# CMPT 733 - Big Data Programming II

# **Anomaly Detection**

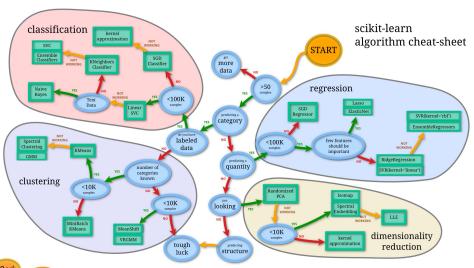
Instructor Steven Bergner

Course website <a href="https://coursys.sfu.ca/2025sp-cmpt-733-g1/pages/">https://coursys.sfu.ca/2025sp-cmpt-733-g1/pages/</a>

Slides by Jiannan Wang & Steven Bergner

# **Outline**

A Brief Introduction of Anomaly Detection Application: Network Intrusion Detection





# What is Anomaly Detection?

# Definition from dictionary

a·nom·a·ly

/ə'näməlē/ •)

noun

1. something that deviates from what is standard, normal, or expected.

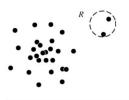


#### Also known as Outlier Detection

# **Anomaly Categories (I)**

# Global Anomaly

- A data point is considered anomalous with respect to the rest of data
- Example: There is a person whose age is 110

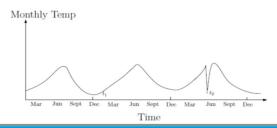


The objects in region R are outliers.

# **Anomaly Categories (II)**

## Context Anomaly

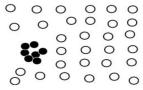
- A data point is considered anomalous with respect to a specific context
- Example: There is a student in our class whose age is 10.



# **Anomaly Categories (III)**

# Collective Anomaly

- A subset of data points as a whole deviates significantly from the entire dataset
- Example: An order may have some delay to be processed. But, what if 1000 orders are processed with delay?



The black objects form a collective outlier.

# **Real-world Applications**

Fraud Detection

Medical Care

**Public Safety and Security** 

**Network Intrusion** 

# **Challenges**

# Modeling normal objects and anomalies effectively:

- Hard to enumerate all possible normal behaviors
- The border between normal objects and anomalies can be gray area

#### Application specific anomaly detection:

· Hard to develop general purpose anomaly detection tools

# Understandability:

Not only detect the anomalies, but also understand why they are anomalies

# **Outline**

# Recap of Anomaly Detection Application: Network Intrusion Detection

"Give a man a fish and you feed him for a day. Teach a man to fish and you feed him for a lifetime." - Chinese Proverb

Teach you a network-intrusion solution vs.

Teach you how to come up with this solution

# **Network Intrusion**



"Our web servers got attacked yesterday. I don't want it to happen again. Please build a system to address it!"

#### TO DO Lists:

- 1. Find related datasets (e.g., /var/log/apache2/access.log)
- 2. Figure out how to detect attacks (anomalies) Key Problem
- 3. Trigger an alert when an attack is detected (e.g., send an email)

# How to come up with a solution?

1. Doing a survey on related work

# **Anomaly Detection Methods**

#### Survey Paper

#### Anomaly detection: A survey

V Chandola, A Baneries, V Kumar. - ACM computing surveys (CSUR), 2009. -d.l.acm.org Abstract Anomaly detection is an important problem that has been researched within diverse research areas and application domains. Many anomaly detection techniques have been specifically developed for certain application domains, while others are more generic. This

☆ 99 Cited by 4705 Related articles All 36 versions

#### Intrusion detection: A survey

F Sabahi, A <u>Movaghar</u> - Systems and Networks ..., 2008 - ieeexplore.ieee.org ... presents a taxonomy of intrusion **detection** systems that is then used to **survey** and classify ... This method works by using the definition "**anomalies** are not normal ... There are many **anomaly detection** that proposed algorithms with differences in the information used for analysis and ...

☆ 99 Cited by 117 Related articles All 4 versions

- 1. Supervised Learning (e.g., Sentiment Analysis)
- 2. Unsupervised Learning (e.g., Find the top-10 hot topics in twitter)

# Why is unsupervised learning more common?

#### No need to label data

Labeling is a tedious and expensive process

#### Able to identify "unknown unknowns"

- Not only detect a known attack pattern (e.g., red apple)
- but also detect an unknown attack pattern (e.g., watermelon)



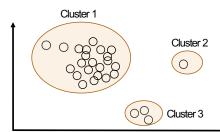
# How to come up with a solution?

