2. Survey of literature

Abstract
This chapter describes the present work that comprises an exhaustive survey of relevant literature containing about 300 most relevant articles on credit risk evaluation from reputed journals such as IEEE Transactions on credit risk, machine intelligence, business journals and proceedings of various symposiums. Some selected articles from the survey are discussed by way of illustration.

The first written document mentioning credit risk was issued in 1790 BC law code is the first written law in recorded human history, which states that a failure to pay a debt is a crime (King, 2005).

The public release of credit risk rating portfolio models began in mid-1990’s. The KMV company released its Portfolio Manager™ product in the year 1993. The RiskMetrics Group (RMG) released its CreditMetrics™ and Credit Manager™ software packages in 1997. Credit Suisse First Boston introduced its CreditRisk+™ product in 1997. McKinsey company introduced CreditPortfolioView™ in 1998; the year witnessed numerous firms evolved their own internal models for credit portfolio management.

Table: 3 Credit risk management products

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<th>Sl. No.</th>
<th>Vendor</th>
<th>Product</th>
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<tr>
<td>1</td>
<td>KMV</td>
<td>Credit Monitor™, Credit Edge™</td>
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<td>2</td>
<td>Kamakura Corporation</td>
<td>KRM-cr™</td>
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<td>3</td>
<td>Loan Pricing Corporation</td>
<td>Risk Rater™</td>
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<td>4</td>
<td>Moody’s</td>
<td>RiskCalc™</td>
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<td>5</td>
<td>Standard &amp; Poor’s</td>
<td>CreditPro™</td>
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<td>Standard &amp; Poor’s</td>
<td>CreditModel™</td>
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<td>7</td>
<td>EnronCredit.com</td>
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The surveyed literature can be classified in to three major categories as casual methods, statistical methods and rulebased methods as shown in Figure-2. There are hybrid methods which are adopting more than one technique for credit risk evaluation.
Paul F. Smith (1964) authored *Measuring Risk on Consumer Installment Credit* paper and developed a relatively simple statistical method for measuring risk on individual accounts that can also be used for measuring and controlling portfolio quality and estimating loss rates. The procedure entails four steps they are

1. Comparison of good and bad accounts in the search for characteristics that are associated with bad accounts
2. Calculation of bad account probabilities for discriminating characteristics
3. Development of risk index from bad account probabilities to be used in grading accounts
4. Evaluation of the risk index. A test of the method on the accounts of commercial banks is described and the judgments implied by the risk index are compared to the criteria used by interviewers in rejecting applicants

A great many similarities are found between the results of the two methods but a number of striking dissimilarities are observed by the authors.

Peter Duchessi and Salvatore Belardo (1987) have designed knowledge-based system prototype to support commercial loan officers in credit risk analysis. The knowledge based system was called Loan Analysis Support System (LASS). This system provides a user interface to deal with variety of data, analytical operations and models in a flexible manner.

Rekha Jain (1989) paper entitled *Expert Systems: A Management Perspective* highlights some of the expert system important features. MARBLE (Managing and Recommending Business Loans Evaluations) expert system is a loan evaluating expert system (Shaw and Gentry, 1988). It combines financial projections with qualitative data. The loan granting decision is a combination of factors related to an analysis of the firm's historical and financial information, qualitative information about its product, market, industry characteristics and overall performance of the management. MARBLE system captures some of these features by analyzing the economic characteristics (size, market share), financial characteristics (profitability, liquidity and leverage), ability to repay loans (cash flow analysis, security), value of collateral, competitive position in industry, etc. Each of the relevant factors is given a certain weightage to evaluate a credit risk weight. The evaluated credit risk weight is compared with an objectively determined standard in order to establish the credit risk classification of the application. Marble system would recommend whether to approve the loan. If the loan is approved, the bank establishes the terms of the loan with the customer. The data and information used in the actual decision process are used as the basis for further performance review of the expert system.
The MARBEL system draws on models related to financial analysis, math programming, forecasting, and regression. In addition, the system also works with knowledge base that stores several rules regarding assessment of different aspects of the applicant, which are gathered by interviewing experienced loan officers. Furthermore, the system can update its own knowledge base while working with specific cases. In a typical session, this system enters into a dialogue with the user to obtain information on the financial and other details of the company. The answers given by the user to the questions asked by the system will trigger off further questions. The user can also ask, as a response to any of the system's questions, the reason why the question is being asked. The system would be able to provide the necessary explanation.

Raymond Beshinske (1991) has developed an expert system for the credit administration department at Merrill Lynch to assist setting up of credit limits on margin accounts. Every account with a debit balance over $100,000 is delivered daily to the system. The system appraises the account by assessing the risk using a combination of analytical and heuristic reasoning. The system considers the factors like fixed income positions on the basis of quality, marketability and overall portfolio diversity in risk assessment of the account. The system warns the credit analyst about problems in the account and gives advice about whether the current debit can be supported and what the credit limits should be. Merrill Lynch has made daily operational use of the system for over two years and uses it now to oversee more than two billion dollars of margin credit.

Hisao Ishibuchi and Tadahiko Murata (1995) presented the paper Selecting Linguistic Classification Rules by Two-Objective Genetic Algorithms and discussed how two objective genetic algorithms can be applied to a rule selection problem of linguistic classification rules. First they briefly describe a generation method of linguistic classification rules from numerical data. Next formulated a rule selection problem of linguistic classification rules. The problem has two objectives to maximize the number of correctly classified training patterns and to minimize the number of selected rules. Authors proposed two objective genetic algorithm for finding non-dominated solutions of the rule selection problem and also extend two objective genetic algorithms to hybrid algorithm, where a learning method is applied to each individual generated in the execution of two objective genetic algorithms.

A.G.Williamson (1995) describes how a simulated genetic process is used to automate the configuration and training of a back propagation trained multi-layer perceptron network used for credit application vetting. The network is trained on past loan case data, and is then used to classify the suitability of issuing credit on new loan applications.
A prototype scheme for using a genetic algorithm to choose the network geometry and back propagation parameters so as to optimize classification accuracy and speed of convergence is described. This optimization relies upon the genetic algorithm assessing a fitness criterion. The novel fitness criteria that has been developed for this application is described with the associated problems, and some suggestions for future research. The particular genetic algorithm used and its mechanisms are detailed. The performance of the final system is compared with the performance of a manually configFigure-d system over common data. The genetic algorithm refined system is seen to outperform the manual system in terms of accuracy, whilst requiring a minimum of operator effort by comparison. Results indicate the successful automation of this aspect of optimization for such a credit application vetting system, although further investigation in to the most suitable fitness criteria is still warranted, so as to incorporate further business information. In spite of the potential improvements to the effectiveness of neural network credit vetting systems oared by the findings of this work, the traditional problem of accountability remains. As loan companies endeavor to present a caring customer image, using a system which does not clearly identify the reasons for refusing credit is still likely to be unpopular.

Barbro Back, Teija Laitinen, Kaisa Sere, Michiel and Van Wezel (1996) authored the article Choosing Bankruptcy Predictors Using Discriminant Analysis, Logit Analysis, and Genetic Algorithms. This paper discusses the use of DA, logit analysis or genetic algorithm all lead to different failure prediction models. The authors studied the group of original variables formed by selecting those variables which in previous central studies have been found good predictors of failure. These variables were then roughly divided into three categories, namely profitability, solidity and liquidity. The results indicated that neural networks outperformed two other methods one and three years prior to failure. The misclassification rate one year prior to failure was extremely low, only 2.7%.

