MARKETING ANALYTICS (MANM533)

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1. Data preparation and pre-processing

1.1 Introduction

1.1.1 Aim

This project aims to develop a predictive model determining the likelihood of a customer responding to an international bank's marketing campaign for promoting a fixed-term savings account.

1.1.2 Data

Dataset 1 consists of campaign contact details (contact type, contact duration) and the corresponding response outcome for each client, whereas Dataset 2 consists of personalized attributes of the customers (age, region, education, balance, etc). The combined dataset comprises 33909 data points, each containing 13 unique attributes.

1.2 Pre-processing

Table 1 – Univariate Statistics for Dataset 1

Univariate Statistics										
				Miss	sing	No. of Ex	tremes ^a			
	N	Mean	Std. Deviation	Count	Percent	Low	High			
custID	33909	22667.10	13040.886	0	.0	0	0			
duration	33909	257.61	256.435	0	.0	0	1568			
contact	33909			0	.0					
response	33909			0	.0					
a. Numbe	er of cases o	utside the ra	ange (Mean - 2*S	D, Mean + 2*	SD).					

All variables in the dataset are complete, with no missing entries. The 'duration' variable presents an average customer contact time of 257.61 seconds. With a substantial standard deviation of 256.435 for 'duration', it suggests there's a wide disparity in how long customers are in contact. Regarding 'duration', the data shows 1,568 instances that exceed the mean by more than double

the standard deviation, pointing to a considerable number of unusually lengthy customer contacts, while there are no notably short durations

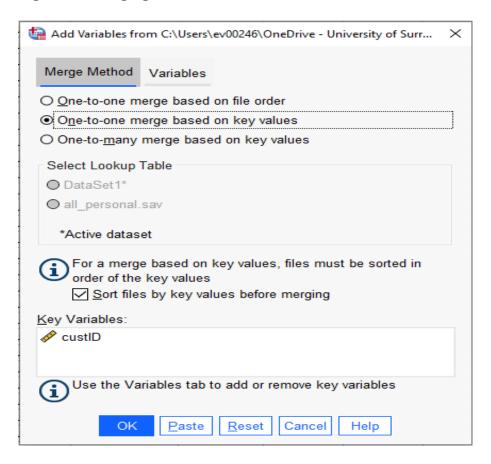
Table 2 - Univariate Statistics for Dataset 2

				Miss	sing	No. of Ext	remesª
	N	Mean	Std. Deviation	Count	Percent	Low	High
custID	33909	22667.10	13040.886	0	.0	0	0
age	33909	40.97	10.628	0	.0	32	720
balance	33909	1569.57	3420.725	0	.0	1	1159
region	33909			0	.0		
job	33909			0	.0		
marital	33909			0	.0		
education	33909			0	.0		
default	33909			0	.0		
housing	33909			0	.0		
Ioan	33909			0	.0		

In Dataset 2, each variable is complete without any missing entries. The 'balance' variable averages at 1,569.57 pounds, indicating the typical account balance for a customer within this data. The substantial standard deviation of 3,420.725 pounds for 'balance' points to a significant diversity in the account balances among customers. For the 'age' variable, there are 32 instances lower and 720 instances higher than the usual age range, based on the mean adjusted by two standard deviations. Similarly, for 'balance', the data shows one extremely low account balance and 1,159 unusually high balances, highlighting notable deviations from the average balance.

1.3 Merging the two datasets

Figure 1 – Merging Datasets



The two datasets 'all_campaign' and 'all_personal' were merged based on the common column 'custID' as shown above.

