

CT050-3-M – DATA ANALYTICAL PROGRAMMING (DAP) MAY-2021-DSBA SEP 2021

INDIVIDUAL ASSIGNMENT

Date Assigned: Thu-7-Oct-2021

Name: ONG WEI AUN (TP063332)

Lecturer: MR. DHASON PADMA KUMAR

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1. INTRODUCTION

Every day, there are companies and individuals that are borrowing money from banks or other financial institutions to finance their activities like a person buying a car or a business buying new machinery equipment to expand their factory. The borrower thereby incurs a debt, which they must repay with interest and within a specified time frame. However, banks are worried of potential loan defaults, thus they do not approve loan applications easily unless they are confident that the borrowers are able to repay the loan. Loan defaults are also known as non-performing loan (NPL), where the borrower did not pay to the bank for 90 days or more.

Therefore, every bank always tries to identify the risk of NPL from the very beginning. However, when the banks avoid risk too much, it can cause income loss from the customers who are able to repay the loans. This is where a good tool is needed to analyze a customer and identify whether they are good or bad customers. Bank loan application filtration process are time consuming and may increase the risk of misidentification.

Nowadays, artificial intelligence (AI) is a rapidly developing technology. AI are now widely used in solving many real-world challenges. Machine learning is a type of AI that is particularly beneficial in prediction systems. Machine learning builds a model based on training data and makes prediction. The algorithm trains the system with a small portion of data and test it with the remaining data. Similarly, this algorithm can be utilized to help banks to analyze the applications to help the banks make better decisions in approving loan applications.

The aim of this assignment is to analyze past data set obtained from past customers and build a most accurate model to predict the approval process as approved or rejected. In the work flow process, a dataset sample will be collected from past history to study the customers backgrounds. Data exploration and modification will be done where necessary before building a model to predict the outcome of loan approval status.

2. BACKGROUND STUDY

The company chosen in this assignment is Lasiandra Finance Inc. (LFI) which is located in New York, USA. It is a leading private financing company which provides funding to Small and Medium Enterprises (SME). By making their loaning process tailor-made and suitable to the customers, they are able to give those business dreams injection of boost. Through the development of internet, it has tremendously increased their business expansion and provide

more funding to more SMEs. In order to speed up the process of loan approval, it needs automation to help process loan eligibility based on the customer portfolio entered online. However, loan approval process is complicated as it requires a lot of verification and validation so that they can give the loans to the most deserving applicants and reduce loan default rate.

3. ASSUMPTION & JUSTIFICATION

It is assumed that the dataset used in this study are actual data from loan applicants to help support the accuracy of the model run in this study.

4. LITERATURE REVIEW

This literature review introduces investigation and discussion for related work on reducing risk for non-performing loans (NPL) or also known as loan defaults.

4.1 Credit Scoring model

In the past works by other researchers, they have used different methods as credit scoring assessment to evaluate whether applications should be approved or not. Imtiaz & J. used variables like gender, education, marital status, age and past payment records to be input their machine learning models as credit risk assessment. (Imtiaz & J., 2017) Other than that, Chen & Xiang even included more detailed variables like loan purpose, loan amount, employment duration, debt service ratio etc. to help filter the applications during risk assessment process. (Chen & Xiang, 2017)

4.2 Applications of Machine Learning in Loan Defaults risk assessment

Thavarith & Liangrokapart (2019) did study on finding the rootcause of NPL and suggested a method about reducing the risks of NPL based on the data from one of the largest banks in Cambodia. They combined the application of both Six Sigma and credit scoring model to help better filter potential clients to reduce the risk of loan defaults. FMEA method are used to analyze the risk priority number for the potential failure causes. Besides, through the credit scoring model, they classified customers into 4 different risk classes. By blending both six sigma and credit scoring model, they are able to reduce the level of RPN by 32.5%, which is from 1446 to 975. (Thavarith & Liangrokapart, 2019)

Furthermore, Coşer et al investigates a database of customers who were unable to repay their loans and got into loan defaults. Predictive models like LightGBM, XGBoost, Logistic Regression and Random Forest were used to calculate the probability of a customer loan turning default status. Model comparison were done to identify the best model by considering the model performance metrics like AUC score, precision, recall and accuracy. The best results obtained was using the Random Forest model which has a representative AUC of 0.89. (Coşer et al., 2019)

Besides, Figini et al. observe the credit risk in small and medium enterprises by using boosting, bagging and random forest. Multivariate outlier detection techniques like Local Outlier Factor (LOF) were mentioned in the study. Unlike univariate outlier detection techniques, the LOF technique is a multivariate technique which is consistent on high dimensional data without resorting to strong assumptions about the distribution. Thus, the authors proposed to improve the out of sample performance of parametric and non-parametric models for credit risk estimation. (Figini et al., 2017)

Other than that, Butaru et al. apply machine learning techniques to predict delinquency in the credit card industry. The authors combined consumer tradeline, credit bureau and macroeconomic variables as part of the model's prediction. Besides, they also found out that decision trees and random forests outperform the logistic regression method in forecasting the credit card delinquencies. (Butaru et al., 2016)

On the other hand, Sudhamathy used decision tree model in R package to help analyze the credibility of the bank loans applicants. They find the correlation between features and rank the features according to importance before building a decision tree model. (Sudhamathy, 2016)

Chen & Xiang also constructed a credit scoring model based on Group Lasso Logistic Regression to manage credit risks. Lasso (Least Absolute Shrinkage and Selection Operator) regression performs both variable selection and regularization to enhance the predictive accuracy and interpretability of the statistical model it produces. For variable selection, the selection of tuning parameter λ is very important and usually the Akaike Information Criterion(AIC), Bayesian Information Criterion(BIC) and Cross Validation prediction errors will determine the tuning parameter. The final results indicated that the Group Lasso method is better than backward elimination in both interpretability and prediction accuracy. (Chen & Xiang, 2017)

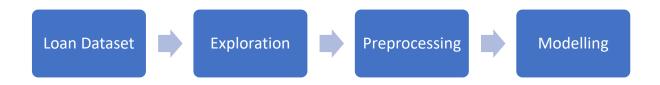
5. DATA EXPLORATION

The dataset used in this assignment contains 614 observations and 13 different variables.

Name of variable	Description	Data	Length	Sample Data
		Type		
SME_LOAN_ID_NO	Loan	Char	8	LP001002/LP001003
	application			
	number			
GENDER	Gender of	Char	6	Female; Male
	the applicant			
MARITAL_STATUS	Marital	Char	11	Married; Not
	Status of the			Married
	applicant;			
	Married or			
	Not Married			
FAMILY_MEMBERS	Number of	Char	2	1, 2, 3+
	family			
	members of			
	the applicant			
QUALIFICATION	Education	Char	14	Graduate; Under
	Qualification			Graduate
	of the			
	applicant			
EMPLOYMENT	Employment	Char	3	Yes; No
	Status of the			
	applicant			
CANDIDATE_INCOME	Income of	Numeric	5	5849, 4583, 3000
	the applicant			
GUARANTEE_INCOME	Income of	Numeric	5	1508, 2358, 4196
	Joint			
	Applicant			
LOAN_AMOUNT	Loan	Numeric	5	128,66,120
	amount			

LOAN_DURATION	Duration of	Numeric	3	71,360
	Loan Tenure			
LOAN_HISTORY	Loan	Numeric	1	0; 1
	History of			
	the applicant			
LOAN_LOCATION	Location of	Char	7	City, Village, Town
	the			
	application			
LOAN_APPROVAL_STATUS	Approval	Char	1	Y; N
	Status of			(Y=Yes, N=No)
	Loan			
	Application			

6. METHODOLOGY

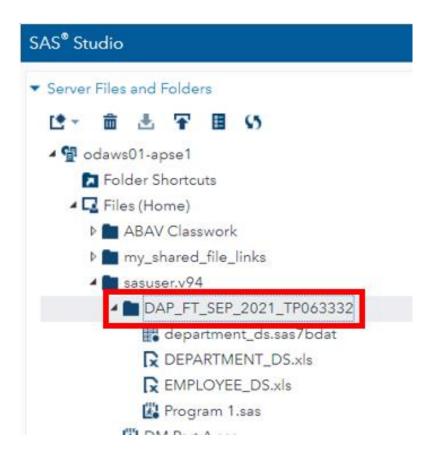


First of all, a dataset consisting of the details of the applicants is obtained. Univariate and bivariate analysis are done on the variables to explore the data. Pre-processing and imputation are done to the missing data in the dataset. Finally, a logistic regression model is created to determine the loan eligibility of the applicants.

7. EXPERIMENTATION

7.1 Create a folder on SAS

Screenshot(s)

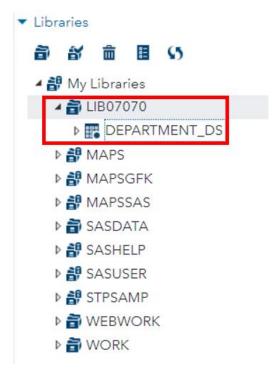


Explanation

- A new folder is created to store all the datasets and SAS programs for the study so that it will not be mixed up with all the other projects.

7.2 Create a permanent library on SAS

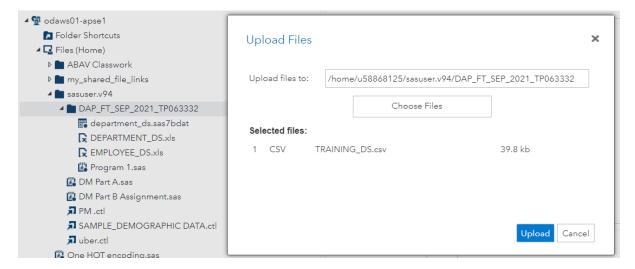
Screenshot

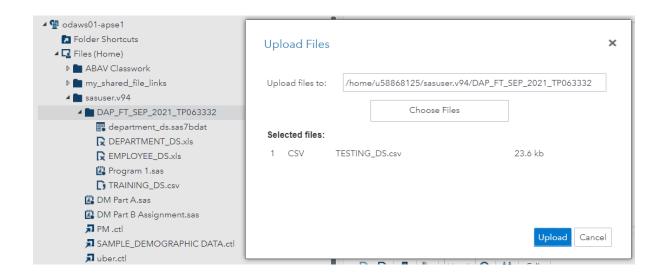


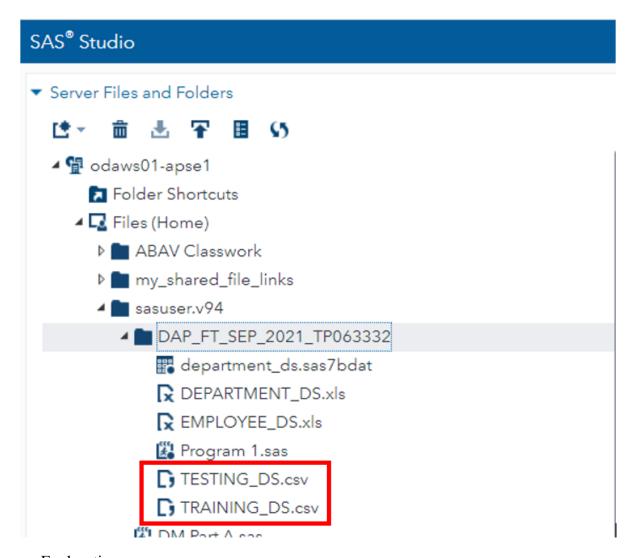
Explanation

- A library is created to store the data schema imported to SAS Studio.
- 7.3 Upload the dataset TRAINING_DS and TESTING_DS to the folder DAP_FT_SEP_2021_TP063332

Screenshot(s)





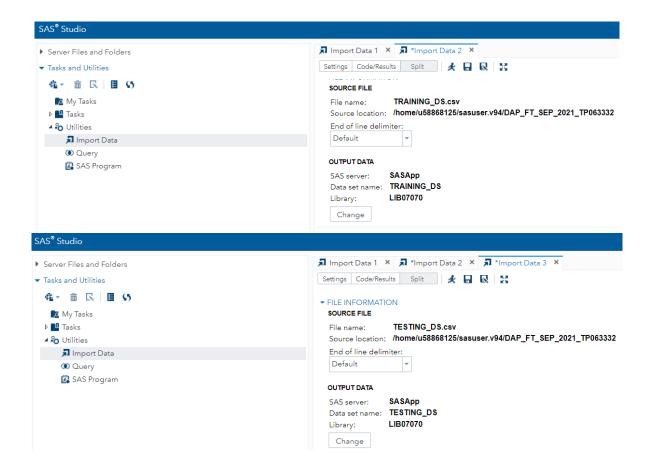


Explanation

- TRAINING_DS and TESTING_DS datasets are uploaded to SAS Studio.