Kasper Rozsbach (1998) presents a Tobit model in his paper bank lending policy, credit scoring and the survival of loans in their paper authors discussed the sample selection and variable censoring thresholds has been constructed and estimated. This model is shown to be a useful tool to predict the expected survival time on the loan to any kind of applicant. A comparison with a nested model that disregards rejected applications, as has been common in studies of creditworthiness, shows that ignoring the sample selection effect leads to a large bias in the parameters estimates. The authors have analyzed the data set consisting of 13,337 applications for loan was processed by a major Swedish lending institution between September 1994 and August 1995. All applications were submitted in stores were potential customers.
Authors claimed that they gained several insights and confirm the findings in Boyes et al. that financial institutions lending policies are not compatible with default risk minimization.

Basel committee on banking supervision (April 1999) task force recognizes that credit risk modeling may indeed prove in better internal risk management, and may have the potential to be used in the supervisory oversight of banking organizations. However, before a portfolio modeling approach could be used in the formal process of setting regulatory capital requirements for credit risk, regulators would have to be confident that models are being used to actively manage risk. The task force observed a range of practices in the conceptual approaches to modeling and welcomed a dialogue with the industry in order to assess the materiality of these choices on a model's accuracy and their impact on the size of required capital if models were to be used for regulatory purposes.

Lyn C.Thomas (2000) carried out A survey of credit and behavioral scoring: forecasting Financial Risk of lending to consumers. Credit scoring and behavioral scoring are the techniques that help organizations deciding whether or not to grant credit to consumers who apply to them. This article surveys the techniques used both statistical and operational research based to support these decisions. It also discusses the need to incorporate economic conditions in to the scoring systems and the way the systems could change from estimating the probability of a consumer defaulting to estimating the probable to consumer will bring to the lending organization. Two of the major developments being attempted in the area and It points out how successful has been this under-researched area of forecasting financial risk.

Sushmita Mitra and Yoichi Hayashi (2000) have conducted exhaustive survey of neuro–fuzzy rule generation algorithms and presented Neuro–Fuzzy Rule Generation: Survey in Soft Computing Framework paper. The neuro–fuzzy approach, symbiotically combining the merits of connectionist and fuzzy approaches constitutes a key component of soft computing at this stage. Authors propose to bring these together under a unified soft computing framework and included rule extraction and rule refinement in a broader perspective of rule generation. Rules learned and generated for fuzzy reasoning and fuzzy control are also considered from this wider view point. This study also provided real life application to medical diagnosis.

Hans Roubos, Magne Setnes and Janos Abonyi (2000) have proposed an iterative approach. An initial model was derived from the observation data and subsequently, feature selection and rule base simplification methods are applied to reduce the model.
The compact, accurate and linguistically interpretable fuzzy rule-based classifiers are obtained from labeled observation data in an iterative fashion. After the model reduction, a real-coded Genetic Algorithm (GA) is applied to improve the classification accuracy and to maintain the interpretability of the rule base.

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The credit analysts read the application form and said yes or no. Their decisions are based on 4 or 5 C of the client. They are Character of the client, the Capital asked for, the Collateral- what the client is willing to put up from their resources, Capacity– what is the repaying capacity of the client how much income they have to repay the loan, The Conditions existing in the market.

*Amir F. Atiya* (2001) has authored the article *The prediction of corporate bankruptcy* and presents two contributions. First part reviews the topic of prediction, with the emphasis on neural-network (NN) models. Secondly developing a NN bankruptcy prediction model. This paper shows how NN models can be better used than conventional models.

*Basel committee* on banking supervision (2001) paper compares the approaches to risk management and capital regulation across the three sectors and was developed by a working group of the joint forum with membership from supervisors in all three sectors. In preparing this report, the working group has drawn on interviews with market participants, rating agencies and analysts, as well as on its own experience. The report was completed in Tendo, Japan, in July 2001 and was updated after consultation with the parent committees in August 2001. It has been found that while there is convergence between the sectors in various respects, there still remain significant differences in the core business activities and the risk management tools that are applied to these activities. There are also significant regulatory capital frameworks, in many cases reflecting differences in the underlying businesses and in supervisory approaches.

*Markus Kern* and Bernd Rudolph (2001) presented *A comparative analysis of alternative credit risk models - an application on German middle market- loan portfolios* discussed the comparison of various models especially with regard to their applicability on typical middle market loan portfolios.
The analysis shows that a difference in the results of an application of the models on a certain loan portfolio is mainly due to different approaches in approximating default correlations. Rodrigo Canales and Ramana Nanda from Harvard Business School have studied the relationship between the organizational structure of banks and the terms of lending to small businesses. Authors found that banks are more likely to restrict credit and to charge higher interests rates when they have market power, more so to smaller firms that have fewer outside options for external finance. Authors have also found that, where branch managers have autonomy over the terms of lending give larger loans to small firms and those with more soft information - particularly in states with weak legal enforcement of financial contracts. The results highlight that the access to soft information and the greater sensitivity of decentralized banks to the local institutional environment can have both positive and negative consequences for small firms. While some of the results complement prior findings by showing the benefits of decentralized lending in weak legal environments, the results also highlight that there may be a dark side to decentralized bank lending in certain instances.

A.J. Feelders (2002) proposed An Overview of Model Based on Reject Inference for Credit Scoring. Reject inference is the process of estimating the risk of defaulting for loan applicants that are rejected under the current acceptance policy. This survey article shows how the problem of reject inference can be viewed as one of statistical inference with incomplete data. Authors use a well-known classification of missing data mechanisms in to ignorable and non-ignorable to organize the discussion of different approaches to reject inference that have been proposed in the literature. From a practical view point, it might be preferable to avoid non-ignorable selection mechanisms. Usually the creditor knows the rule that was used to accept credit in the past, and in the case of over rules it might be worth the effort to find out the reasons for over ruling and recording them in the dataset. In any case, ignorability is a question of degree, and the more variables included that are predictive for acceptance, the closer to ignorability.

Rubens Ricupero, Secretary-General of UNCTAD Geneva (September, 2002) studied Improving the Competitiveness of SMEs, In Developing Countries. This paper discuss the bank’s major constraints in SME lending were (i) a dearth of long-term funding for banks for reasons stated earlier (ii) crowding out of the private sector by government borrowings (iii) low level of banks’ capitalization (iv) absence of long-term benchmark lending rates (v) directed credit albeit in a diluted form (through sovereign guarantees, which could sometimes constitute a moral hazard) (vi) distortions in domestic interest rates which made it difficult for banks to price their lending (vii) credit decisions based on ownership and propinquity rather than on financial criteria and (viii) in countries following restricted exchange practices such as multiple exchange rates which will effect subsidized import of capital goods and taxed
exports. Banks were reluctant to lend in foreign exchange to SMEs whose repayment capacity would have been constrained by any major exchange rate depreciation. Banks also discussed innovative approaches and successful programs in commercial banking for financing SMEs in transitional economies.

Rong Zhouli, Su-Lin Pang and Jian Min Xu (2002) have proposed a neural network credit risk evaluation model by using back propagation algorithm. This model evaluates the credit risk for 120 applicants. The data is separated in three groups, Good credit, Middle credit and Bad credit groups. The simulation shows that the neural network credit risk evaluation model has higher classification accuracy compared to traditional parameter statistical approach.

