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

) - 38013 bytes, last modified: 1/15/2020 - 100% done

Saved successfully!

l) - 21957 bytes, last modified: 1/15/2020 - 100% done

```
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
```

Saved successfully!

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:

Saved successfully! 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.

Saved successfully!

	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)
```

Saved successfully!

> 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]
```

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
				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

Saved successfully!

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

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

Saved successfully!

es	0	Graduate	No	14683	2100.0	304.0
es	1	Graduate	No	6083	4250.0	330.0
lo	0	Graduate	No	2060	2209.0	134.0
lo	1	Graduate	No	3481	0.0	155.0
lo	0	Graduate	No	7200	0.0	120.0
es	1	Graduate	No	2882	1843.0	123.0
es	0	Graduate	NaN	3716	0.0	42.0
es	1	Graduate	No	2491	2054.0	104.0
lo	0	Graduate	Yes	6400	0.0	200.0
lo	0	Graduate	No	8333	3750.0	187.0
es	0	Graduate	No	3416	2816.0	113.0
lo	0	Graduate	Yes	11000	0.0	83.0
lo	2	Graduate	No	4923	0.0	166.0
lo	0	Graduate	No	3244	0.0	80.0
lo	0	Graduate	No	2479	0.0	59.0
lo	0	Graduate	No	3418	0.0	127.0
lo	0	Graduate	No	10000	0.0	214.0
			No	3430	1250.0	128.0
			Yes	7787	0.0	240.0
es	0	Graduate	No	3173	3021.0	137.0
es	0	Graduate	No	150	1800.0	135.0
es	0	Graduate	No	3727	1775.0	131.0
es	2	Graduate	NaN	5000	0.0	72.0
es	2	Graduate	No	4283	2383.0	127.0
es	0	Graduate	No	2221	0.0	60.0
es	2	Graduate	No	4009	1717.0	116.0
lo	0	Graduate	No	2971	2791.0	144.0
es	0	Graduate	No	7578	1010.0	175.0
es	0	Graduate	No	6250	0.0	128.0
es	0	Graduate	No	3250	0.0	170.0
es	2	Graduate	No	6250	1695.0	210.0
N	NaN	Graduate	No	4758	0.0	158.0

Saved successfully!

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
```



```
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
```

Saved successfully!

```
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()
```

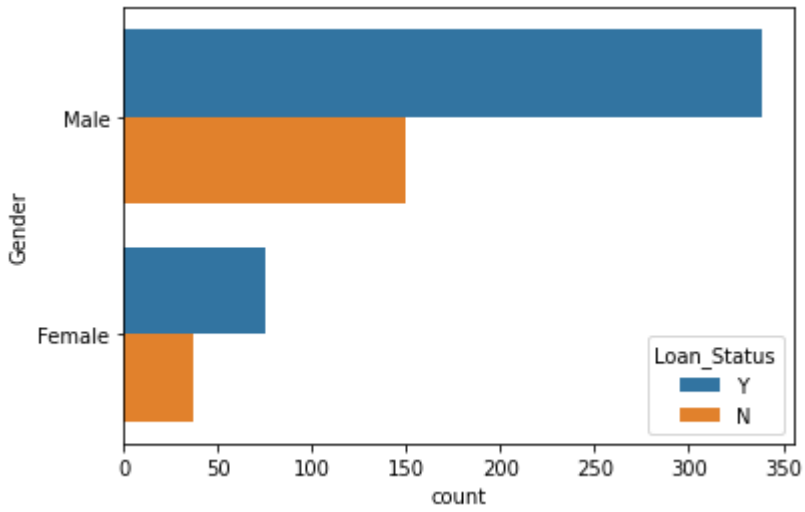
```
            3863,  4028,  4010,  3719,  2858,  3833,  3007,  1850,  2792,
            2982, 18840,  2995,  3579,  3835,  3854,  3508,  1635, 24797,
            2773,  5769,  3634, 29167,  5530,  9000,  8750,  1972,  4983,
            8333,  3667,  3166,  3271,  2241,  1792,  2666,  6478,  3808,
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

Saved successfully!