Figure 2 – Merged dataset

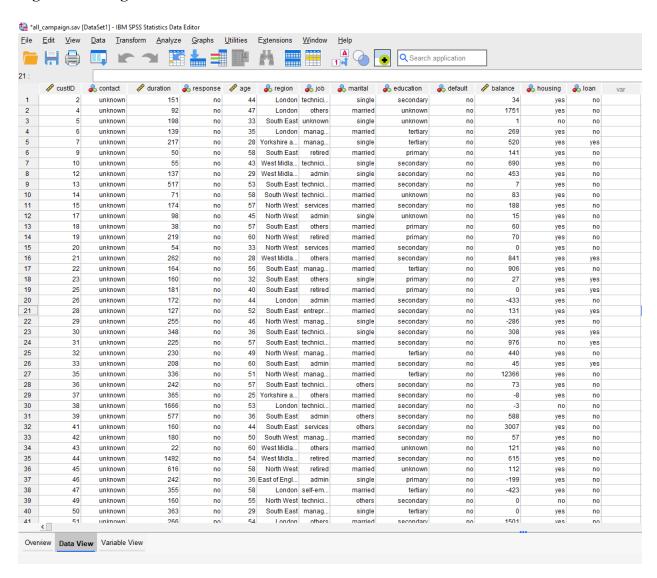


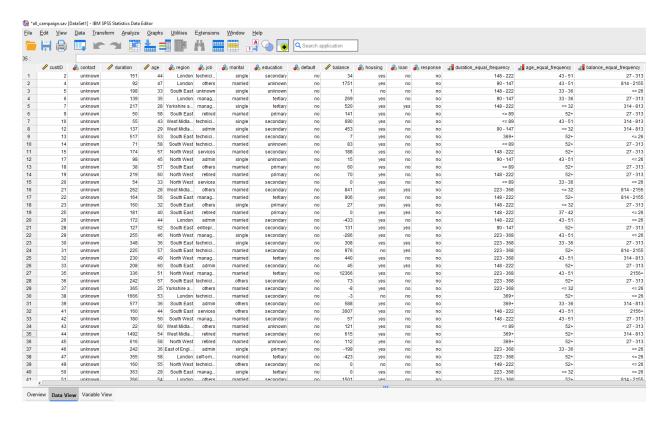
Figure 2 shows the final merged dataset.

1.4 Binning Numeric Variables [Approach 2 - Equal Frequency Binning]

Equal Frequency Binning

Equal frequency binning ensures that each bin has the same number of observations.

Figure 3 – Dataset after Equal Frequency Binning



Approach 2 - numeric variables 'duration', 'age', and 'balance' are binned based on the equal frequency binning method.

Binning details

Duration – [bins =
$$5$$
, width % = 20]

Age – [bins = 5, width
$$\% = 20$$
]

Balance – [bins = 5, width
$$\% = 20$$
]

Figure 4 – Distribution of duration after Equal Frequency Binning

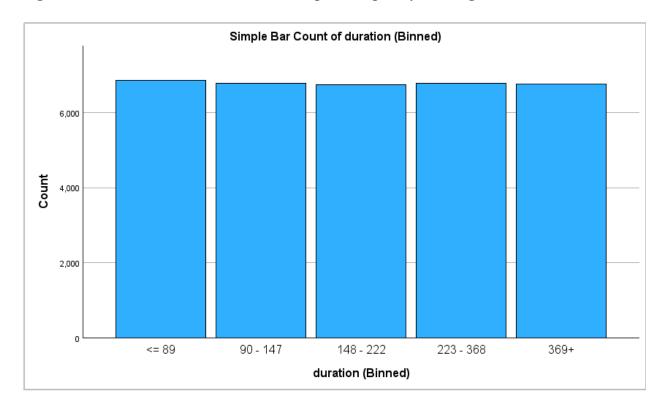


Figure 5 – Distribution of age after Equal Frequency Binning

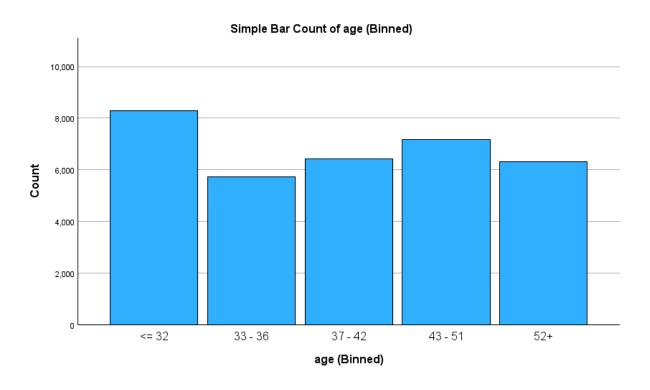
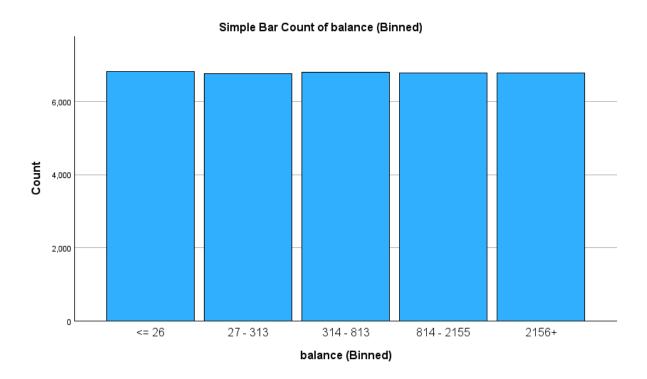


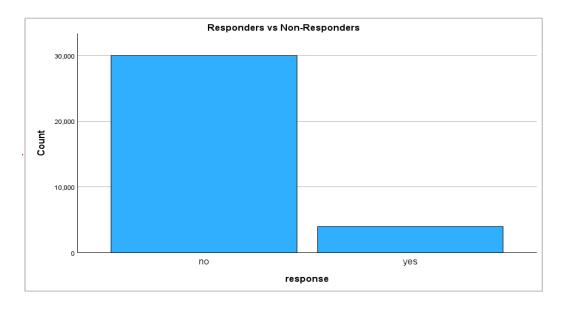
Figure 6 – Distribution of balance after Equal Frequency Binning



