काशी हिन्दू विश्वविद्यालय

BANARAS HINDU UNIVERSITY

DEPARTMENT OF COMPUTER SCIENCE

BANARAS HINDU UNIVERSITY,

VARANASI - 221005.

MCA 2 YEAR, 4 SEMESTER

[CS-303P]-DATA MINING PRACTICAL

DATA MINING ASSIGNMENT

GUIDED BY: - **SUBMITTED BY:**

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Professor **EXAM ROLL NO- 18419MCA003**

INDEX

Please execute the following using WEKA or any other open source data mining tools.

Problem 1: Problem based on association rule mining algorithms.

Association Rule Mining:

Association rule is a rule-based machine learning method for discovering interesting relations between variables in large databases. It is intended to identify strong rules discovered in databases using some measures of interestingness. This rule shows how frequently an item set occurs in a transaction. The main applications of association rule mining are Market Basket Analysis, Cross Marketing and Web Usage Mining.

The equation to calculate support and confidence are
Support(A->B) = P(AUB)
Confidence = P(B/A) = support(AUB)/support(A)

Support (AUB)
Support (A)

Data Set Used:

supermarket.arff
(https://storm.cis.fordham.edu/~gweiss/data-mining/weka-data/supermarket.arff)

This is a dataset of point of sale information. The data is nominal and each instance represents a customer transaction at a supermarket, the products purchased and the departments involved. The data contains 4,627 instances and 217 attributes. The data is denormalized. Each attribute is binary and either has a value ("*t*" for true) or no value ("*?*" for missing). There is a nominal class attribute called "total" that indicates whether the transaction was less than $100 (low) or greater than $100 (high).

Tools Used: WEKA 3.8.4

Algorithm Used: Apriori Algorithm

Apriori is an algorithm for frequent item set mining and association rule learning over relational databases. It proceeds by identifying the frequent individual items in the database and extending them to larger and larger item sets as long as those item sets appear sufficiently often in the database. The frequent item sets determined by Apriori can be used to determine association rules which highlight general trends in the database.

Results:

=== 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: supermarket

Instances: 4627

Attributes: 217

[list of attributes omitted]

=== Associator model (full training set) ===

Apriori

=======

Minimum support: 0.15 (694 instances)

Minimum metric <confidence>: 0.9

Number of cycles performed: 17

Generated sets of large itemsets:

Size of set of large itemsets L(1): 44

Size of set of large itemsets L(2): 380

Size of set of large itemsets L(3): 910

Size of set of large itemsets L(4): 633

Size of set of large itemsets L(5): 105

Size of set of large itemsets L(6): 1

Best rules found:

1. biscuits=t frozen foods=t fruit=t total=high 788 ==> bread and cake=t 723 <conf:(0.92)> lift:(1.27) lev:(0.03) [155] conv:(3.35)

2. baking needs=t biscuits=t fruit=t total=high 760 ==> bread and cake=t 696 <conf:(0.92)> lift:(1.27) lev:(0.03) [149] conv:(3.28)

3. baking needs=t frozen foods=t fruit=t total=high 770 ==> bread and cake=t 705 <conf:(0.92)> lift:(1.27) lev:(0.03) [150] conv:(3.27)

4. biscuits=t fruit=t vegetables=t total=high 815 ==> bread and cake=t 746 <conf:(0.92)> lift:(1.27) lev:(0.03) [159] conv:(3.26)

5. party snack foods=t fruit=t total=high 854 ==> bread and cake=t 779 <conf:(0.91)> lift:(1.27) lev:(0.04) [164] conv:(3.15)

6. biscuits=t frozen foods=t vegetables=t total=high 797 ==> bread and cake=t 725 <conf:(0.91)> lift:(1.26) lev:(0.03) [151] conv:(3.06)

7. baking needs=t biscuits=t vegetables=t total=high 772 ==> bread and cake=t 701 <conf:(0.91)> lift:(1.26) lev:(0.03) [145] conv:(3.01)

8. biscuits=t fruit=t total=high 954 ==> bread and cake=t 866 <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(3)

9. frozen foods=t fruit=t vegetables=t total=high 834 ==> bread and cake=t 757 <conf:(0.91)> lift:(1.26) lev:(0.03) [156] conv:(3)

10. frozen foods=t fruit=t total=high 969 ==> bread and cake=t 877 <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(2.92)

Problem 2: Problem based clustering algorithms.

Cluster Analysis :

Cluster analysis or **clustering** is the task of grouping a set of objects in such a way that objects in the same group (called a **cluster**) are more similar (in some sense) to each other than to those in other groups (**clusters**). It is a main task of exploratory data mining, and a common technique for statistical data analysis, used in many fields, including pattern recognition, image analysis, information retrieval, bioinformatics, data compression, computer graphics and machine learning.

Data Set Used:

glass.arff (https://storm.cis.fordham.edu/~gweiss/data-mining/weka-data/glass.arff)

The glass dataset is a more realistic dataset with 214 instances and 10 attributes. Each instance represents a piece of glass, and its *class* is the type of the glass. There are 7 possible types, corresponding to different glass manufacturing processes.

Tools Used: WEKA 3.8.4

Algorithm Used: Hierarchical Clustering

Hierarchical clustering, also known as *hierarchical cluster analysis,* is an algorithm that groups similar objects into groups called *clusters*. The endpoint is a set of clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other.

Results:

=== Run information ===

Scheme: weka.clusterers.HierarchicalClusterer -N 6 -L SINGLE -A "weka.core.EuclideanDistance -R first-last"

Relation: Glass-weka.filters.unsupervised.attribute.Normalize-S1.0-T0.0

Instances: 214

Attributes: 10

RI

Na

Mg

Al

Si

K

Ca

Ba

Fe

Type

Test mode: evaluate on training data

=== Clustering model (full training set) ===

Time taken to build model (full training data) : 0.33 seconds

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

Clustered Instances

0 191 (89%)

1 9 (4%)

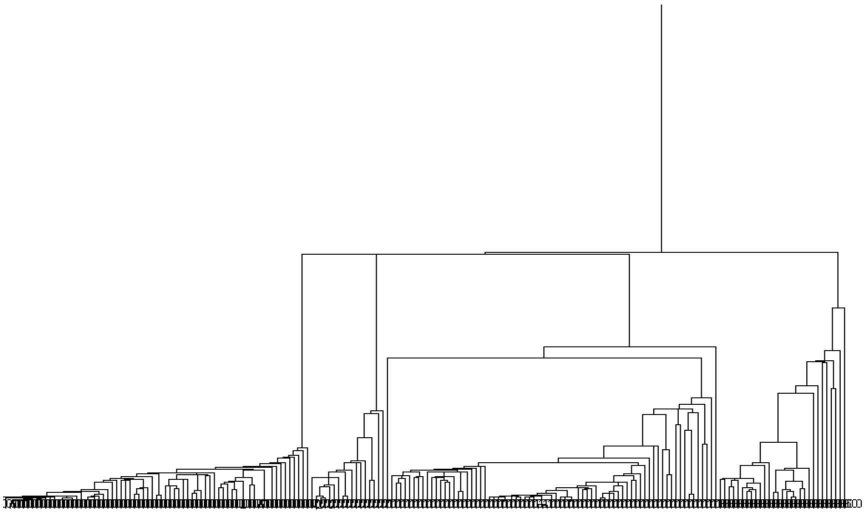
2 10 (5%)

3 1 (0%)

4 1 (0%)

5 2 (1%)

Dendogram:



Problem 3: Problem based on Boolean Association Rules from Transactional Database.

<u>Boolean Association Rules</u>:

In Boolean Association rule, the information is stored in a Boolean database which reveals the connection between two disjoint subsets of the same universe. In single level association rule mining there is only one threshold for support and one for confidence. **Association rules** are if-then statements that help to show the probability of relationships between data items within large data sets in various types of databases. **Association rule** mining has a number of applications and is widely used to help discover sales correlations in transactional data or in medical data sets.

