INDIVIDUAL ASSIGNMENT

TECHNOLOGY PARK MALAYSIA

CT050-3-M-DAP

DATA ANALYTICAL PROGRAMMING

APDMF2310DSBA(DE)

STUDENT's TP: TP077702

STUDENT's NAME: MR. MOHAMMAD ADNAN

LECTURER's NAME: MR. DHASON PADMAKUMAR

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1 Introduction

In the current economic environment, using sophisticated analytical software in banking has transformed how financial institutions manage risk and improve their services. A company situated in New York called Lasiandra Finance Inc. (LFI) which is a leading private mortgage lender is one of the pioneers of this approach. The company uses complex data analysis programs to facilitate fast loan approval processes. This paper focuses on examining the way logistic regression models and data management methods are employed at LFI to support small and medium-sized enterprises (SMEs) decision-making as well as operational efficiency.

There are two main goals for this research study. Firstly, it seeks to determine if logistic regression can be used to predict whether or not loans will be approved based on certain borrower characteristics such as marriage status, income level and employment among others. Secondly, it addresses issues related to missing information by imputing the same so that any model used becomes more robust and accurate.

This task heavily relies on SAS language for automating different data manipulation routines required especially when dealing with large volumes common within bank loan dataset. Furthermore, through univariate analysis alone followed by bivariate analyses also being conducted; specific insights with regards to what each individual variable contributes towards influencing decisions on approving loans shall be brought out.

By incorporating sophisticated types of analysis into their systems, LFI hopes not just to make its operations more efficient but also reliable in serving clients. Consequently, they anticipate that there will be faster processing speeds, decreased cases of defaulting on credit facilities granted while at the same time enhancing overall customer satisfaction levels. Moreover, by strategically embracing such technologies it proves their willingness towards staying ahead of competition within an industry that is highly dynamic thus becoming a role model for other organizations operating in similar sectors.

2 Background Study

Lasiandra Finance Inc. (LFI) is an established and recognized private financing company in New York, USA, with a financial portfolio for support SMEs with custom financial solutions. LFI is committed to many economic solutions in business and business loans, financial consulting, and strategic investment solutions supporting business development and growth.

A key strength of LFI is the innovative use of advanced analytics with machine-learning algorithms that automate the loan approval process. This infusion of technology into LFI would provide loaning services that are even more efficient and precise to decrease the time and effort businesses would have to invest to secure funding. By processing vast amounts of financial data, LFI can make accurate decisions relating to credit, which, in turn, are instrumental in managing the financial risk and lifting the performance of the loans. The operations of LFI are marked with a strong customer orientation. It designs an individual financial solution for each unique need of the business customer, which helps specifically serve challenges and opportunities in their business. The personalized service model allows customers properly to overcome financial challenges and effectively seize opportunities.

In addition to this, the address at 230 Park Avenue, 3rd Floor, New York, NY, is one of the prime addresses of the United States, if not the whole world, of a leading global financial centre. This puts LFI in a position to tap into many resources and networks that the financial industry has to offer. This strategic location further cements LFI's ability to be in touch with a wide range of client interests and to establish firm connections with the industry at large. All this underlines the company's commitment to innovation and delivery of what the customer needs. From several company projects and initiatives details of which can be found on the website and in the repository at GitHub. LFI reinforces its commitment to transparency and continued improvement of its financial services.

In a nutshell, Lasiandra Finance Inc. is a visioned financial institution, incorporating technological innovation within the understanding of client needs towards delivering remarkable financial solutions. Strategically and with an attitude of excellence, Lasiandra Finance Inc. is a vital partner to SMEs desiring success in sustainable growth.

3 Assumption and Justification

Several critical assumptions and justifications resulted in the use of SAS for the above assignment regarding loan prediction data analysis. It proved its aptness in handling complicated data-related tasks. Firstly, it is assumed, that both categorical and continuous variables will dominate the dataset, and consequently, a tool that can apply this wide range of various statistical analyses has to be used. As a propagative statistical software, SAS enables the conduction of all sorts of EDA by performing univariate, bivariate, and multivariate analyses. The robust set of procedures such as PROC FREQ, PROC MEANS, and PROC UNIVARIATE provide elaborate summaries of even the most trivial details for the distribution and relationships of data, along with as much visualization as possible. The use of SAS also implies that large datasets must be manipulated efficiently. SAS has been optimized to handle and analyse vast data, and its speed in doing so is still very high, a factor that may turn out quite valuable for loan prediction given the datasets used are generally massive and hence complex, thus needing much power computationally to run through them properly.

Another critical assumption is the requirement to have advanced data manipulation and transformation. As SAS offers the ultimate data manipulation regarding DATA step programming and various functions, sophisticated data cleaning, transformation, and feature engineering could be carried out. Such flexibility in data preprocessing becomes a must for preparing data for predictive modelling so that all relevant factors get comprehensively captured and analysed. Also, comprehensive support for different types of statistical testing and hypothesis validation justifies using SAS in loan prediction. Here, in the case of loan prediction, understanding the relations between variables such as marital status, employment status, and Loan amounts is crucial. For that, reliable statistical tests should be available. SAS provides the broadest range of tests and diagnosis tools to check for assumptions, data anomalies, and general robustness of analytical results.

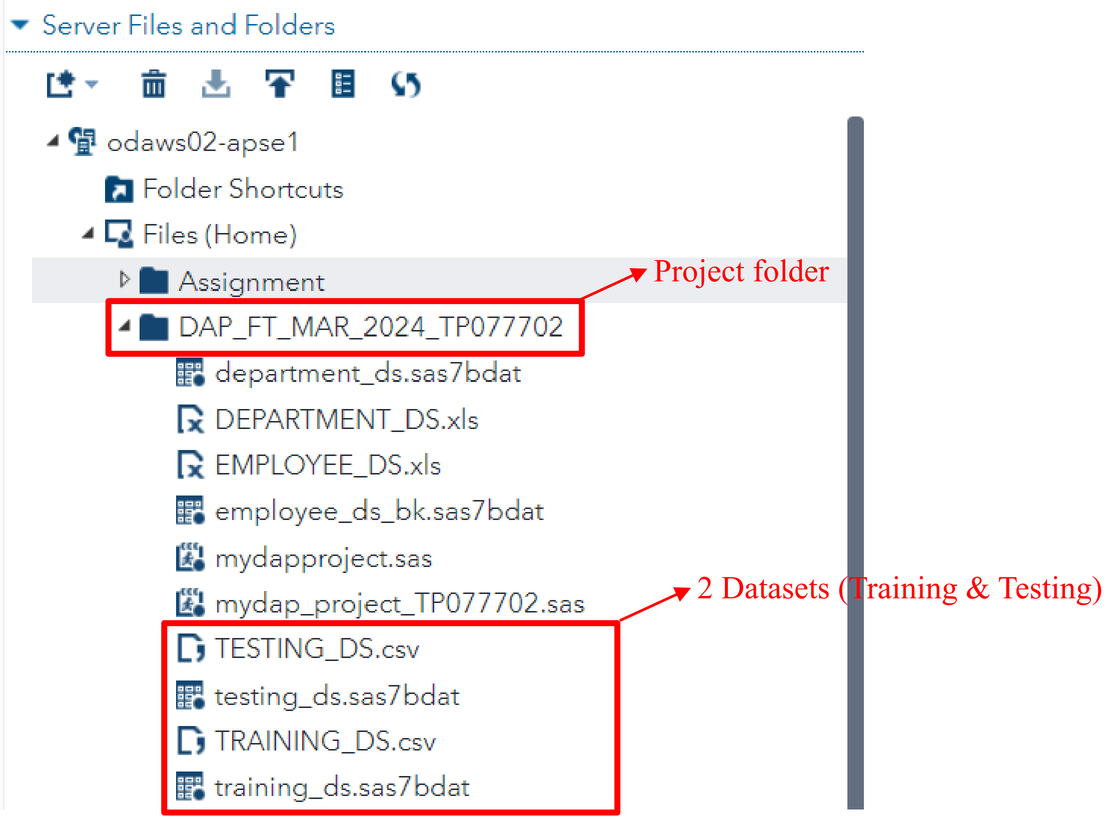
Further, SAS facilitates knowledge distribution by producing reports and visualizations deep in insight. The outputs are marvellous and, thus, best arranged in a way that they explain complex statistical outcomes in such a manner that the user has little bother to acquire insights337 and inform the resolution semblance. Specifically, due to its highly developed statistical powers, effectiveness with large scales of data, advanced powers of data manipulation, totality in statistical testing support, and the capability of producing detailed and interpretable reports, SAS is used in the above loan prediction data analysis.

4 Data Dictionary/ Metadata

Name of Variable	Description	Data Type	Length	Sample Data
SME_LOAN_ID_NO	Loan application number	Char	8	LP001002 LP001003 LP001005
GENDER	Gender of the applicant	Char	6	Female; Male
MARITAL_STATUS	Marital Status of the applicant	Char	11	Married; Not Married
FAMILY_MEMBERS	Number of family members of the applicant	Char	2	1, 2, 3+
QUALIFICATION	Education Qualification of the applicant	Char	14	Graduate; Undergraduate
EMPLOYMENT	Employment Status of the applicant	Char	3	Yes; No
CANDIDATE_INCOME	Income of the applicant	Numeric	5	5849, 4583, 3000
GUARANTEE_INCOME	Income of Joint Applicant	Numeric	5	1508, 2358, 4196
LOAN_AMOUNT	Loan amount	Numeric	5	128, 66, 120
LOAN_DURATION	Duration of Loan Tenure	Numeric	3	71, 360
LOAN_HISTORY	Loan History of the applicant	Numeric	1	0; 1
LOAN_LOCATION	Location of the application	Char	7	City, Village, Town
LOAN_APPROVAL_STATUS	Approval Status of Loan Application	Char	1	Y; N (Y=Yes,N=No)

4.1 Uploading the Dataset

4.1.1.1 Screenshot



Project folder

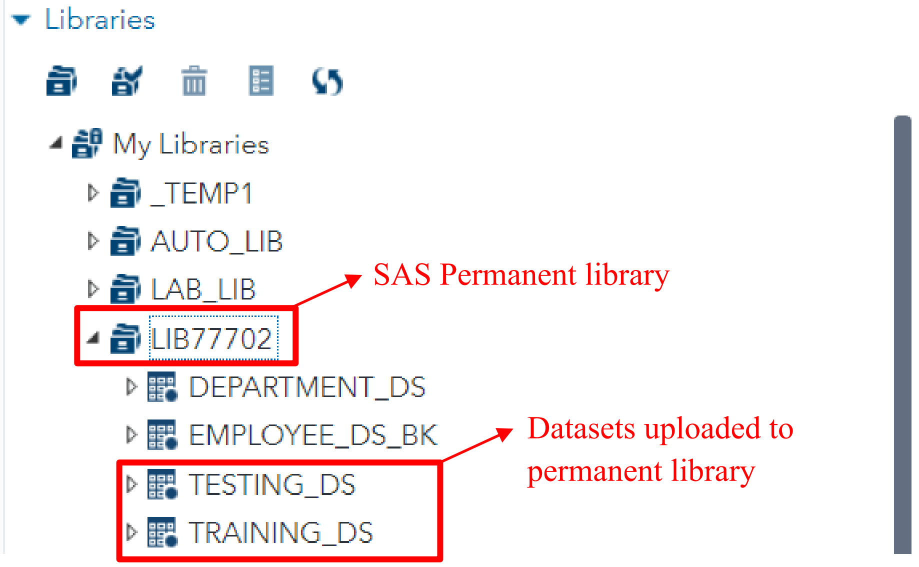
2 Datasets (Training & Testing)

4.1.1.2 Description

The two dataset TRAINING_DS and TESTING_DS is stored in the permanent project folder DAP_FT_MAR_2024_TP077702.

4.2 Transfer Dataset to Permanent SAS Library

4.2.1.1 Screenshot



SAS Permanent library

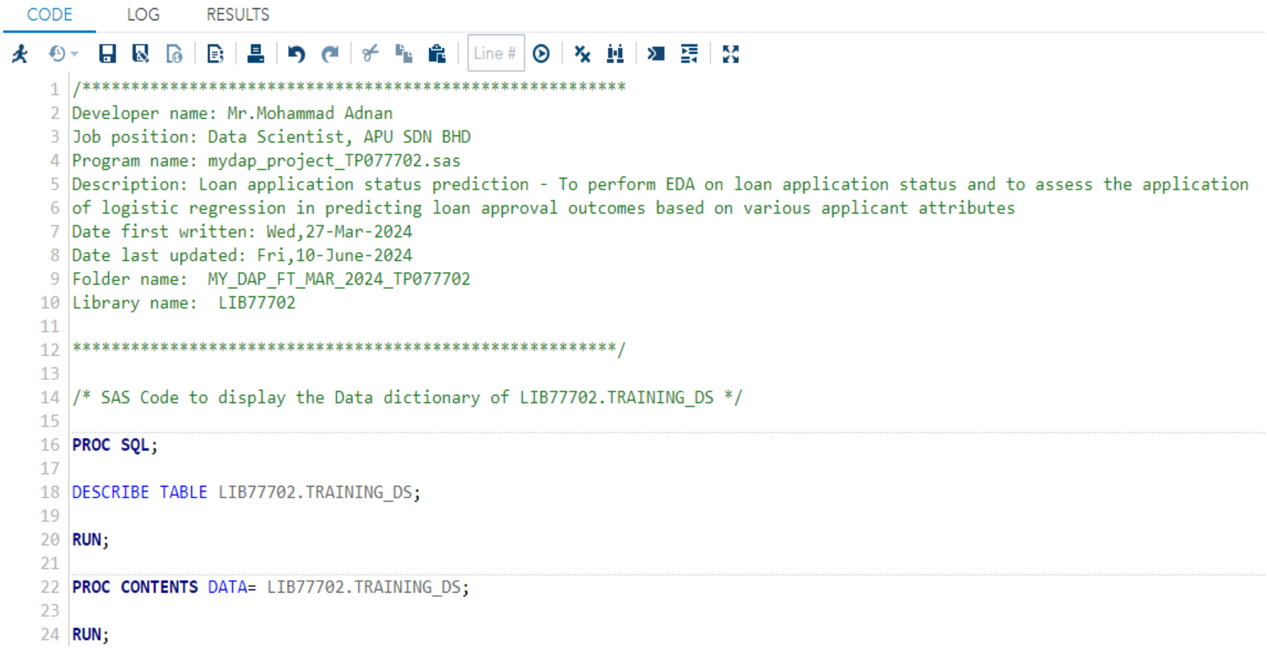
Datasets uploaded to permanent library

4.2.1.2 Description

The dataset TRAINING_DS and TESTING_DS are then uploaded to the SAS permanent library LIB77702 which can be accessed easily.

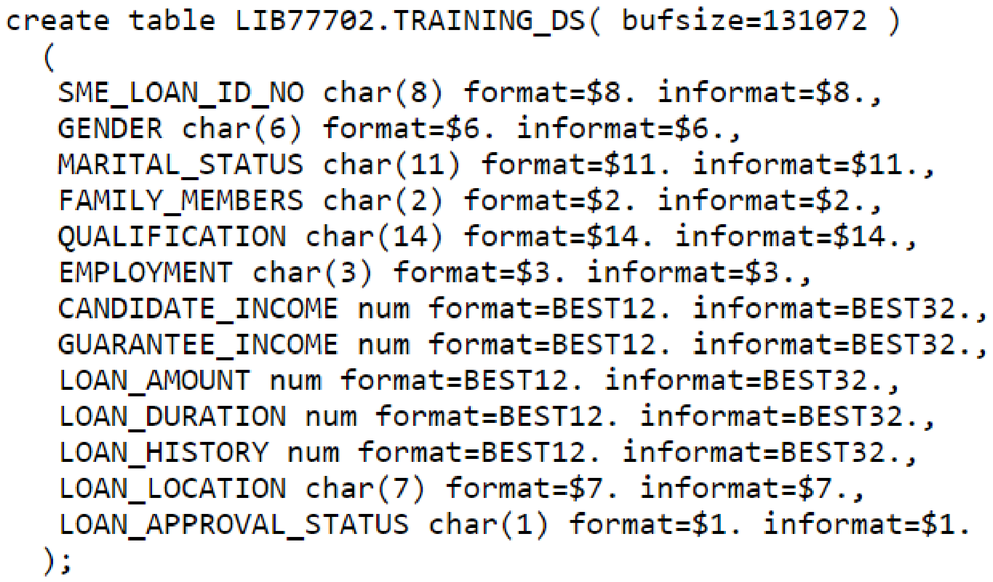
4.3 Data Dictionary

4.3.1.1 Code Snippet



```
/********************************************************
Developer name: Mr.Mohammad Adnan
Job position: Data Scientist, APU SDN BHD
Program name: mydap_project_TP077702.sas
Description: Loan application status prediction - To perform EDA on loan application status and to assess the application
of logistic regression in predicting loan approval outcomes based on various applicant attributes
Date first written: Wed,27-Mar-2024
Date last updated: Fri,10-June-2024
Folder name:  MY_DAP_FT_MAR_2024_TP077702
Library name:  LIB77702

********************************************************/

/* SAS Code to display the Data dictionary of LIB77702.TRAINING_DS */

PROC SQL;

DESCRIBE TABLE LIB77702.TRAINING_DS;

RUN;

PROC CONTENTS DATA= LIB77702.TRAINING_DS;

RUN;
```

4.3.1.2 Output



```
create table LIB77702.TRAINING_DS( bufsize=131072 )
  (
   SME_LOAN_ID_NO char(8) format=$8. informat=$8.,
   GENDER char(6) format=$6. informat=$6.,
   MARITAL_STATUS char(11) format=$11. informat=$11.,
   FAMILY_MEMBERS char(2) format=$2. informat=$2.,
   QUALIFICATION char(14) format=$14. informat=$14.,
   EMPLOYMENT char(3) format=$3. informat=$3.,
   CANDIDATE_INCOME num format=BEST12. informat=BEST32.,
   GUARANTEE_INCOME num format=BEST12. informat=BEST32.,
   LOAN_AMOUNT num format=BEST12. informat=BEST32.,
   LOAN_DURATION num format=BEST12. informat=BEST32.,
   LOAN_HISTORY num format=BEST12. informat=BEST32.,
   LOAN_LOCATION char(7) format=$7. informat=$7.,
   LOAN_APPROVAL_STATUS char(1) format=$1. informat=$1.
  );
```

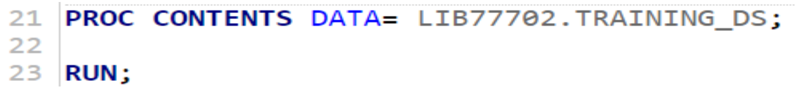
4.3.1.3 Description

Above output using DESCIRBE TABLE from PROC SQL to get brief overview of the data types and size in the dataset.

4.4 Metadata

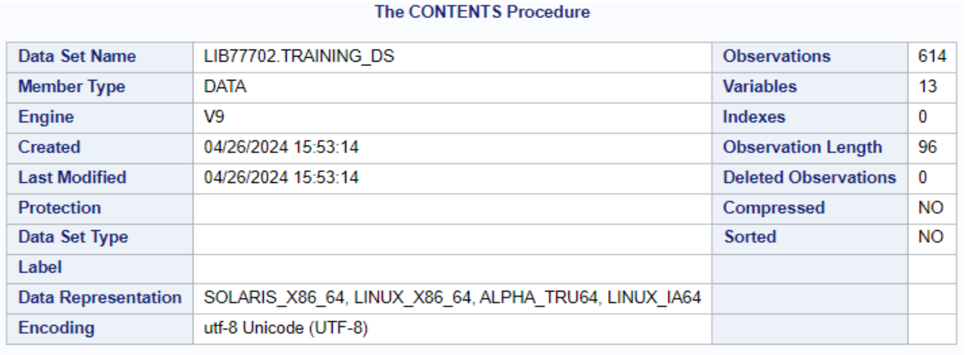
4.4.1 Structure of the Dataset – LIB77702.TRAINING_DS

4.4.1.1 Code Snippet



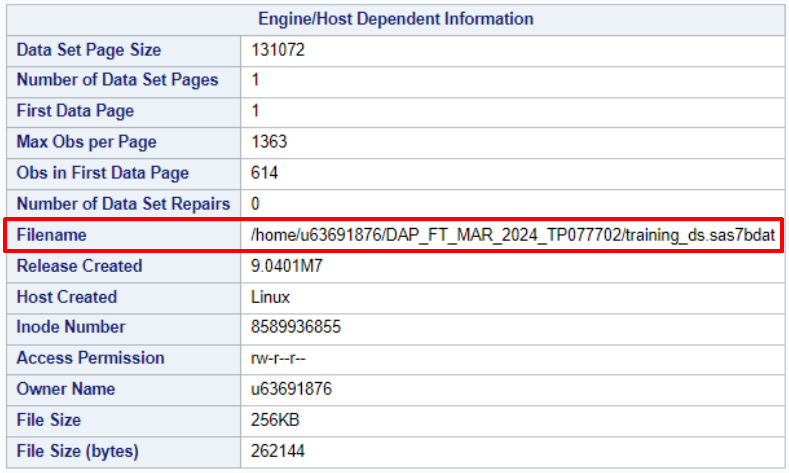
```
PROC CONTENTS DATA= LIB77702.TRAINING_DS;

RUN;
```

4.4.1.2 Output

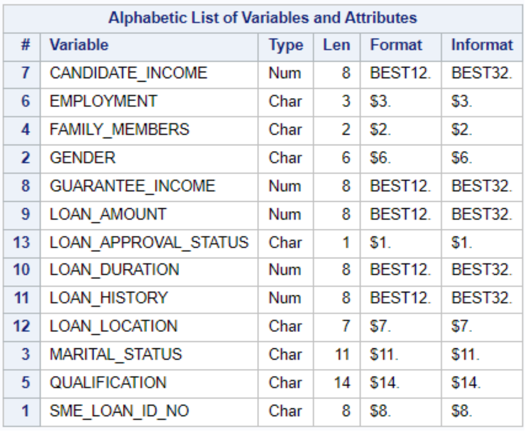


The CONTENTS Procedure

Data Set Name	LIB77702.TRAINING_DS	Observations	614
Member Type	DATA	Variables	13
Engine	V9	Indexes	0
Created	04/26/2024 15:53:14	Observation Length	96
Last Modified	04/26/2024 15:53:14	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/u63691876/DAP_FT_MAR_2024_TP077702/training_ds.sas7bdat
Release Created	9.0401M7
Host Created	Linux
Inode Number	8589936855
Access Permission	rw-r--r--
Owner Name	u63691876
File Size	256KB
File Size (bytes)	262144



Alphabetic List of Variables and Attributes

#	Variable	Type	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.

4.4.1.3 Description

The output above provides a detailed overview of the dataset by identifying the file location, as well as its type, length, format, and other details.

5 Literature Review

The banking sector, in processing loans, assessing the credit risk of prospective borrowers, and managing bad debt, has vividly seen the effect of AI technologies. Advanced document recognition, automated underwriting, and deep learning models have transformed the way we process loans, speeding up loan approval time and reducing errors. The emergence of machine learning algorithms has also improved the ability to predict credit defaults, assisting financial risk management by banks. AI has played a major role in bad debt management by identifying likely defaulters and predicting bankruptcies, effectively mitigating and controlling the risk of non-performing loans. This progress comes with its fair share of challenges, including privacy concerns, bias, and the requirement for new and robust regulatory frameworks. Finally, collaboration with industry experts and researchers, as well as bias-mitigation strategies, will be essential for the ethical and responsible use of AI in banking (Mehndiratta, Arora, & Bathla, 2023).

5.1 Enhancing Loan Processing Efficiency

AI technologies have indeed revolutionized the process of loan processing through the automation of operations, therefore increasing efficiencies and significantly reducing errors. One of the significant developments in this area is intelligent document recognition systems. It consists of the automation of verification of financial statements, performed by different techniques—image segmentation, classification, and the optical character recognition process. As a result, an absolute minimum amount of work remains to be done manually, and the processing time for loan issuance is accelerated dramatically (Hsu, 2020). In the end, banks become more efficient in their operations with fewer errors, eventually reducing their reliance on manual entry of data, which accrues to the good in banks and their customers.

Models developed through AI have also changed the whole process of underwriting credit. It allows a bank to analyse vast sets of data to decide the credit possible for the applicant faster and more accurately than under low-tech regimes (Jain & Verma, 2022). Automation in decision-making speeds up the application process and guarantees that only creditworthy applicants are approved, thus reducing the risk of financial loss to the bank. The implication of AI in banking is beyond the mere integration with processing efficiency; it enhances the service quality and customer experience. As put forward by Rana et al., (2023) AI applications have notably improved customer service and operational efficiency. For example, chatbots can handle periodic customer inquiries, thus freeing up human agents to confront more rigorous issues. This results in quick response times and increased customer satisfaction.

For example, real-time deep learning models have taken the loan approval process to the next level. These use intense neural networks to allow for the analysis of data in real-time, hence making better more reliable, and timely decisions about applicants for loans. In the process, the models can categorize loan applicants as good and bad risks with high precision, recall, and accuracy, thereby shielding only the creditworthy applicants, hence overall improving the loan approval process (Abakarim, Lahby, & Attioui, 2018). In short, AI technologies are driving changes in loan processing via task automation, enhanced accuracy, and better customer service. These advances substantially ease operations and establish a more reliable and efficient banking experience for the people involved.

5.2 AI in Predicting Loan Defaults

The application of machine learning models in the area of prediction of loan default has exhibited phenomenal effectiveness in identifying patterns and trends that might have been red lights for potential defaulters. These models are basically driven by data in their quest to realize patterns and trends that have emerged to show whether loan defaults can occur. For instance, Dong (2022) investigates the capability of a machine-learning model, LightGBM, to predict loan defaults effectively after processing vast volumes of lender information, resulting in a high Area Under the Curve value as a strong indicator of its prediction strength. Other comparison studies have cited the superiority of ensemble learners like XGBoost and AdaBoost in better prediction of loan defaults (Shaheen & Fakharany, 2018) (Odegua, 2020). These algorithms involve advanced technologies in combining multiple models to enhance accuracy, and their performance has been better than the individual models, having high recall, precision, and F1 scores. AdaBoost came on top of all other models based on the findings by Lai (2020) on a real-world dataset from an international bank comparing the performances between AdaBoost, XGBoost, random forest, k-nearest neighbours, and multilayer perceptron’s. The best performance was obtained by AdaBoost, with perfect accuracy in predicting loan defaults.

Besides, it has proven to be an efficient technique to enlarge the model's performance when carried out at a more comprehensive preprocessing and feature selection level (Al-qerem, Alnaymat, & Alhasan, 2020). With the novelty in every possible preprocessing technique and feature extraction algorithm, the augmentation of data quality and choice of relevant features can accordingly enlarge the accuracy and general performance of the prediction models. It has also been implemented along with Synthetic Minority Over-sampling Technique (SMOTE) to correct imbalanced training data, increasing prediction accuracy (Shingi, 2020). Utilizing federated learning, model weights can be shared among organizations without leaks of data, and combined with SMOTE, that is going to increase the teaching of a model from an imbalanced dataset and lead to further accurate predictions.

In summary, AI-driven machine learning models play a critical role in accurately predicting loan defaults, thereby enhancing risk management in banking. By leveraging advanced algorithms, data engineering techniques, and federated learning, banks can improve their ability to predict loan defaults and manage financial risks effectively.

5.3 Managing Bad Debts with AI

Effective management of bad debts is critical to maintaining the financial stability of banks. AI technologies have shown potential in this regard. Predictive models such as Random Forest and data mining algorithms have identified potential defaulters appropriately and helped the banks become proactive (Widiyono & Isa, 2020). Such models help banks properly predict non-performing loans (NPL) to decrease bad debts and improve the financial stability of any bank. Other than that, AI facilitates advanced risk assessment models whereby it has improved the accuracy of bankruptcy assessment, such as logistic and neural network techniques for improved bankruptcy assessment (Chen, 2022). These are models examining data from customer attributes and transaction behaviour to predict the financial default behaviour, hence significantly improving the bankruptcy prediction accuracies and assisting in risk management for the banking industries.

The development of autonomous decision-making AI on credits, based on biometric data and credit history, has significantly increased loan risk management (Pavlikov, 2020). This intelligent engine can, in split seconds, crunch through heaps of data points that include biometric information in making informed decisions related to loans, which will reduce risks of defaults and increase the general process of loan management.

In this line, further transparency and reliability of credit scoring systems, including these XAI models, have increased regulatory compliance and conferred greater trust from the users (Lange et al., 2022). More importantly, the models using the combination of Light GBM with SHAP for model interpretation increase the explainability of predictions, making decisions transparent. The most crucial explanation variable was credit balance volatility, followed by remaining credit percentage and customer relationship lifetime, all indicative of the potential for XAI models to provide insights into the fundamentals driving loan default predictions.

Further, weighted training models using decision tree algorithms are demonstrated to be effective in predicting loan defaults (Pang & Yuan, 2018). These models, being in use with the help of weighted calculating algorithms and combining models with decision trees like C5.0, CART, and CHAID, have enabled high comparison accuracy and warning rates, which confirms effectiveness in revealing potential defaulters which in result helps us in managing bad debts. In short, AI technologies play a crucial role in managing bad debts by improving prediction accuracy, enhancing risk assessment models, and providing transparent and reliable credit scoring systems.

5.4 Challenges and Future Directions

Although there are so many benefits of applying AI in banking, there are still several challenges in this area. The related issues of data privacy and security must be dealt with by the introduction of AI solutions in financial institutions through customer data protection and responsible use to be trusted to be used in a manner consistent with the obligatory requirements on the subject (Rana, et al., 2023). Nonetheless, biases of AI models can still lead to discriminatory outputs, and loan processing and credit scoring remain a significant frontier where the challenge remains paramount (Lange et al., 2022). The dispatch of such a policy is the key to building trustful and fair AI systems, ensured through algorithmic fairness techniques and bias mitigation, where no customer is treated differently from the other.

Other concerns include the need to develop and pursue appropriate regulatory frameworks that will control the application of AI in banking (Mehndiratta, Arora, & Bathla, The use of Artificial Intelligence in the Banking Industry, 2023). It is essential to regularly monitor and update such frameworks to keep pace with technological advances and changing regulatory environments in promoting the ethical use of AI in banking and compliance with financial services regulations. Therefore, future directions will require looking at new directions in AI, including deep reinforcement learning and GAN for improving accuracy in prediction and enabling better decision-making. Adding command-and-control ability may improve decision-making, leading to security and transparency in bank operations, hence more trust and reliability.

Continuous improvement in AI models through advanced data engineering and feature selection techniques would make them superior in performance and reliability. Transfer learning and meta-learning techniques can be used to improve generalization and accommodate new data distributions so that models remain effective in a changing environment. Further, developing the interpretability and explainability of AI models using Explainable AI techniques is very important to get regulatory approval and trust from users, especially in processes such as credit scoring and loan approval (Lange et al., 2022). LIME Technology, like SHAP will help in understanding the model's reasoning and thereby inculcate transparency and accountability.

Collaborations among researchers, financial institutions, and regulatory bodies can yield innovation in banking with AI that is both ethical and value based. Such interdisciplinary teams, made up of data scientists, domain experts, and legal professionals, can thereby translate research to practice most effectively, always considering regulation concerns. Besides, a mitigation strategy of biases in the AI model would be good practice to ensure fairness and equal treatment to all the customers. Adversarial debiasing, calibrated equalization, and many others are factoring techniques that can be effective in bias mitigation (González-Sendino, Serrano, & Bajo, 2024). Algorithm fairness is fostered in loan processing and credit scoring.

To summarize AI technologies have revolutionized the banking industry, driving effectiveness, sound risk management, and efficiencies in processing loans, managing credit risks, and mitigating bad debts. However, the journey to more AI deployments should not forget the requirements to overcome issues covering data privacy, algorithmic bias, and a regulatory fit for the sector. This will involve innovative scientific research in concert with financial institutions and regulatory authorities to support ethical standards and fairness. All these can be achieved with advanced data engineering, developed AI techniques for explanations, and strategies for bias mitigation for continuous model reliability, transparency, and accountability. In this way, the financial sector will be able to unlock the full potential of AI without affecting consumer trust by prioritizing responsible AI practices, fostering interdisciplinary collaborations, and embracing interpretable and unbiased models. The future will see AI being smartly integrated into bank operations in a balanced way: technological advancement and ethical considerations for a robust, transparent, and just financial ecosystem.

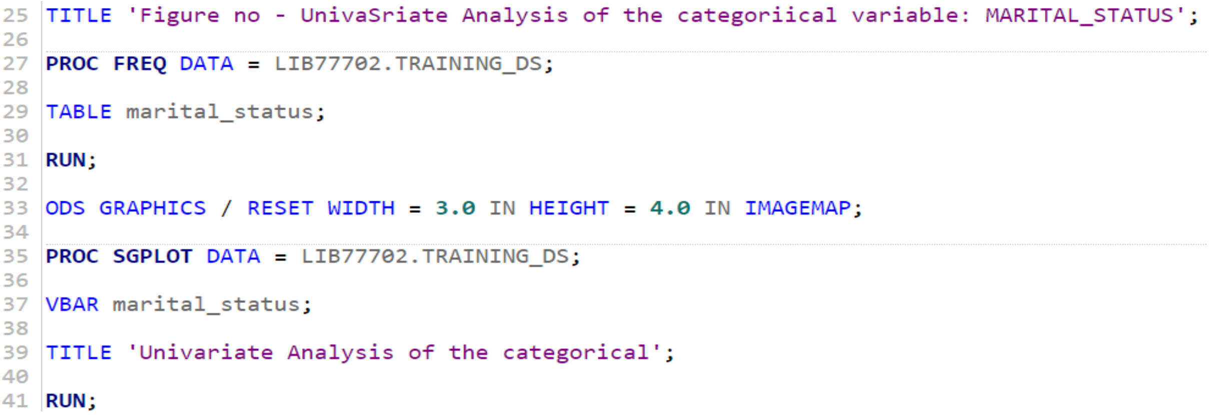
6 Analysis of the Variables – LIB77702.TRAINING_DS

6.1 Univariate Analysis of the Variable in the Dataset LIB77702.TRAINING_DS

6.1.1 Analysis of the Categorical Variables in the Dataset

6.1.1.1 Univariate analysis of the Categorical variables – MARITAL_STATUS

6.1.1.1.1 Code Snippets



```
TITLE 'Figure no - UnivaSriate Analysis of the categoriical variable: MARITAL_STATUS';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE marital_status;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

VBAR marital_status;

TITLE 'Univariate Analysis of the categorical';

RUN;
```

6.1.1.1.2 Output

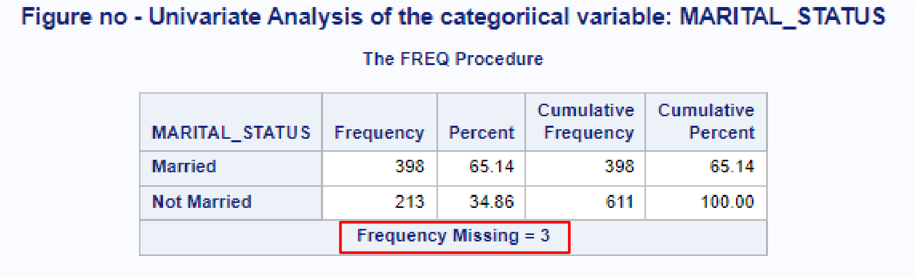
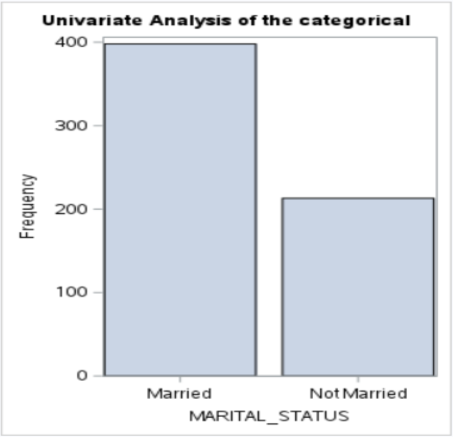


Figure no - Univariate Analysis of the categoriical variable: MARITAL_STATUS

The FREQ Procedure

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				

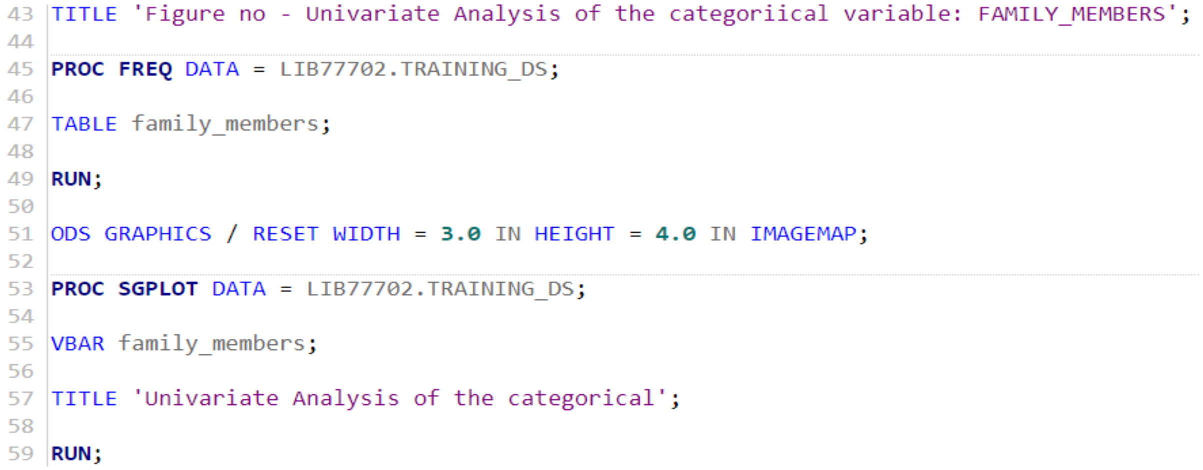


6.1.1.1.3 Description

Both the table and graph show that there are 398 applicants who are married and 213 applicants unmarried. This averages around 65.14% of the applicants are married, and 34.86% are not married. There are presences 3 missing values in the marital status variable.

6.1.1.2 Univariate analysis of the categorical variables – FAMILY_MEMBERS

6.1.1.2.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the categoriical variable: FAMILY_MEMBERS';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE family_members;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

VBAR family_members;

TITLE 'Univariate Analysis of the categorical';

RUN;
```

6.1.1.2.2 Output

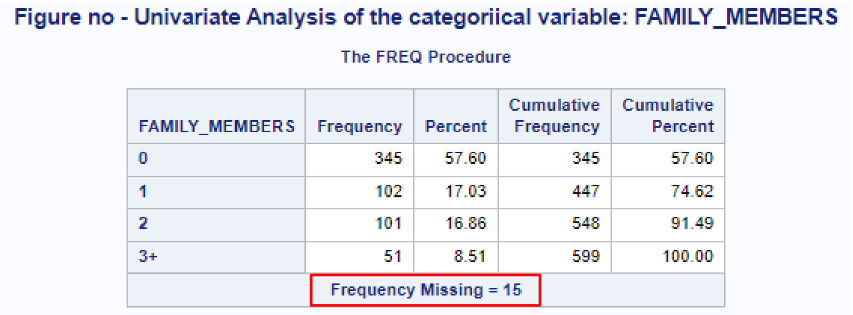
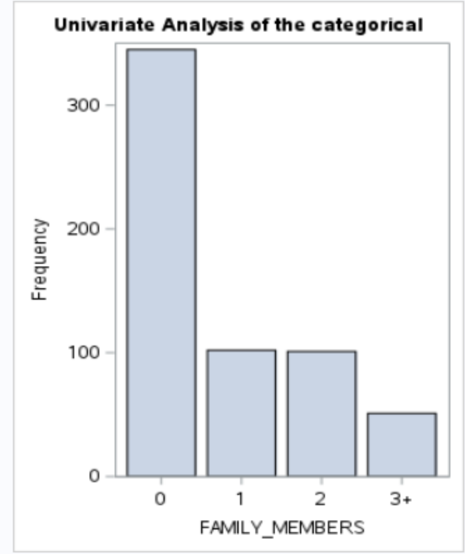


Figure no - Univariate Analysis of the categoriical variable: FAMILY_MEMBERS

The FREQ Procedure

FAMILY_MEMBERS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	345	57.60	345	57.60
1	102	17.03	447	74.62
2	101	16.86	548	91.49
3+	51	8.51	599	100.00

Frequency Missing = 15

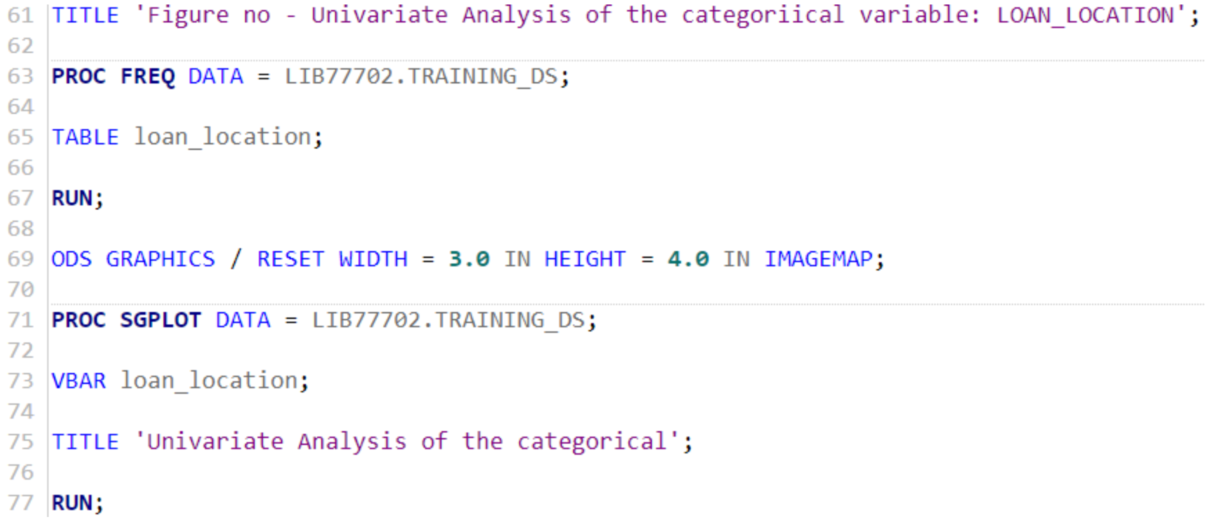


6.1.1.2.3 Description

The table and graph show the distribution of a categorical variable: family members. Most households have no family members (57.6%) followed by households with 1 (17.0%) and 2 (16.9%) family members and 3+ (8.5%) family member. There are also 15 missing values.

6.1.1.3 Univariate analysis of the categorical variables – LOAN_LOCATION

6.1.1.3.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the categoriical variable: LOAN_LOCATION';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE loan_location;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

VBAR loan_location;

TITLE 'Univariate Analysis of the categorical';

RUN;
```

6.1.1.3.2 Output

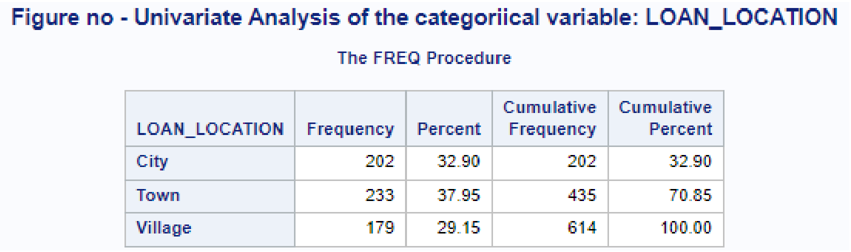
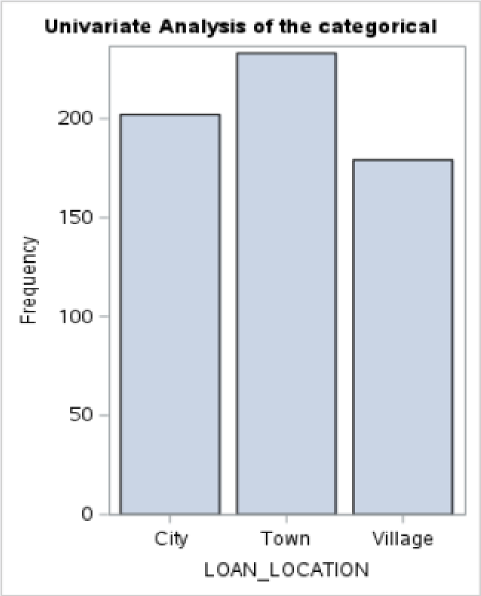


Figure no - Univariate Analysis of the categoriical variable: LOAN_LOCATION

The FREQ Procedure

LOAN_LOCATION	Frequency	Percent	Cumulative Frequency	Cumulative Percent
City	202	32.90	202	32.90
Town	233	37.95	435	70.85
Village	179	29.15	614	100.00

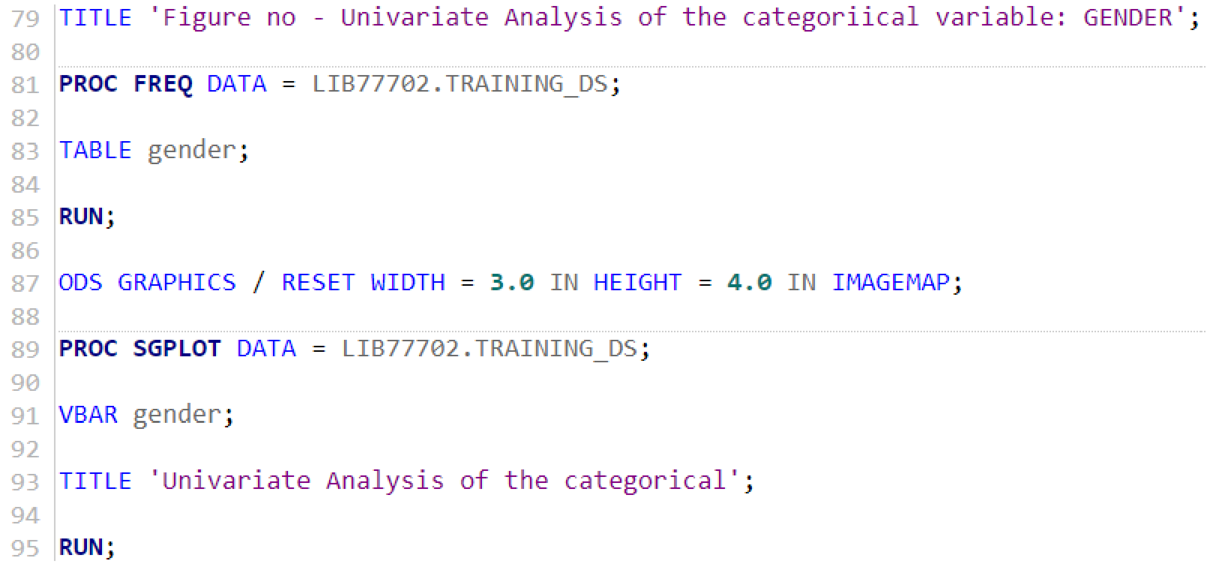


6.1.1.3.3 Description

The table and graph show the frequency of loan repayments for each type of loan location. The frequency of loan repayments for each type of loan varies depending on the location. Town has the highest frequency (37.95%) followed by City (32.90%) and Village (29.15%).

