# Bank Loan Case Study: Exploratory Data Analysis Report

### Introduction

Hello everyone, my name is Hritik Kumar Dutta, and I'm excited to present the findings of my project on the Bank Loan Case Study. This project was assigned to me as part of the data analytics course I'm currently pursuing with Trainity, an edtech platform dedicated to empowering learners with practical data skills.

# **Project Description**

The objective of this project was to analyze a d

ataset containing loan applications from urban customers. Our company, specializing in financial services, faces the challenge of accurately predicting loan defaults to minimize financial losses while maximizing business opportunities. By identifying patterns and factors that influence loan default, we aim to improve our decision-making process regarding loan approvals.

## **Approach**

In tackling this project, I followed a structured approach:

- 1. Data Cleaning and Preprocessing: I began by identifying missing data and outliers in the dataset, ensuring data integrity through appropriate handling techniques.
- 2. Exploratory Data Analysis (EDA): I conducted a thorough analysis to understand the distribution and relationships between customer attributes and loan attributes.
- 3. Data Imbalance Analysis: I assessed the distribution of the target variable to understand any imbalances in the dataset.
- 4. Correlation Analysis: I segmented the dataset based on different scenarios and identified top correlations that indicate loan default.

4	A B	С	D	E	F	G	Н	1	J	K	L	М	N A
1 S					FLAG_OWN_REALTY -	CNT_CHILDREN - AMT_INC							
2	100002	1 Cash loans	М	N	Υ	0	202500	406597.5	24700.5		Unaccompanied	Working	Secondary / secondary speci
3	100003	0 Cash loans	F	N	N	0	270000	1293502.5	35698.5	1129500 I		State servant	Higher education
4	100004	0 Revolving loans	М	Υ	Υ	0	67500	135000	6750	135000	Unaccompanied	Working	Secondary / secondary speci
5	100006	0 Cash loans	F	N	Υ	0	135000	312682.5	29686.5	297000	Unaccompanied	Working	Secondary / secondary speci
6		0 Cash loans	М	N	Υ	0	121500	513000	21865.5	513000	Unaccompanied	Working	Secondary / secondary speci
7	100008	0 Cash loans	M	N	Υ	0	99000	490495.5	27517.5		Spouse, partner	State servant	Secondary / secondary speci
8	100009	0 Cash loans	F	Υ	Υ	1	171000	1560726	41301	1395000 (	Unaccompanied	Commercial associate	Higher education
9	100010	0 Cash loans	M	Υ	Υ	0	360000	1530000	42075	1530000	Unaccompanied	State servant	Higher education
10	100011	0 Cash loans	F	N	Υ	0	112500	1019610	33826.5	913500 (	Children	Pensioner	Secondary / secondary speci
11	100012	0 Revolving loans	М	N	Υ	0	135000	405000	20250	405000	Unaccompanied	Working	Secondary / secondary speci
12	100014	0 Cash loans	F	N	Υ	1	112500	652500	21177	652500 I	Unaccompanied	Working	Higher education
13	100015	0 Cash loans	F	N	Υ	0	38419.155	148365	10678.5	135000 (	Children	Pensioner	Secondary / secondary speci
14	100016	0 Cash loans	F	N	Υ	0	67500	80865	5881.5	67500 I	Unaccompanied	Working	Secondary / secondary speci
