Name: Dhaval Patel

Title: Assignment 1 - Data Preparation

In [233]:
```python
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

In [234]:
```python
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', -1)
```

```
<ipython-input-234-1390d13c0cdd>:4: FutureWarning: Passing a negative integer is depre
cated in version 1.0 and will not be supported in future version. Instead, use None to
not limit the column width.
  pd.set_option('display.max_colwidth', -1)
```

In [235]:
```python
INFILE = "HMEQ_Loss.csv"

TARGET_F = "TARGET_BAD_FLAG"
TARGET_A = "TARGET_LOSS_AMT"

df = pd.read_csv( INFILE )

'''
Print a transpose of the data so that it will fit on the screen
'''
# print( df.head() )
# print( df.head().T )
# df.head()
df.head().T
```

Out[235]:

	0	1	2	3	4
TARGET_BAD_FLAG	1	1	1	1	0
TARGET_LOSS_AMT	641.0	1109.0	767.0	1425.0	NaN
LOAN	1100	1300	1500	1500	1700
MORTDUE	25860.0	70053.0	13500.0	NaN	97800.0
VALUE	39025.0	68400.0	16700.0	NaN	112000.0
REASON	HomeImp	HomeImp	HomeImp	NaN	HomeImp
JOB	Other	Other	Other	NaN	Office
YOJ	10.5	7.0	4.0	NaN	3.0
DEROG	0.0	0.0	0.0	NaN	0.0
DELINQ	0.0	2.0	0.0	NaN	0.0
CLAGE	94.366667	121.833333	149.466667	NaN	93.333333
NINQ	1.0	0.0	1.0	NaN	0.0
CLNO	9.0	14.0	10.0	NaN	14.0
DEBTINC	NaN	NaN	NaN	NaN	NaN

In [236]:
```python
'''
Statistical description of data transposed
'''
# print(df.dtypes)
# print(df.describe())
print(df.dtypes)
df.describe().T
```

```
TARGET_BAD_FLAG    int64
TARGET_LOSS_AMT    float64
LOAN               int64
MORTDUE            float64
VALUE              float64
REASON             object
JOB                object
YOJ                float64
DEROG              float64
DELINQ             float64
CLAGE              float64
NINQ               float64
CLNO               float64
DEBTINC            float64
dtype: object
```

Out[236]:

	count	mean	std	min	25%	50%
TARGET_BAD_FLAG	5960.0	0.199497	0.399656	0.000000	0.000000	0.000000
TARGET_LOSS_AMT	1189.0	13414.576955	10839.455965	224.000000	5639.000000	11003.000000
LOAN	5960.0	18607.969799	11207.480417	1100.000000	11100.000000	16300.000000
MORTDUE	5442.0	73760.817200	44457.609458	2063.000000	46276.000000	65019.000000
VALUE	5848.0	101776.048741	57385.775334	8000.000000	66075.500000	89235.500000
YOJ	5445.0	8.922268	7.573982	0.000000	3.000000	7.000000
DEROG	5252.0	0.254570	0.846047	0.000000	0.000000	0.000000
DELINQ	5380.0	0.449442	1.127266	0.000000	0.000000	0.000000
CLAGE	5652.0	179.766275	85.810092	0.000000	115.116702	173.466667
NINQ	5450.0	1.186055	1.728675	0.000000	0.000000	1.000000
CLNO	5738.0	21.296096	10.138933	0.000000	15.000000	20.000000
DEBTINC	4693.0	33.779915	8.601746	0.524499	29.140031	34.818262

- We have 5960 people whether the loan flag bad or not. The average value for TARGET_BAD_FLAG shows about 19% of the people have bad loans.
- For the TARGET_LOSS_AMT flag counts shows that 1189 people that had bad loans and amount was not repaid. The average loan amount that was not repaid was 13414 dollars but that value went as high as 78987 dollars which is an outlier
- The minimum loan not repaid was 224 dollars that kind of small as well which is kind of unusual to see as well but as we observe 50% of loan amount not repaid is around 11,000 dollars.

In [237]:
```python
'''
Find the variables that are objects (strings), integers, and floats. Put their in a li
'''
dt = df.dtypes

objList = []
intList = []
floatList = []
for i in dt.index:
    if i in ([TARGET_F, TARGET_A]): continue #ignore these two columns
    if dt[i] in (["object"]): objList.append(i)
    if dt[i] in (["float64"]): floatList.append(i)
    if dt[i] in (["int64"]): intList.append(i)

print("OBJECTS ")
print(" ------- ")
for i in objList:
    print(i)
print(" ===============\n")

print("INTEGER ")
print(" ------- ")
for i in intList:
    print(i)
print("===============\n")


print("FLOAT ")
print(" ----- ")
for i in floatList:
    print(i)
print("===============\n")
```

```
OBJECTS
 -------
REASON
JOB
 ===============

INTEGER
 -------
LOAN
===============

FLOAT
 -----
MORTDUE
VALUE
YOJ
DEROG
DELINQ
CLAGE
NINQ
CLNO
DEBTINC
===============
```

In [238]:
```python
'''
EXPLORE THE CATEGORICAL / OBJECT VARIABLES
Group the dataframe by whatever CLASS REASON, JOB in this case save it into g variabl
Calculate mean value for objects based on TARGET flag if they bad loan or not
If the loan was bad calculate average loan amount for all object based on TARGET_A th

'''

for i in objList:
    print(" Class = ", i)
    g = df.groupby(i)  #group the dataframe by whatever CLASS REASON, JOB in this case
    print(g[i].count())
    x = g[ TARGET_F ].mean() #calculate mean value for objects based on TARGET flag i
    print( "Bad Loan Prob (Bank lost Money)", x )
    print( " ................. ")
    x = g[ TARGET_A ].mean()   #If the load was bad calculate average loan amount for
    print( "Loss Amount", x )
    print(" ===============\n\n\n ")
```