[Please refer to appendix section 5.1 to see the explanation for approach 1 – Equal interval Binning]

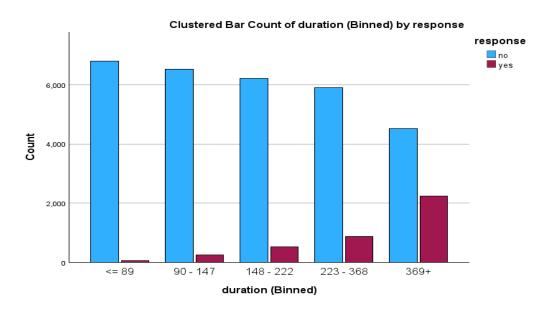
1.5 Exploratory data analysis

Figure 7 – Responders vs Non - Responders



From Figure 7, it is evident that a larger number of customers did not respond to the marketing campaign, as indicated by the "no" bar, which reaches close to the 30,000 mark. In contrast, the "yes" bar, representing the customers who responded positively to the campaign, is significantly lower, suggesting that the campaign had a comparatively low response rate.

Figure 8 – Customer contact duration vs customer response



For shorter contact durations (<= 89 seconds), there's a high number of contacts, but the response rate is very low, suggesting that very short calls are not very effective in generating a positive response. On the other hand, the longest calls (369+ seconds) have a much better chance of yielding a positive response.

Clustered Bar Count of default by response response

default

Figure 9 – Default Credit vs Response

Figure 9 shows that customers without a credit history are more likely to respond to the campaign compared to customers with a credit history.

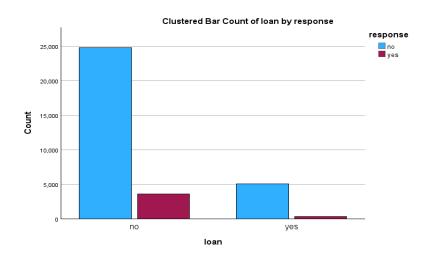
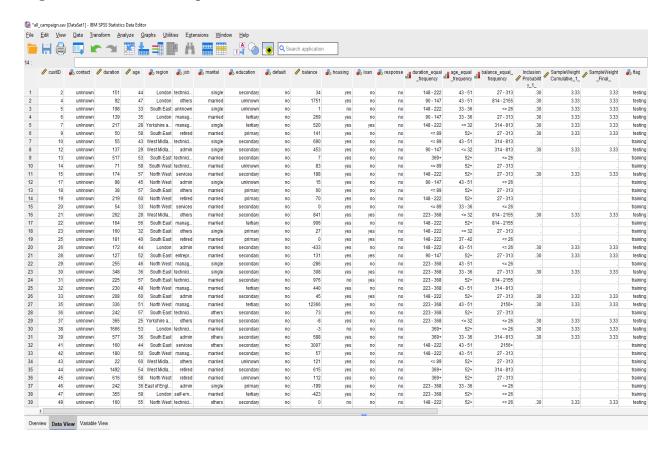


Figure 10 – Personal Loan vs Response

According to Figure 10, there is a higher likelihood of campaign response among consumers who do not possess a personal loan, as opposed to customers who do possess a personal loan.

1.6 Data Splitting

Figure 11 – Train - Test Split



The data is split into training and test sets (70% training and 30% testing) using a stratified sampling approach with a **seed value of 260**. The result of this step is we get 3 new variables and out of 3, the variable of interest is Inclusion probability. If Inclusion probability = 0.3, then it's test data, and If Inclusion probability =. (missing) then its training data. The inclusion probability values are then coded into a new variable named flag. The outcome of this step is we get a new variable flag with values "testing" and "training". Now, the 3 new unwanted columns are removed while the flag column is kept intact. Finally, the data is split into 2 files by putting all flag 1 records into the training dataset and all flag 0 records into the test dataset. Also, the training dataset has 23,736 observations and the test dataset has 10,173 observations respectively.

2. Build a Response Model

2.1 Logistic Regression Model 2 (final model)

Table 3 – Frequency table for the target variable (response)

res	ро	ns	е
-----	----	----	---

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	no	20959	88.3	88.3	88.3
	yes	2777	11.7	11.7	100.0
	Total	23736	100.0	100.0	

Table 3 indicates a response rate of 11.7% from customers to the campaign, demonstrating a relatively low level of engagement.

