Ex5.RobustRandomCutForest

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1 5th exercise: Work with Robust Random Cut Forest (RRCF) algorithms for anomaly detection

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- Date: 28.10.2023

GENERAL NOTE 1: Please make sure you are reading the entire notebook, since it contains a lot of information on your tasks (e.g. regarding the set of certain paramaters or a specific computational trick), and the written mark downs as well as comments contain a lot of information on how things work together as a whole.
GENERAL NOTE 2: * Please, when commenting source code, just use English language only. * When describing an observation please use English language, too.
* This applies to all exercises throughout this course.
* Install the RRCF package per pip:*$ pip install rrcf*
The codes of this exercise is based on the codebase of the following team:
M. Bartos, A. Mullapudi, & S. Troutman, rrcf: Implementation of the Robust Random Cut Forest algorithm for anomaly detection on streams , in: Journal of Open Source Software, The Open Journal, Volume 4, Number 35. 2019

1.0.1 DESCRIPTION:

This notebook allows you for learning Amazon's Robust Random Cut Forest algorithm and its implementation for detecting anomalies. The Robust Random Cut Forest Algorithm for anomaly detection was invented by Guha et al. in 2016. Further reading can be found here (→ paper):

S. Guha, N. Mishra, G. Roy, & O. Schrijvers, Robust random cut forest based anomaly detection on streams, in Proceedings of the 33rd International conference on machine learning, New York, NY, 2016 (pp. 2712-2721).

1.0.2 TASKS:

The tasks that you need to work on within this notebook are always indicated below as bullet points. If a task is more challenging and consists of several steps, this is indicated as well. Make sure you have worked down the task list and commented your doings. This should be done by using markdown. Make sure you don't forget to specify your name and your matriculation number in the notebook.

YOUR TASKS in this exercise are as follows: 1. import the notebook to Google Colab or use your local machine. 2. make sure you specified you name and your matriculation number in the header below my name and date. * set the date too and remove mine. 3. read the entire notebook carefully * add comments whereever you feel it necessary for better understanding * run the notebook for the first time. 4. take the three data sets from exercize 1 and apply the RRCF to them. 5. interpret the results in writing.

1.0.3 Robust random cut trees (part I)

A RRCT can be instantiated from a point set. Points can also be added and removed from an RRCT.

[1]:
```
import numpy as np
import rrcf
# rrcf is pretty much the same as isolation Forest, but works better on high␣
↪dimensional data
```

A (robust) random cut tree can be instantiated from a point set (n x d)

[2]:
```
X = np.random.randn(30, 2)
tree = rrcf.RCTree(X)
print(tree)
```

```
+
   +
      (12)
      +
         +
            (9)
            +
               (29)
               +
                  (28)
                  (18)
         (6)
```

```
+
    +
        +
            (4)
            (14)
        +
            +
                +
                    (1)
                    (25)
                +
                    (7)
                    (20)
            (2)
    +
        +
            +
                (22)
                (5)
            +
                +
                    (16)
                    (11)
                (3)
        +
            (19)
            +
                +
                    +
                        +
                            (10)
                            (0)
                        (8)
                    (24)
                +
                    (15)
                    +
                        +
                            +
                                (26)
                                (23)
                            +
                                (13)
                                (27)
                        +
                            (17)
                            (21)
```

A random cut tree can also be instantiated with no points. The points can be inserted and removed afterwards.

[3]:
```
tree = rrcf.RCTree()

#Inserting points at index i
for i in range(6):
    x = np.random.randn(2)
    #print("x=",x)
    tree.insert_point(x, index=i)

print(tree)

#Deleting points at index i
tree.forget_point(2)

print(tree)
```

```
+
 (1)
 +
    +
       +
          (0)
          (3)
       +
          (2)
          (5)
    (4)

+
 (1)
 +
    +
       +
          (0)
          (3)
       (5)
    (4)
```

1.0.4 Robust random cut trees (part II)

Anomaly score The likelihood that a point is an outlier is measured by the so-called collusive displacement (CoDisp) score: if including a new point significantly changes the model's complexity (i.e. bit depth), then that point is more likely to be an outlier.

