How CRM is going to change the distribution sector in France

Jean-Louis Ermine, Daniel Lang, Philippe van Berten

▶ To cite this version:

Jean-Louis Ermine, Daniel Lang, Philippe van Berten. How CRM is going to change the distribution sector in France. 4th Research Conference on Relationship Marketing and CRM, Nov 2007, Brussels, Belgium. hal-02520445

HAL Id: hal-02520445
https://hal.science/hal-02520445

Submitted on 26 Mar 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

How CRM[1] is going to change the Distribution sector in France.

Jean-Louis ERMINE *Professeur, Directeur du Département SI* - I.N.T.- Institut National des Télécommunications
Daniel LANG *Enseignant chercheur en SI* - I.N.T.- Institut National des Télécommunications
Philippe VAN BERTEN *Chercheur en SI* - I.N.T.- Institut National des Télécommunications

I.N.T.- Institut National des Télécommunications
9 rue Charles Fourier - 91011 EVRY Cedex

Abstract

Helping business for over 15 years, CRM using data mining techniques convinced numerous marketers in various sectors. The distribution sector takes it in turn and is now on the verge of the mine made of proprietary databases supplied with the loyalty card applications.
This paper describes how the CRM becomes part of the management in Distribution and proposes a new systemic model relevant to the sector.

Keywords

Marketing, CRM, Data mining, Loyalty Program, Customer, Distribution, Patron.

[1] Customer Relationship Management

Content

1 Introduction

On 15 June 1963, CARREFOUR opened its first Hypermarket at Sainte-Geneviève des Bois, a southern suburb of Paris. Today the Hypermarkets' formula has been widely replicated, making the marketplace an extremely competitive one. Major French Distributors are Auchan, Carrefour, Casino, Intermarché, and Leclerc. In addition to those Hypermarkets, we have witnessed new formulas intended to target specific customer segments or geographical area: Hard Discount retail, various "Corner Shops" as convenience store formats, Cash & Carry outlets and most recently On-line stores.
The Hypermarkets' products range has become more sophisticated, adding goods labelled after the Distributor's brand. Initially set to be low-priced for high turnover, they later extend to increasingly differentiated and up marketed products (brands of organic, gourmet products, etc.).
Due to ever more regulation, economy slowdown, arrival of the Hard Discount, the environment pushes the Distributors to adapt and think about a new model.
In addition to the changes of the regulatory framework, the now better informed and more demanding customer wants better consideration. Numerous firms are shifting their focus to the customer, hence the increasing importance of customer relationship management (CRM) (Khalifa & al, 2002).
A major challenge for the retailers is to better manage their customer relationship. Based on powerful Data Warehouses gathering customers' purchase and behavioural pattern data, those organisations often attempt to transform raw data into usable knowledge. Data mining is then used to translate structured data into knowledge (Davenport & Grover, 2001).

Any released campaign takes a great deal of resources. Retailers need to measure their real impact, such as the number of new customers per campaign. They save data in large Data Warehouses (Franco, 1997), but knowledge on customer is still lacking. Main monitored indicators are based on sales (e.g. average sale per product and store) but indicators on customers are deficient.
Managing the Information availability is then a main concern: numerous variables impact on promotional campaign. The abundance of overlapping offers skews the evaluation of any particular campaign, making it impossible to know the impact of a given product promotion.
In this paper, we argue that data mining can make a significant contribution to improve knowledge on customer (Freitas, 2002). Our goal is to show how data mining techniques (Jiawei & Kamber, 2000) can be used in building this knowledge in order to improve the profit per customer ratio. Our research presents an initial model introducing the "Patron" concept, splitting the market and making room for the CRM as major part of the organisation.
This paper is organised as follows: Section 2 reviews the literature on CRM and data mining. Section 3 presents the case of a major Distributor in France. We show how data mining can transform data into useful knowledge on sales and promotional actions. Section 4 proposes a new business model.

2 CRM & Data Mining in the Marketing Literature

In this section, we give an overview of key definitions we intend to use in the paper. The concept of knowledge is typically approached through the "data-information-knowledge" sequence. Data are observations, facts or images. Formalized, filtered, contextualized and summarized date constitute information. Finally, information enriched by ideas, rules, procedures that allow actions and decisions constitute knowledge (Liebowitz, 1999). From the organizational perspective, knowledge is viewed as processed information embedded in routines, processes, products, rules and culture that enable actions (Beckman, 1999).

2.1 Data Mining

Depending on the research domain considered and on the goal to achieve, « data mining » encounters various definitions.
We share with Berry & Linoff (Berry & Linoff, 2004) [p.507] a definition that being quite wide though, matches the marketing interest within the distribution sector: "*Data mining is about the successful exploitation of data for decision support purpose, so the choice of variable can bring something to the decider*".
This definition keeps our attention to the variable choice, which puts this selection on the top of interest for marketer.

Giving another definition of data mining, Jambu insists on the variable as well, saying that "*data mining serves [...] as an estimate of unknown entity situation after known entities variables [...]. Every method bears on a cycle of [...] description, modeling and forecast.*" (Jambu, 1999)

2.2 Variables

A variable is a quantity or condition that can be usually measured and whose value may be subject to vary itself or depending on other variables[1].
For instance, the « age » variable is a condition that can be measured, vary itself, or depends on other variable (the age of a person depends on the «time» variable).

2.2.1 Classification of the Variables

Data mining in marketing being historically issued by statisticians, the following paragraph provides a simple classification of variables out of the statistical tools applied to the marketing domain.

The hereafter singled or coordinated attributes apply to the variables.

We can go first from a simple categorisation:

- qualitative or quantitative
- dependent or independent
- continuous or discrete

[1] aggregated definition from www.grand-dictionnaire.com and www.ebsi.umontreal.ca

The relationship that quantitative and qualitative variable have each other, making one to vary the same or opposite way of the other is called correlation[1] which is regularly represented by a theoretical line of best fit (representing a cloud of points) called regression line.

Up to more business goal oriented categorization:

Some authors (Jambu, 1999) prefer to consider the two first categories (qualitative, quantitative) and, like in surveys, divide each in:

- chronological,
- multiple answer,
- sorting variable (classification),
- preference variable
- class variable when the variable accounts for a large data values (categorical, incomes, satisfaction rate, age) e.g. age 0-4, 5-10 etc.

Other authors (Berry & Linoff, 2004), keeping in mind the data miner has to describe a database, propose a classification for numeric variable which value indicates its position along the corresponding axis:

- Categorical variables
- Ranks
- Intervals
- True measures

2.2.2 Qualification of the variables

We'll see that after handling the variable with an algorithm, the information issued can deliver more or less sense to the result. It adds qualification like discriminating or non-discriminating to the variable (Tufféry, 2002) [p.149]

The variables are then recognised as different and it is possible to clearly understand the difference between them. When a question is asked to the data miner, the important point is to identify the discriminating variable, meaning that any variation of this variable has measurable effect on the answer.

After this statement, any released model out of any data mining operation must be readable by the marketer and not remain a statistician issue.