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

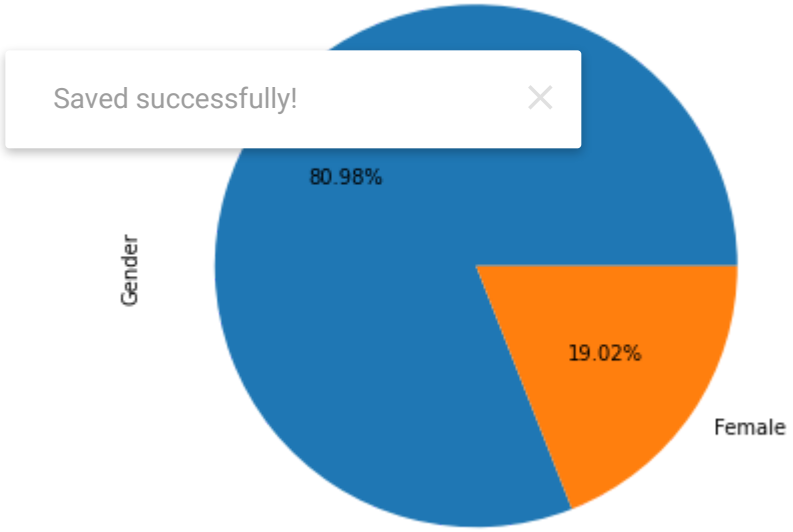
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f39041c2b90>
```



> 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))
```

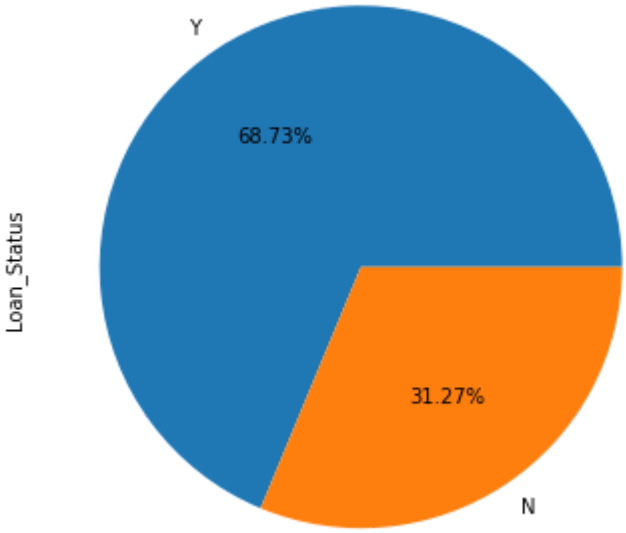
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3903a07710>
```



> 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))
```

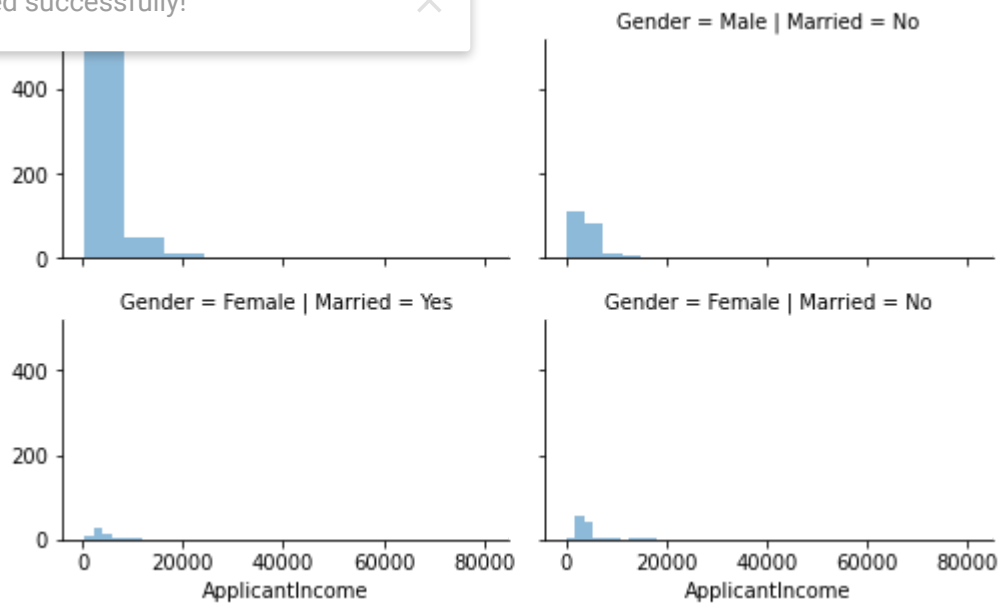
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f39039e0bd0>
```



> 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()
```

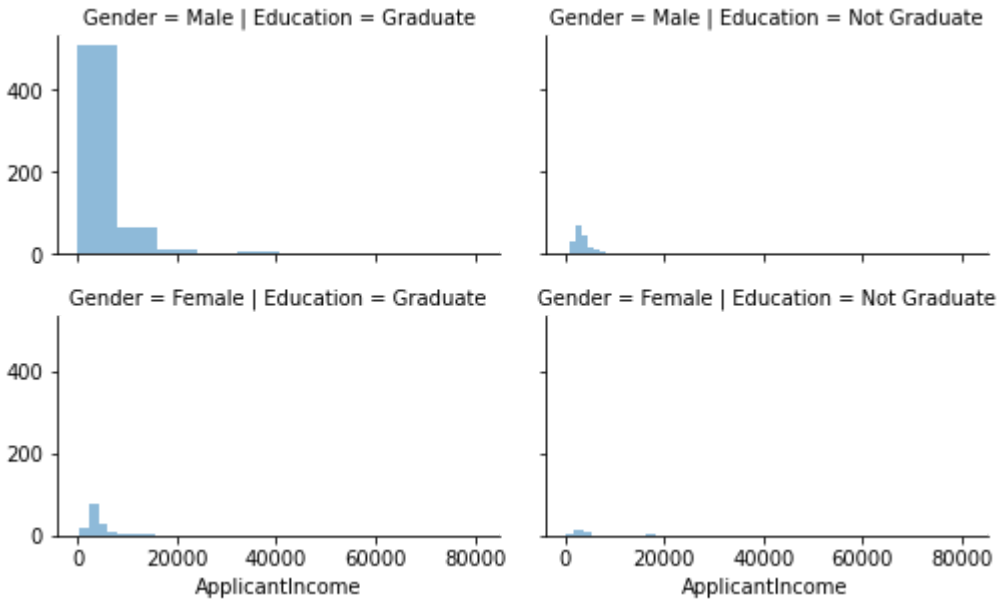
```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:316: UserWarning: The `size`
  warnings.warn(msg, UserWarning)
                                                    0x7f39039abb10>
```

> 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` p
 warnings.warn(msg, UserWarning)
seaborn.axisgrid.FacetGrid at 0x7f38faf7a490>
```



e income than a one whithout and the same goes

Saved successfully!

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.

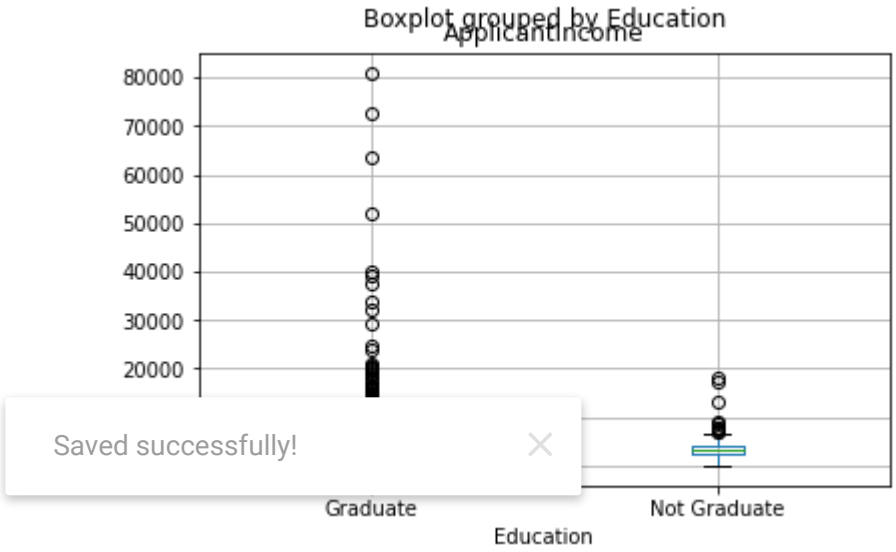
```
sns.distplot(df.ApplicantIncome,kde=False)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f38fad67610>
```

> 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 0x7f38fac43b10>
```



> 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.

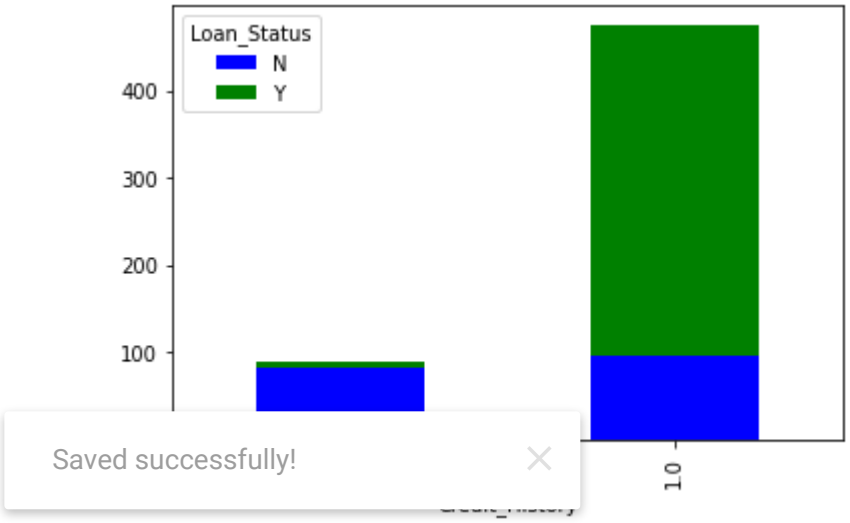
```
sns.boxplot(x='Education',y='ApplicantIncome',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f38fabfc7d0>
```

> 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 0x7f38fab1db90>
```



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> 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.

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)
                                    an': 2, 'Semiurban': 3}
                                    Area'].map(numeric_property)
df ['Dependents'] = df['Dependents'].map(numeric_d)
```


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

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

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplican
0	2.0	1.0	0.0	1	2.0	5720	
1	2.0	1.0	0.0	1	2.0	3076	
2	2.0	1.0	0.0	1	2.0	5000	
3	2.0	1.0	0.0	1	2.0	2340	
4	2.0	2.0	0.0	2	2.0	3276	

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)
```

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	Total	Percent
Dependents	890	0.907238
Loan_Status	367	0.374108
Credit_History	79	0.080530

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.

Gender	24	0.024465

```
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] )
```

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Checking if there any empty values:

Loan_ID_LP001660	0	0.000000

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

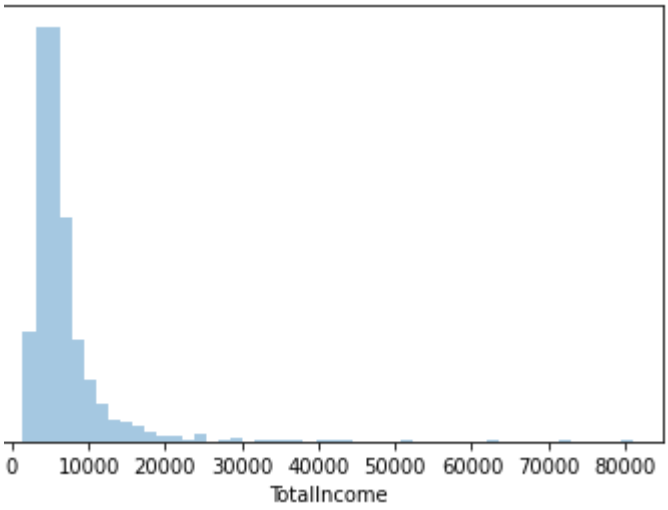
```
Gender              0
Married             0
Dependents          0
Education           0
Self_Employed       0
                   ..
Loan_ID_LP002983    0
Loan_ID_LP002984    0
Loan_ID_LP002986    0
Loan_ID_LP002989    0
Loan_ID_LP002990    0
Length: 993, dtype: int64
```

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)
```

```
local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `distplo
nings.warn(msg, FutureWarning)
lotlib.axes._subplots.AxesSubplot at 0x7f38f69576d0>
```



Modeling:

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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)
```

```
KeyError                                  Traceback (most recent call last)
```

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

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

```
/usr/local/lib/python3.7/dist-packages/pandas/core/indexes/base.py in drop(self,
```

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

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

```
   5289         return self.delete(indexer)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 981 entries, 0 to 613
Columns: 996 entries, Gender to TotalIncome_log
dtypes: float64(12), int64(3), uint8(981)
memory usage: 1.1 MB
```

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

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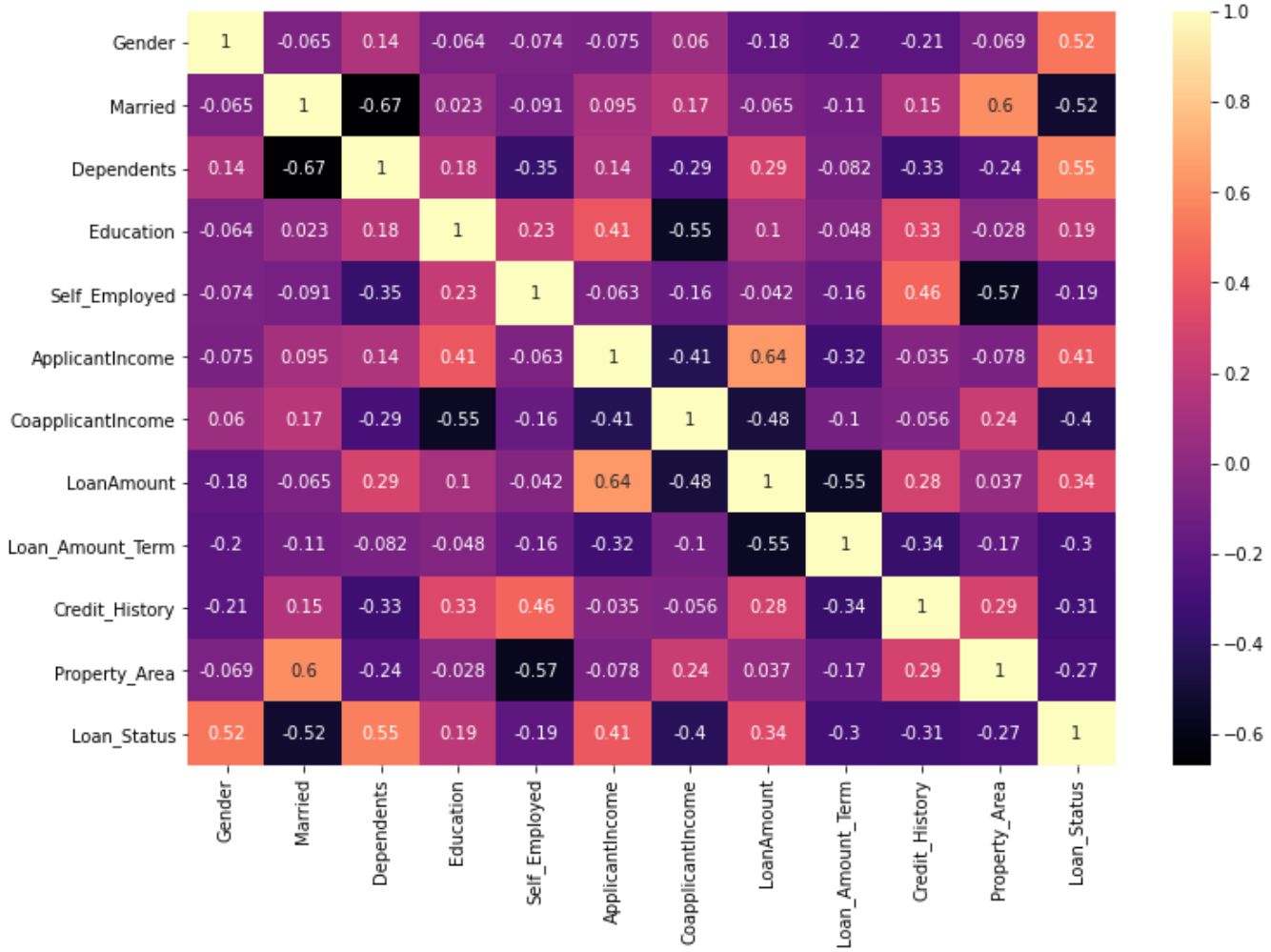
ach axis.

utures 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= ['Gender', 'Married',  'Dependents', 'Education',  'Self_Employed',  'ApplicantIncome'
Cols = ['Gender', 'Married',  'Dependents', 'Education',  'Self_Employed',  'ApplicantIncome'
df_temp = DataFrame(abs(np.random.randn(12, 12)), index=Index, columns=Cols)

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



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```
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',
       ...
       'Loan_ID_LP002979', 'Loan_ID_LP002980', 'Loan_ID_LP002983',
       'Loan_ID_LP002984', 'Loan_ID_LP002986', 'Loan_ID_LP002989',
       'Loan_ID_LP002990', 'LoanAmount_log', 'TotalIncome', 'TotalIncome_log'],
      dtype='object', length=996)
```

```
# 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
```


d 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)
0.8914956011730205
```

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: 495, Score: -0.00848
Feature: 496, Score: 0.00000
Feature: 497, Score: -0.00744
Feature: 498, Score: 0.00000
Feature: 499, Score: -0.00823
Feature: 500, Score: -0.00853
Feature: 501, Score: -0.00850
Feature: 502, Score: -0.00816
Feature: 503, Score: -0.00835
Feature: 504, Score: -0.00702
Feature: 505, Score: -0.00814
Feature: 506, Score: 0.00000
Feature: 507, Score: -0.00818
Feature: 508, Score: -0.00757
Feature: 509, Score: -0.00781
Feature: 510, Score: 0.00000
Feature: 511, Score: -0.00795
Feature: 512, Score: -0.00984
Feature: 513, Score: 0.00000
Feature: 514, Score: -0.00721
Feature: 515, Score: -0.00741
Feature: 516, Score: -0.00770
Feature: 517, Score: 0.03620
Feature: 518, Score: -0.00777
Feature: 519, Score: -0.00732
Feature: 520, Score: -0.00855
Feature: 521, Score: -0.00920
Feature: 522, Score: -0.00809
Feature: 523, Score: -0.00682
Feature: 524, Score: -0.01228
Feature: 525, Score: -0.00863
```

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```
Feature: 529, Score: -0.00893
Feature: 530, Score: -0.01035
Feature: 531, Score: -0.00959
Feature: 532, Score: -0.01204
Feature: 533, Score: -0.00836
Feature: 534, Score: -0.00758
Feature: 535, Score: 0.00000
Feature: 536, Score: -0.00786
Feature: 537, Score: 0.00000
Feature: 538, Score: -0.00884
Feature: 539, Score: -0.00783
Feature: 540, Score: 0.00000
Feature: 541, Score: -0.00870
Feature: 542, Score: -0.00756
Feature: 543, Score: -0.00744
Feature: 544, Score: -0.00876
Feature: 545, Score: -0.00796
Feature: 546, Score: -0.00808
Feature: 547, Score: 0.00000
Feature: 548, Score: -0.00771
Feature: 549, Score: -0.00867
Feature: 550, Score: 0.00000
Feature: 551, Score: -0.01034
```

```
Feature: 552, Score: 0.03432
Feature: 553, Score: 0.00000
Feature: 554, Score: 0.03447
Feature: 555, Score: 0.00000
Feature: 556, Score: -0.00772
Feature: 557, Score: 0.00000
Feature: 558, Score: -0.00830
Feature: 559, Score: -0.00785
Feature: 560, Score: -0.00838
Feature: 561, Score: -0.00698
Feature: 562, Score: 0.00000
Feature: 563, Score: 0.00000
Feature: 564, Score: 0.03417
Feature: 565, Score: -0.00822
Feature: 566, Score: -0.00977
Feature: 567, Score: -0.01051
Feature: 568, Score: -0.00799
Feature: 569, Score: 0.00000
Feature: 570, Score: -0.00838
Feature: 571, Score: 0.00000
Feature: 572, Score: -0.00820
Feature: 573, Score: -0.00792
Feature: 574, Score: -0.00801
Feature: 575, Score: -0.00858
Feature: 576, Score: 0.00000
Feature: 577, Score: -0.00746
Feature: 578, Score: 0.00000
Feature: 579, Score: -0.00864
Feature: 580, Score: 0.03718
Feature: 581, Score: -0.00878
Feature: 582, Score: -0.00779
Feature: 586, Score: -0.00797
Feature: 587, Score: -0.00837
Feature: 588, Score: -0.00774
Feature: 589, Score: -0.00824
Feature: 590, Score: 0.03613
Feature: 591, Score: 0.00000
Feature: 592, Score: 0.00000
Feature: 593, Score: -0.00836
Feature: 594, Score: 0.03595
Feature: 595, Score: 0.03531
Feature: 596, Score: -0.00763
Feature: 597, Score: 0.02714
Feature: 598, Score: -0.00931
Feature: 599, Score: -0.00544
Feature: 600, Score: -0.01062
Feature: 601, Score: -0.00756
Feature: 602, Score: -0.01413
Feature: 603, Score: 0.03563
Feature: 604, Score: -0.00808
Feature: 605, Score: 0.00000
Feature: 606, Score: -0.00761
Feature: 607, Score: -0.00821
Feature: 608, Score: -0.00830
Feature: 609, Score: -0.00741
```

Saved successfully!