[4]:
```python
# Seed the tree with zero-mean, and hence normally distributed data points
X = np.random.randn(100,2)
tree = rrcf.RCTree(X)

# Generate one inlier and one outlier point
inlier = np.array([0, 0])
outlier = np.array([4, 4])

# Insert both points into the tree
tree.insert_point(inlier, index='inlier')
tree.insert_point(outlier, index='outlier')

# Ask for their codisp (anomaly) score
print("tree.codisp('inlier')=",tree.codisp('inlier'))
print("tree.codisp('outlier')=",tree.codisp('outlier'))
```

```
tree.codisp('inlier')= 1.0
tree.codisp('outlier')= 93.0
```

As a rule of thumb: * scores of max(abs(3 * stdev)) are ok * higher scores are an indication of an outlier.

1.0.5 Robust random cut trees (part III)

Batch anomaly detection This example shows how a robust random cut forest can be used to detect outliers in a batch setting. As you already know, outliers correspond to a larger CoDisp score.

[5]:
```python
import numpy as np
import pandas as pd
import rrcf
import matplotlib.pyplot as plt
```

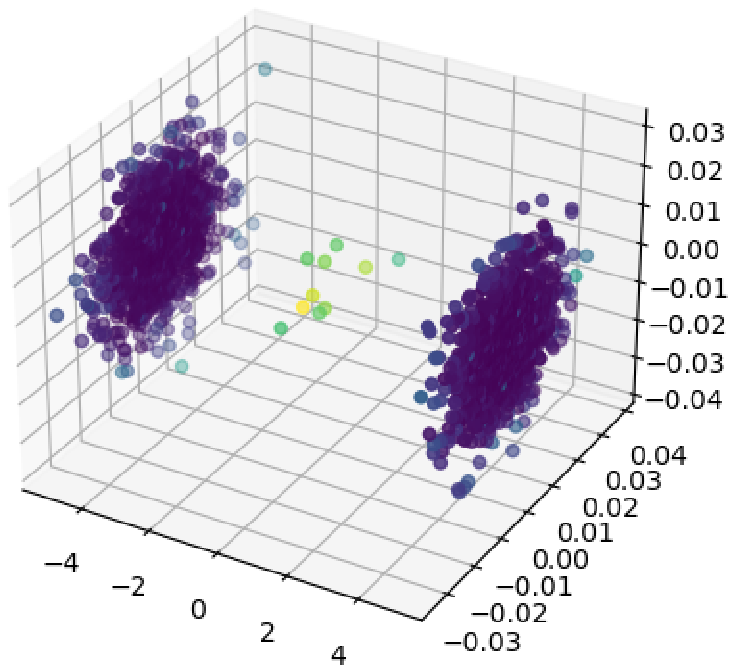
[6]:
```python
'''
In order to create a random forest, we simply create a list of RCTrees,
with each RCTree constructed from a random sample of the input dataset.
Let's create a random forest with 100 trees, each containing 256 points
from the original sample.
'''
# Set parameters
np.random.seed(0)
n = 2010
d = 3
num_trees = 100
tree_size = 256

# Generate a random data set
X = np.zeros((n, d))
```

```python
X[:1000,0] = 5
X[1000:2000,0] = -5
X += 0.01*np.random.randn(*X.shape)


# Construct forest
forest = []
while len(forest) < num_trees:
    # Select random subsets of points uniformly from point set
    ixs = np.random.choice(n, size=(n // tree_size, tree_size),
                           replace=False)
    # Add sampled trees to forest
    trees = [rrcf.RCTree(X[ix], index_labels=ix) for ix in ixs]
    forest += trees

'''
Finally, to determine outliers we compute the average codisp
over all trees for each point in the original sample.
'''
# Compute average CoDisp
avg_codisp = pd.Series(0.0, index=np.arange(n))
index = np.zeros(n)
for tree in forest:
    codisp = pd.Series({leaf : tree.codisp(leaf) for leaf in tree.leaves})
    # print({leaf : tree.codisp(leaf) for leaf in tree.leaves})
    avg_codisp[codisp.index] += codisp
    np.add.at(index, codisp.index.values, 1)

print(index.shape)
avg_codisp /= index

print(avg_codisp)
'''Now, print the average codisp for each set of points.'''
# for the inlier points:
print("AVG_codisp[inlier points]=",round(avg_codisp[:-2000].mean(),2))
# for the outlier points:
print("AVG_codisp[outlier points]=",round(avg_codisp[-10:].mean(),2))
# plt.bar(range(len(avg_codisp)), avg_codisp)
```

```
(2010,)
0        9.421925
1       17.504236
2        3.578805
3        5.145816
4        3.527215
          …
2005    84.226190
```

```
2006    68.506410
2007    68.538889
2008    76.230769
2009    59.571429
Length: 2010, dtype: float64
AVG_codisp[inlier points]= 7.78
AVG_codisp[outlier points]= 73.54
```