```
 Class =  REASON
REASON
DebtCon    3928
HomeImp    1780
Name: REASON, dtype: int64
Bad Loan Prob (Bank lost Money) REASON
DebtCon    0.189664
HomeImp    0.222472
Name: TARGET_BAD_FLAG, dtype: float64
 .................
Loss Amount REASON
DebtCon    16005.163758
HomeImp    8388.090909
Name: TARGET_LOSS_AMT, dtype: float64
 ===============



 Class =  JOB
JOB
Mgr        767
Office     948
Other      2388
ProfExe    1276
Sales      109
Self       193
Name: JOB, dtype: int64
Bad Loan Prob (Bank lost Money) JOB
Mgr        0.233377
Office     0.131857
Other      0.231993
ProfExe    0.166144
Sales      0.348624
Self       0.300518
Name: TARGET_BAD_FLAG, dtype: float64
 .................
Loss Amount JOB
Mgr        14141.536313
Office     13475.304000
Other      11570.102888
ProfExe    14660.966981
Sales      16421.447368
Self       22232.362069
Name: TARGET_LOSS_AMT, dtype: float64
 ===============
```

Analysis: Explore both Input (Categorical) and Target variables

Object: Reason(why do they want a loan)

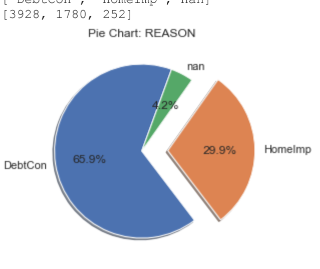
- We observed that 18.9% of the people who are consolidating debt had bad loans(TARGET_F) that might mean they are in financial trouble. The loan amount not repaid (TARGET_A) was 16000 dollars which is double than the amount of the loan that was not repaid with reasoning of home improvement.
- Whereas, 22.2% of the people who had reasoning of home improvement had bad loans (TARGET_F). The loan amount not repaid (TARGET_A) was around 8,000 dollars. Hence, it shows that reasoning consolidating debt is more risker than home improvement loans

Object: JOB(what do they do for living)

- Even though Self and Manager Sales jobs title have higher percentage of 30%(self) and 34% (sales) for bad loans percentage compare to other job titles and the loan amount not repaid is much is around 16,000 dollars for sales and 22,000 dollars for self employee job title. This indicates that these jobs are unstables and more riskier than others.
- The Office, Mgr, and ProfExe job should be stable and less riskier as the probability of bad loans is small and amount of loan not repaid is averaging less compare to others.

In [239]:
```python
'''
EXPLORE THE PIE CHART CATEGORICAL / OBJECT VARIABLES
We are not removing missing value while exploring using pie chart
'''

x = df["REASON"].value_counts(dropna=False)
theLabels = x.axes[0].tolist()
print(theLabels)
theSlices = list(x)
print(theSlices)
explodeList = [ 0 for i in theSlices ]
# print(explodeList)
explodeList[1] = 0.30
# print(explodeList)
plt.pie( theSlices,
        labels=theLabels,
        startangle = 70,
        explode=explodeList,
        shadow=True,
        autopct="%1.1f%%")
plt.title("Pie Chart: REASON")
plt.show()
```

```
['DebtCon', 'HomeImp', nan]
[3928, 1780, 252]
```

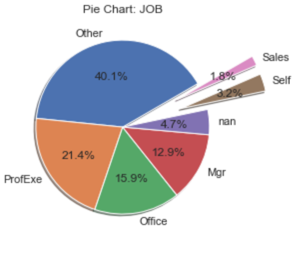


Analysis: Explore both the Input (Categorical) variables using Pie Chart

Pie Chart Analyisis 1: Reason(why do they want a loan)

- Based on the pie chart its shows 29.9% reasoning behind taking loan is for home improvement (HomeImp).
- Also, we see 4.2% of the data falls under the nan category since we haven't removed missing values from our data.
- Lastly, 65.9% of the data has consolidating debt (DebtCon) most common reasoning for taking loan which is risker because based on previous observation it had higher probability of having bad loans and amount not being repaid compare to home improvement loan.
- Since, 'DebtCon' reasoning is most common based on the pie chart will be using to imputate missing values with mode for categorical JOB variable.

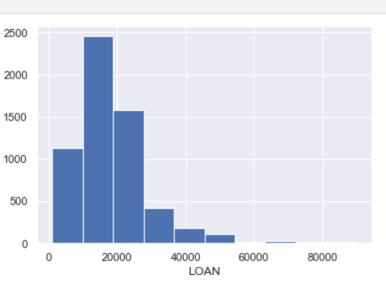
In [240]:
```python
x = df["JOB"].value_counts(dropna=False)
theLabels = x.axes[0].tolist()
# print(theLabels)
theSlices = list(x)
explodeList = [ 0 for i in theSlices ]
# print(explodeList)
explodeList[5] = 0.70
explodeList[6] = 0.70
# print(explodeList)
plt.pie( theSlices,
        labels=theLabels,
        startangle = 30,
        explode=explodeList,
        shadow=True,
        autopct="%1.1f%%")
plt.title("Pie Chart: " + i)
plt.show()
```



Pie Chart Analyisis 2: JOB(what do they do for living)

- Firstly, I was exploded 2 job titles 'Sales' and 'Self' in the pie chart above because even though they cover small portion of the data but based on prior observation they had higher probability of having bad loan and higher amount of loan was not repaid which makes it riskers jobs and less stable after to compare job titles.
- While, 40% of that have job titles 'Others' most common job title in this dataset, and needed further analysis it since we don't know specific job category. But based on prior observation on the probability of having bad loans (TARGET_F) 'Others' and 'Mgr' job title would be consider neutral and slight stable nor risky job titles.
- Since, 'Other' job title is most common based on the pie chart will be using to imputate missing values with mode for categorical JOB variable.
- Lastly, 21.4% of the data lie under 'ProfExec' and 15.9% under 'Office' are the most stable and less risky job titles compare to other job titles.

In [241]:
```python
'''
EXPLORE THE NUMERICAL INTEGER VARIABLES
WITH HISTOGRAM
'''

