# Bank Loan Classification & Analysis

November 28, 2023

## 1 Bank Loan Classification & Analysis

#### 1.0.1 Importing Libraries

[53]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.api as smi
import pylab
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
↪mean_squared_error
from sklearn.metrics import classification_report
from tabulate import tabulate
from sklearn.metrics import confusion_matrix
import warnings
from sklearn.feature_selection import f_regression
warnings.simplefilter('ignore')
```

#### 1.0.2 Data Preprocesing

[54]:
```
df = pd.read_csv(r'C:/Users/PC/Desktop/ML/Data/bankloan.csv')
df.head(5)
```

[54]:

| | ID | Age | Experience | Income | ZIP.Code | Family | CCAvg | Education | Mortgage | \ |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 25 | 1 | 49 | 91107 | 4 | 1.6 | 1 | 0 | |
| 1 | 2 | 45 | 19 | 34 | 90089 | 3 | 1.5 | 1 | 0 | |
| 2 | 3 | 39 | 15 | 11 | 94720 | 1 | 1.0 | 1 | 0 | |
| 3 | 4 | 35 | 9 | 100 | 94112 | 1 | 2.7 | 2 | 0 | |

```
4   5   35          8      45     91330       4    1.0          2          0

   Personal.Loan  Securities.Account  CD.Account  Online  CreditCard
0              0                   1           0       0           0
1              0                   1           0       0           0
2              0                   0           0       0           0
3              0                   0           0       0           0
4              0                   0           0       0           1
```

[55]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   ID                  5000 non-null   int64
 1   Age                 5000 non-null   int64
 2   Experience          5000 non-null   int64
 3   Income              5000 non-null   int64
 4   ZIP.Code            5000 non-null   int64
 5   Family              5000 non-null   int64
 6   CCAvg               5000 non-null   float64
 7   Education           5000 non-null   int64
 8   Mortgage            5000 non-null   int64
 9   Personal.Loan       5000 non-null   int64
 10  Securities.Account  5000 non-null   int64
 11  CD.Account          5000 non-null   int64
 12  Online              5000 non-null   int64
 13  CreditCard          5000 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

[56]:
```
df.describe()
```

[56]:
```
                ID          Age   Experience       Income      ZIP.Code  \
count  5000.000000  5000.000000  5000.000000  5000.000000   5000.000000
mean   2500.500000    45.338400    20.104600    73.774200  93152.503000
std    1443.520003    11.463166    11.467954    46.033729   2121.852197
min       1.000000    23.000000    -3.000000     8.000000   9307.000000
25%    1250.750000    35.000000    10.000000    39.000000  91911.000000
50%    2500.500000    45.000000    20.000000    64.000000  93437.000000
75%    3750.250000    55.000000    30.000000    98.000000  94608.000000
max    5000.000000    67.000000    43.000000   224.000000  96651.000000

            Family        CCAvg    Education     Mortgage  Personal.Loan  \
count  5000.000000  5000.000000  5000.000000  5000.000000    5000.000000
mean      2.396400     1.937938     1.881000    56.498800       0.096000
```

```
std        1.147663     1.747659     0.839869   101.713802       0.294621
min        1.000000     0.000000     1.000000     0.000000       0.000000
25%        1.000000     0.700000     1.000000     0.000000       0.000000
50%        2.000000     1.500000     2.000000     0.000000       0.000000
75%        3.000000     2.500000     3.000000   101.000000       0.000000
max        4.000000    10.000000     3.000000   635.000000       1.000000

       Securities.Account  CD.Account       Online   CreditCard
count         5000.000000  5000.00000  5000.000000  5000.000000
mean             0.104400     0.06040     0.596800     0.294000
std              0.305809     0.23825     0.490589     0.455637
min              0.000000     0.00000     0.000000     0.000000
25%              0.000000     0.00000     0.000000     0.000000
50%              0.000000     0.00000     1.000000     0.000000
75%              0.000000     0.00000     1.000000     1.000000
max              1.000000     1.00000     1.000000     1.000000
```

[57]:
```
df.mean()
```

[57]:
```
ID                     2500.500000
Age                      45.338400
Experience               20.104600
Income                   73.774200
ZIP.Code              93152.503000
Family                    2.396400
CCAvg                     1.937938
Education                 1.881000
Mortgage                 56.498800
Personal.Loan             0.096000
Securities.Account        0.104400
CD.Account                0.060400
Online                    0.596800
CreditCard                0.294000
dtype: float64
```

[58]:
```
df.skew()
```

[58]:
```
ID                     0.000000
Age                   -0.029341
Experience            -0.026325
Income                 0.841339
ZIP.Code             -12.500221
Family                 0.155221
CCAvg                  1.598443
Education              0.227093
Mortgage               2.104002
Personal.Loan          2.743607
```

```
Securities.Account     2.588268
CD.Account             3.691714
Online                -0.394785
CreditCard             0.904589
dtype: float64
```

[59]:
```
df.isnull().sum()
```

[59]:
```
ID                    0
Age                   0
Experience            0
Income                0
ZIP.Code              0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Personal.Loan         0
Securities.Account    0
CD.Account            0
Online                0
CreditCard            0
dtype: int64
```

[60]:
```
df.columns
```

[60]:
```
Index(['ID', 'Age', 'Experience', 'Income', 'ZIP.Code', 'Family', 'CCAvg',
       'Education', 'Mortgage', 'Personal.Loan', 'Securities.Account',
       'CD.Account', 'Online', 'CreditCard'],
      dtype='object')
```

[61]:
```
df.shape
```

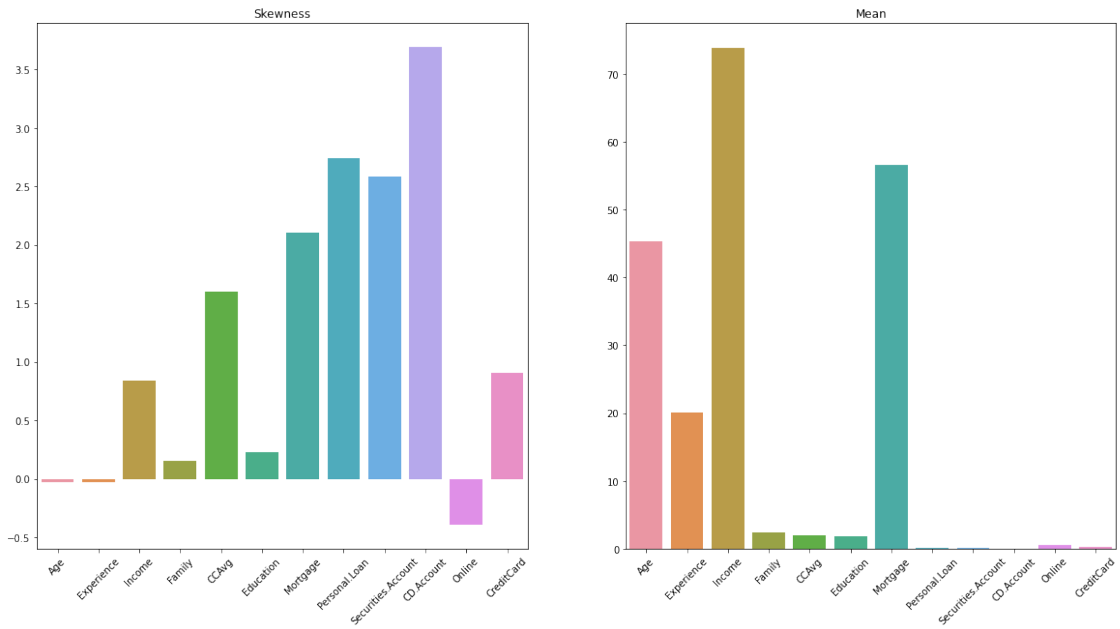
[61]:
```
(5000, 14)
```

[62]:
```
df = df.drop(['ID','ZIP.Code'],axis=1)
```

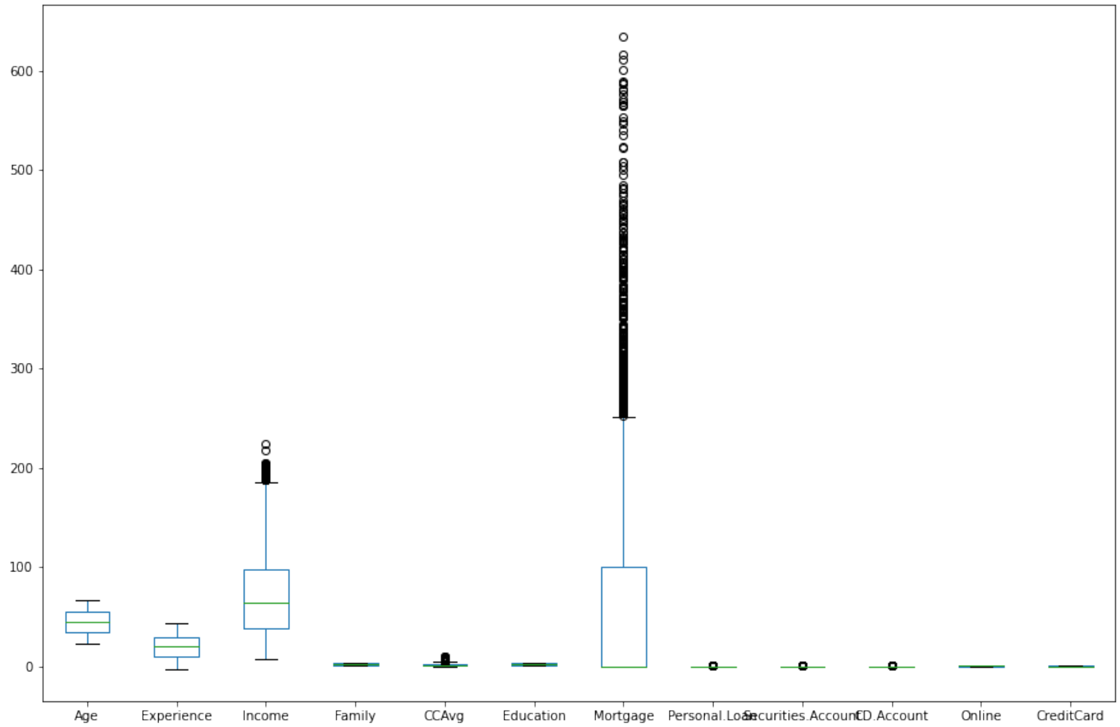
### 1.0.3 Exploratory Data Analysis

[63]:
```
skewness_values = df.skew()
mean_values = df.mean()

fig, ax = plt.subplots(1, 2, figsize=(20, 10))

sns.barplot(x=skewness_values.index, y=skewness_values.values, ax=ax[0])
ax[0].set_title('Skewness')
ax[0].tick_params(axis='x', rotation=45)
```

```python
sns.barplot(x=mean_values.index, y=mean_values.values, ax=ax[1])
ax[1].set_title('Mean')
ax[1].tick_params(axis='x', rotation=45)

plt.show()
```

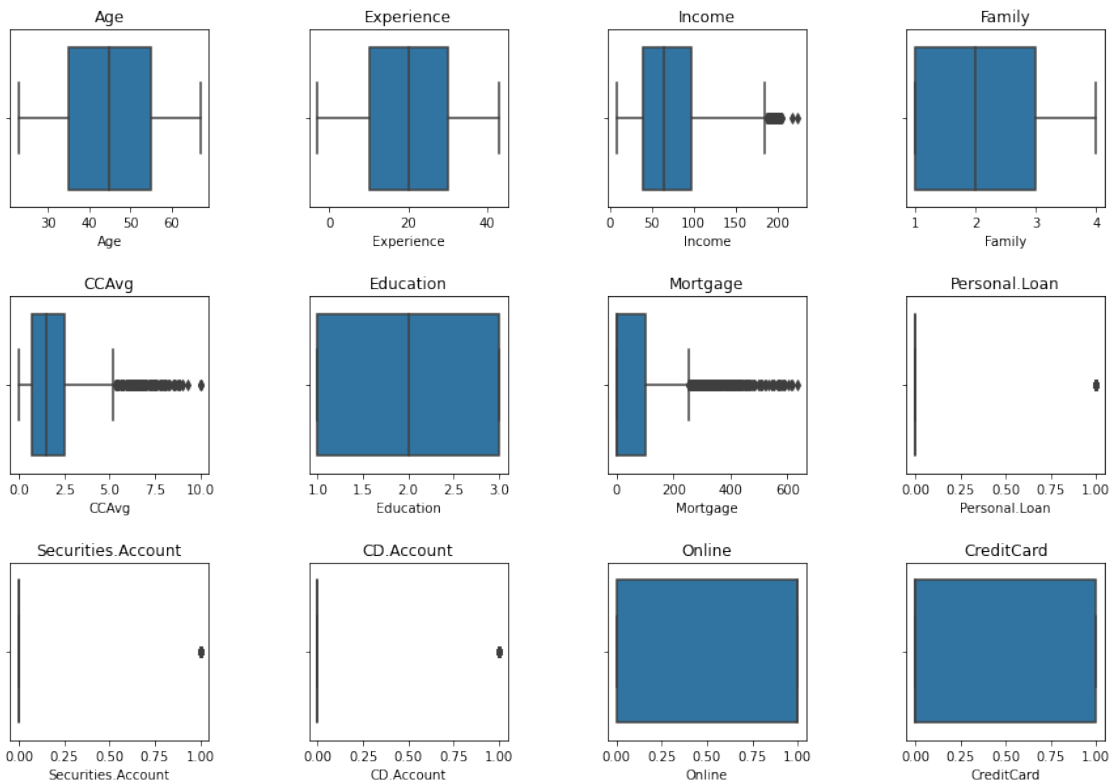



[64]:
```python
df.boxplot(figsize =(15,10), grid = False)
plt.show()
```

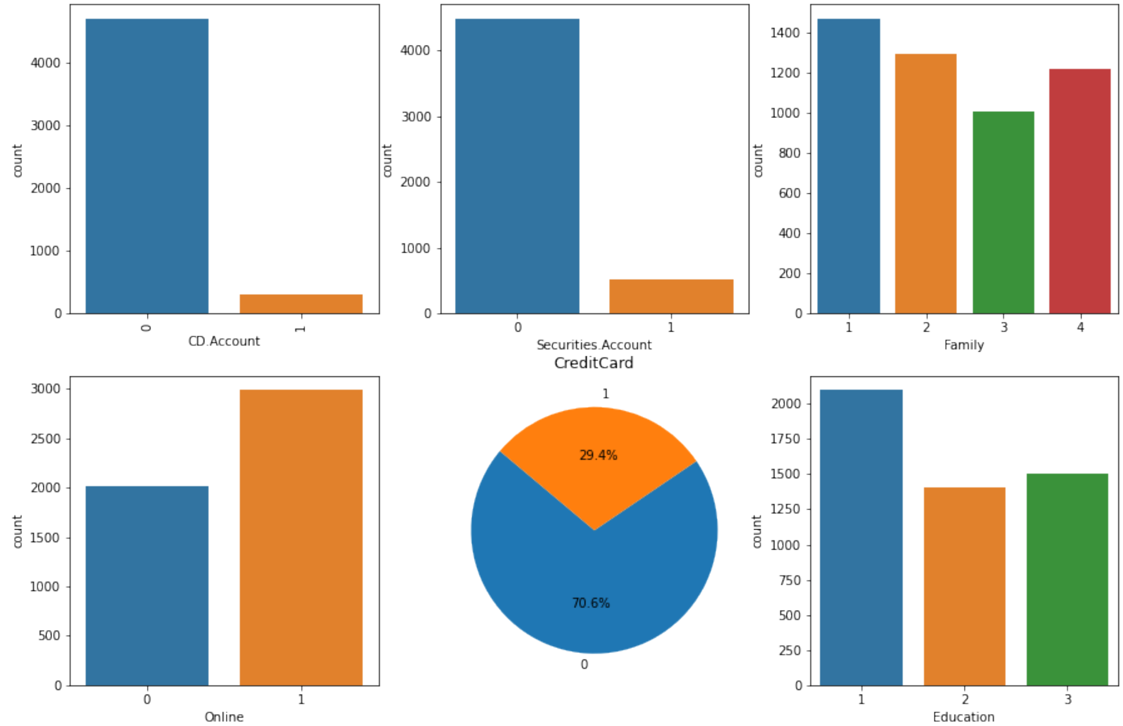



[65]:

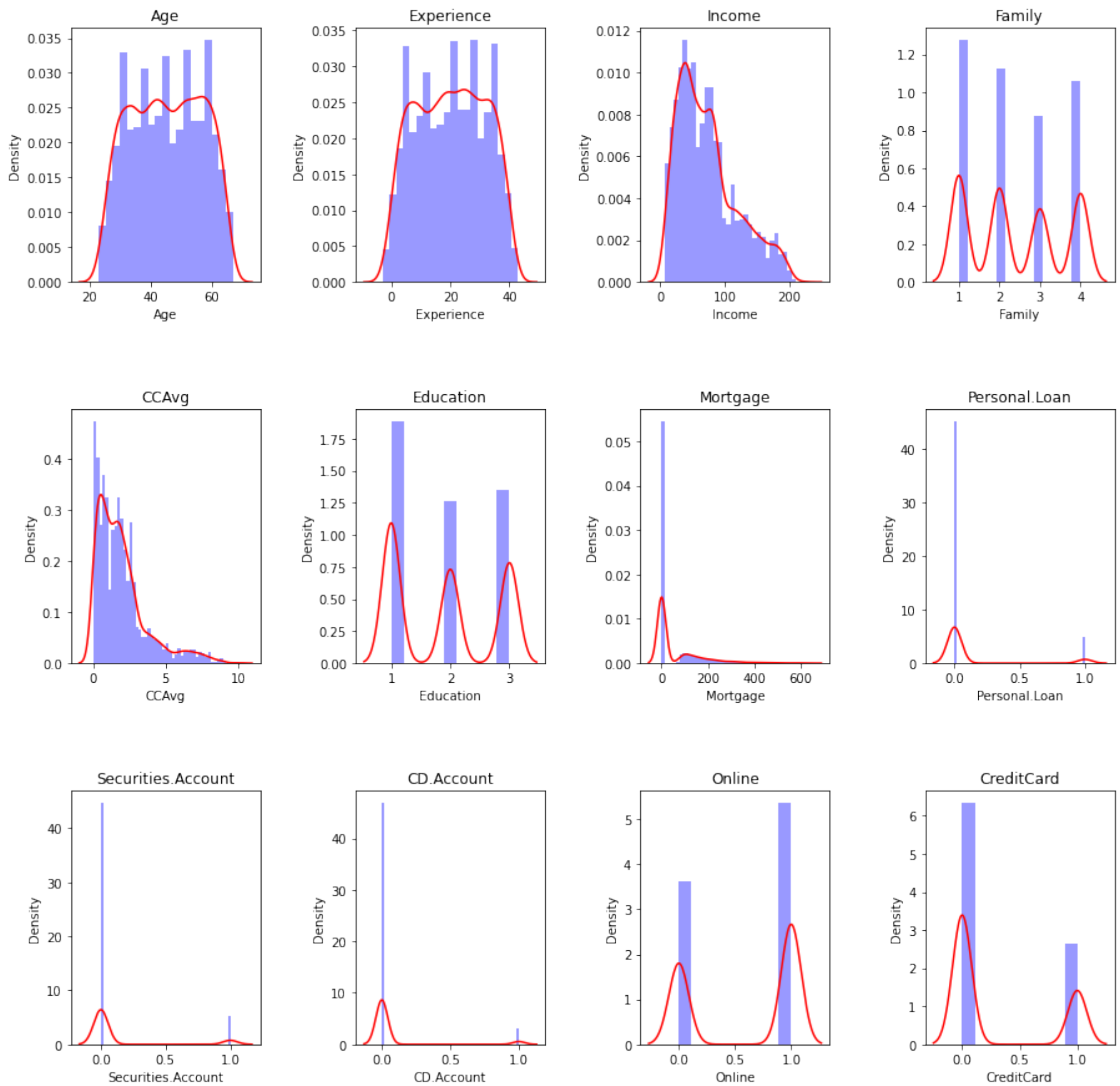
```
columnas_por_fila = 4

num_columnas = len(df.describe().columns)
num_filas = -(-num_columnas // columnas_por_fila)

fig, ax = plt.subplots(num_filas, columnas_por_fila, figsize=(15, 10))

plt.subplots_adjust(wspace=0.5, hspace=0.5)
for i, columna in enumerate(df.describe().columns):
    fila_actual = i // columnas_por_fila
    columna_actual = i % columnas_por_fila

    sns.boxplot(df[columna], ax=ax[fila_actual, columna_actual])
    ax[fila_actual, columna_actual].set_title(columna)
plt.show()
```




[66]:
```
fig, ax = plt.subplots(2, 3, figsize=(15, 10))

sns.countplot(data = df, x ='CD.Account', ax=ax[0,0])
sns.countplot(data = df, x ='Securities.Account', ax=ax[0,1])
sns.countplot(data = df, x ='Family', ax=ax[0,2])
sns.countplot(data = df, x ='Online', ax=ax[1,0])
sns.countplot(data = df, x ='Education', ax=ax[1,2])
ax[1,1].pie(df['CreditCard'].value_counts(), labels=df['CreditCard'].
 ↪value_counts().index, autopct='%1.1f%%', startangle=140)
ax[1,1].set_title('CreditCard')
ax[0,0].tick_params(axis='x', rotation=90)

