loan-data-prediction-1

January 14, 2024

[ ]:

[2]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
from IPython import display
```

Loading the data

[3]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

Copy the path of the file in the drive. You can also change the Directory.

[4]:
```python
df = pd.read_csv('/content/drive/MyDrive/datasets/credit_risk_dataset.csv')
```

[5]:
```python
df.head(10)
```

[5]:
```
   person_age  person_income person_home_ownership  person_emp_length  \
0          22          59000                  RENT              123.0
1          21           9600                   OWN                5.0
2          25           9600              MORTGAGE                1.0
3          23          65500                  RENT                4.0
4          24          54400                  RENT                8.0
5          21           9900                   OWN                2.0
6          26          77100                  RENT                8.0
7          24          78956                  RENT                5.0
8          24          83000                  RENT                8.0
9          21          10000                   OWN                6.0

  loan_intent loan_grade  loan_amnt  loan_int_rate  loan_status  \
0    PERSONAL          D      35000          16.02            1
1   EDUCATION          B       1000          11.14            0
2     MEDICAL          C       5500          12.87            1
```

```
3     MEDICAL          C      35000         15.23            1
4     MEDICAL          C      35000         14.27            1
5     VENTURE          A       2500          7.14            1
6   EDUCATION          B      35000         12.42            1
7     MEDICAL          B      35000         11.11            1
8    PERSONAL          A      35000          8.90            1
9     VENTURE          D       1600         14.74            1

   loan_percent_income cb_person_default_on_file  cb_person_cred_hist_length
0                 0.59                         Y                           3
1                 0.10                         N                           2
2                 0.57                         N                           3
3                 0.53                         N                           2
4                 0.55                         Y                           4
5                 0.25                         N                           2
6                 0.45                         N                           3
7                 0.44                         N                           4
8                 0.42                         N                           2
9                 0.16                         N                           3
```

Size and information of the dataset

[6]:
```
df.shape
```

[6]:
```
(32581, 12)
```

[7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32581 entries, 0 to 32580
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   person_age                  32581 non-null  int64
 1   person_income               32581 non-null  int64
 2   person_home_ownership       32581 non-null  object
 3   person_emp_length           31686 non-null  float64
 4   loan_intent                 32581 non-null  object
 5   loan_grade                  32581 non-null  object
 6   loan_amnt                   32581 non-null  int64
 7   loan_int_rate               29465 non-null  float64
 8   loan_status                 32581 non-null  int64
 9   loan_percent_income         32581 non-null  float64
 10  cb_person_default_on_file   32581 non-null  object
 11  cb_person_cred_hist_length  32581 non-null  int64
dtypes: float64(3), int64(5), object(4)
memory usage: 3.0+ MB
```

checking the null values in the dataset

[8]:
```
df.isnull().sum()
```

[8]:
```
person_age                      0
person_income                   0
person_home_ownership           0
person_emp_length             895
loan_intent                     0
loan_grade                      0
loan_amnt                       0
loan_int_rate                3116
loan_status                     0
loan_percent_income             0
cb_person_default_on_file       0
cb_person_cred_hist_length      0
dtype: int64
```

Filling null values with mode or median rather then deleting it due to more number of null values almost 10%.

[9]:
```
print('person_emp_length mode {}'.format(df['person_emp_length'].mode()[0]))
print('person_emp_length median {}'.format(df['person_emp_length'].median()))
print('loan_int_rate mode {}'.format(df['loan_int_rate'].mode()[0]))
print('loan_int_rate median {}'.format(df['loan_int_rate'].median()))
```

```
person_emp_length mode 0.0
person_emp_length median 4.0
loan_int_rate mode 7.51
loan_int_rate median 10.99
```

[10]:
```
df['person_emp_length'].fillna(df['person_emp_length'].mode()[0], inplace=True)
df['loan_int_rate'].fillna(df['loan_int_rate'].median(), inplace=True)
```

After filling the null values

[22]:
```
df.isnull().sum()
```

[22]:
```
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_grade                    0
loan_amnt                     0
loan_int_rate                 0
loan_status                   0
loan_percent_income           0
```

```
cb_person_default_on_file     0
cb_person_cred_hist_length    0
dtype: int64
```

[11]:
```
print('person_emp_length mode {}'.format(df['person_emp_length'].mode()[0]))
print('person_emp_length median {}'.format(df['person_emp_length'].median()))
print('loan_int_rate mode {}'.format(df['loan_int_rate'].mode()[0]))
print('loan_int_rate median {}'.format(df['loan_int_rate'].median()))
```

```
person_emp_length mode 0.0
person_emp_length median 4.0
loan_int_rate mode 10.99
loan_int_rate median 10.99
```

There is change in mode of Loan interest rate after filling null values with median

[12]:
```
df.dtypes #checking the datatype of values in the column
```

[12]:
```
person_age                      int64
person_income                   int64
person_home_ownership          object
person_emp_length             float64
loan_intent                    object
loan_grade                     object
loan_amnt                       int64
loan_int_rate                 float64
loan_status                     int64
loan_percent_income           float64
cb_person_default_on_file      object
cb_person_cred_hist_length      int64
dtype: object
```

Number of defaulter and non defaulter are to be checked to know the dataset

[13]:
```
df['loan_status'].value_counts()
```

[13]:
```
0    25473
1     7108
Name: loan_status, dtype: int64
```

[14]:
```
df['person_home_ownership'].unique()
```

[14]:
```
array(['RENT', 'OWN', 'MORTGAGE', 'OTHER'], dtype=object)
```

[15]:
```
df['loan_intent'].unique()
```

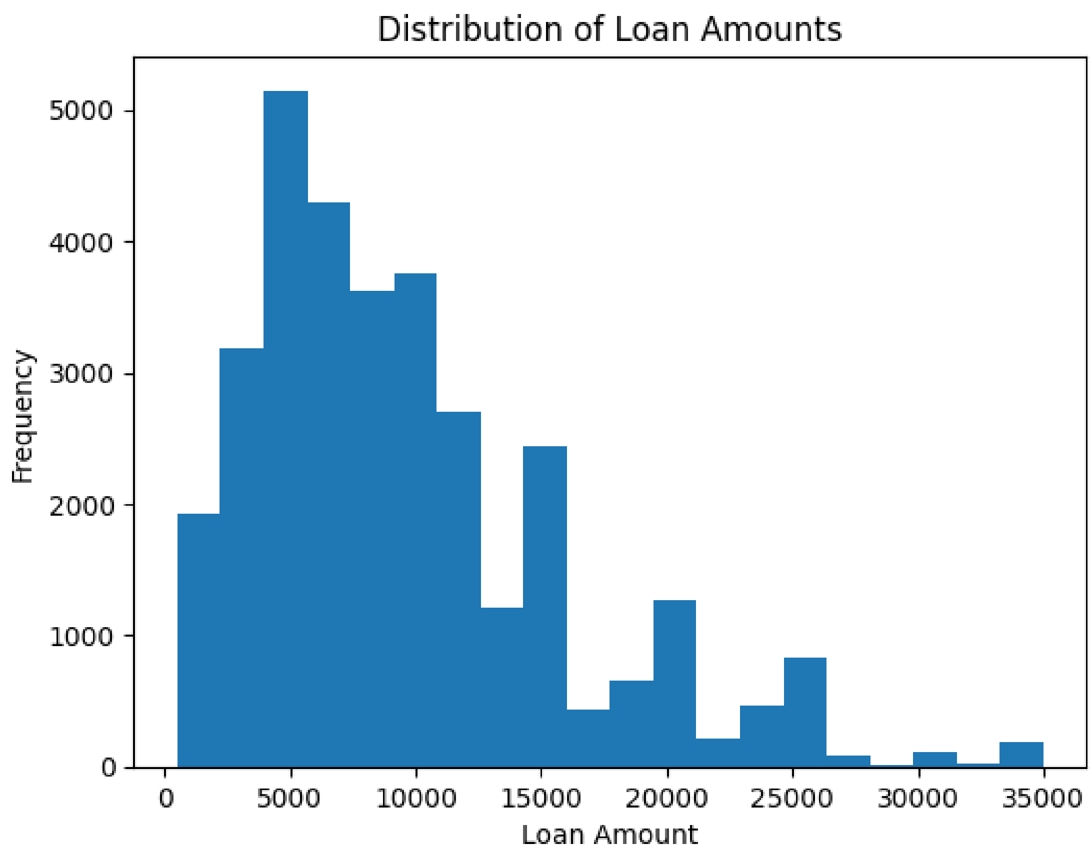
[15]:
```
array(['PERSONAL', 'EDUCATION', 'MEDICAL', 'VENTURE', 'HOMEIMPROVEMENT',
       'DEBTCONSOLIDATION'], dtype=object)
```

