Data Mining Models Applied in Customer Relationship Management System

Titus Felix FURTUNĂ, Alexandru BĂRBULESCU
Academy of Economic Studies, Bucharest, Romania
titus@ase.ro, alexbarbulescu@ie.ase.ro

In the last years the competition between companies has increased. In many industry fields, because of the global economy crisis, important companies have problems such low cash flow and limited customers. But, the market is the same for everybody. In that context what it is right to do? Gaining an advantage over the competing companies is a good answer and can be also a big opportunity. This can't be done without software solutions able to extract information from data. The information is the key in economy, very valuable these days. The information at the right time can make the difference between going to bankruptcy or not. Customer Relationship Management (CRM) software solutions have the ability to help people to improve the profitability and the interactions with the customers. This can be done only when operational of the CRM systems is better sustained by the analytical of CRM. The second is represented by analytic models and data mining techniques. This paper focuses on using data mining algorithms integrated with CRM systems directly in the user interface, making analytics available to the operational people. Also we present a case study based on Microsoft Dynamics CRM and data mining graphic results.
Keywords: *Data Mining, Clustering, CRM Systems*

1 Introduction

In the field literature there were many CRM definitions. From the technical point of view there are packaged software applications, which help management of the company to improve the interaction between the company and his customers. Starting from the idea that a good and for a long term relation with the customer is the key in business competition, the companies are trying to achieve the customer centric business attitude. The CRM systems mean more than operational relationship management which include sales, marketing and service processes management. It means using the customer data including basic data and recorded interactions to improve the relations and also to increase the revenue by up sell and cross-sell.
Most CRM systems don't have specialized data mining modules useful in business intelligence applications. So, the only possible solution would be using data mining implementations that already exist in the Data Base Management System used by that CRM. For instance, for CRM systems that utilize Microsoft SQL Server there is SQL Server Data Mining. Oracle has developed Oracle Data Mining application developers based on Java Technologies having Java Data Mining in the background, and Oracle Data Miner graphical user interface that helps data analysis mine in Oracle. These solutions have one disadvantage: they are limited by what these implementations offers. A more flexible solution would be the implementation of the desired data mining algorithms using those integrated technologies that CRM system allows such as writing a C#NET class library and its integration, within CRM environment.

2 CRM Software Solutions

Investment in aCRM system is an important issue for a company because it imply most of the times a big investment, which include financial but also human effort.
The references of aCRM system are important, but the most important in the success of an implementation is the consulting company. The impacts of poor implementation in any organization cannot

be estimated, but most of the times the costs are higher.

The most important benefit from investing substantial financial and human resources in CRM implementation is the achievement of strategic competitive advantage in three major areas of business activity: accurate and timely information for strategic decision making, business process improvement and a good customer centric attitude. Other benefits of CRM systems include: good operational sales processes and monitoring; quantification of the customer value; Increased revenues anticipation of the market trends; increased customer retention; and increased IT infrastructure capability and business flexibility and reduced IT costs.

Achieving business processes improvement and control play a key investment role. These include operational or tangible benefits (cost reduction, improvements in cycle times, productivity, quality and customer services) and managerial benefits (improved data about the customer).

The first such systems were focused in simplifying the company's management of the customers and customer related processes. There were created customer databases which recorded the customer general data and also the interactions between the company and the customer. Interactions are represented by actions between customer's peoples and organization's peoples like meeting, presenting and negotiating offer, phone calls, fax, emails, marketing campaigns, products returned to service (warranty or not), etc.

In the operational area CRM offer the integration on all channels of communication with customers. The whole picture of the CRM functionalities includes operational sales management, marketing management, call centre (or contact centre) and client services management.

Operational sales management include the following functional areas:

- ⇨ Management of accounts (or clients),
- ⇨ Customer centric functionalities, which also permit to see all customer interaction with the company on all communication areas and with all company departments in one screen, related to the client entity,
- ⇨ Sales process automation. Those processes start from a lead and go through offering stage and in final step closing and deliver a contract. All those spetps can be very complex depending by the company size and type of business.
- ⇨ Partner relationship management is very often an important component of an CRM systems. This functionality extends the relationship concept to the partners instead of clients.
- ⇨ Quote management
- ⇨ Portal used to interact with end user clients (B2C) or with partners B2B

Marketing Management is composed by the following functional areas:

- ⇨ Marketing campaigns management. Those functionalities is delivered to permit the definition of marketing campaigns and after that monitor those campaigns in the mean of cost, clients targeting, involved people from the company
- ⇨ Electronics marketing is the functionality focused on the web marketing. It includes tools to deliver and record marketing campaigns made on the internet.
- ⇨ Client feedback functionality which consist of using web forms to find out the feedback from the customer

Call centre (or contact centre) is a very important functionality especially in a recession period when the customers are very carefully regarding to the cost and the satisfaction. More than that, the competition is always at the corner waiting unhappy clients from the competing companies. Is very clear when the marketing is not going up one chance to go up is to attract clients from the completion. In this context this component is very important. Also the usage is critical by the company users.

- ⇨ Management of the technicians and queues of incidents

- ⇨ Messaging system to interact with the clients
- ⇨ Knowledgebase consist in a database with information regarding to other similar cases
- ⇨ Tools for self-assistance based on the knowledgebase cases.