[7]:
```python
fig = plt.figure()
ax = fig.add_subplot(projection='3d')
ax.scatter(X[:, 0], X[:, 1], X[:, 2], c=avg_codisp)
plt.show()
```



[8]:
```python
'''
Note that the outlier points again have a larger codisp.
To classify the original points into inlier and outlier classes,
perform a simple threshold test on the codisp result.
'''
# For example:
print("Is outlier?\n",avg_codisp > avg_codisp.quantile(0.99))
```

```
Is outlier?
 0       False
1       False
```

```
2        False
3        False
4        False
         …
2005      True
2006      True
2007      True
2008      True
2009      True
Length: 2010, dtype: bool
```

1.0.6 Robust random cut trees (part IV)

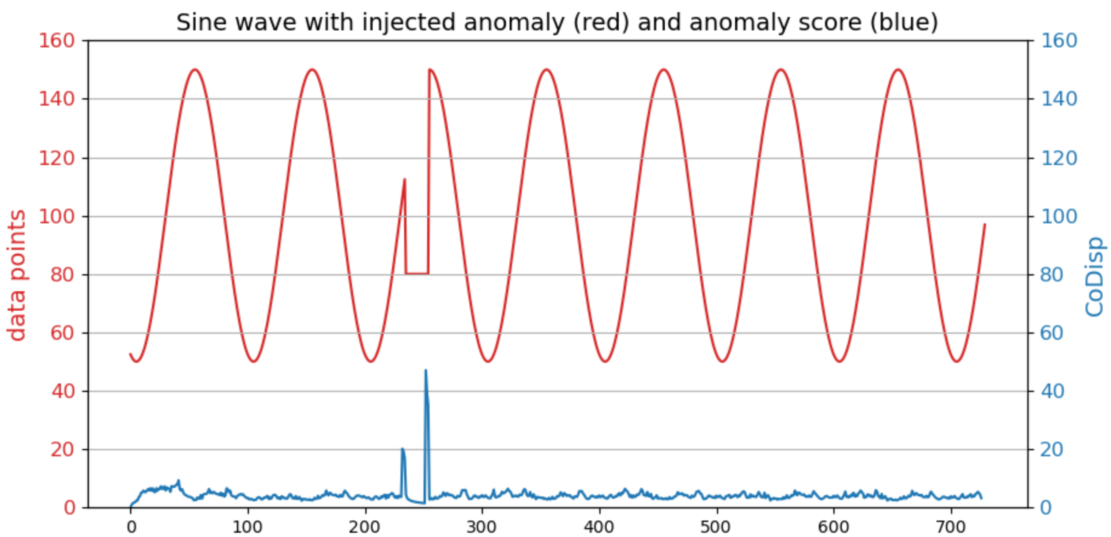
Streaming anomaly detection This example shows how the algorithm can be used to detect anomalies in streaming time series data.