Table 4 – Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
duration	23736	0	3785	258.08	255.136
age	23736	18	93	40.98	10.587
balance	23736	-3852	94423	1558.56	3351.981
Valid N (listwise)	23736				

Table 4 presents descriptive statistics for three variables, duration, age, and balance across a dataset of 23,736 entries. The duration varies from 0 to 3,785 seconds with an average of about 258, suggesting a wide range of values with substantial variation, as indicated by the standard deviation of approximately 255. The age of participants ranges from 18 to 93 years, with the average age being around 41 years and relatively less variability (standard deviation of approximately 10.6). The balance has an extensive range from a deficit of -3,852£ to a positive balance of 94,423£, averaging at 1,558.56, but with a very high standard deviation of about 3,351.981, pointing to significant disparities in financial standing among the participants.

Table 5 – Categorical Variable Coding for Logistic Regression Model 2

		Catego	orical Varia	ables Cod	ings						
	Parameter coding										
		Frequency	(1)	(2)	(3)	(4)	(5)	(6)			
job_update	admin	2672	1.000	.000	.000	.000	.000	.000			
	management	4964	.000	1.000	.000	.000	.000	.000			
	retired	1170	.000	.000	1.000	.000	.000	.000			
	student	471	.000	.000	.000	1.000	.000	.000			
	technician	4027	.000	.000	.000	.000	1.000	.000			
	unemployed	689	.000	.000	.000	.000	.000	1.000			
	others	9743	.000	.000	.000	.000	.000	.000			
contact	mobile	15467	1.000	.000							
	telephone	1531	.000	1.000							
	unknown	6738	.000	.000							
marital	others	2708	1.000	.000							
	married	14330	.000	1.000							
	single	6698	.000	.000							
default	no	23333	1.000								
	yes	403	.000								
education_update	tertiary	6962	1.000								
	others	16774	.000								
Ioan	no	19918	1.000								
	yes	3818	.000								
housing	no	10506	1.000								
	yes	13230	.000								

Table 6 - Logistic Regression Model 2

Variables in the Equation

		•						
		В	S.E.	Wald	df	Sig.	Exp(B)	
Step 1ª	contact			354.701	2	<.001		
	contact(1)	1.443	.077	354.624	1	<.001	4.234	
	contact(2)	1.268	.115	121.986	1	<.001	3.554	
	duration	.004	.000	2210.022	1	<.001	1.004	
	marital			44.059	2	<.001		
	marital(1)	211	.082	6.646	1	.010	.810	
	marital(2)	355	.054	44.004	1	<.001	.701	
	default(1)	.468	.233	4.022	1	.045	1.597	
	balance	.000	.000	14.401	1	<.001	1.000	
	housing(1)	.714	.050	203.122	1	<.001	2.043	
	loan(1)	.617	.077	63.378	1	<.001	1.853	
	job_update			177.637	6	<.001		
	job_update(1)	.547	.079	48.177	1	<.001	1.728	
	job_update(2)	.270	.077	12.413	1	<.001	1.310	
	job_update(3)	.983	.093	111.013	1	<.001	2.674	
	job_update(4)	1.084	.127	72.910	1	<.001	2.956	
	job_update(5)	.213	.072	8.772	1	.003	1.237	
	job_update(6)	.368	.131	7.922	1	.005	1.444	
	education_update(1)	.221	.061	13.017	1	<.001	1.247	
	Constant	-6.060	.256	560.287	1	<.001	.002	

a. Variable(s) entered on step 1: contact, duration, marital, default, balance, housing, loan, job_update, education_update.

Using a significance threshold of 0.1, the logistic regression model under discussion includes 7 categorical variables (contact, job, marital, education, default, housing, loan) and 2 numerical variables (duration, balance). The insignificant variables (p > 0.1) 'age' and 'region' were removed from the model. The insignificant subcategories 'others', 'entrepreneur', 'domestic worker', 'self-employed', and 'services' in the 'job' variable are merged with the reference category 'unknown' to form a new variable 'job_update' with only 7 subcategories. Similarly, the insignificant subcategories 'primary', and 'secondary' in the 'education' variable are merged with the reference category 'unknown' to form a new variable education update which now has only 2 subcategories.

Impact of Input Variables on the Target

Duration

- Significant relationship with response (at 0.1 level)
- A higher "duration" of contact is more likely to respond to the offer.
- Keeping all other variables constant, for a one-unit increase in contact duration, it is estimated to see a 0.4% increase in the odds of response.

Balance

• Keeping all other variables constant, for each unit increase in balance, the odds of response increases by 0%, indicating a minimal effect.

Contact

- There is a significant difference among different categories of contact (at 0.1 level)
- As all regression coefficients are positive and significant (at 0.1), all other categories are more likely to respond than "Unknown". Comparing the magnitudes, it is estimated that customers contacted through "Mobile" are the most likely to respond.
- Keeping other variables constant, the odds of "Mobile" customers responding are 4.234 times greater than those of "Unknown" customers. For the other group of customers, the odds of customers in "Telephone" are 3.554 times higher than those of "Unknown" customers.

