In [123]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
warnings.filterwarnings('ignore')
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score
```

In [2]:

```
loan = pd.read_csv('Loan_Modelling.csv')
```

In [4]:

```
data=loan.copy()
```

In [6]:

```
data.head(15)
```

Out[6]:

| | ID | Age | Experience | Income | ZIPCode | Family | CCAvg | Education | Mortgage | Personal_Loan | Securities_Account | CD_Ac |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 25 | 1 | 49 | 91107 | 4 | 1.6 | 1 | 0 | 0 | 1 | |
| **1** | 2 | 45 | 19 | 34 | 90089 | 3 | 1.5 | 1 | 0 | 0 | 1 | |
| **2** | 3 | 39 | 15 | 11 | 94720 | 1 | 1.0 | 1 | 0 | 0 | 0 | |
| **3** | 4 | 35 | 9 | 100 | 94112 | 1 | 2.7 | 2 | 0 | 0 | 0 | |
| **4** | 5 | 35 | 8 | 45 | 91330 | 4 | 1.0 | 2 | 0 | 0 | 0 | |
| **5** | 6 | 37 | 13 | 29 | 92121 | 4 | 0.4 | 2 | 155 | 0 | 0 | |
| **6** | 7 | 53 | 27 | 72 | 91711 | 2 | 1.5 | 2 | 0 | 0 | 0 | |
| **7** | 8 | 50 | 24 | 22 | 93943 | 1 | 0.3 | 3 | 0 | 0 | 0 | |
| **8** | 9 | 35 | 10 | 81 | 90089 | 3 | 0.6 | 2 | 104 | 0 | 0 | |
| **9** | 10 | 34 | 9 | 180 | 93023 | 1 | 8.9 | 3 | 0 | 1 | 0 | |
| **10** | 11 | 65 | 39 | 105 | 94710 | 4 | 2.4 | 3 | 0 | 0 | 0 | |
| **11** | 12 | 29 | 5 | 45 | 90277 | 3 | 0.1 | 2 | 0 | 0 | 0 | |
| **12** | 13 | 48 | 23 | 114 | 93106 | 2 | 3.8 | 3 | 0 | 0 | 1 | |
| **13** | 14 | 59 | 32 | 40 | 94920 | 4 | 2.5 | 2 | 0 | 0 | 0 | |
| **14** | 15 | 67 | 41 | 112 | 91741 | 1 | 2.0 | 1 | 0 | 0 | 1 | |

In [7]:

```
data.tail(15)
```

Out[7]:

| | ID | Age | Experience | Income | ZIPCode | Family | CCAvg | Education | Mortgage | Personal_Loan | Securities_Account | CI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

|  | ID | Age | Experience | Income | ZIPCode | Family | CCAvg | Education | Mortgage | Personal_Loan | Securities_Account | CI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **4985** | 4986 | 48 | 23 | 30 | 94720 | 3 | 1.70 | 2 | 162 | 0 | 0 | |
| **4986** | 4987 | 32 | 6 | 78 | 95825 | 1 | 2.90 | 3 | 0 | 0 | 0 | |
| **4987** | 4988 | 48 | 23 | 43 | 93943 | 3 | 1.70 | 2 | 159 | 0 | 0 | |
| **4988** | 4989 | 34 | 8 | 85 | 95134 | 1 | 2.50 | 1 | 136 | 0 | 0 | |
| **4989** | 4990 | 24 | 0 | 38 | 93555 | 1 | 1.00 | 3 | 0 | 0 | 0 | |
| **4990** | 4991 | 55 | 25 | 58 | 95023 | 4 | 2.00 | 3 | 219 | 0 | 0 | |
| **4991** | 4992 | 51 | 25 | 92 | 91330 | 1 | 1.90 | 2 | 100 | 0 | 0 | |
| **4992** | 4993 | 30 | 5 | 13 | 90037 | 4 | 0.50 | 3 | 0 | 0 | 0 | |
| **4993** | 4994 | 45 | 21 | 218 | 91801 | 2 | 6.67 | 1 | 0 | 0 | 0 | |
| **4994** | 4995 | 64 | 40 | 75 | 94588 | 3 | 2.00 | 3 | 0 | 0 | 0 | |
| **4995** | 4996 | 29 | 3 | 40 | 92697 | 1 | 1.90 | 3 | 0 | 0 | 0 | |
| **4996** | 4997 | 30 | 4 | 15 | 92037 | 4 | 0.40 | 1 | 85 | 0 | 0 | |
| **4997** | 4998 | 63 | 39 | 24 | 93023 | 2 | 0.30 | 3 | 0 | 0 | 0 | |
| **4998** | 4999 | 65 | 40 | 49 | 90034 | 3 | 0.50 | 2 | 0 | 0 | 0 | |
| **4999** | 5000 | 28 | 4 | 83 | 92612 | 3 | 0.80 | 1 | 0 | 0 | 0 | |

In [8]:

```
data.shape
```

Out[8]:

```
(5000, 14)
```

- **Dataset has 12330 rows and 18 columns**

In [9]:

```
data[data.duplicated()].count()
```

Out[9]:

```
ID                    0
Age                   0
Experience            0
Income                0
ZIPCode               0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Personal_Loan         0
Securities_Account    0
CD_Account            0
Online                0
CreditCard            0
dtype: int64
```

In [10]:

```
data.drop_duplicates(inplace=True)
```

In [11]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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   ZIPCode             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: 585.9 KB
```

- **Most of the data-types are either int64 or float64.**

## Check for missing values

In [13]:

```
data.isnull().sum()
```

Out[13]:

```
ID                    0
Age                   0
Experience            0
Income                0
ZIPCode               0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Personal_Loan         0
Securities_Account    0
CD_Account            0
Online                0
CreditCard            0
dtype: int64
```

In [14]:

```
data.isna().apply(pd.value_counts)   #null value
```

Out[14]:

| | ID | Age | Experience | Income | ZIPCode | Family | CCAvg | Education | Mortgage | Personal_Loan | Securities_Account |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **False** | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 |

- **No Null Values**
- **No Missing Values**

In [15]:

```
data.describe().T
```

Out[15]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **ID** | 5000.0 | 2500.500000 | 1443.520003 | 1.0 | 1250.75 | 2500.5 | 3750.25 | 5000.0 |
| **Age** | 5000.0 | 45.338400 | 11.463166 | 23.0 | 35.00 | 45.0 | 55.00 | 67.0 |

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Experience** | 5000.0 | 20.104600 | 11.467954 | -3.0 | 10.00 | 20.0 | 30.00 | 43.0 |
| **Income** | 5000.0 | 73.774200 | 46.033729 | 8.0 | 39.00 | 64.0 | 98.00 | 224.0 |
| **ZIPCode** | 5000.0 | 93169.257000 | 1759.455086 | 90005.0 | 91911.00 | 93437.0 | 94608.00 | 96651.0 |
| **Family** | 5000.0 | 2.396400 | 1.147663 | 1.0 | 1.00 | 2.0 | 3.00 | 4.0 |
| **CCAvg** | 5000.0 | 1.937938 | 1.747659 | 0.0 | 0.70 | 1.5 | 2.50 | 10.0 |
| **Education** | 5000.0 | 1.881000 | 0.839869 | 1.0 | 1.00 | 2.0 | 3.00 | 3.0 |
| **Mortgage** | 5000.0 | 56.498800 | 101.713802 | 0.0 | 0.00 | 0.0 | 101.00 | 635.0 |
| **Personal_Loan** | 5000.0 | 0.096000 | 0.294621 | 0.0 | 0.00 | 0.0 | 0.00 | 1.0 |
| **Securities_Account** | 5000.0 | 0.104400 | 0.305809 | 0.0 | 0.00 | 0.0 | 0.00 | 1.0 |
| **CD_Account** | 5000.0 | 0.060400 | 0.238250 | 0.0 | 0.00 | 0.0 | 0.00 | 1.0 |
| **Online** | 5000.0 | 0.596800 | 0.490589 | 0.0 | 0.00 | 1.0 | 1.00 | 1.0 |
| **CreditCard** | 5000.0 | 0.294000 | 0.455637 | 0.0 | 0.00 | 0.0 | 1.00 | 1.0 |

- **Negative value in the *Experience* field (-3.0).**

In [16]:

```
# Replacing -ve value with mean of Experience field
any(data['Experience'] < 0)
```

Out[16]:

```
True
```

In [17]:

```
asgn_medn_expn = data.loc[:,"Experience"].median()
data.loc[:, 'Experience'].replace([-1, -2, -3], [asgn_medn_expn, asgn_medn_expn, asgn_me
dn_expn], inplace=True)
```

In [18]:

```
any(data['Experience'] < 0)
```

Out[18]:

```
False
```

In [19]:

```
data.describe().T
```

Out[19]:

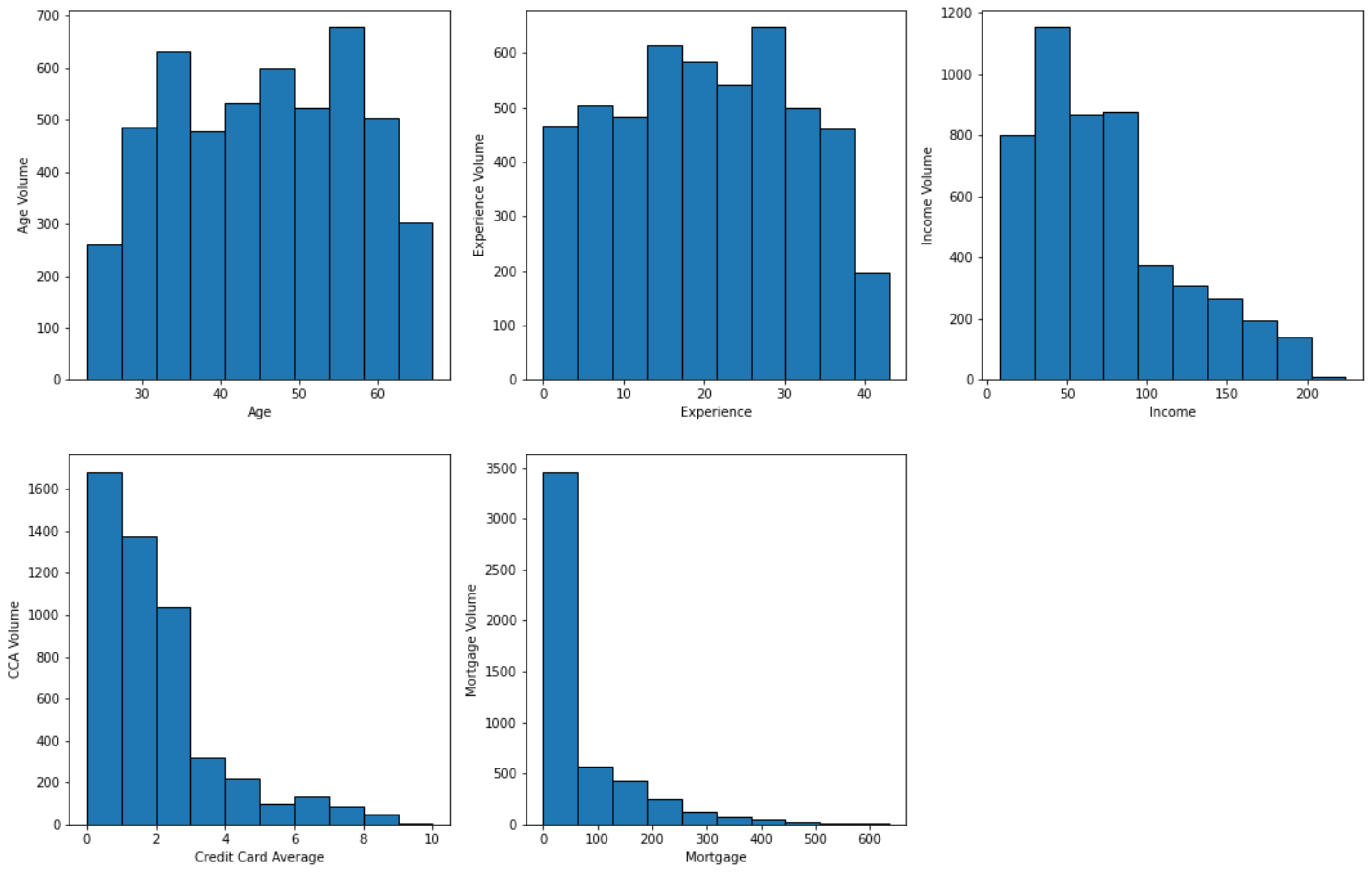
| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **ID** | 5000.0 | 2500.500000 | 1443.520003 | 1.0 | 1250.75 | 2500.5 | 3750.25 | 5000.0 |
| **Age** | 5000.0 | 45.338400 | 11.463166 | 23.0 | 35.00 | 45.0 | 55.00 | 67.0 |
| **Experience** | 5000.0 | 20.327600 | 11.253035 | 0.0 | 11.00 | 20.0 | 30.00 | 43.0 |
| **Income** | 5000.0 | 73.774200 | 46.033729 | 8.0 | 39.00 | 64.0 | 98.00 | 224.0 |
| **ZIPCode** | 5000.0 | 93169.257000 | 1759.455086 | 90005.0 | 91911.00 | 93437.0 | 94608.00 | 96651.0 |
| **Family** | 5000.0 | 2.396400 | 1.147663 | 1.0 | 1.00 | 2.0 | 3.00 | 4.0 |
| **CCAvg** | 5000.0 | 1.937938 | 1.747659 | 0.0 | 0.70 | 1.5 | 2.50 | 10.0 |
| **Education** | 5000.0 | 1.881000 | 0.839869 | 1.0 | 1.00 | 2.0 | 3.00 | 3.0 |
| **Mortgage** | 5000.0 | 56.498800 | 101.713802 | 0.0 | 0.00 | 0.0 | 101.00 | 635.0 |
| **Personal_Loan** | 5000.0 | 0.096000 | 0.294621 | 0.0 | 0.00 | 0.0 | 0.00 | 1.0 |
| **Securities_Account** | 5000.0 | 0.104400 | 0.305809 | 0.0 | 0.00 | 0.0 | 0.00 | 1.0 |

|  | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **CD_Account** | 5000.0 | 0.060400 | 0.238250 | 0.0 | 0.00 | 0.0 | 0.00 | 1.0 |
| **Online** | 5000.0 | 0.596800 | 0.490589 | 0.0 | 0.00 | 1.0 | 1.00 | 1.0 |
| **CreditCard** | 5000.0 | 0.294000 | 0.455637 | 0.0 | 0.00 | 0.0 | 1.00 | 1.0 |

## Univariate Analysis for the continuous variables

In [25]:

```
plt.figure(figsize= (18,18))
plt.subplot(3,3,1)
plt.hist(data.Age, edgecolor = 'black')
plt.xlabel('Age')
plt.ylabel('Age Volume')

plt.subplot(3,3,2)
plt.hist(data.Experience, edgecolor = 'black')
plt.xlabel('Experience')
plt.ylabel('Experience Volume')

plt.subplot(3,3,3)
plt.hist(data.Income, edgecolor = 'black')
plt.xlabel('Income')
plt.ylabel('Income Volume')

plt.subplot(3,3,4)
plt.hist(data.CCAvg, edgecolor = 'black')
plt.xlabel('Credit Card Average')
plt.ylabel('CCA Volume')

plt.subplot(3,3,5)
plt.hist(data.Mortgage, edgecolor = 'black')
plt.xlabel('Mortgage')
plt.ylabel('Mortgage Volume')

plt.show()
```



- **Age and Experience has normal distribution.**
- **Income, Credit Card Average and Mortage are highly skewness**

In [28]:

```
# Skewness for the above data
Uni_data_skew = pd.DataFrame({'Skewness' : [stats.skew(data.Age),stats.skew(data.Experien
ce),stats.skew(data.Income)
                                                ,stats.skew(data.CCAvg),stats.skew(data.Mortgage)
]}
                                                ,index=['Age','Experience','Income','CCAvg','Mort
gage'])
Uni_data_skew
```

Out[28]:

| | Skewness |
|---|---|
| **Age** | -0.029332 |
| **Experience** | -0.014096 |
| **Income** | 0.841086 |
| **CCAvg** | 1.597964 |
| **Mortgage** | 2.103371 |

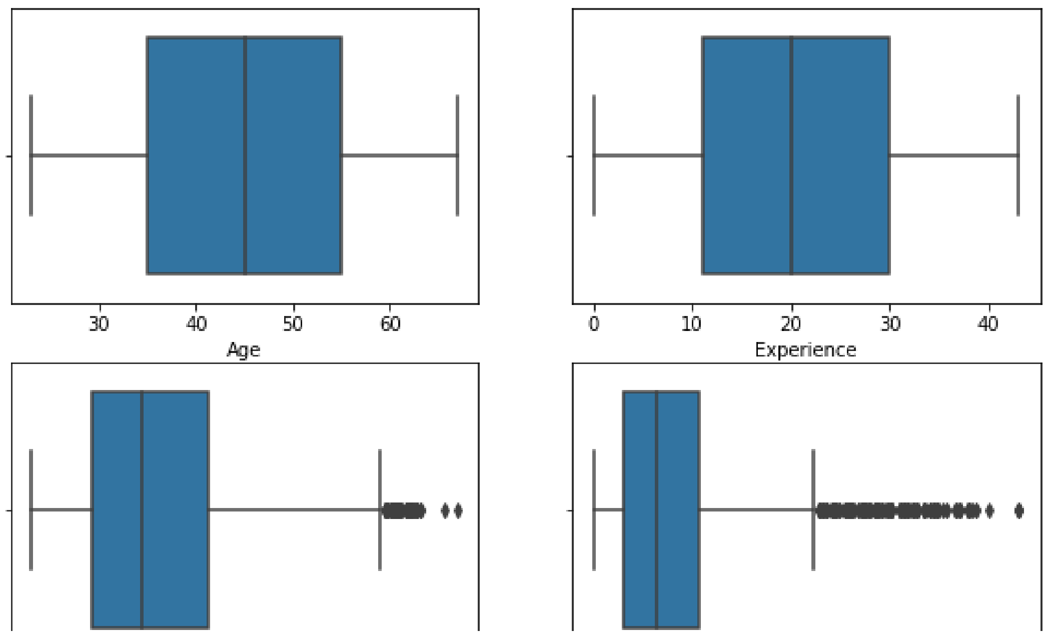
- **Age & Experience has similar skewness**
- **Income, CCAvg & Mortage has positive value**

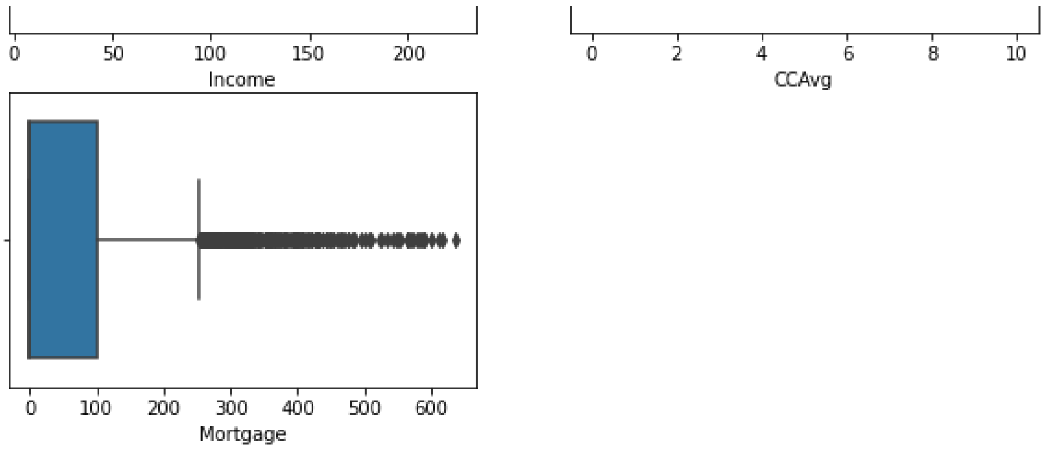
In [36]:

```
plt.figure(figsize= (10,10))
plt.subplot(3,2,1)
sns.boxplot(x= data.Age)

plt.subplot(3,2,2)
sns.boxplot(x= data.Experience)

plt.subplot(3,2,3)
sns.boxplot(x= data.Income)

plt.subplot(3,2,4)
sns.boxplot(x= data.CCAvg)

plt.subplot(3,2,5)
sns.boxplot(x= data.Mortgage)
```

Out[36]:

```
<AxesSubplot:xlabel='Mortgage'>
```





- **Age has normally distributed, 35 to 55 age**
- **Experience has normal distribution, 11 to 30 years**
- **Remaining field has positive skewness**

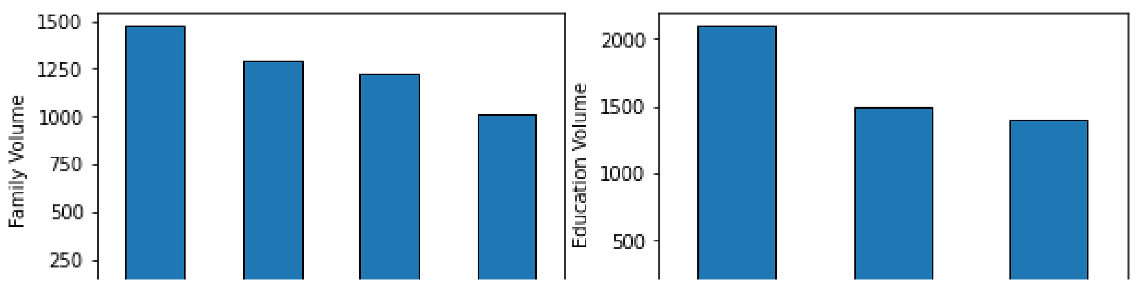
## Univariate Analysis of the descrete variables

