In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import collections

import seaborn as sns;
sns.set()

import warnings
warnings.filterwarnings('ignore')

from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import normalize
from sklearn.metrics import\
    classification_report,\
    plot_confusion_matrix,\
    confusion_matrix,\
    roc_curve,\
    auc
from tqdm import tqdm

from mlxtend.plotting import plot_confusion_matrix
```

In [2]:
```
# Macros
PATH_DATA_TRAIN = '20_Percent_Training_Set.csv'
PATH_DATA_TEST = 'KDDTest+.csv'
PATH_DATA_FEATURES = 'Field_Names.csv'
PATH_DATA_ATTACK = 'Attack_Types.csv'

class IDs:
    """
        Data resource: https://github.com/defcom17/NSL_KDD
    """

    def __init__(self, mode='Anomaly'):
        self.import_features()
        self.import_data()
        self.mode = mode
        self.models = []

    def import_features(self):
        data = pd.read_csv(
            './data/' + PATH_DATA_FEATURES,
            header=None,
            names=['feature_name', 'data_type'])
        self.features_meta = data

    def import_data(self):
        # Last two columns indicate attack type and its severity
        target_features = np.array(['class', 'severity'])
        features = np.concatenate(
            (self.features_meta['feature_name'].values,
             target_features)
        )

        self.data_train = pd.read_csv(
            './data/' + PATH_DATA_TRAIN,
            names=features
```

```
        )
        self.data_test = pd.read_csv(
            './data/' + PATH_DATA_TEST,
            names=features
        )

    def import_attack_types(self):
        data = pd.read_csv(
            './data/' + PATH_DATA_ATTACK,
            header=None,
            names=['attack_name', 'attack_type'])
        types = {}
        for i in range(len(data)):
            types[str(data['attack_name'][i])] = str(data['attack_type'][i])
        self.attack_types = types

    def preprocess(self):
        # Drop the un-needed column
        self.data_train = self.data_train.drop(columns=['severity'])
        self.data_test = self.data_test.drop(columns=['severity'])

        # Drop the symbolic column
        symbolic = self.features_meta.loc[self.features_meta['data_type'] == 's
        symbolic = symbolic['feature_name'].values
        self.data_train = self.data_train.drop(columns=symbolic)
        self.data_test = self.data_test.drop(columns=symbolic)

        # Extract normal for Anomaly Detection
        if self.mode == 'Anomaly':
            self.data_train = self.data_train[self.data_train['class'] == 'norm

    def split(self):
        i = len(self.data_train.columns) - 1
        self.X_train = self.data_train.iloc[:, :i]
        self.y_train = self.data_train.iloc[:, i:]
        self.X_test = self.data_test.iloc[:, :i]
        self.y_test = self.data_test.iloc[:, i:]

        # Normalized data
        if self.mode == 'Anomaly' or self.mode == 'Misuse':
            self.X_train = normalize(self.X_train, axis=0, norm='max')
            self.X_test = normalize(self.X_test, axis=0, norm='max')

        # Convert class to binary
        self.y_train['class'] = (self.data_train['class'] != 'normal').astype(i
        self.y_test['class'] = (self.data_test['class'] != 'normal').astype(int

    def construct_knn(self, args=None):
        if self.mode == 'Anomaly':
            self.X_train = self.data_train[self.data]
        model = KNeighborsClassifier(n_neighbors=args['n_neighbors'])
        model.fit(self.X_train, self.y_train)
        self.models.append(model)
        return model

    def predict_nearests(self):
        nearests = []
        for i in tqdm(range(len(self.X_test))):
            distances = np.linalg.norm(self.X_train - self.X_test[i], axis=1)
            sorted_distances = np.sort(distances)
```

```
            sorted_ids = distances.argsort()
            nearest = [sorted_ids[0], distances[sorted_ids[0]]]
            #print('Nearest neighbor: (id, distacne) = ', nearest)
            nearests.append(nearest)
        return nearests

    def evaluate_nearests_by_threshold(self, nearests, plt_config=None):
        thresholds = self.compute_thresholds(nearests)
        y_dist = np.array([i[1] for i in nearests])
        for th in thresholds:
            y_pred = y_dist.copy()

            y_pred[y_pred < th] = 0
            y_pred[y_pred >= th] = 1

            if plt_config:
                self.plot_ROC(self.y_test, y_pred, plt_config)

    def evaluate_nearests_by_class(self, nearests, plt_config=None):
        # Convert predicted attack to its type
        nearest_ids = np.array([i[0] for i in nearests])
        y_pred = [self.data_train['class'][i] for i in nearest_ids]
        for i in range(len(y_pred)):
            y_pred[i] = self.attack_types[y_pred[i]]

        # Catorgorize attack in test data
        y_test = y_pred.copy()
        for i, key in enumerate(self.data_test['class']):
            if key in self.attack_types:
                y_test[i] = self.attack_types[key]

        return y_test, y_pred

    def evaluate_knn(self, plt_config=None):
        # Obtain the first 10 odd numbers
        neighbors = [k for k in range(1, 20, 2)]

        for k in tqdm(neighbors):
            it = self.construct_knn({'n_neighbors': k})
            y_pred = it.predict(self.X_test)
            self.plot_ROC(self.y_test, y_pred, plt_config)

    @staticmethod
    def compute_thresholds(nearests):
        thresholds = []

        # Use the min and max in nearest distances as threshold range
        threshold_range = [i[1] for i in nearests]
        threshold_range = [min(threshold_range), max(threshold_range)]
        print('Threshold Range: ', threshold_range)

