

Drive Link for the project-

<https://drive.google.com/drive/u/0/folders/1x-1--FVNwEKp7fOmcoAmgW9lumv8tYhE>

Presentation Link for the project-

<https://www.loom.com/share/e451eebee6f14e70aed6fe15ed9596a6>

Tableau Workbook for the project-

https://public.tableau.com/app/profile/mohd.faiz2106/viz/BankLoanCaseStudy_16813027062140/No_ofApplicationvsPaymentTypevsStatus?publish=yes

Project by –

Mohd Faiz

faiz.mohd340@gmail.com

Bank Loan Case Study

Project Description

This project will go through to find some of the insights on Bank Loan Case Study.

Project Approach

In order to find the insights, Excel and Tableau were used. Using Excel, we performed Data Cleaning and transformation first like understanding data columns, checking for missing data, checking and removing outliers, etc. After that, for Exploratory Analysis we used Tableau to get the insights we needed.

Tech Stack Used

Microsoft Excel 2021, Tableau, Microsoft Word 2021, and Google Drive.

Project Insight

1.Cleaning the data

At first, removed all the rows which were empty. Found out the number of blank cells in the particular column. After that, we find the percentage of the null values.

To find the blank values we used COUNTBLANK function in Excel.

We removed those columns whose null value percentage for that particular column is greater than **5%** for “application_data” dataset and **20%** and above for “previous_application” dataset.

A	B	C	D	E	F	G	H	I	J	K	L	M
Percentage of null values	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total null row count	0	0	0	0	0	0	0	0	0	12	278	1292
Total row count 307511	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	NAME_TYPE_SUITE
	100002	1	Cash loans	M	N	N	Y	0	202500	406597.5	24700.5	351000 Unaccompanied
	100003	0	Cash loans	F	N	N	N	0	270000	1293502.5	35698.5	1129500 Family
	100004	0	Revolving loans	M	Y	Y	Y	0	67500	135000	6750	135000 Unaccompanied
	100006	0	Cash loans	F	N	Y	Y	0	135000	312682.5	29686.5	297000 Unaccompanied
	100007	0	Cash loans	M	N	Y	Y	0	121500	513000	21865.5	513000 Unaccompanied
	100008	0	Cash loans	M	N	Y	Y	0	99000	490495.5	27517.5	454500 Spouse, partner
	100009	0	Cash loans	F	Y	Y	Y	1	171000	1560726	41301	1395000 Unaccompanied
	100010	0	Cash loans	M	Y	Y	Y	0	360000	1530000	42075	1530000 Unaccompanied
	100011	0	Cash loans	F	N	Y	Y	0	112500	1019610	33826.5	913500 Children
	100012	0	Revolving loans	M	N	Y	Y	0	135000	405000	20250	405000 Unaccompanied
	100014	0	Cash loans	F	N	Y	Y	1	112500	652500	21177	652500 Unaccompanied
	100015	0	Cash loans	F	N	Y	Y	0	38419.155	148365	10678.5	135000 Children
	100016	0	Cash loans	F	N	Y	Y	0	67500	80865	5881.5	67500 Unaccompanied
	100017	0	Cash loans	M	Y	N	N	1	225000	918468	28966.5	697500 Unaccompanied
	100018	0	Cash loans	F	N	Y	Y	0	189000	773680.5	32778	679500 Unaccompanied
	100019	0	Cash loans	M	Y	Y	Y	0	157500	299772	20160	247500 Family
	100020	0	Cash loans	M	N	N	N	0	108000	509602.5	26149.5	387000 Unaccompanied
	100021	0	Revolving loans	F	N	Y	Y	1	81000	270000	13500	270000 Unaccompanied
	100022	0	Revolving loans	F	N	Y	Y	0	112500	157500	7875	157500 Other_A
	100023	0	Cash loans	F	N	Y	Y	1	90000	544491	17563.5	454500 Unaccompanied
	100024	0	Revolving loans	M	Y	Y	Y	0	135000	427500	21375	427500 Unaccompanied
	100025	0	Cash loans	F	Y	Y	Y	1	202500	1132573.5	37561.5	927000 Unaccompanied
	100026	0	Cash loans	F	N	N	N	1	450000	497520	32521.5	450000 Unaccompanied
	100027	0	Cash loans	F	N	Y	Y	0	83250	239850	23850	225000 Unaccompanied
	100029	0	Cash loans	M	Y	N	N	2	135000	247500	12703.5	247500 Unaccompanied
	100030	0	Cash loans	F	N	Y	Y	0	90000	225000	11074.5	225000 Unaccompanied
	100031	0	Cash loans	F	N	Y	Y	0	112500	652500	21177	652500 Unaccompanied

