INSTITUTE OF MANAGEMENT, NIRMA UNIVERSITY

SUMMER INTERNSHIP FINAL REPORT

CREDIT RISK MODELING OF HOUSING FINANCE LOANS

Name of the organization: National Institute of Bank Management, Pune

Location: Work from home

SUBMITTED TO:	**SUBMITTED BY:**
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Date of Submission: 5th July, 2020

TITLE PAGE

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Designation: Finance Intern

Faculty Guide: Prof. Khyati Desai

Organization Guide: Dr. M Manickaraj

Submitted in: Institute of Management Nirma University

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ACKNOWLEDGEMENT

At the beginning of this report, I would like to extend my gratitude towards Institute of Management, Nirma University, which allowed us to undertake summer internship that provided first hand exposure of working in the real world's research based project.

I would also like to thank National Institute of Bank Management, Pune for providing me the opportunity to undertake this Internship, which will undoubtedly prove to be very beneficial to me in my future assignments, my studies and my career ahead. I wish to place on record, my deep sense of gratitude to Vittarth (The Finance Club of NIBM) and Vittnivesh (The Investment Club of NIBM) team. They have always supported me and provided constant guidance and advice.

I am also grateful to my faculty mentor, Prof. Khyati Desai, for her constant guidance and support in the completion of my project, as well as for being available all time for advice and mentorship.

I would like to extend my heartfelt and sincere obligation towards all the people who have helped me in this endeavor. Without their active guidance, help, cooperation & encouragement, I would not have made headway in the project.

EXECUTIVE SUMMARY

This report consists of project undertaken during my summer internship at National Institute of Bank Management, Pune from 9th April to 8th June 2020. I was assigned to work upon ‘Credit Risk Modeling of Housing Finance Loans in India.’

This project report contains three divisions- A, B and C respectively. Part A comprises of explanation of Training and Education Industry, details about NIBM including its vision, mission, role, services catered, governing board members, etc. Part B consists of thesis that examined the factors considering for sanctioning housing loans and predicting the probability of loan default. It covers methodology to conduct research work through logistic regression. The process contains data handling, calculation of derived variables, binning and conversion of continuous to categorical variables, descriptive statistics, hypothesis formation, variable selection, running regression model through machine learning and final model testing. It has mentioned the model output that rejects null hypothesis and conclusion part has shown the positive/negative and magnitude of relationship between independent and dependent variable. Managerial implication of credit risk modeling and drawbacks & recommendation is also presented in the report. Part C talks about learning from my summer internship project. This opportunity has given me an extensive exposure to learn about credit risk and its modeling in housing finance industry. Application of already known techniques and methods like descriptive statistics, hypothesis, regression analysis, p value, etc. were used during the research and lot of new concepts and processes like machine learning, logistic regression, correlation matrix, WOE and IV test, KS Statistics, confusion matrix and ROC curve I encountered during these two months. It has also mentioned the insights about the managerial role that I’ve learnt during working in this domain.

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PART A

PROFILE OF THE ORGANISATION & INDUSTRY

ABOUT THE ORGANIZATION

The National Bank Management Institute (NIBM) was established in September 1969 by the Reserve Bank of India, in consultation with the Government of India, as an autonomous apex body, with the mandate to play a proactive role as a 'think-tank' for the banking system. It is an autonomous educational institution, whose highest policy-making body is governed by a Council. The Chairman of the Governing Board is the Governor of Reserve Bank of India (the country's central bank). NIBM offers a wide variety of specialized executive development programs all across major Finance, Human resources, International banking, Strategic planning , Marketing, IT and Rural finance sectors. The Institute has partnered with Kellogg School of Management, USA; LSE, UK; CME Group, Chicago; New York's Federal Reserve Bank; and Frankfurt School of Finance & Management, Germany to implement global best practices. It also provides a bunch of international programs at the expense of the Ministry of Foreign Affairs, GoI. Every year, around 5000 participants, especially near 800 from developing nations, visit NIBM. In 2019, it has hit the mark of 50 years and celebrated Golden Jubilee. The Institute has a campus of over 60-acre in sylvan surroundings in a picturesque valley within the Maharashtra's city Pune.

VISION

"The National Institute of Bank Management will be the trustee for India for helping to create world-class, competitive banking and financial services capabilities. The Institute would endeavor to offer knowledge-based products and services in the field of bank management that are as good as, if not better than, the best anywhere in the world. While much of the products of the NIBM would be of universal interest, there would also be a focus on the legal and institutional aspects specific to India. The NIBM will be the preferred partner for enabling vision, strategies, organization, systems, technical, managerial and leadership competencies in the banking and financial sector, so as to help retain a high share of the domestic market, as well as capture a significant share of the global market."

MISSION

NIBM is part of the grand vision of giving a new direction to the banking industry in India and making the industry a more cost-effective instrument for national development. Therefore, helping the managers in their endeavor to make their organizations competitive both in domestic and international markets is the mission of the Institute.

ROLE OF THE INSTITUTE

- To be the banking industry's primary research and academic arm for constantly developing the expertise and skills applicable to its top management.
- To be a data and knowledge storehouse for both existing and emerging banking sector problems.
- To help the banks secure their financial position and make them world class.
- To be the agent of reform in the overall functioning of the banking system and to promote the implementation of professionalism in the country's banking and financial sector.

PRODUCTS/SERVICES

Since, NIBM is an educational institute, so it does not have any product. Although to fulfill the roles laid by the institute, it caters following services:

Training

The Institute is engaged in Bank senior officials' training & education. As an advanced learning institution, NIBM trains executives to work in a multi-cultural, multi-national environment. The participants are prepared to become experts in problem-solving by offering interdisciplinary theory and practical learning modules. The Institute conducts an average of around 150 training programs in different functional areas in one year, as well as conferences and seminars discussing topical areas of importance to the banking and financial services sector. Every year, more than 3,500 participants, including around 250 from different developing countries, attend NIBM training sessions. These programs include 128 institutional offerings upon many business and functional areas encompassing recent developments such as Insolvency and Bankruptcy Code, Prompt Corrective Action, IFRS Implementation, IT and Cyber Security, Supervision and Risk Management, etc.

PGDM Education Course

Since, academic year 2003-04, the Institute launched a one-year Post-Graduate Program in Banking and Finance (PGPBF). Taking into account the expectations of the banking system, the

Institute reoriented PGPBF with enhanced academic insights and deeper banking and finance specialization on a two-year course from 2009-10. PGPBF is called Post-Graduate Diploma in Management (PGDM)-Banking and Financial Services, after obtaining AICTE recognition in April 2013. However, as an integrated and mutually inclusive field of specialization, the Post-Graduate Program continues to concentrate on banking and finance, and is an additional primary identity of the institute. The batch strength of the course PGDM (Banking and Financial Services) was increased from 90 to 120 during 2018-19, which is the level approved by AICTE.

Research and Consultancy

NIBM offers valued consulting and research services to banking and financial sector organizations in their day-to-day activities to tackle various emerging or challenging issues. The institute completed six assignments in 2019 in the fields of risk management, accounting and audit, rural development and human resource management. These assignments are as follows: Validation of the Framework, Systems and Models used in the Allahabad Bank and Syndicate Bank Department of Risk Management, Review of Punjab National Bank 's Internal Audit System and Audit Procedures, Impact Study for Farmers for Commonwealth of Learning (CoL), Project on Weighted Average Cost of Capital (WACC) for Indian Telecom Service Sector assigned by Telecom Regulatory Authority of India (TRAI) and Internal Promotion Exercise for Middle Level Executives of Andhra Pradesh State Financial Corporation (APSFC).

Certification Courses

Following Reserve Bank of India's Directives on Capacity Building in Banks and AIFIs, which emphasized the need for Certification Programs to enhance the skills and competencies of bank executives in India working in four areas, namely Credit Management, Risk Management, Treasury Management, and Accounts & Audit, NIBM launched various courses on September 30th, 2017. These were subsequently followed by other programs on Retail Credit Management and Small Finance Banks Credit Management. The institute is now successfully running seven e-certificate courses. The courses were designed to be blended with a mix of online and classroom learning. The online element is based on the 'Moodle'- an open-source platform which supplies all the course material including practice quizzes for the participants to learn at their own rate. Video-based sessions, which are also offered on the Moodle website, offer classroom learning experience. An extensive assessment program has placed in place for participants to receive certification. Assessment involves several steps of module testing, assignments and a final examination. Since the inception of the courses, 2484 participants have completed and earned their certification, out of a total of 4136 enrolled.

