How to Determine the Optimal Anomaly Detection Method For Your Application

Cynthia Freeman
Research Engineer

Jonathan Merriman
Software Engineer

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Background

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Time Series

- A time series is a sequence of data points indexed in order of time.
- How are time series used?
  - Stock Market
  - Tracking KPIs
  - Medical Sensors
  - Weather Patterns

Anomalies

An anomaly in a time series is a pattern that does not conform to past patterns of behavior.

Applications:

- Efficient troubleshooting
- Fraud detection
- Ensuring undisrupted business
- Saving lives in system health monitoring

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Anomaly Detection is Hard

- What is anomalous?
- Online anomaly detection
- Lack of labeled data
- Data imbalance
- Minimize false positives
- Plethora of anomaly detection methods

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Which anomaly detection method should I use?

- Base this decision off of the characteristics the time series possesses
- Evaluate anomaly detection methods on 4 time series characteristics as an example
- Experiment with 2 evaluation criteria
  - Window-based F-score
  - Numenta Anomaly Benchmark (NAB) Score

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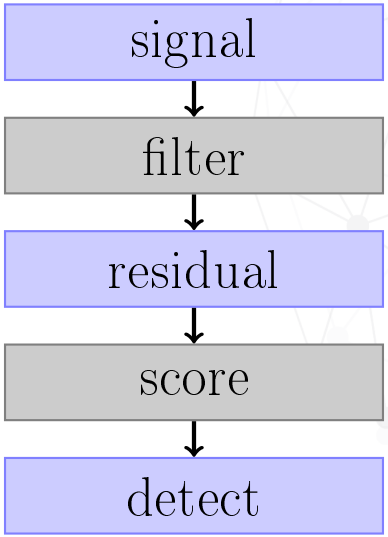
Signal Processing Flow for Anomaly Detection



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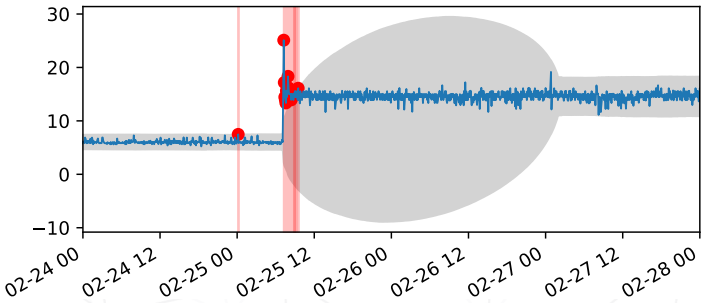
Simple Example: Gaussian

- Estimate mean and variance over sliding window
- Compute a score based on the tail probability

$$S(y_t) = P(y_t \leq \tau | \mu, \sigma^2)$$

- Use max relative to upper and lower extremes



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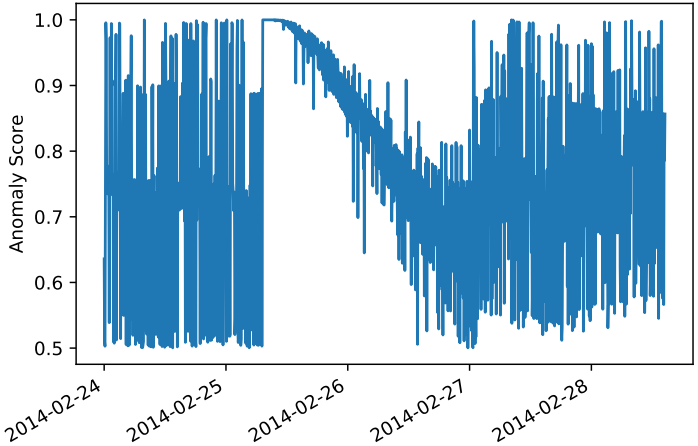
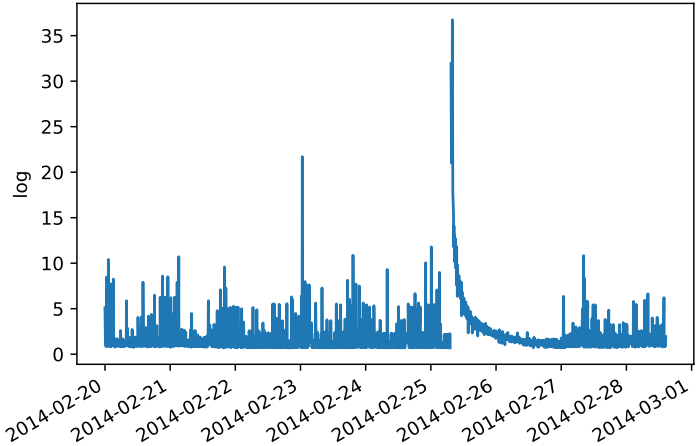
Simple Example: Gaussian





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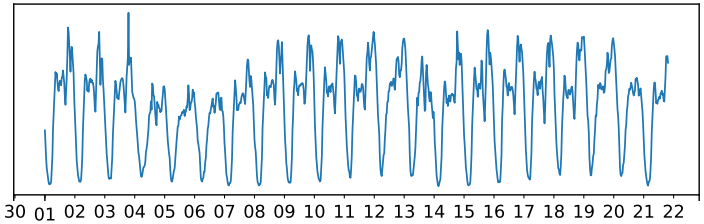
Time Series Characteristics

Seasonality

- Presence of variations that occur at specific regular intervals
- Real data often exhibits seasonal effects at multiple time scales.
  - Day-of-week
  - Hour-of-day
  - Can be irregular
    - Day-of-month
    - Holidays
- ACF plot is one way to detect seasonality



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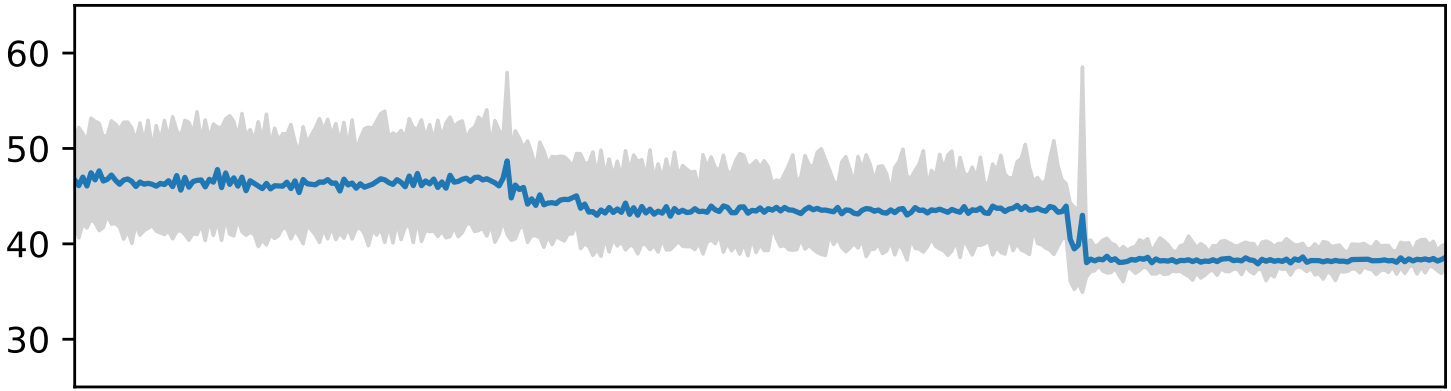
Concept Drift

The underlying process can change over time.

