

▼ 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 several 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)
```

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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 training 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 training 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 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 columns 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 quantitative columns.

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

```
['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'Credit_History']
```

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 dataframe.

```
#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 training 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	LP001402	Male	No	0	Graduate	No	11000

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

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.)

422	LP001731	Male	Yes	0	Graduate	No	3250
------------	----------	------	-----	---	----------	----	------

```
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()
```

```
array([ 5720,  3076,  5000,  2340,  3276,  2165,  2226,  3881, 13633,
        2400,  3091,  2185,  4166, 12173,  4666,  5667,  4583,  3786,
        9226,  1300,  1888,  2083,  3909,  3765,  5400,    0,  4363,
        7500,  3772,  2942,  2478,  6250,  3268,  2783,  2740,  3150,
        7350,  2267,  5833,  3643,  5629,  3644,  1750,  6500,  3666,
        4260,  4163,  2356,  6792,  8000,  2419,  3500,  4116,  5293,
        2750,  4402,  3613,  2779,  4720,  2415,  7016,  4968,  2101,
        4490,  2917,  4700,  3445,  7666,  2458,  3250,  4463,  4083,
        3900,  4750,  3583,  3189,  6356,  3413,  7950,  3829, 72529,
        4136,  8449,  4456,  4635,  3571,  3066,  3235,  5058,  3188,
       13518,  4364,  4766,  4609,  6260,  3333,  9719,  6835,  4452,
        2262,  3901,  2687,  2243,  3417,  1596,  4513,  4500,  4523,
        4742,  4082,  2922,  4167,  4243,  1516,  1762,   724,  3125,
        2333,  3350,  2500, 12500,  4667,  3073,  3321,  3391,  3343,
        3620,  4000,  4258,   2014,  4727,  3089,  6794, 32000, 10890,
       12941,  8703,  5900,   3071,  2463,  4855,  1599,  4246,  4333,
        5823,  7895,  4150,  2964,  5583,  2708,  3180,  2268,  1141,
        3042,  3564,  3958,  4483,  5225,  3017,  2431,  4912,  2918,
        5128, 15312,  4334,  4358, 10166,  4521,  9167, 13083,  7874,
        3785,  2654, 10000,  4796,  2000,  2540,  1900,  8706,  2855,
        3016,  3159,  1937,  2613,  4960,  3074,  4213,  2038,  2362,
        5333,  5384,  5708,  3754,  2914,  2747,  7830,  3507,  3747,
        2166,  2896,  5062,  5184,  2545,  2553,  3436,  2412,  5180,
       14911,  2860,  1173,  7600,  2157,  2231,  2274,  6166,  2513,
        3844,  3887,  3510,  2539,  2107,  3186,  3943,  2925,  3242,
        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,
        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,
```

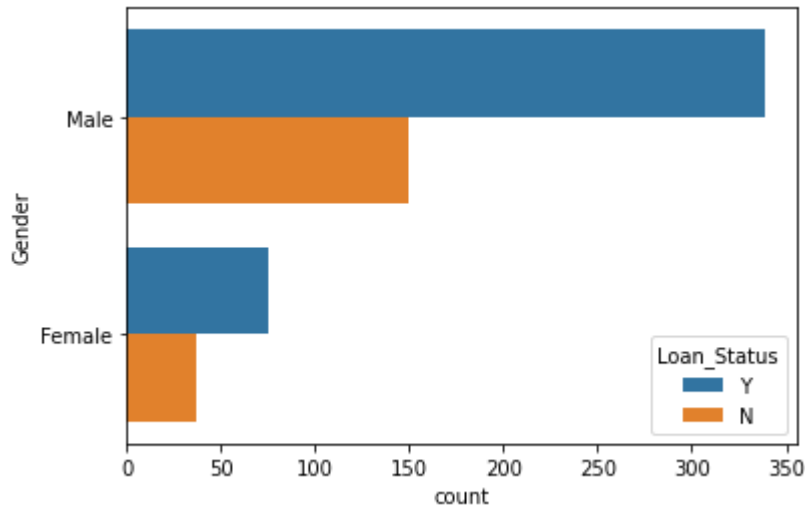
```

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,
1053, 3027, 2301, 1811, 20667, 3158, 3701, 1121, 9508

```

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

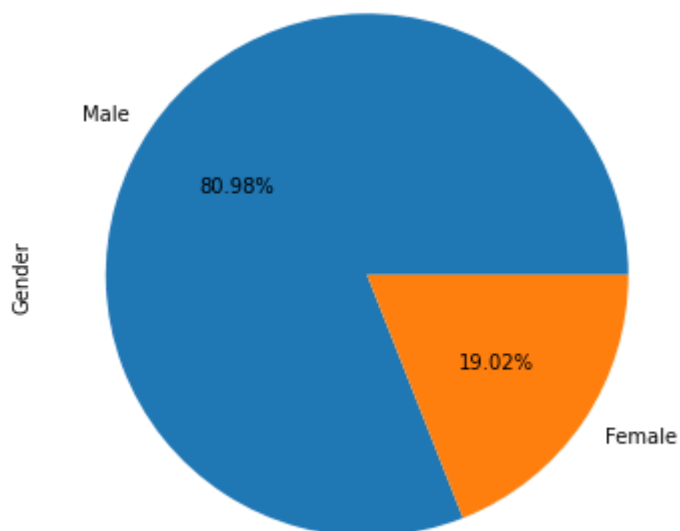
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d75513610>
```



The diagram shows on one hand that there are more male applicants than female and on other hand, there are more approved loans than disapproved.

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

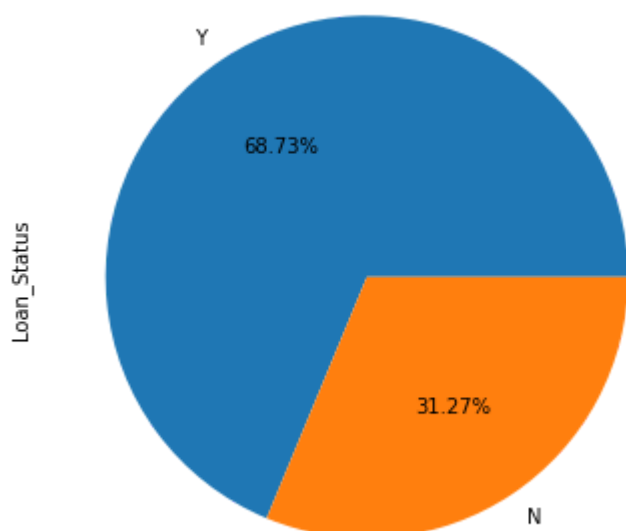
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d75497e90>
```



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>

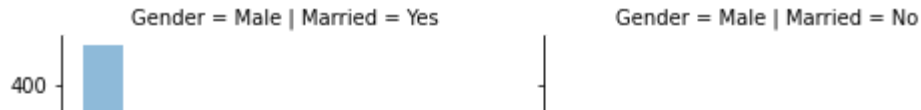


According to the pie chart, there are more approved loans than disapproved.

▼ 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>
```

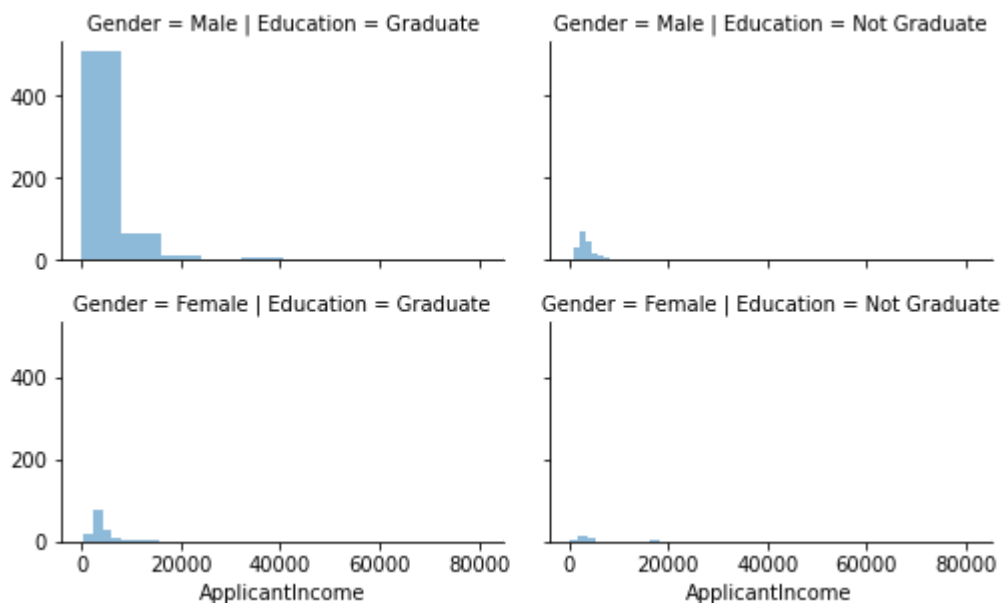


Males have the highest income according to the data. Males that are married have greater income than unmarried male. And the same goes for females.

Gender = Female | Married = Yes Gender = Female | Married = No

```
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>
```



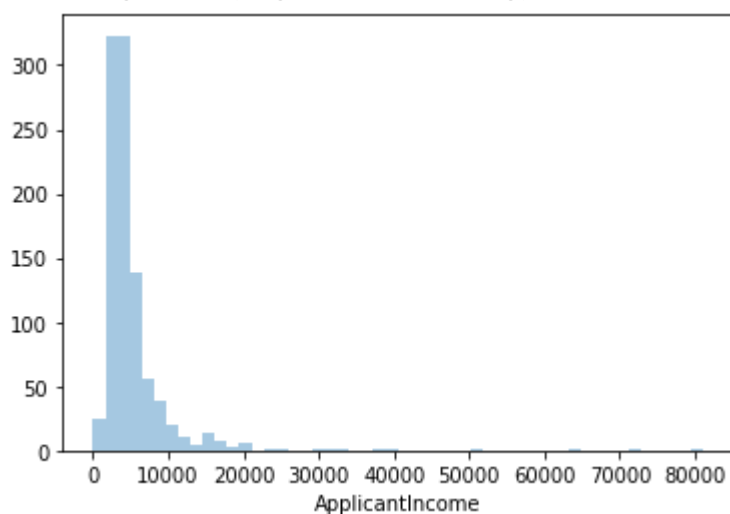
A graduate who is a male has more income than a one without and the same goes for females.

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.

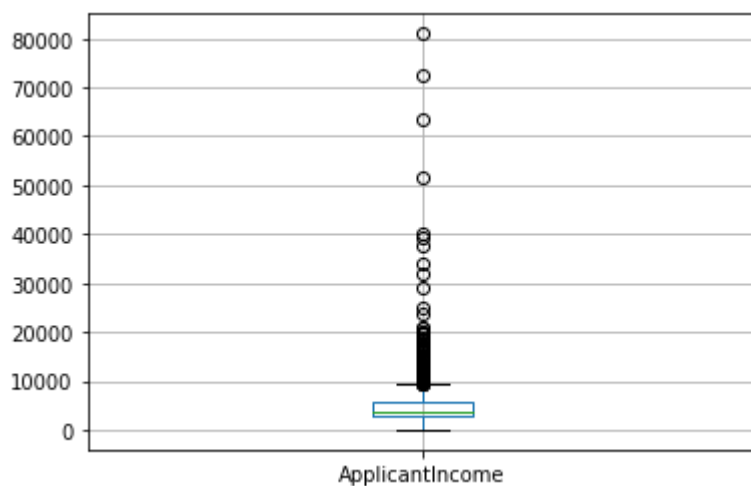
```
sns.distplot(df.ApplicantIncome,kde=False)
plt.show()
```

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

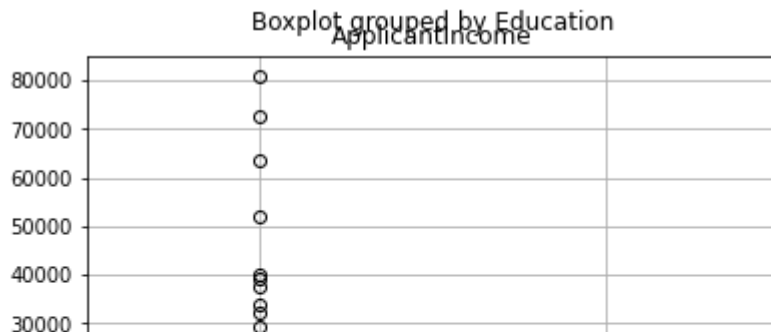
```
df.boxplot(column='ApplicantIncome')
plt.show()
```



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



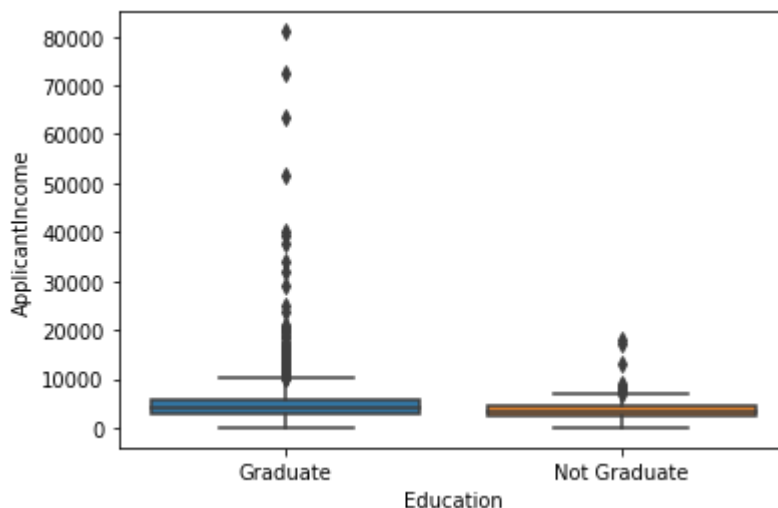
```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:83: VisibleDeprecationWarning
return array(a, dtype, copy=False, order=order)
```



We can conclude that there is no substantial difference 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>
```

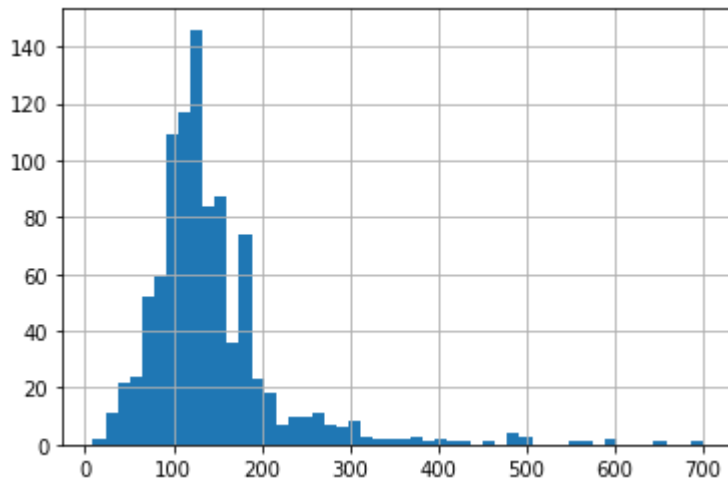


The distributions show that the graduates have more outliers which means that the people with huge income are most likely to be educated.

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.

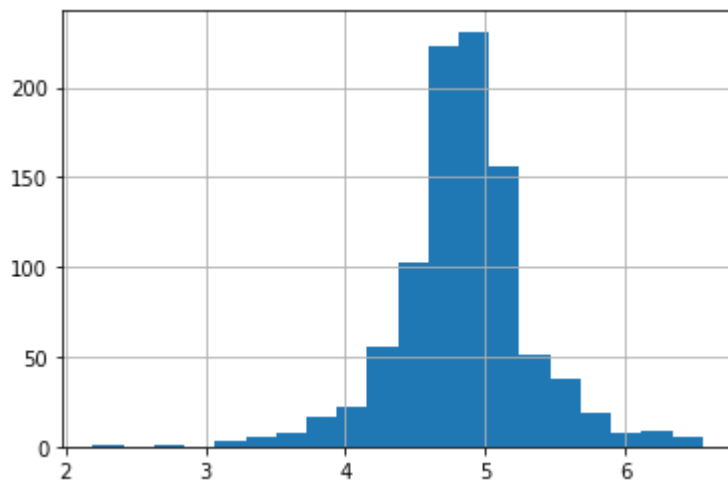
```
df['LoanAmount'].hist(bins=50)
plt.show()
```



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 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.

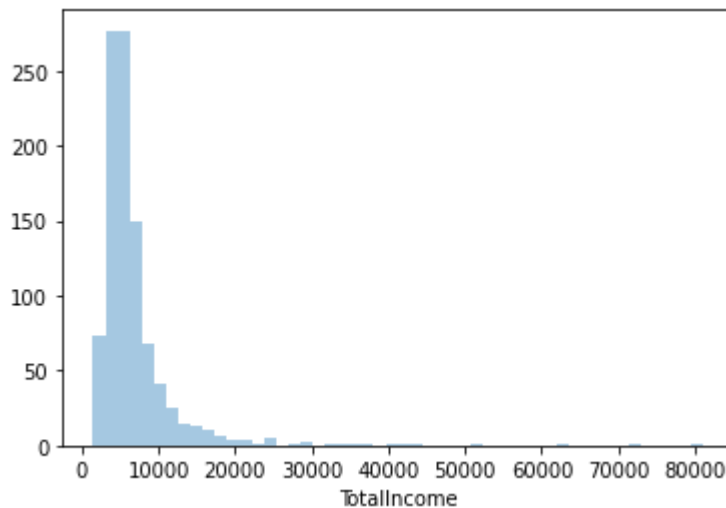
Sometimes loan will be also given based on the co applicant income. Some people might have a low income, but strong CoapplicantIncome, so a good idea would be to combine them in a

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
warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f6d74df8ad0>
```



► Probability of getting a loan

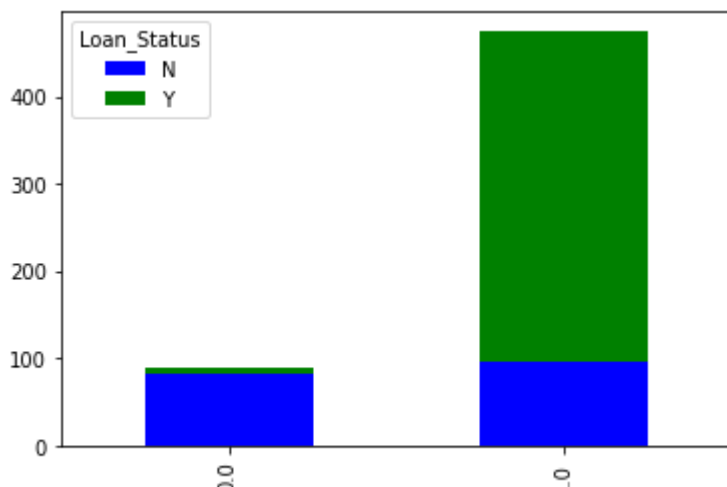
Checking the credit history from the dataset because it is a vital part of the decision whether a person is proper for a loan.

```
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 features 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()
```

```
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 which 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=['MissvalCount', 'Percent'])

# 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.shape[0]))
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 the Exploratory Data Analysis, it can be concluded:

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 than 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.