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CAPSTONE PROJECT

FINAL REPORT

**PROJECT SUMMARY**

**Batch Details**

**Team Members**

**Project Domain**

**Proposed Title**

**Group No**

**Team Leader**

**Mentor**

**July 2022 DSE Online**

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Banking & Finance

Defaulter Prediction using ML Techniques

10

**Neha Goyal**

Trupti Mathapati

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**Part-01**

**Summary of Problem Statement,**

**Data & Findings**

* 1. **Problem Statement Summary**

The goal of the project is to build a classification model, which can classify a loan applicant can become a defaulter or not. By accurately identifying such risky applicants the lending club can take decision whether or not to grant the loan to a particular applicant. This helps the business to reduce having the risk of unrecovered loans and can help to identify the better applicants with low risk to offer loans and increase profitability of the business

* 1. **Data Summary**

The data we have is a huge dataset from organization called Lending club which offer loans to retail customers. This is a structured data with 27 features and 3.9+ Lakh records in it. The source of the dataset is Kaggle. The features consist various data points before the application, while the application process and granting the loan and loan status. Prior to analysis the data was processed to remove missing values and outliers.

* 1. **Findings Summary**

Through analysis we found that there are multiple features which are strongly correlated with the target variable. The features are …………. The model achieved an accuracy of 92% which is 16% above the baseline model. Further the model also suggested the areas for taking necessary decision to avoid the defaulting of loan which can decrease the defaulting rate by 90%.

**Part-02**

**Final Process Overview**

**2.1. Data Preprocessing Steps**

* The redundant columns are dropped.
* Numerical Variables:
  + The distributions were plotted for each variable and found that hardly any variables have normal distribution.
  + The features are skewed, Null values are present, outliers are included.
  + **Null values** – We have treated the Null values **mean imputation**.
  + **Outliers & Skewness** – The outliers are treated based in **IQR Method.**
  + **Scaling** – The data is transformed to a common scale across variables using **standard scaler**.
* Categorical Variables:
  + The categorical data which has large number of categories are dropped.
  + **Null Values** – The null values are imputed with the **mode** of the category.
  + The categories are encoded with **dummy encoding**.
* Test & Train Dataset:
  + Using the scikit learn Test train split function have created two separate data sets with **0.66** of the total data which can be used for **training** & **0.33** of the total data for **testing**.

**2.2. Algorithms Used**

* Since the task is classification, there are many Algorithms which can be used for training the model.
* The algorithms we considered for training are
  + **Logistic Regression** – Logistic Regression is a regression algorithm where we calculate the Log odds value and which then converted in to the probability. Based on the limit of probability we classify which class a particular applicant belongs.
  + **Decision Tree** – Decision Tree uses information gain for creating rules based on which we classify the data in to buckets. This is done in such a way to attain less noise in the model. The algorithms form a set of rules based on the values of the features and classify a particular applicant belongs to which category.
  + **Naïve Bayes** – Naïve Bayes algorithm calculates the conditional probability of the applicant based on the values of the other features and this probability value decides which category a particular applicant belongs to.

**2.3 Combination of Techniques**

* We also used ensembled techniques for modelling the data. Which are
  + **Random Forest** – Random Forest is an ensembled bagging technique which uses multiple decision tree algorithms which runs on multiple subsets of the data and the entire results are summarized and then decides the category of an applicant.
  + **XG Boost** – XG Boost is an ensembled boosting technique in which multiple algorithms are executed in a series where the data in which the previous algorithm made errors are passed to the next and it works and this repeats for a maximum number of iterations which ensures for the best possible performance among all the other models.

**Part-03**

**Step by Step Walk through of the solution**

**3.1. Data Exploration**

**Dataset**

The dataset we chose for analysis is a Loan Dataset which belongs to a bank. Let’s import the data into the jupyter notebook and save it in a variable called df.

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**Check The Size of Dataset**

The Dataset has 2,12,999 Records and 53 Variables

**Check the Size of Dataset**

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**Data Dictionary**

|  |  |  |
| --- | --- | --- |
| Sno | Variable | Description |
| 0 | loan\_amnt | The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value. |
| 1 | term | The number of payments on the loan. Values are in months and can be either 36 or 60. |
| 2 | int\_rate | Interest Rate on the loan |
| 3 | installment | The monthly payment owed by the borrower if the loan originates. |
| 4 | grade | LC assigned loan grade |
| 5 | sub\_grade | LC assigned loan subgrade |
| 6 | emp\_title | The job title supplied by the Borrower when applying for the loan. |
| 7 | emp\_length | Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years. |
| 8 | home\_ownership | The home ownership status provided by the borrower during registration or obtained from the credit report. Our values are RENT, OWN, MORTGAGE, OTHER |
| 9 | annual\_inc | The self-reported annual income provided by the borrower during registration. |
| 10 | verification\_status | Indicates if income was verified by LC, not verified, or if the income source was verified |
| 11 | issue\_d | The month which the loan was funded |
| 12 | loan\_status | Status of the loan |
| 13 | purpose | A category provided by the borrower for the loan request. |
| 14 | title | The loan title provided by the borrower |
| 15 | zip\_code | The first 3 numbers of the zip code provided by the borrower in the loan application. |
| 16 | addr\_state | The state provided by the borrower in the loan application |
| 17 | dti | A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income. |
| 18 | earliest\_cr\_line | The month the borrower's earliest reported credit line was opened |
| 19 | open\_acc | The number of open credit lines in the borrower's credit file. |
| 20 | pub\_rec | Number of derogatory public records |
| 21 | revol\_bal | Total credit revolving balance |
| 22 | revol\_util | Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit. |
| 23 | total\_acc | The total number of credit lines currently in the borrower's credit file |
| 24 | initial\_list\_status | The initial listing status of the loan. Possible values are – W, F |
| 25 | application\_type | Indicates whether the loan is an individual application or a joint application with two co-borrowers |
| 26 | mort\_acc | Number of mortgage accounts. |
| 27 | pub\_rec\_bankruptcies | Number of public record bankruptcies |

**Understanding the basic information of the variables**

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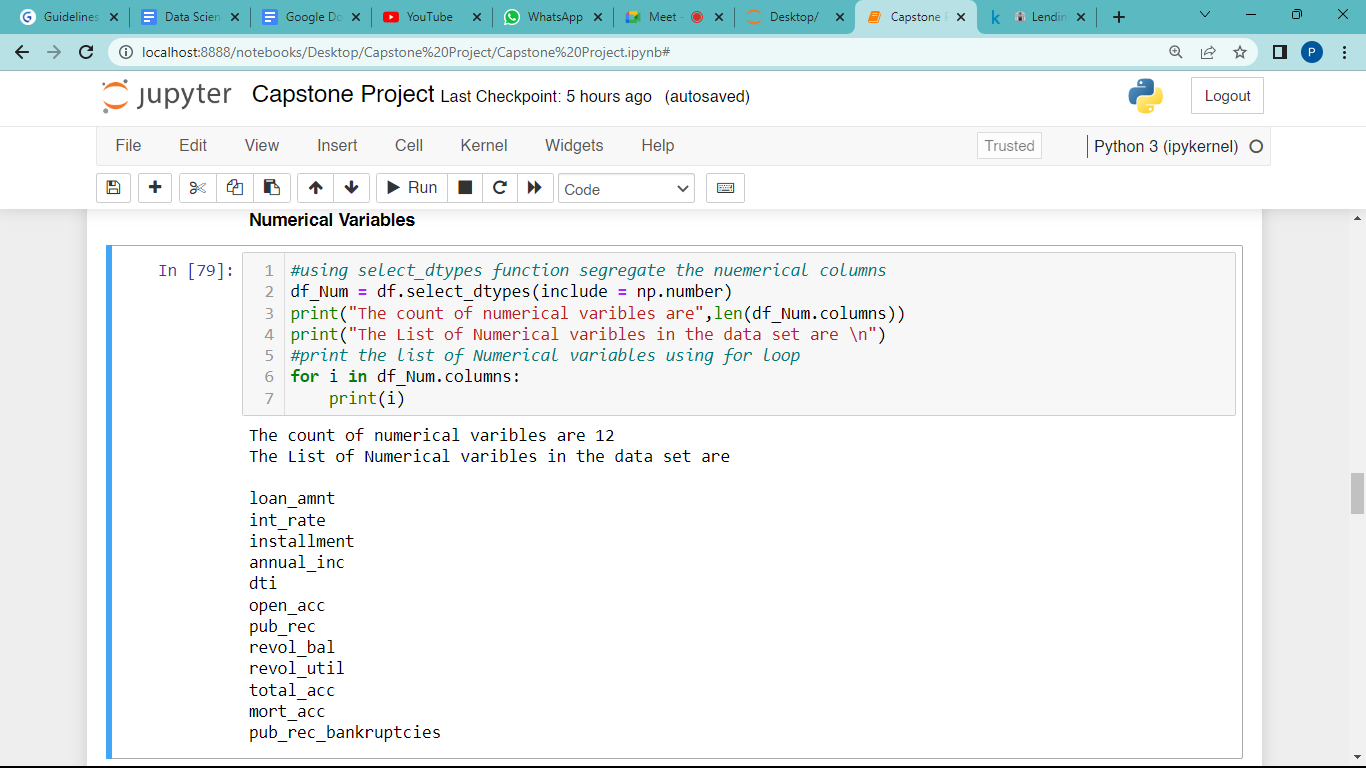
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Interpretation:

* Now we know there are both categorical and numerical variables in the data.
* The methods of analyzing data are based on the nature of the variables, especially what type of data it contains.
* It is better if we can classify the numerical and categorical variables in the data for analysis purposes.

