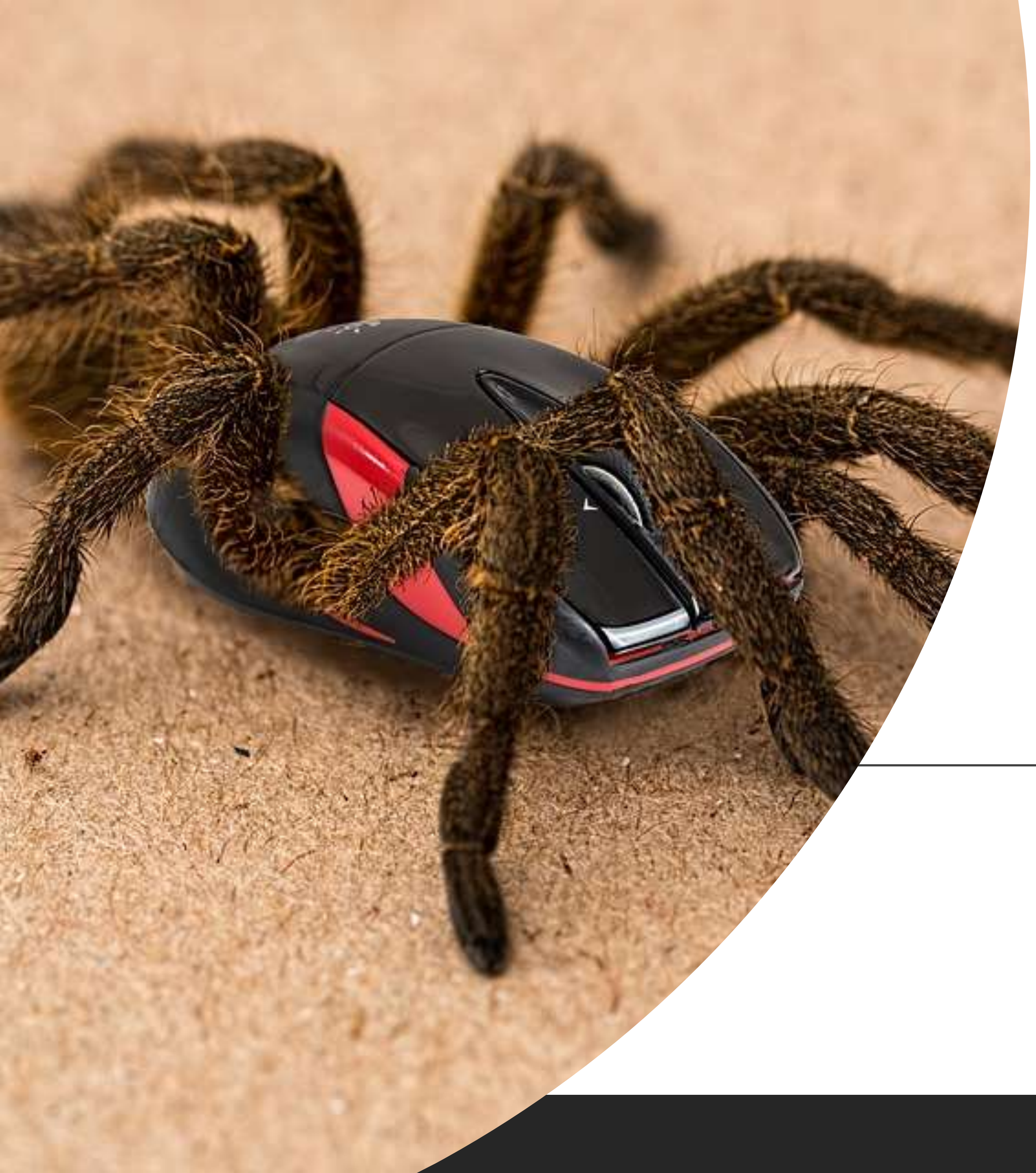


Developing your inner Spidey Sense

Anomaly Detection for IoT apps

RON DAGDAG

Spidey Sense?

- tingling sensation on the back of Peter Parker's skull

- ability to sense and react to danger before it happens.

Uses

- Increases his ability to detect evil (and even clones)

- Helps him navigate if he is impaired (disoriented or unable to see/hear)

- Aids him in discovering secret passageways and find hidden/lost objects

- Helps fire his Web Shooters and swing instinctively

Real Spider Sense

“hyper-awareness”

long, thin hairs, *trichobothria*

- low-level vibrations through their web

- can detect the vibrations of faint sounds

- small insects moving up to 3 meters away

Any new web developers here?

Spidey Sense?