Sulin Pang, Yanming Wang and Yuanhuai Bai (2002) discussed the Incentive mechanism to credit risk decision model with incentive effects in their paper on Credit risk decision model and credit rating with asymmetric information. The authors observed that as the loan interest rate increases, high-risk borrowers drop out the market before low-risk borrowers. Meanwhile, they showed that low-risk borrowers choose contracts with low interest rates and high collateral requirements, whereas high-risk borrowers choose contracts with high interest rates and low collateral requirements. In general, in the case of information asymmetry, the borrowers always have more private information than banks. Therefore, when a borrower applies for a loan, the bank is often unable to judge risk of the project from client files.

Karel Komorad (2002) in his thesis on Credit Scoring Estimation gave a short overview of credit scoring and its methods. Author investigates the usage of some other methods and their performance on a data set from a French bank. Their results indicate that the methods, namely the logistic regression, Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) neural networks give very similar results; however, the traditional logit model seems to be the best one. Authors described RBF architecture and a simple RBF program to implement in the statistical computing environment XploRe. Their analysis thus showed that neural network models did not manage to beat logit in prediction. However, due to the flat-Maximum effect (Lovie and Lovie, 1986) one is unlikely to achieve a great deal of improvement from better statistical modeling on the same set of matching variables.

Gianluca Oderda (13th November, 2002) developed a framework to assess the statistical significance of expected default frequency calculated by credit risk models. This framework is then used to analyze the quality of two commercially available models that have become popular among practitioners: KMV Credit Monitor and RiskCalc from Moody's. Using a unique database of expected default probability from both vendors, Authors studied both the consistency of the prediction and its timeliness.
This paper introduces the concept of cumulative accuracy profile (CAP) that allows seeing in one curve the percentage of defaulting companies captured by the models one year in advance. Authors also used the Miller's information test to see if the models add information to the S&P rating. The result of this analysis indicates that these models indeed add relevant information not accounted for by rating alone. Moreover, with respect to rating agencies, the models predict defaults more than ten months in advance on average.

Uwe Schmock and Ernst Young (2003) in their master thesis on *Performance of modern techniques for rating model design* discuss and compare the various techniques of credit rating system. The methods presented in the first part of their thesis are logistic regression, polynomial regression and K-nearest neighborhood. These methods are intended to produce immediate results. The multi layered network causes lot of problems, as there are too many parameters to set in the architecture, transfer function, learning rate and learning strategy. Uwe Schmock and Ernst Young tried several pruning algorithms without any tangible results. In authors view, radial basis neural network based on hidden layer of neurons derived from the K-means clustering algorithm is the most efficient way to produce desired results.

Meliha Handzic, Felix Tjandrawibawa and Julia Yeo (2003) have applied multi-layer perceptron, ensemble averaging and boosting by filtering technique to credit loan application classification. Author’s goal was to find the best tool among the three neural network models for this kind of decision context. The experimental results indicate that committee machine models were superior to a single multilayer perceptron model and that boosting by filtering outperformed ensemble averaging.

Bart Baesens, Rudy Setiono, Christophe Mues and Jan Vanthienen (2003) in their paper *Using Neural Network Rule Extraction and Decision Tables for Credit Risk Evaluation* present the results from analyzing three real life credit risk data set using neural network rule extraction techniques. Clarifying the neural network decisions by explanatory rules that capture the learned knowledge embedded in the networks can help the credit risk manager in explaining why a particular applicant is classified as either bad or good. Authors also discussed how these rules can be visualized as a decision table in a compact and intuitive graphical format that facilitates easy consultation. It is concluded that neural network rule extraction and decision tables are powerful management tools that allow us to build advanced and user friendly decision support systems for credit risk evaluation.
Keshav Dahal and Zabeer Hussain (2004) in their paper *Loan risk analyzer based on Fuzzy Logic* presented the fuzzy logic approach to analyze the client loan applications by taking fuzzy linguistic variables like age of the applicant, loan amount, salary, employment, no. of repayment years etc. They have designed the fuzzy inference mechanism, rule base design and rating of the clients.

Kolari Shin and Berger (2004) conclude that small business lending has a strong positive effect on bank profitability and believed that lending to SMEs is riskier than to large corporates (see also Saurina and Trucharte (2004), Dietsch and Petey (2004)). The survey reveals that banks should develop credit risk models specifically addressed to MSME in order to minimize their expected and unexpected losses.

Adam Czub (2004) authored *Statistical methods of valuation and risk assessment empirical analysis of equity markets and Hedge fund strategies* and stated that mathematical models of valuation and risk assessment are at the core of modern risk management systems. Author used ETHZ a risk meter - a web-based tool, which was designed and implemented using a statistical methodology. It returns the different Value-at-Risk and related measures of risk (expected shortfall, volatility) using standard methods and the most recent state-of-the-art methods. In the present version riskometer focuses principally on three major stock indices: the Dow Jones Industrial Average (DJIA), the Standard & Poor’s 500 (S&P 500), and the Deutsche Aktienindex (DAX). The data is collected daily and added to the historical daily time series dataset, providing risk measures that may be interpreted as prognoses for a one-day time horizon. The underlying methods included in the riskometer may be applied to any stock price, exchange rate, commodity price or portfolio comprising combinations of these underlying risk factors.

Fabio Wendling and Muniz de Andrade (2004) proposed *Structural Models in Consumer Credit* a structural credit risk model for consumer lending using option theory and the concept of the value of the consumer’s reputation. Using Brazilian empirical data and a credit bureau weight as proxy for creditworthiness. Authors compared a number of alternative models before suggesting one that leads to a simple analytical solution for the probability of default. The proposed model was also applied to portfolios of consumer loans introducing a factor to account for the mean influence of systemic economic factors on individuals. The results in a hybrid structural-reduced-form model and comparisons are made with the Basel II approach. Author’s conclusions partially support that approach for modeling the credit risk of portfolios of retail credit.
Abdulrahman Altahhan and M. Bassam Alkurdy (2005) have introduced a knowledge representation model that depends structurally on fuzzy and crisp set theories. This model uses algebraic operations and a series of stages to reach a solution of the problem under study. This reasoning model operates in a manner very close to how human experts usually use their domain knowledge. This unified knowledge and inference model’s accuracy was verified on an expert system for medical diagnosis. The results are compared with that of domain expert experiments on selected patient samples that were taken under the supervision.

Jeffry R. Haber (2005) studied Assessing How Bankruptcy Prediction Models Are Evaluated. Authors discovered that in the real world, of the 10,000 companies that trade on exchanges, only 600 will go bankrupt - this is a 6% failure rate, so any model should do better than 94% accuracy, not 50%. Some companies might be eligible for bankruptcy, but choose not to file. They might instead threaten to file, and negotiate concessions from creditors. If this company was classified as bankrupt, would that be a correct or incorrect prediction? The classic evaluation model would classify that as a miss, but is it really. This paper addresses the shortcomings of bankruptcy prediction evaluation models and suggests that bankruptcy is better represented as a continuum, rather than a dichotomous situation. The current dichotomous classification test, the standard used in evaluating bankruptcy prediction research, fails to correctly classify situations that would be very important to users outside of an academic environment. A company might be eligible to file for bankruptcy, but chooses not to, using the potential as leverage to obtain concessions from creditors. A prediction model might have predicted the company to be bankrupt and since there was no filing, this would be counted as an error. However, the company used the potential of filing as a way to negotiate every benefit they might have gotten from a filing, and therefore the model should be considered to have correctly classified this. Real-world use starts with a list of companies without a priori knowledge of how many are/will be bankrupt and then the model is asked to classify each. This is how users will apply the model, and this is how the evaluation of the model should proceed.

