*Iranian Journal of Management Studies (IJMS)* *http://ijms.ut.ac.ir/*
*Vol. 11, No. 1, Winter 2018* *Print ISSN: 2008-7055*
*pp. 91-111* *Online ISSN: 2345-3745*
*DOI: 10.22059/ijms.2018.242718.672842*

# Matrix Sequential Hybrid Credit Scorecard Based on Logistic Regression and Clustering

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(Received: August 31, 2017; Revised: December 26, 2017; Accepted: January 7, 2018)

## Abstract

The Basel II Accord pointed out benefits of credit risk management through internal models to estimate Probability of Default (PD). Banks use default predictions to estimate the loan applicants' PD. However, in practice, PD is not useful and banks applied credit scorecards for their decision making process. Also the competitive pressures in lending industry forced banks to use profit scorecards, which show the profitability of customers. Applying these scorecards together makes the loan decision making process for banks more confusing. This paper has an obvious and clean solution for facilitating the confusion of loan decision making process by combining the credit and profit scorecards through introducing a matrix sequential hybrid credit scorecard. The applicability of the introduced matrix sequential hybrid scorecard results are shown using data from an Iranian bank.

## Keywords

Credit scoring, banking industry, credit scorecard, profit scoring, matrix scorecard.

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## Introduction

Credit scoring is used widely in banking industry. Banks use individuals' and companies' information to determine their profit and credit risk. Credit scoring is one of the main issues in the process of lending (Van Gestel & Baesens, 2009). It is used to answer the question of what the probability of default is. Credit scoring uses banks' historical loans and external credit scoring/rating bureaus' reported data to classify customers as good or bad, but banks faces some serious constraints by the application of the probability of default including regulation compliances and customer satisfaction.

Credit scorecards fill this gap intelligently (Hand, 2005; Koo et al., 2009; Dong, et al., 2010; Hand & Adams, 2014). The competitive pressures in lending industry forced banks to use profit scorecards which show the profitability of customers. Applying profit scorecard with credit scorecard together makes the loan decision making process for banks more confusing. Therefore, matrix sequential hybrid credit scorecards are introduced (Siddiqi, 2017).

## Literature Review

Credit scoring is a classification problem. There are many techniques suggested to perform classification on the credit scoring problems including statistical and mathematical programming, and intelligent techniques.

Mathematical programming approaches to the credit scoring problem, as a mathematical problem in which there could be a hyperplane that can separate the good applicants from the bad ones; the objective function of the mathematical model is to minimize the errors of that hyperplane; it is a traditional method and is not used recently. Logistic regression and discriminant analysis are the most favorite statistical methods used to assess the credit score (Wiginton, 1980). There are many intelligent techniques applied to the problem including support vector machines, case based reasoning, decision trees, Bayesian networks, neural networks and etcetera. Ben-David introduced a method for rule pruning (Ben-David, 2008). Hoffmann et al. provide a new learning method for fuzzy rule induction based on the evolutionary algorithms (Hoffmannet al., 2007). Martens et al. used the SVM for rule induction (Martenset al., 2007). There are studies that show intelligent techniques including decision trees, support vector machines, neural networks, and others are superior to statistical techniques (Huang et al., 2004; Onget al., 2005; Crook et al., 2007), and some studies show their vulnerability changes due to population characteristics (Thomas, 2009).

Because of the auditing process done by auditors, and transparency and robustness, banks cannot use many of the mentioned black box techniques including NN and SVM (Thomas, 2009). By using credit scorecards, banks can easily interpret the results and explore the rejecting reasons to the applicant and regulatory auditors.

There is a good literature in the field of credit scorecards. Usually, classification trees, logistic regression, linear programming, and linear regression have been used by banks to develop credit scorecards (Dong, et al., 2010). logistic regression is the most commonly used method due to its distinguishing features (Thomas, 2009). In a credit scorecard, there are some extracted features, each feature is categorized in different ranges; according to the feature value, decision trees or other usual discretization techniques are used, then a point or score is allocated to each range using logistic regression. By multiplying the points by a number, which is usually a multiple of ten, the final score is obtained. Finally a cutoff point is selected to finalize the loan decision making.

