Streaming Outlier Analysis for Fun and Scalability

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Table of Contents

Streaming Analytics

Framework

Example: Streaming Financial Audit

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

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- The Good: Outlier analysis or anomaly detection is a killer-app
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- 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

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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

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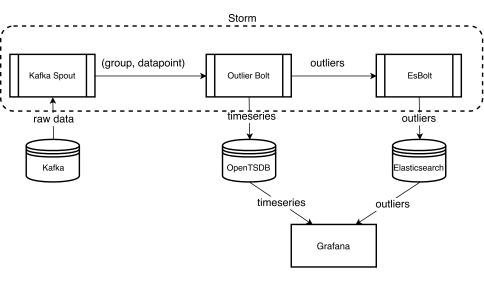
This becomes a data filter which can be attached to a timeseries data stream within a distributed computational framework (i.e. Storm, Spark, Flink, NiFi) to detect outliers.

Example: Streaming Financial Audit

Sometimes, doctors and hospitals have financial relationships with health care manufacturing companies. These relationships can include money for research activities, gifts, speaking fees, meals, or travel. The Social Security Act requires CMS to collect information from applicable manufacturers and group purchasing organizations (GPOs) in order to report information about their financial relationships with physicians and hospitals.

Let's treat each type (e.g. gifts, travel expenses) and physician specialty as a timeseries and look for anomalous payments.

Example Architecture



Questions

Thanks for your attention! Questions?

- Code & scripts for this talk available at http://github.com/cestella/streaming_outliers
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