Assignment 1: Data Preparation

A collection of observations and interpretations based on the results of the analyses performed during the data preparation phase.

Overall Inspection of the Dataset

Column	Non-Null Count	Dtype
TARGET_BAD_FLAG	5960	int64
TARGET_LOSS_AMT	1189	float64
LOAN	5960	int64
MORTDUE	5442	float64
VALUE	5848	float64
REASON	5708	object
JOB	5681	object
YOJ	5445	float64
DEROG	5252	float64
DELINQ	5380	float64
CLAGE	5652	float64
NINQ	5450	float64
CLNO	5738	float64
DEBTINC	4693	float64
RangeIndex: 5960 entries, 0 to 5959		
Data columns (total 14 columns):		
dtypes: float64(10), int64(2), object(2)		

Observations:

- There are 14 variables in our dataset (2 target variables [`TARGET_BAD_FLAG` & `TARGET_LOSS_AMT`] and 12 other variables with information about the characteristics of the borrowers).
- There are 5960 entries in the dataset, and only two columns don't have any null/missing values (`TARGET_BAD_FLAG` and `LOAN`).
- All of the variable's data types appear to be assigned appropriately to what the variable represents.
- Two variables are objects (strings), and 12 are numerical (10 float & 2 integers).

Statistical Description of the Data

Variable	count	mean	std	min	25%	50%	75%	max
TARGET_BAD_FLAG	5960.0	0.199497	0.399656	0.000000	0.000000	0.000000	0.000000	1.000000
TARGET_LOSS_AMT	1189.0	13414.576955	10839.455965	224.000000	5639.000000	11003.000000	17634.000000	78987.000000
LOAN	5960.0	18607.969799	11207.480417	1100.000000	11100.000000	16300.000000	23300.000000	89900.000000
MORTDUE	5442.0	73760.817200	44457.609458	2063.000000	46276.000000	65019.000000	91488.000000	399550.000000
VALUE	5848.0	101776.048741	57385.775334	8000.000000	66075.500000	89235.500000	119824.250000	855909.000000
YOJ	5445.0	8.922268	7.573982	0.000000	3.000000	7.000000	13.000000	41.000000
DEROG	5252.0	0.254570	0.846047	0.000000	0.000000	0.000000	0.000000	10.000000
DELINQ	5380.0	0.449442	1.127266	0.000000	0.000000	0.000000	0.000000	15.000000
CLAGE	5652.0	179.766275	85.810092	0.000000	115.116702	173.466667	231.562278	1168.233561
NINQ	5450.0	1.186055	1.728675	0.000000	0.000000	1.000000	2.000000	17.000000
CLNO	5738.0	21.296096	10.138933	0.000000	15.000000	20.000000	26.000000	71.000000
DEBTINC	4693.0	33.779915	8.601746	0.524499	29.140031	34.818262	39.003141	203.312149

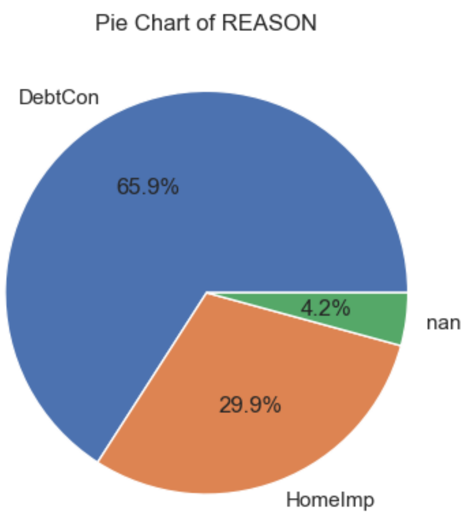
Observations of the Statistical Description

- The median amount lost on a defaulted loan (`TARGET_LOSS_AMT`) was $11,003.00 (mean of $13,414.58)