Competitive forces for banks in recent years make single credit scorecards non-competitive. Dual or multiple scorecards fill this gap. There is a little literature in the field of multiple credit scorecards. Siddiqi introduces three methods to implement multiple scorecards (Siddiqi 2017); Sequential, in which the applicant is scored on each scorecard sequentially for different reasons including fraud, bankruptcy, external bureau and etcetera; Matrix, in which multiple scorecards are used simultaneously with decision making based on a combination of the cutoffs for various scorecards, and finally, Matrix-sequential hybrid, in which a hybrid of the previous methods are applied, whereby applicants are prequalified using a sequential method, and then put through a matrix method. Chi et al. introduced a Matrix scorecard by combining the internal behavioral score and credit bureau score (Chi & Hsu, 2012). They also introduced the appropriate strategies for retention and collection.

Table 1 shows the structured review of the problem space, the horizontal line shows the problem solving category and the vertical line shows the types of credit scorecard which are categorized into enterprise companies, small and midsize technology companies and individual applicants.

**Table 1. Structured Review**

| Reference | Contribution | Type of scorecard |
|---|---|---|
| (Whittaker, 2007) | A dynamic scorecard for monitoring baseline performance | single |
| (Bonacchi, 2008) | drivers of customer profitability in the internet sector | single |
| (Koo, 2009) | number of cut points is extracted using simulated annealing | single |
| (Dong, 2010) | logistic regression with random coefficients | single |
| (Choy, 2011) | determine the optimal performance period and bad definition for credit scorecard | single |
| (Chi & Hsu, 2012) | Single discretization and regression | matrix |
| (Schreiner, 2014) | Micro lending in Bosnia-Herzegovina using logit | single |
| (Gao, 2016) | Loan origination decisions using a multinomial scorecard | single |

This paper looks forward to answering the key questions: “Can we build a model which can combine the profit and credit scoring attributes to make the final decision of lending for banks?” and “ How can we better decide to lend money to grey applicants?”. In order to respond to these questions, we filtered the customers to the current and potential ones sequentially. Then, for each type of the customers, a matrix scorecard is built. The applicability of the model is shown using an Iranian bank’s dataset. The results show the superiority of the built model in the real application.

The rest of the paper is structured as follows: Section 2 describes the research method used. Section 3 introduces the empirical results including dataset introduction, main approaches for dealing with missing values, experiment settings and performance analysis approaches, finally, the study conclusion is described in Section 5.

## Overview of the Research Method

This paper introduces matrix sequential hybrid scorecards in the credit scoring context. Five steps are designed carefully for this purpose. The development process of matrix sequential hybrid scorecards in this study is shown in Figure 1.

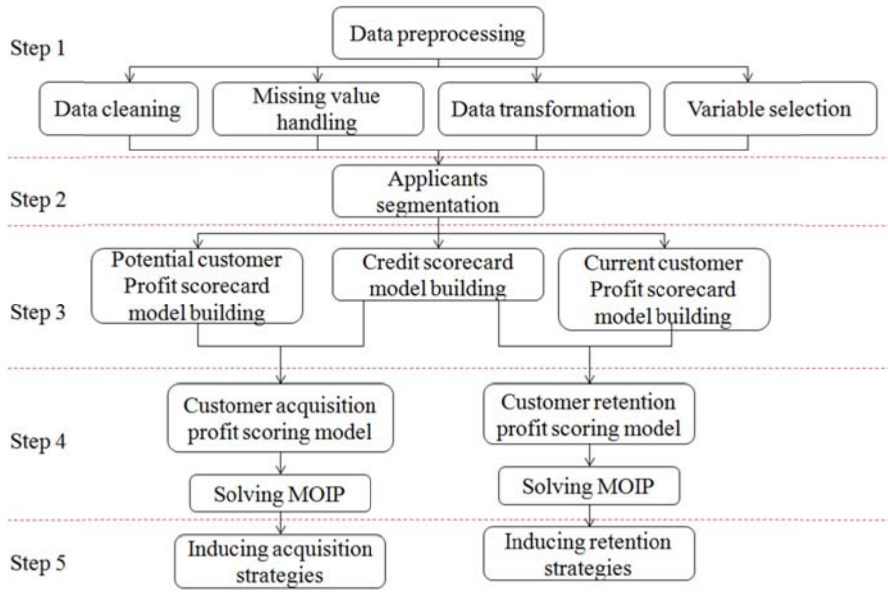


**Figure. 1. Research steps**

A brief description of the steps used in this paper is presented below.