**Variable categorization**

**Numerical variables**



Interpretation

* We can see there are 12 numerical variables.
* They are [ loan\_amnt, int\_rate, installment, annual\_inc, dti, open\_acc, pub\_rec,

revol\_bal, revol\_util, total\_acc, mort\_acc, pub\_rec\_bankruptcies]

**Categorical Variables**

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Interpretation:

* We can see there are 15 variables.
* They are [ term, grade, sub\_grade, emp\_title, emp\_length, home\_ownership, verification\_status, issue\_d, loan\_status, purpose, title, earliest\_cr\_line, initial\_list\_status, application\_type, address]

Let’s Plot a pie plot for comparing the proportion of the Numerical vs Categorical variables.

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Graphical user interface, application

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Interpretation:

* Numerical variables – 44.44%
* Categorical Variables – 55.56%

**Statistical Summary**

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* Using describe function we can look in to the counts, Mean & 5point summary of each variable, which is used for inferring a lot of things about the features.
* We can infer the mean, skewness, outliers of the variables, but over time due to development of advanced visual techniques this piece of info has lost its importance.

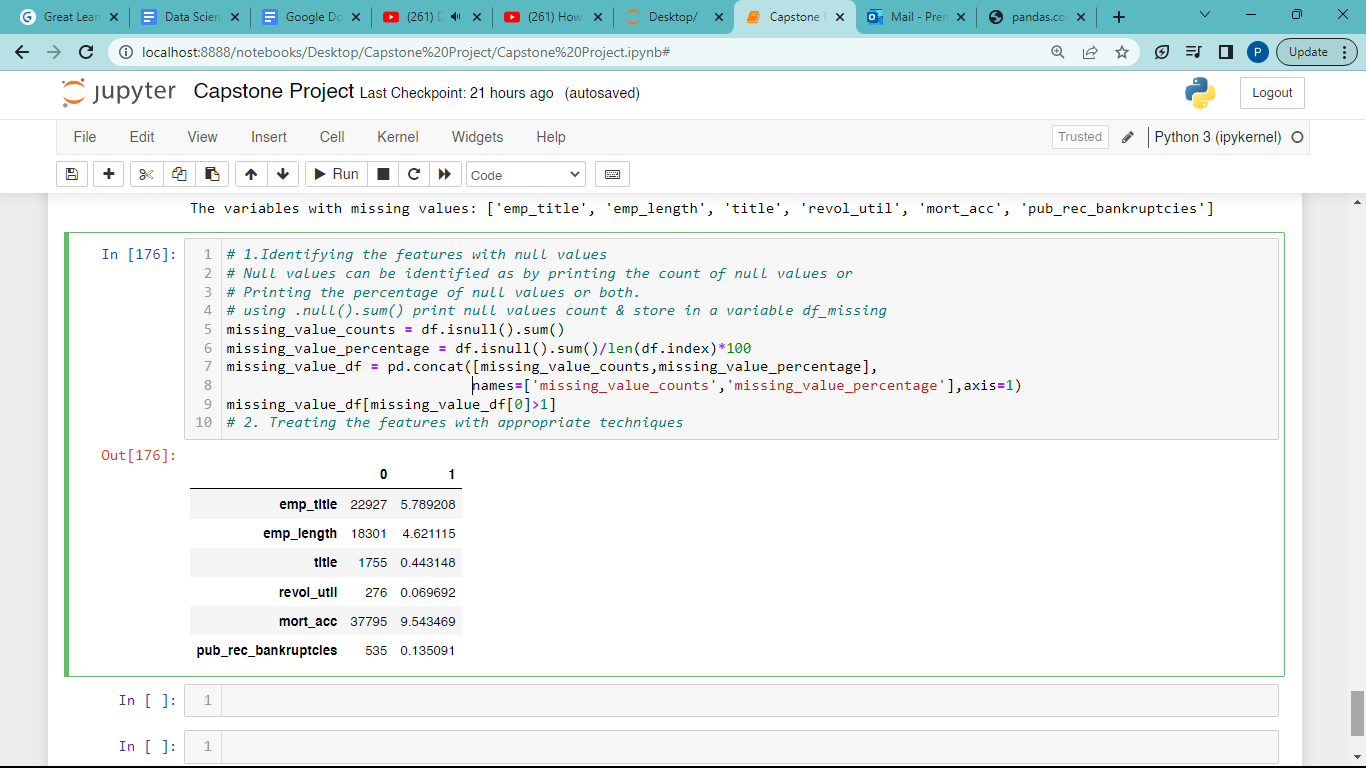
**3.2. Data Preprocessing**

**Redundant Columns Removal**

* Now let’s investigate the columns which we may not need for the analysis.
* Columns like IDs, Names, Null columns are considered redundant columns and can be removed from the dataset.
* When we look in the data frame, we can find there are no such columns which are redundant.
* Now let’s continue to explore null values and treat them.

**Null Values & Treatment**

* + Null values treatment has two steps.
    1. Identifying Null values.



* We made a data frame with columns counts & percentage of null values and filtered the rows with more than one null value.
* We can see there 6 variables with not more than 10% null values.
* We need to treat these null values as per the distribution of the variables individually.

**Project Justification**

Project Statement:

“Determining weather, a given applicant for loan can be a defaulter or non-defaulter through machine learning models within available data. ”

* Within this project we first identify what kind of behavior that most of the defaulters exhibit and through which variables we captured it.
* Transform data and make it suitable for machine learning algorithms.
* Build a model which will help us to predict the defaulter.

Complexity involved:



If we look in to the heatmap there are only two variables which are having strong correlation rest are not strongly correlated, we need to do further processing and see the significance of the variables. To comment on the complexity, it is moderate complex.

Project Outcome:

* The project outcome would be a well-trained model which do classification of a person based on given inputs of information with best accuracy possible.

Commercial, Academic or Social value:

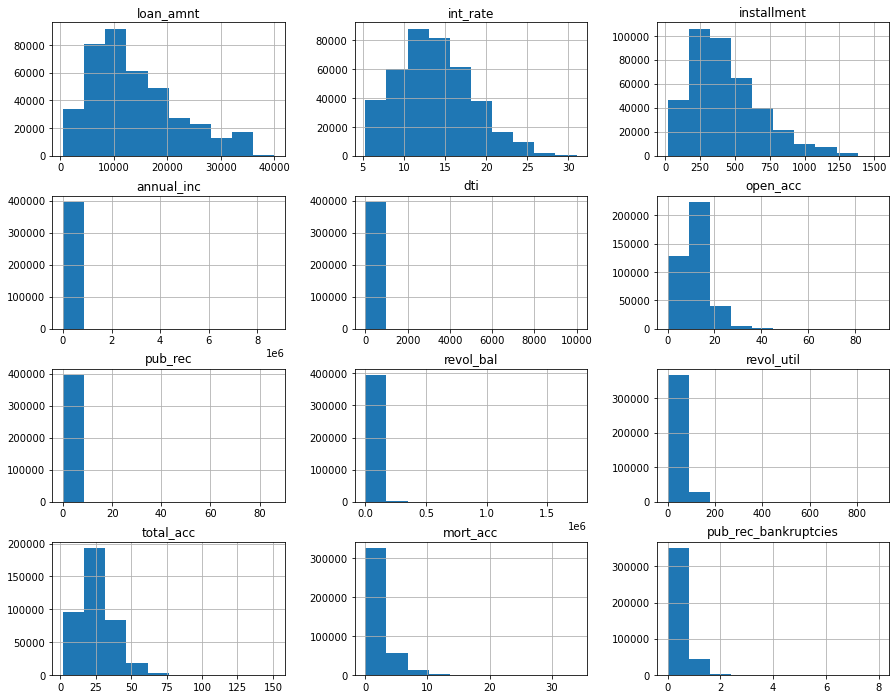
* This project’s main aim is to create commercial value in terms of reducing defaulters for banks which can save banks from more losses.
* As an academic endeavor this project helped us to get work with real time data and learn how to apply data science techniques for real-time applications.
* Socially, the model not only helps detect defaulters but also non-defaulters which can help banks in identifying the right people for offering loans and support them in their financial needs.