Client services management consist in the following functionalities:

- ⇨ Client service, meaning management of warranties and post warranties incidents
- ⇨ Client support, meaning management of all kind of client incidents.
- ⇨ Incidents monitoring and invoicing
- ⇨ Services contracts management

3 Data Mining Techniques

Data mining is the process of extracting knowledge from data. That knowledge can be used to understand the nature of a business or scientific problem, or applied to new data to make predictions or classifications [7] [8]. Data mining is becoming an important technology used in different industries such as financial services, retail, healthcare, telecommunications, and higher education, and businesses such as marketing, manufacturing, customer experiences, customer service and sales. Many of the business problems that data mining can solve cut across industries such as customer retention and acquisition, cross-sell, and response modeling. The data mining algorithm is the mechanism that implements a data mining technique. Mining algorithms provide the ability to specify how it should be done, often with implementer-specific features. Algorithms allow users to tailor data mining results, and allow implementers to expose details of their algorithms supporting a given function.

In our solution we have implemented the following mining algorithms: Principal Component Analysis, Clustering algorithms (Hierarchical Clustering, K-Means clustering algorithm, Bisecting K-Means algorithm), Classification algorithms (Bayesian classification, Decision Tree).

Principal component analysis (PCA) seeks the axis which the cloud of points representing the instances, are closest to. This criterion is that the variance of the projection be as great as possible. PCA is very useful for identify the informational structure of data. The PCA results can be used to building clustering and classification models.

Typical goals for *clustering algorithm s*can include finding representative cases from a large dataset to support data reduction, identifying natural clusters in a dataset to give insight into what cases are grouped together. Essentially, clustering analysis identifies clusters that exist in a given dataset, where a cluster is a collection of cases that are more similar to another than cases in other clusters. A set of clusters is considered to be of high quality if the similarity between clusters is low, yet the similarity of cases within a cluster is high. Most of the works published in cluster analysis outline the possibility of using two types of algorithms: hierarchical algorithms, non–hierarchical algorithms, mixed algorithms. The pseudocode for a hierarchical algorithm is shown in Table 1.

One of the most employed hierarchical methods is the *minimum variance method* (*Ward method*). The minimum variance method is based on dispersing the points which form the groups (classes). The use of dispersions in the grouping criteria link the grouping result with other techniques of data analysis, as it substantially implies a variance decomposition. For instance, the principal component analysis searches the main axes in relation to those points of maximum distance. By using the minimum variance, as a criterion to forming the groups (classes), an additional analysis is achieved, to the principal component analysis, applied to the same set of data, which allows the identification of groups (classes) with a maximum homogeneity.

Table 1. Clustering hierarchical algorithm

```
Procedure Hierarchy (D, n)
// D - the distance matrix
// n - the number of cases
List[] H// the vector of lists representing the hierarchy
for i=1,n
      H[i] = {i}
endfor
for i=1,n-1
// select the two clusters according of the grouping criterion
      call Select(D;k,j)
// agglomerate clusters k and i and replace them with new cluster k
      H[k] = H[k] + H[j]
      H[j] = {}
// update the distances between clusters
      callUpdate(D,k,j)
// write the hierarchy
      callWrite(H)
endfor
return
end
```

The aggregation technique by using the minimum variance is positive to hierarchy, as:

- the homogeneity and separation of groups (classes) are included into the minimum variance criterion;
- this method defines the centroids within groups (classes);
- a top-down hierarchy may be used to retrieve the hierarchical information.

Generally, these are symmetric or balanced and consequently easily to be rendered.The minimum dispersion method leads to identifying certain groups or classes which maintain the density and isolation criteria for working out hierarchies**.** In other words, we pursue to aggregate two groups C_1 and C_2 so that the between class variance to be maximum, and the within class variation of partition to be minimum.To this end, we consider P a partition with n instances and k classes. Let O denote the general centroid and O_k the centroid of the k class.The total varianceis decomposed into between class variance and within class variance.Consequently:

- the total variance is $\frac{1}{n}\sum_{i=1}^{n} d(i,O)^2$, where n is the total number of instances, and $d(i,O)^2$ is the distance between i instance and O;
- the between class variance is $\frac{1}{n}\sum_{k=1}^{p} n_k d(O_k,O)^2$, where n_k is the number of instances from the k class, O_k is the centroid of the k class and $d(O_k,O)$ is the distance between O_k and O;
- the within class variance is $\frac{1}{n}\sum_{k=1}^{p}\sum_{i\in k} d(i,O_k)^2$, where p is the number of classes.

The criterion is formalized as follows:

$\underset{i,j}{Min}\frac{n_i n_j}{n_i+n_j} d(O_i,O_j)^2$, where $d(O_i,O_j)^2$ is the distance between the both classes, i and j.

Another usual hierarchical clustering method is the centroid method. According to centroid method, the aggregation criterion is the minimum distance between centers of groups. The new centroid is computed as a weighted average between the centers of the merging clusters. The weights are given by the number of instances in each group. e distance of merging is getting smaller from one step to another. his is an undesirable feature of the method, because it can lead in the final steps to groups with a high degree of heterogeneity.