[16]:
```
df.describe()
```

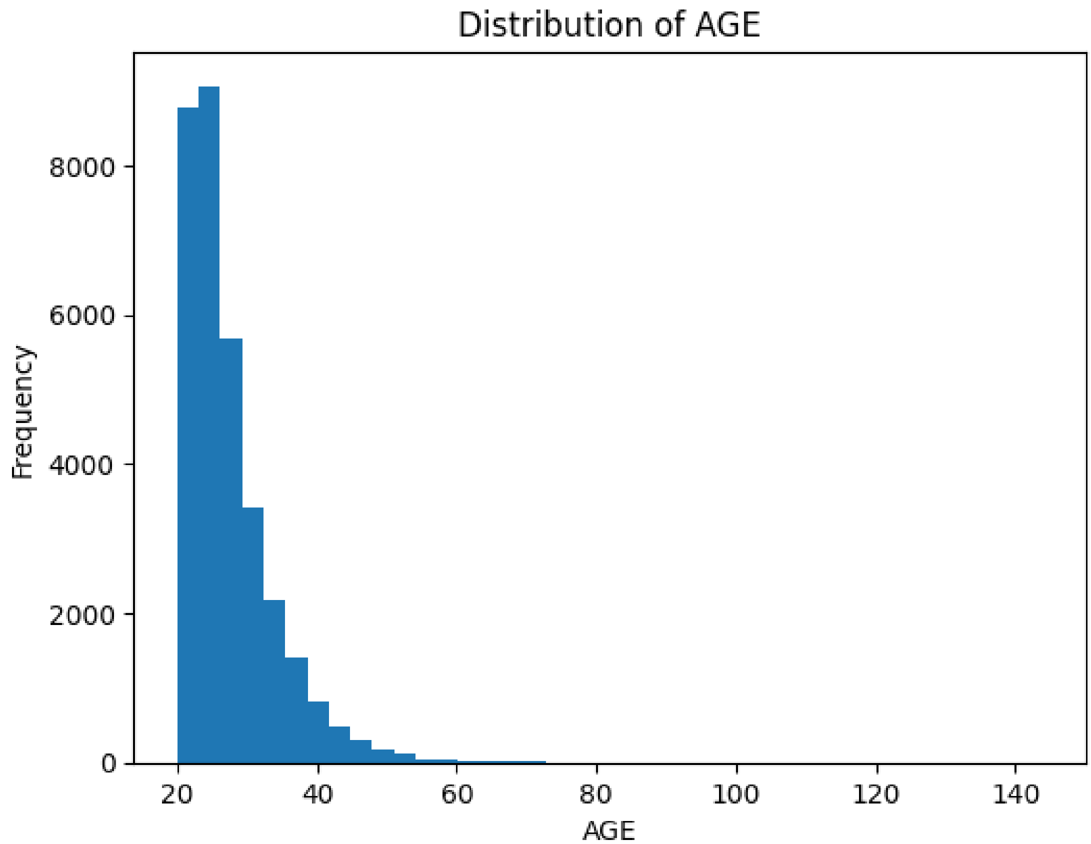
[16]:
```
        person_age  person_income  person_emp_length     loan_amnt  \
count  32581.000000   3.258100e+04       32581.000000  32581.000000
mean      27.734600   6.607485e+04           4.658114   9589.371106
std        6.348078   6.198312e+04           4.159669   6322.086646
min       20.000000   4.000000e+03           0.000000    500.000000
25%       23.000000   3.850000e+04           2.000000   5000.000000
50%       26.000000   5.500000e+04           4.000000   8000.000000
75%       30.000000   7.920000e+04           7.000000  12200.000000
max      144.000000   6.000000e+06         123.000000  35000.000000

       loan_int_rate   loan_status  loan_percent_income  \
count   32581.000000  32581.000000         32581.000000
mean       11.009620      0.218164             0.170203
std         3.081611      0.413006             0.106782
min         5.420000      0.000000             0.000000
25%         8.490000      0.000000             0.090000
50%        10.990000      0.000000             0.150000
75%        13.110000      0.000000             0.230000
max        23.220000      1.000000             0.830000

       cb_person_cred_hist_length
count                32581.000000
mean                     5.804211
std                      4.055001
min                      2.000000
25%                      3.000000
50%                      4.000000
75%                      8.000000
max                     30.000000
```

After observing the above values, there are some outlier which are impossible, i.e, MAX of persons age is 144 years, and MAX of person employment lenth is 123 years which cannot be possible.