**3.3. Data Exploration (EDA)**

**Distribution of variables**

* We have divided variables into numerical and categorical variables. Now we will check how the variables are distributed in the dataset and their shape of distribution in the given range of values.

**Numerical Features**



Interpretation: All the variables are distributed from slightly right skewed too highly right skewed. So, we need to normalize data before we move to modelling.

Categorical Variables

A picture containing calendar

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**Interpretation:**

The categorical variables mostly seemed biased except the verification status column has each category uniformly distributed. The column application\_type is very biased towards individual.

**Relationship between variables**

****

There are two pairs of variables showing linear relationship is.

* Loan\_amnt & Installments – We know that for a huge loan the number of installments will be more though it also depends on the tenure. This is related by a formula that relates the loan amount, tenure, interest rate & installments.
* Total\_acc & open\_acc – Open accounts are always subset of the total accounts, so it has a proportional relationship.

**Multi-collinearity**

* Multicollinearities exist only between two sets of variables Loan\_amnt & installments, Total\_acc & open\_acc. To handle this interaction effect, we can reduce these pairs into a single variable for representation of the values. We can simply consider total accounts rather than having both open and total accounts.

Presence of outliers and its treatment

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* Using the above code, we print the columns with outliers. There are 12 columns with outliers. They are loan\_amnt, int\_rate, installment, annual\_inc, dti, open\_acc, pub\_rec, revol\_bal, revol\_util, total\_acc, mort\_acc, pub\_rec\_bankruptcies.

**Treatment**

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* In the above code we calculate Q1, Q3,IQR, upper limit =Q3+1.5IQR, lower limit = Q1-1.5IQR and using these values we write a for loop and if statement to filter out values which don’t lie between the upper & lower limits and replace them with median of corresponding column to impute outliers.

**Chart, box and whisker chart

Description automatically generatedBefore Outlier’s Treatment**

**After Outlier Treatment**

**Chart, box and whisker chart

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* Almost most of the outliers are imputed with medians.

**statistical significance of variables**

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Graphical user interface, text, application, email

Description automatically generated

Using t test we have found all the significant variables.

**Feature Engineering**

**Whether any transformations required**

We need not any transformation to do further as already the data follows normal distribution when the outliers are treated. We just scale the data for efficiency purposes.

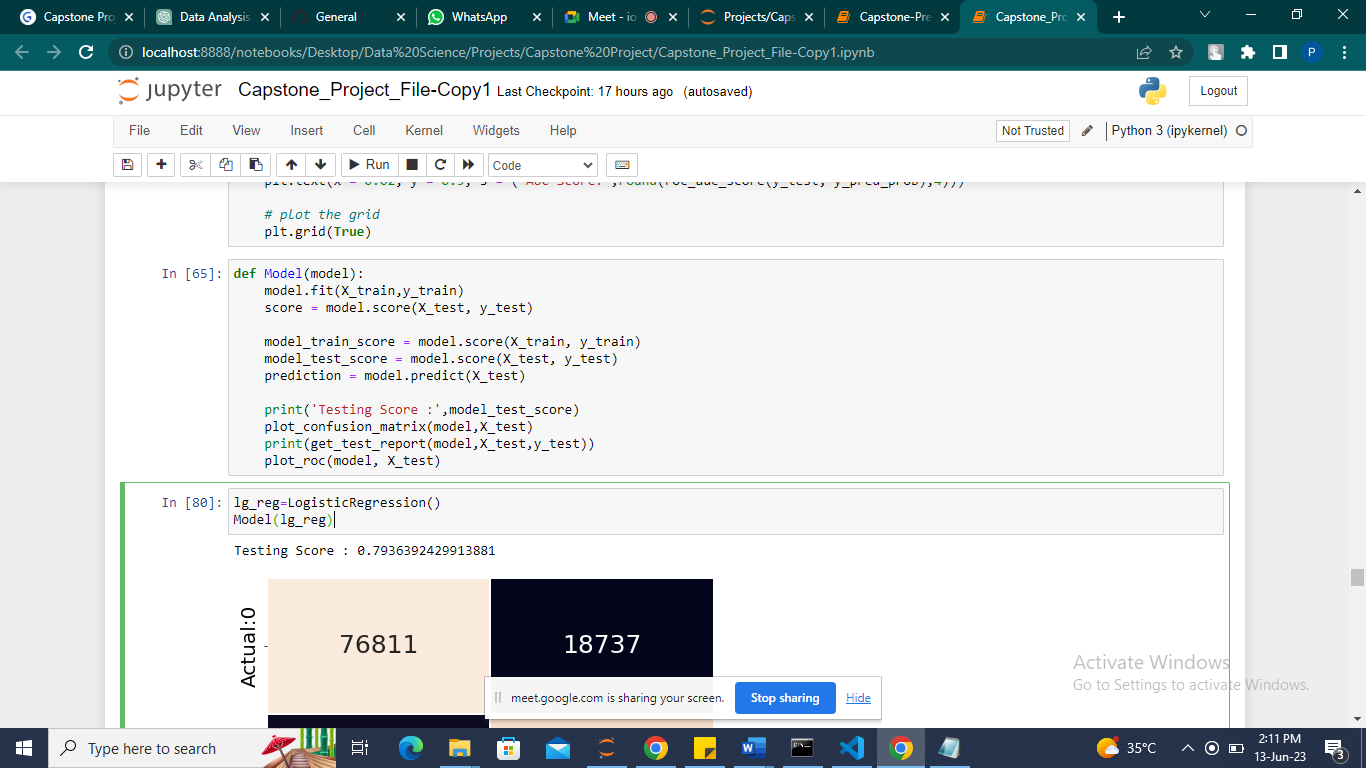
**Scaling the data**

Graphical user interface, application

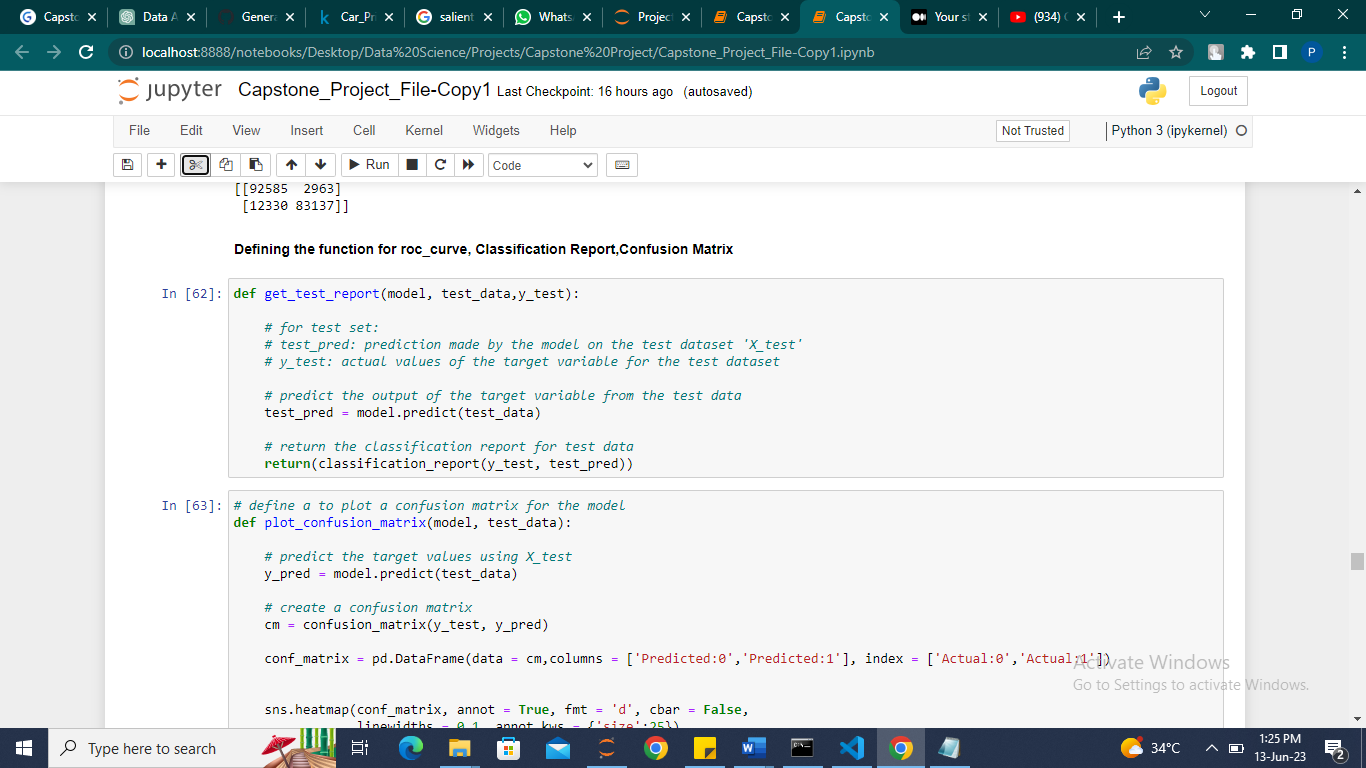
Description automatically generated with medium confidence

Using the min max scaler function, we scaled the data. We can see the data values ranging from 0 to 1, As we used min max scaler the minimum value gets 0 and max value gets 1. This dataset saved in df\_num\_scaled variable.