GOVERNING BOARD MEMBERS

Mr. Shaktikanta Das

Mr. Shaktikanta Das is the Chairman of NIBM Governing Board. He is also the incumbent Governor of Reserve Bank of India (the country's central bank).

Dr. M D Patra

Dr. M D Patra is the member of NIBM Governing Board. He is also the Deputy Governor of Reserve Bank of India.

Mr. Rajnish Kumar

Mr. Rajnish Kumar is the member of NIBM Governing Board and the Chairman of State Bank of India.

Dr. Harsh Kumar Bhanwala

Dr. Harsh Kumar Bhanwala is the member of NIBM Governing Board and the Chairman of National Bank for Agriculture & Rural Development.

Ms. Nanda S Dave

Ms. Nanda S Dave is the member of NIBM Governing Board and the Executive Director of Reserve Bank of India.

Mr. Karnam Sekar

Mr. Karnam Sekar is the member of NIBM Governing Board and the Managing Director & Chief Executive Officer of Indian Overseas Bank.

Mr. Pallav Mohapatra

Mr. Pallav Mohapatra is the member of NIBM Governing Board and the Managing Director & Chief Executive Officer of Central Bank of India.

Mr. Amitabh Chaudhry

Mr. Amitabh Chaudhry is the member of NIBM Governing Board and the Managing Director & Chief Executive Officer of Axis Bank.

Dr. T T Ram Mohan

Dr. T T Ram Mohan is the member of NIBM Governing Board and the Professor under Finance & Economics area at Indian Institute of Management, Ahmedabad.

Mr. H N Panda

Mr. H N Panda is the member of NIBM Governing Board and the Chief General Manager, Corporate Strategy and Budget Department of RBI.

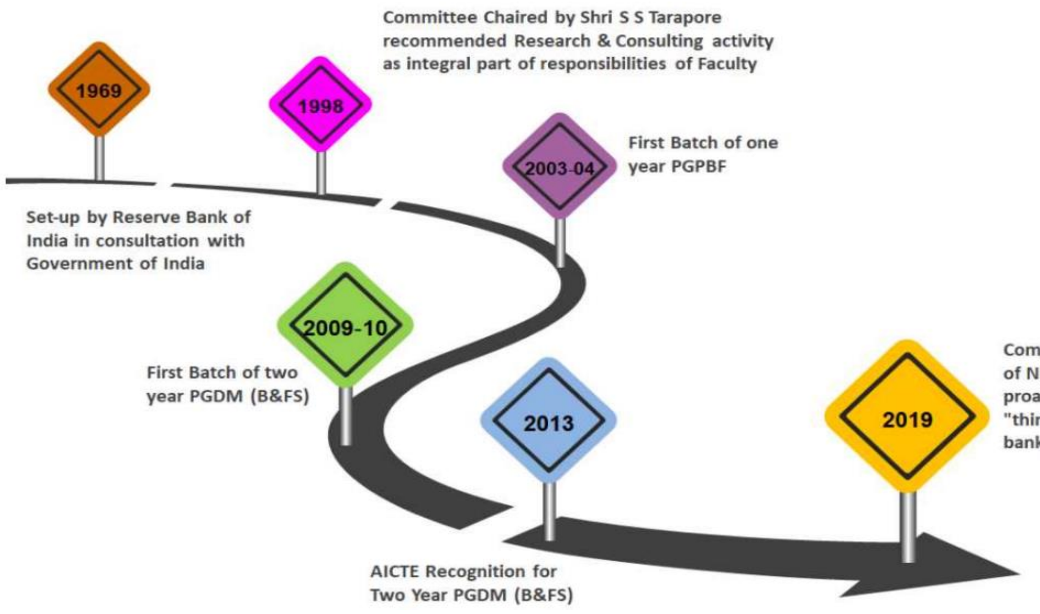
Ms. Zarin Daruwala

Ms. Zarin Daruwala is the member of NIBM Governing Board and the Chief Executive Officer of Standard Chartered Bank, India.

Dr. Sanjay Basu

Dr. Sanjay Basu is the Associate Professor & Associate Dean- Research Faculty Representative on the Governing Board of NIBM.

JOURNEY SO FAR

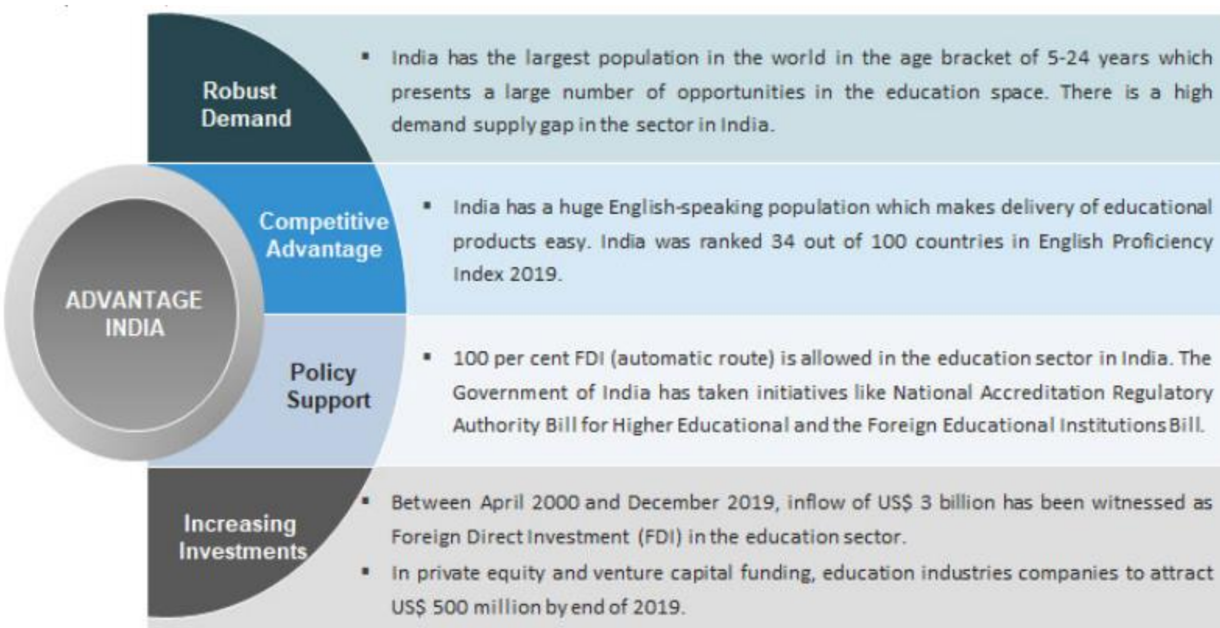


INDUSTRY

India holds an important place in the global education industry. It has one of the largest networks of higher education institutions in the world. However, there is still a lot of potential for further development in the education system.

Market Size

India has the world's largest population of about 500 million in the age bracket of 5-24 years and this provides a great opportunity for the education sector. The education sector in India is estimated at US$ 101.1 billion in FY19. Number of colleges and universities in India reached 39,931 and 993, respectively in 2018-19. India had 37.4 million students enrolled in higher education in 2018-19. Gross Enrolment Ratio in higher education reached 26.3 per cent in 2018-19. The country has become the second largest market for e-learning after the US. The sector is expected to reach US$ 1.96 billion by 2021 with around 9.5 million users. The market for corporate training in India has been a niche market that has witnessed steady growth but is yet to be explored in full potential and has a huge scope for expansion in the coming years. The market has been growing at a double digit growth rate during the period 2013-2018.



Education & Training Industry in India

COMPETITIVE POSITION IN INDUSTRY

Using Porter's framework, competitive position of NIBM in the industry is represented.

- **Threat of negotiation power of supplier:** As an educator, suppliers can be in the form of teachers and infrastructure. The Institute's Faculty consists of academicians from a wide range of disciplines - Agricultural Sciences, Commerce and Business Administration, Computer Science, Economics, Mathematics, Political Science, Psychology, Sociology, Statistics, etc. Practicing bankers strengthen the faculty by serving the Institute for varying periods of duration. The present faculty strength is 25. Below attached is the excerpt from NIBM's hiring notification. As per the data given on glassdoor.com, the national average salary of an Assistant professor in India is INR 5,63,549.00 p.a. If we double this average pay considering B-schools gives higher pay to professors, still NIBM is at par. However, India is facing dearth of highly erudite professors having industry experience. But, most of the tier three institutions are facing the same issue. As far as infrastructure is concerned, NIBM is spread across 60 acre area and is equipped with all coveted facilities. All the assets depreciated have been written off as per the principles (shown in their books of accounts). Therefore, bargaining power of supplier is **less**.