for i in intList :
    plt.hist(df[i])
    plt.xlabel(i)
    plt.show()
```

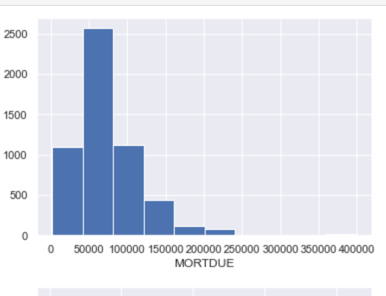


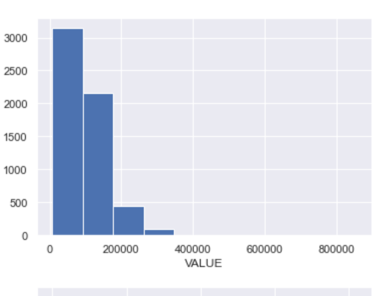
Analysis: Explore both the Input (Numerical) variables using Histogram

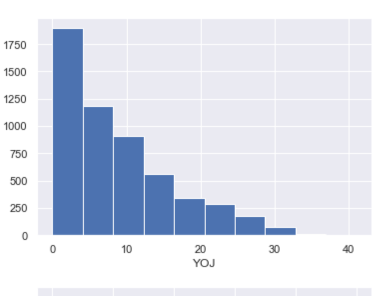
Histogram Analyisis 1: LOAN(HMEQ Credit Line)

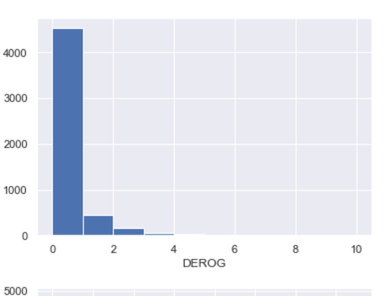
- The loan distribution based on the histogram plot shows data is right positively skewed because of outliers. Around 2500 people have taken loan amount of around 20,0000 dollars which would show that it would a good choice if we pick the median for the loan amount distribution to fillup missing values for the loan amount column
- Most of the data lies below loan amount of estimating 30,000 dollars, after that we observe that as load amount gradually increases less people are taking loans which makes sense based on different job titles, and reasoning for taking loans.
- Mild outliers to be consider based on distribution after 300,000 dollars less than 500 people took loan above that amount, and we see one extreme outlier someone took a loan of above 600,000 dollars

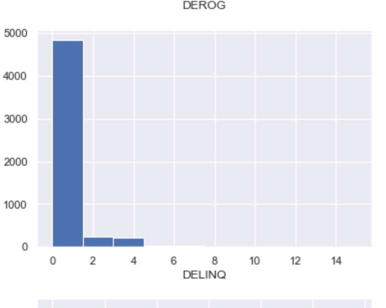
In [242]:
```python
'''
EXPLORE THE NUMERICAL FLOAT VARIABLES
WITH HISTOGRAM
'''