[9]:
```
import numpy as np
import rrcf

# Generate a data set (sine wave with an anomaly inside)
n = 730
A = 50
center = 100
phi = 30
T = 2*np.pi/100
t = np.arange(n)
sin = A*np.sin(T*t-phi*T) + center
sin[235:255] = 80

# Set tree parameters
num_trees = 40
shingle_size = 4
tree_size = 256

# Construct again a forest of empty trees
forest = []
for _ in range(num_trees):
    tree = rrcf.RCTree()
    forest.append(tree)

# Insert streaming points into tree and compute anomaly score
# Use the "shingle" generator to create a rolling window
points = rrcf.shingle(sin, size=shingle_size)

# Create a dict to store anomaly score of each point
avg_codisp = {}

# For each shingle...
```

```python
for index, point in enumerate(points):
    # For each tree in the forest...
    for tree in forest:
        # If tree is above permitted size, drop the oldest point (FIFO)
        if len(tree.leaves) > tree_size:
            tree.forget_point(index - tree_size)
        # Insert the new point into the tree
        tree.insert_point(point, index=index)
        # Compute codisp on the new point and take the average among all trees
        if not index in avg_codisp:
            avg_codisp[index] = 0
        avg_codisp[index] += tree.codisp(index) / num_trees
```

[10]:

```python
'''visualize the originil time series and the CoDisp score'''
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

fig, ax1 = plt.subplots(figsize=(10, 5))

color = 'tab:red'
ax1.set_ylabel('data points', color=color, size=14)
ax1.plot(sin, color=color)
ax1.tick_params(axis='y', labelcolor=color, labelsize=12)
ax1.set_ylim(0,160)
ax2 = ax1.twinx()
color = 'tab:blue'
ax2.set_ylabel('CoDisp', color=color, size=14)
ax2.plot(pd.Series(avg_codisp).sort_index(), color=color)
ax2.tick_params(axis='y', labelcolor=color, labelsize=12)
ax2.grid('off')
ax2.set_ylim(0, 160)
plt.title('Sine wave with injected anomaly (red) and anomaly score (blue)',␣
 ↪size=14)
plt.show()
```



[11]:
```
import pandas as pd

data = pd.read_csv("data/exercise_1/StudentsPerformance.csv")
data.head()
```

[11]:
```
   gender race/ethnicity parental level of education         lunch  \
0  female        group B           bachelor's degree      standard
1  female        group C                some college      standard
2  female        group B             master's degree      standard
3    male        group A          associate's degree  free/reduced
4    male        group C                some college      standard

  test preparation course  math score  reading score  writing score
0                    none          72             72             74
1               completed          69             90             88
2                    none          90             95             93
3                    none          47             57             44
4                    none          76             78             75
```

[12]:
```
# Select random data from data

def rrcf_anom_detection(data: pd.DataFrame, num_trees: int, tree_size: int,␣
 ↪quantile:float) -> pd.DataFrame:
    forest =[]
    for n_tree in range(num_trees):
        ixs = np.random.choice(data.index, tree_size, replace=False)
        forest.append(rrcf.RCTree(data.loc[ixs].to_numpy().astype(float)[:, np.
 ↪newaxis], index_labels=ixs))
```

```
    codisp_sum = np.zeros_like(data.index).astype(float)
    counter = np.zeros_like(data.index)
    for tree in forest:
        for leaf in tree.leaves:
            np.add.at(codisp_sum, leaf, tree.codisp(leaf))
            np.add.at(counter, leaf, 1)
    if np.any(~counter.astype(bool)):
        raise ValueError("Not enough trees or tree size too small")
    return  codisp_sum / counter,  codisp_sum / counter > np.
 ↪quantile((codisp_sum / counter), quantile), np.quantile((codisp_sum /␣
 ↪counter), quantile)

score, outlier_label, threshold = rrcf_anom_detection(data["math score"], 300,␣
 ↪300, .995)
data[outlier_label]
```