6.1.1.4 Univariate analysis of the categorical variables – GENDER

6.1.1.4.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the categoriical variable: GENDER';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE gender;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

VBAR gender;

TITLE 'Univariate Analysis of the categorical';

RUN;
```

6.1.1.4.2 Output

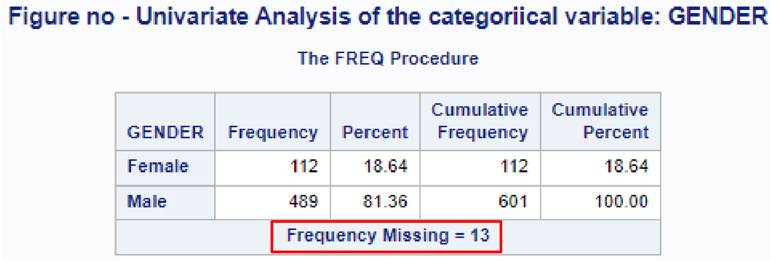
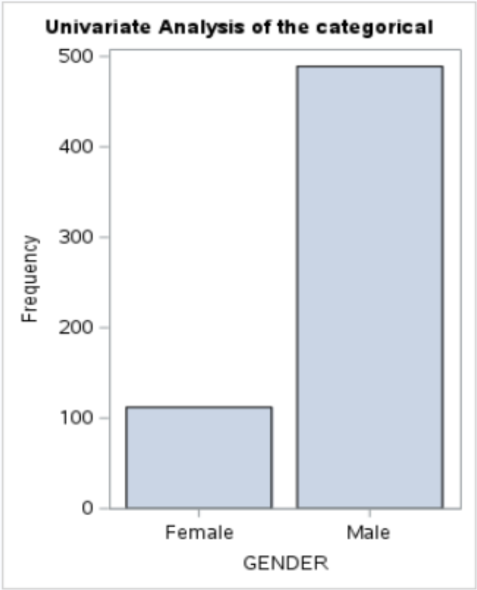


Figure no - Univariate Analysis of the categoriical variable: GENDER

The FREQ Procedure

GENDER	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Female	112	18.64	112	18.64
Male	489	81.36	601	100.00
Frequency Missing = 13				

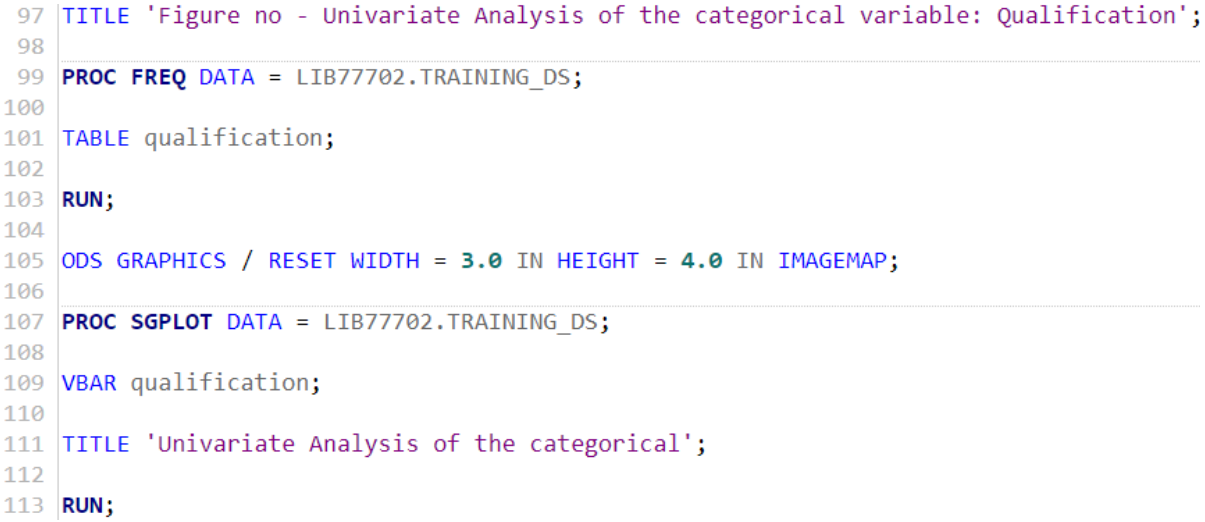


6.1.1.4.3 Description

The table and graph show the frequency distribution for each gender in a categorical variable. There are 112 females (18.64%) and 489 males (81.36%) with data recorded, and 13 entries missing gender data. Overall, the table shows a higher frequency of males in the dataset.

6.1.1.5 Univariate analysis of the categorical variables – Qualification

6.1.1.5.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the categorical variable: Qualification';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE qualification;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

VBAR qualification;

TITLE 'Univariate Analysis of the categorical';

RUN;
```

6.1.1.5.2 Output

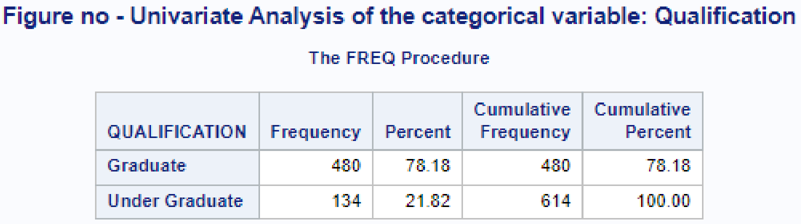
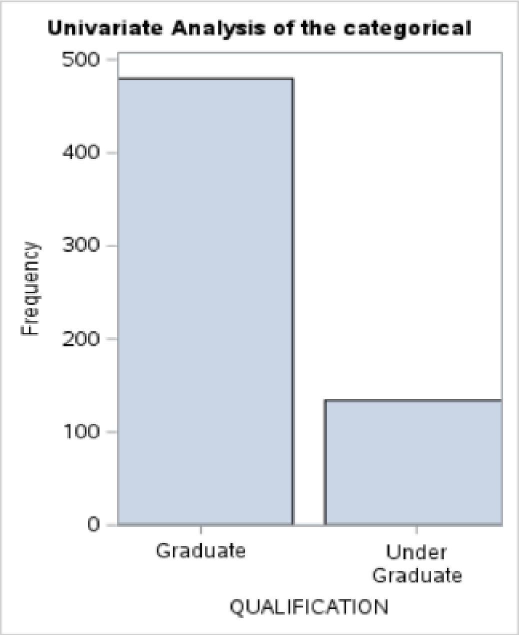


Figure no - Univariate Analysis of the categorical variable: Qualification

The FREQ Procedure

QUALIFICATION	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Graduate	480	78.18	480	78.18
Under Graduate	134	21.82	614	100.00



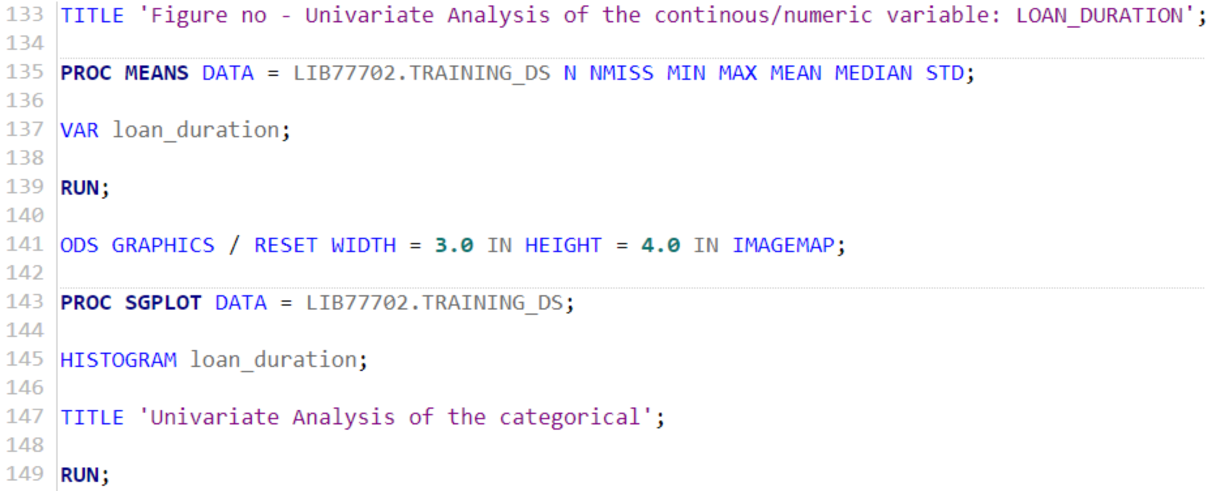
6.1.1.5.3 Description

The table and graph show the frequency of graduates and undergraduates. There are 480 graduates (78.18%) and 134 undergraduates (21.82%). This suggests a higher frequency of graduates in the data set.

6.1.2 Analysis of the Continuous Variable in the dataset

6.1.2.1 Univariate Analysis of the Continuous Variable – LOAN_AMOUNT

6.1.2.1.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the continous/numeric variable: LOAN_DURATION';

PROC MEANS DATA = LIB77702.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;

VAR loan_duration;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

HISTOGRAM loan_duration;

TITLE 'Univariate Analysis of the categorical';

RUN;
```

6.1.2.1.2 Output

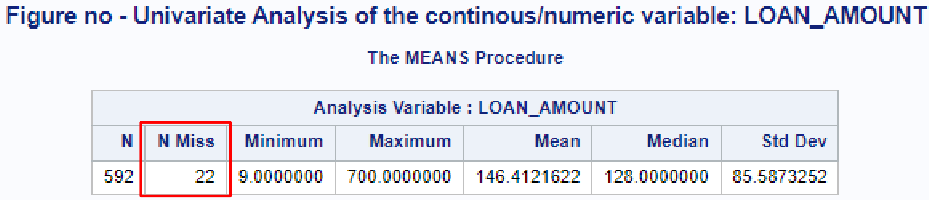
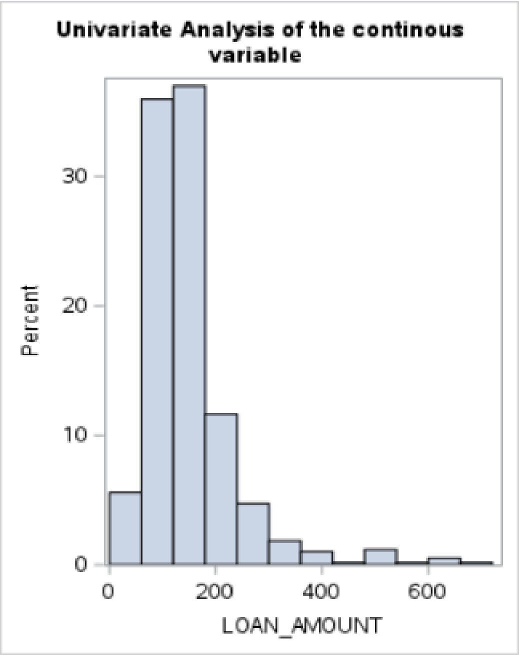


Figure no - Univariate Analysis of the continous/numeric variable: LOAN_AMOUNT

The MEANS Procedure

Analysis Variable : LOAN_AMOUNT						
N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
592	22	9.0000000	700.0000000	146.4121622	128.0000000	85.5873252

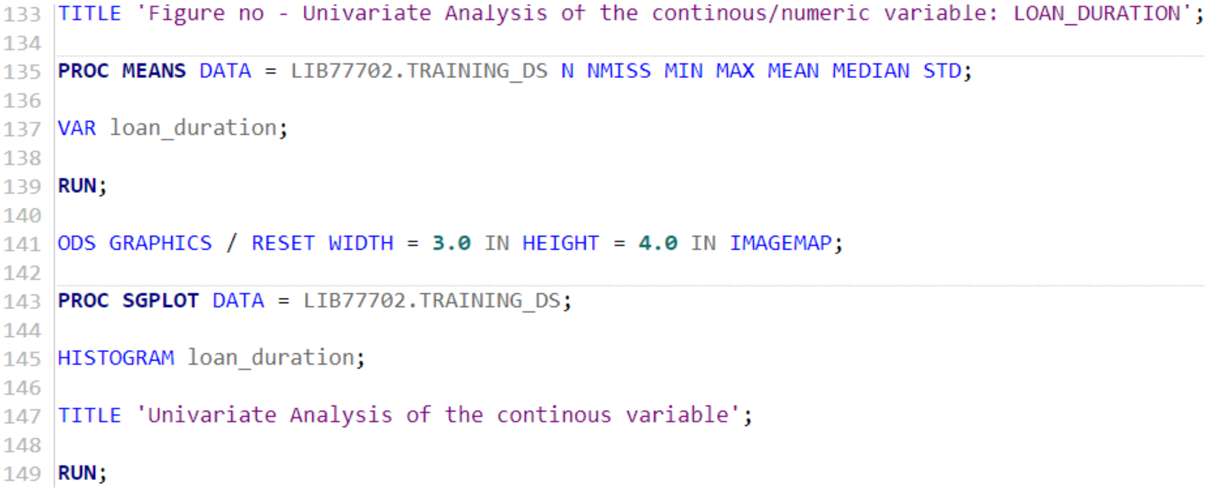


6.1.2.1.3 Description

The univariate analysis shows that the average loan amount is $146.41 with a standard deviation of $85.58. There are 592 loans included in the analysis, with a minimum loan amount of $9 and a maximum loan amount of $700. There are also 22 missing values.

6.1.2.2 Univariate Analysis of the continuous variable – LOAN_DURATION

6.1.2.2.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the continous/numeric variable: LOAN_DURATION';

PROC MEANS DATA = LIB77702.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;

VAR loan_duration;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

HISTOGRAM loan_duration;

TITLE 'Univariate Analysis of the continous variable';

RUN;
```

6.1.2.2.2 Output

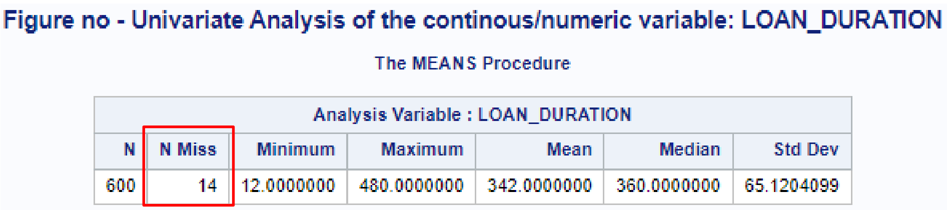
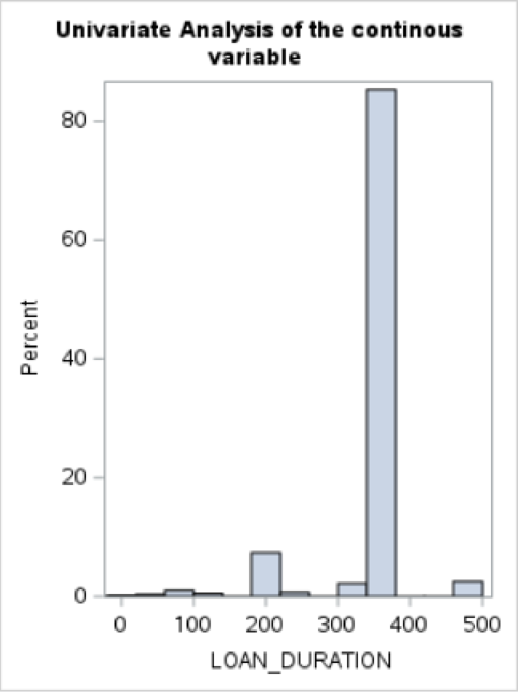


Figure no - Univariate Analysis of the continous/numeric variable: LOAN_DURATION

The MEANS Procedure

Analysis Variable : LOAN_DURATION						
N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
600	14	12.0000000	480.0000000	342.0000000	360.0000000	65.1204099

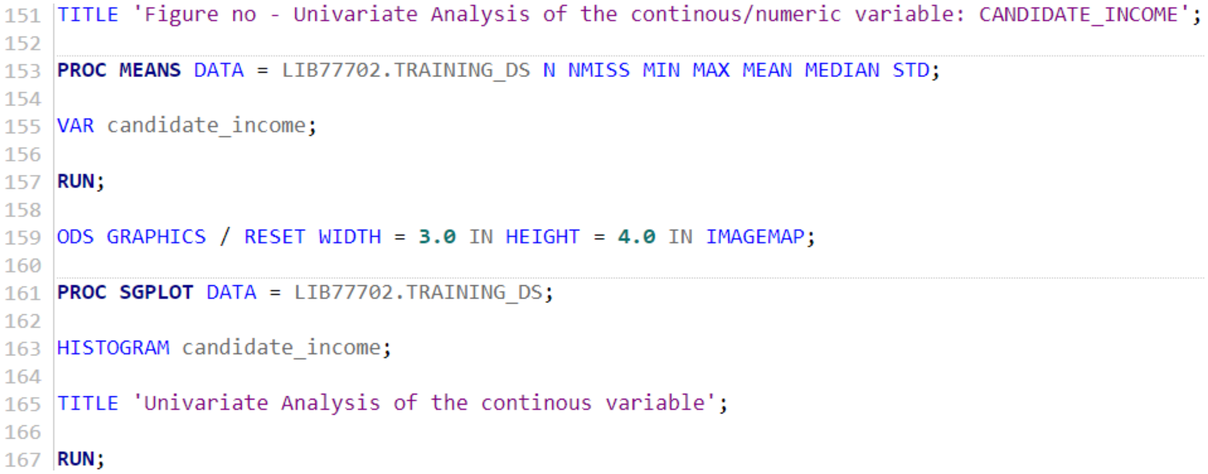


6.1.2.2.3 Description

The univariate analysis shows values for loan duration. The univariate analysis shows an average loan duration of 342 days, with a median of 360 days. The loan duration ranges from 12 days to 480 days. There are 600 loans included in the analysis, with 14 missing values.

6.1.2.3 Univariate Analysis of the continuous variable – CANDIDATE_INCOME

6.1.2.3.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the continous/numeric variable: CANDIDATE_INCOME';

PROC MEANS DATA = LIB77702.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;

VAR candidate_income;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

HISTOGRAM candidate_income;

TITLE 'Univariate Analysis of the continous variable';

RUN;
```

6.1.2.3.2 Output

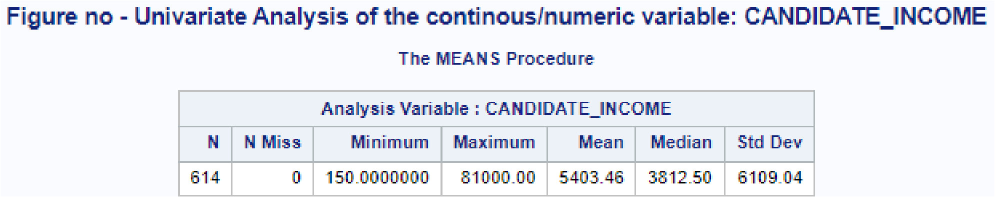
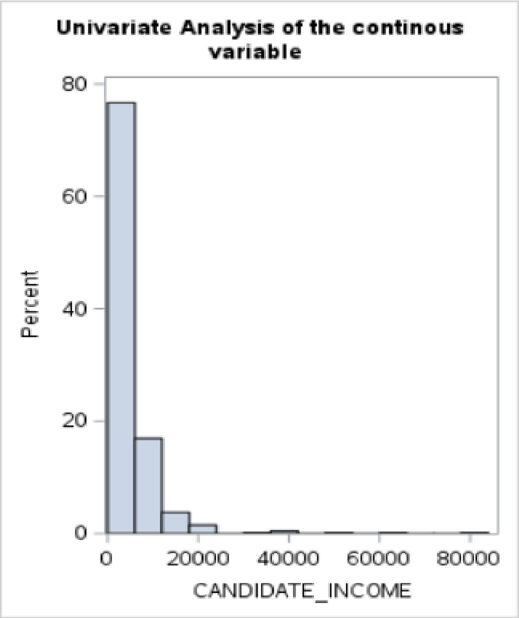


Figure no - Univariate Analysis of the continous/numeric variable: CANDIDATE_INCOME

The MEANS Procedure

Analysis Variable : CANDIDATE_INCOME						
N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
614	0	150.0000000	81000.00	5403.46	3812.50	6109.04

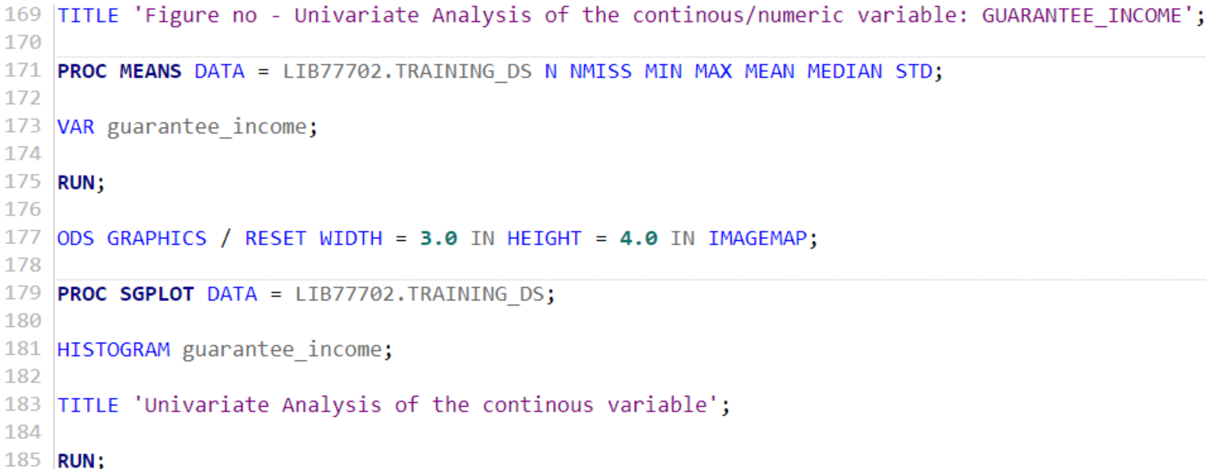


6.1.2.3.3 Description

The univariate analysis shows a summary of a candidate's income. The average income is $5,403.46 with a standard deviation of $6,109.04. The minimum income is $150, and the maximum income is $81,000.

6.1.2.4 Univariate Analysis of the continuous variable – GUARENTEE_INCOME

6.1.2.4.1 Code Snippet



```
TITLE 'Figure no - Univariate Analysis of the continous/numeric variable: GUARANTEE_INCOME';

PROC MEANS DATA = LIB77702.TRAINING_DS N NMISS MIN MAX MEAN MEDIAN STD;

VAR guarantee_income;

RUN;

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

PROC SGPLOT DATA = LIB77702.TRAINING_DS;

HISTOGRAM guarantee_income;

TITLE 'Univariate Analysis of the continous variable';

RUN;
```

6.1.2.4.2 Output

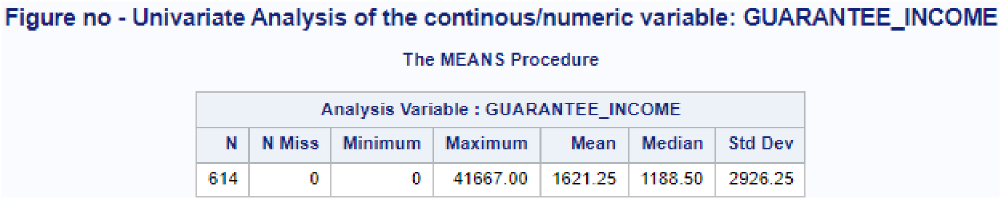
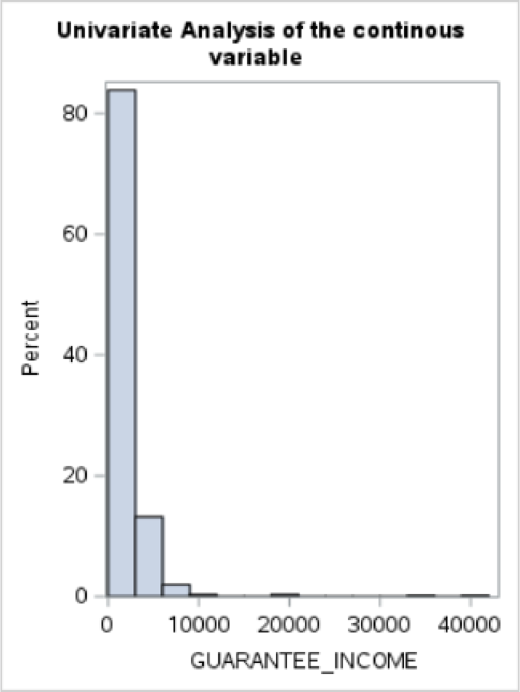


Figure no - Univariate Analysis of the continous/numeric variable: GUARANTEE_INCOME

The MEANS Procedure

Analysis Variable : GUARANTEE_INCOME						
N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
614	0	0	41667.00	1621.25	1188.50	2926.25



6.1.2.4.3 Description

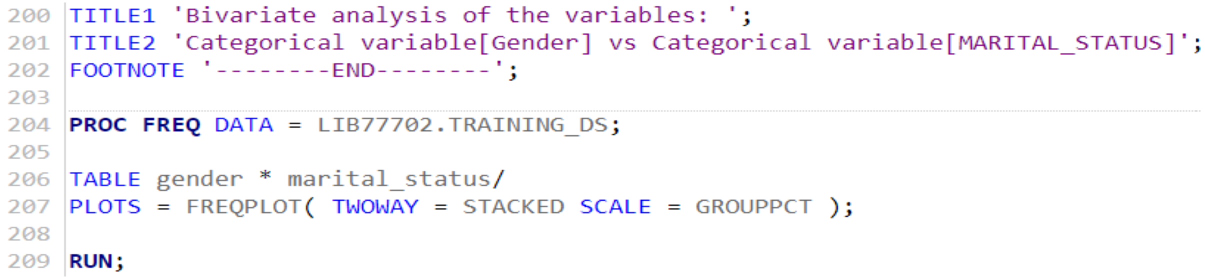
The univariate analysis shows a summary of annual variable guaranteed income. The average annual income is $1,621.25, with a standard deviation of $2,926.25. The minimum annual income is $0, and the maximum annual income is $41,667.

6.2 Bivariate Analysis of Variables in the Dataset LIB77702.TRAINING_DS

6.2.1 Bivariate Analysis of the Variable (Categorical vs Categorical)

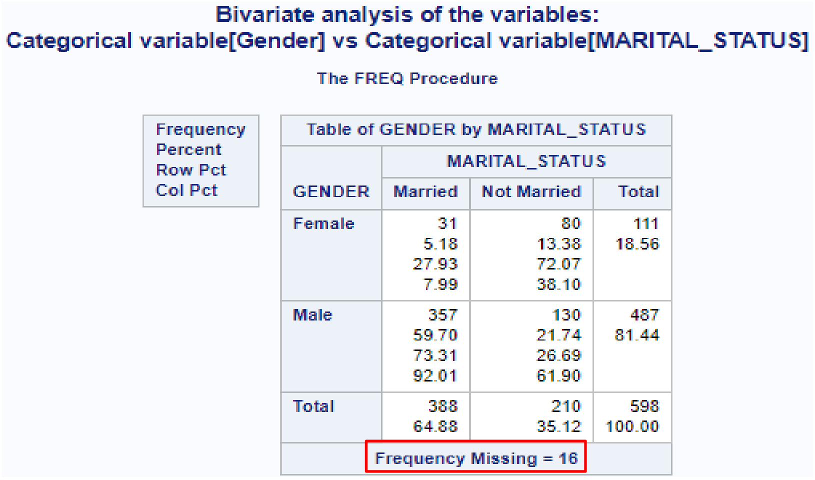
6.2.1.1 Bivariate Analysis of the variable (GENDER vs MARITAL_STATUS)

6.2.1.1.1 Code Snippet



```
TITLE1 'Bivariate analysis of the variables: ';
TITLE2 'Categorical variable[Gender] vs Categorical variable[MARITAL_STATUS]';
FOOTNOTE '--------END--------';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE gender * marital_status/
PLOTS = FREQPLOT( TWOWAY = STACKED SCALE = GROUPPCT );

RUN;
```

6.2.1.1.2 Output



Bivariate analysis of the variables:
Categorical variable[Gender] vs Categorical variable[MARITAL_STATUS]

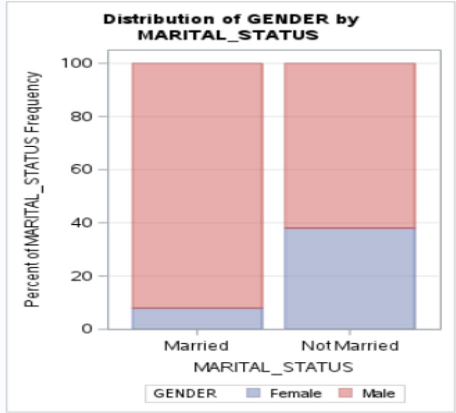
The FREQ Procedure

Frequency
Percent
Row Pct
Col Pct

Table of GENDER by MARITAL_STATUS

	MARITAL_STATUS		
GENDER	Married	Not Married	Total
Female	31 5.18 27.93 7.99	80 13.38 72.07 38.10	111 18.56
Male	357 59.70 73.31 92.01	130 21.74 26.69 61.90	487 81.44
Total	388 64.88	210 35.12	598 100.00

Frequency Missing = 16

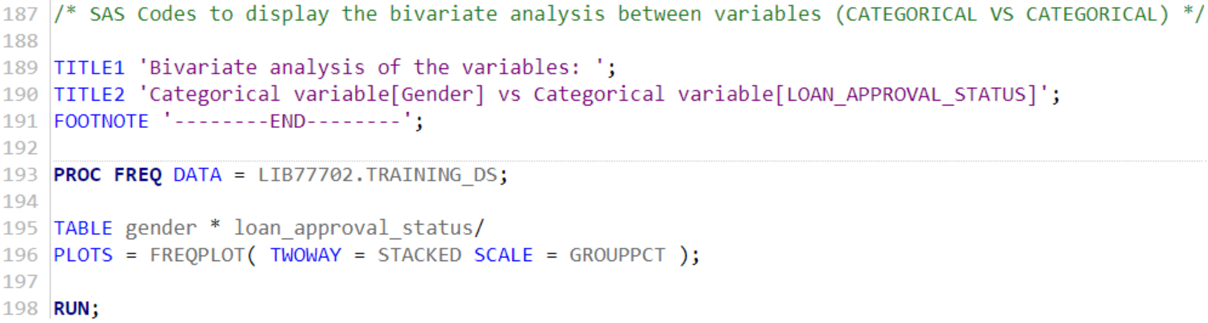


6.2.1.1.3 Description

The bivariate analysis shows a cross-tabulation of gender and marital status. Among females, 27.93% are married and 72.07% are not. Among males, 73.31% are married and 26.69% are not. Overall, 64.88% of the applicants are married, while 35.12% are not. There are 16 missing values.

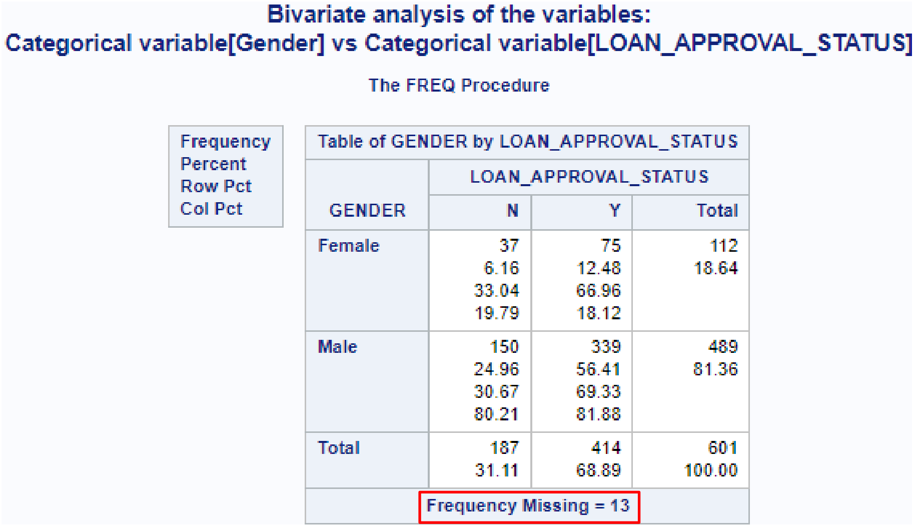
6.2.1.2 Bivariate Analysis of the variable (GENDER vs LOAN_APPROVAL_STATUS)

6.2.1.2.1 Code Snippet



```
/* SAS Codes to display the bivariate analysis between variables (CATEGORICAL VS CATEGORICAL) */

TITLE1 'Bivariate analysis of the variables: ';
TITLE2 'Categorical variable[Gender] vs Categorical variable[LOAN_APPROVAL_STATUS]';
FOOTNOTE '--------END--------';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE gender * loan_approval_status/
PLOTS = FREQPLOT( TWOWAY = STACKED SCALE = GROUPPCT );

RUN;
```

6.2.1.2.2 Output



Bivariate analysis of the variables:
Categorical variable[Gender] vs Categorical variable[LOAN_APPROVAL_STATUS]

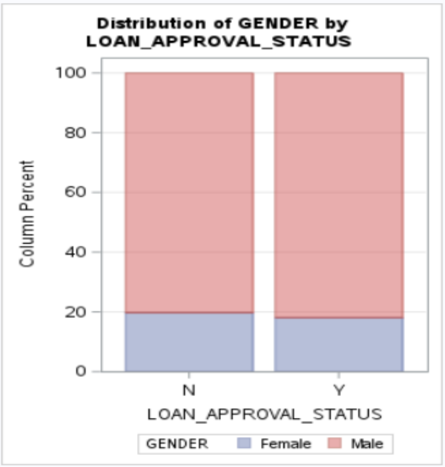
The FREQ Procedure

Frequency Percent Row Pct Col Pct

Table of GENDER by LOAN_APPROVAL_STATUS

GENDER	LOAN_APPROVAL_STATUS N	Y	Total
Female	37 6.16 33.04 19.79	75 12.48 66.96 18.12	112 18.64
Male	150 24.96 30.67 80.21	339 56.41 69.33 81.88	489 81.36
Total	187 31.11	414 68.89	601 100.00

Frequency Missing = 13

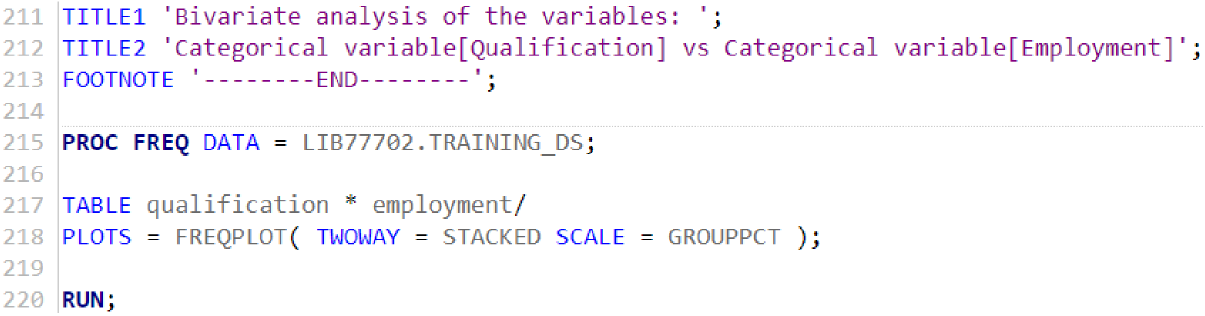


6.2.1.2.3 Description

The bivariate analysis shows a cross-tabulation of gender and loan approval status. Among females, 33.04% of the loan is not approved and 66.96% of the loan is approved. Among males, 30.67% of the loan is not approved and 69.33% are approved. Overall, 31.11% of the applicant's loan are not approved, while 68.89% are approved. There are 13 missing values.

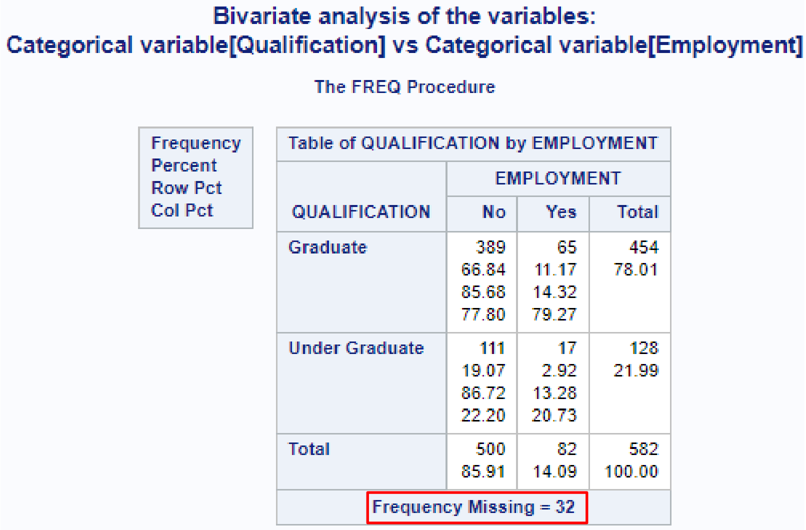
6.2.1.3 Bivariate Analysis of the variable (QUALIFICATION vs EMPLOYMENT)

6.2.1.3.1 Code Snippet



```
TITLE1 'Bivariate analysis of the variables: ';
TITLE2 'Categorical variable[Qualification] vs Categorical variable[Employment]';
FOOTNOTE '--------END--------';

PROC FREQ DATA = LIB77702.TRAINING_DS;

TABLE qualification * employment/
PLOTS = FREQPLOT( TWOWAY = STACKED SCALE = GROUPPCT );

RUN;
```

6.2.1.3.2 Output

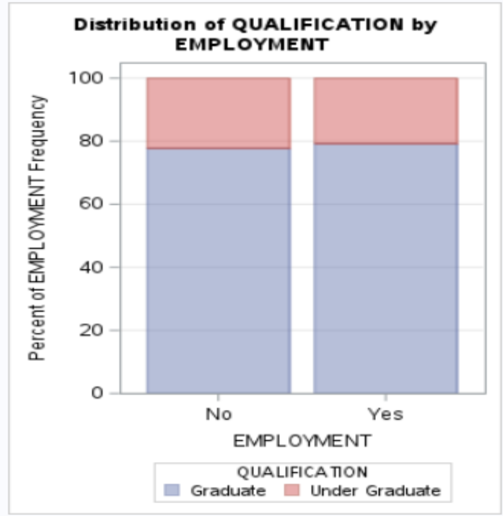


Bivariate analysis of the variables:
Categorical variable[Qualification] vs Categorical variable[Employment]

The FREQ Procedure

Frequency Percent Row Pct Col Pct

Table of QUALIFICATION by EMPLOYMENT			
	EMPLOYMENT		
QUALIFICATION	No	Yes	Total
Graduate	389 66.84 85.68 77.80	65 11.17 14.32 79.27	454 78.01
Under Graduate	111 19.07 86.72 22.20	17 2.92 13.28 20.73	128 21.99
Total	500 85.91	82 14.09	582 100.00
Frequency Missing = 32			



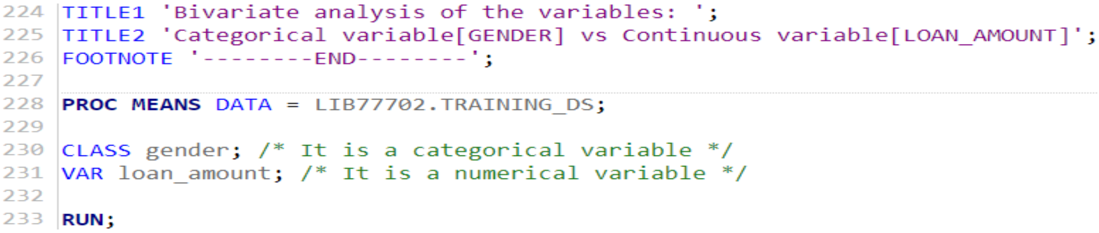
6.2.1.3.3 Description

The bivariate analysis shows the relationship between qualification and employment status. Among graduates, 85.68% are unemployed and 14.32% are employed. Among undergraduates, 86.72% are unemployed and 13.28% are employed. Overall, 85.91% of applicants are unemployed, and 14.09% are employed. There are presences 32 missing values.

6.2.2 Bivariate Analysis of the Variable (Categorical vs Continuous)

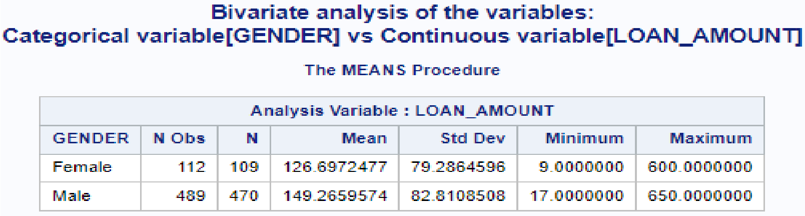
6.2.2.1 Bivariate Analysis of the variable (GENDER vs LOAN_AMOUNT)

6.2.2.1.1 Code Snippet



```
TITLE1 'Bivariate analysis of the variables: ';
TITLE2 'Categorical variable[GENDER] vs Continuous variable[LOAN_AMOUNT]';
FOOTNOTE '--------END--------';

PROC MEANS DATA = LIB77702.TRAINING_DS;

CLASS gender; /* It is a categorical variable */
VAR loan_amount; /* It is a numerical variable */

RUN;
```

6.2.2.1.2 Output



Bivariate analysis of the variables:
Categorical variable[GENDER] vs Continuous variable[LOAN_AMOUNT]

The MEANS Procedure

Analysis Variable : LOAN_AMOUNT

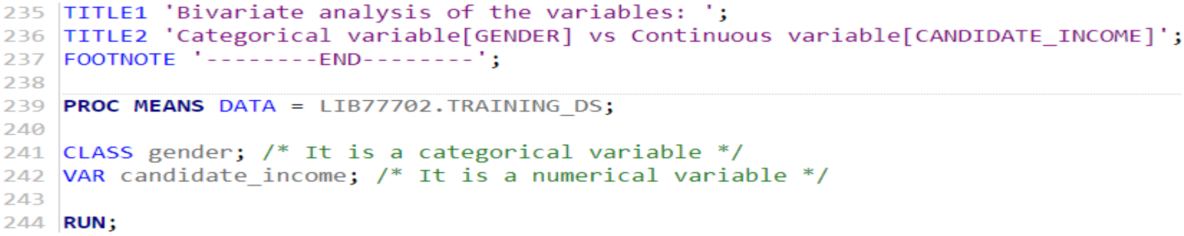
GENDER	N Obs	N	Mean	Std Dev	Minimum	Maximum
Female	112	109	126.6972477	79.2864596	9.0000000	600.0000000
Male	489	470	149.2659574	82.8108508	17.0000000	650.0000000

6.2.2.1.3 Description

The bivariate analysis between gender and loan amount reveals that the average loan amount for females is approximately $126.70 with a standard deviation of $79.29, ranging from $9 to $600. For males, the average is around $149.27 with a standard deviation of $82.81, ranging from $17 to $650.

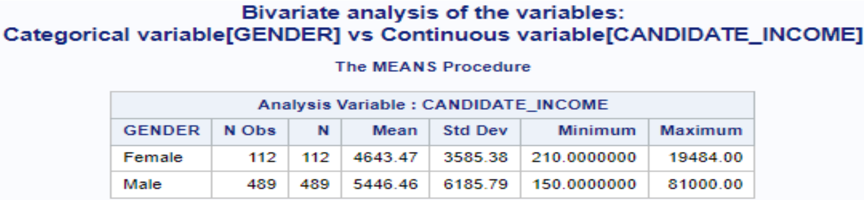
6.2.2.2 Bivariate Analysis of the variable (GENDER vs CANDIDATE_INCOME)

6.2.2.2.1 Code Snippet



```
TITLE1 'Bivariate analysis of the variables: ';
TITLE2 'Categorical variable[GENDER] vs Continuous variable[CANDIDATE_INCOME]';
FOOTNOTE '--------END--------';

PROC MEANS DATA = LIB77702.TRAINING_DS;

CLASS gender; /* It is a categorical variable */
VAR candidate_income; /* It is a numerical variable */

RUN;
```

6.2.2.2.2 Output



Bivariate analysis of the variables:
Categorical variable[GENDER] vs Continuous variable[CANDIDATE_INCOME]

The MEANS Procedure

Analysis Variable : CANDIDATE_INCOME

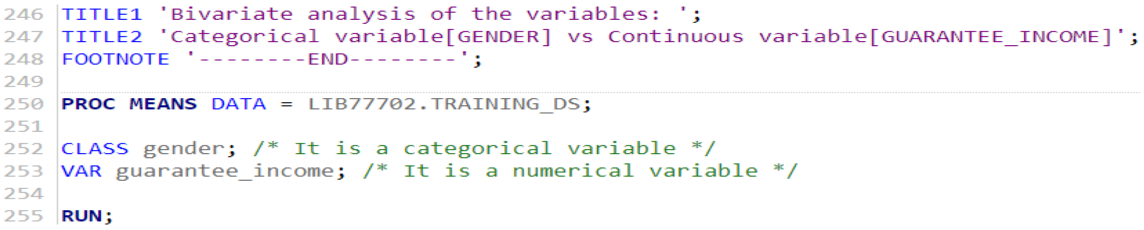
GENDER	N Obs	N	Mean	Std Dev	Minimum	Maximum
Female	112	112	4643.47	3585.38	210.0000000	19484.00
Male	489	489	5446.46	6185.79	150.0000000	81000.00

6.2.2.2.3 Description

The bivariate analysis between gender and candidate income reveals that the average income for females is approximately $4643.47 with a standard deviation of $3585.38, ranging from $210 to $19484. For males, the average is around $5446.46 with a standard deviation of $6185.79, ranging from $150 to $81000.

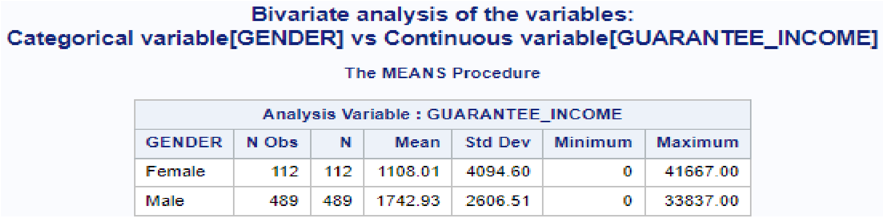
6.2.2.3 Bivariate Analysis of the variable (GENDER vs GUARANTEE_INCOME)

6.2.2.3.1 Code Snippet



```
TITLE1 'Bivariate analysis of the variables: ';
TITLE2 'Categorical variable[GENDER] vs Continuous variable[GUARANTEE_INCOME]';
FOOTNOTE '--------END--------';

PROC MEANS DATA = LIB77702.TRAINING_DS;

CLASS gender; /* It is a categorical variable */
VAR guarantee_income; /* It is a numerical variable */

RUN;
```

6.2.2.3.2 Output



Bivariate analysis of the variables:
Categorical variable[GENDER] vs Continuous variable[GUARANTEE_INCOME]

The MEANS Procedure

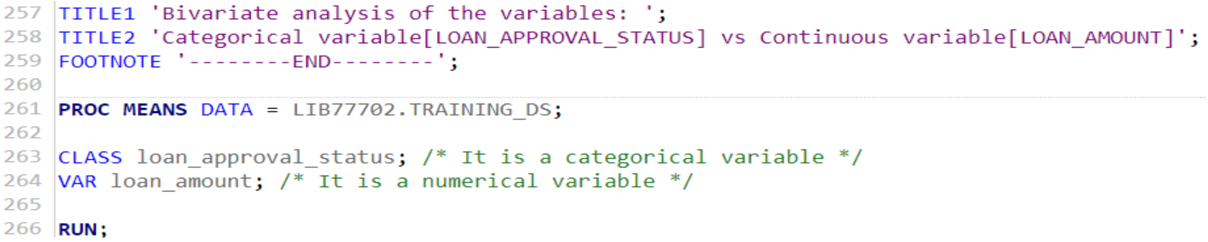
Analysis Variable : GUARANTEE_INCOME						
GENDER	N Obs	N	Mean	Std Dev	Minimum	Maximum
Female	112	112	1108.01	4094.60	0	41667.00
Male	489	489	1742.93	2606.51	0	33837.00

6.2.2.3.3 Description

The bivariate analysis between gender and candidate income reveals that the average income for females is approximately $1108.01 with a standard deviation of $4094.60, ranging from $210 to $19484. For males, the average is around $1742.93 with a standard deviation of $2606.51, ranging from $0 to $33837.

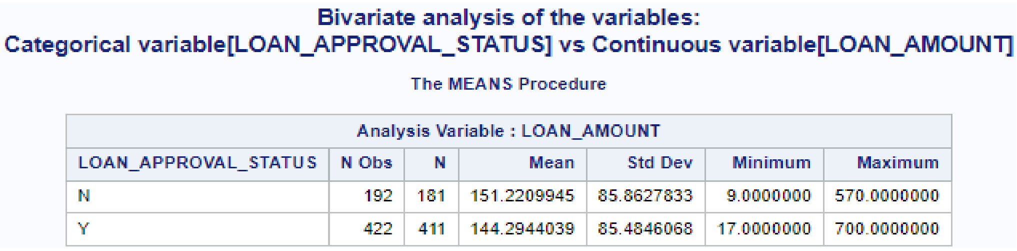
6.2.2.4 Bivariate Analysis of the variable (LOAN_APPROVAL_STATUS vs LOAN_AMOUNT)

6.2.2.4.1 Code Snippet



```
TITLE1 'Bivariate analysis of the variables: ';
TITLE2 'Categorical variable[LOAN_APPROVAL_STATUS] vs Continuous variable[LOAN_AMOUNT]';
FOOTNOTE '--------END--------';

PROC MEANS DATA = LIB77702.TRAINING_DS;

CLASS loan_approval_status; /* It is a categorical variable */
VAR loan_amount; /* It is a numerical variable */

RUN;
```

6.2.2.4.2 Output



Bivariate analysis of the variables:
Categorical variable[LOAN_APPROVAL_STATUS] vs Continuous variable[LOAN_AMOUNT]

The MEANS Procedure

Analysis Variable : LOAN_AMOUNT						
LOAN_APPROVAL_STATUS	N Obs	N	Mean	Std Dev	Minimum	Maximum
N	192	181	151.2209945	85.8627833	9.0000000	570.0000000
Y	422	411	144.2944039	85.4846068	17.0000000	700.0000000

6.2.2.4.3 Description

The bivariate analysis between loan approval status and loan amount shows that for approved loans (Y), the average loan amount is approximately 144.29 with a standard deviation of 85.48, ranging from 17 to 700. For unapproved loans (N), the average is higher at 151.22 with a standard deviation of 85.86, ranging from 9 to 570.

7 Analysis of Variables – LIB77702.TESTING_DS

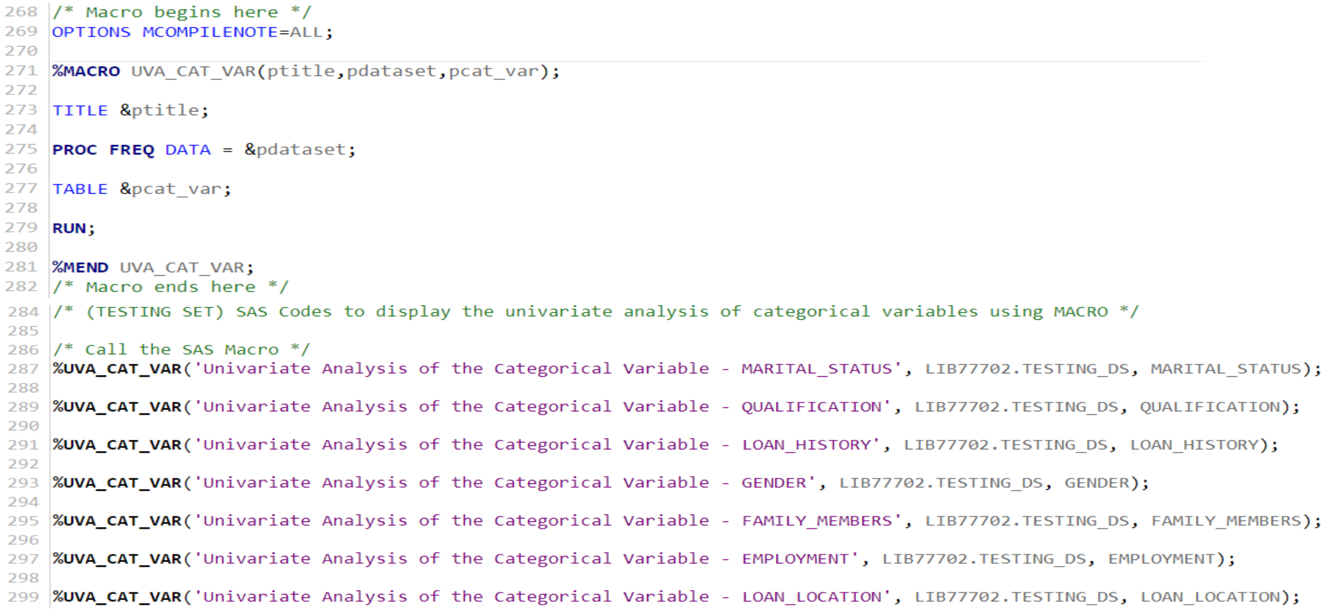
7.1 Introduction to SAS MACRO

The SAS Macro facility is a powerful feature in the SAS programming language. Using the macro, one can automate procedures and clean up code, making it more flexible. Macros take that ability to write fully dynamic programs that drive themselves using data conditions without applying manual interference to the extreme. At the most superficial level, an SAS macro can be defined as a collection of instructions that can be reused as many times as required within any SAS program-opening route to get rid of redundancy and be effective. Macros especially find applications in large-scale data processing and analysis where similar operations need to be applied over several datasets or variables. They dynamically create code according to the values that the macro variables take, hence making the programs more flexible concerning any changes. For example, one can quickly write one macro that cleans up whatever dataset one desires, as opposed to needing to individually write the codes for cleaning each data set. This thereby not only conserves time but also precludes the possibility of committing errors by code duplication. Some features that are associated with the macro language in SAS include the macro variables, macro functions, and macro programs, which allow more compact and maintainable codes (Debikaghosh, 2024).

7.2 Univariate Analysis of the Variables using SAS MACRO – LIB77702.TESTING_DS

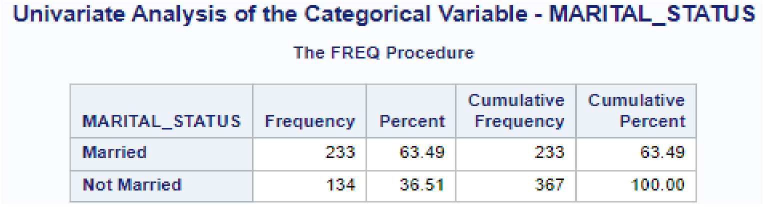
7.2.1 Analysis of the Categorical Variables in the Dataset

7.2.1.1 Code Snippet



```
/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;

%MACRO UVA_CAT_VAR(ptitle,pdataset,pcat_var);

TITLE &ptitle;

PROC FREQ DATA = &pdataset;

TABLE &pcat_var;

RUN;

%MEND UVA_CAT_VAR;
/* Macro ends here */
/* (TESTING SET) SAS Codes to display the univariate analysis of categorical variables using MACRO */

/* Call the SAS Macro */
%UVA_CAT_VAR('Univariate Analysis of the Categorical Variable - MARITAL_STATUS', LIB77702.TESTING_DS, MARITAL_STATUS);

%UVA_CAT_VAR('Univariate Analysis of the Categorical Variable - QUALIFICATION', LIB77702.TESTING_DS, QUALIFICATION);

%UVA_CAT_VAR('Univariate Analysis of the Categorical Variable - LOAN_HISTORY', LIB77702.TESTING_DS, LOAN_HISTORY);

%UVA_CAT_VAR('Univariate Analysis of the Categorical Variable - GENDER', LIB77702.TESTING_DS, GENDER);

%UVA_CAT_VAR('Univariate Analysis of the Categorical Variable - FAMILY_MEMBERS', LIB77702.TESTING_DS, FAMILY_MEMBERS);

%UVA_CAT_VAR('Univariate Analysis of the Categorical Variable - EMPLOYMENT', LIB77702.TESTING_DS, EMPLOYMENT);

%UVA_CAT_VAR('Univariate Analysis of the Categorical Variable - LOAN_LOCATION', LIB77702.TESTING_DS, LOAN_LOCATION);
```

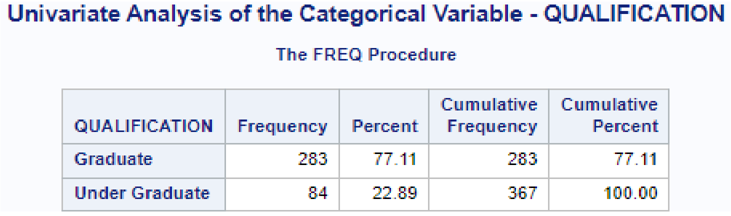
7.2.1.2 Output



Univariate Analysis of the Categorical Variable - MARITAL_STATUS

The FREQ Procedure

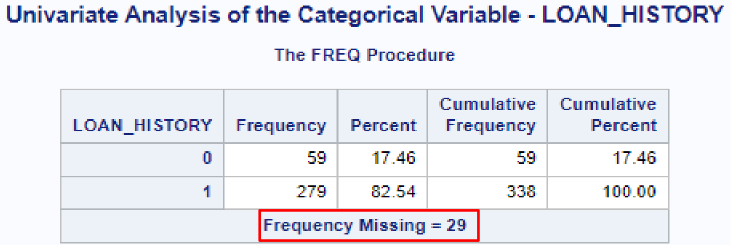
MARITAL_STATUS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Married	233	63.49	233	63.49
Not Married	134	36.51	367	100.00



Univariate Analysis of the Categorical Variable - QUALIFICATION

The FREQ Procedure

QUALIFICATION	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Graduate	283	77.11	283	77.11
Under Graduate	84	22.89	367	100.00

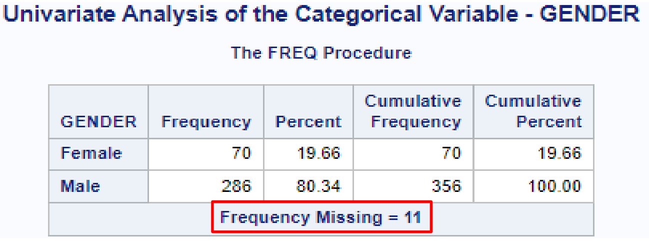


Univariate Analysis of the Categorical Variable - LOAN_HISTORY

The FREQ Procedure

LOAN_HISTORY	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	59	17.46	59	17.46
1	279	82.54	338	100.00

Frequency Missing = 29

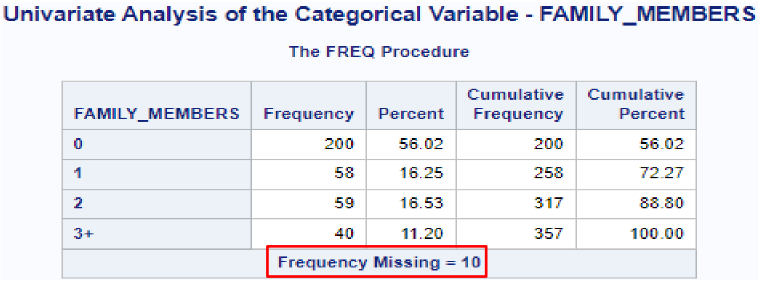


Univariate Analysis of the Categorical Variable - GENDER

The FREQ Procedure

GENDER	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Female	70	19.66	70	19.66
Male	286	80.34	356	100.00

Frequency Missing = 11

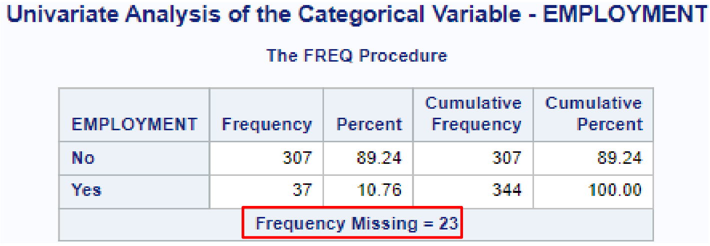


Univariate Analysis of the Categorical Variable - FAMILY_MEMBERS

The FREQ Procedure

FAMILY_MEMBERS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	200	56.02	200	56.02
1	58	16.25	258	72.27
2	59	16.53	317	88.80
3+	40	11.20	357	100.00

Frequency Missing = 10

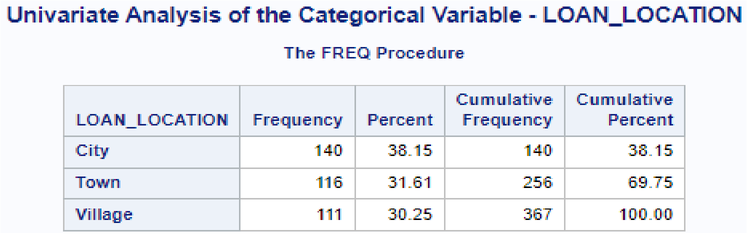


Univariate Analysis of the Categorical Variable - EMPLOYMENT

The FREQ Procedure

EMPLOYMENT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
No	307	89.24	307	89.24
Yes	37	10.76	344	100.00

Frequency Missing = 23



Univariate Analysis of the Categorical Variable - LOAN_LOCATION

The FREQ Procedure

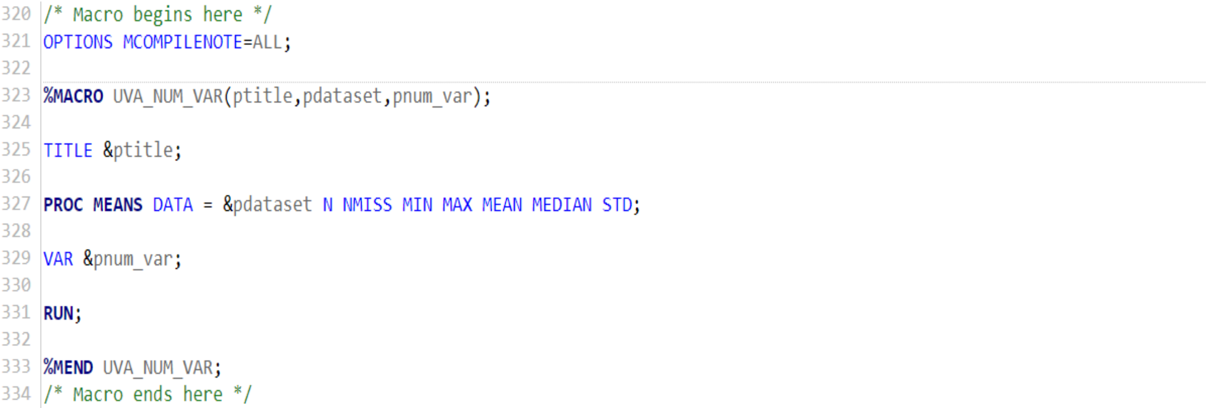
LOAN_LOCATION	Frequency	Percent	Cumulative Frequency	Cumulative Percent
City	140	38.15	140	38.15
Town	116	31.61	256	69.75
Village	111	30.25	367	100.00

7.2.1.3 Description

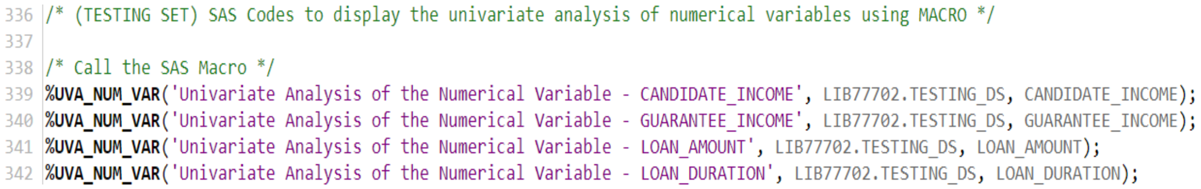
The univariate analysis of categorical variables in testing set reveals several key insights. A majority of the applicants, 63.49%, are married, while 36.51% are not. Regarding qualifications, 77.11% are graduates, and 22.89% are undergraduates. In terms of loan history, 82.54% have a loan history, while 17.46% do not, with 29 missing values. The gender distribution shows that 80.34% of the applicants are male, and 19.66% are female, with 11 missing values. These summaries indicate that the dataset predominantly consists of married graduates, primarily male, who generally have a loan history. The analysis of family member shows that 56.02% of applicants have no family members, 16.25% have one, 16.53% have two, and 11.20% have three or more, with 10 missing values. In employment, 89.24% are unemployed, and 10.76% are employed, with 23 missing values. For loan location, 38.15% are in cities, 31.61% in towns, and 30.25% in villages.

7.2.2 Analysis of the Continuous Variables in the Dataset

7.2.2.1 Code Snippet

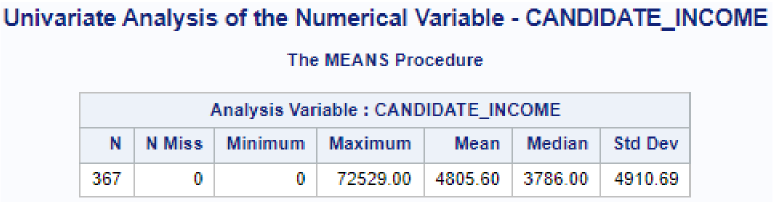


```
/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;

%MACRO UVA_NUM_VAR(ptitle,pdataset,pnum_var);

TITLE &ptitle;

PROC MEANS DATA = &pdataset N NMISS MIN MAX MEAN MEDIAN STD;

VAR &pnum_var;

RUN;

%MEND UVA_NUM_VAR;
/* Macro ends here */
```



```
/* (TESTING SET) SAS Codes to display the univariate analysis of numerical variables using MACRO */

/* Call the SAS Macro */
%UVA_NUM_VAR('Univariate Analysis of the Numerical Variable - CANDIDATE_INCOME', LIB77702.TESTING_DS, CANDIDATE_INCOME);
%UVA_NUM_VAR('Univariate Analysis of the Numerical Variable - GUARANTEE_INCOME', LIB77702.TESTING_DS, GUARANTEE_INCOME);
%UVA_NUM_VAR('Univariate Analysis of the Numerical Variable - LOAN_AMOUNT', LIB77702.TESTING_DS, LOAN_AMOUNT);
%UVA_NUM_VAR('Univariate Analysis of the Numerical Variable - LOAN_DURATION', LIB77702.TESTING_DS, LOAN_DURATION);
```

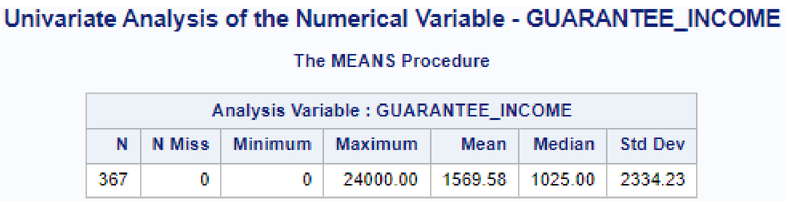
7.2.2.2 Output



Univariate Analysis of the Numerical Variable - CANDIDATE_INCOME

The MEANS Procedure

Analysis Variable : CANDIDATE_INCOME						
N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
367	0	0	72529.00	4805.60	3786.00	4910.69

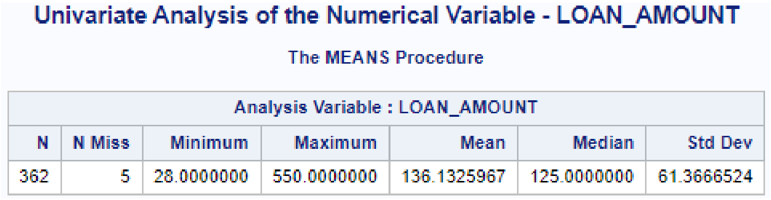


Univariate Analysis of the Numerical Variable - GUARANTEE_INCOME

The MEANS Procedure

Analysis Variable : GUARANTEE_INCOME

N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
367	0	0	24000.00	1569.58	1025.00	2334.23

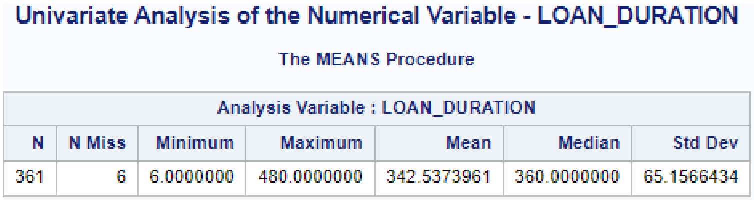


Univariate Analysis of the Numerical Variable - LOAN_AMOUNT

The MEANS Procedure

Analysis Variable : LOAN_AMOUNT

N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
362	5	28.0000000	550.0000000	136.1325967	125.0000000	61.3666524



Univariate Analysis of the Numerical Variable - LOAN_DURATION

The MEANS Procedure

Analysis Variable : LOAN_DURATION

N	N Miss	Minimum	Maximum	Mean	Median	Std Dev
361	6	6.0000000	480.0000000	342.5373961	360.0000000	65.1566434

7.2.2.3 Description

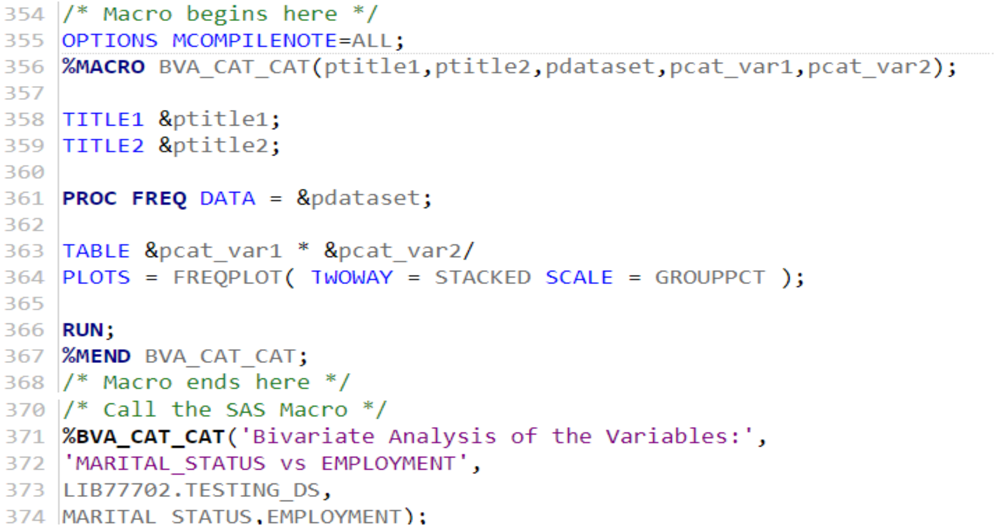
The univariate analysis of the testing set provides a detailed summary of various variables. For candidate's income, the average is $4,805.60 with a standard deviation of $4,910.69, ranging from $0 to $72,529. In terms of guarantee income, the average is $1,569.58 with a standard deviation of $2,334.23, and it ranges from $0 to $24,000. The loan amount analysis shows an average of $136.13 with a standard deviation of $61.36. This analysis includes 362 values, with amounts ranging from $28 to $550, and 5 missing values. For loan duration, the average is 342.53 days, with a median of 360 days, ranging from 6 to 480 days. This analysis includes 361 values, with 6 missing values.

7.3 Bivariate Analysis of the variable Using SAS MACRO – LIB7702.TESTING_DS

7.3.1 Bivariate Analysis of the variable (Categorical vs Categorical)

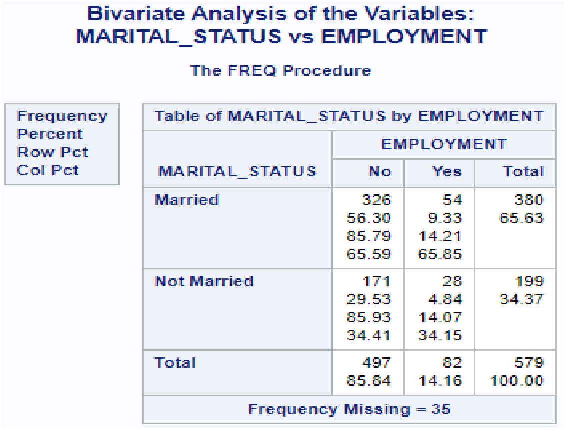
7.3.1.1 Bivariate Analysis of the variable (MARITAL_STATUS vs EMPLOYMENT)

7.3.1.1.1 Code Snippet



```
/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;
%MACRO BVA_CAT_CAT(ptitle1,ptitle2,pdataset,pcat_var1,pcat_var2);

TITLE1 &ptitle1;
TITLE2 &ptitle2;

PROC FREQ DATA = &pdataset;

TABLE &pcat_var1 * &pcat_var2/
PLOTS = FREQPLOT( TWOWAY = STACKED SCALE = GROUPPCT );

RUN;
%MEND BVA_CAT_CAT;
/* Macro ends here */
/* Call the SAS Macro */
%BVA_CAT_CAT('Bivariate Analysis of the Variables:',
'MARITAL_STATUS vs EMPLOYMENT',
LIB77702.TESTING_DS,
MARITAL STATUS,EMPLOYMENT);
```

7.3.1.1.2 Output



Bivariate Analysis of the Variables:
MARITAL_STATUS vs EMPLOYMENT

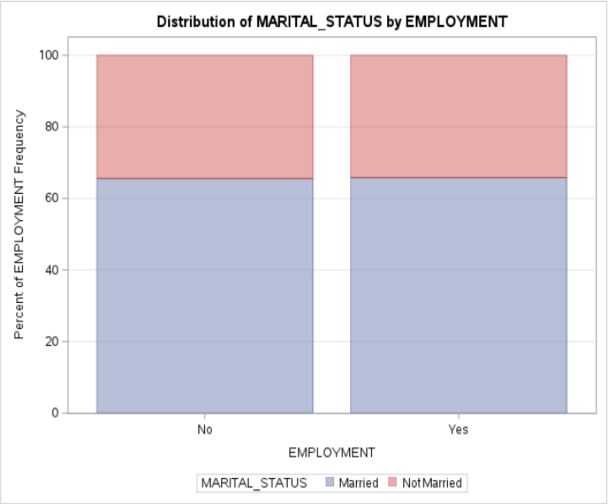
The FREQ Procedure

Frequency
Percent
Row Pct
Col Pct

Table of MARITAL_STATUS by EMPLOYMENT

	EMPLOYMENT		
MARITAL_STATUS	No	Yes	Total
Married	326 56.30 85.79 65.59	54 9.33 14.21 65.85	380 65.63
Not Married	171 29.53 85.93 34.41	28 4.84 14.07 34.15	199 34.37
Total	497 85.84	82 14.16	579 100.00

Frequency Missing = 35

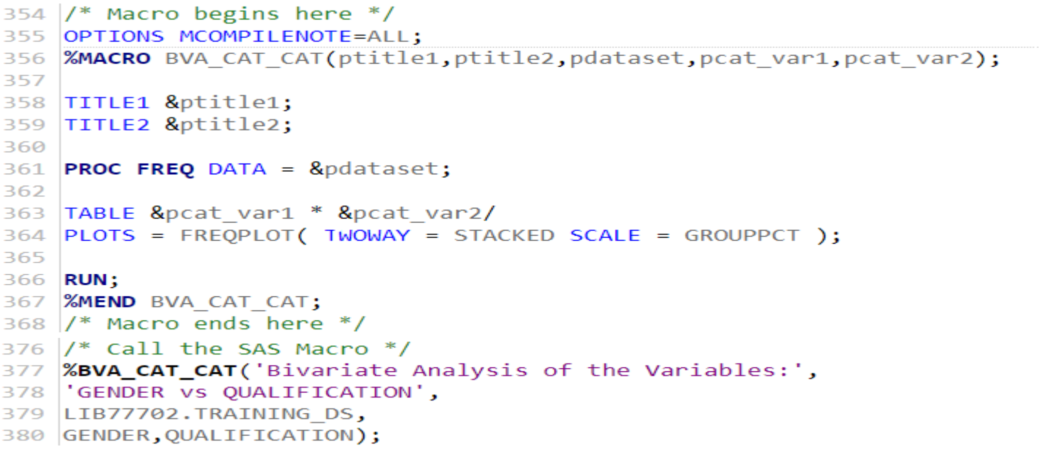


7.3.1.1.3 Description

The bivariate analysis of marital status versus employment shows that among the 579 individuals, 65.63% are married, with 14.21% of them employed. Among the 34.37% who are not married, 14.07% are employed. Overall, 14.16% of the total population is employed, with 35 missing values.

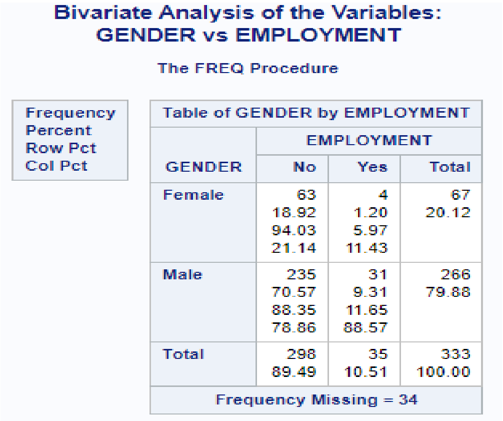
7.3.1.2 Bivariate Analysis of the variable (GENDER vs EMPLOYEMENT)

7.3.1.2.1 Code Snippet



```
/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;
%MACRO BVA_CAT_CAT(ptitle1,ptitle2,pdataset,pcat_var1,pcat_var2);

TITLE1 &ptitle1;
TITLE2 &ptitle2;

PROC FREQ DATA = &pdataset;

TABLE &pcat_var1 * &pcat_var2/
PLOTS = FREQPLOT( TWOWAY = STACKED SCALE = GROUPPCT );

RUN;
%MEND BVA_CAT_CAT;
/* Macro ends here */
/* Call the SAS Macro */
%BVA_CAT_CAT('Bivariate Analysis of the Variables:',
'GENDER vs QUALIFICATION',
LIB77702.TRAINING_DS,
GENDER,QUALIFICATION);
```

7.3.1.2.2 Output



Bivariate Analysis of the Variables:
GENDER vs EMPLOYMENT

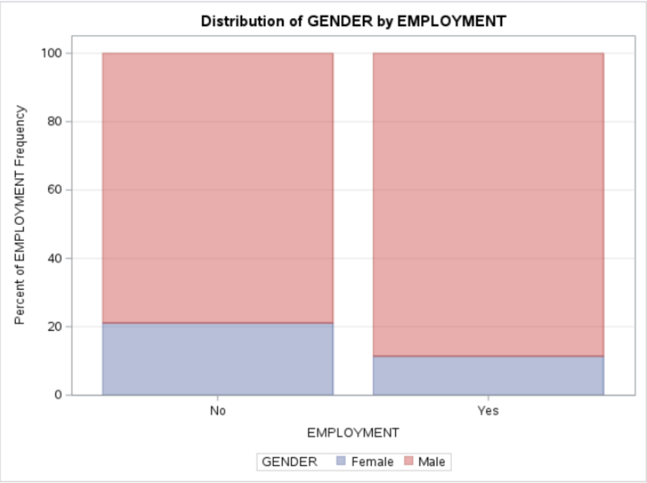
The FREQ Procedure

Frequency
Percent
Row Pct
Col Pct

Table of GENDER by EMPLOYMENT

	EMPLOYMENT		
GENDER	No	Yes	Total
Female	63 18.92 94.03 21.14	4 1.20 5.97 11.43	67 20.12
Male	235 70.57 88.35 78.86	31 9.31 11.65 88.57	266 79.88
Total	298 89.49	35 10.51	333 100.00

Frequency Missing = 34

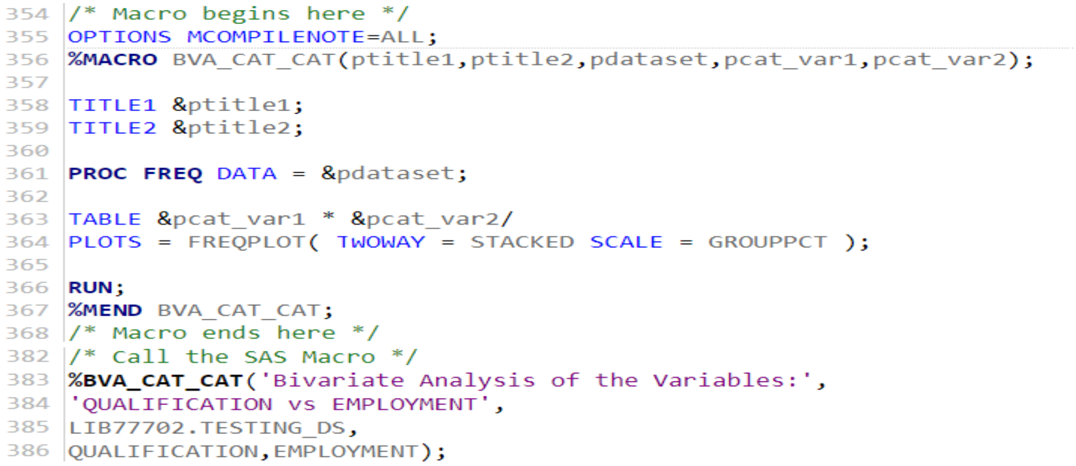


7.3.1.2.3 Description

The bivariate analysis of gender versus employment reveals that among 333 individuals, 20.12% are female, with 5.97% employed and 94.03% are unemployed. Males comprise 79.88% of the data, with 11.65% employed and 88.35% are unemployed. Overall, 10.51% of the total population is employed and 89.49% are unemployed, with 34 missing values.

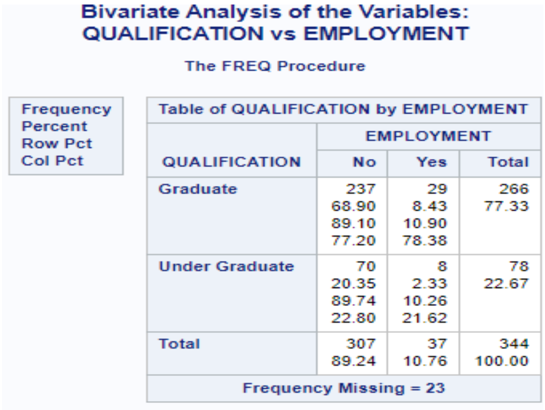
7.3.1.3 Bivariate Analysis of the variable (QUALIFICATION vs EMPLOYEMENT)

7.3.1.3.1 Code Snippet



```
/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;
%MACRO BVA_CAT_CAT(ptitle1,ptitle2,pdataset,pcat_var1,pcat_var2);

TITLE1 &ptitle1;
TITLE2 &ptitle2;

PROC FREQ DATA = &pdataset;

TABLE &pcat_var1 * &pcat_var2/
PLOTS = FREQPLOT( TWOWAY = STACKED SCALE = GROUPPCT );

RUN;
%MEND BVA_CAT_CAT;
/* Macro ends here */
/* Call the SAS Macro */
%BVA_CAT_CAT('Bivariate Analysis of the Variables:',
'QUALIFICATION vs EMPLOYMENT',
LIB77702.TESTING_DS,
QUALIFICATION,EMPLOYMENT);
```

7.3.1.3.2 Output



Bivariate Analysis of the Variables:
QUALIFICATION vs EMPLOYMENT

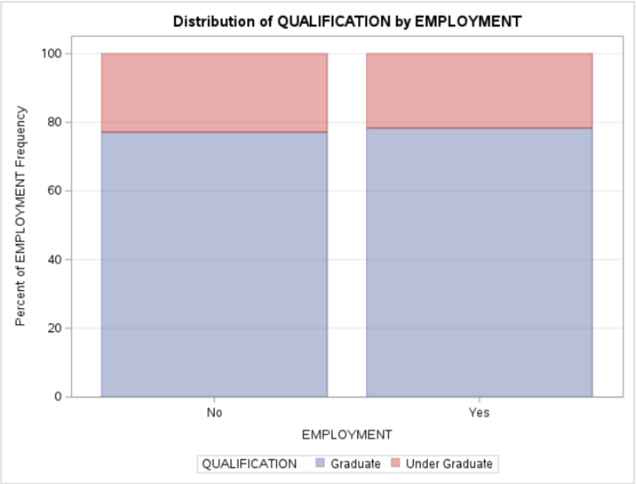
The FREQ Procedure

Frequency
Percent
Row Pct
Col Pct

Table of QUALIFICATION by EMPLOYMENT

	EMPLOYMENT		
QUALIFICATION	No	Yes	Total
Graduate	237 68.90 89.10 77.20	29 8.43 10.90 78.38	266 77.33
Under Graduate	70 20.35 89.74 22.80	8 2.33 10.26 21.62	78 22.67
Total	307 89.24	37 10.76	344 100.00

Frequency Missing = 23



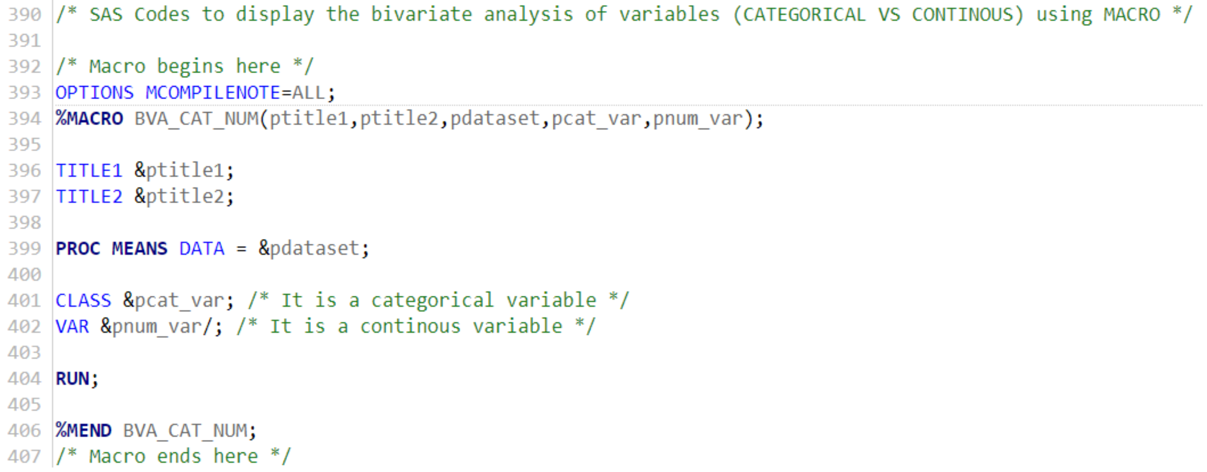
7.3.1.3.3 Description

The bivariate analysis of qualification versus employment reveals that among 344 individuals, 77.33% are graduate, with 10.9% employed and 89.1% are unemployed. Undergraduates comprise 22.67% of the data, with 10.26% employed and 89.74% are unemployed. Overall, 10.76% of the total population is employed and 89.24% are unemployed, with 23 missing values.

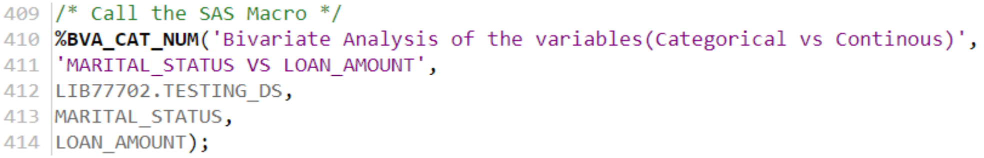
7.3.2 Bivariate Analysis of the variable (Categorical vs Continuous)

7.3.2.1 Bivariate Analysis of the variable (MARITAL_STATUS vs LOAN_AMOUNT)

7.3.2.1.1 Code Snippet

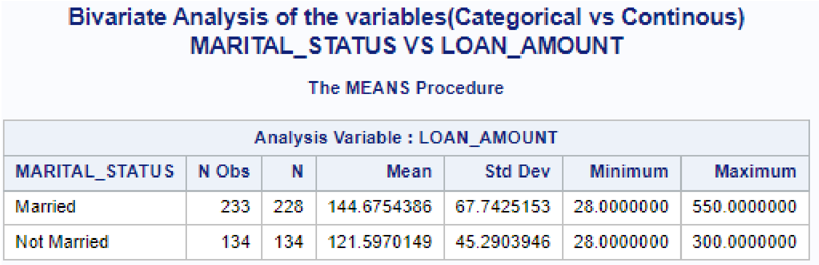


```
/* SAS Codes to display the bivariate analysis of variables (CATEGORICAL VS CONTINOUS) using MACRO */

/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;
%MACRO BVA_CAT_NUM(ptitle1,ptitle2,pdataset,pcat_var,pnum_var);

TITLE1 &ptitle1;
TITLE2 &ptitle2;

PROC MEANS DATA = &pdataset;

CLASS &pcat_var; /* It is a categorical variable */
VAR &pnum_var/; /* It is a continous variable */

RUN;

%MEND BVA_CAT_NUM;
/* Macro ends here */
```



```
/* Call the SAS Macro */
%BVA_CAT_NUM('Bivariate Analysis of the variables(Categorical vs Continous)',
'MARITAL_STATUS VS LOAN_AMOUNT',
LIB77702.TESTING_DS,
MARITAL_STATUS,
LOAN_AMOUNT);
```

7.3.2.1.2 Output



Bivariate Analysis of the variables(Categorical vs Continous)
MARITAL_STATUS VS LOAN_AMOUNT

The MEANS Procedure

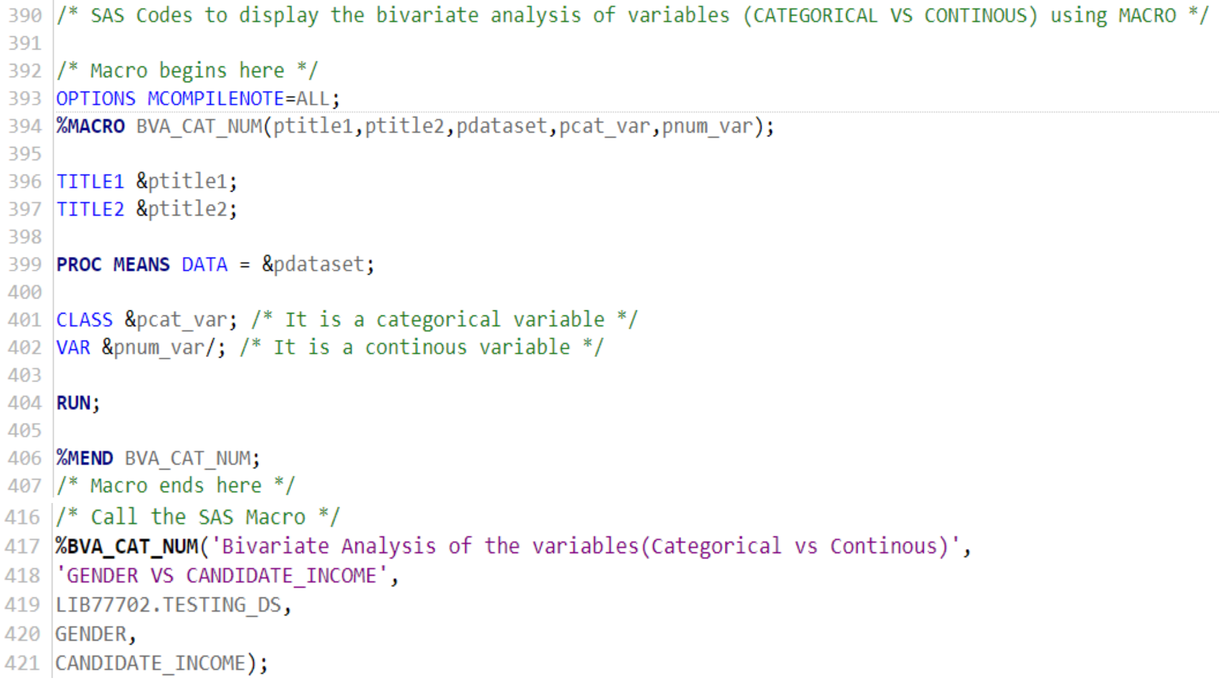
Analysis Variable : LOAN_AMOUNT						
MARITAL_STATUS	N Obs	N	Mean	Std Dev	Minimum	Maximum
Married	233	228	144.6754386	67.7425153	28.0000000	550.0000000
Not Married	134	134	121.5970149	45.2903946	28.0000000	300.0000000

7.3.2.1.3 Description

The bivariate analysis between marital status and loan amount reveals that the average loan amount for married is approximately $144.7 with a standard deviation of $67.74, ranging from $28 to $550. For Not married, the average is around $121.6 with a standard deviation of $45.3, ranging from $28 to $300.

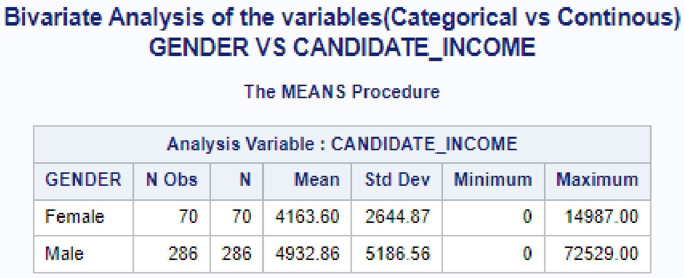
7.3.2.2 Bivariate Analysis of the variable (GENDER vs CANDIDATE_INCOME)

7.3.2.2.1 Code Snippet



```
/* SAS Codes to display the bivariate analysis of variables (CATEGORICAL VS CONTINOUS) using MACRO */

/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;
%MACRO BVA_CAT_NUM(ptitle1,ptitle2,pdataset,pcat_var,pnum_var);

TITLE1 &ptitle1;
TITLE2 &ptitle2;

PROC MEANS DATA = &pdataset;

CLASS &pcat_var; /* It is a categorical variable */
VAR &pnum_var/; /* It is a continous variable */

RUN;

%MEND BVA_CAT_NUM;
/* Macro ends here */
/* Call the SAS Macro */
%BVA_CAT_NUM('Bivariate Analysis of the variables(Categorical vs Continous)',
'GENDER VS CANDIDATE_INCOME',
LIB77702.TESTING_DS,
GENDER,
CANDIDATE_INCOME);
```

7.3.2.2.2 Output



Bivariate Analysis of the variables(Categorical vs Continous)
GENDER VS CANDIDATE_INCOME

The MEANS Procedure

Analysis Variable : CANDIDATE_INCOME

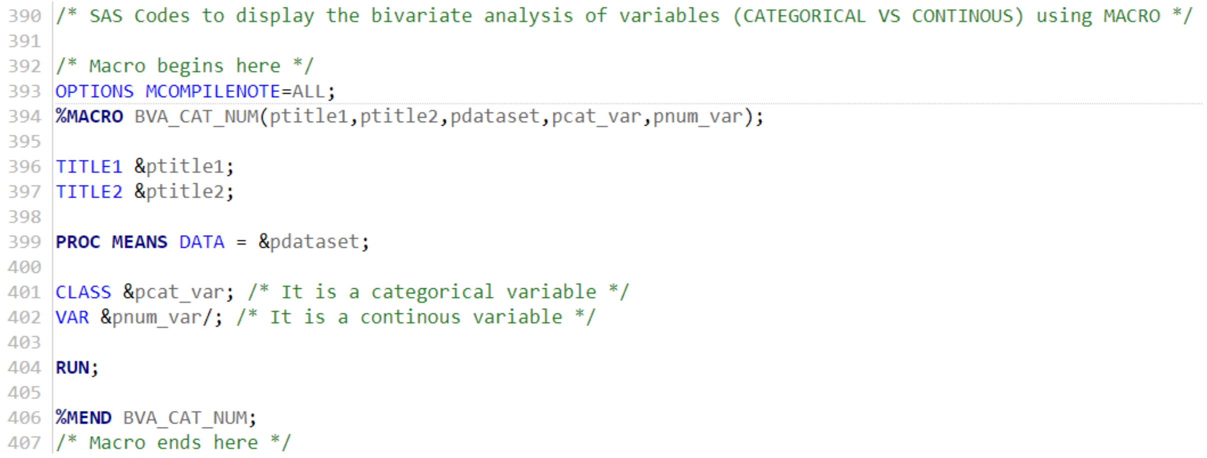
GENDER	N Obs	N	Mean	Std Dev	Minimum	Maximum
Female	70	70	4163.60	2644.87	0	14987.00
Male	286	286	4932.86	5186.56	0	72529.00

7.3.2.2.3 Description

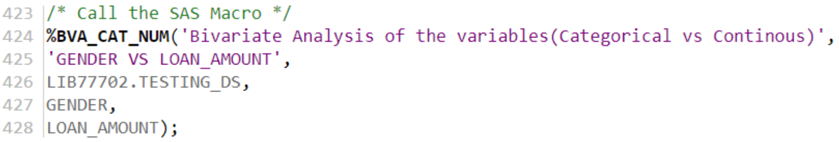
The bivariate analysis between gender and candidate income reveals that the average income for females is approximately $4163.60 with a standard deviation of $2644.87, ranging from $0 to $14987. For males, the average is around $4932 with a standard deviation of $72529, ranging from $0 to $72529.

7.3.2.3 Bivariate Analysis of the variable (GENDER vs LOAN_AMOUNT)

7.3.2.3.1 Code Snippet

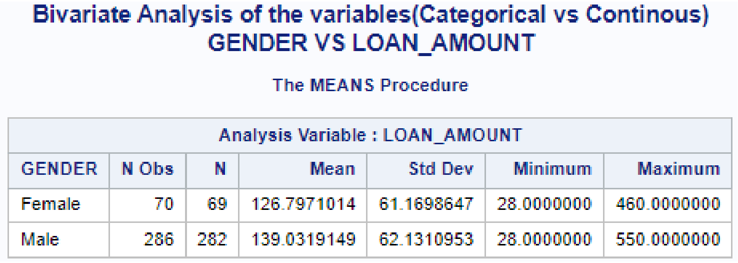


```
/* SAS Codes to display the bivariate analysis of variables (CATEGORICAL VS CONTINOUS) using MACRO */

/* Macro begins here */
OPTIONS MCOMPILENOTE=ALL;
%MACRO BVA_CAT_NUM(ptitle1,ptitle2,pdataset,pcat_var,pnum_var);

TITLE1 &ptitle1;
TITLE2 &ptitle2;

PROC MEANS DATA = &pdataset;

CLASS &pcat_var; /* It is a categorical variable */
VAR &pnum_var/; /* It is a continous variable */

RUN;

%MEND BVA_CAT_NUM;
/* Macro ends here */
```



```
/* Call the SAS Macro */
%BVA_CAT_NUM('Bivariate Analysis of the variables(Categorical vs Continous)',
'GENDER VS LOAN_AMOUNT',
LIB77702.TESTING_DS,
GENDER,
LOAN_AMOUNT);
```

7.3.2.3.2 Output



Bivariate Analysis of the variables(Categorical vs Continous)
GENDER VS LOAN_AMOUNT

The MEANS Procedure

Analysis Variable : LOAN_AMOUNT						
GENDER	N Obs	N	Mean	Std Dev	Minimum	Maximum
Female	70	69	126.7971014	61.1698647	28.0000000	460.0000000
Male	286	282	139.0319149	62.1310953	28.0000000	550.0000000

7.3.2.3.3 Description

The bivariate analysis between gender and loan amount reveals that the average loan amount for females is approximately $126.80 with a standard deviation of $61.2, ranging from $28 to $460. For males, the average is around $139.03 with a standard deviation of $62.1, ranging from $28 to $550.

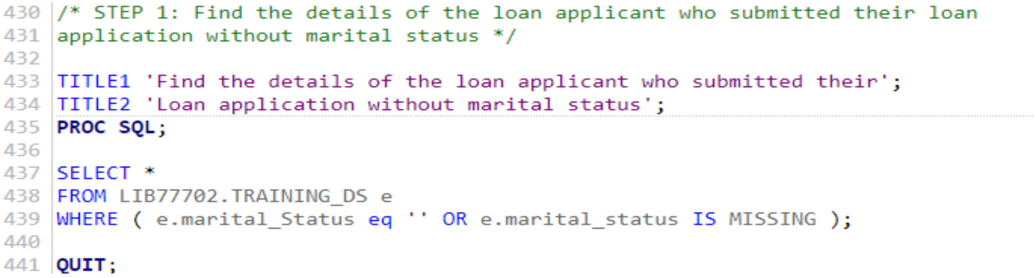
8 Imputation of Missing Values

8.1 Imputing the Missing Values in Categorical Variables – LIB7702.TRAINING_DS

8.1.1 Handling Missing Values in MARITAL_STATUS

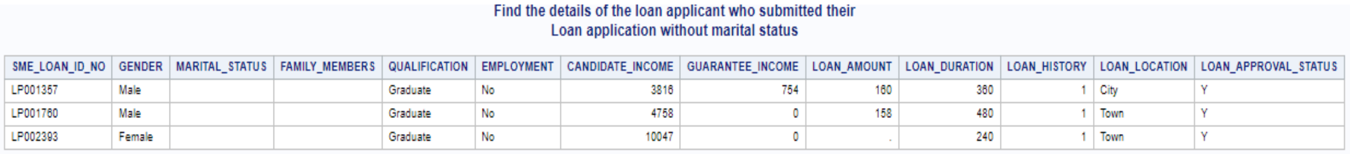
8.1.1.1 Find Missing Value – MARITAL_STATUS

8.1.1.1.1 Code Snippet



```
/* STEP 1: Find the details of the loan applicant who submitted their loan
application without marital status */

TITLE1 'Find the details of the loan applicant who submitted their';
TITLE2 'Loan application without marital status';
PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.marital_Status eq '' OR e.marital_status IS MISSING );

QUIT;
```

8.1.1.1.2 Output



Find the details of the loan applicant who submitted their
Loan application without marital status

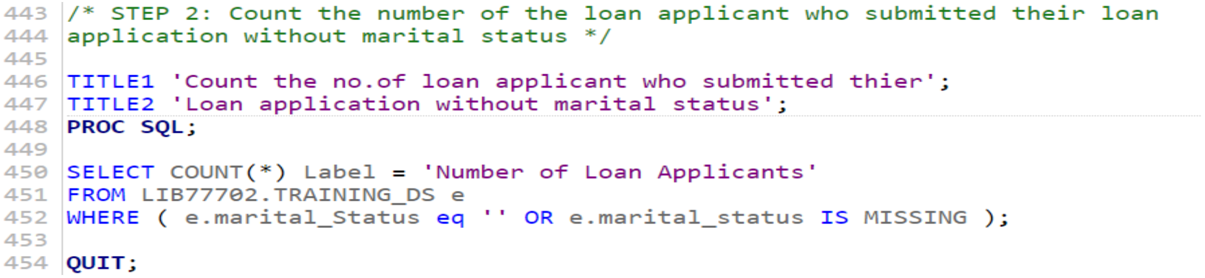
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION	LOAN_APPROVAL_STATUS
LP001357	Male			Graduate	No	3816	754	160	360	1	City	Y
LP001760	Male			Graduate	No	4758	0	158	480	1	Town	Y
LP002393	Female			Graduate	No	10047	0	.	240	1	Town	Y

8.1.1.1.3 Description

From the output above, we observe that the training set contains missing values for marital status; these values will be imputed later.

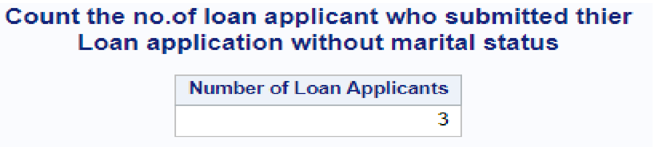
8.1.1.2 Counting Number of Missing Values – MARITAL_STATUS

8.1.1.2.1 Code Snippet



```
/* STEP 2: Count the number of the loan applicant who submitted their loan
application without marital status */

TITLE1 'Count the no.of loan applicant who submitted thier';
TITLE2 'Loan application without marital status';
PROC SQL;

SELECT COUNT(*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS e
WHERE ( e.marital_Status eq '' OR e.marital_status IS MISSING );

