Anomaly Detection

Softnix Technology

Chakrit Phain

Agenda Day 1

- Introduction to Anomaly Detection
- Anomaly Detection with Distribution
- Anomaly Detection with Boxplot
- Anomaly Detection with DB-Scan
- Anomaly Detection with Local Outlier Factor

Agenda Day 2

- Anomaly Detection and Supervised Learning
- Neural Network & Deep Learning
- Anomaly Detection with LSTM & GRU
- Anomaly Detection with Autoencoder
- Anomaly Detection with Variational Autoencoder

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Anomaly Detection

Day 1

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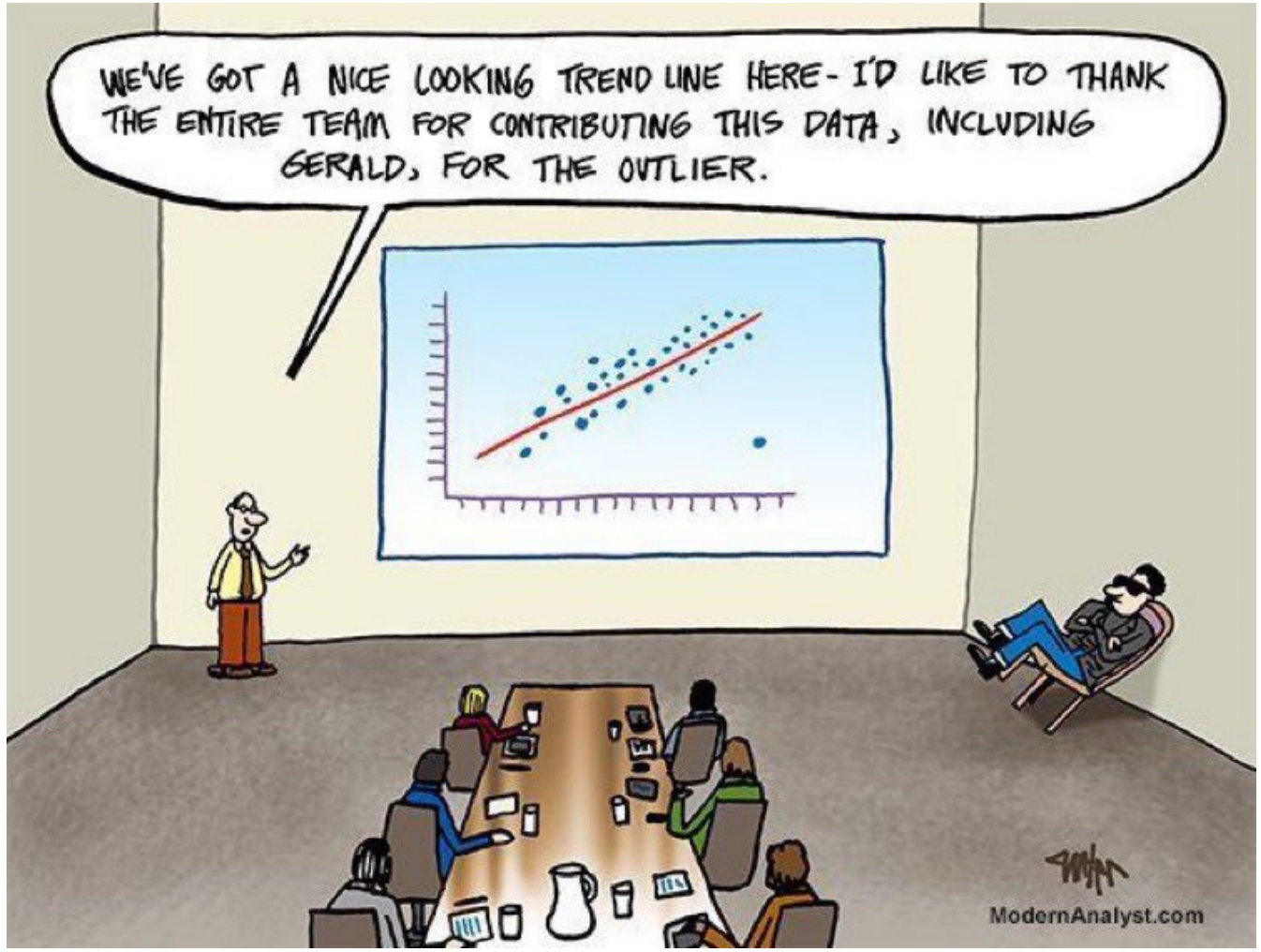
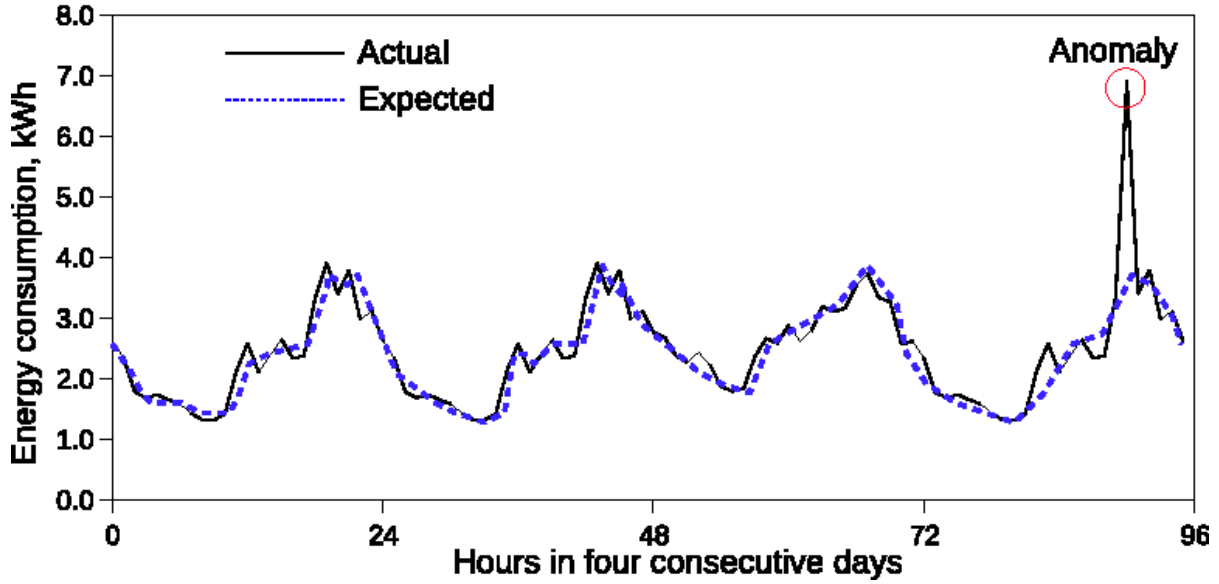
Introduction to Anomaly Detection

Introduction



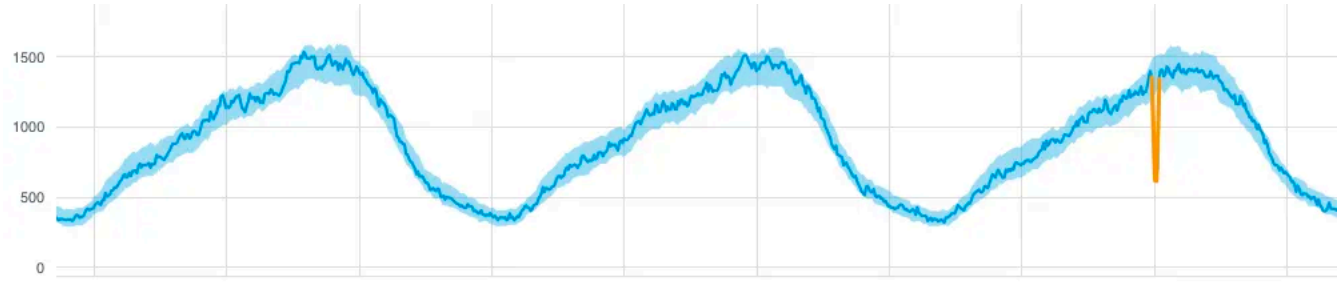
Introduction

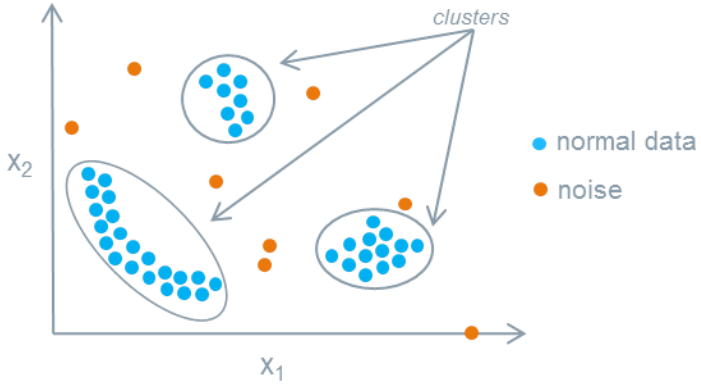
In data mining, **anomaly detection** (also **outlier detection**[1]) is the identification of rare items, events or observations which raise suspicions by differing significantly from the majority of the data.



https://en.wikipedia.org/wiki/Anomaly_detection

Introduction





https://www.anodot.com/blog/what-is-anomaly-detection/

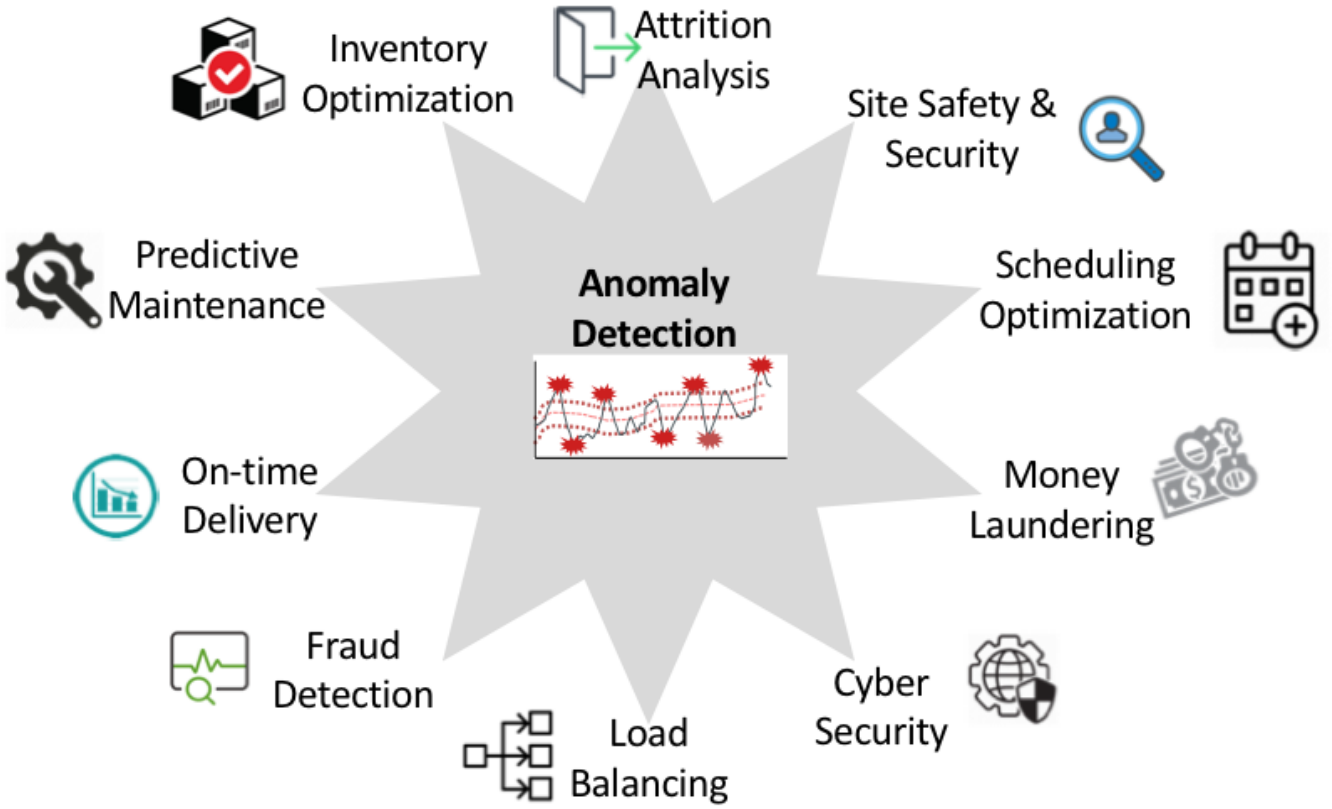
https://developer.mindsphere.io/apis/analytics-anomalydetection/api-anomalydetection-overview.html

Applications of Anomaly Detection in the Business world

- Intrusion detection
  - Attacks on computer systems and computer networks.
- Fraud detection
  - The purchasing behavior of some one who steals a credit card is probably different from that of the original owner.
- Ecosystem Disturbance.
  - Hurricanes , floods , heat waves … etc
- Medicine.
  - Unusual symptoms or test result may indicate potential health problem.

https://zindi.africa/blog/introduction-to-anomaly-detection-using-machine-learning-with-a-case-study

Applications of Anomaly Detection in the Business world



https://www.datasciencecentral.com/profiles/blogs/driving-ai-revolution-with-pre-built-analytic-modules

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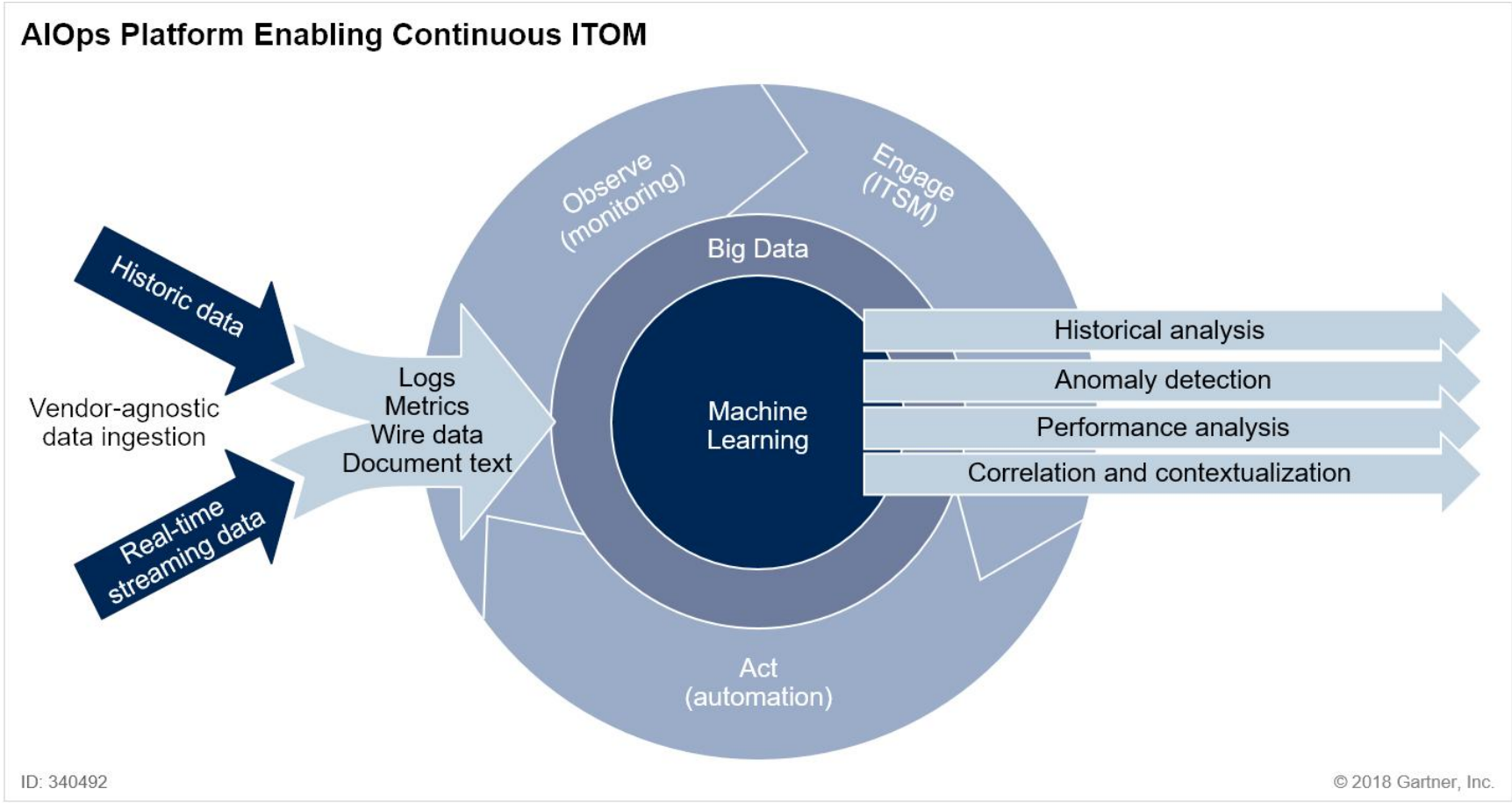
AIOps

