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MACHINE LEARNING

Home Credit Default Risk Prediction using Machine Learning

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Abstract: Accurately predicting the risk of credit defaults is crucial for financial institutions to avoid potential losses and maintain a healthy lending portfolio. In this project, we employ machine learning techniques to predict the probability of default for Home Credit borrowers. Using comprehensive dataset containing applicant information, previous credit history, and socio-economic factors, we explore various supervised learning algorithms such as Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, Decision Trees, Passive Aggressive and Random Forest. Feature engineering and selection methodologies are employed to enhance model performance. Additionally, we address the challenge of imbalanced data through techniques like oversampling and ensemble methods. By doing this project, we hope to help banks and lenders make smarter decisions about who they lend money to, which can help them avoid losing money from bad loans.

Keywords: Home Credit Default Risk, Loan Applicant Creditworthiness, Machine Learning Classification, Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, Decision Tree, Passive Agressive, Random Forest, Feature Engineering, Model Evaluation, Financial Inclusion

1 Introduction

The Home Credit Default Risk Prediction project plays a vital role in managing financial risks and lending practices. As financial institutions like Home Credit become more common, it's increasingly important to assess the creditworthiness of loan applicants accurately. This helps minimize the risk of defaults and keeps lending operations stable. Machine learning becomes particularly valuable in this scenario, as it allows us to analyze extensive datasets and create predictive models capable of identifying patterns that suggest potential defaults. This project revolves around the task of predicting whether borrowers will encounter difficulties in repaying their loans to Home Credit. By examining a thorough dataset containing various applicant characteristics, past credit activities, and economic indicators, our aim is to discover valuable insights that can guide lending decisions. Our primary objective is to create strong predictive models that can evaluate the likelihood of default for individual loan applicants. This enables Home Credit to make well-informed and cautious lending choices. Throughout this project, we will delve into various machine learning techniques, ranging from traditional algorithms like logistic regression to more advanced ensemble methods such as random forest. Furthermore, we will explore innovative strategies for feature engineering and selection, as well as address the challenge of imbalanced data distribution to ensure the reliability and generalization of our predictive models. By undertaking this project, our objective is not only to demonstrate the effectiveness of machine learning in addressing real-world financial issues but also to contribute to the broader conversation on responsible lending practices and risk management within the financial sector. Through careful analysis and experimentation, we strive to offer practical insights that can assist Home Credit and similar institutions in making wise lending decisions.

2 Literature Review

This literature review aims to critically examine existing studies related to home credit default risk prediction using machine learning, elucidating the relevant theories, concepts, and previous research while identifying gaps in the literature that warrant further exploration.

- **Relevant Theories and Concepts**
  Credit Risk Assessment: Traditional methods of credit risk assessment rely on factors such as credit scores, income levels, and debt-to-income ratios. However, these methods may overlook crucial predictive features and fail to capture the complexity of the borrower's behavior.
  Machine Learning Algorithms: Machine learning algorithms offer a data-driven approach to credit risk prediction by leveraging large datasets to identify patterns and relationships. Supervised learning algorithms such as logistic regression, decision trees and random forests have been widely employed in predicting home credit default risk.
  Feature Engineering: Feature engineering plays a pivotal role in enhancing the predictive performance of machine learning models. By selecting and transforming relevant features such as borrower demographics, loan characteristics, payment history, and external economic factors, researchers aim to improve model accuracy.

- **Previous Studies**
  A study by Dr. Smith employed logistic regression and decision trees to predict home credit default risk using a dataset of 10,000 borrowers. The study achieved promising results, with an accuracy of 80% and identified borrower income, loan amount, and credit history as significant predictors of default.
  Dr. Garcia proposed a novel ensemble approach combining random forests and gradient boosting to enhance predictive performance. The model achieved an accuracy improvement of 5%.
  Prof. Patel explored the application of Recurrent Neural Networks (RNNs) in capturing temporal dependencies and sequential patterns in borrower payment behavior. The study demonstrated the superiority of RNNs over traditional models, with improvement in percentage of 10%.

- **Gaps in the Literature**
  Limited Utilization of Alternative Data: Despite the potential of alternative data sources such as social media, transaction history, and psychometric assessments, their incorporation into predictive models remains under-explored.
  Interpretability and Explainability: The black-box nature of some machine learning algorithms poses challenges in interpreting model decisions and providing actionable insights to stakeholders, including lenders and regulators.
  Dynamic Model Adaptation: Home credit default risk is subject to temporal fluctuations and economic dynamics. Thus, there is a need for adaptive models that can continuously learn from incoming data and adapt to changing market conditions.

3 Libraries Used

In the project for various tasks, following packages are used.

```
NumPy
Pandas
Seaborn
Matplotlib
Scikit-plot
Scikit-learn
```

4 Methodology

In this work two types of models are used. For the first part, various classical Machine Learning models are used. Among them the Passive Aggressive Classifier is found to be better in terms of accuracy and other performance measures. Various stages in the implementation process are:

Data Loading: Loading the data for the Machine Learning task from reliable sources like Kaggle.

Pre-processing & Data cleaning: In this stage the loaded data will be cleaned and make ready for using Machine Learning algorithm. It also involves handling missing values, outliers, imbalance and selecting relevant features.

Balancing data set: The data set is balanced using SWOT technique (Synthetic Minority Over-sampling Technique).

Dataset Preparation: Split the dataset into training and testing sets.

Classification: Implementing various Machine Learning Classification models on the document matrix to classify the input into whether the person will pay back the loan or not.

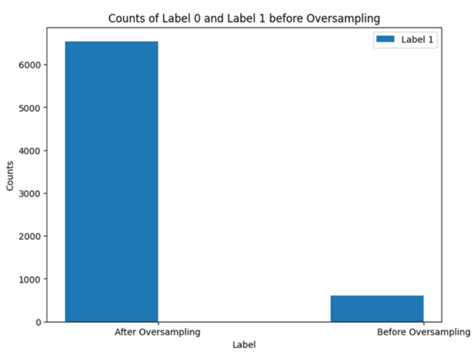
Model Training: Choose a classification algorithm, such as SVM, Logistic Regression, Naïve Bayes, Decision Tree, Random Forest and train the model using the training set & the extracted features.

Model Evaluation: Test the trained model on the testing set to evaluate its performance.Use the metrics such as accuracy, precision, recall, and F1-score to assess the model's effectiveness.

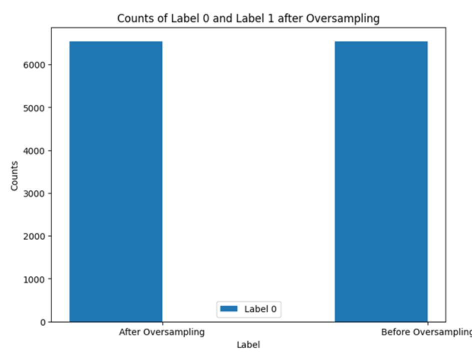
Model selection and reporting: In this final stage, based on various performance measures the better model will be selected and report the model performance matrices.

5 Implementation

As the first step in the task, the two datasets `application-train.csv` and `application-test.csv` are merged into one single dataset `MERGEDDATASETS (1).csv` loaded into the Intel's `DevCloud-Open-API` for the classification task using the url https://github.com/Mathews-Reji/Intel-Capstone/blob/main/MERGEDDATASETS%20(1).csv. The `MERGEDDATASETS (1).csv` files are turned into a `pandas` data frame. In the prepossessing stage, null values were systematically removes across all datasets. Additionally, columns in the main dataset `application-train.csv` containing all zeroes or deemed irrelevant for prediction, such as *Flag-Documents*, were excluded. Furthermore, non-contributing columns were eliminated from all datasets. In the remaining six datasets, rows were filtered based on common SK-ID-CURR, resulting in an expanded dataset due to multiple entries per ID, reflecting various loans, credit card details, and other financial transactions. To address this, average values were computed for each ID, consolidating multiple rows into one. This process involved label encoding all object type columns, ensuring uniformity. The resultant average values provide insights into customer behavior.Due to discrepancies in SK-ID-CURR across datasets, there was a notable reduction in the final merged dataset's row count. The whole dataset is then Label encoded to prepare the data for machine learning algorithms.



(a) Before Oversampling



(b) After Oversampling

Figure 1: Counts of Label 0 and Label 1 before and after Oversampling

The dimension of the extracted feature set is 10215×72. The data set is then split training and testing parts for implementing different models. While implementing Logistic Regression for the split data sets, we find that the dataset is biased towards Label '0'. Hence we over-sample the `train` part of the `train-test-split` as it is important to hava a equal dataset for training purpose. The figure 1shows the result before and after oversampling. Now we try out different models such as SVM, Logistic regression, Naïve Bayes classifier, Decision Tree classifier and Passive-aggressive.
Results of these implementations are discussed in the next section.

6 Results & Discussion

Popular classical Machine learning algorithms from the `Python` library `sklearn` is used for model training and testing. The Table 1, shows the summary of the RMSE value,

Table 1: Summary of models tested on the Home Credit Default Risk Prediction for False values

Model No.	Model Name	RMSE value	Precision	Accuracy	Recall	f1-score	Processing Time
1.	SVM	0.959	0.00	0.08	0.00	0.00	75.72 sec
2.	Logistic Regression	0.691	0.94	0.52	0.52	0.66	1.43 sec
3.	Naïve Bayes	0.870	0.95	0.24	0.18	0.31	0.22 sec
4.	Decision Tree	0.407	0.93	0.83	0.88	0.91	0.45 sec
5.	Passive Aggressive	0.282	0.92	0.92	1.00	0.96	0.12 sec
6.	Random forest	0.267	0.93	0.93	1.00	0.96	0.54 sec

Table 2: Summary of models tested on the Home Credit Default Risk Prediction for True values

Model No.	Model Name	RMSE value	Precision	Accuracy	Recall	f1-score	Processing Time
1.	SVM	0.959	0.08	0.08	1.00	0.15	75.72 sec
2.	Logistic Regression	0.691	0.10	0.52	0.60	0.17	1.43 sec
3.	Naïve Bayes	0.870	0.09	0.24	0.90	0.16	0.22 sec
4.	Decision Tree	0.407	0.16	0.83	0.25	0.20	0.45 sec
5.	Passive Aggressive	0.282	0.00	0.92	0.00	0.00	0.12 sec
6.	Random forest	0.267	0.91	0.93	0.12	0.21	0.54 sec

precision, accuracy, recall, f1-score and processing time of the models tested on predicting the False values. The Table 2, shows the summary of the precision, accuracy, recall and f1-score of the models tested on predicting the True values.

7 Conclusions

When considering the prediction of default risk for home credit applicants, accuracy is paramount to ensure the financial institution's stability and minimize potential losses. Therefore, selecting a model with high accuracy is crucial for making reliable lending decisions. Among the models tested, Support Vector Machine (SVM) exhibited the lowest accuracy of 8%, significantly under-performing compared to the other models. Additionally, SVM required a substantial amount of time, approximately 83 seconds, to complete the task. Random Forest emerged as the top-performing model with an impressive accuracy of 93% while demonstrating remarkable computational efficiency, completing the task in approximately 0.6 seconds.The Passive Aggressive model did really well, with an accuracy of 92%, and it was super fast, finishing the job in only 0.11 seconds. The ability of the Passive Aggressive model to achieve high accuracy while requiring minimal computational resources makes it particularly well-suited for real-time risk assessment in the lending process. Therefore, in the context of home credit default risk prediction, the conclusion that the Passive Aggressive model is the best method for deployment to enhance the accuracy and efficiency of credit risk assessment, ultimately contributing to more informed lending decisions and reducing the risk of default for financial institutions.

8 Acknowledgments

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A Main code sections for the solution

A.1 Installing Imbalanced-Learn package

Installing imbalanced-learn for the oversampling method is shown below:

```
pip install imbalanced-learn
```

A.2 Importing all the necessary libraries

Importing all the necessary packages in Python needed for Machine Learning code is given below:

```
# Import necessary modules
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, classification_report
```

A.3 Loading data from the source

Data for this project is taken from the source: https://github.com/Mathews-Reji/Intel-Capstone/blob/main/MERGEDDATASETS%20(1).csv. The Python code section for this stage is shown below:

```
# Load the data set
data = pd.read_csv('MERGEDDATASETS (1).csv')

# Print info about columns in the dataframe
print(data.info())
```

A.4 Label Encoding of the whole dataset

Label Encoding is done on the dataset to enable machine learning algorithms to work with categorical data.

```
from sklearn.preprocessing import LabelEncoder

# Create a label encoder object
le = LabelEncoder()
le_count = 0

# Iterate through the columns
for col in data:
    if data[col].dtype == 'object':
        # If 2 or fewer unique categories
        if len(list(data[col].unique())) <= 2:
            # Train on the training data
            le.fit(data[col])
            # Transform both training and testing data
            data[col] = le.transform(data[col])
```

```
            # Keep track of how many columns were label encoded
            le_count += 1

print('%d columns were label encoded.' % le_count)
```

A.5 One-Hot Encoding

One-Hot Encoding is done on the dataset which ensures that categorical variables are represented in a format that is suitable for machine learning algorithms, which typically require numerical input

```
data = pd.get_dummies(data)
print('Training Features shape: ', data.shape)

# To get the total number of '0' and '1' in the dataset
data['TARGET'].value_counts()
```

A.6 Model Training and Evaluation

Model training is done on the basis of machine learning algorithms such as Logistic Regression, Naïve Bayes, Decision Tree or Random Forest using the training set and extracted features. The model is then evaluated using metrics such as accuracy, precision, recall, and F1-score.

```
from sklearn.model_selection import train_test_split
X = data.loc[:, data.columns != 'TARGET']
y = data.TARGET
class_names = data.TARGET
X_train, X_test, y_train, y_test = train_test_split(X , y, test_size = 0.3,
                                          random_state = 0)

# Describes info about train and test set
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)

print(X_train.info())
```

