# Loan Prediction

The aim of this project is to predict real-estate prices using the machine learning algorithms: Logistic Regression, Decision tree, Random Forest.

This file is the EDA and its purpose is to go through the sevarl steps of working with data - data gathering, data understanding, data preparation. Visualization of the information is made for better understanding.

# Loading the data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from google.colab import files
from datetime import datetime
import seaborn as sns
%matplotlib inline

import io
```

Using two files which later will be integrated into one dataframe.

```
# Load the data
local_file = files.upload()
train_data = io.BytesIO(local_file['train1.csv'])
train_data2 = io.BytesIO(local_file['train.csv'])
df1 = pd.read_csv(train_data)
df2 = pd.read_csv(train_data2)
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving train.csv to train (2).csv
Saving train1.csv to train1 (2).csv
```

# Data integration

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            367 non-null    object 
 1   Gender             356 non-null    object 
 2   Married            367 non-null    object 
 3   Dependents         357 non-null    object 
 4   Education          367 non-null    object 
 5   Self_Employed      344 non-null    object 
 6   ApplicantIncome    367 non-null    int64  
 7   CoapplicantIncome  367 non-null    int64  
 8   LoanAmount         362 non-null    float64
 9   Loan_Amount_Term   361 non-null    float64
 10  Credit_History     338 non-null    float64
 11  Property_Area      367 non-null    object 
dtypes: float64(3), int64(2), object(7)
memory usage: 34.5+ KB
```

> It can be seen that there are some numeric values and also categorical ones. Later, the categorical will have to be converted into either float or int in order to be plotted and then used for the trainig of the models. There are also missing values in the dataset.

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

> It can be seen that there are some numeric values and also categorical ones. Later, the categorical will have to be converted into either float or int in order to be plotted and then used for the trainig of the models. There are also missing values in the dataset.

Creating one dataframe out of the two dataframes from the csv files.

```
frames = [df1, df2]


df = pd.concat(frames)
df
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome |
|---|---|---|---|---|---|---|---|
| **0** | LP001015 | Male | Yes | 0 | Graduate | No | 5720 |
| **1** | LP001022 | Male | Yes | 1 | Graduate | No | 3076 |
| **2** | LP001031 | Male | Yes | 2 | Graduate | No | 5000 |
| **3** | LP001035 | Male | Yes | 2 | Graduate | No | 2340 |
| **4** | LP001051 | Male | No | 0 | Not Graduate | No | 3276 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **609** | LP002978 | Female | No | 0 | Graduate | No | 2900 |
| **610** | LP002979 | Male | Yes | 3+ | Graduate | No | 4106 |
| **611** | LP002983 | Male | Yes | 1 | Graduate | No | 8072 |
| **612** | LP002984 | Male | Yes | 2 | Graduate | No | 7583 |
| **613** | LP002990 | Female | No | 0 | Graduate | Yes | 4583 |

981 rows × 13 columns

# Data storage solution:

An essential part of Machine Learning is the data storage solution for the selected data and machine learning model. In order to accomplish the most efficient manner of working with data during this project, the following tools were used:

- Git Version Control
- Data Version Control (DVC)

**Git Version Control:** Git has been a popular tool among programmers and it is so for a reason. It allows tracking changes in any set of files, usually used for coordinating work among programmers collaboratively developing source code during software development.

**Data Version Control (DVC):** Data Version Control is a new type of data versioning, workflow, and experiment management software that builds upon Git (although it can work stand-alone). Using Git and DVC, machine learning teams can version experiments, manage large datasets, and make projects reproducible. By utilizing DVC data will be tracked and stored in an effective and efficient way because the data is accessible from everywhere via internet connection for every contributor.

**Summary:**

- DVC will create reference files to data versions
- Git will store the DVC files

At the current stage, the dataset has been loaded after integrating it. Changes were made to like cleaning and processing it so as to make it more suitable to work with and acceptable to store

# Data analysis:

## Checking the dimension of the dataset and the features.

Take a look at the summary of the numerical fields.

```
df.describe()
```

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History |
|---|---|---|---|---|---|
| **count** | 981.000000 | 981.000000 | 954.000000 | 961.000000 | 902.000000 |
| **mean** | 5179.795107 | 1601.916330 | 142.511530 | 342.201873 | 0.835920 |
| **std** | 5695.104533 | 2718.772806 | 77.421743 | 65.100602 | 0.370553 |
| **min** | 0.000000 | 0.000000 | 9.000000 | 6.000000 | 0.000000 |
| **25%** | 2875.000000 | 0.000000 | 100.000000 | 360.000000 | 1.000000 |
| **50%** | 3800.000000 | 1110.000000 | 126.000000 | 360.000000 | 1.000000 |
| **75%** | 5516.000000 | 2365.000000 | 162.000000 | 360.000000 | 1.000000 |
| **max** | 81000.000000 | 41667.000000 | 700.000000 | 480.000000 | 1.000000 |

```
df.shape
```

```
(981, 13)
```

> Here it can be seen the shape of our data with the `.shape`. Here are the the rows and columns(981, 13).

To view what data that is stored the `columns` should be explored. This will return the colums of the data.

```
df.columns
```

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

After reviewing all the columns, in the next cell is outlined only the quantitive columns.

```
quantitative = [f for f in df.columns if df.dtypes[f] != 'object']
print(quantitative)
```

```
['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'Credit_Histo
```

To look at the data I'll use the .head() method from pandas. This will show the first 5 items in the dataframe.

