2. Model building using cleaned Credit Risk Data

FSDS Machine Learning Workshop , October 16, 2022

> *Description: Applying the random forest on cleaned data and deploying the model.*

Pre requisites:

1. Make sure the user has all the data science packages installed.

Input Files:

- cleaned_dataset.csv

Output File:

- rf_model.pkl

1. Import Required Packages

In [4]:
```python
# Import Required Packages
import pandas as pd
import numpy as np
import pandas_profiling
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import sklearn
import pickle
import os

from sklearn import metrics
from sklearn.model_selection import train_test_split
```

In [5]:
```python
# to remove the printing barrier - displays all columns and rows
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

In [6]:
```python
# TO print multiple outputs in single line
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

2. Data analysis before model building

In [7]:
```python
# TASK:Please load the cleaned_dataset.csv to the variable 'df'
# hint: please refer the 1.EDA notebook
df = --
```

In [8]:
```python
df.head()
```

Out[8]:

	loan_percent_income	loan_grade	person_income	person_home_ownership	loan_int_rate	loan_status
0	0.59	3	59000	0	16.02	1
1	0.10	1	9600	2	11.14	0
2	0.57	2	9600	1	12.87	1
3	0.53	2	65500	0	15.23	1
4	0.55	2	54400	0	14.27	1

In [9]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28514 entries, 0 to 28513
Data columns (total 6 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   loan_percent_income    28514 non-null  float64
 1   loan_grade             28514 non-null  int64
 2   person_income          28514 non-null  int64
 3   person_home_ownership  28514 non-null  int64
 4   loan_int_rate          28514 non-null  float64
 5   loan_status            28514 non-null  int64
dtypes: float64(2), int64(4)
memory usage: 1.3 MB
```

- `.sample()` is used to return a random sample of rows or columns from the df.

In [10]:
```python
# TASK: Using above hint please print the sample of 5 records and observe
# please note the output might be different from displayed
--
```

Out[10]:

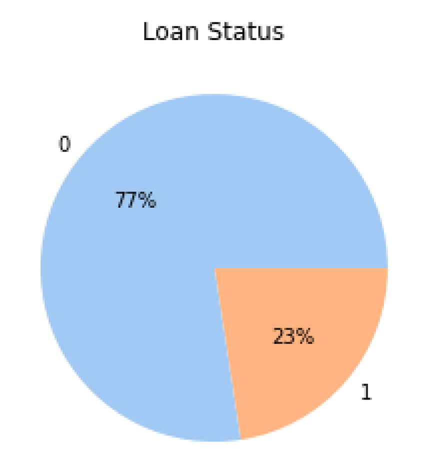
	loan_percent_income	loan_grade	person_income	person_home_ownership	loan_int_rate	loan_status
5081	0.07	0	44000	1	7.51	0
20063	0.21	2	47004	1	13.61	1
28130	0.16	0	150000	1	6.62	0
384	0.24	2	100000	0	12.87	0
11629	0.04	1	76300	1	11.86	0

Loan Status pie chart

Refer: https://www.geeksforgeeks.org/how-to-create-a-pie-chart-in-seaborn/ for more information on how to create more elegant pie charts.

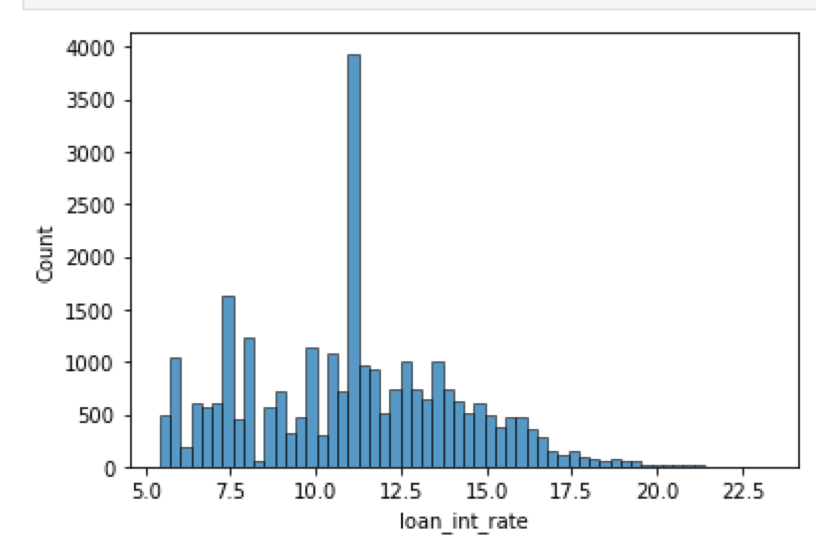
In [9]:
```python
# create pie chart
# define Seaborn color palette to use
colors = sns.color_palette('pastel')[0:2]
labels= df['loan_status'].value_counts().index

plt.pie(df['loan_status'].value_counts(),labels = labels, colors=colors,  autopct='%.0f%%')
plt.title('Loan Status')
plt.show();
```

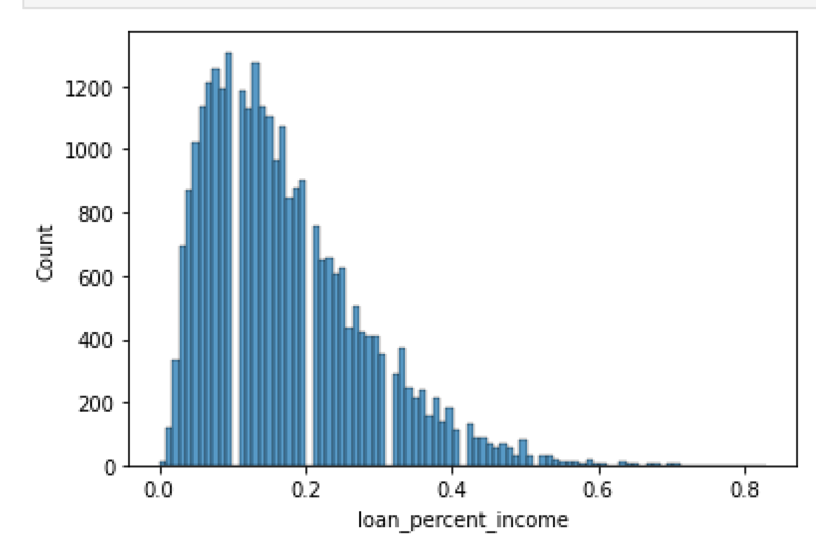


Loan interest rate Disturbution

In [12]:
```python
fig = sns.histplot(df.loan_int_rate)
```



In [12]:
```python
# TASK: Similar to above could please plot an histogram for the column 'loan_percent_income'
# you filter a column by using command 'df.loan_int_rate' or 'df["df.loan_int_rate"]'
fig = --
```



3. Model Training

3.1 Prepare data for training

In [13]:
```python
# TASK: separating features and target variable
# you can try using the same filtering method as above eg. df[['a','b','c']] for multiple columns
# and "df['a']" for single column dataframe
X = --
y = --
```

3.2 Train and test split

Dividing the dataset into 2 dataframes: 1) Train df - 70 % of records

2) Train df - 20 % of the records

In [14]:
```python
#TASK : Please split the whole data set into 70% for Train and 30% for Test
# please assign the value for test_size
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=--, random_state=62, stratify=y)
```

In [15]:
```python
# Printing the train and test dataframe dimensions
print("Target Training Data Shape:" , y_train.shape)
print("Target Test Data Shape:" , y_test.shape)
print("Variables Training Data Shape:" , X_train.shape)
print("Variable Test Data Shape:" , X_test.shape)
```

```
Target Training Data Shape: (19959,)
Target Test Data Shape: (8555,)
Variables Training Data Shape: (19959, 5)
Variable Test Data Shape: (8555, 5)
```

3.3 Loading the model

In [16]:
```python
# initialising the random forest model from sklearn library
# TASK : please intialise a RandomForestClassifier with 1000 estimators  , max_depth of 4
# and set random_state=7
# Hint: please refer the below reference links on the model intialised , fitted and predicted.


# ref: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
# if you are curious how to perform hyperparameter tuning: https://towardsdatascience.com/hyperparameter-tuning

from sklearn.ensemble import RandomForestClassifier

forest = --
```

In [17]:
```python
# TASK : Fitting the model on Train Data i.e "X_train", "y_train"
rf_model = --
```

In [18]:
```python
# Making predictions
pred = rf_model.predict(X_test)
```

In [19]:
```python
pred
```

Out[19]:
```
array([0, 1, 0, ..., 0, 0, 0], dtype=int64)
```

3.4 Feature importance

Ref: https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-random-forest-d9166011959e

In [20]:
```python
Final_df = pd.DataFrame()
```

In [21]:
```python
Final_df['columns'] = X_train.columns
Final_df['feature_importance'] = rf_model.feature_importances_
```

In [22]:
```python
Final_df.sort_values('feature_importance', ascending=False)
```

Out[22]:

	columns	feature_importance
0	loan_percent_income	0.357677
1	loan_grade	0.241564
3	person_home_ownership	0.152480
4	loan_int_rate	0.124349
2	person_income	0.123931

3.5 Checking the model quality

Ref: https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234

In [23]:
```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
def generate_model_report(y_actual, y_predicted):
    print("Accuracy = " , accuracy_score(y_actual, y_predicted))
    print("Precision = " ,precision_score(y_actual, y_predicted))
    print("Recall = " ,recall_score(y_actual, y_predicted))
    print("F1 Score = " ,f1_score(y_actual, y_predicted))
```

In [24]:
```python
# Train Metrics
# TASK : Just observe and enjoy
generate_model_report(y_test, pred)
```

```
Accuracy =  0.8893045002922267
Precision =  0.8402489626556017
Recall =  0.629207664422579
F1 Score =  0.7195735860230975
```

4. Exporting the Model

We save the model as a pickle file. The model can be then used on other machines.

- Ref: https://towardsdatascience.com/do-not-use-python-pickle-unless-you-know-all-these-facts-d9e8695b7d43

In [25]:
```python
with open('rf_model.pkl', 'wb') as f:  # Python 3: open(..., 'wb')
    pickle.dump(rf_model, f)
```