- 1. Doing a survey on related work
- 2. Choosing an unsupervised learning approach

# **Clustering-based**

#### Basic Idea

- Cluster data points into groups.
- Decide which points are anomalies:
  - Points in small clusters
  - Using distance to the closest cluster



# How to come up with a solution?

- 1. Doing a survey on related work
- 2. Choosing an unsupervised learning approach
- 3. Picking up a clustering algorithm

# K-Means

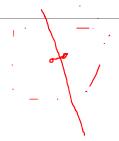
#### Iterative Algorithm

This is the initial motivation for creating Spark

## Algorithm Overview

- 1. Picking up K random points as cluster centers
- Assigning each point to the closest center
- 3. Updating cluster centers accordingly
- 4. Repeat Steps 2 and 3 until some termination conditions are met

https://web.stanford.edu/class/engr108/visualizations/kmeans/kmeans.html



# How to come up with a solution?

- 1. Doing a survey on related work
- 2. Choosing an unsupervised learning approach
- 3. Picking up a clustering algorithm
- 4. Selecting and transforming features

# **Feature Extraction**

#### **Raw Data**

#### **Turning Raw Data into Connection Data**

A connection is a sequence of HTTP requests starting and ending at some well-defined times

#### **Tuming Connection Data into Feature Vectors**

- Requiring a fair bit of domain knowledge
- Asking yourself how to distinguish attacks from normal connections (e.g., number of failed login attempts, duration of the connection)

# **Feature Scaling**

#### Feature Vector

```
e.g., [http, BC, 0, 105, 146, 0, ..., 0.00, 0.00]

Categorical Numerical feature feature
```

#### Will this feature vector work for KMeans?

- What's the distance between "http" and "ftp"?
- The distance between two feature vectors will be dominated by the features with a broad range of values (e.g., the 4th feature)

# Categorical Features → Numerical Features

#### Naïve solution

- http→ 0
- ftp → 1
- ∘ ssh → 2

# One-hot encoding

- $\circ$  http  $\rightarrow$  [1,0,0]
- ftp  $\rightarrow$  [0,1,0]
- $\circ$  ssh  $\rightarrow$  [0,0,1]



Distance("http", "ssh") > Distance("http", "ftp")

# **Scaling Numerical Features**

1. Rescaling

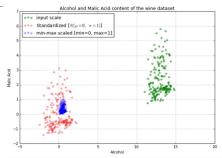
$$x' = \frac{x - min(x)}{max(x) - min(x)}$$

2. Standardization

$$x' = \frac{x - \bar{x}}{\sigma}$$

3. Scaling to unit length





The impact of Standardization and Normalisation on the Wine dataset

Which one to use? It depends on requirements:

- Hard bounds: (1), (3)
  Tree-based models: no need

# **Feature Selection**

# What? and Why?

#### Data are often in the form of a table

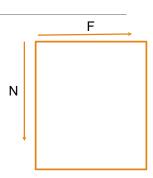
- N: # of training examples (e.g., tweets, images)
- F: # of features (e.g., bag of words, color histogram)

#### Feature Selection

• Selecting a subset of features for use in model construction.

#### What's bad about "Big F"?

- Slow (training time)
- Inaccurate (due to overfitting and the curse of dimensionality)
- Hard to interpret models



# How?

# Feature Selection Learning Algorithm Learning Algorithm Learning Algorithm Feature Selection Learning Algorithm Feature Selection

# **Filter Method**

#### Basic Idea

- Assign a score to each feature
- Filter out useless features based on the scores

#### Many popular scores [see Yang and Pederson '97]

- · Classification: Chi-squared, information gain, document frequency
- Regression: correlation, mutual information

# **Wrapper Method**

#### Basic Idea

- Evaluate subsets of features
- Select the best subset

#### How to evaluate a subset of features?

Test Error (estimated by cross validation)

#### How to find the best subset?

Greedy Algorithms (e.g., forward selection, backward elimination)

# **Embedded Method**

#### Basic Idea

Modify a learning algorithm such that it can automatically penalize useless features

#### Lasso Regression

$$\underset{\beta}{\operatorname{argmin}} \ \|y - X\beta\|_{\text{"}}^2 \ + \overbrace{\lambda \|\beta\|_1}$$
 Penalize useless features

# **Comparisons**

#### Filter Method

Efficient
Robust to overfitting
Fails to capture relationships between features

#### Wrapper Method

Capture relationships between features Inefficient May suffer from overfitting

#### **Embedded Method**

Combine the advantages of the above methods Specific to a learning algorithm

# **Dimensionality Reduction**

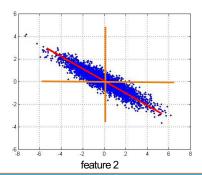
#### **Feature Selection**

 New features have to be a subset of old features

# Feature Transformation (e.g., PCA)

 New features may NOT be a subset of old features

feature 1



# How to come up with a solution?

- 1. Doing a survey on related work
- 2. Choosing an unsupervised learning approach
- 3. Picking up a clustering algorithm
- 4. Selecting and transforming features
- 5. Parameter tuning and evaluation

# **Parameter Tuning and Evaluation**

#### **Evaluation**

- Ground-truth Label?
- Fvaluation Metric?

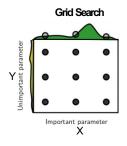
# **Parameter Tuning**

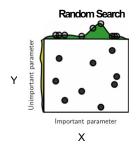
- Grid Search
- Random Search
- Bayesian Optimization

# **Grid Search & Random Search**

x: # of working hours (1, 2, ..., 12) y: # of sleeping hours (1, 2, ..., 12)

Income(x, y) = Work(x) + Sleep(y)

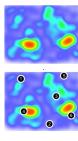




# **Bayesian Optimization**

#### Intuition

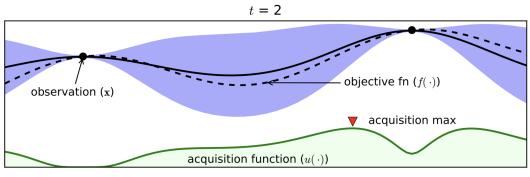
- Want to find the <u>peak point of objective function</u> (eg. accuracy as a function of parameters)
- Fit a <u>statistical model</u> to the observed points and pick next best point where we believe the maximum will be
- Next point is determined by an acquisition function that trades off exploration(objective) and exploitation(uncertainty)





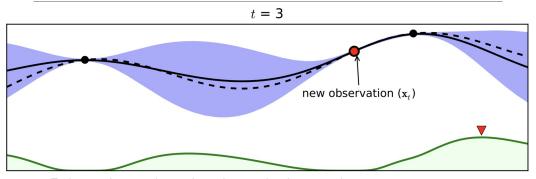


# **Example**



Find next point that max the acquisition function

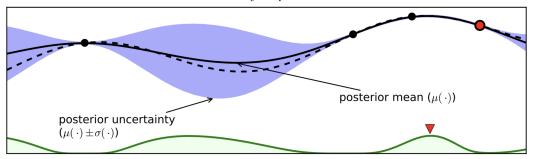
# **Example**



Evaluate at the new observation point x<sub>1</sub> and update posterior Update acquisition function from new posterior and find the next best point

# **Example**





# How to come up with a solution?

- 1. Doing a survey on related work
- 2. Choosing an unsupervised learning approach
- 3. Picking up a clustering algorithm
- 4. Selecting and transforming features
- 5. Tuning parameters and evaluation
- 6. If not satisfied, go back to previous steps

# How to come up with the solution?

- 1. Doing a survey on related work
- 2. Choosing an unsupervised learning approach
- 3. Picking up a clustering algorithm
- 4. Selecting and transforming features
- 5. Tuning Parameters and evaluation
- 6. If not satisfied, go back to previous steps
- 7. Deploying your model in production

# **Model Serving**

## **Very Important Topic**

- · Model has to reflect to the latest data updates.
  - Kmeans → Streaming Kmeans
- Predictions have to be made in real-time.
  - Deploy a Model in Amazon SageMaker
  - TensorFlow Serving
  - Deploy models with Azure Machine Learning
  - Serving of ML models in Kubeflow
  - Announcing MLflow Model Serving on Databricks

# Summary

#### How to come up with the solution?

- 1. Doing a survey on related work
- 2. Choosing an unsupervised learning approach
- 3. Picking up a clustering algorithm
- 4. Selecting and transforming features
- 5. Tuning parameters and evaluation
- 6. If not satisfied, go back to previous steps
- 7. Deploying your model in production

