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Credit Risk Evaluation as a Service (CREaaS) based on ANN and Machine Learning

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Abstract—Credit risk evaluation is the major concern of the banks and financial institutions since there is a huge competition between them to find the minimum risk and maximum amount of credits supplied. Comparing with the other services of the banks like credit cards, value added financial services, account management and money transfers, the majority of their capitals has been used for various types of credits. Even there is a competition among them for finding and serving the low risk customers, these institution shares limited information about the risk and risk related information for the common usage. The purpose of this paper is to explain the service oriented architecture and the decision model for those banks which shares the information about their customers and makes potential customer analysis. Credit Risk Evaluation as a Service system, provides a novel service based information retrieval system submitted by the banks and institutions. The system itself has a sustainable, supervised learning with continuous improvement with the new data submitted. As a main concern of conflict of interest between the institutions trade and privacy information secured for internal usage and full encrypted data gathering and as well as storing architecture with encryption. Proposed system architecture and model is designed mainly for the commercial credits for SME's due to the complexity and variety of other credits.

Keywords*-machine learning, artificial neural networks, credit risk, information as a service, CRIaaS, clustering, classification*

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I. INTRODUCTION

Credit risk scoring or commonly credit risk evaluation is one of the most crucial and important part of the credit application and approval process. Various kind of financial institutions deals with this decision making process continuously even starting from micro credit supplying for consumer product credits in the electronic markets and household stores up to macro credits for the investment of huge projects by the governments and international company consortiums dealing with construction projects like renewable energy investments, bridges and tunnels. Actually the whole decision process output is as simple as common classification problems of machine learning and statistical approaches. Even the classification is based on already defined risk levels like low risk, medium risk or high risk for the credit or sometimes there is only a Boolean decision of bad risk versus good risk. Depending on the approach, decision makers can make their decisions based on credit risk assessment by the type, payback time and value of the credit moreover type of the customer and properties of the customer. Financial institutions that are able to give credits also deal with the common aim of increasing the capital and amount of their funds rather than the other financial investment tools like bonds, investments, stock exchange, funds, share equity, debts and other financial tools.

As a result of their commercial structures, SME's apply for different levels and types of credits in order to improve and obtain the stability of their trade and manufacturing operations, sometimes those credits are used for adding a new machine or equipment to the inventory or sometimes just to fulfill the raw material supplies before starting production. Since the amount of the credit is within the limits of banks daily and weekly operations, the decision is made mostly within 2-3 business days after the application by examining the information supplied by the applicant company. This is a very time consuming process and it is open for errors and human mistakes. There are four possible situations about the credit application; two of them as correct decisions like natural results as approving or rejecting the credit and remaining two are wrong or false decisions. These false decisions have different consequences depending on which wrong classification class assigned for the applicant to the company namely "False Positive-Good Risk" and "False Negative-Bad Risk". (Alpaydin, 2014)

"False positive" or "false good risk" is the major mistake decision that can be taken, as defining a credit application for a good risk and giving the credit however the actual case is a high risk where a credit should not be supplied because the most possible outcome is the credit will not be payed back and resulting a loss for the financial institution. This type of false classifications should be strictly avoided. On the other hand "false negative" or "false bad risk" classification is the case of rejecting a potential good customer with the loss of profit that can be earned as a result of credit supplying which is not an actual loss of money like the former one.

Credit scoring methods for predicting credit worthiness have proven very effective in consumer finance. (Pavlidis, Tasoulis, Adams, & Hand, 2012) The main purpose of this system is making the correct credit scoring resulting to the classification of good and bad risk customers as well as avoiding primarily false positive decisions and decreasing the amount of false negative decisions. The misfit or noisy data will result in medium risk classification where more data should be requested from the applicant company or more detailed decision making process has to take place.

II. CREDIT RISK EVALUATION

Credit risk evaluation or credit risk scoring allows the decision makers in the financial institutions to make a decision about the credit application. It is not as easy as classifying all customers as good credit or bad credit customers since all credits has a different and variant risk level. For example a customer with bad credit background or inadequate income or profitability is not suitable for a midsize credit but can suit for a small or micro credit.

