1_EDA

October 23, 2022

0.1 # 1. Exploratory Data Analysis on Credit Risk Data

FSDS Machine Learning Workshop , October 15, 2022

> Description: Dataset will be cleaned and EDA performed to get more insights on the data.

0.1.1 Pre requisites:

1. Make sure the user has all the data science packages installed.
2. `pip install pandas-profiling`

Input Files: - credit_risk_data.csv

Output File: - cleaned_dataset.csv

0.2 1. Import Required Packages

[3]:
```
# below command will install a python package
!pip install pandas-profiling
```

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
# import the dataset and store it as the variable 'df'
df = pd.read_csv('credit_risk_data.csv')
```

0.3 2. Data Cleaning

- `.head()` returns the first n (here 10) rows of the imported dataframe. It is useful for quickly inspecting the df and what kind of data it contains.

[3]:
```
df.head(10)
```

[3]:
```
   loan_percent_income loan_grade  person_income person_home_ownership  \
0                 0.59          D          59000                  RENT
```

```
1                 0.10          B           9600                  OWN
2                 0.57          C           9600             MORTGAGE
3                 0.53          C          65500                 RENT
4                 0.55          C          54400                 RENT
5                 0.25          A           9900                  OWN
6                 0.45          B          77100                 RENT
7                 0.44          B          78956                 RENT
8                 0.42          A          83000                 RENT
9                 0.16          D          10000                  OWN
```

```
   loan_int_rate  loan_status
0          16.02            1
1          11.14            0
2          12.87            1
3          15.23            1
4          14.27            1
5           7.14            1
6          12.42            1
7          11.11            1
8           8.90            1
9          14.74            1
```

- `.info()` prints information about a df (shape) and its columns (type of column, count of non-null values) and memory usage.

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32581 entries, 0 to 32580
Data columns (total 6 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   loan_percent_income    32581 non-null  float64
 1   loan_grade             32581 non-null  object
 2   person_income          32581 non-null  int64
 3   person_home_ownership  32581 non-null  object
 4   loan_int_rate          29465 non-null  float64
 5   loan_status            32581 non-null  int64
dtypes: float64(2), int64(2), object(2)
memory usage: 1.5+ MB
```

- `.describe()` returns descriptive statistics for all the numeric columns in the df.

[5]:
```
df.describe()
```

[5]:
```
       loan_percent_income  person_income  loan_int_rate   loan_status
count         32581.000000   3.258100e+04   29465.000000  32581.000000
mean              0.170203   6.607485e+04      11.011695      0.218164
std               0.106782   6.198312e+04       3.240459      0.413006
```

```
min              0.000000   4.000000e+03       5.420000       0.000000
25%              0.090000   3.850000e+04       7.900000       0.000000
50%              0.150000   5.500000e+04      10.990000       0.000000
75%              0.230000   7.920000e+04      13.470000       0.000000
max              0.830000   6.000000e+06      23.220000       1.000000
```

- `include='object'` parameter is used to show the decriptive statistic for object columns.

[6]:
```
df.describe(include='object')
```

[6]:
```
        loan_grade person_home_ownership
count        32581                32581
unique           7                    4
top              A                 RENT
freq         10777                16446
```

0.3.1 2.1 Drop Duplciates

- `.duplicated()` will identify the duplicated records in a df.

[3]:
```
# Printing the duplcated records in the dataset
df[df.duplicated()]
```

[3]:
```
       loan_percent_income loan_grade  person_income person_home_ownership  \
161                   0.42          B          60000                  RENT
171                   0.42          B          60000                  RENT
637                   0.36          A          55000                  RENT
666                   0.33          B          60000                  RENT
712                   0.28          D          71004                  RENT
…                        …          …              …                     …
32576                 0.11          C          53000              MORTGAGE
32577                 0.15          A         120000              MORTGAGE
32578                 0.46          B          76000                  RENT
32579                 0.10          B         150000              MORTGAGE
32580                 0.15          B          42000                  RENT

       loan_int_rate  loan_status
161            10.99            1
171            10.99            1
637             6.91            1
666              NaN            1
712            14.09            0
…                 …            …
32576          13.16            0
32577           7.49            0
32578          10.99            1
32579          11.48            0
32580           9.99            0
```

```
[4067 rows x 6 columns]
```

[4]:
```
# dropping duplicated rows
df = df.drop_duplicates()
```

0.3.2 2.2 Filling the missing values

[5]:
```
# counting empty values for each column
df.isnull().sum()
```

[5]:
```
loan_percent_income         0
loan_grade                  0
person_income               0
person_home_ownership       0
loan_int_rate            2612
loan_status                 0
dtype: int64
```

- `.value_counts()` returns containing counts of unique values. Resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default, `dropna=False` includes the empty values.

[10]:
```
df['loan_grade'].value_counts(dropna=False)
```

[10]:
```
A    9218
B    9116
C    5679
D    3331
E     890
F     224
G      56
Name: loan_grade, dtype: int64
```

[11]:
```
df['person_home_ownership'].value_counts(dropna=False)
```

[11]:
```
RENT        14380
MORTGAGE    11745
OWN          2290
OTHER          99
Name: person_home_ownership, dtype: int64
```

- `loan_grade` and `person_home_ownership` are object columns that need to be transformed into numeric values.
- Label Encoding refers to converting the labels into a numeric form so as to convert them into the machine-readable form.

[6]:
```
df = df.replace(to_replace={'person_home_ownership': {'RENT': 0,
                                                      'MORTGAGE': 1,
                                                      'OWN': 2,
                                                      'OTHER': 3},
                            'loan_grade': {'A': 0, 'B': 1, 'C': 2, 'D': 3, 'E':␣
↪4, 'F': 5, 'G': 6}})
```

[7]:
```
df['loan_grade'].value_counts(dropna=False)
```

[7]:
```
0    9218
1    9116
2    5679
3    3331
4     890
5     224
6      56
Name: loan_grade, dtype: int64
```

[8]:
```
df['person_home_ownership'].value_counts(dropna=False)
```

[8]:
```
0    14380
1    11745
2     2290
3       99
Name: person_home_ownership, dtype: int64
```

[15]:
```
df['loan_status'].value_counts(dropna=False) # target variable
```

[15]:
```
0    22078
1     6436
Name: loan_status, dtype: int64
```

[9]:
```
# since there are missing values in the column 'loan_int_rate', we fill them␣
↪with the average interest rate
df['loan_int_rate'].mean()
```

[9]:
```
11.077177051964604
```

[11]:
```
df['loan_int_rate'] = df['loan_int_rate'].fillna(df['loan_int_rate'].mean())
```

