Import Libraries

In [1]:
```
# LIME and SHAP packages have to be installed via pip
# The %%capture command hide code cell output in Google Colab
%%capture
!pip install lime
!pip install shap
```

In [2]:
```
from google.colab import files
import io

import pandas as pd
import numpy as np
import tensorflow as tf
import time

# Plot results
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Data preparation and pre-processing
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

# Model classifiers
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier

# Classifier metrics
from sklearn import metrics
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix, f1_score, precision_score, recall_score, roc_auc_score

# Resample dataset
import collections
from imblearn.over_sampling import SMOTE

# Explainability
import lime
from lime.lime_tabular import LimeTabularExplainer
from lime import submodular_pick
import shap

import warnings
warnings.filterwarnings("ignore")
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the functions in the publi
c API at pandas.testing instead.
  import pandas.util.testing as tm
/usr/local/lib/python3.6/dist-packages/sklearn/externals/six.py:31: FutureWarning: The module is deprecated in version 0.21 and will be removed in versio
n 0.23 since we've dropped support for Python 2.7. Please rely on the official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:144: FutureWarning: The sklearn.neighbors.base module is  deprecated in version 0.22
and will be removed in version 0.24. The corresponding classes / functions should instead be imported from sklearn.neighbors. Anything that cannot be imp
orted from sklearn.neighbors is now part of the private API.
  warnings.warn(message, FutureWarning)
```

Data Upload and Cleaning

In [3]:
```
# Upload the Credit Card Default dataset with google.colab.files
# Wait till the upload is 100%
uploaded = files.upload()
```

Dateien auswählen Keine ausgewählt

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving DefaultOfCreditCardClients.csv to DefaultOfCreditCardClients.csv
```

In [4]:
```
# Read the dataset from the excel file
data = pd.read_csv(io.BytesIO(uploaded['DefaultOfCreditCardClients.csv']), sep=";", header=1)
```

In [5]:
```
data.head(3)
```

Out[5]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1
0	1	20000	2	2	1	24	2	2	-1	-1	-2	-2	3913	3102	689	0	0	0	0
1	2	120000	2	2	2	26	-1	2	0	0	0	2	2682	1725	2682	3272	3455	3261	0
2	3	90000	2	2	2	34	0	0	0	0	0	0	29239	14027	13559	14331	14948	15549	1518

In [6]:
```
# Dataset without the ID column
data.drop('ID',axis=1, inplace=True)
```

In [7]:
```
# Checking missing values - there aren't any non-null values
#data.isnull().sum()
```

In [8]:
```python
# Statistical description
data.describe()
# There are unusal values for PAY_0-PAY_6 the -2, for MARRIAGE the 0 or EDUCATION the 6
# Therefore clean the data
```

Out[8]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	BILL
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000
mean	167484.322667	1.603733	1.853133	1.551867	35.485500	-0.016700	-0.133767	-0.166200	-0.220667	-0.266200	-0.291100	51223.330900	49179
std	129747.661567	0.489129	0.790349	0.521970	9.217904	1.123802	1.197186	1.196868	1.169139	1.133187	1.149988	73635.860576	71173
min	10000.000000	1.000000	0.000000	0.000000	21.000000	-2.000000	-2.000000	-2.000000	-2.000000	-2.000000	-2.000000	-165580.000000	-69777
25%	50000.000000	1.000000	1.000000	1.000000	28.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	3558.750000	2984
50%	140000.000000	2.000000	2.000000	2.000000	34.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	22381.500000	21200
75%	240000.000000	2.000000	2.000000	2.000000	41.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	67091.000000	64006
max	1000000.000000	2.000000	6.000000	3.000000	79.000000	8.000000	8.000000	8.000000	8.000000	8.000000	8.000000	964511.000000	983931

In [9]:
```python
# Rename PAY_0 and Target column
data = data.rename(columns={'PAY_0': 'PAY_1', 'default payment next month': 'Default Payment'})
```

In [10]:
```python
data.loc[data['SEX']==2,'SEX'] = 0
data.loc[data['MARRIAGE'] == 0, 'MARRIAGE'] = 3
clean_education = (data['EDUCATION'] == 0) | (data['EDUCATION'] == 5) | (data['EDUCATION'] == 6)
data.loc[clean_education, 'EDUCATION'] = 4
```

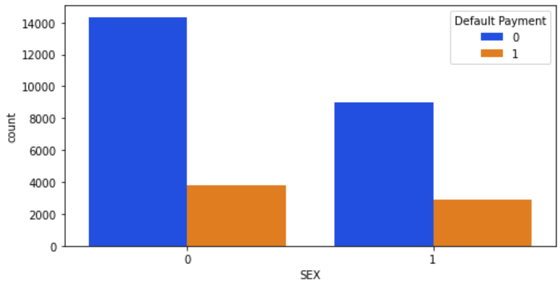
In [11]:
```python
clean_pay1 = (data['PAY_1'] == -2) | (data['PAY_1'] == -1)
data.loc[clean_pay1, 'PAY_1'] = 0
clean_pay2 = (data['PAY_2'] == -2) | (data['PAY_2'] == -1)
data.loc[clean_pay2, 'PAY_2'] = 0
clean_pay3 = (data['PAY_3'] == -2) | (data['PAY_3'] == -1)
data.loc[clean_pay3, 'PAY_3'] = 0
clean_pay4 = (data['PAY_4'] == -2) | (data['PAY_4'] == -1)
data.loc[clean_pay4, 'PAY_4'] = 0
clean_pay5 = (data['PAY_5'] == -2) | (data['PAY_5'] == -1)
data.loc[clean_pay5, 'PAY_5'] = 0
clean_pay6 = (data['PAY_6'] == -2) | (data['PAY_6'] == -1)
data.loc[clean_pay6, 'PAY_6'] = 0
#data[['PAY_1', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']].describe()
```

Simple Exploratory Data Analysis

In [12]:
```python
print(data['SEX'].value_counts())
plt.figure(figsize=(8,4))
sns.countplot(x='SEX', data=data, hue='Default Payment', palette='bright')
```

```
0    18112
1    11888
Name: SEX, dtype: int64
```

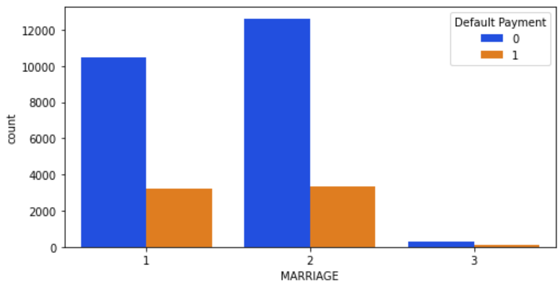
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbb0d6c25c0>



In [13]:
```python
print(data['MARRIAGE'].value_counts())
plt.figure(figsize=(8,4))
sns.countplot(x='MARRIAGE', data=data, hue='Default Payment', palette='bright')
```

```
2    15964
1    13659
3      377
Name: MARRIAGE, dtype: int64
```

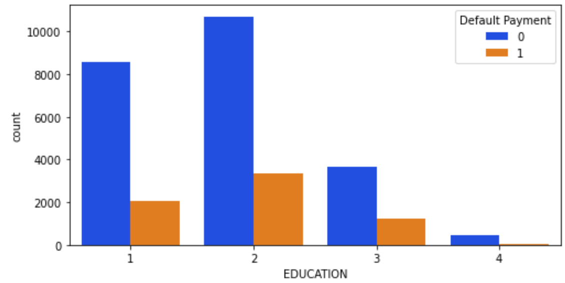
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbb0d6cf438>



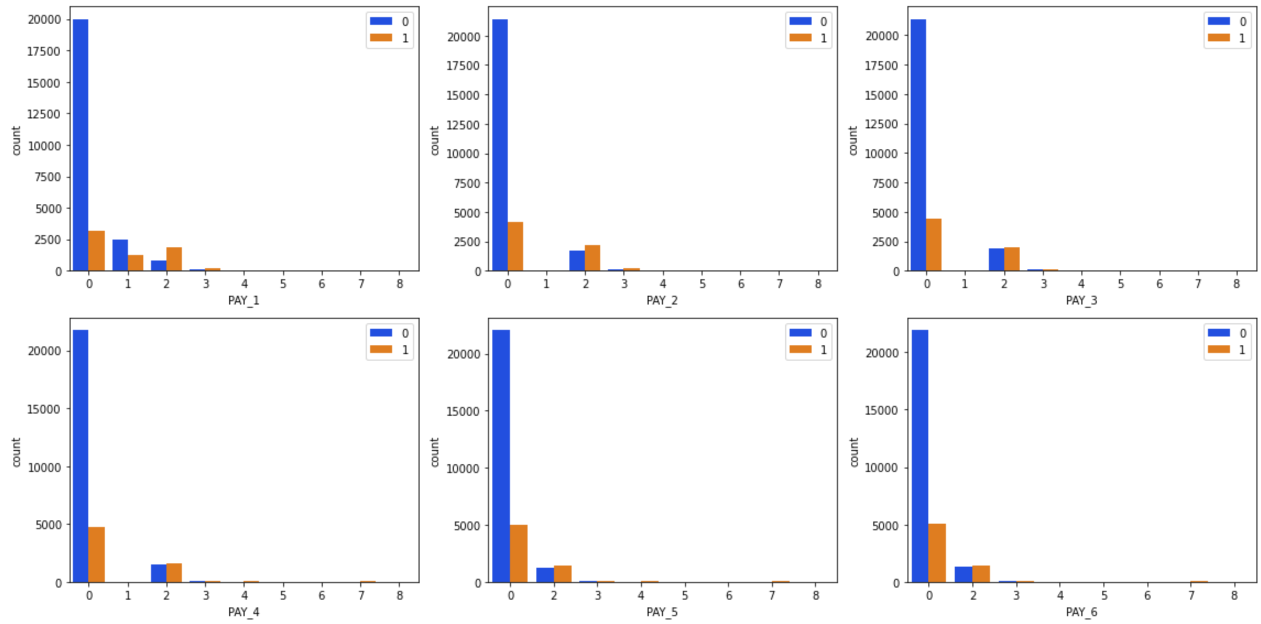
In [14]:
```
print(data['EDUCATION'].value_counts())
plt.figure(figsize=(8,4))
sns.countplot(x='EDUCATION', data=data, hue='Default Payment', palette='bright')
```

```
2    14030
1    10585
3     4917
4      468
Name: EDUCATION, dtype: int64
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbb0e2d35f8>



In [15]:
```
fig, ax =plt.subplots(2,3)
fig.set_size_inches(16,8)
sns.countplot(x='PAY_1', data=data, hue='Default Payment', palette='bright', ax=ax[0,0]).legend(loc="upper right")
sns.countplot(x='PAY_2', data=data, hue='Default Payment', palette='bright', ax=ax[0,1]).legend(loc="upper right")
sns.countplot(x='PAY_3', data=data, hue='Default Payment', palette='bright', ax=ax[0,2]).legend(loc="upper right")
sns.countplot(x='PAY_4', data=data, hue='Default Payment', palette='bright', ax=ax[1,0]).legend(loc="upper right")
sns.countplot(x='PAY_5', data=data, hue='Default Payment', palette='bright', ax=ax[1,1]).legend(loc="upper right")
sns.countplot(x='PAY_6', data=data, hue='Default Payment', palette='bright', ax=ax[1,2]).legend(loc="upper right")
fig.tight_layout()
fig.show()
```



In [16]:
```
#data[['BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6']].describe()
```

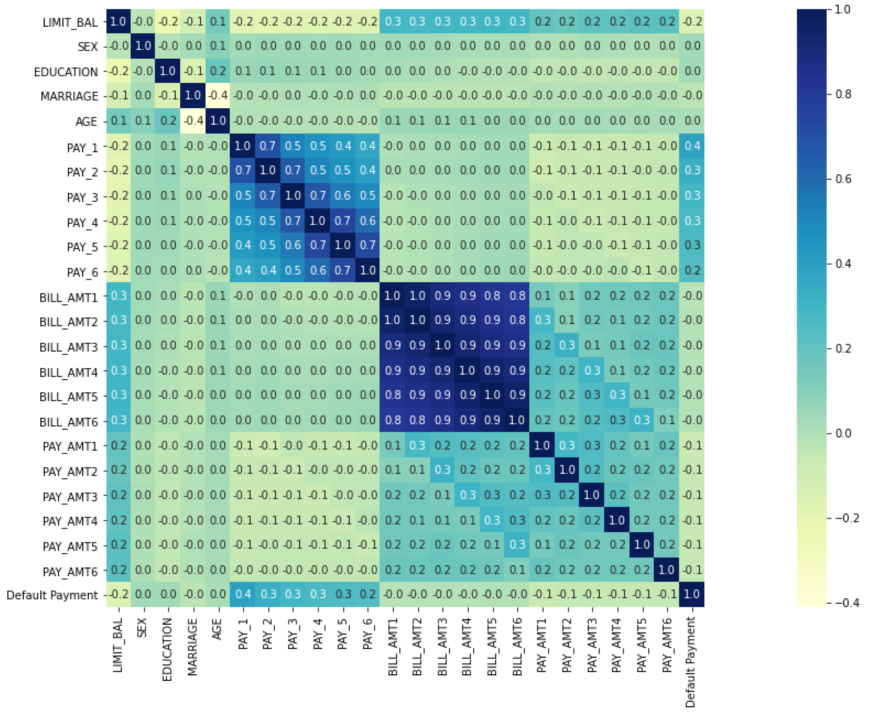
In [17]:
```
#data[['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']].describe()
```

In [18]:
```
#data[['LIMIT_BAL']].describe()
```

In [19]:
```
#plt.figure(figsize=(16,8))
#sns.countplot(x='AGE', data=data, hue='Default Payment', palette='bright')
```

In [20]:
```python
# Correlation analysis
plt.subplots(figsize=(30,10))
sns.heatmap(data.corr(), square=True, annot=True, fmt=".1f", cmap="YlGnBu")
# It seems that PAY_1 has the highest correlation to the target Default Payment
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbb0d0beb70>
```



Simple Feature Engineering and Preprocessing

In [21]:
```python
Y = data['Default Payment']
#Y.head()
```

In [22]:
```python
# Order features first categorical and second continuous
feature_order = ['SEX',
                 'EDUCATION',
                 'MARRIAGE',
                 'PAY_1',
                 'PAY_2',
                 'PAY_3',
                 'PAY_4',
                 'PAY_5',
                 'PAY_6',
                 'LIMIT_BAL',
                 'AGE',
                 'BILL_AMT1',
                 'BILL_AMT2',
                 'BILL_AMT3',
                 'BILL_AMT4',
                 'BILL_AMT5',
                 'BILL_AMT6',
                 'PAY_AMT1',
                 'PAY_AMT2',
                 'PAY_AMT3',
                 'PAY_AMT4',
                 'PAY_AMT5',
                 'PAY_AMT6']

X = data[feature_order]
#X.head()
```

In [23]:
```python
# List of categorical features - preparation for LIME input
categorical_names = {}
categorical_names[0] = ['female', 'male']
categorical_names[1] = [1, 2, 3, 4]
categorical_names[2] = [1, 2, 3]
categorical_names[3] = [0, 1, 2, 3, 4, 5, 6, 7, 8]
categorical_names[4] = [0, 1, 2, 3, 4, 5, 6, 7, 8]
categorical_names[5] = [0, 1, 2, 3, 4, 5, 6, 7, 8]
categorical_names[6] = [0, 1, 2, 3, 4, 5, 6, 7, 8]
categorical_names[7] = [0, 1, 2, 3, 4, 5, 6, 7, 8]
categorical_names[8] = [0, 1, 2, 3, 4, 5, 6, 7, 8]

# List of continuous features
continuous_features = list(X.columns[9:])
```

In [24]:
```python
# Scale the data
scaler = MinMaxScaler(feature_range=(0, 1))

def scaleColumns(X, cols_to_scale):
  for col in cols_to_scale:
    X[col] = pd.DataFrame(scaler.fit_transform(pd.DataFrame(X[col])),
                          columns=[col])
    return X

X_scaled = scaleColumns(X,[continuous_features])
#X_scaled.head()
```

In [25]:
```python
# Split the data into train/test datasets
X_train, X_test, Y_train, Y_test = train_test_split(X_scaled, Y, test_size=0.2, random_state=12345)
#print(len(X_train)) 24000
#print(len(X_test)) 6000
```

Resampling

In [26]:
```python
# Set random state and make the outputs stable
np.random.seed(12345)
```

In [27]:
```python
# Number of default payment and the ratio of it
# clearly imbalanced data, therefore resample with SMOTE
print(data["Default Payment"].value_counts())
print("Default Payment Percentage 0: {0:.2f} %".format(data[data["Default Payment"]==0].shape[0] / data.shape[0] * 100) )
print("Default Payment Percentage 1: {0:.2f} %".format(data[data["Default Payment"]==1].shape[0] / data.shape[0] * 100) )
```

```
0    23364
1     6636
Name: Default Payment, dtype: int64
Default Payment Percentage 0: 77.88 %
Default Payment Percentage 1: 22.12 %
```

In [28]:
```python
print(collections.Counter(Y_train))
#print(len(Y_train)) 24000
# The minority class 1 have just 5331 instances while the majority class 0 have 18669
```

```
Counter({0: 18669, 1: 5331})
```

In [29]:
```python
# Resample the train data
X_resampled, Y_resampled = SMOTE().fit_sample(X_train, Y_train)
# Convert the data to the same type as before SMOTE
X_train = pd.DataFrame(X_resampled, columns=feature_order)
Y_train = pd.Series(Y_resampled)
```

In [30]:
```python
print(collections.Counter(Y_train))
#print(len(Y_train)) 37338
# After applying SMOTE Method the classes are balanced
```

```
Counter({0: 18669, 1: 18669})
```

In [31]:
```python
# Already tested the Black-Box models for unbalanced and balanced data
# --> the balanced data have better recall and f1 score
# Metrics without SMOTE:
# Model  Precision   Recall  F1 Score  Accuracy       ROC
#  SVC   0.651106  0.406130  0.500236  0.823500  0.672820
#  RFC   0.637191  0.375479  0.472517  0.817667  0.658027
#  MLP   0.660274  0.369349  0.473710  0.821500  0.658263

# Metrics with SMOTE:
#Model   Precision   Recall  F1 Score  Accuracy       ROC
#  SVC   0.545605  0.504215  0.524094  0.800833  0.693747
#  RFC   0.521073  0.521073  0.521073  0.791667  0.693976
#  MLP   0.403059  0.686590  0.507937  0.710667  0.701974
```

Black-Box Model Training

In [32]:
```python
# Fitting a Support Vector Machine Classifier
# Actually the SVC model don't need so much computing time
# but the lime package requires probabilities and
# therefore the default probability=False has to be changed to True
svc = SVC(kernel='linear', probability=True, random_state=12345)
%time svc.fit(X_train, Y_train)
svc_pred = svc.predict(X_test)
```

```
CPU times: user 5min 45s, sys: 733 ms, total: 5min 45s
Wall time: 5min 46s
```

In [33]:
```python
# Confusion Matrix
pd.crosstab(Y_test, svc_pred, rownames=['Actual'], colnames=['Predicted'])
```

Out[33]:

Predicted	0	1
Actual		
0	4073	622
1	628	677

In [34]:
```python
# Model performs
print(classification_report(Y_test, svc_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.87      0.87      4695
           1       0.52      0.52      0.52      1305

    accuracy                           0.79      6000
   macro avg       0.69      0.69      0.69      6000
weighted avg       0.79      0.79      0.79      6000
```

In [35]:
```python
# Fitting a Random Forest Classifier
rfc = RandomForestClassifier(n_estimators=150, criterion='entropy', random_state=12345)
%time rfc.fit(X_train, Y_train)
rfc_pred = rfc.predict(X_test)
```

```
CPU times: user 29.4 s, sys: 16.9 ms, total: 29.4 s
Wall time: 29.5 s
```

In [36]:
```python
# Confusion Matrix
pd.crosstab(Y_test, rfc_pred, rownames=['Actual'], colnames=['Predicted'])
```

Out[36]:

Predicted	0	1
Actual		
0	4073	622
1	635	670

In [37]:
```python
# Model performs
print(classification_report(Y_test, rfc_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.87      0.87      4695
           1       0.52      0.51      0.52      1305

    accuracy                           0.79      6000
   macro avg       0.69      0.69      0.69      6000
weighted avg       0.79      0.79      0.79      6000
```

In [38]:
```python
# Fitting a Multi-Layer Perceptron Classifier
mlp = MLPClassifier(hidden_layer_sizes=(10, 10, 10), max_iter=1000, random_state=12345)
%time mlp.fit(X_train, Y_train.values.ravel())
mlp_pred = mlp.predict(X_test)
```

```
CPU times: user 54 s, sys: 38.9 ms, total: 54 s
Wall time: 54.1 s
```

In [39]:
```python
# Confusion Matrix
pd.crosstab(Y_test, mlp_pred, rownames=['Actual'], colnames=['Predicted'])
```

Out[39]:

Predicted	0	1
Actual		
0	3566	1129
1	479	826

In [40]:
```python
# Model performs
print(classification_report(Y_test,mlp_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.76      0.82      4695
           1       0.42      0.63      0.51      1305

    accuracy                           0.73      6000
   macro avg       0.65      0.70      0.66      6000
weighted avg       0.78      0.73      0.75      6000
```

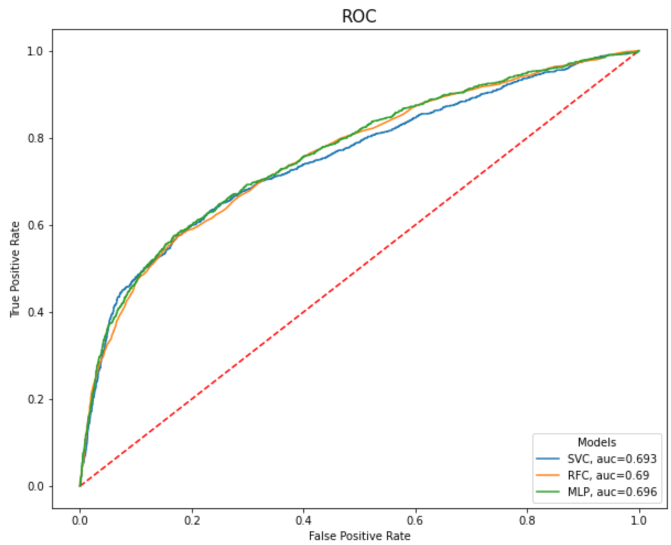
In [41]:
```
# Get a table for the metrics of the model performs
svc_prec = precision_score(Y_test, svc_pred)
svc_rec = recall_score(Y_test, svc_pred)
svc_f1 = f1_score(Y_test, svc_pred)
svc_acc = accuracy_score(Y_test, svc_pred)
svc_roc = roc_auc_score(Y_test, svc_pred)

rfc_prec = precision_score(Y_test, rfc_pred)
rfc_rec = recall_score(Y_test, rfc_pred)
rfc_f1 = f1_score(Y_test, rfc_pred)
rfc_acc = accuracy_score(Y_test, rfc_pred)
rfc_roc = roc_auc_score(Y_test, rfc_pred)

mlp_prec = precision_score(Y_test, mlp_pred)
mlp_rec = recall_score(Y_test, mlp_pred)
mlp_f1 = f1_score(Y_test, mlp_pred)
mlp_acc = accuracy_score(Y_test, mlp_pred)
mlp_roc = roc_auc_score(Y_test, mlp_pred)

metric = pd.DataFrame([['SVC', svc_prec, svc_rec, svc_f1, svc_acc, svc_roc]],
                      columns = ['Model', 'Precision', 'Recall', 'F1 Score', 'Accuracy', 'ROC'])

metric2 = pd.DataFrame([['RFC', rfc_prec, rfc_rec, rfc_f1, rfc_acc, rfc_roc]],
                      columns = ['Model', 'Precision', 'Recall', 'F1 Score', 'Accuracy', 'ROC'])

metric3 = pd.DataFrame([['MLP', mlp_prec, mlp_rec, mlp_f1, mlp_acc, mlp_roc]],
                      columns = ['Model', 'Precision', 'Recall', 'F1 Score', 'Accuracy', 'ROC'])

metric = metric.append([metric2, metric3], sort=False)
metric
```

Out[41]:

	Model	Precision	Recall	F1 Score	Accuracy	ROC
0	SVC	0.521170	0.518774	0.519969	0.791667	0.693146
0	RFC	0.518576	0.513410	0.515980	0.790500	0.690464
0	MLP	0.422506	0.632950	0.506748	0.732000	0.696241

In [42]:
```
# ROC Curve
probs_svc = svc.predict_proba(X_test)[:,1]
FPR1, TPR1, _ = metrics.roc_curve(Y_test, probs_svc)

probs_rfc = rfc.predict_proba(X_test)[:,1]
FPR2, TPR2, _ = metrics.roc_curve(Y_test, probs_rfc)

probs_mlp = mlp.predict_proba(X_test)[:,1]
FPR3, TPR3, _ = metrics.roc_curve(Y_test, probs_mlp)

plt.figure(figsize=(10,8))
plt.plot([0, 1], [0, 1], 'r--')
plt.plot(FPR1,TPR1,label="SVC, auc="+str(round(svc_roc,3)))
plt.plot(FPR2,TPR2,label="RFC, auc="+str(round(rfc_roc,3)))
plt.plot(FPR3,TPR3,label="MLP, auc="+str(round(mlp_roc,3)))
plt.legend(loc=4, title='Models', facecolor='white')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC', size=15)
```

Out[42]: `Text(0.5, 1.0, 'ROC')`



Explainability

Compare the LIME explanations of the Black-Box models at 4 different instances, additionally the Kernel SHAP explanation for MLP

In [43]:
```
predict_svc = lambda x: svc.predict_proba(x).astype(float)
predict_rfc = lambda x: rfc.predict_proba(x).astype(float)
predict_mlp = lambda x: mlp.predict_proba(x).astype(float)
#rfc.predict(X_test) array([1, 0, 0, ..., 0, 0, 0])
#rfc.predict_proba(X_test) array([[0.31333333, 0.68666667], [0.86, 0.14], [0.8, 0.2], ..]
```

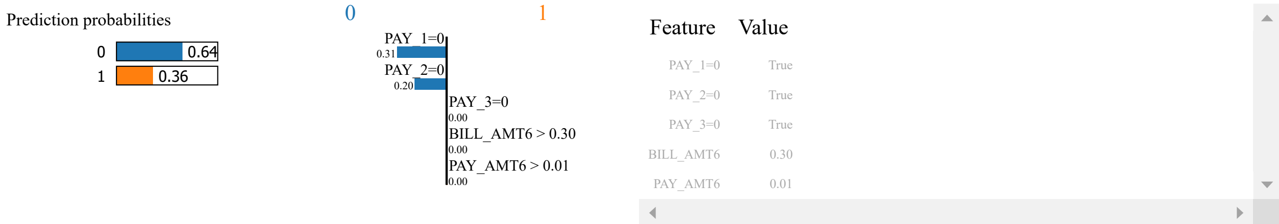
In [44]:
```python
explainer_lime = lime.lime_tabular.LimeTabularExplainer(X_train.values,
                                                        class_names=Y_train.unique(),
                                                        feature_names = X_train.columns,
                                                        categorical_features = categorical_names,
                                                        verbose=True)
# verbose = True, so the intercept the LIME and Black-Box Modell prediction will be shown
```

Instance 1 - Actual Label: 0, Predicted Label: 0

In [45]:
```python
#i = 35
#print(X_test.iloc[i]) shows the instance as the actual data point
#print(Y_test.iloc[i])     0
#print(svc_pred[i])        0
#print(rfc_pred[i])        0
#print(mlp_pred[i])        0
```

In [46]:
```python
i = 35
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_svc, num_features=5)
print(exp.score)
exp.show_in_notebook()
#exp.local_exp
exp.as_list()
```

```
Intercept 0.8694245959934388
Prediction_local [0.36850833]
Right: 0.35691118306794845
CPU times: user 3.98 s, sys: 324 ms, total: 4.3 s
Wall time: 3.97 s
0.862279738698042
```



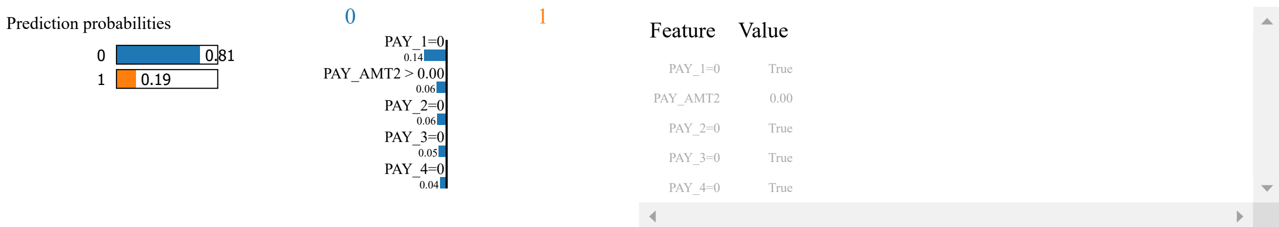
Out[46]:
```
[('PAY_1=0', -0.31115890778276223),
 ('PAY_2=0', -0.20141194001493934),
 ('PAY_3=0', 0.003953150195173049),
 ('BILL_AMT6 > 0.30', 0.00391378520958269),
 ('PAY_AMT6 > 0.01', 0.00378764933835298)]
```

In [47]:
```python
# The prediction of LIME model is the sum of the intercept and coefficients
0.8694245959934388 + (-0.31115890778276223) + (-0.20141194001493934) + 0.003953150195173049 + 0.00391378520958269 + 0.00378764933835298
```

Out[47]:
```
0.36850833293884594
```

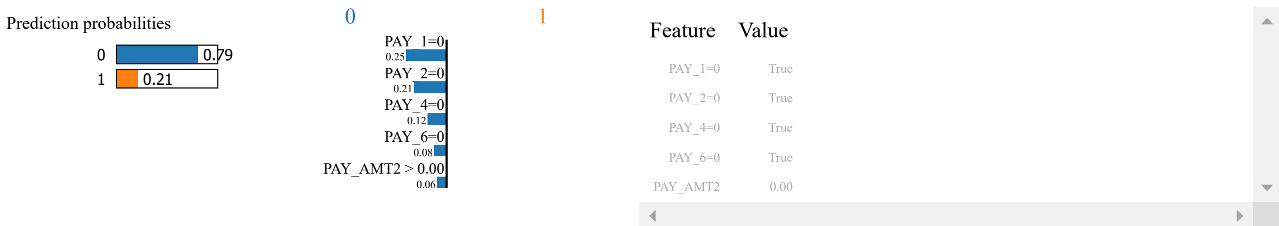
In [48]:
```python
i = 35
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_rfc, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 0.6814565699659403
Prediction_local [0.32728557]
Right: 0.18666666666666668
CPU times: user 1.17 s, sys: 322 ms, total: 1.49 s
Wall time: 1.12 s
0.3749560960082812
```



In [49]:
```python
i = 35
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 1.011229539754286
Prediction_local [0.2923108]
Right: 0.2066158066500271
CPU times: user 979 ms, sys: 250 ms, total: 1.23 s
Wall time: 930 ms
0.44401059872943155
```

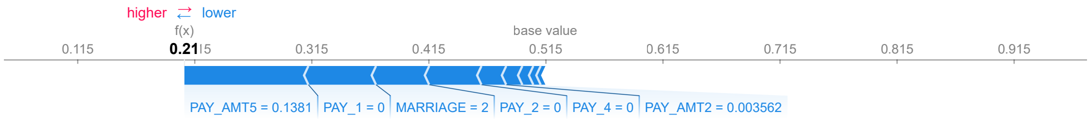


In [50]:
```python
explainer = shap.KernelExplainer(predict_mlp, X_train)
shap.initjs()

i = 35
%time shap_values = explainer.shap_values(X_test.iloc[i], nsamples=100)
shap.force_plot(explainer.expected_value[1], shap_values[1], X_test.iloc[i], link="identity")
```

```
Using 37338 background data samples could cause slower run times. Consider using shap.sample(data, K) or shap.kmeans(data, K) to summarize the background as K samples.
```

```
CPU times: user 43.7 s, sys: 1.74 s, total: 45.4 s
Wall time: 41.6 s
```

Out[50]:



In [51]:
```python
shap_values[1]
```

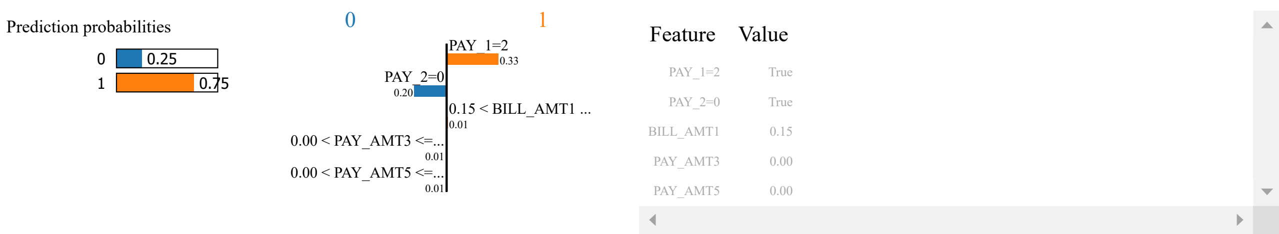
Out[51]:
```
array([-0.00403602,  0.        , -0.04542741, -0.05777129, -0.04465046,
       -0.00629676, -0.02115615, -0.00933667,  0.        ,  0.        ,
        0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
        0.        ,  0.        ,  0.        , -0.01378795,  0.        ,
        0.        , -0.10593468,  0.        ])
```

Instance 2 - Actual Label: 1, Predicted Label: 1

In [52]:
```python
#i = 2675
#print(X_test.iloc[i])
#print(Y_test.iloc[i])     1
#print(svc_pred[i])        1
#print(rfc_pred[i])        1
#print(mlp_pred[i])        1
```

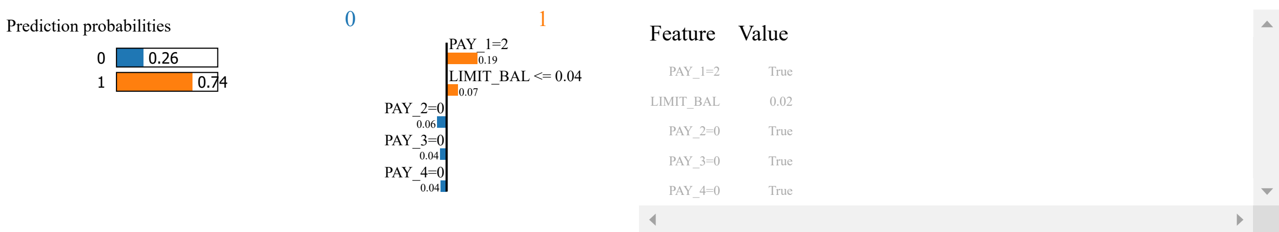
In [53]:
```python
i = 2675
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_svc, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 0.6165365833753855
Prediction_local [0.73449843]
Right: 0.7547813416124128
CPU times: user 3.99 s, sys: 312 ms, total: 4.3 s
Wall time: 3.95 s
0.6501115199111637
```



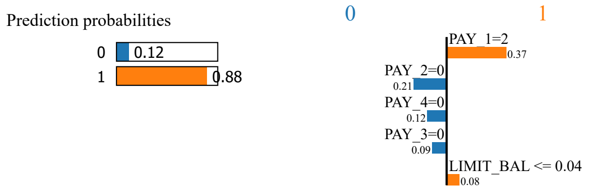
In [54]:
```python
i = 2675
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_rfc, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 0.5174806674038772
Prediction_local [0.6404675]
Right: 0.74
CPU times: user 1.13 s, sys: 300 ms, total: 1.43 s
Wall time: 1.09 s
0.39781062691381536
```



In [55]:
```
i = 2675
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 0.7628486133153582
Prediction_local [0.79443109]
Right: 0.881724734200468
CPU times: user 966 ms, sys: 267 ms, total: 1.23 s
Wall time: 930 ms
0.5244831116770893
```



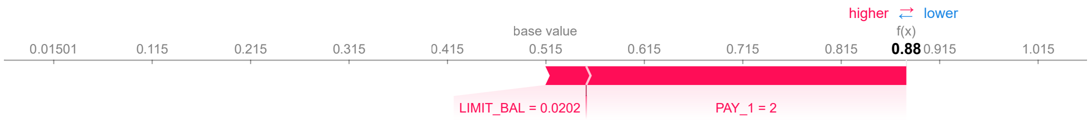
Feature	Value
PAY_1=2	True
PAY_2=0	True
PAY_4=0	True
PAY_3=0	True
LIMIT_BAL	0.02

In [56]:
```
explainer = shap.KernelExplainer(predict_mlp, X_train)
shap.initjs()

i = 2675
%time shap_values = explainer.shap_values(X_test.iloc[i], nsamples=100)
shap.force_plot(explainer.expected_value[1], shap_values[1], X_test.iloc[i], link="identity")
```

```
Using 37338 background data samples could cause slower run times. Consider using shap.sample(data, K) or shap.kmeans(data, K) to summarize the background as K samples.
```

```
CPU times: user 44.4 s, sys: 618 ms, total: 45 s
Wall time: 41.7 s
```

Out[56]:



In [57]:
```
shap_values[1]
```

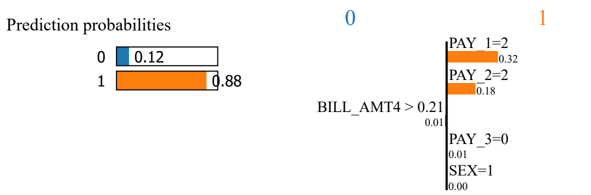
Out[57]:
```
array([0.        , 0.        , 0.        , 0.32525366, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.04145788,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        ])
```

Instance 3 - Actual Label: 0, Predicted Label: 1

In [58]:
```
#i = 555
#print(X_test.iloc[i])
#print(Y_test.iloc[i])    0
#print(svc_pred[i])       1
#print(rfc_pred[i])       1
#print(mlp_pred[i])       1
```

In [59]:
```
i = 555
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_svc, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

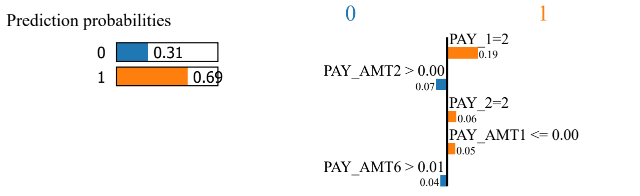
```
Intercept 0.42261127891875716
Prediction_local [0.92256416]
Right: 0.8792847399742162
CPU times: user 3.98 s, sys: 294 ms, total: 4.28 s
Wall time: 3.92 s
0.5653251192321365
```



Feature	Value
PAY_1=2	True
PAY_2=2	True
BILL_AMT4	0.33
PAY_3=0	True
SEX=1	True

```
In [60]: i = 555
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_rfc, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

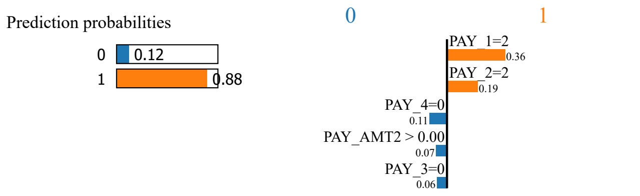
```
Intercept 0.42565547811343807
Prediction_local [0.61834952]
Right: 0.6933333333333334
CPU times: user 1.15 s, sys: 316 ms, total: 1.46 s
Wall time: 1.11 s
0.4065419550916338
```



Feature	Value
PAY_1=2	True
PAY_AMT2	0.00
PAY_2=2	True
PAY_AMT1	0.00
PAY_AMT6	0.01

```
In [61]: i = 555
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 0.575174170239024
Prediction_local [0.88712598]
Right: 0.8822306520804934
CPU times: user 973 ms, sys: 245 ms, total: 1.22 s
Wall time: 922 ms
0.47404336021716476
```



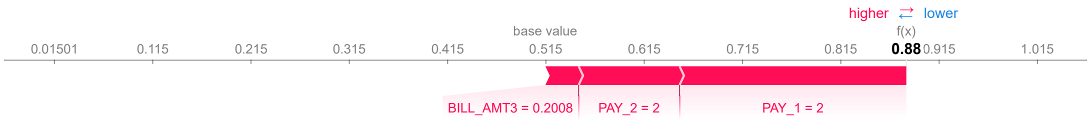
Feature	Value
PAY_1=2	True
PAY_2=2	True
PAY_4=0	True
PAY_AMT2	0.00
PAY_3=0	True

```
In [62]: explainer = shap.KernelExplainer(predict_mlp, X_train)
shap.initjs()

i = 555
%time shap_values = explainer.shap_values(X_test.iloc[i], nsamples=100)
shap.force_plot(explainer.expected_value[1], shap_values[1], X_test.iloc[i], link="identity")
```

```
Using 37338 background data samples could cause slower run times. Consider using shap.sample(data, K) or shap.kmeans(data, K) to summarize the background as K samples.
```

```
CPU times: user 44.5 s, sys: 573 ms, total: 45.1 s
Wall time: 41.7 s
```

Out[62]:




```
In [63]: shap_values[1]
```

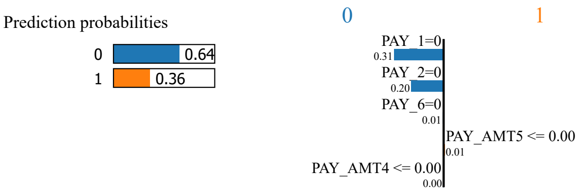
```
Out[63]: array([0.        , 0.        , 0.        , 0.23069281, 0.10266177,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.03386288, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        ])
```

Instance 4 - Actual Label: 1, Predicted Label: 0

```
In [64]: #i = 1880
#print(X_test.iloc[i])
#print(Y_test.iloc[i])    1
#print(svc_pred[i])       0
#print(rfc_pred[i])       0
#print(mlp_pred[i])       0
```

In [65]:
```python
i = 1880
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_svc, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

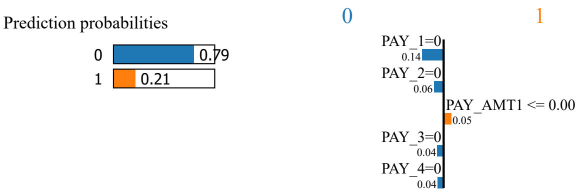
```
Intercept 0.882546408232073
Prediction_local [0.36422746]
Right: 0.3569330122544934
CPU times: user 4.04 s, sys: 317 ms, total: 4.36 s
Wall time: 4 s
0.8700084063477235
```



Feature	Value
PAY_1=0	True
PAY_2=0	True
PAY_6=0	True
PAY_AMT5	0.00
PAY_AMT4	0.00

In [66]:
```python
i = 1880
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_rfc, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

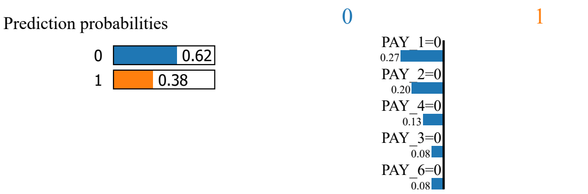
```
Intercept 0.64399487276505
Prediction_local [0.41942654]
Right: 0.21333333333333335
CPU times: user 1.17 s, sys: 308 ms, total: 1.48 s
Wall time: 1.11 s
0.3326753833437992
```



Feature	Value
PAY_1=0	True
PAY_2=0	True
PAY_AMT1	0.00
PAY_3=0	True
PAY_4=0	True

In [67]:
```python
i = 1880
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 1.0729312450809303
Prediction_local [0.32117]
Right: 0.3831789850241079
CPU times: user 965 ms, sys: 255 ms, total: 1.22 s
Wall time: 918 ms
0.47499633409421527
```



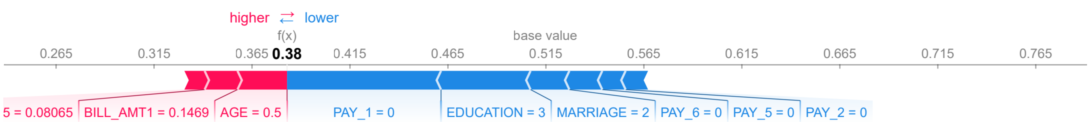
Feature	Value
PAY_1=0	True
PAY_2=0	True
PAY_4=0	True
PAY_3=0	True
PAY_6=0	True

In [68]:
```python
explainer = shap.KernelExplainer(predict_mlp, X_train)
shap.initjs()

i = 1880
%time shap_values = explainer.shap_values(X_test.iloc[i], nsamples=100)
shap.force_plot(explainer.expected_value[1], shap_values[1], X_test.iloc[i], link="identity")
```

```
Using 37338 background data samples could cause slower run times. Consider using shap.sample(data, K) or shap.kmeans(data, K) to summarize the background as K samples.
```

```
CPU times: user 44 s, sys: 632 ms, total: 44.6 s
Wall time: 41.1 s
```

Out[68]:



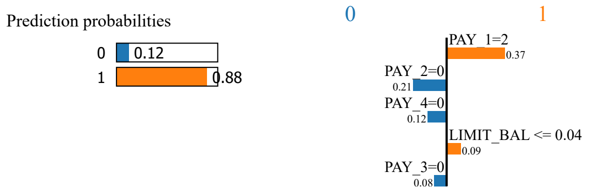
```
In [69]: shap_values[1]
```

```
Out[69]: array([ 0.        , -0.04568959, -0.01980776, -0.07857919, -0.0114412 ,
          0.        ,  0.        , -0.01191077, -0.01679955,  0.        ,
          0.02530845,  0.01675877,  0.        ,  0.        ,  0.        ,
          0.01032664,  0.        ,  0.        ,  0.        ,  0.        ,
          0.        ,  0.        ,  0.        ])
```

Choose the MLP model at the Instance 2 and compare LIME results for different kernels

```
In [81]: explainer_lime = lime.lime_tabular.LimeTabularExplainer(X_train.values,
                                                         class_names=Y_train.unique(),
                                                         feature_names = X_train.columns,
                                                         categorical_features = categorical_names,
                                                         kernel_width=5,
                                                         verbose=True)

         i = 2675
         %time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
         print(exp.score)
         exp.show_in_notebook()
```

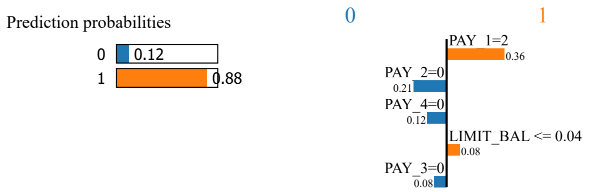
```
Intercept 0.7524639858316332
Prediction_local [0.79832487]
Right: 0.881724734200468
CPU times: user 985 ms, sys: 272 ms, total: 1.26 s
Wall time: 940 ms
0.525888938508656
```



Feature	Value
PAY_1=2	True
PAY_2=0	True
PAY_4=0	True
LIMIT_BAL	0.02
PAY_3=0	True

```
In [82]: explainer_lime = lime.lime_tabular.LimeTabularExplainer(X_train.values,
                                                         class_names=Y_train.unique(),
                                                         feature_names = X_train.columns,
                                                         categorical_features = categorical_names,
                                                         kernel_width=4,
                                                         verbose=True)

         i = 2675
         %time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
         print(exp.score)
         exp.show_in_notebook()
```

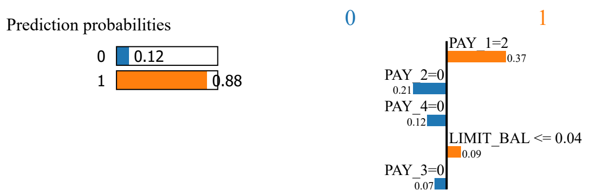
```
Intercept 0.7517766638664278
Prediction_local [0.79204986]
Right: 0.881724734200468
CPU times: user 962 ms, sys: 261 ms, total: 1.22 s
Wall time: 921 ms
0.529183404046643
```



Feature	Value
PAY_1=2	True
PAY_2=0	True
PAY_4=0	True
LIMIT_BAL	0.02
PAY_3=0	True

```
In [83]: explainer_lime = lime.lime_tabular.LimeTabularExplainer(X_train.values,
                                                         class_names=Y_train.unique(),
                                                         feature_names = X_train.columns,
                                                         categorical_features = categorical_names,
                                                         kernel_width=3,
                                                         verbose=True)

         i = 2675
         %time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
         print(exp.score)
         exp.show_in_notebook()
```

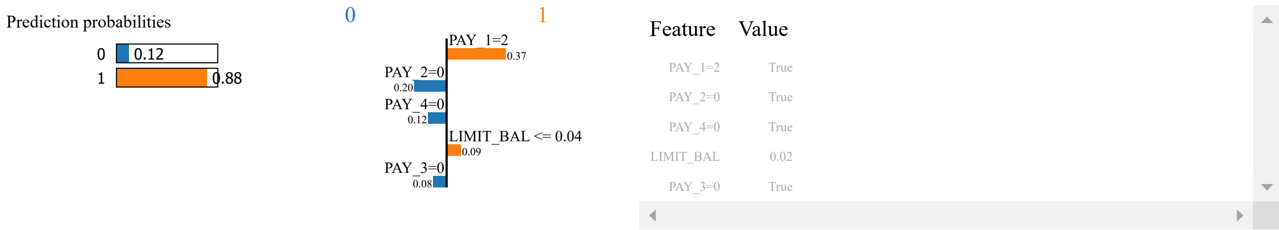
```
Intercept 0.744718161731869
Prediction_local [0.80177693]
Right: 0.881724734200468
CPU times: user 961 ms, sys: 258 ms, total: 1.22 s
Wall time: 915 ms
0.5362884852763443
```



Feature	Value
PAY_1=2	True
PAY_2=0	True
PAY_4=0	True
LIMIT_BAL	0.02
PAY_3=0	True

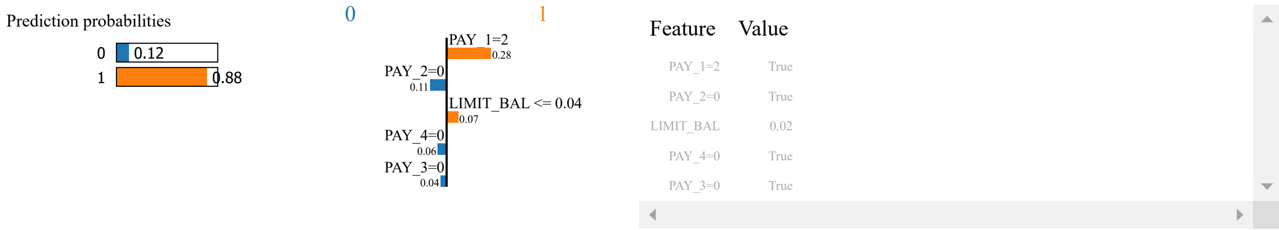
In [84]:
```python
explainer_lime = lime.lime_tabular.LimeTabularExplainer(X_train.values,
                                                        class_names=Y_train.unique(),
                                                        feature_names = X_train.columns,
                                                        categorical_features = categorical_names,
                                                        kernel_width=2,
                                                        verbose=True)

i = 2675
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 0.7452880577664628
Prediction_local [0.80482674]
Right: 0.881724734200468
CPU times: user 982 ms, sys: 252 ms, total: 1.23 s
Wall time: 944 ms
0.5581746440247689
```



In [85]:
```python
explainer_lime = lime.lime_tabular.LimeTabularExplainer(X_train.values,
                                                        class_names=Y_train.unique(),
                                                        feature_names = X_train.columns,
                                                        categorical_features = categorical_names,
                                                        kernel_width=1,
                                                        verbose=True)

i = 2675
%time exp = explainer_lime.explain_instance(X_test.iloc[i], predict_fn = predict_mlp, num_features=5)
print(exp.score)
exp.show_in_notebook()
```

```
Intercept 0.6136595605085354
Prediction_local [0.76491398]
Right: 0.881724734200468
CPU times: user 956 ms, sys: 264 ms, total: 1.22 s
Wall time: 921 ms
0.6020468732140188
```



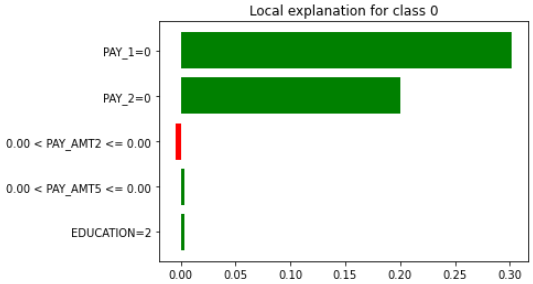
Compare the SP-LIME across the three Black-Box models, additionally the global Kernel SHAP explanation for MLP

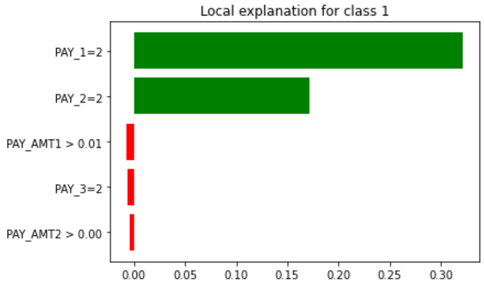
In [90]:
```python
explainer_lime = lime.lime_tabular.LimeTabularExplainer(X_train.values,
                                                        class_names=Y_train.unique(),
                                                        feature_names = X_train.columns,
                                                        categorical_features = categorical_names,
                                                        verbose=False)

#verbose=false, so the information about local explainder don't show up
```

In [94]:
```
%time sp_obj = submodular_pick.SubmodularPick(explainer_lime, X_train.values, predict_svc, sample_size=20, num_features=5, num_exps_desired=2)
[exp.as_pyplot_figure(label=exp.available_labels()[0]) for exp in sp_obj.sp_explanations]
```

```
CPU times: user 1min 22s, sys: 8.07 s, total: 1min 30s
Wall time: 1min 21s
```

Out[94]: `[<Figure size 432x288 with 1 Axes>, <Figure size 432x288 with 1 Axes>]`

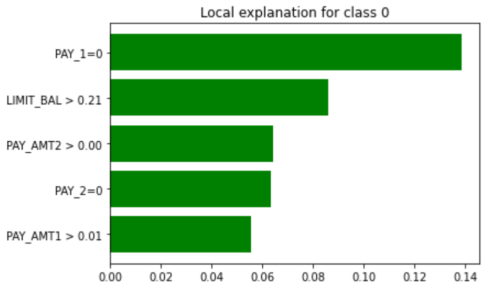


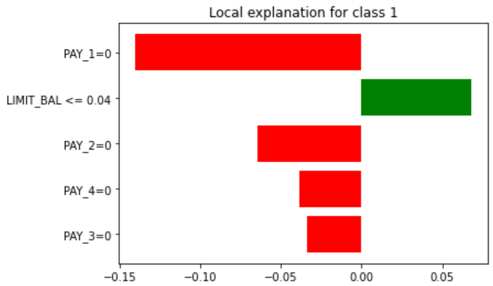


In [98]:
```
%time sp_obj = submodular_pick.SubmodularPick(explainer_lime, X_train.values, predict_rfc, sample_size=20, num_features=5, num_exps_desired=2)
[exp.as_pyplot_figure(label=exp.available_labels()[0]) for exp in sp_obj.sp_explanations]
```

```
CPU times: user 24.1 s, sys: 8.19 s, total: 32.3 s
Wall time: 22.8 s
```

Out[98]: `[<Figure size 432x288 with 1 Axes>, <Figure size 432x288 with 1 Axes>]`

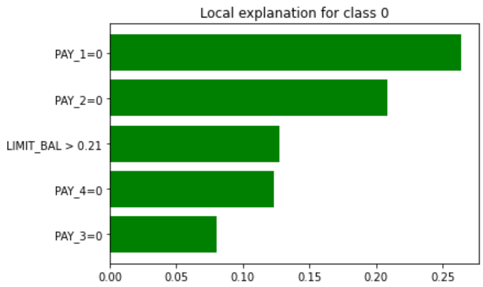


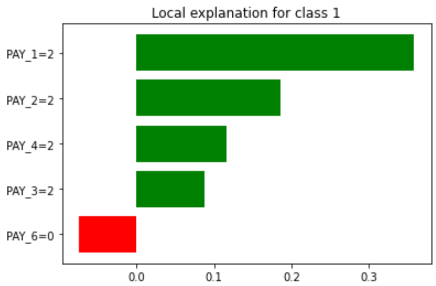


In [99]:
```
%time sp_obj = submodular_pick.SubmodularPick(explainer_lime, X_train.values, predict_mlp, sample_size=20, num_features=5, num_exps_desired=2)
[exp.as_pyplot_figure(label=exp.available_labels()[0]) for exp in sp_obj.sp_explanations]
```

```
CPU times: user 22.4 s, sys: 6.87 s, total: 29.3 s
Wall time: 22.9 s
```

Out[99]:
```
[<Figure size 432x288 with 1 Axes>, <Figure size 432x288 with 1 Axes>]
```





In [100]:
```
# Sampling data from the training set to reduce time
# Running without the kmeans end up with ram crash
X_train_summary = shap.kmeans(X_train, 10)
```

In [101]:
```
explainer = shap.KernelExplainer(predict_mlp, X_train_summary)
%time shap_values = explainer.shap_values(X_test)
shap.initjs()
shap.summary_plot(shap_values, X_test)
```

Error rendering Jupyter widget: missing widget manager

```
CPU times: user 30min 48s, sys: 18min 35s, total: 49min 23s
Wall time: 26min 35s
```