==

CSML1010 Coding Excercise, Week 4, Dec 15

======

PART 2

======

Resampling strategies for imbalanced datasets

Based on code at: https://www.kaggle.com/kernels/scriptcontent/1756536/download (https://www.kaggle.com/kernels/scriptcontent/1756536/download)

==

Index

Imbalanced datasets

In this kernel we will know some techniques to handle highly unbalanced datasets, with a focus on resampling. The Porto Seguro's Safe Driver Prediction competition, used in this kernel, is a classic problem of unbalanced classes, since insurance claims can be considered unusual cases when considering all clients. Other classic examples of unbalanced classes are the detection of financial fraud and attacks on computer networks.

Let's see how unbalanced the dataset is:

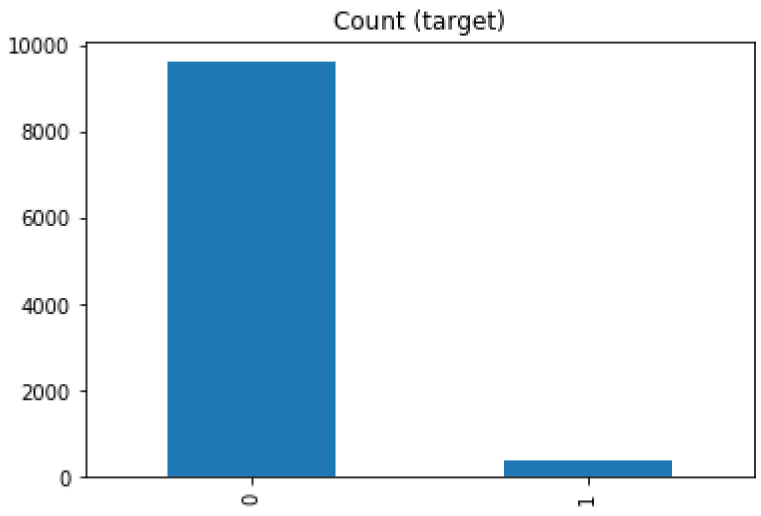
In [1]:
```
import numpy as np
import pandas as pd

df_train = pd.read_csv('train.csv')

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')

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

```
Class 0: 573518
Class 1: 21694
Proportion: 26.44 : 1
```

Shrink it to something I can run, re-check for imbalance

In [2]:
```
df_train = df_train[0:10000]

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')

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

```
Class 0: 9621
Class 1: 379
Proportion: 25.39 : 1
```



The metric trap

One of the major issues that novice users fall into when dealing with unbalanced datasets relates to the metrics used to evaluate their model. Using simpler metrics like `accuracy_score` can be misleading. In a dataset with highly unbalanced classes, if the classifier always "predicts" the most common class without performing any analysis of the features, it will still have a high accuracy rate, obviously illusory.

Let's do this experiment, using simple cross-validation and no feature engineering:

In [3]:
```
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Remove 'id' and 'target' columns
labels = df_train.columns[2:]

X = df_train[labels]
y = df_train['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

model = XGBClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
```

```
Accuracy: 96.55%
```

Now let's run the same code, but using only one feature (which should drastically reduce the accuracy of the classifier):

In [4]:
```
model = XGBClassifier()
model.fit(X_train[['ps_calc_01']], y_train)
y_pred = model.predict(X_test[['ps_calc_01']])

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
```

```
Accuracy: 96.55%
```

As we can see, the high accuracy rate was just an illusion. In this way, the choice of the metric used in unbalanced datasets is extremely important. In this competition, the evaluation metric is the Normalized Gini Coefficient, a more robust metric for imbalanced datasets, that ranges from approximately 0 for random guessing, to approximately 0.5 for a perfect score.

