CREDIT RISK ANALYSIS

```
import numpy as np
import pandas as pd
df1=pd.read_csv(r"C:\Users\radhi\OneDrive\Desktop\PythonProject\application_data.csv")
df1.describe()
<div>
<style scoped>
 .dataframe tbody tr th:only-of-type {
   vertical-align: middle;
 }
 .dataframe tbody tr th {
   vertical-align: top;
 }
 .dataframe thead th {
   text-align: right;
 }
</style>
<thead>
 SK_ID_CURR
  TARGET
  CNT_CHILDREN
  AMT_INCOME_TOTAL
  AMT_CREDIT
  AMT_ANNUITY
  AMT_GOODS_PRICE
```

```
REGION_POPULATION_RELATIVE
 DAYS_BIRTH
 DAYS_EMPLOYED
 ...
 FLAG_DOCUMENT_18
 FLAG_DOCUMENT_19
 FLAG_DOCUMENT_20
 FLAG_DOCUMENT_21
 AMT_REQ_CREDIT_BUREAU_HOUR
 AMT_REQ_CREDIT_BUREAU_DAY
 AMT_REQ_CREDIT_BUREAU_WEEK
 AMT_REQ_CREDIT_BUREAU_MON
 AMT_REQ_CREDIT_BUREAU_QRT
 AMT_REQ_CREDIT_BUREAU_YEAR
</thead>
count
 307511.000000
 307511.000000
 307511.000000
 3.075110e+05
 3.075110e+05
 307499.000000
 3.072330e+05
 307511.000000
 307511.000000
 307511.000000
 ...
 307511.000000
```

```
307511.000000
```

307511.000000

265992.000000

265992.000000

265992.000000

265992.000000

265992.000000

265992.000000

mean

278180.518577

0.080729

0.417052

1.687979e+05

5.990260e+05

27108.573909

5.383962e+05

0.020868

-16036.995067

63815.045904

...

0.008130

0.000595

0.000507

0.000335

0.006402

0.007000

0.034362

```
0.265474
1.899974
std
102790.175348
0.272419
0.722121
2.371231e+05
4.024908e+05
14493.737315
3.694465e+05
0.013831
4363.988632
141275.766519
...
0.089798
0.024387
0.022518
0.018299
0.083849
0.110757
0.204685
0.916002
0.794056
1.869295
min
100002.000000
0.000000
```

```
0.000000
```

2.565000e+04

4.500000e+04

1615.500000

4.050000e+04

0.000290

-25229.000000

-17912.000000

...

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

25%

189145.500000

0.000000

0.000000

1.125000e+05

2.700000e+05

16524.000000

2.385000e+05

0.010006

-19682.000000

```
-2760.000000
```

...

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

50%

278202.000000

0.000000

0.000000

1.471500e+05

5.135310e+05

24903.000000

4.500000e+05

0.018850

-15750.000000

-1213.000000

...

0.000000

0.000000

0.000000

0.000000

```
0.000000
```

0.000000

0.000000

1.000000

75%

367142.500000

0.000000

1.000000

2.025000e+05

8.086500e+05

34596.000000

6.795000e+05

0.028663

-12413.000000

-289.000000

...

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

0.000000

3.000000

```
max
 456255.000000
 1.000000
 19.000000
 1.170000e+08
 4.050000e+06
 258025.500000
 4.050000e+06
 0.072508
 -7489.000000
 365243.000000
 ...
 1.000000
 1.000000
 1.000000
 1.000000
 4.000000
 9.000000
 8.000000
 27.000000
 261.000000
 25.000000
 8 rows × 106 columns
</div>
df1.isnull()
<div>
<style scoped>
 .dataframe tbody tr th:only-of-type {
```

```
vertical-align: middle;
 }
 .dataframe tbody tr th {
  vertical-align: top;
 }
 .dataframe thead th {
  text-align: right;
 }
</style>
<thead>
 SK_ID_CURR
 TARGET
 NAME_CONTRACT_TYPE
 CODE_GENDER
 FLAG_OWN_CAR
 FLAG_OWN_REALTY
 CNT_CHILDREN
 AMT_INCOME_TOTAL
 AMT_CREDIT
 AMT_ANNUITY
 ...
 FLAG_DOCUMENT_18
 FLAG_DOCUMENT_19
 FLAG_DOCUMENT_20
 FLAG_DOCUMENT_21
 AMT_REQ_CREDIT_BUREAU_HOUR
```

```
AMT_REQ_CREDIT_BUREAU_DAY
AMT_REQ_CREDIT_BUREAU_WEEK
AMT_REQ_CREDIT_BUREAU_MON
AMT_REQ_CREDIT_BUREAU_QRT
AMT_REQ_CREDIT_BUREAU_YEAR
</thead>
0
False
...
False
```

1 False ... False 2 False False False False

- False
- False
- False
- False
- False
- False
- ...
- False

- 3
- False
- ...

- False
- False
- False
- False
- True
- True
- True
- True
- True
- True

- 4
- False
- ...
- False

```
False
False
False
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
307506
```

False

- False
- False
- False
- False
- False
- False
- False
- False
- False
- ...
- False
- False
- False
- False
- True
- True
- True
- True
- True
- True

- 307507
- False

- False
- False
- ...
- False
- False
- False
- False
- True
- True
- True
- True
- True
- True

- 307508
- False
- ...
- False
- False
- False
- False

False False False False False False 307509 False ... False False False False False False False False

False

False

```
307510
 False
 ...
 False
 307511 rows × 122 columns
</div>
text_dict=df1.isnull().sum()
df1.isnull()
<div>
```

```
<style scoped>
 .dataframe tbody tr th:only-of-type {
  vertical-align: middle;
 }
 .dataframe tbody tr th {
  vertical-align: top;
 }
 .dataframe thead th {
  text-align: right;
 }
</style>
<thead>
 SK_ID_CURR
  TARGET
  NAME_CONTRACT_TYPE
  CODE_GENDER
  FLAG_OWN_CAR
  FLAG_OWN_REALTY
  CNT_CHILDREN
  AMT_INCOME_TOTAL
  AMT_CREDIT
  AMT_ANNUITY
  ...
  FLAG_DOCUMENT_18
  FLAG_DOCUMENT_19
  FLAG_DOCUMENT_20
```

```
FLAG_DOCUMENT_21
AMT_REQ_CREDIT_BUREAU_HOUR
AMT_REQ_CREDIT_BUREAU_DAY
AMT_REQ_CREDIT_BUREAU_WEEK
AMT_REQ_CREDIT_BUREAU_MON
AMT_REQ_CREDIT_BUREAU_QRT
AMT_REQ_CREDIT_BUREAU_YEAR
</thead>
0
False
...
False
False
False
False
False
False
False
 False
```

```
False
False
1
False
...
False
2
False
False
```

- False
- ...
- False

- 3
- False

- False
- ...
- False
- False
- False
- False
- True
- True
- True
- True
- True
- True

- 4
- False
- ...
- False
- False
- False
- False
- False

- False
- False
- False
- False
- False

- :..
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...

- 307506
- False
- ...
- False
- False
- False
- False
- True
- True
- True
- True
- True
- True

- 307507
- False
- False
- False
- False
- False
- False

- False
- False
- False
- False
- ...
- False
- False
- False
- False
- True
- True
- True
- True
- True
- True

- 307508
- False
- ...
- False
- False

- False
- False
- False
- False
- False
- False
- False
- False

- 307509
- False
- ...
- False

```
False
307510
 False
 ...
 False
 False
 False
 False
 False
 False
 False
 False
 False
 False
307511 rows × 122 columns
</div>
```

#data cleaning,- REMOVING UNWANTED COLOUMNS IN THE FIRST DATA TABLE

#df1.drop(columns=['NAME_TYPE_SUITE','OCCUPATION_TYPE','CNT_FAM_MEMBERS','FLAG_WORK_PHONE'])

#df1

dfn=df1.drop(columns=['CNT CHILDREN','NAME TYPE SUITE','OCCUPATION TYPE','CNT FAM MEM BERS', 'FLAG WORK PHONE', 'FLAG DOCUMENT 18', 'FLAG DOCUMENT 19', 'FLAG DOCUMENT 20', 'AMT_REQ_CREDIT_BUREAU_HOUR','AMT_REQ_CREDIT_BUREAU_DAY','AMT_REQ_CREDIT_BUREAU WEEK','AMT REQ CREDIT BUREAU QRT','AMT REQ CREDIT BUREAU YEAR','FLAG DOCUMENT 21', 'REGION RATING CLIENT W CITY', 'WEEKDAY APPR PROCESS START', 'HOUR APPR PROCESS S TART','APARTMENTS_AVG','BASEMENTAREA_AVG','YEARS_BEGINEXPLUATATION_AVG','YEARS_BUILD AVG','COMMONAREA AVG','ELEVATORS AVG','ENTRANCES AVG','FLOORSMAX AVG','FLOORSMIN AVG', 'LANDAREA AVG', 'LIVINGAPARTMENTS AVG', 'LIVINGAREA AVG', 'NONLIVINGAPARTMENTS AV G','NONLIVINGAREA_AVG','APARTMENTS_MODE','BASEMENTAREA_MODE','YEARS_BEGINEXPLUATAT ION MODE', 'YEARS BUILD MODE', 'COMMONAREA MODE', 'ELEVATORS MODE', 'ENTRANCES MOD E','FLOORSMAX MODE','FLOORSMIN MODE','LANDAREA MODE','LIVINGAPARTMENTS MODE','LIVI NGAREA_MODE','NONLIVINGAPARTMENTS_MODE','NONLIVINGAREA_MODE','APARTMENTS_MEDI',' BASEMENTAREA MEDI', 'YEARS BEGINEXPLUATATION MEDI', 'YEARS BUILD MEDI', 'COMMONAREA MEDI', 'ELEVATORS MEDI', 'ENTRANCES MEDI', 'FLOORSMAX MEDI', 'FLOORSMIN MEDI', 'LANDAREA MEDI', 'LIVINGAPARTMENTS_MEDI', 'LIVINGAREA_MEDI', 'NONLIVINGAPARTMENTS_MEDI', 'NONLIVIN GAREA MEDI', 'FONDKAPREMONT MODE', 'TOTALAREA MODE', 'WALLSMATERIAL MODE', 'DEF 30 C NT_SOCIAL_CIRCLE','OBS_60_CNT_SOCIAL_CIRCLE','FLAG_DOCUMENT_3','FLAG_DOCUMENT_4','FL AG_DOCUMENT_5','FLAG_DOCUMENT_6','FLAG_DOCUMENT_7','FLAG_DOCUMENT_8','FLAG_DOCU MENT_9','FLAG_DOCUMENT_10','FLAG_DOCUMENT_11','FLAG_DOCUMENT_12','FLAG_DOCUMENT 13','FLAG DOCUMENT 14','FLAG DOCUMENT 15','FLAG DOCUMENT 16','FLAG DOCUMENT 17', 'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21'])

```
dfn
<div>
<style scoped>
    .dataframe tbody tr th:only-of-type {
      vertical-align: middle;
    }

    .dataframe tbody tr th {
      vertical-align: top;
    }

    .dataframe thead th {
      text-align: right;
    }
```

```
</style>
<thead>
 SK_ID_CURR
 TARGET
 NAME_CONTRACT_TYPE
 CODE_GENDER
 FLAG_OWN_CAR
 FLAG_OWN_REALTY
 AMT_INCOME_TOTAL
 AMT_CREDIT
 AMT_ANNUITY
 AMT_GOODS_PRICE
 ...
 EXT_SOURCE_1
 EXT_SOURCE_2
 EXT_SOURCE_3
 HOUSETYPE_MODE
 EMERGENCYSTATE_MODE
 OBS_30_CNT_SOCIAL_CIRCLE
 DEF_60_CNT_SOCIAL_CIRCLE
 DAYS_LAST_PHONE_CHANGE
 FLAG_DOCUMENT_2
 AMT_REQ_CREDIT_BUREAU_MON
 </thead>
0
```

```
100002
1
Cash loans
M
N
Y
202500.0
406597.5
24700.5
351000.0
...
0.083037
0.262949
0.139376
block of flats
No
2.0
2.0
-1134.0
0
0.0
1
100003
0
Cash loans
F
N
N
270000.0
```

```
1293502.5
```

1129500.0

...

0.311267

0.622246

NaN

block of flats

No

1.0

0.0

-828.0

0

0.0

2

100004

0

Revolving loans

M

Y

Y

67500.0

135000.0

6750.0

135000.0

...

