SMARTINTERNZ

Credit Card Approval Prediction Using Machine Learning

Project Report

introduction

1.1 overview

Credit risk as the board in banks basically centers around deciding the probability of a customer's default or credit decay and how expensive it will end up being assuming it happens. It is important to consider major factors and predict beforehand the probability of consumers defaulting given their conditions. Which is where a machine learning model comes in handy and allows the banks and major financial institutions to predict whether the customer, they are giving the loan to, will default or not. This project builds a machine learning model with the best accuracy possible using python. First we load and view the dataset. The dataset has a combination of both mathematical and non-mathematical elements, that it contains values from various reaches, in addition to that it contains a few missing passages. We preprocess the dataset to guarantee the AI model we pick can make great expectations. After the information is looking great, some exploratory information examination is done to assemble our instincts. Finally, we will build a machine learning model that can predict if an individual's application for a credit card will be accepted. Using various tools and techniques we then try to improve the accuracy of the model. This project uses Jupyter notebook for python programming to build the machine learning model. Using Data Analysis and Machine Learning, we attempted to determine the most essential parameters for obtaining credit card acceptance in this project.

1.2 Purpose :

It uses personal information and data submitted by credit card applicants to predict the probability of future defaults and credit card borrowings. The bank is able to decide whether to issue a credit card to the applicant. Credit scores can objectively quantify the magnitude of risk.

2 LITERATURE SURVEY

2.1 Existing problem :

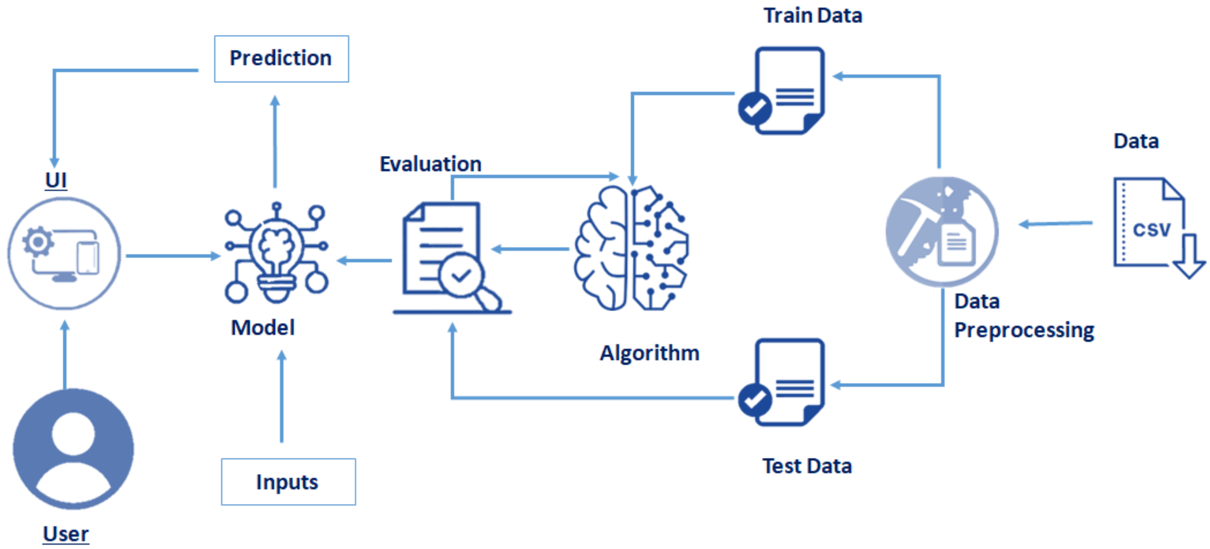
This is a prediction problem in which we need to predit whether a person eligiable for credit card or not

2.2 Proposed solution

A good machine learning model should be able to accurately predict the status of the applications with respect to these statistics.Predicting if a credit card application will be approved or not is a classification task

