



Selected topics in Advanced Machine Learning

Lecture 03 – Anomalies

January 24, 2022

+ Objectives

- Nature of the data
- Data labels
- Types of Outlier/Anomaly techniques

+ 1. Nature of the Data: Input Data

- Most common form of data handled by anomaly detection techniques is *Record Data*

- Univariate
- Multivariate

- Nature of attributes

- Binary
- Categorical
- Continuous
- Hybrid

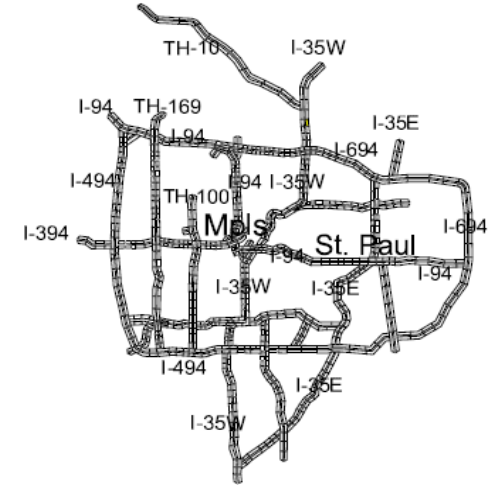
	categorical	continuous	categorical	continuous	Binary	
<i>Tid</i>	SrcIP	Start time	Dest IP	Dest Port	Number	Attack
1	206.135.38.95	11:07:20	160.94.179.223	139	192	No
2	206.163.37.95	11:13:56	160.94.179.219	139	195	No
3	206.163.37.95	11:14:29	160.94.179.217	139	180	No
4	206.163.37.95	11:14:30	160.94.179.255	139	199	No
5	206.163.37.95	11:14:32	160.94.179.254	139	19	Yes
6	206.163.37.95	11:14:35	160.94.179.253	139	177	No
7	206.163.37.95	11:14:36	160.94.179.252	139	172	No
8	206.163.37.95	11:14:38	160.94.179.251	139	285	Yes
9	206.163.37.95	11:14:41	160.94.179.250	139	195	No
10	206.163.37.95	11:14:44	160.94.179.249	139	163	Yes

+ 1. Nature of the Data: Input Data

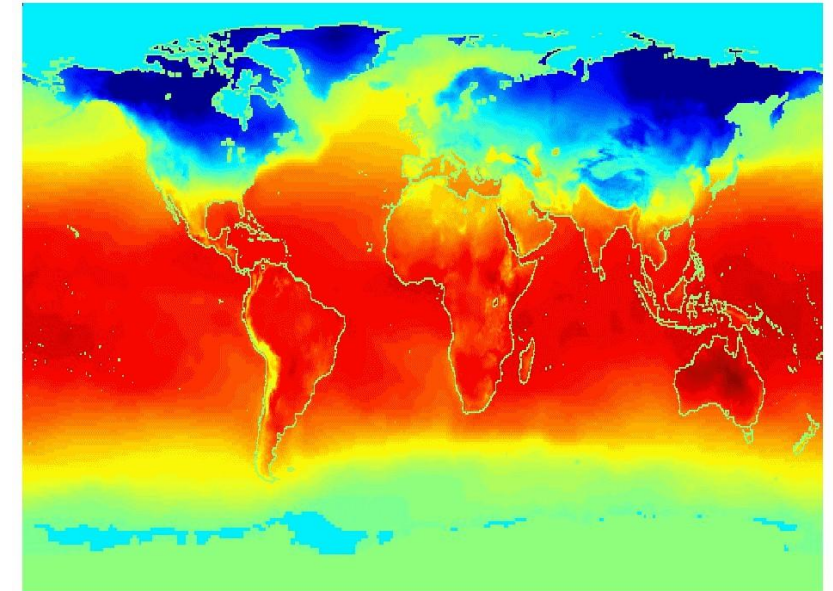
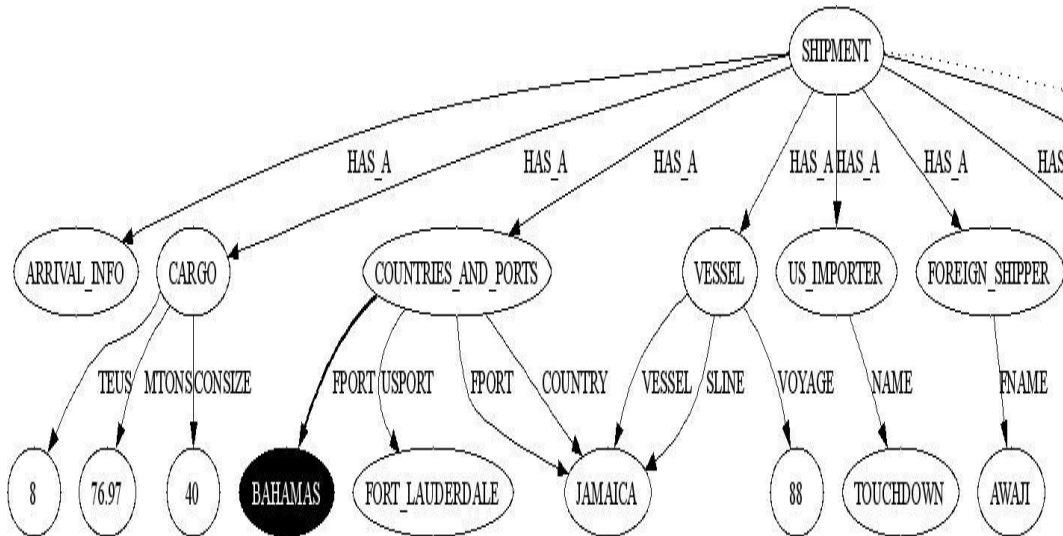
■ Relationship among data instances