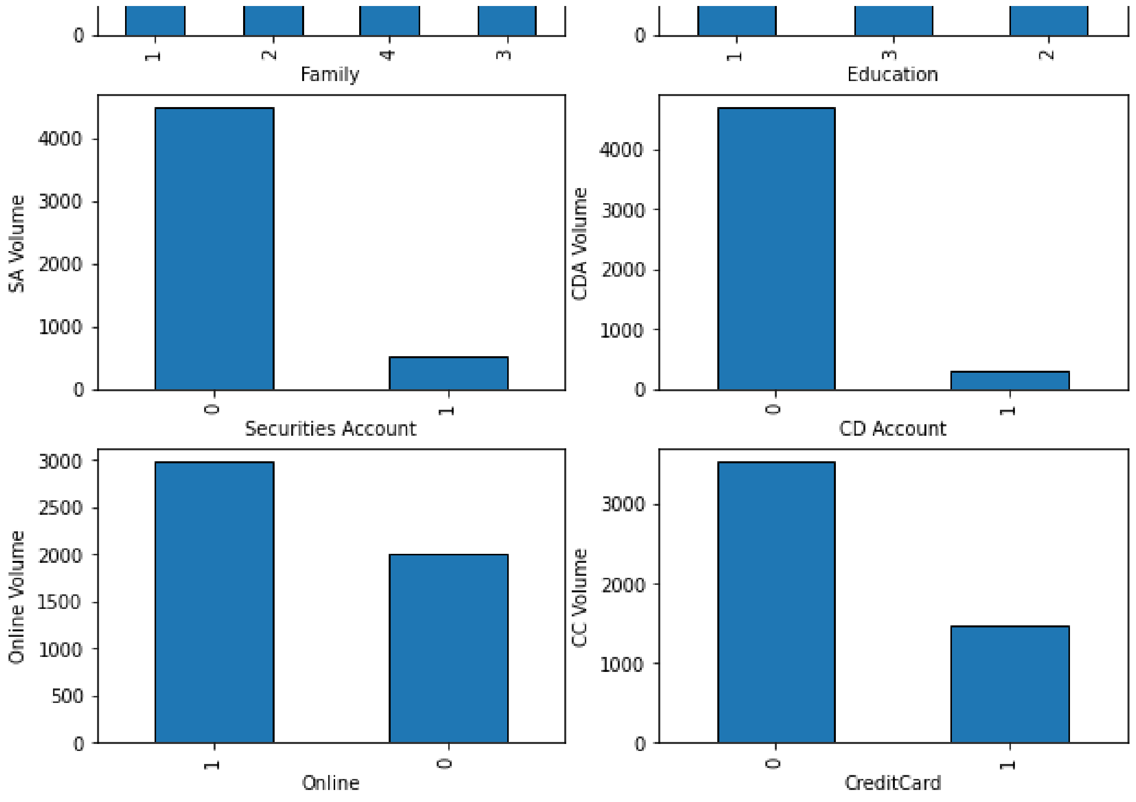
In [41]:

```
plt.figure(figsize=(10,10))


plt.subplot(3,2,1)
data['Family'].value_counts().plot(kind="bar", edgecolor = 'black')
plt.xlabel("Family")
plt.ylabel("Family Volume")

plt.subplot(3,2,2)
data['Education'].value_counts().plot(kind="bar", edgecolor = 'black')
plt.xlabel('Education')
plt.ylabel('Education Volume ')

plt.subplot(3,2,3)
data['Securities_Account'].value_counts().plot(kind="bar", edgecolor = 'black')
plt.xlabel('Securities Account')
plt.ylabel('SA Volume')

plt.subplot(3,2,4)
data['CD_Account'].value_counts().plot(kind="bar", edgecolor = 'black')
plt.xlabel('CD Account')
plt.ylabel('CDA Volume')

plt.subplot(3,2,5)
data['Online'].value_counts().plot(kind="bar", edgecolor = 'black')
plt.xlabel('Online')
plt.ylabel('Online Volume')

plt.subplot(3,2,6)
data['CreditCard'].value_counts().plot(kind="bar", edgecolor = 'black')
plt.xlabel('CreditCard')
plt.ylabel('CC Volume')
```

Out[41]:

```
Text(0, 0.5, 'CC Volume')
```





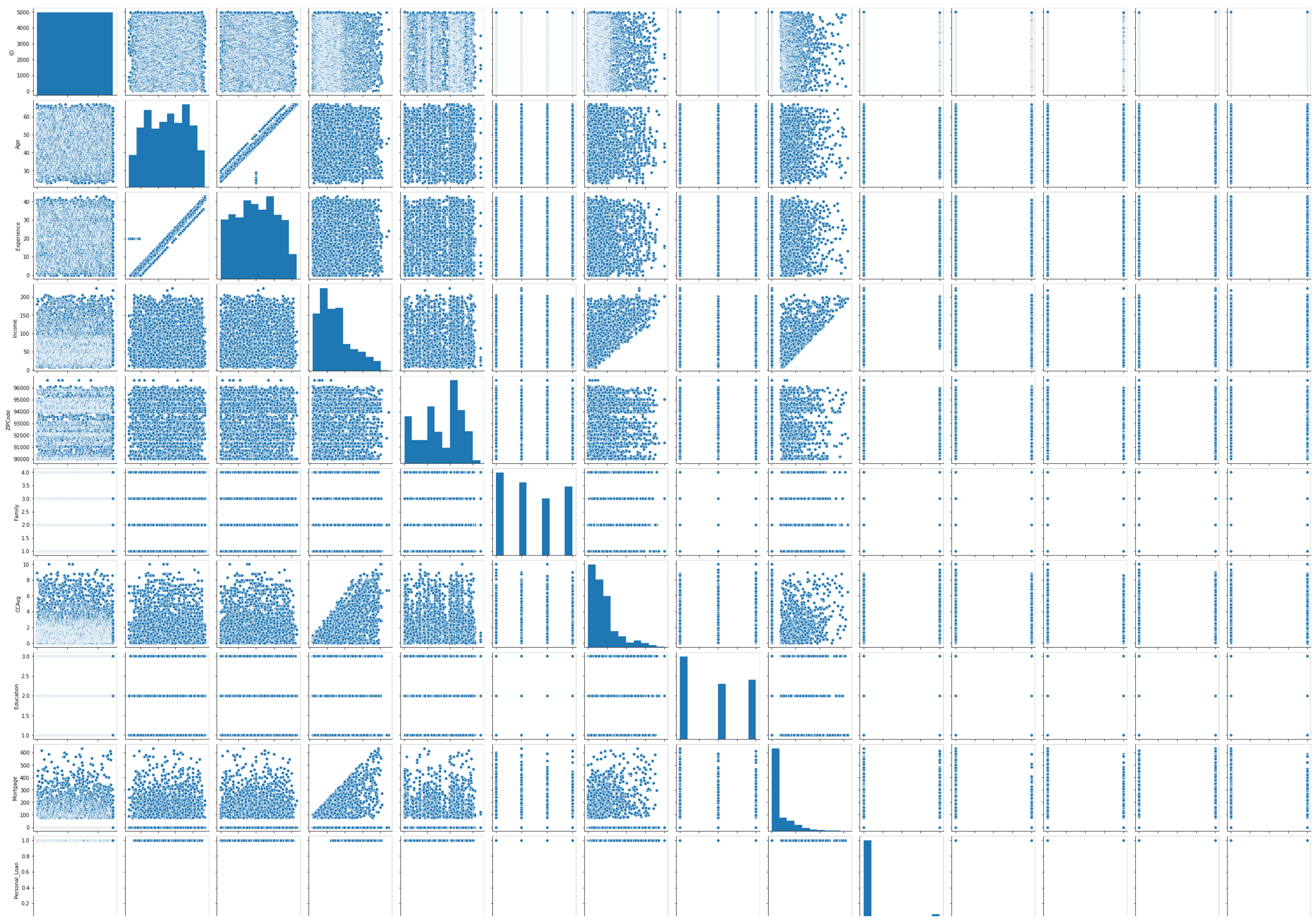
- **Family and Education has normal distribution**
- **Variate in the Securities Account and CD Account**

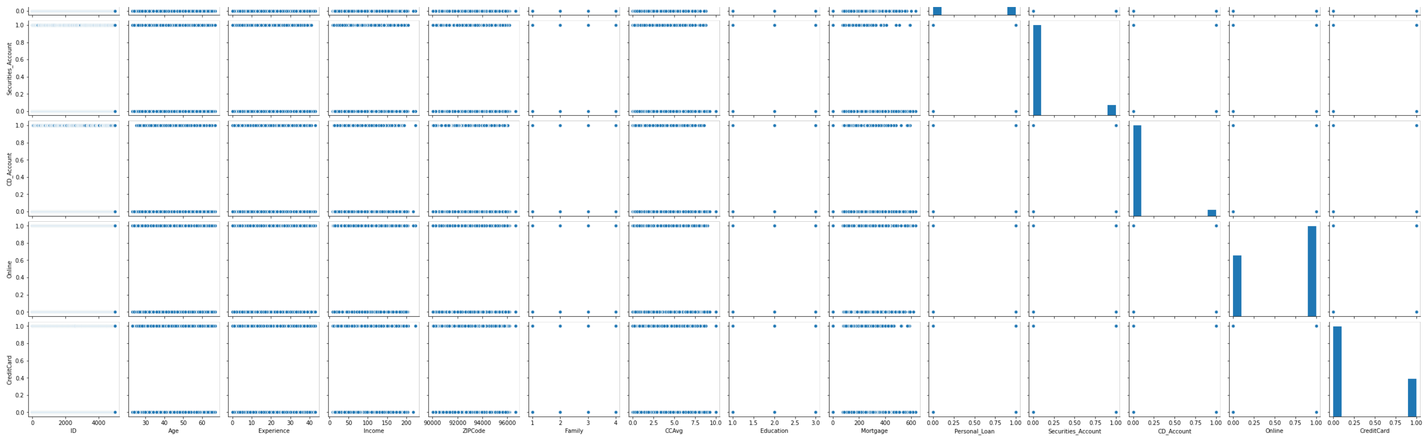
In [42]:

```
# pair plot
sns.pairplot(data)
```

Out[42]:

```
<seaborn.axisgrid.PairGrid at 0x21c5eb00308>
```





## Checking dependent variable

In [45]:

```
data["Personal_Loan"].value_counts()
```

Out[45]:

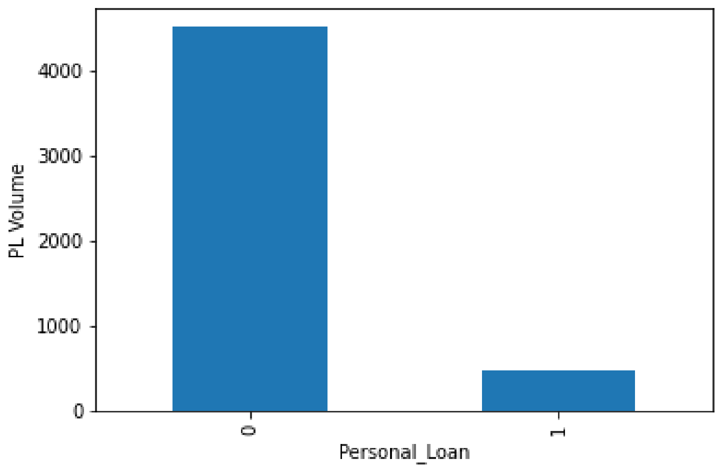
```
0    4520
1     480
Name: Personal_Loan, dtype: int64
```

In [53]:

```
pd.value_counts(data["Personal_Loan"]).plot(kind="bar")
plt.xlabel("Personal_Loan")
plt.ylabel("PL Volume")
```

Out[53]:

```
Text(0, 0.5, 'PL Volume')
```



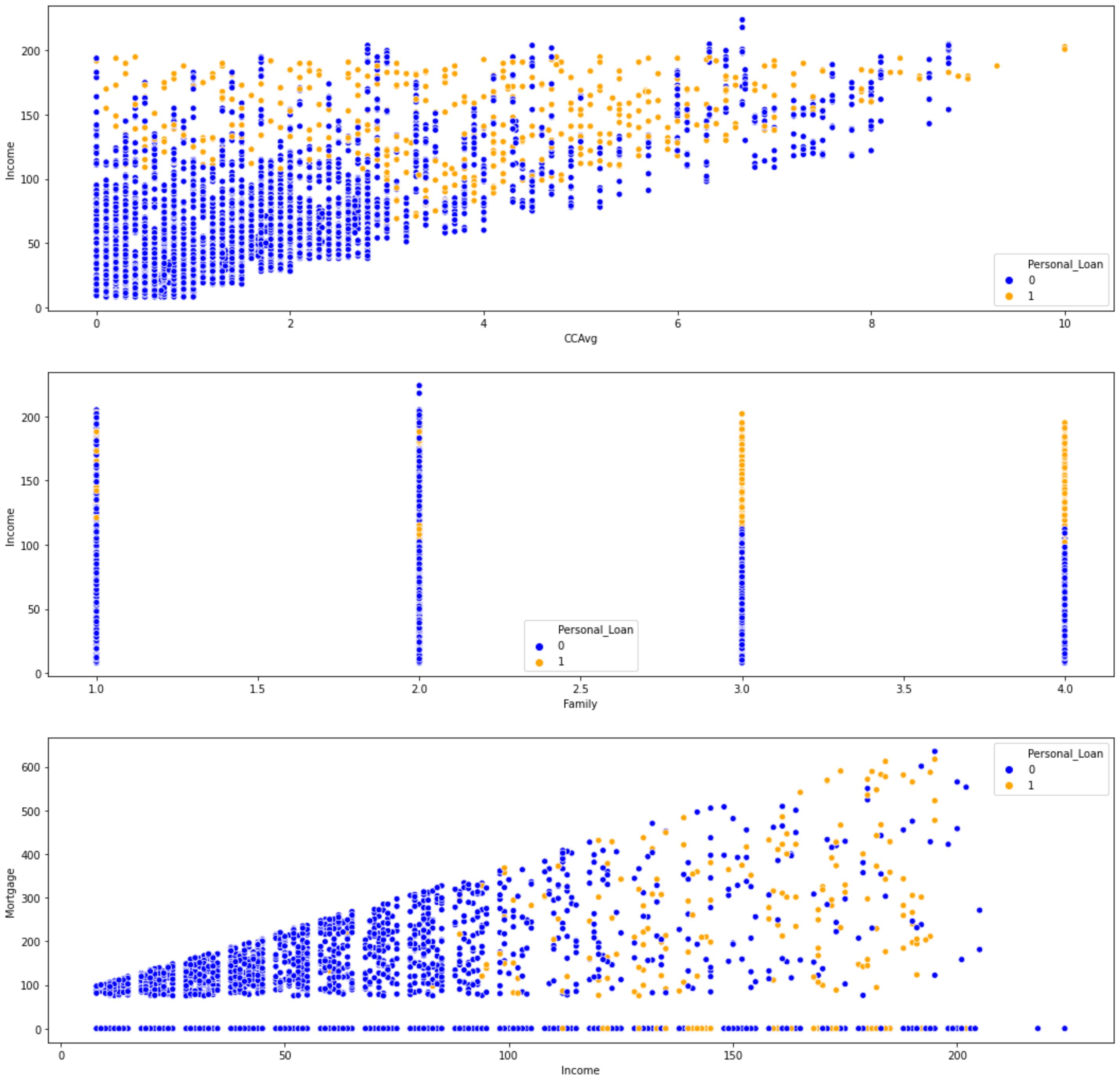
## Comparison charts using different variables by dapendent variable

In [60]:

```
plt.figure(figsize=(18,18))

plt.subplot(3,1,1)
sns.scatterplot(data.CCAvg, data.Income, hue = data['Personal_Loan'], palette= ['blue','
orange'])

plt.subplot(3,1,2)
sns.scatterplot(data.Family, data.Income, hue = data['Personal_Loan'], palette= ['blue',
'orange'])

plt.subplot(3,1,3)
sns.scatterplot(data.Income, data.Mortgage, hue = data['Personal_Loan'], palette= ['blue
','orange'])
```

Out[60]:

```
<AxesSubplot:xlabel='Income', ylabel='Mortgage'>
```



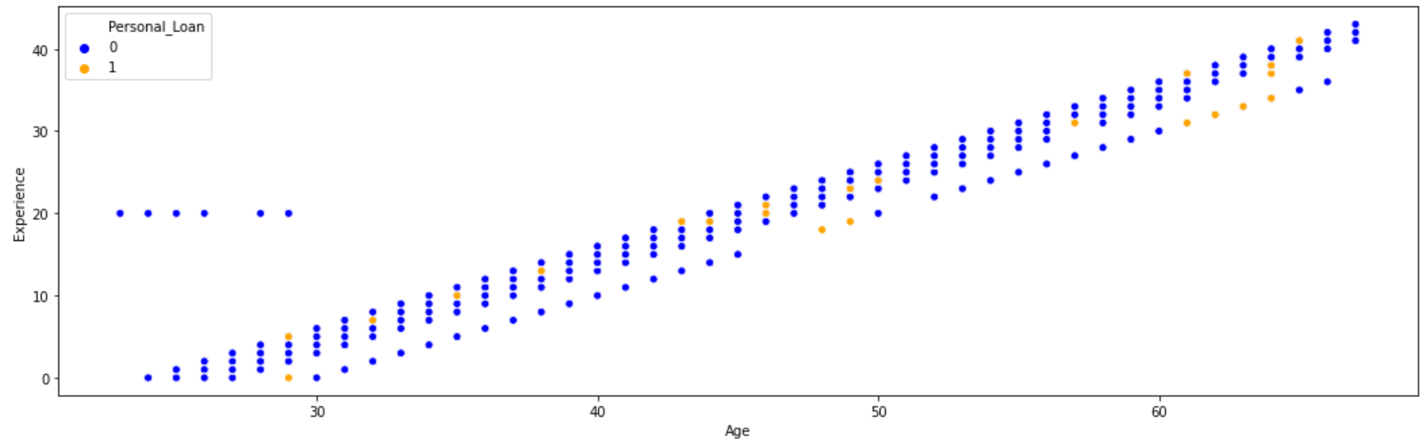
- **Based on CCAvg, Family & Income increases, personal loan also got increasing**

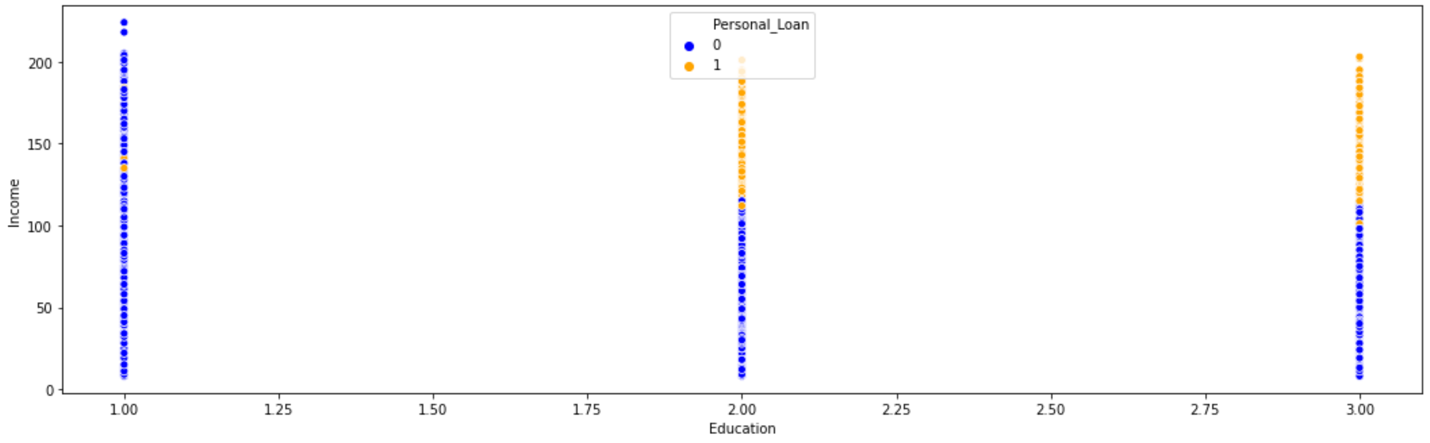
In [61]:

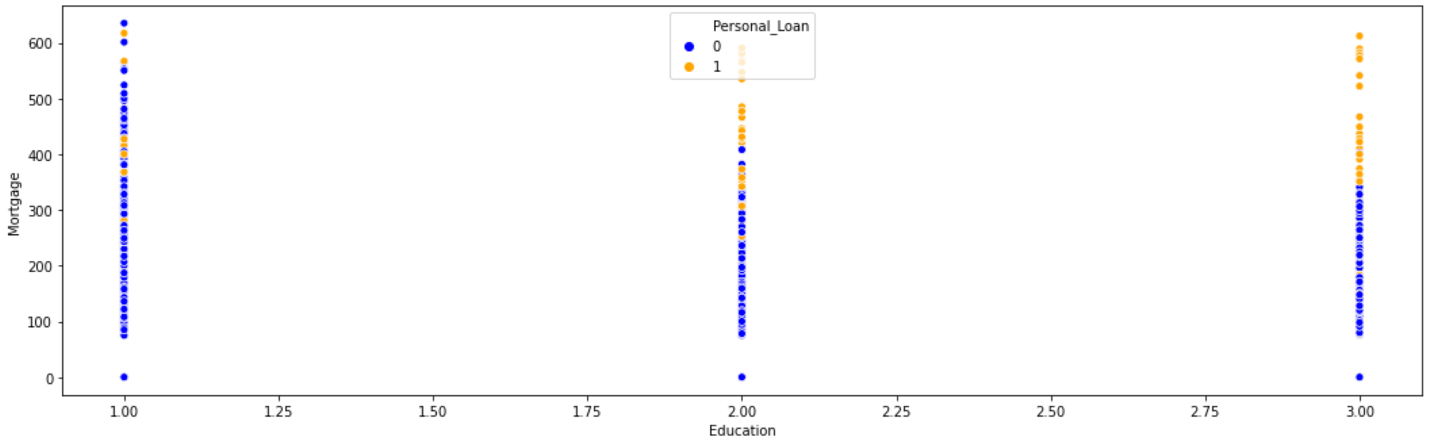
```
plt.figure(figsize=(18,18))

plt.subplot(3,1,1)
sns.scatterplot(data.Age, data.Experience, hue = data['Personal_Loan'], palette= ['blue'
,'orange'])

plt.subplot(3,1,2)
sns.scatterplot(data.Education, data.Income, hue = data['Personal_Loan'], palette= ['blu
e','orange'])

plt.subplot(3,1,3)
sns.scatterplot(data.Education, data.Mortgage, hue = data['Personal_Loan'], palette= ['bl
ue','orange'])
```

Out[61]:

```
<AxesSubplot:xlabel='Education', ylabel='Mortgage'>
```







## Comparing Categorical data by Personal Loan

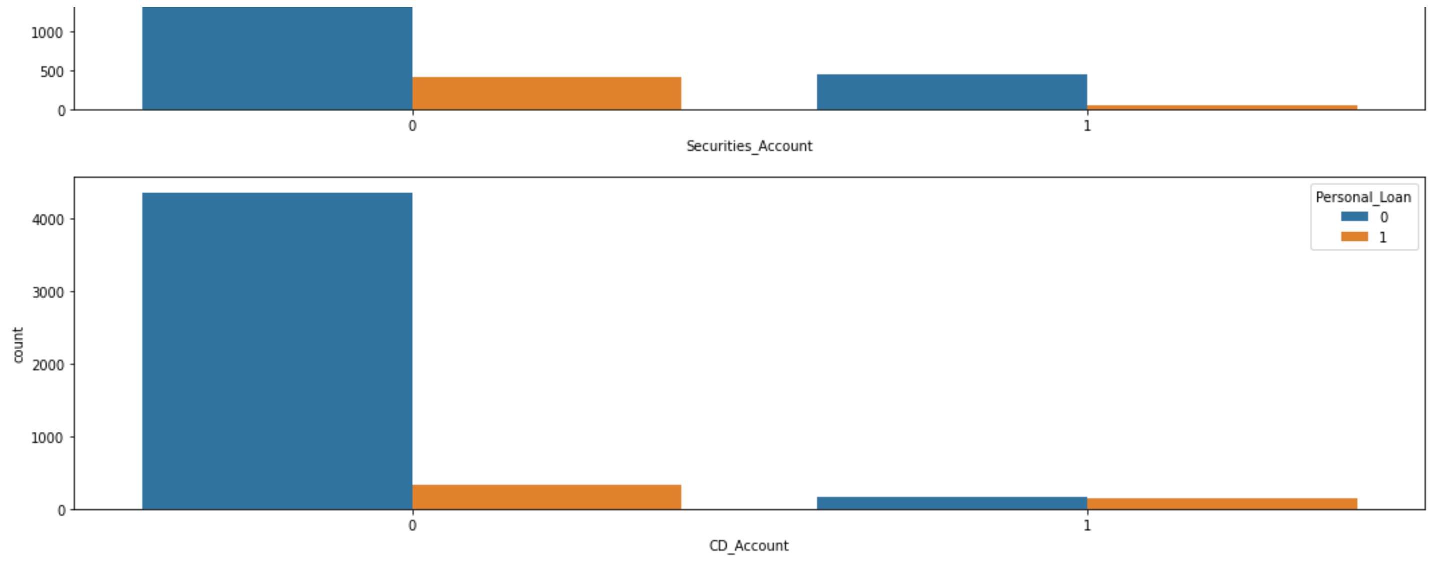
In [64]:

```
plt.figure(figsize=(18,10))

plt.subplot(2,1,1)
sns.countplot(x="Securities_Account", data=data ,hue="Personal_Loan")

plt.subplot(2,1,2)
sns.countplot(x='CD_Account' ,data=data ,hue='Personal_Loan')
```

Out[64]:

```
<AxesSubplot:xlabel='CD_Account', ylabel='count'>
```

Personal_Loan
0
1
count

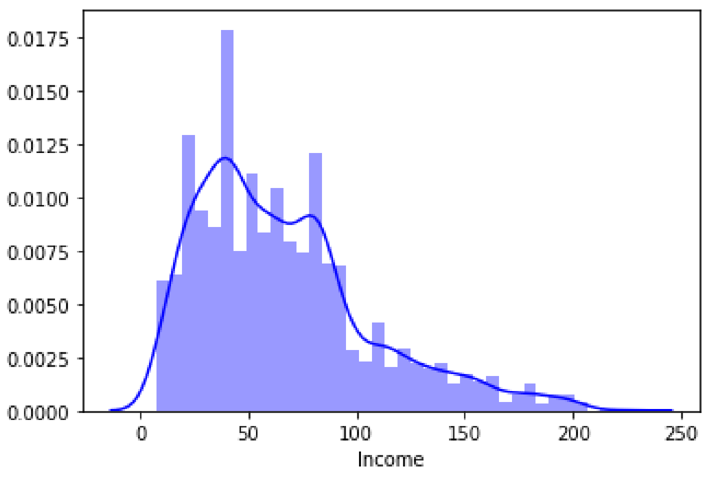


In [68]:

```
sns.distplot(data[data["Personal_Loan"] == 0]['Income'], color = 'blue')
```

Out[68]:

```
<AxesSubplot:xlabel='Income'>
```

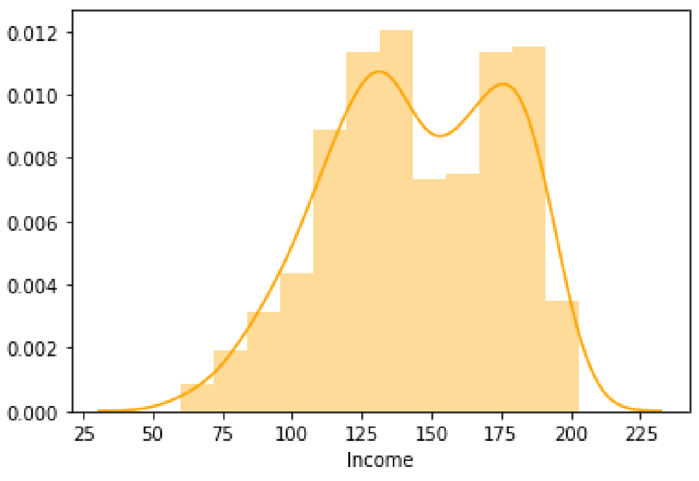


In [70]:

```
sns.distplot(data[data["Personal_Loan"] == 1]['Income'], color = 'orange')
```

Out[70]:

```
<AxesSubplot:xlabel='Income'>
```



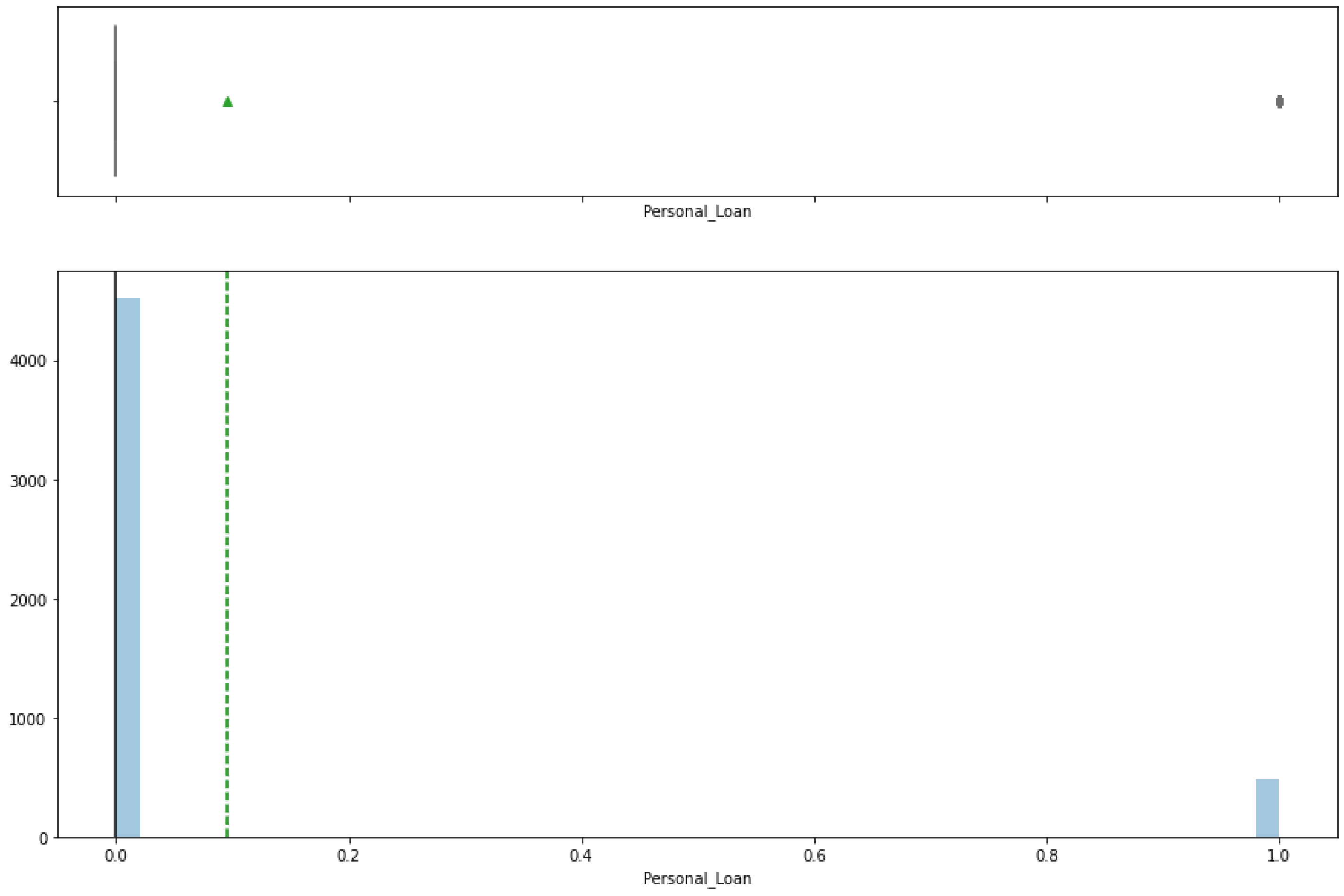
- **Above comparison chart, based on income vs personal loan**

In [71]:

```
def histogram_boxplot(feature, figsize=(15,10), bins = None):

    f2, (ax_box2, ax_hist2) = plt.subplots(nrows = 2,
                                           sharex = True,
                                           gridspec_kw = {"height_ratios": (.25, .75)},

                                           figsize = figsize
                                           )
    sns.boxplot(feature, ax=ax_box2, showmeans=True, color='violet')
    sns.distplot(feature, kde=F, ax=ax_hist2, bins=bins,palette="winter") if bins else s
ns.distplot(feature, kde=False, ax=ax_hist2)
    ax_hist2.axvline(np.mean(feature), color='green', linestyle='--')
    ax_hist2.axvline(np.median(feature), color='black', linestyle='-')
```

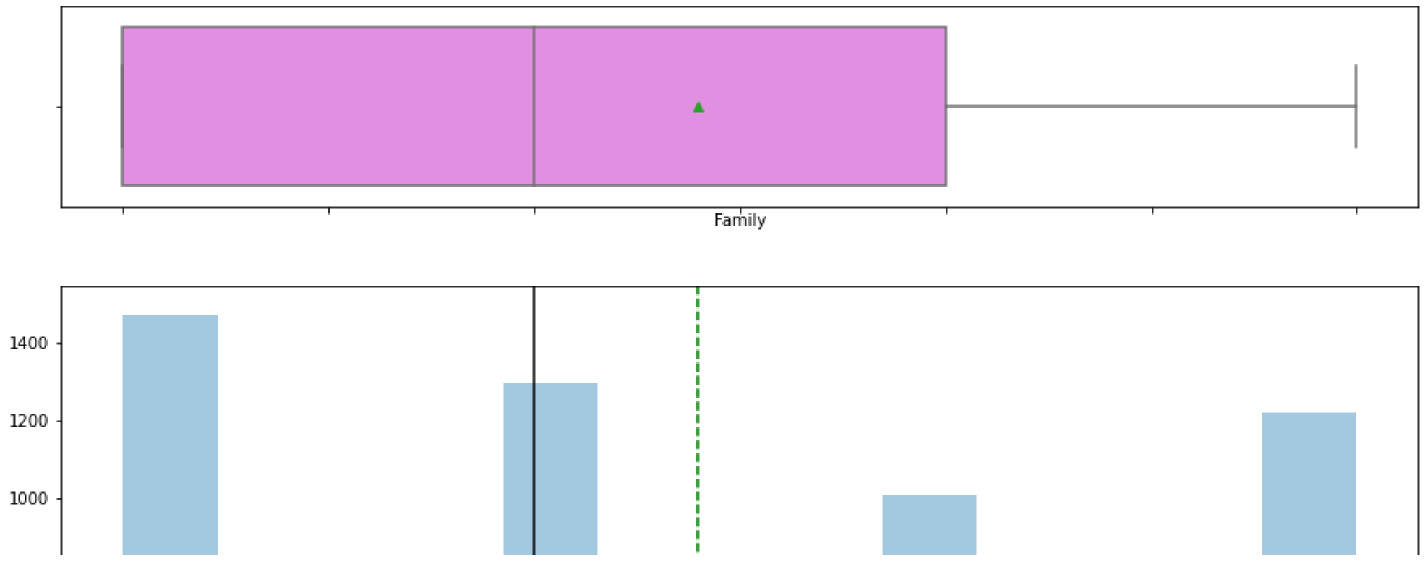
In [72]:

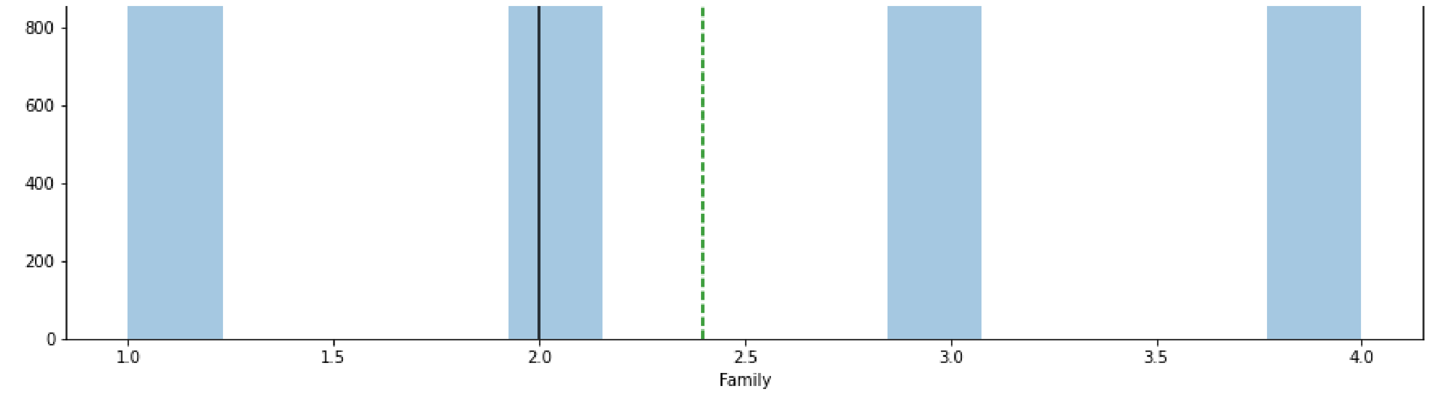
```
histogram_boxplot(data["Personal_Loan"])
```



In [73]:

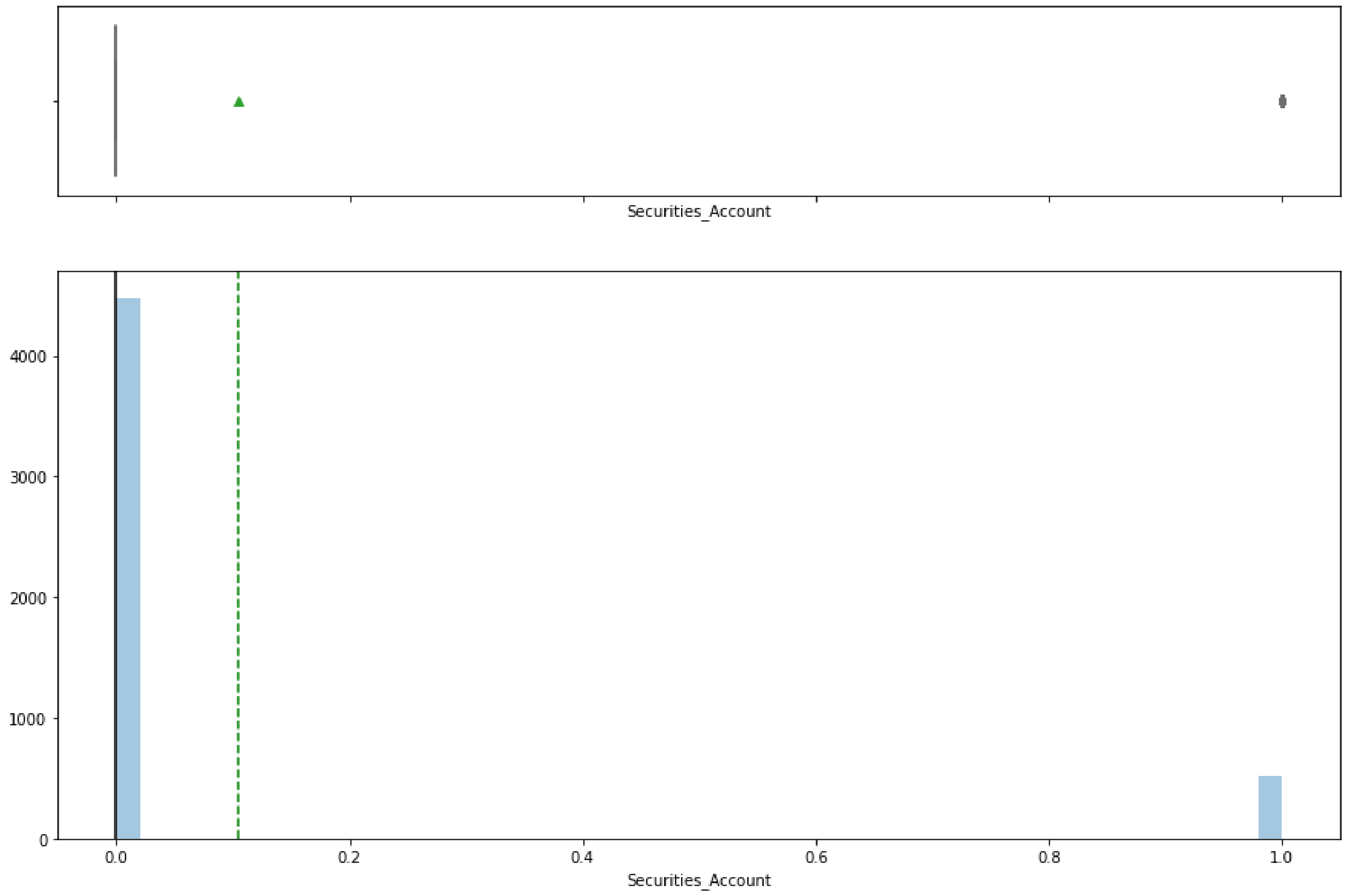
```
histogram_boxplot(data["Family"])
```





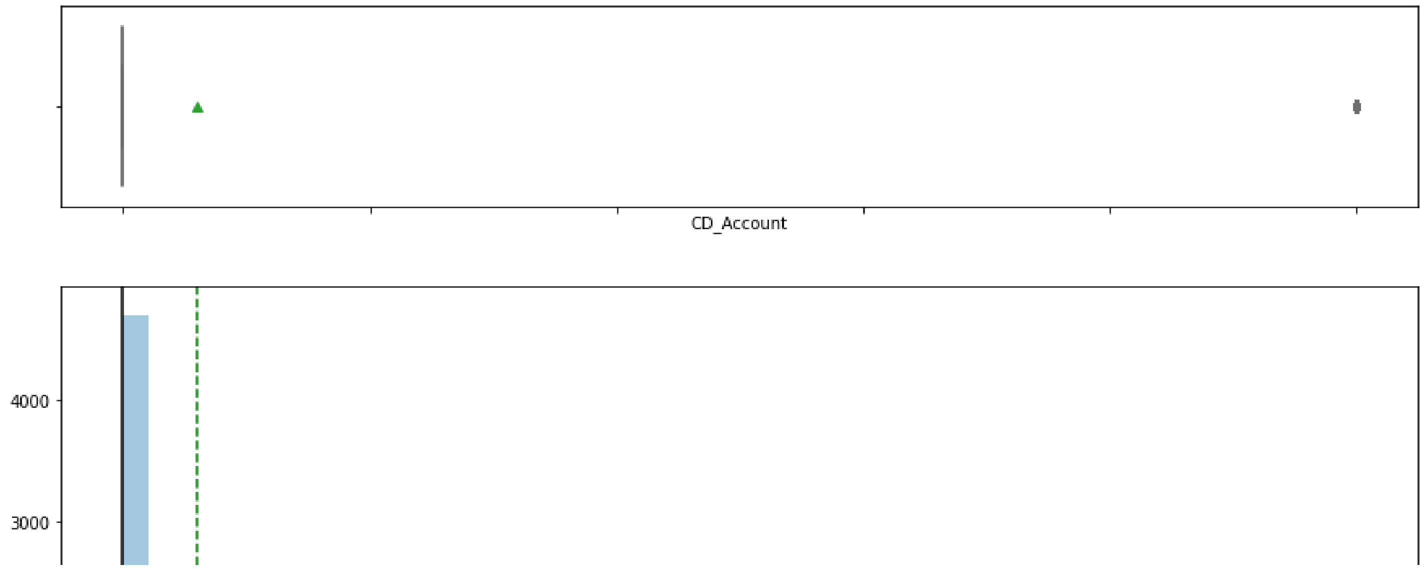
In [74]:

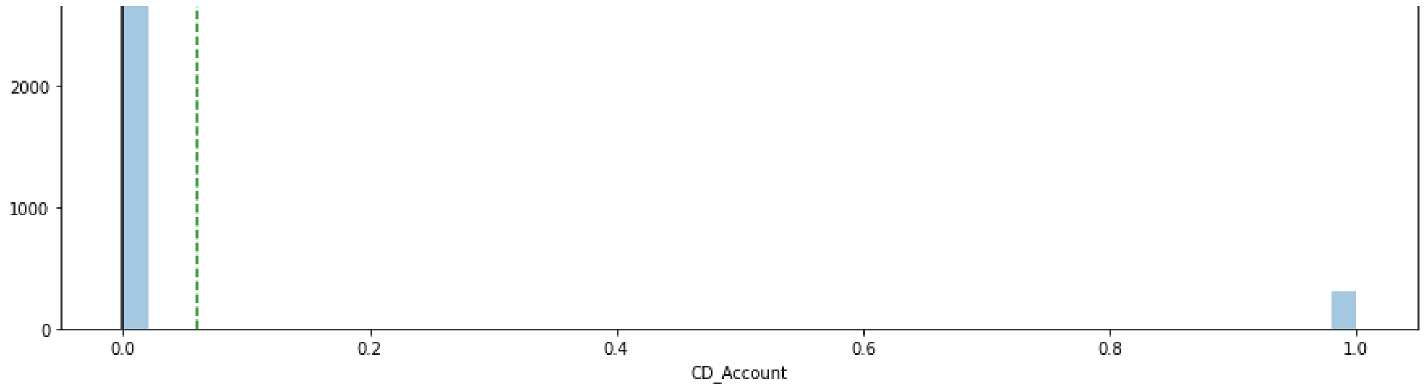
```
histogram_boxplot(data["Securities_Account"])
```



In [75]:

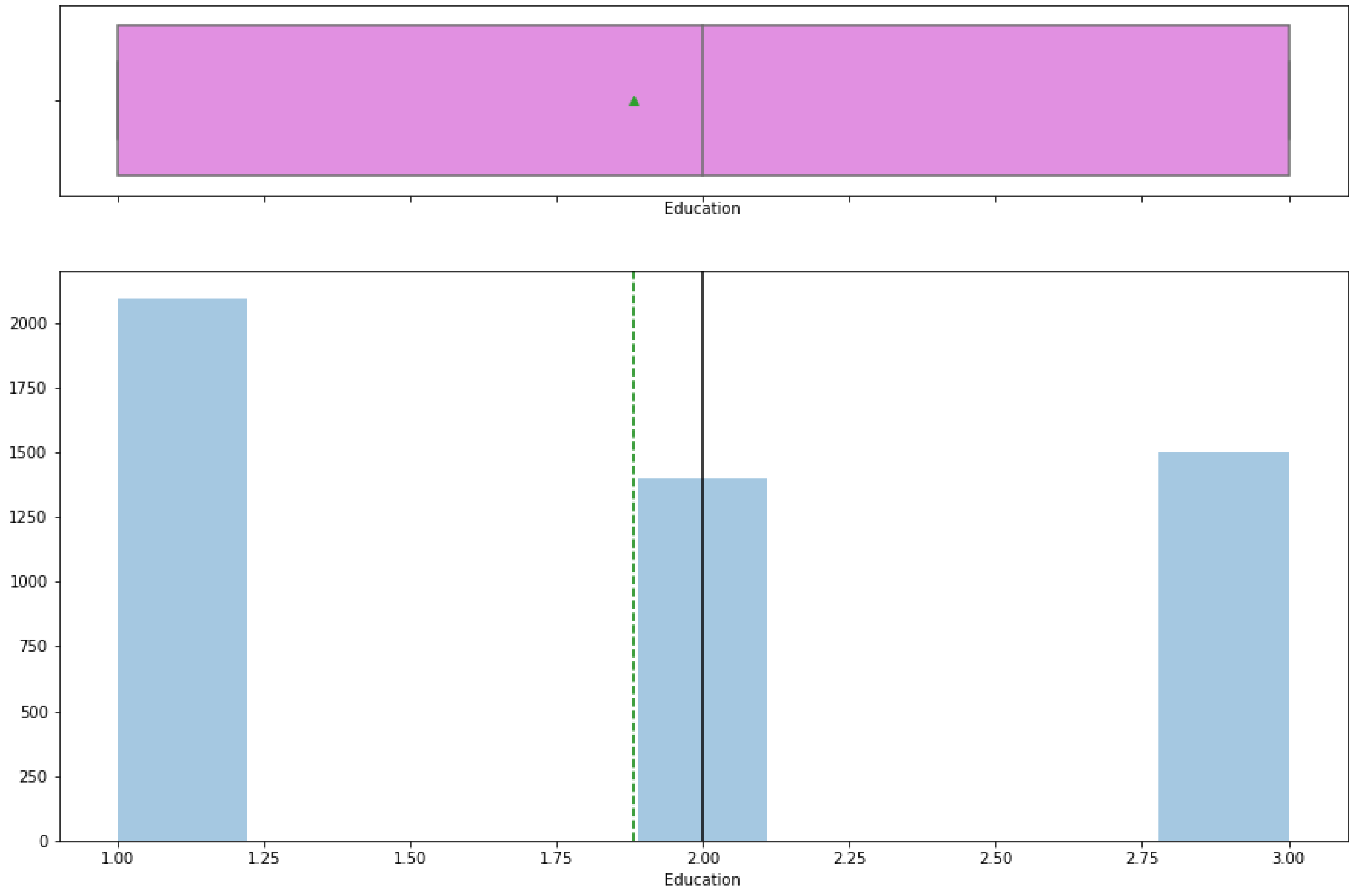
```
histogram_boxplot(data["CD_Account"])
```





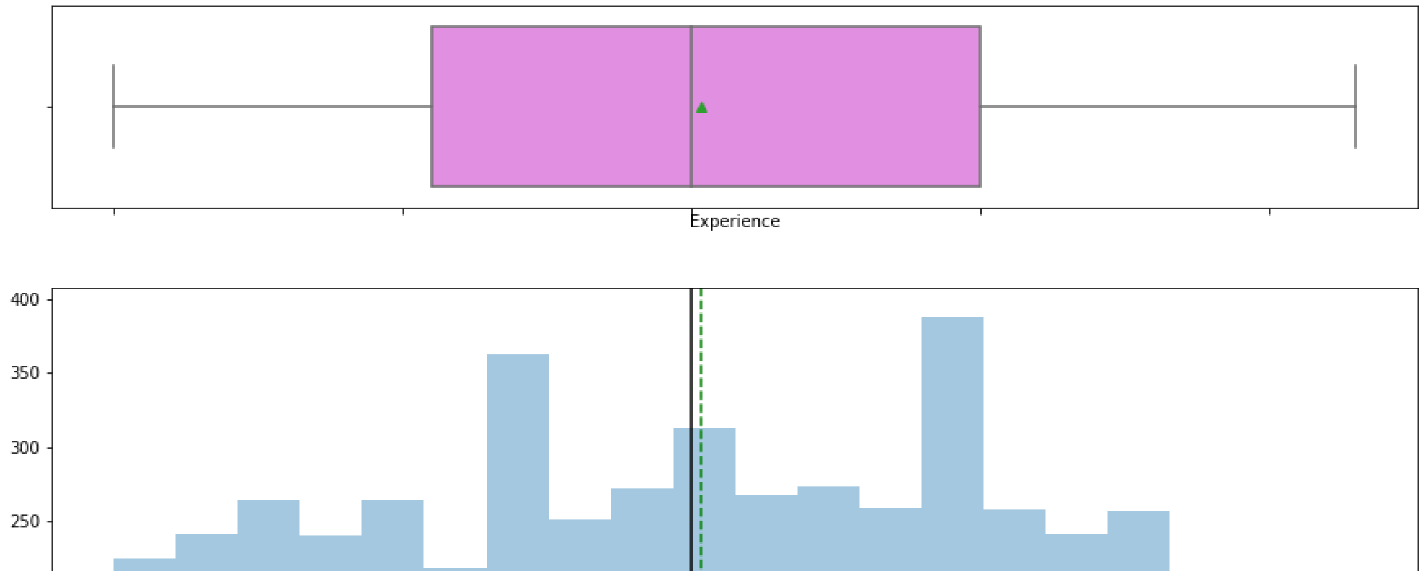
In [76]:

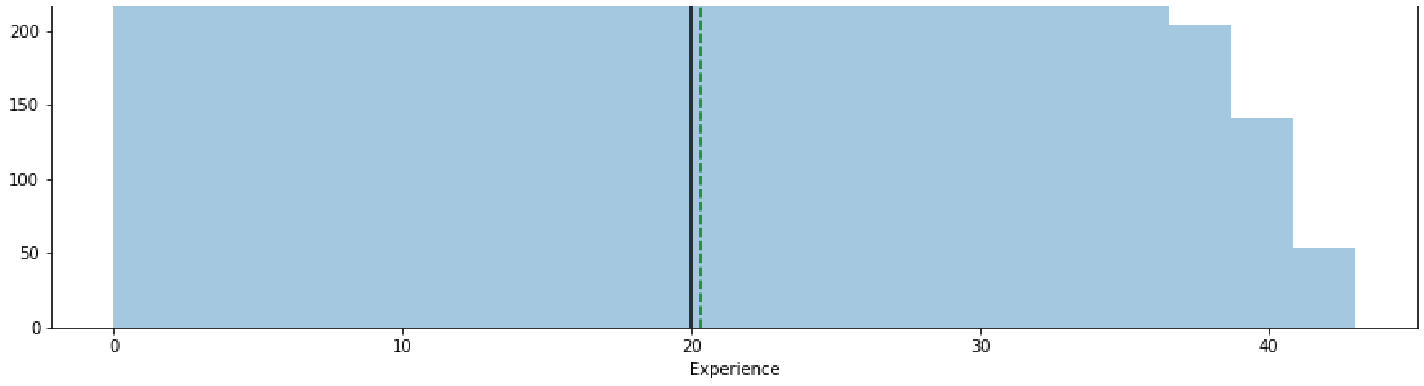
```
histogram_boxplot(data["Education"])
```



In [77]:

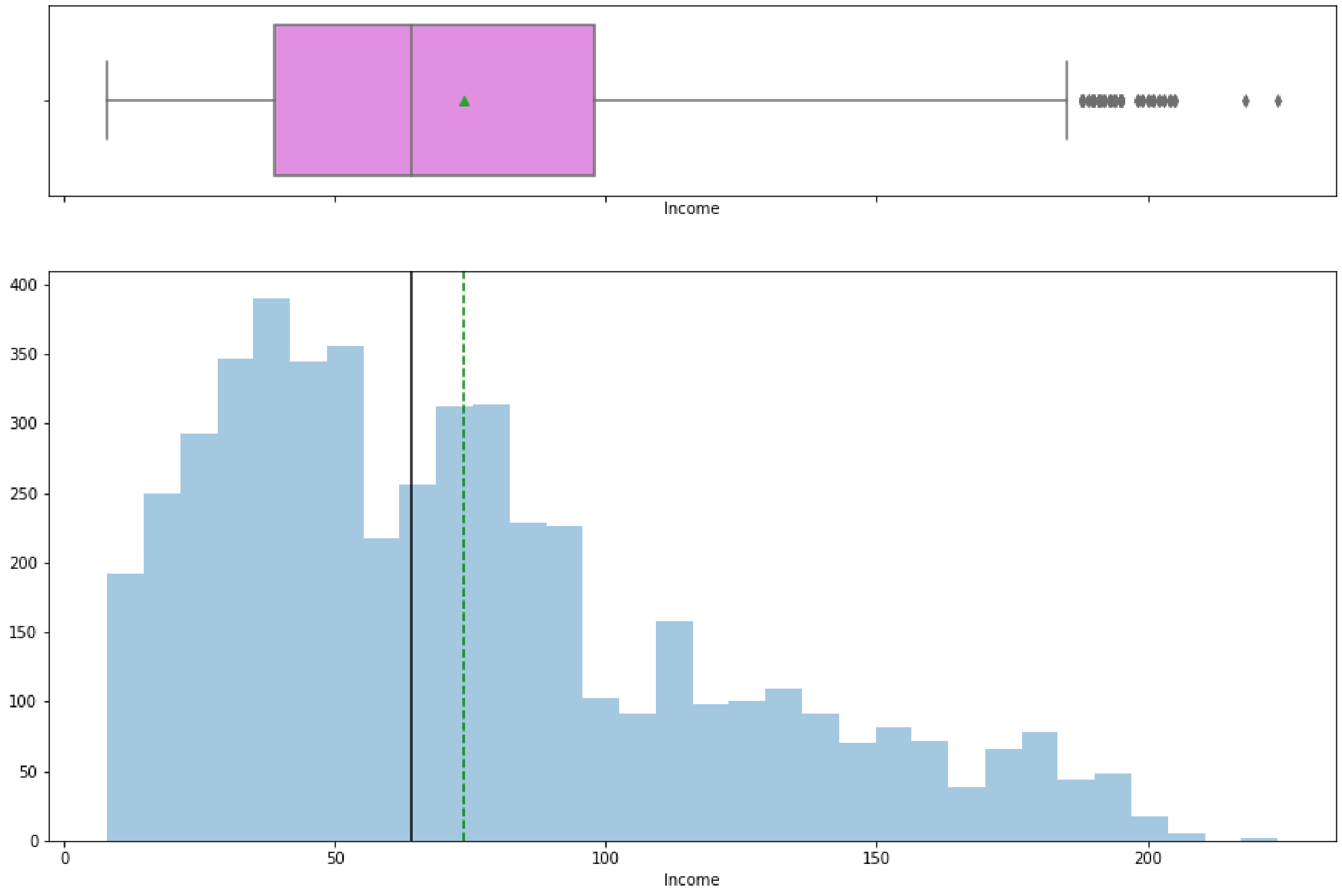
```
histogram_boxplot(data["Experience"])
```





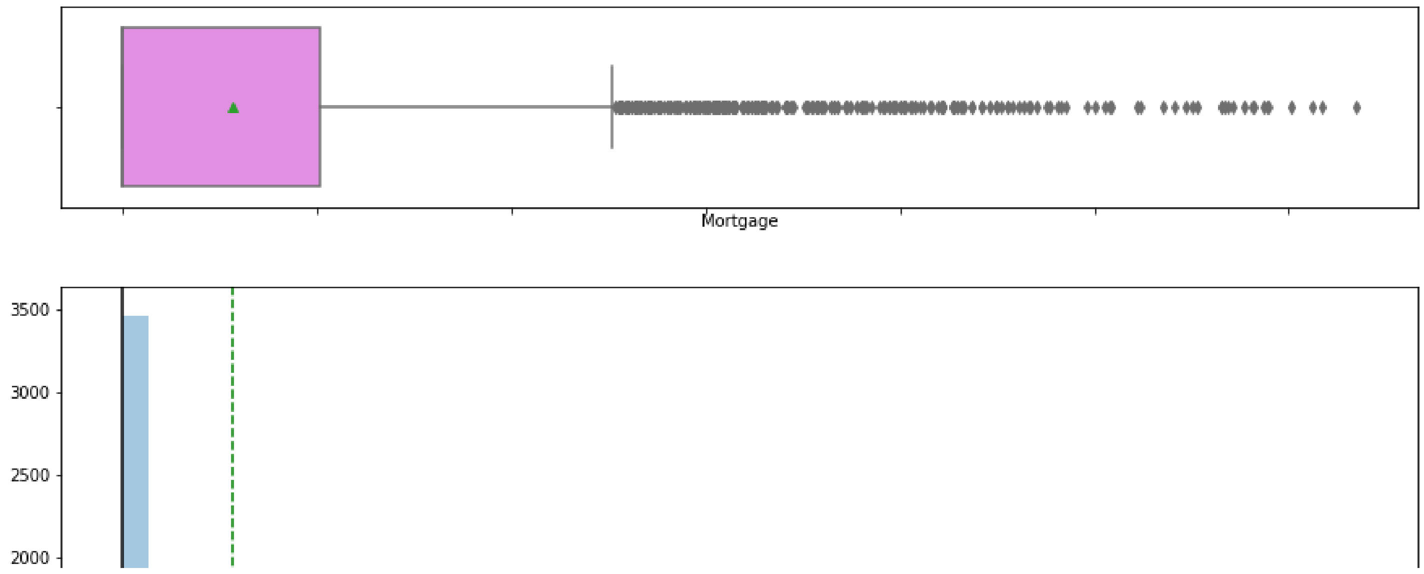
In [78]:

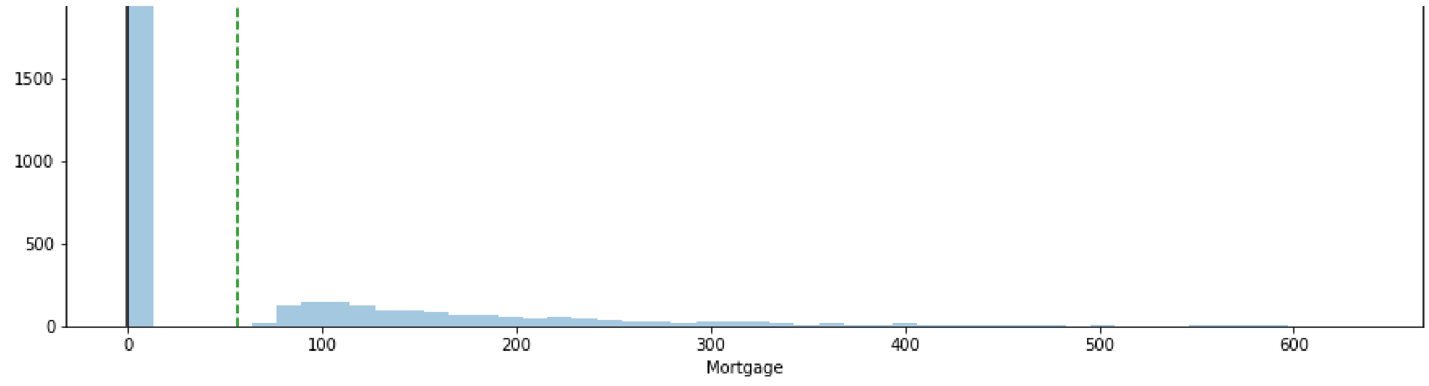
```
histogram_boxplot(data["Income"])
```



In [79]:

```
histogram_boxplot(data["Mortgage"])
```

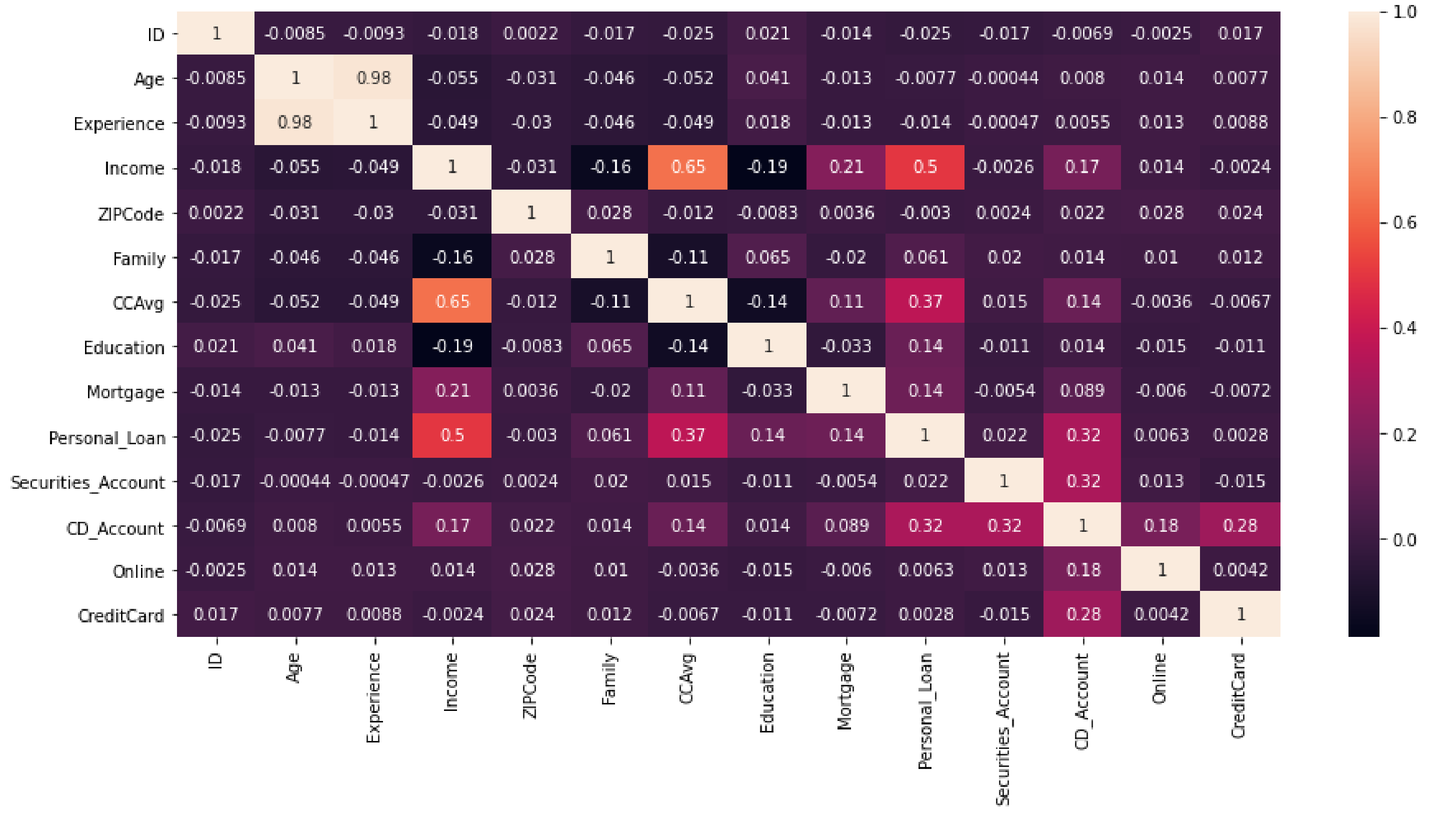




## Bivariate Analysis

In [80]:

```
plt.figure(figsize=(15,7))
sns.heatmap(data.corr(),annot=True)
plt.show()
```



| | ID | Age | Experience | Income | ZIPCode | Family | CCAvg | Education | Mortgage | Personal_Loan | Securities_Account | CD_Account | Online | CreditCard |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID | 1 | -0.0085 | -0.0093 | -0.018 | 0.0022 | -0.017 | -0.025 | 0.021 | -0.014 | -0.025 | -0.017 | -0.0069 | -0.0025 | 0.017 |
| Age | -0.0085 | 1 | 0.98 | -0.055 | -0.031 | -0.046 | -0.052 | 0.041 | -0.013 | -0.0077 | -0.00044 | 0.008 | 0.014 | 0.0077 |
| Experience | -0.0093 | 0.98 | 1 | -0.049 | -0.03 | -0.046 | -0.049 | 0.018 | -0.013 | -0.014 | -0.00047 | 0.0055 | 0.013 | 0.0088 |
| Income | -0.018 | -0.055 | -0.049 | 1 | -0.031 | -0.16 | 0.65 | -0.19 | 0.21 | 0.5 | -0.0026 | 0.17 | 0.014 | -0.0024 |
| ZIPCode | 0.0022 | -0.031 | -0.03 | -0.031 | 1 | 0.028 | -0.012 | -0.0083 | 0.0036 | -0.003 | 0.0024 | 0.022 | 0.028 | 0.024 |
| Family | -0.017 | -0.046 | -0.046 | -0.16 | 0.028 | 1 | -0.11 | 0.065 | -0.02 | 0.061 | 0.02 | 0.014 | 0.01 | 0.012 |
| CCAvg | -0.025 | -0.052 | -0.049 | 0.65 | -0.012 | -0.11 | 1 | -0.14 | 0.11 | 0.37 | 0.015 | 0.14 | -0.0036 | -0.0067 |
| Education | 0.021 | 0.041 | 0.018 | -0.19 | -0.0083 | 0.065 | -0.14 | 1 | -0.033 | 0.14 | -0.011 | 0.014 | -0.015 | -0.011 |
| Mortgage | -0.014 | -0.013 | -0.013 | 0.21 | 0.0036 | -0.02 | 0.11 | -0.033 | 1 | 0.14 | -0.0054 | 0.089 | -0.006 | -0.0072 |
| Personal_Loan | -0.025 | -0.0077 | -0.014 | 0.5 | -0.003 | 0.061 | 0.37 | 0.14 | 0.14 | 1 | 0.022 | 0.32 | 0.0063 | 0.0028 |
| Securities_Account | -0.017 | -0.00044 | -0.00047 | -0.0026 | 0.0024 | 0.02 | 0.015 | -0.011 | -0.0054 | 0.022 | 1 | 0.32 | 0.013 | -0.015 |
| CD_Account | -0.0069 | 0.008 | 0.0055 | 0.17 | 0.022 | 0.014 | 0.14 | 0.014 | 0.089 | 0.32 | 0.32 | 1 | 0.18 | 0.28 |
| Online | -0.0025 | 0.014 | 0.013 | 0.014 | 0.028 | 0.01 | -0.0036 | -0.015 | -0.006 | 0.0063 | 0.013 | 0.18 | 1 | 0.0042 |
| CreditCard | 0.017 | 0.0077 | 0.0088 | -0.0024 | 0.024 | 0.012 | -0.0067 | -0.011 | -0.0072 | 0.0028 | -0.015 | 0.28 | 0.0042 | 1 |

- **Income shows the highest correlation with CCAvg (0.65)**
- **Age and Experience are very highly correlated(0.98) with each other.**
- **Age and Experience are highly correlated and the correlation is almost 1.**
- **'Income' and 'CCAvg' is moderately correlated.**
- **We can see in above heat map there is association of 'CD Account' with 'Credit Card', 'Securities Account', 'Online', 'CCAvg' and 'Income'.**
- **'Income' influences 'CCAvg', 'Personal Loan', 'CD Account' and 'Mortgage'.**

In [83]:

```
data[['Personal_Loan', 'Age', 'Income', 'CCAvg', 'Mortgage', 'Experience']].corr()
```

Out[83]:

```
              Personal_Loan        Age     Income      CCAvg   Mortgage  Experience
Personal_Loan      1.000000  -0.007726   0.502462   0.366889   0.142095   -0.014013
          Age     -0.007726   1.000000  -0.055269  -0.052012  -0.012539    0.977182
```

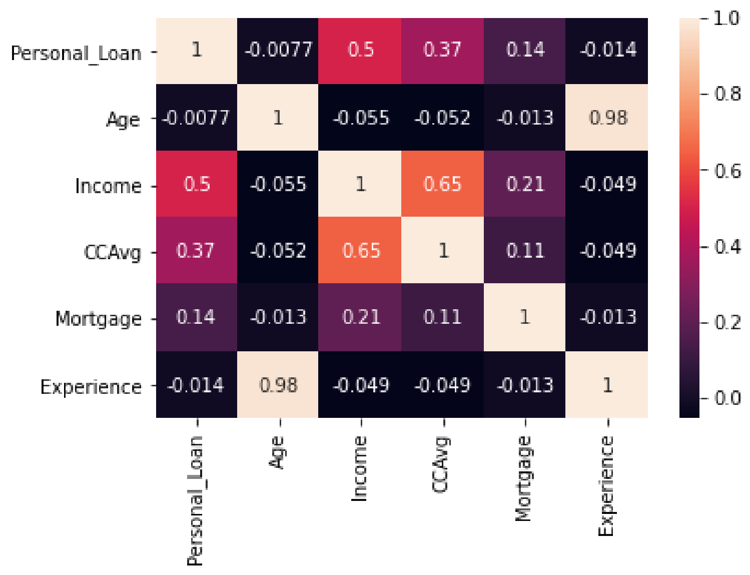
| | Personal_Loan | Age | Income | CCAvg | Mortgage | Experience |
|---|---|---|---|---|---|---|
| **Income** | 0.502462 | -0.055269 | 1.000000 | 0.645984 | 0.206806 | -0.049046 |
| **CCAvg** | 0.366889 | -0.052012 | 0.645984 | 1.000000 | 0.109905 | -0.048718 |
| **Mortgage** | 0.142095 | -0.012539 | 0.206806 | 0.109905 | 1.000000 | -0.013365 |
| **Experience** | -0.014013 | 0.977182 | -0.049046 | -0.048718 | -0.013365 | 1.000000 |

In [85]:

```
sns.heatmap(data[['Personal_Loan', 'Age', 'Income', 'CCAvg', 'Mortgage', 'Experience']].
corr(), annot = True)
```

Out[85]:

```
<AxesSubplot:>
```

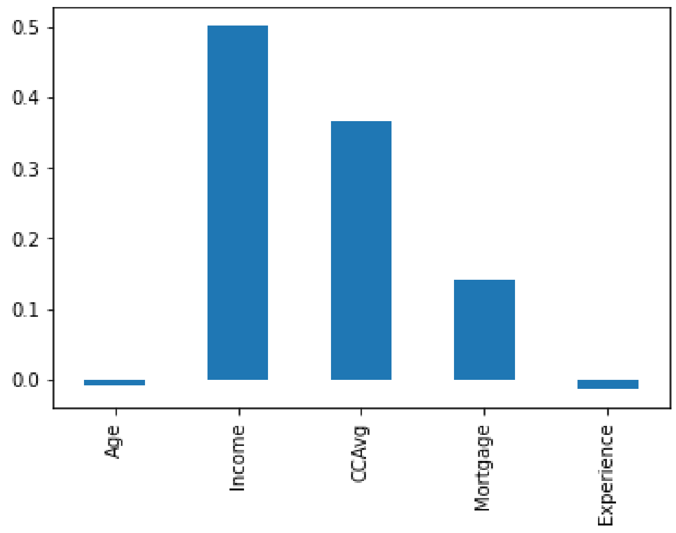


In [88]:

```
data[['Personal_Loan', 'Age', 'Income', 'CCAvg', 'Mortgage', 'Experience']].corr()['Pers
onal_Loan'][1:].plot.bar()
```

Out[88]:

```
<AxesSubplot:>
```



- **Income & CCAvg shows the highest correlation**

**Model Building - Approach**

1. **Data preparation**
2. **Partition the data into train and test set.**
3. **Built a CART model on the train data.**

4. **Tune the model and prune the tree, if required.**
5. **Test the data on test set.**

In [169]:

```
column_names = list(data.columns)
column_names.remove('Personal_Loan')
#column_names.remove('ID')
#column_names.remove('ZIPCode')
feature_names = column_names
print(feature_names)
```

```
['Age', 'Experience', 'Income', 'Family', 'CCAvg', 'Education', 'Mortgage', 'Securities_A
ccount', 'CD_Account', 'Online', 'CreditCard']
```

In [91]:

```
train_set, test_set = train_test_split(data.drop(['ID','Experience'], axis=1), test_size
=0.3 , random_state=100)
```

In [93]:

```
train_labels = train_set.pop('Personal_Loan')
test_labels = test_set.pop('Personal_Loan')
```

In [95]:

```
train_set_indep = data.drop(['Experience' ,'ID'] , axis = 1).drop(labels= "Personal_Loan
" , axis = 1)
train_set_dep = data["Personal_Loan"]
X = np.array(train_set_indep)
Y = np.array(train_set_dep)
X_Train = X[ :3500, :]
X_Test = X[3501: , :]
Y_Train = Y[:3500, ]
Y_Test = Y[3501:, ]
```

In [108]:

```
logmodel = LogisticRegression()
logmodel.fit(X_Train,Y_Train)
```

Out[108]:

```
LogisticRegression()
```

In [99]:

```
X = data.drop('Personal_Loan',axis=1)
y = data['Personal_Loan'].astype('int64')
```

In [100]:

```
# Splitting data into training and test set:
X_train, X_test, y_train, y_test =train_test_split(X, y, test_size=0.3, random_state=1)
print(X_train.shape, X_test.shape)
```

```
(3500, 13) (1500, 13)
```

## Logistic Regression

In [116]:

```
logmodel = LogisticRegression()
logmodel.fit(X_Train,Y_Train)
```

Out[116]:

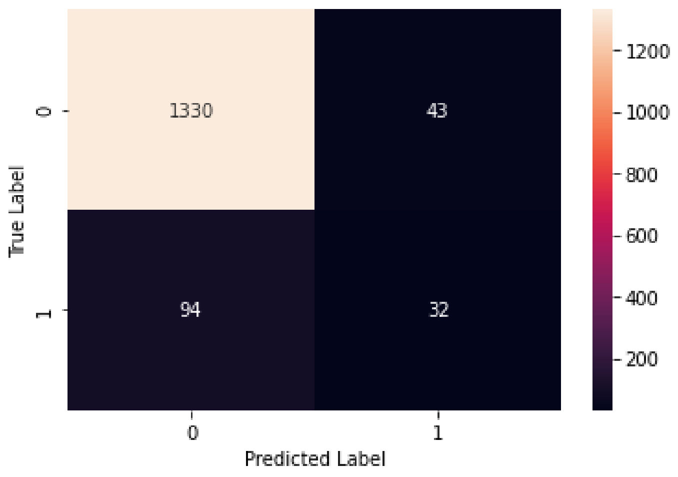
```
LogisticRegression()
```

In [117]:

```
predict = logmodel.predict(X_Test)
predictProb = logmodel.predict_proba(X_Test)
```

In [361]:

```
# Confusion Matrix
cm = confusion_matrix(Y_Test, predict)

class_label = ["0", "1"]
df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
sns.heatmap(df_cm, annot = True, fmt = "d")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [121]:

```
# Classification Report
print(classification_report(Y_Test, predict))
```

```
              precision    recall  f1-score   support

           0       0.93      0.97      0.95      1373
           1       0.43      0.25      0.32       126

    accuracy                           0.91      1499
   macro avg       0.68      0.61      0.63      1499
weighted avg       0.89      0.91      0.90      1499
```

In [345]:

```
print('Accuracy on train set: {:.2f}'.format(logmodel.score(X_Train, Y_Train)))
print('Accuracy on test set: {:.2f}'.format(logmodel.score(X_Test, Y_Test)))
print('Recall score: {:.2f}'.format(recall_score(Y_Test,predicted)))
print('ROC AUC score: {:.2f}'.format(roc_auc_score(Y_Test,predicted)))
print('Precision score: {:.2f}'.format(precision_score(Y_Test,predicted)))
```

```
Accuracy on train set: 0.91
Accuracy on test set: 0.91
Recall score: 0.25
ROC AUC score: 0.61
Precision score: 0.43
```

## Insights:

- **True Positive (observed=0,predicted=0): Model predicted that 1330 customers shall take Personal loan and they customer took it**
- **False Positive (observed=0,predicted=1): Model Predicted 43 Personal loan will take and the customer did not take it but bank didn't loose any money**

- **True Negative (observed=1,predicted=1): Model Predicted 32 Personal loan will not take and the customer did not take it**
- **False Negative (observed=1,predicted=1): Model Predicted 94 Personal loan will not take and the customer took it - This is where model should have done better**

## Build Decision Tree Model

In [145]:

```
model = DecisionTreeClassifier(criterion='gini',class_weight={0:0.15,1:0.85},random_stat
e=1)
```

In [147]:

```
model.fit(X_Train, Y_Train)
```

Out[147]:

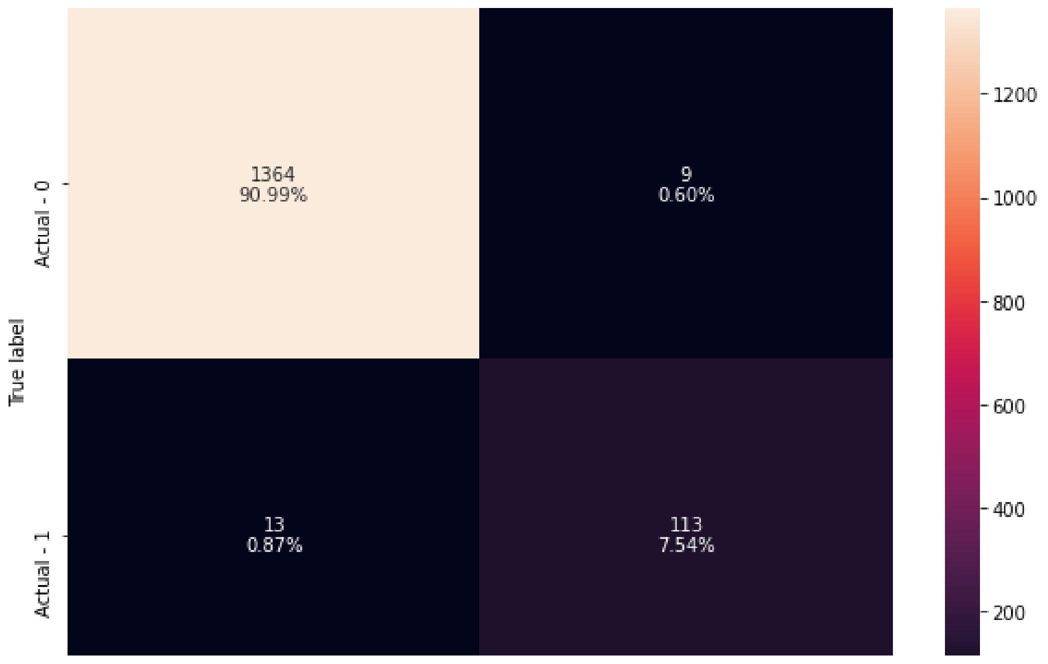
```
DecisionTreeClassifier(class_weight={0: 0.15, 1: 0.85}, random_state=1)
```

In [362]:

```
def make_confusion_matrix(model,y_actual,labels=[1, 0]):
    '''
    model : classifier to predict values of X
    y_actual : ground truth

    '''
    y_predict = model.predict(X_Test)
    cm=metrics.confusion_matrix( y_actual, y_predict, labels=[0, 1])
    df_cm = pd.DataFrame(cm, index = [i for i in ["Actual - 0","Actual - 1"]],
                  columns = [i for i in ['Predicted - 0','Predicted - 1']])
    group_counts = ["{0:0.0f}".format(value) for value in
                cm.flatten()]
    group_percentages = ["{0:.2%}".format(value) for value in
                         cm.flatten()/np.sum(cm)]
    labels = [f"{v1}\n{v2}" for v1, v2 in
              zip(group_counts,group_percentages)]
    labels = np.asarray(labels).reshape(2,2)
    plt.figure(figsize = (10,7))
    sns.heatmap(df_cm, annot=labels,fmt='')
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [363]:

```
make_confusion_matrix(model,Y_Test)
```



In [365]:

```
y_train.value_counts(1)
```

Out[365]:

```
0    0.905429
1    0.094571
Name: Personal_Loan, dtype: float64
```

**We have 90.99% of positive.**

In [160]:

```
##  Function to calculate recall score
def get_recall_score(model):
    '''
    model : classifier to predict values of X

    '''
    pred_train = model.predict(X_Train)
    pred_test = model.predict(X_Test)
    print("Recall on training set : ",metrics.recall_score(Y_Train,pred_train))
    print("Recall on test set : ",metrics.recall_score(Y_Test,pred_test))
```

In [161]:

```
get_recall_score(model)
```

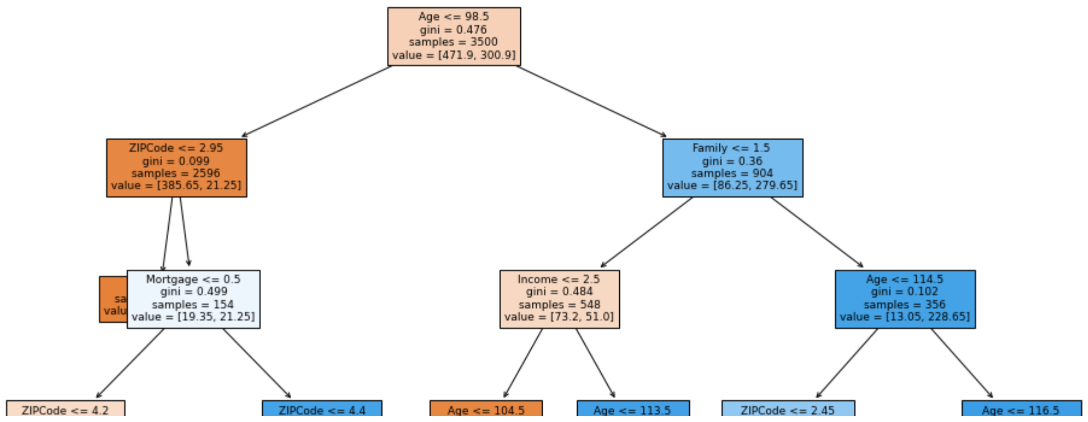
```
Recall on training set :  1.0
Recall on test set :  0.8968253968253969
```

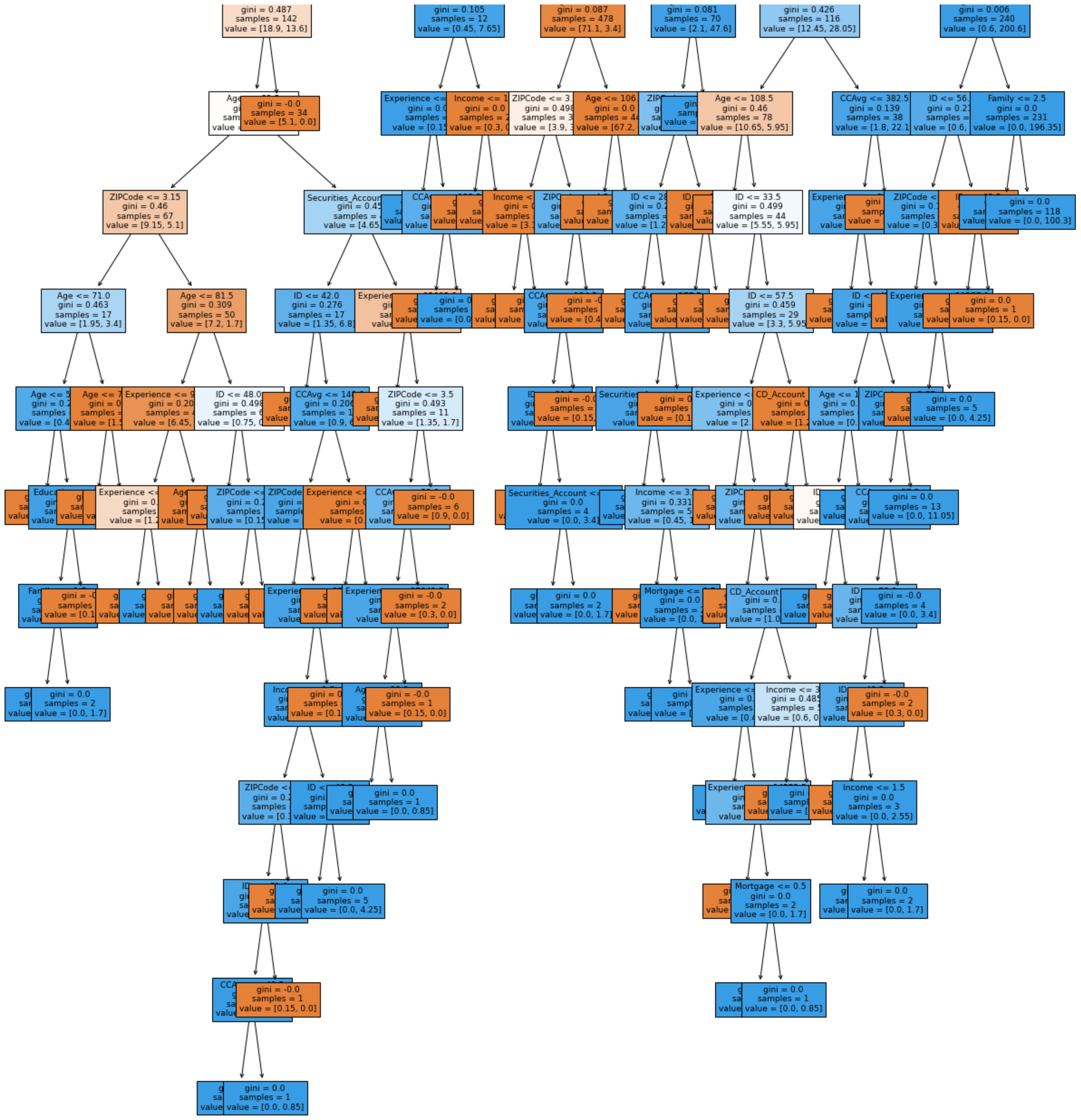
- **There is no huge disparity in performance of model on training set and test set**

## Visualizing the Decision Tree

In [165]:

```
plt.figure(figsize=(20,30))
out = tree.plot_tree(model,feature_names=feature_names,filled=True,fontsize=9,node_ids=Fa
lse,class_names=None,)
#below code will add arrows to the decision tree split if they are missing
for o in out:
     arrow = o.arrow_patch
     if arrow is not None:
        arrow.set_edgecolor('black')
        arrow.set_linewidth(1)
plt.show()
```





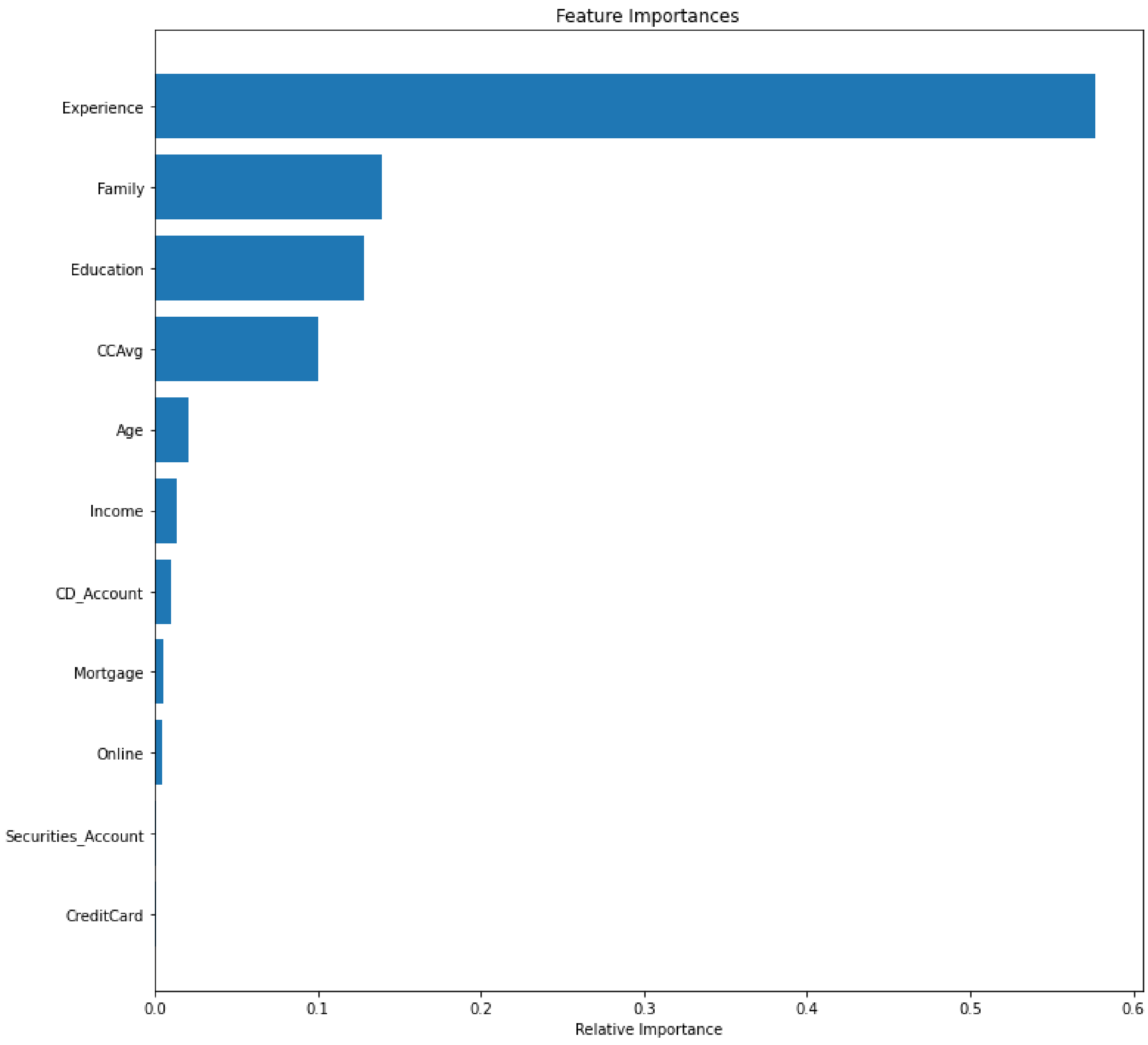
In [170]:

```
# Text report showing the rules of a decision tree
print(tree.export_text(model,feature_names=feature_names,show_weights=True))
```

```
|--- Experience <= 98.50
|   |--- CCAvg <= 2.95
|   |   |--- weights: [366.30, 0.00] class: 0
|   |--- CCAvg >  2.95
|   |   |--- CD_Account <= 0.50
|   |   |   |--- CCAvg <= 4.20
|   |   |   |   |--- Experience <= 82.50
|   |   |   |   |   |--- CCAvg <= 3.15
|   |   |   |   |   |   |--- Experience <= 71.00
|   |   |   |   |   |   |   |--- Experience <= 59.50
|   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |--- Experience >  59.50
|   |   |   |   |   |   |   |   |--- Securities_Account <= 0.50
|   |   |   |   |   |   |   |   |   |--- Education <= 1.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.70] class: 1
|   |   |   |   |   |   |   |   |   |--- Education >  1.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.70] class: 1
|   |   |   |   |   |   |   |   |--- Securities_Account >  0.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |--- Experience >  71.00
|   |   |   |   |   |   |   |--- Experience <= 73.50
|   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |--- Experience >  73.50
|   |   |   |   |   |   |   |   |--- weights: [1.20, 0.00] class: 0
|   |   |   |   |   |--- CCAvg >  3.15
|   |   |   |   |   |   |--- Experience <= 81.50
|   |   |   |   |   |   |   |--- Income <= 91257.00
|   |   |   |   |   |   |   |   |--- Income <= 90974.00
|   |   |   |   |   |   |   |   |   |--- weights: [1.20, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Income >  90974.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |--- Income >  91257.00
|   |   |   |   |   |   |   |   |--- Experience <= 53.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Experience >  53.00
|   |   |   |   |   |   |   |   |   |--- weights: [5.10, 0.00] class: 0
|   |   |   |   |   |   |--- Experience >  81.50
|   |   |   |   |   |   |   |--- Age <= 48.00
|   |   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |   |   |--- Age >  48.00
|   |   |   |   |   |   |   |   |--- CCAvg <= 3.75
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |   |--- CCAvg >  3.75
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |--- Experience >  82.50
|   |   |   |   |   |--- Online <= 0.50
|   |   |   |   |   |   |--- Age <= 42.00
|   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |--- Age >  42.00
|   |   |   |   |   |   |   |--- Mortgage <= 148.00
|   |   |   |   |   |   |   |   |--- CCAvg <= 3.05
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- CCAvg >  3.05
|   |   |   |   |   |   |   |   |   |--- Income <= 95327.50
|   |   |   |   |   |   |   |   |   |   |--- Family <= 1.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |   |--- Family >  1.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |--- Income >  95327.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- Mortgage >  148.00
|   |   |   |   |   |   |   |   |--- Income <= 92319.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Income >  92319.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- Online >  0.50
|   |   |   |   |   |   |--- Income <= 93603.00
|   |   |   |   |   |   |   |--- weights: [1.95, 0.00] class: 0
|   |   |   |   |   |   |--- Income >  93603.00
|   |   |   |   |   |   |   |--- CCAvg <= 3.50
|   |   |   |   |   |   |   |   |--- Mortgage <= 89.00
|   |   |   |   |   |   |   |   |   |--- Income <= 95041.50
|   |   |   |   |   |   |   |   |   |   |--- Experience <= 88.00
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |   |   |   |--- Experience >  88.00
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |   |   |--- Income >  95041.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Mortgage >  89.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |--- CCAvg >  3.50
|   |   |   |   |   |   |   |   |--- weights: [0.90, 0.00] class: 0
|   |   |   |--- CCAvg >  4.20
|   |   |   |   |--- weights: [5.10, 0.00] class: 0
|   |   |--- CD_Account >  0.50
|   |   |   |--- CCAvg <= 4.40
|   |   |   |   |--- Income <= 94506.00
|   |   |   |   |   |--- weights: [0.00, 6.80] class: 1
|   |   |   |   |--- Income >  94506.00
|   |   |   |   |--- Income >  94506.00
|   |   |   |   |   |--- Mortgage <= 123.50
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- Mortgage >  123.50
|   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |--- CCAvg >  4.40
|   |   |   |   |--- Family <= 1.50
|   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |--- Family >  1.50
|   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|--- Experience >  98.50
|   |--- Education <= 1.50
|   |   |--- Family <= 2.50
|   |   |   |--- Experience <= 104.50
|   |   |   |   |--- CCAvg <= 3.31
|   |   |   |   |   |--- Family <= 1.50
|   |   |   |   |   |   |--- weights: [1.20, 0.00] class: 0
|   |   |   |   |   |--- Family >  1.50
|   |   |   |   |   |   |--- weights: [1.95, 0.00] class: 0
|   |   |   |   |--- CCAvg >  3.31
|   |   |   |   |   |--- CCAvg <= 4.50
|   |   |   |   |   |   |--- Mortgage <= 124.50
|   |   |   |   |   |   |   |--- Age <= 31.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- Age >  31.50
|   |   |   |   |   |   |   |   |--- Online <= 0.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.70] class: 1
|   |   |   |   |   |   |   |   |--- Online >  0.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.70] class: 1
|   |   |   |   |   |   |--- Mortgage >  124.50
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- CCAvg >  4.50
|   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |--- Experience >  104.50
|   |   |   |   |--- Experience <= 106.50
|   |   |   |   |   |--- weights: [1.05, 0.00] class: 0
|   |   |   |   |--- Experience >  106.50
|   |   |   |   |   |--- weights: [66.15, 0.00] class: 0
|   |   |--- Family >  2.50
|   |   |   |--- Experience <= 113.50
|   |   |   |   |--- CCAvg <= 4.20
|   |   |   |   |   |--- Age <= 28.50
|   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |--- Age >  28.50
|   |   |   |   |   |   |--- Mortgage <= 377.50
|   |   |   |   |   |   |   |--- Online <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 4.25] class: 1
|   |   |   |   |   |   |   |--- Online >  0.50
|   |   |   |   |   |   |   |   |--- Family <= 3.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Family >  3.50
|   |   |   |   |   |   |   |   |   |--- CD_Account <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |   |   |--- CD_Account >  0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |--- Mortgage >  377.50
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |--- CCAvg >  4.20
|   |   |   |   |   |--- Age <= 55.50
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- Age >  55.50
|   |   |   |   |   |   |--- weights: [0.75, 0.00] class: 0
|   |   |   |--- Experience >  113.50
|   |   |   |   |--- weights: [0.00, 41.65] class: 1
|   |--- Education >  1.50
|   |   |--- Experience <= 114.50
|   |   |   |--- CCAvg <= 2.45
|   |   |   |   |--- Experience <= 108.50
|   |   |   |   |   |--- weights: [5.10, 0.00] class: 0
|   |   |   |   |--- Experience >  108.50
|   |   |   |   |   |--- Age <= 33.50
|   |   |   |   |   |   |--- weights: [2.25, 0.00] class: 0
|   |   |   |   |   |--- Age >  33.50
|   |   |   |   |   |--- Age >  33.50
|   |   |   |   |   |   |--- Age <= 57.50
|   |   |   |   |   |   |   |--- Income <= 91539.00
|   |   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |   |   |--- Income >  91539.00
|   |   |   |   |   |   |   |   |--- CCAvg <= 0.30
|   |   |   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- CCAvg >  0.30
|   |   |   |   |   |   |   |   |   |--- CreditCard <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- Income <= 93596.00
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 3.40] class: 1
|   |   |   |   |   |   |   |   |   |   |--- Income >  93596.00
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |--- CreditCard >  0.50
|   |   |   |   |   |   |   |   |   |   |--- Family <= 3.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- Family >  3.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |--- Age >  57.50
|   |   |   |   |   |   |   |--- CreditCard <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |   |   |--- CreditCard >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |--- CCAvg >  2.45
|   |   |   |   |--- Mortgage <= 382.50
|   |   |   |   |   |--- Income <= 90283.00
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- Income >  90283.00
|   |   |   |   |   |   |--- Age <= 42.00
|   |   |   |   |   |   |   |--- Experience <= 104.50
|   |   |   |   |   |   |   |   |--- Age <= 29.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |   |--- Age >  29.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.90, 0.00] class: 0
|   |   |   |   |   |   |   |--- Experience >  104.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 4.25] class: 1
|   |   |   |   |   |   |--- Age >  42.00
|   |   |   |   |   |   |   |--- CCAvg <= 3.85
|   |   |   |   |   |   |   |   |--- Mortgage <= 57.50
|   |   |   |   |   |   |   |   |   |--- Age <= 58.00
|   |   |   |   |   |   |   |   |   |   |--- Age <= 48.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- Age >  48.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |--- Age >  58.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Mortgage >  57.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 3.40] class: 1
|   |   |   |   |   |   |   |--- CCAvg >  3.85
|   |   |   |   |   |   |   |   |--- weights: [0.00, 11.05] class: 1
|   |   |   |   |--- Mortgage >  382.50
|   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |--- Experience >  114.50
|   |   |   |--- Experience <= 116.50
|   |   |   |   |--- Age <= 56.00
|   |   |   |   |   |--- CCAvg <= 1.10
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- CCAvg >  1.10
|   |   |   |   |   |   |--- Income <= 90577.00
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |--- Income >  90577.00
|   |   |   |   |   |   |   |--- weights: [0.00, 4.25] class: 1
|   |   |   |   |--- Age >  56.00
|   |   |   |   |   |--- Age <= 63.50
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- Age >  63.50
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |--- Experience >  116.50
|   |   |   |   |--- Education <= 2.50
|   |   |   |   |   |--- weights: [0.00, 96.05] class: 1
|   |   |   |   |--- Education >  2.50
|   |   |   |   |   |--- weights: [0.00, 100.30] class: 1
```

In [317]:

```
importances = model.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(12,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



- **Experience & Family are at the top two important features to predict**

## Reducing over fitting

In [204]:

```
from sklearn.model_selection import GridSearchCV
```

In [208]:

```
# Choose the type of classifier.
estimator = DecisionTreeClassifier(random_state=1,class_weight = {0:.15,1:.85})
```

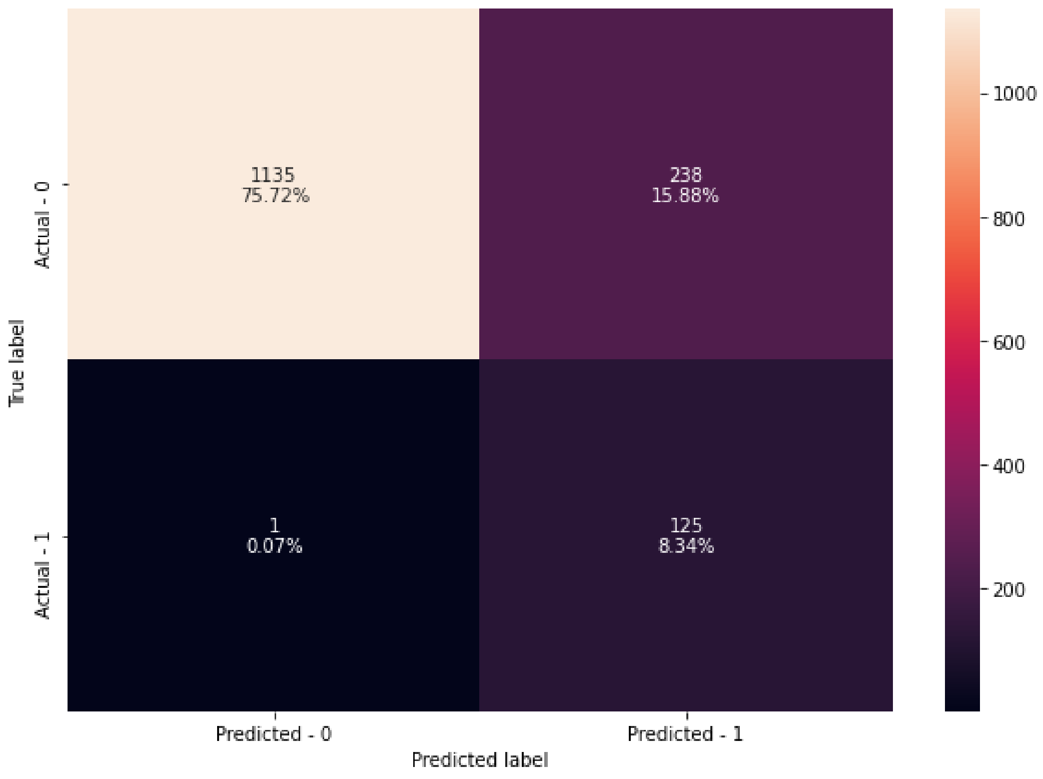
```
parameters = {
            'max_depth': np.arange(1,10),
            'criterion': ['entropy','gini'],
            'splitter': ['best','random'],
            'min_impurity_decrease': [0.000001,0.00001,0.0001],
            'max_features': ['log2','sqrt']
             }

scorer = metrics.make_scorer(metrics.recall_score)

grid_obj = GridSearchCV(estimator, parameters, scoring=scorer,cv=5)
grid_obj = grid_obj.fit(X_Train, Y_Train)

estimator = grid_obj.best_estimator_

estimator.fit(X_Train, Y_Train)
```

Out[208]:

```
DecisionTreeClassifier(class_weight={0: 0.15, 1: 0.85}, max_depth=3,
                       max_features='log2', min_impurity_decrease=1e-06,
                       random_state=1)
```

In [367]:

```
make_confusion_matrix(estimator,Y_Test)
```



In [210]:

```
get_recall_score(estimator)
```

```
Recall on training set :  0.9774011299435028
Recall on test set :  0.9920634920634921
```

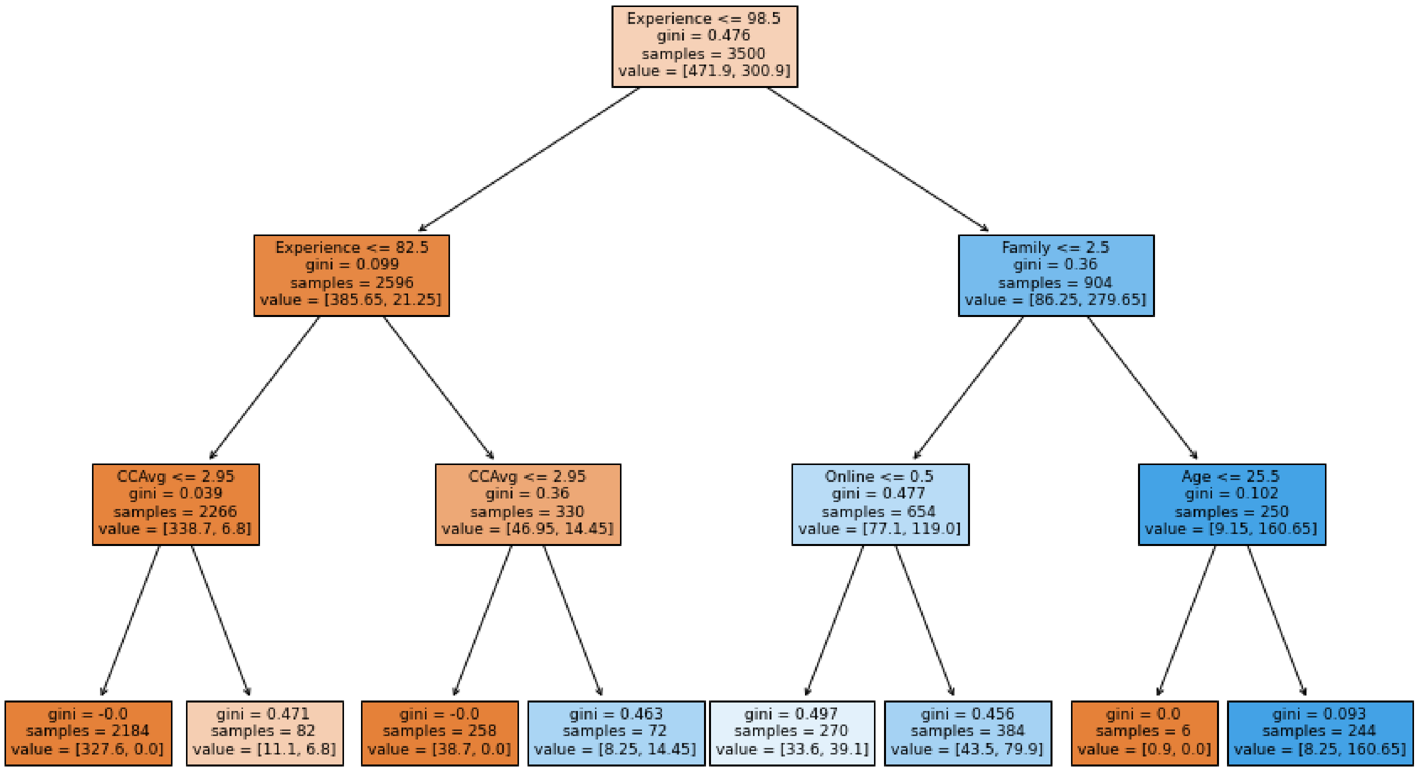
**Recall has improved for both train and test set after hyperparameter tuning and we have a generalized model.**

## Visualizing the Decision Tree

In [211]:

```
plt.figure(figsize=(15,10))
out = tree.plot_tree(estimator,feature_names=feature_names,filled=True,fontsize=9,node_id
s=False,class_names=None)
```

```
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor('black')
        arrow.set_linewidth(1)
plt.show()
```



In [212]:

```
# Text report showing the rules of a decision tree -

print(tree.export_text(estimator,feature_names=feature_names,show_weights=True))
```

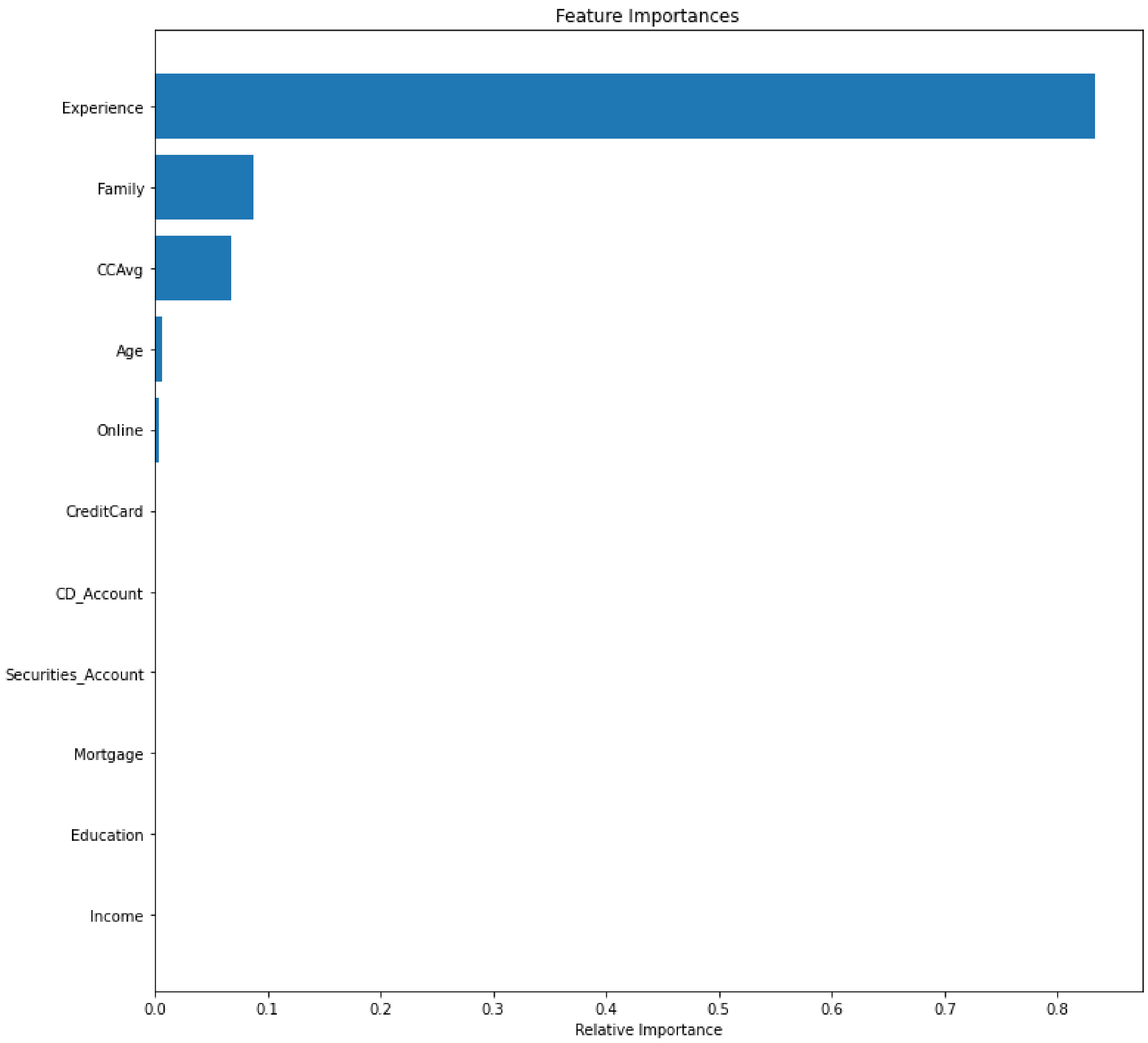
```
|--- Experience <= 98.50
|   |--- Experience <= 82.50
|   |   |--- CCAvg <= 2.95
|   |   |   |--- weights: [327.60, 0.00] class: 0
|   |   |--- CCAvg >  2.95
|   |   |   |--- weights: [11.10, 6.80] class: 0
|   |--- Experience >  82.50
|   |   |--- CCAvg <= 2.95
|   |   |   |--- weights: [38.70, 0.00] class: 0
|   |   |--- CCAvg >  2.95
|   |   |   |--- weights: [8.25, 14.45] class: 1
|--- Experience >  98.50
|   |--- Family <= 2.50
|   |   |--- Online <= 0.50
|   |   |   |--- weights: [33.60, 39.10] class: 1
|   |   |--- Online >  0.50
|   |   |   |--- weights: [43.50, 79.90] class: 1
|   |--- Family >  2.50
|   |   |--- Age <= 25.50
|   |   |   |--- weights: [0.90, 0.00] class: 0
|   |   |--- Age >  25.50
|   |   |   |--- weights: [8.25, 160.65] class: 1
```

In [215]:

```
columns_ = data.iloc[:1, 3:12].columns
```

In [316]:

```
importances = estimator.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(12,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



- **Experience & Family are at the top two important features to predict**

## Cost Complexity Pruning

In [219]:

```
clf = DecisionTreeClassifier(random_state=1,class_weight = {0:0.15,1:0.85})
path = clf.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas, impurities = path.ccp_alphas, path.impurities
```

In [220]:

```
pd.DataFrame(path)
```

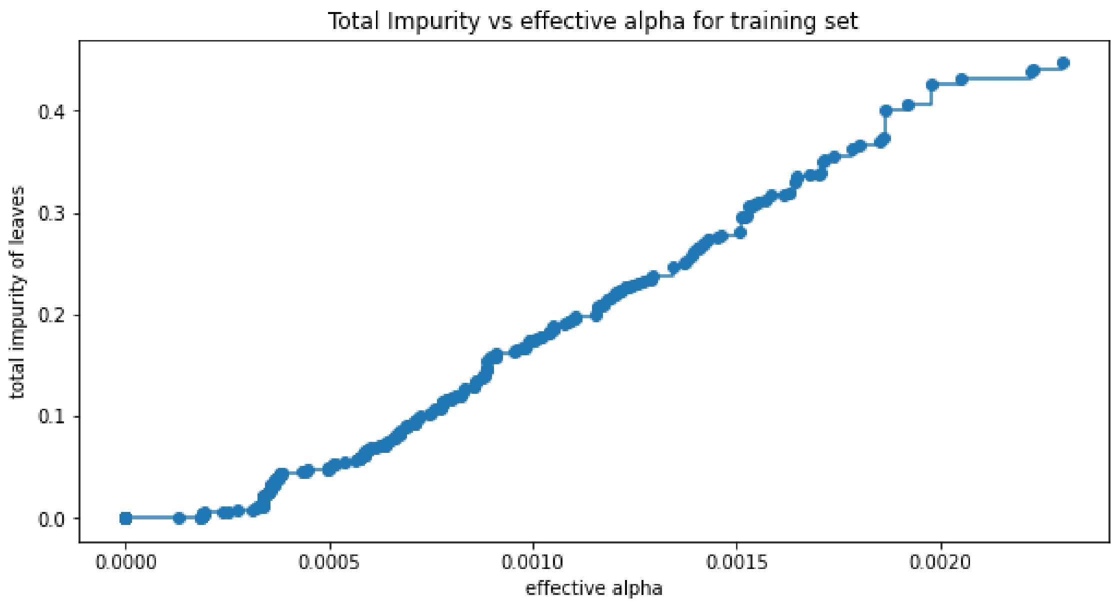
Out[220]:

| | ccp_alphas | impurities |
|---|---|---|
| 0 | 0.000000e+00 | -4.911640e-16 |
| 1 | 1.320471e-19 | -4.910320e-16 |
| 2 | 4.401571e-19 | -4.905918e-16 |
| 3 | 7.482671e-19 | -4.898435e-16 |
| 4 | 7.482671e-19 | -4.890953e-16 |
| ... | ... | ... |
| 361 | 2.051615e-03 | 4.312055e-01 |
| 362 | 2.223356e-03 | 4.378755e-01 |
| 363 | 2.227902e-03 | 4.401034e-01 |
| 364 | 2.299737e-03 | 4.470027e-01 |
| 365 | 2.516616e-03 | 4.671356e-01 |

**366 rows × 2 columns**

In [221]:

```
fig, ax = plt.subplots(figsize=(10,5))
ax.plot(ccp_alphas[:-1], impurities[:-1], marker='o', drawstyle="steps-post")
ax.set_xlabel("effective alpha")
ax.set_ylabel("total impurity of leaves")
ax.set_title("Total Impurity vs effective alpha for training set")
plt.show()
```



In [222]:

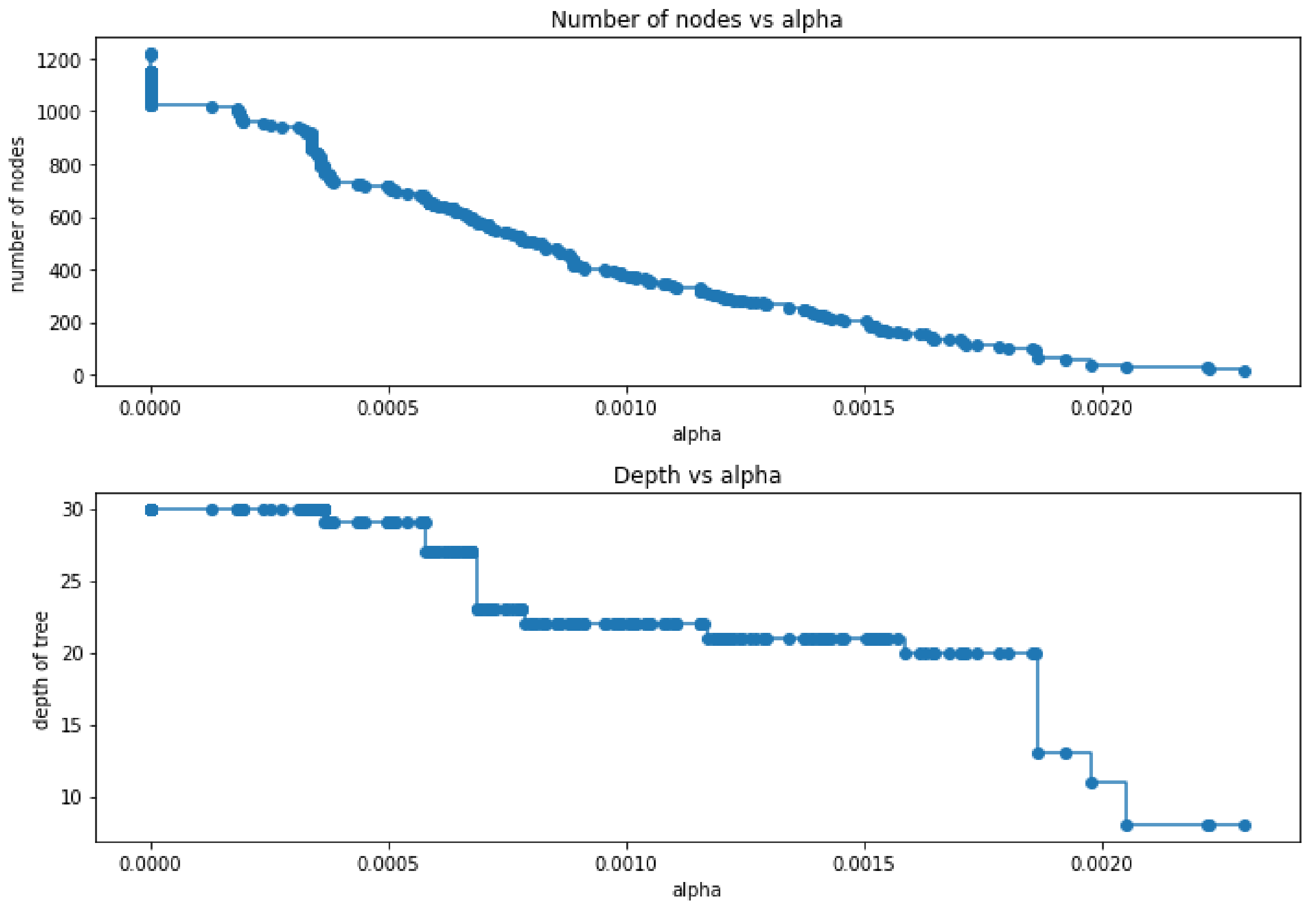
```
clfs = []
for ccp_alpha in ccp_alphas:
    clf = DecisionTreeClassifier(random_state=1, ccp_alpha=ccp_alpha,class_weight = {0:0
.15,1:0.85})
    clf.fit(X_train, y_train)
    clfs.append(clf)
print("Number of nodes in the last tree is: {} with ccp_alpha: {}".format(
      clfs[-1].tree_.node_count, ccp_alphas[-1]))
```

```
Number of nodes in the last tree is: 1 with ccp_alpha: 0.0025166156542417786
```

**For the remainder, we remove the last element in clfs and ccp_alphas**

In [223]:

```
clfs = clfs[:-1]
ccp_alphas = ccp_alphas[:-1]

node_counts = [clf.tree_.node_count for clf in clfs]
depth = [clf.tree_.max_depth for clf in clfs]
fig, ax = plt.subplots(2, 1,figsize=(10,7))
ax[0].plot(ccp_alphas, node_counts, marker='o', drawstyle="steps-post")
ax[0].set_xlabel("alpha")
ax[0].set_ylabel("number of nodes")
ax[0].set_title("Number of nodes vs alpha")
ax[1].plot(ccp_alphas, depth, marker='o', drawstyle="steps-post")
ax[1].set_xlabel("alpha")
ax[1].set_ylabel("depth of tree")
ax[1].set_title("Depth vs alpha")
fig.tight_layout()
```



In [224]:

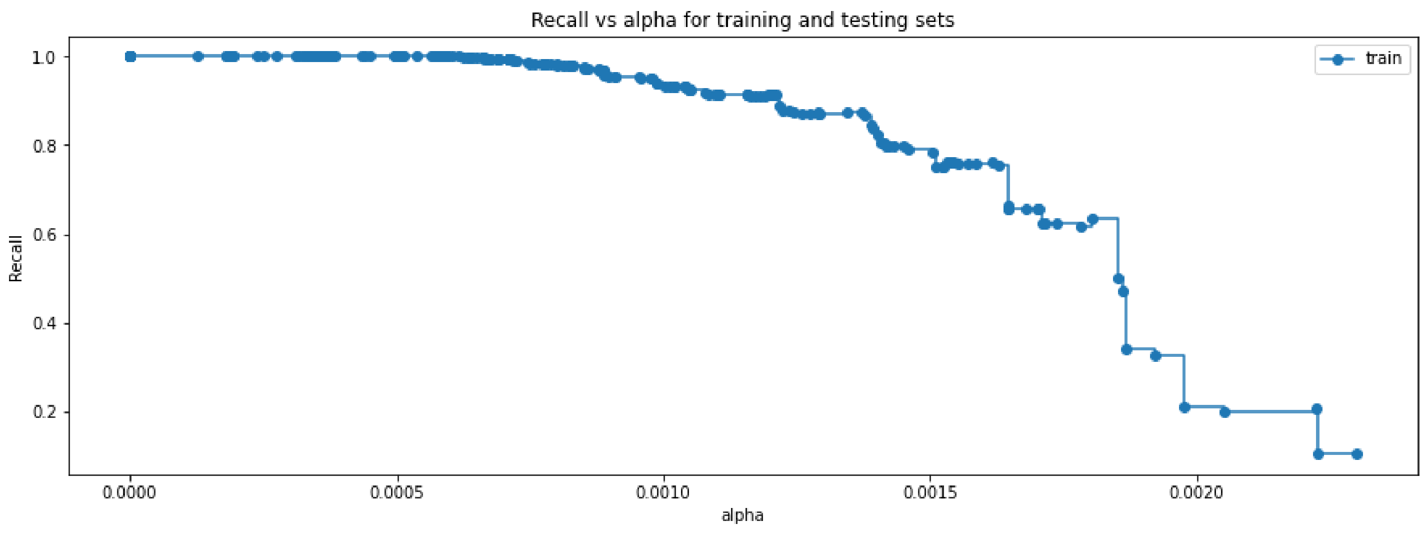
```
recall_train=[]
for clf in clfs:
    pred_train3=clf.predict(X_train)
    values_train=metrics.recall_score(y_train,pred_train3)
    recall_train.append(values_train)
```

In [231]:

```
train_scores = [clf.score(X_train, y_train) for clf in clfs]
```

In [265]:

```
fig, ax = plt.subplots(figsize=(15,5))
ax.set_xlabel("alpha")
ax.set_ylabel("Recall")
ax.set_title("Recall vs alpha for training and testing sets")
ax.plot(ccp_alphas, recall_train, marker='o', label="train",
        drawstyle="steps-post",)

ax.legend()
plt.show()
```



In [277]:

```
# creating the model where we get highest train and test recall
index_best_model = np.argmax(recall_train)
best_model = clfs[index_best_model]
print(best_model)
```

```
DecisionTreeClassifier(class_weight={0: 0.15, 1: 0.85}, random_state=1)
```

In [291]:

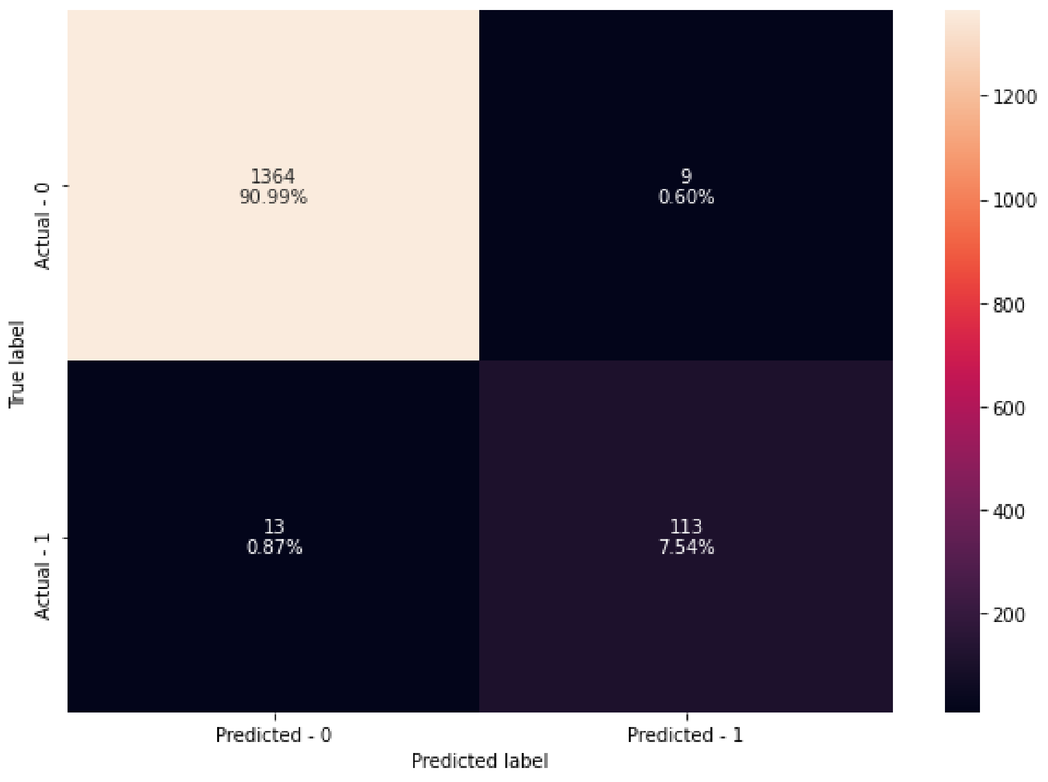
```
best_model.fit(X_Train, Y_Train)
```

Out[291]:

```
DecisionTreeClassifier(class_weight={0: 0.15, 1: 0.85}, random_state=1)
```

In [368]:

```
make_confusion_matrix(best_model,Y_Test)
```

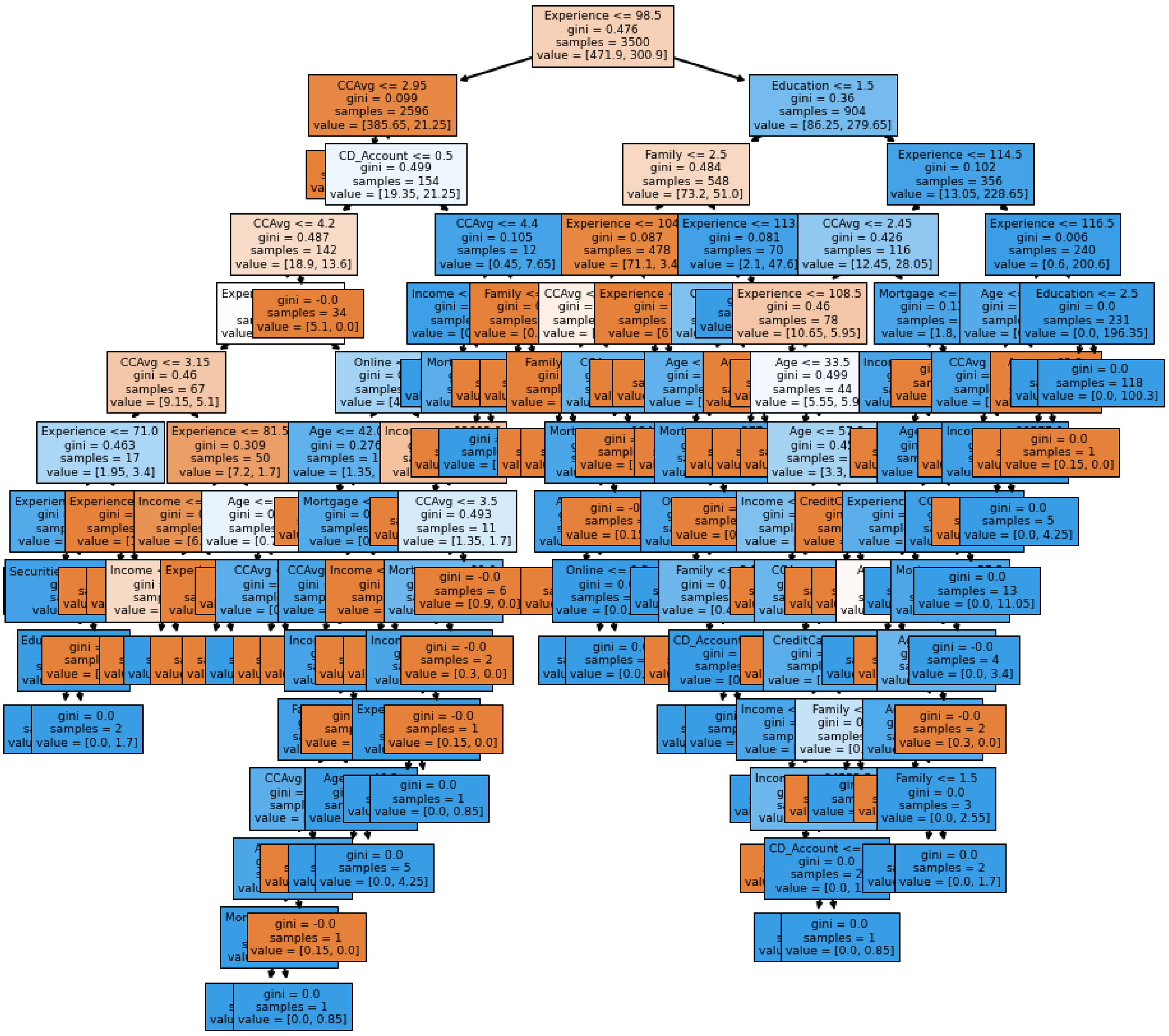


## Visualizing the Decision Tree

In [308]:

```
plt.figure(figsize=(15,15))
```

```
out = tree.plot_tree(best_model,feature_names=feature_names,filled=True,fontsize=9,node_i
ds=False,class_names=None)
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor('black')
        arrow.set_linewidth(2)
plt.show()
```



In [287]:

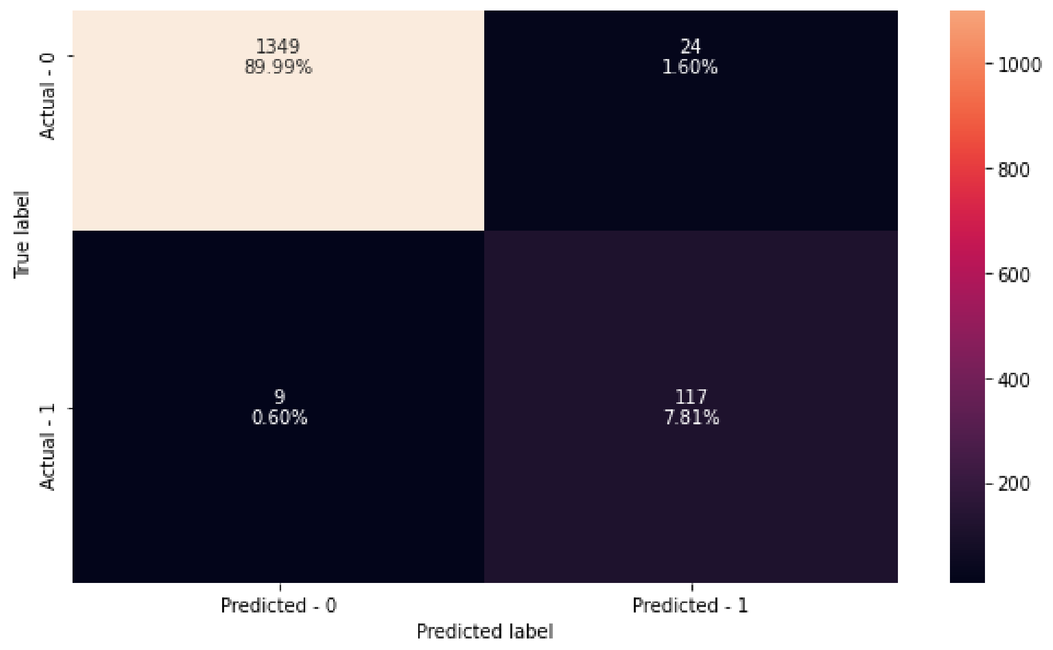
```
best_model2 = DecisionTreeClassifier(ccp_alpha=0.002,
                        class_weight={0: 0.15, 1: 0.85}, random_state=1)
best_model2.fit(X_Train, Y_Train)
```

Out[287]:

```
DecisionTreeClassifier(ccp_alpha=0.002, class_weight={0: 0.15, 1: 0.85},
                       random_state=1)
```

In [369]:

```
make_confusion_matrix(best_model2,Y_Test)
```



- **We are able to identify more True positives - 89.99%**

In [309]:

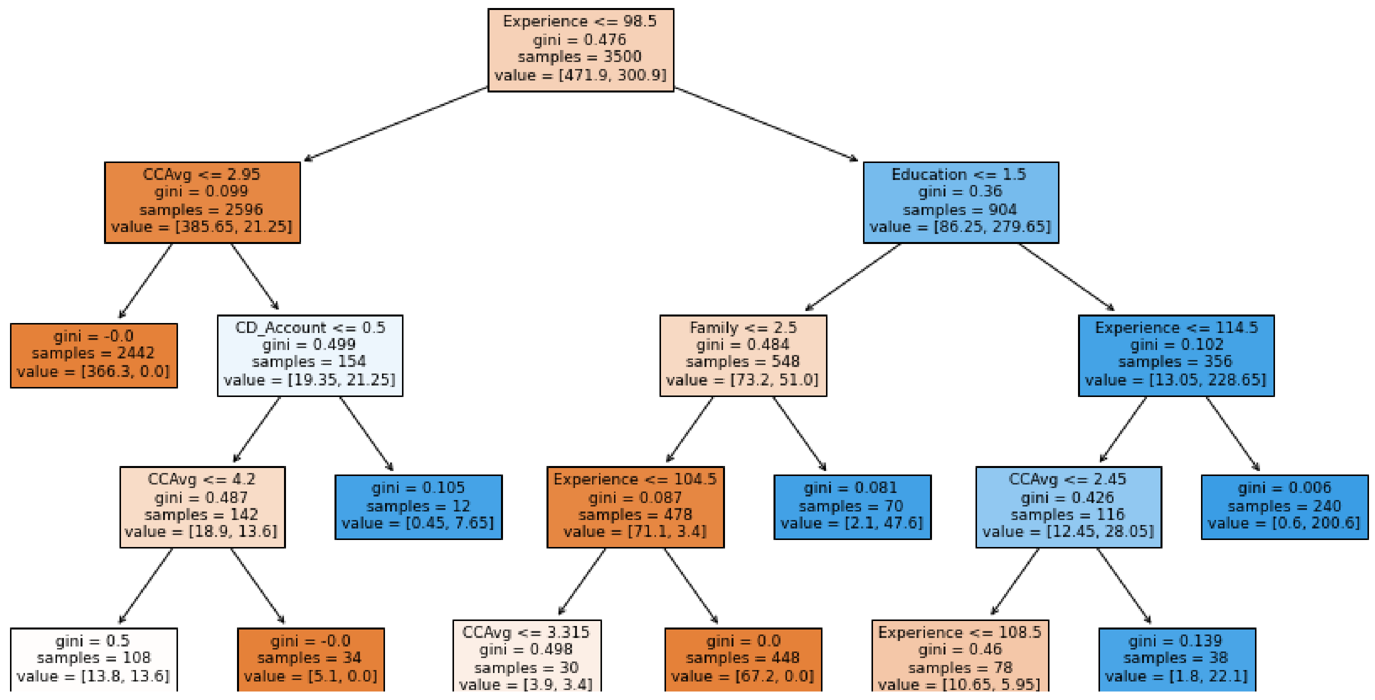
```
get_recall_score(best_model2)
```

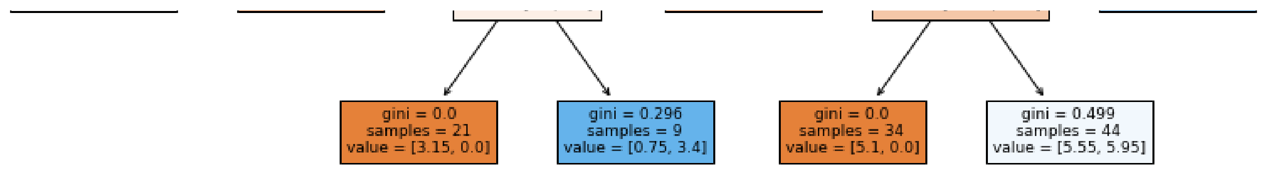
```
Recall on training set :  0.9548022598870056
Recall on test set :  0.9285714285714286
```

## Visualizing the Decision Tree

In [310]:

```
plt.figure(figsize=(15,10))

out = tree.plot_tree(best_model2,feature_names=feature_names,filled=True,fontsize=9,node_
ids=False,class_names=None)
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor('black')
        arrow.set_linewidth(1)
plt.show()
```





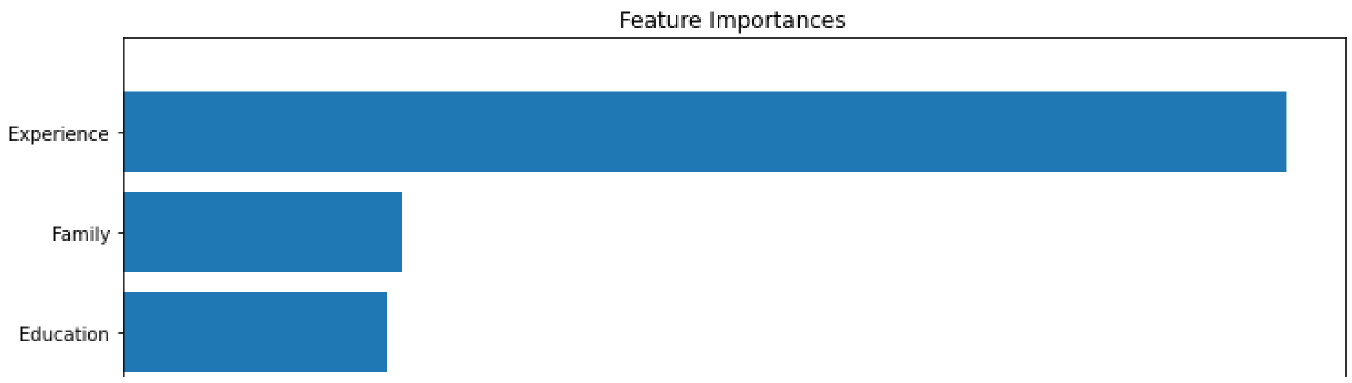
In [311]:

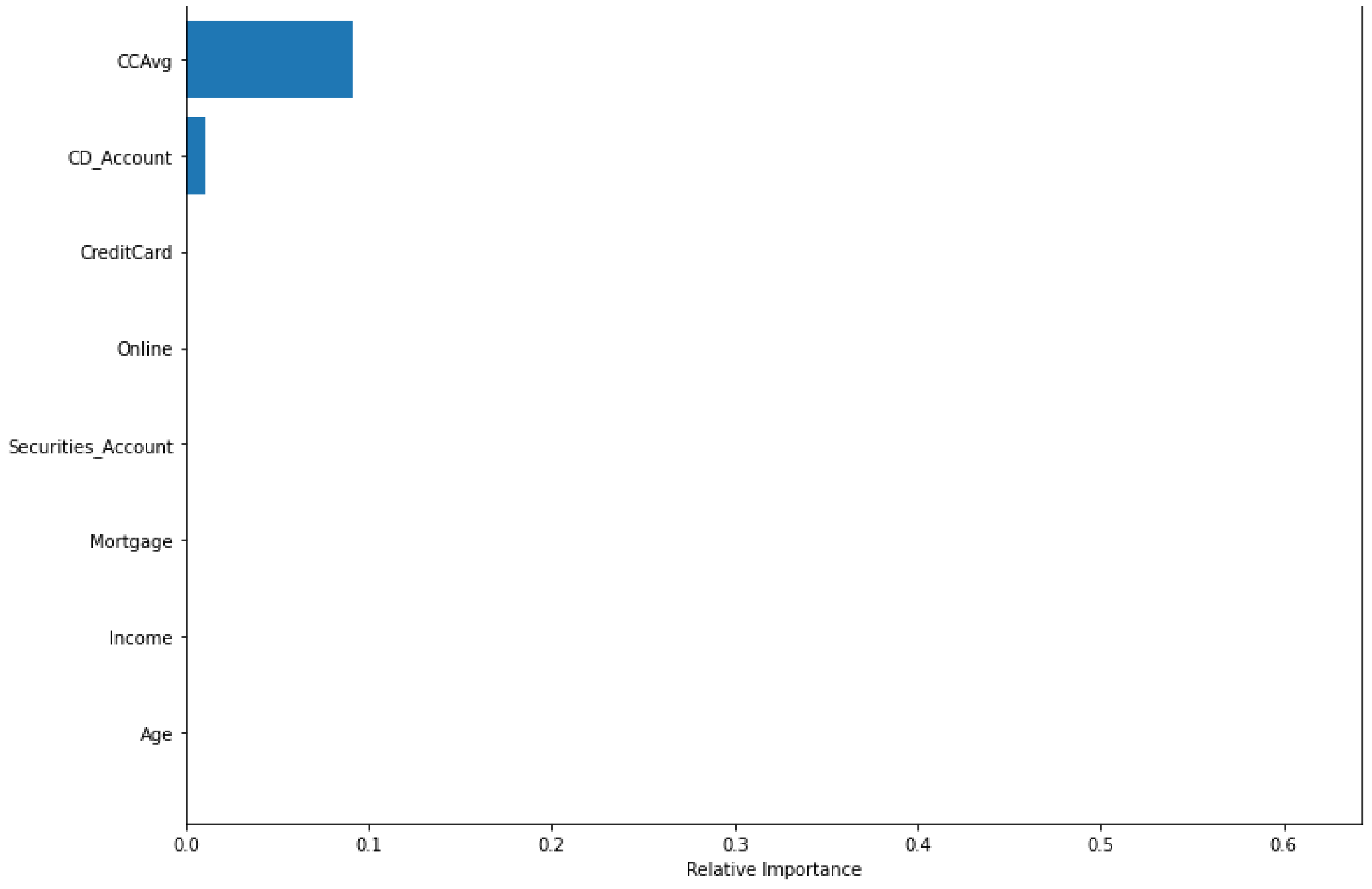
```
print(tree.export_text(best_model2,feature_names=feature_names,show_weights=True))
```

```
|--- Experience <= 98.50
|   |--- CCAvg <= 2.95
|   |   |--- weights: [366.30, 0.00] class: 0
|   |--- CCAvg >  2.95
|   |   |--- CD_Account <= 0.50
|   |   |   |--- CCAvg <= 4.20
|   |   |   |   |--- weights: [13.80, 13.60] class: 0
|   |   |   |--- CCAvg >  4.20
|   |   |   |   |--- weights: [5.10, 0.00] class: 0
|   |   |--- CD_Account >  0.50
|   |   |   |--- weights: [0.45, 7.65] class: 1
|--- Experience >  98.50
|   |--- Education <= 1.50
|   |   |--- Family <= 2.50
|   |   |   |--- Experience <= 104.50
|   |   |   |   |--- CCAvg <= 3.31
|   |   |   |   |   |--- weights: [3.15, 0.00] class: 0
|   |   |   |   |--- CCAvg >  3.31
|   |   |   |   |   |--- weights: [0.75, 3.40] class: 1
|   |   |   |--- Experience >  104.50
|   |   |   |   |--- weights: [67.20, 0.00] class: 0
|   |   |--- Family >  2.50
|   |   |   |--- weights: [2.10, 47.60] class: 1
|   |--- Education >  1.50
|   |   |--- Experience <= 114.50
|   |   |   |--- CCAvg <= 2.45
|   |   |   |   |--- Experience <= 108.50
|   |   |   |   |   |--- weights: [5.10, 0.00] class: 0
|   |   |   |   |--- Experience >  108.50
|   |   |   |   |   |--- weights: [5.55, 5.95] class: 1
|   |   |   |--- CCAvg >  2.45
|   |   |   |   |--- weights: [1.80, 22.10] class: 1
|   |   |--- Experience >  114.50
|   |   |   |--- weights: [0.60, 200.60] class: 1
```

In [315]:

```
importances = best_model2.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(12,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```





- **Experience & Family are at the top two important features to predict**

## Comparing all the decision tree models

In [319]:

```
comparison_frame = pd.DataFrame({'Model':['Initial decision tree model','Decision treee with hyperparameter tuning',
                                          'Decision tree with post-pruning'], 'Train_Recall':[1,0.97,0.95], 'Test_Recall':[0.89,0.99,0.93]})
comparison_frame
```

Out[319]:

| | Model | Train_Recall | Test_Recall |
|---|---|---|---|
| 0 | Initial decision tree model | 1.00 | 0.89 |
| 1 | Decision treee with hyperparameter tuning | 0.97 | 0.99 |
| 2 | Decision tree with post-pruning | 0.95 | 0.93 |

**Decision tree model with hyperparameter tuning has given the best recall score on data.**

## Conclusion and Recommendations

- **I have analyzed the "Personal Loan" using different techniques and used Decision Tree Classifier to build a predictive model for the same.**
- **The model built can be used to predict which feature is going to contribute to Personal loan generation.**
- **Visualized different trees and their confusion matrix to get a better understanding of the model. Easy interpretation is one of the key benefits of Decision Trees.**
- **Verified the fact that how much less data preparation is needed for Decision Trees and such a simple model gave good results even with outliers and imbalanced classes which shows the robustness of Decision Trees.**
- **Experience, Family, Education, CCAvg and CC_Account are the most important variable in predicting the customers that will contribute to the revenue.**

- **The aim of the Bank is to convert there liability customers into loan customers.**
- **It seems like 'Logistic Regression' algorithm & Decision tree model with hyperparameter tuning' have the highest accuracy and we can choose that as our final model**

In [ ]:

```

```