for i in floatList :
    plt.hist(df[i])
    plt.xlabel(i)
    plt.show()
```

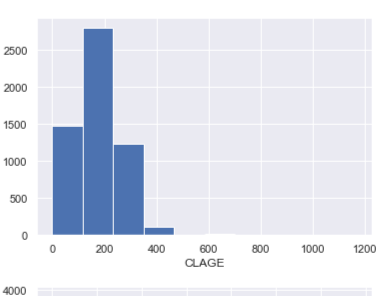


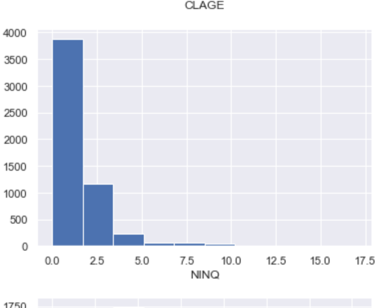


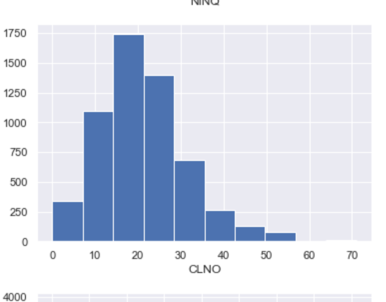


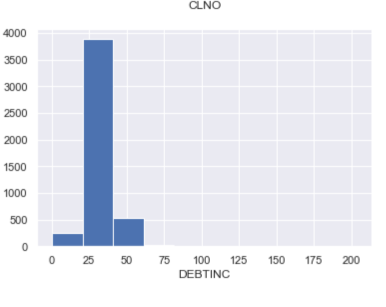








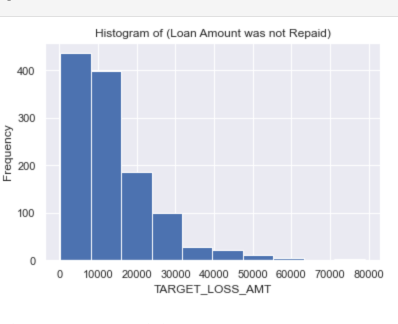




Histogram Analysis 2: Input (float Numerical variables)

- Based on all the histogram plot the credit line age (CLAGE), number of credit lines (CLNO), and debt income ratio (DEBTINC) distribution is almost normally distributed but slightly skewed to the right these variable have relationship with each other.
- For debt income ratio (DEBTINC) distribution the average of data lies above 25% to below 50% ideally is good sign that people with lower debt income ratio below 25% and between 25%-40% this (DEBTINC) ratio have better chance to get the loan or credit they want.
- All the other numerical variables such as outstanding mortgage balance (MORTDUE), home value (VALUE), years on job (YOJ), derogatory marks on credit (DEROG), delinquencies on the current report (DELINQ), and number of inquiries (NINQ) distribution of data is right positively skewed because of outliers. Analyzing the histogram it indicates that picking median to fill up missing value for these column would be good technqiue for now.

In [243]:
```python
'''
EXPLORE THE NUMERICAL FLOAT VARIABLES
WITH HISTOGRAM
'''
plt.hist(df[TARGET_A])
plt.title("Histogram of (Loan Amount was not Repaid)")
plt.ylabel("Frequency")
plt.xlabel("TARGET_LOSS_AMT")
plt.show()
```



Histogram Analysis 3: TARGET_LOSS_AMOUNT

- The pattern of skewness can be analyzed from histogram of loan distribution is showing more skewed to the right because of outliers.
- Most of the data lies be under 250,000 dollars of loan that was not repaid after that there mild outliers because less than 100 people that have not repaid amount higher than that 250,000 dollars
- We can see one extreme outlier loan amount of 600,000 dollars that was not repaid to the bank

In [244]:
```python
for i in objList:
    print(i)
    print(df[i].unique())
    g = df.groupby(i)
    print(g[i].count())
    print( "MOST COMMON = ", df[i].mode()[0]) #this is going to give string
    print( "MISSING = ", df[i].isna().sum())
    print( "\n")
```

```
REASON
['HomeImp' nan 'DebtCon']
REASON
DebtCon    3928
HomeImp    1780
Name: REASON, dtype: int64
MOST COMMON =  DebtCon
MISSING =  252


JOB
['Other' nan 'Office' 'Sales' 'Mgr' 'ProfExe' 'Self']
JOB
Mgr        767
Office     948
Other      2388
ProfExe    1276
Sales      109
Self       193
Name: JOB, dtype: int64
MOST COMMON =  Other
MISSING =  279
```

Exploration Analysis: Object Variables

- First, we tried find the unique value and count of our categorical variables.
- We found out that consolidating debt(DebtCon) is most common reasoning to taking loans in our dataset, and it has 252 missing values.
- Similarly, most common job title is Other in our dataset, the JOB column has 279 missing values.

In [245]:
```python
"""
IMPUTATED Means fixing missing value
FILL IN MISSING WITH THE MODE
"""

for i in objList:
    if df[i].isna().sum() == 0: continue
    print(i)
    print("HAS MISSING")
    NAME = "IMP_"+i
    print( NAME )
    df[NAME] = df[i]  #create an exact copy of job into IMP_JOB has an example
    df[NAME] = df[NAME].fillna(df[NAME].mode()[0]) #Other is what we filled it with mo
    print( "variable",i," has this many missing", df[i].isna().sum() )
    print( "variable",NAME," has this many missing", df[NAME].isna().sum() )

    g = df.groupby(NAME)
    print(g[NAME].count())
    print("\n")
#     df = df.drop( i, axis = 1)
```

```
REASON
HAS MISSING
IMP_REASON
variable REASON  has this many missing 252
variable IMP_REASON  has this many missing 0
IMP_REASON
DebtCon    4180
HomeImp    1780
Name: IMP_REASON, dtype: int64


JOB
HAS MISSING
IMP_JOB
variable JOB  has this many missing 279
variable IMP_JOB  has this many missing 0
IMP_JOB
Mgr        767
Office     948
Other      2667
ProfExe    1276
Sales      109
Self       193
Name: IMP_JOB, dtype: int64
```

Exploration Analysis 1: Missing Values (Object Variables)

- Always create a new variable "IMP_" Imputated_value variable to fix missing values. Because if anyone else is using the dataset they would assume original variable has missing values. We created imputated job (IMP_JOB) and imputated reason (IMP_REASON) as new variables so there is no confusion.
- We are filling up the missing value using mode which most common job and reasoning in our dataset based on pie chart.
- This is one of the technique we are using to fill up the missing values since we don't have a lot of missing values in our dataset for these columns. But based business rules after further exploratory data analysis if some of these value are highly predictive we came back to revisit the technique we are using to fill up missing values

In [246]:
```python
for i in objList:
    print(" Class = ", i)
    print(df[i].unique())
    g = df.groupby(i)  #group the dataframe by whatever CLASS REASON, JOB in this case
    x = g[ TARGET_F ].mean() #calculate mean value for objects based on TARGET flag i
    print( "Bad Loan Prob (Bank lost Money)", x )
    print( " ................. ")
    x = g[ TARGET_A ].mean()   #If the load was bad calculate average loan amount for
    print( "Loss Amount (Loan amount not repaid)", x )
    print(" ===============\n\n\n ")
```

```
 Class =  REASON
['HomeImp' nan 'DebtCon']
Bad Loan Prob (Bank lost Money) REASON
DebtCon    0.189664
HomeImp    0.222472
Name: TARGET_BAD_FLAG, dtype: float64
 .................
Loss Amount (Loan amount not repaid) REASON
DebtCon    16005.163758
HomeImp    8388.090909
Name: TARGET_LOSS_AMT, dtype: float64
 ===============



