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Credit Risk Management Model Optimization Using Complex Event Processing

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ABSTRACT

There are several arguments that the current global financial meltdown is the consequence of abusive use of risky holistic risk management methods such as Monte Carlo techniques by management and professionals. Note that Monte Carlo is a very opportunistic short term solution method that does not reflect real risk. By using such method bankers' were encouraged to risky lending and resulted in financial credit crisis. They prescribed risk models which in essence hide risk involved so it is a time to implement sound predictive risk management model based on empirical data as described in this paper by using Complex Event Processing which a an emerging technology. Event processing has helped companies to identify and react to situations quickly and effectively, and there are many solutions that monitor various events happening both within an enterprise and outside. However, there are some situations that still require manual effort and intelligence to identify and react to those situations. Financial Institutions and Credit Rating Agencies today hope to gain a competitive edge based on their ability to respond quickly to threats and opportunities. That edge can come from highly responsive, near-real-time systems based on complex event processing (CEP) techniques used for financial applications. Now these CEP techniques are being used more widely in enterprise applications.

This paper introduces the methodology of complex event processing to Credit Risk Management model. This involves the in-memory retention and processing of information, allowing the user to minimize the time taken to identify a situation (Risk Category) and the initiation of subsequent actions, business credit authorization and monitoring decisions.

Keywords: CEP, rules, Credit risk, Discriminant, Business Intelligence.

I. INTRODUCTION

Continuous and periodical Credit risk analysis (Liquidity risk, Operational Risk, Finance risk and comprehensive Business Risk analysis, loan default risk analysis) and credit risk management is important to financial institutions which provide loans to businesses and individuals. Credit can occur for various reasons: Working Capital Loans, Corporate short term loan bank mortgages, even such as home loans, motor vehicle purchase finances, credit card purchases, installment purchases, and so on. Credit loans and finances have risk of being defaulted. To understand risk levels of credit users, credit providers normally collect vast amount of information on borrowers. Statistical predictive analytic techniques can be used to analyze or to determine risk levels involved in credits, finances, and loans, i.e., default risk levels. In this paper special focus on Small and Medium Enterprises Loans.

Why credit score is required?

Credit scores are computed from information available and daily, monthly, quarterly financial data provided by the borrower or Credit rating information is collected from the external credit agencies such as CRISIL, CARE, etc. Credit scores may present details on loonies' financial history and current situation. However, it does not indentify exactly what constitutes a "good" score from a "bad" score. More specifically, it does not reveal the level of risk for the lending financial institution may be considering. Weighted Credit Scoring Model developed by Srinivas Gumparthi and Manickavasagm (2010) was used as base model and subsequent improvising was done for enhancing processing speed and accuracy for timely decision making. The improvised model by Complex Event Processing can also be used for credit rating large commercial credits as well.

What is Complex Event Processing?

Dynamic change in the business environment is constant. Business Environment is triggered by internal as well as external events. Every event represents a business change and therefore does not exist without the business. Every event needs to be interpreted so that subsequent business related actions can be triggered. This interpretation and triggering of subsequent actions is known as dynamic event processing (DEP).

There can be business scenarios where information is hidden across multiple events. This information is known as business intelligence (BI) and identification of this intelligence and initiation of subsequent actions is known as complex event processing (CEP).

CEP makes difference in Business?

Typically, current solutions store data in a database management system (DBMS), and then fire queries across this data. But CEP inverts this common design pattern by first storing and indexing the queries/rules into an efficient structure and then streaming data through structures.

This approach has the following advantages:

- CEP helps to analyse information as soon as it is available.
- Time and effort spent on data base interaction and management is saved.
- In CEP most of the comparisons are in memory which makes it a real-time solution.

Dynamic maintenance of rules/queries helps the solution to scale dynamically and effectively.

Alexander Widder et.al [2] have proposed a method of using CEP with Discriminant analysis for identifying the unknown patterns in the banking domain for the use case of credit card frauds.

Credit Risk Management - Complex Event Processing.