R.S. Raghavan (2005) has authored an article on credit as well as credit risk management in banks. Credit portfolio is the real dynamic activity that requires close monitoring and constant management. The role of banks has changed from financial intermediately to risk intermediary. An integrated and proactive approach is required for managing the credit risk. It is very much essential to conduct credit investigation before taking up a proposal for consideration. The preliminary study should lead to valuable information on borrower’s integrity, honesty, reliability, credit worthiness, management competency, expertise, associate concern, guarantor etc. A due diligence report shall invariably accompany the
credit proposal evaluation. Banks have to strictly adhere to the KYC (Know Your Customer) norms to ensure bonafide identification of borrowers and should also follow the prescribed Fair Practice Code on lenders liability, by evolving their own best practices to be followed by the field functionaries, so as to avoid any complaints from customer at a later date. At present, due to lack of credit appraisal skill at the field level, manned by many generalist officials spread across the branch network, there is greater duplication of work at the sanctioning level at HO causing enormous and avoidable delay as papers pass through more than a dozen senior officials before they are placed before sanctioning authority. Author advised that banks should move from credit rating to credit risk rating and detailed discussion on cash flow generation should made compulsory part of project proposal. Credit decision will not get better by how many people review it, but who review it are knowledgeable and how much experience they carry with them in credit portfolio.

**Thomas Parnitzke** (2005) authored *Credit scoring and the sample selection bias* paper and stated that for creating or adjusting credit scoring rules, usually only the accepted applicants data and default information are available. The missing information for the rejected applicants and the sorting mechanism of the preceding scoring can lead to a sample selection bias. In other words, mostly inferior classification results are achieved if the new rules are applied to the whole population of applicants. Methods for coping with this problem are known by the term reject inference. These techniques attempt to get additional data for the rejected applicants or try to infer the missing information. We apply some of these reject inference methods as well as two extensions to a simulated and a real data set in order to test the adequacy of different approaches. The suggested extensions are an improvement in comparison to the known techniques. Furthermore, the size of the sample selection effect and its influencing factors are examined.

**Oliver Buchtala**, Manuel Klimek and Bernhard Sick (2005) discuss the *Evolutionary Optimization of Radial Basis Function Classifiers for Data Mining Applications*. This paper describes an evolutionary algorithm (EA) that performs feature and model selection simultaneously for radial basis function (RBF) classifiers. In order to reduce the optimization effort various techniques are integrated that accelerate and improve the EA significantly. Hybrid training of RBF networks, lazy evolutions, consideration of soft constraints by means of penalty terms and temperature based adoptive control of the EA. The feasibility and benefits of the approach are demonstrated by means of four data mining problems, intrusion detection in computer networks biometric signature verification, customer acquisition with direct marketing methods and optimization of chemical production processes.
It is shown that compared to earlier EA based RBF. Optimization techniques reduce the runtime up to 99% while error rated are lowered up to 86%, depending upon the application the algorithm is dependent of specific applications, so that many ideas and solutions can be transferred to other classifier paradigms.

Chorng-Shyong Ong, Jih-JengHuang and Gwo-Hshiung Tzeng (2005) presented the paper *Building credit scoring models using genetic programming*. Authors realized that an improvement in accuracy of a fraction of a percent might translate into significant savings, a more sophisticated model should be proposed to significantly improving the accuracy of the credit scoring mode. In this paper, genetic programming (GP) is used to build credit scoring models. Two numerical examples will be employed here to compare the error at other credit scoring models including the ANN, decision trees, rough sets, and logistic regression. On the basis of the results, authors concluded that GP can provide better performance than other models. Compared to their models, authors considered that GP is more suitable for the credit scoring problems for the following reasons. Unlike the traditional statistical methods need the assumptions of data set and attributes, GP is a non-parametric tool and suitable for any situations and datasets. Compared to ANNs, GP can determine the adequate discriminant function automatically rather than assigned the transfer function by decision-makers. In addition, GP can also select the important variable automatically. Finally, the discriminant function which is derived by GP can provide the better forecasting performance than the induction based algorithms.

Chihli I Hung, Jing-Hong Chen and Stefan Wermter (2006) divided the bankruptcy prediction and non-bankruptcy prediction techniques in the paper *Hybrid probability based ensemble for Bankruptcy Prediction* this paper. Based on analyzing the expected probability of both bankruptcy and non-bankruptcy predictions for a training set. They have built an ensemble of the three well known classification techniques, i.e. the decision tree, the back propagation neural network and the support vector machine. This ensemble provides an approach which inherits advantages and avoids disadvantages of different classification techniques. This paper describes results which demonstrate that our expected probability based ensemble outperforms other stacking ensemble based on weighting or voting strategy.

Maria Teresinha, Arns Steiner, Pedro José Steiner Neto, Nei Yoshihiro Soma, Tamio Shimizu and Júlio Cesar Nievola (May 2006) have presented a real-life credit-risk data set and analyze it by using the Neuro rule extraction technique and the WEKA (Waikato Environment for Knowledge Analysis) software. This paper presented a way of extracting classification rules from a problem whose attributes were coded, making them binary, and whose patterns were trained with a NN. The extraction was accomplished by applying the neuro rule
algorithm and with the help of the WEKA software. Maria Teresinha Arns Steiner et al. believe that the results were satisfactory.

Lean Yu, Kin Keung Lai and Shouyang Wang (2006) in their paper *Credit risk assessment with least squares Fuzzy Support Vector Machines* have discussed a least squares version of fuzzy support vector machine (FSVM) for designing a credit risk assessment system. This model could discriminate good creditors from bad ones. Relative to the classical FSVM, the least squares FSVM (LSFSVM) can transform a quadratic programming problem into a linear programming problem thus reducing the computational complexity.

**Credit Risk Assessment** Revisited Methodological Issues and Practical Implications working group on risk assessment (2007) discusses implementation methods and provide solutions to practical problems in credit risk measurement. In most of the papers, empirical examples are carried out from the special perspective of a central bank as most of the participants stem from such institutions. Two interesting papers provide empirical evidence on credit scoring and default prediction in central banks. The second paper on credit scoring was contributed by Ms. Lauria Auria and Mr. Moro. The authors discussed the advantages and disadvantages of support vector machines (SVMs) as a new promising non-linear, non-parametric classification technique, which can be used for credit scoring. This paper proposes a simple mechanism for comparison of the performance of major rating agencies and other credit assessment systems. The aim is to provide a simple validation yardstick to help monitoring the performance of different credit assessment systems, more specifically, those participating in the assessment of eligible collateral for Euro system’s monetary policy operations.