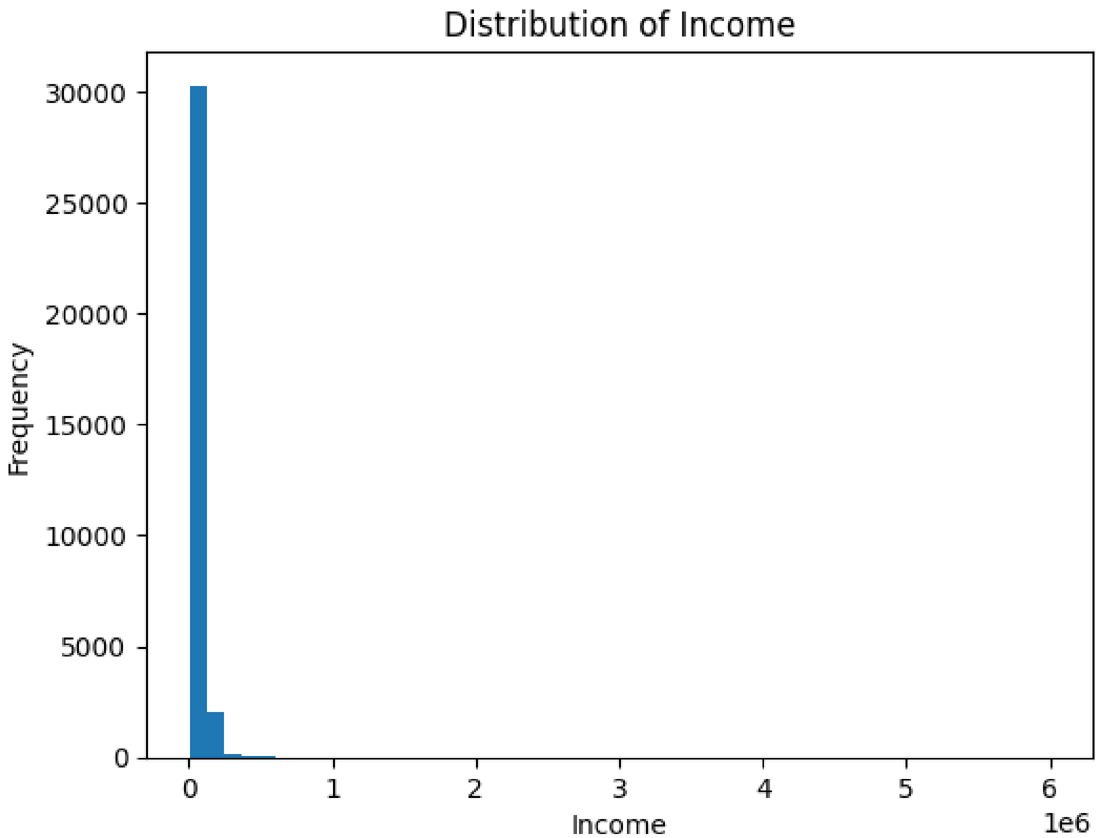
[17]:
```
plt.hist(df['loan_amnt'], bins=20)
plt.xlabel('Loan Amount')
plt.ylabel('Frequency')
plt.title('Distribution of Loan Amounts')
plt.show()
```



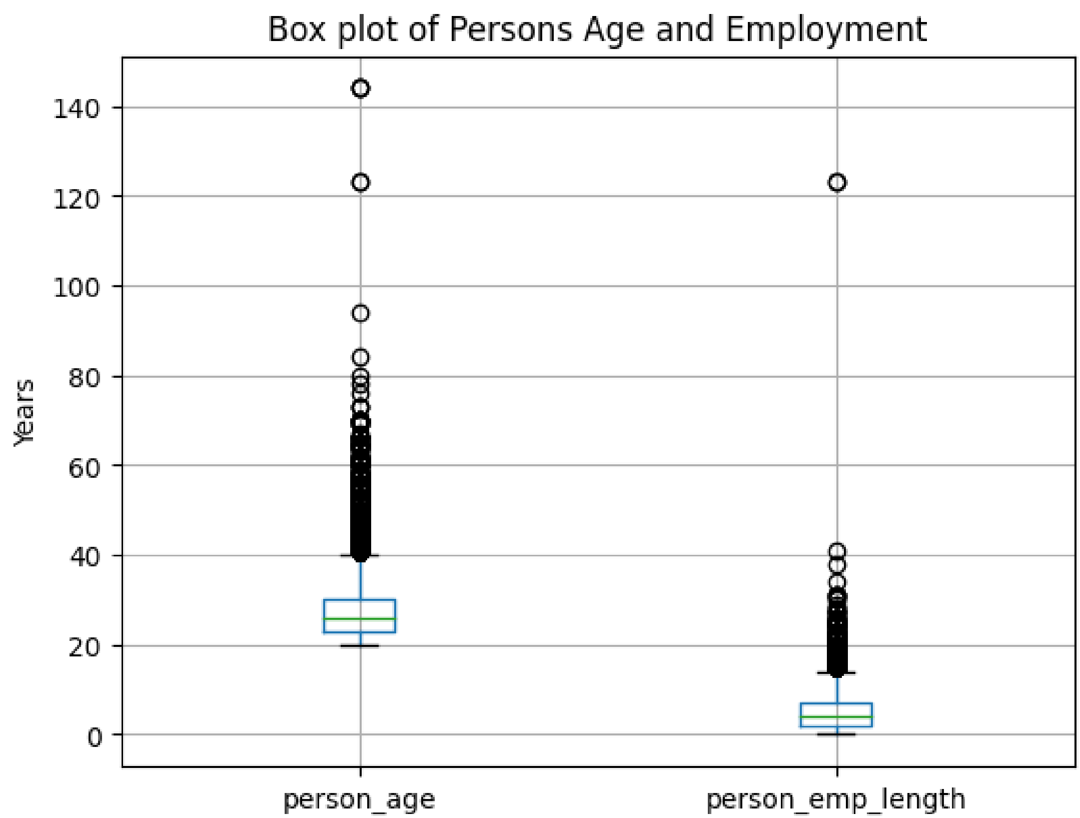

```
[18]: plt.hist(df['person_age'], bins=40)
      plt.xlabel('AGE')
      plt.ylabel('Frequency')
      plt.title('Distribution of AGE')
      plt.show()
```



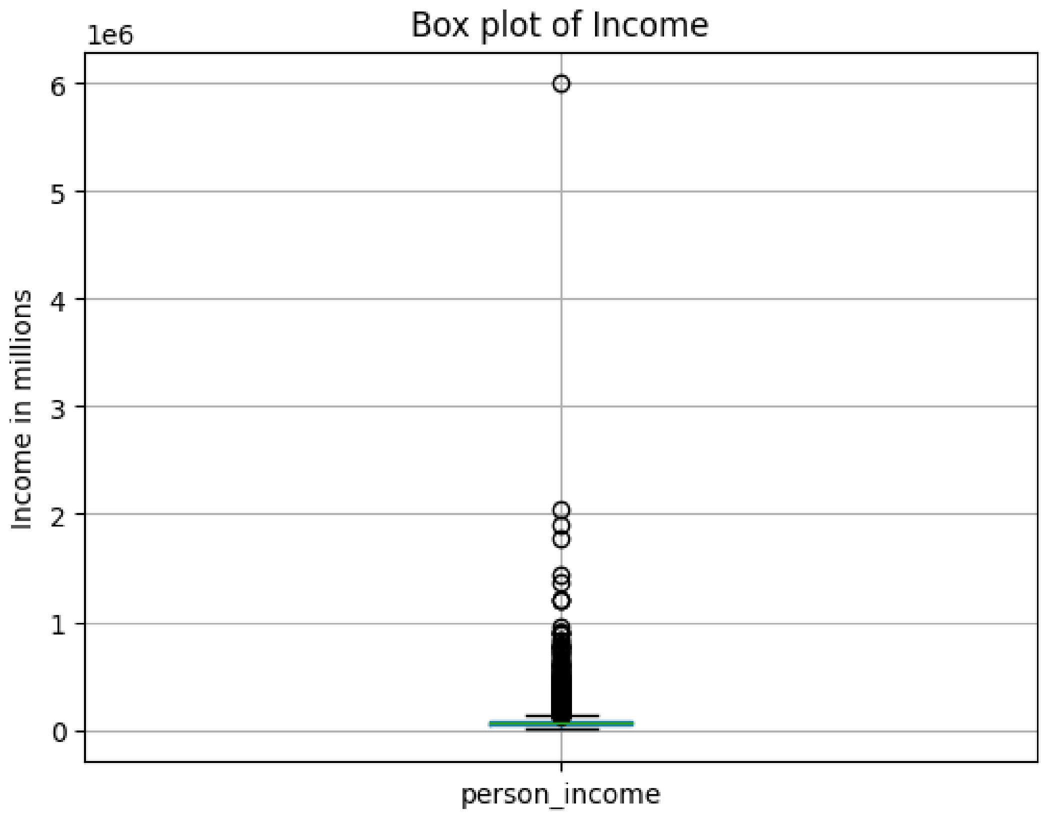
[19]:
```
plt.hist(df['person_income'], bins=50)
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.title('Distribution of Income')
plt.show()
```



