**CASE STUDY - BANKING  
Credit Risk Analytics (PD Models)**

OVERVIEW OF CREDIT SCORING:Credit scoring is perhaps one of the most "classic" applications for predictive  
modelling, to predict whether or not credit extended to an applicant will likely  
result in profit or losses for the lending institution. There are many variations  
and complexities regarding how exactly credit is extended to individuals,  
businesses, and other organizations for various purposes (purchasing  
equipment, real estate, consumer items, and so on), and using various  
methods of credit (credit card, loan, delayed payment plan). But in all cases, a  
lender provides money to an individual or institution, and expects to be paid  
back in time with interest commensurate with the risk of default.  
Credit scoring is the set of decision models and their underlying techniques  
that aid lenders in the granting of consumer credit. These techniques  
determine who will get credit, how much credit they should get, and what  
operational strategies will enhance the profitability of the borrowers to the  
lenders. Further, they help to assess the risk in lending. Credit scoring is a  
dependable assessment of a person’s credit worthiness since it is based on  
actual data.  
A lender commonly makes two types of decisions: first, whether to grant credit  
to a new applicant, and second, how to deal with existing applicants, including  
whether to increase their credit limits. In both cases, whatever the techniques  
used, it is critical that there is a large sample of previous customers with their  
application details, behavioural patterns, and subsequent credit history  
available. Most of the techniques use this sample to identify the connection  
between the characteristics of the consumers (annual income, age, number of  
years in employment with their current employer, etc.) and their subsequent  
history.

Typical application areas in the consumer market include: credit cards, auto  
loans, home mortgages, home equity loans, mail catalog orders, and a wide  
variety of personal loan products.  
**MODEL BUILDING:**When the training data set on which the modelling is based contains a binary  
indicator variable of "Paid back" vs. "Default", or "Good Credit" vs. "Bad  
Credit", then Logistic Regression models are well suited for subsequent  
predictive modelling. Logistic regression yields prediction probabilities for  
whether or not a particular outcome (e.g., Bad Credit) will occur. Furthermore,  
logistic regression models are linear models, in that the logit-transformed  
prediction probability is a linear function of the predictor variable values. Thus,  
a final score card model derived in this manner has the desirable quality that the final credit score (credit risk) is a linear function of the predictors, and with  
some additional transformations applied to the model parameter, a simple  
linear function of scores that can be associated with each predictor class value  
after coarse coding. So the final credit score is then a simple sum of individual  
score values that can be taken from the scorecard  
**BUSINESS OBJECTIVES:**The application of scoring models in today’s business environment covers a  
wide range of objectives. The original task of estimating the risk of default has  
been augmented by credit scoring models to include other aspects of credit  
risk management: at the pre-application stage (identification of potential  
applicants), at the application stage (identification of acceptable applicants),  
and at the performance stage (identification of possible behaviour of current  
customers). Scoring models with different objectives have been developed.  
They can be generalized into four categories as listed below.

1. MARKETING ASPECT:Purposes:Identify credit-worthy customers most likely to respond to promotional activity  
   in order to reduce the cost of customer acquisition and minimize customer  
   dissatisfaction.  
   Predict the likelihood of losing valuable customers and enable organizations to  
   formulate effective customer retention strategy.  
   Examples:Response scoring: The scoring models that estimate how likely a consumer  
   would respond to a direct mailing of a new product.  
   Retention/attrition scoring: The scoring models that predict how likely a  
   consumer would keep using the product or change to another lender after the  
   introductory offer period is over.

2. APPLICATION ASPECTPurposesDecide whether to extend credit, and how much credit to extend.  
Forecast the future behaviour of a new credit applicant by predicting loandefault chances or poor repayment behaviours at the time the credit is granted.  
Examples:

Applicant scoring: The scoring models that estimate how likely a new applicant  
of credit will become default.  
**3. PERFORMANCE ASPECT  
Purpose:**Predict the future payment behaviour of existing debtors in order to  
identify/isolate bad customers to direct more attention and assistance to  
them, thereby reducing the likelihood that these debtors will later become a problem.  
**Examples:**Behavioural scoring. Scoring models that evaluate the risk levels of existing  
debtors.  
**4. BAD DEBT MANAGEMENT  
Purpose:**Select optimal collections policies in order to minimize the cost of  
administering collections or maximizing the amount recovered from a  
delinquent’s account.  
**Examples:**Scoring models for collection decisions: Scoring models that determine when actions should be taken on the accounts of delinquents and which of several alternative collection techniques might be more appropriate and successful.  
Thus, the overall objective of credit scoring is not only to determine whether the applicant is credit worthy, but also to attract quality credit applicants who can subsequently be retained and controlled while maintaining an overall profitable portfolio.  
**DATA AVAILABLE:**⮚Bankloans.csv  
The data contains the credit details about credit borrowers:  
**Data Description:**age - Age of Customer, ed - Education level of customer  
employ: Tenure with current employer (in years)  
address: Number of years in same address  
income: Customer Income  
debtinc: Debt to income ratio  
creddebt: Credit to Debt ratio  
othdebt: Other debts  
default: Customer defaulted in the past (1= defaulted, 0=Never defaulted)