QUIT;
```

8.1.1.2.2 Output



Count the no.of loan applicant who submitted thier
Loan application without marital status

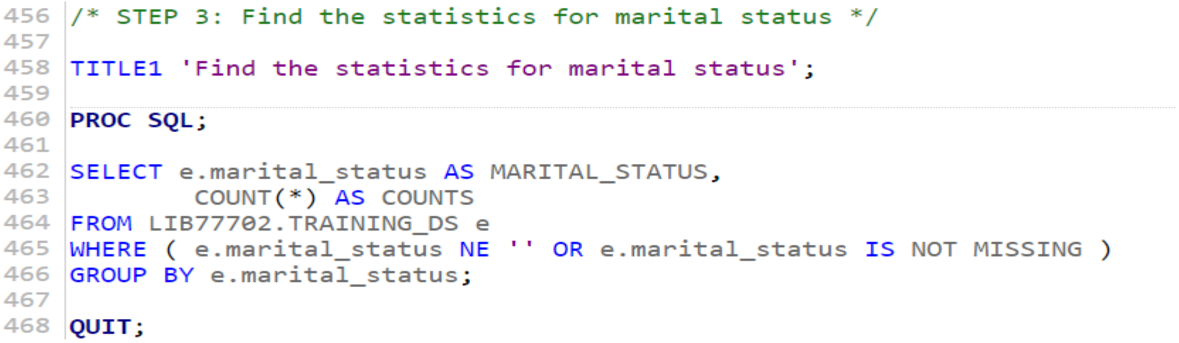
Number of Loan Applicants
3

8.1.1.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their marital status, which is 3 loan applicants.

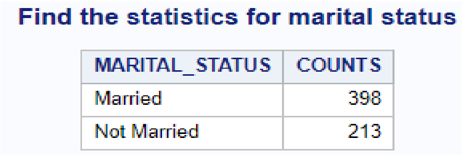
8.1.1.3 Finding the Statistics – MARITAL_STATUS

8.1.1.3.1 Code Snippet



```
/* STEP 3: Find the statistics for marital status */

TITLE1 'Find the statistics for marital status';

PROC SQL;

SELECT e.marital_status AS MARITAL_STATUS,
        COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.marital_status NE '' OR e.marital_status IS NOT MISSING )
GROUP BY e.marital_status;

QUIT;
```

8.1.1.3.2 Output



Find the statistics for marital status

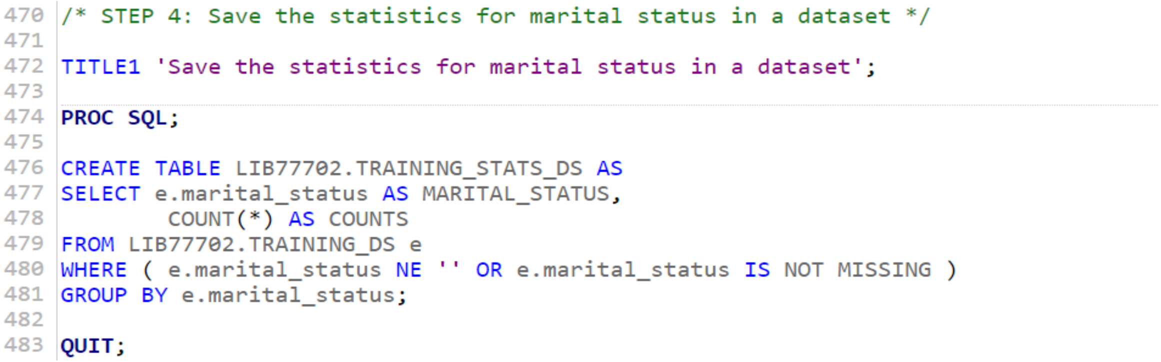
MARITAL_STATUS	COUNTS
Married	398
Not Married	213

8.1.1.3.3 Description

The statistics for marital status show that out of the total applicants, 398 are married and 213 are unmarried. This indicates that most of the applicants are married, while rest are not married.

8.1.1.4 Saving the Statistics – MARITAL_STATUS

8.1.1.4.1 Code Snippet



```
/* STEP 4: Save the statistics for marital status in a dataset */

TITLE1 'Save the statistics for marital status in a dataset';

PROC SQL;

CREATE TABLE LIB77702.TRAINING_STATS_DS AS
SELECT e.marital_status AS MARITAL_STATUS,
        COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.marital_status NE '' OR e.marital_status IS NOT MISSING )
GROUP BY e.marital_status;

QUIT;
```

8.1.1.4.2 Output

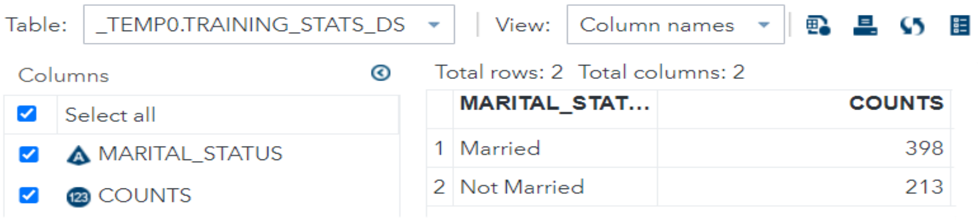


Table: _TEMP0.TRAINING_STATS_DS | View: Column names

Columns

☑ Select all
☑ MARITAL_STATUS
☑ COUNTS

Total rows: 2 Total columns: 2

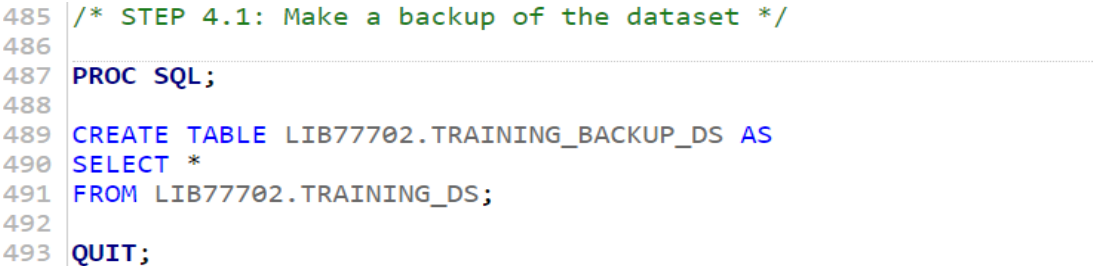
	MARITAL_STAT...	COUNTS
1	Married	398
2	Not Married	213

8.1.1.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TRAINING_STATS_DS.

8.1.1.5 Backup of the Dataset – MARITAL_STATUS

8.1.1.5.1 Code Snippet



```
/* STEP 4.1: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TRAINING_BACKUP_DS AS
SELECT *
FROM LIB77702.TRAINING_DS;

QUIT;
```

8.1.1.5.2 Output

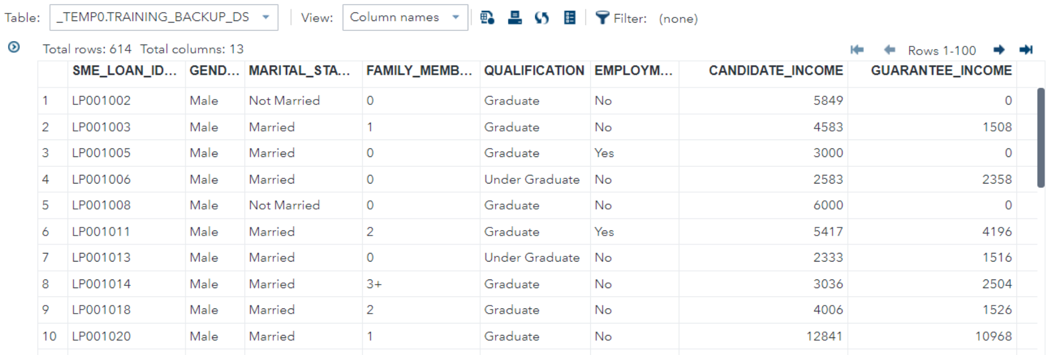


Table: _TEMP0.TRAINING_BACKUP_DS View: Column names Filter: (none)

Total rows: 614 Total columns: 13 Rows 1-100

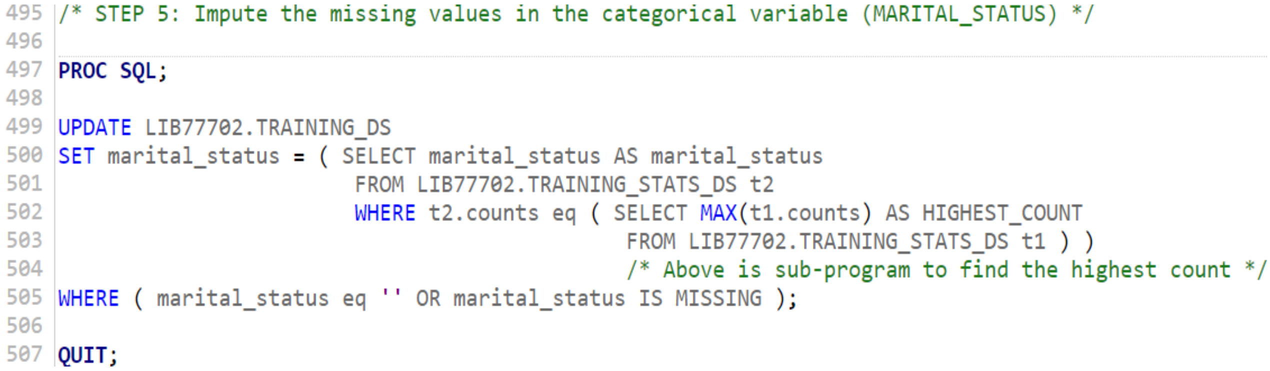
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001002	Male	Not Married	0	Graduate	No	5849	0
2	LP001003	Male	Married	1	Graduate	No	4583	1508
3	LP001005	Male	Married	0	Graduate	Yes	3000	0
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358
5	LP001008	Male	Not Married	0	Graduate	No	6000	0
6	LP001011	Male	Married	2	Graduate	Yes	5417	4196
7	LP001013	Male	Married	0	Under Graduate	No	2333	1516
8	LP001014	Male	Married	3+	Graduate	No	3036	2504
9	LP001018	Male	Married	2	Graduate	No	4006	1526
10	LP001020	Male	Married	1	Graduate	No	12841	10968

8.1.1.5.3 Description

The newly formed backup table LIB77702.TRAINING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

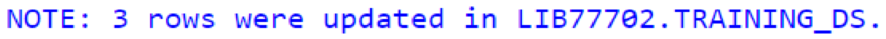
8.1.1.6 Imputing the missing values– MARITAL_STATUS

8.1.1.6.1 Code Snippet



```
/* STEP 5: Impute the missing values in the categorical variable (MARITAL_STATUS) */

PROC SQL;

UPDATE LIB77702.TRAINING_DS
SET marital_status = ( SELECT marital_status AS marital_status
                       FROM LIB77702.TRAINING_STATS_DS t2
                       WHERE t2.counts eq ( SELECT MAX(t1.counts) AS HIGHEST_COUNT
                                            FROM LIB77702.TRAINING_STATS_DS t1 ) )
                                            /* Above is sub-program to find the highest count */
WHERE ( marital_status eq '' OR marital_status IS MISSING );

QUIT;
```

8.1.1.6.2 Output



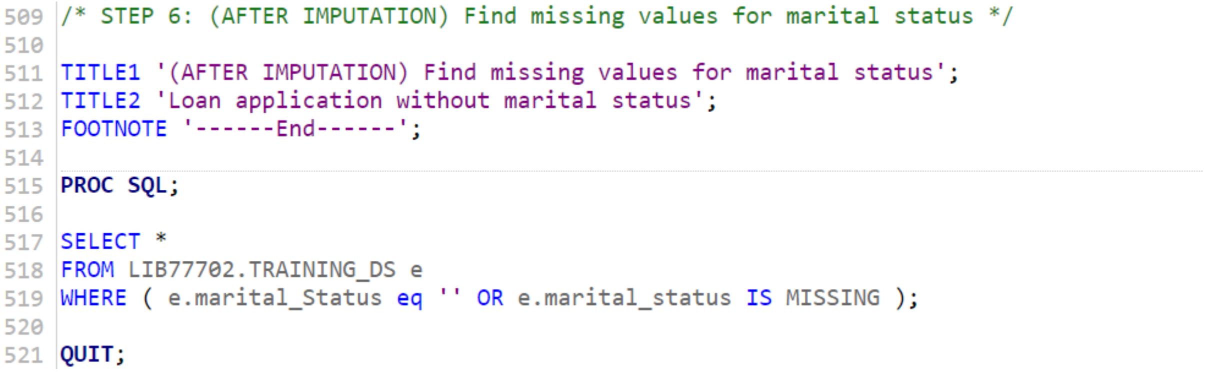
```
NOTE: 3 rows were updated in LIB77702.TRAINING_DS.
```

8.1.1.6.3 Description

The above output shows that the 3 missing values were successfully imputed and updated in marital status.

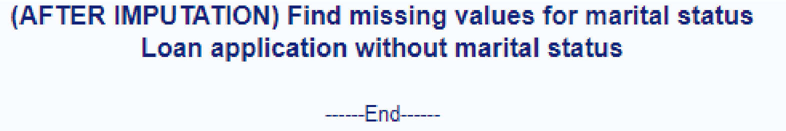
8.1.1.7 After imputing the missing values – MARITAL_STATUS

8.1.1.7.1 Code Snippet



```
/* STEP 6: (AFTER IMPUTATION) Find missing values for marital status */

TITLE1 '(AFTER IMPUTATION) Find missing values for marital status';
TITLE2 'Loan application without marital status';
FOOTNOTE '------End------';

PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.marital_Status eq '' OR e.marital_status IS MISSING );

QUIT;
```

8.1.1.7.2 Output



(AFTER IMPUTATION) Find missing values for marital status

Loan application without marital status

------End------

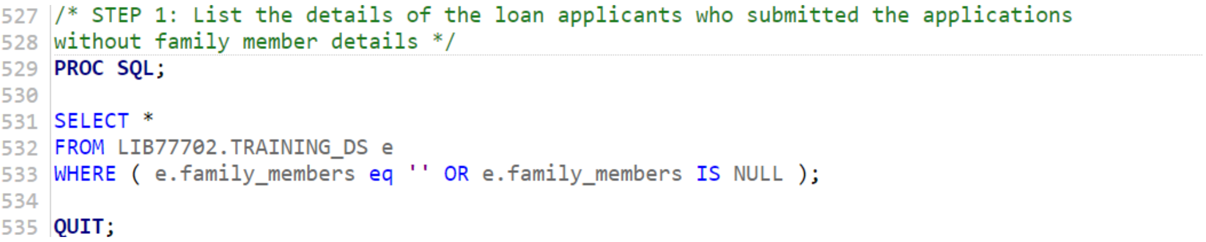
8.1.1.7.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.1.2 Handling Missing Values in FAMILY_MEMBERS

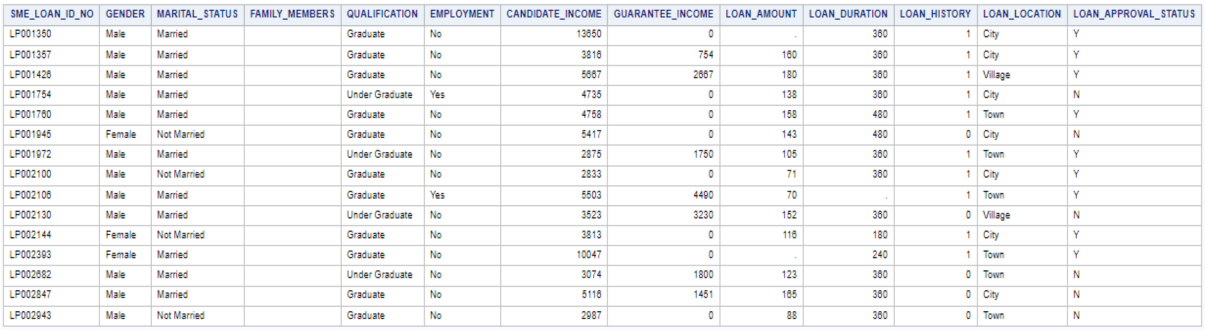
8.1.2.1 Find missing values – FAMILY_MEMBERS

8.1.2.1.1 Code Snippet



```
/* STEP 1: List the details of the loan applicants who submitted the applications
without family member details */
PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.family_members eq '' OR e.family_members IS NULL );

QUIT;
```

8.1.2.1.2 Output



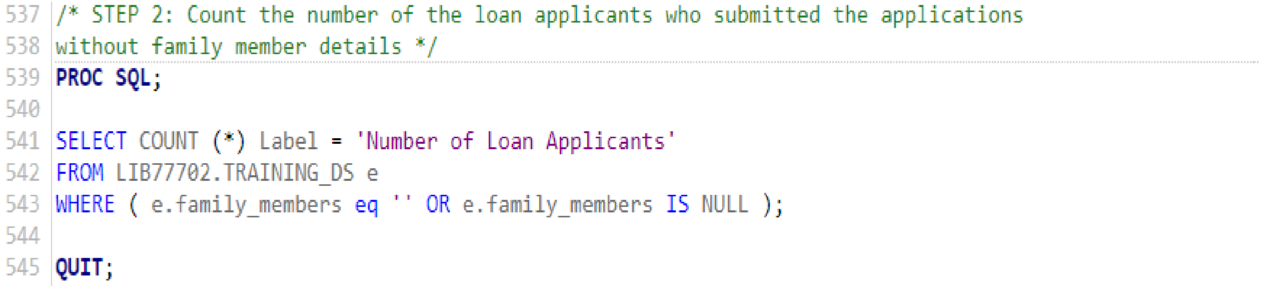
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION	LOAN_APPROVAL_STATUS
LP001350	Male	Married		Graduate	No	13650	0	.	360	1	City	Y
LP001357	Male	Married		Graduate	No	3816	754	160	360	1	City	Y
LP001426	Male	Married		Graduate	No	5667	2667	180	360	1	Village	Y
LP001754	Male	Married		Under Graduate	Yes	4735	0	138	360	1	City	N
LP001760	Male	Married		Graduate	No	4758	0	158	480	1	Town	Y
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	Y
LP002100	Male	Not Married		Graduate	No	2833	0	71	360	1	City	Y
LP002106	Male	Married		Graduate	Yes	5503	4490	70	.	1	Town	Y
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	Y
LP002393	Female	Married		Graduate	No	10047	0	.	240	1	Town	Y
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

8.1.2.1.3 Description

From the output above, we observe that the training set contains missing values for family members; these values will be imputed later.

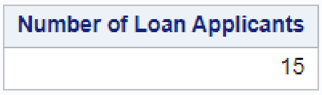
8.1.2.2 Counting the Number of Missing values – FAMILY_MEMBERS

8.1.2.2.1 Code Snippet



```
/* STEP 2: Count the number of the loan applicants who submitted the applications
without family member details */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS e
WHERE ( e.family_members eq '' OR e.family_members IS NULL );

QUIT;
```

8.1.2.2.2 Output



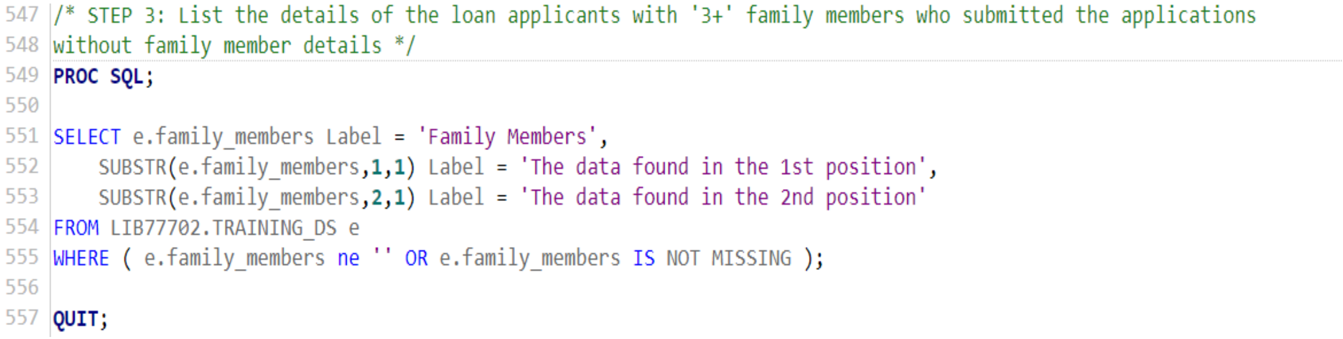
Number of Loan Applicants
15

8.1.2.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their family members, which is 15 loan applicants.

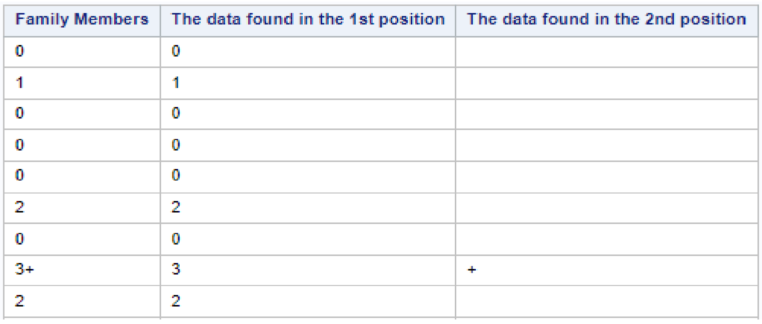
8.1.2.3 List Details of Family with ‘3+’ Members

8.1.2.3.1 Code Snippet



```
/* STEP 3: List the details of the loan applicants with '3+' family members who submitted the applications
without family member details */
PROC SQL;

SELECT e.family_members Label = 'Family Members',
    SUBSTR(e.family_members,1,1) Label = 'The data found in the 1st position',
    SUBSTR(e.family_members,2,1) Label = 'The data found in the 2nd position'
FROM LIB77702.TRAINING_DS e
WHERE ( e.family_members ne '' OR e.family_members IS NOT MISSING );

QUIT;
```

8.1.2.3.2 Output



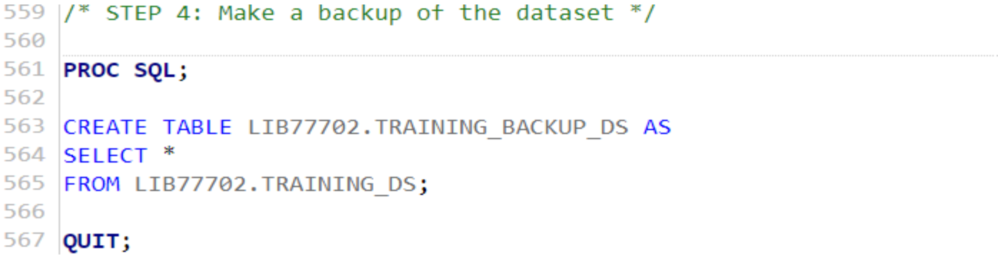
Family Members	The data found in the 1st position	The data found in the 2nd position
0	0	
1	1	
0	0	
0	0	
0	0	
2	2	
0	0	
3+	3	+
2	2	

8.1.2.3.3 Description

From the above output we can see that applicant with 3+ family member is split into two positions to remove ‘+’ sign in the later stage.

8.1.2.4 Backup of Dataset – FAMILY_MEMBERS

8.1.2.4.1 Code Snippet



```
/* STEP 4: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TRAINING_BACKUP_DS AS
SELECT *
FROM LIB77702.TRAINING_DS;

QUIT;
```

8.1.2.4.2 Output

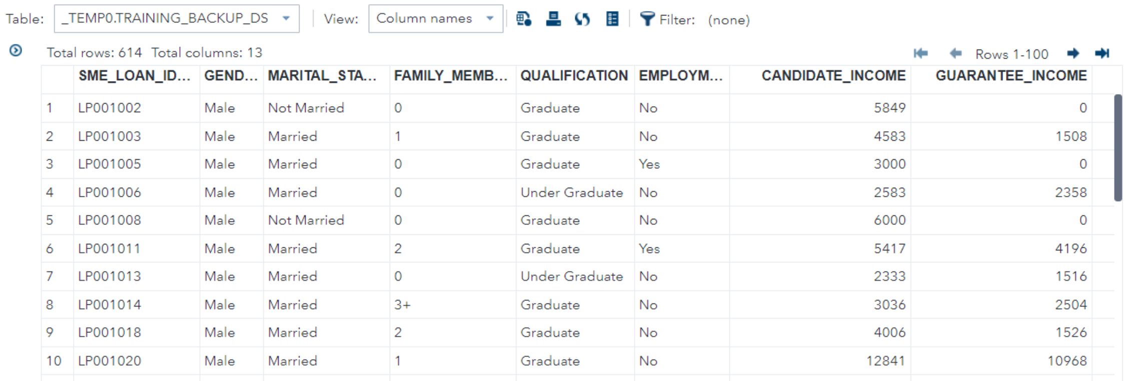


Table: _TEMP0.TRAINING_BACKUP_DS View: Column names Filter: (none)

Total rows: 614 Total columns: 13 Rows 1-100

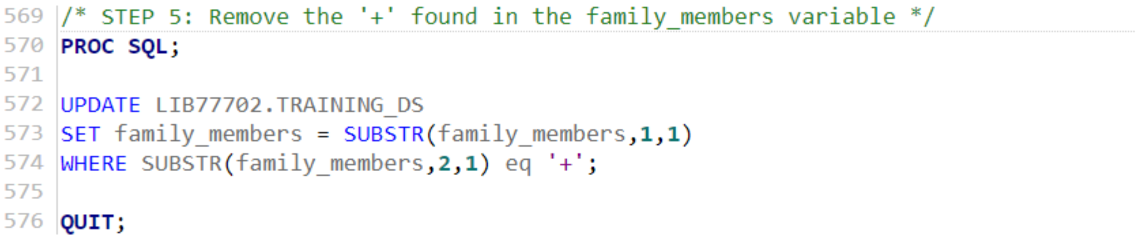
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001002	Male	Not Married	0	Graduate	No	5849	0
2	LP001003	Male	Married	1	Graduate	No	4583	1508
3	LP001005	Male	Married	0	Graduate	Yes	3000	0
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358
5	LP001008	Male	Not Married	0	Graduate	No	6000	0
6	LP001011	Male	Married	2	Graduate	Yes	5417	4196
7	LP001013	Male	Married	0	Under Graduate	No	2333	1516
8	LP001014	Male	Married	3+	Graduate	No	3036	2504
9	LP001018	Male	Married	2	Graduate	No	4006	1526
10	LP001020	Male	Married	1	Graduate	No	12841	10968

8.1.2.4.3 Description

The newly formed backup table LIB77702.TRAINING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

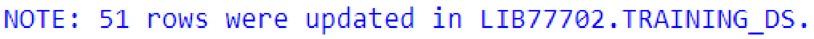
8.1.2.5 Removing ‘+’ Found in Family Member

8.1.2.5.1 Code Snippet



```
/* STEP 5: Remove the '+' found in the family_members variable */
PROC SQL;

UPDATE LIB77702.TRAINING_DS
SET family_members = SUBSTR(family_members,1,1)
WHERE SUBSTR(family_members,2,1) eq '+';

QUIT;
```

8.1.2.5.2 Output



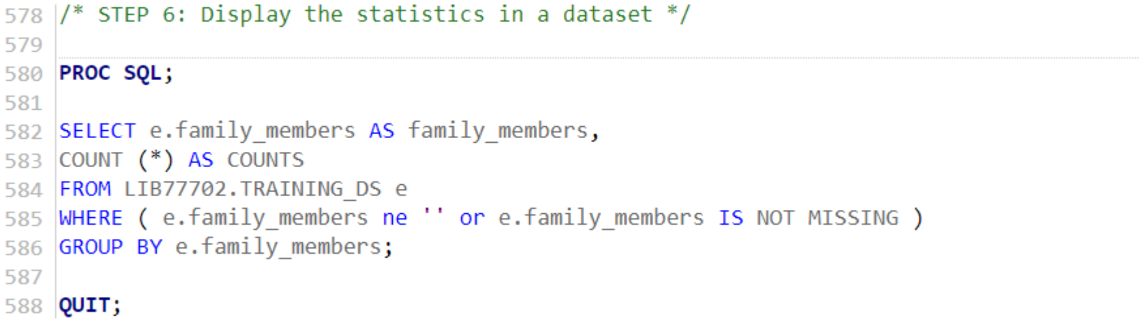
```
NOTE: 51 rows were updated in LIB77702.TRAINING_DS.
```

8.1.2.5.3 Description

From the above output we can see that the ‘+’ sign has been removed successfully and the rows have been updated in family members.

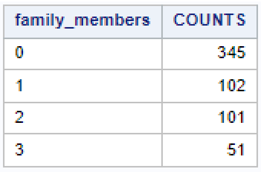
8.1.2.6 Finding the Statistics – FAMILY_MEMBERS

8.1.2.6.1 Code Snippet



```
/* STEP 6: Display the statistics in a dataset */

PROC SQL;

SELECT e.family_members AS family_members,
COUNT (*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.family_members ne '' or e.family_members IS NOT MISSING )
GROUP BY e.family_members;

QUIT;
```

8.1.2.6.2 Output



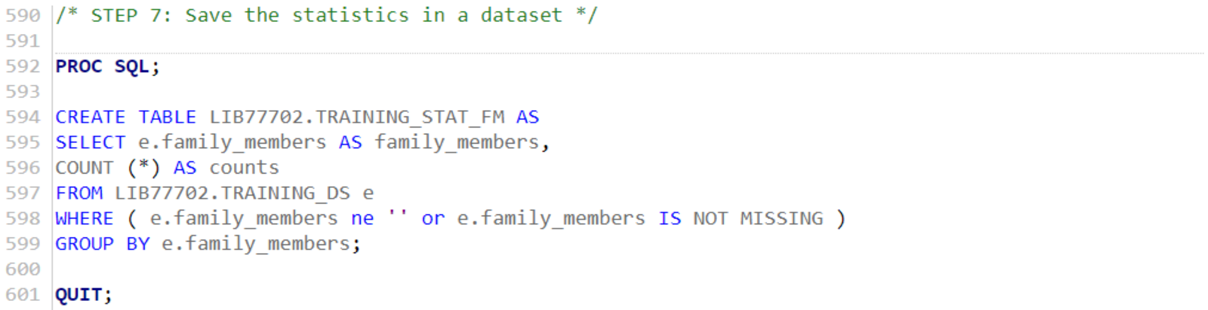
family_members	COUNTS
0	345
1	102
2	101
3	51

8.1.2.6.3 Description

The statistics for family members show that out of the total applicants, 345 are having 0 family members, 102 having 1 member, 101 having 2 members and 51 having 3 members. This indicates that most of the applicants are having no family members.

8.1.2.7 Save the Statistics – FAMILY_MEMBERS

8.1.2.7.1 Code Snippet



```
/* STEP 7: Save the statistics in a dataset */

PROC SQL;

CREATE TABLE LIB77702.TRAINING_STAT_FM AS
SELECT e.family_members AS family_members,
COUNT (*) AS counts
FROM LIB77702.TRAINING_DS e
WHERE ( e.family_members ne '' or e.family_members IS NOT MISSING )
GROUP BY e.family_members;

QUIT;
```

8.1.2.7.2 Output

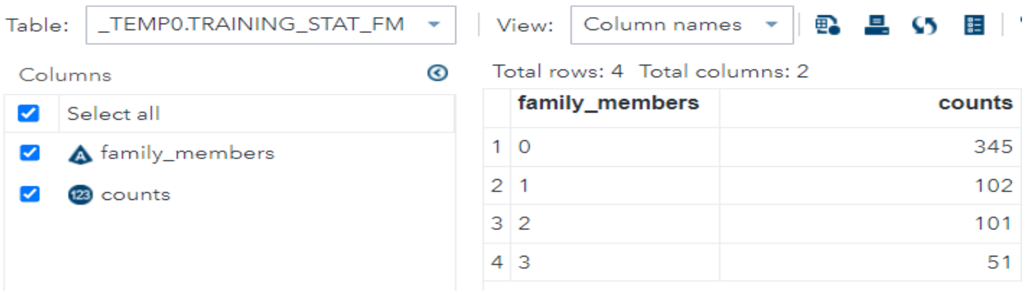


Table: _TEMP0.TRAINING_STAT_FM

View: Column names

Columns

☑ Select all

☑ family_members

☑ counts

Total rows: 4 Total columns: 2

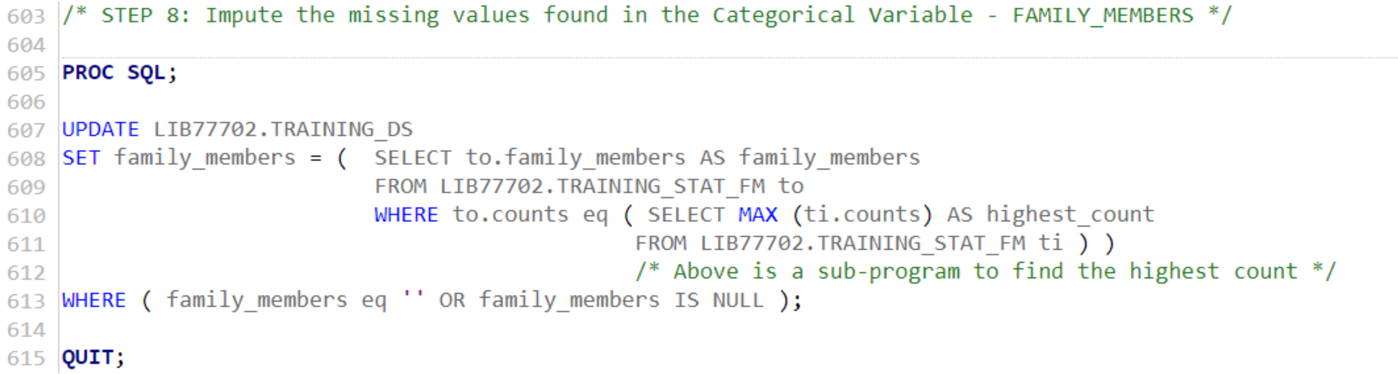
	family_members	counts
1	0	345
2	1	102
3	2	101
4	3	51

8.1.2.7.3 Description

The above output shows that the statistics performed earlier is saved successfully in TRAINING_STATS_DS.

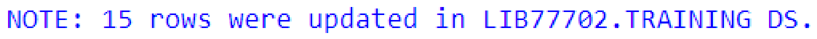
8.1.2.8 Imputing the Missing Value – FAMILY_MEMBERS

8.1.2.8.1 Code Snippet



```
/* STEP 8: Impute the missing values found in the Categorical Variable - FAMILY_MEMBERS */

PROC SQL;

UPDATE LIB77702.TRAINING_DS
SET family_members = (  SELECT to.family_members AS family_members
                        FROM LIB77702.TRAINING_STAT_FM to
                        WHERE to.counts eq ( SELECT MAX (ti.counts) AS highest_count
                                            FROM LIB77702.TRAINING_STAT_FM ti ) )
                                            /* Above is a sub-program to find the highest count */
WHERE ( family_members eq '' OR family_members IS NULL );

QUIT;
```

8.1.2.8.2 Output



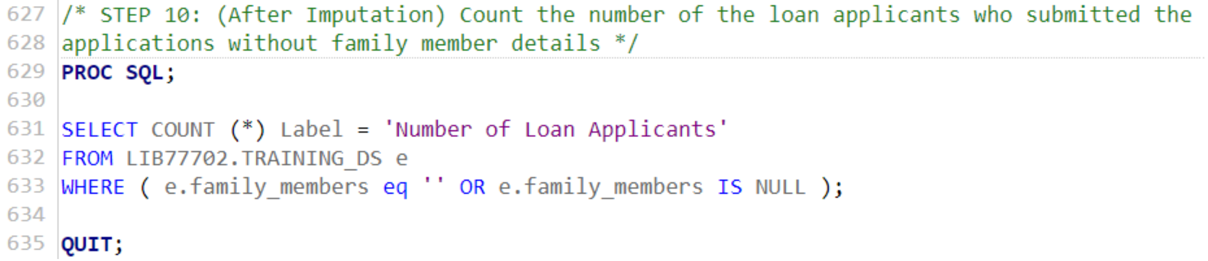
```
NOTE: 15 rows were updated in LIB77702.TRAINING_DS.
```

8.1.2.8.3 Description

The above output shows that the 15 missing values rows were successfully imputed and updated in family members.

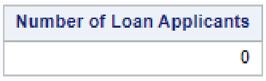
8.1.2.9 After Imputing Missing Value – FAMILY_MEMBERS

8.1.2.9.1 Code Snippet



```
/* STEP 10: (After Imputation) Count the number of the loan applicants who submitted the
applications without family member details */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS e
WHERE ( e.family_members eq '' OR e.family_members IS NULL );

QUIT;
```

8.1.2.9.2 Output



Number of Loan Applicants
0

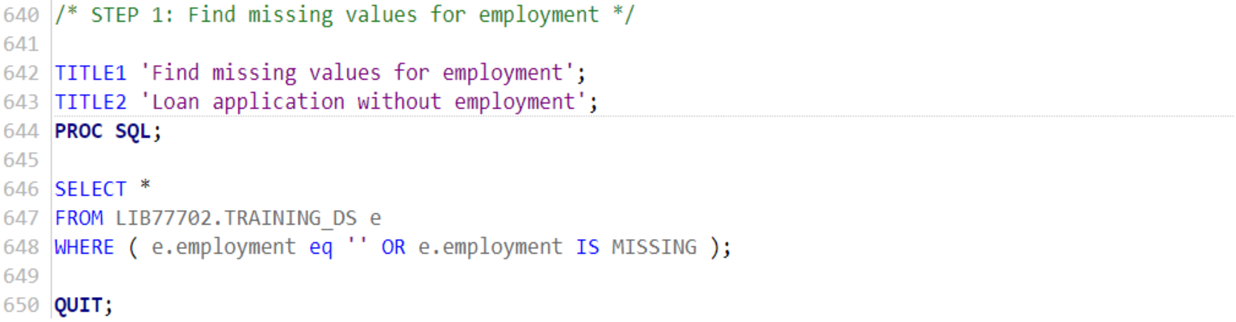
8.1.2.9.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.1.3 Handling Missing Values in EMPLOYMENT

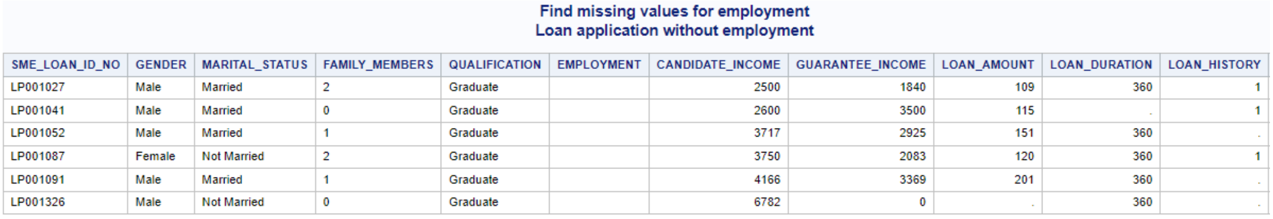
8.1.3.1 Find Missing Value – EMPLOYMENT

8.1.3.1.1 Code Snippet



```
/* STEP 1: Find missing values for employment */

TITLE1 'Find missing values for employment';
TITLE2 'Loan application without employment';
PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.employment eq '' OR e.employment IS MISSING );

QUIT;
```

8.1.3.1.2 Output



Find missing values for employment
Loan application without employment

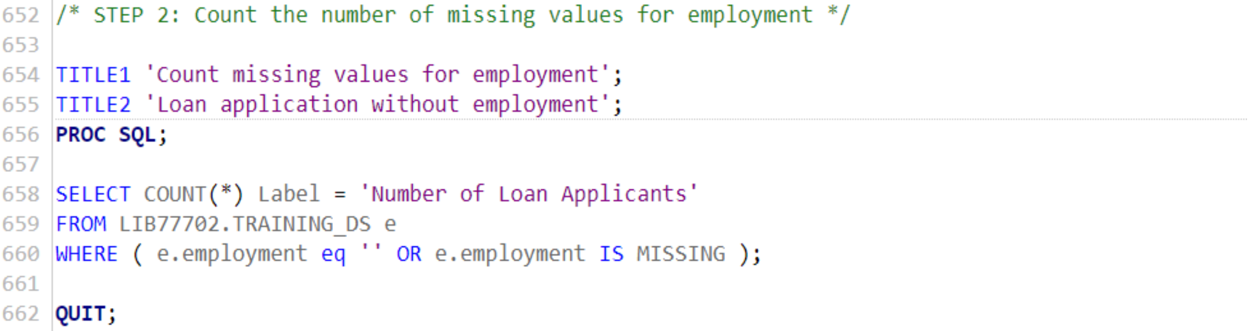
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY
LP001027	Male	Married	2	Graduate		2500	1840	109	360	1
LP001041	Male	Married	0	Graduate		2600	3500	115	.	1
LP001052	Male	Married	1	Graduate		3717	2925	151	360	.
LP001087	Female	Not Married	2	Graduate		3750	2083	120	360	1
LP001091	Male	Married	1	Graduate		4166	3369	201	360	.
LP001326	Male	Not Married	0	Graduate		6782	0	.	360	.

8.1.3.1.3 Description

From the output above, we observe that the training set contains missing values for employment; these values will be imputed later.

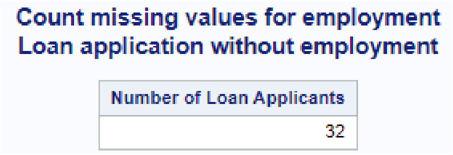
8.1.3.2 Counting Number of Missing Values – EMPLOYMENT

8.1.3.2.1 Code Snippet



```
/* STEP 2: Count the number of missing values for employment */

TITLE1 'Count missing values for employment';
TITLE2 'Loan application without employment';
PROC SQL;

SELECT COUNT(*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS e
WHERE ( e.employment eq '' OR e.employment IS MISSING );

QUIT;
```

8.1.3.2.2 Output



Count missing values for employment
Loan application without employment

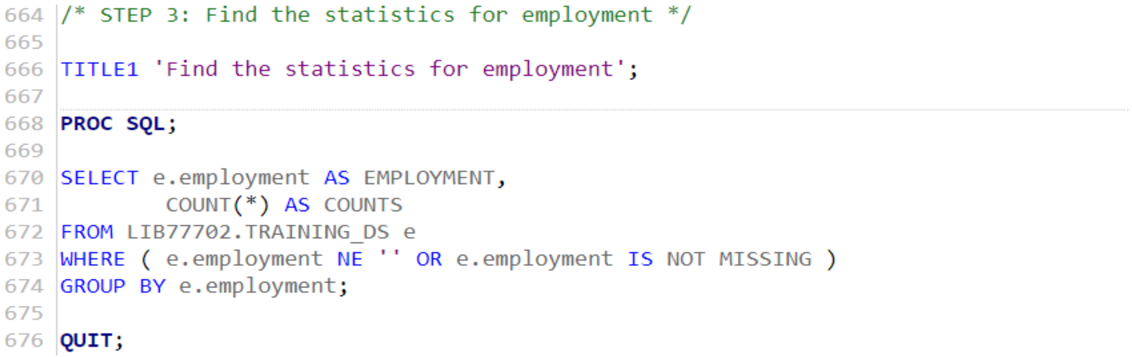
Number of Loan Applicants
32

8.1.3.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their employment status, which is 32 loan applicants.

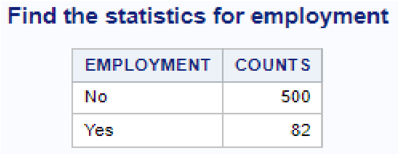
8.1.3.3 Finding the Statistics – EMPLOYMENT

8.1.3.3.1 Code Snippet



```
/* STEP 3: Find the statistics for employment */

TITLE1 'Find the statistics for employment';

PROC SQL;

SELECT e.employment AS EMPLOYMENT,
        COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.employment NE '' OR e.employment IS NOT MISSING )
GROUP BY e.employment;

QUIT;
```

8.1.3.3.2 Output



Find the statistics for employment

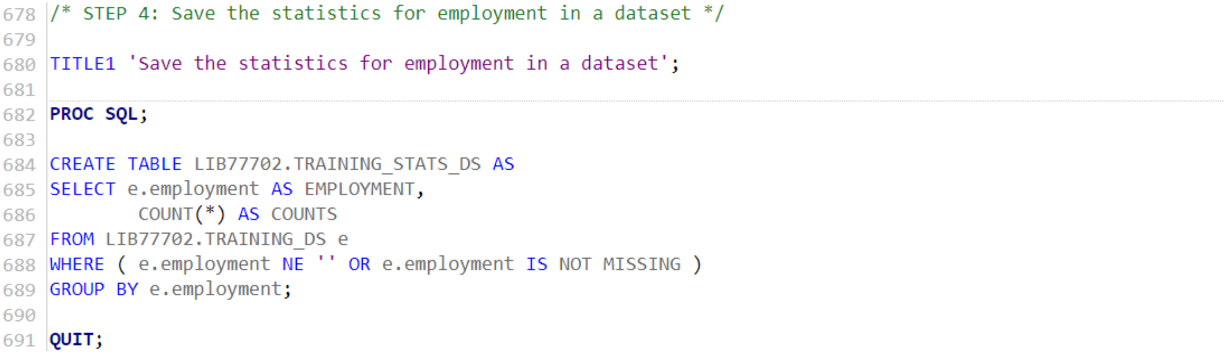
EMPLOYMENT	COUNTS
No	500
Yes	82

8.1.3.3.3 Description

The statistics for employment show that out of the total applicants, 500 are employed and 82 are not employed. This indicates that most of the applicants are employed, while rest are not employed.

8.1.3.4 Saving the Statistics – EMPLOYMENT

8.1.3.4.1 Code Snippet



```
/* STEP 4: Save the statistics for employment in a dataset */

TITLE1 'Save the statistics for employment in a dataset';

PROC SQL;

CREATE TABLE LIB77702.TRAINING_STATS_DS AS
SELECT e.employment AS EMPLOYMENT,
        COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.employment NE '' OR e.employment IS NOT MISSING )
GROUP BY e.employment;

QUIT;
```

8.1.3.4.2 Output

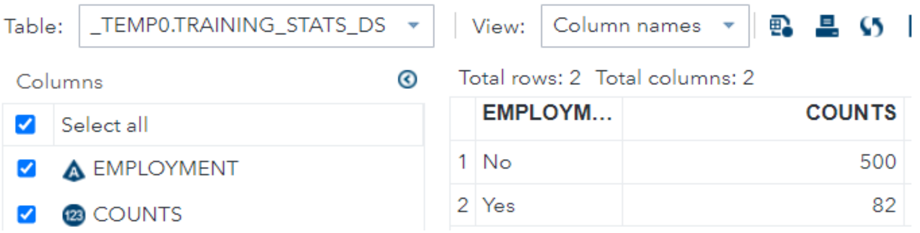


Table: _TEMP0.TRAINING_STATS_DS View: Column names

Columns

☑ Select all
☑ EMPLOYMENT
☑ COUNTS

Total rows: 2 Total columns: 2

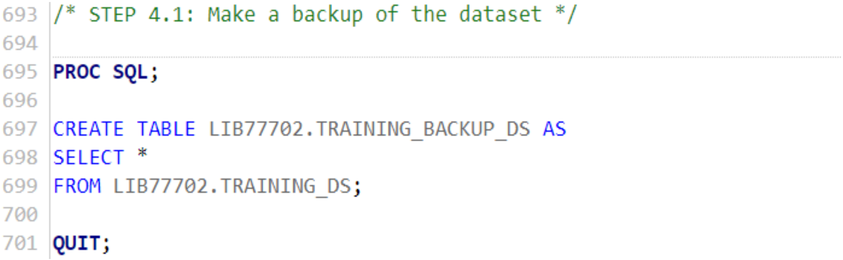
	EMPLOYM...	COUNTS
1	No	500
2	Yes	82

8.1.3.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TRAINING_STATS_DS.

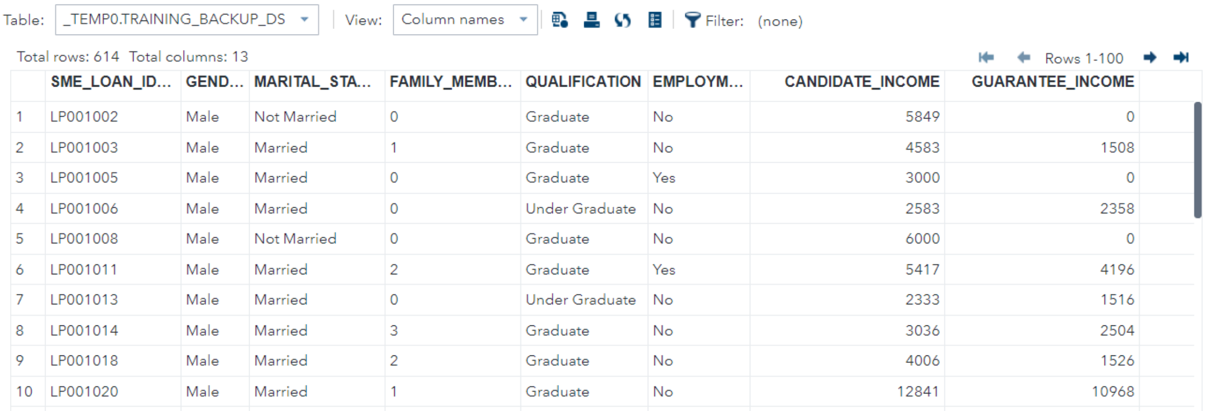
8.1.3.5 Backup of the Dataset – EMPLOYMENT

8.1.3.5.1 Code Snippet



```
/* STEP 4.1: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TRAINING_BACKUP_DS AS
SELECT *
FROM LIB77702.TRAINING_DS;

QUIT;
```

8.1.3.5.2 Output



Total rows: 614 Total columns: 13

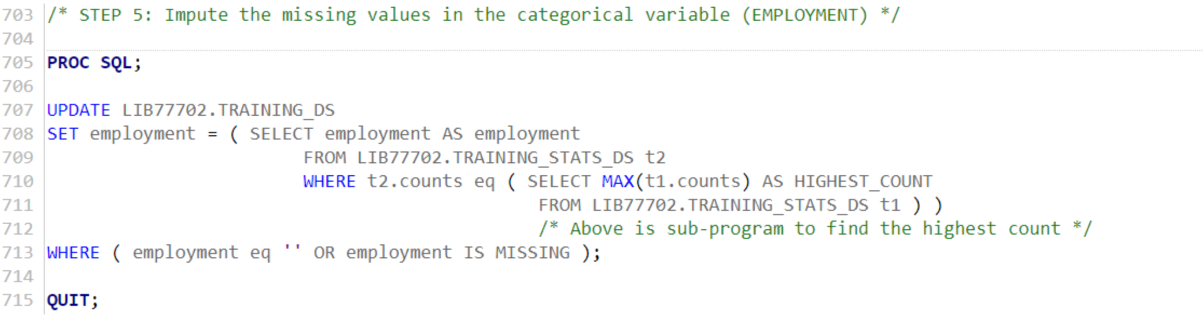
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001002	Male	Not Married	0	Graduate	No	5849	0
2	LP001003	Male	Married	1	Graduate	No	4583	1508
3	LP001005	Male	Married	0	Graduate	Yes	3000	0
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358
5	LP001008	Male	Not Married	0	Graduate	No	6000	0
6	LP001011	Male	Married	2	Graduate	Yes	5417	4196
7	LP001013	Male	Married	0	Under Graduate	No	2333	1516
8	LP001014	Male	Married	3	Graduate	No	3036	2504
9	LP001018	Male	Married	2	Graduate	No	4006	1526
10	LP001020	Male	Married	1	Graduate	No	12841	10968

8.1.3.5.3 Description

The newly formed backup table LIB77702.TRAINING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

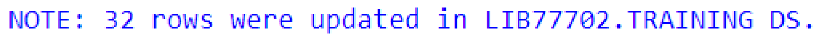
8.1.3.6 Imputing the missing values– EMPLOYMENT

8.1.3.6.1 Code Snippet