[12]:

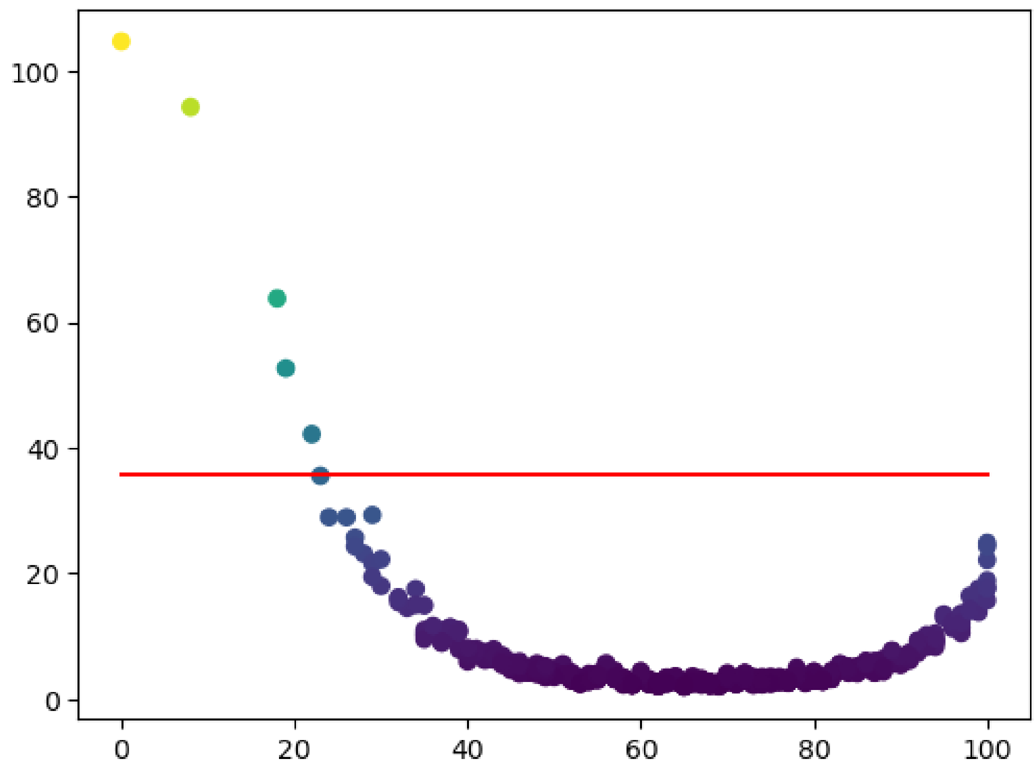
```
     gender race/ethnicity parental level of education         lunch  \
17   female        group B            some high school  free/reduced
59   female        group C            some high school  free/reduced
145  female        group C                some college  free/reduced
787  female        group B                some college      standard
980  female        group B                 high school  free/reduced

    test preparation course  math score  reading score  writing score
17                     none          18             32             28
59                     none           0             17             10
145                    none          22             39             33
787                    none          19             38             32
980                    none           8             24             23
```

[13]:

```
plt.plot([data["math score"].min(), data["math score"].max()], [threshold,␣
 ↪threshold], color="r")
plt.scatter(data["math score"], score, c=score)
```

[13]:

```
<matplotlib.collections.PathCollection at 0x7ff49550e8d0>
```



[14]:
```
data = pd.read_csv("data/exercise_1/city_temperature.csv")
data.drop(data[data["AvgTemperature"] == -99].index, inplace=True)
data["AvgTemperature"] = (data["AvgTemperature"] - 32) * 5/9
data["date"] = pd.to_datetime(data[["Year", "Month", "Day"]])
data = data.set_index("date").groupby(["City", pd.
 ↪Grouper(freq="D")])["AvgTemperature"].mean()
data = data.reset_index()
```

```
/tmp/ipykernel_4887/3201813435.py:1: DtypeWarning: Columns (2) have mixed types.
Specify dtype option on import or set low_memory=False.
  data = pd.read_csv("data/exercise_1/city_temperature.csv")
```

[15]:
```
p_data = data[data["City"] == "Brasilia"]
score, outlier_label, threshold = rrcf_anom_detection(p_data.
 ↪reset_index()["AvgTemperature"], 1000, 400, .995)
p_data[outlier_label]
```

[15]:

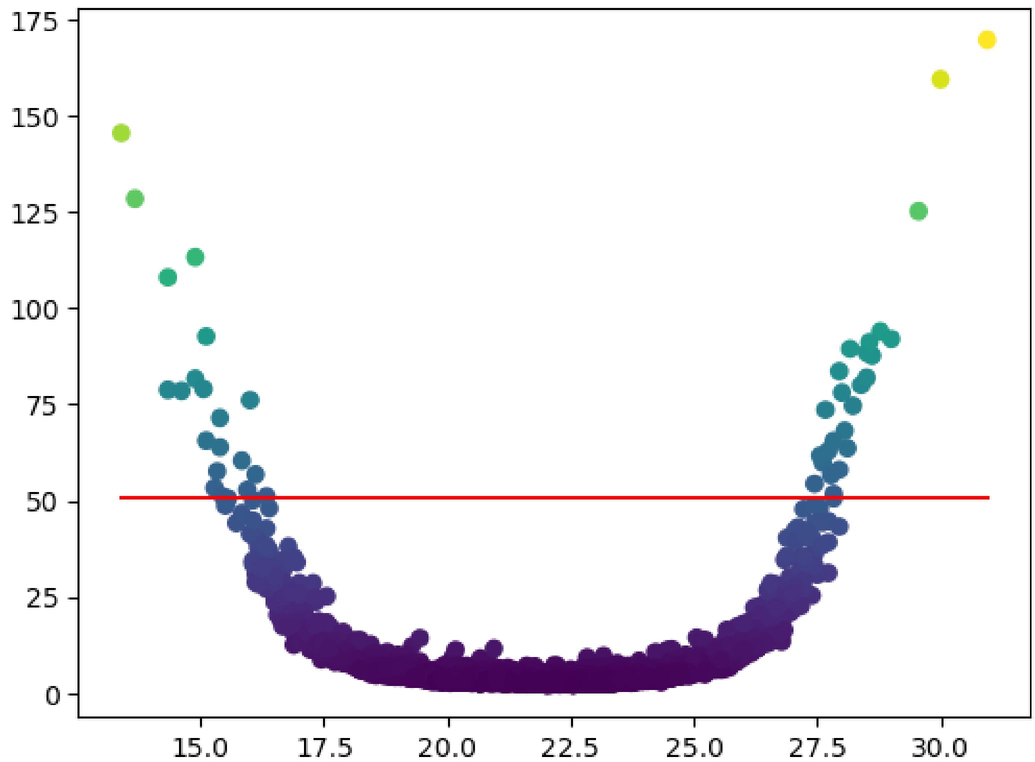
	City	date	AvgTemperature
406288	Brasilia	1996-06-29	13.666667
406289	Brasilia	1996-06-30	14.333333
406632	Brasilia	1997-06-08	15.944444
406633	Brasilia	1997-06-09	15.111111

```
406771   Brasilia 1997-10-25       28.611111
406842   Brasilia 1998-01-04       27.833333
406925   Brasilia 1998-03-30       28.000000
407080   Brasilia 1998-09-06       30.000000
407223   Brasilia 1999-02-17       28.500000
408563   Brasilia 2002-10-26       30.944444
409198   Brasilia 2004-07-24       15.277778
409266   Brasilia 2004-09-30       28.055556
409548   Brasilia 2005-07-09       15.388889
409549   Brasilia 2005-07-10       14.333333
409550   Brasilia 2005-07-11       14.611111
409908   Brasilia 2006-07-04       15.388889
409909   Brasilia 2006-07-05       15.833333
409919   Brasilia 2006-07-15       14.888889
410642   Brasilia 2008-07-09       14.888889
410643   Brasilia 2008-07-10       15.444444
410647   Brasilia 2008-07-14       15.333333
410650   Brasilia 2008-07-17       16.000000
410751   Brasilia 2008-10-28       27.611111
412213   Brasilia 2012-10-30       27.722222
412541   Brasilia 2013-09-23       27.944444
412909   Brasilia 2014-09-28       27.833333
412910   Brasilia 2014-09-29       28.388889
412925   Brasilia 2014-10-14       27.666667
412926   Brasilia 2014-10-15       28.111111
412927   Brasilia 2014-10-16       28.166667
412929   Brasilia 2014-10-18       28.777778
412930   Brasilia 2014-10-19       27.833333
413914   Brasilia 2017-07-04       15.111111
413915   Brasilia 2017-07-05       15.055556
413916   Brasilia 2017-07-06       15.555556
413937   Brasilia 2017-07-27       16.333333
414017   Brasilia 2017-10-15       29.000000
414262   Brasilia 2018-06-18       13.388889
414282   Brasilia 2018-07-08       16.111111
414712   Brasilia 2019-09-20       28.222222
414713   Brasilia 2019-09-21       29.555556
414726   Brasilia 2019-10-04       27.555556
414742   Brasilia 2019-10-20       28.555556
414754   Brasilia 2019-11-01       27.944444
414765   Brasilia 2019-11-12       28.500000
414766   Brasilia 2019-11-13       27.777778
414828   Brasilia 2020-01-14       27.444444
```

[16]:

```
plt.plot([p_data["AvgTemperature"].min(), p_data["AvgTemperature"].max()],␣
  ↪[threshold, threshold], color="r")
plt.scatter(p_data["AvgTemperature"], score, c=score)
```

```
plt.show()
```



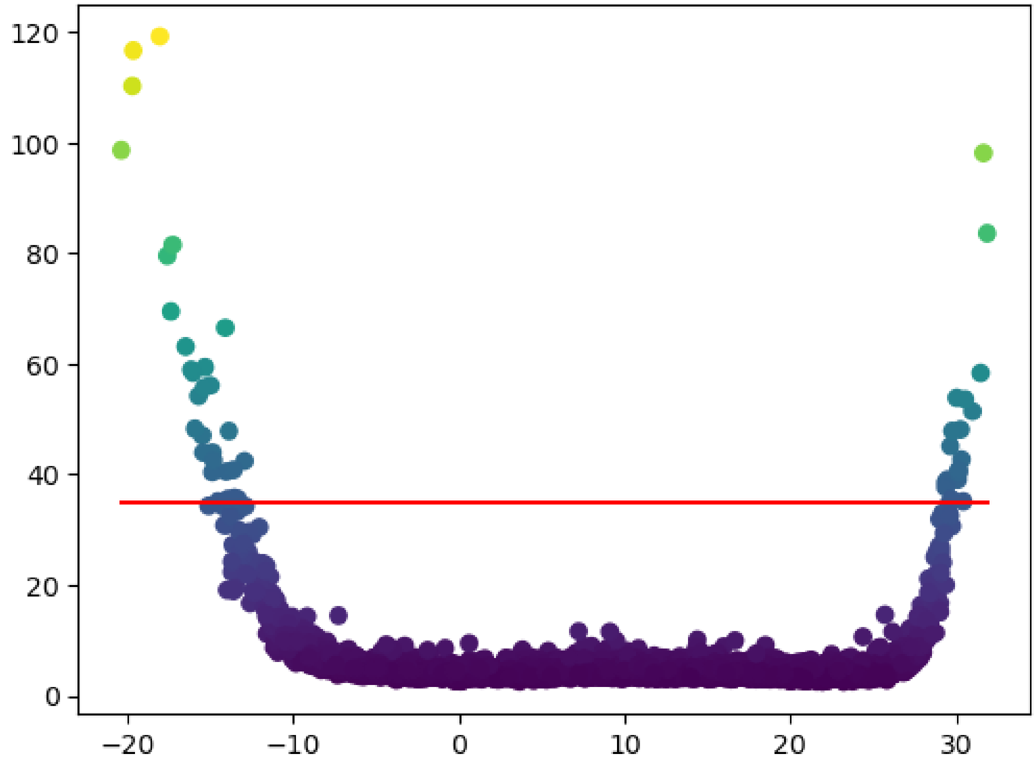
[17]:
```
p_data = data[data["City"] == "Pyongyang"]
score, outlier_label, threshold = rrcf_anom_detection(p_data.
 ↪reset_index()["AvgTemperature"], 1000, 400, .995)
p_data[outlier_label]
```

[17]:

	City	date	AvgTemperature
2008873	Pyongyang	1997-01-21	-14.055556
2009059	Pyongyang	1997-07-26	29.500000
2009060	Pyongyang	1997-07-27	30.111111
2010165	Pyongyang	2000-08-17	31.000000
2010309	Pyongyang	2001-01-11	-17.388889
2010310	Pyongyang	2001-01-12	-18.055556
2010311	Pyongyang	2001-01-13	-17.611111
2010312	Pyongyang	2001-01-14	-19.666667
2010313	Pyongyang	2001-01-15	-20.388889
2010314	Pyongyang	2001-01-16	-19.722222
2011018	Pyongyang	2003-01-05	-15.722222
2011019	Pyongyang	2003-01-06	-15.000000
2011042	Pyongyang	2003-01-29	-14.111111
2011396	Pyongyang	2004-01-21	-17.277778

```
2011397  Pyongyang 2004-01-22      -14.555556
2012907  Pyongyang 2008-08-11       29.388889
2013402  Pyongyang 2009-12-31      -13.888889
2013415  Pyongyang 2010-01-13      -14.888889
2013780  Pyongyang 2011-01-15      -14.888889
2014159  Pyongyang 2012-02-01      -15.333333
2014160  Pyongyang 2012-02-02      -16.055556
2014471  Pyongyang 2012-12-09      -12.944444
2014488  Pyongyang 2012-12-26      -13.611111
2014495  Pyongyang 2013-01-02      -16.166667
2014496  Pyongyang 2013-01-03      -16.500000
2014531  Pyongyang 2013-02-07      -13.555556
2015069  Pyongyang 2014-08-01       29.388889
2015070  Pyongyang 2014-08-02       30.333333
2015608  Pyongyang 2016-01-23      -15.500000
2016292  Pyongyang 2017-12-12      -13.388889
2016321  Pyongyang 2018-01-11      -13.944444
2016333  Pyongyang 2018-01-23      -15.388889
2016334  Pyongyang 2018-01-24      -15.944444
2016335  Pyongyang 2018-01-25      -15.444444
2016336  Pyongyang 2018-01-26      -14.833333
2016515  Pyongyang 2018-07-24       30.555556
2016520  Pyongyang 2018-07-29       30.166667
2016522  Pyongyang 2018-07-31       30.166667
2016523  Pyongyang 2018-08-01       31.666667
2016524  Pyongyang 2018-08-02       31.500000
2016525  Pyongyang 2018-08-03       31.888889
2016526  Pyongyang 2018-08-04       29.666667
2016528  Pyongyang 2018-08-06       29.722222
2016872  Pyongyang 2019-07-27       30.055556
2016882  Pyongyang 2019-08-06       30.277778
2016886  Pyongyang 2019-08-10       29.777778
```

[18]:
```python
plt.plot([p_data["AvgTemperature"].min(), p_data["AvgTemperature"].max()],␣
 ↪[threshold, threshold], color="r")
plt.scatter(p_data["AvgTemperature"], score, c=score)
plt.show()
```



Just as the Isolation Forest this works well for normally and non-normally distributed dataset to detect outliers.

[ ]: