

Project Description

To find trends that can be used to determine whether a customer has trouble making their payments, which may be used to decide whether to refuse the loan, reduce the loan's size, or lend to a riskier applicant. More expensive interest rates, etc. By doing this, it will be ensured that only borrowers who can repay the loan will be accepted.

There are two sections to the analysis, or should I say two datasets:

1. Application data
2. Previous application data

Approach

Prior to analysis, data must be understood and cleaned. Finding null values, outliers, and identifying each column in our dataset to determine how many of them are irrelevant for analysis are all part of the cleaning process.

After data cleaning, we must analyse the data using univariate and bivariate methods, which aid in data analysis and provide insightful information about the relationship between two variables, or the interdependence of one and more factors.

Tech-Stack Used

Here I am using Microsoft Excel 2016, I will be able to clean the data and develop a pivot table, which is useful for data analysis. We can visualize data using graphs in Excel as well. Due to the size of the dataset, I'm also using a Jupyter notebook to help me analyse the data.

Insights

Application Dataset – NULL values

First, the proportion of null values must be examined, and any columns with more than 50% of the data being null must be removed. Additionally, any columns with less than 50% of null data must be replaced with the mean, median, or the category variable with the highest frequency.

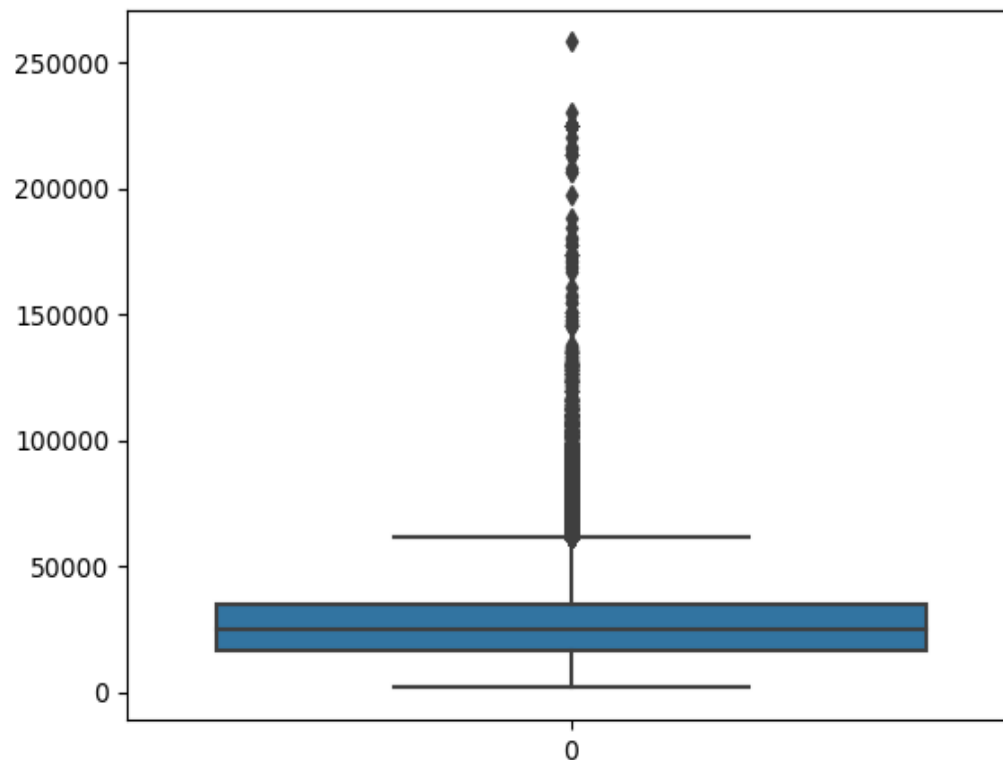
As all of the below column names have null values greater than or equal to 50%, they can all be dropped down.

Column name	Total number of null values	Percentage of null value in that column
OWN_CAR_AGE	202930	65.99%
EXT_SOURCE_1	173379	56.38%
APARTMENTS_AVG	156061	50.75%
BASEMENTAREA_AVG	179943	58.52%
YEARS_BUILD_AVG	204488	66.50%
COMMON_AREA_AVG	214865	69.87%
ELEVATORS_AVG	163891	53.30%
ENTRANCES_AVG	154828	50.35%
FLOORSMAX_AVG	153021	49.76%
FLOORSMIN_AVG	208642	67.85%
LANDAREA_AVG	182590	59.38%
LIVINGAPARTMENTS_AVG	210199	68.35%
LIVINGAREA_AVG	154350	50.19%
NONLIVINGAPARTMENTS_AVG	213514	69.43%
NONLIVINGAREA_AVG	169682	55.18%
APARTMENTS_MODE	156061	50.75%
BASEMENTAREA_MODE	179943	58.52%
YEARS_BUILD_MODE	204488	66.50%
COMMON_AREA_MODE	214865	69.87%
ELEVATORS_MODE	163891	53.30%
ENTRANCES_MODE	154828	50.35%
FLOORSMAX_MODE	153020	49.76%
FLOORSMIN_MODE	208642	67.85%
LANDAREA_MODE	182590	59.38%
LIVINGAPARTMENTS_MODE	210199	68.35%
LIVINGAREA_MODE	154350	50.19%
NONLIVINGAPARTMENTS_MODE	213514	69.43%
NONLIVINGAREA_MODE	169682	55.18%
APARTMENTS_MEDIAN	156061	50.75%
BASEMENTAREA_MEDIAN	179943	58.52%
YEARS_BUILD_MEDIAN	204488	66.50%
COMMON_AREA_MEDIAN	214865	69.87%
ELEVATORS_MEDIAN	163891	53.30%
ENTRANCES_MEDIAN	154828	50.35%
FLOORSMAX_MEDIAN	153020	49.76%
FLOORSMIN_MEDIAN	208642	67.85%
LANDAREA_MEDIAN	182590	59.38%
LIVINGAPARTMENTS_MEDIAN	210199	68.35%
LIVINGAREA_MEDIAN	154350	50.19%
NONLIVINGAPARTMENTS_MEDIAN	213514	69.43%
NONLIVINGAREA_MEDIAN	169682	55.18%
FONDKAPREMONT_MODE	210295	68.39%
HOUSETYPE_MODE	154297	50.18%
WALLSMATERIAL_MODE	156341	50.84%

As they are irrelevant columns for doing our analysis, ALL OF THE FOLLOWING COLUMN NAMES NEED TO BE DROPPED DOWN.

Column name	Total number of null values	Percentage of null value
FLAG_MOBIL	1	0.00%
FLAG_EMPLOY_PHONE	55387	18.01%
FLAG_WORK_PHONE	0	0.00%
FLAG_CONT_MOBILE	0	0.00%
FLAG_PHONE	0	0.00%
FLAG_EMAIL	0	0.00%
CNT_FAMILY_MEMBERS	2	0.00%
REGION_RATING_CLIENT	0	0.00%
REGION_RATING_CLIENT_W_CITY	0	0.00%
EXT_SOURCE_3	60965	19.83%
YEAR_BEGINEXPLUATATION_A	150008	48.78%
YEAR_BEGINEXPLUATATION_N	150007	48.78%
YEAR_BEGINEXPLUATATION_N	150007	48.78%
TOTAL_AREA_MODE	148431	48.27%
EMERGENCYSTATE_MODE	145755	47.40%
DAYS_LAST_PHONE_CHANGE	1	0.00%
FLAG_DOC_2	0	0.00%
FLAG_DOC_3	0	0.00%
FLAG_DOC_4	0	0.00%
FLAG_DOC_5	0	0.00%
FLAG_DOC_6	0	0.00%
FLAG_DOC_7	0	0.00%
FLAG_DOC_8	0	0.00%
FLAG_DOC_9	0	0.00%
FLAG_DOC_10	0	0.00%
FLAG_DOC_11	0	0.00%
FLAG_DOC_12	0	0.00%
FLAG_DOC_13	0	0.00%
FLAG_DOC_14	0	0.00%
FLAG_DOC_15	0	0.00%
FLAG_DOC_16	0	0.00%
FLAG_DOC_17	0	0.00%
FLAG_DOC_18	0	0.00%
FLAG_DOC_19	0	0.00%
FLAG_DOC_20	0	0.00%
FLAG_DOC_21	0	0.00%

Replacing blanks in the Application Dataset's **AMT_ANNUTY** column with the median value of AMT_ANNUTY since the column contains outliers.



AMT_ANNUTY

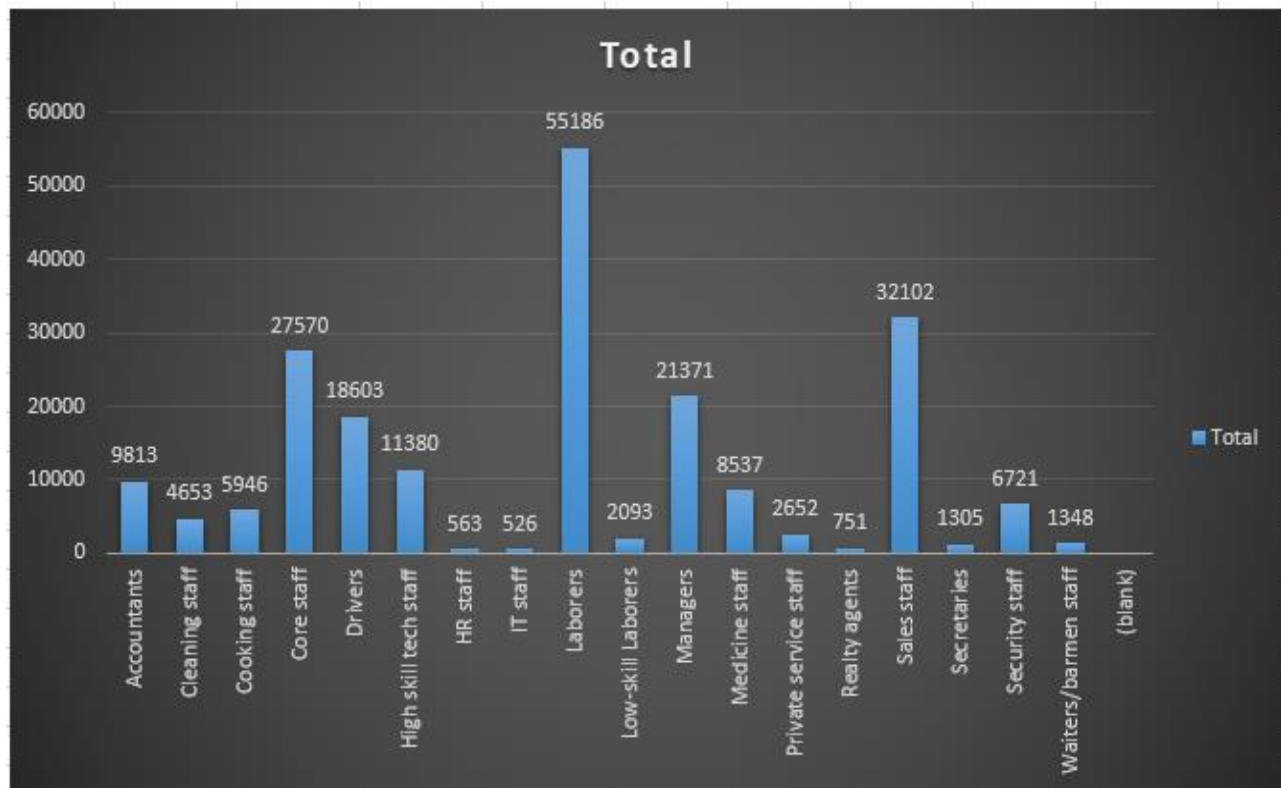
Median	24903
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Replacing Blanks with
Median

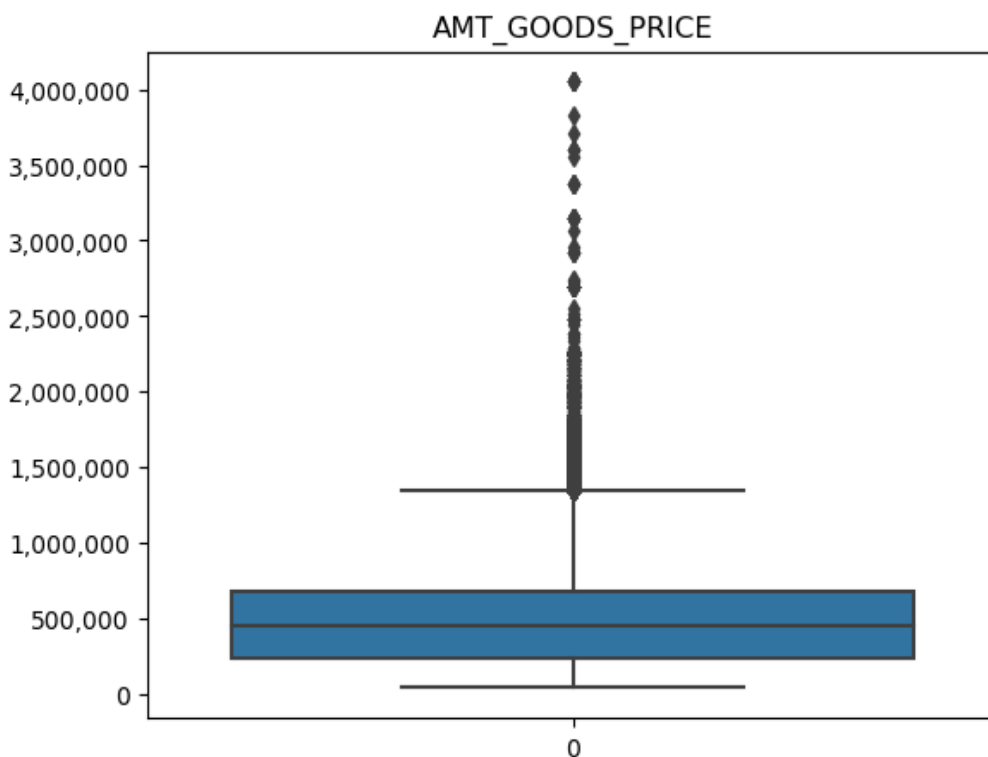
Filling in blanks in the Application Dataset's **Occupation_Type** column with the categorical variable with the highest frequency

Row Labels	Count of OCCUPATION_TYPE
Accountants	9813
Cleaning staff	4653
Cooking staff	5946
Core staff	27570
Drivers	18603
High skill tech staff	11380
HR staff	563
IT staff	526
Laborers	55186
Low-skill Laborers	2093
Managers	21371
Medicine staff	8537
Private service staff	2652
Realty agents	751
Sales staff	32102
Secretaries	1305
Security staff	6721
Waiters/barmen staff	1348
(blank)	
Grand Total	211120

Highest occurring
categorical
variable is
'Laborers'



Blanks in the Application Dataset's AMT_GOODS_PRICE column should be replaced with the median of AMT_GOODS_PRICE since the column contains outliers.