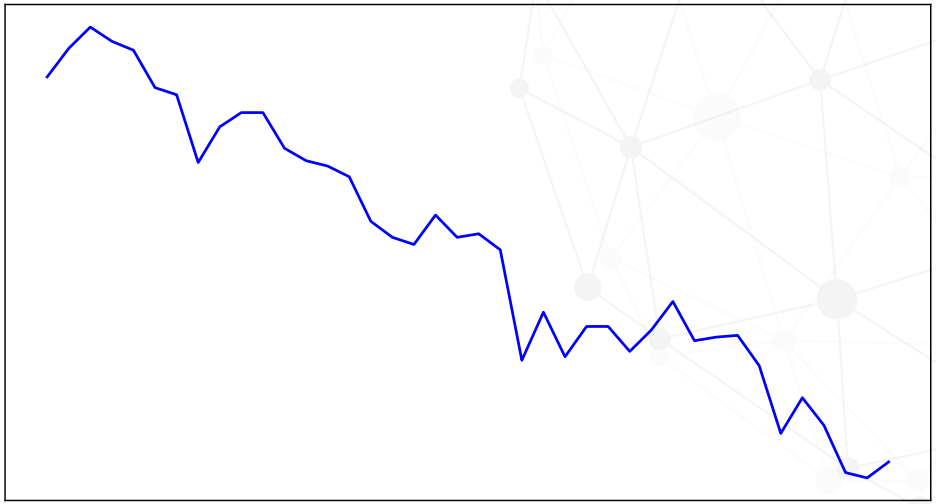
- Bayesian Online Changepoint Detection
- ecp package in R



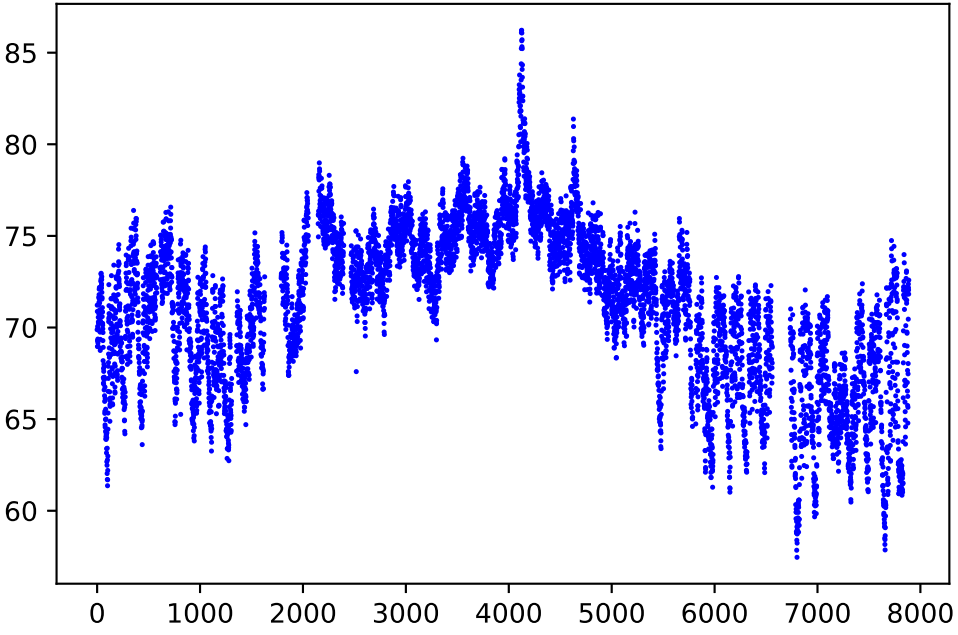
https://github.com/hildensia/bayesian_changepoint_detection

Trend

The process mean can change over time.



Missing Time Steps



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Time Series Modeling for Anomaly Detection

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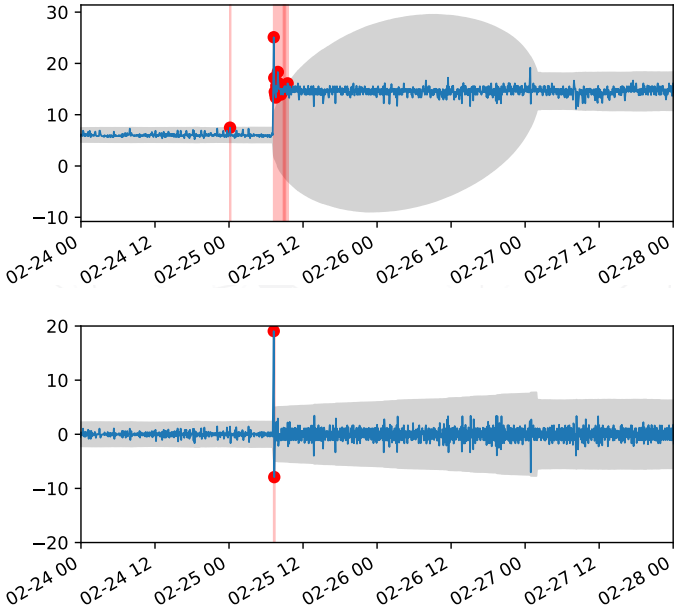
Nonstationarity: Differencing

- First-order difference to remove trend:

$$[\Delta y](t) = y(t) - y(t-1)$$

- Seasonal differencing with period s:

$$[\Delta_s y](t) = y(t) - y(t-s)$$



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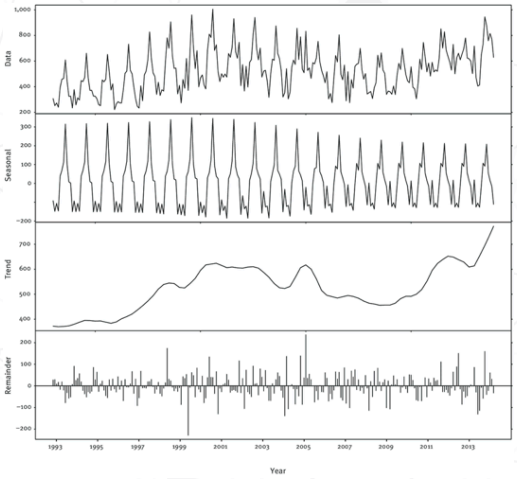
Nonstationarity: Decomposition STL

Local regression with LOESS

$$y(t) = S(t) + T(t) + \epsilon(t)$$

- Decompose into season and trend
- LOESS smoothing can interpolate missing data
- Residual should look more stationary



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ARMA

A family of Gaussian models with temporal correlation.

$$y(t) - \underbrace{\sum_{i=1}^{p} \theta_i y(t-i)}_{\text{AR}} = \epsilon(t) + \underbrace{\sum_{j=1}^{q} \phi_j \epsilon(t-j)}_{\text{MA}}$$

Autoregressive (AR)

The value at time t is a linear combination of p past values plus current noise signal.

Moving Average (MA)

The value at time t is a linear combination of q past values of noise.

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ARMA for Nonstationary Signals

ARIMA
: ARMA on differenced signal.

SARIMA
: Extend ARIMA to incorporate longer-term seasonal correlation.

SARIMAX
: Add eXogenous variables.

ARMA

- Generative model having Gaussian distribution at each timestep
- Optimal model order selection is not straightforward
- See: Box-Jenkins method

Prophet

Uses an additive model:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

- $g(t)$ is linear/logistic growth trend
- $s(t)$ is yearly/weekly seasonal component
- $h(t)$ is user-provided list of holidays

https://github.com/facebook/prophet

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Extreme Studentized Deviate Test

How many outliers does the data set contain?
ESD test requires an upper bound on the number of outliers.
Assuming data is approximately normally distributed,

1. Compute the statistic,

$$R_i = \frac{\max_i |x_i - \bar{x}|}{s}$$

2. Remove observation that maximizes $|x_i - \bar{x}|$, and repeat
3. Compare R_i up to critical value

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Twitter AnomalyDetection

- Uses STL but replaces trend with median
  - Anomalies can affect trend estimation
  - Leads to artificial anomalies in the residual
- Apply Extreme Studentized Deviate (ESD) test
  - Need to specify an upper limit on the # of outliers
  - $\bar{x}$ is median and s is Median Absolute Deviation

https://github.com/twitter/AnomalyDetection

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Recurrent Neural Network

- Given a window of n_{lag} time steps in the past, predict a window of n_{seq} time steps in the future
- Anomaly score is an average of the prediction error
- Adaptive: uses online gradient-based optimizer, built to deal with concept drift
- Choice of n_{seq} can greatly affect false positive rate

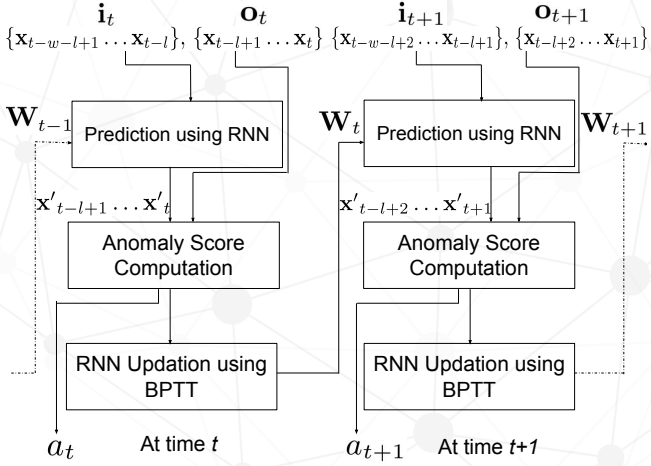

Illustration from Saurav et al. '18

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HTM for Anomaly Detection

Hierarchical Temporal Memory Network

- HTM outputs sparse representation of input and next prediction step to determine the prediction error modeled as a rolling normal distribution
- HTM not implmented in a widely accessible way
- Cannot handle missing time steps innately

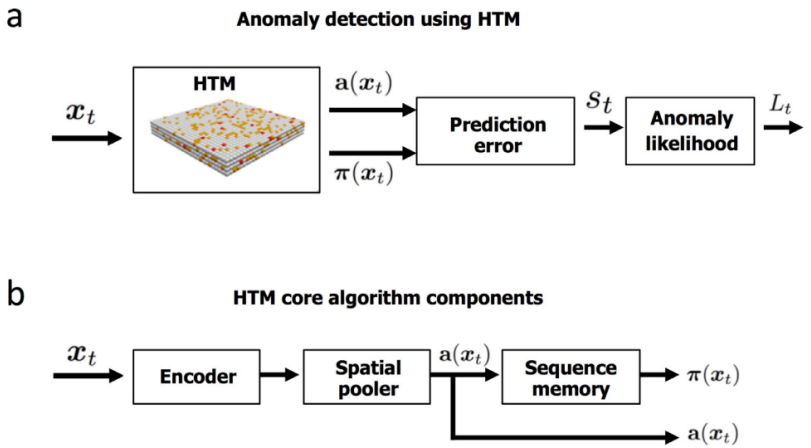

Illustration from Ahmad et al. '17

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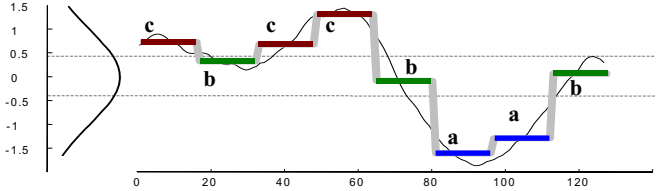
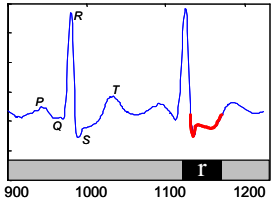
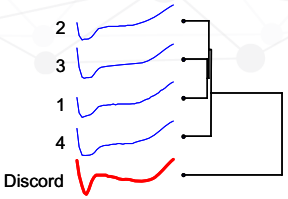
HOT-SAX

Heuristically Ordered Timeseries - Symbolic Aggregated ApproXimation

- Finds Discords: Subsequences of time series that are maximally different from all remaining subsequences
- Transform timeseries into alphabetical symbols and compare the distances between words
- Not built for concept drift detection
- Inefficient for very large time series







Illustrations from Keough et al. 2005

Evaluation Strategies

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Anomaly Scores

Anomaly detectors are adapted to output a score between 0 and 1

- HTM: Use provided score
- Twitter AD and HOT-SAX: Use binary determination
- Windowed gaussian: Apply Q function to standardized signal
- STL, SARIMA, Prophet: Apply Q function to standardized residual

Numenta Anomaly Benchmark Scoring

- For every predicted anomaly y, its score $\sigma(y)$ is determined by its position relative to its containing window or an immediately preceding window
- For every ground truth anomaly, construct an anomaly window with the anomaly in the center.

$$\frac{.1 \times \text{length of time series}}{\#\text{ of true anomalies}}$$

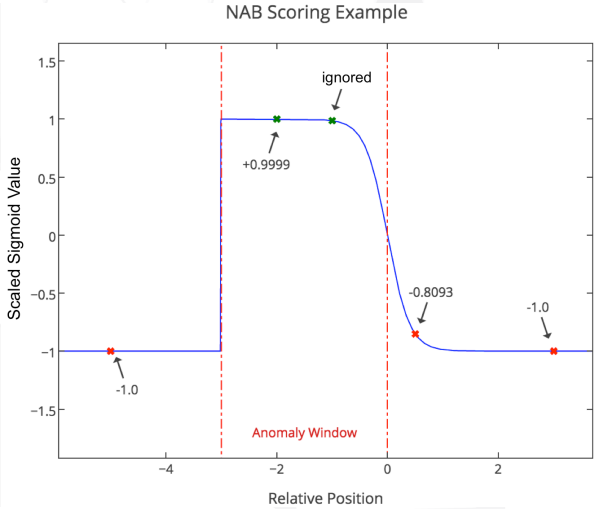

Illustration from Lavin & Ahmad '15

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Numenta Anomaly Benchmark Scoring (Continued)

- The raw score is computed as:

$$S_d = \left(\sum_{y \in Y_d} \sigma(y) \right) + A_{FN} f_d$$

A_{FN} is cost of false negatives

- Then rescale to get summary score:

$$100 \times \frac{S - S_{null}}{S_{perfect} - S_{null}}$$

- Choose threshold that maximizes score

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Window-based F-score

- Segment into nonoverlapping windows
- Window is anomalous if it contains an anomaly
- Treat like binary classification and report F_1
- Choose threshold that minimizes # of errors
- Prefer detection in case of tie

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Results and Conclusions

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Characteristic Corpora

Seasonality 10 datasets 63,336 samples 23 ground truth anomalies	Trend 10 datasets 31,596 samples 17 ground truth anomalies
Concept Drift 10 datasets 32,402 samples 27 ground truth anomalies	Missing Timesteps 10 datasets 33,245 samples 22 ground truth anomalies 1,254 missing samples

https://github.com/numenta/NAB

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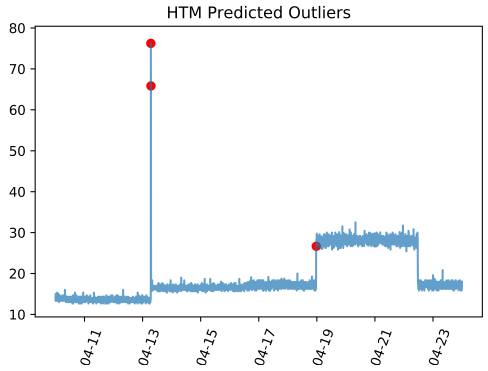
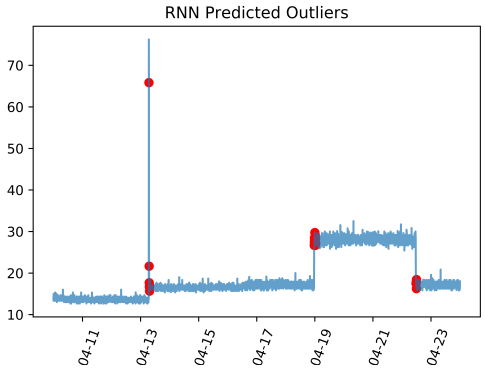
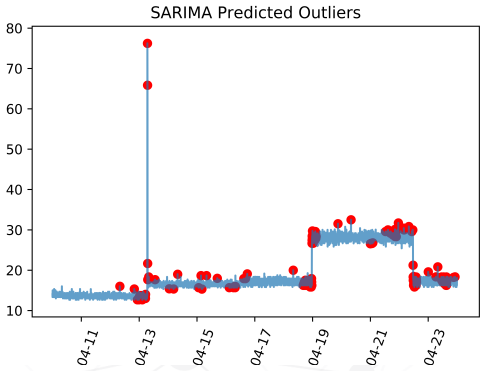
Example







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Which methods are promising given a characteristic?

Seasonality and Trend

STL, SARIMA, Prophet

Concept Drift

Requires more complex methods such as HTMs

Missing Time Steps

- Performance varies based on evaluation strategy
- Area for future work: more methods needed!

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Which evaluation strategy should I use?

- F-score scheme is more restrictive
- NAB scores have more wiggle room for false positives due to reward for early detection
- What evaluation metric to use is entirely based on the needs of the user

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In Summary

- The existence of an anomaly detection method that is optimal for all domains is a myth
- Determine the characteristics present in the data to narrow down the choices for anomaly detection methods

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Questions?

Cynthia Freeman
cynthia.freeman@verint.com

Jonathan Merriman
jonathan.merriman@verint.com

https://github.com/cynthiaw2004/adclasses

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Cyberconflict: A new era of war, sabotage, and fear

See passes & pricing

David Sanger (The New York Times)
9:55am-10:10am Wednesday, March 27, 2019
Location: Ballroom
Secondary topics: Security and Privacy

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We're living in a new era of constant sabotage, misinformation, and fear, in which everyone is a target, and you're often the collateral damage in a growing conflict among states. From crippling infrastructure to sowing discord and doubt, cyber is now the weapon of choice for democracies, dictators, and terrorists.

David Sanger explains how the rise of cyberweapons has transformed geopolitics like nothing since the invention of the atomic bomb. Moving from the White House Situation Room to the dens of Chinese, Russian, North Korean, and Iranian hackers to the boardrooms of Silicon Valley, David reveals a world coming face-to-face with the perils of technological revolution—a conflict that the United States helped start when it began using cyberweapons against Iranian nuclear plants and North Korean missile launches. But now we find ourselves in a conflict we're uncertain how to control, as our adversaries exploit vulnerabilities in our hyperconnected nation and we struggle to figure out how to deter these complex, short-of-war attacks.

David Sanger
The New York Times

David E. Sanger is the national security correspondent for the *New York Times* as well as a national security and political contributor for CNN and a frequent guest on *CBS This Morning*, *Face the Nation*, and many PBS shows.

Session page on conference website

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Cyberconflict: A new era of war, sabotage, and fear

9:55 AM - 10:10 AM, Wed, Mar 27, 2019

Speakers

David Sanger
National Security Correspondent
The New York Times

Ballroom

Keynotes

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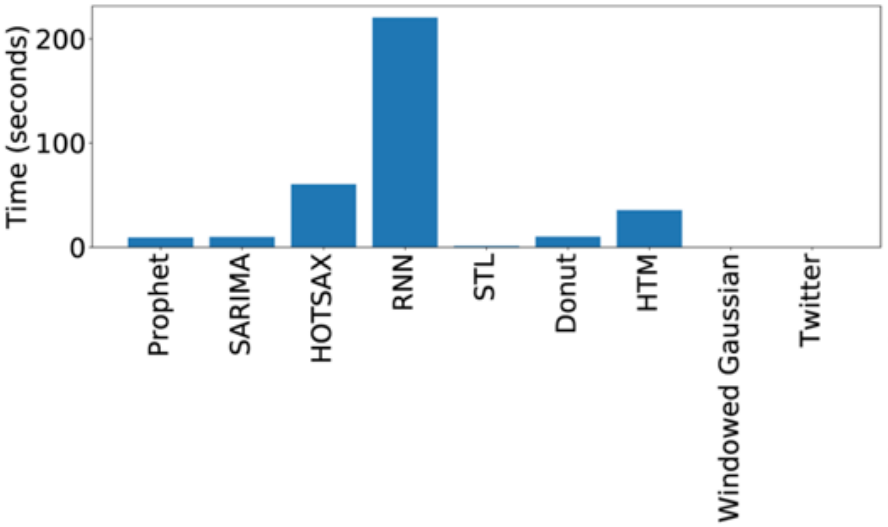
SESSION EVALUATION

O’Reilly Events App

Timing

Average time to generate anomaly scores:



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