[1] http://www.ebsi.umontreal.ca/jetrouve/illustre/gra_voca.htm#discrete

2.2.3 Suitable Variables for CRM

Within the distribution domain, it is now admitted that "*the current model of customer relationship in the marketing field tends to consider the customer as an asset of the retail company, introducing the customer life time value*" (Jong Woo K. &al, 2001).
The customer relationship management (CRM) comes after this paradigm, considering the customer no more as a mass market entity with few consideration for individuals, but as a single and valuable entity (Kale Sudhir, 2004). This concept though, in use for decades in the marketing literature and most of industrial sectors, is quite new in distribution in France where mass marketed catalogues are still the rule[1].
To "see at values of data over the time" (Berry & Linoff, 2004) [p.162] implies to select stable variables throughout the description level.
As customer's reactions to marketing efforts change over the time, only stable variables should be put in the columns.

The following list (Lefébure&Venturi, 1998) [p. 290] gathers independent variables considered at an early stage of the data mining process:

- Date of birth
- RFM (recently, frequency, monetary and type of payment)
- spending
- products & services purchased
- length of relationship
- additional products and services
- geography (size of city, address, telephone, Email and type of housing)
- gender
- child(ren)
- centres of interest
- occupation and length in position
- family situation

After showing that variable selection should be kept simple and limited, the choice of the right algorithm, being the miner's tool, is of primary interest.

2.3 Algorithms

The data miner has to consider applicability and constraints of his/her project, and have to cope with, in order to select the proper algorithm which most suits the project.
The choice of the right algorithm will consequently lead to put the choice of the variable at first.

If we want to use the data mining tools, we need to know more on the variable which has consequently to be strictly defined.
In order the work done with algorithms to be efficient, the selection of the variable must be properly made after clear categorization.

[1] Some French retailers drop in mailboxes up to 18 millions of the same paper copy catalogue, many times a year.

2.3.1 Descriptive Algorithms

Two categories of descriptive algorithms can be reported in marketing: the Clustering algorithms and the Market Basket Analysis.

2.3.1.1 Clustering techniques

Our natural tendency, as human being, is to break a complex problem into smaller pieces much easier to understand and manipulate.
Cluster stands for things gathered together in a small group, when segmentation stands for the division of something. Since the computer's hardware vocabulary took the word « cluster » to design actual small part of a drive, it is common to understand the « cluster » as a part of a database. The word « segmentation » can design the making of many partitions out of database, which are physically located on multiple clusters. A segment/part of a database can handle thousands or more data.
« Clustering » used as well as « segmentation » allows describing and explaining the structure of complex database. Many algorithms are supposed to do that and we list helpful ones in the marketing field.

The Hertzprung-Russel[1] diagram.
As the number of dimensions[2] (meaning here independent variables) increases, giving a n-dimensions space, it is necessary, in order to maintain a clear understandable 2 or 3 dimensions representation graph, to attribute a vector value to a particular point in this space. The value of each variable represents a distance along the corresponding axis in an n-dimensions space.

Kohonen network.
This type of clustering algorithm learns from data structure and doesn't intend to make any prediction over output variable. The characteristics of the structure allow the Kohonen network to identify clusters.

K-means clustering[3]
This nonhierarchical method initially takes the number of components of the population equal to the final required number of clusters. In this step itself the final required number of clusters is chosen such that the points are mutually farthest apart. Next, it examines each component in the population and assigns it to one of the clusters depending on the minimum distance to the center. The centroid's position is recalculated overtime a component is added to the cluster and this continues until all the components are grouped into the final required number of clusters (http://cne.gmu.edu/modules/dau/stat/clustgalgs/clust5_bdy.html).
With the K-means method, when a new member shall change the neighbors' centroids with the Kohonen method which in addition reduces the dimensions of the variables space.

McQueen's clustering
This iterative algorithm of KM clustering can be described with the help of the Infrared spectra. Infrared spectra are illustrated as points in a p-dimensional space (p is the number of features of the spectra). In this space a number of k points is initially chosen, where each point stands for a cluster to be made. Then, distance values between the points and all objects (spectra) are calculated. Objects are assigned to a cluster on the basis of a minimal distance

[1] also known as "main components analysis" or "multiple components analysis"
[2] dimension is each of the data which must be measured independently
[3] J.B. McQueen. In L.M. LeCam and J. Neymann (eds) Proceedings of Fifth Berkeley Symposium on Mathematical Statistics and Probability. 281-297 (1967)

value. Next, centroids of the clusters are calculated and distance values between the centroids and each of the objects are re-calculated. Then, if the closest centroid is not associated with the cluster to which the object currently belongs, the object will switch its cluster membership to the cluster with the closest centroid. The centroid's positions are re-calculated every time a component has changed the cluster membership. This continues until none of the objects has been re-assigned.

2.3.1.2 Market Basket Analysis

This algorithm is about the lookup of rules existing between variables in the form of the following statement: If *condition* then *result*. (Decker & Monien, 2003)
As it is still an "on statistics" based technique, the driven rules have to be measured in order to evaluate

- with a *support* index which is the probability the rule (condition and result) is true
- with a *confidence (or trust)* index which shows often when the "if" part is true that the "then" part is also true.

However, compared to a simple chance of the result being obtained, the rule reduces uncertainty. This enhancement is the *lift.*

This can be summarized as follow:
rule's lift = trust index/result probability =support/prob condition x prob result
The rule is efficient if the lift is >1 which means in actual marketing that action should be undergone if the lift is above a predefined value.

Market Basket Analysis produces three types of rules (Berry & Linoff, 2004) [p.319]: inexplicable, trivial and actionable, the latter being easy to justify and suggesting more prominent product placement.

Lesson learned from Clustering techniques
We saw from the K-means algorithm that the database can be divided in groups, but how many mutually exclusive groups exist in the database?
This is not as obvious as it seams in the distribution sector dealing with real people and hundreds of thousands of products. The data mining software, making computerised application of the described algorithms, are able to cluster a data base by segmenting too much, which can lead to almost as many cluster as individuals in the group. The data miner must make a relevant request which introduce subjectivity in the process.
It has been shown as well by Fitzpatrick (Fitzpatrick, 2001): "clustering is a very subjective method [which] gives always an even irrelevant solution".
Though clustering techniques provide true statistical result, it doesn't mean that the larger cluster comes first in term of marketing interest. Numerous marketing case studies have proven that great marketing successes came from "niches" that were simply ignored by statistical market studies.

2.3.2 Predictive Algorithms

2.3.2.1 Regression Analysis

"*Regression analysis uses software and professional expertise to search among available characteristics to identify the most important item: [...] independent variable which are able to predict response [...]. Regression analysis gauges the relationship between dependent and* *independent variables*" (Fitzpatrick, 2001), using the value of one in order to predict the value of the other (Berry & Linoff, 2004) [p.139].

Fitzpatrick (Fitzpatrick, 2001) proposes the following operations:

1. select the potentially independent variable
   - Recency, Frequency, Monetary (Derks, 1994)
   - geography
   - gender
   - age
   - presence of children
   - number of time mailed

2. assign a weight to each or rank each by order of importance

3. determine what you want to predict as dependant variable

2.3.2.2 Decision Trees

"*Decision tree is used to determine the most discriminating variable in order to explain the targeted variable*" (Tufféry, 2002) [p.125].

