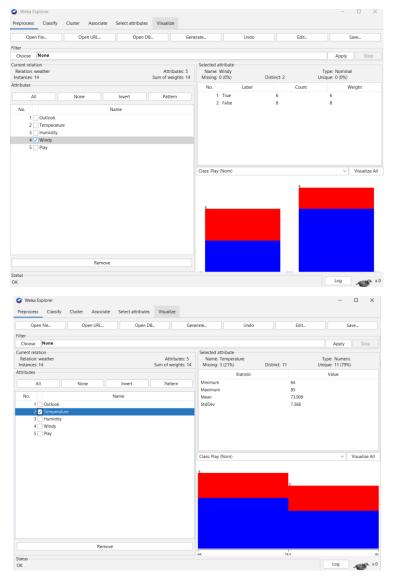
- Open WEKA GUI Chooser.
- Click on **Explorer** to open the main data mining environment.

Step 2: Load Dataset

- 1. Click on "Open file...".
- 2. Select a dataset file (.arff or .csv).
- 3. The dataset will load into the **Preprocess** tab.

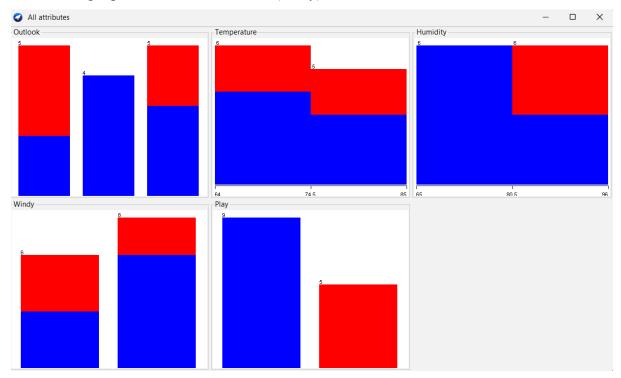
For each attribute, WEKA shows:

- Type: Nominal / Numeric
- Missing Values
- Distinct Values
- Minimum, Maximum, Mean, Standard Deviation (for numeric)
- Class distribution (for nominal/categorical)



Step 4: Visualize Data Distribution

- In the Preprocess tab, click on an attribute \rightarrow it shows a **histogram** of the distribution.
- Color coding represents different classes (if any).



4. Experiment to demonstrate various data pre-processing techniques

Step 1: Open WEKA and Load Dataset

- 1. Launch WEKA GUI Chooser.
- 2. Click Explorer.
- 3. Click **Open file...** and load a dataset (.arff or .csv).
- 4. The dataset will appear in the **Preprocess** tab.

Step 2: View Summary Information

- In the **Preprocess** tab:
 - o Select each attribute to see its type, missing values, distinct values, etc.

Step 3: Apply Data Pre-processing Techniques

a. Handling Missing Values:

Filter Path:

unsupervised → attribute → ReplaceMissingValues

Steps:

- 1. Click on **Choose** under Filter.
- 2. Select: unsupervised \rightarrow attribute \rightarrow ReplaceMissingValues
- 3. Click Apply.

This replaces missing values with:

- Mean for numeric attributes
- **Mode** for nominal attributes
 - b. Normalization: Rescales attributes to range [0,1]

Filter Path:

unsupervised → attribute → Normalize

Steps:

- 1. Click Choose \rightarrow unsupervised \rightarrow attribute \rightarrow Normalize
- 2. Click Apply.
 - c. Standardization: Converts data to zero mean and unit variance

Filter Path:

unsupervised → attribute → Standardize

Steps:

- 1. Choose unsupervised → attribute → Standardize
- 2. Click Apply
 - d. Discretization: Converts numeric attributes to nominal

Filter Path:

unsupervised → attribute → Discretize

Steps:

- 1. Choose unsupervised \rightarrow attribute \rightarrow Discretize
- 2. Click Apply
 - e. Remove Unnecessary Attributes: Remove attributes that don't contribute to analysis, like IDs, serial numbers, timestamps, etc.

Filter Path:

unsupervised \rightarrow attribute \rightarrow Remove

Steps:

- 1. Click **Choose** \rightarrow unsupervised \rightarrow attribute \rightarrow Remove
- 2. Click on the filter to set attribute indices to remove.
- 3. Click Apply

5. Experiment to select prominent feature subsets of various datasets.

• Feature Importance Identification:

It helps determine which features (attributes) in the dataset have the most influence on the output variable.

