CREDIT CARD APPROVAL USING MACHINE LEARNING

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 :

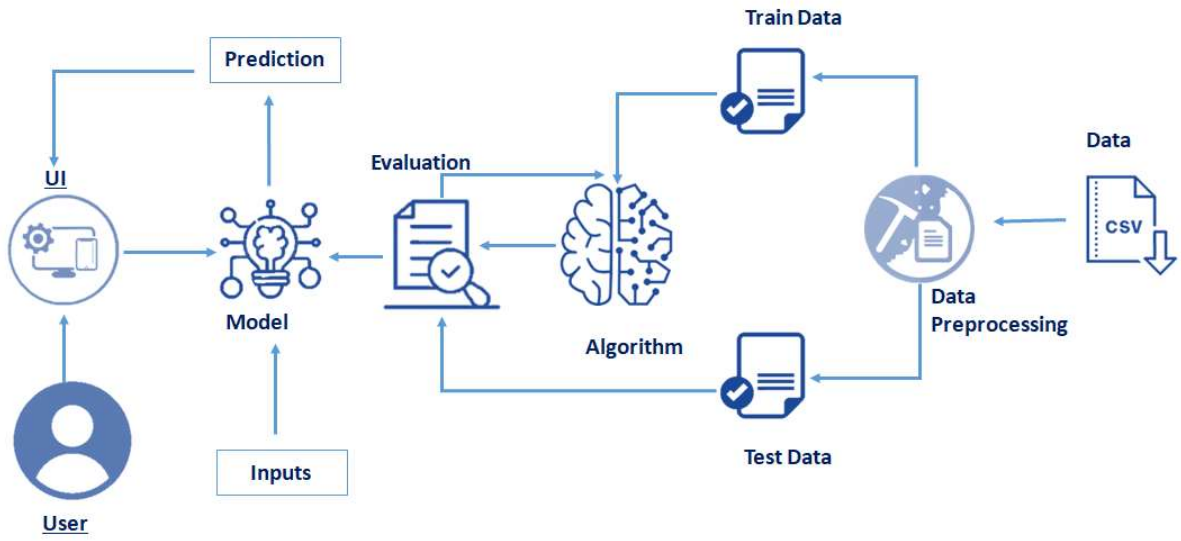
This is a prediction problem in which we need to predit whether a person eligiable for credit card or not.

2.2 Proposed solution :

It's means the combination of software, hardware, other products or equipment, and any and all services (including any installation, implementation, training, maintenance and support services) necessary to implement the solution described by user in its Proposal.

3 THEORITICAL ANALYSIS

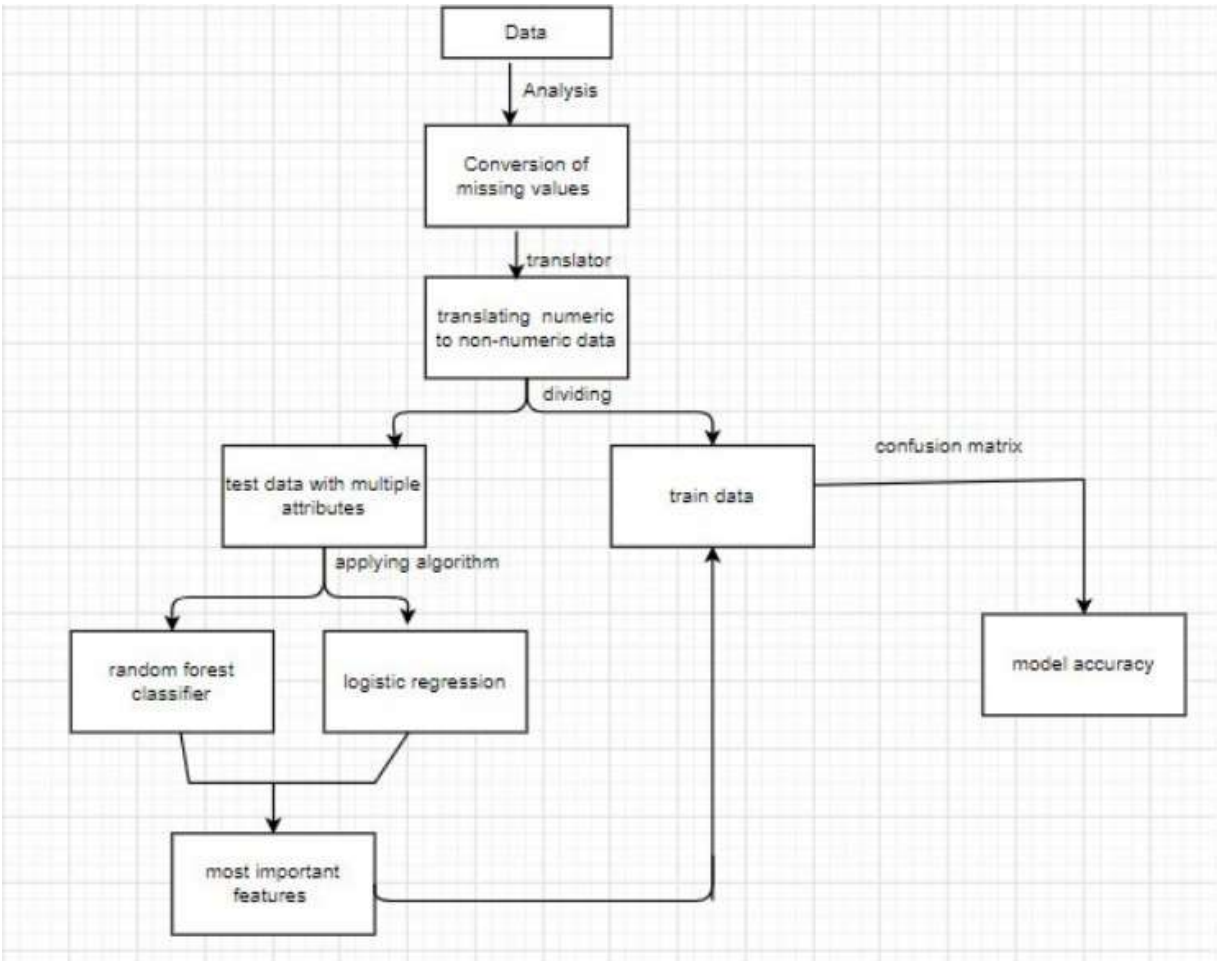
3.1 BLOCK DIAGRAM :