Formerly called « relevance trees » or « tree classification technique » (Green, 2004), and described as a set of if/then statements (Jambu, 1999)[p.47], decision tree is an inductive technique (Parks, 2004) used for classification and prediction.
The decision tree discriminates classes of objects and works for continuous and discrete variable. A classification/regression tree partitions a data set in discrete subgroups based on independent variable.

Many other decision trees exist such as:

- Chi-square Automatic Interaction Detector (CHAID) for detecting statistical relationship between the variables.
- Fischer's test which provides a measure of the probability that samples with different means and variances come from the same population.
- Classification and Regression trees (CART) which is a pruning algorithm that identifies sets of subtrees and contributes to increase purity as long as new splits can be found.
- C5, a decision tree algorithm released by J. Ross Quinlan, which uses the same data set to grow and prune the tree.

The decision tree algorithm appears at a very early stage of the data mining process, and some authors (Berry & Linoff, 2004) [p.209] recommend it at the beginning of any data mining project and specify that it is a good choice when the task is:

- Classification
- Prediction of discrete outcomes

Generating rules with decision trees is easily translated into natural language or SQL[1]. Features that are most important predictors for the wanted purpose have to be put at the upper level of the tree.

With decision tree, it is fairly easy to follow the path through the tree to a particular leaf, and easy to give explanation for any prediction or particular classification. The robustness of a decision tree comes at the cost of throwing away some of the information available in the training data.
However, decision trees can identify the most informative features in the data relative to a particular outcome (Berry & Linoff, 2004) [p.507].

The variable selection problem is a common issue for statisticians and in practice, decision trees provide a good method for choosing the best variables: "segments (the place where the customer is put) are built with respect to a marketing goal such as subscription renewal or high spending levels. Decision trees techniques are ideal for this sort of segmentation (Berry & Linoff, 2004) [p.112 & 233]."

Other advantage of the decision tree is its ability to make outcomes understandable and to deliver rule that can be readily expressed in (plain) English (Jambu, 1999).
This opinion is widely shared among the authors, this technique being highly interpretable and intuitive.

2.3.2.3 Neural Networks

After disappointing results in the 1950s, the Neural Network algorithm based on similarity with the brain histology came back in the 1980s thanks to the "back propagation" published by John Hopfield (Hopfield, 1982).
Nowadays, Neural Network algorithms are part of statistical tools and are used in segmentation, classification, prediction, in various domains such as automated handwriting recognition, signal analysis, weather forecast etc.

Neural networks work best when there are only a few input variables. Though the power of this algorithm grows with the size and number of layers, the risk of overfitting is real.
This technique itself doesn't help choose which variable to use.
"Other techniques such as decision tree can come to the rescue" (Berry & Linoff, 2004) [p.255]. A combination of decision tree to select variables and of Neural Network which is good at classification and at prediction, should produce a good model.
However, Neural Network cannot explain what it is doing and cannot produce an accurate set of rules.
Making sense of this is described as beyond our human powers of comprehension and since Tufféry (Tufféry, 2002) [p.125] states that "neural network isn't good at marketing", we must keep in mind that putting this algorithm at work requires great attention.

2.3.2.4 Genetic algorithm

The last data mining algorithm we briefly describe is an analogy with genetics.

[1] Structured Query Language after simple structures as tables are proposed for storage by Edgar Frank Codd '*A relational model of data for large shared data banks*' Association for Computing Machinery magazine, June 1970, Vol. 13, No. 6, pp. 377-387

Discovering the predictive or classifying most adapted rules existing during interaction between the variables leads to genetic algorithms[1]. The said rules can be a set of variables that describes real people as for instance: gender, aged 35-50, homeowner, with monthly income>3k€.

Genetic algorithms have three steps (Tufféry, 2002) [p.146]:

1. primary rules setting from randomised number of variables
2. selection of the best rules which implies the analysis of the past behavioural variables analysis; e.g. within a rule, knowing the percentage (see the amount required infra) who did buy which product leads to select stable rules that can be hold for future use.
3. new rules production after mutation or crossing-over of rules previously held at step 2 maximise the fitness of individuals (the discovered rules)

The application of those three processes produces a new generation which fitness should be greater than the original (Berry & Linoff, 2004) [p.446].

In conclusion, we strongly encourage (Berry & Linoff, 2004) [p.233] the data miner, after selecting algorithm and variable, to use intuition, to start with a handful of variables that make sense and to experiment by trying other variables to see which one improves the model.
Figure 1 summarizes the process.
When the choice of the variables is done, feeding properly the data base, it is then interesting to identify "*the customers who have the potential of highest value to the firm*" (Jong Woo & al, 2001).

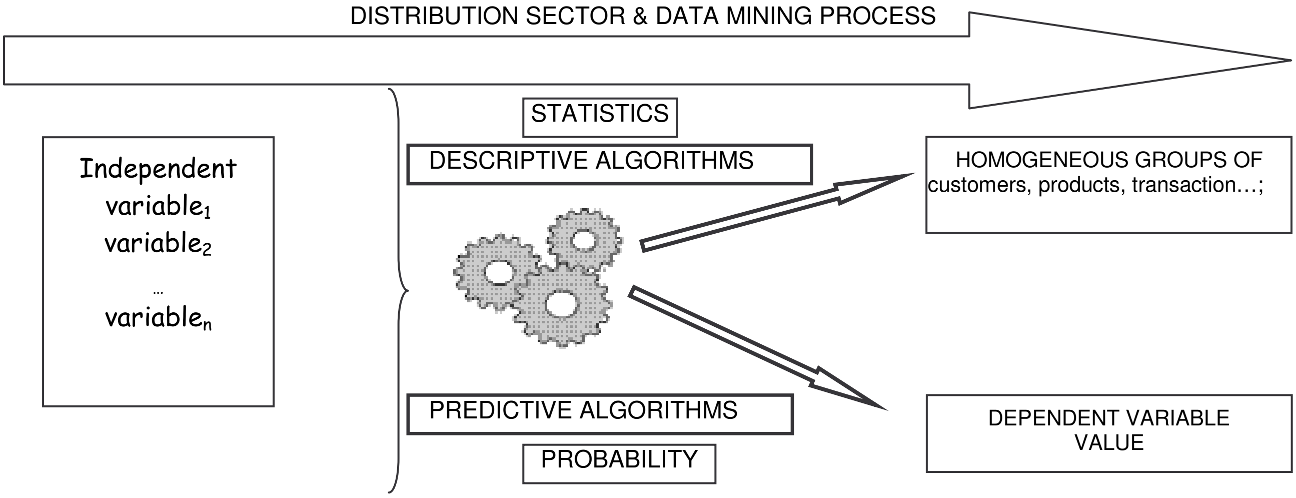


Figure 1 Data mining process within the Distribution Sector.

