CAPSTONE PROJECT 1:
HOME LOAN PREDICTION

An analytical approach

Capstone Project 1 (Link)

Aditya Jakka
October 2018

Abstract

Dream Housing is a financial institution that grants loans to people for the purpose of acquiring property. There are a number of variables that are taken into account when granting a loan. Some of them are: the type of property being acquired (urban, rural, semi-urban), the applicant's income, the loan term, marital status, number of dependents, level of education, their credit history and various other variables.

I hope we can all agree that there is a certain degree of risk involved when granting loans to applicants. For example, it would definitely be a lot riskier to grant loans to people with no credit history. The company is also taking into account if the applicants are self-employed. Will they be able to continue making payments if they suffer a loss in business? Should applicants with incomes on the lower scale be granted large loan amounts? A 'risk analysis' is performed before a final decision is made.

This is clearly a complex and time consuming process which is also prone to human error (if done manually). Hence, with this project, a prediction model will be built which will make decisions on behalf of the company. That is, human intervention will not be necessary.

TABLE OF CONTENTS

INTRODUCTION

Financial institutions in recent years are trying to automate the process of loan approvals. One of the major motivating factors is that it eliminates the scope for human error. The loan approvals could be for a car, education, house or any other property. As discussed in the abstract, there are certain "**variables**" like **gender, income, loan amount, loan term, type of property** that are taken into consideration. These are all **independent variables.** These **independent variables** are taken into consideration when determining the outcome, which is our **dependent variable**, the **Loan_status.**

The key goal of this project is to design a prediction model that will make decisions (in this case predict the value of the **dependent variable**) in real time. For the design of this model, historical data will be used. This ***historical data*** is available in the csv file, '***train_data.csv'.*** The historical data contains information about the applicants (all the **independent variables)** and whether they were approved for a loan or not (i.e the **dependent variable**, the **Loan_status)**. The information of applicants for whom the loan approval decision is yet to be determined (**Loan_status)** is present in the ***test*** data file, '***test_data.csv***'.

The next part of the question is – "Who can benefit from this model?". A model of this nature could benefit any financial institutions that is in the business of granting loans. Depending on the type of loan granted, the dependent variables to be considered could vary. However, the crux of the concept and approach remains the same. This model is by no means a "perfect prediction model" and this project serves as a model upon which better prediction models can be built.

Proposed Approach

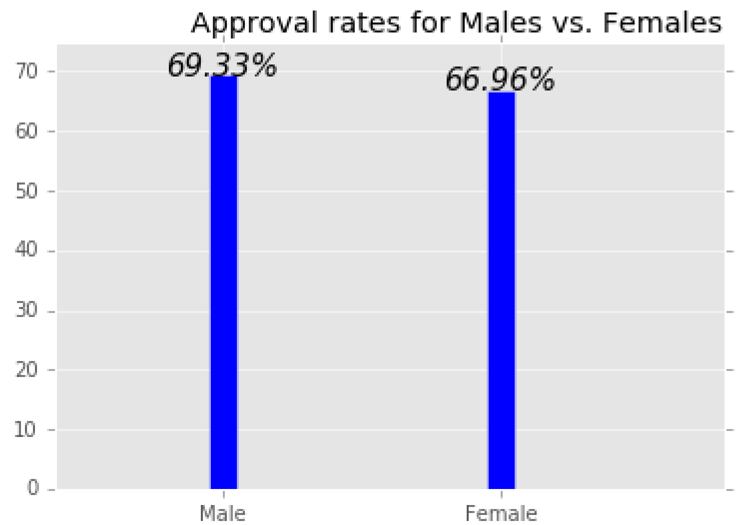
The dataset consists of a total of thirteen columns. The last column in the dataset, the **Loan_Status** is the **dependent variable**. Initially, the assumption is that all the other **independent variables** are critical in determining the loan approval. However, it is clear that the '**Loan_ID'** column plays no role in determining a decision. Similarly, through a statistical analysis, we need to determine which other dependent variables play little or no part in determining the loan approval. For example, it's possible that the "**CoApplicantIncome" variable** really doesn't affect the decision process. We may also find similar results with "**Gender**".

Once we have determined all such variables that play no role in the decision making process, we omit these variables from our analysis.

Initial Hypotheses

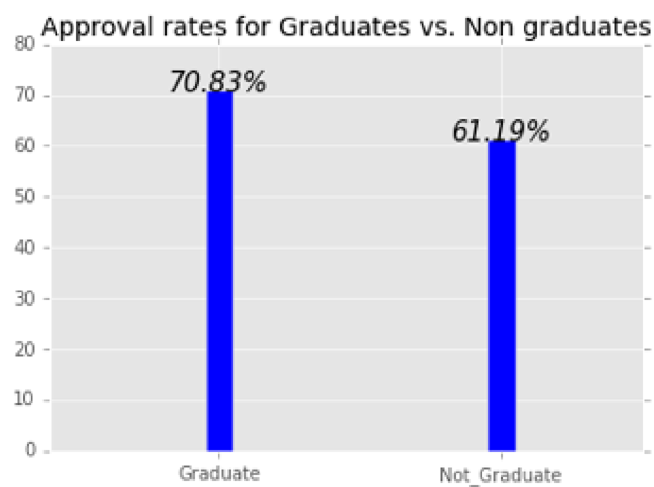
Before we clean the data and get into the nuts and bolts of predictive modeling, let us try and make a hypotheses and observe if the data echoes our assumptions.