Salary & Other Benefits

Pay Band and AGP as on January 2016

Position			*Pay Band*	*AGP*	*Gross Monthly Pay***
1)	Professor	PB-IV	Rs. 37,400 – 67,000	10500	Rs. 1,52,673
2)	Associate Professor	PB-IV	Rs. 37,400 – 67,000	9500	Rs. 1,37,235
3)	Assistant Professor*	PB-III*	Rs. 15,600 – 39,100	8000	Rs. 1,01,628
4)	Faculty Research Associate	PB-III	Rs. 15,600 – 39,100	6000	Rs. 60,792

Note: * To be upgraded to PB-IV with AGP of Rs 9,000/- after completion of 3 years as Assistant Professor.
** with DA, HRA & TA.

Salary benefits such as Contributory PF, Gratuity, LTC, Medical, Housing Loan Subsidy, House Furnishing Loan, Consultancy (up to a maximum of Rs. 5 lakhs p.a.), etc., are admissible as per the Institute's rules. Suitable residential accommodation at nominal license fee subject to availability will be provided on the campus in lieu of HRA.

- **Threat of negotiation power of customers:** For training, many banks such as SBI, ICICI, Dena bank have either hired or started their in house training centers, but still NIBM (being promoted by RBI) maintains a strong hold in this sector for banks across the globe. For PGDM degree, it offers specialization in banking with limited intake of 120 students and scholarship offer; MBA aspirants are still desirable of the institute. Also, the application process of institute ends in April month, so aspirants who scored good marks in aptitude test but cannot convert the further admission process of different b-schools apply in NIBM. Average Placement of INR 8-10 LPA with the investment of INR 12 Lakhs fee is still advisable by many coaching centers in India. So, bargaining power of customer is also **low**.
- **Threat of Substitution:** For-profit institutes, distance learning and online degree can be the probable substitute of higher educational degree residential program. In India, there is a large part of institutes work For-profit motive, but they often face criticism of compromising with quality education. Online or distance learning these days are receiving huge support, but for training and development, still, residential program has been given priority. On the job training is also preferred by many people. But, these days very few employers want to invest this much on every employee. So, threat of substitution is **low**.
- **Threat of New Entrant:** For training purposes, many private training centers are also entering such as Centum Learning, etc. Various banks have started collaborating with different institutes for that purpose. But, still profound network with banks and financial institution has led NIBM to have a strong foothold on this sector. In PGDM education, it takes time for any institute /college to develop value among management aspirants and therefore, for any institute to enter into tier 3 with banking specialization is not so easy. For online certifications, it has high threat of new entrant. Various online platforms are providing e-certificate courses.
- **Rivalry among competitors:** Both in training and PGDM education field, NIBM has marked a different position for inclining more towards BFSI sector. But, there are various other institutes of tier 3 with exceptional infrastructure like IFMR, KJ Somaiya, Wellingkar, etc. who have majority of their finance major students placed into BFSI sector. College like IFMR also has trustees from different banks of India. This helps the

institute to use their networking for providing good placement offer In order to compete with such institutes; it has to continuously being progressive in its pedagogy, curriculum, faculty and placements. So, rivalry among competitors is **high.**

NIBM'S STRATEGIC FRAMEWORK

- **Strategy:** NIBM is regulated by RBI and its Governing Board is headed by the Governor of RBI. So, they enjoy the benefit of strategic policies that come directly from India's apex bank. NIBM has been mandated to play a constructive role in the financial and banking sector.
- **Structure:** It is headed by a Board of Governors composed of leading banking sector personalities. NIBM society has Member Banks and Associate Member Banks. Those banks have been admitted for specific purposes by the Governing Board. All the Member Banks contribute on a non-temporary basis to the NIBM budget, and ten of these banks are also represented on a rotational basis in the Governing Board. The Associate Member Banks, on the other hand, contribute only a specific amount to the NIBM's Budget. The working of the Institute is overlooked by the Director of the Institute.
- **Systems:** The Institute has emerged as an epicenter in all banking and finance areas for education, capacity growth, research and advanced learning. Rapid technical advances, succession planning for top management, compliance with legislation, enhancement of competencies, financial inclusion, etc. are some areas that have emerged as a challenge for the banking sector in the modern times. Identifying and incorporating these things into the courses and regular curriculum changes are unique features of this Institute.
- **Shared Values:** The Institute believes in the notion of Learning while working. They have programs not only for the graduate students but also for experts in the industry. They thus foster equality between experts and students, and also provide a safe forum for all classes to learn and demonstrate their skills. The Institute's courses recognize the value of ethics and morality in the banking industry, and concentrate on instilling them into potential manager.
- **Style:** NIBM has adopted a transformation and democratic approach that puts emphasis on the use by the faculties there of versatile teaching styles. Their goal is to include all stakeholders in the institution's brain storming and effective administration. This further

leads the Institute to sustained growth. The Institute also provides Online Certification Courses in keeping with the demand and availability of technology. Such courses were planned with the intention of imparting ability, aptitude and experience, leading to an enhancement of the skills of students and officers in carrying out their jobs.

- **Staff:** The Institute's faculty staff comprises researchers from a wide variety of disciplines including Commerce and Business Administration, Economics, Political Science, Sociology, Agricultural Sciences, Computer Science, Mathematics, Statistics, Psychology, and so on. Practicing bankers contribute to this pool by representing the Institute for temporary periods; thus for this time, improving the faculty staff.
- **Skills:** The faculties are experts in various management areas and are divided into seven separate focus groups, namely Finance, Information Technology, Rural Finance and Development, Human Resource Management, Money International Banking and Finance, Strategic Planning, Marketing and Control. The staff is also routinely provided with various training programs for continuous improvement of their skills.