[1] See John Holland and genetic algorithms circa 1970

2.4 CRM

This concept though, in use for decades in the marketing literature and most of industrial sectors, is quite new in distribution in France where mass marketed campaigns are still the rule[1].
Today, companies' wealth relies on their customers' loyalty. Information gathered, added to efficient knowledge management, is the key points of success of any CRM project (Tufféry, 2002) [p.5]. We extract from the literature what causes CRM's success or failure.

Success first (Reinartz & al, 2004) with the model shown Figure 2 built up after a survey of over 200 companies having led a satisfactory CRM project:

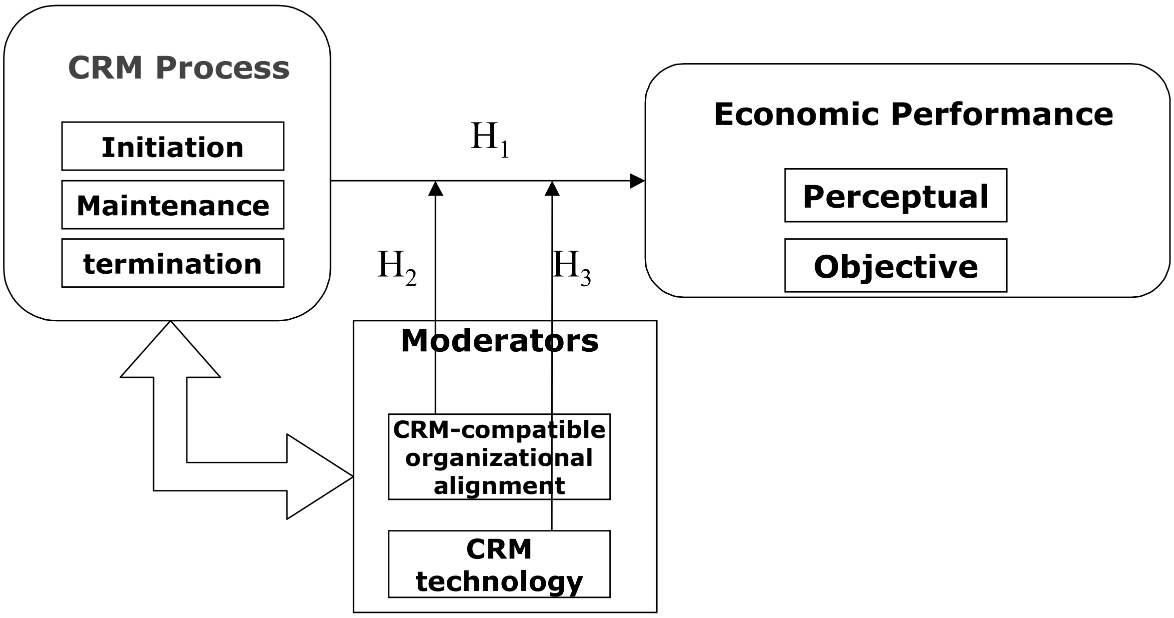


Figure 2 Reinartz, Kraft, Hoyer CRM success model

Failures of CRM Projects (Kale, 2004) have their origin in the mismanagement of many stages of the process. Considering CRM as technology, lack of customer centric vision, ignoring the customer's life time value and long-term relationship, poor involvement of both executives and employees, bad conversion of information into knowledge are major failure causes.

[1] Carrefour among others drops in mailboxes up to 18 millions of the same paper copy catalogue, many times a year!

3 From Data Mining to CRM, a case study

3.1 First Project out of Proprietary Credit Card

A large distribution company in France running over 200 hypermarkets has provided to its willing customers a proprietary credit card program for over 20 years up to date. The customer has to pay for and must provide name, address, household income and banking reference when filling up the card application. The marketing management decided in 2001 to link the cashier ticket database to those informations in order to obtain a purchase behavioral typology and subsequently better customer knowledge.

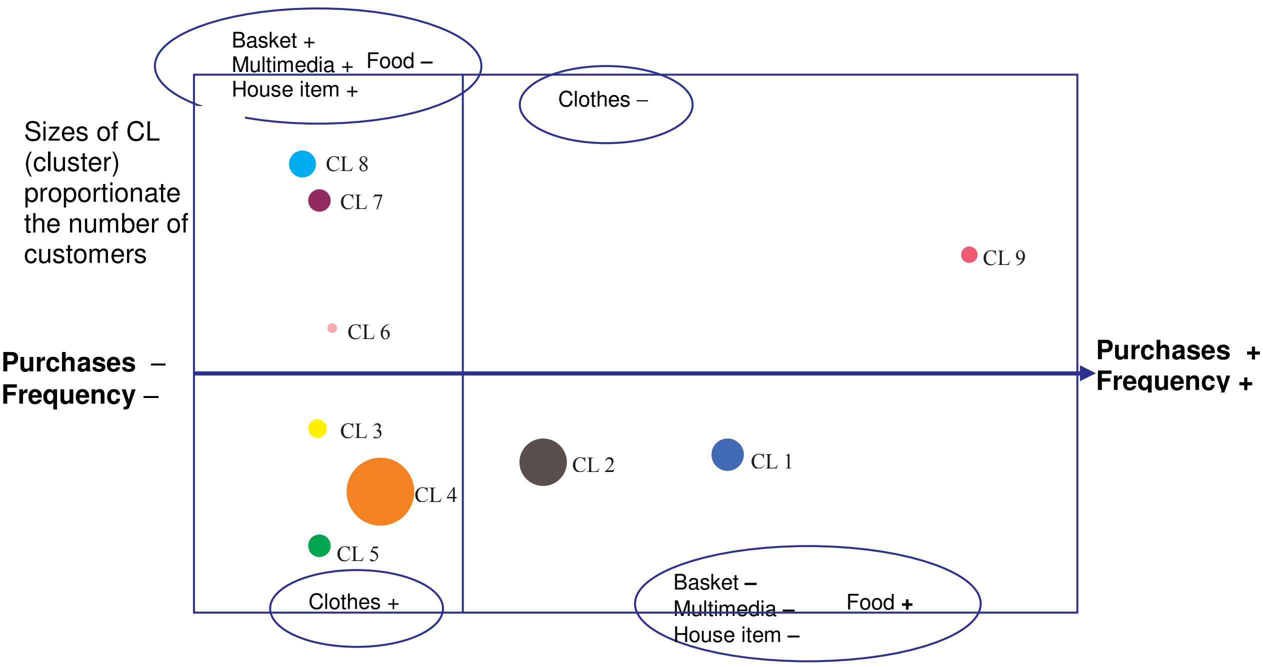
3.1.1 Methodology

The first step shown Figure 3, as in any database exploration of a data mining process consists in establishing a clear objective to the project (Tufféry, 2002). Segmentation is done into relatively homogeneous, sizeable, responsive to marketing effort and stable over the time groups. The then analyzed variables after the credit cardholder tickets are listed on column 1 of Table 1 below.
The second step, after obtaining a typology, makes the data miner wonder for each cluster what the purchase behavior per store section is.

The data mining is done using the SQL language running an Oracle hosted database.
The tickets' database is processed by Informix base™.
The SAS™ Enterprise Miner module is part of the process.
Main components analysis (see§2.3.1) gives the essential components of the customer's database and from there determines clusters. The result got tested with many trials, checking that each individual belongs actually only to one cluster. It is important that the testing rule pays attention to individuals who don't switch clusters when the targeted variable changes.

3.1.2 Released Model: a behavioral typology.

Figure 3: a two dimensions representation of the segmentation into nine clusters.



Using a classification tree (see §2.3.2) on the clusters gives the following result. For instance, from cluster Nr.3, when the question is about the most attended store's sections.

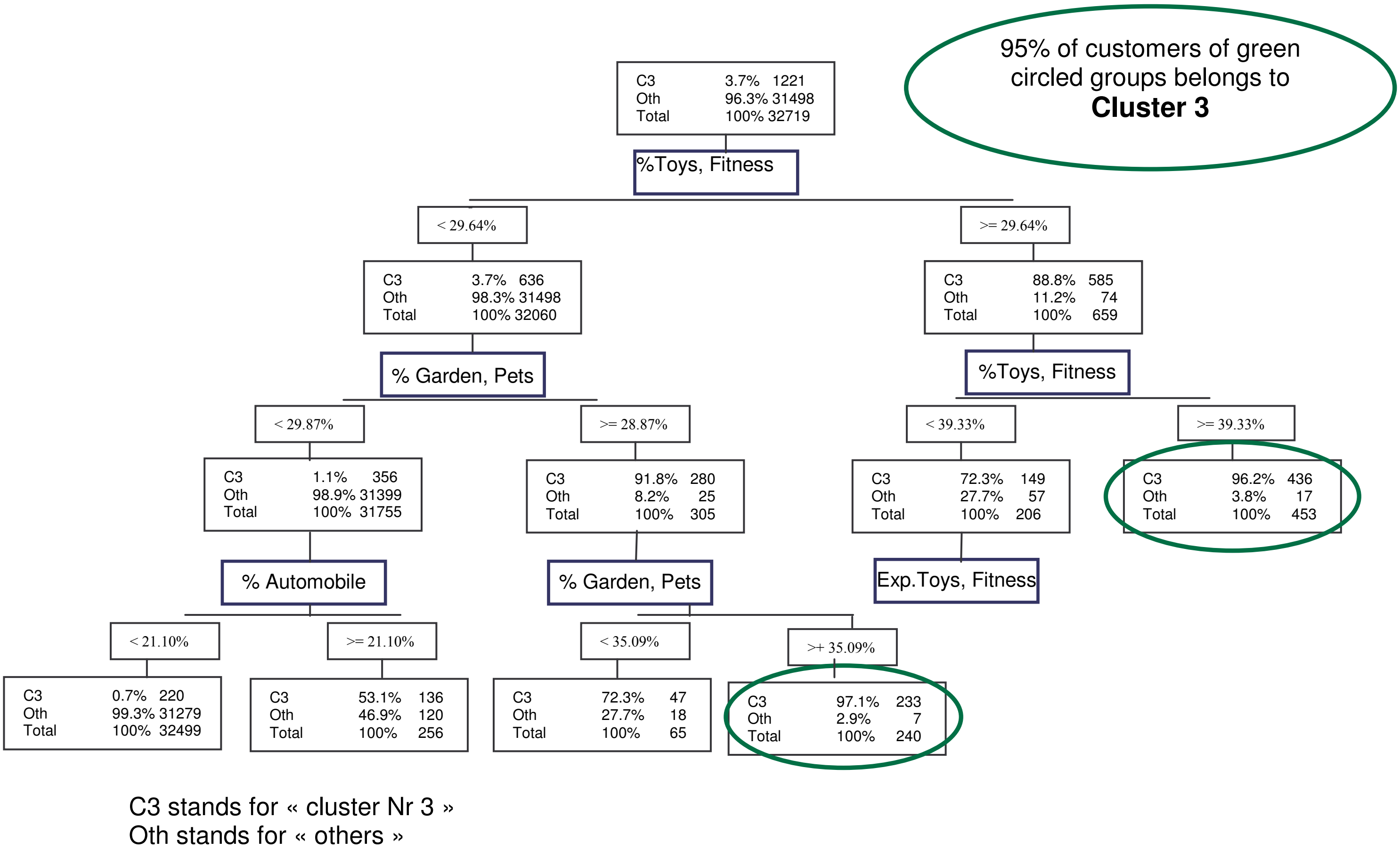


Figure 5: Purchase behavior per store section

What do cluster Nr.3 customers buy the most?
Figure 5 shows that 96.2% buy toys and fitness products and 97.1% shop at Garden & Pets department.

At this point, let's quote the data mining project manager comment:

"*The Main components analysis method is descriptive and the classification tree method is predictive. Decision trees are part of a modelling process able to predict a percentage of return on a targeted variable.*"
However, this segmentation and per cluster's predictive tree did appear useless to the marketing team. Knowing that such type of client behaves in such a way doesn't tell which marketing action or targeting means to undertake.

3.2 Current Project out of loyalty card program

"*Our past experience (§3.1) discourages us to get numerous groups of customers*," the data mining manager said, thinking that the remaining issue of the first project was linked to the amount of clusters.
The data mining work was given up after the failure of this first data mining project.
However, under the market pressure, being the only large distribution chain in France with no loyalty card program, the marketing management decided in 2004 to launch a new fidelity card.
The application that the customer has to fill up in order to get this card gathers various informations.
As an introduction of this new list of variables, let's compare the specificity of this card with the proprietary credit card: Name, Address, Occupation and Household's income are common to the two applications. Comparison of the remaining variables is shown on Table 1.

proprietary credit card project-**2001**	loyalty rewarding card project-**2004**
• frequency ➢ monetary ❖ monthly basket value ❖ number of basket's items ❖ percentage of per store's section expense ❖ per type of brand expense (distributor's, national brands, first price's) not a free card used as a regular credit card.	• frequency ➢ monetary ❖ store's sections expense ➢ geography ➢ date of birth (of both spouse if available) ➢ phone & email ➢ household party with DOB & gender of children ➢ single house Y/N • other cards hold from competitors Y/N ➢ center of interest : multiple choice of 12 possible • already proprietary credit card holder ❖ other services member (kid's club) free card not a debit, nor credit card.

Table 1 Evolution of the variables' selection

❖ data linked to the products offer,
➢ data linked to the customer's personal information

Table 1shows an amazing difference between 2001 and 2004, the data linked to the product's offer go from 4 to 2 when the data linked to the customer's personal information go from 1 to 7. Is it a clue that CRM is on the track?

The data mining made out of this new multi-million loyalty cards database extracts monthly reports on customer's expense. (Table 2)

monthly expense	June - 04	July - 04	Aug. - 04	Sept-04	Oct-04	Nov-04
Gold	484,2	442,5	437,2	456,7	454,2	477,6
Silver	179,6	186,7	183,2	191,2	197,4	199,9
Bronze	89,7	104,4	106,2	107,8	112,1	111,3
Switcher	36,7	48,2	53,0	55,3	58,6	59,7
Total store holder	253,8	230,1	223,6	242,7	239,1	247,9
Total holder exploitation	260,2	254,6	241,0	252,8	256,6	259,8

Table 2 : remains from the 2001 project, a four segment clustering of the database.