Jozef Zurada (2007) examined the historical data from consumer loans issued by a financial institution to individuals that the financial institution deemed to be qualified customers in their paper *University of Louisville Rule Induction Methods For Credit Scoring*. The data set consists of the financial attributes of each customer and includes a mixture of loans that the customers paid off or defaulted upon. The paper uses rule induction methods (decision trees) to predict whether a particular applicant paid off or defaulted upon his/her loan. The main advantage of decision trees is their ability to generate if-then classification rules which are intuitive and easy to understand. Rules could be explained to business managers who would need to approve their implementation as well as loan applicants as the reason for denying a loan. The paper compares the correct classification accuracy rates of several decision tree algorithms with other data mining methods proposed in earlier works.
Jonathan N.Crook, David B. Edelman and Lyn C. Thomas (2007) Recent developments in consumer credit risk assessment, Consumer credit risk assessment involves the use of risk assessment tools to manage a borrower’s account from the time of pre-screening a potential application through the management of the account during its life and possible write-off. The riskiness of ending to a credit applicant is usually estimated using a logistic regression model though researchers have considered many other types of classifier and whilst preliminary evidence suggest that support vector machines seem to be the most accurate, data quality issues may prevent these laboratory based results from being achieved in practice. The training of a classifier on a sample of accepted applicants rather than on a sample representative of the applicant population seems not to result in bias though it does result in difficulties in setting the cut off profit scoring is a promising line of research. Basel accord has profound implications for the way in which credit applicants are assessed and bank policies adopted.

Arturo Leccadito, Sergio Ortobelli Lozza and Emilio Russo (2007) proposed Markovian models in portfolio theory and risk management in the paper Portfolio Selection and Risk Management with Markov Chains. At first, authors described discrete time optimal allocation models and examined the investor’s optimal choices either when the returns are uniquely determined by their mean and variance or when they are modeled by a Markov chain. Authors subjected these models to back-testing on out-of-sample data, in order to assess their forecasting ability. Finally, proposed some models to compute VaR and CVaR when the returns are modeled by a Markov chain. In this paper pursued two objectives: the first one is to propose different markovian models that may be used to determine optimal portfolio strategies and to value opportunely the risk of a given portfolio; the second one is to compare portfolio selection strategies obtained either by modeling the return distributions by a Markov chain or by using a mean-variance analysis.

YUAN Hua and CHEN Xiaohong (2007) in the article A study of growth evaluation system for Small and Medium scale Enterprises (SME) s Considering credit risk have considered capital turnover ratio, sales gross profit ratio, debt ratio, growth ratio of major business period expenditure ratio and built the judgment model for the growth of listed companies based on these five factors and added credit risk into the growth evaluation system. The empirical study of small-medium sized listed companies found that that the reliability and validity of the new evaluation system has greatly increased when compared with the old one. The authors have adopted Altman’s Z-Weight model to measure the credit risk of Chinese listed SMEs.
Viresh Moonasar (2007) has applied LVQ artificial neural networks accurately to South African consumer credit risk analysis in his paper *Credit Risk Analysis using Artificial Intelligence: Evidence from a Leading South African Banking Institution*. This study investigates if relationships between biographic and demographic characteristics of consumers and their credit risk weights existed. Authors investigated the effect of varying the ANN network architecture on its ability to detect credit risk at the customer level. The relationship exist between age groups, marital status, race groups, employment and the credit risk grades of customers.

HA Min and ZHUANG Xintian (2007) have discussed how the commercial banks control the credit risk problem in the face of supervision of the laws, regulations and risks of the enterprise in their paper *Control model of bank credit risks based on commercial age of Enterprises*. Authors have proposed the two-stage optimization models of the bank asset-liability structure and credit risk control.

Ming Xu and Chu Zhang (2007) have authored *Bankruptcy prediction: the case of Japanese listed companies* paper and investigated bankruptcy prediction of Japanese listed companies. Accounting variables used in Altman’s Z-Weight, Ohlson's O-Weight and the option pricing theory-based distance-to-default measure, previously developed for the US market, are useful in predicting bankruptcy of Japanese companies. Traditional accounting variables form the basis for predicting bankruptcy, while the stock market variables provide more forward-looking information about a company's future prospects. Authors found that, for Japanese listed companies, the option pricing theory-based bankruptcy measure is more successful than the accounting variable-based measures alone, but it does not subsume the accounting measures. These variables and models all have their own strengths and cover certain aspects of bankruptcy prediction.

Alhassan G Abdul Muhmin (2007) studied *Credit card ownership and usage behavior in Saudi Arabia* and the impact of demo graphics and attitudes toward debt. In this study, authors empirically examined the extent and nature of credit card ownership and usage in Saudi Arabia, and how these are impacted by consumer demographics and attitudes toward debt using data from a structured survey. It was found credit card penetration in the country was relatively low, female Saudis are more likely than males to own the cards. Card usage tends to be selective, attitude toward debt was a significant determinant of card ownership but not usage behavior, and evaluation of card attributes is fairly positive among cardholders.
Theoretical, managerial and public policy implications of the findings are discussed. This study takes the parameters like income, education, age, nationality, gender and attitude towards debt.

Kingkarn Sookhanaphibarn, Piruna Polsiri, Worawat Choensawat and Frank C. Lin (2007) worked on *Application of Neural Networks to Business Bankruptcy Analysis in Thailand*. This study analyses financial data of the business bankruptcy prediction problem using neural networks for bankruptcy forecasting, the obtained features are fed into neural networks as input data. Their experiments examined the predictive performance of the three neural networks, Learning vector quantization, Probabilistic neural networks and feed forward network with back propagation learning. All these approaches are applied to data sets of 41 Thailand financial institutions for the period 1993-2003. Authors are of the opinion that Probabilistic Neural Network (PNN) provides consistent results every running time but its accuracy is lowest. Feed forward network with back propagation learning provide superior accuracy results to those results but its bias is considerably higher than that of the other two methods in an emerging market economy where ownership concentration is common.

Eduardo Rodriguez and John S. Edwards (2008) aimed to design a methodology to improve the risk modeling process using Knowledge Management (KM) concepts and tools. The risk modeling process is considered a support structure of the decision-making process in order to pursue a strategic planning process and strategy implementation. The article identifies different perspectives of the problem of risk modeling and proposes a methodological solution through: the use of the theory in Enterprise Risk Management (ERM) and KM using the context of a new view of organizational problems, the review of the historical episodes that created mathematical knowledge when groups shared knowledge and the analysis of the modeling process of three risk model example. This article sees enterprise risk management as a specific application of knowledge in order to control deviations from strategic objectives, shareholders’ values and relationships. Before and after a modeling process it is necessary to find insights into how the application of knowledge management processes can improve the understanding of risk and implementation of enterprise risk management. The article presents a proposed methodology to contribute in providing a guide for developing risk modeling knowledge and a reduction of knowledge silos, in order to improve the quality and quantity of solutions related to risk inquiries across the organization.

WEI Ran (2008) has developed the traditional credit risk model to evaluate the credit risk of the commercial banks based on the fuzzy theory. The membership functions for the model are designed with the evaluating indexes from credit risk weights of commercial banks.
The principle component analysis was also used to reduce the factors, which have diverse impact on the credit risk degree of the commercial banks. Author’s results indicated that their study can be used to make a quantitative evaluation of the credit risk of the commercial banks. Their case study shows that this new credit risk model has a good application for the commercial banks in China and shown a new method for risk management.


Gerhard Winkler (2008) presented Assessment of Credit Risk of the Companies Sector which aims at ensuring accuracy and reliability of credit ratings by means of validation which is of critical importance to many different market participants motivated by their specific objectives. The main “Ingredients” of Credit Risk Probability of Default (PD) - the probability that the obligor will default over the next year, Exposure at Default (EAD) - the amount outstanding in the case of default. This amount may exceed the current amount outstanding if the obligor is granted a credit line and they increase the amount borrowed prior to the default, Loss Given Default (LGD). Authors said that today, many banks adopt an enterprise-wide credit risk management approach for an integrated risk view. Best practices in credit risk management should demonstrate objectivity, prioritization, speed and accuracy, timeliness and active portfolio management. The pressure from regulatory requirements such as Basel II for International Swap Derivatives Association (ISDA) also encourages this. Credit risk analytics makes all this possible. An important prerequisite for effectively using credit risk analytics is to have appropriate organizational skill sets capable of understanding, building and maintaining risk models. Otherwise, banks should consider outsourcing, also important are consistent and accurate data and integrated technology.

Gary Chen (2008) discussed the overview of credit risk measurement under BIS II framework using block diagram in their paper Experiences in the Implementation of Credit Risk Management for Basel II. Authors also reviewed internal rating system tasks, role of different entities in Credit Risk Management (CRM) of banks with block diagram. Authors also designed requirements for rating systems, IRB requirements for credit ratings, overview of model development process and validation of the model. Paper also discusses the data collection and maintenance of systems.
Helsinki (2008) authored the article *Political Risk in Credit Evaluation Empirical Studies and Survey Results*, Swedish School of economics and Business Administration & Annika Sandstrom discuss the phenomenon of political risk in the context of international credit risk evaluation has been an exciting and stimulating, but at times exhausting and difficult endeavor. Not only the definitions of political risk indeterminate and more of a disciplinary perspective than objective statement, but to incorporate such phenomena in the academic literature on credit risk is far from an exact science. Authors interacted with distinctive group of academics and practitioners in the field of finance and related disciplines who have contributed substantially to author’s understanding on various issues concerning this research. Accordingly this thesis would not appear in its present form without the kind assistance and support of the following individuals and organizations.

David Shimko (2008) proposed management of counterparty credit risk in their paper *Credit Risk Management Policy Best practices in Credit Risk Management* which focuses on counterparty initiation and monitoring, contracting standards, credit authorities and limits, transaction approval process, credit risk reporting and reserving and capital policy. Improved risk measurement and reporting techniques paired with comprehensive credit risk policies can provide extremely effective protection against credit risk losses. The best risk management techniques are operational and legal, with collateral providing the best financial risk mitigation. Credit insurance and credit default swaps offer financial protection against default, but each at its own cost—which must be compared to the benefits of reducing the specific risk it is intended to mitigate.

Jingping Chen and Haiwei Pan (2008) in their paper *Credit risk assessment model based on domain knowledge* discussed the application of decision tree algorithm for the measurement of individual housing loan credit risk. The sample records have 11 fields they are identity cards number, no. of months in arrears, marriage status, gender, age, post, occupation, educational background, ratio of housing price to income, ratio of payment to income, insurance. The analysis result of decision tree algorithm shows that the ratio of payment to income is the most important factor to choose and the second is ratio of housing price to income. These two factors are important attributes that affect the degree of borrower’s credit risk, so they should be selected as main basis to assess credit risk of borrowers housing loan.
Xuemei Zhu and Ping Wang (2008) in their paper *The credit risk assessment method based on Dempster-Shafer combining evidence theory - Reasoning of the methods* evolved an expert methodology known as CAMPARI factor analysis, which assesses the customer credit worthiness by applying seven criterions. The word CAMPARI stands for C-Character, A-Ability, M-Margin, P-Purpose, A-Amount, R-Repayment and I-Insurance. This method largely depends on the ability of the expert in assessing the credit risk. Such an expert method can prove quite efficient in assessing the debtor credit as it relies on the historic information of the debtor and the subjective judgment to be taken by the experts. This method is usually applicable for qualitative rather than quantitative analysis and hence lacks an objective appraisal.

Wai Chuen Wong, Yao Xiao, Le Lei and Xinjiang Guo (2008) in their article *Research on credit risk evaluation model based on LVQ neural networks* proposed a credit risk evaluation model based on Learning Vector Quantization. This method produces good results marked by high research value.

Joao A. Bastos (2008) authored *Credit scoring with boosted decision trees* paper and proposed a credit scoring model based on boosted decision trees, a powerful learning technique that aggregates several decision trees to form a classifier given by a weighted majority vote of classifications predicted by individual decision trees. The performance of boosted decision trees is evaluated using two publicly available credit card application datasets. The prediction accuracy of boosted decision trees is benchmarked against two alternative data mining techniques: the multilayer perceptron and support vector machines. The results showed that boosted decision trees are a competitive technique for implementing credit scoring models.

B. S. Bodla and Richa Verma (2009) *Credit Risk Management Framework at Banks in India* The present paper is designed to study the implementation of the Credit Risk Management Framework by Commercial Banks in India. To achieve the above mentioned objective a primary survey was conducted. The results show that the authority for approval of Credit Risk vests with ‘Board of Directors’ in case of 94.4% and 62.5% of the public sector and private sector banks, respectively. This authority in the remaining banks, however, is with the ‘Credit Policy Committee’. For Credit Risk Management, most of the banks (if not all) are found performing several activities like industry study, periodic credit calls, periodic plant visits, developing MIS, risk scoring and annual review of accounts. However, the banks in India are abstaining from the use of derivatives products as risk hedging tool.
The survey has brought out that irrespective of sector and size of bank, credit risk management framework in India is on the right track and it is fully based on the RBI's guidelines issued in this regard.

Ross Gayler (2009) writes the *Guide to Credit Scoring in R*. This document is the first guide to credit scoring using the R system. This is a brief practical guide based on experience showing how to do common credit scoring development and validation using R. In addition the paper highlights cutting edge algorithms available in R system and not in other commercial packages and discusses an approach to improving existing credit weight cards using the Random forest package.

Guilio, Marco Grazzi and Federico Tamagni (2009) investigated the relevance of financial and economic variables as determinants of firm defaults in their paper *Financial and Economic Determinants of Firms Default*. Author's study is not only limited to publicly traded companies but extends to a large sample of limited liability firms. The study considered size, growth, profitability and productivity together with a standard set of financial indicators. Non parametric tests allow to assess to what extent defaulting firms differs from the non-defaulting group. Bootstrap probit regressions confirm that economic variables play both a long and short term effect. This paper's findings are robust with respect to the inclusion of distance to default and risk ratings among the regressors. This study shows that the industrial or economic characteristics of firms like size, growth, productivity and profitability do play a relevant role as determinant of default.

Zulkarnain Muhamad Sori and Hasbullah Abd Jalil (2009) studied *Financial Ratios, Discriminant Analysis and the Prediction of Corporate Distress*. This study developed a failure prediction model for Singaporean companies. The results showed a good performance with a highly correct categorization factuality rate of more than 80%. Two ratios were determined significant out of 64 financial ratios utilized in this analysis to discriminate among failed and non-failed companies. In their opinion the outcome shows good performance with a highly correct categorization factuality rate of more than 80%. The outcomes are very significant variables to identifying distress of the Singaporean firms.

Lidia Mandru, Adnan Khashman, Claudia Carstea, Nicoleta David and Lucian Patrascu (2009) worked on evaluating bankruptcy risk in their article *The Diagnosis of Bankruptcy Risk Using Weight Function*. Discriminant analysis can be used to assess companies using a linear combination with a limited number of financial ratios, which are used in financial analysis to identify the company's present and future situation. This paper uses Weight functions to determine the bankruptcy probability for private companies. Significant for the
concerned economic sectors. These indicators should base on the main economic and social key factors appropriate for the environment in analyzing risk of bankruptcy.