7.4 Import the dataset TRAINING_DS and TESTING_DS to the library LIB07070

Screenshot(s)



Explanation

- TRAINING_DS and TESTING_DS datasets are imported into the library created in previous step. These datasets serve as the database for the SQL programs to run.

7.5 Initial Exploration of the Dataset

Screenshot(s)

```
TITLE1 'Structure of the Dataset (Data Dictionary)';
PROC CONTENTS DATA = LIB07070.TRAINING_DS;
RUN;
```

	Structure of the Dataset (Data Dictionary)		
	The CONTENTS Procedure		
Data Set Name	LIB07070.TRAINING_DS	Observations	614
Member Type	DATA	Variables	13
Engine	V9	Indexes	0
Created	11/10/2021 17:25:41	Observation Length	96
Last Modified	11/10/2021 17:25:41	Deleted Observations	0
Protection		Compressed	NO
Data Set Type		Sorted	NO
Label			
Data Representation	SOLARIS_X86_64, LINUX_X86_64, ALPHA_TRU64, LINUX_IA64		
Encoding	utf-8 Unicode (UTF-8)		

Engine/Host Dependent Information				
Data Set Page Size	131072			
Number of Data Set Pages	1			
First Data Page	1			
Max Obs per Page	1363			
Obs in First Data Page	614			
Number of Data Set Repairs	0			
Filename	/home/u58868125/sasuser.v94/DAP_FT_SEP_2021_TP063332/training_ds.sas7bdat			
Release Created	9.0401M6			
Host Created	Linux			
Inode Number	235407138			
Access Permission	TW-TF			
Owner Name	u58868125			
File Size	256KB			
File Size (bytes)	262144			

Alphabetic List of Variables and Attributes					
#	Variable	Туре	Len	Format	Informat
7	CANDIDATE_INCOME	Num	8	BEST12.	BEST32.
6	EMPLOYMENT	Char	3	\$3.	\$3.
4	FAMILY_MEMBERS	Char	2	\$2.	\$2.
2	GENDER	Char	6	\$6.	\$6.
8	GUARANTEE_INCOME	Num	8	BEST12.	BEST32.
9	LOAN_AMOUNT	Num	8	BEST12.	BEST32.
13	LOAN_APPROVAL_STATUS	Char	1	\$1.	\$1.
10	LOAN_DURATION	Num	8	BEST12.	BEST32.
11	LOAN_HISTORY	Num	8	BEST12.	BEST32.
12	LOAN_LOCATION	Char	7	\$7.	\$7.
3	MARITAL_STATUS	Char	11	\$11.	\$11.
5	QUALIFICATION	Char	14	\$14.	\$14.
1	SME_LOAN_ID_NO	Char	8	\$8.	\$8.

Explanation

- Initial understanding of the dataset is done by running the program. There are 5 numerical variables and 8 string variables.

7.6 Univariate Analysis of categorical variables found in the dataset LIB07070.TRAINING DS

7.6.1 Univariate Analysis of the categorical variable MARITAL STATUS

SAS Codes

```
TITLE 'Univariate Analysis of the categorical variable: MARITAL_STATUS';

PROC FREQ DATA = LIB07070.TRAINING_DS;

TABLE MARITAL_STATUS;

RUN;

ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;

PROC SGPLOT DATA = LIB07070.TRAINING_DS;

VBAR MARITAL_STATUS;

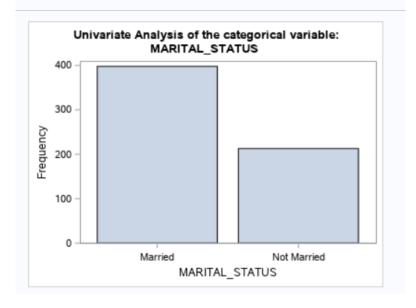
TITLE 'Univariate Analysis of the categorical variable: MARITAL_STATUS';

RUN;
```

Screenshot(s)

Univariate Analysis of the categorical variable: MARITAL_STATUS

	morne	Q I TOCCUU			
MARITAL_STATUS	Frequency	Percent	Cumulative Frequency	Cumulative Percent	
Married	398	65.14	398	65.14	
Not Married	213	34.86	611	100.00	
Frequency Missing = 3					



Explanation

There are 398 married applicants and 213 applicants who are not married. However, there are 3 missing values in the MARITAL_STATUS variable.

7.6.2 Univariate Analysis of the categorical variable GENDER

SAS Codes

```
TITLE 'Univariate Analysis of the categorical variable: GENDER';

PROC FREQ DATA = LIB07070.TRAINING_DS;

TABLE GENDER;

RUN;

ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;

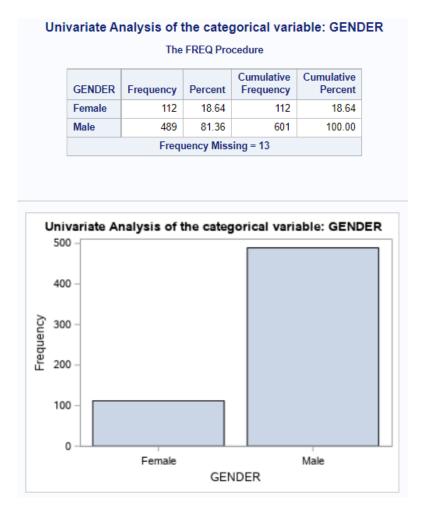
PROC SGPLOT DATA = LIB07070.TRAINING_DS;

VBAR GENDER;

TITLE 'Univariate Analysis of the categorical variable: GENDER';

RUN;
```

Screenshot(s)



Explanation

There are mostly male in the dataset, consisting as high as 81.36% of the dataset. Other than that, there are also 13 missing data in this GENDER variable.

7.6.3 Univariate Analysis of the categorical variable LOAN_LOCATION

SAS Codes

```
TITLE 'Univariate Analysis of the categorical variable: LOAN_LOCATION';

PROC FREQ DATA = LIB07070.TRAINING_DS;

TABLE LOAN_LOCATION;

RUN;

ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;

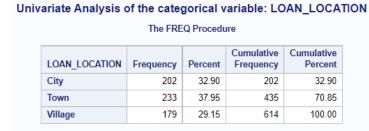
PROC SGPLOT DATA = LIB07070.TRAINING_DS;

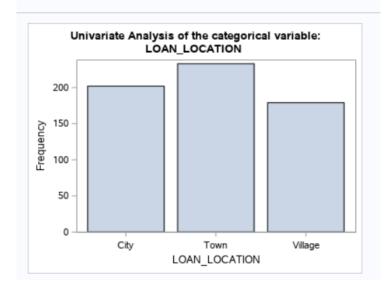
VBAR LOAN_LOCATION;

TITLE 'Univariate Analysis of the categorical variable: LOAN_LOCATION';

RUN;
```

Screenshot(s)





Explanation

The loan applicants are mainly from town area, amounting to 233 of them. City area have 202 loan applicants while village have the least number of applicants, only 179 of them. This variable has no missing data.

7.6.4 Univariate Analysis of the categorical variable QUALIFICATION

SAS Codes

```
TITLE 'Univariate Analysis of the categorical variable: QUALIFICATION';

PROC FREQ DATA = LIB07070.TRAINING_DS;

TABLE QUALIFICATION;

RUN;

ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;

PROC SGPLOT DATA = LIB07070.TRAINING_DS;

VBAR QUALIFICATION;

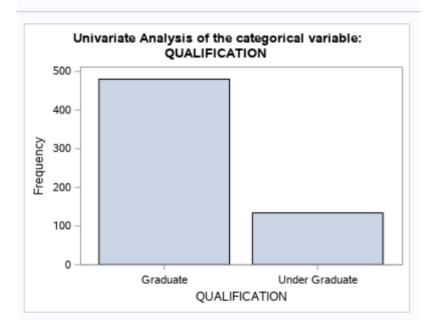
TITLE 'Univariate Analysis of the categorical variable: QUALIFICATION';

RUN;
```

Screenshot(s)

Univariate Analysis of the categorical variable: QUALIFICATION

The FREQ Procedure Cumulative Cumulative QUALIFICATION Frequency Percent Frequency Percent 78.18 Graduate 480 78.18 480 **Under Graduate** 134 21.82 614 100.00



Explanation

A total of 78.18% (480 of them) from the loan applicants are graduates while only 134 of them are under graduates. This QUALIFICATION variable does not have any missing data as well.

7.6.5 Univariate Analysis of the categorical variable FAMILY_MEMBERS

SAS Codes

```
TITLE 'Univariate Analysis of the categorical variable: FAMILY_MEMBERS';

PROC FREQ DATA = LIB07070.TRAINING_DS;

TABLE FAMILY_MEMBERS;

RUN;

ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;

PROC SGPLOT DATA = LIB07070.TRAINING_DS;

VBAR FAMILY_MEMBERS;

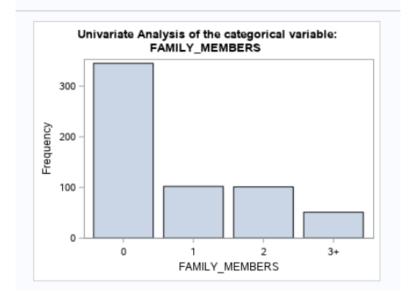
TITLE 'Univariate Analysis of the categorical variable: FAMILY_MEMBERS';

RUN;
```

Screenshot(s)

Univariate Analysis of the categorical variable: FAMILY_MEMBERS





Explanation

Most of the loan applicants (57.60%) do not have any family members. This actually indicates that they may be lesser financial commitments with lesser dependent family members. On the other hand, there are 51 of them who have more than 2 family members. This may affect their loan eligibility as banks may prefer individuals with lesser financial commitments reduce loan defaults rate.

