taiwan-credit

August 21, 2022

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import xlrd
```

[2]:
```
filename = 'default of credit card clients.xls'
```

[3]:
```
DATA = os.path.relpath('/Users/ben/Benborg/ml-blog/credit/data/' + filename)
```

[4]:
```
df = pd.read_excel(DATA, 'Data', index_col=[0], header=[1], na_values='NA')
df.head()
```

[4]:
```
    LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
ID
1       20000    2          2         1   24      2      2     -1     -1
2      120000    2          2         2   26     -1      2      0      0
3       90000    2          2         2   34      0      0      0      0
4       50000    2          2         1   37      0      0      0      0
5       50000    1          2         1   57     -1      0     -1      0

    PAY_5  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
ID         …
1      -2  …          0          0          0         0       689         0
2       0  …       3272       3455       3261         0      1000      1000
3       0  …      14331      14948      15549      1518      1500      1000
4       0  …      28314      28959      29547      2000      2019      1200
5       0  …      20940      19146      19131      2000     36681     10000

    PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
ID
1          0         0         0                           1
2       1000         0      2000                           1
3       1000      1000      5000                           0
4       1100      1069      1000                           0
5       9000       689       679                           0

[5 rows x 24 columns]
```

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30000 entries, 1 to 30000
Data columns (total 24 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   LIMIT_BAL                   30000 non-null  int64
 1   SEX                         30000 non-null  int64
 2   EDUCATION                   30000 non-null  int64
 3   MARRIAGE                    30000 non-null  int64
 4   AGE                         30000 non-null  int64
 5   PAY_0                       30000 non-null  int64
 6   PAY_2                       30000 non-null  int64
 7   PAY_3                       30000 non-null  int64
 8   PAY_4                       30000 non-null  int64
 9   PAY_5                       30000 non-null  int64
 10  PAY_6                       30000 non-null  int64
 11  BILL_AMT1                   30000 non-null  int64
 12  BILL_AMT2                   30000 non-null  int64
 13  BILL_AMT3                   30000 non-null  int64
 14  BILL_AMT4                   30000 non-null  int64
 15  BILL_AMT5                   30000 non-null  int64
 16  BILL_AMT6                   30000 non-null  int64
 17  PAY_AMT1                    30000 non-null  int64
 18  PAY_AMT2                    30000 non-null  int64
 19  PAY_AMT3                    30000 non-null  int64
 20  PAY_AMT4                    30000 non-null  int64
 21  PAY_AMT5                    30000 non-null  int64
 22  PAY_AMT6                    30000 non-null  int64
 23  default payment next month  30000 non-null  int64
dtypes: int64(24)
memory usage: 5.7 MB
```

- Split the dataset, **train, test, split**

[6]:
```
X = df.iloc[:, :22]
y = df.iloc[:, 23]
```

[7]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)
```

0.0.1 k-Means Clustering

[8]:
```
from sklearn.cluster import KMeans
```

[9]:
```
kmeans = KMeans(init='random', n_clusters=2, n_init=10, max_iter=200,␣
↪random_state=42).fit(X_train)
```

[10]:
```
kmeans.labels_
```

[10]:
```
array([1, 1, 1, …, 1, 1, 1], dtype=int32)
```

[11]:
```
kmeans.cluster_centers_
```

[11]:
```
array([[ 2.83674183e+05,  1.57331731e+00,  1.80468750e+00,
         1.50600962e+00,  3.68996394e+01,  2.76442308e-01,
         2.47896635e-01,  2.17247596e-01,  1.76682692e-01,
         1.44531250e-01,  1.46935096e-01,  1.90051442e+05,
         1.85602306e+05,  1.80108695e+05,  1.66677600e+05,
         1.55567471e+05,  1.49142236e+05,  1.46585198e+04,
         1.60775589e+04,  1.33720249e+04,  1.18201352e+04,
         1.16559153e+04],
       [ 1.48479683e+05,  1.61000387e+00,  1.86193885e+00,
         1.55872678e+00,  3.52681405e+01, -6.38544892e-02,
        -1.92434211e-01, -2.30214783e-01, -2.84345975e-01,
        -3.31124226e-01, -3.58891254e-01,  2.85298009e+04,
         2.69093469e+04,  2.52887110e+04,  2.31047658e+04,
         2.15692457e+04,  2.09935957e+04,  4.22389140e+03,
         4.33244505e+03,  3.95200353e+03,  3.76368619e+03,
         3.71814512e+03]])
```

[12]:
```
centroids = kmeans.cluster_centers_
```

[13]:
```
def plot_data(X):
    plt.scatter(X[0], X[1],  c='k', s=30)

def plot_centroids(centroids, weights=None, circle_color='k', cross_color='w'):
    if weights is not None:
        centroids =  centroids[weights > weights.max() / 10]
    plt.scatter(centroids[:, 0], centroids[:, 1], marker='o', s=35,␣
↪linewidths=8,
                color=circle_color, zorder=10, alpha=0.9)
    plt.scatter(centroids[:, 0], centroids[:, 1], marker='x', s=2,␣
↪linewidths=12,
                color=cross_color, zorder=11, alpha=1)

def plot_decision_boundaries(clusterer, X, resolution=1000,␣
↪show_centroids=True, show_xlabels=True, show_ylabels=True):
    mins = X.min(axis=0) - 0.1
    maxs = X.max(axis=0) + 0.1
    xx, yy = np.meshgrid(np.linspace(mins[0], maxs[0], resolution),
                         np.linspace(mins[1], maxs[1], resolution))
```

```
    Z = clusterer.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    plt.contourf(Z, extent=(mins[0], maxs[0], mins[1], maxs[1]),
                 cmap='viridis')
    plt.contour(Z, extent=(mins[0], maxs[0], mins[1], maxs[1]),
                linewidths=1, colors='k')

    plot_data(X)
    if show_centroids:
        plot_centroids(clusterer.cluster_centers_)

    if show_xlabels:
        plt.xlabel("$x_1$", fontsize=14)
    else:
        plt.tick_params(labelbottom=False)
    if show_ylabels:
        plt.ylabel("$x_2$", fontsize=14, rotation=0)
    else:
        plt.tick_params(labelleft=False)
```

[14]:
```
plt.figure(figsize=(10,7))
plot_decision_boundaries(kmeans, X_train)
plt.savefig('voronoi_exempts.png')
plt.show()
```

```
/Users/ben/Benborg/ml-blog/mlenv/lib/python3.10/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but KMeans was fitted with feature names
  warnings.warn(
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Input In [14], in <cell line: 2>()
      1 plt.figure(figsize=(10,7))
----> 2 plot_decision_boundaries(kmeans, X_train)
      3 plt.savefig('voronoi_exempts.png')
      4 plt.show()

Input In [13], in plot_decision_boundaries(clusterer, X, resolution,␣
 ↪show_centroids, show_xlabels, show_ylabels)
     14 maxs = X.max(axis=0) + 0.1
     15 xx, yy = np.meshgrid(np.linspace(mins[0], maxs[0], resolution),
     16                      np.linspace(mins[1], maxs[1], resolution))
---> 17 Z = clusterer.predict(np.c_[xx.ravel(), yy.ravel()])
     18 Z = Z.reshape(xx.shape)
     20 plt.contourf(Z, extent=(mins[0], maxs[0], mins[1], maxs[1]),
     21              cmap='viridis')
```

```
File ~/Benborg/ml-blog/mlenv/lib/python3.10/site-packages/sklearn/cluster/
↪_kmeans.py:1021, in _BaseKMeans.predict(self, X, sample_weight)
    999 """Predict the closest cluster each sample in X belongs to.
   1000
   1001 In the vector quantization literature, `cluster_centers_` is called
   (…)
   1017     Index of the cluster each sample belongs to.
   1018 """
   1019 check_is_fitted(self)
-> 1021 X = self._check_test_data(X)
   1022 x_squared_norms = row_norms(X, squared=True)
   1023 sample_weight = _check_sample_weight(sample_weight, X, dtype=X.dtype)

File ~/Benborg/ml-blog/mlenv/lib/python3.10/site-packages/sklearn/cluster/
↪_kmeans.py:897, in _BaseKMeans._check_test_data(self, X)
    896 def _check_test_data(self, X):
--> 897     X = self._validate_data(
    898         X,
    899         accept_sparse="csr",
    900         reset=False,
    901         dtype=[np.float64, np.float32],
    902         order="C",
    903         accept_large_sparse=False,
    904     )
    905     return X

File ~/Benborg/ml-blog/mlenv/lib/python3.10/site-packages/sklearn/base.py:600,␣
↪in BaseEstimator._validate_data(self, X, y, reset, validate_separately,␣
↪**check_params)
    597     out = X, y
    599 if not no_val_X and check_params.get("ensure_2d", True):
--> 600     self._check_n_features(X, reset=reset)
    602 return out

File ~/Benborg/ml-blog/mlenv/lib/python3.10/site-packages/sklearn/base.py:400,␣
↪in BaseEstimator._check_n_features(self, X, reset)
    397     return
    399 if n_features != self.n_features_in_:
--> 400     raise ValueError(
    401         f"X has {n_features} features, but {self.__class__.__name__} "
    402         f"is expecting {self.n_features_in_} features as input."
    403     )

ValueError: X has 2 features, but KMeans is expecting 22 features as input.
```

```
<Figure size 720x504 with 0 Axes>
```

[ ]:
```
# from scipy.spatial import Voronoi, voronoi_plot_2d
#
# vor = Voronoi(X_train)
# fig = voronoi_plot_2d(vor, show_vertices=True)
# plt.show()
```

0.1 Principal Component Analysis

[14]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
X_train_reduce = pca.fit_transform(X_train)
```

[15]:
```
pca.n_components_, pca.explained_variance_ratio_
```

[15]:
```
(2, array([0.61072272, 0.29729969]))
```

- Almost all the **variance** is explained by these two components. Let's try `k-Means` again with only these two.

[16]:
```
X_train_reduce
```

[16]:
```
array([[   -977.60220334, -100584.93299971],
       [-114722.50953568,  -92885.0797815 ],
       [ -75597.74683556,   57990.49015691],
       …,
       [-154241.34324944,  -47130.34187774],
       [ -39566.13383388,  -90111.51714451],
       [ -91963.87331176,   44506.13176602]])
```

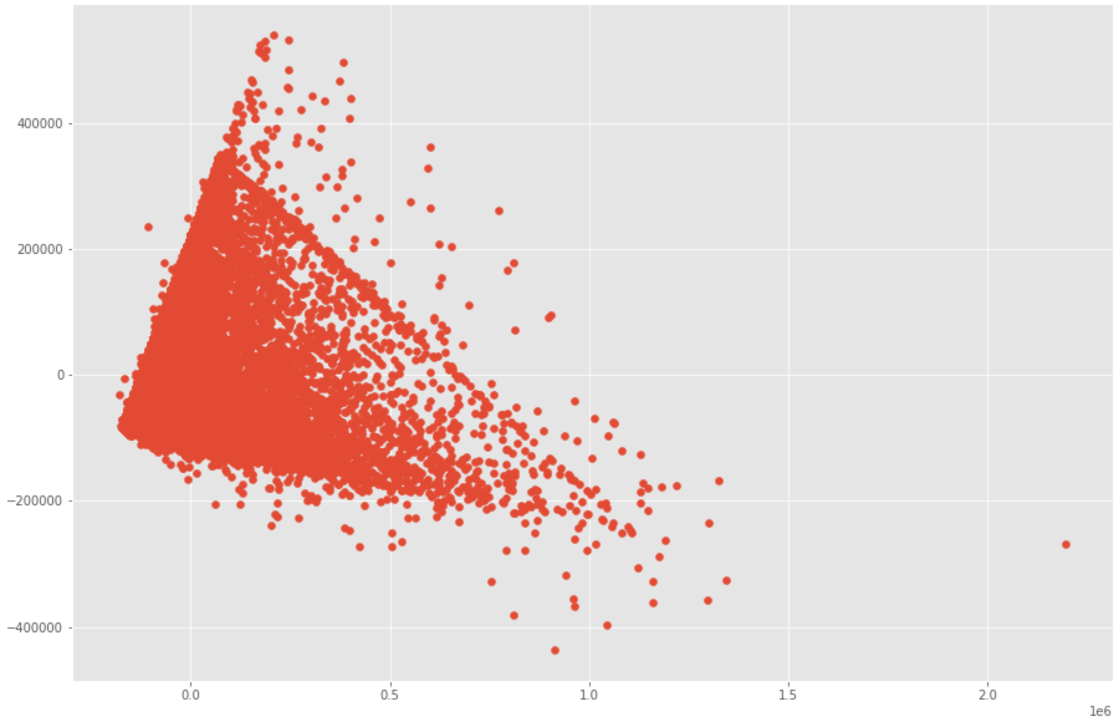
[17]:
```
from sklearn.cluster import KMeans
```

[18]:
```
kmeans_pca = KMeans(n_clusters=2, init='k-means++', max_iter=200,␣
 ↪random_state=42).fit(X_train_reduce)
```

[19]:
```
pca_centroids = kmeans_pca.cluster_centers_
```

[21]:
```
plt.style.use('ggplot')
plt.figure(figsize=(15,10))
plt.scatter(X_train_reduce[:, 0], X_train_reduce[:, 1])
```

[21]:
```
<matplotlib.collections.PathCollection at 0x11dbb9930>
```

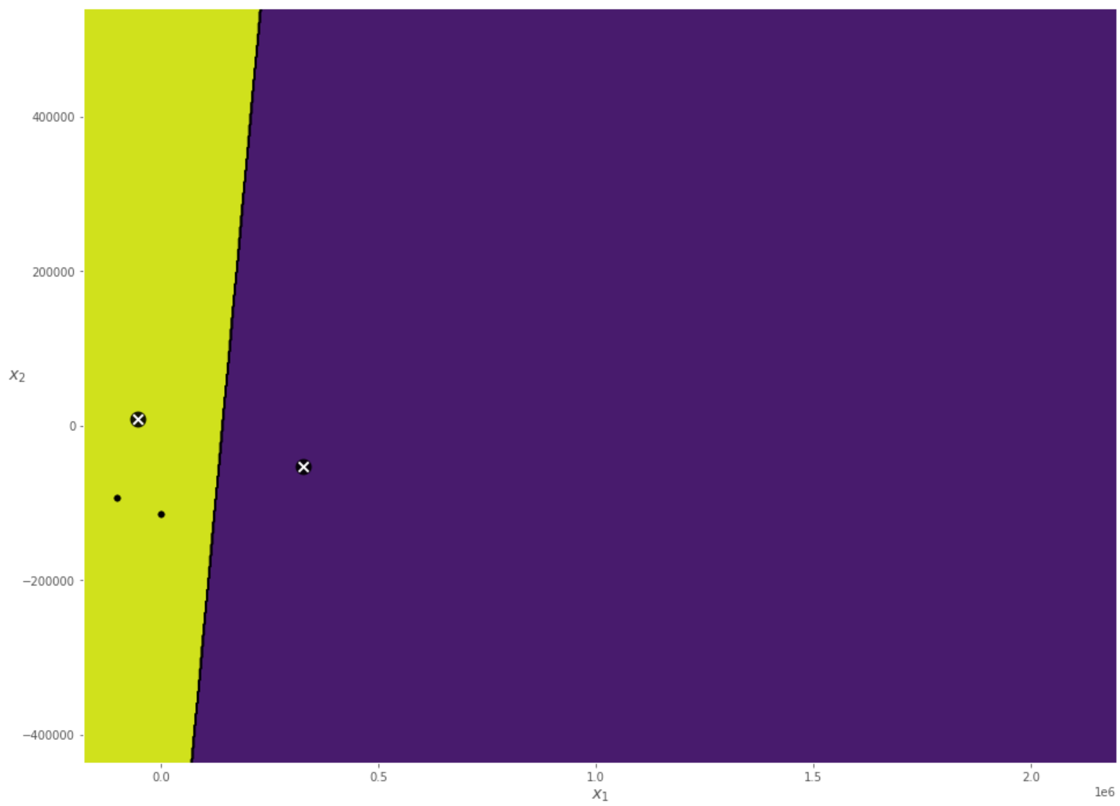


[22]:
```
kmeans_pca.labels_
```

[22]:
```
array([1, 1, 1, …, 1, 1, 1], dtype=int32)
```

[23]:
```
# from scipy.spatial import Voronoi, voronoi_plot_2d
#
# vor = Voronoi(pca_centroids)
# fig = voronoi_plot_2d(vor, show_points=True, show_vertices=True)
# # fig.set_size_inches(6,6)
#
# plt.show()
```

[24]:
```
plt.figure(figsize=(16,12))
plot_decision_boundaries(kmeans_pca, X_train_reduce)
plt.savefig('voronoi_credit.png')
plt.show()
```

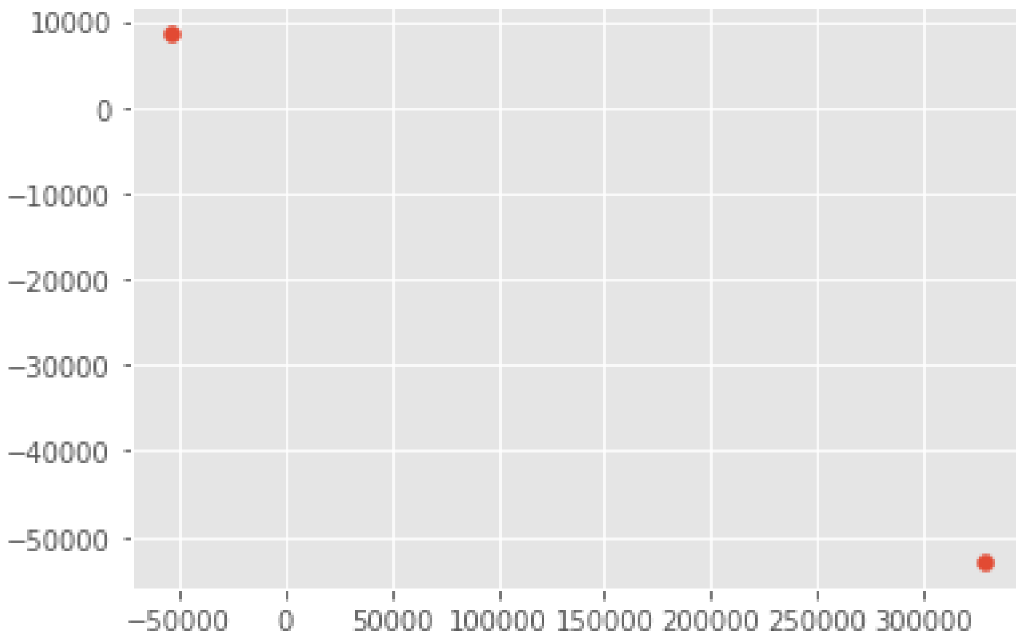


[25]:
```
pca_centroids
```

[25]:
```
array([[327875.66668953, -53170.77487821],
       [-52877.03087416,   8574.93553341]])
```

[26]:
```
plt.scatter(pca_centroids[0], pca_centroids[1])
```

[26]:
```
<matplotlib.collections.PathCollection at 0x1395abac0>
```



- Clustering seems a bit extreme. The PCA analysis highlighted that almost 97% of the variance in the dataset was explained by the two principal components that were discovered. However, clustering the data with k-Means seems to show a very large discrepancy between one cluster and the other. This data point appears to be an outlier. Next, we will need to look to eliminate singular non-representative data points, then re-run the PCA algorithm.

[27]:
```
X_train.describe()
```

[27]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE \
count	24000.000000	24000.000000	24000.000000	24000.000000	24000.000000
mean	167226.653333	1.604917	1.854000	1.551417	35.494375
std	129734.959196	0.488879	0.792176	0.522766	9.235160
min	10000.000000	1.000000	0.000000	0.000000	21.000000
25%	50000.000000	1.000000	1.000000	1.000000	28.000000
50%	140000.000000	2.000000	2.000000	2.000000	34.000000
75%	240000.000000	2.000000	2.000000	2.000000	42.000000
max	1000000.000000	2.000000	6.000000	3.000000	79.000000

	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5 \
count	24000.000000	24000.000000	24000.000000	24000.000000	24000.000000
mean	-0.016667	-0.131375	-0.168167	-0.220417	-0.265167
std	1.126473	1.197675	1.191685	1.168107	1.132949
min	-2.000000	-2.000000	-2.000000	-2.000000	-2.000000
25%	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000

```
max        8.000000      8.000000      8.000000      8.000000      8.000000

       …      BILL_AMT2     BILL_AMT3      BILL_AMT4      BILL_AMT5  \
count  …   24000.000000  2.400000e+04   24000.000000   24000.000000
mean   …   48914.770500  4.675708e+04   43013.532167   40150.333000
std    …   70923.493353  6.926506e+04   64069.494705   60635.882129
min    …  -69777.000000 -1.572640e+05 -170000.000000  -81334.000000
25%    …    2989.750000  2.699500e+03    2329.000000    1763.000000
50%    …   21140.500000  2.005000e+04   19010.000000   18085.000000
75%    …   63035.250000  5.952925e+04   53927.750000   50007.500000
max    …  983931.000000  1.664089e+06  891586.000000  927171.000000

           BILL_AMT6       PAY_AMT1      PAY_AMT2       PAY_AMT3  \
count   24000.000000   24000.000000  2.400000e+04   24000.000000
mean    38763.540458    5670.826542  5.961101e+03    5258.246500
std     59281.986863   17084.401034  2.428412e+04   18242.618988
min   -209051.000000       0.000000  0.000000e+00       0.000000
25%      1271.750000    1000.000000  8.615000e+02     390.000000
50%     17108.500000    2100.000000  2.007000e+03    1800.000000
75%     49101.750000    5005.000000  5.000000e+03    4500.000000
max    961664.000000  873552.000000  1.684259e+06  896040.000000

            PAY_AMT4       PAY_AMT5
count   24000.000000   24000.000000
mean     4880.847125    4818.849250
std     16304.718844   15619.425964
min         0.000000       0.000000
25%       285.750000     240.750000
50%      1500.000000    1500.000000
75%      4000.000000    4021.000000
max    621000.000000  426529.000000

[8 rows x 22 columns]
```

0.2 Support Vector Machines

[28]:
```python
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
```

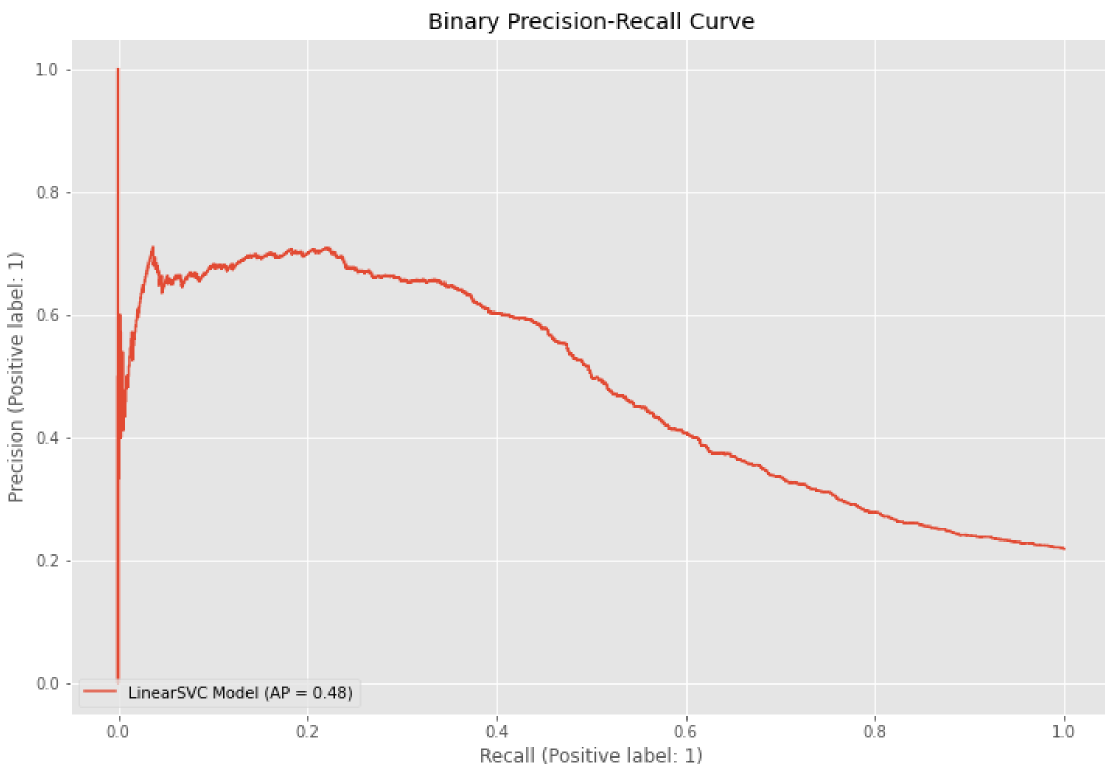
[29]:
```python
svm_clf = make_pipeline(StandardScaler(),
                        LinearSVC(C=1, dual=False, random_state=42,␣
 ↪max_iter=1000))
svm_clf.fit(X_train, y_train)
```

