# A Novel Algorithm Developed with Integrated Metrics for Dynamic and Smart Credit Rating of Bank Customers

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**Abstract** There are a wide variety of algorithms for bank customer credit rating. Over-allocation or under-allocation of credit arises from weakness in algorithms and lack of software programs involving efficient metrics. This in turn gives rise to legal and criminal issues between banks and customers, poor utilization of customer capabilities, and inappropriate provision of banking services. This study intended to propose qualitative metrics to identify the best customer credit rating model with a focus on financial transitions. Instead of focusing on customer credit, this study employed a concept known as discredit derived from the concepts concerning system quality assurance. The new model was validated through efficiently developed software including metric information and customer data. Over the past four years, the account information about 56,000 customers of an international bank branch was studied to determine the criteria and metrics of their credits using different modeling techniques. The developed software was used to define, analyze, and statistically test multiple financial metrics for the financial information of an international bank branch, while fitting the best metrics in a dynamic model for discredit detection. The best coefficients for combination of financial metric were calculated by weighting based on time, while extracting and validating appropriate equations for the newly proposed model. More specifically, the current year account balance was correlated with discredit, whereas the previous year account balances were not correlated. In addition, the discredit data involved a somewhat greater regression than the numerical discredit data.

**Keywords** Dynamic credit rating · Discredited · Integrated metrics

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# 1 Introduction

From the bank's perspective, the credit of a customer depends on their fulfillment of liabilities [1]. Particularly, clearing of cheques and repayment of loans can be two criteria to allocate credit to a customer [2]. In terms of quality assurance, however, credit violations are more reliable. More specifically, discredit can be demonstrated based on the relationship between the amount of cleared cheques and the amount of bounced cheques.

When a cheque-account customer draws a cheque, money is simply generated. In fact, a customer obtains goods/services by providing a cheque with a credit equivalent [3]. The cheque is supposed to be credible to its minimum amount from the date of drawing until the date of cashing at the bank. When the cheque is bounced on due date because of insufficient balance, it shows that false credit has been assigned to the customer, at least as much as the difference between the current balance and the cheque amount. Nonetheless, there might have been other cheques drawn.

# 2 Modeling for Dynamic Discredit Calculation

As noted earlier, the banking codes of conduct prescribe that cheque-account balance cannot be an indicator of credit or discredit [4]. That is because the real-time or average balance over a given banking period cannot indicate the issuance of cheques, and the account holder is at full elbow-room. Nonetheless, the account balance is supposed to be sufficient when the cheque is submitted to the bank for collection. However, balance and, in particular, the average balance of an account in a specific interval, e.g. three months, is the easiest way to allocate credit to customers for a new chequebook or loans. It can also leave a loophole for abuse or fraud [5].

## *2.1 Discredit*

Failure to fulfill liabilities leads to discredit [6]. Nevertheless, the decision on credit usually depends on recorded and registered data as well as official actions rather than exchanged information [7]. Specifically, we defined discredit as official action of cheque owners when they are informed that the account balance is insufficient for clearance and request a certificate of absence for judicial authorities. In this perspective, the following metrics can be defined:

N-CoA-x-d: The number of discredit events per day d for customer X (the number of issued certificates of absence)
A-CoA-x-d: The amount of discredit events per day d for customer X (the number of issued certificates of absence)

### 2.2 Discredit in a Fiscal Year

The number of discredit events for a customer in one fiscal year can be calculated through the following equation:

$$\mathrm{N-CoA-x_{-y}} = \sum_{d=1}^{d=\text{number of working days}} N - CoA - x - d \tag{1}$$

(Number of certificates of absence issued during one fiscal year)

The amount of discredit events for a customer in one fiscal year can be calculated through the following equation:

$$\mathrm{A-CoA-x_{-y}} = \sum_{d=1}^{d=\text{number of working days}} A - CoA - x - d \tag{2}$$

(Amount of certificates of absence issued during one fiscal year)

## 3 Hypotheses

This study involved three pairs of hypotheses as follows:

### 3.1 Hypothesis One

H1—There is a significant relationship between average balance and discredit for the number of cheques.
H0—There is no significant relationship between average balance and discredit for the number of cheques.