SOFTWARE REQUIREMENTS :

- ANACONDA NAVIGATOR
- JUPYTER
- SPYDER

FLOW CHART:

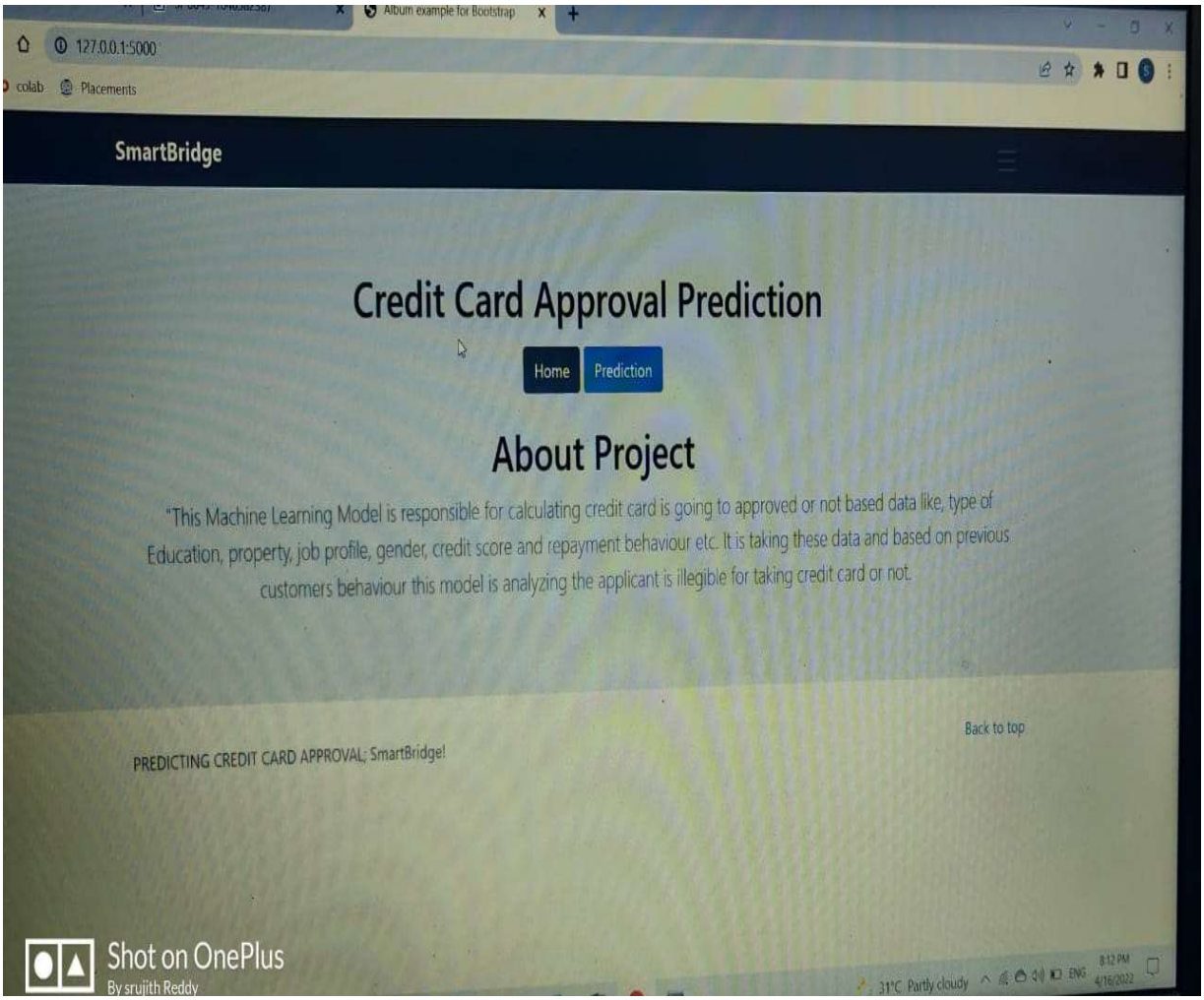


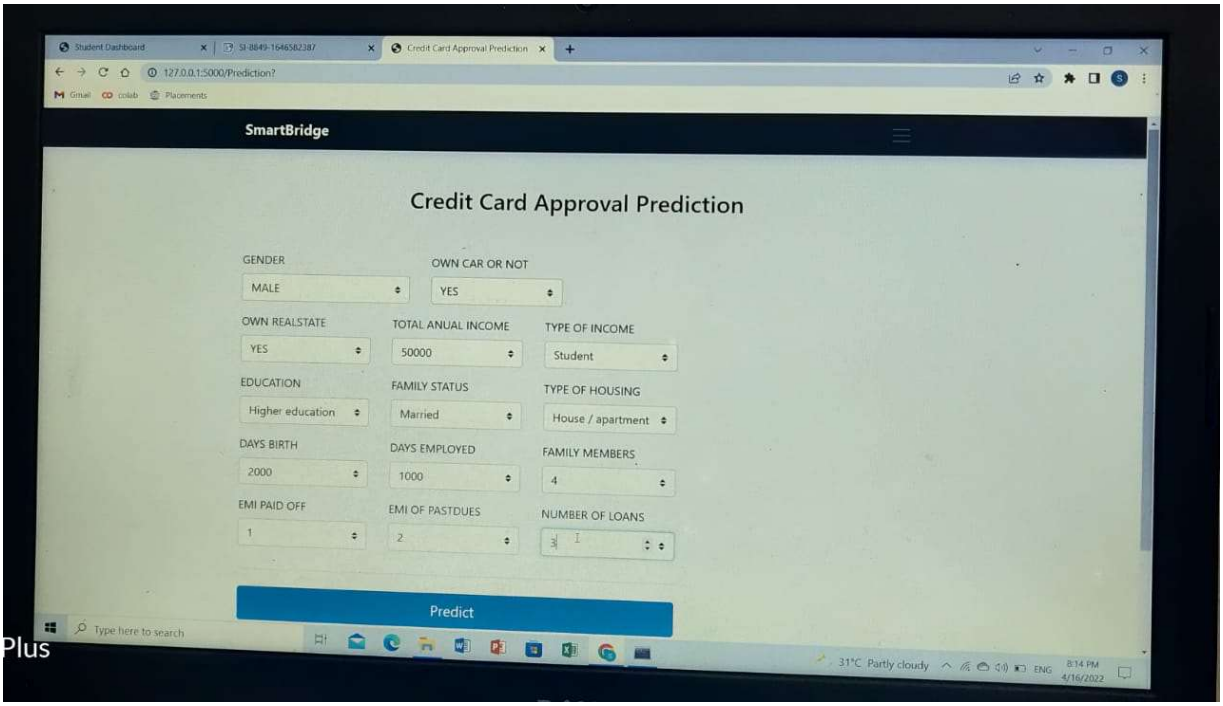
4. PROJECT FLOW :

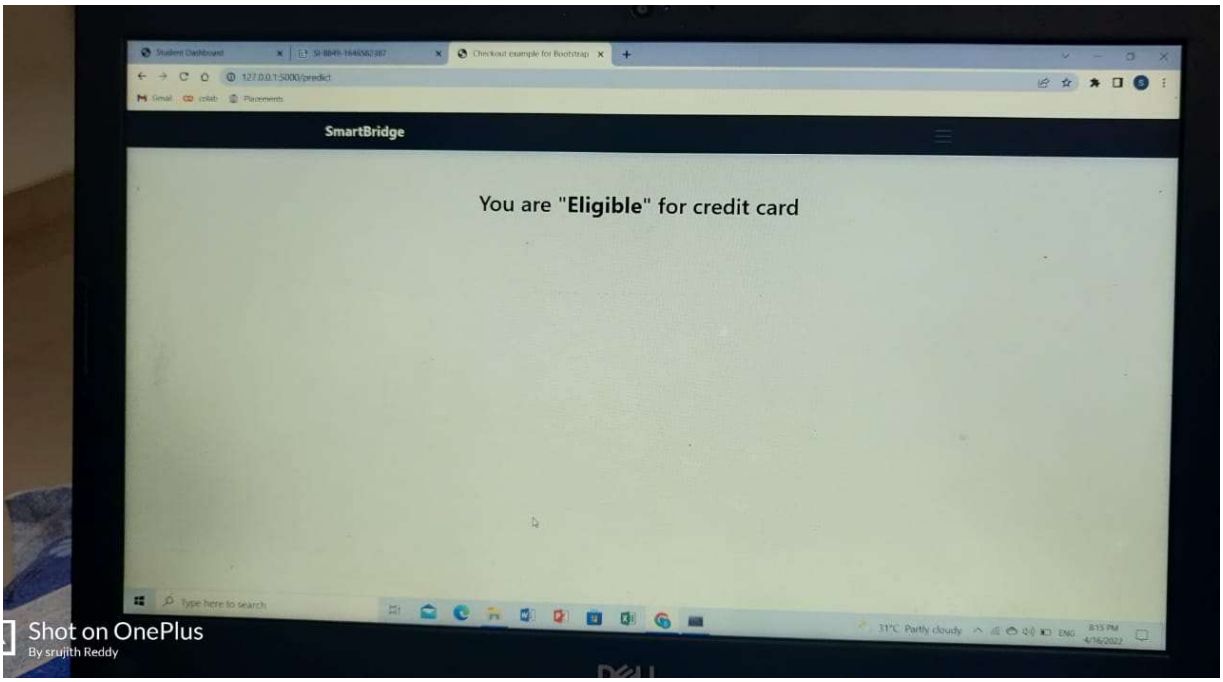
- DATA COLLECTION
- DATA VISUALIZATION
- DATA PRE-PROCESSING

- MODEL BUILDING
- APPLICATION BUILDING

5 RESULT:




SmartBridge
Credit Card Approval Prediction
GENDER
MALE
OWN CAR OR NOT
YES
OWN REALSTATE
YES
TOTAL ANUAL INCOME
50000
TYPE OF INCOME
Student
EDUCATION
Higher education
FAMILY STATUS
Married
TYPE OF HOUSING
House / apartment
DAYS BIRTH
2000
DAYS EMPLOYED
1000
FAMILY MEMBERS
4
EMI PAID OFF
1
EMI OF PASTDUES
2
NUMBER OF LOANS
3
Predict