% Card Holders expenses				
	Store		Region	
Business Income rate	54,4%	⬀	53,2%	⬀
Food purchase rate	59,3%	⬀	58,3%	⬀
Non Food purchase rate	44,9%	⬀	44,8%	⬀

⬀ comparison with previous month

Table 3 Report (partial) sent monthly to store's manager

Figure 6 below is obtained by crossing information from fidelity card with phone book directory and produces an accurate map of card-holders geographical location which is provided to the stores managers.

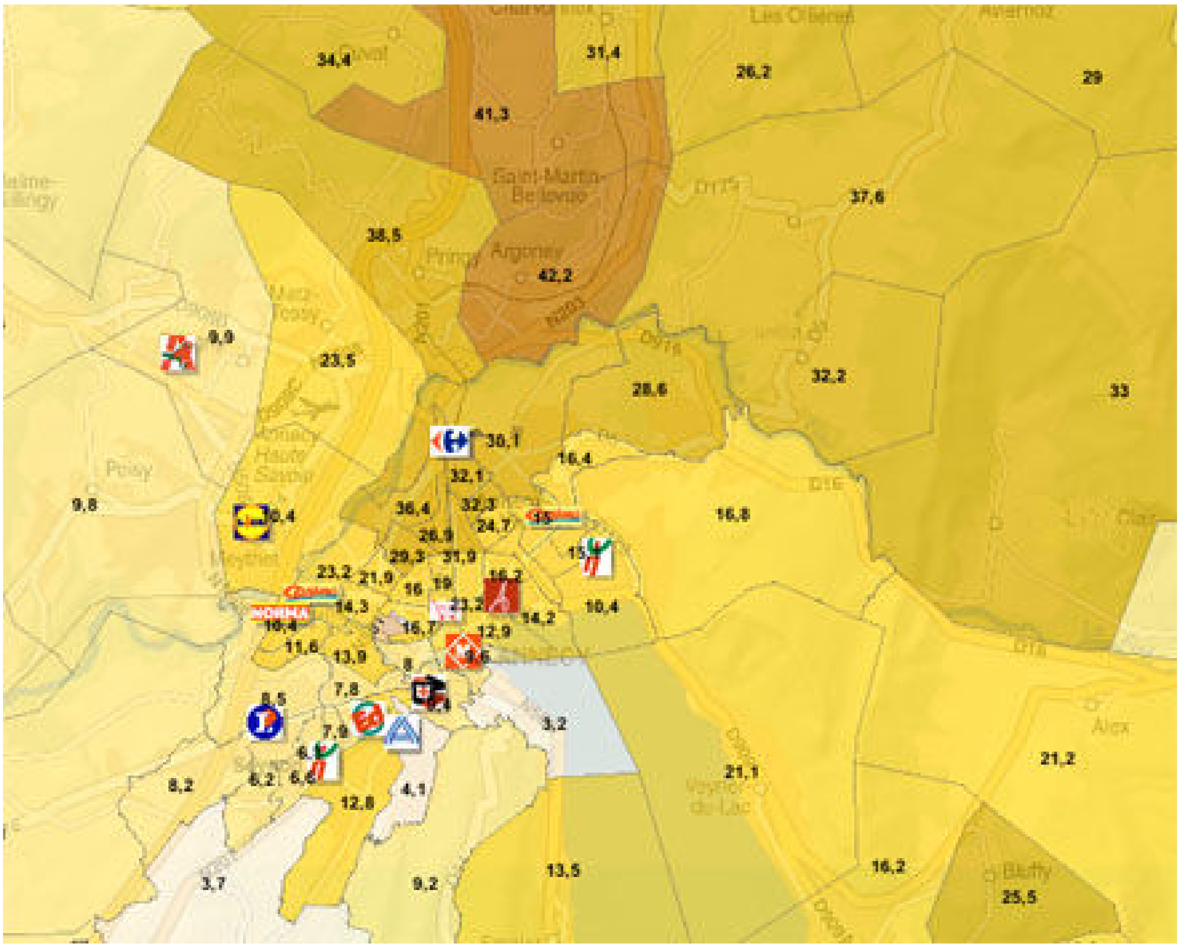


Figure 6: Map of Cardholder’s rate showing location of competitors.

Another part of the reporting concerns the product and special offer of the fidelity card. This will allow measuring the return’s rate of targeted customers.

At this early descriptive stage of the project, the stores managers have already changed their perception of the clientele. The data sheet obtained from the data mining department gives a clear picture of a few variables. In term of market knowledge, this makes a big difference with the former reports driven out of panelists surveys.

Through the evolution of these two projects, it is clear that the data mining within the distribution sector leads to CRM. Moreover the lesson learned from the first project failure added to literature’s recommendation provide a stable panel of essential variables which have to be harvested directly out of an application, filled up by the client at registration time.

4 The issue: Distribution, Marketing and CRM

The question that any CRM project must answer is how to improve the quality of the relationship between the company and its loyal customers and subsequently how to increase profit per customer. This purpose need, as an essential matter of success, mastering information provided by or gained on customers (Tufféry, 2002).

On Figure 7 below S. Tufféry (2002) proposes to summarize this statement.

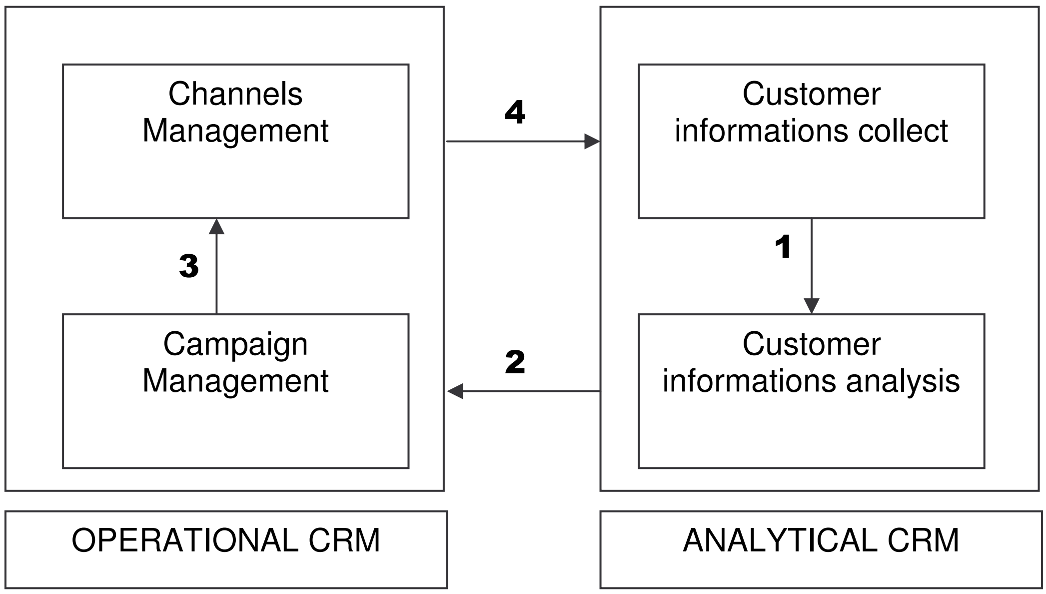


Figure 7: Customers Relationship Management after S. Tuffery, 2002

This model splits Analytical and Operational CRM and inspires the upper part of Figure 8.

