Task 1: Data Analysis and Insights Generation

Instructions:

1. Obtain a real-world dataset related to a specific domain (e.g., sales, marketing, customer behavior).
2. Perform exploratory data analysis using appropriate tools (Python, R, data visualization platforms).
3. Clean and preprocess the data, handling missing values, outliers, and inconsistent formats.
4. Conduct statistical analysis, applying measures like mean, median, standard deviation, and correlation coefficients.
5. Apply advanced analytical methods (regression analysis, clustering) to identify patterns and trends.
6. Use data visualization techniques to present findings effectively (charts, graphs).
7. Interpret results, providing actionable insights and recommendations aligned with business objectives.
8. Prepare a comprehensive report summarizing the analysis approach, key findings, and recommendations.

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('ggplot')
import numpy as np
```

In [2]:
```
data = pd.read_csv("Datasets/credit_approval/crx.data",header=None,na_values="?")
```

In [3]:
```
# data.head()
data.info()
# data[0].value_counts()
data.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 16 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       678 non-null    object 
 1   1       678 non-null    float64
 2   2       690 non-null    float64
 3   3       684 non-null    object 
 4   4       684 non-null    object 
 5   5       681 non-null    object 
 6   6       681 non-null    object 
 7   7       690 non-null    float64
 8   8       690 non-null    object 
 9   9       690 non-null    object 
 10  10      690 non-null    int64  
 11  11      690 non-null    object 
 12  12      690 non-null    object 
 13  13      677 non-null    float64
 14  14      690 non-null    int64  
 15  15      690 non-null    object 
dtypes: float64(4), int64(2), object(10)
memory usage: 86.4+ KB
```

Out[3]:

	1	2	7	10	13	14
count	678.000000	690.000000	690.000000	690.00000	677.000000	690.000000
mean	31.568171	4.758725	2.223406	2.40000	184.014771	1017.385507
std	11.957862	4.978163	3.346513	4.86294	173.806768	5210.102598
min	13.750000	0.000000	0.000000	0.00000	0.000000	0.000000
25%	22.602500	1.000000	0.165000	0.00000	75.000000	0.000000
50%	28.460000	2.750000	1.000000	0.00000	160.000000	5.000000
75%	38.230000	7.207500	2.625000	3.00000	276.000000	395.500000
max	80.250000	28.000000	28.500000	67.00000	2000.000000	100000.000000

1 .Real world dataset

Dataset details:

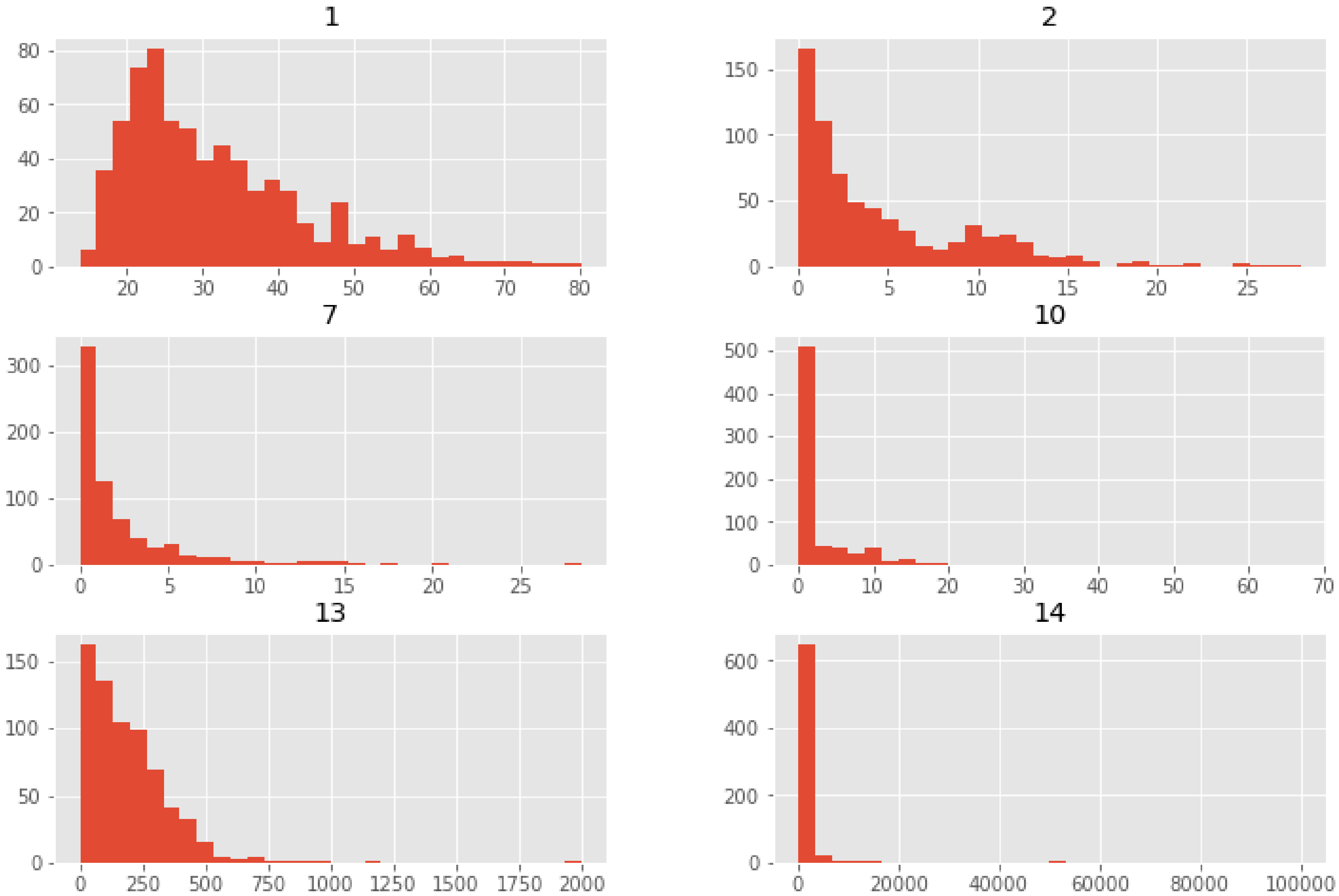
- Male   A1: b, a.
- Age   A2: continuous.
- Debt   A3: continuous.
- Married   A4: u, y, l, t.
- BankCustomer   A5: g, p, gg.
- EducationLevel   A6: c, d, cc, i, j, k, m, r, q, w, x, e, aa, ff.
- Ethnicity   A7: v, h, bb, j, n, z, dd, ff, o.
- YearsEmployed   A8: continuous.
- PriorDefault   A9: t, f.
- Employed   A10: t, f.
- CreditScore   A11: continuous.
- DriversLicense   A12: t, f.
- Citizen   A13: g, p, s.
- ZipCode   A14: continuous.
- Income   A15: continuous.
- Approved   A16: +,- (class attribute)
- (from crx.names file, Source:https://archive.ics.uci.edu/dataset/27/credit+approval)
- (Column descriptions, Reference:http://rstudio-pubs-static.s3.amazonaws.com/73039_9946de135c0a49daa7a0a9eda4a67a72.html)

2. EDA

In [4]:
```
data.hist(bins=30,figsize=(12,8))
```

Out[4]:

```
array([[<AxesSubplot:title={'center':'1'}>,
        <AxesSubplot:title={'center':'2'}>],
       [<AxesSubplot:title={'center':'7'}>,
        <AxesSubplot:title={'center':'10'}>],
       [<AxesSubplot:title={'center':'13'}>,
        <AxesSubplot:title={'center':'14'}>]], dtype=object)
```



In [5]:

```
numeric = [1, 2, 7, 10, 14]
#A14 is zip code. Should be treated as categorical rather than numeric "data[13]"
```

```python
data_num = data[numeric]
data_num.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   1       678 non-null    float64
 1   2       690 non-null    float64
 2   7       690 non-null    float64
 3   10      690 non-null    int64  
 4   14      690 non-null    int64  
dtypes: float64(3), int64(2)
memory usage: 27.1 KB
```

In [6]:
```python
categorical = [0, 3, 4, 5, 6, 8, 9, 11, 12, 13]
data_cat = data[categorical]
data_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       678 non-null    object 
 1   3       684 non-null    object 
 2   4       684 non-null    object 
 3   5       681 non-null    object 
 4   6       681 non-null    object 
 5   8       690 non-null    object 
 6   9       690 non-null    object 
 7   11      690 non-null    object 
 8   12      690 non-null    object 
 9   13      677 non-null    float64
dtypes: float64(1), object(9)
memory usage: 54.0+ KB
```

In [7]:
```python
data_target = data[15].replace({'+':1, '-':0})
data_target.info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 690 entries, 0 to 689
Series name: 15
Non-Null Count  Dtype
--------------  -----
690 non-null    int64
dtypes: int64(1)
memory usage: 5.5 KB
```

3. Pre-processing

Data Pre-processing cleaning, missing values and outliers

- Taking mean for Age column in data_num
- Checking for outliers in Numerical columns and removing outliers
- Filling categorical columns with mode value of that column in data_cat
- Converting Categorical values to numerical by Label Encoder

In [24]:

```
# data_num.info()
data_num = data_num.fillna(data_num.mean())
# data_num.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   1       690 non-null    float64
 1   2       690 non-null    float64
 2   7       690 non-null    float64
 3   10      690 non-null    int64  
 4   14      690 non-null    int64  
dtypes: float64(3), int64(2)
memory usage: 27.1 KB
```

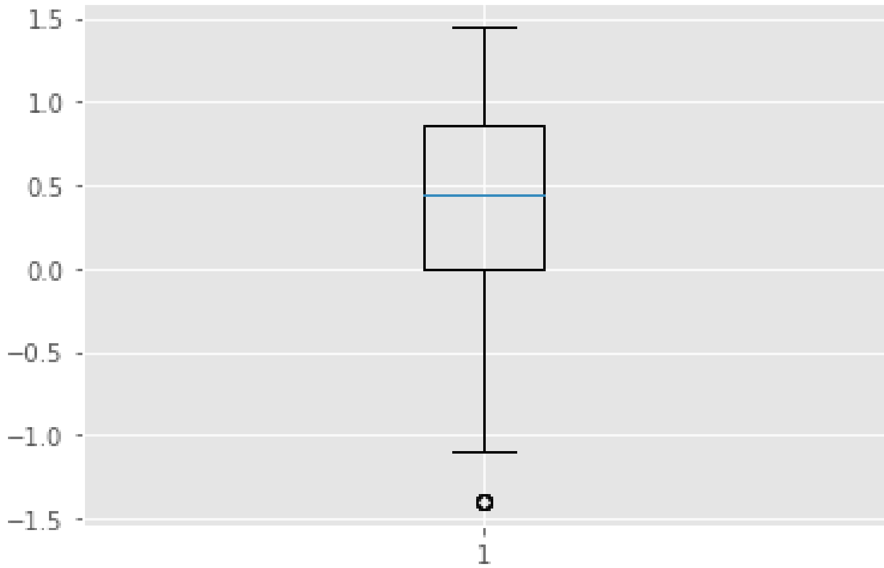
In [9]:

```
# numeric = [1,2,7,10,14]
plt.boxplot(np.log10(data_num[2]))
data_num[2].describe()
```

```
C:\Users\MAHAVIR\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarning: divide by zero encount
ered in log10
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

Out[9]:

```
count    690.000000
mean       4.758725
std        4.978163
min        0.000000
25%        1.000000
50%        2.750000
75%        7.207500
max       28.000000
Name: 2, dtype: float64
```

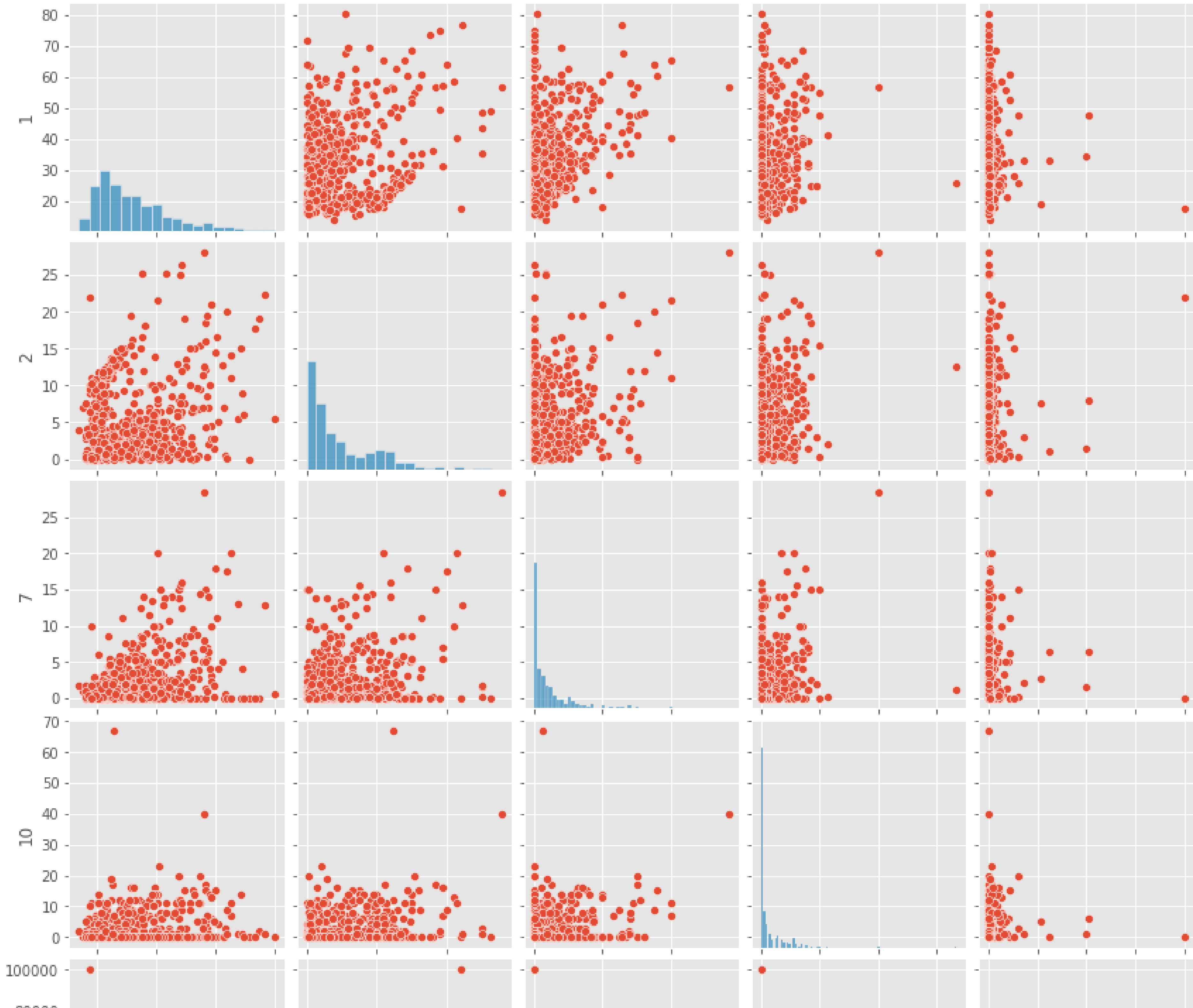


In [10]:

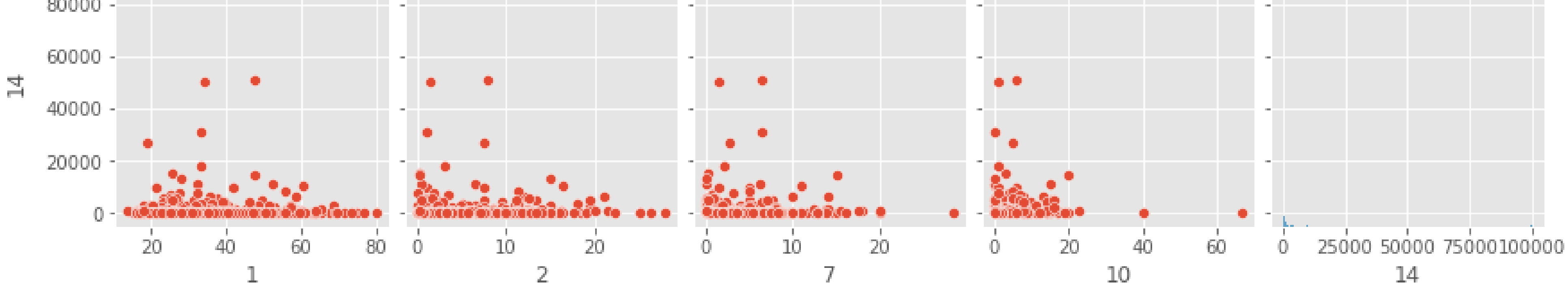
```
sns.pairplot(data[[1,2,7,10,14]])
```

Out[10]:

```
<seaborn.axisgrid.PairGrid at 0x2687c1d13a0>
```



1
2
7
10



In [25]:

```python
for column in data_cat.columns:
  data_cat[column] = data_cat[column].fillna(data_cat[column].value_counts().index[0])
# data_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       690 non-null    int32
 1   3       690 non-null    int32
 2   4       690 non-null    int32
 3   5       690 non-null    int32
 4   6       690 non-null    int32
 5   8       690 non-null    int32
 6   9       690 non-null    int32
 7   11      690 non-null    int32
 8   12      690 non-null    int32
 9   13      690 non-null    int64
dtypes: int32(9), int64(1)
memory usage: 29.8 KB
```

In [26]:

```python
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

for column in data_cat.columns:
    data_cat[column] = label_encoder.fit_transform(data_cat[column])

# data_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       690 non-null    int32
 1   3       690 non-null    int32
 2   4       690 non-null    int32
 3   5       690 non-null    int32
 4   6       690 non-null    int32
 5   8       690 non-null    int32
 6   9       690 non-null    int32
 7   11      690 non-null    int32
 8   12      690 non-null    int32
 9   13      690 non-null    int64
dtypes: int32(9), int64(1)
memory usage: 29.8 KB
```

In [27]:

```
data_cleaned = pd.concat([data_num,data_cat,data_target],axis=1)
# data_cleaned.info()
# data_cleaned.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 16 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   1       690 non-null    float64
 1   2       690 non-null    float64
 2   7       690 non-null    float64
 3   10      690 non-null    int64  
 4   14      690 non-null    int64  
 5   0       690 non-null    int32  
 6   3       690 non-null    int32  
 7   4       690 non-null    int32  
 8   5       690 non-null    int32  
 9   6       690 non-null    int32  
 10  8       690 non-null    int32  
 11  9       690 non-null    int32  
 12  11      690 non-null    int32  
 13  12      690 non-null    int32  
 14  13      690 non-null    int64  
 15  15      690 non-null    int64  
dtypes: float64(3), int32(9), int64(4)
memory usage: 62.1 KB
```

Out[27]:

	1	2	7	10	14	0	3	4	5	6	8	9	11	12	13	15
0	30.83	0.000	1.25	1	0	1	1	0	12	7	1	1	0	0	68	1
1	58.67	4.460	3.04	6	560	0	1	0	10	3	1	1	0	0	11	1
2	24.50	0.500	1.50	0	824	0	1	0	10	3	1	0	0	0	96	1
3	27.83	1.540	3.75	5	3	1	1	0	12	7	1	1	1	0	31	1
4	20.17	5.625	1.71	0	0	1	1	0	12	7	1	0	0	2	37	1

- Scaling the Data using MinMaxScaler and saving clean dataset for Predictive modelling and advance analytics

In [14]:
```
from sklearn.preprocessing import MinMaxScaler
```

```
scaler = MinMaxScaler(feature_range=(0, 1))
clean_data = scaler.fit_transform(data_cleaned)
```

In [28]:
```
clean_data = pd.DataFrame(clean_data)
# clean_data.head()
clean_data.to_csv('Datasets/credit_approval/clean_data.data')
```

Out[28]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Cluster
0	0.256842	0.000000	0.043860	0.014925	0.00000	1.0	0.5	0.0	0.923077	0.875	1.0	1.0	0.0	0.0	0.402367	1.0	0
1	0.675489	0.159286	0.106667	0.089552	0.00560	0.0	0.5	0.0	0.769231	0.375	1.0	1.0	0.0	0.0	0.065089	1.0	0
2	0.161654	0.017857	0.052632	0.000000	0.00824	0.0	0.5	0.0	0.769231	0.375	1.0	0.0	0.0	0.0	0.568047	1.0	0
3	0.211729	0.055000	0.131579	0.074627	0.00003	1.0	0.5	0.0	0.923077	0.875	1.0	1.0	1.0	0.0	0.183432	1.0	0
4	0.096541	0.200893	0.060000	0.000000	0.00000	1.0	0.5	0.0	0.923077	0.875	1.0	0.0	0.0	1.0	0.218935	1.0	0

4. Statistical Analysis and 5. Advance Analytics

Performing Analysis of Data through plots

- Statistical analysis of dataset (mean, std, min, max)
- Performing Kmeans clustering on 2 principal components
- Generating Heatmap for checking correlation
- Checking correlation between target and each feature using scatter plots

In [16]:
```
data_cleaned.describe()
```

Out[16]:

	1	2	7	10	14	0	3	4	5	6	
count	690.000000	690.000000	690.000000	690.00000	690.000000	690.000000	690.000000	690.000000	690.000000	690.000000	690.
mean	31.568171	4.758725	2.223406	2.40000	1017.385507	0.695652	1.233333	0.475362	5.698551	5.098551	0.
std	11.853273	4.978163	3.346513	4.86294	5210.102598	0.460464	0.430063	0.850238	4.285748	2.510731	0.
min	13.750000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.
25%	22.670000	1.000000	0.165000	0.00000	0.000000	0.000000	1.000000	0.000000	1.000000	3.000000	0.
50%	28.625000	2.750000	1.000000	0.00000	5.000000	1.000000	1.000000	0.000000	5.000000	7.000000	1.
75%	37.707500	7.207500	2.625000	3.00000	395.500000	1.000000	1.000000	0.000000	10.000000	7.000000	1.
max	80.250000	28.000000	28.500000	67.00000	100000.000000	1.000000	2.000000	2.000000	13.000000	8.000000	1.

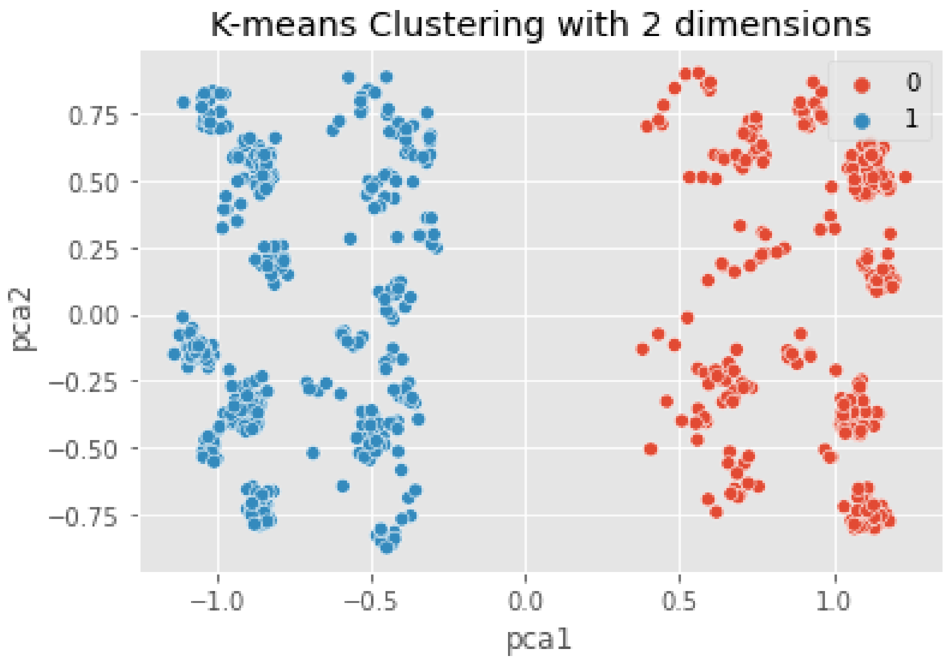
In [17]:

```
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

In [18]:

```
kmeans = KMeans(n_clusters=2)

y = kmeans.fit_predict(clean_data)
clean_data['Cluster'] = y

### Run PCA on the data and reduce the dimensions in pca_num_components dimensions

reduced_data = PCA(n_components=2).fit_transform(clean_data)
results = pd.DataFrame(reduced_data,columns=['pca1','pca2'])

sns.scatterplot(x="pca1", y="pca2", hue=y, data=results)
plt.title('K-means Clustering with 2 dimensions')
plt.show()
```

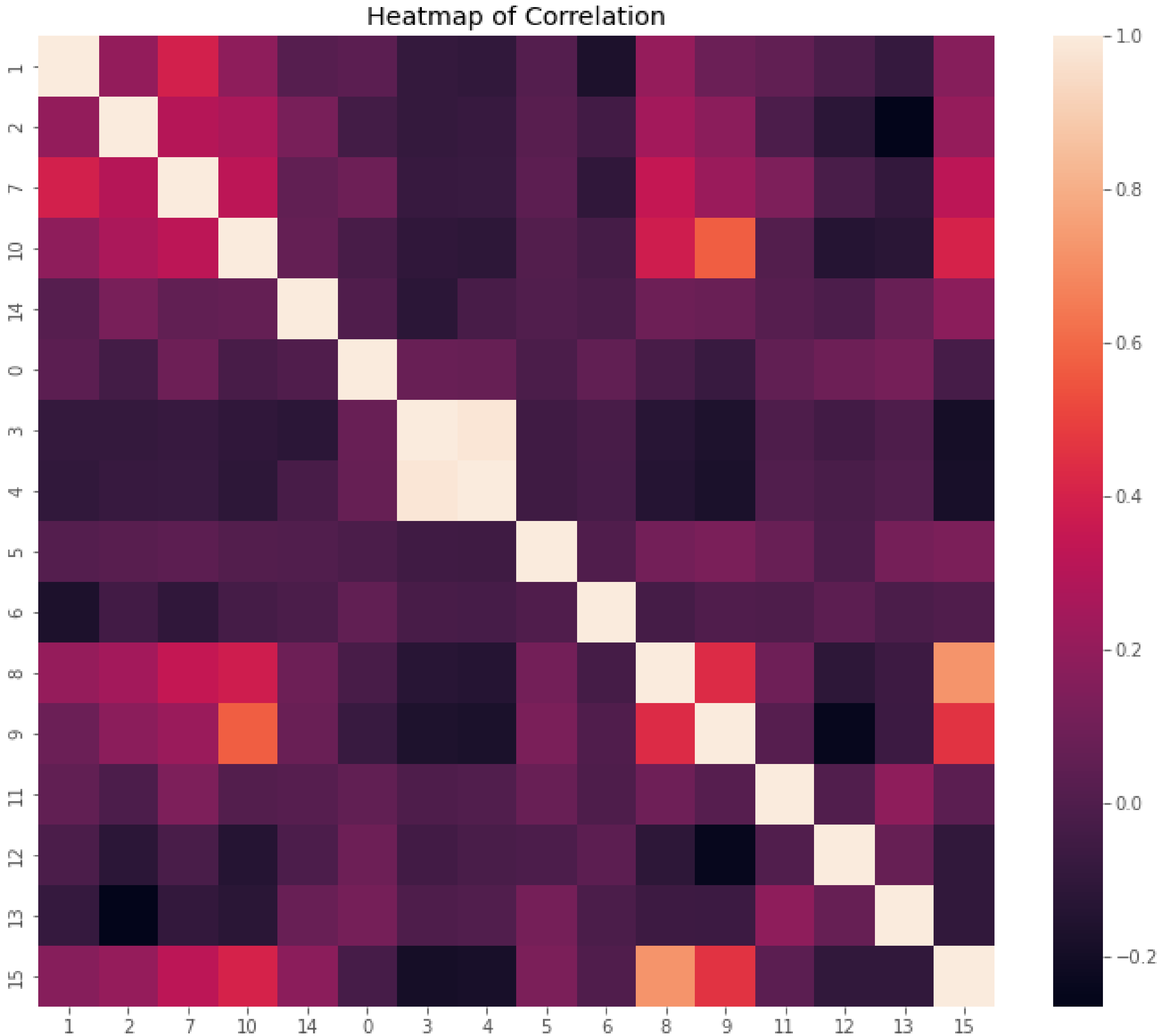
```
C:\Users\MAHAVIR\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1334: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=3.
  warnings.warn(
C:\Users\MAHAVIR\anaconda3\lib\site-packages\sklearn\utils\validation.py:1858: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```



- We can clearly see that the clusters can be separated easily based on pca1, there is high correlation between pca1 with Approval rate

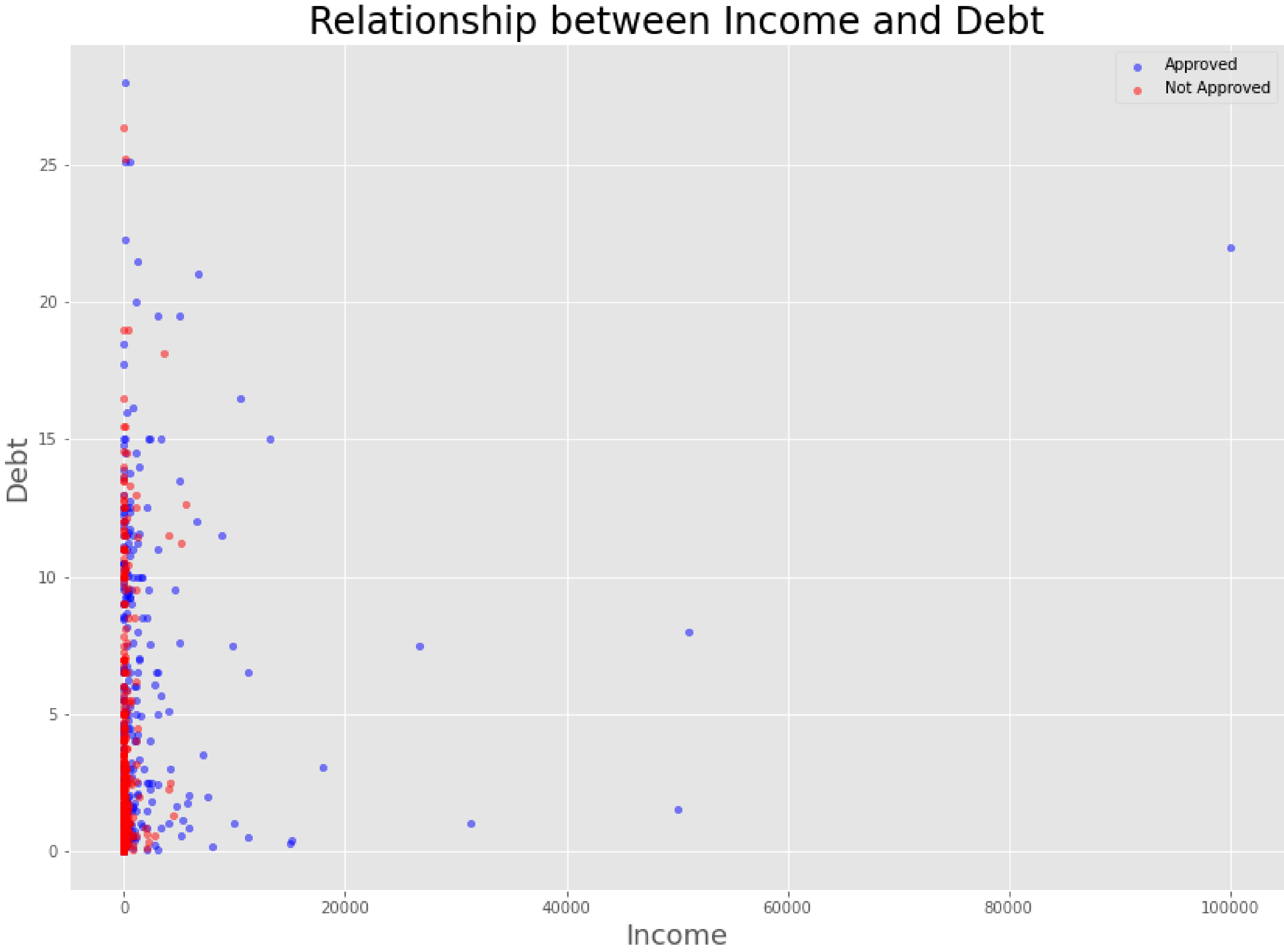
In [19]:
```python
corr = data_cleaned.corr()
plt.figure(figsize=(12,10))
heat = sns.heatmap(data=corr)
plt.title('Heatmap of Correlation')
```

Out[19]:
```
Text(0.5, 1.0, 'Heatmap of Correlation')
```



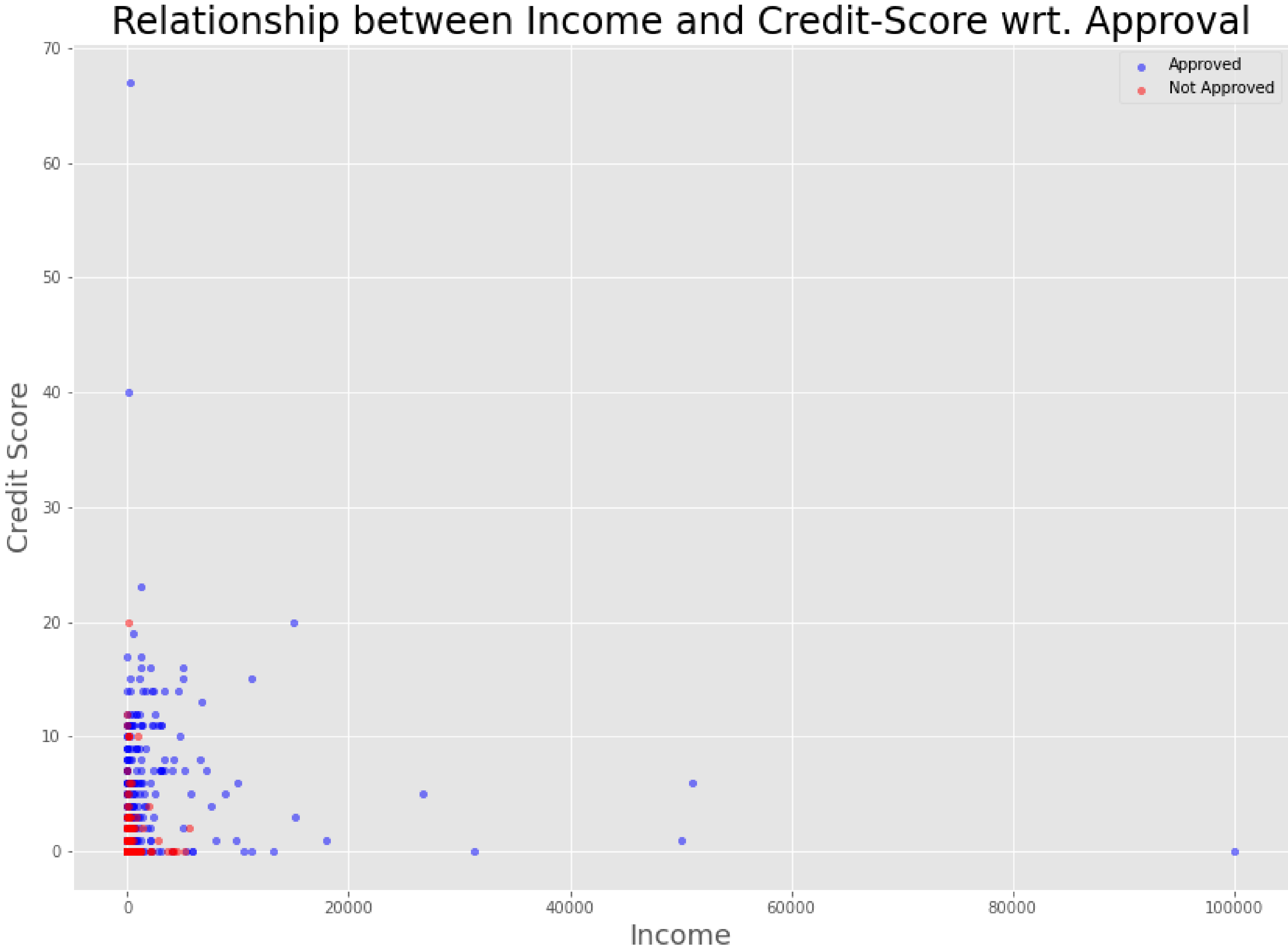
In [20]:
```
ax1 = data_cleaned[data_cleaned[15] == 1].plot(kind='scatter', x=14, y=2, color='blue', alpha=0.5, figsize=(14, 1
data_cleaned[data_cleaned[15] == 0].plot(kind='scatter', x=14, y=2, color='red', alpha=0.5, figsize=(14, 10), ax=
plt.legend(labels=['Approved', 'Not Approved'])
```

```
plt.title('Relationship between Income and Debt', size=24)
plt.xlabel('Income', size=18)
plt.ylabel('Debt', size=18);
```



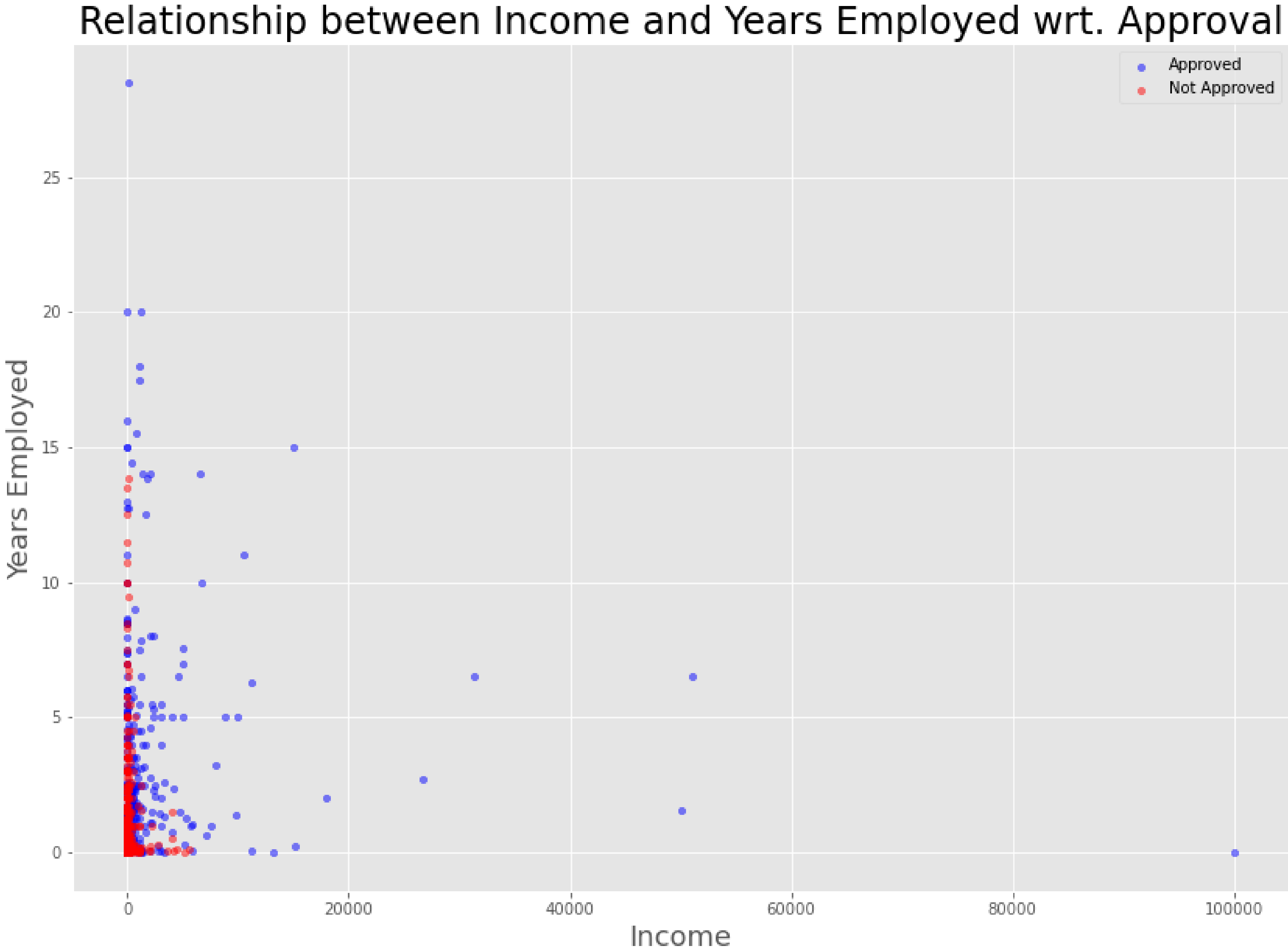
In [21]:
```
ax1 = data_cleaned[data_cleaned[15] == 1].plot(kind='scatter', x=14, y=10, color='blue', alpha=0.5, figsize=(14,
data_cleaned[data_cleaned[15] == 0].plot(kind='scatter', x=14, y=10, color='red', alpha=0.5, figsize=(14, 10), ax
```

```
plt.legend(labels=['Approved', 'Not Approved'])
plt.title('Relationship between Income and Credit-Score wrt. Approval', size=24)
plt.xlabel('Income', size=18)
plt.ylabel('Credit Score', size=18);
```



In [22]:
```
ax1 = data_cleaned[data_cleaned[15] == 1].plot(kind='scatter', x=14, y=7, color='blue', alpha=0.5, figsize=(14, 1
data_cleaned[data_cleaned[15] == 0].plot(kind='scatter', x=14, y=7, color='red', alpha=0.5, figsize=(14, 10), ax=
```

```
plt.legend(labels=['Approved', 'Not Approved'])
plt.title('Relationship between Income and Years Employed wrt. Approval', size=24)
plt.xlabel('Income', size=18)
plt.ylabel('Years Employed', size=18);
```



6. Insights and Visulaizations above

Insights from Visualizations

- We can see that Credit Score, Income, Years-Employed, Debt have high correlation with Credit Card Approval
- Higher Income, Lower debt, More no. of Years of Employment and High Credit score gives High Approval rate
- Further Analysis is needed to arrive at actionable insights

7. Actionable insights and Recommendations

Recommendations

- Based upon the analysis done on the data, Credit score, Income, Years of Employment and Debt are high deciding factors on credit approval decision.
- However, it must be noted that Credit score and Debt indirectly depends on Credit card usage thus, business must focus more on Income and Employment years.