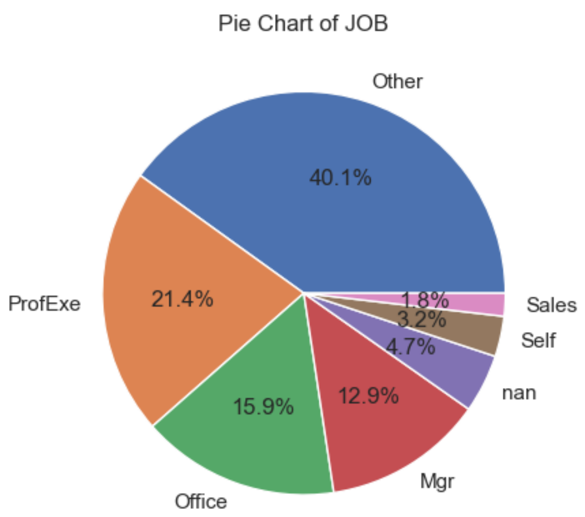
- The median value of the loans (`LOAN`) is $16,300.00 (mean of $18,607.97), and the median amount of the mortgage still due is $65.019 (mean of $73,760.82)
- The average number of delinquencies (`DELINQ`) among the borrowing population is 0.25, with the highest number being 10.
- The median lines of credit (`CLNO`) among the borrowers is 20 (mean of 21.3)

Visual Exploration of the Inputs and Target Variables Using Graphs and Other Visualizations

Pie Charts of Categorical Variables

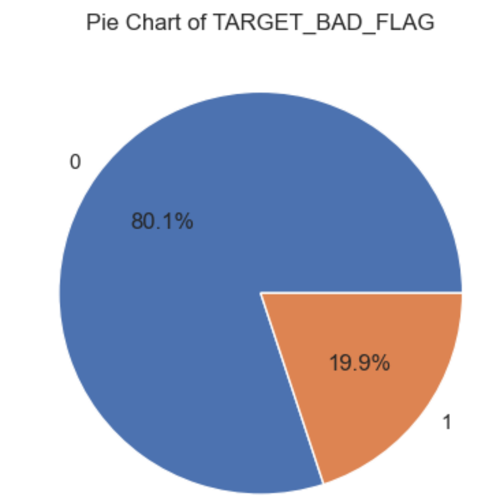


- Most loans are being taken out for debt consolidation (65.9%), while 29.9% are being taken out for home improvement projects, and the remaining 4.2% don't have a recorded reason for the loan.



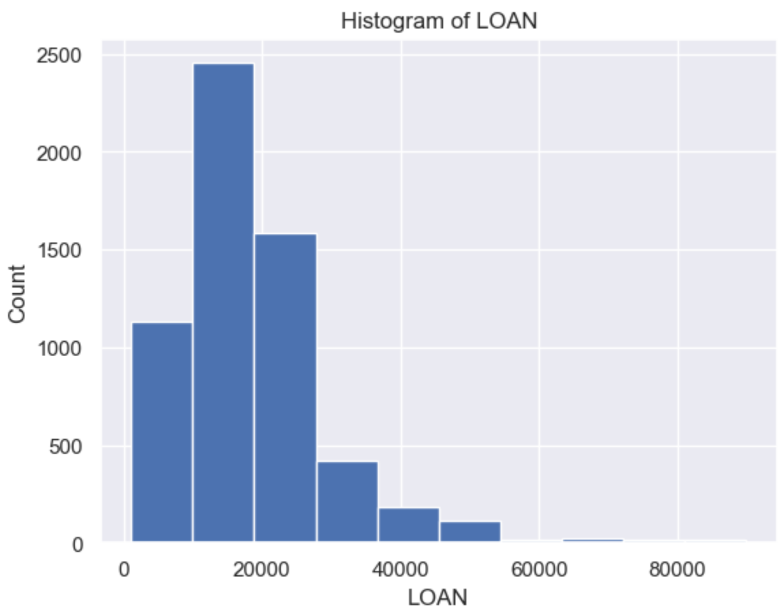
- Most borrowers have a job that doesn't fall into one of the dataset's defined titles (40.1%). The next most common job among barrowers is 'ProfExe' (21.4%), followed by those with office jobs (12.9%), managers (12.9%), self-employed (3.2%), Sales (1.8%), and 4.7% of barrowers don't have a job type specified (nan).