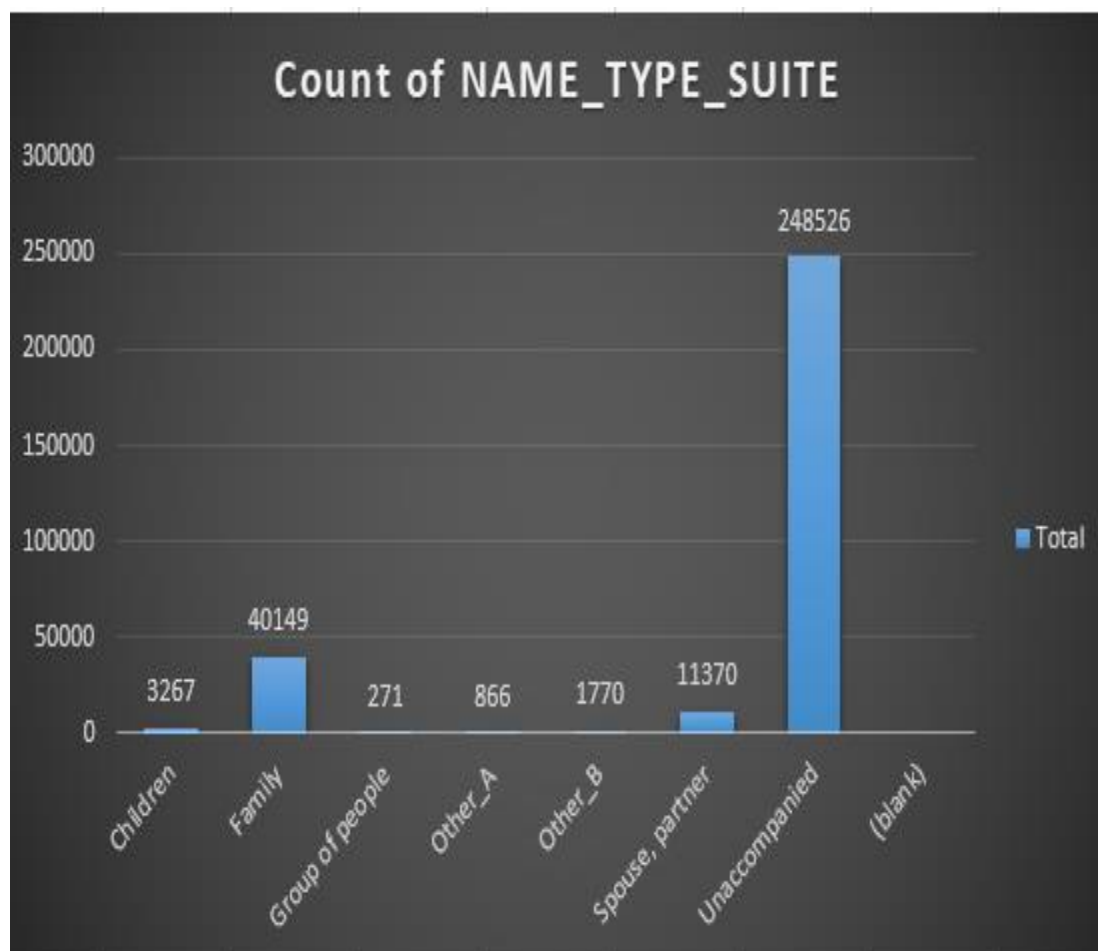


AMT_GOODS_PRICE	
Median	450000
Replacing Blanks with Median	

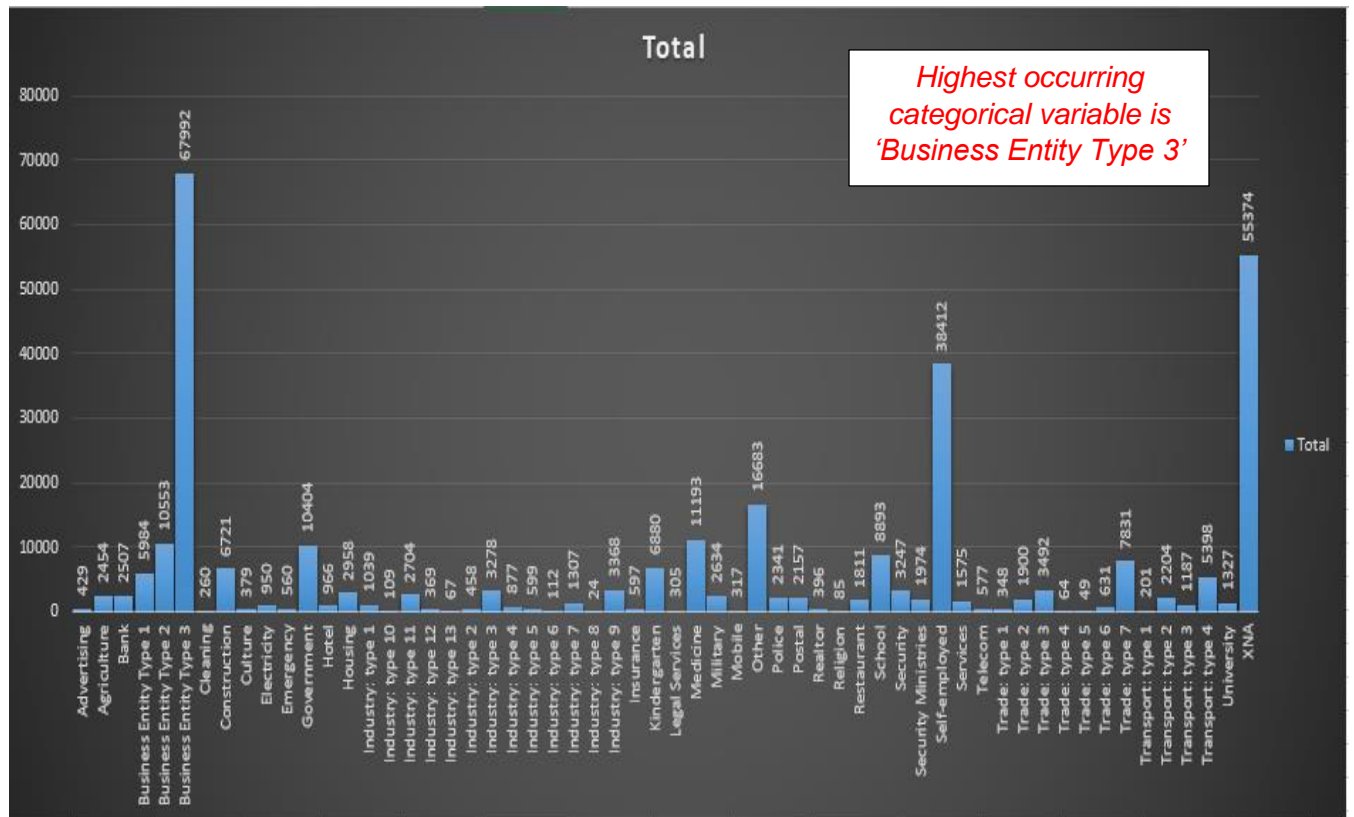
Filling in blanks in the Name_Type_Suite column of the Application Dataset with the categorical variable with the highest frequency

Row Labels	Count of NAME_TYPE_SUITE
Children	3267
Family	40149
Group of people	271
Other_A	866
Other_B	1770
Spouse, partner	11370
Unaccompanied	248526
(blank)	
Grand Total	306219

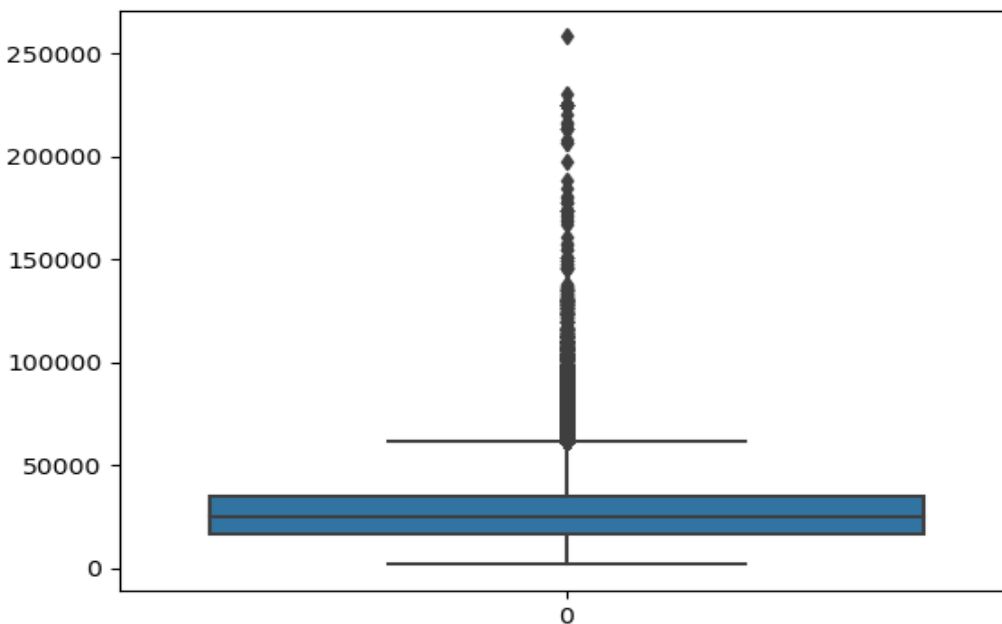
Highest occurring categorical variable is 'Unaccompanied'



Filling in blanks in the Application Dataset's Organization_type column with the most frequent categorical variable

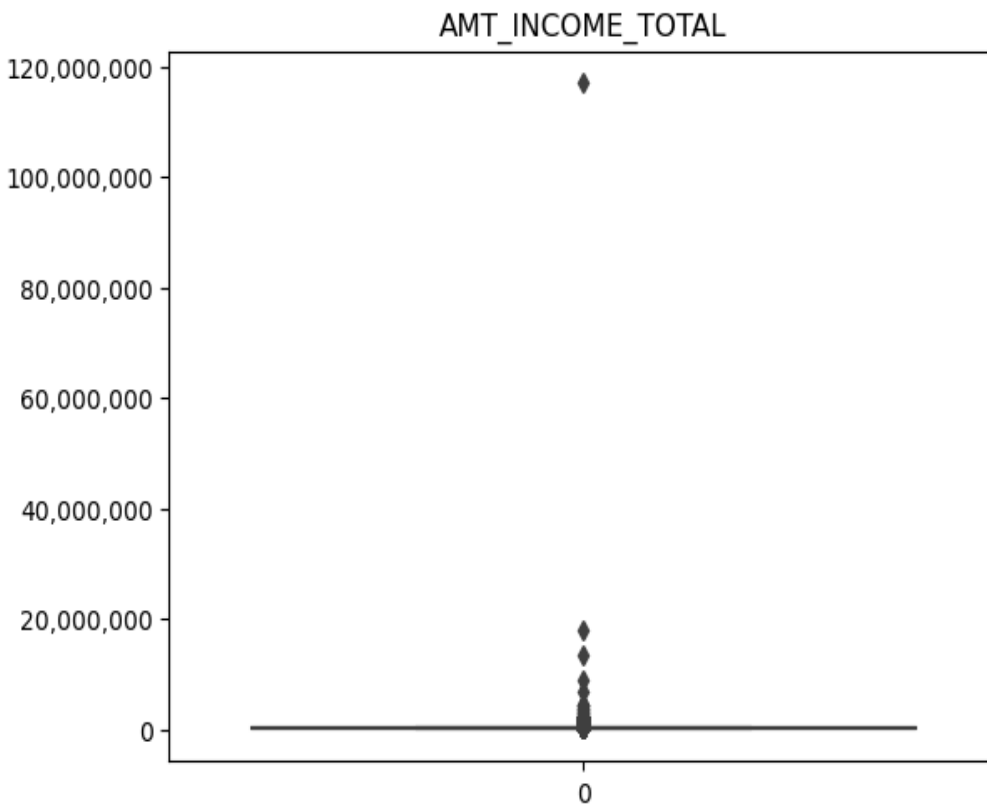


Application Dataset – Outliers



Quartiles at AMT_INCOME_TOTAL	
count	307511
mean	168798
std	237123
min	25650
25%	112500
50%	147150
75%	202500
max	117000000

Here, we can see that the existence of outliers causes a significant difference between the 25%, 50%, and 75% quartiles. We won't get rid of the outliers though because overall income differs from person to person.