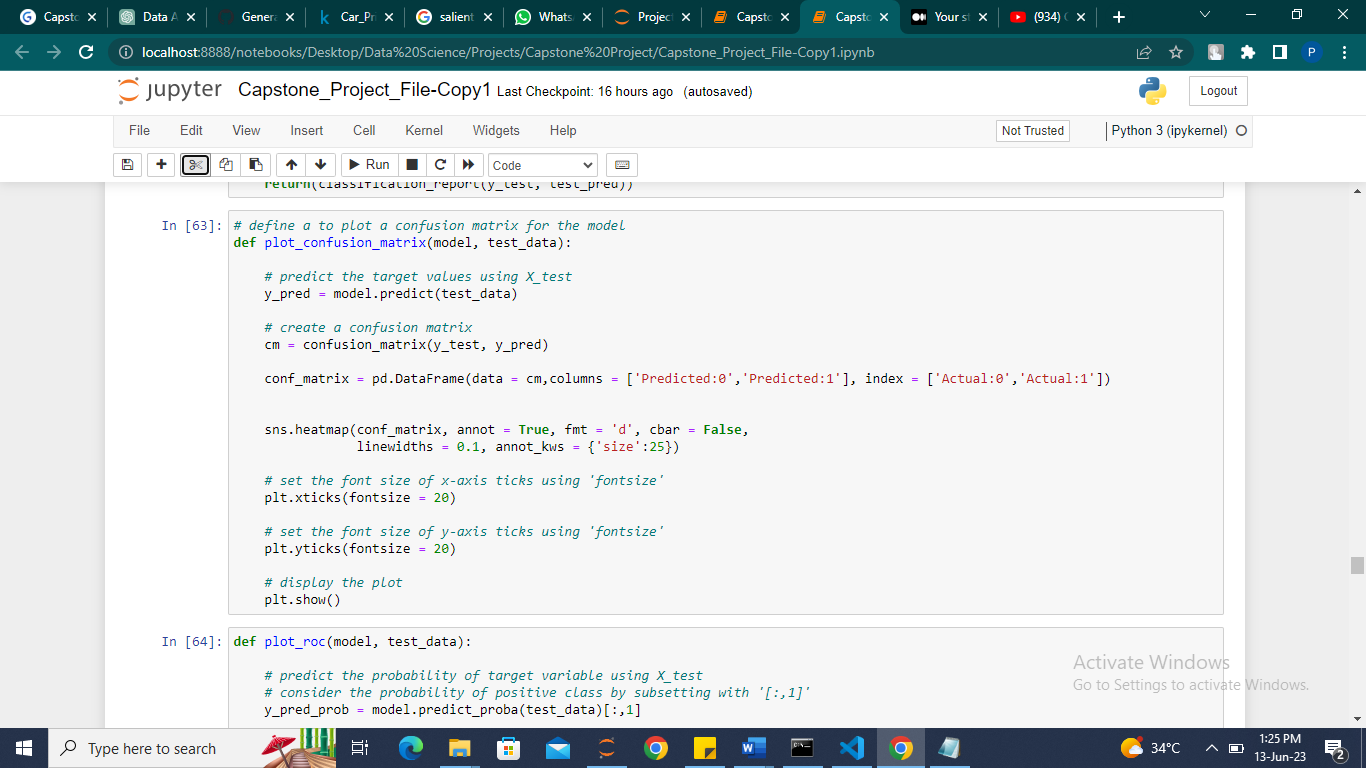
**3.4. Model Building**

**Defining a function for training the model. Model ( )**

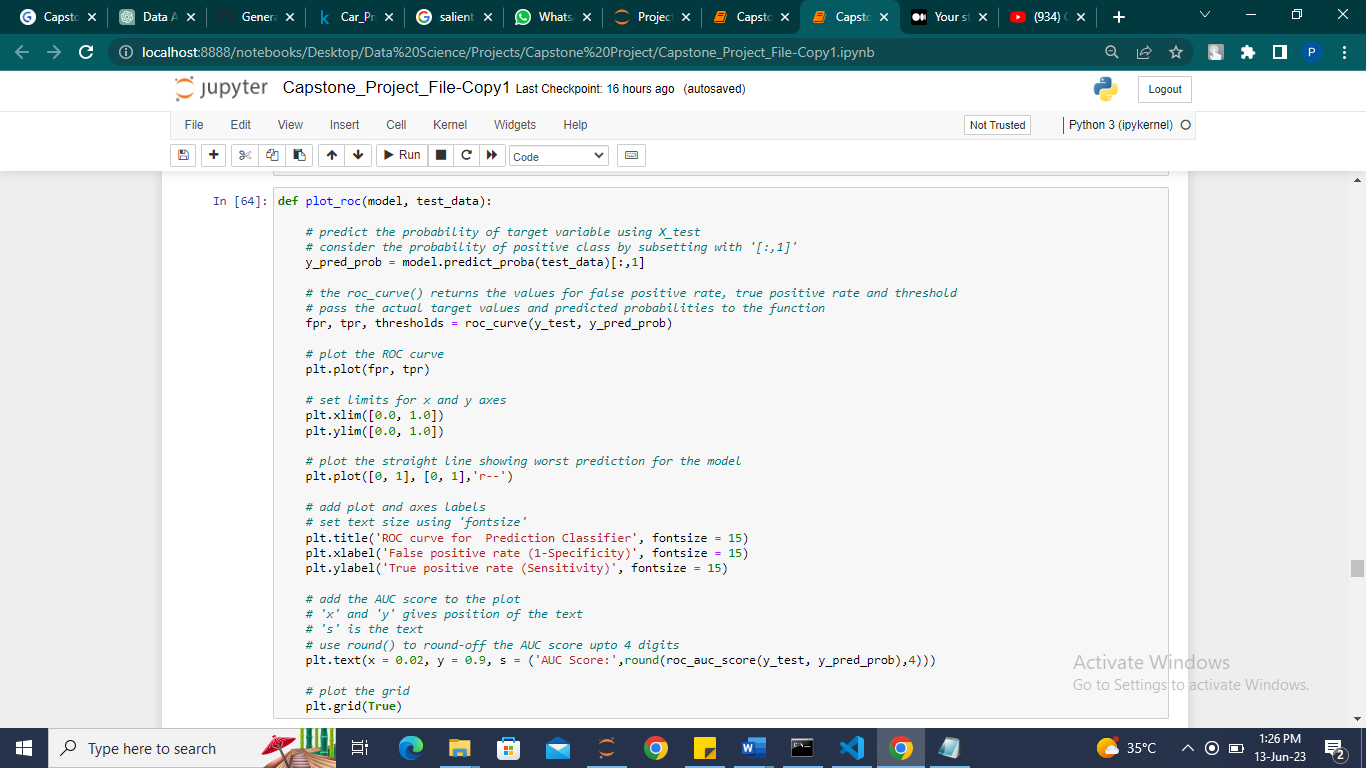
**Defining a function for getting the test report get\_test\_report ( )**



