Personal Loan Campaign Modelling Project

Description

Background and Context

AllLife Bank is a US bank that has a growing customer base. The majority of these customers are liability customers (depositors) with varying sizes of deposits. The number of customers who are also borrowers (asset customers) is quite small, and the bank is interested in expanding this base rapidly to bring in more loan business and in the process, earn more through the interest on loans. In particular, the management wants to explore ways of converting its liability customers to personal loan customers (while retaining them as depositors).

A campaign that the bank ran last year for liability customers showed a healthy conversion rate of over 9% success. This has encouraged the retail marketing department to devise campaigns with better target marketing to increase the success ratio.

You as a Data scientist at AllLife bank have to build a model that will help the marketing department to identify the potential customers who have a higher probability of purchasing the loan.

Objective

1. To predict whether a liability customer will buy a personal loan or not.
2. Which variables are most significant.
3. Which segment of customers should be targeted more.

Data Dictionary

LABELS	DESCRIPTION
ID	Customer ID
Age	Customer’s age in completed years
Experience	#years of professional experience
Income	Annual income of the customer (in thousand dollars)
ZIP Code	Home Address ZIP code.
Family	the Family size of the customer
CCAvg	Average spending on credit cards per month (in thousand dollars)
Education	Education Level. 1: Undergrad; 2: Graduate;3: Advanced/Professional
Mortgage	Value of house mortgage if any. (in thousand dollars)
Personal_Loan	Did this customer accept the personal loan offered in the last campaign?
Securities_Account	Does the customer have securities account with the bank?

LABELS	DESCRIPTION
CD_Account	Does the customer have a certificate of deposit (CD) account with the bank?
Online	Do customers use internet banking facilities?
CreditCard	Does the customer use a credit card issued by any other Bank (excluding All life Bank)?

Import libraries and load dataset

Import libraries

```
import pandas as pd
import numpy as np
import math
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from sklearn import metrics, tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import (confusion_matrix, classification_report,
                             accuracy_score, precision_score,
recall_score, f1_score)

import warnings
warnings.filterwarnings("ignore")  # ignore warnings

%matplotlib inline
sns.set()

from google.colab import drive
drive.mount('/content/drive/')
```

```
Mounted at /content/drive/
```

Read Dataset

```
# Read the data
df =
pd.read_csv('/content/drive/MyDrive/LoanModelling/Loan_Modelling.csv')
# Returns the first 5 rows
df.head()

print(f"There is {df.shape[0]} rows and {df.shape[1]} columns in this
dataset.")
```

```
There is 5000 rows and 14 columns in this dataset.
```

Overview of Dataset

```python
pd.concat([df.head(10), df.tail(10)])
```

```
        ID  Age  Experience  Income  ZIPCode  Family  CCAvg  Education  \
0        1   25           1      49    91107       4   1.60          1
1        2   45          19      34    90089       3   1.50          1
2        3   39          15      11    94720       1   1.00          1
3        4   35           9     100    94112       1   2.70          2
4        5   35           8      45    91330       4   1.00          2
5        6   37          13      29    92121       4   0.40          2
6        7   53          27      72    91711       2   1.50          2
7        8   50          24      22    93943       1   0.30          3
8        9   35          10      81    90089       3   0.60          2
9       10   34           9     180    93023       1   8.90          3
4990  4991   55          25      58    95023       4   2.00          3
4991  4992   51          25      92    91330       1   1.90          2
4992  4993   30           5      13    90037       4   0.50          3
4993  4994   45          21     218    91801       2   6.67          1
4994  4995   64          40      75    94588       3   2.00          3
4995  4996   29           3      40    92697       1   1.90          3
4996  4997   30           4      15    92037       4   0.40          1
4997  4998   63          39      24    93023       2   0.30          3
4998  4999   65          40      49    90034       3   0.50          2
4999  5000   28           4      83    92612       3   0.80          1

      Mortgage  Personal_Loan  Securities_Account  CD_Account  Online  \
0            0              0                   1           0       0
1            0              0                   1           0       0
```

2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	155	0	0	0	1
6	0	0	0	0	1
7	0	0	0	0	0
8	104	0	0	0	1
9	0	1	0	0	0
4990	219	0	0	0	0
4991	100	0	0	0	0
4992	0	0	0	0	0
4993	0	0	0	0	1
4994	0	0	0	0	1
4995	0	0	0	0	1
4996	85	0	0	0	1
4997	0	0	0	0	0
4998	0	0	0	0	1
4999	0	0	0	0	1

	CreditCard
0	0
1	0
2	0
3	0
4	1
5	0
6	0
7	1
8	0
9	0
4990	1
4991	1

```
4992        0
4993        0
4994        0
4995        0
4996        0
4997        0
4998        0
4999        1
```

```
df.columns
```

```
Index(['ID', 'Age', 'Experience', 'Income', 'ZIPCode', 'Family',
'CCAvg',
       'Education', 'Mortgage', 'Personal_Loan', 'Securities_Account',
       'CD_Account', 'Online', 'CreditCard'],
      dtype='object')
```

Edit column names

```
df.columns = df.columns.str.lower()
df.columns = df.columns.str.replace("creditcard", "credit_card")
df.columns
```

```
Index(['id', 'age', 'experience', 'income', 'zipcode', 'family',
'ccavg',
       'education', 'mortgage', 'personal_loan', 'securities_account',
       'cd_account', 'online', 'credit_card'],
      dtype='object')
```

```
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   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  credit_card         5000 non-null   int64
```

```
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

Observation

- All column names are lowercase
- There are 5000 observations in this dataset.
- All values are of a numerical type (int, float).
- There are zero missing values in all columns. We will confirm.

Check for duplicates

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

```
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
credit_card           0
dtype: int64
```

Describe dataset

```
df.nunique()
```

```
id                    5000
age                     45
experience              47
income                 162
zipcode                467
family                   4
ccavg                  108
education                3
mortgage               347
personal_loan            2
securities_account       2
cd_account               2
online                   2
credit_card              2
dtype: int64
```

Observations

- `id` has 5000 unique values. We can drop this column.
- We can change `family, education` to categorical.

```
df.drop(['id'], axis=1, inplace=True)
df.head()

   age  experience  income  zipcode  family  ccavg  education
mortgage  \
0   25           1      49    91107       4    1.6          1
0
1   45          19      34    90089       3    1.5          1
0
2   39          15      11    94720       1    1.0          1
0
3   35           9     100    94112       1    2.7          2
0
4   35           8      45    91330       4    1.0          2
0

   personal_loan  securities_account  cd_account  online  credit_card

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
```

Change dtypes

```
cat_features = ['family', 'education']

for feature in cat_features:
    df[feature] = pd.Categorical(df[feature])

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   age                 5000 non-null   int64
 1   experience          5000 non-null   int64
 2   income              5000 non-null   int64
 3   zipcode             5000 non-null   int64
```

```
 4   family              5000 non-null   category
 5   ccavg               5000 non-null   float64
 6   education           5000 non-null   category
 7   mortgage            5000 non-null   int64
 8   personal_loan       5000 non-null   int64
 9   securities_account  5000 non-null   int64
 10  cd_account          5000 non-null   int64
 11  online              5000 non-null   int64
 12  credit_card         5000 non-null   int64
dtypes: category(2), float64(1), int64(10)
memory usage: 439.9 KB
```

```python
df.describe(include='all').T
```

```
                     count  unique  top    freq          mean
std  \
age                 5000.0     NaN  NaN     NaN     45.338400
11.463166
experience          5000.0     NaN  NaN     NaN     20.104600
11.467954
income              5000.0     NaN  NaN     NaN     73.774200
46.033729
zipcode             5000.0     NaN  NaN     NaN  93169.257000
1759.455086
family              5000.0     4.0  1.0  1472.0           NaN
NaN
ccavg               5000.0     NaN  NaN     NaN      1.937938
1.747659
education           5000.0     3.0  1.0  2096.0           NaN
NaN
mortgage            5000.0     NaN  NaN     NaN     56.498800
101.713802
personal_loan       5000.0     NaN  NaN     NaN      0.096000
0.294621
securities_account  5000.0     NaN  NaN     NaN      0.104400
0.305809
cd_account          5000.0     NaN  NaN     NaN      0.060400
0.238250
online              5000.0     NaN  NaN     NaN      0.596800
0.490589
credit_card         5000.0     NaN  NaN     NaN      0.294000
0.455637

                        min      25%      50%      75%      max
age                    23.0     35.0     45.0     55.0     67.0
experience             -3.0     10.0     20.0     30.0     43.0
income                  8.0     39.0     64.0     98.0    224.0
zipcode             90005.0  91911.0  93437.0  94608.0  96651.0
family                  NaN      NaN      NaN      NaN      NaN
ccavg                   0.0      0.7      1.5      2.5     10.0
```

```
education                 NaN      NaN      NaN      NaN      NaN
mortgage                  0.0      0.0      0.0    101.0    635.0
personal_loan             0.0      0.0      0.0      0.0      1.0
securities_account        0.0      0.0      0.0      0.0      1.0
cd_account                0.0      0.0      0.0      0.0      1.0
online                    0.0      0.0      1.0      1.0      1.0
credit_card               0.0      0.0      0.0      1.0      1.0
```

Observations

- All columns have a count of 5000, meaning there are zero missing values in these columns.
- There are 4 unique values in `family` and 3 unique values in the `education` column.
- There are only 2 unique values in the `personal_loan, securities_account, cd_account, online and credit_card` columns.
- `age` has a mean of 45 and a standard deviation of about 11.4. The min `age` is 23 and the max is 67.
- `experience` has a mean of 20 and a standard deviation of 11.5. The min is -3 and the max is 43 years. We will inspect the negative value further. -`income` has a mean of 74K and a standard deviation of 46K. The values range from 8K to 224K.
- `ccavg` has a mean of 1.93 and a standard deviation of 1.7. The values range from 0.0 to 10.0.
- `mortgage` has a mean of 56.5K and a standard deviation of 101K. The standard deviation is greater than the mean. We will investigate further.
- There are zero values in the `mortgage` column. We will inspect.

```
df.isnull().sum().sort_values(ascending=False)
```

```
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
credit_card           0
dtype: int64
```

```
df.isnull().values.any() # If there are any null values in data set
```

```
False
```

Observations

- Confirming dtype changed to categorical variables for the columns mentioned previously.
- Confirming there are zero missing values. Not to be confused with values that are zero. We have alot of those in the `mortgage` column. Also, we will investigate the outliers.

```
numerical_feature_df = df.select_dtypes(include=['int64','float64'])
numerical_feature_df.skew()
```

```
age                   -0.029341
experience            -0.026325
income                 0.841339
zipcode               -0.296165
ccavg                  1.598443
mortgage               2.104002
personal_loan          2.743607
securities_account     2.588268
cd_account             3.691714
online                -0.394785
credit_card            0.904589
dtype: float64
```

Observations

- `income`, `ccavg` and `mortgage` are heavily skewed. We will investigate further.

Exploratory Data Analysis

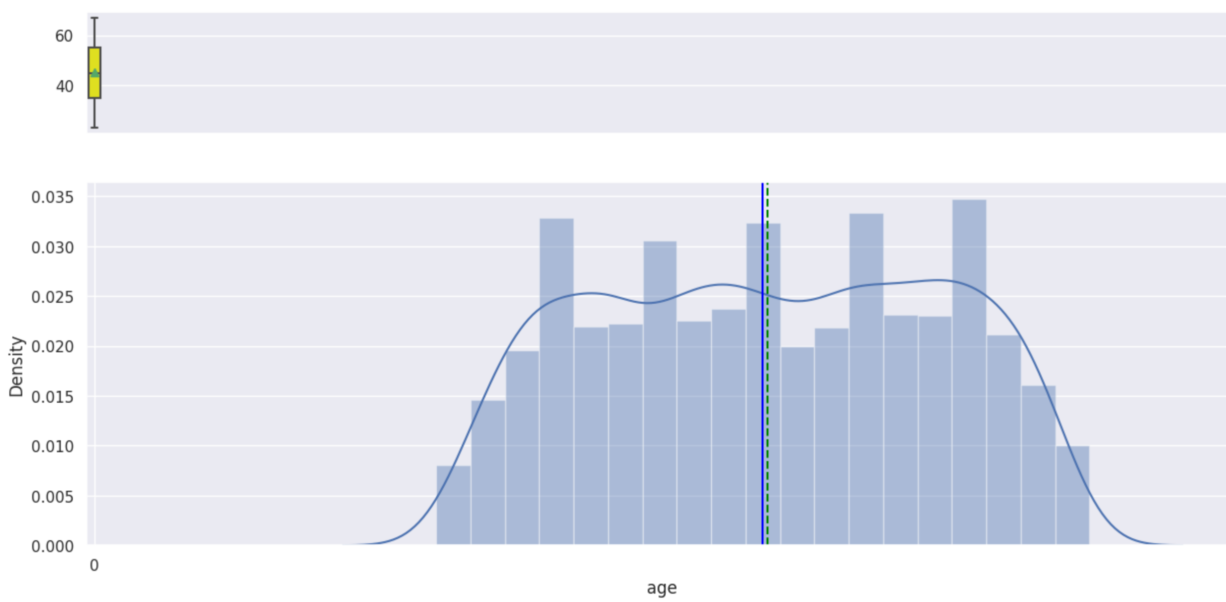
Univariate Analysis

```
def histogram_boxplot(feature, figsize=(15, 7), bins=None):
    """
    Boxplot and histogram combined
    feature: 1-d feature array
    figsize: size of fig (default (15,10))
    bins: number of bins (default None / auto)
    """
    f2, (ax_box2, ax_hist2) = plt.subplots(nrows = 2, # Number of rows
of the subplot grid= 2
                                           sharex = True, # x-axis
will be shared among all subplots
                                           gridspec_kw =
{"height_ratios": (.25, .75)},
                                           figsize = figsize
                                           ) # creating the 2 subplots

    sns.boxplot(feature, ax=ax_box2, showmeans=True, color='yellow') #
boxplot will be created and a star will indicate the mean value of the
column
    sns.distplot(feature, kde=True, ax=ax_hist2, bins=bins) if bins
else sns.distplot(feature, kde=True, ax=ax_hist2) # For histogram
```

```
    ax_hist2.axvline(np.mean(feature), color='green', linestyle='--')
# Add mean to the histogram
    ax_hist2.axvline(np.median(feature), color='blue',
linestyle='-');# Add median to the histogram

def create_outliers(feature: str, data=df):
    """
    Returns dataframe object of feature outliers.
    feature: 1-d feature array
    data: pandas dataframe (default is df)
    """
    Q1 = data[feature].quantile(0.25)
    Q3 = data[feature].quantile(0.75)
    IQR = Q3 - Q1
    #print(((df.Mileage < (Q1 - 1.5 * IQR)) | (df.Mileage > (Q3 + 1.5
* IQR))).sum())
    return data[((data[feature] < (Q1 - 1.5 * IQR)) | (data[feature] >
(Q3 + 1.5 * IQR)))]
```

Observations on age

```
histogram_boxplot(df.age)
```



Observations

- No outliers in the age column. The mean is near the median.
- Average age is about 45 years old.
- The age column distribution is uniform.

Observations on `income`

```
histogram_boxplot(df.income)
```

Observations

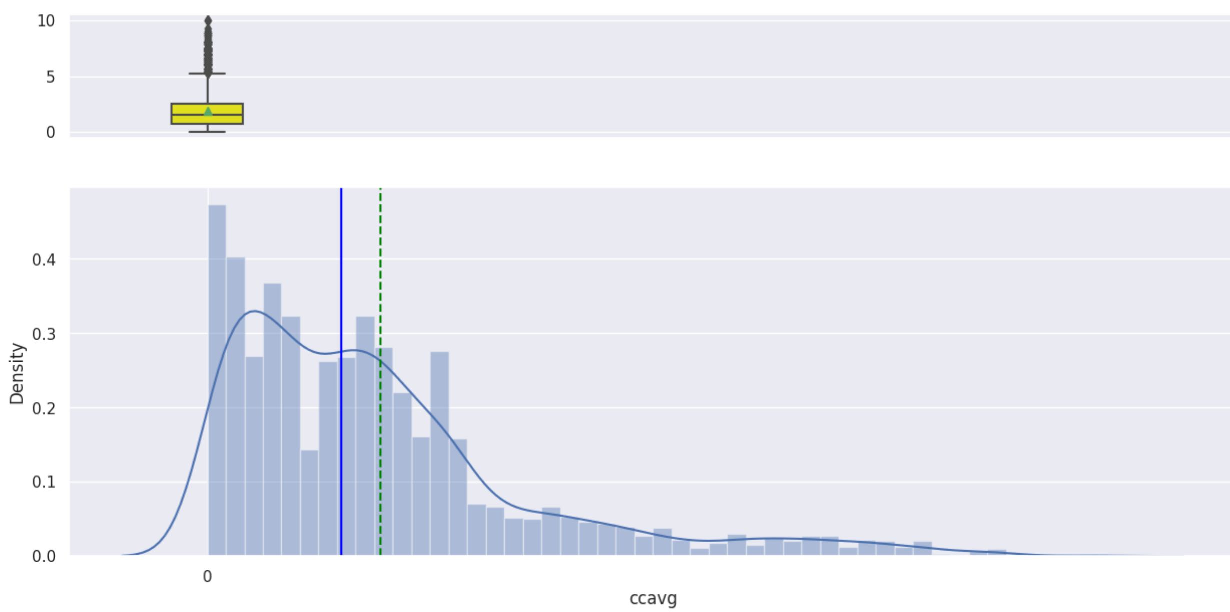
- The average `income` is about 60K, with a median value of about 70K.
- `income` column is right skewed and has many outliers to the upside.

Observations on `income` outliers

```
outliers = create_outliers('income')
outliers.sort_values(by='income', ascending=False).head(20)

print(f"There are {outliers.shape[0]} outliers.")

There are 96 outliers.
```

Observations on `ccavg`

```
histogram_boxplot(df.ccavg)
```



Observations

- `ccavg` has an average of about 1.5 and a median of about 2.
- `ccavg` column is right skewed and has many outliers to the upside.

Observations on `ccavg` outliers

```
outliers = create_outliers('ccavg')
outliers.sort_values(by='ccavg', ascending=False).head(20)
```

```
      age  experience  income  zipcode family  ccavg education
mortgage  \
2337   43          16     201    95054      1   10.0         2
0
787    45          15     202    91380      3   10.0         3
0
2101   35           5     203    95032      1   10.0         3
0
3943   61          36     188    91360      1    9.3         2
0
3822   63          33     178    91768      4    9.0         3
0
1339   52          25     180    94545      2    9.0         2
297
9      34           9     180    93023      1    8.9         3
0
1277   45          20     194    92110      2    8.8         1
428
3312   47          22     190    94550      2    8.8         1
0
4225   43          18     204    91902      2    8.8         1
0
2988   46          21     205    95762      2    8.8         1
181
2447   44          19     201    95819      2    8.8         1
0
881    44          19     154    92116      2    8.8         1
0
917    45          20     200    90405      2    8.8         1
0
2769   33           9     183    91320      2    8.8         3
582
3804   47          22     203    95842      2    8.8         1
0
1797   35          10     143    91365      1    8.6         1
0
4156   37          12     193    92780      1    8.6         1
0
614    37          12     180    90034      1    8.6         1
0
4603   37          12     179    91768      1    8.6         1
0

      personal_loan  securities_account  cd_account  online
credit_card
2337              1                   0           0       0
1
787               1                   0           0       0
0
2101              1                   0           0       0
```

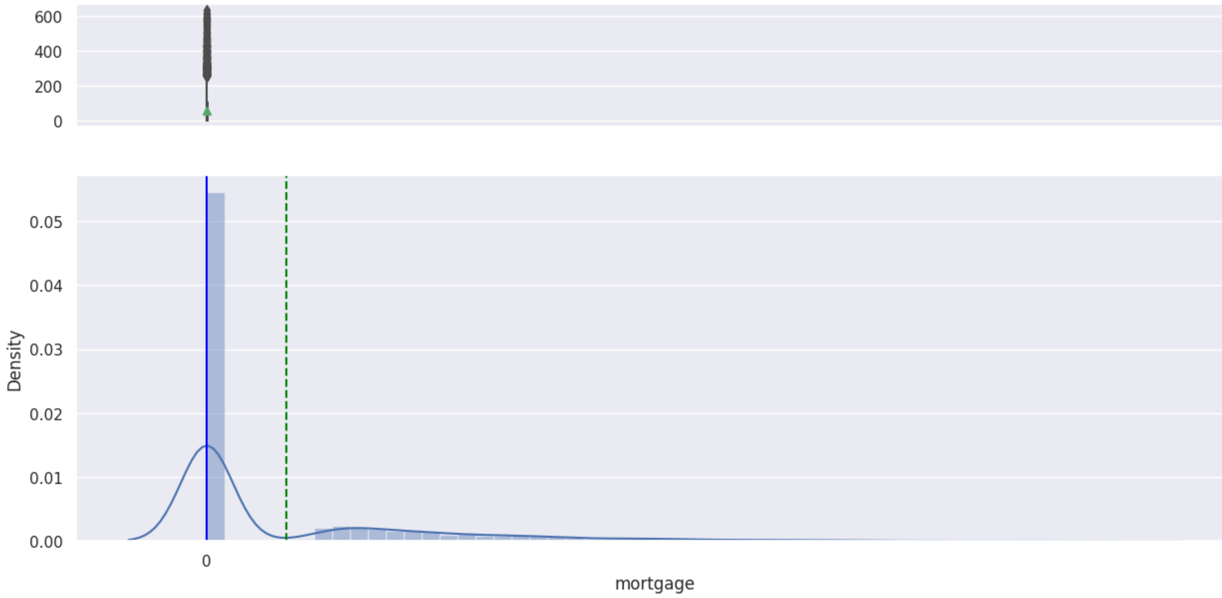
```
0
3943                1                   0            0        0
0
3822                1                   0            0        0
0
1339                1                   0            0        1
0
9                   1                   0            0        0
0
1277                0                   0            0        0
0
3312                0                   0            0        0
0
4225                0                   0            0        1
0
2988                0                   1            0        1
0
2447                0                   0            0        1
1
881                 0                   0            0        1
0
917                 0                   0            0        1
1
2769                1                   0            0        1
0
3804                0                   0            0        1
0
1797                0                   0            0        1
1
4156                0                   0            0        0
0
614                 0                   0            0        1
1
4603                0                   0            0        1
0
```

```
print(f"There are {outliers.shape[0]} outliers.")
```

```
There are 324 outliers.
```

Observations on `mortgage`

```
histogram_boxplot(df.mortgage)
```



Observations

- `mortgage` has many values that aren't null but are equal to zero. We will dissect further.
- `mortgage` column has many outliers to the upside.

Observations on `mortgage` outliers

```
outliers = create_outliers('mortgage')
outliers.sort_values(by='mortgage', ascending=False)
```

```
      age  experience  income  zipcode  family  ccavg  education  
mortgage  \
2934   37          13     195    91763       2    6.5          1
635
303    49          25     195    95605       4    3.0          1
617
4812   29           4     184    92126       4    2.2          3
612
1783   53          27     192    94720       1    1.7          1
601
4842   49          23     174    95449       3    4.6          2
590
...   ...         ...     ...      ...     ...    ...        ...         .
..
1522   25          -1     101    94720       4    2.3          3
256
3950   38          14      62    94143       1    1.5          3
255
2159   61          35      99    94085       1    4.8          3
255
3138   36          11     103    93555       1    4.6          1
255
```

```
3948   37          12      123     94304       4     3.1          2
253

      personal_loan  securities_account  cd_account  online
credit_card
2934              0                   0           0       1
0
303               1                   0           0       0
0
4812              1                   0           0       1
0
1783              0                   0           0       1
0
4842              1                   0           0       0
0
...             ...                 ...         ...     ...          .
..
1522              0                   0           0       0
1
3950              0                   0           0       1
0
2159              1                   0           0       0
1
3138              0                   0           0       1
0
3948              1                   0           1       1
1

[291 rows x 13 columns]
```

```
print(f"There are {outliers.shape[0]} outliers in the outlier
column.")
```

```
There are 291 outliers in the outlier column.
```

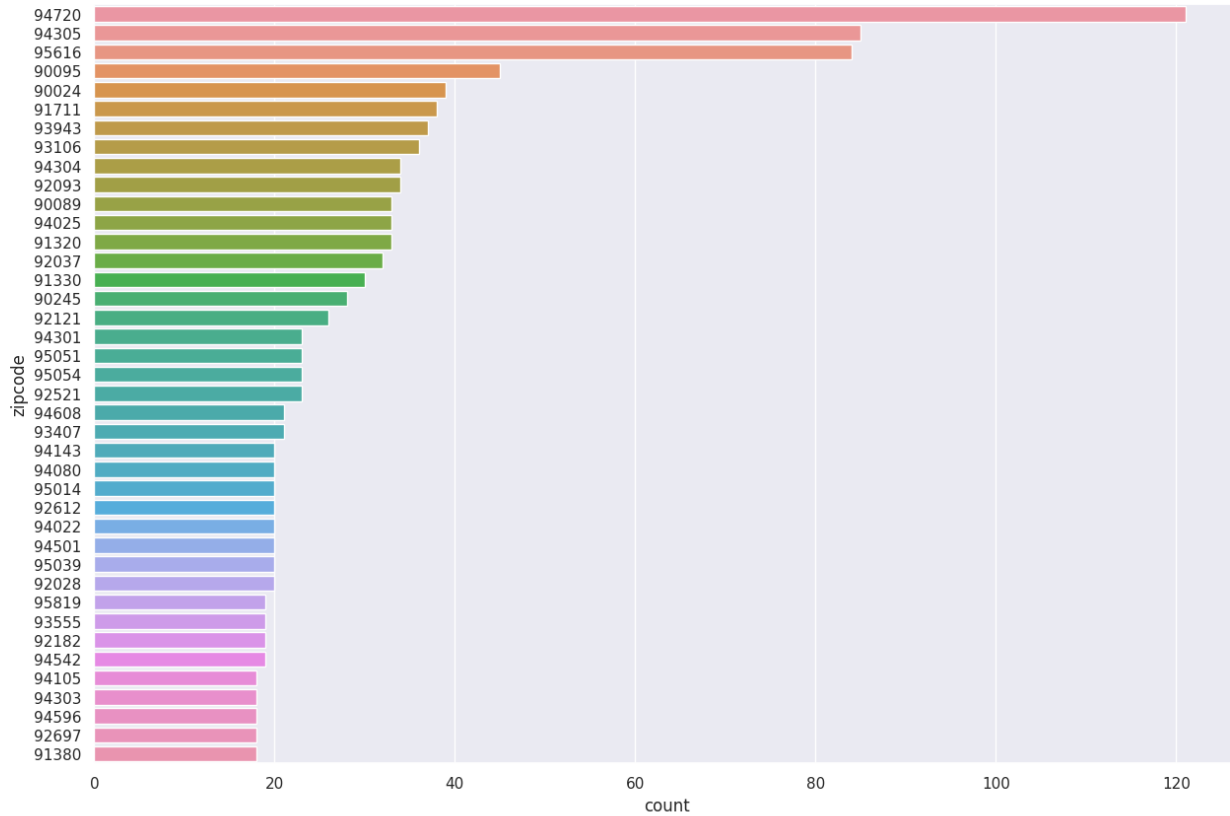
Check zero values in `mortgage` column

```
print(f'There are {df[df.mortgage==0].shape[0]} rows where mortgage
equals to ZERO!')
```

```
There are 3462 rows where mortgage equals to ZERO!
```

Check `zipcodes` frequency where `mortgage` equals zero.