A non-hierarchical algorithm is *classical K-Means* algorithm. The main idea is to define from the beginning, the *k* group centers, one for each group. How are selected these centers is important, because it affects the number of subsequent iterations. After the initial choice of centers, an iterative process of adjusting their positions so that each center to group around his the nearest instances, is started. The optimization function used at each iteration is: $F = \sum_{j=1}^{k}\sum_{i=1}^{n} d(c_j, x_i)$, where k is the number of groups, n is the number of instances and $d(c_j, x_i)$ is the distance between the i instance and the j group [7][8].The pseudo-code for classical K-Means algorithm is shown in following table (Table 2).

Table 2. Classical K-Means

```
ProcedureKMeans(X,k)
// Initialization of the k centroids
callInitCentroids(X;G)
List[] H
do
       // Identify the new composition of classes
       call Groups(X,G;H)
       // Identify the new centroids
       call Centroids(X,H;C)
       // Calculate the distance between the old and new centroids
       call Distance(G,C;dist)
       G = C
whiledist>eps
// Write the hierarchy
call Write(G,H)
return
end
```

K-means results are highly dependent on the initialization procedure used. We used to initialize the first principal component, because it cumulate the maximum of information.

Bisecting K-Means algorithm is an improved version of the classical K-Means algorithm, which is closer to the hierarchical algorithms.Bisecting K-Means builds a hierarchy in a top-down manner, as the Greedy technique.At each step is divided the cluster with the maximum variance or the cluster with maximum number of instances.The splitting of a cluster into two disjoint clusters is similar to that of classical K-means algorithm. The algorithm is described in Table 3.

Table 3. Bisecting K-Means

```
ProcedureBisectingKMeans(X,n,m,k)
List L// List of the clusters.
call Add(L,X)
for i=1,k
       callSelectCluster(L;M)
       call Centroid(M;g)
       call Select(M;gl)
       gr = 2*g - gl
       do
              call Divide(M,gl,gr;ML,MR)
              call Centroid(ML;cl)
              call Centroid(MR;cr)
       while cl!=gl || cr!=gr
       call Add(L,ML)
       call Add(L,MR)
endfor
callWrite(L)
return
end
```

Consider a set of n instances measured on each of m attributes or variables. The $n \times m$ matrix of values will be denoted by X. A cluster is represented by a matrix M that contains into the lines, the values recorded for an instance. So the lines of matrix M are lines from the matrix X, corresponding to instances belonging to the cluster. Clusters are stored in a list L. The procedures have the following functionalities:

Add - add a cluster to the list;

SelectCluster- choosing the cluster to be divided according to the splitting criterion;

Centroid -compute the centroid;

Select - Compute the first centroid, using the first principal component as criterion;

Divide - Determine instances belonging to the two clusters using a particular distance;

Write - Write the list of clusters.

Bayesian classification algorithm is one of the fastest classification algorithms. It produces results comparable to other algorithms, often outperforming other classifications algorithms. Bayesian classification is the most frequent used method for assigning a group of objects into previous established groups. Consider the x an array representing an instance belonging to a set of n instances and k the number of groups. The Bayes' rule for the assignment this instance to group i rather than to any other group, j, is as follows:

$P(i/x) > P(j/x)$, for all $i \neq j$ (1)

Where $P(i/x)$ is the probability that x belongs to group i, and $P(j/x)$ is the probability that x belongs to group j. These are a posteriori probabilities and they have to be determined. The a priori probabilities are those probabilities that determine belonging to a certain class in case that no information about the words of the classes is available. Usually, a priori probabilities are either determined based on groups weights and equal to $1/k$ ratio or have values chosen subjectively.

Consider apriori probability for any given group i, $P(i)=\frac{m_i}{n}$, where m_i is the number of instances from group i.

Bayes' theorem binds a priori and a posteriori probabilities as shown below:

$$P(i/x) = \frac{P(x/i)\cdot P(i)}{\sum_{j=1}^{k} P(x/j)P(j)}, \quad (2)$$

In equation (2), $P(x/j)$ is the probability of having a given instance, x, within group j. These probabilities are the conditioned probabilities in Bayes' theorem .They are calculated based on Gaussian or normal distribution.

Assuming that each group, i, is a Gaussian, the Bayes' rule (1) becomes:

- assign the instance x to class i if $P(x/i)P(i) > P(x/j)P(j)$, for all groups $j \neq i$. (3)

If we use a normal Gaussian distribution for estimating the conditional probabilities, we get:

$$P(x/i) = (2\pi)^{-\frac{m}{2}} \left|V\right|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(x-g_i)^t V^{-1}(x-g_i)\right)$$

,

where V is the variance-covariance matrix, and g_i is the centre of class i.

Substituting this into equation (3), taking natural logs of both sides of the inequality and cancelling common terms on both sides, given the following assignment rule:

- assign instance x to class i if:

$$\frac{1}{2}\ln\left|V\right| + \frac{1}{2}(x-g_i)^t V^{-1}(x-g_i) + \ln P(i) < \frac{1}{2}\ln\left|V\right| + \frac{1}{2}(x-g_j)^t V^{-1}(x-g_j) + \ln P(j)$$

for all groups $i \neq j$. (4)

This rule is simplified by defining a discriminating score as follows:

$$\delta_i(x) = \frac{1}{2}\ln\left|V_c\right| + \frac{1}{2}(x-g_i)^t V_c^{-1}(x-g_i) \quad (5)$$

The assignment rule then becomes:

- assign x to class i if:

$\delta_i(x) + \ln P(i) < \delta_j(x) + \ln P(j)$, for all $i \neq j$. (6)

The decision tree algorithm produces rules that explain how a prediction was made, as well as showing which grouping of cases produce a certain outcome. Decision trees create rules that include the instances in one group or another. The algorithm is relatively easy to understand and implement. The name comes from the major output of the technique: decision tree. The basic idea is to divide the dataset into groups as homogeneous in terms of values of target variable. The name comes from the major output of the technique: decision tree. The basic idea is to divide the dataset into groups as homogeneous in terms of values of target variable. This algorithm has better results for categorical variables type.