```
#First 5 rows of our dataset
df.head()
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | Co |
|---|---|---|---|---|---|---|---|---|
| **0** | LP001015 | Male | Yes | 0 | Graduate | No | 5720 | |
| **1** | LP001022 | Male | Yes | 1 | Graduate | No | 3076 | |
| **2** | LP001031 | Male | Yes | 2 | Graduate | No | 5000 | |
| **3** | LP001035 | Male | Yes | 2 | Graduate | No | 2340 | |
| **4** | LP001051 | Male | No | 0 | Not Graduate | No | 3276 | |

To look at the data I'll use the .tail() method from pandas. This will show us the last 5 items in the

```
#Last 5 rows of our dataset
df.tail()
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome |
|---|---|---|---|---|---|---|---|
| **609** | LP002978 | Female | No | 0 | Graduate | No | 2900 |
| **610** | LP002979 | Male | Yes | 3+ | Graduate | No | 4106 |
| **611** | LP002983 | Male | Yes | 1 | Graduate | No | 8072 |
| **612** | LP002984 | Male | Yes | 2 | Graduate | No | 7583 |
| **613** | LP002990 | Female | No | 0 | Graduate | Yes | 4583 |

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 981 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            981 non-null    object 
 1   Gender             957 non-null    object 
 2   Married            978 non-null    object 
 3   Dependents         956 non-null    object 
 4   Education          981 non-null    object 
 5   Self_Employed      926 non-null    object 
 6   ApplicantIncome    981 non-null    int64  
 7   CoapplicantIncome  981 non-null    float64
 8   LoanAmount         954 non-null    float64
 9   Loan_Amount_Term   961 non-null    float64
 10  Credit_History     902 non-null    float64
 11  Property_Area      981 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 107.3+ KB
```

> It can be seen that there are features that are numeric and also objects. Later, the ones that are not numeric will have to be converted into either float or int in order to be plotted and then used for the trainig of the models. There are also missing values in the dataset, which will be handled later.

Sorting the data by `Loan_Status` and showing 50 elements.

```
df.sort_values('Loan_Status', ascending = True)[:50]
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome |
|---|---|---|---|---|---|---|---|
| **613** | LP002990 | Female | No | 0 | Graduate | Yes | 4583 |
| **489** | LP002556 | Male | No | 0 | Graduate | No | 2435 |
| **186** | LP001641 | Male | Yes | 1 | Graduate | Yes | 2178 |
| **487** | LP002547 | Male | Yes | 1 | Graduate | No | 18333 |
| **486** | LP002545 | Male | No | 2 | Graduate | No | 3547 |
| **191** | LP001656 | Male | No | 0 | Graduate | No | 12000 |
| **192** | LP001657 | Male | Yes | 0 | Not Graduate | No | 6033 |
| **195** | LP001665 | Male | Yes | 1 | Graduate | No | 3125 |
| **199** | LP001673 | Male | No | 0 | Graduate | Yes | 11000 |
| **479** | LP002533 | Male | Yes | 2 | Graduate | No | 2947 |
| **202** | LP001682 | Male | Yes | 3+ | Not Graduate | No | 3992 |
| **477** | LP002530 | NaN | Yes | 2 | Graduate | No | 2873 |
| **209** | LP001702 | Male | No | 0 | Graduate | No | 3418 |
| **210** | LP001708 | Female | No | 0 | Graduate | No | 10000 |
| **211** | LP001711 | Male | Yes | 3+ | Graduate | No | 3430 |
| **471** | LP002517 | Male | Yes | 1 | Not Graduate | No | 2653 |
| **469** | LP002505 | Male | Yes | 0 | Graduate | No | 4333 |
| **216** | LP001722 | Male | Yes | 0 | Graduate | No | 150 |
| **218** | LP001732 | Male | Yes | 2 | Graduate | NaN | 5000 |
| **466** | LP002500 | Male | Yes | 3+ | Not Graduate | No | 2947 |
| **220** | LP001736 | Male | Yes | 0 | Graduate | No | 2221 |
| **464** | LP002493 | Male | No | 0 | Graduate | No | 4166 |
| **225** | LP001751 | Male | Yes | 0 | Graduate | No | 3250 |
| **226** | LP001754 | Male | Yes | NaN | Not Graduate | Yes | 4735 |
| **459** | LP002473 | Male | Yes | 0 | Graduate | No | 8334 |
| **457** | LP002467 | Male | Yes | 0 | Graduate | No | 3708 |
| **236** | LP001786 | Male | Yes | 0 | Graduate | NaN | 5746 |
| **452** | LP002448 | Male | Yes | 0 | Graduate | No | 3948 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **183** | LP001637 | Male | Yes | 1 | Graduate | No | 33846 |
| **450** | LP002446 | Male | Yes | 2 | Not Graduate | No | 2309 |
| **181** | LP001634 | Male | No | 0 | Graduate | No | 1916 |
| **179** | LP001630 | Male | No | 0 | Not Graduate | No | 2333 |
| **524** | LP002697 | Male | No | 0 | Graduate | No | 4680 |
| **135** | LP001488 | Male | Yes | 3+ | Graduate | No | 4000 |
| **136** | LP001489 | Female | Yes | 0 | Graduate | No | 4583 |
| **519** | LP002684 | Female | No | 0 | Not Graduate | No | 3400 |
| **138** | LP001492 | Male | No | 0 | Graduate | No | 14999 |
| **139** | LP001493 | Male | Yes | 2 | Not Graduate | No | 4200 |
| **140** | LP001497 | Male | Yes | 2 | Graduate | No | 5042 |
| **518** | LP002683 | Male | No | 0 | Graduate | No | 4683 |
| **517** | LP002682 | Male | Yes | NaN | Not Graduate | No | 3074 |
| **514** | LP002652 | Male | No | 0 | Graduate | No | 5815 |
| **513** | LP002648 | Male | Yes | 0 | Graduate | No | 2130 |
| **148** | LP001519 | Female | No | 0 | Graduate | No | 10000 |
| **150** | LP001528 | Male | No | 0 | Graduate | No | 6277 |
| **510** | LP002637 | Male | No | 0 | Not Graduate | No | 3598 |
| **152** | LP001531 | Male | No | 0 | Graduate | No | 9166 |
| **153** | LP001532 | Male | Yes | 2 | Not Graduate | No | 2281 |
| **507** | LP002625 | NaN | No | 0 | Graduate | No | 3583 |
| **503** | LP002618 | Male | Yes | 1 | Not Graduate | No | 4050 |

Sorting the data by `Education` and showing 50 elements.

