

# Bank Loan Case Study

analysis performed on Application dataset

# Approach

The approach will be to perform the tasks in an organized way, creating separate sheets in the workbook for different tasks performed.

The project analysis follows the below mentioned steps:

Step 1: Data Cleaning (Null values removal & imputation, duplicates removal, outliers detection, irrelevant columns removal)

Step 2: Univariate Analysis

Step 3: Fraud Analysis

Step 4: Bivariate Analysis

Step 5: Correlation Analysis

# Irrelevant columns deleted

89 irrelevant columns were deleted which were not required for our analysis

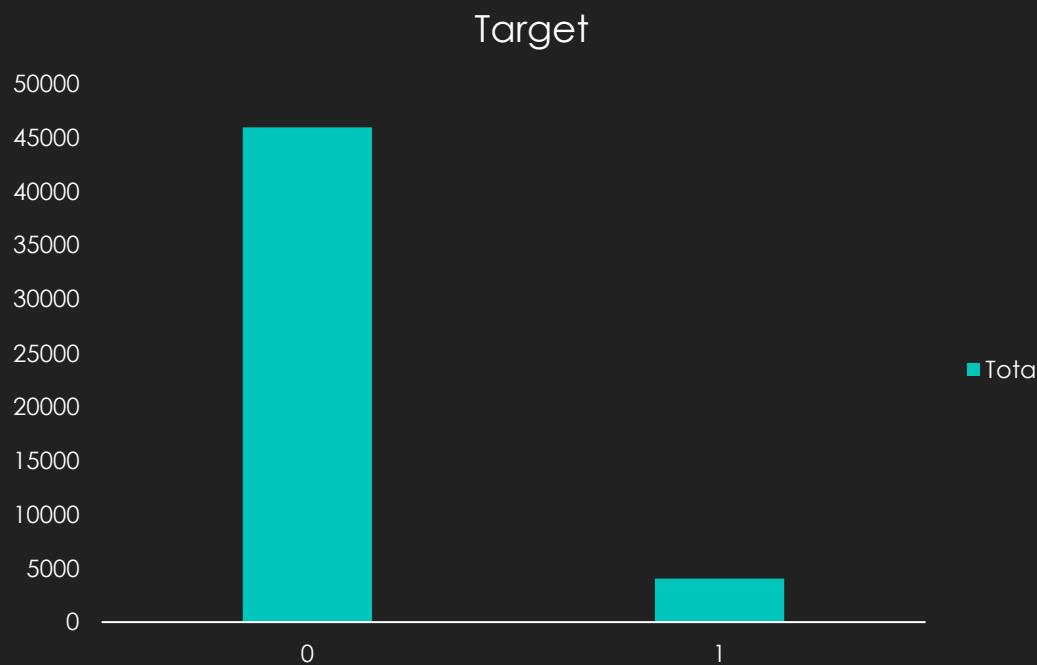
NAME CONTRACT TYPEa	NONLIVINGAPARTMENTS AVG	FONDKAPREMONT MODE
FLAG OWN CAR	NONLIVINGAREA AVG	HOUSETYPE MODE
CNT CHILDREN	APARTMENTS MODE	TOTALAREA MODE
AMT GOODS PRICE	BASEMENTAREA MODE	WALLSMATERIAL MODE
NAME TYPE SUITE	YEARS BEGINEXPLUATATION MODE	EMERGENCYSTATE MODE
NAME INCOME TYPE	YEARS BUILD MODE	OBS 30 CNT SOCIAL CIRCLE
REGION POPULATION RELATIVE	COMMONAREA MODE	DEF 30 CNT SOCIAL CIRCLE
DAYS EMPLOYED	ELEVATORS MODE	OBS 60 CNT SOCIAL CIRCLE
DAYS REGISTRATION	ENTRANCES MODE	DEF 60 CNT SOCIAL CIRCLE
OWN CAR AGE	FLOORSMAX MODE	FLAG DOCUMENT 2
FLAG EMAIL	FLOORSMIN MODE	FLAG DOCUMENT 3
REGION RATING CLIENT	LANDAREA MODE	FLAG DOCUMENT 4
REGION RATING CLIENT W CITY	LIVINGAPARTMENTS MODE	FLAG DOCUMENT 5
WEEKDAY APPR PROCESS START	LIVINGAREA MODE	FLAG DOCUMENT 6
HOUR APPR PROCESS START	NONLIVINGAPARTMENTS MODE	FLAG DOCUMENT 7
EXT SOURCE 1	NONLIVINGAREA MODE	FLAG DOCUMENT 8
EXT SOURCE 2	APARTMENTS MEDI	FLAG DOCUMENT 9
EXT SOURCE 3	BASEMENTAREA MEDI	FLAG DOCUMENT 10
APARTMENTS AVG	YEARS BEGINEXPLUATATION MEDI	FLAG DOCUMENT 11
BASEMENTAREA AVG	YEARS BUILD MEDI	FLAG DOCUMENT 12
YEARS BEGINEXPLUATATION AVG	COMMONAREA MEDI	FLAG DOCUMENT 13
YEARS BUILD AVG	ELEVATORS MEDI	FLAG DOCUMENT 14
COMMONAREA AVG	ENTRANCES MEDI	FLAG DOCUMENT 15
ELEVATORS AVG	FLOORSMAX MEDI	FLAG DOCUMENT 16
ENTRANCES AVG	FLOORSMIN MEDI	FLAG DOCUMENT 17
FLOORSMAX AVG	LANDAREA MEDI	FLAG DOCUMENT 18
FLOORSMIN AVG	LIVINGAPARTMENTS MEDI	FLAG DOCUMENT 19
LANDAREA AVG	LIVINGAREA MEDI	FLAG DOCUMENT 20
LIVINGAPARTMENTS AVG	NONLIVINGAPARTMENTS MEDI	FLAG DOCUMENT 21
LIVINGAREA AVG	NONLIVINGAREA MEDI	

# Null values analysis

Colu mn Name	SK ID RR	T A CU G	COD E_G END ER	FLAG OWN REA LTY	AMT_I E_TOT RE	AMT_C T_C NUI	NAME EDUCA TION_T YPE	NAME FAMIL Y_STA TUS	NAME HOUS ING_T YPE	DA S_ID BIR ISH	DAY G MO PHO	FLAG FLA WOR K_PH NE	FLAG FLA G ONE	FLAG FLA CON G_P ON_T YPE	OCCU PATI EMBE RS	CNT AM_M ON_NOT LIVE REG	FREG REGI ON_NOT WORK REG	REG REGI ON_NOT WORK REG	LIVE REGI ON_NOT WORK REG	REG CI TY_NO T_LIVE CITY	REG CI TY_NOT WORK CITY	LIVE CI TY_NOT WORK CITY	ORG ANIZAT ION_T YPE	DAYS_L AST_PH ONE_CH ANGE	AMT_REQ CREDIT BUREAU DAY	AMT_REQ CREDIT BUREAU WEEK	AMT_REQ CREDIT BUREAU MON	AMT_REQ CREDIT BUREAU QRT	AMT_REQ CREDIT BUREAU YEAR
Null Value %age	0	0	0	0	0	0	0.00	0	0	0	0	0	0	0	0	31.308	6	0.002	0	0	0	0	0.002	13.4683	13.4683	13.4683	13.4683	13.4683	13.4683

Occupation\_type column has been dropped due to the presence of > 30% null values

# Data Imbalance

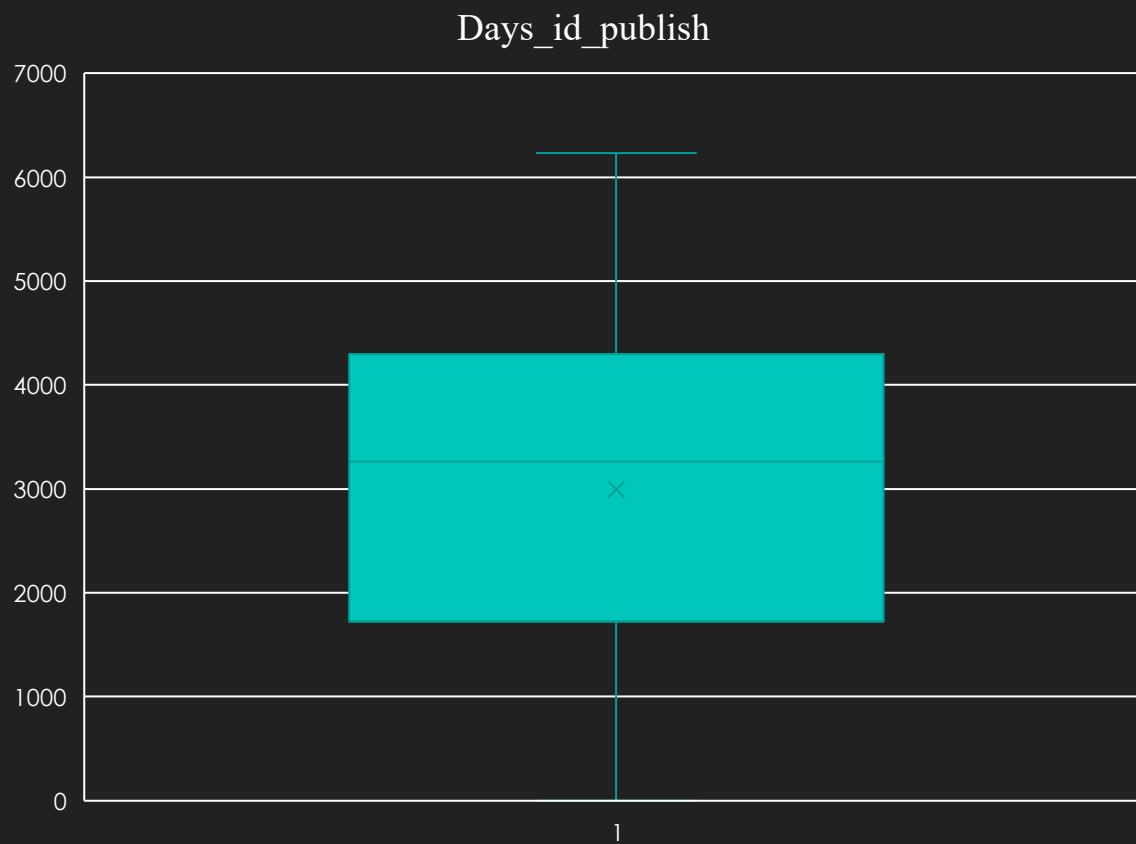


We have data imbalance in our dataset, hence, the results would be skewed, we cannot generalize the findings of target 1 as it only represents 8% of our sample, rest 92% represents target 0.

# Feature Engineering

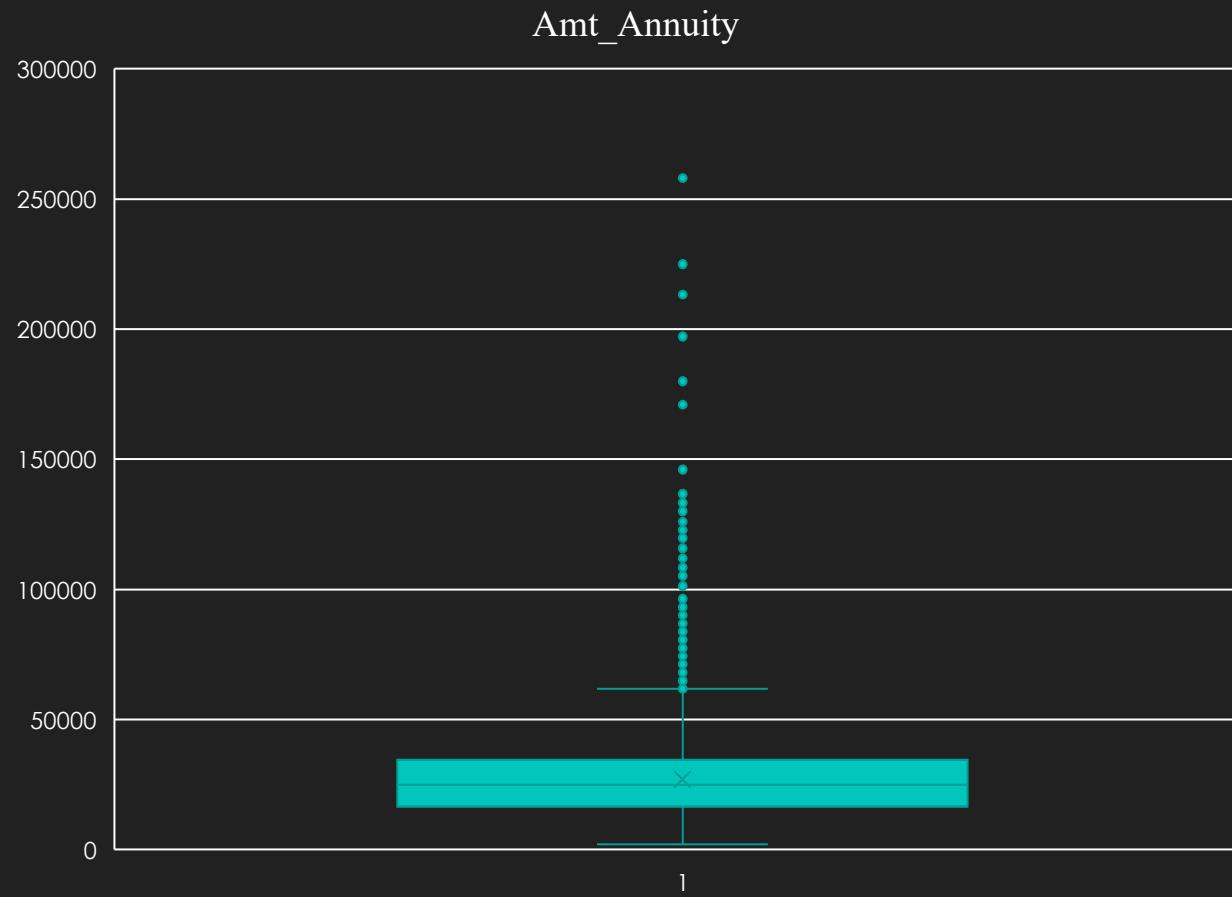
1. AMT\_REQ\_CREDIT\_BUREAU\_YEAR\_Total – Following 6 columns were clubbed to create a new column
  - AMT\_REQ\_CREDIT\_BUREAU\_HOUR
  - AMT\_REQ\_CREDIT\_BUREAU\_DAY
  - AMT\_REQ\_CREDIT\_BUREAU\_WEEK
  - AMT\_REQ\_CREDIT\_BUREAU\_MON
  - AMT\_REQ\_CREDIT\_BUREAU\_QRT
  - AMT\_REQ\_CREDIT\_BUREAU\_YEAR
2. DAYS\_ID\_PUBLISH – Values were converted into positive values through absolute function.
3. Days\_Birth – The column values were converted into positive year values.
4. Days\_last\_phone\_change - The column values were converted into positive values.

# Data distribution



The data contains no outliers and no null values.

# Data distribution

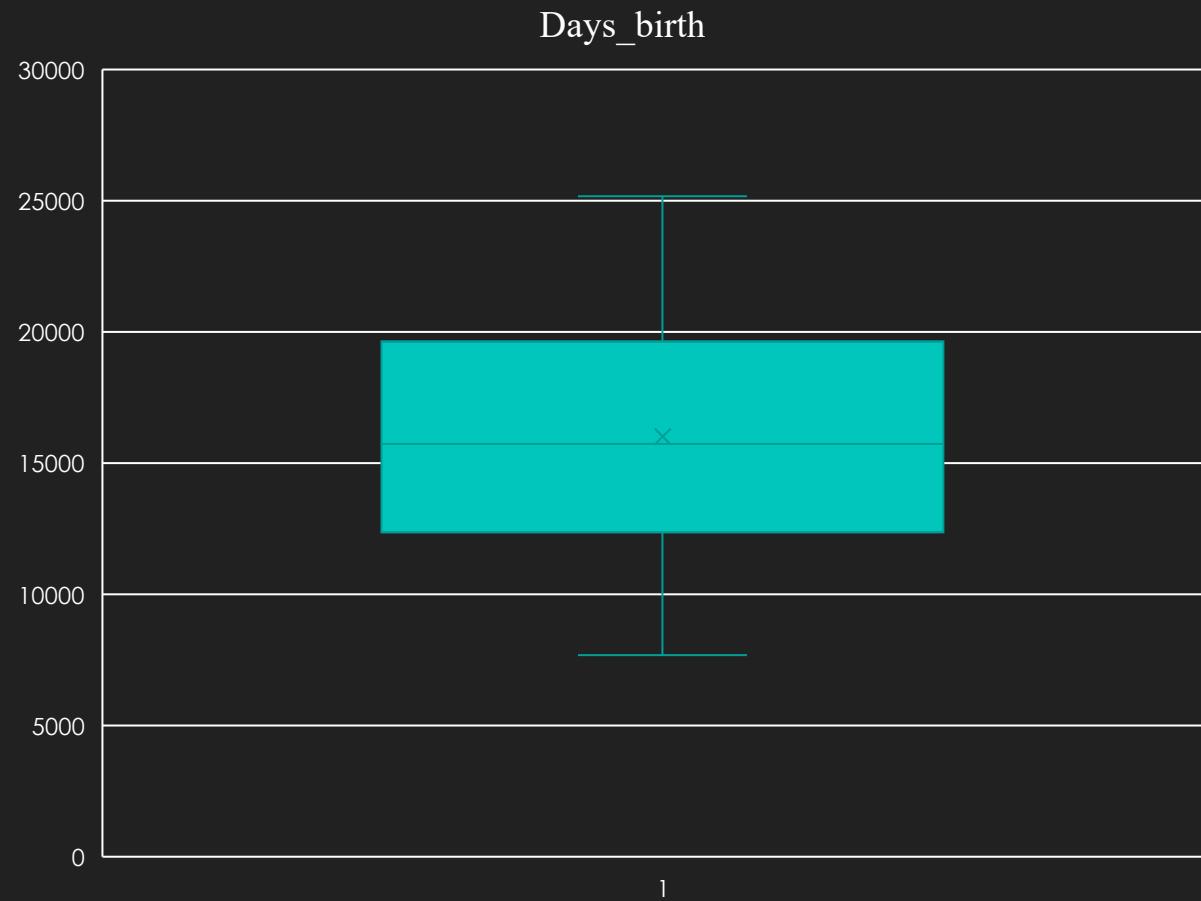


Quartiles	AMT_ANNUITY
Q1	112500
Q2 (median)	146250
Q3	202500
Q4	117000000
Q3-Q1	90000
Lower Bound	-22500
Upper Bound	337500

Null values in Amt\_Annuity column have been replaced with median value due to the presence of outliers in our data.  
Median = 24939

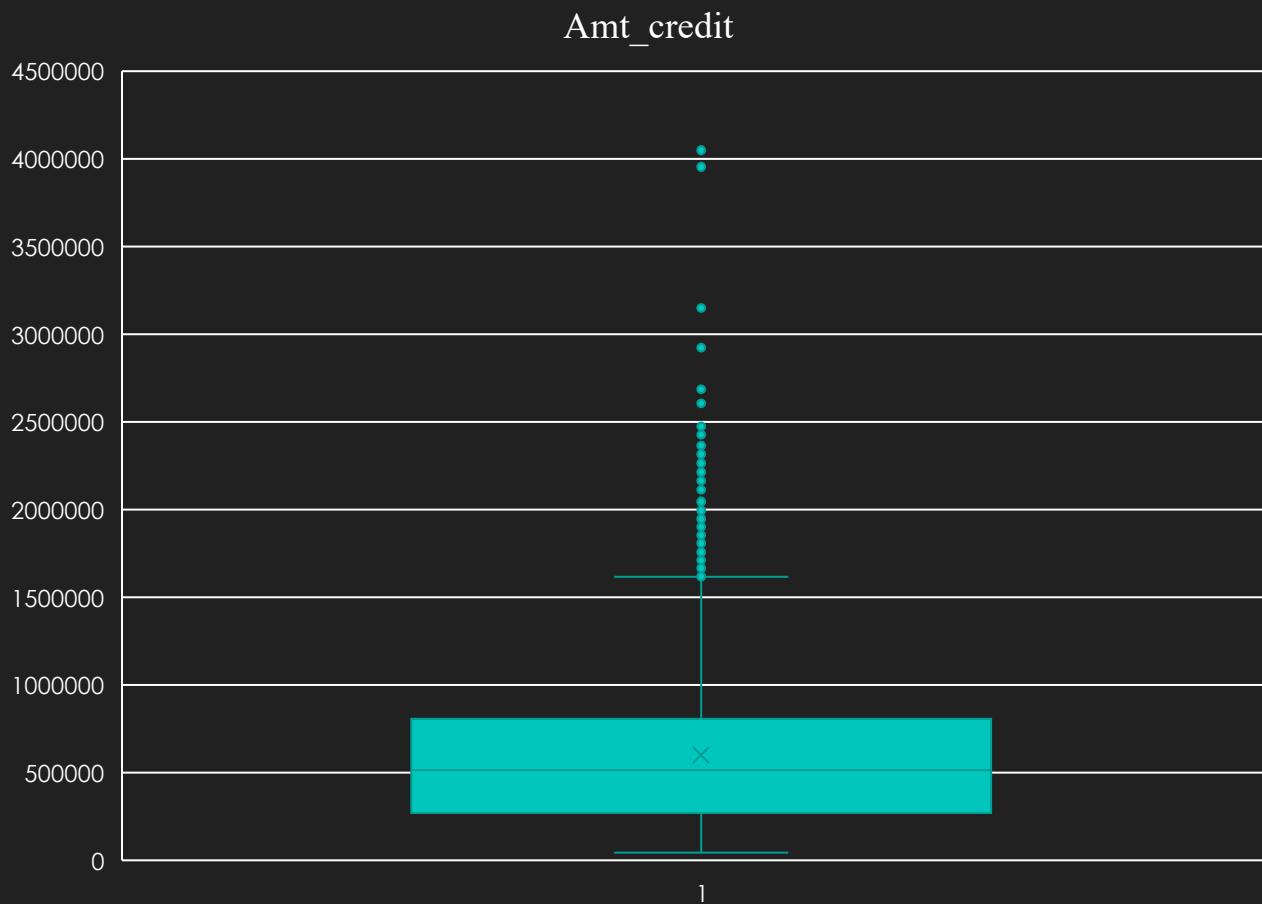
The values beyond lower and upper bound were identified as outliers. But these values were not replaced as extremes in annuity are possible.

# Data distribution



The data contains no outlier and no null value.

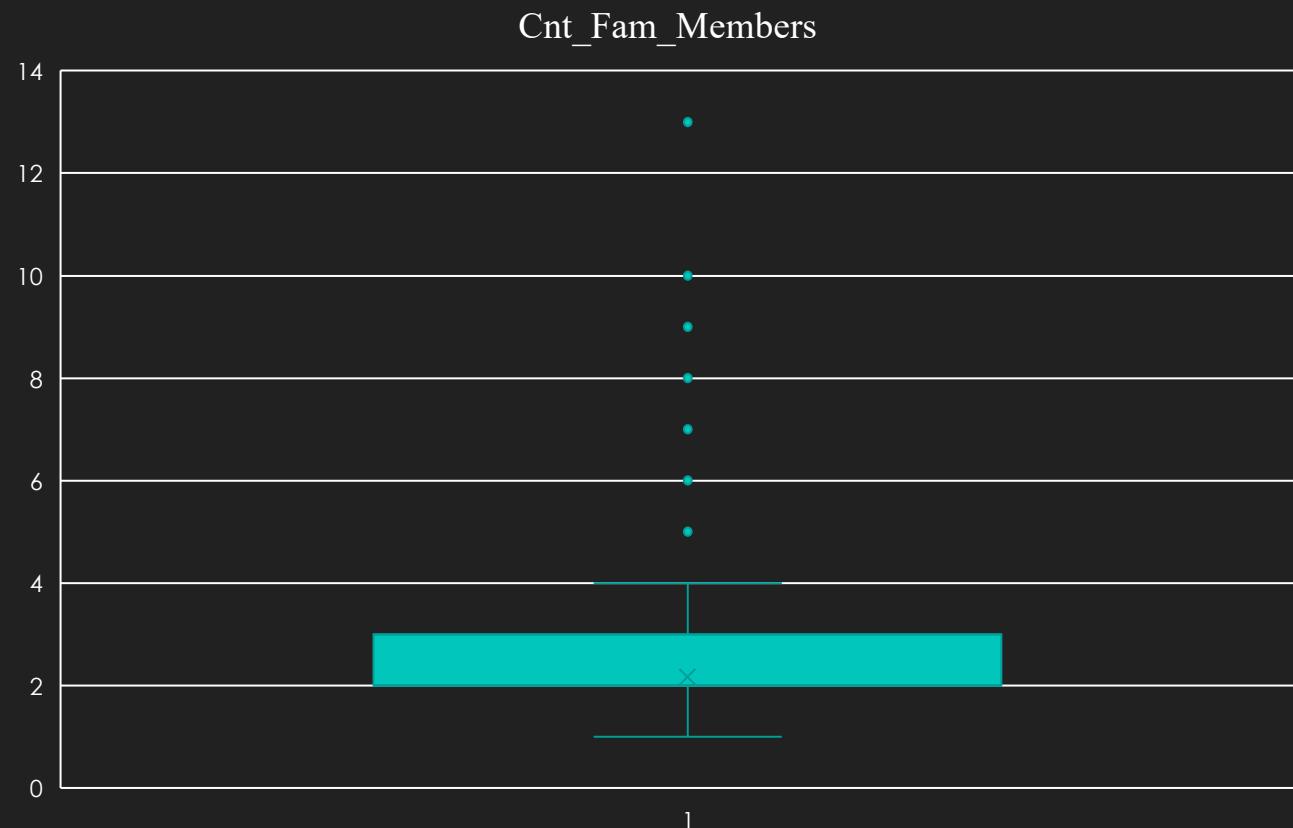
# Data distribution



The dataset contains outliers but replacing these data points is not an ideal choice as credit amount varies highly for customers.

Also, no null values were found.

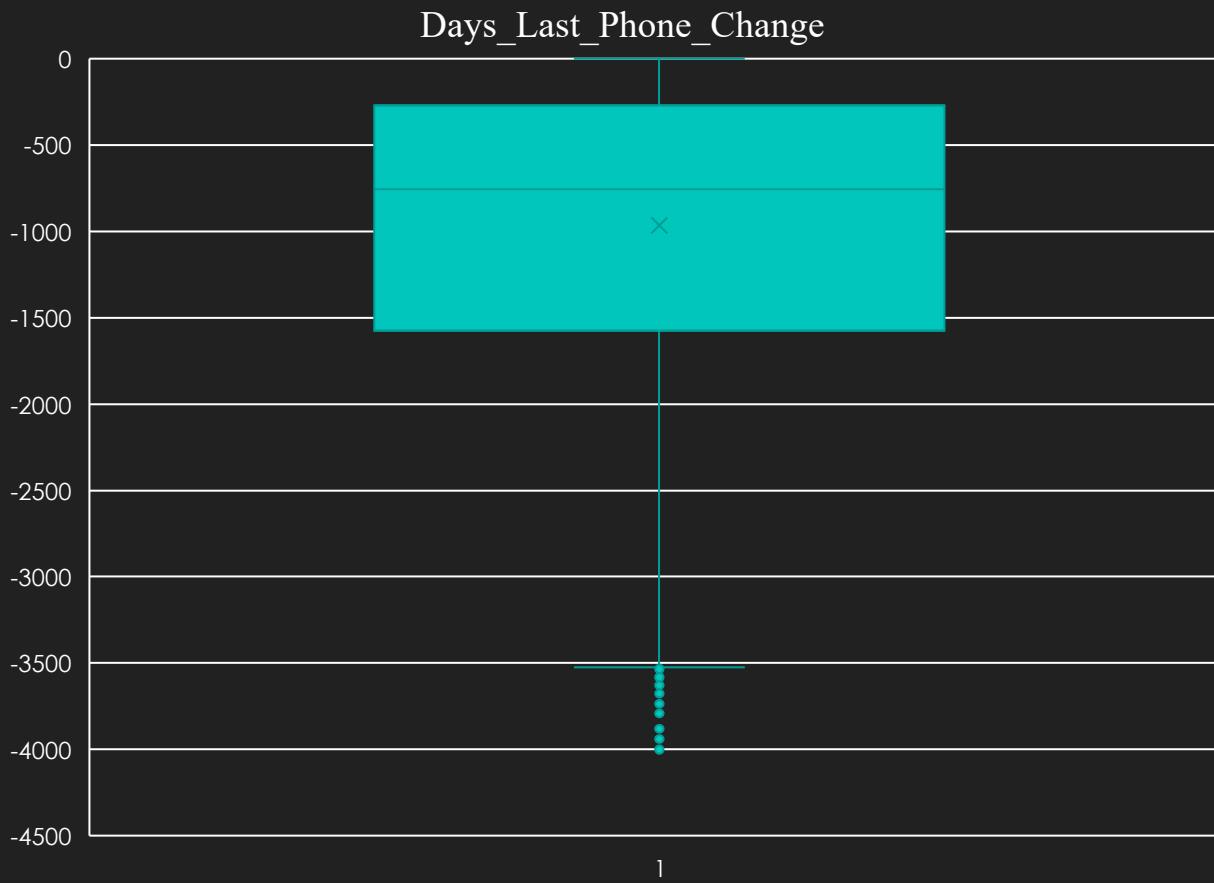
# Data distribution



Null values in Cnt\_Fam\_Members column have been replaced with median value due to the presence of outliers in our data.  
Median = 2

But outliers have not been replaced as the highest value in the dataset is 13 which is possible. A family can have 13 members.

# Data distribution



Quartiles	DAYS LAST PHONE CHANGE
Q1	270
Q2 (median)	755
Q3	1573
Q4	4002
Q3-Q1	1303
Lower Bound	-1684.5
Upper Bound	3527.5

- Null values in Days\_Last\_Phone\_Change column have been replaced with median value due to the presence of outliers in our data.
- The data points were converted into positive values with ABS function.
- Outliers have also been replaced with median value. Values beyond lower and upper bound are outliers.

# Attribute analysis

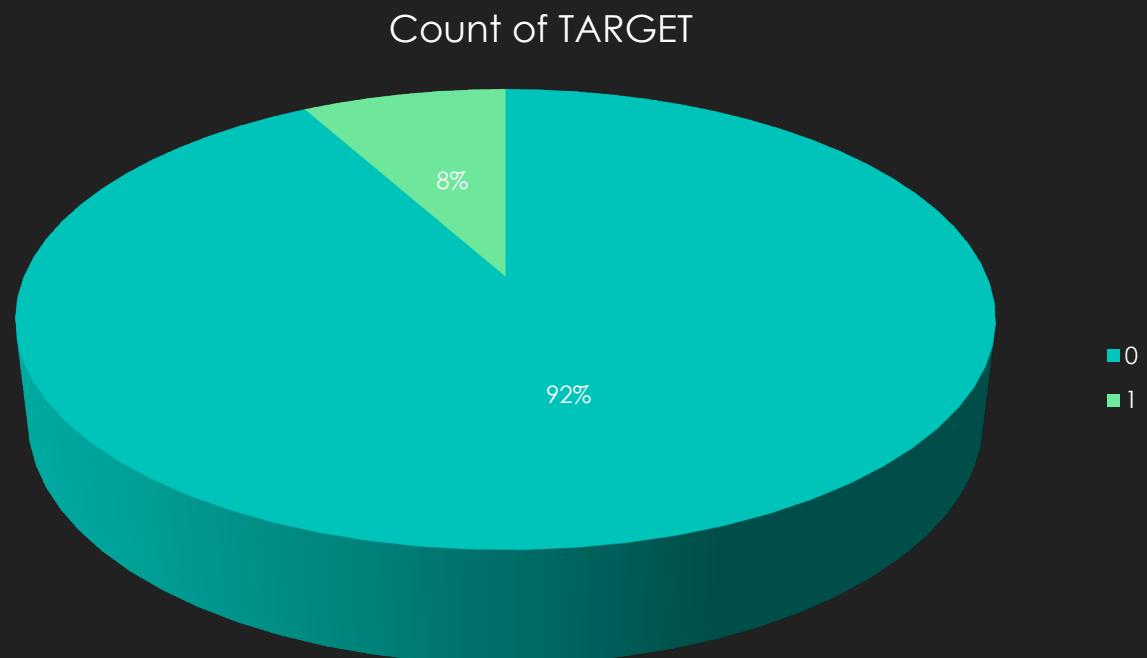


# Univariate Analysis

# TARGET

Row Labels	Count of TARGET
0	45973
1	4026
Grand Total	49999

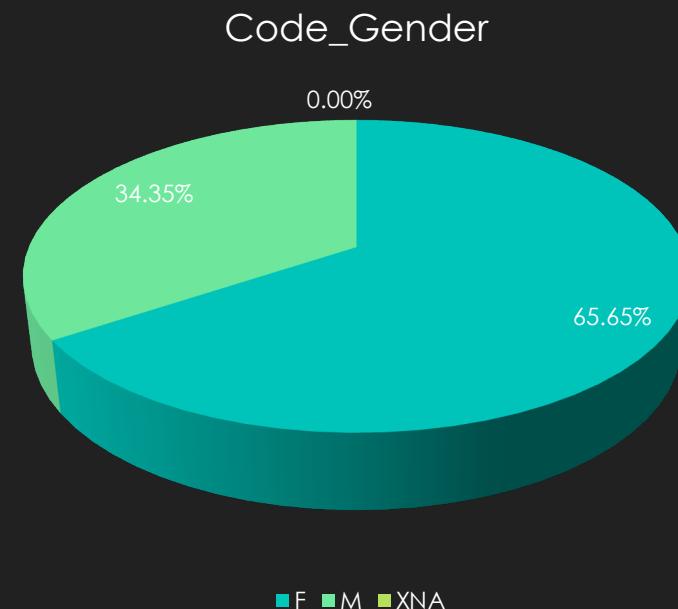
Label	Representation
0	Customers with no payment difficulties
1	Customers with payment difficulties



Most of the customers had no payment difficulties, only 8% customers made late payment of installment

# CODE\_GENDER

Row Labels	Count of CODE_GENDER	Count of CODE_GENDER (%)
F	32823	65.65%
M	17174	34.35%
XNA	2	0.00%
Grand Total	49999	100.00%

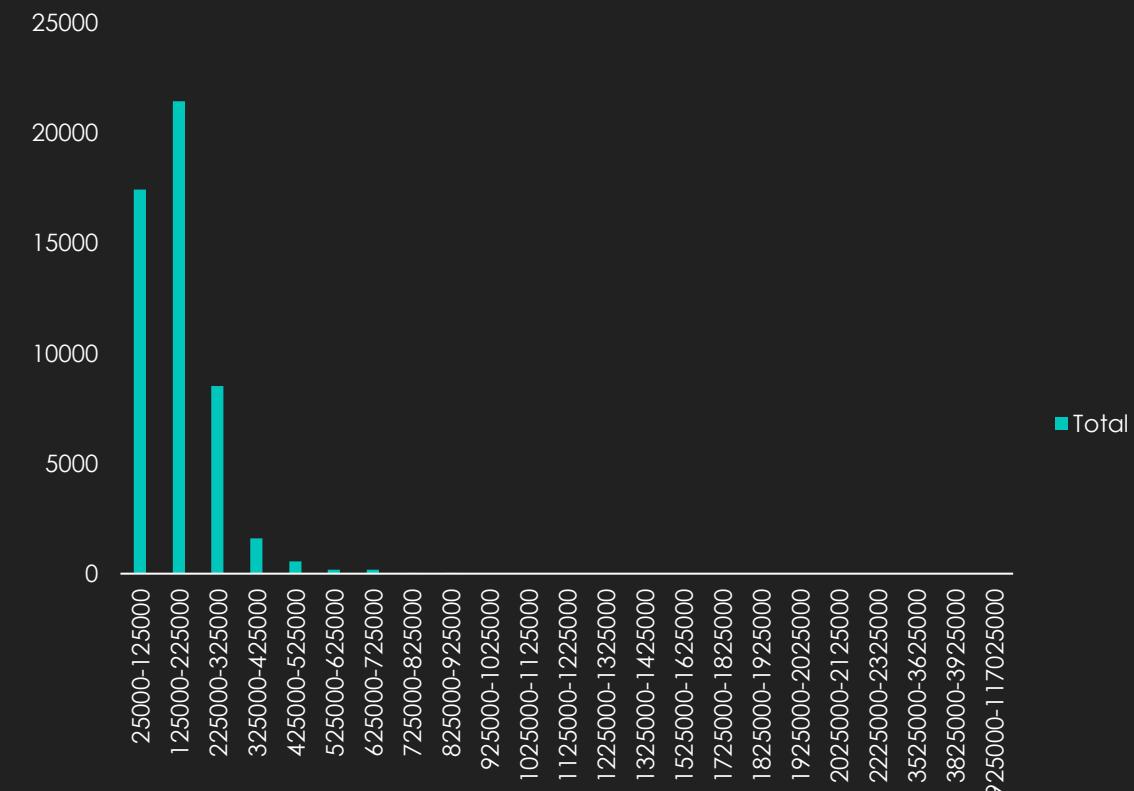


Approximately 65% of bank's customers are females and rest are males.

# AMT\_INCOME\_TOTAL

Row Labels	Count of AMT_INCOME_TOTAL
25000-125000	17440
125000-225000	21447
225000-325000	8506
325000-425000	1592
425000-525000	569
525000-625000	169
625000-725000	165
725000-825000	34
825000-925000	35
925000-1025000	2
1025000-1125000	4
1125000-1225000	13
1225000-1325000	1
1325000-1425000	10
1525000-1625000	1
1725000-1825000	2
1825000-1925000	1
1925000-2025000	1
2025000-2125000	2
2225000-2325000	2
3525000-3625000	1
3825000-3925000	1
116925000-117025000	1
Grand Total	49999

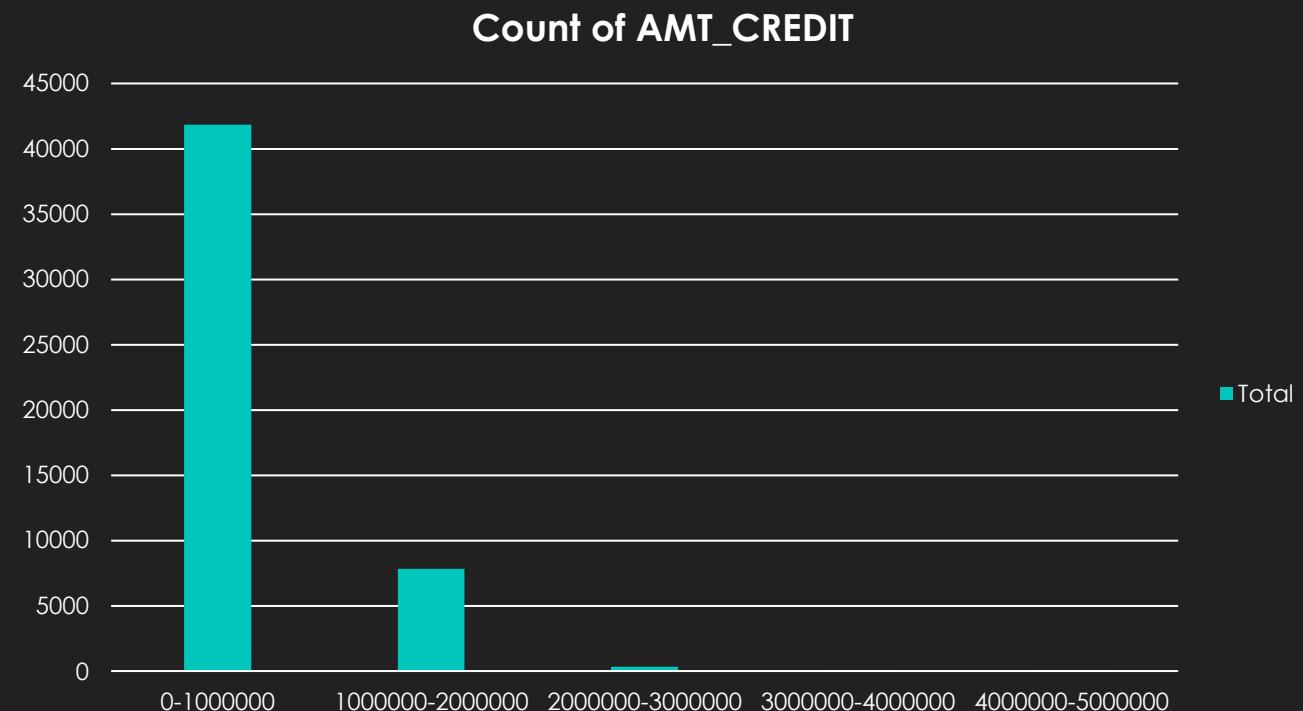
Count of AMT\_INCOME\_TOTAL



Customers belonging to 125000-225000 income range are highest applicants of credit and as the income increases, the less customers apply for credit.

# AMT\_CREDIT

Row Labels	Count of AMT_CREDIT
0-1000000	41853
1000000-2000000	7823
2000000-3000000	319
3000000-4000000	2
4000000-5000000	2
Grand Total	49999

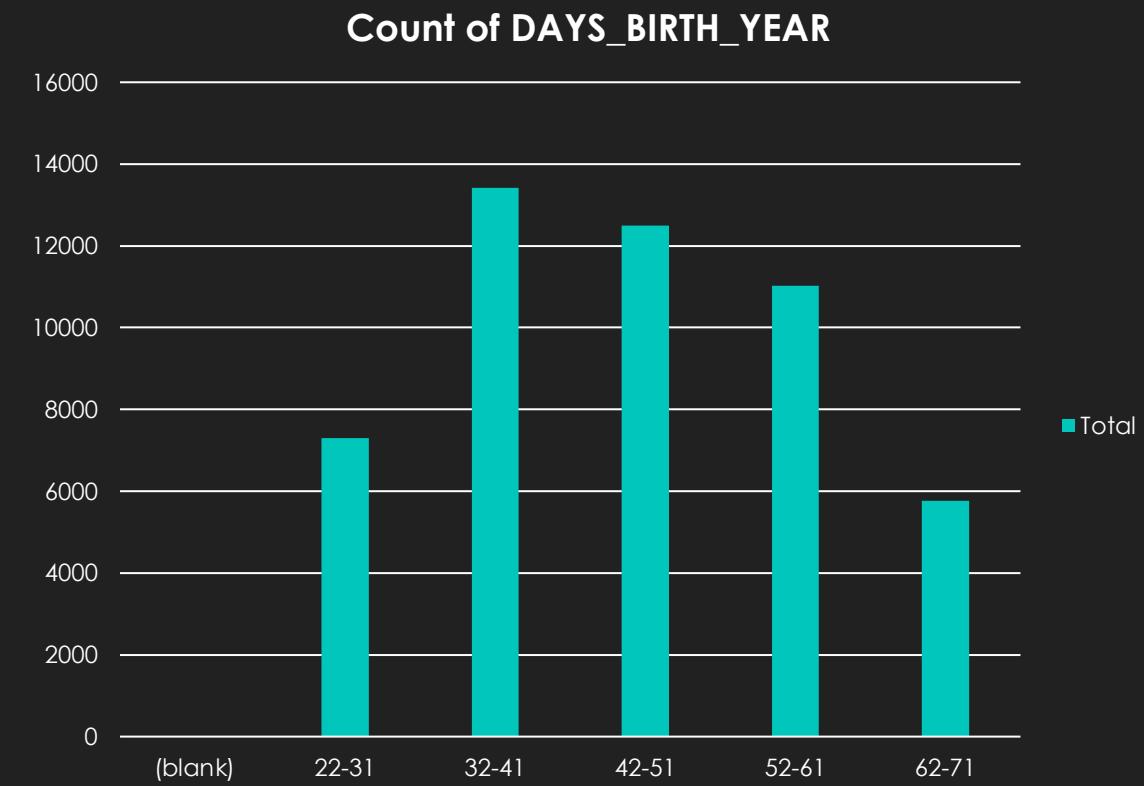


Smaller value loans of upto Rs. 100000 are mostly applied for.

# DAYs\_BIRTH\_YEAR

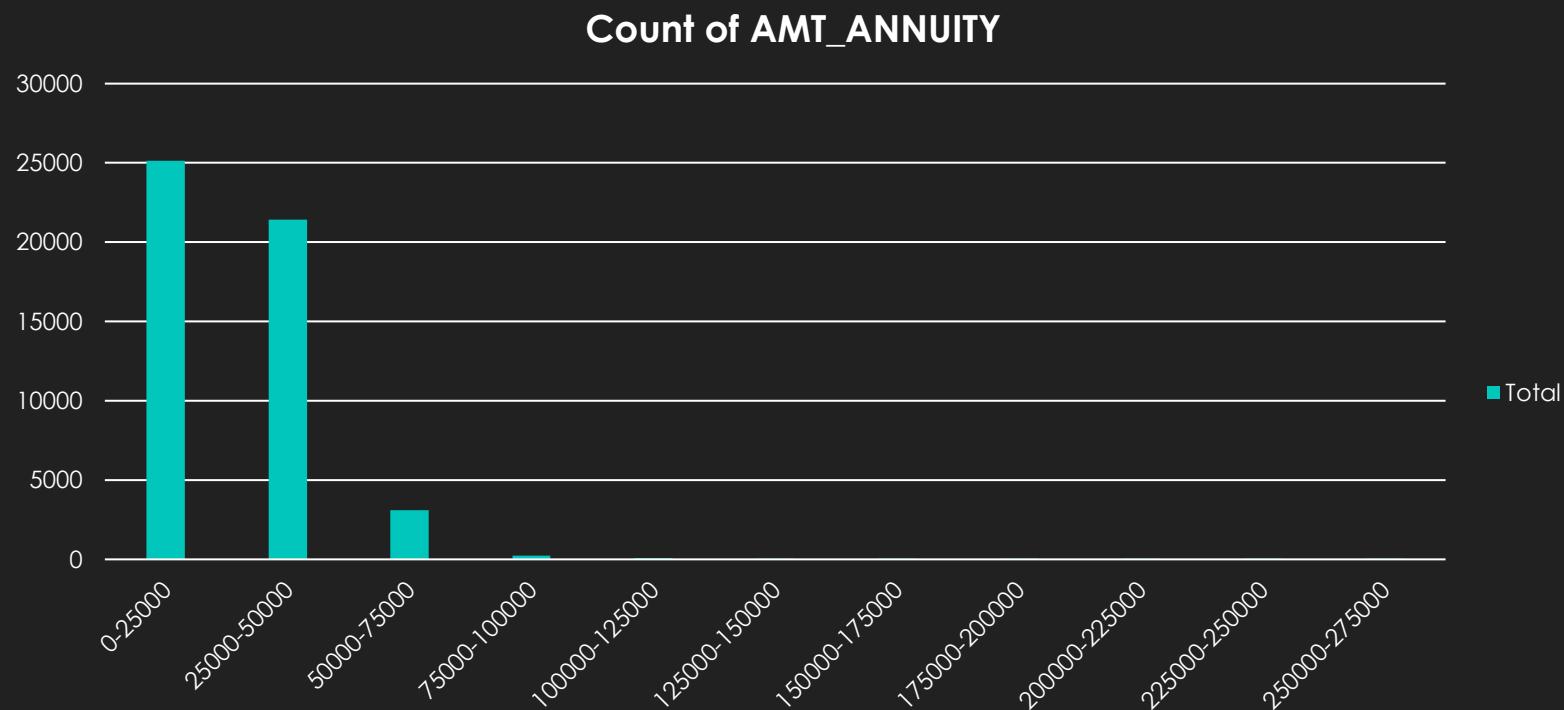
Row Labels	Count of DAYs_BIRTH_year
22-31	7302
32-41	13422
42-51	12489
52-61	11020
62-71	5766
Grand Total	49999

Most of the applicants belong to the 32-51 years age bracket.



# AMT\_ANNUITY

Row Labels	Count of AMT_ANNUITY
0-25000	25128
25000-50000	21434
50000-75000	3107
75000-100000	245
100000-125000	55
125000-150000	17
150000-175000	4
175000-200000	2
200000-225000	1
225000-250000	5
250000-275000	1
Grand Total	49999



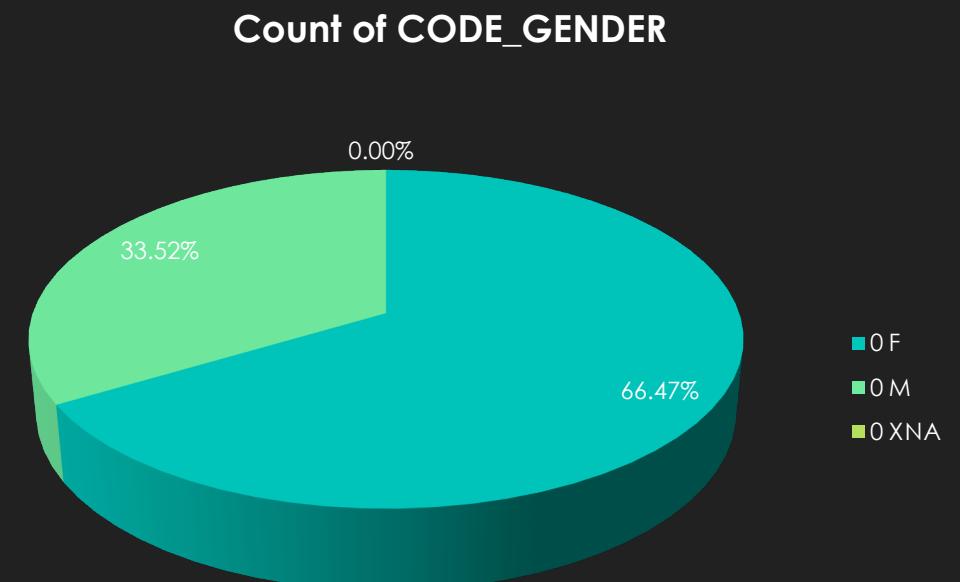
Most of the annuities are lower in value and annuities beyond Rs. 150000 are very less in number.

# Segmented Univariate Analysis

# 0 – Customers with no payment difficulties

## CODE\_GENDER

Row Labels 0	Count of CODE_GENDER	Count of CODE_GENDER(%)
F	30559	66.47%
M	15412	33.52%
XNA	2	0.00%
Grand Total	45973	100.00%

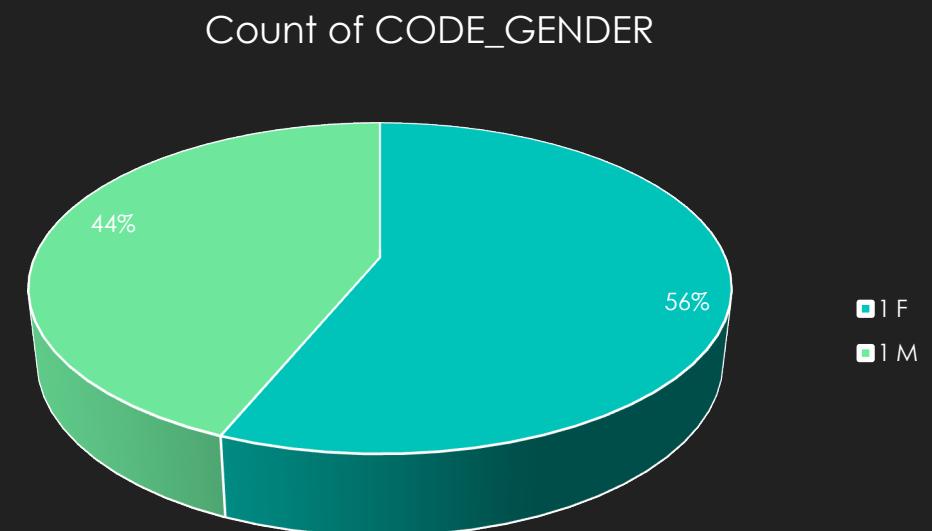


Approximately 66% of customers who faced no payment difficulties were females.

# 1 – Customers with payment difficulties

## CODE\_GENDER

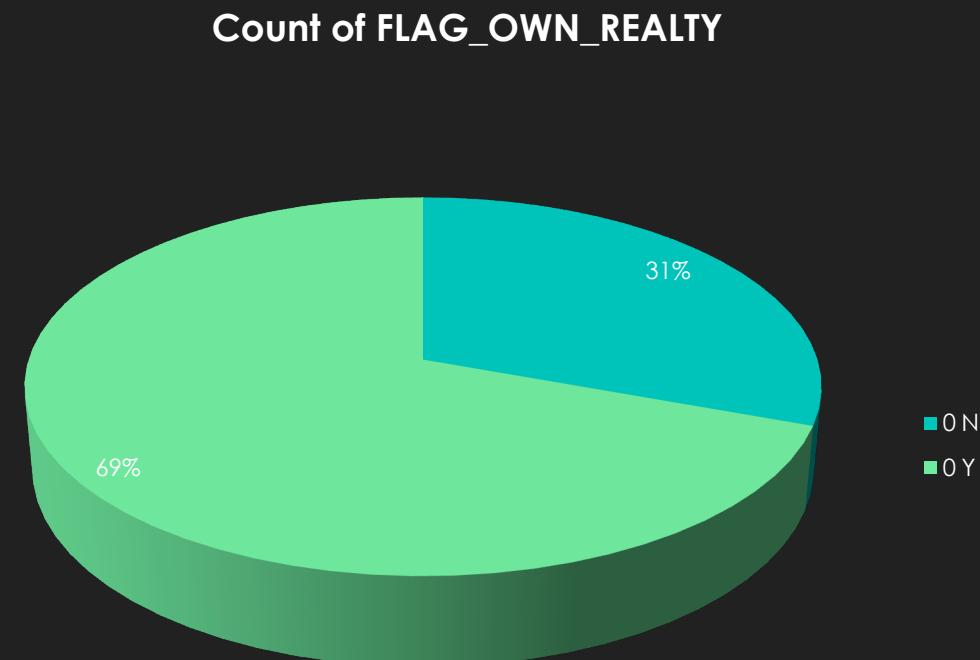
Row Labels 1	Count of CODE_GENDER	Count of CODE_GENDER(%)
F	2264	56.23%
M	1762	43.77%
Grand Total	4026	100.00%



Females faced more payment difficulties in comparison to males.

# 0 – Customers with no payment difficulties FLAG\_OWN\_REALTY

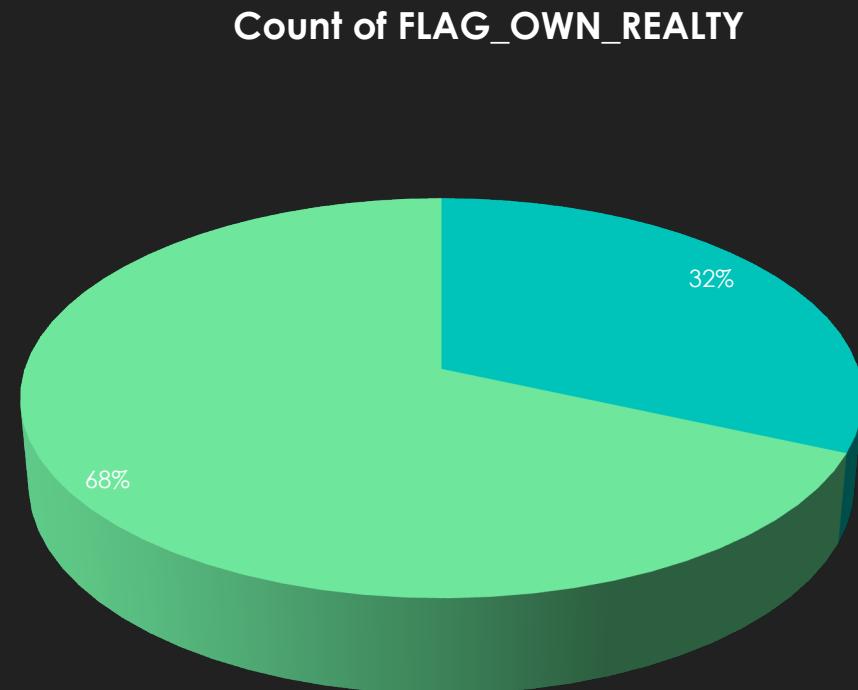
Row Labels (0)	Count of FLAG_OWN_REALTY
N	14034
Y	31939
Grand Total	45973



69% of customers who had no payment issues had own property

# 1 – Customers with payment difficulties FLAG\_OWN\_REALTY

Row Labels (1)	Count of FLAG_OWN_REALTY
N	1274
Y	2752
Grand Total	4026

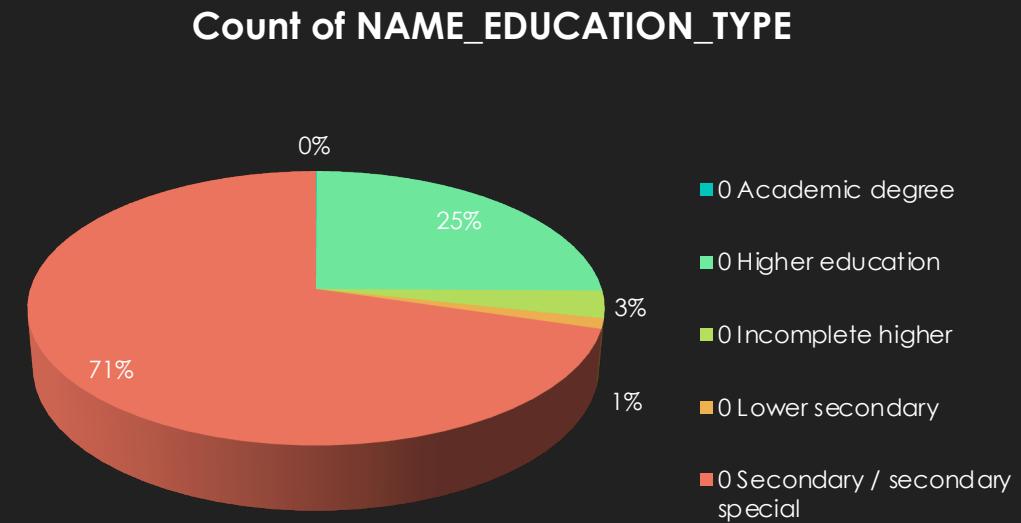


68% of customers who had payment difficulties had own property.

# 0 – Customers with no payment difficulties

## NAME\_EDUCATION\_TYPE

Row Labels	Count of NAME_EDUCATION_TYPE
Academic degree	20
Higher education	11561
Incomplete higher	1482
Lower secondary	547
Secondary / secondary special	32363
Grand Total	45973



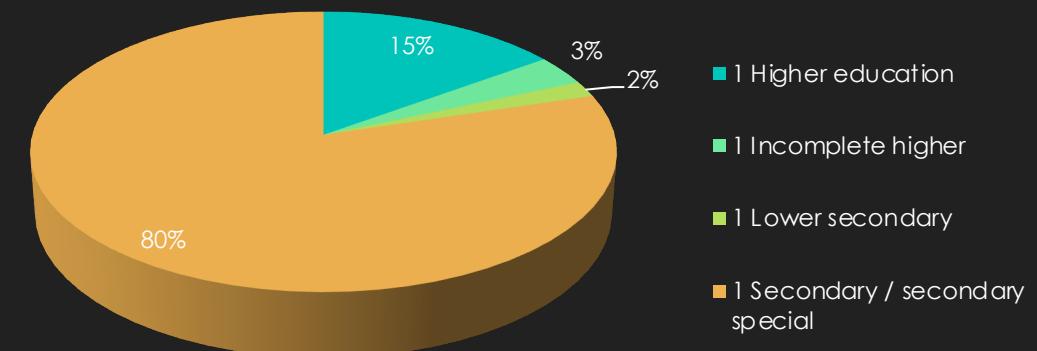
71% of the customers who faced no payment difficulties had education level upto secondary/ secondary special.

# 1 – Customers with payment difficulties

## NAME\_EDUCATION\_TYPE

Row Labels	Count of NAME_EDUCATION_TYPE
Higher education	606
Incomplete higher	138
Lower secondary	73
Secondary / secondary special	3209
Grand Total	4026

Count of NAME\_EDUCATION\_TYPE



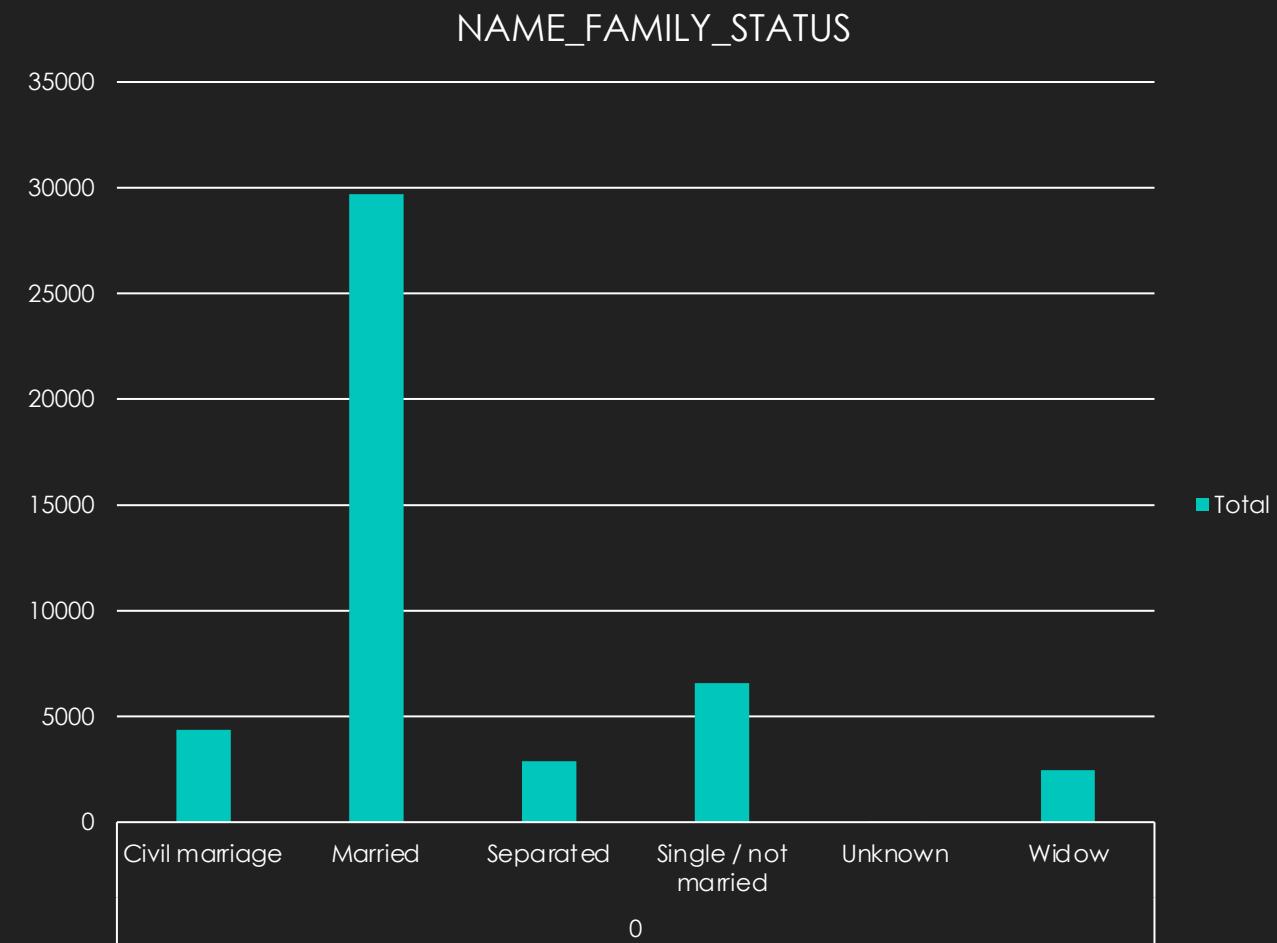
80% of the customers who faced payment difficulties had education level upto secondary/ secondary special.

# 0 – Customers with no payment difficulties

## NAME\_FAMILY\_STATUS

Row Labels	Count of NAME_FAMILY_STATUS
Civil marriage	4377
Married	29699
Separated	2870
Single / not married	6577
Unknown	1
Widow	2449
Grand Total	45973

Most of the customers who did not face payment difficulties were married.

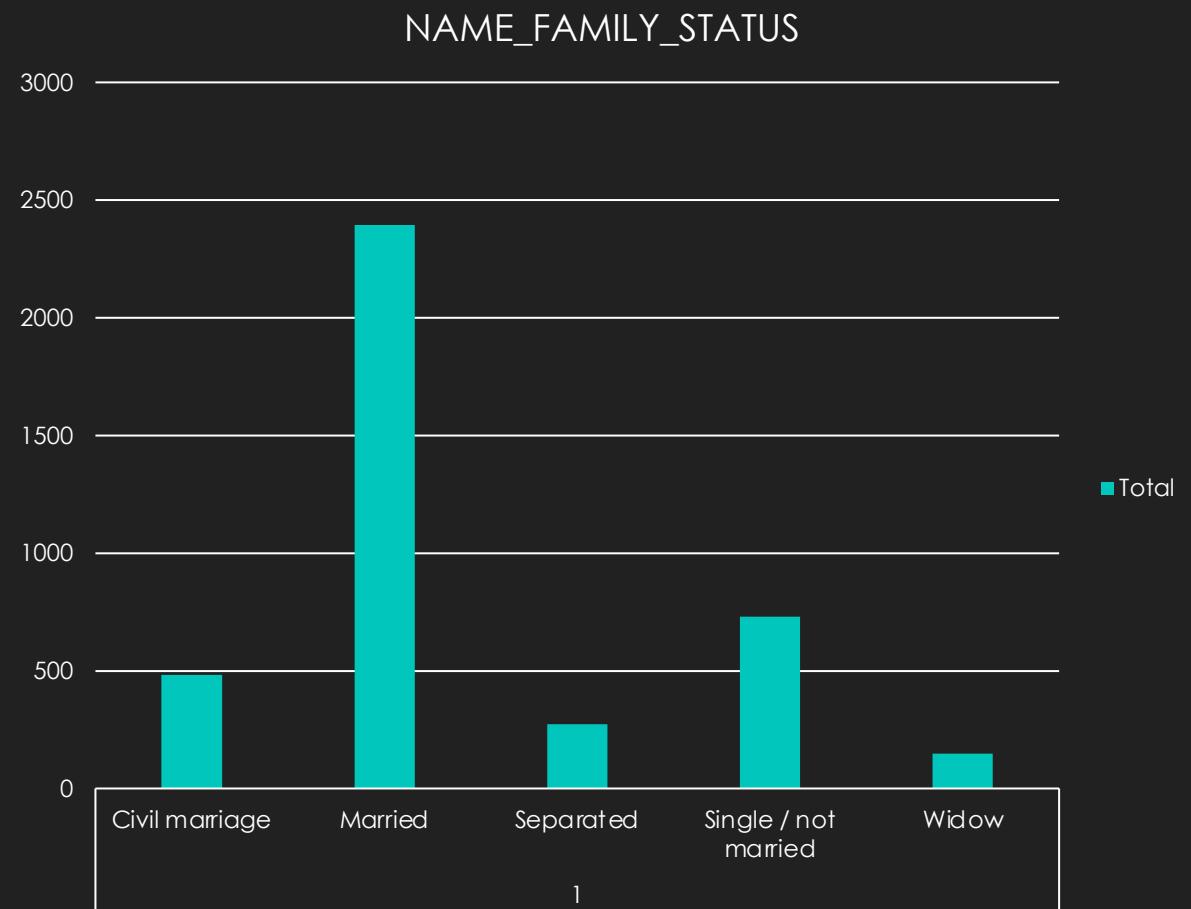


# 1 – Customers with payment difficulties

## NAME\_FAMILY\_STATUS

Row Labels	Count of NAME_FAMILY_STATUS
Civil marriage	482
Married	2395
Separated	272
Single / not married	729
Widow	148
Grand Total	4026

Most of the customers who faced payment difficulties were also married.

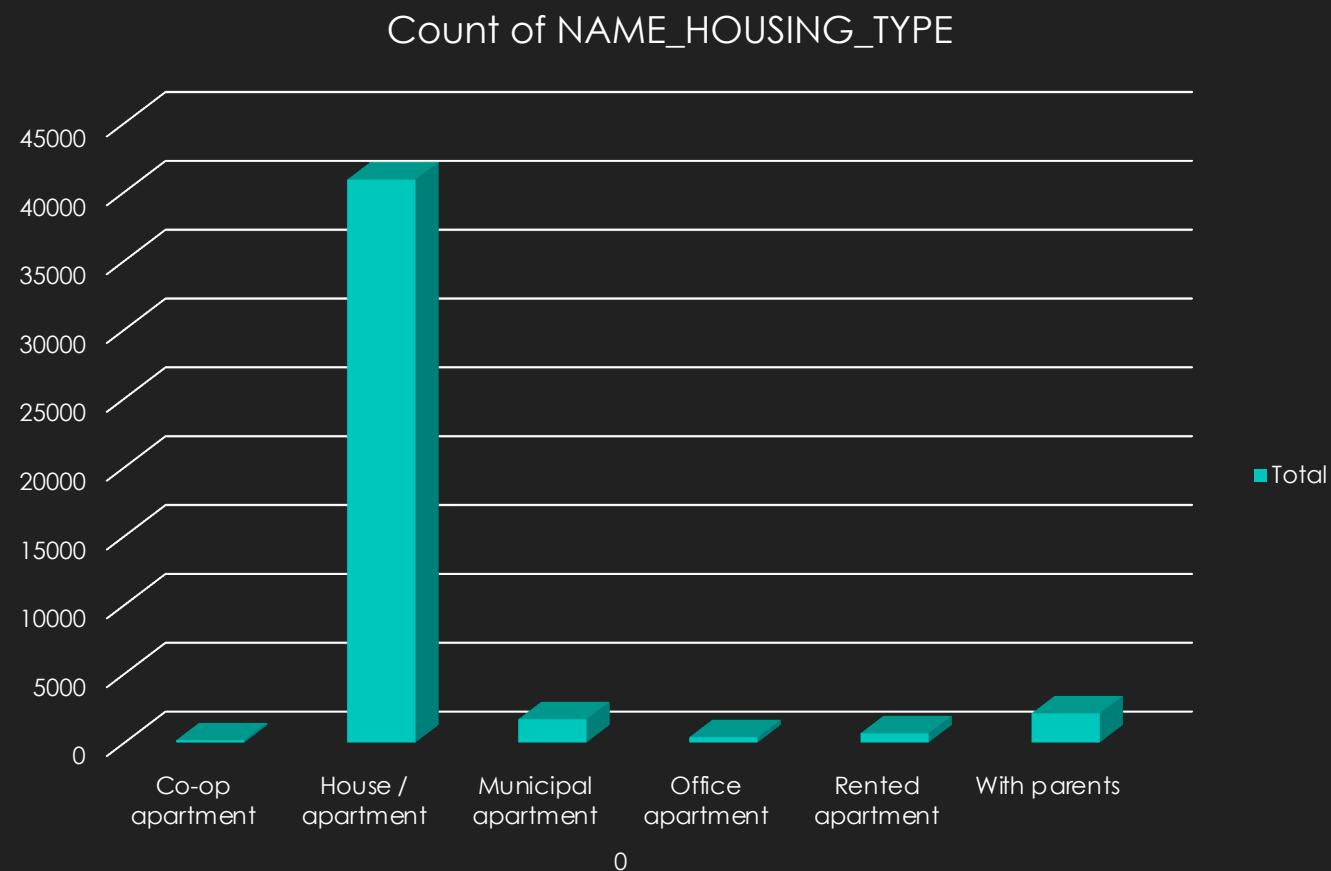


# 0 – Customers with no payment difficulties

## NAME\_HOUSING\_TYPE

Row Labels	Count of NAME_HOUSING_TYPE
Co-op apartment	176
House / apartment	40895
Municipal apartment	1700
Office apartment	398
Rented apartment	682
With parents	2122
Grand Total	45973

Most of the customers who faced no payment difficulties lived in own house/ apartment.

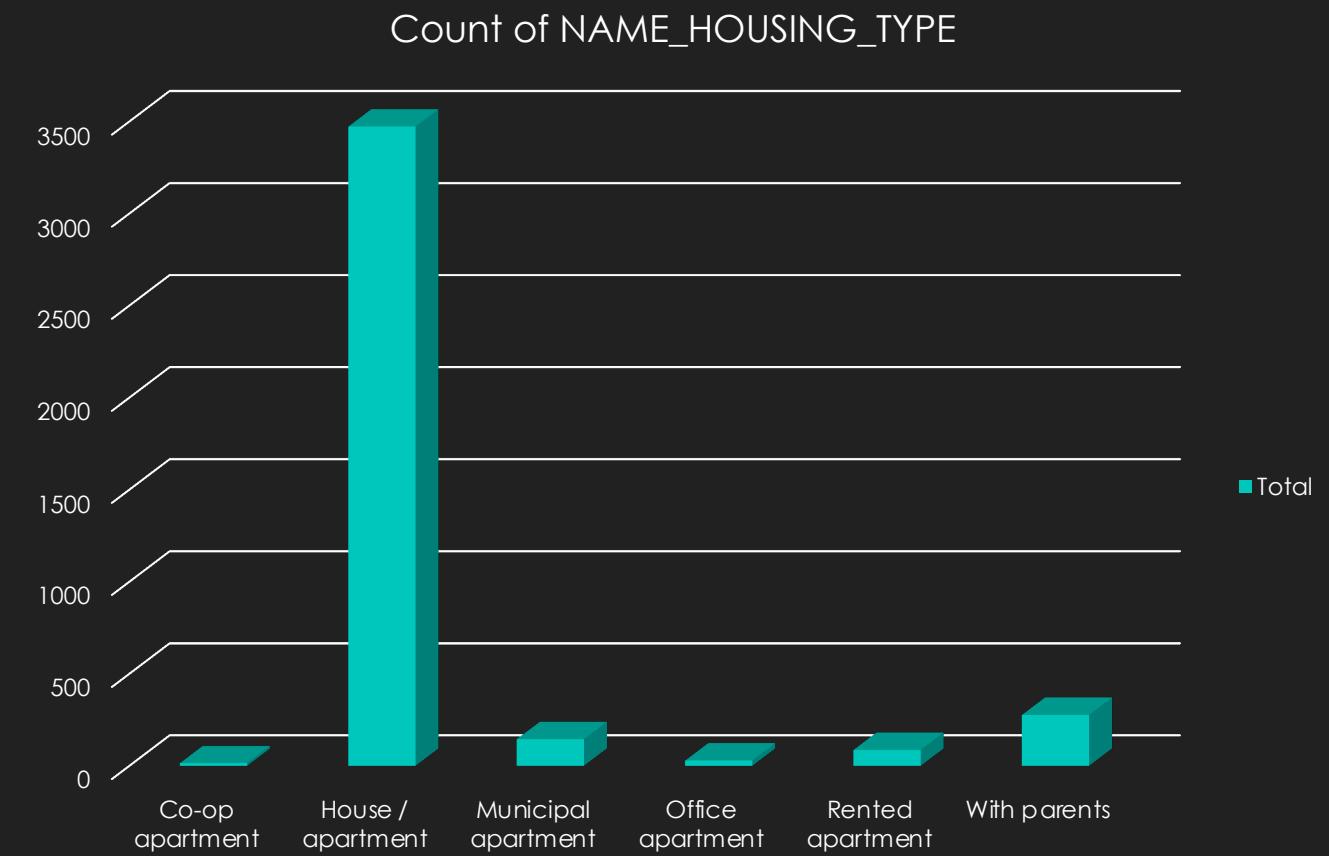


# 1 – Customers with payment difficulties

## NAME\_HOUSING\_TYPE

Row Labels	Count of NAME_HOUSING_TYPE
Co-op apartment	15
House / apartment	3473
Municipal apartment	145
Office apartment	29
Rented apartment	87
With parents	277
Grand Total	4026

Most of the customers who faced payment difficulties also lived in own house/ apartment.

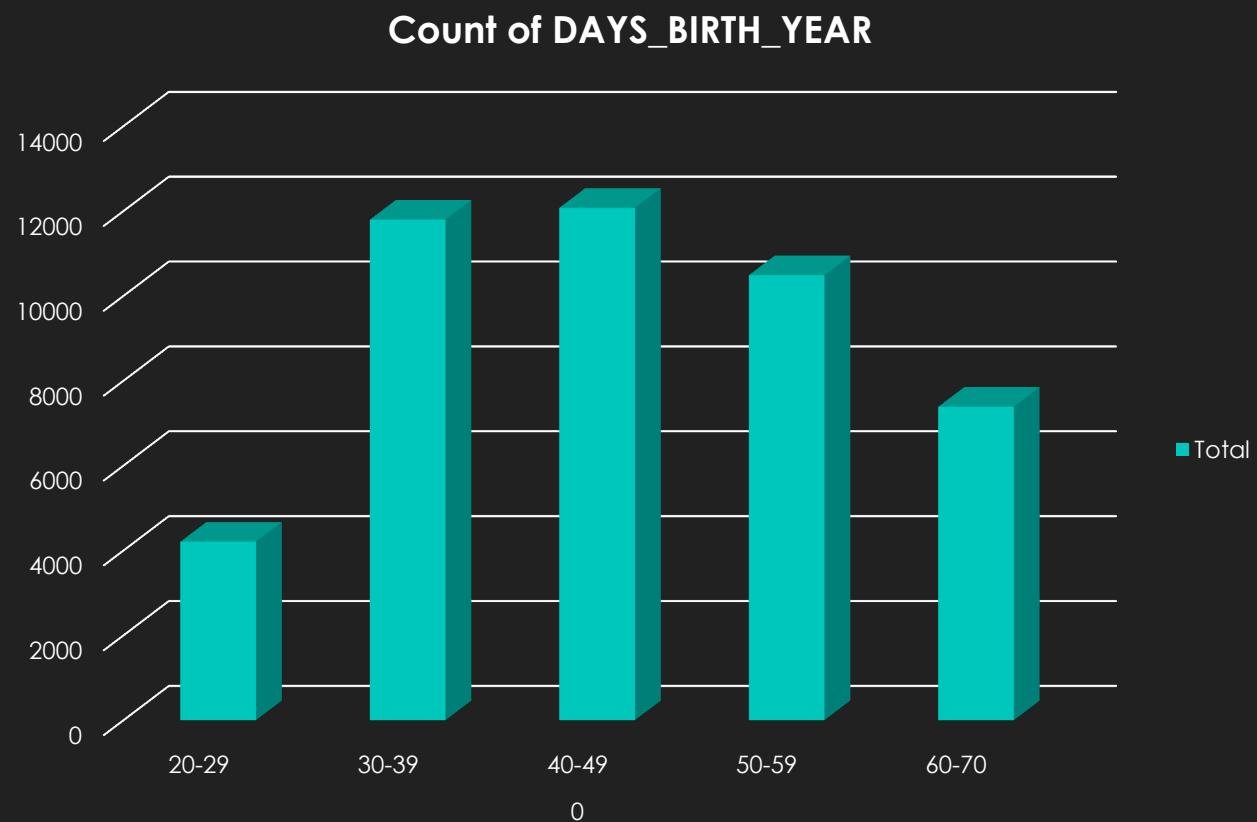


# 0 – Customers with no payment difficulties

## DAY\_S\_BIRTH\_YEAR

Row Labels	Count of SK_ID_CURR
20-29	4211
30-39	11801
40-49	12079
50-59	10491
60-70	7391
Grand Total	45973

Most of the customers with no payment difficulties belonged to 40-49 years.

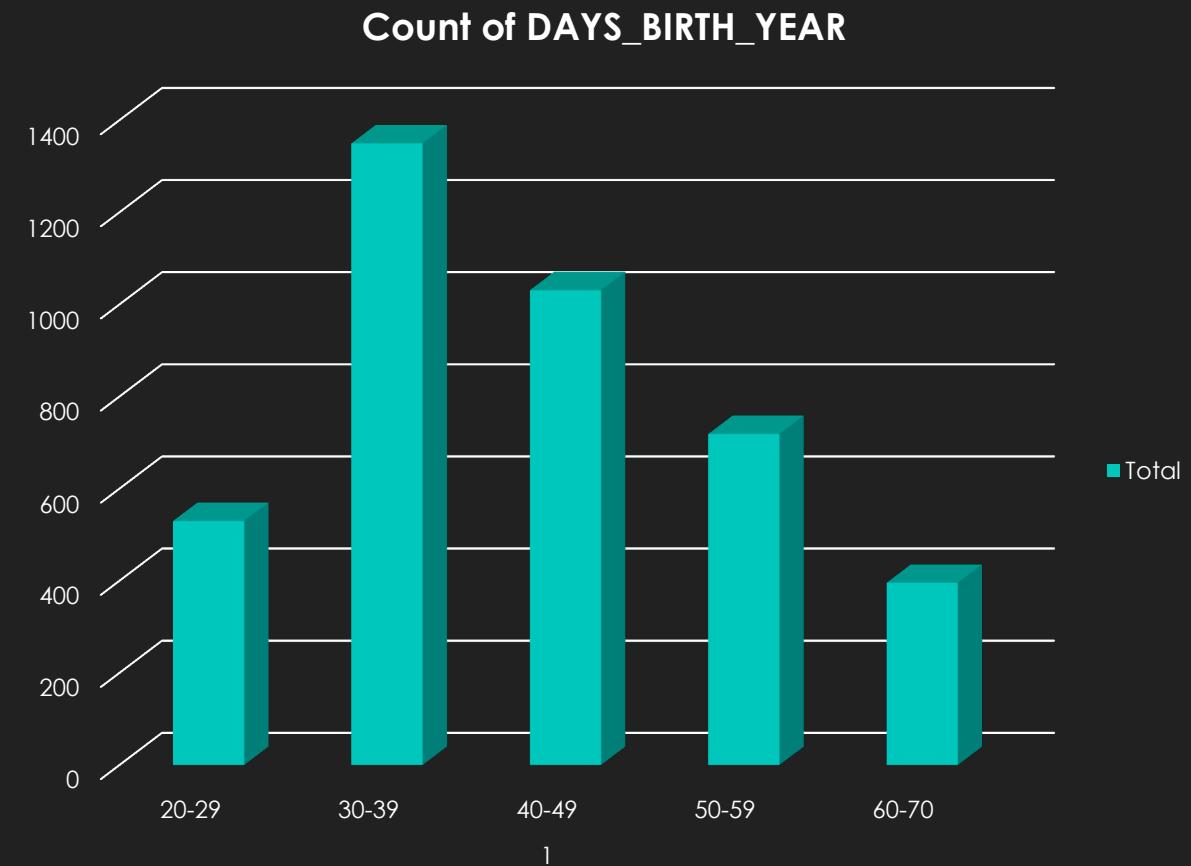


# 1 – Customers with payment difficulties

## DAY\_S\_BIRTH\_YEAR

Row Labels	Count of SK_ID_CURR
20-29	530
30-39	1350
40-49	1031
50-59	719
60-70	396
Grand Total	4026

Most of the customers with payment difficulties belonged to 30-39 years.

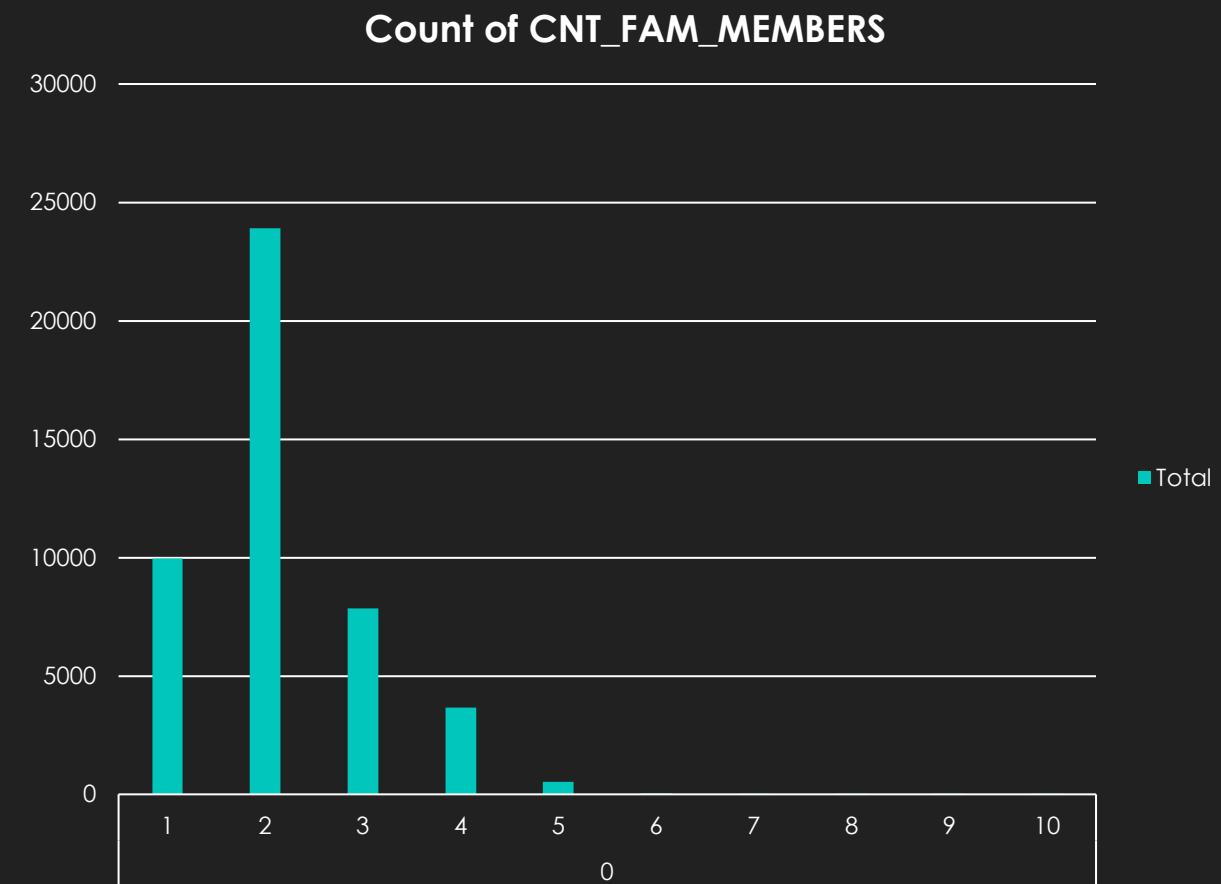


# 0 – Customers with no payment difficulties

## CNT\_FAM\_MEMBERS

Row Labels	Count of CNT_FAM_MEMBERS
1	9951
2	23902
3	7858
4	3651
5	538
6	55
7	9
8	6
9	2
10	1
Grand Total	45973

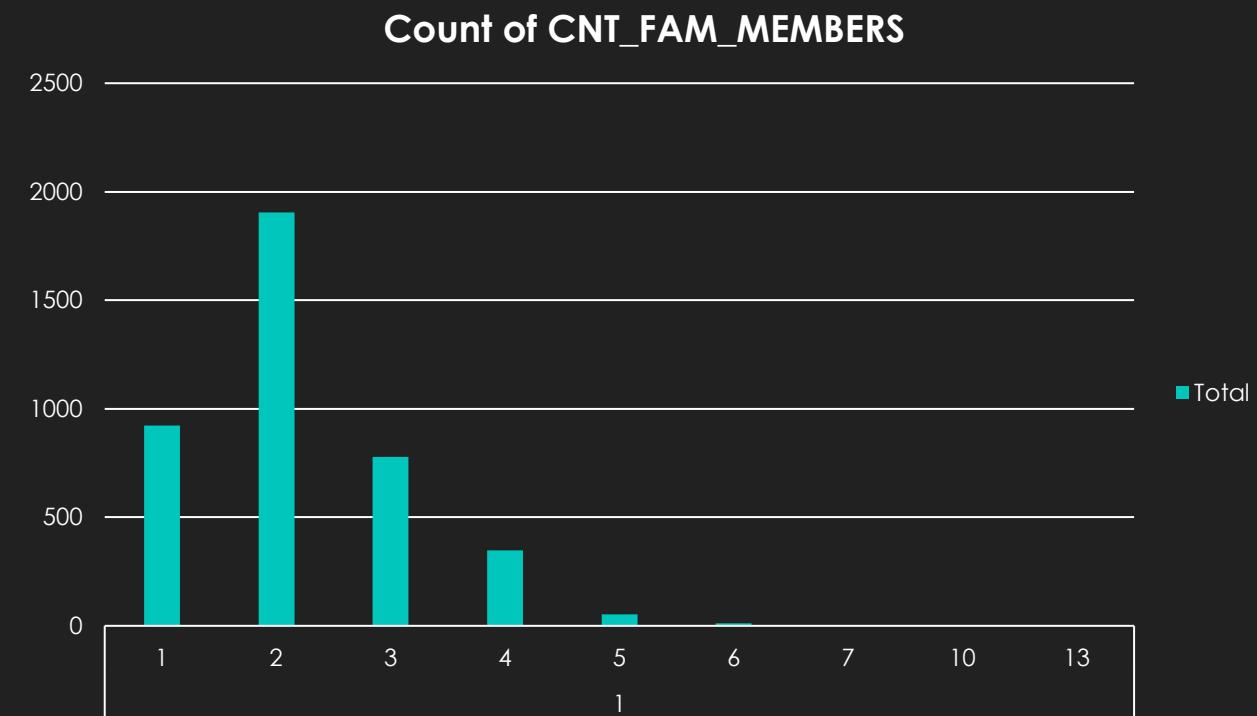
Most of the customers with no payment difficulties had 2 members in family.



# 1 – Customers with payment difficulties

## CNT\_FAM\_MEMBERS

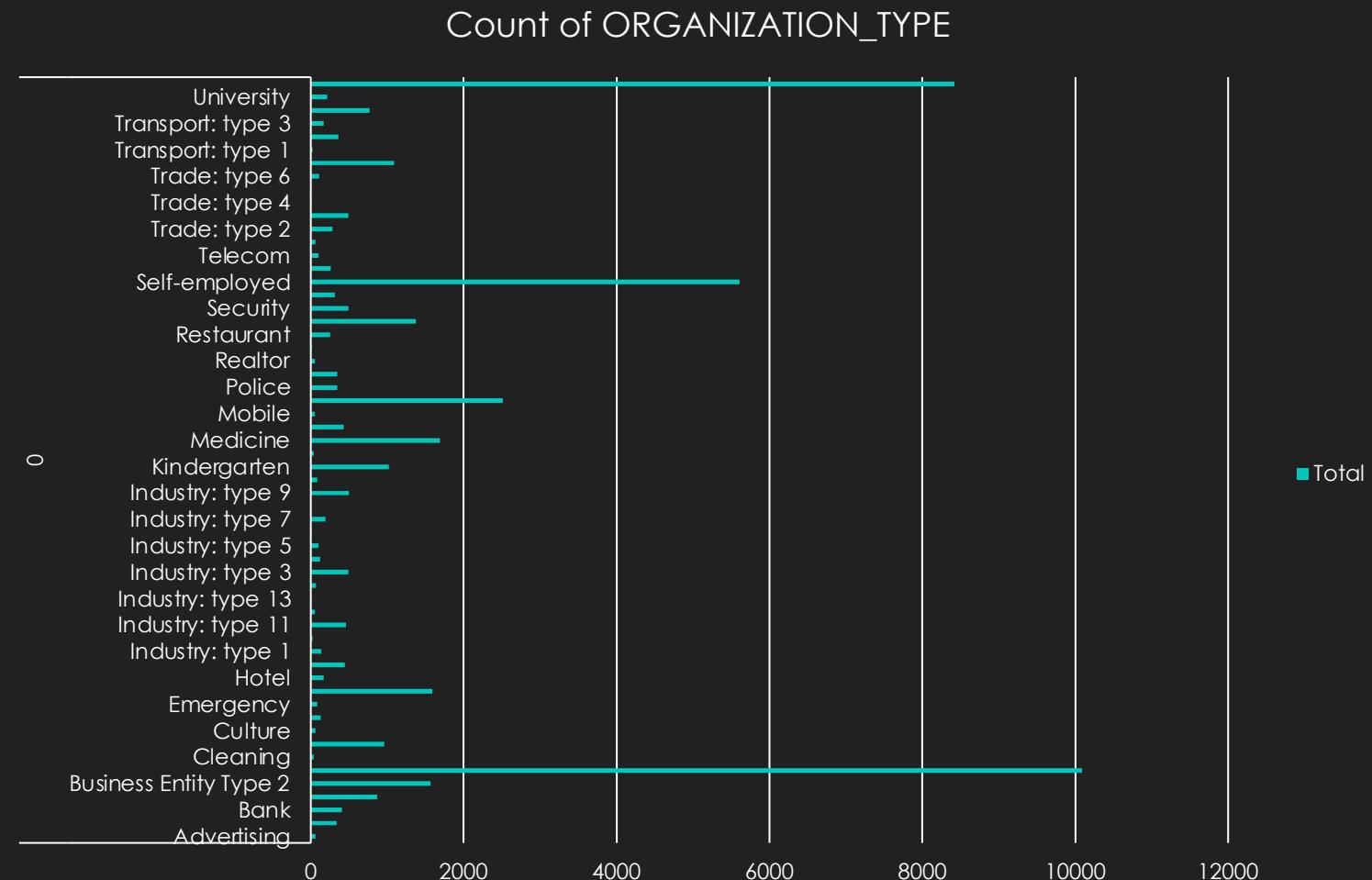
Row Labels	Count of CNT_FAM_MEMBERS
1	4026
1	922
2	1906
3	777
4	349
5	54
6	13
7	3
10	1
13	1
Grand Total	4026



Most of the customers with payment difficulties also had 2 members in family.

# 0 – Customers with no payment difficulties ORGANIZATION\_TYPE

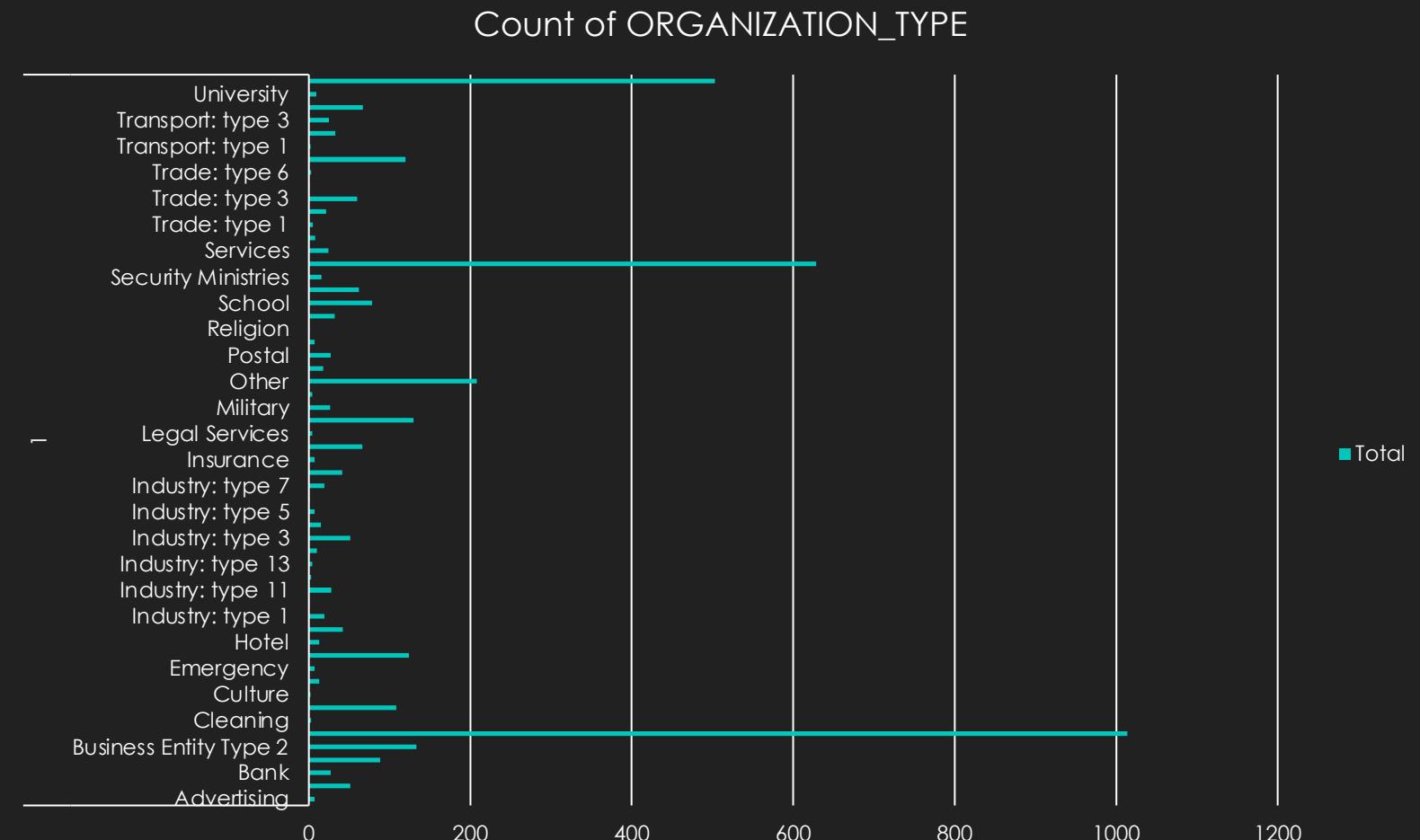
Most of the customers with no payment difficulties work in Business Entity type 3, and majority were also self employed.



# 1 – Customers with payment difficulties

## ORGANIZATION\_TYPE

Most of the customers with payment difficulties work in Business Entity type 3, and majority were also self employed.

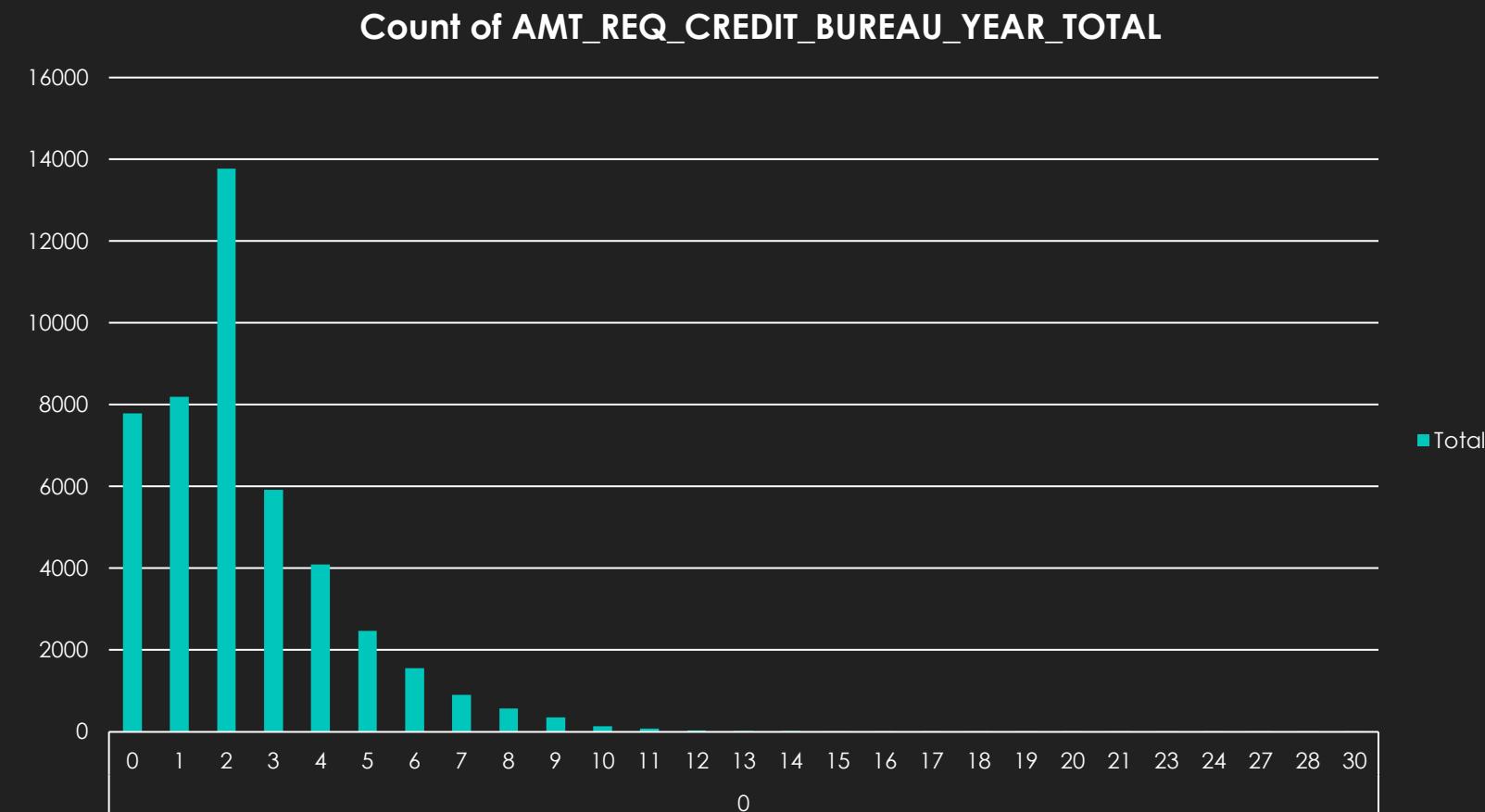


# 0 – Customers with no payment difficulties

## AMT\_REQ\_CREDIT\_BUREAU\_YEAR\_TOTAL

The inquiries to credit bureau twice for most of the customers with no payment difficulties.

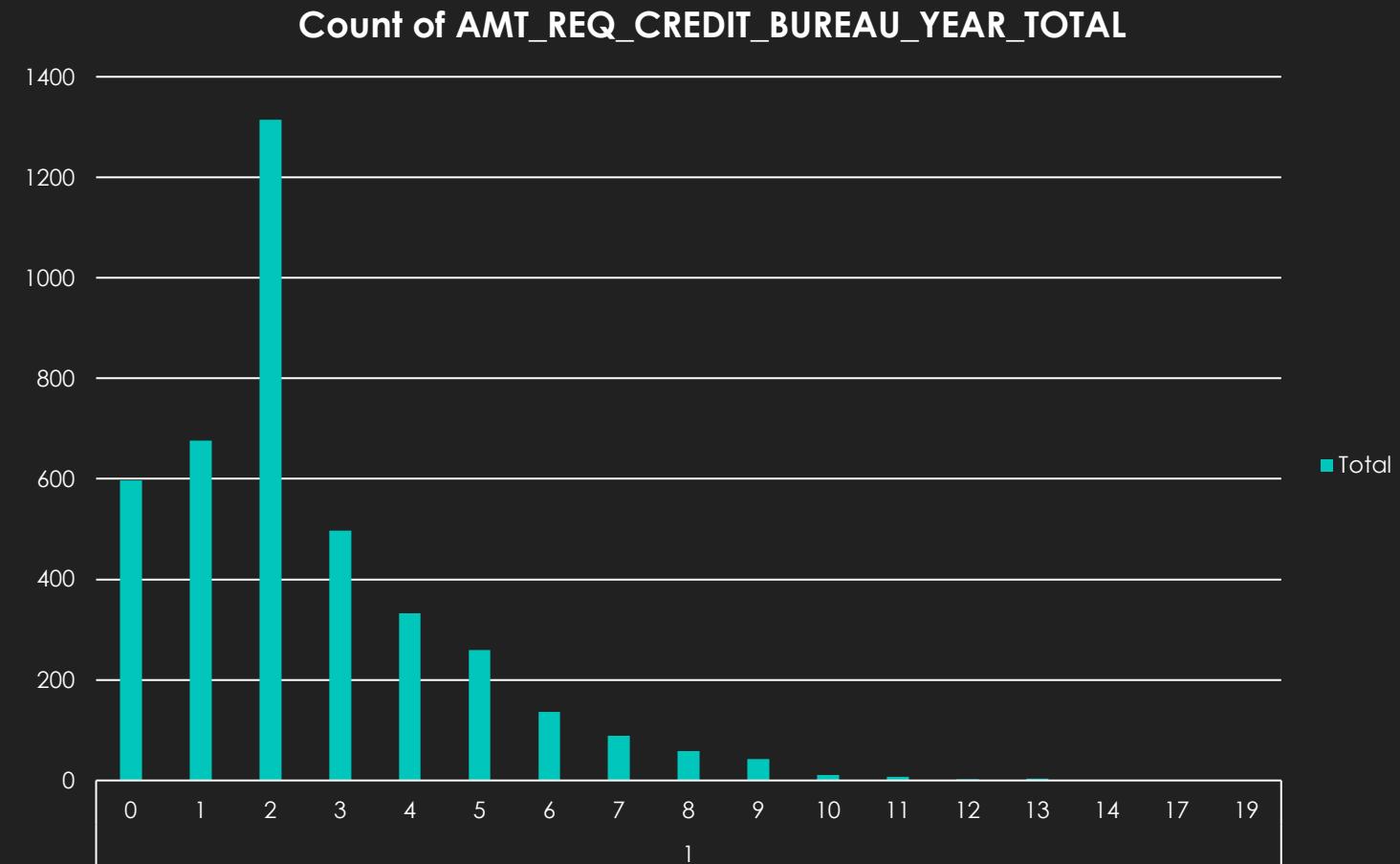
The columns have been clubbed to sum up the count upto 1 year.



# 1 – Customers with payment difficulties

## AMT\_REQ\_CREDIT\_BUREAU\_YEAR\_TOTAL

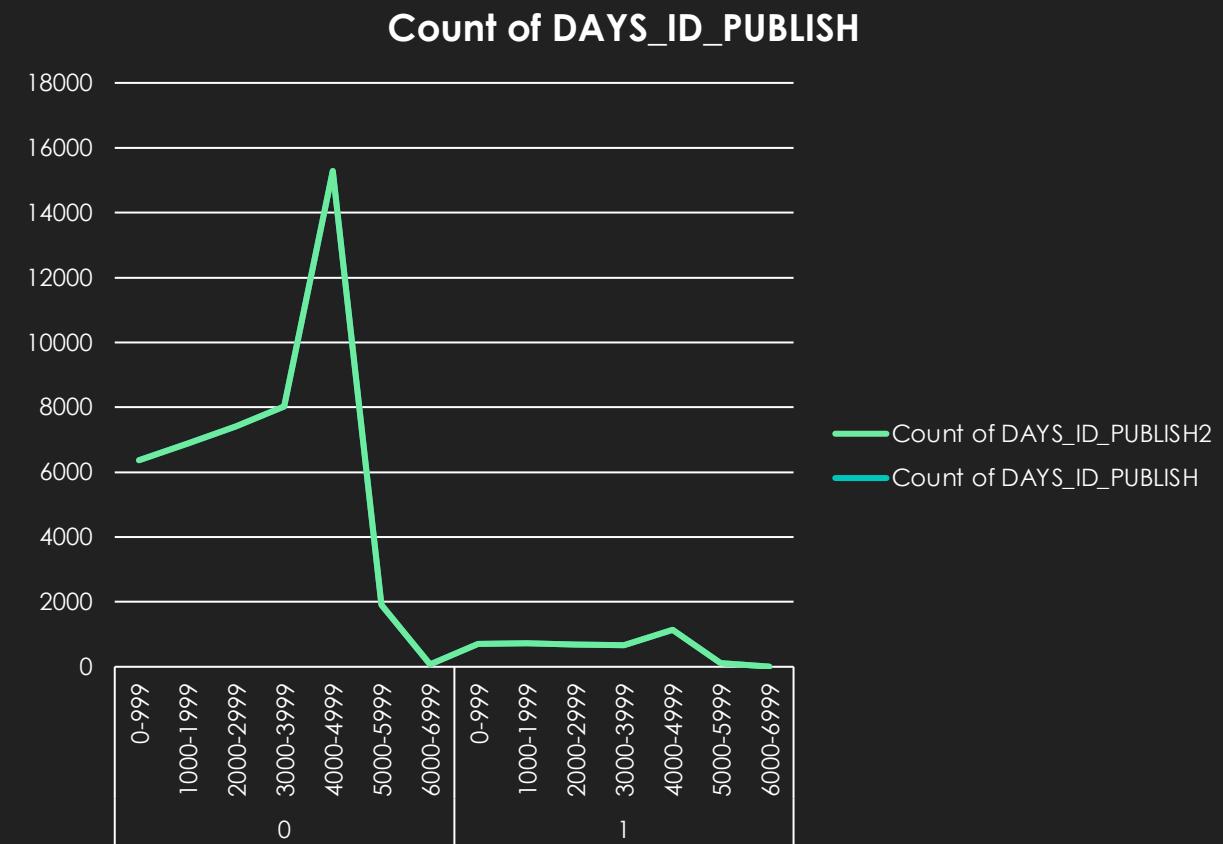
- The columns have been clubbed to sum up the count upto 1 year.
- The inquiries to credit bureau twice for most of the customers with payment difficulties.
- But the stats are same for customers with no payment difficulties, so it can be understood that on an average inquiries were made two times for a customer in last 1 year.



# Fraud Analysis

Row Labels	Count of DAYS_ID_PUBLISH	Count of DAYS_ID_PUBLISH2
0	45973	91.95%
0-999	6376	13.87%
1000-1999	6887	14.98%
2000-2999	7421	16.14%
3000-3999	8033	17.47%
4000-4999	15285	33.25%
5000-5999	1902	4.14%
6000-6999	69	0.15%
1	4026	8.05%
0-999	700	17.39%
1000-1999	719	17.86%
2000-2999	687	17.06%
3000-3999	671	16.67%
4000-4999	1132	28.12%
5000-5999	112	2.78%
6000-6999	5	0.12%
Grand Total	49999	100.00%

No specific trend could be found.



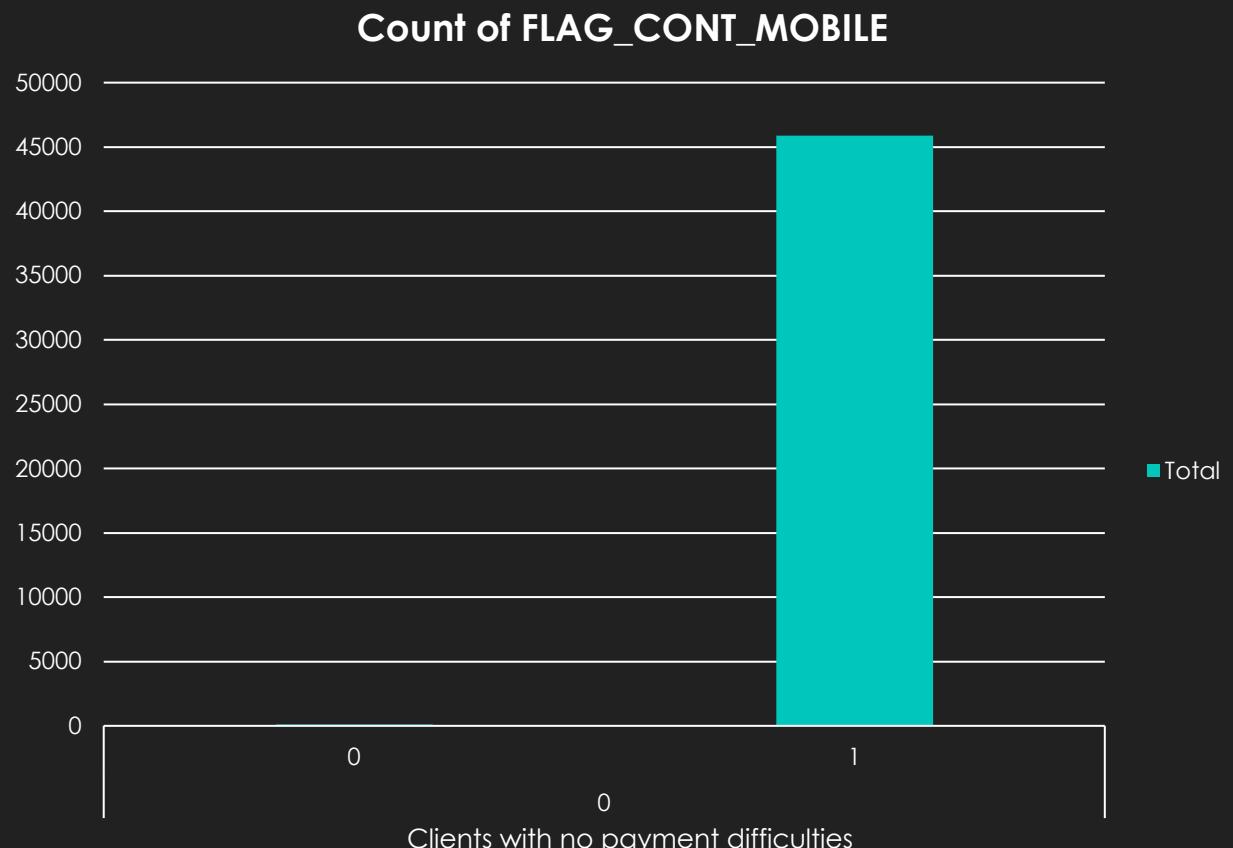
# Fraud Analysis

Row Labels	Count of FLAG_CONT_MOBILE
0	97
1	45876
Grand Total	45973

This column whether the client's phone was reachable or not.

Here, 0 represents no  
1 represents yes

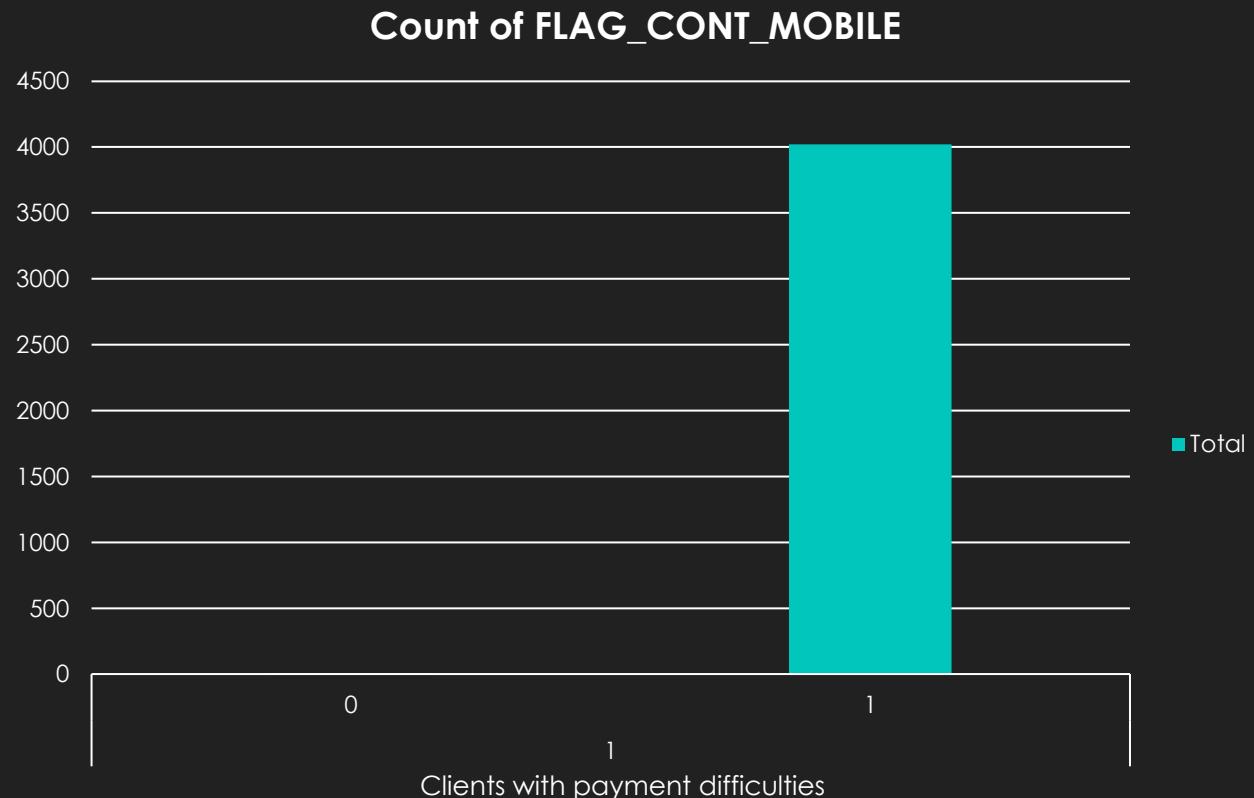
Majority of the clients who faced no payment difficulties had their phone reachable.



# Fraud Analysis

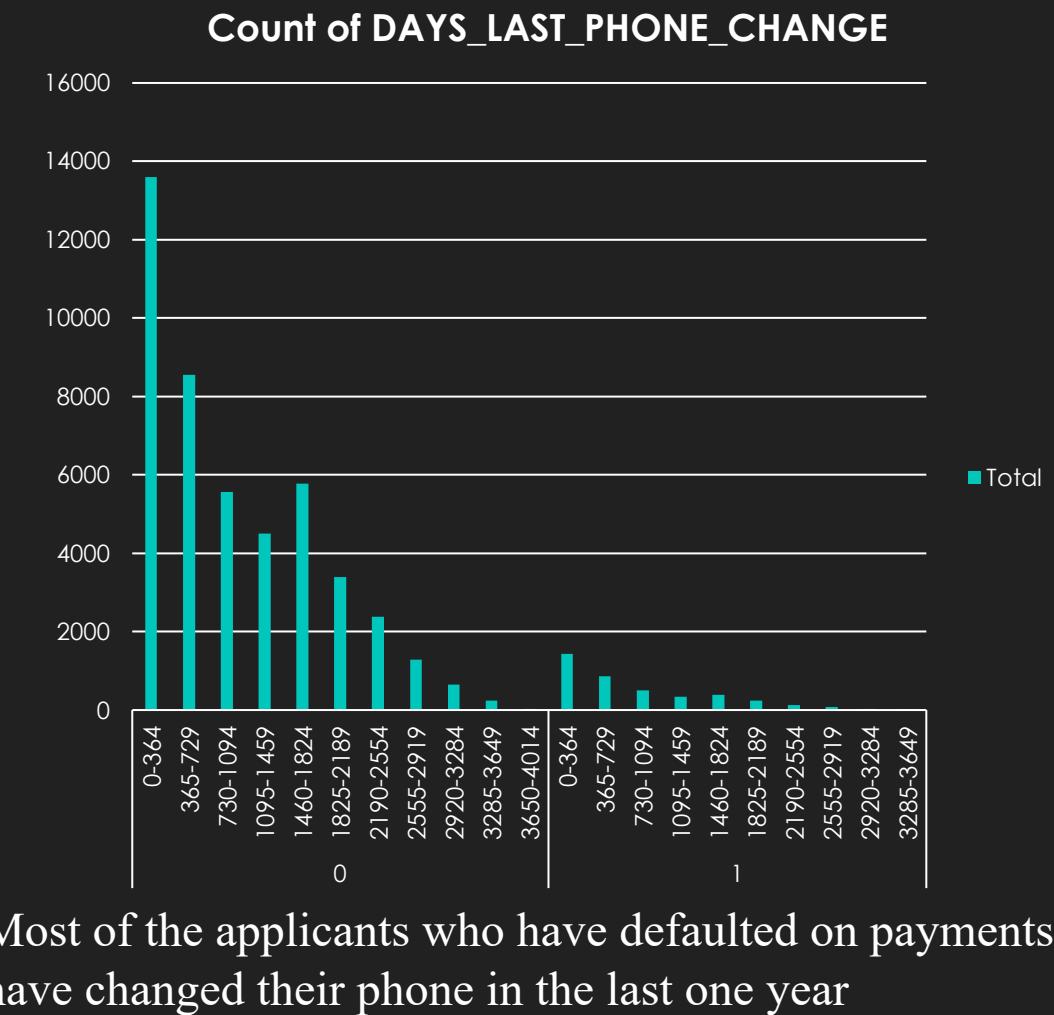
Row Labels	Count of FLAG_CONT_MOBILE
0	4
1	4022
Grand Total	4026

Majority of the clients who faced payment difficulties had their phone reachable. So, it does not seem to be a deliberate fraudulent practice of clients to bounce payments.



# Fraud Analysis

Row Labels	Count of DAYS_LAST_PHONE_CHANGE
0	45973
0-364	13600
365-729	8555
730-1094	5565
1095-1459	4509
1460-1824	5773
1825-2189	3388
2190-2554	2373
2555-2919	1293
2920-3284	649
3285-3649	238
3650-4014	30
1	4026
0-364	1440
365-729	866
730-1094	508
1095-1459	343
1460-1824	389
1825-2189	235
2190-2554	125
2555-2919	81
2920-3284	25
3285-3649	14
Grand Total	49999



# Correlation Matrix

Overall	AMT INCOME TOTAL	AMT CREDIT	AMT ANNUITY	DAYS BIRTH year	DAYS ID PUBLISH	CNT FAM MEMBERS	DAYS LAST PHONE CHANGE NEW	AMT REQ CREDIT BUREAU YEAR Total
AMT INCOME TOTAL	1							
AMT CREDIT	0.069315897	1						
AMT ANNUITY	0.083008438	0.76949879	1					
DAYS BIRTH year	-0.015871498	0.05911226	-0.00804581	1				
DAYS ID PUBLISH	-0.003506646	0.01222876	-0.006716927	0.271609378	1			
CNT FAM MEMBERS	0.011225511	0.06399716	0.07737959	-0.276365674	0.026074278	1		
DAYS LAST PHONE CHANGE NEW	0.004141658	0.07528529	0.065246635	0.079837875	0.090774609	0.022506978	1	
AMT REQ CREDIT BUREAU YEAR Total	0.007286752	-0.00024933	0.015002696	0.060532471	0.038116142	-0.024501112	0.111847863	1

AMT\_ANNUITY and AMT\_CREDIT have high positive correlation as expected while no other attribute show significant correlation.

0	AMT INCOME TOTAL	AMT CREDIT	AMT ANNUITY	DAYS BIRTH year	DAYS ID PUBLISH	CNT FAM MEMBERS	DAYS LAST PHONE CHANGE NEW	AMT REQ CREDIT BUREAU YEAR Total
AMT INCOME TOTAL	1							
AMT CREDIT	0.377965752	1						
AMT ANNUITY	0.451135167	0.77077282	1					
DAYS BIRTH year	-0.073966771	0.05092406	-0.010167705	1				
DAYS ID PUBLISH	-0.032286356	0.00829019	-0.00942697	0.270944996	1			
CNT FAM MEMBERS	0.041599302	0.06487694	0.077892626	-0.283548577	0.025054258	1		
DAYS LAST PHONE CHANGE NEW	0.045978573	0.07048628	0.062421355	0.072071995	0.084246321	0.025018128	1	
AMT REQ CREDIT BUREAU YEAR Total	0.054557569	0.00017615	0.014432023	0.059726216	0.035696206	-0.025894464	0.114187737	1

Clients with no payment difficulties

There is high positive correlation between AMT\_ANNUITY & AMT\_CREDIT , no other substantial correlation is observed.

1	AMT INCOME TOTAL	AMT CREDIT	AMT ANNUITY	DAYS BIRTH year	DAYs ID PUBLISH	CNT FAM MEMBERS	DAYs LAST PHONE CHANGE NEW	AMT REQ CREDIT BUREAU YEAR Total
AMT INCOME TOTAL	1							
AMT CREDIT	0.015271444	1						
AMT ANNUITY	0.018004594	0.7496652	1					
DAYS BIRTH year	-0.008419044	0.14130676	0.007248662	1				
DAYs ID PUBLISH	0.009122006	0.0437719	0.02132109	0.247697382	1			
CNT FAM MEMBERS	0.013121678	0.06124869	0.075838463	-0.197711093	0.044037815	1		
DAYs LAST PHONE CHANGE NEW	-0.012642088	0.12091321	0.098610858	0.125790656	0.140069979	0.003474821	1	
AMT REQ CREDIT BUREAU YEAR Total	-0.008196542	-0.00024734	0.025387094	0.084832424	0.073252128	-0.011741962	0.094573561	1

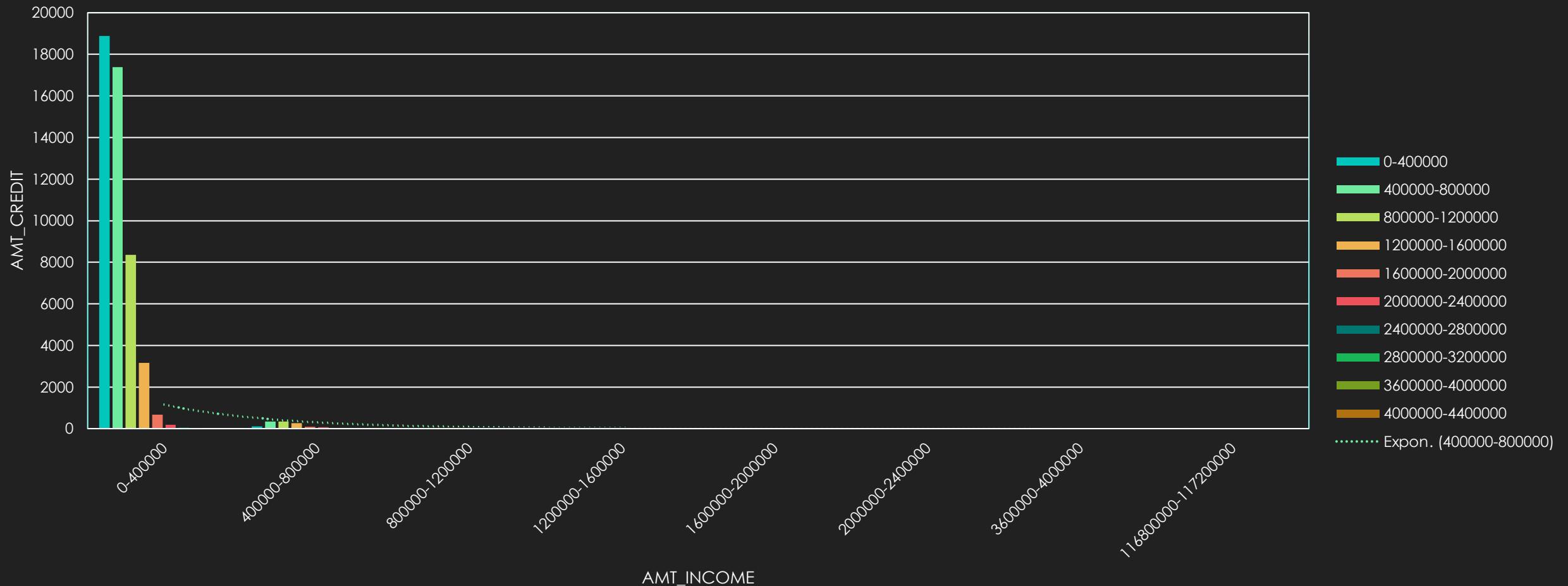
## Clients with payment difficulties

As expected there is high positive correlation between AMT\_CREDIT & AMT\_ANNUITY, no other significant value is observed.

# Bivariate Analysis

# AMT\_INCOME TO AMT\_CREDIT

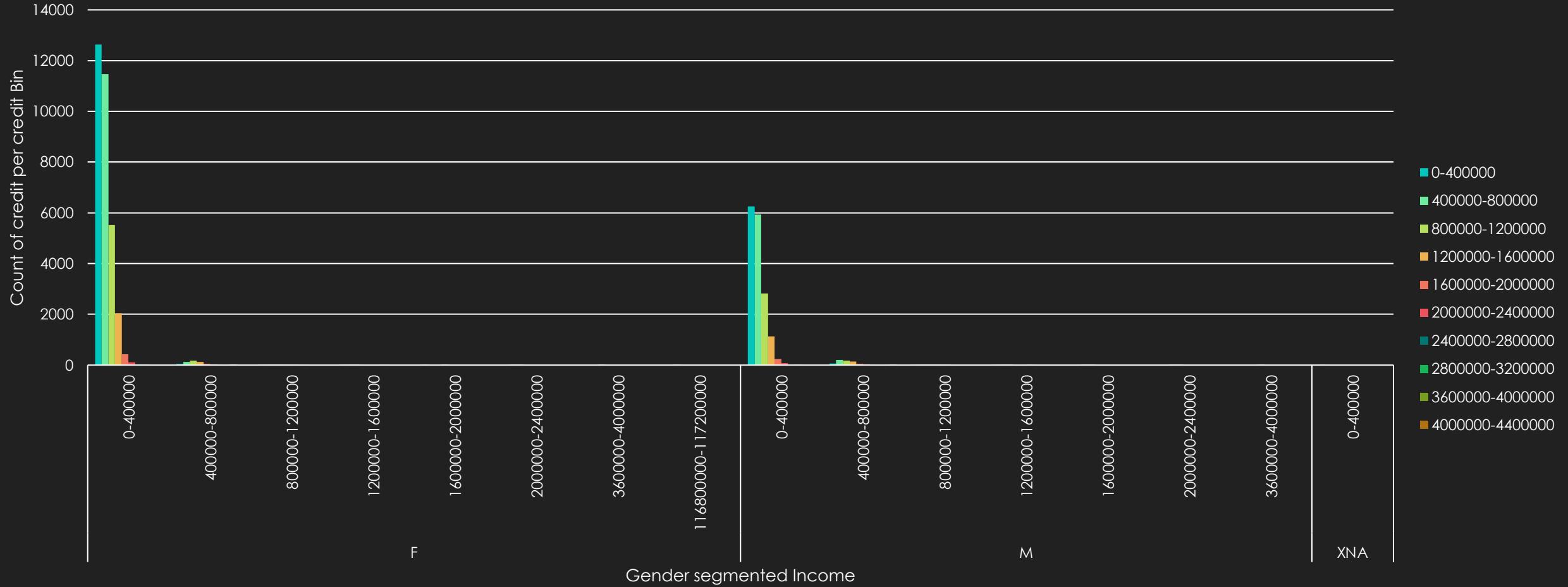
Count of SK_ID_CURR	Column Labels	400000- 800000	800000- 1200000	1200000- 1600000	1600000- 2000000	2000000- 2400000	2400000- 2800000	2800000- 3200000	3600000- 4000000	4000000- 4400000	Grand Total
Row Labels	0-400000	18881	17394	8351	3169	670	185	42	4		
0-400000		18881	17394	8351	3169	670	185	42	4		48696
400000-800000	110	333	338	259	84	61	18		1	2	1206
800000-1200000	11	19	13	15	8	7	1				74
1200000-1600000	2	4	4			1	1				12
1600000-2000000	1	1	1	1							4
2000000-2400000		1	2	1							4
3600000-4000000			1	1							2
116800000- 117200000											1
Grand Total	19005	17753	8710	3446	762	254	62	4	1	2	49999



Most of the applicants belong to the lower income range and also apply for low amount of credit. The distribution follows Poisson distribution being heavily skewed on the left.

# Gender, Credit And Income

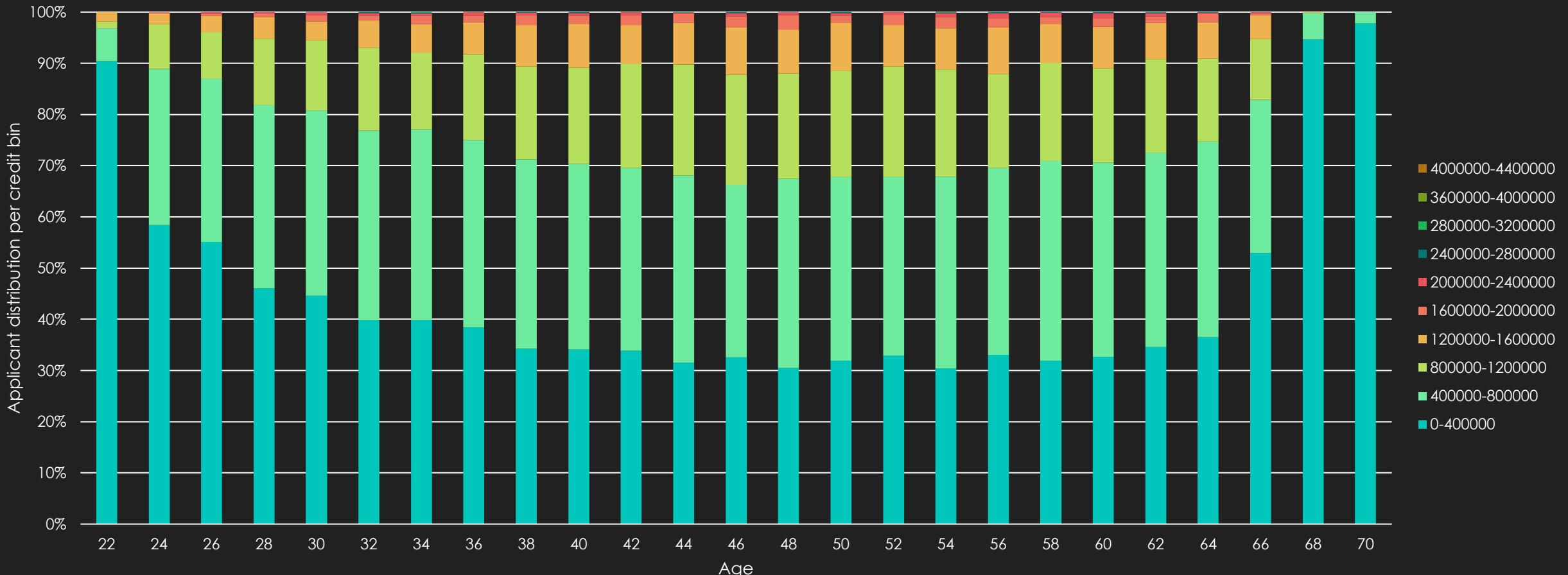
Count of SK_ID_CURR	Column Labels										
Row Labels	0-400000	400000-800000	800000-1200000	1200000-1600000	1600000-2000000	2000000-2400000	2400000-2800000	2800000-3200000	3600000-4000000	4000000-4400000	Grand Total
F	12689	11608	5700	2168	476	142	38	1	1		32823
0-400000	12632	11468	5524	2043	432	114	26	1			32240
400000-800000	51	131	165	120	43	26	10		1		547
800000-1200000	4	5	7	4	1	2	1				24
1200000-1600000	1	2	2				1				6
1600000-2000000	1			1							2
2000000-2400000		1	1								2
3600000-4000000			1								1
116800000-117200000		1									1
M	6314	6145	3010	1278	286	112	24	3		2	17174
0-400000	6247	5926	2827	1126	238	71	16	3			16454
400000-800000	59	202	173	139	41	35	8			2	659
800000-1200000	7	14	6	11	7	5					50
1200000-1600000	1	2	2			1					6
1600000-2000000		1	1								2
2000000-2400000			1	1							2
3600000-4000000				1							1
XNA	2										2
0-400000	2										2
Grand Total	19005	17753	8710	3446	762	254	62	4	1	2	49999



The highest number of applicants, both male and female belong to the lower income range and apply for the low amount of credit.

# AGE to CREDIT

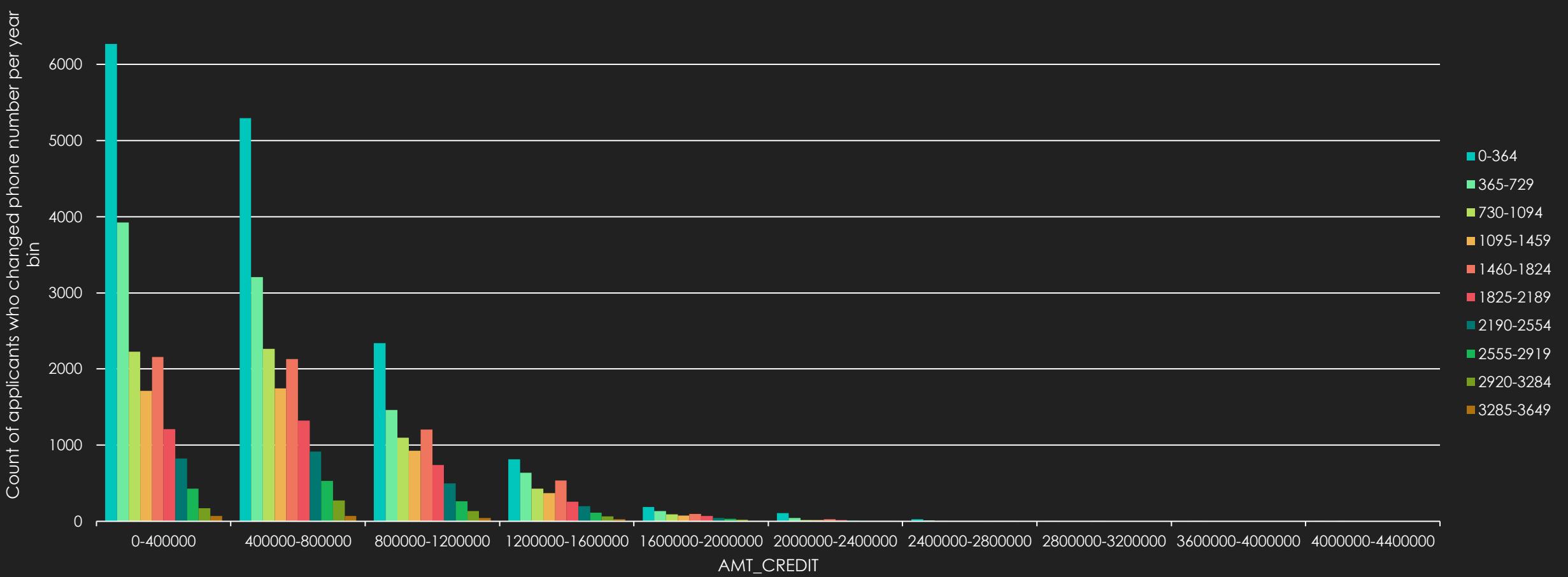
Count of SK ID CURR	Column Labels											
Row Labels	0-400000	400000-800000	800000-1200000	1200000-1600000	1600000-2000000	2000000-2400000	2400000-2800000	2800000-3200000	3600000-4000000	4000000-4400000	Grand Total	
22	197	14	3	4							218	
24	682	356	102	25	2	1					1168	
26	725	418	121	42	4	5					1315	
28	940	729	265	86	14	6					2040	
30	1142	926	353	94	31	13	2				2561	
32	1071	997	435	143	25	13	6				2690	
34	1043	979	392	146	43	11	7	1			2622	
36	951	905	416	155	31	15	1			1	2475	
38	961	1035	509	226	55	13	4				2803	
40	966	1027	532	241	47	14	5				2832	
42	963	1014	580	214	55	15	1			1	2843	
44	834	966	573	213	47	6	2	2			2643	
46	794	820	525	227	50	15	6				2437	
48	718	870	485	202	66	12	2				2355	
50	706	793	459	207	31	11	4				2211	
52	706	751	464	173	43	12					2149	
54	714	881	493	189	53	16	4		1		2351	
56	757	835	421	206	44	21	5				2289	
58	706	861	423	169	31	17	3				2210	
60	660	766	374	164	34	18	5				2021	
62	659	723	348	136	24	12	3	1			1906	
64	631	660	281	123	28	4	2				1729	
66	689	389	155	60	4	4					1301	
68	660	35	1	1							697	
70	130	3									133	
Grand Total	19005	17753	8710	3446	762	254	62	4	1	2	49999	



Applicants belonging to lower age groups and upper age groups above 60 years mostly apply for smaller amount of credit, while middle age applicants apply for the larger amount.

# CREDIT vs PHONE NUMBER CHANGES

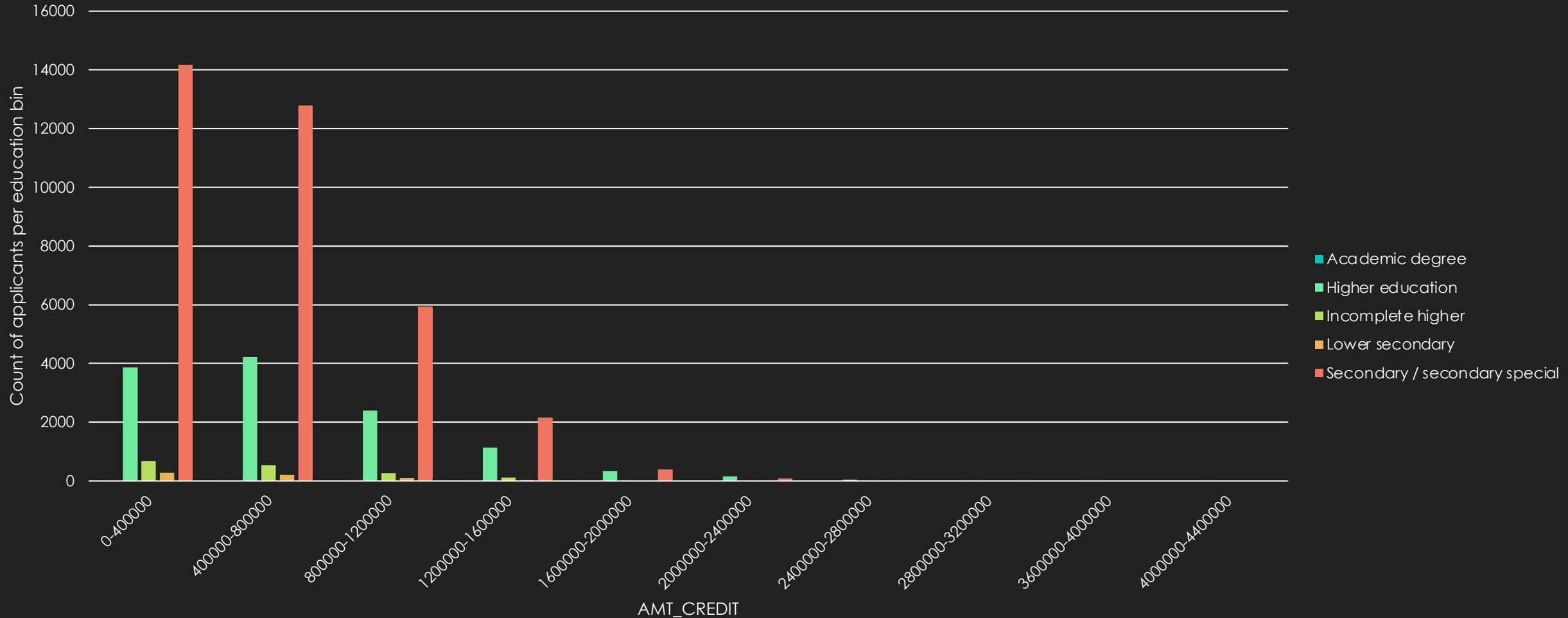
Count of SK_ID_CURR	Column Labels										
Row Labels	0-364	365-729	730-1094	1095-1459	1460-1824	1825-2189	2190-2554	2555-2919	2920-3284	3285-3649	Grand Total
0-400000	6269	3927	2227	1714	2160	1210	825	430	173	70	19005
400000-800000	5293	3206	2264	1746	2133	1323	917	528	271	72	17753
800000-1200000	2340	1463	1097	927	1203	738	501	263	136	42	8710
1200000-1600000	813	638	429	370	536	260	197	112	66	25	3446
1600000-2000000	186	136	92	76	99	71	45	32	20	5	762
2000000-2400000	106	41	19	16	26	18	11	7	5	5	254
2400000-2800000	29	9	7	3	4	3	2	2	3		62
2800000-3200000	3					1					4
3600000-4000000			1								1
4000000-4400000	1		1								2
Grand Total	15040	9421	6136	4852	6162	3623	2498	1374	674	219	49999



Highest number of applicants have changed their phone number in the last year in all the credit bins..

# CREDIT to DEGREE

Count of SK_ID_CURR	Column Labels						
Row Labels	Academic degree	Higher education	Incomplete higher	Lower secondary	Secondary / secondary special	Grand Total	
0-400000	7	3863	675	283	14177	19005	
400000-800000	4	4216	529	213	12791	17753	
800000-1200000	3	2399	273	94	5941	8710	
1200000-1600000	4	1142	118	24	2158	3446	
1600000-2000000	2	339	20	4	397	762	
2000000-2400000		161	4	2	87	254	
2400000-2800000		42	1		19	62	
2800000-3200000		2			2	4	
3600000-4000000		1				1	
4000000-4400000		2				2	
Grand Total	20	12167	1620	620	35572	49999	



Highest number of applicants in all the credit ranges have education upto secondary/ secondary special.

## Video Link

<https://www.loom.com/share/a95d13c8b6ef4f3fb0ad73845f5a7a88?sid=63fa5ff8-823b-4521-b237-0d3dba89a33a>

## Bivariate Analysis Excel Sheet

[https://docs.google.com/spreadsheets/d/1aHfwWSbqmhHyGth01-OCEUVpL2zZZEcI/edit?usp=share\\_link&ouid=101949921485202693908&rtpof=true&sd=true](https://docs.google.com/spreadsheets/d/1aHfwWSbqmhHyGth01-OCEUVpL2zZZEcI/edit?usp=share_link&ouid=101949921485202693908&rtpof=true&sd=true)

## Univariate Analysis Excel Sheet

[https://docs.google.com/spreadsheets/d/1bcKn2xjE\\_m-4x3lEyiOavscVFcbXHLA3/edit?usp=sharing&ouid=101949921485202693908&rtpof=true&sd=true](https://docs.google.com/spreadsheets/d/1bcKn2xjE_m-4x3lEyiOavscVFcbXHLA3/edit?usp=sharing&ouid=101949921485202693908&rtpof=true&sd=true)