• Dimensionality Reduction:

Removes irrelevant or redundant features, reducing the number of input variables — this simplifies models and avoids overfitting.

• Improved Model Performance:

Using only the most significant features often increases classification or prediction accuracy and reduces computation time.

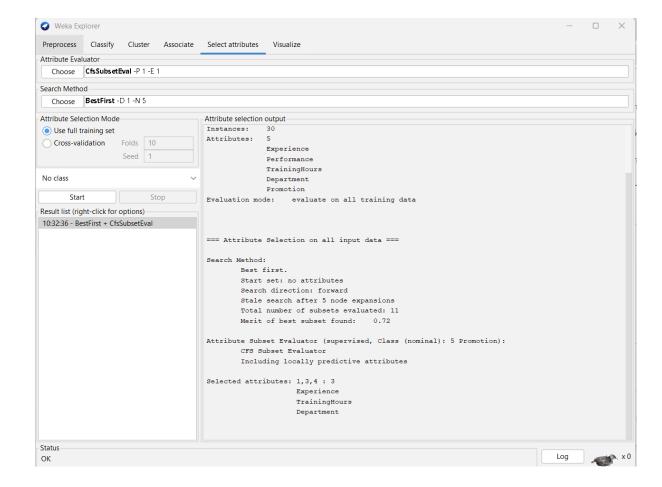
• Better Interpretability:

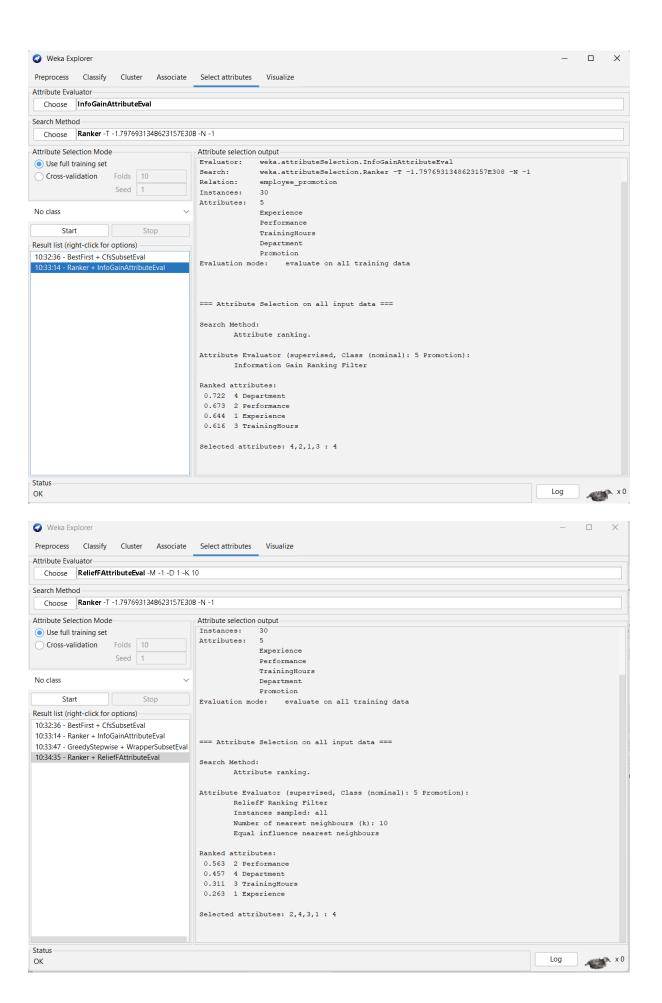
With fewer features, the resulting model becomes easier to understand and explain.

• Preprocessing Step in Data Mining:

Feature selection is a crucial step before applying algorithms like Decision Trees, SVM, Naïve Bayes, etc., improving their efficiency

- 1. Open WEKA \rightarrow Explorer.
- 2. Load the dataset file.
- 3. Click on "Select attributes" tab.
- 4. Apply various evaluators (InfoGain, CfsSubsetEval, ReliefF).
- 5. Compare the selected feature subsets.





6. Experiment to Evaluate Information Gain of an attribute in the student database

Information Gain: Information Gain (IG) measures how much knowing an attribute reduces the uncertainty (entropy) about the class. It is based on Entropy, which measures impurity or randomness in the data.

Step 1: Load Data

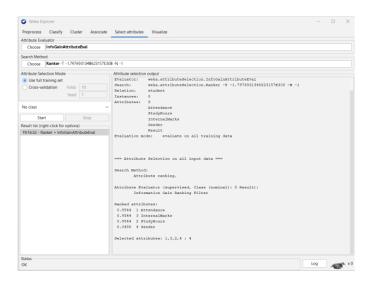
- Open Weka → Explorer → Preprocess
- Load student.arff
- Set Result as class attribute.

Step 2: Select InfoGain

- Go to Select Attributes tab
- In Attribute Evaluator choose: InfoGainAttributeEval
- In Search Method choose: Ranker

Step 3: Run

Click Start → Weka gives you Information Gain values for each attribute.



- @relation student
- @attribute Attendance {Low, Medium, High}
- @attribute StudyHours numeric
- @attribute InternalMarks numeric
- @attribute Gender {Male, Female}
- @attribute Result {Pass, Fail}
- @data

High, 8, 25, Male, Pass

Medium, 5, 20, Female, Pass

Low, 2, 12, Male, Fail

High, 7, 22, Female, Pass

Low, 1, 10, Female, Fail

Medium, 4, 18, Male, Pass

High,9,26,Female,Pass

Low, 3, 15, Male, Fail

7. Demonstration of classification rule process using j48 decision tree algorithm

J48 generates a tree based on the **attribute with the highest Information Gain Ratio** at each node. The tree can then be converted into **IF-THEN classification rules**.

Step 1: Open Weka Explorer

• Launch Weka → Explorer.

Step 2: Load Data

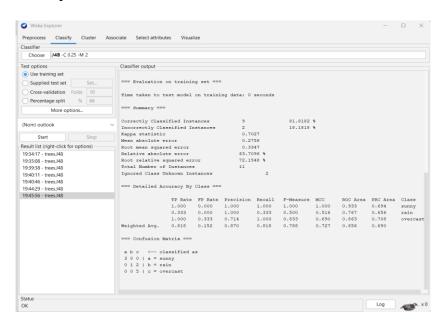
- Load student.arff.
- Go to Classify tab.
- Ensure Result is the class attribute.

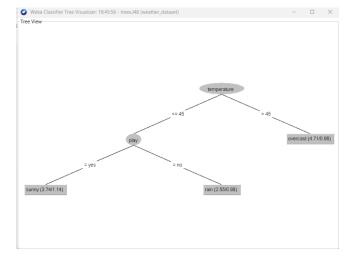
Step 3: Choose Classifier

- Click Choose \rightarrow Select trees \rightarrow J48.
- In "Test options", select **Use training set** (not cross-validation).

Step 4: Run the Classifier

- Click Start.
- Weka will output the **decision tree model** and evaluation metrics.

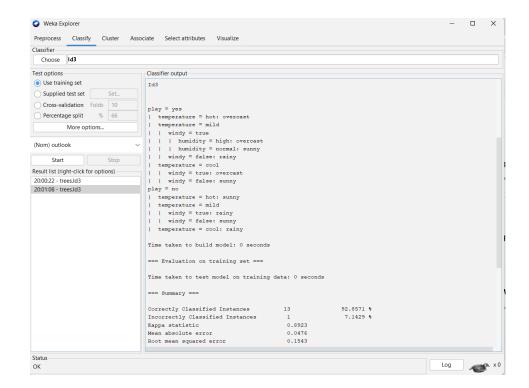




8. Demonstration of classification rule process using ID3 decision tree algorithm

ID3 (Iterative Dichotomiser 3)

- A decision tree algorithm developed by Quinlan.
- Builds the tree using **Information Gain** to select the best attribute at each step.
- Works well with categorical data, but cannot handle numeric values directly.
- Does **not support pruning**, so trees may overfit.
 - Open Weka Explorer → Preprocess.
 - Load dataset.
 - Go to Classify → Choose → trees → Id3
 - Run classifier.
 - Weka will display the decision tree and evaluation



9. Experiment to predict the class using the Bayesian classification

Naive Bayes

- A probabilistic classifier based on Bayes' Theorem.
- Assumes attributes are **independent** given the class (hence "naïve").
- Works well with both categorical and numeric data.
- Fast, simple, and effective, even with small datasets.

Based on Bayes' Theorem:

$$P(Class|Data) = rac{P(Data|Class) imes P(Class)}{P(Data)}$$

- In Weka, the most common is **Naïve Bayes**, which assumes that attributes are **conditionally independent** given the class.
- It works well on both categorical and numeric attributes.

Step 1: Load Dataset

- Open Weka Explorer → Preprocess.
- Load weather.arff.

Step 2: Set Class Attribute

• The last attribute play is the **class** (yes/no).

Step 3: Select Classifier

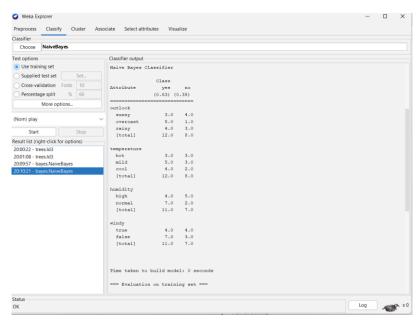
- Go to the Classify tab.
- Choose: bayes \rightarrow NaiveBayes.

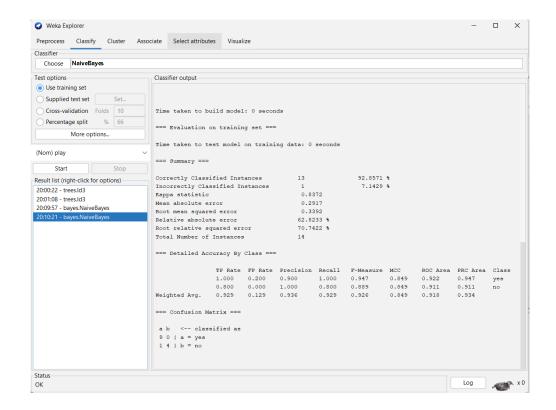
Step 4: Test Options

• Choose 10-fold cross-validation (default), or Use training set for a small dataset.

Step 5: Run

• Click Start.

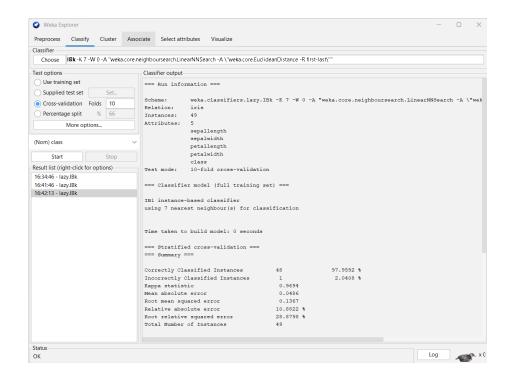


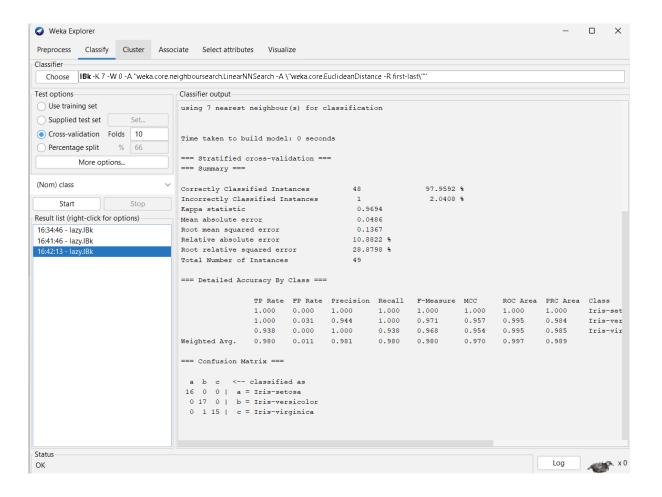


10. Experiment to predict the class using the k-Nearest Neighbor classification

KNN: k-Nearest Neighbor (KNN) is a simple, supervised machine learning algorithm commonly used for both classification and regression tasks. It works on the principle of finding the k nearest data points to a query instance based on distance measures such as Euclidean distance and assigning the majority class (for classification) or the average value (for regression). Unlike other algorithms, KNN has no explicit training phase and is therefore known as an instance-based learning method. Its main strength lies in its simplicity, non-parametric nature, and effectiveness on small datasets with irregular decision boundaries, making it useful in applications such as pattern recognition, medical diagnosis, recommendation systems, and image classification. However, KNN has limitations: it becomes computationally expensive for large datasets, is sensitive to irrelevant or unscaled features, suffers from the curse of dimensionality in high-dimensional data, and its performance highly depends on the choice of k.

- 1. Open WEKA \rightarrow Explorer \rightarrow Preprocess.
- 2. Load iris.arff.
- 3. Go to Classify tab \rightarrow Choose \rightarrow lazy \rightarrow IBk (k-NN).
- 4. Try different k values (1,3,5,7,9).
- 5. Use 10-fold Cross-Validation for evaluation.
- 6. Record Accuracy, Confusion Matrix, and per-class Precision/Recall/F1.





11. Experiment to implement weight & bias updating using the Back propagation Neural Network

A Backpropagation Neural Network (BPNN) is a supervised learning model consisting of input, hidden, and output layers.

It uses the **backpropagation algorithm** for training:

- 1. **Forward pass** inputs are passed through the network to calculate outputs.
- 2. **Error computation** difference between predicted and target values.
- 3. Backward pass gradients of the error are propagated backward using the chain rule.
- 4. Weight and bias update parameters are adjusted using Gradient Descent:

$$w_{new} = w_{old} - \eta \cdot rac{\partial E}{\partial w}$$

$$b_{new} = b_{old} - \eta \cdot rac{\partial E}{\partial b}$$

where η = learning rate, **E** = error function (e.g., Mean Squared Error).

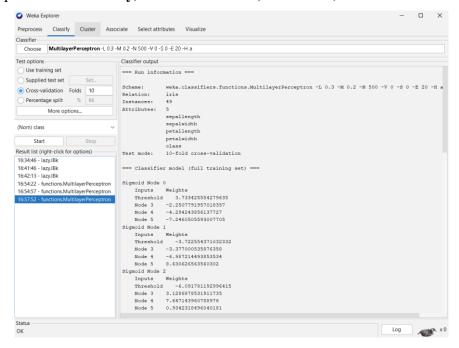
Multilayer Perceptron (MLP) in WEKA is a feedforward neural network trained with backpropagation.

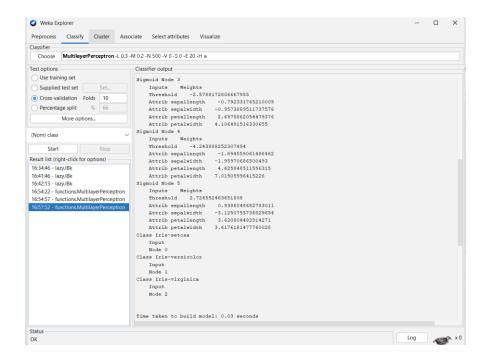
It has input, hidden, and output layers.

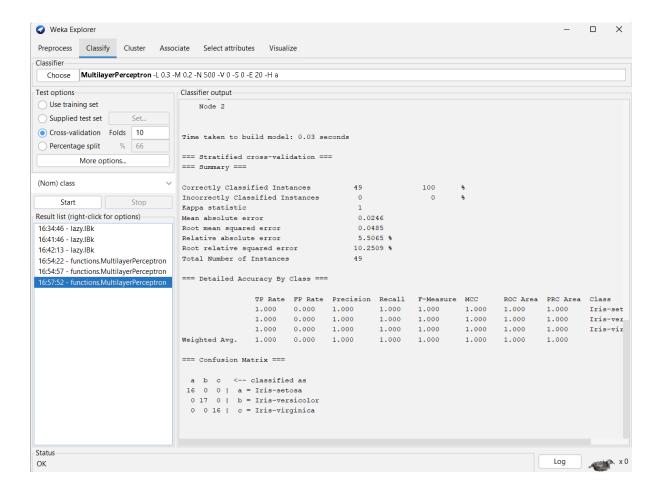
Backpropagation updates **weights and biases** iteratively to minimize error using **gradient descent**.

- 1. Open WEKA Explorer.
- Go to Preprocess → Open file → load a dataset (e.g., iris.arff or your custom dataset).
- Ensure the **class attribute** is set (usually last column).
 - 2. Go to Classify tab.
- Click Choose → functions → MultilayerPerceptron.
- This is WEKA's backpropagation neural network.
 - 3. Configure the Neural Network.
- Click on **MultilayerPerceptron** (blue text) to open parameters:
 - Learning rate (η): controls weight update step size (default 0.3).
 - Momentum: helps escape local minima by smoothing updates (default 0.2).
 - o **Training time (epochs):** number of iterations (default 500).
 - o **Hidden layers:** structure of hidden layer(s)
 - Use a = (attributes+classes)/2 (default)
 - You can try 1, 2, or 3 hidden units.
- Press OK.
 - 4. Choose evaluation method.

- At the top, select:
 - o Cross-validation (10 folds) (recommended), or
 - o Percentage split (e.g., 70% train, 30% test).
 - 5. Run training.
- Click Start.
- WEKA trains the network using backpropagation.
- The output shows accuracy, confusion matrix, error rate, etc.



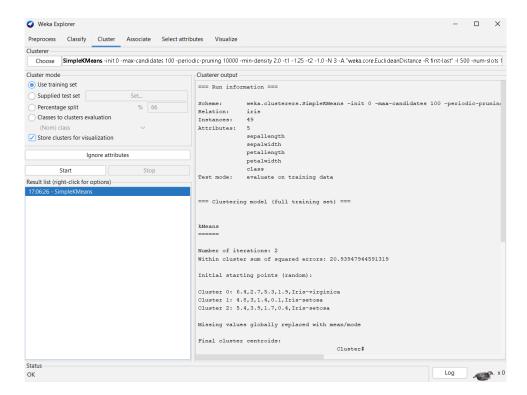


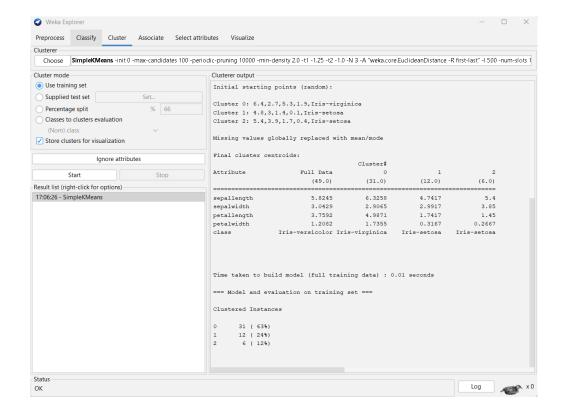


- 12. Demonstration of clustering process using k-means algorithm
- Clustering is an unsupervised learning technique where data is grouped into clusters based on similarity.
- K-Means is the most widely used clustering algorithm.
- It works as follows:
 - > Choose the number of clusters (k).
 - > Randomly initialize k centroids.
 - Assign each data point to the **nearest centroid** (using distance measure, e.g., Euclidean).
 - ➤ Recalculate centroids as the mean of points in each cluster.
 - Repeat until centroids do not change significantly (convergence).

> Open WEKA Explorer.

- Go to Preprocess → Open file → load a dataset (e.g., iris.arff or your custom dataset).
- 2. Remove the **class attribute** (optional) since clustering is unsupervised.
- ➤ Go to the Cluster tab.
 - 1. Click Choose \rightarrow SimpleKMeans.
- > Configure K-Means parameters.
 - 1. Click SimpleKMeans (blue text) to open options:
 - 1. **NumClusters:** Set k (e.g., 3 for iris dataset).
 - 2. Seed: Random initialization (default 10).
 - 3. **Distance function:** Euclidean Distance (default).
 - 2. Click OK.
- > Run the algorithm.
 - 1. At the top, select **Use training set** (to cluster all data).
 - 2. Click Start.





13. Demonstration of mining frequent patterns using Apriori algorithm

- The Apriori algorithm is a classic data mining algorithm used for association rule mining.
- It finds frequent itemsets in large transactional databases and then generates association rules from them.
- o It uses support and confidence measures:
 - Support \rightarrow How often an itemset appears in the dataset.
 - Confidence → How often items in Y appear in transactions that contain X (for rule X → Y).
- Widely used in market basket analysis (e.g., "If a customer buys Milk, they are likely to buy Bread")

1. Start Weka and open Explorer

- Launch the Weka GUI (double-click the weka.jar or use your Weka launcher).
- Click Explorer.

2. Load your dataset

• In the Preprocess tab click Open file

3. Switch to the Associate tab

•	Click the Associate tab at the top of the Explorer window.									
	□ Choo	se Aprio	ri							
•	Click	the	Choose	button	(top	left)	and	select:		
	weka.associations.Apriori → Apriori .									
	□ Set A	priori pa	rameters							
	Click the small text label that says Apriori (or double-click) to open the configuration									

- Click the small text label that says Apriori (or double-click) to open the configuration dialog.
- Important parameters to set:
 - o **lowerBoundMinSupport** (minimum support): enter a fraction such as 0.20 for 20% (for 20 transactions, $0.20 \rightarrow$ requires itemset in at least 4 transactions).
 - o **minMetric** (minimum confidence / metric): set 0.60 for 60% confidence (or use a value you need).
 - o **numRules** (max number of rules to output): set something like 100 so you don't truncate useful rules.
- Notes: Weka typically accepts these as decimal fractions (0.2 = 20%). If the dialog tooltip shows a different format, follow the dialog's guidance.

Run		

- Click **OK** to close the parameter dialog.
- Click **Start** (lower left) to run Apriori on your loaded dataset.

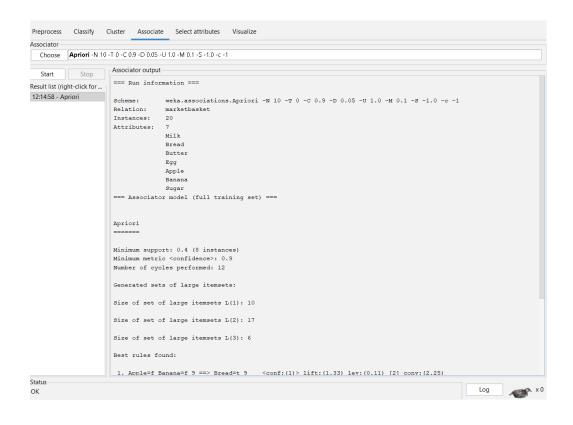
☐ Read the output

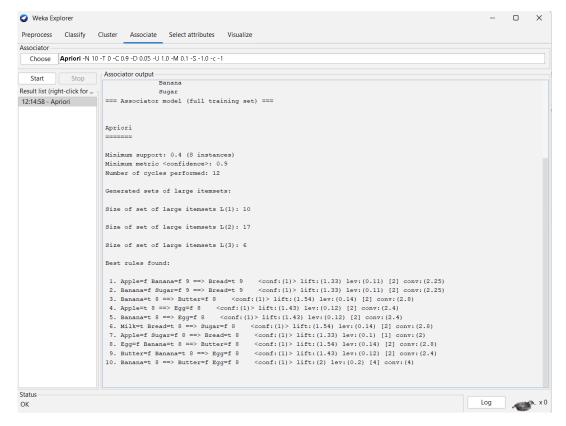
Dataset:

- @relation marketbasket
- @attribute Milk {t, f}
- @attribute Bread {t, f}
- @attribute Butter {t, f}
- @attribute Egg {t, f}
- @attribute Apple {t, f}
- @attribute Banana {t, f}
- @attribute Sugar {t, f}

@data

- t, t, t, f, f, f, f
- t, t, f, t, f, f, f
- t, f, f, f, t, t, f
- f, t, t, f, f, f, t
- t, t, f, f, t, f, f
- f, t, f, t, f, f, t
- t, f, f, f, t, t
- f, t, t, t, f, f, f
- t, t, f, f, f, t, f
- f, f, f, f, t, t, t
- t, t, t, f, t, f, f
- f, t, f, t, f, f, f
- t, f, f, f, t, f, t
- t, t, t, f, f, f
- f, t, f, f, f, t, t
- t, t, f, f, t, t, f
- f, t, t, f, f, f, f
- t, f, f, f, t, t, t
- f, t, t, t, f, f, f
- t, t, f, f, t, t, f

