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Automated Credit Decision Process - an insight into developing a credit-scoring model within the Nepalese Banking Sector.

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Abstract

There has been significant growth post-2000 in consumer credit within transition economies. Credit scoring, established within Western institutions, has the potential to be used to assess consumer creditworthiness here. This paper presents challenges and complexities relating to credit-scoring model development within the Nepalese banking sector. The research incorporates a mixed methods approach, involving model development using secondary data, supported by five in-depth interviews involving lending managers.

A model was developed deploying binary logistic regression comprising six customer characteristics. Its overall ability to predict known outcome was high, particularly repayment success, although challenges remain in terms of predicting failure, pointing to a relative absence of current data on such customers. Implementation challenges also exist, reliance on traditional judgement prevails, together with ignorance of possible approaches to modelling. Decision overrides occur due to conflict between restricting defaulting customers and growth targets, traditional practice retention and desire to demonstrate expertise amongst lending managers.

1. Introduction

Transition economies like Nepal are characterised by the presence of a *"bank-centred financial market"* (Adhikary, 2006). Here, the role of banks and financial institutions (referred to collectively as banks hereinafter) is crucial in mobilising capital, creating credit and allocating it efficiently within the economy. Within Nepal, these banks represent over 83% (160) of the 192 listed companies (Nepalese Stock Exchange Ltd., 2010). For an established period of time, these banks have been focussed on commercial and industrial lending as their sole source of revenue earnings. However, in the late 1990s, as a combined consequence of economic slowdown, infrastructural constraints, disintermediation and the rise in non-performing loans (Rao, 2004), these banks realised the necessity for diversification and expansion into additional lending areas in order to avoid concentration risk. From the new millennium onwards, consumer credit emerged as a new lending paradigm across numerous transition economies, Nepal included, at a time when the associated capital markets were not yet well developed (Ramamurthy, 2005). These developments have enabled associated middle class consumers to acquire and own assets such as houses/flats, vehicles, to obtain credit cards and also take out personal and educational loans. Within a short space of time, consumer credit growth in Nepal has been staggering, rising from around 15% per annum in 2004 up to 65-75% by 2009-2010, and in doing so constituting about 65% of the total credit portfolio of Nepalese banks by that endpoint in time (Nepal Rastra Bank, 2010).

Out of the credit crisis of 2007-2008, the Bank of International Settlements (BIS, 2009) directed transition economies exhibiting high consumer credit growth rates to be aware of inherent credit risks and the need to measure and manage such risk, and in doing so, allocating proper capital for any related exposure. Given this growth in consumer credit, it has become important to emphasise the need for a prudent credit decision making process to be adopted by the banks in such an economy if they are to undertake objective, fair, consistent and risk-based assessment of their growing numbers of consumers, Nepal being no exception.

The objective of this paper is to evaluate present consumer credit decision systems operating within Nepalese banks, with the intention of determining the feasibility of developing and implementing an automated credit decision-making technique known as a credit-scoring model, analogous to those long established within the Western banking sectors. If these developments are achievable, it could be argued that their full and proper implementation by Nepalese banks could enhance their credit decision-making processes and risk management systems, and by doing so, raise the credibility amongst consumers of the individual banks and the banking sector as a whole. With this objective, the research questions presented in this paper are:

- To what extent does the quality of existing data permit the development of formal credit scoring models?
- To what extent are the Nepalese banks geared up to credit scoring in terms of data availability and quantity?
- To what extent do the existing data permit accurate prediction of good and bad credit?
- What are the current challenges in terms of system implementation within a banking sector renowned for making decisions in a judgmental way, where the name and family of the customer and personal relations often play an important part in the final decision and where the onus on the banks is to continue growth in consumer credit?

2.   Literature Review

The literature review will provide a background to credit decision-making, before assessing the benefits of objectivity over subjectivity in the context of this type of decision-making. Consideration will be given to the benefits afforded by credit scoring, before looking at model selection and performance criteria. The review will look, from a quantitative perspective, at the relevance of these interventions to new markets.

2.1.   Background

Consumer credit has developed significantly since its launch from the early finance houses established in the 1920s, GE Capital and GM Finance being examples (Lewis, 1992), to the arrival of the credit cards in the 1960s, subsequently being matched by the growth in credit offered through an array of consumer products (Chandler and Coffman, 1979; Allen, DeLong and Saunders, 2004; Thomas, Oliver and Hand, 2005). Thomas (2000) made the observation that when credit was granted to a limited number of applicants, the banks evaluated their creditworthiness by means of subjective or judgmental process driven by the 5Cs, namely "*Character, Capital, Collateral, Capacity, and Condition*". However, as customer bases have grown significantly, the application of subjective techniques were rendered unviable because of their subjectivity around selection, being time consuming and not being grounded in assessment of risk (Hand and Henley, 1997; Thomas, 2000). To cope with this vastly changing market in consumer credit market, the banks active in developed economies have used automated credit decision processes known as credit scoring, based on statistical techniques used "*to predict the probability that an loan applicant or existing borrower will default or become delinquent*" (Mester, 1997, p.3).

