Streaming Outlier Analysis for Fun and Scalability

Casey Stella



2016

Table of Contents

Streaming Analytics

Framework

Demos

Questions

Introduction

Hi, I'm Casey Stella!

- The future involves non-trivial analytics done on streaming data
- It's not just IoT
- There is a need for insights to keep pace with the velocity of your data

• The Good: Much of the data can be coerced into timeseries

- The Good: Much of the data can be coerced into timeseries
- The Bad: There is a lot of data and it comes at you fast

- The Good: Much of the data can be coerced into timeseries
- The Bad: There is a lot of data and it comes at you fast
- The Good: Outlier analysis or anomaly detection is a killer-app

- The Good: Much of the data can be coerced into timeseries
- The Bad: There is a lot of data and it comes at you fast
- The Good: Outlier analysis or anomaly detection is a killer-app
- The Bad: Outlier analysis can be computationally intensive

- The Good: Much of the data can be coerced into timeseries
- The Bad: There is a lot of data and it comes at you fast
- The Good: Outlier analysis or anomaly detection is a killer-app
- The Bad: Outlier analysis can be computationally intensive
- The Good: There is no shortage of computational frameworks to handle streaming

- The Good: Much of the data can be coerced into timeseries
- The Bad: There is a lot of data and it comes at you fast
- The Good: Outlier analysis or anomaly detection is a killer-app
- The Bad: Outlier analysis can be computationally intensive
- The Good: There is no shortage of computational frameworks to handle streaming
- The Bad: There are not an overabundance of high-quality outlier analysis frameworks

Outlier Analysis

Outlier analysis or anomaly detection is the analytical technique by which "interesting" points are differentiated from "normal" points. Often "interesting" implies some sort of error or state which should be researched further.

¹http://arxiv.org/pdf/1603.00567v1.pdf

Outlier Analysis

Outlier analysis or anomaly detection is the analytical technique by which "interesting" points are differentiated from "normal" points. Often "interesting" implies some sort of error or state which should be researched further.

Macrobase¹, an outlier analysis system built for IoT by MIT and Stanford and Cambridge Mobile Telematics, noted several properties of IoT data:

- Data produced by IoT applications often have come from some "ordinary" distribution
- IoT anomalies are often systemic
- They are often fairly rare

¹http://arxiv.org/pdf/1603.00567v1.pdf

In order to function at scale, a two-phase approach is taken

For every data point

- For every data point
 - Detect outlier candidates using a robust estimator of variability (e.g. median absolute deviation) that uses distributional sketching (e.g. Q-trees)
 - Gather a biased sample (biased by recency)

- For every data point
 - Detect outlier candidates using a robust estimator of variability (e.g. median absolute deviation) that uses distributional sketching (e.g. Q-trees)
 - Gather a biased sample (biased by recency)
 - Extremely deterministic in space and cheap in computation

- For every data point
 - Detect outlier candidates using a robust estimator of variability (e.g. median absolute deviation) that uses distributional sketching (e.g. Q-trees)
 - Gather a biased sample (biased by recency)
 - Extremely deterministic in space and cheap in computation
- For every outlier candidate
 - Use traditional, more computationally complex approaches to outlier analysis (e.g. Robust PCA) on the biased sample

- For every data point
 - Detect outlier candidates using a robust estimator of variability (e.g. median absolute deviation) that uses distributional sketching (e.g. Q-trees)
 - Gather a biased sample (biased by recency)
 - Extremely deterministic in space and cheap in computation
- For every outlier candidate
 - Use traditional, more computationally complex approaches to outlier analysis (e.g. Robust PCA) on the biased sample
 - Expensive computationally, but run infrequently

In order to function at scale, a two-phase approach is taken

- For every data point
 - Detect outlier candidates using a robust estimator of variability (e.g. median absolute deviation) that uses distributional sketching (e.g. Q-trees)
 - Gather a biased sample (biased by recency)
 - Extremely deterministic in space and cheap in computation
- For every outlier candidate
 - Use traditional, more computationally complex approaches to outlier analysis (e.g. Robust PCA) on the biased sample
 - Expensive computationally, but run infrequently

This becomes a data filter which can be attached to a timeseries data stream within a distributed computational framework (i.e. Storm, Spark, Flink, NiFi) to detect outliers.

Median absolute deviation (or MAD) is a robust statistic

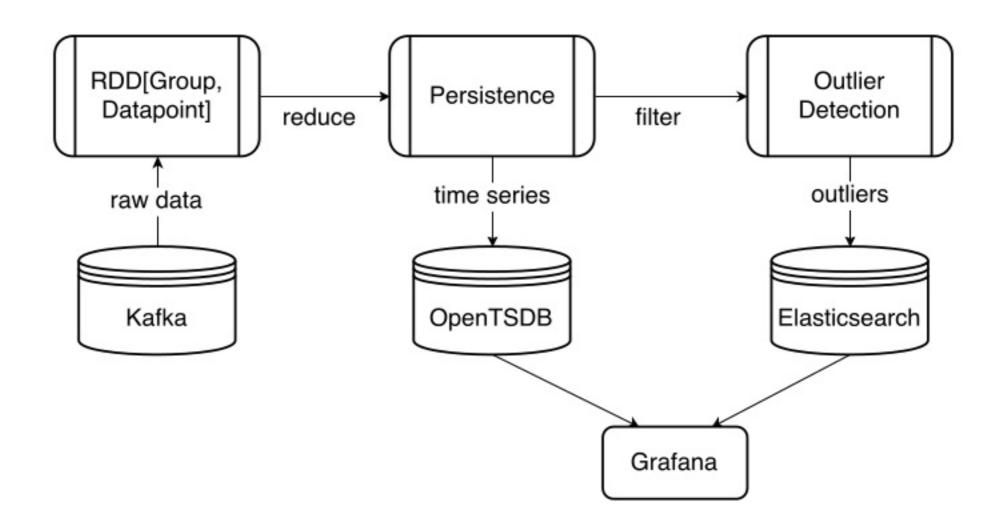
- Median absolute deviation (or MAD) is a robust statistic
 - Robust statistics are statistics with good performance for data drawn from a wide range of non-normally distributed probability distributions
 - Unlike the standard mean/standard deviation combo, MAD is not sensitive to the presence of outliers.

- Median absolute deviation (or MAD) is a robust statistic
 - Robust statistics are statistics with good performance for data drawn from a wide range of non-normally distributed probability distributions
 - Unlike the standard mean/standard deviation combo, MAD is not sensitive to the presence of outliers.
- The median absolute deviation is defined for a series of univariate samples X with $\tilde{x} = \text{median}(X)$, $\text{MAD}(X) = \text{median}(\{\forall x_i \in X | |x_i \tilde{x}|\})$.

- Median absolute deviation (or MAD) is a robust statistic
 - Robust statistics are statistics with good performance for data drawn from a wide range of non-normally distributed probability distributions
 - Unlike the standard mean/standard deviation combo, MAD is not sensitive to the presence of outliers.
- The median absolute deviation is defined for a series of univariate samples X with $\tilde{x} = \text{median}(X)$, $\text{MAD}(X) = \text{median}(\{\forall x_i \in X | |x_i \tilde{x}|\})$.
- A point is considered an outlier if its distance from the current window median, scaled by the MAD for the previous window, is above a threshold.

- Median absolute deviation (or MAD) is a robust statistic
 - Robust statistics are statistics with good performance for data drawn from a wide range of non-normally distributed probability distributions
 - Unlike the standard mean/standard deviation combo, MAD is not sensitive to the presence of outliers.
- The median absolute deviation is defined for a series of univariate samples X with $\tilde{x} = \text{median}(X)$, $\text{MAD}(X) = \text{median}(\{\forall x_i \in X | |x_i \tilde{x}|\})$.
- A point is considered an outlier if its distance from the current window median, scaled by the MAD for the previous window, is above a threshold.

tl;dr: A formal way to encode our intuition: If a point is far away from the "central" point of our window, then it's likely an outlier.



This kind of architecture has a few characteristics that are interesting

Aimed primarily at many different low to medium velocity time series data

This kind of architecture has a few characteristics that are interesting

- Aimed primarily at many different low to medium velocity time series data
- Aimed at many different one-dimensional data streams instead of outliers in multidimensional data streams.

This kind of architecture has a few characteristics that are interesting

- Aimed primarily at many different low to medium velocity time series data
- Aimed at many different one-dimensional data streams instead of outliers in multidimensional data streams.
- Because probabalistic sketches are extremely compact, you can look much farther back for your context than a naive windowing solution

This kind of architecture has a few characteristics that are interesting

- Aimed primarily at many different low to medium velocity time series data
- Aimed at many different one-dimensional data streams instead of outliers in multidimensional data streams.
- Because probabalistic sketches are extremely compact, you can look much farther back for your context than a naive windowing solution
- Send outliers (lower velocity and number) and send raw time series to a TSDB capable of handling scale. Investigate the data via a dashboard that can marry the two into a single pane of glass.

Demos

Demos

Questions

Thanks for your attention! Questions?

- Code & scripts for this talk available at http://github.com/cestella/streaming_outliers
- Find me at http://caseystella.com
- Twitter handle: @casey_stella
- Email address: cstella@hortonworks.com