# Anomaly detection A very brief introduction

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# **Quick Introduction**



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- Research Scientist at Numerica Corp. (Fort Collins, CO)
- PhD in Applied Mathematics from University of Colorado Boulder
- Hydrogeologist at Golder Inc. (Lakewood, CO)
- MS in Hydrogeology from Colorado School of Mines
- BA in Physics from Dartmouth College



# **Anomaly Detection**



## What is Anomaly Detection?

- The identification of rare items, events or observations which raise suspicions by differing significantly from the majority of the data.
- Outlier detection
  - The <u>training data contains outliers</u> which are defined as observations that are far from the others. Outlier detection estimators thus <u>try to fit the regions where the training data is the most concentrated</u>, ignoring the deviant observations.
  - Unsupervised anomaly detection.

#### Novelty Detection

- The <u>training data is not polluted by outliers</u> and we are interested in detecting <u>whether a new observation is an outlier</u>. In this context an outlier is also called a novelty.
- Semi-supervised anomaly detection.



## The good and the bad

- Pros
  - Potential to detect of anomalous events you hadn't anticipated
  - Threats you've never seen before (e.g. zero-day attacks)
  - Identify data quality / consistency issues (e.g. changes and/or problems with data collection pipelines)
- Cons
  - Can be difficult to detect the things you want to find
  - Anomalies != bad things
  - Difficult to tune thresholds (often find way too many anomalies or few to none)
  - Potentially manually intensive process of diagnosing root cause of anomaly
  - Alert fatigue



# Lots of algorithms for outlier detection

- Robust Covariance (Minimum Covariance Determinant)
- Isolation Forest
- One-class SVM
- Local Outlier Factor
- Robust PCA
- And many more...



# **Robust Covariance (Minimum Covariance Determinant)**

- Assumes inliers have a (multivariate) Gaussian distribution.
- Conceptually
  - Attempts to find the smallest ellipsoid which contains "most" of the data.
- A bit more precisely
  - Objective is to find h observations (out of n > h) whose covariance matrix has the smallest determinant.

Rousseeuw, P.J., Van Driessen, K. "A fast algorithm for the minimum covariance determinant estimator" Technometrics 41(3), 212 (1999)







# **Robust Covariance (Minimum Covariance Determinant)**





### **Isolation Forest**

- Non-parametric method (no assumptions about distribution of inliers)
- Randomized method for detecting outliers
- Ensemble tree-based approach
  - Random selection of features
  - Random cutoffs on each feature between min and max values
  - Length of path to isolate a data point is an indicator of anomalous-ness
    - Short paths to isolation imply a likely outlier
    - Long paths to isolation imply a likely inlier

Liu, Fei Tony, Ting, Kai Ming and Zhou, Zhi-Hua. "Isolation forest." Data Mining, 2008. ICDM'08. Eighth IEEE International Conference on.



10

50

no. of tree (log scale)

100

0



500 1000

### **Isolation Forest**





#### To the codes!





### **Next Steps**

- Tune algorithm parameters
- Add (or synthesize) more features
  - Other device data
  - Shopping cart data
  - Customer history
- Get more data (more events)
  - May require a distributed compute platform like Spark
- Experiment with other anomaly detection algorithms
- Investigate correlation with variables or outcomes of interest (e.g. fraud)



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#### Lessons

- Get super familiar with the data
- Think carefully about feature set to ensure anomalies are more likely to be interesting
- Align anomaly detection algorithm with the distribution of "normal data"
- Tune thresholds carefully