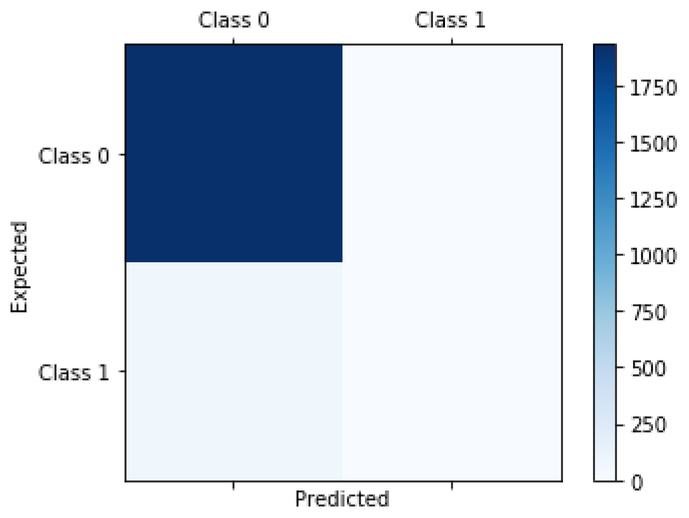
Confusion matrix

An interesting way to evaluate the results is by means of a confusion matrix, which shows the correct and incorrect predictions for each class. In the first row, the first column indicates how many classes 0 were predicted correctly, and the second column, how many classes 0 were predicted as 1. In the second row, we note that all class 1 entries were erroneously predicted as class 0.

Therefore, the higher the diagonal values of the confusion matrix the better, indicating many correct predictions.

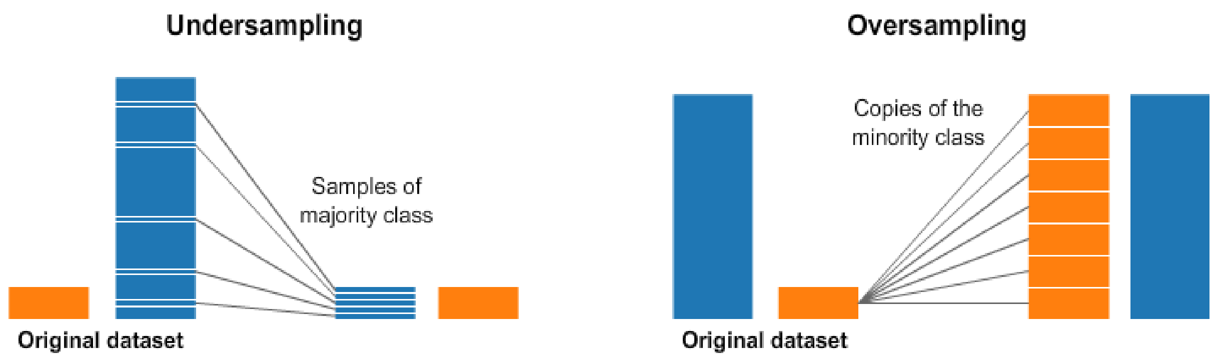
In [5]:
```python
from sklearn.metrics import confusion_matrix
from matplotlib import pyplot as plt

conf_mat = confusion_matrix(y_true=y_test, y_pred=y_pred)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Blues)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

```
Confusion matrix:
 [[1931    0]
 [  69    0]]
```



Resampling

A widely adopted technique for dealing with highly unbalanced datasets is called resampling. It consists of removing samples from the majority class (under-sampling) and / or adding more examples from the minority class (over-sampling).



Despite the advantage of balancing classes, these techniques also have their weaknesses (there is no free lunch). The simplest implementation of over-sampling is to duplicate random records from the minority class, which can cause overfitting. In under-sampling, the simplest technique involves removing random records from the majority class, which can cause loss of information.

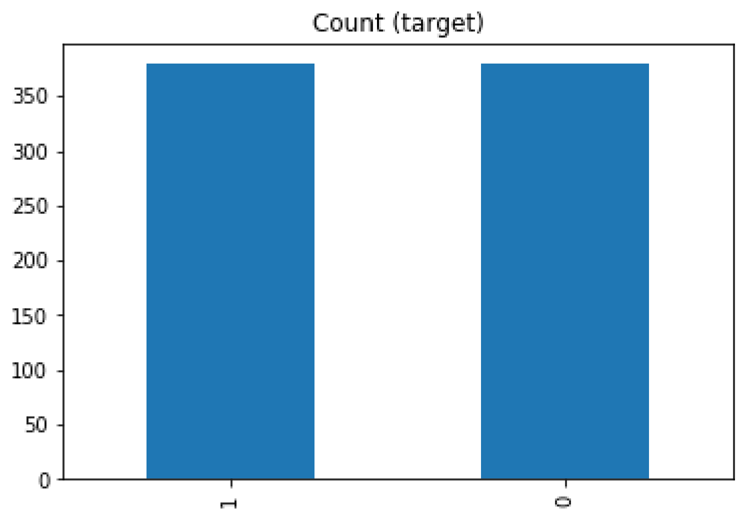
Let's implement a basic example, which uses the `DataFrame.sample` method to get random samples each class:

In [6]:
```
# 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]
```

Random under-sampling

```
In [7]: df_class_0_under = df_class_0.sample(count_class_1)
        df_test_under = pd.concat([df_class_0_under, df_class_1], axis=0)

        print('Random under-sampling:')
        print(df_test_under.target.value_counts())

        df_test_under.target.value_counts().plot(kind='bar', title='Count (target)');
```

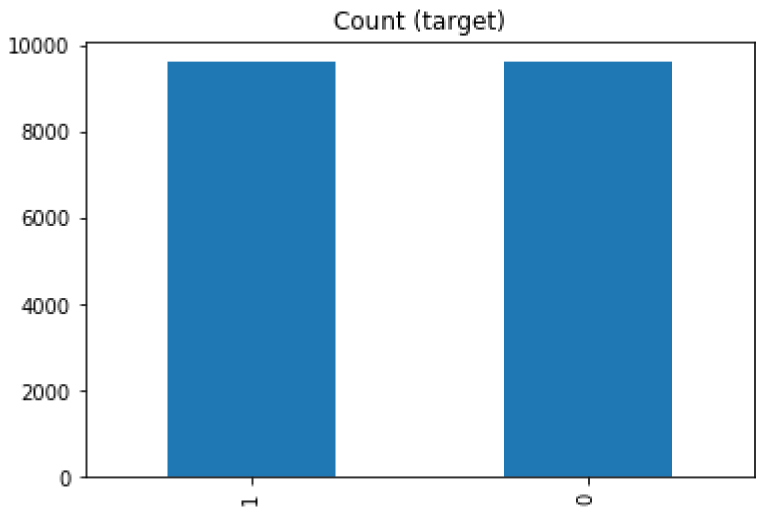
```
Random under-sampling:
1    379
0    379
Name: target, dtype: int64
```



Random over-sampling

In [8]:
```
df_class_1_over = df_class_1.sample(count_class_0, replace=True)
df_test_over = pd.concat([df_class_0, df_class_1_over], axis=0)

print('Random over-sampling:')
print(df_test_over.target.value_counts())

df_test_over.target.value_counts().plot(kind='bar', title='Count (target)');
```

```
Random over-sampling:
1    9621
0    9621
Name: target, dtype: int64
```



Python imbalanced-learn module

A number of more sophisticated resapling techniques have been proposed in the scientific literature.

For example, we can cluster the records of the majority class, and do the under-sampling by removing records from each cluster, thus seeking to preserve information. In over-sampling, instead of creating exact copies of the minority class records, we can introduce small variations into those copies, creating more diverse synthetic samples.

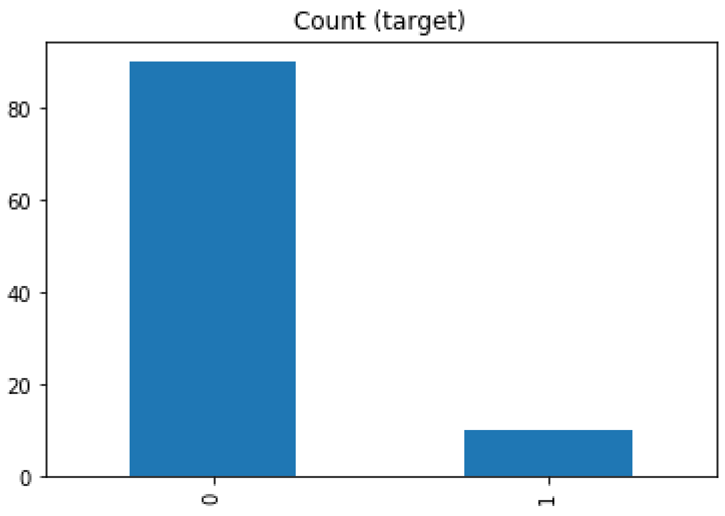
Let's apply some of these resampling techniques, using the Python library imbalanced-learn (http://contrib.scikit-learn.org/imbalanced-learn/stable/). It is compatible with scikit-learn and is part of scikit-learn-contrib projects.

In [9]:
```
import imblearn
```

```
Using TensorFlow backend.
```

For ease of visualization, let's create a small unbalanced sample dataset using the `make_classification` method:

```
In [10]: from sklearn.datasets import make_classification

         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
         )

         df = pd.DataFrame(X)
         df['target'] = y
         df.target.value_counts().plot(kind='bar', title='Count (target)');
```

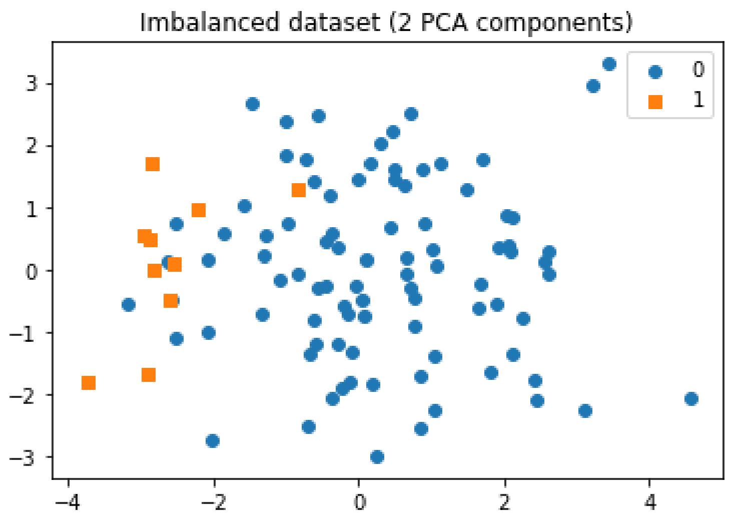


We will also create a 2-dimensional plot function, `plot_2d_space`, to see the data distribution:

```
In [11]: def plot_2d_space(X, y, label='Classes'):
             colors = ['#1F77B4', '#FF7F0E']
             markers = ['o', 's']
             for l, c, m in zip(np.unique(y), colors, markers):
                 plt.scatter(
                     X[y==l, 0],
                     X[y==l, 1],
                     c=c, label=l, marker=m
                 )
             plt.title(label)
             plt.legend(loc='upper right')
             plt.show()
```

Because the dataset has many dimensions (features) and our graphs will be 2D, we will reduce the size of the dataset using Principal Component Analysis (PCA):

In [12]:
```
from sklearn.decomposition import PCA

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

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



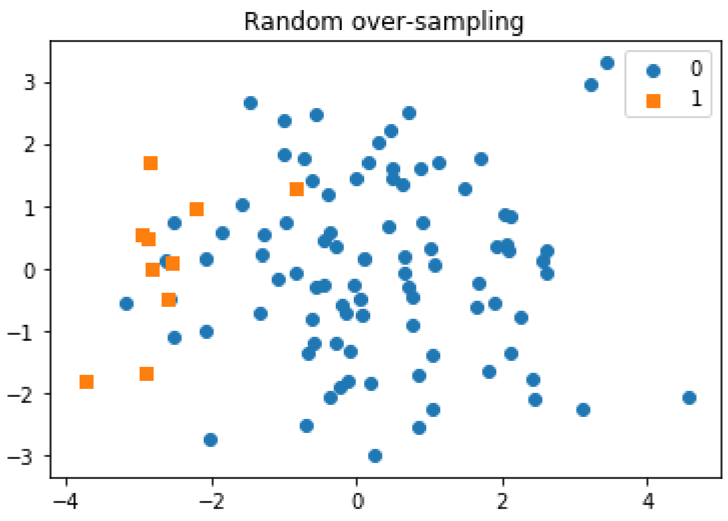
Random under-sampling and over-sampling with imbalanced-learn

In [13]:
```
from imblearn.under_sampling import RandomUnderSampler

rus = RandomUnderSampler(return_indices=True)
X_rus, y_rus, id_rus = rus.fit_sample(X, y)

print('Removed indexes:', id_rus)

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

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-13-300b656fed46> in <module>
      1 from imblearn.under_sampling import RandomUnderSampler
      2 
----> 3 rus = RandomUnderSampler(return_indices=True)
      4 X_rus, y_rus, id_rus = rus.fit_sample(X, y)
      5 

TypeError: __init__() got an unexpected keyword argument 'return_indices'
```

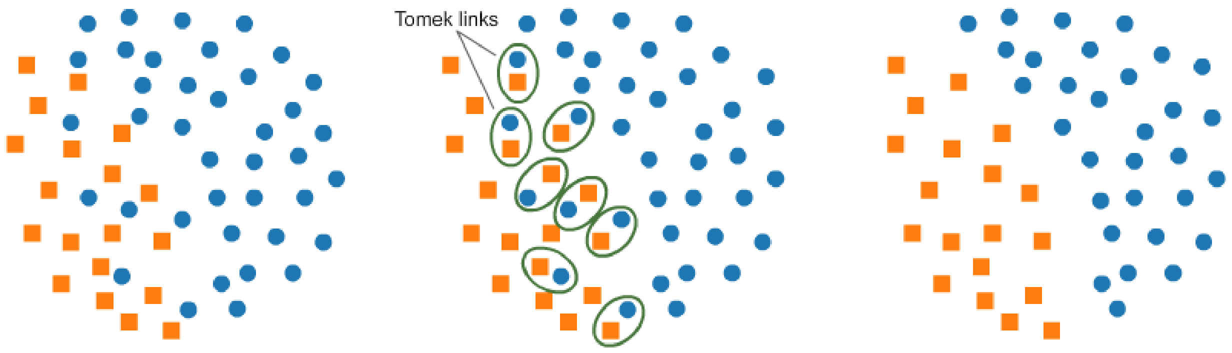
In [14]:
```python
from imblearn.over_sampling import RandomOverSampler

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
```



Under-sampling: Tomek links

Tomek links are pairs of very close instances, but of opposite classes. Removing the instances of the majority class of each pair increases the space between the two classes, facilitating the classification process.



In the code below, we'll use `ratio='majority'` to resample the majority class.

In [15]:
```python
from imblearn.under_sampling import TomekLinks

tl = TomekLinks(return_indices=True, ratio='majority')
X_tl, y_tl, id_tl = tl.fit_sample(X, y)

print('Removed indexes:', id_tl)

plot_2d_space(X_tl, y_tl, 'Tomek links under-sampling')
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-15-0ccea873bc32> in <module>
      1 from imblearn.under_sampling import TomekLinks
      2 
----> 3 tl = TomekLinks(return_indices=True, ratio='majority')
      4 X_tl, y_tl, id_tl = tl.fit_sample(X, y)
      5 

TypeError: __init__() got an unexpected keyword argument 'return_indices'
```

Under-sampling: Cluster Centroids

This technique performs under-sampling by generating centroids based on clustering methods. The data will be previously grouped by similarity, in order to preserve information.

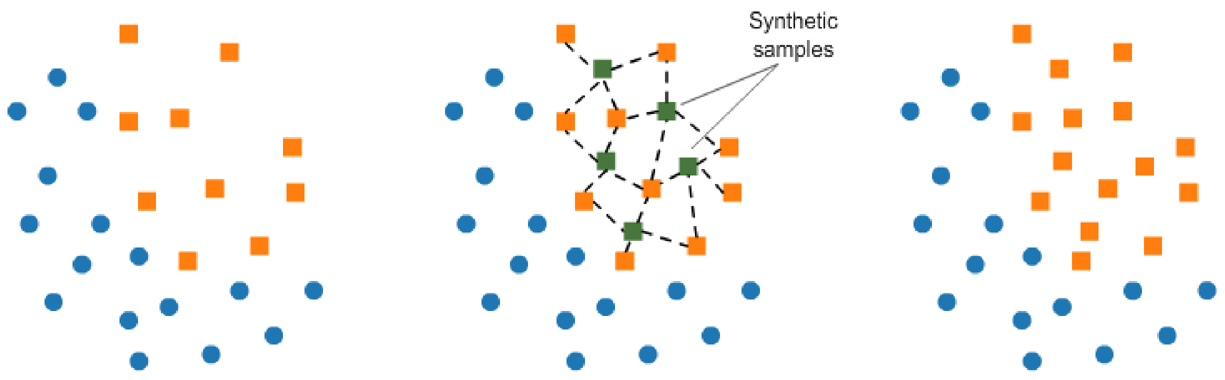
In this example we will pass the `{0: 10}` dict for the parameter `ratio` , to preserve 10 elements from the majority class (0), and all minority class (1) .

In [16]:
```python
from imblearn.under_sampling import ClusterCentroids

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

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

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-16-09efd36bb60c> in <module>
      1 from imblearn.under_sampling import ClusterCentroids
      2 
----> 3 cc = ClusterCentroids(ratio={0: 10})
      4 X_cc, y_cc = cc.fit_sample(X, y)
      5 

TypeError: __init__() got an unexpected keyword argument 'ratio'
```

Over-sampling: SMOTE

SMOTE (Synthetic Minority Oversampling TEchnique) consists of synthesizing elements for the minority class, based on those that already exist. It works randomly picingk a point from the minority class and computing the k-nearest neighbors for this point. The synthetic points are added between the chosen point and its neighbors.



We'll use `ratio='minority'` to resample the minority class.

In [17]:
```
from imblearn.over_sampling import SMOTE

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

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

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-17-56dec43e4907> in <module>
      1 from imblearn.over_sampling import SMOTE
      2 
----> 3 smote = SMOTE(ratio='minority')
      4 X_sm, y_sm = smote.fit_sample(X, y)
      5 

TypeError: __init__() got an unexpected keyword argument 'ratio'
```

Over-sampling followed by under-sampling

Now, we will do a combination of over-sampling and under-sampling, using the SMOTE and Tomek links techniques:

In [18]:
```
from imblearn.combine import SMOTETomek

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

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

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-18-492b5cb1e15d> in <module>
      1 from imblearn.combine import SMOTETomek
      2 
----> 3 smt = SMOTETomek(ratio='auto')
      4 X_smt, y_smt = smt.fit_sample(X, y)
      5 

TypeError: __init__() got an unexpected keyword argument 'ratio'
```

Recommended reading

The imbalanced-learn documentation:
http://contrib.scikit-learn.org/imbalanced-learn/stable/index.html (http://contrib.scikit-learn.org/imbalanced-learn/stable/index.html)

The imbalanced-learn GitHub:
https://github.com/scikit-learn-contrib/imbalanced-learn (https://github.com/scikit-learn-contrib/imbalanced-learn)

Comparison of the combination of over- and under-sampling algorithms:
http://contrib.scikit-learn.org/imbalanced-learn/stable/auto_examples/combine/plot_comparison_combine.html (http://contrib.scikit-learn.org/imbalanced-learn/stable/auto_examples/combine/plot_comparison_combine.html)

Chawla, Nitesh V., et al. "SMOTE: synthetic minority over-sampling technique." Journal of artificial intelligence research 16 (2002):
https://www.jair.org/media/953/live-953-2037-jair.pdf (https://www.jair.org/media/953/live-953-2037-jair.pdf)

In [ ]:
```

```