**Defining a function for plotting confusion matrix plot\_confusion\_matrix ( )**



**Defining a function for plotting the ROC curve plot\_roc()**

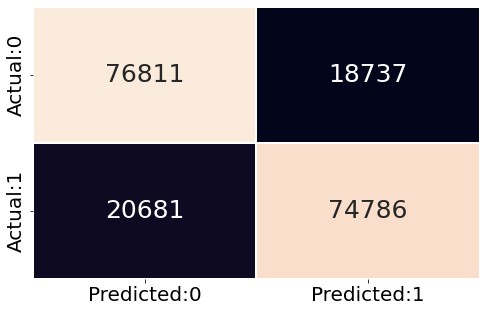
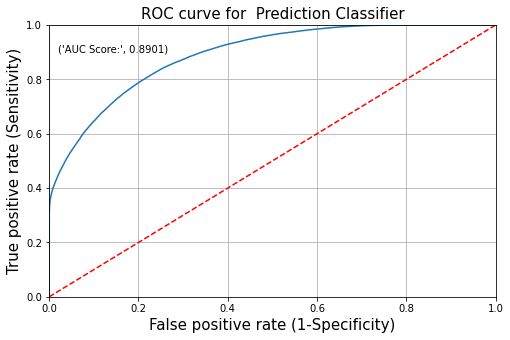


**Model 01: Trained on Logistic Regression Algorithm**

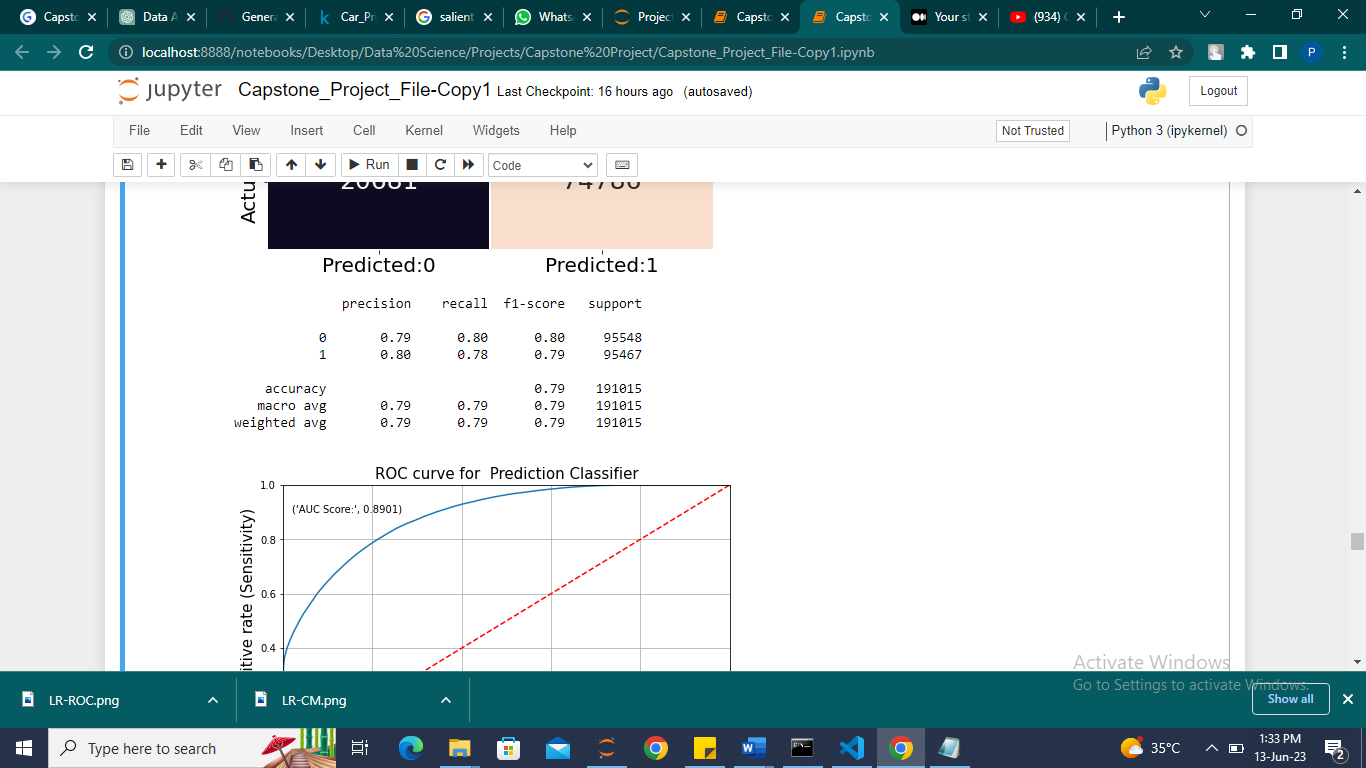
**Training the model**

Lg\_reg = LogisticRegression ()

Model (Lg\_reg)

******Confusion Matrix of Logistic Regression ROC Curve for Prediction Classifier**

**Test report for the model Logistic Regression**

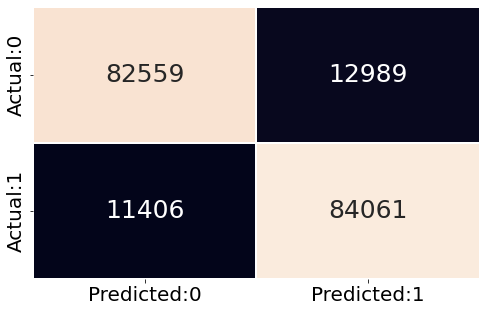
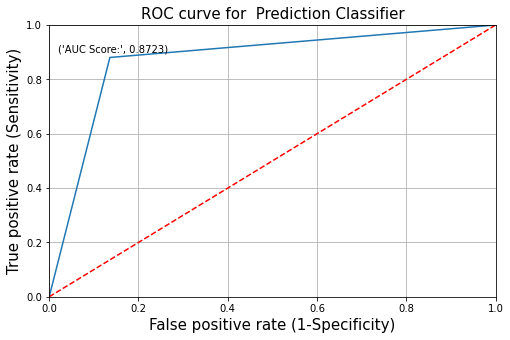


**Model -02: Trained using Decision Tree Algorithm**

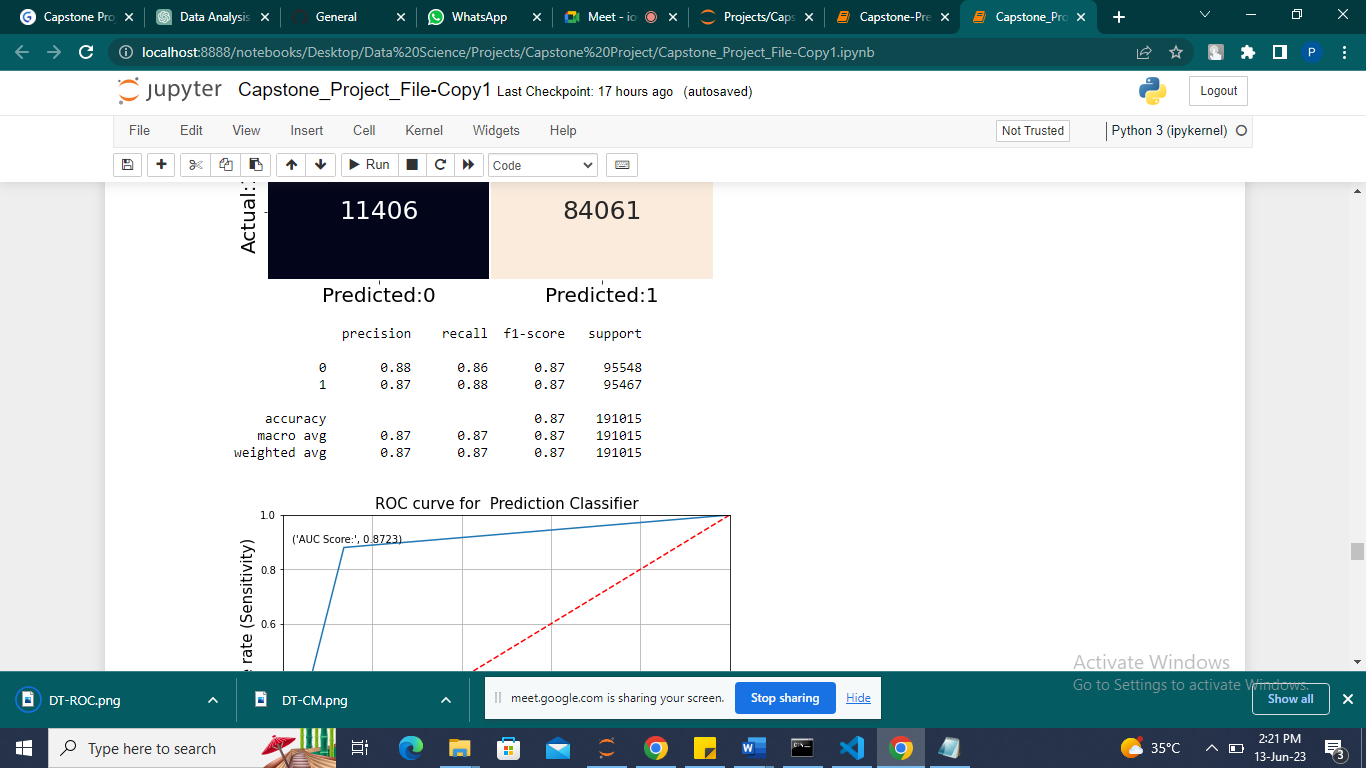
**Training the model Decision Tree**

DTC=DecisionTreeClassifier ()