<u>Data Set Used:</u>

TEST_ITEM_TRANS.arff (https://arxiv.org/ftp/arxiv/papers/1406/1406.7371.pdf)

Our Dataset contains 15 transactions that have made for a shopping center. Each transaction has specific list of items. Here we have demonstrated use of Apriori algorithm for association rule mining using WEKA.

Transaction table:

Trans ID	Items
1	A,B,C,D,G,H
2	A,B,C,D,E,F,H
3	B,C,D,E,H
4	B,E,G,H
5	A,B,D,E,G,H
6	A,C,F,G,H
7	B,D,E,G,H
8	A,C,D,E,G,H
9	B,C,D,E,H
10	A,C,E,F,H
11	C,E,H

12	A,D,E,F,H
13	B,C,E,F,H
14	A,B,C,F,H
15	A,B,E,F,H

<u>Tools Used</u>: WEKA 3.8.4

<u>Algorithm Used:</u> Apriori Algorithm

Apriori is a classic algorithm for learning association rules. Apriori is designed to operate on databases containing transactions (for example, collections of items bought by customers, or details of a website frequentation). The Apriori Algorithm is an influential algorithm for mining frequent itemsets for boolean association rules. Some key concepts for Apriori algorithm are:

• Frequent Itemsets: The sets of item which has minimum support (denoted by Li for ith-Itemset).

• Apriori Property: Any subset of frequent itemset must be frequent.

• Join Operation: To find Lk , a set of candidate k itemsets is generated by joining Lk-1 with itself.

Using the Apriori Algorithm we want to find the association rules that have minSupport=50% and minimum confidence=50%

<u>Results:</u>

=== Run information ===

Scheme: weka.associations.Apriori -N 20 -T 0 -C 0.5 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1

Relation: TEST_ITEM_TRANS

Instances: 15

Attributes: 8

A

B

C

D

E

F

G

H

=== Associator model (full training set) ===

Apriori

=======

Minimum support: 0.5 (7 instances)

Minimum metric <confidence>: 0.5

Number of cycles performed: 10

Generated sets of large itemsets:

Size of set of large itemsets L(1): 10

Size of set of large itemsets L(2): 12

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

Best rules found:

1. E=TRUE 11 ==> H=TRUE 11 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
2. B=TRUE 10 ==> H=TRUE 10 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
3. C=TRUE 10 ==> H=TRUE 10 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
4. A=TRUE 9 ==> H=TRUE 9 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
5. G=FALSE 9 ==> H=TRUE 9 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
6. D=TRUE 8 ==> H=TRUE 8 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
7. F=FALSE 8 ==> H=TRUE 8 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
8. D=FALSE 7 ==> H=TRUE 7 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
9. F=TRUE 7 ==> H=TRUE 7 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
10. B=TRUE E=TRUE 7 ==> H=TRUE 7 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
11. C=TRUE G=FALSE 7 ==> H=TRUE 7 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
12. E=TRUE G=FALSE 7 ==> H=TRUE 7 <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
13. G=FALSE 9 ==> C=TRUE 7 <conf:(0.78)> lift:(1.17) lev:(0.07) [1] conv:(1)
14. G=FALSE 9 ==> E=TRUE 7 <conf:(0.78)> lift:(1.06) lev:(0.03) [0] conv:(0.8)
15. G=FALSE H=TRUE 9 ==> C=TRUE 7 <conf:(0.78)> lift:(1.17) lev:(0.07) [1] conv:(1)
16. G=FALSE 9 ==> C=TRUE H=TRUE 7 <conf:(0.78)> lift:(1.17) lev:(0.07) [1] conv:(1)
17. G=FALSE H=TRUE 9 ==> E=TRUE 7 <conf:(0.78)> lift:(1.06) lev:(0.03) [0] conv:(0.8)

18. G=FALSE 9 ==> E=TRUE H=TRUE 7 <conf:(0.78)> lift:(1.06) lev:(0.03) [0] conv:(0.8)

19. H=TRUE 15 ==> E=TRUE 11 <conf:(0.73)> lift:(1) lev:(0) [0] conv:(0.8)

20. B=TRUE 10 ==> E=TRUE 7 <conf:(0.7)> lift:(0.95) lev:(-0.02) [0] conv:(0.67)

Conclusion:

Apriori is the simplest algorithm which is used for mining of frequent patterns from the transaction database. The purpose of reducing the number of scans of database to extract frequent item set will be resolved in future. We have tried to implement the Apriori algorithm and also we have utilized WEKA for referring the process of association rule mining.

Problem 4: Problems based on Mining multilevel association rules from transaction databases

Multilevel Association Rule:

Association rules generated from mining data at multiple levels of abstraction are called multiple-level or multilevel association rules. Quantitative association rules are Multidimensional association rules in which numeric attributes are dynamically discretized. The relational association rule mining looks for patterns that involves multiple tables. Efficient rule mining algorithms are developed to discover knowledge from the databases.

In multilevel association rule mining there are as many support and confidence thresholds as there are levels of abstraction except for level 0 (the root node). When working with multilevel association rules, the support and confidence are called minimum support and minimum confidence and these are defined for each level of the concept hierarchy.

Multi-level association rule mining consists of two steps the first step is finding all frequent k-itemsets for all levels of the concept hierarchy. The second step is to generate multi-level association rules for all levels where each frequent k-itemset in any level can produce up to 2 k - 2 multi-level association rules in k^{th} level. The generation of multi-level association rules is a straight forward step.

Data Set Used:

supermarket.arff
(https://storm.cis.fordham.edu/~gweiss/data-mining/weka-data/supermarket.arff)

This is a dataset of point of sale information. The data is nominal and each instance represents a customer transaction at a supermarket, the products purchased and the departments involved. The data contains 4,627 instances and 217 attributes. The data is denormalized. Each attribute is binary and either has a value ("*t*" for true) or no value ("*?*" for missing). There is a nominal class attribute called "total" that indicates whether the transaction was less than \$100 (low) or greater than \$100 (high).

<u>Tools Used</u>: WEKA 3.8.4

<u>Algorithm Used:</u> Apriori Algorithm

Apriori is an algorithm for frequent item set mining and association rule learning over relational databases. It proceeds by identifying the frequent individual items in the database and extending them to larger and larger item sets as long as those item sets appear sufficiently often in the database. The frequent item sets determined by Apriori can be used to determine association rules which highlight general trends in the database.

<u>Results:</u>

Problem 5: Problems based on Classification by Decision Tree induction

Decision Tree Induction:

Decision Tree is a supervised learning method used in data mining for classification and regression methods. It is a tree that helps us in decision-making purposes. The decision tree creates classification or regression models as a tree structure. It separates a data set into smaller subsets, and at the same time, the decision tree is steadily developed. The final tree is a tree with the decision nodes and leaf nodes. A decision node has at least two branches. The leaf nodes show a classification or decision. We can't accomplish more split on leaf nodes-The uppermost decision node in a tree that relates to the best predictor called the root node. Decision trees can deal with both categorical and numerical data.

Data Set Used:

iris.arff (https://storm.cis.fordham.edu/~gweiss/data-mining/weka-data/iris.arff)

The data set contains 3 classes of 50 instances each, % where each class refers to a type of iris plant. One class is % linearly separable from the other 2; the latter are NOT linearly % separable from each other.

Tools Used: WEKA 3.8.4

Algorithm Used: J48

J48, an open source Java implementation of the C4.5 decision tree algorithm. Quinlan's C4.5 algorithm actualizes J48 to create a trimmed C4.5 decision tree. The every aspect of the information is to split into minor subsets to base on a decision. J48 look at the standardized data gain that really the results the split the information by choosing an attribute. To summarize, the attribute extreme standardized data gained is utilized. The minor subsets are returned by the algorithm. The split strategies stop if a subset has a place with a similar class in all the instances. J48 develops a decision node utilizing the expected estimations of the class. J48 decision tree can deal with particular characteristics, lost or missing attribute estimations of the data and varying attribute costs. Here accuracy can be expanded by pruning.

