Datasets

- [pageb_benchmarks.zip (https://ir.library.oregonstate.edu/concern/parent/47429f155/file_sets/1g05fh87w)](https://ir.library.oregonstate.edu/concern/parent/47429f155/file_sets/1g05fh87w)

要求

使用[Python Outlier Detection (PyOD) (https://github.com/yzhao062/pyod)](https://github.com/yzhao062/pyod)或其他已知的工具包来完成分析工作

提交的内容

- 完整的分析代码
- 分析报告：展示分析的思路，详细过程，结果及你的分析
- 所选择的数据集在README中说明，数据文件不要上传到Github中

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

warnings.filterwarnings('ignore')

# timekeeping
timekeeping = time.time()
```

In [2]:
```
PAGEB_ROOT = 'pageb/benchmarks'
benchmark_list = os.listdir(PAGEB_ROOT)
print(len(benchmark_list))
```

```
940
```

数据来源说明

根据论文[1]可知，数据集中会引入4种不同的层次的不相关特征（i.e., noise）。

要创建新的不相关特征，首先从原始母集中随机选择一个特征。 然后，对于原始数据集中的每个数据点，通过从原始数据点的值进行统一采样（替换）来为此特征选择一个值。 结果是新添加的特征与某些原始特征具有相同的边缘分布，但是其值不包含有关数据点异常状态的信息。这保留了真实数据的特质，同时允许引入噪声。

为了简化确定需要多少不相关特征的过程，如果数据集已经具有d维特征，而我们想评估d'维，即将成对平均距离增加一个因子α所需的维数，那么

$$d' = \left(\alpha\sqrt{d}\right)^2 \quad (1),$$

其中$\alpha \in \{1.0, 1.2, 1.5, 2.0\}$.

[1] Emmott A, Das S, Dietterich T G, et al. A Meta-Analysis of the Anomaly Detection Problem[J]. arXiv: Artificial Intelligence, 2015.

随机选取一个csv文件，确定该数据集的原始特征有哪些?

In [3]:
```
df = pd.read_csv(os.path.join(PAGEB_ROOT, benchmark_list[0]))
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4654 entries, 0 to 4653
Data columns (total 16 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   point.id        4654 non-null   object 
 1   motherset       4654 non-null   object 
 2   origin          4654 non-null   object 
 3   original.label  4654 non-null   int64  
 4   diff.score      4654 non-null   float64
 5   ground.truth    4654 non-null   object 
 6   V               4654 non-null   float64
 7   V.1             4654 non-null   float64
 8   V.2             4654 non-null   float64
 9   V.3             4654 non-null   float64
 10  V.4             4654 non-null   float64
 11  V.5             4654 non-null   float64
 12  V.6             4654 non-null   float64
 13  V.7             4654 non-null   float64
 14  V.8             4654 non-null   float64
 15  V.9             4654 non-null   float64
dtypes: float64(11), int64(1), object(4)
memory usage: 581.9+ KB
```

Out[3]:

	point.id	motherset	origin	original.label	diff.score	ground.truth	V	
0	pageb_point_2156	pageb	multiclass	1	0.050799	nominal	-0.077700	-0.(
1	pageb_point_4574	pageb	multiclass	3	0.012214	anomaly	3.244986	0.(
2	pageb_point_1655	pageb	multiclass	1	0.013439	nominal	-0.183182	-0.(
3	pageb_point_0667	pageb	multiclass	5	0.011605	anomaly	2.190165	3.:
4	pageb_point_2081	pageb	multiclass	1	0.054793	nominal	-0.183182	1.(

根据以上的信息我们可以确定，pageb这个数据集的原始特征维度$d = 10$(`V` , `V.1` ~ `V.9`)。因此，由等式（1）可知，所有csv文件所包含的列数可能为$16 = \left(1.0 \times \sqrt{10}\right)^2 + 6, 20 = \left(1.2 \times \sqrt{10}\right)^2 + 6, 28 = \left(1.5 \times \sqrt{10}\right)^2 + 6, 46 = \left(2.0 \times \sqrt{10}\right)^2 + 6.$

下面我们遍历所有csv文件，验证一下。

In [4]:
```
d_set = set()
d_count = 0
for i in range(len(benchmark_list)):
    df = pd.read_csv(os.path.join(PAGEB_ROOT, benchmark_list[i]))
    d_set.add(len(df.columns))
    d_count += len(df)
print('Possible columns of all csv files:', d_set)
print('Total amount:', d_count)
```

```
Possible columns of all csv files: {16, 20, 28, 46}
Total amount: 3180315
```

数据特征选择

为了充分利用所提供的数据集完成离群点分析与异常检测，将提取所有csv文件共同的特征（即原始特征, `V` , `V.1` ~ `V.9` ）作为算法或模型的输入，用于检测该条数据是否属于异常点。

In [5]:
```
ORIGIN_FEATURES = ['V', 'V.1', 'V.2', 'V.3', 'V.4', 'V.5', 'V.6', 'V.
7', 'V.8', 'V.9', 'ground.truth']
def feature_section(benchmark_list):
    concat_data = pd.DataFrame()
    for i in benchmark_list:
        df = pd.read_csv(os.path.join(PAGEB_ROOT, i))
        concat_data = concat_data.append(df[ORIGIN_FEATURES])
    return concat_data
```

In [6]:
```
concat_data = feature_section(benchmark_list=benchmark_list)
concat_data.info()
concat_data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3180315 entries, 0 to 4465
Data columns (total 11 columns):
 #   Column        Dtype  
---  ------        -----  
 0   V             float64
 1   V.1           float64
 2   V.2           float64
 3   V.3           float64
 4   V.4           float64
 5   V.5           float64
 6   V.6           float64
 7   V.7           float64
 8   V.8           float64
 9   V.9           float64
 10  ground.truth  object 
dtypes: float64(10), object(1)
memory usage: 291.2+ MB
```

Out[6]:

	V	V.1	V.2	V.3	V.4	V.5	V.6	V.7	
0	-0.077700	-0.031103	-0.087518	-0.136725	-0.886844	-1.570670	-0.071357	-0.159746	-0.181
1	3.244986	0.056064	1.178212	-0.404543	0.671466	-1.189799	0.137100	2.367937	1.745
2	-0.183182	-0.667426	-0.228360	-0.387477	-0.588683	-0.803068	-0.069620	-0.269166	-0.362
3	2.190165	3.237675	4.696190	-0.159231	-0.993731	-3.146892	0.076734	3.338549	2.762
4	-0.183182	1.023622	0.051676	0.515150	-0.673068	-0.082342	-0.071357	-0.003881	0.199

数据集划分

train set : test set = 8 : 2

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

train, test = train_test_split(concat_data, test_size=0.2, random_sta
te=2020)

def data_label_split(data, label_column='ground.truth'):
    x = data.drop(label_column, axis=1)
    y = []
    for i in data[label_column].values:
        if i == 'nominal':
            y.append(0)
        else:
            y.append(1)
    y = np.array(y)
    return x, y

X_train, y_train = data_label_split(train)
X_test, y_test = data_label_split(test)
```

In [8]:
```
from sklearn.utils.multiclass import type_of_target
type_of_target(y_train)
```

Out[8]:
```
'binary'
```

t-SNE降维，用于可视化

In [9]:
```
from sklearn.manifold import TSNE
# T-SNE Implementation
t0 = time.time()
X_train_reduced_tsne = TSNE(n_components=2, random_state=2020, init=
'pca', n_iter=2000).fit_transform(X_train.values)
X_test_reduced_tsne = TSNE(n_components=2, random_state=2020, init='p
ca', n_iter=2000).fit_transform(X_test.values)
t1 = time.time()
print("T-SNE took {:.2} s".format(t1 - t0))
```

```
T-SNE took 1.7e+04 s
```

模型比较

单一模型

- KNN
- PCA
- LOF

组合模型

- **Average**: average scores of all detectors
- **Maximization**: maximum score across all detectors.
- **Average of Maximum (AOM)**
- **Maximum of Average (MOA)**

ref: [https://github.com/yzhao062/pyod/tree/master/examples (https://github.com/yzhao062/pyod/tree/master/examples)](https://github.com/yzhao062/pyod/tree/master/examples)

kNN

初始化一个 `pyod.models.knn.KNN` 检测器, 模型拟合, 然后给出预测。

In [10]:
```
# train the KNN detector
from pyod.models.knn import KNN

clf_name = 'KNN'
clf = KNN()
clf.fit(X_train)

# get the prediction labels and outlier scores of the training data
y_train_pred = clf.labels_  # binary labels (0: inliers, 1: outliers)
y_train_scores = clf.decision_scores_  # raw outlier scores

# get the prediction on the test data
y_test_pred = clf.predict(X_test)  # outlier labels (0 or 1)
y_test_scores = clf.decision_function(X_test)  # outlier scores
```

利用 ROC 和 Precision @ Rank 评估预测。

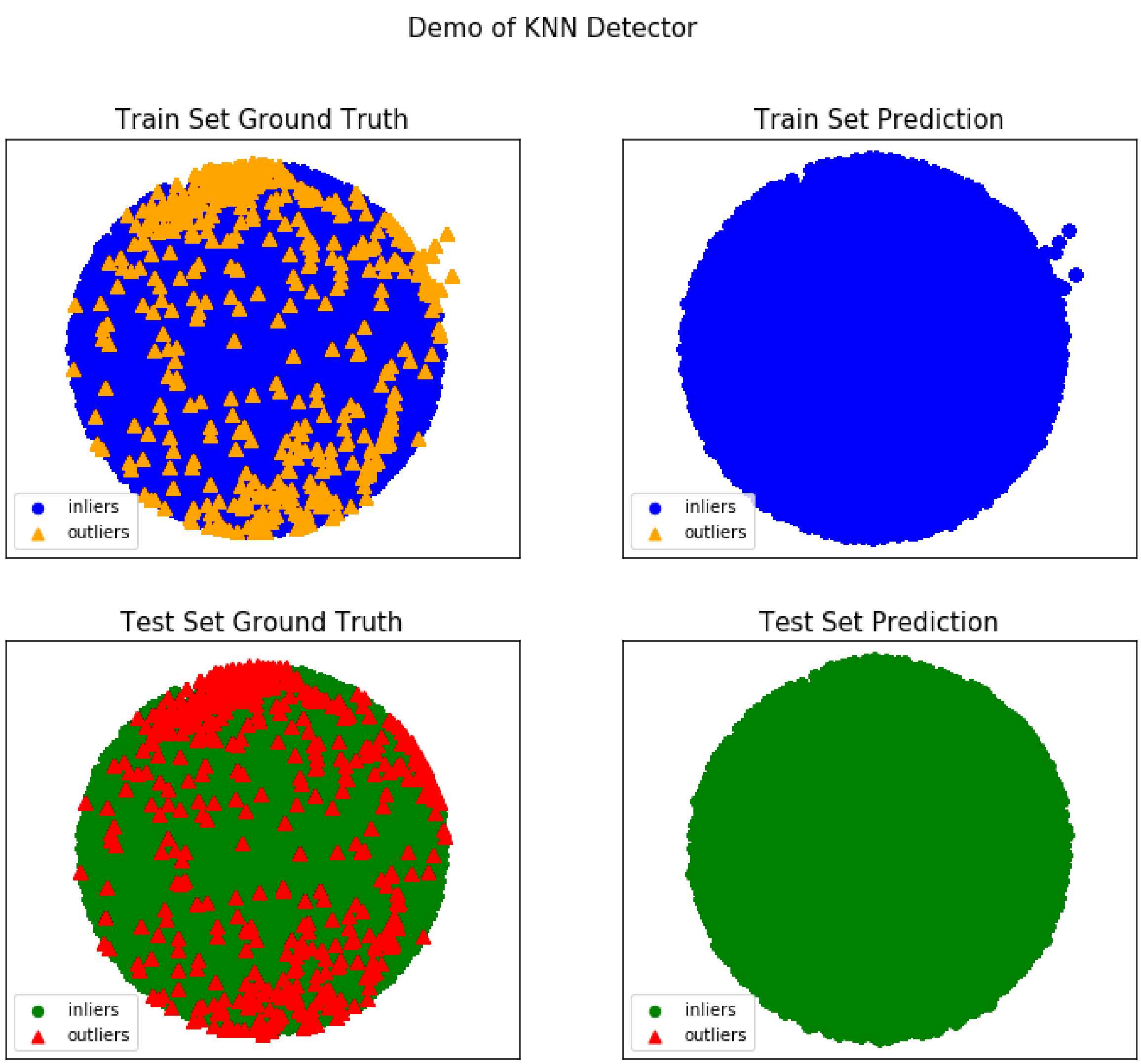
In [11]:
```python
from pyod.utils.data import evaluate_print
# evaluate and print the results
print("\nOn Training Data:")
evaluate_print(clf_name, y_train, y_train_scores)
print("\nOn Test Data:")
evaluate_print(clf_name, y_test, y_test_scores)
```

```
On Training Data:
KNN ROC:0.5, precision @ rank n:0.0

On Test Data:
KNN ROC:0.5, precision @ rank n:0.0
```

可视化 KNN 的结果

In [12]:
```python
from pyod.utils.example import visualize
visualize(clf_name, X_train_reduced_tsne, y_train, X_test_reduced_tsn
e, y_test, y_train_pred,
          y_test_pred, show_figure=True, save_figure=False)
```



PCA

初始化一个 `pyod.models.pca.PCA` 检测器, 模型拟合, 然后给出预测。

In [13]:
```
# train PCA detector
from pyod.models.pca import PCA

clf_name = 'PCA'
clf = PCA(n_components=3)
clf.fit(X_train)

# get the prediction labels and outlier scores of the training data
y_train_pred = clf.labels_  # binary labels (0: inliers, 1: outliers)
y_train_scores = clf.decision_scores_  # raw outlier scores

# get the prediction on the test data
y_test_pred = clf.predict(X_test)  # outlier labels (0 or 1)
y_test_scores = clf.decision_function(X_test)  # outlier scores
```

利用 ROC 和 Precision @ Rank 评估预测

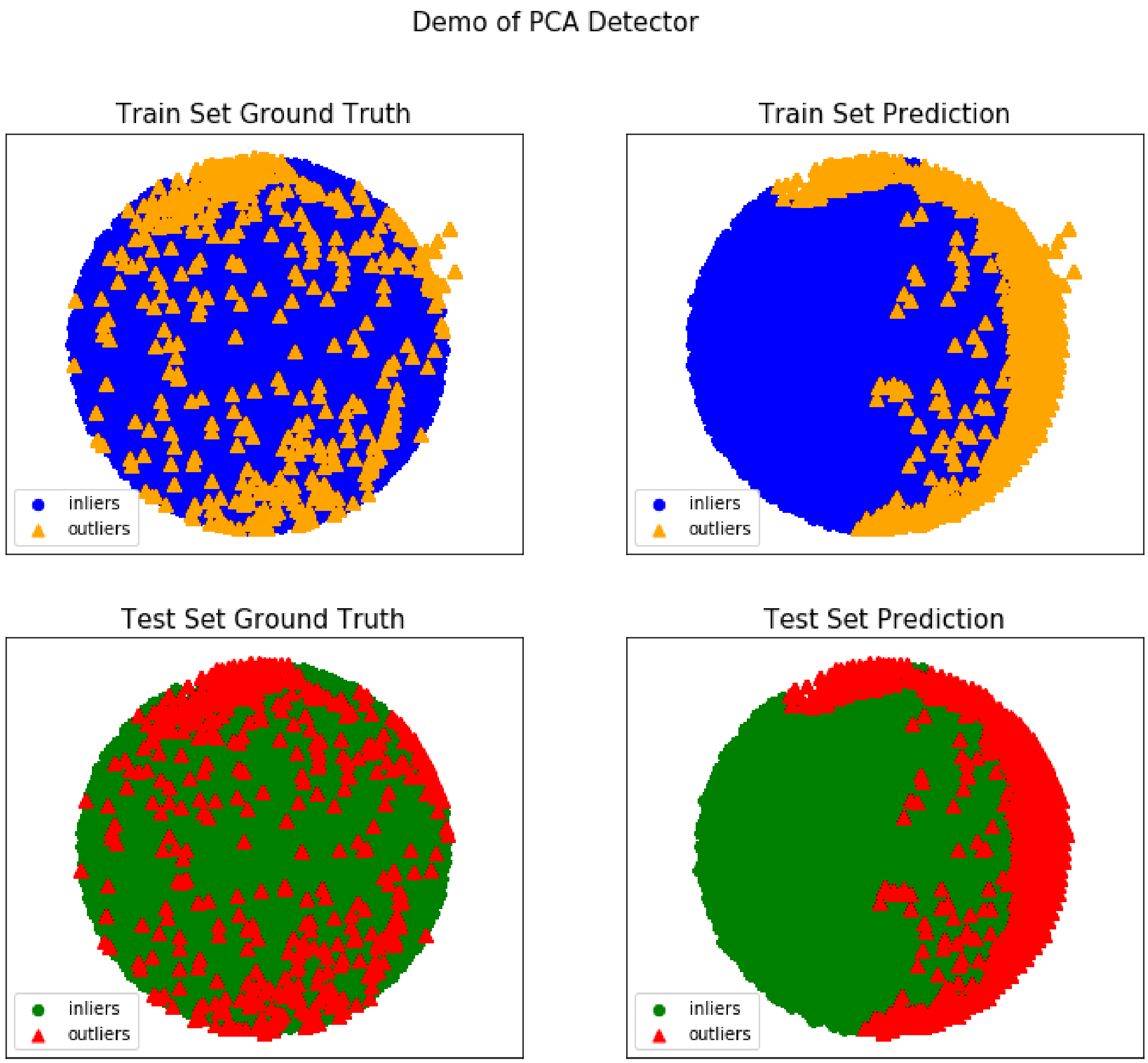
In [14]:
```
# evaluate and print the results
print("\nOn Training Data:")
evaluate_print(clf_name, y_train, y_train_scores)
print("\nOn Test Data:")
evaluate_print(clf_name, y_test, y_test_scores)
```

```
On Training Data:
PCA ROC:0.8928, precision @ rank n:0.2423

On Test Data:
PCA ROC:0.8925, precision @ rank n:0.2426
```

可视化 PCA 的结果

```
In [15]: visualize(clf_name, X_train_reduced_tsne, y_train, X_test_reduced_tsn
e, y_test, y_train_pred,
          y_test_pred, show_figure=True, save_figure=False)
```



LOF

初始化一个 `pyod.models.lof.LOF` 检测器, 模型拟合, 然后给出预测。

```
In [16]: # train LOF detector
from pyod.models.lof import LOF
clf_name = 'LOF'
clf = LOF()
clf.fit(X_train)

# get the prediction labels and outlier scores of the training data
y_train_pred = clf.labels_  # binary labels (0: inliers, 1: outliers)
y_train_scores = clf.decision_scores_  # raw outlier scores

# get the prediction on the test data
y_test_pred = clf.predict(X_test)  # outlier labels (0 or 1)
y_test_scores = clf.decision_function(X_test)  # outlier scores
```

利用 ROC 和 Precision @ Rank 评估预测

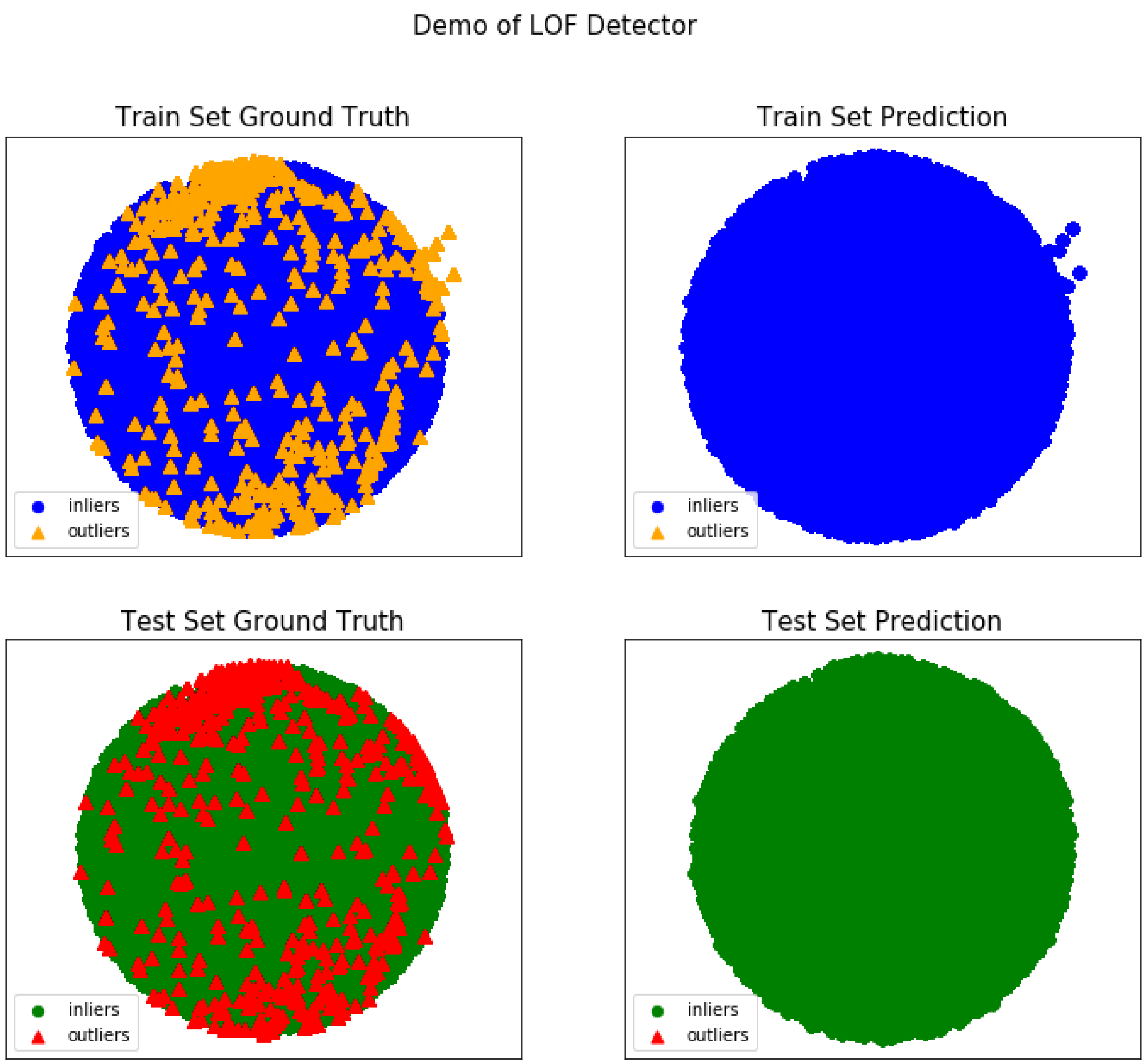
In [17]:
```
# evaluate and print the results
print("\nOn Training Data:")
evaluate_print(clf_name, y_train, y_train_scores)
print("\nOn Test Data:")
evaluate_print(clf_name, y_test, y_test_scores)
```

```
On Training Data:
LOF ROC:0.5, precision @ rank n:0.0

On Test Data:
LOF ROC:0.5, precision @ rank n:0.0
```

可视化 LOF 的结果

In [18]:
```
# visualize the results
visualize(clf_name, X_train_reduced_tsne, y_train, X_test_reduced_tsn
e, y_test, y_train_pred,
          y_test_pred, show_figure=True, save_figure=False)
```



Model Combination

用不同的k(10 ～ 200)初始化20个 kNN 离群点检测器，然后得到所有的离群点的分数。

In [19]:
```
from pyod.models.knn import KNN  # kNN detector
from pyod.models.combination import aom, moa, average, maximization
from pyod.utils.utility import standardizer
```

In [20]:
```
# standardizing data for processing
X_train_norm, X_test_norm = standardizer(X_train, X_test)

n_clf = 20  # number of base detectors

# initialize 20 base detectors for combination
k_list = [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140
, 150, 160, 170, 180, 190, 200]

train_scores = np.zeros([X_train.shape[0], n_clf])
test_scores = np.zeros([X_test.shape[0], n_clf])

print('Combining {n_clf} kNN detectors'.format(n_clf=n_clf))

for i in range(n_clf):
    k = k_list[i]

    clf = KNN(n_neighbors=k, method='largest')
    clf.fit(X_train_norm)

    train_scores[:, i] = clf.decision_scores_
    test_scores[:, i] = clf.decision_function(X_test_norm)
```

```
Combining 20 kNN detectors
```

In [21]:
```
# Decision scores have to be normalized before combination
train_scores_norm, test_scores_norm = standardizer(train_scores, test
_scores)

# Combination by average
y_by_average = average(test_scores_norm)
# Combination by max
y_by_maximization = maximization(test_scores_norm)
# Combination by aom
y_by_aom = aom(test_scores_norm, n_buckets=5)
# Combination by moa
y_by_moa = moa(test_scores_norm, n_buckets=5)
```

In [22]:
```
print("\nOn Test Data:")
evaluate_print('Combination by Average', y_test, y_by_average)
evaluate_print('Combination by Maximization', y_test, y_by_maximizati
on)
evaluate_print('Combination by AOM', y_test, y_by_aom)
evaluate_print('Combination by MOA', y_test, y_by_moa)
```

```
On Test Data:
Combination by Average ROC:0.6484, precision @ rank n:1.0
Combination by Maximization ROC:0.6484, precision @ rank n:1.0
Combination by AOM ROC:0.6484, precision @ rank n:1.0
Combination by MOA ROC:0.6484, precision @ rank n:1.0
```

In [23]:
```
m, s = divmod(time.time()-timekeeping, 60)
h, m = divmod(m, 60)
print ('run time: %02d:%02d:%02d' % (h, m, s))
```

```
run time: 06:27:28
```