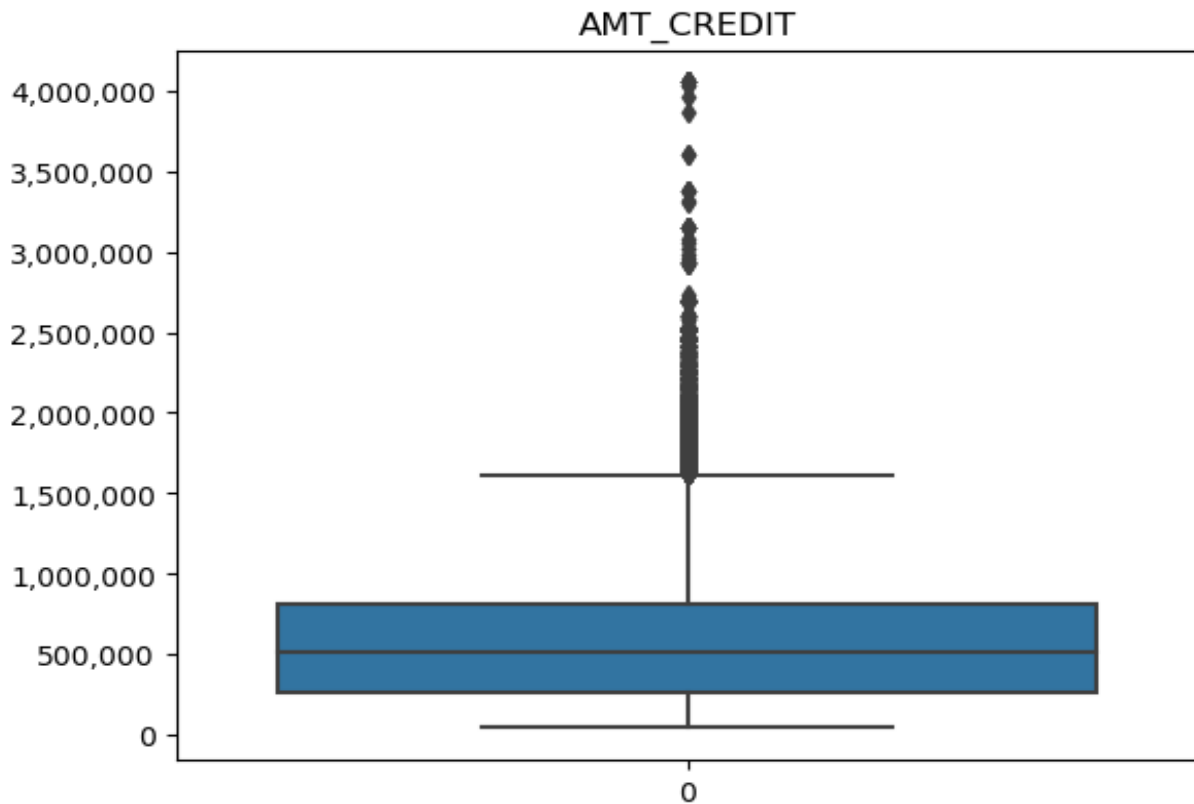


outliers at extreme points i.e. max 117000000

Quartiles at AMT_CREDIT	
count	307511
mean	599026
std	402491
min	45000
25%	270000
50%	513531
75%	808650
max	4050000

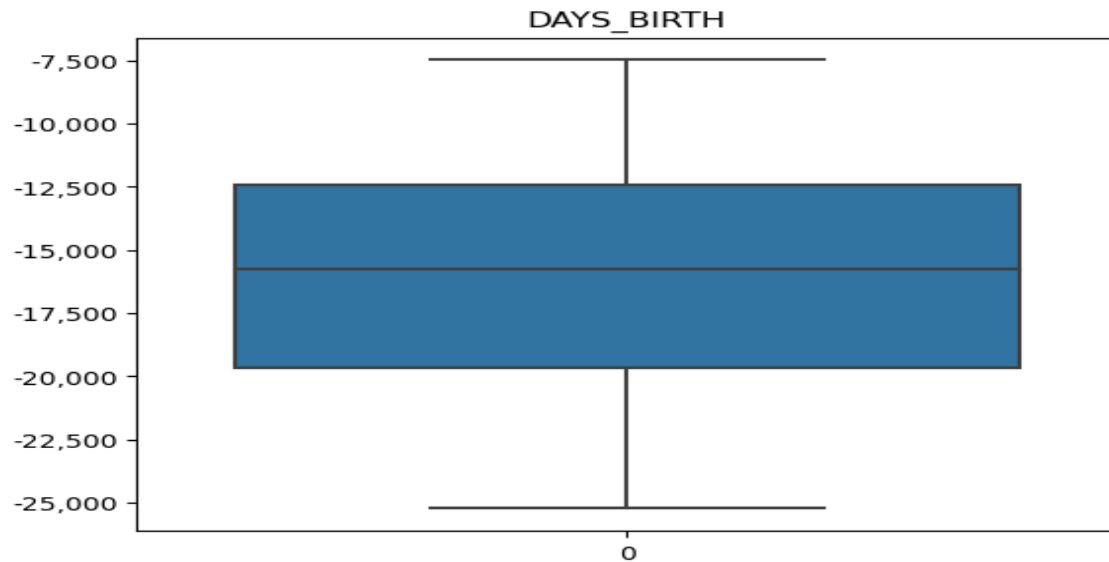
It is evident from the figure that outliers are located on the 98% and close to the maximum side of the box plot. Additionally, there is a large discrepancy between the 75% quartile and the maximum value, which is caused by the existence of outliers.

But because each person receives a different amount of credit, we won't eliminate the outliers.



Quartiles at DAYS_BIRTH	
count	307511
mean	-16037
std	4364
min	-252229
25%	-19682
50%	-15750
75%	-12413
max	-7489

As seen from the boxplot it is clear that there are no outliers The data of DAYS_BIRTH is well distributed.



Quartiles at DAYS_EMPLOYED	
count	307511
mean	63815
std	141276
min	-17912
25%	-2760
50%	-1213
75%	-289
max	365243

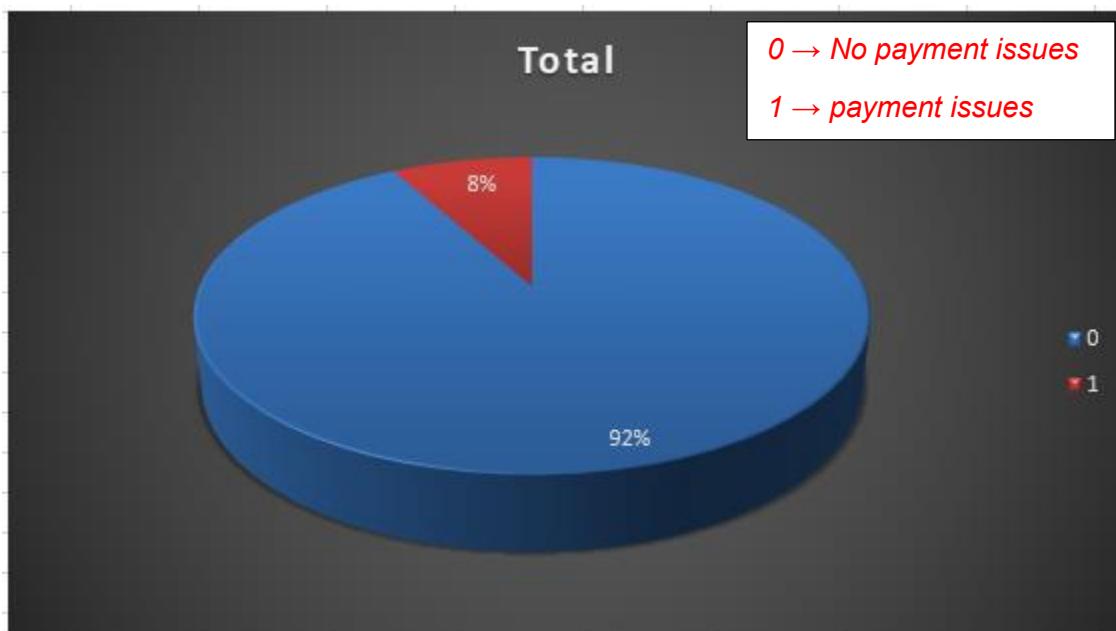
There is only one outlier, which is + or 365243; the median value is -1213.00.



Application Dataset –Univariate Analysis

TARGET VARIABLE

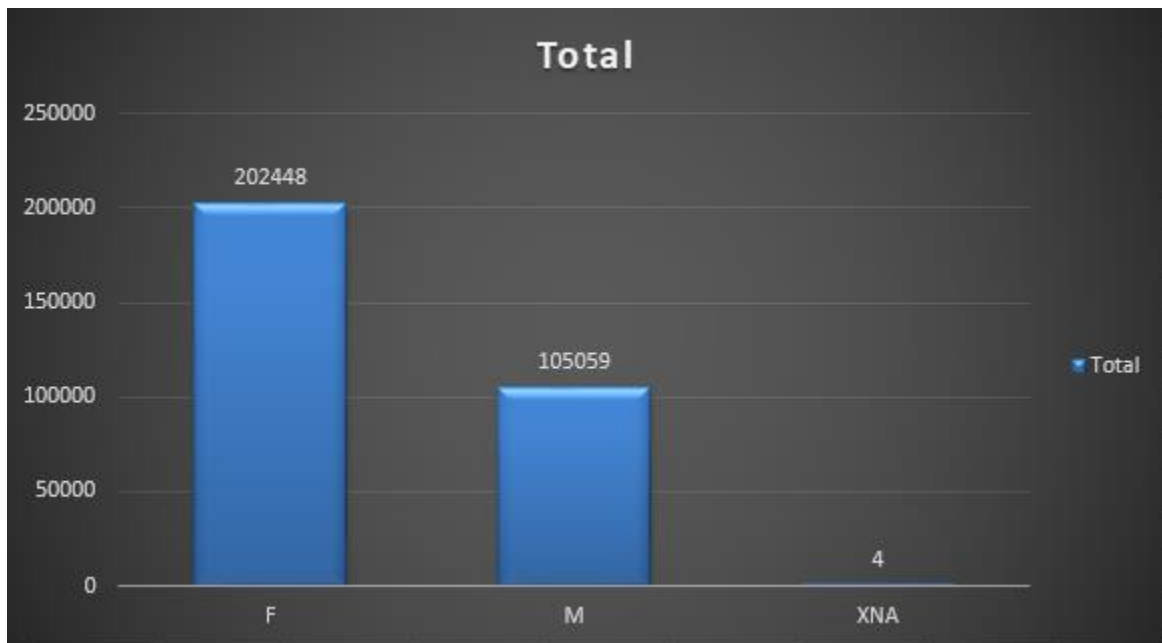
Row Labels	Count of TARGET
0	282686
1	24825
Grand Total	307511



Nearly 92% of all clients had the target variable, according to the Target Variable Pie Chart. Whereas 8% of clients had some sort of issue upon payment, there were no problems.

GENDER VARIABLE

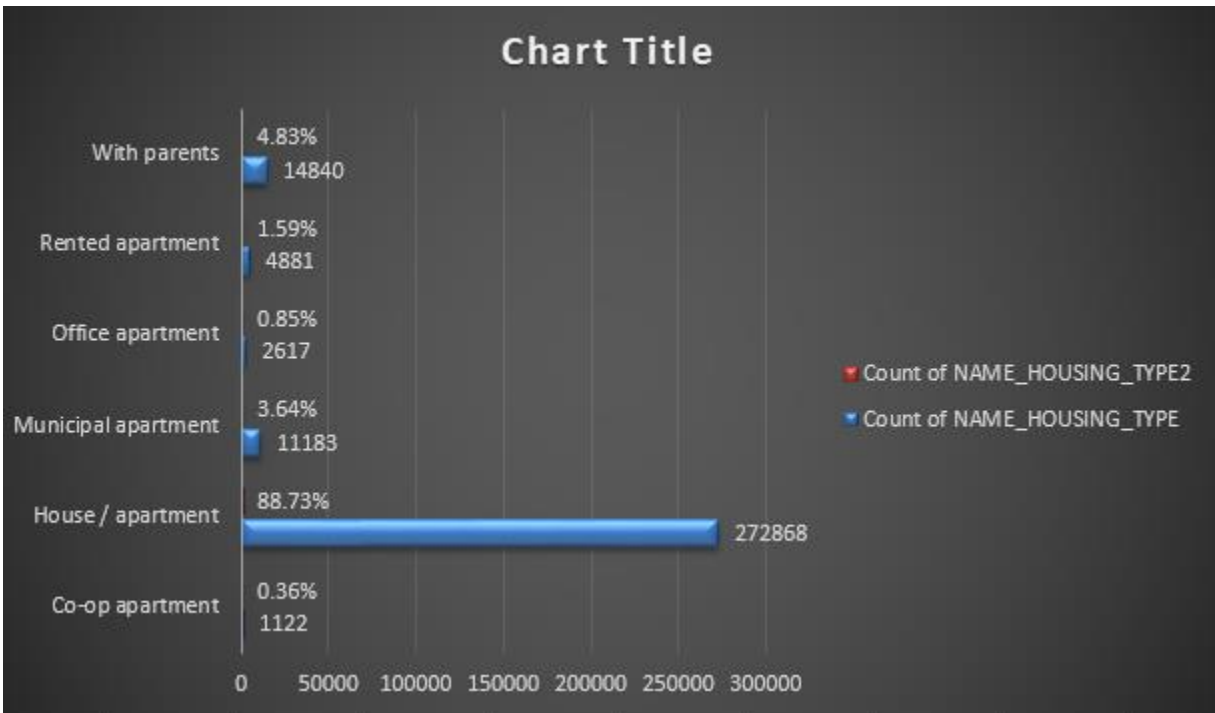
Row Labels	Count of CODE_GENDER
F	202448
M	105059
XNA	4
Grand Total	307511



We may deduce that around 66% of clients are female and 34% are male based on the GENDER_VARIABLE pie chart. The four applicants' XNA gender designations can be disregarded.

NAME_HOUSING_TYPE

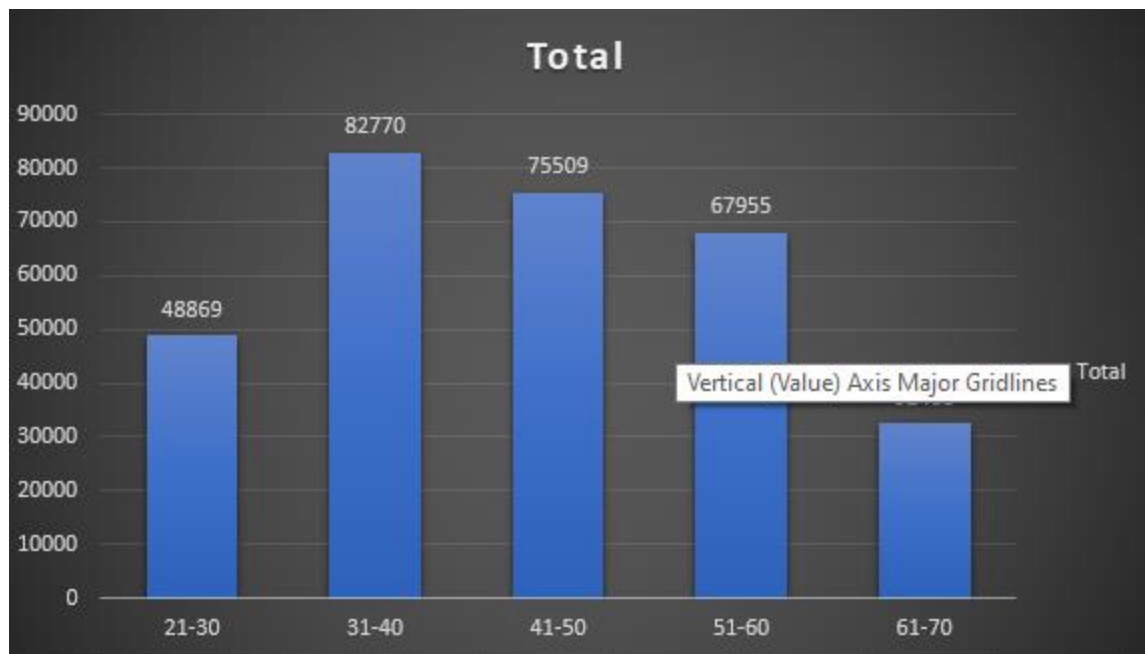
Row Labels	Count of NAME_HOUSING_TYPE	Count of NAME_HOUSING_TYPE2
Co-op apartment	1122	0.36%
House / apartment	272868	88.73%
Municipal apartment	11183	3.64%
Office apartment	2617	0.85%
Rented apartment	4881	1.59%
With parents	14840	4.83%
Grand Total	307511	100.00%



Based on the count and percentage bar graphs. The bank can focus on those populations that do not have their own apartments, such as those who live in co-ops, municipal apartments, rented apartments, and those who live with their parents.

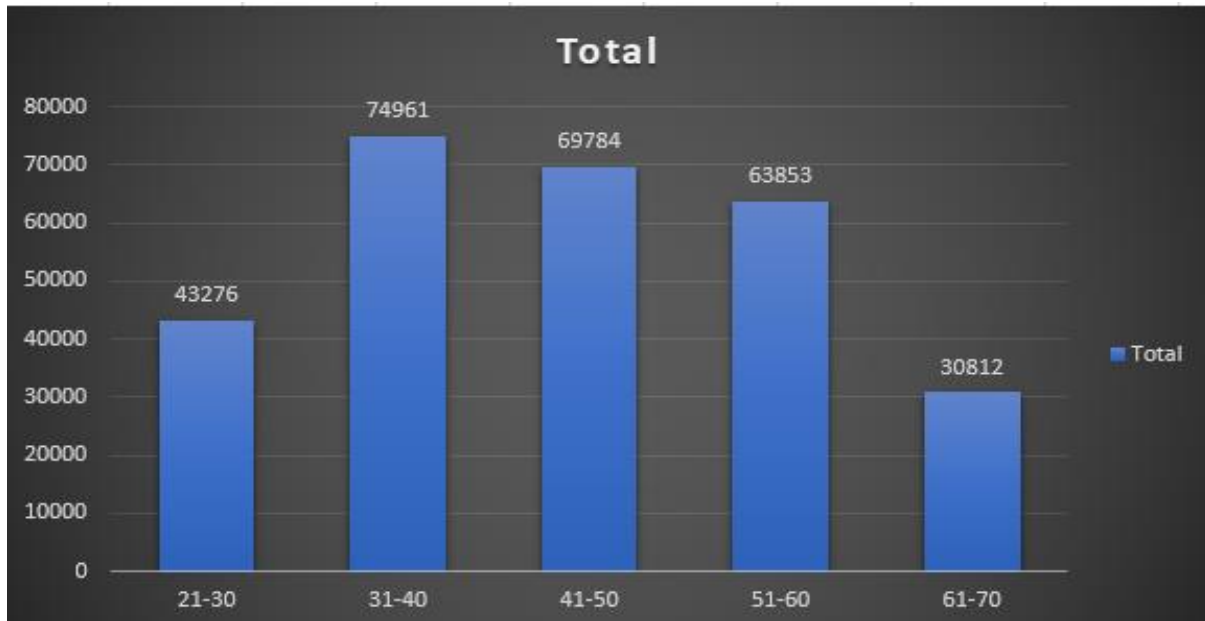
AGE GROUP

Row Labels	Count of Year_Birth
21-30	48869
31-40	82770
41-50	75509
51-60	67955
61-70	32408
Grand Total	307511



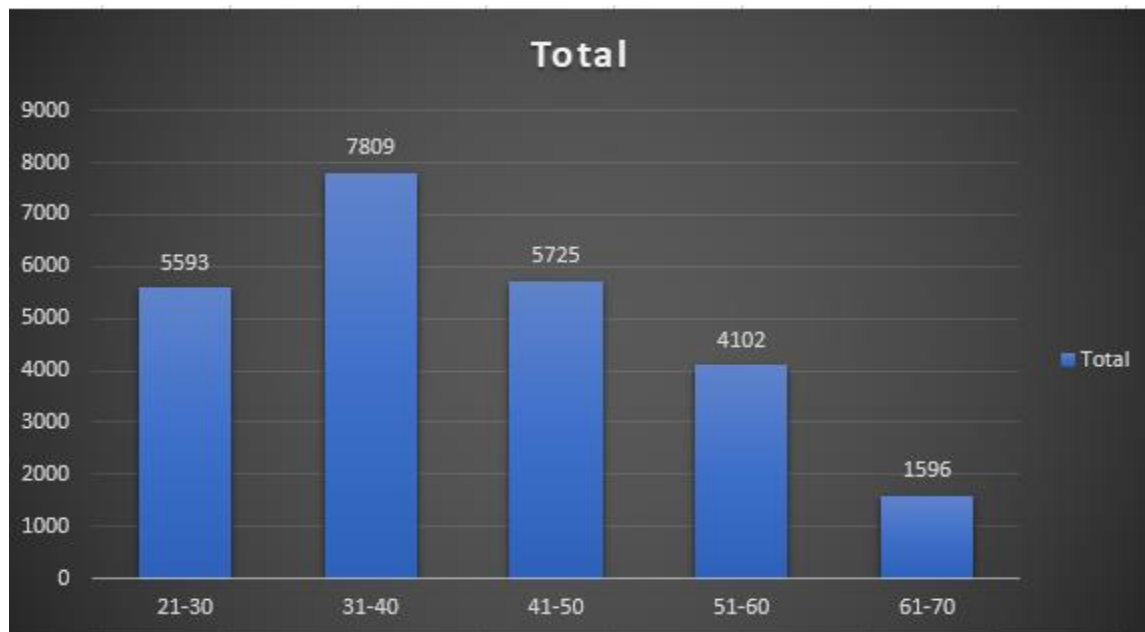
We may deduce that the majority of applicants fall into the Age Group "31-40" from the nearby pub layout.

Row Labels	Count of Year_Birth
21-30	43276
31-40	74961
41-50	69784
51-60	63853
61-70	30812
Grand Total	282686



We may deduce from the adjacent bar plot that customers/applicants in the age group "31-40" have the biggest number when it comes to making or returning payments to banks.

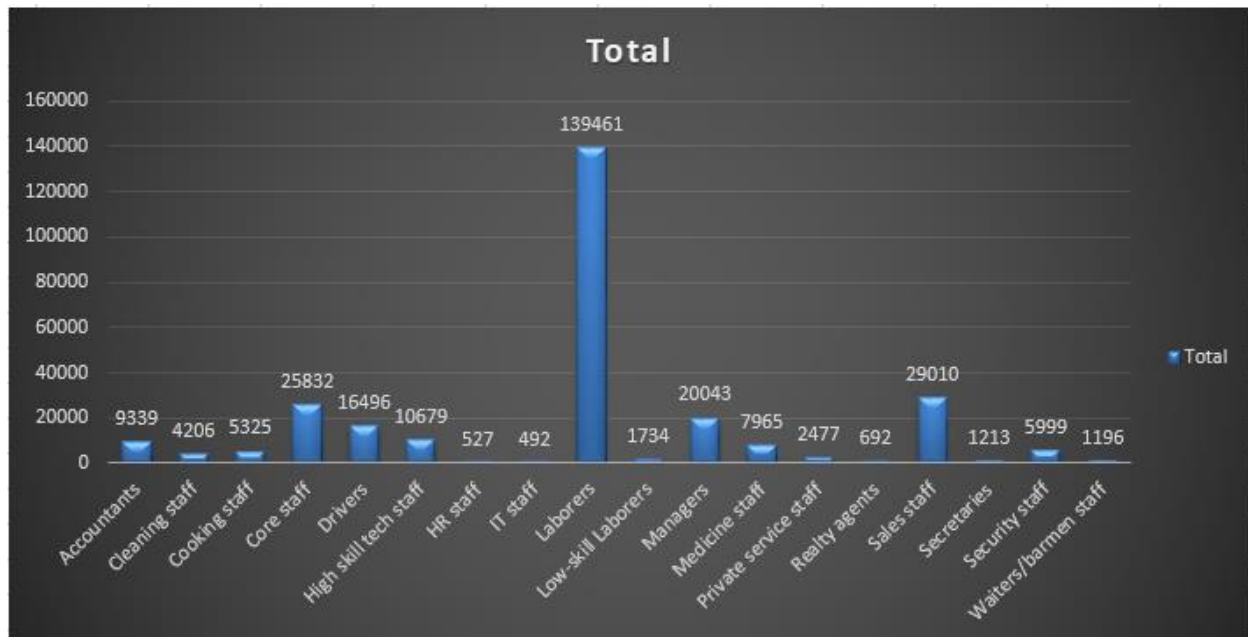
TARGET 1		
Row Labels		Count of Year_Birth
21-30		5593
31-40		7809
41-50		5725
51-60		4102
61-70		1596
Grand Total		24825



According to the adjacent bar plot, customers/applicants in the age group "31-40" experience the most payment problems while making or returning payments to banks.

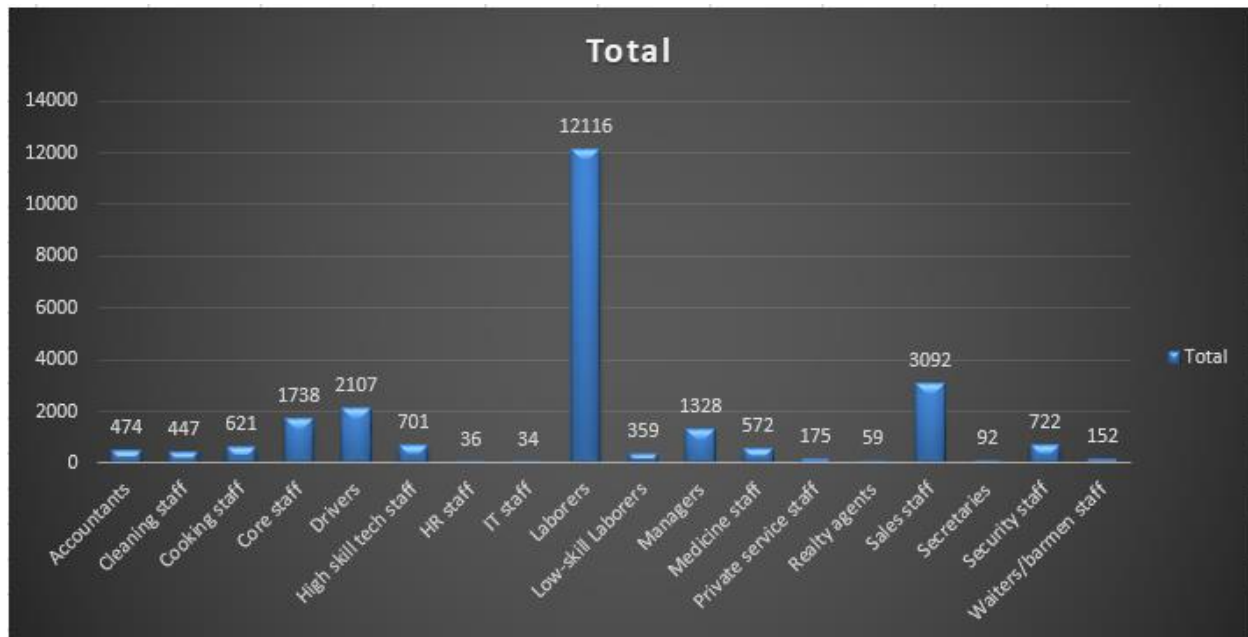
OCCUPATION_TYPE

TARGET	0
Row Labels	Count of OCCUPATION_TYPE
Accountants	9339
Cleaning staff	4206
Cooking staff	5325
Core staff	25832
Drivers	16496
High skill tech staff	10679
HR staff	527
IT staff	492
Laborers	139461
Low-skill Laborers	1734
Managers	20043
Medicine staff	7965
Private service staff	2477
Realty agents	692
Sales staff	29010
Secretaries	1213
Security staff	5999
Waiters/barmen staff	1196
Grand Total	282686



'Labourers' occupation_type clients have the largest count when it comes to clients with no payment concerns, according to the above bar plot, it can be deduced.

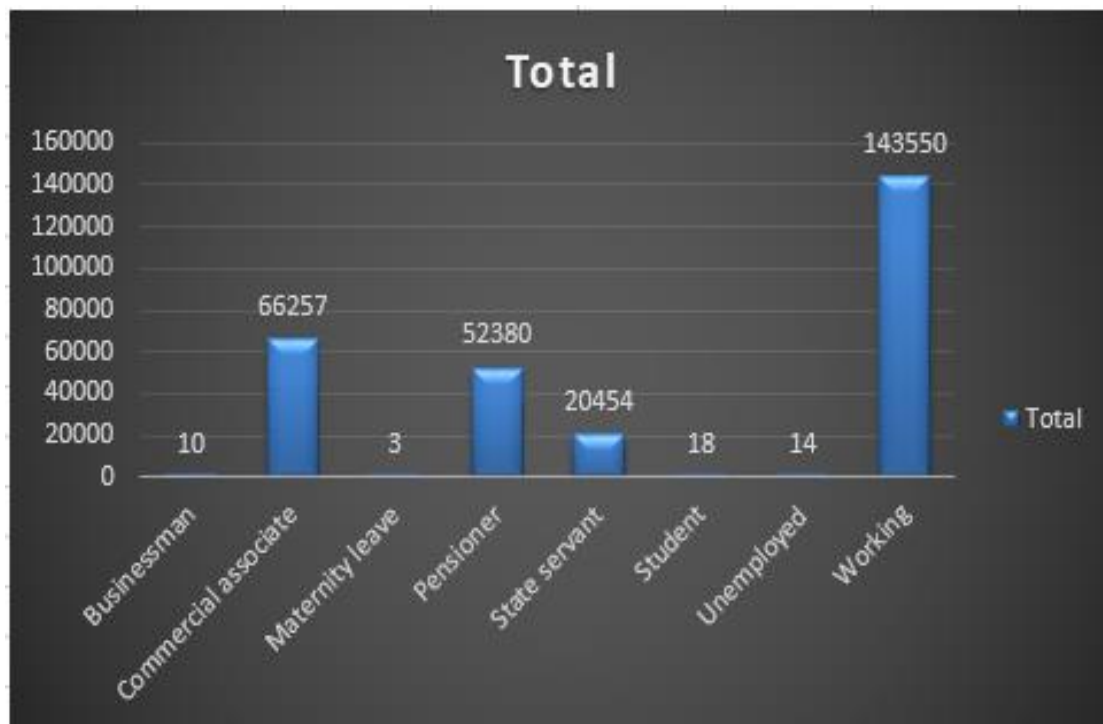
TARGET 1	
Row Labels	Count of OCCUPATION_TYPE
Accountants	474
Cleaning staff	447
Cooking staff	621
Core staff	1738
Drivers	2107
High skill tech staff	701
HR staff	36
IT staff	34
Laborers	12116
Low-skill Laborers	359
Managers	1328
Medicine staff	572
Private service staff	175
Realty agents	59
Sales staff	3092
Secretaries	92
Security staff	722
Waiters/barmen staff	152
Grand Total	24825



From the above bar plot we can infer that clients with occupation_type 'Laborers' have the highest number of count when it comes to clients with payment issues.

