# **Applied Analytic Modeling**

# **Group Project- Loan Set Model**

Model Assessment-SAS Miner

# Submitted to Prof. David Parent

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INTRODUCTION

The choice to approve a loan is crucial for both banks and borrowers. Efficient loan approval

procedures are essential for banks and other organizations to maintain profitability and lower the

chance of defaults. Loan approvals are necessary for borrowers to fulfill their financial objectives.

In this project, we make decisions about loan approval for clients using SAS. Our goal is to create

a model that can determine how likely a borrower is to repay a loan. The bank can now make

better-informed decisions as a result.

This model's successful use will greatly impact banks and borrowers alike. It will result in lower

loan default rates, higher loan acceptance rates, and better risk management techniques for banks.

It will make credit more accessible to borrowers and make it easier for them to realize their

financial goals.

We will use a strict research process in this capstone project that includes data collection, data

exploration, model construction, model evaluation, and model deployment. Our goal is to create a

reliable and broadly applicable model that can accurately forecast the results of loan approvals and

support the banking sector.

**OBJECTIVES** 

Creating a model: This will be used to forecast the approval or denial of a loan.

Boost approval rates: The model will make bank approval rates higher.

Cut down on loan defaults:

Customized loan selections: Make personalized loan decisions by applying the predictive model

to inform your decision-making and accounting for the distinct features and financial profiles of

each application.

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#### **EXPLORATORY ANALYSIS**

#### **METHODOLOGY**

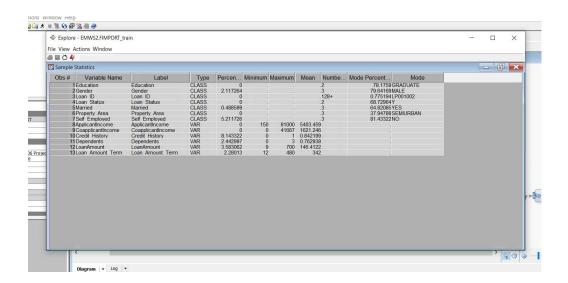
Reviewing the data, we can confirm that there is no bad data. The data seem to be within the normal range and analysis can be done on it.

We used the Loan Prediction Dataset in our machine learning project to create a predictive model that will automate and improve the loan approval procedure. This dataset provides a comprehensive perspective of the attributes of loan applicants by encapsulating important information about them.

Let us examine the salient characteristics.

- 1. Loan ID: An exclusive number assigned to every loan application that makes thorough monitoring and referencing easier.
- 2. Gender: Gain insight into the applicant's gender and identify any possible relationships with loan acceptance.
- 3. Married: A signal indicating marital status, which is frequently taken into consideration when determining whether to approve a loan.
- 4. Dependents: Unveiling the number of dependents associated with an applicant, revealing insight into familial duties.
- 5. Education: A summary of the applicant's educational background that distinguishes between graduates and non-graduates.
- 6. Self-Employed: Indicates in binary terms if the applicant works for themselves, providing information about their professional standing.
- 7. Applicant Income: A numerical depiction of the applicant's overall income, which is a crucial component in determining their financial capability.
- 8. Co-applicant Income: This feature tracks any co-applicant income like the applicant's income.
- 9. Loan Amount: The applicant's requested financial amount, which is a deciding factor in the loan

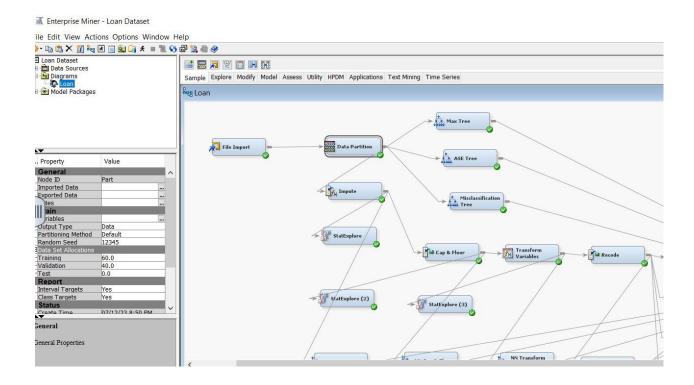
approval process.



The data we used are within acceptable parameters.