### 3.2 Hypothesis Two

H1—There is a significant relationship between average balance and discredit for the monetary amount of cheques.

H0—There is no significant relationship between average balance and discredit for the monetary amount of cheques.

### 3.3 Model Description

Figure 1 illustrates the conceptual model proposed in this paper. The following steps were sequentially included in the model:

- Data of cleared and bounced cheques by time
- Monetary amount of cleared cheques
- Monetary amount of bounced cheques
- Access to cheque-account database and archives
- Calculating balance for current year accounts and previous years
- Calculating metrics designed for discredit
- Calculating data regression and specifying the significant relationship between metrics

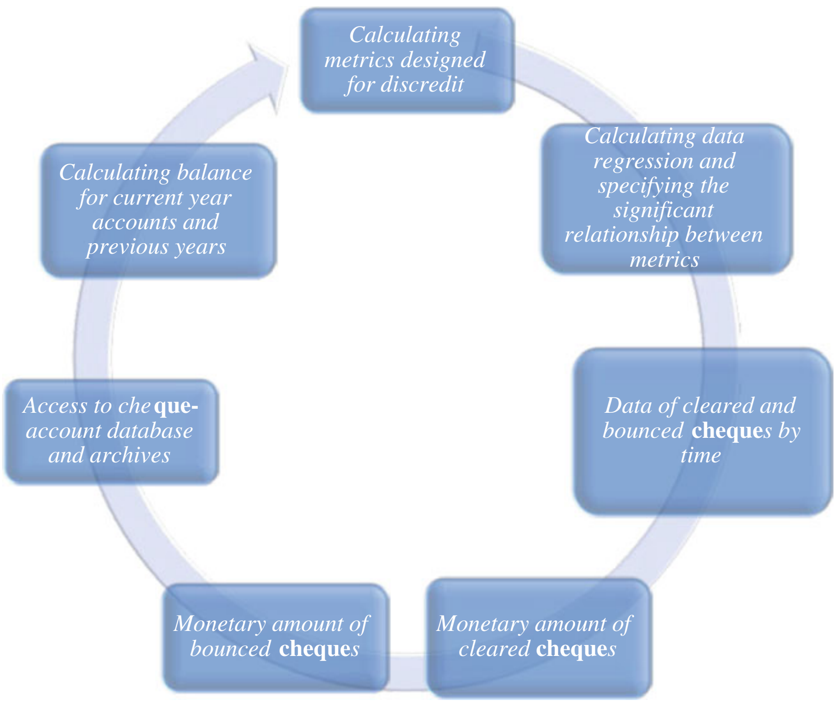


**Fig. 1** The conceptual model for account credit

### 3.4 Main Input Variables of the Model

We selected a total of 56,000 customers holding cheque-accounts with available records over the past three years. For each customer, the account balance information and the number and amount of cleared and bounced cheques were extracted and calculated. The variables in Table 1 were adopted for calculations.

**Table 1** Main input variables

| Variable | Description |
|---|---|
| Bal – Ave – x − 3y | Average account balance of customer X over three years |
| Bal – Ave – x – py | Average account balance of customer X over the past year |
| Bal – Ave – x – ty | Average account balance of customer X from the beginning of the year to the study day |
| N – C – x – d | The total number of cheques submitted to the bank on day d for customer X |
| A – C – x – d | The total amount of cheques submitted to the bank on day d for customer X |
| –B – C – x – d | The number of bounced cheques on day d for customer X |
| A – B – C – x – d | The amount of bounced cheques on day d for customer X |
| N – P – C – x – d | The number of cleared cheques on day d for customer X |
| N – P – C – x – d | The amount of cleared cheques on day d for customer X |
| N – P – C – pctg = N – P – C – x – d / N – C – x – d * 100 | Percentage ratio (number) of cleared cheques to total cheques drawn on day d for customer X |
| N – B – C – B – pctg = N – P – C – x – d / N – C – x – d * 100 | Percentage ratio (number) of bounced cheques to total cheques drawn on day d for customer X |
| A – P – C – pctg = A – P – C – x – d / A – C – x – d * 100 | Percentage ratio (amount) of cleared cheques to total cheques drawn on day d for customer X |
| A – B – C – B – pctg = A – P – C – x – d / A – C – x – d * 100 | Percentage ratio (amount) of bounced cheques to total cheques drawn on day d for customer X |