 Class =  JOB
['Other' nan 'Office' 'Sales' 'Mgr' 'ProfExe' 'Self']
Bad Loan Prob (Bank lost Money) JOB
Mgr        0.233377
Office     0.131857
Other      0.231993
ProfExe    0.166144
Sales      0.348624
Self       0.300518
Name: TARGET_BAD_FLAG, dtype: float64
 .................
Loss Amount (Loan amount not repaid) JOB
Mgr        14141.536313
Office     13475.304000
Other      11570.102888
ProfExe    14660.966981
Sales      16421.447368
Self       22232.362069
Name: TARGET_LOSS_AMT, dtype: float64
 ===============
```

Convert the Object variables to Numerical variables Using One-Hot Encoding.

- Creating flag variables for JOB and REASON based on category. In one-hot encoding flag variable that matches criteria will hot set to 1 rest of the flag variables will set to 0
- One-Hot encoding for REASON as category variable and JOB as categorical variable will be used in following method below
- Both variables JOB and REASON (categorical) are predictive of both prob of bad loans and amount loan not repaid
- z_ flag for categorical variables

In [247]:
```python
for i in objList:
    if (i in objList):
        print("Class = ", i )
        thePrefix = "z_" + i #z_ Categorical Variables
        print( thePrefix )
        y = pd.get_dummies(df[i], prefix=thePrefix, dummy_na=False) #pd.get_dummies t
        print(type(y))
        print(y.head().T)
        df = pd.concat([df, y], axis=1)
        df = df.drop( i, axis = 1)
```

```
Class =  REASON
z_REASON
<class 'pandas.core.frame.DataFrame'>
                 0  1  2  3  4
z_REASON_DebtCon  0  0  0  0  0
z_REASON_HomeImp  1  1  1  0  1
Class =  JOB
z_JOB
<class 'pandas.core.frame.DataFrame'>
              0  1  2  3  4
z_JOB_Mgr      0  0  0  0  0
z_JOB_Office   0  0  0  0  1
z_JOB_Other    1  1  1  0  0
z_JOB_ProfExe  0  0  0  0  0
z_JOB_Sales    0  0  0  0  0
z_JOB_Self     0  0  0  0  0
```

In [248]:
```python
df.head().T
```

Out[248]:

	0	1	2	3	4
TARGET_BAD_FLAG	1	1	1	1	0
TARGET_LOSS_AMT	641.0	1109.0	767.0	1425.0	NaN
LOAN	1100	1300	1500	1500	1700
MORTDUE	25860.0	70053.0	13500.0	NaN	97800.0
VALUE	39025.0	68400.0	16700.0	NaN	112000.0
YOJ	10.5	7.0	4.0	NaN	3.0
DEROG	0.0	0.0	0.0	NaN	0.0
DELINQ	0.0	2.0	0.0	NaN	0.0
CLAGE	94.366667	121.833333	149.466667	NaN	93.333333
NINQ	1.0	0.0	1.0	NaN	0.0
CLNO	9.0	14.0	10.0	NaN	14.0
DEBTINC	NaN	NaN	NaN	NaN	NaN
IMP_REASON	HomeImp	HomeImp	HomeImp	DebtCon	HomeImp
IMP_JOB	Other	Other	Other	Other	Office
z_REASON_DebtCon	0	0	0	0	0
z_REASON_HomeImp	1	1	1	0	1

z_JOB_Mgr	0	0	0	0	0
z_JOB_Office	0	0	0	0	1
z_JOB_Other	1	1	1	0	0
z_JOB_ProfExe	0	0	0	0	0
z_JOB_Sales	0	0	0	0	0
z_JOB_Self	0	0	0	0	0

In [249…

```
#Adding IMP_JOB and IMP_REASON to the object list
dt = df.dtypes
objList = []
for i in dt.index:
    if i in ([TARGET_F, TARGET_A]) : continue
    if dt[i] in (["object"]) : objList.append(i)
objList
```

Out[249…

```
['IMP_REASON', 'IMP_JOB']
```

In [250…

```
#Analysis to see if we can throw one of the one-encoding flag variables
SomeData = df.head().T
for r in range( SomeData.shape[0] ):
    print( SomeData.iloc[r,] )
    print("---")
```

```
0    1
1    1
2    1
3    1
4    0
Name: TARGET_BAD_FLAG, dtype: object
---
0    641.0
1    1109.0
2    767.0
3    1425.0
4    NaN
Name: TARGET_LOSS_AMT, dtype: object
---
0    1100
1    1300
2    1500
3    1500
4    1700
Name: LOAN, dtype: object
---
0    25860.0
1    70053.0
2    13500.0
3    NaN
4    97800.0
Name: MORTDUE, dtype: object
---
0    39025.0
1    68400.0
2    16700.0
3    NaN
4    112000.0
Name: VALUE, dtype: object
---
0    10.5
1    7.0
2    4.0
3    NaN
4    3.0
Name: YOJ, dtype: object
---
0    0.0
1    0.0
2    0.0
3    NaN
4    0.0
Name: DEROG, dtype: object
---
0    0.0
1    2.0
2    0.0
3    NaN
4    0.0
Name: DELINQ, dtype: object
---
0    94.366667
1    121.833333
2    149.466667
3    NaN
4    93.333333
Name: CLAGE, dtype: object
---
0    1.0
1    0.0
2    1.0
3    NaN
4    0.0
Name: NINQ, dtype: object
---
0    9.0
1    14.0
2    10.0
3    NaN
4    14.0
Name: CLNO, dtype: object
---
0    NaN
1    NaN
2    NaN
3    NaN
4    NaN
Name: DEBTINC, dtype: object
---
0    HomeImp
1    HomeImp
2    HomeImp
3    DebtCon
4    HomeImp
Name: IMP_REASON, dtype: object
---
0    Other
1    Other
2    Other
3    Other
4    Office
Name: IMP_JOB, dtype: object
---
0    0
1    0
2    0
3    0
4    0
Name: z_REASON_DebtCon, dtype: object
---
0    1
1    1
2    1
3    0
4    1
Name: z_REASON_HomeImp, dtype: object
---
0    0
1    0
2    0
3    0
4    0
Name: z_JOB_Mgr, dtype: object
---
0    0
1    0
2    0
3    0
4    1
Name: z_JOB_Office, dtype: object
---
0    1
1    1
2    1
3    0
4    0
Name: z_JOB_Other, dtype: object
---
0    0
1    0
2    0
3    0
4    0
Name: z_JOB_ProfExe, dtype: object
---
0    0
1    0
2    0
3    0
4    0
Name: z_JOB_Sales, dtype: object
---
0    0
1    0
2    0
3    0
4    0
Name: z_JOB_Self, dtype: object
---
```

In [251…