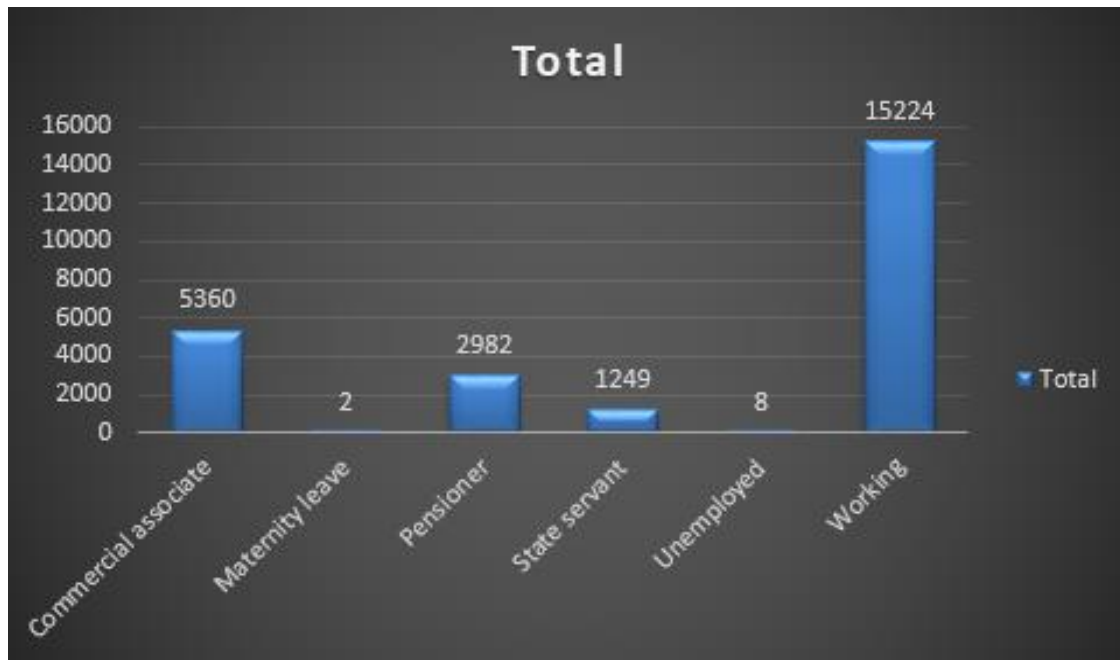
NAME_INCOME_TYPE

TARGET	0
Row Labels	Count of NAME_INCOME_TYPE
Businessman	10
Commercial associate	66257
Maternity leave	3
Pensioner	52380
State servant	20454
Student	18
Unemployed	14
Working	143550
Grand Total	282686



The 'WORKING' income_type customers have the largest count of those who have no payment concerns, according to the aforementioned Bar plot.

TARGET	1
Row Labels	Count of NAME_INCOME_TYPE
Commercial associate	5360
Maternity leave	2
Pensioner	2982
State servant	1249
Unemployed	8
Working	15224
Grand Total	24825

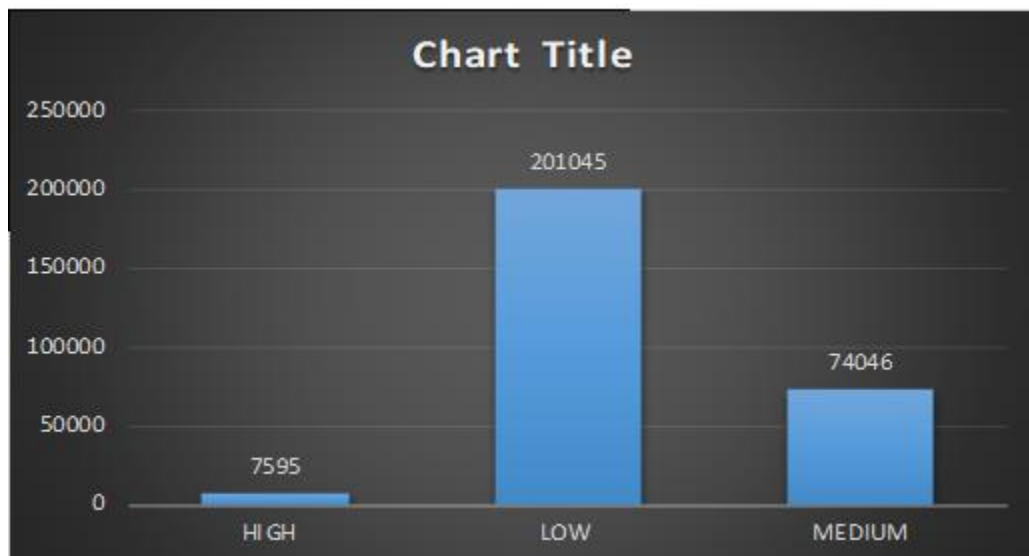


The 'WORKING' income_type customers have the largest count of clients experiencing payment concerns, according to the aforementioned Bar plot.

AMT_TOTAL INCOME

Row Labels	Count of AMT_TOTAL INCOME
HIGH	7595
LOW	201045
MEDIUM	74046
Grand Total	282686

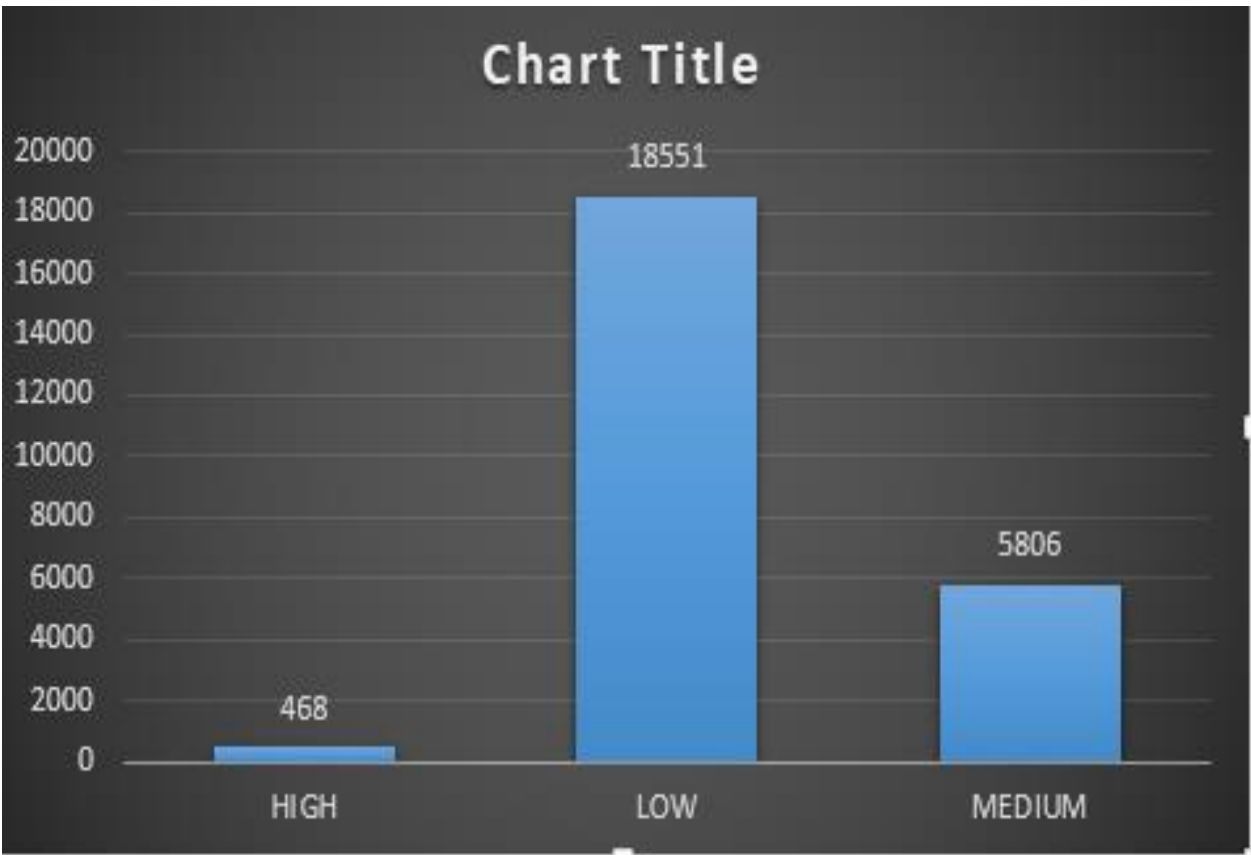
AMT_TOTAL_INCOME with no payment issues



The customer having the whole income range as 'LOW' has the largest count when it comes to clients having no payment concerns, according to the aforementioned bar plot.

AMT_TOTAL_INCOME with payment issues

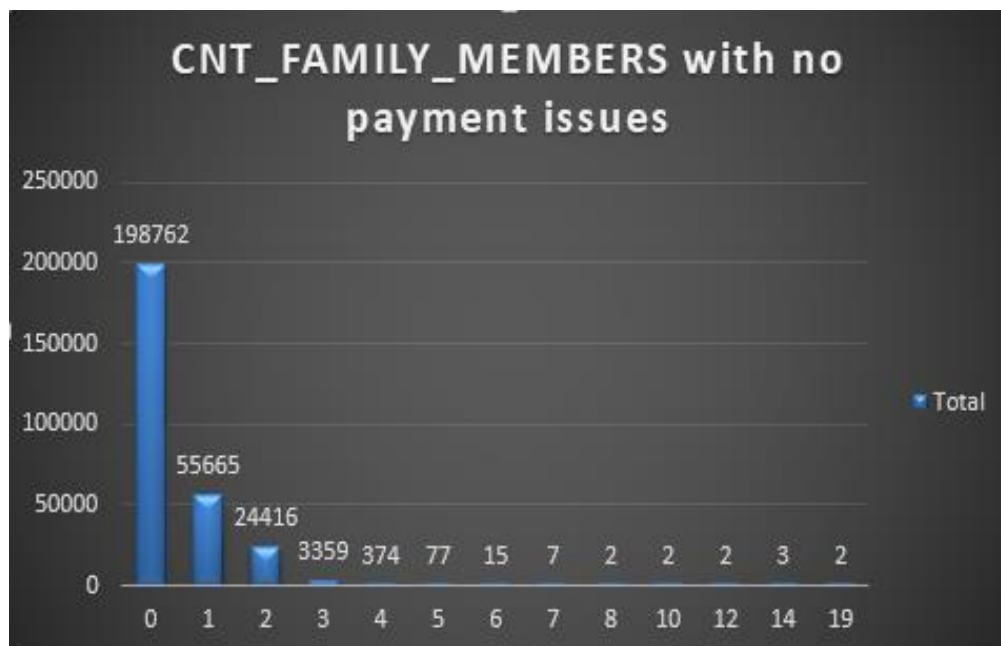
Count of TARGET	
Row Labels	1
HIGH	468
LOW	18551
MEDIUM	5806
Grand Total	24825



The accompanying bar plot indicates that clients with total income ranges that are "LOW" have the largest percentage of clients with payment difficulties.

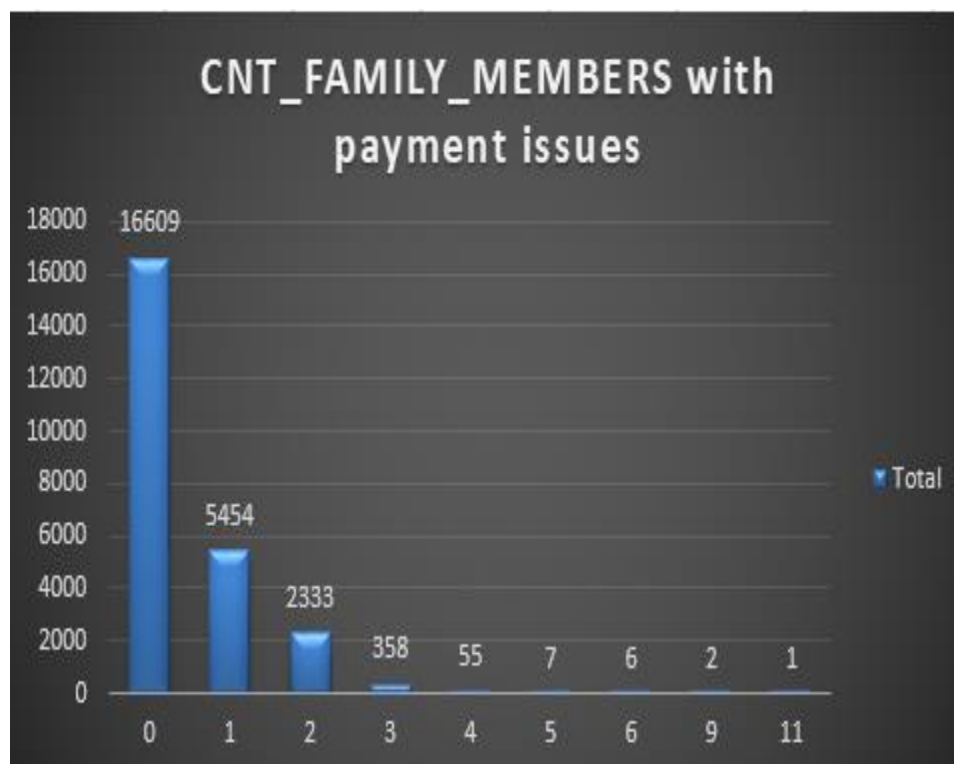
CNT_FAMILY

TARGET	0
Row Labels	Count of CNT_CHILDREN
0	198762
1	55665
2	24416
3	3359
4	374
5	77
6	15
7	7
8	2
10	2
12	2
14	3
19	2
Grand Total	282686



According to the above Bar Plot, clients with no family members have the highest percentage of clients with no payment concerns.