**Step 1: Data preprocessing.**

The existing bank's internal data for customers are collected, then, data cleaning, integration, and transformation are done.

**Step 2: Applicant segmentation**

Banks usually consider the applicants' marketing situation to handle the credit applications. This paper used the concept of potential and current bank customers, to model the behavior of the banks.

**Step 3: Building three one-dimensional credit/profit scoring models.**

A one-dimensional credit scoring and two one-dimensional profit scoring models are induced.

**Step 4: Building two matrix scorecard models and finding the optimized cutoff points**

The risk ranks of the two profit scoring models are combined with the credit scoring model separately and two credit/profit matrices are built. The performance measures are used to evaluate the results carefully. Finally a multi objective problem is solved in order to find the best cutoff points.

**Step 5: Inducing credit application strategy.**

Based on two credit/profit matrices, a credit strategy to lend or avoid the lending or other secondary strategies can be put into action. The amount of letter of grantee (LG) limit and a loan line limit can be allocated to each applicant.

## Empirical Analysis

In this section the six steps of model building are described carefully.

**Step 1: Data Preprocessing.**

An Iranian bank's datasets are used to build the scorecards. Table 1 shows the characteristics of the dataset. The initial dataset includes 1431 corporate applicants and 46 financial and non-financial features in the period of 2007 to 2012, from which 909 are credit worthy (90.9%) and the other 91 are non-worthy (9.1%). Default was defined by Basel definition and used to generate a binary (1/0) target variable for modeling purposes (credit worthy = 1, non-worthy = 0). Descriptions of the variables and their missing value percentages are shown in Table 9 in Appendix 1. There are a few missing values for some corporates, where 33 features (71.7%) have complete data and 813 (81.3%) applicants' data records are complete. Table 2 summarizes the dataset characteristics before and after cleaning steps and displays a brief description of data preprocessing done on the dataset. In order to recognize the datasets better in the research, each one of them is labeled with a dataset code which is shown at the first column of Table 2. Maximum Likelihood (ML) is performed as well on credit risk missing data compared to other missing data handling methods, therefore, SPSS statistics 23.0 ML function is used to handle the missing data (Florez-Lopez, 2010). Then, the dataset is normalized by scaling attribute values to fall within a specified range using SPSS modeler 18.0 functions.

**Table 2. Dataset Description**

| Data set code | Description | Data size | Inputs variables | | | | Complete features% | Complete applicant records% |
|---|---|---|---|---|---|---|---|---|
| | | | Total | Continuous | Categorical | Features with Missing value | | |
| 1 | Initial dataset | 1431 | 46 | 38 | 8 | 13 | NA | NA |
| 2 | Dataset (1) with variables converted | 1431 | 46 | 38 | 8 | 13 | NA | NA |
| 3 | 431 records from Dataset (2) are eliminated because their loan are current process of repay | 1000 | 46 | 38 | 8 | 13 | 71.7 | 81.3 |
| 4 | Data set (3) variable are changed and categorical variables are converted to dummy variables | 1000 | 54 | 34 | 20 | 13 | 75.93 | 81.3 |
| 5 | Data set (4) missing values are replaced using maximum likelihood | 1000 | 54 | 34 | 20 | 13 | 100 | 100 |

### Step 2: Applicant Segmentation

Banks usually consider the applicants’ marketing situation to handle the credit applications. This paper used the concept of potential and current bank customers’ segmentation, to model the potential strategy of the bank facing different customers. This is mainly because the customers in each segment can have similar behavior and characteristics. Therefore, on one hand, checking the customer account’s turnover, checking account’s weighted average and experience with the bank which shows the number of years of the customer working with the bank variables are selected to rank the customers in a spectrum of disloyal to loyal (profitable), used for the applicants who are currently the banks’ customers; on the other hand, the current period sales, current assets, accounts receivable, other accounts receivable, and sales which show the liquidity are selected for the applicants who are not currently the banks' customers. The selection of these variables is due to the limitations of the research and lack of availability of the other variables in the research dataset, although, these variables can play the role of the substitute for those variables in the local market from experts' point of view.