```
plt.figure(figsize=(15, 10))
sns.countplot(y=df[df.mortgage==0]['zipcode'],
              data=df,
              order=df[df.mortgage==0]
['zipcode'].value_counts().index[:40]);
```

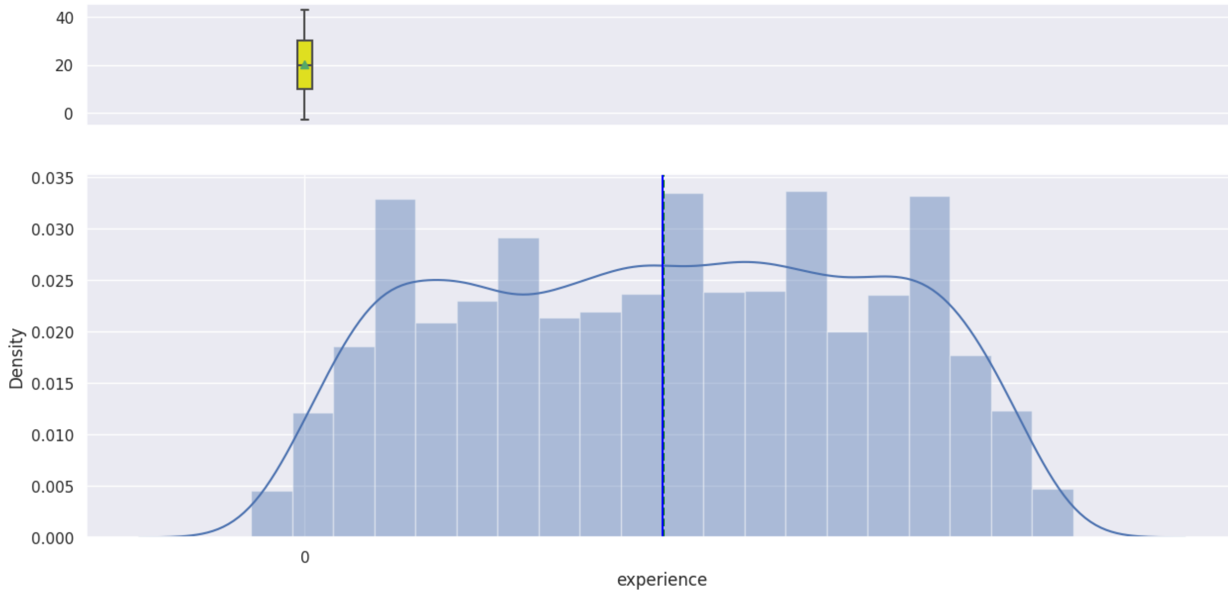


Observations

- The `zipcode` 94720 has the most frequent number of mortgages that equal zero with over 120 values.
- The second highest number of zero values is 94305, and the third highest is 95616.

Observations on `experience`

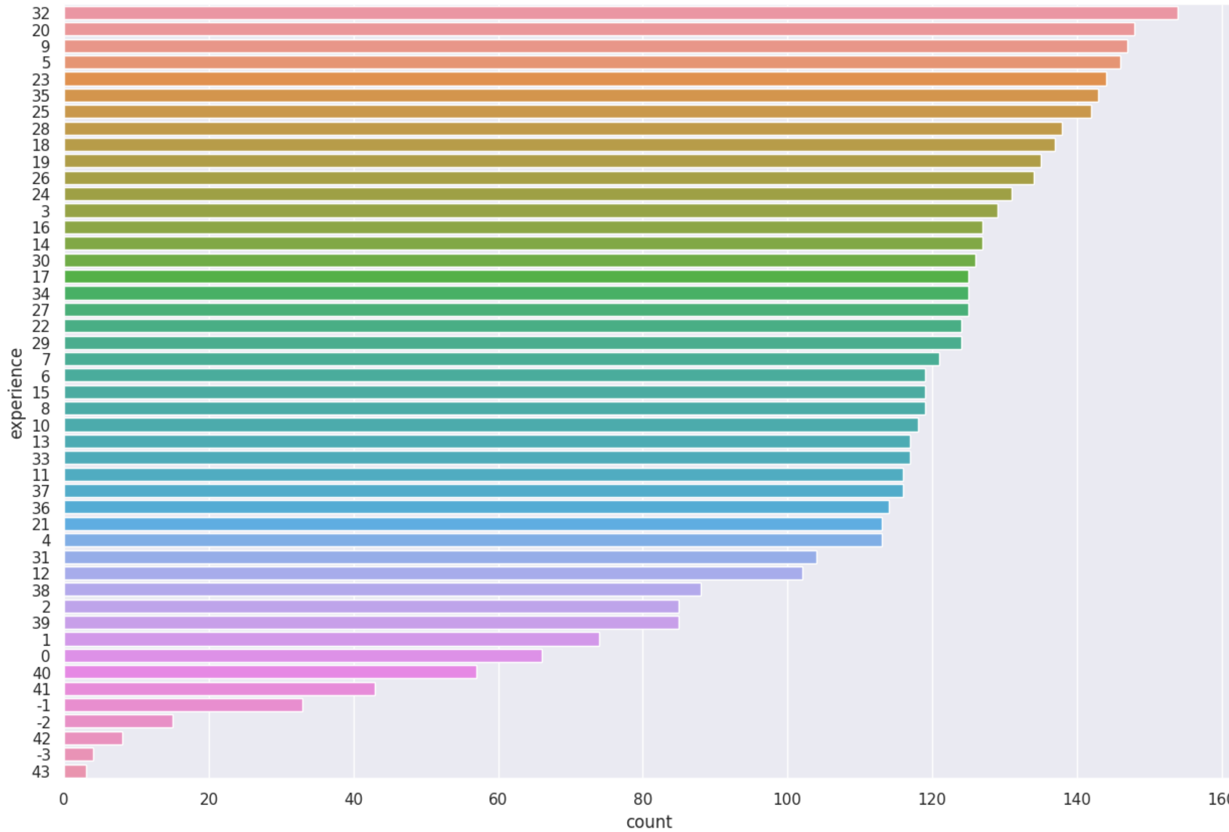
```
histogram_boxplot(df.experience)
```



Observations

- The `experience` column is uniform and has no outliers.
- The average and median `experience` is about 20 years.
- `experience` column is uniformly distributed. The mean is close to the median.

```
plt.figure(figsize=(15, 10))
sns.countplot(y=df.experience,
              data=df,
              order=df.experience.value_counts().index[:]);
```



Observations

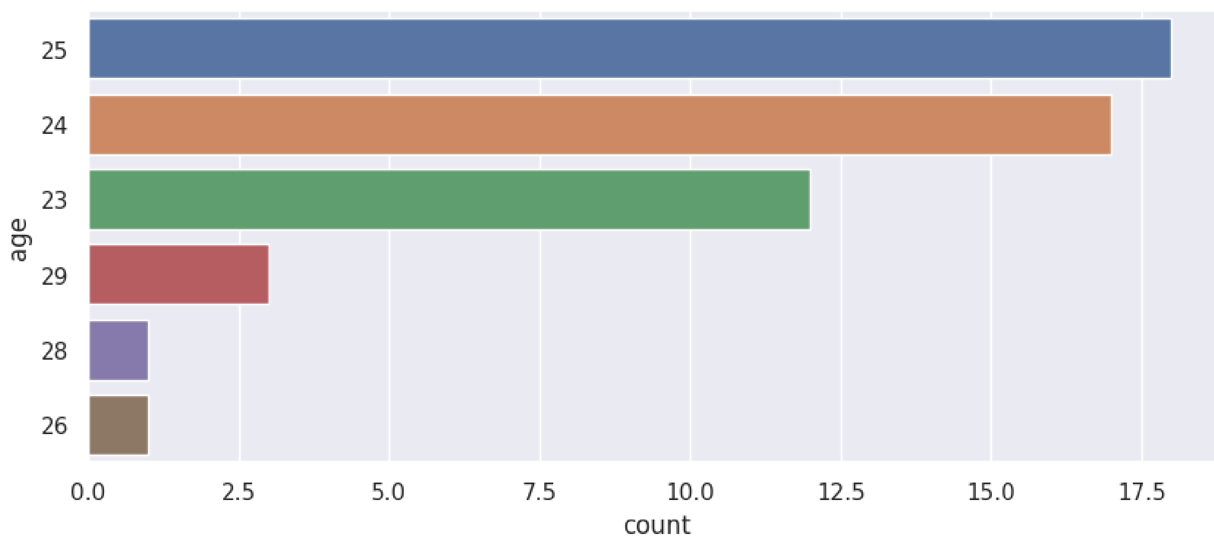
- 32 years is the greatest number of `experience` years observed with about 150 observations.
- The plot shows negative values.

```
print(f"There are {df[df.experience<0].shape[0]} rows that have
professional experience less than zero.")
df[df.experience<0].sort_values(by='experience',
ascending=True).head()

There are 52 rows that have professional experience less than zero.

      age  experience  income  zipcode  family  ccavg  education
mortgage  \
4514   24          -3      41    91768       4    1.0          3
0
2618   23          -3      55    92704       3    2.4          2
145
4285   23          -3     149    93555       2    7.2          1
0
3626   24          -3      28    90089       4    1.0          3
0
2717   23          -2      45    95422       4    0.6          2
0
```

```
      personal_loan  securities_account  cd_account  online
credit_card
4514              0                   0           0       1
0
2618              0                   0           0       1
0
4285              0                   0           0       1
0
3626              0                   0           0       0
0
2717              0                   0           0       1
1
```

Countplot for `experience` less than zero vs. `age`.

```
plt.figure(figsize=(10, 4))
sns.countplot(y=df[df.experience<0]['age'],
              data=df,
              order=df[df.experience<0]
['age'].value_counts().index[:]);
```



Observations

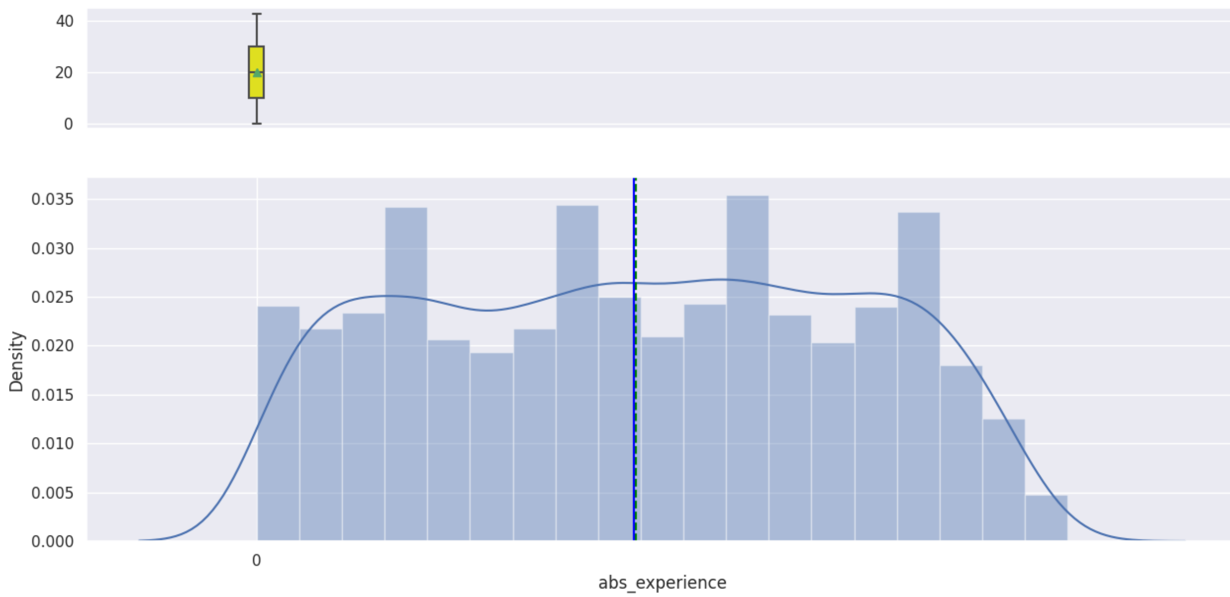
- Most of the negative values are from the 25 year old `age` group with over 17.
- This is a error in the data entry. You can't have negative years of `experience` so we will take the absolute value of the `experience`.

Taking absolute values of the `experience` column

```
df['abs_experience'] = np.abs(df.experience)
df.sort_values(by='experience', ascending=True).head(10)
```

```
      age  experience  income  zipcode family  ccavg education
mortgage  \
4514   24          -3      41    91768      4    1.0         3
0
2618   23          -3      55    92704      3    2.4         2
145
4285   23          -3     149    93555      2    7.2         1
0
3626   24          -3      28    90089      4    1.0         3
0
3796   24          -2      50    94920      3    2.4         2
0
2717   23          -2      45    95422      4    0.6         2
0
4481   25          -2      35    95045      4    1.0         3
0
3887   24          -2     118    92634      2    7.2         1
0
2876   24          -2      80    91107      2    1.6         3
238
2962   23          -2      81    91711      2    1.8         2
0

      personal_loan  securities_account  cd_account  online
credit_card  \
4514              0                   0           0       1
0
2618              0                   0           0       1
0
4285              0                   0           0       1
0
3626              0                   0           0       0
0
3796              0                   1           0       0
0
2717              0                   0           0       1
1
4481              0                   0           0       1
0
3887              0                   1           0       1
0
2876              0                   0           0       0
0
2962              0                   0           0       0
0

      abs_experience
4514               3
2618               3
4285               3
```

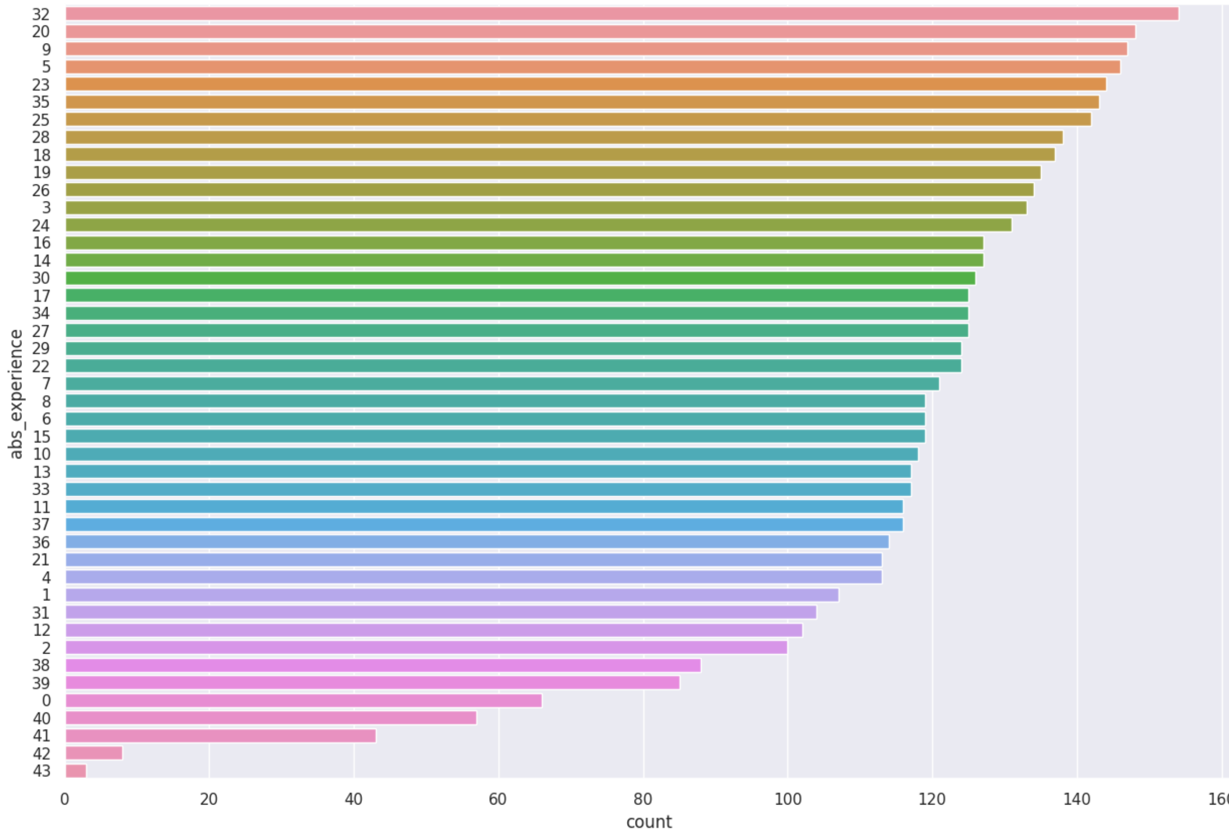
```
3626    3
3796    2
2717    2
4481    2
3887    2
2876    2
2962    2

histogram_boxplot(df.abs_experience)
```



Observations

- It didn't change the distribution that much.

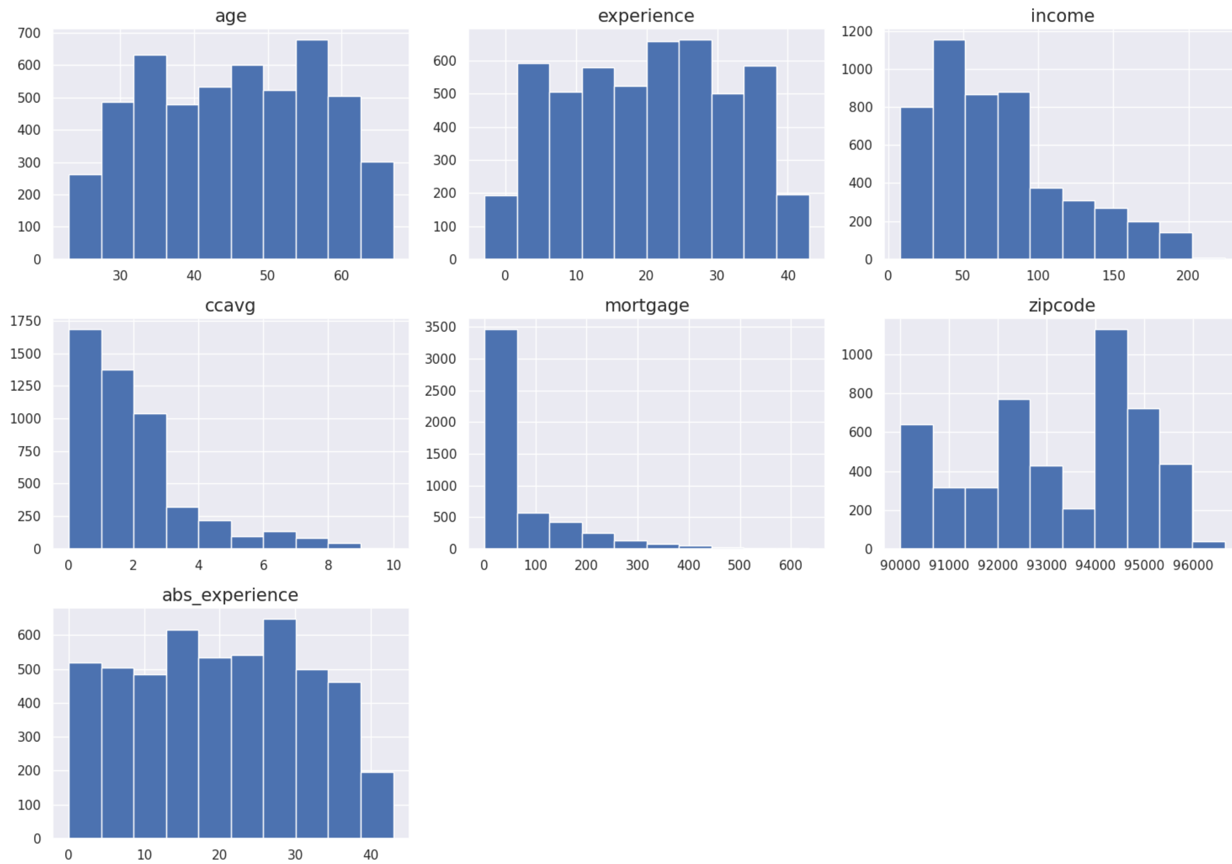
```
plt.figure(figsize=(15, 10))
sns.countplot(y=df.abs_experience,
              data=df,
              order=df.abs_experience.value_counts().index[:]);
```



- There are no more negative `experience` values.

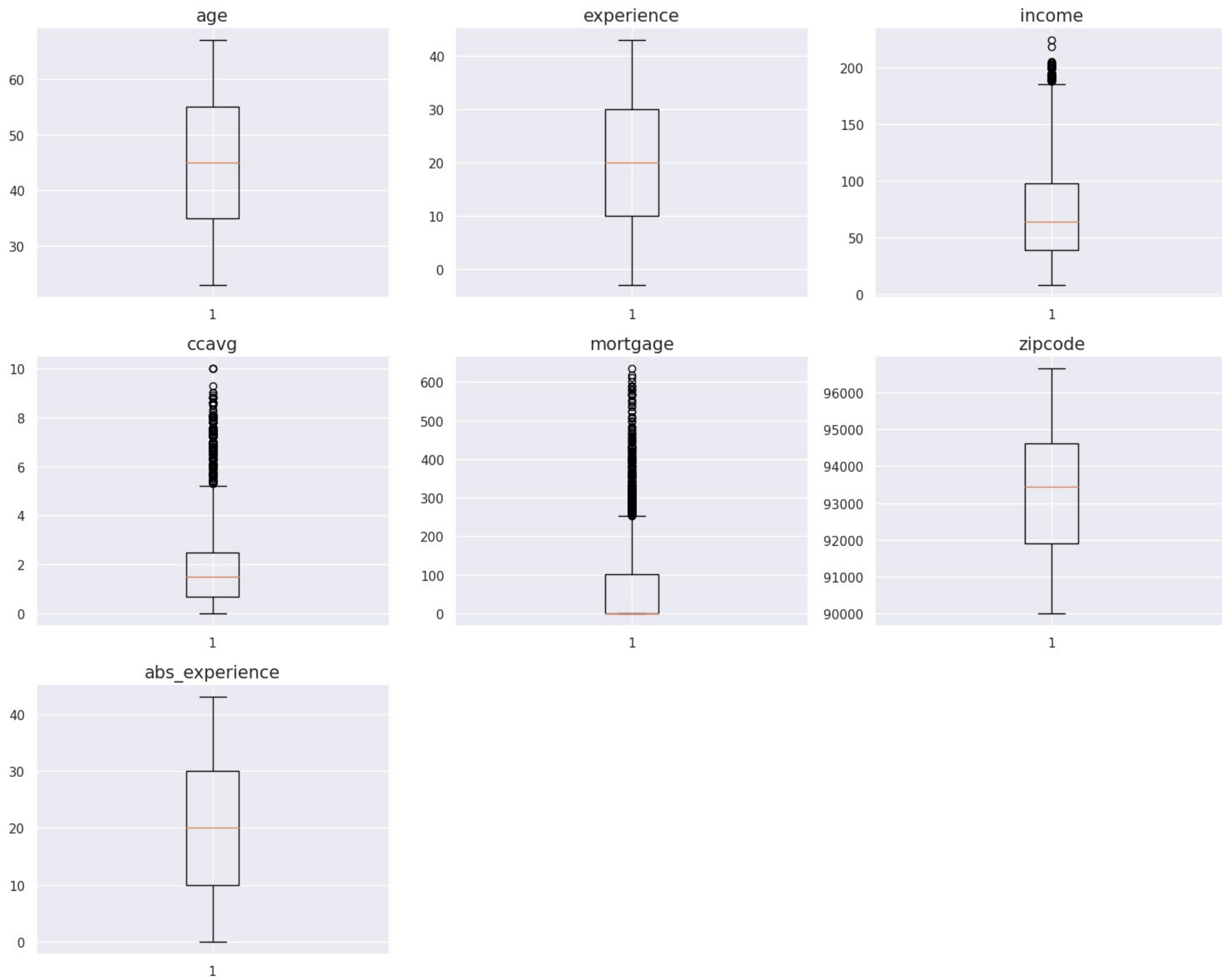
Overview on distributions of numerical columns.