# 4 Dynamic, Weighted Discredit Calculation Model for Cheque-Account Customers

Discredit is calculated through two methods: (1) the number of bounced cheques to the total cheques submitted to the bank, and (2) the amount of bounced cheques to the total amount of cheques submitted to the bank. The calculations covered discredit for chequeing-account customers of the branch holding a chequebook for three years and available banking history of at least three years. Discredit was also calculated separately for the previous year. Finally, discredit was calculated from the beginning of the year to the day of empirical study. There were three separate criteria inserted into the model:

- Three-year discredits
- Recent-year discredits
- Discredit from the beginning of the year to the study day.

The final metric was selected because the fiscal year for individuals and companies are mainly specified by closing the previous year account, opening new ones, and transferring over items from accounts of the previous year. Usually, a separate budgeting is assigned to each year; and resources, costs, and capital are supplied using the new plan.

## *4.1 Model Validation Through Developing Discredited Software*

The presented model was completed and checked through designing new software in which the mentioned metrics were embedded and the cheque-account information was presented without personal information. The information about cheques issued by cheque-account customers, including cleared and bounced cheques were imported into the software, while calculating the values of metrics separately.

The information was compiled into four databases, covering three current and archived time periods. Several fetches were run through SQL Query in Discredited software developed in this phase (see Fig. 2) until essential data were extracted from numerous tables involved in each database. There were no system tabs in databases. Fetches were run on log files which were extremely time-consuming. Most core banking systems do not store but calculate balances. Therefore, the data sources were adopted to make the essential calculations for balance inquiry. A more precise average balance was obtained by accumulating the individual day balances instead of dividing the difference between the first day and last day of the period by working days.

```
T-SQL applying OVER() to get summary total and percent on base
SELECT  MONTH = MONTH(OrderDate),
        SUM(TotalDue)                   AS SalesByMonth,
        100.0 * ((SUM(TotalDue)) / (SUM(SUM(TotalDue))
                            OVER())) AS PctSalesByMonth
FROM    AdventureWorks2008.Sales.SalesOrderHeader
WHERE   YEAR(OrderDate) = 2003
GROUP BY MONTH(OrderDate)
ORDER BY MONTH
*/

/*
SELECT CHQ_Date, CHQ_Account, count(CHQ_Account),
CAST(( (COUNT(CHQ_Account) over () / (COUNT(CHQ_Account) OVER() ) ) * 100.00) as decimal(30,2))
AS Pctg
FROM CHQData WHERE CHQ_Status = 'R' GROUP BY CHQ_Date , CHQ_Account ORDER BY
CHQ_Date, CHQ_Account
*/

/*
COUNT(CHQ_Account) AS N_COA_X_D,
SUM(CHQ_Amount) AS A_COA_X_D FROM CHQData WHERE CHQ_Status = 'R' GROUP BY
CHQ_Date , CHQ_Account ORDER BY CHQ_Date, CHQ_Account
SELECT CHQ_Date, CHQ_Account, COUNT(CHQ_Account) AS N_P_X_D, SUM(CHQ_Amount) AS
A_P_X_D FROM CHQData WHERE CHQ_Status = 'G' GROUP BY CHQ_Date , CHQ_Account ORDER
BY CHQ_Date, CHQ_Account
SELECT CHQ_Date, CHQ_Account, COUNT(CHQ_Account) AS N_C_X_D, SUM(CHQ_Amount) AS
A_C_X_D FROM CHQData GROUP BY CHQ_Date , CHQ_Account ORDER BY CHQ_Date,
CHQ_Account
```

**Fig. 2** A sample of SQL script using in this study

## *4.2 Discussion*

We selected the relationship between the average balance and the percentage of discredit was one of the most important issues explored in this paper [8]. Therefore, the model included and sorted the relationship between average balance in three years and percentage of discredit over three years, the relationship between average balance over one year and percentage of discredit over one year, and the credit of high-ranking and low-ranking customers. The ratio of these rankings to the values of metrics was inserted into the following mathematical models below and the corresponding charts were discussed.

Table 2 was derived from the data on average balances for the current year, previous year and past three years by bounced cheques. The results indicated that the average balance of people who had at least three bounced cheques from the beginning of the current year until the research period was 50% less than the average balance of those with one bounced cheque and 35% less than those who had two bounced cheques, which is significant. The ratio was much stronger for previous year in that the average balance of people who had at least three bounced cheques was 95% less than the average balance of those with one bounced cheque and 55% less than those who had two bounced cheques. The ratio does not suggest a significant relationship for the past three years. It implies that the recent data has more weight and is the current criterion of the account holders.

**Table 2** The relationship between the number of bounced cheques and the average balance

| Current year | | Previous year | | Past three years | |
|---|---|---|---|---|---|
| Title | Amount ($) | Title | Amount ($) | Title | Amount ($) |
| The average balance of those who had a bounced cheque in the past three years | 136,127.38 | The average balance of those who had a bounced cheque previous year | 241,816.18 | The average balance of those who have a bounced cheque bcurrent year | 101,682.82 |
| The average balance of those who had two bounced cheques over the past three years | 119,602.02 | The average balance of those who had two bounced cheques previous year | 77,117.47 | The average balance of those who had two bounced cheques bcurrent year | 695,067.34 |
| The average balance of those who had at least three bounced cheques over the past three years | 73,699.08 | The average balance of those who had at least three bounced cheques previous year | 12,196.39 | The average balance of those who have at least three bounced cheques bcurrent year | 692,653.06 |

As shown in the charts (Figs. 3 and 4), there is significant relationship between the number of bounced cheques, discredit, and account balances. This relationship was insignificant for all three periods of the current year, the past year, and the last three years. Nonetheless, there was a significant relationship between balance and amount of bounced cheques in all three periods. Furthermore, there was a significant relationship between discredit and account balances for the last period of current year.

Focusing on the "bounced cheque to the average balance" metric led to significant results and relationships. To this end, three levels of balances were considered. The balances were divided into deciles and customers were identified at each level. The first three deciles were regarded as low level, the three upper deciles as high level and the three middle deciles as medium level. By pressing the necessary scripts at each level, the amount of each customer's bounced cheques in the current year, previous year and past three years was determined. Table 3 contains the results of the metric data.

The hypothesis of inverse relationship between the average balance and the bounced cheque rate was confirmed. Figures 5, 6 and 7 are pictorial view of