```
#Adding both Integer and Floating type numerical variables into numList
dt = df.dtypes
numList = []
for i in dt.index:
    if i in ([TARGET_F, TARGET_A]): continue #ignore these two columns
    if dt[i] in (["int64", "float64"]): numList.append(i)
numList
```

Out[251…

```
['LOAN',
 'MORTDUE',
 'VALUE',
 'YOJ',
 'DEROG',
 'DELINQ',
 'CLAGE',
 'NINQ',
 'CLNO',
 'DEBTINC']
```

Exploration Analysis 1: Missing Values (For VALUE Numerical Variables)

- To imputate missing for 'VALUE' of the house variable based on the analysis we first grouped by imputated job with median of missing value was one good technique.
- When we grouped 'IMP_JOB' with other variables such as 'DEBTINC' ratio but the median was constant for all job category that's reason when grouped by 'VALUE' with 'IMP_JOB' the median value of the house was more reasonable in term of job title.
- If loan was not repaid to the bank by people their property held as collateral for loans. Therefore, the value of the house tieing with job category would have further build better predictive model. Also analyzing person's information ability to pay loan to the bank.

In [252…

```
g = df.groupby("IMP_JOB")
i = "VALUE"
print( g[i].median())
```

```
IMP_JOB
Mgr        101258.0
Office      89094.5
Other       76864.5
ProfExe    110007.0
Sales       84473.5
Self       130631.0
Name: VALUE, dtype: float64
```

In [253…

```
i = "VALUE"
FLAG = "M_" + i
IMP = "IMP_"+ i

df[FLAG] = df[i].isna() + 0
df[IMP] = df[i]
df.loc[df[IMP].isna() & df["IMP_JOB"].isin(["Other"]), IMP] = 76864.5
df.loc[df[IMP].isna() & df["IMP_JOB"].isin(["Sales"]), IMP] = 84473.5
df.loc[df[IMP].isna() & df["IMP_JOB"].isin(["Office"]), IMP] = 89094.5
df.loc[df[IMP].isna() & df["IMP_JOB"].isin(["Mgr"]), IMP] = 101258.0
df.loc[df[IMP].isna() & df["IMP_JOB"].isin(["ProfExe"]), IMP] = 110007.0
df.loc[df[IMP].isna() & df["IMP_JOB"].isin(["Self"]), IMP] = 130631.0
df.loc[df[IMP].isna(), IMP] = df[i].median()
df = df.drop( i, axis=1)
# df = df.drop(["IMP_JOB", "IMP_REASON"], axis=1)
numList.remove(i)
```

Exploration Analysis 2: Missing Values (For All Numerical Variables)

- Always create a new variable "IMP_" Imputated_value variable to fix missing values. Because if anyone else is using the dataset they would assume original variable has missing values. We created imputated as new variables so there is no confusion.
- The FLAG variables = "M_" is to show that the following column had missing value we fixed this data. Sometimes data missing is highly predictive. Instead of boolean TRUE or FALSE, the flag is to 1 if the data is missing in that column
- We are filling up the missing value using median compare to the mean because it safest techniques especially when the flag is created it tends to count of any outliers that could skewing the data compare to average.
- This is one of the safest technique for starting off we are using to fill up the missing values since there could be a lot of variables less time for analysis. But based business rules after further exploratory data analysis if someone of these value are highly predictive we came back to revisit the technique we using to fill up missing values

In [254…

```
for i in numList:
    if df[i].isna().sum() == 0: continue  # If na.value == 0 we continue since there
    FLAG = "M_" + i  # Flag that this column had missing value I fixed this data
    IMP = "IMP_" + i
#     print(i)
#     print(df[i].isna().sum())
#     print(FLAG)
#     print(IMP)
#     print(" -------- ")
    df[FLAG] = df[i].isna() + 0  # If missing it is = 1, and if not missing = 0
    df[IMP] = df[i]  # copy the value and created an imputated value out of it
    df.loc[df[IMP].isna(), IMP] = df[i].median()  # If the value is missing fill it i
    df = df.drop( i, axis=1)
df = df.drop(["IMP_JOB", "IMP_REASON"], axis=1)
```

In [255…

```
print("DATA TYPES")
print(df.dtypes)
print("\n")

print("To see there are no mssing values except TARGET variables")
print(df.isna().sum())
```