Gut feeling

Vibe

Feeling

Intuition

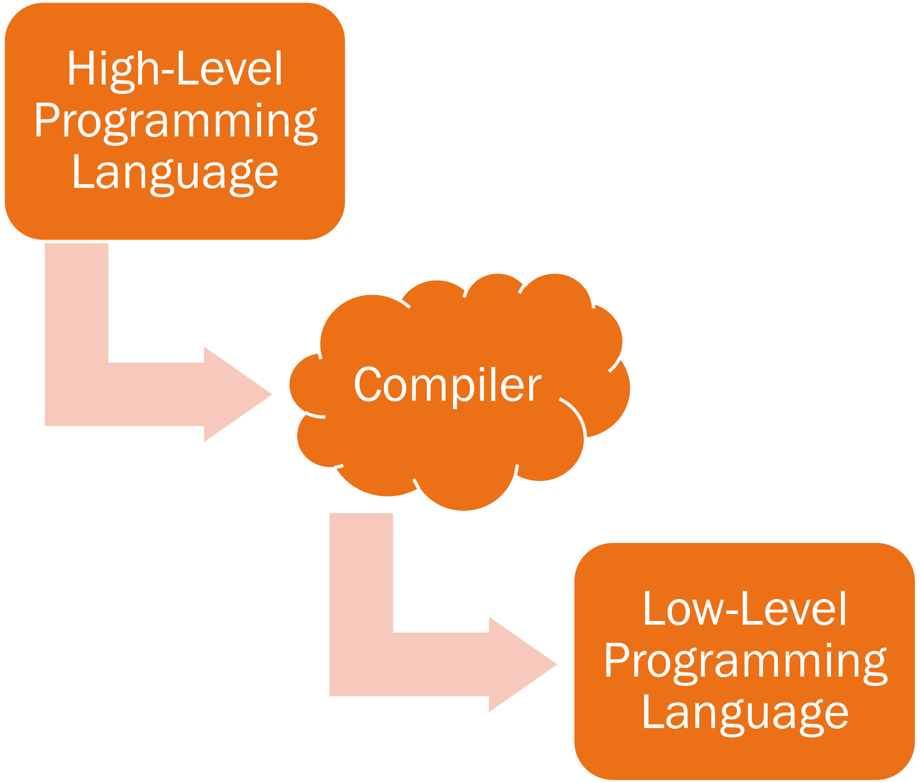
Discover Blind Spots

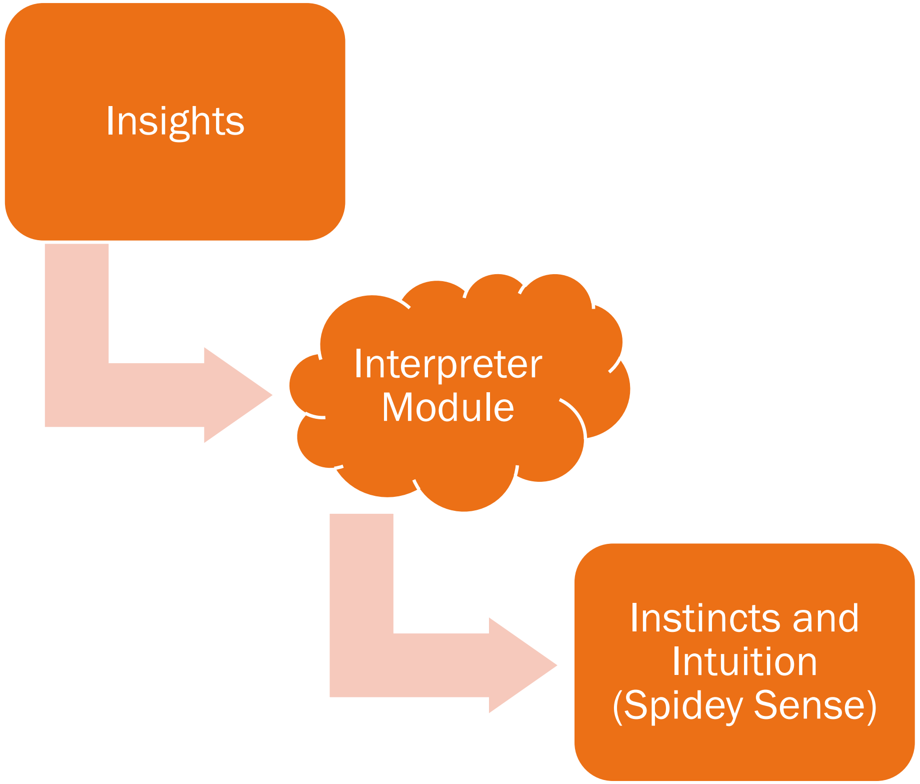
Learning from the past

“Experience is the teacher of all things.”

Julius Caesar

IDE


High-Level Programming Language
Compiler
Low-Level Programming Language


Insights
Interpreter Module
Instincts and Intuition (Spidey Sense)

Agenda

What is Anomaly Detection?

Time Series Anomaly Detection

Demo

Takeaways

Anomaly Detection

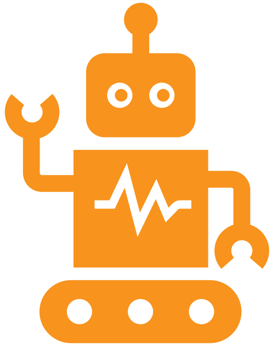
Identifying unexpected items or events in data sets, which differ from the norm

An Outlier

Assumptions:

- Anomalies only occur very rarely in the data.
- Their features differ from the normal instances significantly.

Causes of Outliers

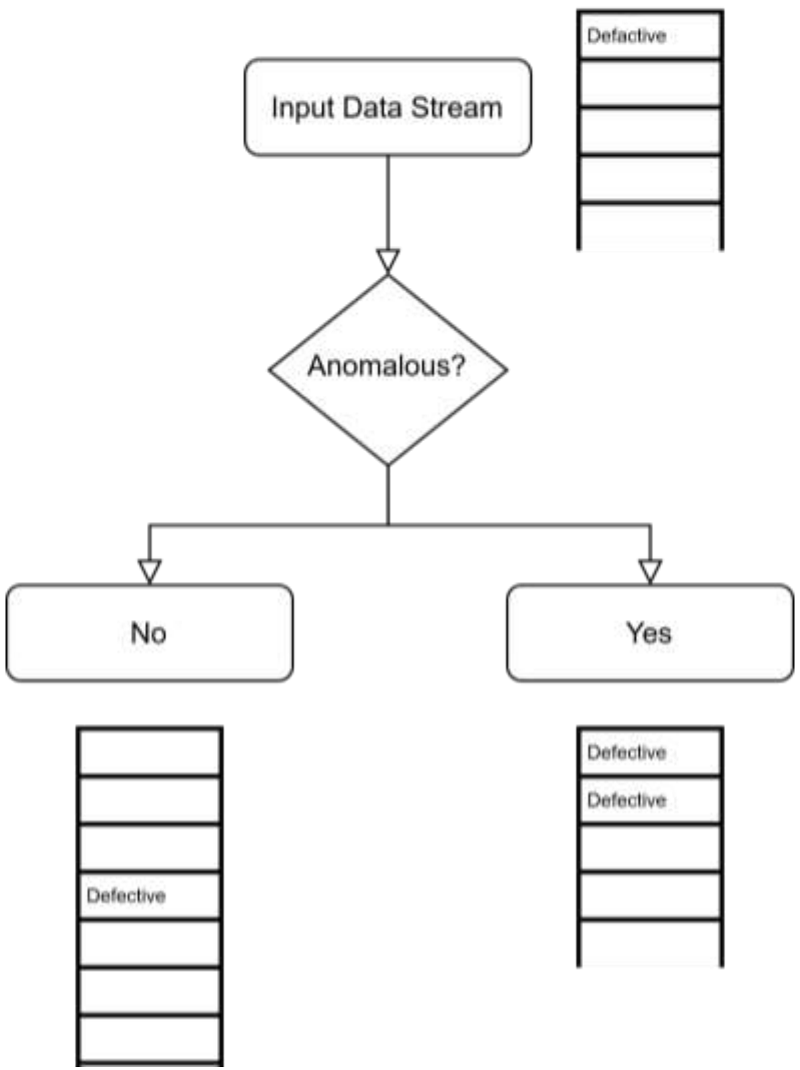


Artificial (Error) / Non-natural

Natural

Causes of Outliers

- Data Entry Errors: 100,000 vs 1,000,000 - fat fingered
- Measurement Error: common
- Experimental Error: start late in sprint
- Intentional Outlier: underreporting alcohol consumption
- Data Processing Error: extraction errors
- Sampling Error: reporting height for all athletes and included most basketball players
- Natural Outlier: When it's not artificial


Defactive
Input Data Stream
Anomalous?
No
Yes
Defective
Defective
Defective

Confusion Matrix

Truth

Guess		true	false
	positive	$true\ positive$	$false\ positive$
	negative	$false\ negative$	$true\ negative$

$$precision = \frac{tp}{tp + fp}$$

$$recall = \frac{tp}{tp + fn}$$

$$accuracy = \frac{tp + tn}{tp + tn + fp + fn}$$

Needle in a haystack

Methods

- Rule-based Systems
- Statistical Techniques
- Machine Learning

Rule-based Systems

Specific Rules

Assign Threshold and limits

Experience of Industry Experts to detect “known anomalies”

Doesn’t Adapt as patterns change

Data Labeling

Statistical Techniques

- flags the data points => deviate from common statistical properties (mean, median, mode, quantiles)
- a rolling average or a moving average
- n-period simple moving average
  "low pass filter.“ e.g. Kalman Filters
- Histogram-based Outlier Detection (HBOS)
- More Interpretable and sometimes more useful than ML methods

ANOMALY DETECTION	SUPERVISED LEARNING
Very small number of positive examples	Large number of positive and negative examples
Large number of negative examples	Enough positive examples for algorithm to learn.
Many different “types” of anomalies. Hard to learn from positive examples	Future positive examples likely to be similar to training set
Future anomalies may not be discovered yet.	

ANOMALY DETECTION

- Fraud Detection
- Manufacturing (engines/machineries)
- Monitoring Data Center
- Internet of Things

SUPERVISED LEARNING

- Email spam classification
- Weather prediction
- Cancer classification

Machine Learning Methods

Supervised
(e.g. Decision Tree, SVM, LSTM Forecasting)

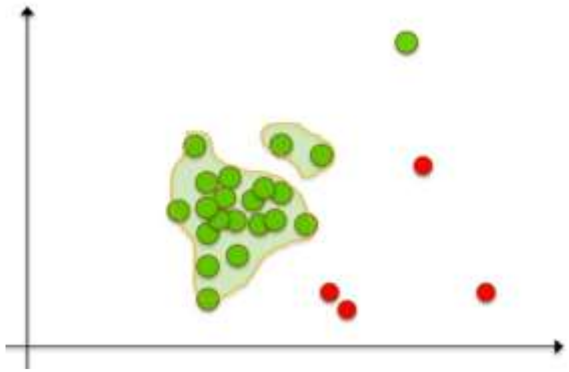
Unsupervised
(e.g. K-Means, Hierarchical Clustering, DBSCAN)

Self-Supervised
(e.g. LSTM Autoencoder)

Machine Learning

Density-Based Anomaly Detection

- based on the k-nearest neighbors algorithm.
- *Assumption:* Normal data points occur around a dense neighborhood and abnormalities are far away.



