A NEW WAY OF PREDICTING THE LOAN APPROVAL PROCESS USING ML TECHNIQUES

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Abstract

Loans account for a large portion of bank profits. Despite the fact that many people are looking for loans. Finding a legitimate applicant who will return the loan is difficult. There may be many errors made when selecting the real applicant when the process is done manually. As a result, we are creating a machine learning-based loan prediction system that will choose the qualified applicants on its own. Both the applicant and the bank staff will benefit from this. There will be a significant reduction in the loan sanctioning period of time. In this research, we use different machine learning techniques to predict the loan data.

Keywords: loan, bank, legitimate applicant, loan prediction, Machine Learning, Vector system.

Introduction

A loan is the foundation of a bank's operations. The majority of the bank's profits are derived directly from the money made from the loans. Even when the bank authorizes the loan following a lengthy verification and testimonial process, there is no guarantee that the chosen hopeful is the appropriate hopeful. When done manually, this operation requires additional time. We are able to foretell if a specific hopeful is secure or not, and the entire testimonial procedure is mechanized using machine literacy.Credit risk is the chance that the loan won't be paid back on time or at all; liquidity risk is the chance that too many deposits will be withdrawn too quickly, leaving the bank cash-strapped; and interest rate risk is the chance that interest rates on bank loans will be too low to generate enough revenue for the bank. For bank clients as well as potential borrowers, loan prognostic is quite beneficial.

The goal of this project is to provide a quick, easy, and immediate technique for choosing qualified applications. The bank may gain in a number of ways, such as by imposing a deadline for applicants to check and confirm whether or not their loan will be approved. This forecasting approach might be useful in that it allows bankers to concentrate more on valuable assets rather than on unqualified applicants. The applicant's loan application process will take less time as a result. "Results for a certain Loan Id can be sent to other bank departments so they can handle applications in a suitable manner. This facilitates the completion of other formalities by all other departments.

Methodology

We have used different classification algorithms to find out which one best predicts the loan status with most accuracy.

Random Forest:In Supervised Machine Learning, Random Forest is a well-known learning technique that works well for Regression & Classification applications.It creates random forests and then searches through them for solutions.It is an ensemble learning method where a sizable number of classifiers are employed to address a challenging issue.To avoid overfitting difficulties, random forest considers each tree for prediction rather than just one.

Support Vector Machine (SVM):A popular supervised machine learning algorithm is SVM. The SVM classifier is currently the most popular classifier.SVM has proven to have a wide variety of excellent skills, especially in classification issues.

Logistic Regression (LR):Logistic regression, which belongs to the supervised learning approach, is one of the most popular machine learning algorithms. The sample size for LR should be large. It is employed for categorical target variable prediction. It does not produce 0 or 1, but rather returns the probability value.

Data Collection:

A training set and a testing set are created using the dataset gathered for loan failure prediction customers. The 80/20 rule is typically used to separate the training set from the testing set. Forecasting for the test set is done using the data model that was developed using a decision tree and applied to the training set. the following characteristics:

- Loan_id-Unique loan id
- Gender-Male / female
- Married-Applicant Married(Y/N)
- Dependents-Number of dependents
- Education-Applicant education(graduate/undergraduate)
- Self_employed-Self employed(Y/N)
- Applicant income-Applicant income
- Co-Application income-Co_application income
- LoanAmount-Loan amount in thousands
- Loan_Amount_term-Term of loan in months
- Credit_history-Credit history meets guidelines
- Property_area Urban /semi urban /rural
- Loan_status-Loan approved(Y/N)

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```
import numpy as np
import pandas as pd
```