Marital

- "Single" is the reference category of "Marital". As all regression coefficients are negative and significant (at 0.1), all other categories are less likely to respond than "single".
- marital(1) represents "others". As the regression coefficient is significant (i.e. 0.010) and negative (i.e. -.211), this means: that compared with the reference category (i.e. single), customers with "others" marital status are less likely to respond.
- Compared to single individuals (reference category), being married (marital(2)) decreases the odds of response by a factor of 0.701.

Housing

• Not having a housing loan (housing(1)) increases the odds of response by a factor of 2.043 compared to having one.

Loan

• Not having a personal loan (loan(1)) increases the odds of response by a factor of 1.853 compared to having one.

Job

- Significant difference among different categories (at 0.1 level)
- As all regression coefficients are positive and significant (at 0.1), all other categories are more likely to respond than the reference category "others". Comparing the magnitudes, it is estimated that "student" is the most likely to respond. The second group is those in "retired" followed by "admin".
- Keeping other variables constant, the odds of "student" customers responding are 2.956 times greater than those of "other" customers. The odds of customers in "retired" and "admin" are 2.674 and 1.728 times higher than those of "other" customers.

Education

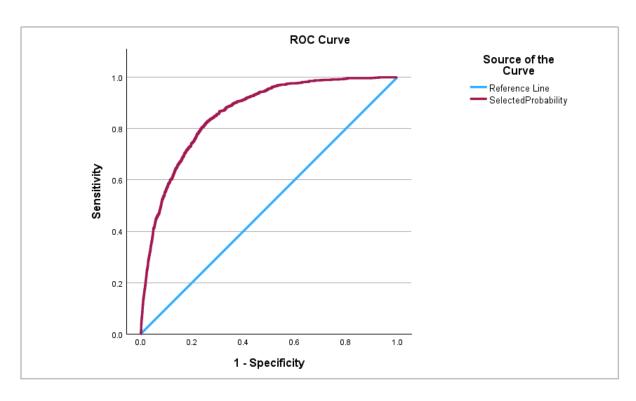
• Compared to the reference education level (ie others), having a tertiary education (education_update(1)) increases the odds of response by a factor of 1.247.

Default credit

• Not having a credit default (default(1)) increases the odds of response by a factor of 1.597 compared to having a credit default.

Performance of logistic regression model

Figure 12 – ROC Curve



Area Under the ROC Curve

Test Result Variable(s): SelectedProbability

Area .859

The test result variable (s): SelectedProbability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

Figure 12 shows that the model has an AUC value of 0.859, which indicates a very good ability to discriminate between respondents and non-respondents. The curve and the AUC indicate that the logistic regression model has a high level of performance in predicting customer responses to the marketing campaign.

[Refer to section 5.2 in the appendix to see the explanation for the baseline model]

3. Marketing Campaign

Based on the findings from the logistic regression analysis, the following marketing campaign plan is designed to target the customer segments most likely to respond.

3.1 Target Customers

Engagement Focus: Prioritize customers who have engaged longer in calls (369+ seconds), as the data indicates a higher chance of a positive response from this group. These are likely to be individuals who have shown interest in the conversation about the offer.

Marital Status: Target single individuals more aggressively than married ones, as singles have shown a greater likelihood to respond to the campaign.

Housing and Personal Loans: Segment customers based on their loan status. Those without housing or personal loans are more responsive and thus should be a focus.

Occupation: Direct specific campaign efforts towards students and retired individuals, who are more inclined to respond than other job categories.

Education: Aim at customers with tertiary education, who have been identified as more likely to engage with the campaign.

Credit History: Customers with no credit default should be considered safer targets for the campaign since they are more likely to respond.

3.2 Channels

Mobile Marketing: Utilize mobile communication as the primary channel for outreach, capitalizing on the higher response rates observed from customers contacted through mobile phones. Leverage SMS and mobile app notifications, which can be personalized and are known to have a high open rate of 98% and a response rate of 45% (Memud, 2023).

Social Media: Deploy targeted ads on social media platforms popular among students and younger demographics, as well as platforms frequented by retirees.

3.3 Strategies

Personalized Messaging: Create messages that resonate with each segment, like offering financial planning tips for students and retirees.

Value Proposition: Emphasize freedom and flexibility in the offer, which is often more appealing to single individuals and those without the financial burden of loans.

Educational Content: Develop content that educates customers on financial health, which aligns with the interests of those with tertiary education and demonstrates value beyond the product.

Incentives: Introduce incentives for early responses to encourage quick decision-making among target demographics

Data-Driven Duration Analysis: Implement analytics to identify calls reaching the critical 369+ second threshold and flag them for follow-up communications.

Training: Equip call center staff with insights on how to extend productive calls and provide training on dealing with target segments like students and retired individuals.

4. Reference

Memud, S. (2023). Customer Engagement via Email and SMS for Financial Services. [online] www.linkedin.com. Available at: https://www.linkedin.com/pulse/customer-engagement-via-email-sms-financial-services-shina-memud/ [Accessed 31 Mar. 2024].