4 Case Study

Dynamics CRM 4.0 is the CRM system provided by Microsoft for managing the relation with customers. The solution is based on three main areas: sales, services and marketing. All functionalities are developed based on customer centric approach. As we see in the figure 1 there is in the system a window which structures all the information related to a customer (left side of the window). There is “Details” which include fields like addresses, sub-accounts or branches, contacts, relationships, etc. below there are three main areas of information: “Sales” which include all interaction regarding sales activity and processes with the customer, “Service” which present the cases or incidents and services contracts related with the customer and “Marketing” area which include information about marketing campaigns of the selected customer.

All areas which have in the centre the customer are interconnected. The study consists in creating the integration between a new developed module for data mining (in C# .NET) and Dynamics CRM system. The result will be a solution that can empower the system end user with the power of the data mining analysis directly into the usual Dynamics CRM interface not in other tool or third party application most of the time accessible in a reporting section of the application.

According to producer (Microsoft) the main platform components are: MS SQL database, web services, system services (workflow, metadata, and integration), a query processor that supports the entity model, secured ad hoc queries that use an XML fetch statement to protect the physical database, plug-ins for business logic extensibility, reporting services. The core system has an extension used for integrating with email desktop client Outlook. The integration is made by synchronization services with replicate some of data on desktop client computer. Developing application over the system implies web-services to communicate with the platform layer.

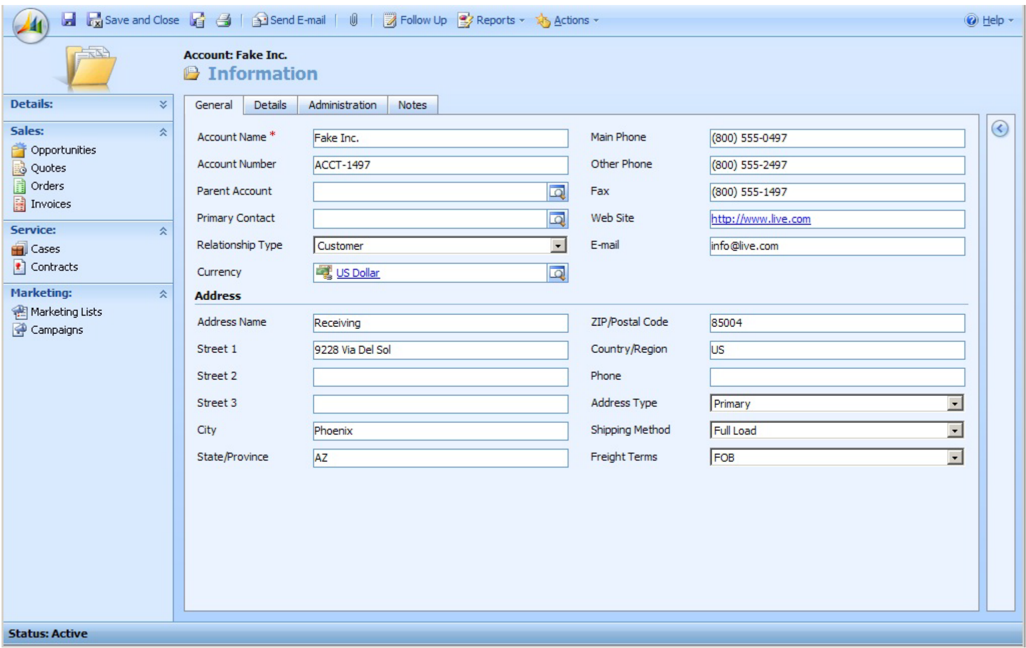

Fig. 1. Customer view

In Figure 2there are marked several types of changing standard functionalities of the system, orange color. Customization Tools: Customize, add, and rename entities. There are [10]:

- ISV Script/Form Customization allow customization of the forms by using the client-side scripting,
- ISV Code is used to add custom features to the application by using the application configuration file and the Software Development Kit (SDK),
- Custom Reports is used to create custom reports using the advanced built in filtered vies mechanism,
- Import/Export is a built in mechanism which allow to migrate the customization from one installation to another only in few simple steps,
- Plug-ins can be used for integration to external systems,
- Workflow Custom Activities is a mechanism that uses workflow and custom activities for calling external systems.