[29]:
```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('linearsvc', LinearSVC(C=1, dual=False, random_state=42))])
```

[30]:
```python
y_pred = svm_clf.predict(X_test)
```

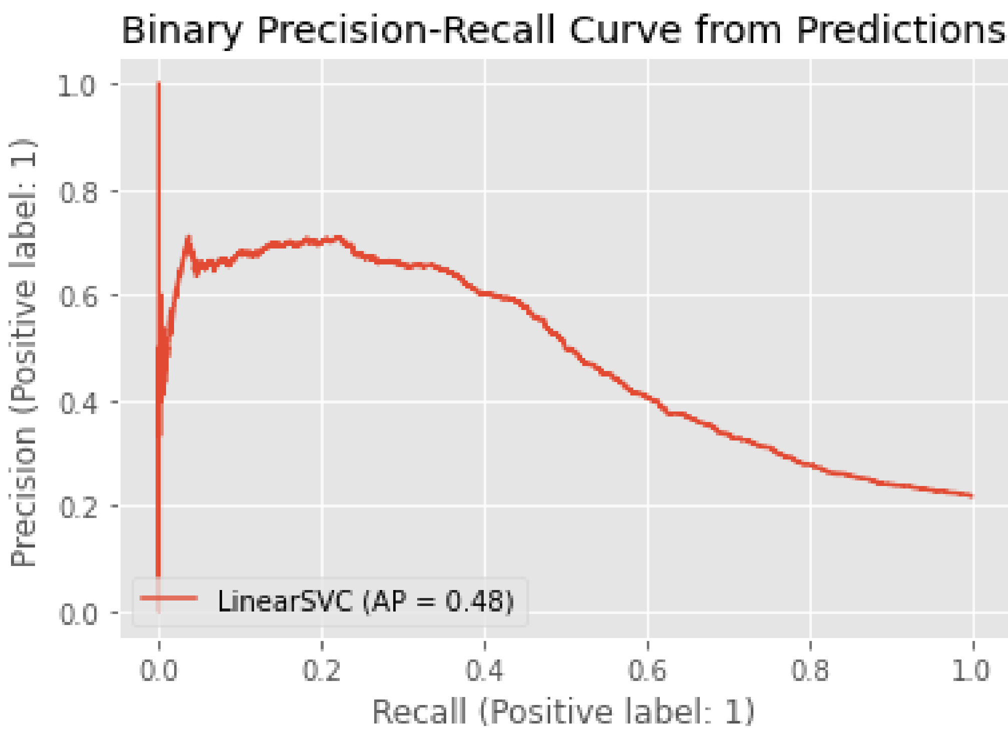
[31]:
```python
from sklearn.metrics import PrecisionRecallDisplay, accuracy_score

display = PrecisionRecallDisplay.from_estimator(svm_clf, X_test, y_test,␣
    ↪name='LinearSVC Model')
display.figure_.set_size_inches(12, 8)
_ = display.ax_.set_title('Binary Precision-Recall Curve')
```



[122]:
```python
y_score = svm_clf.decision_function(X_test)
```

[123]:
```python
display = PrecisionRecallDisplay.from_predictions(y_test, y_score,␣
    ↪name='LinearSVC')
_ = display.ax_.set_title('Binary Precision-Recall Curve from Predictions')
```



[34]:
```
linsvm_acc = accuracy_score(y_test, y_pred)
print('LinearSVC Accuracy: ', round(linsvm_acc, 3))
```

```
LinearSVC Accuracy:  0.801
```

This is probably not a **linear** boundary.

[127]:
```
from sklearn.metrics import confusion_matrix

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

```
[[4594   93]
 [1099  214]]
```

[131]:
```
svc_err = (1099 + 93) / (4594 + 93 + 1099 + 214)
print('LinearSVC Error: ', round(svc_err, 3))
print('LinearSVC Accuracy: ', round(1 - svc_err, 3))
```

```
LinearSVC Error:  0.199
LinearSVC Accuracy:  0.801
```

0.2.1 XGBoost for Feature Selection

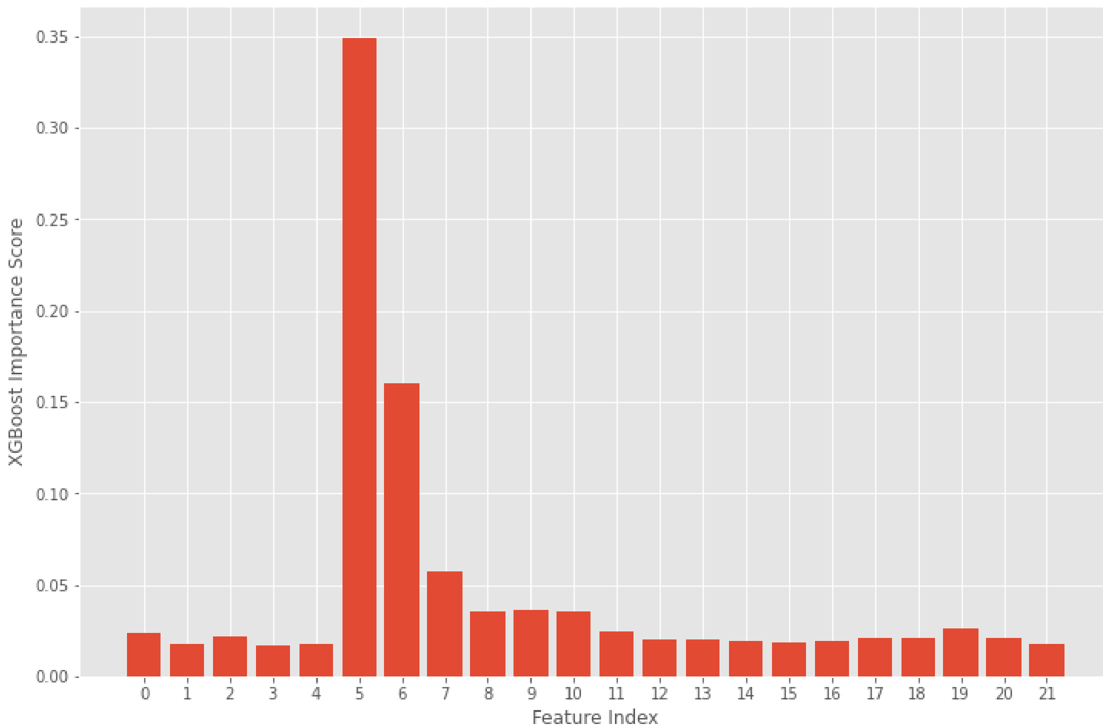
[42]:
```
from xgboost import XGBClassifier
```

[54]:
```
xgb_model = XGBClassifier()
xgb_model.fit(X_train, y_train)
xgb_import = xgb_model.feature_importances_

for i, v in enumerate(xgb_import):
    print("Feature: %0d, Score: %.5f" % (i, v))

plt.figure(figsize=(12, 8))
plt.bar([x for x in range(len(xgb_import))], xgb_import)
plt.xticks(range(len(xgb_import)))
plt.xlabel('Feature Index')
plt.ylabel('XGBoost Importance Score')
plt.savefig('xgb_boost_importance.png')
plt.show()
```

```
Feature: 0, Score: 0.02381
Feature: 1, Score: 0.01781
Feature: 2, Score: 0.02181
Feature: 3, Score: 0.01665
Feature: 4, Score: 0.01787
Feature: 5, Score: 0.34939
Feature: 6, Score: 0.16002
Feature: 7, Score: 0.05737
Feature: 8, Score: 0.03554
Feature: 9, Score: 0.03649
Feature: 10, Score: 0.03515
Feature: 11, Score: 0.02405
Feature: 12, Score: 0.01977
Feature: 13, Score: 0.02011
Feature: 14, Score: 0.01946
Feature: 15, Score: 0.01838
Feature: 16, Score: 0.01897
Feature: 17, Score: 0.02112
Feature: 18, Score: 0.02127
Feature: 19, Score: 0.02621
Feature: 20, Score: 0.02103
Feature: 21, Score: 0.01773
```



[56]:
```
from sklearn.feature_selection import SelectFromModel
# from sklearn.svm import SVC

feat_sel = SelectFromModel(XGBClassifier())
feat_sel.fit(X_train, y_train)
X_train_feat_sel = feat_sel.transform(X_train)
X_test_feat_sel = feat_sel.transform(X_test)
```

0.2.2 Non-Linear SVM

[35]:
```
from sklearn.svm import SVC
from sklearn.pipeline import Pipeline

rbf_kernel_svm = Pipeline([
    ('scaler', StandardScaler()),
    ('svm_clf', SVC(kernel='rbf', gamma=5, C=0.001))
])

rbf_kernel_svm.fit(X_train, y_train)
```

[35]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svm_clf', SVC(C=0.001, gamma=5))])
```

[37]:
```
def plot_dataset(X, y, axes):
    plt.plot(X[:, 0][y==0], X[:, 1][y==0], "bs")
    plt.plot(X[:, 0][y==1], X[:, 1][y==1], "g^")
    plt.axis(axes)
    plt.grid(True, which='both')
    plt.xlabel(r"$x_1$", fontsize=20)
    plt.ylabel(r"$x_2$", fontsize=20, rotation=0)
```

[38]:
```
rbf_dec_func = rbf_kernel_svm.decision_function
```

[39]:
```
y_pred = rbf_kernel_svm.predict(X)
y_decision = rbf_kernel_svm.decision_function(X)
plt.contourf(x0, x1, y_pred, cmap=plt.cm.brg, alpha=0.2)
plt.contourf(x0, x1, y_decision, cmap=plt.cm.brg, alpha=0.1)
```

[39]:
```
<bound method Pipeline.decision_function of Pipeline(steps=[('scaler',
StandardScaler()),
                ('svm_clf', SVC(C=0.001, gamma=5))])>
```

[57]:
```
rbf_kernel_svm_fs = Pipeline([
    ('scaler', StandardScaler()),
    ('svm_clf_fs', SVC(kernel='rbf', gamma=5, C=0.001))
])

rbf_kernel_svm_fs.fit(X_train_feat_sel, y_train)
```

[57]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svm_clf_fs', SVC(C=0.001, gamma=5))])
```

[58]:
```
y_hat_fs = rbf_kernel_svm_fs.predict(X_test_feat_sel)
```

[68]:
```
fs_accuracy = accuracy_score(y_test, y_hat_fs)
print('RBF kernel SVM Classifier with XGBoosted Feature Selection Accuracy,␣
 ↪SelectFromModel: ', round(fs_accuracy, 3))
```

```
RBF kernel SVM Classifier with XGBoosted Feature Selection Accuracy,
SelectFromModel:  0.781
```

- Try without the `SelectFromModel` class...

[62]:
```
X_fs_train = X_train.iloc[:, 5:7]
X_fs_test = X_test.iloc[:, 5:7]
X_fs_train.head(), X_fs_test.head()
```

[62]:
```
(       PAY_0  PAY_2
 ID
 21754      0      0
 252        0      0
 22942      0      0
```

```
619         0      0
17091       0      0,
       PAY_0  PAY_2
ID
2309        0      0
22405       0      0
23398       0      0
25059       0      0
2665        0      0)
```

[64]:
```
rbf_kernel_svm_fs_two = Pipeline([
    ('scaler', StandardScaler()),
    ('svm_clf_fs', SVC(kernel='rbf', gamma=5, C=0.001, random_state=42))
])

rbf_kernel_svm_fs_two.fit(X_fs_train, y_train)
```

[64]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svm_clf_fs', SVC(C=0.001, gamma=5))])
```

[65]:
```
y_hat_fs_two = rbf_kernel_svm_fs_two.predict(X_fs_test)
```

[67]:
```
fs_two_accuracy = accuracy_score(y_test, y_hat_fs_two)
print('RBF kernel SVM Classifier with XGBoosted Feature Selection Accuracy,␣
 ↪Manual Selection: ', round(fs_two_accuracy, 3))
```

```
RBF kernel SVM Classifier with XGBoosted Feature Selection Accuracy, Manual
Selection:  0.781
```

[75]:
```
lin_kernel_svm_fs = Pipeline([
    ('scaler', StandardScaler()),
    ('svm_clf_fs_lin', SVC(kernel='linear', gamma='scale', C=1.0,␣
 ↪random_state=42))
])

lin_kernel_svm_fs.fit(X_fs_train, y_train)

y_hat_fs_lin = lin_kernel_svm_fs.predict(X_fs_test)

fs_lin_accuracy = accuracy_score(y_test, y_hat_fs_lin)
print('Linear kernel SVM Classifier with XGBoosted Feature Selection Accuracy,␣
 ↪Manual Selection: ', round(fs_lin_accuracy, 3))
```

```
Linear kernel SVM Classifier with XGBoosted Feature Selection Accuracy, Manual
Selection:  0.81
```

- Raising `C=1.0` instead of `0.001`, with `gamma='scale'`, the **default** setting, the accuracy improves to **81%**, which is about where it was prior to trying **feature selection with XGBoost**.

Three features, not just two

[76]:
```
X_fs_three_train = X_train.iloc[:, 5:8]
X_fs_three_test = X_test.iloc[:, 5:8]
X_fs_three_train.head(), X_fs_three_test.head()
```

[76]:
```
(       PAY_0  PAY_2  PAY_3
 ID
 21754      0      0      0
 252        0      0      0
 22942      0      0     -1
 619        0      0      0
 17091      0      0      0,
        PAY_0  PAY_2  PAY_3
 ID
 2309       0      0      0
 22405      0      0      0
 23398      0      0      0
 25059      0      0      0
 2665       0      0      0)
```

[83]:
```
lin_kernel_svm_fs_three = Pipeline([
    ('scaler', StandardScaler()),
    ('svm_clf_fs_lin', SVC(kernel='linear', gamma=1, C=1.0, random_state=42))
])

lin_kernel_svm_fs_three.fit(X_fs_three_train, y_train)
```

[83]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('svm_clf_fs_lin',
                 SVC(gamma=1, kernel='linear', random_state=42))])
```

[84]:
```
y_hat_fs_lin_three = lin_kernel_svm_fs_three.predict(X_fs_three_test)

fs_lin_three_accuracy = accuracy_score(y_test, y_hat_fs_lin_three)
print('Linear kernel SVM Classifier with XGBoosted Feature Selection Accuracy,␣
 ↪Manual Selection: ', round(fs_lin_three_accuracy, 3))
```

```
Linear kernel SVM Classifier with XGBoosted Feature Selection Accuracy, Manual
Selection:  0.81
```

[ ]:
```

```