At this point, a systemic model which could incorporate CRM techniques supplied with data mining processes and marketing in the distribution sector is needed.
Mixing Tuffery's model with our empirical analysis of the case study above leads us to Figure 8 below.

4.1 When Patronage is changing the rule: a new marketing model in Distribution

Up to date, many generations of marketers used, after J. McCarthy & Neil H. Borden the well known Marketing Mix "4 P", product oriented, strategy. As a reminder of this mnemonic, let's introduce a Customer oriented "4 P" within the distribution sector:

- The Patron (Collins, 1992) [p.1053] holds a loyalty card.
- The Panelist belongs to classic panels used in market studies.
- The Prospect is potentially a client who actually never came to the store.
- The Purchaser shops the store but hasn't signed up the fidelity program.

This concept of "Patron" is essential to the following model on Figure 8.

Since the fidelity, loyalty or rewarding card programs are now part of the basic offer within the distribution sector in France, it is time to consider the then card-holders as a special entity, out of the environment and therefore out of the traditional market.
The issue is no longer to bring products to the mass-market through a distribution organization but how to use accurate Knowledge gathered on "voluntary captive" customers to sell more and tune up the offer.
Strong knowledge on customers is a tremendous competitive advantage that no company can ignore any more.
The distribution sector may use the computerized power of the data mining tools to enhance this Knowledge. Customers become Patrons, thanks to those special programs.
Large amount of customers of the distribution sector wants to be rewarded and treated. They're ready for tight cooperation with distributors, willing to patronize them with a win-win relationship.
We suggest that the concept of "Customer Knowledge inside the company" is embedded to the model.

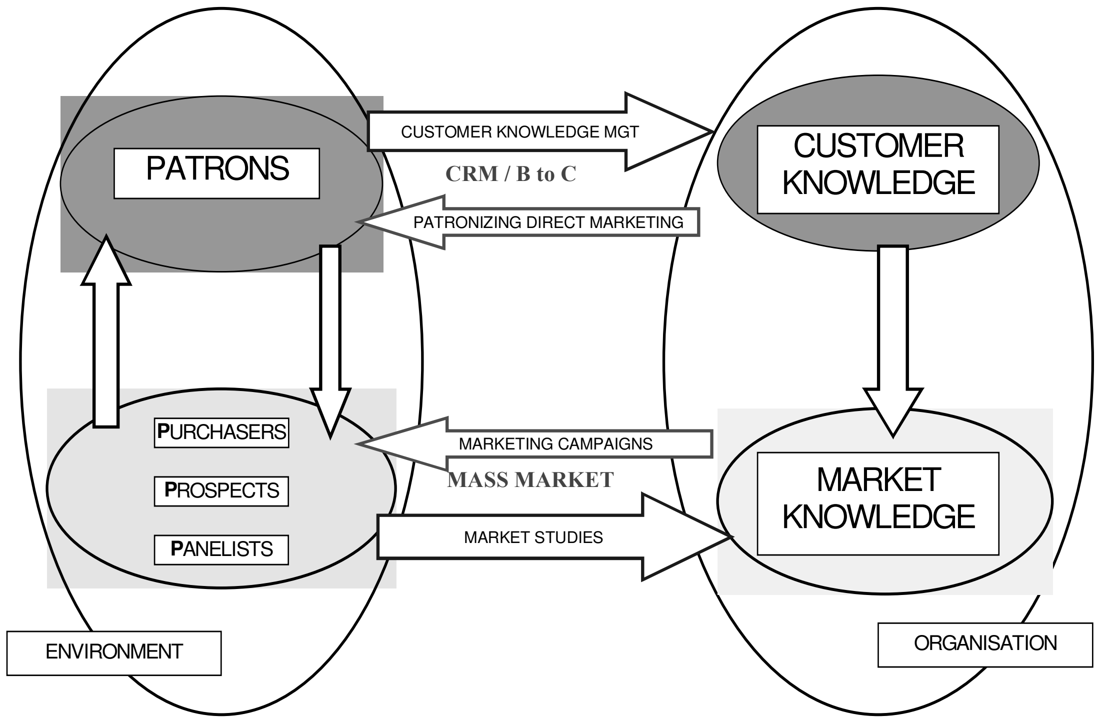
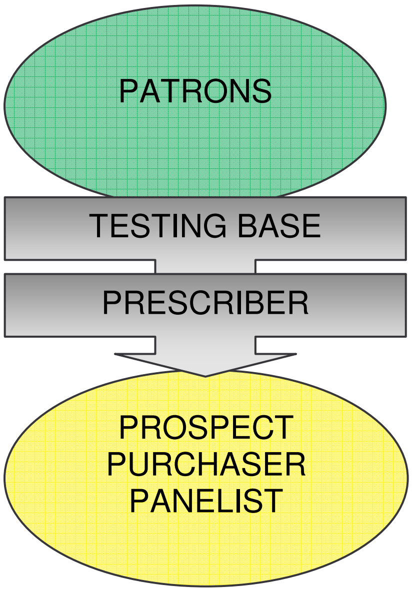


Figure 8 CRM & Distribution, the "CRM/Patron" Model.

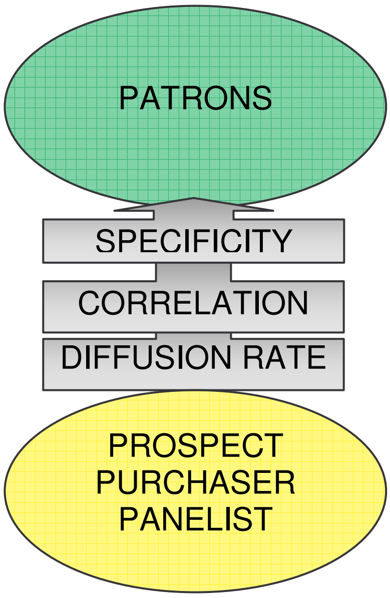
4.2 Testing the model

As a test set of the model, we propose to test the relationship represented by the vertical arrows. First from the loyalty card database down to the three remaining “P”:



To what extend should the Patrons database be taken as an actual test base of the rest of the environment? Geography and Size of the Patrons database are for sure variables to be observed in order to answer this question.
What is the recommendation effect coming from the Patrons group as Prescriber of the loyalty card to the environment? Adding a question to the fidelity card application or making a survey on the reason why people of the “3P” group join the program should make it.

Exploring the other arrow going up, three variables should be tested:



The diffusion rate of the card should measure external influences (media, cashier's recommendation, in store animation, etc.) onto the process.
Correlation between the "3P" and the "Patrons" should be tested in order to found the variables involved. Knowing if the Correlation summarizes "diffusion" and "specificity" or if it is a separate factor will enhance the model as well.
Last but not least, since we do expect more ideas to come, is the Specificity of the "3P" switching over to the "Patrons". Which variable is specific to the people who sign up the card application? Becoming a "Patrons" obeys not the same motivation at the beginning of the loyalty program and after this group gathers multi-million members. What size of the "Patrons" group makes "Specificity" to be considered? Answering this question will give strong value to the arrow up.

As soon as those tests are performed, running the model clockwise gives to the marketing management a much powerful tool. Out of the CRM, easy retrieval of knowledge on the "Patrons" and consequently on the "3P" allows accurate targeting through marketing campaign already tested and which efficiency is measured thanks to the proprietary database. Moreover, it is obvious that this new business model in Distribution is very attractive to the Brands. The approach of the market, changed in a direct approach of the customer through the Distributor's database unbalances the Distributor/Brands relationship. This point should also bring brick to the model.

This model gives a much more accurate and predictive measure of the ROI of the marketing campaign. Giving to the distributor hand on its customer by no more relying on external market studies, the Patron Model on its upper part (Figure 8) makes market studies and from there deducted marketing mix obsolete. Further research will say how those classical studies shall adapt to the arrival of the CRM/Patron management within the Distribution sector and how the model gets improved.

5 Conclusion

The 2001 and 2004 data mining projects of DDD-France, a large Distributor, brought independent variables describing the customer. Statistical work out of the market basket has proved to produce model non-suitable for marketers. Gaining expertise on the issue, this distributor is, in 2005, still working on a data mining project embedding as many independent variables as possible out of its proprietary fidelity card program. This project, at its 2004 first stage, produced reports delivered to the stores, bringing a sharp picture of the fidelity card-holder behavior.
Managing this new knowledge on customer is expected to bring a competitive advantage.
The emergence of CRM inside this type of organization obliges their forty years old business model to evolve.
As shown on model Figure 8, Knowledge management, CRM and Patronizing become now an essential point of any marketing strategy within the Distribution Sector in France. Long after other sectors such as Banking, Insurance, Remote Sale, this will allow the switch from the Mass-Market towards the Business to Customer model thanks to unlimited data storage capacity, efficient algorithms and well performed CRM.

6 References

Almquist Eric, Wyner Gordon. (2001) *'Boost your marketing ROI with experimental design'*, Harvard Business Review. Oct. 2001, Vol.79, Issue 9, p.135, Boston.

Berry Michael J.A, Linoff Gordon S. (2004) *'Data mining techniques'*, Wiley, Indianapolis.

Collins, Cobuild (1992) English Language Dictionary, HarperCollins Publishers, London.

Crone Sven F, Lessmann Stefan, Stahlbock Robert. (2004) *'Empirical Comparison and Evaluation of Classifier Performance for Data Mining in Customer Relationship Management'* Proceedings of IEEE International Joint Conference on Neural Networks, 2004 (IJCNN 2004), vol.1, pp.443-448, Budapest.

Decker Reinhold, Monien Katharina. (2003) *'Market basket analysis with neural gas networks and self-organising maps'*, Journal of Targeting, Measurement and Analysis for Marketing. Jun. 2003, Vol.11, Issue 4, p. 373, London.

Derks Richard P. (1994) '*Business trends : The competitive advantages of data base marketing'*, Information Strategy : The executive's Journal. vol. 10, no 3, pp. 5-11, New York : Auerbach Publications Inc., Spring 1994

De Ville Barry. (1997) *'Intelligent Tools for Marketing Research'*, Marketing Research. Spring 1997, p.40-43, Chicago.

De Ville Barry. (1998) *'SAS Enterprise Miner-First Looks'*, Marketing Research Spring 1998, Vol.10, Issue 1, p.37-41, Chicago.

Franco Jean-Michel, EDS-Institut Prometheus. (1997) *'Le Data warehouse, le data mining'*, Eyrolles, Paris.

Fitzpatrick Michele. (2001) *'Statistical analysis for direct marketers in plain English',* Direct Marketing, Hoke Communication Inc., Aug.2001, Vol.64, Issue 4, pp.54-56, New York.

Freitas Alex A. (2002*) 'Data mining and knowledge discovery with evolutionary algorithms'*, Springer, Berlin, New York.

Green Paul E., (2004) *'Practice makes perfect'*, Marketing research, vol. 16, no 2, pp. 8-14, Chicago : American Marketing Association, Summer 2004

Jiawei Han, Kamber Micheline, (2000) *Data mining : concepts and techniques.* San Francisco : Morgan Kaufmann Publishers, August 2000

Hopfield, J. (1982) *'Neural Networks and Physical Systems with Emergent Collective Computational Abilities.'* Proceedings of the National Academy of Sciences, 1982:79:2554-2558.

Jambu Michel, France Télécom-CNET. (1999*) 'Introduction au data mining : analyse intelligente des données'*, Eyrolles, Paris.

Jong Woo Kim, Byung Hun Lee, Michael J. Shaw, Hsin-Lu Chang, Matthew Nelson. (2001) *'Application of Decision-Tree Induction Techniques to Personalized Advertisement on Internet Storefronts'*, International Journal of Electronic Commerce, Vol.5, Issue 3, p.45-62, New York : M.E. Sharpe Inc., Spring 2001.

Kale Sudhir H. (2004) *'CRM Failure and the Seven Deadly Sins'*, Marketing Management, Sep.-Oct. 2004, Vol.13, Issue 5, Chicago: American Marketing Association.

Lefébure René, Venturi Gilles. (1998) *'Le data mining'*, Eyrolles, Paris.

Lefébure René, Venturi Gilles. (2001) *'Data mining : gestion de la relation client, personnalisation de sites web'*, Eyrolles, Paris.

Mladenic Dunja. (2003) *'Data mining and decision support: integration and collaboration'*, Kluwer Academic Publishers, Boston, London.

Morin Annie, Bosc Patrick, Hebrail Georges. (2002*) 'Bases de données et statistiques'*, Dunod, Paris.

Naïm Patrick, Bazsalicza Mylène. (2001) *'Data mining pour le web : profiling, filtrage collaboratif, personnalisation client'*, Eyrolles, Paris.

Parks Liz. (2004) *'Nectar Finds Loyalty's Sweet Spot'*, New York Stores, Jul.2004, Vol.86, Issue 7, p.66, New York.

Peacock Peter R. (1998) *'Data mining in Marketing'*, Marketing Management, Winter 1998, Vol.6, Issue 4, p.8-19, Chicago.

Perner Petra. (2002) *'Data mining on multimedia data'*, Springer, Berlin, New York.

Pearson Nigel. (2005) *'Customer management requires top-to-bottom company culture'* Precision Marketing, Feb.2005, p.12.

Popper Karl R. (1934) '*Logik des Vorschung'* Julius Springer, Wien.

Pyle Dorian. (2003) *'Business modelling and data mining'*, Morgan Kaufmann Publishers, Amsterdam, Boston.

Reinartz Werner, Kraft Manfred, Hoyer Wayne D.(2004) *'The customer Relationship Management Process: Its Measurement and Impact on Performance'* Journal of Marketing Research, Aug.2004, p. 293-305.

Tufféry Stéphane. (2002) 'Data mining et scoring : bases de données et gestion de la relation client', Dunod, Paris.