Adel Lahsasna (2009) in his article *Evaluation of credit risk using evolutionary-fuzzy logic scheme discusses the transparency and the accuracy of credit scoring model*. The author investigates credit risk using two different types of fuzzy models namely Takagi-Sugeno (TS) and Mamdani using generic software called *Evolutionary-Fuzzy-Neuro-System (EvoFNS)*. This software is used for fuzzy identification, (generation and optimization) prediction, classification and knowledge extraction.

Shaomei Yang and Junyan Zhao (2009) in their paper *Study on commercial banks credit risk based on CAMEL rating system* identifies five areas such as Capital adequacy, Asset quality, Management ability, Earnings and Liquidity. The initials of five words form the term *CAMEL* and the CAMEL rating system is used for the assessment of commercial banks credit rating system.

D.K.Sreekantha and R.V.Kulkarni (2009) authored *Small-scale industry loan processing using neuro fuzzy logic* and designed a credit rating framework by organizing the five areas of risks such as Technical Feasibility, Management Commitment, Commercial Variability, Financial Feasibility and Economic Feasibility. They have used fuzzy logic to capture the domain expert knowledge and assigned the standard weights to each of these risks. The client’s Weight is evaluated against these standard Weights. This client Weight is used in determining the client risk rating, which ranges from AAA-Highest Safety to D-Default.

Lidia Mandru, Adnan Khashman, Claudia Carstea et al. (2009) discuss discriminant analysis method to assay companies and particularly to evaluate their bankruptcy risk in their paper *The Diagnosis of Bankruptcy Risk Using Weight Function*. Weight functions are based on discriminant analysis and they are formed of a linear combination with a limited number of financial ratios; they are used in financial analysis but not only to identify the companies' present situation but also to assay their future. The Z - Weight for each enterprise is calculated as follows

\[
Z = V_1X_1 + V_2X_2 + V_3X_3 + \ldots \ldots + V_nX_n, \quad X_i \text{ - Independent Variables, } V_i \text{ - Discriminant Coefficients,}
\]

The discriminant function transforms the individual variable values to a single discriminant Weight which is used to classify the analyzed company.

Hamadi Matoussi and Aida Abelmoula (2009) Using a Neural Network-Based Methodology for Credit–Risk Evaluation of a Tunisian Bank. Credit–risk evaluation is a very important and challenging problem to financial institutions. Many classification methods have been
suggested in the literature to tackle this problem. Neural networks, especially, have received a lot of attention because of their universal approximation property. Their study contributes to the credit risk evaluation literature in MENA region.

Adel Lahsasna, Raja Noor Ainon and Teh Ying Wah (2010) studied Credit Scoring Models using Soft Computing Methods. Neural networks, genetic algorithms and support vector machines have been reported to be the most accurate methods as compared to the other methods. The classification accuracy is the key determinant of success in financial lending industry. During the last few years many studies have been conducted to overcome the main drawback of the soft computing methods which is the lack of interpretability. This survey illustrated different approaches used to overcome this problem. Among the approaches used are extraction rules from neural networks, using hybrid methods like neuro fuzzy or genetic fuzzy or using unsupervised neural networks learning methods like self-organizing map. This study has shown the benefits of using hybrid methods to overcome some limitations of single methods by using fuzzy system, artificial methods like neural networks, genetic algorithms.

D.K.Sreekantha and R.V.Kulkarni (2010) authored Expert System Design for credit risk evaluation using Neuro Fuzzy logic and presented credit risk evaluation technique for Trading industry client credit worthiness. This paper identifies all the credit risk parameters and organizes them in to a credit rating framework. The paper uses a Expert System Builder tool to design a Expert System prototype. This tool provides facilities to build knowledge base and query facilities. The inference engine interprets the client data entered and gives the credit advice to sanction a loan or reject the loan request. This paper also discusses these explanation facility to justify the credit decision taken. The results are tabulated and compared with that of manual system. Authors claim that results are satisfactory.

Amir E. Khandani, Adlar J. Kim and Andrew W.Lo (2010) authored Consumer Credit Risk Models via Machine-Learning Algorithms. They applied machine-learning techniques to construct nonlinear non parametric forecasting models of consumer credit risk. By combining customer transactions and credit bureau data from January 2005 to April 2009 for a sample of a major commercial banks customers. Authors are able to construct out-of-sample forecasts that significantly improve the classification rates of credit-card-holder delinquencies and defaults, with linear regression $R^2$'s of forecasted/realized delinquencies of 85%. This study has developed a machine-learning model for consumer credit default and delinquency that is surprisingly accurate in forecasting credit events 3 to 12 months in advance.
Shorouq Fathi Eletter, Saad Ghaleb Yaseen and Ghaleb Awad Elrefae (2010) in their paper entitled *Neuro-Based Artificial Intelligence Model for Loan Decisions* proposed a model that identifies artificial neural network as an enabling tool for evaluating credit applications to support loan decisions in the Jordanian Commercial banks. A multi-layer feed-forward neural network with back propagation learning algorithm was used to build up the proposed model. The study covers different representative cases of loan applications based on the guidelines of different banks in Jordan, to validate the neural network model. The results indicated that artificial neural networks are a successful technology that can be used in loan application evaluation in the Jordanian commercial banks.

D.K.Sreekantha and R.V.Kulkarni (2010) have published *The survey of Credit Risk Assessment Techniques* paper and discussed the various techniques used by researchers around the world for credit risk evaluation. The paper discusses about 40 research papers. The present research survey papers from 1964 to 2013. Authors have identified about 150 out of 300 papers which most relevant and included in this chapter. The techniques discussed covers from basic statistical methods to most recent methods such as soft computing and data mining approaches.

RC Chakraborty (2010) discussed the characteristics of hybrid systems employing fuzzy logic, neural networks and genetic algorithms. Hybrid system is Integration of neural networks, fuzzy logic & genetic algorithms. The hybridization of technologies can have pitfalls and therefore need to be done with care. Authors suggested that if one technology only solves the problem, hybrid technology ought to be used if it provides better solution. There are two types of hybrid systems one is sequential hybrid system and auxiliary hybrid system. Hybridization of fuzzy logic, neural networks and genetic algorithms has led to creation of a perspective scientific trend known as soft computing. Neural networks mimic our ability to adapt to circumstances and learn from past experiences. Fuzzy logic addresses the imprecision or vagueness in input and output. Genetic algorithms are inspired by biological evolution, can systemize random search and reach to optimum characteristics.

Basel III is an international regulatory framework was published on 16th December 2010, which encompasses a set of reform measures agreed upon by the Basel committee on banking supervision. Those reforms aim at strengthening: (i) the regulation, to avoid or at least reduce systemic risks, (ii) the supervision of the banking sector by requiring more transparency and disclosures and (iii) the risk management and governance of the banking sector. The three major components of credit risk are the probability of default, the exposure at default and the loss given default. Credit risk can be expressed as a function of those
parameters: Credit risk = f(PD, EAD, LGD) where PD: probability of default EAD: Exposure at default LGD: loss given default the credit VaR is another key element of credit risk.

D.K.Sreekantha and R.V.Kulkarni (2010) authored Knowledgebase design for Credit Risk Evaluation is using Evolutionary Neuro Fuzzy Logic have designed a prototype for evaluating the creditworthiness of MSME client from manufacturing and trading sector using knowledge management tool called WEKA tools. They have identified the risk parameters and shown the credit risk evaluation process using flow chart. This paper compares the results derived from WEKA tool with that of manual decisions and results are matching the extent of 95%.

Guy Ellena (April, 2011) International Finance Corporation from World Bank group has published a Guide for Investors in Private Health Care in Emerging Markets. This section provides an overview for financial institutions interested in learning more about the health sector. It defines the private health sector and discusses growth patterns and key business drivers, trends by subsector and future outlook. It also outlines factors to determine the private health sector’s scale and viability in a given country so that investors may identify the risks and take advantage of opportunities in this rapidly growing and capital-intensive sector.

Abbas Keramati and Niloofar Yousefi (2011) recognized that credit scoring has become very important issue due to the recent growth of the credit industry, so the credit department of the bank faces a large amount of credit data. Clearly it is impossible analyzing this huge amount of data both in economic and manpower terms, so data mining techniques were employed for this purpose. So far many data mining methods are proposed to handle credit scoring problems that each of them, has some prominences and limitations than the others, but there is no comprehensive reference introducing most used data mining method in credit scoring problem. The aim of this study is providing a comprehensive literature survey related to applied data mining techniques in credit scoring context. Such reference can help the researchers to be aware of most common methods in credit scoring evaluation, find their limitations, improve them and suggest new method with better capabilities. At the end authors noticed the limitation of the most proposed methods and suggest the more applicable method than other proposed.

Risk Management Advisory & Consulting Healthcare Industry (January 2012) has discussed the key issues noticed in healthcare, illustrated a business model for hospitals, governance, risk and compliance offering and enterprise risk management in hospitals.

Linda Delamaire (February 2012) proposed the implementation of credit risk management system based on innovative scoring techniques. Their thesis presents a credit scoring system which aims at setting credit lines and thus, controlling credit risk. It includes three types of
models: application weightcards, early detection weightcards and behavioral weightcards. They have been built on real and recent data coming from a German credit card company. The models have been built with a training sample and validated accordingly, using logistic regression. Information value and validation charts have been used for comparing the models. In the scoring process described, the Weightcards are used in a sequential order. The author shows that minimizing losses might not be optimal in order to maximize profit. Finally, the author presents possible extensions to the research and hopes that the technique described in this thesis can play some part in preventing future financial crisis.

Drew D.Creal, Robert B.Gramacy and Ruey S.Tsay (September 24, 2012) in their paper Market-based Credit Ratings presented a methodology for rating the credit worthiness of public companies in the U.S. from the prices of traded assets. Our approach uses as set pricing data to impute a term structure of risk neutral survival functions or default probabilities. Firms are then clustered in to ratings categories based on their survival functions using a functional clustering algorithm. This allows all public firms whose assets are traded to be directly rated by market participants. For firms whose assets are not traded, authors shown that how they can be indirectly rated through the use of matching estimators and show how the resulting ratings can be used to construct loss distributions for portfolios of bonds. Their approach has the advantages of being transparent, computationally tractable, simple to implement, and easy to interpret economically.

Frans Labuschagne and Patrik Desmares (November 2012) European Credit risk Outlook Results of Sixth European Credit Risk Managers Summary found that Eurozone crisis dragged on through summer of 2012 and in to fall and presents dismal picture of credit market. Authors given a clear message that banks owns customers must provide the growth and banks must do a better job of building customer loyalty, understanding customer needs, risks and improving communications. Authors pointed out that the findings from this survey will help to inform the risk manager’s council in better risk management.

Alejandro Correa, Andrés González, Catherine Nieto and Darwin Amezquita (2012) Constructing a Credit Risk Weightcard using Predictive Cluster. The main objective of this paper is to improve the development of credit risk weightcards by using cluster analysis, not only as a methodology to classify individuals with some specific characteristics (variables), but also as a part of a prediction process; obtaining efficient results when it comes to classifying and getting to know the profiles of the new clients that join the financial business. To do this, a comparison of two different methodologies is performed in four different databases in order to obtain an unbiased conclusion. The first methodology consists on developing Weightcard models for the entire population using a logistic regression and a
Multi-Layer Perceptron neural network (MLP). The second methodology involves four steps; first to carry out a cluster analysis for the entire population using K-means and Kohonen self-organizing map algorithms. Then, to develop an algorithm to assign a new client to any of the resulting clusters; the techniques used for this purpose are the multinomial logistic regression, MLP neural network, minimum Euclidian distance, minimum adjusted distance and Mahalanobis distance. The third step is to develop a weightcard for each of the clusters using also a logistic regression and a MLP neural network. Lastly, a final weight is computed using three different techniques: cluster weight, weight ensemble and classifier average vote ensemble. To conclude, a contrast between these methodologies is conducted using the F1 Weight statistic as a measure of comparison. This paper is divided into five sections. First, some descriptive statistics of the databases used in the analysis are presented. Then, an introduction to the most general concepts of the methodologies used along the paper is made. Subsequently, there is an explanation of the modeling process and the particularities of the algorithms and measures of comparison applied in this paper. In the fourth section the experimental results are shown and finally the conclusions are presented.

D.K.Sreekantha and R.V.Kulkarni (2012) authored Credit Risk Evaluation Using Knowledge Mining paper that focuses on the design of expert system model for credit risk evaluation by mining the knowledge bank of credit rating experts. This expert system is named as Credit Risk Evaluation Expert system (CREES). This expert system performance resembles human expert credit risk executives thought process in decision making. CREES uses soft computing technique called evolutionary neuro fuzzy logic. Authors have designed a Credit Rating Framework (CRF) comprising a large number of risk parameters such as financial, business, industry and management areas. Authors have tested CREES using the selected sample data. The results obtained from CREES are compared with manual decisions to evaluate the accuracy. This CREES needs to be tested using international standard German and Australian credit data sets.

Trends in lending report from Bank of England (January 2013) a quarterly publication presents the Bank of England’s assessment of the latest trends in lending to the UK economy. It draws mainly on long-established official data sources, such as the existing monetary and financial statistics collected by the bank that covers all monetary financial institutions, and on newer data collections, established since the start of the financial crisis. These data are supplemented by discussions between the major UK lenders and bank staff, giving staff a better understanding of the business developments driving the figures, and this intelligence is reflected in the report. The focus of the report is on lending, but broader credit market developments, such as those relating to capital market issuance or trade credit, are discussed where relevant.
Ovidiu Costin, Michael B. Gordy, Min Huang and Pawel J. Szerszen (February 26, 2013) authored the paper on *Expectations of functions of stochastic time with application to credit risk modeling*. Authors have developed two novel approaches to solving for the Laplace transform of a time-changed stochastic process. Authors discard the standard assumption that the background process (X) is Levy maintaining the assumption that the business clock (T) and the background process are independent, developed two different series solutions for the Laplace transform of the time-changed process \( X = X(T) \). Infact, their methods apply only to Laplace transforms, but more generically to expectations of smooth functions of random time. They apply the methods to introduce stochastic time change to the standard class of default intensity models of credit risk, and show that stochastic time-change has a very large effect on the pricing of deepout-of-the-money options on credit default.