PART B

THE PROJECT WORK

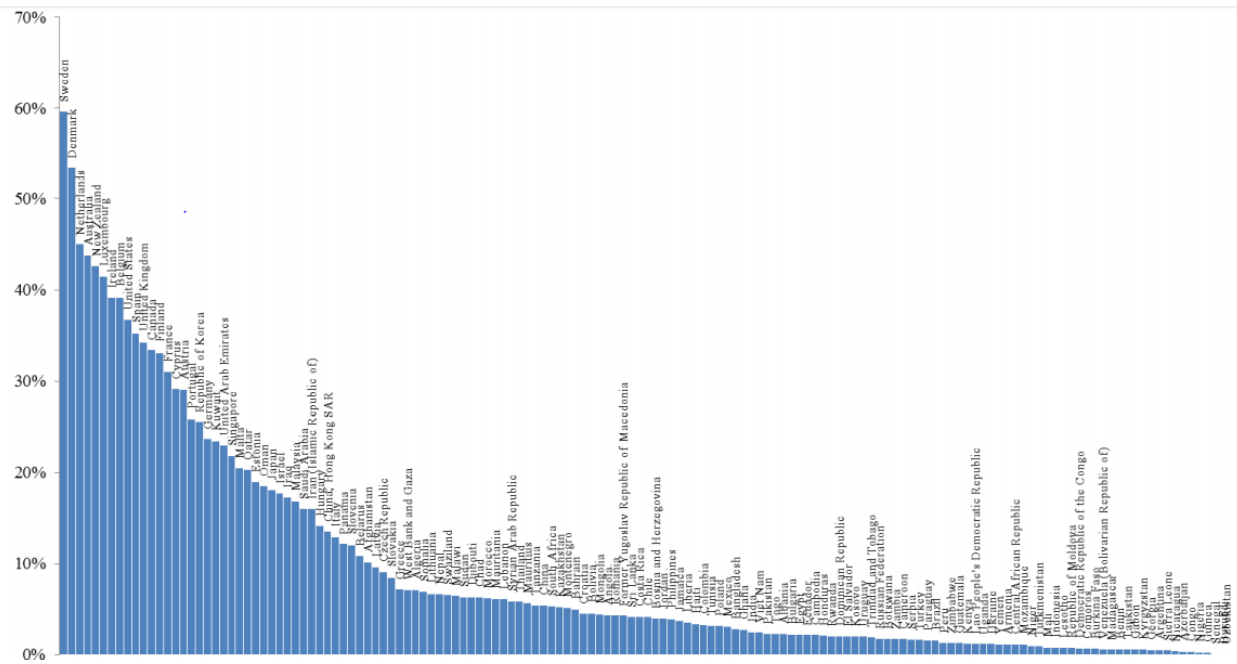
INTRODUCTION

Prior to the research work, plenty of journals, articles and research papers on housing loans in India had been referred by interns. From the study, it has been found that owning a house is considered to be an individual's single biggest investment in India. Most of the citizens rely on after retirement perks, to buy a home. But, now people of different ages have started seeking housing finance institutions (both banks and housing finance companies). India has progressed in social terms and today there is no stigma associated to going for bank loans. According to **Chandrasekar, V. (2010)**, Indian home loan industry has witnessed the different phases: Phase-I Government Control pre 1970, Phase-II 1970-1980 HUDCO and HDFC establishes, Phase-III 1980-1990 Foundation of NHB, Phase-IV 1990-2000 Interest Rate Liberalization & Phase-V 2000 to Present High Growth. A paper by **Sreelaxmi P. (2007) entitled "Housing Finance Sector in India- An Overview,"** claimed that housing has always been an essential subject for India's government. It stimulates national income through job creation and assists the individuals in their socio-economic growth. It gives economy a boost by increasing the capacity utilization of industries such as steel, cement, transport, etc. The new generation of young buyers, whose affordability is high, spends even more on paying EMI instead of paying massive amounts on rentals, thus owning a home. A paper by **Rao K. N. entitled "Retail Banking- Emerging Issue in Home Loan." et.al. (2005)**, the author reported that banks' housing loans grew at a high rate of growth of greater than 100 per cent during 2002-03. The factors that led to such a rapid growth in the portfolio of banks' housing loans and HFC are: (i) Accessibility of housing loans (ii) Increasing population (iii) Nuclear family system (iv) Newer segments for finance (v) Urbanization of the Indian economy (vi) Shortage of housing units (viii) Decreasing house value-to-income ratio, (viii) Incentives on tax repayment of principal and interest (ix) Growing middle-class income levels, (x) dropping interest rates, (xi) Steady real estate values, (x) lower returns on market-accessible investment opportunities.

In India, as a result of population explosion, migration from rural to urban areas, decline of existing housing stock and disintegration of joint families, demand for housing has rapidly inflated. In addition, in recent years the IT revolution and the rapid growth of knowledge-based industries have resulted to the acute housing shortage in urban areas. Since housing requires huge capital, the lack of finance is an important constraint for housing. The housing sector has faced a massive boom in the last couple of decades with the entrance of commercial banks into housing finance. The rising demand for housing finance has led to the rapid growth of the attitude of banks towards the housing sector. Housing finance has now emerged as a crucial component of the banks ' credit portfolio. In India SBI is the biggest loan provider of housing, constitute around 34% followed by HDFC, LIC Housing Finance, etc.

It has been observed that rise in housing loans over the last few years is quick enough to cause regulator concern. For example, the unprecedented interest shown by most banks in acquiring new customers for their housing loans throughout the year of 2003 led to a significant 55 per cent increase in housing finance. The Reserve Bank of India expressed its concern in its Annual

Report 2002-03 in a box captioned 'Housing Finance: New Driver of Bank Credit'. It discovered that the cause of potential concern is that banks are approaching the price of funds by lowering disposition rates. It went on to caution that 'banks want to be alert against unchecked growth in housing finance and may take due precaution with regard to interest rates, margins, residual amounts and documentation.' Thereafter the growth in housing financing continued. The rate of growth of housing finance has been close to 40% since 2000-01. On the other hand, overgrowth results in losses. That is evident from the large number of non-performing assets (NPAs). It turns out to be around 3-4 percent of advances on the Internet. It was also confirmed that three key players in the housing finance sector have approached Asset Reconstruction Company of India Ltd. (ARCIL) to sell unhealthy loans from their portfolios of home loans. However, housing finance has also been at the forefront of several banking crises, most recently in the United States, Ireland and Spain, and latest evidence has shown that banking crises related to housing boom and bust cycles are usually worse than other upheavals **(Claessens et al., 2011).**



Source: Research paper "Housing Finance Across Countries" by Anton Badev, Thorsten Beck, Ligia Vado & Simon Walley

Objective of the Study

Government's boost to housing sector & increased access to housing loans have a positive effect on consumers' housing purchase decision and thereafter increase the default rate. This increasing trend of delinquency has led **a) to find out the possible factors to be considered pre-sanctioning of housing loan; and b) discover the factors that have a greater impact on the default of housing loans**. That was the main objective of our study project.

METHODOLOGY

Approach:

The two months of internship was entirely a work from home research based project. In the first two weeks, interns were provided the necessary reference material related to Credit rules and regulations in the banking sector, Data analytics, Regression analysis and Introduction to machine learning. In the third week, the literature review upon credit risk in housing finance loans had been drafted by us. In the subsequent weeks, we were introduced with the customers' data and learnt data handling and running regression model. The research undertaken to ascertain probability of default was conducted through Logistic regression. It has been chosen because of the binary nature of the dependent variable

Data:

Team Vittarth and Vittnivesh provided us the dummy data of 7499 loan accounts (alike what is used in Housing finance industry to find out the delinquency rate). Out of total 7499 borrowers, we had derived 3.83% borrowers were defaulters, 88.78% were solvent and 7.25% accounts to data missing category.

[Insert Table 1]

From the given independent variables we derived other variables, vital for our research. In order to make observation, logistic regression was performed. Most of the raw variables provided were in continuous form (continuous variables are numerical variables with an infinite number of values for two different values), so they had been converted into categorical variables (categorical variables consist a finite number of different categories or groups) through binning. The categories were coded in quantitative numbers and missing values had been given an additional code.

[Insert Table 2&3]

PROJECT FLOWCHART

Method of data analysis:

Our research was focused upon estimating log of the odds of default as a linear function of loan application attributes, therefore logistic regression had been considered as a simple and effective method to be used. A logistic/logit model has the agility to incorporate both the qualitative and quantitative factors and is more efficient than the linear regression probability model. In a set of logistic regression exercises, we actually predicted the likelihood of a housing loan default based on the financial, non-financial (qualitative borrower characteristics), situational factors (location and local factors). Since, logistic regression was conducted in research; therefore, Maximum Likelihood Estimation (MLE) method had been used. But, before running the model, descriptive statistics calculation, hypothesis formation and final variables selection had been performed.

Descriptive Statistics calculation- For descriptive statistics, missing values was replaced by their WOE scores. Out of total 7499 data points, 6877 data points had been selected for conducting final regression test. Descriptive statistics for the variables had been performed. This had given an idea about the profile of the borrowers and their distribution. It had been observed that mean age of the borrowers was 44 years, average monthly income was Rs.20289.53 and average moratorium period was of 297 days (nearly 10 months). 19% of the total borrowers had business, 1.28% had house property, 38.08% had others, 4.56% had profession & 37.04% had salary as their source of income. Similarly, 81.93% borrowers were male and only 18.06% were female. And the borrowers belong to central region (comprises of states such as MP & CHH) were 21.05%, eastern region (AN, ASM, NAGA, ORI, SIK, TRI & WB) were 5%, north eastern region (UP, BHR & JHK) were 10%, north region (CHN, DEL, HAR, HP, JNK, PUN, UTTAR) were 7.66%, southern region (AP, KAR, KER, POND, TN & TS) were 30.47% and western region (DAMAN, DNH, GOA, GUJ, MAH & RAJ) were 25.8%.

[Insert Table 4&5]

Hypothesis formation & variable selection- In order to test our objective, following hypothesis had been laid down:

H0: The borrower characteristics will not affect the probability of loan default.
H1: The borrower characteristics will affect the probability of loan default.

For the selection of final variables, correlation matrix and IV test had been performed. A correlation matrix is a table which shows coefficients of correlation between variables. The correlation between two variables is displayed by each cell in the table. A matrix of correlation is used to summarize the data, as an input to a more detailed analysis, and as a diagnosis to advanced analysis. The information value is one of the most effective methods in a predictive model for selecting important variables It helps rank variables according to their significance. The IV is determined using the following formula: IV = ∑ (% of non-events - % of events) * WOE. This had eliminated highly correlated and less significant variables which are unfit for final regression test.

[Insert Table 6]

Running regression model- Regression analysis is a series of statistical functions in statistical modeling to estimate the relationship between a dependent variable (often referred to as the 'outcome variable') and one or more independent variables (often referred to as 'predictors,' 'covariates' or 'features'). The most popular type of regression analysis is linear regression, which aims to model the relationship between two variables by applying a linear equation to actual observed data. One variable is called an explanatory variable, and another a dependent variable. However, since we had categorical variables, so we conducted logistic regression. Logistic regression is defined as:

$$\ln\left[\frac{\Pr ob(Default)}{\Pr ob(Solvency)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + ... + \beta_k X_k.$$

To perform regression, data had been divided into Train data (4.07% default accounts) & Test data (4.35% default accounts) in 7:3 ratio. Through KS Statistics, threshold of 0.0373 was decided to define the default probability.

Model testing- Regression ran for the Train data and three variables i.e. Cust_Status, Sanct_lim and Tenure had dropped due to p>lzl value greater than level of significance i.e. 0.05. After iterative stepwise regression, we got the final model. Through P value approach, it had been observed that p value of the above variables was less than 0.05 (level of significance), hence we **rejected the null hypothesis**. In confusion matrix, we received the precision of 10.25%, Recall of 75.9% and Accuracy of 72.1%. Precision was found low since the data has only 3.83% default accounts. In the test data, we calculated the probability of default for 2064 accounts. The calculated probability of default in case of greater than 0.0373 had been marked as the final default accounts. The calculated defaults results were compared with actual default cases and the Test confusion matrix had been designed. For Test data, we received Precision as 8.14%, Recall as 62.22% and Accuracy as 70.43%. These three parameters were almost in line with the same observed in Train confusion matrix.

[Insert Table 7, 8, 9]

Recall measures the proportion of a correctly defined model (True Positive) for the actual result. The numerator is the number of true positives or the presence of positive ones properly identified by the model. The denominator is the number of real positives that the model predicts and the number of positive ones that the model wrongly predicts as negative.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

Precision assesses just how accurate a model is in projecting positive marks. Precision addresses the question, how many times was it right out of the amount of times that a model predicted positive?

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Accuracy is a metric of assessment that facilitates the calculation of the overall number of estimates a model is getting correct. Accuracy would answer the question, what percent of predictions for models is correct? True Positives and True Negatives has been looked at accuracy.

$$Accuracy = \frac{TrueNegatives + TruePositive}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

In our research work, True Positive is that no. of customer’s accounts which our model predicted as defaults and in reality also they defaulted. True Negative indicates those customers’ accounts which our model predicted to be defaults, but in reality they were solvents. False Negative contains those accounts which our model predicted as solvents but they defaulted in reality. True Negative symbolize those accounts which are solvents as per our model and in reality too.

We had also built the ROC curve. In a ROC curve, the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off/threshold points of a parameter. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish between two diagnostic groups. We had received 0.7942 as Area under ROC Curve; hence accuracy of the curve was justified.

[Insert Graph 10]

ANALYSIS & DISCUSSION

Observation & Conclusions:

The estimated coefficients actually explain how the probability of default changes with one unit change in the parameters (independent variables). Table results document that Annual_Income has a strong predicting result on the response variable i.e. default. Negative sign of coefficient indicates that both have an inverse relationship. Hence as the annual income increases, the likelihood of default will reduce. Moratorium has positive coefficient and hence signifies the probability of default will increase with the increase in moratorium period. Therefore, these days banks mostly keeps maximum one year of moratorium period. Loan_duration also has a positive impact on chances of default. This means, the more duration of loan is, more is the chances of default. Networth_to_Loan has positive impact on default. EMI_to_Monthly_Income has inverse relationship with default, hence indicates as the EMI to monthly income increases, the probability of loan default reduces. Similarly, increment in loan to value ratio will raise the chance of default. Therefore these days' banks mostly sanction loan of 60-75% of total security value. State has negative and SRC_of_Income has positive coefficient. However, since we have not used dummy variables, so can't predict the default chances of each category of State and SRC_of_Income. The intercept value we obtained is -4.091216.

In our research, we collected and derived various variables important to be considered before loan sanctioning. However to run the regression model, some variables had to be dropped. And the final result showed that annual income of the borrower has the strongest impact upon likelihood of loan default. It is followed by source of income, moratorium period, loan to value ratio, net worth to loan ratio, state of the borrower, EMI to monthly income ratio and duration of loan.

Managerial Implications:

Greater accessibility to housing loans is predicted to have a positive effect on consumers' housing purchase decision. However, this has impacted the burgeoning NPAs in NBFCs, HFCs and commercial banks. A credit risk model enables the bank management to identify the factors impacting the most upon probability of loan default. Hence, the customer profile can be checked upon those factors and a sound decision can be taken before approving the loan. The banks can charge lofty rate of interest from customers whose traits indicates higher risk of committing default. Hence, credit risk modeling serves as a vital tool for management in the banking sector.

Recommendations:

It has been observed that some of the customers' data provided to us was not organized and certain information was missing. The reason cited behind this mismanagement was mistakes occurred due to manual entry done by the clerks. In our model testing, the precision we received was very low. This was occurred due to data provided to us which had only 3.83% borrowers as defaulters. Also the availability of inadequate data led us to ignore some macro & micro factors affecting the probability of loan default. We could not include GDP growth rate. **"Factors Driving Demand and Default Risk in Residential Housing Loans: Indian Evidence"** by **Arindam Bandyopadhyay & Asish Saha** revealed, an increase in GDP growth rate significantly reduces the likelihood of default. Interest rates are also a significant factor that we have not reckoned here. Since, it can be predicted that lower the interest rate, lesser is the probability of default. A borrower with a relatively low income is often more likely to be charged at a higher rate of interest to cover the risk associated with a loan. The debt-to-income ratio is related positively to the interest charged on loans. As the debt-to-income ratio increases, so too does the interest rate **(Sanchez-Arellano, 2006; Ceyhan et al., 2011)**. Credit history in current days is one of the prime and initial factor, banks and HFCs consider. Better the credit history, lessen the chances of default. Ignoring borrower data like education details, marital status, employment situation, regional locations, city locations, age profile, no. of years at current address, house preference that prevent lenders from properly assessing credit risk in the home loan market, as our study indicates, these parameters also act as default triggers. In cases where the house is larger in size, monthly income is higher, asset value is higher and borrower age is lower, we found that the default is lower. The involvement of more co-borrowers and their level of income considerably decrease the probability of default. We have also skipped the recovery prospect which indicates higher is the actual margin better is the likelihood of recovery on the loan. Medium and Smaller cities have higher rates of recovery than the Big cities.

Regarding the manner internship was conducted by NIBM, Pune, I didn’t find any flaw while experiencing those two months. My mentor was very cooperative and zealous in assisting me. However, in context of the project work, our research would have been more accurate if the organization had provided additional data points with less or no missing values.

PRESENTATIONS OF DATA

VARIABLES	EXPLANATION
ACCT ID	Account ID is a unique ID provided to each borrower
ACCT_OPN_DATE	Account opening date is the date at which loan has been sanctioned
ACCT_CLS_DATE	Account closing date is the date at which loan account has been closed
STATE	State which borrower belongs to.
DATE_OF_BIRTH	Date of birth of the borrower
CUST_SEX	Gender of the borrower
CUST_FIRST_ACCT_DATE	Date at which an existing customer has opened bank account or a borrower opened new account
OCCP_CODE_DESC	Occupation of borrower
ANNUAL_INCOME	Annual income of the borrower
SRC_OF_INCOME	Source of Income of the borrower
NETWORTH	Networth of the borrower
DMD_OVDU_DATE	Date at which installment is overdue
MAX_LAST_ADJ_DATE	Date at which installment is paid.
SANCT_LIM	Loan amount sanctioned
SEC_VALUE	Security value
FLOW_START_DATE	Date at which installment starts
NUM_OF_FLOWS	Total no. of installments charged for the repayment of loan
FLOW_AMT	Installment amount
NUM_OF_EMI_PAID	Number of installments paid

Table 1: Given Data

DERIVED VARIABLES	EXPLANATION	CALCULATION
CUST_STATUS	Customer status defines if the new or an existing customer has availed the loan.	CUST_FIRST_ACCT_DATE (-) ACCT_OPN_DATE
AGE	Age of the customer	DATE_OF_DATA_COLLECTION (-) DATE_OF_BIRTH
MORATORIUM	Moratorium period is a time (in no. of days) during the loan term when the borrower is not required to make any payment.	FLOW_START_DATE (-) ACCT_OPN_DATE
LOAN_DURATION (IN MONTHS)	Loan duration (in no. of months) is the time period in which loan account is closed or settled.	[MAX_LAST_ADJ_DATE (-) ACCT_OPN_DATE]/12
NETWORTH_TO_LOAN	Net worth to loan is the ratio of borrower's net worth and the loan sanctioned.	(NETWORTH_AMT/SANCT_LIM)*100
EMI_TO_MONTHLY_INCOME	EMI to monthly income is the ratio of EMI borrower has to pay and his monthly income.	(FLOW_AMT/MONTHLY_INCOME)*100
LTV_RATIO	Loan to value is the ratio of loan sanctioned and the security value customer owns.	(SANCT_LIM/SEC_VALUE)*100
Tenure	Tenure is the period (in no. of years) for which the bank has given loan, calculated from the total no. of installments.	NO_FLOWS/12
DPD	Days Past Due signify the no. of days for which payment is outstanding	MAX_LAST_ADJ_DATE (-) DMD_OVDU_DATE
Default	Default arises when DPD > 90 days	If(DPD>90,1,0)

Table 2: Derived variables

VARIABLES	CATEGORY DETAILS	VARIABLES	CATEGORY DETAILS
STATE_CODE_NO.	Central Region	**NETWORTH_TO_LOAN CODE**	Less than 50
	Eastern Region		Between 50 to 100
	North Eastern Region		Between 100 to 250
	North Region		Between 250 to 500
	Southern Region		More than 500
	Western Region		#N/A (Data missing)
GENDER CODE	Female	**CUST_STATUS CODE**	New Customer
	Male		Existing Customer
LTV_RATIO CODE	Less than 25%	**TENURE**	Less than 10 years
	Between 25 to 50%		Between 10 to 20 years
	Between 50 to 75%		Between 20 to 30 years
	More than 75%		More than or equal to 30 years
	#N/A (Data missing)		#N/A (Data missing)
EMI_TO_MONTHLY_INCOME CODE	Less than 100%	**MORATORIUM CODE**	Less than 100 days
	Between 100 to 200%		Between 100 to 500 days
	Between 200 to 300%		Between 500 to 1000 days
	Between 300 to 400%		Between 1000 to 1500 days
	Between 400 to 500%		Between 1500 to 2000 days
	More than 500%		More than 2000 days
	#N/A (Data missing)		#N/A (Data missing)
ANNUAL_INCOME CODE	Less than Rs. 1.00 lac	SANCT_LIM CODE	Less than Rs. 10 lakhs
	Rs. 1.00 lac to Rs. 5.00 lacs		Rs. 10 lakhs to 20 lakhs
	Rs. 5.00 Lacs to 10.00 Lacs		Rs 20 lakhs to 30 lakhs
	Rs. 10.00 Lacs to Rs. 25.00 Lacs		Rs. 30 lakhs to 40 lakhs
	Above Rs. 25.00 Lacs		Above Rs 40 lakhs
	#N/A (Data missing)		#N/A (Data missing)
SRC_OF_INCOME CODE	Salary	**LOAN_DURATION CODE**	Less than 50 months
	Others		Between 50 to 100 months
	Business		Between 100 to 150 months
	Profession		Between 150 to 200 months
	House Property		More than 200 months

Table 3: Binning details

Variables	Mean	Median	Mode	S.D.	Kurtosis	Minimum	Maximum
MONTHLY_INCOME (IN RS.)	20289.53557	4166.666667	4166.666667	45060.65898	61.4175709	4166.666667	416666.6667
SEC_VALUE (IN RS.)	1900331.591	1482000	100000	2823495.896	109.7883314	60000	45500000
AGE (IN YEARS)	44.75158368	44.9260274	43.77534247	9.180421019	-0.230900588	24.17260274	76.62465753
SANCT_LIM (IN RS.)	838287.5396	600000	100000	1070705.392	42.39343321	-0.540331559	12700000
NETWORTH_AMT (IN RS.)	1111111.111	500000	500000	3649870.514	231.330547	500000	70000000
SEC_VALUE (IN RS.)	1900331.591	1482000	100000	2823495.896	109.7883314	60000	45500000
MORATORIUM (IN DAYS)	297.5233143	183	-0.9176	425.3048508	6.238545355	-0.9176	2253
TENURE (IN YEARS)	14.59769721	14.5	15	7.219959007	-0.006165832	-0.578960089	30

Table 4: Descriptive statistics for continuous variables

STATE CATEGORY	Frequency	in %age of total
Central Region	1461	21.0518732
Eastern Region	347	5
North Eastern Region	694	10
North Region	532	7.665706052
Southern Region	2115	30.47550432
Western Region	1791	25.80691643
Grand Total	**6940**	**100**

OCCP_CODE_CATEGORY	Frequency	in %age of total
Government employee	1223	17.62247839
Core products mfg industry	128	1.844380403
Professionals	1095	15.77809798
Service Industry	1332	19.19308357
Non earners	475	6.844380403
Agricultarists	1268	18.27089337
Miscellaneous	296	4.265129683
Non core products mfg industry	78	1.123919308
Financial sector	1045	15.05763689
Grand Total	**6940**	**100**

SRC_OF_INC_CATEGORY	Frequency	in %age of total
Business	1317	19.02079723
House Property	89	1.285384171
Others	2637	38.08492201
Profession	316	4.563835933
Salary	2565	37.04506066
Grand Total	**6924**	**100**

GENDER CATEGORY	Frequency	in %age of total
Male	5686	81.93083573
Female	1254	18.06916427
Grand Total	**6940**	**100**

Table 5: Statistics for Categorical variables

VARIABLE	STATUS
ANNUAL_INCOME	Taken
SRC_OF_INC	Taken
STATE	Taken
GENDER	Dropped due to low IV Value
CUST_STATUS	Taken
AGE	Dropped due to low IV Value
MORATORIUM	Taken
LOAN_DURATION	Taken
SANCT_LIM	Taken
NETWORTH_TO_LOAN	Taken
EMI_MONTHLY_INC_RATIO	Taken
TENURE	Taken
LTV RATIO	Taken
NETWORTH_AMT	Dropped due to high correlation
FLOW_AMT	Dropped due to high correlation
FLOW_START_DATE	Dropped due to high correlation
OCCUPATION	Dropped due to high correlation

Table 6: Final variables for regression

Default	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
state_code_no	-0.1685417	0.0495596	-3.4	0.001	-0.2656768	-0.0714066
annual_income	-0.7662037	0.1564022	-4.9	0	-1.072746	-0.459661
src_of_income	0.3386117	0.0929036	3.64	0	0.156524	0.5206995
moratorium	0.2013376	0.0640895	3.14	0.002	0.0757244	0.3269508
loan_duration	0.1487394	0.0742018	2	0.045	0.0033066	0.2941722
networth_to_loan	0.1997328	0.060735	3.29	0.001	0.0806944	0.3187712
emi_to_monthly_income	-0.1665106	0.0590798	-2.82	0.005	-0.2823048	-0.0507163
ltv_ratio	0.2018283	0.0899015	2.24	0.025	0.0256245	0.378032
_cons	-4.091216	0.4398084	-9.3	0	-4.953225	-3.229208

Number of observation	4813
LR Chi^2 statistic (degrees of freedom)	223.65
Prob>Chi^2	0
Pseudo R^	0.137

Table 7: Model output

		TRUE		
		Default (1)	**Solvent (0)**	**Total**
MODEL PREDICTED	**Default (1)**	148 TP	1296 FP	1444
	Solvent (0)	47 FN	3322 TN	3369
	Total	**195**	**4618**	**4813**

Precision	TP/TP+FP	**10.25%**
Recall	TP/TP+FN	**75.90%**
Accuracy	TP+TN/Total	**72.10%**

Table 8: Confusion matrix for Train data

		TRUE		
		Default (1)	**Solvent (0)**	**Total**
MODEL PREDICTED	**Default (1)**	56 TP	576 FP	632
	Solvent (0)	34 FN	1397 TN	1431
	Total	**90**	**1973**	**2063**

Precision	TP/TP+FP	**8.14%**
Recall	TP/TP+FN	**62.22%**
Accuracy	TP+TN/Total	**70.43%**