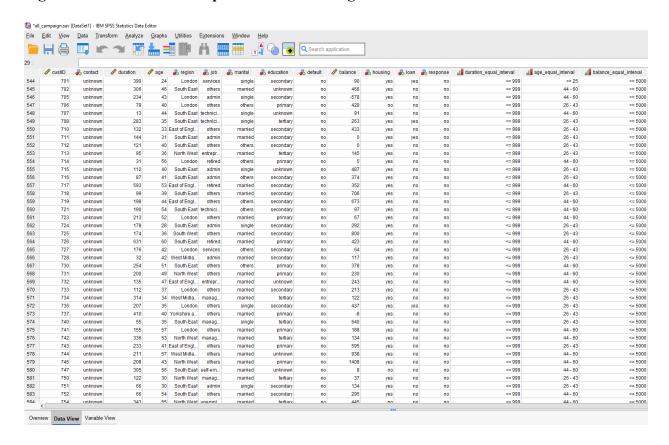
5. Appendix

5.1 Binning Numeric Variables [Approach 1 - Equal Interval Binning]

Equal Interval Binning

This method divides the range of data into intervals of equal size

Figure 13 – Dataset after Equal Interval Binning



Approach 1 - numeric variables 'duration', 'age', and 'balance' are binned based on the equal interval binning method.

Binning details

Duration – [bins = 5, bin width = 979 seconds]

Age - [bins = 5, bin width = 17 years]

Balance – [bins = 5, bin width = 27360 £]