SmartBridge
You are "Eligible" for credit card
Shot on OnePlus
By srujith Reddy

6 ADVANTAGES AND DISADVANTAGES

6.1 ADVANTAGES:

- 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 DISADVANTAGES:

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

7 CONCLUSION:

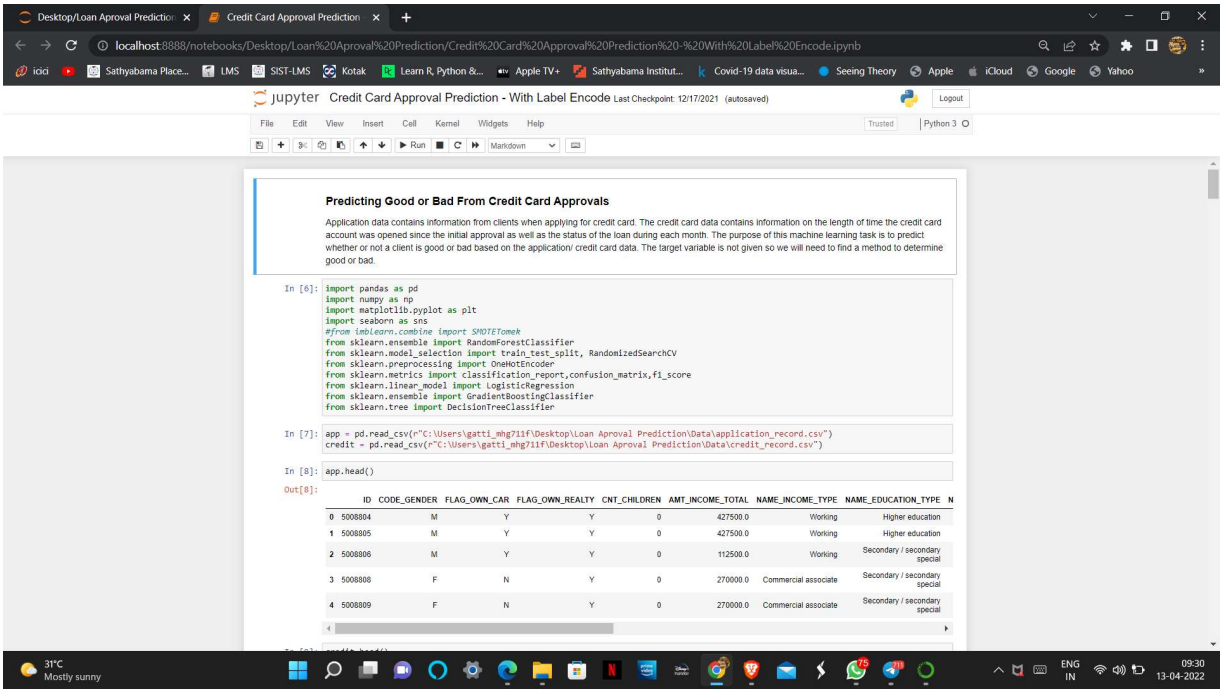
Currently, factors considered are regular details related to gender, age of the consumer, his/her credit reports and worthiness, yearly income, and the number of years he/she has been working. Further, to improve this work, various other factors or conditions can be considered like their history related to any offense and their assets which can be both physical and liquid cash. These features can improve the model to be more effective and can help the institutes to make better decisions so that they can avoid experiencing frauds and loss. Various classification algorithms can be used to build a

model and compare the rates or levels of accuracy to improve the model for better use.

8 FUTURE SCOPE :

machine learning needs you to know computer programming, statistics and data evaluation, the future scope of your machine learning career can also be in leadership roles in automation or analytics environments.

9 APPENDIX:



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In [9]:
```
credit.head()
```

Out[9]:

	ID	MONTHS_BALANCE	STATUS
0	5001711	0	X
1	5001711	-1	0
2	5001711	-2	0
3	5001711	-3	0
4	5001712	0	C

Data Visulization

In [10]:
```
print("Number of people working status :")
print(app['OCCUPATION_TYPE'].value_counts())
sns.set(rc = {'figure.figsize':(18,6)})
sns.countplot(x='OCCUPATION_TYPE', data=app, palette = 'Set2')
```

```
Number of people working status :
Laborers                 78240
Core staff               43007
Sales staff              41098
Managers                 35487
Drivers                  26090
High skill tech staff    17289
Accountants              15985
Medicine staff           13520
Cooking staff             8076
Security staff            7993
Cleaning staff            5845
Private service staff     3456
Low-skill Laborers        2140
Secretaries               2044
Waiters/barmen staff      1665
Realty agents             1041
HR staff                   774
IT staff                   604
Name: OCCUPATION_TYPE, dtype: int64
```

Out[10]: <AxesSubplot:xlabel='OCCUPATION_TYPE', ylabel='count'>

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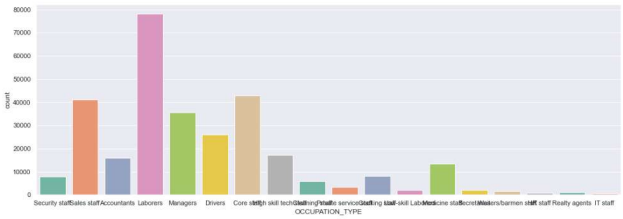
Out[10]: <AxesSubplot:xlabel='OCCUPATION_TYPE', ylabel='count'>



In [11]:
```
print("Types of house of the peoples :")
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 peoples :
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
```

