Anomaly detection using K-means

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Clustering: basics

Clustering analysis *is a collection of statistical methods that can be used to assign units to groups, where group members share some characteristic*.

- **data reduction**: reduce data that are homogeneous (similar)
- **find natural clusters** and describe their unknown properties
- **find** useful and suitable **groupings**
- **find** unusual data objects (i.e. outlier detection).

The aim is to find a way of **grouping statistical units** (or variables) in a data set in such a way that: **units are similar within groups and dissimilar among groups**.

Clustering algorithm

The essentials steps for a clustering algorithm are the following:

1. Define a **metric** to evaluate distances between units;
2. Define an **algorithm** to form groups.

A **grouping** algorithm can be:

- **Hierarchical**
- **Non Hierarchical**

Non-hierarchical clustering: K-means

K-means clustering is one of the simplest and popular unsupervised machine learning algorithms. The aim is to find a partition of the dataset into a set of K clusters that optimizes the chosen partitioning criterion.

1. choose K points at random as cluster centers (centroids);
2. assign each unit to its closest centroid, using an opportune distance measure (usually Euclidean or Manhattan);
3. calculate the centroid of each cluster and use it as the new cluster center;
4. go back to step 2, stop when cluster centers do not change any more.

K-means: implementation (1)

- First of all the algorithm choose K random centroid.

```
z = self.rng.permutation(len(X))[:self.k]
X = np.array(X, dtype= "float64")
centers = X[z]
```

K-means: implementation (2)

- The second step of the fit() method is to **calculate the Euclidean distance** between all the dataset points in respect to the K centroids. The distances are used to assign all the points to the nearest cluster, using K labels.

$$d(x, y) = \sqrt[2]{\sum_{i=0}^{n}(x_i - y_i)^2}$$

```
for i in range(self.k):
        distances[:,i] = np.linalg.norm(X - centers[i],
                axis=1)

        labels= np.argmin(distances, axis = 1)
```

K-means: implementation (3)

- For each cluster the algorithm **calculates the new centroid** as the mean of the points assigned to them:

```
for i in range(self.k):
        if(i in labels):
                new_centers = X[labels == i].mean(0)
                center_temp.append(new_centers)
        else:
                center_temp.append(self.farthest(X,
                        distances, labels))
                new_centers = np.array(center_temp,
                        dtype= "float64")
```

K-means: implementation (4)

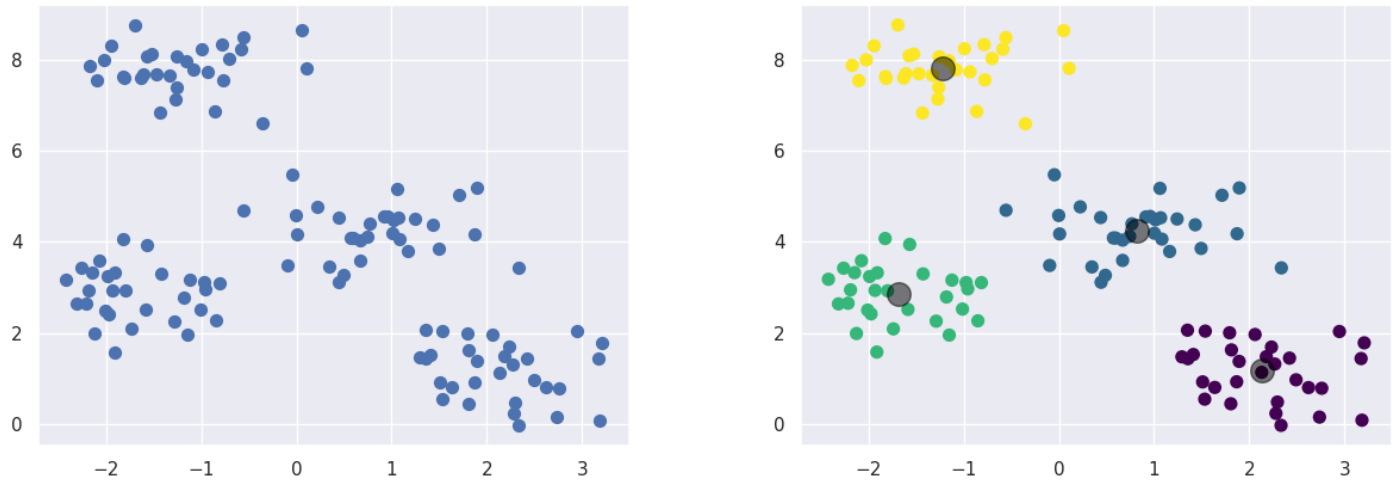
Repeats from point 2 to point 3 until the new centroids are equal to the centroids from the previous step.

```
if np.all(centers == new_centers):
        break

        centers = new_centers
```

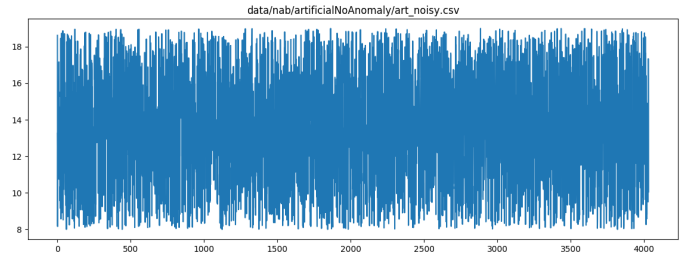
K-means: example

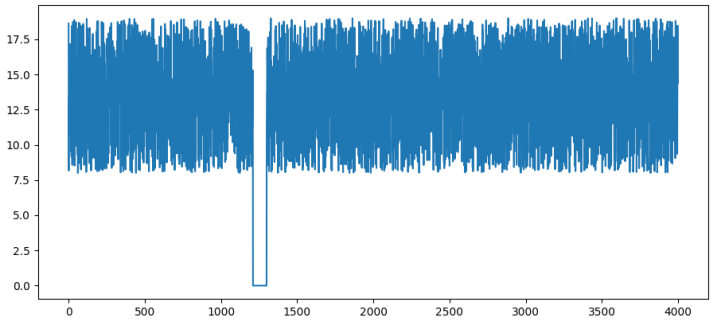
The ***kmeans_sk.py*** file contains an example of usage for the algorithm. The artificial data presents 4 distinct points aggregates. Using the ***fit()*** method with $K = 4$ the algorithm, as we expected, identifies the 4 aggregates of points as 4 clusters.



Anomaly detection using K-means

K-means algorithm can be used to spot anomalies given the normal behaviour.





Anomaly detection using K-means: implementation (1)

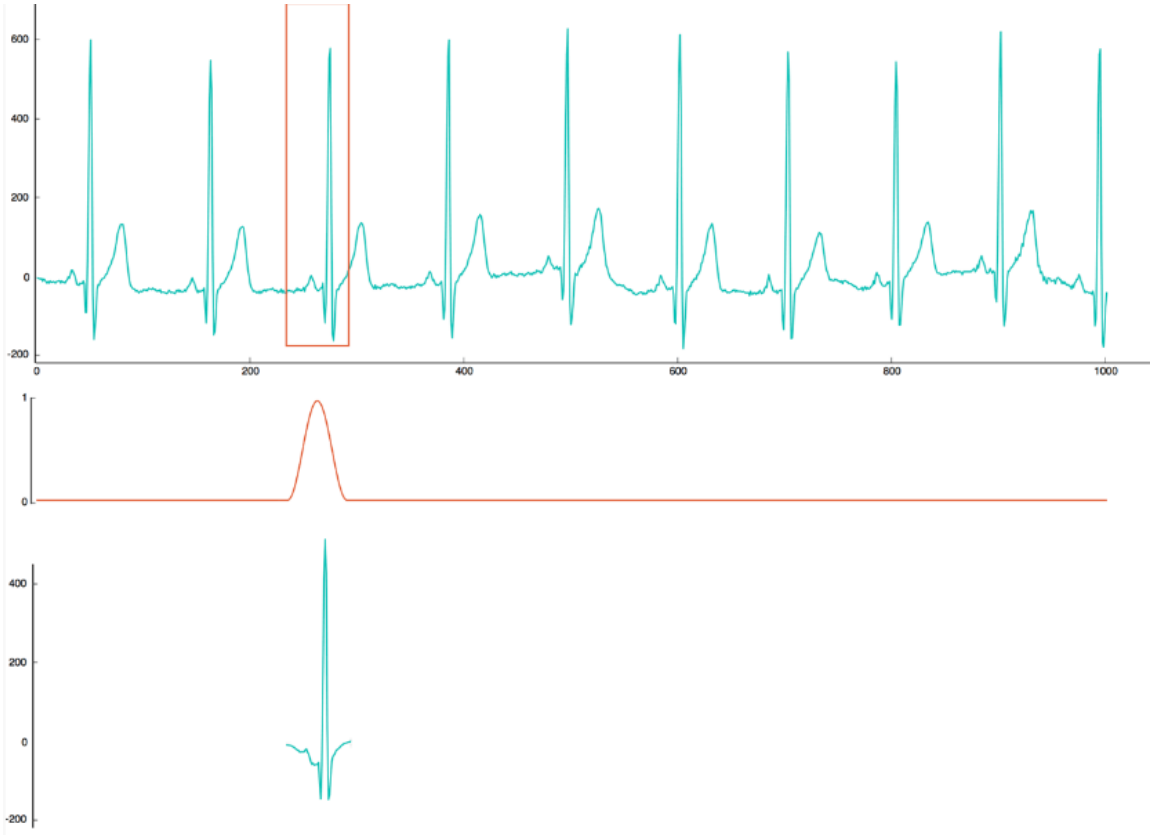
The idea is the following:

- split the waweform into ***n*** segments of length ***l***: every segment is considered a statistical unit;
- apply the K-means algorithm over the l-dimension points obtained (segments). The results are K cluster's *centroids*;
- a centroid is a segments itself that can be used to reconstruct the original waweform: for every segments the nearest centroid is used to approximate the current;

Anomaly detection using K-means: implementation (2)

- once obtained a recostructed waweform using only centroids, we can subtract it from the original: the result is also a waweform that rapresents the noise signal between the two;
- the last step is to use a treshold value to detect where the error between the original and the reconstructed waweforms is anomalous in respect to the noise obtained.

Segmentation



Segmentation

The segmentation is done using the *segmentation()* function implemented in the K-means class.

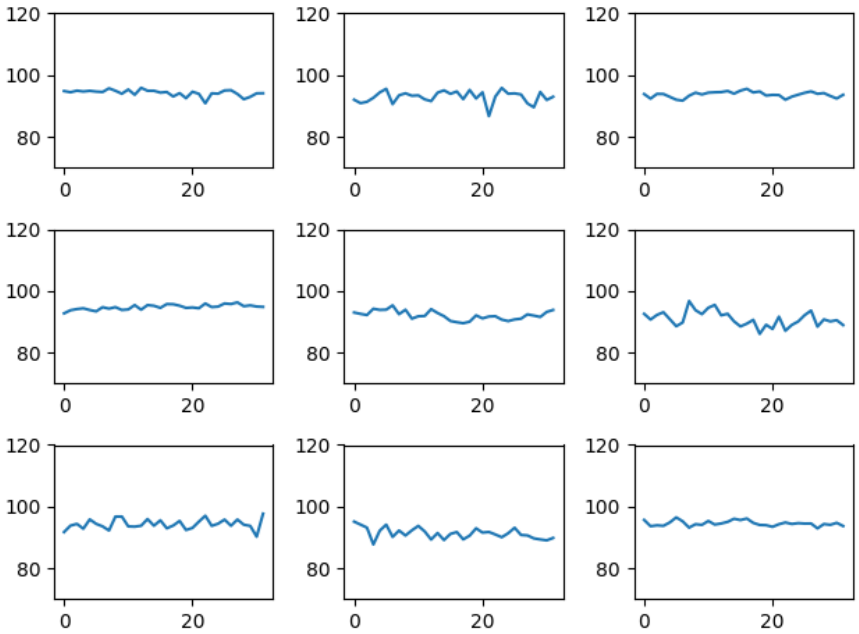
```
segment_len = 32
slide_len = 16
km = skmeans.K_means(30)
segments = km.segmentation(train_array, segment_len, slide_len)
```

The output would be a Numpy's array containing the segments obtained.

Calculate centroids

```
centr = km.fit(segments)
learn_utils.plot_waves(centr, step=3)
```

The output would be a Numpy's array containing K centroids of the dataset. The picture below shows some of the normal waveform obtained.



Reconstruction (1)

Once obtained the centroids we can use them to reconstruct the original waweform. First of all we have to apply again the segmentation process, this time over the entire dataset.

```
segments = km.segmentation(dataset_array, segment_len, slide_len)
lab = km.predict(centr, segments)
```

Reconstruction (2)

Then the ***predict()*** function is used to find, for all the segments obtained, the nearest centroid. The output would be an array wich store in the n-th position a label referring to the nearest centroid for the n-th segment.

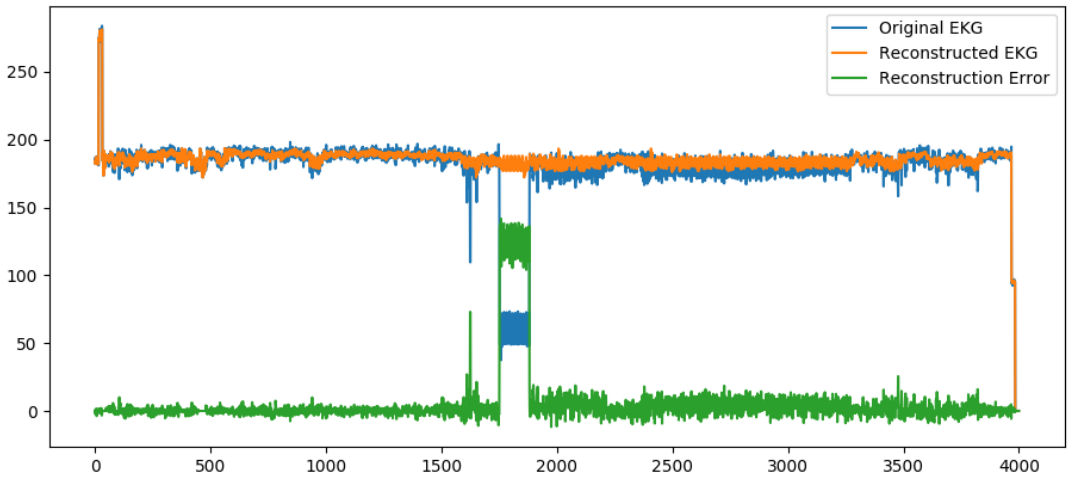
```
Predicted Labels
[12 27 3 14 23 22 27 16 12 26 12 19 4 5 7 6 6 6 28 10 9 1 10 4
29 16 6 21 20 15 13 9 24 7 12 2 17 17 11 1 23 9 10 9 11 11 10 6
6 8 0 8 9 9 1 11 0 23 0 21 26 27 6 8 24 23 25 25 10 23 25 8
9 10 25 1 11 10 5 23 24 0 10 8 9 10 23 23 0 23 23 18 10 10 7 23
                        ..................
20 21 26 21 26 26 21 21 26 21 21 26 20 27  6  7 27 12 27 14  6
21 21 15 21 13 13 27 6 10 0 23 9 0 12 21 12 12 20 20 27 12 27 12
27 21 21 20 23 23 9 0 9 10 10 8 9]
```

Reconstruction (3)

Finally the reconstruction algorithm is used to obtain the whole waweform.

```
noise = detection.reconstruction(dataset_array, segments, lab,
centr, slide_len, segment_len)
```

The noise obtained as output is ploted along with the original and the reconstructed waweform.



Detecting anomalies (1)

The noise obtained from previous step can be analized to detect anomalies:

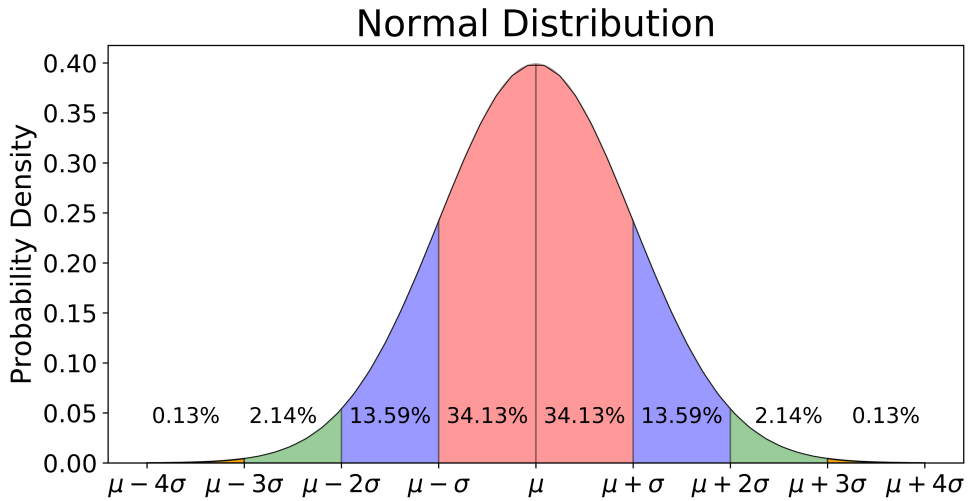
1. the noise signal is defined as being normally distributed with a mean of zero;
2. if it suddenly changes into another distribution, something unusual or anomalous is happening;
3. to spot outliers values in the noise distribution we use a treshold value defined as:

$$mean \pm 4\sigma$$

Detecting anomalies (2)

In fact values lower than $mean - 4\sigma$ deviation and higher than $mean + 4\sigma$ should be extremely rare and could be considered as an anomaly:

- 68% of all values fall between $[mean - \sigma; mean + \sigma]$;
- 95% of all values fall between $[mean - 2\sigma; mean + 2\sigma]$;
- $99,7\%$ of all values fall between $[mean - 3\sigma; mean + 3\sigma]$



Detecting anomalies (3)

```
pos_treshold = np.mean(noise) + coef * np.std(noise)
neg_treshold = np.mean(noise) - coef * np.std(noise)
anomalies = []

for i in range(0,len(noise)):
        if(noise[i] <= neg_treshold):
                anomalies.append((i,noise[i]))
        if(noise[i] > pos_treshold):
                anomalies.append((i, noise[i]))
```

Detecting anomalies (4)

The *if* branches are used to detect and store anomalies in a Python list, returned as output of the function.

```
[[1752.     136.241]
[1753.     136.351]
[1754.     137.356]
[1755.     137.524]
.
.
.
[1875.     133.178]
[1876.     127.938]
[1877.     135.216]
[1878.     135.596]
[1879.     109.638]
[1880.     136.132]]
```

Libraries

```
import skmeans
import matplotlib.pyplot as plt
import learn_utils
import numpy as np
import import_dataset as imp
import detection
```

Conclusion

The first part of the code (noise production) can be used as base to implement an anomaly detection wich use different approach for detection:

- a sliding window can be used to detect changes in the noise distribution rather then use a treshold value to detect outliers values;
- if the mean and standard derivation of this window change too much from their expected values, we can deduce an anomaly.
- the use of the sliding windows could be combined with the outliers detection to improve the detection precision.

Dataset

The dataset used is the Numenta Anomaly Benchmark (NAB) that is a benchmark for evaluating algorithms for anomaly detection in streaming and online applications.

The dataset is open source and available for dowload at: github.com/numenta/NAB.

Project's repository

The code of the project can be reached at https://github.com/GeorgeSmiley/masl.