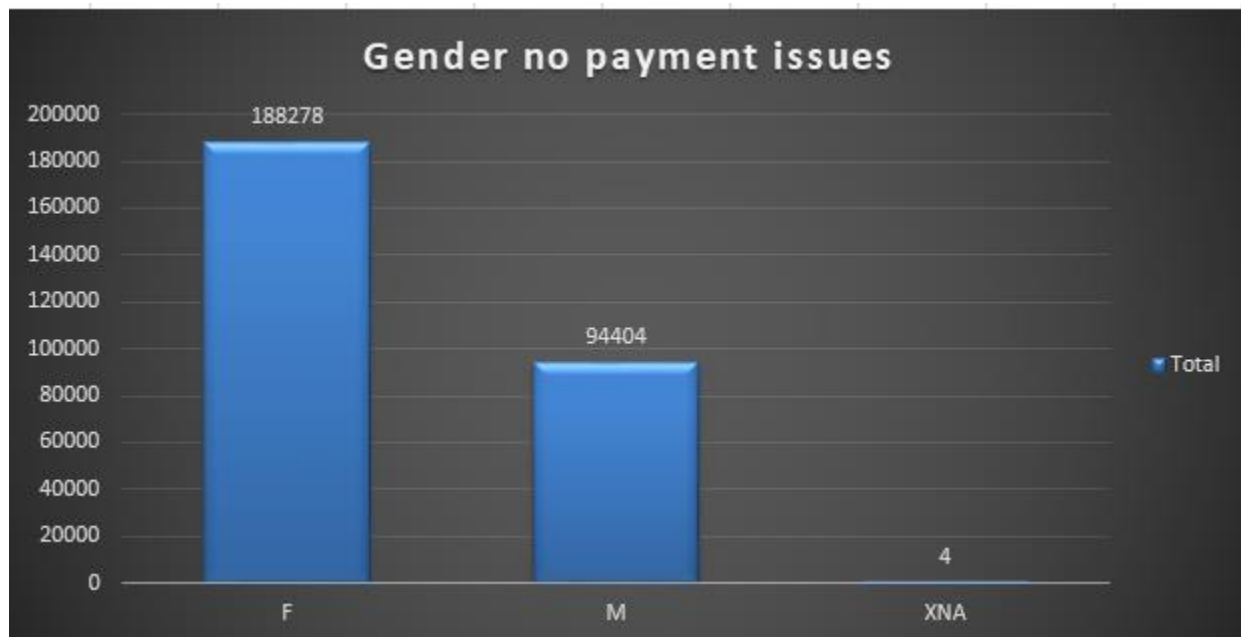
TARGET	1	
Row Labels		Count of CNT_CHILDREN
0		16609
1		5454
2		2333
3		358
4		55
5		7
6		6
9		2
11		1
Grand Total		24825



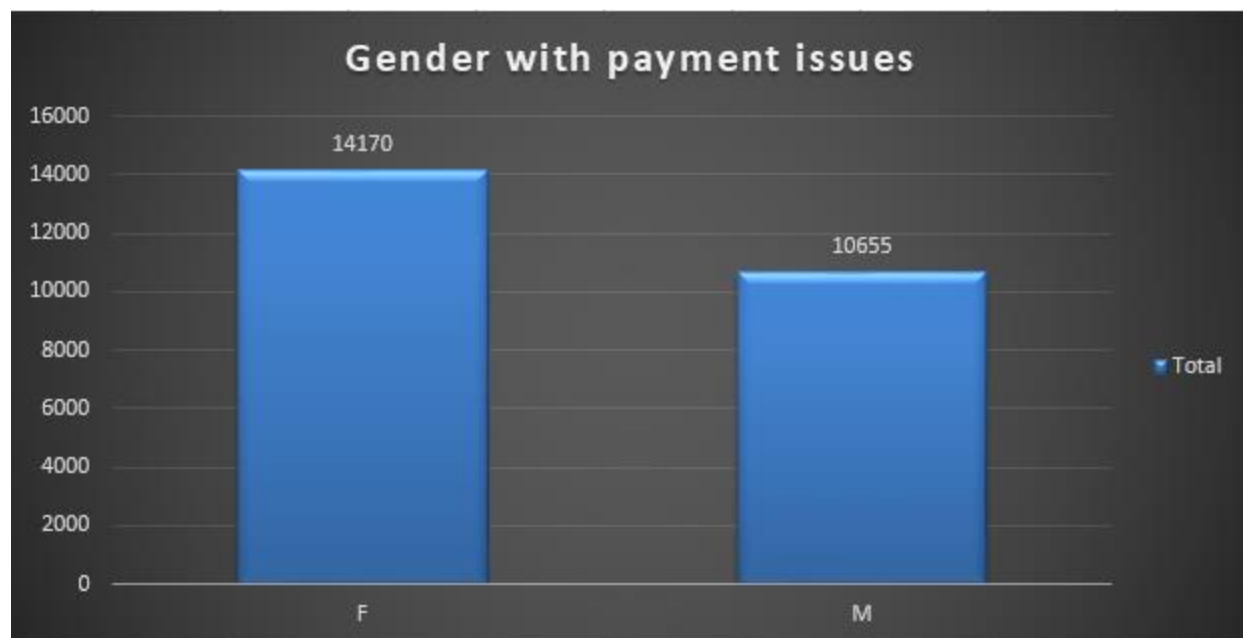
According to the aforementioned bar plot, customers with no family members are the ones who have the most number of payment problems.

CODE_GENDER

TARGET	0	
Row Labels	Count of CODE_GENDER	
F	188278	
M	94404	
XNA	4	
Grand Total	282686	



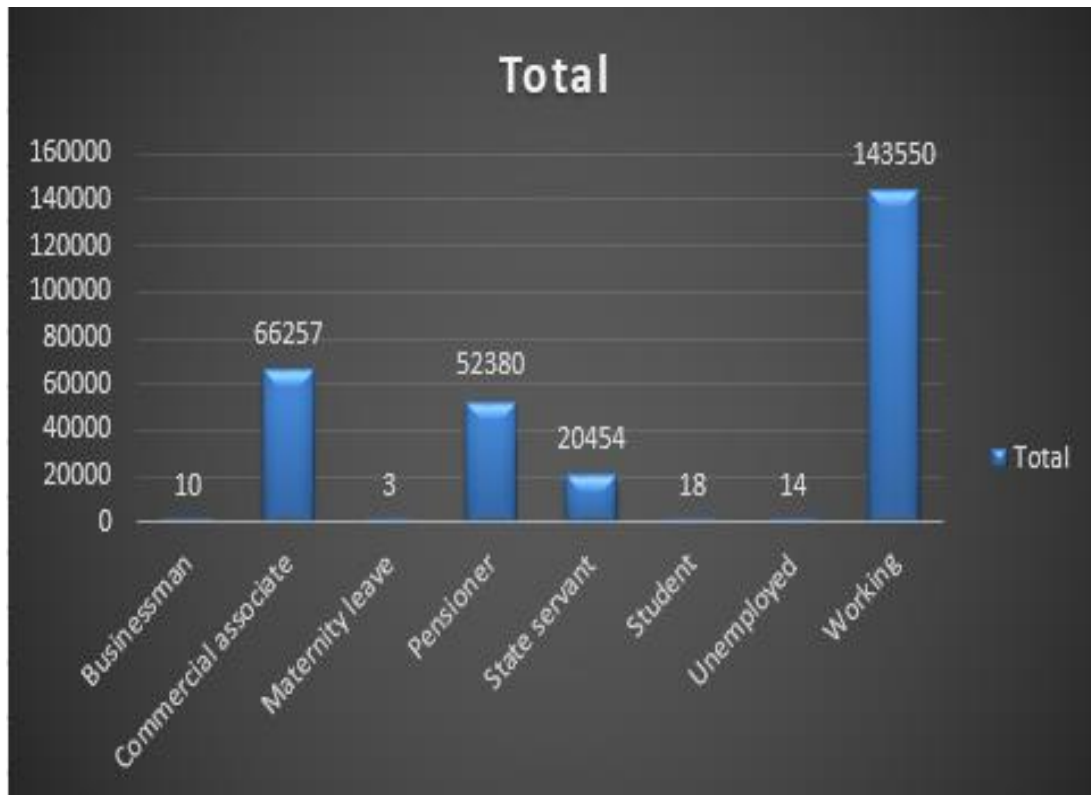
TARGET	1	
Row Labels	Count of CODE_GENDER	
F	14170	
M	10655	
Grand Total	24825	



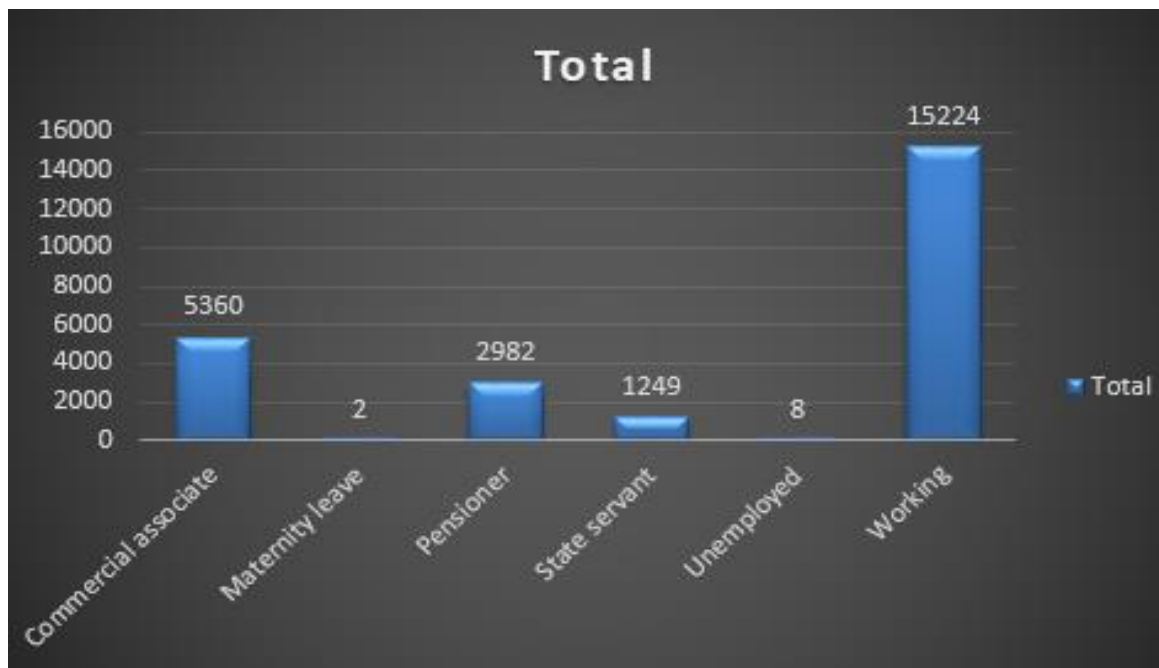
According to the above bar plot, clients with CODE_GENDER = 'F' had the most non-defaulters ($188278 - 14170 = 174108$).

NAME_INCOME_TYPE

TARGET	0	
Row Labels	▼	Count of NAME_INCOME_TYPE
Businessman		10
Commercial associate		66257
Maternity leave		3
Pensioner		52380
State servant		20454
Student		18
Unemployed		14
Working		143550
Grand Total		282686



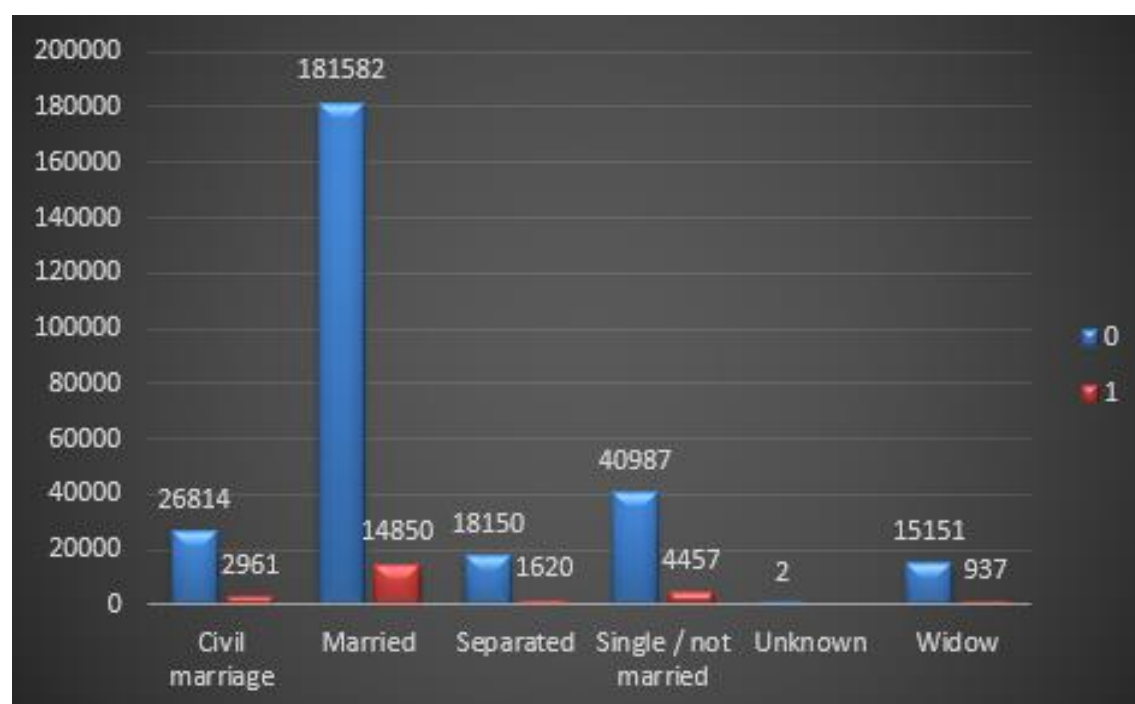
TARGET	1	
Row Labels		Count of NAME_INCOME_TYPE
Commercial associate		5360
Maternity leave		2
Pensioner		2982
State servant		1249
Unemployed		8
Working		15224
Grand Total		24825



According to the adjacent bar plot, customers with NAME_INCOME_TYPE = "WORKING" have the largest number of non-defaulters, or $143550 - 15224 = 128326$.

NAME_FAMILY_STATUS

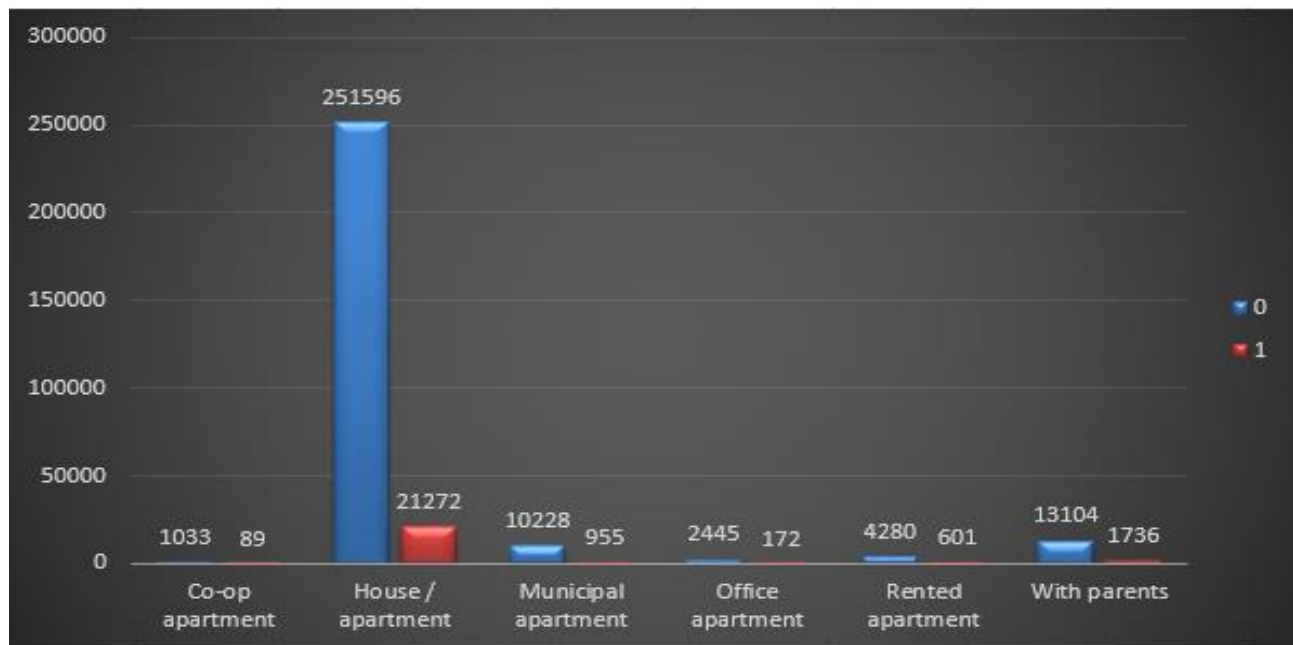
Count of NAME_FAMILY_STATUS		Column Labels	
Row Labels		0	1 Grand Total
Civil marriage	26814	2961	29775
Married	181582	14850	196432
Separated	18150	1620	19770
Single / not married	40987	4457	45444
Unknown	2		2
Widow	15151	937	16088
Grand Total	282686	24825	307511



customers with NAME_FAMILY_STATUS = 'MARRIED' are, according to the adjacent Bar Plot, customers had the most nondefaulters, with a total of 166732 (181582 - 14850).

NAME_HOUSING_TYPE

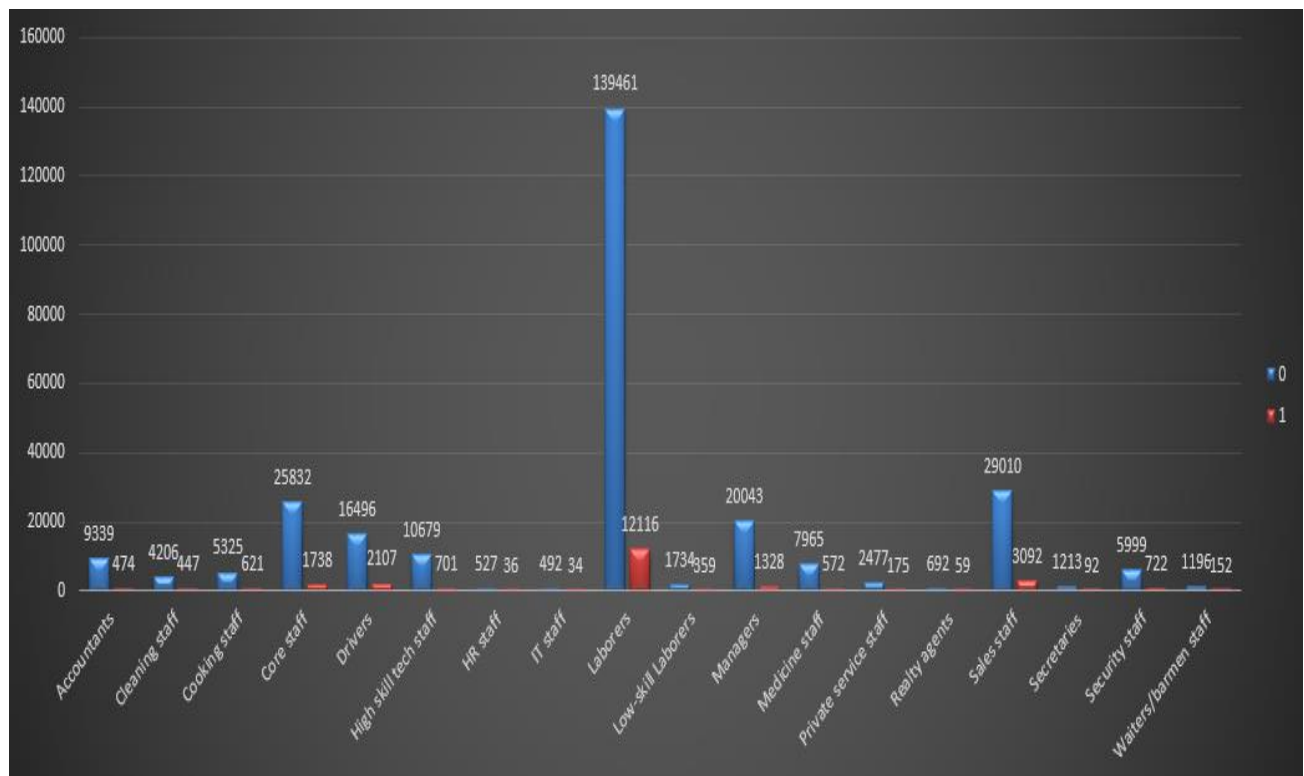
Count of NAME_HOUSING_TYPE Column Labels ▼			
Row Labels ▼	0	1	Grand Total
Co-op apartment	1033	89	1122
House / apartment	251596	21272	272868
Municipal apartment	10228	955	11183
Office apartment	2445	172	2617
Rented apartment	4280	601	4881
With parents	13104	1736	14840
Grand Total	282686	24825	307511



According to the above bar plot, clients with NAME_HOUSING_TYPE = "House/Apartment" had the largest number of non-defaulters, with a total of 251596-21272 = 230324.

OCCUPATION_TYPE

Count of OCCUPATION_TYPE Column Labels			
Row Labels	0	1	Grand Total
Accountants	9339	474	9813
Cleaning staff	4206	447	4653
Cooking staff	5325	621	5946
Core staff	25832	1738	27570
Drivers	16496	2107	18603
High skill tech staff	10679	701	11380
HR staff	527	36	563
IT staff	492	34	526
Laborers	139461	12116	151577
Low-skill Laborers	1734	359	2093
Managers	20043	1328	21371
Medicine staff	7965	572	8537
Private service staff	2477	175	2652
Realty agents	692	59	751
Sales staff	29010	3092	32102
Secretaries	1213	92	1305
Security staff	5999	722	6721
Waiters/barmen staff	1196	152	1348
Grand Total	282686	24825	307511

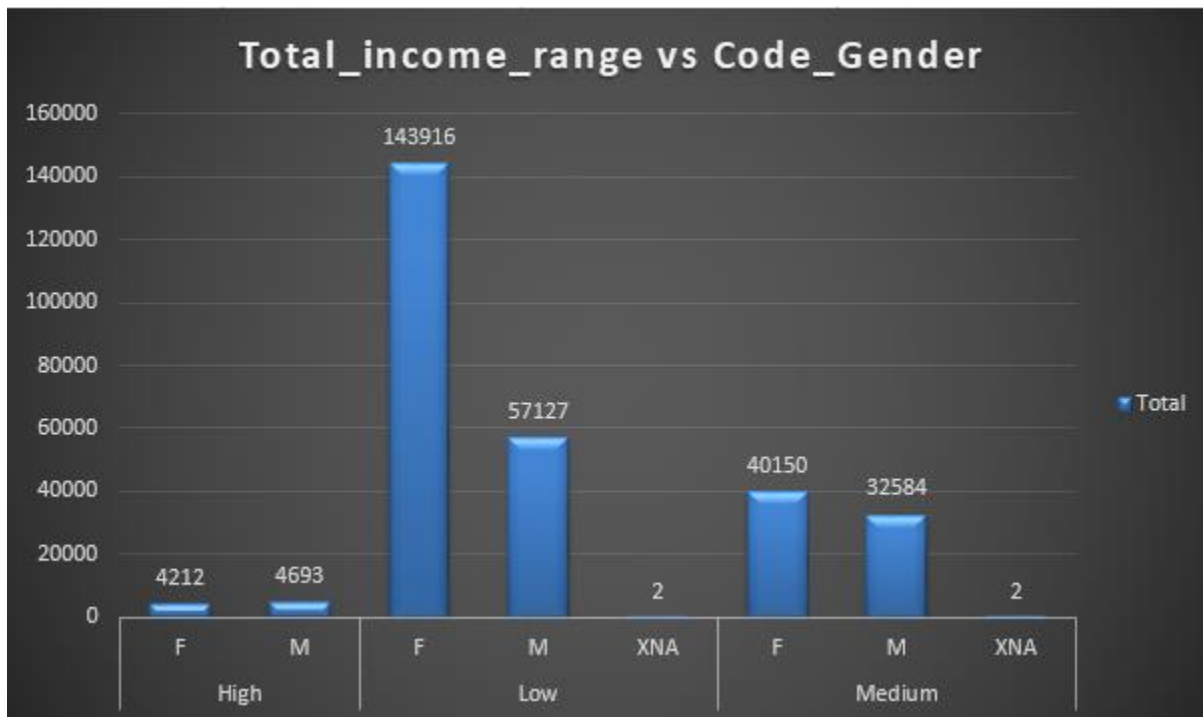


The customers with occupation_type = "Labourers" have the greatest count for non-defaulters, which is $139461 - 12116 = 127345$, according to the adjacent Bar plot.

Bivariate Analysis for TARGET variable

Target 0: Total_income_range vs Code_gender

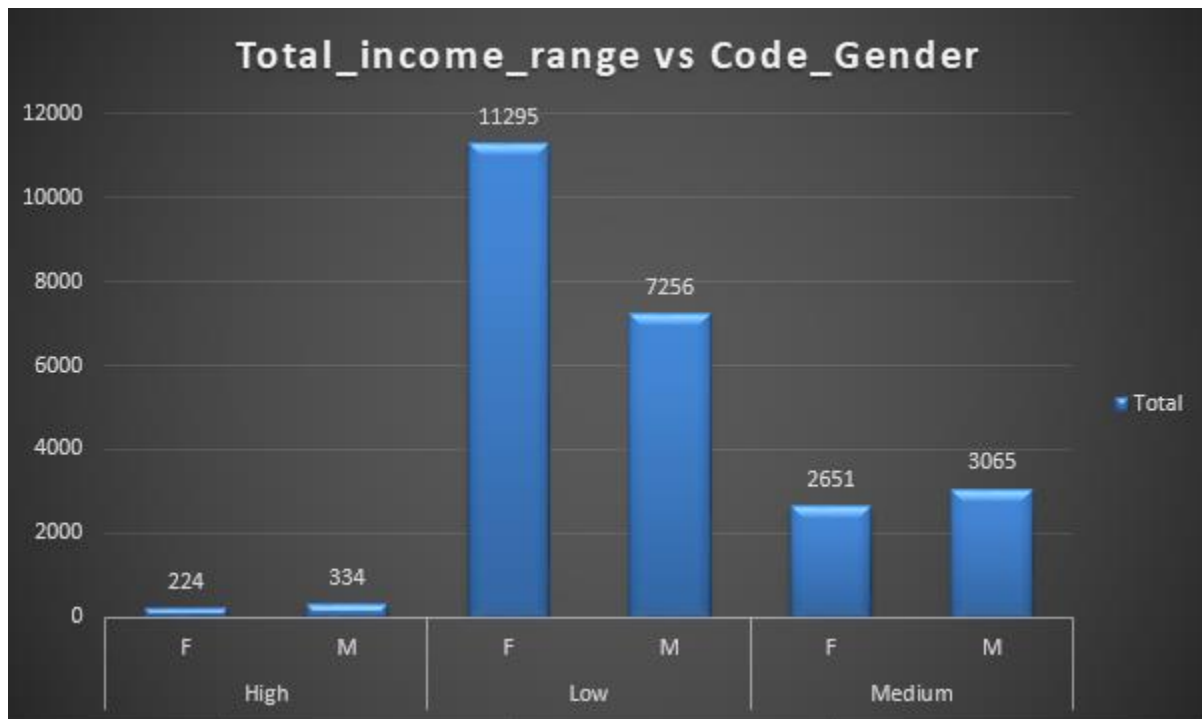
TARGET		0
Row Labels		Count of CODE_GENDER
High		8905
F		4212
M		4693
Low		201045
F		143916
M		57127
XNA		2
Medium		72736
F		40150
M		32584
XNA		2
Grand Total		282686



The majority of consumers without payment concerns are women who are in the low income bracket, according to the aforementioned bar map.

Target 1: Total_income_range vs Code_gender

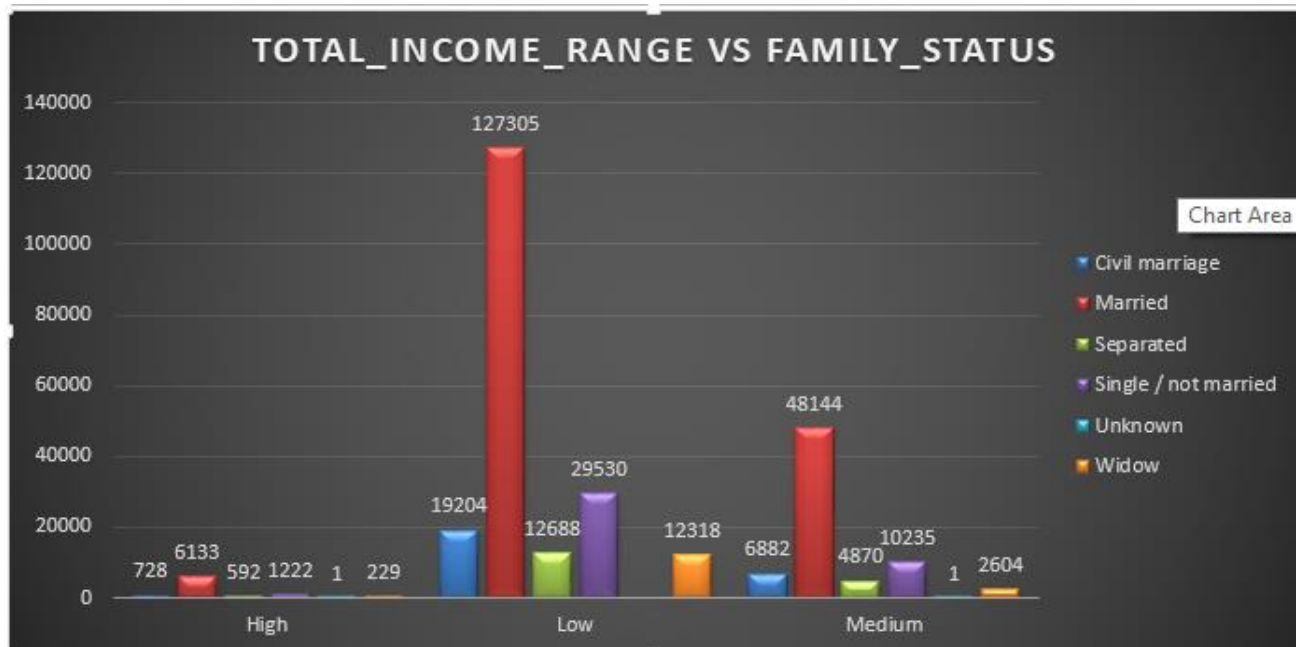
TARGET	1
Row Labels	Count of CODE_GENDER
High	558
F	224
M	334
Low	18551
F	11295
M	7256
Medium	5716
F	2651
M	3065
Grand Total	24825



The accompanying bar plot indicates that the majority of clients that have payment concerns are women who fall into the low income group.

Target 0: Total Income vs Family status

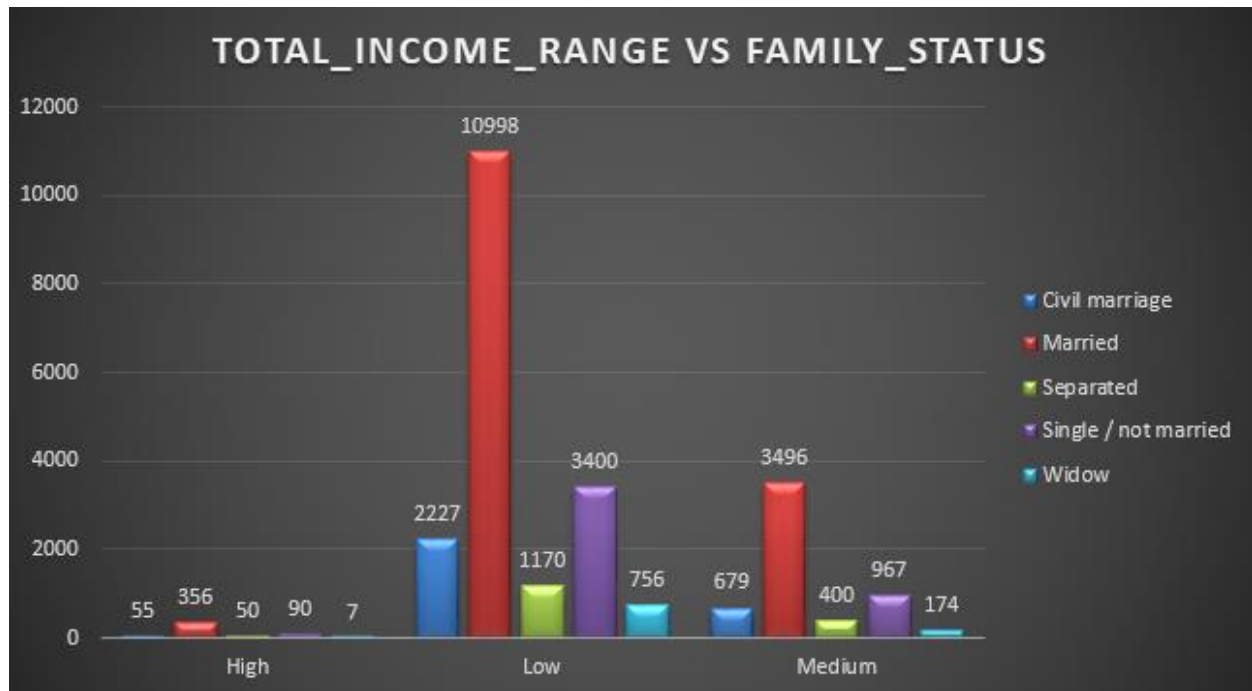
TARGET	0						
Count of NAME_FAMILY_STATUS Column Labels							
Row Labels	Civil marriage	Married	Separated	Single / not married	Unknown	Widow	Grand Total
High	728	6133	592	1222	1	229	8905
Low	19204	127305	12688	29530		12318	201045
Medium	6882	48144	4870	10235	1	2604	72736
Grand Total	26814	181582	18150	40987	2	15151	282686



Clients with a family status of "Married" and a total income range of "Low" are those most likely to have no payment troubles, according to the adjacent Bar plot.

Target 1: Total Income vs Family status

TARGET	1						
Count of NAME_FAMILY_STATUS	Column Labels						
Row Labels	Civil marriage	Married	Separated	Single / not married	Widow	Grand Total	
High	55	356	50		90	7	558
Low	2227	10998	1170		3400	756	18551
Medium	679	3496	400		967	174	5716
Grand Total	2961	14850	1620		4457	937	24825



Clients with a total income range of "Low" and a family status of "Married" are those most likely to experience payment troubles, according to the adjacent Bar plot.

Previous Application Dataset – Dropping, Imputing and analyzing Null values

The following columns from the preceding datasets for applications must be removed since they are unnecessary for doing data analysis.

1. HOUR_APPR_PROCESS_START
2. WEEKDAY_APPR_PROCESS_START_PREV
3. FLAG_LAST_APPL_PER_CONTRACT
4. NFLAG_LAST_APPL_IN_DAY
5. SK_ID_CURR
6. WEEKDAY_APPR_PROCESS_START
7. Removing the rows with the values 'XNA' & 'XAP' for the column: NAME_TYPE_SUITE

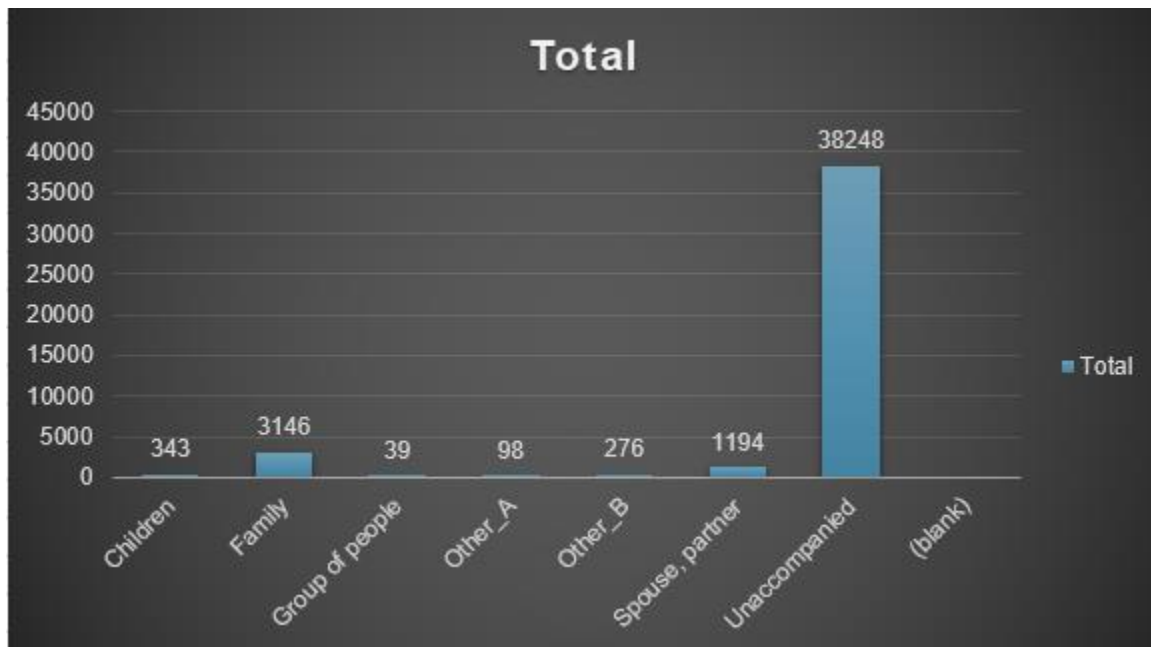
AMT_ANNUIITY

AMT_ANNUIITY	
Mean	25598.36
Standard Error	83.89295
Median	21340
Mode	25996.37
Standard Deviation	17465.86
Sample Variance	3.05E+08
Kurtosis	29.07112
Skewness	2.813956
Range	418058.1

Replace Blanks with 21340

NAME_TYPE_SUITE

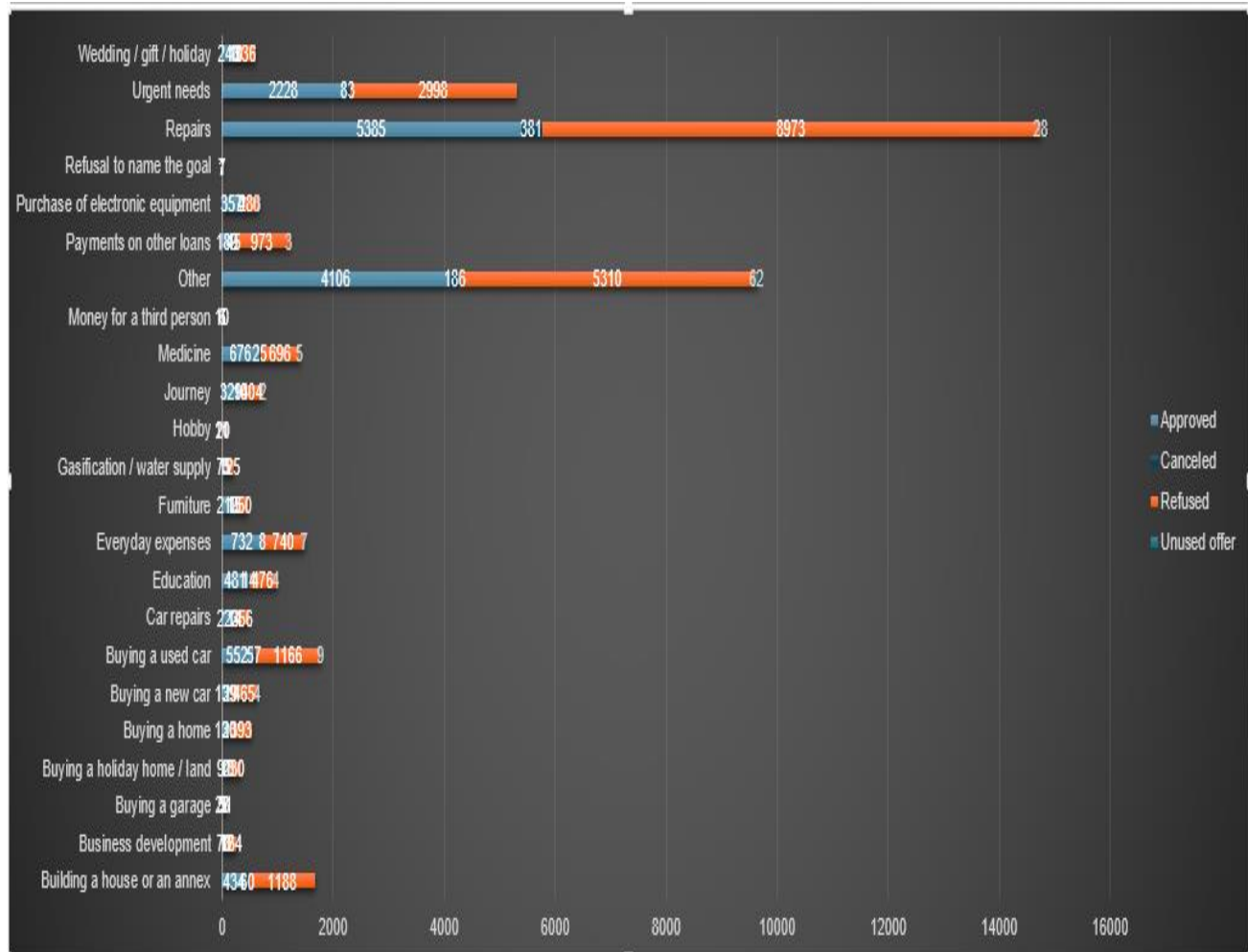
Row Labels	Count of NAME_TYPE_SUITE
Children	343
Family	3146
Group of people	39
Other_A	98
Other_B	276
Spouse, partner	1194
Unaccompanied (blank)	38248
Grand Total	43344



Replace Blanks with Unaccompanied

Distribution of Name Contract Status

Count of NAME_CONTRACT_STATUS	Column Labels				
Row Labels	Approved	Canceled	Refused	Unused offer	Grand Total
Building a house or an annex	434	60	1188		1682
Business development	78	12	164		254
Buying a garage	28	5	51		84
Buying a holiday home / land	91	13	230		334
Buying a home	130	23	393		546
Buying a new car	139	29	465	4	637
Buying a used car	552	57	1166	9	1784
Car repairs	223	14	256		493
Education	481	14	476	4	975
Everyday expenses	732	8	740	7	1487
Furniture	210	15	250		475
Gasification / water supply	75	3	125		203
Hobby	11		20		31
Journey	329	10	404	2	745
Medicine	676	25	696	5	1402
Money for a third person	10		6		16
Other	4106	186	5310	62	9664
Payments on other loans	189	45	973	3	1210
Purchase of electronic equipment	357	4	280	3	644
Refusal to name the goal	1		7		8
Repairs	5385	381	8973	28	14767
Urgent needs	2228	83	2998		5309
Wedding / gift / holiday	248	10	336		594
Grand Total	16713	997	25507	127	43344



Result

The analysis that was done led to the following conclusions:

1. The Name of Contract status, i.e., Repairs work, has the largest number of Loans that have been approved, according to the above Bar Plot.
2. So, both the Applications Dataset and the Precious Applications Dataset are being used for the analysis.
3. The percentage of defaulters (target = 1) is around 8%, whereas the percentage of non-defaulters (target = 0) is approximately 92%.
4. The Bank often loans more money to female customers than to male customers since there are fewer female customers on the list of defaulters. If the credit amount is met, the bank may still hunt for additional male customers.
5. Additionally, customers from the Working Class are more likely than those from the Commercial Associate category to make their loan payments on time.

6. Consumers with education levels of secondary or higher secondary or above have a tendency to repay loans on schedule, allowing banks to prioritise lending to those consumers.
7. Clients with LOW credit amounts tend to pay off their loans on time as opposed to HIGH and MEDIUM credit amounts. Clients in the Age Groups 31–40 have the greatest rate of timely loan repayment, followed by clients in the Age Groups 41–60.
8. Compared to other housing types, customers who live with their parents often pay off their debts rapidly. Therefore, a bank may extend credit to customers who live with their parents.
9. consumers who are taking out loans to buy a new home, or who are taking out loans to buy a new car, or who have an income type like "State Servant," have a tendency to repay their debts on time, thus banks should favour consumers with this background.
10. The Bank should exercise greater caution when providing loans to customers for repairs since they have a high number of defaulters in addition to a high number of defaulters.