3.THEORITICAL ANALYSIS

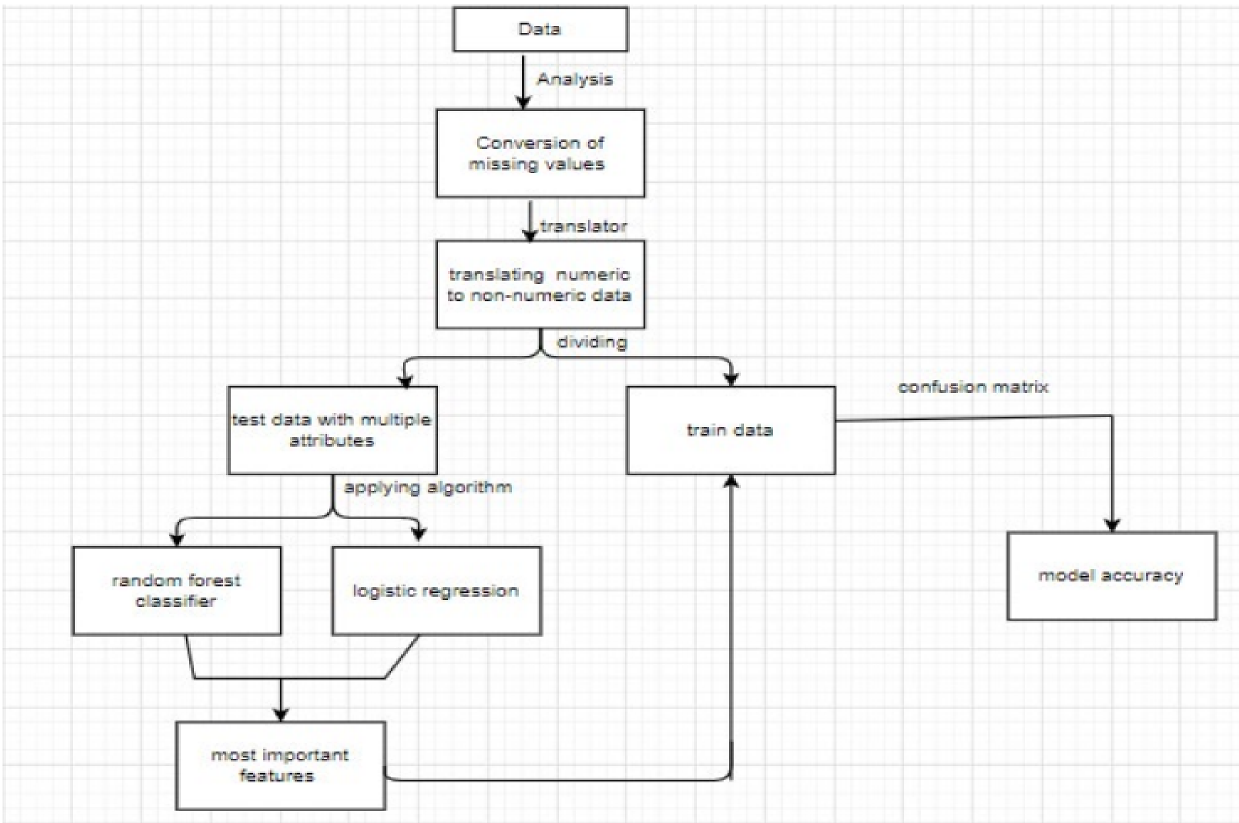
3.1 Block Diagram :