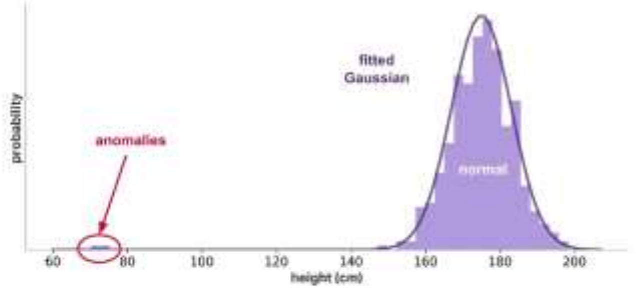
Clustering-Based Anomaly Detection

- *Assumption:* Data points that are similar tend to belong to similar groups or clusters, as determined by their distance from local centroids.
- K-means

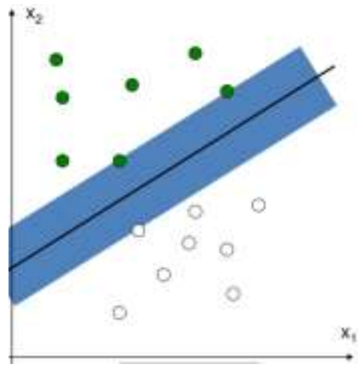
Machine Learning

Gaussian Distribution

- Gaussian Distribution and given a new data-point,
- Compute the probability of the data-point
- If the probability is below a threshold => outlier or anomalous.



Machine Learning



Support Vector Machine-Based Anomaly Detection

- *OneClassSVM*
- *>100 features, aggressive boundary*
- find a function that is positive for regions with high density of points, and negative for small densities

PCA-Based Anomaly Detection

- analyzing available features to determine what constitutes a "normal" class
- applying distance metrics
- Fast training

Internet of Things

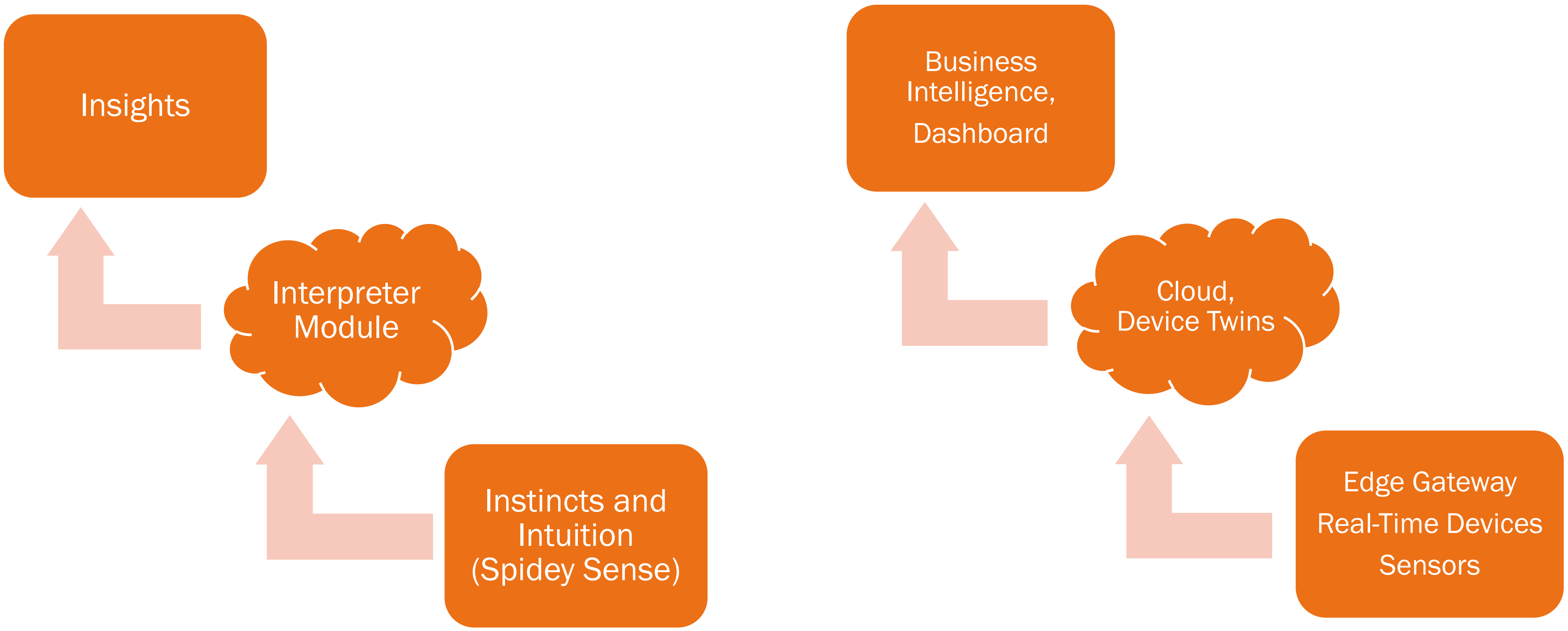
Increasing Data Volume
(sensors are cheaper)

Increased Data Speed
(improved networking)

Risk environment that are moving very fast but failures are not tolerated.