Pie Chart for `TARGET_BAD_FLAG`, since this is a binary indicator of loan default.

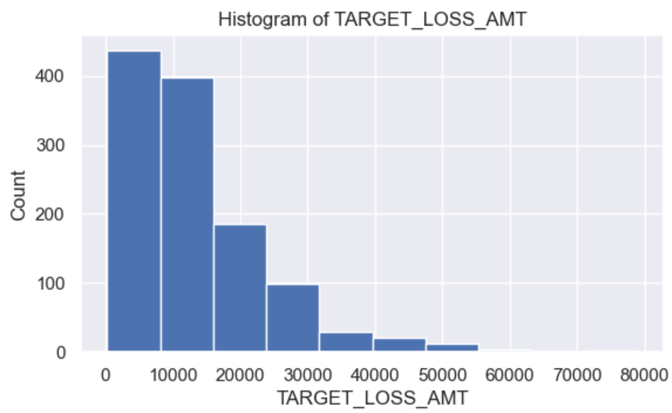


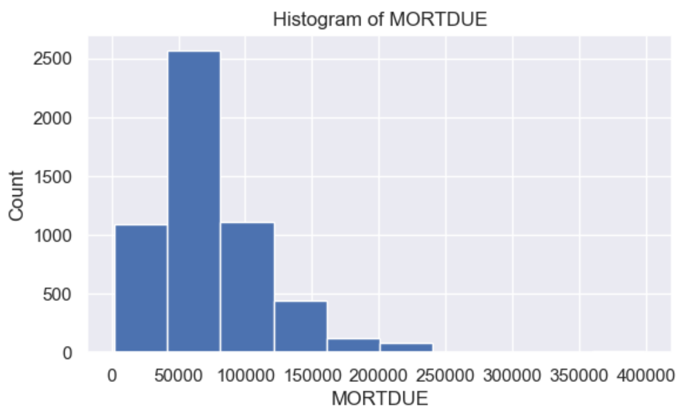
- 19.9% of borrowers defaulted on their loans (have a value of 1), and 80.1% of borrowers were good on their loans.

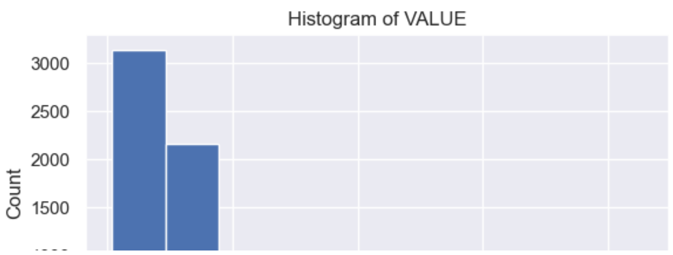
Histograms of Continuous Variables (Integer & Float)