plt.show()
```

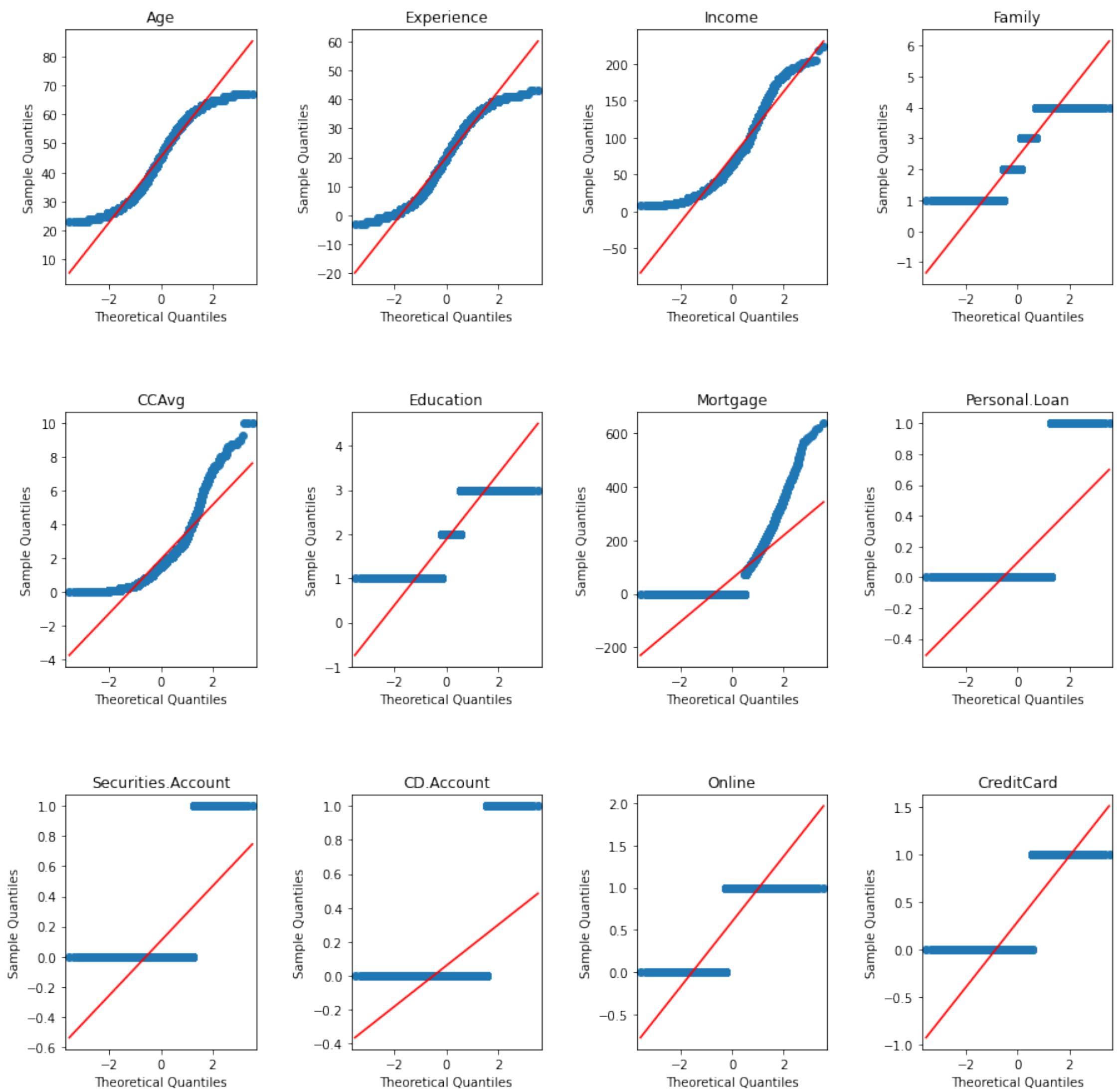



[67]:
```
columnas_por_fila = 4

num_columnas = len(df.describe().columns)
num_filas = -(-num_columnas // columnas_por_fila)

fig, ax = plt.subplots(num_filas, columnas_por_fila, figsize=(15, 15))

plt.subplots_adjust(wspace=0.5, hspace=0.5)
for i, columna in enumerate(df.describe().columns):
    fila_actual = i // columnas_por_fila
    columna_actual = i % columnas_por_fila

    sns.distplot(df[columna], ax=ax[fila_actual, columna_actual], color='red', hist_kws={'color': 'blue'})
    ax[fila_actual, columna_actual].set_title(columna)
plt.show()
```

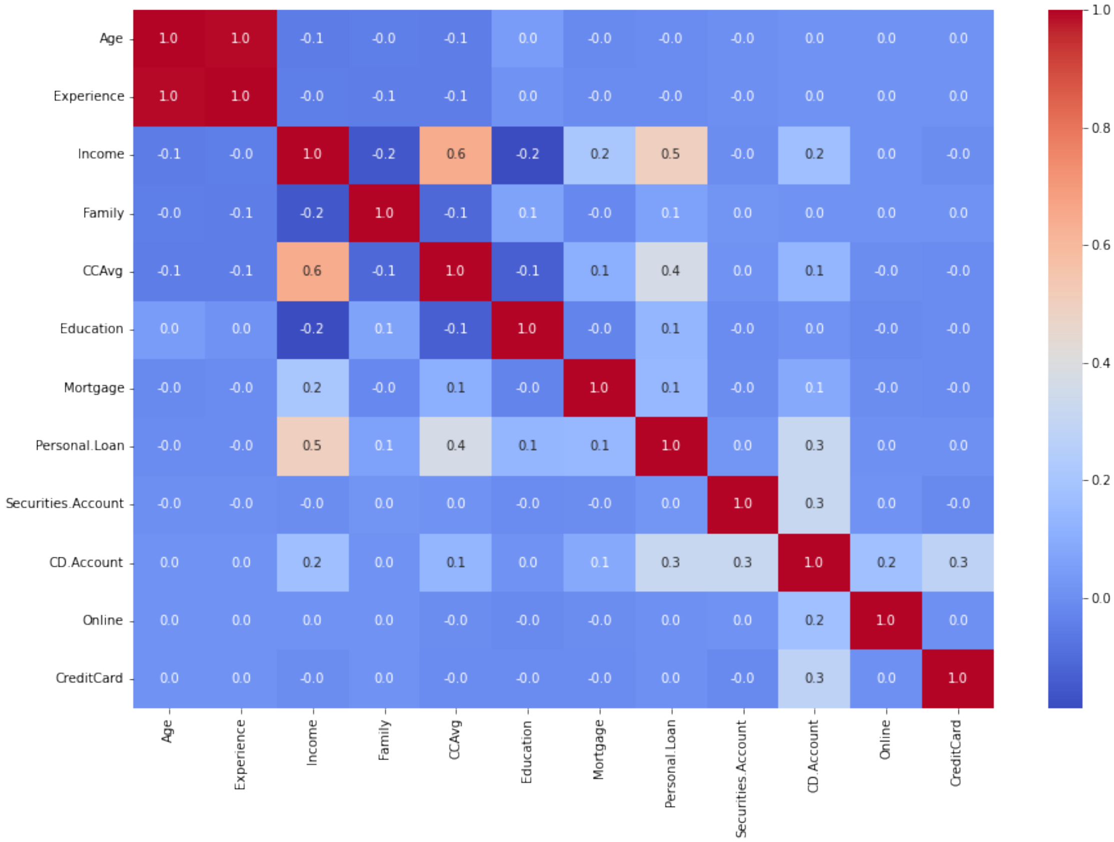



[68]:
```
columnas_por_fila = 4

num_columnas = len(df.describe().columns)
num_filas = -(-num_columnas // columnas_por_fila)

fig, ax = plt.subplots(num_filas, columnas_por_fila, figsize=(15, 15))

plt.subplots_adjust(wspace=0.5, hspace=0.5)
for i, columna in enumerate(df.describe().columns):
    fila_actual = i // columnas_por_fila
    columna_actual = i % columnas_por_fila

    smi.qqplot(df[columna], ax=ax[fila_actual, columna_actual],line="r")
```

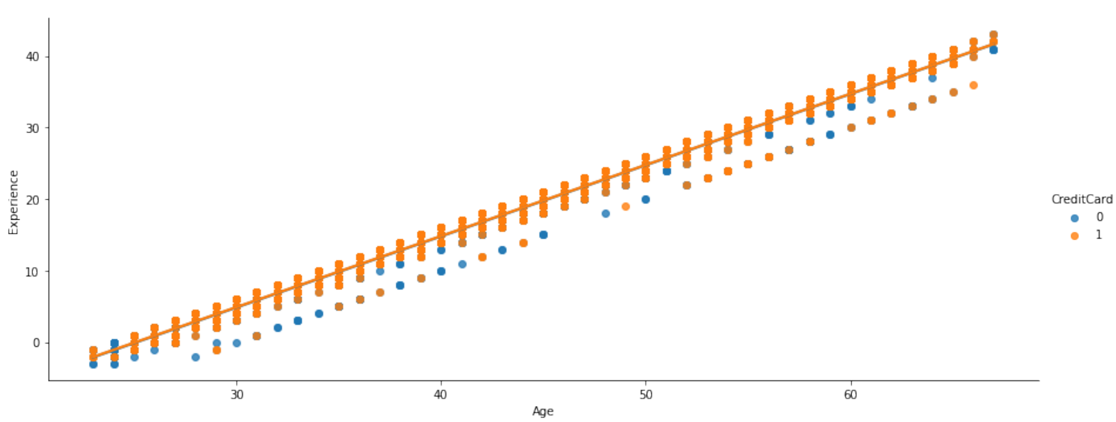
```
    ax[fila_actual, columna_actual].set_title(columna)
plt.show()
```

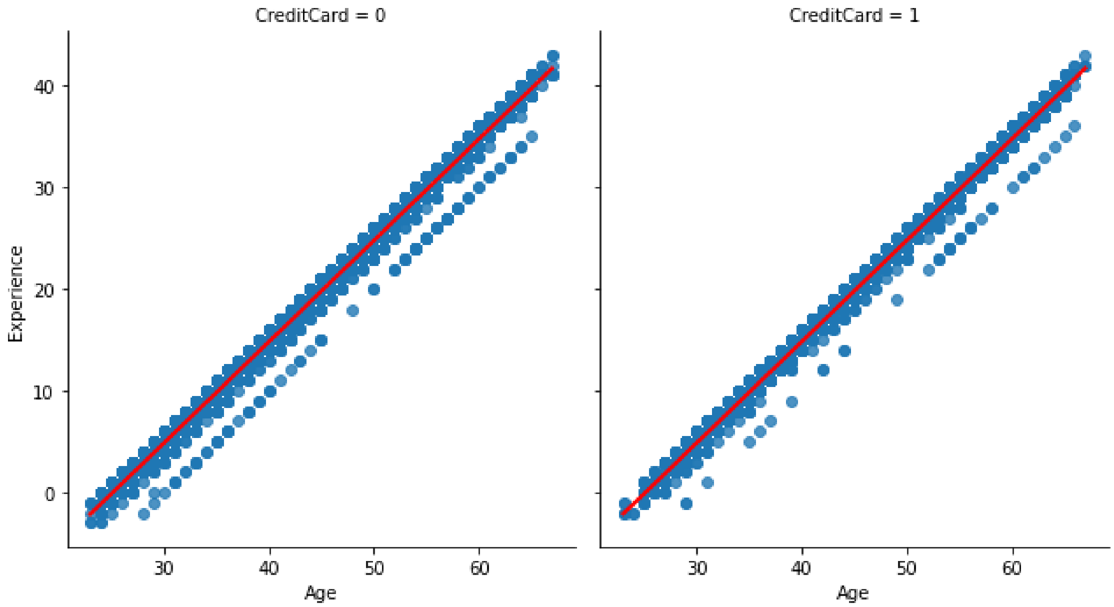



[69]:
```
plt.figure(figsize=(15, 10))
sns.heatmap(df.corr(), annot = True, fmt = '.1f', cmap = 'coolwarm')
plt.show()
```

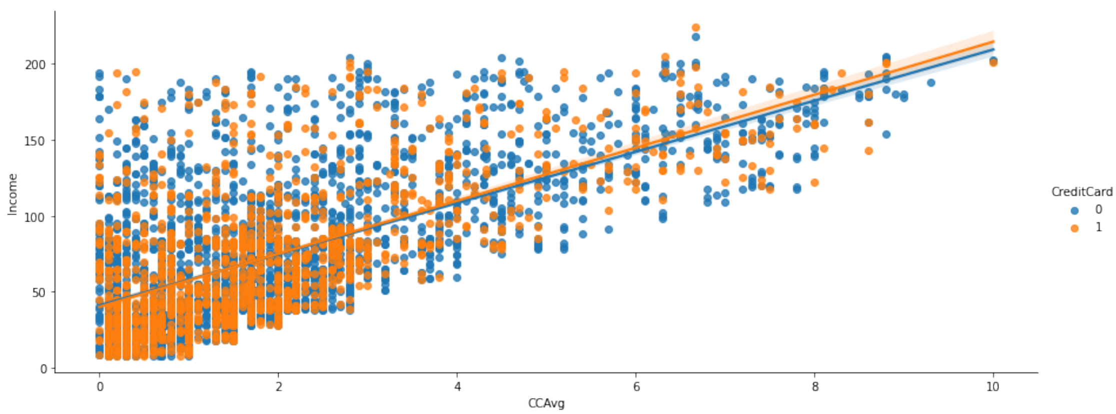


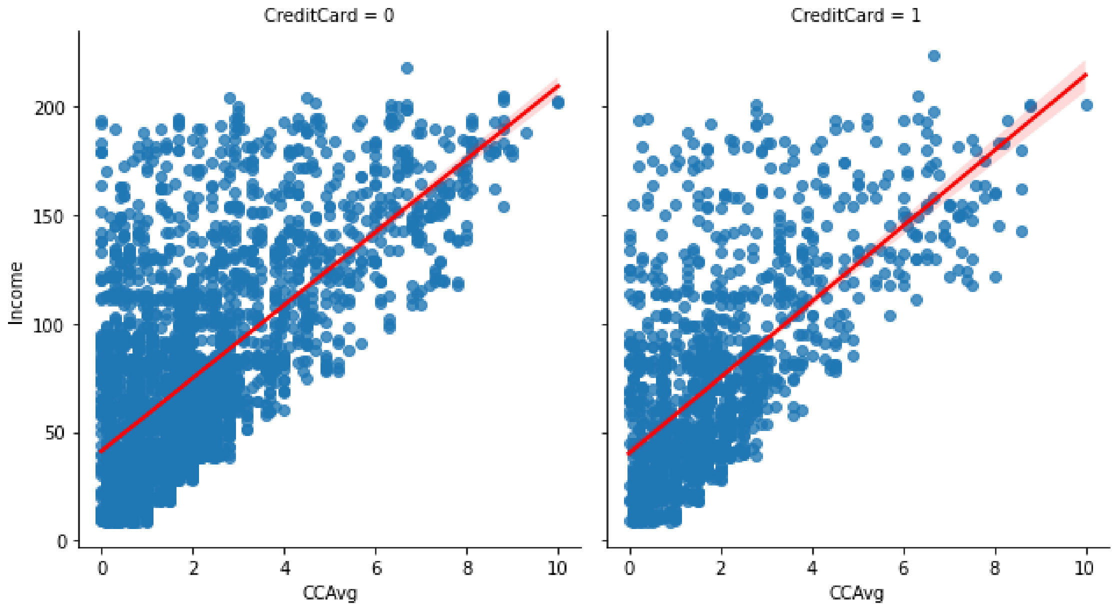

```
[70]: sns.lmplot(data=df, x='Age', y='Experience', hue = 'CreditCard', aspect=2.5)
      sns.lmplot(data=df, x='Age', y='Experience', col ='CreditCard', aspect=0.9,␣
       ↪line_kws={'color': 'red'})

      plt.show()
```



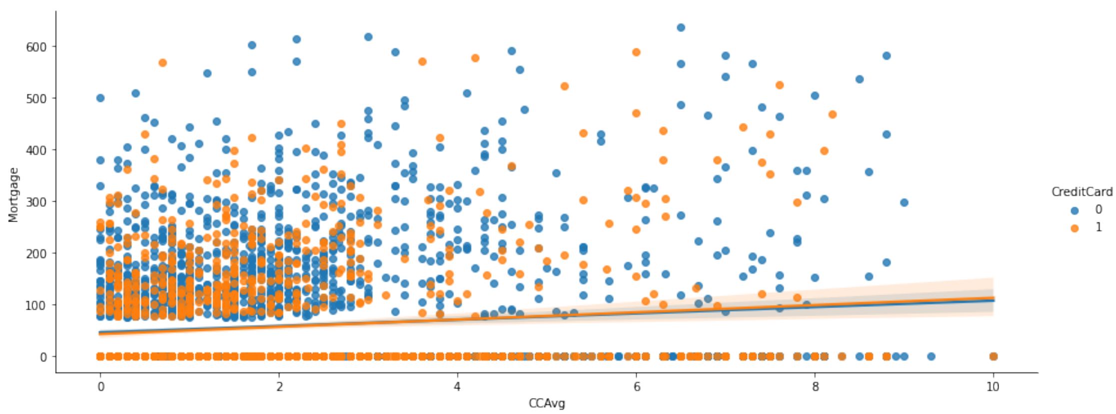


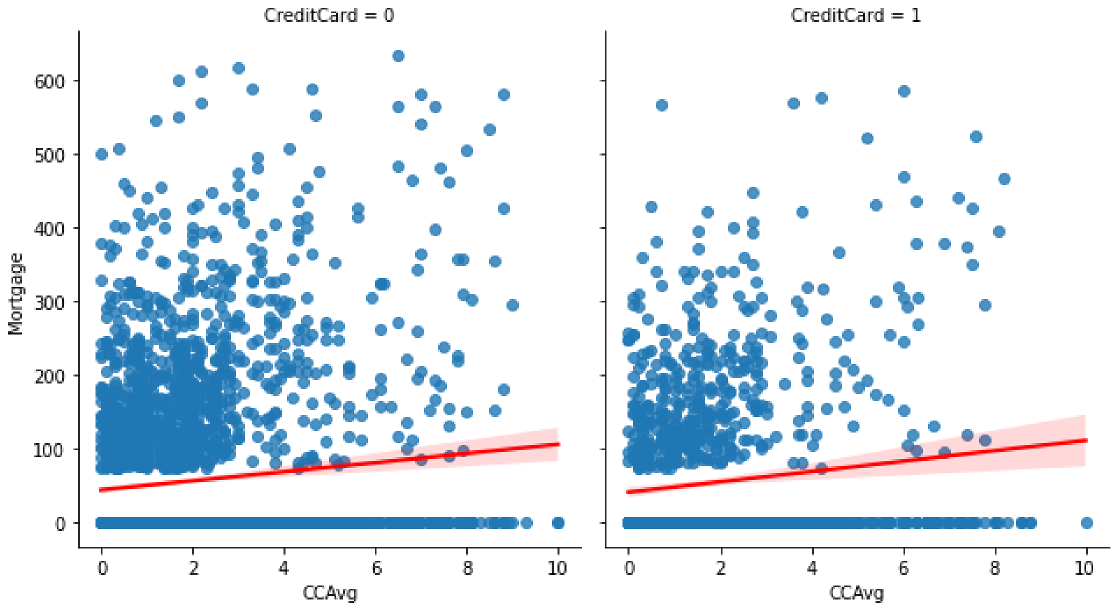

[71]:
```
sns.lmplot(data=df, x='CCAvg', y='Income', hue = 'CreditCard', aspect=2.5)
sns.lmplot(data=df, x='CCAvg', y='Income', col ='CreditCard', aspect=0.9,␣
 ↪line_kws={'color': 'red'})

plt.show()
```



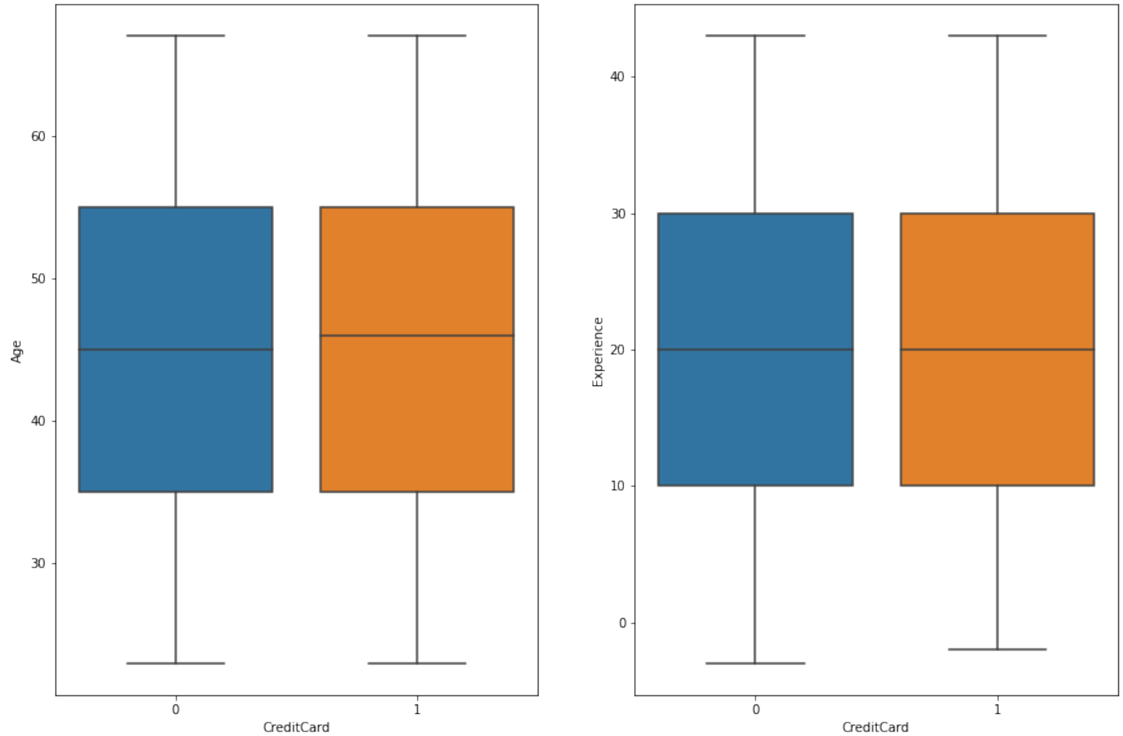



[72]:
```
sns.lmplot(data=df, x='CCAvg', y='Mortgage', hue = 'CreditCard', aspect=2.5)
sns.lmplot(data=df, x='CCAvg', y='Mortgage', col ='CreditCard', aspect=0.9,␣
 ↪line_kws={'color': 'red'})

plt.show()
```

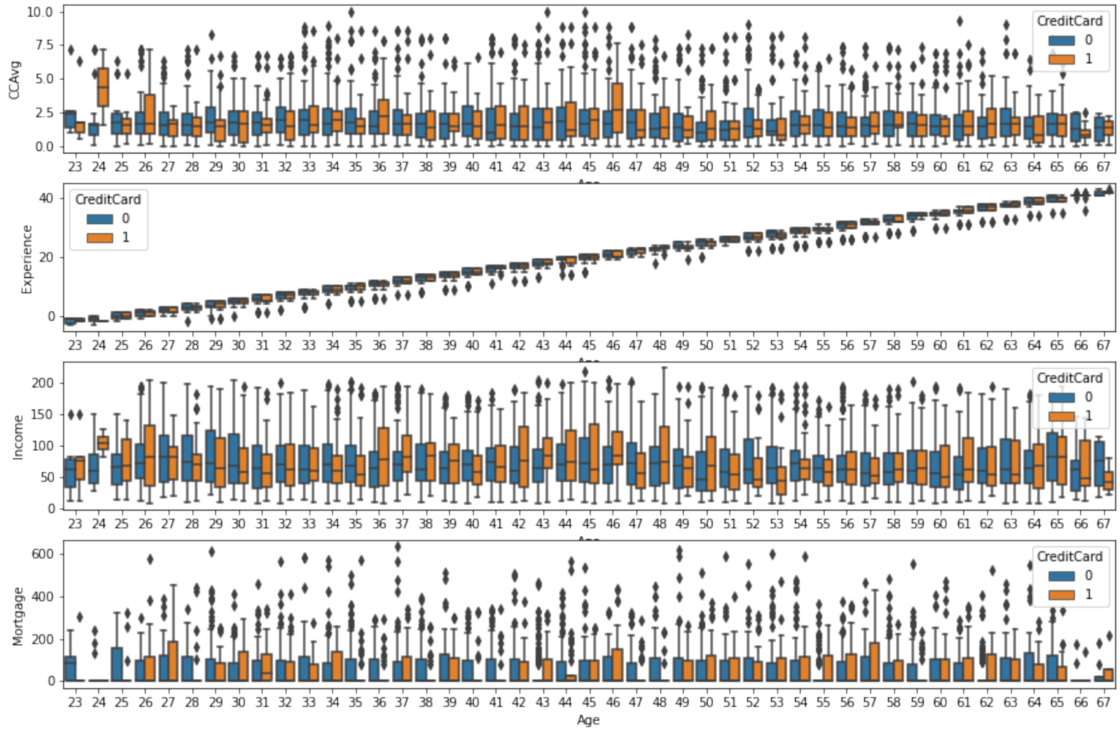





[73]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 10))

sns.boxplot(data = df, x ='CreditCard', y='Age',ax=ax[0])
sns.boxplot(data = df, x ='CreditCard', y='Experience',ax=ax[1])

plt.show()
```

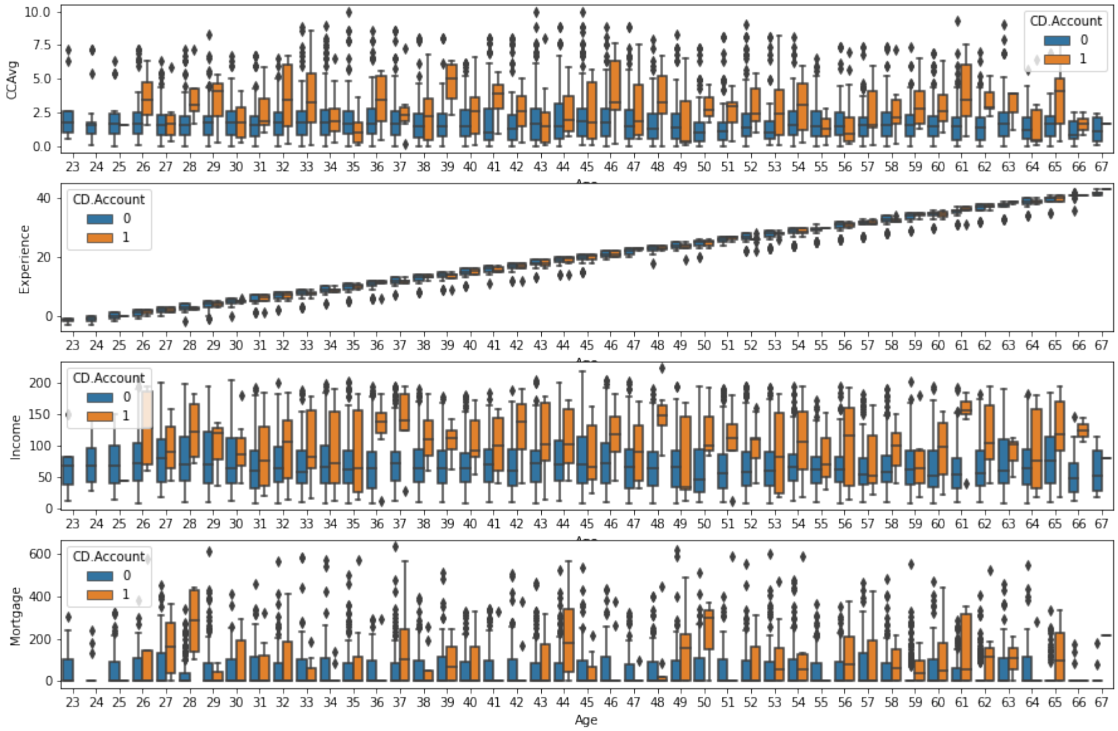



[74]:
```
fig, ax = plt.subplots(4, 1, figsize=(15, 10))

sns.boxplot(data = df, x ='Age', y='CCAvg', hue = 'CreditCard',ax=ax[0])
sns.boxplot(data = df, x ='Age', y='Experience', hue = 'CreditCard',ax=ax[1])
sns.boxplot(data = df, x ='Age', y='Income', hue = 'CreditCard',ax=ax[2])
sns.boxplot(data = df, x ='Age', y='Mortgage', hue = 'CreditCard',ax=ax[3])

plt.show()
```

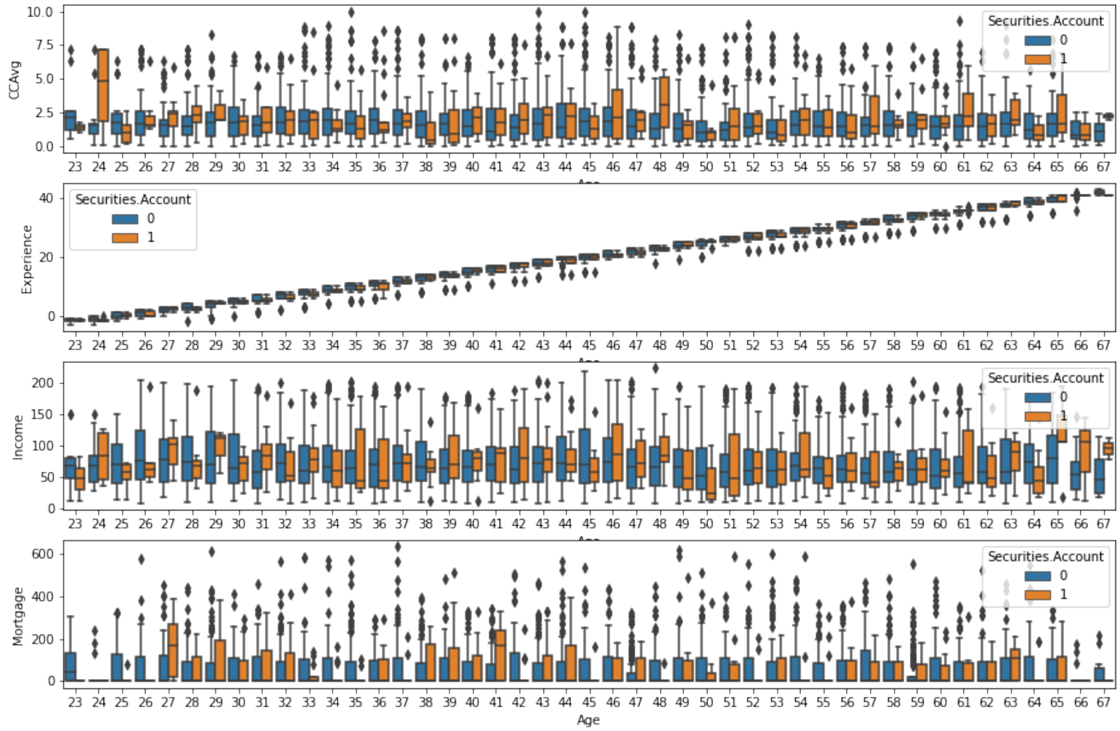



[75]:

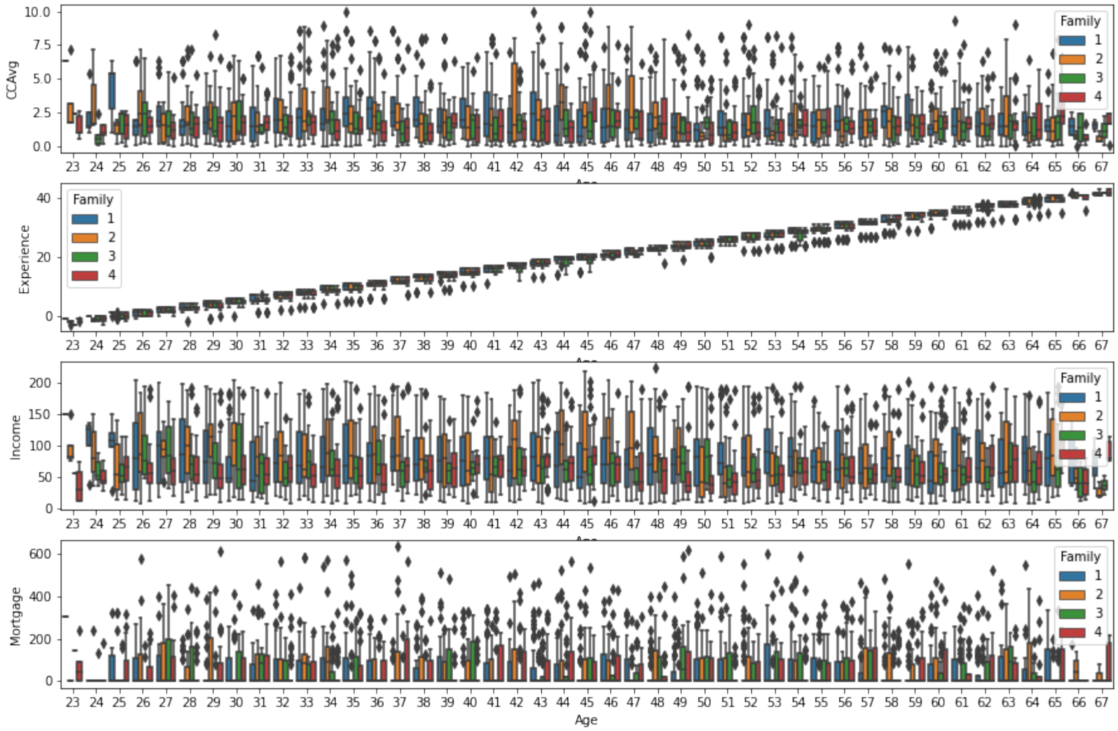
```
fig, ax = plt.subplots(4, 1, figsize=(15, 10))

sns.boxplot(data = df, x ='Age', y='CCAvg', hue = 'CD.Account',ax=ax[0])
sns.boxplot(data = df, x ='Age', y='Experience', hue = 'CD.Account',ax=ax[1])
sns.boxplot(data = df, x ='Age', y='Income', hue = 'CD.Account',ax=ax[2])
sns.boxplot(data = df, x ='Age', y='Mortgage', hue = 'CD.Account',ax=ax[3])

plt.show()
```



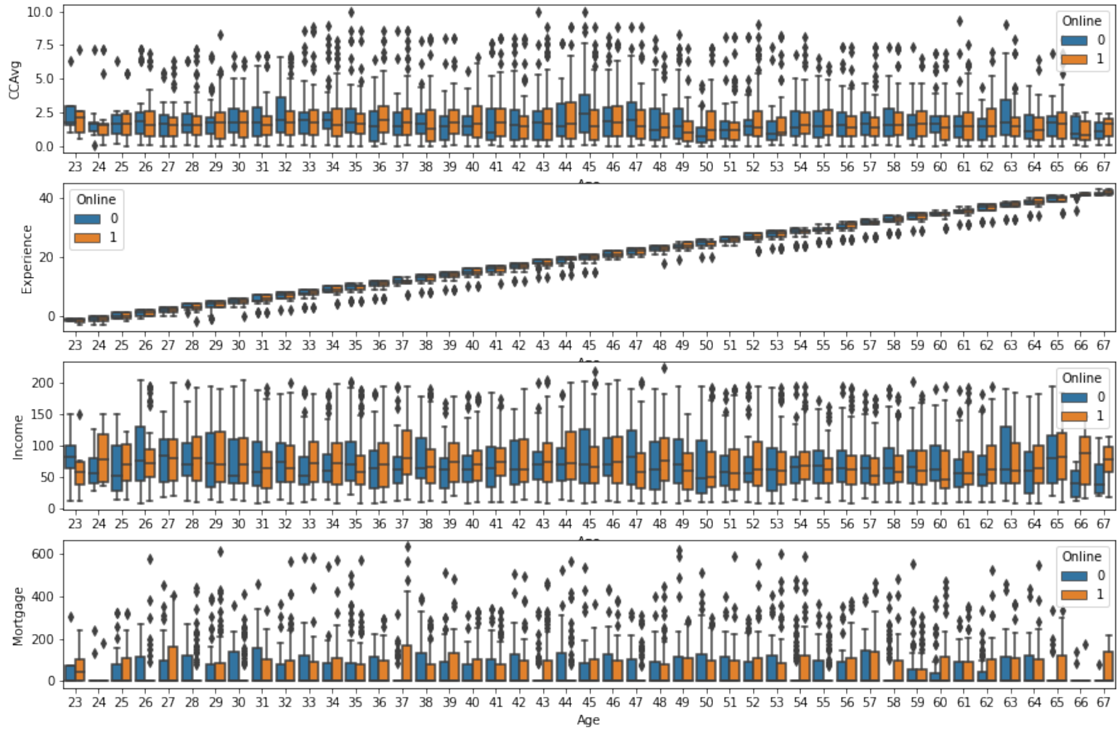

[76]:
```
fig, ax = plt.subplots(4, 1, figsize=(15, 10))

sns.boxplot(data = df, x ='Age', y='CCAvg', hue = 'Securities.Account',ax=ax[0])
sns.boxplot(data = df, x ='Age', y='Experience', hue = 'Securities.Account',ax=ax[1])
sns.boxplot(data = df, x ='Age', y='Income', hue = 'Securities.Account',ax=ax[2])
sns.boxplot(data = df, x ='Age', y='Mortgage', hue = 'Securities.Account',ax=ax[3])

plt.show()
```



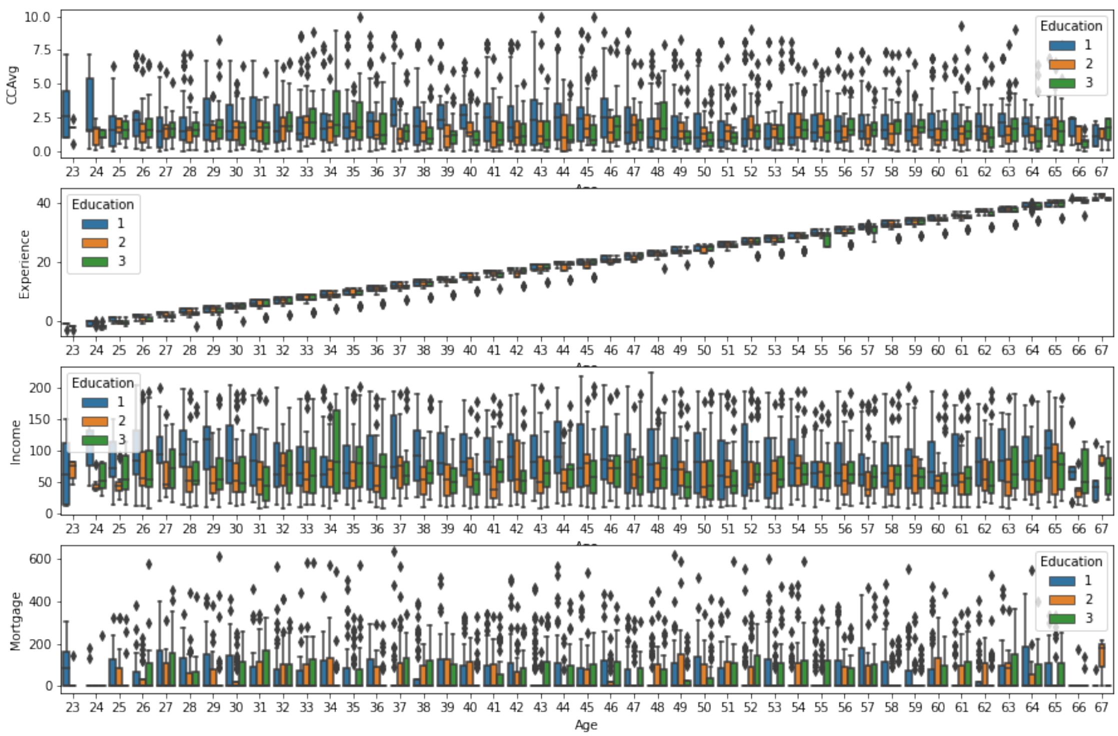

[77]:
```
fig, ax = plt.subplots(4, 1, figsize=(15, 10))

sns.boxplot(data = df, x ='Age', y='CCAvg', hue = 'Family',ax=ax[0])
sns.boxplot(data = df, x ='Age', y='Experience', hue = 'Family',ax=ax[1])
sns.boxplot(data = df, x ='Age', y='Income', hue = 'Family',ax=ax[2])
sns.boxplot(data = df, x ='Age', y='Mortgage', hue = 'Family',ax=ax[3])

plt.show()
```



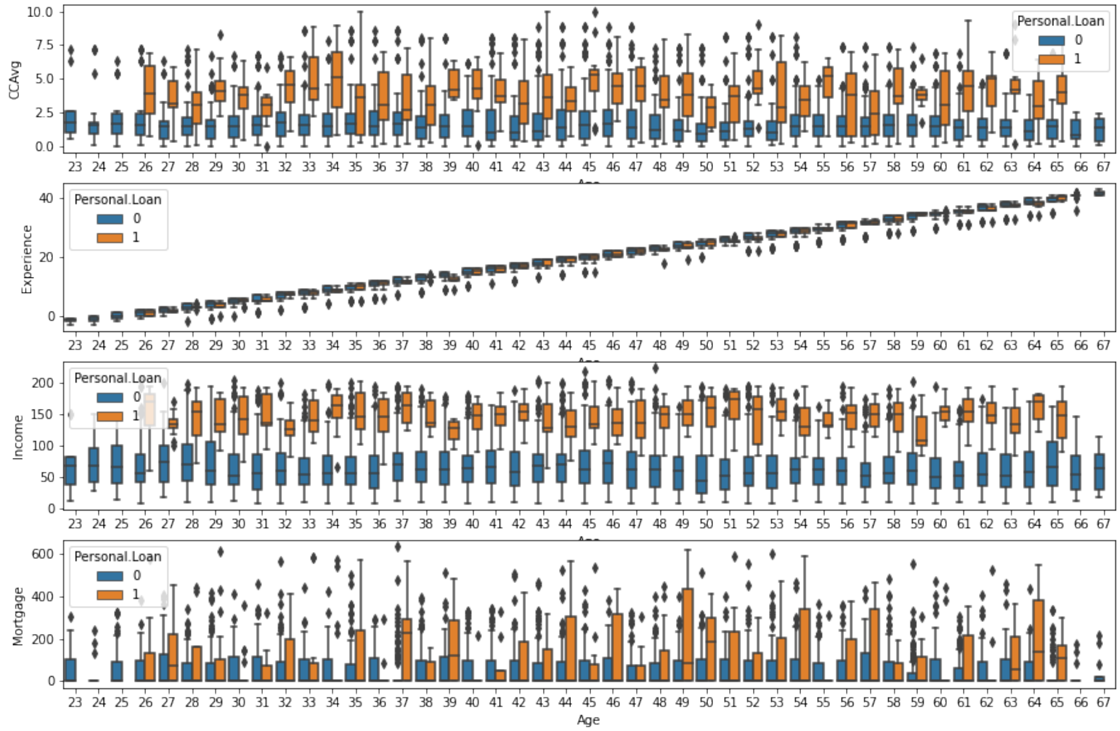

[78]:
```
fig, ax = plt.subplots(4, 1, figsize=(15, 10))

sns.boxplot(data = df, x ='Age', y='CCAvg', hue = 'Online',ax=ax[0])
sns.boxplot(data = df, x ='Age', y='Experience', hue = 'Online',ax=ax[1])
sns.boxplot(data = df, x ='Age', y='Income', hue = 'Online',ax=ax[2])
sns.boxplot(data = df, x ='Age', y='Mortgage', hue = 'Online',ax=ax[3])

plt.show()
```