Figure 14 – Distribution of duration

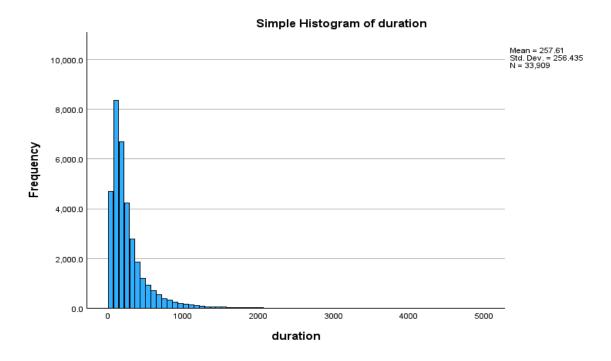


Figure 15 – Distribution of age

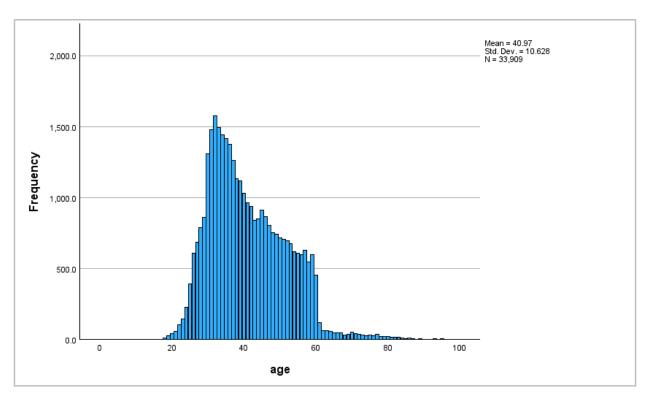


Figure 16 – Distribution of balance

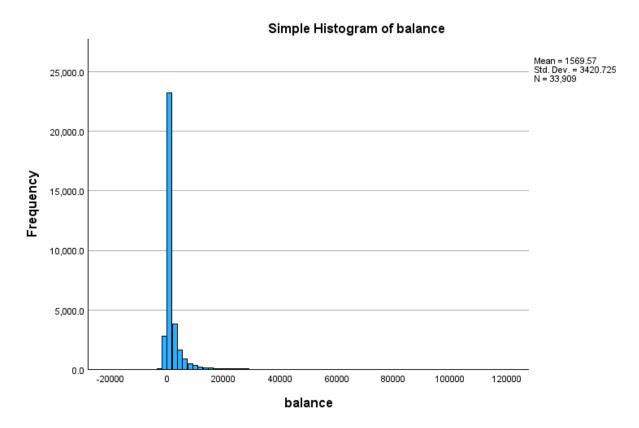


Figure 17 – Distribution of duration after binning

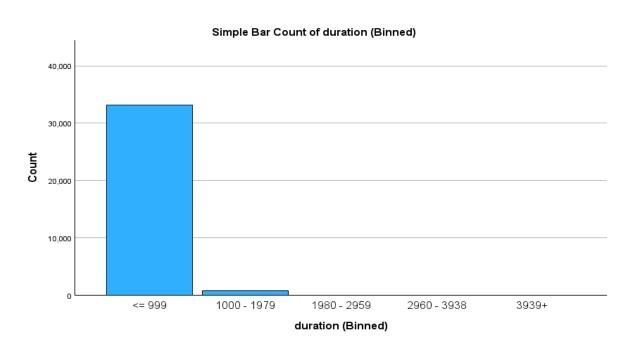


Figure 18 – Distribution of age after binning

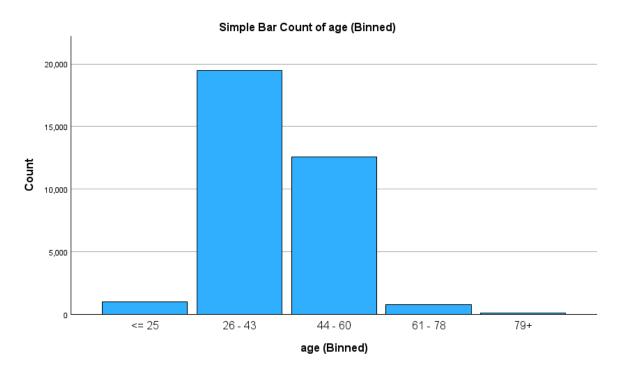
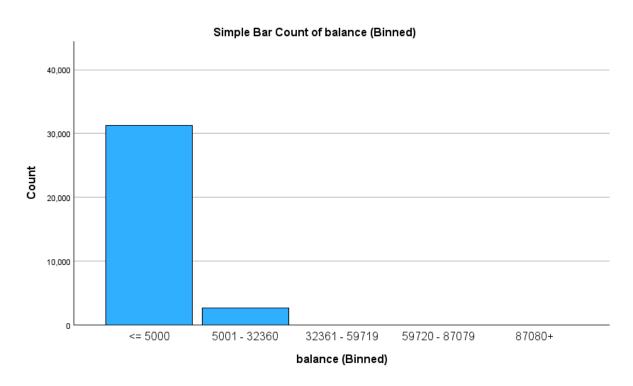


Figure 19 – Distribution of balance after binning



Since the numeric variables 'duration', 'age', and 'balance' have skewed or long-tailed distributions it is not appropriate to use this binning method as these lead to many data points being concentrated in a few bins while leaving others empty or sparsely populated. Equal frequency binning, on the other hand, ensures that each bin has the same number of observations, which can be more appropriate for handling outliers and skewed distributions.

5.2 Logistic Regression Model 1 (Initial baseline model)

Table 7 – Categorical Variable Coding for Logistic Regression Model 1

				Categ	orical Var	ables Cod	lings						
	Parameter coding												
		Frequency	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
job	admin	2672	1.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	others	5120	.000	1.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	entrepreneur	760	.000	.000	1.000	.000	.000	.000	.000	.000	.000	.000	.000
	domestic worker	681	.000	.000	.000	1.000	.000	.000	.000	.000	.000	.000	.000
	management	4964	.000	.000	.000	.000	1.000	.000	.000	.000	.000	.000	.000
	retired	1170	.000	.000	.000	.000	.000	1.000	.000	.000	.000	.000	.000
	self-employed	872	.000	.000	.000	.000	.000	.000	1.000	.000	.000	.000	.000
	services	2176	.000	.000	.000	.000	.000	.000	.000	1.000	.000	.000	.000
	student	471	.000	.000	.000	.000	.000	.000	.000	.000	1.000	.000	.000
	technician	4027	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000	.000
	unemployed	689	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000
	unknown	134	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
region	North East	115	1.000	.000	.000	.000	.000	.000	.000	.000			
	South West	725	.000	1.000	.000	.000	.000	.000	.000	.000			
	East of England	2604	.000	.000	1.000	.000	.000	.000	.000	.000			
	London	5141	.000	.000	.000	1.000	.000	.000	.000	.000			
	South East	6501	.000	.000	.000	.000	1.000	.000	.000	.000			
	North West	5205	.000	.000	.000	.000	.000	1.000	.000	.000			
	West Midlands	2575	.000	.000	.000	.000	.000	.000	1.000	.000			
	Yorkshire and the Humber	782	.000	.000	.000	.000	.000	.000	.000	1.000			
	East Midlands	88	.000	.000	.000	.000	.000	.000	.000	.000			
education	primary	3598	1.000	.000	.000								
	secondary	12224	.000	1.000	.000								
	tertiary	6962	.000	.000	1.000								
	unknown	952	.000	.000	.000								
marital	others	2708	1.000	.000									
	married	14330	.000	1.000									
	single	6698	.000	.000									
contact	mobile	15467	1.000	.000									
	telephone	1531	.000	1.000									
	unknown	6738	.000	.000									
default	no	23333	1.000										
	yes	403	.000										
housing	no	10506	1.000										
	yes	13230	.000										
Ioan	no	19918	1.000										
	yes	3818	.000										

Table 8 - Logistic Regression Model 1

Variables in the Equation

Step 1a contact 352.800 contact(1) 1.442 .077 352.733 contact(2) 1.267 .116 119.649 duration .004 .000 2205.863 age .003 .003 1.358 region 5.547 region(1) .235 .632 .138 region(2) .635 .497 1.634 region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(8) .623 .495 1.588 job 163.200 1.588 job 163.200 1.585 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(3) .415 .408 1.038 job(4) .366 .411 .796 jo	2 1 1 1 1 8 1 1 1 1 1	<.001 <.001 <.001 <.001 .244 .698 .711 .201 .171	4.230 3.550 1.004 1.003 1.264 1.887
contact(1) 1.442 .077 352.733 contact(2) 1.267 .116 119.649 duration .004 .000 2205.863 age .003 .003 1.358 region 5.547 region(1) .235 .632 .138 region(2) .635 .497 1.634 region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383	1 1 8 1 1 1 1	<.001 <.001 .244 .698 .711 .201	3.550 1.004 1.003 1.264 1.887
duration .004 .000 2205.863 age .003 .003 1.358 region 5.547 .547 region(1) .235 .632 .138 region(2) .635 .497 1.634 region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 1.588 1.588 job 163.200 1.588 1.588 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485	1 1 8 1 1 1 1	<.001 .244 .698 .711 .201	1.004 1.003 1.264 1.887
region 5.547 region(1) .235 .632 .138 region(2) .635 .497 1.634 region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital marital(1)233 .087 7.117	1 8 1 1 1 1	.244 .698 .711 .201 .171	1.003 1.264 1.887
region(1) .235 .632 .138 region(2) .635 .497 1.634 region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1)233 .087 7.117	8 1 1 1 1 1	.698 .711 .201 .171	1.264 1.887
region(1) .235 .632 .138 region(2) .635 .497 1.634 region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383	1 1 1 1	.711 .201 .171	1.887
region(2)	1 1 1 1	.201 .171	1.887
region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914	1 1 1	.171	
region(3) .662 .483 1.877 region(4) .697 .481 2.102 region(5) .665 .480 1.919 region(6) .627 .481 1.700 region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914	1		
region(4)	1	.147	1.939
region(6)			2.008
region(7) .746 .483 2.386 region(8) .623 .495 1.588 job 163.200 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.166	1.945
region(8)		.192	1.872
region(8)	1	.122	2.110
job 163.200 job(1) 1.071 .385 7.720 job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.208	1.865
job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	11	<.001	
job(2) .585 .385 2.316 job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.005	2.917
job(3) .415 .408 1.038 job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.128	1.796
job(4) .366 .411 .796 job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.308	1.515
job(5) .803 .383 4.387 job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.372	1.442
job(6) 1.485 .388 14.614 job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.036	2.232
job(7) .638 .398 2.562 job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	<.001	4.413
job(8) .602 .390 2.390 job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.109	1.892
job(9) 1.643 .397 17.134 job(10) .737 .383 3.697 job(11) .914 .398 5.270 marital 39.496 marital(1) 233 .087 7.117	1	.122	1.826
job(11) .914 .398 5.270 marital 39.496 marital(1)233 .087 7.117	1	<.001	5.172
marital 39.496 marital(1)233 .087 7.117	1	.054	2.090
marital(1)233 .087 7.117	1	.022	2.494
	2	<.001	
marital(2)367 .059 39.211	1	.008	.792
	1	<.001	.693
education 16.369	3	<.001	
education(1)182 .137 1.764	1	.184	.834
education(2)017 .121 .021	1	.886	.983
education(3) .189 .127 2.207	1	.137	1.208
default(1) .468 .234 4.009	1	.045	1.596
balance .000 .000 13.367	1	<.001	1.000
housing(1) .716 .051 195.808	4	<.001	2.045
loan(1) .618 .078 63.232	1	<.001	1.854
Constant -7.350 .677 117.865	1	<.001	

a. Variable(s) entered on step 1: contact, duration, age, region, job, marital, education, default, balance, housing, loan.

Using a significance threshold of 0.1, the logistic regression model under discussion includes 8 categorical variables (contact, region, job, marital, education, default, housing, loan) and 3 numerical variables (duration, age, balance). The 'age' variable is not significant since its p-value exceeds 0.1, suggesting that it can be excluded from the final model. The remaining two numerical variables show statistical significance under this threshold.

The categorical variable 'region', along with all its subcategories, does not show significance at the 0.1 level, leading to its removal from the final model. The 'job' category is significant overall, however, some specific subcategories (job(2), job(3), job(4), job(7), and job(8)) do not meet the significance criterion. These non-significant job categories will be merged with the baseline "unknown" category in a revised final model.

Likewise, the 'education' variable is significant as a whole, but the subcategories 'education(1)' and 'education(2)' are not. These will also be combined with the "unknown" reference category for the final refined model. All other variables are considered significant at the 0.1 significance level.