        # Increment 1/10 upon the previous for each threshold
        offset = (threshold_range[1] - threshold_range[0]) * 0.1
        for i in np.arange(threshold_range[0], threshold_range[1], offset):
            thresholds.append(i)
        print('Thresholds: ', thresholds)

        return thresholds

    @staticmethod
```

```
    def plot_ROC(y_test, y_pred, plt_config):
        fpr, tpr, threshold = roc_curve(y_test, y_pred)
        print('False positive, True positive: ', fpr, tpr)

        roc_auc = auc(fpr, tpr)

        plt.figure(figsize=plt_config['figsize'])
        plt.title('ROC for ' + plt_config['model'])
        plt.plot(fpr, tpr, 'b', label='ROC-AUC = %0.2f' % roc_auc)
        plt.plot([0,1], [0,1], 'y--', label='baseline')

        plt.ylabel('True Positive Rate')
        plt.xlabel('False Positive Rate')
        plt.legend(loc='best')
        plt.show()

    def check_shape(self):
        #print(self.data_train.head())
        print('Train data shape: ', self.data_train.shape)
        print('Test data shape: ', self.data_test.shape)
        print('Data features: ', self.data_train.columns, len(self.data_train.c
        print('Shape of X_train, y_train, X_test, y_test: ',
              self.X_train.shape, self.y_train.shape, self.X_test.shape, self.y
```

(1) Extract normal instances from the training dataset; process the data according to the need as necessary; normalize the attribute values for better classification performance.

In [51]:

```
# A.1
ad = IDs('Anomaly')
ad.preprocess()
ad.split()
ad.check_shape()
```

```
Train data shape:  (13449, 39)
Test data shape:  (22543, 39)
Data features:  Index(['duration', 'src_bytes', 'dst_bytes', 'land', 'wrong_fr
agment',
       'urgent', 'hot', 'num_failed_logins', 'logged_in', 'num_compromised',
       'root_shell', 'su_attempted', 'num_root', 'num_file_creations',
       'num_shells', 'num_access_files', 'num_outbound_cmds', 'is_host_login',
       'is_guest_login', 'count', 'srv_count', 'serror_rate',
       'srv_serror_rate', 'rerror_rate', 'srv_rerror_rate', 'same_srv_rate',
       'diff_srv_rate', 'srv_diff_host_rate', 'dst_host_count',
       'dst_host_srv_count', 'dst_host_same_srv_rate',
       'dst_host_diff_srv_rate', 'dst_host_same_src_port_rate',
       'dst_host_srv_diff_host_rate', 'dst_host_serror_rate',
       'dst_host_srv_serror_rate', 'dst_host_rerror_rate',
       'dst_host_srv_rerror_rate', 'class'],
      dtype='object') 39
Shape of X_train, y_train, X_test, y_test:  (13449, 38) (13449, 1) (22543, 38)
(22543, 1)
```

(2) For every instance in the testing dataset, find the nearest “neighbor” instance in the normal profile and calculate the corresponding distance to it.

In [52]:

```
# A.2
nearests = ad.predict_nearests()
print('Nearest neighbors = ', nearests[:5])
```

```
100%|██████████████████████████████████████████████████████████████████████████| 22543/22543 [01:17<00:00, 289.28it/s]
Nearest neighbors =  [[8073, 1.3940272867028123], [8073, 1.398023406443181], [11704, 0.047388972828311504], [9857, 0.36566526415352013], [10738, 0.8093912662149911]]
```

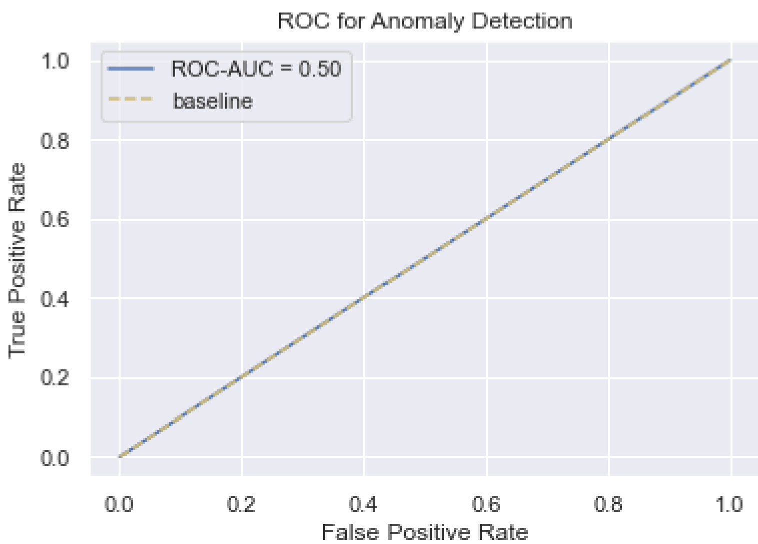
(3) Vary the control threshold to appropriately cover the value range of this distance (using at least 10 different values), and classify each new instance as normal or attack (binary classification) accordingly.

(4) Calculate the False Positive Rate (FPR) and True Positive Rate (TPR) pair for each control threshold value used and plot the Receiver Operating Characteristic (ROC) curve.

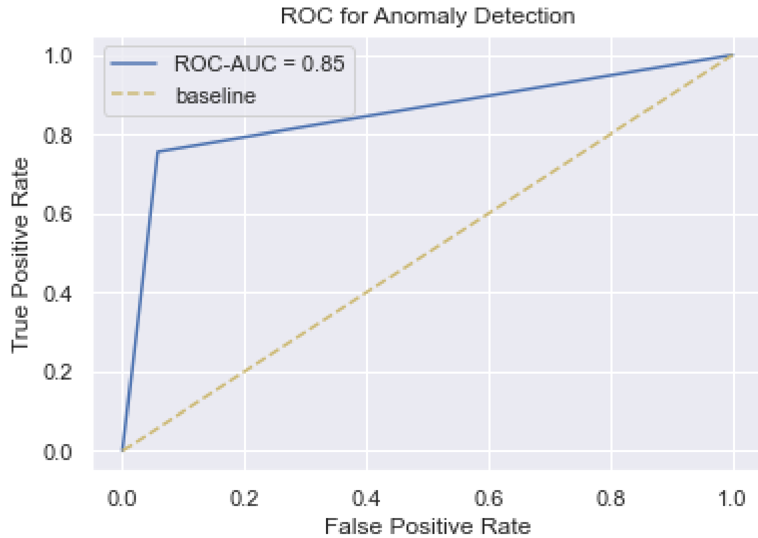
(5) Please calculate the Area Under the Curve (AUC) for this ROC.

In [53]:
```python
# Customize plot
plt_config = {
    'figsize': (6, 4),
    'model': ad.mode + ' Detection'
}

