ANALYSIS ON

LOAN APPLICANT

Data Exploration Project Report

ABSTRACT:

Applying loan for immediate/essential financial needs is almost done by everyone. The only factor that varies is the reason and the amount required.

There are many factors that are involved in determining if the applicant is going repay the loan or not.

Through this analysis process, I have tried to find if there are any correlations which has impact on the loan defaulters.

AKSHAYA KUMAR CHANDRASEKARAN

ID: 31021301

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FACTORS INFLUENCING LOAN REPAYMENT.

1.INTRODUCTION:

Almost all of us apply for loan for some of the essential needs and requirements in an intention to repay to the loan within the stipulated date and time. However, few of them are unfortunately not able to repay the loan as planned and end up being a defaulter.

So what loan providers generally do is collect required basic information about the person to assess the application and then decide to proceed with the application or not.

1.1 PROBLEM SUMMARY:

The more the number of defaulters, the more the loss is for the loan providers. Hence before processing and granting any type loan for the applicants, the loan providers do some ground works and analyse if they can proceed. Analysis and explorations are done to identify any such factors which will influence the granting on loan.

1.2 MOTIVATION:

Primary focus of this analysis is on some important factors like Annual Income, Employment length, House ownership, type of application, grade of the applicant, loan amount requested and other few factors.

1.3 QUESTIONS:

1. Does the **type of application** have impact on loan repayment?

2. Does the applicant's **annual income** have any influence towards loan repayment?

3. How does **employment length, home ownership** have influence on loan repayment individually?

2.DATA WRANGLING:

As part of data wrangling process, columns that were insignificant for the analysis were removed and the analysis were done after data cleansing was done.

2.1 DATASET REFERENCE:

The dataset used for the analysis is taken from the site Kaggle. One large data set is used for analysis.

1. **Dataset** → Tabular data consisting of 855696 records and 74 variables. (All kinds of variables such as **location, continuous, categorical** and **simple text with punctuations and numbers** are present in the dataset)
   Source Link : https://www.kaggle.com/sonujha090/xyzcorp-lendingdata

   This data source will help me to answer the above mentioned 3 questions.

Dataset Description: Attributes mentioned below are **used in analysis** from the dataset. Other columns were removed as part of the data wrangling process as their contribution in the analysis were found insignificant.

Attribute Name	Description
annual_inc	The self-reported annual income provided by the borrower during registration.
Application_type	Indicates whether the loan is an individual application or a joint application with two co-borrowers
loan_amnt	The listed amount of the loan applied for by the borrower.
Emp_length	Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
Home_ownership	The home ownership status provided by the borrower during registration. Our values are: RENT, OWN, MORTGAGE, OTHER.
Sub_grade	XYZ assigned loan subgrade
verification_status	Was the income source verified
Purpose	A category provided by the borrower for the loan request.
Title	The loan title provided by the borrower.
Emp_title	The job title supplied by the Borrower when applying for the loan. (Text Data)
addr_state	The state provided by the borrower in the loan application (Geo Location)
default_ind	If he is a defaulter or not. 0 is Non defaulter and 1 is defaulter.

Table 2.1 Major Attributes used for analysis

2.2 DATA WRANGLING AND EXPLORATION:

To start with, few packages were imported. Additional packages were added when new functions were introduced. Setting up working directory was one of the important tasks that was carried out that ensured the code and the environment variables were saved and available in the IDE instance.

Data auditing was carried out as a first step to have some understanding on the data using basic commands like *describe(), summary()* function in R and observed data anomalies like missing values, inconsistencies, correlation and data type error.
Below is **the sample summary output** and the highlighted columns consisting of the above-mentioned anomalies.

```
> summary(dataSet)
       id              member_id          loan_amnt       funded_amnt     funded_amnt_inv          term           int_rate      installment
 Min.   :   54734   Min.   :   70699   Min.   :  500   Min.   :  500   Min.   :    0   36 months:600221   Min.   : 5.32   Min.   :  15.69
 1st Qu.: 9067986   1st Qu.:10792732   1st Qu.: 8000   1st Qu.: 8000   1st Qu.: 8000   60 months:255748   1st Qu.: 9.99   1st Qu.: 260.55
 Median :34313546   Median :36975319   Median :13000   Median :13000   Median :13000                      Median :12.99   Median : 382.55
 Mean   :32240726   Mean   :34762690   Mean   :14746   Mean   :14732   Mean   :14700                      Mean   :13.19   Mean   : 436.24
 3rd Qu.:54463114   3rd Qu.:58035586   3rd Qu.:20000   3rd Qu.:20000   3rd Qu.:20000                      3rd Qu.:15.99   3rd Qu.: 571.56
 Max.   :68616867   Max.   :73519693   Max.   :35000   Max.   :35000   Max.   :35000                      Max.   :28.99   Max.   :1445.46
 grade        sub_grade                emp_title         emp_length      home_ownership     annual_inc          verification_status
 A:145665   B3     : 54958                   : 49439   10+ years:282090   ANY      :     3   Min.   :      0   Not Verified   :257742
 B:247998   B4     : 54116   Teacher         : 12965   2 years  : 75986   MORTGAGE:429106   1st Qu.:  45000   Source Verified:318178
 C:236855   C1     : 51588   Manager         : 10821   < 1 year : 67597   NONE     :    45   Median :  65000   Verified       :280049
 D:132802   C2     : 50457   Registered Nurse:  5341   3 years  : 67392   OTHER    :   144   Mean   :  75071
 E: 66448   C3     : 48337   RN              :  5182   1 year   : 54855   OWN      : 84136   3rd Qu.:  90000
 F: 21328   B2     : 47589   Owner           :  5157   5 years  : 53812   RENT     :342535   Max.   :9500000
 G:  4873   (Other):548924   (Other)         :767064   (Other)  :254237
    issue_d      pymnt_plan                                                                  desc                        purpose
 Oct-15 : 48212   n:855964                                                                      :734156   debt_consolidation:505392
 Jul-15 : 44906   y:     5                                                                    :   231   credit_card       :200144
 Oct-14 : 37442                Borrower added on 03/10/14 > Debt consolidation<br>:    10   home_improvement  : 49956
 Nov-15 : 37211                Borrower added on 03/17/14 > Debt consolidation<br>:    10   other             : 40949
 Dec-15 : 35638                Debt Consolidation                                 :    10   major_purchase    : 16587
 Aug-15 : 35267                Borrower added on 02/19/14 > Debt consolidation<br>:     9   small_business    :  9785
 (Other):617293                (Other)                                            :121543   (Other)           : 33156
                    title             zip_code       addr_state          dti            delinq_2yrs       earliest_cr_line inq_last_6mths
 Debt consolidation     :398089   945xx  :  9466   CA     :125172   Min.   :    0.00   Min.   : 0.0000   Aug-01 :  6433   Min.   :0.0000
 Credit card refinancing:159228   750xx  :  9111   NY     : 71114   1st Qu.:   11.88   1st Qu.: 0.0000   Aug-00 :  6322   1st Qu.:0.0000
 Home improvement       : 38633   112xx  :  8894   TX     : 68708   Median :   17.61   Median : 0.0000   Oct-00 :  6117   Median :0.0000
 Other                  : 30522   606xx  :  8370   FL     : 58639   Mean   :   18.12   Mean   : 0.3116   Oct-01 :  5924   Mean   :0.6809
 Debt Consolidation     : 15469   300xx  :  7820   IL     : 34379   3rd Qu.:   23.90   3rd Qu.: 0.0000   Aug-02 :  5858   3rd Qu.:1.0000
 Major purchase         : 11519   100xx  :  7348   NJ     : 32061   Max.   :9999.00   Max.   :39.0000   Sep-00 :  5712   Max.   :8.0000
 (Other)                :202509   (Other):804960   (Other):465896                                       (Other):819603
 mths_since_last_major_derog  policy_code   application_type  annual_inc_joint   dti_joint      verification_status_joint acc_now_delinq
 Min.   :  0.0                Min.   :1   INDIVIDUAL:855527   Min.   : 17950   Min.   : 3.0                    :855527   Min.   : 0.000000
 1st Qu.: 27.0                1st Qu.:1   JOINT     :   442   1st Qu.: 75000   1st Qu.:13.2   Not Verified     :   252   1st Qu.: 0.000000
 Median : 44.0                Median :1                      Median :100000   Median :17.7   Source Verified:    51   Median : 0.000000
 Mean   : 44.1                Mean   :1                      Mean   :107412   Mean   :18.3   Verified       :   139   Mean   : 0.004944
 3rd Qu.: 61.0                3rd Qu.:1                      3rd Qu.:130750   3rd Qu.:22.6                             3rd Qu.: 0.000000
 Max.   :188.0                Max.   :1                      Max.   :410000   Max.   :43.9                             Max.   :14.000000
 NA's   :642830                                              NA's   :855527   NA's   :855529
  tot_coll_amt      tot_cur_bal       open_acc_6m      open_il_6m      open_il_12m     open_il_24m     mths_since_rcnt_il  total_bal_il
 Min.   :      0   Min.   :      0   Min.   : 0.0   Min.   : 0.0   Min.   : 0.0   Min.   : 0.0   Min.   :  0.0   Min.   :     0
 1st Qu.:      0   1st Qu.:  29870   1st Qu.: 0.0   1st Qu.: 1.0   1st Qu.: 0.0   1st Qu.: 0.0   1st Qu.:  6.0   1st Qu.: 10390
 Median :      0   Median :  81008   Median : 1.0   Median : 2.0   Median : 0.0   Median : 1.0   Median : 12.0   Median : 24960
 Mean   :    225   Mean   : 139766   Mean   : 1.1   Mean   : 2.9   Mean   : 0.7   Mean   : 1.7   Mean   : 20.8   Mean   : 36512
 3rd Qu.:      0   3rd Qu.: 208703   3rd Qu.: 2.0   3rd Qu.: 4.0   3rd Qu.: 1.0   3rd Qu.: 2.0   3rd Qu.: 23.0   3rd Qu.: 47493
 Max.   :9152545   Max.   :8000078   Max.   :12.0   Max.   :40.0   Max.   :12.0   Max.   :15.0   Max.   :300.0   Max.   :634217
 NA's   :67313     NA's   :67313     NA's   :842681 NA's   :842681 NA's   :842681 NA's   :842681 NA's   :843035  NA's   :842681
  inq_last_12m    default_ind
 Min.   :-4.0   Min.   :0.00000
 1st Qu.: 0.0   1st Qu.:0.00000
 Median : 2.0   Median :0.00000
 Mean   : 1.8   Mean   :0.05429
3rd Qu.: 3.0   3rd Qu.:0.00000
 Max.   :32.0   Max.   :1.00000
 NA's   :842681
```

2.3 DATA WRANGLING:

From the above output, the following key features were found.

1. Every grade has 5 different sub-grades, so if we know the sub-grade, the applicant's grade can be found.
2. The attributes "Title" and "Purpose" were almost equal. They depict the same meaning in different kinds.
3. There were few attributes with missing values more than 95% in them.

Attributes that exhibited the above-mentioned properties were identified and removed as part of wrangling process for exploration.

3. DATA CHECKING AND HANDLING ANOMALIES:

3.1 MISSING VALUES:

Few attributes were found to have more number of missing values as shown in the below figure 3.1. While analysing I found the **reason** for very high number of missing values are, **a particular application type "joint"** were found to **have all records**. When the application type is **"JOINT" those columns had values** and, if the **application type is individual** the attribute's **value will be NA**. Those columns were dropped using *dplyr* and *plyr* libraries in R as their contribution were insignificant for the analysis. Other attributes such as "emp_length" that had few missing values were handled and the missing values were imputed with the method "measure of central tendency" (**median** for **continuous** data type and **mode** for **categorical** data type)