15	100017	0 Cash loans	M	Υ	N	1	225000	918468	28966.5	697500 U	Unaccompanied	Working	Secondary / secondary speci
16	100018	0 Cash loans	F	N	Υ	0	189000	773680.5	32778	679500 I	Unaccompanied	Working	Secondary / secondary speci
17	100019	0 Cash loans	М	Υ	Υ	0	157500	299772	20160	247500 I	Family	Working	Secondary / secondary speci
18	100020	0 Cash loans	М	N	N	0	108000	509602.5	26149.5	387000 (	Unaccompanied	Working	Secondary / secondary speci
19	100021	0 Revolving loans	F	N	Υ	1	81000	270000	13500	270000 (	Unaccompanied	Working	Secondary / secondary speci
20	100022	0 Revolving loans	F	N	Υ	0	112500	157500	7875	157500	Other_A	Working	Secondary / secondary speci
21	100023	0 Cash loans	F	N	Υ	1	90000	544491	17563.5	454500 I	Unaccompanied	State servant	Higher education
22	100024	0 Revolving loans	М	Υ	Υ	0	135000	427500	21375	427500 U	Unaccompanied	Working	Secondary / secondary speci
23	100025	0 Cash loans	F	Υ	Υ	1	202500	1132573.5	37561.5	927000 (	Unaccompanied	Commercial associate	Secondary / secondary speci
24	100026	0 Cash loans	F	N	N	1	450000	497520	32521.5	450000 U	Unaccompanied	Working	Secondary / secondary speci
25	100027	0 Cash loans	F	N	Υ	0	83250	239850	23850	225000	Unaccompanied	Pensioner	Secondary / secondary speci
26	100029	0 Cash loans	М	Υ	N	2	135000	247500	12703.5	247500 (	Unaccompanied	Working	Secondary / secondary speci
27	100030	0 Cash loans	F	N	Υ	0	90000	225000	11074.5	225000	Unaccompanied	Working	Secondary / secondary speci
28	100031	1 Cash loans	F	N	Υ	0	112500	979992	27076.5	702000 (	Unaccompanied	Working	Secondary / secondary speci
29	100032	0 Cash loans	М	N	Υ	1	112500	327024	23827.5	270000 1	Family	Working	Secondary / secondary speci
30	100033	0 Cash loans	M	Υ	Υ	0	270000	790830	57676.5	675000 I	Unaccompanied	State servant	Higher education
31	100034	0 Revolving loans	М	N	Υ	0	90000	180000	9000	180000	Unaccompanied	Working	Higher education
32	100035	0 Cash loans	F	N	Υ	0	292500	665892	24592.5	477000 (	Unaccompanied	Commercial associate	Secondary / secondary speci
33	100036	0 Cash loans	F	N	Υ	0	112500	512064	25033.5	360000 1	Family	Working	Secondary / secondary speci
34	100037	0 Cash loans	F	N	N	0	90000	199008	20893.5	180000	Unaccompanied	Working	Secondary / secondary speci
35	100039	0 Cash loans	М	Υ	N	1	360000	733315.5	39069		Unaccompanied	Commercial associate	Secondary / secondary speci
36	100040	0 Cash loans	F	N	Υ	0	135000	1125000	32895	1125000	Unaccompanied	State servant	Higher education
37	100041	0 Cash loans	F	N	N	0	112500	450000	44509.5	450000	Unaccompanied	Working	Higher education 🔻
<	> application	on_data (1) columns_descri	ption previous_a	application Sheet1	Null Value Chart	HANDLING MISSING VALUES	FULL DATA W	+ ;	-			-	•

### **Tech-Stack Used**

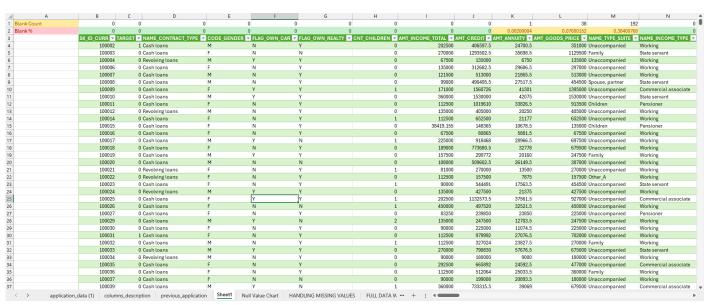
**Microsoft Excel 2022**: This was my primary tool for data cleaning, analysis, and visualization. I utilized functions such as `COUNT`, `ISBLANK`, `QUARTILE`, `CORREL`, and `COUNTIF`, alongside Excel's features like pivot tables, charts, and conditional formatting.

# **Insights**

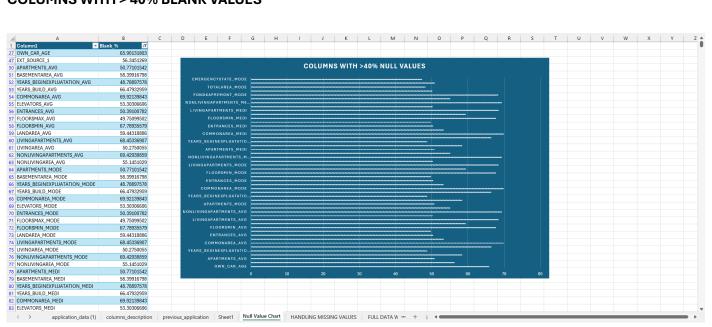
### **Handling Missing Data**

Missing values were identified using the `ISBLANK` function and imputed with `AVERAGE` or `MEDIAN`, ensuring that the dataset remained unbiased and reliable.

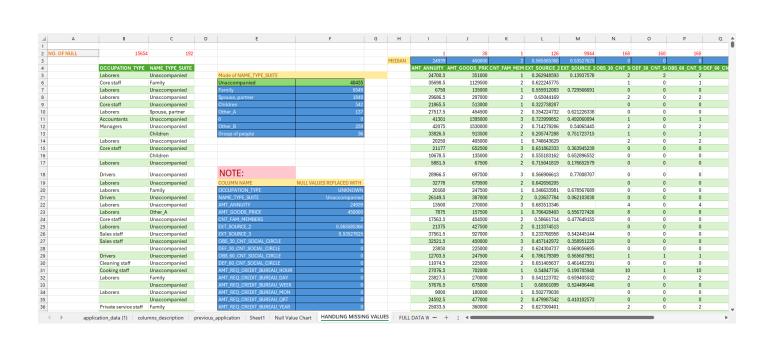
#### **CALCULATING BLANK PERCENTAGE**



#### **COLUMNS WITH > 40% BLANK VALUES**



#### HANDLING MISSING VALUES



#### **FULL DATA WITHOUT MISSING VALUES**

SK ID CURR 1000 1000 1000 1000 1000 1000 1000 1	002 003 004 006 007 008	NAME_CONTRACT_TYPE 1 Cash loans 0 Cash loans 0 Revolving loans 0 Cash loans	M F M	N N Y	FLAG_OWN_REALTY Y N	CNT_CHILDREN C	202500	406597.5	AMT_ANNUITY  24700.5		IAME_TYPE_SUITE   Inaccompanied	NAME_INCOME_TYPE Working	NAME_EDUCATION_TYPE Secondary / secondary speci
1000 1000 1000 1000 1000 1000	003 004 006 007 008	0 Cash loans 0 Revolving loans 0 Cash loans 0 Cash loans	F M F	N Y					24700.5	351000 U	Inaccompanied	Working	Secondary / secondary speci
1000 1000 1000 1000 1000 1000	004 006 007 008 009	0 Revolving loans 0 Cash loans 0 Cash loans	M F	Υ		0							
1000 1000 1000 1000 1000	006 007 008 009	0 Cash loans 0 Cash loans	F		V		270000	1293502.5	35698.5	1129500 F	amily	State servant	Higher education
1000 1000 1000	007 008 009	0 Cash loans			T	(	67500	135000	6750	135000 U	Inaccompanied	Working	Secondary / secondary speci
100 100 100	008 009			N	Υ	0	135000	312682.5	29686.5	297000 U	Inaccompanied	Working	Secondary / secondary speci
100	009	0 Cash loans	M	N	Υ	(	121500	513000	21865.5	513000 U	Inaccompanied	Working	Secondary / secondary speci
100			M	N	Υ		99000	490495.5	27517.5	454500 S	pouse, partner	State servant	Secondary / secondary speci
	110	0 Cash loans	F	Υ	Υ	1	171000	1560726	41301	1395000 U	Inaccompanied	Commercial associate	Higher education
100	110	0 Cash loans	M	Υ	Υ	(	360000	1530000	42075	1530000 U	Inaccompanied	State servant	Higher education
	11	0 Cash loans	F	N	Υ	0	112500	1019610	33826.5	913500 C	hildren	Pensioner	Secondary / secondary speci
100	)12	0 Revolving loans	M	N	Υ		135000	405000	20250	405000 U	Inaccompanied	Working	Secondary / secondary speci
100	14	0 Cash loans	F	N	Υ	1	112500	652500	21177	652500 U	Inaccompanied	Working	Higher education
100	15	0 Cash loans	F	N	Υ	0	38419.155	148365	10678.5	135000 C	hildren	Pensioner	Secondary / secondary speci
100	16	0 Cash loans	F	N	Υ		67500	80865	5881.5	67500 U	Inaccompanied	Working	Secondary / secondary speci
100	17	0 Cash loans	М	Υ	N	1	225000	918468	28966.5	697500 U	Inaccompanied	Working	Secondary / secondary speci
100	18	0 Cash loans	F	N	Υ	(	189000	773680.5	32778	679500 U	Inaccompanied	Working	Secondary / secondary speci
100	119	0 Cash loans	М	Υ	Υ	0	157500	299772	20160	247500 F	amily	Working	Secondary / secondary speci
100	020	0 Cash loans	М	N	N		108000	509602.5	26149.5	387000 U	Inaccompanied	Working	Secondary / secondary speci
100	021	0 Revolving loans	F	N	Υ	1	81000	270000	13500	270000 U	Inaccompanied	Working	Secondary / secondary speci
100	)22	0 Revolving loans	F	N	Υ		112500	157500	7875	157500 O	Other_A	Working	Secondary / secondary speci
100	023	0 Cash loans	F	N	Υ	1	90000	544491	17563.5	454500 U	Inaccompanied	State servant	Higher education
100	024	0 Revolving loans	М	Υ	Υ		135000	427500	21375	427500 U	Inaccompanied	Working	Secondary / secondary speci
100	)25	0 Cash loans	F	Υ	Υ	1	202500	1132573.5	37561.5	927000 U	Inaccompanied	Commercial associate	Secondary / secondary speci
100	26	0 Cash loans	F	N	N	1	450000	497520	32521.5	450000 U	Inaccompanied	Working	Secondary / secondary spec
100	)27	0 Cash loans	F	N	Υ		83250	239850	23850	225000 U	Inaccompanied	Pensioner	Secondary / secondary spec
100	129	0 Cash loans	М	Υ	N	2	135000	247500	12703.5	247500 U	Inaccompanied	Working	Secondary / secondary spec
100	030	0 Cash loans	F	N	Υ		90000	225000	11074.5	225000 U	Inaccompanied	Working	Secondary / secondary spec
100	031	1 Cash loans	F	N	Υ		112500	979992	27076.5	702000 U	Inaccompanied	Working	Secondary / secondary spec
100	32	0 Cash loans	М	N	Υ	1	112500	327024	23827.5	270000 F	amily	Working	Secondary / secondary spec
100	33	0 Cash loans	М	Υ	Υ	(	270000	790830	57676.5	675000 U	Inaccompanied	State servant	Higher education
100	34	0 Revolving loans	М	N	Υ	0	90000	180000	9000	180000 U	Inaccompanied	Working	Higher education
100	35	0 Cash loans	F	N	Υ		292500	665892	24592.5	477000 U	Inaccompanied	Commercial associate	Secondary / secondary spec
100	036	0 Cash loans	F	N	Υ		112500	512064	25033.5	360000 F	amily	Working	Secondary / secondary spec
100	37	0 Cash loans	F	N	N	0	90000	199008	20893.5	180000 U	Inaccompanied	Working	Secondary / secondary speci
100	)39	0 Cash loans	М	Υ	N	1	360000	733315.5	39069		Jnaccompanied	Commercial associate	Secondary / secondary spec
100	040	0 Cash loans	F	N	Υ	0	135000	1125000	32895	1125000 U	Inaccompanied	State servant	Higher education
100	041	0 Cash loans	F	N	N		112500	450000	44509.5	450000 U	Inaccompanied	Working	Higher education
< >	proviewe	application Sheet1 Nu	II Value Chart H	ANDLING MISSING V	ALLIES FULL DATA W	ITHOUT NULL VALU	JES OUTLIERS DA	ΓA + :	4			-	