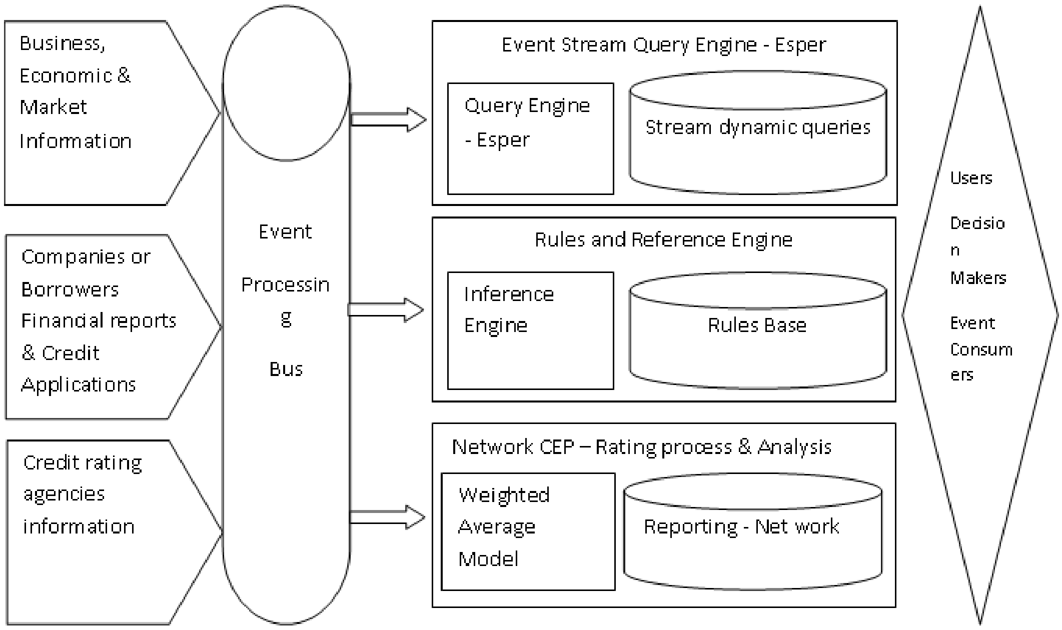


Figure 1: Credit Risk Management with CEP

Credit Risk Management

Credit risk analysis (Liquidity Risk, Operational Risk, Finance risk Business Risk analysis, loan default risk analysis) is part comprehensive effective credit risk management is important to financial institutions which provide loans to Large, Medium and Small Business Enterprises. Credit can occur for various reasons: bank mortgage loans, Working Capital Loan, Seed Capital Loan or any other short term loan

Pitfalls of classification modeling techniques and Justification for the present model

Classification models predict events into categorical classes, say, "risky" or "safe". Classification methods are supported by decision tree, SVM, neural network, etc. Intuitively, this is a very appealing approach as prediction is made using terms that anyone can understand! However, there is a serious drawback in applying classification techniques to credit risk management. The problem lies with the fact that credit defaults are in general very low ratio events, say, less than 10%. Developing predictive models with skewed data is very difficult, especially with decision tree classification. Decision trees develop predictive models by segmenting populations into smaller groups' recursively. It uses the dominant category (or most frequent value) of each segment as the predicted value for the segment. Dominant categories are the values represented by over 50% segment population. Credit users are already well screened. It is possible that no segments may contain risky customers in excess over 50%! Even it exists, it may be slightly over 50%! Segments in which 49% customers have default-history will be predicted as "not" risky, although they are in very high risk segments! This type of models will have very low accuracy in predicting risky customers as "risky". Much worse is that, as a consequence, more non-risky customers may end up being classified as "risky". Not much useful properties! It is important to note that all classification techniques have this limitation. To overcome this problem, you may be tempted to use tricks by introducing extra instances. However, such tricks will necessarily distort overall representation of population. Still the problem remains! A better approach is credit scoring using statistical probability described in the next sections.

Credit Risk Analysis and Modeling

The following credit risk analysis methods are described;

- Credit risk factor profiling or loans default analysis.
- Credit predictive modeling or loans default predictive modeling.
- Credit risk modeling or finance risk modeling.
- Credit scoring (Internal).

II. PROPOSED WORK

STEPS IN DEVELOPMENT OF MODEL

Model has two stages first stage focuses on developing Risk Assessment Framework based on weighted Averages and second stage application of Discriminant Analysis. The following are the steps involved in developing the model. In First Stage there are 6 steps in developing Risk Assessment Framework and in the second stage of the model Discriminant Analysis was used for classification of assets

Step - I: Identification of all the key risk components in the principal business
Step-II: Analysis of the weights given in similar organizations
Step- III: Allocation of weights to risk components
Step- IV: Development of risk rating on the Risk Assessment Model
Step-V: Comparison with previous risk-ratings and checking for Consistency
Step-VI: Use of Discriminant Analysis for Classification of Assets/ Clients

Step 1 – Identification of all the key risk components in the principal business

The first step in the development of the model was the identification of the various parameters to be taken into consideration. For this purpose, various manuals and documents pertaining to appraisal were carefully studied. More factors were added to the list to make it comprehensive and effective. This was done through literature survey and scanning of other leading organization's appraisal systems. The following was the result.