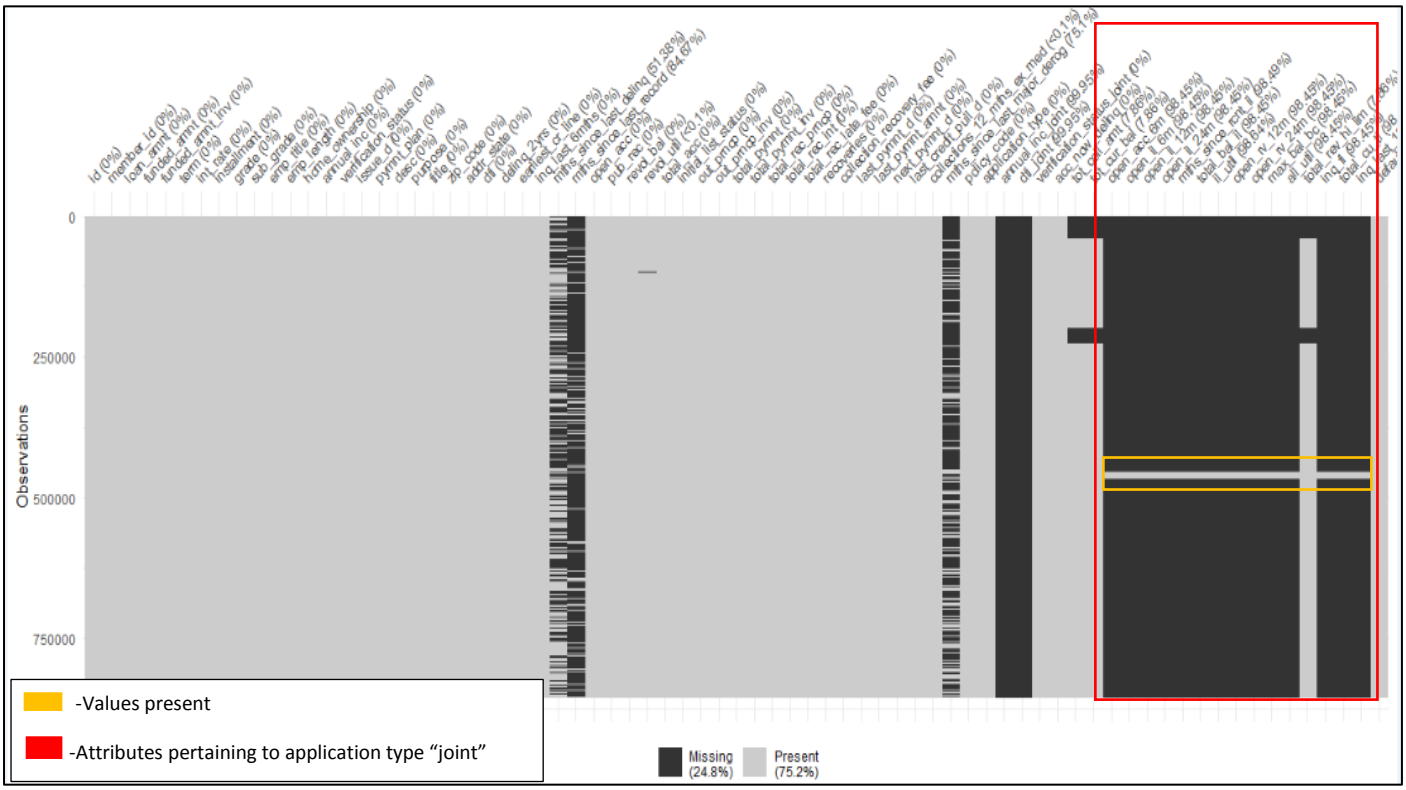

Figure 3.1 Image showing Missing values

3.2 INCONSISTENCY:

Attributes namely "home_ownership"," verification_status" and "emp_title" had inconsistency in them. For eg: attribute "verification_status" had **Source Verified, verified and Not verified** unique values as shown in the figure 3.2. Here, both **source verified and verified means the same**. Home ownership has **Any** and **None** as extra values other than mentioned in business requirement(in table 2.1). Anomalies like these were handled as well as shown in the figure 3.3.

```
> unique(df$home_ownership)
[1] RENT     OWN      MORTGAGE OTHER    NONE     ANY
Levels: ANY MORTGAGE NONE OTHER OWN RENT
> unique(df$verification_status)
[1] Verified        Source Verified Not Verified
Levels: Not Verified Source Verified Verified
>
```

Figure 3.2 Attributes having inconsistency

```
> unique(df$home_ownership)
[1] RENT     OWN      MORTGAGE OTHER
Levels: MORTGAGE OTHER OWN RENT
> unique(df$verification_status)
[1] Source Verified Not Verified
Levels: Not Verified Source Verified
>
```

Figure 3.3 Inconsistency eliminated

3.3 CORRELATION:

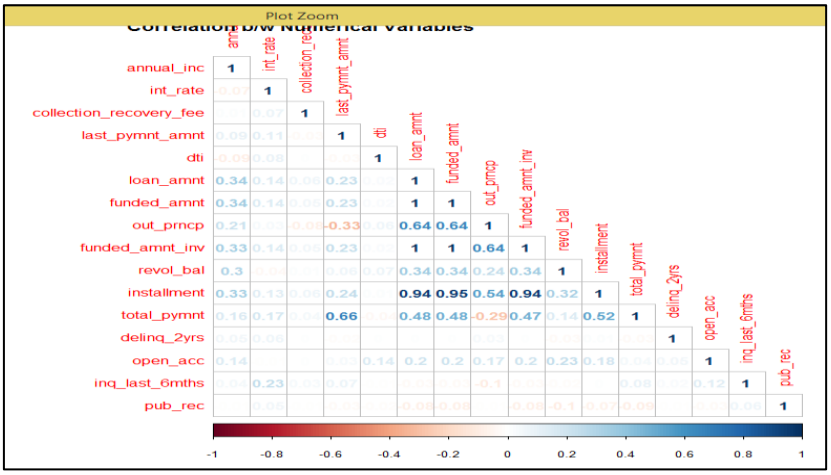

Figure 3.4 Correlation plot of numerical variables

Few attributes were exhibiting correlation. Correlation plot was drawn using *cor()* function the to find the correlation between the attributes as shown in the figure 3.4. Attributes having high correlation value greater than 0.8 was removed using *dplyr* and *plyr* libraries in R.

There was one other interesting property found during the analysis,
Total_payment attribute was having a correlation value of 1 with the sum of *(Principal + Interest + Total Recoveries Late Fee + Recoveries)* attributes. This was also handled

3.4 DATA TYPE ERROR:

```
> str(df$default_ind)
 int [1:855969] 0 1 0 0 0 0 0 0 1 1 ...
> df$default_ind <- as.factor(df$default_ind)
> str(df$default_ind)
 Factor w/ 2 levels "0","1": 1 2 1 1 1 1 1 1 2 2 ...
>
```

Figure 3.5 Imaging showing data type handled

Few attribute's data type was misinterpreted by R. For example, "default_ind" attribute is **of type categorical** with unique values 0 and 1 but R **misinterpreted** it as a **numerical** attribute. Attributes that I considered for the analysis were all checked and reformatted it to correct data type as shown in the figure 3.5.

All the anomalies were handled, and cleaning was done making the data ready for the exploration and analysis.

4.DATA EXPLORATION:

During the process of exploration, analysis was also done parallelly. 4 Major attributes namely,

1. Annual Income
2. Application Type
3. Home Ownership
4. Employment length , are analysed in detail on their influence on the loan payment to answer the question. Other attributes were also analysed additionally.

4.1 ANNUAL INCOME:

It is evident from the figure 4.1 that the **applicants with less than 1000K as their annual income are subject to be defaulters**. On drilling down further, only those whose salary is less than 300k and 1000k was analysed as shown in the figure 4.2(a) and (b) based on their home_ownership. It is understood from figure 4.2(b) that applicants who are salaried less than **750000 and who are either living in a rented house or has mortgaged their house are likely to be defaulters**. Also, people who **own the house but are getting less than 500000 are also likely to be defaulters**.

Since the box-plot was not clearly visible and the stats of a box plot could not be interpreted from figure 4.1, subset of the data was taken with annual salary less than 300k. It was found that the annual salary's 25 percentile (Q1), 50 percentile/median(Q2),75 percentile (Q3) were almost the same for both defaulters and non-defaulters shown in the figure 4.2(a)

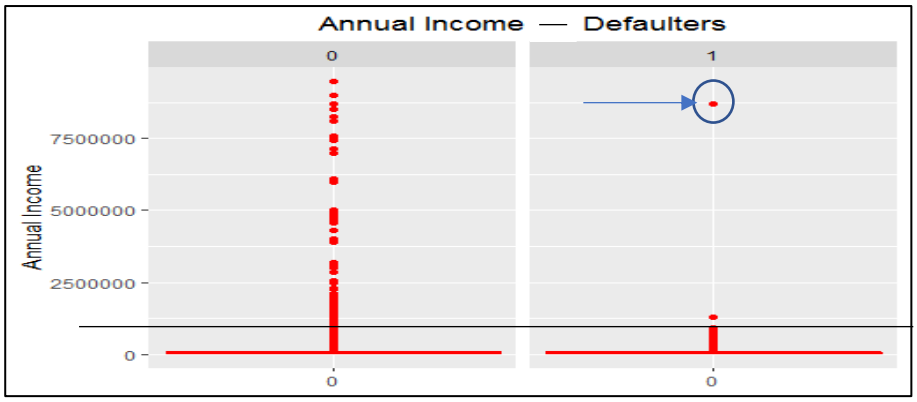

Figure 4.1 Box Plot of annual income(full data set)

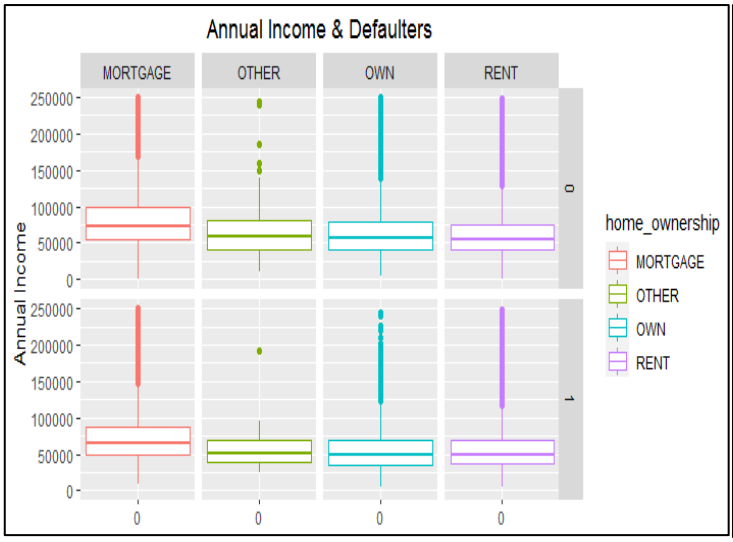

Fig 4.2(a) Box-Plot to understand annual income(<300k)

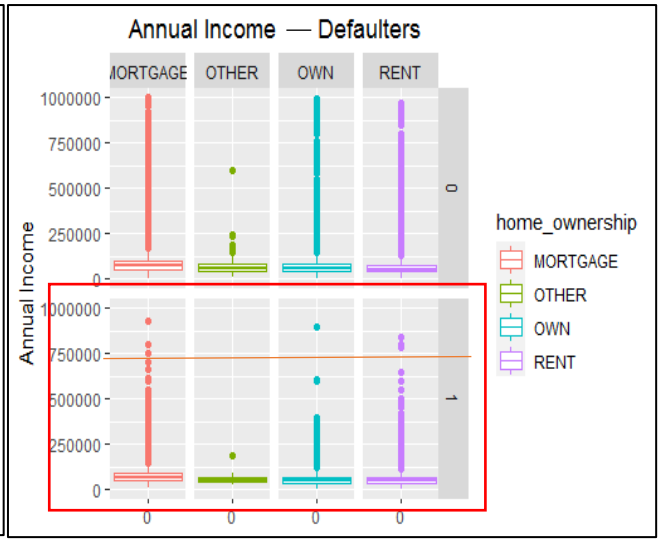

Figure 4.2(b) Box plot of annual income (<1000k)

One interesting factor noticed during this analysis is, one applicant with **annual salary more than 75000000** has been a defaulter. He/She might have started a business and unfortunately didn't turn out to be a profitable one. He/She is **an outlier** in this data.

annual_inc	application_type	loan_amnt	emp_length	home_ownership	sub_grade	verification_status	purpose	title	emp_title	addr_state	default_ind
8706582	INDIVIDUAL	8000	10+ years	MORTGAGE	C3	Source Verified	credit_card	Credit card refinancing	Correctional Sgt.	IL	1

Figure 4.3 Outlier and interesting record

4.2 APPLICATION TYPE

```
> table(finalData$application_type) / sum(table(finalData$application_type))

  INDIVIDUAL        JOINT
0.9994836262 0.0005163738
> table(finalData$application_type)

INDIVIDUAL      JOINT
    855527        442
>
```

Figure 4.4 Table function in R to show the count of application type

In the dataset, only **.05% of the applicants** have got the loan as type "**JOINT**" while the rest **99.95%** of the applicants have applied the loan **individually** which can be seen from the figure 4.4.

Now, the analysis has been done for **both the types separately**.

It is understood that applicants with type as**" joint" have always paid the loan** as shown in the figure 4.5 while there are chances that the applicant **might become a defaulter if the type is "individual"** as shown in figure 4.6. This makes sense as applicants with type "joint" both be the earning members and hence they will be able to repay the loan easily when compared to single person earning and closing the loan.

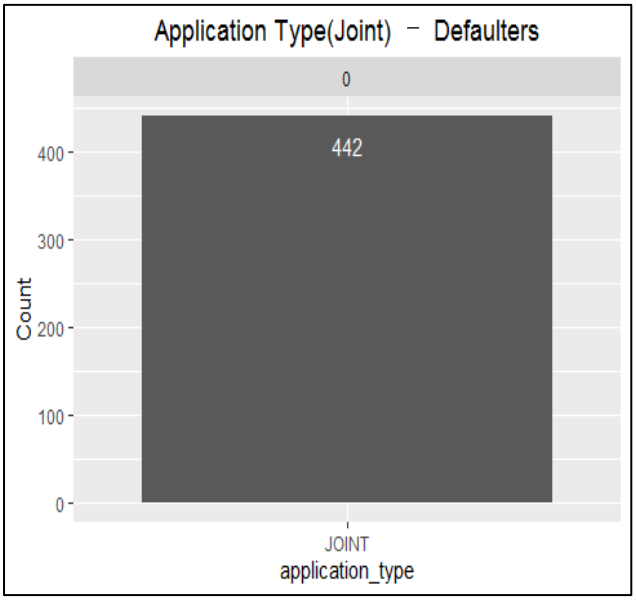

Figure 4.5 Application Type "Joint"

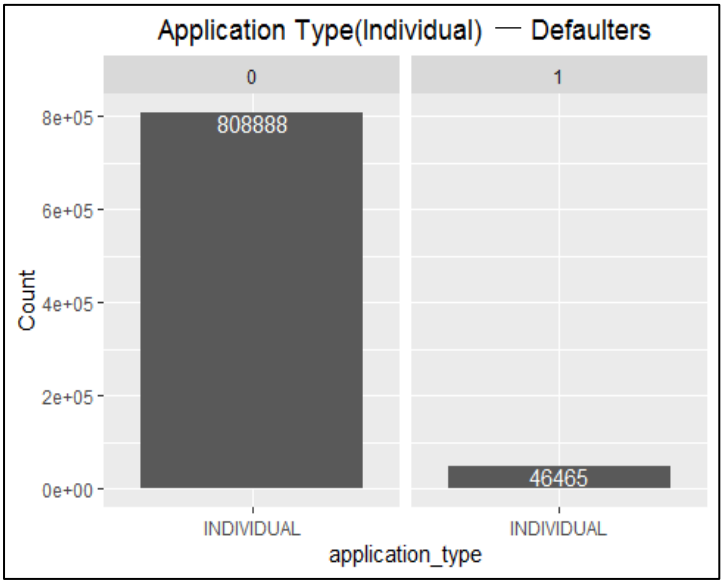

Figure 4.6 Application Type "Individual"

4.3 HOME OWNERSHIP:

From the **analysis outcome based on the annual income in box plot**, it is found that most of the people who are earning less **than 300k as their annual income are found to be defaulters**. Considering the outcome from that analysis, I did a **subset** of data for applicants earning less than **1000k annual income** to analyse in depth on how home ownership has influence on their loan repayment.

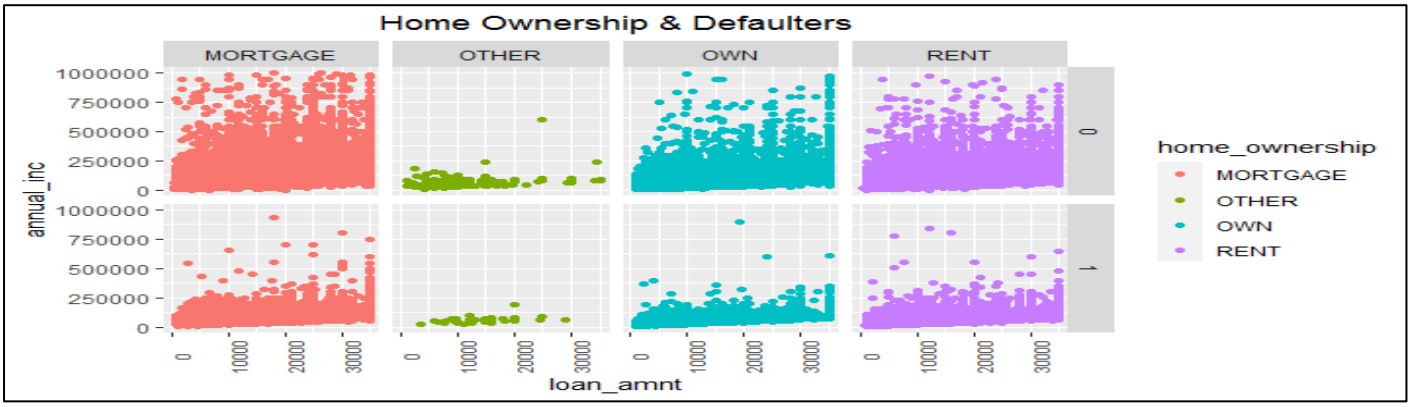

Figure 4.7 House Ownership Vs Defaulters wrt annual income

From the figure 4.7 it is understood that applicants whose **annual income** is less than **250k has their house ownership as "mortgaged" or "rented**".

It can also be seen that applicants who also **owned the house are also subjected to be defaulters**, but **their annual income is less** when compared to applicants whose house is either "mortgaged" or "rented".

4.4 EMPLOYMENT LENGTH:

From the figure 4.8, I concluded that **most of the loan applicants have 10+ years of experience** and **employment length has no significance to determine if they are going to be a defaulter or not**. The more the number of applicants with 10+ years of experience, the number of defaulters is going to be relatively high when compared to other categories. Thus **employment length has no significance** in determining if the applicant is going to be a defaulter or not.

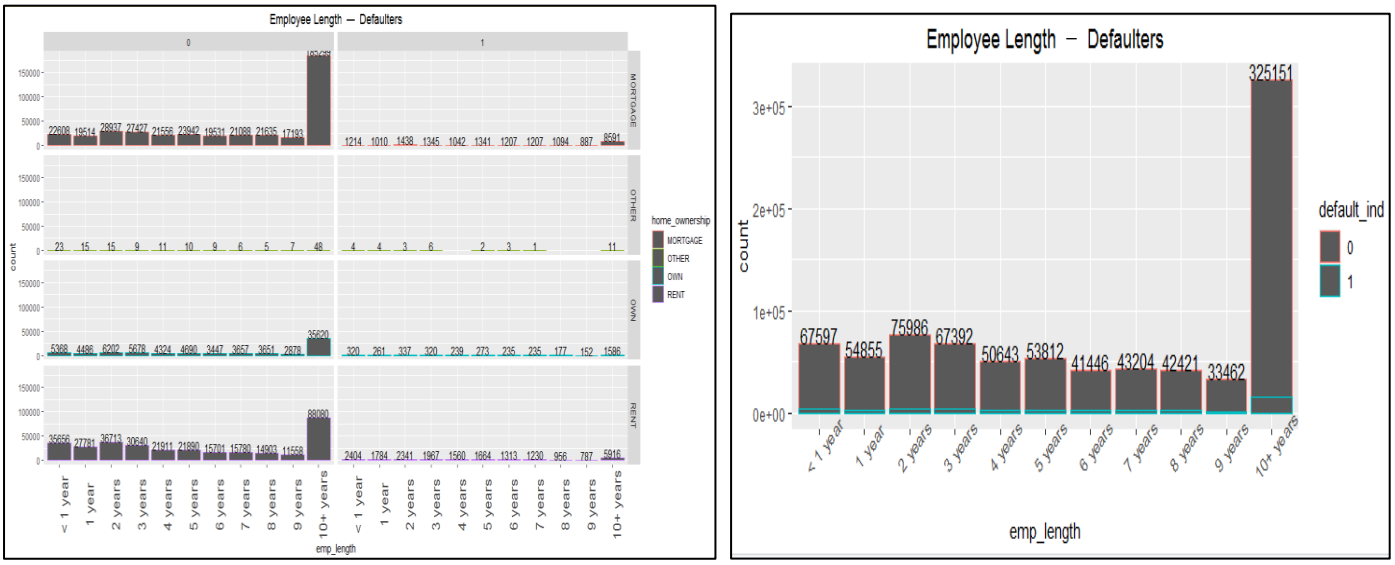

Figure 4.8 Employment length count plotted wrt house ownership and defaulters

4.5 OTHER INSIGHTS AND ANALYSIS PERFORMED WITH THE DATASET:

4.5.1 COUNTRY:

When plotted the map I saw that I **was analysing applicants from The United states**. On Analysing, I saw an **interesting fact** that applicants from the mentioned states **North Dakota and Maine have not defaulted the loan**. Few applicants from other states have been defaulters while others have not. The same was understood from the figure 4.9 below. Also, there are **almost 35% of applicants** from the states **New York, Texas, California and Florida** as the sum of applicants from these states alone were more than approximately 300,000.

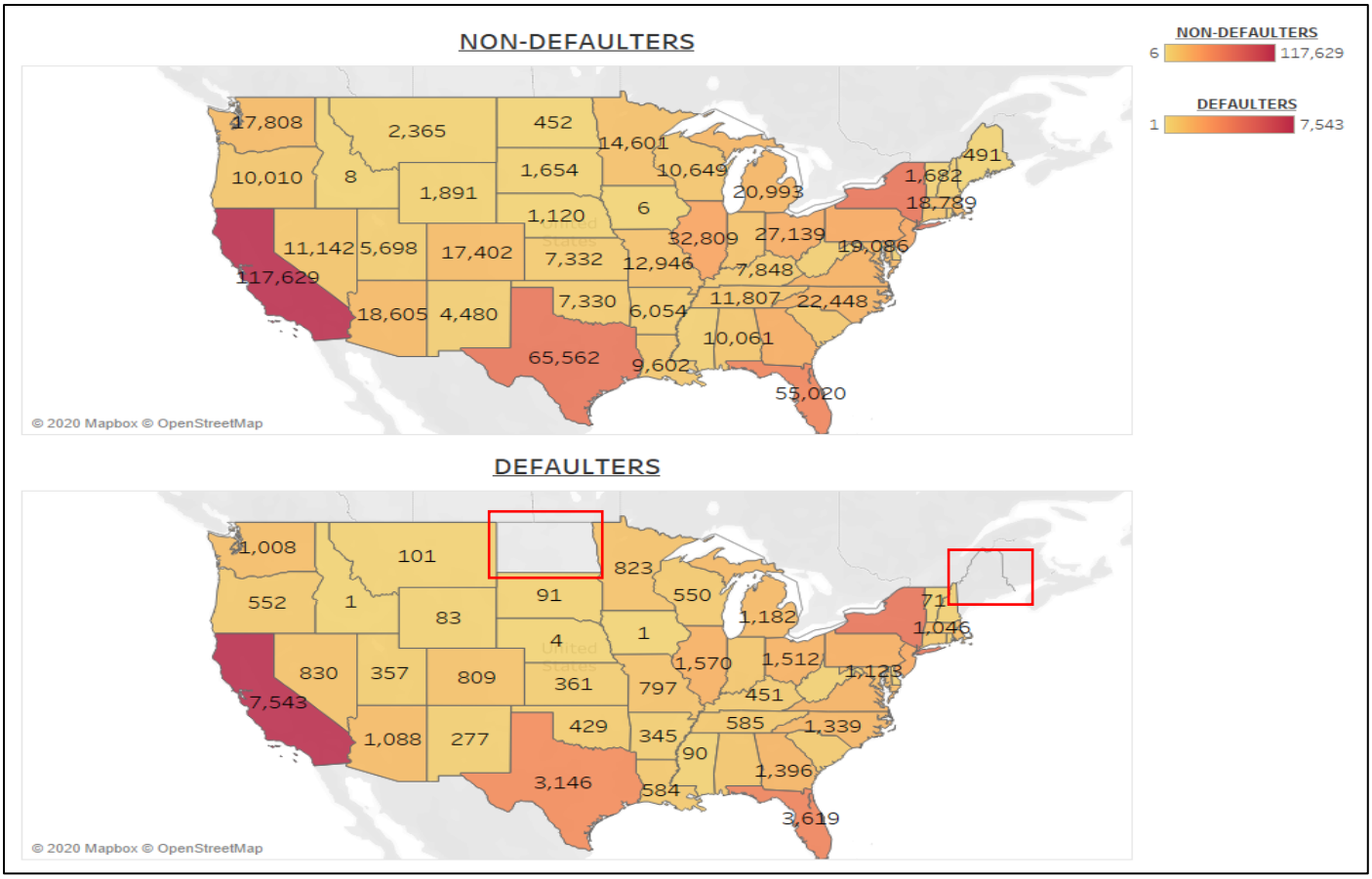

Figure4.9 showing defaulter status state wise

4.5.2 ATTRIBUTE "ANNUAL INCOME" VS "LOAN AMOUNT"

When comparing between the attributes annual income and loan amount to find a relation if any, I was able to conclude that **loan amount sanctioned to each of the applicants were almost same**. But an applicant tends to be a defaulter **based on his/her annual income**. From the below figures 4.10 and 4.11, it can be found that on an **average**, the annual income of a **non-defaulter is close to 1000k** while average remains less than **300k for a defaulter**.

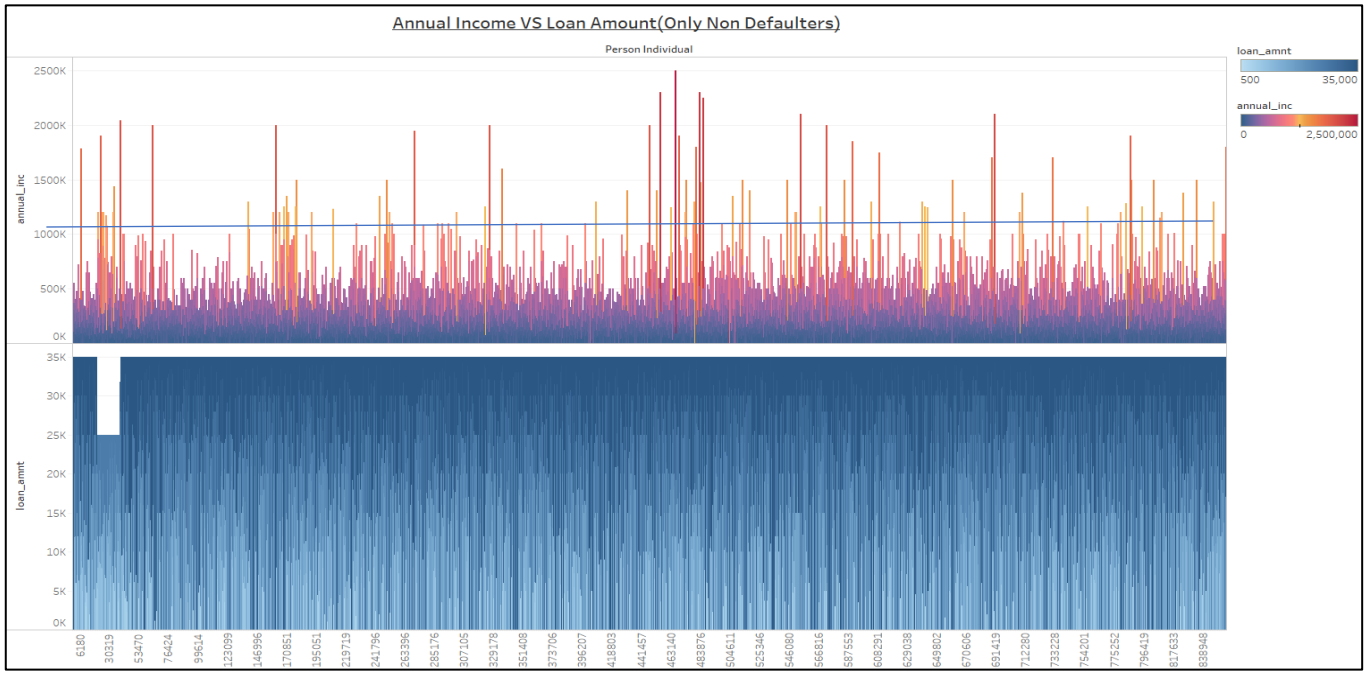

Figure 4.10 Non-Defaulter's annual income vs the loan amount

Figure 4.10 shows the annual income compared to loan amount for non-defaulters and the figure 4.11 shows the annual income compared to loan amount for defaulters.

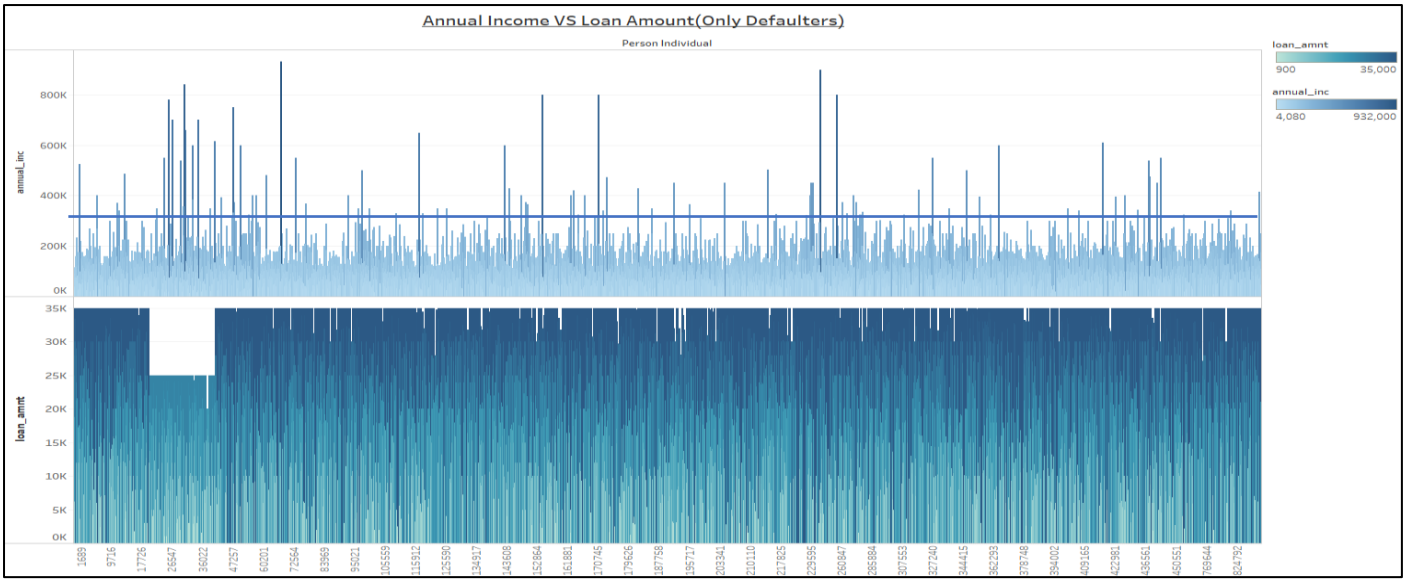

Figure 4.11 Defaulter's annual income vs the loan amount

4.5.3 PURPOSE:

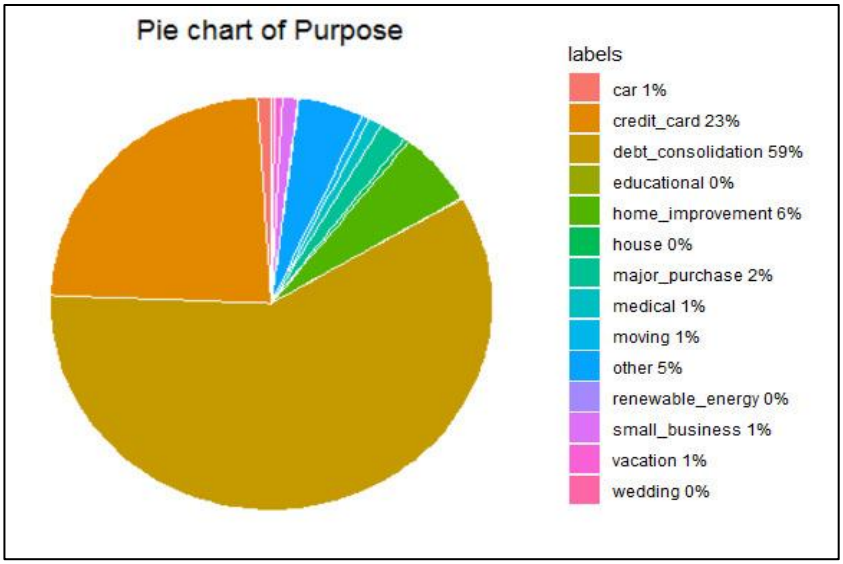

Figure 4.12 Pie showing the purpose of loan (full dataset)

To analyse for what purpose the applicants are applying for a loan, a pie chart got created in R with *geom_bar()* and *coord_polar()*and it is found that **almost 60% of the applicants** have applied loan for the **purpose of debt consolidations** (debt consolidation is process of getting a loan to close of other loans and manage financially).

Next reason for applying loan is to repay their **credit card debts**. Thus, from the figure 4.12, we can conclude **that almost 75%** of the applicants get loan only to **close their previous loans.**

To get some more insights on the purpose, I took the subset of the data excluding both the major purposes (debt consolidation and credit card) and analysed using treemap with *treemap() package* in R. It was found that the next **major purpose to get the loan was for house improvement and other** from the figure 4.13.

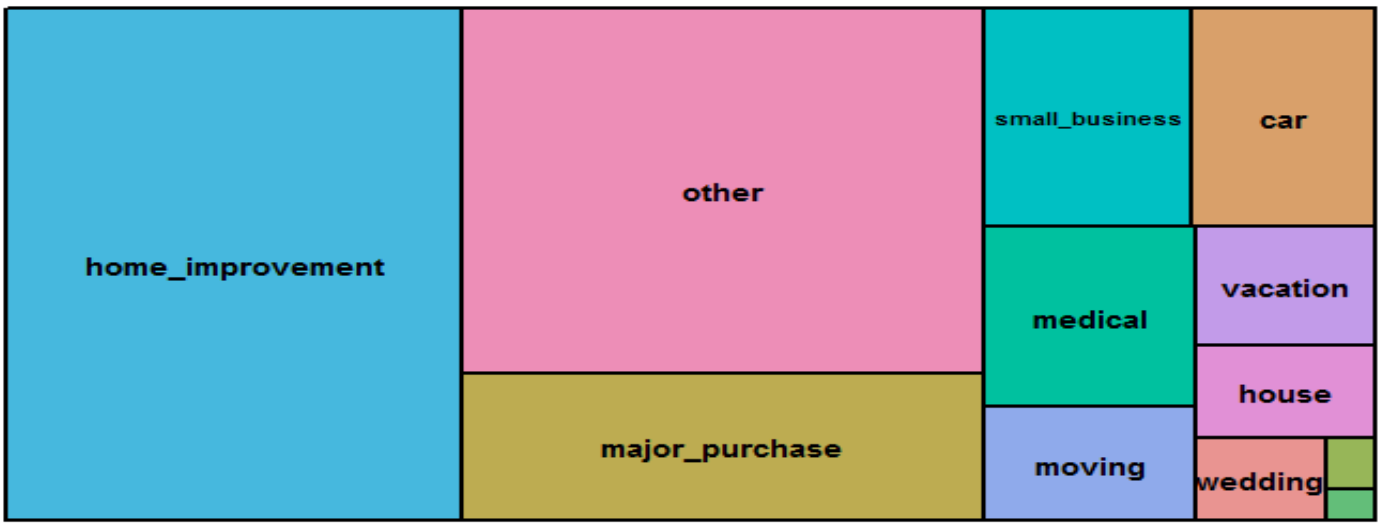

Figure 4.13 Treemap showing the purpose of loan(Subset of dataset excluding debt consolidations and credit card)

4.5.4 EMPLOYEE_TITLE:

The attribute **emp_title was a simple text that consisted of punctuations, numbers and some special characters using *tm and removePunctuation()*** libraries and functions in R as shown in the figure 4.14. Later, a word cloud was created to analyse applicant from which profession has applied for the loan. It can be seen from the figure4.15 **that most of the applicants** are one among **Teacher, Project Managerial roles, Owner, Sales person, Engineer, accountant and supervisors.**

x	freq
	49439
'Property Manager	1
'roduction manager	1

Figure 4.14 DataFrame showing punctuations and special characters

Punctuations, special characters and numbers(for those who worked in more than 1 jobs) were there in the attribute employee title.

All those were removed as part of cleaning and word cloud was created in R to analyse the most employee title who are applying for loan.

Figure 4.15 Word Cloud for the attribute employee title

4.5.5 STATISTICAL TESTS:

Statistical tests like chi-squared tests (for two categorical type attributes) and variance tests (for two continuous type attributes) were performed to understand the correlation between the variables as shown in the figure 4.15. It was found that, all the **variables have less correlation value** (as expected) and the correlation between *annual income, home ownership, application type* with *defaulte_ind* were more when compared to other attributes. Sample statistical output is shown in the figure 4.15.

```
> chisq.test(finalData$home_ownership,finalData$default_ind,correct = T)

        Pearson's Chi-squared test

data:  finalData$home_ownership and finalData$default_ind
X-squared = 1115.8, df = 3, p-value < 2.2e-16

> var.test(finalData$annual_inc,finalData$loan_amnt)

        F test to compare two variances

data:  finalData$annual_inc and finalData$loan_amnt
F = 58.179, num df = 855968, denom df = 855968, p-value < 2.2e-16
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 58.00519 58.35380
sample estimates:
ratio of variances
           58.1791

> chisq.test(finalData$application_type,finalData$emp_length)

        Pearson's Chi-squared test

data:  finalData$application_type and finalData$emp_length
X-squared = 17.285, df = 10, p-value = 0.06828
```

Figure 4.16 Showing statistical test results done in R to find the correlation categorical variables

5.CONCLUSION:

On analysing various attributes which could affect the applicant to be a defaulter or not, below main attributes has their own significance and influence:

- ***Annual Income:*** Applicants with annual income less than 250k are most likely to be a defaulter. Also, we cannot access the applicant's application only with their annual income. Other attributes should also be taken into considerations.
- ***Application Type:*** When the application type is "Joint", then those applicants are not going to default as the earning is twice than that of applicants with application type "individual". When an application is of type individual, several other attributes are required to proceed and process the loan request.
- ***Employment length:*** The attribute employment length has no greater influence in deciding if the person is going to be a defaulter or not. But one quite interesting fact found is, applicants with more than 10 years of experience are applying for loan. This makes sense because the applicant may have planned their future based on their financial status to make progress in their life.
- ***Home Ownership:*** Applicant who are residing in a mortgaged house or in a rented house are likely to default their loan provided their annual salary is less than 250k. Hence only this particular attribute has some influence on determining if the applicant is going to default or not and has greater influence when other attributes are analysed alongside.
- ***Other key attributes and findings:*** Country's state was a new and interesting finding during the analysis. Other attributes were also analysed but per my analysis, they didn't seem to have much impact on determining if a person is going to default a loan or not.

6.REFLECTIONS:

Upon completion of this analysis, I gained knowledge on data wrangling, hypothesis testing,data cleaning, data modelling and data visualization using R and Tableau. Knowledge about various libraries like plyr, dplyr, wordcloud, RcolorBrewer, treemap , ggplot2, randomcoloR, corrplot,leaflet was also gained and also about its appropriate uses.

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