Phase 2

Data preprocessing and analysis

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In [1]:

```
import warnings
warnings.filterwarnings('ignore')
###

%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
df = pd.read_csv("bankloan.csv")
df.head()
```

Out[2]:

	ID	Age	Experience	Income	ZIP.Code	Family	CCAvg	Education	Mortgage	Personal.Loan
0	1	25	1	49	91107	4	1.6	1	0	0
1	2	45	19	34	90089	3	1.5	1	0	0
2	3	39	15	11	94720	1	1.0	1	0	0
3	4	35	9	100	94112	1	2.7	2	0	0
4	5	35	8	45	91330	4	1.0	2	0	0

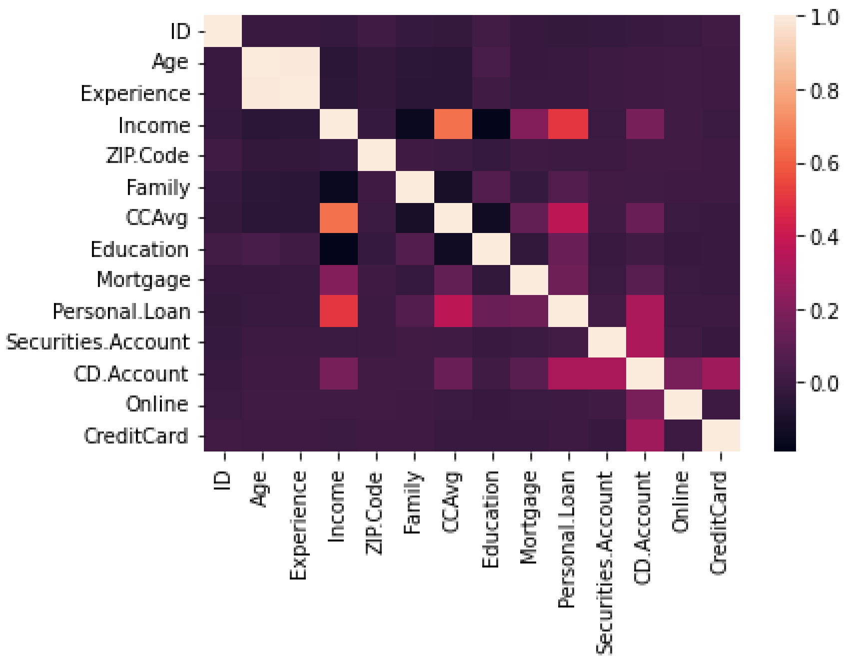
In [3]:

```
df.info()
print("--------------------------------")
print("List of Columns:", df.columns)
print("Shape:", df.shape)
```

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

In [4]:
```
sns.heatmap(df.corr(), annot=False)
```

Out[4]: <AxesSubplot:>



Drop ID, experience, and Zip Code columns since they're irrelevant

In [5]:
```
df = df.drop(columns=['ID','Experience','ZIP.Code'])
df.head()
```

Out[5]:

	Age	Income	Family	CCAvg	Education	Mortgage	Personal.Loan	Securities.Account	CD.Acco
0	25	49	4	1.6	1	0	0	1	
1	45	34	3	1.5	1	0	0	1	
2	39	11	1	1.0	1	0	0	0	
3	35	100	1	2.7	2	0	0	0	
4	35	45	4	1.0	2	0	0	0	

Check for missing values

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
Age                   0
Income                0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Personal.Loan         0
Securities.Account    0
CD.Account            0
Online                0
CreditCard            0
dtype: int64
```

Therefore, there is no missing values as specified by the non-null count and the sum calculated

Check for duplicate values and drop them

In [7]:
```
df.duplicated().sum()
```

Out[7]:
```
13
```

In [8]:
```
df.drop_duplicates(inplace=True)
df.duplicated().sum()
```

Out[8]:
```
0
```

Encodings

Change numeric/continous variables to type float and categorical/discrete variable to type category

In [9]:
```
df['Income']=df['Income'].astype('float')
df['Family']=df['Family'].astype('category')
df['Education']=df['Education'].astype('category')
df['CCAvg']=df['CCAvg'].astype('float')
df['Mortgage']=df['Mortgage'].astype('float')
df['Personal.Loan']=df['Personal.Loan'].astype('category')
df['Securities.Account']=df['Securities.Account'].astype('category')
df['CD.Account']=df['CD.Account'].astype('category')
df['Online']=df['Online'].astype('category')
```

```
df['CreditCard']=df['CreditCard'].astype('category')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4987 entries, 0 to 4999
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Age                 4987 non-null   int64
 1   Income              4987 non-null   float64
 2   Family              4987 non-null   category
 3   CCAvg               4987 non-null   float64
 4   Education           4987 non-null   category
 5   Mortgage            4987 non-null   float64
 6   Personal.Loan       4987 non-null   category
 7   Securities.Account  4987 non-null   category
 8   CD.Account          4987 non-null   category
 9   Online              4987 non-null   category
 10  CreditCard          4987 non-null   category
dtypes: category(7), float64(3), int64(1)
memory usage: 229.8 KB
```

Cut the Age and income into Ranges for better interpretations

In [10]:

```
#minimum age = 23
#maximum age = 67
bins = [23,30,40,50,60,70]
df['Age_r'] = pd.cut(df['Age'], bins=bins, labels=['23-30', '30-40', '40-50', '50-6

#minimum age = 8
#maximum age = 224
bins = [8,20,100,150,200,250]
df['Income_r'] = pd.cut(df['Income'], bins=bins, labels=['Poor', 'Middle_Class', 'U
df.head()
```

Out[10]:

	Age	Income	Family	CCAvg	Education	Mortgage	Personal.Loan	Securities.Account	CD.Acco
0	25	49.0	4	1.6	1	0.0	0	1	
1	45	34.0	3	1.5	1	0.0	0	1	
2	39	11.0	1	1.0	1	0.0	0	0	
3	35	100.0	1	2.7	2	0.0	0	0	
4	35	45.0	4	1.0	2	0.0	0	0	

Unique values of each of the variables

In [11]:

```
print("Unique Family",pd.unique(df['Family']))
print("------------------------------------------")
print("Unique Education",pd.unique(df['Education']))
print("------------------------------------------")
print("Unique Personal.Loan",pd.unique(df['Personal.Loan']))
print("------------------------------------------")
print("Unique Securities.Account",pd.unique(df['Securities.Account']))
print("------------------------------------------")
print("Unique CD.Account",pd.unique(df['CD.Account']))
print("------------------------------------------")
print("Unique Online",pd.unique(df['Online']))
print("------------------------------------------")
print("Unique CreditCard",pd.unique(df['CreditCard']))
```

```
Unique Family [4, 3, 1, 2]
Categories (4, int64): [1, 2, 3, 4]
------------------------------------------
Unique Education [1, 2, 3]
Categories (3, int64): [1, 2, 3]
------------------------------------------
Unique Personal.Loan [0, 1]
Categories (2, int64): [0, 1]
------------------------------------------
Unique Securities.Account [1, 0]
Categories (2, int64): [0, 1]
------------------------------------------
Unique CD.Account [0, 1]
Categories (2, int64): [0, 1]
------------------------------------------
Unique Online [0, 1]
Categories (2, int64): [0, 1]
------------------------------------------
Unique CreditCard [0, 1]
Categories (2, int64): [0, 1]
```

Correlation Matrix along with a heatmap for our Numerical/Continous Variables

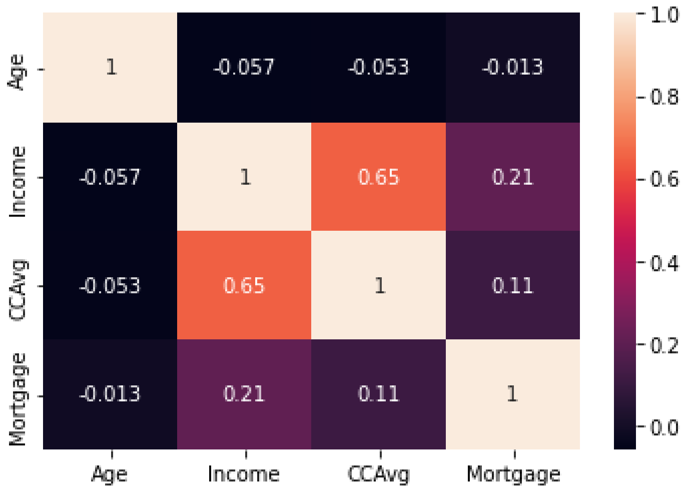
In [12]:
```
df.corr()
```

Out[12]:

	Age	Income	CCAvg	Mortgage
Age	1.000000	-0.056897	-0.052522	-0.013014
Income	-0.056897	1.000000	0.646065	0.206420
CCAvg	-0.052522	0.646065	1.000000	0.109162
Mortgage	-0.013014	0.206420	0.109162	1.000000

In [13]:
```
sns.heatmap(df.corr(), annot=True)
```

Out[13]: <AxesSubplot:>

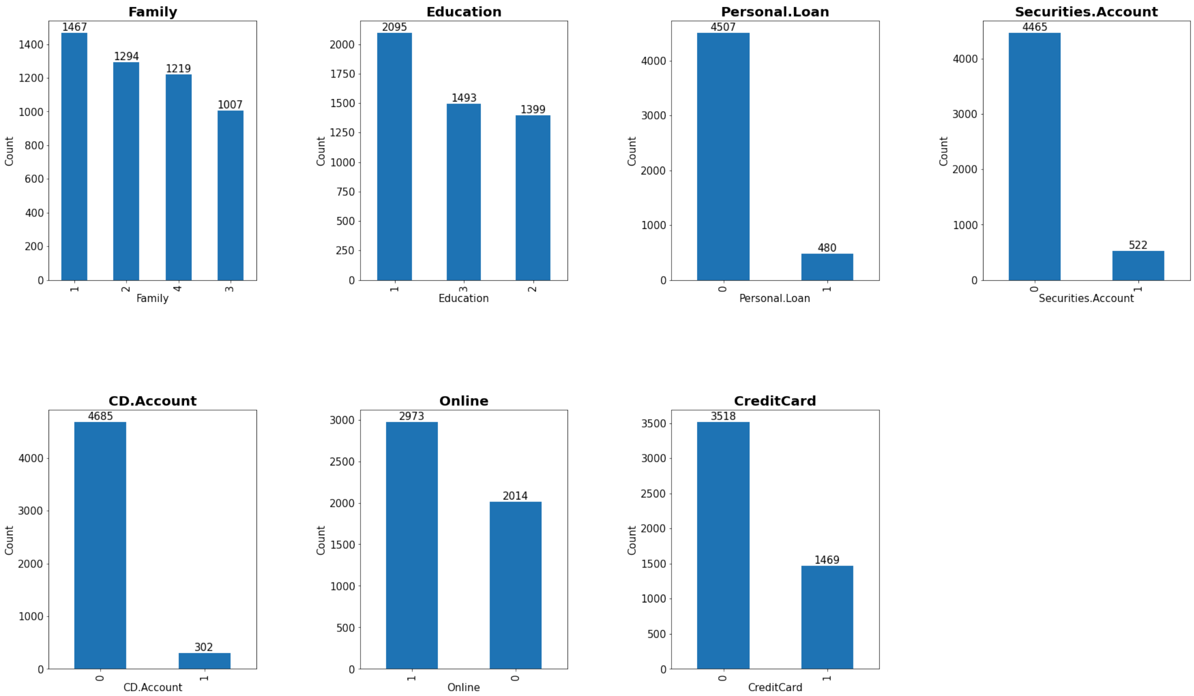


Barplots for our Discrete variables to show their distributions

In [14]:
```
plt.figure(figsize=(30,28))
plt.subplot(3,4,1)
df['Family'].value_counts().plot(kind='bar')
plt.title("Family", fontsize=20, fontweight="bold")
plt.xlabel('Family',fontsize=15)
plt.ylabel('Count',fontsize=15)
```

```python
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
counts=df['Family'].value_counts()
for i, count in enumerate (counts):
    plt.text(i,count+1,str(count), ha='center',va='bottom',fontsize=15)

plt.subplot(3,4,2)
df['Education'].value_counts().plot(kind='bar')
plt.title("Education", fontsize=20, fontweight="bold")
plt.xlabel('Education',fontsize=15)
plt.ylabel('Count',fontsize=15)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
counts=df['Education'].value_counts()
for i, count in enumerate (counts):
    plt.text(i,count+1,str(count), ha='center',va='bottom',fontsize=15)

plt.subplot(3,4,3)
df['Personal.Loan'].value_counts().plot(kind='bar')
plt.title("Personal.Loan", fontsize=20, fontweight="bold")
plt.xlabel('Personal.Loan',fontsize=15)
plt.ylabel('Count',fontsize=15)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
counts=df['Personal.Loan'].value_counts()
for i, count in enumerate (counts):
    plt.text(i,count+1,str(count), ha='center',va='bottom',fontsize=15)

plt.subplot(3,4,4)
df['Securities.Account'].value_counts().plot(kind='bar')
plt.title("Securities.Account", fontsize=20, fontweight="bold")
plt.xlabel('Securities.Account',fontsize=15)
plt.ylabel('Count',fontsize=15)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
counts=df['Securities.Account'].value_counts()
for i, count in enumerate (counts):
    plt.text(i,count+1,str(count), ha='center',va='bottom',fontsize=15)

plt.subplot(3,4,5)
df['CD.Account'].value_counts().plot(kind='bar')
plt.title("CD.Account", fontsize=20, fontweight="bold")
plt.xlabel('CD.Account',fontsize=15)
plt.ylabel('Count',fontsize=15)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
counts=df['CD.Account'].value_counts()
for i, count in enumerate (counts):
    plt.text(i,count+1,str(count), ha='center',va='bottom',fontsize=15)

plt.subplot(3,4,6)
df['Online'].value_counts().plot(kind='bar')
plt.title("Online", fontsize=20, fontweight="bold")
plt.xlabel('Online',fontsize=15)
plt.ylabel('Count',fontsize=15)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
counts=df['Online'].value_counts()
for i, count in enumerate (counts):
    plt.text(i,count+1,str(count), ha='center',va='bottom',fontsize=15)

plt.subplot(3,4,7)
df['CreditCard'].value_counts().plot(kind='bar')
plt.title("CreditCard", fontsize=20, fontweight="bold")
```

```
plt.xlabel('CreditCard',fontsize=15)
plt.ylabel('Count',fontsize=15)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
counts=df['CreditCard'].value_counts()
for i, count in enumerate (counts):
    plt.text(i,count+1,str(count), ha='center',va='bottom',fontsize=15)

plt.subplots_adjust(wspace=0.5,hspace=0.5)
plt.show()
```



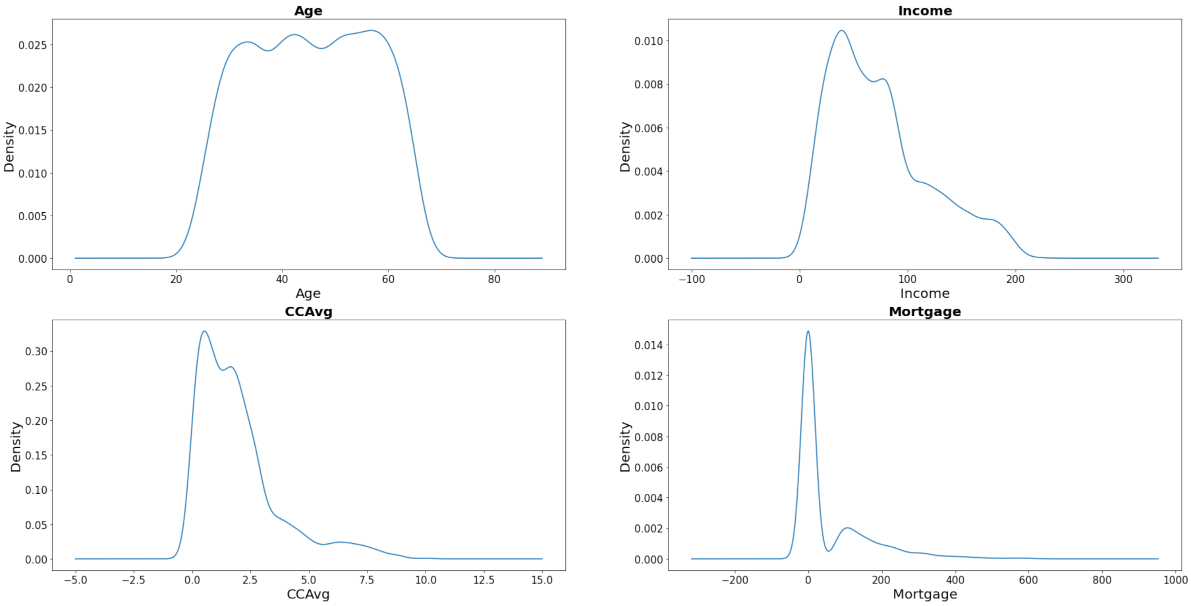
Linegraphs for our Continous variables to show their distributions

In [15]:
```
plt.figure(figsize=(30,15))
plt.subplot(2,2,1)
df['Age'].plot(kind='density')
plt.title("Age", fontsize=20, fontweight="bold")
plt.xlabel('Age',fontsize=20)
plt.ylabel('Density',fontsize=20)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(2,2,2)
df['Income'].plot(kind='density')
plt.xlabel('Income',fontsize=20)
plt.ylabel('Density',fontsize=20)
plt.title("Income", fontsize=20, fontweight="bold")
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(2,2,3)
df['CCAvg'].plot(kind='density')
plt.title("CCAvg", fontsize=20, fontweight="bold")
plt.xlabel('CCAvg',fontsize=20)
plt.ylabel('Density',fontsize=20)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(2,2,4)
df['Mortgage'].plot(kind='density')
plt.title("Mortgage", fontsize=20, fontweight="bold")
```

```
plt.xlabel('Mortgage',fontsize=20)
plt.ylabel('Density',fontsize=20)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
```

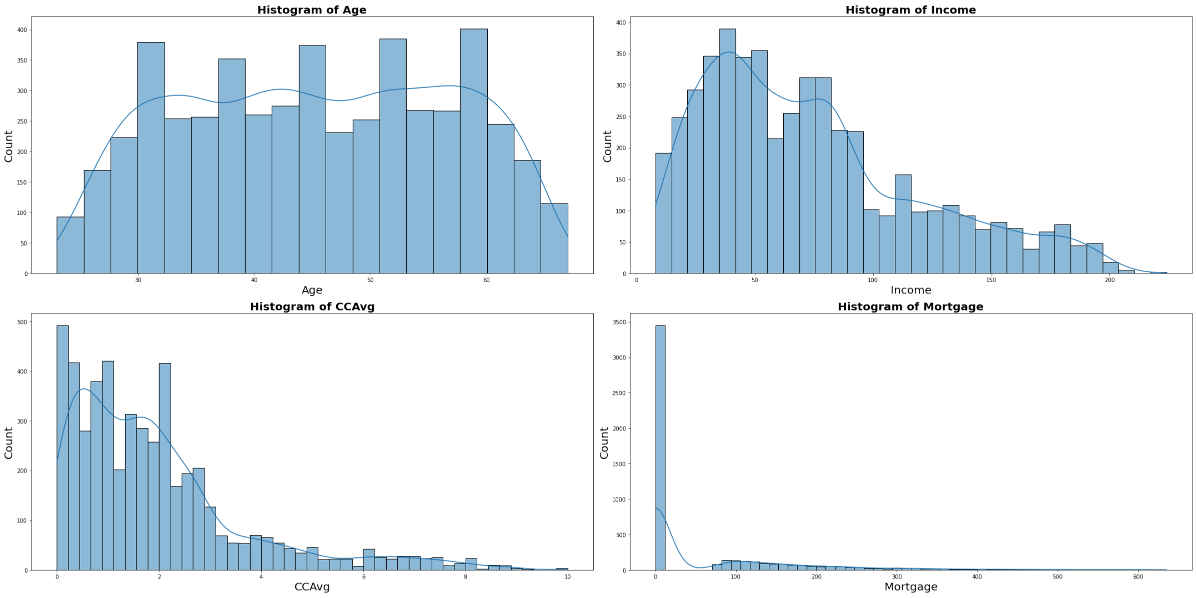
Out[15]:

```
(array([-0.002,  0.   ,  0.002,  0.004,  0.006,  0.008,  0.01 ,  0.012,
         0.014,  0.016]),
 [Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, '')])
```



In [16]:

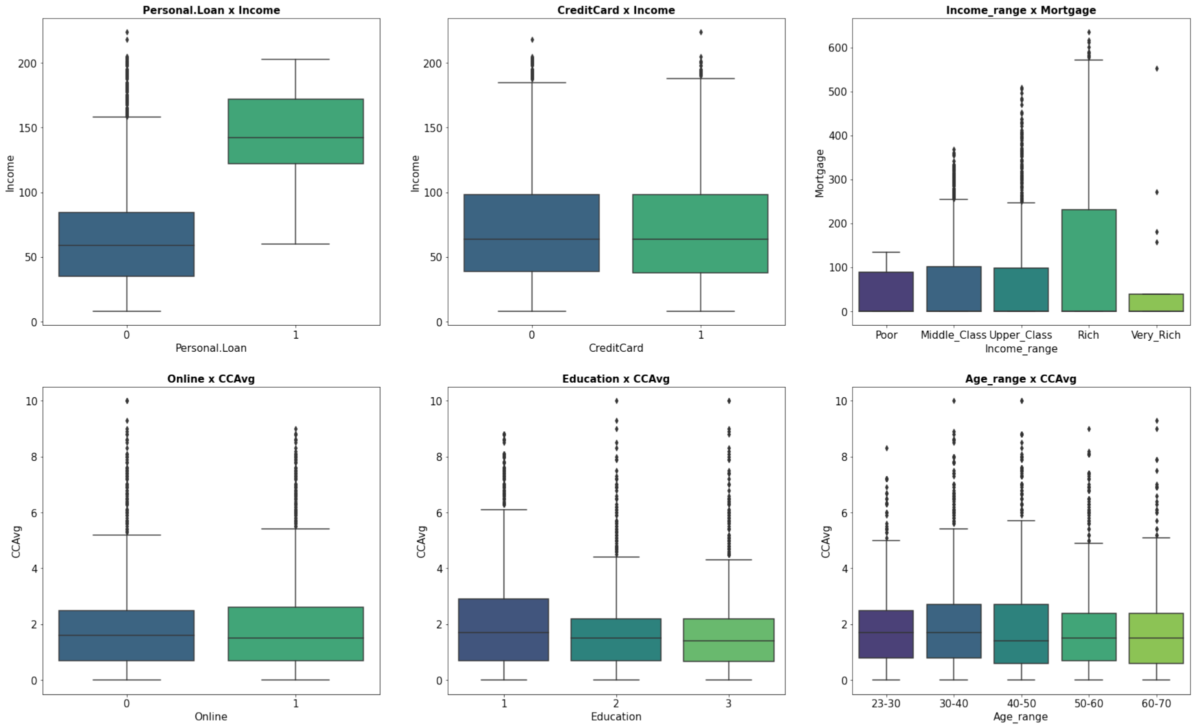
```
dist_columns = ['Age', 'Income', 'CCAvg','Mortgage']

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(30, 15))

axes = axes.flatten()

for i, col in enumerate(dist_columns):
    sns.histplot(df[col], kde=True, ax=axes[i])
    axes[i].set_title(f'Histogram of {col}',fontsize=20,fontweight='bold')
    axes[i].set_xlabel(col,fontsize=20)
    axes[i].set_ylabel('Count',fontsize=20)


plt.tight_layout()
plt.show()
```



Box plots to show the relations and errors between each pair of variables

In [17]:
```python
plt.figure(figsize=(30,28))
plt.subplot(3,3,1)
sns.boxplot(x='Personal.Loan', y='Income', data=df, palette='viridis')
plt.xlabel('Personal.Loan',fontsize=15)
plt.ylabel('Income',fontsize=15)
plt.title('Personal.Loan x Income',fontsize=15, fontweight='bold')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(3,3,2)
sns.boxplot(x='CreditCard', y='Income', data=df, palette='viridis')
plt.xlabel('CreditCard',fontsize=15)
plt.ylabel('Income',fontsize=15)
plt.title('CreditCard x Income',fontsize=15, fontweight='bold')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(3,3,3)
sns.boxplot(x='Income_r', y='Mortgage', data=df, palette='viridis')
plt.xlabel('Income_range',fontsize=15)
plt.ylabel('Mortgage',fontsize=15)
plt.title('Income_range x Mortgage',fontsize=15, fontweight='bold')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(3,3,4)
sns.boxplot(x='Online', y='CCAvg', data=df, palette='viridis')
plt.xlabel('Online',fontsize=15)
plt.ylabel('CCAvg',fontsize=15)
plt.title('Online x CCAvg',fontsize=15, fontweight='bold')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(3,3,5)
sns.boxplot(x='Education', y='CCAvg', data=df, palette='viridis')
plt.xlabel('Education',fontsize=15)
plt.ylabel('CCAvg',fontsize=15)
plt.title('Education x CCAvg',fontsize=15, fontweight='bold')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.subplot(3,3,6)
```

```python
sns.boxplot(x='Age_r', y='CCAvg', data=df, palette='viridis')
plt.xlabel('Age_range',fontsize=15)
plt.ylabel('CCAvg',fontsize=15)
plt.title('Age_range x CCAvg',fontsize=15, fontweight='bold')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)

plt.show()
```



We can identify that income, CCAvg and Mortgage are 3 features containing outliers

Function to identify outliers

In [18]:
```python
def outlier(df):

  Q1=df.quantile(0.25)

  Q3=df.quantile(0.75)

  IQR=Q3-Q1

  out = df[((df<(Q1-1.5*IQR)) | (df>(Q3+1.5*IQR)))]

  return out
```

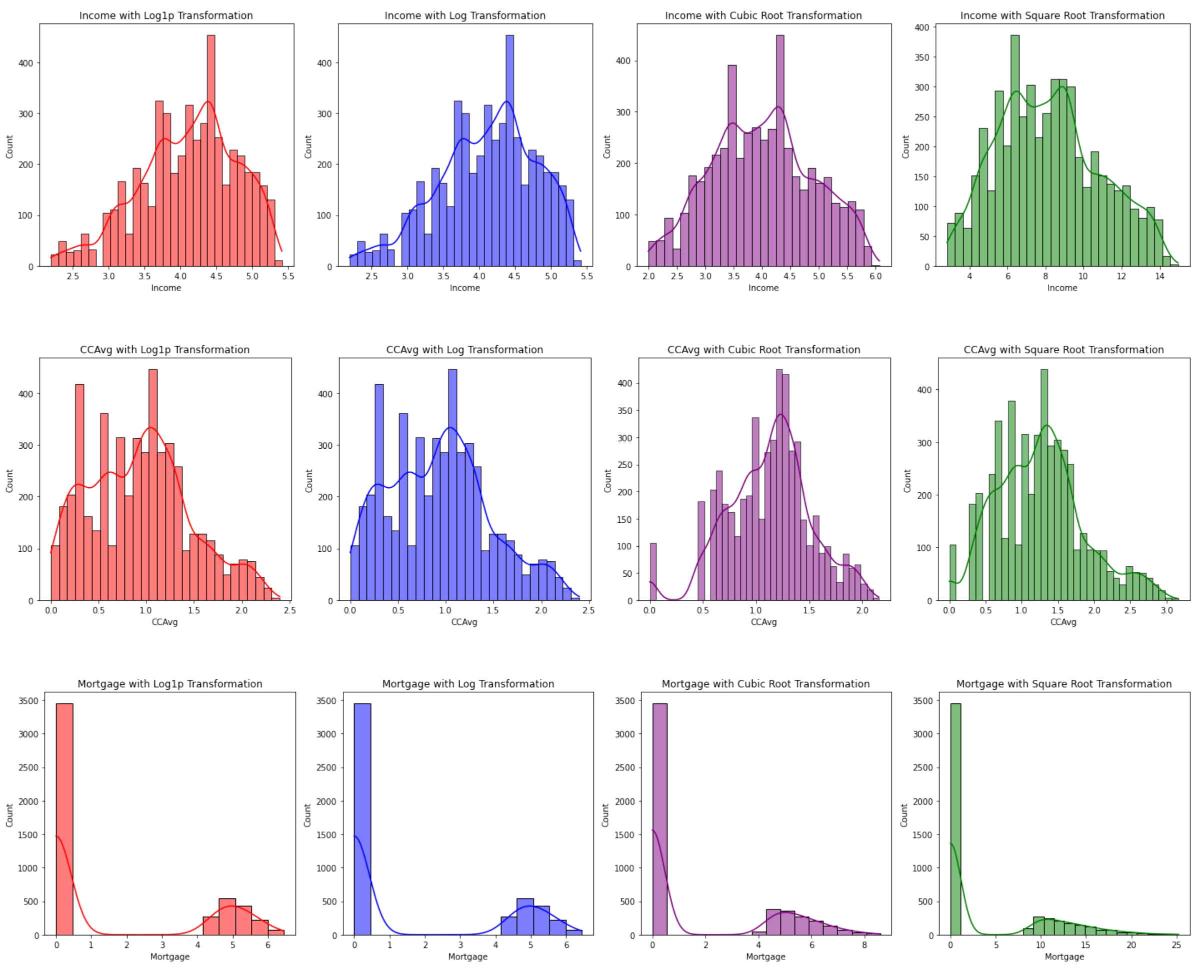
In [19]:
```python
skewed =['Income','CCAvg','Mortgage']
for col in skewed:
    outliers=outlier(df[col])
    print("Number of outliers in",col,":", str(len(outliers)),",It's Percentage is
    print("\n")
```

```
Number of outliers in Income : 96 ,It's Percentage is :  1.925005013033888 %


Number of outliers in CCAvg : 301 ,It's Percentage is :  6.035692801283337 %


Number of outliers in Mortgage : 291 ,It's Percentage is :  5.835171445758974 %
```

Outlier numbers are relatively low, yet they could better. In addition their line graphs and histograms are skewed. We found a solution to the problems by:

Find a suitable transformation for the skewed features

In [20]:
```
skewed =['Income','CCAvg','Mortgage']

for col in skewed:
    fig, axes = plt.subplots(1, 4, figsize=(20, 5))

    # Log1p Transformation
    sns.histplot(np.log1p(df[col]), color='red', ax=axes[0],kde=True)
    axes[0].set_title(f'{col} with Log1p Transformation')

    # Log Transformation
    sns.histplot(np.log(df[col] + 1), color='blue', ax=axes[1],kde=True)
    axes[1].set_title(f'{col} with Log Transformation')

    # Cubic Root Transformation
    sns.histplot(np.cbrt(df[col]), color='purple', ax=axes[2],kde=True)
    axes[2].set_title(f'{col} with Cubic Root Transformation')

    # Square Root Transformation
    sns.histplot(np.sqrt(df[col]), color='green', ax=axes[3],kde=True)
    axes[3].set_title(f'{col} with Square Root Transformation')

    plt.tight_layout()
    plt.show()
    print("\n")
```



Therefore, the best suitable transformation for:

- Income: Cubic root
- CCAvg: Cubic root
- Mortgage: Square root

In [21]:
```
df['Income'] = np.cbrt(df['Income'])
df['CCAvg'] = np.cbrt(df['CCAvg'])
df['Mortgage'] = np.sqrt(df['Mortgage'])
```

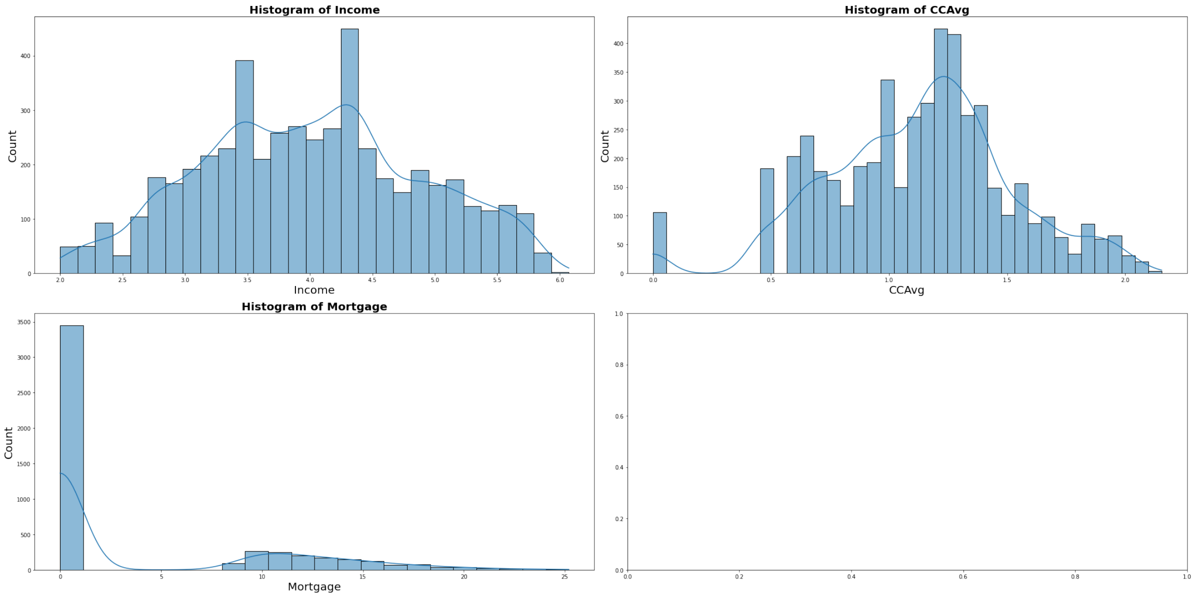
Test for outliers after the transformation and plot the histograms

In [22]:
```
skewed =['Income','CCAvg','Mortgage']
for col in skewed:
    outliers=outlier(df[col])
    print("Number of outliers in",col,":", str(len(outliers)),",It's Percentage is
    print("\n")
```

```
Number of outliers in Income : 0 ,It's Percentage is :  0.0 %


Number of outliers in CCAvg : 109 ,It's Percentage is :  2.1856827752155605 %


Number of outliers in Mortgage : 1 ,It's Percentage is :  0.020052135552436335 %
```

Outliers are significantly reduced after the transformation

In [23]:
```
dist_columns = ['Income', 'CCAvg','Mortgage']

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(30, 15))

axes = axes.flatten()

for i, col in enumerate(dist_columns):
    sns.histplot(df[col], kde=True, ax=axes[i])
    axes[i].set_title(f'Histogram of {col}',fontsize=20,fontweight='bold')
    axes[i].set_xlabel(col,fontsize=20)
    axes[i].set_ylabel('Count',fontsize=20)


plt.tight_layout()
plt.show()
```



Finally, here's a summary of our continous features

In [24]:
```
df.describe()
```

Out[24]:

	Age	Income	CCAvg	Mortgage
count	4987.000000	4987.000000	4987.000000	4987.000000
mean	45.347704	4.006779	1.127270	4.046775
std	11.460838	0.887801	0.392599	6.346477
min	23.000000	2.000000	0.000000	0.000000
25%	35.000000	3.391211	0.887904	0.000000
50%	45.000000	4.000000	1.144714	0.000000
75%	55.000000	4.610436	1.375069	10.049876
max	67.000000	6.073178	2.154435	25.199206