Data Mining Lab File

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Section - 3
Semester - 5
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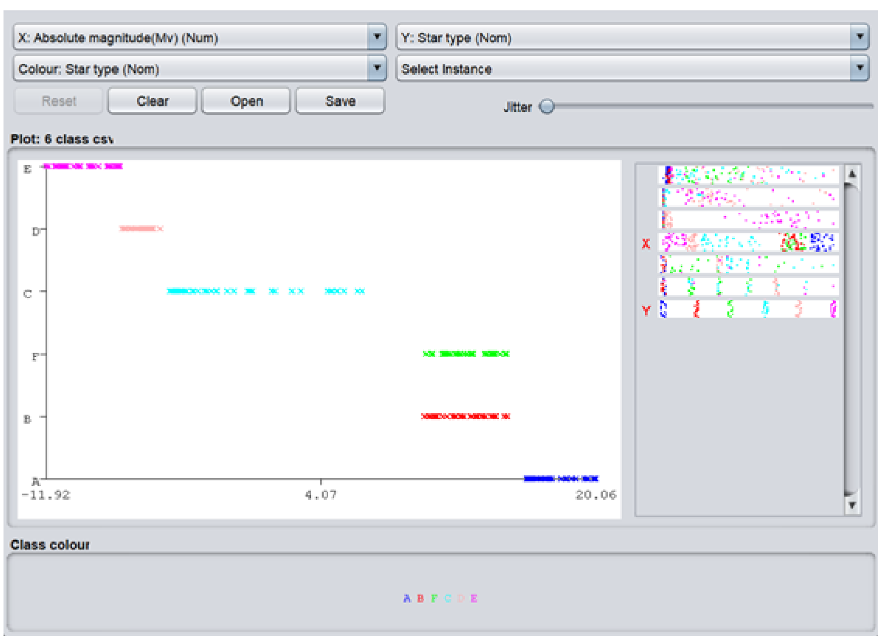
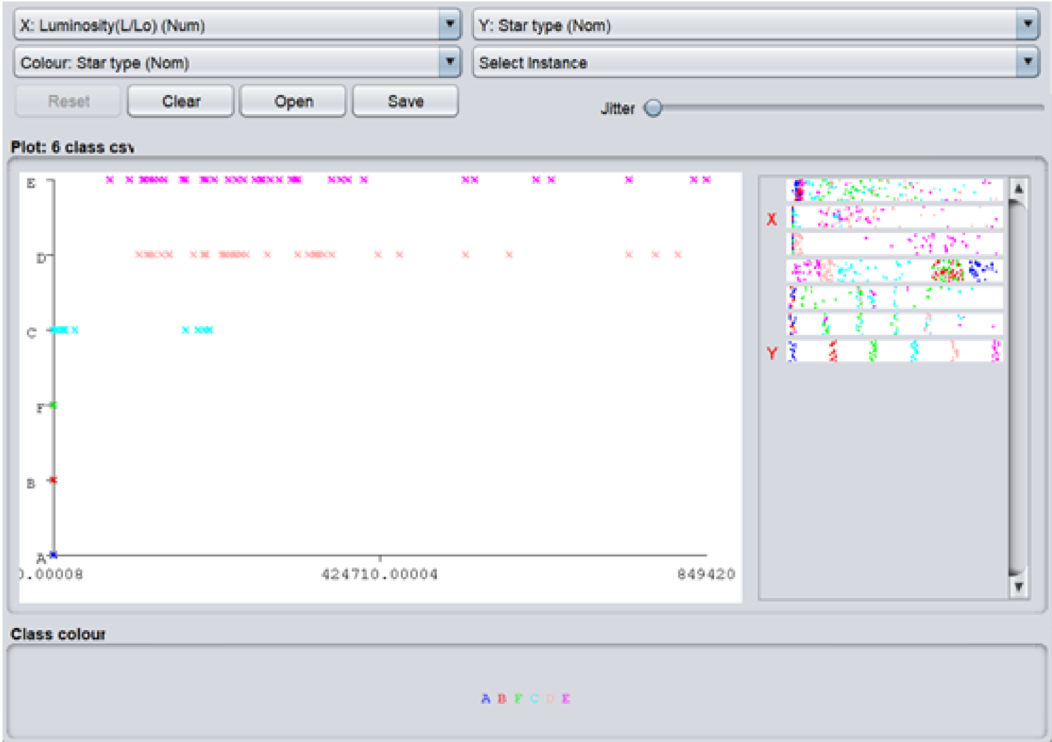
1) Understanding Data Mining & Visualizing data

Data Mining

Data mining, also known as knowledge discovery in data, is the process of extracting patterns and other useful information from large data sets (KDD). The usage of data mining techniques has grown in recent decades, assisting organisations in turning raw data into valuable knowledge, thanks to advancements in data warehousing technologies and the rise of big data. Executives still face scalability and automation difficulties, despite the fact that technology is constantly advancing to manage enormous amounts of data.
Data mining has improved corporate decision-making through clever data analytics. The data mining approaches employed in these research can be divided into two groups: those that describe the target dataset and those that use machine learning algorithms to anticipate results. These tactics are used to organise and filter data, providing the most important information, from fraud detection to user behaviours, bottlenecks, and even security breaches.
When integrated with data analytics and visualisation technologies like Apache Spark, delving into the domain of data mining has never been easier, and collecting significant insights has never been faster. Artificial intelligence advances are hastening implementation in a variety of industries.

Visualising Data




X: Luminosity(L/Lo) (Num)
Y: Star type (Nom)
Colour: Star type (Nom)
Select Instance
Reset
Clear
Open
Save
Jitter
Plot: 6 class csv
E
D
C
F
B
A
0.00008
424710.00004
849420
X
Y
Class colour
A B F C D E

2) Analysis of Data - nominal, ordinal, ratio, interval

Nominal

A nominal scale is used to express a variable that has no natural order or ranking. If you choose, you can code nominal variables with numbers, but the sequence is arbitrary, and any computations, such as estimating a mean, median, or standard deviation, would be useless. Examples of nominal variables include: genotype, blood type, zip code, gender, race, eye color, political party

Ordinal

An ordinal scale is one where the order matters but not the difference between values. Examples of ordinal variables include: socio economic status (“low income”,”middle income”,”high income”), education level (“high school”,”BS”,”MS”,”PhD”), income level (“less than 50K”, “50K-100K”, “over 100K”), satisfaction rating (“extremely dislike”, “dislike”, “neutral”, “like”, “extremely like”).

Interval

An interval scale is one where there is order and the difference between two values is meaningful. Examples of interval variables include: temperature (Farenheit), temperature (Celcius), pH, SAT score (200-800), credit score (300-850).

Ratio

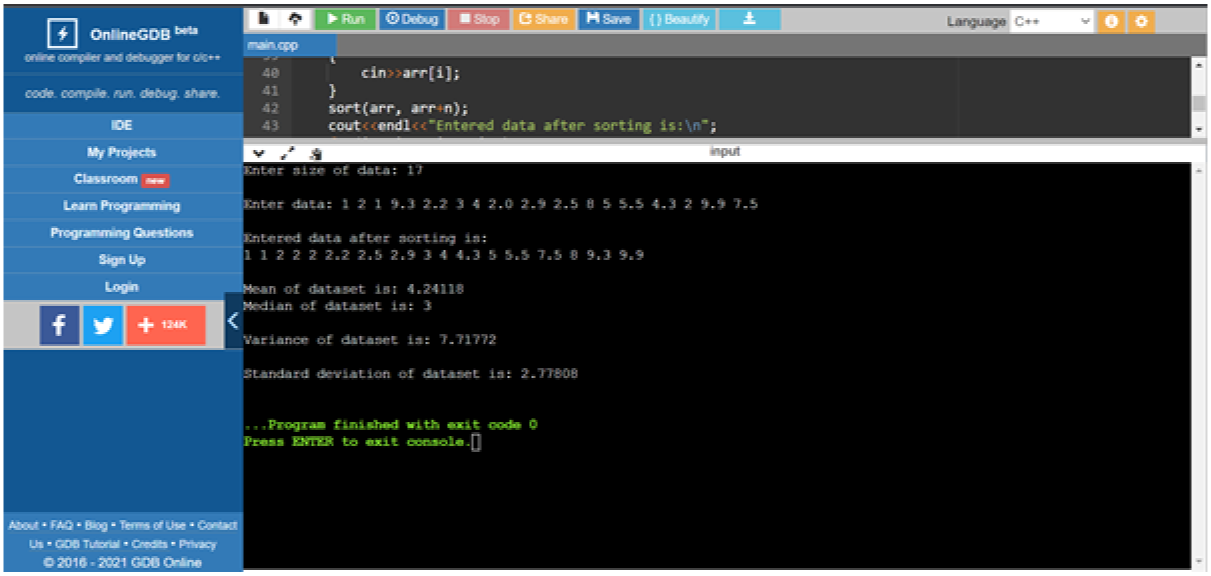
A ratio variable, has all the properties of an interval variable, and also has a clear definition of 0.0. When the variable equals 0.0, there is none of that variable.

Examples of ratio variables include: enzyme activity, dose amount, reaction rate, flow rate, concentration, pulse, weight, length, temperature in Kelvin (0.0 Kelvin really does mean “no heat”), survival time.

3) Find the mean, median, variance and standard deviation of data

```
#include <bits/stdc++.h>

using namespace std;

double meancal(double *arr, int n){

   double sum=accumulate(arr, arr+n, 0.0);

   return sum/n;

}

double median(double *arr, int n){

   if(n%2==1)

        return (double)(arr[n/2]);

   return (double)((arr[n/2]+arr[n/2-1])/2);

}

double variance(double *arr, int n, double mean){

   double t=0.0;

   for(int i=0; i<n; i++){

      double temp=abs(arr[i]-mean);

      t+=temp*temp;

   }

   if(n>50)

        return t/(n-1);

   else

        return t/n;

}


int main() {
```

```
    cout<<"Enter size of data: ";
    int n;
    cin>>n;
    cout<<"\nEnter data: ";
    double arr[n];
    for(int i=0; i<n; i++)
    {
        cin>>arr[i];
    }
    sort(arr, arr+n);
    cout<<endl<<"Entered data after sorting is:\n";
    for(int i=0; i<n; i++)
    cout<<arr[i]<<" ";
    cout<<endl;
    double mean;
    mean=meancal(arr, n);
    cout<<"\nMean of dataset is: "<<mean<<endl;
    cout<<"Median of dataset is: "<<median(arr, n)<<endl;
    double var=variance(arr, n, mean);
    cout<<"\nVariance of dataset is: "<<var<<endl;
    cout<<"\nStandard deviation of dataset is: "<<sqrt(var)<<endl;
    return 0;
}
```


OnlineGDB beta
online compiler and debugger for c/c++
code. compile. run. debug. share.
IDE
My Projects
Classroom new
Learn Programming
Programming Questions
Sign Up
Login
124K
About • FAQ • Blog • Terms of Use • Contact Us • GDB Tutorial • Credits • Privacy
© 2016 - 2021 GDB Online
Run
Debug
Stop
Share
Save
{ } Beautify
Language C++
main.cpp
cin>>arr[i];
}
sort(arr, arr+n);
cout<<endl<<"Entered data after sorting is:\n";
input
Enter size of data: 17
Enter data: 1 2 1 9.3 2.2 3 4 2.0 2.9 2.5 8 5 5.5 4.3 2 9.9 7.5
Entered data after sorting is:
1 1 2 2 2 2.2 2.5 2.9 3 4 4.3 5 5.5 7.5 8 9.3 9.9
Mean of dataset is: 4.24118
Median of dataset is: 3
Variance of dataset is: 7.71772
Standard deviation of dataset is: 2.77808
...Program finished with exit code 0
Press ENTER to exit console.

4) Proximity Measures - Calculate dissimilarity matrix

The pairwise differentiation between M items is described by the dissimilarity matrix (also known as the distance matrix). It's a square symmetrical MxM matrix with the value of a chosen measure of differentiation between the (i)th and (j)th object as the (ij)th member. The diagonal elements are either ignored or equal to zero, implying that the difference between an item and itself is assumed to be zero.

The similarity matrix is a similarly related and opposing idea. For the same data, both sorts of descriptions are frequently utilised.

Any valid measure of dissimilarity, including subjective dissimilarity scores, may be employed. The only stipulation is that the bigger the difference between two objects, the higher the measure of dissimilarity's worth.

Code:

```
#include<bits/stdc++.h>
#define N 3
#define M 4
using namespace std;
void printDistance(int mat[N][M])
{
	int ans[N][M];
	for (int i = 0; i < N; i++)
		for (int j = 0; j < M; j++)
			ans[i][j] = INT_MAX;
	for (int i = 0; i < N; i++)
		for (int j = 0; j < M; j++)
		{
			for (int k = 0; k < N; k++)
				for (int l = 0; l < M; l++)
				{
					if (mat[k][l] == 1)
						ans[i][j] = min(ans[i][j], abs(i-k) + abs(j-l));
				}
		}
	for (int i = 0; i < N; i++)
	{
		for (int j = 0; j < M; j++)
			cout << ans[i][j] << " ";
		cout << endl;
	}
}
int main()
{
```

```
    int mat[N][M] =
    {
        0, 0, 0, 1,
        0, 0, 1, 1,
        0, 1, 1, 0
    };
    printDistance(mat);
    return 0;
}
```

5) Data Preprocessing

Preprocessing data is a crucial task. It is a data mining approach that converts unstructured data into a format that is more comprehensible, usable, and efficient.

Tasks in data preprocessing -

1) Data Cleaning
2) Data Integration
3) Data Transformation
4) Data Reduction
5) Data Discretization

Handling Missing Values -

In a data set, missing values cannot be checked. They must be dealt with. A number of models also don't like missing values. There are numerous methods for dealing with missing data, and picking the proper one is crucial. The strategy used to deal with missing data is determined by the problem domain and the data mining process's purpose. The different ways to handle missing data are:

1) Ignore the data row
2) Fill the missing values manually
3) Use a global constant to fill in for missing values
4) Use attribute mean or median
5) Use forward fill or backward fill method
6) Use a data-mining algorithm to predict the most probable value

Handling Noise & Outliers -

Noise in data can be created as a result of data gathering errors, data entry problems, or data transmission errors, among other things. Different sorts of noise and outliers include unknown encoding (Example: Marital Status — Q), out of range numbers (Example: Age — -10), inconsistent data (Example: DoB — 4th Oct 1999, Age — 50), inconsistent formats (Example: DoJ — 13th Jan 2000, DoL — 10/10/2016), and so on.

Binding can be used to deal with noise. Sorted data is arranged into bins or buckets using this method. Equal-width (distance) or equal-depth (frequency) partitioning can be used to produce bins. Smoothing can be done on these bins. Bin mean, bin median, and bin borders are all options for smoothing.

Binning and then smoothing can be used to smooth outliers. Visual analysis or box plots can be used to detect them. Clustering can be used to find outlier data groups. The detected outliers may be smoothed or removed.

Normalization -

Normalization or Min-Max Scaling is used to transform features to be on a similar scale. The new point is calculated as:

$$X\_new = (X - X\_min)/(X\_max - X\_min)$$

This scales the range to [0, 1] or sometimes [-1, 1]. Geometrically speaking, transformation squishes the n-dimensional data into an n-dimensional unit hypercube. Normalization is useful when there are no outliers as it cannot cope up with them. Usually, we would scale age and not incomes because only a few people have high incomes but the age is close to uniform.

Standardization -

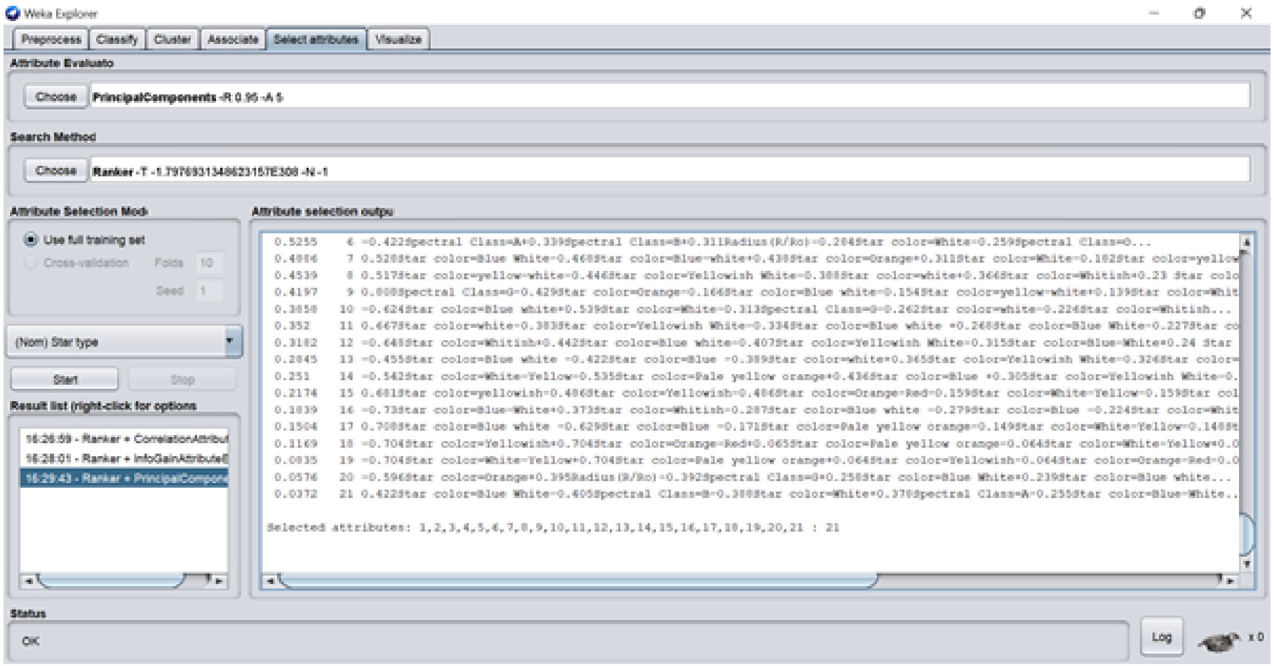
Standardization or Z-Score Normalization is the transformation of features by subtracting from mean and dividing by standard deviation. This is often called a Z-score.

$$X\_new = (X - mean)/Std$$

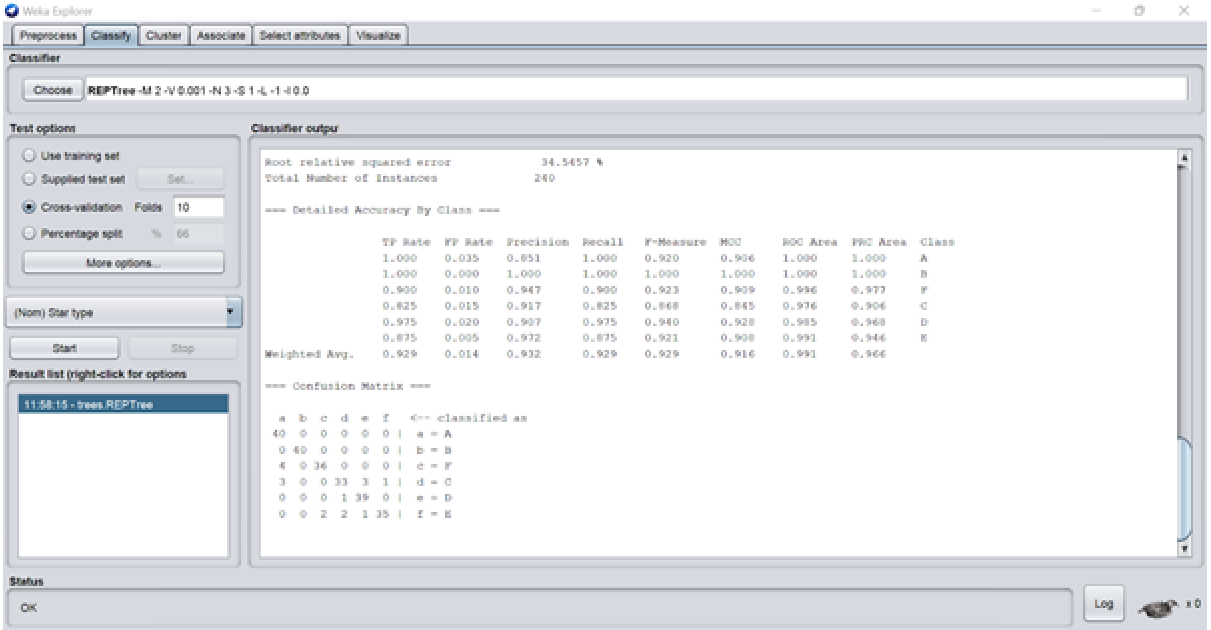
Standardization can be helpful in cases where the data follows a Gaussian distribution. However, this does not have to be necessarily true. Geometrically speaking, it translates the data to the mean vector of original data to the origin and squishes or expands the points if std is 1 respectively. We can see that we are just changing mean and standard deviation to a standard normal distribution which is still normal thus the shape of the distribution is not affected.

Standardization does not get affected by outliers because there is no predefined range of transformed features.

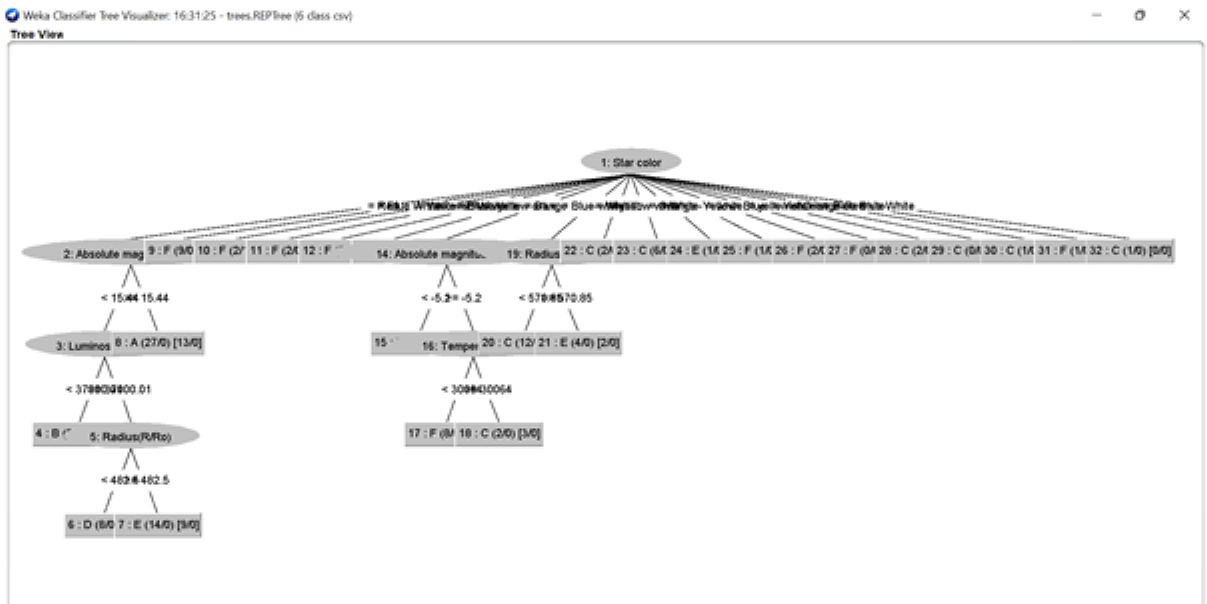
6) Dimensionality reduction using Principal components (PCA)

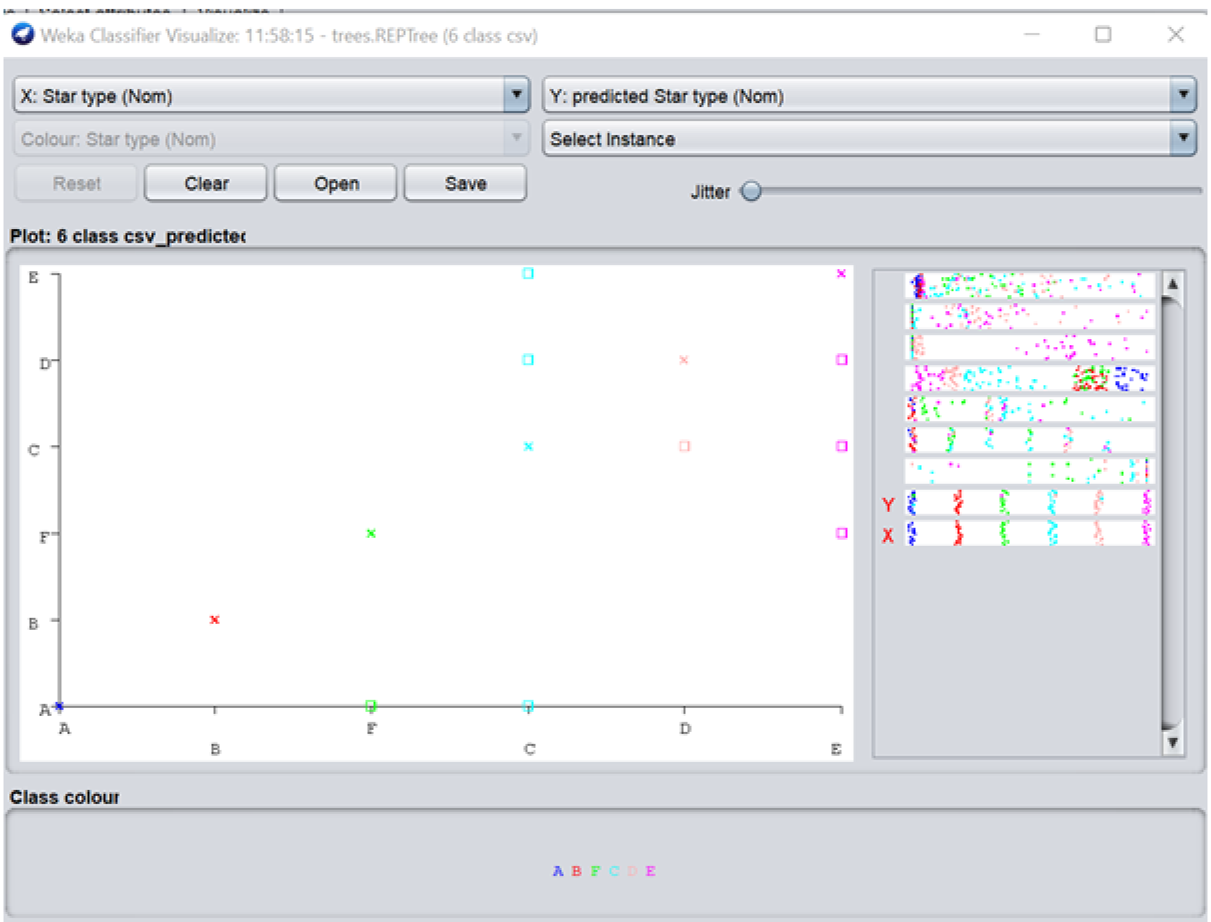


7) Classification using Decision trees

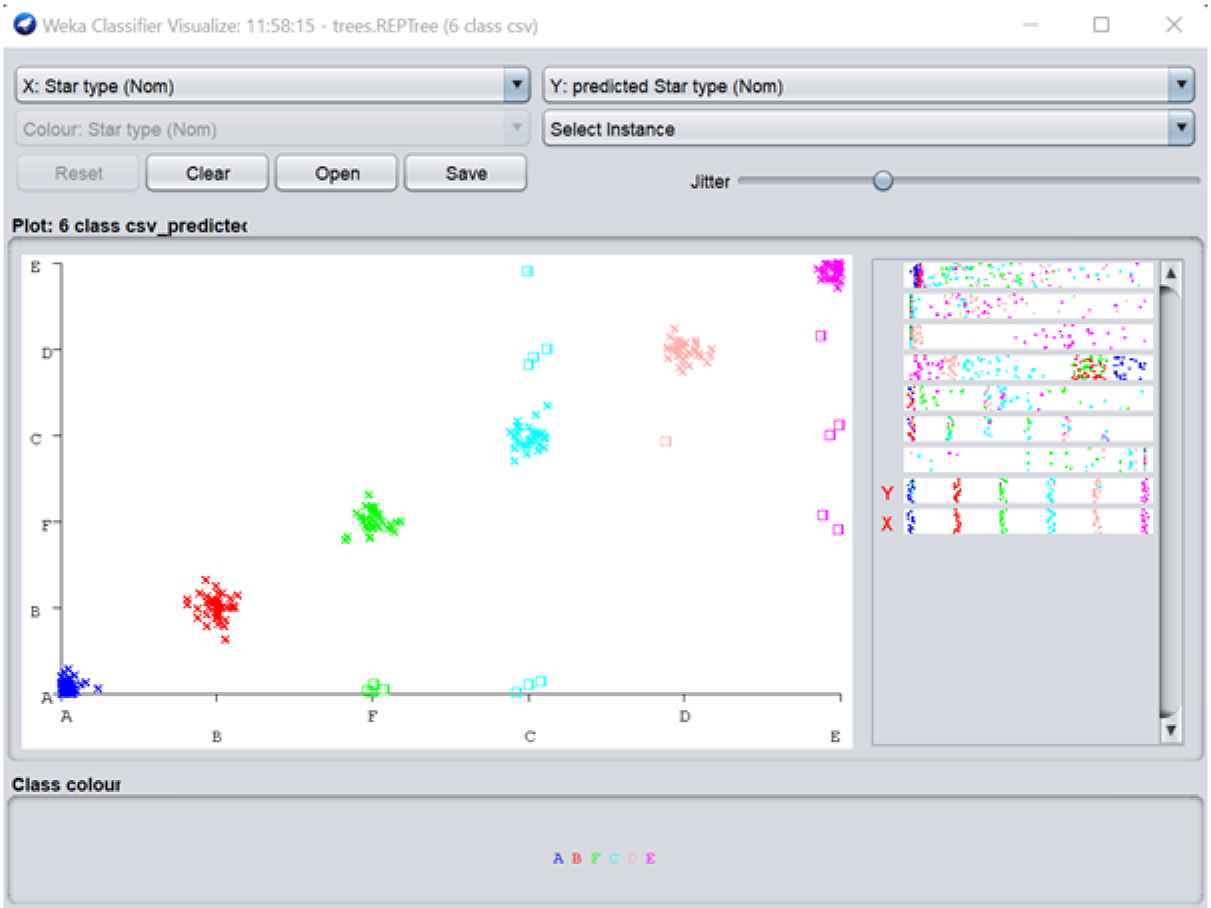



```
Size of the tree : 32

Time taken to build model: 0.01 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         223               92.9167 %
Incorrectly Classified Instances        17                7.0833 %
Kappa statistic                          0.915
Mean absolute error                      0.0271
Root mean squared error                  0.1287
Relative absolute error                  9.7411 %
Root relative squared error             34.5457 %
Total Number of Instances              240
```



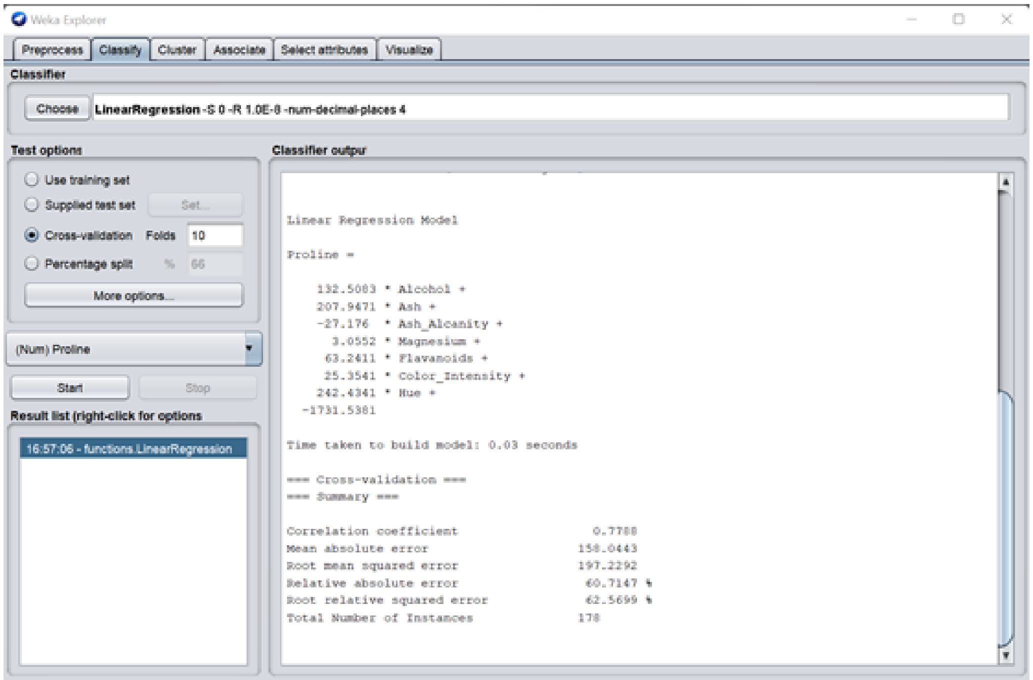


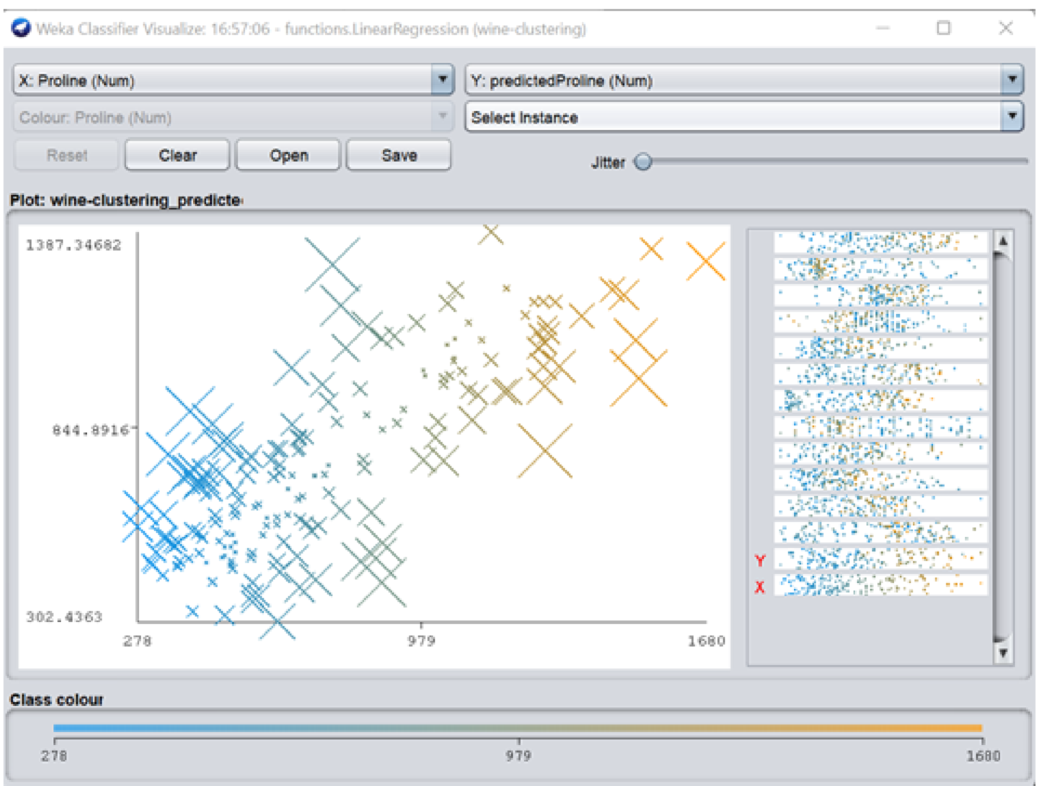
Using some Jitter


Weka Classifier Visualize: 11:58:15 - trees.REPTree (6 class csv)
X: Star type (Nom)
Y: predicted Star type (Nom)
Colour: Star type (Nom)
Select Instance
Reset
Clear
Open
Save
Jitter
Plot: 6 class csv_predictec
E
D
C
F
B
A
A
B
F
C
D
E
Y
X
Class colour
A B F C D E

8) Regression Tasks

Implement linear Regression





Implement logistic regression

16:40:46 - functions.Logistic

Logistic Regression with ridge parameter of 1.0E-8

Coefficients...

Variable	Class A	B	F	C	D
Temperature (K)	-0.0028	0.0019	-0.0009	0.0032	0.0006
Luminosity(L/Lo)	0.0001	-0.0002	-0	-0.0001	-0
Radius(R/Ro)	0.1025	-0.1182	-0.0179	-0.0538	-0.1071
Absolute magnitude(Mv)	18.175	-2.6781	1.7887	-0.2151	-3.5152
Star color=Red	-49.108	15.1471	-19.9149	7.7397	1.7505
Star color=Blue White	-50.8312	4.6768	43.0445	2.4603	26.0063
Star color=White	-90.3027	22.1454	25.5743	33.1626	4.101
Star color=Yellowish White	-97.4297	58.121	30.3236	-5.8311	39.3589
Star color=Blue white	-77.1746	19.056	15.2599	45.1564	22.2079
Star color=Pale yellow orange	-32.3932	9.5621	2.0318	2.9255	42.2033
Star color=Blue	38.0603	3.3557	29.6014	-38.8306	15.7708
Star color=Blue-white	74.3603	-61.8612	-18.2862	24.1565	-54.1701
Star color=Whitish	107.8768	-35.8509	-46.5252	44.1919	-44.6546
Star color=yellow-white	99.9836	-17.4586	-37.7106	14.5591	-34.1429
Star color=Orange	32.6449	114.1015	12.4706	36.6664	71.0603
Star color=White-Yellow	-33.1173	10.1595	1.6009	3.5162	42.1698
Star color=white	-45.1716	20.6891	21.3986	-6.718	34.3057
Star color=Blue	35.4133	-3.6265	23.1439	-32.7696	2.412
Star color=yellowish	41.7433	-7.8328	-52.226	-14.3923	58.5373
Star color=Yellowish	73.6844	-46.5547	25.9194	-14.6628	-12.537
Star color=Orange-Red	60.7389	-17.1273	-5.7423	4.2106	-16.2879
Star color=Blue white	-51.6584	8.3071	13.1004	42.1464	12.8028
Star color=Blue-White	161.2902	-63.9489	-23.3488	28.7284	-53.5763
Spectral Class=M	-52.7066	13.1837	-20.5939	0.0058	8.9949
Spectral Class=B	-15.0796	0.9229	20.2896	-30.5629	16.0907
Spectral Class=A	18.3257	15.1348	7.562	-17.1997	13.4759
Spectral Class=F	-22.6404	-2.322	33.4145	9.6999	7.9858
Spectral Class=O	97.4909	-39.437	-4.9862	23.6415	-38.7934
Spectral Class=K	49.4133	27.3546	-9.9775	76.9718	-36.9831
Spectral Class=G	204.4089	105.9766	38.8751	45.4425	12.6383
Intercept	-158.6944	19.9491	11.1024	-13.5823	33.3988

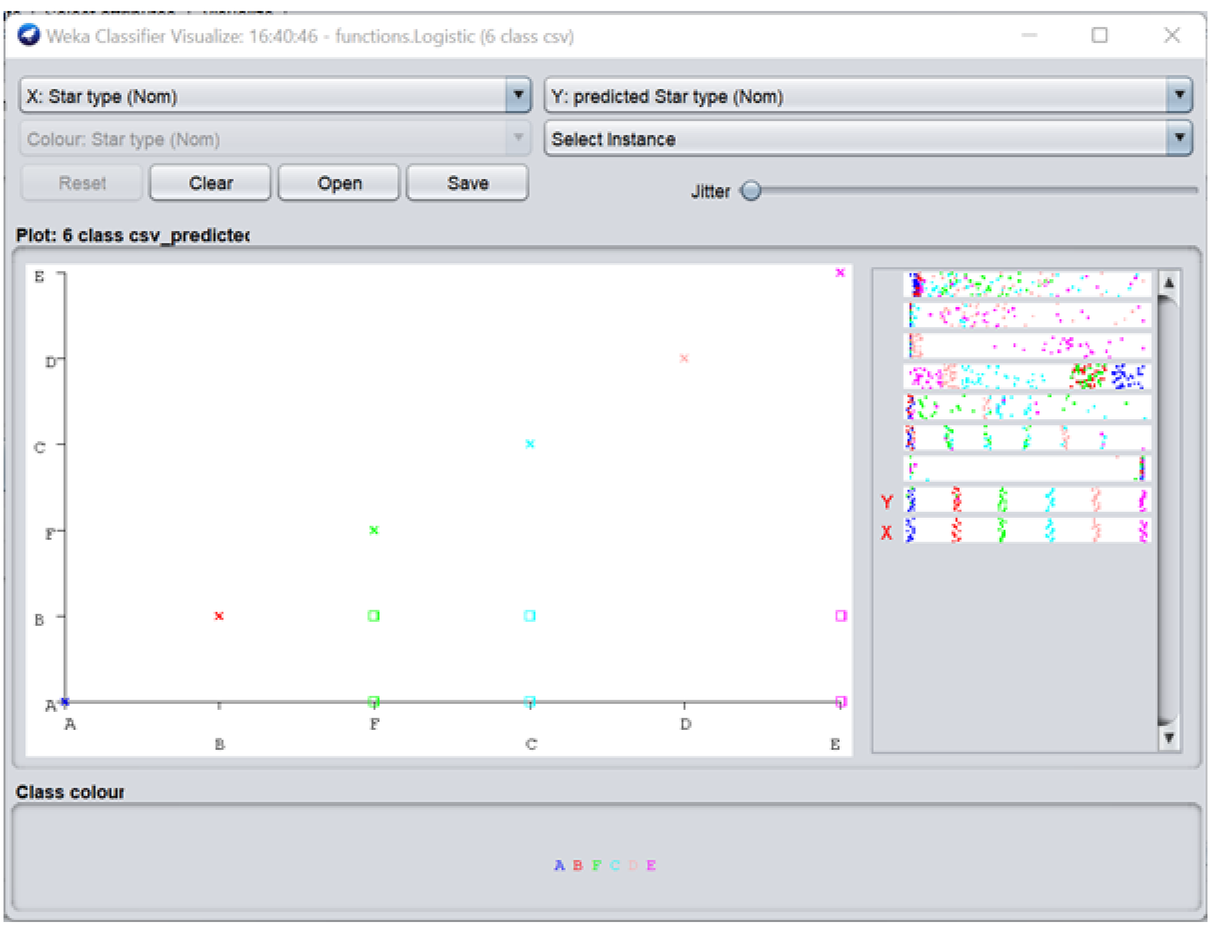
16:40:46 - functions.Logistic

Odds Ratios...

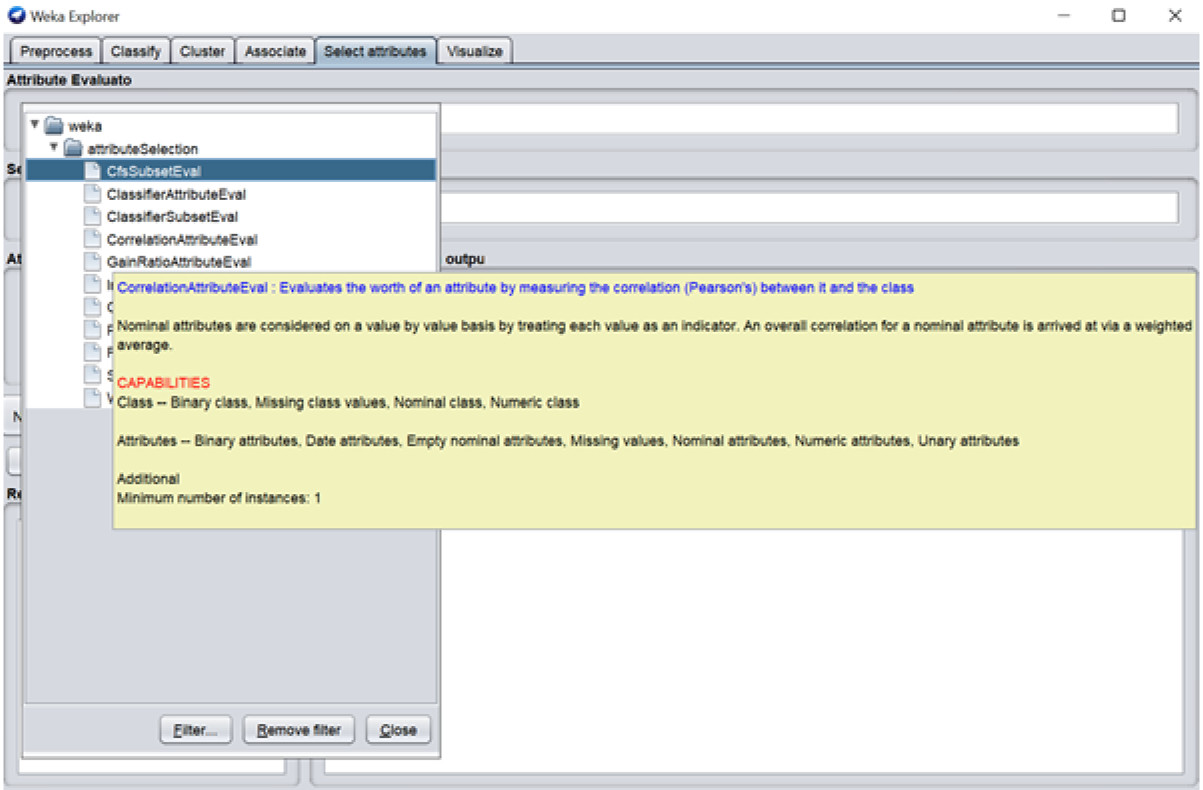
Variable	Class A	B	F	C	D
Temperature (K)	0.9972	1.0019	0.9991	1.0032	1.0006
Luminosity(L/Lo)	1.0001	0.9998	1	0.9999	1
Radius(R/Ro)	1.1079	0.8885	0.9823	0.9477	0.8984
Absolute magnitude(Mv)	78214314.869	0.0687	5.9818	0.8065	0.0297
Star color=Red	0	3786892.6543	0	2297.7035	5.7573
Star color=Blue White	0	107.4268	4.9431022087017892E18	11.7089	1.9696071613771902E11
Star color=White	0	4146155172.5596	1.2787412896255319E11	2.5254171831250975E14	60.4021
Star color=Yellowish White	0	1.7444124222054088E25	1.4769319397642275E13	0.0029	1.2397947059722536E17
Star color=Blue white	0	188768400.1109	4239257.7703	4.0048323222127778E19	4413331398.4746
Star color=Pale yellow orange	0	14216.2942	7.6282	18.6428	2.1313475977261483E18
Star color=Blue	3.3837358189599456E16	28.667	7.1737296180326648E12	0	7066125.1417
Star color=Blue-white	1.9691211371105947E32	0	0	3.0977825480072365E10	0
Star color=Whitish	7.0842938217324938E46	0	0	1.5571024492786872E19	0
Star color=yellow-white	2.6443512922561983E43	0	0	2103376.7282	0
Star color=Orange	1.5049278680187647E14	3.5781744283482168E49	260570.3537	8.3952700048229128E15	7.2623989034817288E30
Star color=White-Yellow	0	25835.0213	4.9577	33.6579	2.0611377933552015E18
Star color=white	0	966439832.7463	1964766591.9054	0.0012	7.9212960343079797E14
Star color=Blue	2.3977726644386898E15	0.0266	1.1252500145968239E10	0	11.1559
Star color=yellowish	1.3454610729638313E18	0.0004	0	0	2.6449257065080806E25
Star color=Yellowish	1.0017005877141715E32	0	1.8058038515579355E11	0	0
Star color=Orange-Red	2.3909030714286743E26	0	0.0032	67.3941	0
Star color=Blue white	0	4052.5748	489145.6356	2.0134444427362823E18	363247.076
Star color=Blue-White	1.1154772243142857E70	0	0	2.9961979571408804E12	0
Spectral Class=M	0	531644.7882	0	1.0058	8061.7006
Spectral Class=B	0	2.5166	648135832.9227	0	9729722.1494
Spectral Class=A	90936060.187	3740583.728	1923.6786	0	712082.5254
Spectral Class=F	0	0.0981	3.2489419606395330E14	16315.3958	2938.9515
Spectral Class=O	2.1865854272401227E42	0	0.0068	1.8509032531859875E10	0
Spectral Class=K	2.8836565582558028E21	7.5848230268159168E11	0	2.6810684613591148E33	0
Spectral Class=G	5.9382186521120338E88	1.0594127670079418E46	7.6428382859898912E16	6.6415479821372128E19	308123.8245

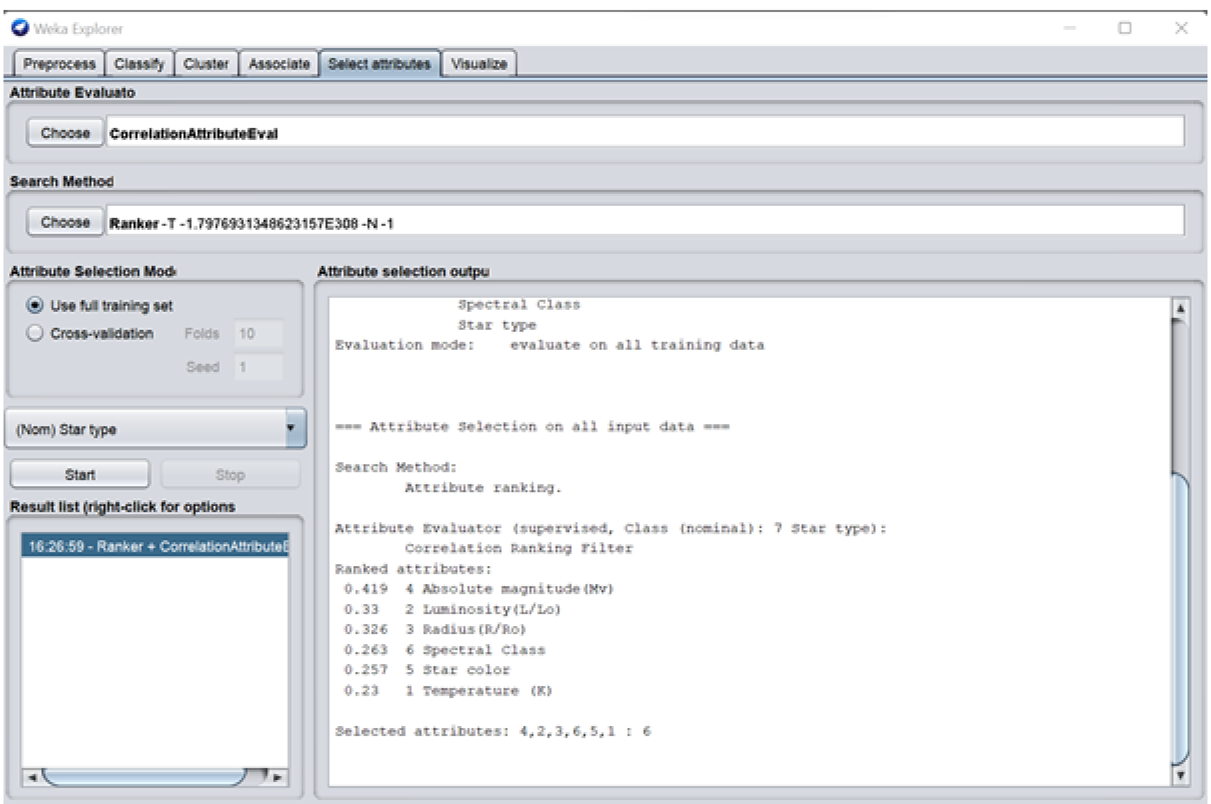
Time taken to build model: 0.17 seconds

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         229               95.4167 %
Incorrectly Classified Instances        11                4.5833 %
Kappa statistic                          0.945
Mean absolute error                      0.016
Root mean squared error                  0.1233
Relative absolute error                  5.7643 %
Root relative squared error             33.076  %
Total Number of Instances              240

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 1.000    0.035    0.851      1.000    0.920      0.906    0.995     0.976     A
                 1.000    0.020    0.909      1.000    0.952      0.944    0.996     0.967     B
                 0.875    0.000    1.000      0.875    0.933      0.924    0.993     0.979     F
                 0.925    0.000    1.000      0.925    0.961      0.955    0.986     0.971     C
                 1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000     D
                 0.925    0.000    1.000      0.925    0.961      0.955    0.978     0.959     E
Weighted Avg.    0.954    0.009    0.960      0.954    0.955      0.947    0.991     0.975