```
/* STEP 5: Impute the missing values in the categorical variable (EMPLOYMENT) */

PROC SQL;

UPDATE LIB77702.TRAINING_DS
SET employment = ( SELECT employment AS employment
                        FROM LIB77702.TRAINING_STATS_DS t2
                        WHERE t2.counts eq ( SELECT MAX(t1.counts) AS HIGHEST_COUNT
                                             FROM LIB77702.TRAINING_STATS_DS t1 ) )
                                             /* Above is sub-program to find the highest count */
WHERE ( employment eq '' OR employment IS MISSING );

QUIT;
```

8.1.3.6.2 Output



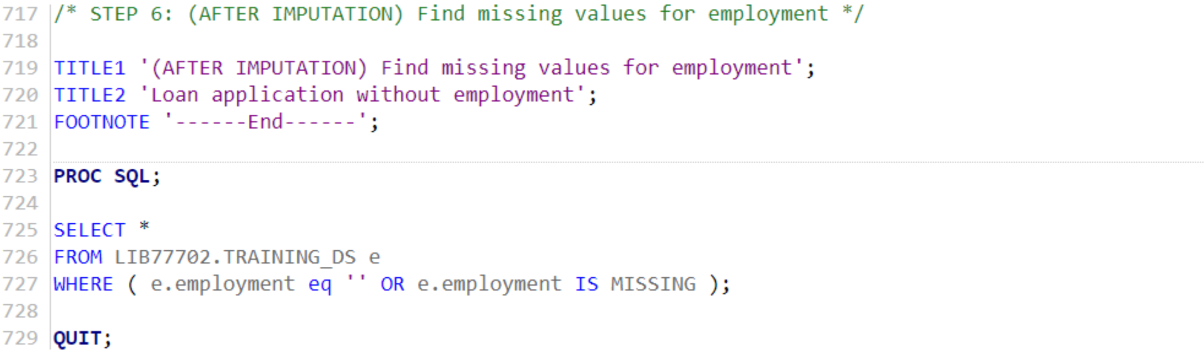
```
NOTE: 32 rows were updated in LIB77702.TRAINING DS.
```

8.1.3.6.3 Description

The above output shows that the 32 missing values rows were successfully imputed and updated in employment.

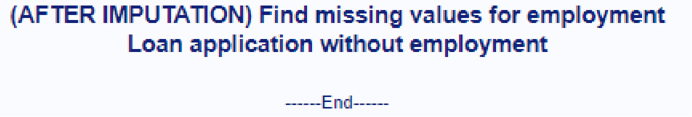
8.1.3.7 After imputing the missing values – EMPLOYMENT

8.1.3.7.1 Code Snippet



```
/* STEP 6: (AFTER IMPUTATION) Find missing values for employment */

TITLE1 '(AFTER IMPUTATION) Find missing values for employment';
TITLE2 'Loan application without employment';
FOOTNOTE '------End------';

PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.employment eq '' OR e.employment IS MISSING );

QUIT;
```

8.1.3.7.2 Output



```
(AFTER IMPUTATION) Find missing values for employment
Loan application without employment

------End------
```

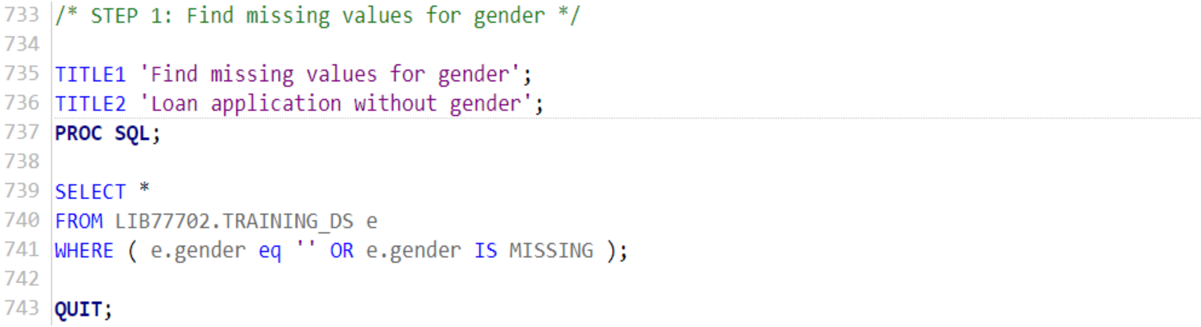
8.1.3.7.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.1.4 Handling Missing Values in GENDER

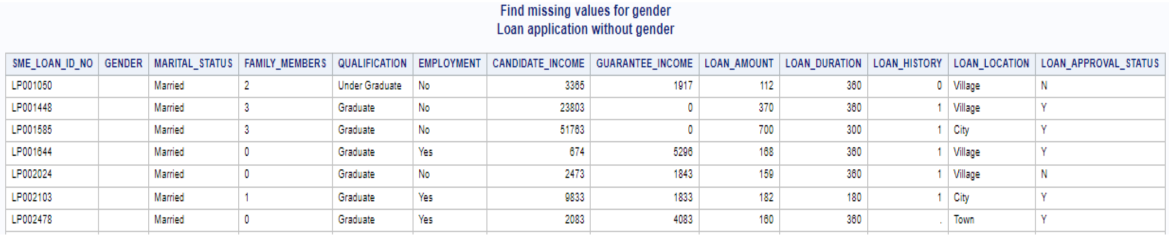
8.1.4.1 Find Missing Value – GENDER

8.1.4.1.1 Code Snippet



```
/* STEP 1: Find missing values for gender */

TITLE1 'Find missing values for gender';
TITLE2 'Loan application without gender';
PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.gender eq '' OR e.gender IS MISSING );

QUIT;
```

8.1.4.1.2 Output



Find missing values for gender
Loan application without gender

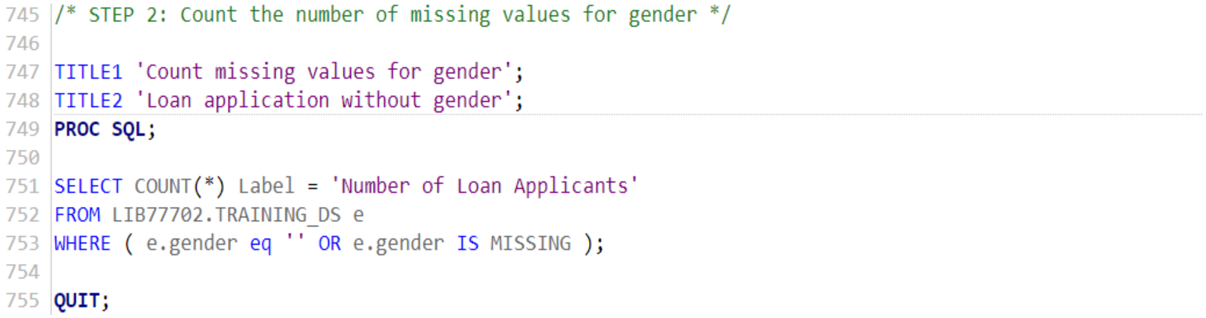
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION	LOAN_APPROVAL_STATUS
LP001050		Married	2	Under Graduate	No	3365	1917	112	360	0	Village	N
LP001448		Married	3	Graduate	No	23803	0	370	360	1	Village	Y
LP001585		Married	3	Graduate	No	51763	0	700	300	1	City	Y
LP001644		Married	0	Graduate	Yes	674	5296	168	360	1	Village	Y
LP002024		Married	0	Graduate	No	2473	1843	159	360	1	Village	N
LP002103		Married	1	Graduate	Yes	9833	1833	182	180	1	City	Y
LP002478		Married	0	Graduate	Yes	2083	4083	160	360	.	Town	Y

8.1.4.1.3 Description

From the output above, we observe that the training set contains missing values for gender; these values will be imputed later.

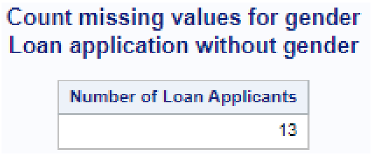
8.1.4.2 Counting Number of Missing Values – GENDER

8.1.4.2.1 Code Snippet



```
/* STEP 2: Count the number of missing values for gender */

TITLE1 'Count missing values for gender';
TITLE2 'Loan application without gender';
PROC SQL;

SELECT COUNT(*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS e
WHERE ( e.gender eq '' OR e.gender IS MISSING );

QUIT;
```

8.1.4.2.2 Output



Count missing values for gender
Loan application without gender

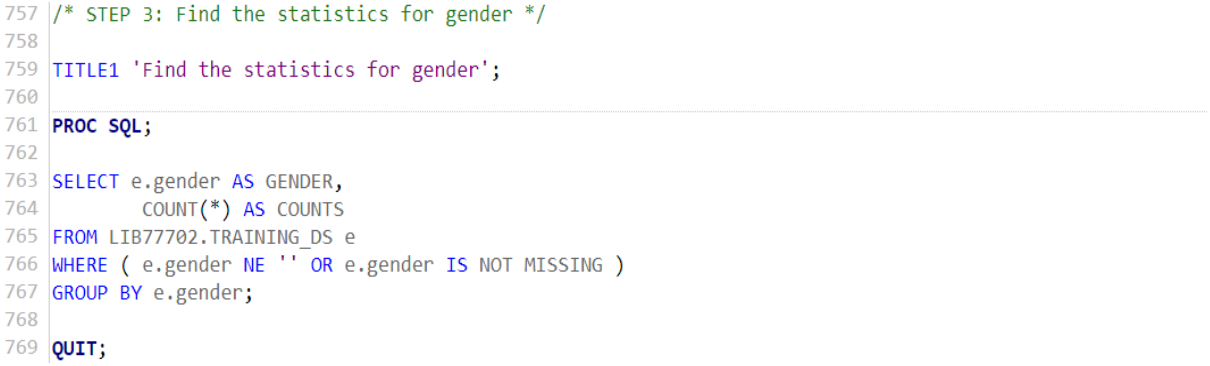
Number of Loan Applicants
13

8.1.4.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their gender, which is 13 loan applicants.

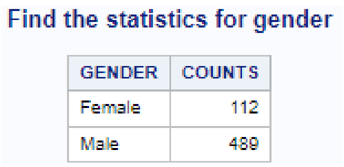
8.1.4.3 Finding the Statistics – GENDER

8.1.4.3.1 Code Snippet



```
/* STEP 3: Find the statistics for gender */

TITLE1 'Find the statistics for gender';

PROC SQL;

SELECT e.gender AS GENDER,
       COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.gender NE '' OR e.gender IS NOT MISSING )
GROUP BY e.gender;

QUIT;
```

8.1.4.3.2 Output



Find the statistics for gender

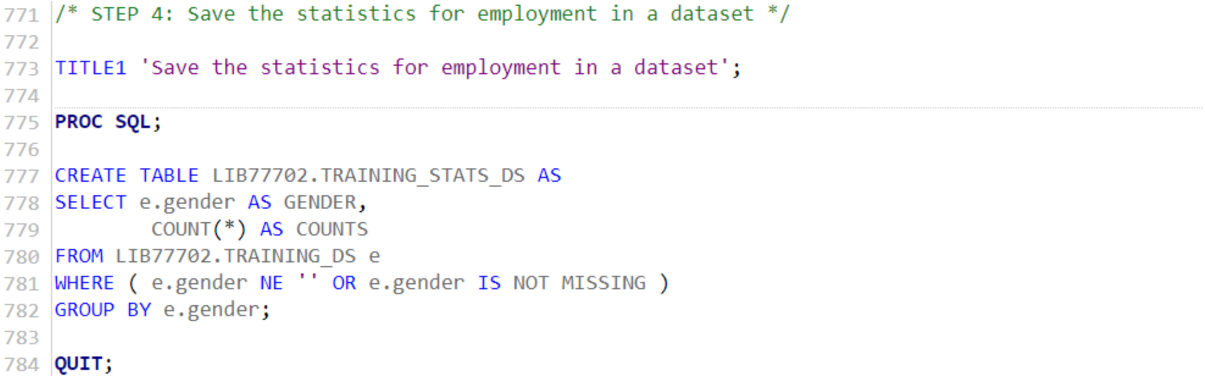
GENDER	COUNTS
Female	112
Male	489

8.1.4.3.3 Description

The statistics for gender show that out of the total applicants, 112 are female and 489 are male. This indicates that most of the applicants are male.

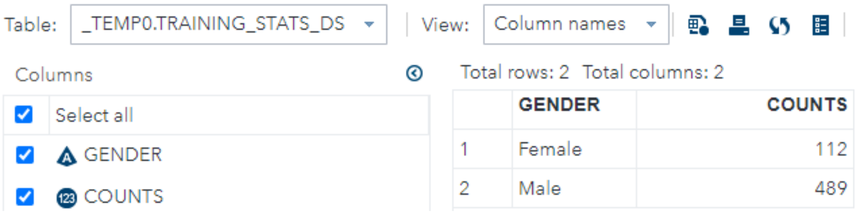
8.1.4.4 Saving the Statistics – GENDER

8.1.4.4.1 Code Snippet



```
/* STEP 4: Save the statistics for employment in a dataset */

TITLE1 'Save the statistics for employment in a dataset';

PROC SQL;

CREATE TABLE LIB77702.TRAINING_STATS_DS AS
SELECT e.gender AS GENDER,
        COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.gender NE '' OR e.gender IS NOT MISSING )
GROUP BY e.gender;

QUIT;
```

8.1.4.4.2 Output



Total rows: 2 Total columns: 2

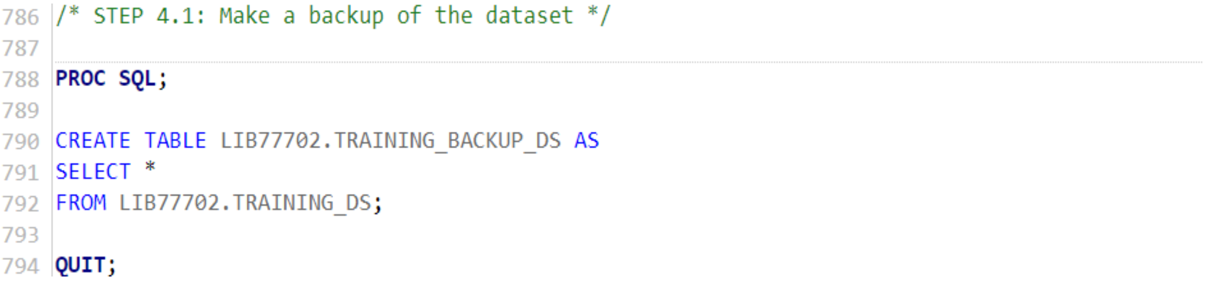
	GENDER	COUNTS
1	Female	112
2	Male	489

8.1.4.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TRAINING_STATS_DS.

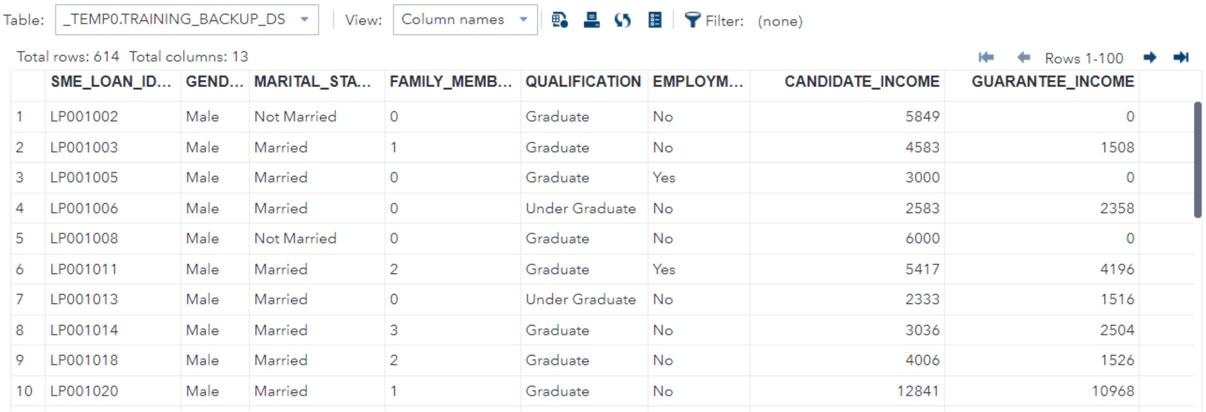
8.1.4.5 Backup of the Dataset – GENDER

8.1.4.5.1 Code Snippet



```
/* STEP 4.1: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TRAINING_BACKUP_DS AS
SELECT *
FROM LIB77702.TRAINING_DS;

QUIT;
```

8.1.4.5.2 Output



Total rows: 614 Total columns: 13

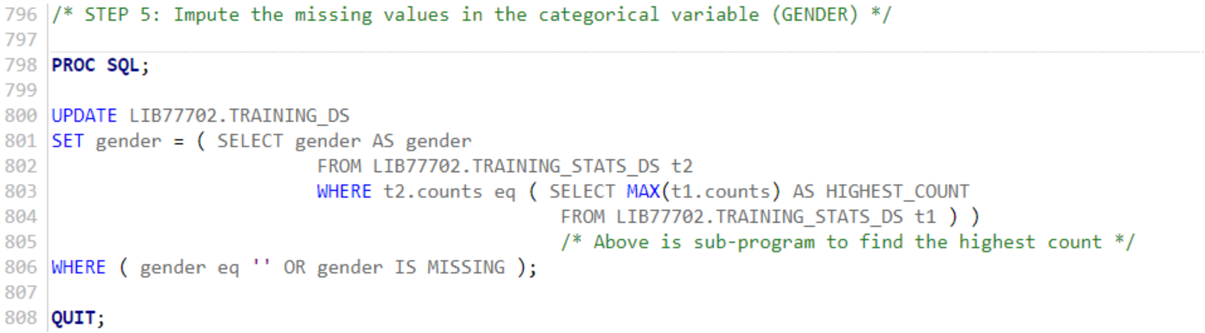
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001002	Male	Not Married	0	Graduate	No	5849	0
2	LP001003	Male	Married	1	Graduate	No	4583	1508
3	LP001005	Male	Married	0	Graduate	Yes	3000	0
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358
5	LP001008	Male	Not Married	0	Graduate	No	6000	0
6	LP001011	Male	Married	2	Graduate	Yes	5417	4196
7	LP001013	Male	Married	0	Under Graduate	No	2333	1516
8	LP001014	Male	Married	3	Graduate	No	3036	2504
9	LP001018	Male	Married	2	Graduate	No	4006	1526
10	LP001020	Male	Married	1	Graduate	No	12841	10968

8.1.4.5.3 Description

The newly formed backup table LIB77702.TRAINING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

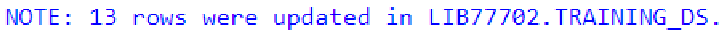
8.1.4.6 Imputing the missing values– GENDER

8.1.4.6.1 Code Snippet



```
/* STEP 5: Impute the missing values in the categorical variable (GENDER) */

PROC SQL;

UPDATE LIB77702.TRAINING_DS
SET gender = ( SELECT gender AS gender
                        FROM LIB77702.TRAINING_STATS_DS t2
                        WHERE t2.counts eq ( SELECT MAX(t1.counts) AS HIGHEST_COUNT
                                             FROM LIB77702.TRAINING_STATS_DS t1 ) )
                                             /* Above is sub-program to find the highest count */
WHERE ( gender eq '' OR gender IS MISSING );

QUIT;
```

8.1.4.6.2 Output



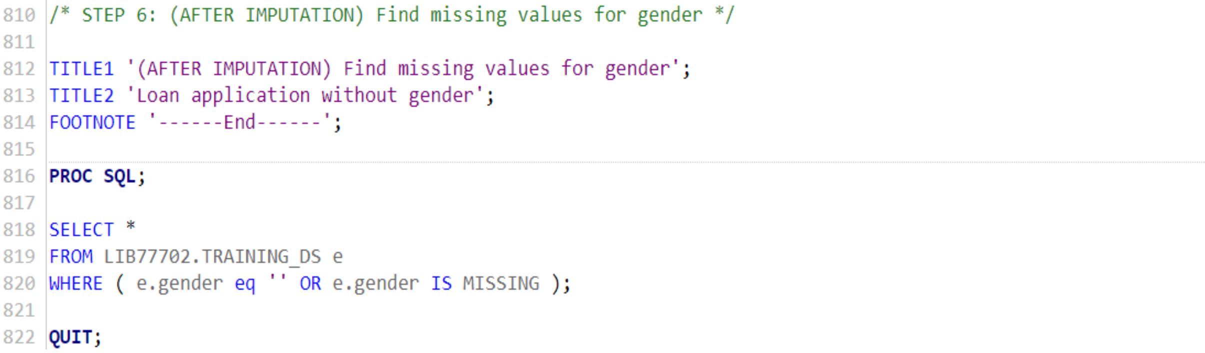
```
NOTE: 13 rows were updated in LIB77702.TRAINING_DS.
```

8.1.4.6.3 Description

The above output shows that the 13 missing values rows were successfully imputed and updated in gender.

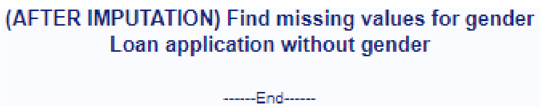
8.1.4.7 After imputing the missing values – GENDER

8.1.4.7.1 Code Snippet



```
/* STEP 6: (AFTER IMPUTATION) Find missing values for gender */

TITLE1 '(AFTER IMPUTATION) Find missing values for gender';
TITLE2 'Loan application without gender';
FOOTNOTE '------End------';

PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.gender eq '' OR e.gender IS MISSING );

QUIT;
```

8.1.4.7.2 Output



(AFTER IMPUTATION) Find missing values for gender
Loan application without gender

------End------

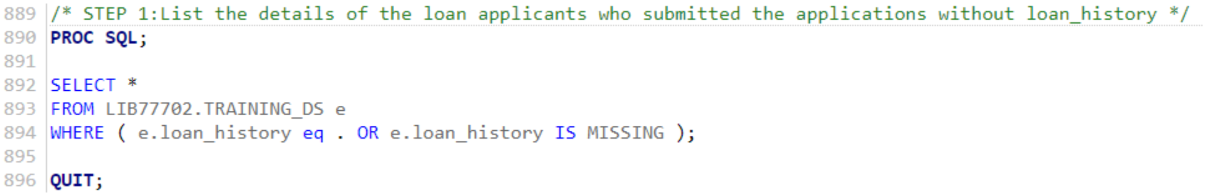
8.1.4.7.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.1.5 Handling Missing Values in LOAN_HISTORY

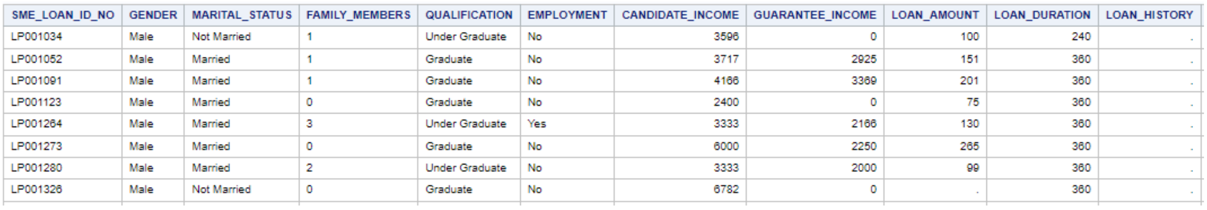
8.1.5.1 Find Missing Value – LOAN_HISTORY

8.1.5.1.1 Code Snippet



```
/* STEP 1:List the details of the loan applicants who submitted the applications without loan_history */
PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.loan_history eq . OR e.loan_history IS MISSING );

QUIT;
```

8.1.5.1.2 Output



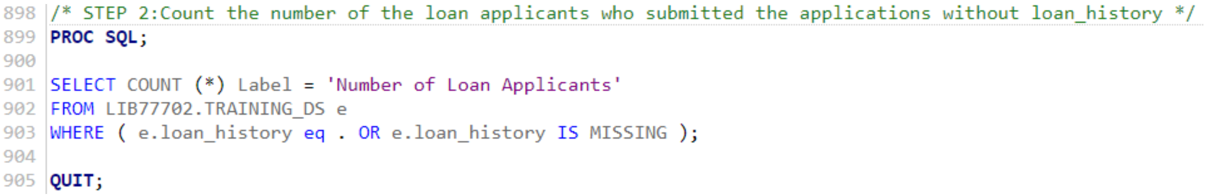
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY
LP001034	Male	Not Married	1	Under Graduate	No	3596	0	100	240	.
LP001052	Male	Married	1	Graduate	No	3717	2925	151	360	.
LP001091	Male	Married	1	Graduate	No	4166	3369	201	360	.
LP001123	Male	Married	0	Graduate	No	2400	0	75	360	.
LP001264	Male	Married	3	Under Graduate	Yes	3333	2166	130	360	.
LP001273	Male	Married	0	Graduate	No	6000	2250	265	360	.
LP001280	Male	Married	2	Under Graduate	No	3333	2000	99	360	.
LP001326	Male	Not Married	0	Graduate	No	6782	0	.	360	.

8.1.5.1.3 Description

From the output above, we observe that the training set contains missing values for loan history; these values will be imputed later.

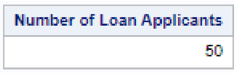
8.1.5.2 Counting Number of Missing Values – LOAN_HISTORY

8.1.5.2.1 Code Snippet



```
/* STEP 2:Count the number of the loan applicants who submitted the applications without loan_history */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS e
WHERE ( e.loan_history eq . OR e.loan_history IS MISSING );

QUIT;
```

8.1.5.2.2 Output



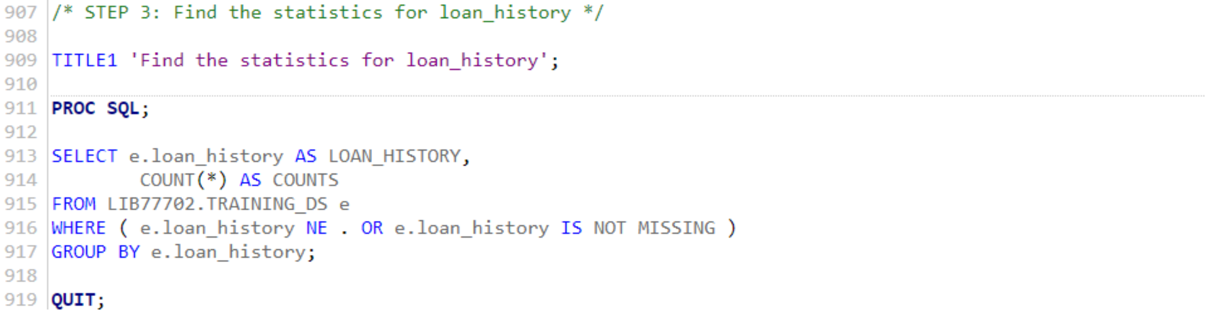
Number of Loan Applicants
50

8.1.5.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their loan history, which is 50 loan applicants.

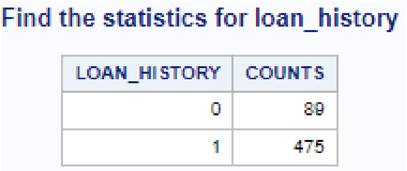
8.1.5.3 Finding the Statistics – LOAN_HISTORY

8.1.5.3.1 Code Snippet



```
/* STEP 3: Find the statistics for loan_history */

TITLE1 'Find the statistics for loan_history';

PROC SQL;

SELECT e.loan_history AS LOAN_HISTORY,
        COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.loan_history NE . OR e.loan_history IS NOT MISSING )
GROUP BY e.loan_history;

QUIT;
```

8.1.5.3.2 Output



Find the statistics for loan_history

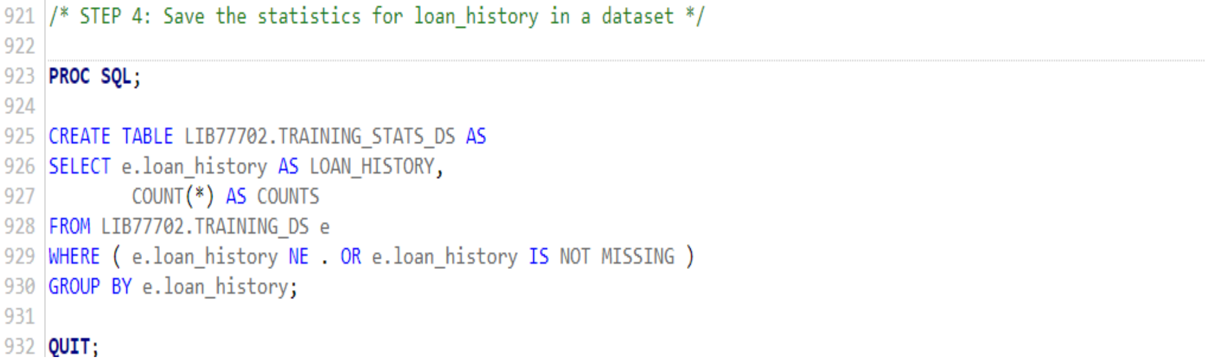
LOAN_HISTORY	COUNTS
0	89
1	475

8.1.5.3.3 Description

The statistics for loan history show that out of the total applicants, 89 had no past loans and 475 had loans in the past. This indicates that most of the applicants had loans in the past.

8.1.5.4 Saving the Statistics – LOAN_HISTORY

8.1.5.4.1 Code Snippet



```
/* STEP 4: Save the statistics for loan_history in a dataset */

PROC SQL;

CREATE TABLE LIB77702.TRAINING_STATS_DS AS
SELECT e.loan_history AS LOAN_HISTORY,
        COUNT(*) AS COUNTS
FROM LIB77702.TRAINING_DS e
WHERE ( e.loan_history NE . OR e.loan_history IS NOT MISSING )
GROUP BY e.loan_history;

QUIT;
```

8.1.5.4.2 Output

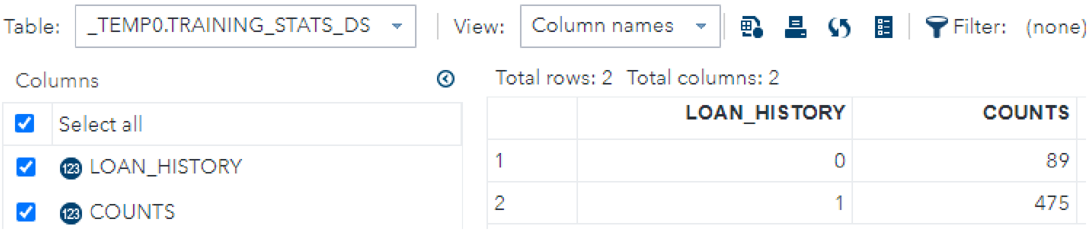


Table: _TEMP0.TRAINING_STATS_DS

View: Column names

Filter: (none)

Columns

☑ Select all

☑ LOAN_HISTORY

☑ COUNTS

Total rows: 2 Total columns: 2

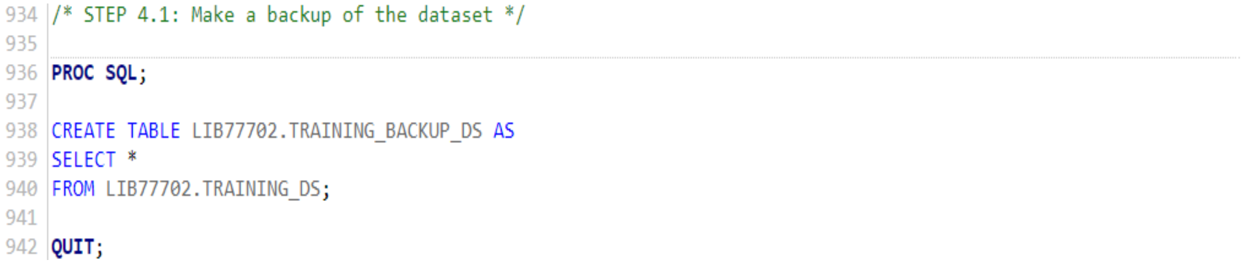
	LOAN_HISTORY	COUNTS
1	0	89
2	1	475

8.1.5.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TRAINING_STATS_DS.

8.1.5.5 Backup of the Dataset – LOAN_HISTORY

8.1.5.5.1 Code Snippet



```
/* STEP 4.1: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TRAINING_BACKUP_DS AS
SELECT *
FROM LIB77702.TRAINING_DS;

QUIT;
```

8.1.5.5.2 Output

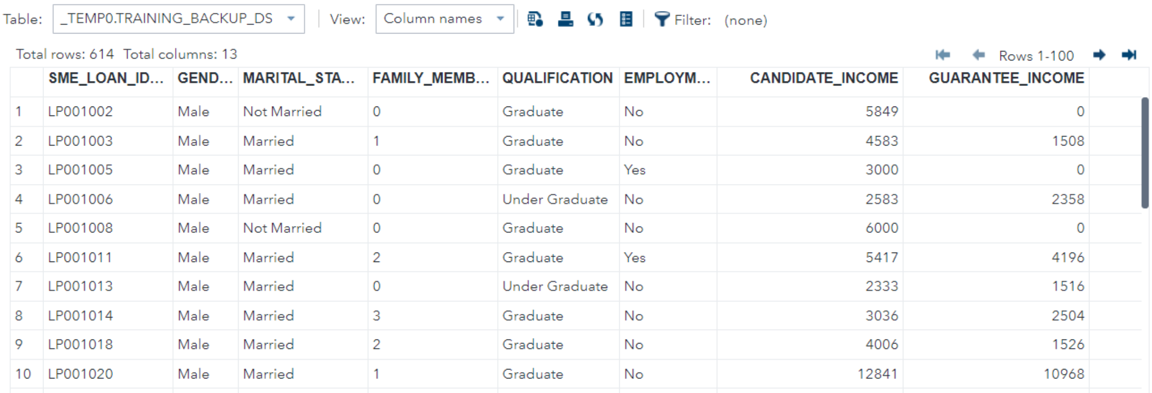


Table: _TEMP0.TRAINING_BACKUP_DS View: Column names Filter: (none)

Total rows: 614 Total columns: 13

Rows 1-100

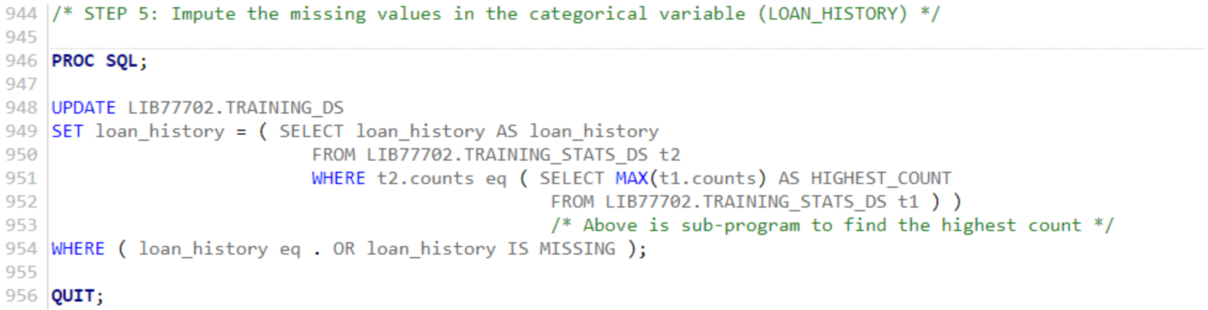
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001002	Male	Not Married	0	Graduate	No	5849	0
2	LP001003	Male	Married	1	Graduate	No	4583	1508
3	LP001005	Male	Married	0	Graduate	Yes	3000	0
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358
5	LP001008	Male	Not Married	0	Graduate	No	6000	0
6	LP001011	Male	Married	2	Graduate	Yes	5417	4196
7	LP001013	Male	Married	0	Under Graduate	No	2333	1516
8	LP001014	Male	Married	3	Graduate	No	3036	2504
9	LP001018	Male	Married	2	Graduate	No	4006	1526
10	LP001020	Male	Married	1	Graduate	No	12841	10968

8.1.5.5.3 Description

The newly formed backup table LIB77702.TRAINING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

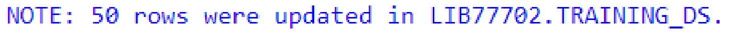
8.1.5.6 Imputing the missing values– LOAN_HISTORY

8.1.5.6.1 Code Snippet



```
/* STEP 5: Impute the missing values in the categorical variable (LOAN_HISTORY) */

PROC SQL;

UPDATE LIB77702.TRAINING_DS
SET loan_history = ( SELECT loan_history AS loan_history
                        FROM LIB77702.TRAINING_STATS_DS t2
                        WHERE t2.counts eq ( SELECT MAX(t1.counts) AS HIGHEST_COUNT
                                              FROM LIB77702.TRAINING_STATS_DS t1 ) )
                                              /* Above is sub-program to find the highest count */
WHERE ( loan_history eq . OR loan_history IS MISSING );

QUIT;
```

8.1.5.6.2 Output



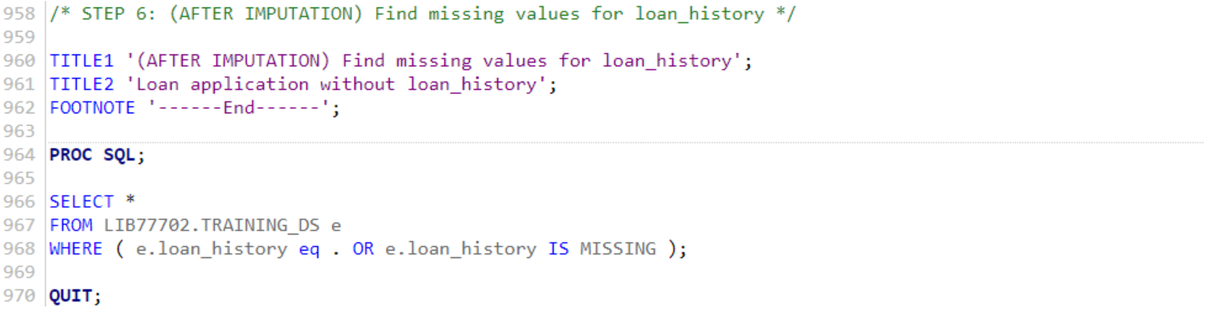
```
NOTE: 50 rows were updated in LIB77702.TRAINING_DS.
```

8.1.5.6.3 Description

The above output shows that the 50 missing values rows were successfully imputed and updated in loan history.

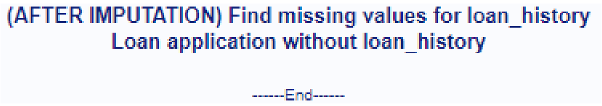
8.1.5.7 After imputing the missing values – LOAN_HISTORY

8.1.5.7.1 Code Snippet



```
/* STEP 6: (AFTER IMPUTATION) Find missing values for loan_history */

TITLE1 '(AFTER IMPUTATION) Find missing values for loan_history';
TITLE2 'Loan application without loan_history';
FOOTNOTE '------End------';

PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS e
WHERE ( e.loan_history eq . OR e.loan_history IS MISSING );

QUIT;
```

8.1.5.7.2 Output



(AFTER IMPUTATION) Find missing values for loan_history
Loan application without loan_history

------End------

8.1.5.7.3 Description

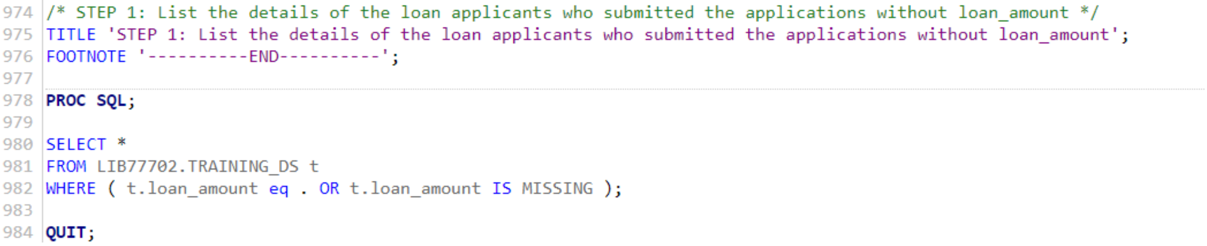
The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.2 Imputing the missing values in Continuous variables – LIB7702.TRAINING_DS

8.2.1 Handling Missing Values in LOAN_AMOUNT

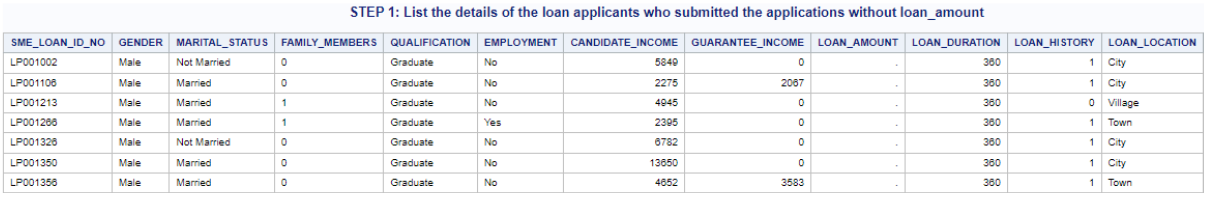
8.2.1.1 Find Missing Value – LOAN_AMOUNT

8.2.1.1.1 Code Snippet



```
/* STEP 1: List the details of the loan applicants who submitted the applications without loan_amount */
TITLE 'STEP 1: List the details of the loan applicants who submitted the applications without loan_amount';
FOOTNOTE '----------END----------';

PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS t
WHERE ( t.loan_amount eq . OR t.loan_amount IS MISSING );

QUIT;
```

8.2.1.1.2 Output



STEP 1: List the details of the loan applicants who submitted the applications without loan_amount

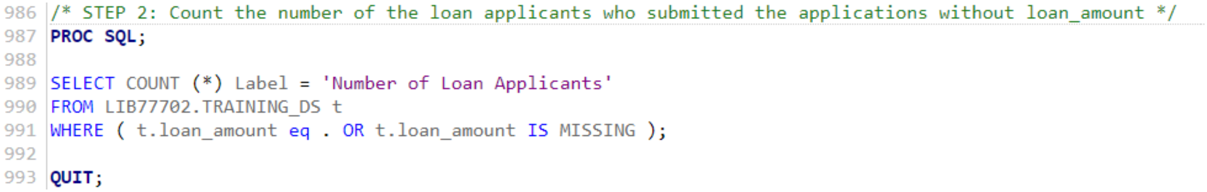
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION
LP001002	Male	Not Married	0	Graduate	No	5849	0	.	360	1	City
LP001106	Male	Married	0	Graduate	No	2275	2067	.	360	1	City
LP001213	Male	Married	1	Graduate	No	4945	0	.	360	0	Village
LP001266	Male	Married	1	Graduate	Yes	2395	0	.	360	1	Town
LP001326	Male	Not Married	0	Graduate	No	6782	0	.	360	1	City
LP001350	Male	Married	0	Graduate	No	13650	0	.	360	1	City
LP001356	Male	Married	0	Graduate	No	4652	3583	.	360	1	Town

8.2.1.1.3 Description

From the output above, we observe that the training set contains missing values for loan amount; these values will be imputed later.

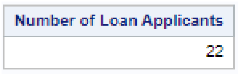
8.2.1.2 Counting Number of Missing Values – LOAN_AMOUNT

8.2.1.2.1 Code Snippet



```
/* STEP 2: Count the number of the loan applicants who submitted the applications without loan_amount */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS t
WHERE ( t.loan_amount eq . OR t.loan_amount IS MISSING );

QUIT;
```

8.2.1.2.2 Output



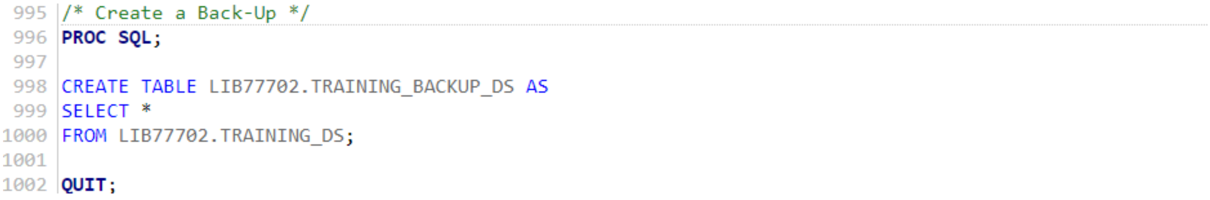
Number of Loan Applicants
22

8.2.1.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their loan amount, which is 22 loan applicants.

8.2.1.3 Backup of the Dataset – LOAN_AMOUNT

8.2.1.3.1 Code Snippet



```
/* Create a Back-Up */
PROC SQL;

CREATE TABLE LIB77702.TRAINING_BACKUP_DS AS
SELECT *
FROM LIB77702.TRAINING_DS;

QUIT;
```

8.2.1.3.2 Output

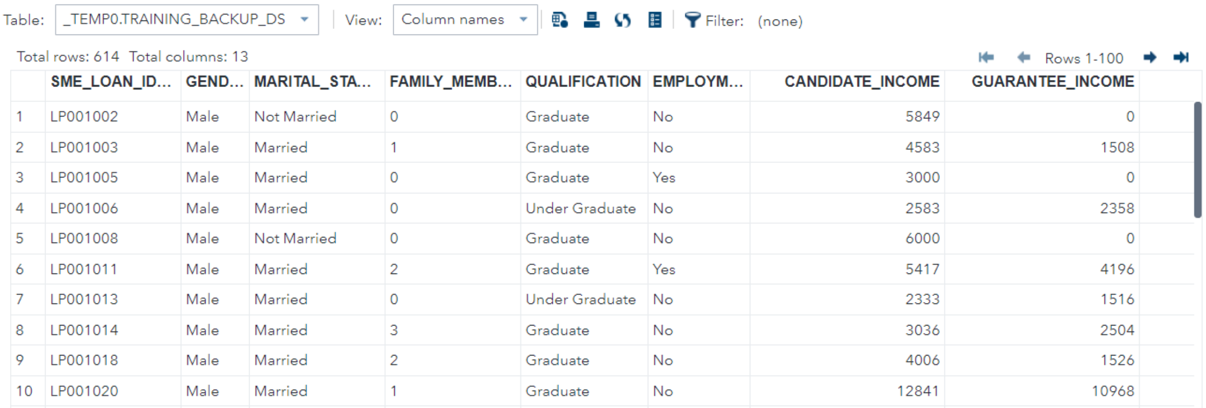


Table: _TEMP0.TRAINING_BACKUP_DS View: Column names Filter: (none)

Total rows: 614 Total columns: 13 Rows 1-100

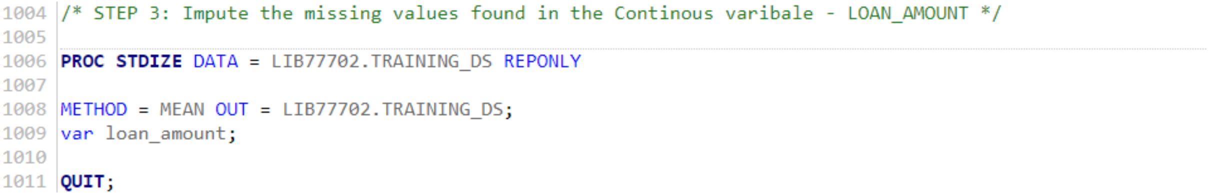
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001002	Male	Not Married	0	Graduate	No	5849	0
2	LP001003	Male	Married	1	Graduate	No	4583	1508
3	LP001005	Male	Married	0	Graduate	Yes	3000	0
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358
5	LP001008	Male	Not Married	0	Graduate	No	6000	0
6	LP001011	Male	Married	2	Graduate	Yes	5417	4196
7	LP001013	Male	Married	0	Under Graduate	No	2333	1516
8	LP001014	Male	Married	3	Graduate	No	3036	2504
9	LP001018	Male	Married	2	Graduate	No	4006	1526
10	LP001020	Male	Married	1	Graduate	No	12841	10968

8.2.1.3.3 Description

The newly formed backup table LIB77702.TRAINING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

8.2.1.4 Imputing the missing values– LOAN_AMOUNT

8.2.1.4.1 Code Snippet



```
/* STEP 3: Impute the missing values found in the Continous varibale - LOAN_AMOUNT */

PROC STDIZE DATA = LIB77702.TRAINING_DS REPONLY

METHOD = MEAN OUT = LIB77702.TRAINING_DS;
var loan_amount;

QUIT;
```

8.2.1.4.2 Output

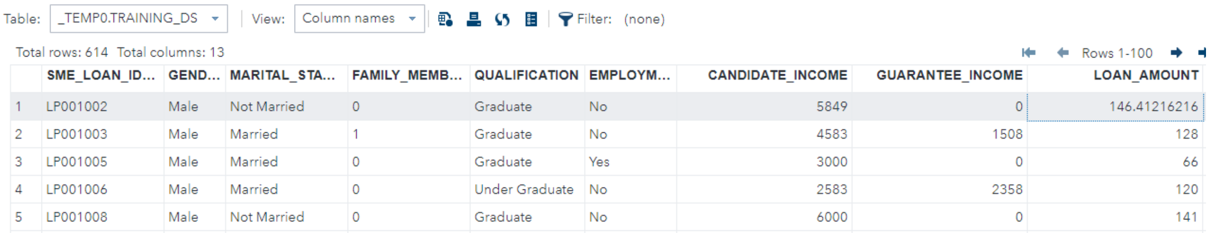


Table: _TEMP0.TRAINING_DS View: Column names Filter: (none)

Total rows: 614 Total columns: 13 Rows 1-100

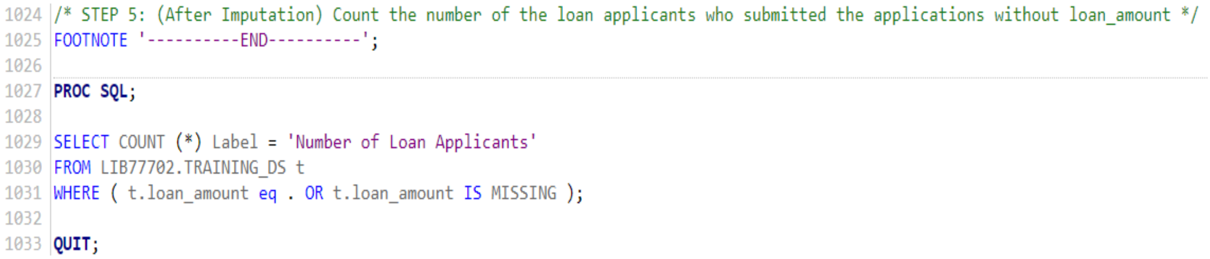
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT
1	LP001002	Male	Not Married	0	Graduate	No	5849	0	146.41216216
2	LP001003	Male	Married	1	Graduate	No	4583	1508	128
3	LP001005	Male	Married	0	Graduate	Yes	3000	0	66
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358	120
5	LP001008	Male	Not Married	0	Graduate	No	6000	0	141

8.2.1.4.3 Description

The above output shows that the missing value of the loan amount was successfully imputed using the loan amount's average value.

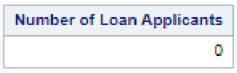
8.2.1.5 After imputing the missing values – LOAN_AMOUNT

8.2.1.5.1 Code Snippet



```
/* STEP 5: (After Imputation) Count the number of the loan applicants who submitted the applications without loan_amount */
FOOTNOTE '----------END----------';

PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS t
WHERE ( t.loan_amount eq . OR t.loan_amount IS MISSING );

QUIT;
```

8.2.1.5.2 Output



Number of Loan Applicants
0

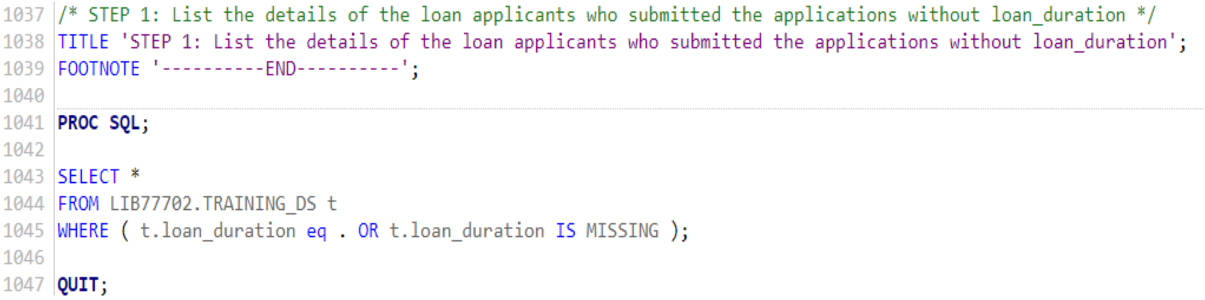
8.2.1.5.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.2.2 Handling Missing Values in LOAN_DURATION

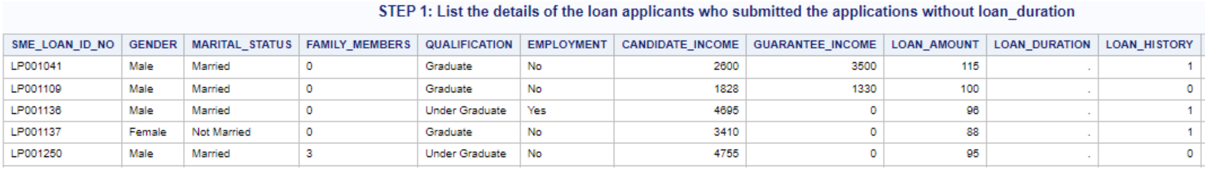
8.2.2.1 Find Missing Value – LOAN_DURATION

8.2.2.1.1 Code Snippet



```
/* STEP 1: List the details of the loan applicants who submitted the applications without loan_duration */
TITLE 'STEP 1: List the details of the loan applicants who submitted the applications without loan_duration';
FOOTNOTE '----------END----------';

PROC SQL;

SELECT *
FROM LIB77702.TRAINING_DS t
WHERE ( t.loan_duration eq . OR t.loan_duration IS MISSING );

QUIT;
```

8.2.2.1.2 Output



STEP 1: List the details of the loan applicants who submitted the applications without loan_duration

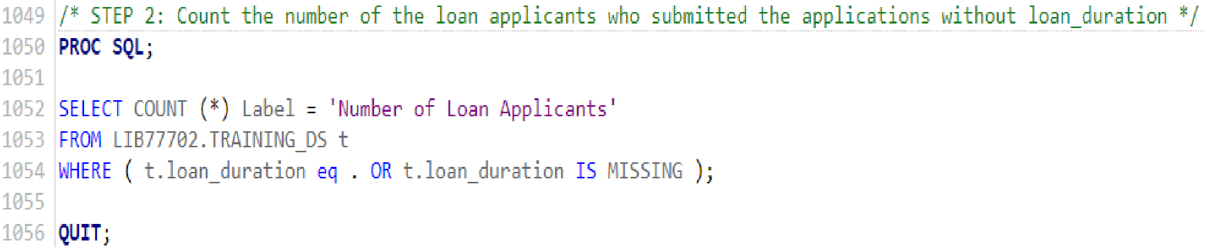
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY
LP001041	Male	Married	0	Graduate	No	2600	3500	115	.	1
LP001109	Male	Married	0	Graduate	No	1828	1330	100	.	0
LP001136	Male	Married	0	Under Graduate	Yes	4695	0	96	.	1
LP001137	Female	Not Married	0	Graduate	No	3410	0	88	.	1
LP001250	Male	Married	3	Under Graduate	No	4755	0	95	.	0

8.2.2.1.3 Description

From the output above, we observe that the training set contains missing values for loan duration; these values will be imputed later.

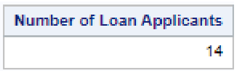
8.2.2.2 Counting Number of Missing Values – LOAN_DURATION

8.2.2.2.1 Code Snippet



```
/* STEP 2: Count the number of the loan applicants who submitted the applications without loan_duration */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS t
WHERE ( t.loan_duration eq . OR t.loan_duration IS MISSING );

QUIT;
```

8.2.2.2.2 Output



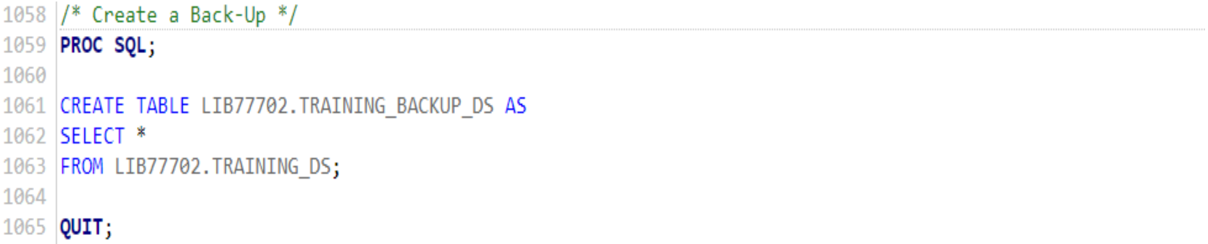
Number of Loan Applicants
14

8.2.2.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their loan duration, which is 14 loan applicants.

8.2.2.3 Backup of the Dataset – LOAN_DURATION

8.2.2.3.1 Code Snippet



```
/* Create a Back-Up */
PROC SQL;

CREATE TABLE LIB77702.TRAINING_BACKUP_DS AS
SELECT *
FROM LIB77702.TRAINING_DS;

QUIT;
```

8.2.2.3.2 Output

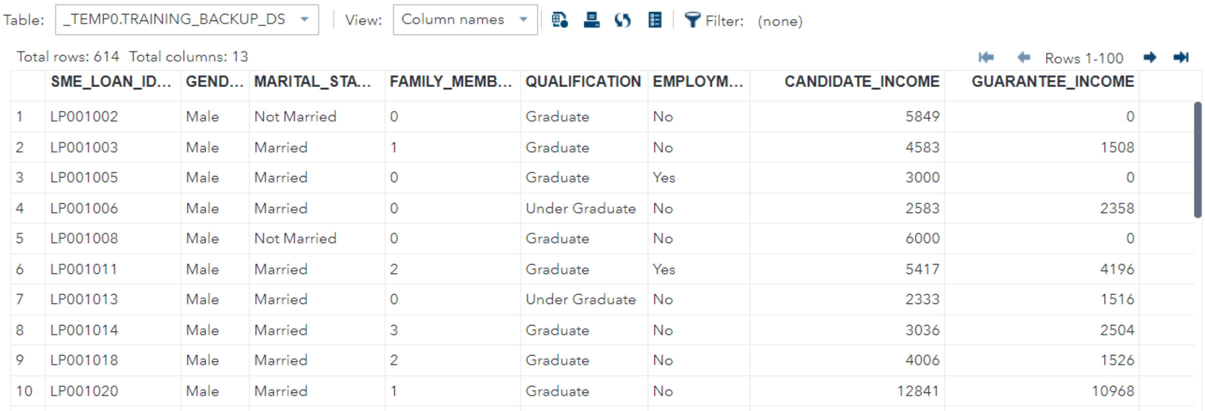


Table: _TEMP0.TRAINING_BACKUP_DS View: Column names Filter: (none)

Total rows: 614 Total columns: 13 Rows 1-100

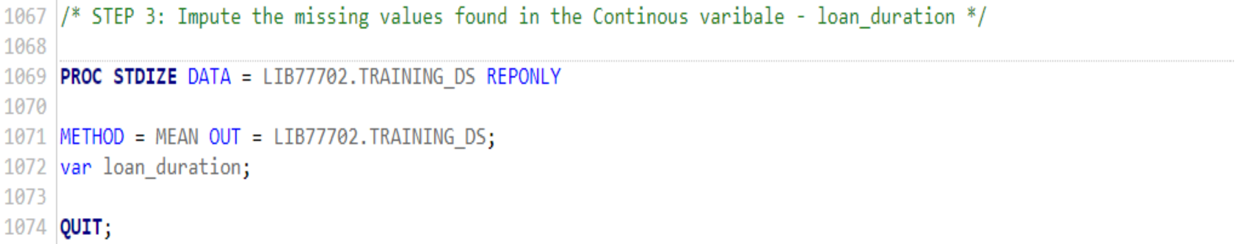
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001002	Male	Not Married	0	Graduate	No	5849	0
2	LP001003	Male	Married	1	Graduate	No	4583	1508
3	LP001005	Male	Married	0	Graduate	Yes	3000	0
4	LP001006	Male	Married	0	Under Graduate	No	2583	2358
5	LP001008	Male	Not Married	0	Graduate	No	6000	0
6	LP001011	Male	Married	2	Graduate	Yes	5417	4196
7	LP001013	Male	Married	0	Under Graduate	No	2333	1516
8	LP001014	Male	Married	3	Graduate	No	3036	2504
9	LP001018	Male	Married	2	Graduate	No	4006	1526
10	LP001020	Male	Married	1	Graduate	No	12841	10968

8.2.2.3.3 Description

The newly formed backup table LIB77702.TRAINING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

8.2.2.4 Imputing the missing values– LOAN_DURATION

8.2.2.4.1 Code Snippet



```
/* STEP 3: Impute the missing values found in the Continous varibale - loan_duration */

PROC STDIZE DATA = LIB77702.TRAINING_DS REPONLY

METHOD = MEAN OUT = LIB77702.TRAINING_DS;
var loan_duration;

QUIT;
```

8.2.2.4.2 Output

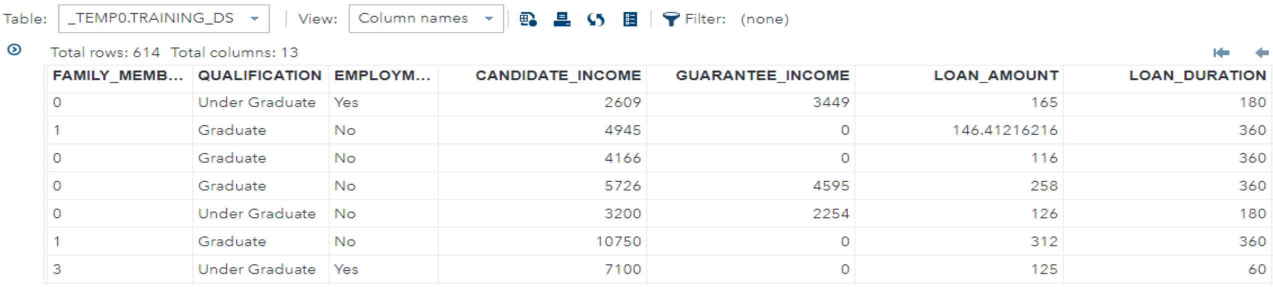


Table: _TEMP0.TRAINING_DS View: Column names Filter: (none)

Total rows: 614 Total columns: 13

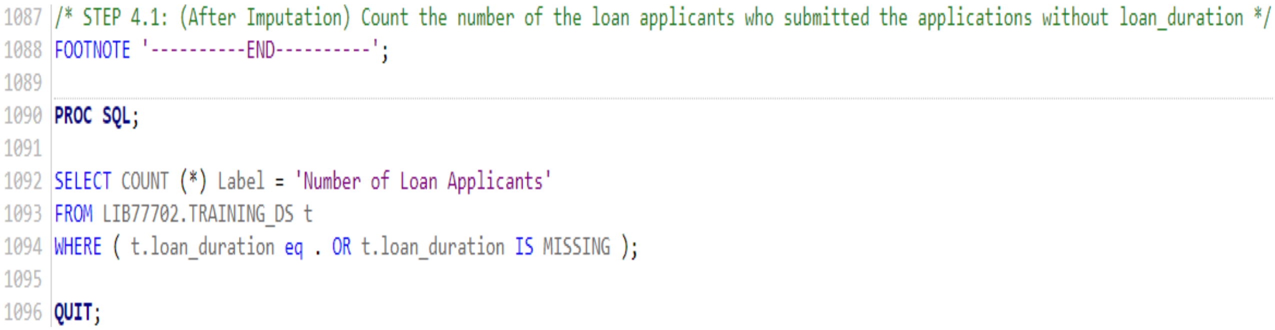
FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION
0	Under Graduate	Yes	2609	3449	165	180
1	Graduate	No	4945	0	146.41216216	360
0	Graduate	No	4166	0	116	360
0	Graduate	No	5726	4595	258	360
0	Under Graduate	No	3200	2254	126	180
1	Graduate	No	10750	0	312	360
3	Under Graduate	Yes	7100	0	125	60

8.2.2.4.3 Description

The above output shows that the missing value of the loan duration was correctly imputed using the loan duration's average value.

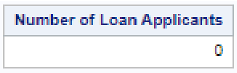
8.2.2.5 After imputing the missing values – LOAN_DURATION

8.2.2.5.1 Code Snippet



```
/* STEP 4.1: (After Imputation) Count the number of the loan applicants who submitted the applications without loan_duration */
FOOTNOTE '----------END----------';

PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TRAINING_DS t
WHERE ( t.loan_duration eq . OR t.loan_duration IS MISSING );

QUIT;
```

8.2.2.5.2 Output



Number of Loan Applicants
0

8.2.2.5.3 Description

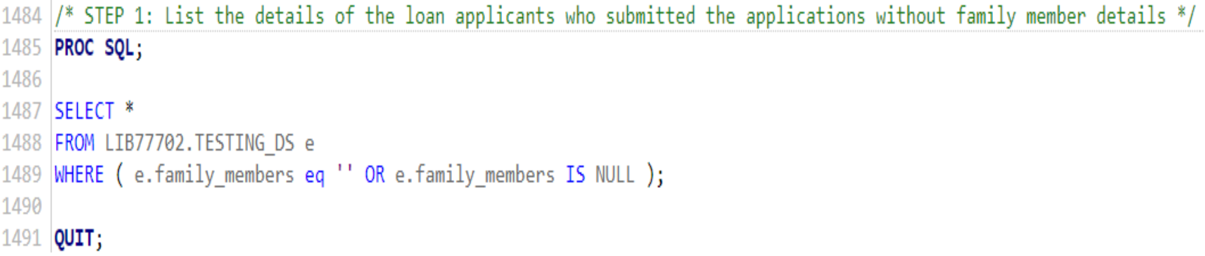
The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.3 Imputing the missing values in Categorical variables – LIB7702.TESTING_DS

8.3.1 Handling Missing Values in FAMILY_MEMBERS

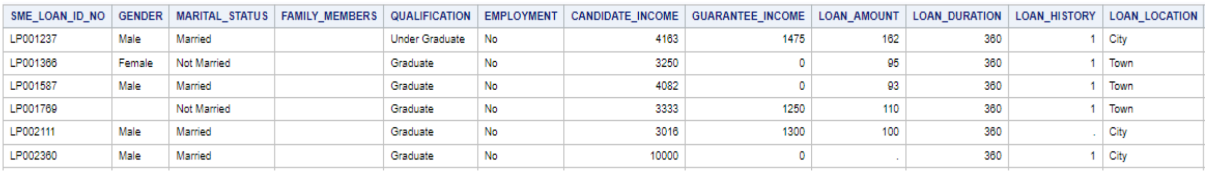
8.3.1.1 Find missing values – FAMILY_MEMBERS

8.3.1.1.1 Code Snippet



```
/* STEP 1: List the details of the loan applicants who submitted the applications without family member details */
PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS e
WHERE ( e.family_members eq '' OR e.family_members IS NULL );

QUIT;
```

8.3.1.1.2 Output



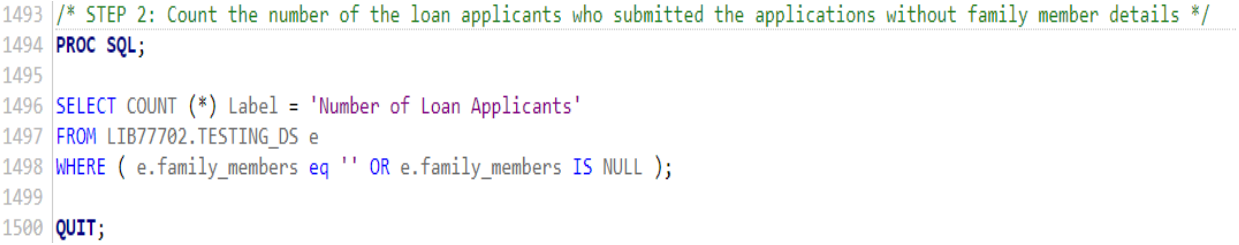
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION
LP001237	Male	Married		Under Graduate	No	4163	1475	162	360	1	City
LP001366	Female	Not Married		Graduate	No	3250	0	95	360	1	Town
LP001587	Male	Married		Graduate	No	4082	0	93	360	1	Town
LP001769		Not Married		Graduate	No	3333	1250	110	360	1	Town
LP002111	Male	Married		Graduate	No	3016	1300	100	360	.	City
LP002360	Male	Married		Graduate	No	10000	0	.	360	1	City

8.3.1.1.3 Description

From the output above, we observe that the testing set contains missing values for family members; these values will be imputed later.

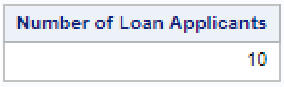
8.3.1.2 Counting the Number of Missing values – FAMILY_MEMBERS

8.3.1.2.1 Code Snippet



```
/* STEP 2: Count the number of the loan applicants who submitted the applications without family member details */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS e
WHERE ( e.family_members eq '' OR e.family_members IS NULL );

QUIT;
```

8.3.1.2.2 Output



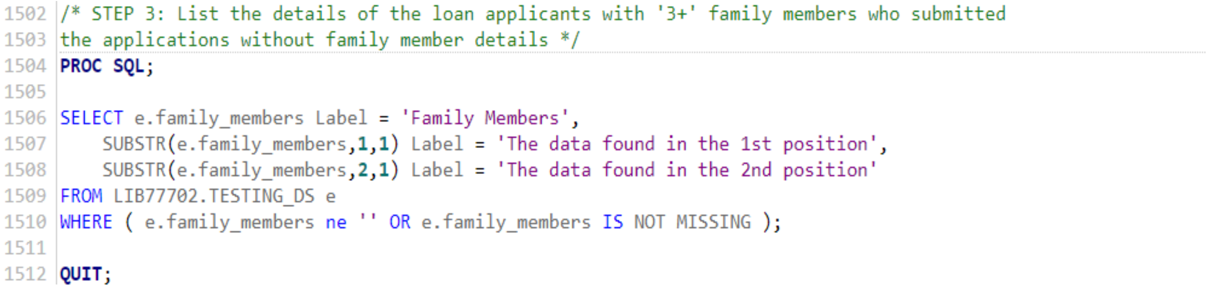
Number of Loan Applicants
10

8.3.1.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their family members, which is 10 loan applicants.

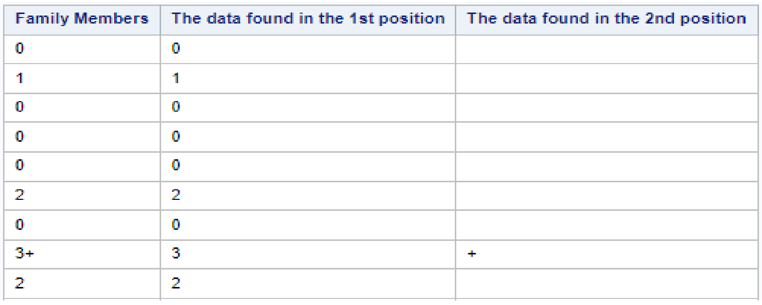
8.3.1.3 List Details of Family with '3+' Members

8.3.1.3.1 Code Snippet



```
/* STEP 3: List the details of the loan applicants with '3+' family members who submitted
the applications without family member details */
PROC SQL;

SELECT e.family_members Label = 'Family Members',
    SUBSTR(e.family_members,1,1) Label = 'The data found in the 1st position',
    SUBSTR(e.family_members,2,1) Label = 'The data found in the 2nd position'
FROM LIB77702.TESTING_DS e
WHERE ( e.family_members ne '' OR e.family_members IS NOT MISSING );

QUIT;
```

8.3.1.3.2 Output



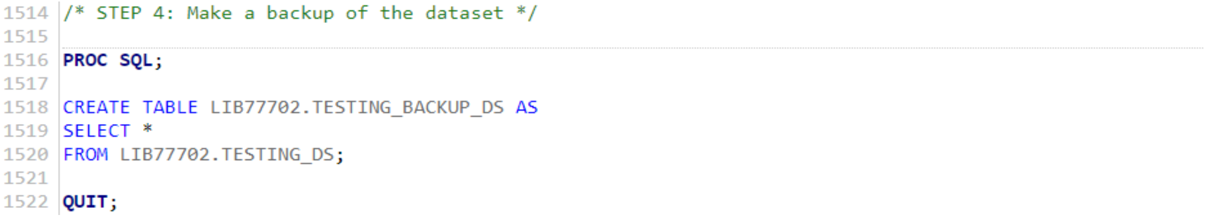
Family Members	The data found in the 1st position	The data found in the 2nd position
0	0	
1	1	
0	0	
0	0	
0	0	
2	2	
0	0	
3+	3	+
2	2	

8.3.1.3.3 Description

From the above output we can see that applicant with 3+ family member is split into two positions to remove '+' sign in the later stage.

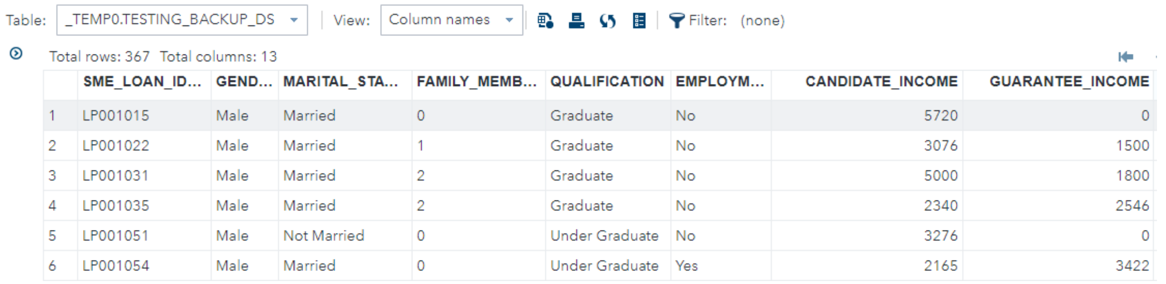
8.3.1.4 Backup of Dataset – FAMILY_MEMBERS

8.3.1.4.1 Code Snippet



```
/* STEP 4: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TESTING_BACKUP_DS AS
SELECT *
FROM LIB77702.TESTING_DS;

QUIT;
```

8.3.1.4.2 Output



Total rows: 367 Total columns: 13

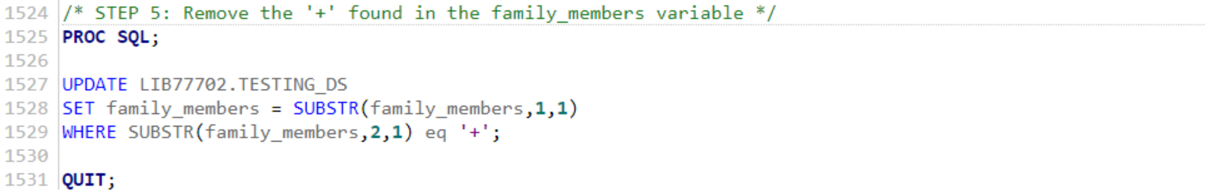
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001015	Male	Married	0	Graduate	No	5720	0
2	LP001022	Male	Married	1	Graduate	No	3076	1500
3	LP001031	Male	Married	2	Graduate	No	5000	1800
4	LP001035	Male	Married	2	Graduate	No	2340	2546
5	LP001051	Male	Not Married	0	Under Graduate	No	3276	0
6	LP001054	Male	Married	0	Under Graduate	Yes	2165	3422

8.3.1.4.3 Description

The newly formed backup table LIB77702.TESTING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

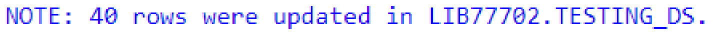
8.3.1.5 Removing '+' Found in Family Member

8.3.1.5.1 Code Snippet



```
/* STEP 5: Remove the '+' found in the family_members variable */
PROC SQL;

UPDATE LIB77702.TESTING_DS
SET family_members = SUBSTR(family_members,1,1)
WHERE SUBSTR(family_members,2,1) eq '+';

QUIT;
```

8.3.1.5.2 Output



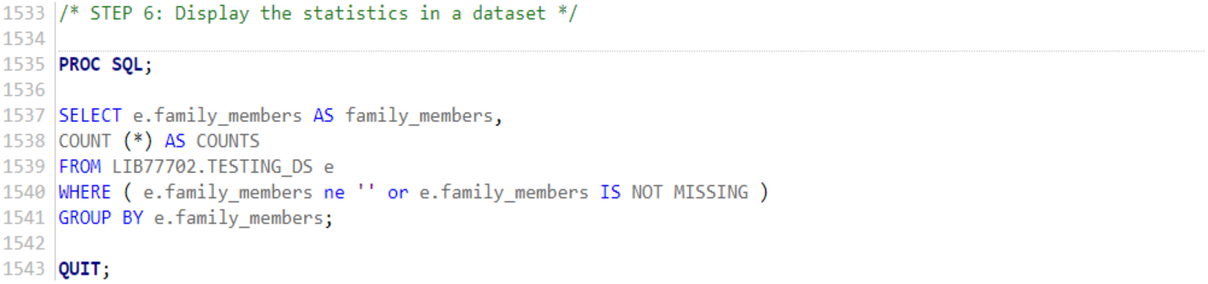
```
NOTE: 40 rows were updated in LIB77702.TESTING_DS.
```

8.3.1.5.3 Description

From the above output we can see that the '+' sign has been removed successfully and the 40 rows have been updated in family members.

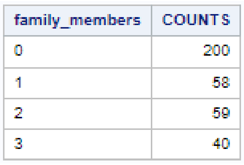
8.3.1.6 Finding the Statistics – FAMILY_MEMBERS

8.3.1.6.1 Code Snippet



```
/* STEP 6: Display the statistics in a dataset */

PROC SQL;

SELECT e.family_members AS family_members,
COUNT (*) AS COUNTS
FROM LIB77702.TESTING_DS e
WHERE ( e.family_members ne '' or e.family_members IS NOT MISSING )
GROUP BY e.family_members;

QUIT;
```

8.3.1.6.2 Output



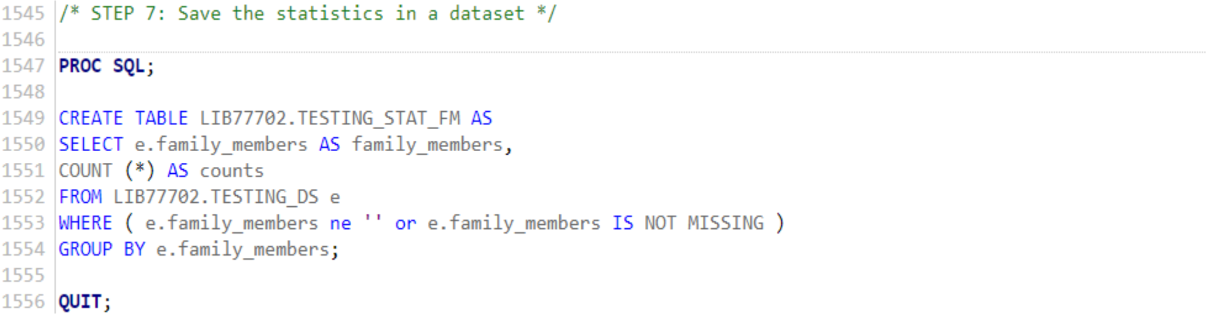
family_members	COUNTS
0	200
1	58
2	59
3	40

8.3.1.6.3 Description

The statistics for family members show that out of the total applicants, 200 are having 0 family members, 58 having 1 member, 59 having 2 members and 40 having 3 members. This indicates that most of the applicants are having no family members.

8.3.1.7 Saving the Statistics – FAMILY_MEMBERS

8.3.1.7.1 Code Snippet



```
/* STEP 7: Save the statistics in a dataset */

PROC SQL;

CREATE TABLE LIB77702.TESTING_STAT_FM AS
SELECT e.family_members AS family_members,
COUNT (*) AS counts
FROM LIB77702.TESTING_DS e
WHERE ( e.family_members ne '' or e.family_members IS NOT MISSING )
GROUP BY e.family_members;

QUIT;
```

8.3.1.7.2 Output

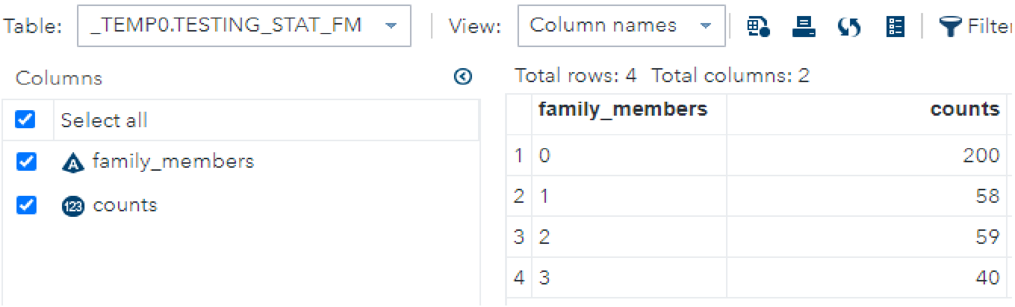


Table: _TEMP0.TESTING_STAT_FM

View: Column names

☑ Select all
☑ family_members
☑ counts

Total rows: 4 Total columns: 2

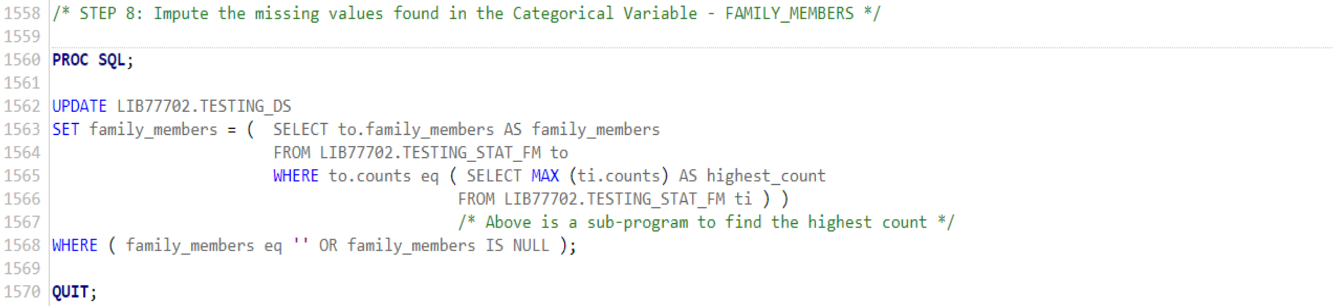
	family_members	counts
1	0	200
2	1	58
3	2	59
4	3	40

8.3.1.7.3 Description

The above output shows that the statistics performed earlier is saved successfully in TESTING_STATS_DS.

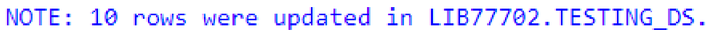
8.3.1.8 Imputing the Missing Value – FAMILY_MEMBERS

8.3.1.8.1 Code Snippet



```
/* STEP 8: Impute the missing values found in the Categorical Variable - FAMILY_MEMBERS */

PROC SQL;

UPDATE LIB77702.TESTING_DS
SET family_members = (  SELECT to.family_members AS family_members
                        FROM LIB77702.TESTING_STAT_FM to
                        WHERE to.counts eq ( SELECT MAX (ti.counts) AS highest_count
                                             FROM LIB77702.TESTING_STAT_FM ti ) )
                                             /* Above is a sub-program to find the highest count */
WHERE ( family_members eq '' OR family_members IS NULL );

QUIT;
```

8.3.1.8.2 Output



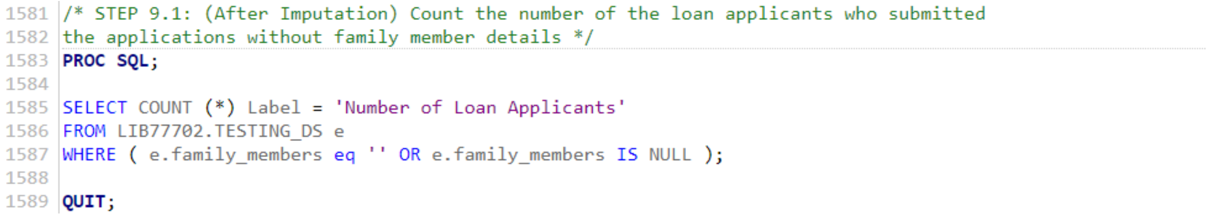
```
NOTE: 10 rows were updated in LIB77702.TESTING_DS.
```

8.3.1.8.3 Description

The above output shows that the 10 missing values rows were successfully imputed and updated in family members.

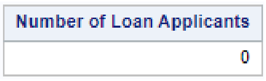
8.3.1.9 After Imputing Missing Value – FAMILY_MEMBERS

8.3.1.9.1 Code Snippet



```
/* STEP 9.1: (After Imputation) Count the number of the loan applicants who submitted
the applications without family member details */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS e
WHERE ( e.family_members eq '' OR e.family_members IS NULL );

QUIT;
```

8.3.1.9.2 Output



Number of Loan Applicants
0

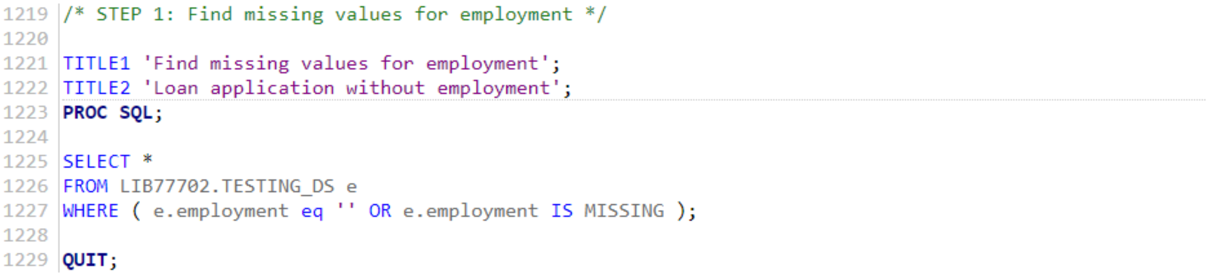
8.3.1.9.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.3.2 Handling Missing Values in EMPLOYMENT

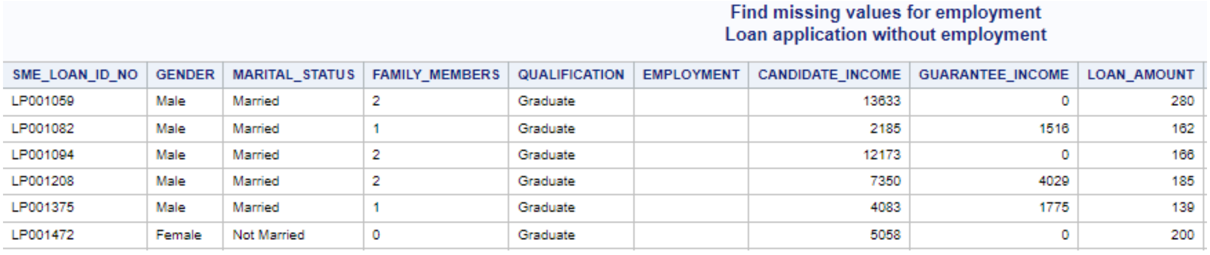
8.3.2.1 Find Missing Value – EMPLOYMENT

8.3.2.1.1 Code Snippet



```
/* STEP 1: Find missing values for employment */

TITLE1 'Find missing values for employment';
TITLE2 'Loan application without employment';
PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS e
WHERE ( e.employment eq '' OR e.employment IS MISSING );

QUIT;
```

8.3.2.1.2 Output



Find missing values for employment
Loan application without employment

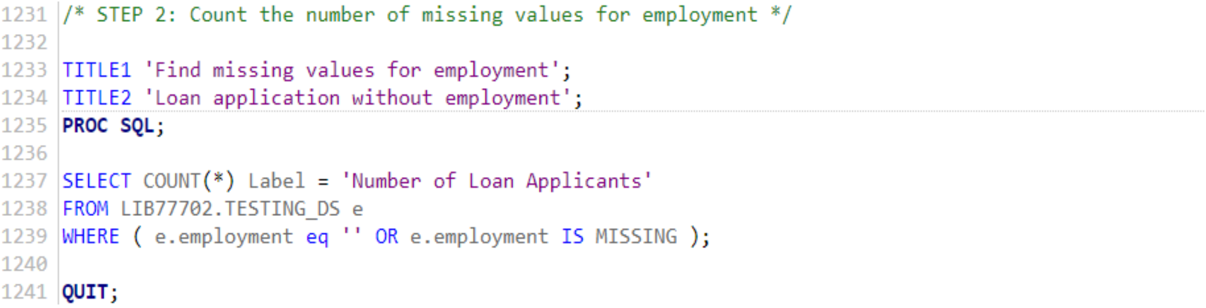
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT
LP001059	Male	Married	2	Graduate		13633	0	280
LP001082	Male	Married	1	Graduate		2185	1516	162
LP001094	Male	Married	2	Graduate		12173	0	166
LP001208	Male	Married	2	Graduate		7350	4029	185
LP001375	Male	Married	1	Graduate		4083	1775	139
LP001472	Female	Not Married	0	Graduate		5058	0	200

8.3.2.1.3 Description

From the output above, we observe that the testing set contains missing values for employment; these values will be imputed later.

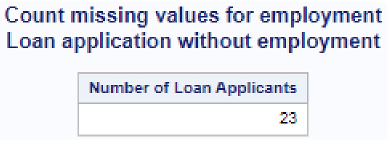
8.3.2.2 Counting Number of Missing Values – EMPLOYMENT

8.3.2.2.1 Code Snippet



```
/* STEP 2: Count the number of missing values for employment */

TITLE1 'Find missing values for employment';
TITLE2 'Loan application without employment';
PROC SQL;

SELECT COUNT(*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS e
WHERE ( e.employment eq '' OR e.employment IS MISSING );

QUIT;
```

8.3.2.2.2 Output



Count missing values for employment
Loan application without employment

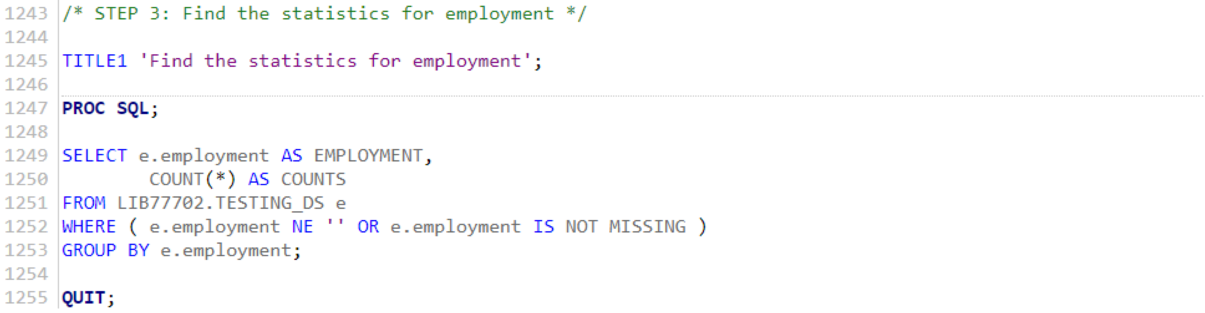
Number of Loan Applicants
23

8.3.2.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their employment status, which is 23 loan applicants.

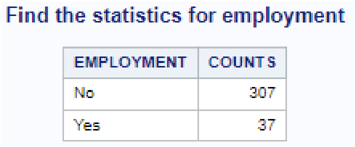
8.3.2.3 Finding the Statistics – EMPLOYMENT

8.3.2.3.1 Code Snippet



```
/* STEP 3: Find the statistics for employment */

TITLE1 'Find the statistics for employment';

PROC SQL;

SELECT e.employment AS EMPLOYMENT,
       COUNT(*) AS COUNTS
FROM LIB77702.TESTING_DS e
WHERE ( e.employment NE '' OR e.employment IS NOT MISSING )
GROUP BY e.employment;

QUIT;
```

8.3.2.3.2 Output



Find the statistics for employment

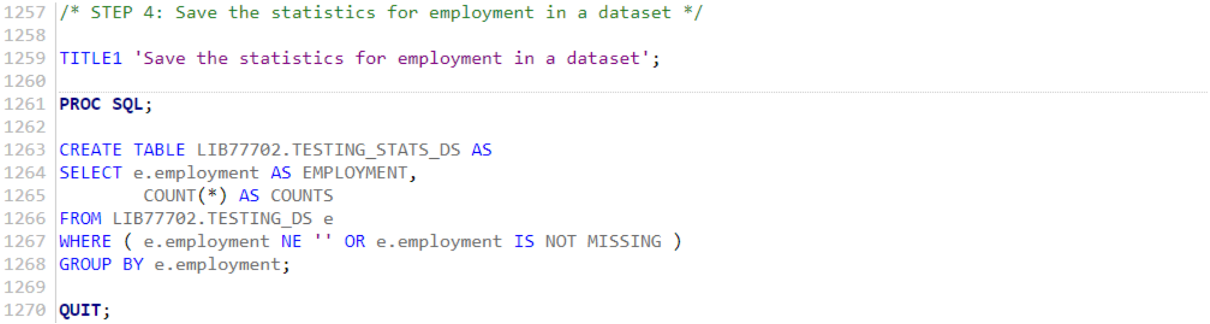
EMPLOYMENT	COUNTS
No	307
Yes	37

8.3.2.3.3 Description

The statistics for employment show that out of the total applicants, 307 are employed and 37 are not employed. This indicates that most of the applicants are employed, while rest are not employed.

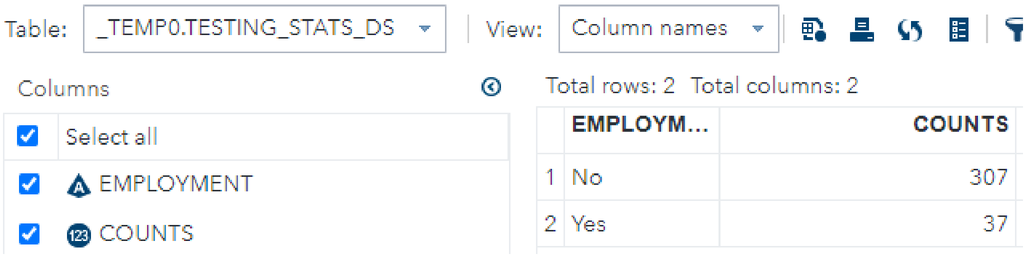
8.3.2.4 Saving the Statistics – EMPLOYMENT

8.3.2.4.1 Code Snippet



```
/* STEP 4: Save the statistics for employment in a dataset */

TITLE1 'Save the statistics for employment in a dataset';

PROC SQL;

CREATE TABLE LIB77702.TESTING_STATS_DS AS
SELECT e.employment AS EMPLOYMENT,
       COUNT(*) AS COUNTS
FROM LIB77702.TESTING_DS e
WHERE ( e.employment NE '' OR e.employment IS NOT MISSING )
GROUP BY e.employment;

QUIT;
```

8.3.2.4.2 Output



Total rows: 2 Total columns: 2

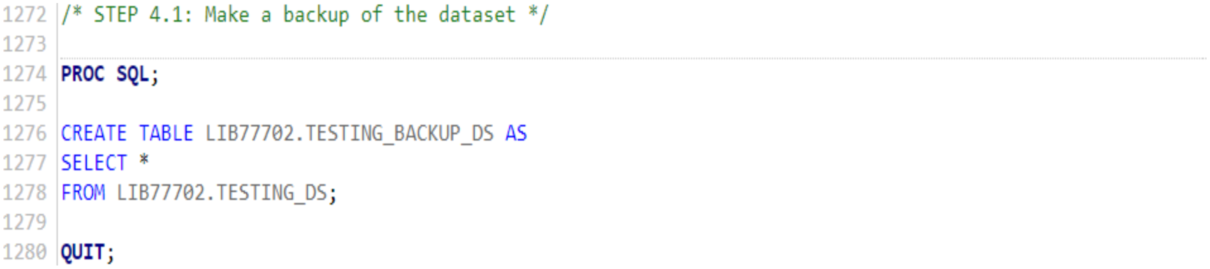
	EMPLOYM...	COUNTS
1	No	307
2	Yes	37

8.3.2.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TESTING_STATS_DS.

8.3.2.5 Backup of the Dataset – EMPLOYMENT

8.3.2.5.1 Code Snippet



```
/* STEP 4.1: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TESTING_BACKUP_DS AS
SELECT *
FROM LIB77702.TESTING_DS;

QUIT;
```

8.3.2.5.2 Output

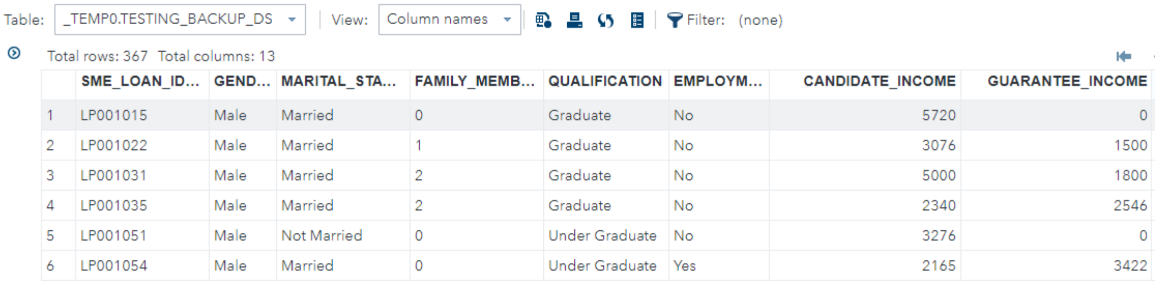


Table: _TEMP0.TESTING_BACKUP_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 13

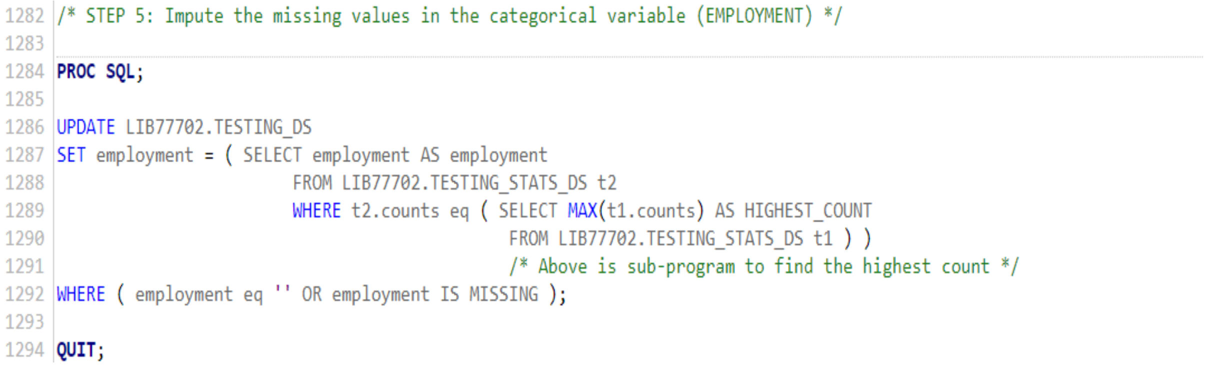
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001015	Male	Married	0	Graduate	No	5720	0
2	LP001022	Male	Married	1	Graduate	No	3076	1500
3	LP001031	Male	Married	2	Graduate	No	5000	1800
4	LP001035	Male	Married	2	Graduate	No	2340	2546
5	LP001051	Male	Not Married	0	Under Graduate	No	3276	0
6	LP001054	Male	Married	0	Under Graduate	Yes	2165	3422

8.3.2.5.3 Description

The newly formed backup table LIB77702.TESTING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

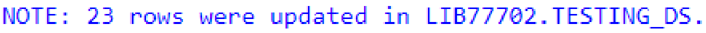
8.3.2.6 Imputing the missing values– EMPLOYMENT

8.3.2.6.1 Code Snippet



```
/* STEP 5: Impute the missing values in the categorical variable (EMPLOYMENT) */

PROC SQL;

UPDATE LIB77702.TESTING_DS
SET employment = ( SELECT employment AS employment
                        FROM LIB77702.TESTING_STATS_DS t2
                        WHERE t2.counts eq ( SELECT MAX(t1.counts) AS HIGHEST_COUNT
                                              FROM LIB77702.TESTING_STATS_DS t1 ) )
                                              /* Above is sub-program to find the highest count */
WHERE ( employment eq '' OR employment IS MISSING );

QUIT;
```

8.3.2.6.2 Output



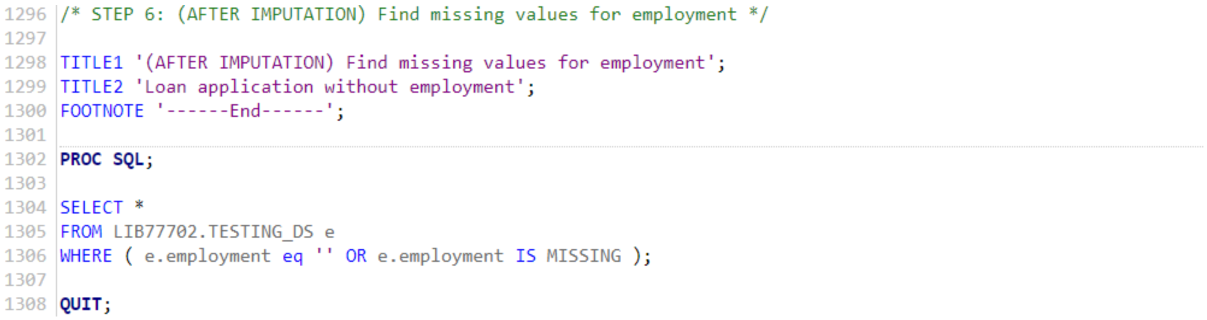
```
NOTE: 23 rows were updated in LIB77702.TESTING_DS.
```

8.3.2.6.3 Description

The above output shows that the 23 missing values rows were successfully imputed and updated in employment.

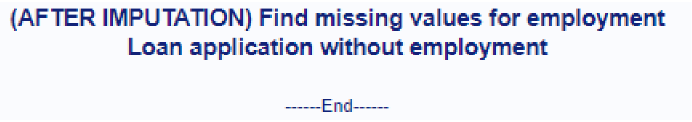
8.3.2.7 After imputing the missing values – EMPLOYMENT

8.3.2.7.1 Code Snippet



```
/* STEP 6: (AFTER IMPUTATION) Find missing values for employment */

TITLE1 '(AFTER IMPUTATION) Find missing values for employment';
TITLE2 'Loan application without employment';
FOOTNOTE '------End------';

PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS e
WHERE ( e.employment eq '' OR e.employment IS MISSING );

QUIT;
```

8.3.2.7.2 Output



(AFTER IMPUTATION) Find missing values for employment
Loan application without employment

------End------

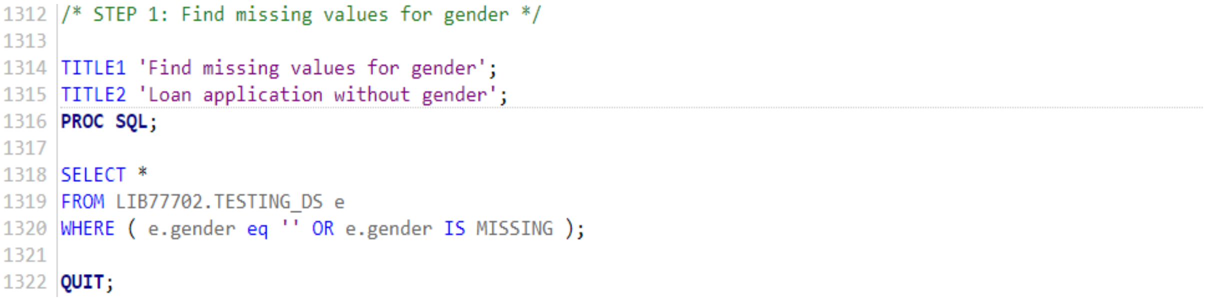
8.3.2.7.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.3.3 Handling Missing Values in GENDER

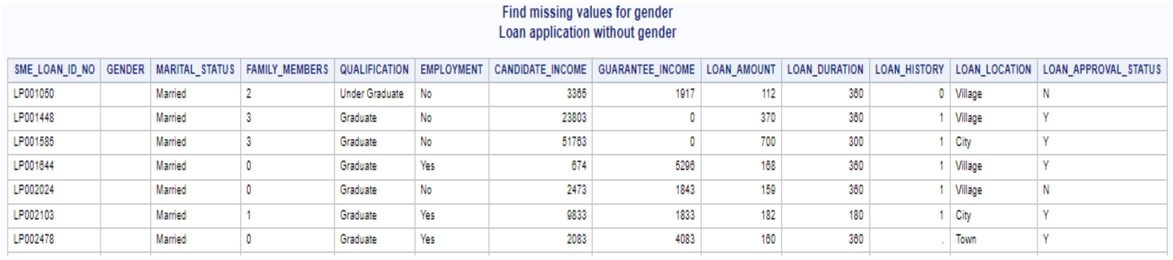
8.3.3.1 Find Missing Value – GENDER

8.3.3.1.1 Code Snippet



```
/* STEP 1: Find missing values for gender */

TITLE1 'Find missing values for gender';
TITLE2 'Loan application without gender';
PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS e
WHERE ( e.gender eq '' OR e.gender IS MISSING );

QUIT;
```

8.3.3.1.2 Output



Find missing values for gender
Loan application without gender

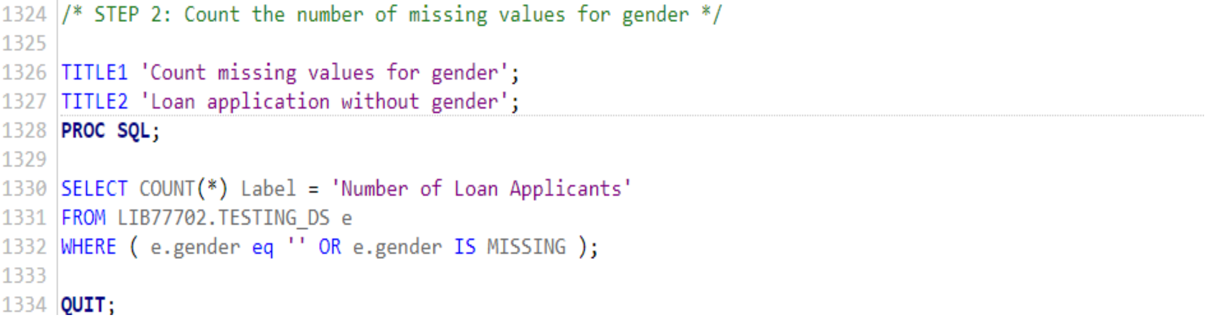
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY	LOAN_LOCATION	LOAN_APPROVAL_STATUS
LP001050		Married	2	Under Graduate	No	3365	1917	112	360	0	Village	N
LP001448		Married	3	Graduate	No	23803	0	370	360	1	Village	Y
LP001585		Married	3	Graduate	No	51763	0	700	300	1	City	Y
LP001644		Married	0	Graduate	Yes	674	5296	168	360	1	Village	Y
LP002024		Married	0	Graduate	No	2473	1843	159	360	1	Village	N
LP002103		Married	1	Graduate	Yes	9833	1833	182	180	1	City	Y
LP002478		Married	0	Graduate	Yes	2083	4083	160	360	.	Town	Y

8.3.3.1.3 Description

From the output above, we observe that the testing set contains missing values for gender; these values will be imputed later.

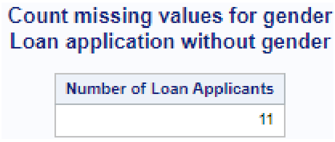
8.3.3.2 Counting Number of Missing Values – GENDER

8.3.3.2.1 Code Snippet



```
/* STEP 2: Count the number of missing values for gender */

TITLE1 'Count missing values for gender';
TITLE2 'Loan application without gender';
PROC SQL;

SELECT COUNT(*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS e
WHERE ( e.gender eq '' OR e.gender IS MISSING );

QUIT;
```

8.3.3.2.2 Output



Count missing values for gender
Loan application without gender

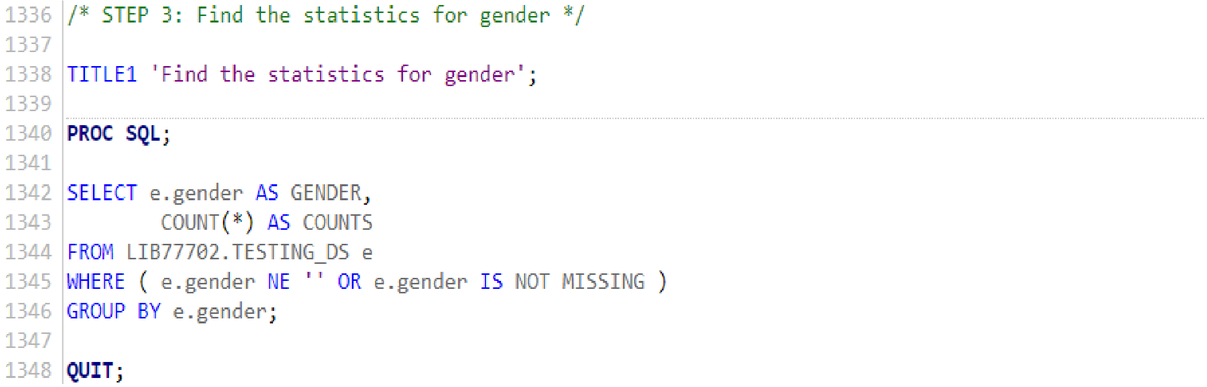
Number of Loan Applicants
11

8.3.3.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their gender, which is 11 loan applicants.

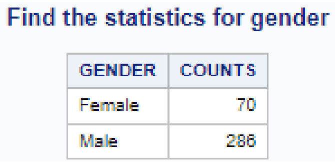
8.3.3.3 Finding the Statistics – GENDER

8.3.3.3.1 Code Snippet



```
/* STEP 3: Find the statistics for gender */

TITLE1 'Find the statistics for gender';

PROC SQL;

SELECT e.gender AS GENDER,
        COUNT(*) AS COUNTS
FROM LIB77702.TESTING_DS e
WHERE ( e.gender NE '' OR e.gender IS NOT MISSING )
GROUP BY e.gender;

QUIT;
```

8.3.3.3.2 Output



Find the statistics for gender

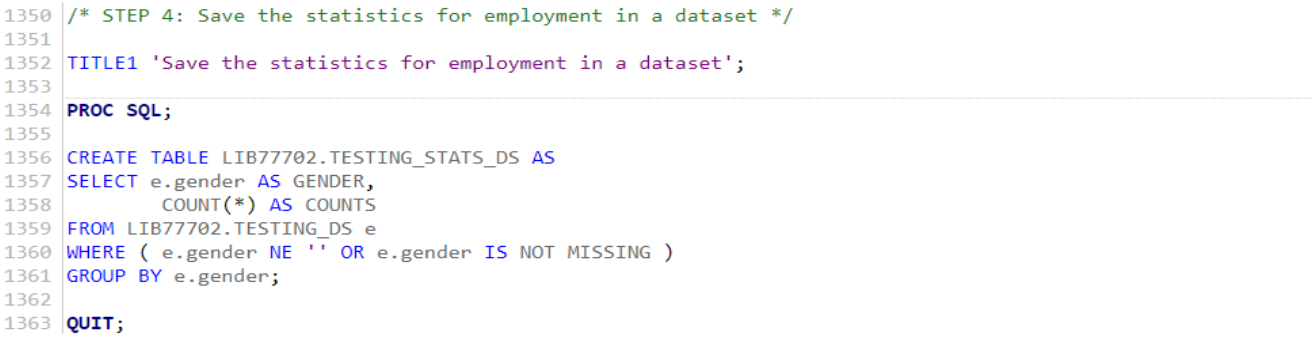
GENDER	COUNTS
Female	70
Male	286

8.3.3.3.3 Description

The statistics for marital status show that out of the total applicants, 70 are female and 286 are male. This indicates that most of the applicants are male.

8.3.3.4 Saving the Statistics – GENDER

8.3.3.4.1 Code Snippet



```
/* STEP 4: Save the statistics for employment in a dataset */

TITLE1 'Save the statistics for employment in a dataset';

PROC SQL;

CREATE TABLE LIB77702.TESTING_STATS_DS AS
SELECT e.gender AS GENDER,
        COUNT(*) AS COUNTS
FROM LIB77702.TESTING_DS e
WHERE ( e.gender NE '' OR e.gender IS NOT MISSING )
GROUP BY e.gender;

QUIT;
```

8.3.3.4.2 Output

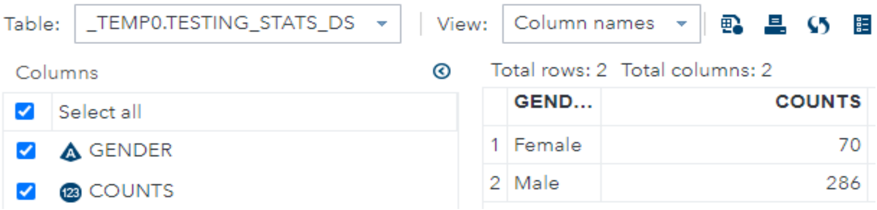


Table: _TEMP0.TESTING_STATS_DS View: Column names

Columns

☑ Select all
☑ GENDER
☑ COUNTS

Total rows: 2 Total columns: 2

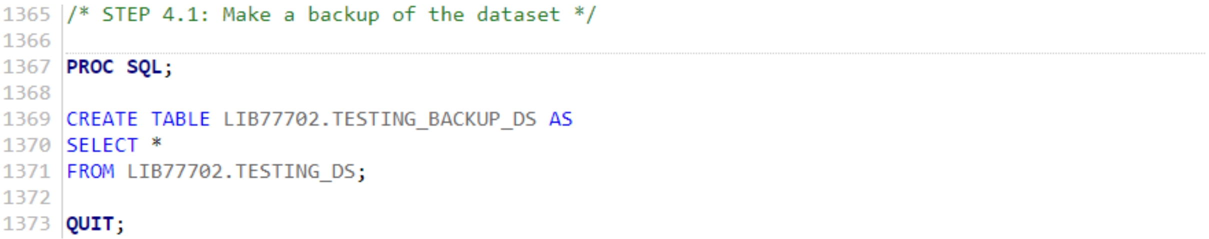
	GEND...	COUNTS
1	Female	70
2	Male	286

8.3.3.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TESTING_STATS_DS.

8.3.3.5 Backup of the Dataset – GENDER

8.3.3.5.1 Code Snippet



```
/* STEP 4.1: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TESTING_BACKUP_DS AS
SELECT *
FROM LIB77702.TESTING_DS;

QUIT;
```

8.3.3.5.2 Output

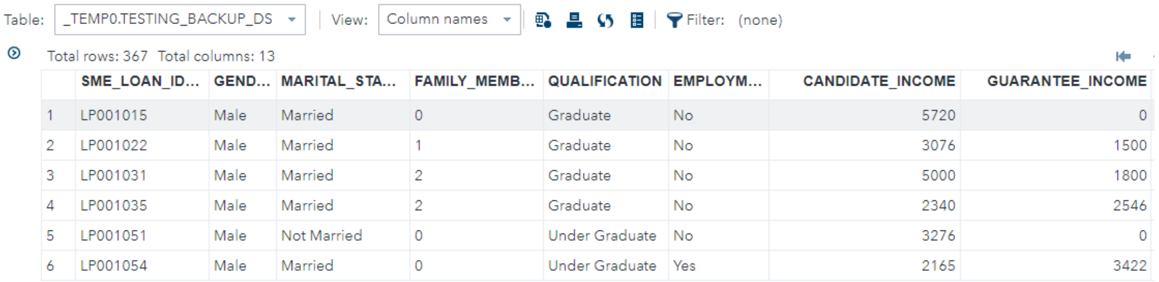


Table: _TEMP0.TESTING_BACKUP_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 13

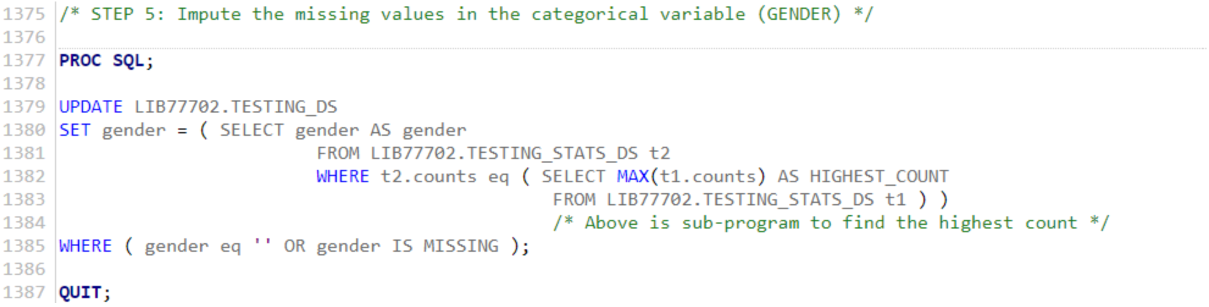
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001015	Male	Married	0	Graduate	No	5720	0
2	LP001022	Male	Married	1	Graduate	No	3076	1500
3	LP001031	Male	Married	2	Graduate	No	5000	1800
4	LP001035	Male	Married	2	Graduate	No	2340	2546
5	LP001051	Male	Not Married	0	Under Graduate	No	3276	0
6	LP001054	Male	Married	0	Under Graduate	Yes	2165	3422

8.3.3.5.3 Description

The newly formed backup table LIB77702.TESTING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

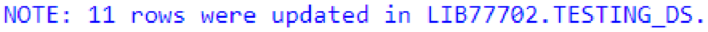
8.3.3.6 Imputing the missing values– GENDER

8.3.3.6.1 Code Snippet



```
/* STEP 5: Impute the missing values in the categorical variable (GENDER) */

PROC SQL;

UPDATE LIB77702.TESTING_DS
SET gender = ( SELECT gender AS gender
                    FROM LIB77702.TESTING_STATS_DS t2
                    WHERE t2.counts eq ( SELECT MAX(t1.counts) AS HIGHEST_COUNT
                                          FROM LIB77702.TESTING_STATS_DS t1 ) )
                                          /* Above is sub-program to find the highest count */
WHERE ( gender eq '' OR gender IS MISSING );

QUIT;
```

8.3.3.6.2 Output



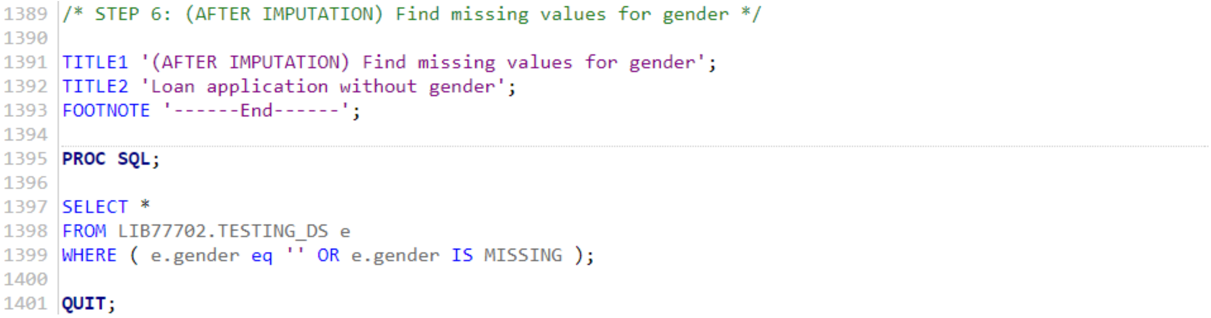
```
NOTE: 11 rows were updated in LIB77702.TESTING_DS.
```

8.3.3.6.3 Description

The above output shows that the 11 missing values rows were successfully imputed and updated in gender.

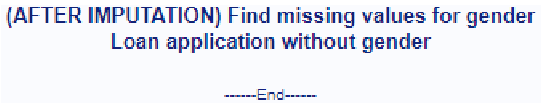
8.3.3.7 After imputing the missing values – GENDER

8.3.3.7.1 Code Snippet



```
/* STEP 6: (AFTER IMPUTATION) Find missing values for gender */

TITLE1 '(AFTER IMPUTATION) Find missing values for gender';
TITLE2 'Loan application without gender';
FOOTNOTE '------End------';

PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS e
WHERE ( e.gender eq '' OR e.gender IS MISSING );

QUIT;
```

8.3.3.7.2 Output



(AFTER IMPUTATION) Find missing values for gender
Loan application without gender

------End------

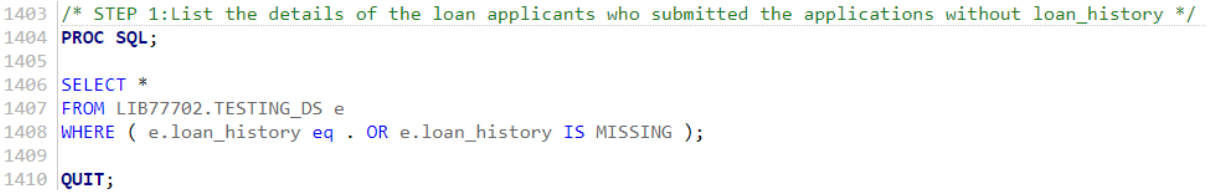
8.3.3.7.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.3.4 Handling Missing Values in LOAN_HISTORY

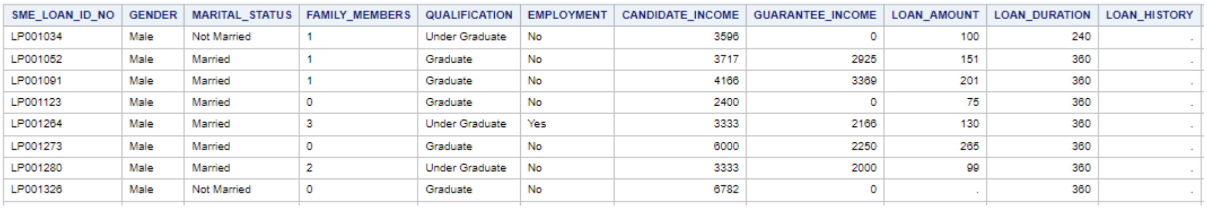
8.3.4.1 Find Missing Value – LOAN_HISTORY

8.3.4.1.1 Code Snippet



```
/* STEP 1:List the details of the loan applicants who submitted the applications without loan_history */
PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS e
WHERE ( e.loan_history eq . OR e.loan_history IS MISSING );

QUIT;
```

8.3.4.1.2 Output



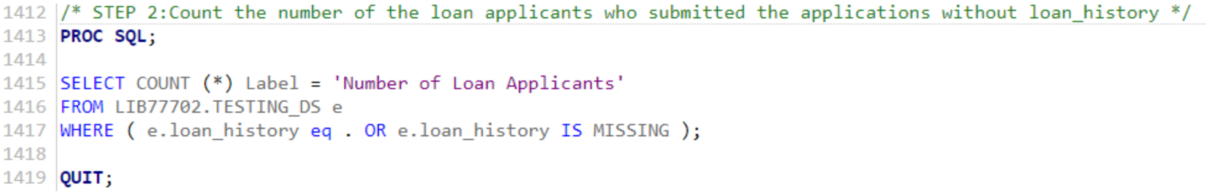
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY
LP001034	Male	Not Married	1	Under Graduate	No	3596	0	100	240	.
LP001052	Male	Married	1	Graduate	No	3717	2925	151	360	.
LP001091	Male	Married	1	Graduate	No	4166	3369	201	360	.
LP001123	Male	Married	0	Graduate	No	2400	0	75	360	.
LP001264	Male	Married	3	Under Graduate	Yes	3333	2166	130	360	.
LP001273	Male	Married	0	Graduate	No	6000	2250	265	360	.
LP001280	Male	Married	2	Under Graduate	No	3333	2000	99	360	.
LP001326	Male	Not Married	0	Graduate	No	6782	0	.	360	.

8.3.4.1.3 Description

From the output above, we observe that the testing set contains missing values for loan history; these values will be imputed later.

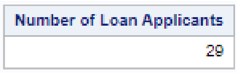
8.3.4.2 Counting Number of Missing Values – LOAN_HISTORY

8.3.4.2.1 Code Snippet



```
/* STEP 2:Count the number of the loan applicants who submitted the applications without loan_history */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS e
WHERE ( e.loan_history eq . OR e.loan_history IS MISSING );

QUIT;
```

8.3.4.2.2 Output



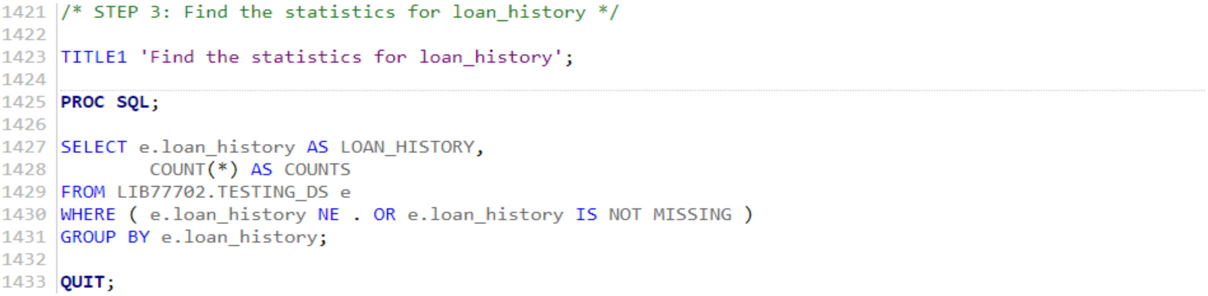
Number of Loan Applicants
29

8.3.4.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their loan history, which is 29 loan applicants.

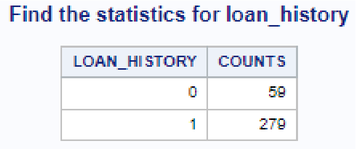
8.3.4.3 Finding the Statistics – LOAN_HISTORY

8.3.4.3.1 Code Snippet



```
/* STEP 3: Find the statistics for loan_history */

TITLE1 'Find the statistics for loan_history';

PROC SQL;

SELECT e.loan_history AS LOAN_HISTORY,
       COUNT(*) AS COUNTS
FROM LIB77702.TESTING_DS e
WHERE ( e.loan_history NE . OR e.loan_history IS NOT MISSING )
GROUP BY e.loan_history;

QUIT;
```

8.3.4.3.2 Output



Find the statistics for loan_history

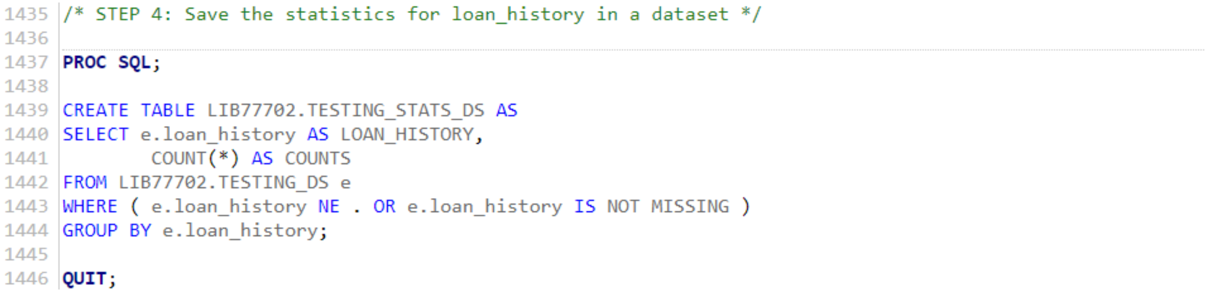
LOAN_HISTORY	COUNTS
0	59
1	279

8.3.4.3.3 Description

The statistics for loan history show that out of the total applicants, 59 had no past loan and 279 had past loan. This indicates that most of the applicants are married, while rest are not married.

8.3.4.4 Saving the Statistics – LOAN_HISTORY

8.3.4.4.1 Code Snippet



```
/* STEP 4: Save the statistics for loan_history in a dataset */

PROC SQL;

CREATE TABLE LIB77702.TESTING_STATS_DS AS
SELECT e.loan_history AS LOAN_HISTORY,
       COUNT(*) AS COUNTS
FROM LIB77702.TESTING_DS e
WHERE ( e.loan_history NE . OR e.loan_history IS NOT MISSING )
GROUP BY e.loan_history;

QUIT;
```

8.3.4.4.2 Output

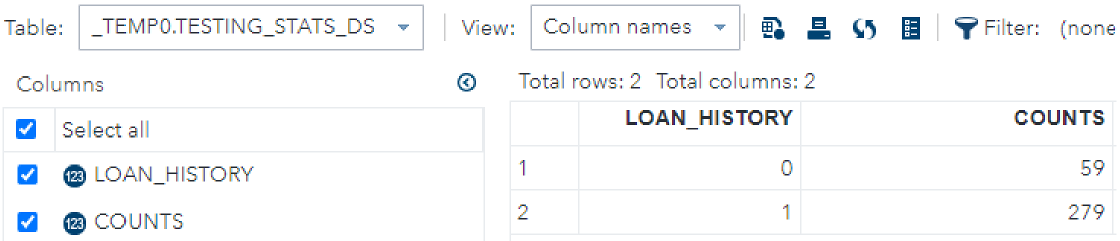


Table: _TEMP0.TESTING_STATS_DS View: Column names Filter: (none

Columns

☑ Select all
☑ LOAN_HISTORY
☑ COUNTS

Total rows: 2 Total columns: 2

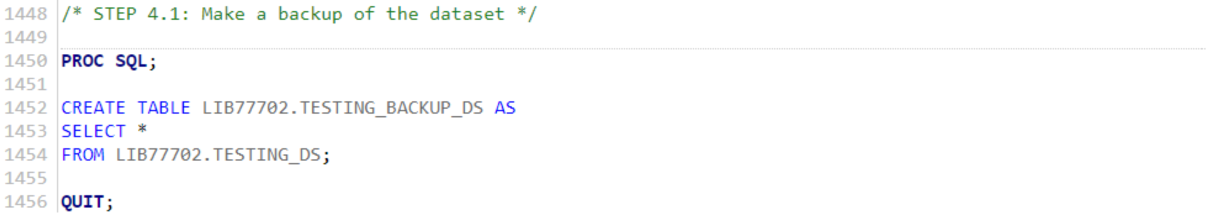
	LOAN_HISTORY	COUNTS
1	0	59
2	1	279

8.3.4.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TESTING_STATS_DS.

8.3.4.5 Backup of the Dataset – LOAN_HISTORY

8.3.4.5.1 Code Snippet



```
/* STEP 4.1: Make a backup of the dataset */

PROC SQL;

CREATE TABLE LIB77702.TESTING_BACKUP_DS AS
SELECT *
FROM LIB77702.TESTING_DS;

QUIT;
```

8.3.4.5.2 Output

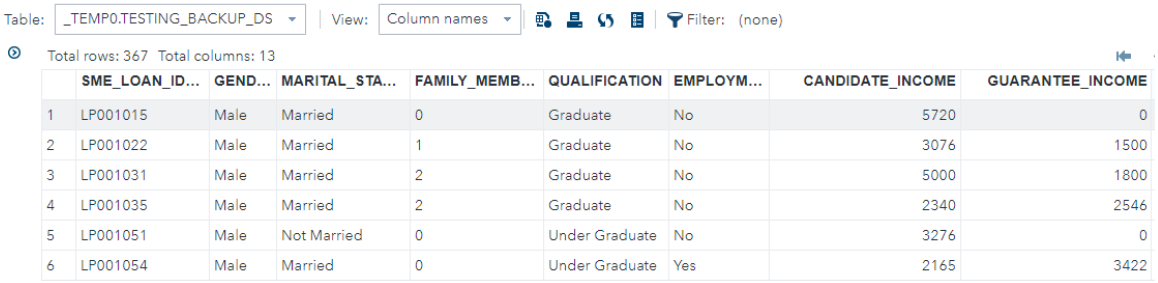


Table: _TEMP0.TESTING_BACKUP_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 13

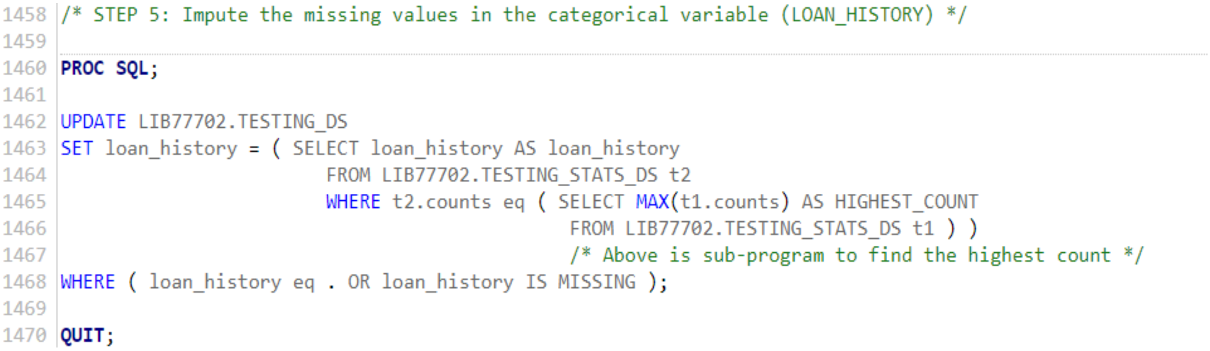
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001015	Male	Married	0	Graduate	No	5720	0
2	LP001022	Male	Married	1	Graduate	No	3076	1500
3	LP001031	Male	Married	2	Graduate	No	5000	1800
4	LP001035	Male	Married	2	Graduate	No	2340	2546
5	LP001051	Male	Not Married	0	Under Graduate	No	3276	0
6	LP001054	Male	Married	0	Under Graduate	Yes	2165	3422

8.3.4.5.3 Description

The newly formed backup table LIB77702.TESTING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

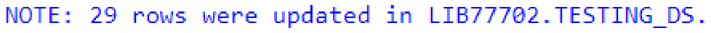
8.3.4.6 Imputing the missing values– LOAN_HISTORY

8.3.4.6.1 Code Snippet



```
/* STEP 5: Impute the missing values in the categorical variable (LOAN_HISTORY) */

PROC SQL;

UPDATE LIB77702.TESTING_DS
SET loan_history = ( SELECT loan_history AS loan_history
                        FROM LIB77702.TESTING_STATS_DS t2
                        WHERE t2.counts eq ( SELECT MAX(t1.counts) AS HIGHEST_COUNT
                                              FROM LIB77702.TESTING_STATS_DS t1 ) )
                                              /* Above is sub-program to find the highest count */
WHERE ( loan_history eq . OR loan_history IS MISSING );

QUIT;
```

8.3.4.6.2 Output



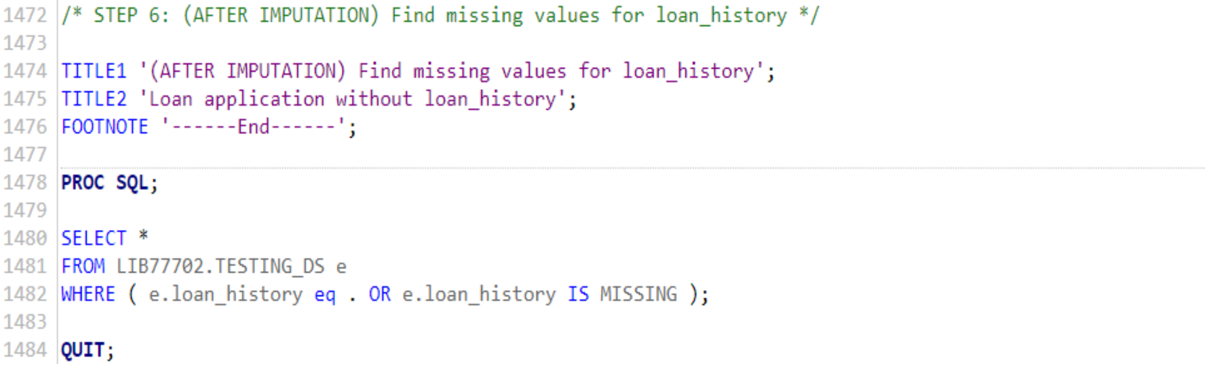
```
NOTE: 29 rows were updated in LIB77702.TESTING_DS.
```

8.3.4.6.3 Description

The above output shows that the 29 missing values rows were successfully imputed and updated in loan history.

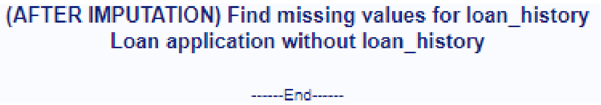
8.3.4.7 After imputing the missing values – LOAN_HISTORY

8.3.4.7.1 Code Snippet



```
/* STEP 6: (AFTER IMPUTATION) Find missing values for loan_history */

TITLE1 '(AFTER IMPUTATION) Find missing values for loan_history';
TITLE2 'Loan application without loan_history';
FOOTNOTE '------End------';

PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS e
WHERE ( e.loan_history eq . OR e.loan_history IS MISSING );

QUIT;
```

8.3.4.7.2 Output



(AFTER IMPUTATION) Find missing values for loan_history
Loan application without loan_history

------End------

8.3.4.7.3 Description

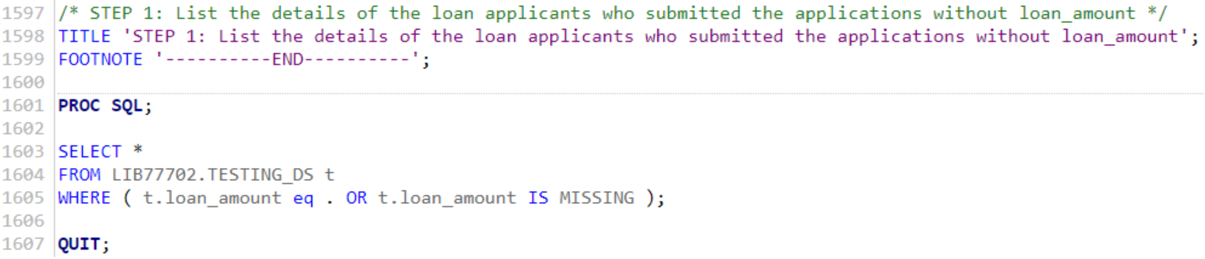
The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.4 Imputing the missing values in Continuous variables – LIB7702.TESTING_DS

8.4.1 Handling Missing Values in LOAN_AMOUNT

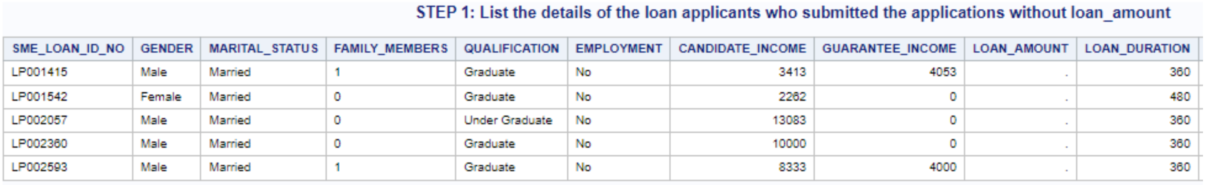
8.4.1.1 Find Missing Value – LOAN_AMOUNT

8.4.1.1.1 Code Snippet



```
/* STEP 1: List the details of the loan applicants who submitted the applications without loan_amount */
TITLE 'STEP 1: List the details of the loan applicants who submitted the applications without loan_amount';
FOOTNOTE '----------END----------';

PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS t
WHERE ( t.loan_amount eq . OR t.loan_amount IS MISSING );

QUIT;
```

8.4.1.1.2 Output



STEP 1: List the details of the loan applicants who submitted the applications without loan_amount

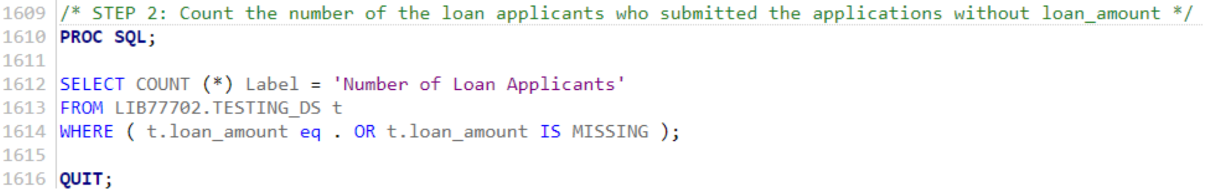
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION
LP001415	Male	Married	1	Graduate	No	3413	4053	.	360
LP001542	Female	Married	0	Graduate	No	2262	0	.	480
LP002057	Male	Married	0	Under Graduate	No	13083	0	.	360
LP002360	Male	Married	0	Graduate	No	10000	0	.	360
LP002593	Male	Married	1	Graduate	No	8333	4000	.	360

8.4.1.1.3 Description

From the output above, we observe that the testing set contains missing values for loan amount; these values will be imputed later.

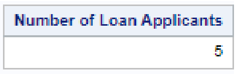
8.4.1.2 Counting Number of Missing Values – LOAN_AMOUNT

8.4.1.2.1 Code Snippet



```
/* STEP 2: Count the number of the loan applicants who submitted the applications without loan_amount */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS t
WHERE ( t.loan_amount eq . OR t.loan_amount IS MISSING );

QUIT;
```

8.4.1.2.2 Output



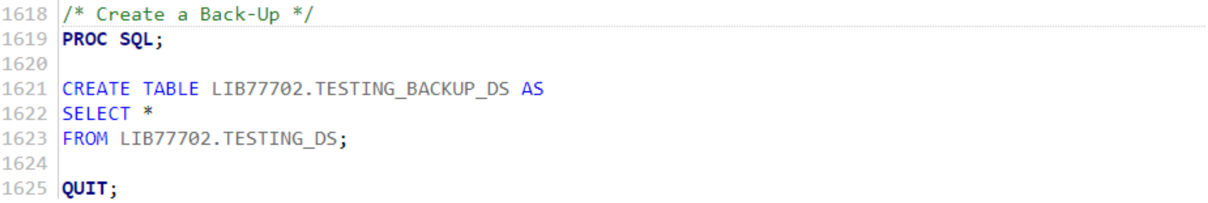
Number of Loan Applicants
5

8.4.1.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their loan amount, which is 5 loan applicants.

8.4.1.3 Backup of the Dataset – LOAN_AMOUNT

8.4.1.3.1 Code Snippet



```
/* Create a Back-Up */
PROC SQL;

CREATE TABLE LIB77702.TESTING_BACKUP_DS AS
SELECT *
FROM LIB77702.TESTING_DS;

QUIT;
```

8.4.1.3.2 Output

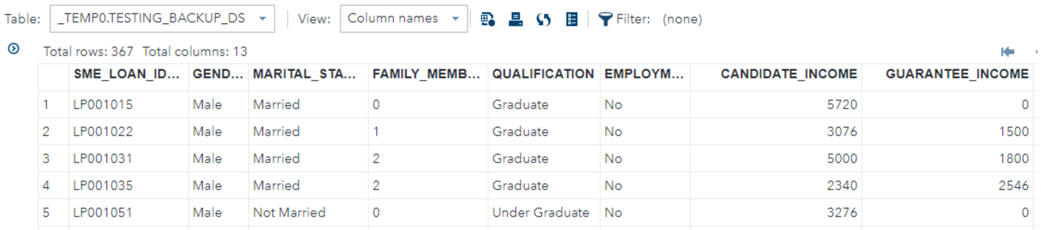


Table: _TEMP0.TESTING_BACKUP_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 13

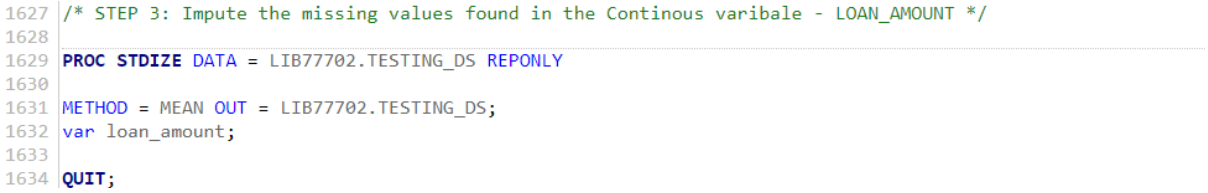
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001015	Male	Married	0	Graduate	No	5720	0
2	LP001022	Male	Married	1	Graduate	No	3076	1500
3	LP001031	Male	Married	2	Graduate	No	5000	1800
4	LP001035	Male	Married	2	Graduate	No	2340	2546
5	LP001051	Male	Not Married	0	Under Graduate	No	3276	0

8.4.1.3.3 Description

The newly formed backup table LIB77702.TESTING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

8.4.1.4 Imputing the missing values– LOAN_AMOUNT

8.4.1.4.1 Code Snippet



```
/* STEP 3: Impute the missing values found in the Continous varibale - LOAN_AMOUNT */

PROC STDIZE DATA = LIB77702.TESTING_DS REPONLY

METHOD = MEAN OUT = LIB77702.TESTING_DS;
var loan_amount;

QUIT;
```

8.4.1.4.2 Output

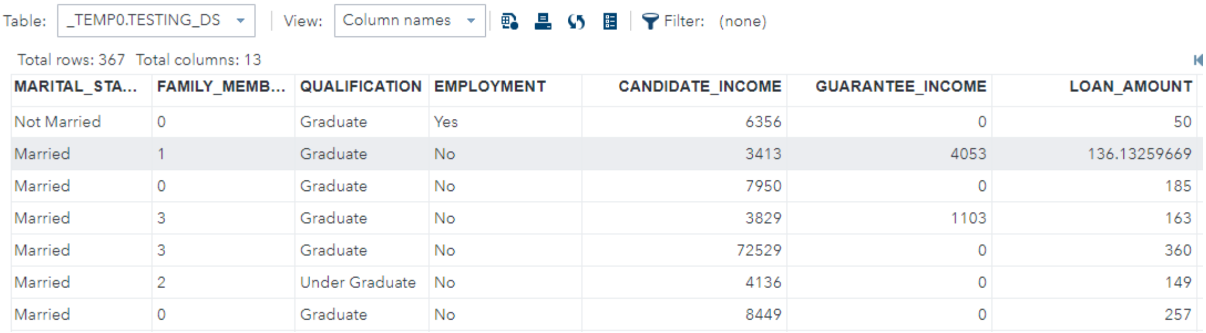


Table: _TEMP0.TESTING_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 13

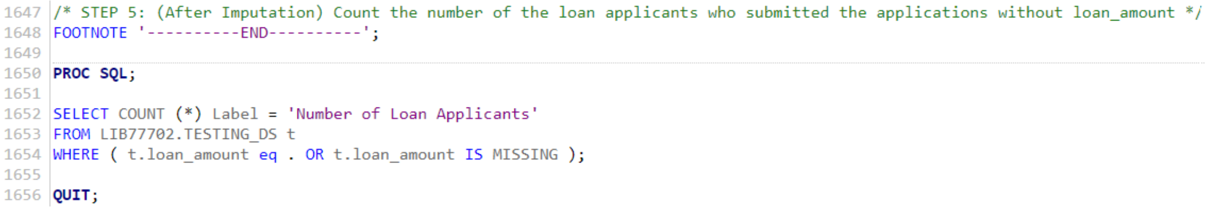
MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT
Not Married	0	Graduate	Yes	6356	0	50
Married	1	Graduate	No	3413	4053	136.13259669
Married	0	Graduate	No	7950	0	185
Married	3	Graduate	No	3829	1103	163
Married	3	Graduate	No	72529	0	360
Married	2	Under Graduate	No	4136	0	149
Married	0	Graduate	No	8449	0	257

8.4.1.4.3 Description

The above output shows that the missing value of the loan amount was correctly imputed using the loan amount's average value.

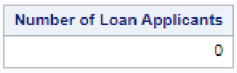
8.4.1.5 After imputing the missing values – LOAN_AMOUNT

8.4.1.5.1 Code Snippet



```
/* STEP 5: (After Imputation) Count the number of the loan applicants who submitted the applications without loan_amount */
FOOTNOTE '----------END----------';

PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS t
WHERE ( t.loan_amount eq . OR t.loan_amount IS MISSING );

QUIT;
```

8.4.1.5.2 Output



Number of Loan Applicants
0

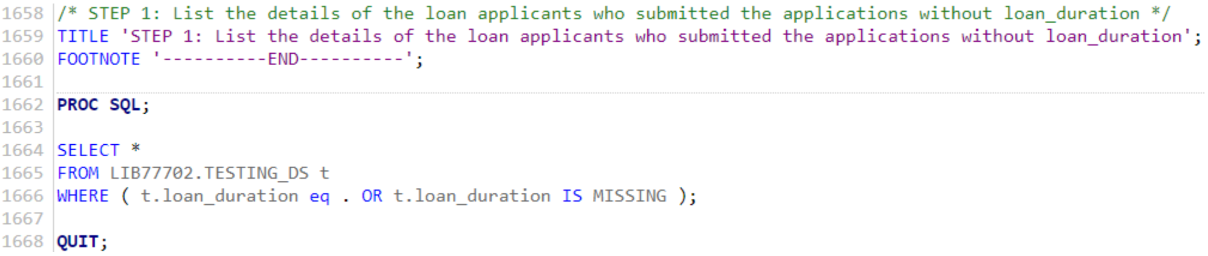
8.4.1.5.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

8.4.2 Handling Missing Values in LOAN_DURATION

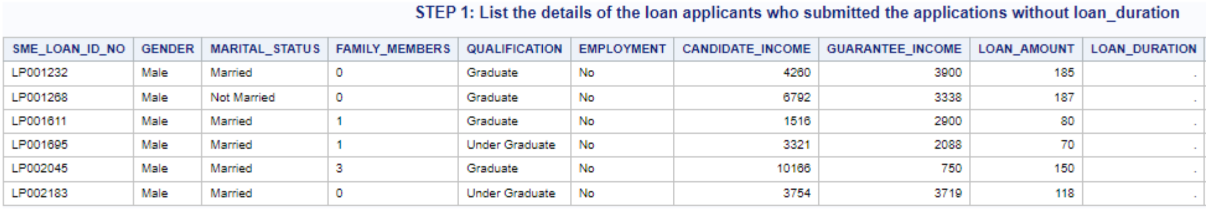
8.4.2.1 Find Missing Value – LOAN_DURATION

8.4.2.1.1 Code Snippet



```
/* STEP 1: List the details of the loan applicants who submitted the applications without loan_duration */
TITLE 'STEP 1: List the details of the loan applicants who submitted the applications without loan_duration';
FOOTNOTE '----------END----------';

PROC SQL;

SELECT *
FROM LIB77702.TESTING_DS t
WHERE ( t.loan_duration eq . OR t.loan_duration IS MISSING );

QUIT;
```

8.4.2.1.2 Output



STEP 1: List the details of the loan applicants who submitted the applications without loan_duration

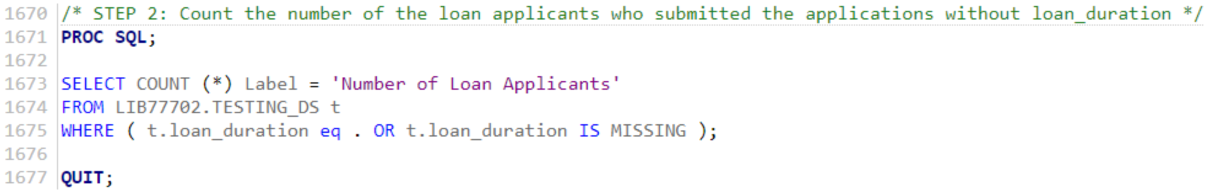
SME_LOAN_ID_NO	GENDER	MARITAL_STATUS	FAMILY_MEMBERS	QUALIFICATION	EMPLOYMENT	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION
LP001232	Male	Married	0	Graduate	No	4260	3900	185	.
LP001268	Male	Not Married	0	Graduate	No	6792	3338	187	.
LP001611	Male	Married	1	Graduate	No	1516	2900	80	.
LP001695	Male	Married	1	Under Graduate	No	3321	2088	70	.
LP002045	Male	Married	3	Graduate	No	10166	750	150	.
LP002183	Male	Married	0	Under Graduate	No	3754	3719	118	.

8.4.2.1.3 Description

From the output above, we observe that the testing set contains missing values for loan duration; these values will be imputed later.

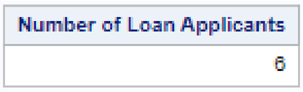
8.4.2.2 Counting Number of Missing Values – LOAN_DURATION

8.4.2.2.1 Code Snippet



```
/* STEP 2: Count the number of the loan applicants who submitted the applications without loan_duration */
PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS t
WHERE ( t.loan_duration eq . OR t.loan_duration IS MISSING );

QUIT;
```

8.4.2.2.2 Output



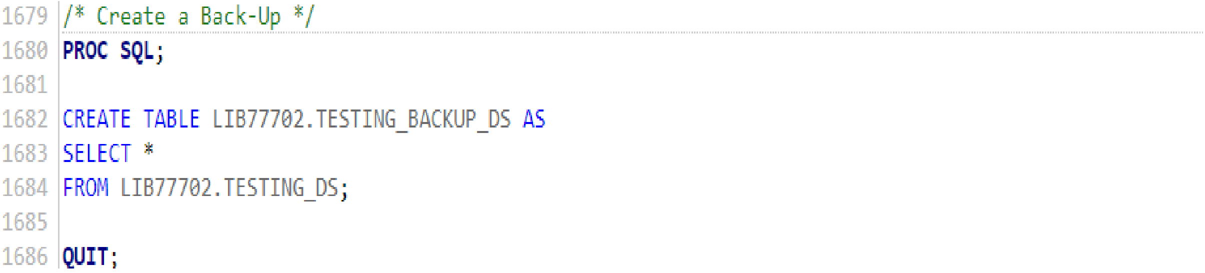
Number of Loan Applicants
6

8.4.2.2.3 Description

The above output displays the number of loan applicants who submitted without disclosing their loan duration, which is 6 loan applicants.

8.4.2.3 Backup of the Dataset – LOAN_DURATION

8.4.2.3.1 Code Snippet



```
/* Create a Back-Up */
PROC SQL;

CREATE TABLE LIB77702.TESTING_BACKUP_DS AS
SELECT *
FROM LIB77702.TESTING_DS;

QUIT;
```

8.4.2.3.2 Output

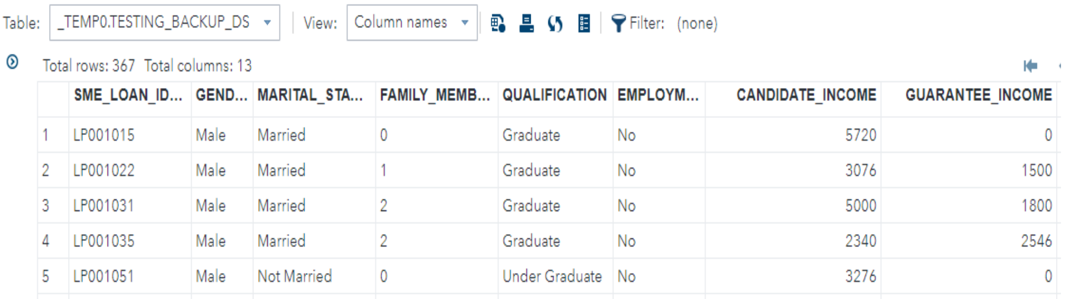


Table: _TEMP0.TESTING_BACKUP_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 13

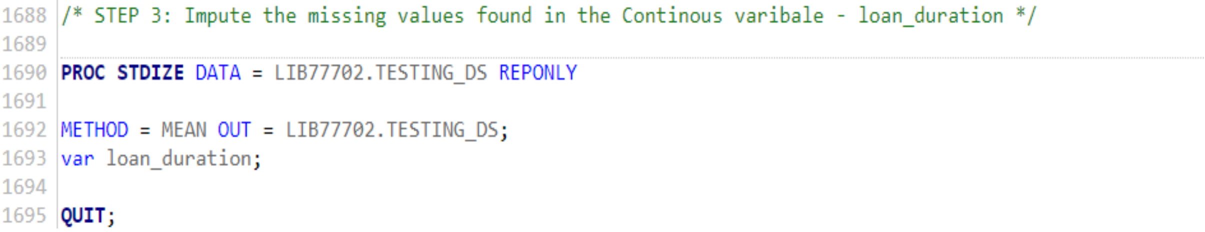
	SME_LOAN_ID...	GEND...	MARITAL_STA...	FAMILY_MEMB...	QUALIFICATION	EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME
1	LP001015	Male	Married	0	Graduate	No	5720	0
2	LP001022	Male	Married	1	Graduate	No	3076	1500
3	LP001031	Male	Married	2	Graduate	No	5000	1800
4	LP001035	Male	Married	2	Graduate	No	2340	2546
5	LP001051	Male	Not Married	0	Under Graduate	No	3276	0

8.4.2.3.3 Description

The newly formed backup table LIB77702.TESTING_BACKUP_DS's content is displayed in the output. The screenshot ensures that the data may be retrieved or referenced as needed without changing the primary dataset by verifying that the backup was correctly made and contains detailed records that are equal to those in the original dataset.

8.4.2.4 Imputing the missing values– LOAN_DURATION

8.4.2.4.1 Code Snippet



```
/* STEP 3: Impute the missing values found in the Continous varibale - loan_duration */

PROC STDIZE DATA = LIB77702.TESTING_DS REPONLY

METHOD = MEAN OUT = LIB77702.TESTING_DS;
var loan_duration;

QUIT;
```

8.4.2.4.2 Output

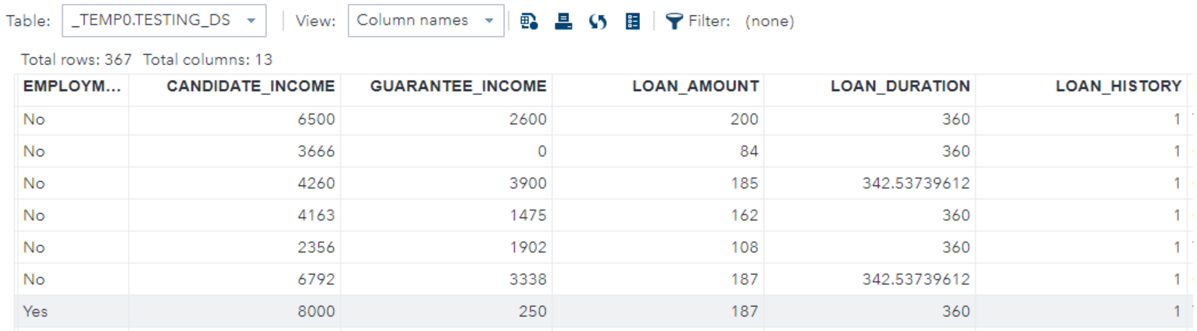


Table: _TEMP0.TESTING_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 13

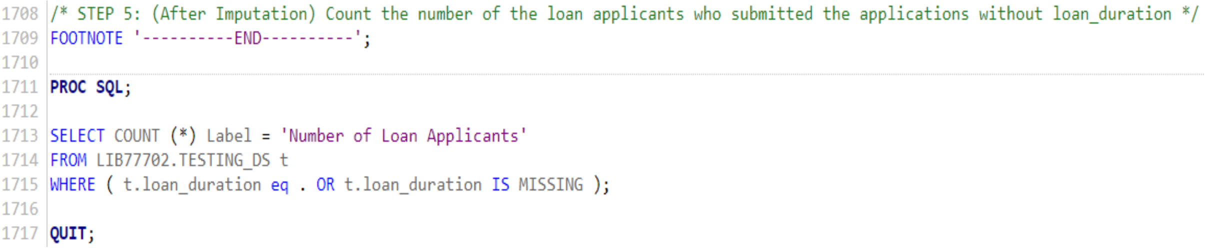
EMPLOYM...	CANDIDATE_INCOME	GUARANTEE_INCOME	LOAN_AMOUNT	LOAN_DURATION	LOAN_HISTORY
No	6500	2600	200	360	1
No	3666	0	84	360	1
No	4260	3900	185	342.53739612	1
No	4163	1475	162	360	1
No	2356	1902	108	360	1
No	6792	3338	187	342.53739612	1
Yes	8000	250	187	360	1

8.4.2.4.3 Description

The above output shows that the statistics performed earlier is saved successfully in TESTING_STATS_DS.

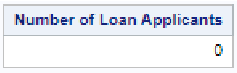
8.4.2.5 After imputing the missing values – LOAN_DURATION

8.4.2.5.1 Code Snippet



```
/* STEP 5: (After Imputation) Count the number of the loan applicants who submitted the applications without loan_duration */
FOOTNOTE '----------END----------';

PROC SQL;

SELECT COUNT (*) Label = 'Number of Loan Applicants'
FROM LIB77702.TESTING_DS t
WHERE ( t.loan_duration eq . OR t.loan_duration IS MISSING );

QUIT;
```

8.4.2.5.2 Output



Number of Loan Applicants
0

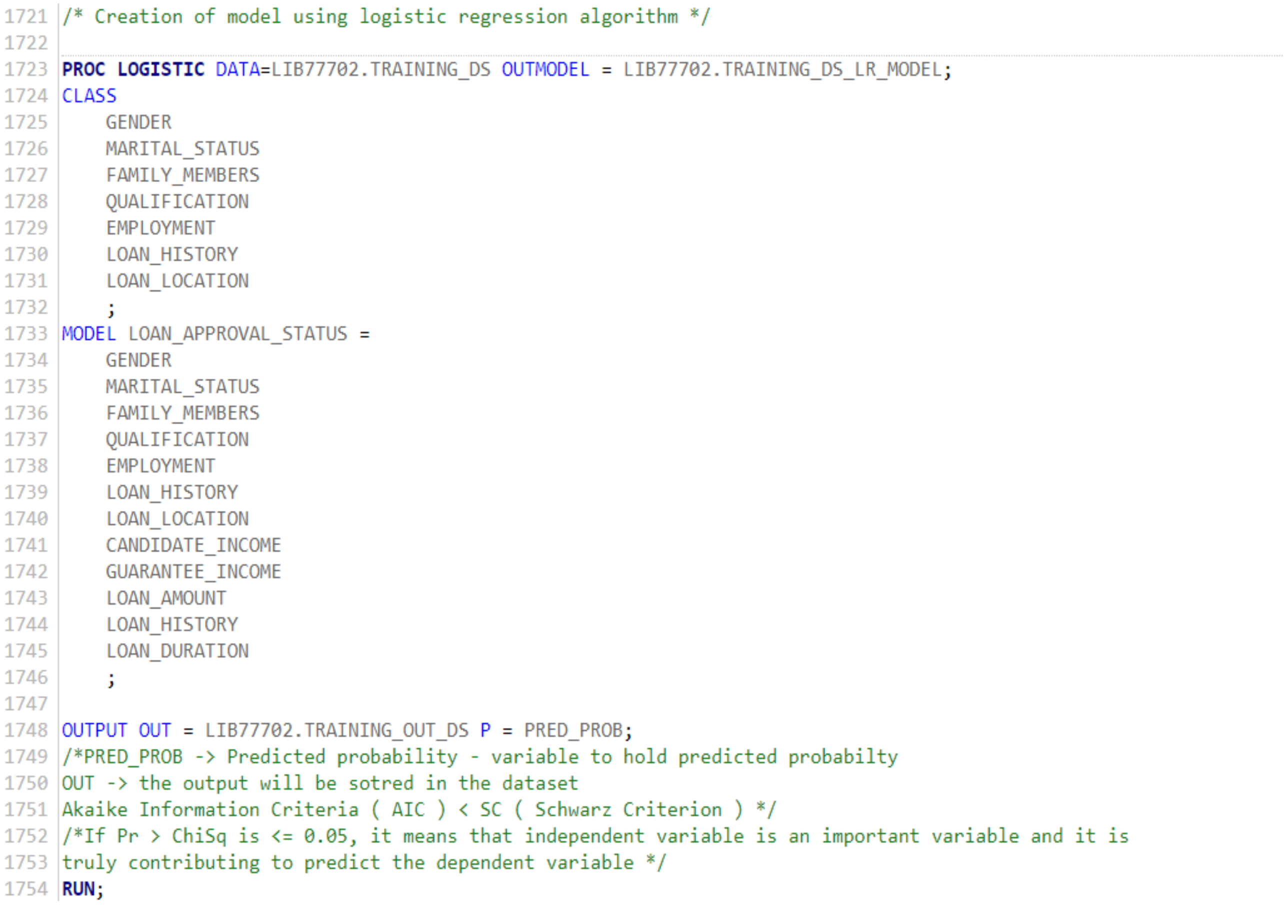
8.4.2.5.3 Description

The above output shows that the missing values are absent after the imputation, indicating that the imputation was successfully implemented.

9 Logistic Regression

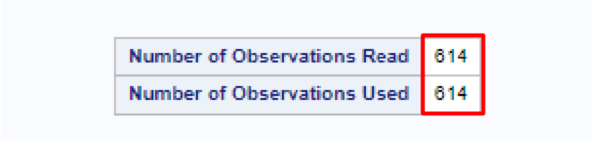
9.1 Creation of the Model using Logistic Regression Algorithm

9.1.1.1 Code Snippet



```
/* Creation of model using logistic regression algorithm */

PROC LOGISTIC DATA=LIB77702.TRAINING_DS OUTMODEL = LIB77702.TRAINING_DS_LR_MODEL;
CLASS
    GENDER
    MARITAL_STATUS
    FAMILY_MEMBERS
    QUALIFICATION
    EMPLOYMENT
    LOAN_HISTORY
    LOAN_LOCATION
    ;
MODEL LOAN_APPROVAL_STATUS =
    GENDER
    MARITAL_STATUS
    FAMILY_MEMBERS
    QUALIFICATION
    EMPLOYMENT
    LOAN_HISTORY
    LOAN_LOCATION
    CANDIDATE_INCOME
    GUARANTEE_INCOME
    LOAN_AMOUNT
    LOAN_HISTORY
    LOAN_DURATION
    ;

OUTPUT OUT = LIB77702.TRAINING_OUT_DS P = PRED_PROB;
/*PRED_PROB -> Predicted probability - variable to hold predicted probabilty
OUT -> the output will be sotred in the dataset
Akaike Information Criteria ( AIC ) < SC ( Schwarz Criterion ) */
/*If Pr > ChiSq is <= 0.05, it means that independent variable is an important variable and it is
truly contributing to predict the dependent variable */
RUN;
```

9.1.1.2 Output

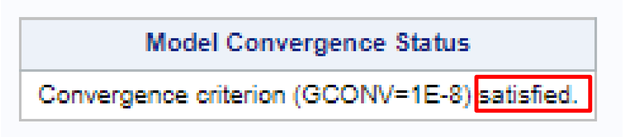


Number of Observations Read	614
Number of Observations Used	614

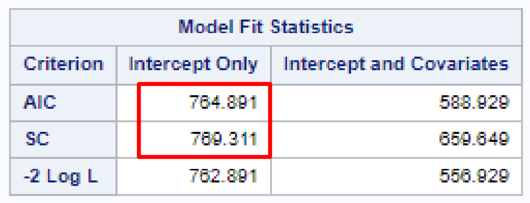
9.1.1.3 Description

The training dataset is well imputed and contains no missing data, as evidenced by the matched number of observations utilised and read (614 observations total). Additionally, 422 applications were expected to be accepted and 192 to be rejected.

9.1.1.4 Output



Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

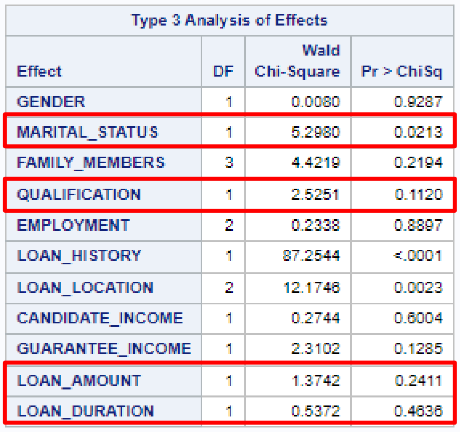


Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	784.891	588.929
SC	789.311	659.649
-2 Log L	782.891	556.929

9.1.1.5 Description

The model convergence status indicates that the convergence criterion is satisfied. Comparing model fit statistics, the AIC and SC values decrease significantly from 784.891 and 789.311 (intercept only) to 558.929 and 659.646 (with covariates), suggesting a better fit with the covariates.

9.1.1.6 Output



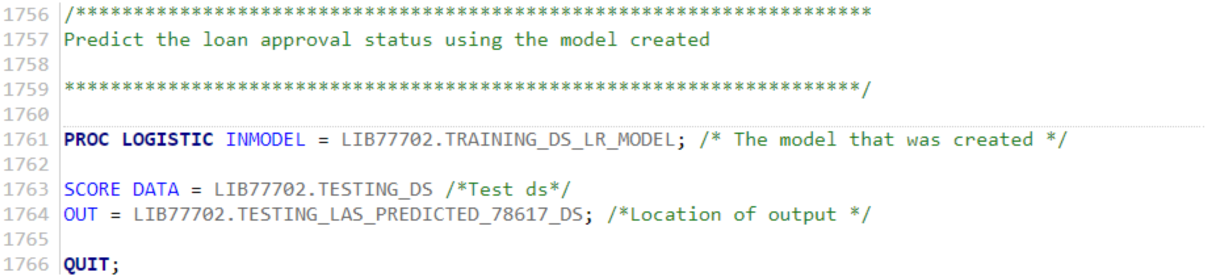
Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
GENDER	1	0.0080	0.9287
MARITAL_STATUS	1	5.2980	0.0213
FAMILY_MEMBERS	3	4.4219	0.2194
QUALIFICATION	1	2.5251	0.1120
EMPLOYMENT	2	0.2338	0.8897
LOAN_HISTORY	1	87.2544	<.0001
LOAN_LOCATION	2	12.1746	0.0023
CANDIDATE_INCOME	1	0.2744	0.6004
GUARANTEE_INCOME	1	2.3102	0.1285
LOAN_AMOUNT	1	1.3742	0.2411
LOAN_DURATION	1	0.5372	0.4636

9.1.1.7 Description

When Pr > ChiSq is less than 0.05, it indicates that the independent variable plays a significant role in the prediction of the dependent variable. In this instance, the prediction depends on LOAN_LOCATION, MARITAL_STATUS, and LOAN_HISTORY.

9.2 Predicting the Loan Approval Status Using Logistic Regression

9.2.1.1 Code Snippet



```
/************************************************************************
Predict the loan approval status using the model created

***********************************************************************/

PROC LOGISTIC INMODEL = LIB77702.TRAINING_DS_LR_MODEL; /* The model that was created */

SCORE DATA = LIB77702.TESTING_DS /*Test ds*/
OUT = LIB77702.TESTING_LAS_PREDICTED_78617_DS; /*Location of output */

QUIT;
```

9.2.1.2 SAS Output

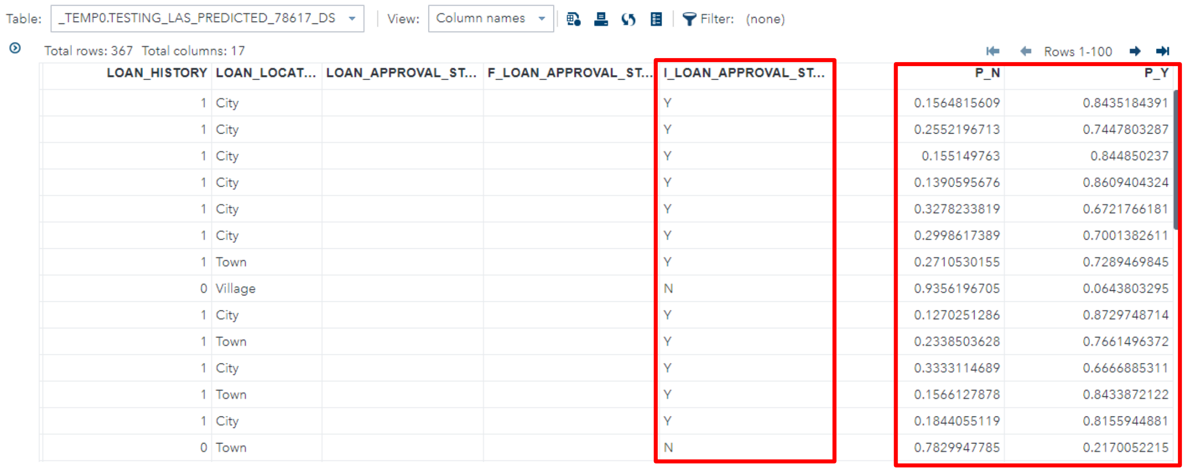


Table: _TEMP0.TESTING_LAS_PREDICTED_78617_DS View: Column names Filter: (none)

Total rows: 367 Total columns: 17 Rows 1-100

LOAN_HISTORY	LOAN_LOCAT...	LOAN_APPROVAL_ST...	F_LOAN_APPROVAL_ST...	I_LOAN_APPROVAL_ST...		P_N	P_Y
1	City			Y		0.1564815609	0.8435184391
1	City			Y		0.2552196713	0.7447803287
1	City			Y		0.155149763	0.844850237
1	City			Y		0.1390595676	0.8609404324
1	City			Y		0.3278233819	0.6721766181
1	City			Y		0.2998617389	0.7001382611
1	Town			Y		0.2710530155	0.7289469845
0	Village			N		0.9356196705	0.0643803295
1	City			Y		0.1270251286	0.8729748714
1	Town			Y		0.2338503628	0.7661496372
1	City			Y		0.3333114689	0.6666885311
1	Town			Y		0.1566127878	0.8433872122
1	City			Y		0.1844055119	0.8155944881
0	Town			N		0.7829947785	0.2170052215

9.2.1.3 Description

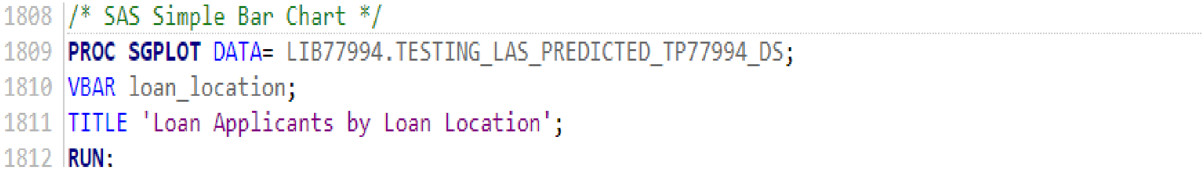
The models predict whether the status is accepted (Y) or not approved (N) based on the P_N and P_Y, as seen in the output above. Predicted is what the letter P stands for. In the event that the P_Y exceeds the P_N, the loan approval status will be Y (approved), or vice versa.

10 Data Visualization and Report Generation

10.1 Data Visualization

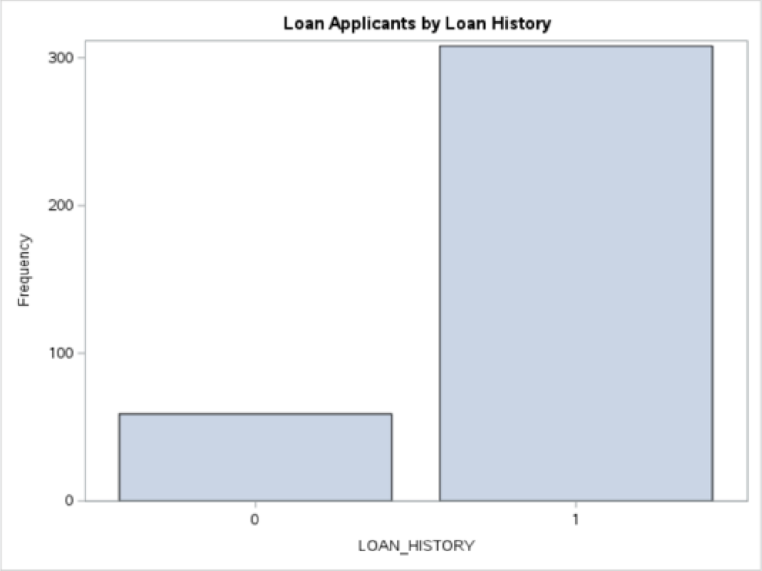
10.1.1 Simple Bar Chart

10.1.1.1 Code Snippet



```
/* SAS Simple Bar Chart */
PROC SGPLOT DATA= LIB77994.TESTING_LAS_PREDICTED_TP77994_DS;
VBAR loan_location;
TITLE 'Loan Applicants by Loan Location';
RUN:
```

10.1.1.2 Output

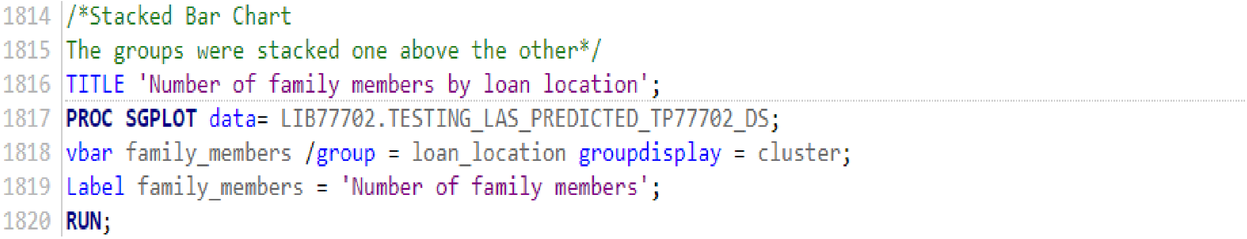


10.1.1.3 Description

The output above is a simple bar chart that displays the loan history from the dataset. It can be seen from the bar chart that the majority of applicants had already taken out a loan before reapplying.

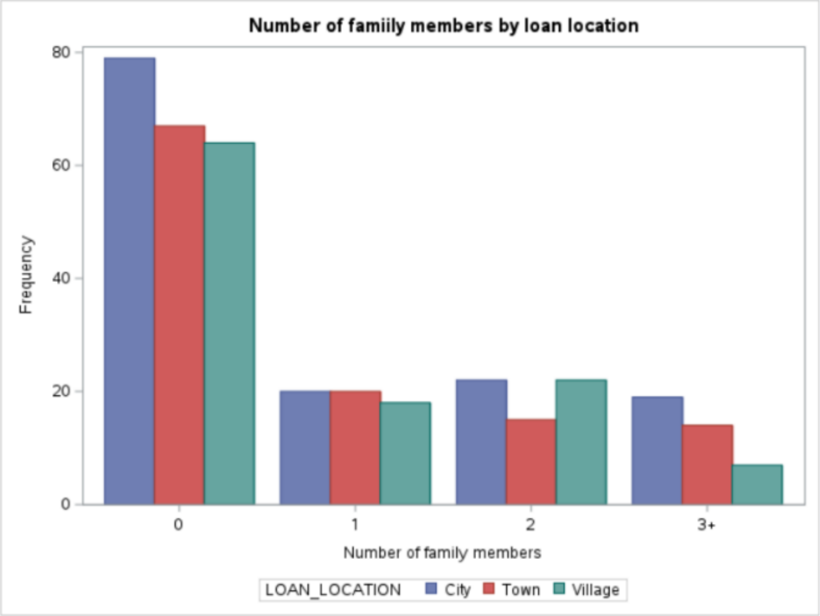
10.1.2 Stacked Bar Chart

10.1.2.1 Code Snippet



```
/*Stacked Bar Chart
The groups were stacked one above the other*/
TITLE 'Number of family members by loan location';
PROC SGPLOT data= LIB77702.TESTING_LAS_PREDICTED_TP77702_DS;
vbar family_members /group = loan_location groupdisplay = cluster;
Label family_members = 'Number of family members';
RUN;
```

10.1.2.2 Output

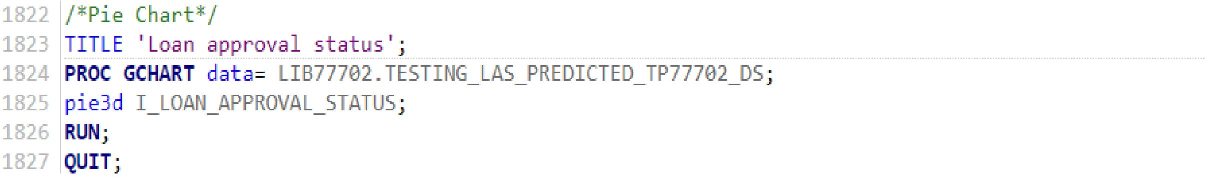


10.1.2.3 Description

The output shown above is a stacked bar chart from the dataset that shows the number of family members by loan location. According to the stacked bar chart, the majority of applicants from cities, towns, and villages are alone.

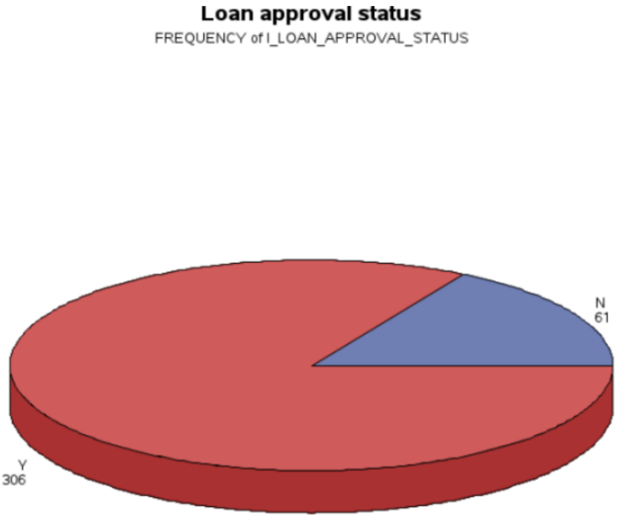
10.1.3 Pie chart

10.1.3.1 Code Snippet



```
/*Pie Chart*/
TITLE 'Loan approval status';
PROC GCHART data= LIB77702.TESTING_LAS_PREDICTED_TP77702_DS;
pie3d I_LOAN_APPROVAL_STATUS;
RUN;
QUIT;
```

10.1.3.2 Output

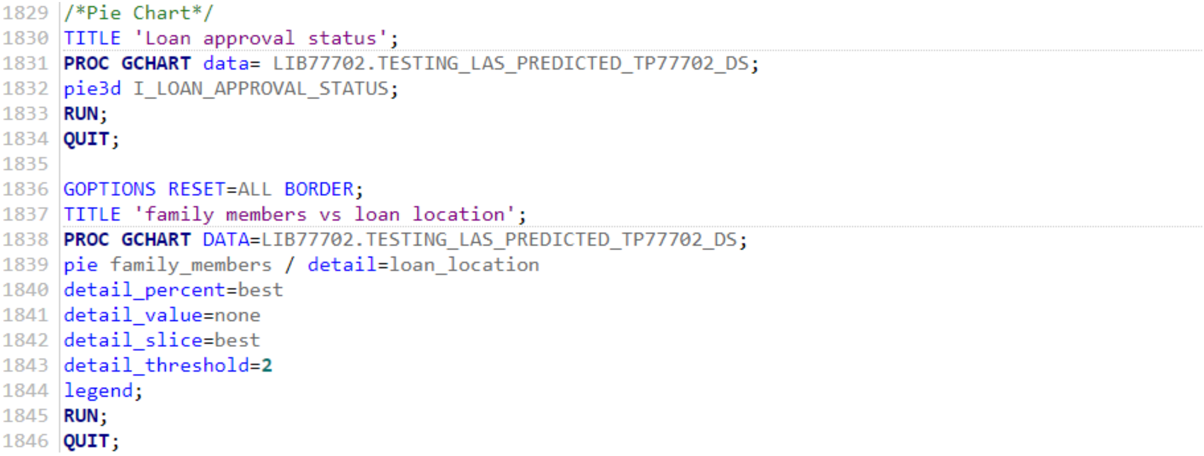


10.1.3.3 Description

A pie chart representing the loan approval status in the dataset is shown in the output above. As can be seen from the pie chart, 356 of the total loans that were reviewed were approved, or yes, while 61 of the loans were not approved, or no.

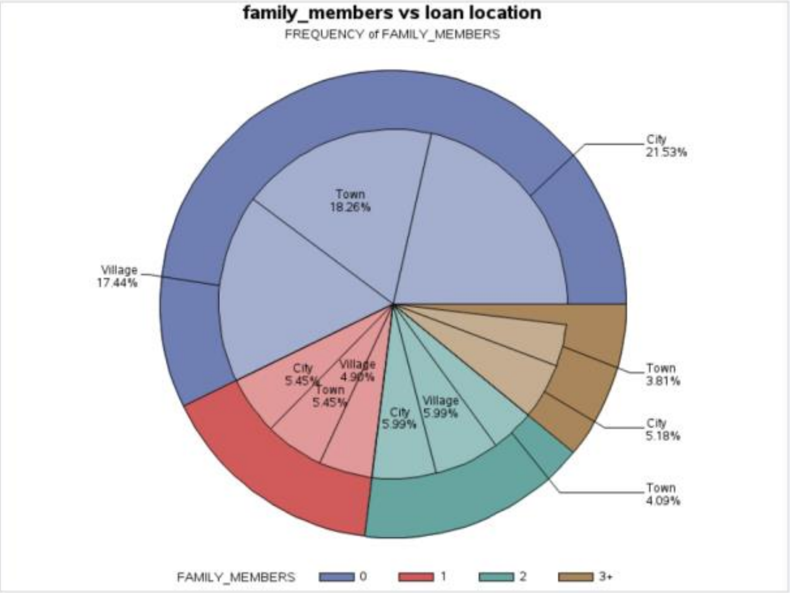
10.1.4 Stacked Pie Chart

10.1.4.1 Code Snippet



```
/*Pie Chart*/
TITLE 'Loan approval status';
PROC GCHART data= LIB77702.TESTING_LAS_PREDICTED_TP77702_DS;
pie3d I_LOAN_APPROVAL_STATUS;
RUN;
QUIT;

GOPTIONS RESET=ALL BORDER;
TITLE 'family members vs loan location';
PROC GCHART DATA=LIB77702.TESTING_LAS_PREDICTED_TP77702_DS;
pie family_members / detail=loan_location
detail_percent=best
detail_value=none
detail_slice=best
detail_threshold=2
legend;
RUN;
QUIT;
```

10.1.4.2 Output



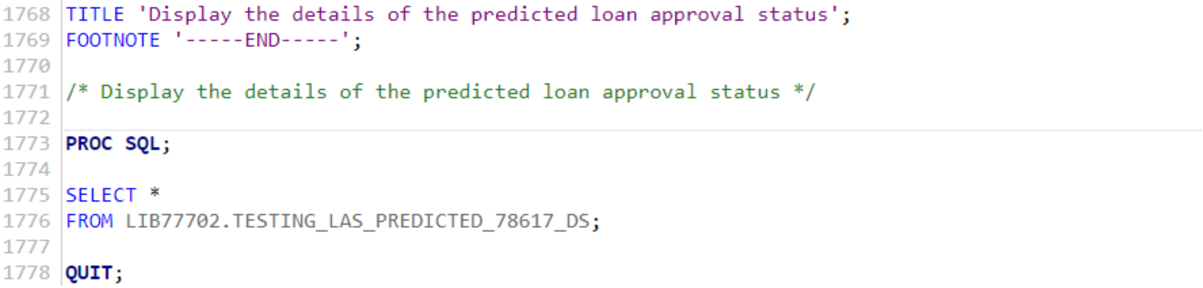
10.1.4.3 *Description*

Another pie chart that shows how family members are distributed among loan sites is produced using the above output. Whereas towns and villages are home to a variety of family sizes, the majority of loan applicants from cities are alone.

10.2 Report Generation using SAS ODS

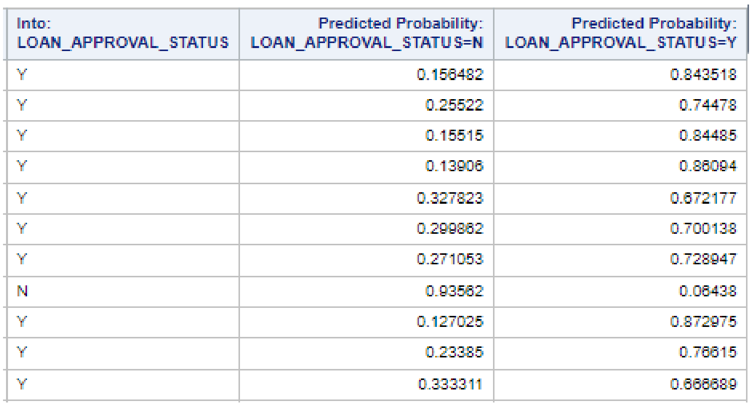
10.2.1 Display Details of Predicted Loan Approvals Status

10.2.1.1 Code Snippet



```
TITLE 'Display the details of the predicted loan approval status';
FOOTNOTE '-----END-----';

/* Display the details of the predicted loan approval status */

PROC SQL;

SELECT *
FROM LIB77702.TESTING_LAS_PREDICTED_78617_DS;

QUIT;
```

10.2.1.2 Output



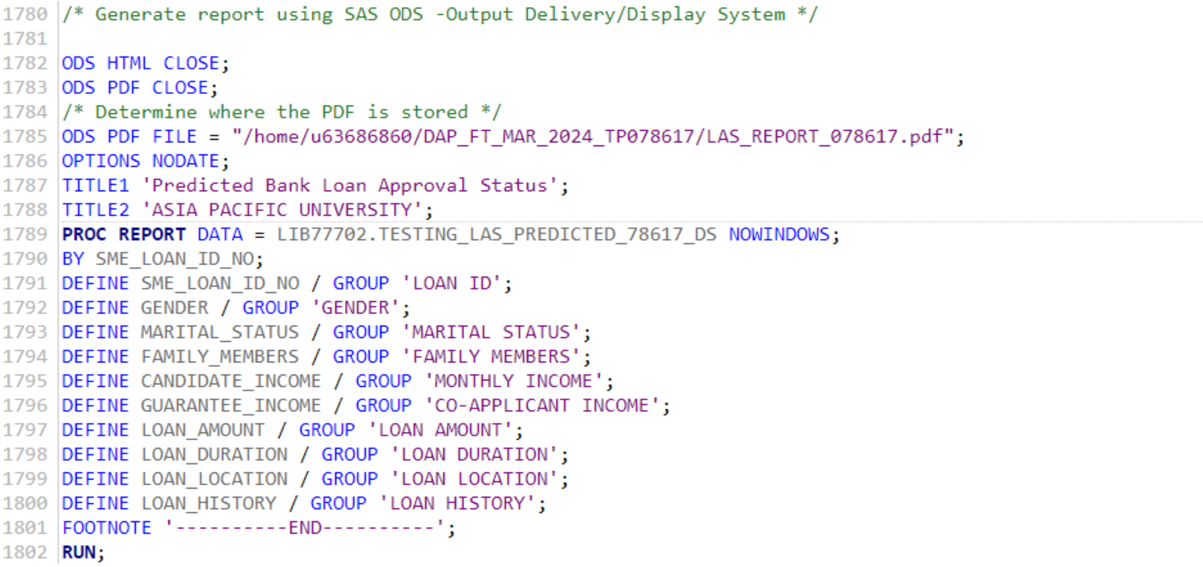
Into: LOAN_APPROVAL_STATUS	Predicted Probability: LOAN_APPROVAL_STATUS=N	Predicted Probability: LOAN_APPROVAL_STATUS=Y
Y	0.156482	0.843518
Y	0.25522	0.74478
Y	0.15515	0.84485
Y	0.13906	0.86094
Y	0.327823	0.672177
Y	0.299862	0.700138
Y	0.271053	0.728947
N	0.93562	0.06438
Y	0.127025	0.872975
Y	0.23385	0.76615
Y	0.333311	0.666689

10.2.1.3 Description

The above output shows the details about the predicted probability of loan approval status of approved and not approved loans.

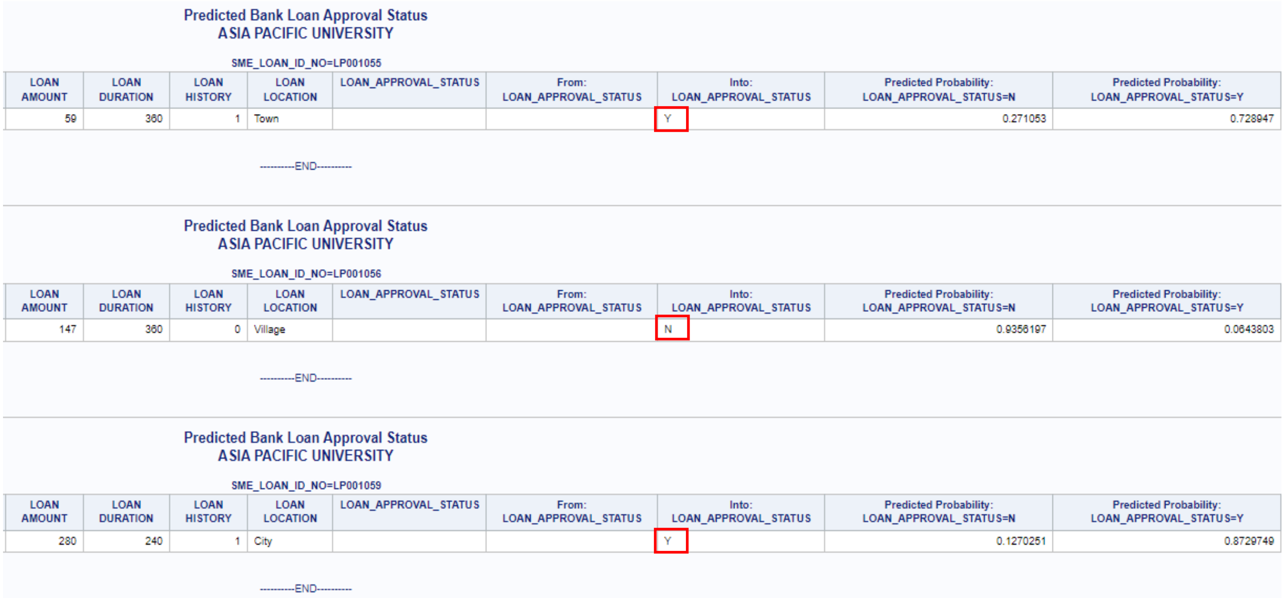
10.2.2 Generated Report from SAS ODS

10.2.2.1 Code Snippet



```
/* Generate report using SAS ODS -Output Delivery/Display System */

ODS HTML CLOSE;
ODS PDF CLOSE;
/* Determine where the PDF is stored */
ODS PDF FILE = "/home/u63686860/DAP_FT_MAR_2024_TP078617/LAS_REPORT_078617.pdf";
OPTIONS NODATE;
TITLE1 'Predicted Bank Loan Approval Status';
TITLE2 'ASIA PACIFIC UNIVERSITY';
PROC REPORT DATA = LIB77702.TESTING_LAS_PREDICTED_78617_DS NOWINDOWS;
BY SME_LOAN_ID_NO;
DEFINE SME_LOAN_ID_NO / GROUP 'LOAN ID';
DEFINE GENDER / GROUP 'GENDER';
DEFINE MARITAL_STATUS / GROUP 'MARITAL STATUS';
DEFINE FAMILY_MEMBERS / GROUP 'FAMILY MEMBERS';
DEFINE CANDIDATE_INCOME / GROUP 'MONTHLY INCOME';
DEFINE GUARANTEE_INCOME / GROUP 'CO-APPLICANT INCOME';
DEFINE LOAN_AMOUNT / GROUP 'LOAN AMOUNT';
DEFINE LOAN_DURATION / GROUP 'LOAN DURATION';
DEFINE LOAN_LOCATION / GROUP 'LOAN LOCATION';
DEFINE LOAN_HISTORY / GROUP 'LOAN HISTORY';
FOOTNOTE '----------END----------';
RUN;
```

10.2.2.2 Output



Predicted Bank Loan Approval Status
ASIA PACIFIC UNIVERSITY

SME_LOAN_ID_NO=LP001055

LOAN AMOUNT	LOAN DURATION	LOAN HISTORY	LOAN LOCATION	LOAN_APPROVAL_STATUS	From: LOAN_APPROVAL_STATUS	Into: LOAN_APPROVAL_STATUS	Predicted Probability: LOAN_APPROVAL_STATUS=N	Predicted Probability: LOAN_APPROVAL_STATUS=Y
59	360	1	Town			Y	0.271053	0.728947

----------END----------

Predicted Bank Loan Approval Status
ASIA PACIFIC UNIVERSITY

SME_LOAN_ID_NO=LP001056

LOAN AMOUNT	LOAN DURATION	LOAN HISTORY	LOAN LOCATION	LOAN_APPROVAL_STATUS	From: LOAN_APPROVAL_STATUS	Into: LOAN_APPROVAL_STATUS	Predicted Probability: LOAN_APPROVAL_STATUS=N	Predicted Probability: LOAN_APPROVAL_STATUS=Y
147	360	0	Village			N	0.9356197	0.0643803

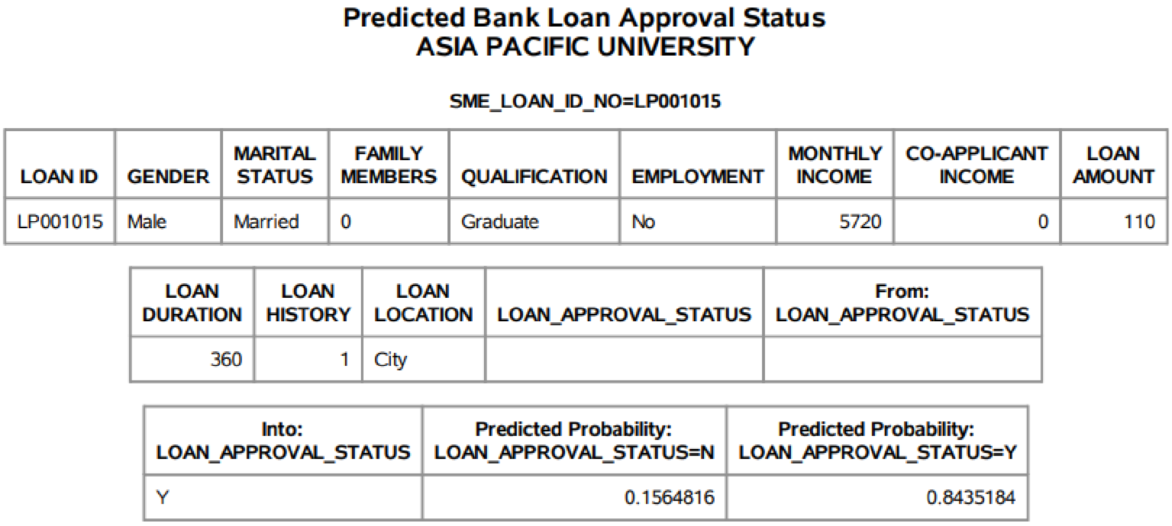
----------END----------

Predicted Bank Loan Approval Status
ASIA PACIFIC UNIVERSITY

SME_LOAN_ID_NO=LP001059

LOAN AMOUNT	LOAN DURATION	LOAN HISTORY	LOAN LOCATION	LOAN_APPROVAL_STATUS	From: LOAN_APPROVAL_STATUS	Into: LOAN_APPROVAL_STATUS	Predicted Probability: LOAN_APPROVAL_STATUS=N	Predicted Probability: LOAN_APPROVAL_STATUS=Y
280	240	1	City			Y	0.1270251	0.8729749

----------END----------



Predicted Bank Loan Approval Status
ASIA PACIFIC UNIVERSITY

SME_LOAN_ID_NO=LP001015

LOAN ID	GENDER	MARITAL STATUS	FAMILY MEMBERS	QUALIFICATION	EMPLOYMENT	MONTHLY INCOME	CO-APPLICANT INCOME	LOAN AMOUNT
LP001015	Male	Married	0	Graduate	No	5720	0	110

LOAN DURATION	LOAN HISTORY	LOAN LOCATION	LOAN_APPROVAL_STATUS	From: LOAN_APPROVAL_STATUS
360	1	City		

Into: LOAN_APPROVAL_STATUS	Predicted Probability: LOAN_APPROVAL_STATUS=N	Predicted Probability: LOAN_APPROVAL_STATUS=Y
Y	0.1564816	0.8435184

10.2.2.3 Description

Using PROC REPORT, the output produced a report that shows loan approval forecasts depending on several variables, including income, marital status, and gender. The result displays each loan case together with the expected chances of acceptance and rejection. Generated reports are need in order to evaluate the predictions made by the models, confirm the accuracy, and effectively convey the findings to decision-makers involved in loan approval procedures.

11 Conclusion

In conclusion, by exploring the loan approval process in Lasiandra Finance Inc., it is evident that there has been a huge step towards the use of AI and machine learning in financial services. In this research, we have learned that logistic regression can predict loans awarded and understood more the importance proper data management such as filling in missing values in ensuring trustworthy predictions. The study further states that advanced data analysis greatly increases accuracy and speed while at the same time reducing risks involved with financial transactions. Moreover, SAS Macro application has made it possible for us to handle larger sets of information easily without slowing down our processing power.

Integrating complex analytical tools and techniques into banking systems represents not just an upgrade but a survival strategy within today's fast-changing world of money matters. It is therefore not shocking that such a move will serve to improve operations at Lasiandra Finance Inc apart from acting as a yardstick for creativity in provision of money-related services as well.

12 References

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