```
df.sort_values('Education')[:50]
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome |
|---|---|---|---|---|---|---|---|
| **0** | LP001015 | Male | Yes | 0 | Graduate | No | 5720 |
| **234** | LP001778 | Male | Yes | 1 | Graduate | No | 3155 |
| **235** | LP001784 | Male | Yes | 1 | Graduate | No | 5500 |
| **236** | LP001786 | Male | Yes | 0 | Graduate | NaN | 5746 |
| **237** | LP001788 | Female | No | 0 | Graduate | Yes | 3463 |
| **238** | LP001790 | Female | No | 1 | Graduate | No | 3812 |
| **239** | LP001792 | Male | Yes | 1 | Graduate | No | 3315 |
| **240** | LP001798 | Male | Yes | 2 | Graduate | No | 5819 |
| **242** | LP001806 | Male | No | 0 | Graduate | No | 2965 |
| **243** | LP001807 | Male | Yes | 2 | Graduate | Yes | 6250 |
| **245** | LP001813 | Male | No | 0 | Graduate | Yes | 6050 |
| **233** | LP001776 | Female | No | 0 | Graduate | No | 8333 |
| **246** | LP001814 | Male | Yes | 2 | Graduate | No | 9703 |
| **249** | LP001825 | Male | Yes | 0 | Graduate | No | 1809 |
| **251** | LP001836 | Female | No | 2 | Graduate | No | 3427 |
| **254** | LP001844 | Male | No | 0 | Graduate | Yes | 16250 |
| **255** | LP001846 | Female | No | 3+ | Graduate | No | 3083 |
| **257** | LP001854 | Male | Yes | 3+ | Graduate | No | 5250 |
| **258** | LP001859 | Male | Yes | 0 | Graduate | No | 14683 |
| **260** | LP001865 | Male | Yes | 1 | Graduate | No | 6083 |
| **261** | LP001868 | Male | No | 0 | Graduate | No | 2060 |
| **262** | LP001870 | Female | No | 1 | Graduate | No | 3481 |
| **263** | LP001871 | Female | No | 0 | Graduate | No | 7200 |
| **248** | LP001824 | Male | Yes | 1 | Graduate | No | 2882 |
| **231** | LP001768 | Male | Yes | 0 | Graduate | NaN | 3716 |
| **230** | LP001765 | Male | Yes | 1 | Graduate | No | 2491 |
| **229** | LP001761 | Male | No | 0 | Graduate | Yes | 6400 |
| **196** | LP001666 | Male | No | 0 | Graduate | No | 8333 |
| **198** | LP001671 | Female | Yes | 0 | Graduate | No | 3416 |
| **199** | LP001673 | Male | No | 0 | Graduate | Yes | 11000 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **201** | LP001677 | Male | No | 2 | Graduate | No | 4923 |
| **206** | LP001693 | Female | No | 0 | Graduate | No | 3244 |
| **208** | LP001699 | Male | No | 0 | Graduate | No | 2479 |
| **209** | LP001702 | Male | No | 0 | Graduate | No | 3418 |
| **210** | LP001708 | Female | No | 0 | Graduate | No | 10000 |
| **211** | LP001711 | Male | Yes | 3+ | Graduate | No | 3430 |
| **212** | LP001713 | Male | Yes | 1 | Graduate | Yes | 7787 |
| **214** | LP001716 | Male | Yes | 0 | Graduate | No | 3173 |
| **216** | LP001722 | Male | Yes | 0 | Graduate | No | 150 |
| **217** | LP001726 | Male | Yes | 0 | Graduate | No | 3727 |
| **218** | LP001732 | Male | Yes | 2 | Graduate | NaN | 5000 |
| **219** | LP001734 | Female | Yes | 2 | Graduate | No | 4283 |
| **220** | LP001736 | Male | Yes | 0 | Graduate | No | 2221 |
| **221** | LP001743 | Male | Yes | 2 | Graduate | No | 4009 |
| **222** | LP001744 | Male | No | 0 | Graduate | No | 2971 |
| **223** | LP001749 | Male | Yes | 0 | Graduate | No | 7578 |
| **224** | LP001750 | Male | Yes | 0 | Graduate | No | 6250 |
| **225** | LP001751 | Male | Yes | 0 | Graduate | No | 3250 |
| **227** | LP001758 | Male | Yes | 2 | Graduate | No | 6250 |
| **228** | LP001760 | Male | NaN | NaN | Graduate | No | 4758 |

This is a representation of one row content, which helps by showing what to look for and what to expect to be in each other row.

```
df.iloc[0]
```

```
Loan_ID              LP001015
Gender                   Male
Married                   Yes
Dependents                  0
Education            Graduate
Self_Employed              No
ApplicantIncome          5720
CoapplicantIncome           0
LoanAmount                110
Loan_Amount_Term          360
Credit_History              1
Property_Area           Urban
Loan_Status               NaN
Name: 0, dtype: object
```

Get the unique values and their frequency of variable. (Checking how many times the certain value occurs.)

```
df['Loan_Status'].value_counts()
```

```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

```
df['ApplicantIncome'].value_counts()
```

```
2500     13
5000     11
3333     10
3500      9
2600      8
         ..
5391      1
15000     1
14999     1
7830      1
1811      1
Name: ApplicantIncome, Length: 752, dtype: int64
```

```
df['Gender'].value_counts()
```

```
Male      775
Female    182
Name: Gender, dtype: int64
```

```
df['Married'].value_counts()
```

```
Yes    631
No     347
Name: Married, dtype: int64
```

```
df['CoapplicantIncome'].value_counts()
```

```
0.0       429
2500.0      6
1666.0      5
2000.0      5
2083.0      5
          ...
6250.0      1
1742.0      1
189.0       1
1868.0      1
4266.0      1
Name: CoapplicantIncome, Length: 437, dtype: int64
```

```
df['Dependents'].value_counts()
```

```
0     545
2     160
1     160
3+     91
Name: Dependents, dtype: int64
```

```
df['Education'].value_counts()
```

```
Graduate        763
Not Graduate    218
Name: Education, dtype: int64
```

```
df['Self_Employed'].value_counts()
```

```
No     807
Yes    119
Name: Self_Employed, dtype: int64
```

```
df['Loan_Status'].unique()
```

```
array([nan, 'Y', 'N'], dtype=object)
```

```
df['ApplicantIncome'].unique()
```

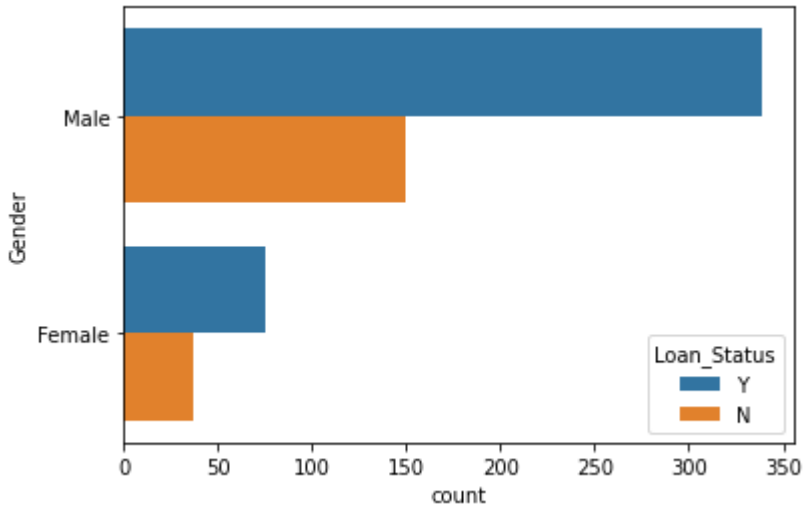
```
            3863,  4028,  4010,  3719,  2858,  3833,  3007,  1850,  2792,
            2982, 18840,  2995,  3579,  3835,  3854,  3508,  1635, 24797,
            2773,  5769,  3634, 29167,  5530,  9000,  8750,  1972,  4983,
            8333,  3667,  3166,  3271,  2241,  1792,  2666,  6478,  3808,
            3729,  4120,  6300, 14987,   570,  2600,  2733,  3859,  6825,
            3708,  5314,  2366,  2066,  3767,  7859,  4283,  1700,  4768,
            3083,  2667,  1647,  3400, 16000,  2875,  5041,  6958,  5509,
            9699,  3621,  4709,  3015,  2292,  2360,  2623,  3972,  3522,
            6858,  8334,  2868,  3418,  8667,  2283,  5817,  5119,  5316,
            7603,  3791,  3132,  8550,  2269,  4009,  4158,  9200,  5849,
            3000,  2583,  6000,  5417,  3036,  4006, 12841,  3200,  1853,
            1299,  4950,  3596,  4887,  7660,  5955,  3365,  3717,  9560,
            2799,  4226,  1442,  3750,  3167,  4692,  2275,  1828,  3748,
            3600,  1800,  3941,  4695,  3410,  5649,  5821,  2645,  1928,
            3086,  4230,  4616, 11500,  2132,  3366,  8080,  3357,  3029,
            2609,  4945,  5726, 10750,  7100,  4300,  3208,  1875,  4755,
            5266,  1000,  3846,  2395,  1378,  3988,  8566,  5695,  2958,
            3273,  4133,  6782,  2484,  1977,  4188,  1759,  4288,  4843,
           13650,  4652,  3816,  3052, 11417,  7333,  3800,  2071,  2929,
            3572,  7451,  5050, 14583,  2214,  5568, 10408,  2137,  2957,
            3692, 23803,  3865, 10513,  6080, 20166,  2718,  3459,  4895,
            3316, 14999,  4200,  5042,  6950,  2698, 11757,  2330, 14866,
            1538,  4860,  6277,  2577,  9166,  2281,  3254, 39999,  9538,
            2980,  1863,  7933,  9323,  3707,  2439,  2237,  1820, 51763,
            4344,  3497,  2045,  5516,  6400,  1916,  4600, 33846,  3625,
           39147,  2178,  2383,   674,  9328,  4885, 12000,  6033,  3858,
            4191,  1907,  3416, 11000,  4923,  3992,  3917,  4408,  3244,
```

```
 4191,  1907,  5416, 11000,  4923,  5992,  5917,  4408,  3244,
 3975,  2479,  3430,  7787,  5703,  3173,  3850,   150,  3727,
 2221,  2971,  7578,  4735,  4758,  2491,  3716,  3155,  5500,
 5746,  3463,  3812,  3315,  5819,  2510,  2965,  3406,  6050,
 9703,  6608,  2882,  1809,  1668,  3427,  2661, 16250,  6045,
 5250, 14683,  4931,  6083,  2060,  3481,  7200,  5166,  4095,
 4708,  2876,  3237, 11146,  2833,  2620,  3993,  3103,  4100,
 4053,  3927,  2301,  1811, 20667,  3158,  3704,  4124,  9508,
 3075,  4400,  3153,  4416,  6875,  1625,  3762, 20233,  7667,
 2927,  2507,  2473,  3399,  2058,  3541,  4342,  3601, 15000,
 8666,  4917,  5818,  4384,  2935, 63337,  9833,  5503,  1830,
 4160,  2647,  2378,  4554,  2499,  3523,  6333,  2625,  9083,
 2423,  3813,  3875,  5167,  4723,  3013,  6822,  6216,  5124,
 6325, 19730, 15759,  5185,  3062,  2764,  4817,  4310,  3069,
 5391,  5941,  7167,  4566,  2346,  3010,  5488,  9504,  1993,
 3100,  3033,  3902,  1500,  2889,  2755,  1963,  7441,  4547,
 2167,  2213,  8300, 81000,  3867,  6256,  6096,  2253,  2149,
 1600,  1025,  3246,  5829,  2720,  7250, 14880,  4606,  5935,
 2920,  2717,  8624, 12876,  2425, 10047,  1926, 10416,  7142,
 3660,  7901,  4707, 37719,  3466,  3539,  3340,  2769,  2309,
 1958,  3948,  2483,  7085,  4301,  4354,  7740,  5191,  2947,
16692,   210,  3450,  2653,  4691,  5532, 16525,  6700,  2873,
16667,  4350,  3095, 10833,  3547, 18333,  2435,  2699,  3691,
17263,  3597,  3326,  4625,  2895,  6283,   645,  4865,  4050,
 3814, 20833, 13262,  3598,  6065,  3283,  2130,  5815,  2031,
 4683,  2192,  5677,  7948,  4680, 17500,  3775,  5285,  2679,
 6783,  4281,  3588, 11250, 18165,  2550,  6133,  3617,  6417,
 4608,  2138,  3652,  2239,  2768,  3358,  2526,  2785,  6633,
 2492,  2454,  3593,  5468, 10139,  4180,  3675, 19484,  5923,
 5800,  8799,  4467,  5116, 16666,  6125,  6406,  3087,  3229,
 1782,  3182,  6540,  1836,  1880,  2787,  2297,  2726,  9357,