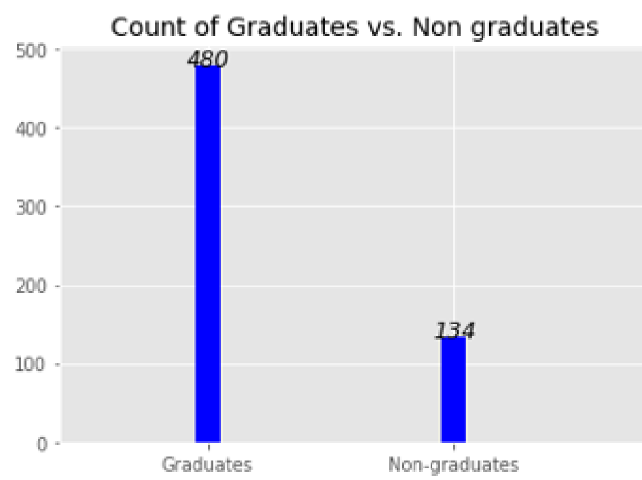
- Let us explore the data and see if males have a greater chance of approval. I computed the percentages of males vs. females approved for the loan.



  From the bar plot above, we observe that indeed males do have a higher approval rating than females. However, the difference in percentage isn't significant enough to definitively confirm our hypothesis.

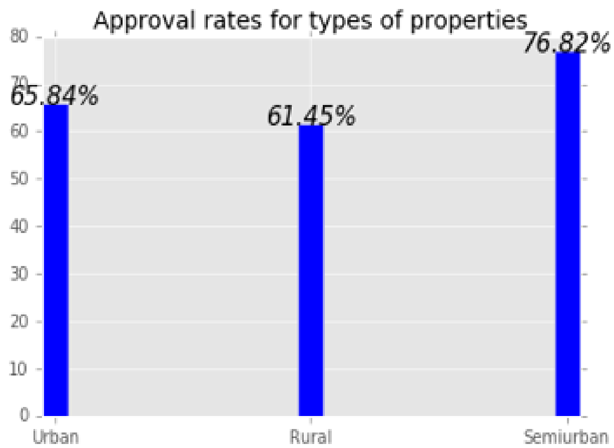
- Next, let us explore to see if Graduates have a higher chance of approval in comparison to non-graduates. From the bar graphs below, we see that graduates indeed have a ~10% higher approval chance. However, let's also see how many graduates and non-graduates were in the list. ***If there are an insignificant number of non-graduates in comparison to graduates or vice-versa, then we might have to consider rejecting the hypothesis as there aren't enough samples to support our hypothesis. [Note: This process will be followed for evaluating the other variables as well.]***

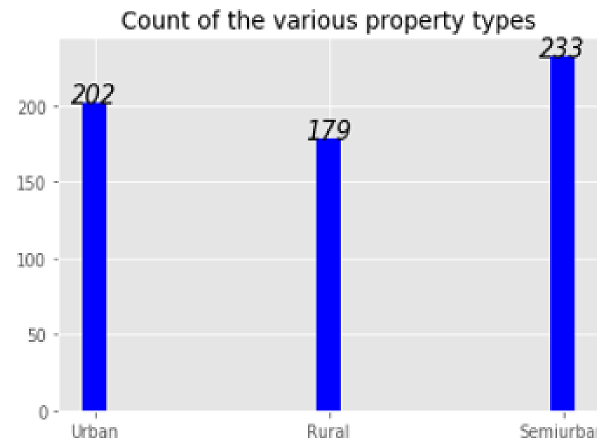




For a total of 614 applicants, 134 were non-graduates. Hence, we can argue that our hypotheses could be true.

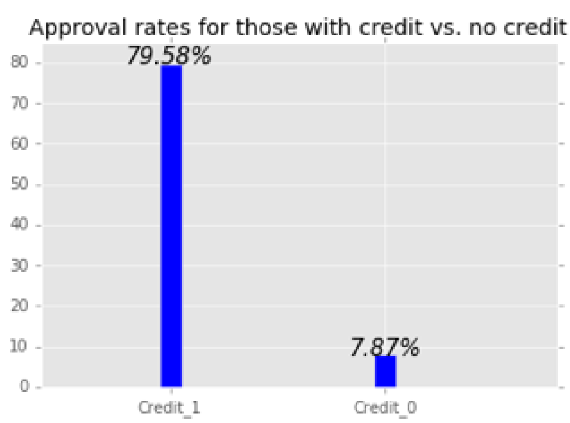
- Next, let us consider the property type and the percentage approvals. We see that semi-urban areas have a higher approval rate. They have a 15% higher approval rate than rural properties and more than 10% approval rate than urban areas. But let us also consider the count of the number of Urban, rural and semiurban properties in question. Two bar plots has been illustrated below.

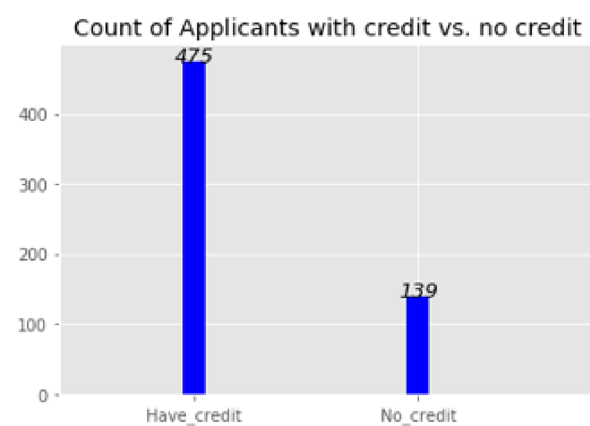




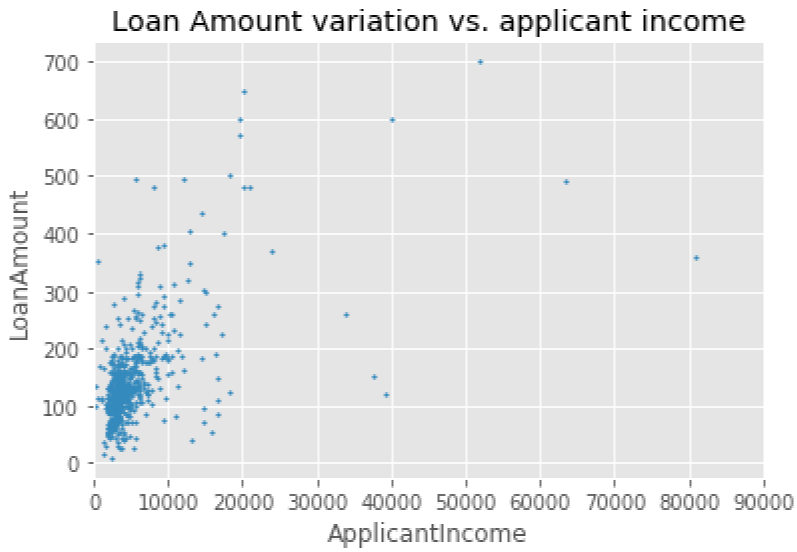
We see a significant number of loan applications for each of the property types. Hence, we could again argue that perhaps, our hypotheses holds true.

- Next, we will try to determine if people with a credit history has a higher chance of loan approval as opposed to those who don't. Let us explore the bar graph below. It would seem that applicants with a credit history are 10 times more likely to get approved. But before we confirm our hypothesis, let's investigate the number of people with credit vs no credit. Again, there are a significant number of samples for people with no credit. Hence, we could again argue that for now, our hypothesis holds good.