=== Confusion Matrix ===

  a  b  c  d  e  f   <-- classified as
 40  0  0  0  0  0 |  a = A
  0 40  0  0  0  0 |  b = B
  4  1 35  0  0  0 |  c = F
  1  2  0 37  0  0 |  d = C
  0  0  0  0 40  0 |  e = D
  2  1  0  0  0 37 |  f = E
```



Calculate correlation matrix for numerical attributes.





9) Association rule mining

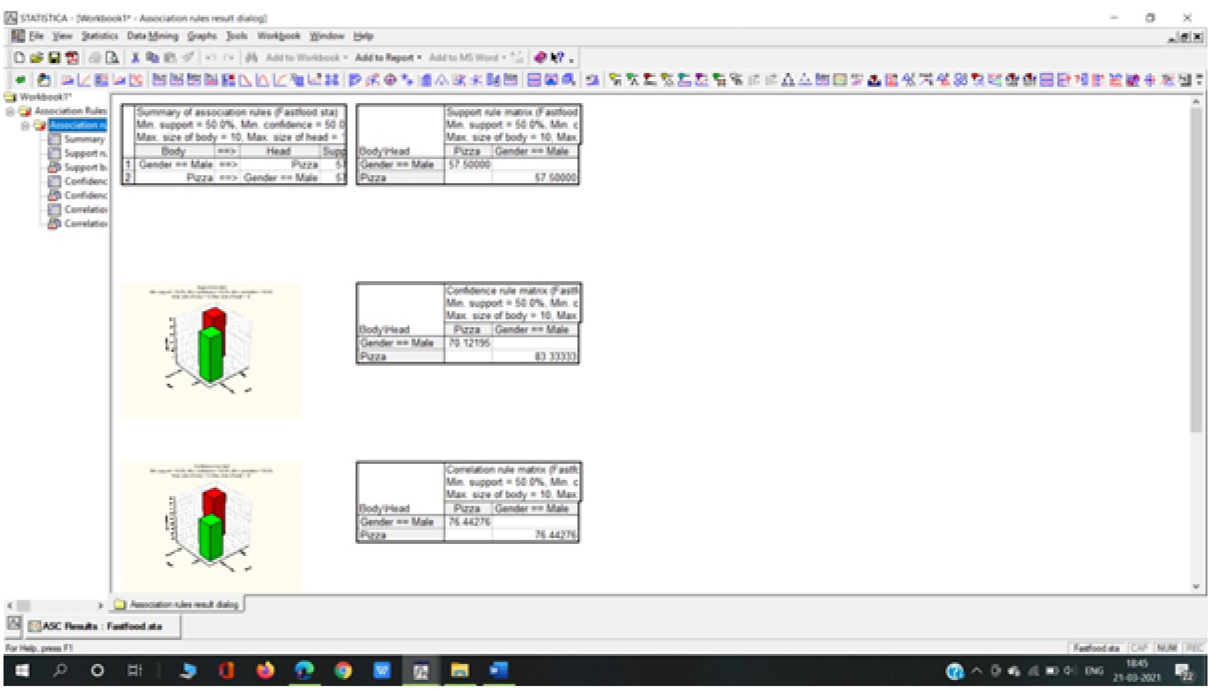
Association rule learning has become a popular approach for uncovering hidden associations between variables in huge data sets. Association rules can be used to express the discovered relationships. Association rules are rules that show the connection or correlation between two or more objects. A correlation matrix is a table that displays the coefficients of correlation between variables. The correlation between two variables is shown in each cell of the table. A correlation matrix can be used to summarise data, as an input to a more sophisticated study, or as a diagnostic tool for advanced analyses.

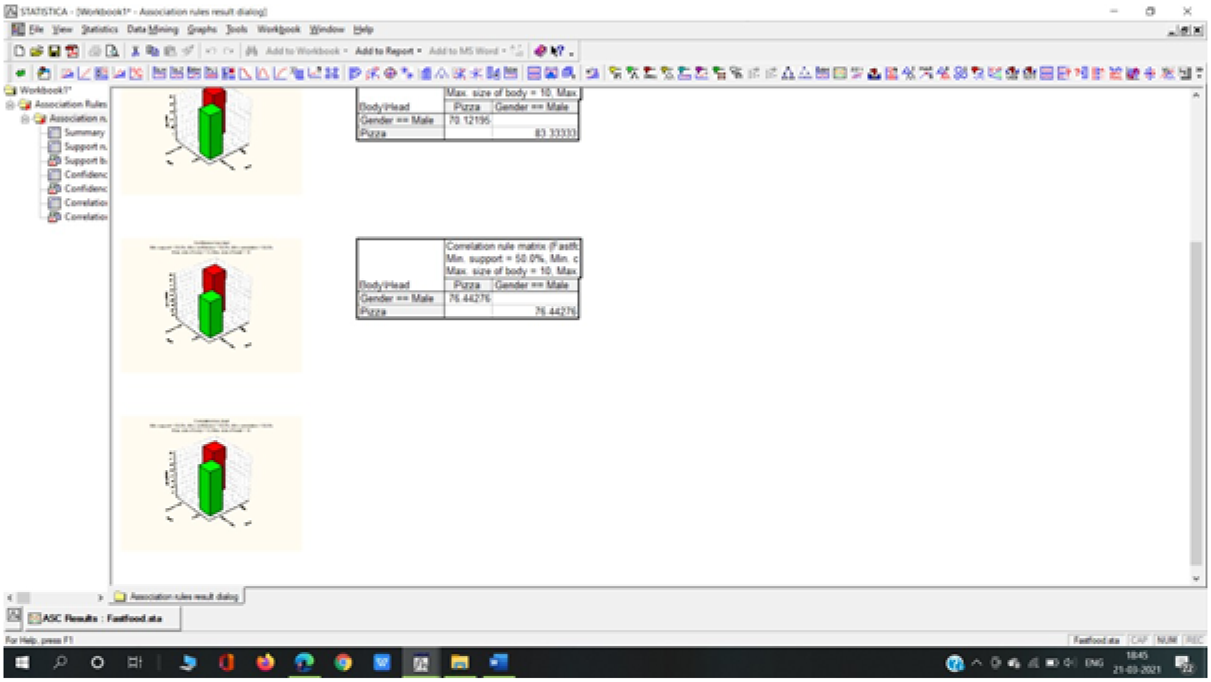
1) Summary of Association Rule
2) Support Rule Matrix
3) Support Bar Chart
4) Correlation Rule Matrix
5) Correlation Bar Chart

Done in three ways

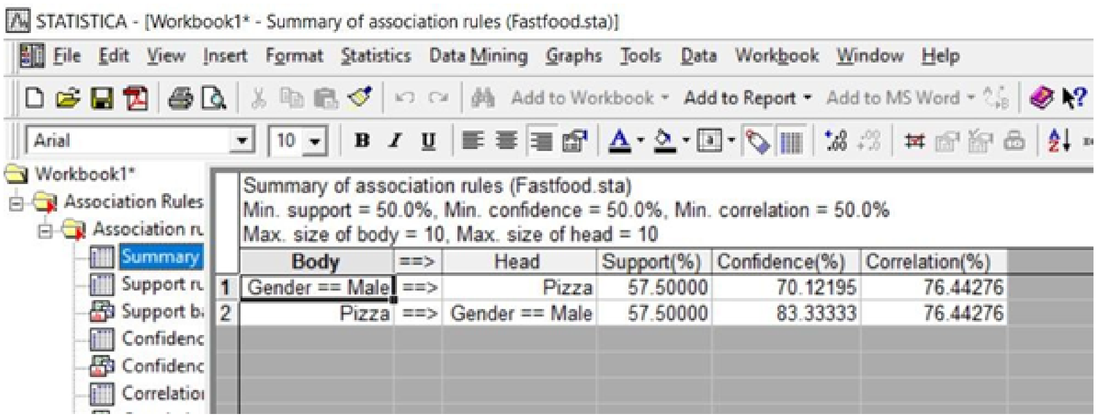
1) On statistical tool
2) On WEKA with WEKA explorer window
3) On WEKA with knowledge window

Implementing on Statistical tool (OUTPUT):





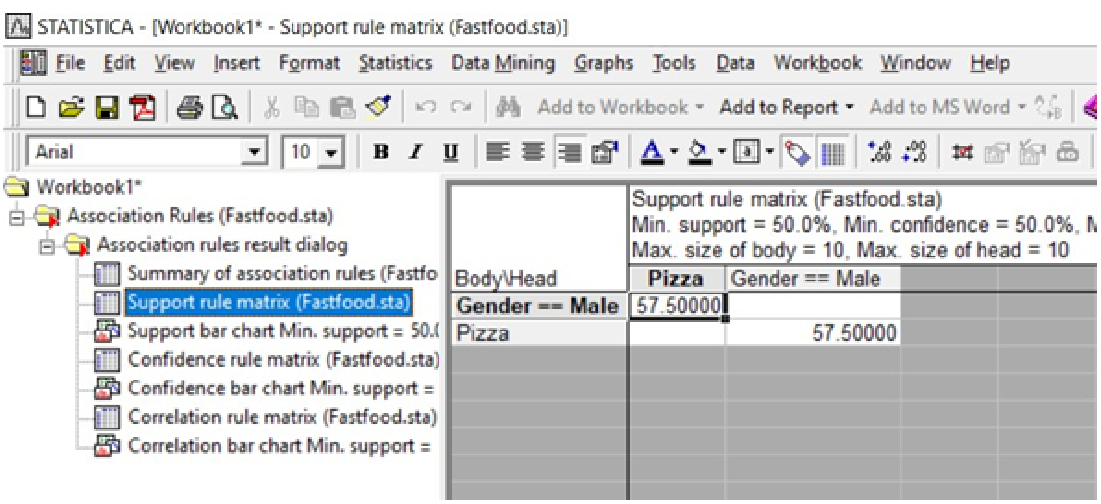
Summary of Association Rules



Summary of association rules (Fastfood.sta)
Min. support = 50.0%, Min. confidence = 50.0%, Min. correlation = 50.0%
Max. size of body = 10, Max. size of head = 10

	Body	==>	Head	Support(%)	Confidence(%)	Correlation(%)
1	Gender == Male	==>	Pizza	57.50000	70.12195	76.44276
2	Pizza	==>	Gender == Male	57.50000	83.33333	76.44276

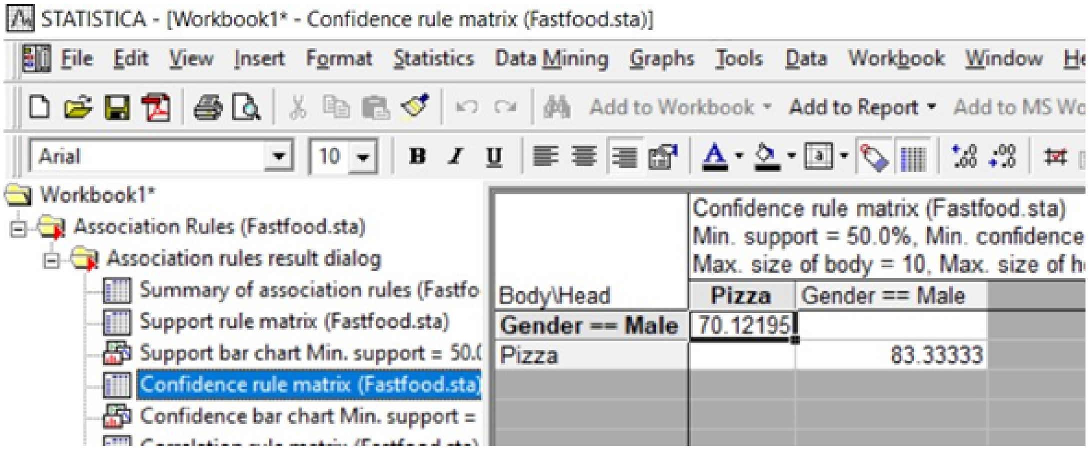
Support Rule Matrix



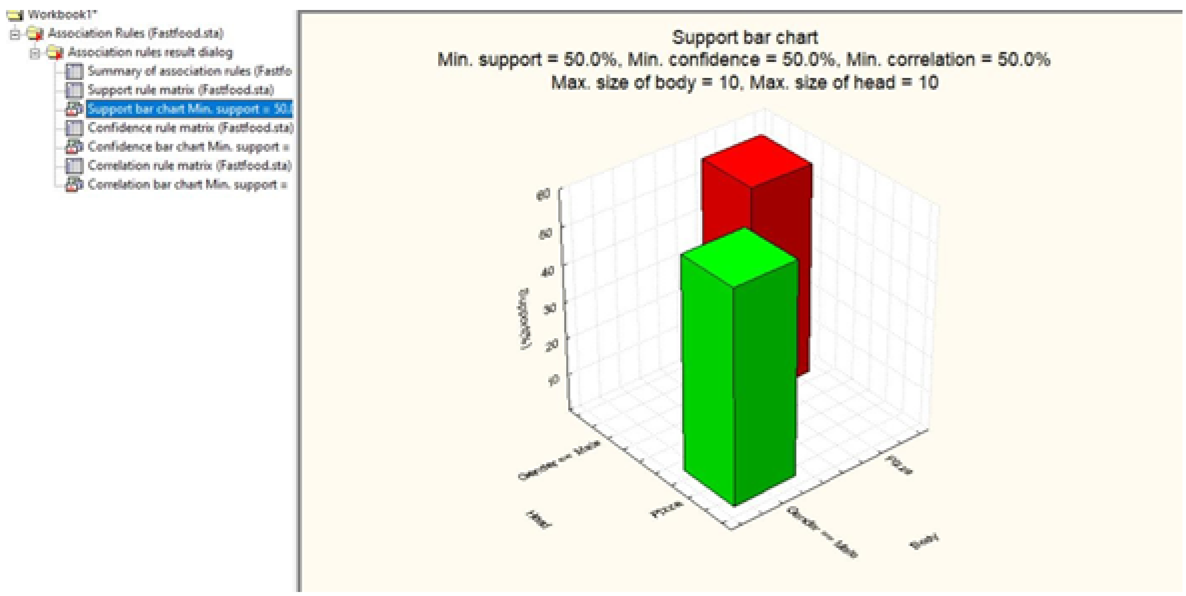
Support rule matrix (Fastfood.sta)
Min. support = 50.0%, Min. confidence = 50.0%, M
Max. size of body = 10, Max. size of head = 10

Body\Head	Pizza	Gender == Male
Gender == Male	57.50000	
Pizza		57.50000

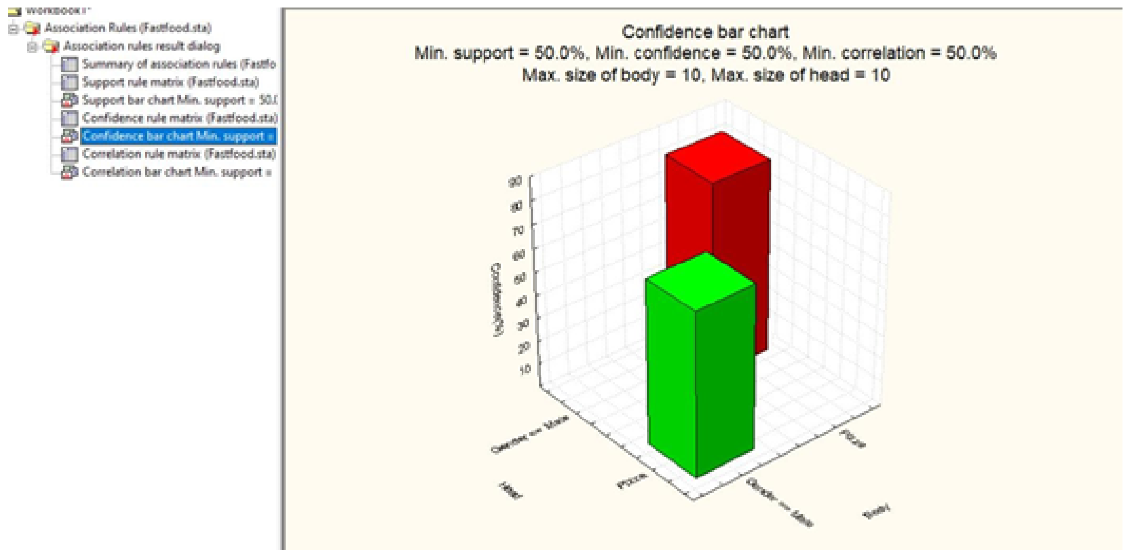
Confidence Rule Matrix



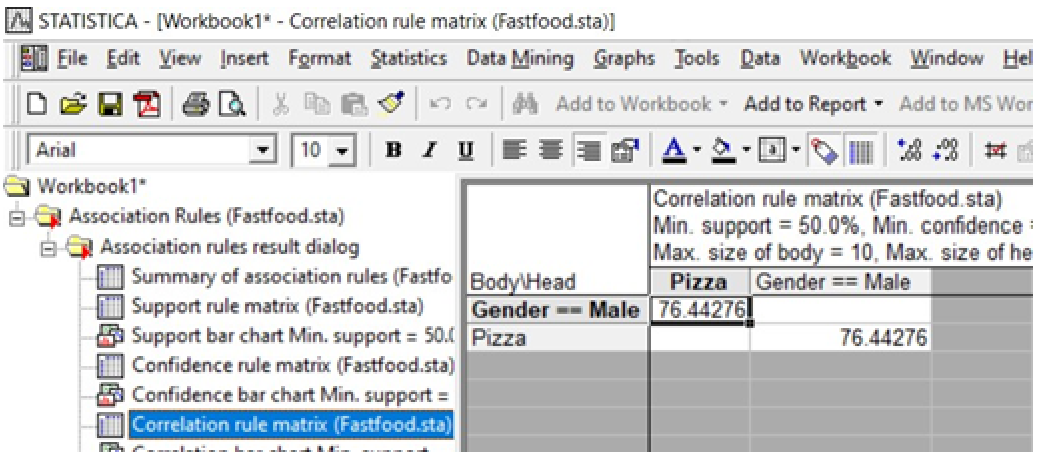
Support Bar Chart



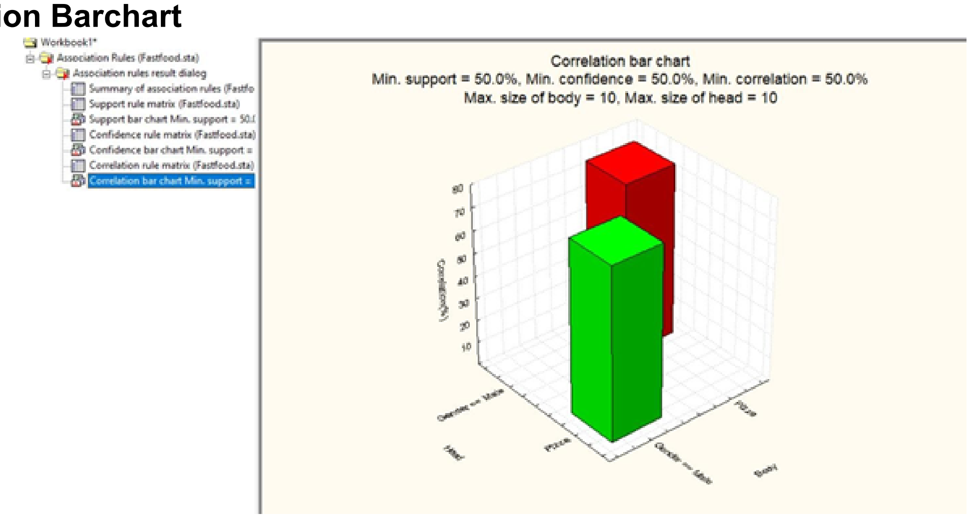
Confidence Bar Chart



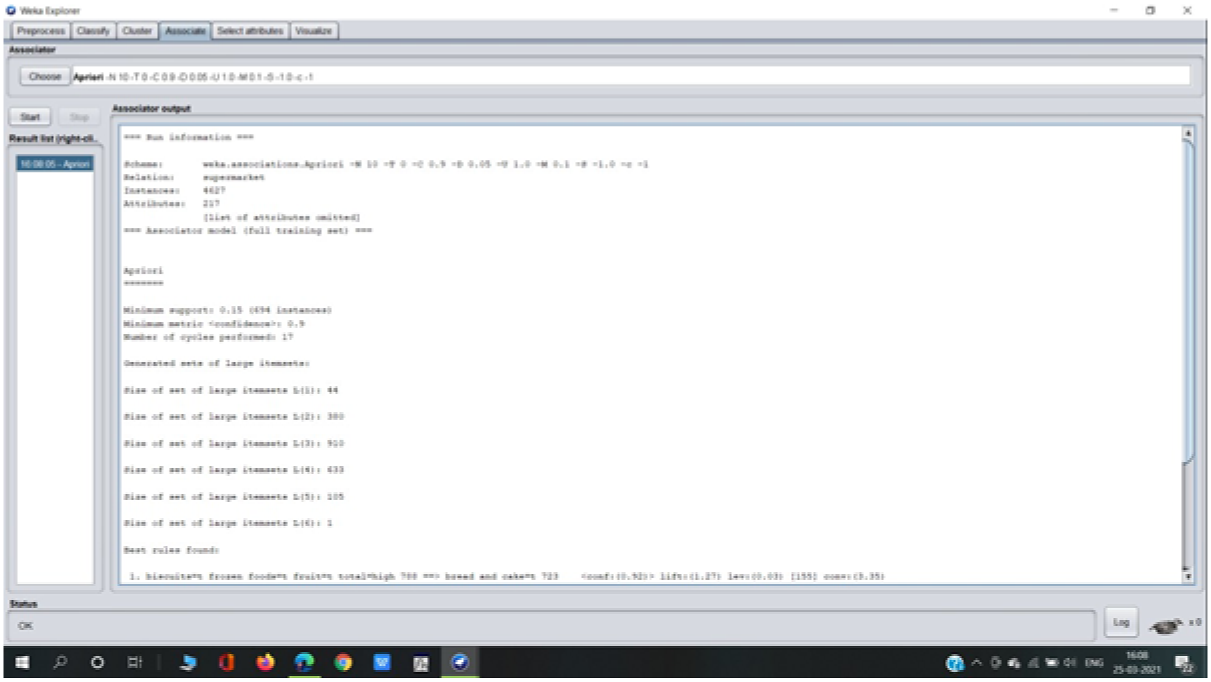
Correlation Matrix

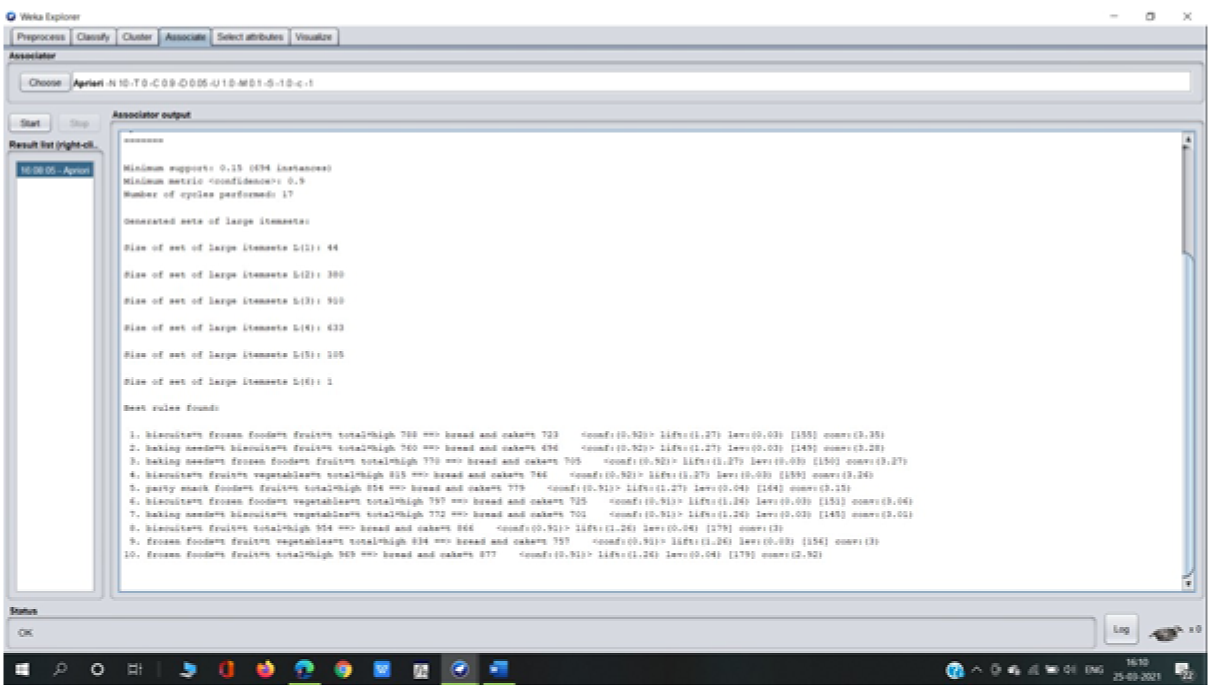


Correlation Barchart

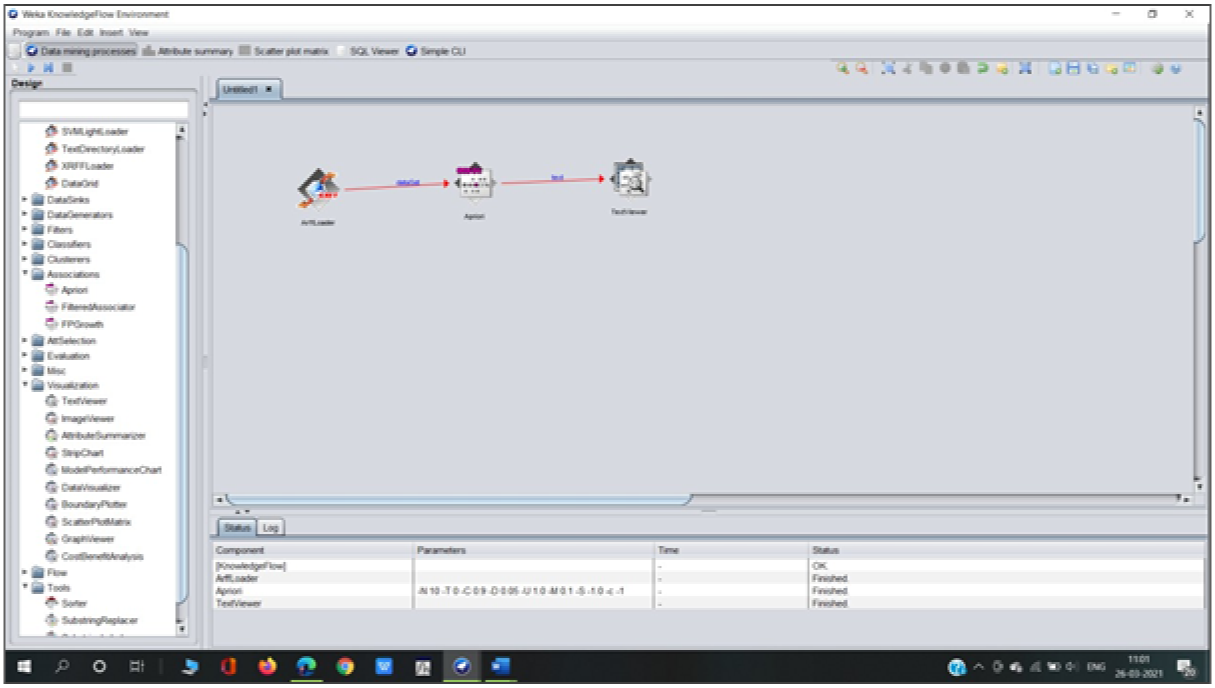


Implementation on WEKA(Output)

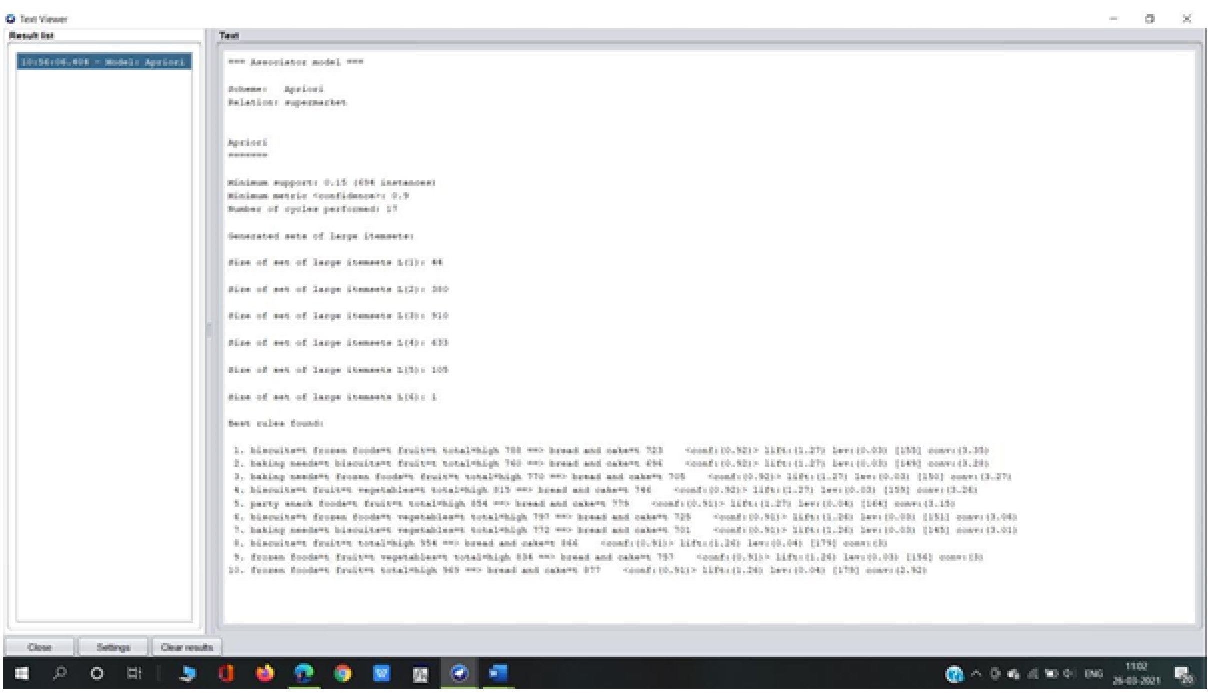




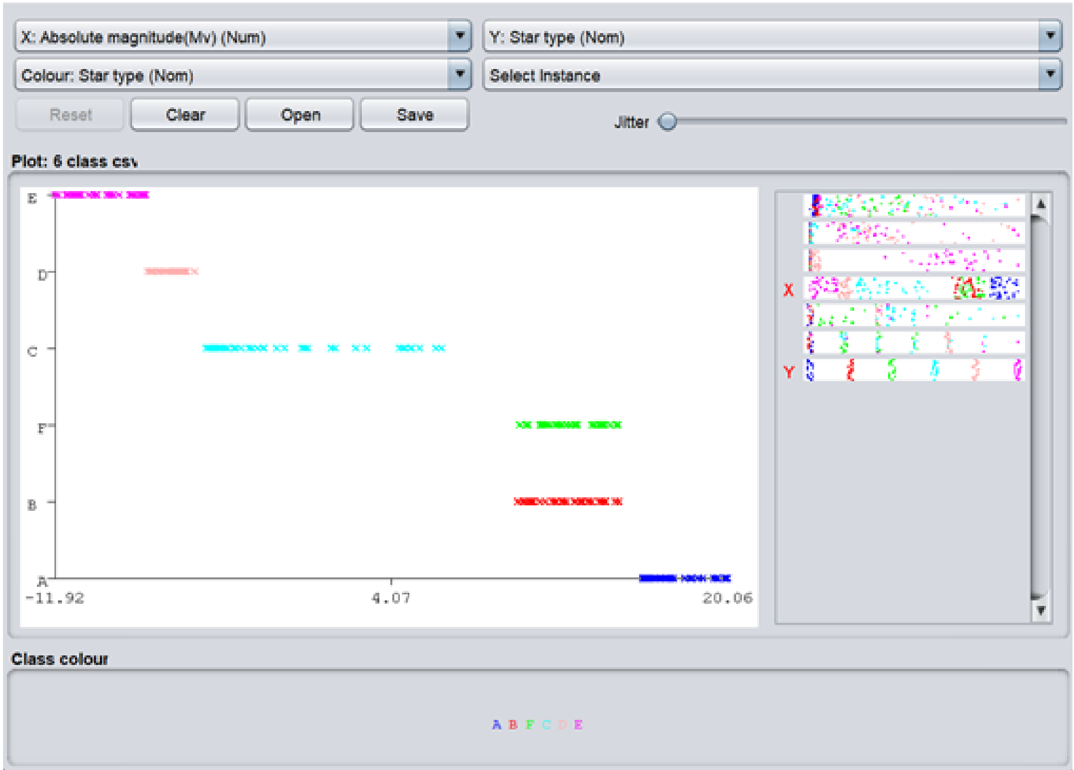
On Knowledge Flow working with apriori after selecting a data set of supermarkets. Using text viewer for result finding full information after using algorithm.

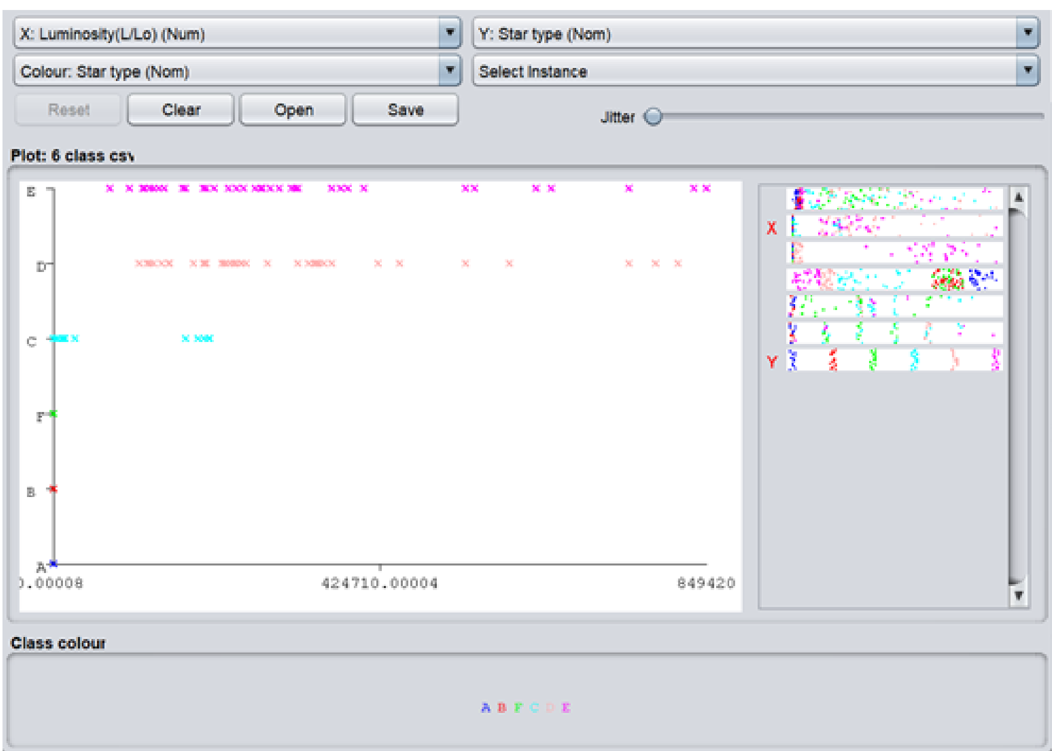


TEXTVIEWER RESULT

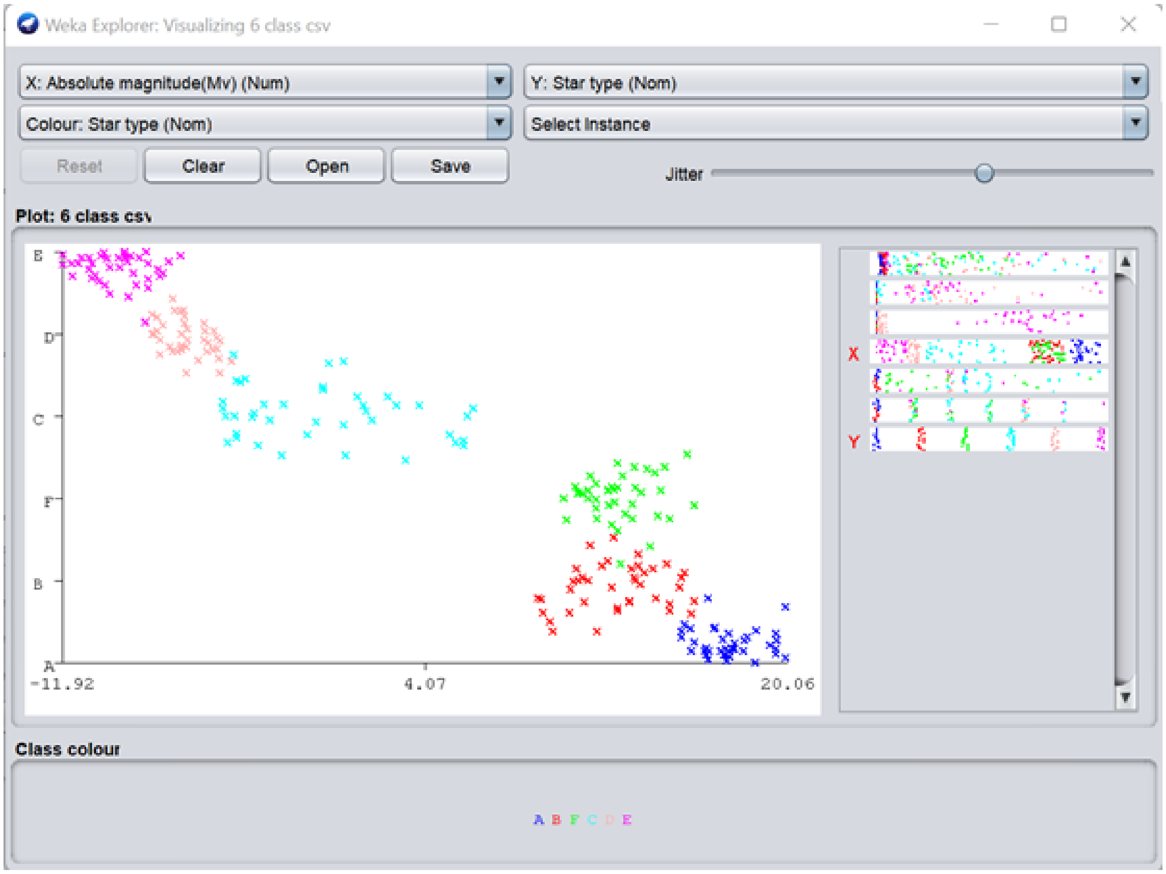


10) Visualization Techniques

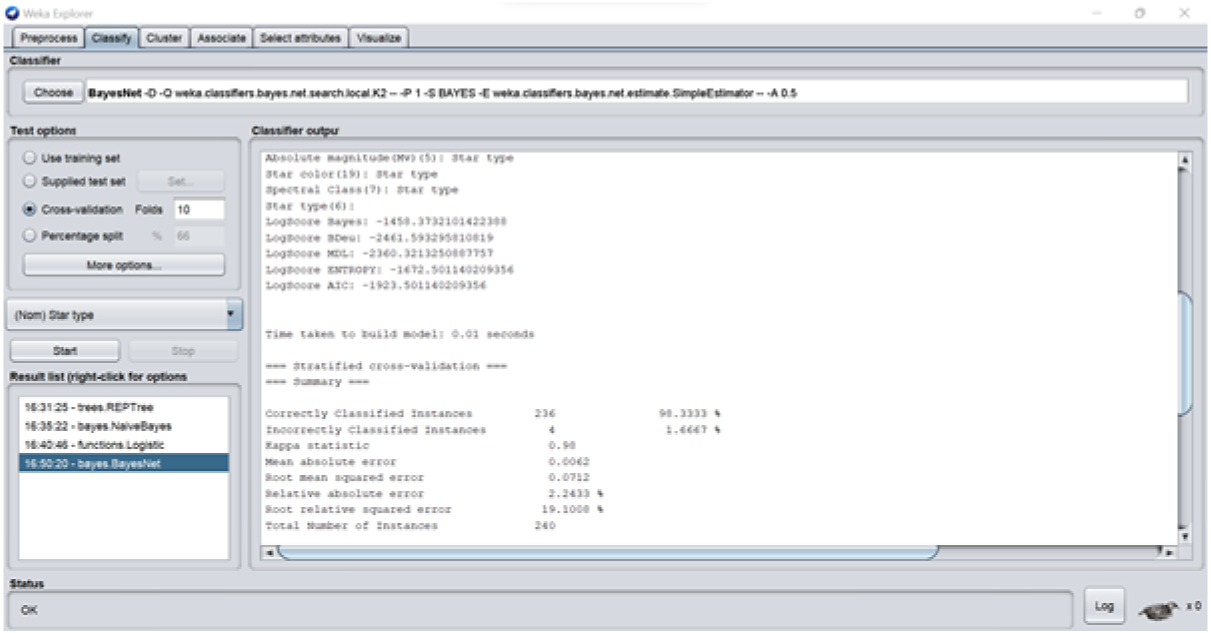


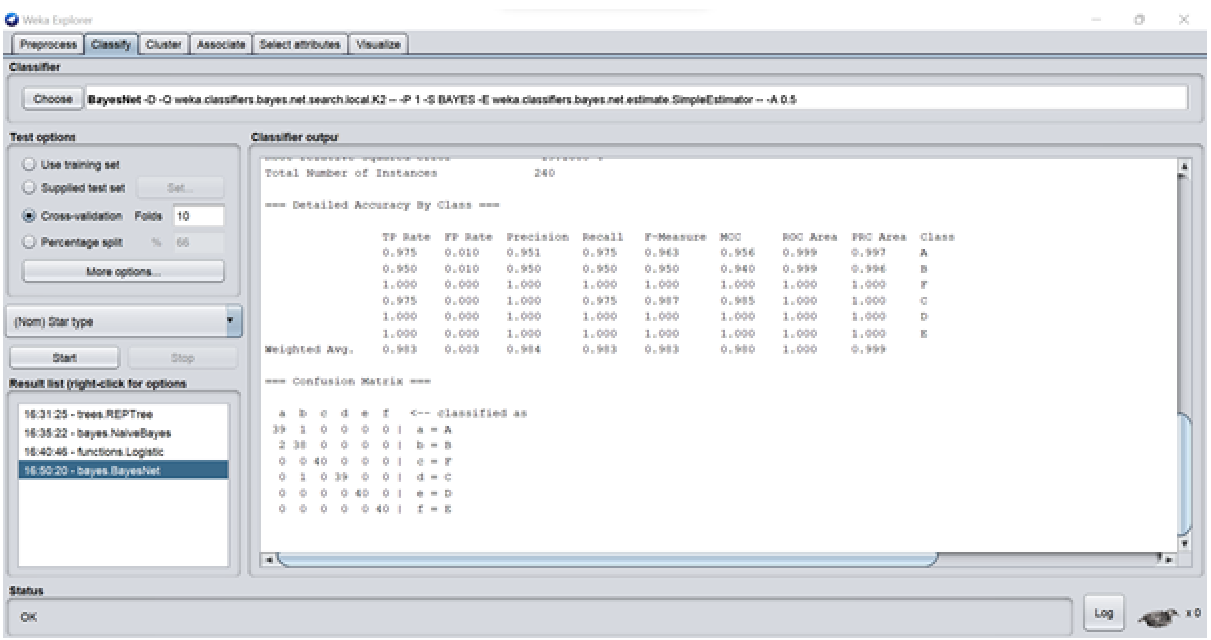


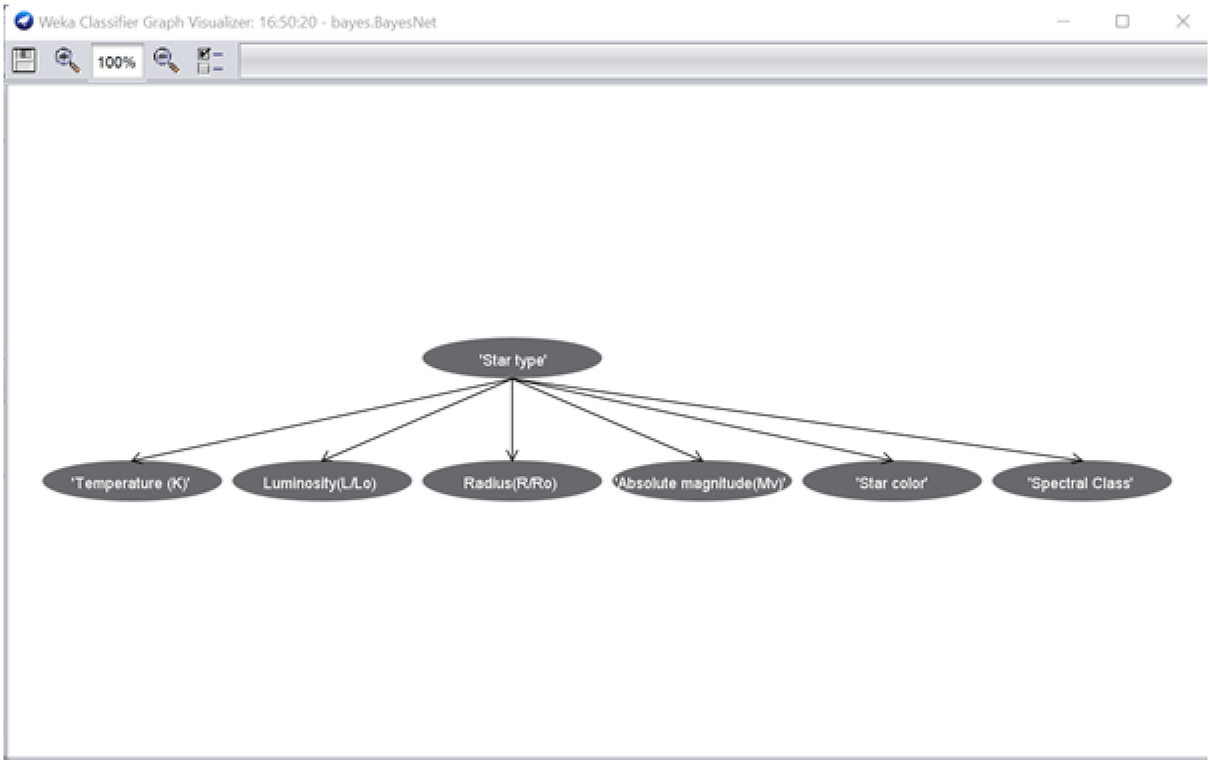
Using Jitter - Jitter is used to introduce random noise to the dataset so as to classify data points (separate them)

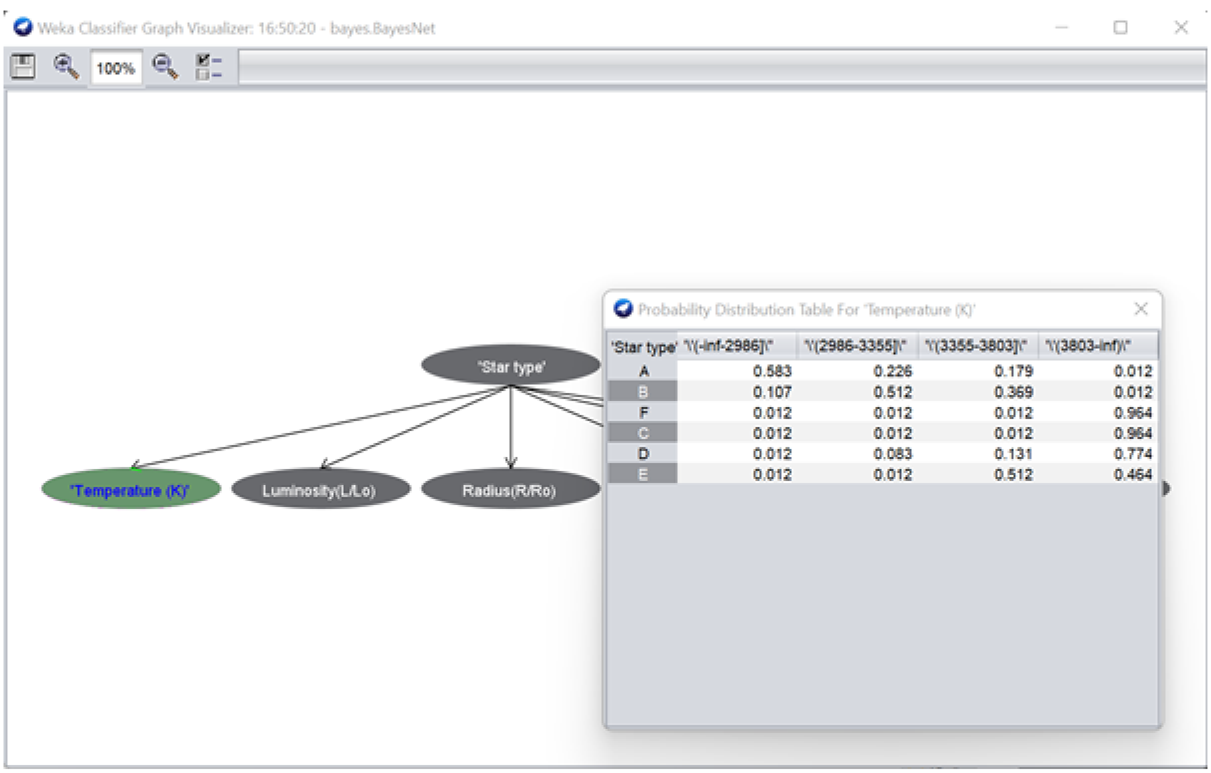


11) Use Bayesian Learning for classification

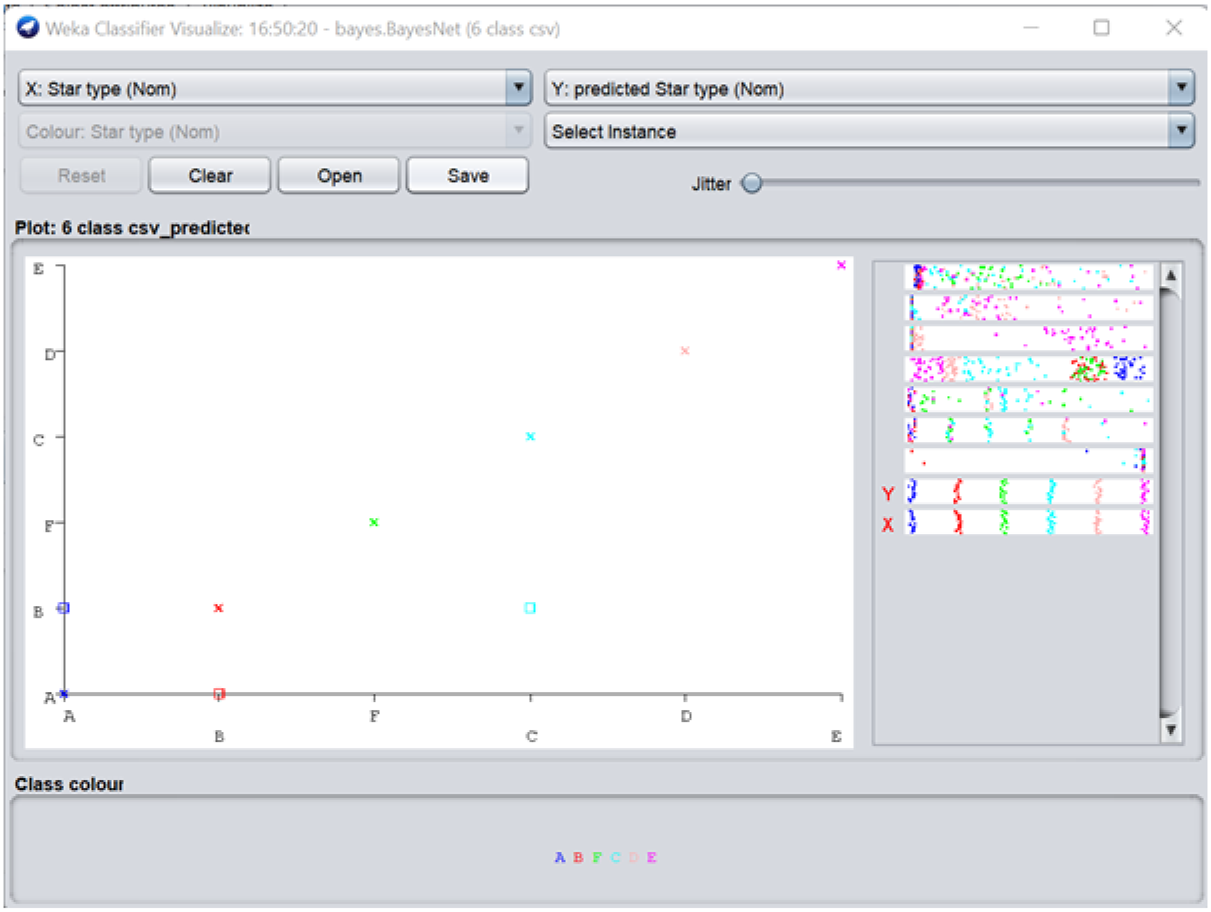





Weka Classifier Graph Visualizer: 16:50:20 - bayes.BayesNet
100%
'Star type'
'Temperature (K)'
Luminosity(L/Lo)
Radius(R/Ro)
'Absolute magnitude(Mv)'
'Star color'
'Spectral Class'


Weka Classifier Graph Visualizer: 16:50:20 - bayes.BayesNet
100%
'Star type'
'Temperature (K)'
Luminosity(L/Lo)
Radius(R/Ro)
Probability Distribution Table For 'Temperature (K)'

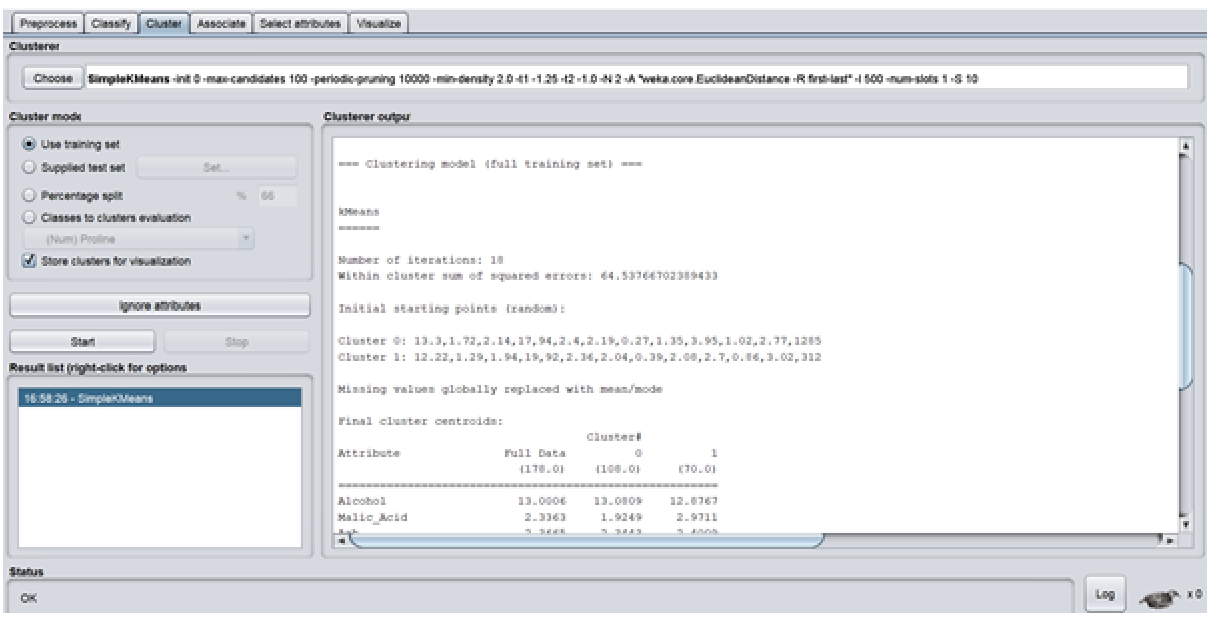
'Star type'	'\'(-inf-2986]\''	'\'(2986-3355]\''	'\'(3355-3803]\''	'\'(3803-inf)\''
A	0.583	0.226	0.179	0.012
B	0.107	0.512	0.369	0.012
F	0.012	0.012	0.012	0.964
C	0.012	0.012	0.012	0.964
D	0.012	0.083	0.131	0.774
E	0.012	0.012	0.512	0.464


Weka Classifier Visualize: 16:50:20 - bayes.BayesNet (6 class csv)
X: Star type (Nom)
Y: predicted Star type (Nom)
Colour: Star type (Nom)
Select Instance
Reset
Clear
Open
Save
Jitter
Plot: 6 class csv_predicted
E
D
C
F
B
A
A
B
F
C
D
E
Y
X
Class colour
A B F C D E

12) Implement clustering algorithm

K-means Clustering is a popular exploratory data analysis tool for gaining an understanding of the data's structure. It is the task of identifying subgroups in data so that data points within the same subgroup (cluster) are extremely similar while data points within different clusters are very dissimilar. To put it another way, we strive to discover homogeneous subgroups within the data so that data points in each cluster are as comparable as feasible based on a similarity measure like euclidean-based distance or correlation-based distance. The choice of the similarity measure to utilise depends on the application.

K Means algorithm is an iterative procedure that attempts to split a dataset into K unique non-overlapping subgroups (clusters), each of which contains only one data point. It attempts to make intra-cluster data points as comparable as possible while maintaining clusters as distinct (far) as possible. It distributes data points to clusters in such a way that the sum of the squared distances between them and the cluster's centroid (arithmetic mean of all the data points in that cluster) is as small as possible. Within clusters, the less variance there is, the more homogenous (similar) the data points are.



```
Final cluster centroids:
                                       Cluster#
Attribute                Full Data            0            1
                           (178.0)      (108.0)       (70.0)
==============================================================
Alcohol                    13.0006      13.0809      12.8767
Malic_Acid                  2.3363       1.9249       2.9711
Ash                         2.3665       2.3443       2.4009
Ash_Alcanity               19.4949      18.5296      20.9843
Magnesium                  99.7416     100.9352         97.9
Total_Phenols               2.2951       2.6738       1.7109
Flavanoids                  2.0293       2.6898       1.0101
Nonflavanoid_Phenols        0.3619       0.3008        0.456
Proanthocyanins             1.5909       1.8576       1.1794
Color_Intensity             5.0581       4.4097       6.0584
Hue                         0.9574       1.0671       0.7882
OD280                       2.6117       3.0891       1.8751
Proline                   746.8933     844.6852     596.0143




Time taken to build model (full training data) : 0.02 seconds

=== Model and evaluation on training set ===

Clustered Instances

0      108 ( 61%)
1       70 ( 39%)
```