Out[11]: <AxesSubplot:xlabel='NAME_HOUSING_TYPE', ylabel='count'>

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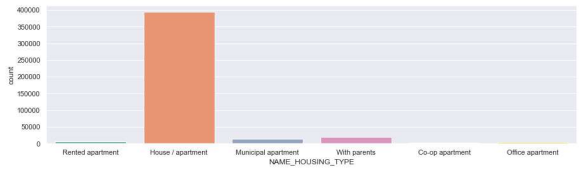
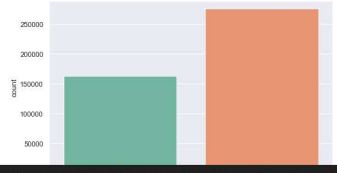
Out[11]: <AxesSubplot:xlabel='NAME_HOUSING_TYPE', ylabel='count'>



In [12]:
```
print("How many peoples own car :")
print(app['FLAG_OWN_CAR'].value_counts())
sns.set(rc = {'figure.figsize':(8,5)})
sns.countplot(x='FLAG_OWN_CAR', data=app, palette = 'Set2')
```

```
How many peoples own car :
N    275459
Y    163098
Name: FLAG_OWN_CAR, dtype: int64
```

Out[12]: <AxesSubplot:xlabel='FLAG_OWN_CAR', ylabel='count'>



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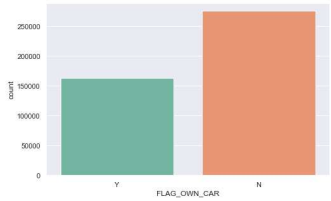

In [13]:
```
print("Income Types Of the Person :")
print(app['NAME_INCOME_TYPE'].value_counts())
sns.set(rc = {'figure.figsize':(8,5)})
sns.countplot(x='NAME_INCOME_TYPE', data=app, palette = 'Set2')
```

```
Income Types Of the Person :
Working                 226104
Commercial associate    100757
Pensioner                75493
State servant            36186
Student                     17
Name: NAME_INCOME_TYPE, dtype: int64
```

Out[13]: <AxesSubplot:xlabel='NAME_INCOME_TYPE', ylabel='count'>

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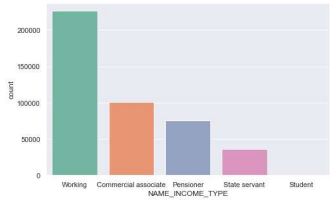
```
Name: NAME_INCOME_TYPE, dtype: int64
```

Out[13]: <AxesSubplot:xlabel='NAME_INCOME_TYPE', ylabel='count'>



In [14]:
```
fig, ax = plt.subplots(figsize=(8,6))
sns.heatmap(app.corr(),annot=True)
```

Out[14]: <AxesSubplot:>

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In [15]:
```
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
```

In [16]:
```
app.shape,credit.shape
```

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In [16]:
```
app.shape,credit.shape
```

Out[16]:
```
((438557, 18), (1048575, 3))
```

In [17]:
```
app.describe()
```

Out[17]:

	ID	CNT_CHILDREN	AMT_INCOME_TOTAL	DAYS_BIRTH	DAYS_EMPLOYED	FLAG_MOBIL	FLAG_WORK_PHONE	FLAG_PHONE	FLAG_EMA
count	4.385570e+05	438557.000000	4.385570e+05	438557.000000	438557.000000	438557.0	438557.000000	438557.000000	438557.0000
mean	6.022176e+06	0.427390	1.875243e+05	-15997.904649	60563.675328	1.0	0.206133	0.287771	0.1082
std	5.716370e+05	0.724882	1.100869e+05	4185.030007	138767.799647	0.0	0.404527	0.452724	0.3106
min	5.008804e+06	0.000000	2.610000e+04	-25201.000000	-17531.000000	1.0	0.000000	0.000000	0.0000
25%	5.609375e+06	0.000000	1.215000e+05	-19483.000000	-3103.000000	1.0	0.000000	0.000000	0.0000
50%	6.047745e+06	0.000000	1.607805e+05	-15630.000000	-1467.000000	1.0	0.000000	0.000000	0.0000
75%	6.456971e+06	1.000000	2.250000e+05	-12514.000000	-371.000000	1.0	0.000000	1.000000	0.0000
max	7.999952e+06	19.000000	6.750000e+06	-7489.000000	365243.000000	1.0	1.000000	1.000000	1.0000

In [18]:
```
app.isnull().sum()
```

Out[18]:
```
ID                     0
CODE_GENDER            0
FLAG_OWN_CAR           0
FLAG_OWN_REALTY        0
CNT_CHILDREN           0
AMT_INCOME_TOTAL       0
NAME_INCOME_TYPE       0
NAME_EDUCATION_TYPE    0
NAME_FAMILY_STATUS     0
NAME_HOUSING_TYPE      0
DAYS_BIRTH             0
DAYS_EMPLOYED          0
FLAG_MOBIL             0
FLAG_WORK_PHONE        0
FLAG_PHONE             0
FLAG_EMAIL             0
OCCUPATION_TYPE   134203
CNT_FAM_MEMBERS        0
dtype: int64
```