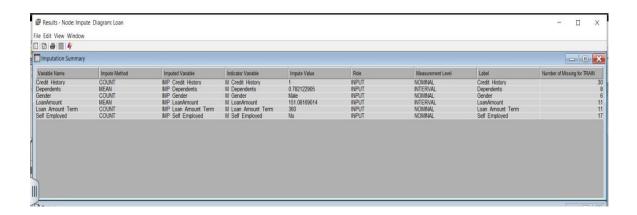
# **DATA PARTITION**

The data was split into 60% training and 40% validation. This ensures that there is more data to train our model on.



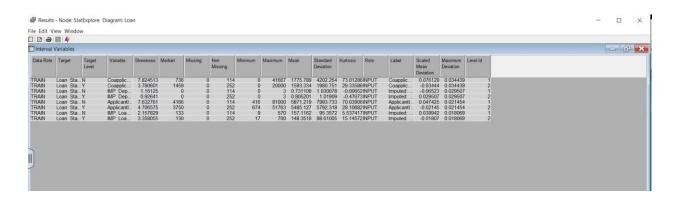
#### **DATA IMPUTATION**

In our commitment to making well-informed loan decisions, we recognize that missing data can compromise the accuracy of our analysis. To address this, we employ a sophisticated technique known as imputation, which utilizes statistical methods to estimate and fill in any gaps in the data. This ensures that we have a more complete and precise understanding of each borrower's financial profile. By enhancing the quality of our data, we can make more equitable and informed decisions regarding loan approvals.



#### SKEWNESS THRESHOLD OF 1

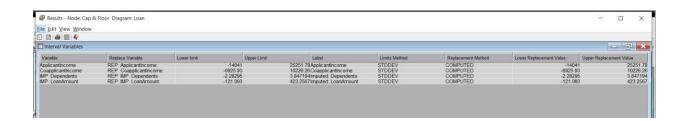
Loan companies rely heavily on data analysis, but biased data can lead to unfair decisions. Describes identifying such bias, where information leans towards an extreme (e.g., mostly high incomes). This skews the model and could disadvantage some borrowers. Cleaning the data, such as skewness techniques helps ensure a fairer assessment, ultimately influencing whether a loan is granted.

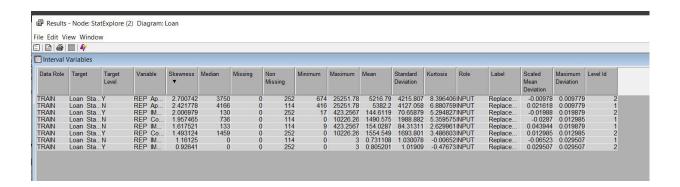


#### **OUTLIERS AND EXTREME VALUES**

Our initial data exploration revealed a potential bias in the loan application data set. The values skewed towards one extreme, which could lead to inaccurate assessments and unfair lending

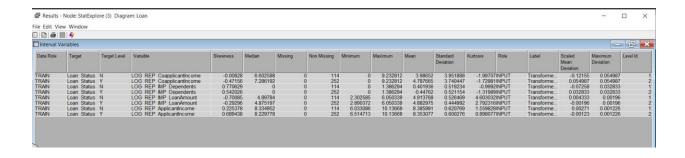
practices. To address this, we're implementing 'Cap & Floor' techniques to establish reasonable limits on the data points. While this is a positive step, further data cleaning procedures may be necessary to guarantee a fully unbiased and reliable data set for informed loan approval decisions.





#### **DATA TRANSFORM**

We identified a bias in the loan application data, where certain variables were skewed towards one extreme. To mitigate this and ensure a more balanced representation, we're employing a mathematical transformation technique on key variables like income and loan amount. This process effectively evens out the data distribution, creating a more accurate picture of each applicant's financial profile. By using unbiased and reliable data, we can make confident and responsible loan approval decisions.



#### **DATA SIMPLIFICATION**

Data efficiency is paramount in loan analysis. "RECODE" tackles this by consolidating a multitude of specific loan terms into just two major categories. This strategic grouping, achieved with specialized tools, simplifies analysis without sacrificing valuable insights. By streamlining data categorization, we gain a clearer view of repayment trends across different loan types. This empowers us to make informed decisions regarding future loan offerings and optimize our overall loan approval criteria.