3.2 Software Requirements :

- ANACONDA NAVIGATOR
- JUPYTER NOTEBOOK
- SPIDER

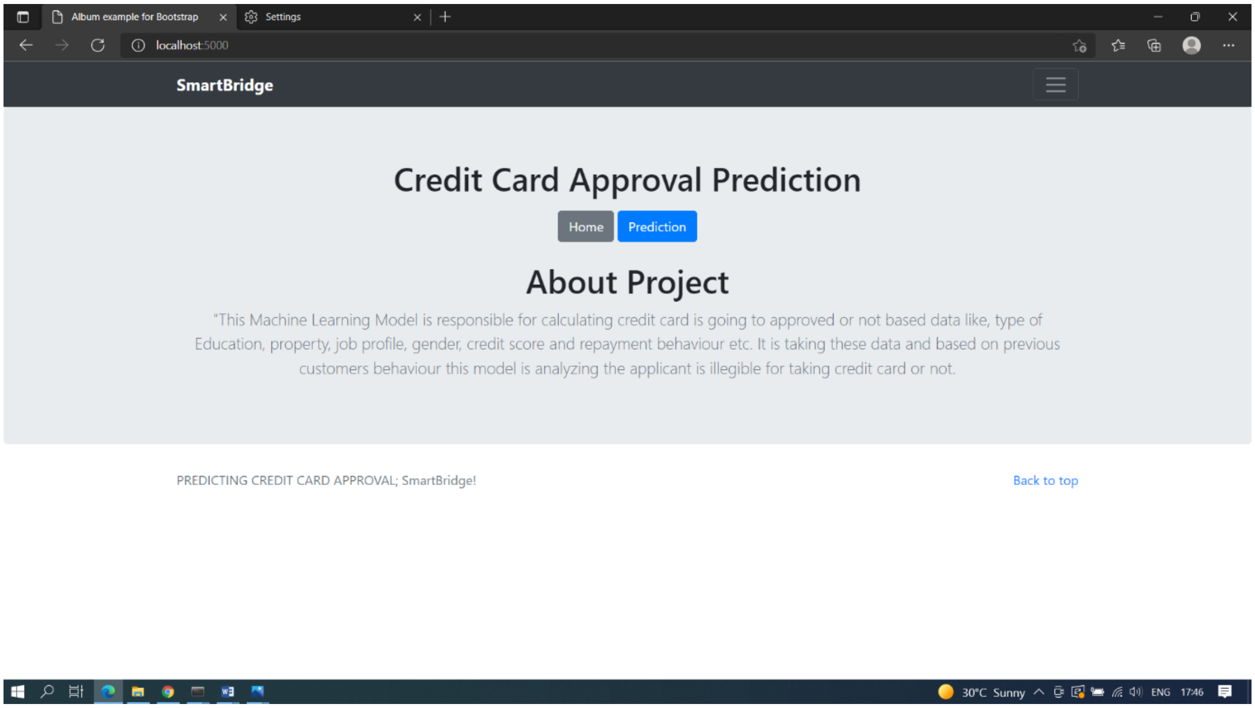
3.3 FLOW CHART

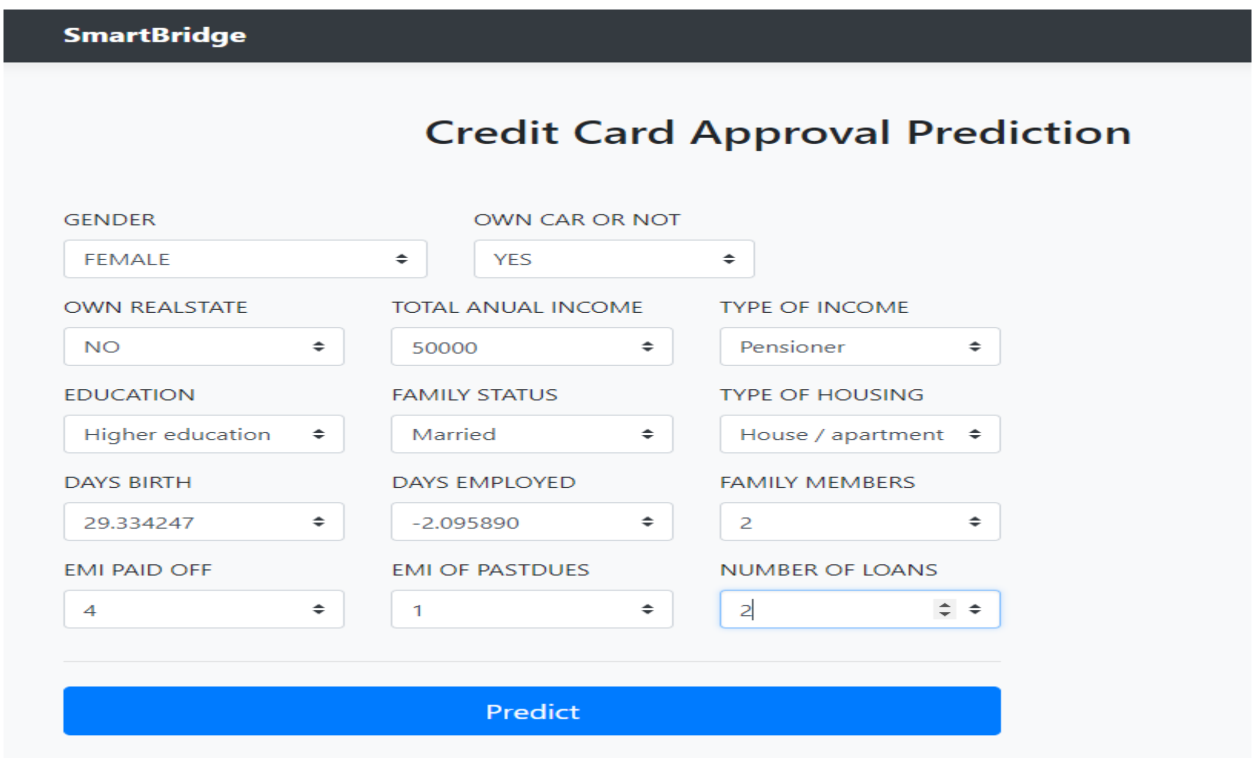


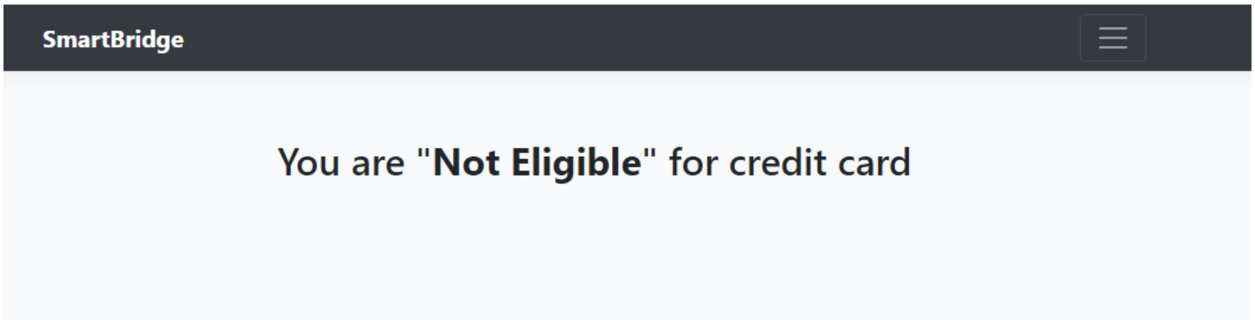
4. Project Flow

- Data Collection.
- Data Visualization
- Data Pre-processing
- Model Building
- Application Building

5.RESULT


Album example for Bootstrap
Settings
localhost:5000
SmartBridge
Credit Card Approval Prediction
Home
Prediction
About Project
"This Machine Learning Model is responsible for calculating credit card is going to approved or not based data like, type of Education, property, job profile, gender, credit score and repayment behaviour etc. It is taking these data and based on previous customers behaviour this model is analyzing the applicant is illegible for taking credit card or not.
PREDICTING CREDIT CARD APPROVAL; SmartBridge!
Back to top
30°C Sunny
ENG
17:46


SmartBridge
Credit Card Approval Prediction
GENDER
FEMALE
OWN CAR OR NOT
YES
OWN REALSTATE
NO
TOTAL ANUAL INCOME
50000
TYPE OF INCOME
Pensioner
EDUCATION
Higher education
FAMILY STATUS
Married
TYPE OF HOUSING
House / apartment
DAYS BIRTH
29.334247
DAYS EMPLOYED
-2.095890
FAMILY MEMBERS
2
EMI PAID OFF
4
EMI OF PASTDUES
1
NUMBER OF LOANS
2
Predict



6 . ADAVANTAGES AND DISADAVANTAGES :

6.1 ADAVANTAGES

- Opportunity to build credit
- Earn rewards such as cash back or miles points
- Protection against credit card fraud
- Free credit score information
- No foreign transaction fees

6.2 DISADAVANTAGES

- Minimum due trap
- Hidden costs
- Ease of overuse
- High intrest rate

7. CONCLUSION :

Currently, factors considered are regular details related to gender, age of the consumer, his/hercredit reports and worthiness, yearly income, and the number of years he/she has been working.Further, to improve this work, various other factors or conditions can be considered like theirhistory related to any offense and their assets which can be both physical and liquid cash. Thesefeatures can improve the model to be more effective and can help the institutes to make betterdecisions so that they can avoid experiencing frauds and loss. Various classification algorithmscan be used to build a model and compare the rates or levels of accuracy to improve the model for better use.

7. FUTURE SCOPE :

From this initial analysis, we are able to conclude that the most significant factors in determining the outcome of a credit application are Employment, Income, Credit Score and Prior Default.

Based on these insights, we can work on building some predictive models. They can be used by analysts in financial sector and be incorporated to automate the credit approval process. These results can also serve as a source of information for the consumers.

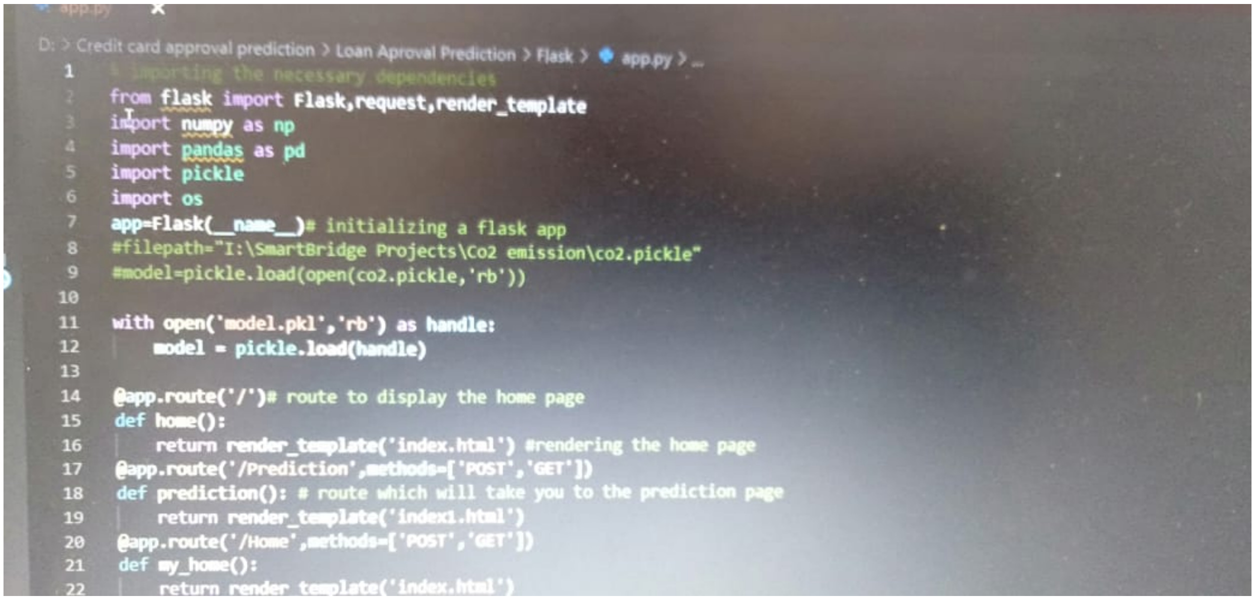
8.REFERENCE :

