Isolation Forest for Anomaly Detection

Sahand Hariri
PhD Student, MechSE UIUC

Matias Carrasco Kind
Senior Research Scientist, NCSA

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Overview

Goal: Build a resilient scalable anomaly detection service.

Motivation: Astronomical data (both literal and figurative)

Algorithm: Extended Isolation Forest

Infrastructure: Kubernetes cluster

Mapreduce package: Spark
Astronomy is just one example where data exploration needs to be automated.

Large catalogs, Large number of images, many unexpected objects/problems → Anomaly detection
Isolation Forest (Liu et al. 2008 IEEE on Data Mining)

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- Nominal points in more
Isolation Forest

Single Tree scores for **anomaly** and **nominal** points

Forest plotted radially. Scores for **anomaly** and **nominal** shown as lines

\[ s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \]
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- Readily applicable to high dimensional data
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  - Randomly select an **intercept**
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- Generate multiple trees $\rightarrow$ forest
- No artificial extra slicing
- Same rules about scoring apply
- Checking for which side of the line the point lies:

$$ (\mathbf{x} - \mathbf{p}) \cdot \mathbf{n} \leq 0 $$
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- Consistent scoring
Anomaly Detection with Extended Isolation Forest

Algorithm 2 iTree(X, e, l)

Require: X - input data, e - current tree height, l - height limit

Ensure: an iTree

1: if e ≥ l or |X| ≤ 1 then
2:     return exNode{Size ← |X|}
3: else
4:     randomly select a normal vector \( \mathbf{n} \in \mathbb{R}^{|X|} \) by drawing each coordinate of \( \mathbf{n} \) from a uniform distribution.
5:     randomly select an intercept point \( \mathbf{p} \in \mathbb{R}^{|X|} \) in the range of \( X \)
6:     set coordinates of \( \mathbf{n} \) to zero according to extension level
7:     \( X_l \leftarrow \text{filter}(X, (X - \mathbf{p}) \cdot n \leq 0) \)
8:     \( X_r \leftarrow \text{filter}(X, (X - \mathbf{p}) \cdot n > 0) \)
9:     return inNode{Left ← iTree(X_l, e + 1, l),
               \hspace{1cm} Right ← iTree(X_r, e + 1, l),
               \hspace{1cm} Normal ← n,
               \hspace{1cm} Intercept ← \mathbf{p}}
10: end if
Multi-Dimensional Data

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\[(\vec{x} - \vec{p}) \cdot \vec{n} \leq 0\]
Technology Stack For Anomaly Service

- Use Extended Isolation Forest as core algorithm
- Use Spark to parallelize trees and scoring
- Use Redis as a broker communicator
- To easily deploy in any environment, use Docker
- For orchestration of Docker containers, use Kubernetes
- Kubernetes cluster built on top of OpenStack, but it can be deployed also in AWS, GKE, etc.
Framework Architecture

There are three main components:

1. Storage
2. Computation Stage
3. User Interface / Streaming
Framework Architecture

Storage:
- NFS (Kubernetes PV/PVC)
- Redis
- RDD for Trees and Spark

User Interface:
- Jupyter notebooks
- Interactive web app for submitting jobs
- Streaming service

Computation Stage:
- Spark Master and Workers
- Communicator with Spark Master
- Subscription
Deployment

- Kubernetes allows very easy deployment, orchestration, scalability, resilience, replication, workloads and more
- Federation of services and Jobs
- From 0 to anomaly service → in minutes and config files
- Scale up/down (spark cluster and front-end) → Auto-scaling as an option
- Prototype support multiple users/projects, batch and streaming process
- Fault tolerant, disaster recovery
Example: Jupyter Notebooks
Example: Jupyter Notebooks
Examples: User interface
Conclusions

- Open source anomaly detection software package for scientific application using fast and efficient isolation forest
- Fault tolerant, robust, scalable deployment
- Train and scoring using Spark
- Ready-to-deploy infrastructure on Kubernetes
- Production services for large datasets
Thank you!

Questions?

Sahand Hariri -- NCSA
hariria2@illinois.edu
github.com/sahandha
sahandhariri.com
Variance

(a) Data
(b) Score Mean
(c) Score Variance

(a) 3-D Blob, mean of the scores
(b) 3-D Blob, variance of the scores
(a) 4-D Blob, mean of the scores
(b) 4-D Blob, variance of the scores
Convergence
Streaming

- 2 cases: Time evolving data, Time accumulative data
- Streaming isolation forest exists, not extended
- We can adapt and retrain trees as new data is presented
- Replace trees one by one until whole forest is replaced
- Work with window size to retrain trees