```
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import accuracy_score, roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
```

import matplotlib.pyplot as plt
!pip install xgboost
import xgboost as xgb
from xgboost import XGBClassifier



Preprocessing: The collected data may contain missing values that may lead to inconsistency. To gain better results data needs to be preprocessed and so it'll better the effectiveness of the algorithm. We should remove the outliers and we need to convert the variables. In order to cover these issues we use a chart function.

Train model on training data set:

Now that the model has been trained on the training data, predictions should be made for the test data. Our train dataset may be split into two tracts: testimony and train. On the basis of the training portion, we can train the model to generate predictions for the testimony portion. We can validate our prophecies in this way since we have the actual prophecies for the testimony portion (which we do not have for the test dataset).

	Loan_ID	Gender	Married	Dependents	E	ducation	Self_Employed	1	
0	LP001002	Male	No	0		Graduate	No		
1	LP001003	Male	Yes	1		Graduate	No		
2	LP001005	Male	Yes	0		Graduate	Yes		
3	LP001006	Male	Yes	0	Not	Graduate	No		
4	LP001008	Male	No	0		Graduate	No		
	Annlicont	Tacomo	Coopple	contIncomo	Loon	Amount	Loon Amount Tonm		
~	Applicant	LTUCOIIIe	COappi	LCantincome	LOan	M-N	Loan_Amount_Term	1	
0		5649		0.0		NaN	560.0		
1		4583		1508.0		128.0	360.0		
2		3000		0.0		66.0	360.0		
3		2583		2358.0		120.0	360.0		
4		6000		0.0		141.0	360.0		
	e		200000000000000000000000000000000000000		22102000				
	Credit_History Property_Area Loan_Status								
0		1.0	l	Jrban	Ŷ	ſ			
1		1.0	[Rural	N	J			
2		1.0	ι	Jrban	Ŷ	1			
3		1.0	J	Jrban	γ	(
4		1.0	ι	Jrban	γ	1			

Apply Model:

Before applying, we find out which classifier best predicts the loan status and after that we applied the model to the suitable one. Apply the built model on a test dataset.

NOVATEUR PUBLICATIONS INTERNATIONAL JOURNAL OF INNOVATIONS IN ENGINEERING RESEARCH AND TECHNOLOGY [IJIERT] ISSN: 2394-3696 Website: ijiert.org VOLUME 6, ISSUE 12, Dec. -2019

<pre>1 total_null = loan_train.isnull().sum().sort_values(ascending=False) 2 total_null.head(10)</pre>					
Credit History	50				
Self_Employed	32				
LoanAmount	22				
Dependents	15				
Loan_Amount_Term	14				
Gender	13				
Married	3				
Loan_ID	0				
Education	0				
ApplicantIncome dtype: int64	0				

Generating the prediction:

Classify the applicants based on the applicant's information and bank's criteria using random forest classifier. **Output**

Loan Status Pre	-		\times
Loan Status	Predictio	on	
Gender [1:Male ,0:Female]	1		
Married [1:Yes,0:No]	1		
Dependents [1,2,3,4]	2		
Education	0		
Self_Employed	0		
ApplicantIncome	2889		
CoapplicantIncome	0		
LoanAmount	45		
Loan_Amount_Term	108		
Credit_History	0		
Property_Area	1		
Predict			
Loan Not Approved			

Next, we can try a single decision tree with the max depth ranging from 4 to 25 and minimum samples for leaf and split between 10 and 100. 4 is the best max depth, while the ideal criterion is the default 'Gini' index.

```
Appendices
import pandas as pd
data = pd.read_csv('loan_prediction.csv')
data.head()
data.tail()
Data.shape
data.info()
data.isnull().sum()
data.isnull().sum()*100 / len(data)data = data.drop('Loan_ID',axis=1)
data.head(1)
columns = ['Gender', 'Dependents', 'LoanAmount', 'Loan Amount Term']
data = data.dropna(subset=columns)
data.isnull().sum()*100 / len(data)
data['Self_Employed'].mode()
[0]data['Gender'].unique()
data['Self_Employed'].unique()
data['Credit History'].mode()[0]
data['Credit_History']=data['Credit_History'].fillna(data['Credit_History'].mode()[0])
data.isnull().sum()*100 / len(data)
data['Dependents']=data['Dependents'].replace(to_replace="3+",value='4')
data['Dependents'].unique()
data['Loan Status'].unique()
data.head()
X = data.drop('Loan_Status',axis=1)
y = data['Loan_Status']
y
data.head()
cols = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan Amount Term']
from sklearn.preprocessing import StandardScaler
st = StandardScaler()
X[cols]=st.fit_transform(X[cols])
Х
from sklearn.model selection import train test split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
import numpy as np
model df
```

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model_val(model,X,y)
from sklearn import svm
model = svm.SVC()
model_val(model,X,y)
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model val(model,X,y)
from sklearn.ensemble import RandomForestClassifier
model =RandomForestClassifier()
model_val(model,X,y)
from sklearn.ensemble import GradientBoostingClassifier
model =GradientBoostingClassifier()
model val(model,X,y)
from sklearn.model_selection import RandomizedSearchCV
\log_{reg_grid} = \{"C":np.logspace(-4,4,20),
        "solver":['liblinear']}
rs_log_reg=RandomizedSearchCV(LogisticRegression(),
           param_distributions=log_reg_grid,
          n iter=20,cv=5,verbose=True)
rs log reg.fit(X,y)
rs_log_reg.best_score_
rs_log_reg.best_params_
svc_grid = \{ 'C': [0.25, 0.50, 0.75, 1], "kernel": ["linear"] \}
rs_svc=RandomizedSearchCV(svm.SVC(),
          param_distributions=svc_grid,
           cv=5,
           n_iter=20,
          verbose=True)
rs_svc.fit(X,y)
rs_svc.best_score_
rs svc.best params
RandomForestClassifier()
rf_grid={'n_estimators':np.arange(10,1000,10),
 'max_features':['auto','sqrt'],
'max_depth':[None,3,5,10,20,30],
'min_samples_split':[2,5,20,50,100],
'min_samples_leaf':[1,2,5,10]
rs_rf=RandomizedSearchCV(RandomForestClassifier(),
          param_distributions=rf_grid,
```

cv=5. n_iter=20, verbose=True) rs rf.fit(X,y) rs_rf.best_score_ rs_rf.best_params_ $X = data.drop('Loan_Status',axis=1)$ $y = data['Loan_Status']$ rf = RandomForestClassifier(n estimators=270, min_samples_split=5, min_samples_leaf=5, max_features='sqrt', max_depth=5) rf.fit(X,y) import joblib joblib.dump(rf,'loan_status_predict') model = joblib.load('loan_status_predict') import pandas as pd $df = pd.DataFrame({$ 'Gender':1, 'Married':1. 'Dependents':2, 'Education':0, 'Self_Employed':0, 'ApplicantIncome':2889, 'CoapplicantIncome':0.0, 'LoanAmount':45, 'Loan_Amount_Term':180, 'Credit_History':0, 'Property_Area':1 ,index=[0])df result = model.predict(df) if result==1: print("Loan Approved") else: print("Loan Not Approved") from tkinter import * import joblib import pandas as pd def show_entry():

p2 = float(e2.get()) p3 = float(e3.get()) p4 = float(e4.get()) p5 = float(e5.get()) p6 = float(e6.get()) p7 = float(e7.get()) p8 = float(e8.get())p9 = float(e9.get())

p1 = float(e1.get())

- p10 = float(e10.get())
- p11 = float(e11.get())

```
model = joblib.load('loan_status_predict')
  df = pd.DataFrame({
  'Gender':p1,
  'Married':p2,
  'Dependents':p3,
  'Education':p4,
  'Self_Employed':p5,
  'ApplicantIncome':p6,
  'CoapplicantIncome':p7,
  'LoanAmount':p8,
  'Loan_Amount_Term':p9,
  'Credit_History':p10,
  'Property_Area':p11
,index=[0]
  result = model.predict(df)
  if result == 1:
    Label(master, text="Loan approved").grid(row=31)
  else:
    Label(master, text="Loan Not Approved").grid(row=31)
master = Tk()
master.title("Loan Status Prediction Using Machine Learning")
label = Label(master,text = "Loan Status Prediction",bg = "black",
         fg = "white").grid(row=0,columnspan=2)
Label(master,text = "Gender [1:Male ,0:Female]").grid(row=1)
Label(master,text = "Married [1:Yes,0:No]").grid(row=2)
```

```
Label(master,text = "Dependents [1,2,3,4]").grid(row=3)
```

```
Label(master,text = "Education").grid(row=4)
```

Label(master,text = "Self_Employed").grid(row=5)
Label(master,text = "ApplicantIncome").grid(row=6)
Label(master,text = "CoapplicantIncome").grid(row=7)
Label(master,text = "LoanAmount").grid(row=8)
Label(master,text = "Loan_Amount_Term").grid(row=9)
Label(master,text = "Credit_History").grid(row=10)
Label(master,text = "Property_Area").grid(row=11)
e1 = Entry(master)
e2 = Entry(master)
e3 = Entry(master)
e4 = Entry(master)
e5 = Entry(master)
e6 = Entry(master)
e7 = Entry(master)
e8 = Entry(master)
e9 = Entry(master)
e10 = Entry(master)
e11 = Entry(master)
e1.grid(row=1,column=1)
e2.grid(row=2,column=1)
e3.grid(row=3,column=1)
e4.grid(row=4,column=1)
e5.grid(row=5,column=1)
e6.grid(row=6,column=1)
e7.grid(row=7,column=1)
e8.grid(row=8,column=1)
e9.grid(row=9,column=1)
e10.grid(row=10,column=1)
e11.grid(row=11,column=1)

Button(master,text="Predict",command=show_entry).grid()

mainloop()

Conclusion :

From a proper point of view of analysis this system can be Perfectly used to find customers who qualify Loan approval. The software is perfect and can work To be used for all banking needs. This may be the system Can be easily uploaded to any operating system. Since then As technology moves online, there is more to this system Space for the coming days. This system is more secure and reliable. Since we used random forest Algorithm system gives very accurate results. There There is no problem if many customers are applying Loan This system accepts data for N no. of customers. In In the future we may add more algorithms to this system Get more accurate results.

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