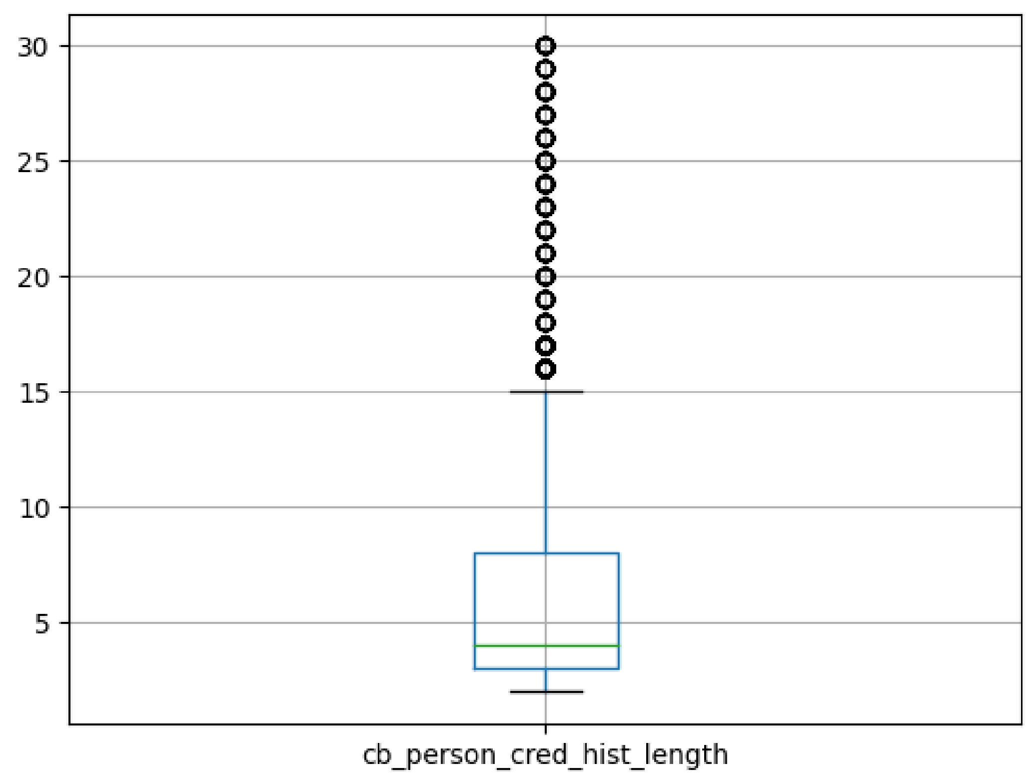
[20]:
```
df.boxplot(['person_age','person_emp_length'])
plt.title('Box plot of Persons Age and Employment')
plt.ylabel('Years')
plt.show()
```




```
[21]: df.boxplot(['person_income'])
plt.title('Box plot of Income')
plt.ylabel('Income in millions')
plt.show()
```



[22]:
```
df.boxplot(['cb_person_cred_hist_length'])
plt.show()
```



From above box plot we can observe the outliers

[23]:
```
df = df[df['person_age']<=100]
df = df[df['person_emp_length']<=60]
df = df[df['person_income']<=3.000000e+06]
```

Removing the outiers using above condition

[24]:
```
df.shape
```

[24]: (32574, 12)

Checking the correlation chart using the Heatmap.

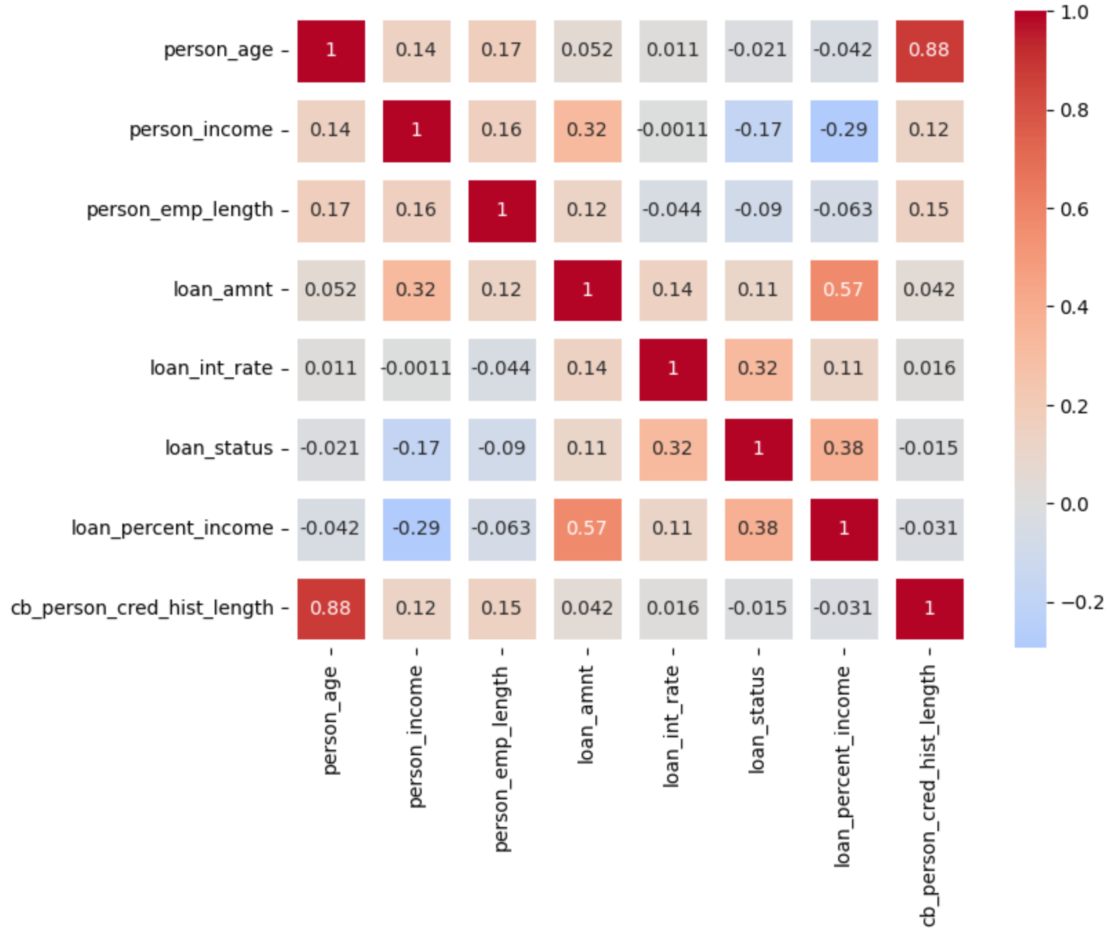
[26]:
```
f , ax = plt.subplots(figsize=(8,6))
print(f)
sns.heatmap(df.corr(),annot=True,linewidths=8,center =0,ax=ax,cmap="coolwarm")
```

```
Figure(800x600)
```

```
<ipython-input-26-1110c77e98d2>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
```

```
to silence this warning.
  sns.heatmap(df.corr(),annot=True,linewidths=8,center =0,ax=ax,cmap="coolwarm")
```

[26]: `<Axes: >`



One hot encoding of categorical columns.

[27]:
```
dfohc= pd.get_dummies(df, columns=['person_home_ownership', 'loan_intent',␣
↪'loan_grade', 'cb_person_default_on_file'], drop_first=True)
dfohc.head(30)
```

[27]:
```
   person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
1          21           9600                5.0       1000          11.14
2          25           9600                1.0       5500          12.87
3          23          65500                4.0      35000          15.23
4          24          54400                8.0      35000          14.27
5          21           9900                2.0       2500           7.14
6          26          77100                8.0      35000          12.42
```

7	24	78956	5.0	35000	11.11
8	24	83000	8.0	35000	8.90
9	21	10000	6.0	1600	14.74
10	22	85000	6.0	35000	10.37
11	21	10000	2.0	4500	8.63
12	23	95000	2.0	35000	7.90
13	26	108160	4.0	35000	18.39
14	23	115000	2.0	35000	7.90
15	23	500000	7.0	30000	10.65
16	23	120000	0.0	35000	7.90
17	23	92111	7.0	35000	20.25
18	23	113000	8.0	35000	18.25
19	24	10800	8.0	1750	10.99
20	25	162500	2.0	35000	7.49
21	25	137000	9.0	34800	16.77
22	22	65000	4.0	34000	17.58
23	24	10980	0.0	1500	7.29
24	22	80000	3.0	33950	14.54
25	24	67746	8.0	33000	12.68
26	21	11000	3.0	4575	17.74
27	23	11000	0.0	1400	9.32
28	24	65000	6.0	32500	9.99
29	21	11389	5.0	4000	12.84
30	21	11520	5.0	2000	11.12

	loan_status	loan_percent_income	cb_person_cred_hist_length	\
1	0	0.10	2	
2	1	0.57	3	
3	1	0.53	2	
4	1	0.55	4	
5	1	0.25	2	
6	1	0.45	3	
7	1	0.44	4	
8	1	0.42	2	
9	1	0.16	3	
10	1	0.41	4	
11	1	0.45	2	
12	1	0.37	2	
13	1	0.32	4	
14	0	0.30	4	
15	0	0.06	3	
16	0	0.29	4	
17	1	0.32	4	
18	1	0.31	4	
19	1	0.16	2	
20	0	0.22	4	
21	0	0.25	2	

```
22          1              0.52                         4
23          0              0.14                         3
24          1              0.42                         4
25          1              0.49                         3
26          1              0.42                         3
27          0              0.13                         3
28          1              0.50                         3
29          1              0.35                         2
30          1              0.17                         3

    person_home_ownership_OTHER  person_home_ownership_OWN  …  \
1                             0                          1  …
2                             0                          0  …
3                             0                          0  …
4                             0                          0  …
5                             0                          1  …
6                             0                          0  …
7                             0                          0  …
8                             0                          0  …
9                             0                          1  …
10                            0                          0  …
11                            0                          1  …
12                            0                          0  …
13                            0                          0  …
14                            0                          0  …
15                            0                          0  …
16                            0                          0  …
17                            0                          0  …
18                            0                          0  …
19                            0                          0  …
20                            0                          0  …
21                            0                          0  …
22                            0                          0  …
23                            0                          1  …
24                            0                          0  …
25                            0                          0  …
26                            0                          0  …
27                            0                          1  …
28                            0                          0  …
29                            1                          0  …
30                            0                          1  …

    loan_intent_MEDICAL  loan_intent_PERSONAL  loan_intent_VENTURE  \
1                     0                     0                    0
2                     1                     0                    0
3                     1                     0                    0
4                     1                     0                    0
```

5	0	0	1
6	0	0	0
7	1	0	0
8	0	1	0
9	0	0	1
10	0	0	1
11	0	0	0
12	0	0	1
13	0	0	0
14	0	0	0
15	0	0	0
16	0	0	0
17	1	0	0
18	0	0	0
19	0	0	0
20	0	0	1
21	0	1	0
22	0	0	0
23	0	1	0
24	0	1	0
25	0	0	0
26	0	0	1
27	0	1	0
28	0	0	0
29	0	0	0
30	1	0	0

	loan_grade_B	loan_grade_C	loan_grade_D	loan_grade_E	loan_grade_F	\
1	1	0	0	0	0	
2	0	1	0	0	0	
3	0	1	0	0	0	
4	0	1	0	0	0	
5	0	0	0	0	0	
6	1	0	0	0	0	
7	1	0	0	0	0	
8	0	0	0	0	0	
9	0	0	1	0	0	
10	1	0	0	0	0	
11	0	0	0	0	0	
12	0	0	0	0	0	
13	0	0	0	1	0	
14	0	0	0	0	0	
15	1	0	0	0	0	
16	0	0	0	0	0	
17	0	0	0	0	1	
18	0	0	1	0	0	
19	1	0	0	0	0	

20	0	0	0	0	0
21	0	0	0	1	0
22	0	0	1	0	0
23	0	0	0	0	0
24	0	0	1	0	0
25	0	1	0	0	0
26	0	0	0	1	0
27	0	0	0	0	0
28	1	0	0	0	0
29	0	1	0	0	0
30	1	0	0	0	0

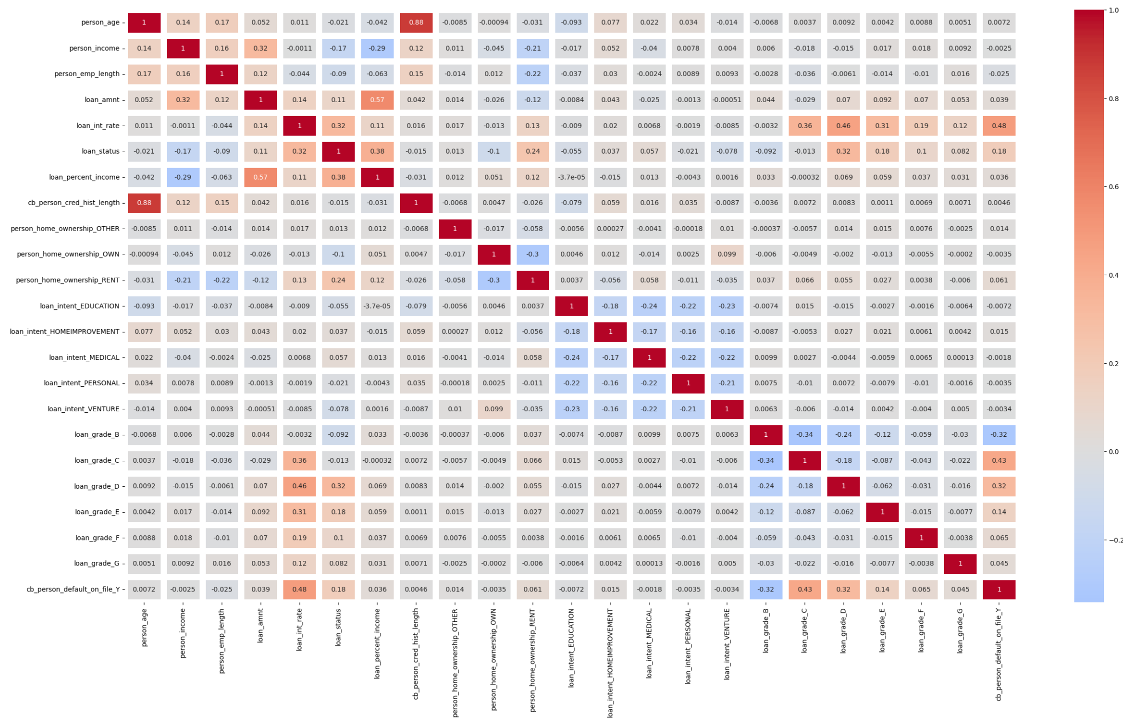
	loan_grade_G	cb_person_default_on_file_Y
1	0	0
2	0	0
3	0	0
4	0	1
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	0
21	0	1
22	0	0
23	0	0
24	0	1
25	0	0
26	0	1
27	0	0
28	0	0
29	0	1
30	0	0

[30 rows x 23 columns]

[28]:
```python
f , ax = plt.subplots(figsize=(30,16))
print(f)
sns.heatmap(dfohc.corr(), annot=True,linewidths=8,center␣
 ↪=0,ax=ax,cmap="coolwarm")
```

```
Figure(3000x1600)
```

[28]:
```
<Axes: >
```



Separating the input and out (X & Y).

[29]:
```python
Y=dfohc['loan_status']
X= dfohc.drop('loan_status',axis=1)
```

[52]:
```python
X
```

[52]:
```
       person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
1              21           9600                5.0       1000          11.14
2              25           9600                1.0       5500          12.87
3              23          65500                4.0      35000          15.23
4              24          54400                8.0      35000          14.27
5              21           9900                2.0       2500           7.14
…             …             …                …         …             …
32576          57          53000                1.0       5800          13.16
32577          54         120000                4.0      17625           7.49
```

```
32578           65          76000                   3.0      35000             10.99
32579           56         150000                   5.0      15000             11.48
32580           66          42000                   2.0       6475              9.99

       loan_percent_income  cb_person_cred_hist_length  \
1                     0.10                           2
2                     0.57                           3
3                     0.53                           2
4                     0.55                           4
5                     0.25                           2
…                      …                          …
32576                 0.11                          30
32577                 0.15                          19
32578                 0.46                          28
32579                 0.10                          26
32580                 0.15                          30

       person_home_ownership_OTHER  person_home_ownership_OWN  \
1                                0                          1
2                                0                          0
3                                0                          0
4                                0                          0
5                                0                          1
…                              …                          …
32576                            0                          0
32577                            0                          0
32578                            0                          0
32579                            0                          0
32580                            0                          0

       person_home_ownership_RENT  …  loan_intent_MEDICAL  \
1                               0  …                    0
2                               0  …                    1
3                               1  …                    1
4                               1  …                    1
5                               0  …                    0
…                             …  …                  …
32576                           0  …                    0
32577                           0  …                    0
32578                           1  …                    0
32579                           0  …                    0
32580                           1  …                    1

       loan_intent_PERSONAL  loan_intent_VENTURE  loan_grade_B  loan_grade_C  \
1                         0                    0             1             0
2                         0                    0             0             1
3                         0                    0             0             1
```

```
4                        0                    0             0             1
5                        0                    1             0             0
...                    ...                  ...           ...           ...
32576                    1                    0             0             1
32577                    1                    0             0             0
32578                    0                    0             1             0
32579                    1                    0             1             0
32580                    0                    0             1             0

       loan_grade_D  loan_grade_E  loan_grade_F  loan_grade_G  \
1                 0             0             0             0
2                 0             0             0             0
3                 0             0             0             0
4                 0             0             0             0
5                 0             0             0             0
...             ...           ...           ...           ...
32576             0             0             0             0
32577             0             0             0             0
32578             0             0             0             0
32579             0             0             0             0
32580             0             0             0             0

       cb_person_default_on_file_Y
1                                0
2                                0
3                                0
4                                1
5                                0
...                            ...
32576                            0
32577                            0
32578                            0
32579                            0
32580                            0

[32574 rows x 22 columns]
```

Performing the Train test split of (0.75:0.25)

[30]:
```python
from sklearn.model_selection import train_test_split

X_train , X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.
 ↪25,random_state=10)
print(X_train.shape,Y_train.shape)
print(X_test.shape,Y_test.shape)
```

```
(24430, 22) (24430,)
(8144, 22) (8144,)
```

Data Transformation

[33]:
```
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()

X_train_trans = scale.fit_transform(X_train)
print(X_train_trans.shape)
X_test_trans = scale.transform(X_test)
print(X_test_trans.shape)
```

```
(24430, 22)
(8144, 22)
```

[34]:
```
X_train_trans
```

[34]:
```
array([[-0.76047974, -0.26579741,  0.57866681, …, -0.08542872,
         -0.04390413, -0.46178989],
        [-0.76047974,  0.99037087,  0.57866681, …, -0.08542872,
         -0.04390413, -0.46178989],
        [ 0.37467066,  0.01442474,  0.08617155, …, -0.08542872,
         -0.04390413, -0.46178989],
        …,
        [ 2.4828071 ,  2.20788783,  0.08617155, …, -0.08542872,
         -0.04390413, -0.46178989],
        [-0.92264408, -0.69096206, -0.16007608, …, -0.08542872,
         -0.04390413,  2.165487  ],
        [-0.76047974, -0.30444874,  0.08617155, …, -0.08542872,
         -0.04390413, -0.46178989]])
```

The above code is creating array as output, To create dataframe below code is written

[35]:
```
cols=['person_age','person_income','person_emp_length','loan_amnt','loan_int_rate','loan_perce
```

[36]:
```
scale = StandardScaler()

X_train_transformed = pd.DataFrame(scale.
 ↪fit_transform(X_train),columns=cols,index = X_train.index)
X_test_transformed = pd.DataFrame(scale.transform(X_test),columns=cols,index =␣
 ↪X_test.index)

X_train_transformed.head()
```