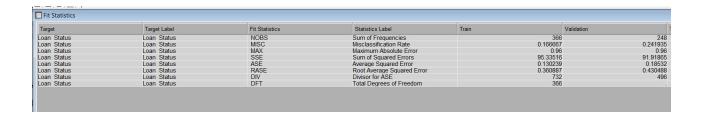
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Variable	Formatted Value	Value	Frequency Count	Туре	Value	Numeric Value	
ducation	Graduate		283 C		Graduate		^
ducation	Not Graduate		83 C		Not Graduate		
ducation	_UNKNOWN_	_DEFAULT_	. С				
MP_Credit_History	1		309N			1	
MP_Credit_History	0		57N			0	
MP_Credit_History	_UNKNOWN_	_DEFAULT_	. N				
MP_Gender	Male		303C		Male		
MP_Gender	Female		63 C		Female		
MP_Gender	_UNKNOWN_	_DEFAULT_	. с				
MP_Loan_Amount_Term	360	360	317N			360	
MP_Loan_Amount_Term	180	999	28 N			180	
MP_Loan_Amount_Term	480	999	6N			480	
MP_Loan_Amount_Term	300	999	5N			300	
MP_Loan_Amount_Term	84	999	3N			84	
MP_Loan_Amount_Term	120	999	2 N			120	
MP_Loan_Amount_Term	240	999	2 N			240	
MP_Loan_Amount_Term	12	999	1N			12	
MP_Loan_Amount_Term	36	999	1N			36	
MP_Loan_Amount_Term	60	999	1N			60	
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MP_Self_Employed	Yes		50 C		Yes		
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#### **ANALYSIS**

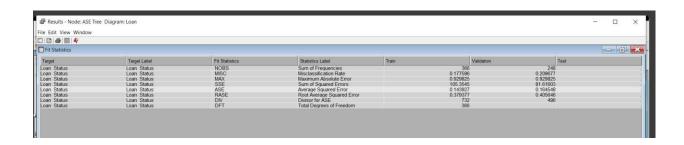
#### TREE ANALYSIS

Our tree analysis identified credit history as the key driver for model performance, with both the ASE and misclassification trees achieving a strong score of 0.164458. These models outperformed the maximal tree (score: 0.18532) which, while comprehensive, might be overfitting the data (i.e. using more variables). This analysis highlights the optimal balance achieved between model complexity and efficiency.

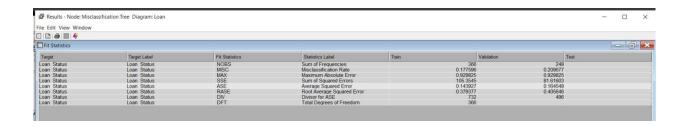
#### **MAX TREE**



#### **ASE TREE**

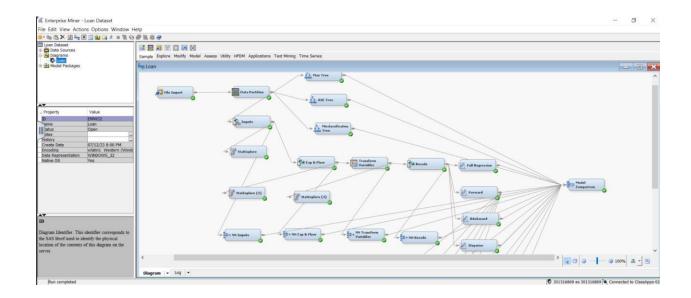


# MISCLASSIFICATION TREE



#### **REGRESSION ANALYSIS**

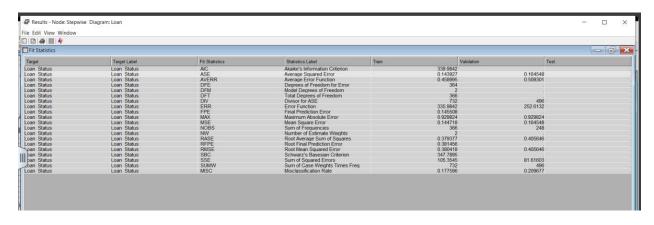
Our logistic regression analysis explored various approaches to identify the most impactful factors influencing the model. We compared the full regression model to forward selection, backward elimination, and stepwise regression. All models achieved strong performance, with scores ranging from 0.164548 to 0.172466. Notably, the forward selection and stepwise regression yielded identical average squared error (ASE) scores of 0.164548, suggesting a streamlined model can achieve comparable effectiveness. This analysis helps us optimize model complexity while maintaining robust performance.