```
# lets plot histogram of all plots
features = ['age', 'experience', 'income',
            'ccavg', 'mortgage', 'zipcode',
            'abs_experience']

n_rows = math.ceil(len(features)/3)
plt.figure(figsize=(15, n_rows*3.5))
for i, feature in enumerate(list(features)):
    plt.subplot(n_rows, 3, i+1)
    plt.hist(df[feature])
    plt.tight_layout()
    plt.title(feature, fontsize=15);
```



Overview on the dispersion of numerical columns.

```
# outlier detection using boxplot
plt.figure(figsize=(15, n_rows*4))
for i, feature in enumerate(features):
    plt.subplot(n_rows, 3, i+1)
    plt.boxplot(df[feature], whis=1.5)
    plt.tight_layout()
    plt.title(feature, fontsize=15);
```



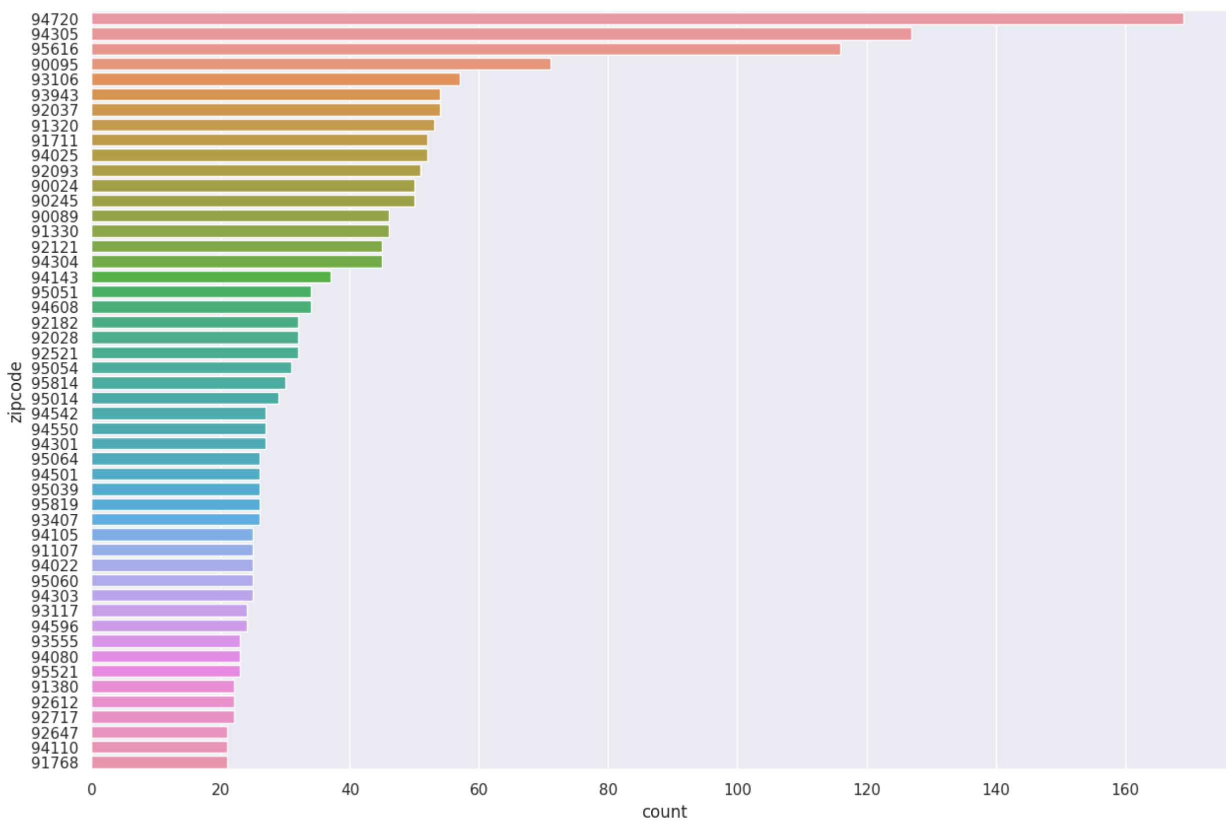
Display value counts from categorical columns

```
# looking at value counts for non-numeric features
num_to_display = 10  # defining this up here so it's easy to change later if I want
for colname in df.dtypes[df.dtypes=='category'].index:
    val_counts = df[colname].value_counts(dropna=False)  # i want to see NA counts
    print(f"Column: {colname}")
    print("="*40)
    print(val_counts[:num_to_display])
    if len(val_counts) > num_to_display:
        print(f"Only displaying first {num_to_display} of {len(val_counts)} values.")
    print("\n") # just for more space between

Column: family
========================================
1    1472
2    1296
```

```
4    1222
3    1010
Name: family, dtype: int64


Column: education
========================================
1    2096
3    1501
2    1403
Name: education, dtype: int64
```

Observations on `zipcode`

```
plt.figure(figsize=(15, 10))
sns.countplot(y="zipcode", data=df,
order=df.zipcode.value_counts().index[0:50]);
```



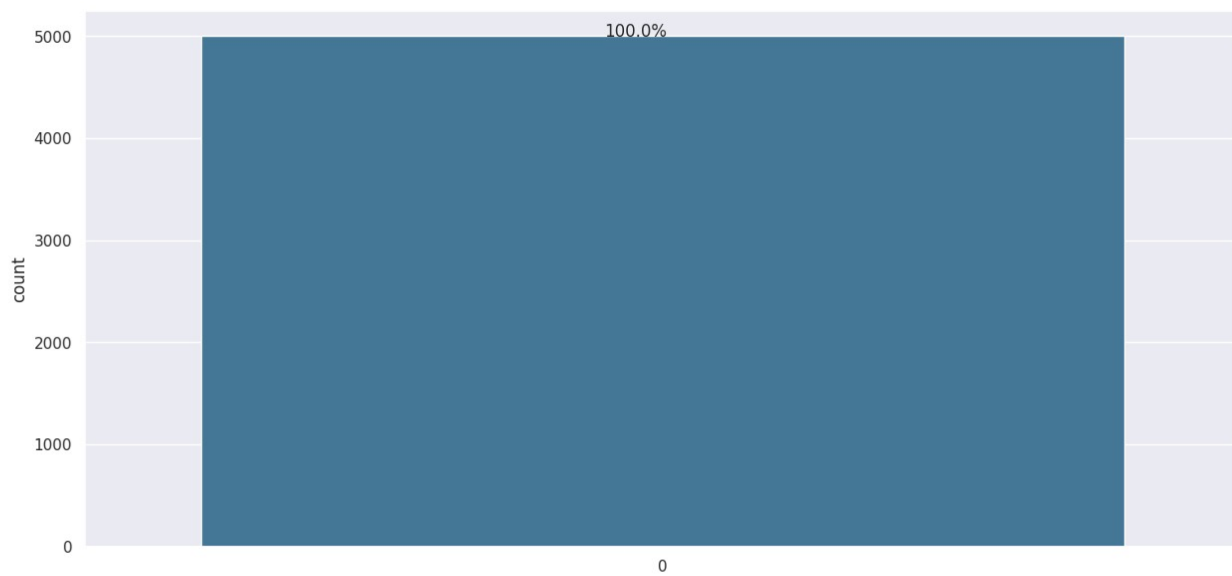
Observations

- Most of the values come from the `zipcode` 94720 with over 160.

```
def perc_on_bar(plot, feature):
    """
    Shows the percentage on the top of bar in plot.
    feature: categorical feature
    The function won't work if a column is passed in hue parameter
    """
    total = len(feature) # length of the column
    for p in ax.patches:
        # percentage = '{:.1f}%'.format(100 * p.get_height()/total) #
percentage of each class of the category
        percentage = 100 * p.get_height()/total
        percentage_label = f"{percentage:.1f}%"
        x = p.get_x() + p.get_width() / 2 - 0.05 # width of the plot
        y = p.get_y() + p.get_height()           # hieght of the plot
        ax.annotate(percentage_label, (x, y), size = 12) # annotate
the percantage
    plt.show() # show the plot
```

Observations on `family`

```
plt.figure(figsize=(15, 7))
ax = sns.countplot(df.family, palette='mako')
perc_on_bar(ax, df.family)
```

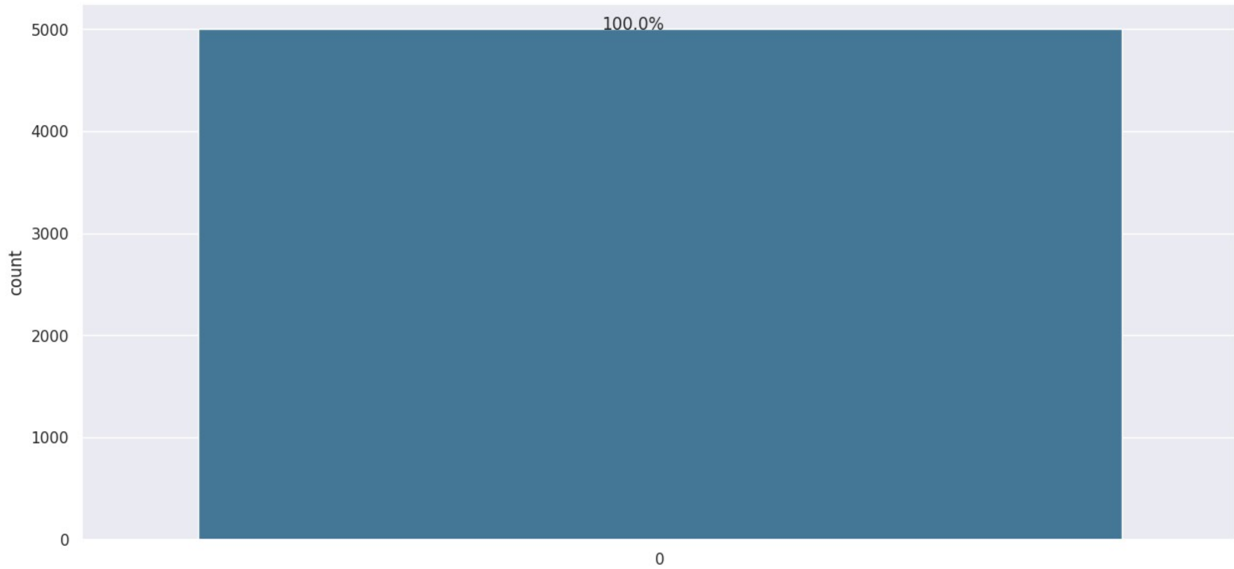


Observations

- The largest category of the `family` column is 1 with a percentage of 29.4%.
- The second largest category of the `family` column is a size of 2, then 4. A size of 3 is the smallest portion in our dataset.

Observations on `education`

```
plt.figure(figsize=(15, 7))
ax = sns.countplot(df.education, palette='mako')
perc_on_bar(ax, df.education)
```

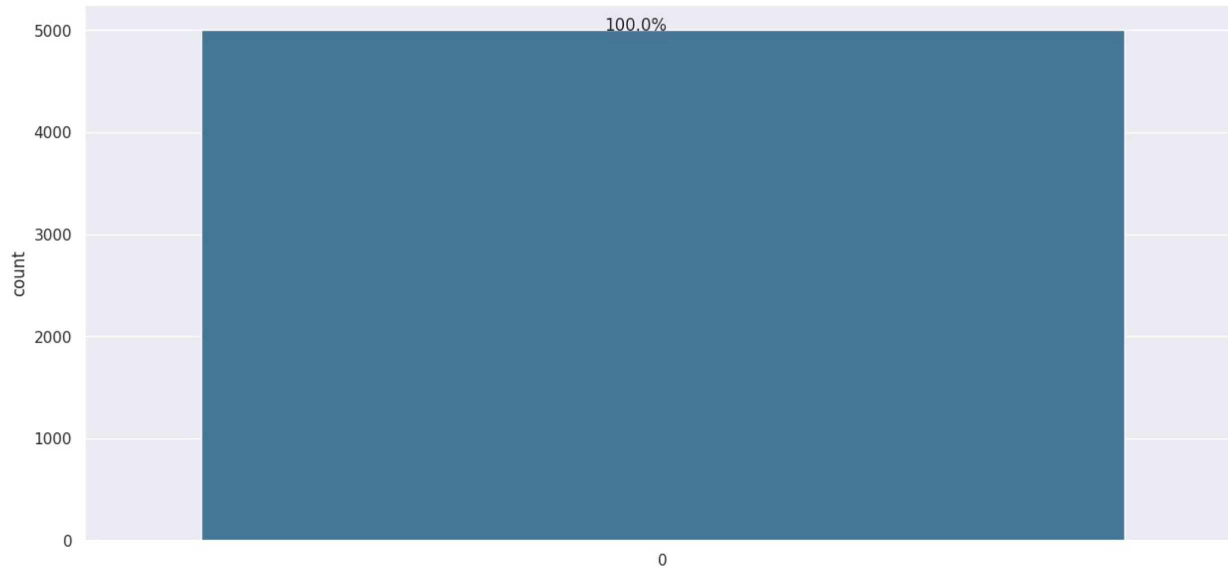


Observations

- The `education` column has 3 categories.
- Category 1 (undergrad) hold the greatest proportion with 41.9%.
- Category 3 holds the second highest with 30%.
- Category 2 holds the third highest proportion with 28.1%.

Oberservations on `personal_loan`

```
plt.figure(figsize=(15, 7))
ax = sns.countplot(df.personal_loan, palette='mako')
perc_on_bar(ax, df.personal_loan)
```

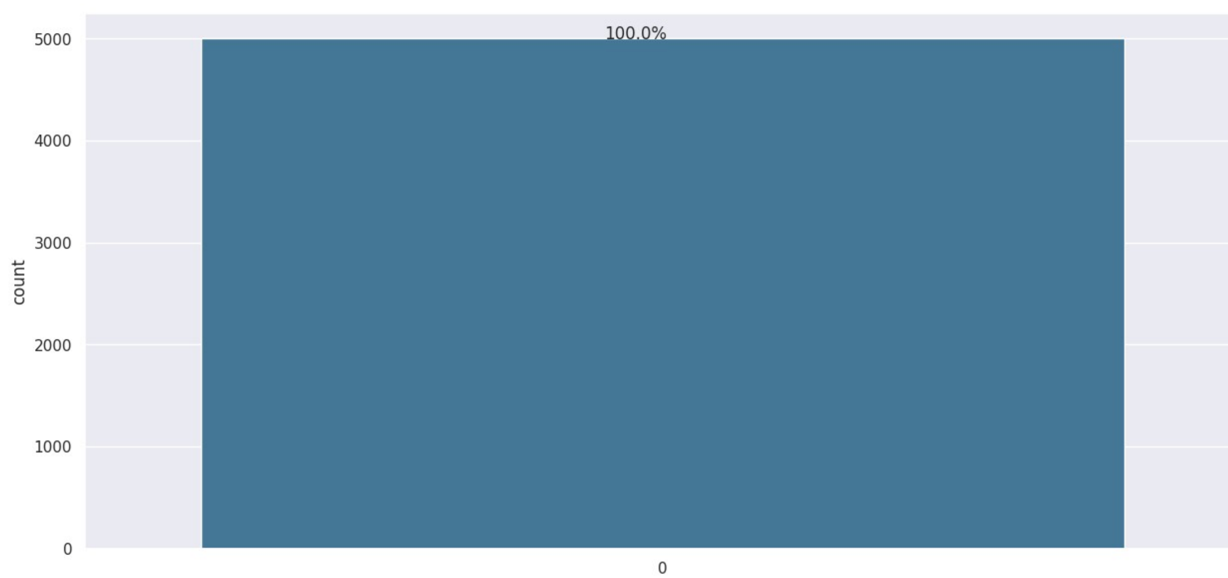


Observations

- Those that didn't accept a `personal_loan` from the last campaign make up the greatest percentage with 90.4%.

Observations on `securities_account`

```
plt.figure(figsize=(15,7))
ax = sns.countplot(df.securities_account, palette='mako')
perc_on_bar(ax, df.securities_account)
```

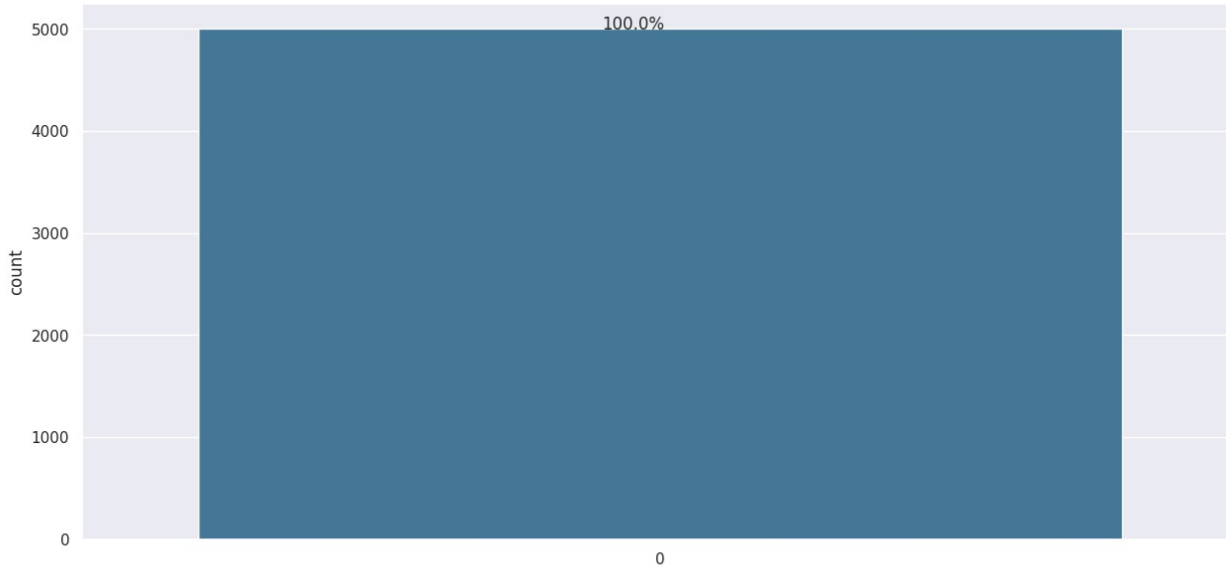


Observations

- Those customers without a `securities_account` make up the greatest proportion with 89.6%.

Observations on `cd_account`

```
plt.figure(figsize=(15, 7))
ax = sns.countplot(df.cd_account, palette='mako')
perc_on_bar(ax, df.cd_account)
```

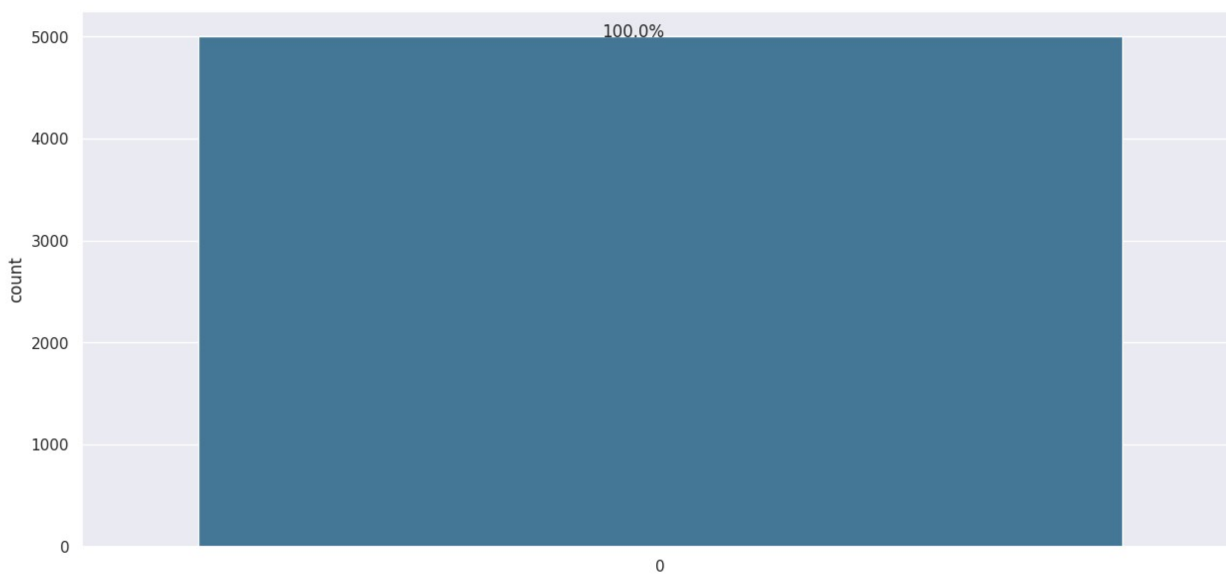


Observations

- Those customers without a `cd_account` make up the greatest percentage with 94%

Observations on `online`

```
plt.figure(figsize=(15, 7))
ax = sns.countplot(df.online, palette='mako')
perc_on_bar(ax, df.online)
```

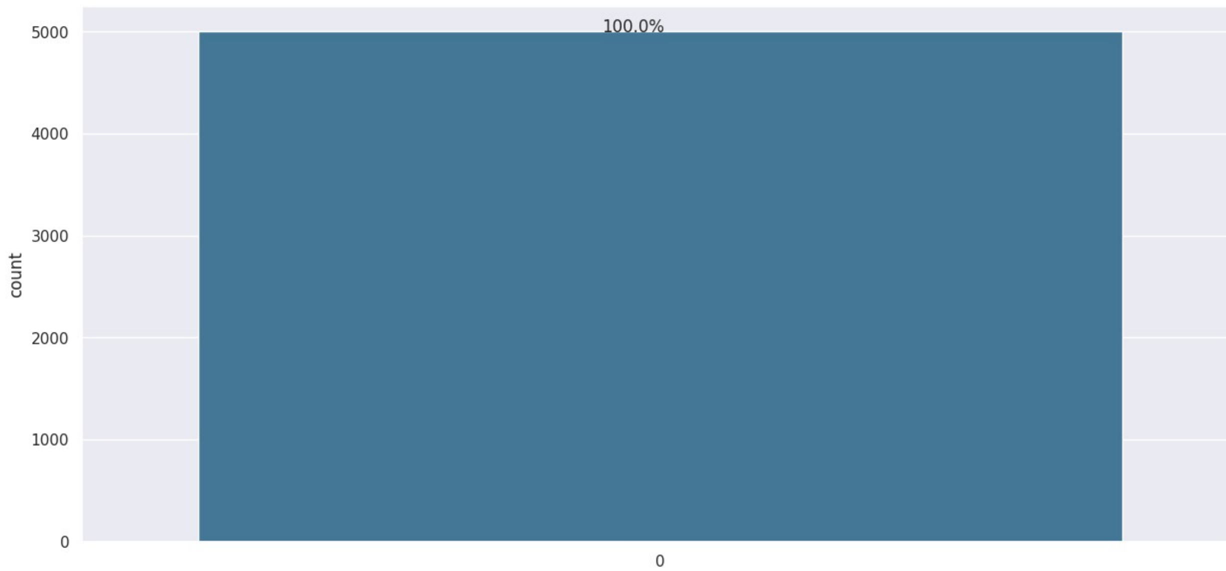


Observations

- Those customers that use `online` banking facilities makes up the majority with 59.7%.

Observations on `credit_card`

```
plt.figure(figsize=(15, 7))
ax = sns.countplot(df.credit_card, palette='mako')
perc_on_bar(ax, df.credit_card)
```



Observations

- Those customers that don't use `credit_cards` issued by other banks makes up the majority with 70.6%.

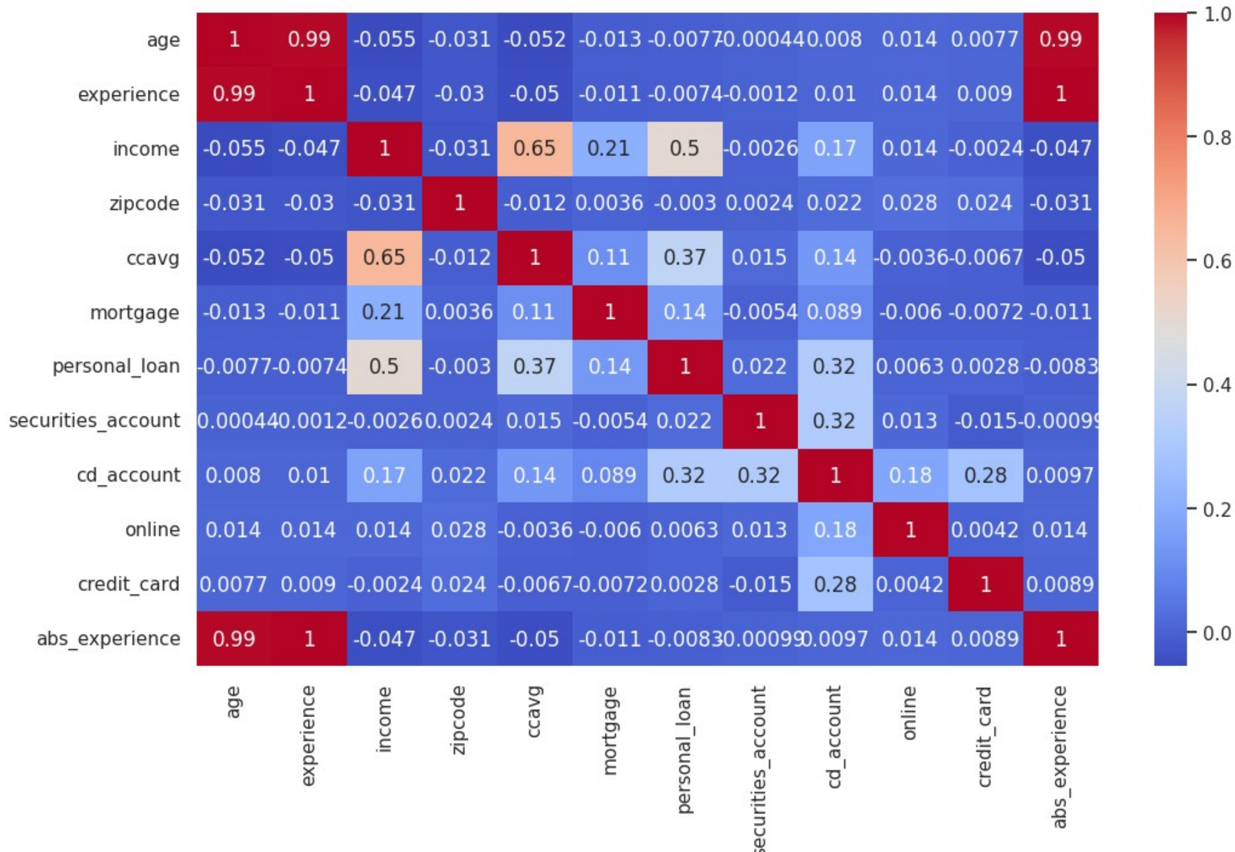
Bivariate Analysis

```
## Function to plot stacked bar chart
def stacked_plot(x, y):
    """
    Shows stacked plot from x and y pandas data series
    x: pandas data series
    y: pandas data series
    """
    info = pd.crosstab(x, y, margins=True)
    info['% - 0'] = round(info[0]/info['All']*100, 2)
    info['% - 1'] = round(info[1]/info['All']*100, 2)
    print(info)
    print('='*80)
    visual = pd.crosstab(x, y, normalize='index')
    visual.plot(kind='bar', stacked=True, figsize=(10,5));
```

```
def show_boxplots(cols: list, feature: str, show_fliers=True,
data=df): #method call to show bloxplots
    n_rows = math.ceil(len(cols)/2)
    plt.figure(figsize=(15, n_rows*5))
    for i, variable in enumerate(cols):
        plt.subplot(n_rows, 2, i+1)
        if show_fliers:
            sns.boxplot(data[feature], data[variable], palette="mako",
showfliers=True)
        else:
            sns.boxplot(data[feature], data[variable], palette="mako",
showfliers=False)
        plt.tight_layout()
        plt.title(variable, fontsize=12)
    plt.show()
```

Correlation and heatmap

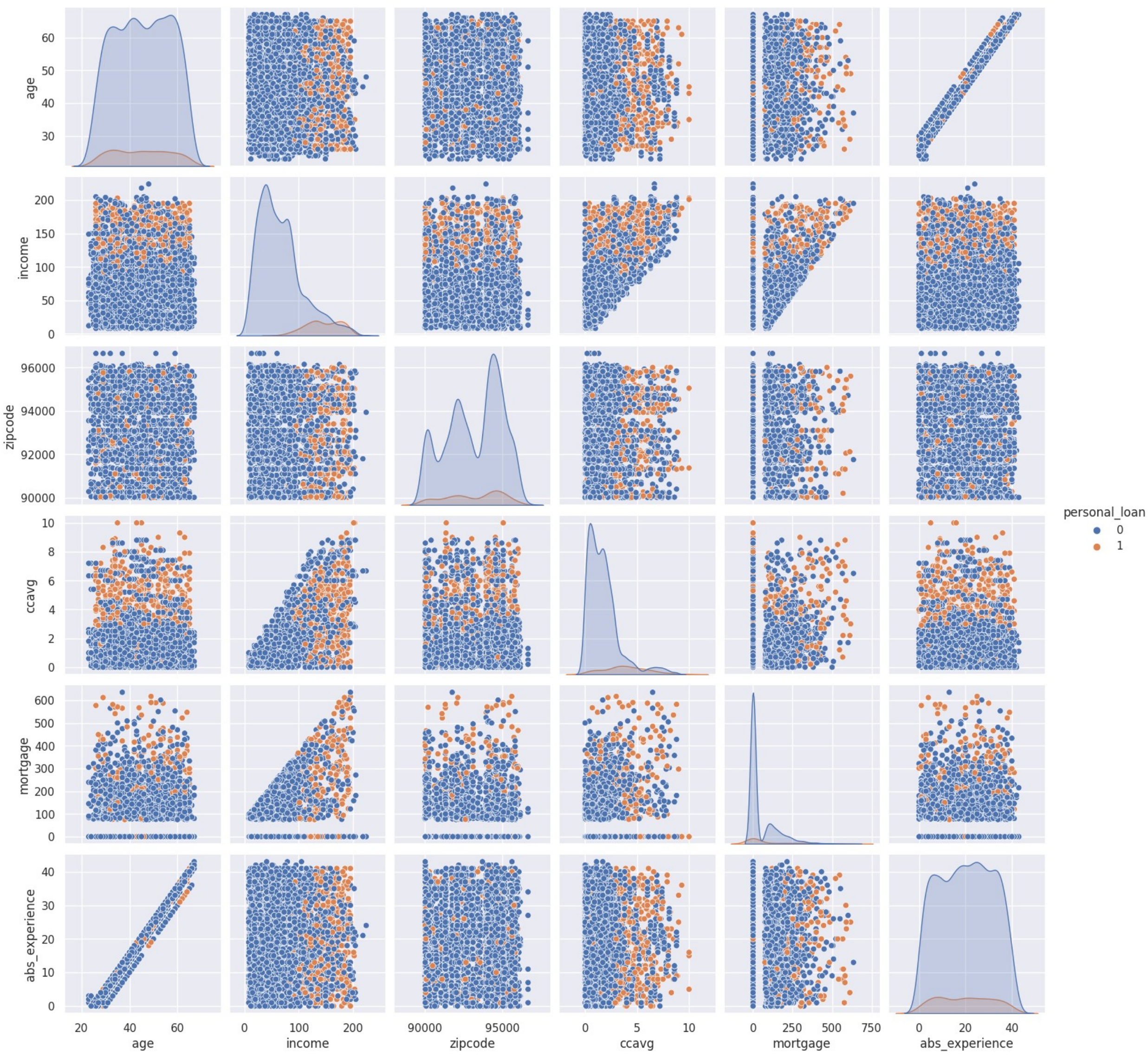
```
plt.figure(figsize=(12, 7))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm");
```



Observations

- `age` and `experience` are heavily positively correlated.
- `ccavg` and `income` are positively correlated.

```
sns.pairplot(data=df[['age','income','zipcode','ccavg',
                      'mortgage','abs_experience','personal_loan']],
             hue='personal_loan');
```



Observations

- Plot show that income is higher among those customers with personal loans.
- ccavg is higher among those customers with personal loans. we will investigate.

Show without outliers in boxplots

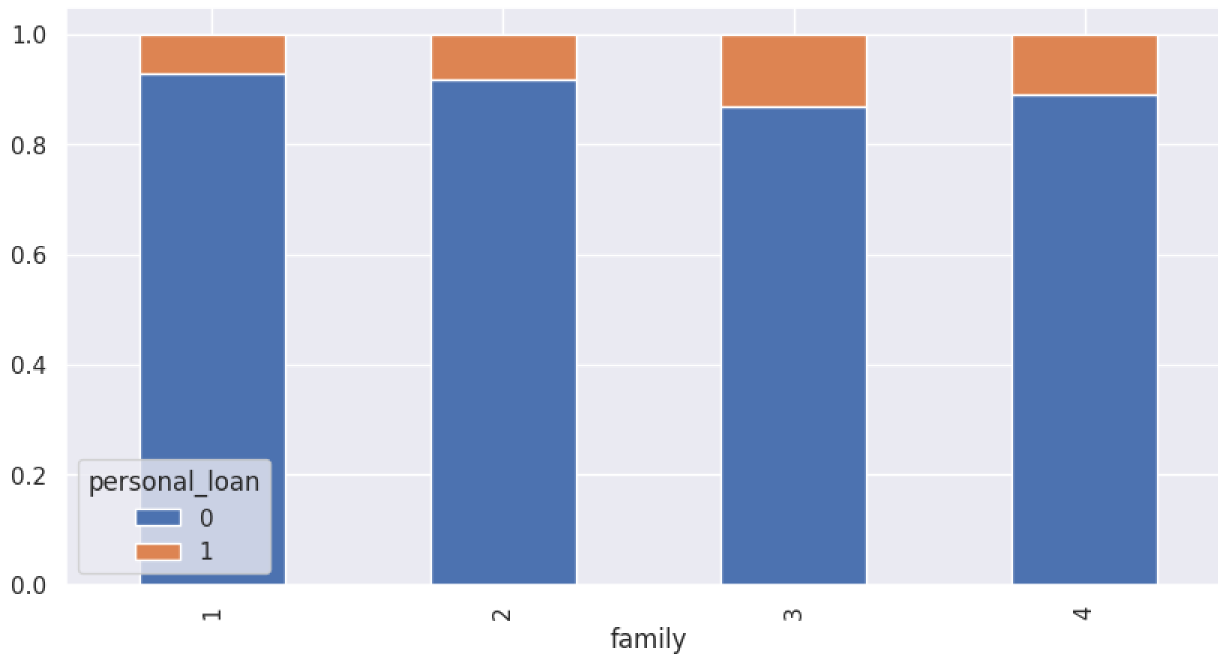
Observations

- On average, those customers with higher incomes have personal loans.

- On average, those customers with higher credit card usage have personal loans.
- 75% of those customers with personal loans have a mortgage payments of 500K or less.

`personal_loan` vs `family`

```
stacked_plot(df.family, df.personal_loan)

personal_loan     0    1   All  % - 0  % - 1
family
1              1365  107  1472  92.73   7.27
2              1190  106  1296  91.82   8.18
3               877  133  1010  86.83  13.17
4              1088  134  1222  89.03  10.97
All            4520  480  5000  90.40   9.60
======================================================================
==========
```



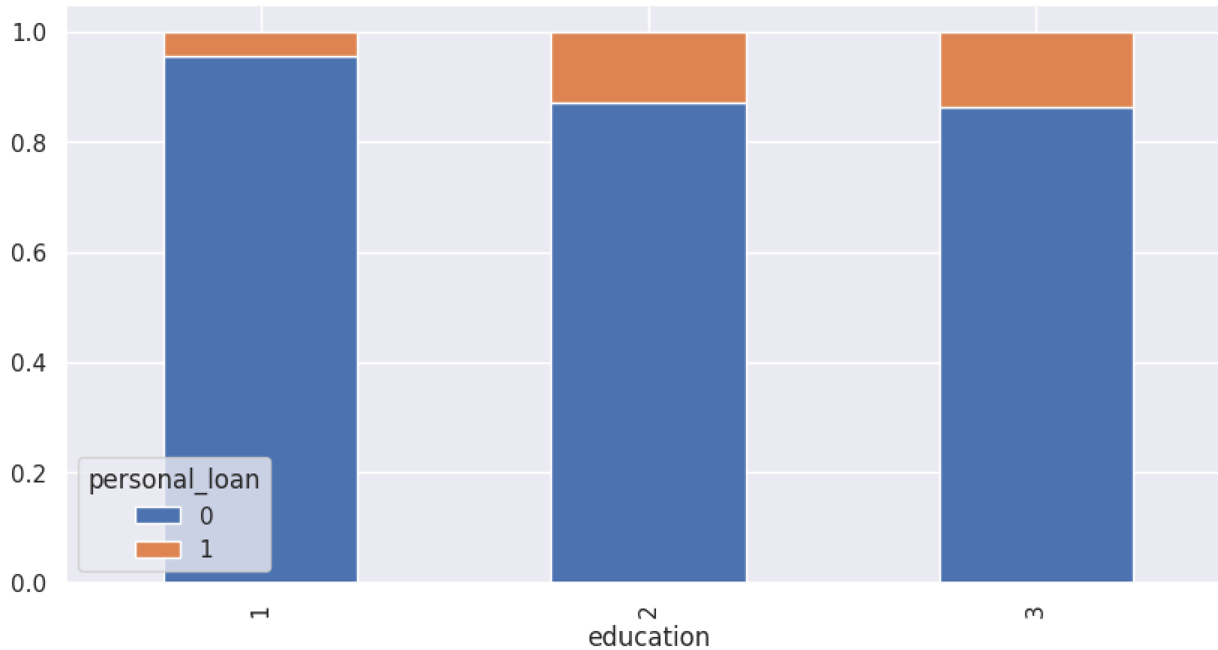
Observations

- Those customers with a `family` of 4 have more `personal loans`.
- A family of 3 have the second most personal loans followed by a family of 1 and 2.

`personal_loan` vs `education`

```
stacked_plot(df.education, df.personal_loan)

personal_loan     0    1   All  % - 0  % - 1
education
1              2003   93  2096  95.56   4.44
2              1221  182  1403  87.03  12.97
```

```
3                 1296  205  1501  86.34  13.66
All               4520  480  5000  90.40   9.60
======================================================================
==========
```

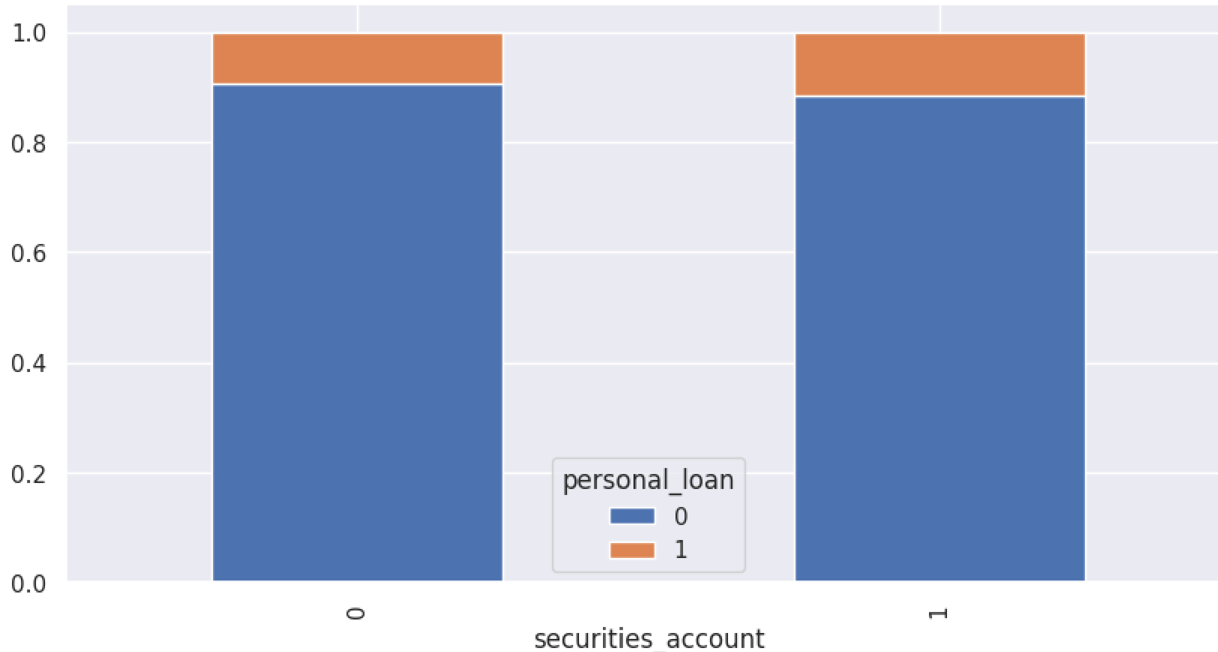


Observations

- Those customers with an education of '2' and '3' hold a greater percentage of personal loans that those customer with an education of '1'.

`personal_loan` vs `secuities_account`

```
stacked_plot(df.securities_account, df.personal_loan)

personal_loan          0    1   All  % - 0  % - 1
securities_account
0                   4058  420  4478  90.62   9.38
1                    462   60   522  88.51  11.49
All                 4520  480  5000  90.40   9.60
======================================================================
==========
```

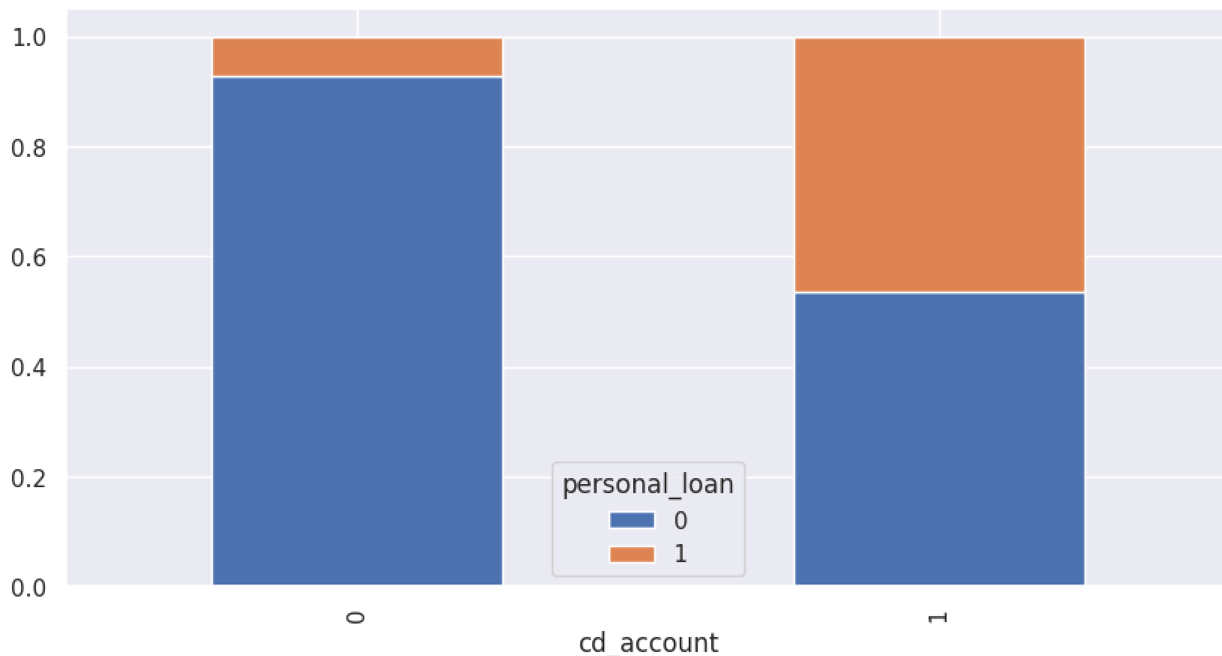


Observations

- There is not much difference in securities account versus personal loans

`personal_loan` vs `cd_account`

```
stacked_plot(df.cd_account, df.personal_loan)

personal_loan     0    1   All   % - 0   % - 1
cd_account
0              4358  340  4698   92.76    7.24
1               162  140   302   53.64   46.36
All            4520  480  5000   90.40    9.60
======================================================================
==========
```



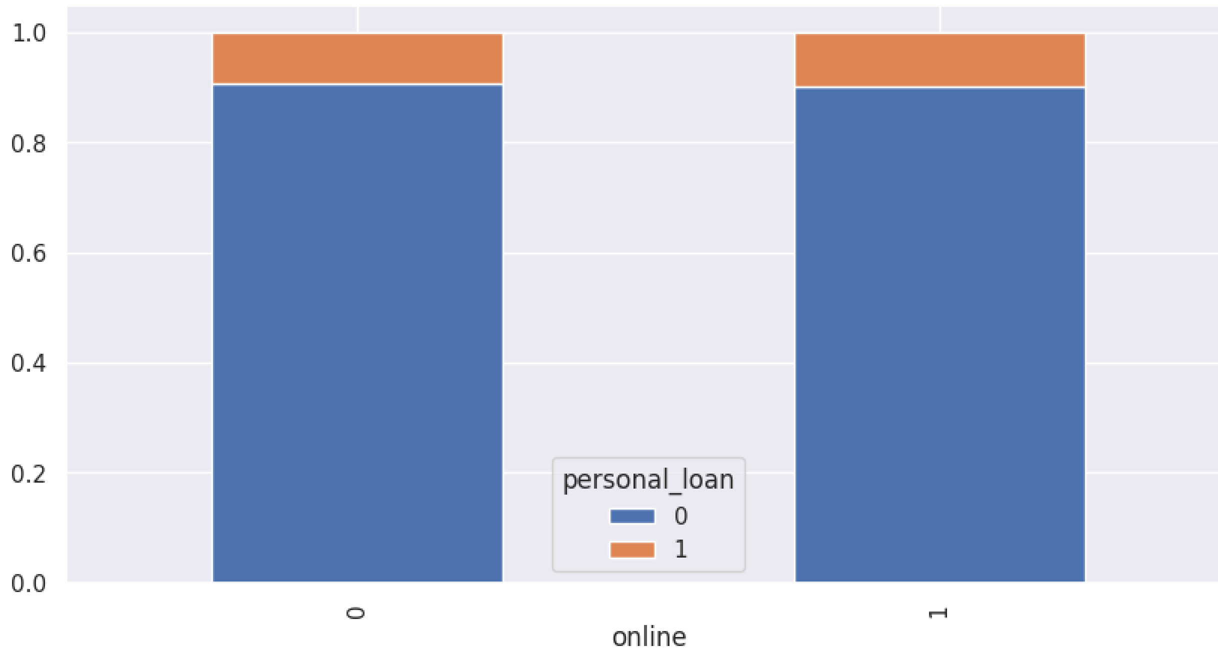
Observations

- Those customers with cd accounts. have a greater percentage of personal loans than those customer without a cd account.

`personal_loan` vs `online`