The traditional approach to decision making based on judgement or subjectivity has been criticised for exhibiting weakness around decision-making error, an absence of quantification, inconsistency and slowness in decision-making and higher associated costs (Capon, 1982; Lewis, 1992; Hand, 1998). In contrast, there is greater credibility attached to objective decision-making around assessment of risk benefit, decision-making speed, consistency and fairness, especially where legislation governs the variables that can be used in this assessment. These attributes are generally regarded as drivers of process improvement in this arena (MacNeill, 2000).

Underpinning this objective approach to decision making, is the principle that the chosen scoring technique estimate the creditworthiness of an applicant upon his/her quantifiable attributes, an approach which has its predominance within developed countries to evaluate credit applicants (Hand and Henley, 1997; Thomas, 2000; Allen, DeLong and Saunders, 2004), with recognition given to its economic benefits (Blochlinger and Leippold, 2006). In contrast, evidence relating to emerging and transition economies suggests credit scoring was had at best limited application, even after 2000, during a period when consumer credit has exhibited considerable growth (Schreiner, 2000; Rao, 2005; de Andrade and Thomas, 2007; Kordichev and Katilova, 2007; Thanh and Kleimeier, 2007). An example of this is the Nepalese banking sector, where credit scoring is still at the stage of development (Ramamurthy, 2004; Upadhyay, 2005; Nepal Rastra Bank, 2008), despite increases in supply of consumer credit supply, driven by the growth in numbers of commercial banks, from 13 in 2000 to 25 in 2008 to 32 banks in 2011 (Nepal Rastra Bank, 2011). The introduction however, of credit scoring as a framework for risk-based credit assessment is perhaps inevitable, given the rapid upsurge in consumer credit and regulator driven emphasis on risk-based lending (Nepal Rastra Bank, 2008).

2.2. Role of predictive models, model selection and performance criteria

Early stimulus for credit scoring was provide by the "*Z-Score*" model developed by Altman (1968), which led to the principal of decision tools being developed around a suite of historical customer characteristics, available internally to the lending organisation, that are used in conjunction with appropriate statistical techniques (Hand and Henley, 1997; Thomas, 2000; Crook, Edelman and Thomas, 2007). To develop, maintain and update such processes, the lenders are required to upkeep robust databases containing customer characteristics and associated credit histories. The combination of timely data to represent lender experience and statistical process aims to provide a predictive model which uses probabilities to define an individual credit application as being good or bad in the future, the resultant credit scoring model transforming the selected characteristics into a single numerical value (analogous to the *Z-score*) to classify the credit applicant as good or bad credit, and in turn, recommending to accept or reject their application as appropriate.

Central to this development is the selection of an appropriate statistical technique to underpin the subsequent model development process. Various scoring approaches have been put in place, including application, behavioural, collection and bureau scoring as examples (Thomas, 2000; Mays, 2004; Bhatia, 2006; Anderson, 2007). Technique choice is driven by a combination of suitability of statistical approach to the scoring approach, development time, flexibility of the model to change and user friendliness defined by development ease, alongside user understanding and ease of application (Hand and Henley, 1997; Thomas, 2000; Crook, Edelman and Thomas, 2007). The latter is particularly relevant to arenas where the movement towards objective customer assessment is in its infancy. Consistent for all such models, transparency of output is crucial in affording these end users an understanding of the assumptions that underpin the models, thereby promoting acceptance and an ongoing ability to identify anomalies and any inaccuracies encountered in the decision making process.

Hand and Henley (1997) critically assessed various statistical techniques employed in credit model development, concluding that no individual "*best*" model existed, this being dependent on a combination of classification criteria, data structure and consumer characteristics assessed. Building on this assessment, Crook, Edelman and Thomas (2007) presented an overview of relative predictive accuracy for a range of established modelling approaches, defined in terms of the recognised "*percentage correctly classified*" (PCC) measure of fit, the key findings presented in Table 1.

[Table 1 here]

An interesting feature emerging from Table 1 is the similarity in accuracy afforded by a number of the commonly applied approaches, the assessment of Henley (1995) suggested little difference between linear regression, logistic regression and decision tress. Consequently, the final choice of adopted approach may then rest on various additional factors, perhaps specific to the scenario and the developing organisation. Lenders in an arena where credit scoring is highly embedded have a recognised history of utilising various linear techniques, as well as discriminant analysis, the benefit of the latter in establishing category membership beyond the binary stated predicted by logistic regression (Srinivasan and Kim, 1987; Boyle *et al.,* 1992; Henley, 1995; Crook *et al.,* 2007). Where situations required lenders to provide a credit score central to which is an estimation of default probability, capital adequacy scenarios being an example of this, binary logistic regression represents a widely used approach (West, 2000; Lee *et al.,* 2002; Baesens *et al.,* 2003). Further to this, certain non-parametric techniques including neural networks and decision trees, referred to

generically as expert systems (Thomas, 2000) have been used to score corporations, these situations being classic examples of modelling scenarios involving much less data, especially in comparison with consumers scoring developments (Baesens *et al*., 2003; Ong *et al.,* 2005).