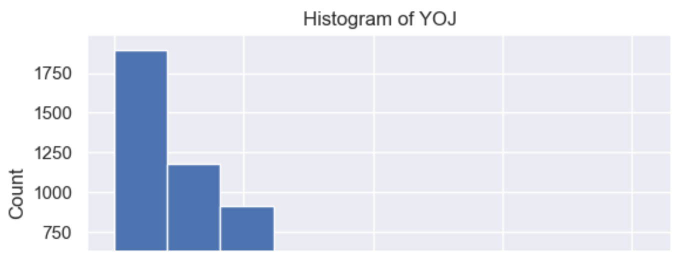


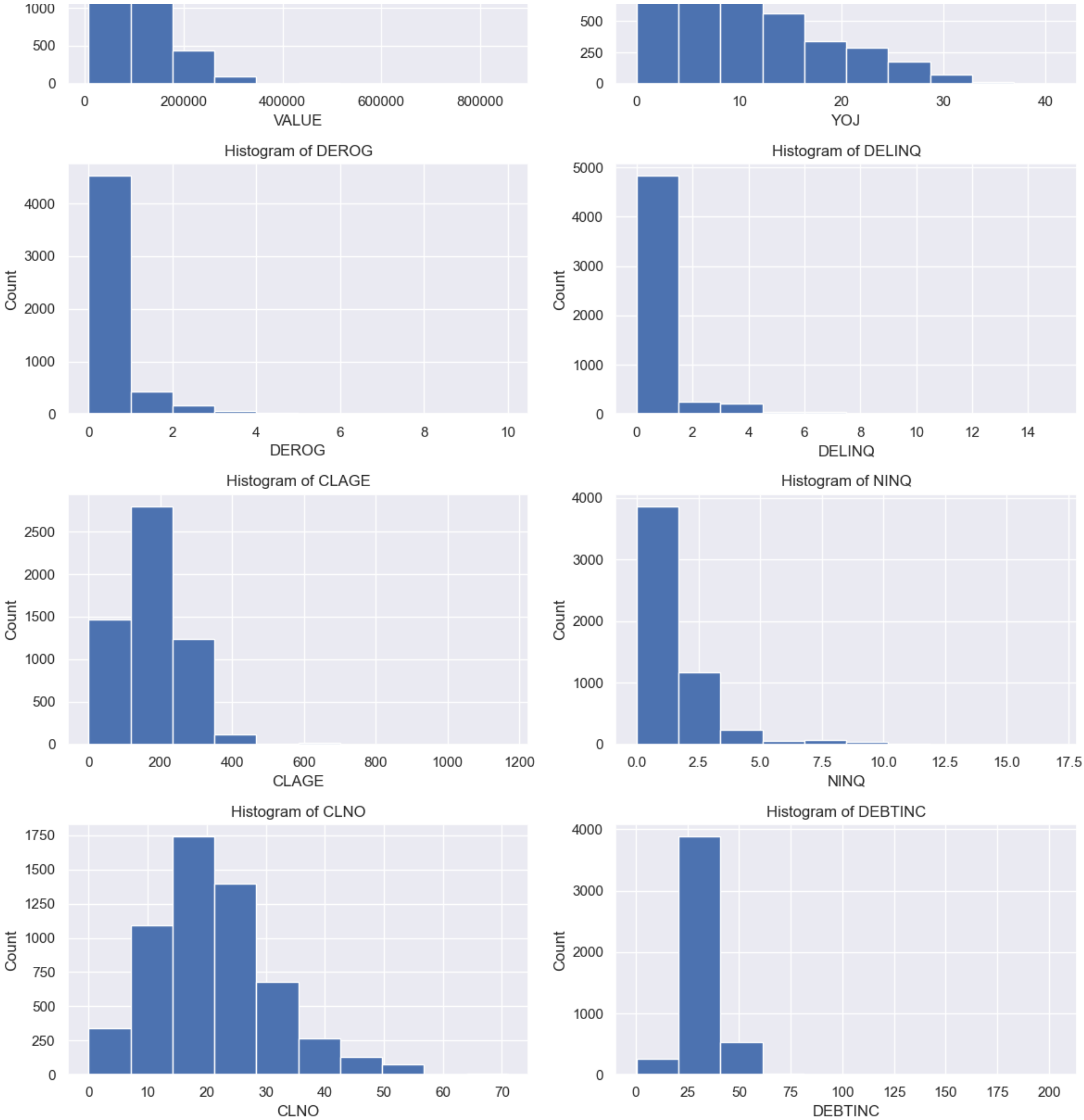
- The distribution of loan amounts is positively skewed.











- For the target variable `TARGET_LOSS_AMT`, the distribution of the amount of money lost on the defaulted loan is very positively skewed.
- The float type variables represent the amount still due on the barrow's mortgage, the value of the borrower's home, the years the borrower has held their job, the number of derogatory marks on the borrower's credit record, the number of delinquencies the borrower has, and the number of credit inquiries the borrower has all have distributions that are positively skewed.
- The float type variables representing the borrower's number of lines of credit, age of credit, and debt-to-income ratio are more normally distributed.

Exploring the Relationships Between the Input and Target Variables

Exploration of Categorical Variables

Class = JOB (The borrower's occupation)

JOB	Probability of Loan Default
Mgr	0.233377
Office	0.131857
Other	0.231993
ProfExe	0.166144
Sales	0.348624

JOB	Probability of Loan Default
Self	0.300518

JOB	Average Loss Amount
Mgr	14141.536313
Office	13475.304000
Other	11570.102888
ProfExe	14660.966981
Sales	16421.447368
Self	22232.362069

Observations

- Those borrowers who work in sales have the highest probability of defaulting on a loan (0.348624), followed by those who are self-employed (0.300518). Additionally, self-employed borrowers tend to have the most significant default amount ($22,232.36), which is almost 6 thousand dollars higher than the next most significant job type (sales at $16,421.45)
- Borrowers who work office jobs are the least likely to default on their loans (0.131857), followed by those who are 'ProfExe' (0.166144). This likely indicates the stability of these jobs since borrowers in these professions are less likely to experience a situation where they can't repay their loans. Borrowers in these professions also tend to have relatively lower amounts lost upon default ($13,475.30 and $14,660); however, borrowers with the profession of 'Other' have the lowest average default amount at $11,570.10.

Class = REASON (The reason the borrower took out the loan)

REASON	Probability of Loan Default
DebtCon	0.189664
HomeImp	0.222472

REASON	Average Loss Amount
DebtCon	16005.163758
HomeImp	8388.090909

Observations

- Those who take out a loan for home improvement purposes are slightly more likely to default on their loans; however, when these borrowers default, the amount they default on is almost half of that of borrowers who default on loans for debt consolidation ($8,388 vs. $16,005).

Exploration of Continuous (Numerical) Variables

Variable = LOAN (The loan amount)

TARGET_BAD_FLAG	Value of Loan
0	19028.107315
1	16922.119428
Correlation with Loss Amount	83.71 %

- Borrowers who don't default on their loans generally have a higher loan value ($19,082.11), and those who default on their loans have an average loan value of $16,922.12.
- The value of a borrower's loan is significantly correlated with the loss amount upon default (83.71%)

Variable = MORTDUE (The borrower's current outstanding mortgage)

- The average mortgage amount for loans that did not default is $74,829.25; for loans that did default, the average mortgage amount is $69,460.45. There is a moderate correlation, 34.87%, between the amount of a borrower's mortgage still due and the amount lost when a loan defaults.

Variable = VALUE (The value of the borrower's house)

- For loans that did not default, the average value of the borrower's home is $102,595.92; for loans that did default, the average value of the borrower's home is $98,172.85. There is a moderate correlation, 36.69%, between the value of a borrower's house and the amount lost when a loan defaults.

Variable = YOJ (The number of years the borrower has been at their job)

- For loans that did not default, the average length on the job is 9.15; for loans that did default, the average length is 8.03. There is very little correlation, 1.76%, between a borrower's years on the job and the amount lost when a loan defaults.

Variable = DEROG (The number of derogatory marks on the borrower's credit record)

- For loans that did not default, the borrowers had, on average, 0.25 derogatory marks on their credit record; for loans that did default, the borrowers had, on average, 0.71 derogatory marks on their record. There is little correlation, 9.53%, between the number of derogatory marks on a borrower's record and the amount lost when a loan defaults.
  - Those borrower with more derogatory marks on their records likely have much more difficulty getting larger loans, which might be why we don't see a higher correlation between the number of derogatory marks and the amount lost when a loan defaults.

Variable = DELINQ (The number of delinquencies on the borrower's credit report)

- For loans that did not default, the borrowers had, on average, 0.25 delinquencies on their credit report; for loans that did default, the borrowers had, on average, 1.23 delinquencies on their credit report. There is a slight correlation, 22.66%, between the number of delinquents on a borrower's credit report and the amount lost when a loan defaults.
  - It is interesting to note that the correlation for delinquencies is higher than for derogatory marks. This makes me wonder whether lenders should consider delinquents with a similar weight to derogatory marks when deciding how much to lend borrowers.

Variable = CLAGE (The age of the borrower's line of credit)

- For loans that did not default, the borrowers had, on average, a credit line age of 187.00. For loans that did default, the borrowers had, on average, a credit line age of 150.19. Despite the difference in credit line age between those who did and did not default, there is very little correlation, 1.41%, between the credit line age and the amount lost when a loan defaults.

Variable = NINQ (The number of credit inquiries the borrower has on their credit report within the last three years)

- For loans that did not default, the borrowers had, on average, 1.03 credit inquiries; for loans that did default, the borrowers had, on average, a slightly higher number of credit inquiries--1.78. There is only a slight correlation, 14.28%, between the number of credit inquiries on a borrower's credit report and the amount lost when a loan defaults.

Variable = CLNO (Number of lines of credit)

- For both the borrowers that did and did not default on their loans, their number of lines of credit was very similar (default = 21.21; good = 21.32); however, there is a moderate correlation, 40.0%, between a borrower's number of lines of credit and the amount lost when a loan defaults.

Variable - DEBTINC (The barrower's debt-to-income-ratio)

- Among the borrowers who did not default on their loans, the average debt-to-income ratio was 33.25. On the other hand, among borrowers defaulting on their loans, the average debt-to-income ratio was 39.39. A moderate correlation, 37.77%, exists between the borrower's debt-to-income-ration and the amount lost when a loan defaults.

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Data Preparation

Filling in Missing Data for Categorical Data

**We will use the second method of imputation discussed in the lectures (filling in missing with entries with the category "MISSING").

- The two categorical variables that were identified as having missing data were:
  1. REASON (The reason that the borrower is taking out the loan)
  2. JOB (What the borrower does for a living)

Missing Categorical Value Imputation for `REASON` variable:

> Original variable = REASON
> HAS MISSING
> New (imputed) variable = IMP_REASON
> New (flag) variable = M_REASON
> Variable REASON has this many missing 252
> Variable IMP_REASON has this many missing 0
>
> > IMP_REASON
> > DebtCon 3928
> > HomeImp 1780
> > MISSING 252
> > Name: IMP_REASON, dtype: int64

Missing Categorical Value Imputation for `JOB` variable:

> Original variable = JOB
> HAS MISSING
> New (imputed) variable = IMP_JOB
> New (flag) variable = M_JOB
> Variable JOB has this many missing 279
> Variable IMP_JOB has this many missing 0
>
> > IMP_JOB
> > MISSING 279

> > Mgr 767
> > Office 948
> > Other 2388
> > ProfExe 1276
> > Sales 109
> > Self 193
> > Name: IMP_JOB, dtype: int64

Perform Missing Value Imputation for Numerical Variables

It is my hunch that for the numerical variables, `VALUE`, `LOAN`, and `DEBTINC` it would be best to fill in the missing values with the median of the groups in the `JOB` class. This is because the value of a person's home is likely to be related to how much they make and what their job is.

Therefore, it would make sense to fill in the missing values with the median of the group that the individual belongs to. The same logic applies to the `LOAN` variable--the more a person makes at their job, the more they will likely be able to barrow. I also believe that this same approach is appropriate for the `DEBTINC` variable.

For the rest of the numerical variables, I will fill in the missing values with the median of all entries within the field.

Missing Numerical Value Imputation for `VALUE` Based on `JOB` Class

> **Name: VALUE, dtype: float64**
> **IMP_JOB**
>
> | GROUP | MEDIAN VALUE |
> | --- | --- |
> | MISSING | 78227.0 |
> | Mgr | 101258.0 |
> | Office | 89094.5 |
> | Other | 76599.5 |
> | ProfExe | 110007.0 |
> | Sales | 84473.5 |
> | Self | 130631.0 |
>
> Original variable = VALUE
> New (Flag) variable = M_VALUE
> New (Imputed) variable = IMP_VALUE

Missing Numerical Value Imputation for `LOAN` Based on `JOB` Class

> **Name: LOAN, dtype: float64**
> **IMP_JOB**
>
> | GROUP | MEDIAN LOAN |
> | --- | --- |
> | MISSING | 13400.0 |
> | Mgr | 18100.0 |
> | Office | 16200.0 |
> | Other | 15650.0 |
> | ProfExe | 17300.0 |
> | Sales | 14300.0 |
> | Self | 24000.0 |
>
> Original variable = LOAN
> New (Flag) variable = M_LOAN
> New (Imputed) variable = IMP_LOAN

Missing Numerical Value Imputation for `DEBTINC` Based on `JOB` Class

> **Name: DEBTINC, dtype: float64**
> **IMP_JOB**
>
> | GROUP | MEDIAN DEBTINC |
> | --- | --- |
> | MISSING | 30.311902 |
> | Mgr | 35.661118 |
> | Office | 36.158718 |

> | GROUP | MEDIAN DEBTINC |
> |---|---|
> | Other | 35.247328 |
> | ProfExe | 33.378041 |
> | Sales | 35.764058 |
> | Self | 34.830194 |
>
> Original variable = DEBTINC
> New (Flag) variable = M_DEBTINC
> New (Imputed) variable = IMP_DEBTINC

`.info()` Table After Performing Missing Value Imputation of the Rest of The Numerical Variables

- Note that there are no more missing values.

Column	Non-Null Count	Dtype
TARGET_BAD_FLAG	5960	int64
TARGET_LOSS_AMT	5960	float64
M_REASON	5960	int64
IMP_REASON	5960	object
M_JOB	5960	int64
IMP_JOB	5960	object
M_VALUE	5960	int64
IMP_VALUE	5960	float64
M_LOAN	5960	int64
IMP_LOAN	5960	int64
M_DEBTINC	5960	int64
IMP_DEBTINC	5960	float64
M_MORTDUE	5960	int64
IMP_MORTDUE	5960	float64
M_YOJ	5960	int64
IMP_YOJ	5960	float64
M_DEROG	5960	int64
IMP_DEROG	5960	float64
M_DELINQ	5960	int64
IMP_DELINQ	5960	float64
M_CLAGE	5960	int64
IMP_CLAGE	5960	float64
M_NINQ	5960	int64
IMP_NINQ	5960	float64
M_CLNO	5960	int64
IMP_CLNO	5960	float64
Range Index: 5960 entries, 0 to 5959		
Data columns (total 26 columns)		
dtypes: float64(10), int64(14), object(2)		

Performing One Hot Encoding on the Categorical Variables

`.head()` Preview of the Dataset after Completion of Imputation and One Hot Encoding

	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

	0	1	2	3	4
M_REASON	0.000000	0.000000	0.000000	1.000000	0.000000
M_JOB	0.000000	0.000000	0.000000	1.000000	0.000000
M_VALUE	0.000000	0.000000	0.000000	1.000000	0.000000
IMP_VALUE	39025.000000	68400.000000	16700.000000	78227.000000	112000.000000
M_LOAN	0.000000	0.000000	0.000000	0.000000	0.000000
IMP_LOAN	1100.000000	1300.000000	1500.000000	1500.000000	1700.000000
M_DEBTINC	1.000000	1.000000	1.000000	1.000000	1.000000
IMP_DEBTINC	35.247328	35.247328	35.247328	30.311902	36.158718
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
z_IMP_REASON_DebtCon	0.000000	0.000000	0.000000	0.000000	0.000000
z_IMP_REASON_HomeImp	1.000000	1.000000	1.000000	0.000000	1.000000
z_IMP_REASON_MISSING	0.000000	0.000000	0.000000	1.000000	0.000000
z_IMP_JOB_MISSING	0.000000	0.000000	0.000000	1.000000	0.000000
z_IMP_JOB_Mgr	0.000000	0.000000	0.000000	0.000000	0.000000
z_IMP_JOB_Office	0.000000	0.000000	0.000000	0.000000	1.000000
z_IMP_JOB_Other	1.000000	1.000000	1.000000	0.000000	0.000000
z_IMP_JOB_ProfExe	0.000000	0.000000	0.000000	0.000000	0.000000
z_IMP_JOB_Sales	0.000000	0.000000	0.000000	0.000000	0.000000
z_IMP_JOB_Self	0.000000	0.000000	0.000000	0.000000	0.000000