Streaming Outlier Analysis for Fun and Scalability

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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: 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.

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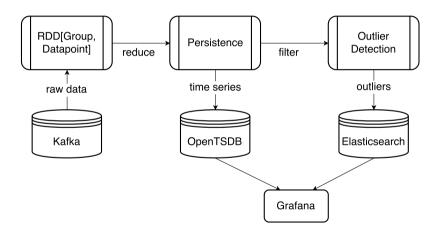
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tl;dr: A formal way to encode our intuition: If a point is far away from the "central" point of our window, then it's likely an outlier.



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- 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

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