K. Chaudhary, J. Yadav, and B. Mallick, "A review of fraud detection techniques: Credit card,"

International Journal of Computer Applications

9.APPENDIX

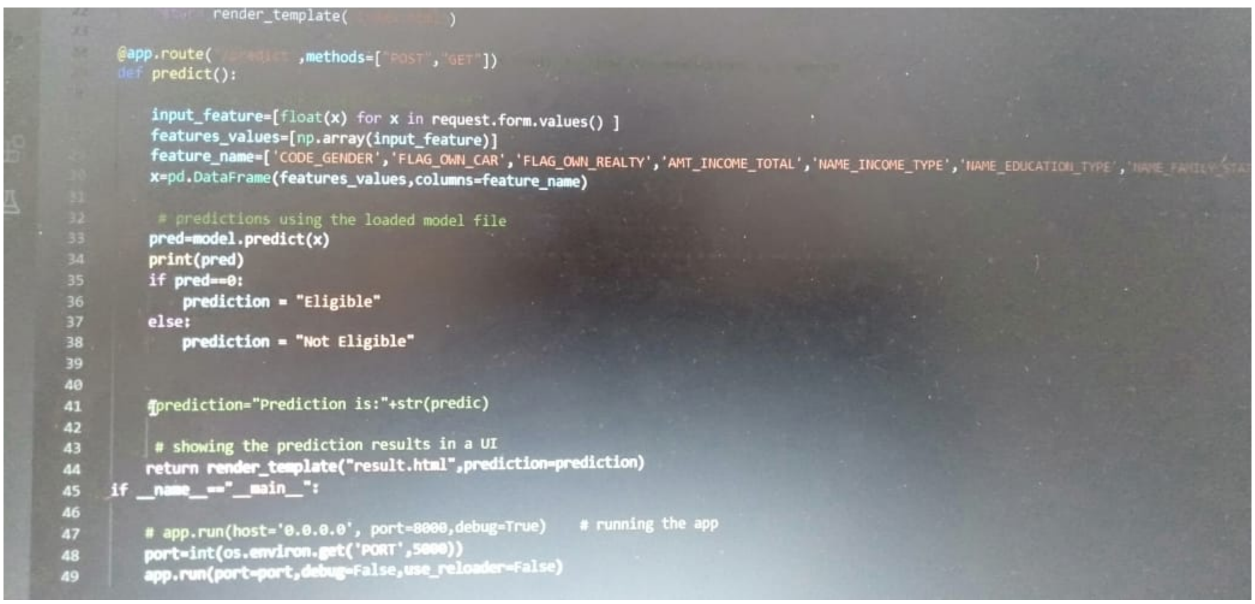
9.1 source code



```
D: > Credit card approval prediction > Loan Aproval Prediction > Flask > app.py > ...
# importing the necessary dependencies
from flask import Flask,request,render_template
import numpy as np
import pandas as pd
import pickle
import os
app=Flask(__name__)# initializing a flask app
#filepath="I:\SmartBridge Projects\Co2 emission\co2.pickle"
#model=pickle.load(open(co2.pickle,'rb'))

with open('model.pkl','rb') as handle:
    model = pickle.load(handle)

@app.route('/')# route to display the home page
def home():
    return render_template('index.html') #rendering the home page
@app.route('/Prediction',methods=['POST','GET'])
def prediction(): # route which will take you to the prediction page
    return render_template('index1.html')
@app.route('/Home',methods=['POST','GET'])
def my_home():
    return render_template('index.html')
```



```
    return render_template(           )

@app.route(           ,methods=['POST','GET'])
def predict():

    input_feature=[float(x) for x in request.form.values() ]
    features_values=[np.array(input_feature)]
    feature_name=['CODE_GENDER','FLAG_OWN_CAR','FLAG_OWN_REALTY','AMT_INCOME_TOTAL','NAME_INCOME_TYPE','NAME_EDUCATION_TYPE','NAME_FAMILY_STAT
    x=pd.DataFrame(features_values,columns=feature_name)

    # predictions using the loaded model file
    pred=model.predict(x)
    print(pred)
    if pred==0:
        prediction = "Eligible"
    else:
        prediction = "Not Eligible"


    #prediction="Prediction is:"+str(predic)

    # showing the prediction results in a UI
    return render_template("result.html",prediction=prediction)
if __name__=="__main__":

    # app.run(host='0.0.0.0', port=8000,debug=True)    # running the app
    port=int(os.environ.get('PORT',5000))
    app.run(port=port,debug=False,use_reloader=False)
```

SOURCE CODE:

In [2]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import classification_report,confusion_matrix,f1_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
```

In [3]:

```python
app = pd.read_csv('application_record.csv')
credit = pd.read_csv('credit_record.csv')
```

In [4]:

```python
app.head()
```

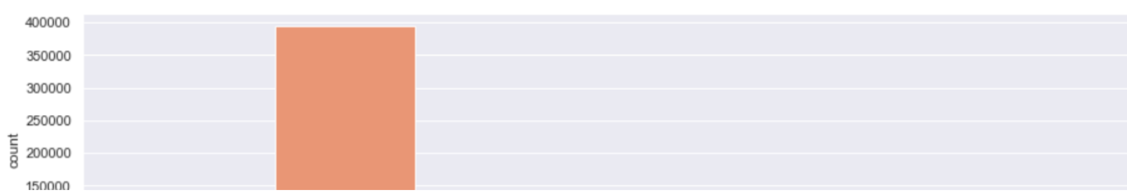
Out[4]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	N
0	5008804	M	Y	Y	0	427500.0	Working	Higher education	
1	5008805	M	Y	Y	0	427500.0	Working	Higher education	
2	5008806	M	Y	Y	0	112500.0	Working	Secondary / secondary special	
3	5008808	F	N	Y	0	270000.0	Commercial associate	Secondary / secondary special	
4	5008809	F	N	Y	0	270000.0	Commercial associate	Secondary / secondary special	

```python
print('Types of house of the people:')
print(app['NAME_HOUSING_TYPE'].value_counts())
sns.set(rc = {'figure.figsize':(15,4)})
sns.countplot(x='NAME_HOUSING_TYPE',data=app,palette ='Set2')
```

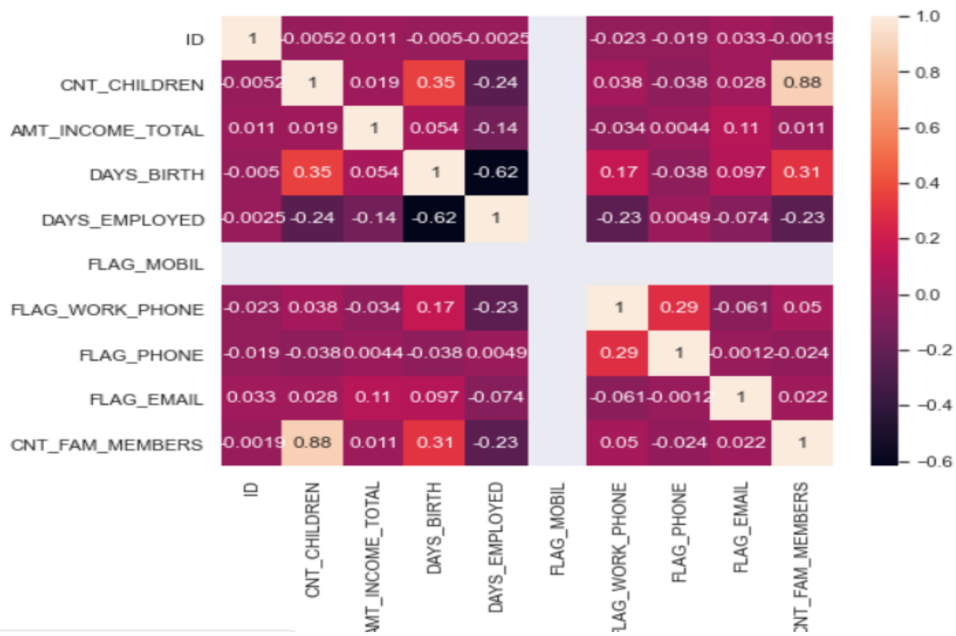
```
Types of house of the people:
House / apartment      393831
With parents            19077
Municipal apartment     14214
Rented apartment         5974
Office apartment         3922
Co-op apartment          1539
Name: NAME_HOUSING_TYPE, dtype: int64