**Step 3: Building Three One-Dimensional Credit/Profit Scoring Models.**

All the experiments in this paper are done using Table 2 datasets and tests are reported using Dataset 4.

### Credit scoring model

Credit scorecards are widely used in banks and novel models are of interest in recent years. In this section of the paper, the credit scorecard model is built. Logistic Regression (LR) has been widely used in building the credit scoring models. There are studies showing that LR is the best traditional model (West, 2000). Also, there are some studies which show the superiority of LR against NN and other intelligent methods (West, 2000). LR is a linear model, in which the logit-transformed prediction probability is a linear function of the predictor variable values. Thus, a final credit score is a linear function of the predictor variables and can be taken from the scorecard.

**Table 3. Performance Measures on Different Missing Value Handling Methods Reported for Test Dataset**

| Model code | Variable feed method | Accuracy% | Gini | AUC | Type II error | Type I error |
|---|---|---|---|---|---|---|
| LRE | Enter | 87.67 | 0.368 | 0.684 | 0.921 | 0.007 |
| LRS | Stepwise | 87.33 | 0.27 | 0.635 | 1 | 0 |
| LRF | Foreword | 87.33 | 0.27 | 0.635 | 1 | 0 |
| LRB | Backward | 87.67 | 0.638 | 0.684 | 0.921 | 0.007 |
| LRBS | Backward stepwise | 87.67 | 0.638 | 0.684 | 0.921 | 0.007 |

The scorecard model has been built, Table 3 shows classification accuracy, Gini index, and Area Under Curve (AUC) which are measured for each model based on the tested dataset. The models are labeled with a unique code at the first column of the Table 3. The best classification accuracy, the lowest Gini and higher AUC are of interest. It can be seen from Table 3 that there is not a best performer model in all the three performance analysis measures.

On one hand, credit scoring datasets are usually low default portfolios, meaning that the number of defaults is usually1 to 10 ratio, on the other hand, the cost of predicting a bad applicant as a good one is significantly higher than predicting a good applicant as a bad one. Therefore, Type I error rate is much more important that other performance measures, this gets us the result to put aside the LRF and LRS models. Selecting the other models is equal, because all of performance measures are the same, therefore, we select the LRE method for the credit scoring model.

**Customer retention profit scoring model**

Profit scoring is usually computed at two levels: Account level and customer level, the current study is seeking to estimate the profit at the customer level. There are many studies in the field of profit scoring, they mainly discussed that the development of profit scoring models is troublesome, because banks' datasets usually lack data related to time and the loss of given defaults and profits from other bank services which are used by the customers including letter of guarantee, letter of credit, other transactional service fees which form the revenue of the banks (Lessmannet al., 2015). There are also studies which use a simple approach to distinguish scorecard profitability by investigating costs of classification errors (Eisenbeis, 1977).

This paper just like other mentioned studies lacks the variables needed for profit scoring. Therefore, the substitute scenario is used. Considering the comments of experts, we used the variables in the dataset including: checking account's turnover, checking account's weighted average and customer's experience with the bank to segment the current customers into different levels of profitability. Therefore, the customers are segmented to $k_R$ different clusters using different clustering algorithms. The correct choice of $k_R$ is often ambiguous and it depends on the clustering resolution of the bank and its customer retention strategies. In order to handle the simplicity of the scorecard and by gathering the expert opinions, 3 to 5 cluster are selected finally. The silhouette is used for assessing the best clusters 3, 4 or 5 at last. It is a measure that shows how near an applicant is to others within its cluster and how far it is to applicants of the other neighboring clusters (Rousseeuw, 1987). If the silhouette measure was close to 1, the data are in an appropriate cluster; on the other hand, if silhouette measure is close to −1, the data are clustered wrongly. Kohonen (KO), Two Step (TS), and K-Means (KM) methods are used for clustering. The parameters' settings are done in order to finely tune the algorithms, the width and length parameters are set from one to three, learning rate decays linearly and exponentially separately in the neighborhood of one and two for Kohonen, the number of clusters is from two to five, and Euclidean distance for k-means and the distance methods of log-likelihood and Euclidean, both clustering Schwarz's Bayesian and Akaike's information criteria, and number of clusters from two to five are selected for two-step algorithm, which finally yields to 56 implementations. Table 4 shows the results of selected eight clustering implementations among 56 with the silhouette measure almost higher or equal to 0.75 and the number of clusters between 2 to 5 by feeding three variables which are mentioned to SPSS modeler 18.0 auto cluster node.