In order to improve this, a well designed and operated credit scoring mechanism should be included in the credit risk management. However, with the fierce competition, the credit scoring has also been expanded from only controlling the credit default risk to maximizing the profit. In the 1950s, it was first noticed that the statistical classification methods could be applied in discriminating the good and bad loans. The money-making ability has become the most significant business in credit decision making. In order to make a better classification for credit evaluation, customer's should be in a money-making state, and the lenders need more smart models which can guess a number the patterns of relationships, trade or financial movements of operations avoiding risk creation and generate income over time. For example, when making the credit condition decisions, lenders need to carefully figure out not only the customers' risk but also their possible income. The higher credit level can drive the usage of credit and bring more income, however, if customers are SME’s, then the higher credit level may also cause bigger loss to lenders. So, the lenders need to foreseeor calculate the chance of default and early payoff over time so that they can calculate the expected income and loss as a result of this credit operation.(Luo, Kong, & Nie)

There are many mathematical approaches and finance models like statistical approaches logistic regression (Bensic, Sarlija, & Zekic‐Susac, 2005; Hosmer Jr & Lemeshow, 2004; Joanes, 1993; Maher & Sen, 1997; Menard, 2002), nearest neighbor analysis (Blume et al., 2005; Hand & Henley, 1997; Henley, 1997; C.-L. Huang, Chen, & Wang, 2007), Bayesian network(Alexander, 2000; Chin, Tang, Yang, Wong, & Wang, 2009; Sanford & Moosa, 2012; Shenoy & Shenoy, 2000), support vector machines (Danenas, Garsva, & Gudas, 2011; Z. Huang, Chen, Hsu, Chen, & Wu, 2004; Lai, Yu, Zhou, & Wang, 2006; Shin, Lee, & Kim, 2005; Yu, Yue, Wang, & Lai, 2010), genetic algorithms (Chen & Huang, 2003; Mukerjee, Biswas, Deb, & Mathur, 2002; Ong, Huang, & Tzeng, 2005; Oreski, Oreski, & Oreski, 2012), multiple criteria decision making (Figueira, Greco, & Ehrgott, 2005; Shi, Peng, Kou, & Chen, 2005; Yoon & Hwang, 1995; Zopounidis & Doumpos, 2002), decision tables (Baesens, Setiono, Mues, & Vanthienen, 2003; Kirk, 1965), particle swarm optimization (Cao, Lu, Wang, & Wang, 2012; Jiang & Yuan, 2007; Xuchuan, 2008), ant colony algorithm (Marinakis, Marinaki, Doumpos, & Zopounidis, 2009; Martens et al., 2007; Martens et al., 2010), fuzzy logic (Capotorti & Barbanera, 2012; Malhotra & Malhotra, 2002; Tang & Chi, 2005) and so others like loss distribution function, portfolio credit risk, default correlation, Black-Scholes, Large portfolio approximation, Monte Carlo simulation, Conditional vs. unconditional loss distributions in the literature and theory about the risk scoring (Bomfim, 2016)

There are also different classification approaches for the customers credit rating evaluation similar to those former traditional evaluation techniques commercial banks employ to evaluate the risk levels of borrowers and applicants. Some financial institutions and consulting firms assign and uses of different risk groups. For example, Prosper uses a seven-level risk rating (i.e., AA, A, B, C, D, E, NR). This “rating-based” model provides basic evaluation of loans’ credit risk, and the loans within each rating group are assumed to bear the same level of risk. In order to diversify their portfolios, investors are allowed to pick loans from different risk groups, according to their risk-return preferences.(Guo, Zhou, Luo, Liu, & Xiong, 2016)

In summary, use of all the above mentioned techniques, approaches and combining them with local and global information, market and sector reports, a credit scoring model can be time and resource consuming, easily ranging from 9 to 18 months from system analysis, data collection and knowhow generation to the application deployment. Hence, it is not rare that banks use unchanged credit scoring models for several years. Bearing in mind that models are built using a sample file frequently comprising 2 or more years of past data, in the best case scenario, data used in the models are shifted 3 years away from the point they will be used. Should conditions remain unchanged, then this would not significantly affect the accuracy of the models, otherwise, their performance can greatly deteriorate over time.(Sousa, Gama, & BrandÃ£o, 2016)

III. ANN AND MACHINE LEARNING

ANN Artificial Neural Networks introduced in to machine learning serving commonly in supervised learning methodology has been widely used in the last fifty years in the common applications. In general artificial neural networks inspired from human neural information processing structure which formed by biological neurons. (Yegnanarayana, 2009)

As by supervised learning principle an artificial neural network needs an adaptation, or in other words, a learning process to understand and interpret the information flow according to inputs and outputs which is the credit risk evaluation parameters and the output as the classification of the risk application and the applicant.