- Sequential
- Temporal
- Spatial
- Spatio-temporal
- Graph

GGTTCCG CCTTCAGCCCCGCGCC
CGCAGGGCCCGCCCCGCGCCGTC
GAGAAGGGCCCGCCTGGCGGGCG
GGGGGAGGCGGGGCGCCCCGAGC
CCAACCGAGTCCGACCAGGTGCC
CCCTCTGCTCGGCCCTAGACCTGA
GCTCATTAGGCGGCAGCGGACAG
GCCAAGTAGAACACGCGAAGCGC
TGGGCTGCCTGCTGCGACCAGGG



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+ 2. Availability of supervision: Data Labels

■ *Supervised Anomaly Detection*

- Labels available for both normal data and anomalies
- Similar to rare class mining/imbalanced classification

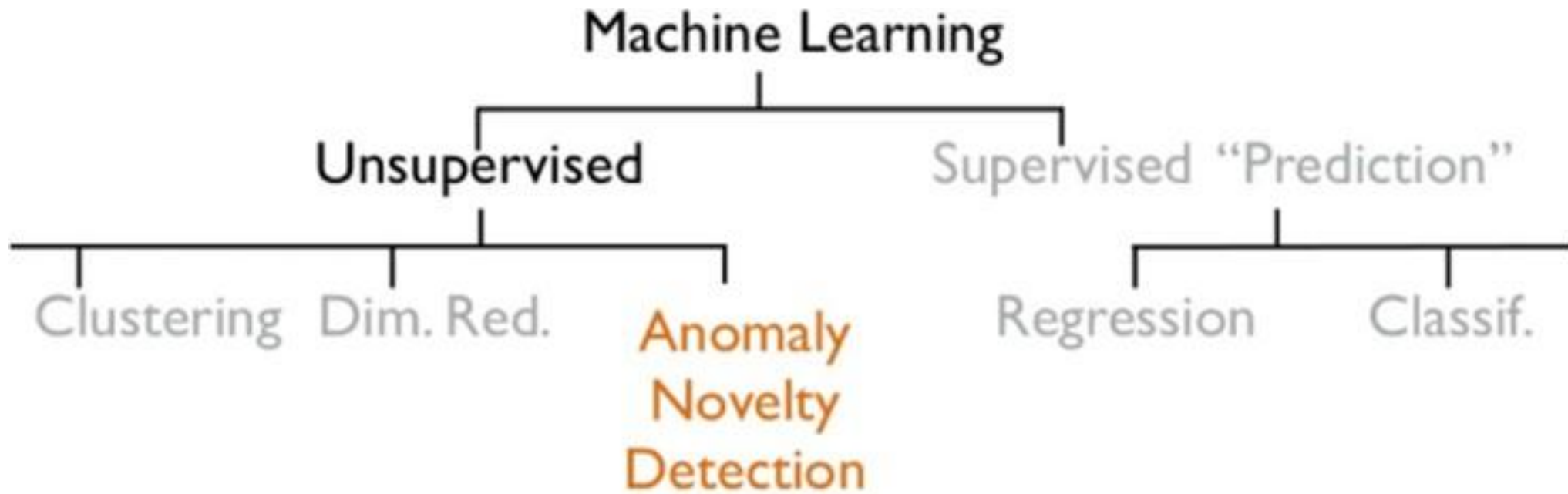
■ *Semi-supervised (Anomaly/novelty Detection)*