```
DATA TYPES
TARGET_BAD_FLAG      int64
TARGET_LOSS_AMT      float64
LOAN                 int64
z_REASON_DebtCon     uint8
z_REASON_HomeImp     uint8
z_JOB_Mgr            uint8
z_JOB_Office         uint8
z_JOB_Other          uint8
z_JOB_ProfExe        uint8
z_JOB_Sales          uint8
z_JOB_Self           uint8
M_VALUE              int64
IMP_VALUE            float64
M_MORTDUE            int64
IMP_MORTDUE          float64
M_YOJ                int64
IMP_YOJ              float64
M_DEROG              int64
IMP_DEROG            float64
M_DELINQ             int64
IMP_DELINQ           float64
M_CLAGE              int64
IMP_CLAGE            float64
M_NINQ               int64
IMP_NINQ             float64
M_CLNO               int64
IMP_CLNO             float64
M_DEBTINC            int64
IMP_DEBTINC          float64
dtype: object


To see there are no mssing values except TARGET variables
TARGET_BAD_FLAG      0
TARGET_LOSS_AMT      4771
LOAN                 0
z_REASON_DebtCon     0
z_REASON_HomeImp     0
z_JOB_Mgr            0
z_JOB_Office         0
z_JOB_Other          0
z_JOB_ProfExe        0
z_JOB_Sales          0
z_JOB_Self           0
M_VALUE              0
IMP_VALUE            0
M_MORTDUE            0
IMP_MORTDUE          0
M_YOJ                0
IMP_YOJ              0
M_DEROG              0
IMP_DEROG            0
M_DELINQ             0
IMP_DELINQ           0
M_CLAGE              0
IMP_CLAGE            0
M_NINQ               0
IMP_NINQ             0
M_CLNO               0
IMP_CLNO             0
M_DEBTINC            0
IMP_DEBTINC          0
dtype: int64
```

Converted all categorical variables numeric variables

In [256…