2.3. Relevance to new markets

In any market new to objective customer assessment, a pivotal question for the lending organisation centres on determining, which if any, represents the most appropriate technique to underpin the development of their credit scoring system. In these arena, Thomas (2000) and Crook *et al.,* (2007) have recommended, particularly for newcomers to credit scoring, the application of binary logistic regression, given its specific design for predicting a binary two-sate outcome (analogous to repay or default) and well-established relative levels of accuracy. This recommendation accords with the scenario presented in this study, particularly around newness to the credit-scoring concept, coupled with modelling opportunities that are constrained by relatively small data sets, these issues being explored in the next section of the paper.

However, credit scoring in itself is neither new nor restricted to the developed markets found in Western economies. Furthermore, within these various arenas, alternative modelling techniques to that recommended above are in place, and as such, it is worth considering why they are potentially inappropriate for application in a setting such as the Nepalese banking sector. Within the emerging markets, evidence from the literature suggests that lenders have been recently developing credit-scoring system (Schreiner, 2000; Rao, 2005; de Andrade and Thomas, 2007; Kordichev and Katilova, 2007; Thanh and Kleimeier, 2007). There is a common experience in play here around the availability of only small data sets, the application of logistic regression and barriers to overcome in establishing an appropriate foothold in the consumer credit decision making processes. In contrast, in the mature markets of the West, the UK and USA representing two key examples, the developers of consumer credit models are afforded more mature and extensive customer databases, and as such, have been able to develop decision models with a much greater level of sophistication that arguably too complex than is practicable for an arena such as the Nepalese banking sector.

Customer characteristics, income level, behaviour of repayment and associated credit history being a small number of examples, used to develop models in these established markets are arguably different from those relevant to Nepal. The Credit Information Centre data available to the Nepalese financial institutions has historically been used only for blacklisting borrowers rather than to assess new credit applicants (Ramamurthy, 2004; Credit Information Centre, 2011). Consequently, it is crucial that in any model development, the nature and availability of data is given paramount consideration.

3. Data and Methodology for Model Development:
3.1. Mixed Methods Research – approach and benefits

A two-stage analysis took place in this study, the first involving model development through objective, quantitative analysis which has been well served in the literature pertaining to credit scoring (Hand and Henley, 1997; Thomas, 2000; Crook *et al*., 2007), the second, more subjective, by means of in-depth interviews with experts from the lending profession who were able to provide context and practical assessment of the analysis and how it relates to current lending practice and the support available internally to the organisation. This mixed approach to research is reviewed appropriately given the provision of broader perspective and subsequent depth of understanding (Easterby-Smith *et al*., 2002; Creswell, 2003).

3.2. Data sources, methods of variable selection and model development

In the Nepalese banking sector, where until recently, no formal history of credit scoring existed, one of the major challenges relates to extraction of historical customer information in relation to those granted credit. It is vital that the data cover a single time period and relate to an individual credit product to ensure that the applicants were subjected to consistent policy and procedures for granting credit, thus supporting the recommendations in selecting data for model creation made by Thomas *et al*. (2002) and Thomas (2002). Following this guidance, customer application data was sourced from a population of 202 historical home loan customers from an individual and typical Nepalese bank. The data for this study were collected from home loans granted during the period of 2005-2006 (one year) over a time horizon of one year (July 2007), assuring that both borrower's characteristics and their subsequent default status could be observed. In absolute terms, the sample size is perhaps small, being constrained by bank support and actual data availability, although the extant research indicates model development involving data sets covering varying sizes, Boyle *et al*. (1992) - 139; Vigano (1993) - 131; Desai *et al*. (1997) - 293; Baesens *et al*. (2003) - 200, 264, and 1438 and Abdou *et al*. (2008) - 581 being examples of this. One additional issue to consider is the recognised biased that occurs when models are developed using only accepted customer applications (Thomas, 1998; Banasik and Crook, 2007; Wu and Hand, 2007), this being rectified, where possible using reject inference and involving information from rejected applications. This additional aspect of the modelling process was not incorporated here, given the lack of maintenance of such data within the providing lending organisation.

3.3. Modelling technique adopted

The data derived from the source described comprised a range of customer measures, some continuous data, e.g. monthly income, others categorical in nature, e.g. gender. Crook (1997) and Thomas (2000) have indicated the suitability of binary logistic regression in handling a combination of both data forms in assessing a binary dependent measure, in this case loan status, i.e. default/bad credit and no default/good credit respectively. In this application of logistic regression, the historical customer home loan database comprised twenty independent measures, alongside loan status.

The model assumes the existence of a dependent outcome 'Y', defined in this application as the probability that a borrower is classified either a "*good*" or "*bad*" credit risk. This is modelled using a linear function comprising the various independent measures 'X' (Sharma, 1996; Field, 2005; Tabachnick and Fidell, 2006), expressed below in Equation 1 as:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots + \beta_n X_n \qquad \text{(Equation 1)}$$

Where, α is the intercept term,

β_n is the coefficient of the nth characteristic, and

X_n is the value of the characteristics n.