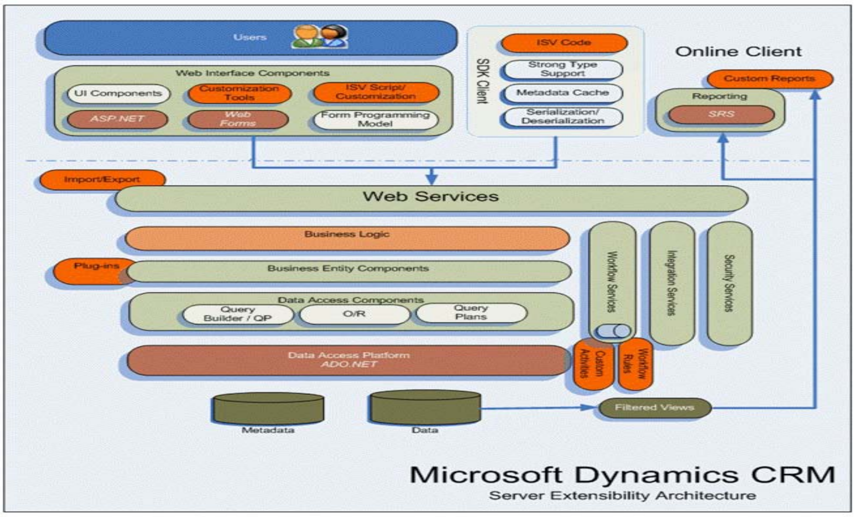

Fig. 2. MS Dynamics CRM Architecture (MSDN website)

In this case study we have used the list of customers from the demonstrative database Dynamics CRM 4.0. In our customers database we have 491 customers. The data columns are:

- *customertypecodename* represents the name of the code for type of customers (Sample of values: Grand stores, eCommerce, instant store);
- *accountcategorycodename* which records the category of the customers (sample of values: standard, preferred customer);
- *address1_city* is the city of the customer;
- *address1_country* is the country of the customer;
- *address1_freighttermscodename* represents the freight term code (sample of data: FOB, No Charge);
- *address1_shippingmethodcodename* represents the shipping method (Sample of data: Postal Mail, DHL, UPS);
- *address1_stateorprovince* represents the province of the customer;
- *creditlimit* is the credit limit of the customer;
- *customertypecodename* represents the type of the customer (sample of values: Prospect, Reseller, Customer);
- *industrycodename* is the name of the industry of the customer (Sample of values: Service Retail, Business Services, Consumer Services);
- *numberofemployees* is the number of the employees of the customer;
- *ownershipcodename* is the ownership name of the customer (Sample of values: Subsidiary, Public, Private);

- *paymenttermscodename* is the payment terms for the customer (Sample of values: Net 30, Net 45);
- *revenue* is the amount of the revenue invoiced with the customer;
- *statecodename* is the state of the customer in the database, active or inactive

For the integration of data mining algorithms, we developed a class hierarchy as shown in Figure 3.The hierarchy was developed using Visual Studio Class Library project template. The resulting dll file may be used in any Visual Studio .NET application [11]. For exemplification, we used the ISV Script/Form Customization, ISV Code and our library, to discover patterns and relationships in data. In additional to the main class hierarchy (data mining classes), we developed a graphics class hierarchy for specific graphics representations. The root of this hierarchy is *Plot* class. This class is derived in specific classes one for each type of graphic [10].

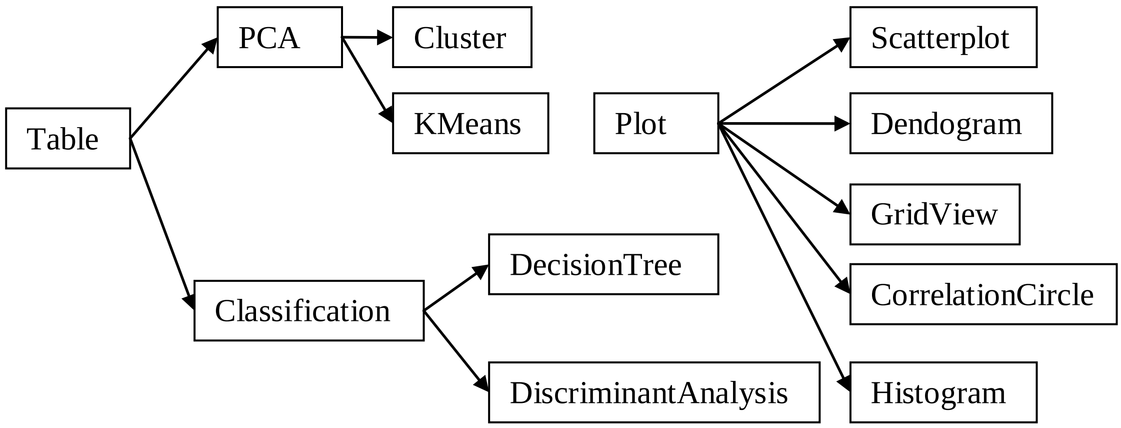

Fig. 3. Class Hierarchy

Next we will present some significant graphical outputs for each type of analysis. Principal components analysis underlines a great variability at data level. Figure 4 shows the projection of individuals on the plane of the first two principal components. As we can see in our case study, the first two principal components explain only 32% of variance (figure 5) and only the first seven principal components explain over 80% of the variance. These results demonstrate the large variability in the data.PCA class also contains methods by which the following results can be presented:

- factor coordinates of cases (table);
- correlation circle between components (graphics plot);
- eigen values and variance distribution (table and graphics plot);
- correlation matrix (table);
- variables contribution (table).

