A Geometric Framework for Unsupervised Anomaly Detection: Detecting Intrusions in Unlabeled Data

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Agenda

- **Introduction**
- **Feature spaces and kernels**
- **Detection algorithms**
- **Experiments**

Introduction (1)

- Intrusion detection systems (IDS)
  - detects malicious activities such as DoS attacks, port scans, etc. by monitoring network traffic and/or system activities
- Most deployed systems use signature-based detection
  - compares feature values to attack signatures provided by experts
  - need a new signature for every new attack
- *Supervised* machine learning approach
  - train a classifier using data of normal usage and known attacks
  - can retrain to include more known attacks
  - can detect unknown attacks if *perfect* model of normality is available

Introduction (2)

- *Unsupervised* machine learning approach
  - Use unlabeled data as input
  - Attempt to separate the *anomalous* instances from the *normal* instances
  - Separate the two classes of instances, then train a traditional anomaly detection algorithm on the *clean* data
- Geometric framework for unsupervised anomaly detection
  - Map the data to a R^d feature space
  - Label points in the sparse regions of the feature space as anomalies

Unsupervised Anomaly Detection

- Detect intrusions in unlabeled data
- Can be used to semi-automate manual inspection of data in forensic analysis
- Two main assumptions:
  1) The number of normal instances vastly outnumbers the number of anomalies
  2) The anomalies are qualitatively different from the normal instances

Feature Space (1)

- Instances $x_1, x_2, \ldots, x_n$ in input space X
  - for example, X can be the space of all possible network connection records, event logs, system call traces, etc.
- Define a mapping

$$\varphi: X \rightarrow Y$$

where Y is R^d, or more generally a Hilbert space

- Define the distance between x_1 and x_2:

$$d_{\varphi}(x_1, x_2)$$
$$= \| \varphi(x_1) - \varphi(x_2) \|$$
$$= \sqrt{<\varphi(x_1),\varphi(x_1)> - 2 <\varphi(x_1),\varphi(x_2)> + <\varphi(x_2),\varphi(x_2)>}$$

Feature Space (2)

- Some mappings correspond to a kernel function K where

$$K_{\varphi}(x_1, x_2) = <\varphi(x_1),\varphi(x_2)>$$

- Some kernel functions correspond to an infinite dimension mapping!
- Example (radial basis kernel):

$$K_{rb}(x_1, x_2) = e^{-\frac{\|x_1 - x_2\|^2}{\sigma^2}}$$

  – This kernel corresponds to an infinite dimension mapping

Detection Algorithms (1)

Algorithm 1: Cluster-based Estimation

  – computes how many points are “near” each point in the feature space, i.e., $d(x1,x2) \leq w$

- Straightforward computation takes $O(n^2)$
- Fixed width clustering algorithm (approximation)
  – First point is center of the first cluster
  – For each subsequent point, if it is within w of some cluster’s center, it is added to that cluster. Otherwise, it is a center of a new cluster
  – Some points may be added to multiple clusters!
  – Complexity is $O(cn)$ where c is the number of clusters

Detection Algorithms (2)

- For points in dense regions, the estimate is inaccurate
  - not an issue, as long as we classify it as a normal point
- For points in sparse regions, the estimate is (more) accurate

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Detection Algorithms (3)

Algorithm 2: K-nearest neighbors

- computes the sum of the distance to the *k*-nearest neighbors of each point in the feature space
- Refer to this sum as k-NN score

- To be useful, *k* needs to be larger than the number of instances of any one attack
- Straightforward computation: $O(n^2)$

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Detection Algorithms (4)

- Approximation algorithm
  - Use the fixed-width cluster algorithm from algorithm 1, with a variation that each element is only placed in one cluster
- Let $c(x)$ denote the center of the cluster that contains x
- If x_1 and x_2 are in the same cluster:

$$d_{\varphi}(x_1, x_2) \leq 2w$$

- In all cases:

$$d_{\varphi}(x_1, x_2) \leq d_{\varphi}(x_1, c(x_2)) + w$$
$$d_{\varphi}(x_1, x_2) \geq d_{\varphi}(x_1, c(x_2)) - w$$

Detection Algorithms (5)

- The algorithm uses these three inequalities to find the *k*-nearest neighbors
- Note that choice of *w* does not affect the k-NN score; it only affects the efficiency of computing the score

Detection Algorithms (6)

Algorithm 3: One Class SVM (Support Vector Machine)

- Standard SVM algorithm is a supervised learning algorithm
  - tries to maximally separate two classes of data in feature space by a hyperplane
- Unsupervised (one class) SVM tries to separate the entire set of training data from the origin
- Objective function:

$$\min_{w \in Y, \zeta_i \in \Re, \rho \in \Re} \quad \frac{1}{2}||w||^2 + \frac{1}{vl}\sum_i^l \zeta_i - \rho$$

$$\text{subject to:} \quad (w \cdot \phi(x_i)) \geq \rho - \zeta_i, \zeta_i \geq 0$$

v : parameter that controls tradeoff between maximizing the distance from origin and containing most of the data (essentially the ratio of expected anomalies in the dataset)

l : the number of data points

w: the hyperplane's normal vector in the feature space

ρ: the origin

ζ: slack variables

Experiments (1)

- Two datasets:
  - KDD Cup 1999
    - Wide variety of simulated intrusions in a military network environment
    - 4,900,000 instances
    - The features are extracted from connection records
      - examples are duration, protocol type, number of bytes transferred, normal or error status of the connection
    - Four categories of attacks (total 24 attack types):
      1) Denial of Service (e.g. syn flood)
      2) Unauthorized access from a remote machine (e.g. password guessing)
      3) Unauthorized access to superuser functions (e.g. buffer overflow attacks)
      4) Probing (e.g. port scanning)
    - Filter out attacks so that dataset consists of 1-1.5% attacks

Experiments (2)

- System call data from BSM (Basic Security Module) portion of 1999 DARPA Intrusion Detection Evaluation data
  - consists of 5 weeks of BSM data of all processes on a Solaris machine
  - consider two programs: *eject* and *ps*
  - An attack can correspond to multiple processes because a malicious process can spawn other processes. Consider an attack detected if one of the processes corresponding to the attack is detected

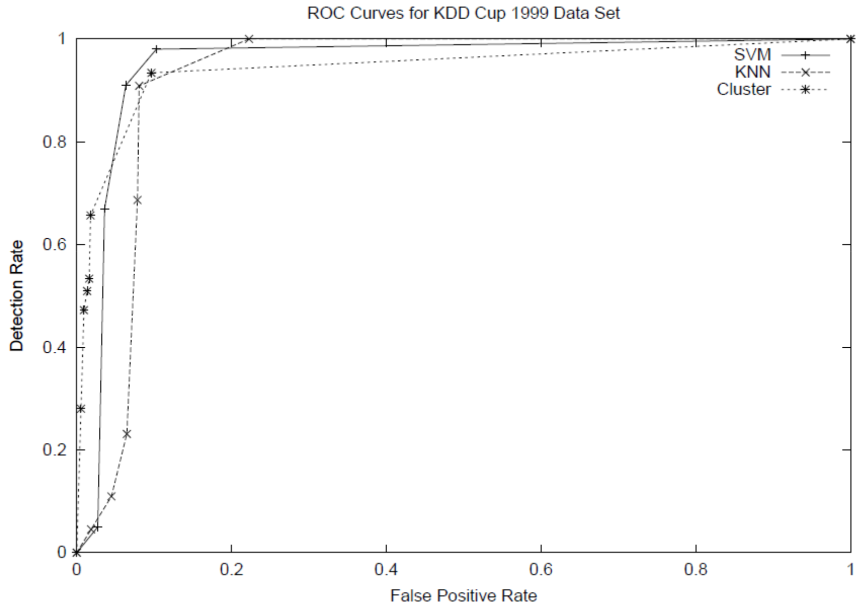
Program Name	Total # of Attacks	# Intrusion Traces	# Intrusion System Calls	# Normal Traces	# Normal System Calls	% Intrusion Traces
ps	3	21	996	208	35092	2.7%
eject	3	6	726	7	1278	36.3%

Experiments (3)

- The datasets are divided into two parts: one for training and one for testing
- Parameters:
  - cluster-based algorithm:
    - For network connection data, the width is 40
    - For *eject* system call traces, the width is 5
    - For *ps* traces, the width is 10
  - k-nearest neighbor algorithm:
    - For network connection data, k=10,000
    - For *eject* system call traces, k=2
    - For *ps* traces, k=15
  - SVM-based algorithm:
    - For network connection data, ν=0.01 and σ^2=12
    - For system call traces, ν=0.05 and σ^2=1

Experiments (4)

- Result for KDD cup data (network connection data)



Experiments (5)

Algorithm	Detection rate	False positive rate
Cluster	93%	10%
Cluster	66%	2%
Cluster	47%	1%
Cluster	28%	.5%
K-NN	91%	8%
K-NN	23%	6%
K-NN	11%	4%
K-NN	5%	2%
SVM	98%	10%
SVM	91%	6%
SVM	67%	4%
SVM	5%	3%

Table 2: Selected points from the ROC curves of the performance of each algorithm over the KDD Cup 1999 Data.

Experiment (6)

- For system call traces, **all three** algorithms perform perfectly (100% accuracy)!
- Features used: sub-sequences of system calls
  - Malicious process traces have many sub-sequences that do not occur in normal processes
  - Normal processes have similar sub-sequences of system calls