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In [19]:
```
def unique_values():
    a = app.CODE_GENDER.unique()
    print("-------------CODE_GENDER-----------------------------------------")
    print(a)
    print()
    b = app.FLAG_OWN_CAR.unique()
    print("--------------------FLAG_OWN_CAR-----------------------------------")
    print(b)
    print()
    c = app.FLAG_OWN_REALTY.unique()
    print('---------------------FLAG_OWN_REALTY-----------------------------------------')
    print(c)
    print()
    d = app.CNT_CHILDREN.unique()
    print('-------------------------CNT_CHILDREN----------------------------------------')
    print(d)
    print()
    e = app.NAME_INCOME_TYPE.unique()
    print( '-------------------------NAME_INCOME_TYPE----------------------------------------')
    print(e)
    print()
    f = app.NAME_EDUCATION_TYPE.unique()
    print('-------------------------NAME_EDUCATION_TYPE----------------------------------------')
    print(f)
    print()
    g = app.NAME_FAMILY_STATUS.unique()
    print('-------------------------NAME_FAMILY_STATUS----------------------------------------')
    print(g)
    print()
    h = app.NAME_HOUSING_TYPE.unique()
    print('-------------------------NAME_HOUSING_TYPE----------------------------------------')
    print(h)
    print()
    i = app.OCCUPATION_TYPE.unique()
    print('----------------------OCCUPATION_TYPE----------------------------------------')
    print(i)
    print()
    j = app.CNT_FAM_MEMBERS.value_counts()
    print('-------------------------CNT_FAM_MEMBERS----------------------------------------')
    print(j)
    print()
    return unique_values
```

In [20]:
```
unique_values()
```

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Run Markdown

In [20]:
```
unique_values()
```

```
--------------CODE_GENDER--------------------------------------------
['M' 'F']

----------------------FLAG_OWN_CAR--------------------------------
['Y' 'N']

----------------------FLAG_OWN_REALTY-----------------------------------------
['Y' 'N']

-------------------------CNT_CHILDREN--------------------------------------
[ 0  1  3  2  4  5 14 19  7  9 12  6]

-------------------------NAME_INCOME_TYPE----------------------------------------
['Working' 'Commercial associate' 'Pensioner' 'State servant' 'Student']

-------------------------NAME_EDUCATION_TYPE-------------------------------------------
['Higher education' 'Secondary / secondary special' 'Incomplete higher'
 'Lower secondary' 'Academic degree']

-------------------------NAME_FAMILY_STATUS--------------------------------------------
['Civil marriage' 'Married' 'Single / not married' 'Separated' 'Widow']

-------------------------NAME_HOUSING_TYPE---------------------------------------------
['Rented apartment' 'House / apartment' 'Municipal apartment'
 'With parents' 'Co-op apartment' 'Office apartment']

-----------------------OCCUPATION_TYPE-----------------------------------------
[nan 'Security staff' 'Sales staff' 'Accountants' 'Laborers' 'Managers'
 'Drivers' 'Core staff' 'High skill tech staff' 'Cleaning staff'
 'Private service staff' 'Cooking staff' 'Low-skill Laborers'
 'Medicine staff' 'Secretaries' 'Waiters/barmen staff' 'HR staff'
 'Realty agents' 'IT staff']

---------------------------CNT_FAM_MEMBERS-----------------------------------
2.0    233891
1.0     84492
3.0     77128
4.0     37356
5.0      5081
6.0       459
7.0       124
9.0         9
```

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Run Markdown

Out[20]:
```
<function __main__.unique_values()>
```

In [21]:
```
# dropping duplicate rows
app.drop_duplicates(subset = ['CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN',
       'AMT_INCOME_TOTAL', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'DAYS_BIRTH',
       'DAYS_EMPLOYED', 'FLAG_MOBIL', 'FLAG_WORK_PHONE', 'FLAG_PHONE',
       'FLAG_EMAIL', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS'], keep = 'first', inplace = True)

app.shape
```

Out[21]:
```
(90085, 18)
```

Data Cleaning

In [22]:
```
def data_cleansing(data):
    # Adding number of family members with number of children to get overall family members.
    data['CNT_FAM_MEMBERS'] = data['CNT_FAM_MEMBERS'] + data['CNT_CHILDREN']

    dropped_cols = ['FLAG_MOBIL', 'FLAG_WORK_PHONE', 'FLAG_PHONE',
       'FLAG_EMAIL','OCCUPATION_TYPE','CNT_CHILDREN']
    data = data.drop(dropped_cols, axis = 1)

    #converting birth years and days employed to years.
    data['DAYS_BIRTH'] = np.abs(data['DAYS_BIRTH']/365) #Absolute
    data['DAYS_EMPLOYED'] = data['DAYS_EMPLOYED']/365

    #Cleaning up categorical values to lower the count of dummy variables.
    housing_type = {'House / apartment' : 'House / apartment',
                    'With parents': 'With parents',
                    'Municipal apartment' : 'House / apartment',
                    'Rented apartment': 'House / apartment',
                    'Office apartment': 'House / apartment',
                    'Co-op apartment': 'House / apartment'}

    income_type = {'Commercial associate':'Working',
                   'State servant':'Working',
                   'Working':'Working',
                   'Pensioner':'Pensioner',
                   'Student':'Student'}
    education_type = {'Secondary / secondary special':'secondary',
                      'Lower secondary':'secondary',
```