application_data_EDA

Final Dataset

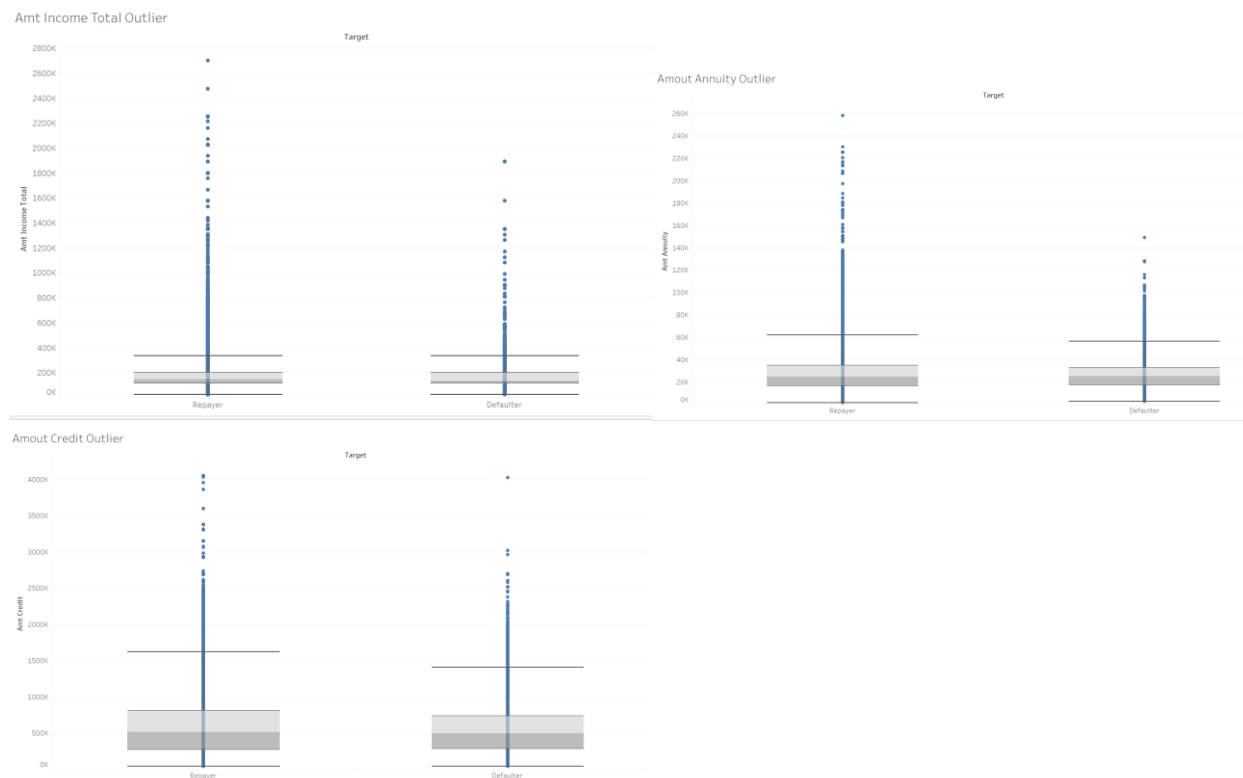
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
Percentage of null values	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total null row count	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total row count	1048573	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_APPLICATION	AMT_CREDIT	WEEKDAY	HOUR_APPRaisal	FLAG_LAST_PAYMENT	LA_NAME_CURRENT	NAME_CODE_REJECT	NAME_CLIENT	NAME_GENDER	NAME_PHONE_CHANNEL	SELLER_PLATFORM							
		2030495	271877	Consumer	17145	17145	SATURDAY	15	Y	1	XAP	Approved	-73	Cash thro	XAP	Repeater	Mobile	POS	XNA	Country-w	35 Co
		2802425	108129	Cash loans	607500	679671	THURSDAY	11	Y	1	XNA	Approved	-164	XNA	XAP	Repeater	XNA	Cash	x-sell	Contract ce	-1 XN
		2523466	122040	Cash loans	112500	136445	TUESDAY	11	Y	1	XNA	Approved	-301	Cash thro	XAP	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		2819243	176158	Cash loans	450000	470790	MONDAY	7	Y	1	XNA	Approved	-512	Cash thro	XAP	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		1784265	202054	Cash loans	337500	404055	THURSDAY	9	Y	1	Repairs	Refused	-781	Cash thro	HC	Repeater	XNA	Cash	walk-in	Credit and	-1 XN
		1383531	199383	Cash loans	315000	340574	SATURDAY	8	Y	1	Everyday	Approved	-684	Cash thro	XAP	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		2315218	175704	Cash loans	0	0	TUESDAY	11	Y	1	XNA	Canceled	-14	XNA	XAP	Repeater	XNA	XNA	XNA	Credit and	-1 XN
		1656711	296299	Cash loans	0	0	MONDAY	7	Y	1	XNA	Canceled	-21	XNA	XAP	Repeater	XNA	XNA	XNA	Credit and	-1 XN
		2367563	342292	Cash loans	0	0	MONDAY	15	Y	1	XNA	Canceled	-386	XNA	XAP	Repeater	XNA	XNA	XNA	Credit and	-1 XN
		2579447	334349	Cash loans	0	0	SATURDAY	15	Y	1	XNA	Canceled	-57	XNA	XAP	Repeater	XNA	XNA	XNA	Credit and	-1 XN
		1715995	447712	Cash loans	270000	335754	FRIDAY	7	Y	1	XNA	Approved	-735	Cash thro	XAP	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		2257824	161140	Cash loans	211500	246398	FRIDAY	10	Y	1	XNA	Approved	-815	Cash thro	XAP	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		2330894	258628	Cash loans	148500	174362	TUESDAY	15	Y	1	XNA	Approved	-860	Cash thro	XAP	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		1397919	321676	Consumer	53779.5	57564	SUNDAY	15	Y	1	XAP	Approved	-408	Cash thro	XAP	New	Consumer	POS	XNA	Country-w	200 Co
		2723188	270658	Consumer	26550	27252	SATURDAY	10	Y	1	XAP	Approved	-726	Cash thro	XAP	New	Constructi	POS	XNA	Stone	83 Co
		1232483	151612	Consumer	126490.5	119853	TUESDAY	7	Y	1	XAP	Approved	-699	Cash thro	XAP	New	Auto Acce	POS	XNA	Regional /	130 Inc
		2163253	154602	Consumer	26955	27297	SATURDAY	12	Y	1	XAP	Approved	-1473	Cash thro	XAP	Repeater	Photo / Cl	POS	XNA	Stone	130 Co
		1285768	142748	Revolving	180000	180000	FRIDAY	13	Y	1	XAP	Approved	-336	XNA	XAP	Repeater	XNA	Cash	x-sell	AP+ (Cash	6 XN
		2393109	396305	Cash loans	180000	180000	THURSDAY	14	Y	1	XNA	Approved	-700	Cash thro	XAP	Repeater	XNA	Cash	x-sell	AP+ (Cash	6 XN
		1173070	199178	Cash loans	45000	49455	SATURDAY	16	Y	1	Everyday	Refused	-584	XNA	HC	Repeater	XNA	Cash	walk-in	AP+ (Cash	6 XN
		1172842	302212	Cash loans	0	0	TUESDAY	9	Y	1	XNA	Refused	-239	XNA	HC	Repeater	XNA	XNA	XNA	Credit and	-1 XN
		1172937	302212	Cash loans	1129500	1277105	THURSDAY	5	Y	1	XNA	Refused	-594	Cash thro	HC	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		1555330	199353	Cash loans	0	0	SATURDAY	6	Y	1	XNA	Canceled	-202	XNA	XAP	Repeater	XNA	XNA	XNA	Credit and	-1 XN
		1543131	275707	Cash loans	229500	241920	THURSDAY	8	Y	1	XNA	Approved	-370	Cash thro	XAP	Repeater	XNA	Cash	x-sell	Credit and	-1 XN
		2536650	338725	Cash loans	369000	369000	WEDNESDAY	13	Y	1	XNA	Approved	-1487	XNA	XAP	Repeater	XNA	Cash	x-sell	Country-w	-1 Co
		1676258	433468	Cash loans	247500	268083	THURSDAY	14	Y	1	XNA	Approved	-1883	XNA	XAP	Repeater	XNA	Cash	x-sell	Country-w	-1 Co
		2075578	418383	Consumer	74610	65610	MONDAY	14	Y	1	XAP	Approved	-2702	Cash thro	XAP	New	Mobile	POS	XNA	Stone	61 Co
		1583704	315664	Cash loans	0	0	WEDNESDAY	15	Y	1	XNA	Refused	-430	XNA	HC	Repeater	XNA	XNA	XNA	Credit and	-1 XN