The historical data or in other words the training data is continuously provided by the members of this system during operation. As in this paper previously credit applications and their classification are used to train the network and also some part of the data is used for testing and cross correlation in order to prevent memorizing instead of learning the process.

So for the test samples the input data is propagated forward through the ANN network model defined in the beginning. The output data from the system compared with the correct classification outputs and depending on the bias and the errors if obtained, the next step is to change the weights programmatically and use the new weights to start all over. This learning progress similar to a learning progress of a intern in the bank of financial institutions where their decisions should be screen by a supervisor. So in this type of supervised learning a set of input vectors and output vector used and considered to be learning a mapping from input set of parameters to a output classification. There is also a second type of learning is the unsupervised learning and is mostly used as a part of machine learning systems for making classifications and segmentations without a supervisor which cannot be used in this type of credit risk.

There are various applications of ANN to the credit risk evaluations using different ANN approaches in the literature, some of them using pure ANN for the solution based on general scoring and finding the risk values (Altman, Marco, & Varetto, 1994; Z. Huang et al., 2004; Jensen, 1992; Trippi &

Turban, 1992; West, 2000), as well as some hybrid approaches with other metaheuristic and machine learning algorithms like genetic algorithms (Oreski et al., 2012), with fuzzy logic (Lin, Hwang, & Becker, 2003), multivariate adaptive regression splines(Lee & Chen, 2005), Bayesian networks (Lee & Chen, 2005), particle swarm optimization (Gao, Zhou, Gao, & Shi, 2006), support vector machines (Z. Huang et al., 2004).

IV. Cloud Based Services and XaaS

Cloud computing is commonly and widely used information technology hot subject for the current status of the evolution with the genotypes of computational power within cloud computing is based on parallel processing, extensive storage and virtualization of computer systems as the system genes which results in the latest phenotypes like massive flexibility, scalability and complex computing. The common principle of the cloud computing is delivering, offering, providing the all suitable types of information technology related products and services via high speed internet as a service based business model namely “X as a Service” (XaaS) or “Everything as a Service” (EaaS) model. This paper introduces a new syntax to the X or E as Credit Risk Evaluation CRE, like well-known services like software (SaaS), infrastructure (IaaS) and platform (PaaS) as well as lots of unique or extended possibilities like network (NaaS), communication (CaaS), education (EaaS) and so on.(Mell & Grance, 2011)

The requirement for proving this information as a service is this type of knowhow and data should be shared between all financial institutions in order to protect the stability of the market from bad credits. The current financial market is to dynamic and responsive as a whole both for local and global markets. The overall system involves both local and global decision parameters to adapt itself for different situations.

One common problem using the cloud based services related with financial records is the issue of privacy and trade secrets. So the cloud system offers the service based on the hybrid cloud architectures, where the privacy and trade secrets stored in the local servers of the financial institutions and not shared within the public cloud system, and referenced with the encrypted key also generated on the private side of the cloud. So the identity of the customers and their information is protected as well as the amount of the credit and the sensitive information never opened for the public use. Service act as a black box agent where getting the information and returns the credit score and risk depending on the input.

It will not be possible to query the historical data as well as the results from the system. Only the weights and the information about the neural network architecture of the system open for public view.

V. Design Of Credit Risk Evaluation as a Service (CREaaS) Architecture

A. General Architecture of CREaaS

CREaaS service can be activated via standard SOA architecture either by XML or JSON queries over web services. In order to make a request the following inputs should be send to service over HTTP. Database server stores the previous credit application information and their current status. Banks stores the information belonging to their own company and record id’s in their private cloud systems. In the private cloud system private and sensitive information about the companies are stored and not shared to public cloud. All the information on the public cloud encrypted with asymmetric keys and the keys of all banks are different from each other. The information processing in the ANN Engine works without the identity of the customers.

Public cloud should be operated by a certified 3rd party company approved by all the banks and financial institutions and frequently audit by independent audits. ISO/IEC 27032 directives and common ethical rules also applied for standard operating procedures within the public cloud.

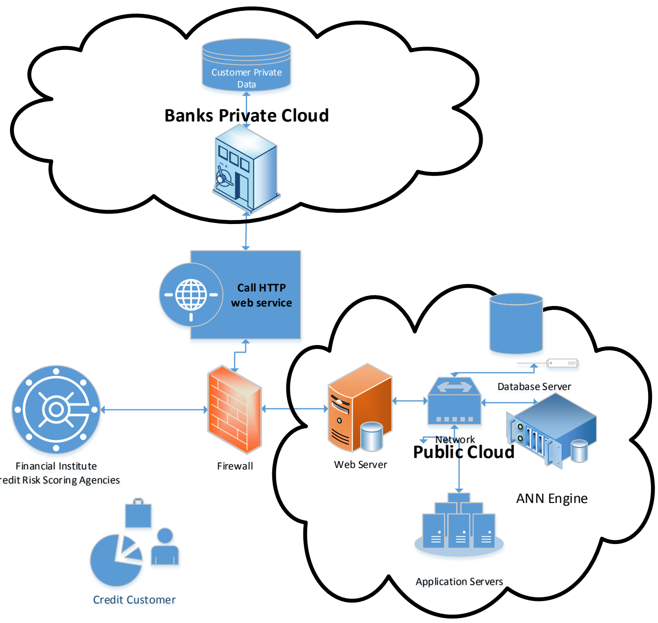

Figure 1. Architecture of CREaaS System.

B. CREaaS Input Parameters and Sample Data for Training

1) Applied Credit Amount

The amount of money that the borrower applies for. This has to be specified in the initial stage of documentation which also provides the essential financial and other information about the borrower on which the lender bases the decision to lend.

2) Age and Gender of the Borrower

Refers to the age and sex of the real person who applies for the credit. The age/sex scale in the risk evaluation is analyzed by the loan officer. The risk levels of younger male and female are higher. This parameter is not valid for legal companies.

3) Short term, medium term and long term risk

Maturity risk is defined as the type of risk which occurs due to the fact that the cash flow table does not fit the planned schedule because the maturity of receivables and payables do not match, and sudden losses are incurred due to financing failure. Maturity risk occurs when the average maturity term of the payables does not match that of the receivables. In the opposite case, where the maturity term of the payables and receivables match, maturity risk is eliminated.

For example, if the maturity term of a customer’s total payables to banks is 6 years on the average, and the term of the credit planned to be financed is 4 years, maturity risk occurs. However, if the maturity of the total payables is 5 years and that of the approved credit is also 5 years, there will be no maturity risk. Short, medium and long term maturities are determined by banks on the basis of the number of installments. The risk of short and medium term is always higher compared to that of long term.

4) Cheque Limit;

A cheque is a bill of exchange qualified as a commercial paper, and yet, it is an order for money transfer. Cheques can be drawn by banks only and can be used with cheque books issued by banks. A cheque is issued by a "drawer"; the person that will collect the relevant payment is "beneficiary"; and the party that will make the payment is "drawee". A cheque that is issued without any matching amount in the bank account is called a "bad cheque". Cheque limit is the total cheque limit value defined by the banks for a customer. However, cheque risk is equal to only the amount of the cheque limit that is used by the customer. The cheque limit value variable actually constitutes the cheque risk.

5) Credit Limit;

A credit limit is the maximum amount of credit that a financial institution will extend to a debtor for a particular line of credit. This limit is based on a variety of factors ranging from an individual's ability to make interest payments, an organization's cash flow and ability to repay the credit card debt and is an obligation of the consumer to pay just like all other parts of the balance

6) Total Risk;

The sum of both credit and cheque limit and short, middle and long term maturity risk. Limit and maturity risk, examined in different documents, are set out in two different ways to make it convenient for the allocation officer in credit risk analysis measurement. The maturity of the credit and cheque limit may be reviewed depending on the total value.

7) Accrued Interest;

Accrued interest is used to describe an accrual accounting method when interest that is either payable or receivable has been recognized, but not yet paid or received.

The accrued interest variable has been seen in 6 customers in the sample dataset that will be used in this study. Their loan application is rejected by credit authorites even though the good intelligence about some of the customers.

8) Legal and Administrative Prosecution;

If a period of 90 days has passed since the last payment day for a customer's credit card and credit, the relevant bank submits a notification to the customer, requesting to fulfill the payment within 7 days. This situation is called "administrative prosecution". Following this, the bank monitors the customer and analyzes whether the customer is capable of making the payment, before initiating executive proceedings. Should the problem continue, such situation shall be registered with the Credit Registration Bureau and the customer's future applications for credit card or credit may be rejected. After this phase, if the customer fails to make the payment by the end of the period that the bank grants, the bank shall sue the customer and initiate legal proceedings

Administrative proceedings phase does not involve judiciary proceedings, where the bank offers a payment plan and options for the customer. If the customer accepts such plan, then a debt structuring process is initiated. 50 customers included in the relevant database have not been subjected to any legal or administrative proceedings in the last five years.

9) Factoring Account;

Factoring is a financial transaction and a type of debtor finance in which a business sells its account receivable to a third party at a discount. This is done so that the business can receive cash more quickly than it would by waiting 30 to 60 days for a customer payment. It can be reached to factoring account documents of all commercial group customers on the Bank's internal financial records under the control of BRSA. 24 out of 50 customers in the database has factoring account.

10) Consumer Indebtedness Index- CII

CII is a tool designed to help identify individuals who may currently be able to fulfill their current repayment obligations but whose overall level of indebtedness means that they would struggle to keep up with their payments if they were to increase their commitments. It is as important for lenders to be able to identify those people who are in danger of over-committing themselves, as it is for them to be aware of those who are already in financial difficulties or have a record of poor payment and, therefore, pose a high risk of defaulting. The Consumer Indebtedness Index has been designed to support responsible lending by helping lenders to avoid granting further credit to consumers who are already heavily in debt and may be pushed beyond their ability to pay.

11) Credit Score from a National Institute

Lenders want to make sure individuals can comfortably afford to manage any new borrowing. To do so, they usually calculate a credit score, weighing up all the relevant information at their disposal - this helps them to assess the chances that borrower will be able to repay what they owe. The amount of debt borrower has is one of the biggest factors that goes into credit score. The credit scoring calculation considers credit utilization – the ratio between borrower's credit card balance and their credit limit – for each of their credit cards and overall credit utilization. The higher borrower's credit card balances are relative to their credit limit, the more it hurts their credit score. Credit score also takes into account how close borrower's loan balance is to the original loan amount. Carrying a lot of debt, especially high credit card debt hurts your credit score and your ability to get approved for new credit cards and loans.

For example in Turkey, KKB is a company that was established in the partnership of 11 banks and with the support of The Banks Association of Turkey in 1995 to realize the sharing of information necessary to ensure the monitoring and control of individual loans. The score given by KKB is an important reference in the credit decision process for most institutions.

12) Number of Credit Applications;

Number of applications only to the related bank. In the database, this number refers to the number of commercial applications and excludes individual and other type of applications.

13) Number of Late Payments

Number of late payments refers to the number of any payments that the borrower missed to pay the related bank by the statement due date. These late payments also classified into three types as T1, T2 and T3.

14) Guarantee

Guarantee is all kinds of movable and non-movable guarantees or provisions that are in the form of cash or that can be liquidated, received from the debtor for protection against the damages that the financing bank may incur in the event that the debtor fails to pay the relevant credit or fulfill his obligations.

For the training and test data a guarantee was received from 42 of the 50 customers in the database, whereas in the rest of the cases, no guarantee was requested since the financial data were determined to be solid. 26 of the 42 customers are legal persons, and 16 are companies owned by real persons. As indicated earlier, during the credit application, all female applicants provided personal guarantees, namely, a joint guarantor.

15) Intelligence

Refers to all the relevant information about the borrower which is collected by the authorized loan officers under the privacy, impartiality, accuracy and continuity principles and that may affect the bank's acceptance of credit application.

16) The Year of Establishment

The establishment year is the year that the company becomes subject to corporate tax.

17) Business Sector and Land Registry

Business sector refers to the segment of the economy that the company operates in. The sample dataset includes the companies established between 1981-2012 and the construction, PVC production, textile and supermarket sectors. Land registry shows the ownership of land and property in/on which the company operates. The sample dataset shows 15 customer or partners' ownerships and 35 rentals.

18) Customer Type

Refers to the customer being a real or legal person. Real person (sometimes referred to as natural person) is a living human being. Legal systems can attach rights and duties to natural persons without their express consent

Legal person refers to a non-human entity that is treated as a person for limited legal purposes-corporations, for example. Legal persons can sue and be sued, own property, and enter into contracts, in the sample data set 26 sample customers are legal person whereas 24 of them are real person.

19) Turnover

The amount of business that a company does in a period of time.

20) Profit and Loss

Profit refers to the amount of revenue when you get from selling goods or services exceeds the expenses, costs and taxes Loss is the result that occurs when expenses exceed the income or total revenue produced for a given period of time In the sample dataset 7 of the customers are in loss, 4 of whose have been denied, 2 partially approved and 1 accepted.

C. *The Result of Credit Application*

The decision made to grant or deny any installment to the customer after evaluating the information obtained and the risk assessment process. In the sample dataset 32 of the customer applications have been accepted (Low Risk classification), 6 have been partially accepted (Medium Risk classification) and 12 have been denied (High risk classification). The most important reasons that lie behind the deny decisions are,

a) The lack of liquidity available to pay the debt

b) Inadequacy of company equity, the high debt ratio, showing high profit and equity through fictitious (non- real) operations

c) Operating results of the previous years the company fails or found to be insufficient

VI. ANN RESULTS

Figure 2 shows the schematic representation of the classification artificial neural network created by the software neuro solutions.

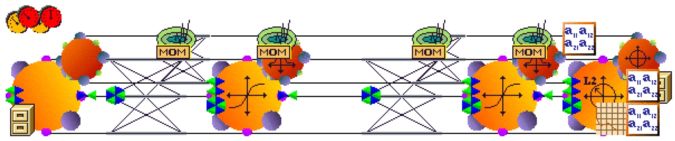

Figure 2. Architecture ANN Engine

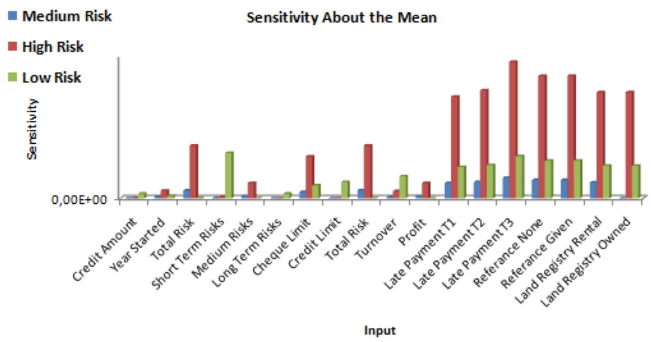

Figure 3. Data sensitivity about the mean

Figure 3 shows the senstivity about the mean and effective input items for the risk evaluation. Table 1 show the preliminary results from the sample data which will be promising for the future of the system.

TABLE I. ANN LEARNING PERFORMANCE

Performance	Table Column Head		
	Low Risk Accept	*Medium Risk Analyze*	*High Risk Reject*
MSE	0,0986	0,0013	0,1932
NMSE	0,4068	0,3854	0,7968
MAE	0,1371	0,0315	0,2073
Min Abs Error	0,0352	0,0030	0,0030
Max Abs Error	1,0303	0,0472	1,0521
r	0,8893	0,9264	0,8664
Percent Correct	80%	95%	89%

VII. CONCLUSIONS

This papers introduces a new cloud based service oriented architecture as CREaaS Credit Risk Evaluation as a Service for all kinds of financial institutions providing credits especially SME's and personal companies. The proposed ANN system receives the input parameters from the related financial institution, send this data for the ANN decision engine. The credit result and the risk is returned from the sample. The data is also stored in the system for further investigation of the credit. So the financial institutions also provides the payment status and the activity of the credit until its closed or classified differently. So the system is continuously improving itself by delayed supervised system by following the status of accepted credits.

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