1. Use yeast dataset from UCI http://archive.ics.uci.edu/ml/machine-learning-databases/yeast/yeast.data

2. Remove the first column and use the last column as the target

3. Only leave CYT and VAC classes

4. Replace [0.3, 0.5, 0.7] in feature 2 to null

5. Replace [0.26, 0.36, 0.64] in feature 3 to null

6. Split the data

In [1]:

```
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import mglearn
from IPython.display import display

from matplotlib import rc
font = {'family' : 'monospace', 'weight' : 'bold', 'size'   : 25}
rc('font', **font)

plt.rcParams['figure.figsize'] = [20, 10]
plt.rcParams['lines.linewidth'] = 5.0
plt.rcParams['lines.markersize'] = 15.0

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore", category=FutureWarning)
```

In [2]:

```
df = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/ye
df
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9
0	ADT1_YEAST	0.58	0.61	0.47	0.13	0.5	0.0	0.48	0.22	MIT
1	ADT2_YEAST	0.43	0.67	0.48	0.27	0.5	0.0	0.53	0.22	MIT
2	ADT3_YEAST	0.64	0.62	0.49	0.15	0.5	0.0	0.53	0.22	MIT
3	AAR2_YEAST	0.58	0.44	0.57	0.13	0.5	0.0	0.54	0.22	NUC
4	AATM_YEAST	0.42	0.44	0.48	0.54	0.5	0.0	0.48	0.22	MIT
...	...	...	...	...	...	...	...	...	...	...
1479	YUR1_YEAST	0.81	0.62	0.43	0.17	0.5	0.0	0.53	0.22	ME2
1480	ZIP1_YEAST	0.47	0.43	0.61	0.40	0.5	0.0	0.48	0.47	NUC
1481	ZNRP_YEAST	0.67	0.57	0.36	0.19	0.5	0.0	0.56	0.22	ME2
1482	ZUO1_YEAST	0.43	0.40	0.60	0.16	0.5	0.0	0.53	0.39	NUC
1483	G6PD_YEAST	0.65	0.54	0.54	0.13	0.5	0.0	0.53	0.22	CYT

1484 rows × 10 columns

In [3]:

```
target = 9
df.drop(0, axis=1, inplace=True)
```

In [4]:

```
df = df[df[target].isin(['CYT', 'VAC'])]
df.head(50)
```

Out[4]:

	1	2	3	4	5	6	7	8	9
5	0.51	0.40	0.56	0.17	0.5	0.5	0.49	0.22	CYT
9	0.40	0.39	0.60	0.15	0.5	0.0	0.58	0.30	CYT
12	0.40	0.42	0.57	0.35	0.5	0.0	0.53	0.25	CYT
15	0.46	0.44	0.52	0.11	0.5	0.0	0.50	0.22	CYT
16	0.47	0.39	0.50	0.11	0.5	0.0	0.49	0.40	CYT
20	0.45	0.40	0.50	0.16	0.5	0.0	0.50	0.22	CYT
21	0.43	0.44	0.48	0.22	0.5	0.0	0.51	0.22	CYT
22	0.73	0.63	0.42	0.30	0.5	0.0	0.49	0.22	CYT
23	0.43	0.53	0.52	0.13	0.5	0.0	0.55	0.22	CYT
24	0.46	0.53	0.52	0.15	0.5	0.0	0.58	0.22	CYT
26	0.59	0.45	0.53	0.19	0.5	0.0	0.59	0.27	CYT

27	0.57	0.47	0.60	0.18	0.5	0.0	0.51	0.22	CYT
32	0.38	0.61	0.61	0.12	0.5	0.0	0.53	0.47	CYT
37	0.40	0.45	0.57	0.18	0.5	0.0	0.56	0.26	CYT
44	0.37	0.36	0.56	0.18	0.5	0.0	0.48	0.26	VAC
48	0.74	0.57	0.51	0.28	0.5	0.0	0.58	0.22	VAC
50	0.48	0.39	0.51	0.21	0.5	0.0	0.52	0.28	CYT
53	0.56	0.48	0.58	0.27	0.5	0.0	0.51	0.22	CYT
54	0.64	0.59	0.56	0.23	0.5	0.0	0.46	0.22	CYT
55	0.64	0.56	0.56	0.22	0.5	0.0	0.45	0.22	CYT
56	0.66	0.62	0.49	0.10	0.5	0.0	0.49	0.22	CYT
57	0.53	0.44	0.51	0.33	0.5	0.0	0.55	0.22	CYT
58	0.38	0.49	0.53	0.19	0.5	0.0	0.50	0.22	CYT
64	0.54	0.48	0.44	0.08	0.5	0.0	0.52	0.27	CYT
65	0.60	0.47	0.45	0.22	0.5	0.0	0.51	0.29	CYT
66	0.34	0.46	0.57	0.09	0.5	0.0	0.55	0.22	CYT
67	0.48	0.54	0.55	0.12	0.5	0.0	0.51	0.22	CYT
68	0.47	0.39	0.59	0.15	0.5	0.0	0.57	0.22	CYT
70	0.48	0.42	0.52	0.24	0.5	0.0	0.56	0.22	CYT
71	0.58	0.51	0.49	0.27	0.5	0.0	0.57	0.29	CYT
89	0.42	0.47	0.52	0.41	0.5	0.0	0.53	0.32	CYT
90	0.36	0.46	0.62	0.46	0.5	0.0	0.51	0.33	CYT
92	0.40	0.45	0.56	0.20	0.5	0.0	0.45	0.22	CYT
94	0.49	0.61	0.49	0.25	0.5	0.0	0.50	0.28	CYT
99	0.64	0.57	0.57	0.27	0.5	0.0	0.37	0.22	CYT
102	0.47	0.52	0.50	0.40	0.5	0.0	0.41	0.22	CYT
104	0.47	0.39	0.55	0.24	0.5	0.0	0.47	0.22	CYT
106	0.42	0.35	0.54	0.18	0.5	0.0	0.56	0.22	CYT
107	0.30	0.56	0.55	0.18	0.5	0.0	0.50	0.22	CYT
108	0.65	0.65	0.52	0.16	0.5	0.0	0.60	0.22	CYT
109	0.27	0.60	0.48	0.23	0.5	0.0	0.55	0.22	CYT
129	0.41	0.40	0.59	0.47	0.5	0.0	0.48	0.43	CYT
130	0.50	0.64	0.57	0.15	0.5	0.0	0.47	0.22	CYT

131	0.40	0.62	0.52	0.31	0.5	0.0	0.49	0.31	CYT
132	0.60	0.50	0.57	0.25	0.5	0.0	0.41	0.26	CYT
135	0.34	0.54	0.50	0.21	0.5	0.0	0.54	0.31	CYT
138	0.29	0.32	0.58	0.15	0.5	0.0	0.50	0.30	CYT
140	0.39	0.47	0.56	0.16	0.5	0.0	0.47	0.22	CYT
144	0.43	0.57	0.53	0.16	0.5	0.0	0.54	0.22	CYT
146	0.59	0.48	0.50	0.14	0.5	0.0	0.45	0.25	CYT

In [5]:

```
df[2] = df[2].replace([0.3, 0.5, 0.7], np.nan)
df[3] = df[3].replace([0.26, 0.36, 0.64], np.nan)

df[2]
```

```
<ipython-input-5-2d0c3bee9743>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[2] = df[2].replace([0.3, 0.5, 0.7], np.nan)
<ipython-input-5-2d0c3bee9743>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[3] = df[3].replace([0.26, 0.36, 0.64], np.nan)
```

Out[5]:

```
5       0.40
9       0.39
12      0.42
15      0.44
16      0.39
        ...
1475     NaN
1476    0.48
1477    0.32
1478    0.40
1483    0.54
Name: 2, Length: 493, dtype: float64
```

In [6]:

```
y = df[target] == 'CYT'
df[target]
```

Out[6]:
```
5       CYT
9       CYT
12      CYT
15      CYT
16      CYT
       ...
1475    CYT
1476    CYT
1477    CYT
1478    CYT
1483    CYT
Name: 9, Length: 493, dtype: object
```

In [7]:
```
features = [1,2,3,4,5,6,7,8]
```

In [8]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(df[features], y, test_siz
```

In [9]:
```
y_test
```

Out[9]:
```
1105    True
321     True
517     True
733     True
1021    True
        ...
1307    True
1121    True
1459    True
934     True
365     True
Name: 9, Length: 163, dtype: bool
```

In [10]:
```
y_train
```

Out[10]:
```
244     True
1326    True
821     True
68      True
277     True
        ...
931     True
213     True
1237    True
848     True
106     True
Name: 9, Length: 330, dtype: bool
```

7. Impute the data (or not, it's your call)

In [11]:

```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')

imputer.fit(X_train)
X_train_imputed = imputer.transform(X_train)
X_test_imputed = imputer.transform(X_test)
```

In [12]:

```
X_train_imputed
```

Out[12]:

```
array([[0.2 , 0.26, 0.52, ..., 0.  , 0.53, 0.44],
       [0.47, 0.59, 0.56, ..., 0.  , 0.5 , 0.22],
       [0.55, 0.63, 0.54, ..., 0.  , 0.45, 0.27],
       ...,
       [0.59, 0.48, 0.49, ..., 0.  , 0.52, 0.22],
       [0.48, 0.56, 0.49, ..., 0.  , 0.5 , 0.22],
       [0.42, 0.35, 0.54, ..., 0.  , 0.56, 0.22]])
```

In [13]:

```
X_test_imputed
```

Out[13]:

```
array([[0.37, 0.55, 0.52, ..., 0.  , 0.42, 0.8 ],
       [0.35, 0.36, 0.57, ..., 0.  , 0.52, 0.22],
       [0.52, 0.48, 0.58, ..., 0.  , 0.48, 0.22],
       ...,
       [0.41, 0.45, 0.46, ..., 0.  , 0.5 , 0.7 ],
       [0.61, 0.38, 0.57, ..., 0.  , 0.44, 0.21],
       [0.59, 0.43, 0.52, ..., 0.  , 0.55, 0.27]])
```

In [14]:

```
from sklearn.svm import SVC

model = SVC()
model.fit(X_train_imputed, y_train)
model.predict(X_test_imputed)
```

Out[14]:
```
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,  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,  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,  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,  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])
```

8. Build a outlier detection model to classify VAC from CYT, i.e. 0 from 1

In [15]:
```
# from sklearn.ensemble import IsolationForest
# from numpy import quantile, where, random
```

In [16]:
```
from sklearn.cluster import DBSCAN
# from sklearn.datasets import make_blobs
from numpy import random, where, quantile

# random.seed(3)
# x, _ = make_blobs(n_samples=200, centers=1, cluster_std=.3, center_box=(20,

# # We'll check the dataset by visualizing it in a plot.

# plt.scatter(x[:,0], x[:,1])
# plt.show()
```

In [17]:
```
dbscan = DBSCAN(eps = 0.28, min_samples = 20)
print(dbscan)
```

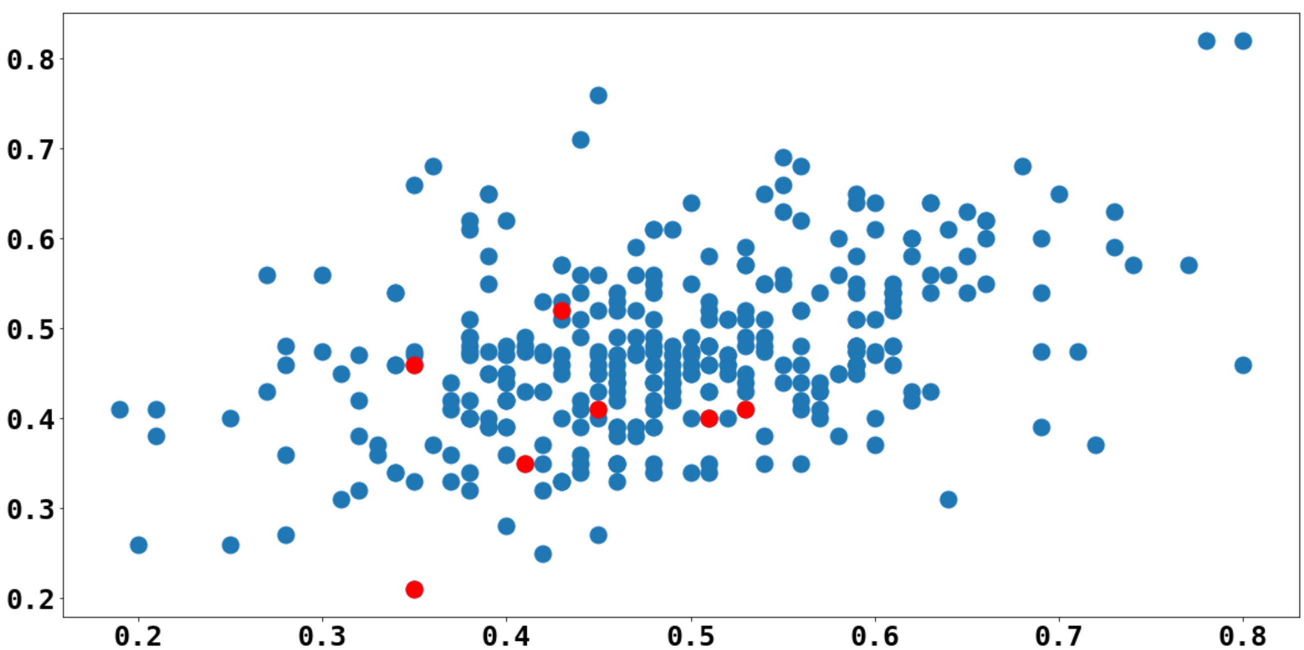
```
DBSCAN(eps=0.28, min_samples=20)
```

In [18]:
```
#  We'll fit the model with x dataset and get the prediction data with the fi

y_pred = dbscan.fit_predict(X_train_imputed)
y_pred
```

Out[18]:
```
array([ 0,  0,  0,  0,  0,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
       -1,  0,  0,  0,  0,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0, -1,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0])
```

In [19]:
```python
# the negative outputs as the outliers.
anom_index = where(y_pred == -1)
values = X_train_imputed[anom_index]
```

In [20]:
```python
plt.scatter(X_train_imputed[:,0], X_train_imputed[:,1])
plt.scatter(values[:,0], values[:,1], color='r')
plt.show()
```



9. Build a classifer using sample augmentation techniques to flassify VAC from CYT, i.e. 0 from 1

In [21]:

```
import numpy as np
import pandas as pd
```

In [22]:

```
color = ['blue','orange']
df_train = df[df[target].isin(['CYT', 'VAC'])]
```

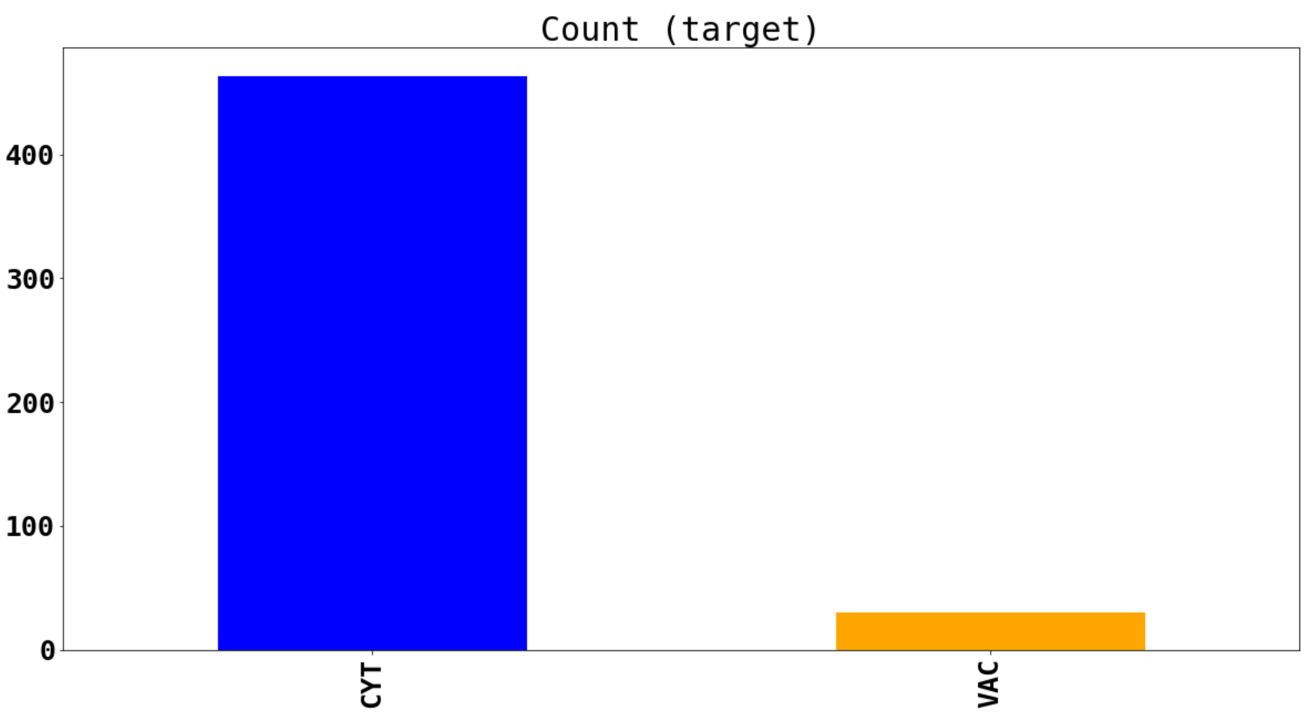
In [23]:

```
target_count = df_train[target].value_counts()
print('Class 0:', target_count[0])
print('Class 1:', target_count[1])
print('Proportion:', round(target_count[0] / target_count[1], 2), ': 1')
```

```
Class 0: 463
Class 1: 30
Proportion: 15.43 : 1
```

In [24]:

```
target_count.plot(kind='bar', title='Count (target)', color = color);
```



In [25]:

```
# Class count
count_class_0, count_class_1 = df_train[target].value_counts()

# Divide by class
df_class_0 = df_train[df_train[target] == 0]
df_class_1 = df_train[df_train[target] == 1]
```

In [26]:

```
#Random under-sampling and over-sampling with imbalanced-learn

!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in /Users/macbookpro/opt/anaco
nda3/lib/python3.8/site-packages (0.7.0)
Requirement already satisfied: scikit-learn>=0.23 in /Users/macbookpro/opt/ana
conda3/lib/python3.8/site-packages (from imbalanced-learn) (0.23.1)
Requirement already satisfied: joblib>=0.11 in /Users/macbookpro/opt/anaconda3
/lib/python3.8/site-packages (from imbalanced-learn) (0.16.0)
Requirement already satisfied: numpy>=1.13.3 in /Users/macbookpro/opt/anaconda
3/lib/python3.8/site-packages (from imbalanced-learn) (1.18.5)
Requirement already satisfied: scipy>=0.19.1 in /Users/macbookpro/opt/anaconda
3/lib/python3.8/site-packages (from imbalanced-learn) (1.5.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /Users/macbookpro/opt/a
naconda3/lib/python3.8/site-packages (from scikit-learn>=0.23->imbalanced-lear
n) (2.1.0)
```

In [27]:

```
from sklearn.datasets import make_classification
import imblearn

X, y = make_classification(
    n_classes=2, class_sep=1.5, weights=[0.9, 0.1],
    n_informative=3, n_redundant=1, flip_y=0,
    n_features=20, n_clusters_per_class=1,
    n_samples=100, random_state=10
)
```

In [28]:

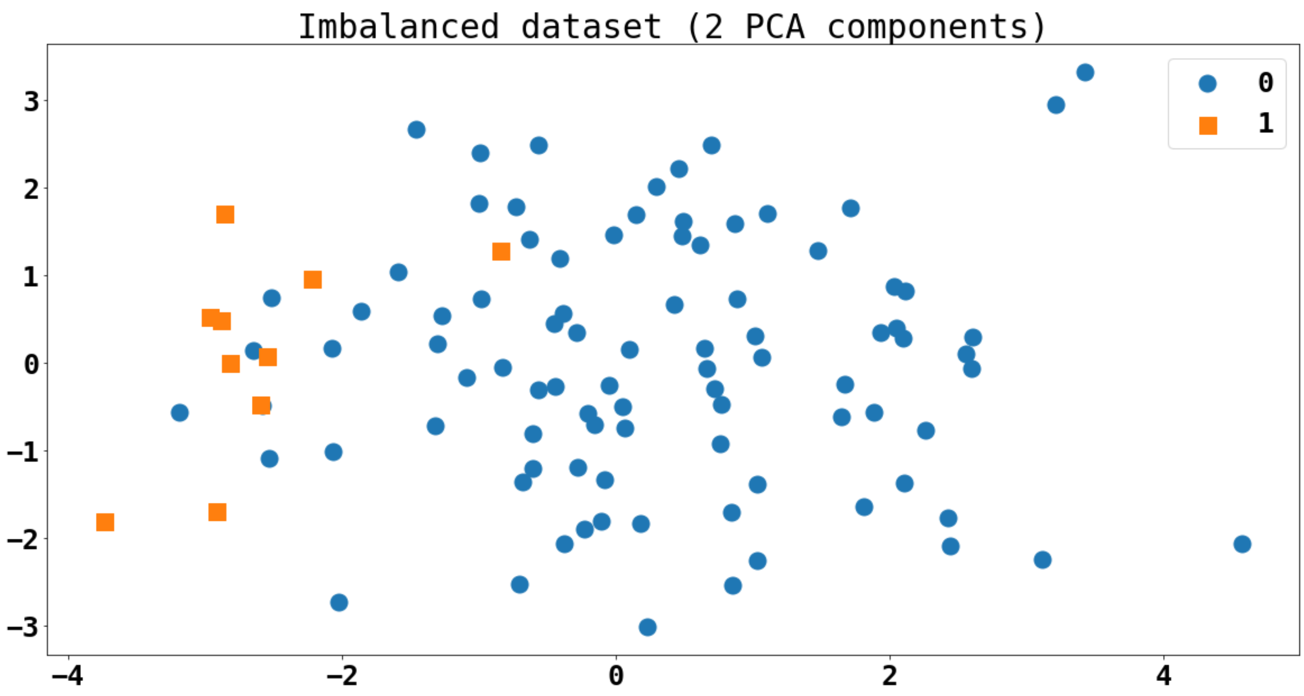
```
def plot_2d_space(X_train_imputed, y, label='Classes'):
    colors = ['#1F77B4', '#FF7F0E']
    markers = ['o', 's']
    for l, c, m in zip(np.unique(y), colors, markers):
        plt.scatter(
            X_train_imputed[y==l, 0],
            X_train_imputed[y==l, 1],
            c=c, label=l, marker=m
        )
    plt.title(label)
    plt.legend(loc='upper right')
    plt.show()
```

In [29]:

```
def plot_2d_space(X_train_imputed, y, label='Classes'):
    colors = ['#1F77B4', '#FF7F0E']
    markers = ['o', 's']
    for l, c, m in zip(np.unique(y), colors, markers):
        plt.scatter(
            X_train_imputed[y==l, 0],
            X_train_imputed[y==l, 1],
            c=c, label=l, marker=m
        )
    plt.title(label)
    plt.legend(loc='upper right')
    plt.show()
```

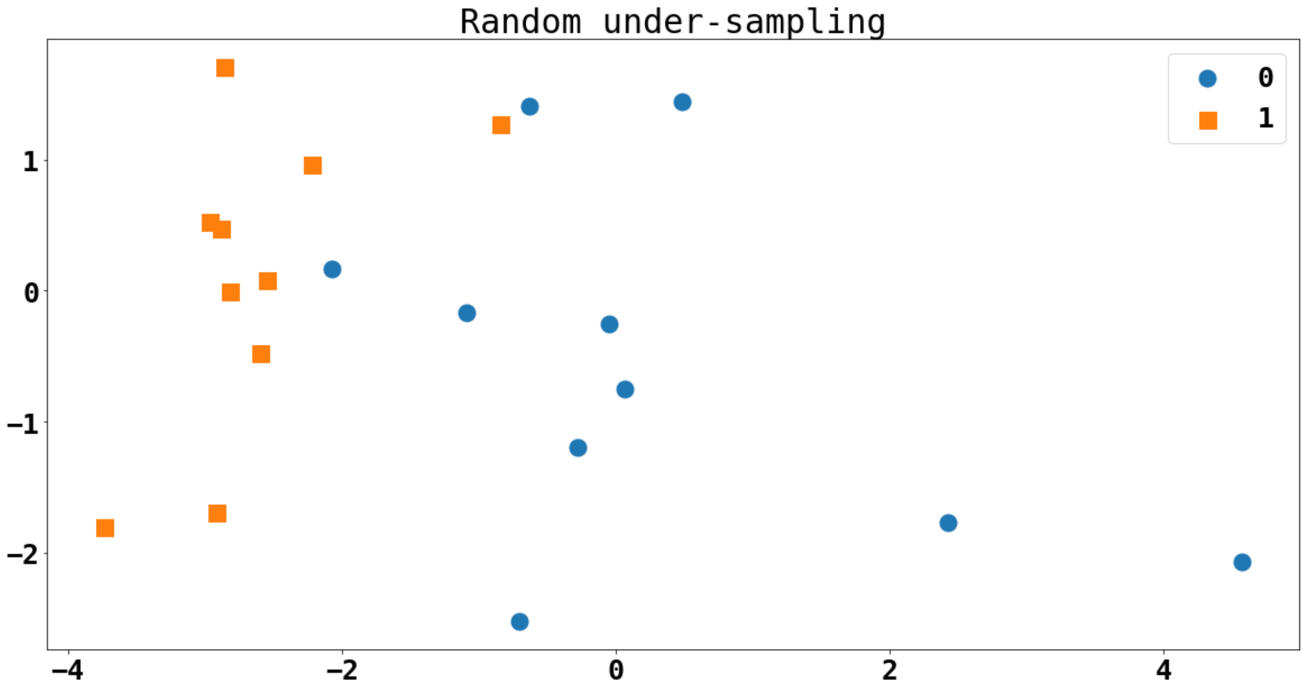
In [30]:

```
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
Xpca = pca.fit_transform(X)

plot_2d_space(Xpca, y, 'Imbalanced dataset (2 PCA components)')
```



In [31]:

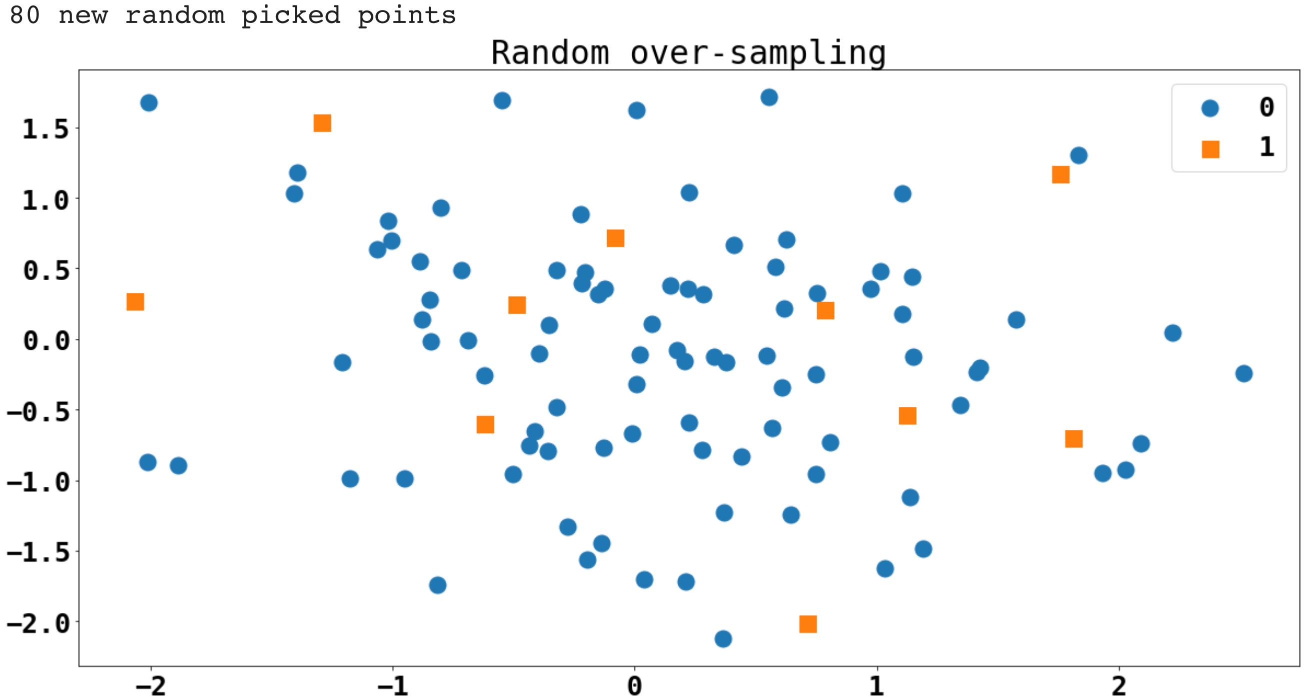
```
from imblearn.under_sampling import RandomUnderSampler

rus = RandomUnderSampler()
X_rus, y_rus = rus.fit_resample(Xpca, y)

plot_2d_space(X_rus, y_rus, 'Random under-sampling')
```



In [32]:

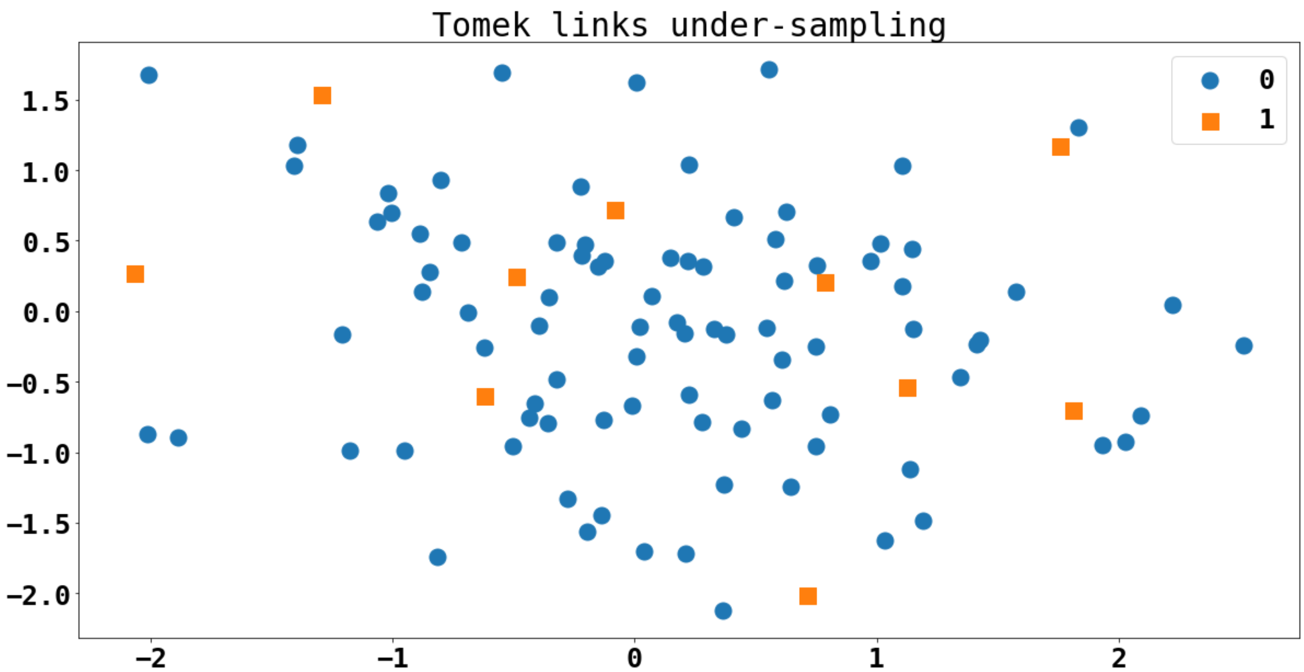
```
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler()
X_ros, y_ros = ros.fit_sample(X, y)

print(X_ros.shape[0] - X.shape[0], 'new random picked points')

plot_2d_space(X_ros, y_ros, 'Random over-sampling')
```

80 new random picked points



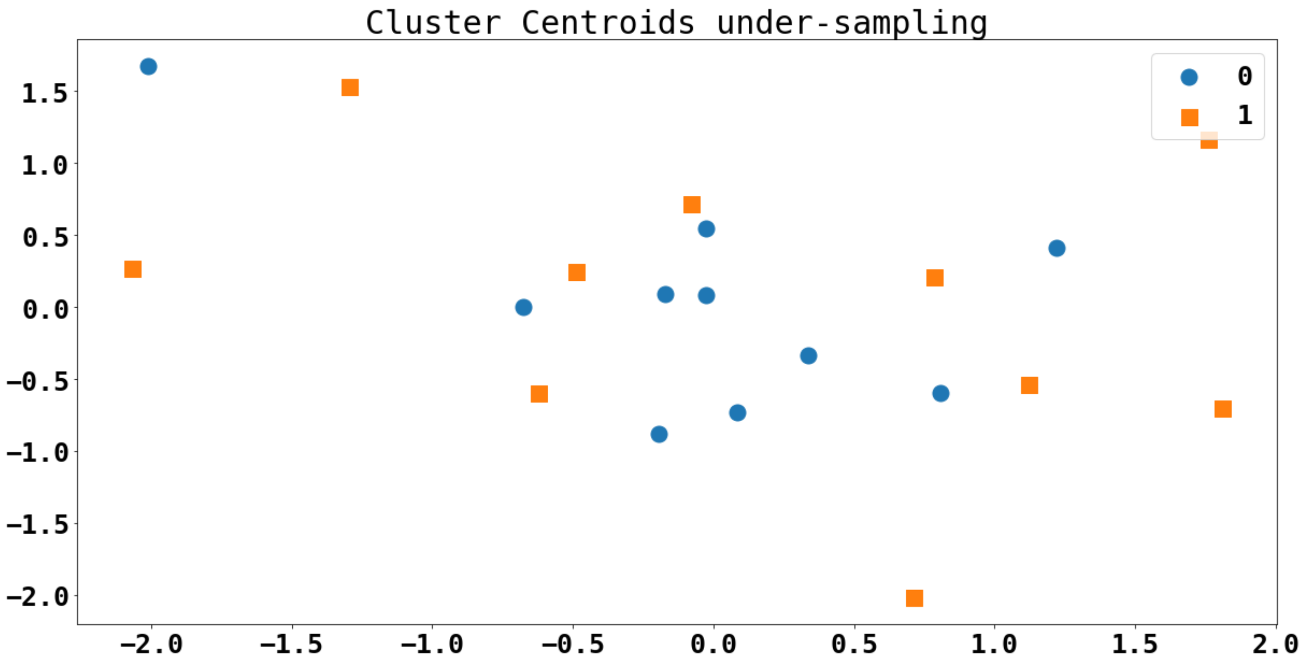
In [33]:

```
#Other method #1: Under-sampling: Tomek links

from imblearn.under_sampling import TomekLinks

tl = TomekLinks(sampling_strategy='majority')
X_tl, y_tl = tl.fit_sample(X, y)
plot_2d_space(X_tl, y_tl, 'Tomek links under-sampling')
```



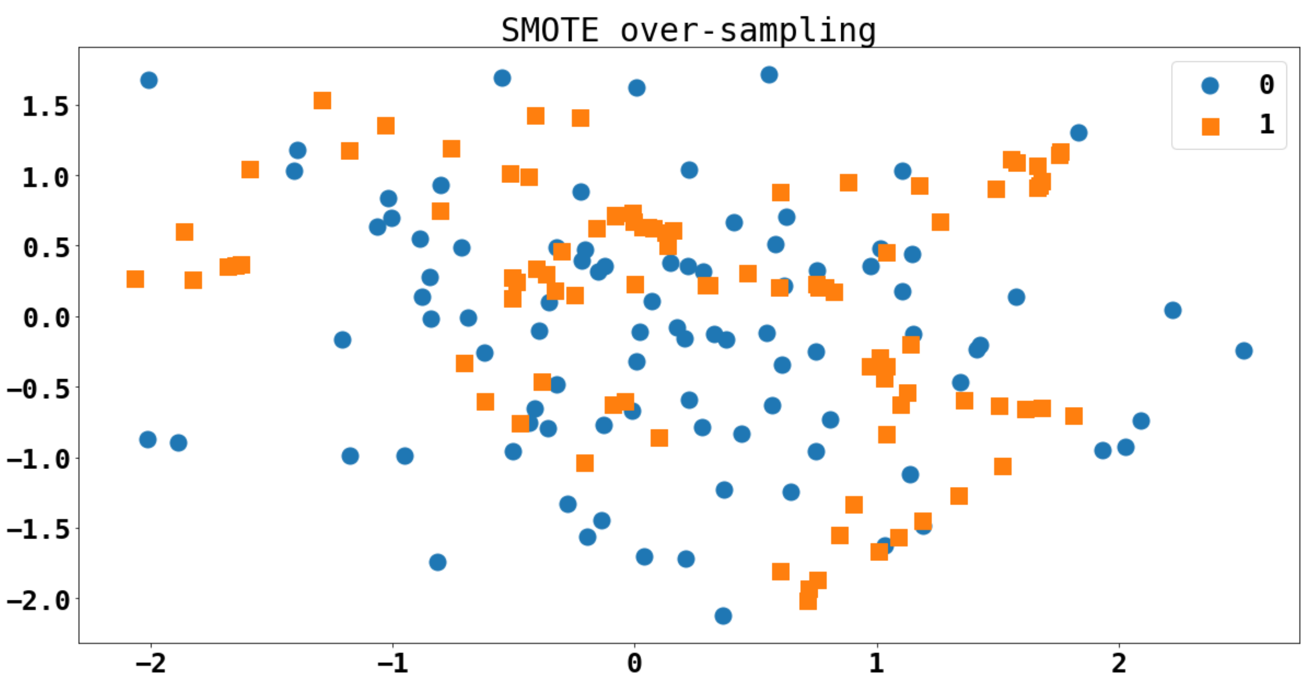
In [34]:

```
#Other method #2: Under-sampling _ Cluster Centroids

from imblearn.under_sampling import ClusterCentroids

cc = ClusterCentroids(sampling_strategy ={0: 10})
X_cc, y_cc = cc.fit_sample(X, y)

plot_2d_space(X_cc, y_cc, 'Cluster Centroids under-sampling')
```



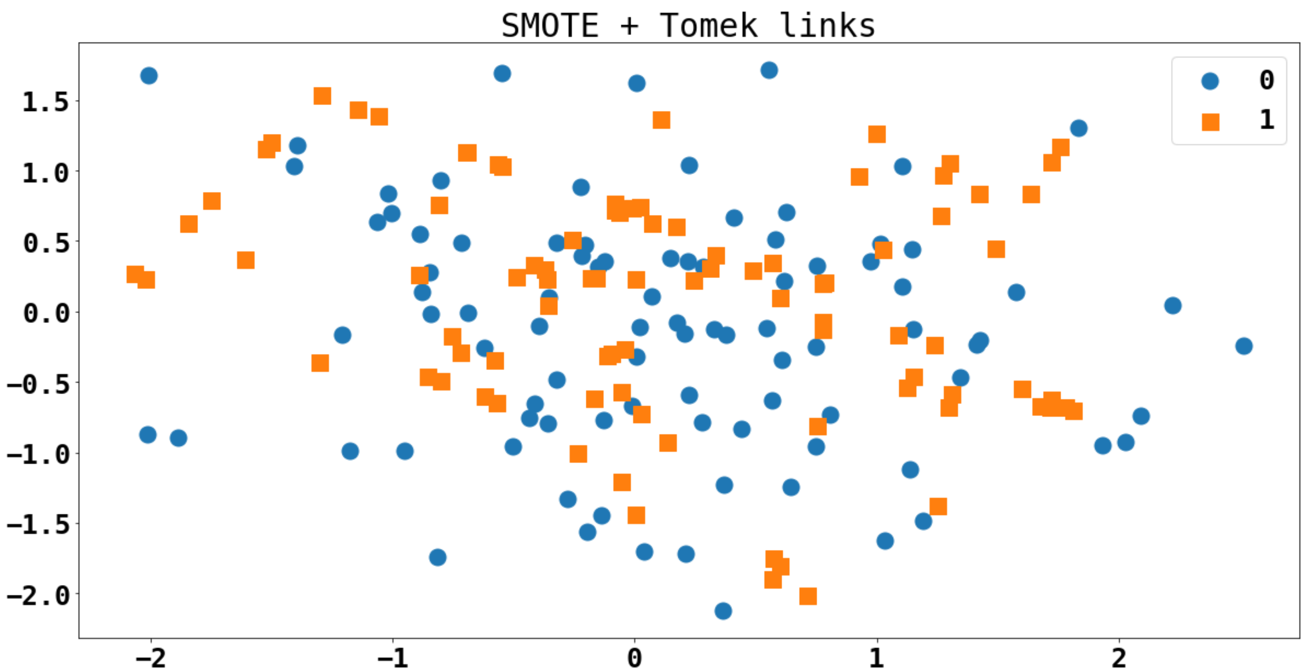
In [35]:

```
#Other method #4: Over-sampling: SMOTE

from imblearn.over_sampling import SMOTE

smote = SMOTE(sampling_strategy='minority')
X_sm, y_sm = smote.fit_sample(X, y)

plot_2d_space(X_sm, y_sm, 'SMOTE over-sampling')
```



In [36]:

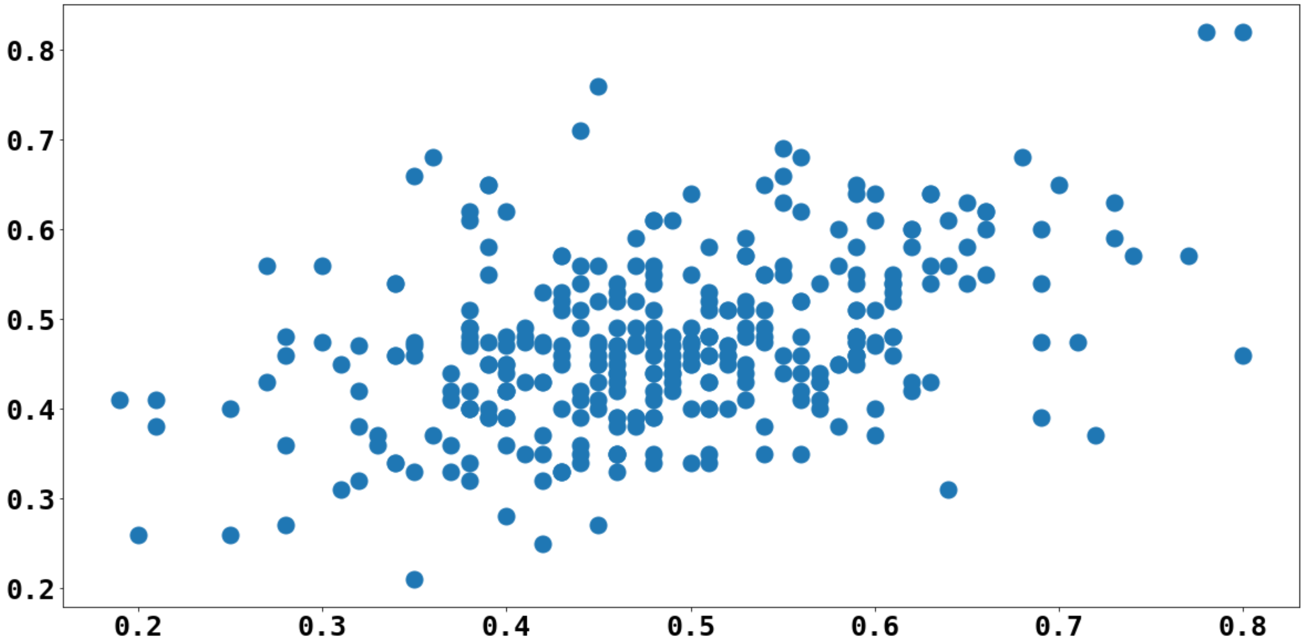
```
#Other method #4: Over-sampling followed by under-sampling

from imblearn.combine import SMOTETomek

smt = SMOTETomek(sampling_strategy='auto')
X_smt, y_smt = smt.fit_sample(X, y)

plot_2d_space(X_smt, y_smt, 'SMOTE + Tomek links')
```



10. Try different methods and hyper paramters

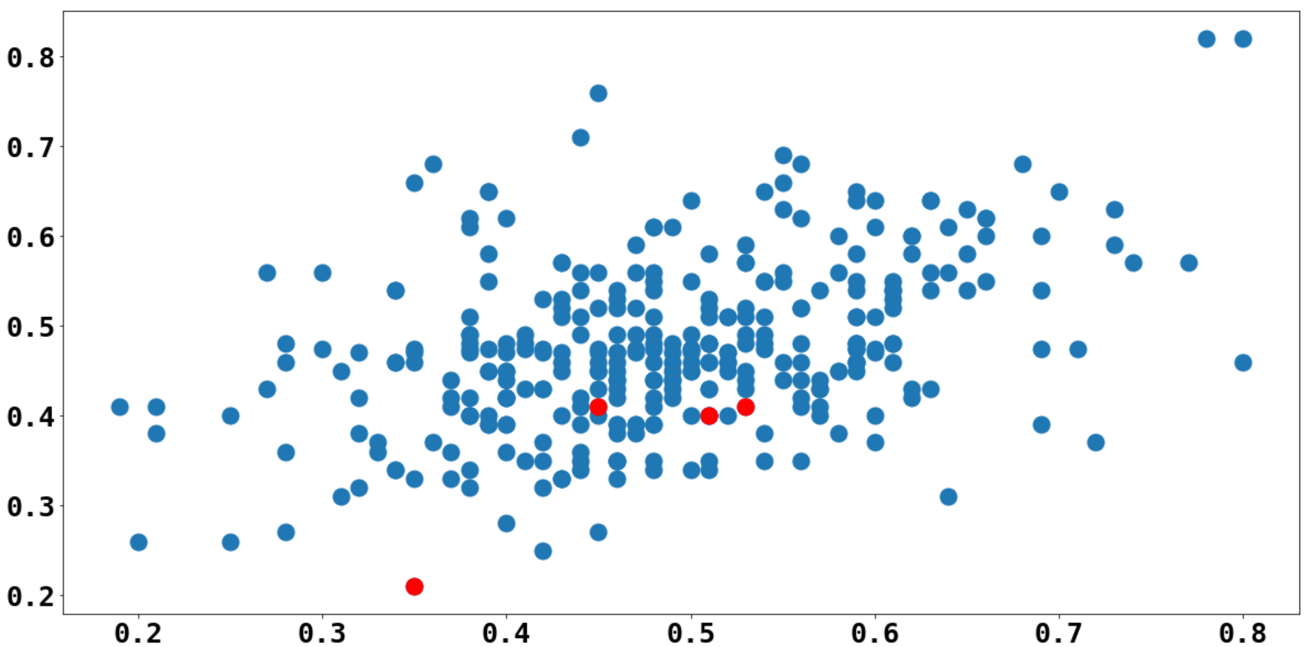
In [37]:

```
#Local Outlier Factor Method

from sklearn.neighbors import LocalOutlierFactor

plt.scatter(X_train_imputed[:,0], X_train_imputed[:,1])
plt.show()
```



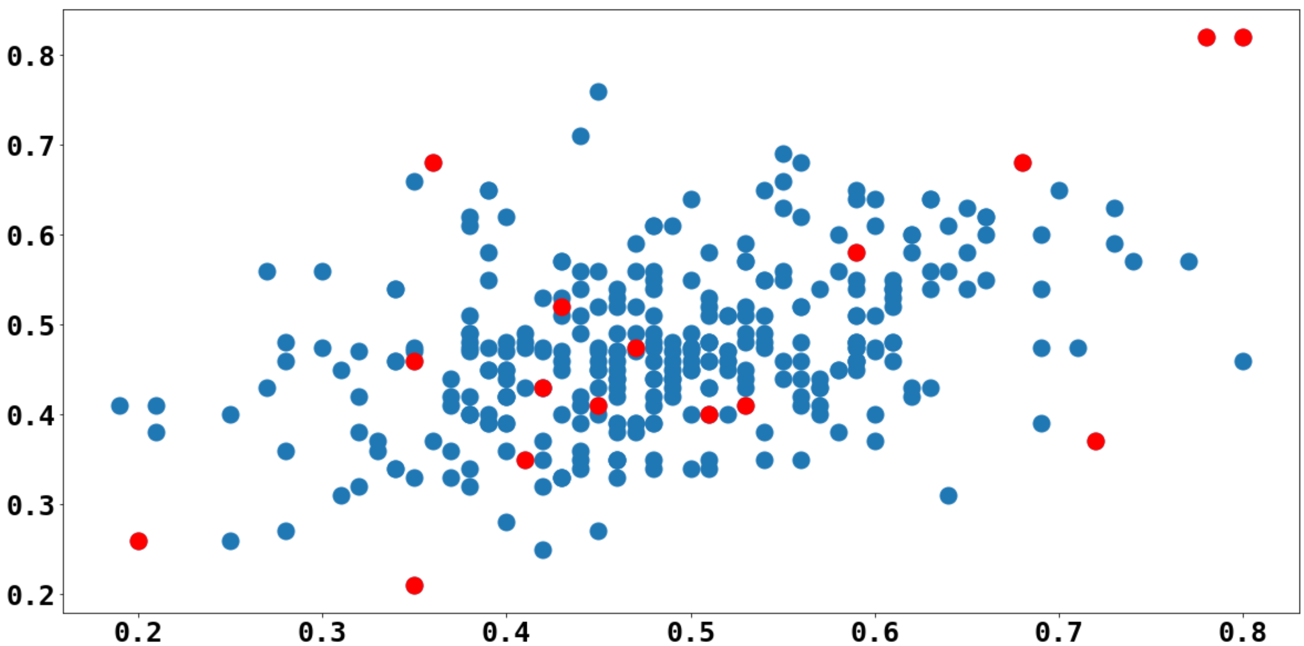
In [38]:

```
lof = LocalOutlierFactor(n_neighbors=100, contamination=.01)

y_pred = lof.fit_predict(X_train_imputed)

lofs_index = where(y_pred==-1)
values = X_train_imputed[lofs_index]

plt.scatter(X_train_imputed[:,0], X_train_imputed[:,1])
plt.scatter(values[:,0],values[:,1], color='r')
plt.show()
```



In [39]:
```
#Isolation Forest Method

from sklearn.ensemble import IsolationForest
from numpy import quantile, where, random

# plt.scatter(X_train_imputed[:,0], X_train_imputed[:,1])
# plt.show()
```

In [40]:
```
# The model by using the IsolationForest class of Scikit-learn API.
# We'll set estimators number and contamination value in arguments of the cla

iforest = IsolationForest(n_estimators=300, contamination=.05) # contaminatio
pred = iforest.fit_predict(X_train_imputed)
anom_index = where(pred==-1)
values = X_train_imputed[anom_index]

plt.scatter(X_train_imputed[:,0], X_train_imputed[:,1])
plt.scatter(values[:,0], values[:,1], color='r')
plt.show()
```



11. Report perfromance using F-1 score

In [41]:
```
X = df.iloc[:,:8].values
X
```

Out[41]:
```
array([[0.51, 0.4 , 0.56, ..., 0.5 , 0.49, 0.22],
       [0.4 , 0.39, 0.6 , ..., 0.  , 0.58, 0.3 ],
       [0.4 , 0.42, 0.57, ..., 0.  , 0.53, 0.25],
       ...,
       [0.38, 0.32,  nan, ..., 0.  , 0.44, 0.11],
       [0.38, 0.4 , 0.66, ..., 0.  , 0.43, 0.11],
       [0.65, 0.54, 0.54, ..., 0.  , 0.53, 0.22]])
```

In [42]:
```
y = df.iloc[:,8].values
```

In [43]:
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
# df_encoded = pd.DataFrame()
le.fit(y)

y = le.fit_transform(df.iloc[:,8])
import collections
from collections import Counter

y
```

Out[43]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [44]:
```
import collections
from collections import Counter


print(Counter(y))
```

```
Counter({0: 463, 1: 30})
```

In [45]:
```
print(Counter(y_train))
```

```
Counter({True: 309, False: 21})
```

In [46]:
```
print(Counter(y_pred))
```

```
Counter({1: 326, -1: 4})
```

In [47]:
```
# z =  y.copy()
# my_dict = {'CYT':0, 'VAC':-1}
# z = [my_dict[zi] for zi in z]
# print(Counter(z))
```

In [48]:
```
from sklearn.metrics import f1_score

# print("f1 score most frequent: {:.2f}".format(
# f1_score(y_train, y)))

f1_score(y_pred, y_train, average = None)
```

Out[48]:
```
array([0.        , 0.        , 0.96062992])
```

In [ ]: