Machine Learning Applications in Finance

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***Abstract*—Now is an opportune time to for everyone. Let us acknowledge that now because it is very important that the current credit scoring system in place needs to be improved and accurate to avoid any risk going forward. We know for sure that Artificial Intelligence can help in the credit scoring systems process.**

***Index Terms*—Machine learning, Finance, Regression Analysis,Credit**

I. Introduction

To understand creditworthiness, first, we need to understand the meaning of this concept. Creditworthiness is based on how the borrower handled debt and credit. Creditworthiness is how a lender decides if the person or company who requests for money can repay the loan that will be borrowed. The first step to get a loan is to complete and fill an application. Based on the applicant's current credit score, the lender takes into consideration how likely the applicant will repay the obligations of the debt on time. Once the lender determines if the applicant [1], [2]

is deemed not a risk and is worthy of credit, the decision will be made if eligible to get the loan. There are some very important factors other than credit score that determine the approval of a loan application status. In other words, proving to the creditors and lenders that timely payments will be made will establish trust with any applicant. Throughout this project, we will attempt to examine other factors and find some patterns using datasets to determine who can establish creditworthiness, without the use of institutional discriminations [1]. [3] [4] . [5]

[6] [7]. . [6]–[8]

II. Literature review

It is important to encourage and develop a great sense of money management. Managing how applicants spend their money will ease the stress down the road. The fundamental practice of paying bills on time and saving money will eventually help. The path to financial freedom is not always an easy task. In this research, we have identified that loans are widely used around the world, and we have revealed that there are many reasons why people want to get money from banks or any other financial companies that offer loan services. Some similarities and differences exist amongst the various existing crediting systems. S&P, Moody, and Fitch, are three rating agencies that established corporate customer credit rating systems. FICO credit rating systems evaluate customer credit status from at least five aspects, such as length of customer's building credit time and historical records of customers' paying credit. Small and medium sized customer credit ratings may also be evaluated using the "5C principle": Character, Capital, Capacity, Collateral and Condition of Business [9]. From the previous charts, we can see that many factors affect loan approval stronger than others—for example, gender shows how a male can get approval more than a female. Also, the education level is one factor that affects the application decision.Machine learning models for business [3] [4] [10]–[21] [5], [22]and Health [7], [11] [6] [6] and Social Media [7], [8], [23]–[32] Can be used to improve Data discovery.

Through various references, it is clear that the current credit lending system is broken due to various reasons. [33], [34] Within their research, Kumar Arun, Garg Ishan, and Kaur Sanmeet [35] demonstrated that it is indeed possible to use machine learning to predict loan approval odds. Machine Learning can determine new relationships that a person would never think to test. This is the legality of ethics of using machine learning. Another such attempt is done by Mridul Bhandari, using IBM Watson technology suite. [36]

Similarly, there are other studies that have identified other factors other than credit score that could foster the inclusion of information that will impact creditworthiness [37]. This can include data points such as payment of utility bills, rent, and personal habits.

The goal is to incorporate new data and harness AI to expand credit to consumers who need it on better terms than are currently provided. AI can easily go in the other direction to exacerbate existing bias, creating cycles that reinforce biased credit allocation while making discrimination in lending even harder to find. Protection against discrimination in a risk-based pricing system layered on top of a society with centuries of institutional discrimination. [38]

AI will build on our existing system's dual goals of pricing financial services based on the true risk the individual consumer poses while aiming to prevent discrimination (e.g., race, gender, DNA, marital status, etc.). Currently, there are not enough sources of standardized information to base decisions and too little credit being made available. Those conditions allowed rampant discrimination by loan officers who could simply deny people because they "didn't look credit worthy." [38], [39]

It is important to encourage and develop a great sense of money management. Managing how applicants spend their money will ease the stress down the road. The fundamental practice of paying bills on time and saving money will eventually help. The path to financial freedom is not always an easy task. In this research, we have identified that loans are widely used around the world, and we have revealed that there are many reasons why people want to get money from banks or any other financial companies that offer loan services. Some similarities and differences exist amongst the various existing crediting systems. S&P, Moody, and Fitch, are three rating agencies that established corporate customer credit rating systems. FICO credit rating systems evaluate customer credit status from at least five aspects, such as length of customer's building credit time and historical records of customers' paying credit. Small and medium sized customer credit ratings may also be evaluated using the "5C principle": Character, Capital, Capacity, Collateral and Condition of Business [9]. From the previous charts, we can see that many factors affect loan approval stronger than others—for example, gender shows how a male can get approval more than a female. Also, the education level is one factor that affects the application decision.

III. Datasets

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

A. BigML.com. The dataset title: Loan Risk Data [40]

The dataset is taken from BigML.com. The dataset title: Loan Risk Data [40] link: *https://bigml.com/user/bigml/gallery/dataset/4f89c38f1552686459000033#info* The dataset is about loan risk data. It is having around 1000 records which shows the creditworthiness of applications and contains 21 attributes.

B. Lending Club Loan Dataset 2007_2011

The other dataset we use in our project is "Lending Club Loan Dataset 2007_2011" which is a big data set; it contains around 39,000 rows and 111 columns [41]. *Link: https://www.kaggle.com/imsparsh/lending-club-loan- dataset-2007-2011?select=loan.csv*

C. Data on loan delinquency

The dataset is about loan delinquency, data has around 50,000 loans data and 19 attributes. The size of the dataset is 4.3 MB. [42]

Link: *https://bigml.com/user/bigml/gallery/dataset/4f8b5eae155268783e00000d?reload*

IV. Purposed approach

Like any other data science project, the approach we are planning to use includes multiple steps. The steps we are planning to follow are described in Figure 2.

The goal is already defined for this project, which is to find the impact of social and economic factors on Creditworthiness. While we already found one dataset [43], [44] to start with the research, we will continue the research for more data sources, which could help us investigate the problem. Subsequently a data clean up activity is planned and then normalization and grouping of data is also planned. In the next stage, we will be looking for patterns and derive the required knowledge to address the topic under consideration. Finding insights and visualizing the same will be done at this stage. Next step of using machine learning is a bit ambitious for us, with which we will try to find clusters within the dataset(s) under consideration to gain necessary wisdom to solve the problem under consideration.

Fig. 1. ATTRIBUTES FROM LOAN RISK DATA

Sl No	Attribute Name	Data type	Description
1	checking_status	Categorical	Status of the loan (status can be in process, grace, repayment, forbearance, etc.,)
2	duration	Numeric	Measure of the bond with sensitivity of price, or other debt to change in interest rates.
3	credit_history	Categorical	Records of how a person maintained their credit history in the past.
4	purpose	Categorical	Purpose of the loan
5	credit_amount	Numeric	Amount the customer promises to repay
6	savings_status	Categorical	Status of the savings account
7	employment	Categorical	The customer's employment
8	installment_commitment	Numeric	Includes all the terms and conditions as per amount
9	personal_status	Categorical	Personal Status of the customer

V. Framework

Through the research done so far, we identified that the below attributes have a significant impact on determining the credit worthiness of a person.

- Education
- Marital Status
- Employment
- Income
- Property Type
- Rent and/or Utility payments
- Purchase history

In the next phase we are looking to find patterns among them and the weightage of those attributes on determining creditworthiness.

In typical situations, lenders use the credit score as the main factor to determine if people were eligible for a loan. Since 45

10	other_parties	Categorical	All other parties included in the loan agreement
11	residence_since	Numeric	Dates of since when a person is living at a particular residence.
12	property_magnitude	Categorical	Type and importance of the loan
13	age	Numeric	Age of the customer
14	other_payment_plans	Categorical	Other payment plans included in the bank
15	housing	Categorical	Housing status of the customer
16	existing_credits	Numeric	Available information/ history of the customer
17	job	Categorical	A customer's basic job information
18	num_dependents	Numeric	Number of dependents included in the loan
19	own_telephone	Categorical	If customers have a contact number
20	foreign_worker	Categorical	If the customer is a foreign worker.
21	class	Categorical	Two different classes of loan-good/bad

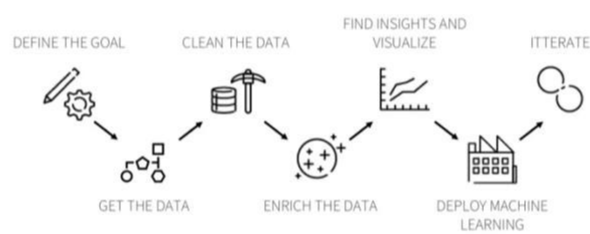

Fig. 2. attributes information for Loan Risk Data

million people do not have a credit score, we will use the AI, ML to create a new framework called "qualification score". The qualification score is a calculation of multiple factors such as social, educational, and financial factors to name a few. Based on this information, then the lender can use the "qualification score" instead of the credit score to determine creditworthiness for those who do not have one.

We will use AI to adopt a new system to find a proper way to rank each element based on the datasets we have. As a result, a will inherit and then calculate the "qualification score". [39], [45]

VI. Findings

VII. Feature walk through

VIII. Conclusion

Ultimately, measuring creditworthiness without institutional discriminations should be the law. Fairness is the act of treating an individual equally or in a way that is right or reasonable. This is what we learn from our life experience. However, in life, there are instances where there are misinterpretations and different views of the meaning of the term, fairness.

All applications should be given an equal opportunity and accommodations to help gain access to the same lender model. With the help of the most powerful tool available in the world, artificial intelligence and bank institutions are collaborating to provide new and alternative approaches to help increase credit scores. With the help of alternative data source, Artificial Intelligence and Machine Learning will make the decision-making process for the lender much faster and provide an insight on whom will repay their loans. [46]–[48]

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