<AxesSubplot:xlabel='NAME_HOUSING_TYPE', ylabel='count'>
```



```
flg, ax=plt.subplots(figsize=(8,6))
sns.heatmap(app.corr(),annot=True)
```

```
<AxesSubplot:>
```



```
app.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 438557 entries, 0 to 438556
Data columns (total 18 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   ID                   438557 non-null  int64
 1   CODE_GENDER          438557 non-null  object
 2   FLAG_OWN_CAR         438557 non-null  object
 3   FLAG_OWN_REALTY      438557 non-null  object
 4   CNT_CHILDREN         438557 non-null  int64
 5   AMT_INCOME_TOTAL     438557 non-null  float64
 6   NAME_INCOME_TYPE     438557 non-null  object
 7   NAME_EDUCATION_TYPE  438557 non-null  object
 8   NAME_FAMILY_STATUS   438557 non-null  object
 9   NAME_HOUSING_TYPE    438557 non-null  object
 10  DAYS_BIRTH           438557 non-null  int64
 11  DAYS_EMPLOYED        438557 non-null  int64
 12  FLAG_MOBIL           438557 non-null  int64
 13  FLAG_WORK_PHONE      438557 non-null  int64
 14  FLAG_PHONE           438557 non-null  int64
 15  FLAG_EMAIL           438557 non-null  int64
 16  OCCUPATION_TYPE      304354 non-null  object
 17  CNT_FAM_MEMBERS      438557 non-null  float64
dtypes: float64(2), int64(8), object(8)
memory usage: 60.2+ MB
```

```
def logistic_reg(xtrain,xtest, ytrain, ytest):
  Ir-LogisticRegression (solver-'liblinear')
  lr.fit(xtrain, ytrain)
  ypred-lr.predict(xtest)
  print('***LogisticRegression***')
  print('Confusion matrix')
  print(confusion_matrix(ytest,ypred))
  print('Classification report')
  print(classification_report(ytest, ypred))
```

```
def random_forest(xtrain, xtest, ytrain,ytest):
  rf=RandomForestClassifier()
  rf.fit(xtrain, ytrain)
  ypred-rf.predict(xtest)
  print('***RandomForestClassifier***')
  print('Confusion matrix')
  print(confusion_matrix(ytest,ypred))
  print('Classification report')
  print(classification_report(ytest,ypred))
```

```
def g_boosting (xtrain, xtest, ytrain,ytest):
   gb=GradientBoostingClassifier()
   gb.fit(xtrain, ytrain)
   ypred=gb.predict(xtest)
   print('***Gradient BoostingClassifier***')
   print('Confusion matrix')
   print(confusion_matrix(ytest,ypred))
   print('Classification report')
   print(classification_report(ytest, ypred))
```

```
def compare_model (xtrain,xtest, ytrain,ytest):
  logistic_reg(xtrain, xtest, ytrain,ytest)
  print('-'*100)
  random_forest(xtrain, xtest, ytrain,ytest)
  print('-'*100)
  g_boosting(xtrain, xtest, ytrain,ytest)
  print('-'*100)
  d_tree(xtrain, xtest, ytrain,ytest)
```

```
dt = DecisionTreeClassifier()
dt.fit(xtrain,ytrain)
ypred = dt.predict(xtest)
```

```
import pickle
pickle.dump(dt,open("model.pk1","wb"))
```

THANK YOU