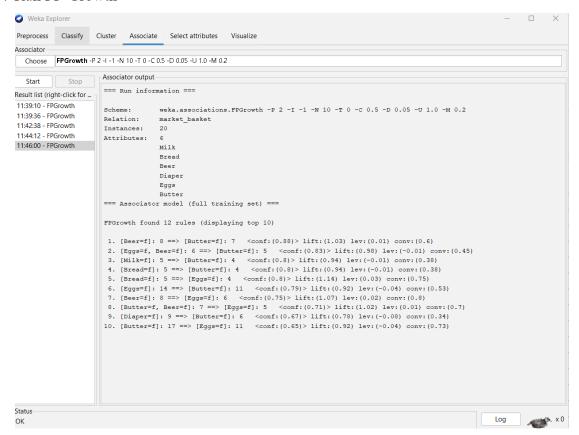




- 14. Demonstration of mining frequent patterns using FP-Growth algorithm
 - Frequent Pattern Growth (FP-Growth) is an efficient algorithm for mining frequent itemsets without candidate generation (unlike Apriori).
 - It compresses the dataset into a **Frequent Pattern Tree (FP-Tree)** and then recursively extracts frequent patterns.
 - Works better than Apriori for **large datasets** because it avoids repeated database scans.

Procedure:

- 1. Prepare the dataset
- 2. Open Weka
- 3. Load the dataset
- 4. Go to Associate tab
 Click on Choose → select weka.associations.FPGrowth.
- 5. Select FP-Growth
- 6. Configure FP-Growth Parameters
 - minSupport \rightarrow set as fraction (e.g., 0.2 = 20% support threshold).
 - numRulesToFind \rightarrow set how many rules you want (e.g., 10).
 - $metricType \rightarrow choose confidence$, lift, or leverage (default is confidence).
 - minMetric \rightarrow set minimum confidence (e.g., 0.5).
- 7. Run FP-Growth



Dataset:

@relation market_basket

- @attribute Milk {t,f}
- @attribute Bread {t,f}
- @attribute Beer $\{t,f\}$
- @attribute Diaper {t,f}
- @attribute Eggs {t,f}
- @attribute Butter {t,f}

@data

t,t,t,f,f,f

t,t,t,f,f

t,t,f,t,f,f

f,t,t,t,f

t,f,t,t,f,f

t,t,f,f,t,f

t,t,t,f,t,f

t,f,f,t,f,f

t,t,f,f,f,t

f,t,t,f,t,f

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- 15. Experiment to compare the performance of various data mining algorithms on the give database.
 - 1. Open WEKA \rightarrow Explorer \rightarrow Open File \rightarrow employee promotion.arff
 - 2. Set **Promotion** as the class attribute
 - 3. Run each algorithm:
 - **>J48** (trees)
 - **≻**NaiveBayes
 - >IBk (default k=1, then try k=3)
 - ≻SMO (SVM)
 - 4. Compare metrics (Accuracy, Precision, Recall, F1).

Dataset:

- @relation employee promotion
- @attribute Experience numeric
- @attribute Performance {Low, Medium, High}
- @attribute TrainingHours numeric
- @attribute Department {HR,Sales,IT,Finance}
- @attribute Promotion {Yes,No}
- @data
- 2,Low,5,Sales,No
- 5, Medium, 12, HR, No
- 7,High,20,IT,Yes
- 10, High, 18, Finance, Yes
- 3,Low,6,Sales,No
- 8,High,15,IT,Yes
- 4, Medium, 8, HR, No
- 6, Medium, 10, Finance, Yes
- 1,Low,3,Sales,No
- 9,High,22,IT,Yes
- 2,Low,4,HR,No
- 5,Medium,9,Finance,Yes
- 7,High,19,IT,Yes
- 3,Medium,7,Sales,No
- 8, High, 16, Finance, Yes

- 4,Low,5,HR,No
- 6,Medium,12,Sales,No
- 9,High,20,IT,Yes
- 10, High, 21, Finance, Yes
- 2,Low,6,Sales,No
- 5, Medium, 10, HR, No
- 7, High, 18, IT, Yes
- 3, Medium, 8, Finance, No
- 8,High,19,IT,Yes
- 4,Low,6,Sales,No
- 6, Medium, 13, Finance, Yes
- 9,High,20,IT,Yes
- 10, High, 22, Finance, Yes
- 1,Low,4,Sales,No
- 7, Medium, 12, HR, Yes