# A.3 ~ 5
ad.evaluate_nearests_by_threshold(nearests, plt_config)
```

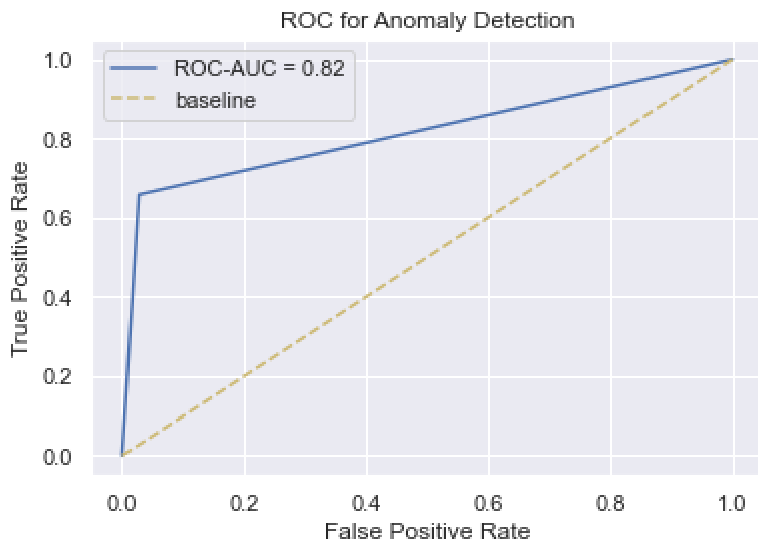
```
Threshold Range:  [5.512885536068322e-05, 2.0624348053245796]
Thresholds:  [5.512885536068322e-05, 0.20629309650228259, 0.4125310641492045, 0.6187690317961263, 0.8250069994430482, 1.0312449670899702, 1.237482934736892, 1.443720902383814, 1.649958870030736, 1.8561968376776579]
False positive, True positive:  [0. 1.] [0. 1.]
```



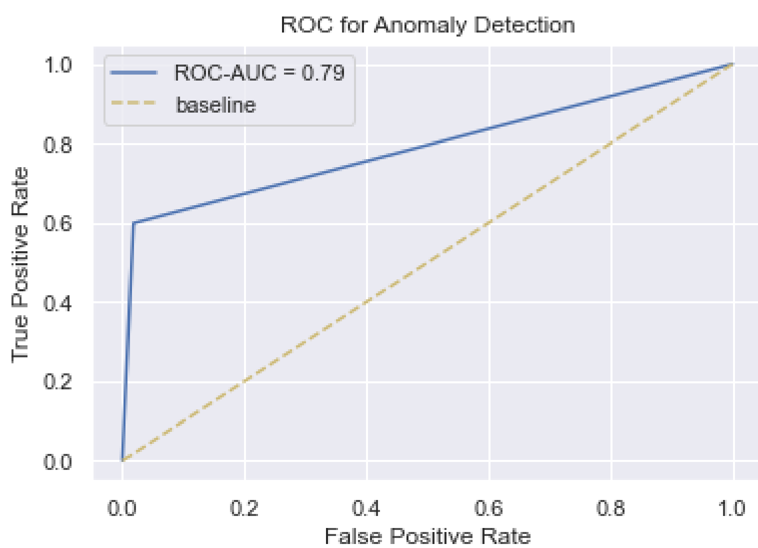

```
False positive, True positive:  [0.         0.05736354 1.        ] [0.
0.75617549 1.        ]
```



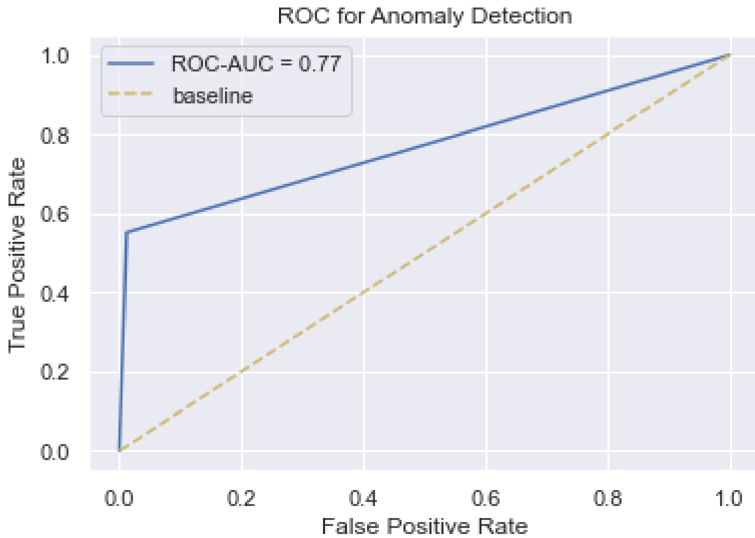

```
False positive, True positive:  [0.         0.02687951 1.        ] [0.
0.65838074 1.        ]
```



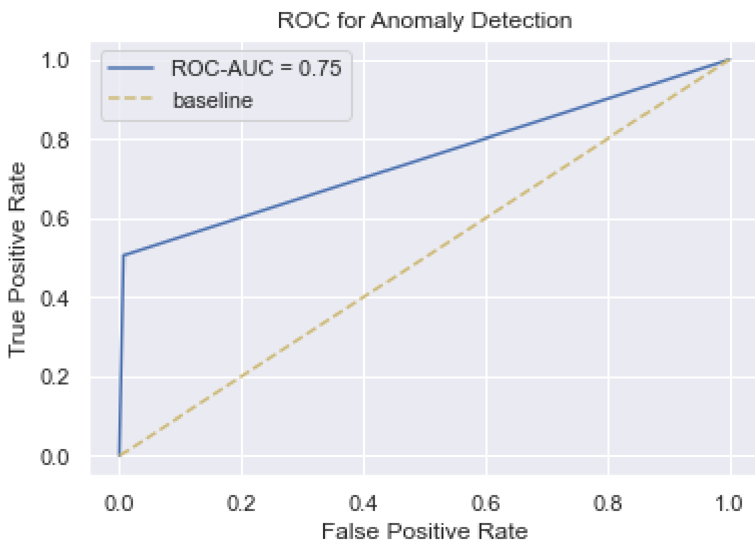

```
False positive, True positive:  [0.         0.01750772 1.        ] [0.
0.59915842 1.        ]
```



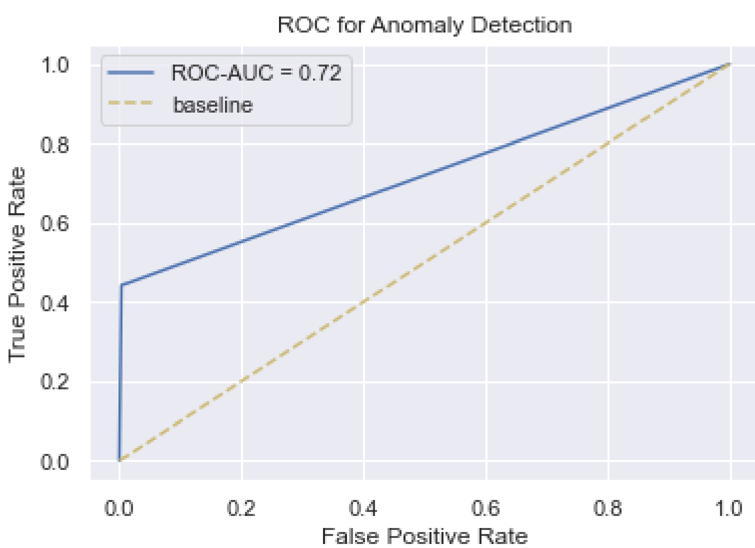

```
False positive, True positive:  [0.         0.01163749 1.        ] [0.
0.55209226 1.        ]
```



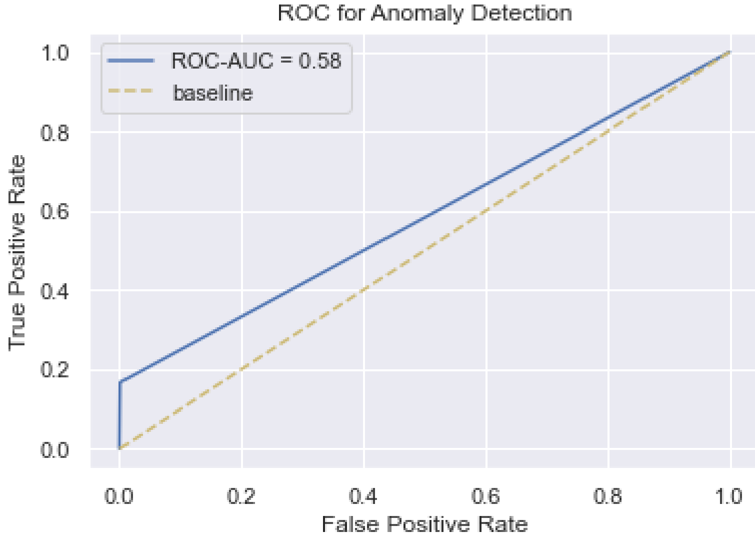

```
False positive, True positive:  [0.         0.00679712 1.        ] [0.
0.50596119 1.        ]
```



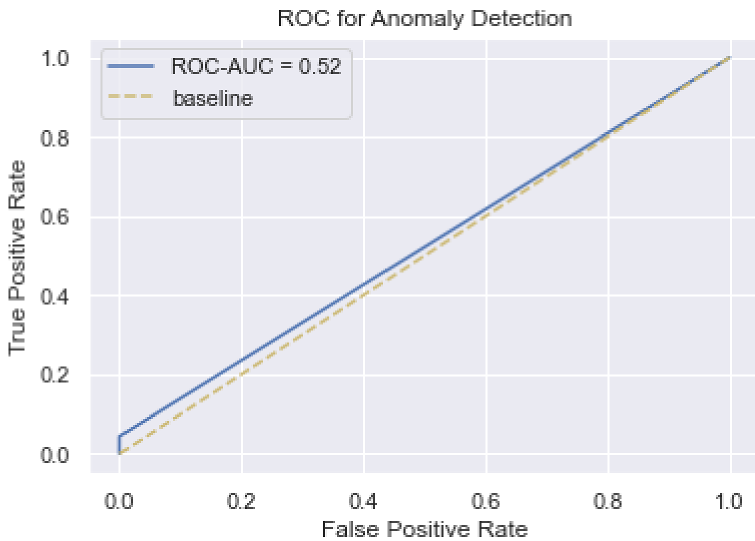

```
False positive, True positive:  [0.         0.00339856 1.        ] [0.
0.4422972 1.        ]
```



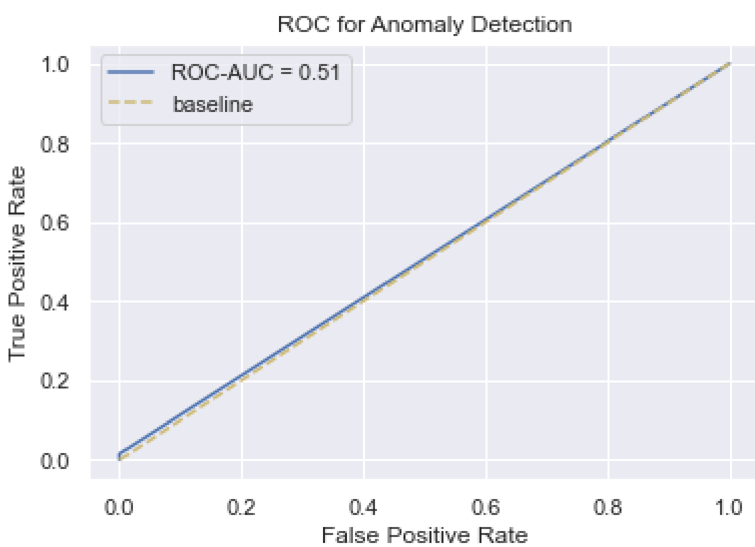