**Table 4. Performance Measures on Different Clustering Methods for Customer Retention Strategies**

| Model | TS51 | TS52 | KM2 | KM3 | TS31 | TS32 | TS33 | TS34 |
|---|---|---|---|---|---|---|---|---|
| Clustering method | Two step | Two step | K-means | K-means | K-means | Two step | Two step | Two step |
| Distance method | Log-likelihood | Log-likelihood | Euclidean | Euclidean | Log-likelihood | Euclidean | Log-likelihood | Euclidean |
| Clustering criterion | Schwarz's Bayesian | Akaike's Information | NA | NA | Schwarz's Bayesian | Akaike's Information | Schwarz's Bayesian | Akaike's Information |
| silhouette | 0.888 | 0.888 | 0.762 | 0.749 | 0.749 | 0.749 | 0.749 | 0.749 |
| Number of clusters | 5 | 5 | 2 | 3 | 3 | 3 | 3 | 3 |

It can be seen from Table 3 that the silhouette measure is higher for TS51 and TS52. These models differ because of their clustering criterion, as this criterion makes no difference in other clustering performance measures which could not be reported in this paper including size of the largest and smallest clusters, so the TS51 method is selected for customer retention profit scoring model.

**Customer acquisition profit scoring model**

Measuring the profitability of a potential customer is much more sophisticated than measuring the profit of a current customer mainly because the assumptions and facts about a potential customer are not real and can or cannot take place in the future. Using the comments of experts, after scaling the variables between zero and one using z-score transformation, the study used principal component analysis to convert three variables of customer profitability (checking account's turnover, checking account's weighted average and customer's experience with bank) into one principal component. This principal component is then used to select features using Pearson correlation for building the customer acquisition profit scoring model. This procedure is done because the three profit scoring variables are not available for potential customers, therefore, we select other variables which are available at the time of applying for loan. Considering the cutoff point of 0.95 for important variables, 32 variables are finally selected for clustering.

Just like the customer retention profit scoring model, the potential customers are segmented to $k_A$ different clusters using different clustering algorithms. The correct choice of $k_A$ is often ambiguous and it depends on the clustering resolution of the bank and its customer acquisition strategies.

**Table 5. Performance Measures on Different Clustering Methods for Customer Acquisition Strategies**

| Model | KM3 | KM4 | TS51 | TS52 | TS41 | TS42 |
|---|---|---|---|---|---|---|
| Clustering method | K-means | K-means | Two step | Two step | Two step | Two step |
| Distance method | Euclidean | Euclidean | Log-likelihood | Log-likelihood | Log-likelihood | Log-likelihood |
| Clustering criterion | NA | NA | Schwarz's Bayesian | Akaike's Information | Schwarz's Bayesian | Schwarz's Bayesian |
| Silhouette | 0.702 | 0.611 | 0.366 | 0.366 | 0.194 | 0.194 |
| Number of clusters | 3 | 4 | 5 | 5 | 4 | 4 |

Table 5 shows the results of seven-time selected clustering among 52 implementations, the number of clusters between 3 to 5 using Kohonen (KO), Two-Step (TS), and K-Means (KM) methods and in different clustering settings by feeding 32 variables to SPSS modeler 18.0 auto cluster node.

It can be seen from Table 4 that the silhouette measure is higher for KM3 and KM4, but the data distribution in these two models are granular, the smallest cluster size is so much little and the data are not separated well, Therefore, TS51 is selected for building customer acquisition profit scoring model.

**Step 4: Determining Score Cutoffs and Building Final Matrix Sequential Hybrid Scorecard Models.**

Once, three good one-dimensional credit/profit scoring models have been built, choosing the cutoff values for accepting or rejecting the credit and profit happens. The most straightforward and simple way is to put the cutoff point at sections in the situations that separate good and bad credit cases better. However, many other considerations typically enter into this decision when the creditworthiness and profitability of customers are divided into more than just two segments. In these cases, several cutoff points should be selected.

**Table 6. Matrix Credit-Retention Scorecard**

| | | | | Current customer profitability score | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | non | | weak | | middle | | highly | | Very highly | |
| | | | | prediction | | | | | | | | | |
| | | | | B | G | B | G | B | G | B | G | B | G |
| Credit score | 600 or less | real | B | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| | | | G | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| | 600-700 | | B | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 2 |
| | | | G | 0 | 5 | 1 | 3 | 0 | 0 | 0 | 3 | 0 | 2 |
| | 700-800 | | B | 0 | 1 | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 2 |
| | | | G | 0 | 7 | 0 | 4 | 0 | 0 | 0 | 10 | 0 | 4 |
| | 800-900 | | B | 0 | 5 | 0 | 1 | 0 | 0 | 0 | 3 | 0 | 5 |
| | | | G | 0 | 19 | 0 | 24 | 0 | 0 | 1 | 19 | 0 | 23 |
| | 900-1000 | | B | 3 | 2 | 0 | 2 | 0 | 2 | 0 | 3 | 0 | 2 |
| | | | G | 0 | 30 | 0 | 26 | 0 | 0 | 0 | 35 | 0 | 41 |

The cutoff point should be selected to maximize the profit based on the model's predictions of risk. Due to lack of the data regarding the amount of loans, unfortunately, profit criteria in terms of monetary cannot be considered. Table 6 and Table 7 show the matrix credit-retention and matrix credit-acquisition scorecards, respectively. Each table shows a matrix for each of 25 cells which are shaped by crossing five credit and five profit categories, each applicant fell into just one of these cells. In order to better handle the computation, the confusion for each 25 cell is also described.

**Table 7. Matrix Credit-Acquisition Scorecard**

| | | | | Current customer profitability score | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | non | | weak | | middle | | highly | | Very highly | |
| | | | | prediction | | | | | | | | | |
| | | | | B | G | B | G | B | G | B | G | B | G |
| Credit score | 600 or less | real | B | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 2 |
| | | | G | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| | 600-700 | | B | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 |
| | | | G | 1 | 0 | 0 | 3 | 0 | 2 | 0 | 0 | 0 | 8 |
| | 700-800 | | B | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 3 |
| | | | G | 0 | 0 | 0 | 7 | 0 | 4 | 0 | 0 | 0 | 14 |
| | 800-900 | | B | 0 | 0 | 0 | 5 | 0 | 2 | 0 | 0 | 0 | 7 |
| | | | G | 1 | 0 | 0 | 22 | 0 | 14 | 0 | 0 | 0 | 49 |
| | 900-1000 | | B | 1 | 0 | 1 | 0 | 0 | 4 | 0 | 0 | 0 | 5 |
| | | | G | 0 | 1 | 0 | 26 | 0 | 32 | 0 | 0 | 0 | 72 |

In order to determine the cutoff points, the paper used two multi objective mathematical models. The aim of the multi objective problems in the designed scorecard is to find the cutoffs in each of the two scorecards in a manner that Type I and II errors are in their minimum value and accuracy is in its maximum value. We have $\frac{10!}{5!\times5!}$ =252 in each of the two scorecards. Each of 252 cuts have their own accuracy, Type I and II errors. The mathematical model are described in the following for finding the best cutoffs.

## Notations

### Units

Steps (Baesens et al., 2003),

**Indices and Sets**

$h$: Index of horizontal axis $X_{HV}$ matrix, H={1,…,10},

$v$: Index of vertical axis of $X_{HV}$ matrix, V={1,2},

**Decision Variable**

$X_{HV}$ : $10 \times 2$ dimension matrix of 10 couples of $x_{hv}$ which shows 10 vertical or horizontal steps from down-left of the scorecard to up-right of it (a full cutoff in a scorecard).

