Project 1 - Classification

Machine Learning Spring 2021

Default of Credit card

Source of Dataset

https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients
(https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients)

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import model_selection
from sklearn.preprocessing import MinMaxScaler,StandardScaler
from sklearn import svm
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import recall_score, precision_score, f1_score
from sklearn.metrics import precision_recall_curve
from sklearn import svm
```

In [2]:

```
dcc = pd.read_excel('default of credit card clients.xls',skiprows=1)
dcc.drop(['ID'], axis=1, inplace=True)
```

In [3]:

```
dcc
```

Out[3]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AM
0	20000	2	2	1	24	2	2	-1	-1	-2	...	
1	120000	2	2	2	26	-1	2	0	0	0	...	32
2	90000	2	2	2	34	0	0	0	0	0	...	143
3	50000	2	2	1	37	0	0	0	0	0	...	283
4	50000	1	2	1	57	-1	0	-1	0	0	...	209
...	...	...	...	...	...	...	...	...	...	...	...	
29995	220000	1	3	1	39	0	0	0	0	0	...	880
29996	150000	1	3	2	43	-1	-1	-1	-1	0	...	89

In [4]:

```
dcc.head()
```

Out[4]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...
0	20000	2	2	1	24	2	2	-1	-1	-2	...
1	120000	2	2	2	26	-1	2	0	0	0	...
2	90000	2	2	2	34	0	0	0	0	0	...
3	50000	2	2	1	37	0	0	0	0	0	...
4	50000	1	2	1	57	-1	0	-1	0	0	...

5 rows × 24 columns

In [5]:

```
dcc.describe()
```

Out[5]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	167484.322667	1.603733	1.853133	1.551867	35.485500	-0.016700
std	129747.661567	0.489129	0.790349	0.521970	9.217904	1.123802
min	10000.000000	1.000000	0.000000	0.000000	21.000000	-2.000000
25%	50000.000000	1.000000	1.000000	1.000000	28.000000	-1.000000
50%	140000.000000	2.000000	2.000000	2.000000	34.000000	0.000000
75%	240000.000000	2.000000	2.000000	2.000000	41.000000	0.000000
max	1000000.000000	2.000000	6.000000	3.000000	79.000000	8.000000

8 rows × 24 columns

In [6]:

```
dcc.isnull().sum()
```

Out[6]:

```
LIMIT_BAL                    0
SEX                          0
EDUCATION                    0
MARRIAGE                     0
AGE                          0
PAY_0                        0
PAY_2                        0
PAY_3                        0
PAY_4                        0
PAY_5                        0
PAY_6                        0
BILL_AMT1                    0
BILL_AMT2                    0
BILL_AMT3                    0
BILL_AMT4                    0
BILL_AMT5                    0
BILL_AMT6                    0
PAY_AMT1                     0
```

Delete 5.5% of random values, Categorical variables and Age are left alone

In [7]:

```
np.random.seed(seed=0)
masking_array= np.random.randint(100,size=(dcc.shape[0], 19)) < 94.5
masking_array

```

Out[7]:

```
array([[ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       ...,
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True, False,  True]])
```

In [8]:

```
dcc[dcc.columns[5:25]]=dcc[dcc.columns[5:25]].where(masking_array, np.nan)
```

In [9]:

```
dcc.isna().sum()
```

Out[9]:

```
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                      1496
PAY_2                      1490
PAY_3                      1550
PAY_4                      1502
PAY_5                      1437
PAY_6                      1474
BILL_AMT1                  1459
BILL_AMT2                  1473
BILL_AMT3                  1514
BILL_AMT4                  1432
BILL_AMT5                  1462
BILL_AMT6                  1530
PAY_AMT1                   1466
PAY_AMT2                   1518
PAY_AMT3                   1491
PAY_AMT4                   1440
PAY_AMT5                   1475
PAY_AMT6                   1612
default payment next month    1518
dtype: int64
```

Function to find missing data in percentage

In [10]:

```
def missing_data_percentage(df):
    x = ['column_name','missing_values', 'missing_in_percentage']
    missing_data = pd.DataFrame(columns=x)
    columns = dcc.columns
    for col in columns:
        iscolumn_name = col
        ismissing_values = dcc[col].isnull().sum()
        ismissing_in_percentage = (dcc[col].isnull().sum()/dcc[col].shape[0])*100

        missing_data.loc[len(missing_data)] = [iscolumn_name, ismissing_values, ismiss:
    print(missing_data.round(2))


```

In [11]:

```
missing_data_percentage(dcc)
```

```
                  column_name missing_values  missing_in_percentage
0                   LIMIT_BAL              0                   0.00
1                         SEX              0                   0.00
2                   EDUCATION              0                   0.00
3                    MARRIAGE              0                   0.00
4                         AGE              0                   0.00
5                       PAY_0           1496                   4.99
6                       PAY_2           1490                   4.97
7                       PAY_3           1550                   5.17
8                       PAY_4           1502                   5.01
9                       PAY_5           1437                   4.79
10                      PAY_6           1474                   4.91
11                  BILL_AMT1           1459                   4.86
12                  BILL_AMT2           1473                   4.91
13                  BILL_AMT3           1514                   5.05
14                  BILL_AMT4           1432                   4.77
15                  BILL_AMT5           1462                   4.87
16                  BILL_AMT6           1530                   5.10
17                   PAY_AMT1           1466                   4.89
18                   PAY_AMT2           1518                   5.06
19                   PAY_AMT3           1491                   4.97
20                   PAY_AMT4           1440                   4.80
21                   PAY_AMT5           1475                   4.92
22                   PAY_AMT6           1612                   5.37
23 default payment next month           1518                   5.06
```

Data Cleaning

In [12]:

```
print(dcc.apply(lambda col: col.unique()))
```

```
LIMIT_BAL                     [20000, 120000, 90000, 50000, 500000, 100000,
...
SEX                                                                      [2,
1]
EDUCATION                                                   [2, 1, 3, 5, 4, 6,
0]
MARRIAGE                                                              [1, 2, 3,
0]
AGE                           [24, 26, 34, 37, 57, 29, 23, 28, 35, 51, 41,
3...
PAY_0                         [2.0, -1.0, 0.0, nan, 1.0, -2.0, 3.0, 4.0, 8.
0...
PAY_2                         [2.0, 0.0, nan, -2.0, -1.0, 3.0, 5.0, 7.0, 4.
0...
PAY_3                         [-1.0, 0.0, 2.0, -2.0, nan, 3.0, 4.0, 6.0, 7.
0...
PAY_4                         [-1.0, 0.0, -2.0, 2.0, nan, 3.0, 4.0, 5.0, 7.
0...
PAY_5                         [-2.0, 0.0, -1.0, 2.0, nan, 3.0, 5.0, 4.0, 7.
0...
PAY_6                         [-2.0, 2.0, 0.0, -1.0, nan, 3.0, 4.0, 6.0, 7.
0...
BILL_AMT1                     [3913.0, 2682.0, 29239.0, 46990.0, 8617.0, 64
4...
BILL_AMT2                     [3102.0, 1725.0, 14027.0, 48233.0, 5670.0, 57
0...
BILL_AMT3                     [689.0, 2682.0, 13559.0, 49291.0, 35835.0, 57
6...
BILL_AMT4                     [0.0, 3272.0, 14331.0, 28314.0, 20940.0, 1939
4...
BILL_AMT5                     [0.0, 3455.0, 14948.0, 28959.0, 19146.0, nan,
...
BILL_AMT6                     [0.0, 3261.0, 15549.0, 29547.0, 19131.0, 2002
4...
PAY_AMT1                      [0.0, 1518.0, 2000.0, 2500.0, 55000.0, 380.0,
...
PAY_AMT2                      [689.0, 1000.0, 1500.0, 2019.0, 36681.0, 181
5....
PAY_AMT3                      [0.0, nan, 1000.0, 1200.0, 10000.0, 657.0, 38
0...
PAY_AMT4                      [0.0, 1000.0, 1100.0, 9000.0, 20239.0, 581.0,
...
PAY_AMT5                      [0.0, 1000.0, 1069.0, 689.0, 13750.0, 1687.0,
...
PAY_AMT6                      [0.0, 2000.0, 5000.0, 1000.0, nan, 800.0, 137
7...
default payment next month                                     [1.0, 0.0, n
an]
dtype: object
```

Content of Data

LIMIT_BAL: Amount of given credit in NT dollars (includes individual and family/supplementary credit

SEX: Gender (1=male, 2=female)

EDUCATION: (0=?, 1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)

MARRIAGE: Marital status (0=?,1=married, 2=single, 3=others)

AGE: Age in years

PAY_0: Repayment status in September, 2005 (-1=pay duly, 1=payment delay for one month, 2=payment delay for two months, ... 8=payment delay for eight months, 9=payment delay for nine months and above)

PAY_2: Repayment status in August, 2005

PAY_3: Repayment status in July, 2005

PAY_4: Repayment status in June, 2005

PAY_5: Repayment status in May, 2005

PAY_6: Repayment status in April, 2005)

BILL_AMT1: Amount of bill statement in September, 2005 (NT dollar)

BILL_AMT2: Amount of bill statement in August, 2005 (NT dollar)

BILL_AMT3: Amount of bill statement in July, 2005 (NT dollar)

BILL_AMT4: Amount of bill statement in June, 2005 (NT dollar)

BILL_AMT5: Amount of bill statement in May, 2005 (NT dollar)

BILL_AMT6: Amount of bill statement in April, 2005 (NT dollar)

PAY_AMT1: Amount of previous payment in September, 2005 (NT dollar)

PAY_AMT2: Amount of previous payment in August, 2005 (NT dollar)

PAY_AMT3: Amount of previous payment in July, 2005 (NT dollar)

PAY_AMT4: Amount of previous payment in June, 2005 (NT dollar)

PAY_AMT5: Amount of previous payment in May, 2005 (NT dollar)

PAY_AMT6: Amount of previous payment in April, 2005 (NT dollar)

default.payment.next.month: Default payment (1=yes, 0=no)

Education type for levels 0,4,5,6 is unknown. We combine and label them as 0

In [13]:

```
dcc.loc[dcc.EDUCATION >= 4, 'EDUCATION'] = 0
```

In [14]:

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

Out[14]:

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

Marriage status for 0 and 3 is unknown. We combine and label them as 0

In [15]:

```
dcc.loc[dcc.MARRIAGE == 3, 'MARRIAGE'] = 0
```

In [16]:

```
dcc['MARRIAGE'].unique()

```

Out[16]:

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

Filling up missing values

In [17]:

```
dcc['PAY_0'].fillna(dcc['PAY_0'].mode()[0],inplace= True)
dcc['PAY_2'].fillna(dcc['PAY_2'].mode()[0],inplace= True)
dcc['PAY_3'].fillna(dcc['PAY_3'].mode()[0],inplace= True)
dcc['PAY_4'].fillna(dcc['PAY_4'].mode()[0],inplace= True)
dcc['PAY_5'].fillna(dcc['PAY_5'].mode()[0],inplace= True)
dcc['PAY_6'].fillna(dcc['PAY_6'].mode()[0],inplace= True)
```

In [18]:

```
dcc['PAY_AMT1'].fillna(dcc['PAY_AMT1'].mean(),inplace= True)
dcc['PAY_AMT2'].fillna(dcc['PAY_AMT2'].mean(),inplace= True)
dcc['PAY_AMT3'].fillna(dcc['PAY_AMT3'].mean(),inplace= True)
dcc['PAY_AMT4'].fillna(dcc['PAY_AMT4'].mean(),inplace= True)
dcc['PAY_AMT5'].fillna(dcc['PAY_AMT5'].mean(),inplace= True)
dcc['PAY_AMT6'].fillna(dcc['PAY_AMT6'].mean(),inplace= True)
```

In [19]:

```
dcc['BILL_AMT1'].fillna(dcc['BILL_AMT1'].mean(),inplace= True)
dcc['BILL_AMT2'].fillna(dcc['BILL_AMT1'].mean(),inplace= True)
dcc['BILL_AMT3'].fillna(dcc['BILL_AMT1'].mean(),inplace= True)
dcc['BILL_AMT4'].fillna(dcc['BILL_AMT1'].mean(),inplace= True)
dcc['BILL_AMT5'].fillna(dcc['BILL_AMT1'].mean(),inplace= True)
dcc['BILL_AMT6'].fillna(dcc['BILL_AMT1'].mean(),inplace= True)

```

In [20]:

```
dcc['default payment next month'].fillna(dcc['default payment next month'].mode()[0],ir
```

In [21]:

```
dcc.shape
```

Out[21]:

```
(30000, 24)
```

In [22]:

```
dcc.rename(columns={'default payment next month':'Default_Payment'}, inplace=True)
```

In [23]:

```
dcc.isna().sum()
```

Out[23]:

```
LIMIT_BAL      0
SEX            0
EDUCATION      0
MARRIAGE       0
AGE            0
PAY_0          0
PAY_2          0
PAY_3          0
PAY_4          0
PAY_5          0
PAY_6          0
BILL_AMT1      0
BILL_AMT2      0
BILL_AMT3      0
BILL_AMT4      0
BILL_AMT5      0
BILL_AMT6      0
PAY_AMT1       0
```

In [24]:

```
dcc
```

Out[24]:

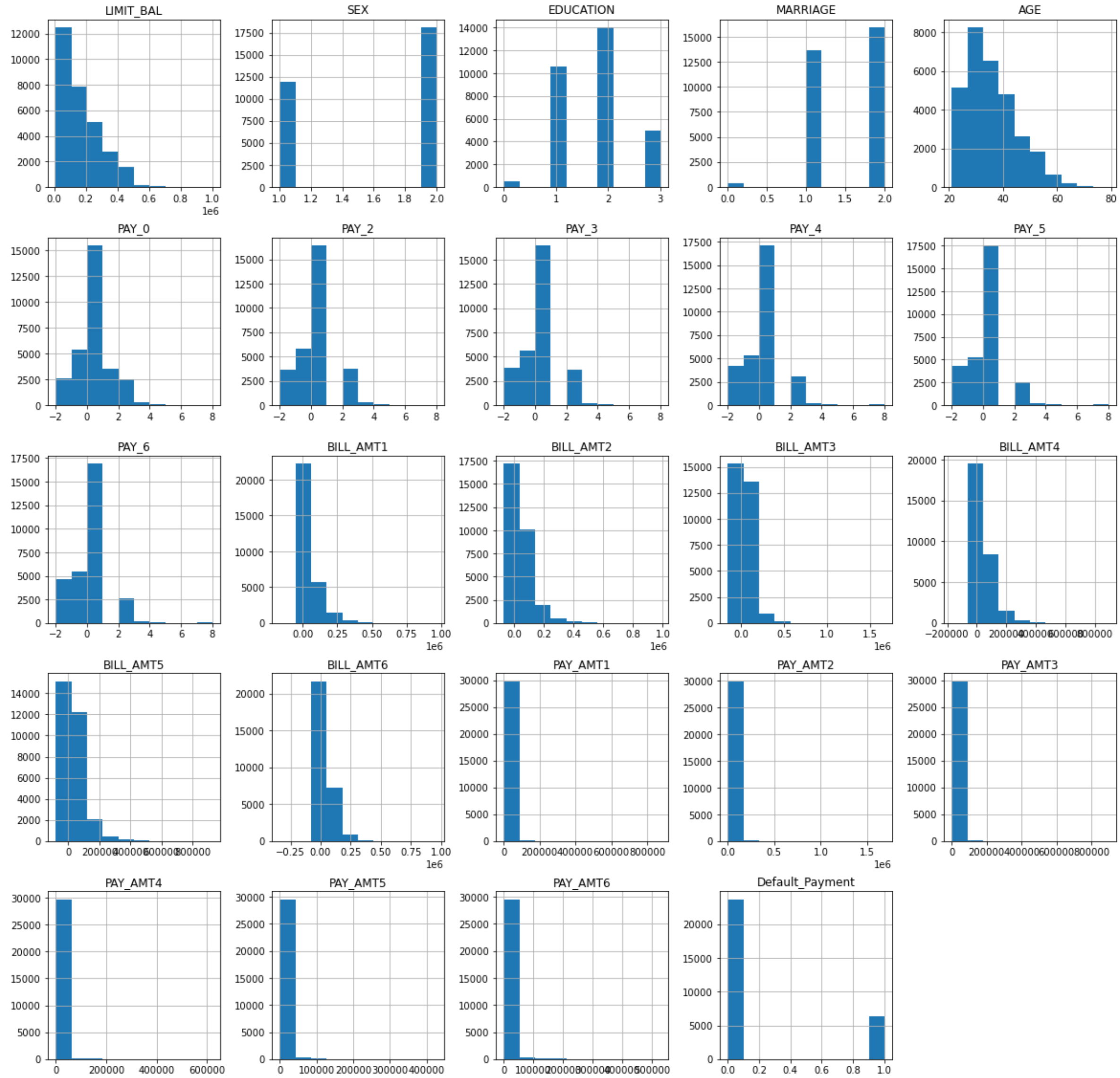
	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5
0	20000	2	2	1	24	2.0	2.0	-1.0	-1.0	-2.0
1	120000	2	2	2	26	-1.0	2.0	0.0	0.0	0.0
2	90000	2	2	2	34	0.0	0.0	0.0	0.0	0.0
3	50000	2	2	1	37	0.0	0.0	0.0	0.0	0.0
4	50000	1	2	1	57	-1.0	0.0	-1.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...
29995	220000	1	3	1	39	0.0	0.0	0.0	0.0	0.0
29996	150000	1	3	2	43	-1.0	-1.0	-1.0	-1.0	0.0
29997	30000	1	2	2	37	4.0	3.0	2.0	-1.0	0.0
29998	80000	1	3	1	41	1.0	-1.0	0.0	0.0	0.0
29999	50000	1	2	1	46	0.0	0.0	0.0	0.0	0.0

30000 rows × 24 columns

Exploratory Data Analysis

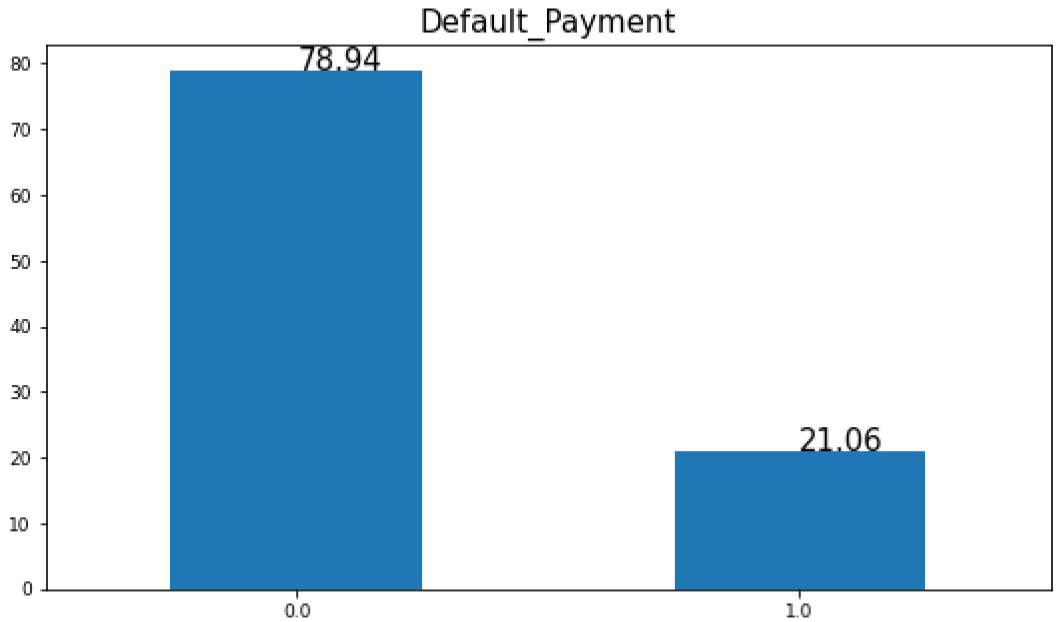
In [25]:

```
dcc.hist(figsize=(20,20));
```



In [26]:

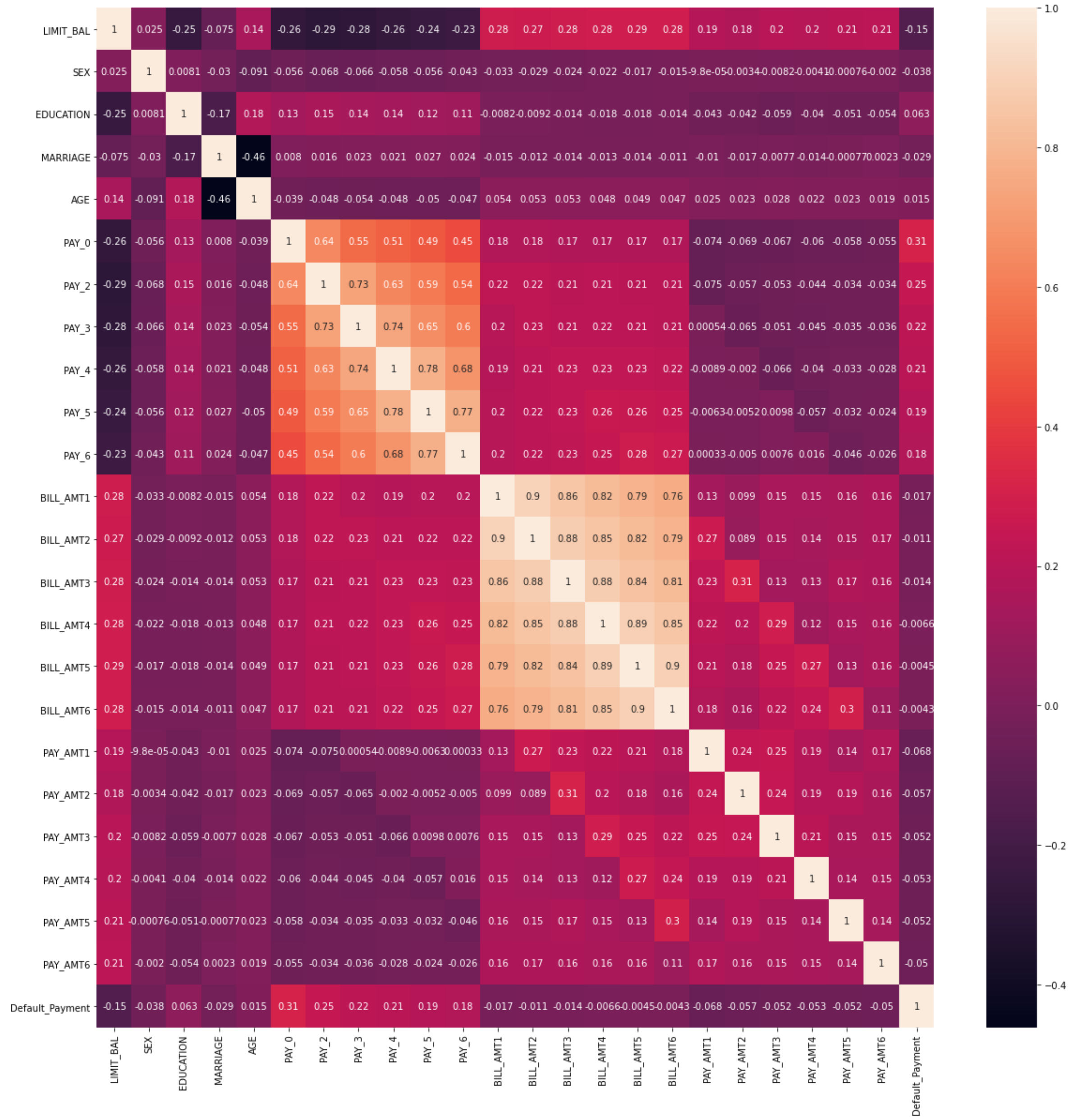
```
a = (dcc.Default_Payment.value_counts(normalize=True)*100)
a.plot.bar(figsize=(9,5))
plt.xticks(fontsize=9, rotation=0)
plt.yticks(fontsize=9)
plt.title("Default_Payment", fontsize=15)
for x,y in zip([0,1],a):
    plt.text(x,y,round(y,2),fontsize=15)
plt.show()
```



We can see that the dataset consists of **78.9%** clients are not expected to default payment whereas **21.0%** clients are expected to default the payment. This graph also indicates the our target data column(**Default_Payment**) is **imbalanced**.

In [27]:

```
plt.figure(figsize=(20,20))
sns.heatmap(dcc.corr(), annot=True);
```



There is a weak correlation between all the columns of PAY and BILL_AMT and There is Negative correlation between LIMIT_BAL and PAY column values

Data Prepartion for Analysis and classification

1. Train Test Split

In [28]:

```
X = dcc.drop('Default_Payment',axis =1)
y = dcc['Default_Payment']
X_train_org, X_test_org, y_train, y_test = train_test_split(X, y, random_state = 0)
```

2. Scaling

In [29]:

```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train_org)
X_test = scaler.transform(X_test_org)
```

Classification Model

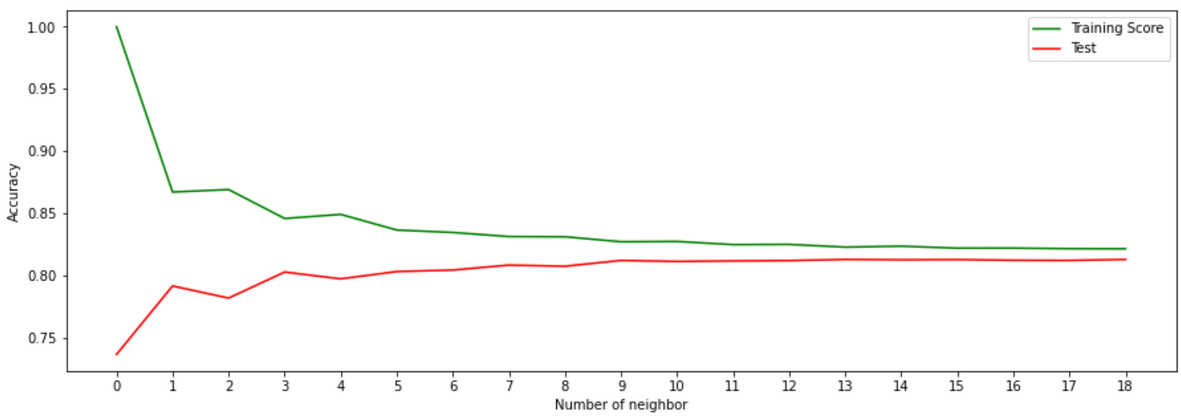
1. k-nearest neighbors (KNN)

In [30]:

```
%matplotlib inline
from sklearn.neighbors import KNeighborsClassifier

knn_training = []
knn_testing = []
xvalues = range(1,20)

for i in range(1,20):
    knn=KNeighborsClassifier(n_neighbors = i)
    knn.fit(X_train,y_train)
    train_score_knn=knn.score(X_train,y_train)
    test_score_knn=knn.score(X_test,y_test)
    knn_training.append(train_score_knn)
    knn_testing.append(test_score_knn)

plt.subplots(figsize = (15,5))
plt.plot(xvalues, knn_training, color='g', label = 'Training Score')
plt.plot(xvalues, knn_testing, color='r', label = 'Test')
plt.xticks(xvalues, range(19))
plt.xlabel('Number of neighbor')
plt.ylabel('Accuracy')
plt.legend()


```

Out[30]:

```
<matplotlib.legend.Legend at 0x233135e9400>
```



In [31]:

```
knn=KNeighborsClassifier(n_neighbors = 9)
knn.fit(X_train, y_train)

```

Out[31]:

```
KNeighborsClassifier(n_neighbors=9)
```

neighbors(k) = 9 is the best parameter for knn model

In [32]:

```
print('Training score: {:.3f}'.format(knn.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(knn.score(X_test, y_test)))
```

```
Training score: 0.831
Testing score: 0.807
```

In [33]:

```
X_train.shape
```

Out[33]:

```
(22500, 23)
```

Cross validation scores for KNN Classifier

In [34]:

```
knn_CV_scores = cross_val_score(knn, X_train, y_train, cv=7)

pd.DataFrame({'Train Score - Cross Validation  ': knn_CV_scores})
```

Out[34]:

	Train Score - Cross Validation
0	0.805910
1	0.808087
2	0.815184
3	0.809583
4	0.807716
5	0.805227
6	0.808650

Grid Search on KNN Classifier

In [35]:

```
grid_knn_parameters = {'n_neighbors':range(1,20), 'p': [1,2],
            'weights': ['uniform','distance'],
            'metric': ['euclidean','manhattan']}

knn_CV = GridSearchCV(KNeighborsClassifier(), grid_knn_parameters, verbose = 1, cv = 7,

Knn_results = knn_CV.fit(X_train, y_train)
```

```
Fitting 7 folds for each of 152 candidates, totalling 1064 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   11.2s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:   55.0s
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 784 tasks      | elapsed:  4.4min
[Parallel(n_jobs=-1)]: Done 1064 out of 1064 | elapsed:  6.5min finished
```

In [36]:

```
round(knn_CV.score(X_test,y_test),2)
```

Out[36]:

```
0.81
```

In [37]:

```
print("KNN grid search Best Parameters ")
best_parameters_knn=Knn_results.best_params_
best_parameters_knn
```

```
KNN grid search Best Parameters
```

Out[37]:

```
{'metric': 'manhattan', 'n_neighbors': 19, 'p': 1, 'weights': 'distance'}
```

In [38]:

```
best_para_Knn = KNeighborsClassifier(metric= 'manhattan', n_neighbors = 19, p = 1, weig
best_para_Knn.fit(X_train, y_train)
Knn_value_y = best_para_Knn.predict(X_test)


```

In [39]:

```
print('Training score: {:.3f}'.format(best_para_Knn.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(best_para_Knn.score(X_test, y_test)))
```

```
Training score: 1.000
Testing score: 0.810
```

In [40]:

```
print(classification_report(y_pred = Knn_value_y, y_true = y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.83      0.96      0.89      5950
         1.0       0.60      0.25      0.35      1550

    accuracy                           0.81      7500
   macro avg       0.71      0.60      0.62      7500
weighted avg       0.78      0.81      0.78      7500
```

In [41]:

```
print(confusion_matrix(y_pred = Knn_value_y, y_true = y_test))
```

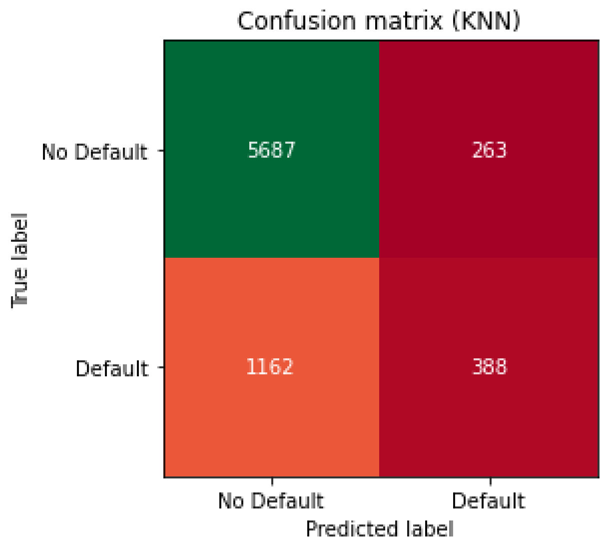
```
[[5687  263]
 [1162  388]]
```

In [42]:

```
import mglearn
```

In [43]:

```
heatmap = mglearn.tools.heatmap(
    confusion_matrix(y_pred = Knn_value_y, y_true = y_test), xlabel = 'Predicted label'
    ylabel='True label', xticklabels = ['No Default','Default'], yticklabels=['No Defau
plt.title("Confusion matrix (KNN)")
plt.gca().invert_yaxis()
```



In [44]:

```
Knn_precision_score=precision_score(y_test, best_para_Knn.predict(X_test))
print('Precision score : {:.2f} '.format(Knn_precision_score))
```

```
Precision score : 0.60
```

In [45]:

```
Knn_recall_score = recall_score(y_test, best_para_Knn.predict(X_test))
print('Recall score : {:.2f} '.format(Knn_recall_score))
```

```
Recall score : 0.25
```

In [46]:

```
Knn_f1_score = f1_score(y_test,best_para_Knn.predict(X_test))
print('f1 score : {:.2f} '.format(Knn_f1_score))
```

```
f1 score : 0.35
```

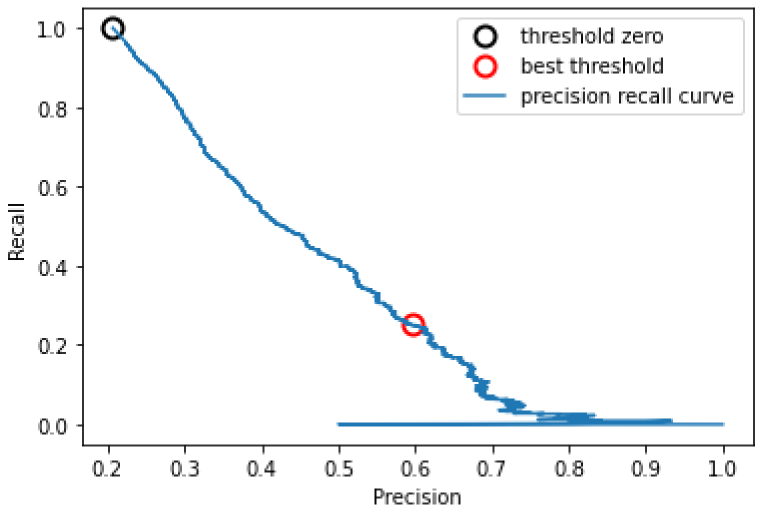
The precision-recall curve is used for evaluating the performance of binary classification algorithms. It is often used in situations where classes are heavily imbalanced

In [47]:

```
import mglearn

%matplotlib inline

precision, recall, thresholds = precision_recall_curve(y_test, best_para_Knn.predict_pr

close_zero = np.argmin(np.abs(thresholds))

plt.plot(precision[close_zero], recall[close_zero], 'o', markersize=10, label="thresho]

plt.plot(Knn_precision_score, Knn_recall_score, 'o', markersize=10, label="best thresho

plt.plot(precision, recall, label="precision recall curve")
plt.xlabel("Precision")
plt.ylabel("Recall")
plt.legend(loc="best")
```

Out[47]:

```
<matplotlib.legend.Legend at 0x2330e428ca0>
```



In [48]:

```
Summary_Knn= {'Type': 'K-nearest Neighbors (KNN) Classification Model', 'Training Score
              'Testing Score':best_para_Knn.score(X_test, y_test)*100,
              'f1 Score':f1_score(y_test, best_para_Knn.predict(X_test))};
```

In [49]:

```
Summary_Knn
```

Out[49]:

```
{'Type': 'K-nearest Neighbors (KNN) Classification Model',
 'Training Score': 100.0,
 'Testing Score': 81.0,
 'f1 Score': 0.35256701499318494}
```

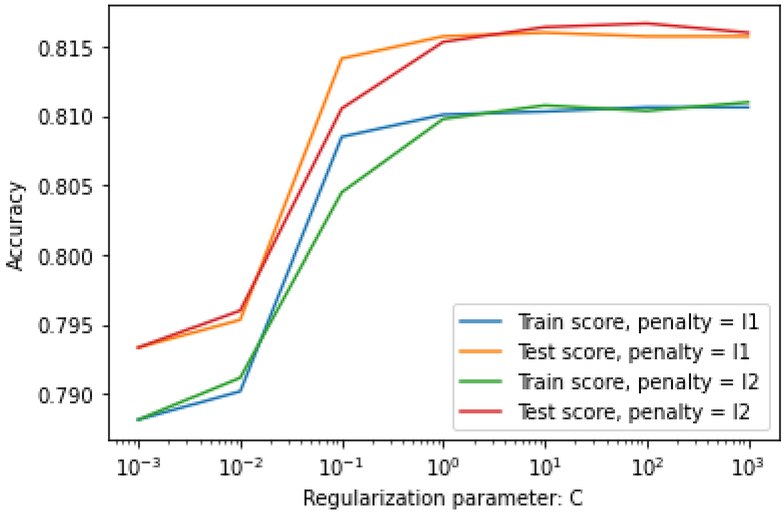
2. Logistic Regression

In [50]:

```
c_range = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
l1_training = []
l1_testing = []
l2_training = []
l2_testing = []
#As liblinear and saga handle 'l1 and l2' penalty, for small datasets, 'liblinear' is c
for c in c_range:
    l1_logistic = LogisticRegression(penalty = 'l1', C = c,solver='liblinear', n_jobs =
    l2_logistic = LogisticRegression(penalty = 'l2', C = c,solver = 'lbfgs', n_jobs = -
    l1_logistic.fit(X_train, y_train)
    l2_logistic.fit(X_train, y_train)
    l1_training.append(l1_logistic.score(X_train, y_train))
    l1_testing.append(l1_logistic.score(X_test, y_test))
    l2_training.append(l2_logistic.score(X_train, y_train))
    l2_testing.append(l2_logistic.score(X_test, y_test))
```

In [51]:

```
plt.plot(c_range, l1_training, label = 'Train score, penalty = l1')
plt.plot(c_range, l1_testing, label = 'Test score, penalty = l1')
plt.plot(c_range, l2_training, label = 'Train score, penalty = l2')
plt.plot(c_range, l2_testing, label = 'Test score, penalty = l2')
plt.legend()
plt.xlabel('Regularization parameter: C')
plt.ylabel('Accuracy')
plt.xscale('log')

```



According to above graph, C=100 & l2 penalty, test accuracy is best.

In [52]:

```
logistic = LogisticRegression(penalty = 'l2', C=100)

logistic.fit(X_train, y_train)

print('Training score: {:.3f}'.format(logistic.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(logistic.score(X_test, y_test)))
```

```
Training score: 0.810
Testing score: 0.817
```

In [53]:

```
logistic_CV_scores = cross_val_score(logistic, X_train, y_train, cv=5)

pd.DataFrame({'Train Score - Cross Validation  ': logistic_CV_scores})
```

Out[53]:

	Train Score - Cross Validation
0	0.811333
1	0.812000
2	0.812444
3	0.805111
4	0.811111

In [54]:

```
print("Average cross-validation score is : {:.2f}".format(logistic_CV_scores.mean()))
```

```
Average cross-validation score is : 0.81
```

Applying Grid Search with Logistic Regression

In [55]:

```
logistic.get_params()
```

Out[55]:

```
{'C': 100,
 'class_weight': None,
 'dual': False,
 'fit_intercept': True,
 'intercept_scaling': 1,
 'l1_ratio': None,
 'max_iter': 100,
 'multi_class': 'auto',
 'n_jobs': None,
 'penalty': 'l2',
 'random_state': None,
 'solver': 'lbfgs',
 'tol': 0.0001,
 'verbose': 0,
 'warm_start': False}
```

In [56]:

```
param_grid_logit = { 'max_iter' : range(1,200), 'penalty' : ['l1','l2'],
             'C' : [0.001, 0.01, 0.1, 1, 10, 100, 1000]}
logit_class_CV = GridSearchCV(estimator = logistic, param_grid = param_grid_logit, cv =
GS_results_logit = logit_class_CV.fit(X_train, y_train)

best_parameters_logit = logit_class_CV.best_params_

```

```
Fitting 5 folds for each of 2786 candidates, totalling 13930 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  56 tasks      | elapsed:    0.3s
[Parallel(n_jobs=-1)]: Done 1200 tasks      | elapsed:    8.0s
[Parallel(n_jobs=-1)]: Done 3200 tasks      | elapsed:   27.2s
[Parallel(n_jobs=-1)]: Done 4768 tasks      | elapsed:   48.7s
[Parallel(n_jobs=-1)]: Done 5218 tasks      | elapsed:   58.6s
[Parallel(n_jobs=-1)]: Done 5768 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 6874 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 7624 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 8930 tasks      | elapsed:  2.8min
[Parallel(n_jobs=-1)]: Done 9880 tasks      | elapsed:  3.7min
[Parallel(n_jobs=-1)]: Done 11386 tasks      | elapsed:  4.5min
[Parallel(n_jobs=-1)]: Done 13104 tasks      | elapsed:  5.7min
[Parallel(n_jobs=-1)]: Done 13930 out of 13930 | elapsed:  6.6min finished
```

In [57]:

```
print("Logistic grid search Best score ")
GS_results_logit.best_score_
```

```
Logistic grid search Best score
```

Out[57]:

```
0.8110666666666667
```

In [58]:

```
best_parameters = logit_class_CV.best_params_
print("Logistic grid search Best parameters: ")
best_parameters_logit
```

```
Logistic grid search Best parameters:
```

Out[58]:

```
{'C': 1000, 'max_iter': 90, 'penalty': 'l2'}
```

Grid Search on Logistic Regressio with C=1000, max_iter=90, penalty=l2

In [59]:

```
best_para_logistic = LogisticRegression( C = 1000, max_iter = 90, penalty ='l2',)

best_para_logistic.fit(X_train,y_train)
logistic_value_y = best_para_logistic.predict(X_test)

print('Training score: {:.3f}'.format(best_para_logistic.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(best_para_logistic.score(X_test, y_test)))
```

```
Training score: 0.811
Testing score: 0.817
```

In [60]:

```
print(classification_report(y_pred = logistic_value_y, y_true = y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.82      0.98      0.89      5950
         1.0       0.71      0.19      0.30      1550

    accuracy                           0.82      7500
   macro avg       0.77      0.58      0.60      7500
weighted avg       0.80      0.82      0.77      7500
```

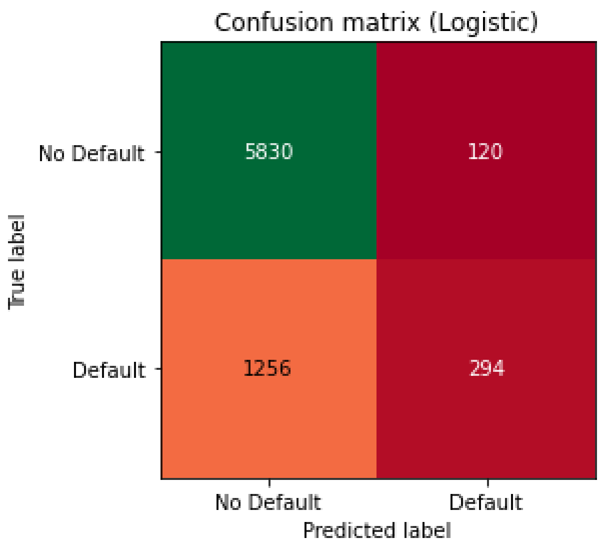
In [61]:

```
print(confusion_matrix(y_pred =logistic_value_y, y_true = y_test))
```

```
[[5830  120]
 [1256  294]]
```

In [62]:

```
heatmap = mglearn.tools.heatmap(
    confusion_matrix(y_pred = logistic_value_y, y_true = y_test), xlabel = 'Predicted l
    ylabel='True label', xticklabels = ['No Default','Default'],yticklabels=['No Defaul
plt.title("Confusion matrix (Logistic)")
plt.gca().invert_yaxis()
```



In [63]:

```
print("Logistic grid search Best Score ")
GS_results_logit.best_score_
```

```
Logistic grid search Best Score
```

Out[63]:

```
0.8110666666666667
```

In [64]:

```
logistic_precision_score=precision_score(y_test, best_para_logistic.predict(X_test))
print('Precision score : {:.2f} '.format(logistic_precision_score))
```

```
Precision score : 0.71
```

In [65]:

```
logistic_recall_score = recall_score(y_test, best_para_Knn.predict(X_test))
print('Recall score : {:.2f} '.format(logistic_recall_score))
```

```
Recall score : 0.25
```

In [66]:

```
logistic_f1_score = f1_score(y_test, best_para_logistic.predict(X_test))
print('f1 score : {:.2f} '.format(logistic_f1_score))
```

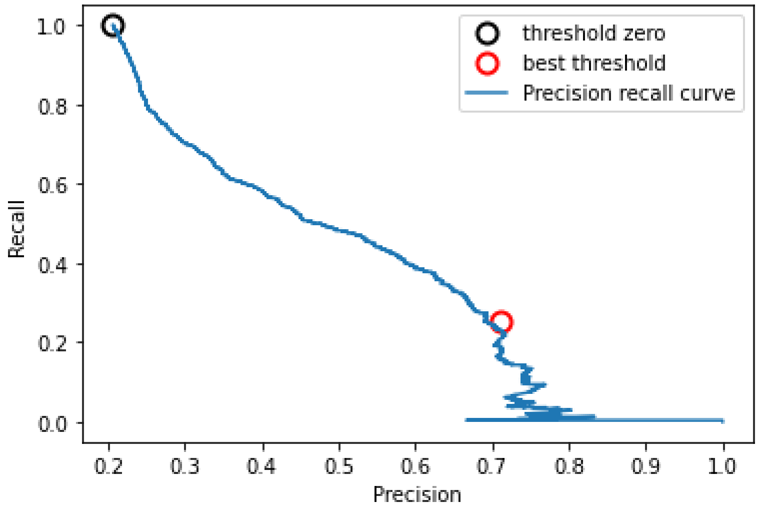
```
f1 score : 0.30
```

In [67]:

```
precision, recall, thresholds = precision_recall_curve(y_test, best_para_logistic.predi

plt.plot(precision[close_zero], recall[close_zero], 'o', markersize=10,
         label="threshold zero", fillstyle="none", c='k', mew=2)

plt.plot(logistic_precision_score, logistic_recall_score, 'o', markersize=10,
         label="best threshold", fillstyle="none", c='r', mew=2)

plt.plot(precision, recall, label="Precision recall curve")
plt.xlabel("Precision")
plt.ylabel("Recall")
plt.legend(loc="best")
```

Out[67]:

```
<matplotlib.legend.Legend at 0x23311bde790>
```



In [68]:

```
Summary_Logistic= {'Type': 'Logistic Regression', 'Train Score': best_para_logistic.sco
              'Testing Score':best_para_logistic.score(X_test, y_test)*100,
              'f1 Score':f1_score(y_test, best_para_logistic.predict(X_test))};
```

In [69]:

```
Summary_Logistic
```

Out[69]:

```
{'Type': 'Logistic Regression',
 'Train Score': 81.05333333333333,
 'Testing Score': 81.65333333333334,
 'f1 Score': 0.2993890020366599}
```

3. Linear Support Vector Machine Classifier

In [70]:

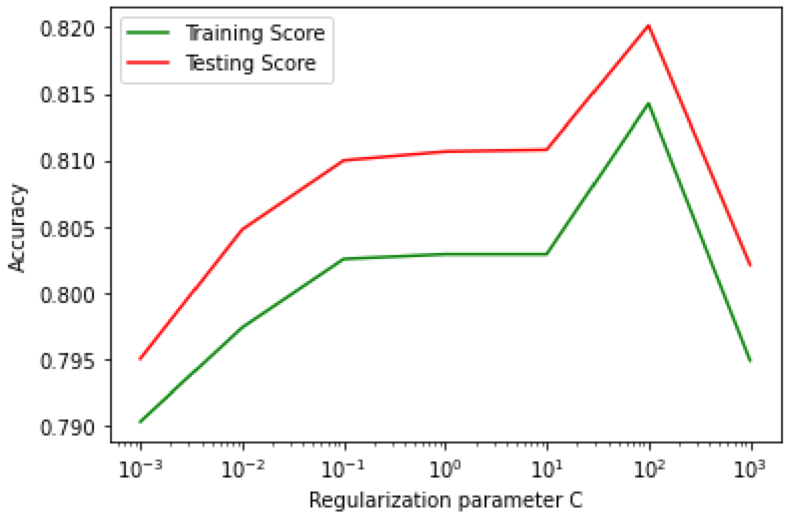
```
from sklearn.svm import LinearSVC,SVC

c_val = [0.001, 0.01, 0.1, 1, 10, 100, 1000]

lin_train_score =[]
lin_test_score =[]

for c in c_val:
    lin_svm = LinearSVC(C = c)
    lin_svm.fit(X_train, y_train)
    lin_train_score.append(lin_svm.score(X_train, y_train))
    lin_test_score.append(lin_svm.score(X_test, y_test))
```

In [71]:

```
plt.plot(c_val, lin_train_score, label = 'Training Score', c = 'g')
plt.plot(c_val, lin_test_score, label = 'Testing Score', c = 'r')
plt.xscale('log')
plt.xlabel('Regularization parameter C')
plt.ylabel('Accuracy')
plt.legend()
```

Out[71]:

```
<matplotlib.legend.Legend at 0x23314457790>
```



Based on above graph C=100,test accuracy is best.

In [72]:

```
linear_svm = LinearSVC(C = 100)
linear_svm.fit(X_train, y_train)

print('Training score: {:.3f}'.format(linear_svm.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(linear_svm.score(X_test, y_test)))
```

```
Training score: 0.795
Testing score: 0.802
```

In [73]:

```
linear_svm_cv = cross_val_score(linear_svm, X_train, y_train, cv=5)

pd.DataFrame({'Train Score - Cross Validation ': linear_svm_cv})
```

Out[73]:

	Train Score - Cross Validation
0	0.789778
1	0.791778
2	0.808667
3	0.791556
4	0.791333

In [74]:

```
print("Average cross-validation score: {:.2f}".format(linear_svm_cv.mean()))
```

```
Average cross-validation score: 0.79
```

Applying Grid Search with Linear Support Vector Machine Classifier

In [75]:

```
param_linearSVM = { 'max_iter' : range(1,200),'C' : [ 0.001,0.01, 0.1, 1, 10, 100, 100

CV_linearSVM = GridSearchCV(estimator = lin_svm, param_grid = param_linearSVM ,cv = 5,
GS_results_linearSVM = CV_linearSVM.fit(X_train, y_train)

best_parameters_linearSVM = CV_linearSVM.best_params_
print(best_parameters_linearSVM)
```

```
Fitting 5 folds for each of 1393 candidates, totalling 6965 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  52 tasks      | elapsed:    1.0s
[Parallel(n_jobs=-1)]: Done 352 tasks      | elapsed:    8.0s
[Parallel(n_jobs=-1)]: Done 852 tasks      | elapsed:   20.4s
[Parallel(n_jobs=-1)]: Done 1552 tasks      | elapsed:   35.5s
[Parallel(n_jobs=-1)]: Done 2452 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 3392 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 4042 tasks      | elapsed:  3.8min
[Parallel(n_jobs=-1)]: Done 4792 tasks      | elapsed:  5.6min
[Parallel(n_jobs=-1)]: Done 5642 tasks      | elapsed:  7.6min
[Parallel(n_jobs=-1)]: Done 6592 tasks      | elapsed: 10.0min
[Parallel(n_jobs=-1)]: Done 6965 out of 6965 | elapsed: 11.6min finished

{'C': 10, 'max_iter': 128}
```

In [76]:

```
print("Best score : Linear SVM grid search ")
GS_results_linearSVM.best_score_
```

```
Best score : Linear SVM grid search
```

Out[76]:

```
0.8086666666666666
```

In [77]:

```
print("Best parameters : Linear SVM grid search ")
best_parameters_linearSVM
```

```
Best parameters : Linear SVM grid search
```

Out[77]:

```
{'C': 10, 'max_iter': 128}
```

GridSearch for Linear SVM Classification with C=10 and max_iter=128

In [78]:

```
best_para_lin_SVM = LinearSVC(C = 10,max_iter = 128)
best_para_lin_SVM.fit(X_train, y_train)
SVM_value_y = best_para_lin_SVM.predict(X_test)

print('Training score: {:.3f}'.format(best_para_lin_SVM.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(best_para_lin_SVM.score(X_test, y_test)))


```

```
Training score: 0.796
Testing score: 0.803
```

In [79]:

```
print(classification_report(y_pred = SVM_value_y, y_true = y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.80      0.99      0.89      5950
         1.0       0.76      0.07      0.12      1550

    accuracy                           0.80      7500
   macro avg       0.78      0.53      0.51      7500
weighted avg       0.79      0.80      0.73      7500
```

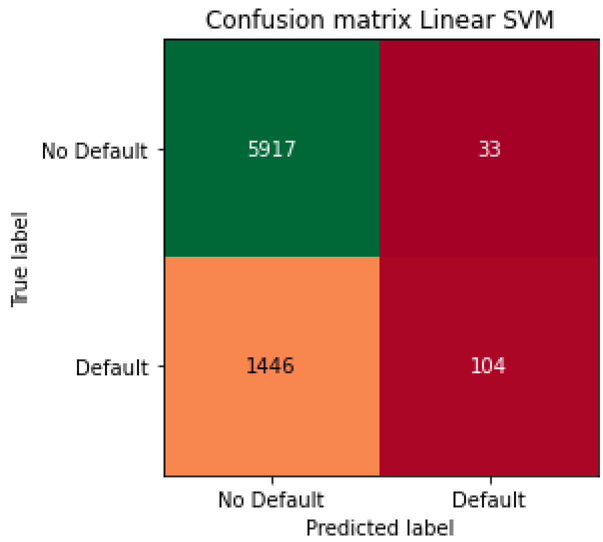
In [80]:

```
print(confusion_matrix(y_pred = SVM_value_y, y_true = y_test))
```

```
[[5917   33]
 [1446  104]]
```

In [81]:

```
heatmap = mglearn.tools.heatmap(
    confusion_matrix(y_pred = SVM_value_y, y_true = y_test), xlabel = 'Predicted label'
    ylabel='True label', xticklabels = ['No Default','Default'],yticklabels=['No Defau
plt.title("Confusion matrix Linear SVM")
plt.gca().invert_yaxis()
```



In [82]:

```
lin_SVM_precision_score=precision_score(y_test, best_para_lin_SVM.predict(X_test))
print('Precision score : {:.2f} '.format(lin_SVM_precision_score))
```

```
Precision score : 0.76
```

In [83]:

```
lin_SVM_recall_score = recall_score(y_test, best_para_lin_SVM.predict(X_test))
print('Recall score : {:.2f} '.format(lin_SVM_recall_score))
```

```
Recall score : 0.07
```

In [84]:

```
lin_SVM_f1_score = f1_score(y_test,  best_para_lin_SVM.predict(X_test))
print('f1 score : {:.2f} '.format(lin_SVM_f1_score))
```

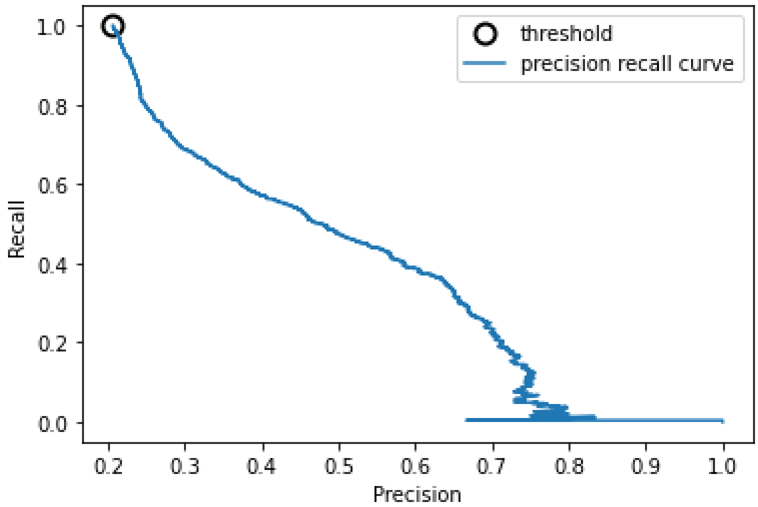
```
f1 score : 0.12
```

In [85]:

```
import mglearn
%matplotlib inline

precision, recall, thresholds = precision_recall_curve(y_test, best_para_lin_SVM.decisi

plt.plot(precision[close_zero], recall[close_zero], 'o', markersize=10,
         label="threshold", fillstyle="none", c='k', mew=2)

plt.plot(precision, recall, label="precision recall curve")
plt.xlabel("Precision")
plt.ylabel("Recall")
plt.legend(loc="best")
```

Out[85]:

<matplotlib.legend.Legend at 0x23311f8afa0>



In [86]:

```
Summary_lin_SVM= {'Type': 'Linear SVM', 'Train Score': best_para_lin_SVM.score(X_train,
              'Testing Score':best_para_lin_SVM.score(X_test, y_test)*100,
              'f1 Score':f1_score(y_test, best_para_lin_SVM.predict(X_test))};
```

In [87]:

```
Summary_lin_SVM
```

Out[87]:

```
{'Type': 'Linear SVM',
 'Train Score': 79.63555555555556,
 'Testing Score': 80.28,
 'f1 Score': 0.12329579134558386}
```

4.Kerenilzed Support Vector Machine (rbf, poly, and linear)

Reducing sample size to 1000 samples with subsampling, map the training samples with random feature mapping to obtain training set and train linear SVMs in parallel to get a unified model on the training set.

In [88]:

```
dcc_k = dcc.sample(n = 1000, random_state= 0)

dcc_k.shape
```

Out[88]:

```
(1000, 24)
```

In [89]:

```
dcc_k.head()
```

Out[89]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5
8225	20000	1	1	2	33	1.0	2.0	0.0	2.0	2.0
10794	20000	2	2	2	35	0.0	0.0	2.0	0.0	0.0
9163	230000	2	1	1	44	1.0	-1.0	-1.0	-1.0	-1.0
26591	100000	1	2	1	42	0.0	0.0	0.0	0.0	0.0
6631	150000	1	1	2	29	-2.0	-2.0	-2.0	-2.0	-2.0

5 rows × 24 columns

In [90]:

```
X_k = dcc_k.drop(['Default_Payment'],axis =1)

y_k = dcc_k['Default_Payment']

X_train_org_k, X_test_org_k, y_train_k, y_test_k = train_test_split(X_k, y_k, random_st
```

Scaling the small sample

In [91]:

```
from sklearn.preprocessing import MinMaxScaler,StandardScaler
scaler_new = MinMaxScaler()
X_train_k = scaler_new.fit_transform(X_train_org_k)
X_test_k = scaler_new.transform(X_test_org_k)

```

In [92]:

```
pd.DataFrame(X_train_k).head()
```

Out[92]:

	0	1	2	3	4	5	6	7	8	9	...	
0	0.229730	0.0	0.666667	1.0	0.458333	0.166667	0.125	0.000000	0.333333	0.000000	...	0
1	0.351351	0.0	0.666667	1.0	0.125000	0.333333	0.250	0.285714	0.333333	0.285714	...	0
2	0.081081	0.0	0.333333	1.0	0.166667	0.333333	0.250	0.285714	0.666667	0.285714	...	0
3	0.148649	0.0	0.333333	1.0	0.250000	0.333333	0.250	0.285714	0.333333	0.285714	...	0
4	0.391892	1.0	0.333333	1.0	0.104167	0.333333	0.250	0.285714	0.333333	0.285714	...	0

5 rows × 23 columns

In [93]:

```
pd.DataFrame(X_test_k).head()
```

Out[93]:

	0	1	2	3	4	5	6	7	8	9	...	
0	0.148649	1.0	0.333333	0.5	0.458333	0.333333	0.25	0.285714	0.333333	0.285714	...	0.(
1	0.000000	1.0	0.666667	1.0	0.125000	0.500000	0.50	0.571429	0.333333	0.285714	...	0.(
2	0.554054	0.0	0.333333	1.0	0.229167	0.333333	0.00	0.000000	0.000000	0.000000	...	0.(
3	0.054054	1.0	0.666667	0.5	0.395833	0.333333	0.25	0.285714	0.333333	0.285714	...	0.(
4	0.202703	0.0	0.333333	0.5	0.187500	0.166667	0.25	0.285714	0.333333	0.285714	...	0.(

5 rows × 23 columns

In [94]:

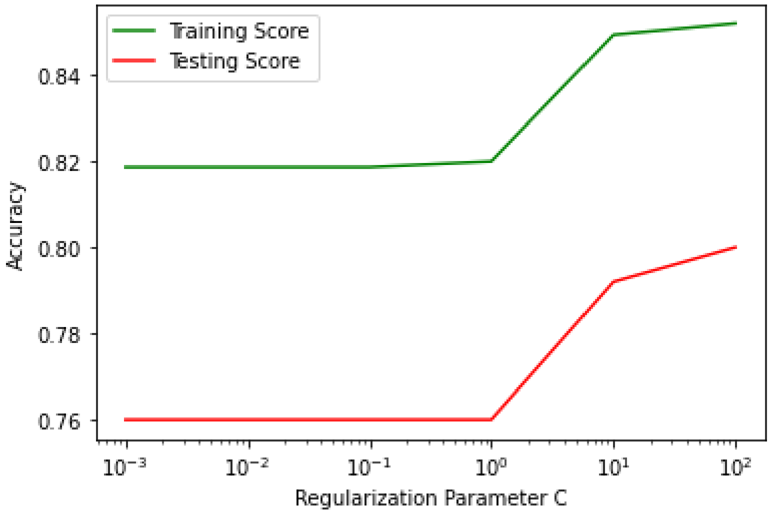
```
c_range = [0.001,0.01, 0.1, 1, 10,100]
k1_train_score = []
k1_test_score = []
for C in c_range:
    kernal_new = svm.SVC(kernel = 'linear', C=C)
    kernal_new.fit(X_train_k,y_train_k)
    k1_train_score.append(kernal_new.score(X_train_k,y_train_k))
    k1_test_score.append(kernal_new.score(X_test_k, y_test_k))
```

In [95]:

```
plt.plot(c_range, k1_train_score, label = 'Training Score', c = 'g')
plt.plot(c_range, k1_test_score, label = 'Testing Score', c='r')
plt.xscale('log')
plt.xlabel('Regularization Parameter C')
plt.ylabel('Accuracy')

plt.legend()
```

Out[95]:

```
<matplotlib.legend.Legend at 0x23311123ca0>
```



In [96]:

```
from sklearn.svm import LinearSVC,SVC
kernal_new = svm.SVC(kernel = 'linear', C=10)
kernal_new.fit(X_train_k, y_train_k)
print("train score {:.3f}".format(kernal_new.score(X_train_k, y_train_k)))
print("test score: {:.3f}".format(kernal_new.score(X_test_k, y_test_k)))

```

```
train score 0.849
test score: 0.792
```

In [97]:

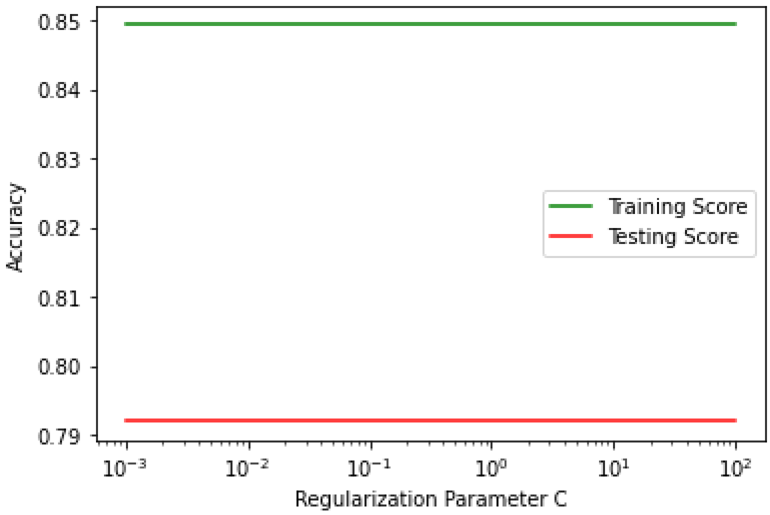
```
from sklearn import svm
from sklearn.svm import SVC
c_range = [0.001,0.01, 0.1, 1, 10,100]
k2_train_score = []
k2_test_score = []
for C in c_range:
    kernal_new2 = svm.SVC(kernel = 'poly', C=C)
    kernal_new2.fit(X_train_k,y_train_k)
    k2_train_score.append(kernal_new.score(X_train_k,y_train_k))
    k2_test_score.append(kernal_new.score(X_test_k, y_test_k))
```

In [98]:

```
plt.plot(c_range, k2_train_score, label = 'Training Score', c = 'g')
plt.plot(c_range, k2_test_score, label = 'Testing Score', c='r')
plt.xscale('log')
plt.xlabel('Regularization Parameter C')
plt.ylabel('Accuracy')

plt.legend()
```

Out[98]:

```
<matplotlib.legend.Legend at 0x23311203d90>
```



In [99]:

```
from sklearn.svm import LinearSVC,SVC
kernal_new2 = svm.SVC(kernel = 'poly', C=10)
kernal_new2.fit(X_train_k, y_train_k)
print("train score {:.3f}".format(kernal_new2.score(X_train_k, y_train_k)))
print("test score: {:.3f}".format(kernal_new2.score(X_test_k, y_test_k)))

```

```
train score 0.892
test score: 0.796
```

In [100]:

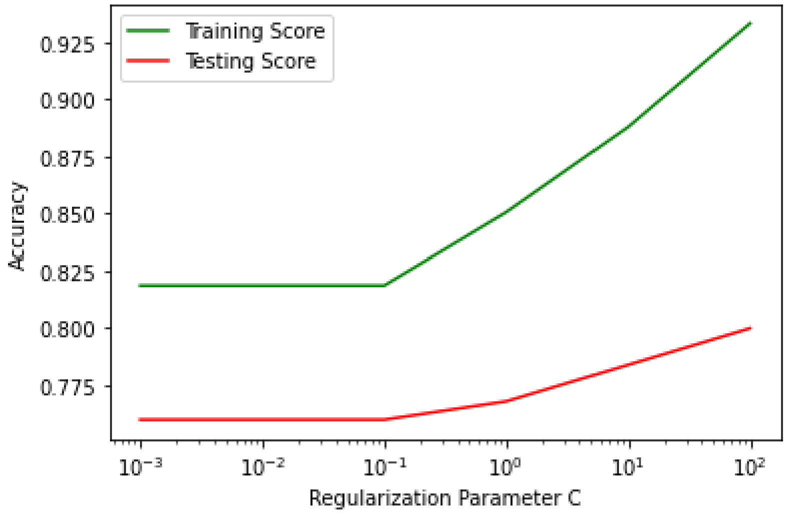
```
from sklearn import svm
from sklearn.svm import SVC
c_range = [0.001,0.01, 0.1, 1, 10,100]
k3_train_score = []
k3_test_score = []
for C in c_range:
    kernal_new3 = svm.SVC(kernel = 'rbf', C=C)
    kernal_new3.fit(X_train_k,y_train_k)
    k3_train_score.append(kernal_new3.score(X_train_k,y_train_k))
    k3_test_score.append(kernal_new3.score(X_test_k, y_test_k))
```

In [101]:

```
plt.plot(c_range, k3_train_score, label = 'Training Score', c = 'g')
plt.plot(c_range, k3_test_score, label = 'Testing Score', c='r')
plt.xscale('log')
plt.xlabel('Regularization Parameter C')
plt.ylabel('Accuracy')

plt.legend()
```

Out[101]:

```
<matplotlib.legend.Legend at 0x23311fa41c0>
```



In [102]:

```
from sklearn.svm import LinearSVC,SVC
kernal_new3 = svm.SVC(kernel = 'rbf', C=10)
kernal_new3.fit(X_train_k, y_train_k)
print("train score {:.3f}".format(kernal_new3.score(X_train_k, y_train_k)))
print("test score: {:.3f}".format(kernal_new3.score(X_test_k, y_test_k)))
```

```
train score 0.888
test score: 0.784
```

GridSearch for Kerenilzed Support Vector Machine (rbf, poly, and linear)

In [103]:

```
best_score=0

for gamma in [0.001, 0.01, 0.1, 1, 10, 100]:
    for C in [0.001, 0.01, 0.1, 1, 10, 100]:


        svm = SVC(gamma = gamma, C=C)

        CV_scores = cross_val_score(svm, X_train_k, y_train_k, cv=5)

        CV_score = np.mean(CV_scores)

        if CV_score > best_score:
            best_score = CV_score
            best_parameters = {'C': C, 'gamma': gamma}

# rebuild a model on the combined training and validation set
svm = SVC(**best_parameters)
svm.fit(X_train_k, y_train_k)
```

Out[103]:

```
SVC(C=10, gamma=0.1)
```

In [104]:

```
kernelSVC_parameters = {'C':[0.001, 0.01, 0.1, 1, 10, 100],'gamma':[0.001, 0.01, 0.1, 1
```

In [105]:

```
print(classification_report(y_pred = SVM_value_y, y_true = y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.80      0.99      0.89      5950
         1.0       0.76      0.07      0.12      1550

    accuracy                           0.80      7500
   macro avg       0.78      0.53      0.51      7500
weighted avg       0.79      0.80      0.73      7500
```

In [106]:

```
from sklearn.model_selection import GridSearchCV

KernelSVC = SVC()
GS_KernelSVC = GridSearchCV(KernelSVC, kernelSVC_parameters, cv = 5, return_train_score
GS_KernelSVC.fit(X_train_k,y_train_k)
```

Out[106]:

```
GridSearchCV(cv=5, estimator=SVC(), n_jobs=-1,
             param_grid={'C': [0.001, 0.01, 0.1, 1, 10, 100],
                         'gamma': [0.001, 0.01, 0.1, 1, 10, 100],
                         'kernel': ['rbf', 'poly', 'linear']},
             return_train_score=True)
```

In [107]:

```
print("Best score : KernelSVM grid search ")
round(GS_KernelSVC.best_score_,2)
```

```
Best score : KernelSVM grid search
```

Out[107]:

```
0.84
```

In [108]:

```
print("Best parameters- KernelSVM grid search ")
GS_KernelSVC.best_params_
```

```
Best parameters- KernelSVM grid search
```

Out[108]:

```
{'C': 0.1, 'gamma': 1, 'kernel': 'poly'}
```

kernel = poly

In [109]:

```
best_para_svm_poly = SVC(C = 0.1, gamma = 1, kernel = 'poly', verbose = 1)

best_para_svm_poly.fit(X_train_k,y_train_k)
SVM_value_y_poly = best_para_svm_poly.predict(X_test_k)
print('Training score: {:.3f}'.format(best_para_svm_poly.score(X_train_k, y_train_k)))
print('Testing score: {:.3f}'.format(best_para_svm_poly.score(X_test_k, y_test_k)))
```

```
[LibSVM]Training score: 0.856
Testing score: 0.768
```

In [110]:

```
print(classification_report(SVM_value_y_poly,y_test_k))
```

```
              precision    recall  f1-score   support

         0.0       0.98      0.78      0.87       240
         1.0       0.10      0.60      0.17        10

    accuracy                           0.77       250
   macro avg       0.54      0.69      0.52       250
weighted avg       0.94      0.77      0.84       250
```

In [111]:

```
import mglearn
```

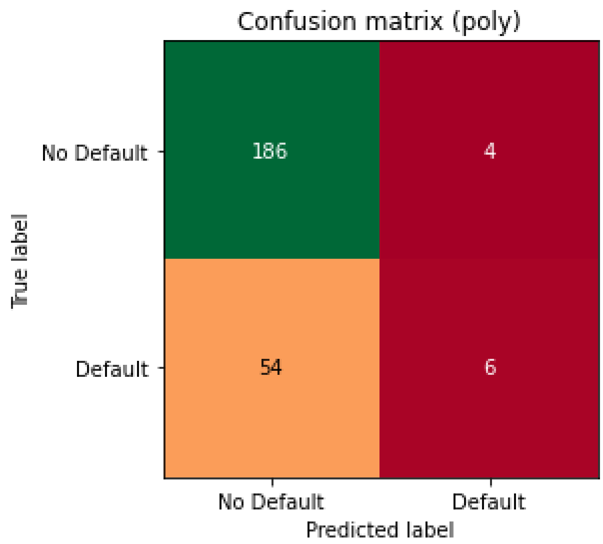
In [112]:

```
print(confusion_matrix(y_pred = SVM_value_y_poly,y_true = y_test_k))
```

```
[[186   4]
 [ 54   6]]
```

In [113]:

```
%matplotlib inline

heatmap = mglearn.tools.heatmap(
    confusion_matrix(y_pred = SVM_value_y_poly, y_true = y_test_k), xlabel = 'Predicted
    ylabel='True label', xticklabels = ['No Default','Default'], yticklabels=['No Defau
plt.title("Confusion matrix (poly)")
plt.gca().invert_yaxis()
```



In [114]:

```
Kernel_poly_precision_score=precision_score(y_test_k,best_para_svm_poly.predict(X_test_
print('Precision score : {:.2f} '.format(Kernel_poly_precision_score))

```

```
Precision score : 0.60
```

In [115]:

```
Kernel_poly_f1_score=f1_score(y_test_k, best_para_svm_poly.predict(X_test_k))
print('f1 Score : {:.2f} '.format(Kernel_poly_f1_score))

```

```
f1 Score : 0.17
```

In [116]:

```
Kernel_poly_recall_score=recall_score(y_test_k, best_para_svm_poly.predict(X_test_k))
print('Recall score : {:.2f} '.format(Kernel_poly_recall_score))

```

```
Recall score : 0.10
```

In [117]:

```
Summary_Kernelized_poly= {'Type': 'Kernalized poly ', 'Train Score': best_para_svm_poly
              'Testing Score':best_para_svm_poly.score(X_test_k, y_test_k)*100,
              'f1 Score':f1_score(y_test_k, best_para_svm_poly.predict(X_test_k))};
```

In [118]:

```
Summary_Kernelized_poly
```

Out[118]:

```
{'Type': 'Kernalized poly ',
 'Train Score': 85.6,
 'Testing Score': 76.8,
 'f1 Score': 0.17142857142857143}
```

Kernel = rbf

In [119]:

```
best_para_svm_rbf = SVC(C = 0.1, gamma = 1, kernel = 'rbf', verbose = 1)

best_para_svm_rbf.fit(X_train_k,y_train_k)
SVM_value_y_rbf = best_para_svm_rbf.predict(X_test_k)
print('Training score: {:.3f}'.format(best_para_svm_rbf.score(X_train_k, y_train_k)))
print('Testing score: {:.3f}'.format(best_para_svm_rbf.score(X_test_k, y_test_k)))

```

```
[LibSVM]Training score: 0.819
Testing score: 0.760
```

In [120]:

```
print(classification_report(SVM_value_y_rbf,y_test_k))
```

```
              precision    recall  f1-score   support

         0.0       1.00      0.76      0.86       250
         1.0       0.00      0.00      0.00         0

    accuracy                           0.76       250
   macro avg       0.50      0.38      0.43       250
weighted avg       1.00      0.76      0.86       250
```

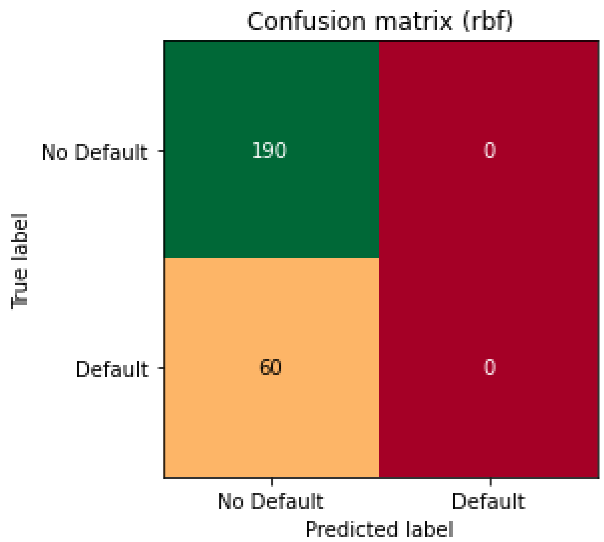
In [121]:

```
print(confusion_matrix(y_pred = SVM_value_y_rbf,y_true= y_test_k))
```

```
[[190   0]
 [ 60   0]]
```

In [122]:

```
%matplotlib inline

heatmap = mglearn.tools.heatmap(confusion_matrix(y_pred = SVM_value_y_rbf, y_true = y_t
plt.title("Confusion matrix (rbf)")
plt.gca().invert_yaxis()

```



In [123]:

```
Kernel_rbf_precision_score=precision_score(y_test_k,best_para_svm_rbf.predict(X_test_k)
print('Precision score : {:.2f} '.format(precision_score(y_test_k,best_para_svm_rbf.pre

```

```
Precision score : 0.00
```

In [124]:

```
Kernel_rbf_f1_score=f1_score(y_test_k, best_para_svm_rbf.predict(X_test_k))
print('f1 Score : {:.2f} '.format(Kernel_rbf_f1_score))

```

```
f1 Score : 0.00
```

In [125]:

```
Kernel_rbf_recall_score=recall_score(y_test_k, best_para_svm_rbf.predict(X_test_k))
print('Recall score : {:.2f} '.format(Kernel_rbf_recall_score))

```

```
Recall score : 0.00
```

In [126]:

```
Summary_Kernelized_rbf= {'Type': 'Kernalized rbf ', 'Train Score': best_para_svm_rbf.sc
              'Testing Score':best_para_svm_rbf.score(X_test_k, y_test_k)*100,
              'f1 Score':f1_score(y_test_k, best_para_svm_rbf.predict(X_test_k))};
```

In [127]:

```
Summary_Kernelized_rbf
```

Out[127]:

```
{'Type': 'Kernalized rbf ',
 'Train Score': 81.86666666666666,
 'Testing Score': 76.0,
 'f1 Score': 0.0}
```

Kernel = linear

In [128]:

```
best_para_svm_linear = SVC(C = 0.1, cache_size = 200, gamma = 1, kernel = 'linear', ver

best_para_svm_linear.fit(X_train_k,y_train_k)
SVM_value_y_linear = best_para_svm_linear.predict(X_test_k)
print('Training score: {:.3f}'.format(best_para_svm_linear.score(X_train_k, y_train_k))
print('Testing score: {:.3f}'.format(best_para_svm_linear.score(X_test_k, y_test_k)))

```

```
[LibSVM]Training score: 0.819
Testing score: 0.760
```

In [129]:

```
print(classification_report(SVM_value_y_linear,y_test_k))
```

```
              precision    recall  f1-score   support

         0.0       1.00      0.76      0.86       250
         1.0       0.00      0.00      0.00         0

    accuracy                           0.76       250
   macro avg       0.50      0.38      0.43       250
weighted avg       1.00      0.76      0.86       250
```

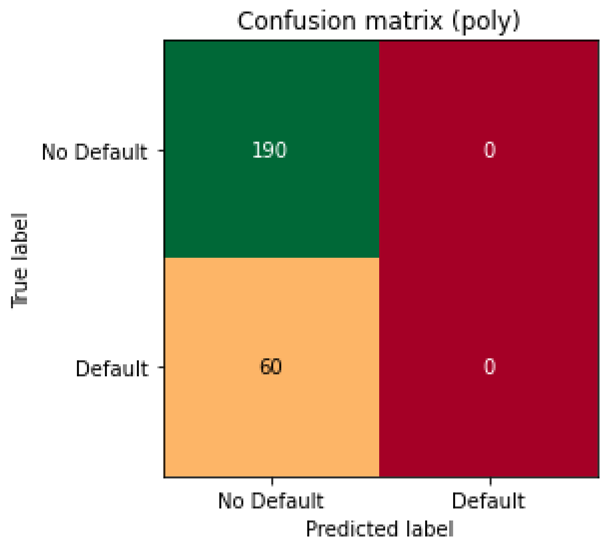
In [130]:

```
print(confusion_matrix(y_pred = SVM_value_y_linear,y_true = y_test_k))
```

```
[[190   0]
 [ 60   0]]
```

In [131]:

```
%matplotlib inline

heatmap = mglearn.tools.heatmap(
    confusion_matrix(y_pred = SVM_value_y_linear, y_true = y_test_k), xlabel = 'Predict
    yticklabels=['No Default','Default'], cmap = "RdYlGn", fmt = "%d")
plt.title("Confusion matrix (poly)")
plt.gca().invert_yaxis()
```



In [132]:

```
Kernel_linear_precision_score=precision_score(y_test_k,best_para_svm_linear.predict(X_t
print('Precision score : {:.2f} '.format(precision_score(y_test_k,best_para_svm_linear.

```

```
Precision score : 0.00
```

In [133]:

```
Kernel_linear_f1_score=f1_score(y_test_k, best_para_svm_linear.predict(X_test_k))
print('f1 Score : {:.2f} '.format(Kernel_linear_f1_score))

```

```
f1 Score : 0.00
```

In [134]:

```
Kernel_linear_recall_score=recall_score(y_test_k, best_para_svm_linear.predict(X_test_k
print('Recall score : {:.2f} '.format(Kernel_linear_recall_score))

```

```
Recall score : 0.00
```

In [135]:

```
Summary_Kernelized_linear= {'Type': 'Kernalized linear ', 'Train Score': best_para_svm_
              'Testing Score':best_para_svm_linear.score(X_test_k, y_test_k)*100,
              'f1 Score':f1_score(y_test_k, best_para_svm_linear.predict(X_test_k))};
```

In [136]:

```
Summary_Kernelized_linear
```

Out[136]:

```
{'Type': 'Kernalized linear ',
 'Train Score': 81.86666666666666,
 'Testing Score': 76.0,
 'f1 Score': 0.0}
```

```
<b>5.Decision Tree Classification.</b>
```

In [137]:

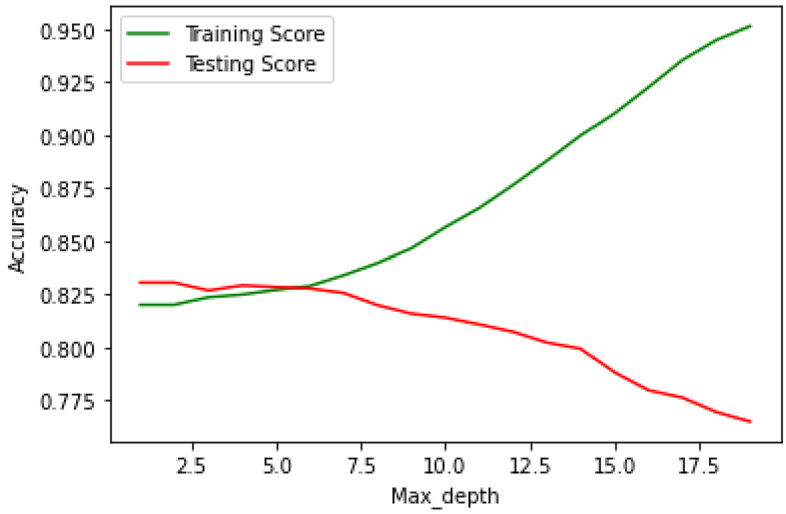
```
from sklearn.tree import DecisionTreeClassifier

dtree_training = []
dtree_testing = []

for depth in range(1,20):
    dtree = DecisionTreeClassifier(max_depth = depth, random_state = 0)
    dtree.fit(X_train, y_train)
    dtree_training.append(dtree.score(X_train, y_train))
    dtree_testing.append(dtree.score(X_test, y_test))
```

In [138]:

```
xvalues = range(1,20)

plt.plot(xvalues, dtree_training, label = 'Training Score', c = 'g')
plt.plot(xvalues, dtree_testing, label = 'Testing Score', c = 'r')
plt.xlabel('Max_depth')
plt.ylabel('Accuracy')
plt.legend()
```

Out[138]:

```
<matplotlib.legend.Legend at 0x2331167e580>
```



Based on above graph max_depth = 7

In [139]:

```
dtree = DecisionTreeClassifier(max_depth = 7)

dtree.fit(X_train, y_train)
dtree_value_y = dtree.predict(X_test)

print('Training score: {:.3f}'.format(dtree.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(dtree.score(X_test, y_test)))
```

```
Training score: 0.834
Testing score: 0.826
```

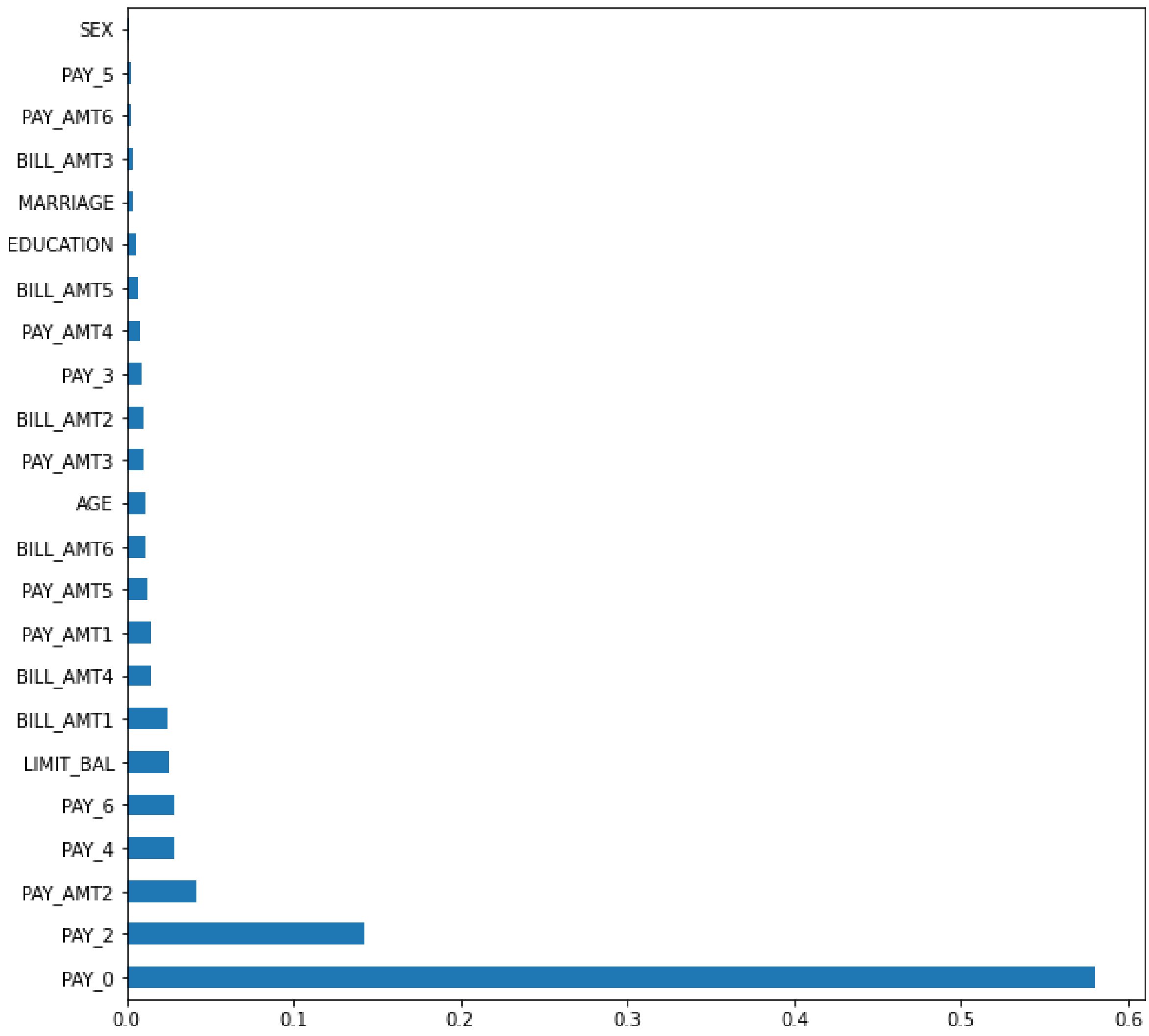
Decision Tree Feature Selection

In [140]:

```
feat_importance = pd.Series(dtree.feature_importances_, index=X.columns)
feat_importance.nlargest(X.shape[1]).plot(kind='barh', figsize=(10, 10))
```

Out[140]:

```
<AxesSubplot:>
```



PAY_O: Repayment status in September, 2005 is the most important feature.

Cross validation scores for Decision Tree Classifier

In [141]:

```
dtree_CV_scores = cross_val_score(dtree, X_train,y_train, cv = 7)

pd.DataFrame({"Cross-Validation scores": dtree_CV_scores})
```

Out[141]:

	Cross-Validation scores
0	0.814619
1	0.820840
2	0.822029
3	0.813317
4	0.817984
5	0.813939
6	0.821717

In [142]:

```
print("cross-validation score is : {:.2f}".format(dtree_CV_scores.mean()))
```

```
cross-validation score is : 0.82
```

Grid Search with Decision Tree Classifier

In [143]:

```
dtree.get_params()
```

Out[143]:

```
{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 7,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': 'deprecated',
 'random_state': None,
 'splitter': 'best'}
```

In [144]:

```
param_grid_dtree = {'max_depth': range(1,20),'criterion':['gini','entropy'],'min_sample
CV_dtrees = GridSearchCV(estimator = dtree, cv = 7, param_grid = param_grid_dtree , ver
GS_results_dtrees = CV_dtrees.fit(X_train, y_train)
best_parameters_dtrees = CV_dtrees.best_params_
print(best_parameters_dtrees)


```

```
Fitting 7 folds for each of 1824 candidates, totalling 12768 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done 328 tasks      | elapsed:    3.6s
[Parallel(n_jobs=-1)]: Done 828 tasks      | elapsed:   11.8s
[Parallel(n_jobs=-1)]: Done 1528 tasks      | elapsed:   30.5s
[Parallel(n_jobs=-1)]: Done 2428 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 3528 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 4634 tasks      | elapsed:  2.9min
[Parallel(n_jobs=-1)]: Done 5384 tasks      | elapsed:  3.7min
[Parallel(n_jobs=-1)]: Done 6234 tasks      | elapsed:  4.6min
[Parallel(n_jobs=-1)]: Done 7944 tasks      | elapsed:  5.4min
[Parallel(n_jobs=-1)]: Done 9594 tasks      | elapsed:  6.9min
[Parallel(n_jobs=-1)]: Done 10744 tasks      | elapsed:  8.4min
[Parallel(n_jobs=-1)]: Done 11994 tasks      | elapsed: 10.2min
[Parallel(n_jobs=-1)]: Done 12768 out of 12768 | elapsed: 11.4min finished

{'criterion': 'entropy', 'max_depth': 4, 'min_samples_leaf': 48}
```

In [145]:

```
print("Best score : Decision Tree grid search ")
round(GS_results_dtrees.best_score_,2)
```

```
Best score : Decision Tree grid search
```

Out[145]:

```
0.82
```

In [146]:

```
print("Best parameters : Decision Tree grid search ")
GS_results_dtrees.best_params_
```

```
Best parameters : Decision Tree grid search
```

Out[146]:

```
{'criterion': 'entropy', 'max_depth': 4, 'min_samples_leaf': 48}
```

In [147]:

```
best_dtree = DecisionTreeClassifier(criterion='entropy', max_depth=4, min_samples_leaf=

best_dtree.fit(X_train, y_train)
dtree_value_y = best_dtree.predict(X_test)

print('Training score: {:.3f}'.format(best_dtree.score(X_train, y_train)))
print('Testing score: {:.3f}'.format(best_dtree.score(X_test, y_test)))
```

```
Training score: 0.825
Testing score: 0.829
```

In [148]:

```
print(classification_report(y_pred =dtree_value_y, y_true = y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.85      0.95      0.90      5950
         1.0       0.66      0.35      0.46      1550

    accuracy                           0.83      7500
   macro avg       0.76      0.65      0.68      7500
weighted avg       0.81      0.83      0.81      7500
```

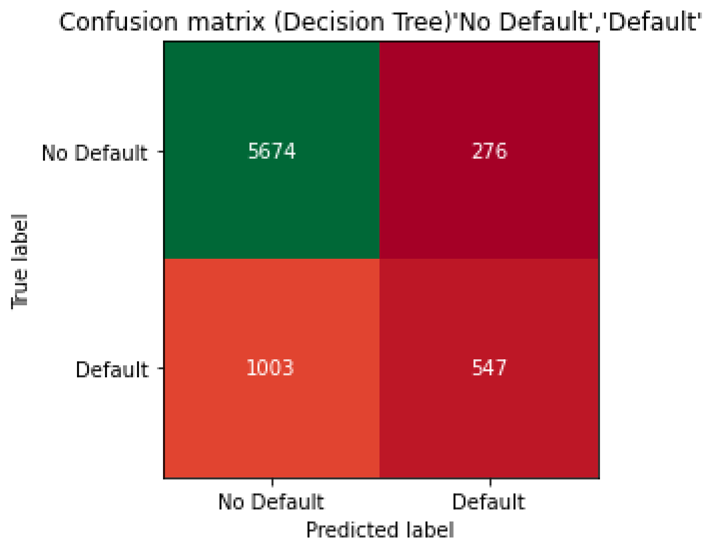
In [149]:

```
print(confusion_matrix(y_pred = dtree_value_y, y_true = y_test))
```

```
[[5674  276]
 [1003  547]]
```

In [150]:

```
%matplotlib inline

heatmap = mglearn.tools.heatmap(
    confusion_matrix(y_pred = dtree_value_y, y_true = y_test), xlabel = 'Predicted labe
    ylabel='True label', xticklabels = ['No Default','Default'],yticklabels=['No Defaul
plt.title("Confusion matrix (Decision Tree)'No Default','Default'")

plt.gca().invert_yaxis()
```



In [151]:

```
dtree_precision_score=precision_score(y_test, best_dtree.predict(X_test))
print('Precision score : {:.2f} '.format(dtree_precision_score))
```

```
Precision score : 0.66
```

In [152]:

```
dtree_recall_score = recall_score(y_test, best_dtree.predict(X_test))
print('Recall score : {:.2f} '.format(dtree_recall_score))
```

```
Recall score : 0.35
```

In [153]:

```
dtree_f1_score = f1_score(y_test,best_dtree.predict(X_test))
print('f1 score : {:.2f} '.format(dtree_f1_score))
```

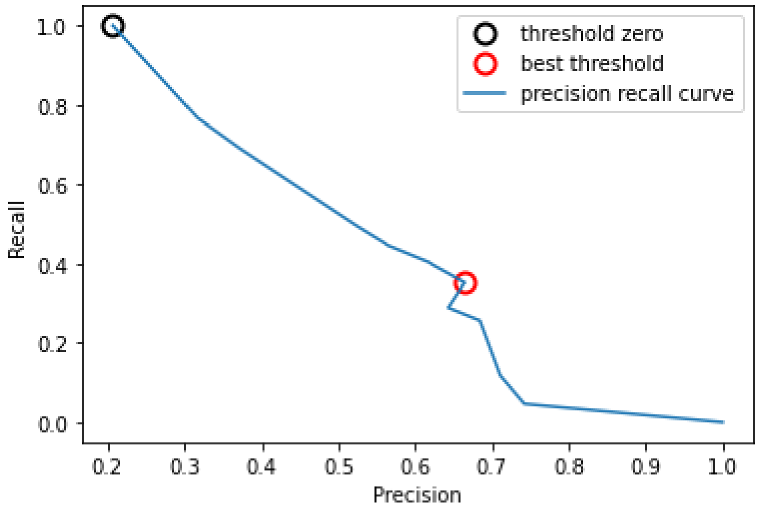
```
f1 score : 0.46
```

In [154]:

```
import mglearn
%matplotlib inline
%matplotlib inline

precision, recall, thresholds = precision_recall_curve(y_test, best_dtree.predict_proba

plt.plot(precision[close_zero], recall[close_zero], 'o', markersize=10,
         label="threshold zero", fillstyle="none", c='k', mew=2)
plt.plot(dtree_precision_score, dtree_recall_score, 'o', markersize=10,
         label="best threshold", fillstyle="none", c='r', mew=2)

plt.plot(precision, recall, label="precision recall curve")
plt.xlabel("Precision")
plt.ylabel("Recall")
plt.legend(loc="best")
```

Out[154]:

```
<matplotlib.legend.Legend at 0x233113e2b80>
```



In [155]:

```
Summary_dtree= {'Type': 'Decision Tree', 'Train Score': best_dtree.score(X_train, y_tra
              'Testing Score':best_dtree.score(X_test, y_test)*100,
              'f1 Score':f1_score(y_test, best_dtree.predict(X_test))};
```

In [156]:

```
Summary_dtree
```

Out[156]:

```
{'Type': 'Decision Tree',
 'Train Score': 82.45333333333333,
 'Testing Score': 82.94666666666667,
 'f1 Score': 0.46101980615254945}
```

Comparing All Models

In [157]:

```
Summary_Knn
```

Out[157]:

```
{'Type': 'K-nearest Neighbors (KNN) Classification Model',
 'Training Score': 100.0,
 'Testing Score': 81.0,
 'f1 Score': 0.35256701499318494}
```

In [158]:

```
Summary_Logistic
```

Out[158]:

```
{'Type': 'Logistic Regression',
 'Train Score': 81.05333333333333,
 'Testing Score': 81.65333333333334,
 'f1 Score': 0.2993890020366599}
```

In [159]:

```
Summary_lin_SVM
```

Out[159]:

```
{'Type': 'Linear SVM',
 'Train Score': 79.63555555555556,
 'Testing Score': 80.28,
 'f1 Score': 0.12329579134558386}
```

In [160]:

```
Summary_Kernelized_rbf
```

Out[160]:

```
{'Type': 'Kernalized rbf ',
 'Train Score': 81.86666666666666,
 'Testing Score': 76.0,
 'f1 Score': 0.0}
```

In [161]:

```
Summary_Kernelized_linear
```

Out[161]:

```
{'Type': 'Kernalized linear ',
 'Train Score': 81.86666666666666,
 'Testing Score': 76.0,
 'f1 Score': 0.0}
```

In [162]:

```
Summary_Kernelized_poly
```

Out[162]:

```
{'Type': 'Kernalized poly ',
 'Train Score': 85.6,
 'Testing Score': 76.8,
 'f1 Score': 0.17142857142857143}
```

In [163]:

```
Summary_dtree
```

Out[163]:

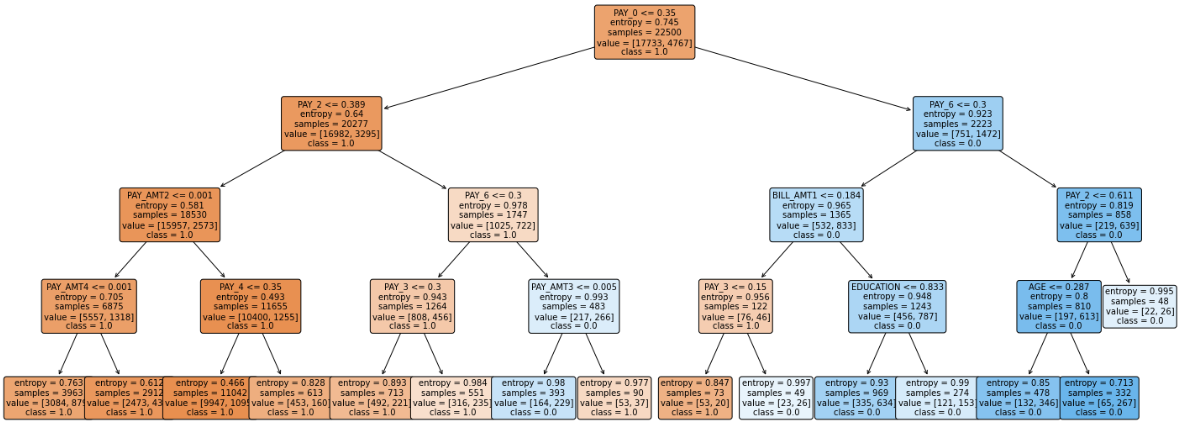
```
{'Type': 'Decision Tree',
 'Train Score': 82.45333333333333,
 'Testing Score': 82.94666666666667,
 'f1 Score': 0.46101980615254945}
```

In [164]:

```
X = dcc.drop('Default_Payment',axis =1)
y = dcc['Default_Payment']
X_train_org, X_test_org, y_train, y_test = train_test_split(X, y, random_state = 0)


```

In [165]:

```python
from sklearn.tree import DecisionTreeClassifier, plot_tree
dtree_feature_names =X.columns
dtree_target_names = y.unique().astype(str).tolist()
plt.figure(figsize=(25,10))
plot_tree(best_dtree,
          feature_names = dtree_feature_names,
          class_names = dtree_target_names,
          filled = True,
          rounded = True, fontsize=10)

plt.savefig('tree_visualization.png')

plt.show()
```



1)From above summary we can state that Decision Tree is the best classification model as the training and test scores are 82.45% and 82.94% respectively with a f1 score of 0.46 which is highest compared to other candidates, since we have different model predicting the same thing, f1 score is a good choice for this purpose as it depends heavily on how imbalanced our training dataset is.

2)Since the target variable in our dataset is highly skewed towards one particular category, thus decision tree performs fairly better than other classification models in this case.

3) PAY_O: Repayment status in September, 2005 is the most important feature

End of Project 1 : Classification

Initials:

-rp