AIOps


AIOps Platform Enabling Continuous ITOM
Historic data
Vendor-agnostic data ingestion
Real-time streaming data
Logs
Metrics
Wire data
Document text
Observe (monitoring)
Engage (ITSM)
Act (automation)
Big Data
Machine Learning
Historical analysis
Anomaly detection
Performance analysis
Correlation and contextualization
ID: 340492
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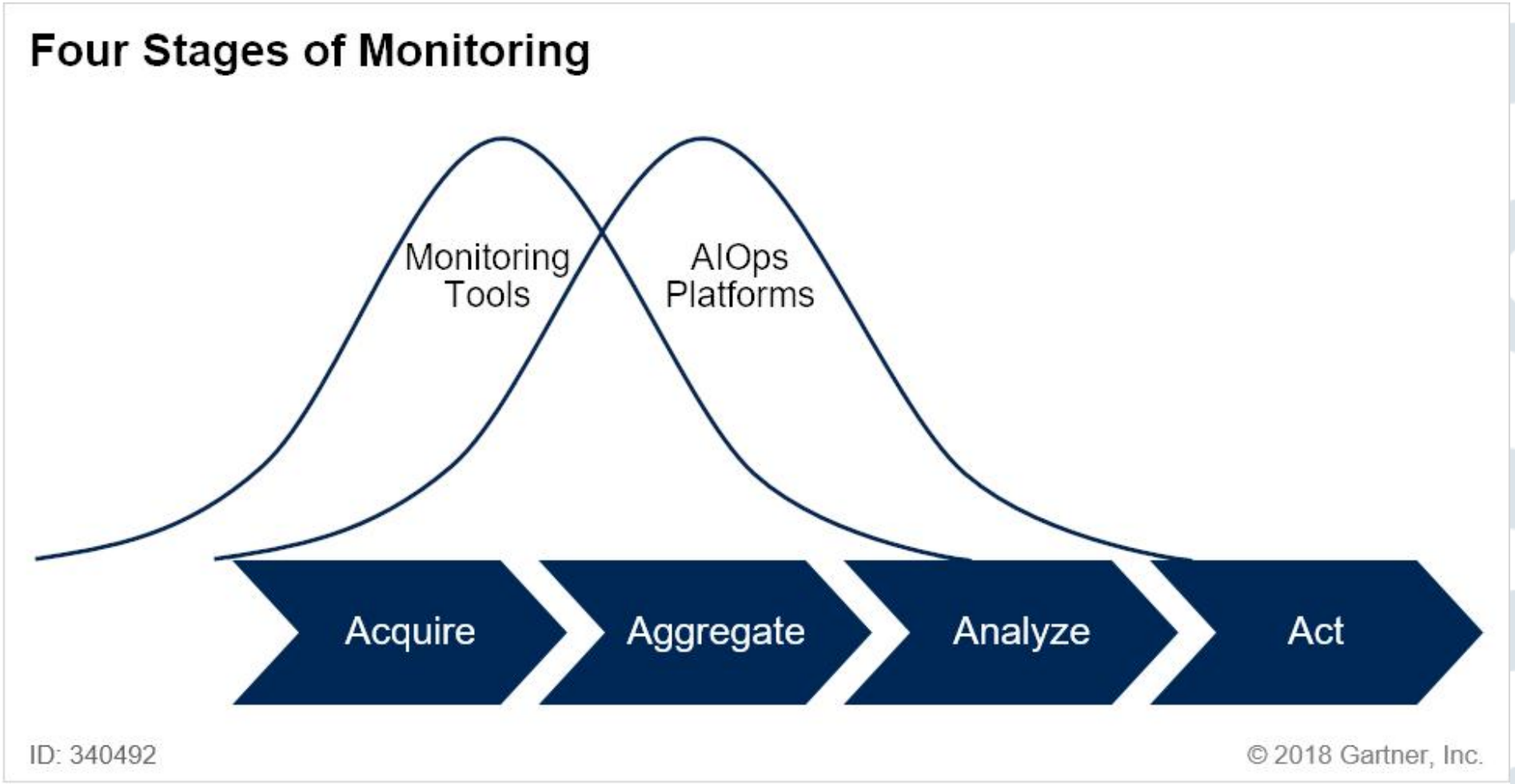
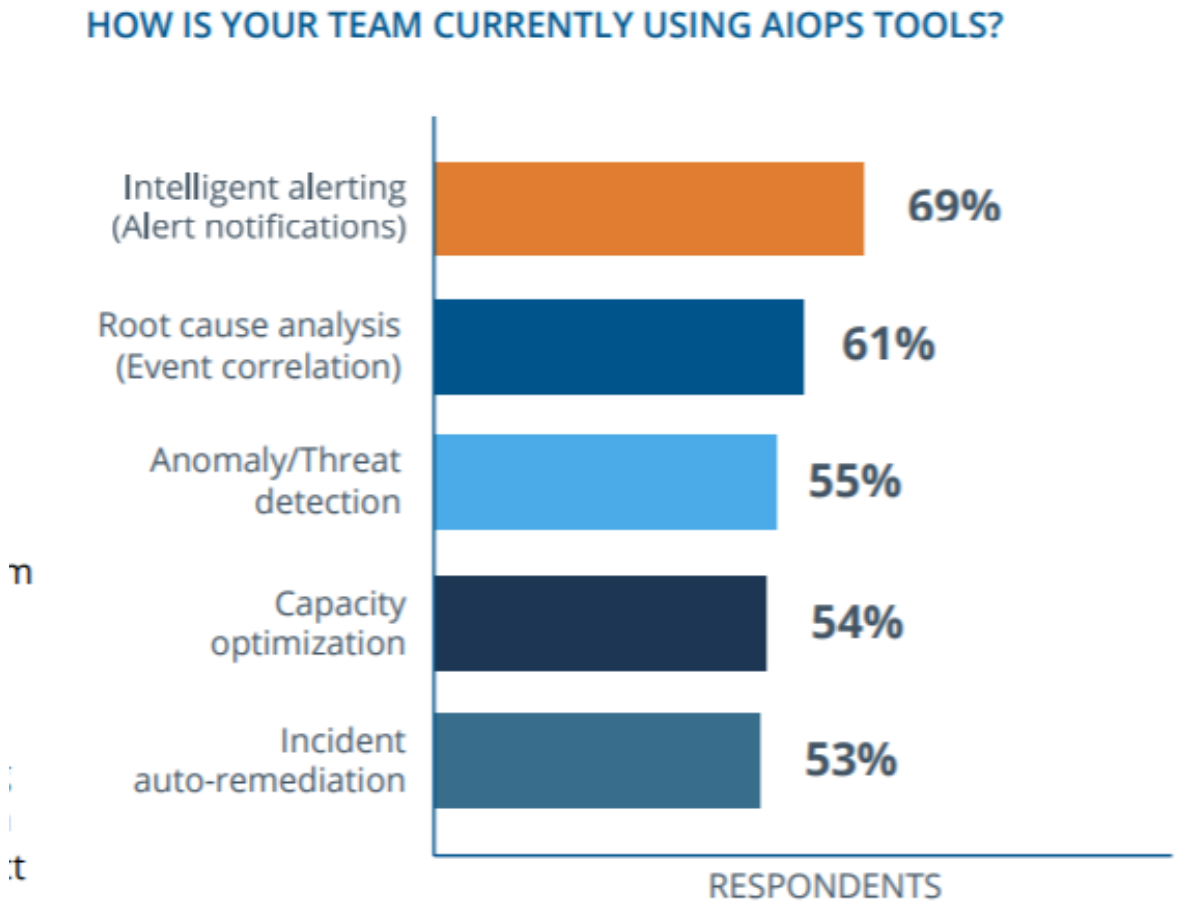


AIOps



https://infrastructureedge.blogspot.com/2019/09/enterprise-it-managers-say-aiops-works.html?utm_source=dlvr.it&utm_medium

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Graph Database

Fraud Detection for Graph analytic

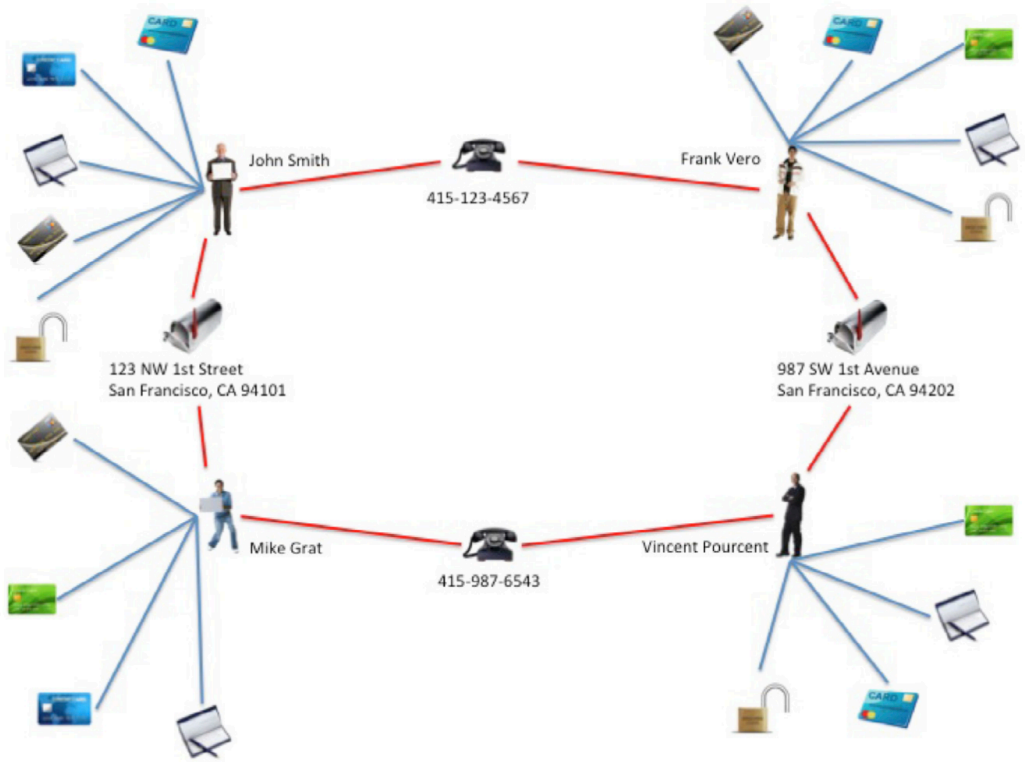

Diagram 1: 2 people sharing 2 pieces of data and creating 4 synthetic identities

https://neo4j.com/whitepapers/fraud-detection-graph-databases/?ref=blog

Insurance Fraud

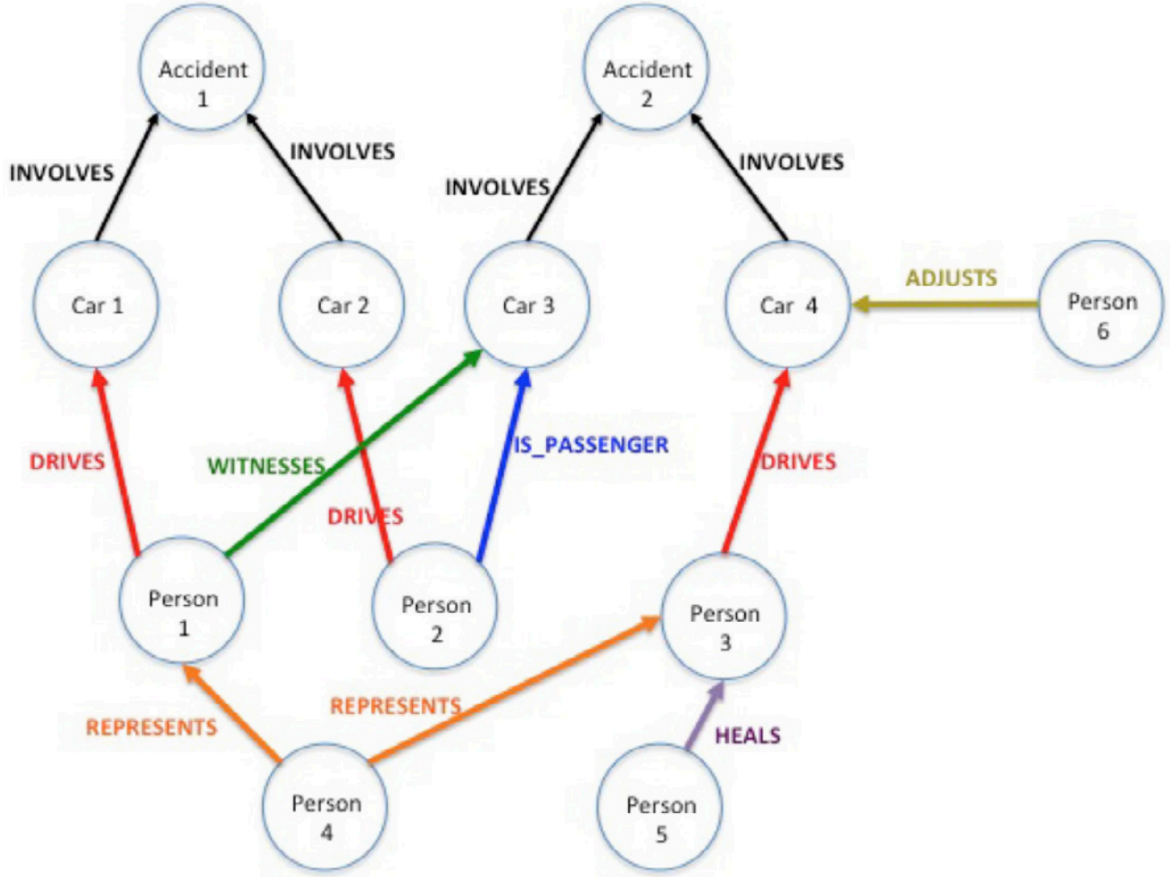

Diagram 7: A Graph Representation of Insurance Fraud

https://neo4j.com/whitepapers/fraud-detection-graph-databases/?ref=blog

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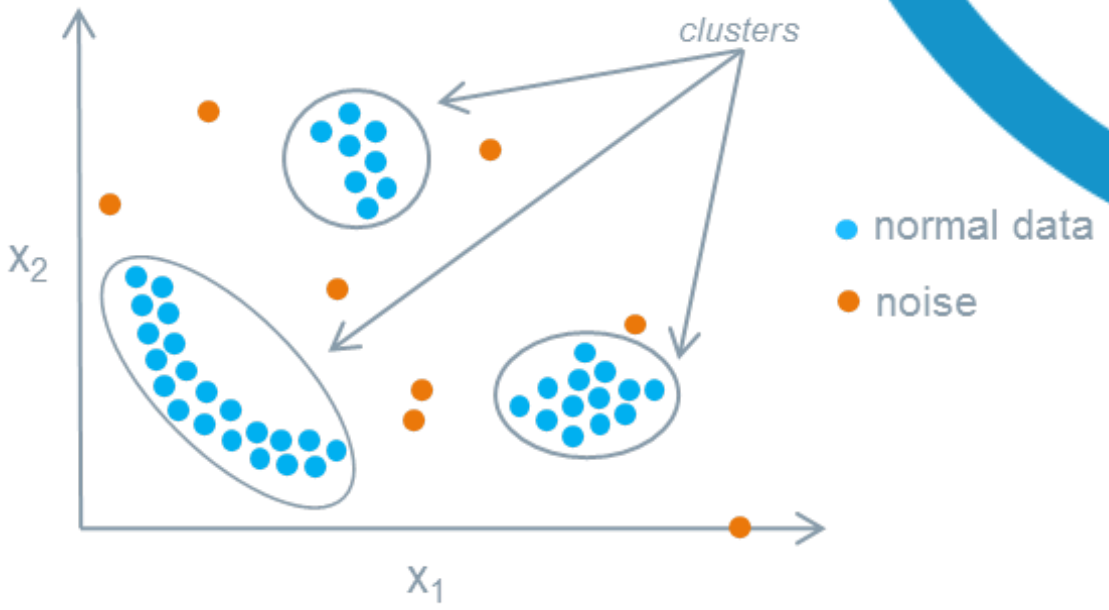
Type of Anomaly

Anomalies can be broadly categorized as

1. **Point Anomalies**
2. Contextual Anomalies
3. Collective Anomalies



If an individual data instance can be considered as anomalous with respect to the rest of data, then the instance is termed as a point anomaly.

Chandola, V., Banerjee, A. & Kumar, V., 2009. Anomaly Detection: A Survey. ACM Computing Surveys, July. 41(3).

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1. Point Anomalies
2. **Contextual Anomalies**
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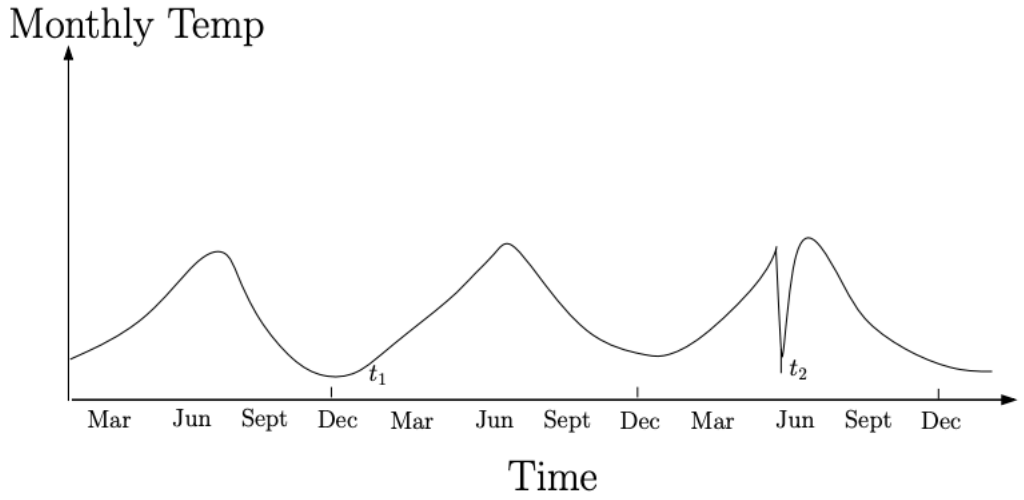
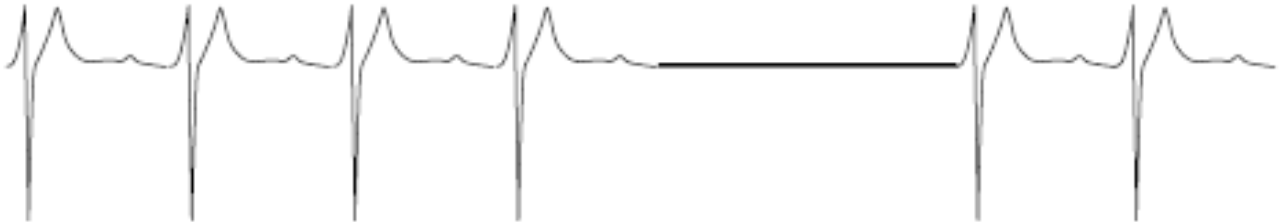


If a data instance is anomalous in a specific context (but not otherwise), then it is termed as a contextual anomaly

Chandola, V., Banerjee, A. & Kumar, V., 2009. Anomaly Detection: A Survey. ACM Computing Surveys, July. 41(3).

Anomalies can be broadly categorized as

1. Point Anomalies
2. Contextual Anomalies
3. **Collective Anomalies**



If a collection of related data instances is anomalous with respect to the entire data set, it is termed as a collective anomaly

Chandola, V., Banerjee, A. & Kumar, V., 2009. Anomaly Detection: A Survey. ACM Computing Surveys, July. 41(3).

How to Identify Outliers in your Data

1. Extreme Value Analysis
2. Proximity Methods
3. Projection Methods
4. Methods Robust to Outliers

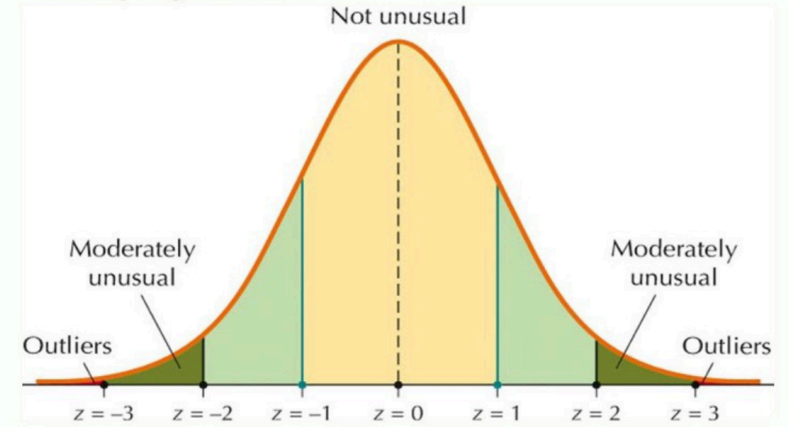
Welcome! I'm **Jason Brownlee** PhD and I help developers get results with machine learning.
Read More

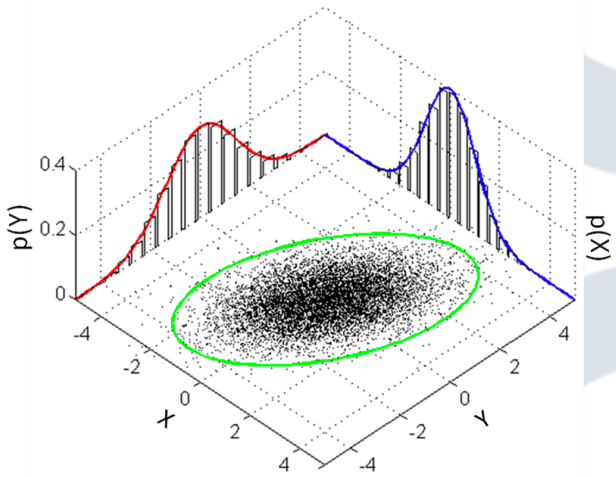
https://machinelearningmastery.com/how-to-identify-outliers-in-your-data/

How to Identify Outliers in your Data

1. **Extreme Value Analysis**
2. Proximity Methods
3. Projection Methods
4. Methods Robust to Outliers

1. Focus on univariate methods
2. Visualize the data using scatterplots, histograms and box and whisker plots and look for extreme values
3. Assume a distribution (Gaussian) and look for values more than 2 or 3 standard deviations from the mean or 1.5 times from the first or third quartile
4. Filter out outliers candidate from training dataset and assess your models performance





https://machinelearningmastery.com/how-to-identify-outliers-in-your-data/
https://en.wikipedia.org/wiki/Multivariate_normal_distribution