Model (DTC)

**Confusion Matrix of Decision Tree** **ROC curve for prediction classifier**

**Test report for Decision Tree Model**

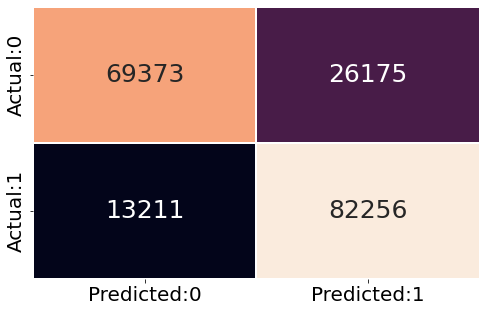
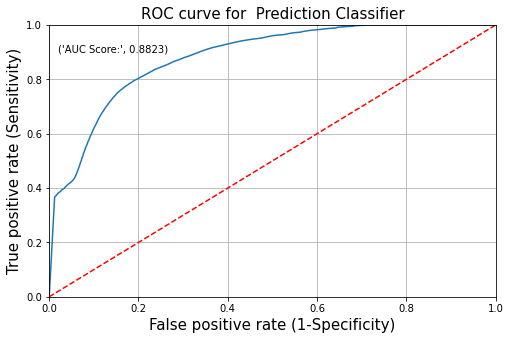


**Model 03: Trained on Naïve Bayes Algorithm**

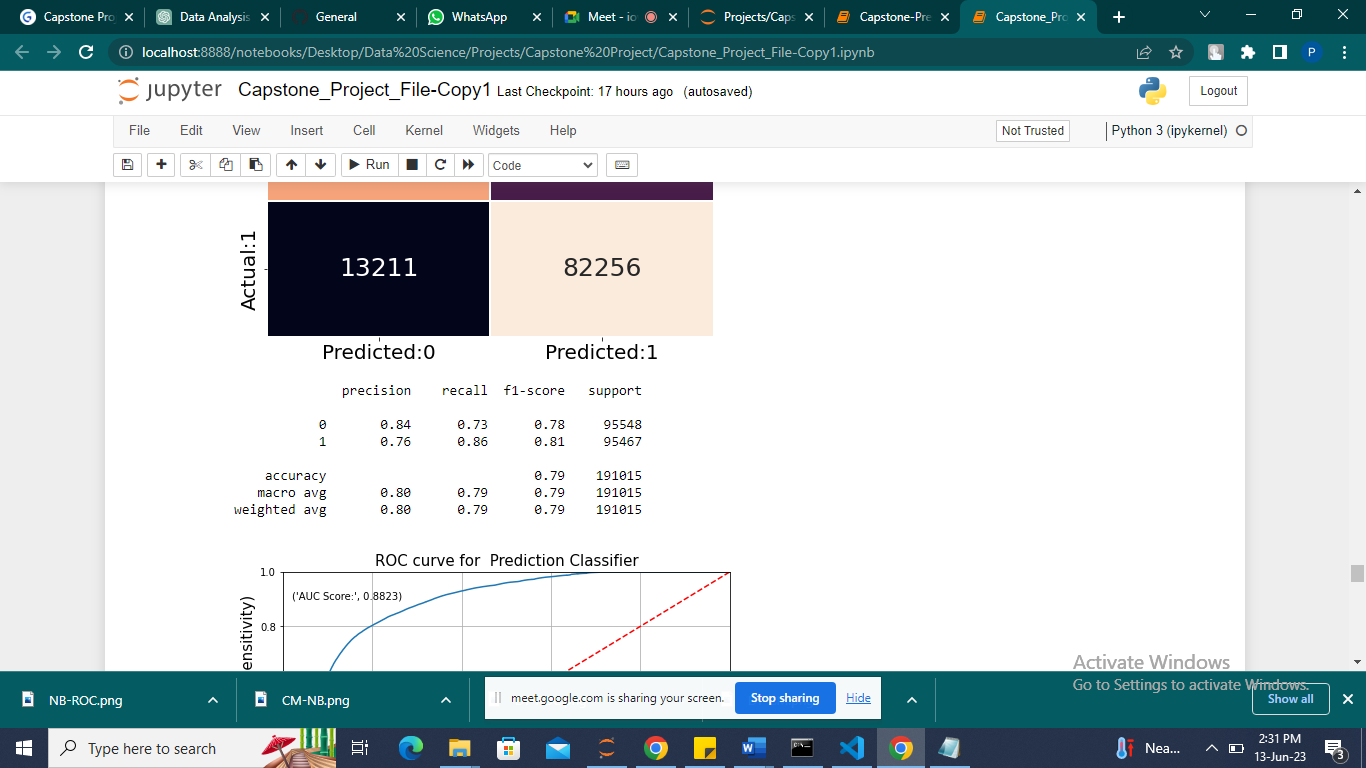
**Training the model Naïve Bayes**

GN=GaussianNB ()

Model (GN)

**Confusion Matrix of Naïve Bayes ROC Curve for Prediction Classifier**

**Test report of Naïve Bayes**

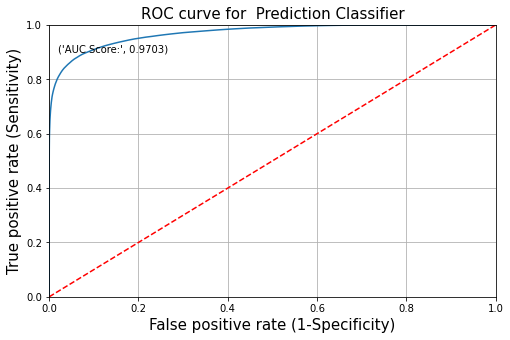
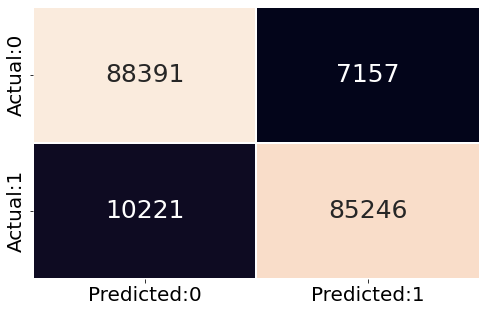


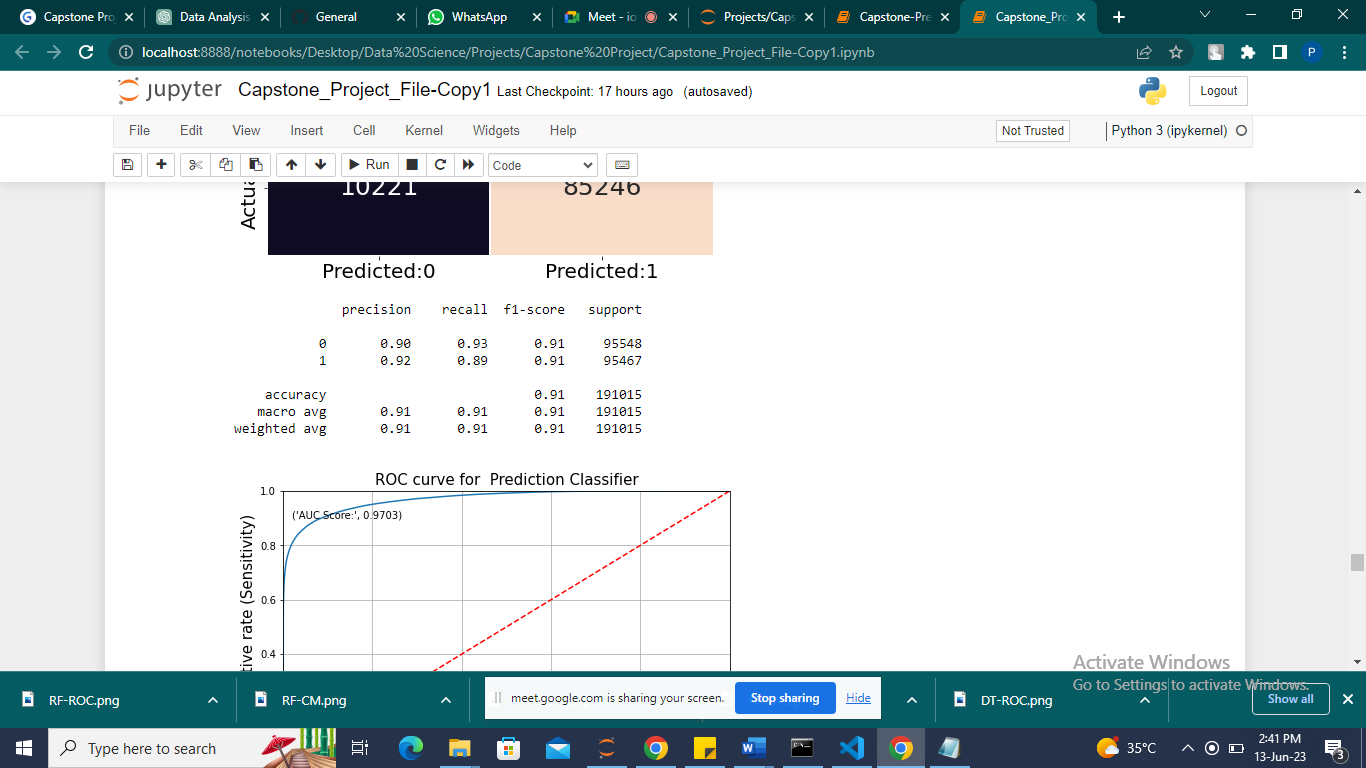
**Model 04: Trained on Random Forest Algorithm**

**Training the model Naïve Bayes**

RF=RandomForestClassifier ()

Model (RF)

**Confusion Matrix for Random Forest ROC curve for Random Forest**

**Test report of Random Forest **

**Part-04**

**Model Evaluation**

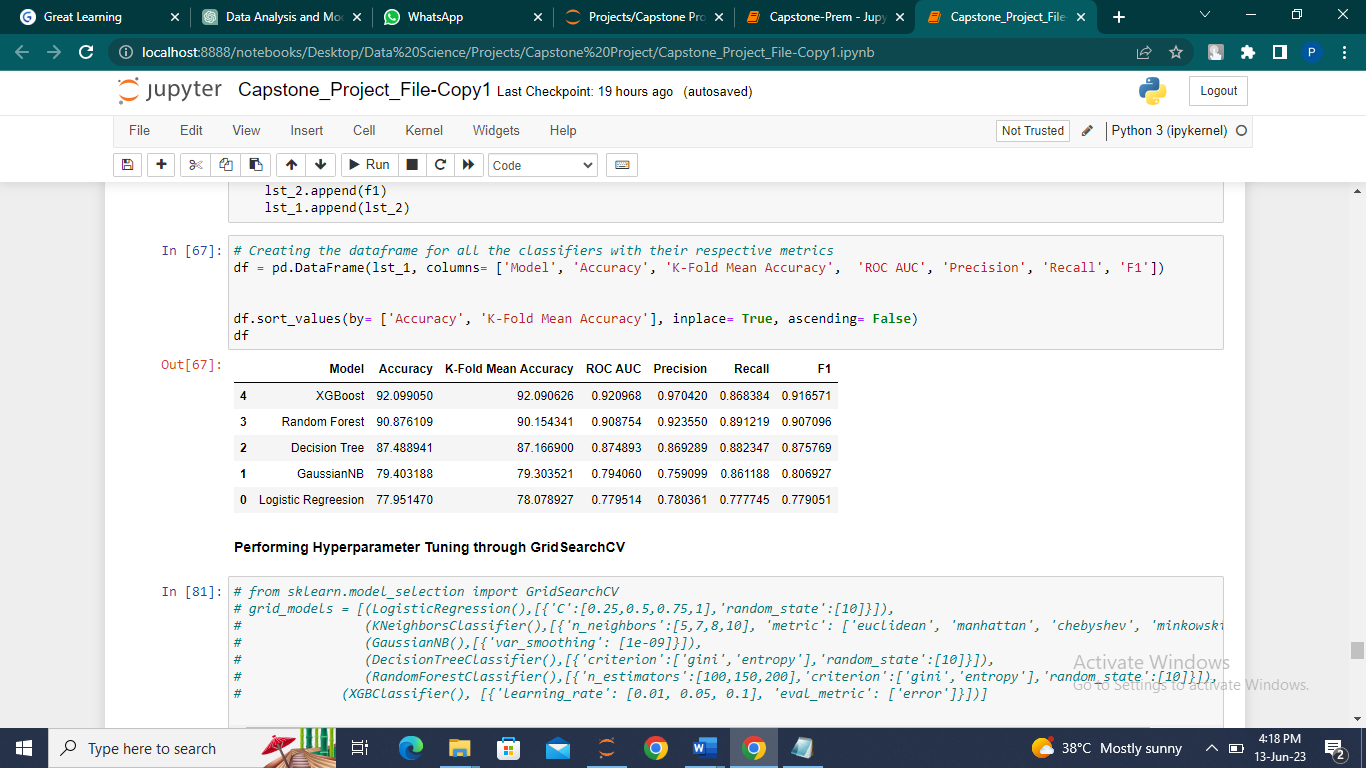
**4.1. Objectives**

We have seen four models trained over Logistic Regression, Naïve Bayes, Decision Tree and ensembled Technique like Random Forest. In this section we are going to discuss about the final model which is trained on XG Boost ensembled technique.

XG Boost is a boosting algorithm which is formed by ensemble of multiple decision tress algorithms which operates as single model. We also evaluate all the above models we build to verify the performance of each model comparing with all the other model.

**4.2. Prominent Parameters**

**4.3. Model Evaluation**



The XG Boost model achieved an accuracy of 92.099050% on the evaluation dataset. This metric indicates the overall correctness of the model's predictions, with a higher accuracy indicating a better-performing model.

The **K-Fold Mean Accuracy** is reported as 92.090626%, which is the average accuracy across multiple folds during cross-validation. Cross-validation helps provide a more reliable estimate of the model's performance by evaluating it on different subsets of the data. The high mean accuracy suggests that the model is consistently performing well across different folds, reducing the chance of overfitting or biased evaluation.

The **ROC AUC** (Area Under the Receiver Operating Characteristic Curve) is reported as 0.920968. ROC AUC measures the model's ability to distinguish between positive and negative instances, with a higher value indicating better discrimination. An AUC of 0.920968 suggests that the model has a strong ability to correctly rank positive instances higher than negative instances.

**Precision**, reported as 0.970420, is a measure of the model's ability to correctly identify positive instances out of all instances predicted as positive. A higher precision indicates fewer false positives, meaning that the model is precise in its positive predictions.

**Recall**, also known as sensitivity or true positive rate, is reported as 0.868384. Recall measures the model's ability to correctly identify positive instances out of all actual positive instances. A higher recall indicates that the model is effective at capturing positive instances, minimizing false negatives.

The **F1-score**, reported as 0.916571, is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall, indicating the overall effectiveness of the model in capturing positive instances while minimizing false positives and false negatives.

Based on these metrics, the XG Boost model demonstrates strong predictive performance, achieving high accuracy and exhibiting a good balance between precision and recall. The ROC AUC value suggests that the model is effective at discriminating between positive and negative instances. These results indicate that the model is performing well and may be suitable for the classification task at hand.

**4.4. Robustness of the Model**

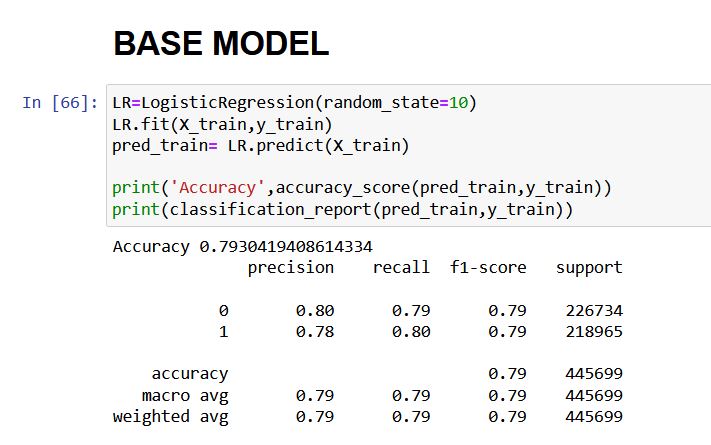
The model we built for classification is robust in many aspects.

* We have seen a consistent performance on cross validation on different subsets of the dataset.
* It is very sensitive to outliers or any type of noise in the data as the model uses decision tree as base model which is efficient working on noise in the data. So any noise in the data may not effect the performance of the data.
* The model has to be deployed and checked with unseen data, but still the model performed with 92% accuracy with the test data which says the model captured the behavior maximum.
* XG Boost is one of the top performing models and efficient in production and scalability.

**Part-05**

**Comparing with Benchmark**

**5.1. Description of the Benchmark**

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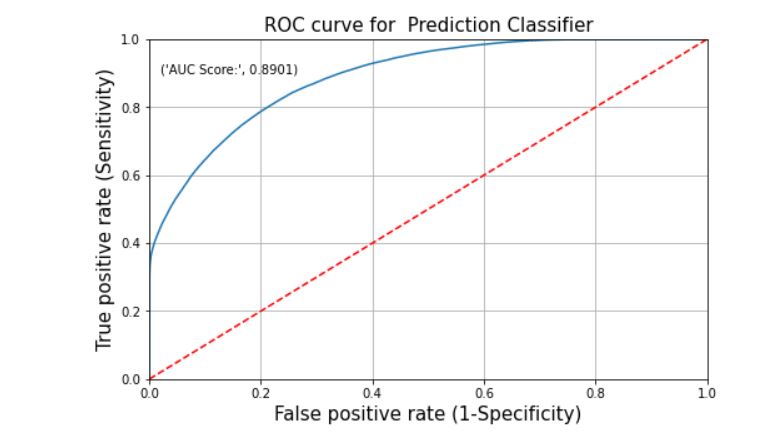
For base model used Logistic Regression algorithm.

0 – Fully Paid Customers

1 – Defaulters

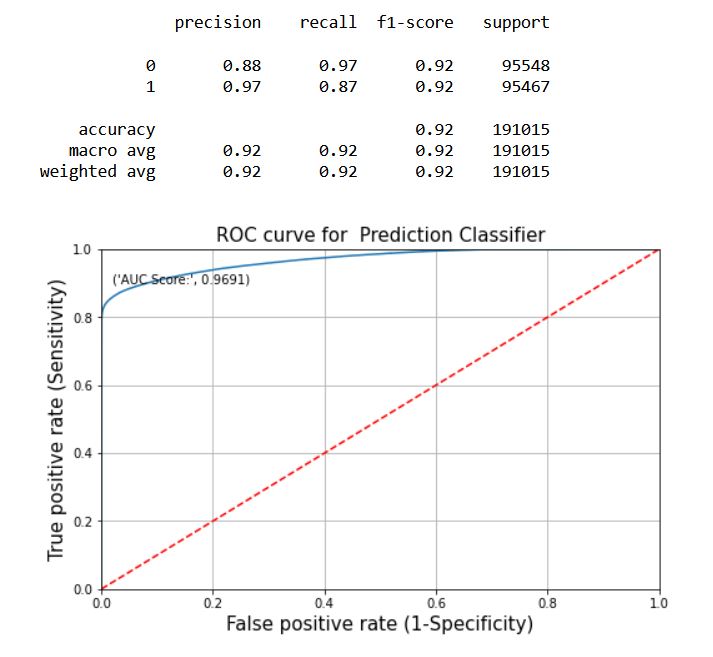
Model has 79.3 % accuracy.

Precision and recall for both classes is average 80 %. ROC score is 0.89.



**5.2. Reasons for Improvement**

To improve the model, we used SMOTE technique to balance the classes. Also, we tried different algorithms like Decision tree, KNN, Naïve bayes, Random Forest and XG Boost. XG Boost showed us improvement in model performance.



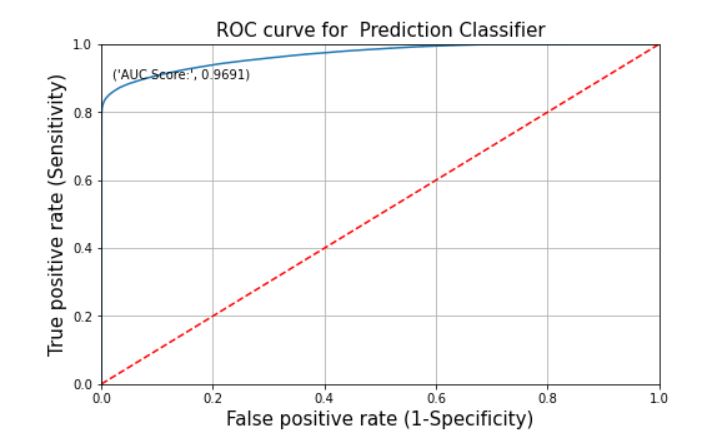
Precision and recall score got improved above 90%. Roc score is 0.96.

**Part-06**

**Visualizations**

In addition to quantifying your model and the solution, please include all relevant visualizations that support the ideas/insights that you gleaned from the data.

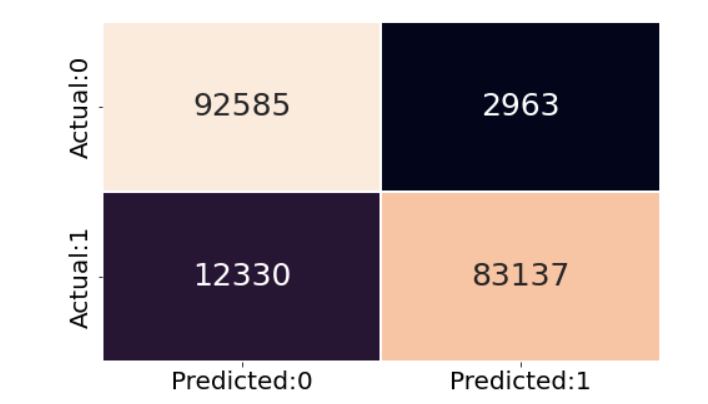
We have visualization of confusion matrix, ROC – AUC curve.



ROC -AUC plots curve on True Positive Rate and False positive rate.

It gives us idea of how classes are separate from each other.

Good model has high auc score and curve must be above the red line.



Confusion matrix gives us how much actual values are predicted correct for both classes.

Here out of 95,467 records of defaulters 83,137 is predicted correctly and 12330 records predicted wrong.

**Part-07**

**Implications**

**7.1. Impact on the Problem**

Identifying a prospect defaulter is very critical for a loan offering company. The model can identify the defaulters with an accuracy of 92% which helps the business process to become more efficient and resulting less losses and more revenue.

7.2. **Recommendations**

* Decrease interest rate to motivate borrowers to payback the loan.
* Decrease the installment amount and increase the tenure of the repayment.
* Employment length and grade are two crucial factors to consider before giving loan.
* Verification of the details can ensure the applicant potential which may reduce the defaulting of the loan.

**7.3. Business Impact Assessments**

* Out of all the loan applicant there are nearly 20% of people who defaulted the loan.
* Most of them are not paid full amount leaving the payment in between.
* Recommendations were made for encouraging such dropping borrowers to payback the amount.
* This will help the business to recover most of the amount.
* Not just recovering the model also warns the company regarding the risk of a person being a defaulter which can be avoided offering loans to such candidates.
* This also impacts business to not incur losses.
* It also helps to find the people who are potentially good for opting for a loan.

**Part-06**

**Limitations**

**6.1. Data Limitations**

* The data consists outliers, missing values and redundant columns. Handling these data was easy but few crucial variables has missed because of missing values are more than 90%
* The data consists just 27 variables which are less compared to the scope. There can be many other variables which are crucial but not covered.

**6.2. Assumptions & Simplifications**

* The model assumes that the variables are normally distributed but the variables are not normally distributed.

**6.3. Computational Resources**

* The data has 3.9+ Lakh records where this has become a challenge to perform some advanced techniques like hyperparameter tuning for the models on the local machine.

**Part-07**

**Closing Reflections**

**7.1. Learnings**

* Got exposure to the real time data and working with data across different phases of the machine learning life cycle.
* Got complete overview of performing classification task over the real time data with various implementations available in the libraries.
* Got hands on experience on Data cleaning, Data manipulation, Data preprocessing, preparation, model building, tuning.
* Introduced how to look the project in a problem-solving perspective and realized that analysis or model building must result in showing impact on business and that impact should also measurable.
* Realized the power of machine learning while solving the business problems.
* Also familiarized with team mode of working over a particular task like in a project management environment.

**7.2. Things to be done differently**

* To build model using Neural Networks.
* Coming up with the better model by including all the performance aspects of the algorithms in production and scaling.
* Looking at the project from a deeper Business Perspective rather just analytical perspective.
* Deploying the model on cloud.
* Analyzing the Business impact of the model in-depth to present the impact in

The End