```
False positive, True positive:  [0.         0.00113285 1.        ] [0.
0.16691343 1.        ]
```




```
False positive, True positive:  [0.00000000e+00 1.02986612e-04 1.00000000e+00]
[0.         0.04418297 1.        ]
```




```
False positive, True positive:  [0. 0. 1.] [0.         0.01542897 1.        ]
```



(6) Please find the “best” control threshold setting and explain how you determine it.

B. Misuse Detection

(1) Use the whole training dataset (both normal and intrusive instances) for detection.

In [3]:
```
# B.1
md = IDs('Misuse')
md.preprocess()
md.split()
md.check_shape()
```

```
Train data shape:  (25192, 39)
Test data shape:  (22543, 39)
Data features:  Index(['duration', 'src_bytes', 'dst_bytes', 'land', 'wrong_fr
agment',
       'urgent', 'hot', 'num_failed_logins', 'logged_in', 'num_compromised',
       'root_shell', 'su_attempted', 'num_root', 'num_file_creations',
       'num_shells', 'num_access_files', 'num_outbound_cmds', 'is_host_login',
       'is_guest_login', 'count', 'srv_count', 'serror_rate',
       'srv_serror_rate', 'rerror_rate', 'srv_rerror_rate', 'same_srv_rate',
       'diff_srv_rate', 'srv_diff_host_rate', 'dst_host_count',
       'dst_host_srv_count', 'dst_host_same_srv_rate',
       'dst_host_diff_srv_rate', 'dst_host_same_src_port_rate',
       'dst_host_srv_diff_host_rate', 'dst_host_serror_rate',
       'dst_host_srv_serror_rate', 'dst_host_rerror_rate',
       'dst_host_srv_rerror_rate', 'class'],
      dtype='object') 39
Shape of X_train, y_train, X_test, y_test:  (25192, 38) (25192, 1) (22543, 38)
(22543, 1)
```

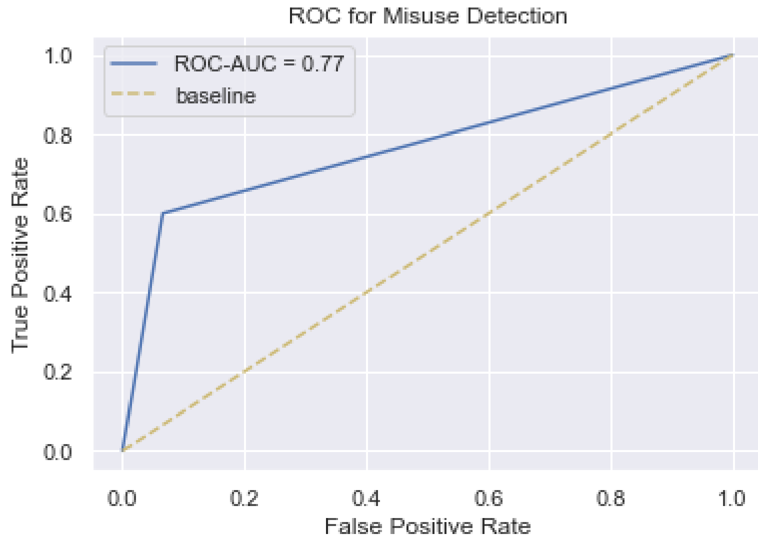
(2) Select different k's (using at least the first 10 odd integer numbers) used in k-NN classification, through majority voting, to classify each instance in the testing dataset as normal or intrusive (binary classification).

(3) Calculate the FPR and TPR pair for each k used and plot the ROC curve over these different k's.

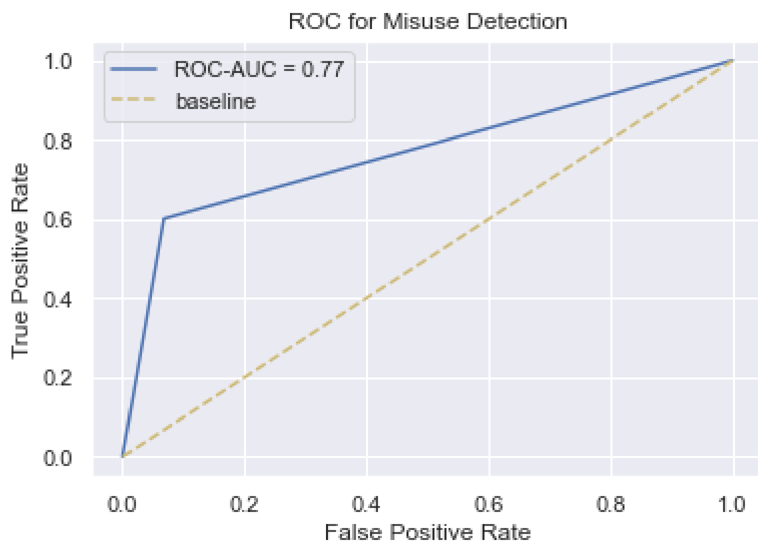
(4) Please calculate the AUC for this ROC.

In [5]:
```
# Customize plot
plt_config = {
    'figsize': (6, 4),
    'model': md.mode + ' Detection'
}

# B.2 ~ 4
md.evaluate_knn(plt_config)
```

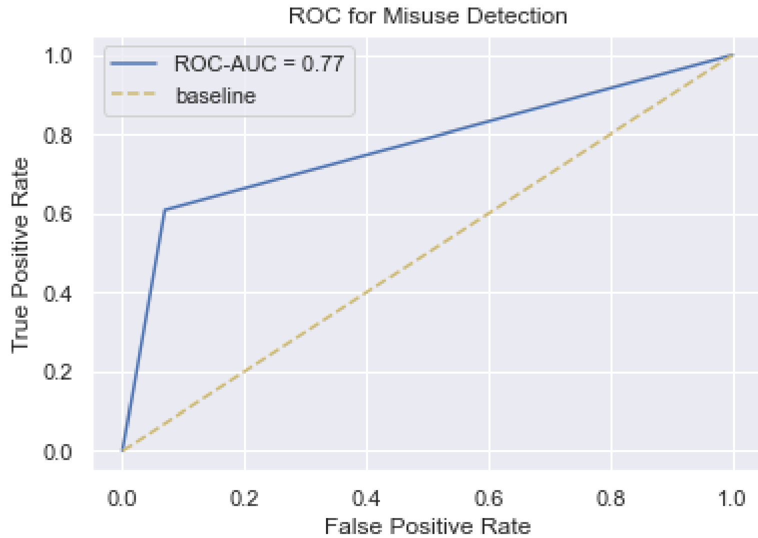
```
  0%|
| 0/10 [00:00<?, ?it/s]
False positive, True positive:  [0.         0.06560247 1.        ] [0.
0.60001558 1.        ]
```



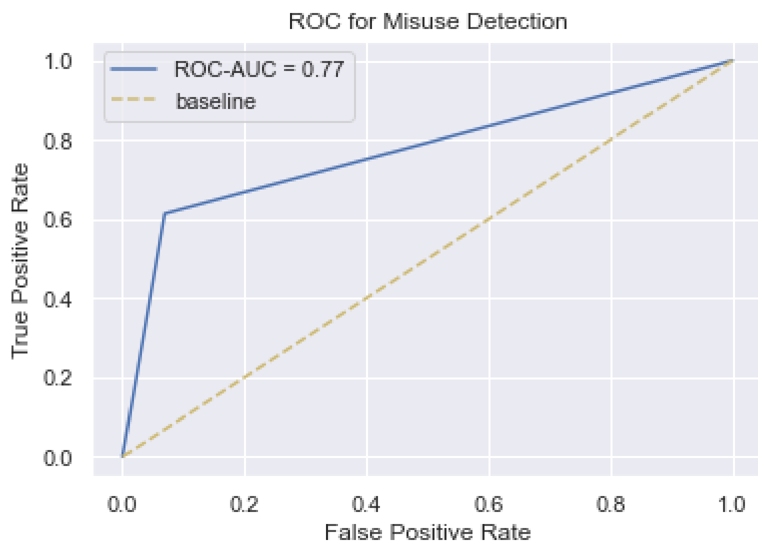

```
 10%|██████████████
| 1/10 [00:09<01:28,  9.79s/it]
False positive, True positive:  [0.         0.06745623 1.        ] [0.
0.60134029 1.        ]
```



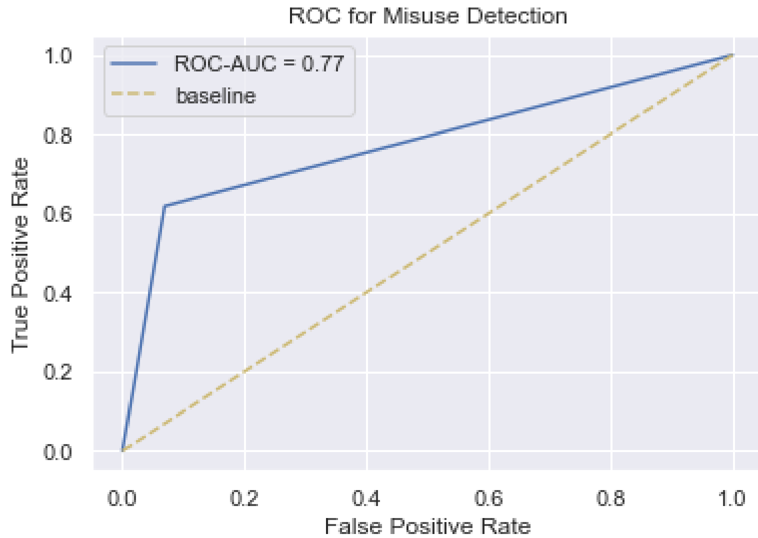

```
 20%|████████████████████████████
| 2/10 [00:20<01:20, 10.11s/it]
False positive, True positive:  [0.         0.06900103 1.        ] [0.
0.60874308 1.        ]
```



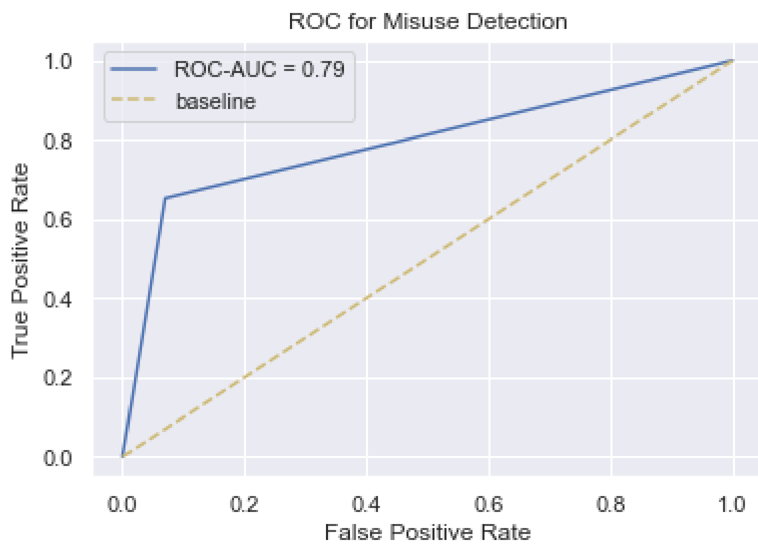

```
 30%|███████████████████████████████████████████
| 3/10 [00:33<01:21, 11.67s/it]
False positive, True positive:  [0.         0.06879506 1.        ] [0.
0.61404192 1.        ]
```



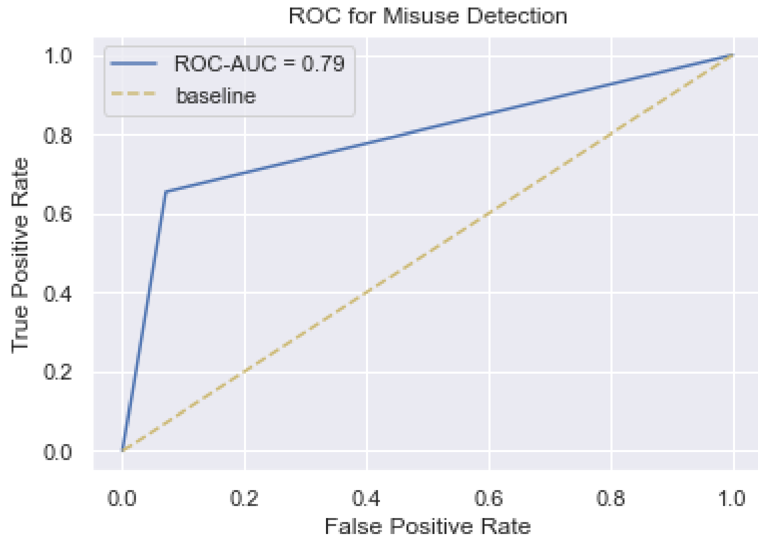

```
 40%|█████████████████████████████████████████████████████████
| 4/10 [00:46<01:12, 12.10s/it]
False positive, True positive:  [0.         0.06869207 1.        ] [0.
0.61832775 1.        ]
```



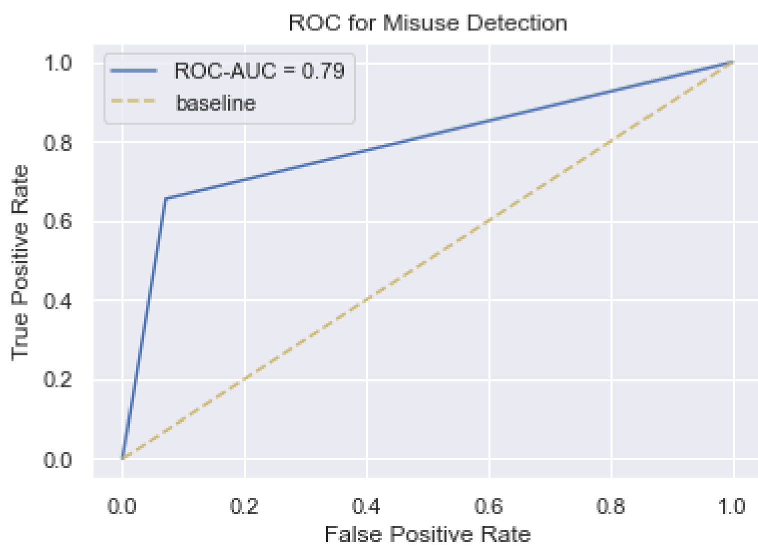

```
 50%|██████████████████████████████████████████████████████████████████████
| 5/10 [01:00<01:04, 12.81s/it]
False positive, True positive:  [0.         0.06961895 1.        ] [0.
0.65284813 1.        ]
```



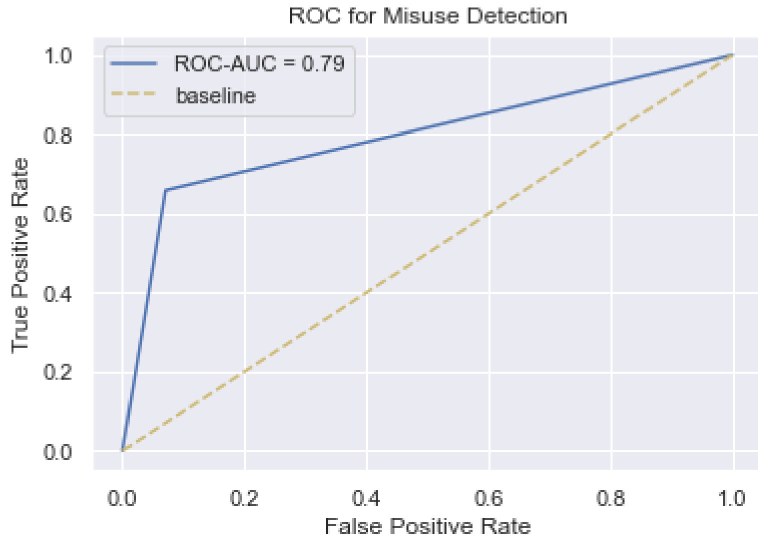

```
 60%|█████████████████████████████████████████████████████████████████████████
██████████                                                          | 6/10 [01:1
3<00:51, 12.78s/it]
False positive, True positive:  [0.         0.07064882 1.        ] [0.
0.6547183 1.       ]
```



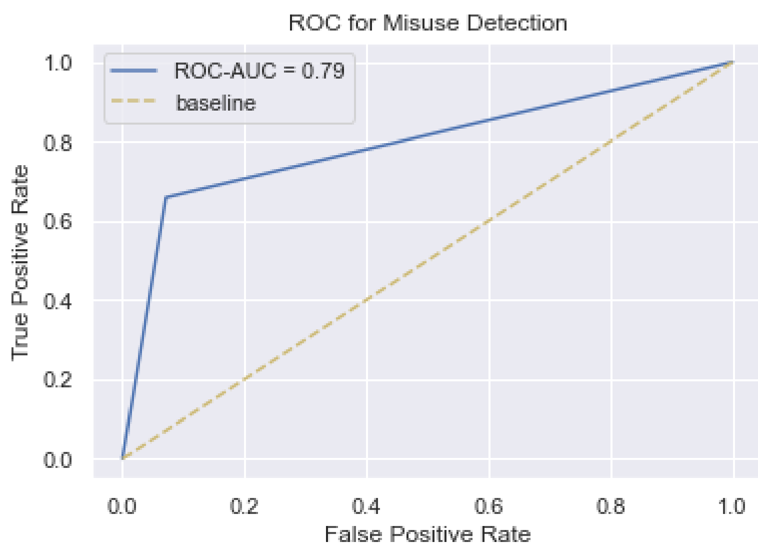

```
 70%|██████████████████████████████████████████████████████████████████████████████████████████                    | 7/10 [01:26<00:38, 12.89s/it]
False positive, True positive:  [0.         0.07033986 1.        ] [0.
0.65518585 1.        ]
```




```
 80%|████████████████████████████████████████████████████████████████████████████████████████████████████          | 8/10 [01:39<00:25, 12.89s/it]
False positive, True positive:  [0.         0.07023687 1.        ] [0.
0.65908205 1.        ]
```




```
 90%|█████████████████████████████████████████████████████████████████████████████████████████████████████████████████████████████              | 9/10 [01:51<00:12, 12.59s/it]
False positive, True positive:  [0.         0.0707518 1.        ] [0.         0.65915998 1.        ]
```




```
100%|████████████████████████████████████████████████████████████████████████████████████████████████████████████████████████████████████████| 10/10 [02:03<00:00, 12.37s/it]
```

(5) Now, use the nearest neighbor method, i.e., k=1, to find the attack category (using the four attack categories) or normal category of each testing instance, and show the resulting confusion matrix.

In [6]:

```python
# B.5
md.import_attack_types()
nearests = md.predict_nearests()
```

```
100%|████████████████████████████████████████████████████████████████████████████████████████████████████████████████| 22543/22543 [02:29<00:00, 150.58it/s]
```

In [14]:

```python
y_test, y_pred = md.evaluate_nearests_by_class(nearests)
print(collections.Counter(y_test))
```

```
target_names = ['normal', 'dos', 'r2l', 'probe','u2r']
```

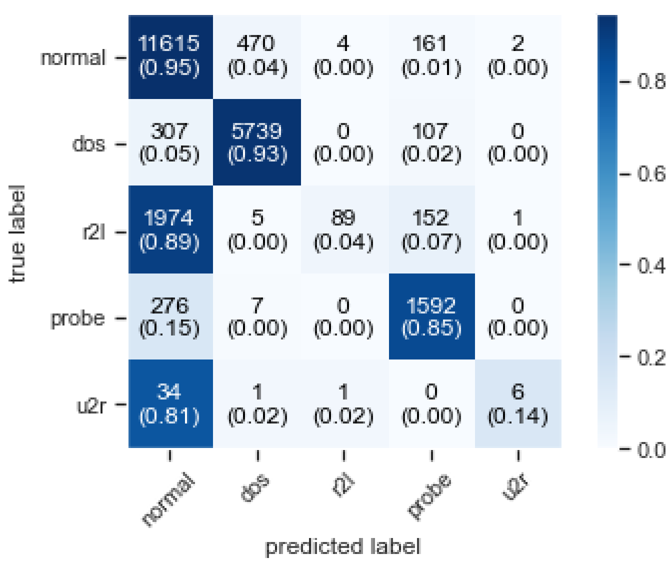
```
Counter({'normal': 12252, 'dos': 6153, 'r2l': 2221, 'probe': 1875, 'u2r': 42})
```

In [15]:
```
print(classification_report(y_test, y_pred, target_names=target_names))
```

```
              precision    recall  f1-score   support

      normal       0.92      0.93      0.93      6153
         dos       0.82      0.95      0.88     12252
         r2l       0.79      0.85      0.82      1875
       probe       0.95      0.04      0.08      2221
         u2r       0.67      0.14      0.24        42

    accuracy                           0.84     22543
   macro avg       0.83      0.58      0.59     22543
weighted avg       0.86      0.84      0.81     22543
```

In [11]:
```
cm = confusion_matrix(y_test, y_pred, labels=target_names)
print('Confusion Matrix: \n', cm)

fig, ax = plot_confusion_matrix(conf_mat=cm, show_absolute=True, show_normed=Tr
plt.show()
```

```
Confusion Matrix:
 [[11615   470     4   161     2]
 [  307  5739     0   107     0]
 [ 1974     5    89   152     1]
 [  276     7     0  1592     0]
 [   34     1     1     0     6]]
```



(6) Lastly, please use the cost matrix for the KDD'99 contest to calculate your average cost score. Now you can compare your performance to other entries in that contest!

COST-BASED SCORING AND TRAINING VS. TEST DISTRIBUTION

The cost matrix used for scoring entries was given as

	normal	probe	DOS	U2R	R2L
normal	0	1	2	2	2
probe	1	0	2	2	2
DOS	2	1	0	2	2
U2R	3	2	2	0	2
R2L	4	2	2	2	0

In [92]:
```
cost_normal = 1*161 + 2*470 + 2*2 + 2*4
cost_probe = 1*276 + 2*7 + 2*0 + 2*0
cost_dos = 2*307 + 1*107 + 2*0 + 2*0
cost_u2r = 3*34 + 2*0 + 2*1 + 2*1
cost_r2l = 4*1974 + 2*152 + 2*5 + 2*1

costs = [cost_normal, cost_probe, cost_dos, cost_u2r, cost_r2l]
cost_total = sum(costs)
cost_avg = cost_total / len(md.y_test)
print('Average cost: ', cost_avg)
```

```
Average cost:  0.46320365523665885
```

Accroding to "Results of the KDD'99 Classifier Learning Contest, " non-winning entries obtained an average cost per test example ranging from 0.2356 to 0.9414.