**Parameters**

$FN_i$: False negative (FN) of the *i*th decision vector,

$TP_i$: True positive (TP) of the *i*th decision vector,

$FP_i$: False positive (FP) of the *i*th decision vector,

$TN_i$: True negative (TN) of the *i*th decision vector,

**Mathematical Model**

$$\text{Min} \quad {}^{FN_i}\!/_{FN_i + TP_i} \tag{1}$$

$$\text{Min} \quad {}^{FP_i}\!/_{FP_i + TN_i} \tag{2}$$

$$\text{Max} \, {}^{TP_i + TN_i}\!/_{TP_i + FP_i + FN_i + TN_i} \tag{3}$$

Subjected to

$$\textstyle\sum_{h=1}^{10} x_{hv} \leq 5 \tag{4}$$

$$\textstyle\sum_{h=1}^{10} \sum_{v=1}^{2} x_{hv} = 10 \tag{5}$$

$$x_{hv} = \{0,1\}, \tag{6}$$

In the model, the banks' first objective function which is expressed in the first line (1) is to minimize Type I error, the second objective (2) is to minimize Type II error and the third and last objective function (3) is to maximize the accuracy of the scorecard. Constraint (4) assures that the steps reach the limits of the steps. Constraint (5) assures that the steps are well defined. Finally the last constraint limits the components of the matrix to $X_{HV}$ 0 or 1. After weighted sum conversion of the objective functions, two models can be solved using GA feeding the 300 records of our test sets in 1000 iterations. The results of the cutoffs are shown in Tables 5 and 6 and the performance criteria are reported in Table 8.

**Table 8. Performance Measures of Three Different Scorecards Built in the Study**

| Model code | Accuracy% | Type II error | Type I error |
|---|---|---|---|
| Single credit scorecard | 87.67 | 0.921 | 0.007 |
| Matrix credit-retention scorecard | 82 | 0.9 | 0.069 |
| Matrix credit-acquisition scorecard | 82.6 | 0.72 | 0.016 |

## Step 5: Inducing Credit Application Strategy.

From the results of the analysis and discussions with the experts, we discovered the following strategies for lending which are mentioned in Table 9.

**Table 9. Loan/Letter of Guarantee Decision**

| Customer type | Credit score | Profit cluster | Loan decision |
|---|---|---|---|
| **Current customer** | 600 or less | Non to highly | Reject loan application |
| **Current customer** | 600 - 700 | Non to middle | Reject loan application |
| **Current customer** | 700 - 800 | non | Reject loan application |
| **Current customer** | 600 or less | Very highly | Loan amount depends on the type of collateral |
| **Current customer** | 700-800 | highly | Lend as much as requested by the borrower |
| **Current customer** | 700-800 | Weak and middle | Loan amount depends on the type of collateral, cross sell deposit services |
| **Current customer** | 800-900 | non | Revolving credit Loan amount depends on the type of collateral. |
| **Current customer** | Other remained | Other remained | Revolving credit Loan amount depends on the type of collateral. |
| Potential customer | 600 or less | Non to highly | Reject loan application |
| Potential customer | 600 - 700 | Non to middle | Loan amount depends on the type of collateral, cross sell deposit services |
| Potential customer | 700 - 800 | Non and weak | Reject loan application |
| Potential customer | Other remained | Other remained | Revolving credit Loan amount depends on the type of collateral, cross sell deposit service, up sell |

## Conclusions and Future Directions

In this paper, a matrix sequential hybrid credit scorecard based on logistic regression and clustering is introduced. Based on the customer type, a matrix scorecard is built and its cutoff points are optimized using multi objective integer programming. There is also a huge amount of work for data preprocessing done which is defined carefully. Finally, using expert opinions, credit strategies are extracted. The proposed model helps the banks to make more precise decisions in the competitive economy, in which the grey customers are the main concern, the grey customers are customers whose profitability is not obvious and their loan applications are rejected in traditional strict credit scorecards. the proposed model can be applied into the real world of decision making by coding it as a software having inputs from banks' softwares including core banking, loan software, and etcetera, and the main output is a decision whether to lend money or not and what actually your strategy should be.