Step II -Analysis of the weights given in similar organizations

Once the parameters were identified, a questionnaire was prepared embracing all the parameters and was circulated among various bankers in order to find out the general practice of assessment. The 31 key players and the 37 Credit managers were chosen in this sector. Their opinions were gathered and considered for the study. Results of the opinion collected are presented according to the Risk Category.

Step III: Allocation of weights to risk components

The data collected was then classified, sorted and weights were assigned. Higher weights were allocated for elements with higher importance and vice versa. The categories within which these factors were classified were also weighed. Quantitative and qualitative factors were given appropriate weights.

The weights assigned to various parameters developed in this study are based on a conceptual understanding of the relative impact of these parameters on the risky ness of an enterprise or an industry to which it belongs. The weights may change if the external economic environment undergoes substantial changes.

It is not possible here to claim full objectivity in assignment of different weights, which requires empirical testing of success and failure experiences of a lending organization over a substantially long period of time.

Whatever weights are assigned to different risk parameters should be held constant for a given period of time across all borrowers, and during this period the weights must not be varied due to subjective consideration, for example to favour a particular borrower. If this consistency were upheld zealously, then even the subjective weights would gain objectivity in application.

Step IV: Development of risk rating on the Risk Assessment Model

Based on the above-mentioned information on weights a standard and comprehensive model was developed. Each of the customers will be rated on each of the parameters based on the key provided. The final score of the customer decides the risk involved in operating with him.

To aid the assessment process and to systematize the entire process, key for assessment has been developed in consultation with people well versed in this field. The key will not only quicken the assessment, but also standardizes it.

The parameters in each risk category should be analyzed based on the key and must be given a score. The scores should be multiplied with the weights assigned, in proportion to the importance of the parameter, to arrive at an aggregate for each risk category.

Each risk category is measured separately and is also expressed as a percentage, which would help to measure the risk easily. After calculating the risks under each category, they must be summed up and the grand score will be on 1000. To get a single point indicator of the risks, it is divided by 10 and expressed as a score on 100.

Based on the final score the company is given a rating by referring to the scoring guide of the model. As mentioned earlier, the grades used in the internal risk grading system should represent, without any ambiguity, the default risks associated with an exposure.

Here, we employ a numeric rating scale. Numeric scales developed for RAM is such that the lower the risk, the lower is the rating on the scale. The rating scale consists of 6 levels, of which levels 0 to 2 represents various grades of acceptable credit risk and levels 3 to 5 represents various grades of unacceptable credit risk associated with an exposure. The scale, starting from "0" (which would represent lowest level credit risk and highest level of safety) and ending at "5" (which would represent the highest level of credit risk and lowest level of safety), is deployed to standardize, benchmark, compare and monitor credit risk associated with the bank's loans and give indicative guidelines for risk management activities.

The model, the key for assessment and the scoring guide along with the interpretation are illustrated below.

The table shown above is The Scoring Guide which is useful in identifying risk category and classifying risk class of an asset or client.

Interpretation

- Risk category 0 - Indicates fundamentally strong position. Risk factors are negligible. There may be circumstances adversely affecting the degree of safety but even such circumstances are not likely to affect the timely payment of principal and interest as per terms.
- Risk category 1 - The risk factors are more variable and greater in periods of economic stress. Any adverse change in circumstances may alter the fundamental strength and affect the timely payment of principal and interest as per terms.
- Risk category 2 - Considerable variability in risk factors. The protective factors are below average. Adverse changes in economic circumstances are likely to affect the timely payment of principal and interest as per terms.
- Risk category 3 - Risk factors indicate that obligations may not be met when due. The protective factors are narrow. Adverse changes in economic conditions could result in inability or unwillingness to service debts on time as per terms.
- Risk category 4 - There are inherent elements of risk. Timely servicing of debts could be possible only in case of continued existence of favourable circumstances.
- Risk category 5 - Extremely speculative. Either already in default in payment of interest and/or principal as per terms or expected to default. Recovery is likely only on liquidation or re-organization.

Step V: Comparison of the previous risk-ratings and checking for consistency

Five of the existing customers were considered and rated, for checking the consistency of performance of the model. The comparison of the rating of the customer and the current status of the performance determines the consistency of the model.

Step VI: Use of Discriminant Analysis for Classification of Assets/ Clients

In this study after assessing the risk category of the Assets/ Client, Discriminant Analysis has been used for classification of assets/ client in to good and non performing asset groups. Given a set of independent variables, Discriminant analysis attempts to find linear combinations of those variables that best separate the groups of cases. These combinations are called Discriminant functions and have the form displayed in the equation.

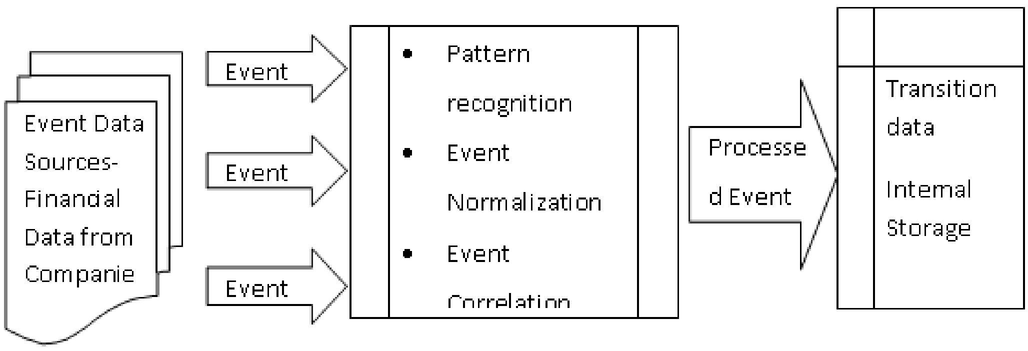
$$Dik = b0k+b1kxi1+...............+bpkxip$$

Where

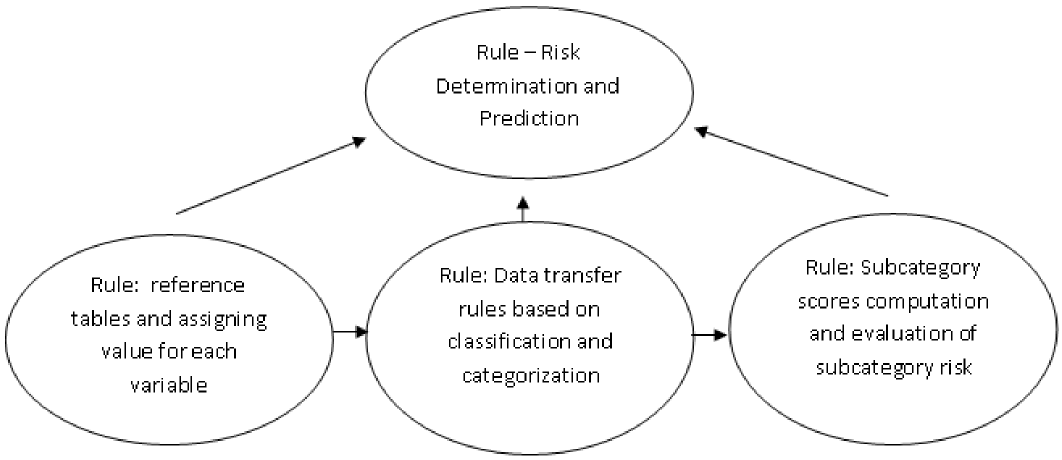
dik -	is the value of the kth discriminant function for the ith case
p -	is the number of predictors
bjk -	is the value of the jth coefficient of the kth function
xij -	is the value of the ith case of the jth predictor

The number of functions equals min (#groups-1, #predictors).

The procedure automatically chooses a first function that will separate the groups as much as possible. It then chooses a second function that is both uncorrelated with the first function and provides as much further separation as possible. The procedure continues adding functions in this way until reaching the maximum number of functions as determined by the number of predictors and categories in the dependent variable.



Rule Defined Nodes



Evolving threat situations demand faster and more reliable decisions to assess the credit risk

III. CEP FOR CREDIT RISK MANAGEMENT

Credit risk assessment using CEP involves the following steps.

Data filtering:

Only the valid data is passed to the CEP engine for further processing. Data is cleansed by filling the missing and invalid data with default values given by the industry standards.

Data Transformation:

Data provided by the customer is transformed into risk scores.

Development of Rules:

Rules are developed for identifying the overall risk and sub categories of the total risk such as liquidity risk, operations risk, financial risk and market risk.

A rule written for identifying Liquidity risk using STRAW EPL looks as follows.

Element	Declarations
Variables	Weights(W_i), Liquidity risk independent variables (V_i), Company Id, Company name
Event Types	Receive(company Id, Company name, V_i)
Relational Operators	$<$
Context Test	$\sum W_i * V_i < 400$
Action	Create liquidityRisk (Company ID, Risk Score)

IV. CONCLUSION

The proposed system is implemented in JAVA. ESPER CEP engine is used for implementing the rules. The proposed system reduces the computation time, improves the accuracy and enhances the predictive power of identifying the risky assets.

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