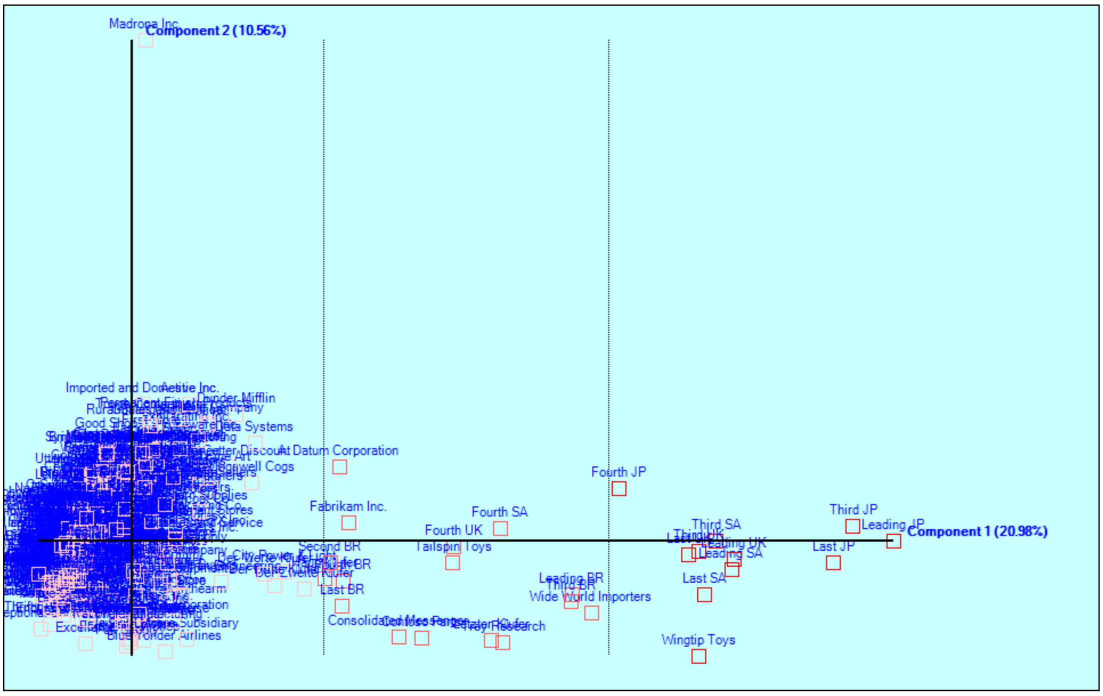

Fig. 4. PCA Scatter plot

Factors	Eigenvalues	Cumulative	Variance (%)	Cumulative (%)
Factor 0	2.518	2.518	20.981	20.981
Factor 1	1.267	3.785	10.562	31.543
Factor 2	1.115	4.9	9.29	40.833
Factor 3	1.063	5.963	8.855	49.688
Factor 4	1.035	6.998	8.629	58.317
Factor 5	0.953	7.951	7.943	66.26
Factor 6	0.925	8.876	7.705	73.964
Factor 7	0.871	9.747	7.257	81.221
Factor 8	0.823	10.569	6.855	88.077
Factor 9	0.675	11.244	5.623	93.7
Factor 10	0.478	11.722	3.982	97.681
Factor 11	0.278	12	2.319	100

Fig. 5. Eigen values and variance distribution

The algorithms of hierarchical classification are implemented using Cluster class. Figure 6 is showing the horizontal hierarchical tree plot (the dendogram) using Ward method. Cluster class can also generate dendogram using centroid method. Other results that can be shown:
- histograms and related statistics for each cluster;
- different partitions taken into account a given distance value;
- maximum stability partition.

K-Means class was developed in order to implement classic and bisecting K-Means algorithms. The clusters map is presented in the plane of the first two principal components in order to have more relevance. Figure 7 shows a three-cluster partition.
DiscriminantAnalysis class implements Naive Bayes classification and discriminant factor analysis. *Classification*, *DiscriminantAnalysis* and *DecisionTree* classes provides methods for computation of:

- covariance matrices (total covariance, covariance between groups, covariance within groups);
- Mahalanobis distances and Mahalanobis distances between groups;
- posterior probabilities;
- confusion matrix and cost;
- classification functions;
- decision tree;
- predictions for the application test;
- scatter-plot of canonical scores.

Figure 8 shows projections of individuals and group centres on the canonical plane (first and second discriminant factors) for Naive Bayes (scatter plot of canonical scores). The graphic's relevance is influenced by the discrimination power of the first two discriminant variables.

Figure 6 underlines the maximum stability partition that contains two clusters (marked by red and green).The data have been taken using Dynamics CRM web-services according to selected variables.

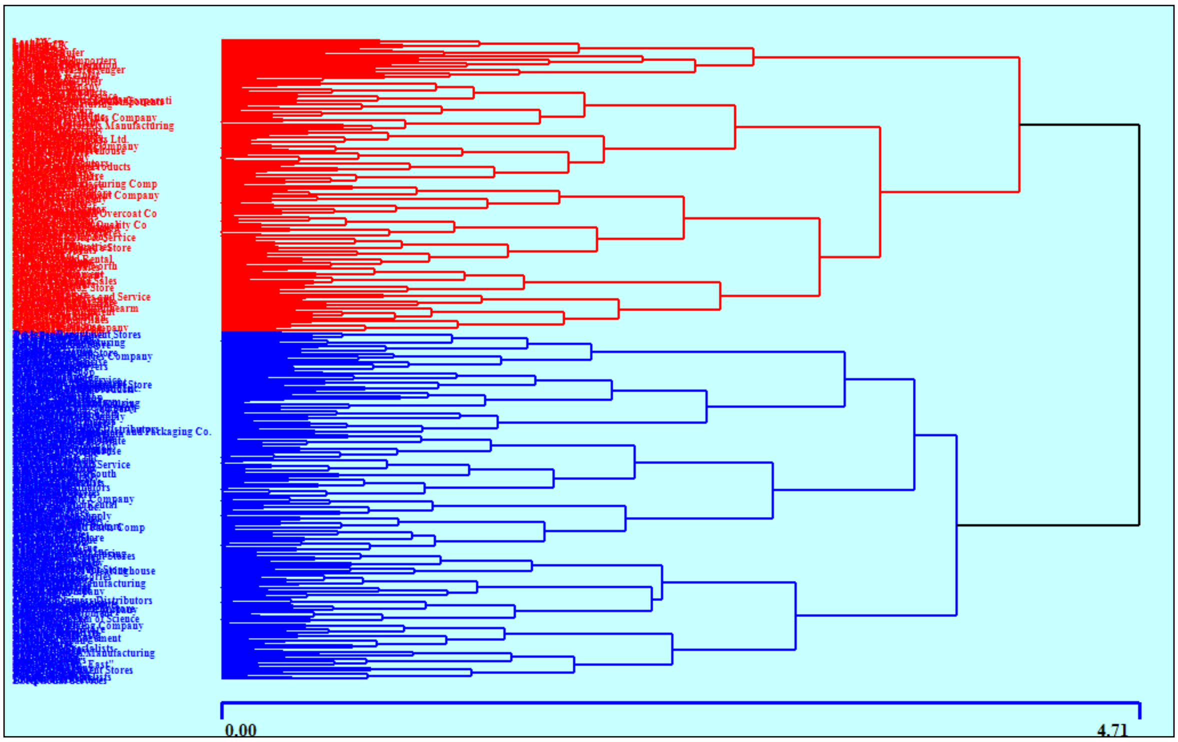

Fig. 6. Horizontal Icicle Plot

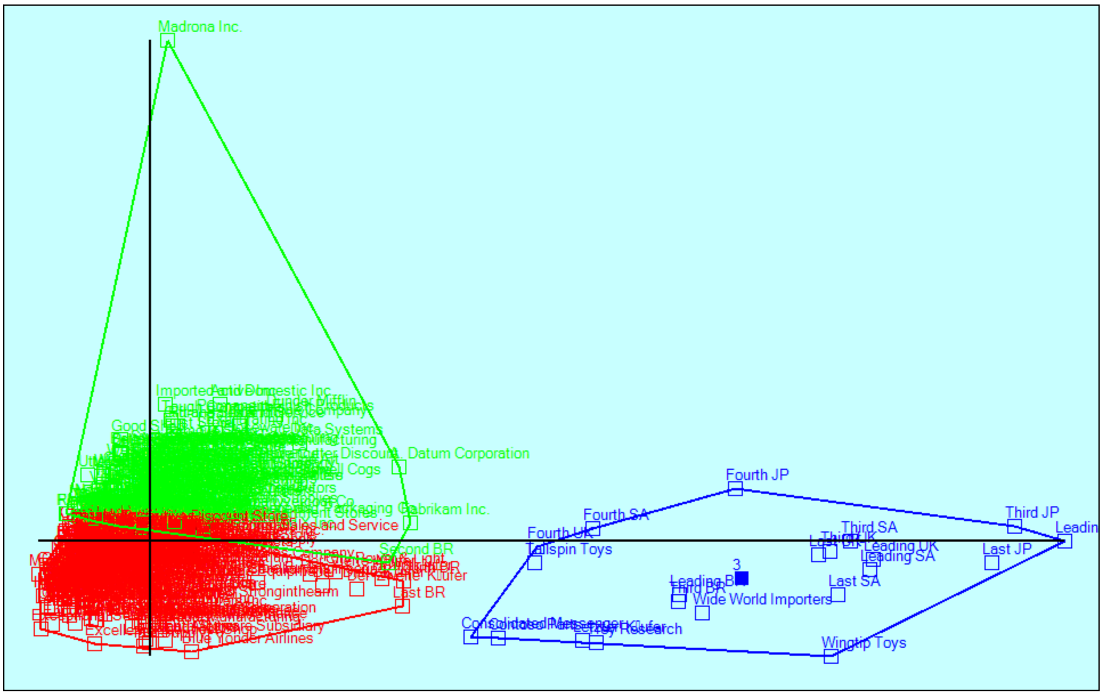

Fig. 7. K-Means Distribution Plot

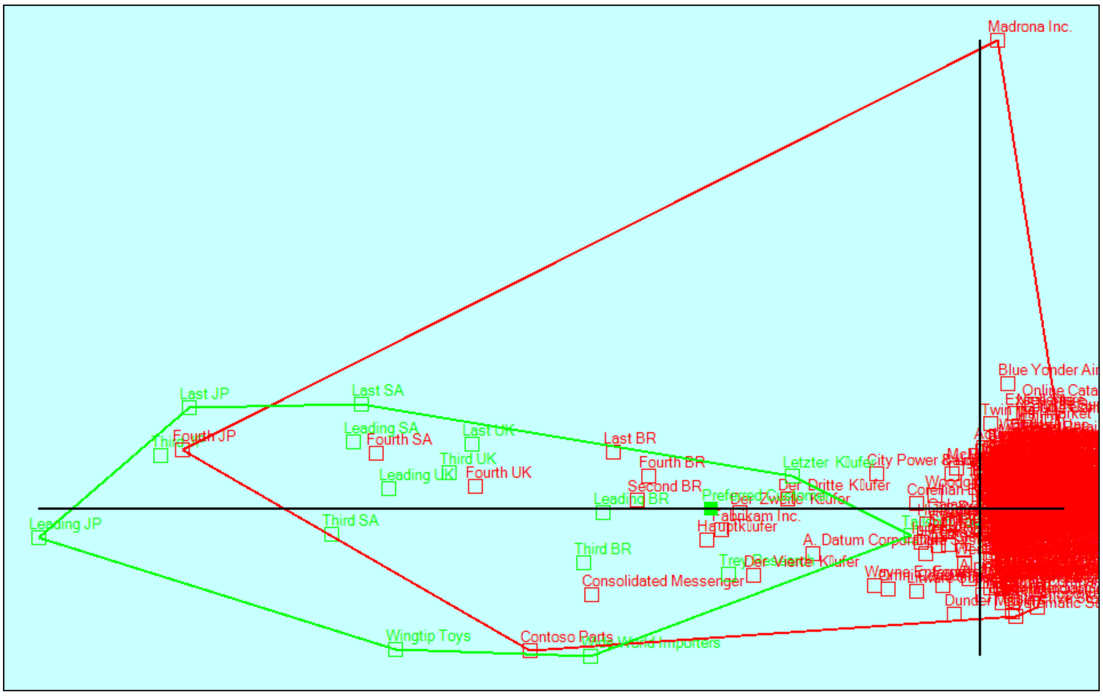

Fig. 8. Scatter plot of canonical scores. Root 1 versus root 2

5 Conclusions

Using a CRM system for managing the relation with customers is a critical point in any company. It is essential, especially in a crisis situation, to understand customers and fit to theirs needs to hold them and maybe increase business with them. This cannot be done successfully without data mining using customized models for a company. Using CRM external modules for data mining is not the best option. The more flexible is to develop and use libraries for implementing customized algorithms and integrating them into the CRM systems interfaces. This is a very practical solution for giving the users the power for analyses and decisions.

References

[1] S. Onut, I. Erdem and B. Hosver, *Customer Relationship Management in Banking Sector and A Model Design for Banking Performance Enhancement*

[2] N. Kanellakis, Sage, *Software Change Management and Customer Relationship Management (CRM) Implementations: Planning for Success*, 2005.

[3] D. Arndt and W. Gersten, *Data Management in Analytical Customer Relationship Management*

[4] CFO Research, *Mining the values in CRM data: a CFO perspective*, 2002.

[5] H. Edelstein, *Building profitable customer relationships with data mining*

[6] P. Phelan and Frey, *Avoiding failure in large IT projects: new risk and project management initiatives*, Gartner, 2002.

[7] J. Han and M. Kamber, *Data Mining: Concepts and Techniques*, Elsevier, 2006.