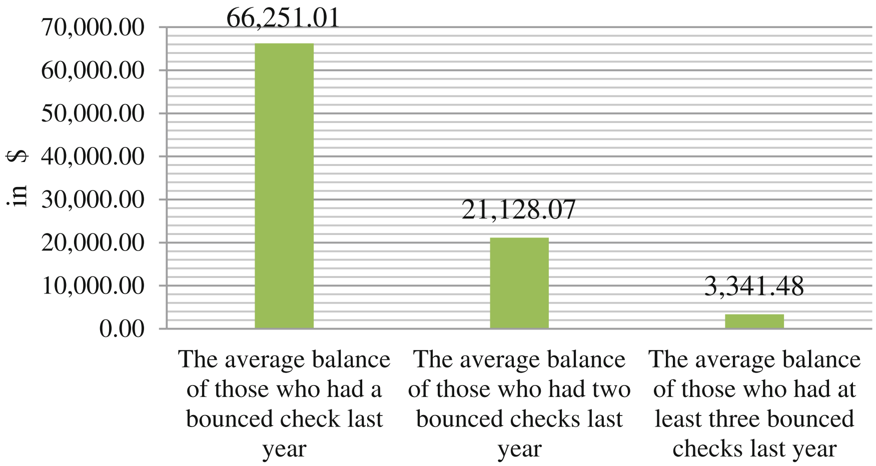


**Fig. 3** The relationship between the number of bounced cheques and the average balance for previous year

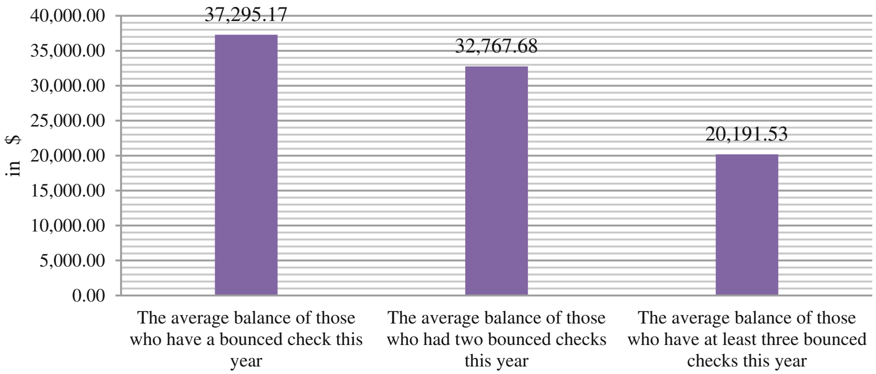


**Fig. 4** The relationship between the number of bounced cheques and the average balance for current year

relations in form of diagrams. The amount of the bounced cheques for low balances bcurrent year was seven times higher than that for medium balances in the same year and 80 times higher than the amount of the bounced cheques for the upper-level customer balances. Similarly, the amount of the bounced cheques for lower balances in the previous year was 3.5 times higher than that for the medium balances in the previous year and 25 times higher than the amount of the bounced cheques for the upper-level customer balances. Finally, the amount of the bounced cheques for lower balances over the past three years was 6 times higher than the amount of the bounced cheques for the medium balances in the past three years and 35 times higher than the amount of the bounced cheques for the upper-level

**Table 3** The relationship between the amount of bounced cheques and the average balance

| Current year | | Previous year | | Past three years | |
|---|---|---|---|---|---|
| Title | Amount ($) | Title | Amount ($) | Title | Amount ($) |
| The amount of bounced checks for high balances in the current year | 8842.24 | The amount of bounced cheques for medium balances in the current year | 91,187.03 | The amount of bounced cheques for low balances in the current year | 649,052.13 |
| The amount of bounced checks for high balances in the previous year | 31,592.96 | The amount of bounced cheques for medium balances in the previous year | 218,491.87 | The amount of bounced cheques for low balances in the previous year | 743,305.28 |
| The amount of bounced checks for high balances over the past three years | 67,336.26 | The amount of bounced cheques for medium balances over the past three years | 455,892.33 | The amount of bounced cheques for low balances over the past three years | 2,554,846.39 |

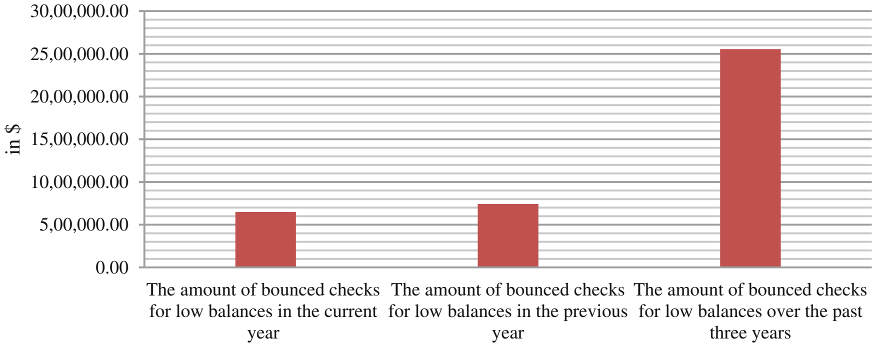


**Fig. 5** The relationship between the amount of bounced cheques and the average balance for Low balances

customer balances over the past three years. Therefore, the average customer balance is negatively correlated with the bounced cheque rate with a statistical strength of tens of times. Unlike the relationship between the number of cheques (and the bounced cheque rate) that was measured with the previous metric, the relationship between balances and the amount of the bounced cheques over the past three years

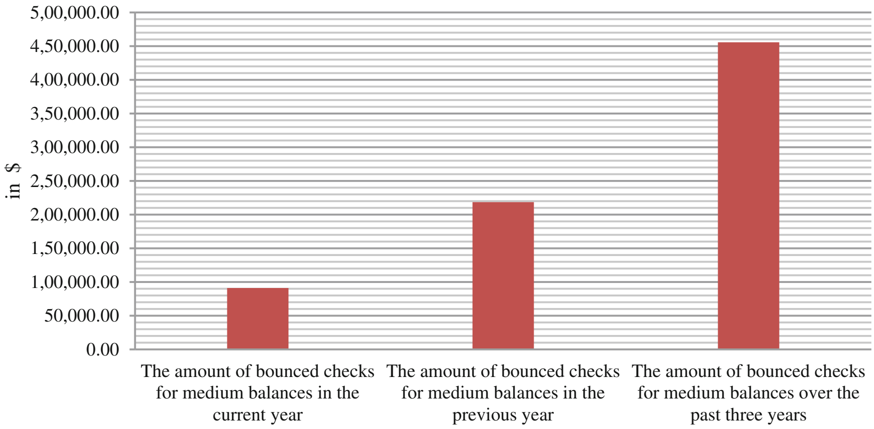


**Fig. 6** The relationship between the amount of bounced cheques and the average balance for Medium balances

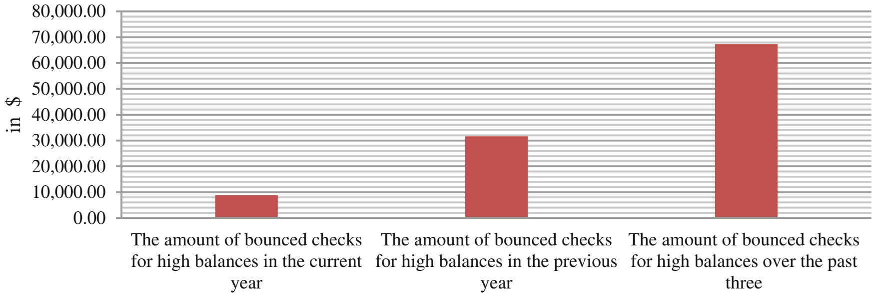


**Fig. 7** The relationship between the amount of bounced cheques and the average balance for High balances

is stronger and more significant than the previous year and current year. Therefore, the average balance over the past three years can be considered a criterion for customer credit.

## 5 Conclusions

The information obtained in this paper suggested that the average discredit over past years was not significantly correlated with current credit of customers. In fact, the average amount of discredit of past year and discredit from the beginning of the year could provide a better criterion. Moreover, the number of cheques was not significantly correlated with customer credit, unlike what is usually applicable. In fact, the amount of discredit provided a more important criterion than the percentage number of discredit. Finally, the new model can be adopted as a desirable criterion for granting financial facilities to bank customers.

## 6 Future Studies

The information Considering the important points and recommendation in this section will pave the way to continue the research from different supplement aspects.

### *6.1 Important Recommendation for All Banking Systems*

We selected The field studies in this paper indicated that cheques exchanged through the banking system between banks and branches are fully recorded and traceable. When individuals visit the banks to cash the cheques and there is insufficient account balance, however, information is not recorded in most cases for defective or incompatible cheques. In this scenario, a certificate of absence is issued and recorded if the customer requests one. However, nothing would be recorded and the bank would remain unaware if the customer decides to personally contact the drawer to increase account balance or resolve other issues. It is strongly recommended to formulate a code of conduct where the information of each bank-submitted cheque is recorded [9].

### *6.2 Limitations and Delimitations*

The modeling could be improved by some information unavailable to the bank. For example, the interval between cheque issuance and bank delivery (due date on the cheque) is unspecified even though it can be an important criterion to determine customer credit. This can be achieved through self-declaration, which tends to be unreliable [10].

### *6.3 Model Improvement by Inserting Other Effective Variables*

The future studies can be more accurate by covering the loans granted, and the repayments with/without delay. Also by presenting a customized method similar to that of the current paper, the amount of discredit in repayment of loans can be obtained and examined. Ultimately, a combination of discredit for cheques and discredit for repayment of loans can double the validity and reliability of customer classification in terms of credit [11]. For this purpose, it is recommended to adopt integrated modeling together with statistical tests involving real information as presented in this paper.

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