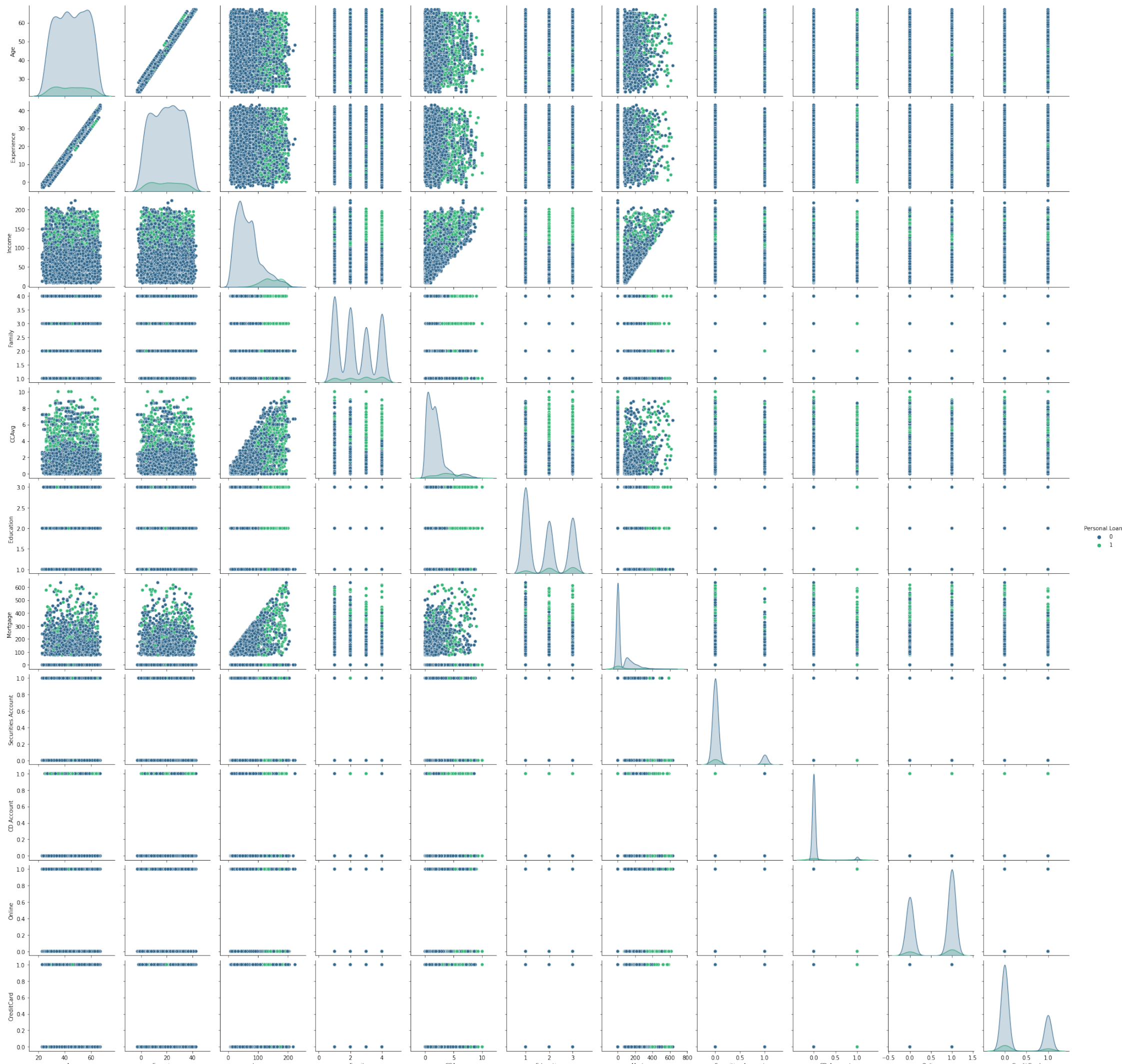

[79]:
```
fig, ax = plt.subplots(4, 1, figsize=(15, 10))

sns.boxplot(data = df, x ='Age', y='CCAvg', hue = 'Education',ax=ax[0])
sns.boxplot(data = df, x ='Age', y='Experience', hue = 'Education',ax=ax[1])
sns.boxplot(data = df, x ='Age', y='Income', hue = 'Education',ax=ax[2])
sns.boxplot(data = df, x ='Age', y='Mortgage', hue = 'Education',ax=ax[3])

plt.show()
```




[80]:
```
fig, ax = plt.subplots(4, 1, figsize=(15, 10))

sns.boxplot(data = df, x ='Age', y='CCAvg', hue = 'Personal.Loan',ax=ax[0])
sns.boxplot(data = df, x ='Age', y='Experience', hue = 'Personal.Loan',ax=ax[1])
sns.boxplot(data = df, x ='Age', y='Income', hue = 'Personal.Loan',ax=ax[2])
sns.boxplot(data = df, x ='Age', y='Mortgage', hue = 'Personal.Loan',ax=ax[3])

plt.show()
```




[81]:
```
sns.pairplot(df, hue='Personal.Loan', palette = 'viridis')
plt.show()
```




### 1.0.4 Select Best Features

[82]:
```python
X = df.drop(columns=['Personal.Loan'], axis = 1)
y = df['Personal.Loan']

f_scores, p_values = f_regression(X, y)

feature_scores_df = pd.DataFrame({'Feature': X.columns, 'F_Score': f_scores,␣
↪'P_Value': p_values})
feature_scores_df = feature_scores_df.sort_values(by='F_Score', ascending=False)
feature_scores_df
```

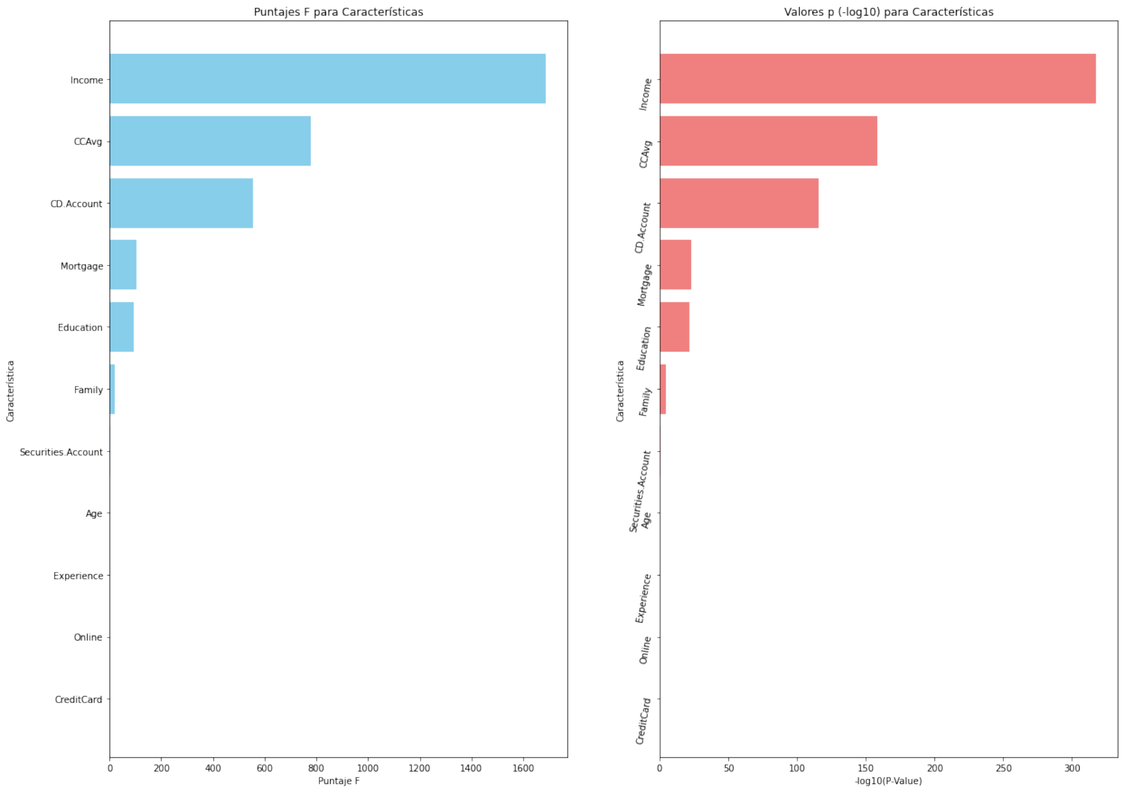
[82]:

| | Feature | F_Score | P_Value |
|---|---|---|---|
| 2 | Income | 1688.004580 | 3.560291e-318 |

```
4                CCAvg   777.413007  3.830266e-159
8           CD.Account   555.829340  1.278403e-116
6             Mortgage   102.994466   5.730342e-24
5            Education    95.206194   2.709663e-22
3               Family    18.893189   1.409904e-05
7   Securities.Account     2.410062   1.206209e-01
0                  Age     0.298324   5.849593e-01
1           Experience     0.274675   6.002359e-01
9               Online     0.196984   6.571858e-01
10          CreditCard     0.039227   8.430079e-01
```

[83]:

```
fig, ax = plt.subplots(1, 2, figsize=(20, 15))

ax[0].barh(feature_scores_df['Feature'], feature_scores_df['F_Score'],␣
 ↪color='skyblue')
ax[0].set_xlabel('Puntaje F')
ax[0].set_ylabel('Característica')
ax[0].set_title('Puntajes F para Características')


ax[1].barh(feature_scores_df['Feature'], -np.
 ↪log10(feature_scores_df['P_Value']), color='lightcoral')
ax[1].set_xlabel('-log10(P-Value)')
ax[1].set_ylabel('Característica')
ax[1].set_title('Valores p (-log10) para Características')

ax[0].invert_yaxis()
ax[1].invert_yaxis()
plt.yticks(rotation=80)
plt.show()
```




[84]:
```
cols = feature_scores_df[feature_scores_df['F_Score']>=1].Feature.to_list()
```

### 1.0.5 Modeling and Evaluation

[85]:
```
X_M = df[cols]
Y_M = df['Personal.Loan']
scaler = MinMaxScaler()
x = scaler.fit_transform(X_M)
```

### 1.0.6 Train Test Split

[86]:
```
X_train, X_test, y_train, y_test = train_test_split(x, Y_M, test_size=0.3,␣
↪random_state=42)
```

### 1.0.7 Logistic Regression

[87]:
```
logistic_model = LogisticRegression(random_state=42)
logistic_model.fit(X_train, y_train)
logistic_model.score(X_train, y_train)
model_pred_L = logistic_model.predict(X_test)

print(classification_report(y_test, model_pred_L))
```

```
print("accuracy: ",accuracy_score(y_test, model_pred_L))
print("mean_absolute_error: ",mean_absolute_error(y_test, model_pred_L))
print("mean_squared_error: ",mean_squared_error(y_test, model_pred_L))
```

```
              precision    recall  f1-score   support

           0       0.95      0.99      0.97      1343
           1       0.89      0.55      0.68       157

    accuracy                           0.95      1500
   macro avg       0.92      0.77      0.82      1500
weighted avg       0.94      0.95      0.94      1500

accuracy:  0.9453333333333334
mean_absolute_error:  0.05466666666666667
mean_squared_error:  0.05466666666666667
```

### 1.0.8 Random Forest Classifier

[88]:
```
random_forest_model = RandomForestClassifier(random_state=42)
random_forest_model.fit(X_train, y_train)
random_forest_model.score(X_train, y_train)
model_pred_R = random_forest_model.predict(X_test)

print(classification_report(y_test, model_pred_R))
print("accuracy: ",accuracy_score(y_test, model_pred_R))
print("mean_absolute_error: ",mean_absolute_error(y_test, model_pred_R))
print("mean_squared_error: ",mean_squared_error(y_test, model_pred_R))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1343
           1       0.98      0.90      0.94       157

    accuracy                           0.99      1500
   macro avg       0.98      0.95      0.97      1500
weighted avg       0.99      0.99      0.99      1500

accuracy:  0.988
mean_absolute_error:  0.012
mean_squared_error:  0.012
```

### 1.0.9 Decision Tree

[89]:
```
decision_tree_model = DecisionTreeClassifier(random_state=42)
decision_tree_model.fit(X_train, y_train)
decision_tree_model.score(X_train, y_train)
model_pred_T = decision_tree_model.predict(X_test)
```

```
print(classification_report(y_test, model_pred_T))
print("accuracy: ",accuracy_score(y_test, model_pred_T))
print("mean_absolute_error: ",mean_absolute_error(y_test, model_pred_T))
print("mean_squared_error: ",mean_squared_error(y_test, model_pred_T))
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1343
           1       0.91      0.90      0.91       157

    accuracy                           0.98      1500
   macro avg       0.95      0.95      0.95      1500
weighted avg       0.98      0.98      0.98      1500

accuracy:  0.9806666666666667
mean_absolute_error:  0.019333333333333334
mean_squared_error:  0.019333333333333334
```

#### 1.0.10 SVC

[90]:
```
model_SVC = SVC(kernel = 'rbf' ,random_state = 42)
model_SVC.fit(X_train, y_train)
model_SVC.score(X_train, y_train)
model_SVC_Pred = model_SVC.predict(X_test)

print(classification_report(y_test, model_SVC_Pred))
print("accuracy: ",accuracy_score(y_test, model_SVC_Pred))
print("mean_absolute_error: ",mean_absolute_error(y_test, model_SVC_Pred))
print("mean_squared_error: ",mean_squared_error(y_test, model_SVC_Pred))
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1343
           1       0.98      0.82      0.89       157

    accuracy                           0.98      1500
   macro avg       0.98      0.91      0.94      1500
weighted avg       0.98      0.98      0.98      1500

accuracy:  0.9793333333333333
mean_absolute_error:  0.020666666666666667
mean_squared_error:  0.020666666666666667
```

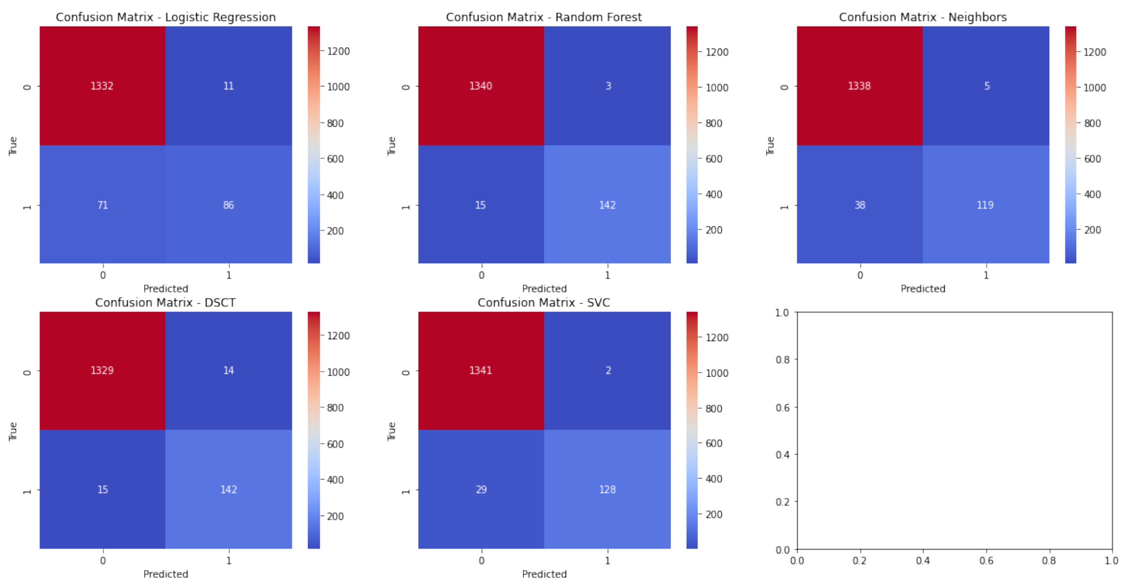
### 1.0.11 KNeighborsClassifier

[91]:
```
model_NEG = KNeighborsClassifier(n_neighbors=5)
model_NEG.fit(X_train, y_train)
model_NEG.score(X_train, y_train)
model_NEG_Pred = model_NEG.predict(X_test)

print(classification_report(y_test, model_NEG_Pred))
print("accuracy: ",accuracy_score(y_test, model_NEG_Pred))
print("mean_absolute_error: ",mean_absolute_error(y_test, model_NEG_Pred))
print("mean_squared_error: ",mean_squared_error(y_test, model_NEG_Pred))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1343
           1       0.96      0.76      0.85       157

    accuracy                           0.97      1500
   macro avg       0.97      0.88      0.92      1500
weighted avg       0.97      0.97      0.97      1500

accuracy:  0.9713333333333334
mean_absolute_error:  0.028666666666666667
mean_squared_error:  0.028666666666666667
```

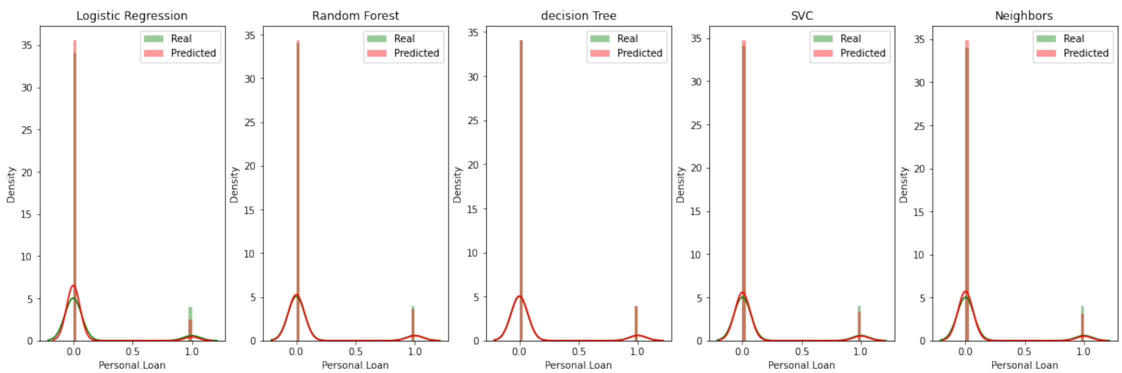
[92]:
```
RLOG = confusion_matrix(y_test, model_pred_L)
RMFC = confusion_matrix(y_test, model_pred_R)
DSCT = confusion_matrix(y_test, model_pred_T)
SVC_ = confusion_matrix(y_test, model_SVC_Pred)
NEG = confusion_matrix(y_test, model_NEG_Pred)

fig, axes = plt.subplots(2, 3, figsize=(20, 10))

sns.heatmap(RLOG, annot=True, cmap='coolwarm', fmt='g', ax=axes[0,0])
axes[0,0].set_title('Confusion Matrix - Logistic Regression')
axes[0,0].set_xlabel('Predicted')
axes[0,0].set_ylabel('True')

sns.heatmap(RMFC, annot=True, cmap='coolwarm', fmt='g', ax=axes[0,1])
axes[0,1].set_title('Confusion Matrix - Random Forest')
axes[0,1].set_xlabel('Predicted')
axes[0,1].set_ylabel('True')

sns.heatmap(DSCT, annot=True, cmap='coolwarm', fmt='g', ax=axes[1,0])
axes[1,0].set_title('Confusion Matrix - DSCT')
axes[1,0].set_xlabel('Predicted')
axes[1,0].set_ylabel('True')
```

```python
sns.heatmap(SVC_, annot=True, cmap='coolwarm', fmt='g', ax=axes[1,1])
axes[1,1].set_title('Confusion Matrix - SVC')
axes[1,1].set_xlabel('Predicted')
axes[1,1].set_ylabel('True')

sns.heatmap(NEG, annot=True, cmap='coolwarm', fmt='g', ax=axes[0,2])
axes[0,2].set_title('Confusion Matrix - Neighbors')
axes[0,2].set_xlabel('Predicted')
axes[0,2].set_ylabel('True')

plt.show()
```




[93]:
```python
fig, ax = plt.subplots(1, 5, figsize=(20, 6))

sns.distplot(y_test, label='Real', ax=ax[0], color = 'Green')
sns.distplot(model_pred_L, label='Predicted', ax=ax[0],  color = 'red')

sns.distplot(y_test, label='Real', ax=ax[1], color = 'Green')
sns.distplot(model_pred_R, label='Predicted', ax=ax[1], color = 'red')

sns.distplot(y_test, label='Real', ax=ax[2], color = 'Green')
sns.distplot(model_pred_T, label='Predicted', ax=ax[2], color = 'red')

sns.distplot(y_test, label='Real', ax=ax[3], color = 'Green')
sns.distplot(model_SVC_Pred, label='Predicted', ax=ax[3], color = 'red')

sns.distplot(y_test, label='Real', ax=ax[4], color = 'Green')
sns.distplot(model_NEG_Pred, label='Predicted', ax=ax[4], color = 'red')
```

```
ax[0].set_title('Logistic Regression')
ax[1].set_title('Random Forest')
ax[2].set_title('decision Tree')
ax[3].set_title('SVC')
ax[4].set_title('Neighbors')

ax[0].legend()
ax[1].legend()
ax[2].legend()
ax[3].legend()
ax[4].legend()
plt.show()
```




[ ]:
```
# End
```