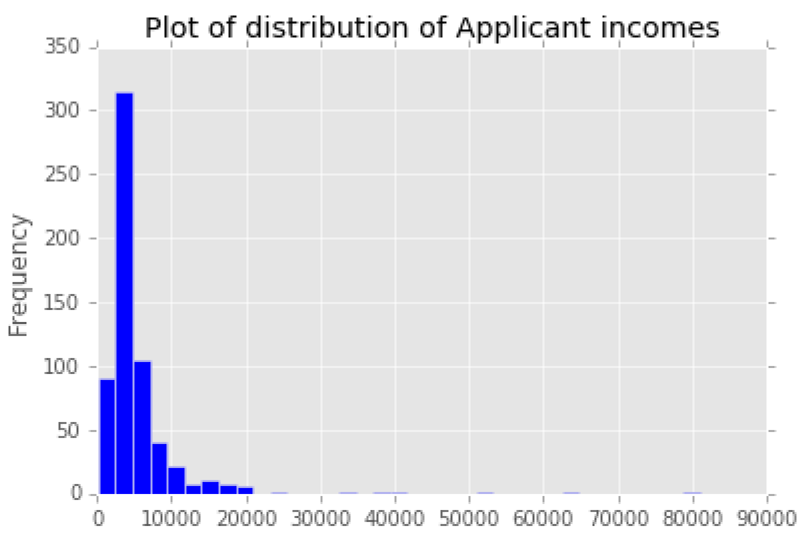




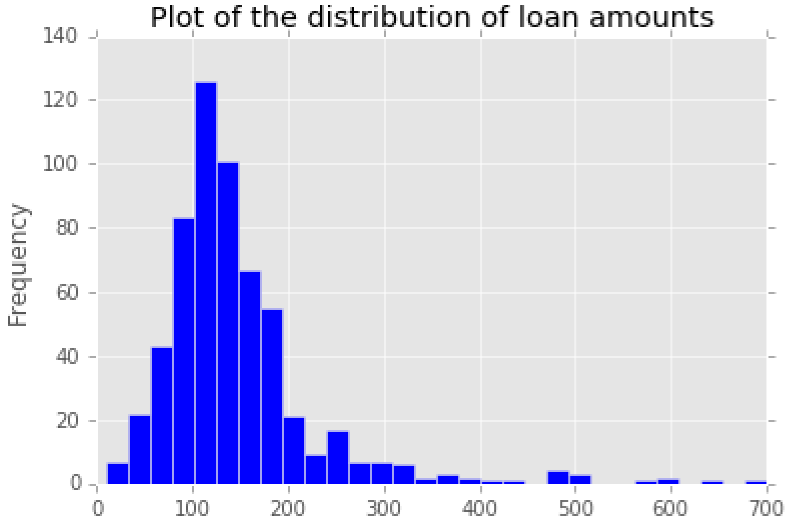
- Next, let us try to see if there is a relationship between the applicants' incomes and their loan amounts requested. While there is some indication that applicants with higher incomes requester larger loan amounts, the data points are diversely spread through the graph and we cannot confidently conclude that there is a solid pattern that supports our hypothesis.



- Next, let us consider the distributions for applicant income. This has been illustrated with a histogram below. From the histogram plot below, it's evident that most of our applicants make $5000 a month or less. In fact, more than 50% of the applicants make between $2500 and $5000.



- Let us also consider the distribution for loan amounts requested. We see that most of the applicants request a loan amount of $200K or less.



Cleaning Steps performed

Before I get started, I will attach a snapshot of all the columns in the dataset.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
Loan_ID              614 non-null object
Gender               601 non-null object
Married              611 non-null object
Dependents           599 non-null object
Education            614 non-null object
Self_Employed        582 non-null object
ApplicantIncome      614 non-null int64
CoapplicantIncome    614 non-null float64
LoanAmount           592 non-null float64
Loan_Amount_Term     600 non-null float64
Credit_History       564 non-null float64
Property_Area        614 non-null object
Loan_Status          614 non-null object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.4+ KB
```

There are 614 observation in total. Some of the columns have missing values. These values had 'NaN' assigned for missing values.

Before we can an in-depth analysis of the cleaning steps performed, I will explain two concepts: Mode, median and Outliers

Mode - The **mode** of a set of data values is the value that appears most often. Let us consider a list, x = [1,2,2,3]. The mode of the list x is 2 since it is the most repeated value.

Median - The median is the value separating the higher half from the lower half of a data sample. Let's consider a list x = [3,4,5,6,7]. The median of x in this case is 5. For an even number of observations, the average of the two middle observations is computed as the median. This is represented by the *50th percentile* line in the box plot below.

Gender – The missing values of the gender column were filled with 'Other'.

Married – Missing values for the married column were filled with the mode value. The 'NaN' or missing values were then substituted with this value. It was '*Married*' for this column.

Dependents – I defined a function that converted the values '3+' to '3'. The mode of the dependents columns was computed next. It was '0'. In the last step, this column was converted to type 'numeric'.

Self Employed – The mode value was computed once again.

LoanAmount – The mean of Loan amounts was computed and assigned to the NaN values.

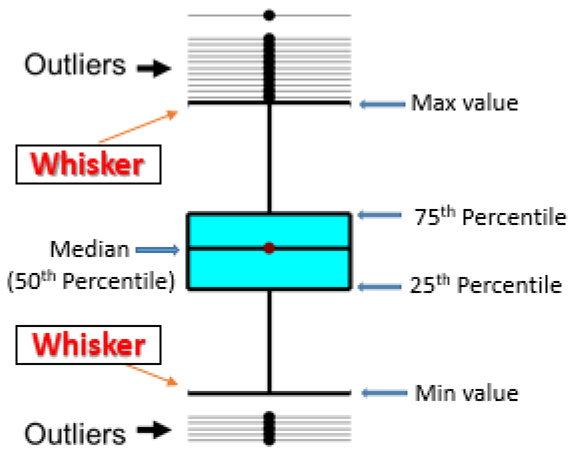
Loan_Amount_Term – The mode was computed and assigned to the missing values. It was 360.

Credit History – The NaN values for credit history were filled with 0.0.

Dealing with Outliers

Outliers - An **outlier** is an observation point that is distant from other observations. These data points could be a result of errors or wrongly recorded observations. These are often excluded from analysis as it could have an adverse effect on the reliability of our model.

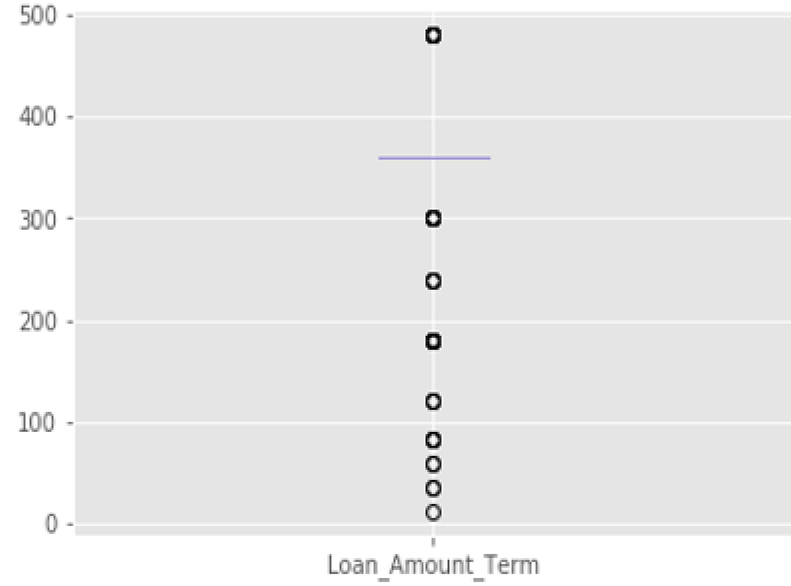
We will identify outliers with the help of box plots. A typical box plot with outliers is illustrated below:



The data points above and below the **whiskers** are our **outliers**. The min and max values in this plot have been plotted by excluding the outliers from the calculation.

I will now outline the steps I took to clean the data:

Loan_Amount_Term – From the box plot, there is one data point > 360. On pulling values from the dataframe for Loan_Amount_term > 360, I observed that there quite a few applicants for loan_amount term = 480 and considering the relatively small size of this dataset, these data points will be taken into consideration for analysis. However, there are a few data points below 100.

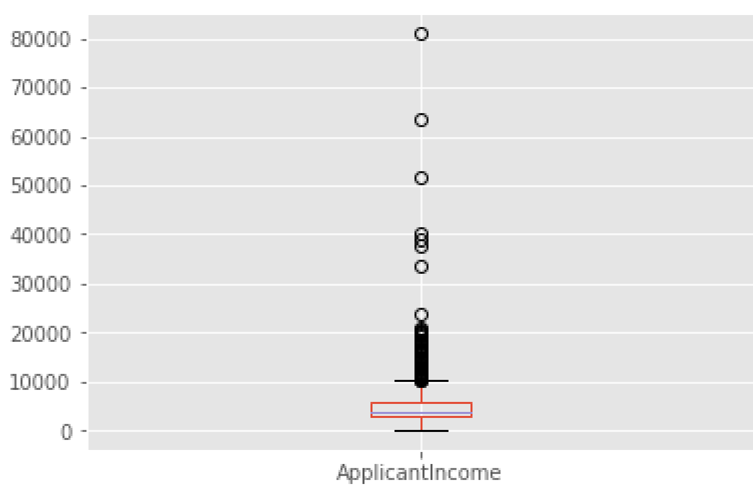


	Loan_Amount_Term
Loan Amount terms < 100	60.0
	60.0
	36.0
	84.0
	84.0
	12.0
	36.0
	84.0
	84.0

So when I take a peek at that data, here's what I get: A total of 9 data points below 100. However, we can see that there are just 2 values below 50: 12 and 24.

Proposed course of action: While it seems highly unlikely that applicants would apply for a 12 or 36 term housing loan, these data points will still be considered for analysis.

<u>ApplicantIncome</u> - By observing the box plot for applicant incomes, we again see quite a few outliers.

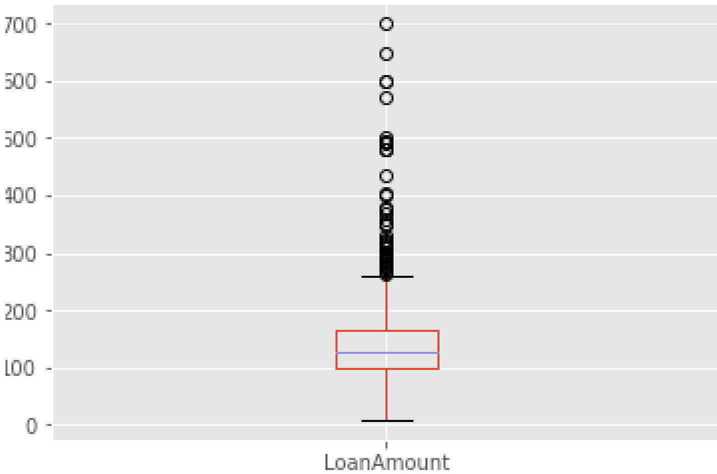


ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
51763	0.0	700.0	300.0	1.0	Urban	Y
63337	0.0	490.0	180.0	1.0	Urban	Y
81000	0.0	360.0	360.0	0.0	Rural	N

All the values in the boxplot from 50000 and above seem pretty far away and we see that there are indeed just three data points.

Proposed course of action: These rows will be considered for our analysis.

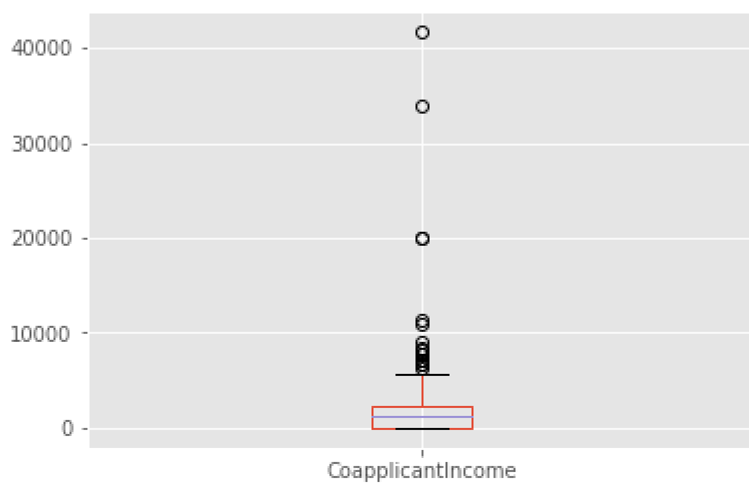
<u>LoanAmount</u> - The box plot shows quite a few outliers. We see that some outliers over 500 (illustrated beside the box plot) that are pretty isolated. We find 3 data points in the 600s and one at 700.



LoanAmount
650.0
600.0
700.0
570.0
600.0

Proposed course of action: Consider all data points.

<u>CoapplicantIncome</u> - On observing the box plot, we again see quite a few outliers but most of them are located close to the box plot. However, there are three data points over the 20000 mark that appear to be pretty isolated.



Proposed course of action: There are only 3 data points above 20000. All rows will be considered for analysis

Statistical Analysis

Now that we have a clean dataset to being our analysis with, this section with deal with statistical analysis of the data set. Before the section digs deep in to the math/statistics, a few definitions will be explained that will help perceive the results of the analysis better.

Hypothesis testing and p-values

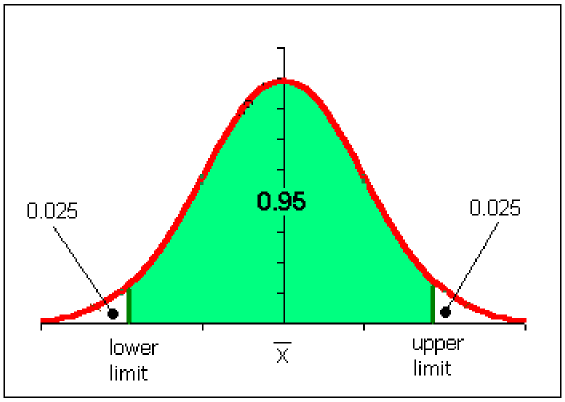
A statistical hypothesis, sometimes called confirmatory data analysis, is an hypothesis that is testable on the basis of observing a process that is modeled via a set of random variables. A statistical hypothesis test is a method of statistical inference. Commonly, two statistical data sets are compared, or a data set obtained by sampling is compared against a synthetic data set from an idealized model. A hypothesis is proposed for the statistical relationship between the two data sets, and this is compared as an alternative to an idealized null hypothesis that proposes no relationship between two data sets. The comparison is deemed statistically significant if the relationship between the data sets would be an unlikely realization of the null hypothesis according to a threshold probability—the significance level. Hypothesis tests are used in determining what outcomes of a study would lead to a rejection of the null hypothesis for a pre-specified level of significance. For more information, follow this link.

p-value

The p-value is the level of marginal significance within a statistical hypothesis test representing the probability of the occurrence of a given event. The p-value is used as an alternative to rejection points to provide the smallest level of significance at which the null hypothesis would be rejected. A smaller p-value means that there is stronger evidence in favor of the alternative hypothesis. For more information on p-values, refer this link.

Our p-value is set in adavance i.e we before we begin our hypothesis testing. If we set a p-value of 5% (0.05), and we get a p-value less than 0.05, this would mean that this data point will not be within the 95% confidence interval. Let us try to visualize this.

(Refer to the illustration and the explanation in the following page.)



If we have a p-value greater than 0.05, then it lies in the green area. Else, it would lie in the white area (indicated by the area of the two tails "0.025", which accounts for the total probability of 5%

In layman terms, if we find the level of significance of our test to be less than 5% (or whatever hypothesis level we set), this would indicate a very rare event and one that didn't happen by random chance alone.

For our tests, let us set the level of significance to 0.05 or 5%.

2-Sample t-tests

Two-sample hypothesis testing is statistical analysis designed to test if there is a difference between two means from two different populations. The two-sample t-test is one of the most commonly used hypothesis tests to compare whether the average difference between two groups is really significant or if it is due instead to random chance.

The null hypothesis here would be that there is no significant difference between the means of the populations and any difference observed is due to random chance. The alternative hypothesis would be that there is indeed a significant difference in means between the two distributions.

For more information on 2 sample t-tests, please refer to this video from Khan Academy.

Pearson Correlation Coefficient (r)

The Pearson correlation coefficient, r, can take a range of values from +1 to -1. A value of 0 indicates that there is no association between the two variables. A value greater than 0 indicates a positive association; that is, as the value of one variable increases, so does the value of the other variable. Conersely, a negative value indicates that if one of the variables increases in value, the other decreases. The formula is displayed below (*refer next page)*:

$$r = r_{xy} = \frac{\text{Cov}(x, y)}{S_x \times S_y}$$

Cov(x,y) represents the covariance of x and y. S_x and S_y represent the standard deviations of x and y respectively. The pearson correlation, r is a dimensionless quantity.

For more on Pearson correlation coefficient, please follow this link.

A series of two sample t tests were carried out. Its results and explanations will now be explored in detail.

- **H_0 : There is no significant difference between males and females in terms of loan approvals`**

  H_a : There is a significant difference between males and females in terms of loan approvals

  The two sample t-test yielded the following results:

  t_statistic = 0.48608, **p_val** = 0.627

  Our p-value of 0.627 is much greater than the set level of 0.05. Hence, we cannot reject our hypothesis as our test doesn't indicate that gender is an influencing factor.

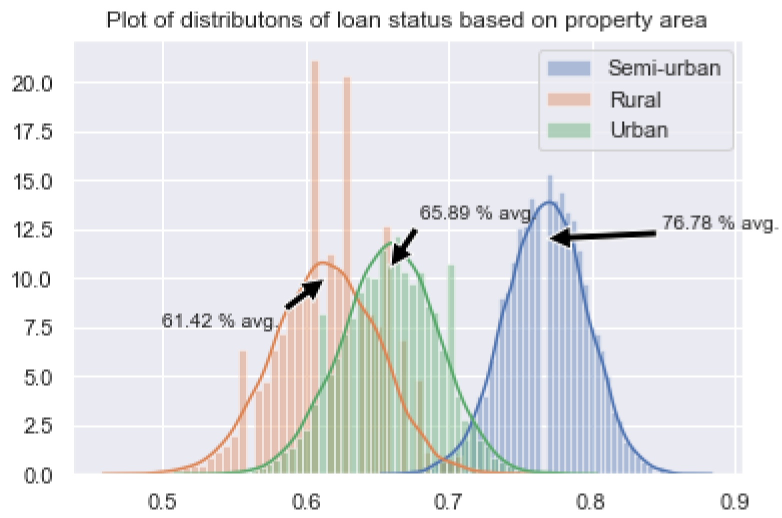
- **H_0: There is no significant difference between loan approvals for semi-urban and rural areas**

  H_a: There is a significant difference between loan approvals for semi-urban and rural areas.

  During our initial hypothesis, we found out that semi-urban areas had a higher loan approval rate in comparison to urban and rural areas. Let us do a significance test for the same. The two sample t-test yielded the following results:

  t_statistic = 3.419, **p_val** = 0.00069

  The small p-value above indicates that property type does matter when granting loan approvals. Hence, this wasn't due to random chance. A plot of the distributions of the various property areas has been plotted below.



We can notice that semiurban property have a significantly higher percentage of approvals.

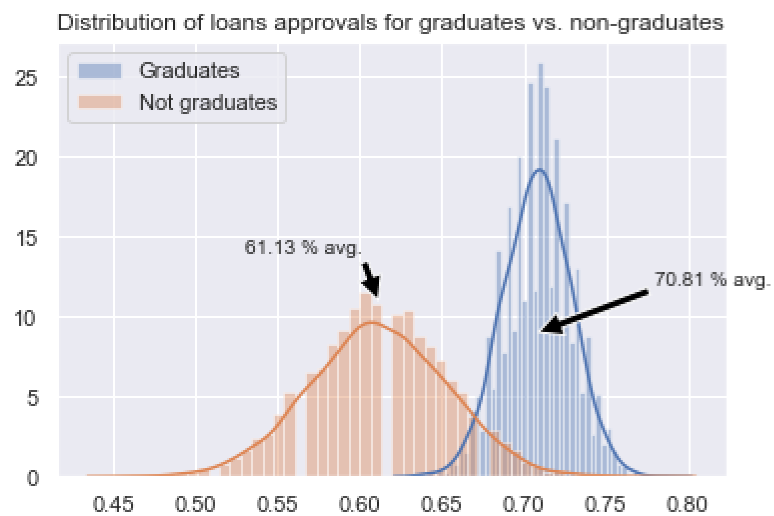
- **H_0: Graduates and non-graduates have an almost equal chance of having their loan approved.**

  H_a: Graduates and non-graduates have an almost equal chance of having their loan approved.

  A two sample test was carried out once again which yielded the results:

  t_statistic = 2.1325, **p_val** = 0.033

  The p-value obtained is < 0.05 which implies statistical significance. The plot below is a mean of the distributions for graduates vs. non graduates.



The significantly higher loan approval rates for graduates has been illustrated in the plot above.

- **H_0: The number of dependents of an applicant has no significance on the loan approval rates.**

  H_a: The number of dependents of an applicant has statistical significance on the loan approval rate.

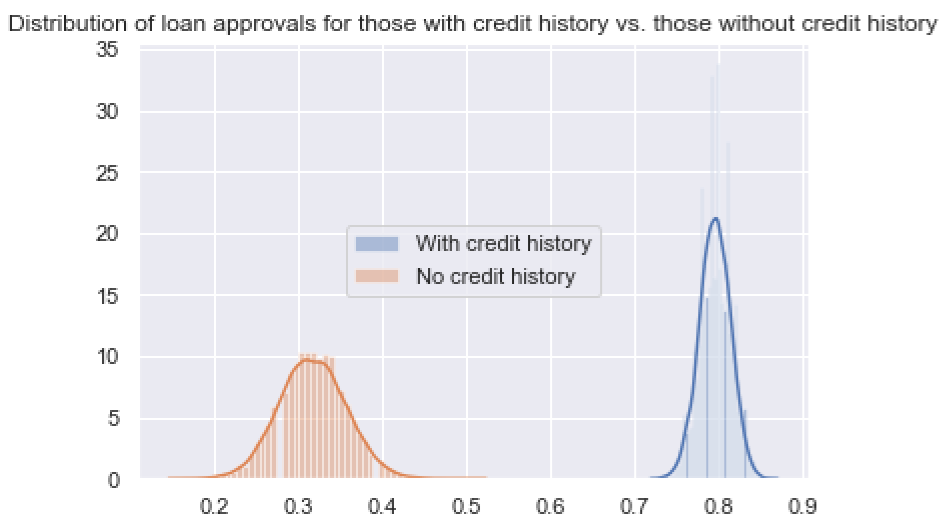
  Various t-sample tests were carried out but none of them yielded a p-value less than 0.05. Hence, we cannot reject our null hypothesis. There were four categories here: 0 dependents, 1 dependent, 2 dependent, and 3 or more dependents. Let us visualize this result below by plotting the means of the distributions for various number of dependents. The p-value from the 2 sample t test for 2 dependents vs. 1 dependent yielded ~0.1 which is close to our significance value. Hence, we can see that these distributions are quite far away from each other. However, since we had our threshold set at 0.05, we didn't reject the null hypothesis.

- **H_0: There is no significant difference in loan approvals for people with credit history vs. those with no credit history.**
- **H_a: There is a significant difference in loan approvals for people with credit history vs. those with no credit history.**

  A two sample t-test was carried out for applicants with credit history vs. for those with no credit history. The results were:

  t_statistic = 11.87, **p_val** = 2.1445*e^-29

  Our p-value is extremely small and hence, this signifies statistical significance. A visualization of the means of the distributions has been plotted below:



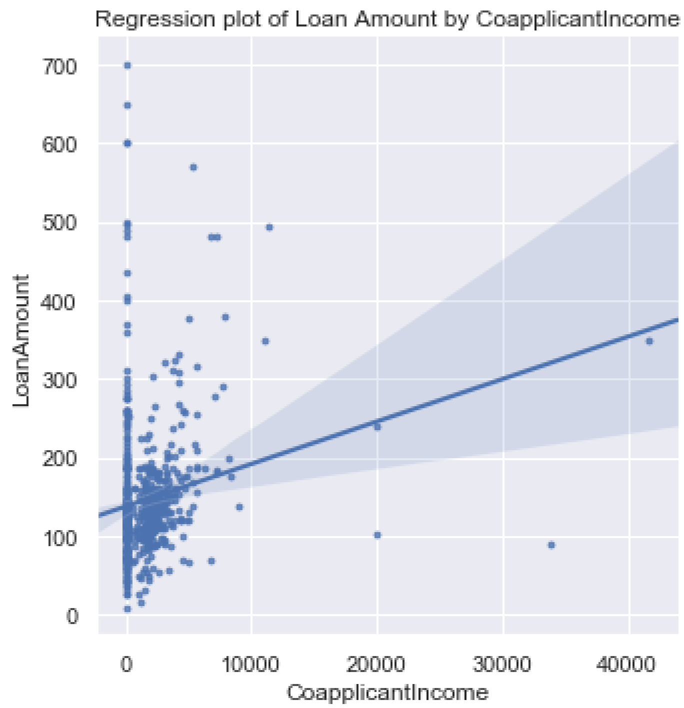
It would seem that applicants with credit history have a much better overall chance of obtaining a loan.

Now, let us try to explore the correlations between some of the independent variables. To achieve this, the Pearson correlation coefficients was computed. A series of the Pearson_r tests and their explanations will be explored below.

- From an intuitive sense, it would make sense for an applicant's income be somewhat proportional to the Loan amount requested. Let's see if this is the case. Computing the pearson_r value yielded 0.5656. This signifies a strong positive correlation. A linear regression plot between these two variables has been illustrated below.

- Next, let us observe the correlation between the Coapplicant income and the Loan Amount.

  The pearson_r value computed was 0.1878 which signifies a positive correlation albeit a weak one. Let us visualize this relation with a regression plot below.



- Let us now see what we can make of the relation between the Loan Amount requested and the loan amount term.

  The pearson_r value was computed to be 0.036. This is indeed a very weak positive correlation that is very close to 0.