In [3]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors as colors
from sklearn.utils import resample
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import scale
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from sklearn.decomposition import PCA
```

In [4]:

```
df = pd.read_csv('default of credit card clients.csv', header = 1)
```

In [8]:

```
df.head()
```

Out[8]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AM
0	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	
1	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	32
2	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	155
3	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	295
4	5	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	191

5 rows × 25 columns

In [10]:

```
df.rename({'default payment next month':'DEFAULT'}, axis = 'columns',inplace = True)
```

In [ ]:

```
df.drop('ID' , axis=1, inplace=True)
df.head()
```

Identifying missing data

either remove or impute(guess)

In [14]:

```
df.dtypes #check the datatypes
```

Out[14]:

```
LIMIT_BAL     int64
SEX           int64
EDUCATION     int64
MARRIAGE      int64
AGE           int64
PAY_0         int64
PAY_2         int64
```

```
PAY_3         int64
PAY_4         int64
PAY_5         int64
PAY_6         int64
BILL_AMT1     int64
BILL_AMT2     int64
BILL_AMT3     int64
BILL_AMT4     int64
BILL_AMT5     int64
BILL_AMT6     int64
PAY_AMT1      int64
PAY_AMT2      int64
PAY_AMT3      int64
PAY_AMT4      int64
PAY_AMT5      int64
PAY_AMT6      int64
DEFAULT       int64
dtype: object
```

In [17]:

```
df['SEX'].unique()
```

Out[17]:

```
array([2, 1], dtype=int64)
```

In [19]:

```
df['EDUCATION'].unique()
```

Out[19]:

```
array([2, 1, 3, 5, 4, 6, 0], dtype=int64)
```

In [21]:

```
df['MARRIAGE'].unique()  #0 is missing data
```

Out[21]:

```
array([1, 2, 3, 0], dtype=int64)
```

Dealing with missing data

In [23]:

```
len(df.loc[(df['EDUCATION'] == 0) | (df['MARRIAGE'] == 0)]) #Check number of rows with m
issing values
```

Out[23]:

```
68
```

In [25]:

```
len(df)
```

Out[25]:

```
30000
```

In [28]:

```
df_no_missing = df.loc[(df['EDUCATION'] != 0) & (df['MARRIAGE'] != 0)]
len(df_no_missing)
```

Out[28]:

```
29932
```

In [36]:

```
print(df_no_missing['EDUCATION'].unique(),df_no_missing['MARRIAGE'].unique())
```

```
[2 1 3 5 4 6] [1 2 3]
```

Downsampling the data

In [38]:

```
len(df_no_missing)
```

Out[38]:

```
29932
```

In [41]:

```
df_no_default = df_no_missing[df_no_missing['DEFAULT'] == 0]
df_default = df_no_missing[df_no_missing['DEFAULT'] == 1]
```

In [44]:

```
df_no_default_downsampled = resample(df_no_default,replace=False,n_samples= 1000,random_s
tate=42)
len(df_no_default_downsampled)
```

Out[44]:

```
1000
```

In [46]:

```
df_default_downsampled = resample(df_default,replace=False,n_samples= 1000,random_state=
42)
len(df_default_downsampled)
```

Out[46]:

```
1000
```

In [49]:

```
df_downsample = pd.concat([df_no_default_downsampled,df_default_downsampled])
len(df_downsample)
```

Out[49]:

```
2000
```

Split data to independent and dependent variables

1. **Columns of data that we use to make classifications (X)**
2. **Column of data that we want to predict (y)**

The reason we deal with missing data before splitting is that if we remove rows, splitting after ensures that each row in X correctly corresponds with appropriate Y value

In [50]:

```
X = df_downsample.drop('DEFAULT', axis=1).copy()
X.head()
```

Out[50]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT3	BILL_AMT4
641	130000	2	3	1	28	0	0	0	0	-2	...	50000	0
4678	170000	1	3	1	29	0	0	0	0	0	...	172307	35234
16004	180000	2	2	1	29	0	0	0	0	0	...	26310	26662

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT3	BILL_AMT4
22974	210000	2	2	2	32	-2	-2	-2	-2	-2	...	410	0
17535	190000	2	3	1	45	0	0	0	0	0	...	80548	81778

5 rows × 23 columns

In [51]:

```
y = df_downsample['DEFAULT'].copy()
y.head()
```

Out[51]:

```
641      0
4678     0
16004    0
22974    0
17535    0
Name: DEFAULT, dtype: int64
```

One-Hot Encoding

LIMIT*Bal - Integer SEX - Category(1=male,2=female) EDUCATION - Category (1=graduate,2=uni,3=high school,4=others) MARRIAGE - Category (1=Married,2=Single,3=Other) AGE - Integer PAY* - Category (-1=On time,1=Delayed by one month,2=Delayed by two ... 9=Delayed by nine or more) BILL_AMT - Integer --> Last 6 bills Pay_AMT - Integer --> Last payments DEFAULT - Category (0=Did not get defaulted,1=Defaulted)

In [53]:

```
pd.get_dummies(X,columns=['MARRIAGE']).head()
```

Out[53]:

	LIMIT_BAL	SEX	EDUCATION	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	...	BILL_AMT6	PAY_AMT1	PAY_
641	130000	2	3	28	0	0	0	0	-2	-2	...	0	2500	
4678	170000	1	3	29	0	0	0	0	0	0	...	33862	7200	
16004	180000	2	2	29	0	0	0	0	0	0	...	26176	1800	
22974	210000	2	2	32	-2	-2	-2	-2	-2	-2	...	0	979	
17535	190000	2	3	45	0	0	0	0	0	0	...	84811	3300	

5 rows × 25 columns

In [55]:

```
X_encoded = pd.get_dummies(X,columns=['SEX','EDUCATION','MARRIAGE','PAY_0','PAY_2','PAY_
3','PAY_4','PAY_5','PAY_6'])
X_encoded.head()
```

Out[55]:

	LIMIT_BAL	AGE	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	PAY_AMT2	.
641	130000	28	100143	50456	50000	0	0	0	2500	1000	.
4678	170000	29	165027	168990	172307	35234	32869	33862	7200	7500	.
16004	180000	29	25781	26000	26310	26662	26166	26176	1800	1800	.
22974	210000	32	355	975	410	0	0	0	979	412	.
17535	190000	45	76433	78472	80548	81778	83082	84811	3300	3331	.

5 rows × 81 columns

Centering and Scaling

The RBF that we are using with our SVM assumes that the data are cenered and scaled ie: each column should have a mean value = 0 and a standard deviation = 1. So we need to do this to both the training and testing datasets

We split the data into training and testing sets and then scale them separately to avoid Data Leakage - when info about training dataset influences testing dataset

In [56]:

```
X_train,X_test,y_train,y_test = train_test_split(X_encoded,y,random_state=42)
X_train_scaled = scale(X_train)
X_test_Scaled = scale(X_test)
```

Building Preliminary SVM

In [61]:

```
clf_svm = SVC(random_state=42)
clf_svm.fit(X_train_scaled,y_train)
```

Out[61]:

```
SVC(random_state=42)
```

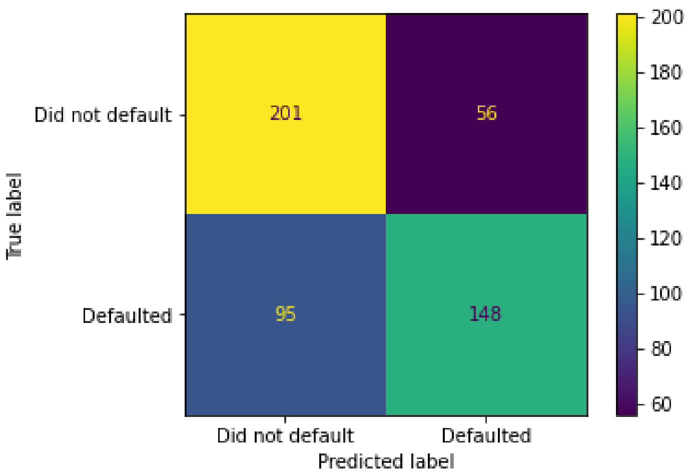
In [62]:

```
# Drawing confusion matrix
plot_confusion_matrix(clf_svm,X_test_Scaled,y_test,values_format='d',display_labels=["Did
not default","Defaulted"])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning
: Function plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is depre
cated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDis
play.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```

Out[62]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2713504f310>
```



In the confusion matrix, out of DID NOT DEFAULT 201(79%) correctly classified, out of DEFAULTED 148(61%) correctly classified.

Optimize parameters using Cross Validation and GridSearchCV ()

Optimizing is about finding best value for gamma, and potentially the regularization parameter C.

We use GridSearchCV() to optimize parameters gamma and c. We specify potential values for gamma and C

In [63]:

```
param_grid = [{'C':[0.5,1,10,100],'gamma':['scale',1,0.1,0.01,0.001,0.0001],'kernel':['r
bf']},]

optimal_params = GridSearchCV(SVC(),param_grid,cv=5,scoring='accuracy',verbose=0)

optimal_params.fit(X_train_scaled,y_train)
print(optimal_params.best_params_)
```

```
{'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}
```

Python has told us that ideal value of C is 100, which means when we will use regularization, ideal gamma value is 0.001

Build, Evaluate, Draw and interpret final SVM

In [64]:

```
clf_svm = SVC(random_state=42,C=100,gamma=0.001)
clf_svm.fit(X_train_scaled,y_train)
```

Out[64]:

```
SVC(C=100, gamma=0.001, random_state=42)
```

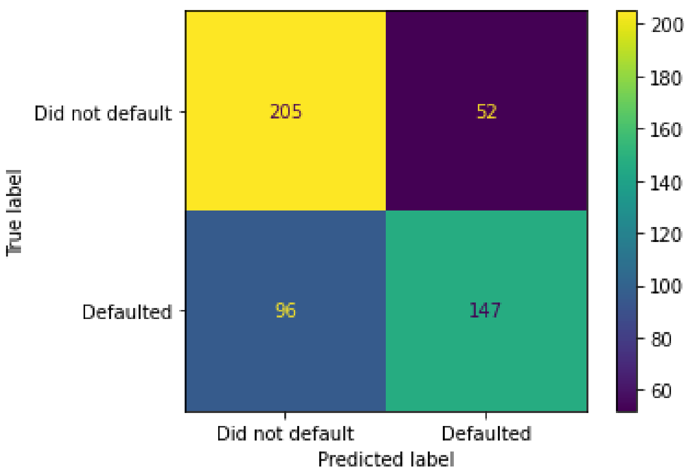
In [65]:

```
plot_confusion_matrix(clf_svm,X_test_Scaled,y_test,values_format='d',display_labels=["Did
not default","Defaulted"])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning
: Function plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is depre
cated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDis
play.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```

Out[65]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2712e966400>
```



Now we have to draw the decision boundary and interpret it

In [66]:

```
len(df_downsample.columns) #tells us number of
```

Out[66]:

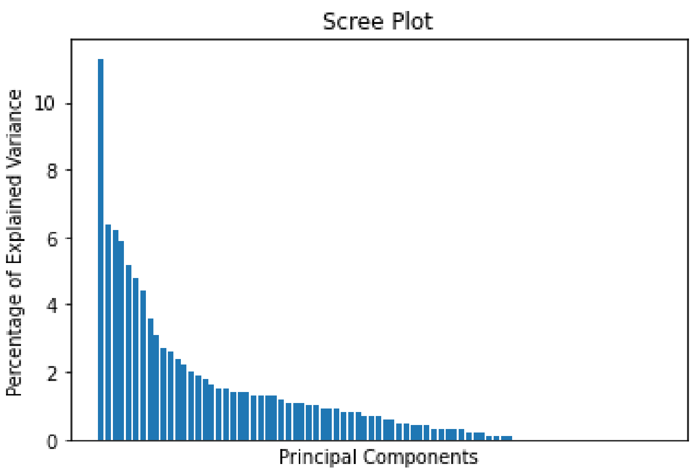
```
24
```

Here we see that there are 24 features(columns) in X. Thus our graph should be 24 dimensions to plot in raw form which is not possible. So we use PCA(Principal Component Analysis) to combine the 24 to 2.

we can obtain the accuracy of the graph by drawing a "scree plot"

In [69]:

```
pca = PCA()
X_train_pca = pca.fit_transform(X_train_scaled)

per_var = np.round(pca.explained_variance_ratio_*100,decimals=1)
labels = [str(x) for x in range(1,len(per_var)+1)]

plt.bar(x=range(1,len(per_var)+1),height=per_var)
plt.tick_params(
    axis = 'x',          # changes apply to the x-axis
    which = 'both',      # both major and minor ticks are affected
    bottom = False,      # ticks along bottom edge turned off
    top = False,         # ticks along top edge turned off
    labelbottom = False) # labels along bottom edge turned off

plt.ylabel('Percentage of Explained Variance')
plt.xlabel('Principal Components')
plt.title('Scree Plot')
plt.show()
```



In [70]:

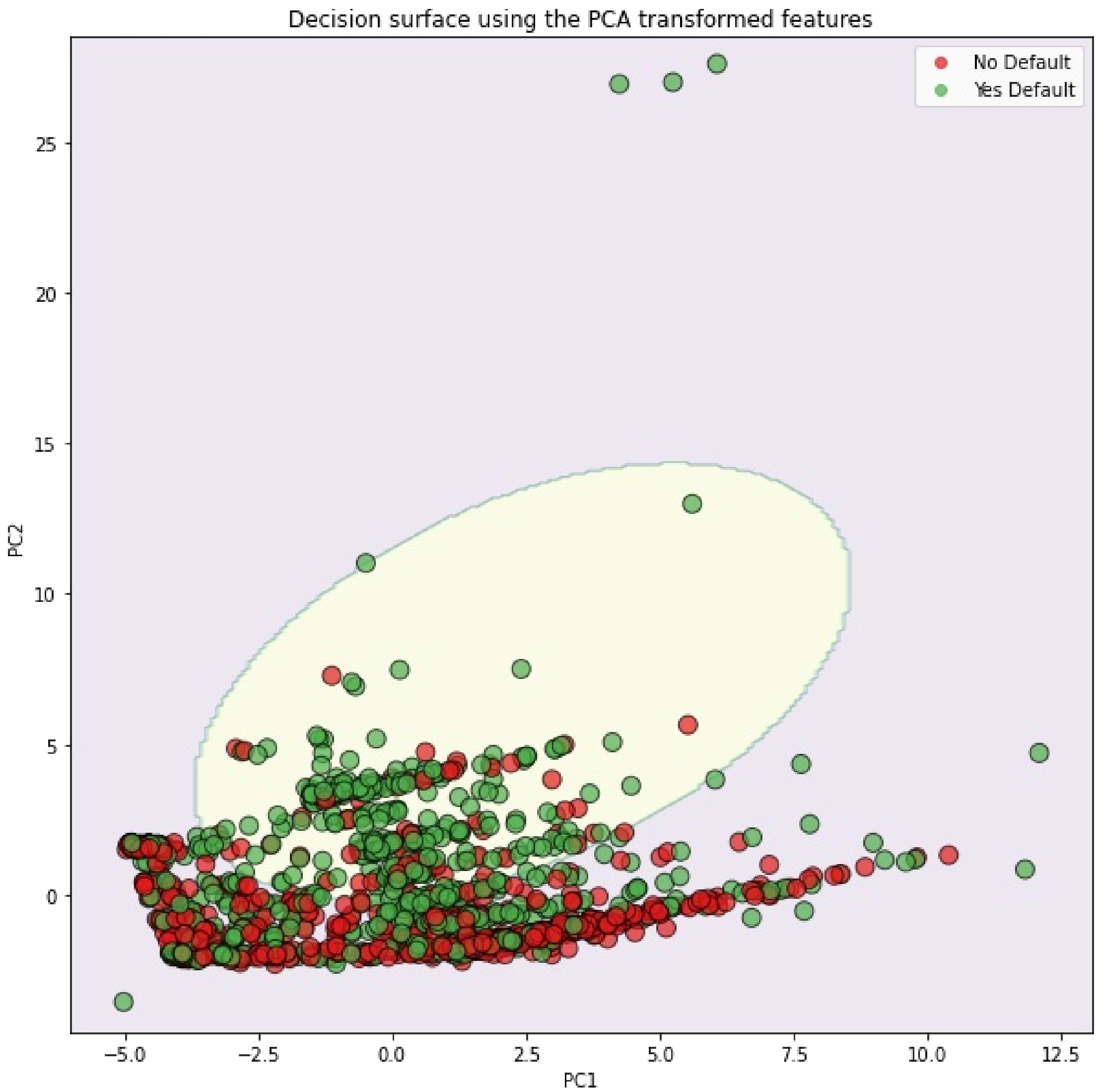
```
train_pc1_coords = X_train_pca[:,0]
train_pc2_coords = X_train_pca[:,1]

pca_train_scaled = scale(np.column_stack((train_pc1_coords,train_pc2_coords)))

param_grid = [{'C':[1,10,100,1000],'gamma':['scale',1,0.1,0.01,0.001,0.0001],'kernel':['
rbf']},]

optimal_params = GridSearchCV(SVC(),param_grid,cv=5,scoring='accuracy',verbose=0)
optimal_params.fit(pca_train_scaled,y_train)
print(optimal_params.best_params_)
```

```
{'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
```

In [75]:

```
clf_svm = SVC(random_state=42,C=1000,gamma=0.001)
clf_svm.fit(pca_train_scaled,y_train)

## Transform the test dataset with PCA
X_test_pca = pca.transform(X_train_scaled)
test_pc1_coords = X_test_pca[:,0]
test_pc2_coords = X_test_pca[:,1]

x_min = test_pc1_coords.min() - 1
x_max = test_pc1_coords.max() + 1

y_min = test_pc2_coords.min() - 1
y_max = test_pc2_coords.max() + 1
```

```
xx, yy = np.meshgrid(np.arange(start=x_min,stop=x_max, step=0.1),
                     np.arange(start = y_min,stop = y_max,step = 0.1))

z = clf_svm.predict(np.column_stack((xx.ravel(),yy.ravel())))
z = z.reshape(xx.shape)

fig, ax = plt.subplots(figsize = (10,10))
ax.contourf(xx,yy,z,alpha = 0.1)

cmap = colors.ListedColormap(['#e41a1c','#4daf4a'])
scatter = ax.scatter(test_pc1_coords,test_pc2_coords, c = y_train,
                     cmap = cmap,
                     s = 100,
                     edgecolors = 'k',
                     alpha = 0.7)

## Creating a legend
legend = ax.legend(scatter.legend_elements()[0],
                   scatter.legend_elements()[1],
                   loc = "upper right")
legend.get_texts()[0].set_text("No Default")
legend.get_texts()[1].set_text("Yes Default")

#add axis labels and titles
ax.set_ylabel('PC2')
ax.set_xlabel('PC1')
ax.set_title("Decision surface using the PCA transformed features")

plt.show()
```



Pink part of the graph is the area where all datapoints are predicted as "Not Defaulted". Yellow part is the area where datapoints are predicted to "have defaulted".

In [ ]:

```
```