Future works can be done on three other directions including gathering the profit data carefully in the banks specially profit from fees of information technology services, letter of guarantee fees, letter of credit fees, marketing costs, and so on, and building sequential hybrid scorecards by combining behavioral and profit scoring; secondly, building sequential hybrid scorecards by combining collection and profit scoring which helps the banks making more precise collection decisions; the third and last future work is using customer lifetime value which can be used in building matrix profit scorecards.

## Acknowledgement

We want to show our gratitude specially to Dr. Morteza Zekavat for his kind assistance with data gathering, technique, and methodology, and also, for his points of view that greatly improved the paper.

## Appendix (1)

**Table 10. List of Variables in an Iranian Bank's Credit Dataset**

| Variable | Type | Complete% | Variable | Type | Complete % |
|---|---|---|---|---|---|
| Net profit | Continuous | 100 | Type of industry: industry and mine (=1, other =0) | Categorical | 100 |
| Active in internal market | Categorical | 100 | Type of industry: agricultural (=1, other =0) | Categorical | 100 |
| number of countries that the company export to | Categorical | 100 | Type of industry: oil and petrochemical (=1, other =0) | Categorical | 100 |
| Sales growth | Categorical | 97.95 | Type of industry: infrastructure and service(=1, other =0) | Categorical | 100 |
| Target market risk (from 1 to 5) | Categorical | 99.56 | Type of industry: chemical (=1, other =0) | Categorical | 100 |
| Seasonal factors | Categorical | 100 | Year of financial ratio | Continuous | 100 |
| Company history(number of years) | Categorical | 100 | Type of book: Tax declaration(=1,other=0) | Categorical | 100 |
| Top Mangers history | Categorical | 100 | Type of book: Audit Organization (=1,other=0) | Categorical | 100 |
| Type of company: Cooperative (=1, other =0) | Categorical | 100 | Type of book: Accredited auditor (=1,other=0) | Categorical | 100 |
| Type of company: Stock Exchange(LLP) (=1, other =0) | Categorical | 100 | Inventory cash | Continuous | 100 |
| Type of company: Generic join stock( PJS) (=1, other =0) | Categorical | 100 | Accounts receivable | Continuous | 100 |
| Type of company: Limited and others (=1, other =0) | Categorical | 100 | Other Accounts receivable | Continuous | 100 |
| Type of company: Stock Exchange (=1, other =0) | Categorical | 100 | Total inventory | Continuous | 100 |
| Experience with Bank(number of years in 5 categories) | Categorical | 100 | Current assets | Continuous | 100 |
| Audit report Reliability | Categorical (binary) | 93 | Non-current assets | Continuous | 100 |
| Current period sales | Continuous | 100 | Total assets | Continuous | 100 |
| Prior period sales | Continuous | 98.98 | Short-term financial liabilities | Continuous | 100 |

| Variable | Type | Complete% | Variable | Type | Complete % |
|---|---|---|---|---|---|
| Two-prior period sales | Continuous | 97.52 | Current liabilities | Continuous | 100 |
| Current period assets | Continuous | 100 | Long-term financial liabilities | Continuous | 100 |
| Prior period assets | Continuous | 98.83 | Non-current liabilities | Continuous | 100 |
| Two-prior period assets | Continuous | 98.1 | Total liabilities | Continuous | 100 |
| Current period shareholder Equity | Continuous | 100 | Capital | Continuous | 100 |
| Prior period shareholder Equity | Continuous | 98.68 | Accumulated gains or losses | Continuous | 100 |
| Two-prior period shareholder Equity | Continuous | 96.94 | shareholder Equity | Continuous | 100 |
| Checking accounts creditor turn over | Continuous | 99.56 | Sale | Continuous | 100 |
| Checking Account Weighted Average | Continuous | 99.41 | Gross profit | Continuous | 100 |
| Last three years average exports | Continuous | 99.56 | Financial costs | Continuous | 100 |
| Last three years average imports | Continuous | 91.98 | worthy/nonworthy) y) | Categorical (binary) | 100 |

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