[8] M. F. Hornick, E.Marcade and S. Venkayala, *Java Data Mining. Strategy, Standard, and Practice*, Elsevier, Morgan Kaufmann Publishers, 2007.

[9] M. J. A. Berry, G.S.Linoff, *Mastering Data Mining: The Art and Science of Customer Relationship Management*, John Wiley & Sons, Inc., 2000.

[10] F. Furtună, "A 3D Graphics Engine for Polyhedral Compounds using GDI+," *Open Source Science Journal*, Vol. 2, No. 2, 2010.

[11] M. Dârdală and A. Reveiu, I. Smeureanu, "Using DLL as Interface between API and VC#.NET Applications," *Informatica Economică*, vol. X, nr. 1, Editura INFOREC, Bucureşti, 2006.

[12] http://msdn.microsoft.com/en-us/library/bb928229.aspx

[13] http://msdn.microsoft.com/en-us/library/bb928227.aspx

Felix FURTUNĂ has graduated the Faculty of Cybernetics, Statistics and Economic Informatics. He holds a PhD diploma in Economic Cybernetics and Statistics. He is senior lecturer in Economic Informatics field and branches within Department of Economic Informatics at faculty of Cybernetics, Statistics and Economic Informatics from Academy of Economic Studies. He is the author and co-author of 7 books and over 30 articles in journal and proceedings of national and international conferences, symposiums, workshops in the fields of computer programming, object oriented programming, computer graphics, data analysis and data mining.

Alexandru BĂRBULESCU has graduated the Faculty of Cybernetics, Statistics and Economic Informatics. He is a PHD Student in the Faculty of Cybernetics, Statistics and Economic Informatics. He is assistant lecturer in Economic Informatics Department. He’s academic fields of interests are object oriented programming, programming algorithms and economic informatics. He is the author and co-author of many articles in the field of informatics systems for management.