- Labels available only for normal data.
- The algorithm learns on normal data only

■ *Unsupervised Anomaly Detection (Outlier Detection)*

- No labels assumed (training set=normal data + abnormal Data)
- Based on the assumption that anomalies are very rare compared to normal data

+ Machine Learning Taxonomy



+ 3. Types of Outlier/Anomaly

- *Three kinds:*

- *Global Outliers* (Point Anomalies)

- *Contextual Outliers* (Conditional Anomalies)

- *Collective Outliers*

- A data set may have *multiple* types of *outlier*

- *One* object may *belong* to *more* than *one* type of *outlier*

Global anomalies affect the entire system uniformly.

Contextual anomalies occur within specific contexts or subsets of data.

Collective anomalies involve collective behavior of multiple data points or entities

+ Global Anomalies

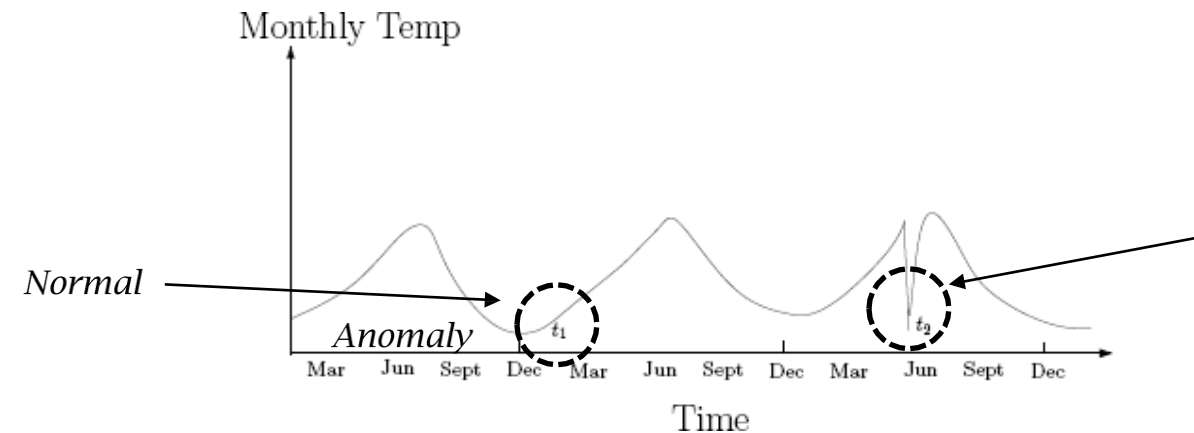
- Affect the entire system uniformly.
- Represent a sudden or consistent deviation across all data points.
- Example: All sensors in a factory show unusually high temperatures at the same time.

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+ Contextual Anomalies

- An individual data instance is anomalous *within a context*
- Requires a *notion* of *context*
- Also referred to as *conditional anomalies**

- Occur in a specific context (such as time, location, or condition).
- The data point is only abnormal under certain circumstances.
- Example: A temperature of 25°C is normal in summer but abnormal in winter.



+ Collective Anomalies

- Involve unusual patterns among a group of data points.
- Each point may look normal alone but abnormal together.
- **Example:** Multiple network devices suddenly show identical traffic spikes.

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+ Applications of Anomaly Detection

- Network intrusion detection
- Insurance / Credit card fraud detection
- Healthcare Informatics / Medical diagnostics
- Industrial Damage Detection
- Image Processing / Video surveillance
- Novel Topic Detection in Text Mining
- ...

+ Application: Intrusion Detection



■ *Intrusion Detection*

- Process of monitoring the *events* occurring in a *computer system* or network and *analyzing* them for *intrusions*
- Intrusions are defined as *attempts to bypass the security mechanisms* of a computer or network

■ *Challenges*

- Traditional *signature-based intrusion detection systems* are based on *signatures* of known *attacks* and cannot *detect emerging cyber threats*
- Substantial latency in deployment of newly created signatures across the computer system
- *Anomaly detection can alleviate these limitations*

+ Applications of Anomaly Detection

■ *Fraud detection:*

- Fraud detection refers to detection of *criminal activities* occurring in *commercial organizations*.
- Malicious users might be the *actual customers* of the *organization* or might be *posing* as a *customer* (also *known as identity theft*).

■ *Types of fraud*

- Credit card fraud.
- Insurance claim fraud
- Mobile / cell phone fraud
- Insider trading

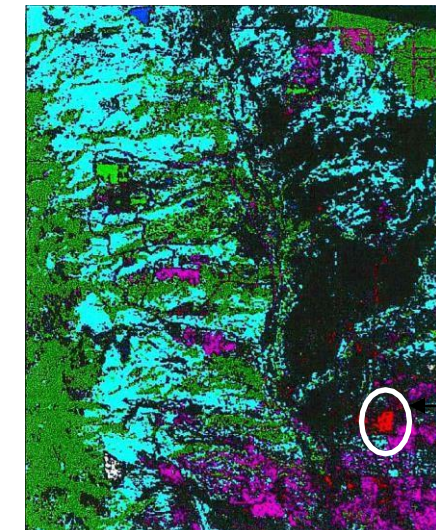
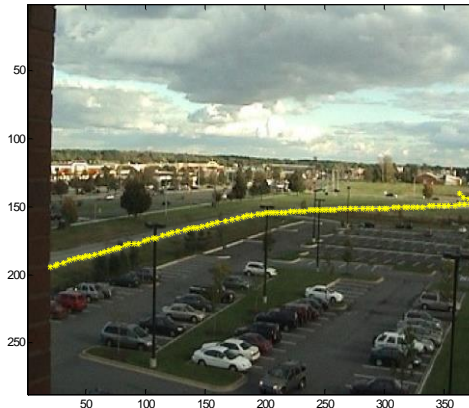
■ *Challenges*

- *Fast* and *accurate* real-time detection.
- *Misclassification* cost is very *high*



+ Image Processing

- Detecting outliers in an image monitored over time
- Detecting anomalous regions within an *image*
- Used in
 - *mammography image analysis*
 - *video surveillance*
 - *satellite image analysis*
- *Key Challenges*
 - Detecting *collective anomalies*
 - Data sets are *very large*



Anomaly

+ Challenges of Anomaly detection

- Modeling *normal objects* and *outliers* properly.
 - Hard to *enumerate all possible normal behaviors in an application*.
 - The *border* between *normal* and *outlier* objects is often a gray area
- Application-specific outlier detection.
 - Choice of *distance measure* among objects and the model of *relationship* among objects are often *application-dependent*.
- *Example: clinic data: a small deviation could be an outlier; while in marketing analysis, larger fluctuations*

+ Challenges of Anomaly detection

■ *Handling noise in outlier detection.*

- *Noise* may *distort* the normal objects and *blur* the *distinction* between *normal* objects and *outliers*.
- Noise may help *hide outliers* and *reduce* the *effectiveness* of outlier detection.

■ *Understandability*

- Understand why these are outliers: *Justification of the detection*.
- Specify the *degree* of an *outlier*: the *unlikelihood* of the object being generated by a *normal* mechanism.
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+ Methods for anomaly detection

- Outlier Detection Methods.
- *Whether user-labeled examples of outliers can be obtained.*
 - Supervised, Semi-Supervised, and Unsupervised Methods.
- *Assumptions about normal data and outliers.*
 - Statistical Methods, Proximity-Based Methods, and Clustering-Based Methods.

+ Supervised Methods

- *Modeling outlier detection as a classification problem.*

- Samples examined by domain experts used for training & testing

- Methods for *Learning* a *classifier* for *outlier detection* effectively:

- Model normal objects & report those not matching the model as outliers, or
- Model outliers and treat those not matching the model as normal

- *Challenges*

- *Imbalanced classes*, i.e., outliers are rare: Boost the outlier class and make up some artificial outliers.
- Catch as many outliers as possible, i.e., *recall* is more important than *accuracy* (i.e., not mislabeling normal objects as outliers)

+ Unsupervised Methods

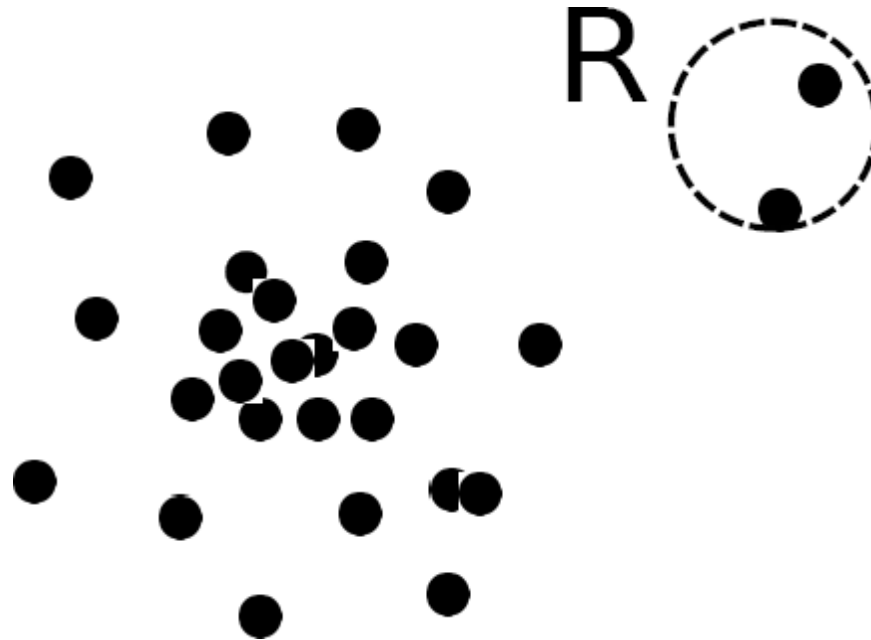
- Assume the normal objects are somewhat “*clustered*” into *multiple groups*, each having some *distinct features*
- An outlier is expected to be *far away* from any groups of normal objects
- *Weakness: Cannot detect collective outlier effectively*
 - Normal objects *may not* share any *strong patterns*, but the collective outliers may share *high similarity in a small area*
- Many clustering methods can be adapted for unsupervised methods.
- *Find clusters, then outliers: not belonging to any cluster*

+ Semi-Supervised Methods

- In many applications, the number of *labeled data is often small*
 - Labels could be on outliers only, normal objects only, or both•
- If some labeled *normal objects are available*
 - Use the *labeled examples* and the *proximate unlabeled* objects to train a model for *normal* objects.
 - Those not *fitting the model of normal objects* are detected as *outliers*
- If only *some labeled outliers* are available, a *small number of labeled outliers many not cover the possible outliers well*.
 - To improve the *quality of outlier detection*, one can get help from models for normal objects learned from unsupervised methods

+ Proximity-based Methods

- An object is an *outlier* if the *nearest neighbors* of the object are *far away*, i.e., the proximity of the object is *significantly deviates* from the *proximity* of *most* of the *other* objects in the *same data set*.

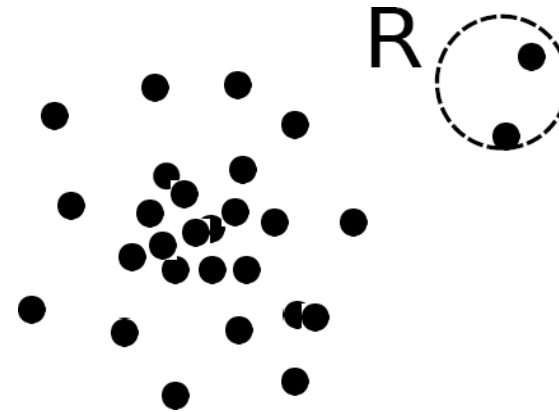


+ Challenges: Proximity based

- The *effectiveness* of proximity-based methods highly relies on the *proximity measure*.
- In some applications, *proximity or distance measures cannot* be *obtained easily*.
- Often have a *difficulty in identifying a group of outliers that stay close to each other*.
- Two major types of proximity-based outlier detection methods.
 - *Distance-based vs. density-based*

+ Clustering-based Methods

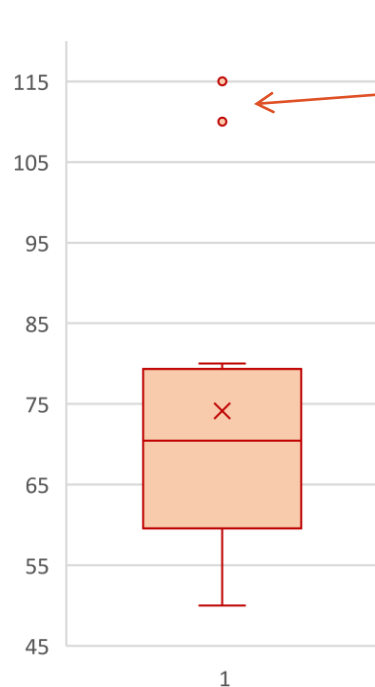
- Normal data belong to *large and dense clusters*, whereas *outliers* belong to *small* or *sparse clusters*, or *do not belong to any clusters*.
- Clustering based
 - Nearest-neighbor based
 - Density based
- *Challenges*
 - Clustering is expensive: straightforward adaption of a clustering method for outlier detection can be costly and does not scale up well for large data sets.



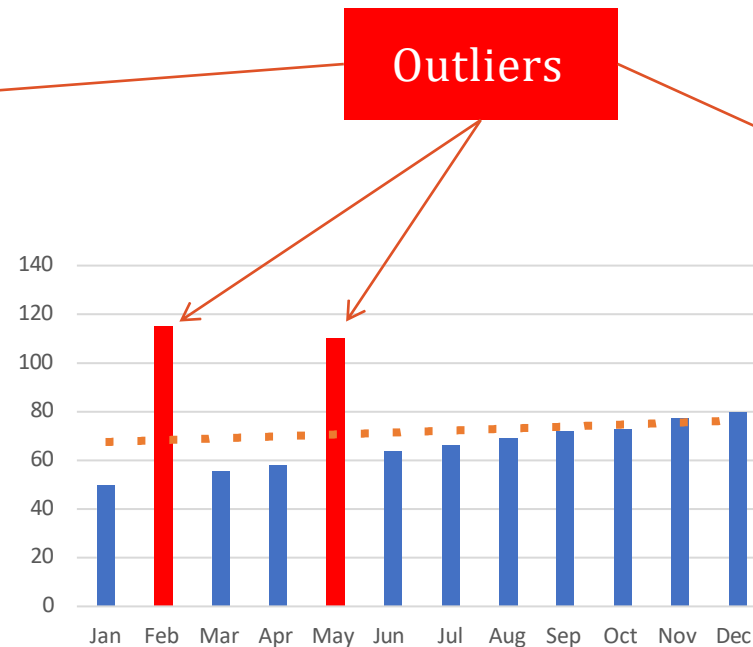
+ Statistical Outlier Analysis

- Most commonly used method to *detect* outliers is visualization.
- Various visualization methods, like *Box-plot, Histogram, Scatter Plot*.

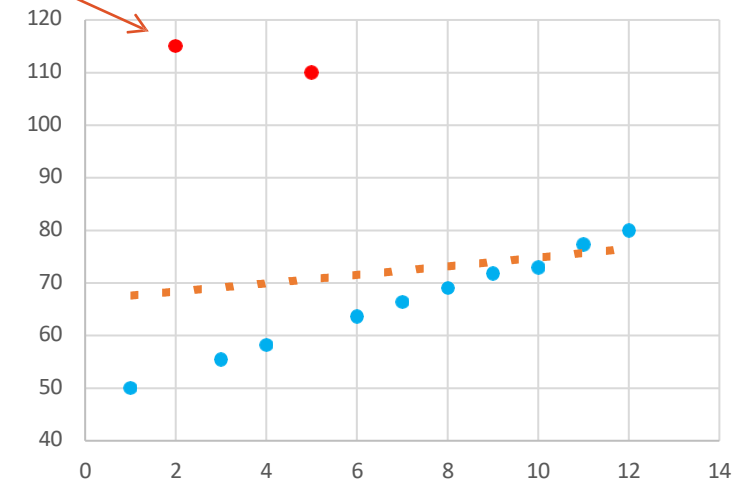
Quarter - Income	2017
Jan	50
Feb	115
Mar	55
Apr	58
May	110
Jun	64
Jul	66
Aug	69
Sep	72
Oct	73
Nov	77
Dec	80



Box-plot



Histogram



Scatter Plot

+ Statistical Outlier Analysis

■ *Apply a statistical test that depends on*

- Data distribution
- Parameter of distribution (e.g., mean, variance)
- Number of expected outliers (confidence limit)

■ *Limitation*

- Most of the tests are for a single attribute
- In many cases, data distribution may not be known
- For high dimensional data, it may be difficult to estimate the true distribution

+ Statistical Outlier Analysis

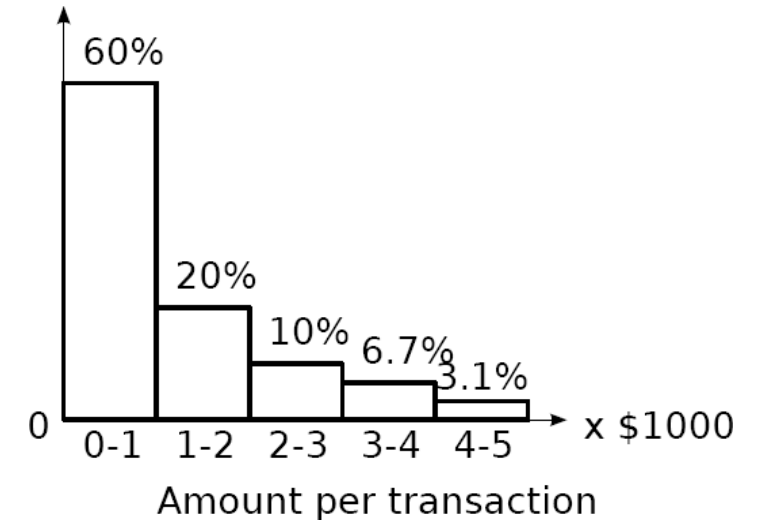
- **Assumption:** the objects in a data set are generated by a *(stochastic) process (a generative model)*.
- Learn a *generative model fitting* the given data set, and then *identify* the *objects* in *low probability regions of the model as outliers*.
- Two categories: *parametric versus nonparametric*.
- Statistical methods (also known as model based methods) assume that the *normal data* follow *some statistical model*.
 - The data not following the model are outliers

+ Parametric Methods

- Assumption: the normal data is generated by a *parametric distribution* with *parameter θ* .
- The probability *density function* of the parametric distribution $f(x \mid \theta)$ gives the *probability that object x is generated by the distribution*
- *The smaller this value, the more likely x is an outlier*

+ Non-parametric Method

- Not assume an *a-priori statistical model, instead, determine the model from the input data.*
 - Not completely parameter free but consider the number and nature of the parameters are flexible and not fixed in advance.
- Examples: *histogram and kernel density estimation.*
- A transaction in the amount of \$7,500 is an outlier, since only 0.2% transactions have an amount higher than \$5,000



+ Challenges: Non Parametric method

- Hard to choose an *appropriate bin size for histogram*.
 - *Too small bin size* → normal objects in empty/rare bins, false positive .
 - *Too big bin size* → outliers in some frequent bins, false negative



End of Lecture – 03