16120,  6383,  2987,  9963,  5780,   416,  2894,  3676,  3987,
 3232,  2900,  4106,  8072,  7583])
```

```
sns.countplot(y = 'Gender', hue = 'Loan_Status', data = df)
```

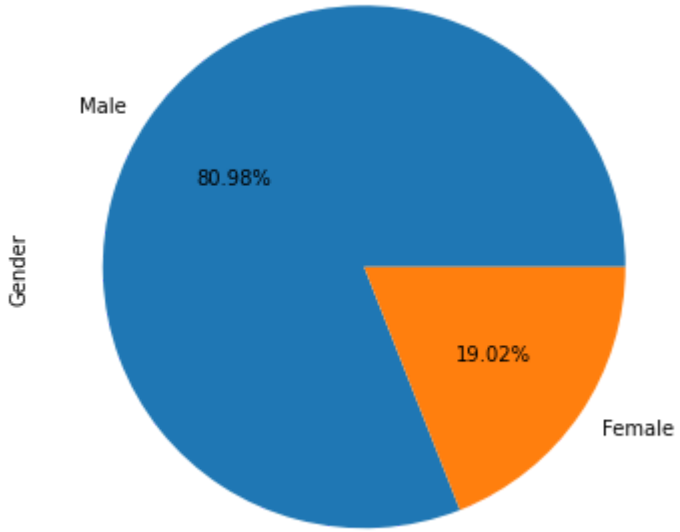
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d75513610>
```



> The diagram shows on one hand that there are more male applicants than female

```
df['Gender'].value_counts().plot(kind='pie', autopct='%1.2f%%', figsize=(6, 6))
```

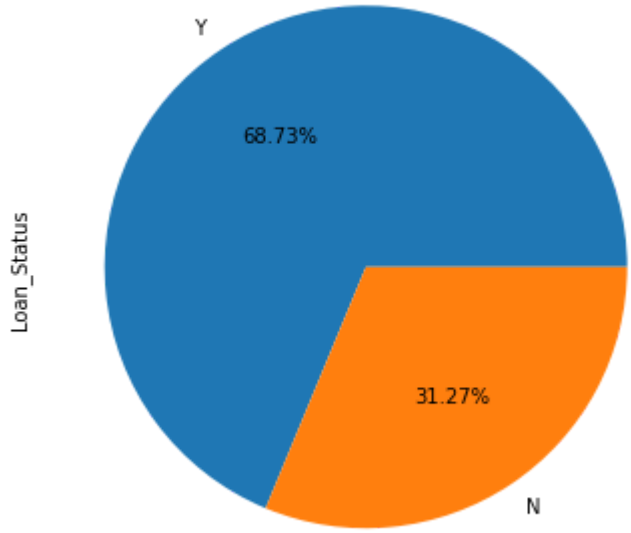
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d75497e90>
```




> The percentage of males who applied for a loan is greater than the one of females.

```
df['Loan_Status'].value_counts().plot(kind='pie', autopct='%1.2f%%', figsize=(6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d75466410>
```

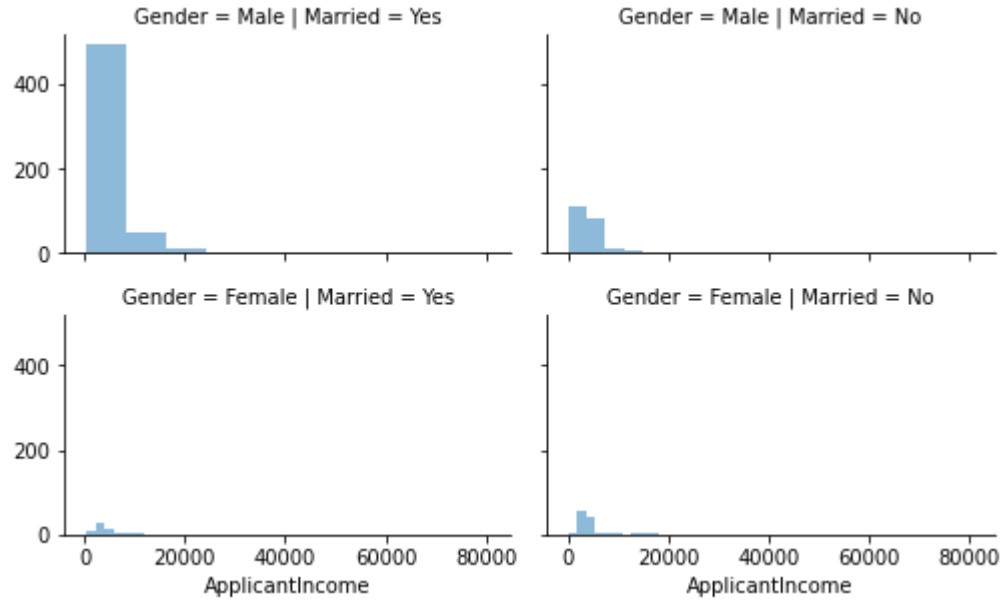


> According to the pie chart, there are more approved loans that disapproved.

# Distribution Analysis

```
grid=sns.FacetGrid(df, row='Gender', col='Married', size=2.2, aspect=1.6)
grid.map(plt.hist, 'ApplicantIncome', alpha=.5, bins=10)
grid.add_legend()
```

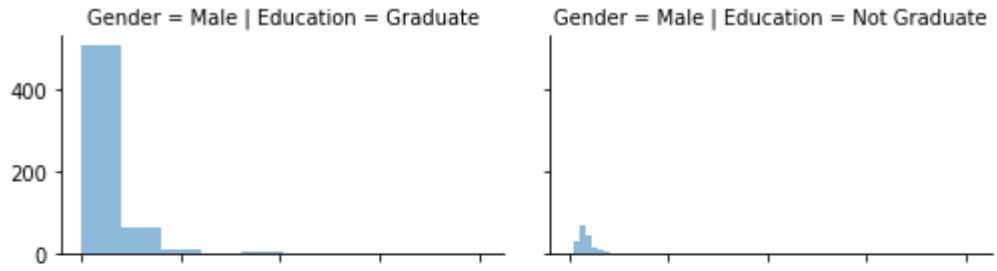
```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:316: UserWarning: The `size`
  warnings.warn(msg, UserWarning)
<seaborn.axisgrid.FacetGrid at 0x7f6d7545e550>
```




> Males have the highest income according to the data. Males that are married have greater income than unmarried male. And the same goes for females.

```
grid=sns.FacetGrid(df, row='Gender', col='Education', size=2.2, aspect=1.6)
grid.map(plt.hist, 'ApplicantIncome', alpha=.5, bins=10)
grid.add_legend()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:316: UserWarning: The `size`
  warnings.warn(msg, UserWarning)
<seaborn.axisgrid.FacetGrid at 0x7f6d75226850>
```



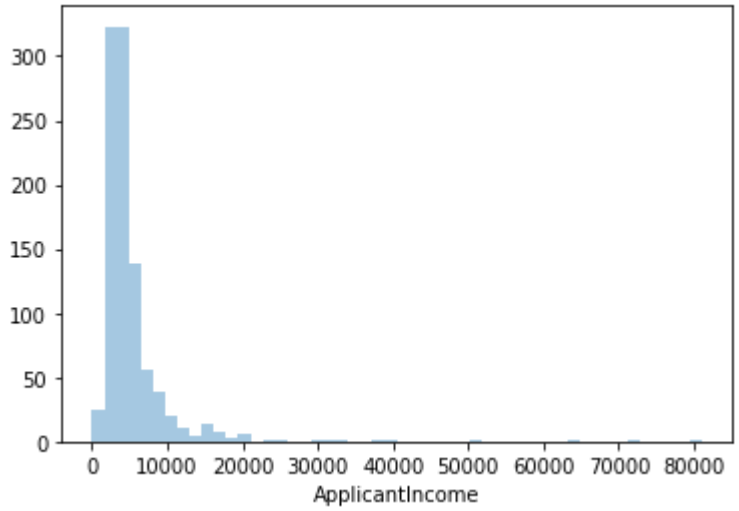

> A graduate who is a male has more income than a one whithout and the same goes for females.

Here I am exploring the distribution of the numerical variables mainly the Applicant income and the Loan amount.

What can be noticed are quite a few outliers.

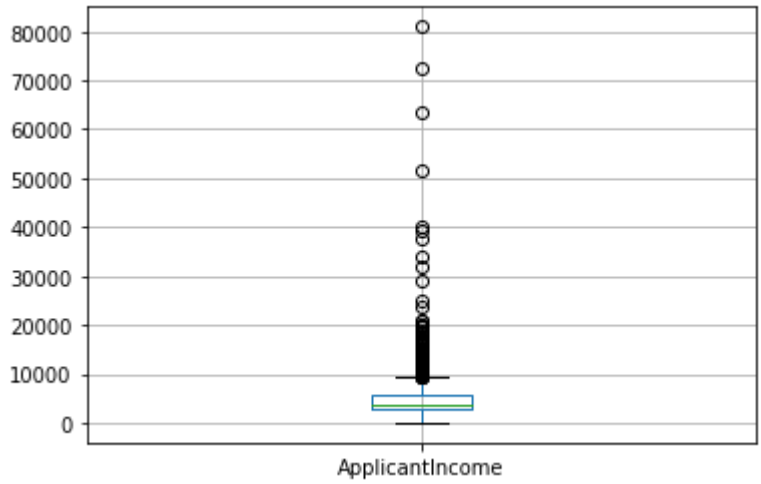
```
sns.distplot(df.ApplicantIncome,kde=False)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
```



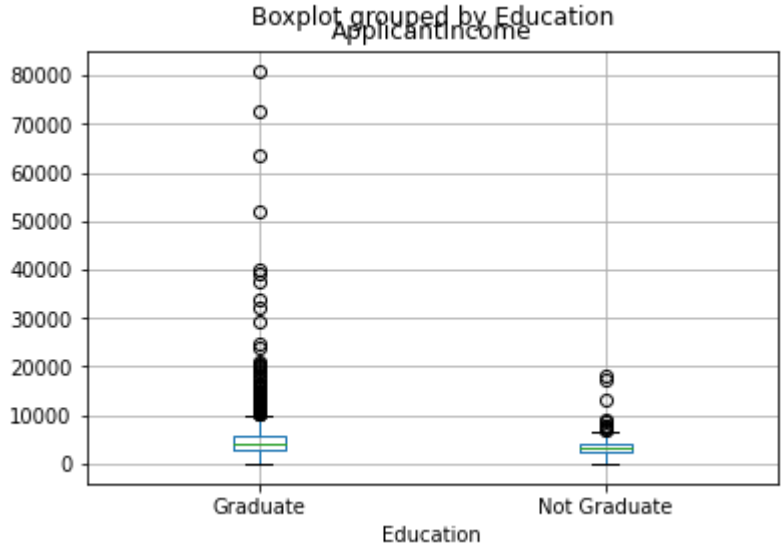

> People with better education should normally have a higher income, we can check that by plotting the education level against the income.

```
df.boxplot(column='ApplicantIncome')
plt.show()
```




```
df.boxplot(column='ApplicantIncome', by = 'Education')
plt.show()
```

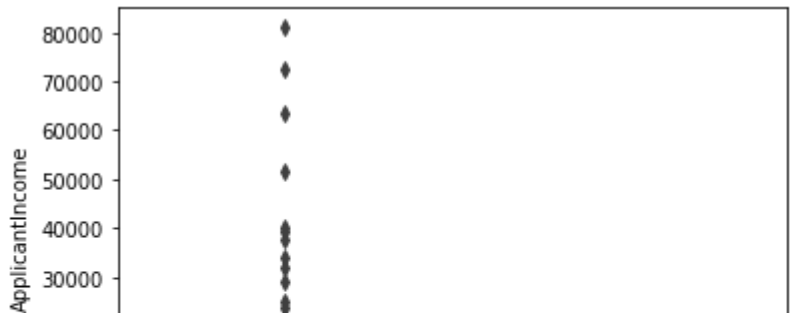
```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:83: VisibleDeprecationWarr
  return array(a, dtype, copy=False, order=order)
```




> We can conclude that there is no substantial different between the mean income of graduate and non-graduates. However, there are a higher number of graduates with very high incomes, which are appearing to be the outliers.

```
sns.boxplot(x='Education',y='ApplicantIncome',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d7502fb10>
```



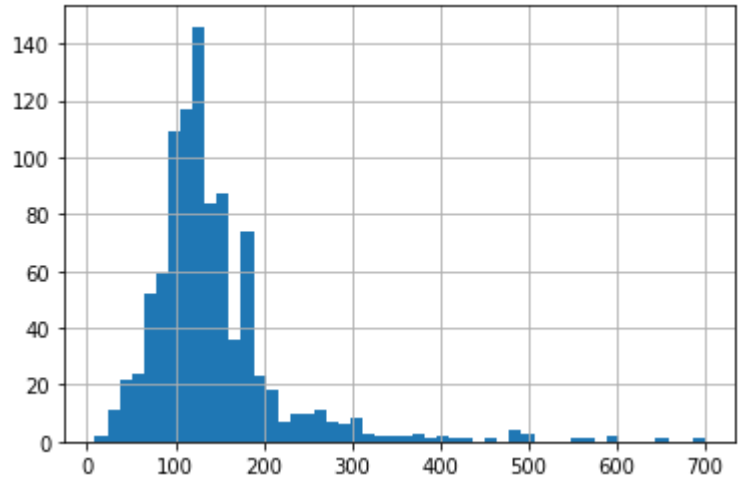

> The distributions shows that the graduates have more outliers which means that the people with huge income are most likely to be educated.

Education

Examining the data distributions of the features. I will start with the target variable, Loan Amount, to make sure it's normally distributed.

This is important because most machine learning algorithms make the assumption that the data is normally distributed. When data fits a normal distribution, statements about the price using analytical techniques will be made.

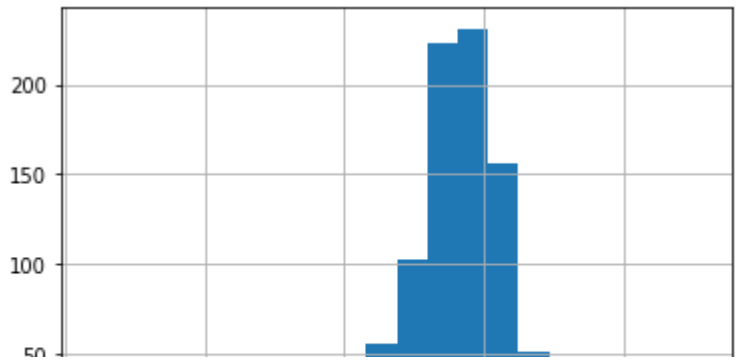
```
df['LoanAmount'].hist(bins=50)
plt.show()
```




Transforming the `Loan Amount` into normal distribution.

```
df['LoanAmount_log'] = np.log(df['LoanAmount'])
df['LoanAmount_log'].hist(bins=20)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d74ea0b50>
```




It can be seen that the `Loan Amount` distribution is not skewed after the transformation, but normally distributed.

> The transformed data will be used in in the dataframe and remove the skewed distribution: **Normally distributed** means that the data is symmetric about the mean, showing that data near the mean are more frequent in occurrence than data far from the mean.

Sometimes loan will be also given based on the co applicant income. Some people might have a low income, but strong CoappliantIncome, so a good idea would be to combine them in a TotalIncome column.

```
df['LoanAmount_log']=np.log(df['LoanAmount'])
df['TotalIncome']= df['ApplicantIncome'] + df['CoapplicantIncome']
df['TotalIncome_log']=np.log(df['TotalIncome'])
```

```
sns.distplot(df.TotalIncome,kde=False)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
```

# Probability of getting a loan

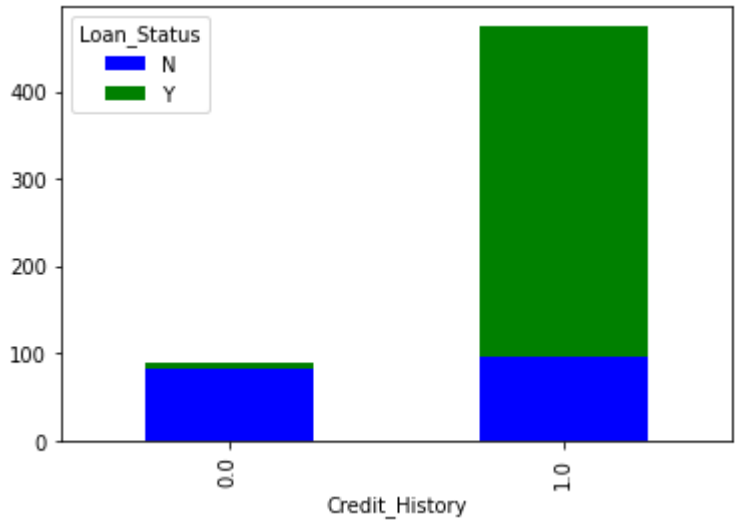
Checking the credit history from the dataset because it is a vital part of the decision whether a person is proper for a loan.

```
temp_credit = df['Credit_History'].value_counts(ascending=True)
print ('Frequency Table for Credit History:')
print (temp_credit)
```

```
Frequency Table for Credit History:
0.0    148
1.0    754
Name: Credit_History, dtype: int64
```

```
temp3 = pd.crosstab(df['Credit_History'], df['Loan_Status'])
temp3.plot(kind='bar', stacked=True, color=['blue','green'], grid=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d74cdd850>
```




> This shows that the chances of getting a loan are higher if the applicant has a valid credit history.

# Data cleaning & Data processing

Converting all categorical variables into numeric ones to use them in the training of the models.

One-Hot Encoding: This process takes categorical variables and converts them to a numerical representation without an arbitrary ordering. What computers know is numbers and for machine learning it is vital to accommodate the feautures into numeric values.

```
numeric_gender = {'Female': 1, 'Male': 2}
df ['Gender'] = df['Gender'].map(numeric_gender)
numeric_married = {'Yes': 1, 'No': 2}
df ['Married'] = df['Married'].map(numeric_married)
numeric_edu = {'Graduate': 1, 'Not Graduate': 2}
df ['Education'] = df['Education'].map(numeric_edu)
numeric_self = {'Yes': 1, 'No': 2}
df ['Self_Employed'] = df['Self_Employed'].map(numeric_self)
numeric_loan = {'Y': 1, 'N': 2}
df ['Loan_Status'] = df['Loan_Status'].map(numeric_loan)
numeric_property = {'Rural': 1, 'Urban': 2, 'Semiurban': 3}
df ['Property_Area'] = df['Property_Area'].map(numeric_property)
numeric_d = {'3+': 3}
df ['Dependents'] = df['Dependents'].map(numeric_d)
```

Checking if there are any null values and if so, which.

```
df.isnull().sum()
```

```
Loan_ID               0
Gender               24
Married               3
Dependents          890
Education             0
Self_Employed        55
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           27
Loan_Amount_Term     20
Credit_History       79
Property_Area         0
Loan_Status         367
LoanAmount_log       27
TotalIncome           0
TotalIncome_log       0
dtype: int64
```

Checking if the percentage of missing values of each value and whic has to be dropped if any.

```
# Find columns with missing values and their percent missing
df.isnull().sum()
miss_val = df.isnull().sum().sort_values(ascending=False)
miss_val = pd.DataFrame(data=df.isnull().sum().sort_values(ascending=False), columns=['Missva
```

```
# Add a new column to the dataframe and fill it with the percentage of missing values
miss_val['Percent'] = miss_val.MissvalCount.apply(lambda x : '{:.2f}'.format(float(x)/df.shap
miss_val = miss_val[miss_val.MissvalCount > 0].style.background_gradient(cmap='Reds')
miss_val
```

| | MissvalCount | Percent |
|---|---|---|
| **Dependents** | 890 | 90.72 |
| **Loan_Status** | 367 | 37.41 |
| **Credit_History** | 79 | 8.05 |
| **Self_Employed** | 55 | 5.61 |
| **LoanAmount_log** | 27 | 2.75 |
| **LoanAmount** | 27 | 2.75 |
| **Gender** | 24 | 2.45 |
| **Loan_Amount_Term** | 20 | 2.04 |
| **Married** | 3 | 0.31 |

> The light red color shows the small amount of NaN values. If the features were with a high than 50% of missing values, they would have to be removed. Yet, in this case, they have relatively low percentage so they can be used in future. Then, the NaN values will be replaced.

Filling up the null values in order to train the model.

Filling the missing values, for categorical we can fill them with the mode (the value with the highest frequency). The best practice is to use mode with data points such as salary field or any other kind of money.

```
df['Gender'] = df['Gender'].fillna(
df['Gender'].dropna().mode().values[0] )
df['Married'] = df['Married'].fillna(
df['Married'].dropna().mode().values[0] )
df['Dependents'] = df['Dependents'].fillna(
df['Dependents'].dropna().mode().values[0] )
df['Self_Employed'] = df['Self_Employed'].fillna(
df['Self_Employed'].dropna().mode().values[0] )
df['LoanAmount'] = df['LoanAmount'].fillna(
df['LoanAmount'].dropna().median() )
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(
df['Loan_Amount_Term'].dropna().mode().values[0] )
df['LoanAmount_log'] = df['LoanAmount_log'].fillna(
df['LoanAmount_log'].dropna().mode().values[0] )
df['Credit_History'] = df['Credit_History'].fillna(
df['Credit_History'].dropna().mode().values[0] )
df['Loan_Status'] = df['Loan_Status'].fillna(
df['Loan_Status'].dropna().mode().values[0] )
```

```
df['TotalIncome_log'] = df['TotalIncome_log'].fillna(
df['TotalIncome_log'].dropna().mode().values[0] )
```

Checking if there are still any empty values after the filling.

```
df.isnull().sum()
```

```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
LoanAmount_log       0
TotalIncome          0
TotalIncome_log      0
dtype: int64
```

Saving the results to a csv file so that the cleaned and processed data can be used in the modelling part of the project.

```
df.to_csv('results.csv')
```

# Conclusion

**From Data Analysis:**

1. There are features that are numeric and also objects. Later, the ones that are not numeric were converted into either float or int in order to be plotted and then used for the trainig of the models.
2. There were also missing values in the dataset, which will be handled later.
3. The shape of the data with the `shape` . Here are the the rows and columns(981, 13).
4. One diagram shows on one hand that there are more male applicants than female and on other hand, there are more approved loans than disapproved.

**From Distribution Analysis**

1. The amount of male applicants seems to be greater than the female ones and they tend to live in the semi suburban areas.
2. There are more positive than negative loan statuses - more approvals.
3. The distributions show that the graduates have more outliers which means that the people with huge income are most likely to be educated.
4. Males have the highest income according to the data. Males that are married have greater income that unmarried male. And the same goes for female. Therefore, there is a greater chance for educated and married people to receive a loan than applicant who are not.

**From Data Cleaning:**

1. There was a variety of values - both categorical and numeric. The categorical values had to be concerted to numeric in order to be used in the modelling part of the project.
2. After the data integration, NaN values occurred so they had to be handled in order to work with the data in the models. The values showed how much they are missing in percentage:

Dependents - 90.72

Loan_Status - 37.41

Credit_History - 8.05

Self_Employed - 5.61

LoanAmount_log - 2.75

LoanAmount - 2.75

Gender - 2.45

Loan_Amount_Term - 2.04

Married - 0.31