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```
                    'Lower secondary':'secondary',
                    'Higher education':'Higher education',
                    'Incomplete higher':'Higher education',
                    'Academic degree':'Academic degree'}
    family_status = {'Single / not married':'Single',
                     'Separated':'Single',
                     'Widow':'Single',
                     'Civil marriage':'Married',
                    'Married':'Married'}
    data['NAME_HOUSING_TYPE'] = data['NAME_HOUSING_TYPE'].map(housing_type)
    data['NAME_INCOME_TYPE'] = data['NAME_INCOME_TYPE'].map(income_type)
    data['NAME_EDUCATION_TYPE']=data['NAME_EDUCATION_TYPE'].map(education_type)
    data['NAME_FAMILY_STATUS']=data['NAME_FAMILY_STATUS'].map(family_status)
    return data
```

In [23]:
```
cleansed_app = data_cleansing(app)
```

In [24]:
```
cleansed_app
```

Out[24]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	NAME_FA
0	5008804	M	Y	Y	427500.0	Working	Higher education	
2	5008806	M	Y	Y	112500.0	Working	secondary	
3	5008808	F	N	Y	270000.0	Working	secondary	
7	5008812	F	N	Y	283500.0	Pensioner	Higher education	
10	5008815	M	Y	Y	270000.0	Working	Higher education	
...	...	...	...	...	...	...	...	
438541	6837707	M	N	Y	202500.0	Working	Higher education	
438545	6839651	F	N	Y	99000.0	Pensioner	secondary	
438547	6839917	F	N	Y	180000.0	Pensioner	Higher education	
438552	6840104	M	N	Y	135000.0	Pensioner	secondary	

In [25]:
```
# Data frame to analyze length of time since initial approval of credit card
# Shows number of past dues, paid off and no loan status.
grouped = credit.groupby('ID')

pivot_tb = credit.pivot(index = 'ID', columns = 'MONTHS_BALANCE', values = 'STATUS')
pivot_tb['open_month'] = grouped['MONTHS_BALANCE'].min()
```

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In [25]:
```
# Data frame to analyze length of time since initial approval of credit card
# Shows number of past dues, paid off and no loan status.
grouped = credit.groupby('ID')

pivot_tb = credit.pivot(index = 'ID', columns = 'MONTHS_BALANCE', values = 'STATUS')
pivot_tb['open_month'] = grouped['MONTHS_BALANCE'].min()
pivot_tb['end_month'] = grouped['MONTHS_BALANCE'].max()
pivot_tb['window'] = pivot_tb['end_month'] - pivot_tb['open_month']
pivot_tb['window'] += 1 # Adding 1 since month starts at 0.

#Counting number of past dues, paid offs and no loans.
pivot_tb['paid_off'] = pivot_tb[pivot_tb.iloc[:,0:61] == 'C'].count(axis = 1)
pivot_tb['pastdue_1-29'] = pivot_tb[pivot_tb.iloc[:,0:61] == '0'].count(axis = 1)
pivot_tb['pastdue_30-59'] = pivot_tb[pivot_tb.iloc[:,0:61] == '1'].count(axis = 1)
pivot_tb['pastdue_60-89'] = pivot_tb[pivot_tb.iloc[:,0:61] == '2'].count(axis = 1)
pivot_tb['pastdue_90-119'] = pivot_tb[pivot_tb.iloc[:,0:61] == '3'].count(axis = 1)
pivot_tb['pastdue_120-149'] = pivot_tb[pivot_tb.iloc[:,0:61] == '4'].count(axis = 1)
pivot_tb['pastdue_over_150'] = pivot_tb[pivot_tb.iloc[:,0:61] == '5'].count(axis = 1)
pivot_tb['no_loan'] = pivot_tb[pivot_tb.iloc[:,0:61] == 'X'].count(axis = 1)
#Setting Id column to merge with app data.
pivot_tb['ID'] = pivot_tb.index
```

In [26]:
```
pivot_tb.head()
```

Out[26]:

MONTHS_BALANCE	-60	-59	-58	-57	-56	-55	-54	-53	-52	-51	...	window	paid_off	pastdue_1-29	pastdue_30-59	pastdue_60-89	pastdue_90-119	pastdu
ID																		
5001711	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	4	0	3	0	0	0	
5001712	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	19	9	10	0	0	0	
5001713	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	22	0	0	0	0	0	
5001714	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	15	0	0	0	0	0	
5001715	NaN	X	X	X	X	X	X	X	X	X	...	60	0	0	0	0	0	

5 rows × 73 columns

Feature Engineering

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Feature Engineering

A ratio based method was used to create the target variable. For example, given a client with a time period of 60 months, if the client had paid off loan 40 times and was late 20 times, this would be considered a fairly good client given that there were more loans that were paid off on time compared to late payments. If a client had no loans throughout the initial approval of the credit card account, by default, this would be considered a good client as well. To identify a bad client, the number of past dues would exceed the number of loans paid off or if the client only has past dues. It may be better to incorporate a set difference between number of paid off loans and number of past dues. Meaning, there needs to be a significant gap between paid off loans and past dues. If a person has 50 past dues and 51 paid off loans, based on the ratio method, this would be considered good. However the difference is only 1 and this may not be a good sign of a good client. For simplicity sake, I will not adjust the algorithm further and keep it at ratio decisioning. Code is also not optimal, adjustment may be needed for the code to compute faster.

In [27]:
```
def feature_engineering_target(data):
    good_or_bad = []
    for index, row in data.iterrows():
        paid_off = row['paid_off']
        over_1 = row['pastdue_1-29']
        over_30 = row['pastdue_30-59']
        over_60 = row['pastdue_60-89']
        over_90 = row['pastdue_90-119']
        over_120 = row['pastdue_120-149'] + row['pastdue_over_150']
        no_loan = row['no_loan']

        overall_pastdues = over_1+over_30+over_60+over_90+over_120

        if overall_pastdues == 0:
            if paid_off >= no_loan or paid_off <= no_loan:
                good_or_bad.append(1)
            elif paid_off == 0 and no_loan == 1:
                good_or_bad.append(1)

        elif overall_pastdues != 0:
            if paid_off > overall_pastdues:
                good_or_bad.append(1)
            elif paid_off <= overall_pastdues:
                good_or_bad.append(0)

        elif paid_off == 0 and no_loan != 0:
            if overall_pastdues <= no_loan or overall_pastdues >= no_loan:
                good_or_bad.append(0)

        else:
            good_or_bad.append(1)
```

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There is data on clients in the credit data that intersect with the application data. the following is a merge between the two data frames given on the data of clients that exist in both data sets. Featured engineered additional columns from the credit data.

In [ ]:
```
target = pd.DataFrame()
target['ID'] = pivot_tb.index
target['paid_off'] = pivot_tb['paid_off'].values
target['#_of_pastdues'] = pivot_tb['pastdue_1-29'].values+ pivot_tb['pastdue_30-59'].values
+ pivot_tb['pastdue_60-89'].values +pivot_tb['pastdue_90-119'].values
+pivot_tb['pastdue_120-149'].values +pivot_tb['pastdue_over_150'].values

target['no_loan'] = pivot_tb['no_loan'].values
target['target'] = feature_engineering_target(pivot_tb)
credit_app = cleansed_app.merge(target, how = 'inner', on = 'ID')
credit_app.drop('ID', axis = 1, inplace = True)
```

In [ ]:
```
credit_app.head()
```

In [ ]:
```
from sklearn.preprocessing import LabelEncoder

cg = LabelEncoder()
oc = LabelEncoder()
own_r = LabelEncoder()
it = LabelEncoder()
et = LabelEncoder()
fs = LabelEncoder()
ht = LabelEncoder()


credit_app['CODE_GENDER'] = cg.fit_transform(credit_app['CODE_GENDER'])
credit_app['FLAG_OWN_CAR'] = oc.fit_transform(credit_app['FLAG_OWN_CAR'])
credit_app['FLAG_OWN_REALTY'] = own_r.fit_transform(credit_app['FLAG_OWN_REALTY'])
credit_app['NAME_INCOME_TYPE'] = it.fit_transform(credit_app['NAME_INCOME_TYPE'])
credit_app['NAME_EDUCATION_TYPE'] = et.fit_transform(credit_app['NAME_EDUCATION_TYPE'])
credit_app['NAME_FAMILY_STATUS'] = fs.fit_transform(credit_app['NAME_FAMILY_STATUS'])
credit_app['NAME_HOUSING_TYPE'] = ht.fit_transform(credit_app['NAME_HOUSING_TYPE'])
```

In [ ]:
```
print("CODE_GENDER",credit_app['CODE_GENDER'].unique())
print(cg.inverse_transform(list(credit_app['CODE_GENDER'].unique())))
print()
print("FLAG_OWN_CAR:",credit_app['FLAG_OWN_CAR'].unique())
```

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In [ ]:
```
print("CODE_GENDER",credit_app['CODE_GENDER'].unique())
print(cg.inverse_transform(list(credit_app['CODE_GENDER'].unique())))
print()
print("FLAG_OWN_CAR:",credit_app['FLAG_OWN_CAR'].unique())
print(oc.inverse_transform(list(credit_app['FLAG_OWN_CAR'].unique())))
print()
print("FLAG_OWN_REALTY", credit_app['FLAG_OWN_REALTY'].unique())
print(own_r.inverse_transform(list(credit_app['FLAG_OWN_REALTY'].unique())))
print()
print("NAME_INCOME_TYPE",credit_app['NAME_INCOME_TYPE'].unique())
print(it.inverse_transform(list(credit_app['NAME_INCOME_TYPE'].unique())))
print()
print("NAME_EDUCATION_TYPE",credit_app['NAME_EDUCATION_TYPE'].unique())
print(et.inverse_transform(list(credit_app['NAME_EDUCATION_TYPE'].unique())))
print()
print("NAME_FAMILY_STATUS",credit_app['NAME_FAMILY_STATUS'].unique())
print(fs.inverse_transform(list(credit_app['NAME_FAMILY_STATUS'].unique())))
print()
print("NAME_HOUSING_TYPE",credit_app['NAME_HOUSING_TYPE'].unique())
print(ht.inverse_transform(list(credit_app['NAME_HOUSING_TYPE'].unique())))
```

In [ ]:
```
x = credit_app[credit_app.drop('target', axis = 1).columns]
y = credit_app['target']
xtrain, xtest, ytrain, ytest = train_test_split(x,y, test_size = 0.3, random_state = 0)
```

Imported SMOTE in case of high imbalance of target variable. However, it does not seem to be highly imbalanced so it is fine not to use an imbalanced technique.

In [ ]:
```
def logistic_reg(xtrain,xtest,ytrain,ytest):
    lr=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))
```

In [ ]:
```
def random_forest(xtrain,xtest,ytrain,ytest):
    rf=RandomForestClassifier()
    rf.fit(xtrain,ytrain)
    ypred=rf.predict(xtest)
```

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

In [ ]:
```
def d_tree(xtrain,xtest,ytrain,ytest):
    dt=DecisionTreeClassifier()
    dt.fit(xtrain,ytrain)
    ypred=dt.predict(xtest)
    print('***DecisionTreeClassifier***')
    print('Confusion matrix')
    print(confusion_matrix(ytest,ypred))
    print('Classification report')
    print(classification_report(ytest,ypred))
```

In [ ]:
```
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)
```

In [ ]:
```
compare_model(xtrain,xtest,ytrain,ytest)
```

In [ ]:
```
dt=DecisionTreeClassifier()
dt.fit(xtrain,ytrain)
ypred=dt.predict(xtest)
```

In [ ]:
```
dt.predict([[1,1,1,112500.0,2,2,0,0,58.832877,-3.106849,2.0,7,7,16]])
```

In [ ]:
```
import pickle
pickle.dump(dt,open("model.pkl","wb"))
```

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