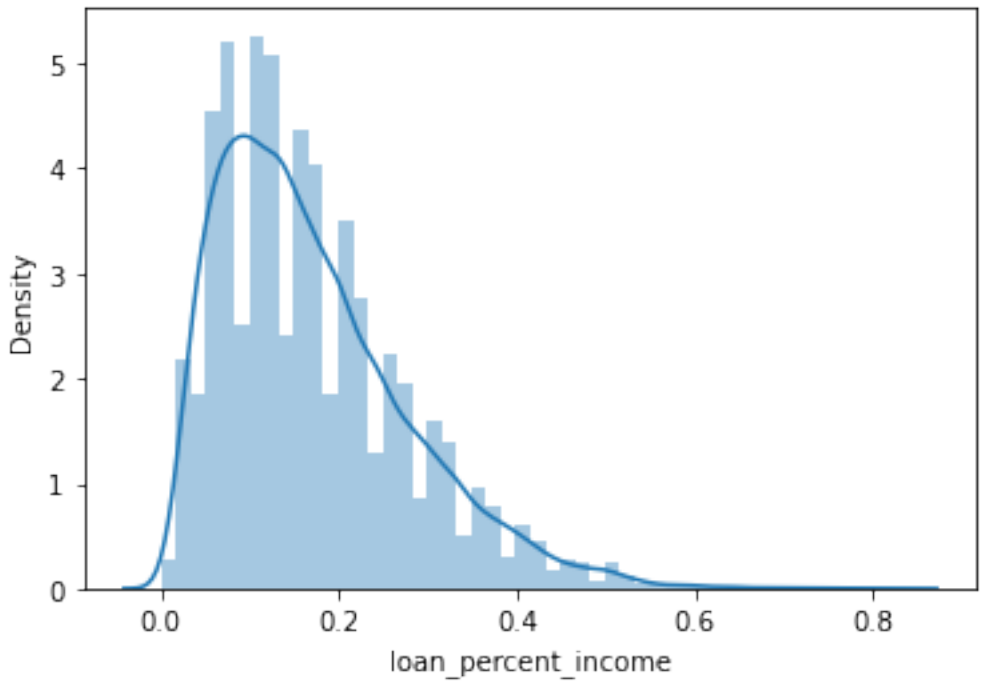
0.3.3 2.3 Plots

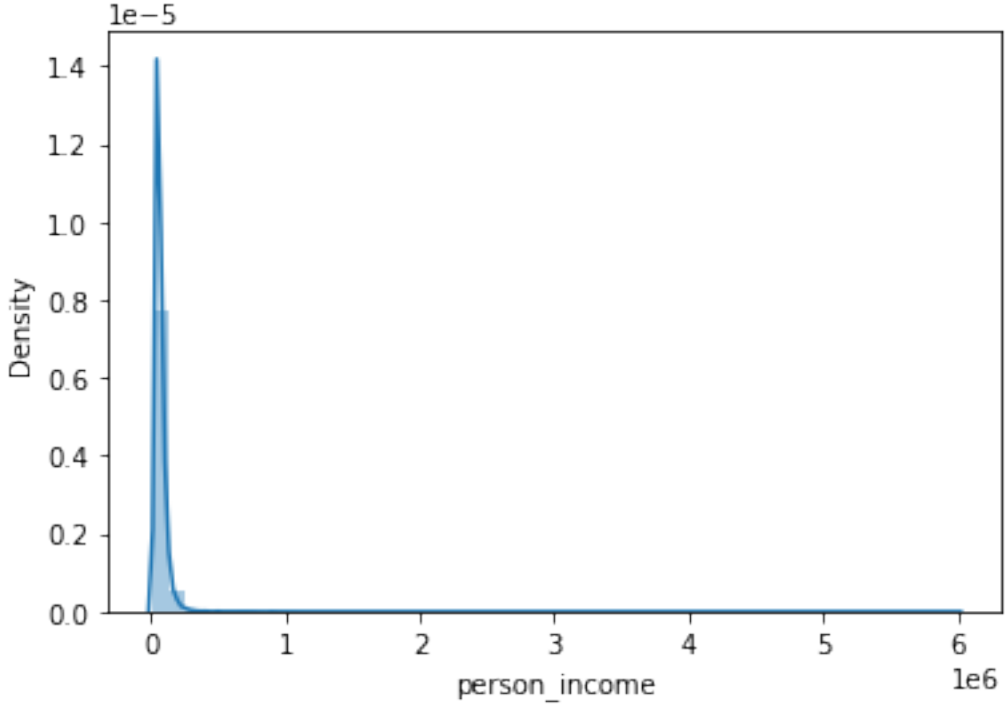
- `sns.distplot()` visualizes the distribution of the data.

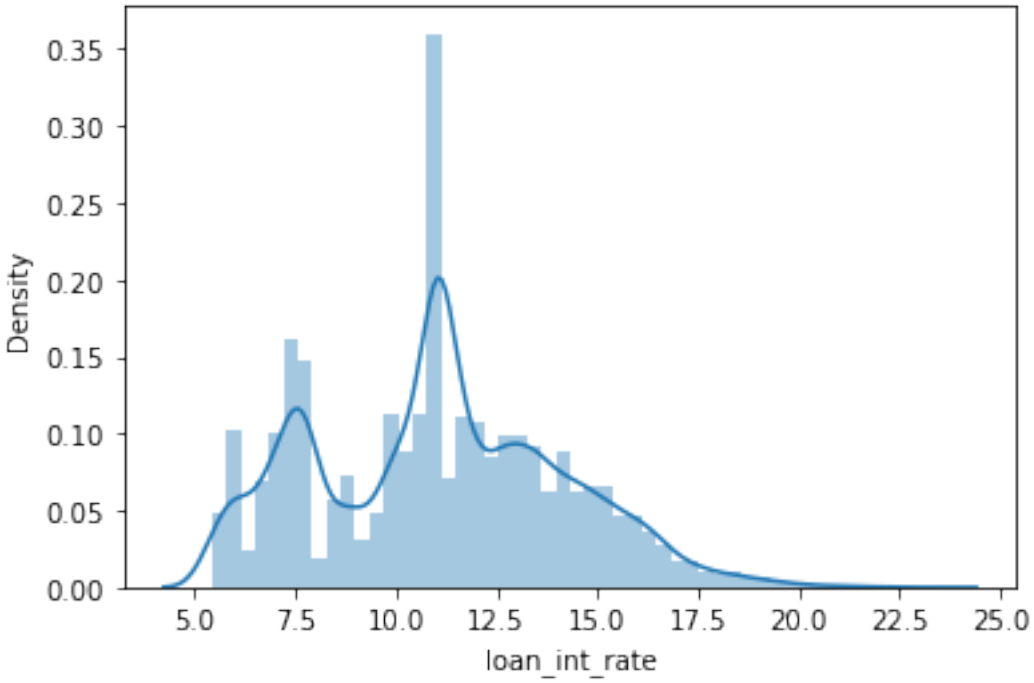
[12]:
```
list_columns = ['loan_percent_income', 'person_income', 'loan_int_rate']

for i in list_columns:
    plt.figure()
```

```
sns.distplot(df[i].dropna())
```







0.4 3. Exporting the cleaned dataset

[19]:
```
df.to_csv("cleaned_dataset.csv", index=None)
```

0.5 4. Pandas profiling

[20]:
```
import pandas_profiling
df = pd.read_csv('credit_risk_data.csv')
profile = pandas_profiling.ProfileReport(df, title="Pandas Profiling Report")
profile.to_file("credit_risk_eda_report.html")
```

```
Summarize dataset:   0%|          | 0/19 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```