Machine Learning and Anomaly Detection in Splunk IT Service Intelligence

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Agenda

- Introductions/History
- Axioms – Problem Domain
- Axioms – Solution Domain
- Time Series Feature Engineering
- Spatial vs. Temporal Analysis
- Other Approaches
- MAD Service Engineering
- ITSI Context
Introductions/History

- **Key team members**
  - Shang
  - Mihai
  - Jacob
  - Iman
  - Touf

- **Presenters**
  - Fred – Data scientist
  - Alex – Architect/Dev Manager
Axioms – Problem Domain

- THE UNIVERSE OF DATA

Time-series data
Axioms – Problem Domain

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Axioms – Problem Domain

- **Detecting anomalies** in this narrow subset of the universe of data:
- Time series
  - *Numeric variables* that change over time

![Graph showing time series data with increasing time](image)
Detecting anomalies in this narrow subset of the universe of data:

- Time series
  - Numeric variables that change over time
- Regular time series
  - The new values arrive on a regular interval (e.g. every five seconds)
Axioms – Problem Domain

- **Detecting anomalies** in this narrow subset of the universe of data:
- Time series
  - *Numeric variables* that change over time
- Regular time series
  - The new values arrive *on a regular interval* *(e.g. every five seconds)*
- Dense, Regular time series
  - New values are *fairly likely* to arrive and *not be null*
Axioms – Solution Domain

- Unsupervised
- Non-Parametric
- Robust
- Streaming
- Adaptive
- Domain-agnostic
Axioms – Solution Domain

- Unsupervised
  - No labelled anomalies
  - What’s normal is learned from observing the data itself, not defined by an expert
- Non-Parametric
- Robust
- Streaming
- Adaptive
- Domain-agnostic
Axioms – Solution Domain

- Unsupervised
- Non-Parametric
  - We make no assumptions about the probability distribution of the values (e.g. Gaussian or stationary)
- Robust
- Streaming
- Adaptive
- Domain-agnostic
Axioms – Solution Domain

- Unsupervised
- Non-Parametric
- Robust
  - Outliers are detected as anomalies, but don’t cause distortions in our expectations
- Streaming
- Adaptive
- Domain-agnostic
Axioms – Solution Domain

- Unsupervised
- Non-Parametric
- Robust
- Streaming
  - No separate training/test periods
  - Anomalies are detected and reported in (near-) real time
- Adaptive
- Domain-agnostic
Axioms – Solution Domain

- Unsupervised
- Non-Parametric
- Robust
- Streaming
- Adaptive
  - No static thresholds, discover normal behaviour patterns automatically
  - Adapt to behavioral changes without end-user feedback
  - What was normal last week might be worrisome today
- Domain-agnostic
Axioms – Solution Domain

- Unsupervised
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- Streaming
- Adaptive
- Domain-agnostic
  - Purely numeric
  - No information about underlying subjects or causes of the behaviour stream
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Getting Data In

Time Series Feature Engineering

- If you already have **dense, regular, numeric** time series (aka “metrics” or “KPIs”) you’re good to go
Getting Data In

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- If you have something else, now you have a time series feature engineering problem
Getting Data In

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• There are inescapable tradeoffs between density and precision
Getting Data In

Time Series Feature Engineering

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- If you have something else, now you have a **time series feature engineering** problem
- There are **inescapable** tradeoffs between **density** and **precision**
- Increased precision implies sparser time series
  - Also increased memory and bandwidth usage!
Getting Data In

Time Series Feature Engineering

• If you already have *dense, regular, numeric* time series (aka “metrics” or “KPIs”) you’re good to go

• If you have something else, now you have a *time series feature engineering* problem

• There are *inescapable* tradeoffs between *density* and *precision*

• Increased precision implies sparser time series
  – Also increased memory and bandwidth usage!

• TSFE requires dealing with *Time, Space* and *Values*
Getting Data In

Time Series Feature Engineering

• Time
  – How frequently do new values arrive?
  – How regularly do new values arrive?
  – How precisely do we want to be able to record the time when the measurement was taken?
    ‣ Finer time resolution increases sparsity: the probability that any event occurred during a particular time window is decreased

• Space

• Values
Getting Data In

Time Series Feature Engineering

• Time

• **Space** - how precisely do we want to be able to relate time series back to the underlying event stream?
  - *How many* dimensions? e.g. IP address, geo. coordinates, MIME type, HTTP response code
    - Adding dimensions increases precision, but also **magnifies the likelihood of sparsity**
  - Within a dimension, *how precise* do we need to be?
    - Full IP address or /24? Distinguish 400, 401, 403, 404 or just 4xx?
    - Country, state/province, city, neighbourhood, building, ...?
    - Extra precision **increases the likelihood of sparsity**

• Values
Getting Data In

Time Series Feature Engineering

- Time
- Space
- **Values**
  - How do we generate a number?
    - Get a numeric field as-is (i.e. a “gauge”)
    - Increment a counter
  - How do we aggregate multiple values?
    - Min, max, mean, etc.
  - How should we handle missing values?
    - "Replace null with zero" only makes sense for something we know is a counter
    - "Take the previous value" might make sense
Proprietary! Not open source or off-the-shelf.

Spatial and temporal algorithms

- What do we mean by “spatial” and “temporal”? 
- Completely orthogonal, irreducible distinction
  - One cannot substitute for the other
  - Neither is always applicable to every time series
Metric Anomaly Detection Algorithms

Temporal Analysis (aka “Trending” algorithm)

- Analyze one time series at a time (embarrassingly parallel)
- Alerting when *present* behaviour is surprising compared to *past* behaviour
Metric Anomaly Detection Algorithms

Trending Algorithm Constraints

• Good results only when there is a history of recurring patterns in the underlying event stream
  – Not necessarily periodic, just recurring

• How much history?
  – Preliminary (usually bad) results after ~2000 points
    ‣ e.g. 1.5 days at 1-minute resolution
  – Great results after a “full period” has been observed (e.g. 7 days)
  – More is better! (modulo memory, storage...)
Metric Anomaly Detection Algorithms

Spatial (“Cohesive”) Algorithm

- Compare *present* behaviour of *multiple* metrics
Metric Anomaly Detection Algorithms

Cohesive Algorithm Constraints

- Given a set\(^*\) of time series that are expected\(^†\) to behave similarly\(^‡\), detect when one or more of them departs from their peers

\(^*\) set
  \[\geq 3\text{ members}\]

\(^†\) expected
  by a human analyst or interesting ML process

\(^‡\) similarly
  Roughly the same shape
  Scale and magnitude invariant
Metric Anomaly Detection Algorithms

Cohesive Algorithm Characteristics

- No periodicity required
- History improves scale/magnitude invariance
- Performance relies on similarity within group
  - What if the group isn’t inherently cohesive?
    ‣ Lots of alerts early on
    ‣ Then, the algorithm adapts to the chaos
    ‣ If the group returns to cohesion, the algorithm will automatically adapt to the “new normal”.
Metric Anomaly Detection Algorithms

Cohesive Algorithm: Example Use Case #1

- A cluster of servers performing a similar role for the same application, behind the same load balancer

- Assuming the load balancer is operating nominally, many server metrics should be roughly correlated, e.g.:
  - CPU usage (user, system, idle)
  - Disk usage (reads, writes, IOPS)
  - Network usage (bandwidth, # active sockets)
  - Application-specific metrics (requests handled per second, 500 errors, authentication failures, active sessions)
Imagine some wind turbines on the same hill
We can’t predict wind direction and speed very well (yet?)
But we expect every turbine should be roughly cohesive in several metrics:
  – rotation speed
  – power generation rate
  – vibration
  – direction
    ‣ * actually, because this is a periodic metric (359° ≈ 1°), we don’t support it well right now
If any metric for any turbine differs significantly from its peers, we should be notified, and maybe send a team to investigate
Other approaches we have tried

- 3-sigma
  - Kolmogorov-Smirnov test over sliding windows
  - Time-series forecasting methods
    - Holt-Winters (previous version of ITSI AD is based on its non-parametric version)
    - ARIMA, etc
  - One-class SVM
  - Clustering methods – DBSCAN, K-means, etc
  - Various R, Python packages
MAD Service Engineering

- MAD = “Metafor Anomaly Detection”
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- MAD = “**Metric** Anomaly Detection”
- Written in Scala
  - using Akka for concurrency
MAD Service Engineering

- **MAD = “Metric Anomaly Detection”**
- Written in Scala
  - using Akka for concurrency
- Uses Search Command Protocol v2 (available since Splunk 6.3)
  - Runs forever, doesn’t get restarted every 50k events
  - Receives data soon after it arrives at an indexer, no polling
MAD Service Engineering

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- Fast!
MAD Service Engineering

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- Fast!
- Designed for general-purpose use, no coupling to ITSI runtime
How to get it

ITSI-AD

- ITSI 2.3 “Batman” (July 2016)
  - ITSI Anomaly Detection replaced with Trending algorithm

- ITSI 2.4 “Catwoman” (.conf 2016)
  - Cohesive algorithm added
  - Compares entities within a KPI
How to get it

ITSI-AD
How to get it

ITSI-AD
How to get it

ITSI Anomaly Detection learns the normal patterns of KPIs continuously in real-time, firing a notable event when a KPI departs from its expected behavior. Certain types of data may not be suitable for use with anomaly detection and produce many false positives. We recommend that you analyze the KPI data to see if it is compatible with ITSI’s Anomaly Detection algorithms.

- Search and Calculate
- Thresholding
- Anomaly Detection
THANK YOU