[36]:
```
       person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
15001   -0.760480      -0.265797           0.578667   0.857754       1.055419
14857   -0.760480       0.990371           0.578667  -0.931503      -0.087376
23863    0.374671       0.014425           0.086172  -0.250636      -1.015897
30338    1.509821      -0.265797          -0.898819   0.857754      -0.006212
1884    -0.598315      -0.207820          -0.160076   0.841920       0.266501
```

```
       loan_percent_income  cb_person_cred_hist_length  \
15001             1.119782                   -0.692179
14857            -1.313617                   -0.692179
23863            -0.471287                    0.794343
30338             1.119782                    2.033111
1884              0.932597                   -0.692179

       person_home_ownership_OTHER  person_home_ownership_OWN  \
15001                    -0.056595                  -0.294195
14857                    -0.056595                  -0.294195
23863                    -0.056595                  -0.294195
30338                    -0.056595                  -0.294195
1884                     -0.056595                  -0.294195

       person_home_ownership_RENT  …  loan_intent_MEDICAL  \
15001                    0.991522  …            -0.477632
14857                   -1.008551  …             2.093664
23863                   -1.008551  …            -0.477632
30338                   -1.008551  …            -0.477632
1884                     0.991522  …            -0.477632

       loan_intent_PERSONAL  loan_intent_VENTURE  loan_grade_B  loan_grade_C  \
15001             -0.452432             2.183088     -0.691511      2.031759
14857             -0.452432            -0.458067      1.446109     -0.492184
23863             -0.452432            -0.458067     -0.691511     -0.492184
30338             -0.452432             2.183088     -0.691511     -0.492184
1884               2.210278            -0.458067      1.446109     -0.492184

       loan_grade_D  loan_grade_E  loan_grade_F  loan_grade_G  \
15001     -0.356226     -0.173386     -0.085429     -0.043904
14857     -0.356226     -0.173386     -0.085429     -0.043904
23863     -0.356226     -0.173386     -0.085429     -0.043904
30338     -0.356226     -0.173386     -0.085429     -0.043904
1884      -0.356226     -0.173386     -0.085429     -0.043904

       cb_person_default_on_file_Y
15001                     -0.46179
14857                     -0.46179
23863                     -0.46179
30338                     -0.46179
1884                      -0.46179

[5 rows x 22 columns]
```

[37]:
```
X_train_transformed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24430 entries, 15001 to 17679
Data columns (total 22 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   person_age                   24430 non-null  float64
 1   person_income                24430 non-null  float64
 2   person_emp_length            24430 non-null  float64
 3   loan_amnt                    24430 non-null  float64
 4   loan_int_rate                24430 non-null  float64
 5   loan_percent_income          24430 non-null  float64
 6   cb_person_cred_hist_length   24430 non-null  float64
 7   person_home_ownership_OTHER  24430 non-null  float64
 8   person_home_ownership_OWN    24430 non-null  float64
 9   person_home_ownership_RENT   24430 non-null  float64
 10  loan_intent_EDUCATION        24430 non-null  float64
 11  loan_intent_HOMEIMPROVEMENT  24430 non-null  float64
 12  loan_intent_MEDICAL          24430 non-null  float64
 13  loan_intent_PERSONAL         24430 non-null  float64
 14  loan_intent_VENTURE          24430 non-null  float64
 15  loan_grade_B                 24430 non-null  float64
 16  loan_grade_C                 24430 non-null  float64
 17  loan_grade_D                 24430 non-null  float64
 18  loan_grade_E                 24430 non-null  float64
 19  loan_grade_F                 24430 non-null  float64
 20  loan_grade_G                 24430 non-null  float64
 21  cb_person_default_on_file_Y  24430 non-null  float64
dtypes: float64(22)
memory usage: 4.3 MB
```

Modeling

Logistic Regression

[38]:
```python
from sklearn.linear_model import LogisticRegression


LR_model = LogisticRegression()

LR_model.fit(X_train_transformed,Y_train)

y_pred_LR = LR_model.predict(X_test_transformed)
```

[41]:
```python
from sklearn import  metrics

from sklearn.metrics import auc, accuracy_score, confusion_matrix,␣
 ↪roc_auc_score, classification_report
```

```
print(classification_report(Y_test, LR_model.predict(X_test_transformed)))
LR_AUC=metrics.accuracy_score(Y_test,y_pred_LR)
print(LR_AUC)
```

```
              precision    recall  f1-score   support

           0       0.89      0.95      0.92      6423
           1       0.76      0.56      0.64      1721

    accuracy                           0.87      8144
   macro avg       0.83      0.76      0.78      8144
weighted avg       0.86      0.87      0.86      8144

0.8699656188605108
```

KNN

[42]:
```
from sklearn.neighbors import  KNeighborsClassifier

KNNcls =  KNeighborsClassifier()
KNNcls.fit(X_train_transformed,Y_train)
y_pred_KNN = KNNcls.predict(X_test_transformed)

print(classification_report(Y_test, KNNcls.predict(X_test_transformed)))
KNN_AUC=metrics.accuracy_score(Y_test,y_pred_KNN)
print(KNN_AUC)
```

```
              precision    recall  f1-score   support

           0       0.91      0.97      0.94      6423
           1       0.85      0.64      0.73      1721

    accuracy                           0.90      8144
   macro avg       0.88      0.80      0.83      8144
weighted avg       0.90      0.90      0.89      8144

0.900171905697446
```

Support vetcor machines (SVM)

[43]:
```
from sklearn.svm import SVC

SVMa = SVC()
SVMa.fit(X_train_transformed,Y_train)
y_pred_SVC = SVMa.predict(X_test_transformed)

print(classification_report(Y_test, SVMa.predict(X_test_transformed)))
SVM_AUC=metrics.accuracy_score(Y_test,y_pred_SVC)
print(SVM_AUC)
```

```
              precision    recall  f1-score   support

           0       0.91      0.99      0.95      6423
           1       0.93      0.66      0.77      1721

    accuracy                           0.92      8144
   macro avg       0.92      0.82      0.86      8144
weighted avg       0.92      0.92      0.91      8144

0.9161345776031434
```

Decision Tree

[44]:
```
from sklearn.tree import DecisionTreeClassifier

DTc = DecisionTreeClassifier()
DTc.fit(X_train_transformed,Y_train)
y_pred_DT = DTc.predict(X_test_transformed)

print(classification_report(Y_test, DTc.predict(X_test_transformed)))
DT_AUC=metrics.accuracy_score(Y_test,y_pred_DT)
print(DT_AUC)
```

```
              precision    recall  f1-score   support

           0       0.94      0.92      0.93      6423
           1       0.73      0.78      0.75      1721

    accuracy                           0.89      8144
   macro avg       0.84      0.85      0.84      8144
weighted avg       0.90      0.89      0.89      8144

0.893172888015717
```