To select the most significant combination of independent measures to include in the logistic regression model, either a forward or backward selection method (Sharma, 1996; Hand and Henley, 1997; Field, 2005) can be employed. The independent variables may be respectively added or withdrawn from the model, and by doing so, the final and optimal combination will maximise the model's predictive accuracy. The selection involves iteration with insignificant predictors discarded as appropriate. Logistic regression applies maximum likelihood estimation (MLE) after transforming the dependent characteristics into a log function, which

provides an assessment of the respective variable coefficients (Field, 2005; Pallant, 2007). The model yields the probability of "Y" occurring for the given values of the predictor (independent) variables "X", as demonstrated by Equation 2:

$$P(Y) = 1/(1+e^{-z}) \hspace{3cm} \text{(Equation 2)}$$
$$\text{where } z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_n x_n$$

From the known data, the dependent variable takes the binary values 0 and 1 (representing good and bad loans respectively); the logistic regression model does not predict 0 and 1, but a continuous range of values in between. Appropriate round either side of a cut off value of 0.5 (the cut-off value is the value, taken by default as 0.5, which maximizes the model accuracy and can be varied as part of the model's sensitivity analysis, see the study findings). In short, larger values of P(Y) would signify a higher probability of default, conversely values of P(Y) less than 0.5 suggest that the applicant would be classified as creditworthy.

3.4. Expert Interviews
Given the newness of this approach to lending decisions, there are understandable issues relating to model acceptance and implementation, quality, volume, completeness and availability of data required to develop these models, the behaviour of credit managers with respect to full or part-replacement of the current judgmental approaches to credit lending and issues relating to model performance and evaluation. Five credit managers participated in these interviews, picked by purposive means from a number of different lending organisations given their lending and customer expertise. The interviews were semi-structured in terms of delivery and the resultant narrative content was analysed by means of a matrix analysis (Miles and Huberman, 1994; Morse and Field, 1995).

3.5. Ethical Considerations
The study has been dependent upon an individual bank providing loan data relating to a group of its credit consumers. In line with the ethics guidelines set out by the researchers' University relating to informed consent and assurances to the bank, this lending organisation will remain anonymous and the customers to whom the data relates cannot be identified in the study, nor were they recognisable from the data stored during the analysis performed. Likewise, the credit managers who participated in the in-depth interviews remained anonymous and cannot be identified by either name or employing lending organisation, demonstrating that both parts of the study ensured participant privacy (Bryman and Bell, 2007).

4. Study Findings
4.1. Empirical Analysis
The sample of 202 customer records, presented in Table 2, comprises 20 independent characteristics, alongside the dependent measure, loan quality, coded as 0 for default/bad credit and 1 for no default/good credit. Nepalese banks classify loan quality as standard (performing loan), sub-standard (loan pass due 3+ to 6 months), doubtful (loan pass due 6+ to 12 months) and loss (loan past due above 12 months) (Nepal Rastra Bank, 2004). All standard loans, 167 in the sample were classified as good, the remainder, 35 loans, as bad.

4.1.1. Assessment of the data
As discussed earlier, for a market without credit scoring history, Crook *et al.,* (2007) recommended logistic regression as the most appropriate statistical technique for model development, given its statistical acceptability and an ability to provide estimates of good or

bad credit (Henley, 1995; Sidiqqi, 2005; Anderson, 2007). This was developed using SPSS. Prior to model development, it is essential to assess multicollinearity between the independent measures (Pallant, 2007), given the detrimental effect on the assessment and significance of characteristics included within the model (Crook *et al.,* (1992). Menard (1995) suggested that tolerance values below 0.1 indicate serious collinearity problems, with Myers (1980) pointing to Variance Inflation Factor (VIF) values greater than 10 signposting concerns. From the correlation coefficients results presented in Table 2, monthly income (tolerance value = 0.003 and VIF = 398.791 (applicant), 27.407 (spouse) and 392.344 (total) represent the key problem measures.

[Table 2 here]

4.1.2. Model Development and Evaluation

A backward stepwise logistic regression analysis was used to select most the significant characteristics out of the 20 characteristics discussed above to be included to the model using the recommendation of Sharma (1996). Initially, the model contains all 20 consumer characteristics, thereafter, at each step; the backward stepwise method eliminates the weakest characteristic so that only the strongest characteristics, significant in combination, are considered for the final CSS.

After fourteen steps, the backward stepwise process concluded with the following six statistically significant characteristics: type of employment (TYP_EMP), type of occupation (TYP_OCC), purpose of the loan (PUR_LN), total cost of the project (TTL_CST), loan amount requested (LN_RQT) and stage of the project (STG_PJT) as the combined group of statistically significant characteristics. The remaining fourteen characteristics were not included because they had statistically insignificant coefficients and did not contribute to the explanation of the dependent variable (QUA_LN) by means of appropriate classification. These six characteristics as well as their coefficients are summarized in Table 3.

[Table 3 here]

The six characteristics in combination with each other were found to be statistically significant in predicting the quality of the home loan. The determined logistic regression model suggests that for a given type of occupation, purpose of the loan, total cost of the project, the amount of loan requested and the stage of the project, the type of employment is a significant predictor at the 5% level (p-value = 0.012). For a given type of employment, purpose of the loan, the total cost of the project, the amount of loan requested and the stage of the project, the type of occupation is a significant predictor at the 1% level (p-value = 0.006). For a given type of employment, type of occupation, the total cost of the project, the amount of loan requested and the stage of construction, the purpose of the loan is a significant predictor at the 1% level (p-value = 0.0099). For a given type of employment, type of occupation, purpose of the loan, the amount of loan requested and the stage of construction, the total cost of the project is a significant predictor at the 5% level (p- value = 0.029). For a given type of employment, type of occupation, purpose of the loan, the total cost of the project and the stage of construction, the loan amount request is a significant predictor at the 5% level (p- value = 0.047). Finally, for a given type of employment, type of occupation, purpose of the loan, the total cost of the project, and the amount of loan requested the stage of construction is a significant predictor at the 5% level (p- value = 0.047).

Thus, the logistic regression equation of our model is given by:
$$P(Y) = 1/(1+e^{-z})$$ (Equation 3)

Where $Z = 2.3645648 + 1.5054261 \text{ TYPE\_EMP} - 0.3110066 \text{ TYPE\_OCC} - 0.8348210 \text{ PUR\_LN} -0.0000004 \text{ TTL\_CST} + 0.0000005 \text{ LN\_RQT} + 0.3737026 \text{ STG\_PJT}$

The final model generated from the historical customer data as presented in Equation 3 could be applied to a new customer to predict their unknown value of the dependent variable 'Y'. Thus, a credit decision can be determined based on the prediction of 'Y'. The prediction can either be the risk class with two categorical values or a continuous score (from 0% to 100%, which may for example be the default probabilities). Although the dependent characteristic takes values 0 and 1, the logistic regression equation does not give the prediction of 0 and 1, but a continuum of fractional values in between. These can be then rounded and compared with the "*cut off value*" of 0.50 (the cut-off value is the value which maximizes the model accuracy and in this model it is taken as 0.5). Thus, if the probability of default is less than 0.50 (50%), then the applicant would be accepted and classified as a good credit and if the probability of default is classified greater than 0.5 (50%), then the applicant would be rejected as classified as a bad credit.

In order to test the performance of the credit scoring model several goodness of fit test were conducted. The results of the omnibus tests of model coefficients gives us an indication of how well the model performs when the predictors were entered to the model. The significance value is 0.003 (compare with the standard rule significance value should be less than 0.005), confirming the final model performance is within acceptable limits. Alternatively, the Homer and Lemeshow Test indicate a poor model fit by means of a significance value less than 0.05. In this modelling scenario, the significance value is 0.276, which supports the performance of the developed logistic regression model.

4.1.3. Sensitivity Analysis
The performance of the model can be further assessed by means of scrutinising its classification accuracy, as presented in Table 4. Superficially, as indicated by its overall attainment, the model has a creditable classification accuracy of 83.7% using the standard 50% cut-off level, comparing well with Srinivasan and Kim (1987) - 89.3%; Henley (1995) - 43.3%; Desai *et al.,* (1997)- 43.3%; West (2000) - 81.8%; Lee *et al*., (2002) - 73.5% and Baesens *et al.,* (2003) - 79.3%.

However, this represents only part of the assessment, given that the percentage of correctly classified bad credit (PCC bad) is only 8.6% (3 out of the 35 bad credits were correctly classified), although the model has performed particularly well in classifying good credit with an accuracy of 99.4% (166 out of the 167 good credits were classified correctly).

[Table 4 here]

As indicated by Baesens *et al.,* (2003), the final model classification might result in two types of errors:
- Type I errors (bad credit classified as good- Bg)
- Type II errors (good credit classified as bad- Gb).

From the lender's perspective, type I errors are understandably more concerning compared with type II errors, although the latter could case problems if large because potentially good customers may be rejected, hence a loss of good name for the bank, as well as future custom and revenue.

The sensitivity (SENS) which is the proportion of correctly classified good credit to the total number of predicted good credits and specificity (SPEC) is the proportion of correctly classified bad credits to the total number of predicted bad credits could be calculated for the model classification matrix (cut off value = 0.50) as:

$$SENS = Gg / (Gg + Bg) = 166/(166 + 32) = 0.8383 = 83.83\ \%$$
$$SPEC = Bb / (Bb + Gb) = 3/(3+1) = 0.75 = 75.00\ \%$$

Since type I errors are more serious, the model could be calibrated to determine the optimal cut-off point based on the sensitivity (SENS) measures. In order to calibrate the model, it is possible to assume that the Nepalese bank wanted to set a target for non-performing home loans at 0.75 per cent (as against the Mid-July 2008 NPL of 6.08 per cent of Class A Nepalese Commercial Banks, Nepal Rastra Bank 2009), then it could calibrate the model to a sensitivity of 99.25 per cent (SENS =100% - 0.75%), which could mean that the Nepalese bank should only accept applicants who have a predicted probability of default of less than 0.75 per cent. With such a cut-off value, the modified classification matrix for the model appears as shown in Table 5.

[Table 5 here]

By comparing the accuracy of the modified classification matrix for the model (cut off = 0.75) with the original classification matrix (cut off = 0.50), the PCC good drops from 99.4% to 88% and PCC bad increases from 8.6% to 40%.

$$SENS = 147 / (147 + 21) = 0.8721 = 87.21\%$$
$$SPEC = 14 / (14 + 20) = 0.4117 = 41.17\%$$

Thus, an improvement of 3.38% (87.21% - 83.83%) in sensitivity is achieved at a cost of a 33.83% (75.00% - 41.17%) reduction in specificity. This means that by calibrating the cut-off value of the model, the percentage of bad credit being classified as good would be reduced, a necessary adjustment given the underlying poor performance of the original model in terms of type I error.

4.2. Implementation issues – the credit manager's perspective

Consistent with setting, judgement dominated the existing approach to decision making (Ramamurthy, 2005, Nepal Rastra Bank, 2008), with measures of character, capacity and collateral underpinning the judgements made (Apilado *et al*., 1974), various interviewees describing the supporting role of their legal department, but typically the set of approaches described offered neither uniformity of standards or consistency of approach. Lack of consistency was also in evidence regarding the understanding of the approaches to modelling or the associated complexities, although dual recognition was given to the increase in consumer credit in this setting, and as such, the inevitability that model development would play a future role, be it created in-house or involving outsourcing to third parties. Limited recognition was also given here to data quality and quantity issues.

The latter is also substantiated by an absence of consistency in organisational policy pertaining to data management, thus raising doubts regarding credit evaluation consistency. Data verification processes were reported here, through the existence of dedicated internal auditors and valuators, with the overall position of data integrity defined by completeness and accuracy being at the behest of judgement exercised by various internal parties within the respective banks. Diligence exercised by bank staff in overseeing the application form processes is recognised, this offsetting discrepancy and exaggeration from the customers with regard to certain information provided, salary being an example. This situation is not helped by a highly competitive banking system where information sharing between organisations is problematic (Ramamurthy, 2005).

Despite problems relating to data integrity, there is a commitment to use historical data in model development, consistent with the literature (Thomas, 2000; Bhatia, 2006; Crook *et al*., 2007), although maintenance challenges pertaining to holding both accepted and rejected applications was conceded, the importance of the latter being around the necessity to account for "*reject inference*" in any thorough model development. The range of consumer measures considered appropriate in model development unearthed no unexpected consumer characteristics, with various responses arguably suggesting a rather limited overview of the potential credit applicants. The potential for a lack of model accuracy is recognised by these credit-lending managers, with a noticeable loyalty towards judgement demonstrated once again and an erosion of their powers to demonstrate expertise. There is a visible desire to permit decision overrides, although the necessity to monitor and seek further reference was acknowledged. However, the drivers of overrides were varied, information, bank policy and lender intuition all playing a part (Siddiqi, 2005; Anderson, 2007), complemented by staff references, customer behaviour and the necessity to achiever sales performance targets.

The practicalities of model implementation in terms of when and where in the credit transaction, system robustness and data maintenance were further recognised as areas for potential problems, as were aspects of culture, given the legislative void, which contrasts sharply with lending arenas such as the UK. In terms of model adoption, acceptance was evident from the lending managers, providing its could be used in tandem with judgement, whilst from the perspective of model performance assessment and complexity, limited responses were provided, perhaps understandably so, given the absence of any such systems locally against which to benchmark. The lack of consideration of performance parallels that being made against the judgemental approach that was operational at the time of the research.

5.   Conclusions

The paper has presented the application of binary logistic regression as an established modelling tool in the prediction of good and bad debts for a case consumer product provided by an individual lending organisation from the Nepalese Banking Sector. The study makes a crucial contribution to professional practice in this arena, given the absence of implemented models of this nature at the time of the research.   In short, this study has achieved its objective to develop a credit-scoring model for a Nepalese bank using a small dataset (given availability), for a part of the world that previously did not have a history of credit scoring. The study has identified that whilst consumer credit is growing, necessary data volume to develop and test the relevant credit scoring tools is potentially limited, and as such, banks and lending organisations with a desire to develop objective tools to support their lending decisions must give the highest priority to the collection and safe storage of consumer records from the point of loan application to completion of the loan activity, be it a success or failure. The sample considered was small, limited by data availability in a useable format and various business issues that have prohibited its collection, a constraint common to such developments in emerging financial markets, this sample being size limited in comparison with samples that have supported equivalent studies. However, the data set considered is representative of the fast growing consumer credit market of the Nepalese banking industry.

There are various examples of appropriate statistical models that are pertinent to modelling in this environment, the most recognised and credible has been put in place, demonstrating that high levels of classification can be achieved using data sets of limited size, although associated sensitivity of the model performance, suggests issues exist relating to data inadequacy because of the relatively small amount of declared bad debt to model, and subsequently, its ability to predict this outcome with any level of acceptable accuracy. In other words, the models have the ability to classify to a high level of accuracy, but the individual assessment of good debt and specifically bad debt represents a recognisable shortcoming, only corrected through the availability of much more data. With this in mind, it may take a long period of time involving high levels of consumer activity to develop a database with comparable and measurable proportions of good and bad debt, as recommended by decision makers adopting the recommended modelling techniques.   This data should incorporate both rejected as well as accepted applicant so that a robust credit-scoring model can be developed. The range of characteristics available, and therefore considered, could be expanded, whilst macroeconomic assessments including inflation and economic growth were not built in the model, thus representing a major limitation. Beyond the latter, the participating lending managers suggested no additional characteristics to be included in any data capture.

In terms of lending manager perspective, there appears to be a loyalty towards existing judgemental approaches, with a desire to see these dovetailed with any formal credit scoring systems, with areas for concern centring on data integrity, alongside a plethora of reasons for overriding decisions. There is acceptance however, that such systems will eventually arrive, although issues of systems' robustness is raised as a concern, whilst a necessity to support understanding of application, an appreciation of model complexity and content as well as assessment of system performance are recognisable areas for employee development.

Additional areas for future research potentially follow from this study. These include, subject to data availability, comparison of model performance across various approaches, assessment of the model from the perspective of implementation and calibrating it in line with established Basel guidelines.

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Appendix 1: List of characteristics used in the proposed credit-scoring model

Characteristics	Code	Descriptions
Applicant Age (in years)	APP_AGE	20-30=1, 30-40=2, 40-50=3, 50-60=4 and 60 and above=5. Boyle *et al.,* (1992) and Thomas (2000) have confirmed that with the rise in the age of the applicant, the propensity to default is reduced.
Type of Employment	TYPE_EMP	Employed =1, Self employed=2, Unemployed = 3. The type of employment determines the source of income for the applicant.
Type of Occupation	TYPE_OCC	Farmer/Agricultural=1, Teacher/Lecturer=2, Housewife=3, Govt. service =4, MNCs/NCs/Banking=5, NGOs/INGOs=6, Professionals=7, Politician=8, Entrepreneur/Business=9, Overseas Employment=10, Any others=11. This represents the depth in the type of occupations held by home loan customers.
Office Telephone	OFF_TEL	Yes=1, No=0. Crook et al., (1992) reported that the propensity of default is higher if the applicant does not have an official telephone.
Home Telephone	HOM_TEL	Yes=1, No=0. Possession of home telephone is an indicator of the behaviour of the applicant.
Number of Dependents	NUM_DEP	Data recorded as actual. Thanh and Kleimeier (2007) reported that as the number of dependents increases, so does the applicant's expenditure and also the propensity to default.
Purpose of the Loan	PUR_LN	Construction of the house=1, Purchase of a House/Flat/Apartment=2, Repair/Renovation of the House/Flat/Apartment=3. It could be argued that the purpose of the loan might be a strong determinant of default within Nepalese banks.
Total Cost of the Project (in Nepalese Rupees)	TTL_CST	These are recorded on an actual and represent the total cost price of the house/flat/apartment or the repair/renovation cost.
Loan Amount Requested (in Nepalese Rupees)	LN_RQT	These are recorded on an actual and represent the amount of loan requested by the applicant less the margin amount from the applicant's own equity which is about 20-30%.
Other sources of Finance (in Nepalese Rupees)	OTH_SRC	These are recorded on an actual and represent the fund available to the applicant from other sources such as loans/grants from relatives, interests on deposits, rental income, dividends and the sale of other property.
Stage of the Project	STG_PJT	Not started=0, Foundation completed=1, Structural work completed=2, Repairs and Finishing=3, Purchase of house/flat/apartment=4. For the purpose of construction of a new house, the credit is granted on an instalment basis linked with the stage of construction so as to ensure that the credit is used for the purpose requested for, which ensures to minimize the default risk.
Total Assets of the applicant (in Nepalese Rupees)	AST_APP	Assets are recorded on an actual and represent all assets the applicant has in the form of savings deposits, investments in shares, furniture and fixtures, motor vehicles, jewelleries. Nepalese banks do not ask for any documentary proof of ownership of these assets and sometimes the applicant exaggerates these figures.
Total Liabilities of the applicant (in Nepalese Rupees)	LBT_APP	Liabilities are recorded on an actual and represent all the liabilities the applicant might have in the form of bank loans, loans from employer, etc. However, these characteristics were not fully completed.
Monthly income of the	MI_APP	Monthly income recorded on an actual basis. Within Nepalese banks, one of the conditions for home loans is that the monthly income should

applicant (in Nepalese Rupees)		be twice the repayment amount. Banks were require the applicant to submit a salary slip or a salary certificate stating the current monthly salary, the applicant position, the terms of employment and the remaining tenure of employment.
Monthly income of the spouse (in Nepalese Rupees)	MI_SPS	Recorded on an actual basis. In case of joint borrowings, the income of the spouse is also taken into consideration for the purpose of loan assessment.
Total Monthly income (self and spouse) (in Nepalese Rupees)	TMI_BTH	Recorded on an actual basis. The total income represents the applicants' financial wealth and his ability to pay.
Applicant's equity (in Nepalese Rupees)	APP_EQY	It represents the applicant's contribution towards the project cost. Nepalese banks specify applicant equity between 20-30% in the property before the loan is sanctioned. A high percentage of applicant's equity could signify low default rates. These characteristics were recorded on an actual basis.
Rate of interest (in per cent)	RT_INT	Recorded on an actual basis, it represents the cost of the loan, which is as per the published rate of the bank at the time of the loan agreement.
Loan duration (in years)	LN_DUR	0-5 years=1, 5-10 years=2, 10-15 years=3, 15-20 years=4, 20-25 years=5. In Nepalese banks the maximum tenure for home loans is 25 years, which is decided by the bank taking into consideration the applicant's repayment ability.
Property value (in Nepalese Rupees)	PPY_VLE	Recorded on an actual basis, it represents the collateral value of the property. The property serves as collateral and is secured in favour of the lender. The higher the value of the property, the higher the motivation for the borrower to repay the loan outstanding as the borrower might not want to lose the property in case of default. It could be argued that the propensity of default is higher in case of negative equity, which is when the value of the property is less than the amount of home loan.
Quality of Loan	QUA_LN	Default/Bad credit=0, No Default/Good credit=1. These constitute the credit behaviour of the applicants who have been granted home loans. From 202 home loans, 167 (82.67%) had non-default or good status and 35 (17.33%) had default/bad status at the time the data was collected for this study.

Table 1 - Relative Predictive Accuracy of Different Modelling Techniques (in per cent):

Author	Linear Regression	Logistic Regression	Decision Trees	Neural Networks
Srinivasan and Kim (1987)	87.5	89.3	93.2	
Boyle *et al.,* (1992)	77.5		75.0	
Henley (1995)	43.4	43.3	43.8	
Desai *et al.,* (1997)	66.5	67.3		66.4
Yobas *et al.,* (2000)	68.4		62.3	62.0
West (2000)	79.3	81.8	77.0	82.6
Lee *et al.,* (2002)	71.4	73.5		73.7
Baesens *et al.,* (2003)	79.3	79.3	77.0	79.4
Ong *et al.,* (2005)	80.8		78.4	81.7

(Source: Crook, Edelman and Thomas (2007) Recent developments in consumer credit risk assessment)

Table 2 - Collinearity statistics of the characteristics used in the proposed credit-scoring model

Characteristics	Collinearity Statistics	
	Tolerance	VIF
APP_AGE	0.819	1.220
TYPE_EMP	0.619	1.615
TYPE_OCC	0.619	1.615
OFF_TEL	0.701	1.426
HOM_TEL	0.846	1.182
NUM_DEP	0.751	1.332
PUR_LN	0.570	1.754
TTL_CST	0.502	1.452
LN_RQT	0.215	4.659
OTH_SRC	0.305	3.278
STG_PJT	0.551	1.816
AST_APP	0.617	1.621
LBT_APP	0.778	1.286
MI_APP	0.003	398.791
MI_SPS	0.036	27.407
TMI_BTH	0.003	392.344
APP_EQY	0.308	3.243
RT_INT	0.822	1.216
LN_DUR	0.721	1.387
PPY_VLE	0.351	1.387
QUA_LN	Dependent Variable.	

Table 3 - Logistic Regression Final Model Parameters:

Characteristics	Coefficients (B) [1]	Standard Errors [2]	Wald [3]	P-Values [4]	Exp (B) [5]	Lower 95% C.I. for Exp (B) [6]	Upper 95% C.I. for Exp (B) [7]
TYPE_EMP	**1.5054261**	0.5980502	6.3364158	0.0118284	4.5060732	1.3955231	14.5498815
TYPE_OCC	**-0.3110066**	0.1141474	7.4234661	0.0064379	0.7327091	0.5858266	0.9164189
PUR_LN	**-0.8348210**	0.3237010	6.6511809	0.0099090	0.4339521	0.2300949	0.8184207
TTL_CST	**-0.0000004**	0.0000002	4.7436454	0.0294067	0.9999996	0.9999993	1.0000000
LN_RQT	**0.0000005**	0.0000003	3.9529864	0.0467883	1.0000005	1.0000000	1.0000011
STG_PJT	**0.3737026**	0.1882177	3.9421338	0.0470910	1.4531049	1.0048143	2.1013971
Constant	**2.3645648**	0.7985188	8.7686390	0.0030645	10.6394076		

1-Coefficients (B) represent the estimates of the predictors (β) and the constant (α) included in the CSS. This value needs to be replaced in the equation to establish the probability that a case falls into certain category.

2-Standard Errors (SE) are the standard deviation of the sample distribution. A small SE signifies that most pairs of samples will have very similar means. A large SE would tell that the sample means can deviate quite a lot from the population mean and so differences between pairs of samples can be quite large by chance alone.

3- Wald statistic has the chi-square distribution and tells whether the coefficient (B) for the predictor is significantly different from zero. If the coefficient is significantly different from zero, than it could be inferred that the predictor is making a significant contribution to the prediction of the dependent characteristics (Y)

4- P-values represent statistical significance of the predictor.

5- Exp (B) represents the odds ratios (OR) for each of the predictor. According to Tabachnick and Fidell (2007, p. 461), the *"OR represents the change in odds of being in one of the categories of outcome when the value of the predictor increases by one unit"*.

6 & 7- For each OR, Exp (B) the lower value and upper value at 95% confidence limit is presented. This shows the range of values at 95% confident encompassing the true value of the odds ratio.

Table 4 - Classification Matrix of the Final Model (at cut off value = 50%)

			Predicted		
			Quality of the Loan		
Observed			Default/Bad Credit	No Default/Good Credit	Percentage Correct
Step14	Quality of the Loan	Default/Bad Credit	3	32	8.6
		No Default/Good Credit	1	166	99.4
		Overall Percentage			83.7

a. The cut value is .500

Table 5 - Modified Classification Matrix for the model (at cut off value = 75%):

			Predicted		
			Quality of the Loan		
Observed			Default/Bad Credit	No Default/Good Credit	Percentage Correct
Step14	Quality of the Loan	Default/Bad Credit	14	21	40.0
		No Default/Good Credit	20	147	88.0
		Overall Percentage			79.7

a. The cut value is .750