credit-score-classification

August 22, 2023

1 About Dataset

This dataset contains information about a sample of over 100 people across the world. The data includes the following informations:

Age: The age of the person in years.

Gender: The gender of the person (male or female).

Income: The annual income of the person in US dollars.

Education: The highest level of education completed by the person.

Marital Status: The marital status of the person (single, married, divorced, or widowed).

Number of Children: The number of children the person has.

Home Ownership: Whether the person owns their home or rents it.

Credit Score: The credit score of the person, which is a measure of their creditworthiness.

1.1 Source and link

Source: Kaggle

Link: https://www.kaggle.com/datasets/sujithmandala/credit-score-classification-dataset

Author: Bao Thai

2 Credit Score Classification

2.1 Import needed libraries and packages

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score,␣
 ↪classification_report
from sklearn.linear_model import LogisticRegression
```

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
```

2.2 Loading Dataset

[2]:
```python
df = pd.read_csv('C:/Users/Admin/Desktop/Projects/Credit Score Classification/
 ↪Credit Score Classification Dataset.csv')
df_original = df.copy()
df_original.head(10)
```

[2]:
```
   Age  Gender  Income            Education Marital Status  \
0   25  Female   50000    Bachelor's Degree         Single
1   30    Male  100000      Master's Degree        Married
2   35  Female   75000            Doctorate        Married
3   40    Male  125000  High School Diploma         Single
4   45  Female  100000    Bachelor's Degree        Married
5   50    Male  150000      Master's Degree        Married
6   26  Female   40000   Associate's Degree         Single
7   31    Male   60000    Bachelor's Degree         Single
8   36  Female   80000      Master's Degree        Married
9   41    Male  105000            Doctorate         Single

   Number of Children Home Ownership Credit Score
0                   0         Rented         High
1                   2          Owned         High
2                   1          Owned         High
3                   0          Owned         High
4                   3          Owned         High
5                   0          Owned         High
6                   0         Rented      Average
7                   0         Rented      Average
8                   2          Owned         High
9                   0          Owned         High
```

2.3 Explore Data

[16]:
```python
df_original.shape
```

[16]:
```
(164, 8)
```

[17]:
```python
df_original.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 164 entries, 0 to 163
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Age                 164 non-null    int64
 1   Gender              164 non-null    object
 2   Income              164 non-null    int64
 3   Education           164 non-null    object
 4   Marital Status      164 non-null    object
 5   Number of Children  164 non-null    int64
 6   Home Ownership      164 non-null    object
 7   Credit Score        164 non-null    object
dtypes: int64(3), object(5)
memory usage: 10.4+ KB
```

[18]:
```
df_original.isna().sum()
```

[18]:
```
Age                   0
Gender                0
Income                0
Education             0
Marital Status        0
Number of Children    0
Home Ownership        0
Credit Score          0
dtype: int64
```

[19]:
```
df_original.describe()
```

[19]:

	Age	Income	Number of Children
count	164.000000	164.000000	164.000000
mean	37.975610	83765.243902	0.652439
std	8.477289	32457.306728	0.883346
min	25.000000	25000.000000	0.000000
25%	30.750000	57500.000000	0.000000
50%	37.000000	83750.000000	0.000000
75%	45.000000	105000.000000	1.000000
max	53.000000	162500.000000	3.000000

[20]:
```
df_original.corr()
```

```
C:\Users\Admin\AppData\Local\Temp\ipykernel_10520\2946492221.py:1:
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.
  df_original.corr()
```

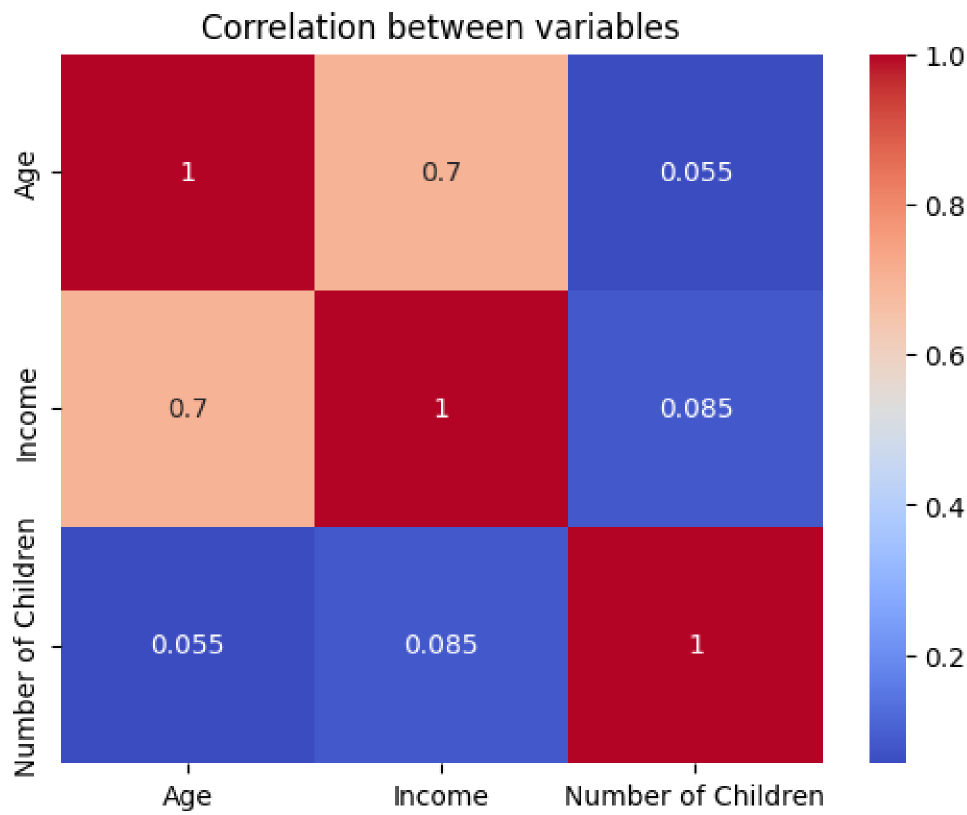
[20]:

	Age	Income	Number of Children
Age	1.000000	0.699464	0.055390
Income	0.699464	1.000000	0.084547
Number of Children	0.055390	0.084547	1.000000

[29]:
```
sns.heatmap(df_original.corr(), annot = True, cmap = 'coolwarm')
plt.title('Correlation between variables')
```

```
C:\Users\Admin\AppData\Local\Temp\ipykernel_10520\434348305.py:1: 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_original.corr(), annot = True, cmap = 'coolwarm')
```

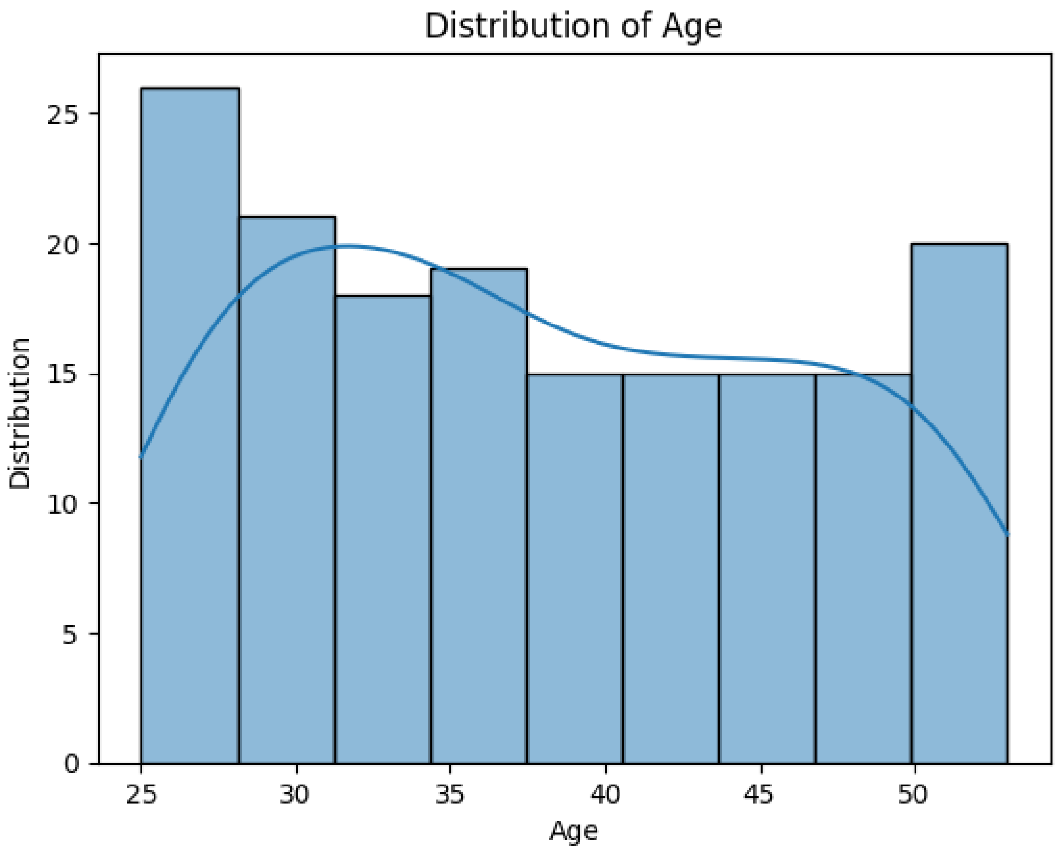
[29]: Text(0.5, 1.0, 'Correlation between variables')



Heatmap shows that there is a high positive correlation between Age and Income

[40]:
```
sns.histplot(df_original, x = df_original['Age'], kde = True)
plt.title('Distribution of Age')
plt.xlabel('Age')
```