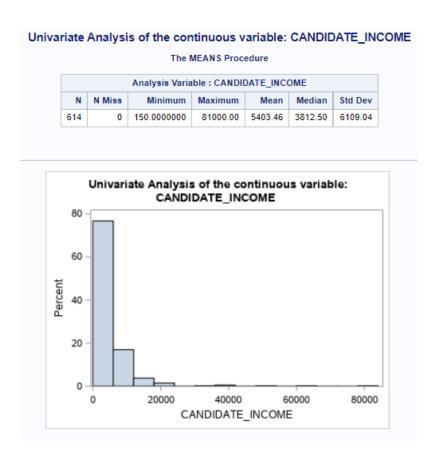
7.7 Univariate Analysis of continuous variables found in the dataset LIB07070.TRAINING DS

7.7.1 Univariate Analysis of the continuous variable CANDIDATE_INCOME

SAS Codes

```
PROC MEANS DATA = LIB07070.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;
VAR CANDIDATE_INCOME;
TITLE 'Univariate Analysis of the continuous variable: CANDIDATE_INCOME';
RUN;
ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;
PROC SGPLOT DATA = LIB07070.TRAINING_DS;
HISTOGRAM CANDIDATE_INCOME;
TITLE 'Univariate Analysis of the continuous variable: CANDIDATE_INCOME';
RUN;
```

Screenshot(s)



Explanation

As observed from the distribution of the histogram above, most of the candidates have an income of below \$20000 with a mean of \$5403, although the maximum income recorded is \$81000.

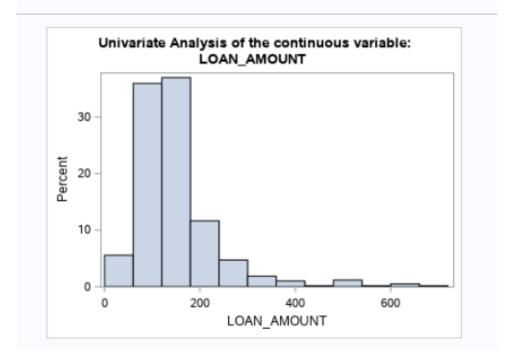
7.7.2 Univariate Analysis of the continuous variable LOAN_AMOUNT

SAS Codes

```
PROC MEANS DATA = LIB07070.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;
VAR LOAN_AMOUNT;
TITLE 'Univariate Analysis of the continuous variable: LOAN_AMOUNT';
RUN;
ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;
PROC SGPLOT DATA = LIB07070.TRAINING_DS;
HISTOGRAM LOAN_AMOUNT;
TITLE 'Univariate Analysis of the continuous variable: LOAN_AMOUNT';
RUN;
```

Screenshot(s)

Univariate Analysis of the continuous variable: LOAN_AMOUNT The MEANS Procedure Analysis Variable: LOAN_AMOUNT N Miss N Minimum Maximum Mean Median Std Dev 700.0000000 592 9 00000000 146.4121622 128.0000000 85.5873252



Explanation

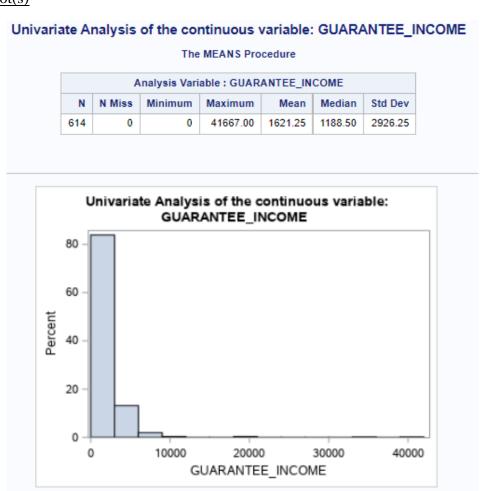
There are 22 missing data in the LOAN_AMOUNT variable. It can be observed that most of the applicants have loan amount of less than \$200 with a median of \$128.

7.7.3 Univariate Analysis of the continuous variable GUARANTEE_INCOME

SAS Codes

```
PROC MEANS DATA = LIB07070.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;
VAR GUARANTEE_INCOME;
TITLE 'Univariate Analysis of the continuous variable: GUARANTEE_INCOME';
RUN;
ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;
PROC SGPLOT DATA = LIB07070.TRAINING_DS;
HISTOGRAM GUARANTEE_INCOME;
TITLE 'Univariate Analysis of the continuous variable: GUARANTEE_INCOME';
RUN;
```

Screenshot(s)



Explanation

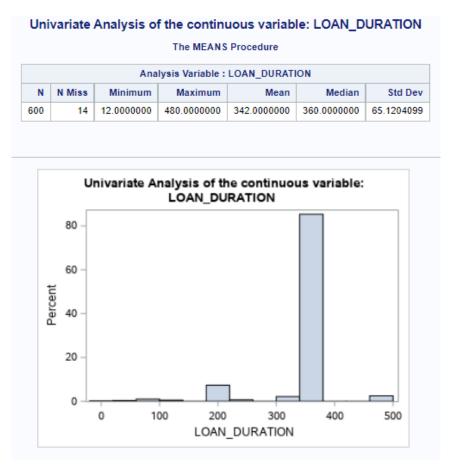
More than 80% of the applicants have guarantee income of less than \$5000.

7.7.4 Univariate Analysis of the continuous variable LOAN_DURATION

SAS Codes

```
PROC MEANS DATA = LIB07070.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;
VAR LOAN_DURATION;
TITLE 'Univariate Analysis of the continuous variable: LOAN_DURATION';
RUN;
ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;
PROC SGPLOT DATA = LIB07070.TRAINING_DS;
HISTOGRAM LOAN_DURATION;
TITLE 'Univariate Analysis of the continuous variable: LOAN_DURATION';
RUN;
```

Screenshot(s)



Explanation

There are 14 missing data in the LOAN_DURATION variable. Other than that, over 80% of the applicants are having a loan duration of 360 months.

7.8 Bivariate Analysis of variables found in the dataset LIB07070.TRAINING_DS

7.8.1 Bivariate Analysis of the variables (LOAN_LOCATION - Categorical variable vs CANDIDATE_INCOME - Continuous variable) found in the LIB07070.TRAINING DS

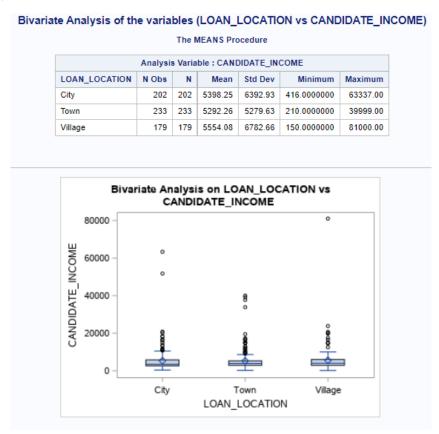
SAS Codes

```
TITLE1 'Bivariate Analysis of the variables (Categorical vs Continuous) found in the LIB07070.TRAINING_DS';
TITLE1 'Bivariate Analysis of the variables (LOAN_LOCATION vs CANDIDATE_INCOME)';

PROC MEANS DATA = LIB07070.TRAINING_DS;
CLASS LOAN_LOCATION; /* CHAR */
VAR CANDIDATE_INCOME; /*NUMERIC*/
RUN;

PROC SGPLOT DATA = LIB07070.TRAINING_DS;
VBOX CANDIDATE_INCOME / CATEGORY=LOAN_LOCATION;
/*LL X-AXIS CI Y-AXIS */
TITLE 'Bivariate Analysis on LOAN_LOCATION vs CANDIDATE_INCOME';
RUN;
```

Screenshot(s)



Explanation

From the boxplot above, we can see that the distribution of data between LOAN_LOCATION and CANDIDATE_INCOME is quite similar across the different loan locations. There are also a few observations that lies as outliers in the dataset.

7.8.2 Bivariate Analysis of the variables (LOAN_HISTORY – categorical variable vs LOAN_APPROVAL_STATUS – categorical variable) found in the LIB07070.TRAINING_DS

SAS Codes

```
TITLE1 'Bivariate Analysis of the variables (Categorical vs Categorical) found in the LIB07070.TRAINING_DS';

TITLE2 'Bivariate Analysis of the variables (LOAN_HISTORY vs LOAN_APPROVAL_STATUS)';

FOOTNOTE '-----END-----';

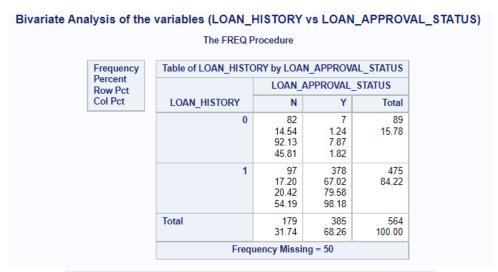
PROC FREQ DATA = LIB07070.TRAINING_DS;

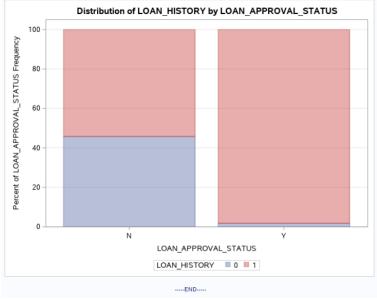
TABLE LOAN_HISTORY * LOAN_APPROVAL_STATUS /

PLOTS = FREQPLOT ( TWOWAY = STACKED SCALE = GROUPPCT );

RUN;
```

Screenshot(s)





Explanation

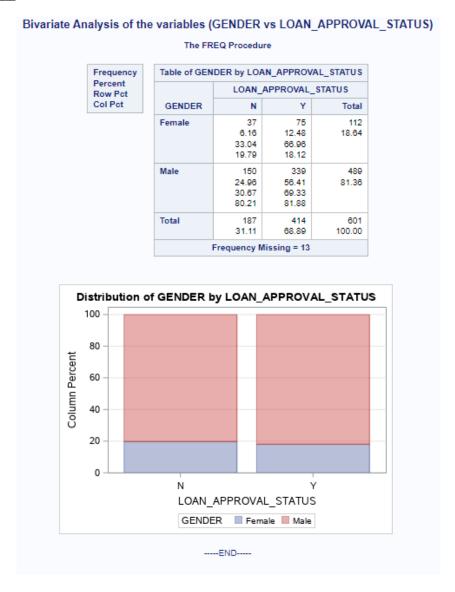
Through the graph plot above, it is observed that a large percentage of LOAN_APPROVAL_STATUS showing Y are also showing 1 in the LOAN_HISTORY. This is a very important finding where it suggested that loan history is quite likely to affect the outcome of the loan approval status.