Table 9: Confusion matrix for Test data

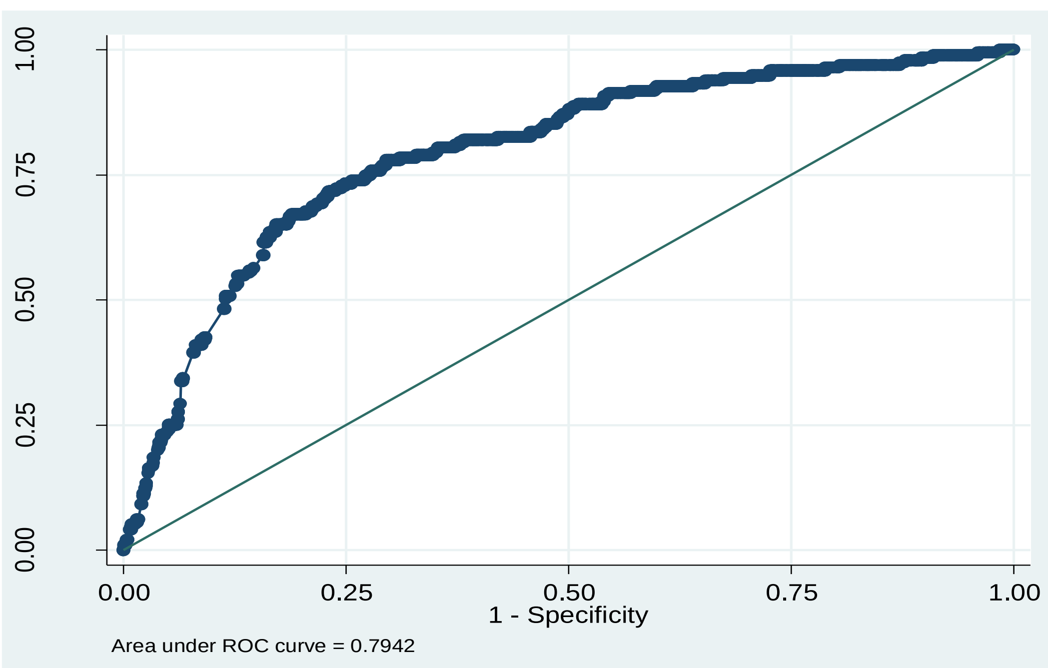


Chart 10: ROC curve

PART C

LEARNING FROM THE SUMMER TRAINING PROJECT.

APPLICATION AND CONCEPTS USED FROM YEAR I

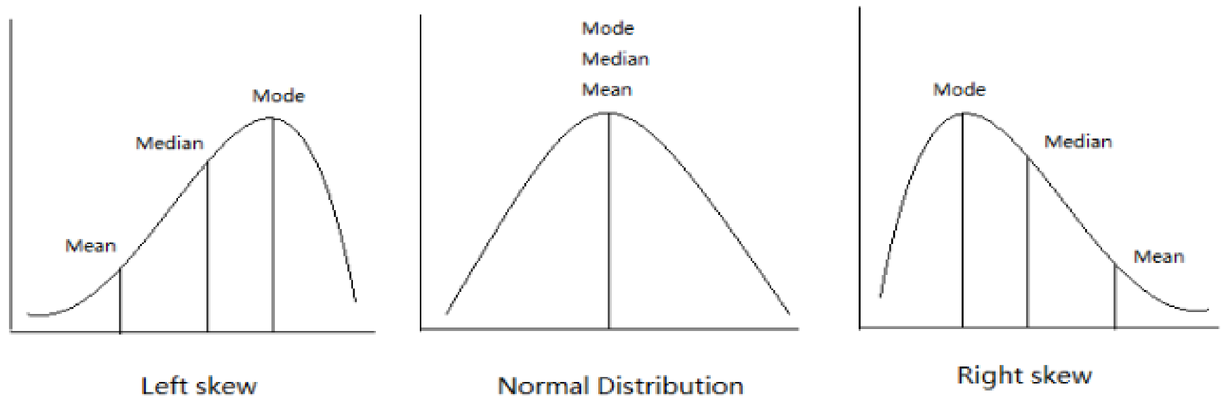
In our research work, we had organized, classified and processed the data using different statistical tools. From the concepts of Data Analytics & Management taught in MBA first year, I was able to use techniques of descriptive statistics, hypothesis formation, regression analysis and significance of z value & p value.

Descriptive statistics helped me to analyze the data provided to us. Central tendency figures such as mean, median & mode represented each variable of the data points & Standard deviation helped in identifying the distribution of the data points in a variable.

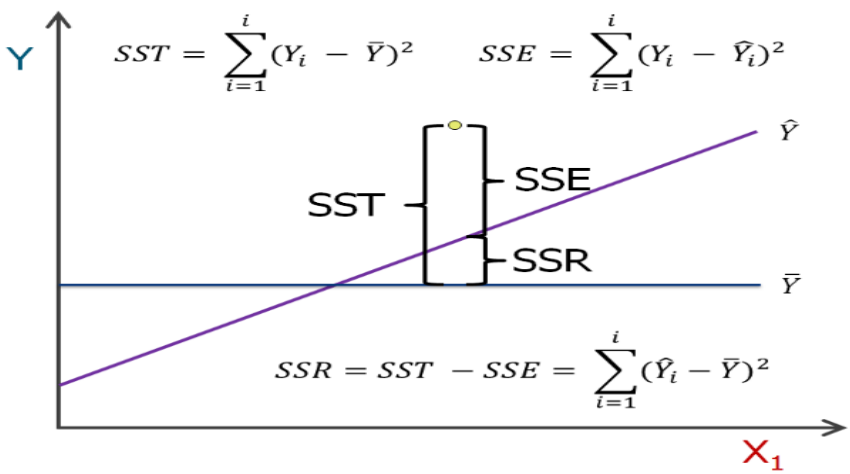
Without forming null and alternative hypothesis, we could not reach the result of our research work. A null hypothesis is a hypothesis that states the two variables don't have statistical significance. It's typically the hypothesis that will seek to disprove or dismiss by a researcher or experimenter. An alternative hypothesis is something that claims the relationship between two variables as statistically significant. The output our model received has rejected null hypothesis and hence proved that there is a statistically significant relationship between variables.

In our regression model output, we received different coefficient values of independent variables. A positive coefficient (in case of source of income, moratorium period, loan duration and loan to value ratio) means that the mean of the dependent variable often appears to increase as the value of the independent variable rises. A negative coefficient (in case of annual income and EMI to monthly income ratio) implies that the dependent variable continues to decrease as the independent variable increases.

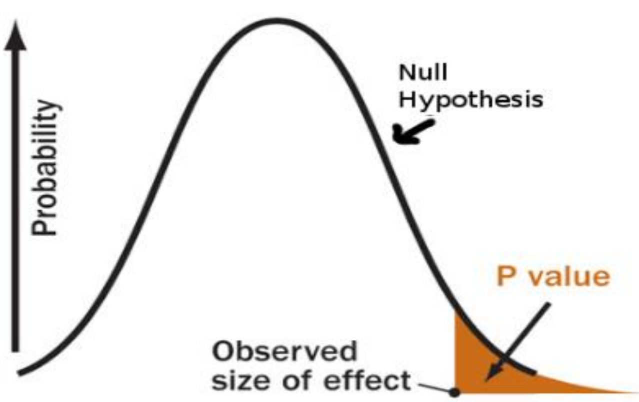
Similarly, I'd studied the significance of p value in MBA first year, according to which, the lower the p-value, the greater the proof that the null hypothesis should be dismissed. A p-value of just under 0.05 is statistically relevant. It implies clear proof against the null hypothesis, as null being correct (and the results being random) in case of the likelihood is less than 5 per cent. For regression, we had taken 11 variables, but due to inefficient p value (i.e. value >0.05) of variables, CUST_STATUS, SANCT_LIM and TENURE had been dropped and multiple iterations were performed. Variables in our final model has p value<0.05.



Example of central tendency values in graph



Graphical representation of SSR, SSE & SST in regression



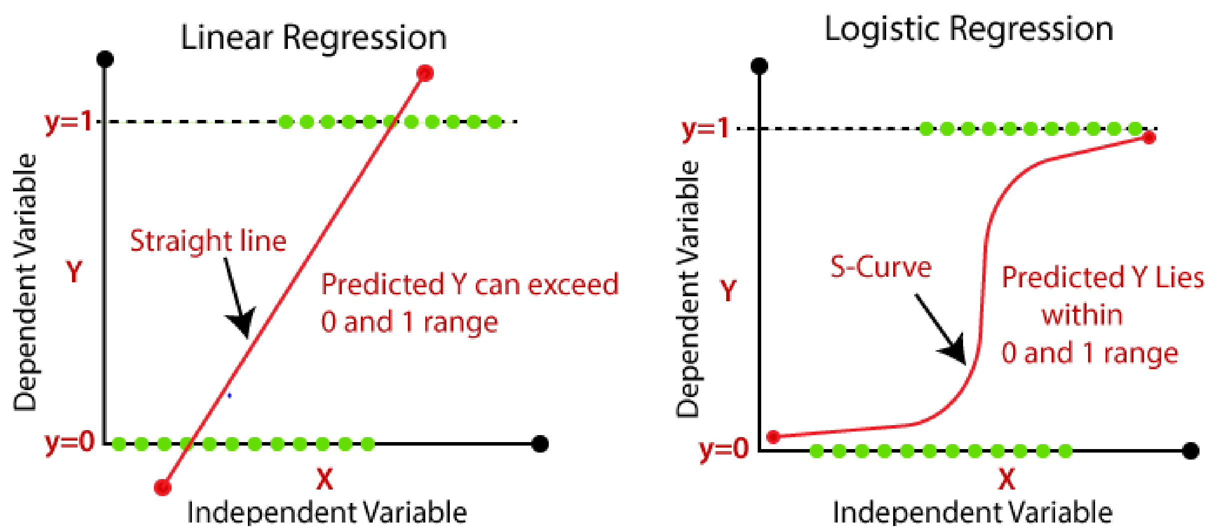
p value

NEW KNOWLEDGE, TOOLS, TECHNIQUES OR SKILLS LEARNT

Prior subject knowledge was required for our research work, therefore credit risk modeling interns were provided with the study material. It included presentations, research papers, topic wise explanation references & video recordings. It added a bunch of new knowledge, tools and techniques to my skill sets.

We referred to **Credit Risk Measurement Under Basel II: An Overview and Implementation Issues for Developing Countries.** The paper has provided an overview of the changes in the calculation of minimum regulatory capital requirements for credit risk that have been drafted by the Basel Committee on Banking Supervision (Basel II). Basel is a series of international banking regulations put forward by the Basel Committee on Bank Supervision (BCBS), which sets out financial institutions' minimum capital requirements with the aim of minimizing credit risk.

In this project work, we came to know about logistic regression and the difference between linear and logistic regression. Linear regression is used when the dependent variable is continuous and logistic regression is being used where there is categorical dependent variable. In our project, dependent variable was 'probability of default' which was categorical i.e. either 0 (No default) or 1 (Default).



Credit Risk Scorecards Developing and Implementing Intelligent Credit Scoring by Naeem Siddiqi explained the usage & treatment of variables**.** In our research we have converted all the independent variables too into categorical form for which, we learnt data binning. For final selection of variables, we conducted Correlation Matrix, Weight of Evidence and Information Value test. A correlation matrix is a table that displays coefficients of correlation between variables. It was used to find and eliminate highly correlated variables, since highly correlated variables don't give the effective output. The weight of evidence in relation to the dependent variable shows the predictive capacity of an independent variable. Because it evolved from the world of credit scoring, it is generally taken as a function of the segregation of good and bad customers. The Statistics of Information Value (IV) is a prominent screener used to pick predictor variables for binary logistic regression.

$$WoE = [ln(\frac{\text{Relative frequecy of Goods}}{\text{Relative frequecy of Bads}})] * 100$$

$$IV = \sum(DistributionGood_i - DistributionBad_i) * WoE_i$$

Logistic regression is a technique borrowed by machine learning from the field of statistics. So, we have gained an overview of machine learning too. At its most basic level, machine learning is the practice that uses algorithms to decipher data, learn from it and then make a judgment or prediction. Types of Machine learning:

- Supervised Learning- In supervised learning, a small training dataset is provided to work with the ML algorithm. This training dataset is a narrower part of the larger dataset and acts to provide the algorithm with a basic understanding of the problem, solution, and data points to be addressed. The training dataset is also quite identical in its features to the final data set and offers the algorithm with the necessary labeled parameters for the problem. Then, the algorithm finds relationships between the given parameters, effectively creating a relation of cause and effect between the variables in the dataset..
- Unsupervised leaning- Unsupervised machine learning has the benefit of working with unlabeled data. This means human effort is not needed to render the dataset readable by machine, enabling the system to operate on much larger datasets
- Reinforcement learning- Reinforcement learning draws cues directly from how human beings learn in their lives from results. It uses an algorithm that builds upon itself and uses a trial-and-error approach to benefit from new circumstances. It promotes or 'reinforce' favorable outputs and prevent or 'punish' non-favorable outputs

In our research, we ran the regression model using supervised machine learning. We learnt how to divide the data into Train and Test. And using Train dataset, estimate the final relationship between dependent and independent variables.

We also learnt the use of KS Statistics to judge the threshold value for deciding the value of dependent variable. Concept of confusion matrix and ROC curve was also learnt to test the credibility of model.

In the area of machine learning, and precisely the issue of statistical classification, a confusion matrix, also known as an error matrix, is a particular table structure that enables the visualization of an algorithm's performance, usually a supervised learning version. Through confusion matrix, indicators like Recall, Precision and Accuracy is calculated.

AUGMENTATION OF SOFT SKILLS

My internship was based upon research based project, so we had virtual meetings every week and the work was assigned to us. Since, it was a work from home internship; I could only interact with my mentor on phone calls or messenger. However, my mentor was very supportive and easily accessible for any guidance or assistance. I had also worked upon a parallel project named **'Arthanomics'** under different mentor, so I got some opportunity to improve my interpersonal relationships

INSIGHTS ABOUT MANAGERIAL ROLE

Credit Risk Modeling is a prominent technique used in Banking, Financial Services and Insurance industry. Various credit rating agencies and research firms also use this model to predict the loan default likelihood. Such companies require Credit Risk Model Developer to work upon this procedure. This managerial role is vital in credit risk domain and besides MBA, Financial Risk Management is a coveted professional designation that opens up the opportunity in this field. The experience I've received has opened up my horizon and motivated me to strive hard for building career in this field.

REFERENCES

- http://www.nibmindia.org/admin/fckImages/Annual%20Report%202018-19%20for%20web(1).pdf
- http://www.nibmindia.org/
- http://www.nibmindia.org/admin/fckImages/Faculty%20Recruitment%20-%20Website(1).pdf
- https://en.wikipedia.org/wiki/National_Institute_of_Bank_Management
- https://www.franchiseindia.com/education/Employee-learning-and-development-a-growth-market-in-India.8862
- https://www.kenresearch.com/blog/2019/12/india-corporate-training-market/
- https://mega.nz/folder/PFNlHaiY#DXrgV6mJUCGY2yCjoOZrDA
- https://www.thebalance.com/how-does-real-estate-affect-the-u-s-economy-3306018
- “Factors Driving Demand and Default Risk in Residential Housing Loans: Indian Evidence” by Arindam Bandyopadhyay & Asish Saha
- "Housing Finance Sector in India- An Overview," by Sreelaxmi P. (2007)
- "Retail Banking- Emerging Issue in Home Loan." et.al.(2005) by Rao K. N.
- “Housing Finance Across Countries” by Anton Badev, Thorsten Beck, Ligia Vado & Simon Walley
- Accessibility of Housing Loan Effect on Homeownership in Urban China by Xia (Cindy) GAO
- Credit Risk Scorecards Developing and Implementing Intelligent Credit Scoring by Naeem Siddiqi
- Development of Indian home loan industry by B .Chandra Mohan Patnaik & Ipseeta Satpathy
- A Research Article entitled “Housing Credit Situation in Eighties” by Lall Vinay (1984)
- The Research Study entitled “Housing in the New Millennium: A Home Without Equity is Just a Rental with Debt” by Joshua Rosner (2001)
- A research article entitled “Home Ownership Risk Beyond a Subprime Crisis: The Role of Delinquency Management” by Jaco Melissa B. (2002)
- "Housing Loan Frauds: Are they Avoidable?" by Manohar Padhi (2007)

ANNEXURE

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Ref: VIT/CRM/2020/009 Date: 08/06/2020

TO WHOMSOEVER IT MAY CONCERN

This is to certify that **Mr. Prakhar Saxena**, a student of **MBA, Institute of Management, Nirma University** has successfully completed **02 months** long internship program, From **9th April 2020 to 8th June 2020**, at the National Institute of Bank Management, Pune - India, under the aegis of Vittarth. During the period of his internship program with us, he has worked on **Credit Risk Modelling**.

We wish his every success in life.

For, NIBM-Pune.

AICTE RECOG. PGDM (BANKING & FINANCIAL SERVICES) NIBM PUNE

Dr. M Manickaraj

Associate Dean, NIBM