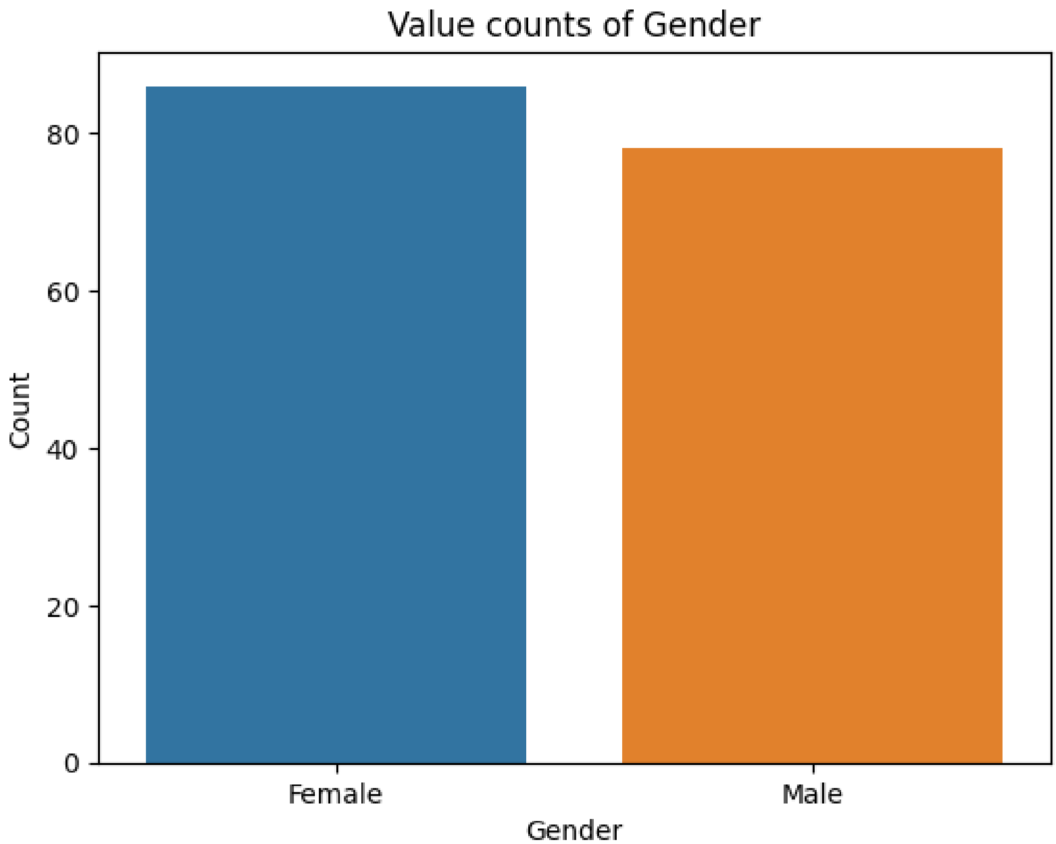
```
plt.ylabel('Distribution')
plt.show()
```



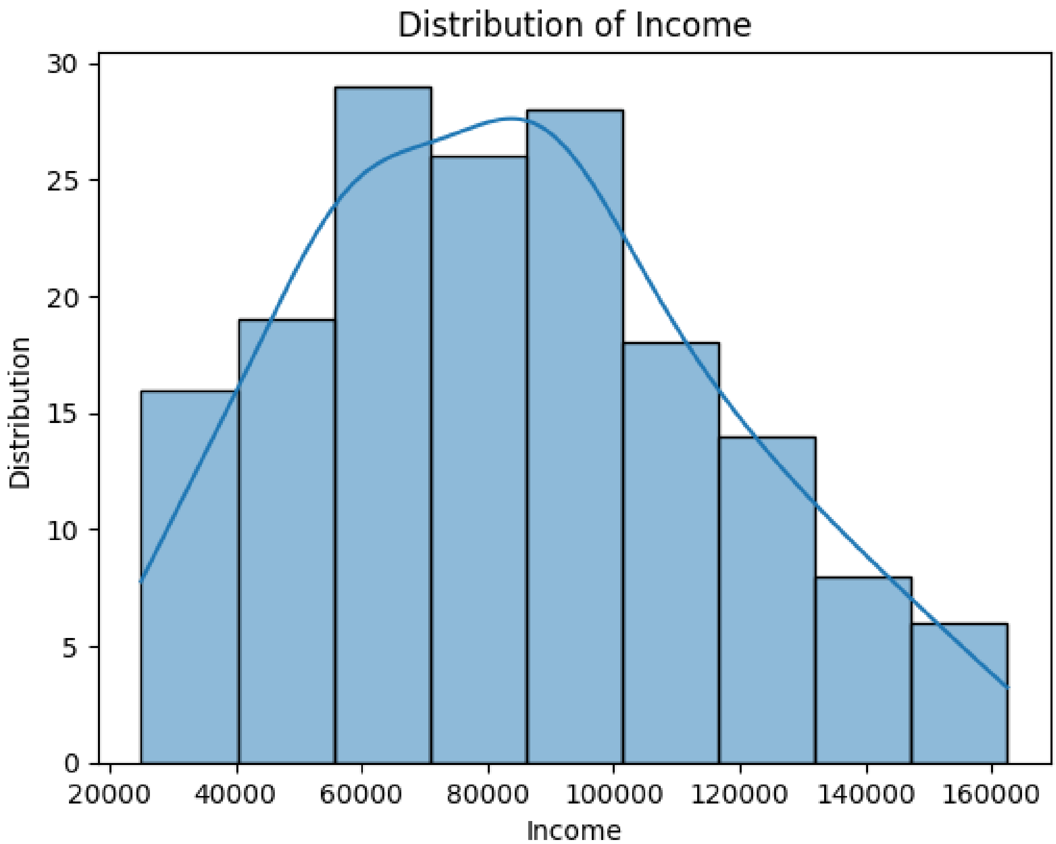
[47]:
```
df_original['Gender'].value_counts()
```

[47]:
```
Female    86
Male      78
Name: Gender, dtype: int64
```

[52]:
```
sns.barplot (x = df_original['Gender'].unique(), y = df_original['Gender'].
 ↪value_counts())
plt.title('Value counts of Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



[54]:
```
sns.histplot(df_original, x = df_original['Income'], kde = True)
plt.title('Distribution of Income')
plt.xlabel('Income')
plt.ylabel('Distribution')
plt.show()
```



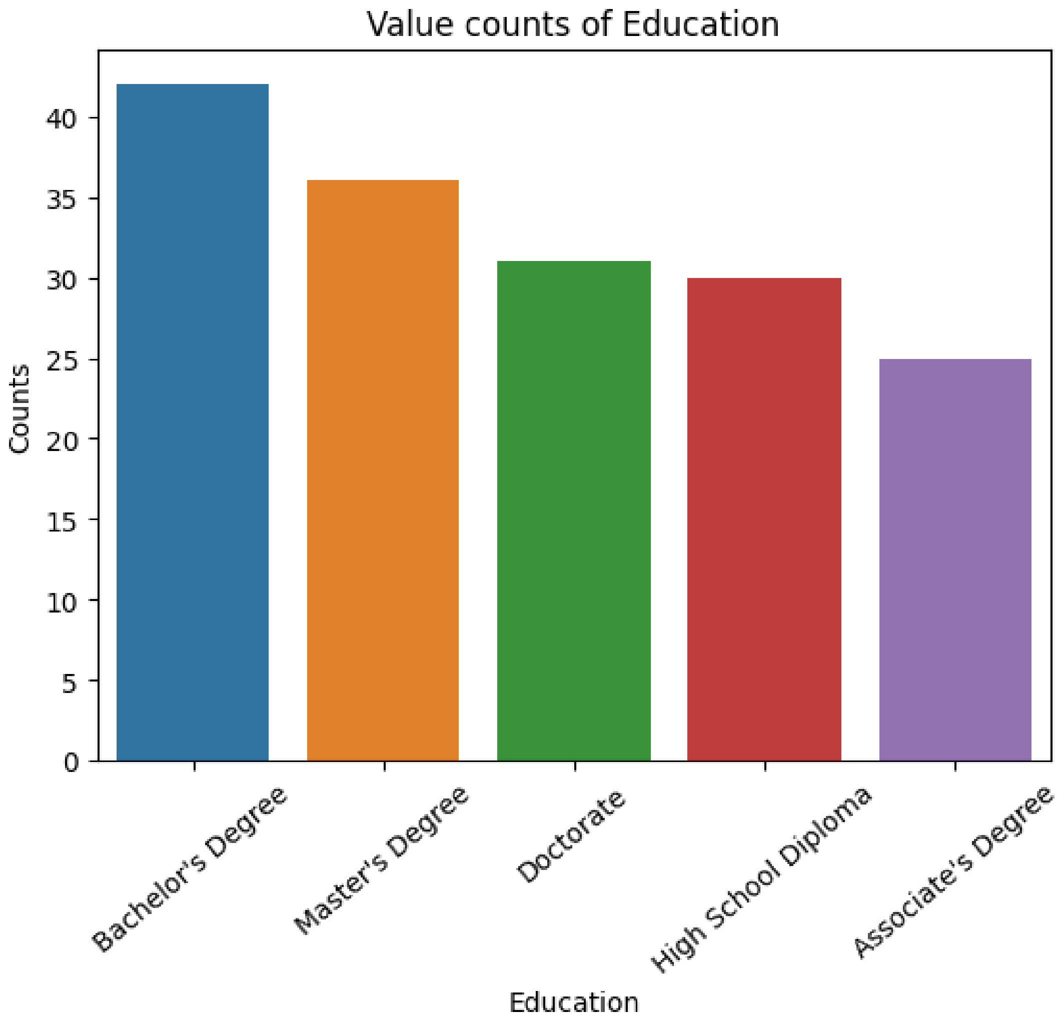

```
[94]: Education = df_original['Education'].value_counts()
Education
```

```
[94]: Bachelor's Degree      42
Master's Degree        36
Doctorate              31
High School Diploma    30
Associate's Degree     25
Name: Education, dtype: int64
```

```
[101]: sns.barplot(x = Education.index, y = Education)
plt.title('Value counts of Education')
plt.xlabel('Education')
plt.ylabel('Counts')
plt.xticks(rotation = 40)
```

