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


# 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 2 files

- **train.csv**(application/vnd.ms-excel) - 38013 bytes, last modified: 1/15/2020 - 100% done
- **train1.csv**(application/vnd.ms-excel) - 21957 bytes, last modified: 1/15/2020 - 100% done

```
Saving train.csv to train.csv
Saving train1.csv to train1.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
```

```
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
```

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

```
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

Data analysis:

Checking the dimension of the dataset and the features.

```
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

Here we can see the shape of our data with the `.shape`. Here we see (981, 13) this means that we have a 981 rows and 13 columns

```
df.shape
```

```
(981, 13)
```

Here we can see the shape of our test data with the .shape. Here we see (367, 12) this means that we have a 367 rows and 12 columns

To view what data that is stored we can use .columns. This will return the colums of our 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')
```

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

```
#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

```
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.

```
# 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
Loan_Status	367	37.41
Credit_History	79	8.05
Self_Employed	55	5.61
LoanAmount	27	2.75
Dependents	25	2.55

> 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.

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

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

Here we can see one row (one person)

```
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
1     160
2     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()
```

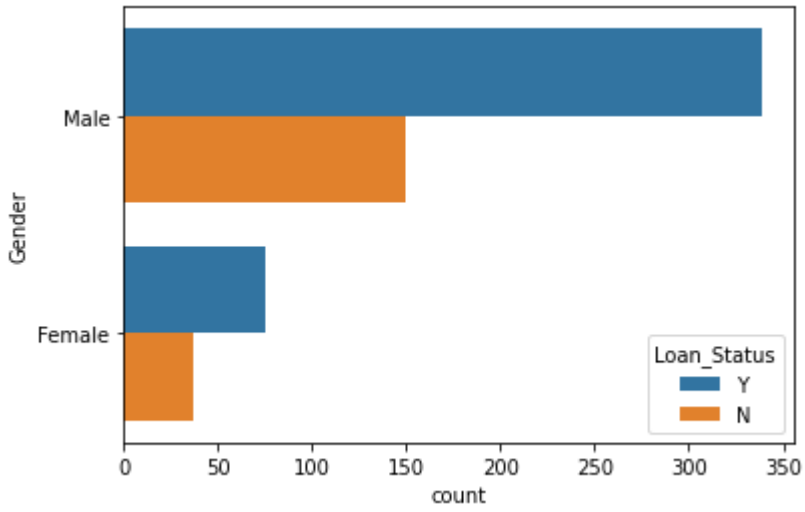
```
3863,  4028,  4010,  3719,  2858,  3833,  3007,  1850,  2792,
2982, 18840,  2995,  3579,  3835,  3854,  3508,  1635, 24797,
2773,  5769,  3634, 29167,  5530,  9000,  8750,  1972,  4983,
8333,  3667,  3166,  3271,  2241,  1792,  2666,  6478,  3808,
3729,  4120,  6300, 14987,   570,  2600,  2733,  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,
 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)
```

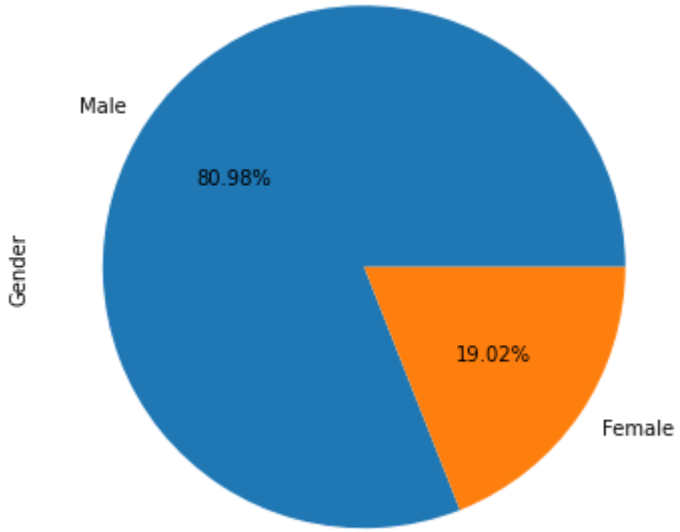
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f78900c5dd0>
```



> 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))
```

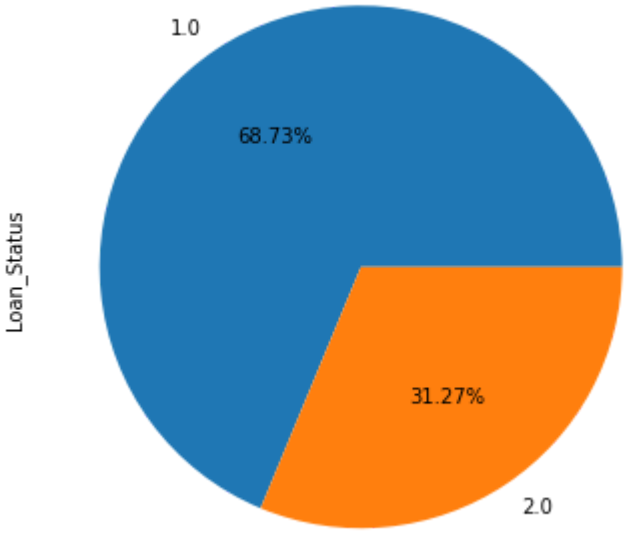
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7862d5cf90>
```



> 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))
```

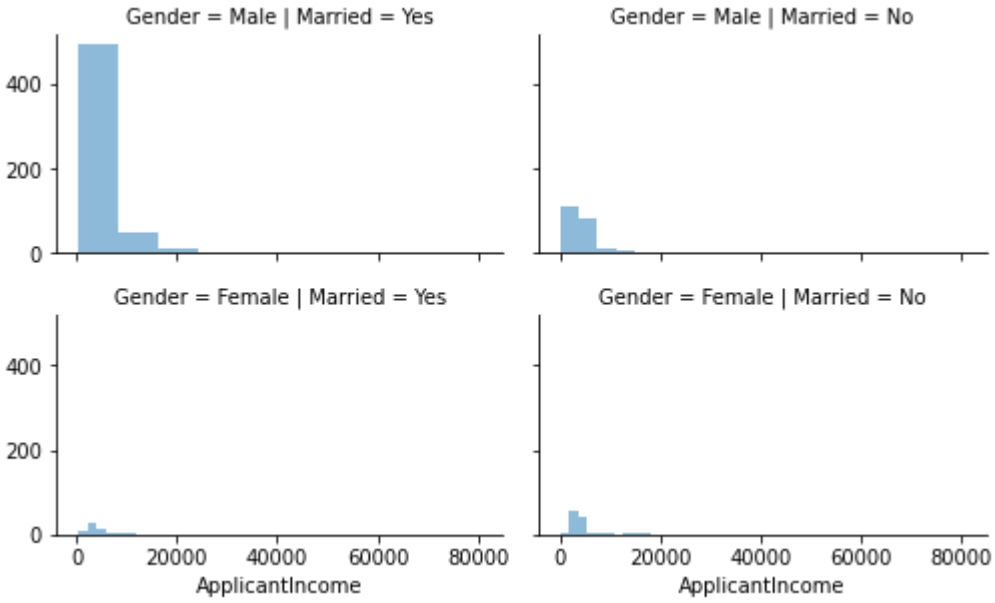
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f99cd11d410>
```



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

```
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()
```

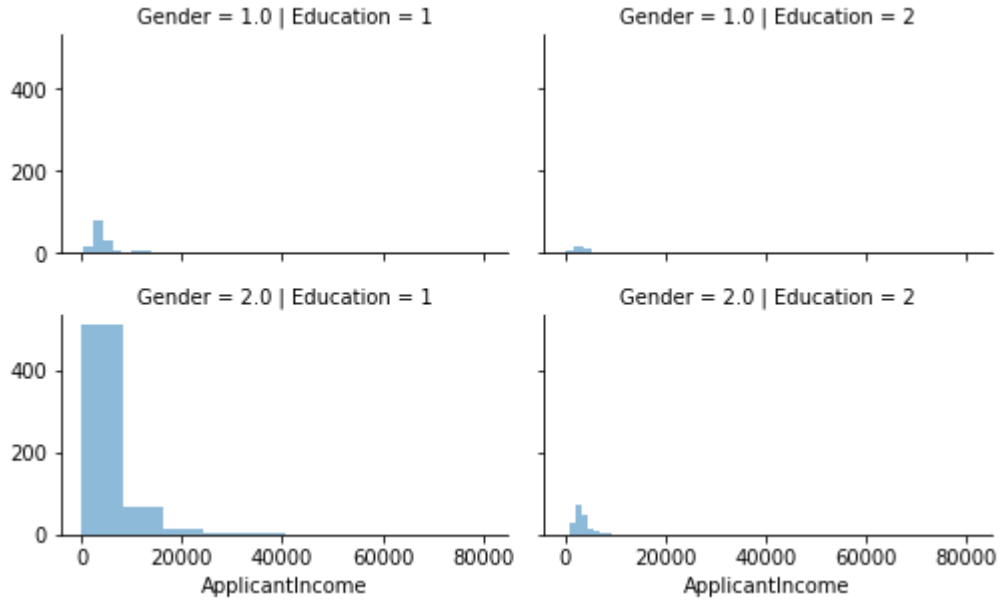
```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:316: UserWarning: The `size`
  warnings.warn(msg, UserWarning)
<seaborn.axisgrid.FacetGrid at 0x7f786227dd10>
```



> 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 0x7f99cb69e3d0>
```



> 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.

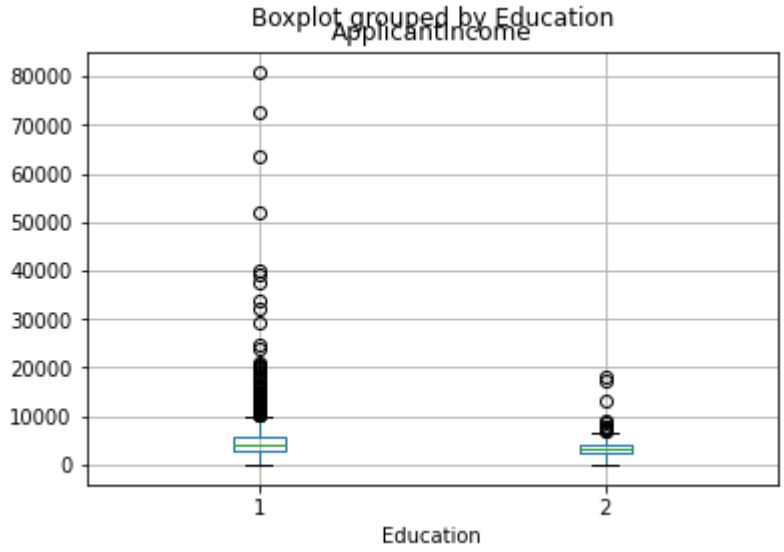
```
sns.distplot(df.ApplicantIncome,kde=False)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f99c262d090>
```

> 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', by = 'Education')
```

```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:83: VisibleDeprecationWarn
  return array(a, dtype, copy=False, order=order)
<matplotlib.axes._subplots.AxesSubplot at 0x7f99c2587fd0>
```



> 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.

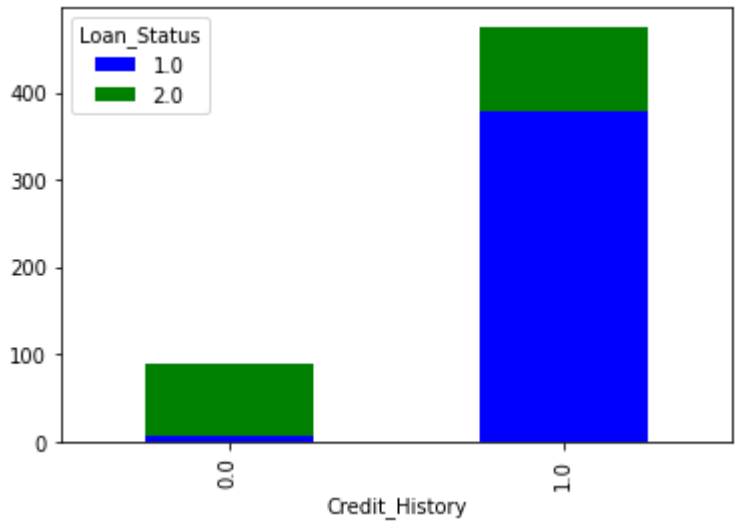
```
sns.boxplot(x='Education',y='ApplicantIncome',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f99c24be3d0>
```

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

```
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 0x7f99c23e5490>
```



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

Data cleaning

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

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

```
Loan_ID               0
Gender               24
Married               3
Dependents           25
Education             0
```

```
Self_Employed         55
ApplicantIncome        0
CoapplicantIncome      0
LoanAmount            27
Loan_Amount_Term      20
Credit_History        79
Property_Area          0
Loan_Status          367
dtype: int64
```

Converting the string values to numeric valuesto use them in the training of the models.

```
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)
```

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

```
df.fillna(0)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001015	2.0	1.0	0.0	1	2.0	5720
1	LP001022	2.0	1.0	0.0	1	2.0	3076

Data processing:

Checking if there are certain missing values that need to be fixed.

```
total = df.isnull().sum().sort_values(ascending=False)
percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(20)
```

	Total	Percent
Dependents	890	0.907238
Loan_Status	367	0.374108
Credit_History	79	0.080530
Self_Employed	55	0.056065
LoanAmount	27	0.027523
Gender	24	0.024465
Loan_Amount_Term	20	0.020387
Married	3	0.003058
Property_Area	0	0.000000
CoapplicantIncome	0	0.000000
ApplicantIncome	0	0.000000
Education	0	0.000000
Loan_ID	0	0.000000

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['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] )
```

Checking if there any empty values.

```
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
dtype: int64
```

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
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f99c2305950>
```

Modeling:

Encoding to numeric data in order to start the training of the models.

```
#drop the uniques loan id
df.drop('Loan_ID', axis = 1, inplace = True)
```

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

```
2.0    799
1.0    182
Name: Gender, dtype: int64
```

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

```
3.0    981
Name: Dependents, dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 981 entries, 0 to 613
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             981 non-null    float64
 1   Married            981 non-null    float64
 2   Dependents         981 non-null    float64
 3   Education          981 non-null    int64  
 4   Self_Employed      981 non-null    float64
 5   ApplicantIncome    981 non-null    int64  
 6   CoapplicantIncome  981 non-null    float64
 7   LoanAmount         981 non-null    float64
 8   Loan_Amount_Term   981 non-null    float64
 9   Credit_History     981 non-null    float64
 10  Property_Area      981 non-null    int64  
 11  Loan_Status        981 non-null    float64
```

```
 12  LoanAmount_log     981 non-null    float64
 13  TotalIncome        981 non-null    float64
 14  TotalIncome_log    981 non-null    float64
dtypes: float64(12), int64(3)
memory usage: 142.6 KB
```

Need to covnvert the object values to numeric ones - `Dependents` needs to become an int.

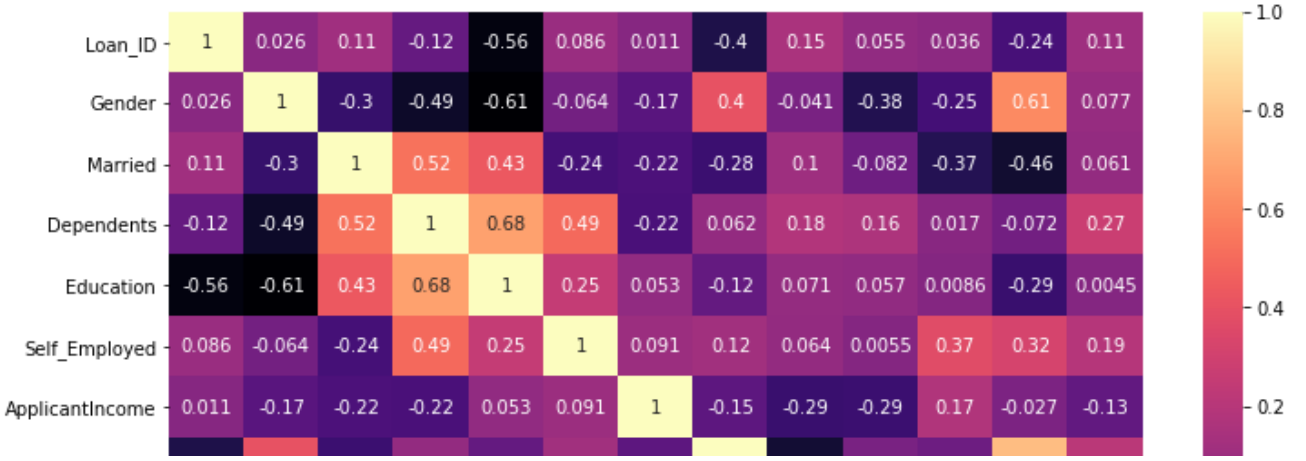
Heatmaps are very useful to find relations between two variables in a dataset and this way the user gets a visualisation of the numeric data. No correlations are extremely high. Each square shows the correlation between the variables on each axis.

- The correlations between the feautures can be explained:

> The close to 1 the correlation is the more positively correlated they are; that is as one increases so does the other and the closer to 1 the stronger this relationship is. It is noticable that the correlation between the `ApplicantIncome` and `LoanAmount` is 0.57, which mean that they have a positive correlation, but not strong.

```
from pandas import DataFrame
%matplotlib inline
plt.figure(figsize=(12, 8))
df_temp = df.copy()
Index= df.columns
Cols = df.columns
df_temp = DataFrame(abs(np.random.randn(13, 13)), index=Index, columns=Cols)

sns.heatmap(df_temp.corr(), annot=True, cmap = 'magma')
plt.show()
```



Importing sklearn libraries

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
```

Splitting into train and test set after choosing the right features X and labels y

```
y = df['Loan_Status']
X = df.drop('Loan_Status', axis = 1)
```

To split the dataset, I will use random sampling with 80/20 train-test split; that is, 80% of the dataset will be used for training and set aside 20% for testing:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=0)
```

Analyzing the numeric features.

```
numeric_features = df.select_dtypes(include=[np.number])
```

```
numeric_features.columns
```

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

```
# use only those input features with numeric data type
df = df.select_dtypes(include=["int64","float64"])
```

```
# set the target and predictors
y = df.Loan_Status  # target

# use only those input features with numeric data type
df_temp = df.select_dtypes(include=["int64","float64"])

X = df_temp.drop(["Loan_Status"],axis=1)  # predictors
```

Three models will be built and evaluated by their performances with R-squared metric. Additionally, insights on the features that are strong predictors of house prices, will be analised .

Logistic Regression

```
model = LogisticRegression()
model.fit(X_train, y_train)
y_reg=model.predict(X_test)
evaluation = f1_score(y_test, y_reg)
evaluation
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:940: Convergenc
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
0.8869565217391304
```

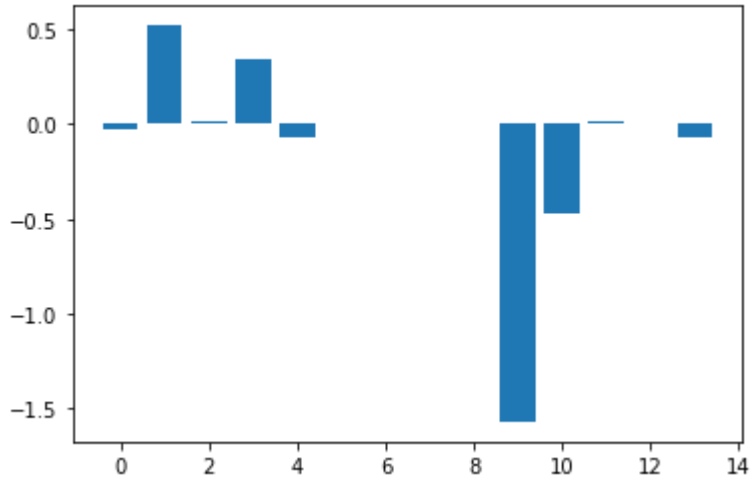
Reporting the coefficient value for each feature. Notice that the coefficients are both positive and negative. The positive scores indicate a feature that predicts class 1, whereas the negative scores indicate a feature that predicts class 0.

> The importance of a feature is measured by calculating the increase in the model's prediction error after permuting the feature. A feature is "important" if shuffling its values increases the model error, because in this case the model relied on the feature for the prediction.

```
# get importance
importance = model.coef_[0]
# summarize feature importance
for i,v in enumerate(importance):
```

```
  print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

```
Feature: 0, Score: -0.03256
Feature: 1, Score: 0.51781
Feature: 2, Score: 0.00937
Feature: 3, Score: 0.34609
Feature: 4, Score: -0.06700
Feature: 5, Score: -0.00001
Feature: 6, Score: 0.00002
Feature: 7, Score: 0.00291
Feature: 8, Score: -0.00062
Feature: 9, Score: -1.56869
Feature: 10, Score: -0.47370
Feature: 11, Score: 0.01679
Feature: 12, Score: 0.00001
Feature: 13, Score: -0.06696
```



> This might mean that your model is underfit (not enough iteration and it has not used the feature enough) or that the feature is not good and you can try removing it to improve final quality.

Decision tree:

1. Creating classifier
2. Fitting classifier with train data

```
tree = DecisionTreeClassifier()
tree.fit(X_train, y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
```

```
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

Do predictions on a test set. **Testing** the model by testing the test data.

```
y_tree=tree.predict(X_test)
print(y_tree)
```

```
[1. 1. 1. 2. 1. 1. 1. 1. 1. 2. 1. 1. 2. 2. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1.
 1. 1. 1. 1. 2. 1. 2. 1. 1. 2. 1. 1. 1. 2. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1.
 2. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1. 2. 1. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1.
 1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 2. 1. 2. 2. 1. 2. 1. 1.
 2. 1. 1. 1. 2. 2. 1. 2. 1. 1. 2. 2. 1. 1. 1. 2. 1. 1. 1. 2. 2. 2. 1. 1.
 1. 1. 2. 1. 1. 1. 1. 1. 2. 1. 2. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1. 2. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 2. 1. 1.
 1. 1. 2. 2. 1.]
```

Evaluate classsifier, measure accuracy, which is 0.76

```
evaluation = f1_score(y_test, y_tree)
evaluation
```

```
0.8737864077669903
```

Random forests

```
forest = RandomForestClassifier()
forest.fit(X_train, y_train)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

Testing the model by testing the test data.

```
y_forest=forest.predict(X_test)
print(y_forest)
```

```
[1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 2. 1. 1. 2. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 2. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1.
```

```
1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 2. 1. 2. 1. 1.
2. 1. 2. 1. 2. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 2. 1. 1.
1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1.
1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 1. 1. 1. 1. 1. 1. 1. 1. 1. 2. 2. 1. 1.
1. 1. 1. 1. 1.]
```

Result of the **accuracy**.

```
evaluation_f= f1_score(y_test, y_forest)
evaluation_f
```

```
0.9003021148036254
```

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 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 the Modelling, it can be concluded:

1. After the exploring of different types of modelling, that the more accurate model is Logistic Regression than Decision tree.
2. From the evaluation of the three models, it can be noticed that the Random forest performed better than others

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