How to Identify Outliers in your Data

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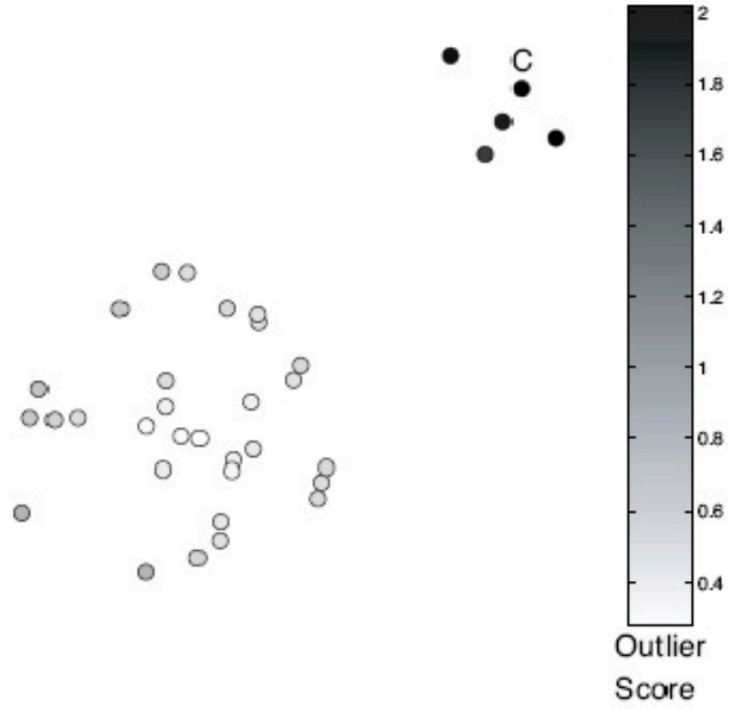

Figure 10.6. Outlier score based on distance to the fifth nearest neighbor. A small cluster becomes an outlier.

https://machinelearningmastery.com/how-to-identify-outliers-in-your-data/

How to Identify Outliers in your Data

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2. Proximity Methods
3. **Projection Methods**
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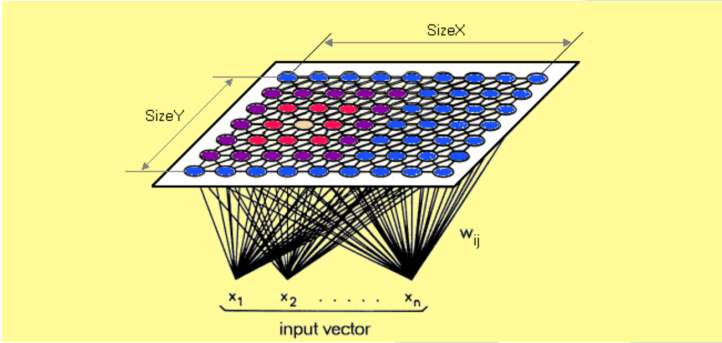
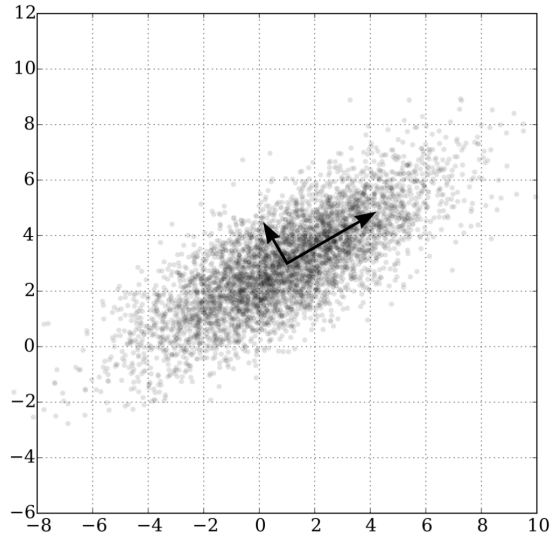




https://machinelearningmastery.com/how-to-identify-outliers-in-your-data/

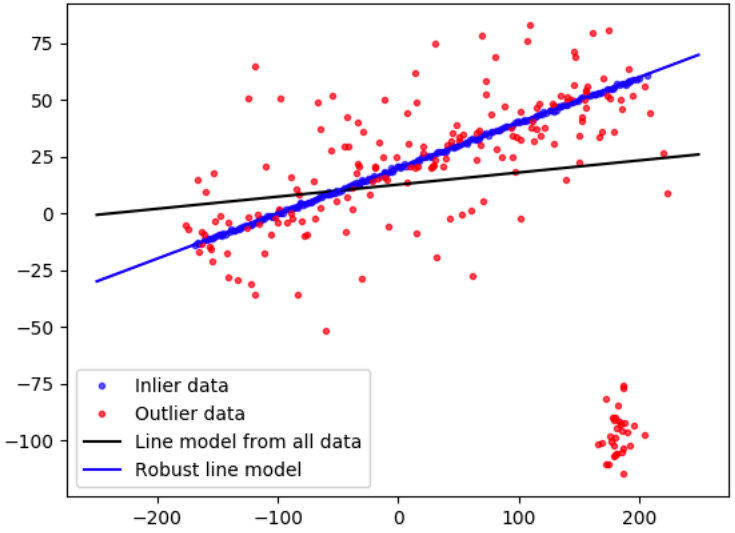
How to Identify Outliers in your Data

1. Extreme Value Analysis
2. Proximity Methods
3. Projection Methods
4. **Methods Robust to Outliers**

$$mean\_squared\_error = \frac{\sum (outputs - targets)^2}{instances\_number}$$

$$MAE = \frac{\sum_{i=1}^{n} |y_i - y_i^p|}{n}$$

$$minkowski\_error = \frac{\sum (outputs - targets)^{minkowski\_parameter}}{instances\_number}$$



https://machinelearningmastery.com/how-to-identify-outliers-in-your-data/

Typology of Anomalies

Cardinality of Relationship		Types of data: Continuous attributes	Types of data: Categorical attributes	Types of data: Mixed attributes
	Univariate Described by individual attributes (independence)	Type I Extreme value anomaly	Type II Rare class anomaly	Type III Simple mixed data anomaly
	Multivariate Described by multi-dimensionality (dependence)	Type IV Multidimensional numerical anomaly	Type V Multidimensional rare class anomaly	Type VI Multidimensional mixed data anomaly

From: Foorthuis (2018), 'A Typology of Data Anomalies', IPMU 2018.

https://tunguska.home.xs4all.nl/Publications/AD_Typology.htm

Anomaly based IDS using Backpropagation Neural Network

- Vrushali D. Mane ME (Electronics) JNEC, Aurangabad
- S.N. Pawar Associate Professor JNEC, Aurangabad
- Neural Network detect 98% accuracy

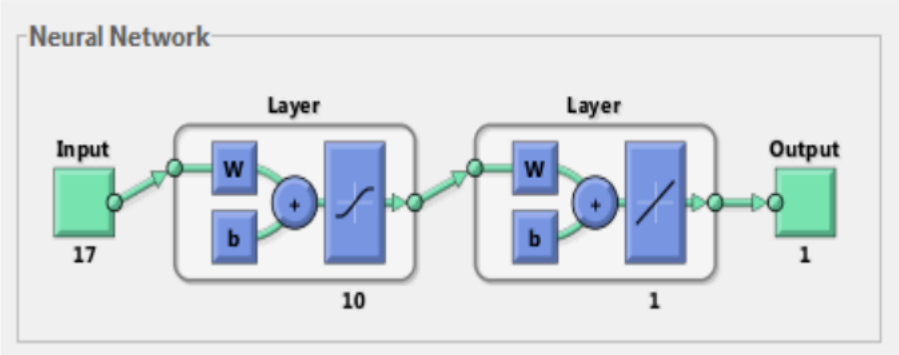
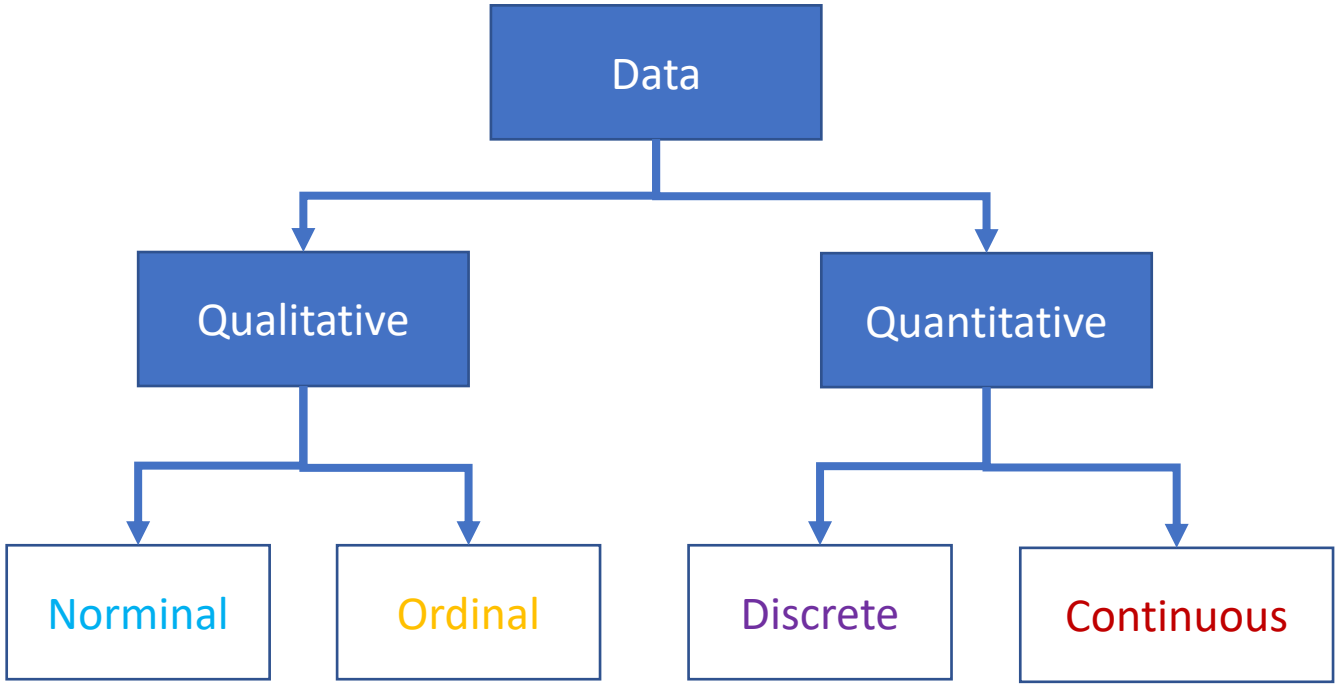


Fig 2: Neural network training model.

https://pdfs.semanticscholar.org/3ac9/37cb50bad238091fba6d1076a78136fe8691.pdf

Type of Data



- ชาย , หญิง
- PC , Notebook , Tablet
- กาแฟ , น้ำเปล่า , น้ำส้ม

- ทองแดง , เงิน , ทอง
- ร้อน , อุ่น , เย็น
- ปานกลาง , สวย , สวยมาก

- 1 , 2 , 3 , 4 , 5

- 1 , 1.1 , 1.5 , 1.6 , 2

EDA Methods

EDA Methods

Descriptive statistics

Central tendency of a distribution

Mean	Sum of all values / Total number of values
Median	Middle value(when data are arranged in order
Mode	Most common value

Measure of Variation

Variance	**how far a set of numbers are spread out from mean**
Interquartile range	divides a data set into quartiles.
Standard deviation	dispersion of a set of data from mean

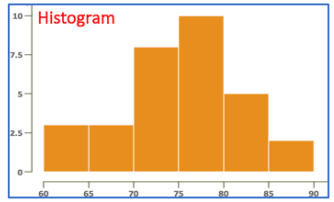
Skewness & Kurtosis

Skewness	**Measure of symmetry**
Kurtosis	**Kurtosis is a measure of "peakedness" relative to a Gaussian shape**

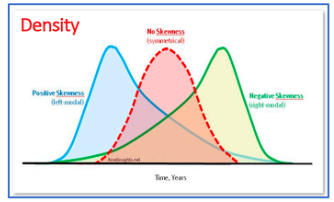
Visualizations

1-dimension

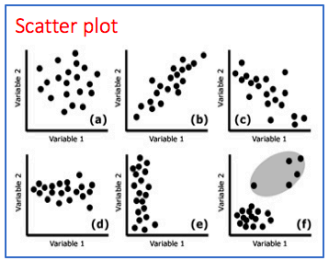
Few data points



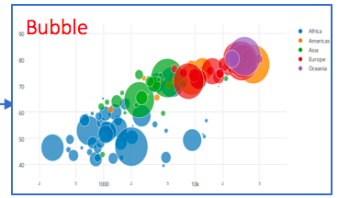
Many data points



2-dimension



3-dimension



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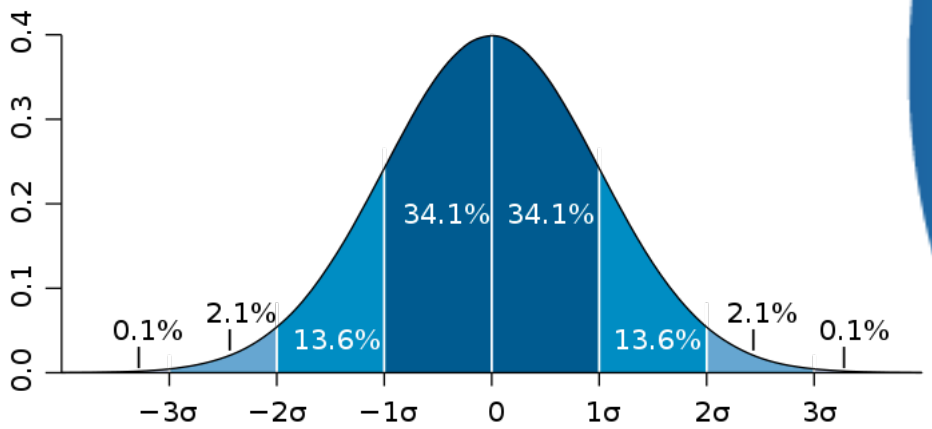
Anomaly Detection with Distribution

Normal Distribution

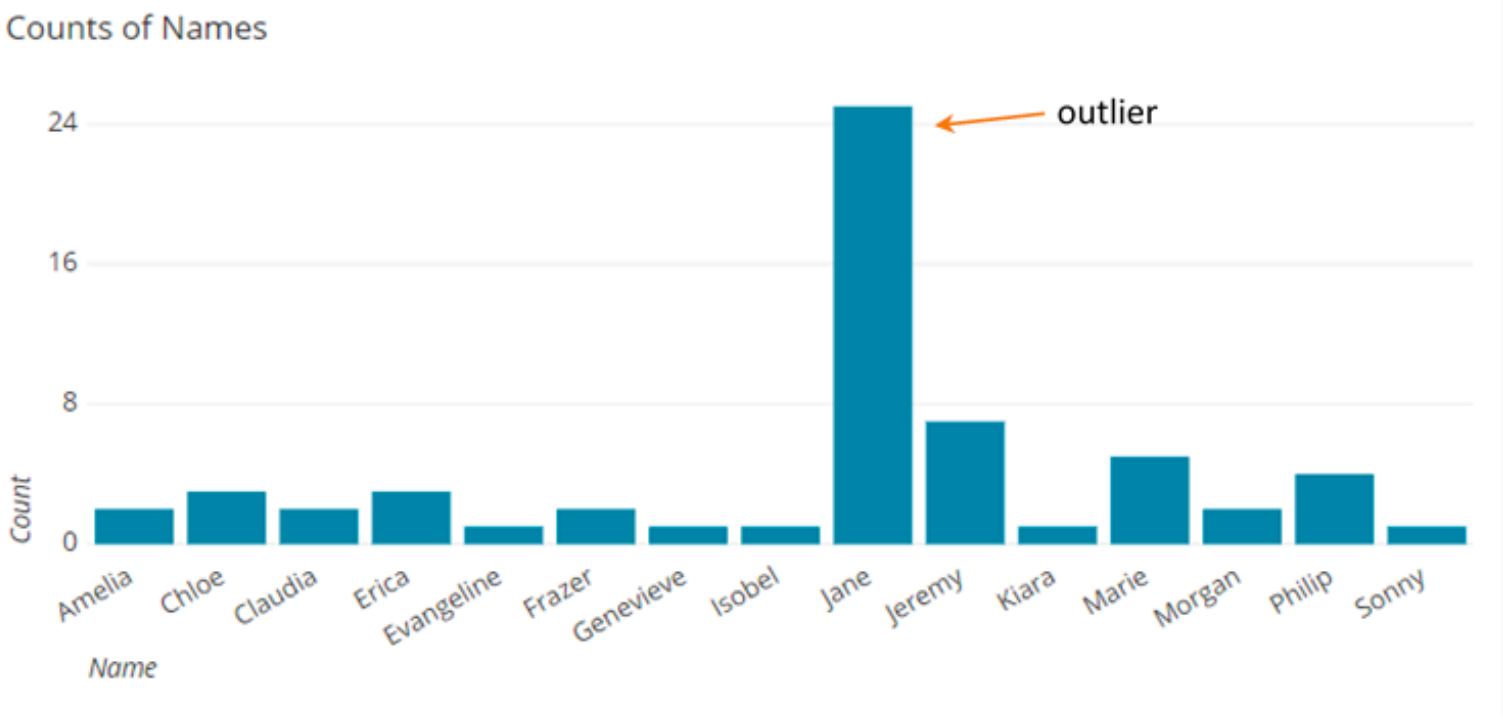
If a continuous random variable has a distribution with a graph that is symmetric and bell-shaped and can be described by the equation

$$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$



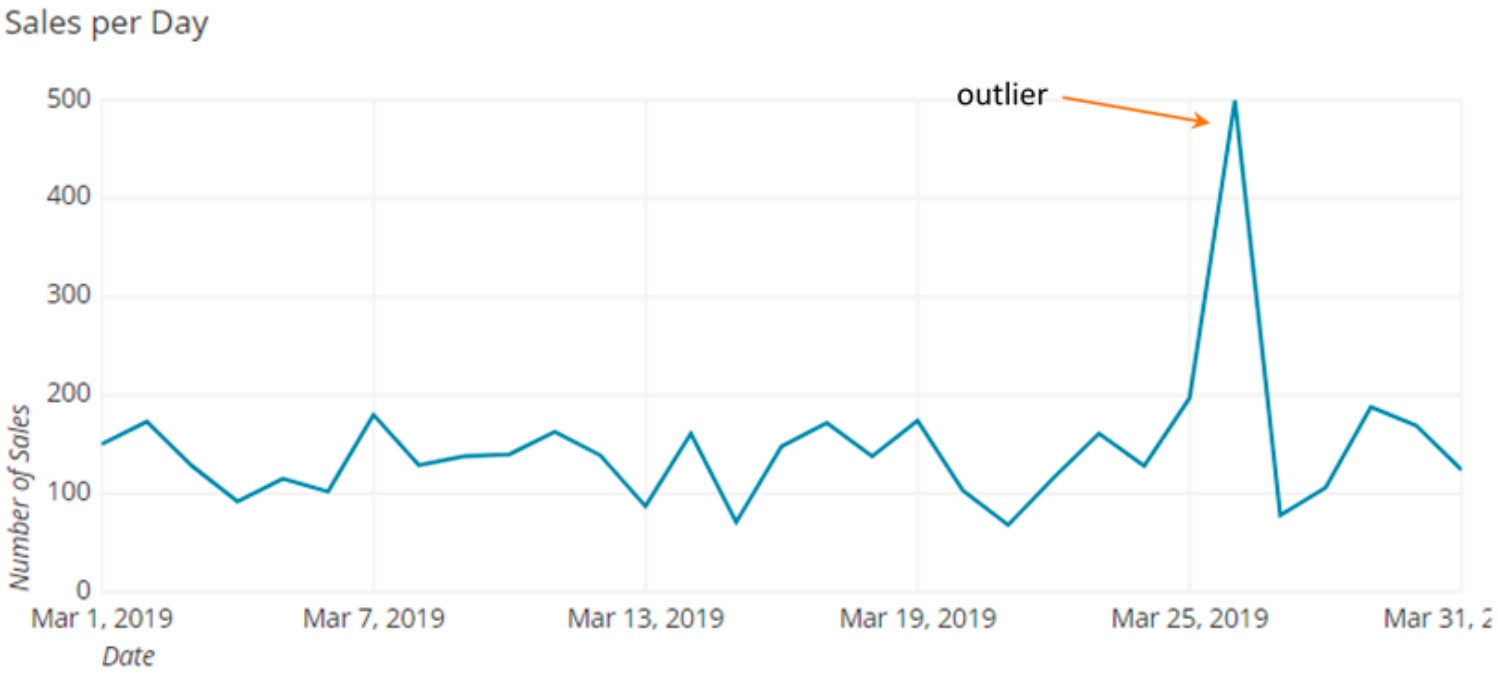
We say that it has a normal distribution

Anomaly Example



https://dataschool.com/fundamentals-of-analysis/what-is-an-outlier/

Anomaly Example



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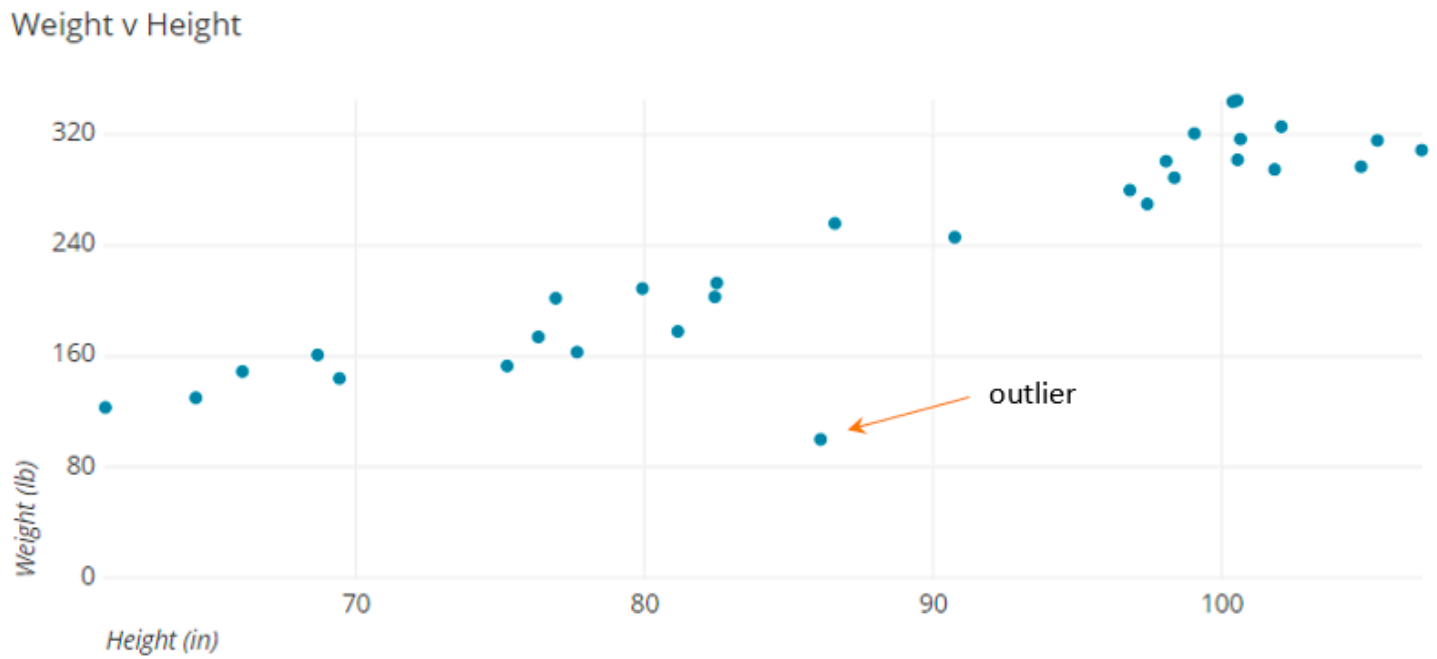
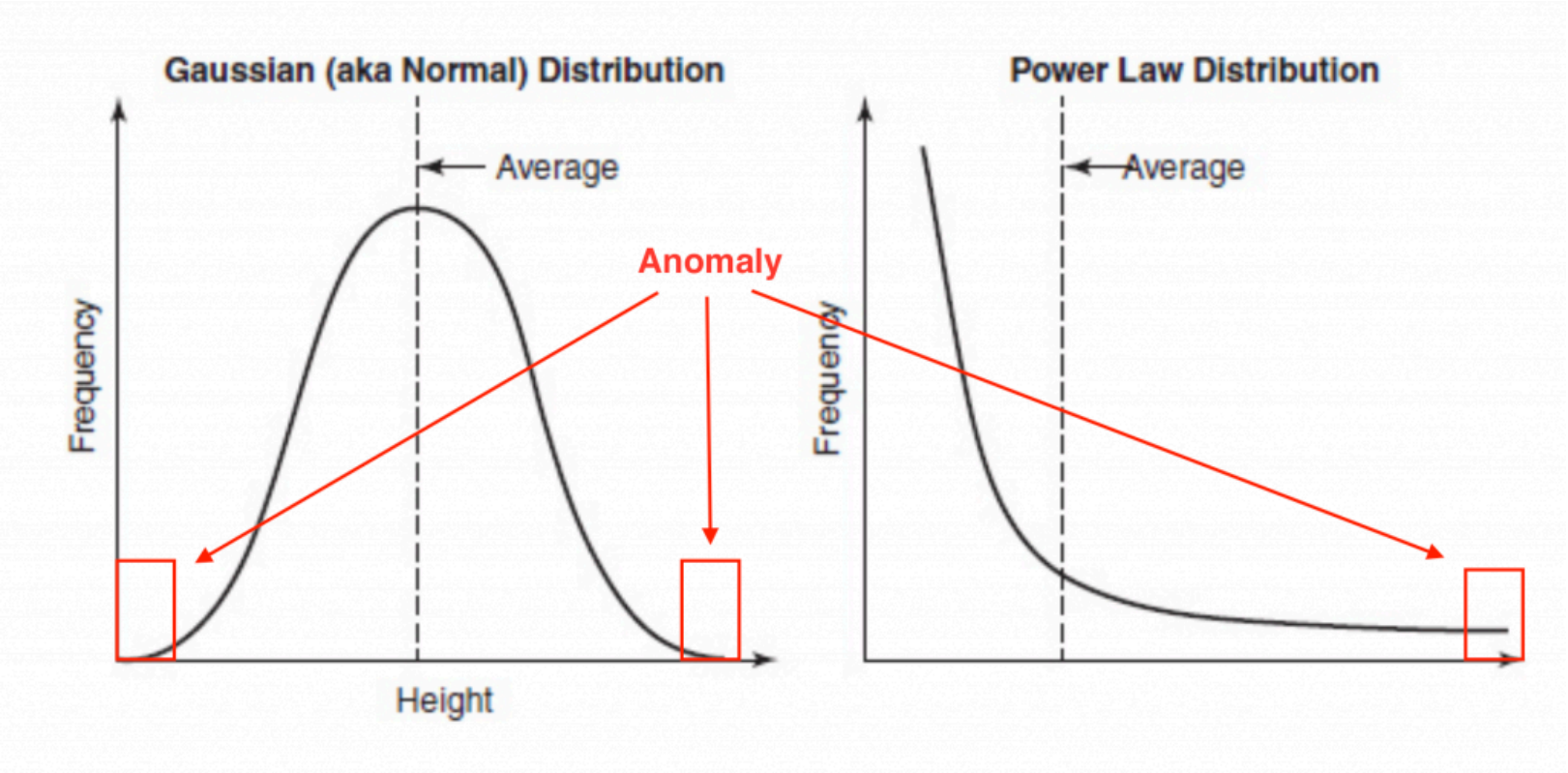
Anomaly Example



https://dataschool.com/fundamentals-of-analysis/what-is-an-outlier/

Others Distributions



Anomaly Detection with Distribution Examples

451 lines (451 sloc) | 393 KB

Raw Blame

Open in Colab

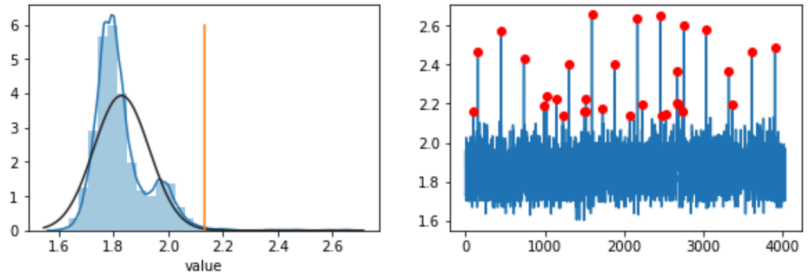
In [ ]:
```
import  pandas as pd
import matplotlib.pyplot as plt
import numpy as  np
import requests
import re
import seaborn as sns
from scipy.stats import norm
```

File display

ตัวอย่าง CPU

In [ ]:
```
cpu = pd.read_csv("https://raw.githubusercontent.com/numenta/NAB/master/data/realAWSCloudwatch/ec2_cpu_utilization_53ea38.csv")
```

In [ ]:
```
f, axes = plt.subplots(1, 2,figsize=(10, 3))
sns.distplot(cpu.value,bins=30,fit=norm,ax=axes[0])
#สร้าง Threshold ที่ 3SD หรือประมาณ 99.7% ของ Data ทั้งหมด
threshold = cpu.value.mean()+3*cpu.value.std()
axes[0].plot([u3sd,u3sd],[0,6])
axes[1].plot(cpu.value)
for  i in range(len(cpu.value)):
  if cpu.value.values[i] > threshold:
    #Remark Threshold
    axes[1].plot(i,cpu.value.values[i],'ro')
```



https://github.com/krmonline/AnomalyDetection/blob/master/Anomaly_Distribution.ipynb

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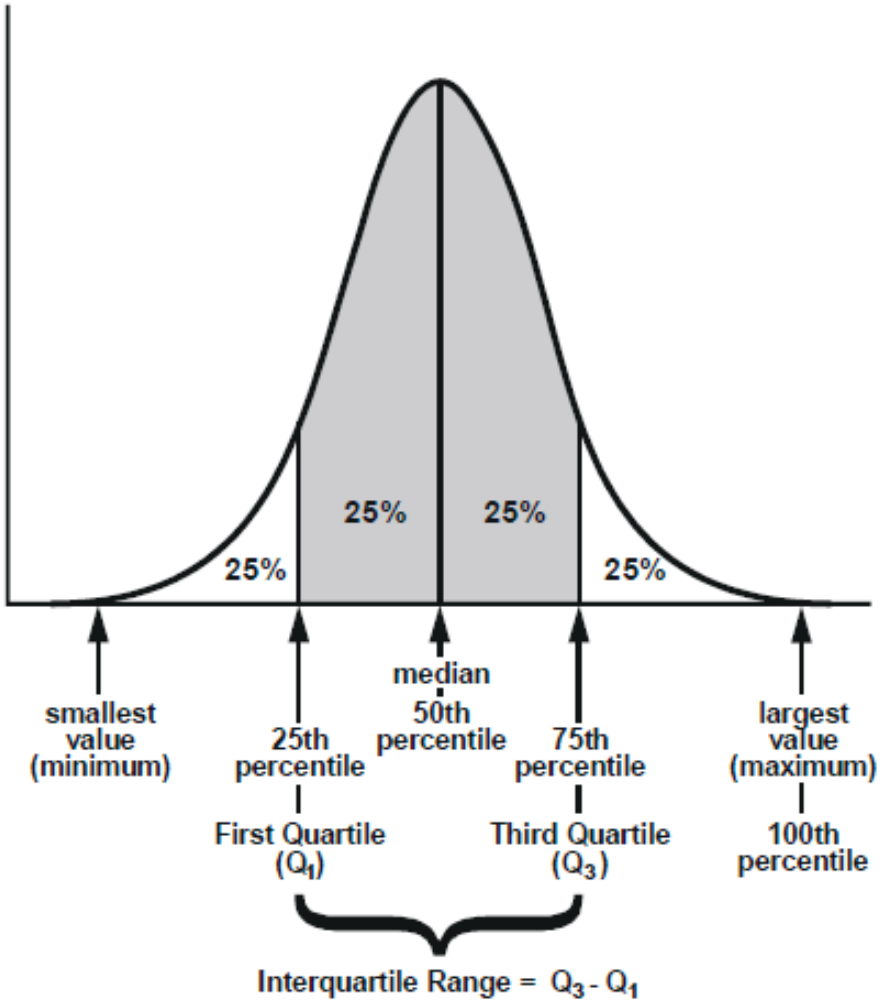
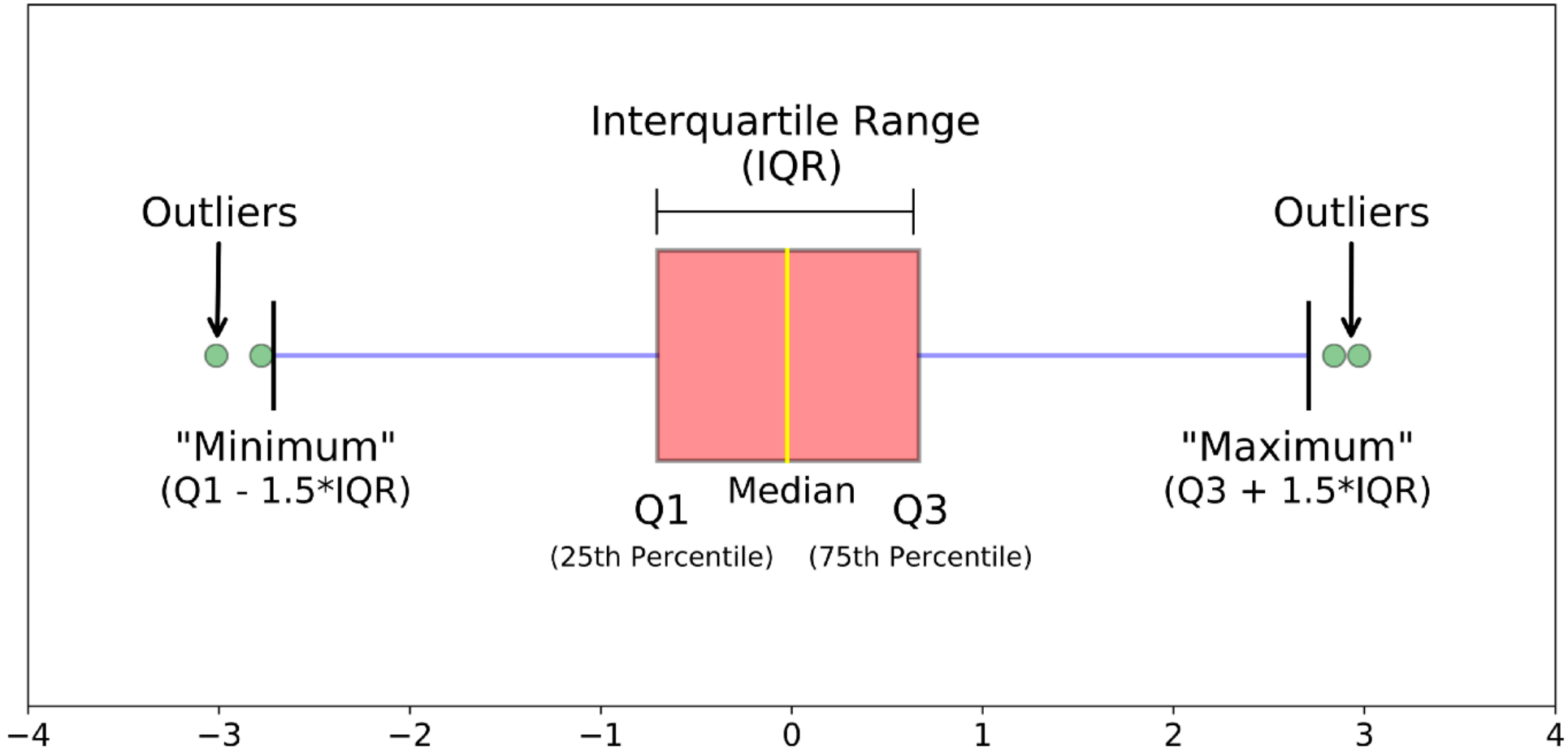
Anomaly Detection with Boxplot

Understanding Boxplots



Understanding Boxplots



Understanding Boxplots

Math Expression

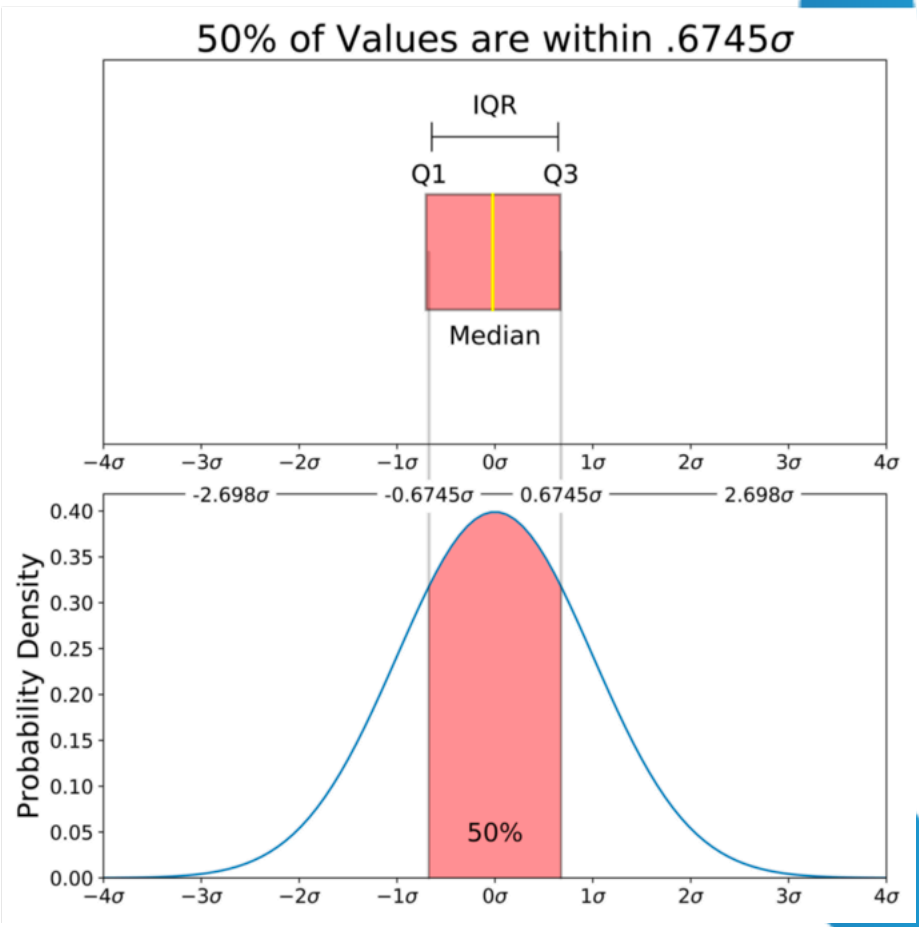
$$\int_{-.6745}^{.6745} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