Random Forest

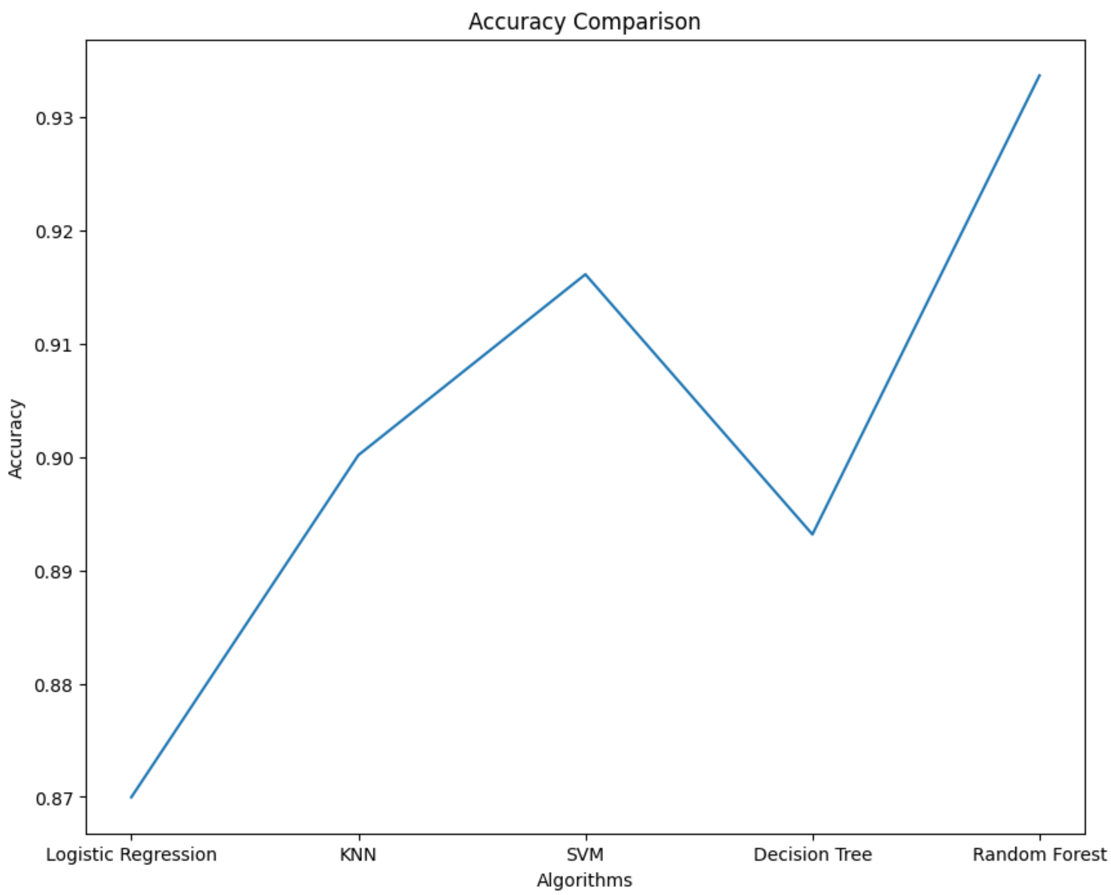
[45]:
```
from sklearn.ensemble import RandomForestClassifier
RFC = RandomForestClassifier()
RFC.fit(X_train_transformed,Y_train)
y_pred_RF = RFC.predict(X_test_transformed)

print(classification_report(Y_test, RFC.predict(X_test_transformed)))
RFC_AUC=metrics.accuracy_score(Y_test,y_pred_RF)
print(RFC_AUC)
```

```
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      6423
           1       0.95      0.73      0.82      1721
```

```
    accuracy                           0.93      8144
   macro avg       0.94      0.86      0.89      8144
weighted avg       0.93      0.93      0.93      8144

0.9336935166994106
```

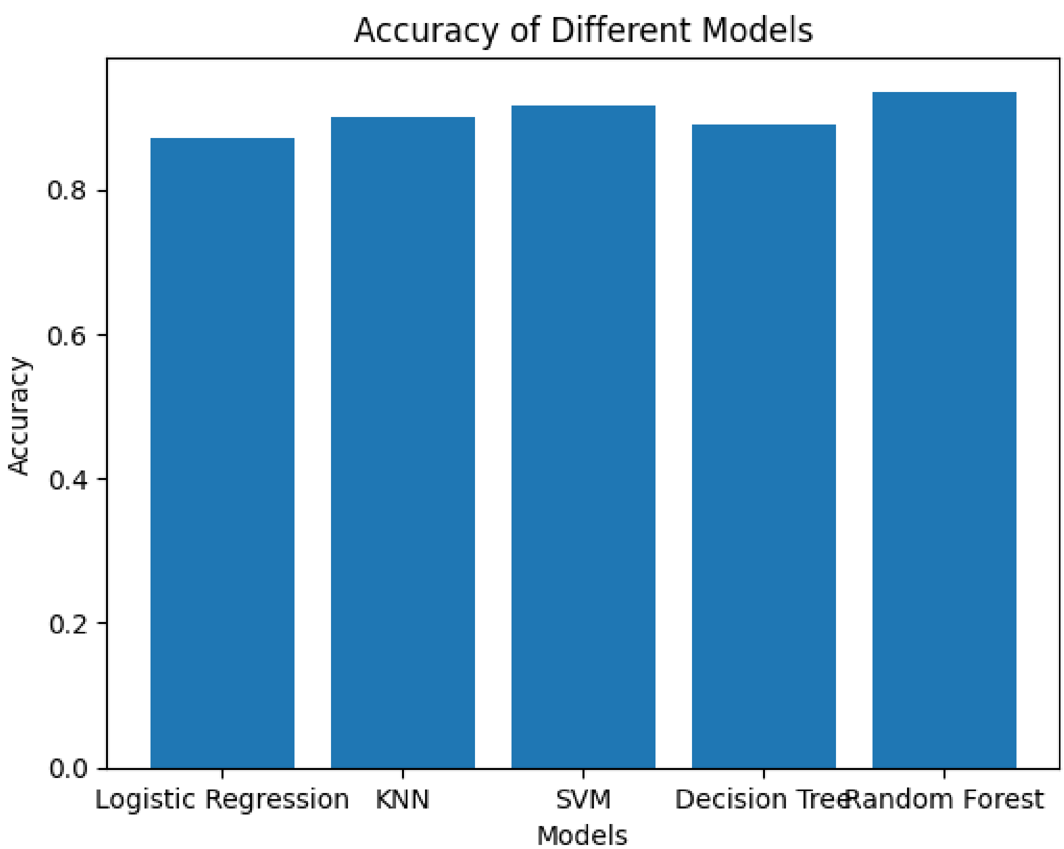
Plot of Accuracy of models

```
[46]: plt.figure(figsize=(10,8))
      plt.plot(['Logistic Regression','KNN','SVM','Decision Tree','Random␣
       ↪Forest'],[LR_AUC,KNN_AUC,SVM_AUC,DT_AUC,RFC_AUC])
      plt.xlabel('Algorithms')
      plt.ylabel('Accuracy')
      plt.title('Accuracy Comparison')
      plt.show()
```



Bar plot of Accuracy

[99]:
```
models = [LR_model, KNNcls, SVMa, DTc, RFC]
models_names = ['Logistic Regression', 'KNN', 'SVM', 'Decision Tree', 'Random␣
 ↪Forest']
accuracies = [LR_AUC, KNN_AUC, SVM_AUC, DT_AUC, RFC_AUC]
plt.bar(models_names, accuracies)
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Accuracy of Different Models')
plt.show()
```



Conclusion: After evaluating the given models the accuracy of Random Forest Classifier gives an accuracy of 0.935, compared to other models and Support vector machines with 0.916 accuracy.

[ ]:
```

```