```
df.head().T
```

Out[256…

	0	1	2	3	4
TARGET_BAD_FLAG	1.000000	1.000000	1.000000	1.000000	0.000000
TARGET_LOSS_AMT	641.000000	1109.000000	767.000000	1425.000000	NaN
LOAN	1100.000000	1300.000000	1500.000000	1500.000000	1700.000000
z_REASON_DebtCon	0.000000	0.000000	0.000000	0.000000	0.000000
z_REASON_HomeImp	1.000000	1.000000	1.000000	0.000000	1.000000
z_JOB_Mgr	0.000000	0.000000	0.000000	0.000000	0.000000
z_JOB_Office	0.000000	0.000000	0.000000	0.000000	1.000000
z_JOB_Other	1.000000	1.000000	1.000000	0.000000	0.000000
z_JOB_ProfExe	0.000000	0.000000	0.000000	0.000000	0.000000
z_JOB_Sales	0.000000	0.000000	0.000000	0.000000	0.000000
z_JOB_Self	0.000000	0.000000	0.000000	0.000000	0.000000
M_VALUE	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_VALUE	39025.000000	68400.000000	16700.000000	76864.500000	112000.000000
M_MORTDUE	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_MORTDUE	25860.000000	70053.000000	13500.000000	65019.000000	97800.000000
M_YOJ	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_YOJ	10.500000	7.000000	4.000000	7.000000	3.000000
M_DEROG	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_DEROG	0.000000	0.000000	0.000000	0.000000	0.000000
M_DELINQ	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_DELINQ	0.000000	2.000000	0.000000	0.000000	0.000000
M_CLAGE	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_CLAGE	94.366667	121.833333	149.466667	173.466667	93.333333
M_NINQ	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_NINQ	1.000000	0.000000	1.000000	1.000000	0.000000
M_CLNO	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_CLNO	9.000000	14.000000	10.000000	20.000000	14.000000
M_DEBTINC	1.000000	1.000000	1.000000	1.000000	1.000000
IMP_DEBTINC	34.818262	34.818262	34.818262	34.818262	34.818262

Summary Report

Hypothesis:

My hunch looking at the data is either correct or incorrect regarding people who have consolidating debt as reasoning for taking loans are more risky have any higher probability of having a bad loans, and more amount would not be repaid to the bank compare to the people who have home improvement reasoning for taking the loan.

Statistical Description Analysis

- We have 5960 people whether the loan flag bad or not. The average value for TARGET_BAD_FLAG shows about 19% of the people have bad loans.
- For the TARGET_LOSS_AMT flag counts shows that 1189 people that had bad loans and amount was not repaid. The average loan amount that was not repaid was 13414 dollars but that value went as high as 78987 dollars which is an outlier
- The minimum loan not repaid was 224 dollars that kind of small as well which is kind of unusual to see as well but as we observe 50% of loan amount not repaid is around 11,000 dollars.

Analysis: Explore both Input (Categorical) and Target variables

Object: Reason(why do they want a loan)

- We observed that 18.9% of the people who are consolidating debt had bad loans(TARGET_F) that might mean they are in financial trouble. The loan amount not repaid (TARGET_A) was 16000 dollars which is double than the amount of the loan that was not repaid with reasoning of home improvement.
- Whereas, 22.2% of the people who had reasoning of home improvement had bad loans (TARGET_F). The loan amount not repaid (TARGET_A) was around 8,000 dollars. Hence, it shows that reasoning consolidating debt is more risker than home improvement loans

Object: JOB(what do they do for living)

- Even though Self and Manager Sales jobs title have higher percentage of 30%(self) and 34% (sales) for bad loans percentage compare to other job titles and the loan amount not repaid is much is around 16,000 dollars for sales and 22,000 dollars for self employee job title. This indicates that these jobs are unstables and more riskier than others.
- The Office, Mgr, and ProfExe job should be stable and less riskier as the probability of bad loans is small and amount of loan not repaid is averaging less compare to others.

Analysis: Explore both the Input (Categorical) variables using Pie Chart

Pie Chart Analyisis 1: Reason(why do they want a loan)

- Based on the pie chart its shows 29.9% reasoning behind taking loan is for home improvement (HomeImp).
- Also, we see 4.2% of the data falls under the nan category since we haven't removed missing values from our data.
- Lastly, 65.9% of the data has consolidating debt (DebtCon) most common reasoning for taking loan which is risker because based on previous observation it had higher probability of having bad loans and amount not being repaid compare to home improvement loan.
- Since, 'DebtCon' reasoning is most common based on the pie chart will be using to imputate missing values with mode for categorical JOB variable.

Pie Chart Analyisis 2: JOB(what do they do for living)

- Firstly, I was exploded 2 job titles 'Sales' and 'Self' in the pie chart above because even though they cover small portion of the data but based on prior observation they had higher probability of having bad loan and higher amount of loan was not repaid which makes it riskers jobs and less stable after to compare job titles.
- While, 40% of that have job tiltes 'Others' most common job title in this dataset, and needed further analysis it since we don't know specific job category. But based on prior observation on the probability of having bad loans (TARGET_F) 'Others' and 'Mgr' job title would be consider neutral and slight stable nor risky job titles.
- Since, 'Other' job title is most common based on the pie chart will be using to imputate missing values with mode for categorical JOB variable.
- Lastly, 21.4% of the data lie under 'ProfExec' and 15.9% under 'Office' are the most stable and less risky job titles compare to other job titles.

Analysis: Explore both the Input (Numerical) variables using Histogram

Histogram Analysis 1: LOAN(HMEQ Credit Line)

- The loan distribution based on the histogram plot shows data is right positively skewed because of outliers. Around 2500 people have taken loan amount of around 20,0000 dollars which would show that it would a good choice if we pick the median for the loan amount distribution to fillup missing values for the loan amount column
- Most of the data lies below loan amount of estimating 30,000 dollars, after that we observe that as load amount gradually increases less people are taking loans which makes sense based on different job titles, and reasoning for taking loans.
- Mild outliers to be consider based on distribution after 300,000 dollars less than 500 people took loan above that amount, and we see one extreme outlier someone took a loan of above 600,000 dollars

Histogram Analysis 2: Input (float Numerical variables)

- Based on all the histogram plot the credit line age (CLAGE), number of credit lines (CLNO), and debt income ratio (DEBTINC) distribution is almost normally distributed but slightly skewed to the right these variable have relationship with each other.
- For debt income ratio (DEBTINC) distribution the average of data lies above 25% to below 50% ideally is good sign that people with lower debt income ratio below 25% and between 25%-40% this (DEBTINC) ratio have better chance to get the loan or credit they want.
- All the other numerical variables such as outstanding mortgage balance (MORTDUE), home value (VALUE), years on job (YOJ), derogatory marks on credit (DEROG), delinquencies on the current report (DELINQ), and number of inquiries (NINQ) distribution of data is right positively skewed because of outliers. Analyzing the histogram it indicates that picking median to fill up missing value for these column would be good technqiue for now.

Convert the Object variables to Numerical variables Using One-Hot Encoding.

- Creating flag variabls for JOB and REASON based on category. In one-hot encoding flag variable that matches criteria will hot set to 1 rest of the flag variables will set to 0
- One-Hot encoding for REASON as category variable and JOB as categorical variable will be used in following method above
- Both variables JOB and REASON (categorical) are predictive of both prob of bad loans and amount loan not repaid
- z_ flag for categorical variables

Exploration Analysis Missing Values (Object Variables)

- Always create a new variable "IMP_+i" Imputated_value variable to fix missing values. Because if anyone else is using the dataset they would assume original variable has missing values. We created imputated job (IMP_JOB) and imputated reason (IMP_REASON) as new variables so there is no confusion.
- We are filling up the missing value using mode which most common job and reasoning in our dataset.
- This is one of the technique we are using to fill up the missing values since we don't have a lot of missing values in our dataset for these columns. But based business rules after further exploratory data analysis if someone of these value are highly predictive we came back to revisit the technique we using to fill up missing values

Exploration Analysis 1: Missing Values (For VALUE Numerical Variables)

- To imputate missing for 'VALUE' of the house variable based on the analysis we first grouped by imputated job with median of missing value was one good technique.
- When we grouped 'IMP_JOB' with other variables such as 'DEBTINC' ratio but the median was constant for all job category that's reason when grouped by 'VALUE' with 'IMP_JOB' the median value of the house was more reasonable in term of job title.
- If loan was not repaid to the bank by people their property held as collateral for loans. Therefore, the value of the house tieing with job category would have further build better predictive model. Also analyzing person's information ability to pay loan to the bank.

Exploration Analysis 2: Missing Values (For All Numerical Variables)

- Always create a new variable "IMP_" Imputated_value variable to fix missing values. Because if anyone else is using the dataset they would assume original variable has missing values. We created imputated as new variables so there is no confusion.
- The FLAG variables = "M_" is to show that the following column had missing value we fixed this data. Sometimes data missing is highly predictive. Instead of boolean TRUE or FALSE, the flag is to 1 if the data is missing in that column
- We are filling up the missing value using median compare to the mean because it safest techniques especially when the flag is created it tends to count of any outliers that could skewing the data compare to average.
- This is one of the safest technique for starting off we are using to fill up the missing values since there could be a lot of variables less time for analysis. But based business rules after further exploratory data analysis if someone of these value are highly predictive we came back to revisit the technique we using to fill up missing values

In [ ]: