In [1]:
```
import numpy as np
import pandas as pd
import os
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
```

In [2]:
```
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
```

In [3]:
```
os.chdir("/Users/serrauzun/Desktop/MSDS_422_Practical")
df = pd.read_csv('HMEQ_Loss_clean.csv')
```

In [4]:
```
df_binary = df[['TARGET_BAD_FLAG', 'REASON_DebtCon', 'REASON_HomeI
mp', 'REASON_Missing', 'JOB_Mgr', 'JOB_Missing', 'JOB_Office', 'JO
B_Other', 'JOB_ProfExe', 'JOB_Sales', 'JOB_Self']]
```

Let's remove the binary variables from our dataset to get the best and most accurate results on our PCA

In [5]:
```
x = df.copy()
x = x.drop(df_binary, axis=1 )
varNames = x.columns
```

In [6]:
```
x.head().T
```

Out[6]:

	0	1	2	3	
TARGET_LOSS_AMT	641.000000	1109.000000	767.000000	1425.000000	0.0000
LOAN	1100.000000	1300.000000	1500.000000	1500.000000	1700.0000
MORTDUE	25860.000000	70053.000000	13500.000000	65019.000000	97800.0000
VALUE	39025.000000	68400.000000	16700.000000	89235.500000	112000.0000
YOJ	10.500000	7.000000	4.000000	7.000000	3.0000
DEROG	0.000000	0.000000	0.000000	0.000000	0.0000
DELINQ	0.000000	2.000000	0.000000	0.000000	0.0000
CLAGE	94.366667	121.833333	149.466667	173.466667	93.3333
NINQ	1.000000	0.000000	1.000000	1.000000	0.0000
CLNO	9.000000	14.000000	10.000000	20.000000	14.0000
DEBTINC	0.000000	0.000000	0.000000	0.000000	0.0000

In [7]:
```
theScaler = StandardScaler()
theScaler.fit(x)
```

Out[7]: StandardScaler(copy=True, with_mean=True, with_std=True)

In [8]:
```
x_std = theScaler.transform(x)
```

In [9]:
```
max_n = x_std.shape[1]
max_n
```

Out[9]: 11

We have 11 variables so now we will set our pca to have 11 components

In [10]:
```
pca = PCA(n_components = max_n)
pca.fit(x_std)
```

Out[10]:
```
PCA(copy=True, iterated_power='auto', n_components=11, random_sta
te=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

We will now look at eigen values to seen how much information is in each component

In [11]:
```
ev = pca.explained_variance_
print("Eigen Values")
print(ev)
```

```
Eigen Values
[2.23602553 1.89155257 1.27424046 1.0488845  0.95815283 0.8412759
8
 0.79714086 0.74358928 0.63790425 0.44104532 0.13206555]
```

We can see that the the first component with 2.24 Eigen Value has the most amount of information. 2.24 Eigen value of component 1 is followed by two with 1.89, three with 1.27 and four with 1.05. Pass the 4th component Eigen value drops below 1.

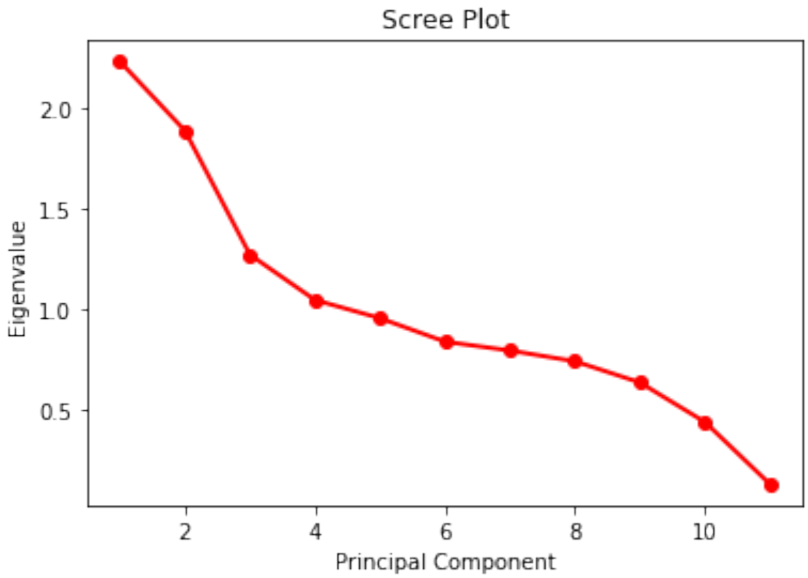
In [12]:
```
varPCT = []
totPCT = []
total = 0
```

In [13]:
```
for i in ev:
    total = total + i
    VAR = int( i / len(ev) * 100)
    PCT = int( total / len(ev) * 100)
    varPCT.append(VAR)
    totPCT.append(PCT)
    print(round(i,2), "variation=", VAR,"%"," total=", PCT,"%")
```

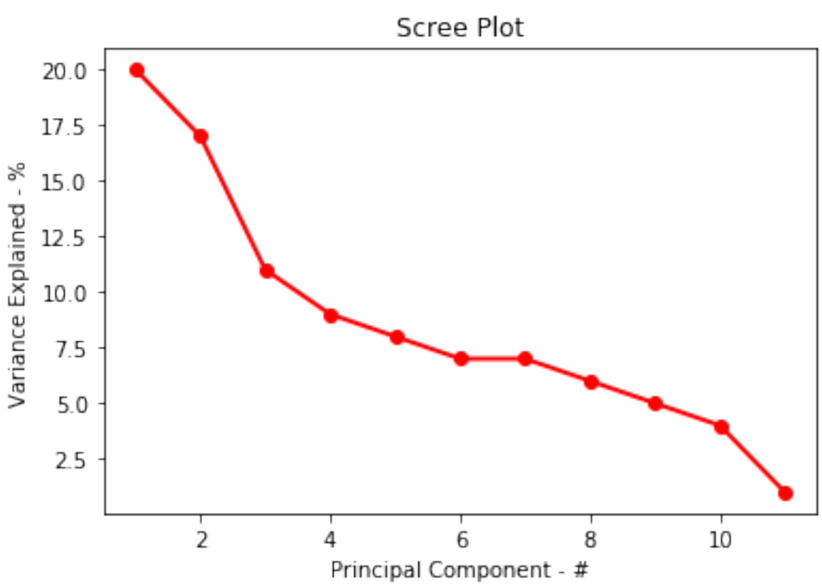
```
2.24 variation= 20 %  total= 20 %
1.89 variation= 17 %  total= 37 %
1.27 variation= 11 %  total= 49 %
1.05 variation= 9 %  total= 58 %
0.96 variation= 8 %  total= 67 %
0.84 variation= 7 %  total= 75 %
0.8 variation= 7 %  total= 82 %
0.74 variation= 6 %  total= 89 %
0.64 variation= 5 %  total= 94 %
0.44 variation= 4 %  total= 98 %
0.13 variation= 1 %  total= 100 %
```

From the above list we can see that component one holds 20 percent of the information. We need all the variables to reach 100%, yet with 8 (0 to 7) variables we cover almost 90 percent of the information.

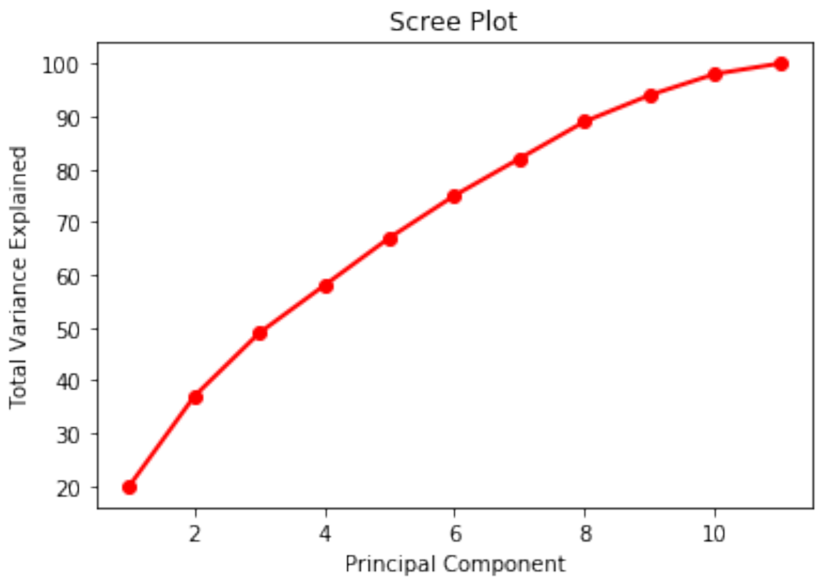
In [14]:
```
PC_NUM = np.arange(max_n) + 1
plt.plot(PC_NUM , ev, 'ro-', linewidth=2)
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Eigenvalue')
plt.show()
```



In [15]:
```
PC_NUM = np.arange(max_n) + 1
plt.plot( PC_NUM , varPCT, 'ro-', linewidth=2)
plt.title('Scree Plot')
plt.xlabel('Principal Component - #')
plt.ylabel('Variance Explained - %')
plt.show()
```



In [16]:
```
PC_NUM = np.arange(max_n) + 1
plt.plot( PC_NUM , totPCT, 'ro-', linewidth=2)
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Total Variance Explained')
plt.show()
```



In [17]:
```
dfc = pd.DataFrame(pca.components_)
dfc.columns = list(x.columns)
print(dfc)
```

```
    TARGET_LOSS_AMT      LOAN   MORTDUE     VALUE       YOJ      D
EROG  \
0          0.081988  0.267405  0.578739  0.606279  0.024087 -0.03
3348
1          0.580699  0.045400 -0.026277 -0.019115 -0.047318  0.40
1818
2          0.014958  0.057149 -0.239904 -0.154050  0.649916 -0.08
5019
3          0.138591  0.781972 -0.169203 -0.025363  0.290481  0.06
3117
4         -0.208936 -0.184319 -0.132445 -0.178111  0.010866  0.22
9842
5         -0.019580  0.162280 -0.120876 -0.098285 -0.273103  0.61
3548
6         -0.171714 -0.078482  0.116244  0.129177  0.112916  0.56
6684
7          0.154276  0.306015 -0.212274 -0.149865 -0.616056 -0.26
9376
8         -0.170722 -0.044487  0.120120  0.128385 -0.115988  0.03
2097
9          0.714045 -0.362403  0.069993 -0.024064  0.094716 -0.04
7150
10         0.017470 -0.135124 -0.684203  0.714209 -0.031740 -0.00
1660

      DELINQ     CLAGE      NINQ      CLNO   DEBTINC
0   0.047594  0.231982 -0.007883  0.375141  0.143853
1   0.454536 -0.141671  0.287081  0.143289 -0.407866
2   0.271562  0.554667 -0.243473  0.183733 -0.105675
3  -0.230984 -0.142703  0.260634 -0.256384  0.210464
4  -0.081271  0.193252  0.655310  0.446150  0.384355
5   0.153985  0.076204 -0.523407  0.060839  0.436818
6  -0.517800  0.298048  0.027629 -0.196335 -0.451679
7  -0.160514  0.525042  0.032287  0.113465 -0.218163
8   0.480197  0.379486  0.289783 -0.663390  0.157543
9  -0.330208  0.213049 -0.031973 -0.211987  0.376488
10 -0.014416 -0.032240  0.011119  0.006971  0.027895
```

In [18]:
```
pca = PCA(n_components = max_n)
pca.fit(x_std)
```

Out[18]:
```
PCA(copy=True, iterated_power='auto', n_components=11, random_sta
te=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

In [19]:
```
x_pca = pca.transform(x_std)
x_pca = pd.DataFrame(x_pca)
x_pca.head()
```

Out[19]:

	0	1	2	3	4	5	6	7
0	-2.865963	0.155170	-0.107874	-0.809012	-0.751538	-1.112336	0.627023	-0.393440
1	-1.417085	0.866563	0.113970	-1.912648	-1.303637	-0.530000	-0.193783	-0.518738
2	-3.172426	0.149320	-0.151269	-1.089726	-0.468637	-0.716039	0.594184	0.677099
3	-0.939059	0.222763	-0.113738	-1.540292	-0.436616	-1.072145	0.875724	0.166829
4	-0.591185	-0.027098	-1.265551	-1.745048	-1.466700	-0.864668	0.833184	-0.375194

Per the Eigen Value results and our scree plots we see that we cover almost 90% of the information with first 8 variables, thus we will grab them for the remainder of our analysis

In [20]:
```
x_pca = x_pca.iloc[:,0:7]
```

In [21]:
```
colNames = x_pca.columns
pcaNames = []
for i in colNames :
    index = int(i) + 1
    theName = "PC_" + str(index)
    pcaNames.append(theName)
```

In [22]:
```
x_pca.columns = pcaNames
```

In [23]:
```
print(x_pca.head())
```

```
       PC_1      PC_2      PC_3      PC_4      PC_5      PC_6      
PC_7
0 -2.865963  0.155170 -0.107874 -0.809012 -0.751538 -1.112336  0.
627023
1 -1.417085  0.866563  0.113970 -1.912648 -1.303637 -0.530000 -0.
193783
2 -3.172426  0.149320 -0.151269 -1.089726 -0.468637 -0.716039  0.
594184
3 -0.939059  0.222763 -0.113738 -1.540292 -0.436616 -1.072145  0.
875724
4 -0.591185 -0.027098 -1.265551 -1.745048 -1.466700 -0.864668  0.
833184
```

In [24]:
```
x_pca["TARGET"] = df.TARGET_BAD_FLAG
print(x_pca.head())
```

```
       PC_1      PC_2      PC_3      PC_4      PC_5      PC_6  
PC_7  \
0 -2.865963  0.155170 -0.107874 -0.809012 -0.751538 -1.112336  0.
627023
1 -1.417085  0.866563  0.113970 -1.912648 -1.303637 -0.530000 -0.
193783
2 -3.172426  0.149320 -0.151269 -1.089726 -0.468637 -0.716039  0.
594184
3 -0.939059  0.222763 -0.113738 -1.540292 -0.436616 -1.072145  0.
875724
4 -0.591185 -0.027098 -1.265551 -1.745048 -1.466700 -0.864668  0.
833184

   TARGET
0       1
1       1
2       1
3       1
4       0
```

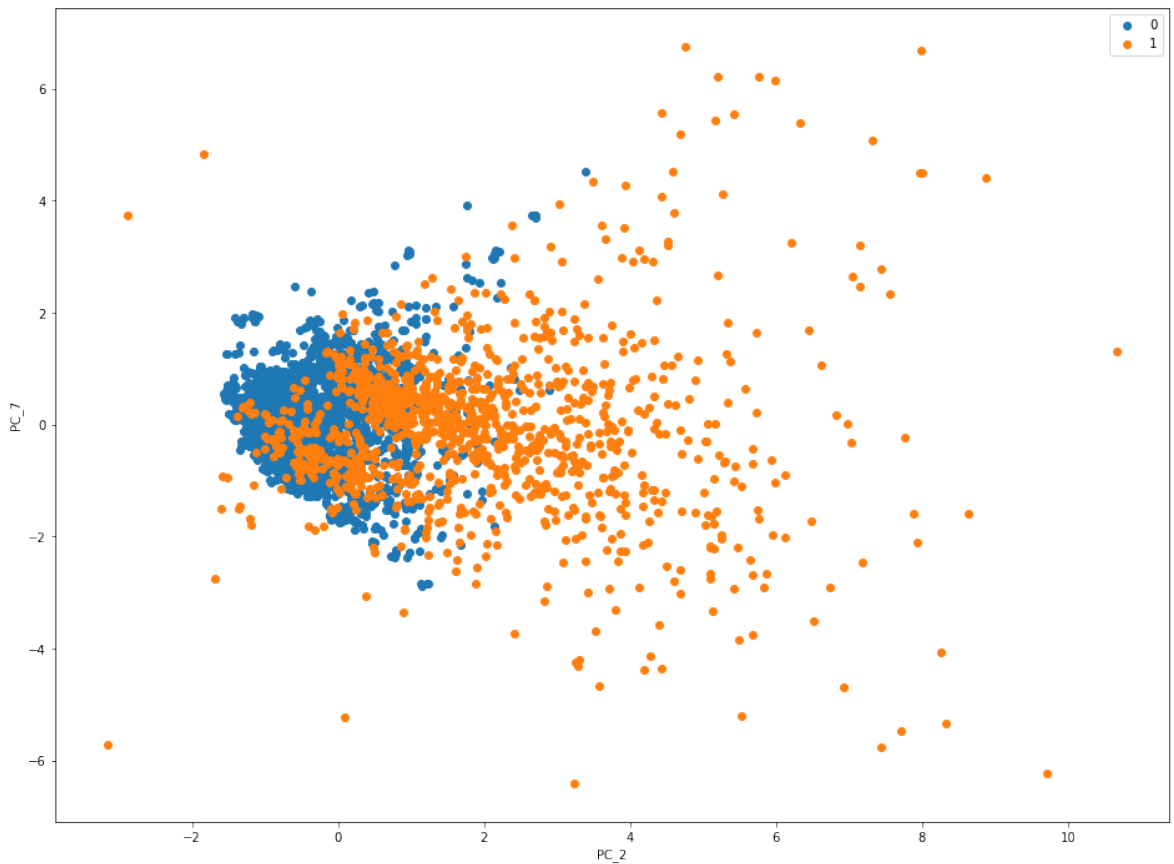
In [25]:
```
for Name, Group in x_pca.groupby("TARGET"):
    print(Group.head(10))
    print("\n")
```

```
        PC_1      PC_2      PC_3      PC_4      PC_5      PC_6  
PC_7  \
4   -0.591185 -0.027098 -1.265551 -1.745048 -1.466700 -0.864668  0
.833184
13 -0.904644  0.067210 -0.462130 -1.928392 -0.676052 -0.566922  0
.638936
19 -0.146466 -0.855330 -1.658999 -1.315499 -0.807840  0.017426 -0
.043264
26 -0.258524 -0.818944 -1.408371 -1.237724 -0.817937 -0.086180  0
.029147
29 -2.643833 -0.179980  0.646058 -1.208316 -0.711424 -0.467028  0
.860727
30 -1.037048 -0.328047  0.513549 -1.569109 -0.964939 -0.748038  1
.347297
34 -0.218958 -0.812748 -1.684461 -1.344950 -0.818949  0.038547 -0
.019040
35 -0.088934 -0.828657 -1.587185 -1.322203 -0.840898 -0.016722  0
.043831
38 -0.055448 -0.843257 -1.690763 -1.287349 -0.785307  0.033489 -0
.090891
48 -0.859664  0.778687  1.264920 -2.079391 -0.552105 -0.430763 -0
.062291

    TARGET
```

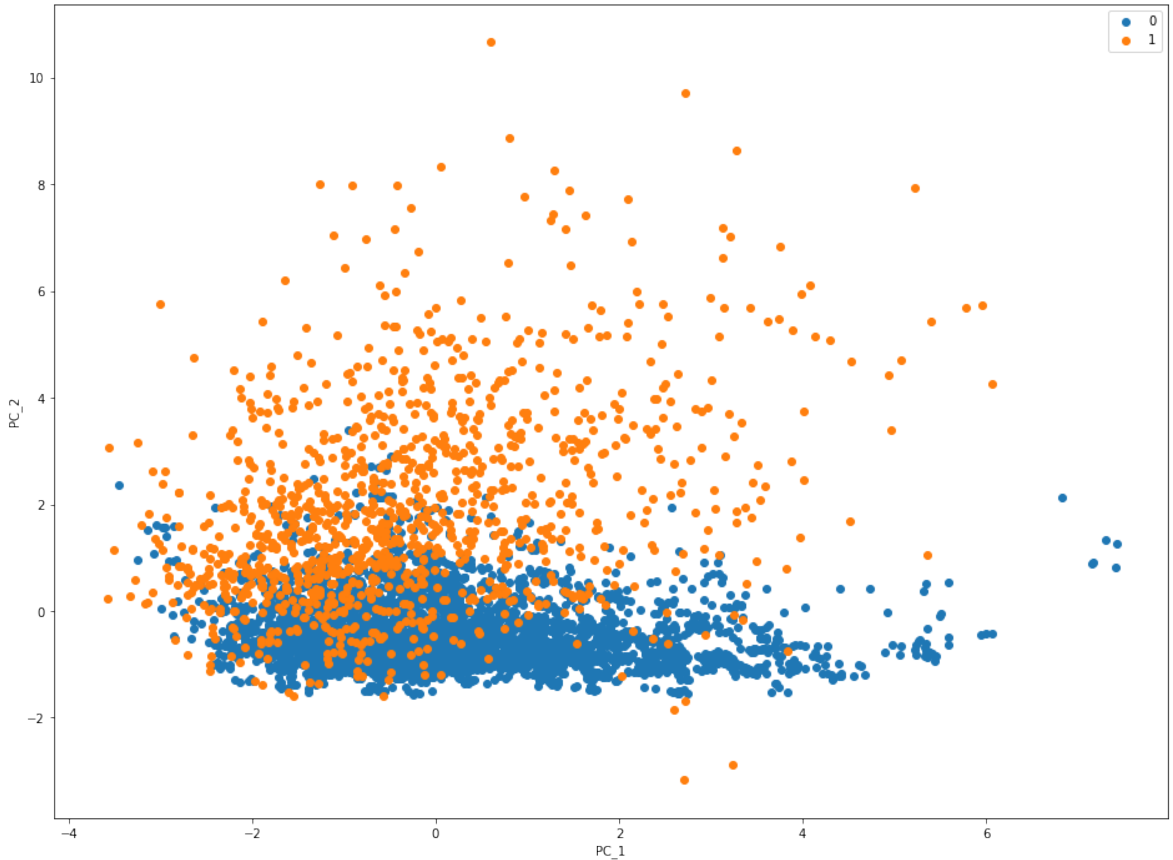
```
4         0
13        0
19        0
26        0
29        0
30        0
34        0
35        0
38        0
48        0


        PC_1      PC_2      PC_3      PC_4      PC_5      PC_6  
PC_7  \
0  -2.865963  0.155170 -0.107874 -0.809012 -0.751538 -1.112336  0
.627023
1  -1.417085  0.866563  0.113970 -1.912648 -1.303637 -0.530000 -0
.193783
2  -3.172426  0.149320 -0.151269 -1.089726 -0.468637 -0.716039  0
.594184
3  -0.939059  0.222763 -0.113738 -1.540292 -0.436616 -1.072145  0
.875724
5  -2.446910 -0.851330 -0.497177 -0.344156  0.101221 -0.032670 -0
.395636
6  -2.031667  2.755495 -0.587214 -1.445323  0.073342  1.597039  1
.564915
7  -2.467609 -1.007007 -0.246877 -0.386908 -0.333347  0.193370 -0
.420512
8  -2.109649  0.924236  0.522703 -1.786284 -0.579729 -0.440789 -0
.048444
9  -1.668549  0.005998  0.422056 -1.001540 -1.181651 -1.128046  0
.854647
10 -1.566230  0.216358  1.162760 -0.854797 -0.284476 -1.340005  0
.897862

    TARGET
0        1
1        1
2        1
3        1
5        1
6        1
7        1
8        1
9        1
10       1
```

As the above values per PC do not present a significant differentiation, let's try scatter plots between certain PCs that may give us a better and more elaborate insight.

In [26]:
```
plt.figure(figsize=(16, 12))
for Name, Group in x_pca.groupby("TARGET"):
    plt.scatter(Group.PC_2, Group.PC_7, label=Name)
plt.xlabel("PC_2")
plt.ylabel("PC_7")
plt.legend()
plt.show()
```



In [27]:
```
plt.figure(figsize=(16, 12))
for Name, Group in x_pca.groupby("TARGET"):
    plt.scatter(Group.PC_1, Group.PC_2, label=Name)
plt.xlabel("PC_1")
plt.ylabel("PC_2")
plt.legend()
plt.show()
```



While the PCA grouped by TARGET variables values do not show a significant differentiation between the principles components, the two scatter plots above show a minor distinction between certain PCs.

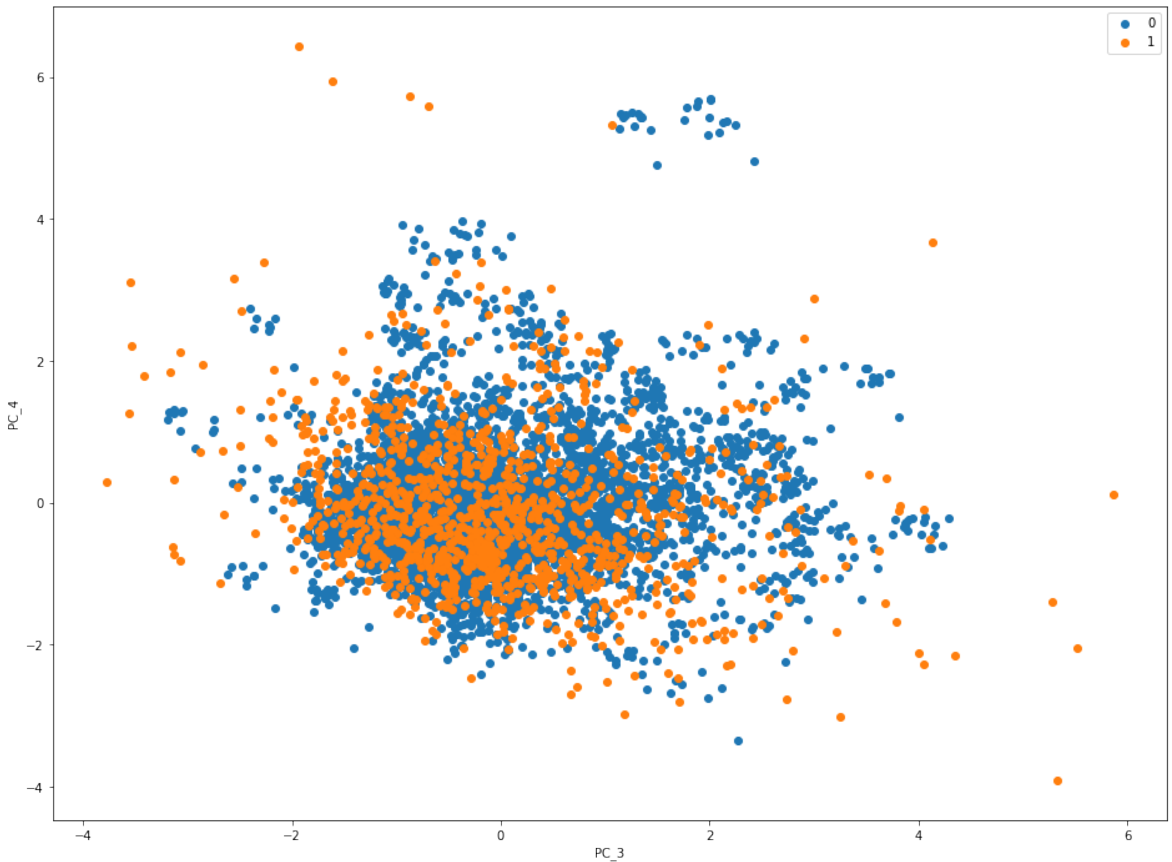
The first graph plots PC_2 against PC_7 and we see that even though there are quite some overlaps, value in PC_2 that is above 2 and value in PC_7 that is above 2 or below -2 is very likely Target = 1, thus a defaulted home credit. For the PC_2 and PC_7 values that are between -2 and 2, we do not see any distinct separation that will give us a clear understanding of the default possibility.

Secondly and finally, when we plot PC_1 against PC_2 we see that any value above 2 in PC_2 is most likely a defaulted credit. We do not see s distinct scatter or clustering for PC_1.

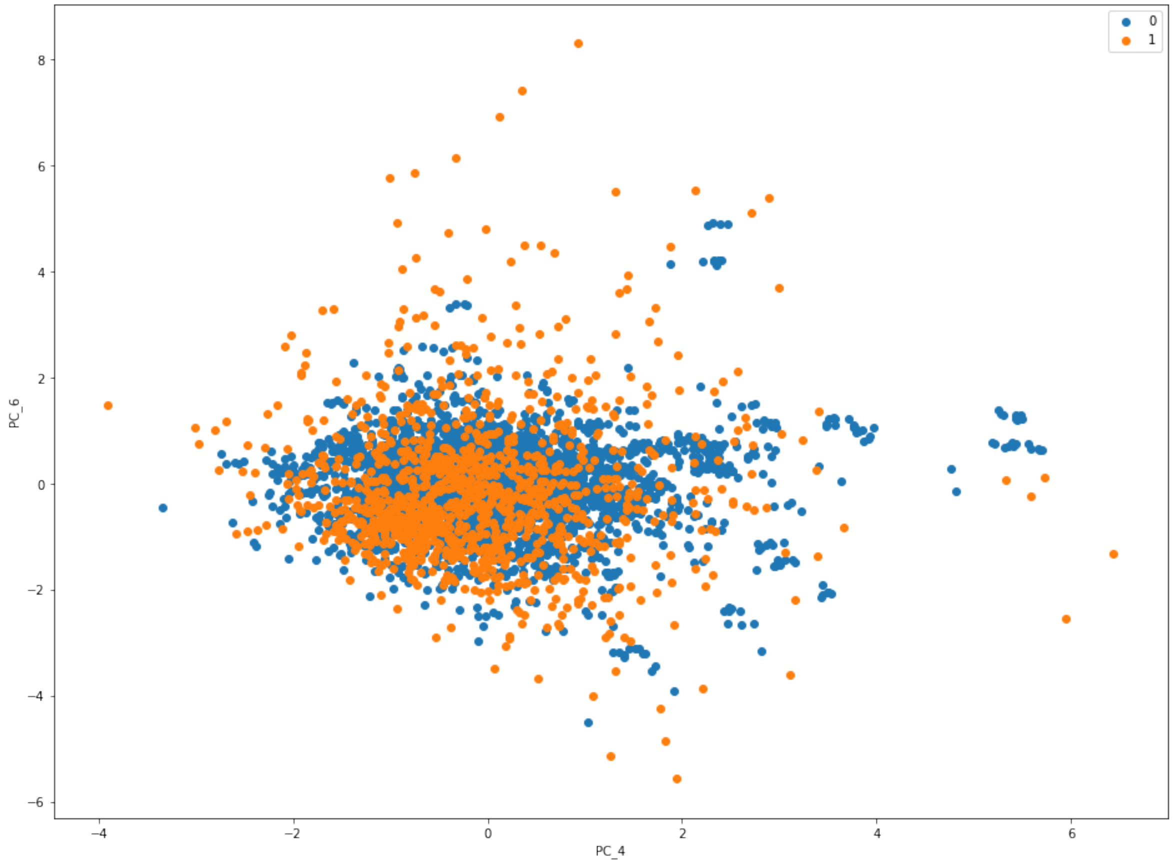
Appendix

Below are some other scatter plots that we plotted yet didn't give us a valuable usable outcome.

In [28]:
```
plt.figure(figsize=(16, 12))
for Name, Group in x_pca.groupby("TARGET"):
    plt.scatter(Group.PC_3, Group.PC_4, label=Name)
plt.xlabel("PC_3")
plt.ylabel("PC_4")
plt.legend()
plt.show()
```



In [29]:
```
plt.figure(figsize=(16, 12))
for Name, Group in x_pca.groupby("TARGET"):
    plt.scatter(Group.PC_4, Group.PC_6, label=Name)
plt.xlabel("PC_4")
plt.ylabel("PC_6")
plt.legend()
plt.show()
```



In [30]:
```
plt.figure(figsize=(16, 12))
for Name, Group in x_pca.groupby("TARGET"):
    plt.scatter(Group.PC_1, Group.PC_5, label=Name)
plt.xlabel("PC_1")
plt.ylabel("PC_5")
plt.legend()
plt.show()
```