7.8.3 Bivariate Analysis of the variables (GENDER – categorical variable vs LOAN_APPROVAL_STATUS – categorical variable) found in the LIB07070.TRAINING_DS

SAS Codes

```
TITLE1 'Bivariate Analysis of the variables (Categorical vs Continuous) found in the LIB07070.TRAINING_DS';
TITLE1 'Bivariate Analysis of the variables (GENDER vs LOAN_APPROVAL_STATUS)';
FOOTNOTE '----END-----';
PROC FREQ DATA = LIB07070.TRAINING_DS;
TABLE GENDER * LOAN_APPROVAL_STATUS /
PLOTS = FREQPLOT ( TWOWAY = STACKED SCALE = GROUPPCT );
RUN;
```

Screenshot(s)



Explanation

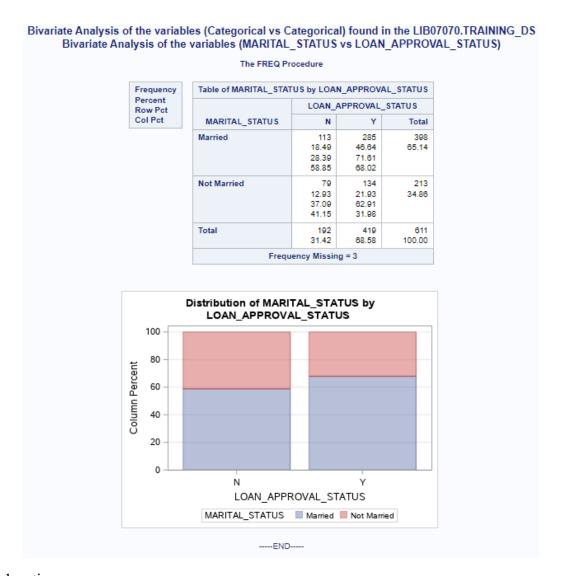
From the graph above, it is observed that number of loan approved between male and female are quite similar, which indicates that the gender does not really contribute to the outcome of the loan approval status.

7.8.4 Bivariate Analysis of the variables (MARITAL_STATUS – categorical variable vs LOAN_APPROVAL_STATUS – categorical variable) found in the LIB07070.TRAINING_DS

SAS Codes

```
TITLE1 'Bivariate Analysis of the variables (Categorical vs Categorical) found in the LIB07070.TRAINING_DS';
TITLE2 'Bivariate Analysis of the variables (MARITAL_STATUS vs LOAN_APPROVAL_STATUS)';
FOOTNOTE '-----END-----';
PROC FREQ DATA = LIB07070.TRAINING_DS;
TABLE MARITAL_STATUS * LOAN_APPROVAL_STATUS /
PLOTS = FREQPLOT ( TWOWAY = STACKED SCALE = GROUPPCT );
RUN:
```

Screenshot(s)



Explanation

From the graph above, it is observed that number of loan approved between married and not married are a little different, which indicates that there are more married applicants who got their loan approved as compared to the not married ones.

7.9 Finding the variables with missing values and data imputation.

SAS Codes

```
TITLE 'Find the Categorical and Continuous variables with missing values';

PROC FORMAT;

VALUE $missfmt ' ' = 'Missing' others = 'Not missing';

VALUE missfmt . = 'Missing' others = 'Not missing';

RUN;

PROC FREQ DATA=LIB07070.TRAINING_DS;

FORMAT _CHAR_ $missfmt.;

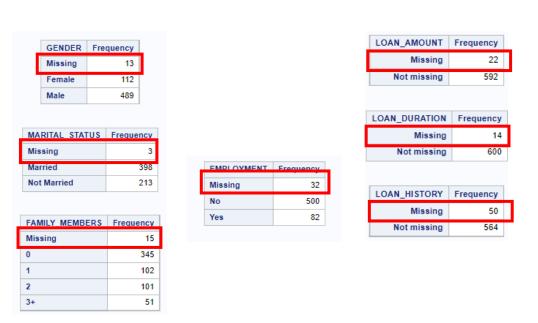
FORMAT _NUMERIC_ missfmt.;

TABLE _CHAR_ / missing nocum nopercent;

TABLE _NUMERIC_ / missing nocum nopercent;

RUN;
```

Screenshot(s)



Explanation

There is total 7 variables with missing values, with the highest being 50 in the LOAN_HISTORY variable. These missing data must be pre-processed first and imputed before performing the next step.

7.9.1 Imputing the missing values in GENDER variable

STEP 1: Making a copy of the dataset: LIB07070.TRAINING_DS and listing the missing values in GENDER variable

SAS Codes

```
TITLE 'STEP 1: Make a copy of the dataset LIB07070.TRAINING_DS before imputing missing values';
PROC SQL;
CREATE TABLE LIB07070.TRAINING DS FI AS
SELECT * FROM LIB07070.TRAINING DS:
QUIT;
TITLE 'LIST THE OBSERVATIONS WITH MISSING VALUES IN GENDER VARIABLE';
FOOTNOTE '----END----';
PROC SQL;
SELECT *
FROM LIB07070.TRAINING DS FI
WHERE ( GENDER IS MISSING );
QUIT;
TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END-----';
PROC SQL;
SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING_DS_FI
WHERE ( GENDER IS MISSING );
QUIT;
```

Screenshot(s)



Explanation

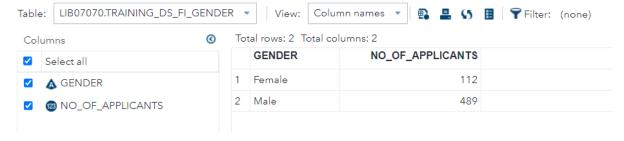
Before imputing all the variables, the dataset should be duplicated before imputation is done so that the imputation is only done on the duplicate dataset and have the original one as backup in case of any necessary situations. (This step is only done once in this section.)

After that, the GENDER variable is checked for missing data and the rows with missing values in the variable are listed.

STEP 2: Create a dataset to hold the gender and number of applicants

SAS Codes

Screenshot(s)



Explanation

Since GENDER is a binary categorical variable, mode imputation will be used to impute the missing values. To do so, a secondary table is required to tabulate the frequency of the variable.

STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_GENDER

SAS Codes

```
TITLE 'STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_GENDER';

PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI_GENDER;

QUIT;
```

Screenshot(s)

STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_GENDER

GENDER	NO_OF_APPLICANTS
Female	112
Male	489

Explanation

After creating the secondary table, the contents are viewed before doing the imputation.

STEP 4: Impute the missing values found in the GENDER variable.

SAS Codes

Screenshot(s)

```
TITLE 'STEP 4: Impute the missing values found in the GENDER variable';
70
          PROC SQL;
71
          UPDATE LIB07070.TRAINING DS FI
73
          SET GENDER = ( SELECT GENDER
74
             FROM LIB07070.TRAINING_DS_FI_GENDER
75
             WHERE NO_OF_APPLICANTS EQ ( SELECT MAX(NO_OF_APPLICANTS) Label 'NO OF APPLICANTS'
             FROM LIB07070.TRAINING_DS_FI_GENDER ) )
76
77
             /*It is a sub-program to find the highest no of applicants*/
78
          WHERE ( ( GENDER IS MISSING ) OR
79
          ( GENDER IS NULL ) OR
          (GENDER EQ ''));
NOTE: 13 rows were updated in LIB07070.TRAINING_DS_FI.
```

Explanation

The missing values in GENDER variables are imputed using the mode, through the secondary table that is created in the previous step.

STEP 5: After imputing missing values, list the observations with missing values in GENDER variable

SAS Codes

```
TITLE 'STEP 5: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN GENDER VARIABLE';
FOOTNOTE '----END-----';
PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI
WHERE ( GENDER IS MISSING );
QUIT;

TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END-----';
PROC SQL;

SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING_DS_FI
WHERE ( GENDER IS MISSING );
QUIT;
```

Screenshot(s)

STEP 5: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN GENDER VARIABLE

	END
NUMBER OF OBSERVAT	TIONS WITH MISSING VALUES
NUMBER OF OBSERVA	ATIONS WITH MISSING VALUES 0
	END

Explanation

After imputation is done, the GENDER variable is double-checked for missing data to ensure there are no more missing data.

7.9.2 Imputing the missing values in MARITAL_STATUS variable

STEP 1: Listing the missing values in MARITAL_STATUS variable

SAS Codes

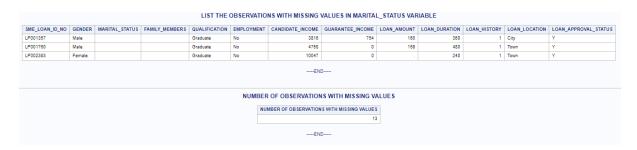
```
TITLE 'LIST THE OBSERVATIONS WITH MISSING VALUES IN MARITAL_STATUS VARIABLE';
FOOTNOTE '----END-----';
PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI
WHERE ( MARITAL_STATUS IS MISSING );
QUIT;

TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END-----';
PROC SQL;

SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING_DS_FI
WHERE ( MARITAL_STATUS IS MISSING );
QUIT;
```

Screenshot(s)



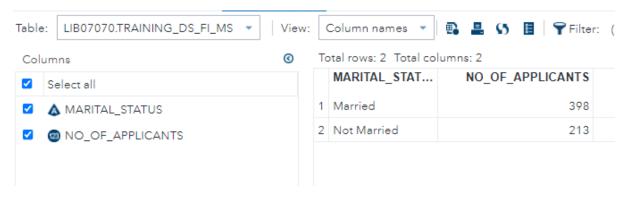
Explanation

The MARITAL_STATUS variable is checked for missing data and the rows with missing values in the variable are listed.

STEP 2: Create a dataset to hold the marital status and number of applicants

SAS Codes

Screenshot(s)



Explanation

Since MARITAL_STATUS is a binary categorical variable, mode imputation will be used to impute the missing values. To do so, a secondary table is required to tabulate the frequency of the variable.

STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_MS

SAS Codes

```
TITLE 'STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_MS';

PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI_MS;

QUIT;
```

Screenshot(s)

STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_MS

MARITAL_STATUS	NO_OF_APPLICANTS
Married	398
Not Married	213

Explanation

After creating the secondary table, the contents are viewed before doing the imputation.

STEP 4: Impute the missing values found in the MARITAL_STATUS variable.

SAS Codes

Screenshot(s)

```
69
           TITLE 'STEP 4: Impute the missing values found in the GENDER variable';
70
           PROC SQL;
71
72
          UPDATE LIB07070.TRAINING_DS_FI
73
          SET MARITAL_STATUS = ( SELECT MARITAL_STATUS
74
                 FROM LIB07070.TRAINING DS FI MS
                WHERE NO_OF_APPLICANTS EQ ( SELECT MAX(NO_OF_APPLICANTS) Label 'NO OF APPLICANTS'
75
76
                FROM LIB07070.TRAINING DS FI MS ) )
77
                 /*It is a sub-program to find the highest no of applicants*/
78
          WHERE ( ( MARITAL_STATUS IS MISSING ) OR
79
           ( MARITAL_STATUS IS NULL ) OR
           ( MARITAL_STATUS EQ '' ) );
NOTE: 3 rows were updated in LIB07070.TRAINING_DS_FI.
```

Explanation

The missing values in MARITAL_STATUS variables are imputed using the mode, through the secondary table that is created in the previous step.

STEP 5: After imputing missing values, list the observations with missing values in MARITAL STATUS variable

SAS Codes

```
TITLE 'STEP 5: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN MARITAL_STATUS VARIABLE';
FOOTNOTE '----END-----';
PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI
WHERE ( MARITAL_STATUS IS MISSING );
QUIT;

TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END-----';
PROC SQL;

SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING_DS_FI
WHERE ( MARITAL_STATUS IS MISSING );
QUIT;
```

Screenshot(s)

STEP 5: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN MARITAL_STATUS VARIABLE

	END		
NUMBER OF OBSERVATIONS WITH MISSING VALUES			
	NUMBER OF OBSERVATIONS WITH MISSING VALUES		
	0		
	END		

Explanation

After imputation is done, the MARITAL_STATUS variable is double-checked for missing data to ensure there are no more missing data.

7.9.3 Imputing the missing values in EMPLOYMENT variable

STEP 1: Listing the missing values in EMPLOYMENT variable

SAS Codes

```
/***********EMPLOYMENT*********/
TITLE 'STEP 1: Make a copy of the dataset LIB07070.TRAINING_DS before imputing missing values';
PROC SQL;
CREATE TABLE LIB07070.TRAINING DS FI AS
SELECT * FROM LIB07070.TRAINING_DS;
QUIT;
TITLE 'LIST THE OBSERVATIONS WITH MISSING VALUES IN EMPLOYMENT VARIABLE';
FOOTNOTE '----END----';
PROC SQL;
SELECT *
FROM LIB07070.TRAINING DS FI
WHERE ( EMPLOYMENT IS MISSING );
QUIT;
TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END----';
PROC SQL;
SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING DS FI
WHERE ( EMPLOYMENT IS MISSING );
QUIT;
```

Screenshot(s)

SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION	LOAN_APPROVAL_STATUS
LP001027	Male	Married	2	Graduate		2500	1840	109	360	1	City	Υ
LP001041	Male	Married	0	Graduate		2600	3500	115		1	City	Υ
LP001052	Male	Married	1	Graduate		3717	2925	151	360		Town	N
LP001087	Female	Not Married	2	Graduate		3750	2083	120	360	1	Town	Υ
LP001091	Male	Married	1	Graduate		4166	3369	201	360		City	N
LP001326	Male	Not Married	0	Graduate		6782	0		360		City	N
LP001370	Male	Not Married	0	Under Graduate		7333	0	120	360	1	Village	N
LP001387	Female	Married	0	Graduate		2929	2333	139	360	1	Town	Υ
LP001398	Male	Not Married	0	Graduate		5050	0	118	360	1	Town	Υ
LP001546	Male	Not Married	0	Graduate		2980	2083	120	360	1	Village	Υ
LP001581	Male	Married	0	Under Graduate		1820	1769	95	360	1	Village	Υ
LP001732	Male	Married	2	Graduate		5000	0	72	360	0	Town	N
LP001768	Male	Married	0	Graduate		3716	0	42	180	1	Village	Υ
LP001786	Male	Married	0	Graduate		5746	0	255	360		City	N
LP001883	Female	Not Married	0	Graduate		3418	0	135	360	1	Village	N
LP001949	Male	Married	3+	Graduate		4416	1250	110	360	1	City	Υ
LP002101	Male	Married	0	Graduate		63337	0	490	180	1	City	Υ
LP002110	Male	Married	1	Graduate		5250	688	160	360	1	Village	Υ
LP002128	Male	Married	2	Graduate		2583	2330	125	360	1	Village	Υ
LP002209	Female	Not Married	0	Graduate		2784	1459	110	360	1	City	Υ
LP002226	Male	Married	0	Graduate		3333	2500	128	360	1	Town	Υ
LP002237	Male	Not Married	1	Graduate		3887	0	113	180	1	City	Υ
LP002319	Male	Married	0	Graduate		6256	0	160	360		City	Υ
LP002386	Male	Not Married	0	Graduate		12876	0	405	360	1	Town	Υ



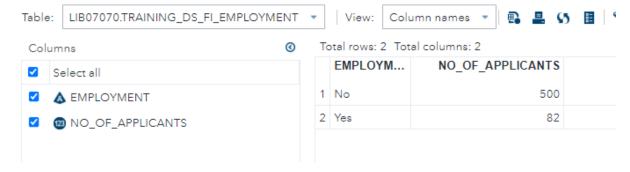
Explanation

The EMPLOYMENT variable is checked for missing data and the rows with missing values in the variable are listed.

STEP 2: Create a dataset to hold the employment and number of applicants

SAS Codes

Screenshot(s)



Explanation

Since EMPLOYMENT is a binary categorical variable, mode imputation will be used to impute the missing values. To do so, a secondary table is required to tabulate the frequency of the variable.

STEP 3: Display the contents of the dataset LIB07070.TRAINING DS FI EMPLOYMENT

```
TITLE 'STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_EMPLOYMENT';

PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI_EMPLOYMENT;

QUIT;
```

Screenshot(s)

STEP 3: Display the contents of the dataset LIB07070.TRAINING_DS_FI_EMPLOYMENT

EMPLOYMENT	NO_OF_APPLICANTS
No	500
Yes	82

Explanation

After creating the secondary table, the contents are viewed before doing the imputation.

STEP 4: Impute the missing values found in the EMPLOYMENT variable.

SAS Codes

Screenshot(s)

```
WHERE NO OF APPLICANTS EQ ( SELECT MAX(NO OF A
75
76
              FROM LIB07070.TRAINING DS FI EMPLOYMENT ) )
77
              /*It is a sub-program to find the highest no c
78
           WHERE ( ( EMPLOYMENT IS MISSING ) OR
79
           ( EMPLOYMENT IS NULL ) OR
           ( EMPLOYMENT EQ '' ) );
80
NOTE: 32 rows were updated in LIB07070.TRAINING DS FI.
81
           QUIT;
NOTE: PROCEDURE SQL used (Total process time):
      real time
                          0.01 seconds
                          0.00 seconds
      user cpu time
                          0.00 seconds
      system cpu time
                          5999 19L
```

Explanation

The missing values in EMPLOYMENT variable are imputed using the mode, through the secondary table that is created in the previous step.

STEP 5: After imputing missing values, list the observations with missing values in EMPLOYMENT variable

SAS Codes

```
TITLE 'STEP 5: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN EMPLOYMENT VARIABLE';
FOOTNOTE '----END-----';
PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI
WHERE ( EMPLOYMENT IS MISSING );
QUIT;

TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END-----';
PROC SQL;

SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING_DS_FI
WHERE ( EMPLOYMENT IS MISSING );
QUIT;
```

Screenshot(s)

STEP 5: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN EMPLOYMENT VARIABLE

	END	
NUM	BER OF OBSERVATIONS WITH MISSING VAI	LUES
	NUMBER OF OBSERVATIONS WITH MISSING VALUES	
	0	
	END	

Explanation

After imputation is done, the EMPLOYMENT variable is double-checked for missing data to ensure there are no more missing data.

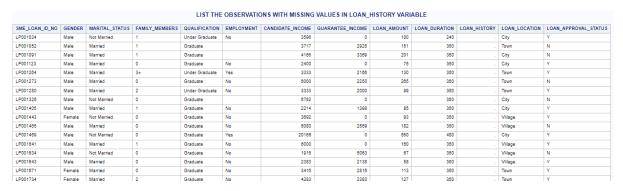
7.9.4 Imputing the missing values in LOAN_HISTORY variable

STEP 1: Listing the missing values in LOAN_HISTORY variable

SAS Codes

```
TITLE 'STEP 1: Make a copy of the dataset LIB07070.TRAINING_DS before imputing missing values';
PROC SQL;
CREATE TABLE LIB07070.TRAINING DS FI AS
SELECT * FROM LIB07070.TRAINING_DS;
QUIT;
TITLE 'LIST THE OBSERVATIONS WITH MISSING VALUES IN LOAN_HISTORY VARIABLE';
FOOTNOTE '----END----';
PROC SQL;
SELECT *
FROM LIB07070.TRAINING DS FI
WHERE ( LOAN_HISTORY IS MISSING );
QUIT;
TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END----';
PROC SQL;
SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING_DS FI
WHERE ( LOAN HISTORY IS MISSING );
QUIT;
```

Screenshot(s)





Explanation

The LOAN_HISTORY variable is checked for missing data and the rows with missing values in the variable are listed.

STEP 2: Display Median value

SAS Codes

Screenshot(s)



Explanation

Since LOAN_HISTORY is a numeric categorical variable, no secondary table is required. Median can be used for the imputation of the missing data.

STEP 3: Impute the missing values found in the LOAN_HISTORY variable

```
TITLE 'STEP 3: Impute the missing values found in the LOAN_HISTORY variable';

PROC SQL;

CREATE TABLE LIB07070.TRAINING_DS_FI_LH AS

SELECT *

FROM LIB07070.TRAINING_DS_FI;

QUIT;

PROC SQL;

UPDATE LIB07070.TRAINING_DS_FI_LH

SET LOAN_HISTORY = ( SELECT MEDIAN(ti.LOAN_HISTORY) Label 'Loan Median'

FROM LIB07070.TRAINING_DS_FI ti

WHERE ( ( ti.LOAN_HISTORY IS NOT MISSING ) OR

( ti.LOAN_HISTORY NE . ) ) ) /* It is a sub-program to find median value */

WHERE ( ( LOAN_HISTORY IS MISSING ) OR

( LOAN_HISTORY EQ . ) );

QUIT;
```

Screenshot(s)

```
69
           PROC SQL;
70
71
           UPDATE LIB07070.TRAINING DS FI LH
72
           SET LOAN_HISTORY = ( SELECT MEDIAN(ti.LOAN_HISTORY) Label 'Loan Median'
73
           FROM LIB07070.TRAINING_DS_FI ti
74
           WHERE ( ( ti.LOAN_HISTORY IS NOT MISSING ) OR
75
           ( ti.LOAN_HISTORY NE . ) ) ) /* It is a sub-program to find median value */
76
77
           WHERE ( ( LOAN_HISTORY IS MISSING ) OR
           ( LOAN_HISTORY EQ . ) );
NOTE: 50 rows were updated in LIB07070.TRAINING_DS_FI_LH.
79
80
           QUIT;
```

Explanation

The missing values in EMPLOYMENT variable are imputed using the median. 50 rows were updated in this imputation step.

STEP 4: After imputing missing values, list the observations with missing values in LOAN HISTORY variable

Screenshot(s)

STEP 4: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN LOAN HISTORY VARIABLE

STEP 4. ALTER IMPOTING MISSING VALO	E3. E131 THE ODSERVATIONS WITH MISSIN	IO VALUES IN LOAN_IIISTORT VARIABLE
	END	
NUM	BER OF OBSERVATIONS WITH MISSING VA	LUES
	NUMBER OF OBSERVATIONS WITH MISSING VALUES	
	0	
	END	

Explanation

After imputation is done, the LOAN_HISTORY variable is double-checked for missing data to ensure there are no more missing data.

7.9.5 Imputing the missing values in LOAN_AMOUNT variable

STEP 1: Listing the missing values in the LOAN_AMOUNT variable

SAS Codes

Screenshot(s)

SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION	LOAN_APPROVAL_STATUS
LP001002	Male	Not Married	0	Graduate	No	5849	0		360	1	City	Υ
LP001108	Male	Married	0	Graduate	No	2275	2087		360	1	City	Υ
LP001213	Male	Married	1	Graduate	No	4945	0		360	0	Village	N
LP001288	Male	Married	1	Graduate	Yes	2395	0		360	1	Town	Υ
LP001326	Male	Not Married	0	Graduate		6782	0		360		City	N
LP001350	Male	Married		Graduate	No	13650	0		360	1	City	Υ
LP001358	Male	Married	0	Graduate	No	4852	3583		360	1	Town	Υ
LP001392	Female	Not Married	1	Graduate	Yes	7451	0		360	1	Town	Υ
LP001449	Male	Not Married	0	Graduate	No	3865	1640		360	1	Village	Υ
LP001682	Male	Married	3+	Under Graduate	No	3992	0		180	1	City	N
LP001922	Male	Married	0	Graduate	No	20667	0		360	1	Village	N
LP001990	Male	Not Married	0	Under Graduate	No	2000	0		360	1	City	N
LP002054	Male	Married	2	Under Graduate	No	3601	1590		360	1	Village	Υ
LP002113	Female	Not Married	3+	Under Graduate	No	1830	0		360	0	City	N
LP002243	Male	Married	0	Under Graduate	No	3010	3138		360	0	City	N
LP002393	Female			Graduate	No	10047	0		240	1	Town	Υ
LP002401	Male	Married	0	Graduate	No	2213	1125		360	1	City	Y
LP002533	Male	Married	2	Graduate	No	2947	1603		380	1	City	N
LP002697	Male	Not Married	0	Graduate	No	4680	2087		360	1	Town	N
LP002778	Male	Married	2	Graduate	Yes	6633	0		360	0	Village	N
LP002784	Male	Married	1	Under Graduate	No	2492	2375		360	1	Village	Y
LP002960	Male	Married	0	Under Graduate	No	2400	3800		180	1	City	N
							D IS WITH MISSING VALUES IS WITH MISSING VALUES 22	1				

Explanation

The LOAN_AMOUNT variable is checked for missing data and the rows with missing values in the variable are listed.

STEP 2: Impute missing values with mean

SAS Codes

```
TITLE 'STEP 2: IMPUTE THE MISSING VALUES IN LOAN_AMOUNT';

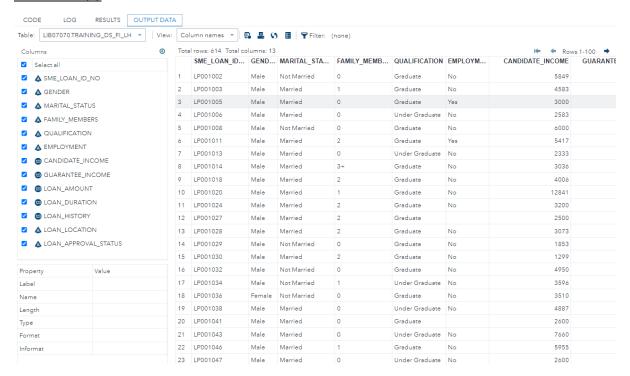
PROC STDIZE DATA=LIB07070.TRAINING_DS_FI_LH REPONLY

METHOD=MEAN OUT=LIB07070.TRAINING_DS_FI_LH;

VAR LOAN_AMOUNT;

QUIT;
```

Screenshot(s)



Explanation

As LOAN_AMOUNT is a numeric continuous variable, mean imputation will be used to impute the missing values in the variable.

STEP 3: After imputing missing values, list the observations with missing values in LOAN AMOUNT variable

SAS Codes

Screenshot(s)

STEP 3: AFTER IMPUTING MISSING VALUES: LIST THE OBSERVATIONS WITH MISSING VALUES IN LOAN_AMOUNT VARIABLE

	END	
NUM	BER OF OBSERVATIONS WITH MISSING VAI	LUES
	NUMBER OF OBSERVATIONS WITH MISSING VALUES	
	0	
	END	

Explanation

After imputation is done, the LOAN_AMOUNT variable is double-checked for missing data to ensure there are no more missing data.

7.9.6 Imputing the missing values in LOAN_DURATION variable

STEP 1: Listing the missing values in the LOAN_DURATION variable

SAS Codes

Screenshot(s)



Explanation

The LOAN_DURATION variable is checked for missing data and the rows with missing values in the variable are listed.

STEP 2: Impute missing values with mean

SAS Codes

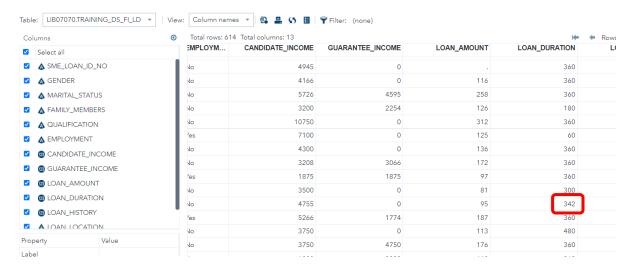
```
TITLE 'STEP 2: IMPUTE THE MISSING VALUES IN LOAN_DURATION';

PROC STDIZE DATA=LIB07070.TRAINING_DS_FI REPONLY

METHOD=MEAN OUT=LIB07070.TRAINING_DS_FI_LD;
VAR LOAN_DURATION;

QUIT;
```

Screenshot(s)



Explanation

As LOAN_DURATION is a numeric continuous variable, mean imputation will be used to impute the missing values in the variable.

STEP 3: After imputing missing values, list the observations with missing values in LOAN DURATION variable

SAS Codes

Screenshot(s)



Explanation

After imputation is done, the LOAN_DURATION variable is double-checked for missing data to ensure there are no more missing data.

7.9.7 Imputing the missing values in FAMILY_MEMBERS variable

STEP 1: List the observations with missing values in FAMILY_MEMBERS variable

SAS Codes

```
TITLE 'STEP 1: LIST THE OBSERVATIONS WITH MISSING VALUES IN FAMILY_MEMBERS VARIABLE';
FOOTNOTE '----END----';
PROC SQL;
SELECT *
FROM LIB07070.TRAINING DS FI
WHERE ( ( FAMILY MEMBERS IS MISSING ) OR
        ( FAMILY MEMBERS IS NULL ) OR
        ( FAMILY_MEMBERS EQ '' ) );
QUIT;
TITLE 'NUMBER OF OBSERVATIONS WITH MISSING VALUES';
FOOTNOTE '----END----';
PROC SQL;
SELECT COUNT (*) LABEL 'NUMBER OF OBSERVATIONS WITH MISSING VALUES'
FROM LIB07070.TRAINING DS FI
WHERE ( ( FAMILY_MEMBERS IS MISSING ) OR
        ( FAMILY_MEMBERS IS NULL ) OR
        ( FAMILY_MEMBERS EQ '' ) );
QUIT;
```

Screenshot(s)

				STEP 1: LIST T	HE OBSERVA	TIONS WITH MISSI	NG VALUES IN FAM	ILY_MEMBERS	VARIABLE			
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION	LOAN_APPROVAL_STATUS
LP001350	Male	Married		Graduate	No	13650	0		360	1	City	Υ
LP001357	Male			Graduate	No	3816	754	160	360	1	City	Υ
LP001426	Male	Married		Graduate	No	5667	2667	180	360	1	Village	Υ
LP001754	Male	Married		Under Graduate	Yes	4735	0	138	360	1	City	N
LP001760	Male			Graduate	No	4758	0	158	480	1	Town	Υ
LP001945	Female	Not Married		Graduate	No	5417	0	143	480	0	City	N
LP001972	Male	Married		Under Graduate	No	2875	1750	105	360	1	Town	Υ
LP002100	Male	Not Married		Graduate	No	2833	0	71	360	1	City	Υ
LP002106	Male	Married		Graduate	Yes	5503	4490	70		1	Town	Υ
LP002130	Male	Married		Under Graduate	No	3523	3230	152	360	0	Village	N
LP002144	Female	Not Married		Graduate	No	3813	0	116	180	1	City	Υ
LP002393	Female			Graduate	No	10047	0		240	1	Town	Υ
LP002682	Male	Married		Under Graduate	No	3074	1800	123	360	0	Town	N
LP002847	Male	Married		Graduate	No	5116	1451	165	360	0	City	N
LP002943	Male	Not Married		Graduate	No	2987	0	88	360	0	Town	N
NUMBER OF OBSERVATIONS WITH MISSING VALUES NUMBER OF OBSERVATIONS WITH MISSING VALUES 15												
						EN	D					

Explanation

The FAMILY_MEMBERS variable is checked for missing data and the rows with missing values in the variable are listed.

STEP 2: Display the details of applicants with 3+ family members

SAS Codes

```
TITLE 'STEP 2 : DISPLAY THE DETAILS OF APPLICANTS WITH 3+ FAMILY MEMBERS';
FOOTNOTE '----END----';

PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI
WHERE ( SUBSTR(FAMILY_MEMBERS,2,1) EQ '+' );
QUIT;

PROC SQL;
SELECT COUNT(*) Label 'No of Applicants'
FROM LIB07070.TRAINING_DS_FI
WHERE ( SUBSTR(FAMILY_MEMBERS,2,1) EQ '+' );
QUIT;
```

Screenshot(s)



STEP 2 : DISPLAY THE DETAILS OF APPLICANTS WITH 3+ FAMILY MEMBERS

No of Applicants

51

----END-----

Explanation

The observations of the applicants with 3 or more family members are listed out and counted. There are total 51 applicants with 3 or more family members

STEP 3: Replace 3+ with 3

```
TITLE 'STEP 3 : Replace 3+ with 3';

PROC SQL;
UPDATE LIB07070.TRAINING_DS_FI
SET FAMILY_MEMBERS = SUBSTR(FAMILY_MEMBERS,1,1)
WHERE ( SUBSTR(FAMILY_MEMBERS,2,1) EQ '+' );
QUIT;
```

Screenshot(s)

```
, _
           THUC DUE,
72
           UPDATE LIB07070.TRAINING DS FI
73
           SET FAMILY MEMBERS = SUBSTR(FAMILY MEMBERS,1,1)
           WHERE ( SUBSTR(FAMILY MEMBERS, 2, 1) EQ '+' );
74
NOTE: 51 rows were updated in LIB07070.TRAINING DS FI.
75
           QUIT;
NOTE: PROCEDURE SQL used (Total process time):
      real time
                          0.00 seconds
      user cou time
                          a al seconde
```

Explanation

The value 3+ have to be replaced with 3 because with the + symbol, it makes the variable become string variable while the other values are numeric. By converting this, it makes the variable as numerical variable before proceeding to the next step.

STEP 4: AFTER REPLACING THE 3+ WITH 3

SAS Codes

```
TITLE 'STEP 4 : After replacing 3+ with 3';
FOOTNOTE '----END-----';

PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI
WHERE ( SUBSTR(FAMILY_MEMBERS,2,1) EQ '+' );
QUIT;

PROC SQL;
SELECT COUNT(*) Label 'No of Applicants'
FROM LIB07070.TRAINING_DS_FI
WHERE ( SUBSTR(FAMILY_MEMBERS,2,1) EQ '+' );
QUIT;
```

Screenshot(s)



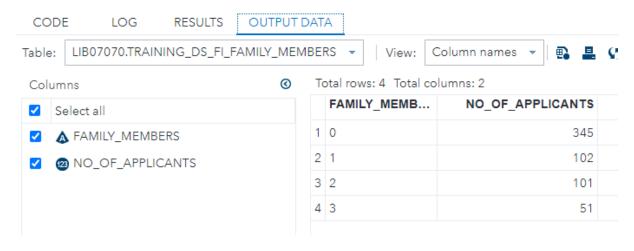
Explanation

All the 3+ values are replaced with number 3.

STEP 5: Create a dataset to hold the family members and number of applicants

SAS Codes

Screenshot(s)



Explanation

A secondary data table is created is tabulate the number of applicants according to the number of their family members.

STEP 6: Display the contents of the dataset LIB07070.TRAINING_DS_FI_FAMILY_MEMBERS

SAS Codes

```
TITLE 'STEP 6: Display the contents of the dataset LIB07070.TRAINING_DS_FI_FAMILY_MEMBERS';

PROC SQL;

SELECT *
FROM LIB07070.TRAINING_DS_FI_FAMILY_MEMBERS;

QUIT;
```

Screenshot(s)

STEP 6: Display the contents of the dataset LIB07070.TRAINING_DS_FI_FAMILY_MEMBERS

FAMILY_MEMBERS	NO_OF_APPLICANTS
0	345
1	102
2	101
3	51

Explanation

The secondary data table is viewed after being created. The highest frequency for the variable is zero family members.

STEP 7: Create a dataset to hold the family members and number of applicants

Screenshot(s)

```
79 (FAMILY_MEMBERS IS NULL) OR
80 (FAMILY_MEMBERS EQ''));
NOTE: 15 rows were updated in LIB07070.TRAINING_DS_FI.

81 QUIT;
NOTE: PROCEDURE SQL used (Total process time):
real time 0.01 seconds
```

Explanation

By using the mode imputation, the missing values are imputed using the 0 value from the secondary data table in previous step.

STEP 8: After imputing missing values, list the observations with missing values in FAMILY_MEMBERS variable

SAS Codes

Screenshot(s)

${\tt STEP~8: AFTER~IMPUTING~THE~MISSING~VALUES, LIST~THE~OBSERVATIONS~WITH~MISSING~VALUES~IN~FAMILY_MEMBERS~VARIABLE}$							
	END						
NUM	BER OF OBSERVATIONS WITH MISSING VAI	LUES					
	NUMBER OF OBSERVATIONS WITH MISSING VALUES						
	0						

Explanation

After imputation is done, the FAMILY_MEMBERS variable is double-checked for missing data to ensure there are no more missing data.

7.10 SAS MACRO

7.10.1 Univariate Analysis of the categorical variable using SAS MACRO

SAS Codes

```
/* MACRO MACRO_FOR_UNIVARIATE ANALYSIS BEGINS HERE */

XMACRO MACRO_FOR_UNIVALIB07070_TESTING_DS(PDS_NAME, PVARI_NAME, PTITLE_NAME);

PROC FREQ DATA = %PDS_NAME;

TABLE %PVARI_NAME;

TITLE %PTITLE_NAME;

QUIT;

XMEND MACRO_UVA_LIB07070_TESTING_DS;

/* MACRO MACRO_FOR_UNIVARIATE ANALYSIS ENDS HERE */

/*CALL/RUN THE SAS MACRO */

XMACRO_UVA_LIB07070_TESTING_DS (LIB07070.TESTING_DS, EMPLOYMENT, "UNIVARIATE ANALYSIS OF THE CATEGORICAL VARIABLE - EMPLOYMENT");

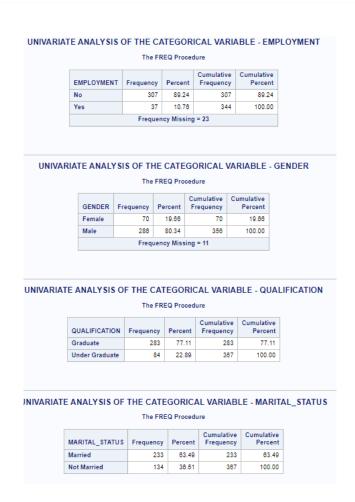
XMACRO_UVA_LIB07070_TESTING_DS (LIB07070.TESTING_DS, GENDER, "UNIVARIATE ANALYSIS OF THE CATEGORICAL VARIABLE - GENDER");

XMACRO_UVA_LIB07070_TESTING_DS (LIB07070.TESTING_DS, QUALIFICATION, "UNIVARIATE ANALYSIS OF THE CATEGORICAL VARIABLE - QUALIFICATION");

XMACRO_UVA_LIB07070_TESTING_DS (LIB07070.TESTING_DS, MARITAL_STATUS, "UNIVARIATE ANALYSIS OF THE CATEGORICAL VARIABLE - QUALIFICATION");

XMACRO_UVA_LIB07070_TESTING_DS (LIB07070.TESTING_DS, MARITAL_STATUS, "UNIVARIATE ANALYSIS OF THE CATEGORICAL VARIABLE - MARITAL_STATUS");
```

Screenshot(s)



7.10.2 Univariate Analysis of the continuous variable using SAS MACRO

```
/* SAS MACRO FOR UNIVARIATE ANALYSIS OF CONTINUOUS VARIABLES*/
%MACRO MACRO_UNIV_CONT_VARI(PDS_NAME, PVARI_NAME, PTITLE_1, PTITLE_NAME_2);
TITLE &PTITLE 1;
PROC MEANS DATA = &PDS NAME N NMISS MIN MAX MEAN MEDIAN STD;
VAR &PVARI NAME;
ODS GRAPHICS / RESET WIDTH=4.0 IN HEIGHT=3.0 IN IMAGEMAP;
PROC SGPLOT DATA = &PDS NAME:
HISTOGRAM &PVARI NAME;
TITLE &PTITLE NAME 2;
RUN;
%MEND MACRO_UNIV_CONT_VARI;
/* To call the SAS MACRO MACRO UNIV CONT VARI */
%MACRO_UNIV_CONT_VARI (LIB07070.TESTING_DS, LOAN_AMOUNT,
'Figure 7.8.3 Univariate Analysis variable: LOAN_AMOUNT',
'Figure 7.8.3 Univariate Analysis variable: LOAN AMOUNT');
%MACRO_UNIV_CONT_VARI (LIB07070.TESTING_DS, CANDIDATE_INCOME,
'Figure 7.8.3 Univariate Analysis variable: CANDIDATE INCOME'
'Figure 7.8.3 Univariate Analysis variable: CANDIDATE_INCOME');
%MACRO_UNIV_CONT_VARI (LIB07070.TESTING_DS, GUARANTEE_INCOME,
'Figure 7.8.3 Univariate Analysis variable: GUARANTEE_INCOME
'Figure 7.8.3 Univariate Analysis variable: GUARANTEE_INCOME');
```

Explanation

SAS MACROS is a programming feature inside SAS studio. It can help the programmer to save a lot of time doing coding because it can help to run repetitive sections of codes without needing to repeat coding.

In this case, SAS MACROS are used to run univariate analysis of the variables in the dataset.

7.10.3 Bivariate Analysis of the categorical variable using SAS MACRO

```
/* SAS MACRO FOR BIVARIATE ANALYSIS OF CATEGORICAL VARIABLES*/
%MACRO_BVAR_CATEG_VARI_TP063332(PDS_NAME, PVARI_1, PVARI_2, PTITLE_1, PTITLE_2);

PROC FREQ DATA = &PDS_NAME;

TABLE &PVARI_1 * &PVARI_2 /
PLOTS=FREQPLOT(TMONAY=STACKED SCALE=GROUPPCT);
TITLE1 &PTITLE_1;
TITLE1 &PTITLE_1;
TITLE2 &PTITLE_2;

RUN;

%MEND MACRO_BVAR_CATEG_VARI_TP063332;

/* To call the macro - MACRO_BVAR_CATEG_VARI_TP063332*/

%MACRO_BVAR_CATEG_VARI_TP063332(LIB07070.TESTING_DS,
MARITAL_STATUS_LOAN_LOCATION, "BIVARIATE ANALYSIS OF CATEGORICAL VARIABLES", "MARITAL_STATUS-Categorical vs LOAN_LOCATION-Categorical")

%MACRO_BVAR_CATEG_VARI_TP063332(LIB07070.TESTING_DS,
EMPLOYMENT_LOAN_HISTORY, "BIVARIATE ANALYSIS OF CATEGORICAL VARIABLES", "EMPLOYMENT-Categorical vs LOAN_HISTORY-Categorical")

%MACRO_BVAR_CATEG_VARI_TP063332(LIB07070.TESTING_DS,
GENDER, FAMILY_MEMBERS, "BIVARIATE ANALYSIS OF CATEGORICAL VARIABLES", "GENDER-Categorical vs FAMILY_MEMBERS-Categorical")

%MACRO_BVAR_CATEG_VARI_TP063332(LIB07070.TESTING_DS,
GENDER, FAMILY_MEMBERS, "BIVARIATE ANALYSIS OF CATEGORICAL VARIABLES", "GENDER-Categorical vs LOAN_LOCATION-Categorical")

%MACRO_BVAR_CATEG_VARI_TP063332(LIB07070.TESTING_DS,
GENDER, FAMILY_MEMBERS, "BIVARIATE ANALYSIS OF CATEGORICAL VARIABLES", "GENDER-Categorical vs LOAN_LOCATION-Categorical")
```

Explanation

SAS MACROS are also used to carry out the bivariate analysis on the variables in the dataset to find any relationships between the variables.

7.11 Variables with missing values found in the LIB07070.TESTING DS

7.11.1 Finding the variables with missing data before imputation

SAS Codes

```
TITLE 'Before imputing the missing values, find the categorical and continuous variables with missing values';

PROC FORMAT;

VALUE $missfmt ' ' = 'Missing' others = 'Not missing';

VALUE missfmt . = 'Missing' others = 'Not missing';

RUN;

PROC FREQ DATA=LIB07070.TESTING_DS;

FORMAT _CHAR_ $missfmt.;

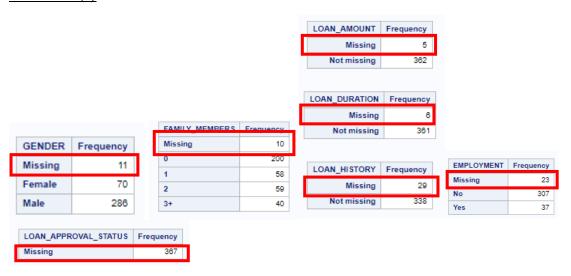
FORMAT _NUMERIC_ missfmt.;

TABLE _CHAR_ / missing nocum nopercent;

TABLE _NUMERIC_ / missing nocum nopercent;

RUN;
```

Screenshot(s)



Explanation

Similar to the TRAINING dataset, TESTING dataset also have missing values, which will be imputed with the same methods as the TRAINING dataset.

7.11.2 Checking all variables to make sure all missing data are imputed

```
TITLE 'Before imputing the missing values, find the categorical and continuous variables with missing values';

PROC FORMAT;

VALUE $missfmt ' ' = 'Missing' others = 'Not missing';

VALUE missfmt . = 'Missing' others = 'Not missing';

RUN;

PROC FREQ DATA=LIB07070.TESTING_DS;

FORMAT _CHAR_ $missfmt.;

FORMAT _NUMERIC_ missfmt.;

TABLE _CHAR_ / missing nocum nopercent;

TABLE _NUMERIC_ / missing nocum nopercent;

RUN;
```

Screenshot(s)

						CANDIDATE_INCOM	E Frequency
GEN	IDER	Frequency				Not missin	g 367
Fem		70		QUALIFICATION	Frequency		
Male	2	297		Graduate	283	GUARANTEE INCOM	E Frequency
				Under Gradu	84	Not missir	
Married		Treque	233	EMPLOYMENT	Frequency	LOAN_AMOUNT	Frequency
MARITAL	CTATI	JS Freque					
Not Marri	ied		134	No	330	Not missing	367
				Yes	37		
						LOAN_DURATION	Frequency
AMILY_N	MEMBE	RS Freque	-	LOAN LOCATION	Frequency	Not missing	367
			210	City	140		
			58	-	-		
			59	Town	116	LOAN_HISTORY	Frequency
2			50				

Explanation

Similar as the TRAINING dataset, all the missing values in the TESTING dataset are made sure imputed before proceeding to build the logistic regression model in the next step.

7.12 Building a Logistic Regression Model

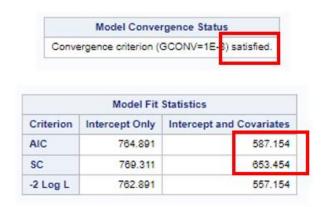
7.13.1 Build a logistic regression model using the dataset LIB07070.TRAINING_DS_FI_LH

```
/*****BUILD LOGISTIC REGRESSION******/
PROC LOGISTIC DATA=LIB07070.TRAINING DS FI LH OUTMODEL=LIB07070.TRAINING DS FI LH MODEL;
CLASS
GENDER
LOAN HISTORY
MARITAL_STATUS
QUALIFICATION
LOAN_LOCATION
FAMILY MEMBERS
EMPLOYMENT;
/* Above are categorical variables */
MODEL LOAN_APPROVAL_STATUS = /*place here all independent variables */
/* LOAN_APPLICATION_STATUS is a dependent variable */
GENDER
LOAN LOCATION
MARITAL STATUS
QUALIFICATION
FAMILY_MEMBERS
LOAN_HISTORY
EMPLOYMENT
CANDIDATE_INCOME
GUARANTEE_INCOME
LOAN_AMOUNT
LOAN DURATION;
OUTPUT OUT = LIB07070.TRAINING_DS_FI_LH_OUT P = PRED_PROB;
/*PRED_PROB ->PRedicted probability - variable to hold predicted probability
OUT -> the output will be stored in the dataset
Akaike Information criterion must ( AIC ) < SC (Schwarz Criterion)
*/
RUN;
```

Output(s)



The number of observations read and used are matched with both showing 614 observations, this indicated that the training dataset is imputed well and has no missing data. It also predicted that 192 applications were rejected while 422 applications were accepted.



To validate that model created is valid, Akaike Information Criterion (AIC) value must be lower than Schwarz Criterion (SC). The convergence criterion is also satisfied.

Analysis of Maximum Likelihood Estimates									
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSo			
Intercept		1	0.0495	0.6972	0.0050	0.943			
GENDER	Female	1	-0.0149	0.1495	0.0100	0.920			
LOAN_LOCATION	City	1	0.1559	0.1519	1.0538	0.304			
LOAN_LOCATION	Town	1	-0.5313	0.1575	11.3806	0.000			
MARITAL_STATUS	Married	1	-0.2915	0.1264	5.3173	0.021			
QUALIFICATION	Graduate	1	-0.2052	0.1299	2.4952	0.114			
FAMILY_MEMBERS	0	1	-0.0394	0.1863	0.0447	0.832			
FAMILY_MEMBERS	1	1	0.4319	0.2258	3.6572	0.055			
FAMILY_MEMBERS	2	1	-0.3310	0.2538	1.6998	0.192			
LOAN_HISTORY	0	1	1.9696	0.2106	87.4798	<.000			
EMPLOYMENT	No	1	-0.0123	0.1586	0.0060	0.938			
CANDIDATE_INCOME		1	-0.00001	0.000024	0.2268	0.633			
GUARANTEE_INCOME		1	0.000053	0.000035	2.2688	0.132			
LOAN_AMOUNT		1	0.00191	0.00160	1.4294	0.231			
LOAN DURATION		1	0.00134	0.00184	0.5322	0.465			

If Pr > ChiSq is <=0.05, it means that the independent variable is an important variable for the dependent variable prediction. In this case, LOAN_LOCATION, MARITAL_STATUS and LOAN_HISTORY is important for the prediction.

7.12.1 Predict the Approval Status using the logistic regression model created

SAS Codes

```
/******PREDICTION MODEL USING LRA**********/
TITLE 'Prediction Model Using the Logistic Regression';
FOOTNOTE '----';
PROC LOGISTIC INMODEL=LIB07070.TRAINING DS FI LH MODEL;
SCORE DATA=LIB07070.TESTING DS FI
OUT=LIB07070.TESTING_DS_FI_PREDICTION;
QUIT;
      TITLE 'Number of Loans Approved';
      FOOTNOTE '----END----';
      PROC SQL;
      SELECT COUNT(*) Label "NUMBER OF OBSERVATIONS WITH 'Y'"
      FROM LIB07070.TESTING_DS_FI_PREDICTION
      WHERE ( I_LOAN_APPROVAL_STATUS EQ 'Y' );
      QUIT;
      TITLE 'Number of Loans Rejected';
      FOOTNOTE '----END----';
      PROC SQL;
      SELECT COUNT(*) Label "NUMBER OF OBSERVATIONS WITH 'N'"
      FROM LIB07070.TESTING DS FI PREDICTION
      WHERE ( I LOAN APPROVAL STATUS EQ 'N' );
      QUIT;
```

Output(s)

From: LOAN_APPROVAL_STATUS	Into: LOAN_APPROVAL_STATUS	Predicted Probability: LOAN_APPROVAL_STATUS=N	Predicted Probability: LOAN_APPROVAL_STATUS=Y
	Υ	0.15823	0.84177
	Υ	0.257444	0.742556
	Υ	0.158193	0.84180
	Υ	0.140894	0.85910
	Υ	0.329375	0.67062
	Υ	0.28222	0.7177
	Υ	0.272703	0.72729
	N	0.93692	0.0630
	Υ	0.131183	0.86881
	Υ	0.236009	0.76399



Explanation

Through the logistic regression model, the loan approval status is predicted. As we can observed from the screenshot above, when the probability of N is more than 0.5, the loan approval status will be N, which means rejected. Otherwise, when the probability of Y is more than 0.5, the loan approval status will be Y, indicating that the loan will be approved. A total of 306 applications were predicted to be approved while only 61 of the applications were predicted to be rejected.

7.13 Output Delivery System (ODS)

In SAS Studio, the SAS output are only designed like a traditional typewriter. This output has some limitations where not everyone is able to access easily. By using the Output Delivery System (ODS) in SAS, it is a method of delivering the outputs in a number of formats. Some of the formats included are like Portable Document Format (PDF) and HTML etc.

After creating the predicted dataset, the outputs can then be delivered to the library folder as PDF for easy access or even create a view for the other data scientists.

7.13.1 Creating VIEW for other users

SAS Codes

```
PROC SQL;
CREATE VIEW LIB07070.VIEW_FOR_WAYNE AS
SELECT SME_LOAN_ID_NO,
GENDER,
FAMILY_MEMBERS,
EMPLOYMENT,
QUALIFICATION
FROM LIB07070.TESTING_DS_FI_PREDICTION;
QUIT;
```

Creating a VIEW for another user

```
PROC DATASETS library=LIB07070 memtype=VIEW; RUN;
```

Output(s)



The user are able to view the VIEW created for him/her

SME_LOAN_ID_NO	GENDER	FAMILY_MEMBERS	EMPLOYMENT	QUALIFICATION
LP001015	Male	0	No	Graduate
LP001022	Male	1	No	Graduate
LP001031	Male	2	No	Graduate
LP001035	Male	2	No	Graduate
LP001051	Male	0	No	Under Graduate
LP001054	Male	0	Yes	Under Graduate
LP001055	Female	1	No	Under Graduate
LP001058	Male	2	No	Under Graduate
LP001059	Male	2	No	Graduate
LP001087	Male	0	No	Under Graduate
LP001078	Male	0	No	Under Graduate
I D004000				0 1 1

The user will only be able to view the variables included in the VIEW dataset.

7.13.2 Creating PDF for other users

SAS Codes

```
ODS HTML CLOSE;
ODS PDF CLOSE;

PDS PDF FILE="/home/u58868125/sasuser.v94/DAP_FT_SEP_2021_TP063332/REPORT.pdf";
OPTIONS NOBYLINE NODATE;
TITLE1 "Bank Loan Approval Status Predicted";
TITLE2 "APU,TPM";
FOOTNOTE '----End of Report-----';

PROC REPORT DATA=LIB07070.TESTING_DS_FI_PREDICTION NOWINDOWS;

BY SME_LOAN_ID_NO; /* To separate each by SME LOAN ID NO */
/* COLUMN SME_LOAN_ID_NO I_LOAN_APPROVAL_STATUS;*/
DEFINE SME_LOAN_ID_NO / GROUP 'LOAN ID';
DEFINE I_LOAN_APPROVAL_STATUS / GROUP 'LOAN APPROVAL STATUS';
FOOTNOTE '----End of Report-----';

RUN;
OPTIONS BYLINE;
```

Output(s)



The observations are exported together with the predicted probability loan approval status and the outcome. This report can then be passed to the person-in-charge to process the loan documents.

8. CONCLUSION

In a nutshell, 2 datasets were used in this study to predict the loan approval status of the applicants, which are TRAINING_DS and TESTING_DS. The datasets are first explored by doing univariate and bivariate analysis. After that, since missing values are found in the datasets, the missing values are imputed by using either mean, median or mode imputation. After cleaning the data, logistic regression model is run on the training dataset to create the model. The predicted dataset on the testing dataset results in 422 applications approved and 192 applications rejected. The model also suggested that loan history, marital status and loan location plays an important role in predicting the outcome of the application approval status.

9. PERSONAL REFLECTION

At the end of this report, the researcher is satisfied that the prediction of the loan approval status is done using the logistic regression model in SAS studio. Compared to the beginning of the module, a better understanding of SQL programming skills and workflow was obtained through the progress of the assignment. This assignment also provided an opportunity to work on a real-life application in loan approvals. Lastly, sincere gratitude also goes to Mr. Dhason who provided his guidance during the study.

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