Results:

=== Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2

Relation: iris

Instances: 150

Attributes: 5

sepallength

sepalwidth

petallength

petalwidth

class

Test mode: split 50.0% train, remainder test

=== Classifier model (full training set) ===

J48 pruned tree

```
petalwidth <= 0.6: Iris-setosa (50.0)
petalwidth > 0.6
|   petalwidth <= 1.7
|   |   petallength <= 4.9: Iris-versicolor (48.0/1.0)
|   |   petallength > 4.9
|   |   |   petalwidth <= 1.5: Iris-virginica (3.0)
|   |   |   petalwidth > 1.5: Iris-versicolor (3.0/1.0)
|   petalwidth > 1.7: Iris-virginica (46.0/1.0)
```

Number of Leaves :   5

Size of the tree :   9

Time taken to build model: 0.09 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.03 seconds

=== Summary ===

Correctly Classified Instances 71 94.6667 %

Incorrectly Classified Instances 4 5.3333 %

Kappa statistic 0.9198

Mean absolute error 0.0519

Root mean squared error 0.192

Relative absolute error 11.6382 %

Root relative squared error 40.5146 %

Total Number of Instances 75

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Iris-setosa
	1.000	0.082	0.867	1.000	0.929	0.892	0.959	0.867	Iris-versicolor
	0.852	0.000	1.000	0.852	0.920	0.887	0.926	0.905	Iris-virginica
Weighted Avg.	0.947	0.028	0.954	0.947	0.946	0.922	0.959	0.920	

=== Confusion Matrix ===

```
  a  b  c   <-- classified as
 22  0  0 |  a = Iris-setosa
  0 26  0 |  b = Iris-versicolor
  0  4 23 |  c = Iris-virginica
```

Problem 6: Problems based Partitioning Algorithm

Partitioning:

Clustering or Partitioning is one of the most common exploratory data analysis technique used to get an intuition about the structure of the data. It can be defined as the task of identifying subgroups in the data such that data points in the same subgroup (cluster) are very similar while data points in different clusters are very different. In other words, we try to find homogeneous subgroups within the data such that data points in each cluster are as similar as possible according to a similarity measure such as euclidean-based distance or correlation-based distance. The decision of which similarity measure to use is application-specific.

Data Set Used:

iris.arff (https://storm.cis.fordham.edu/~gweiss/data-mining/weka-data/iris.arff)

The data set contains 3 classes of 50 instances each, % where each class refers to a type of iris plant. One class is % linearly separable from the other 2; the latter are NOT linearly % separable from each other.

Tools Used: WEKA 3.8.4

Algorithm Used: Simple k-means

Kmeans algorithm is an iterative algorithm that tries to partition the dataset into K pre-defined distinct non-overlapping subgroups (clusters) where each data point belongs to **only one group**. It tries to make the intra-cluster data points as similar as possible while also keeping the clusters as different (far) as possible. It assigns data points to a cluster such that the sum of the squared distance between the data points and the cluster's centroid (arithmetic mean of all the data points that belong to that cluster) is at the minimum. The less variation we have within clusters, the more homogeneous (similar) the data points are within the same cluster.

The way kmeans algorithm works is as follows:

1. Specify number of clusters K.

2. Initialize centroids by first shuffling the dataset and then randomly selecting K data points for the centroids without replacement.
3. Keep iterating until there is no change to the centroids. i.e assignment of data points to clusters isn't changing.

Results:

=== 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 3 -A "weka.core.EuclideanDistance -R first-last" -I 500 -num-slots 1 -S 10

Relation: iris

Instances: 150

Attributes: 5

sepallength

sepalwidth

petallength

petalwidth

Ignored:

class

Test mode: Classes to clusters evaluation on training data

=== Clustering model (full training set) ===

kMeans

======

Number of iterations: 6

Within cluster sum of squared errors: 6.998114004826762

Initial starting points (random):

Cluster 0: 6.1,2.9,4.7,1.4

Cluster 1: 6.2,2.9,4.3,1.3

Cluster 2: 6.9,3.1,5.1,2.3

Missing values globally replaced with mean/mode

Final cluster centroids:

		Cluster#		
Attribute	Full Data	0	1	2
	(150.0)	(61.0)	(50.0)	(39.0)
sepallength	5.8433	5.8885	5.006	6.8462
sepalwidth	3.054	2.7377	3.418	3.0821
petallength	3.7587	4.3967	1.464	5.7026
petalwidth	1.1987	1.418	0.244	2.0795

Time taken to build model (full training data) : 0.04 seconds

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

Clustered Instances

0 61 (41%)

1 50 (33%)

2 39 (26%)

Class attribute: class

Classes to Clusters:

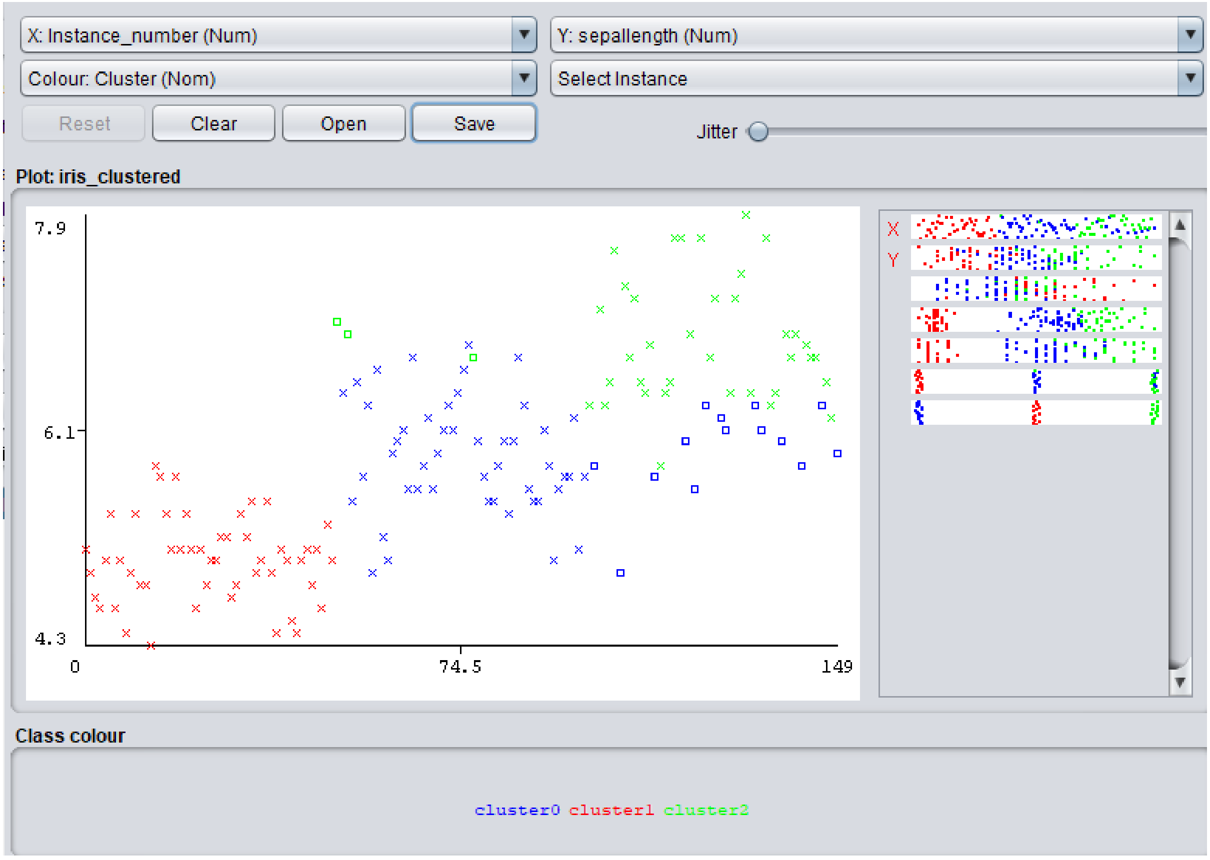
```
  0  1  2  <-- assigned to cluster
  0 50  0 | Iris-setosa
 47  0  3 | Iris-versicolor
 14  0 36 | Iris-virginica
```

Cluster 0 <-- Iris-versicolor

Cluster 1 <-- Iris-setosa

Cluster 2 <-- Iris-virginica

Incorrectly clustered instances : 17.0 11.3333 %



Problem 7: Problems based Time-series and sequence data

<u>Time Series Analysis:</u>

A **time series** is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data. Examples of time series are heights of ocean tides, counts of sunspots, and the daily closing value of the Dow Jones Industrial Average.

Time series are very frequently plotted via line charts. Time series are used in statistics, signal processing, pattern recognition, econometrics, mathematical finance, weather forecasting, earthquake prediction, electroencephalography, control engineering, astronomy, communications engineering, and largely in any domain of applied science and engineering which involves temporal measurements.

Time series *analysis* comprises methods for analysing time series data in order to extract meaningful statistics and other characteristics of the data. **Time series *forecasting*** is the use of a model to predict future values based on previously observed values.

Time series analysis can be applied to real-valued, continuous data, discrete numeric data, or discrete symbolic data.

Methods of time series analysis may also be divided into linear and non-linear, and univariate and multivariate.

Sequential Data Mining:

Sequential pattern mining is a topic of data mining concerned with finding statistically relevant patterns between data examples where the values are delivered in a sequence.[1] It is usually presumed that the values are discrete, and thus time series mining is closely related, but usually considered a different activity. Sequential pattern mining is a special case of structured data mining.

There are several key traditional computational problems addressed within this field. These include building efficient databases and indexes for sequence information, extracting the frequently occurring patterns, comparing sequences for similarity, and recovering missing sequence members. In general, sequence mining problems can be classified as *string mining* which is typically based on string processing algorithms and *itemset mining* which is typically based on association rule learning. *Local process models* [2] extend sequential pattern mining to more complex patterns that can include (exclusive) choices, loops, and concurrency constructs in addition to the sequential ordering construct.

Commonly used algorithms include:

- GSP algorithm
- Sequential Pattern Discovery using Equivalence classes (SPADE)
- FreeSpan
- PrefixSpan
- MAPres[6]

Data Set Used:

test.csv (https://www.kaggle.com/andonians/random-linear-regression)

Tools Used: WEKA 3.8.4

Algorithm Used: Linear Regression for Time Series Analysis

- It is simplest form of regression. Linear regression attempts to model the relationship between two variables by fitting a linear equation to observe the data.
- Linear regression attempts to find the mathematical relationship between variables.
- If outcome is straight line then it is considered as linear model and if it is curved line, then it is a non linear model.
- The relationship between dependent variable is given by straight line and it has only one independent variable.

  $$\mathbf{Y = \alpha + B\,X}$$
- Model **'Y'**, is a linear function of **'X'**.
- The value of 'Y' increases or decreases in linear manner according to which the value of 'X' also changes.

GSP Algorithm for Sequence Mining

GSP algorithm (*Generalized Sequential Pattern* algorithm) is an algorithm used for sequence mining. The algorithms for solving sequence mining problems are mostly based on the *apriori* (level-wise) algorithm. One way to use the level-wise paradigm is to first discover all the frequent items in a level-wise fashion. It simply means counting the occurrences of all singleton elements in the database. Then, the transactions are filtered by removing the non-frequent items. At the end of this step, each transaction consists of only the frequent elements it originally contained. This modified database becomes an input to the GSP algorithm. This process requires one pass over the whole database.

Results:

Linear Regression

=== Run information ===

Scheme: weka.classifiers.functions.LinearRegression -S 0 -R 1.0E-8 -num-decimal-places 4

Relation: test

Instances: 300

Attributes: 2

x

y

Test mode: split 66.0% train, remainder test

=== Classifier model (full training set) ===

Linear Regression Model

x =

0.9751 * y +

1.0045

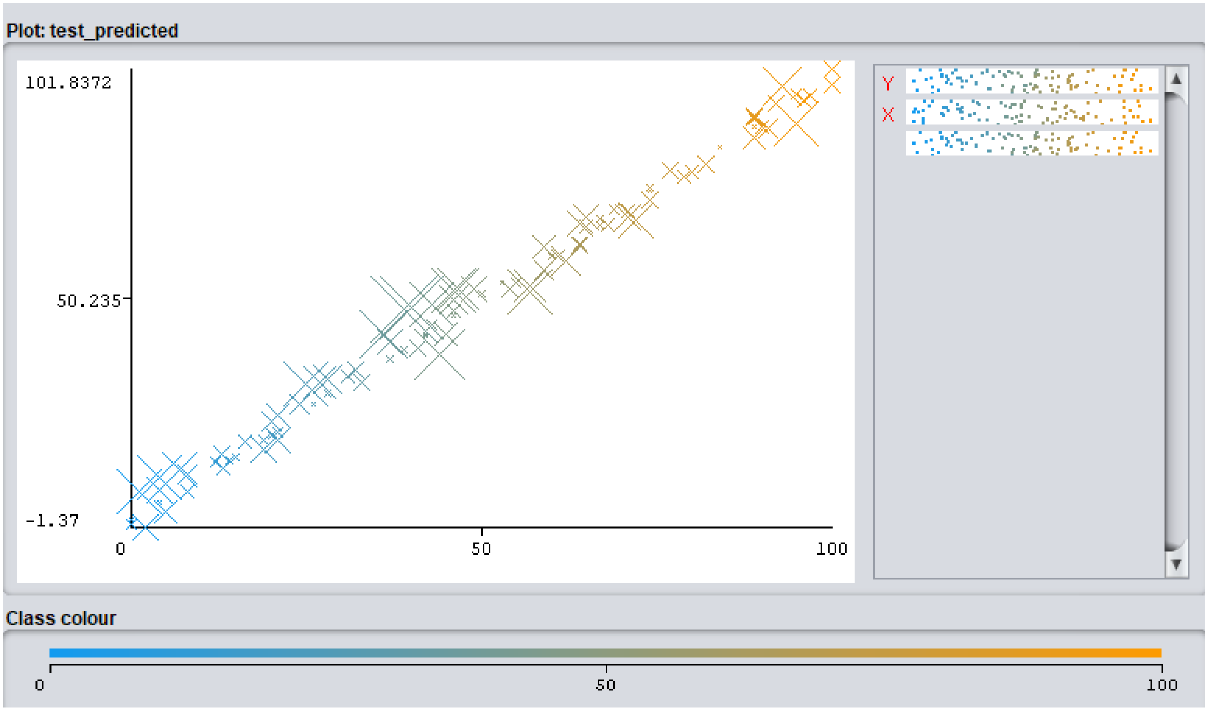
Time taken to build model: 0.01 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.01 seconds

=== Summary ===

Correlation coefficient	0.9949
Mean absolute error	2.3442
Root mean squared error	2.9651
Relative absolute error	9.3844 %
Root relative squared error	10.1762 %
Total Number of Instances	102



GSP Algorithm

Problem 8: Problems based Text databases

Classification on Text Databases:

Text databases consist of huge collection of documents. They collect these information from several sources such as news articles, books, digital libraries, e-mail messages, web pages, etc. Due to increase in the amount of information, the text databases are growing rapidly. In many of the text databases, the data is semi-structured.

For example, a document may contain a few structured fields, such as title, author, publishing_date, etc. But along with the structure data, the document also contains unstructured text components, such as abstract and contents. Without knowing what could be in the documents, it is difficult to formulate effective queries for analyzing and extracting useful information from the data. Users require tools to compare the documents and rank their importance and relevance. Therefore, text mining has become popular and an essential theme in data mining.

Data Set Used: train.arff (https://www.youtube.com/watch?v=jSZ9jQy1sfE)

Relation name is train which initially contains 2 attributes (Document and Class) and 5 instances. Class attribute has two values Yes and No. After converting string to word vector the data contains 5 instances and 31 attributes. All word vector are of numeric type and class attribute is of nominal type. Now the data is ready to be classified by any of the algorithm.

Tools Used: WEKA 3.8.4

Algorithm Used: Naïve Bayes Classifier

Naive Bayes classifiers are a collection of classification algorithms based on **Bayes' Theorem**. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other. They are among the simplest Bayesian network models.

It was introduced into the text retrieval community in the early 1960s,[4] and remains a popular (baseline) method for text categorization, the problem of judging documents as belonging to one category or the other (document categorization)(such as spam or legitimate, sports or politics, etc.) with word frequencies as the features.

Naive Bayes is a learning algorithm commonly applied to text classification.

Some of the applications of the Naive Bayes classifier are:

- **(Automatic) Classification of emails in folders**, so incoming email messages go into folders such as**: "**Family", "Friends", "Updates", "Promotions", etc.
- **(Automatic) Tagging of job listings.** Given a job listing in raw text format, we can assign it tags such as: "software development", "design", "marketing", etc.
- **(Automatic) Categorization of products.** Given a product description, we can assign it into categories such as: "Books", "Electronics", "Clothing", etc.

Results:

=== Run information ===

Scheme: weka.classifiers.bayes.NaiveBayes

Relation: train-weka.filters.unsupervised.attribute.StringToWordVector-R1-W1000-prune-rate-1.0-N0-stemmerweka.core.stemmers.NullStemmer-stopwords-handlerweka.core.stopwords.Null-M1-tokenizerweka.core.tokenizers.WordTokenizer -delimiters " \r\n\t.,;:\'\"()?!"-weka.filters.unsupervised.attribute.Reorder-R2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,1

Instances: 5

Attributes: 31

Crude

Demand

The

crude

for

has

in

increased

is

of

oil

outstrips

price

short

significantly

supply

Some

Use

a

bit

cooking

do

flavor

frying

like

not

olive

pan

people

the

class

Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Naive Bayes Classifier

Class

Attribute yes no

(0.57) (0.43)

================================

Crude

```
  mean          0.3333      0
  std. dev.     0.4714 0.1667
  weight sum         3      2
  precision          1      1
```

Demand

```
  mean          0.3333      0
  std. dev.     0.4714 0.1667
  weight sum         3      2
  precision          1      1
```

The

```
  mean          0.3333      0
  std. dev.     0.4714 0.1667
  weight sum         3      2
  precision          1      1
```

crude

```
  mean          0.6667      0
  std. dev.     0.4714 0.1667
  weight sum         3      2
  precision          1      1
```

for

```
  mean          0.3333      0
  std. dev.     0.4714 0.1667
  weight sum         3      2
```

```
  precision          1      1

has
  mean           0.3333      0
  std. dev.      0.4714 0.1667
  weight sum          3      2
  precision           1      1

in
  mean           0.3333    0.5
  std. dev.      0.4714    0.5
  weight sum          3      2
  precision           1      1

increased
  mean           0.3333      0
  std. dev.      0.4714 0.1667
  weight sum          3      2
  precision           1      1

is
  mean           0.3333      0
  std. dev.      0.4714 0.1667
  weight sum          3      2
  precision           1      1

of
  mean           0.3333      1
  std. dev.      0.4714 0.1667
```

```
  weight sum        3      2
  precision         1      1

oil
  mean              1      1
  std. dev.    0.0017 0.0017
  weight sum        3      2
  precision      0.01   0.01

outstrips
  mean         0.3333      0
  std. dev.    0.4714 0.1667
  weight sum        3      2
  precision         1      1

price
  mean         0.3333      0
  std. dev.    0.4714 0.1667
  weight sum        3      2
  precision         1      1

short
  mean         0.3333      0
  std. dev.    0.4714 0.1667
  weight sum        3      2
  precision         1      1

significantly
  mean         0.3333      0
```

std. dev. 0.4714 0.1667

weight sum 3 2

precision 1 1

supply

mean 0.6667 0

std. dev. 0.4714 0.1667

weight sum 3 2

precision 1 1

Some

mean 0 0.5

std. dev. 0.1667 0.5

weight sum 3 2

precision 1 1

Use

mean 0 0.5

std. dev. 0.1667 0.5

weight sum 3 2

precision 1 1

a

mean 0 0.5

std. dev. 0.1667 0.5

weight sum 3 2

precision 1 1

bit

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

cooking

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

do

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

flavor

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

frying

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

like

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

not

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

olive

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

pan

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

people

mean	0	0.5
std. dev.	0.1667	0.5
weight sum	3	2
precision	1	1

the

mean	0	1
std. dev.	0.1667	0.1667
weight sum	3	2
precision	1	1

Time taken to build model: 0.01 seconds

Problem 9: Dimension reduction techniques to handle multi-dimensional data

Dimension Reduction Technique:

Dimensionality reduction or **dimension reduction** is the process of reducing the number of random variables under consideration by obtaining a set of principal variables.

There are two components of dimensionality reduction:

- **Feature selection:** In this, we try to find a subset of the original set of variables, or features, to get a smaller subset which can be used to model the problem. It usually involves three ways:
  1. Filter
  2. Wrapper
  3. Embedded
- **Feature extraction:** This reduces the data in a high dimensional space to a lower dimension space, i.e. a space with lesser no. of dimensions.

The various methods used for dimensionality reduction include:

- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)
- Generalized Discriminant Analysis (GDA)

Applications of Dimension Reduction:

- It reduces the time and storage space required.
- Removal of multi-collinearity improves the interpretation of the parameters of the machine learning model.
- It becomes easier to visualize the data when reduced to very low dimensions such as 2D or 3D.

- It avoids the curse of dimensionality.

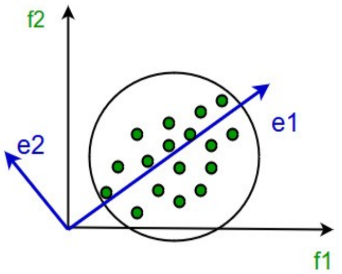
Applications: A dimensionality reduction technique that is sometimes used in neuroscience is maximally informative dimensions which finds a lower-dimensional representation of a dataset such that as much information as possible about the original data is preserved.

Data Set Used: cpu.arff (https://storm.cis.fordham.edu/~gweiss/data-mining/weka-data/cpu.arff)

Tools Used: WEKA 3.8.4

Algorithm Used: PCA (Principal Component Analysis)

This method was introduced by Karl Pearson. It works on a condition that while the data in a higher dimensional space is mapped to data in a lower dimension space, the variance of the data in the lower dimensional space should be maximum.



It involves the following steps:

- Construct the covariance matrix of the data.
- Compute the eigenvectors of this matrix.
- Eigenvectors corresponding to the largest eigenvalues are used to reconstruct a large fraction of variance of the original data.

Hence, we are left with a lesser number of eigenvectors, and there might have been some data loss in the process. But, the most important variances should be retained by the remaining eigenvectors.

Results:

=== Run information ===

Evaluator: weka.attributeSelection.PrincipalComponents -R 0.95 -A 5

Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N 3

Relation: cpu

Instances: 209

Attributes: 8

vendor

MYCT

MMIN

MMAX

CACH

CHMIN

CHMAX

class

Evaluation mode: evaluate on all training data

=== Attribute Selection on all input data ===

Search Method:

Attribute ranking.

Attribute Evaluator (unsupervised):

Principal Components Attribute Transformer

Correlation matrix

1 -0.01 -0.01 -0.01 -0.01 -0.01 -0.01 -0.01 -0.01 -0.01 -0.01 -0.01 -0 -0.01 -0.01 -0.01 -0.02 -0.03 -0.01 -
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-0.01 1 -0.02 -0.02 -0.02 -0.04 -0.04 -0.05 -0.03 -0.04 -0.04 -0.03 -0.01 -0.03 -0.04 -0.04 -0.05 -0.09 -0.04 -
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-0.02 -0.15 0.07 -0.06 0.03 -0.05 0.08 -0.13 -0.09 0.13 0.08 0.36 -0.02 -0.06 -0.07 0.06 0 0.39 -0.1 -0.09
-0.01 -0.17 -0.15 -0 0.02 -0.03 -0.11 -0.1 -0.02 0.1 1 -0.34 -0.38 -0.32 -0.3 -0.25 -0.29

-0.05 0.57 -0.05 0 -0.07 -0.04 -0.11 -0.02 -0.05 -0.09 -0.1 -0.11 -0.04 -0.03 -0.08 -0.11 -0.08 0.02 0.01 -
0.06 -0.04 0.2 0.05 -0.05 -0.07 -0.08 0.09 -0.03 -0.02 -0.05 -0.34 1 0.76 0.53 0.52 0.27 0.82

-0.03 0.46 -0.07 0 -0.03 -0.12 -0.11 -0.05 0 -0.07 -0.06 -0.05 -0.06 0.02 -0.12 -0.08 -0.01 -0.08 -0.01 0
-0.05 0.16 -0.04 -0.07 -0.04 -0.09 0.04 0.24 -0.02 -0.05 -0.38 0.76 1 0.54 0.56 0.53 0.9

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0.03 0.03 0.05 0.01 -0.07 -0.05 -0.08 0.09 0.32 -0.03 -0.07 -0.3 0.52 0.56 0.58 1 0.55 0.61

0.29 0.13 -0.05 -0.04 -0 0.15 -0.08 -0.01 -0.08 -0.08 -0.12 -0.09 0 0.09 0.03 0.05 0.14 -0.19 -0.08 -0.05
0.29 -0.06 -0.05 -0.07 -0.05 -0.05 -0.04 0.35 -0.01 -0.07 -0.25 0.27 0.53 0.49 0.55 1 0.59

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0.04 -0.03 0.12 -0.02 -0.05 -0.05 -0.07 0.03 0.25 -0.03 -0.04 -0.29 0.82 0.9 0.65 0.61 0.59 1

eigenvalue proportion cumulative

4.67768 0.12642 0.12642 -0.425class-0.408MMAX-0.375MMIN-0.352CHMIN-0.351CACH...

1.66189 0.04492 0.17134 -0.397CHMAX+0.353vendor=ibm+0.342MMIN+0.336vendor=amdahl-
0.304vendor=adviser...

1.53365 0.04145 0.21279 -0.53MYCT-0.355vendor=ibm-0.304vendor=formation-0.291CHMAX-0.252vendor=sperry...

1.27287 0.0344 0.24719 0.502vendor=adviser+0.434CACH+0.321vendor=nas-0.232vendor=sperry-
0.23vendor=amdahl...

1.14408 0.03092 0.27811 -0.539vendor=honeywell+0.369vendor=cdc+0.284CHMIN-
0.274vendor=gould+0.272vendor=siemens...

1.11994 0.03027 0.30838 0.453vendor=sperry-0.413vendor=ibm+0.327vendor=formation-0.325vendor=burroughs-
0.264vendor=microdata...

1.08452 0.02931 0.33769 -0.432vendor=ibm+0.38 vendor=formation-0.367vendor=nas+0.325vendor=amdahl-
0.315vendor=sperry...

1.07141 0.02896 0.36665 -0.585vendor=nas-
0.386vendor=burroughs+0.344vendor=ncr+0.259vendor=gould+0.205vendor=honeywell...

1.06348 0.02874 0.39539 -0.661vendor=siemens+0.633vendor=ncr-0.26vendor=honeywell+0.137vendor=nas-
0.127vendor=cdc...

1.0541 0.02849 0.42388 0.495vendor=siemens+0.462vendor=ncr-0.397vendor=cdc-
0.273vendor=amdahl+0.262vendor=honeywell...

1.04972 0.02837 0.45225 0.669vendor=cdc+0.506vendor=honeywell-0.238vendor=gould-0.216vendor=siemens-
0.191vendor=ipl...

1.03678 0.02802 0.48027 0.648vendor=burroughs-0.516vendor=hp-0.458vendor=harris+0.24 vendor=dg-
0.093vendor=microdata...

1.0352 0.02798 0.50825 -0.717vendor=harris+0.586vendor=hp-0.243vendor=magnuson+0.137vendor=c.r.d-0.114vendor=cambex...

1.03322 0.02792 0.53618 -0.84vendor=dg+0.266vendor=dec+0.247vendor=c.r.d+0.233vendor=ipl-0.162vendor=harris...

1.03058 0.02785 0.56403 0.733vendor=magnuson-0.42vendor=ipl-0.392vendor=c.r.d+0.185vendor=hp+0.141vendor=dec...

1.02997 0.02784 0.59187 0.738vendor=c.r.d-0.497vendor=ipl-0.318vendor=dec+0.223vendor=magnuson-0.16vendor=formation...

1.02878 0.0278 0.61967 0.776vendor=dec-0.469vendor=formation-0.321vendor=ipl-0.18vendor=magnuson-0.123vendor=hp...

1.02626 0.02774 0.64741 -0.632vendor=cambex-0.44vendor=prime+0.346vendor=ipl+0.333vendor=magnuson+0.236vendor=c.r.d...

1.02522 0.02771 0.67512 -0.789vendor=prime+0.54 vendor=cambex+0.156vendor=c.r.d-0.135vendor=magnuson+0.113vendor=hp...

1.02117 0.0276 0.70272 0.625vendor=microdata-0.301vendor=burroughs-0.293vendor=nixdorf-0.264vendor=harris-0.241vendor=basf...

1.01765 0.0275 0.73022 0.643vendor=gould-0.434vendor=adviser+0.3 vendor=perkin-elmer-0.252vendor=cambex+0.206vendor=cdc...

1.01588 0.02746 0.75768 -0.666vendor=nixdorf-0.515vendor=perkin-elmer+0.211vendor=gould-0.209vendor=microdata-0.17vendor=apollo...

1.01456 0.02742 0.7851 0.74 vendor=perkin-elmer-0.577vendor=nixdorf-0.191vendor=microdata+0.183vendor=adviser-0.13vendor=gould...

1.01153 0.02734 0.81244 -0.619vendor=wang-0.592vendor=apollo-0.298vendor=bti+0.242vendor=nixdorf+0.211vendor=formation...

1.01044 0.02731 0.83975 -0.827vendor=basf-0.351vendor=bti+0.305vendor=gould-0.19vendor=microdata+0.121vendor=wang...

1.00987 0.02729 0.86704 -0.692vendor=apollo+0.502vendor=bti+0.441vendor=wang-0.223vendor=basf-0.091vendor=microdata...

1.00967 0.02729 0.89433 -0.677vendor=bti+0.551vendor=wang+0.29 vendor=microdata-0.249vendor=apollo+0.216vendor=basf...

1.0065 0.0272 0.92153 -0.928vendor=four-phase-0.183vendor=gould-0.171vendor=sratus+0.132vendor=apollo-0.112vendor=basf...

1.00498 0.02716 0.94869 0.966vendor=sratus-0.167vendor=four-phase+0.106vendor=adviser-0.102vendor=microdata-0.094vendor=basf...

0.58805 0.01589 0.96459 0.597vendor=amdahl+0.402vendor=sperry+0.297vendor=adviser-0.214class-0.161vendor=c.r.d...

Eigenvectors

V1 V2 V3 V4 V5 V6 V7 V8 V9 V10 V11 V12 V13 V14 V15 V16 V17 V18 V19 V20 V21 V22 V23 V24 V25 V26 V27 V28 V29 V30

-0.0712 -0.304 -0.1775 0.5016 -0.0751 -0.1302 0.1385 0.1124 -0.0452 -0.0725 -0.0926 -0.0754 -0.0055 -0.0166 0.0444 0.0376 0.0169 0.0109 0.052 0.0754 -0.4339 -0.1312 0.1828 0.0163 0.0436 0.0507 -0.1016 0.0491 0.1057 0.2972 vendor=adviser

-0.2274 0.3364 0.0044 -0.2295 -0.1249 -0.1433 0.3255 0.038 0.0287 -0.2732 -0.0124 -0.0531 -
0.0049 -0.0126 0.0275 0.0791 0.0464 -0.0253 -0.0147 -0.0002 -0.0556 -0.0569 0.0253 -0.015
0.0148 0.0119 -0.031 -0.031 -0.003 0.5965 vendor=amdahl

0.0387 0.0182 -0.0264 0.009 -0.0122 0.0486 0.0922 -0.0369 0.0247 -0.0211 -0.005 -0.0033
0.0334 0.0242 -0.0196 0.0051 -0.0064 -0.0171 -0.0382 -0.0577 -0.0206 -0.1699 -0.0126 -0.5917
0.1172 -0.6923 -0.2486 0.1317 -0.0197 -0.0926 vendor=apollo

-0.0045 -0.0085 0.0949 0.1511 -0.1023 0.0146 -0.006 0.1696 -0.0446 -0.0997 -0.0999 0.0123 -
0.0071 0.032 -0.0105 0.0011 0.0101 -0.0638 0.0237 -0.2405 0.0585 0.0554 0.0568 -0.0058 -
0.8274 -0.2228 0.2159 -0.1124 -0.0941 -0.0126 vendor=basf

0.0253 -0.0271 -0.0193 -0.065 -0.0233 0.047 0.0079 -0.0195 0.0118 -0.0162 -0.0211 -0.0104 -
0.0135 0.0117 0.014 0.0011 -0.0081 -0.0199 -0.0015 0.1068 0.1284 -0.1191 -0.0272 -0.2979 -
0.3513 0.5018 -0.6775 0.0682 -0.0197 -0.0659 vendor=bti

0.0092 -0.1939 -0.0241 -0.0952 0.0597 -0.3245 0.1672 -0.3864 0.0746 -0.093 -0.1335 0.6479 -
0.0367 0.052 0.0289 -0.0215 -0.0361 -0.0555 0.0663 -0.3012 0.0345 0.1386 0.0407 0.029
0.0228 0.0291 -0.0172 0.0558 -0.0067 -0.038 vendor=burroughs

0.0631 -0.0002 -0.0043 -0.0182 -0.0335 0.1178 0.1075 -0.0217 0.0401 -0.0961 -0.0677 -0.0176
0.1366 0.2468 -0.3922 0.738 0.0292 0.2365 0.1559 0.0993 -0.046 0.1108 0.0048 0.0815
0.0068 0.0046 0.0073 0.0283 -0.0093 -0.1614 vendor=c.r.d

-0.0177 -0.1259 0.1251 0.1477 0.3689 0.0173 0.1052 -0.0106 -0.1271 -0.3968 0.6694 -0.042
0.0186 -0.0151 -0.0581 -0.0577 -0.0469 0.014 -0.0083 0.0942 0.2056 0.0623 -0.0598 -0.0091 -
0.0111 0.0022 0.0476 0.08 -0.0053 0.0016 vendor=cdc

0.0206 -0.0078 0.1528 -0.1181 0.0269 0.1018 -0.13 0.1054 -0.043 -0.108 -0.0556 0.0589 -
0.114 0.068 0.0784 0.011 0.048 -0.632 0.5402 0.239 -0.2525 0.0095 -0.0117 -0.0142
0.0546 -0.0107 0.0306 0.0412 -0.0198 -0.1194 vendor=cambex

0.0557 0.0344 -0.0681 0.0117 -0.0498 0.1719 0.1725 -0.0362 0.0431 -0.048 -0.0102 0.0105
0.075 0.2659 0.1414 -0.3177 0.7756 0.1976 0.0627 0.0808 -0.0238 0.0843 -0.0158 0.0871 -
0.0019 -0.0078 0.0043 0.011 -0.0051 -0.1127 vendor=dec

0.0563 0.0436 0.0153 0.0096 -0.0763 0.2234 0.0843 0.103 0.0059 -0.145 -0.105 0.2404
0.0643 -0.8401 -0.0312 0.0095 0.0647 0.1453 0.0026 0.1477 -0.0682 0.0325 -0.0154 0.0533
0.0116 -0.0095 0.0095 0.0048 -0.01 -0.1419 vendor=dg

0.0716 0.1305 -0.3037 0.0856 -0.1291 0.3273 0.3797 -0.1222 0.0962 0.0783 0.0917 0.0085
0.0702 0.1488 0.1409 -0.1603 -0.4691 -0.1661 0.0227 0.0973 0.0299 0.1071 -0.0734 0.2115 -
0.0576 -0.0473 -0.0126 -0.0511 0.0128 -0.0494 vendor=formation

0.0148 -0.0566 0.0158 -0.0492 0.1312 -0.0197 0.0261 -0.0896 0.0135 -0.0018 0.0457 -0.0086
0.0127 -0.0052 -0.0001 0.0196 0.0165 0.0123 -0.0258 0.0429 -0.1417 -0.1298 0.0206 -0.0367
0.0494 -0.041 -0.1069 -0.9278 -0.1669 -0.0577 vendor=four-phase

-0.0227 -0.1135 0.0207 0.2244 -0.274 -0.0421 -0.0238 0.2587 -0.0609 -0.1441 -0.2384 -0.039 -
0.0479 0.0329 0.0128 0.0002 0.0063 -0.1052 0.088 -0.0297 0.6434 0.2111 -0.1304 0.0054
0.3051 -0.0272 -0.1083 -0.1831 -0.0565 0.0695 vendor=gould

0.0381 -0.121 0.0828 -0.1552 0.021 -0.1593 -0.0022 -0.1549 0.0403 -0.1511 -0.1792 -0.5162
0.5863 -0.1065 0.1854 -0.1076 -0.1231 0.0215 0.113 -0.2085 -0.066 0.1319 0.0545 0.0333
0.0343 0.029 -0.0102 0.0553 -0.0128 -0.1491 vendor=hp

0.04 -0.0908 -0.0773 -0.1143 -0.0008 0.0186 0.1057 -0.1906 0.0621 -0.0241 -0.0315 -0.4578 -
0.7168 -0.1619 -0.133 -0.0038 0.0504 0.0064 0.0286 -0.2642 -0.0367 0.1104 0.0148 0.0489
0.0142 0.0007 -0.0033 0.0311 -0.0032 -0.0861 vendor=harris

0.0222 -0.1284 -0.0636 -0.2294 -0.5389 -0.135 -0.1009 0.2052 -0.2596 0.2624 0.5063 0.061
0.0658 -0.0155 -0.0165 0.0209 0.018 0.0204 -0.0106 -0.1527 -0.1359 0.025 0.0352 0.0191
0.0381 0.0005 -0.0276 -0.0216 -0.0089 -0.046 vendor=honeywell

0.0844 0.3531 -0.3549 0.152 0.2635 -0.4134 -0.4319 0.1237 -0.047 0.0012 -0.028 -0.0044 -
0.0162 -0.0164 0.0022 0.0102 0.0158 0.002 0.0082 0.0124 0.0082 0.0167 -0.0011 0.0257 -
0.0035 0.0016 -0.0039 0.0032 -0.0008 -0.067 vendor=ibm

0.0142 0.016 0.1824 -0.0532 -0.0829 -0.0109 -0.074 0.1531 -0.051 -0.1888 -0.191 0.0748 -
0.0992 0.2326 -0.4202 -0.4974 -0.3205 0.3464 0.0033 0.1578 -0.2032 0.0092 0.0363 0.0054
0.0616 0.0166 -0.0122 0.0122 -0.0245 -0.108 vendor=ipl

0.0146 -0.0379 0.1248 -0.0687 0.019 0.1091 -0.1152 0.1319 -0.0564 -0.1383 -0.08 0.0706 -
0.2428 0.156 0.733 0.2232 -0.1802 0.3325 -0.1345 0.064 -0.1003 0.0161 -0.0244 -0.0087
0.0384 -0.0128 0.0265 0.0309 -0.0153 -0.0886 vendor=magnuson

-0.0116 -0.2226 -0.1519 -0.1798 -0.107 -0.2636 0.0116 -0.1894 0.0434 0.0332 -0.0772 -0.093 -
0.0364 -0.0383 0.0157 -0.0098 -0.0049 0.0574 -0.0133 0.6252 0.198 -0.2091 -0.1912 -0.0558 -
0.1896 -0.0913 0.2899 0.0465 -0.1019 0.0629 vendor=microdata

-0.088 0.106 0.2475 0.3215 -0.2448 0.1812 -0.367 -0.5846 0.1368 0.1842 0.0781 -0.0224
0.0144 -0.0222 -0.0043 0.0083 0.0019 0.0225 -0.0151 0.07 0.0082 -0.0107 -0.0122 -0.0042
0.0124 0.0011 0.0026 0.001 -0.0087 0.1524 vendor=nas

-0.0076 -0.0318 0.2227 0.0497 0.1496 -0.1757 0.2253 0.3436 0.6327 0.4624 0.0809 -0.0128 -
0.0098 -0.0228 0.017 -0.0061 -0.0181 0.0169 0.0123 0.048 0.0321 0.0303 -0.0019 0.0038
0.0126 0.0132 0.0059 0.0342 -0.0101 -0.0545 vendor=ncr

0.0316 -0.006 0.0634 0.0562 -0.023 0.0237 0.0457 0.0468 -0.0037 -0.0799 -0.0555 0.0038
0.0349 0.0383 -0.0397 0.0202 0.0213 -0.061 -0.0466 -0.2932 -0.0306 -0.6662 -0.5773 0.2421
0.0599 0.0564 0.0257 0.0702 -0.0324 -0.1067 vendor=nixdorf

0.0343 -0.0002 0.0203 -0.0621 -0.0065 0.0831 0.0074 0.001 0.0072 -0.0355 -0.0183 0.0054 -
0.0095 0.0281 0.0098 0.0034 -0.0071 -0.0504 -0.0091 -0.0072 0.3002 -0.5151 0.7405 0.2054
0.0633 -0.0182 0.0336 0.053 -0.0174 -0.1033 vendor=perkin-elmer

0.0396 -0.0442 0.08 -0.0216 -0.0339 -0.0002 0.0092 0.0307 0.0011 -0.1189 -0.1125 -0.0198
0.0337 0.0738 -0.0948 0.0679 0.0977 -0.4399 -0.7895 0.1328 -0.1323 0.1496 0.0365 0.0586
0.041 0.022 0.0009 0.042 -0.0196 -0.1392 vendor=prime

-0.0348 0.0192 0.1365 0.0274 0.2721 0.0273 0.2774 -0.0358 -0.6612 0.4947 -0.2163 -0.0354
0.0138 -0.0204 -0.0176 0.0018 -0.0027 0.0102 -0.0048 0.0519 0.0683 0.0216 -0.0212 -0.0012
0.002 0.0041 0.0161 0.0383 -0.0058 0.0433 vendor=siemens

-0.1335 -0.2482 -0.252 -0.232 0.2521 0.453 -0.3152 0.1415 0.118 0.085 -0.0971 0.0691
0.1066 0.0344 -0.1141 -0.0419 -0.002 0.0025 -0.0543 -0.1464 0.041 0.0233 -0.0456 -0.0161 -
0.0084 -0.0322 0.037 0.0168 0.0082 0.4023 vendor=sperry

0.0135 -0.0101 0.0388 -0.0592 -0.0139 -0.0175 -0.0083 -0.0107 0.0026 -0.0216 -0.0234 -0.0028 -
0.004 0.007 -0.0067 -0.0018 0.003 -0.0101 -0.0101 0.0379 0.0769 -0.044 -0.0412 -0.0344 -
0.0713 -0.0352 0.0342 -0.171 0.9661 -0.0597 vendor=sratus

0.0365 0.0423 -0.048 0.0745 -0.0635 0.1031 0.1058 0.0213 0.0141 -0.0278 -0.0191 0.0059
0.0247 0.0347 -0.0069 -0.0045 -0.0219 -0.0342 -0.0128 -0.1405 0.002 -0.0812 0.0516 -0.6187
0.1208 0.4412 0.5511 -0.0549 -0.0231 -0.0686 vendor=wang

0.2301 0.2386 -0.5297 0.1191 -0.0318 0.0495 0.0719 -0.0254 0.0109 0.0143 0.012 -0.0005
0.0032 0.0014 0.002 -0.003 -0.0058 0.0023 0.0001 0.0011 -0.0058 -0.0009 0.0021 -0.0058
0.0037 0.0015 0.0013 0.0037 -0.0016 -0.1329 MYCT

-0.3746 0.3425 0.0902 -0.0115 -0.0224 -0.1505 0.0625 -0.0485 0.0067 0.0064 0.0036 0.0003
0.0061 0.0001 -0.0078 -0.0067 -0.0023 0.0059 -0.0055 0.0051 0.0002 -0.0021 -0.0081 -0.002 -
0.0022 -0.0064 0.008 -0.0003 0.0009 -0.0745 MMIN

-0.4075 0.176 -0.0305 -0.1194 -0.0855 0.114 -0.0646 0.0488 -0.018 0.0099 -0.0004 0.0073 -
0.023 0.001 0.0158 -0.0092 -0.009 -0.0041 0.0149 0.0098 0.0214 0.0158 0.0035 0.007 -
0.0051 0.0072 0.0009 0.0108 0.0002 -0.1421 MMAX

-0.3512 -0.1251 0.0022 0.4342 -0.0342 0.0136 0.0212 0.0501 -0.0143 -0.012 -0.0077 0.0015 -
0.0002 0.002 0.0018 0.0002 -0.0003 -0.0025 0.004 -0.0174 -0.0128 0.0033 0.0064 0.0012
0.0008 0.0012 -0.0019 0.0024 0.0007 -0.1601 CACH

-0.3516 -0.1027 -0.12 -0.0201 0.2841 0.0442 0.0287 -0.0622 0.0021 0.0205 0.0536 0.0035 -
0.0006 -0.0039 0.0079 0.0024 0 0.0061 0.0009 -0.0013 -0.0348 -0.0054 0.0104 0.0029
0.0086 0.0018 -0.0094 -0.0148 -0.0029 -0.1359 CHMIN

-0.3065 -0.3973 -0.2908 -0.1155 -0.108 -0.1066 -0.0017 -0.0261 0.0066 0.0055 -0.0189 -0.0096 -0.0042 -0.0034 0.0007 -0.0022 -0.0013 0.0036 0.0002 0.0328 0.0139 -0.0039 -0.0074 -0.0006 -0.0045 -0.0013 0.0067 0.0049 0.0001 -0.1576 CHMAX

-0.4249 0.1447 -0.1002 -0.0496 -0.0413 0.055 0.0001 0.0306 0.0163 -0.0219 -0.0211 -0.0066 0.0186 0.0007 -0.0124 0.0133 0.0093 -0.0039 -0.0095 -0.0181 0.0007 -0.0045 -0.0011 -0.0056 0.0047 -0.0007 -0.0036 0.001 -0.0008 -0.2141 class

Ranked attributes:

0.874 1 -0.425class-0.408MMAX-0.375MMIN-0.352CHMIN-0.351CACH...

0.829 2 -0.397CHMAX+0.353vendor=ibm+0.342MMIN+0.336vendor=amdahl-0.304vendor=adviser...

0.787 3 -0.53MYCT-0.355vendor=ibm-0.304vendor=formation-0.291CHMAX-0.252vendor=sperry...

Selected attributes: 1,2,3 : 3