```
[101]: (array([0, 1, 2, 3, 4]),
 [Text(0, 0, "Bachelor's Degree"),
  Text(1, 0, "Master's Degree"),
  Text(2, 0, 'Doctorate'),
```

```
 Text(3, 0, 'High School Diploma'),
 Text(4, 0, "Associate's Degree")])
```



[86]:

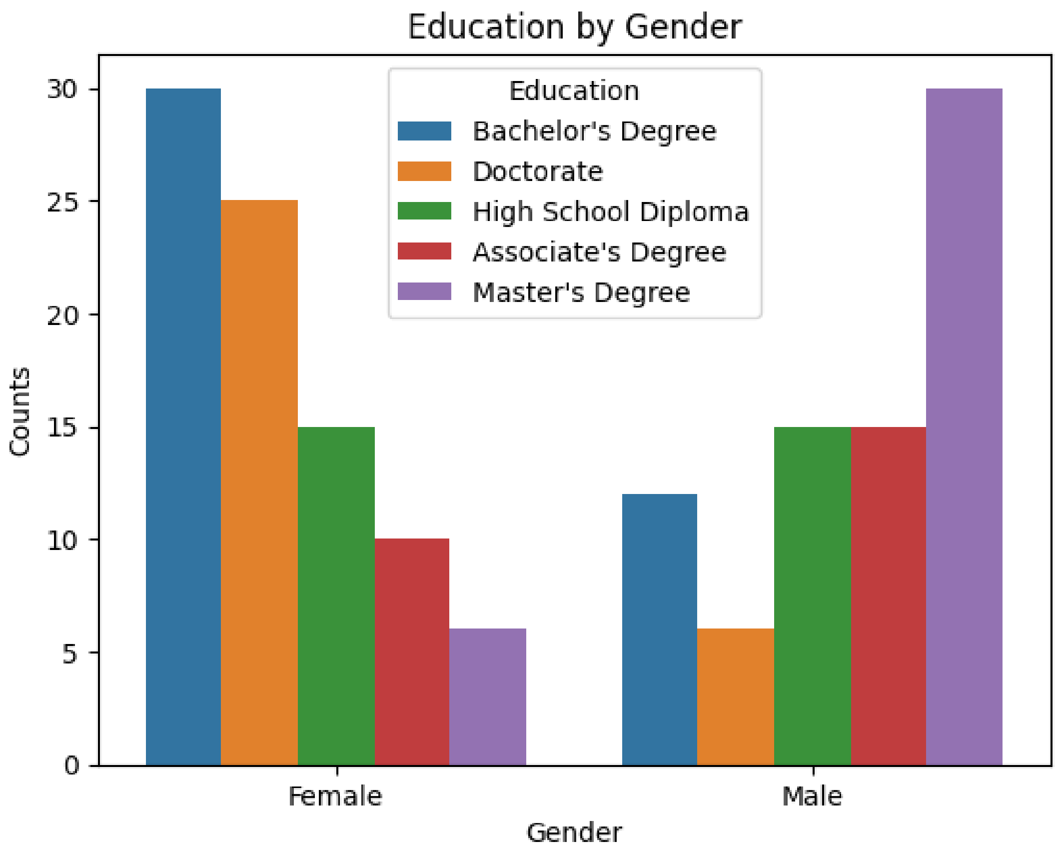
```
Edu_by_Gender = df_original['Education'].groupby(df_original['Gender']).
 ↪value_counts()
Edu_by_Gender = Edu_by_Gender.reset_index(name = 'Count')
Edu_by_Gender
```

[86]:

	Gender	Education	Count
0	Female	Bachelor's Degree	30
1	Female	Doctorate	25
2	Female	High School Diploma	15
3	Female	Associate's Degree	10
4	Female	Master's Degree	6
5	Male	Master's Degree	30

```
6    Male   Associate's Degree     15
7    Male  High School Diploma     15
8    Male    Bachelor's Degree     12
9    Male            Doctorate      6
```

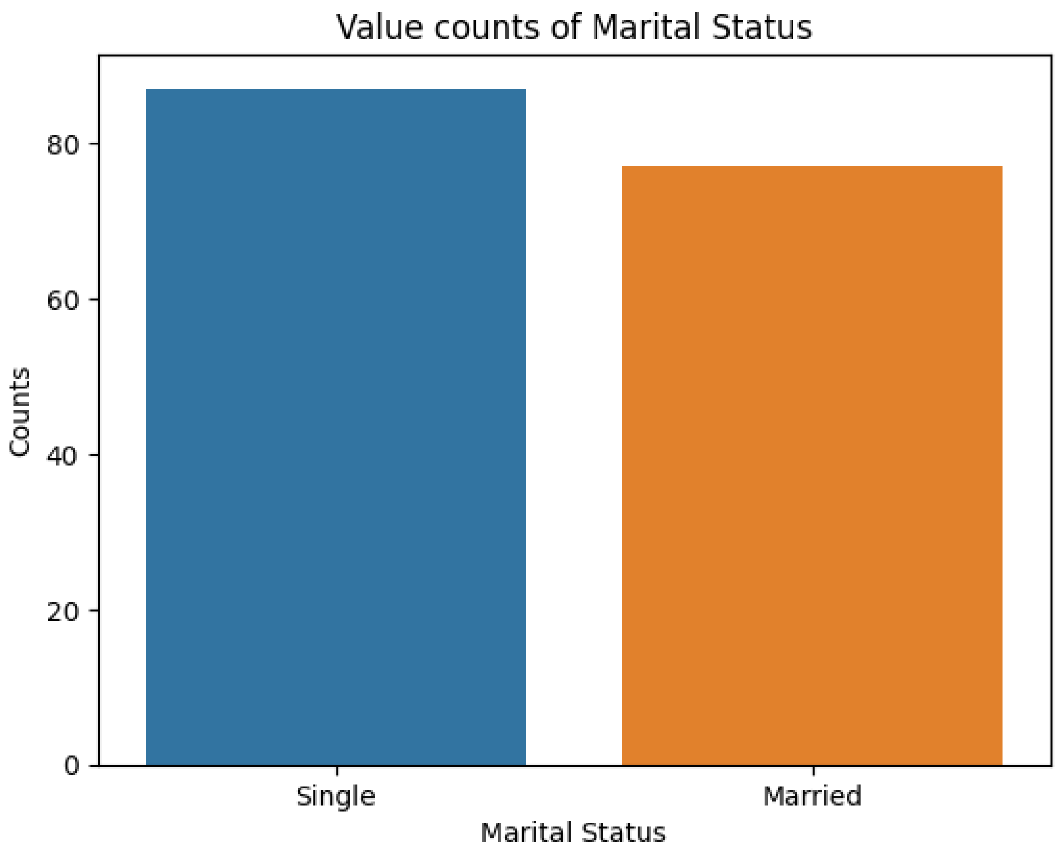
[104]:
```
sns.barplot(x = Edu_by_Gender['Gender'], y = Edu_by_Gender['Count'], hue =␣
 ↪Edu_by_Gender['Education'])
plt.title('Education by Gender')
plt.xlabel('Gender')
plt.ylabel('Counts')
plt.show()
```



[110]:
```
df_original['Marital Status'].value_counts()
```

[110]:
```
Married    87
Single     77
Name: Marital Status, dtype: int64
```

[109]:
```
sns.barplot(x = df_original['Marital Status'].unique(),y = df_original['Marital␣
↪Status'].value_counts())
plt.title('Value counts of Marital Status')
plt.xlabel('Marital Status')
plt.ylabel('Counts')
plt.show()
```

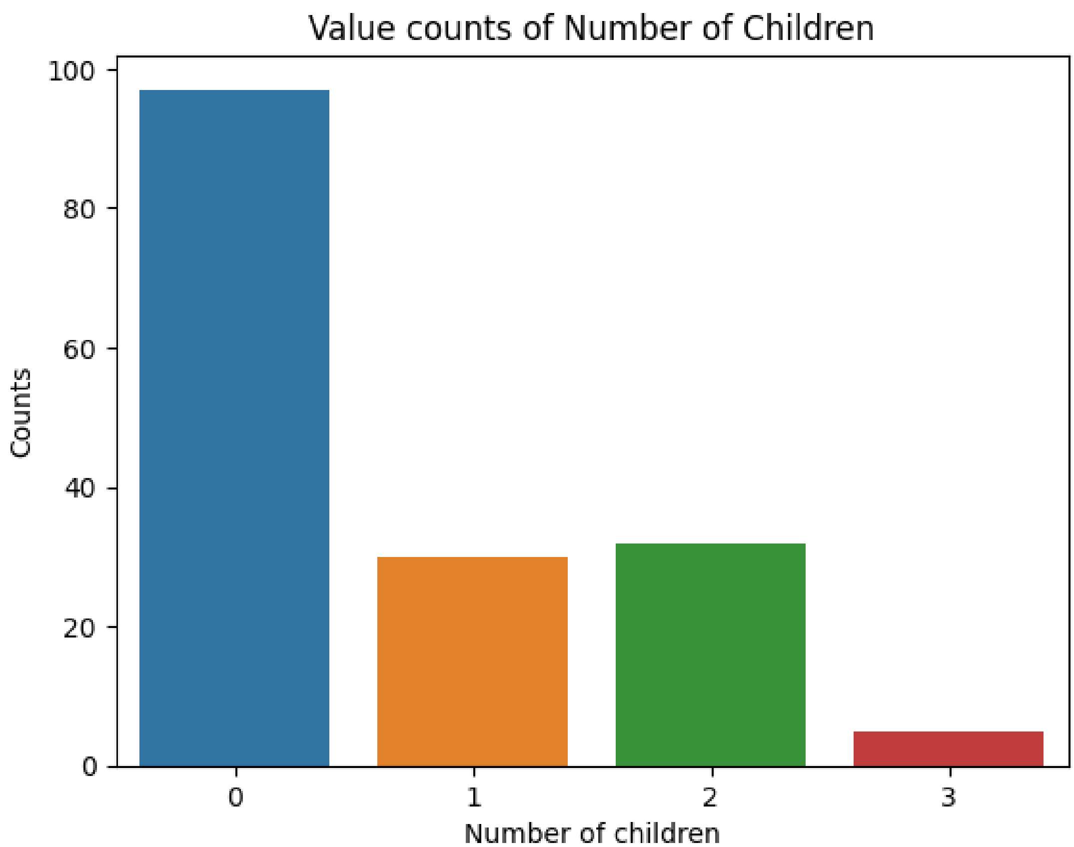


[112]:
```
df_original['Number of Children'].value_counts()
```

[112]:
```
0    97
1    32
2    30
3     5
Name: Number of Children, dtype: int64
```

[114]:
```
sns.barplot(x = df_original['Number of Children'].unique(), y =␣
↪df_original['Number of Children'].value_counts())
plt.title('Value counts of Number of Children')
plt.xlabel('Number of children')
plt.ylabel('Counts')
```

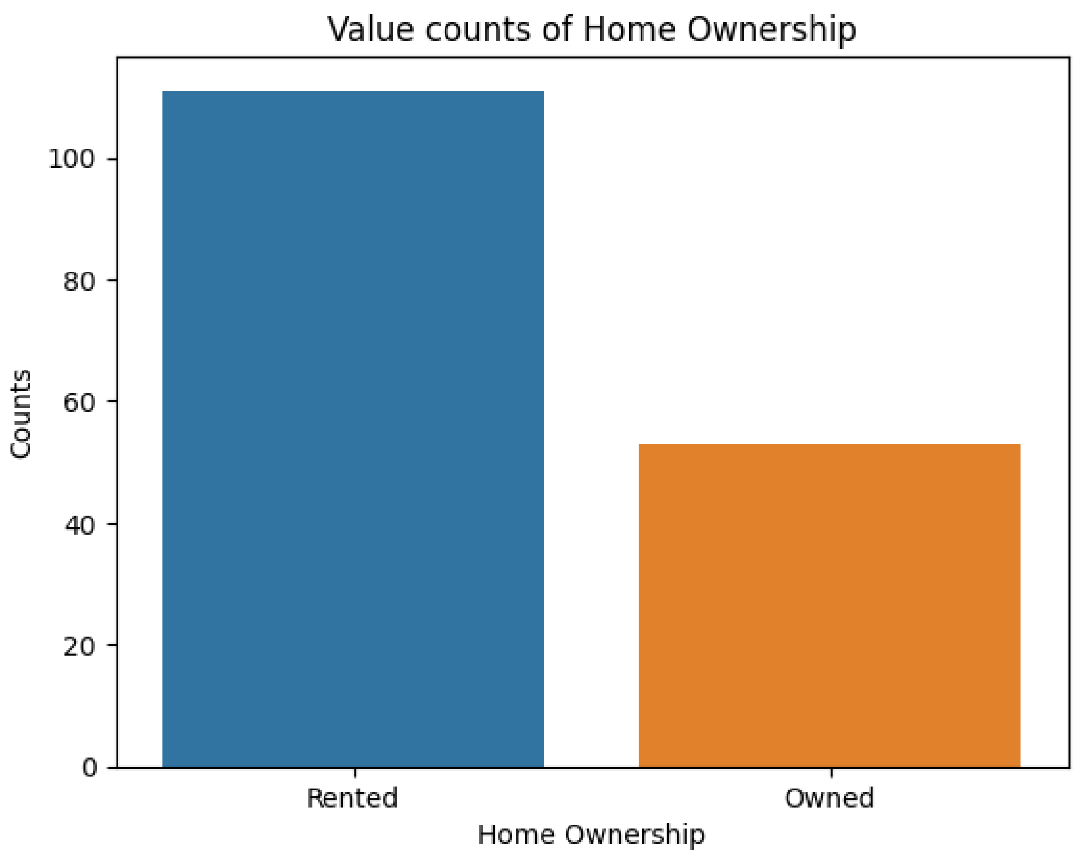
```
plt.show()
```



[115]:
```
df_original['Home Ownership'].value_counts()
```

[115]:
```
Owned      111
Rented      53
Name: Home Ownership, dtype: int64
```

[117]:
```
sns.barplot(x = df_original['Home Ownership'].unique(), y = df_original['Home␣
↪Ownership'].value_counts())
plt.title('Value counts of Home Ownership')
plt.xlabel('Home Ownership')
plt.ylabel('Counts')
plt.show()
```

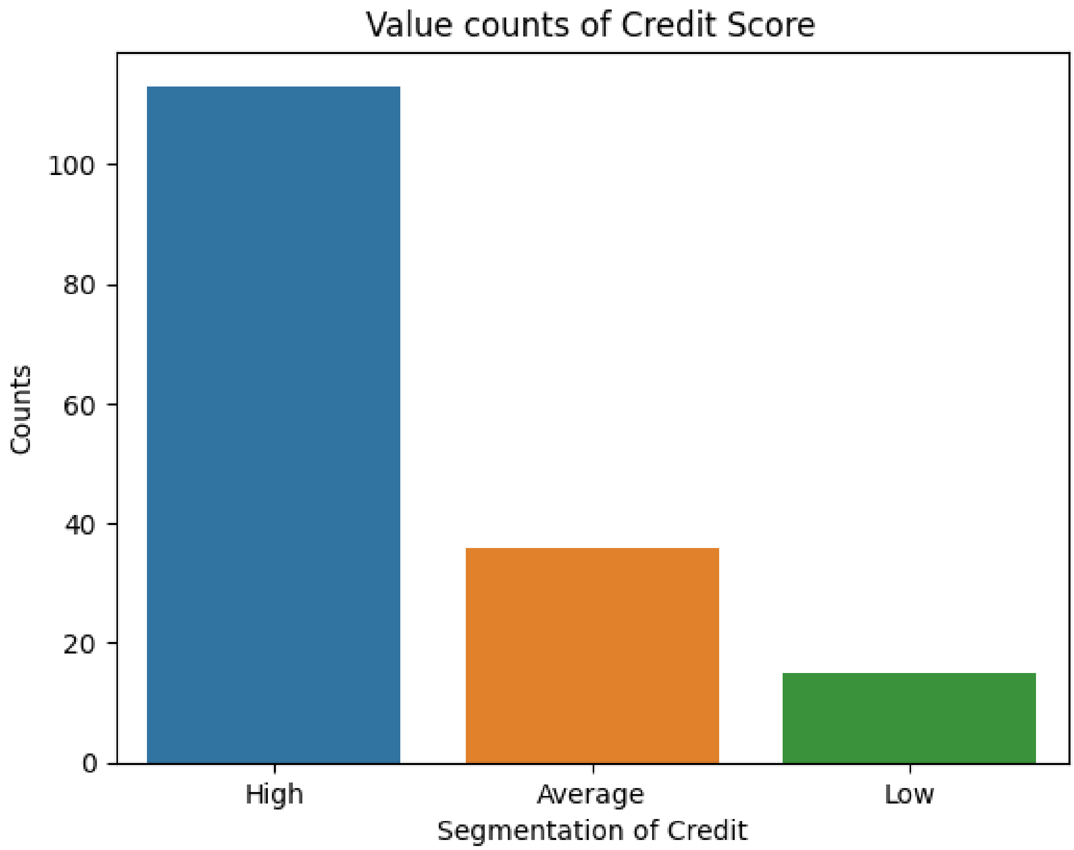


[118]:
```
df_original['Credit Score'].value_counts()
```

[118]:
```
High       113
Average     36
Low         15
Name: Credit Score, dtype: int64
```

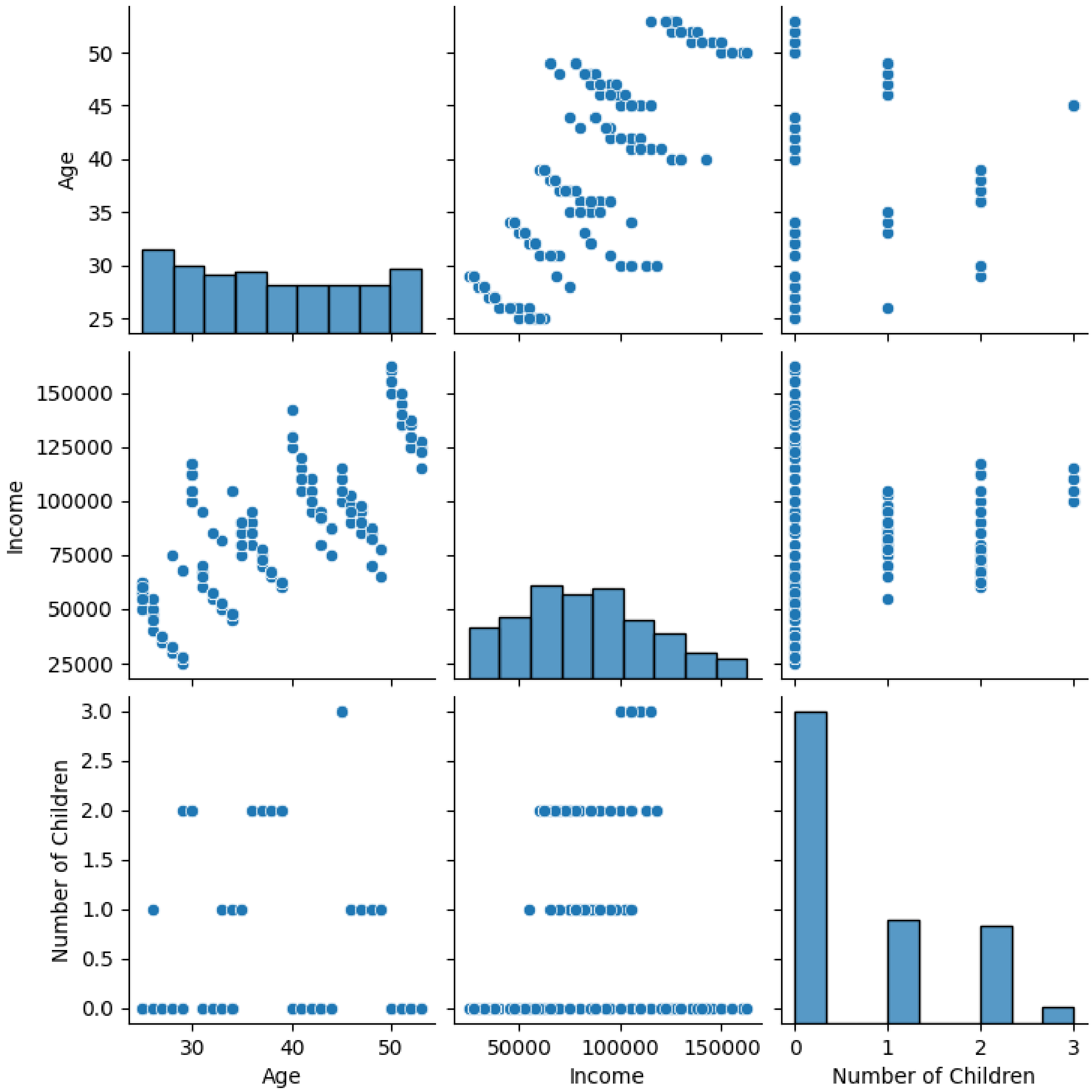
2.4

[121]:
```
sns.barplot(x = df_original['Credit Score'].unique(), y = df_original['Credit␣
↪Score'].value_counts())
plt.title('Value counts of Credit Score')
plt.xlabel('Segmentation of Credit')
plt.ylabel('Counts')
plt.show()
```



[123]:
```
sns.pairplot(data = df_original)
plt.show()
```

```
C:\Users\Admin\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The
figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



2.5 Label Encoding

[4]:
```
le = LabelEncoder()
df_original['Gender'] = le.fit_transform(df_original['Gender'])
df_original['Education'] = le.fit_transform(df_original['Education'])
df_original['Marital Status'] = le.fit_transform(df_original['Marital Status'])
df_original['Home Ownership'] = le.fit_transform (df_original['Home Ownership'])
df_original['Credit Score'] = le.fit_transform(df_original['Credit Score'])
df_original.head()
```

[4]:
```
   Age  Gender  Income  Education  Marital Status  Number of Children  \
0   25       0   50000          1               1                   0
```

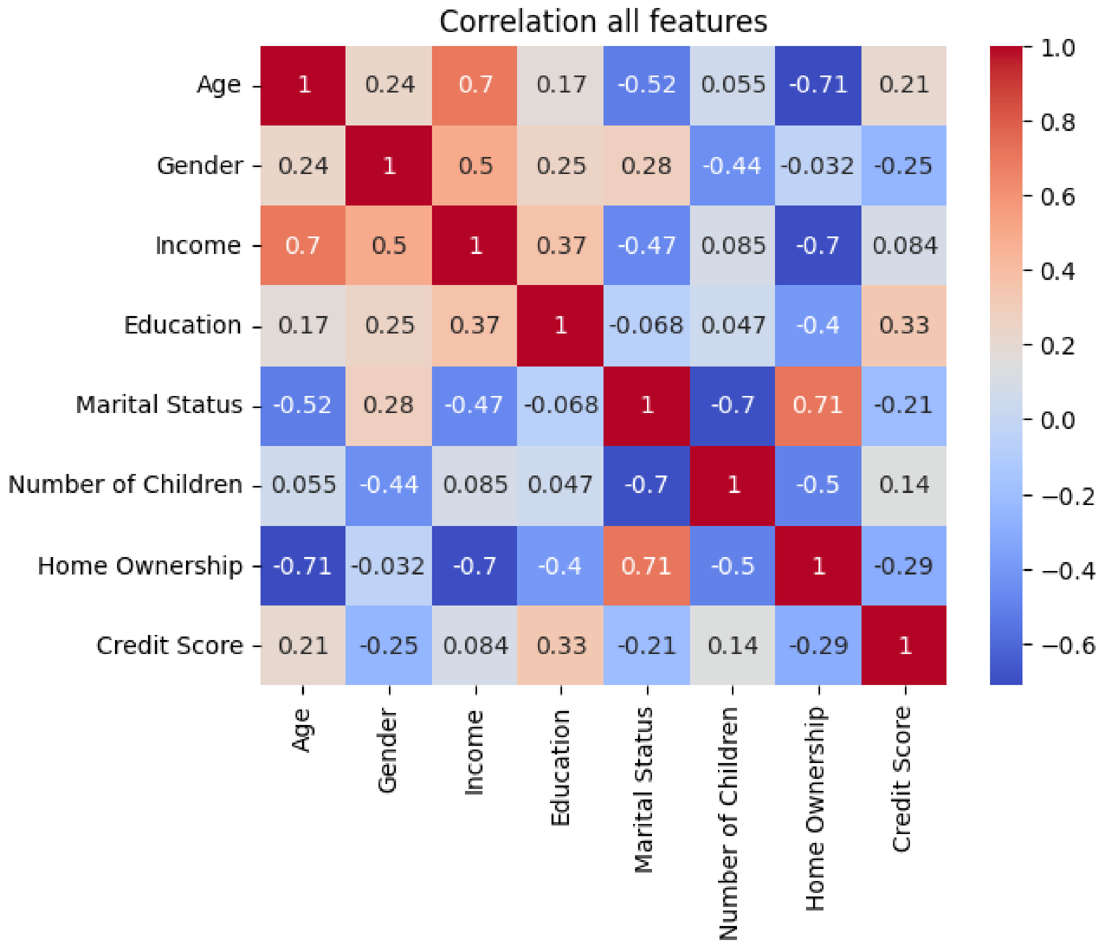
```
1   30      1  100000          4           0                   2
2   35      0   75000          2           0                   1
3   40      1  125000          3           1                   0
4   45      0  100000          1           0                   3

   Home Ownership  Credit Score
0               1             1
1               0             1
2               0             1
3               0             1
4               0             1
```

I pick out 5 categorical columns to label encoder: Gender, Education, Marital Status, Home Ownership, Credit Score.

2.6 Correlation after encoder

[27]:
```python
df_original.corr()
sns.heatmap(df_original.corr(), cmap = 'coolwarm', annot = True)
plt.title('Correlation all features')
plt.show
```

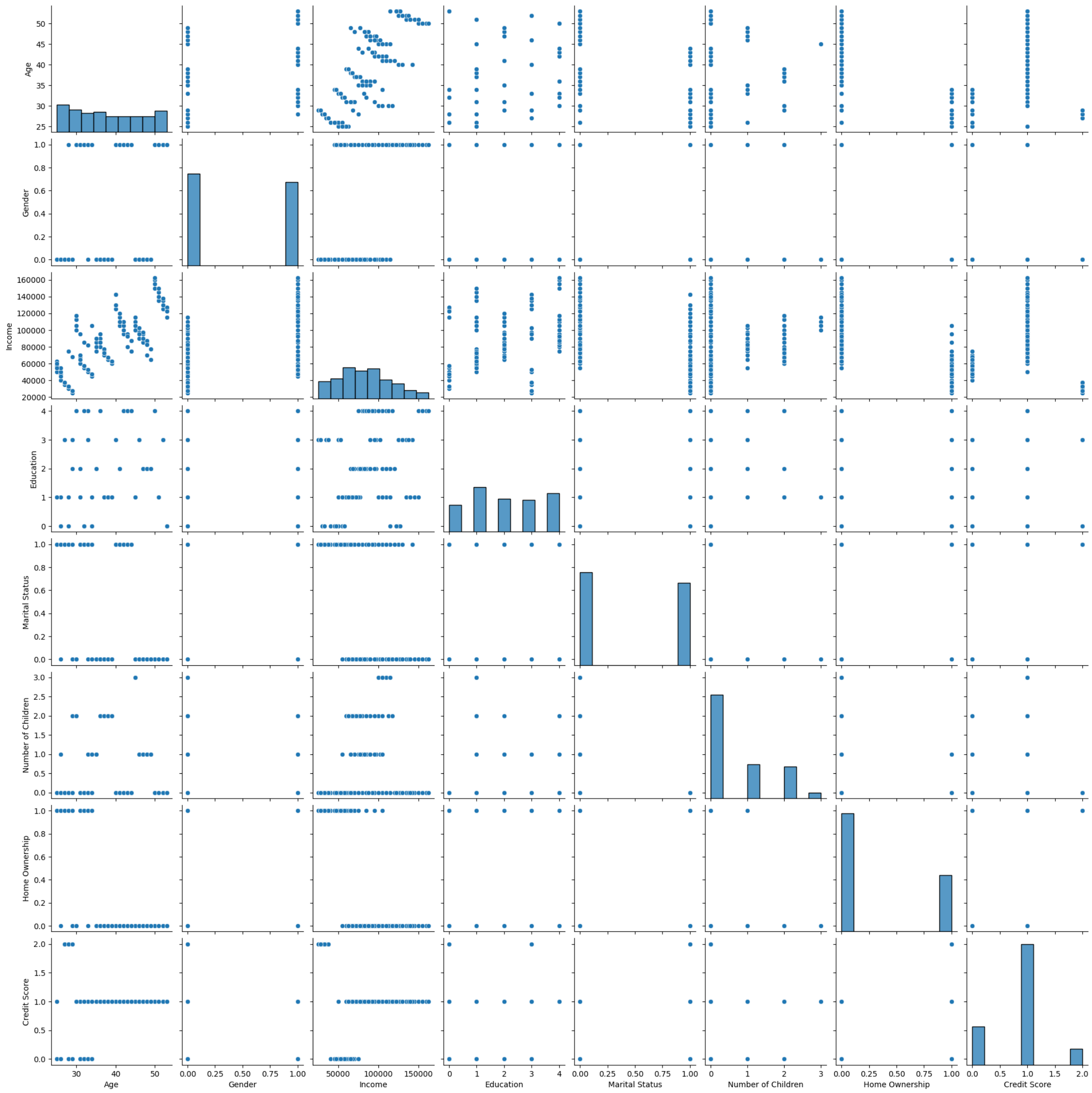
[27]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



[20]:
```
sns.pairplot(df_original)
```

```
C:\Users\Admin\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The
figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

[20]: `<seaborn.axisgrid.PairGrid at 0x19655860dd0>`



[21]:
```
df_original.corr()
```

[21]:
```
                         Age    Gender    Income  Education  Marital Status  \
Age                 1.000000  0.235343  0.699464   0.170254       -0.517723
Gender              0.235343  1.000000  0.495738   0.248671        0.278362
Income              0.699464  0.495738  1.000000   0.369449       -0.471004
Education           0.170254  0.248671  0.369449   1.000000       -0.067797
Marital Status     -0.517723  0.278362 -0.471004  -0.067797        1.000000
Number of Children  0.055390 -0.442139  0.084547   0.047311       -0.696984
Home Ownership     -0.713803 -0.031519 -0.704928  -0.397043        0.708374
Credit Score        0.205362 -0.247729  0.083698   0.334424       -0.205756

                    Number of Children  Home Ownership  Credit Score
```

```
Age                         0.055390   -0.713803    0.205362
Gender                     -0.442139   -0.031519   -0.247729
Income                      0.084547   -0.704928    0.083698
Education                   0.047311   -0.397043    0.334424
Marital Status             -0.696984    0.708374   -0.205756
Number of Children          1.000000   -0.497129    0.136517
Home Ownership             -0.497129    1.000000   -0.293384
Credit Score                0.136517   -0.293384    1.000000
```

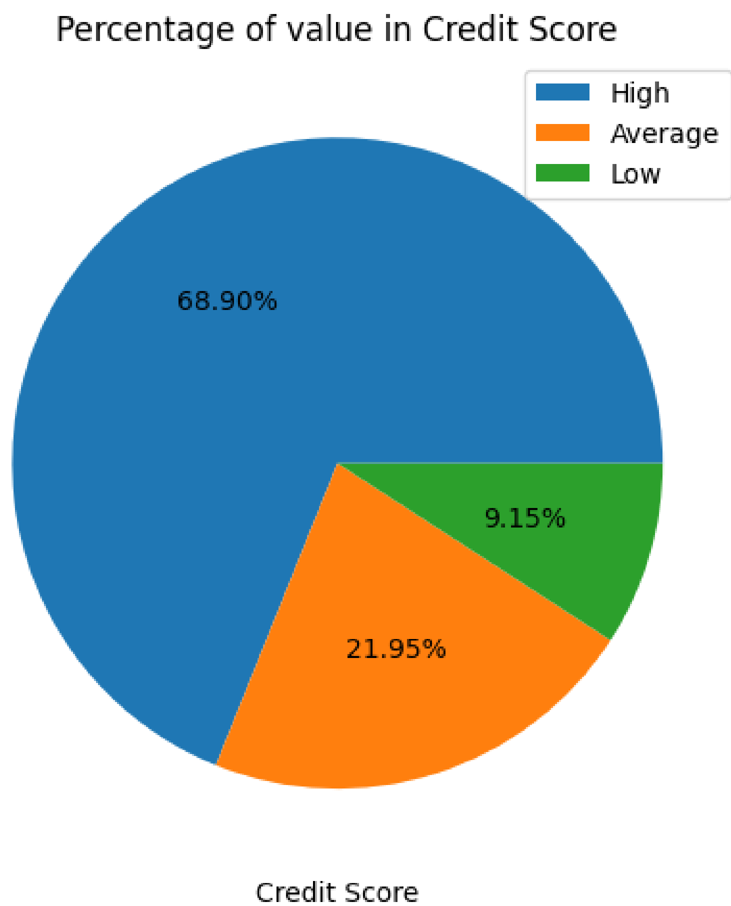
We can see the slightly positive correlation between Education and Credit Score

2.7 Analyzing on target column values 'Credit Score'

[32]:
```
df_original['Credit Score'].value_counts()
```

[32]:
```
1    113
0     36
2     15
Name: Credit Score, dtype: int64
```

[31]:
```
plt.figure(figsize = (5.5,5.5))
plt.pie(df_original['Credit Score'].value_counts(), autopct = '%1.2f%%')
plt.title('Percentage of value in Credit Score')
plt.xlabel('Credit Score')
plt.legend(df['Credit Score'].unique())
plt.show()
```



There is a significant imbalance between 3 unique values in column Credit Score. I need to address this issue by 3 methods later. I will try 3 methods to find out which is the good method for this dataset

2.7.1 Method 1: Undersampling

[115]:
```
df_original['Credit Score'].value_counts()
```

[115]:
```
1    113
0     36
2     15
Name: Credit Score, dtype: int64
```

[5]:
```
under_count_0 = df_original[df_original['Credit Score'] == 0]
under_count_1 = df_original[df_original['Credit Score'] == 1]
under_count_2 = df_original[df_original['Credit Score'] == 2]
undersample_size = 15
undersample_count_0 = under_count_0.sample(undersample_size, random_state = 0)
```

```
undersample_count_1 = under_count_1.sample(undersample_size, random_state = 1)
```

[6]:
```
print('Credit 0: ',undersample_count_0.shape)
print('Credit 1: ',undersample_count_1.shape)
print('Credit 2: ',under_count_2.shape)
```

```
Credit 0:  (15, 8)
Credit 1:  (15, 8)
Credit 2:  (15, 8)
```

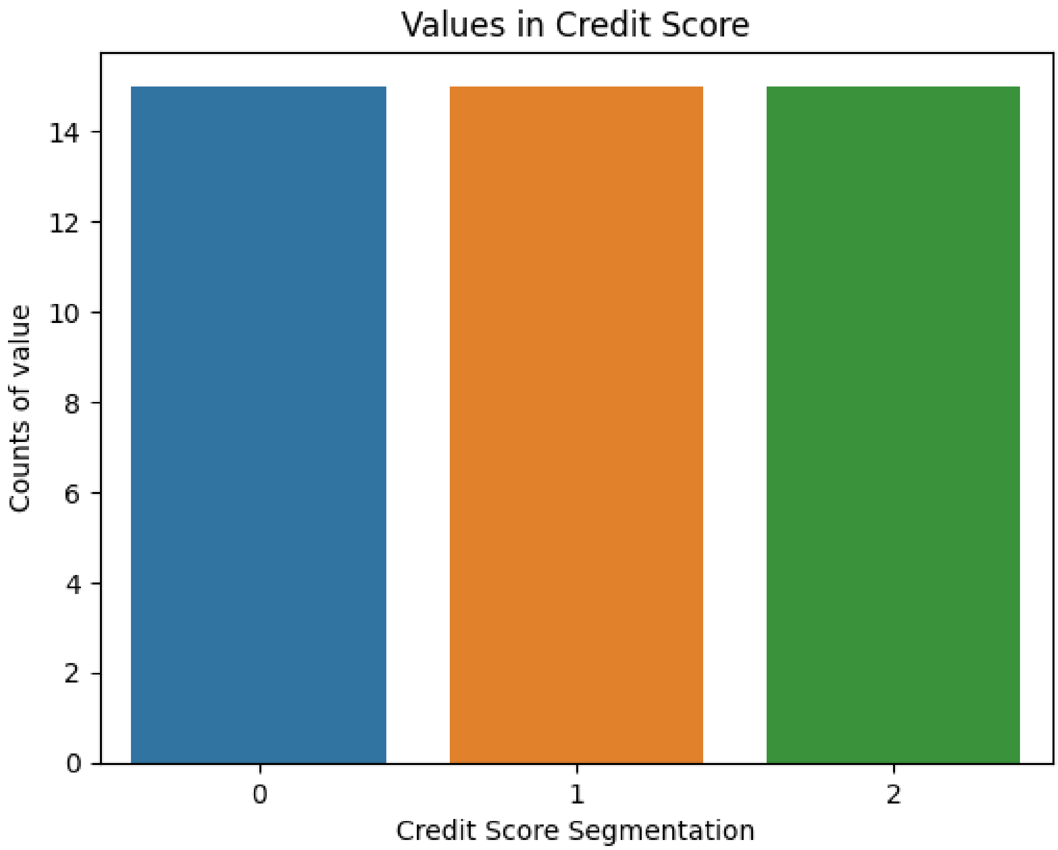
[7]:
```
under_df = pd.concat([undersample_count_0, undersample_count_1, under_count_2],␣
    ↪axis = 0, ignore_index = True)
under_df.shape
```

[7]:
```
(45, 8)
```

[7]:
```
under_df.isna().sum()
```

[7]:
```
Age                   0
Gender                0
Income                0
Education             0
Marital Status        0
Number of Children    0
Home Ownership        0
Credit Score          0
dtype: int64
```

[125]:
```
sns.barplot(x = under_df['Credit Score'].unique(), y = under_df['Credit Score'].
    ↪value_counts())
plt.title('Values in Credit Score')
plt.xlabel('Credit Score Segmentation')
plt.ylabel('Counts of value')
plt.show()
```



2.7.2 Method 2: Oversampling

[8]:
```
df_original['Credit Score'].value_counts()
```

[8]:
```
1    113
0     36
2     15
Name: Credit Score, dtype: int64
```

[9]:
```
over_count_0 = df_original[df_original['Credit Score'] == 0]
over_count_1 = df_original[df_original['Credit Score'] == 1]
over_count_2 = df_original[df_original['Credit Score'] == 2]
oversample_size = 113
oversample_count_0 = over_count_0.sample(oversample_size, random_state = 0,␣
↪replace = True)
oversample_count_2 = over_count_2.sample(oversample_size, random_state = 2,␣
↪replace = True)
```

[10]:
```python
print('Credit 0: ',oversample_count_0.shape)
print('Credit 1: ',over_count_1.shape)
print('Credit 2: ',oversample_count_2.shape)
```