```
stacked_plot(df.online, df.personal_loan)
```

```
personal_loan     0    1   All  % - 0  % - 1
online
0              1827  189  2016  90.62   9.38
1              2693  291  2984  90.25   9.75
All            4520  480  5000  90.40   9.60
======================================================================
==========
```



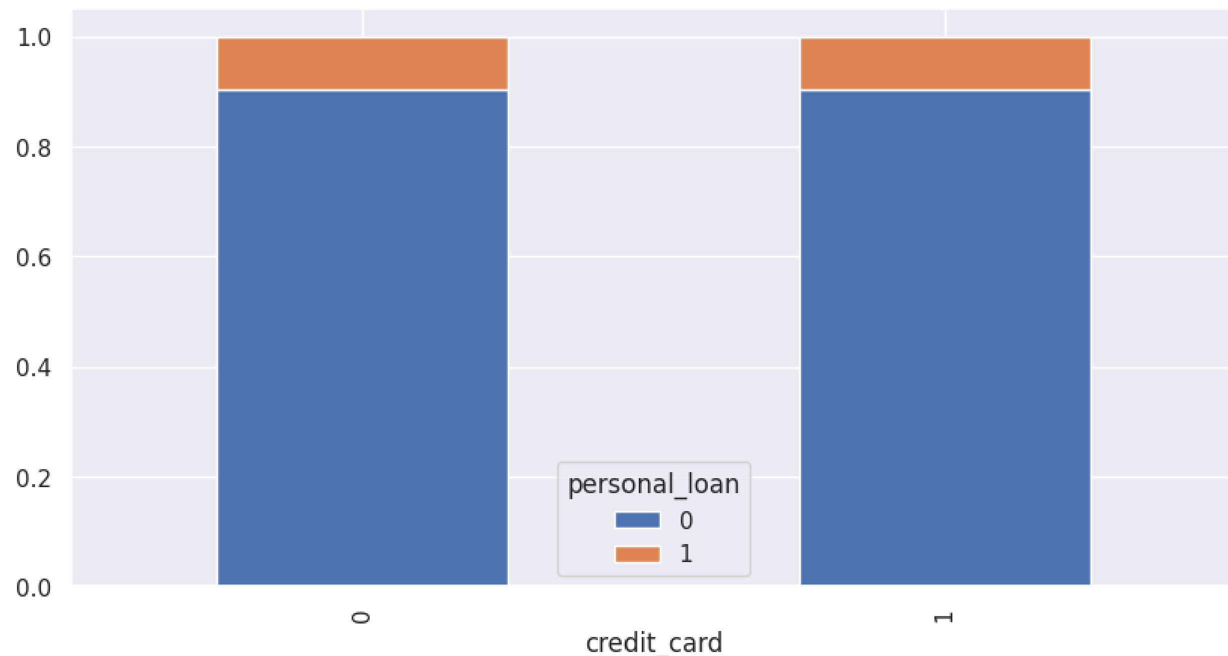
Observations

- There isnt much difference between customers who use online facilities and those who don't versus personal loans.

`personal_loan` vs `credit_card`

```
stacked_plot(df.credit_card, df.personal_loan)
```

```
personal_loan     0    1   All   % - 0  % - 1
credit_card
0              3193  337  3530   90.45   9.55
1              1327  143  1470   90.27   9.73
All            4520  480  5000   90.40   9.60
======================================================================
==========
```

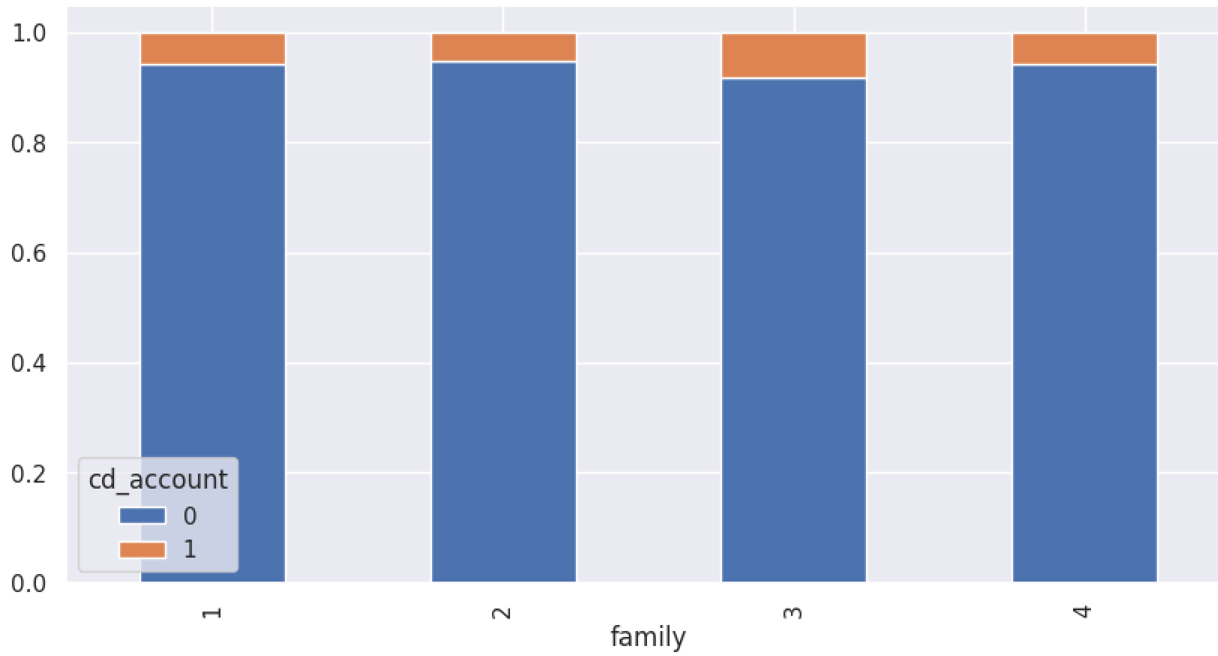


Observations

- There isn't much difference between those who have credit cards from other banks versus personal loans.

`cd_account` vs `family`

```
stacked_plot(df.family, df.cd_account)

cd_account      0    1   All   % - 0  % - 1
family
1            1389   83  1472   94.36   5.64
2            1229   67  1296   94.83   5.17
3             928   82  1010   91.88   8.12
4            1152   70  1222   94.27   5.73
All          4698  302  5000   93.96   6.04
======================================================================
==========
```

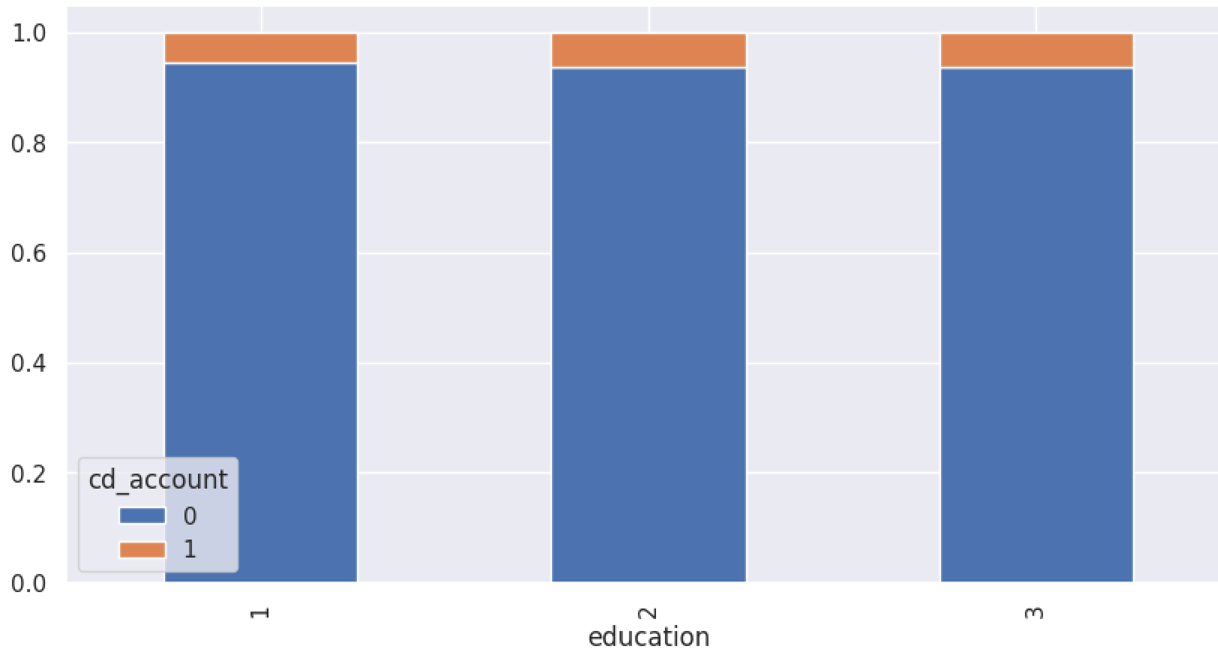


Observations

- A family of 3 has the greatest percentage(8.12) of customers with cd accounts.

`cd_account` vs `education`

```
stacked_plot(df.education, df.cd_account)

cd_account     0    1   All  % - 0  % - 1
education
1           1978  118  2096  94.37   5.63
2           1315   88  1403  93.73   6.27
3           1405   96  1501  93.60   6.40
All         4698  302  5000  93.96   6.04
======================================================================
==========
```



Observations

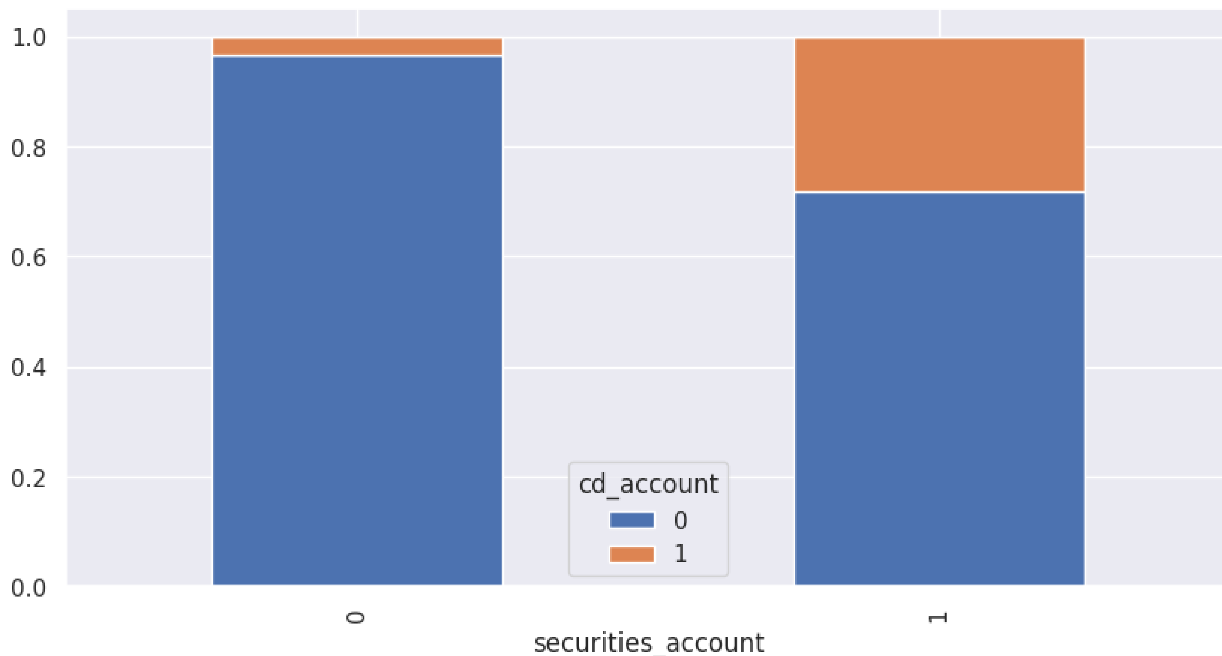
- There isnt much of a difference between education categories.

Observations

`cd_account` vs `securities_account`

```
stacked_plot(df.securities_account, df.cd_account)
```

```
cd_account              0    1   All  % - 0  % - 1
securities_account
0                    4323  155  4478  96.54   3.46
1                     375  147   522  71.84  28.16
All                  4698  302  5000  93.96   6.04
======================================================================
==========
```



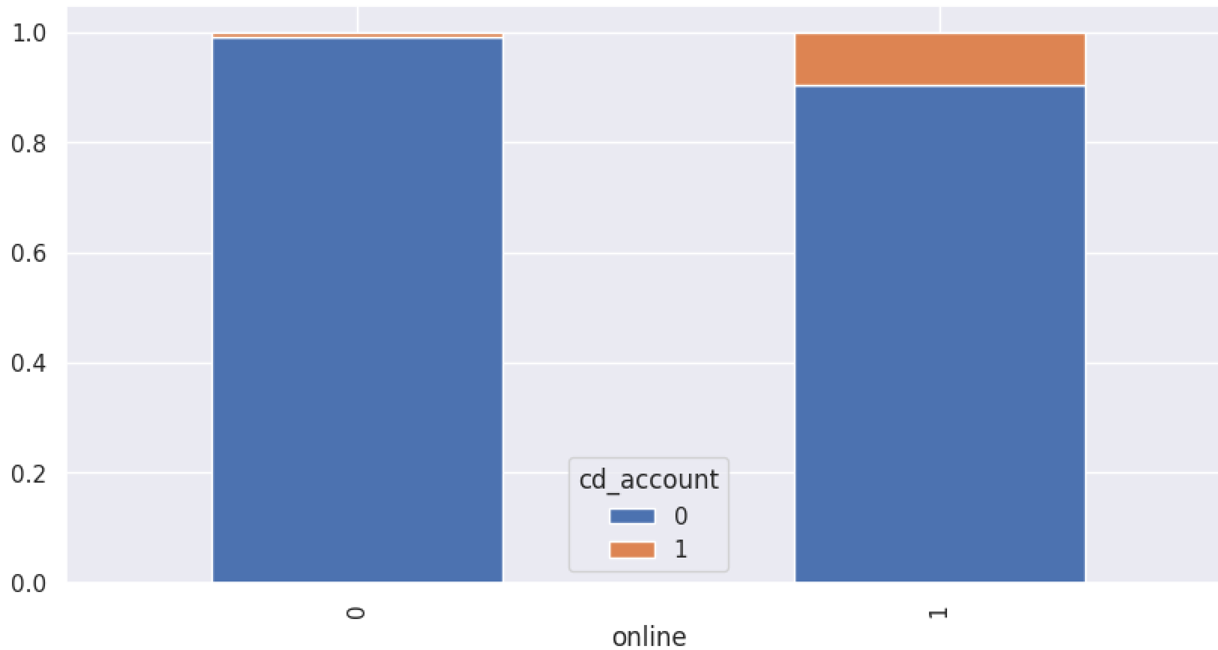
Observations

- A greater percentage of those customers with security accounts also have cd accounts versus those customer that dont have security accounts.

`cd_account` vs `online`

```
stacked_plot(df.online, df.cd_account)
```

```
cd_account     0    1   All  % - 0  % - 1
online
0           1997   19  2016  99.06   0.94
1           2701  283  2984  90.52   9.48
All         4698  302  5000  93.96   6.04
======================================================================
==========
```



Observations

- Customers who use the online facilities have a greater percentage cd accounts than those customer who don't use online facilities.

`cd_account` vs `credit_card`

```
stacked_plot(df.credit_card, df.cd_account)

cd_account      0    1   All   % - 0  % - 1
credit_card
0            3468   62  3530   98.24   1.76
1            1230  240  1470   83.67  16.33
All          4698  302  5000   93.96   6.04
======================================================================
==========
```

Observations

- A greater percentage of those customers who have credit cards with other bank institutions have personal cd accounts than those customers who dont have credit cards from other institutions.

Let us check which of these differences are statistically significant.

The Chi-Square test is a statistical method to determine if two categorical variables have a significant correlation between them.

H_0: There is no association between the two variables.
H_a: There is an association between two variables.

```
def check_significance(feature1: str, feature2: str, data=df):
    """
    Checks the significance of feature1 agaisnt feature2
    feature1: column name
    feature2: column name
    data: pandas dataframe object (defaults to df)
    """
    crosstab = pd.crosstab(data[feature1], data[feature2])  # 
Contingency table of region and smoker attributes
    chi, p_value, dof, expected =  stats.chi2_contingency(crosstab)
    Ho = f"{feature1} has no effect on {feature2}"   # Stating the 
Null Hypothesis
    Ha = f"{feature1} has an effect on {feature2}"   # Stating the 
Alternate Hypothesis
    if p_value < 0.05:  # Setting our significance level at 5%
```

```python
        print(f'{Ha.upper()} as the p_value ({p_value.round(3)}) <
0.05')
    else:
        print(f'{Ho} as the p_value ({p_value.round(3)}) > 0.05')

def show_significance(features: list, data=df):
    """
    Prints out the significance of all the list of features passed.
    features: list of column names
    data: pandas dataframe object (defaults to df)
    """
    for feature in features:
        print("="*30, feature, "="*(50-len(feature)))
        for col in list(data.columns):
            if col != feature: check_significance(col , feature)

show_significance(['personal_loan', 'cd_account'])
```

```
============================== personal_loan
=====================================
age has no effect on personal_loan as the p_value (0.12) > 0.05
experience has no effect on personal_loan as the p_value (0.704) >
0.05
INCOME HAS AN EFFECT ON PERSONAL_LOAN as the p_value (0.0) < 0.05
zipcode has no effect on personal_loan as the p_value (0.76) > 0.05
FAMILY HAS AN EFFECT ON PERSONAL_LOAN as the p_value (0.0) < 0.05
CCAVG HAS AN EFFECT ON PERSONAL_LOAN as the p_value (0.0) < 0.05
EDUCATION HAS AN EFFECT ON PERSONAL_LOAN as the p_value (0.0) < 0.05
MORTGAGE HAS AN EFFECT ON PERSONAL_LOAN as the p_value (0.0) < 0.05
securities_account has no effect on personal_loan as the p_value
(0.141) > 0.05
CD_ACCOUNT HAS AN EFFECT ON PERSONAL_LOAN as the p_value (0.0) < 0.05
online has no effect on personal_loan as the p_value (0.693) > 0.05
credit_card has no effect on personal_loan as the p_value (0.884) >
0.05
abs_experience has no effect on personal_loan as the p_value (0.805) >
0.05
============================== cd_account
========================================
AGE HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.027) < 0.05
experience has no effect on cd_account as the p_value (0.086) > 0.05
INCOME HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.0) < 0.05
zipcode has no effect on cd_account as the p_value (0.675) > 0.05
FAMILY HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.018) < 0.05
CCAVG HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.0) < 0.05
education has no effect on cd_account as the p_value (0.58) > 0.05
MORTGAGE HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.0) < 0.05
PERSONAL_LOAN HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.0) < 0.05
SECURITIES_ACCOUNT HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.0) <
0.05
```

```
ONLINE HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.0) < 0.05
CREDIT_CARD HAS AN EFFECT ON CD_ACCOUNT as the p_value (0.0) < 0.05
abs_experience has no effect on cd_account as the p_value (0.072) >
0.05
```

Key Observations -

- `cd_account`, `family` and `education` seem to be strong indicators of customers received a personal loan.
- `securities_account`, `online` and `credit_card` seem to be strong indicators of customers who have cd accounts.
- Other factors appear to be not very good indicators of those customers that have cd accounts.

Build Model, Train and Evaluate

1. Data preparation
2. Partition the data into train and test set.
3. Build a CART model on the train data.
4. Tune the model and prune the tree, if required.
5. Test the data on test set.

```
try:
    df.drop(['experience'], axis=1, inplace=True)
except KeyError:
    print(f"Column experience must already be dropped.")
df.head()
```

```
   age  income  zipcode  family  ccavg  education  mortgage
personal_loan  \
0   25      49    91107       4    1.6          1         0
0
1   45      34    90089       3    1.5          1         0
0
2   39      11    94720       1    1.0          1         0
0
3   35     100    94112       1    2.7          2         0
0
4   35      45    91330       4    1.0          2         0
0

   securities_account  cd_account  online  credit_card  abs_experience

0                   1           0       0            0               1

1                   1           0       0            0              19

2                   0           0       0            0              15

3                   0           0       0            0               9
```

```
4                    0            0       0            1               8
```

```python
df_dummies = pd.get_dummies(df, columns=['education', 'family'],
drop_first=True)
df_dummies.head()
```

```
   age  income  zipcode  ccavg  mortgage  personal_loan
securities_account  \
0   25      49    91107    1.6         0              0
1
1   45      34    90089    1.5         0              0
1
2   39      11    94720    1.0         0              0
0
3   35     100    94112    2.7         0              0
0
4   35      45    91330    1.0         0              0
0

   cd_account  online  credit_card  abs_experience  education_2
education_3  \
0           0       0            0               1            0
0
1           0       0            0              19            0
0
2           0       0            0              15            0
0
3           0       0            0               9            1
0
4           0       0            1               8            1
0

   family_2  family_3  family_4
0         0         0         1
1         0         1         0
2         0         0         0
3         0         0         0
4         0         0         1
```

```python
df_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 16 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   age                 5000 non-null   int64
 1   income              5000 non-null   int64
 2   zipcode             5000 non-null   int64
```

```
 3   ccavg                 5000 non-null   float64
 4   mortgage              5000 non-null   int64
 5   personal_loan         5000 non-null   int64
 6   securities_account    5000 non-null   int64
 7   cd_account            5000 non-null   int64
 8   online                5000 non-null   int64
 9   credit_card           5000 non-null   int64
 10  abs_experience        5000 non-null   int64
 11  education_2           5000 non-null   uint8
 12  education_3           5000 non-null   uint8
 13  family_2              5000 non-null   uint8
 14  family_3              5000 non-null   uint8
 15  family_4              5000 non-null   uint8
dtypes: float64(1), int64(10), uint8(5)
memory usage: 454.2 KB
```

Partition Data

```
X = df_dummies.drop(['personal_loan'], axis=1)
X.head(10)
```

```
   age  income  zipcode  ccavg  mortgage  securities_account
cd_account  \
0   25      49    91107    1.6         0                   1
0
1   45      34    90089    1.5         0                   1
0
2   39      11    94720    1.0         0                   0
0
3   35     100    94112    2.7         0                   0
0
4   35      45    91330    1.0         0                   0
0
5   37      29    92121    0.4       155                   0
0
6   53      72    91711    1.5         0                   0
0
7   50      22    93943    0.3         0                   0
0
8   35      81    90089    0.6       104                   0
0
9   34     180    93023    8.9         0                   0
0

   online  credit_card  abs_experience  education_2  education_3
family_2  \
0       0            0               1            0            0
0
1       0            0              19            0            0
0
```

```
2        0            0              15           0            0
0
3        0            0               9           1            0
0
4        0            1               8           1            0
0
5        1            0              13           1            0
0
6        1            0              27           1            0
1
7        0            1              24           0            1
0
8        1            0              10           1            0
0
9        0            0               9           0            1
0

   family_3  family_4
0         0         1
1         1         0
2         0         0
3         0         0
4         0         1
5         0         1
6         0         0
7         0         0
8         1         0
9         0         0
```

```
y = df_dummies['personal_loan']
y.head(10)
```

```
0    0
1    0
2    0
3    0
4    0
5    0
6    0
7    0
8    0
9    1
Name: personal_loan, dtype: int64
```

```
# 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("The shape of X_train: ", X_train.shape)
print("The shape of X_test: ", X_test.shape)
```

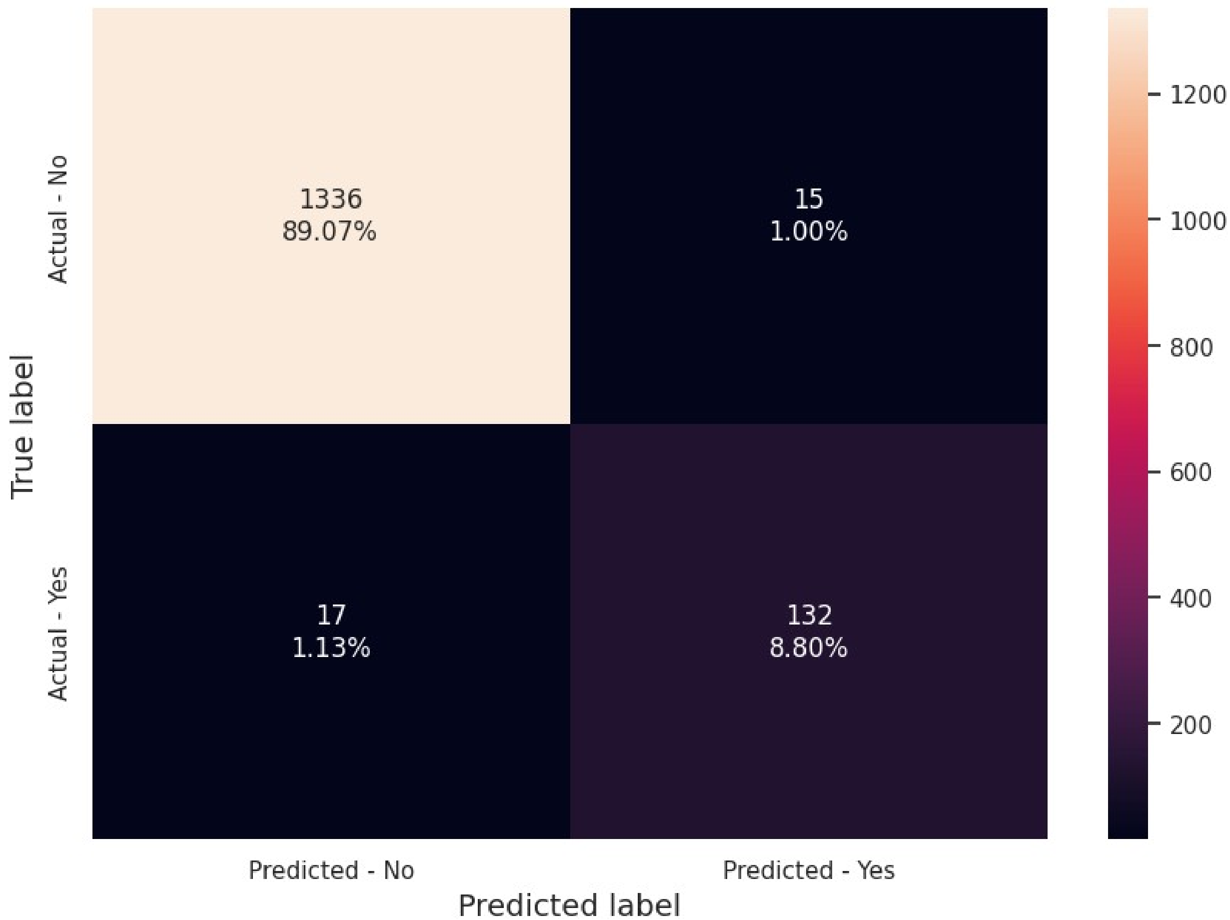
```
The shape of X_train:  (3500, 15)
The shape of X_test:  (1500, 15)
```

Build Initial Decision Tree Model

- We will build our model using the DecisionTreeClassifier function. Using default 'gini' criteria to split.
- If the frequency of class A is 10% and the frequency of class B is 90%, then class B will become the dominant class and the decision tree will become biased toward the dominant classes.
- In this case, we can pass a dictionary {0:0.15,1:0.85} to the model to specify the weight of each class and the decision tree will give more weightage to class 1.
- class_weight is a hyperparameter for the decision tree classifier.

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

model.fit(X_train, y_train)

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

## Function to create confusion matrix
def make_confusion_matrix(model,  y_actual, labels=[1, 0],
xtest=X_test):
    """
    model : classifier to predict values of X
    y_actual : ground truth
    """
    y_predict = model.predict(xtest)
    cm = metrics.confusion_matrix(y_actual, y_predict, labels=[0, 1])
    df_cm = pd.DataFrame(cm, index=["Actual - No","Actual - Yes"],
                         columns=['Predicted - No','Predicted - Yes'])
    #print(df_cm)
    #print("="*80)

    group_counts = [f"{value:0.0f}" for value in cm.flatten()]
    group_percentages = [f"{value:.2%}" for value in
cm.flatten()/np.sum(cm)]

    labels = [f"{gc}\n{gp}" for gc, gp 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', fontsize=14)
    plt.xlabel('Predicted label', fontsize=14);

make_confusion_matrix(model, y_test)
```




```
y_train.value_counts(normalize=True)

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

Observations

- We only have ~10% of positive classes, so if our model marks each sample as negative, then also we'll get 90% accuracy, hence accuracy is not a good metric to evaluate here.

```
##  Function to calculate recall score
def get_recall_score(model):
    '''
    Prints the recall score from 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))
```

Recall score from baseline model.

```
# Recall on train and test
get_recall_score(model)
```

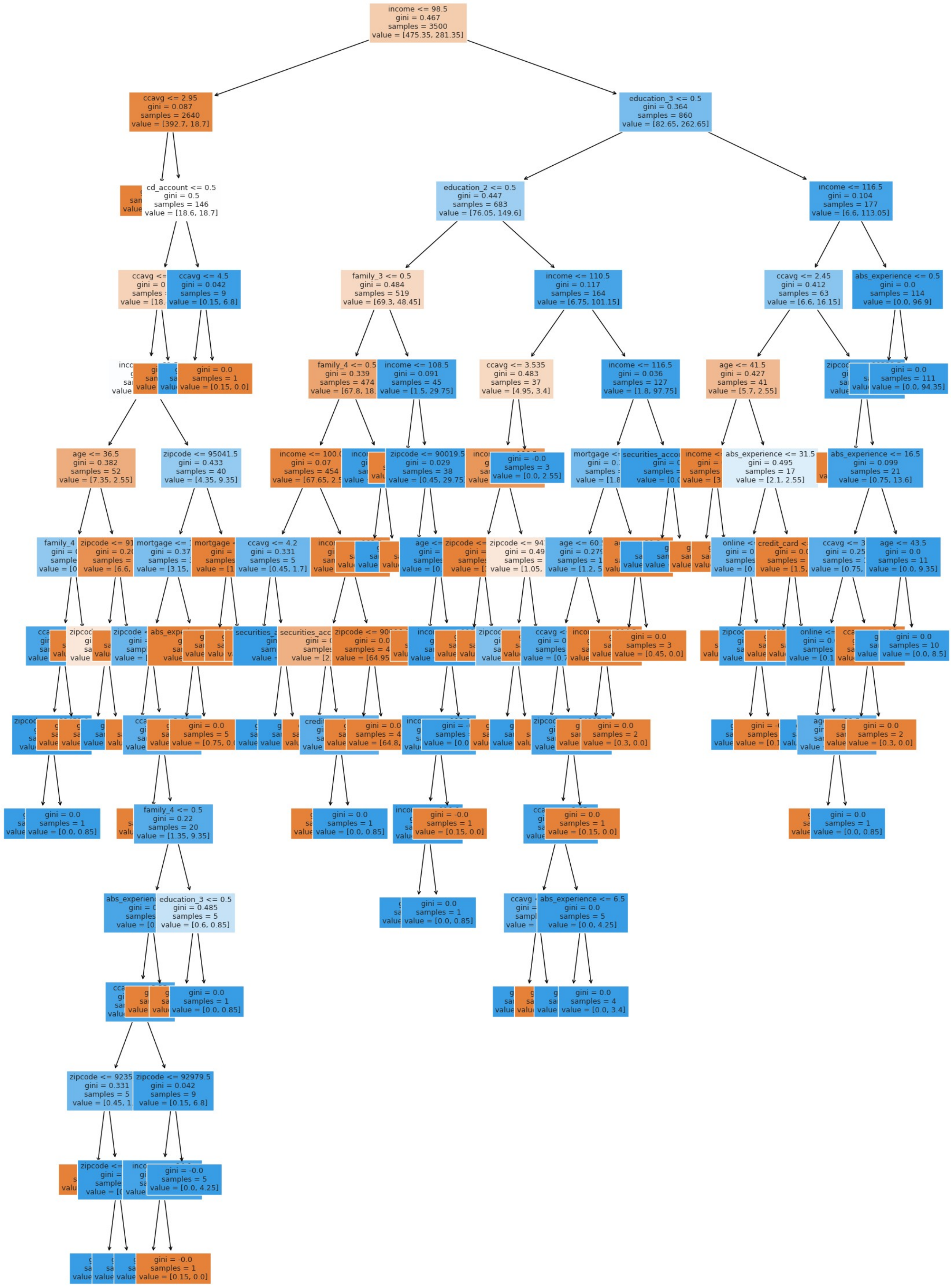
```
Recall on training set :  1.0
Recall on test set :  0.8859060402684564
```

Visualizing the decision tree from baseline model

```
feature_names = list(X.columns)
print(feature_names)
```

```
['age', 'income', 'zipcode', 'ccavg', 'mortgage', 
'securities_account', 'cd_account', 'online', 'credit_card', 
'abs_experience', 'education_2', 'education_3', 'family_2', 
'family_3', 'family_4']
```

```
plt.figure(figsize=(20, 30))
out = tree.plot_tree(model,
                     feature_names=feature_names,
                     filled=True,
                     fontsize=9,
                     node_ids=False,
                     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()
```


income <= 98.5
gini = 0.467
samples = 3500
value = [475.35, 281.35]
ccavg <= 2.95
gini = 0.087
samples = 2640
value = [392.7, 18.7]
education_3 <= 0.5
gini = 0.364
samples = 860
value = [82.65, 262.65]
cd_account <= 0.5
gini = 0.5
samples = 146
value = [18.6, 18.7]
education_2 <= 0.5
gini = 0.447
samples = 683
value = [76.05, 149.6]
income <= 116.5
gini = 0.104
samples = 177
value = [6.6, 113.05]
ccavg <= 4.5
gini = 0.042
samples = 9
value = [0.15, 6.8]
family_3 <= 0.5
gini = 0.484
samples = 519
value = [69.3, 48.45]
income <= 110.5
gini = 0.117
samples = 164
value = [6.75, 101.15]
ccavg <= 2.45
gini = 0.412
samples = 63
value = [6.6, 16.15]
abs_experience <= 0.5
gini = 0.0
samples = 114
value = [0.0, 96.9]
gini = 0.0
samples = 1
value = [0.15, 0.0]
income <= 108.5
gini = 0.091
samples = 45
value = [1.5, 29.75]
ccavg <= 3.535
gini = 0.483
samples = 37
value = [4.95, 3.4]
income <= 116.5
gini = 0.036
samples = 127
value = [1.8, 97.75]
age <= 41.5
gini = 0.427
samples = 41
value = [5.7, 2.55]
gini = 0.0
samples = 111
value = [0.0, 94.35]
age <= 36.5
gini = 0.382
samples = 52
value = [7.35, 2.55]
zipcode <= 95041.5
gini = 0.433
samples = 40
value = [4.35, 9.35]
zipcode <= 90019.5
gini = 0.029
samples = 38
value = [0.45, 29.75]
gini = -0.0
samples = 3
value = [0.0, 2.55]
abs_experience <= 31.5
gini = 0.495
samples = 17
value = [2.1, 2.55]
abs_experience <= 16.5
gini = 0.099
samples = 21
value = [0.75, 13.6]
ccavg <= 4.2
gini = 0.331
samples = 5
value = [0.45, 1.7]
age <= 43.5
gini = 0.0
samples = 11
value = [0.0, 9.35]
gini = 0.0
samples = 3
value = [0.45, 0.0]
gini = 0.0
samples = 10
value = [0.0, 8.5]
gini = 0.0
samples = 5
value = [0.75, 0.0]
gini = 0.0
samples = 2
value = [0.3, 0.0]
gini = 0.0
samples = 1
value = [0.0, 0.85]
family_4 <= 0.5
gini = 0.22
samples = 20
value = [1.35, 9.35]
gini = -0.0
samples = 1
value = [0.15, 0.0]
education_3 <= 0.5
gini = 0.485
samples = 5
value = [0.6, 0.85]
abs_experience <= 6.5
gini = 0.0
samples = 5
value = [0.0, 4.25]
gini = 0.0
samples = 4
value = [0.0, 3.4]
zipcode <= 92979.5
gini = 0.042
samples = 9
value = [0.15, 6.8]
gini = -0.0
samples = 5
value = [0.0, 4.25]

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

```
|--- income <= 98.50
|   |--- ccavg <= 2.95
|   |   |--- weights: [374.10, 0.00] class: 0
|   |--- ccavg >  2.95
|   |   |--- cd_account <= 0.50
|   |   |   |--- ccavg <= 3.95
|   |   |   |   |--- income <= 81.50
|   |   |   |   |   |--- age <= 36.50
|   |   |   |   |   |   |--- family_4 <= 0.50
|   |   |   |   |   |   |   |--- ccavg <= 3.50
|   |   |   |   |   |   |   |   |--- zipcode <= 92453.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class:
1
|   |   |   |   |   |   |   |   |--- zipcode >  92453.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class:
1
|   |   |   |   |   |   |   |--- ccavg >  3.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |--- family_4 >  0.50
|   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |--- age >  36.50
|   |   |   |   |   |   |--- zipcode <= 91269.00
|   |   |   |   |   |   |   |--- zipcode <= 90974.00
|   |   |   |   |   |   |   |   |--- weights: [1.05, 0.00] class: 0
|   |   |   |   |   |   |   |--- zipcode >  90974.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |--- zipcode >  91269.00
|   |   |   |   |   |   |   |--- weights: [5.55, 0.00] class: 0
|   |   |   |   |--- income >  81.50
|   |   |   |   |   |--- zipcode <= 95041.50
|   |   |   |   |   |   |--- mortgage <= 152.00
|   |   |   |   |   |   |   |--- zipcode <= 91335.50
|   |   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |   |   |--- zipcode >  91335.50
|   |   |   |   |   |   |   |   |--- ccavg <= 3.05
|   |   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class:
0
|   |   |   |   |   |   |   |   |--- ccavg >  3.05
|   |   |   |   |   |   |   |   |   |--- family_4 <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- abs_experience <= 39.00
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of
depth 4
|   |   |   |   |   |   |   |   |   |   |--- abs_experience >  39.00
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00]
class: 0
|   |   |   |   |   |   |   |   |   |--- family_4 >  0.50
```

```
|   |   |   |   |   |   |   |   |   |   |--- education_3 <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.60, 0.00]
class: 0
|   |   |   |   |   |   |   |   |   |   |--- education_3 >  0.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85]
class: 1
|   |   |   |   |   |   |--- mortgage >  152.00
|   |   |   |   |   |   |   |--- abs_experience <= 11.00
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- abs_experience >  11.00
|   |   |   |   |   |   |   |   |--- weights: [0.75, 0.00] class: 0
|   |   |   |   |   |--- zipcode >  95041.50
|   |   |   |   |   |   |--- mortgage <= 56.00
|   |   |   |   |   |   |   |--- weights: [0.90, 0.00] class: 0
|   |   |   |   |   |   |--- mortgage >  56.00
|   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |--- ccavg >  3.95
|   |   |   |   |--- weights: [6.75, 0.00] class: 0
|   |   |--- cd_account >  0.50
|   |   |   |--- ccavg <= 4.50
|   |   |   |   |--- weights: [0.00, 6.80] class: 1
|   |   |   |--- ccavg >  4.50
|   |   |   |   |--- weights: [0.15, 0.00] class: 0
|--- income >  98.50
|   |--- education_3 <= 0.50
|   |   |--- education_2 <= 0.50
|   |   |   |--- family_3 <= 0.50
|   |   |   |   |--- family_4 <= 0.50
|   |   |   |   |   |--- income <= 100.00
|   |   |   |   |   |   |--- ccavg <= 4.20
|   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |--- ccavg >  4.20
|   |   |   |   |   |   |   |--- securities_account <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |--- securities_account >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |--- income >  100.00
|   |   |   |   |   |   |--- income <= 103.50
|   |   |   |   |   |   |   |--- securities_account <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [2.10, 0.00] class: 0
|   |   |   |   |   |   |   |--- securities_account >  0.50
|   |   |   |   |   |   |   |   |--- credit_card <= 0.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class:
0
|   |   |   |   |   |   |   |   |--- credit_card >  0.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class:
1
|   |   |   |   |   |   |--- income >  103.50
|   |   |   |   |   |   |   |--- zipcode <= 90006.00
```

```
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- zipcode >  90006.00
|   |   |   |   |   |   |   |   |--- weights: [64.80, 0.00] class: 0
|   |   |   |   |--- family_4 >  0.50
|   |   |   |   |   |--- income <= 102.00
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- income >  102.00
|   |   |   |   |   |   |--- weights: [0.00, 16.15] class: 1
|   |   |   |--- family_3 >  0.50
|   |   |   |   |--- income <= 108.50
|   |   |   |   |   |--- weights: [1.05, 0.00] class: 0
|   |   |   |   |--- income >  108.50
|   |   |   |   |   |--- zipcode <= 90019.50
|   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- zipcode >  90019.50
|   |   |   |   |   |   |--- age <= 26.00
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |--- age >  26.00
|   |   |   |   |   |   |   |--- income <= 118.00
|   |   |   |   |   |   |   |   |--- income <= 112.00
|   |   |   |   |   |   |   |   |   |--- income <= 110.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85]
class: 1
|   |   |   |   |   |   |   |   |   |--- income >  110.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85]
class: 1
|   |   |   |   |   |   |   |   |--- income >  112.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class:
0
|   |   |   |   |   |   |   |--- income >  118.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 28.05] class: 1
|   |   |--- education_2 >  0.50
|   |   |   |--- income <= 110.50
|   |   |   |   |--- ccavg <= 3.54
|   |   |   |   |   |--- income <= 106.50
|   |   |   |   |   |   |--- zipcode <= 90128.50
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |--- zipcode >  90128.50
|   |   |   |   |   |   |   |--- weights: [3.75, 0.00] class: 0
|   |   |   |   |   |--- income >  106.50
|   |   |   |   |   |   |--- zipcode <= 94126.50
|   |   |   |   |   |   |   |--- zipcode <= 92910.50
|   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |--- zipcode >  92910.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |--- zipcode >  94126.50
|   |   |   |   |   |   |   |--- weights: [0.75, 0.00] class: 0
|   |   |   |   |--- ccavg >  3.54
|   |   |   |   |   |--- weights: [0.00, 2.55] class: 1
```

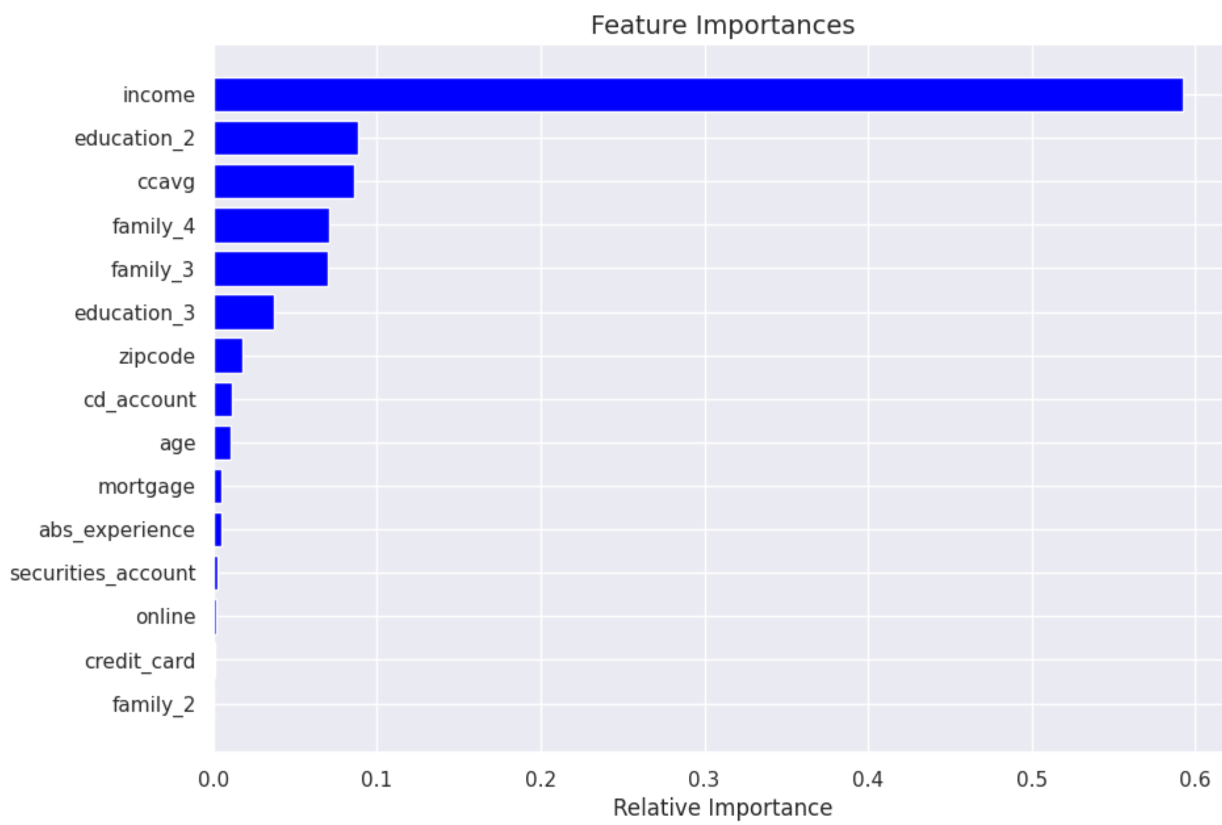
```
|   |   |   |--- income >  110.50
|   |   |   |   |--- income <= 116.50
|   |   |   |   |   |--- mortgage <= 141.50
|   |   |   |   |   |   |--- age <= 60.50
|   |   |   |   |   |   |   |--- ccavg <= 1.20
|   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |--- ccavg >  1.20
|   |   |   |   |   |   |   |   |--- zipcode <= 94887.00
|   |   |   |   |   |   |   |   |   |--- ccavg <= 2.65
|   |   |   |   |   |   |   |   |   |   |--- ccavg <= 1.75
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.70]
class: 1
|   |   |   |   |   |   |   |   |   |   |--- ccavg >  1.75
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00]
class: 0
|   |   |   |   |   |   |   |   |   |--- ccavg >  2.65
|   |   |   |   |   |   |   |   |   |   |--- abs_experience <= 6.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85]
class: 1
|   |   |   |   |   |   |   |   |   |   |--- abs_experience >  6.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 3.40]
class: 1
|   |   |   |   |   |   |   |   |--- zipcode >  94887.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class:
0
|   |   |   |   |   |   |--- age >  60.50
|   |   |   |   |   |   |   |--- income <= 114.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- income >  114.50
|   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |--- mortgage >  141.50
|   |   |   |   |   |   |--- age <= 30.00
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |--- age >  30.00
|   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |--- income >  116.50
|   |   |   |   |   |--- securities_account <= 0.50
|   |   |   |   |   |   |--- weights: [0.00, 80.75] class: 1
|   |   |   |   |   |--- securities_account >  0.50
|   |   |   |   |   |   |--- weights: [0.00, 11.05] class: 1
|   |--- education_3 >  0.50
|   |   |--- income <= 116.50
|   |   |   |--- ccavg <= 2.45
|   |   |   |   |--- age <= 41.50
|   |   |   |   |   |--- income <= 99.50
|   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |--- income >  99.50
|   |   |   |   |   |   |--- weights: [3.30, 0.00] class: 0
|   |   |   |   |--- age >  41.50
```

```
|   |   |   |   |   |--- abs_experience <= 31.50
|   |   |   |   |   |   |--- online <= 0.50
|   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |--- online >  0.50
|   |   |   |   |   |   |   |--- zipcode <= 93596.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 2.55] class: 1
|   |   |   |   |   |   |   |--- zipcode >  93596.00
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- abs_experience >  31.50
|   |   |   |   |   |   |--- credit_card <= 0.50
|   |   |   |   |   |   |   |--- weights: [0.75, 0.00] class: 0
|   |   |   |   |   |   |--- credit_card >  0.50
|   |   |   |   |   |   |   |--- weights: [0.75, 0.00] class: 0
|   |   |   |--- ccavg >  2.45
|   |   |   |   |--- zipcode <= 90389.50
|   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |--- zipcode >  90389.50
|   |   |   |   |   |--- abs_experience <= 16.50
|   |   |   |   |   |   |--- ccavg <= 3.90
|   |   |   |   |   |   |   |--- online <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 3.40] class: 1
|   |   |   |   |   |   |   |--- online >  0.50
|   |   |   |   |   |   |   |   |--- age <= 32.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class:
0
|   |   |   |   |   |   |   |   |--- age >  32.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class:
1
|   |   |   |   |   |   |--- ccavg >  3.90
|   |   |   |   |   |   |   |--- ccavg <= 4.25
|   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |   |   |--- ccavg >  4.25
|   |   |   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |   |   |   |--- abs_experience >  16.50
|   |   |   |   |   |   |--- age <= 43.50
|   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |--- age >  43.50
|   |   |   |   |   |   |   |--- weights: [0.00, 8.50] class: 1
|   |   |--- income >  116.50
|   |   |   |--- abs_experience <= 0.50
|   |   |   |   |--- weights: [0.00, 2.55] class: 1
|   |   |   |--- abs_experience >  0.50
|   |   |   |   |--- weights: [0.00, 94.35] class: 1
```

Feature importance from baseline model

```python
def importance_plot(model):
    """
```

```
    Displays feature importance barplot
    model: decision tree classifier
    """
    importances = model.feature_importances_
    indices = np.argsort(importances)
    size = len(indices)//2 # to help scale the plot.

    plt.figure(figsize=(10, size))
    plt.title("Feature Importances", fontsize=14)
    plt.barh(range(len(indices)), importances[indices], color='blue',
align='center')
    plt.yticks(range(len(indices)), [feature_names[i] for i in
indices])
    plt.xlabel("Relative Importance", fontsize=12);

importance_plot(model=model)
```




```
# importance of features in the tree building ( The importance of a
feature is computed as the
#(normalized) total reduction of the criterion brought by that
feature. It is also known as the Gini importance )
pd.DataFrame(model.feature_importances_,
                   columns=["Imp"],
```

```
                   index=X_train.columns).sort_values(by='Imp',
ascending=False)
```

```
                           Imp
income                0.592431
education_2           0.088134
ccavg                 0.085866
family_4              0.071136
family_3              0.070324
education_3           0.037138
zipcode               0.017887
cd_account            0.011000
age                   0.010398
mortgage              0.005239
abs_experience        0.004911
securities_account    0.002769
online                0.002045
credit_card           0.000721
family_2              0.000000
```

Using GridSearch for hyperparameter tuning of our tree model.

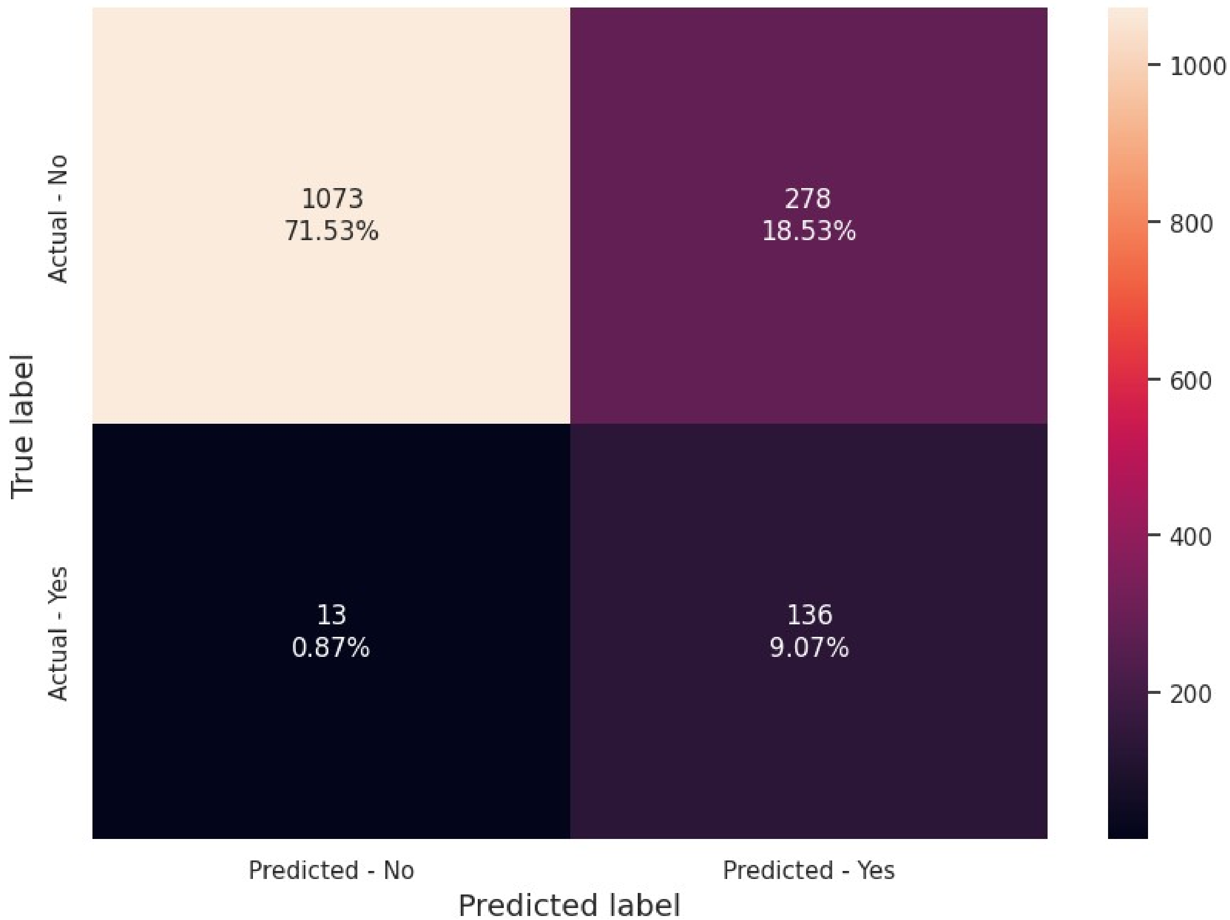
```
# Choose the type of classifier.
estimator = DecisionTreeClassifier(random_state=1,
class_weight={0:.15,1:.85})

# Grid of parameters to choose from
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']}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

# Run the grid search
grid_obj = GridSearchCV(estimator, param_grid=parameters,
scoring=scorer, cv=5)
grid_obj = grid_obj.fit(X_train, y_train)

# Set the clf to the best combination of parameters
estimator = grid_obj.best_estimator_

# Fit the best algorithm to the data.
estimator.fit(X_train, y_train)
```

```
DecisionTreeClassifier(class_weight={0: 0.15, 1: 0.85},
criterion='entropy',
```

```
                            max_depth=3, max_features='log2',
                            min_impurity_decrease=1e-06, random_state=1)
```

Confusion matrix using GridSearchCV

```
make_confusion_matrix(estimator, y_test)
```



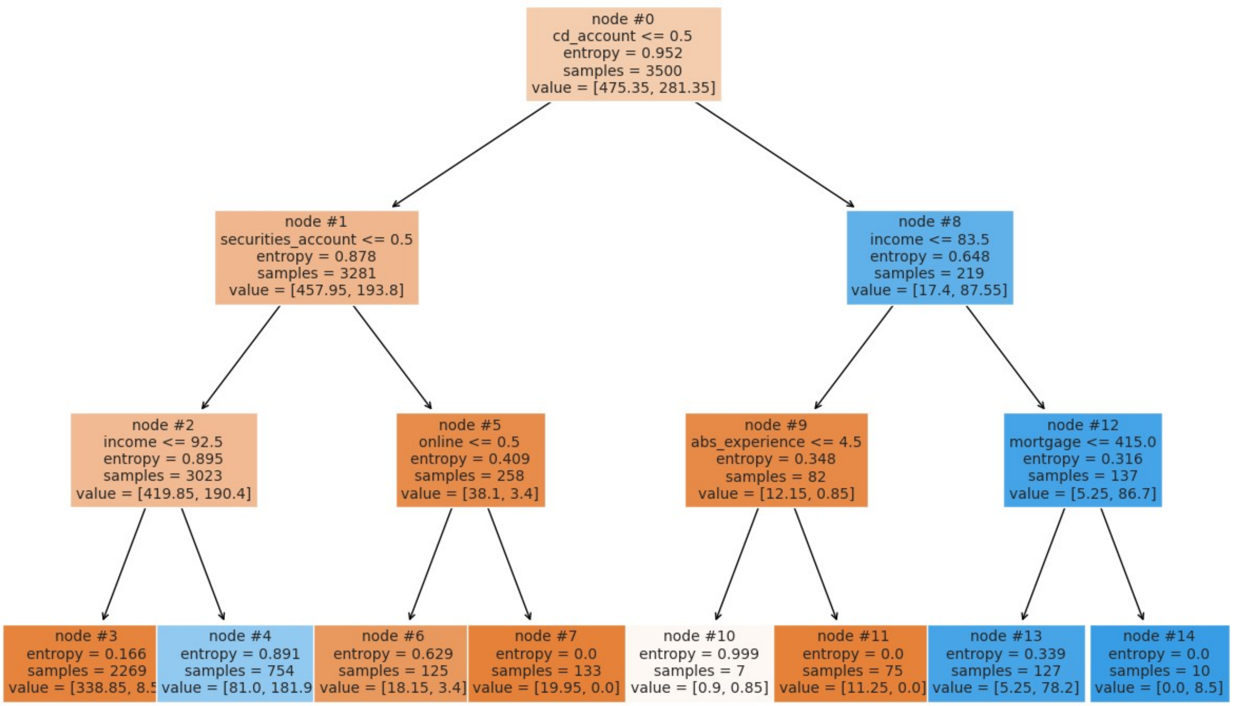
Recall score using GridSearchCV

```
get_recall_score(estimator)

Recall on training set :  0.9546827794561934
Recall on test set :  0.912751677852349
```

Visualizing the decision tree from the best fit estimator using GridSearchCV

```
plt.figure(figsize=(15, 10))
out = tree.plot_tree(estimator,
                     feature_names=feature_names,
                     filled=True,
```

```
                     fontsize=10,
                     node_ids=True,
                     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()
```




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

|--- cd_account <= 0.50
|   |--- securities_account <= 0.50
|   |   |--- income <= 92.50
|   |   |   |--- weights: [338.85, 8.50] class: 0
|   |   |--- income >  92.50
|   |   |   |--- weights: [81.00, 181.90] class: 1
|   |--- securities_account >  0.50
|   |   |--- online <= 0.50
|   |   |   |--- weights: [18.15, 3.40] class: 0
```

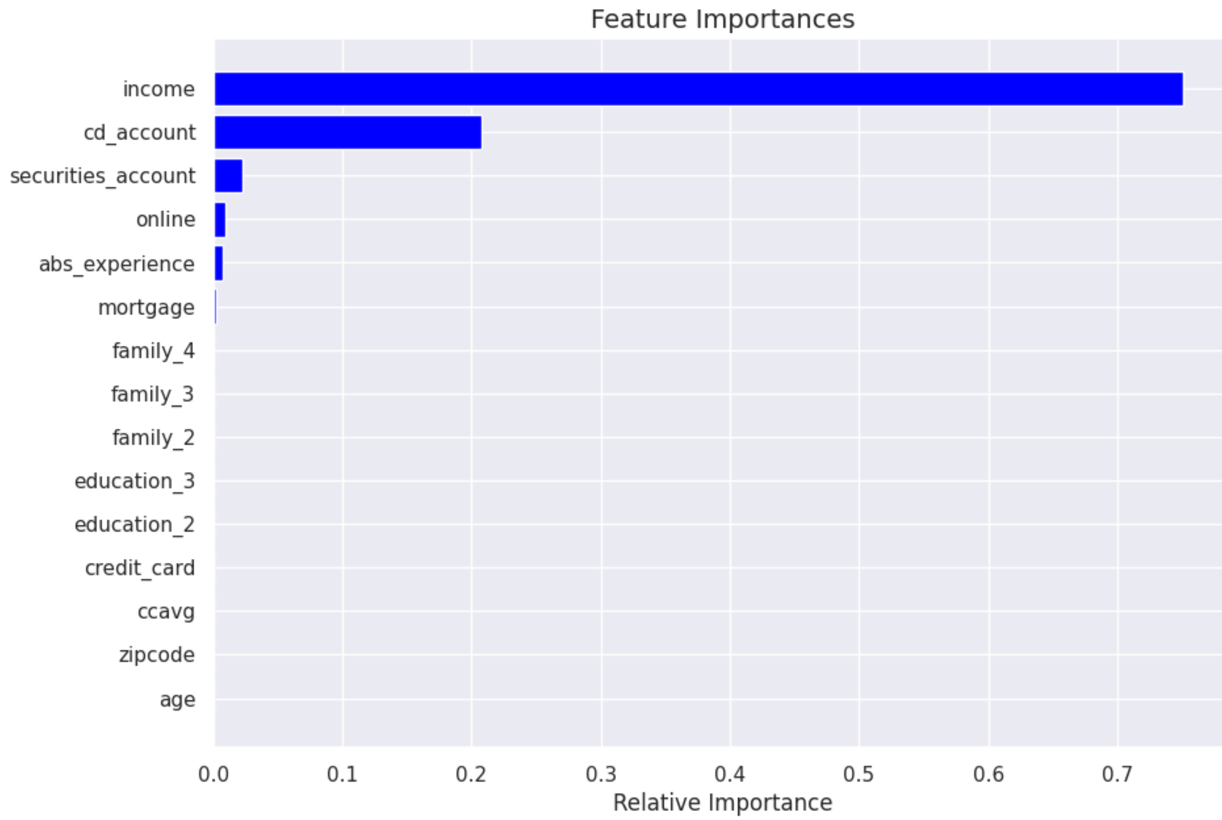
```
|   |   |--- online >  0.50
|   |   |   |--- weights: [19.95, 0.00] class: 0
|--- cd_account >  0.50
|   |--- income <= 83.50
|   |   |--- abs_experience <= 4.50
|   |   |   |--- weights: [0.90, 0.85] class: 0
|   |   |--- abs_experience >  4.50
|   |   |   |--- weights: [11.25, 0.00] class: 0
|   |--- income >  83.50
|   |   |--- mortgage <= 415.00
|   |   |   |--- weights: [5.25, 78.20] class: 1
|   |   |--- mortgage >  415.00
|   |   |   |--- weights: [0.00, 8.50] class: 1
```

Feature importance using GridSearchCV

```
# importance of features in the tree building ( The importance of a
feature is computed as the
#(normalized) total reduction of the 'criterion' brought by that
feature. It is also known as the Gini importance )
pd.DataFrame(estimator.feature_importances_,
             columns=["Imp"],
             index=X_train.columns).sort_values(by='Imp',
ascending=False)
#Here we will see that importance of features has increased
```

	Imp
income	0.750812
cd_account	0.208201
securities_account	0.022921
online	0.008875
abs_experience	0.007224
mortgage	0.001968
age	0.000000
zipcode	0.000000
ccavg	0.000000
credit_card	0.000000
education_2	0.000000
education_3	0.000000
family_2	0.000000
family_3	0.000000
family_4	0.000000

```
importance_plot(model=estimator)
```



Cost Complexity Pruning

The `DecisionTreeClassifier` provides parameters such as `min_samples_leaf` and `max_depth` to prevent a tree from overfiting. Cost complexity pruning provides another option to control the size of a tree. In `DecisionTreeClassifier`, this pruning technique is parameterized by the cost complexity parameter, `ccp_alpha`. Greater values of `ccp_alpha` increase the number of nodes pruned. Here we only show the effect of `ccp_alpha` on regularizing the trees and how to choose a `ccp_alpha` based on validation scores.

Total impurity of leaves vs effective alphas of pruned tree

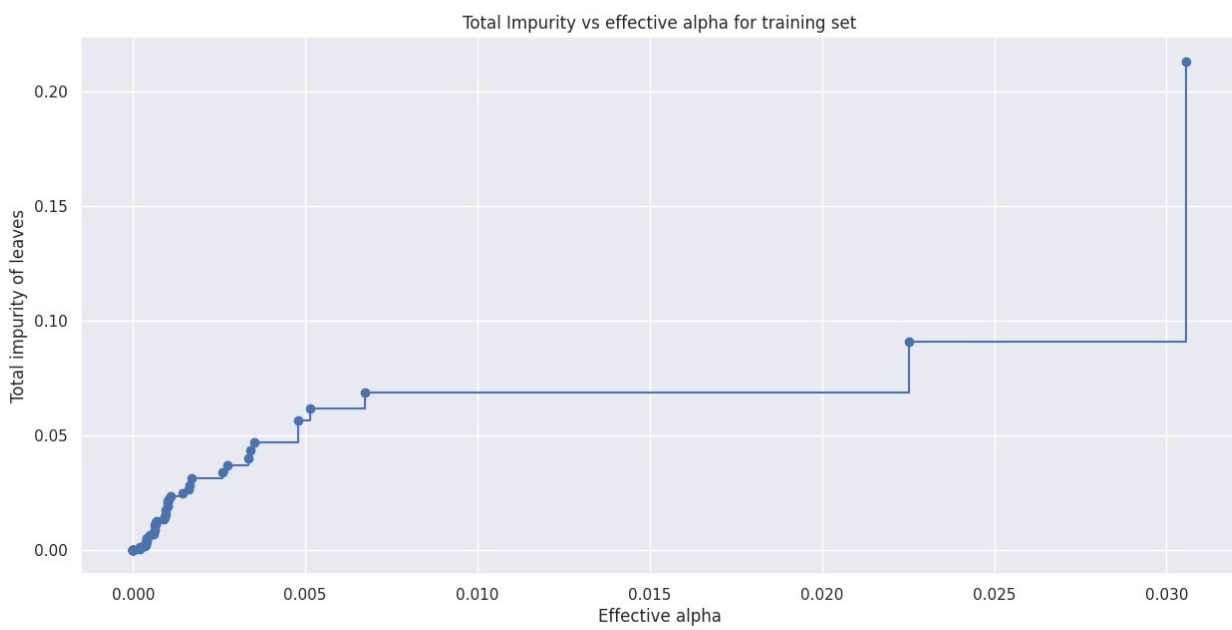
Minimal cost complexity pruning recursively finds the node with the "weakest link". The weakest link is characterized by an effective alpha, where the nodes with the smallest effective alpha are pruned first. To get an idea of what values of `ccp_alpha` could be appropriate, scikit-learn provides `DecisionTreeClassifier.cost_complexity_pruning_path` that returns the effective alphas and the corresponding total leaf impurities at each step of the pruning process. As alpha increases, more of the tree is pruned, which increases the total impurity of its leaves.

```
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

pd.DataFrame(path)
```

	ccp_alphas	impurities
0	0.000000e+00	-6.298297e-15
1	7.482671e-19	-6.297548e-15
2	7.482671e-19	-6.296800e-15
3	7.482671e-19	-6.296052e-15
4	7.482671e-19	-6.295303e-15
5	2.420864e-18	-6.292883e-15
6	2.494224e-18	-6.290388e-15
7	2.905037e-18	-6.287483e-15
8	3.521257e-18	-6.283962e-15
9	4.115469e-18	-6.279847e-15
10	4.665666e-18	-6.275181e-15
11	6.998499e-18	-6.268182e-15
12	7.042514e-18	-6.261140e-15
13	7.394640e-18	-6.253745e-15
14	7.438656e-18	-6.246307e-15
15	8.081285e-17	-6.165494e-15
16	1.143528e-16	-6.051141e-15
17	2.985586e-16	-5.752582e-15
18	1.914713e-04	3.829427e-04
19	1.939508e-04	7.708443e-04
20	1.972347e-04	1.165314e-03
21	3.369896e-04	1.502303e-03
22	3.643130e-04	1.866616e-03
23	3.685823e-04	2.972363e-03
24	3.744328e-04	3.346796e-03
25	3.879017e-04	3.734698e-03
26	3.885915e-04	4.511881e-03
27	3.928099e-04	4.904691e-03
28	4.778878e-04	6.338354e-03
29	5.860688e-04	6.924423e-03
30	6.160535e-04	8.772584e-03
31	6.284400e-04	1.065790e-02
32	6.546462e-04	1.131255e-02
33	6.554717e-04	1.196802e-02
34	6.758139e-04	1.264384e-02
35	8.789656e-04	1.352280e-02
36	9.093369e-04	1.443214e-02
37	9.404360e-04	1.537257e-02
38	9.407728e-04	1.725412e-02
39	9.951370e-04	1.924439e-02
40	1.011155e-03	2.025555e-02
41	1.013173e-03	2.126872e-02
42	1.018946e-03	2.228767e-02
43	1.086501e-03	2.337417e-02
44	1.434181e-03	2.480835e-02
45	1.619124e-03	2.642747e-02
46	1.638043e-03	2.806552e-02
47	1.686407e-03	3.143833e-02
48	2.602631e-03	3.404096e-02

```
49  2.742431e-03  3.678339e-02
50  3.335999e-03  4.011939e-02
51  3.409906e-03  4.352930e-02
52  3.527226e-03  4.705652e-02
53  4.797122e-03  5.665076e-02
54  5.138280e-03  6.178904e-02
55  6.725814e-03  6.851486e-02
56  2.253222e-02  9.104708e-02
57  3.057320e-02  2.133399e-01
58  2.537957e-01  4.671356e-01
```

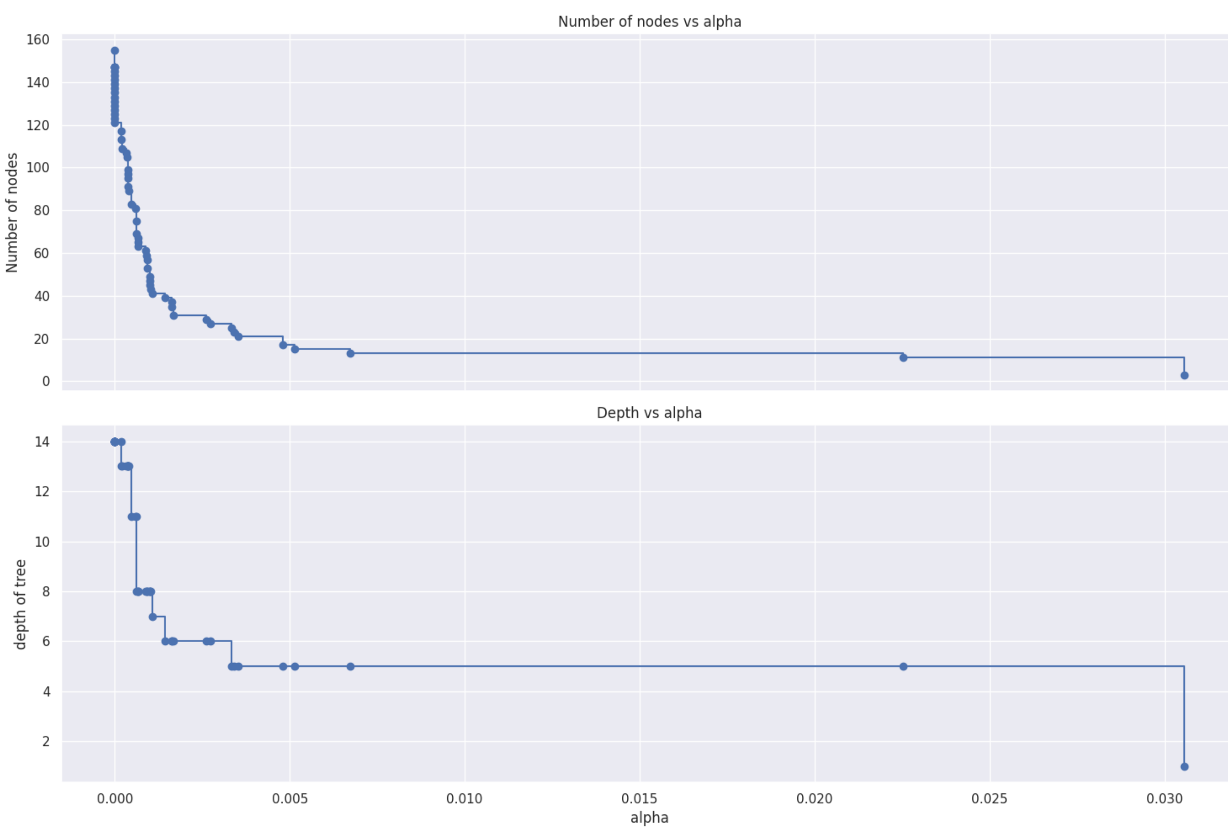
```
fig, ax = plt.subplots(figsize=(15, 7))
ax.plot(ccp_alphas[:-1], impurities[:-1], marker='o',
drawstyle="steps-post")
ax.set_xlabel("Effective alpha")
ax.set_ylabel("Total impurity of leaves")
ax.set_title("Total Impurity vs effective alpha for training set")
plt.show()
```




```
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(f"Number of nodes in the last tree is: {clfs[-
1].tree_.node_count} with ccp_alpha: {ccp_alphas[-1]}")
```

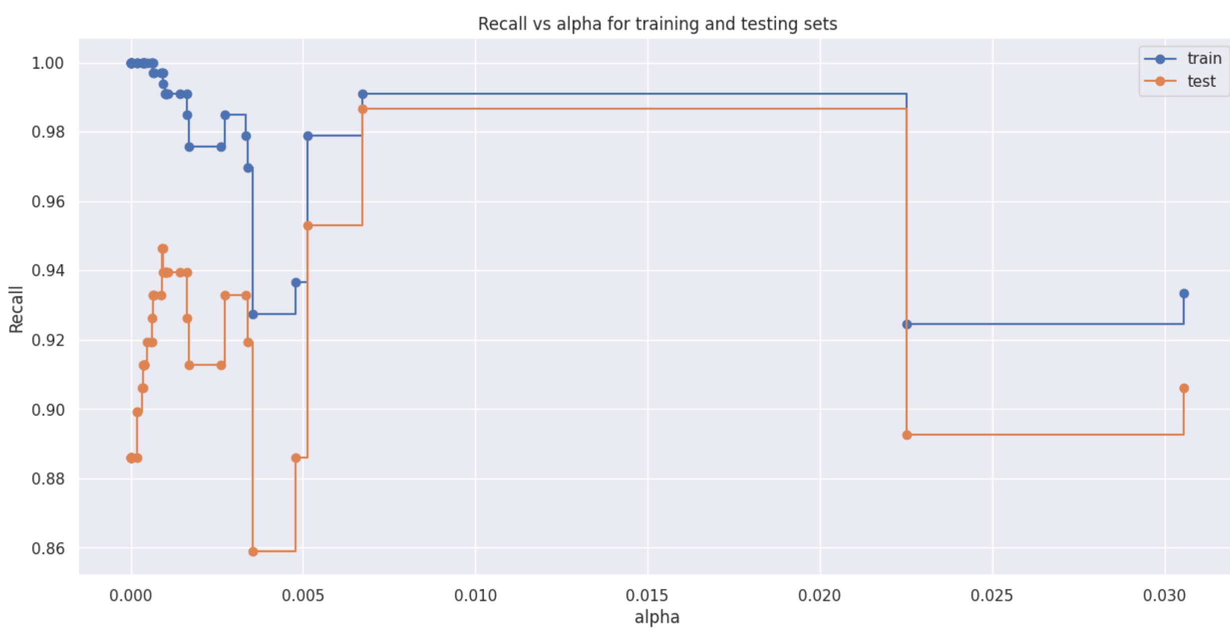
```
Number of nodes in the last tree is: 1 with ccp_alpha:
0.2537957148948104
```

```
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=(15, 10), sharex=True)
ax[0].plot(ccp_alphas, node_counts, marker='o', drawstyle="steps-
post")
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()
```



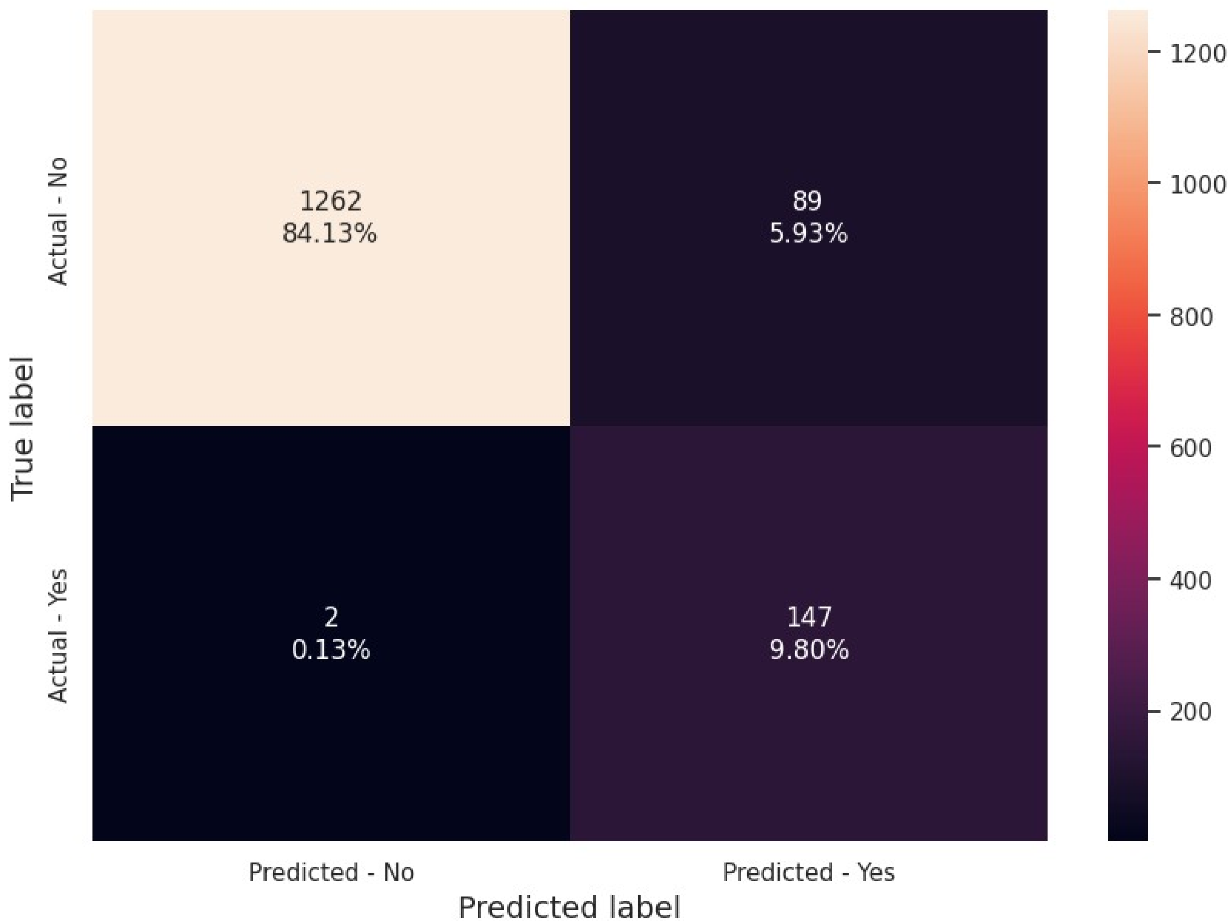

```
recall_train = []
for clf in clfs:
    pred_train3 = clf.predict(X_train)
    values_train = metrics.recall_score(y_train, pred_train3)
    recall_train.append(values_train)
```

```
recall_test = []
for clf in clfs:
    pred_test3 = clf.predict(X_test)
    values_test = metrics.recall_score(y_test, pred_test3)
    recall_test.append(values_test)

train_scores = [clf.score(X_train, y_train) for clf in clfs]
test_scores = [clf.score(X_test, y_test) for clf in clfs]

fig, ax = plt.subplots(figsize=(15, 7))
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.plot(ccp_alphas,
        recall_test,
        marker='o',
        label="test",
        drawstyle="steps-post")
ax.legend()
plt.show()
```




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

```
DecisionTreeClassifier(ccp_alpha=0.006725813690406986,
                       class_weight={0: 0.15, 1: 0.85},
random_state=1)

best_model.fit(X_train, y_train)

DecisionTreeClassifier(ccp_alpha=0.006725813690406986,
                       class_weight={0: 0.15, 1: 0.85},
random_state=1)

make_confusion_matrix(best_model, y_test)
```

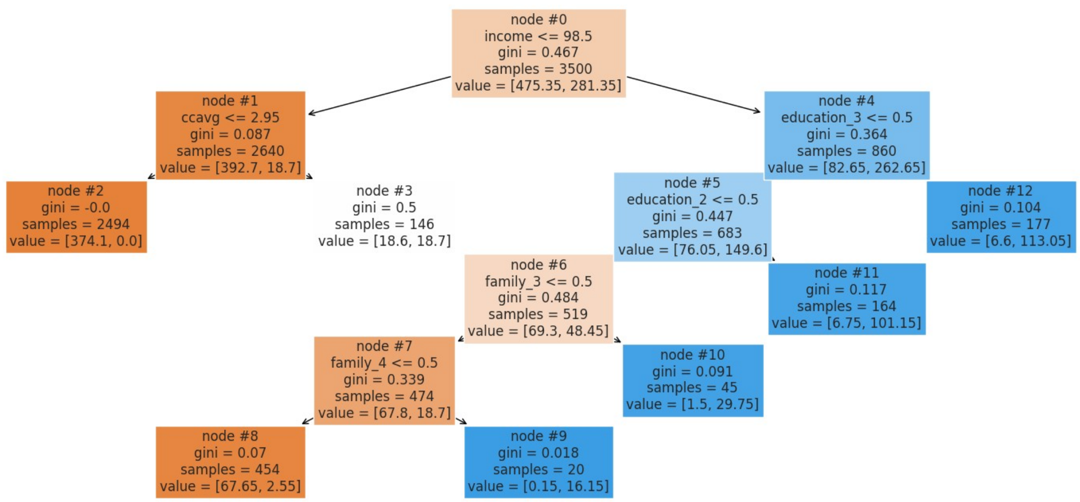



```
get_recall_score(best_model)

Recall on training set :  0.9909365558912386
Recall on test set :  0.9865771812080537
```

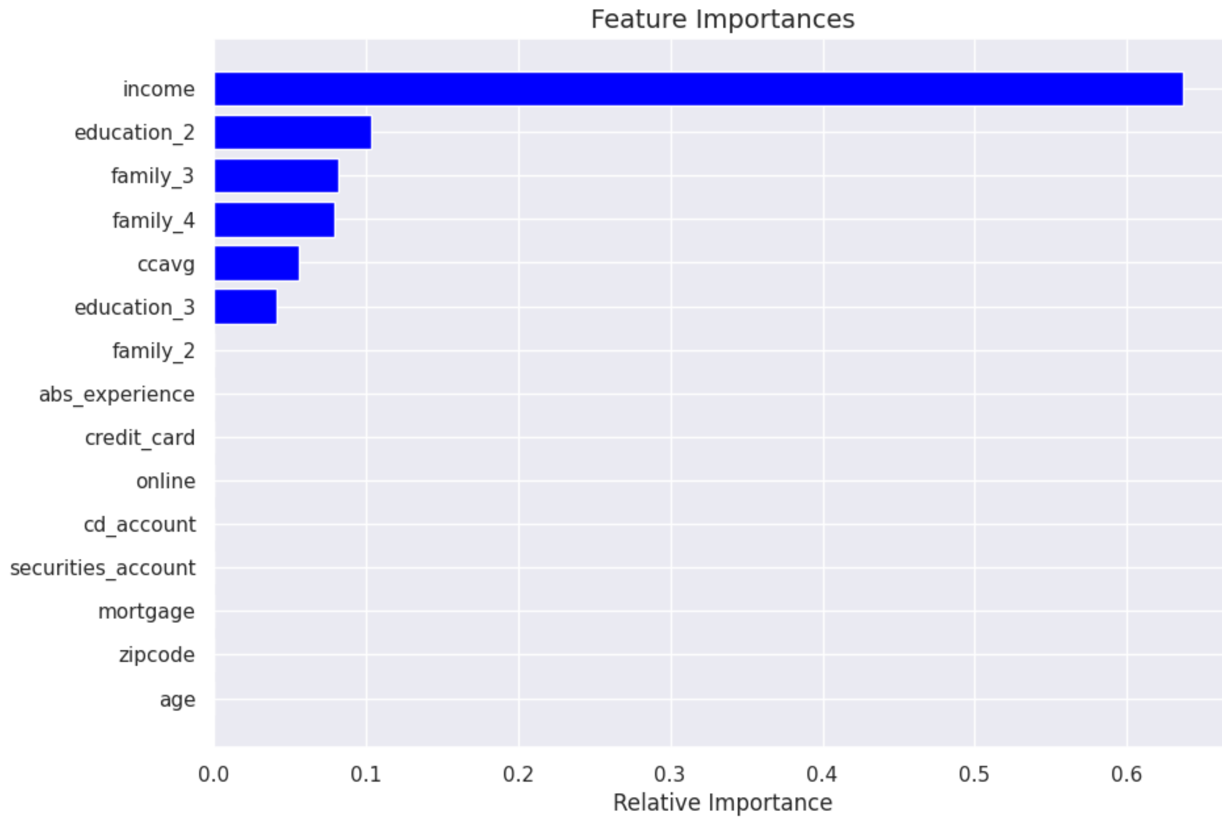
Visualizing the Decision Tree

```
plt.figure(figsize=(20, 8))
```

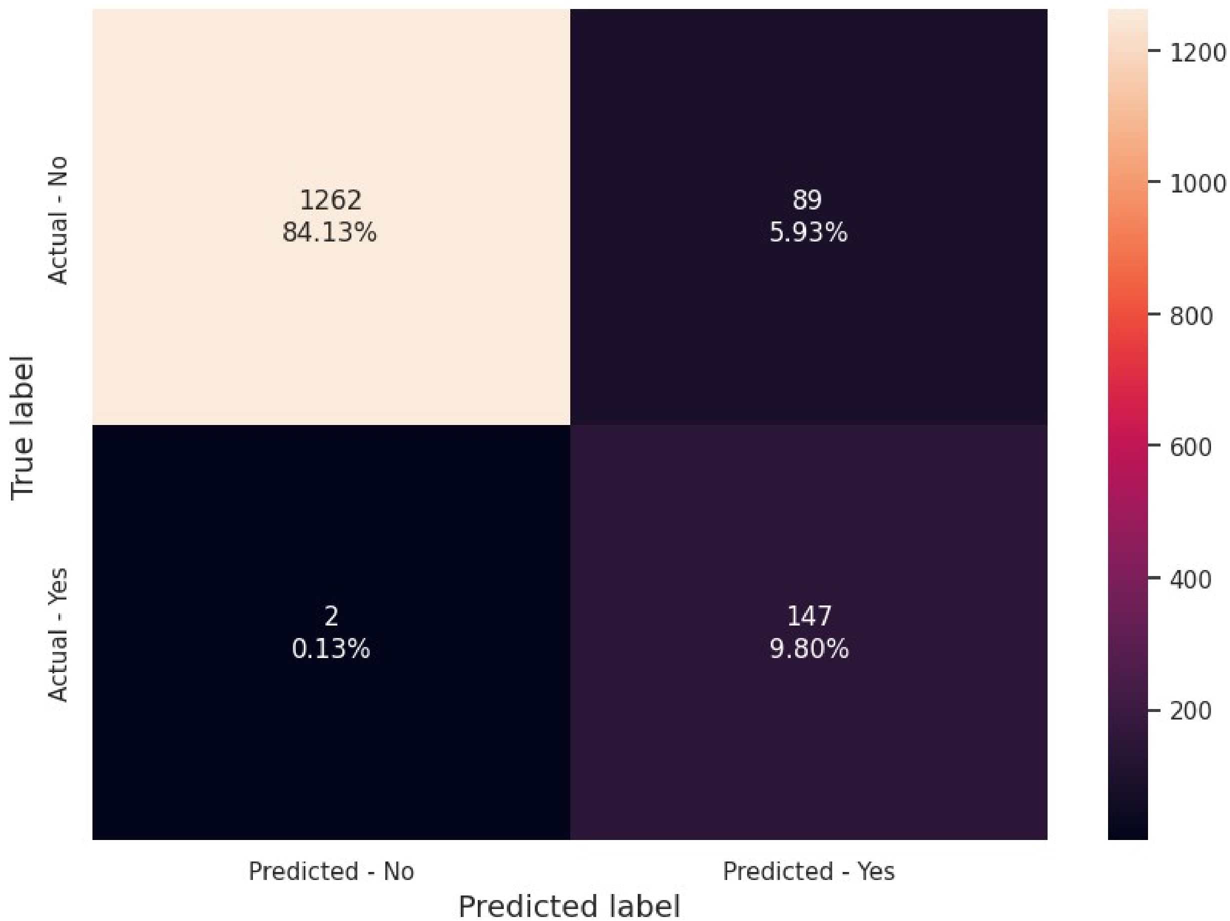
```
out = tree.plot_tree(best_model,
                     feature_names=feature_names,
                     filled=True,
                     fontsize=12,
                     node_ids=True,
                     class_names=None)
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor('black')
        arrow.set_linewidth(1)
plt.show()
```



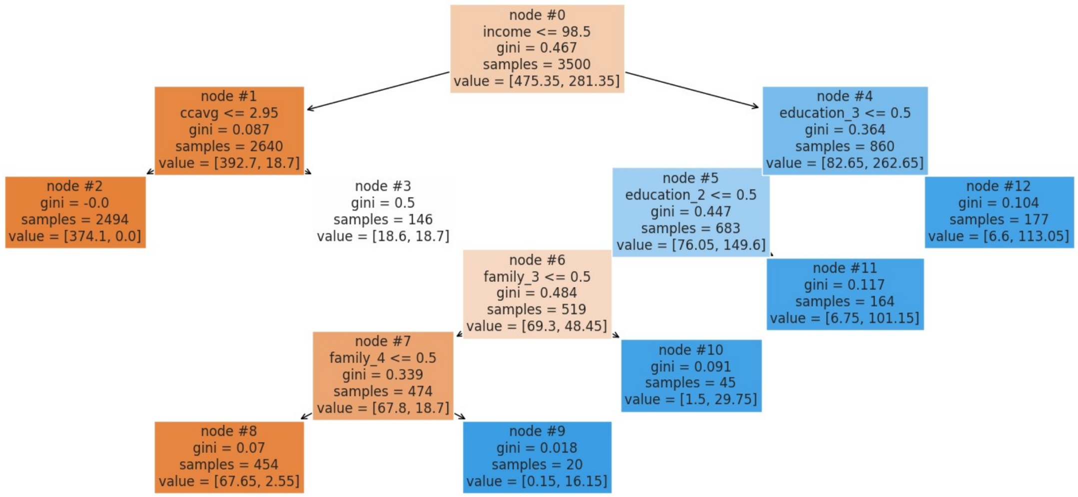

```
# Text report showing the rules of a decision tree -
print(tree.export_text(best_model, feature_names=feature_names,
show_weights=True))

importance_plot(model=best_model)
```




```
best_model2 = DecisionTreeClassifier(ccp_alpha=0.01,
                                     class_weight={0: 0.15, 1: 0.85},
                                     random_state=1)
best_model2.fit(X_train, y_train)

DecisionTreeClassifier(ccp_alpha=0.01, class_weight={0: 0.15, 1:
0.85},
                       random_state=1)

make_confusion_matrix(best_model2, y_test)
```



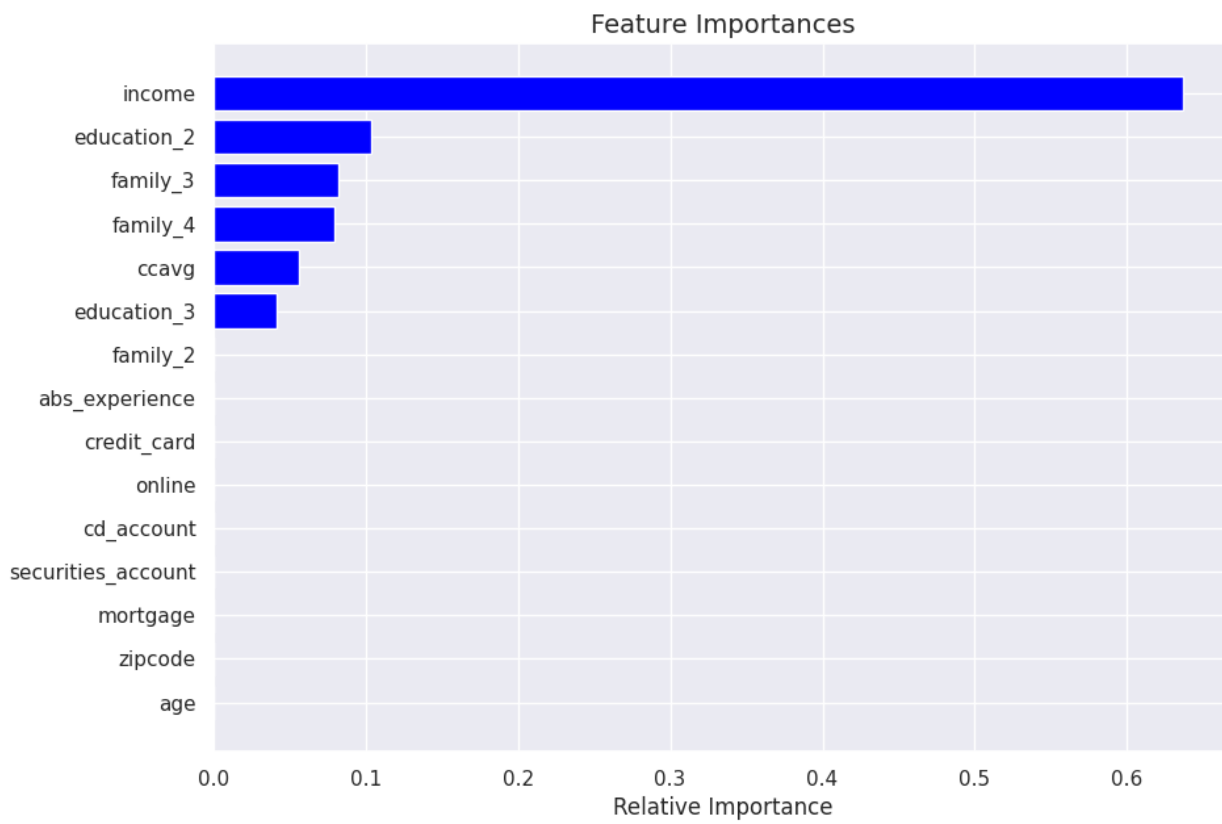

```
get_recall_score(best_model2)

Recall on training set :  0.9909365558912386
Recall on test set :  0.9865771812080537

plt.figure(figsize=(20, 8))

out = tree.plot_tree(best_model2,
                     feature_names=feature_names,
                     filled=True,
                     fontsize=12,
                     node_ids=True,
                     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()
```




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

```
|--- income <= 98.50
|   |--- ccavg <= 2.95
|   |   |--- weights: [374.10, 0.00] class: 0
|   |--- ccavg >  2.95
|   |   |--- weights: [18.60, 18.70] class: 1
|--- income >  98.50
|   |--- education_3 <= 0.50
|   |   |--- education_2 <= 0.50
|   |   |   |--- family_3 <= 0.50
|   |   |   |   |--- family_4 <= 0.50
|   |   |   |   |   |--- weights: [67.65, 2.55] class: 0
|   |   |   |   |--- family_4 >  0.50
|   |   |   |   |   |--- weights: [0.15, 16.15] class: 1
|   |   |   |--- family_3 >  0.50
|   |   |   |   |--- weights: [1.50, 29.75] class: 1
|   |   |--- education_2 >  0.50
|   |   |   |--- weights: [6.75, 101.15] class: 1
|   |--- education_3 >  0.50
|   |   |--- weights: [6.60, 113.05] class: 1
```

```
importance_plot(model=best_model2)
```




```
comparison_frame = pd.DataFrame({'Model':['Initial decision tree
model','Decision treee with hyperparameter tuning',
                                          'Decision tree with post-
pruning'],
                                 'Train_Recall':[1, 0.95, 0.99],
                                 'Test_Recall':[0.91, 0.91, 0.98]})
comparison_frame

                                       Model  Train_Recall
Test_Recall
0                Initial decision tree model          1.00
0.91
1  Decision treee with hyperparameter tuning          0.95
0.91
2            Decision tree with post-pruning          0.99
0.98
```

Decision tree model with post pruning has given the best recall score on data.

Conclusion

- I analyzed the "Potential Loan marketing data" using different techniques and used a Decision Tree Classifier to build a predictive model. The predictive model helps predict whether a liability customer will buy a personal loan or not.

- Income, education, family, and credit card usage are the most important features in predicting potential loan customers.
- Those customers with separate securities and cd accounts are more likely to get a personal loan. Customers who use the bank's online facilities are more likely to get a personal loan versus those customers who don't use the online facilities.
- We established the importance of hyper-parameters/pruning to reduce overfitting during the model selection process.

Recommendations

- From the decision tree model, income is the most important feature. If our customer's yearly income is less than 98.5K, there is a good chance the customer won't have a personal loan.
- From the model, those customers with an income greater than 98.5 and with an education level greater than or equal to 3 (Advanced/Professional) were most likely to have a personal loan. Recommend to target customers that have incomes lower than 98K.
- It was observed that those customers who use the online facilities were more likely to have personal loans. Make the site more user-friendly and encourage those customers who don't use the facilities to use the online facilities. Make the application process to get personal loans easy with a better user experience.