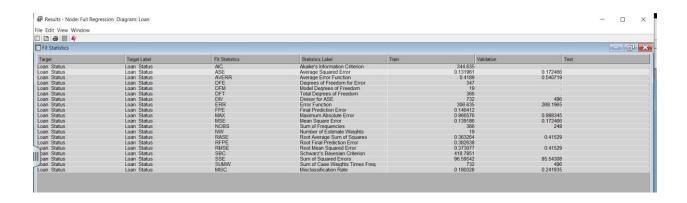
# FORWARD REGRESSION



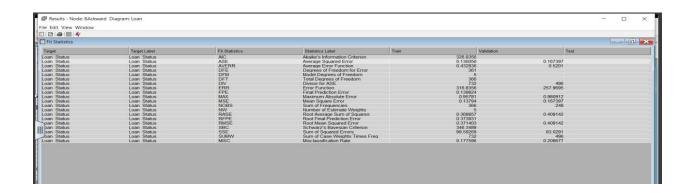
# STEPWISE REGRESSION



# **FULL REGRESSION**

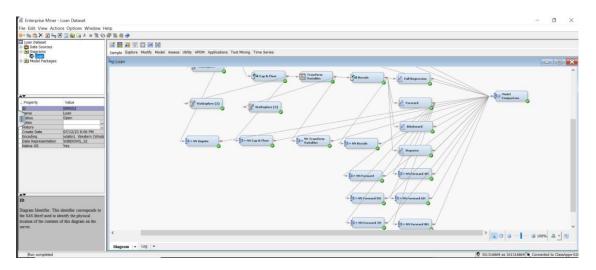


# **BACKWARD REGRESSION**



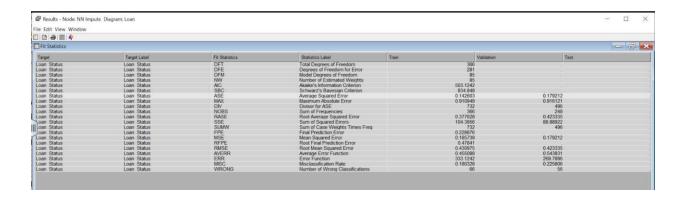
# **NEURAL NETWORKS**

Neural network models were run on the various stages of data cleanup to enable us to verify the best model. The neural network model was run on the impute, Cap and floor, transform, and recode nodes with the image shown below:



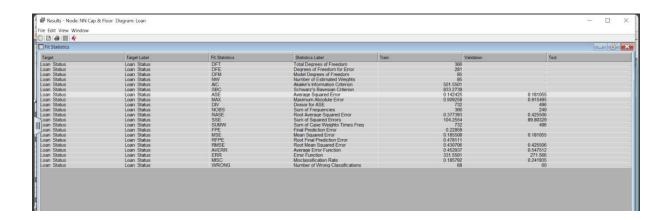
# NEURAL NETWORK IMPUTE (NN IMPUTE)

This was connected to the impute node and we have an ASE score of 0.179212.



# NEURAL NETWORK CAPAND FLOOR (NN CAPAND FLOOR)

This was connected to the cap and floor node, and we have an ASE score of 0.181055.



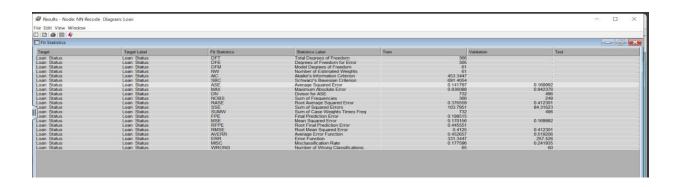
# NEURAL NETWORK NN TRANSFORM

This was connected to the transform node, and we have an ASE score of 0.179294.



# NEURAL NETWORK NN RECODE

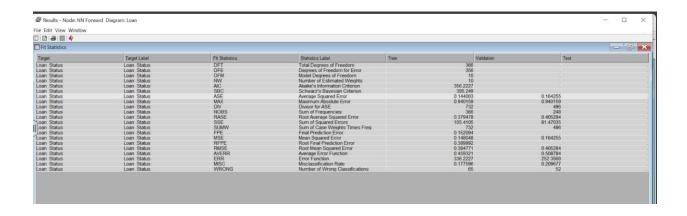
This was connected to the transform node, and we have an ASE score of 0.169992.



# NEURAL NETWORK FORWARD (NN FORWARD)

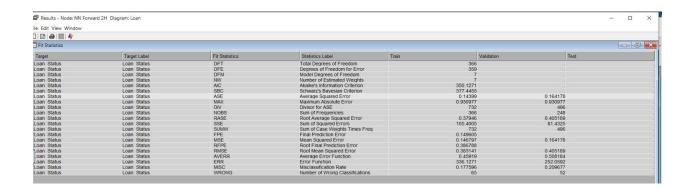
The neural network model was connected to the forward regression model. This gives an ASE score of 0.164255.

We do further analysis with the best model with ASE score by changing the hidden variables. This model has 3 hidden variables.



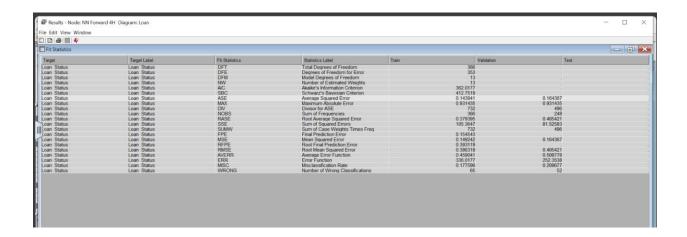
#### **NEURAL NETWORK NN FORWARD 2H**

The neural network model was connected to the forward regression model. This model has the number of hidden variables changed to two (2). The ASE score is 0.164178.



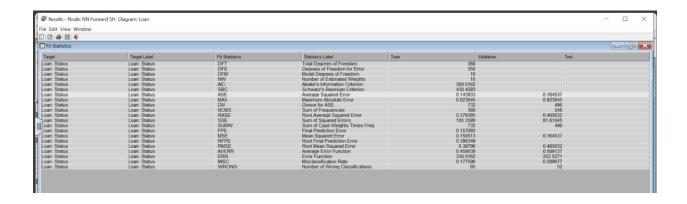
# **NEURAL NETWORK NN FORWARD 4H**

The neural network model was connected to the forward regression model. This model has the number of hidden variables changed to four (4). The ASE score is 0.164367.



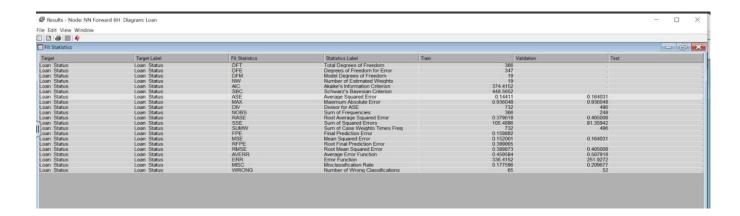
# **NEURAL NETWORK NN FORWARD 5H**

The neural network model was connected to the forward regression model. This model has the number of hidden variables changed to five (5). The ASE score is 0.164537.



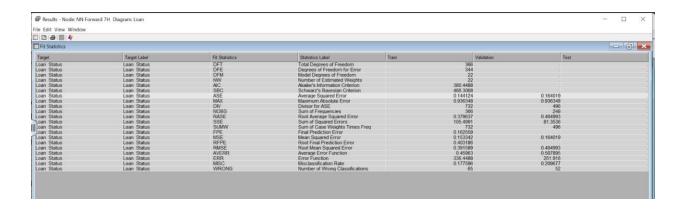
# **NEURAL NETWORK NN FORWARD 6H**

The neural network model was connected to the forward regression model. This model has the number of hidden variables changed to six (6). The ASE score is 0.164031.



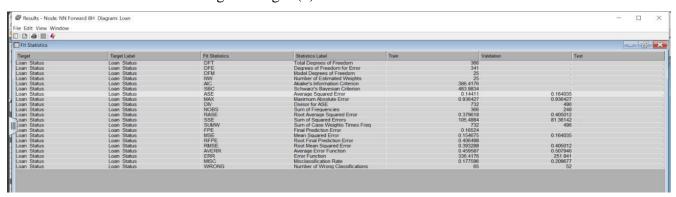
# NEURAL NETWORK FORWARD 7H (NN FORWARD 7H)

The neural network model was connected to the forward regression model. This model has the number of hidden variables changed to seven (7). The ase score is 0.164019.



# NEURAL NETWORK FORWARD 8H (NN FORWARD 8H)

The neural network model was connected to the forward regression model. This model has the number of hidden variables changed to eight (8). The score is 0.164035.



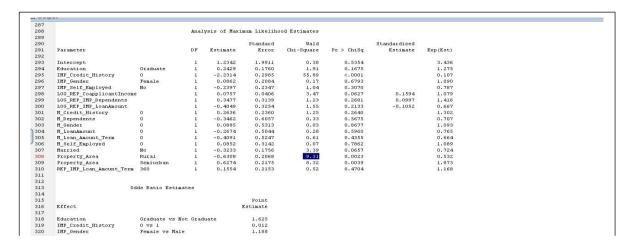
#### **ODDS RATIO**

Using Chi-Sq **IMP\_Credit\_History** and **Property\_Area** recorded the highest Chi-Sq value making them highly statistically significant to our Backward regression model.

- People with **no credit history** are 98.8% less likely to get credit loans when compared to people with **credit history**.
- Customers in **Rural areas** are 47% less likely to get credit loans when compared to people in

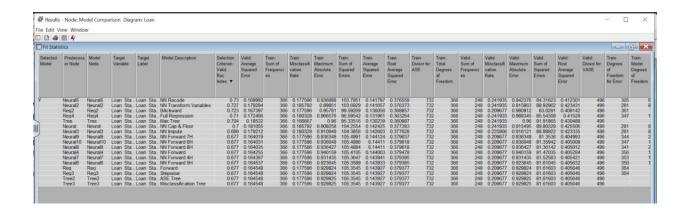
#### Urban area.

• Customers in **semiurban areas** are 86.6% more likely to get credit loans when compared to people in **Urban areas**.



311				
312				
313	0d	lds Ratio Estimates		
314				
315			Point	
316	Effect		Estimate	
317				
318	Education	Graduate vs Not Graduate	1.625	
319	IMP_Credit_History		0.012	
320	IMP_Gender	Female vs Male	1.188	
321	IMP_Self_Employed	No vs Yes	0.619	
322	LOG_REP_CoapplicantIncome		1.079	
323	LOG_REP_IMP_Dependents		1.416	
324	LOG_REP_IMP_LoanAmount		0.667	
325	M_Credit_History	0 vs 1	1.694	
326	M_Dependents	0 vs 1	0.500	
327	M_Gender	0 vs 1	1.194	
328	M_LoanAmount	0 vs 1	0.586	
329	M_Loan_Amount_Term	0 vs 1	0.441	
330	M_Self_Employed	0 vs 1	1.186	
331		No vs Yes	0.524	
332	Property_Area	Rural vs Urban	0.530	
333	Property_Area	Semiurban vs Urban	1.866	
334	REP IMP Loan Amount Term	360 vs 999	1.365	

# MODEL COMPARISON



The best model to predict payment is the neural network recode with the best ROC score of 0.73.

# **CONCLUSION**

- We performed exploratory data analysis on the dataset's features.
- The best model is Neural5 (NN Recode) with an ROC index of 0.73.
- Due to government regulation, we cannot use the best models (neural networks) because we cannot deduce or explain why the loan will be rejected. **Backward regression** is the

third-best model with an **ROC index of 0.723** will be used as this can be explained.

# RECOMMENDATIONS BASED ON THE ODDS RATION AND CHI-SQ

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313	0d	ds Ratio Estimates		
314				
315			Point	
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- Using Chi-Sq IMP\_Credit\_History and Property\_Area recorded the highest Chi-Sq value making them highly statistically significant to our Backward regression model.
- People with **no credit history** are 98.8% less likely to get credit loans when compared to people with **credit history**.
- Customers in **Rural areas** is 47% less likely to get credit loans when compared to people in

#### Urban area.

• Customers in semiurban areas are 86.6% more likely to get credit loans when compared to people in Urban areas.

Customers without a credit history and those who reside in rural areas should also be considered by the business in case they qualify for a credit loan.

This would facilitate the expansion of credit availability for qualified clients and help boost business interest in credit loans.

Also, we should try to check other factors that can lead to a lack of credit history especially in a country with so many immigrants. We can use other factors like work experience and salary to expand the pool of customers who can receive loans.