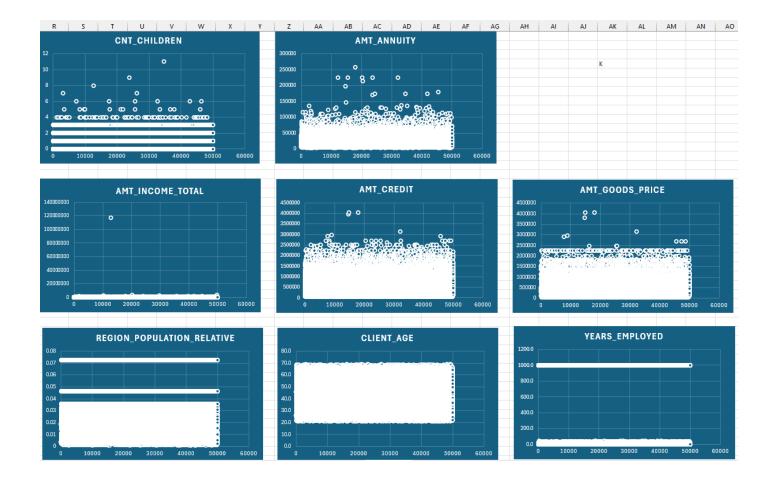
### **Outlier Detection**

Outliers were detected using the IQR method, with box plots illustrating their presence. Validity assessments ensured that the outliers did not distort our analysis.

## FINDING QUARANTILE 1, QUARANTILE 3, IQR, ETC.

K	L	М	N	0	P
COLUMN NAME	Q1	Q3	IQR	<b>UPPER LIMIT</b>	LOWER LIMIT
CNT_CHILDREN	0	1	1	2.5	-1.5
AMT_INCOME_TOTAL	112500	202500	90000	337500	-22500
AMT_CREDIT	270000	808650	538650	1616625	-537975
AMT_ANNUITY	16456.5	34596	18139.5	61805.25	-10752.75
AMT_GOODS_PRICE	238500	679500	441000	1341000	-423000
REGION_POPULATION_RELATIVE	0.010006	0.028663	0.018657	0.0566485	-0.0179795
client_age	33.91233	53.81918	19.90685	83.67945205	4.052054795
Years_employed	2.556164	15.66575	13.10959	35.33013699	-17.10821918
Years_Registration	5.473973	20.44795	14.97397	42.90890411	-16.9869863

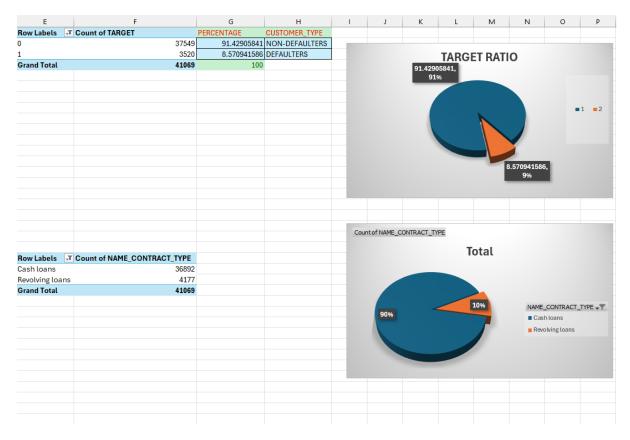
### **OUTLIERS SCATTER PLOT**



### **Data Imbalance**

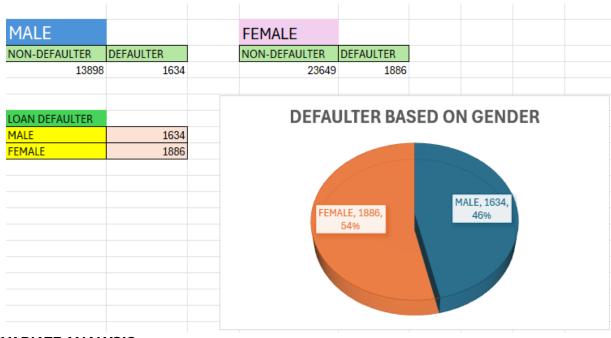
The analysis revealed a significant imbalance, with a higher number of non-defaulters than defaulters. Pie charts were utilized to visualize this imbalance, highlighting the need for balanced data for accurate predictions.

### **RATIO OF DEFAULTERS & NON-DEFAULETRS**



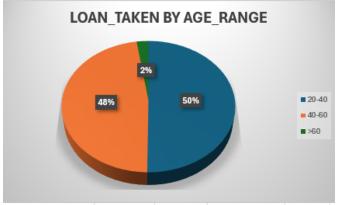
## **Univariate and Segmented Univariate Analysis**

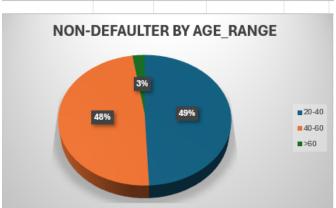
Univariate analysis helped identify key attributes such as income levels and credit history, which emerged as significant indicators of loan defaults. Segmented univariate analysis allowed for comparisons across different customer scenarios, revealing patterns that correlate with default likelihood.

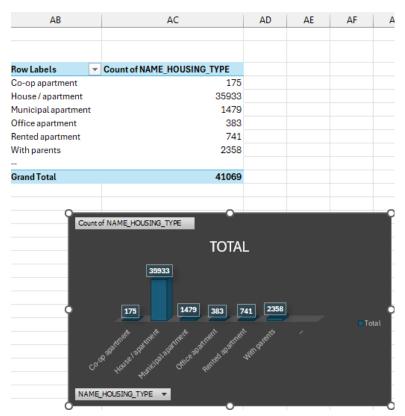


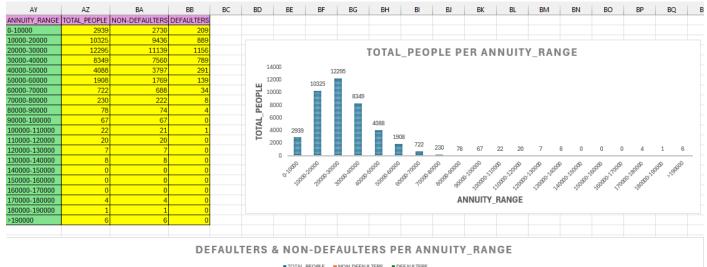
**UNIVARIATE ANALYSIS** 

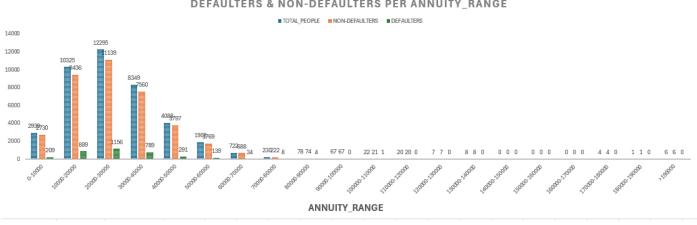
CLIENT_AGE_RANGE	LOAN_TAKEN	DEFAULTER	NON-DEFAULTER
20-40	20616	2114	18502
40-60	19472	1359	18113
>60	981	47	934



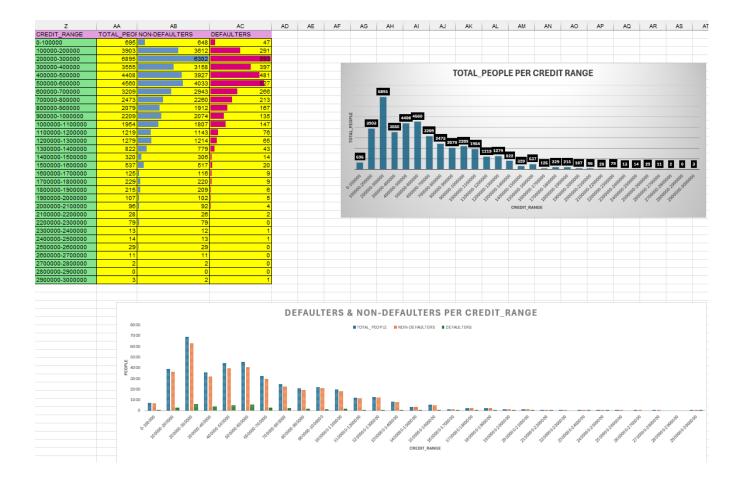












### **Correlation Analysis**

Correlation analysis revealed top correlations using the `CORREL` function. For example, poor credit history was strongly correlated with defaults in customers with payment difficulties, providing actionable insights for risk assessment.

4	Α	В	С	D	Е	F	G	Н	1		
1		Top correlation	of Non-Defaulters				Top Correlation of Defaulters				
2	Rank	▼ Variable 1	Variable 2	▼ Correlation →		Rank	▼ Variable 1	▼ Variable 2	▼ Correlation →		
3		1 AMT_GOODS_PRICE	AMT_CREDIT	0.98635817			1 AMT_GOODS_PRICE	AMT_CREDIT	0.981928143		
4		2 REGION_RATING_CLIENT_W_CITY	REGION_RATING_CLIENT	0.950286525			2 REGION_RATING_CLIENT	REGION_RATING_CLIENT_W_CITY	0.948020808		
5		3 CNT_CHILDREN	CNT_FAM_MEMBERS	0.893735596			3 CNT_FAM_MEMBERS	CNT_CHILDREN	0.895600339		
6		4 REG_REGION_NOT_WORK_REGION -	LIVE_REGION_NOT_WORK_REGION	0.860167703			4 DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.891467244		
7		5 DEF_30_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE	0.853040752			5 LIVE_REGION_NOT_WORK_REGION	REG_REGION_NOT_WORK_REGION	0.805583225		
8		6 REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	0.815604978			6 LIVE_CITY_NOT_WORK_CITY	REG_CITY_NOT_WORK_CITY	0.773107352		
9		7 REGION_RATING_CLIENT	AMT_GOODS_PRICE	0.765201743			7 AMT_ANNUITY	AMT_GOODS_PRICE	0.746422447		
10		8 AMT_ANNUITY	AMT_GOODS_PRICE	0.765201743			8 AMT_ANNUITY	AMT_CREDIT	0.745132112		
11		9 AMT_CREDIT	AMT_ANNUITY	0.760827873							

### **Results**

This project enhanced my understanding of the factors contributing to loan defaults. The insights gained will inform strategies to identify high-risk applicants, adjust loan offerings, and optimize interest rates, ultimately strengthening our company's financial performance. Through this project with Trainity, I've honed my data analytics skills, applying them to real-world challenges.

### **Drive Link**

https://drive.google.com/drive/folders/1PXMUeNplewfeykrXsrqTYzbHUxlFcItm?usp=sharing