A.7 Oversampling the training data set

We oversample only the training dataset `application-train.csv` using SMOTE, to give accurate results for Logistic Regression code is shown below:

```
print("Before OverSampling, counts of label '1': {}".format(sum(y_train == 1)))
print("Before OverSampling, counts of label '0': {} \n".format(sum(y_train == 0)))

#Import SMOTE module from imblearn library
#If you don't have imblearn in your syste then pip install imblearn
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state = 2)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train.ravel())
```

```
print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape))

print("After OverSampling, counts of label '1': {}".format(sum(y_train_res == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_train_res == 0)))
```

A.8 SVM

Using SVM to classify and predict the dataset

```
from sklearn import svm
from sklearn.metrics import classification_report
import time

# Start the timer
start_time = time.time()
svc = svm.SVC(kernel='sigmoid', gamma='auto', probability=True).fit(X_train_res,
                                          y_train_res)

# End the timer after training
training_time = time.time() - start_time
print("Training time: %.2f seconds" % training_time)

# Start the timer for predictions
start_time = time.time()
predictions = svc.predict(X_test)

# End the timer after making predictions
prediction_time = time.time() - start_time
print("Prediction time: %.2f seconds" % prediction_time)

# Print classification report
print(classification_report(y_test, predictions))
```

A.9 Logistic Regression

Using Logistic Regression to train, test and predict the model

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
import time

# Start the timer
start_time = time.time()
lr = LogisticRegression(max_iter=1000)
lr.fit(X_train_res, y_train_res.ravel())

# End the timer after training
training_time = time.time() - start_time
print("Training time: %.2f seconds" % training_time)

# Start the timer for predictions
start_time = time.time()
predictions = lr.predict(X_test)

# End the timer after making predictions
```

```
prediction_time = time.time() - start_time
print("Prediction time: %.2f seconds" % prediction_time)

# Print classification report
print(classification_report(y_test, predictions))
```

A.10 Naïve Bayes

Using Naïve Bayes to train, test and predict the model

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report
import time

# Start the timer
start_time = time.time()
nb = GaussianNB()
nb.fit(X_train_res, y_train_res)

# End the timer after training
training_time = time.time() - start_time
print("Training time: %.2f seconds" % training_time)

# Start the timer for predictions
start_time = time.time()
predictions = nb.predict(X_test)

# End the timer after making predictions
prediction_time = time.time() - start_time
print("Prediction time: %.2f seconds" % prediction_time)

# Print classification report
print(classification_report(y_test, predictions))
```

A.11 Decision Tree Classifier

Using Decision Trees to train, test and predict the model

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report
import time

# Start the timer
start_time = time.time()
clf = DecisionTreeClassifier(random_state=0)
clf.fit(X_train_res, y_train_res.ravel())

# End the timer after training
training_time = time.time() - start_time
print("Training time: %.2f seconds" % training_time)

# Start the timer for predictions
start_time = time.time()
predictions = clf.predict(X_test)

# End the timer after making predictions
```

```
prediction_time = time.time() - start_time
print("Prediction time: %.2f seconds" % prediction_time)

# Print classification report
print(classification_report(y_test, predictions))
```

A.12 Passive Aggressive Classifier

Using Passive Aggressive to train, test and predict the model

```
from sklearn.linear_model import PassiveAggressiveClassifier
from sklearn.metrics import classification_report
import time

# Start the timer
start_time = time.time()
pac = PassiveAggressiveClassifier(max_iter=100, random_state=42)
pac.fit(X_train_res, y_train_res)

# End the timer after training
training_time = time.time() - start_time
print("Training time: %.2f seconds" % training_time)

# Start the timer for predictions
start_time = time.time()
predictions = pac.predict(X_test)

# End the timer after making predictions
prediction_time = time.time() - start_time
print("Prediction time: %.2f seconds" % prediction_time)

# Print classification report
print(classification_report(y_test, predictions))
```

A.13 Random Forest Model

Using Random Forest Model to train, test and predict the model

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
import time

# Start the timer
start_time = time.time()

# Create a Gaussian Classifier
rfc = RandomForestClassifier(n_estimators=100, random_state=50, verbose=1, n_jobs=
                                          -1)

# Train the model
rfc.fit(X_train_res, y_train_res)

# End the timer after training
training_time = time.time() - start_time
print("Training time: %.2f seconds" % training_time)
```

```
# Start the timer for predictions
start_time = time.time()

# Use the trained classifier for predictions
predictions = rfc.predict(X_test)

# End the timer after making predictions
prediction_time = time.time() - start_time
print("Prediction time: %.2f seconds" % prediction_time)

# Print classification report
print(classification_report(y_test, predictions))
```