We also removed some unnecessary columns from both datasets which we were not going to use in our analysis.

2. Finding Outliers

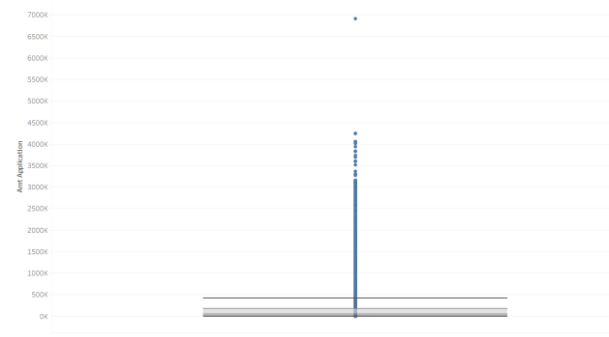
We box-plotted numerical columns to find out the outliers in both datasets.

application_data dataset Outliers-



previous_application dataset Outliers-

Amount Applied Outliers



Amount Credit Outliers

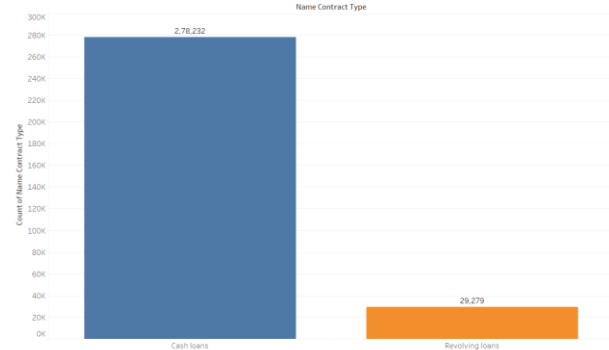


3. Data Imbalance

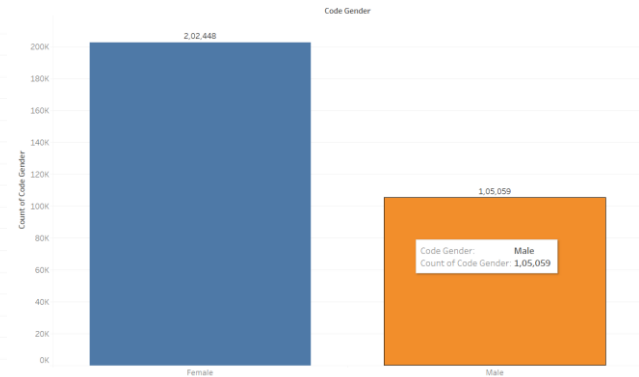
When data is distributed into unequal manner then data imbalance occurs. I plotted data imbalance using Bar/Column Charts in Tableau.

application_data Dataset data imbalance-

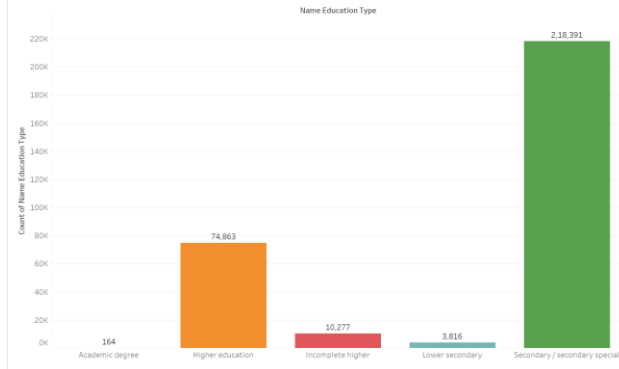
Data Imbalance- Name Contract Type



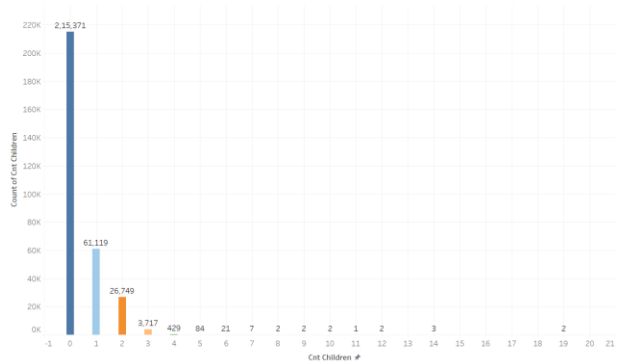
Data Imbalance - Gender



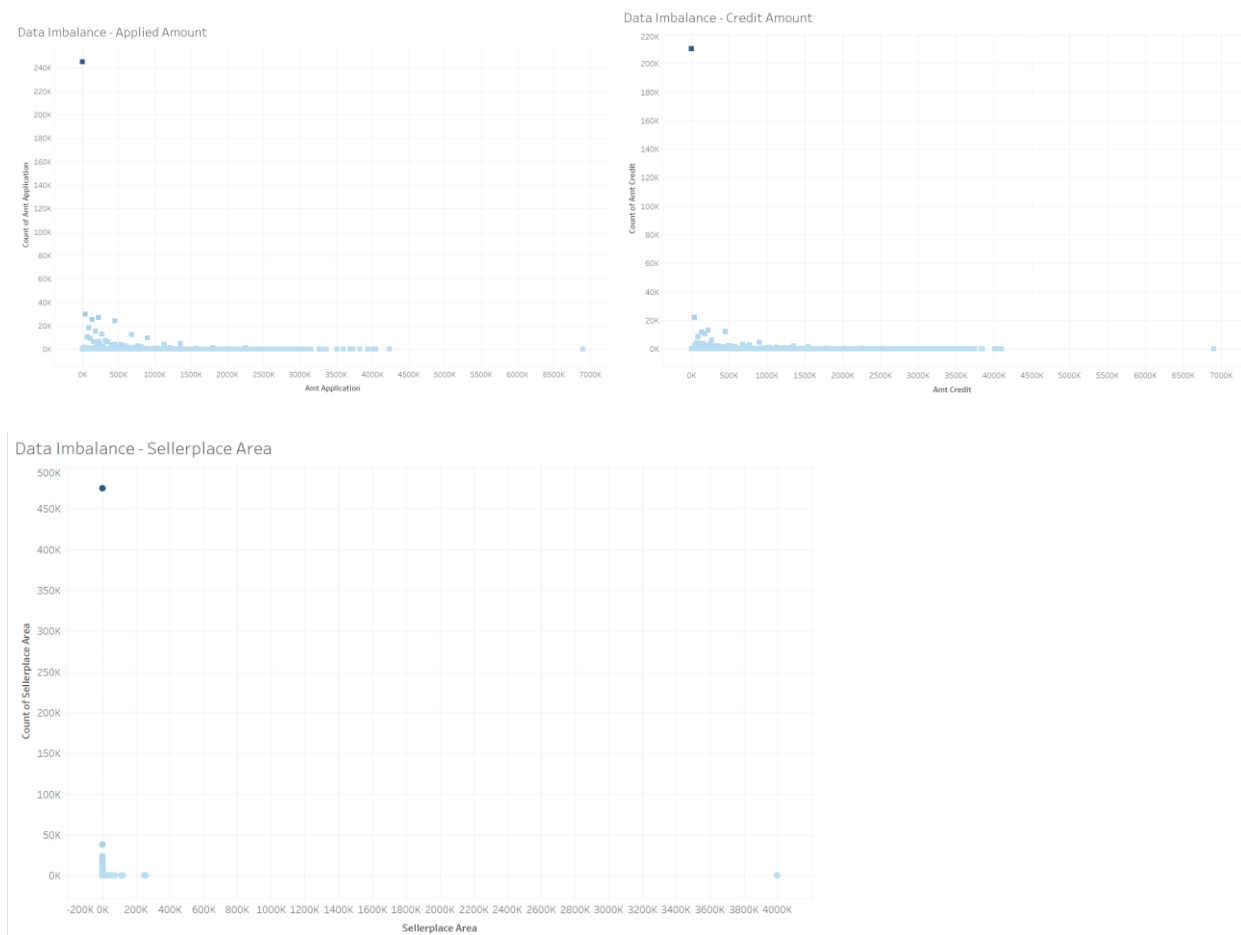
Data Imbalance- Education Type



Data Imbalance - Children Count



previous_application dataset data imbalance-

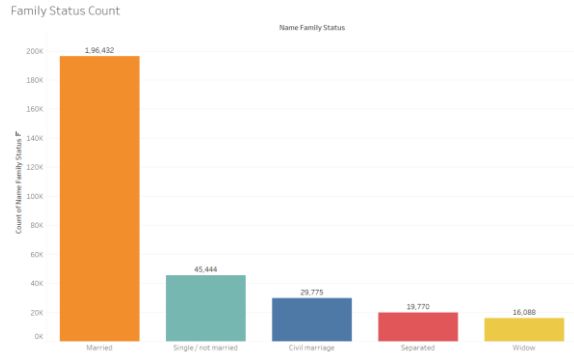
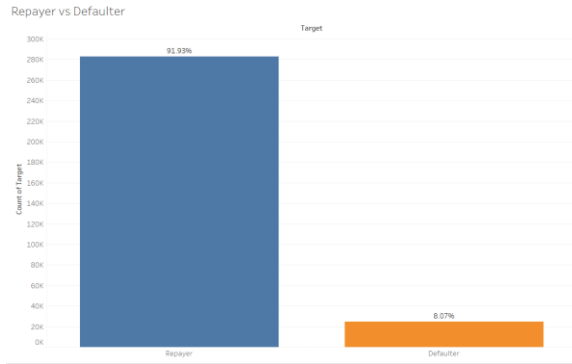


4. Univariate Analysis

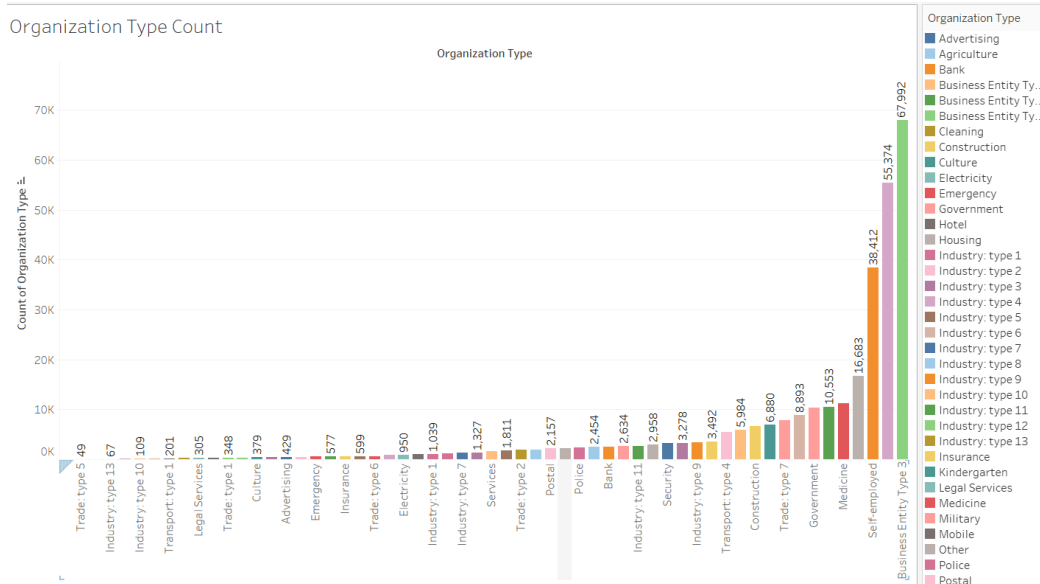
application_data Dataset univariate analysis-

Insights-

- There are more number of Repayers than defaulters.
- Married people have requested more loans.

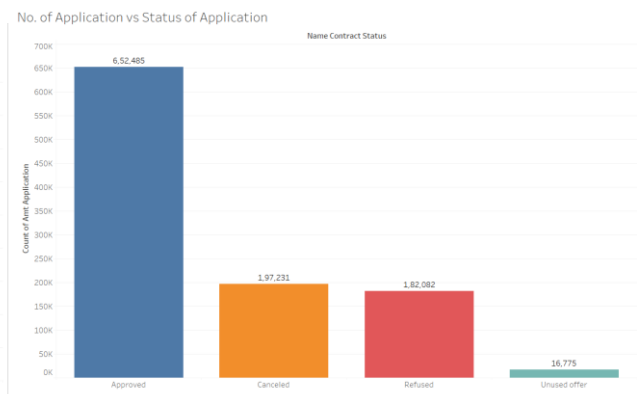
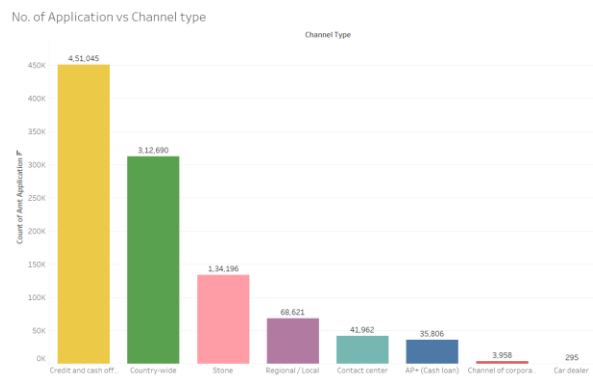


- Maximum No. of loan applications are from Business Type-3 and Industry Type-3 whereas the minimum No. of loan applications are from Trade-Type-5 and Industry Type-13.

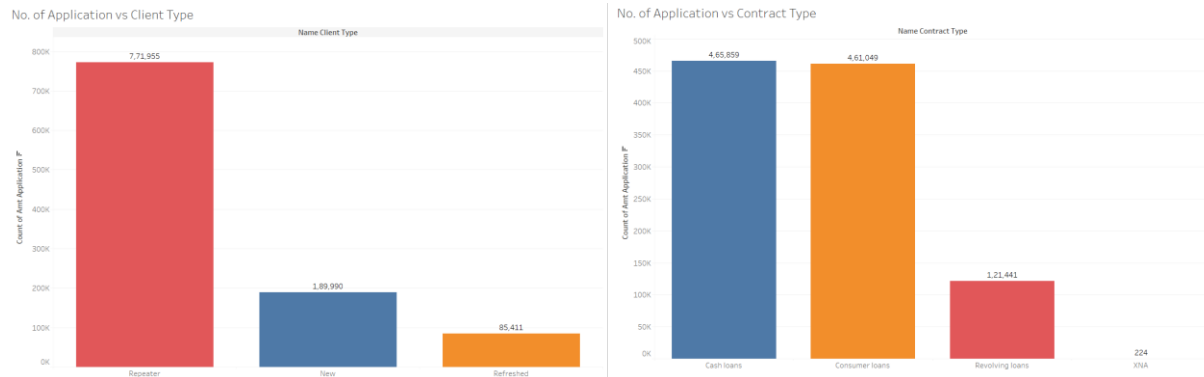


previous_application dataset univariate analysis- Insights-

- Credit and Cash Offices have more number of loan applications than any other group.



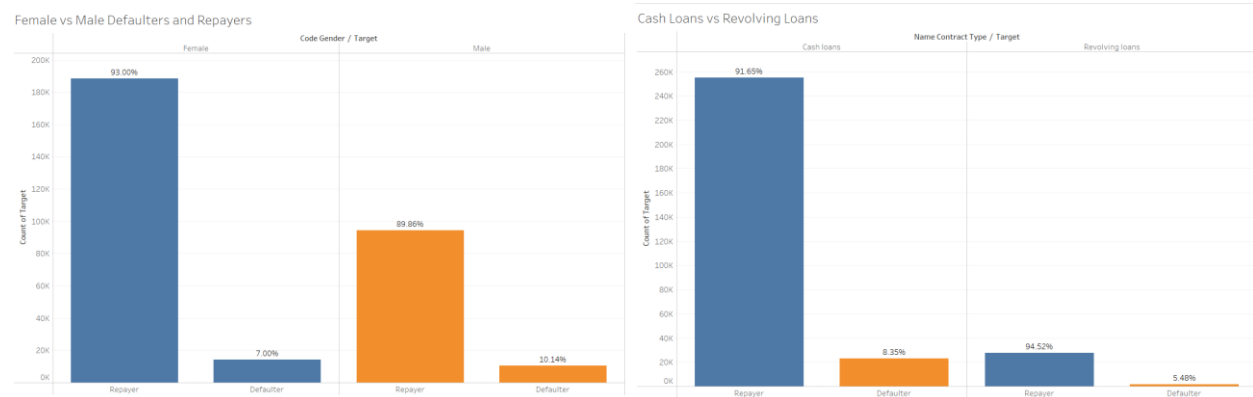
- Repeaters are more likely to apply for loans
- Cash loans and Consumers loans are preferred loan type among all.



5. Bivariate Analysis

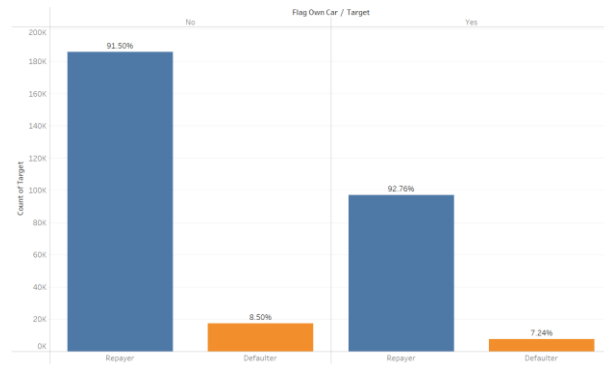
application_data Dataset bivariate analysis-
Insights-

- Females took out more loans and were comparatively less likely to default than males.
- There are a greater number of cash loan applications and they are more likely to be defaulters as well.

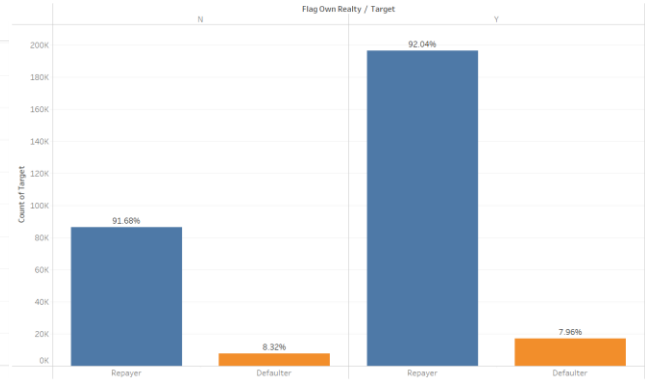


- People with no cars are much more likely to take loans and become defaulters as well.
- Reality Owners are much more likely to take loans and be good re-payers as well.

Car Owner vs Defaulters

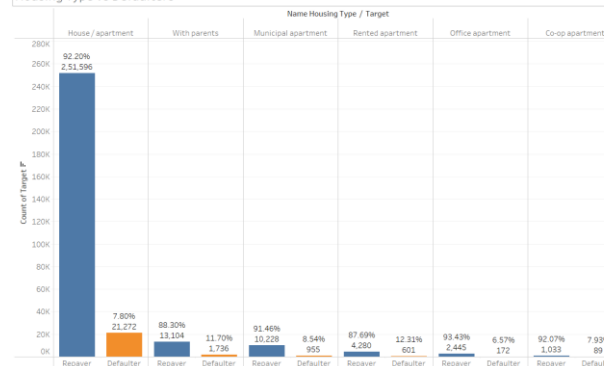


Reality Owner vs Defaulters

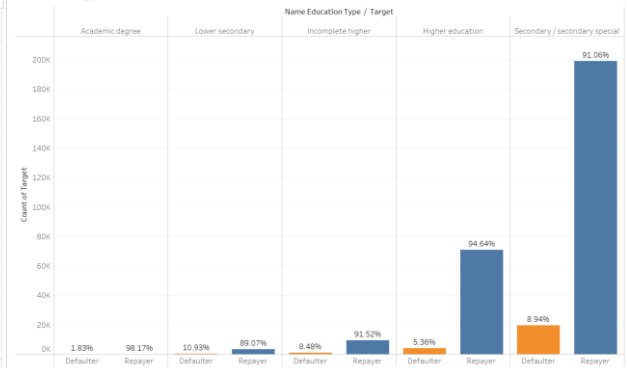


- Among all the Housing types, House/Apartments type receive more loan applications and Rented Apartment Owners are more likely to become defaulters.
- Secondary/Secondary Special has more number of applications and the lower secondary class has more defaulters.

Housing Type vs Defaulters

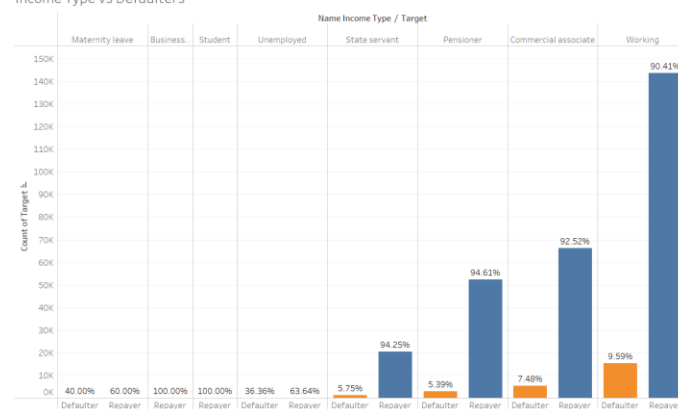


Education Type vs Defaulters



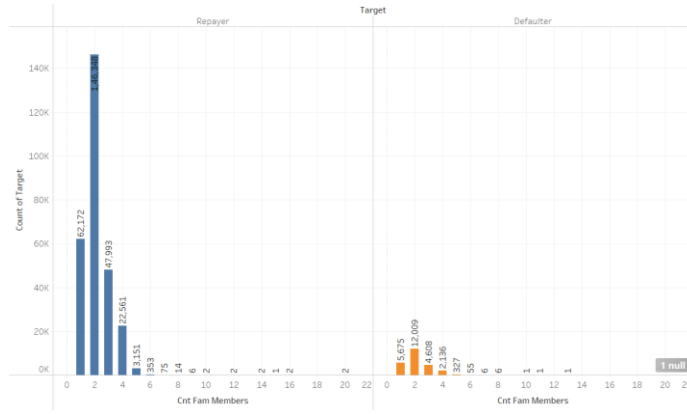
- Working-class people are more likely to take loans and maternity leave ladies are more likely to become defaulters.

Income Type vs Defaulters

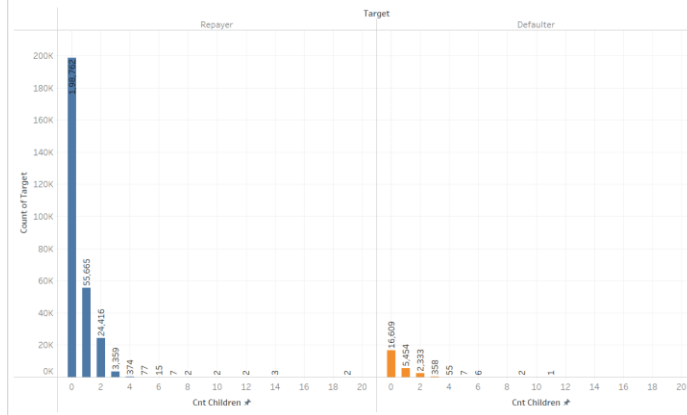


- Customers with no. of family members greater than 4 are more likely to default.

Defaulters vs No. of Family Members



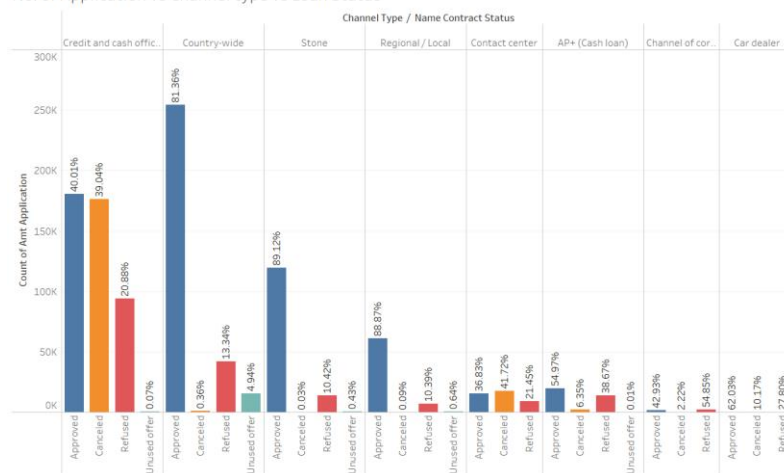
Defaulters vs No. of Children



previous_application dataset bivariate analysis- Insights-

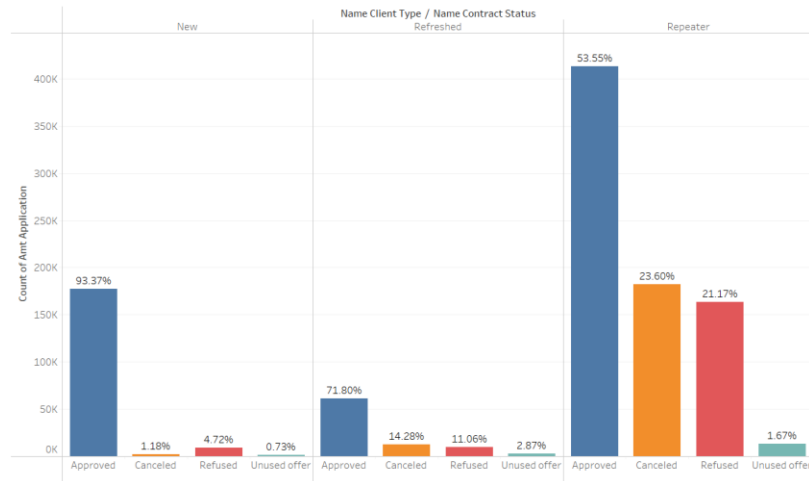
1. Country-wide and Stone are more likely to get their loan application approved whereas Cash loans and channel of correspondence applications are more likely to be refused.

No. of Application vs Channel type vs Loan Status



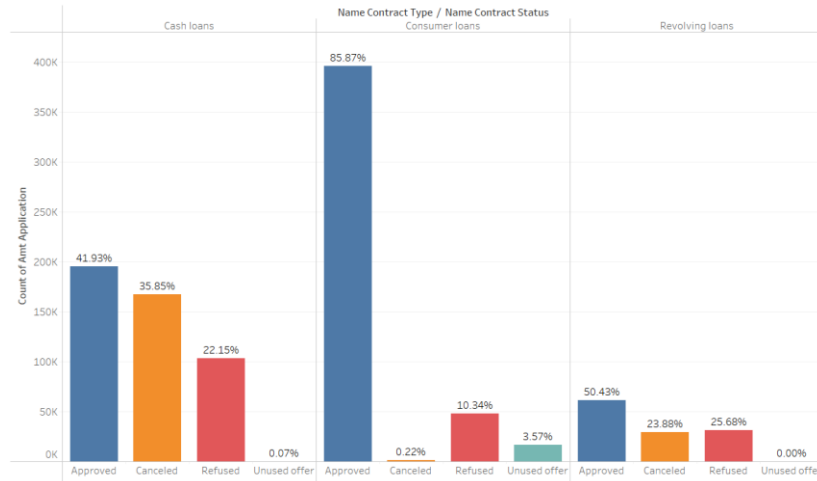
2. New applications are more likely to be accepted. Repeater's application sees the most rejections among all the categories.

No. of Application vs Client Type vs Status of Loan



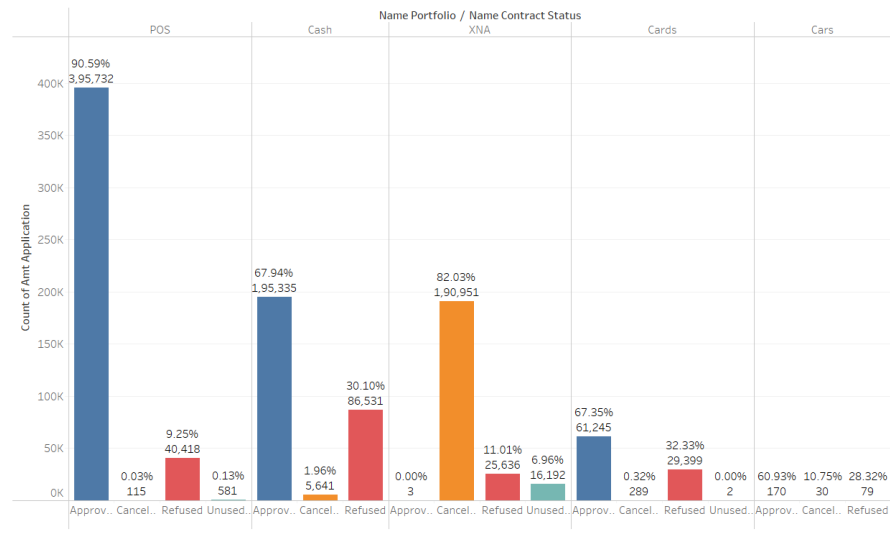
3. Consumer applications have nearly no cancellation and the greatest approval rate.

No. of Application vs Contract Type vs Status



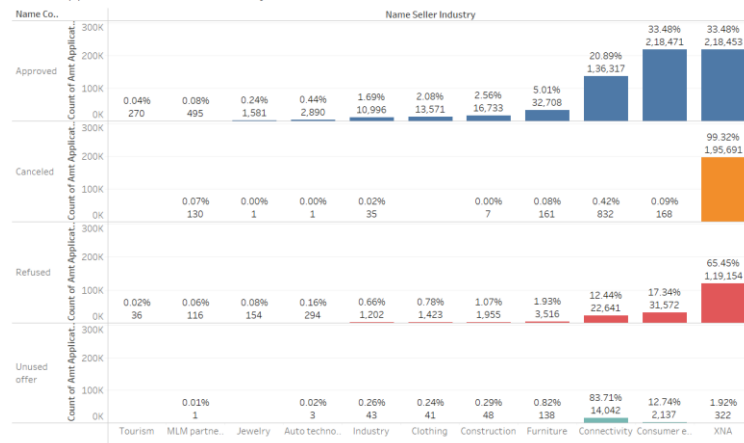
4. POS applications have the greatest approval rate and very low cancellation rate.

No. of Application vs Portfolio vs Status



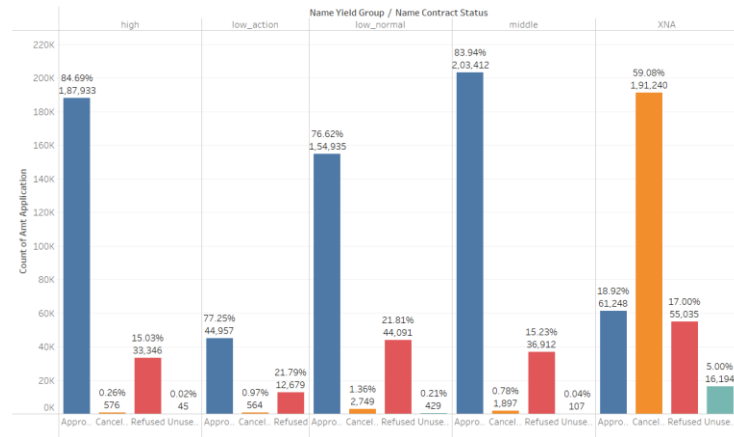
5. Consumer electronics industry have more approval rate of their application

No. of Application vs Seller Industry vs Status



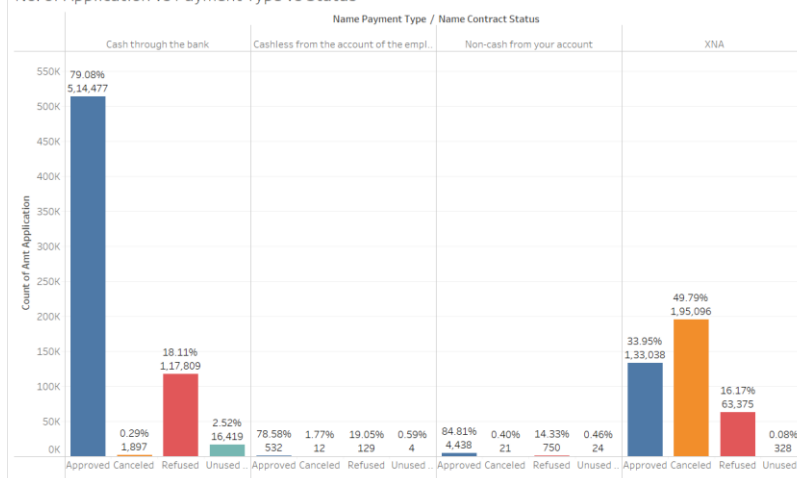
6. High and middle class are more likely to get their application approved whereas low_normal and low_action classes have higher rejection rates among all.

No. of Application vs Yield Group vs Status



7. Applications wanting cash through the bank are more likely to be approved.

No. of Application vs Payment Type vs Status



6. Top Correlations

application_data Dataset-

- Family Status
- Industry Type
- Income Type
- Count of family members
- Count of Children
- Education Type
- Car Owner
- Realtor Owner

previous_application dataset-

- Channel type
- Seller Industry
- Client type
- Contract Type
- Payment Type
- Portfolio
- Yield Group

Summary of Insights

Loan Highly recommended group

- Married Clients
- More educated Clients
- Females
- House/Apartment Owners
- Working Class customers
- Customers with fewer family members (≤ 4)

Loan Highly risky group

- Rented Apartment Owner
- Less Educated Clients
- Car Owner
- Clients on maternity leave
- Customers with higher family members (> 4)
- Unemployed customers

Project Conclusion

While analyzing the data set provided, several meaningful insights were discovered that could not have been discovered by manually searching the dataset for insights.

We could also leverage the Excel-2021 and Tableau tool and got a little more experienced in using the tools and also injecting different formulas and pivot tables and graphs to look for insights.