Internet of Broken Things

Artificial Intelligence of Things



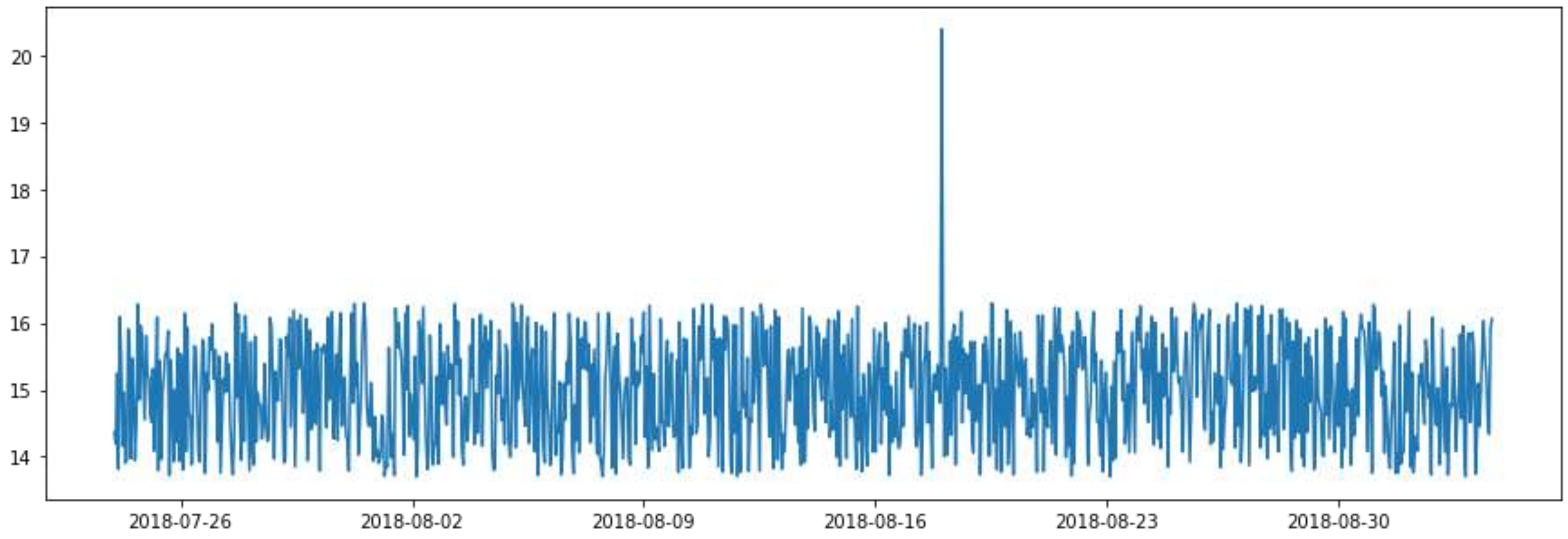
Time Series Anomaly Types

OUTLIER

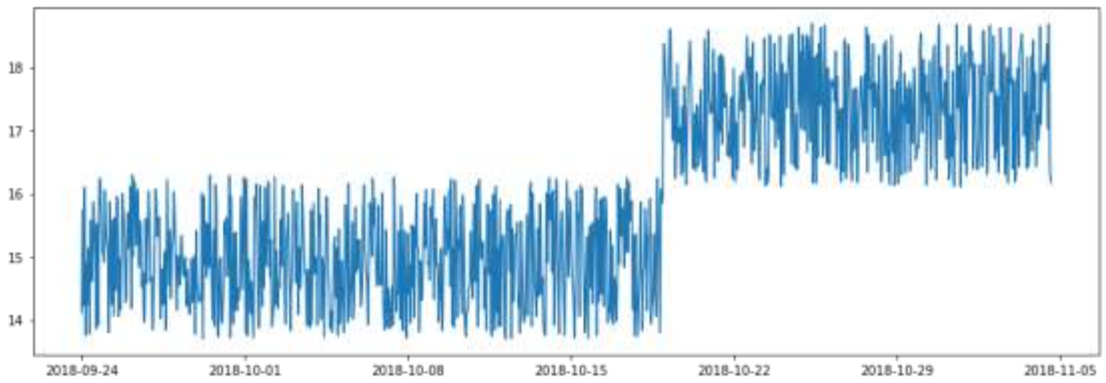
SPIKE AND LEVEL SHIFT

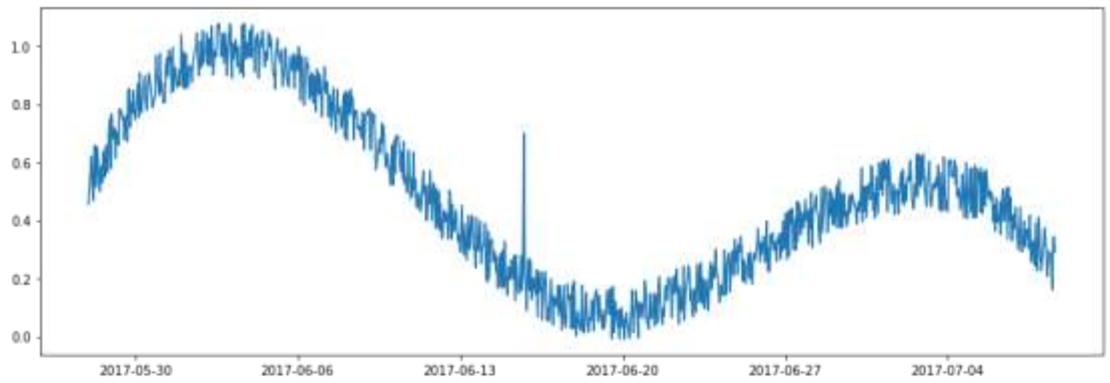
PATTERN CHANGE

SEASONALITY

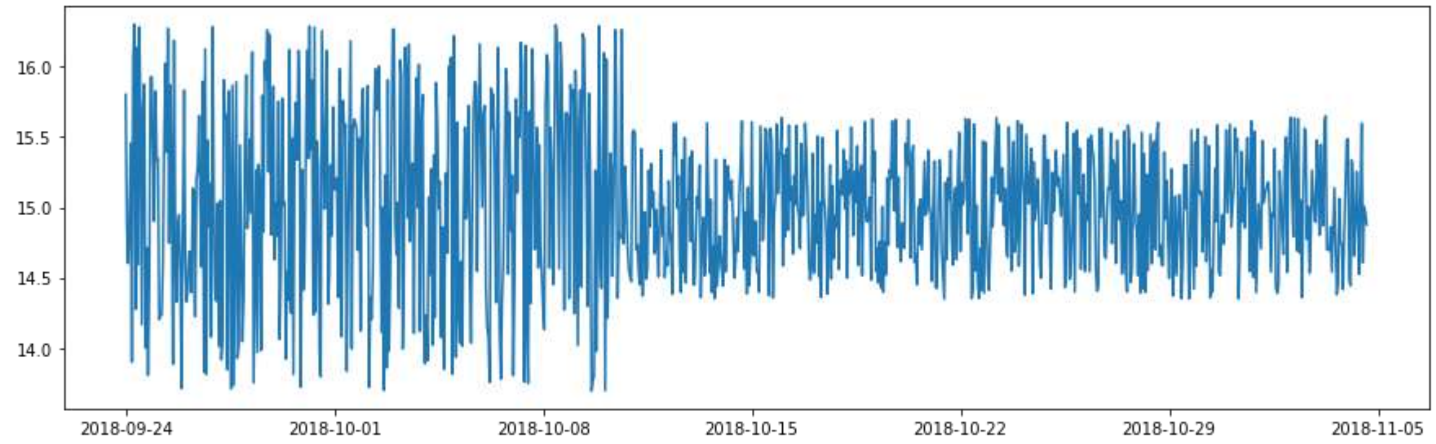

20
19
18
17
16
15
14
2018-07-26
2018-08-02
2018-08-09
2018-08-16
2018-08-23
2018-08-30

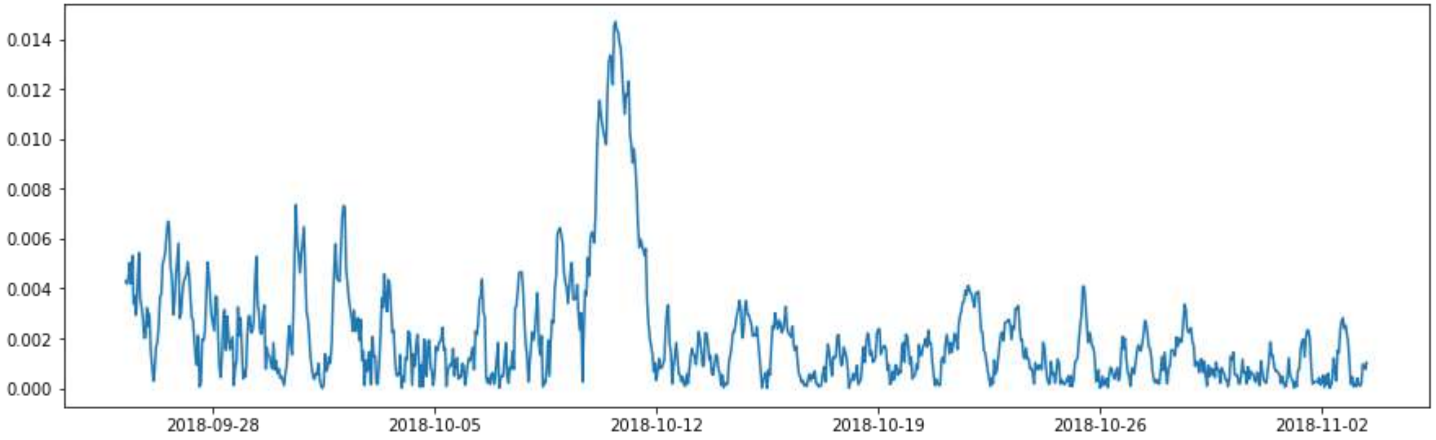
Outlier



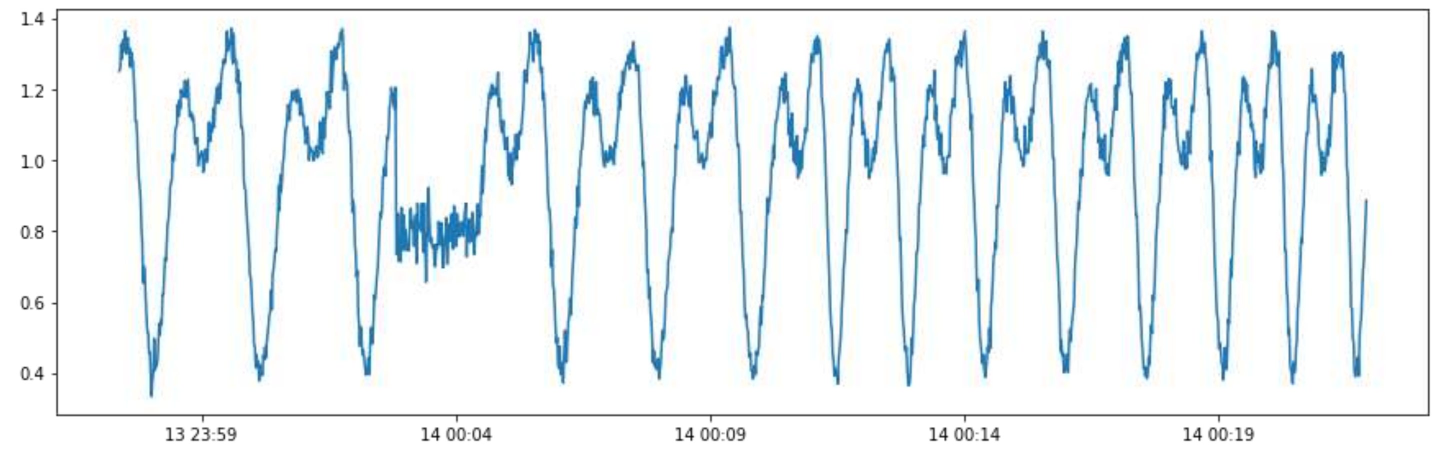


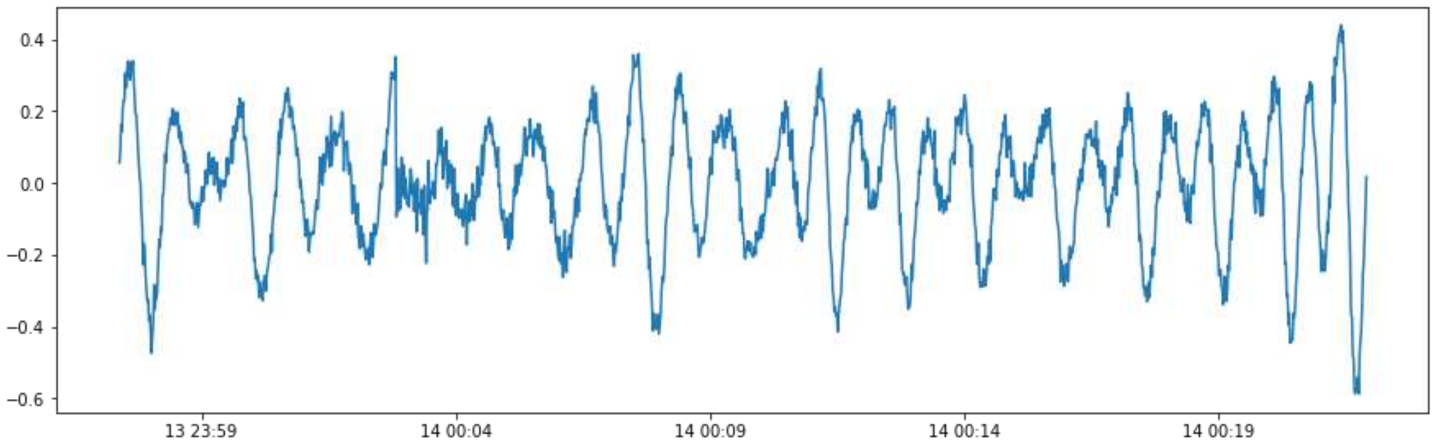
Spike and Level Shift





Pattern Change





Seasonality

Production Issues?

IID datasets

Identically Distributed

- no overall trends – the distribution doesn't fluctuate
- all items in the sample are taken from the same probability distribution

Independent

- Items are all independent events.
- Not connected to each other in any way.

Time Series Anomaly Detection

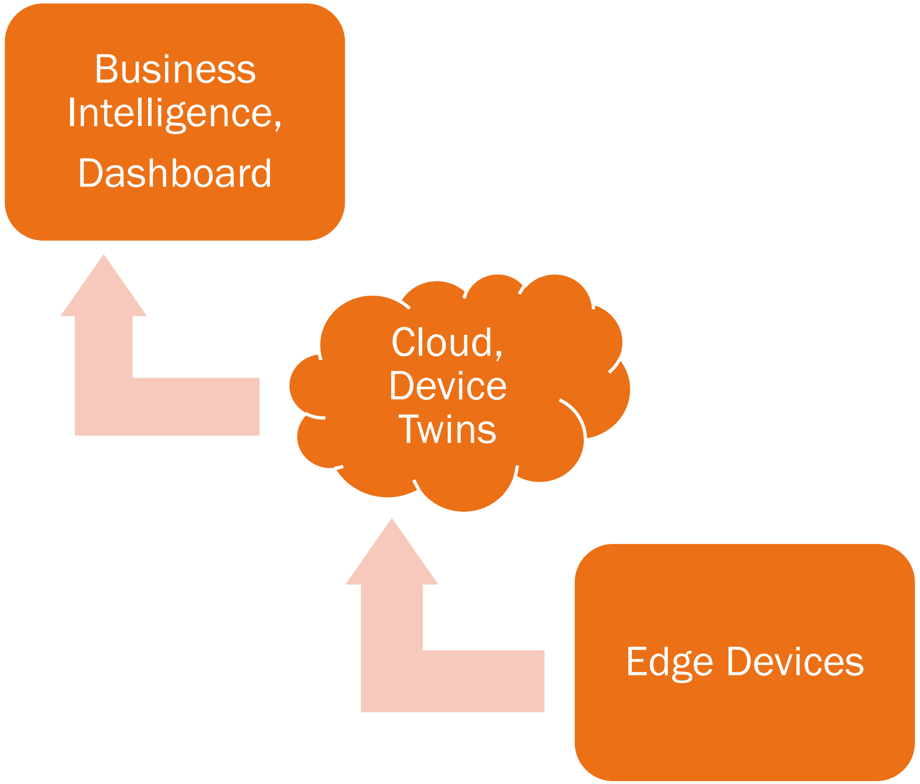
Spikes

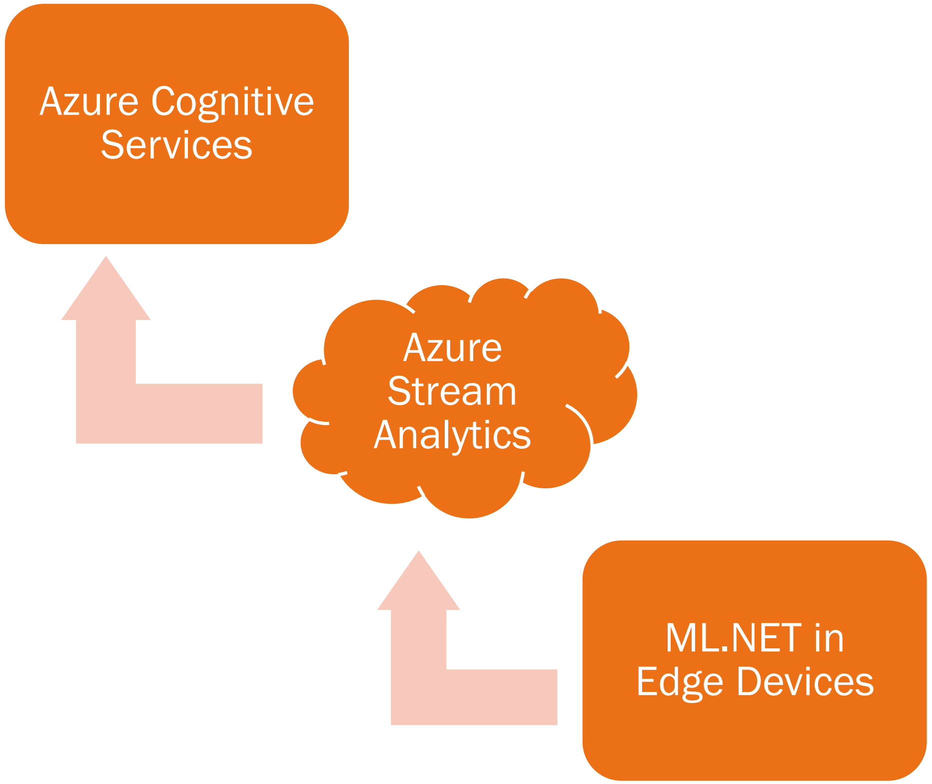
- temporary bursts of anomalous behavior in the system.

Change points

- indicate the beginning of persistent changes over time in the system.
- level changes and trends

Anomaly Detection in IoT





Intelligent Kiosk

https://github.com/microsoft/Cognitive-Samples-IntelligentKiosk

An open source and cross-platform machine learning framework for .NET

ML.NET

Built for

.NET Developers

Can use existing C# and F# skills to integrate ML into .NET apps

Data science & ML experience not required

ML.NET Time Series Catalog

DetectAnomalyBySrCnn
- detects anomalies with the
Spectral Residual Convolutional Neural Network (SRCNN) algorithm

DetectEntireAnomalyBySrCnn
- detects timeseries anomalies for entire input using SRCNN algorithm.

DetectChangePointBySsa
– detects anomalies with the Singular Spectrum Analysis (SSA) algorithm in an independent identically distributed (i.i.d.) time series-based algorithm.

ML.NET Time Series Catalog

DetectIidSpike
– detects changes with an i.i.d. algorithm but predicts spikes instead of change points

DetectSpikeBySsa
– detects spikes in time series using Singular Spectrum Analysis (SSA).

ForecastBySsa
– Uses Singular Spectrum Analysis (SSA) model for singular variable (univariate) based time-series

ML.NET DEMO

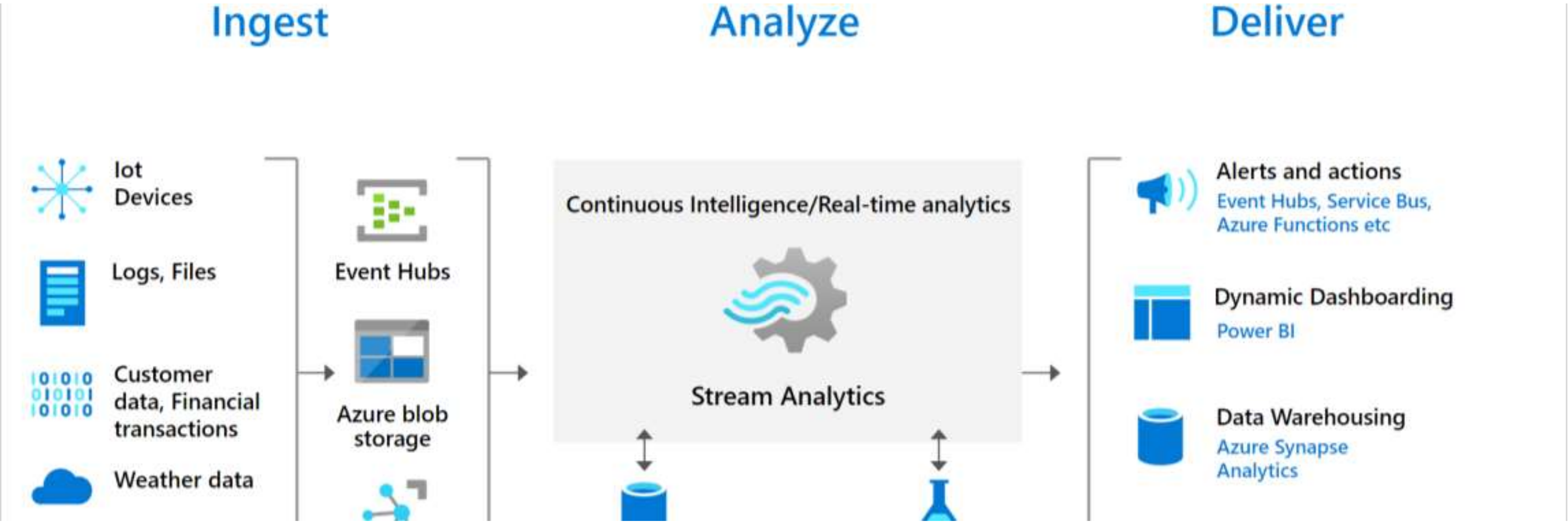
ML.NET 1.5.4 – Time Series

Detecting seasonality in time series

Removing seasonality from time series prior to anomaly detection

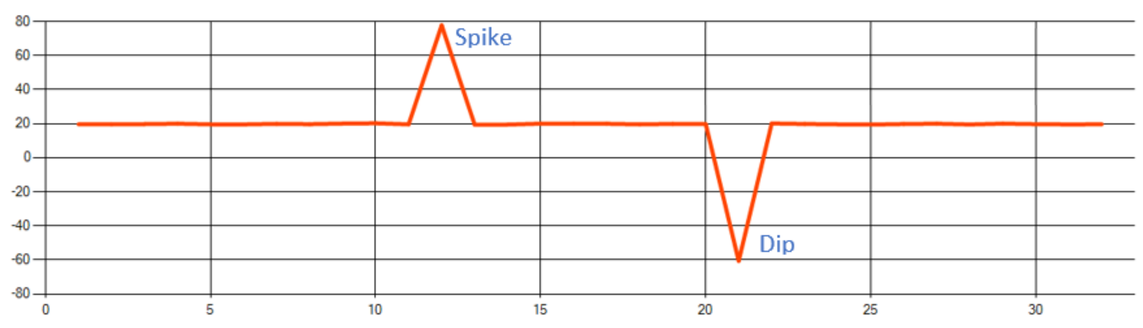
Threshold for root cause analysis (RCA)

RCA for anomaly detection can now return multiple dimensions



Azure Stream Analytics

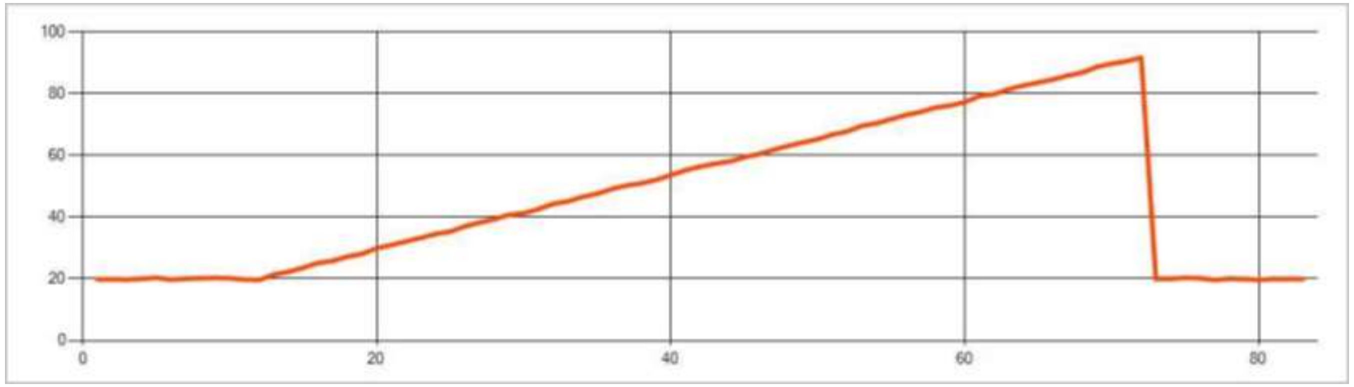
Spike and Dips



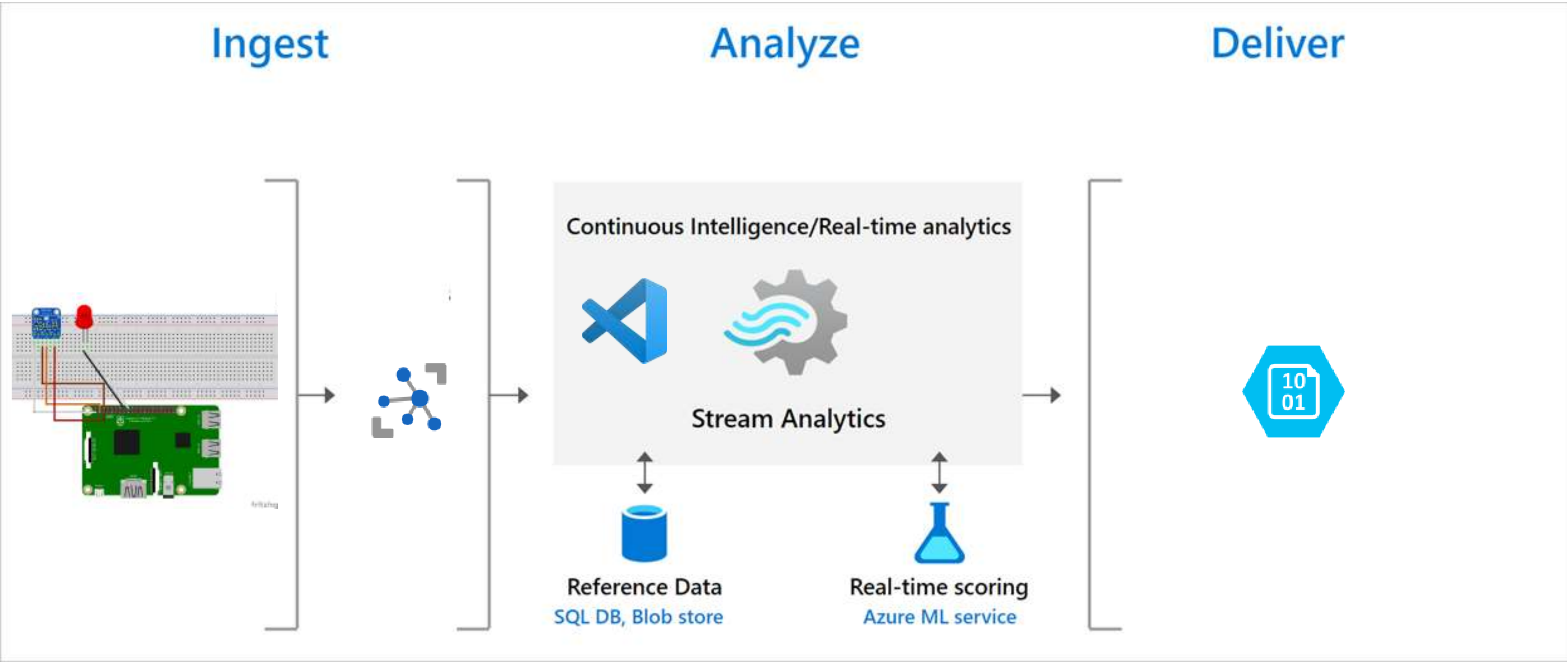
Examples of Spike and Dip anomalies

```
WITH AnomalyDetectionStep AS
(
    SELECT
        EVENTENQUEUEDUTCTIME AS time,
        CAST(temperature AS float) AS temp,
        AnomalyDetection_SpikeAndDip(CAST(temperature AS float), 95, 120, 'spikesanddips')
            OVER(LIMIT DURATION(second, 120)) AS SpikeAndDipScores
    FROM input
)
SELECT
    time,
    temp,
    CAST(GetRecordPropertyValue(SpikeAndDipScores, 'Score') AS float) AS
    SpikeAndDipScore,
    CAST(GetRecordPropertyValue(SpikeAndDipScores, 'IsAnomaly') AS bigint) AS
    IsSpikeAndDipAnomaly
INTO output
FROM AnomalyDetectionStep
```

Change Point




```
WITH AnomalyDetectionStep AS
(
    SELECT
        EVENTENQUEUEDUTCTIME AS time,
        CAST(temperature AS float) AS temp,
        AnomalyDetection_ChangePoint(CAST(temperature AS float), 80, 1200)
        OVER(LIMIT DURATION(minute, 20)) AS ChangePointScores
    FROM input
)
SELECT
    time,
    temp,
    CAST(GetRecordPropertyValue(ChangePointScores, 'Score') AS float) AS
    ChangePointScore,
    CAST(GetRecordPropertyValue(ChangePointScores, 'IsAnomaly') AS bigint) AS
    IsChangePointAnomaly
INTO output
FROM AnomalyDetectionStep
```


Ingest
Analyze
Deliver
Continuous Intelligence/Real-time analytics
Stream Analytics
Reference Data
SQL DB, Blob store
Real-time scoring
Azure ML service
10
01

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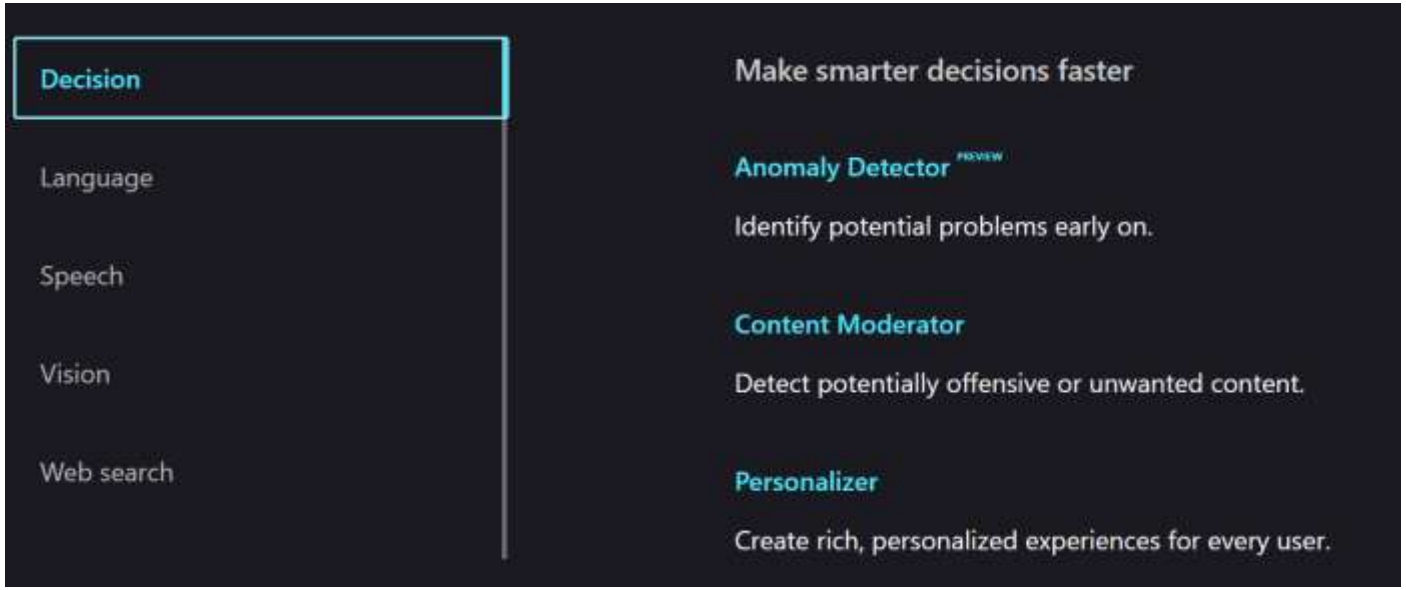
Azure Streaming Analytics DEMO

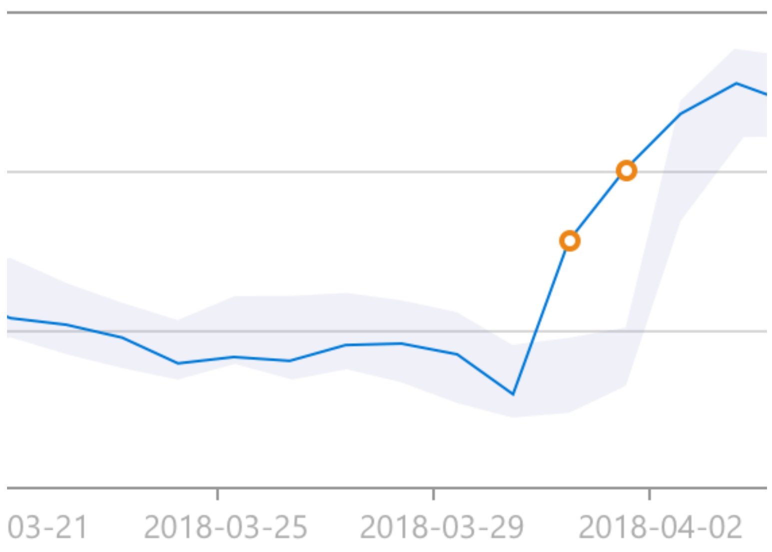
Azure Cognitive Services

- AI for every developer—without requiring machine-learning expertise.
- Just an API call



Anomaly Detector

- Identify potential problems early on
- RESTful API
- monitor and detect abnormalities
- no machine learning expertise needed
- automatically identify and apply the best-fitting models
- Identify boundaries for anomaly detection
- expected values
- Eliminates the need for labeled training data
- Fine-tune sensitivity
- Used by 200 Microsoft product teams



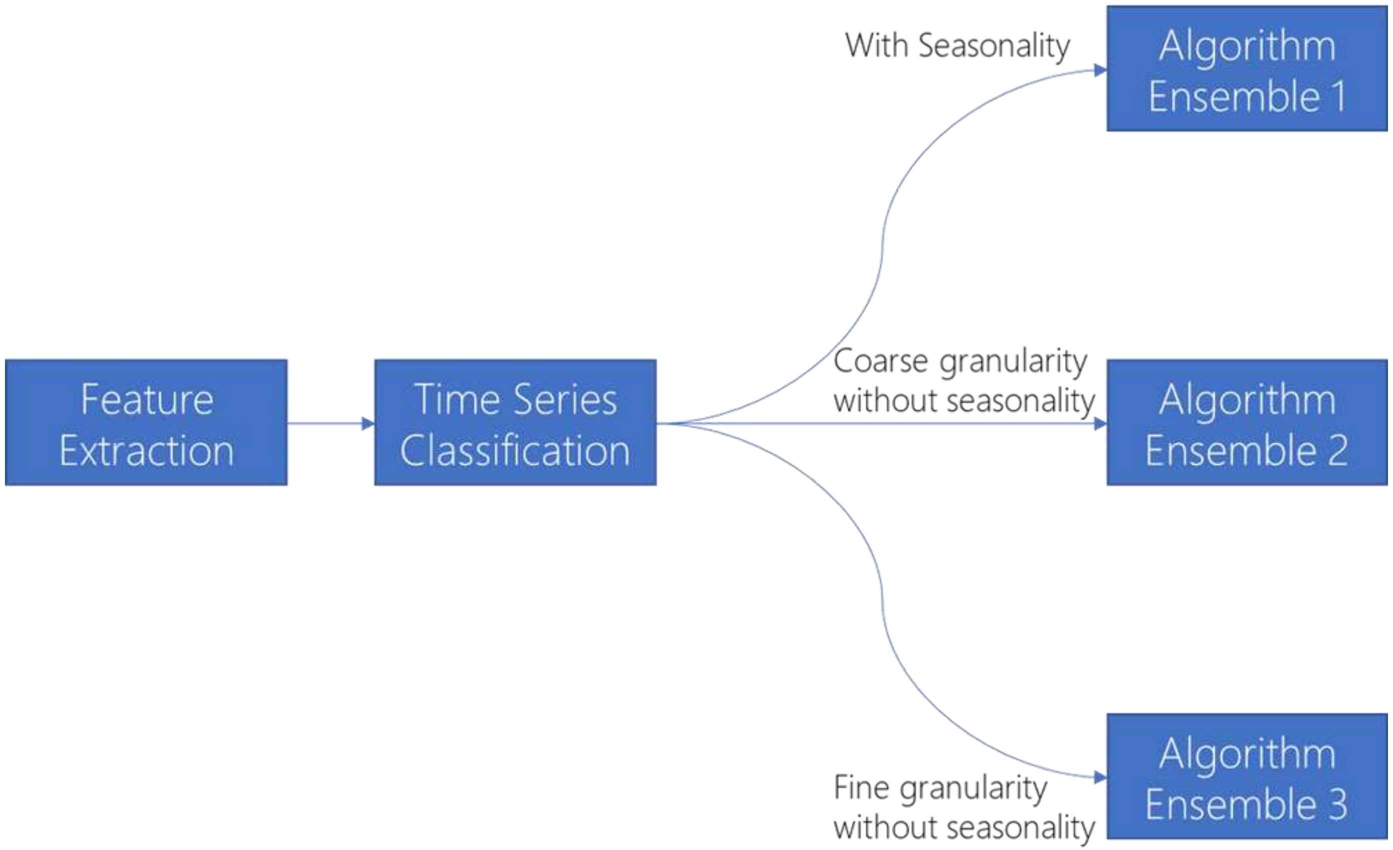
Anomaly Detector Features

Detect anomalies as they occur in real-time.

Detect anomalies throughout your data set as a batch.

Get additional information about your data.

Adjust anomaly detection boundaries.



Gallery of Algorithms

- Fourier Transformation
- Extreme Studentized Deviate (ESD)
- STL Decomposition
- Dynamic Threshold
- Z-score detector
- SR-CNN

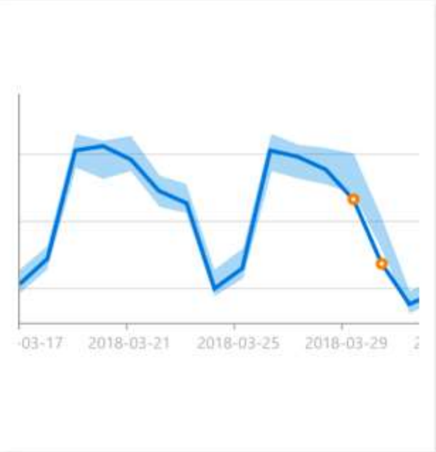
Anomaly Detector Demo

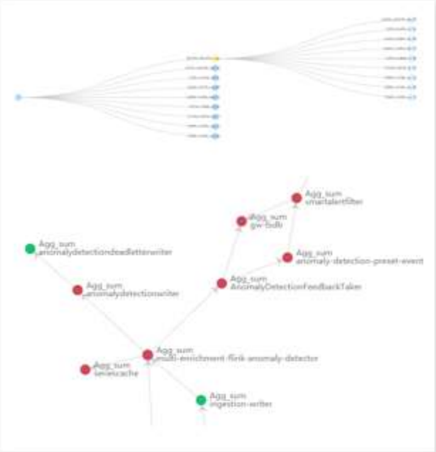
Metrics Advisor

- Part of Azure Cognitive Services
- Performs data monitoring, anomaly detection in time series data
- Automates the process of applying models
- Analyze multi-dimensional data from multiple data sources
- Identify and correlate anomalies
- Configure and fine-tune the anomaly detection model used on your data
- Diagnose anomalies and help with root cause analysis
- REST API and Web Portal

- Currently in preview

Collect time-series data → Detect anomalies → Send incident alerts → Analyze root cause





Where can you use this?

C#, Javascript, Python

https://docs.microsoft.com/en-us/azure/cognitive-services/anomaly-detector/quickstarts/client-libraries?pivots=programming-language-csharp&tabs=linux

Docker Containers

https://docs.microsoft.com/en-us/azure/cognitive-services/anomaly-detector/anomaly-detector-container-howto

Power BI

https://docs.microsoft.com/en-us/azure/cognitive-services/anomaly-detector/tutorials/batch-anomaly-detection-powerbi

Azure Databricks for streaming data

https://docs.microsoft.com/en-us/azure/cognitive-services/anomaly-detector/tutorials/anomaly-detection-streaming-databricks

The best superpower you can give to your IoT project is a “spidey-sense”.

https://bit.ly/spideysense-anomaly

About Me

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  www.linkedin.com/in/rondagdag/
- Thanks for geeking out with me about Spidey Senses and Anomaly Detection