

# Review of Anomaly Detection over Noisy Data using Learned Probability Distributions

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## 1 Background and Motivation

With supervised learning, one of the requirements is that of a clean training set. If there exist anomalies in the training data,

## 2 Application

Eskin's application was in detecting anomalies to systems via UNIX system call traces. Anomalies in this case would be intrusions or access by non-desired users. The data set was from DARPA and Stephanie Forrest's group in University of New Mexico containing multiple months of program traces with attacks on certain components.

## 3 Assumptions

- Normal data can be effectively modelled by any probability distribution
- Anomalous elements are sufficiently distinct from the normal elements
- Anomalies are few ( $< 5\%$ ) of the entire data set else model of the normal distribution will get distorted

## 4 Initial Definitions

- $D$ : generative distribution for entire data
- $M$ : majority distribution
- $A$ : anomalous distribution - a priori assume uniform
- $\lambda$ : probability of anomalous element (generated from  $A$ )
- $(1 - \lambda)$ : probability of normal element (generated from  $M$ )

## 5 Anomaly Detection Method

Generalized Distribution:

$$D = (1 - \lambda)M + \lambda A$$

Probability Distribution Generation with Function  $\Phi$ :

$$P_{M_t}(X) = \Phi_M(M_t)(X)$$

$$P_{A_t}(X) = \Phi_A(A_t)(X)$$

Likelihood of Distribution:

$$L_t(D) = \prod_{i=1}^N P_D(x_i) = \left( (1 - \lambda)^{|M_t|} \prod_{x_i \in M_t} P_{M_t}(x_i) \right) \left( \lambda^{|A_t|} \prod_{x_j \in A_t} P_{A_t}(x_j) \right)$$

Log Likelihood:

$$LL_t(D) = |M_t| \log(1 - \lambda) + \sum_{x_i \in M_t} \log(P_{M_t}(x_i)) + |A_t| \log(\lambda) + \sum_{x_j \in A_t} \log(P_{A_t}(x_j))$$

Treating  $x_i$  as Anomaly:

$$M_t = M_{t-1} \setminus x_t$$

$$A_t = A_{t-1} \cup x_t$$

Score Cutoff:

$$LL_t - LL_{t-1} < c$$

## 6 Baseline Comparisons

Results under conditions that followed the given assumptions listed above gave anomaly detection rates similar to those of stide and t-stide approaches that required training over clean data sets.