NaN

0.555912

- NaN
- NaN
- 0.0
- 0.0
- -815.0
- 0
- 0.0

- 3
- 100006
- 0
- Cash loans
- F
- N
- Y
- 135000.0
- 312682.5
- 29686.5
- 297000.0
- ...
- NaN
- 0.650442
- NaN
- NaN
- NaN
- 2.0
- 0.0
- -617.0
- 0
- NaN

```
4
100007
0
Cash loans
M
N
Y
121500.0
513000.0
21865.5
513000.0
...
NaN
0.322738
NaN
NaN
NaN
0.0
0.0
-1106.0
0
0.0
...
...
...
...
...
```

- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...

- 307506
- 456251
- 0
- Cash loans
- M
- N
- N
- 157500.0
- 254700.0
- 27558.0
- 225000.0
- ...

```
0.145570
```

NaN

block of flats

No

0.0

0.0

-273.0

0

NaN

307507

456252

0

Cash loans

F

N

Y

72000.0

269550.0

12001.5

225000.0

...

NaN

0.115992

NaN

block of flats

No

0.0

```
0.0
0
NaN
307508
456253
0
Cash loans
F
N
Y
153000.0
677664.0
29979.0
585000.0
...
0.744026
0.535722
0.218859
block of flats
No
6.0
0.0
-1909.0
0
1.0
307509
456254
```

```
1
```

Cash loans

F

N

Y

171000.0

370107.0

20205.0

319500.0

...

NaN

0.514163

0.661024

block of flats

No

0.0

0.0

-322.0

0

0.0

307510

456255

0

Cash loans

F

N

N

157500.0

675000.0

```
49117.5
  675000.0
  ...
  0.734460
  0.708569
  0.113922
  block of flats
  No
  0.0
  0.0
  -787.0
  0
  2.0
 307511 rows × 43 columns
</div>
#DATA CLEANING- chnaging the structure of the values in the column data
Dfn
<div>
<style scoped>
 .dataframe tbody tr th:only-of-type {
  vertical-align: middle;
 }
 .dataframe tbody tr th {
   vertical-align: top;
 }
 .dataframe thead th {
```

```
text-align: right;
 }
</style>
<thead>
 SK_ID_CURR
 TARGET
 NAME_CONTRACT_TYPE
 CODE_GENDER
 FLAG_OWN_CAR
 FLAG_OWN_REALTY
 AMT_INCOME_TOTAL
 AMT_CREDIT
 AMT_ANNUITY
 AMT_GOODS_PRICE
 ...
 EXT_SOURCE_1
 EXT_SOURCE_2
 EXT_SOURCE_3
 HOUSETYPE_MODE
 EMERGENCYSTATE_MODE
 OBS_30_CNT_SOCIAL_CIRCLE
 DEF_60_CNT_SOCIAL_CIRCLE
 DAYS_LAST_PHONE_CHANGE
 FLAG_DOCUMENT_2
 AMT_REQ_CREDIT_BUREAU_MON
 </thead>
```

```
0
100002
1
Cash loans
M
N
Y
202500.0
406597.5
24700.5
351000.0
...
0.083037
0.262949
0.139376
block of flats
No
2.0
2.0
-1134.0
0
0.0
1
100003
0
Cash loans
F
N
```

```
N
```

270000.0

1293502.5

35698.5

1129500.0

...

0.311267

0.622246

NaN

block of flats

No

1.0

0.0

-828.0

0

0.0

2

100004

0

Revolving loans

M

Y

Y

67500.0

135000.0

6750.0

135000.0

...

NaN

- 0.555912
- 0.729567
- NaN
- NaN
- 0.0
- 0.0
- -815.0
- 0
- 0.0

- 3
- 100006
- 0
- Cash loans
- F
- N
- Y
- 135000.0
- 312682.5
- 29686.5
- 297000.0
- ...
- NaN
- 0.650442
- NaN
- NaN
- NaN
- 2.0
- 0.0
- -617.0

```
0
NaN
4
100007
0
Cash loans
M
N
Y
121500.0
513000.0
21865.5
513000.0
...
NaN
0.322738
NaN
NaN
NaN
0.0
0.0
-1106.0
0
0.0
...
...
...
```

- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...

- 307506
- 456251
- 0
- Cash loans
- M
- N
- N
- 157500.0
- 254700.0
- 27558.0

```
225000.0
...
0.145570
0.681632
NaN
block of flats
No
0.0
0.0
-273.0
0
NaN
307507
456252
0
Cash loans
F
N
Y
72000.0
269550.0
12001.5
225000.0
...
NaN
0.115992
NaN
block of flats
```

No

```
0.0
0.0
0.0
0
NaN
307508
456253
0
Cash loans
F
N
Y
153000.0
677664.0
29979.0
585000.0
...
0.744026
0.535722
0.218859
block of flats
No
6.0
0.0
-1909.0
0
1.0
```

307509 456254 1 Cash loans FN Y 171000.0 370107.0 20205.0 319500.0 ... NaN 0.514163 0.661024 block of flats No 0.0 0.0 -322.0 0 0.0 307510 456255 0 Cash loans F N

N

```
157500.0
  675000.0
  49117.5
  675000.0
  ...
  0.734460
  0.708569
  0.113922
  block of flats
  No
  0.0
  0.0
  -787.0
  0
  2.0
 307511 rows × 43 columns
</div>
dfn['DAYS_BIRTH'].isnull().sum()
dfn['DAYS_BIRTH']=abs(dfn['DAYS_BIRTH'])#replacing negative values with absolute values
dfn['PERSON_AGE']=dfn.apply( lambda row : int(row.DAYS_BIRTH /365),axis=1)
dfn['PERSON_AGE'].isnull().sum()
dfn['YEARS_EMPLOYED']=dfn.apply( lambda row : int(row.DAYS_EMPLOYED/365),axis=1)
dfn['YEARS_EMPLOYED']=abs(dfn['YEARS_EMPLOYED'])
dfn['DAYS_LAST_PHONE_CHANGE']=abs(dfn['DAYS_LAST_PHONE_CHANGE'])
dfn['AMT_INCOME_TOTAL'].isnull().sum()
```

0

0

dfn.isnull().sum()

SK_ID_CURR 0

TARGET 0

NAME_CONTRACT_TYPE 0

CODE_GENDER 0

FLAG_OWN_CAR 0

FLAG_OWN_REALTY 0

AMT_INCOME_TOTAL 0

AMT_CREDIT 0

AMT_ANNUITY 12

AMT_GOODS_PRICE 278

NAME_INCOME_TYPE 0

NAME_EDUCATION_TYPE 0

NAME_FAMILY_STATUS 0

NAME_HOUSING_TYPE 0

REGION_POPULATION_RELATIVE 0

DAYS_BIRTH 0

DAYS_EMPLOYED 0

DAYS_REGISTRATION 0

DAYS_ID_PUBLISH 0

OWN_CAR_AGE 202929

FLAG_MOBIL 0

FLAG_EMP_PHONE 0

FLAG_CONT_MOBILE 0

FLAG_PHONE 0

FLAG_EMAIL 0

REGION_RATING_CLIENT 0

REG_REGION_NOT_LIVE_REGION 0

REG_REGION_NOT_WORK_REGION 0

LIVE_REGION_NOT_WORK_REGION 0

REG_CITY_NOT_LIVE_CITY 0

```
REG_CITY_NOT_WORK_CITY
LIVE_CITY_NOT_WORK_CITY
ORGANIZATION_TYPE
EXT_SOURCE_1
                      173378
EXT_SOURCE_2
                       660
EXT_SOURCE_3
                      60965
HOUSETYPE_MODE
                        154297
EMERGENCYSTATE_MODE
                           145755
OBS_30_CNT_SOCIAL_CIRCLE
                            1021
DEF_60_CNT_SOCIAL_CIRCLE
                            1021
DAYS_LAST_PHONE_CHANGE
                               1
FLAG_DOCUMENT_2
AMT_REQ_CREDIT_BUREAU_MON
                                41519
PERSON_AGE
                         0
YEARS_EMPLOYED
dtype: int64
dfn.dropna(axis=1,how='any',inplace=True)
dfn
<div>
<style scoped>
 .dataframe tbody tr th:only-of-type {
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 }
 .dataframe tbody tr th {
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 }
 .dataframe thead th {
   text-align: right;
 }
```

```
</style>
<thead>
 SK_ID_CURR
 TARGET
 NAME_CONTRACT_TYPE
 CODE_GENDER
 FLAG_OWN_CAR
 FLAG_OWN_REALTY
 AMT_INCOME_TOTAL
 AMT_CREDIT
 NAME_INCOME_TYPE
 NAME_EDUCATION_TYPE
 ...
 REG_REGION_NOT_LIVE_REGION
 REG_REGION_NOT_WORK_REGION
 LIVE_REGION_NOT_WORK_REGION
 REG_CITY_NOT_LIVE_CITY
 REG_CITY_NOT_WORK_CITY
 LIVE_CITY_NOT_WORK_CITY
 ORGANIZATION_TYPE
 FLAG_DOCUMENT_2
 PERSON_AGE
 YEARS_EMPLOYED
 </thead>
0
```

```
100002
1
Cash loans
M
N
Y
202500.0
406597.5
Working
Secondary / secondary special
...
0
0
0
0
0
0
Business Entity Type 3
0
25
1
1
100003
0
Cash loans
F
N
N
270000.0
```

```
1293502.5
State servant
Higher education
...
0
0
0
0
0
0
School
0
45
3
2
100004
0
Revolving loans
M
Y
Y
67500.0
135000.0
Working
Secondary / secondary special
...
0
0
0
```

```
0
0
0
Government
0
52
0
3
100006
0
Cash loans
F
N
Y
135000.0
312682.5
Working
Secondary / secondary special
...
0
0
0
0
0
0
Business Entity Type 3
0
52
8
```

```
4
100007
0
Cash loans
M
N
Y
121500.0
513000.0
Working
Secondary / secondary special
...
0
0
0
0
1
1
Religion
0
54
8
...
...
...
...
...
```

- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...

- 307506
- 456251
- 0
- Cash loans
- M
- N
- N
- 157500.0
- 254700.0
- Working
- Secondary / secondary special
- ...



```
0
56
1000
307508
456253
0
Cash loans
F
N
Y
153000.0
677664.0
Working
Higher education
...
0
0
0
0
1
1
School
0
41
21
307509
456254
```

```
1
Cash loans
F
N
Y
171000.0
370107.0
Commercial associate
Secondary / secondary special
...
0
0
0
1
1
0
Business Entity Type 1
0
32
13
307510
456255
0
Cash loans
F
N
N
157500.0
675000.0
```

```
Commercial associate
  Higher education
  ...
  0
  0
  0
  0
  1
  1
  Business Entity Type 3
  0
  46
  3
 307511 rows × 33 columns
</div>
import pandas as pd
df2=pd.read_csv(r"C:\Users\radhi\OneDrive\Desktop\PythonProject\previous_application.csv")
df2.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 37 columns):
# Column
              Non-Null Count Dtype
---
             -----
0 SK_ID_PREV 1670214 non-null int64
1 SK_ID_CURR
                1670214 non-null int64
2 NAME_CONTRACT_TYPE 1670214 non-null object
3 AMT_ANNUITY 1297979 non-null float64
4 AMT_APPLICATION 1670214 non-null float64
```

- 5 AMT_CREDIT 1670213 non-null float64
- 6 AMT_DOWN_PAYMENT 774370 non-null float64
- 7 AMT_GOODS_PRICE 1284699 non-null float64
- 8 WEEKDAY_APPR_PROCESS_START 1670214 non-null object
- 9 HOUR_APPR_PROCESS_START 1670214 non-null int64
- 10 FLAG_LAST_APPL_PER_CONTRACT 1670214 non-null object
- 11 NFLAG_LAST_APPL_IN_DAY 1670214 non-null int64
- 12 RATE_DOWN_PAYMENT 774370 non-null float64
- 13 RATE_INTEREST_PRIMARY 5951 non-null float64
- 14 RATE_INTEREST_PRIVILEGED 5951 non-null float64
- 15 NAME_CASH_LOAN_PURPOSE 1670214 non-null object
- 16 NAME_CONTRACT_STATUS 1670214 non-null object
- 17 DAYS_DECISION 1670214 non-null int64
- 18 NAME_PAYMENT_TYPE 1670214 non-null object
- 19 CODE_REJECT_REASON 1670214 non-null object
- 20 NAME_TYPE_SUITE 849809 non-null object
- 21 NAME_CLIENT_TYPE 1670214 non-null object
- 22 NAME_GOODS_CATEGORY 1670214 non-null object
- 23 NAME_PORTFOLIO 1670214 non-null object
- 24 NAME_PRODUCT_TYPE 1670214 non-null object
- 25 CHANNEL_TYPE 1670214 non-null object
- 26 SELLERPLACE_AREA 1670214 non-null int64
- 27 NAME_SELLER_INDUSTRY 1670214 non-null object
- 28 CNT_PAYMENT 1297984 non-null float64
- 29 NAME_YIELD_GROUP 1670214 non-null object
- 30 PRODUCT_COMBINATION 1669868 non-null object
- 31 DAYS_FIRST_DRAWING 997149 non-null float64
- 32 DAYS_FIRST_DUE 997149 non-null float64
- 33 DAYS_LAST_DUE_1ST_VERSION 997149 non-null float64
- 34 DAYS_LAST_DUE 997149 non-null float64
- 35 DAYS_TERMINATION 997149 non-null float64

```
36 NFLAG_INSURED_ON_APPROVAL 997149 non-null float64
dtypes: float64(15), int64(6), object(16)
memory usage: 471.5+ MB
df2.dropna(axis=1,how='any',inplace=True)
df2
df2n=df2.drop(columns=['HOUR_APPR_PROCESS_START','WEEKDAY_APPR_PROCESS_START',])
df2n
<div>
<style scoped>
 .dataframe tbody tr th:only-of-type {
   vertical-align: middle;
 }
 .dataframe tbody tr th {
   vertical-align: top;
 }
 .dataframe thead th {
   text-align: right;
 }
</style>
<thead>
 SK_ID_PREV
  SK_ID_CURR
  NAME_CONTRACT_TYPE
  AMT_APPLICATION
  FLAG_LAST_APPL_PER_CONTRACT
  NFLAG_LAST_APPL_IN_DAY
```

```
NAME_CASH_LOAN_PURPOSE
 NAME_CONTRACT_STATUS
 DAYS_DECISION
 NAME_PAYMENT_TYPE
CODE_REJECT_REASON
NAME_CLIENT_TYPE
 NAME_GOODS_CATEGORY
NAME_PORTFOLIO
NAME_PRODUCT_TYPE
CHANNEL_TYPE
SELLERPLACE_AREA
NAME_SELLER_INDUSTRY
NAME_YIELD_GROUP
</thead>
0
2030495
271877
Consumer loans
17145.0
Y
1
XAP
Approved
-73
 Cash through the bank
 XAP
 Repeater
 Mobile
```

```
POS
XNA
Country-wide
35
Connectivity
middle
1
2802425
108129
Cash loans
607500.0
Y
1
XNA
Approved
-164
XNA
XAP
Repeater
XNA
Cash
x-sell
Contact center
-1
XNA
low_action
2
```

```
2523466
122040
Cash loans
112500.0
Y
1
XNA
Approved
-301
Cash through the bank
XAP
Repeater
XNA
Cash
x-sell
Credit and cash offices
-1
XNA
high
3
2819243
176158
Cash loans
450000.0
Y
1
XNA
Approved
-512
```

```
Cash through the bank
XAP
Repeater
XNA
Cash
x-sell
Credit and cash offices
-1
XNA
middle
4
1784265
202054
Cash loans
337500.0
Y
1
Repairs
Refused
-781
Cash through the bank
HC
Repeater
XNA
Cash
walk-in
Credit and cash offices
-1
XNA
```

```
high
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
1670209
2300464
352015
Consumer loans
267295.5
Y
```

```
1
XAP
Approved
-544
Cash through the bank
XAP
Refreshed
Furniture
POS
XNA
Stone
43
Furniture
low_normal
1670210
2357031
334635
Consumer loans
87750.0
Y
1
XAP
Approved
-1694
Cash through the bank
XAP
New
Furniture
POS
```

```
XNA
Stone
43
Furniture
middle
1670211
2659632
249544
Consumer loans
105237.0
Y
1
XAP
Approved
-1488
Cash through the bank
XAP
Repeater
Consumer Electronics
POS
XNA
Country-wide
1370
Consumer electronics
low_normal
1670212
2785582
```

```
400317
Cash loans
180000.0
Y
1
XNA
Approved
-1185
Cash through the bank
XAP
Repeater
XNA
Cash
x-sell
AP+ (Cash loan)
-1
XNA
low_normal
1670213
2418762
261212
Cash loans
360000.0
Y
1
XNA
Approved
-1193
Cash through the bank
```

```
XAP
  Repeater
  XNA
  Cash
  x-sell
  AP+ (Cash loan)
  -1
  XNA
  middle
 1670214 rows × 19 columns
</div>
df2n.dropna(axis=0,how='any',inplace=True)#removing all null values in the
'previous_application.csv' dataframe
df2n
<div>
<style scoped>
 .dataframe tbody tr th:only-of-type {
   vertical-align: middle;
 }
 .dataframe tbody tr th {
   vertical-align: top;
 }
 .dataframe thead th \{
   text-align: right;
 }
</style>
```

```
<thead>
 SK_ID_PREV
 SK_ID_CURR
 NAME_CONTRACT_TYPE
 AMT_APPLICATION
 FLAG_LAST_APPL_PER_CONTRACT
 NFLAG_LAST_APPL_IN_DAY
 NAME_CASH_LOAN_PURPOSE
 NAME_CONTRACT_STATUS
 DAYS_DECISION
 NAME_PAYMENT_TYPE
 CODE_REJECT_REASON
 NAME_CLIENT_TYPE
 NAME_GOODS_CATEGORY
 NAME_PORTFOLIO
 NAME_PRODUCT_TYPE
 CHANNEL_TYPE
 SELLERPLACE_AREA
 NAME_SELLER_INDUSTRY
 NAME_YIELD_GROUP
 </thead>
0
 2030495
 271877
 Consumer loans
```

```
17145.0
Y
1
XAP
Approved
-73
Cash through the bank
XAP
Repeater
Mobile
POS
XNA
Country-wide
35
Connectivity
middle
1
2802425
108129
Cash loans
607500.0
Y
1
XNA
Approved
-164
XNA
XAP
Repeater
```

```
XNA
Cash
x-sell
Contact center
-1
XNA
low_action
2
2523466
122040
Cash loans
112500.0
Y
1
XNA
Approved
-301
Cash through the bank
XAP
Repeater
XNA
Cash
x-sell
Credit and cash offices
-1
XNA
high
```

```
3
2819243
176158
Cash loans
450000.0
Y
1
XNA
Approved
-512
Cash through the bank
XAP
Repeater
XNA
Cash
x-sell
Credit and cash offices
-1
XNA
middle
4
1784265
202054
Cash loans
337500.0
Y
1
Repairs
Refused
```

-781

Cash through the bank

HC

Repeater

XNA

Cash

walk-in

Credit and cash offices

-1

XNA

high

...

...

...

...

...

...

...

...

...

...

...

...

...

...

...

...

...

...

```
...
...
1670209
2300464
352015
Consumer loans
267295.5
Y
1
XAP
Approved
-544
Cash through the bank
XAP
Refreshed
Furniture
POS
XNA
Stone
43
Furniture
low_normal
1670210
2357031
334635
Consumer loans
87750.0
```

```
Y
1
XAP
Approved
-1694
Cash through the bank
XAP
New
Furniture
POS
XNA
Stone
43
Furniture
middle
1670211
2659632
249544
Consumer loans
105237.0
Y
1
XAP
Approved
-1488
Cash through the bank
XAP
Repeater
Consumer Electronics
```

```
POS
XNA
Country-wide
1370
Consumer electronics
low_normal
1670212
2785582
400317
Cash loans
180000.0
Y
1
XNA
Approved
-1185
Cash through the bank
XAP
Repeater
XNA
Cash
x-sell
AP+ (Cash loan)
-1
XNA
low_normal
1670213
```

```
2418762
           261212
           Cash loans
           360000.0
           Y
           1
           XNA
           Approved
           -1193
           Cash through the bank
           XAP
           Repeater
           XNA
           Cash
           x-sell
           AP+ (Cash loan)
           -1
           XNA
           middle
        1670214 rows × 19 columns
</div>
df 2n. rename (columns = \{'NAME\_CONTRACT\_TYPE': 'PRE\_NAME\_CONTRACT\_TYPE', 'AMT\_CREDIT': 'PRE\_NAME\_CONTRACT\_TYPE', 'AMT\_CREDIT'', 'AMT\_CREDIT'', 'AMT\_CREDIT'', 'AMT\_CREDIT'', 'AMT\_CREDIT'', 'AMT\_CREDIT'', 'AMT\_CREDIT'', 'AMT_CREDIT'', 'AMT_CREDIT''', 'AMT_CREDIT'', 'AMT_CREDIT'''
E_AMT_CREDIT'},inplace=True)
df2n
dfnew=pd.merge(dfn,df2n,on='SK_ID_CURR',how='left') #merged two dataframes
dfnew
for key in dfnew.columns[dfnew.isna().any()]:
        dfnew[key]=dfnew[key].replace(np.NaN,0)
```

dfnew.info()

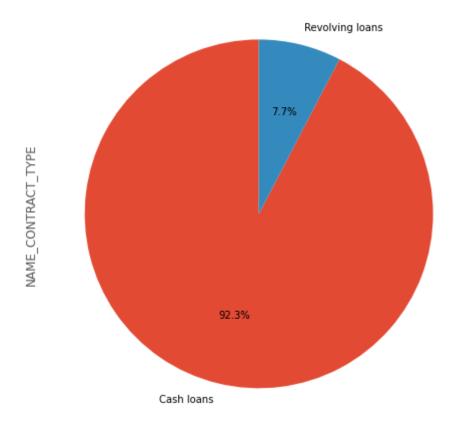
#analysis - COntract type distribution

import matplotlib.pyplot as plt

plt.figure(facecolor='white')

dfnew['NAME_CONTRACT_TYPE'].value_counts().plot(kind='pie',legend=False,autopct='%1.1f%%',fig size=(10,8),startangle=90)

plt.show()

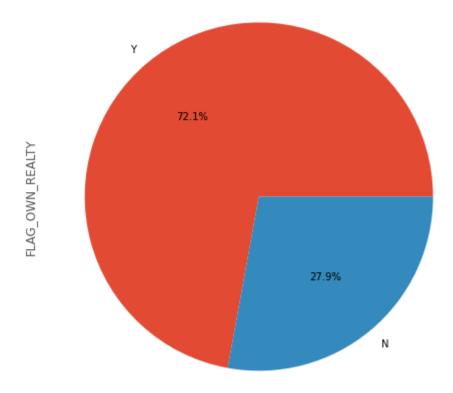


#piechart:property status

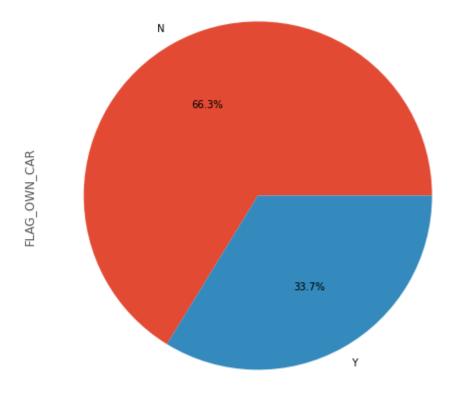
plt.figure(facecolor='white')

 $\label{lem:counts} $$ dfnew['FLAG_OWN_REALTY'].value_counts().plot(kind='pie', legend=False, autopct='\%1.1f\%', figsize=(10,8), startangle=0) $$$

plt.show()



#piechart:car status
plt.figure(facecolor='white')
dfnew['FLAG_OWN_CAR'].value_counts().plot(kind='pie',
legend=False,autopct='%1.1f%%',figsize=(10,8),startangle=0)
plt.show()



```
#dfnew['AMT_INCOME_TOTAL'].max()
#dfnew['AMT_INCOME_TOTAL'].min()
s=dfnew['AMT_INCOME_TOTAL'].astype(int)
dfnew['INCOME_RANGE']=pd.IntervalIndex.from_arrays(s,s+10000,000)
dfnew
<div>
<style scoped>
    .dataframe tbody tr th:only-of-type {
    vertical-align: middle;
    }
    .dataframe tbody tr th {
    vertical-align: top;
    }
    .dataframe thead th {
```

```
text-align: right;
 }
</style>
<thead>
 SK_ID_CURR
 TARGET
 NAME_CONTRACT_TYPE
 CODE_GENDER
 FLAG_OWN_CAR
 FLAG_OWN_REALTY
 AMT_INCOME_TOTAL
 AMT_CREDIT
 NAME_INCOME_TYPE
 NAME_EDUCATION_TYPE
 ...
 CODE_REJECT_REASON
 NAME_CLIENT_TYPE
 NAME_GOODS_CATEGORY
 NAME_PORTFOLIO
 NAME_PRODUCT_TYPE
 CHANNEL_TYPE
 SELLERPLACE_AREA
 NAME_SELLER_INDUSTRY
 NAME_YIELD_GROUP
 INCOME_RANGE
 </thead>
```

```
0
100002
1
Cash loans
M
N
Y
202500.0
406597.5
Working
Secondary / secondary special
...
XAP
New
Vehicles
POS
XNA
Stone
500.0
Auto technology
low_normal
(202500, 212500]
1
100003
0
Cash loans
F
N
```

```
N
270000.0
1293502.5
State servant
Higher education
...
XAP
Repeater
XNA
Cash
x-sell
Credit and cash offices
-1.0
XNA
low_normal
(270000, 280000]
2
100003
0
Cash loans
F
N
N
270000.0
1293502.5
State servant
Higher education
...
XAP
```

```
Refreshed
Furniture
POS
XNA
Stone
1400.0
Furniture
middle
(270000, 280000]
3
100003
0
Cash loans
F
N
N
270000.0
1293502.5
State servant
Higher education
...
XAP
Refreshed
Consumer Electronics
POS
XNA
Country-wide
200.0
Consumer electronics
```

```
middle
(270000, 280000]
4
100004
0
Revolving loans
M
Y
Y
67500.0
135000.0
Working
Secondary / secondary special
...
XAP
New
Mobile
POS
XNA
Regional / Local
30.0
Connectivity
middle
(67500, 77500]
...
...
...
```

- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...
- ...

- 1430150
- 456255
- 0
- Cash loans
- F
- N
- N
- 157500.0
- 675000.0
- Commercial associate

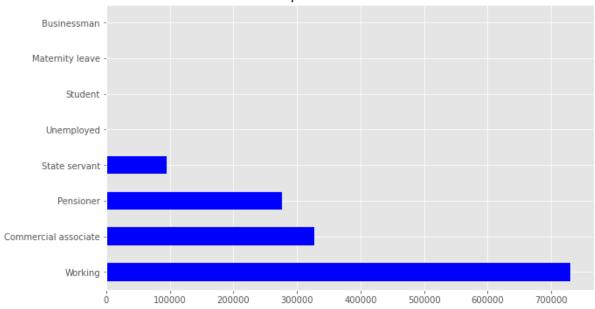
```
Higher education
...
XAP
Repeater
XNA
Cash
x-sell
Credit and cash offices
-1.0
XNA
middle
(157500, 167500]
1430151
456255
0
Cash loans
F
N
N
157500.0
675000.0
Commercial associate
Higher education
...
HC
Repeater
XNA
Cards
walk-in
```

```
Country-wide
20.0
Connectivity
XNA
(157500, 167500]
1430152
456255
0
Cash loans
F
N
N
157500.0
675000.0
Commercial associate
Higher education
...
HC
Repeater
XNA
Cash
walk-in
Credit and cash offices
-1.0
XNA
low_normal
(157500, 167500]
```

```
1430153
456255
0
Cash loans
F
N
N
157500.0
675000.0
Commercial associate
Higher education
...
XAP
Repeater
XNA
Cash
x-sell
AP+ (Cash loan)
6.0
XNA
low_normal
(157500, 167500]
1430154
456255
0
Cash loans
F
N
N
```

```
157500.0
  675000.0
  Commercial associate
  Higher education
  ...
  XAP
  Repeater
  Computers
  POS
  XNA
  Country-wide
  20.0
  Connectivity
  high
  (157500, 167500]
 1430155 rows × 52 columns
</div>
plt.figure(figsize=(10,6),facecolor='white')
dfnew['NAME_INCOME_TYPE'].value_counts().plot.barh(color='blue')
plt.title('Occupation Count of Clients',size=15)
plt.show()
```





```
!pip install seaborn
```

import seaborn as sns

#Outlier analysis of income

create a function for outlier analysis

```
def outlier(column):
```

```
plt.style.use('ggplot')
```

plt.figure(figsize=(12,6))

plt.subplot(1,2,1)

sns.distplot(dfnew[column])

plt.title('Distplot of'+' '+column)

plt.subplot(1,2,2)

sns.boxplot(y=dfnew[column])

plt.title('Boxplot of'+' '+column)

plt.suptitle('Outlier Analysis of'+' '+column ,size=15)

plt.tight_layout(pad=3)

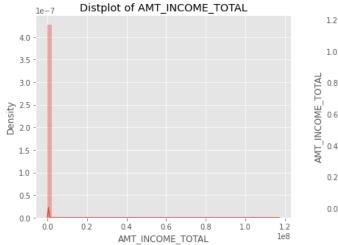
plt.show()

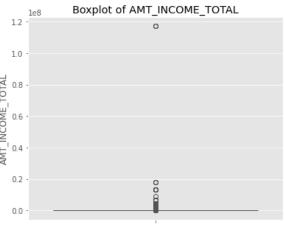
#Analysis of AMT_INCOME_TOTAL

outlier('AMT_INCOME_TOTAL')

#got an understanding of existence of outliers

Outlier Analysis of AMT_INCOME_TOTAL





dfnew['AMT_INCOME_TOTAL'].describe() #statistical info

count 1.430155e+06

mean 1.736036e+05

std 1.983303e+05

min 2.565000e+04

25% 1.125000e+05

50% 1.575000e+05

75% 2.115000e+05

max 1.170000e+08

Name: AMT_INCOME_TOTAL, dtype: float64

dfnew['AMT_INCOME_TOTAL'].quantile([0.9,0.99,0.999,1.0]) #finding the percentile

0.900 270000.0

0.990 450000.0

0.999 900000.0

1.000 117000000.0

Name: AMT_INCOME_TOTAL, dtype: float64

so 99% of values are within 900000 range

#we need to check the data above 9lakh

dfnew[dfnew['AMT_INCOME_TOTAL']>900000]

<div>

<style scoped>

```
.dataframe tbody tr th:only-of-type {
  vertical-align: middle;
 }
 .dataframe tbody tr th {
  vertical-align: top;
 }
 .dataframe thead th {
  text-align: right;
 }
</style>
<thead>
 SK_ID_CURR
 TARGET
 NAME_CONTRACT_TYPE
 CODE_GENDER
 FLAG_OWN_CAR
 FLAG_OWN_REALTY
 AMT_INCOME_TOTAL
 AMT_CREDIT
 NAME_INCOME_TYPE
 NAME_EDUCATION_TYPE
 ...
 CODE_REJECT_REASON
 NAME_CLIENT_TYPE
  NAME_GOODS_CATEGORY
  NAME_PORTFOLIO
```

```
NAME_PRODUCT_TYPE
CHANNEL_TYPE
SELLERPLACE_AREA
NAME_SELLER_INDUSTRY
NAME_YIELD_GROUP
INCOME_RANGE
</thead>
7390
101769
0
Revolving loans
M
Y
Y
1080000.0
180000.0
Commercial associate
Higher education
...
0
0
0
0
0
0
0.0
0
0
```

```
(1080000, 1090000]
8321
102015
0
Cash loans
F
N
Y
1935000.0
269550.0
Pensioner
Secondary / secondary special
...
XAP
New
XNA
Cash
walk-in
AP+ (Cash loan)
50.0
XNA
low_normal
(1935000, 1945000]
16006
103938
0
Cash loans
```

```
F
N
N
1350000.0
2410380.0
Commercial associate
Higher education
...
0
0
0
0
0
0
0.0
0
0
(1350000, 1360000]
21579
105384
0
Revolving loans
F
Y
Y
1350000.0
405000.0
Commercial associate
Higher education
```

```
...
0
0
0
0
0
0
0.0
0
0
(1350000, 1360000]
26451
106637
0
Cash loans
M
Y
Y
967500.0
450000.0
Commercial associate
Higher education
...
XAP
Repeater
Mobile
POS
XNA
Country-wide
```

```
40.0
Connectivity
middle
(967500, 977500]
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
...
```

1423829

```
454746
0
Cash loans
M
Y
Y
949500.0
735579.0
Working
Higher education
...
XAP
Repeater
XNA
XNA
XNA
Credit and cash offices
-1.0
XNA
XNA
(949500, 959500]
1423830
454746
0
Cash loans
M
Y
Y
949500.0
```

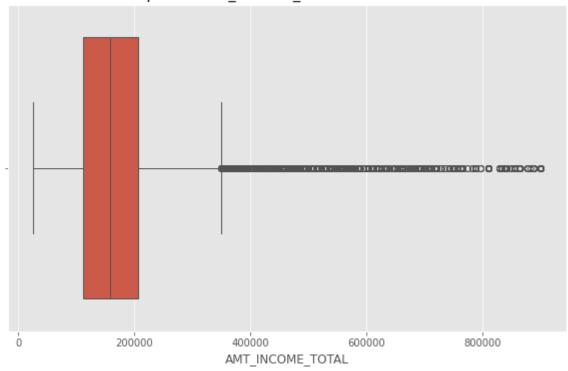
```
735579.0
Working
Higher education
...
XAP
Repeater
XNA
XNA
XNA
Credit and cash offices
-1.0
XNA
XNA
(949500, 959500]
1423831
454746
0
Cash loans
M
Y
Y
949500.0
735579.0
Working
Higher education
...
XAP
Repeater
Clothing and Accessories
```

```
POS
XNA
Country-wide
100.0
Clothing
middle
(949500, 959500]
1424300
454864
0
Cash loans
F
N
N
936000.0
1014493.5
Commercial associate
Higher education
...
XAP
New
XNA
Cards
walk-in
Country-wide
200.0
Connectivity
XNA
(936000, 946000]
```

```
1424301
 454864
 0
 Cash loans
 F
 N
 N
 936000.0
 1014493.5
 Commercial associate
 Higher education
 ...
 XAP
 New
 Furniture
 POS
 XNA
 Regional / Local
 50.0
 Furniture
 middle
 (936000, 946000]
 882 rows × 52 columns
</div>
#plot boxplot for below 9lakh cases
plt.figure(figsize=(10,6))
```

sns.boxplot(x=dfnew[dfnew['AMT_INCOME_TOTAL']<=900000]['AMT_INCOME_TOTAL'])
plt.title("Boxplot of AMT_INCOME_TOTAL within 900000")
plt.show()





#Most values lies between 1lakh and 2.5lakh.Also 99% of data lies below 9lakh. so we can consider anyvalue above 900000 are outliers

Analysis of AMT_CREDIT

dfnew.AMT_CREDIT.describe()

count 1.430155e+06

mean 5.893386e+05

std 3.874204e+05

min 4.500000e+04

25% 2.700000e+05

50% 5.084955e+05

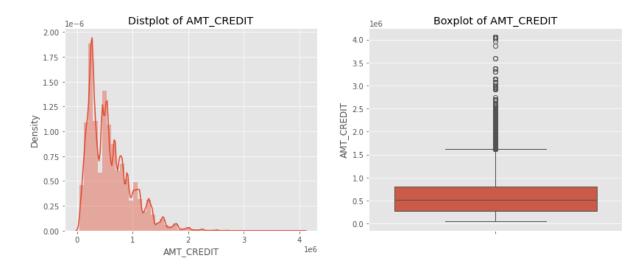
75% 8.086500e+05

max 4.050000e+06

Name: AMT_CREDIT, dtype: float64

outlier('AMT_CREDIT')

Outlier Analysis of AMT_CREDIT



#Most of the values are lying between 200000 and 800000. above 1.6M outliers are visible.

#Analysis of AGE

dfnew.PERSON_AGE.describe()

count 1.430155e+06

mean 4.419713e+01

std 1.190810e+01

min 2.000000e+01

25% 3.400000e+01

50% 4.300000e+01

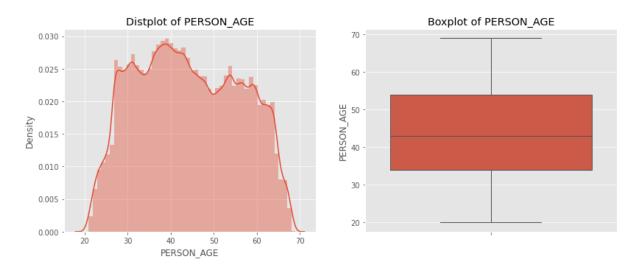
75% 5.400000e+01

max 6.900000e+01

Name: PERSON_AGE, dtype: float64

outlier('PERSON_AGE')

Outlier Analysis of PERSON_AGE



#There are no outliers and most of the applicants are in between 35 and 55 years of age

#Analysis of YEARS_EMPLOYED

dfnew.YEARS_EMPLOYED.describe()

count 1.430155e+06

mean 1.982652e+02

std 3.924261e+02

min 0.000000e+00

25% 2.000000e+00

50% 6.000000e+00

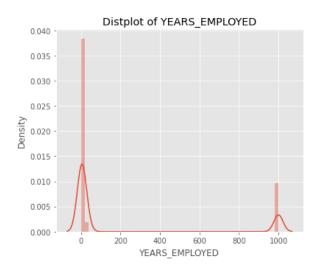
75% 1.700000e+01

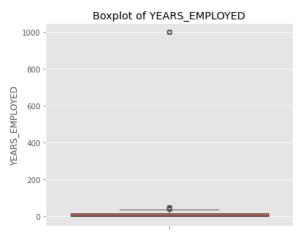
max 1.000000e+03

Name: YEARS_EMPLOYED, dtype: float64

outlier('YEARS_EMPLOYED')

Outlier Analysis of YEARS_EMPLOYED





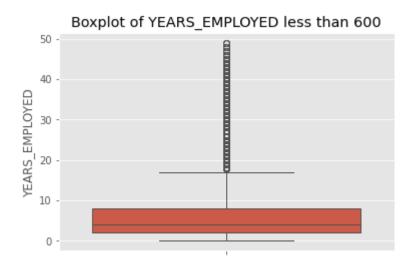
#OBservation: there are outliers

#Check how many values lies above 600

dfnew[dfnew.YEARS_EMPLOYED > 600].shape

(276368, 52)

#there are values at 1000 yrs of employment which is not logical.lets ignore outliers sns.boxplot(y=dfnew[dfnew['YEARS_EMPLOYED']< 600]['YEARS_EMPLOYED']) plt.title("Boxplot of YEARS_EMPLOYED less than 600") plt.show()



#Observation: Most of the values lies within 10 years of employment

#Categorical Analysis- Bucketing age data

dfnew['AGE_GROUP']=pd.cut(dfnew.PERSON_AGE,[0,20,30,40,50,60,999],labels=['0-20','20-30','30-40','40-50','50-60','60+'])

```
dfnew.AGE_GROUP.value_counts(normalize=True)*100
30-40 26.573903
40-50 24.624534
50-60 22.663348
20-30 15.316592
60+
    10.821345
0-20 0.000280
Name: AGE_GROUP, dtype: float64
#create buckets for YEARS_EMPLOYED
dfnew['YEARS_OF_EMPLOYEMENT']=pd.cut(dfnew.YEARS_EMPLOYED,bins=[0,5,10,15,20,25,30,35,40
,9999],labels=['0-5','5-10','10-15','15-20','20-25','25-30','30-35','35-40','40 & above'])
dfnew.YEARS_OF_EMPLOYEMENT.value_counts(normalize=True)*100
0-5
        42.604137
5-10
        21.048733
40 & above 20.994422
10-15
         8.240442
15-20
        3.424295
20-25
        1.869285
25-30
        0.995922
30-35
         0.604613
35-40
         0.218151
Name: YEARS OF EMPLOYEMENT, dtype: float64
#Create buckets for AMT_INCOME_TOTAL
dfnew['AMT_INCOME_RANGE']=pd.qcut(dfnew.AMT_INCOME_TOTAL,q=[0,0.2,0.5,.75,.95,1], labels
= ['VERY_LOW','LOW','MEDIUM','HIGH','VERY_HIGH'])
dfnew.AMT_INCOME_RANGE.value_counts(normalize=True)*100
VERY LOW 29.098524
LOW
         27.065947
HIGH
        19.993917
MEDIUM
           19.161489
```

VERY_HIGH 4.680122

Name: AMT_INCOME_RANGE, dtype: float64

#Analysis of Target variable with Bar graph

plt.figure(figsize=(10,6))

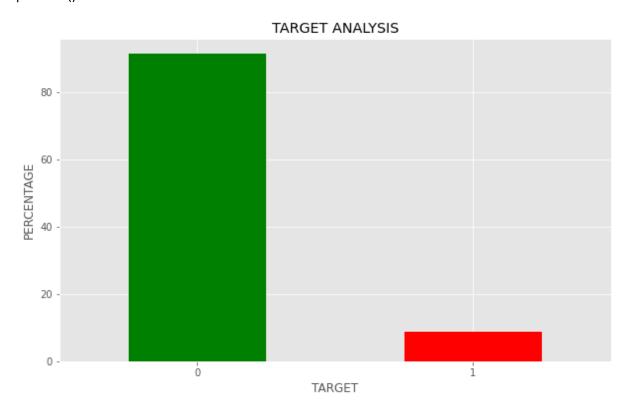
(dfnew.TARGET.value_counts(normalize=True)*100).plot.bar(title='TARGET ANALYSIS',color=['Green','Red'])

plt.xlabel('TARGET')

plt.ylabel('PERCENTAGE')

plt.xticks(rotation=0)

plt.show()



#from the chart it's clear that more than 80% of loan applicants are non defaulters and there are defaulters below 20%

#There is a data imbalance

For finding imbalace ratio split dataframe dfnew to 2,one with Target=1 and other with Target=0

#Create a new df with Target=1

TARGET_1=dfnew[dfnew.TARGET==1]

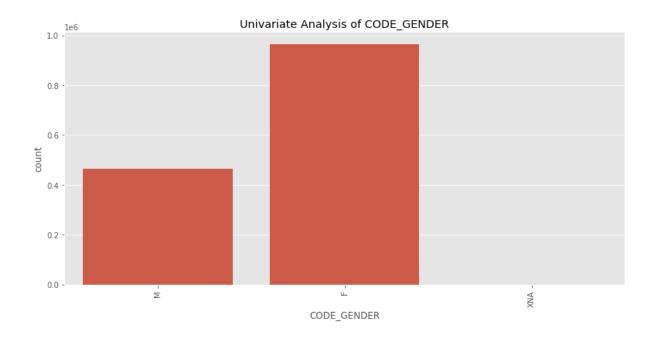
Create df for Target=0

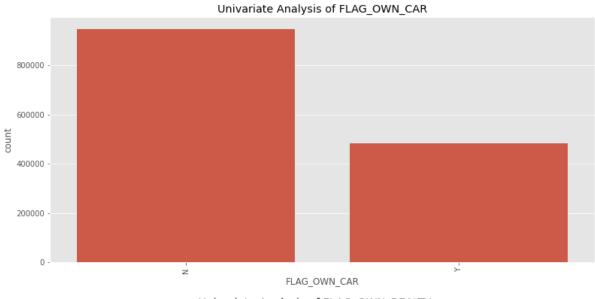
TARGET_0=dfnew[dfnew.TARGET==0]

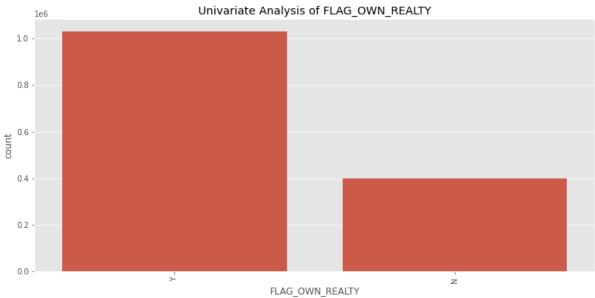
#check IMBALANCE

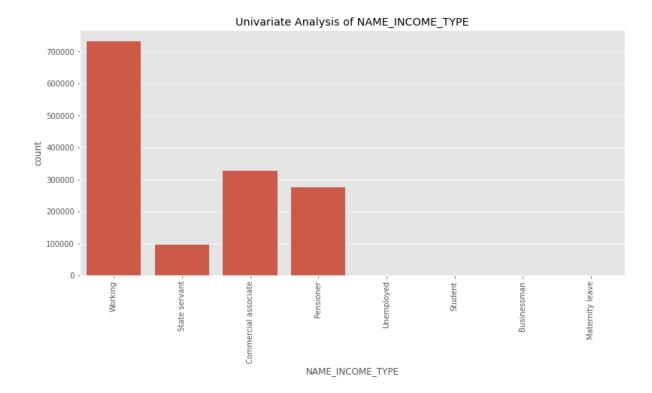
```
imbalace_ratio=len(TARGET_0)/len(TARGET_1)
imbalace_ratio
10.595224582455003
#the imbalance ratio is 10.59
#UNIVARIATE ANALYSIS
# Define function for unsegmented univariate Analysis
def uni_var(column):
  plt.figure(figsize=(13,6))
  sns.countplot(data=dfnew,x=column)
  plt.title("Univariate Analysis of"+ ' '+column)
  plt.xticks(rotation=90)
  Category_cols=['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY',
   'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
   'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE','ORGANIZATION_TYPE', 'AGE_GROUP',
   'YEARS_OF_EMPLOYEMENT','AMT_INCOME_RANGE']
for i in Category_cols:
  uni_var(i)
                             Univariate Analysis of NAME_CONTRACT_TYPE
     1e6
  1.2
  1.0
  0.8
  0.6
  0.4
  0.2
  0.0
```

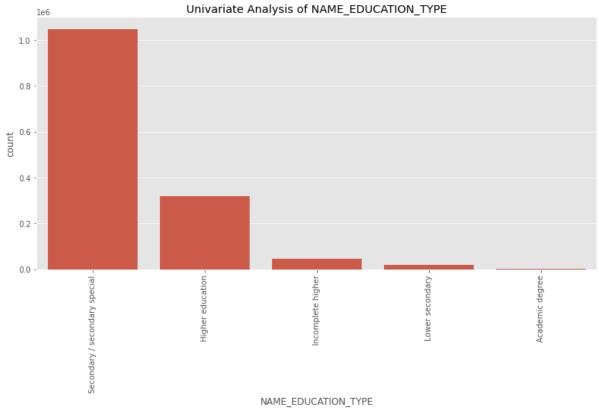
NAME_CONTRACT_TYPE

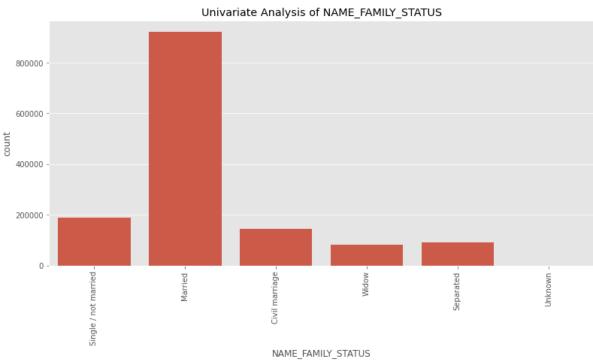


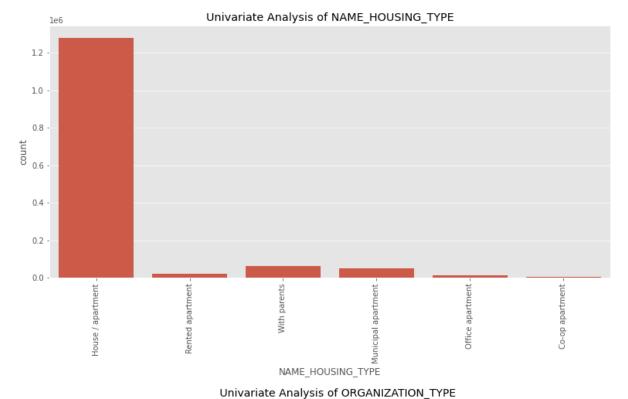


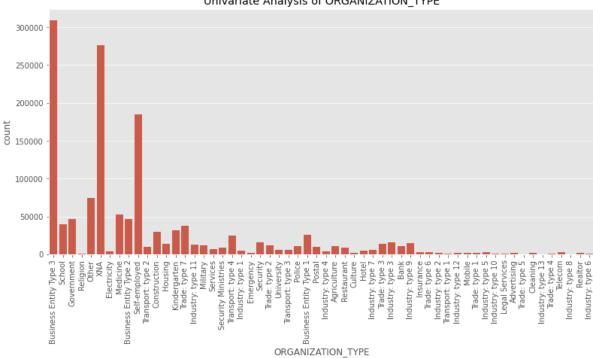


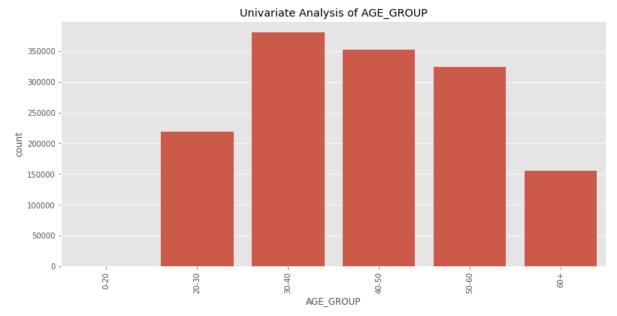




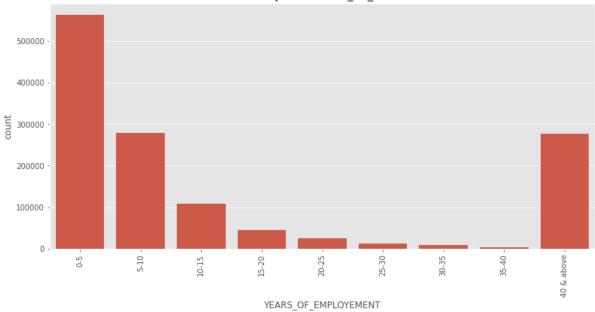


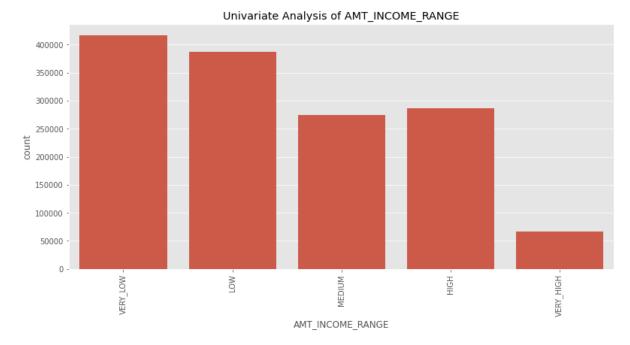












Observations:

- # 1.People rely more on cash loans than revolving loans
- # 2. The applicants are more female than male
- #3. Most of the applicants doesn't own a car
- # 4. But most of them own a property
- # 5. Working class has highest percentage of loans
- # 6. Majority of applicants with secondary education and people with high educatio have applied less
- #7. Most of the loan applicants are Married
- # 8. Business entity needs more money
- # 9. Majority of the applicants are in middle aged group
- #10. People with less employment experience are more applied for loans
- #11. Low and medium income people are more for loan application

#segmented univariate analysis

plt.style.use('default')

%matplotlib inline

plt.style.use('default')

%matplotlib inline

define function for countplot

def univar_count(column):

plt.figure(figsize=(13,6),facecolor='white')

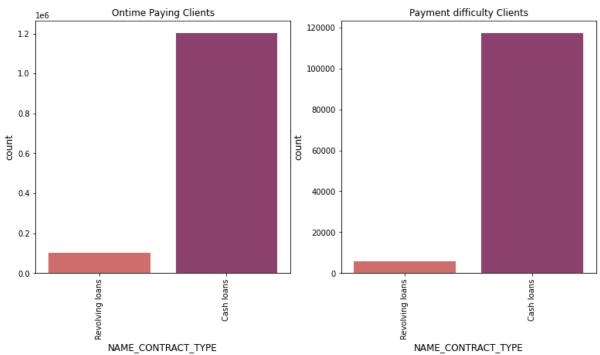
```
plt.rcParams["axes.labelsize"]=12
plt.subplot(1,2,1)

sns.countplot(data=TARGET_0,x=column,order=sorted(TARGET_0[column].value_counts().index,reve rse=True),palette='flare')
plt.title("Ontime Paying Clients")
plt.xticks(rotation=90)
plt.subplot(1,2,2)

sns.countplot(data=TARGET_1,x=column,order=sorted(TARGET_1[column].value_counts().index,reve rse=True),palette='flare')
plt.title("Payment difficulty Clients")
plt.xticks(rotation=90)
plt.suptitle('ANALYSIS OF'+' '+ column)
#Analysis of NAME_CONTRACT_TYPE
```



univar_count('NAME_CONTRACT_TYPE')



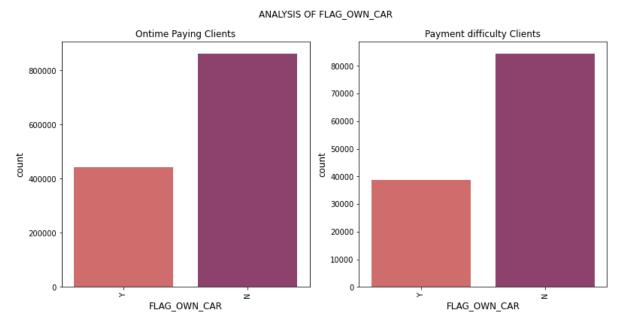
#observation: both ontime payers and default payers took cash loans than revolving loans

#Analysis of FLAG_OWN_CAR & FLAG_OWN_REALTY

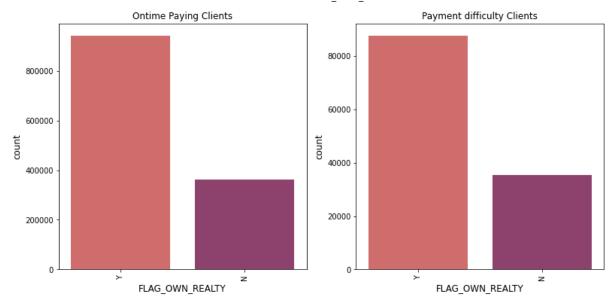
var=['FLAG_OWN_CAR','FLAG_OWN_REALTY']

for i in var:

univar_count(i)

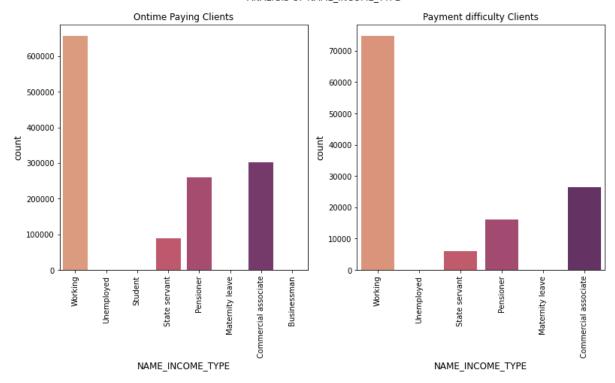






univar_count('NAME_INCOME_TYPE')

ANALYSIS OF NAME_INCOME_TYPE



#Observation: Working Class holds high place in both categories

#Pensioners and Commercial associate tend to pay loans on-time

#Students and Businessman also have no payment difficulties so bank can target them in future

#Analysis of NAME_EDUCATION_TYPE

plt.figure(figsize=(13,6),facecolor='white')

plt.rcParams["axes.labelsize"]=12

plt.subplot(1,2,1)

TARGET_0['NAME_EDUCATION_TYPE'].value_counts().plot.bar(color=['Green','Yellow','Orange','Red',' Black'])

plt.title("Ontime Paying Clients")

plt.xticks(rotation=90)

plt.xlabel('NAME_EDUCATION_TYPE')

plt.ylabel('Count')

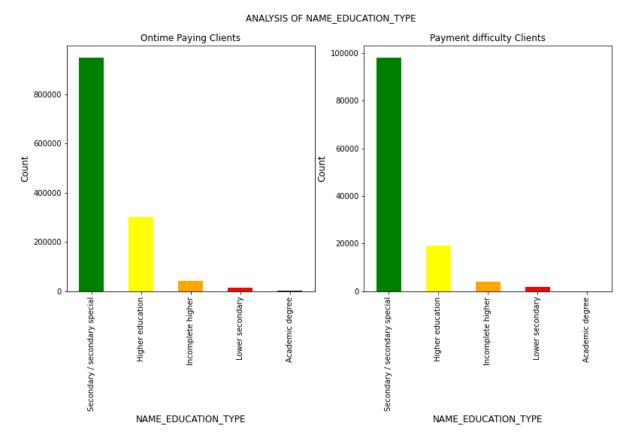
plt.subplot(1,2,2)

TARGET_1["NAME_EDUCATION_TYPE"].value_counts().plot.bar(color=['Green','Yellow','Orange','Red','Black'])

plt.title("Payment difficulty Clients")

plt.xticks(rotation=90)

```
plt.xlabel('NAME_EDUCATION_TYPE')
plt.ylabel('Count')
plt.suptitle('ANALYSIS OF NAME_EDUCATION_TYPE')
plt.show()
```



#observations:

Secondary/secondary special is high in both categories

plt.title("Clients with Payment Difficulties")

#Customers with Higher Education and Academic degree have higher ontime payments than defaulters and this can be because they are settled than others

```
#Analysis of NAME_FAMILY_STATUS

plt.figure(figsize=(13,6),facecolor='white')

plt.subplot(1,2,1)

TARGET_0['NAME_FAMILY_STATUS'].value_counts().plot.pie(autopct='%1.1f%%')

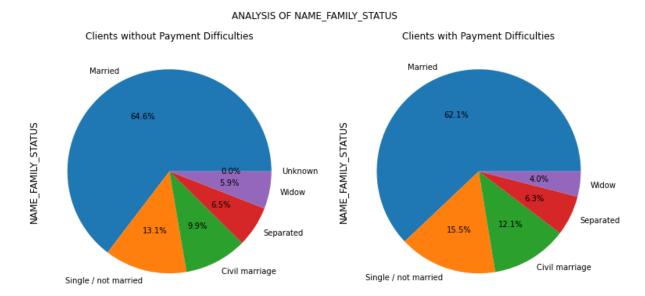
plt.title("Clients without Payment Difficulties")

plt.xticks(rotation=90)

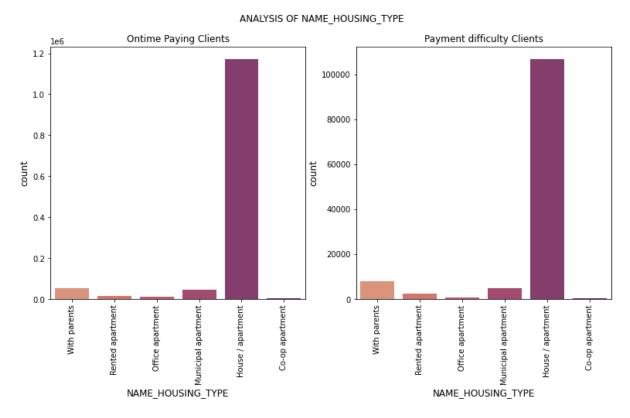
plt.subplot(1,2,2)

TARGET_1['NAME_FAMILY_STATUS'].value_counts().plot.pie(autopct='%1.1f%%')
```

plt.xticks(rotation=90) plt.suptitle('ANALYSIS OF NAME_FAMILY_STATUS') plt.show()



#Analysis of NAME_HOUSING_TYPE univar_count('NAME_HOUSING_TYPE')



Observation:

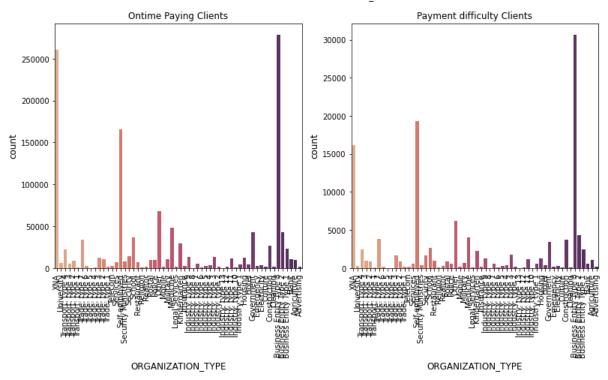
Clients with house/Apartment is high in both categories. This can be because for without payment difficulties they already have house and liability is less and for defaulters it is be because they may have housing loan also. Also this is contrary to FLAG OWN REALTY analysis

#When compared both category people with Rented Apartments and with parents have more payment difficulties than other. It may be because they have more liabilities than others

#Analysis of ORGANIZATION_TYPE

univar_count('ORGANIZATION_TYPE')

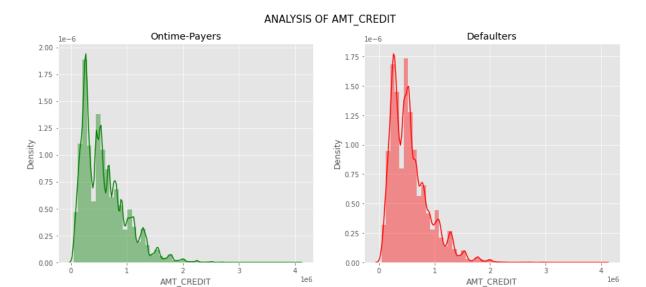
ANALYSIS OF ORGANIZATION_TYPE



#Define function for easy analysis

```
def uni_num(column):
   plt.style.use('ggplot')
   plt.figure(figsize=(15,6))
   plt.subplot(1,2,1)
   sns.distplot(TARGET_0[column],color="green")
   plt.title('Ontime-Payers')
   plt.subplot(1,2,2)
   sns.distplot(TARGET_1[column],color="red")
   plt.title('Defaulters')
   plt.suptitle('ANALYSIS OF'+' '+ column,size=15)
   plt.show()
```

#Analysis of AMT_CREDIT uni_num('AMT_CREDIT')



The graph shows the presence of outliers in both

#Approximately from 3 to 6 lakh there are more clients with difficulty in payments

plt.show()

```
#BIVARIATE ANALYSIS
# Define function for easy access for Analysis
plt.style.use('default')
%matplotlib inline
def scatter_plot(column1,column2):
  plt.figure(figsize=(15,6),facecolor='white')
  plt.subplot(1,2,1)
```

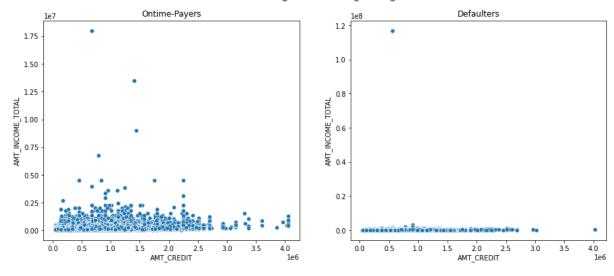
sns.scatterplot(data=TARGET_0,x=column1,y=column2) plt.title('Ontime-Payers') plt.subplot(1,2,2) sns.scatterplot(data=TARGET_1,x=column1,y=column2) plt.title('Defaulters')

plt.suptitle('ANALYSIS OF'+' '+ column1+' and '+column2)

Anaiysis of AMT_CREDIT & AMT_INCOME_TOTAL

scatter_plot('AMT_CREDIT','AMT_INCOME_TOTAL')

ANALYSIS OF AMT_CREDIT and AMT_INCOME_TOTAL



#presence of outliers noticed

Plot AMT_CREDIT,AMT_INCOME_TOTAL

plt.figure(figsize=(15,8),facecolor='white')

plt.subplot(1,2,1)

sns.scatterplot(data=TARGET_0,x=TARGET_0[TARGET_0.AMT_INCOME_TOTAL < 337500].AMT_INCOME_TOTAL,y=TARGET_0[TARGET_0.AMT_CREDIT < 1620000].AMT_CREDIT)

plt.title('Ontime-Payers')

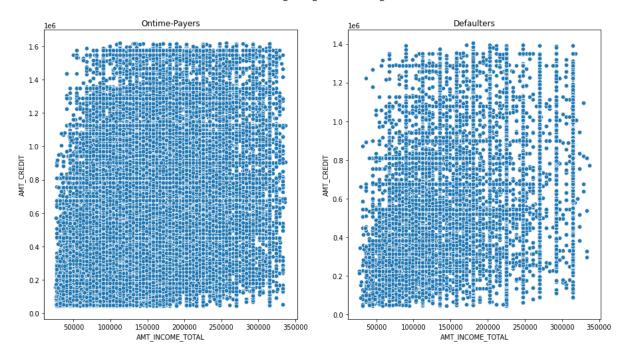
plt.subplot(1,2,2)

sns.scatterplot(data=TARGET_1,x=TARGET_1[TARGET_1.AMT_INCOME_TOTAL < 337500].AMT_INCOME_TOTAL,y=TARGET_1[TARGET_1.AMT_CREDIT < 1406688].AMT_CREDIT)

plt.title('Defaulters')

plt.suptitle('ANALYSIS OF AMT_TOTAL_INCOME vs AMT_CREDIT')

plt.show()



Observation:

#For Ontime payers its densely packed in all regions, but for Defaulters its densely packed in lower income-lower credit regions.

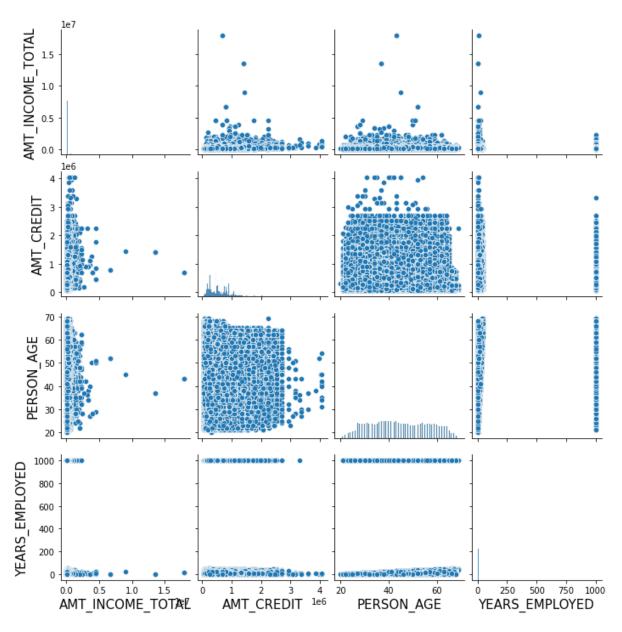
#So most of the defaulters are low income clients and bank should taken this to consideration
Multivariate Analysis

Analysing AMT_INCOME_TOTAL,AMT_CREDIT,PERSON_AGE,YEARS_EMPLOYED for TARGET_0 plt.figure(figsize=(21,6),facecolor='white')

plt.rc('xtick', labelsize=10)

plt.rc('ytick', labelsize=10)

sns.pairplot(TARGET_0[['AMT_INCOME_TOTAL','AMT_CREDIT','PERSON_AGE','YEARS_EMPLOYED']])
plt.show()



#Bivariate Analysis

```
# Using function for easy acess of variables
```

```
def numcat_bivar(column1,column2):

plt.figure(figsize=(21,6),facecolor='white')

plt.rc('xtick', labelsize=12)

plt.rc('ytick', labelsize=12)

plt.rcParams['axes.labelsize']=15

plt.rcParams
```

plt.subplot(1,2,1)

```
sns.boxplot(data=TARGET_0,x=column1,y=column2,order=sorted(TARGET_0[column1].value_counts().index,reverse=True))

plt.title('Ontime-Payers',size=15)

plt.xticks(rotation=90)

plt.subplot(1,2,2)

sns.boxplot(data=TARGET_1,x=column1,y=column2,order=sorted(TARGET_1[column1].value_counts().index,reverse=True))

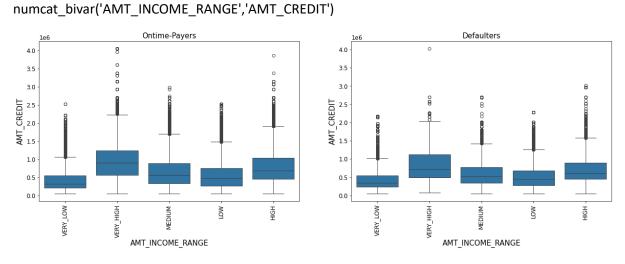
plt.title('Defaulters',size=15)

plt.xticks(rotation=90)

plt.show()

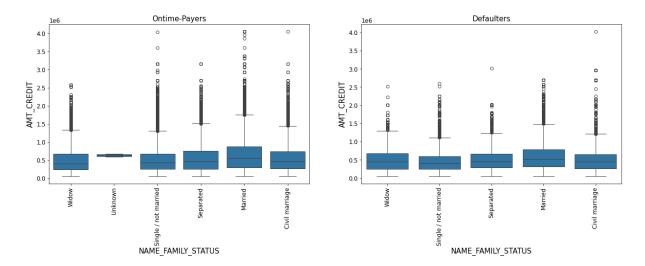
# Analysis of NAME_EDUCATION_TYPE,AMT_CREDIT

#plt.figure(figsize=(5,8),facecolor='white')
```



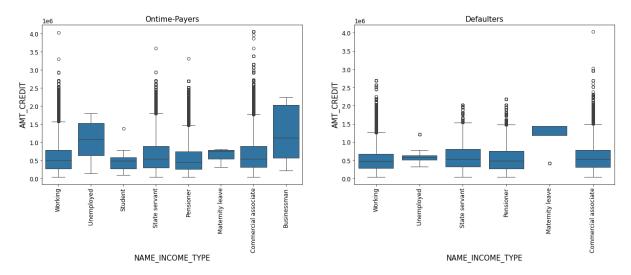
#High and Very_High got more credit amount than lower income categories and their presence is high in Ontime payers category

numcat_bivar('NAME_FAMILY_STATUS','AMT_CREDIT')



#Married follows by Separated got higher credits has no payment difficulties

numcat_bivar('NAME_INCOME_TYPE','AMT_CREDIT')

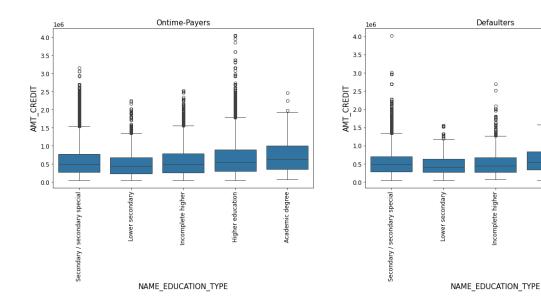


#Bussinessman who got high loan amount tends to pay it ontime

#Similarly Student eventhough credit amount is low tends to pay ontime

#But Maternity leave clients eventhough their representation is less in data tends to have more payement difficulty than ontime payment

numcat_bivar('NAME_EDUCATION_TYPE','AMT_CREDIT')

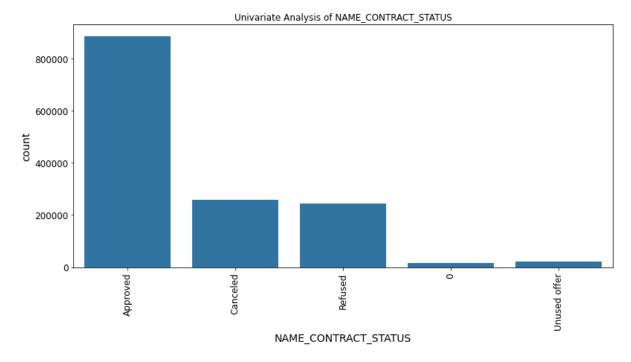


#OBSERVATIONS: Higher Education and Academic degree received more credits and their presence is more in Ontime paying category

Defaulters

ncomplete higher

```
#As Education level is low defaulting tendency is high
plt.style.use('default')
%matplotlib inline
# define function
def uni_var_cat(column):
  plt.figure(figsize=(13,6),facecolor='white')
  plt.rcParams['axes.labelsize']=14
  plt.rc('xtick', labelsize=12)
  plt.rc('ytick', labelsize=12)
  sns.countplot(data=dfnew,x=column)
  plt.title("Univariate Analysis of"+ ' '+column)
  plt.xticks(rotation=90)
  plt.show()
# Select categorical variables for analysis
categorical=['NAME_CASH_LOAN_PURPOSE', 'NAME_PAYMENT_TYPE', 'NAME_CLIENT_TYPE',
'NAME_GOODS_CATEGORY',
   'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE', 'CHANNEL_TYPE',
   'NAME_SELLER_INDUSTRY']
# Analysis of NAME_CONTRACT_STATUS
uni_var_cat('NAME_CONTRACT_STATUS')
```

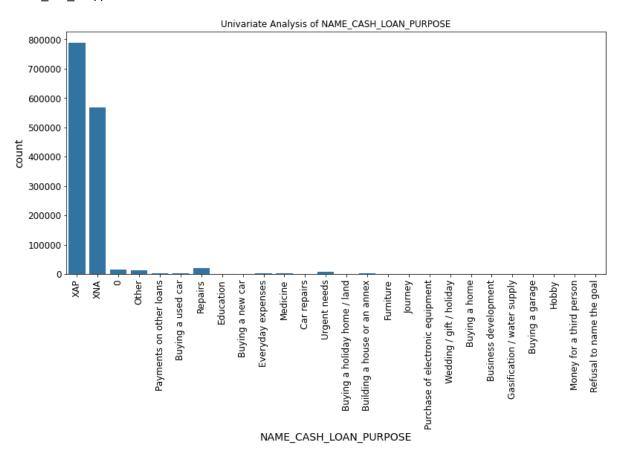


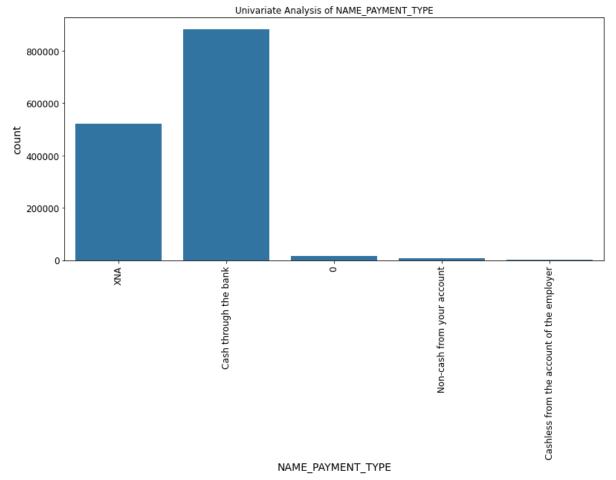
#most of the appplications are approved than canceled or refused

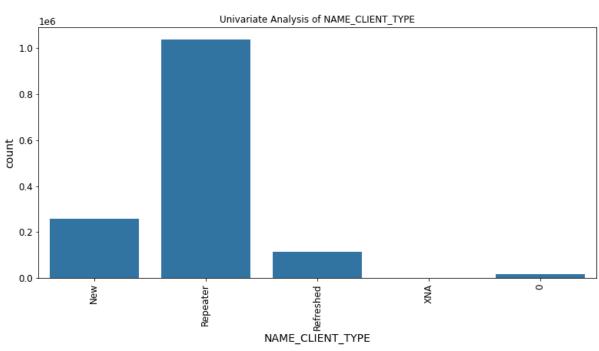
Analysis of other variables

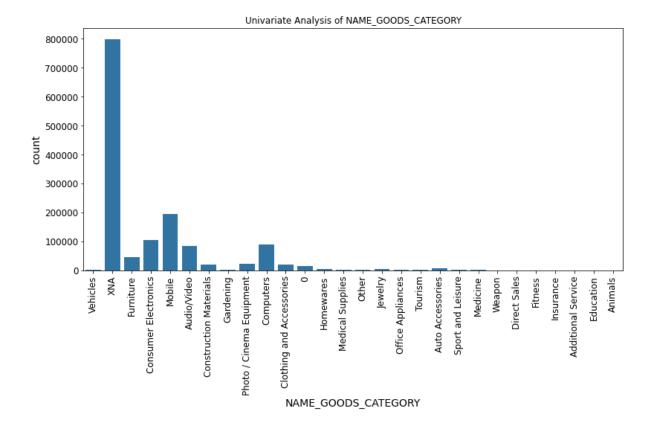
for i in categorical:

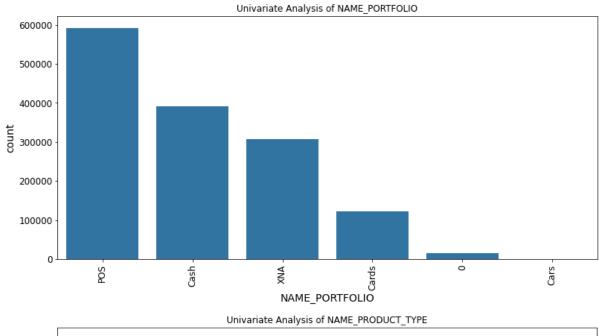
uni_var_cat(i)

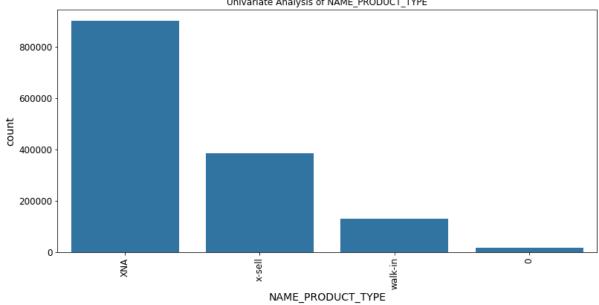


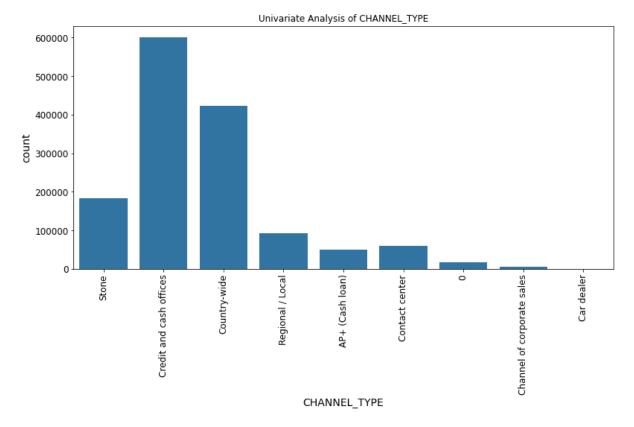


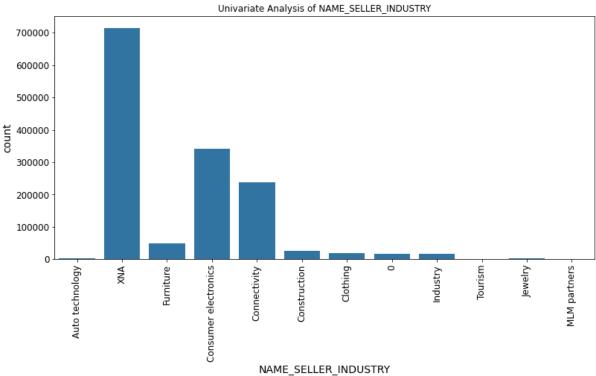












#Majority of the clients use loan for repairs, other and urgent needs. Rest of the parameters have negligible participation

#Clients done loan repayment through bank by cash

#Already existing client outnumbered New clients

#Majority of clients applied for Mobiles in previous Application(Ignoring xna)

#Most of the previous loan applications was for Point of sale followed by Cash and Cards

#Majority of the previuos application was cross shell than walkin.But most of the values was not filled properly

#Through Credit and cash offices and country-wide most of the previous clients were acquired #consumer electronics and Connectivity are the good seller industries(ignoring XNA)

#Bivariate Analysis

```
def num_cat_bivar(column1,column2):

plt.figure(figsize=(20,6),facecolor='white')

plt.rcParams['axes.labelsize']=14

plt.rc('xtick', labelsize=12)

plt.rc('ytick', labelsize=12)

sns.barplot(data=dfnew,x=column1,y=column2,estimator=lambda x:np.quantile(x,0.75),color='yellow')

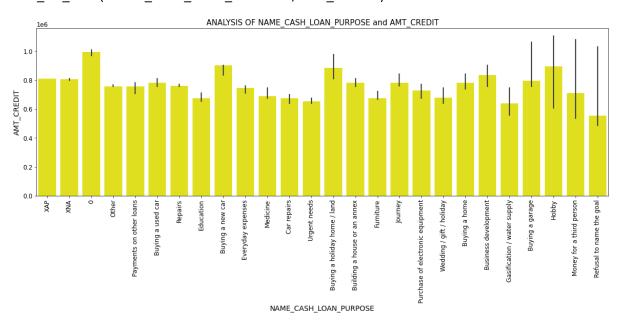
plt.title('ANALYSIS OF'+' '+ column1+' and '+column2,size=15)

plt.xticks(rotation=90)

plt.show()
```

Analysis of NAME_CASH_LOAN_PURPOSE & AMT_CREDIT

num_cat_bivar('NAME_CASH_LOAN_PURPOSE','AMT_CREDIT')



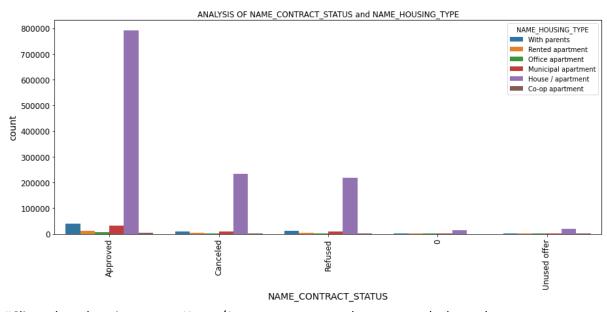
#Buying a home, Buying a car, Buying a holidayhome/land got more credit than other categories. We know for these loans avail funds by providing your asset as collateral to the lender. So bank can promote this type of safer loans

```
# Function definition

def cat_cat_new1(column1,column2):
    plt.figure(figsize=(15,6),facecolor='white')
    plt.rcParams['axes.labelsize']=14
    plt.rc('xtick', labelsize=12)
    plt.rc('ytick', labelsize=12)

sns.countplot(data=dfnew,x=column1,hue=column2,hue_order=sorted(dfnew[column2].value_count s().index,reverse=True))
    plt.title('ANALYSIS OF'+' '+ column1+' and '+column2)
    plt.xticks(rotation=90)
    plt.show()

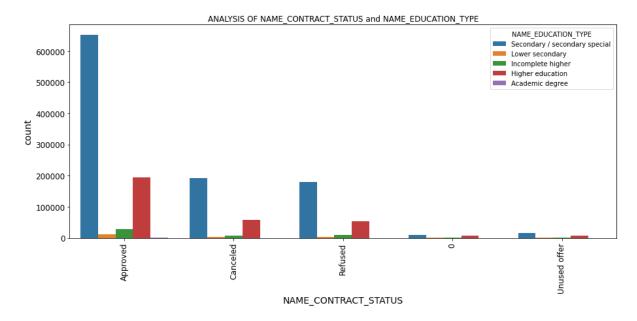
# Analysis of NAME_CONTRACT_STATUS & NAME_HOUSING_TYPE
```



#Clients have housing type as House/Apartment got more loan approvals than others

Analysis of NAME_CONTRACT_STATUS & NAME_EDUCATION_TYPE cat_cat_new1('NAME_CONTRACT_STATUS','NAME_EDUCATION_TYPE')

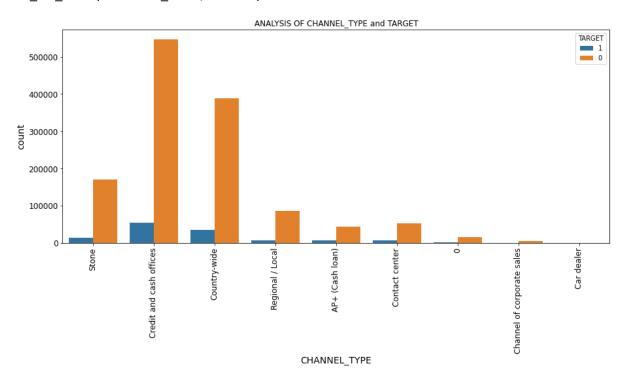
cat_cat_new1('NAME_CONTRACT_STATUS','NAME_HOUSING_TYPE')



#Secondary/Secondary special has got higher loan approvals followed by Higher Education in previous application.But they are high in defaulters category also

Analysis of CHANNEL_TYPE & TARGET

cat_cat_new1('CHANNEL_TYPE','TARGET')

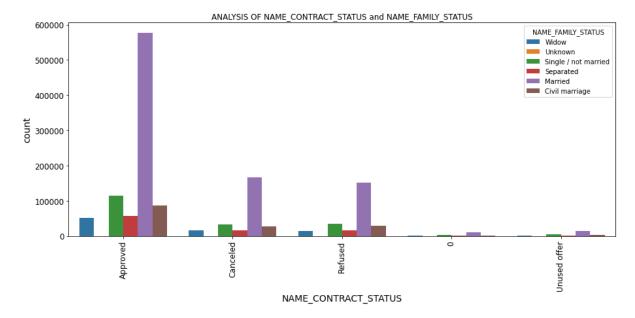


#Credit and cash offices has more clients without payement difficulties followes by country-wide

#Car dealer and Channel of corporate sales have clients who are defaulters

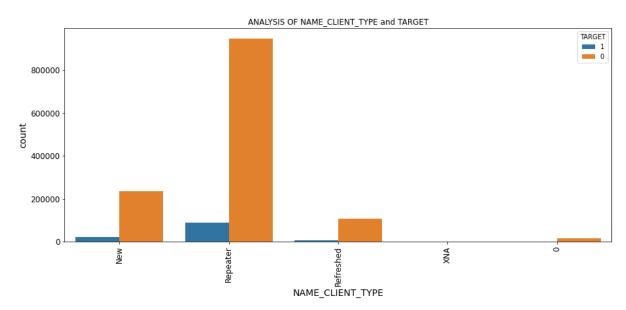
Analysis of NAME_CONTRACT_STATUS & NAME_FAMILY_STATUS

cat_cat_new1('NAME_CONTRACT_STATUS','NAME_FAMILY_STATUS')



Analysis of NAME_CLIENT_TYPE & TARGET

cat_cat_new1('NAME_CLIENT_TYPE','TARGET')



#Generally Repeaters or Old clients are ontime payers than New and Refreshed clients