```
Credit 0:  (113, 8)
Credit 1:  (113, 8)
Credit 2:  (113, 8)
```

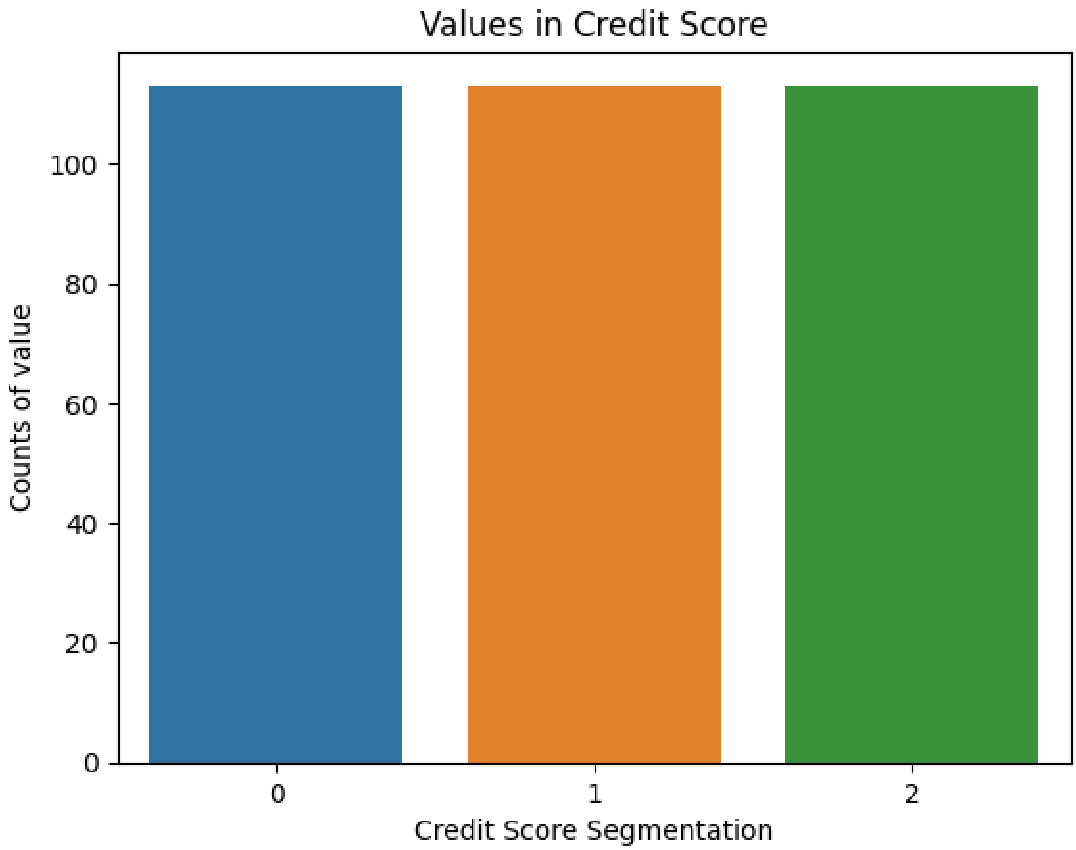
[11]:
```python
over_df = pd.concat([oversample_count_0, over_count_1, oversample_count_2],␣
↪axis = 0, ignore_index = True)
over_df.shape
```

[11]:
```
(339, 8)
```

[12]:
```python
over_df.isna().sum()
```

[12]:
```
Age                   0
Gender                0
Income                0
Education             0
Marital Status        0
Number of Children    0
Home Ownership        0
Credit Score          0
dtype: int64
```

[139]:
```python
sns.barplot(x = over_df['Credit Score'].unique(), y = over_df['Credit Score'].
↪value_counts())
plt.title('Values in Credit Score')
plt.xlabel('Credit Score Segmentation')
plt.ylabel('Counts of value')
plt.show()
```



2.7.3 Method 3: SMOTE

[140]:
```
df_original['Credit Score'].value_counts()
```

[140]:
```
1    113
0     36
2     15
Name: Credit Score, dtype: int64
```

[13]:
```
!pip install imblearn
from imblearn.over_sampling import SMOTE
```

```
[notice] A new release of pip available: 22.3.1 -> 23.2.1
[notice] To update, run: python.exe -m pip install --upgrade pip
```

```
Requirement already satisfied: imblearn in c:\users\admin\lib\site-packages
(0.0)
Requirement already satisfied: imbalanced-learn in c:\users\admin\lib\site-
packages (from imblearn) (0.11.0)
```

```
Requirement already satisfied: numpy>=1.17.3 in c:\users\admin\lib\site-packages
(from imbalanced-learn->imblearn) (1.24.2)
Requirement already satisfied: scipy>=1.5.0 in c:\users\admin\lib\site-packages
(from imbalanced-learn->imblearn) (1.11.1)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\admin\lib\site-
packages (from imbalanced-learn->imblearn) (1.3.0)
Requirement already satisfied: joblib>=1.1.1 in c:\users\admin\lib\site-packages
(from imbalanced-learn->imblearn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\admin\lib\site-
packages (from imbalanced-learn->imblearn) (3.2.0)
```

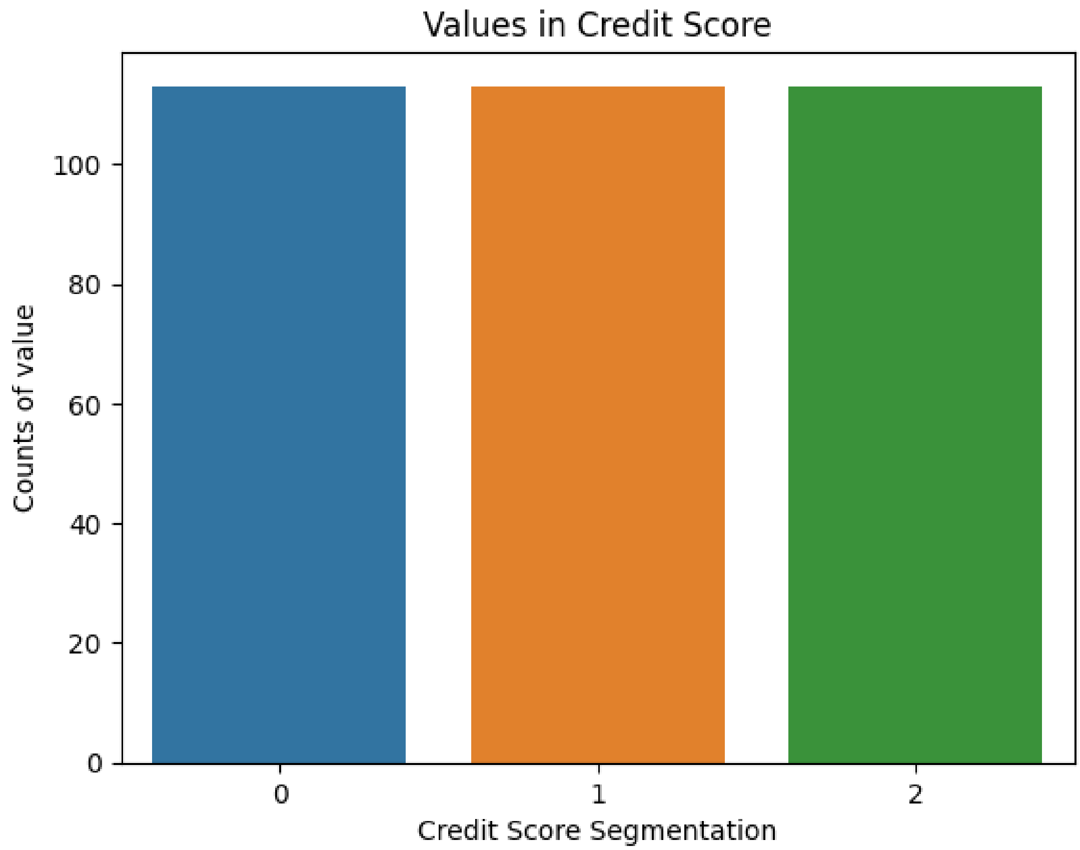
[14]:
```
sm = SMOTE(sampling_strategy = 'all', random_state = 3)
X = df_original.drop('Credit Score', axis = 1)
y = df_original['Credit Score']
X_sm, y_sm = sm.fit_resample(X, y)
sm_df = pd.DataFrame(X_sm, columns = df_original.columns)
sm_df['Credit Score'] = y_sm
sm_df.shape
```

[14]:
```
(339, 8)
```

[13]:
```
sm_df.isna().sum()
```

[13]:
```
Age                   0
Gender                0
Income                0
Education             0
Marital Status        0
Number of Children    0
Home Ownership        0
Credit Score          0
dtype: int64
```

[163]:
```
sns.barplot(x = sm_df['Credit Score'].unique(), y = sm_df['Credit Score'].
 ↪value_counts())
plt.title('Values in Credit Score')
plt.xlabel('Credit Score Segmentation')
plt.ylabel('Counts of value')
plt.show()
```



2.8 Preprocessing model machine learning

2.8.1 For Method 1: Undersampling

[15]:
```
X_under = under_df.drop(['Credit Score'], axis = 1)
y_under = under_df['Credit Score']
X_train_under, X_test_under, y_train_under, y_test_under =␣
↪train_test_split(X_under, y_under, test_size = 0.2, random_state = 10)
```

[16]:
```
sc = StandardScaler()
X_train_under = sc.fit_transform(X_train_under)
X_test_under = sc.transform(X_test_under)
```

2.8.2 For Method 2: Oversampling

[17]:
```
X_over = over_df.drop(['Credit Score'], axis = 1)
y_over = over_df['Credit Score']
X_train_over, X_test_over, y_train_over, y_test_over = train_test_split(X_over,␣
↪y_over, test_size = 0.2, random_state = 10)
```

[18]:
```
sc = StandardScaler()
X_train_over = sc.fit_transform(X_train_over)
X_test_over = sc.transform(X_test_over)
```

2.8.3 For Method 3: SMOTE

[19]:
```
X_sm = sm_df.drop(['Credit Score'], axis = 1)
y_sm = sm_df['Credit Score']
X_train_sm, X_test_sm, y_train_sm, y_test_sm = train_test_split(X_sm, y_sm,␣
 ↪test_size = 0.2, random_state = 10)
```

[20]:
```
sc = StandardScaler()
X_train_sm = sc.fit_transform(X_train_sm)
X_test_sm = sc.transform(X_test_sm)
```

2.9 Building model run on 3 methods

[27]:
```
lr = LogisticRegression()
dtc = DecisionTreeClassifier()
rfc = RandomForestClassifier()
gbc = GradientBoostingClassifier()
knn = KNeighborsClassifier()
svc = SVC()
gnb = GaussianNB()
xgb = XGBClassifier()
```

[29]:
```
models = [lr, dtc, rfc, gbc, knn, svc, gnb, xgb]
```

2.9.1 Method 1: Undersampling

[51]:
```
for model in models:
    model.fit(X_train_under, y_train_under)
    y_pred_under = model.predict(X_test_under)
    Classfication_rp = classification_report(y_test_under, y_pred_under)
    print('-------------------------------------------------------')
    print(type(model).__name__)
    print(Classification_rp)
    print(confusion_matrix(y_test_under, y_pred_under))
```

```
------------------------------------------------------
LogisticRegression
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22
```

```
    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[2 0 0]
 [0 3 0]
 [0 0 4]]
------------------------------------------------------
DecisionTreeClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[2 0 0]
 [1 2 0]
 [0 0 4]]
------------------------------------------------------
RandomForestClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[2 0 0]
 [0 3 0]
 [0 0 4]]
------------------------------------------------------
GradientBoostingClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
```

```
weighted avg       0.99      0.99      0.99        68

[[2 0 0]
 [1 2 0]
 [0 0 4]]
------------------------------------------------------
KNeighborsClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[2 0 0]
 [0 3 0]
 [0 0 4]]
------------------------------------------------------
SVC
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[1 0 1]
 [0 3 0]
 [0 0 4]]
------------------------------------------------------
GaussianNB
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[1 0 1]
```

```
 [1 2 0]
 [0 0 4]]
------------------------------------------------------
XGBClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[2 0 0]
 [0 3 0]
 [0 0 4]]
```

For this undersampling method, we see all models give good outcomes.

2.9.2 Method 2: Oversampling

[52]:
```
for model in models:
    model.fit(X_train_over, y_train_over)
    y_pred_over = model.predict(X_test_over)
    Classification_rp = classification_report(y_test_over, y_pred_over)
    print('------------------------------------------------------')
    print(type(model).__name__)
    print(Classification_rp)
    print(confusion_matrix(y_test_over, y_pred_over))
```

```
------------------------------------------------------
LogisticRegression
              precision    recall  f1-score   support

           0       0.86      0.95      0.90        19
           1       0.96      0.89      0.93        28
           2       1.00      1.00      1.00        21

    accuracy                           0.94        68
   macro avg       0.94      0.95      0.94        68
weighted avg       0.94      0.94      0.94        68

[[18  1  0]
 [ 3 25  0]
 [ 0  0 21]]
------------------------------------------------------
DecisionTreeClassifier
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95        19
           1       1.00      0.93      0.96        28
           2       1.00      1.00      1.00        21

    accuracy                           0.97        68
   macro avg       0.97      0.98      0.97        68
weighted avg       0.97      0.97      0.97        68

[[19  0  0]
 [ 2 26  0]
 [ 0  0 21]]
------------------------------------------------------
RandomForestClassifier
              precision    recall  f1-score   support

           0       0.90      1.00      0.95        19
           1       1.00      0.93      0.96        28
           2       1.00      1.00      1.00        21

    accuracy                           0.97        68
   macro avg       0.97      0.98      0.97        68
weighted avg       0.97      0.97      0.97        68

[[19  0  0]
 [ 2 26  0]
 [ 0  0 21]]
------------------------------------------------------
GradientBoostingClassifier
              precision    recall  f1-score   support

           0       0.86      1.00      0.93        19
           1       1.00      0.89      0.94        28
           2       1.00      1.00      1.00        21

    accuracy                           0.96        68
   macro avg       0.95      0.96      0.96        68
weighted avg       0.96      0.96      0.96        68

[[19  0  0]
 [ 3 25  0]
 [ 0  0 21]]
------------------------------------------------------
KNeighborsClassifier
              precision    recall  f1-score   support

           0       0.86      0.95      0.90        19
```

```
           1       0.96      0.89      0.93        28
           2       1.00      1.00      1.00        21

    accuracy                           0.94        68
   macro avg       0.94      0.95      0.94        68
weighted avg       0.94      0.94      0.94        68

[[18  1  0]
 [ 3 25  0]
 [ 0  0 21]]
------------------------------------------------------
SVC
              precision    recall  f1-score   support

           0       0.89      0.84      0.86        19
           1       0.96      0.93      0.95        28
           2       0.91      1.00      0.95        21

    accuracy                           0.93        68
   macro avg       0.92      0.92      0.92        68
weighted avg       0.93      0.93      0.93        68

[[16  1  2]
 [ 2 26  0]
 [ 0  0 21]]
------------------------------------------------------
GaussianNB
              precision    recall  f1-score   support

           0       0.92      0.58      0.71        19
           1       0.96      0.93      0.95        28
           2       0.72      1.00      0.84        21

    accuracy                           0.85        68
   macro avg       0.87      0.84      0.83        68
weighted avg       0.88      0.85      0.85        68

[[11  1  7]
 [ 1 26  1]
 [ 0  0 21]]
------------------------------------------------------
XGBClassifier
              precision    recall  f1-score   support

           0       0.95      1.00      0.97        19
           1       1.00      0.96      0.98        28
           2       1.00      1.00      1.00        21
```

```
    accuracy                           0.99        68
   macro avg       0.98      0.99      0.99        68
weighted avg       0.99      0.99      0.99        68

[[19  0  0]
 [ 1 27  0]
 [ 0  0 21]]
```

With Oversampling method, although models can give out good outcomes, we clearly see that the outcomes are not as good as in comparision with Undersampling method. In this sample method, XG Boost Classifier is the best performance model.

2.9.3 Method 3: SMOTE

[53]:

```
for model in models:
    model.fit(X_train_sm, y_train_sm)
    y_pred_sm = model.predict(X_test_sm)
    Classification_rp = classification_report(y_test_sm, y_pred_sm)
    print('------------------------------------------------------')
    print(type(model).__name__)
    print(Classification_rp)
    print(confusion_matrix(y_test_sm, y_pred_sm))
```

```
------------------------------------------------------
LogisticRegression
              precision    recall  f1-score   support

           0       0.96      0.96      0.96        27
           1       1.00      0.95      0.97        19
           2       0.96      1.00      0.98        22

    accuracy                           0.97        68
   macro avg       0.97      0.97      0.97        68
weighted avg       0.97      0.97      0.97        68

[[26  0  1]
 [ 1 18  0]
 [ 0  0 22]]
------------------------------------------------------
DecisionTreeClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
```

```
weighted avg       0.99      0.99      0.99        68

[[27  0  0]
 [ 1 18  0]
 [ 0  0 22]]
-------------------------------------------------------
RandomForestClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[27  0  0]
 [ 1 18  0]
 [ 0  0 22]]
-------------------------------------------------------
GradientBoostingClassifier
              precision    recall  f1-score   support

           0       1.00      0.93      0.96        27
           1       0.90      1.00      0.95        19
           2       1.00      1.00      1.00        22

    accuracy                           0.97        68
   macro avg       0.97      0.98      0.97        68
weighted avg       0.97      0.97      0.97        68

[[25  2  0]
 [ 0 19  0]
 [ 0  0 22]]
-------------------------------------------------------
KNeighborsClassifier
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        27
           1       1.00      0.95      0.97        19
           2       1.00      1.00      1.00        22

    accuracy                           0.99        68
   macro avg       0.99      0.98      0.98        68
weighted avg       0.99      0.99      0.99        68

[[27  0  0]
```

```
 [ 1 18  0]
 [ 0  0 22]]
-------------------------------------------------------
SVC
              precision    recall  f1-score   support

           0       0.96      0.93      0.94        27
           1       1.00      0.95      0.97        19
           2       0.92      1.00      0.96        22

    accuracy                           0.96        68
   macro avg       0.96      0.96      0.96        68
weighted avg       0.96      0.96      0.96        68

[[25  0  2]
 [ 1 18  0]
 [ 0  0 22]]
-------------------------------------------------------
GaussianNB
              precision    recall  f1-score   support

           0       0.93      0.52      0.67        27
           1       1.00      0.95      0.97        19
           2       0.63      1.00      0.77        22

    accuracy                           0.79        68
   macro avg       0.85      0.82      0.80        68
weighted avg       0.85      0.79      0.79        68

[[14  0 13]
 [ 1 18  0]
 [ 0  0 22]]
-------------------------------------------------------
XGBClassifier
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        27
           1       1.00      1.00      1.00        19
           2       1.00      1.00      1.00        22

    accuracy                           1.00        68
   macro avg       1.00      1.00      1.00        68
weighted avg       1.00      1.00      1.00        68

[[27  0  0]
 [ 0 19  0]
 [ 0  0 22]]
```

In SMOTE method, all models give very good results, possibly on par with method Undersampling. Particularly, the XGB model across the three methods consistently gives the best outcomes among the models, and in this method, XGB achieves the best performance in all three runs.

2.10 In Conclusion

This is really an interesting project that I have done. After analyzing, I give the following two conclusions: - About the method of handling imbalanced data: I recommend choosing the SMOTE method - About the machine learning model: I recommend choosing the XG Boost Classifier model

Thank you for reading my personal project

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