Code to Integrate

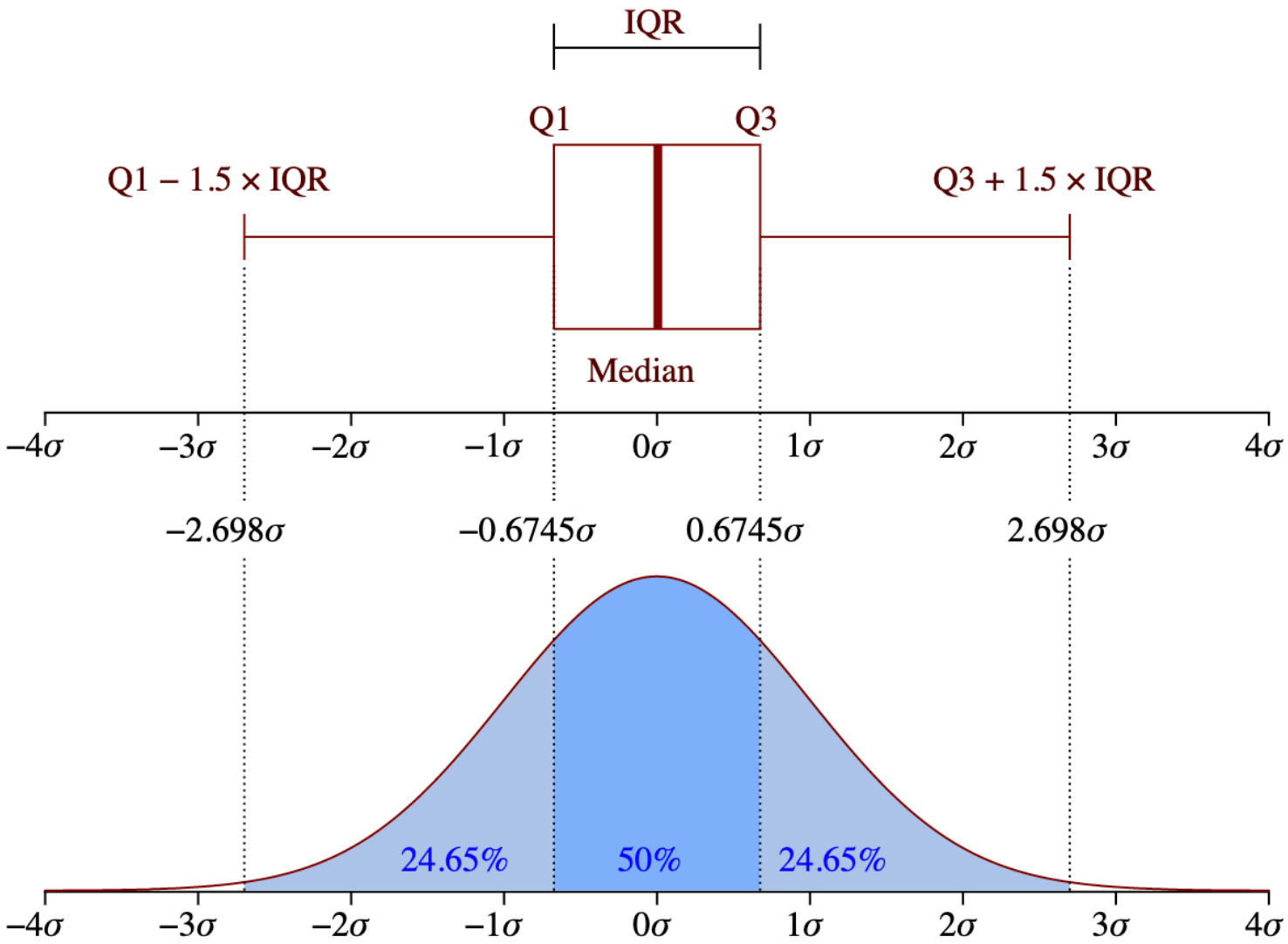
```
# Make a PDF for the normal distribution a function
def normalProbabilityDensity(x):
    constant = 1.0 / np.sqrt(2*np.pi)
    return(constant * np.exp((-x**2) / 2.0) )

# Integrate PDF from -.6745 to .6745
result_50p, _ = quad(normalProbabilityDensity,
                     -.6745,
                     .6745,
                     limit = 1000)
print(result_50p)
```

```
0.500006514273
```



Boxplot on Normal Distribution



Boxplot on Normal Distribution

324 lines (324 sloc) | 11.6 KB

Raw Blame

Open in Colab

In [1]:
```
import  numpy as np
from numpy.random import randn
import matplotlib.pyplot as plt
```

In [14]:
```
data  = np.array([4, 4, 4, 4, 4, 8, 7, 4, 4, 2, 6, 3, 5, 8, 6, 6, 4, 3, 1, 4, 4, 9, 2, 7, 4, 7, 6, 5, 3, 4, 5, 4, 4, 4, 5, 4,1
0,0])
print("Data = ",data)
```

```
Data =  [ 4  4  4  4  4  8  7  4  4  2  6  3  5  8  6  6  4  3  1  4  4  9  2  7
  4  7  6  5  3  4  5  4  4  4  5  4 10  0]
```

In [15]:
```
data.sort()
print(data)
```

```
[ 0  1  2  2  3  3  3  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  5
  5  5  5  6  6  6  6  7  7  7  8  8  9 10]
```

In [16]:
```
q1 = np.percentile(data,25)
q3 = np.percentile(data,75)
iqr = q3-q1
print(q1,q3,iqr)
```

```
4.0 6.0 2.0
```

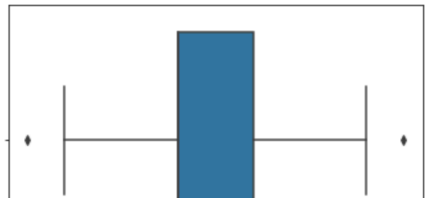
In [17]:
```
lcutoff = q1 - 1.5*iqr
ucutoff = q3 + 1.5*iqr
lcutoff,ucutoff
```

Out[17]: (1.0, 9.0)

In [18]:
```
import seaborn as sns
```

In [19]:
```
sns.boxplot(x=data)
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb43f52aa58>



https://github.com/krmonline/AnomalyDetection/blob/master/IQR_Example.ipynb

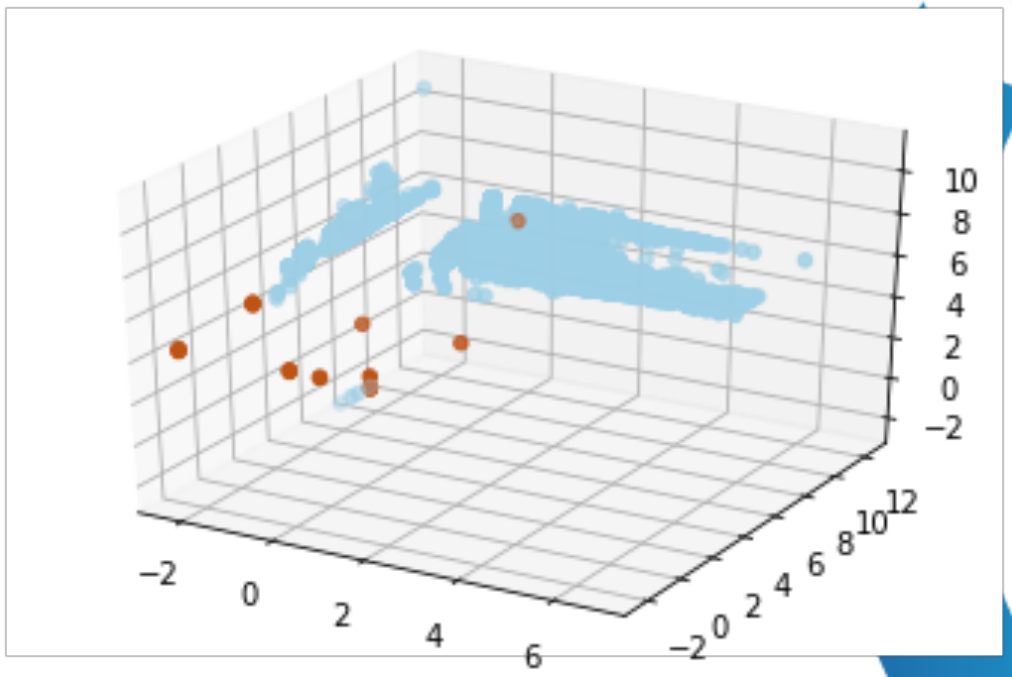
Softnix

Multivariate Anomaly Detection

DB-Scan

	0	1	2	label
0	-3.351119	-1.325486	-4.510206	0
1	-6.762503	-1.837115	5.842649	0
2	-6.143649	6.226966	1.211651	0
3	-7.909054	4.304185	4.259787	0
4	-8.206218	2.532668	6.720400	0
...	...	...	...	...
1595	-4.761516	7.747586	7.979358	1
1596	-1.714259	-0.645442	-6.087254	1
1597	-2.198676	0.934126	-1.519782	1
1598	-2.424503	-4.967541	-8.313585	1
1599	3.550568	-5.749677	6.821268	1

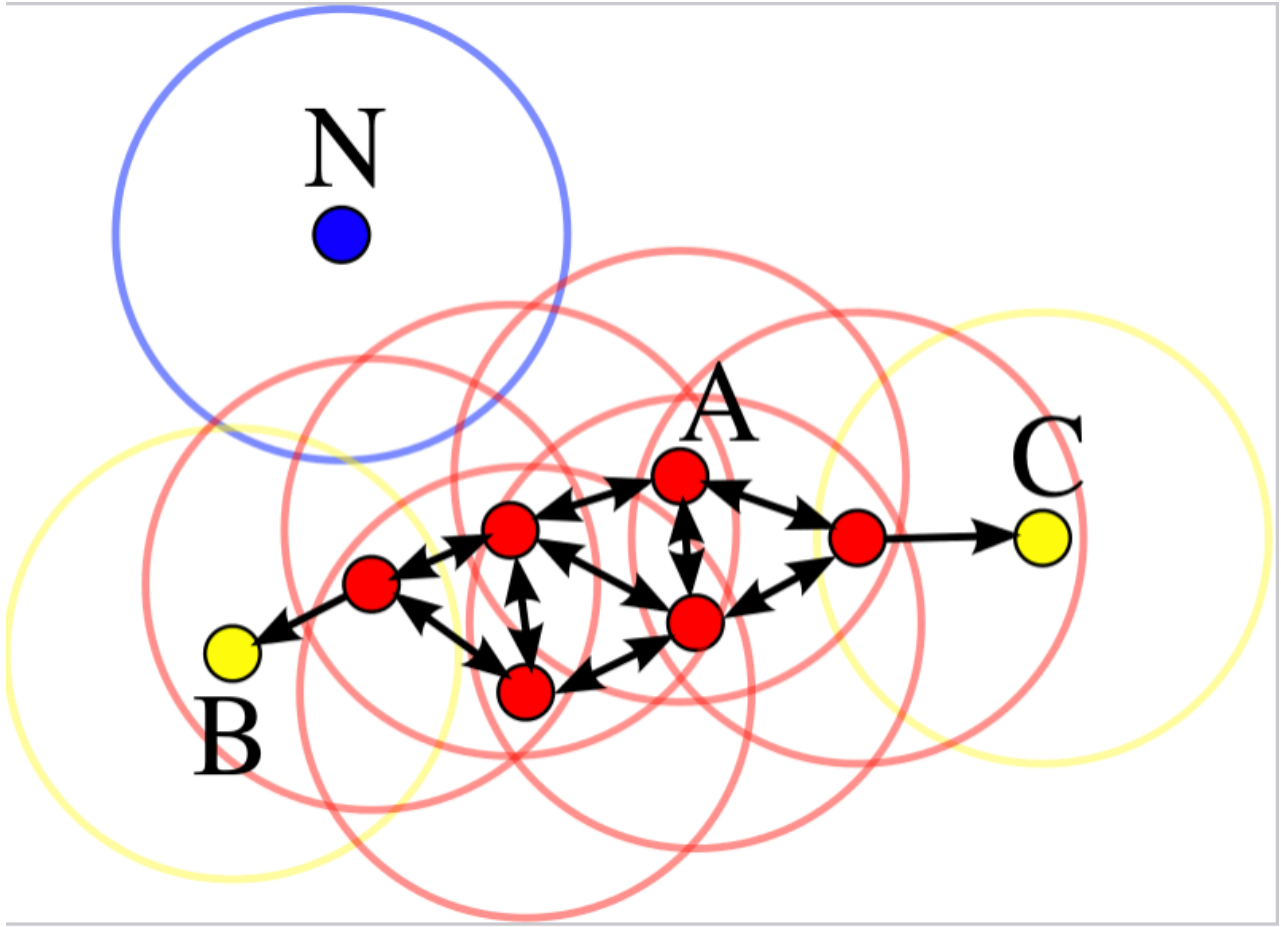
1600 rows × 4 columns



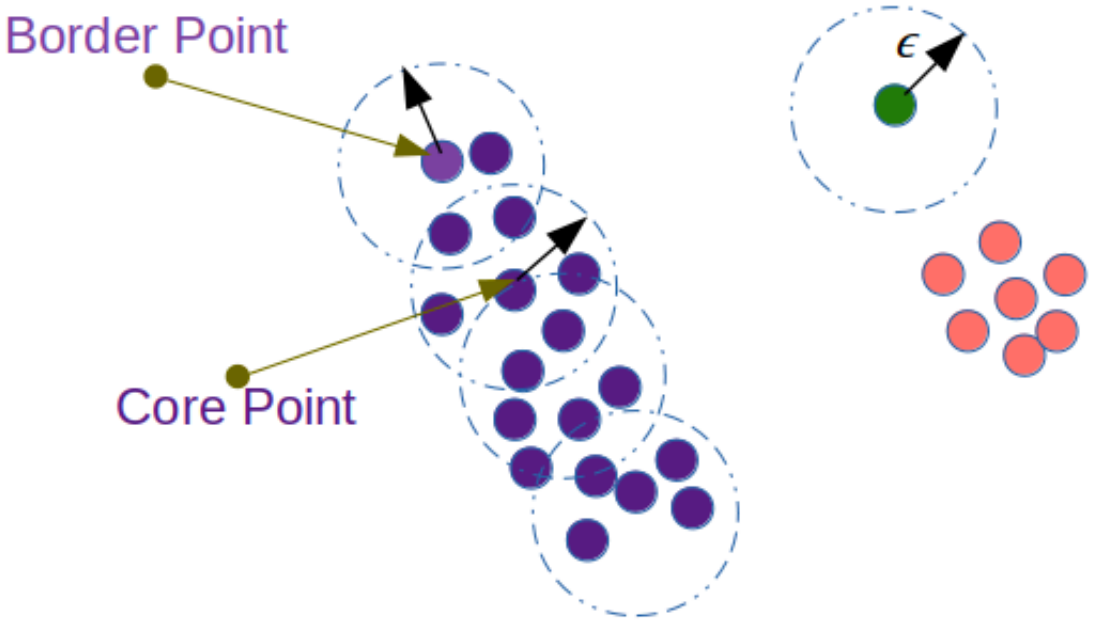
Softnix

Anomaly Detection with DB-Scan

DB-Scan



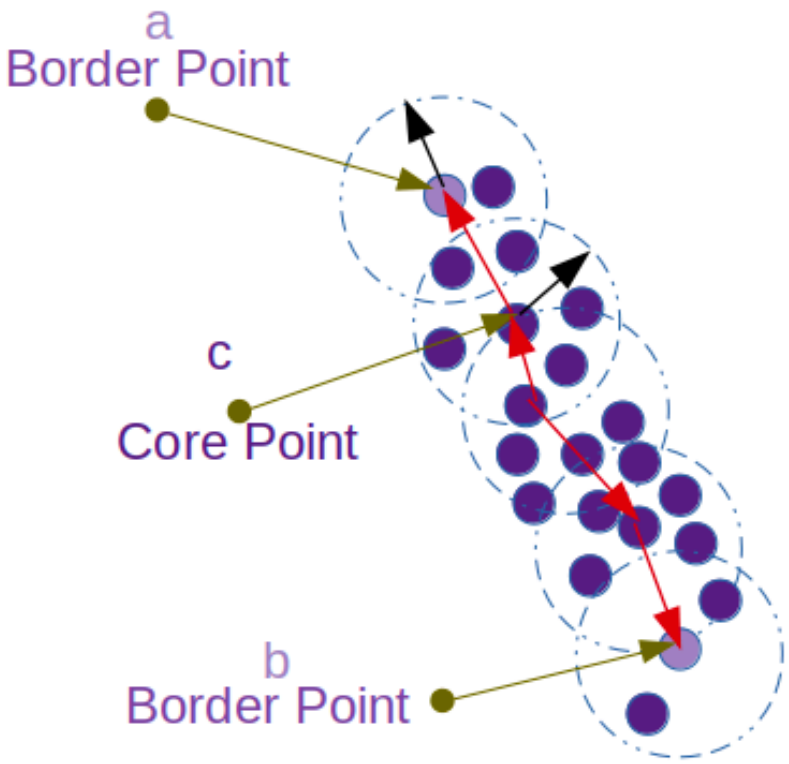
DB-Scan Explain



$$N_{Eps}(p) = \{q \in D \text{ such that } dist(p, q) \leq \epsilon\}$$

ϵ = 1 unit, MinPts = 7

DB-Scan Explain



a, b are Density Reachable from a core point c.

a, b are called Density Connected points.

DB-Scan Example

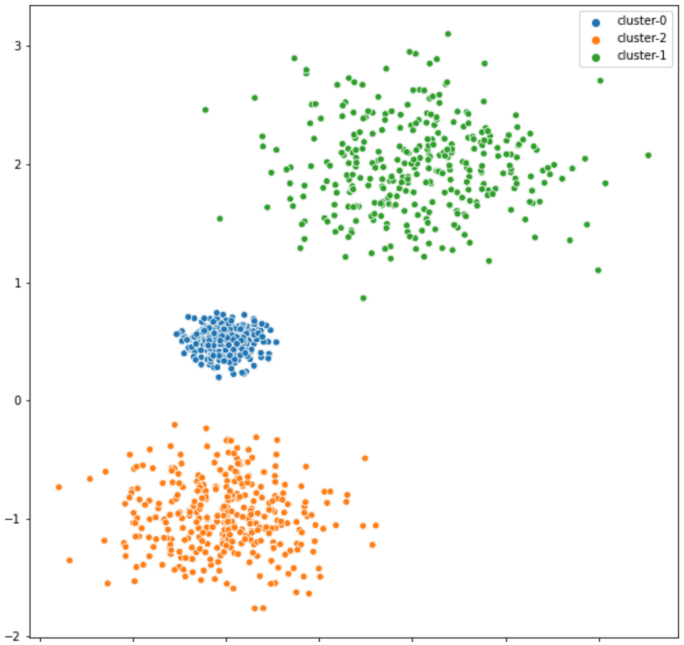
Open in Colab

In [1]:
```
from sklearn.datasets import make_blobs
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use
the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

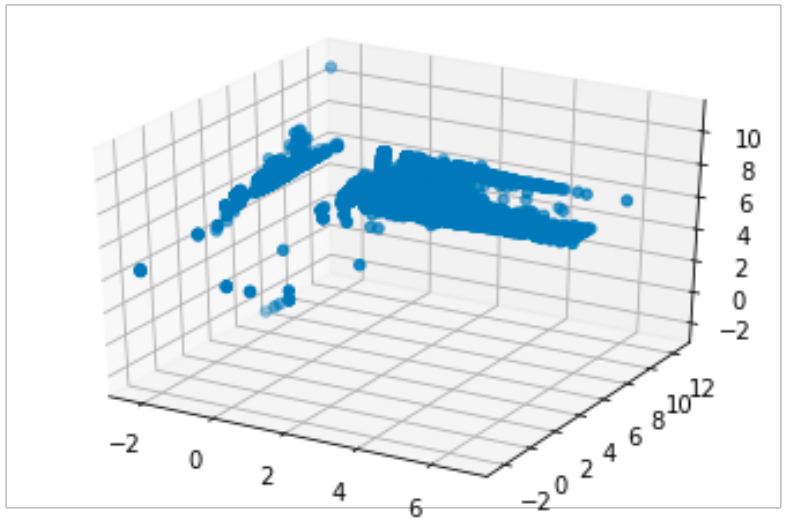
In [2]:
```
centers = [[1, 0.5], [2, 2], [1, -1]]
stds = [0.1, 0.4, 0.3]
X, labels_true = make_blobs(n_samples=1000, centers=centers, cluster_std=stds, random_state=0)
fig = plt.figure(figsize=(10, 10))
sns.scatterplot(X[:,0], X[:,1], hue=["cluster-{}".format(x) for x in labels_true])
```

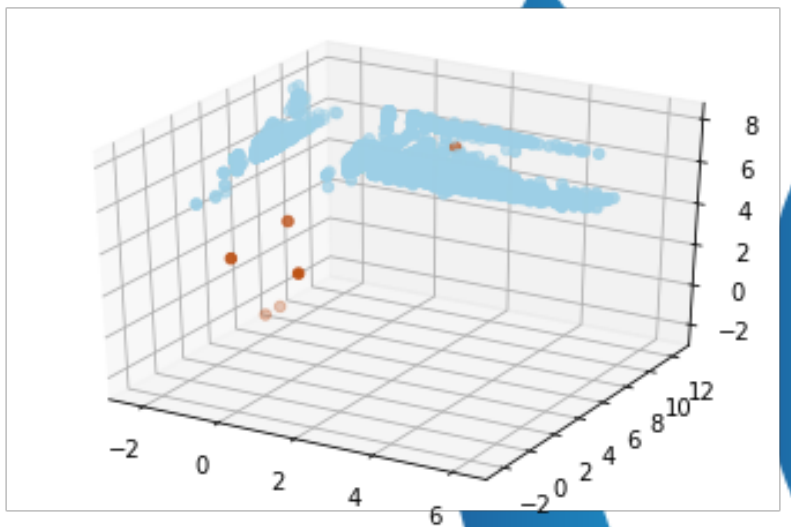
Out[2]: <matplotlib.axes._subplots.AxesSubplot at 0x7f719d239278>



https://github.com/krmonline/AnomalyDetection/blob/master/DBS_Explain.ipynb

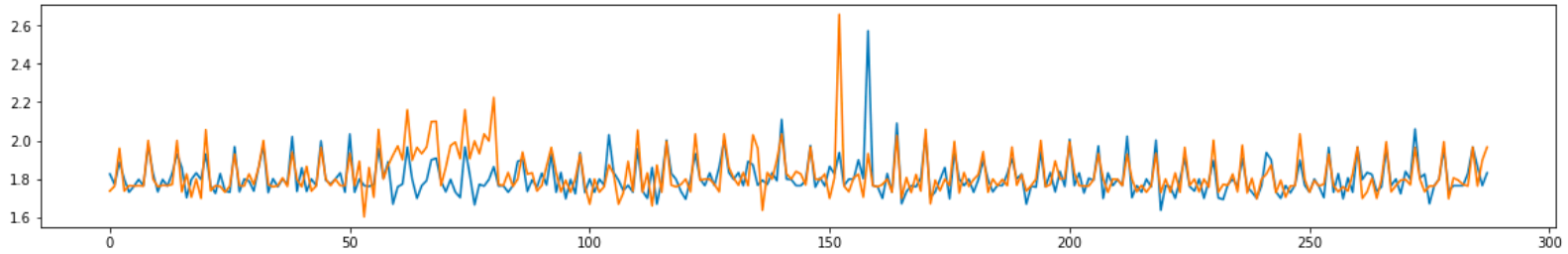
Anomaly with DB-Scan Example

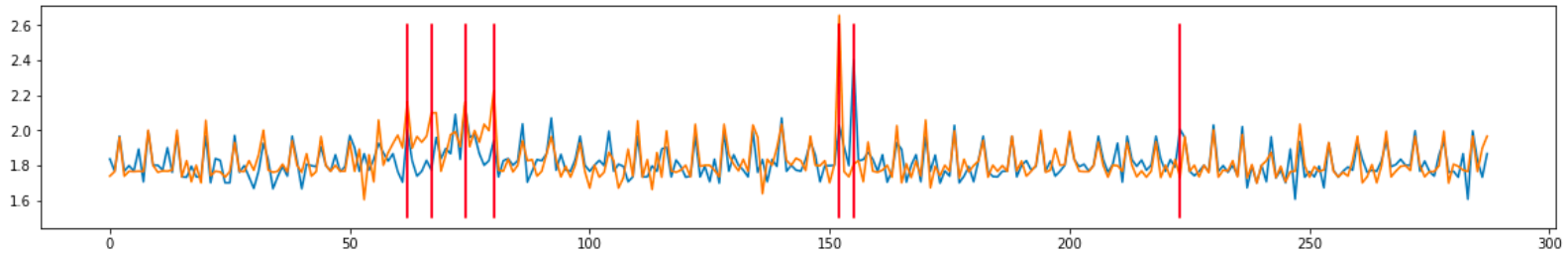


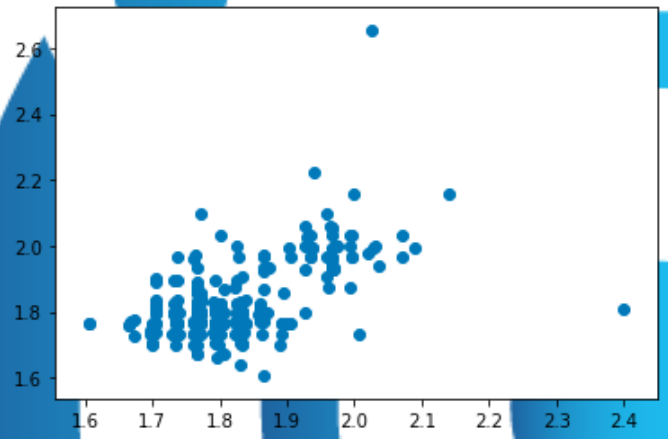


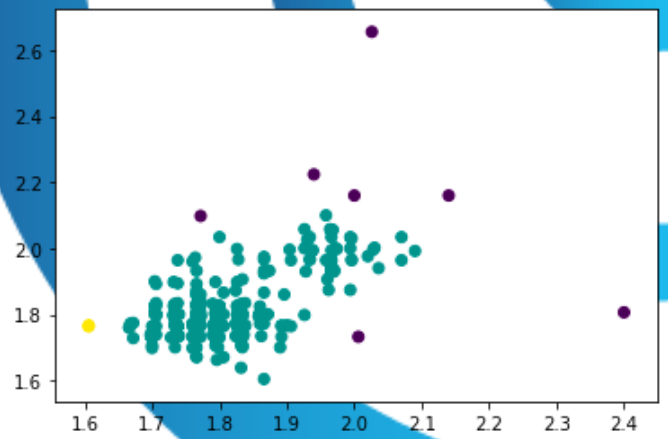
https://github.com/krmonline/AnomalyDetection/blob/master/Anomaly_dbscan.ipynb

DB-Scan Example







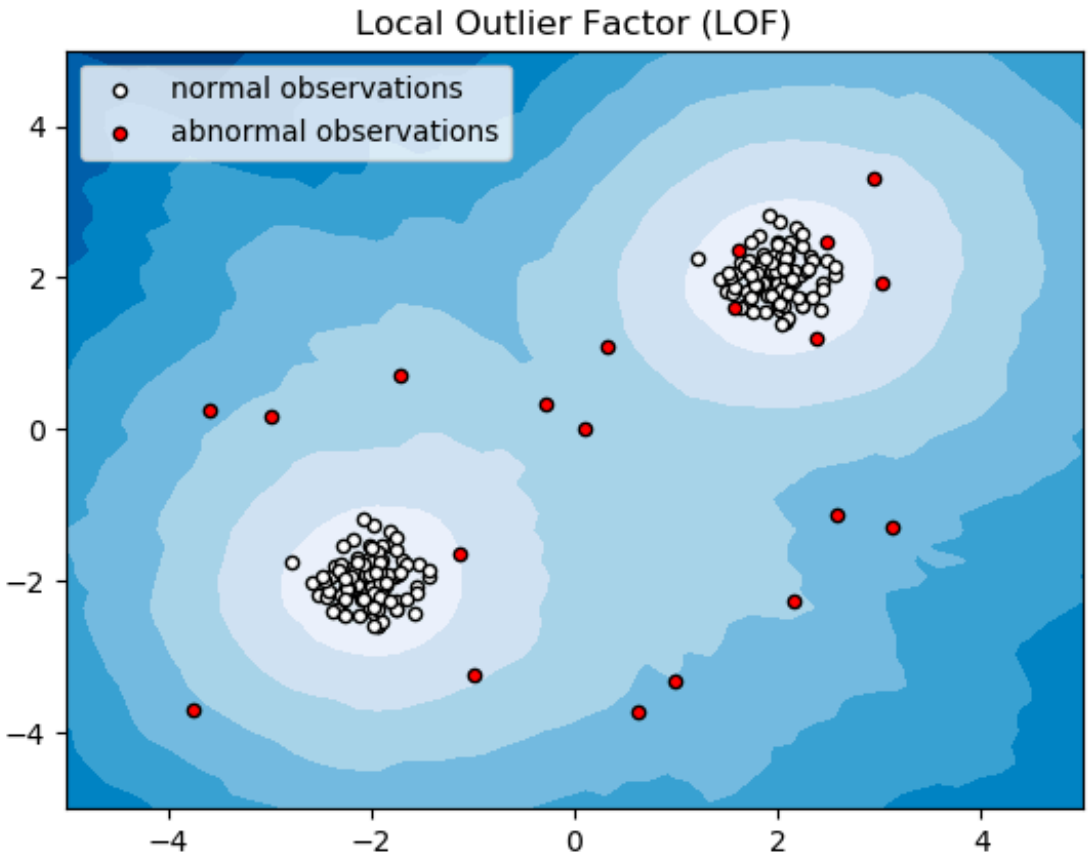


https://github.com/krmonline/AnomalyDetection/blob/master/Anomaly_DBScan_CPU.ipynb

Softnix

Anomaly Detection with Local Outlier Factor

Local Outlier Factor (LOF)



LOF Steps

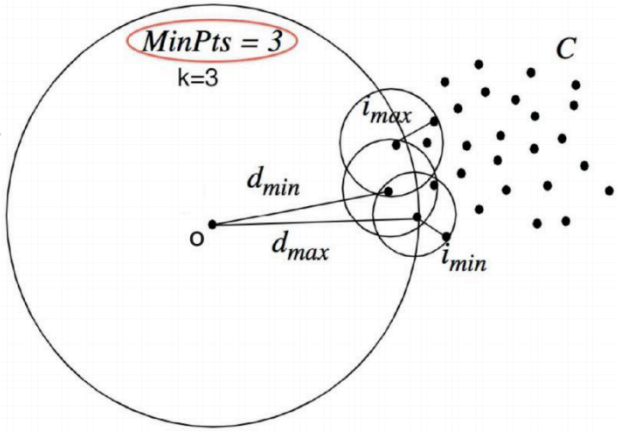
- Reachability distance from *o'* to *o*:

$$reachdist_k(o \leftarrow o') = \max\{dist_k(o), dist(o, o')\}$$

  - where k is a user-specified parameter

- Local reachability density of *o*:

$$lrd_k(o) = \frac{\|N_k(o)\|}{\sum_{o' \in N_k(o)} reachdist_k(o' \leftarrow o)}$$



- LOF (Local outlier factor) of an object o is the average of the ratio of local reachability of *o* and those of *o*'s k-nearest neighbors

$$LOF_k(o) = \frac{\sum_{o' \in N_k(o)} \frac{lrd_k(o')}{lrd_k(o)}}{\|N_k(o)\|} = \sum_{o' \in N_k(o)} lrd_k(o') \cdot \sum_{o' \in N_k(o)} reachdist_k(o' \leftarrow o)$$

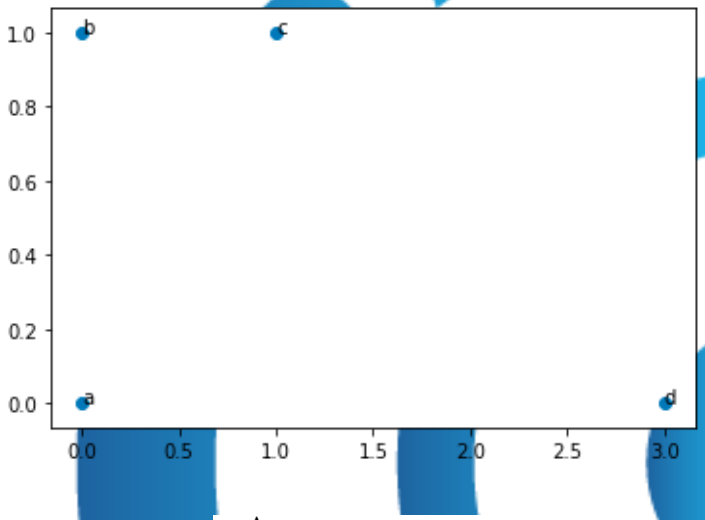
- The lower the local reachability density of o, and the higher the local reachability density of the kNN of o, the higher LOF
- This captures a local outlier whose local density is relatively low comparing to the local densities of its kNN

LOF Calculation

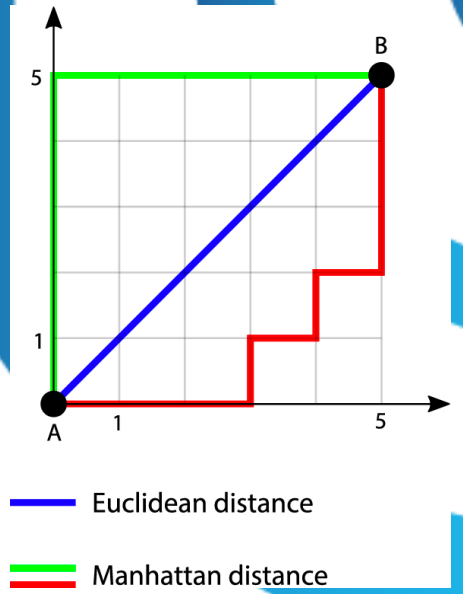
Usaging Manhattan distance with k=2

dist(a,b) = 1
dist(a,c) = 2
dist(a,d) = 3
dist(b,c) = 1
dist(b,d) = 4
dist(c,d) = 3

dist(a) = 2 longest distance is a-c
dist(b) = 1 longest distance is b-a , b-c
dist(c) = 2 longest distance is c-a
dist(d) = 3 longest distance is d-a , d-c



Reachability Density
Ex. rd(b<-a) = max(dist(b),dist(b,a))
rd(b<-a) = max(1,1) = 1
rd(a<-b) = max(2,1) = 2
rd(c<-a) = max(2,2) = 2
rd(d<-a) = max(3,3) = 3
rd(c<-b) = max(2,1) = 2
rd(d<-b) = max(3,4) = 4
rd(c<-d) = max(3,3) = 3



LOF Example

master | AnomalyDetection / Anomaly_LOF_Example.ipynb | Go to file | ...

krmonline Created using Colaboratory — Latest commit e292b63 now — History

1 contributor

350 lines (350 sloc) | 32.1 KB | Raw | Blame

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In [ ]:
```
import numpy as np
import h5py
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.neighbors import LocalOutlierFactor
```

In [ ]:
```
clf = LocalOutlierFactor(n_neighbors=2, contamination=0.4)
(X,Y) = np.asarray([[0,0],[0,1],[1,1],[3,0]]).T
y_pred = clf.fit_predict(np.asarray([X,Y]).T)
clf.negative_outlier_factor_
```

Out[ ]:
```
array([-0.9267767 , -1.17157288, -0.9267767 , -2.16885037])
```

In [ ]:
```
plt.scatter(X,Y)
plt.text(0,0,'a')
plt.text(0,1,'b')
plt.text(1,1,'c')
plt.text(3,0,'d')
```

Out[ ]:
```
Text(3, 0, 'd')
```

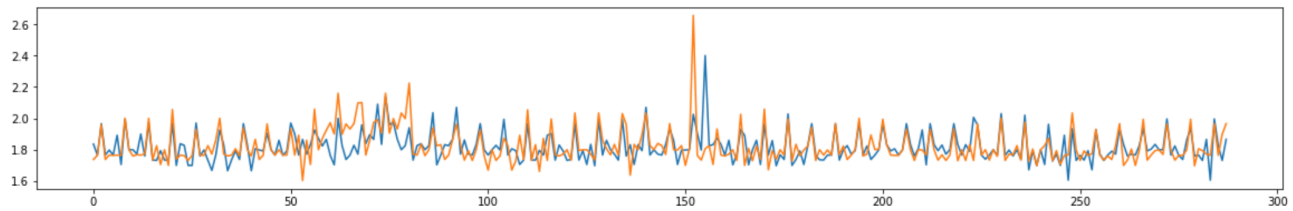
https://github.com/krmonline/AnomalyDetection/blob/master/Anomaly_LOF_Example.ipynb

LOF Example #2

```
In [ ]: X = cpu2[4]
        Y = cpu2[5]
        clf = LocalOutlierFactor(n_neighbors=20, contamination=0.03)
        y_pred = clf.fit_predict(np.asarray([X,Y]).T)
```

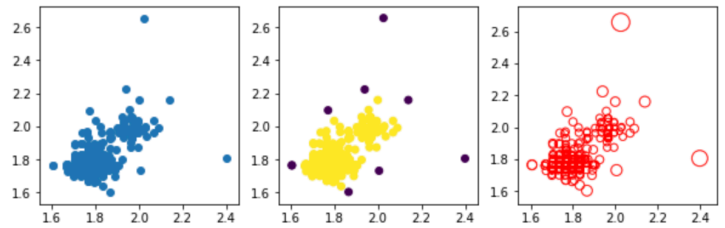
```
In [ ]: plt.figure(figsize=(20, 3))
        plt.plot(X)
        plt.plot(Y)
```

```
Out[ ]: [<matplotlib.lines.Line2D at 0x7fbd6403aba8>]
```




```
In [ ]: plt.figure(figsize=(10, 3))
        plt.subplot(131).scatter(X,Y)
        plt.subplot(132).scatter(X,Y,c=y_pred)
        plt.subplot(133).scatter(X,Y,s=30*np.abs(clf.negative_outlier_factor_),facecolors='none',edgecolors='r')
```

```
Out[ ]: <matplotlib.collections.PathCollection at 0x7fbd63f46f98>
```

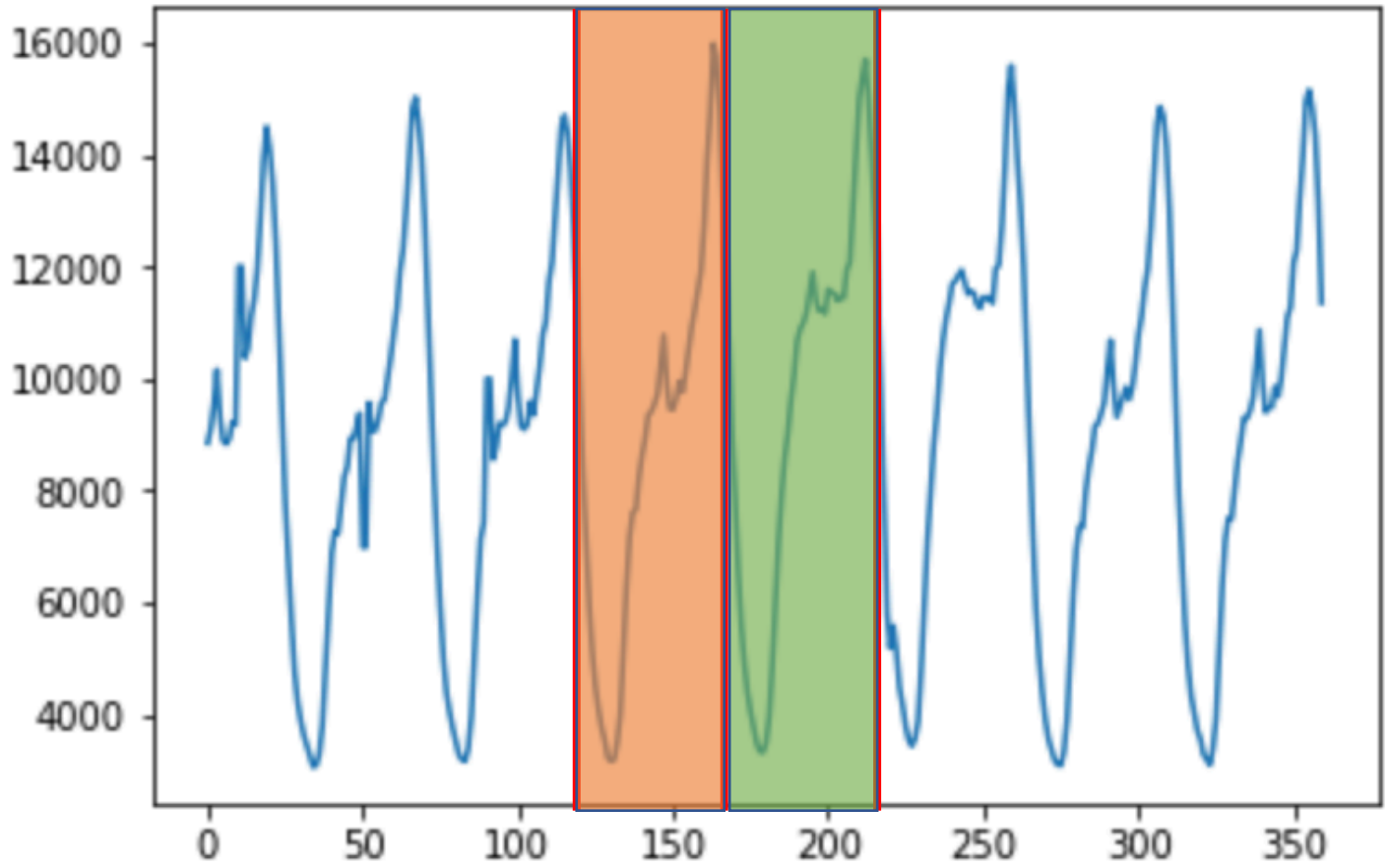



```
In [ ]: plt.figure(figsize=(20, 3))
        plt.plot(X)
        plt.plot(Y)
        for  i in range(len(y_pred)):
          if y_pred[i] == -1:
            plt.plot([i,i],[1.5,2.6],'r-')
```

https://github.com/krmonline/AnomalyDetection/blob/master/Anomaly_LOF.ipynb

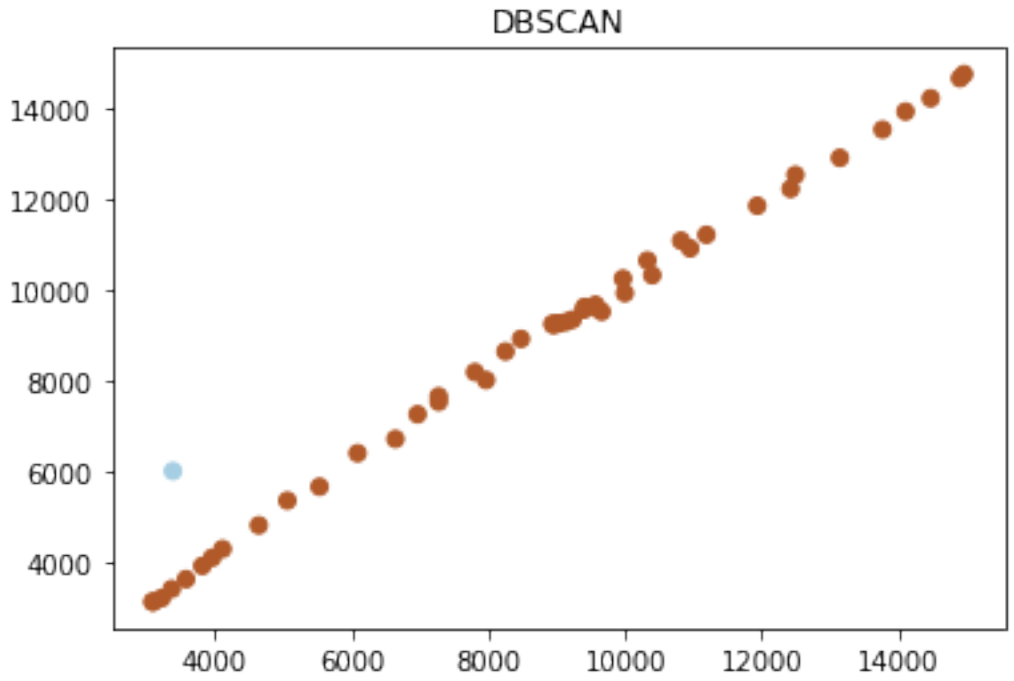
Time series

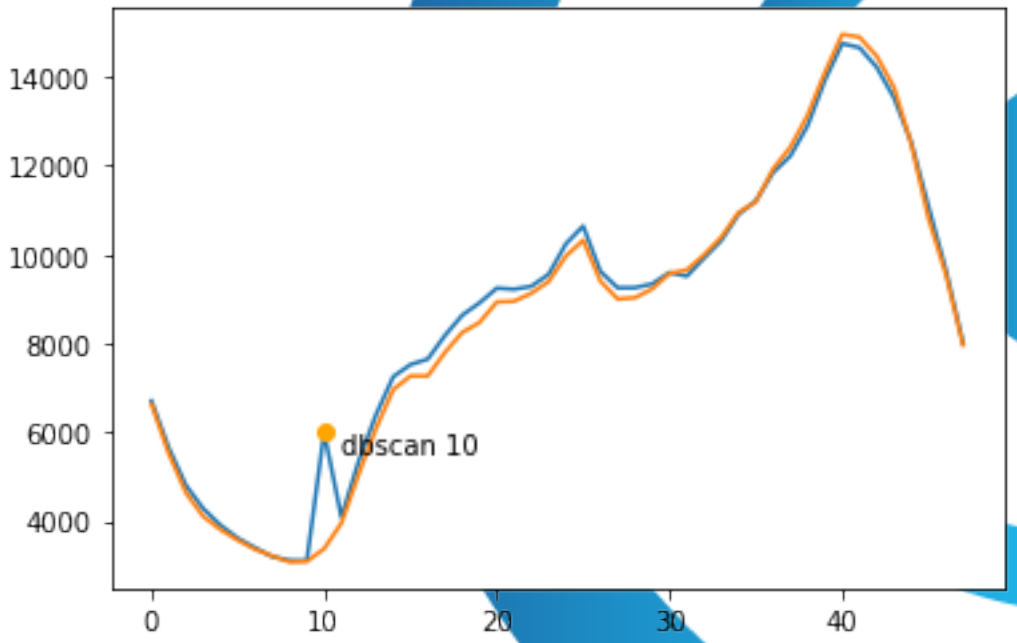
Converse 1 dim to 2 dim



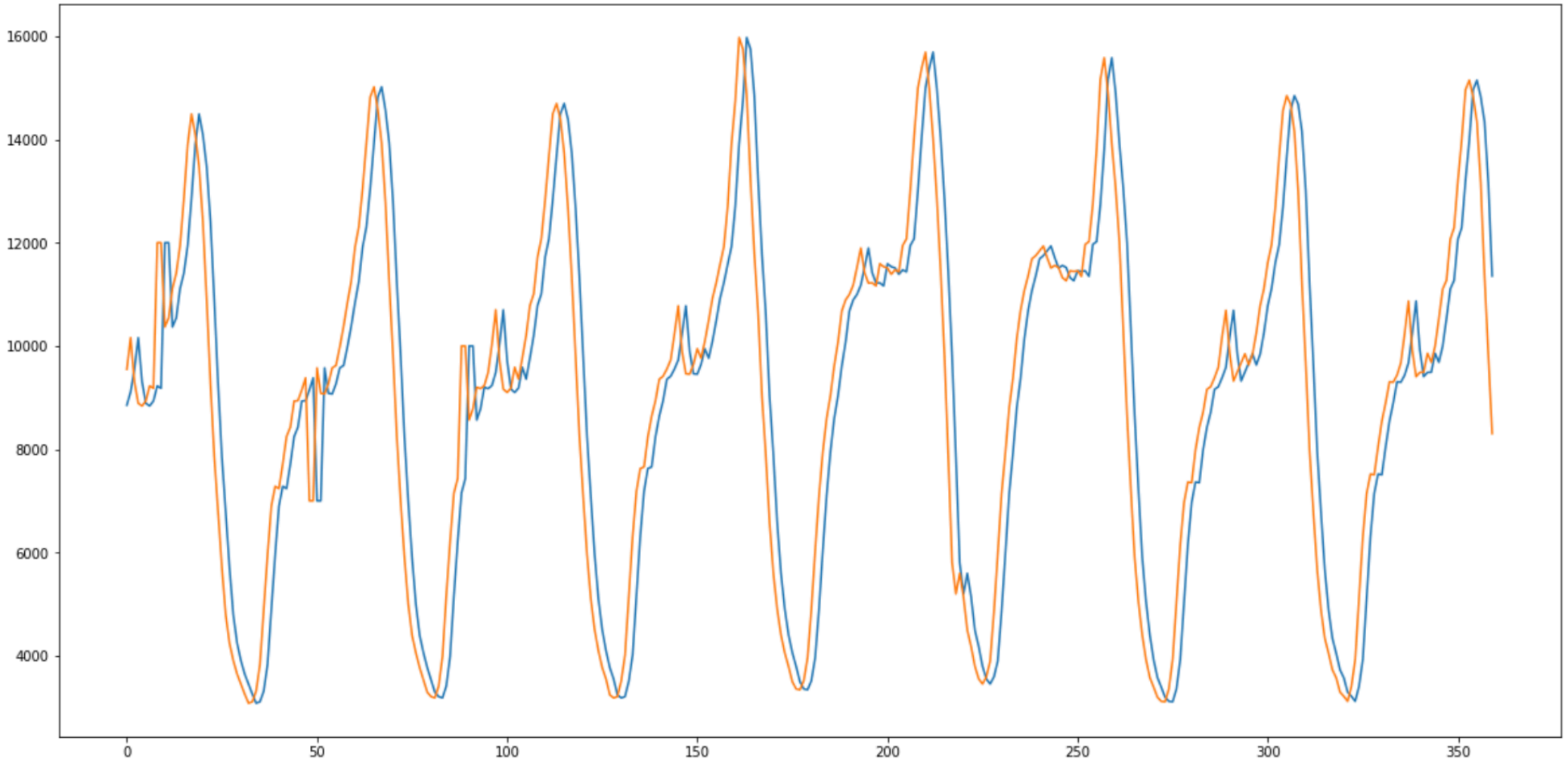
	dataset1	dataset2
0	6636.93	6708.39
1	5525.74	5654.90
2	4636.56	4803.93
3	4106.13	4282.68
4	3809.40	3908.50
5	3571.48	3616.86
6	3362.99	3401.56
7	3215.41	3199.62
8	3079.79	3118.59
9	3093.17	3113.45
10	3380.14	3467.37
11	3954.25	4088.98
12	5054.78	5349.37
13	6082.58	6393.57
14	6960.80	7251.71
15	7269.43	7525.05

Time series

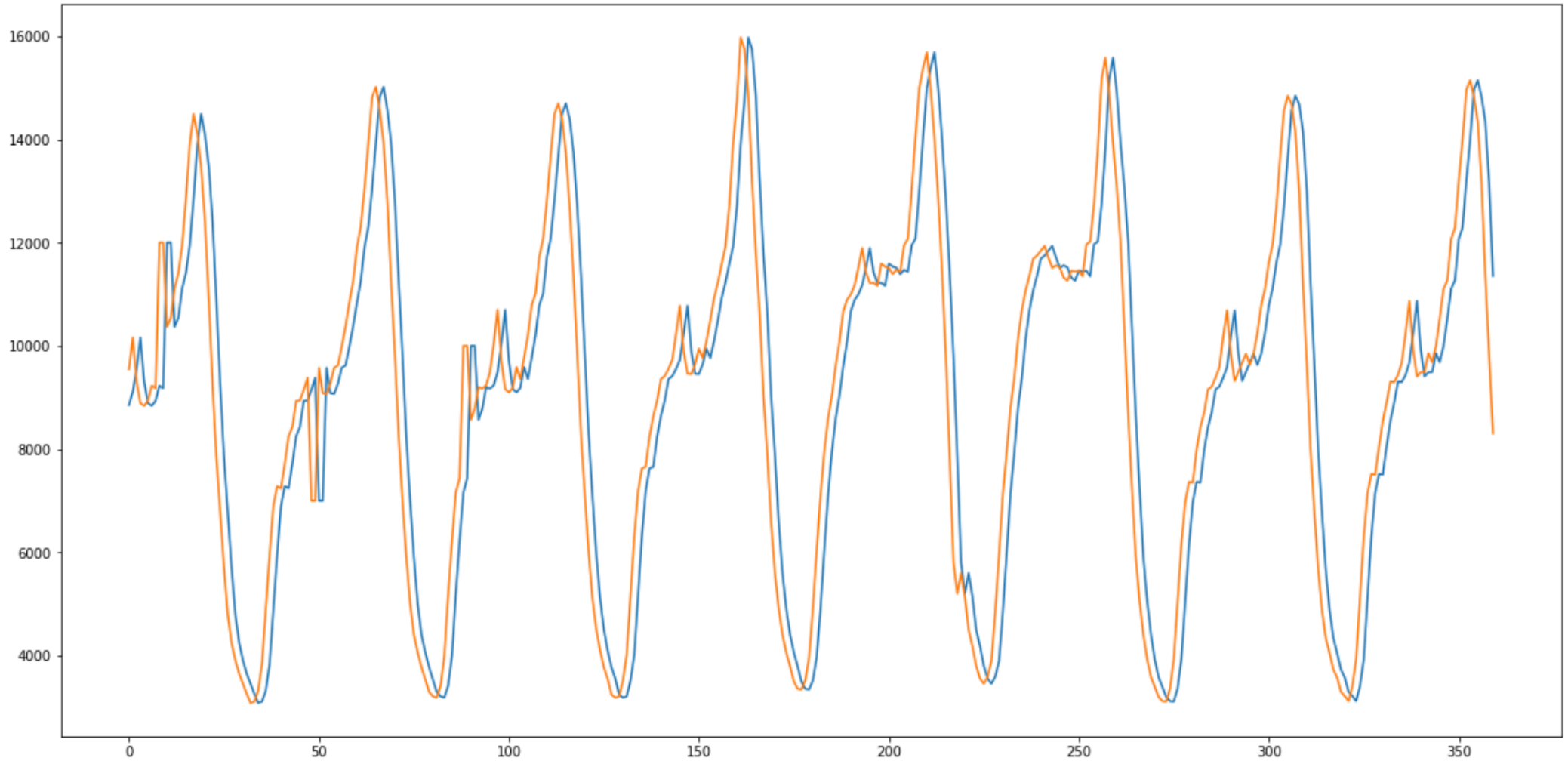

DBSCAN
14000
12000
10000
8000
6000
4000
4000
6000
8000
10000
12000
14000


14000
12000
10000
8000
6000
4000
dbscan 10
0
10
20
30
40

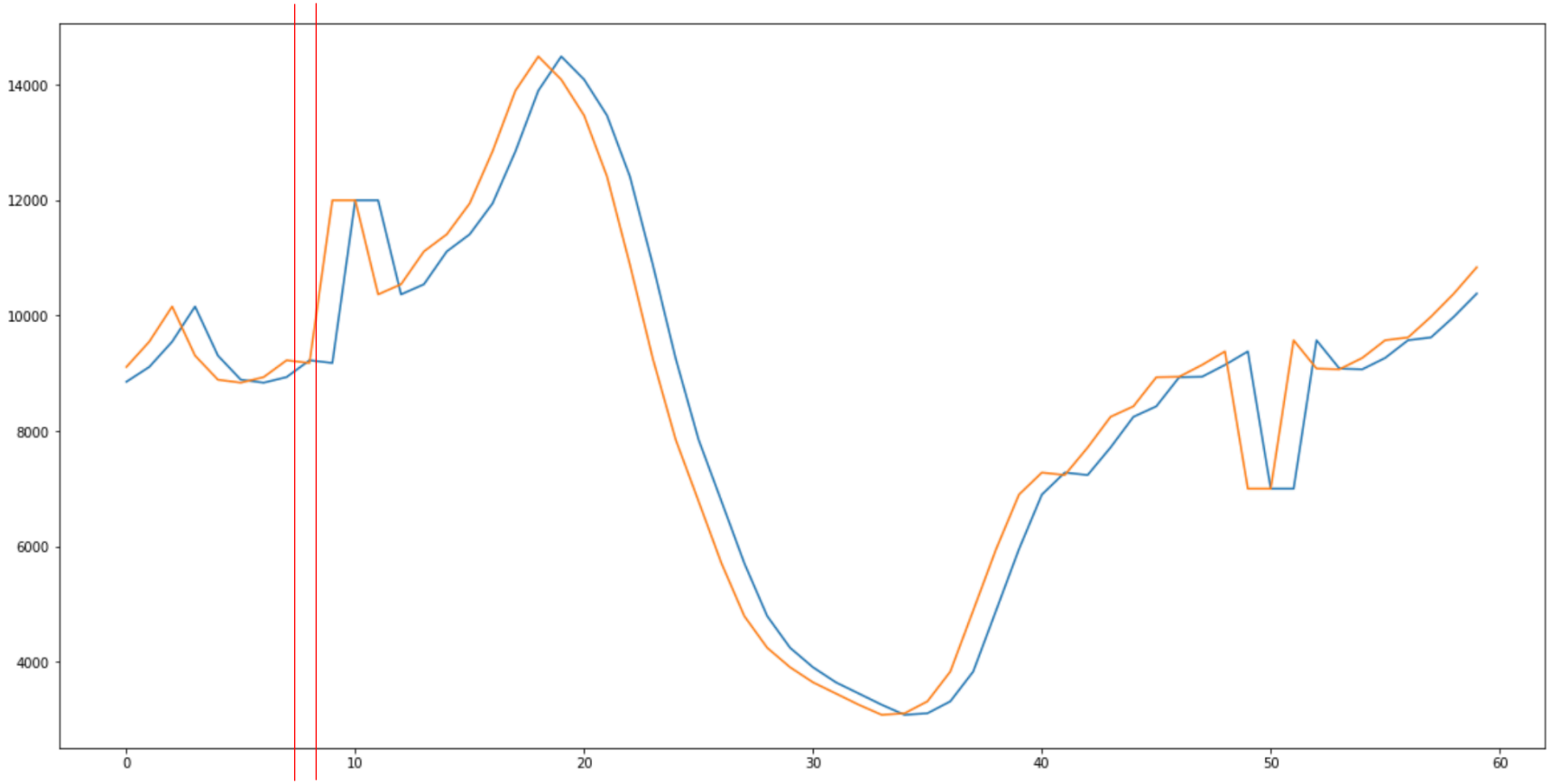
Time Shift Detection



Create new graph with shift to 1 step

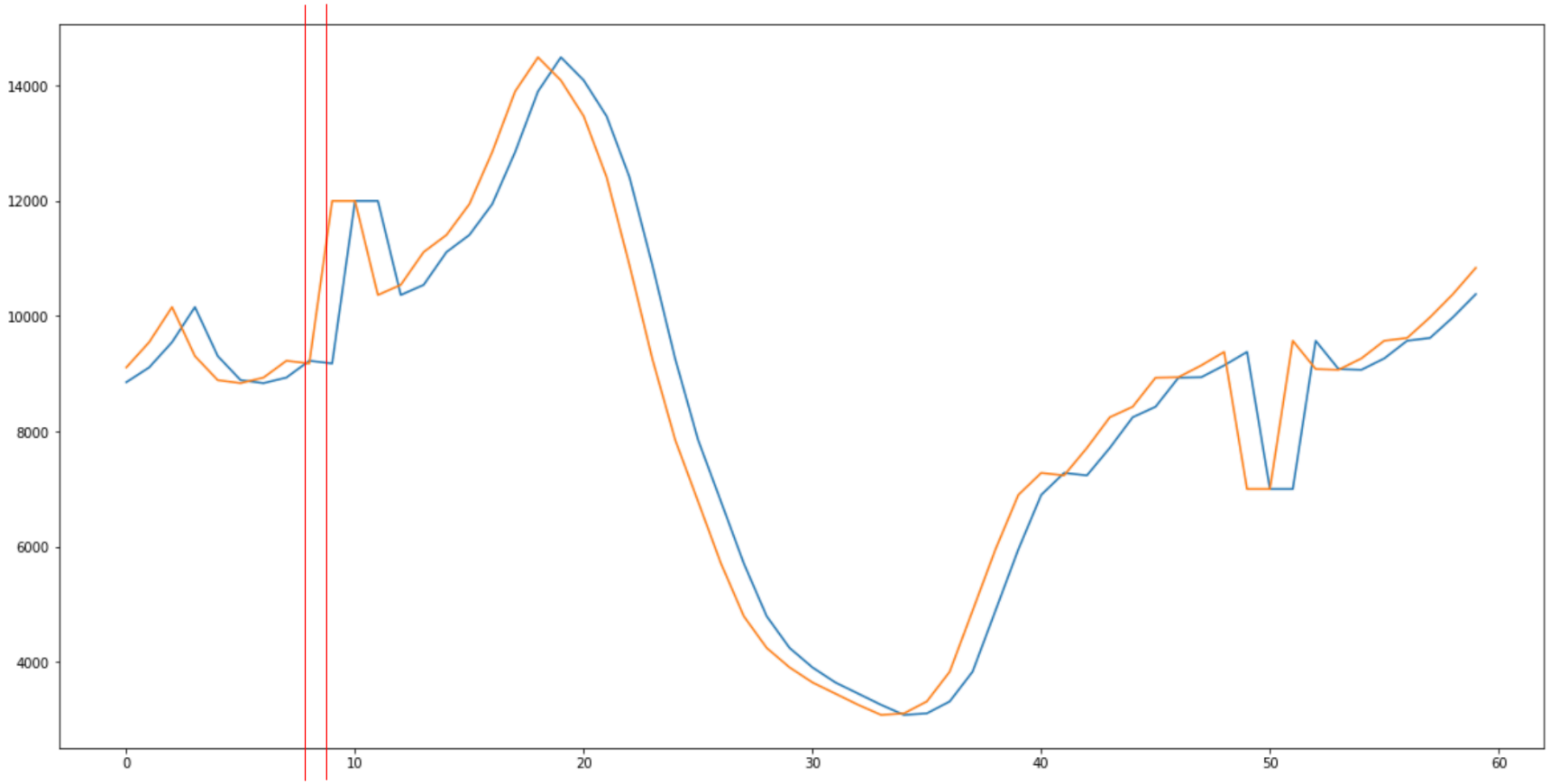


Zoom your graph and shift first 3 step



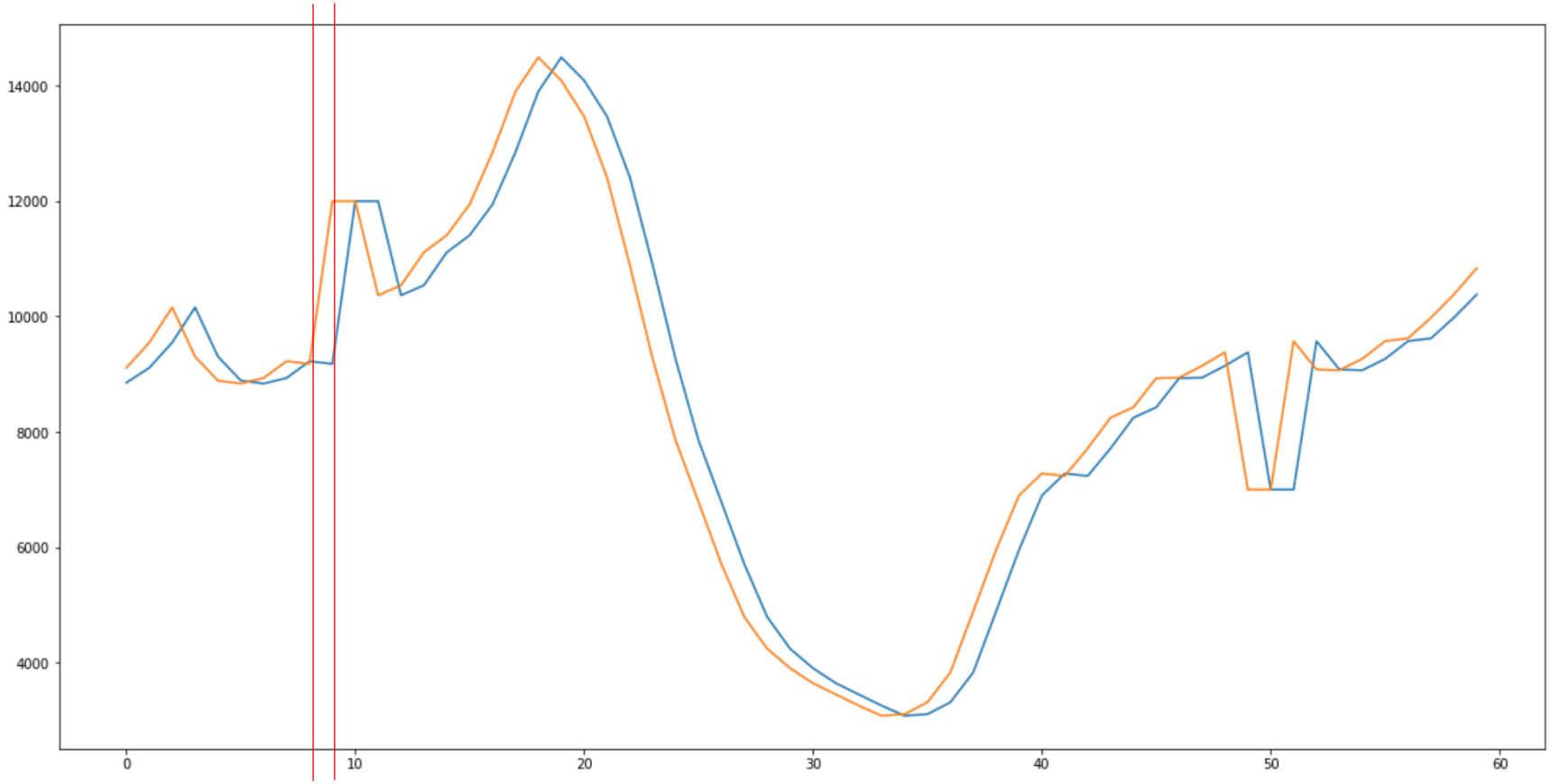

```
0.995416134063
```

Zoom your graph and shift first 3 step



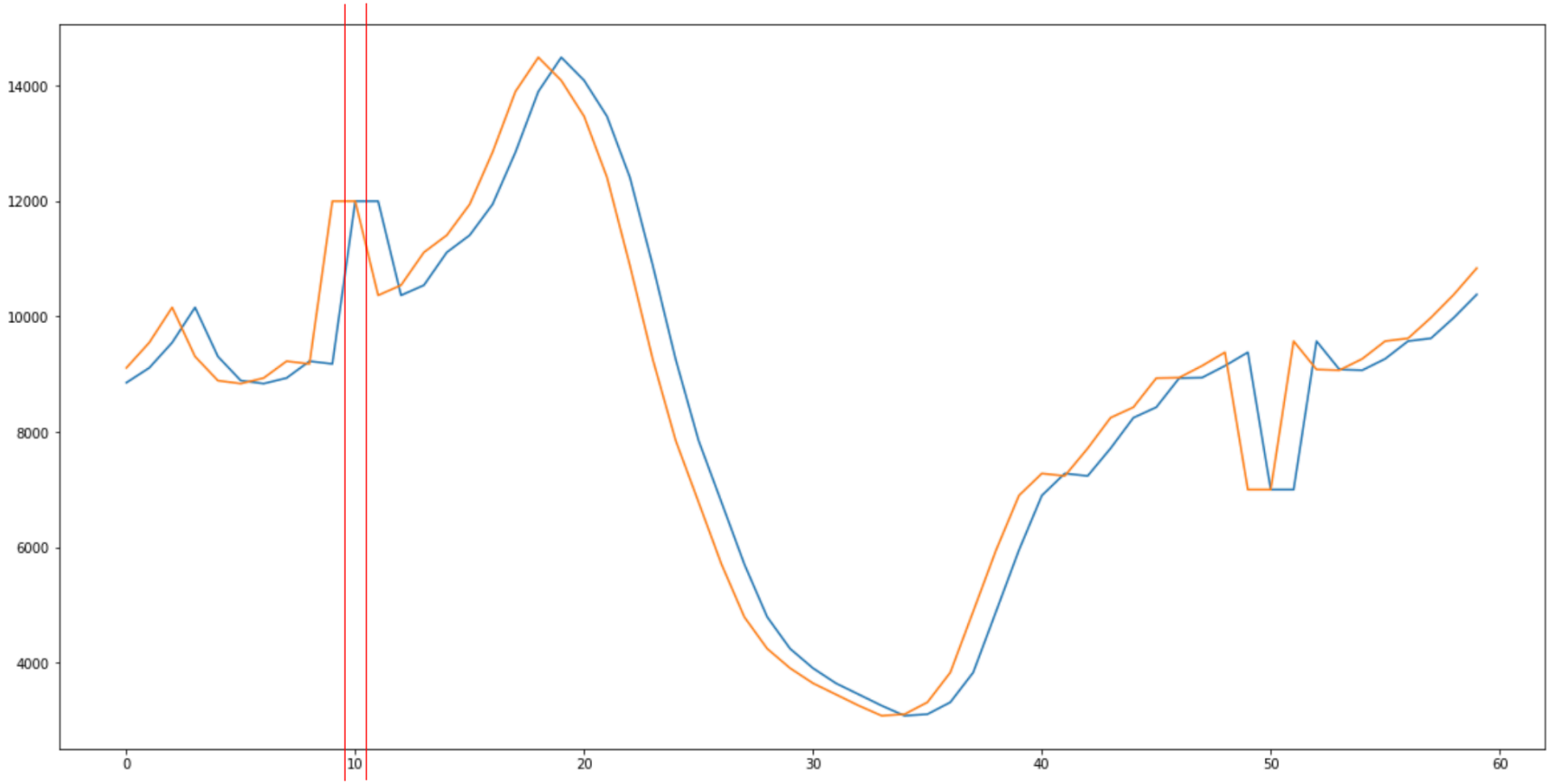

```
0.995416134063
```

Zoom your graph and shift first 3 step



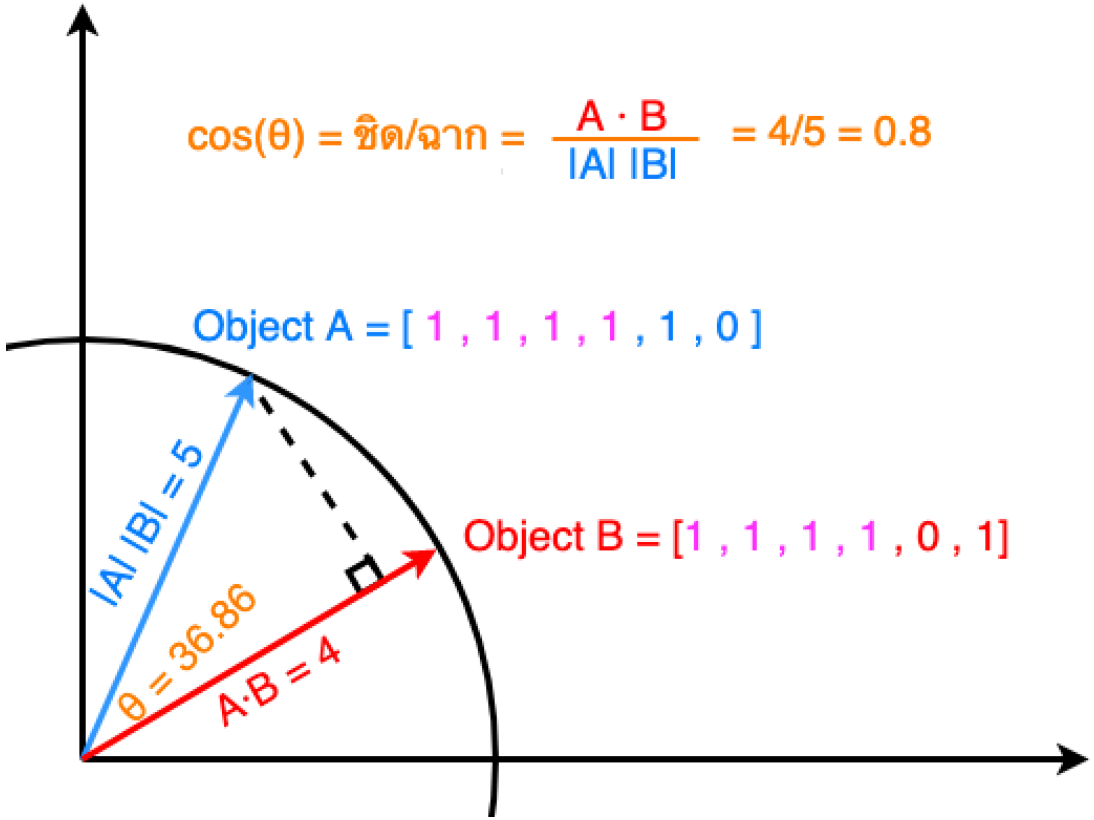

```
0.995416134063
```

Zoom your graph and shift first 3 step



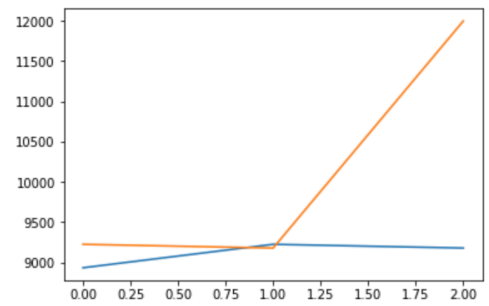

```
0.995416134063
```

Cosine Similarity

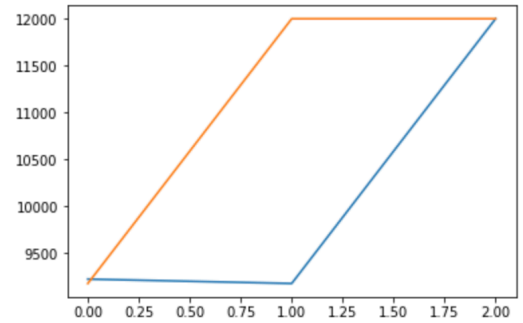


https://www.softnix.co.th/2019/05/29/similarity-%E0%B8%84%E0%B8%A7%E0%B8%B2%E0%B8%A1%E0%B9%80%E0%B8%AB%E

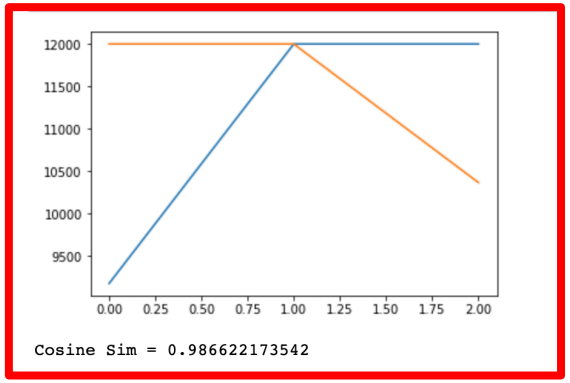
Rotate graph next 3 step and compare with cosine similarity



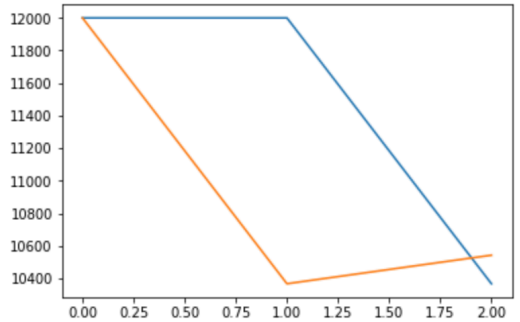
Cosine Sim = 0.99218007699



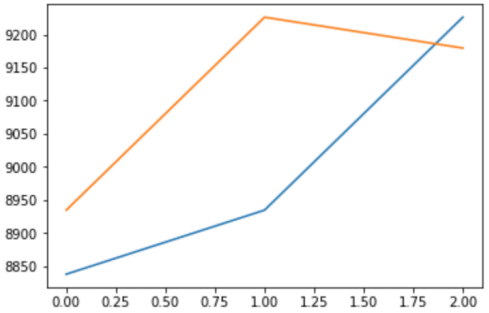
Cosine Sim = 0.992058697927



Cosine Sim = 0.986622173542



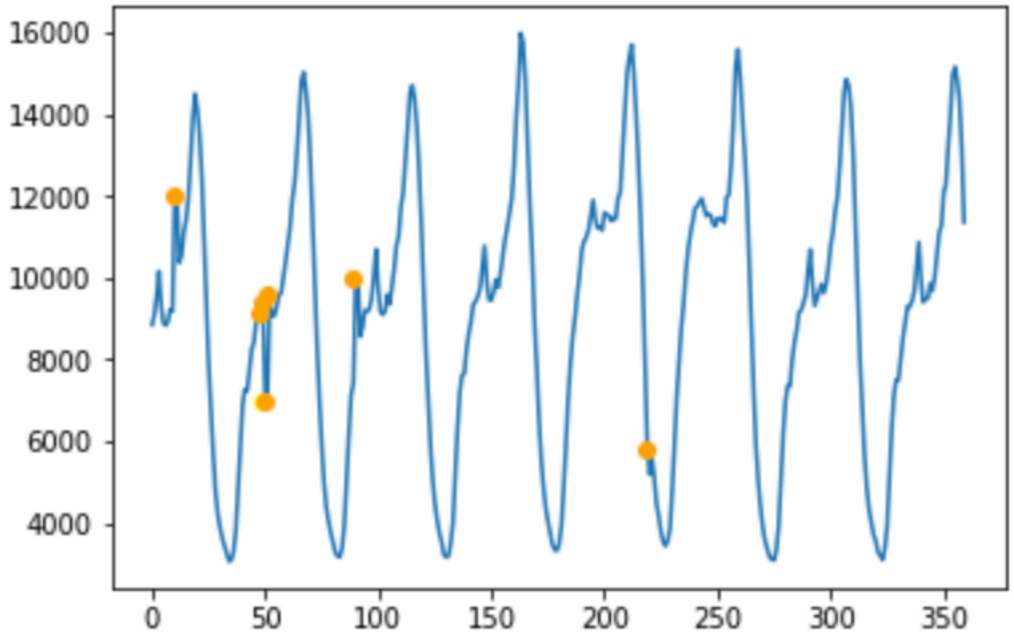
Cosine Sim = 0.997383440828

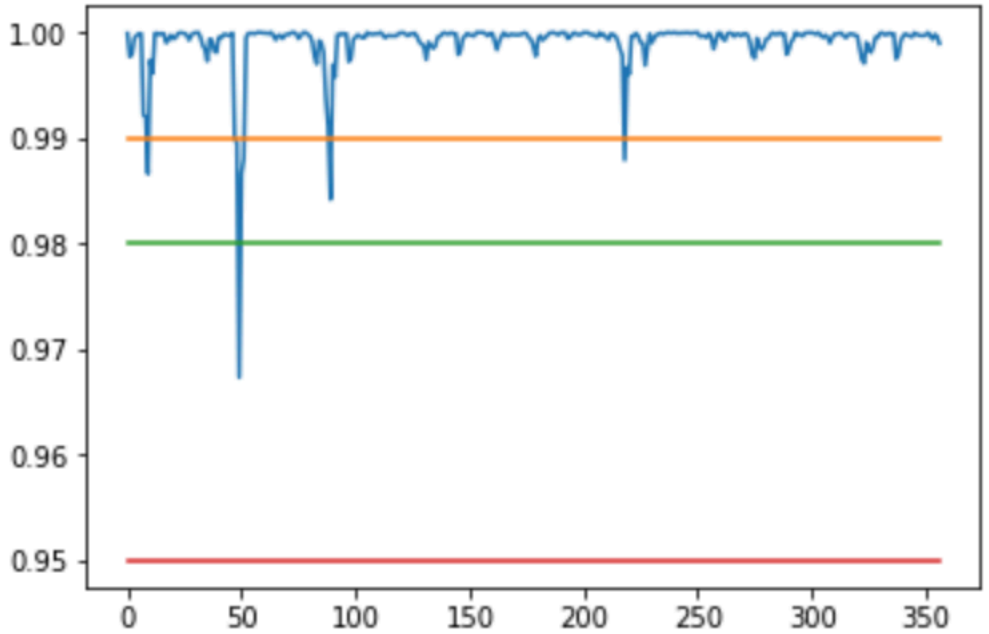


Cosine Sim = 0.999882212445

Remark when value lower than threshold

Anomaly Detection and Cosine Values





Time Shift Detection Example

In [10]:
```
a = np.array([1,2,3,4,5,6,7,7,7,7])
b = np.array([5,5,6,6,7,7,8,8,8,9])

print(a,b)
```

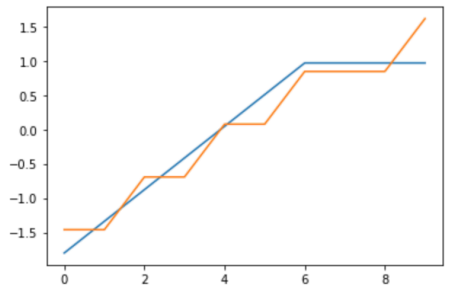
```
[1 2 3 4 5 6 7 7 7 7] [5 5 6 6 7 7 8 8 8 9]
```

In [11]:
```
from sklearn.preprocessing import StandardScaler
#inverse_transform
sa = StandardScaler().fit(a.reshape(-1,1))
sb = StandardScaler().fit(b.reshape(-1,1))
a_Transform = sa.transform(a.reshape(-1,1))
b_Transform = sb.transform(b.reshape(-1,1))
print(a_Transform)
#print(b_Transform)
```

```
[[-1.80085268]
 [-1.33909558]
 [-0.87733848]
 [-0.41558139]
 [ 0.04617571]
 [ 0.50793281]
 [ 0.9696899 ]
 [ 0.9696899 ]
 [ 0.9696899 ]
 [ 0.9696899 ]]
```

In [12]:
```
#print(a_Transform)
plt.plot(a_Transform.reshape(1,-1)[0])
plt.plot(b_Transform.reshape(1,-1)[0])
```

Out[12]: [<matplotlib.lines.Line2D at 0x7fbc56318b70>]



In [13]:
```
#print(a_Tranform)
```

https://github.com/krmonline/AnomalyDetection/blob/master/Cosine_on_TimeSeries.ipynb