Developing Spidey Senses

Anomaly Detection for apps

RON DAGDAG

Spidey Sense?

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

- ability to sense / react to danger

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

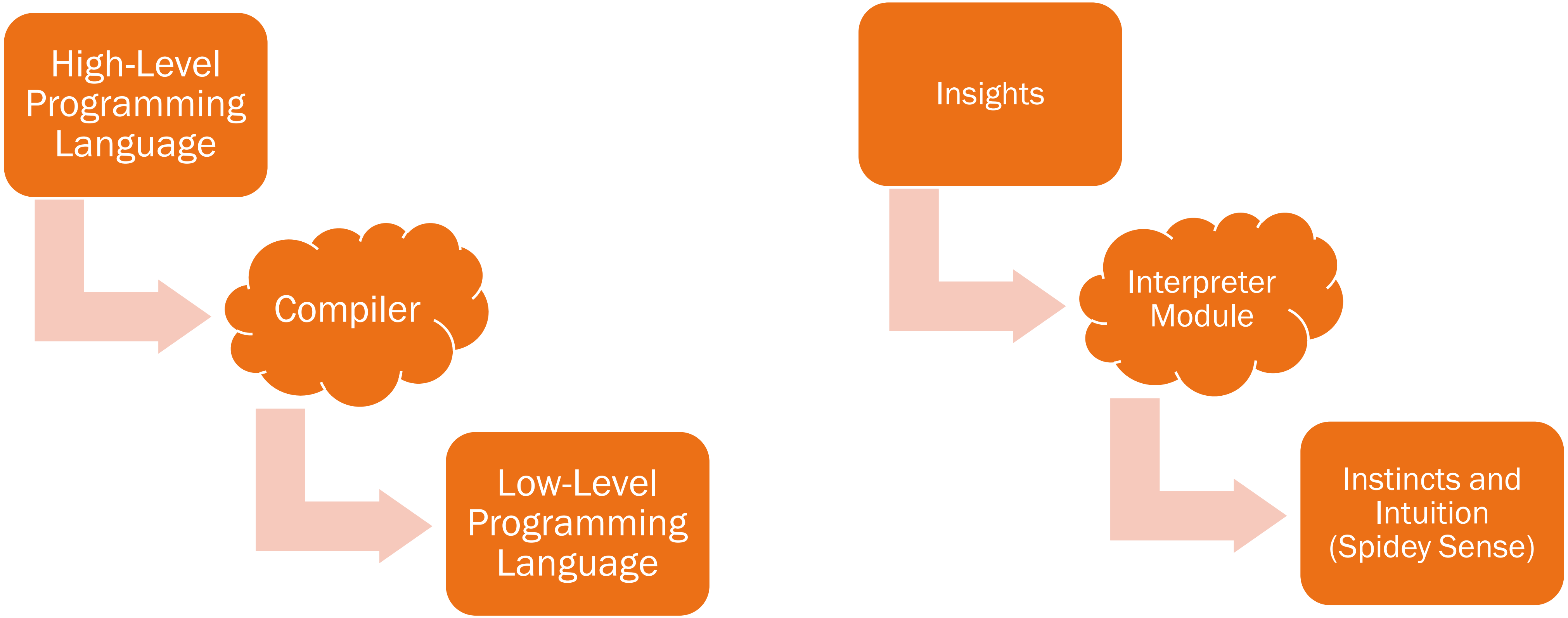
Feeling

Intuition

Discover Blind Spots

Learning from the past

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

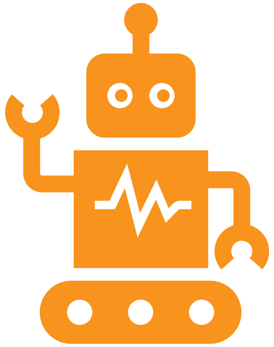
Identifying unexpected items or events in data sets, which differ from the norm

An Outlier

Assumptions:

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

Causes of Outliers

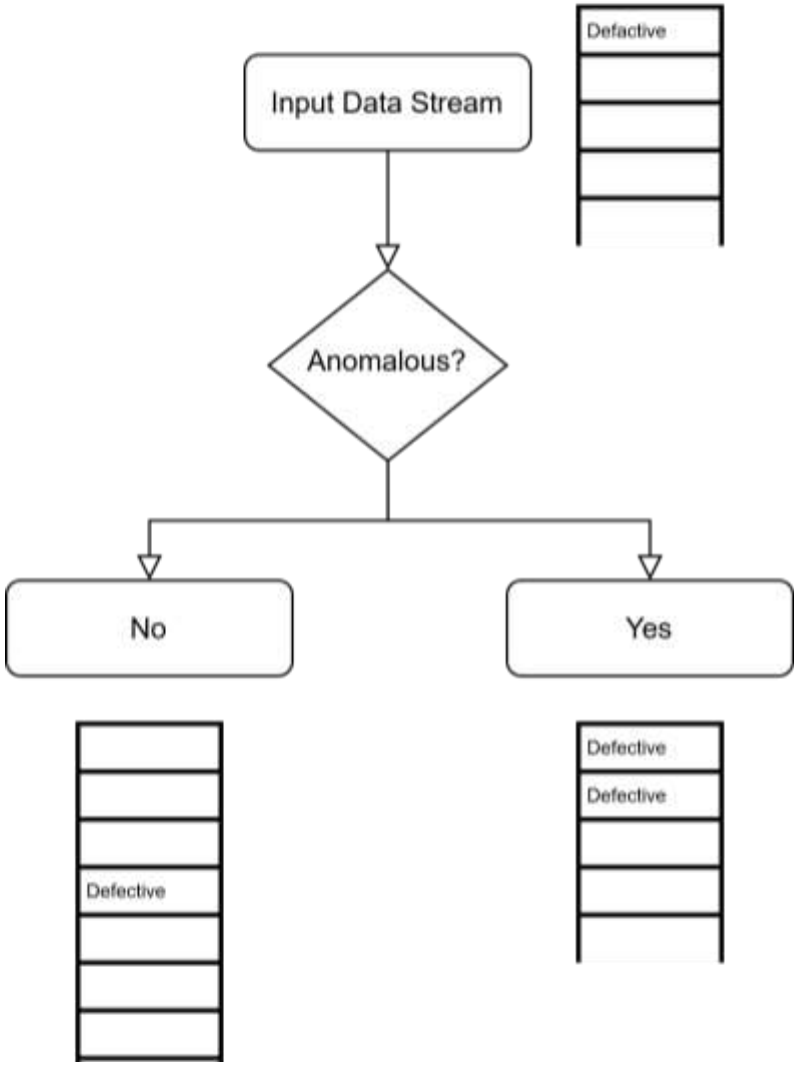


Artificial (Error) / Non-natural

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

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

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)

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

ANOMALY DETECTION

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

SUPERVISED LEARNING

- Email spam classification
- Weather prediction
- Cancer classification

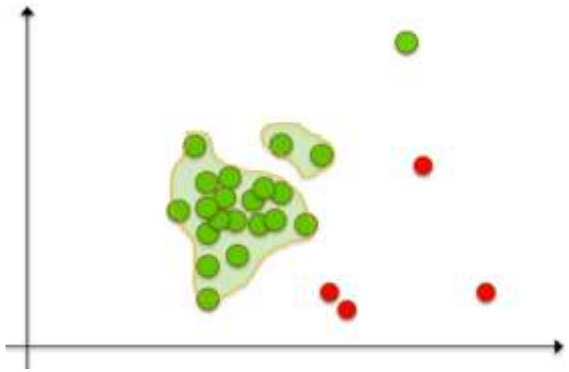
Machine Learning

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

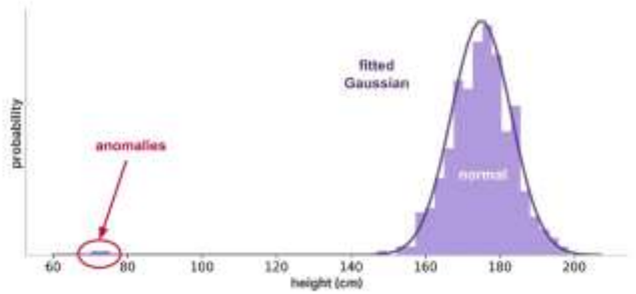
- *Assumption:* Data points that are similar tend to belong to clusters --> distance from local centroids.
- K-means



Machine Learning

Gaussian Distribution

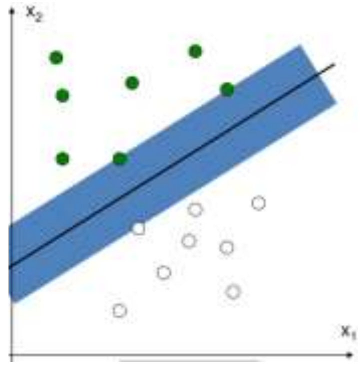
- Gaussian Distribution and given a new data-point,
- Compute the probability of the data-point
- If the probability is below a threshold => outlier or anomalous.



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

Time Series Data

Series of data points indexed in time order

Examples:

- Stock Market
- Sales Data
- Sensors
- Any data captured with Time Stamp

Internet of Things

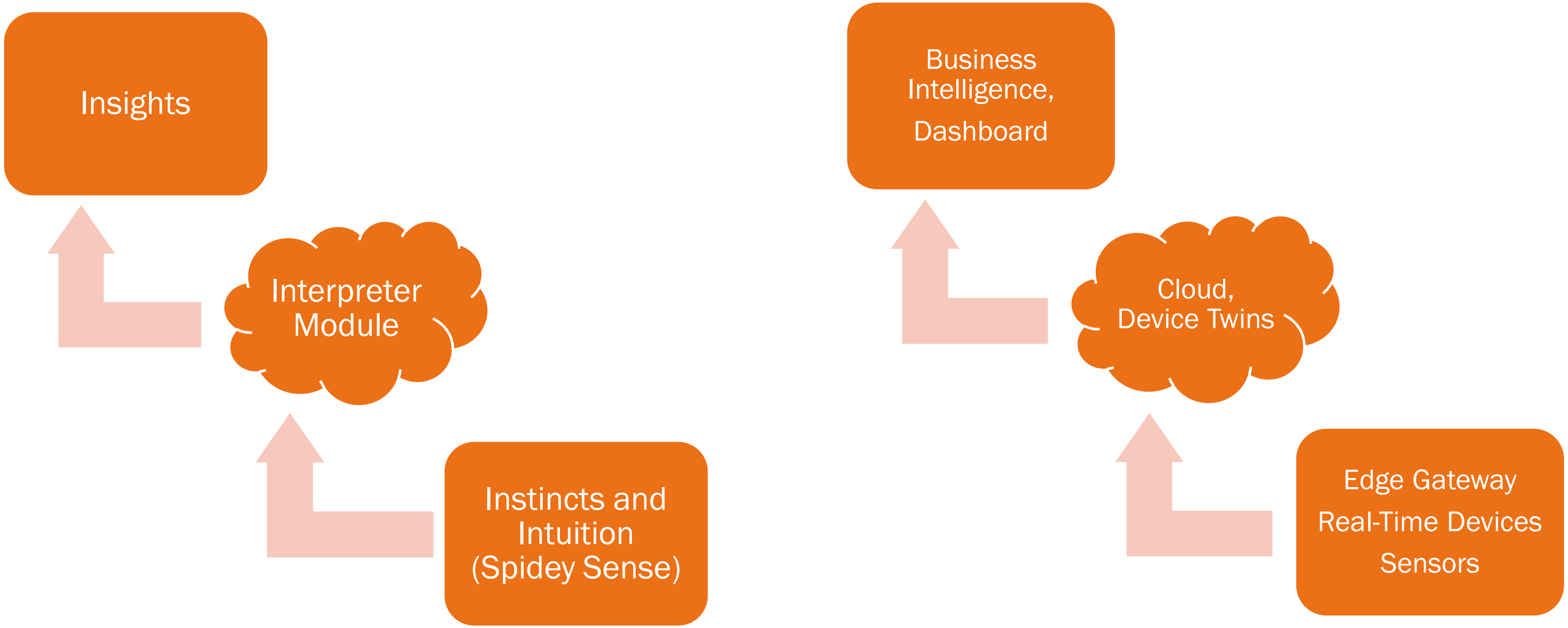
Increasing Data Volume
(sensors are cheaper)

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



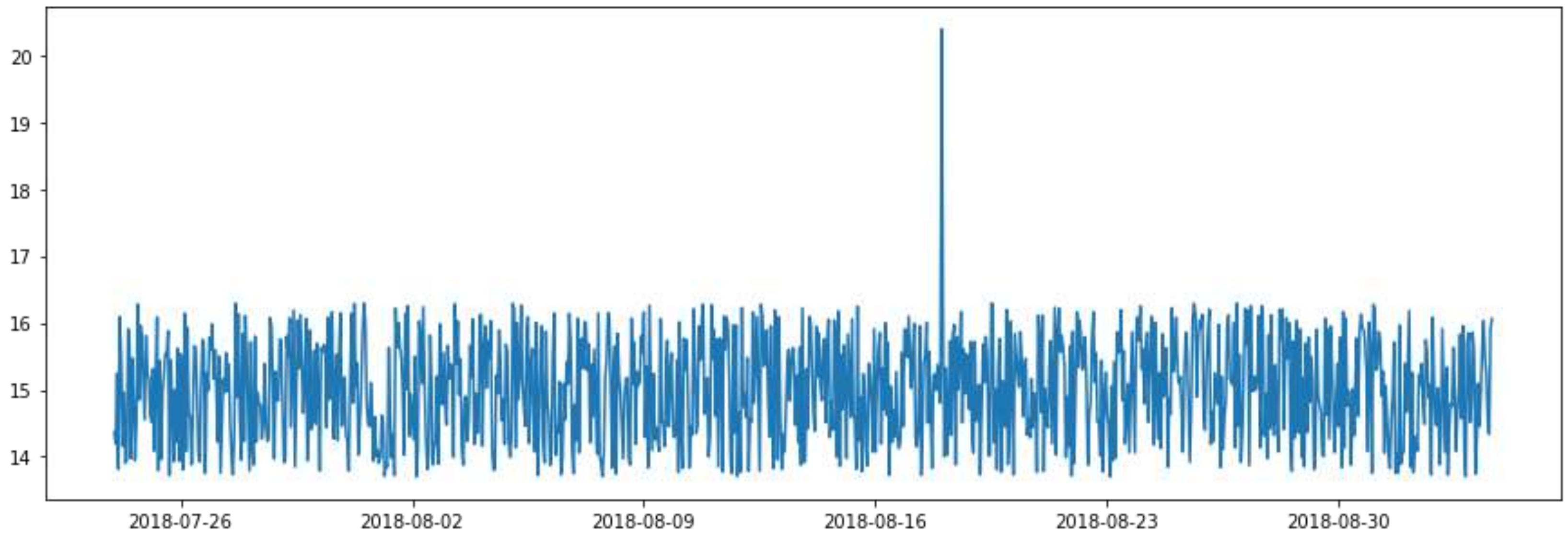
Time Series Anomaly Types

OUTLIER

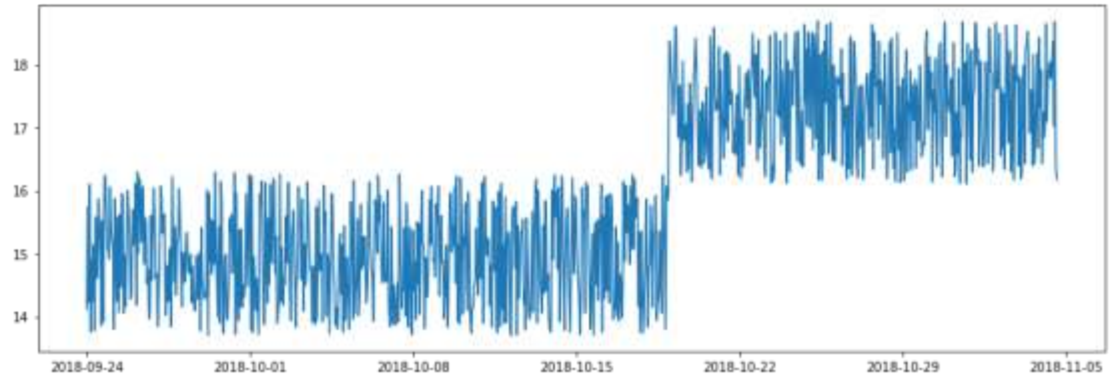
SPIKE AND LEVEL SHIFT

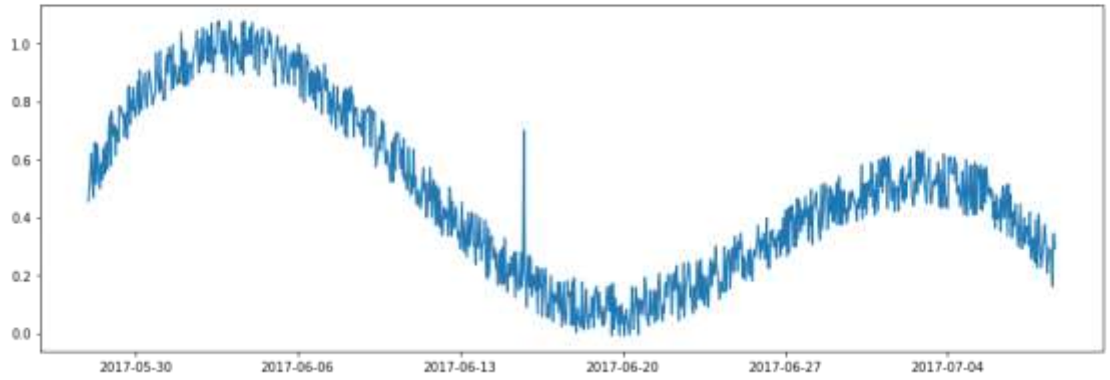
PATTERN CHANGE

SEASONALITY

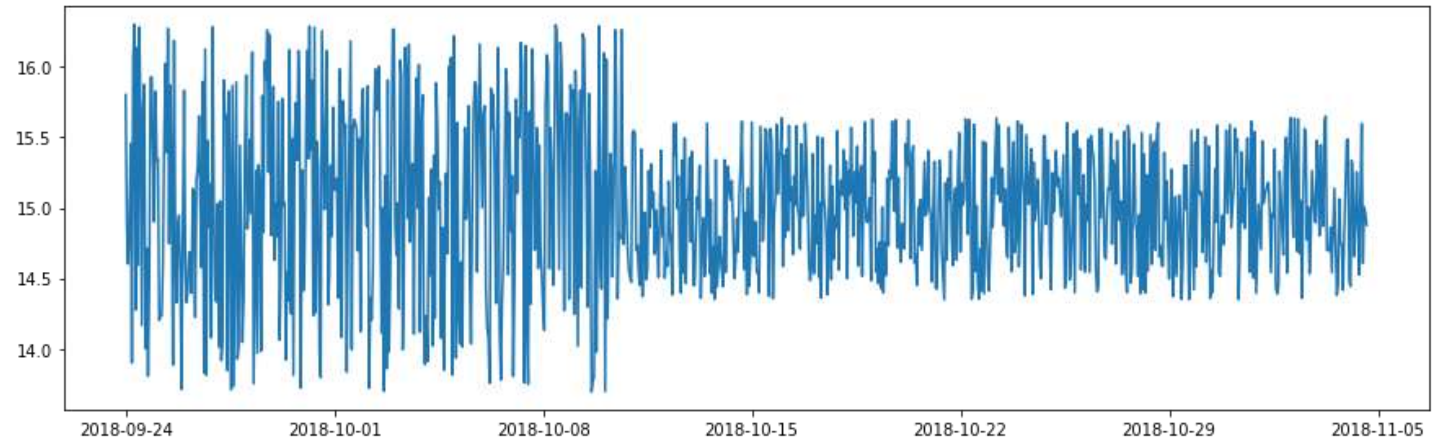

20
19
18
17
16
15
14
2018-07-26
2018-08-02
2018-08-09
2018-08-16
2018-08-23
2018-08-30

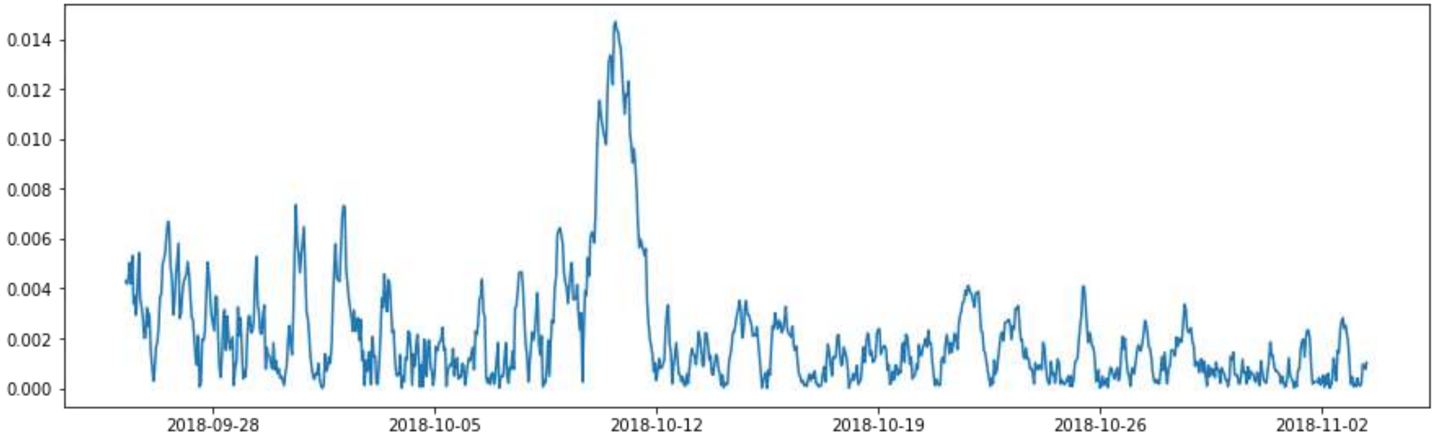
Outlier



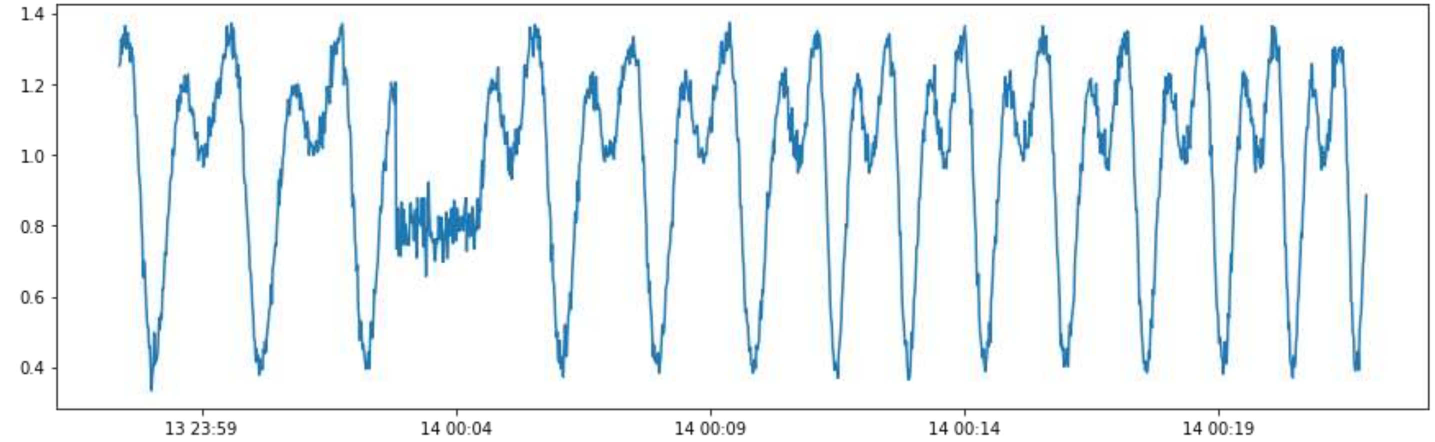


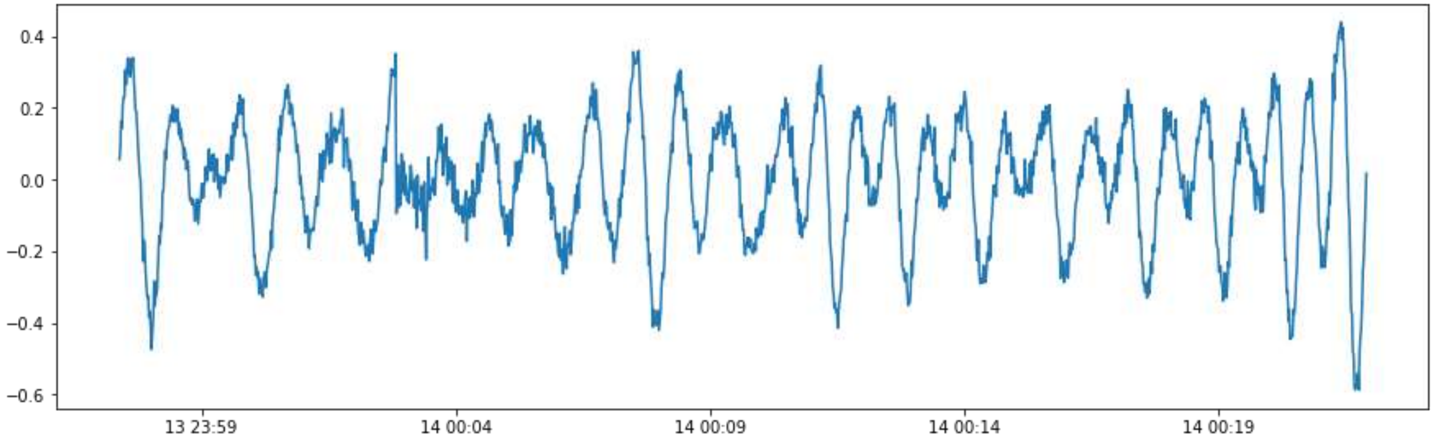
Spike and Level Shift





Pattern Change





Seasonality

Production Issues?

Intelligent Kiosk

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

Time Series Anomaly Detection

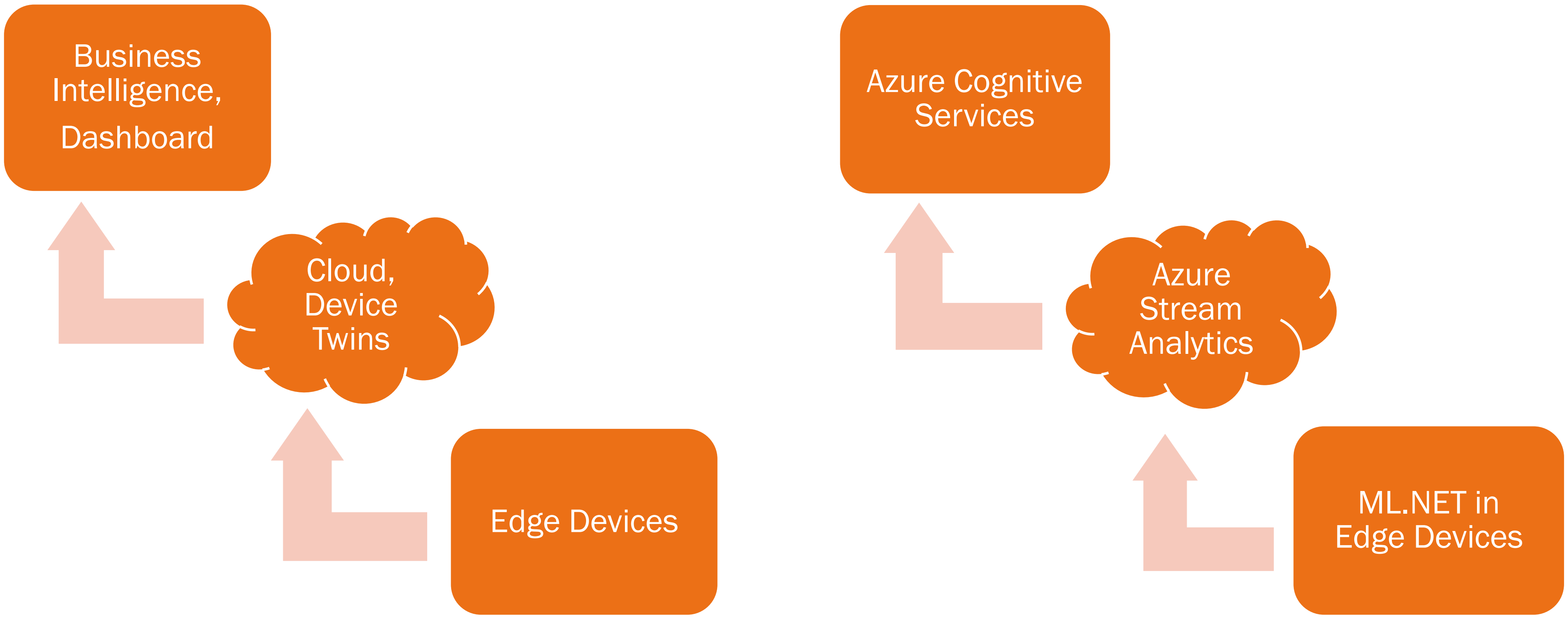
Spikes

- 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



ML.NET

Built for

.NET Developers

Use Existing
C# and F# skills

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.

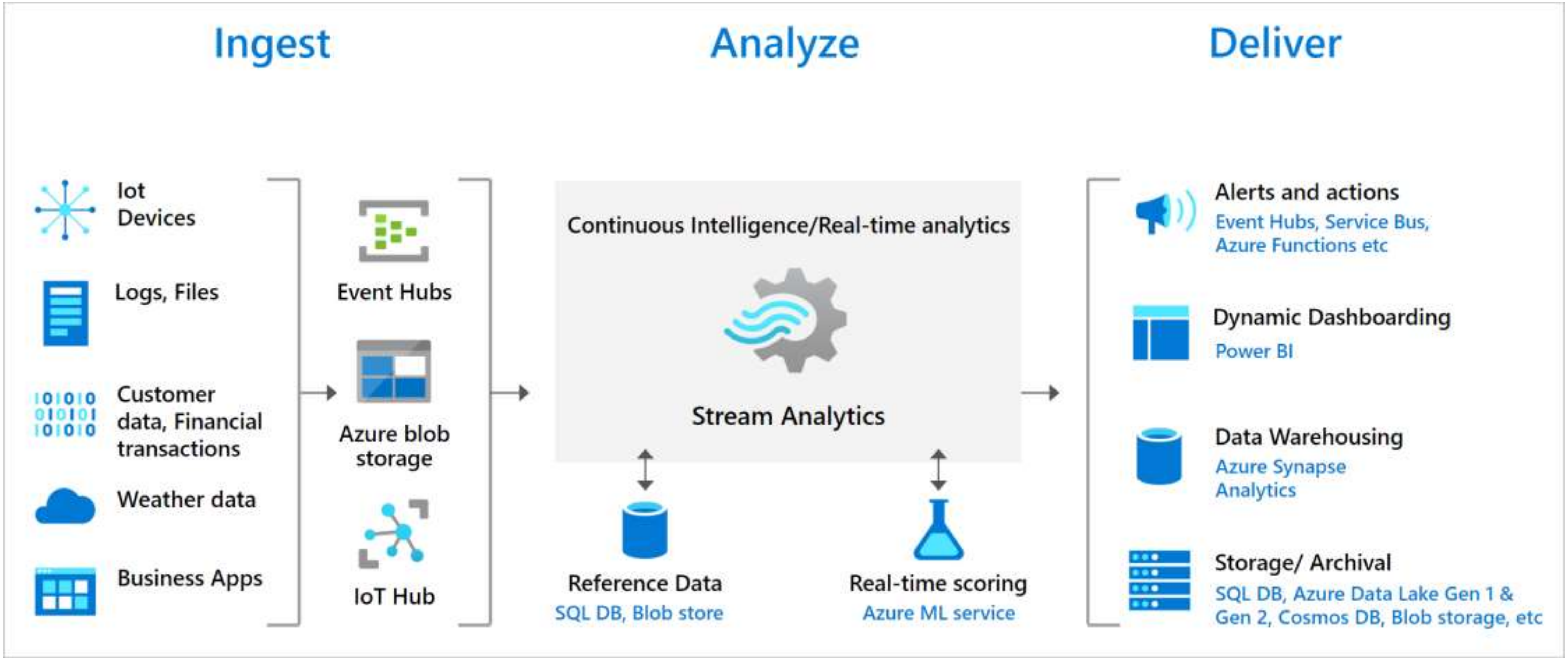
ML.NET Time Series Catalog

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).

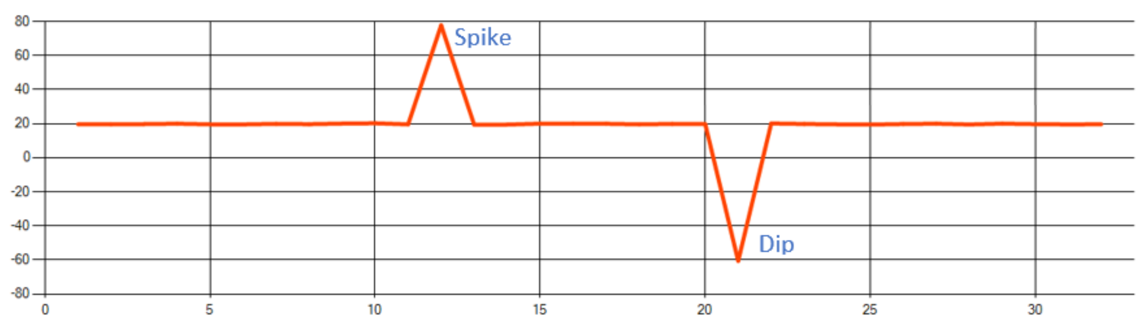
ForecastBySsa
– Uses Singular Spectrum Analysis (SSA) model for singular variable (univariate) based time-series

ML.NET DEMO



Azure Stream Analytics

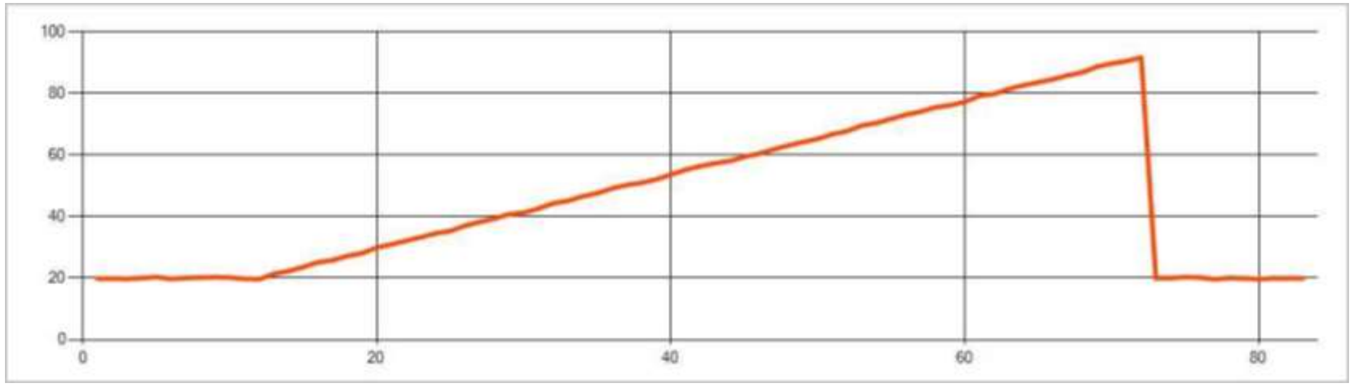
Spike and Dips



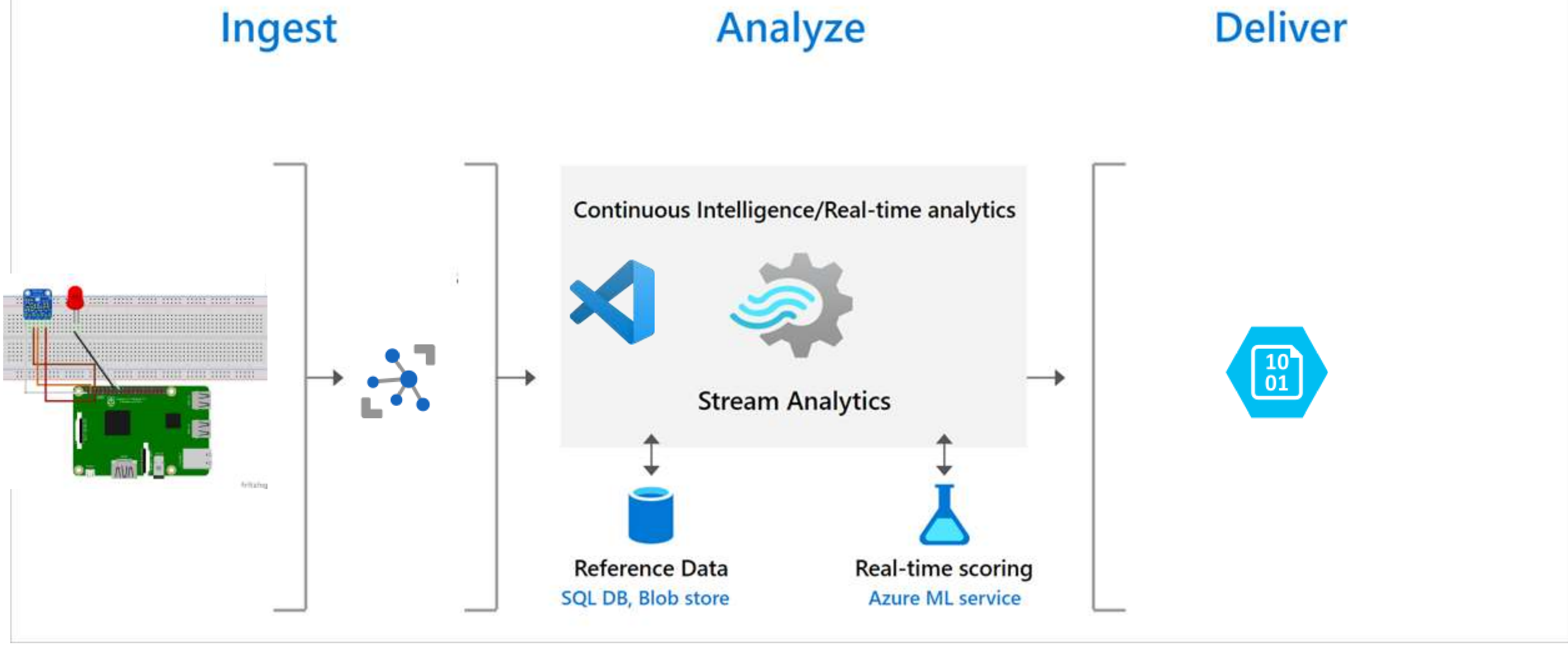
Examples of Spike and Dip anomalies

```
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



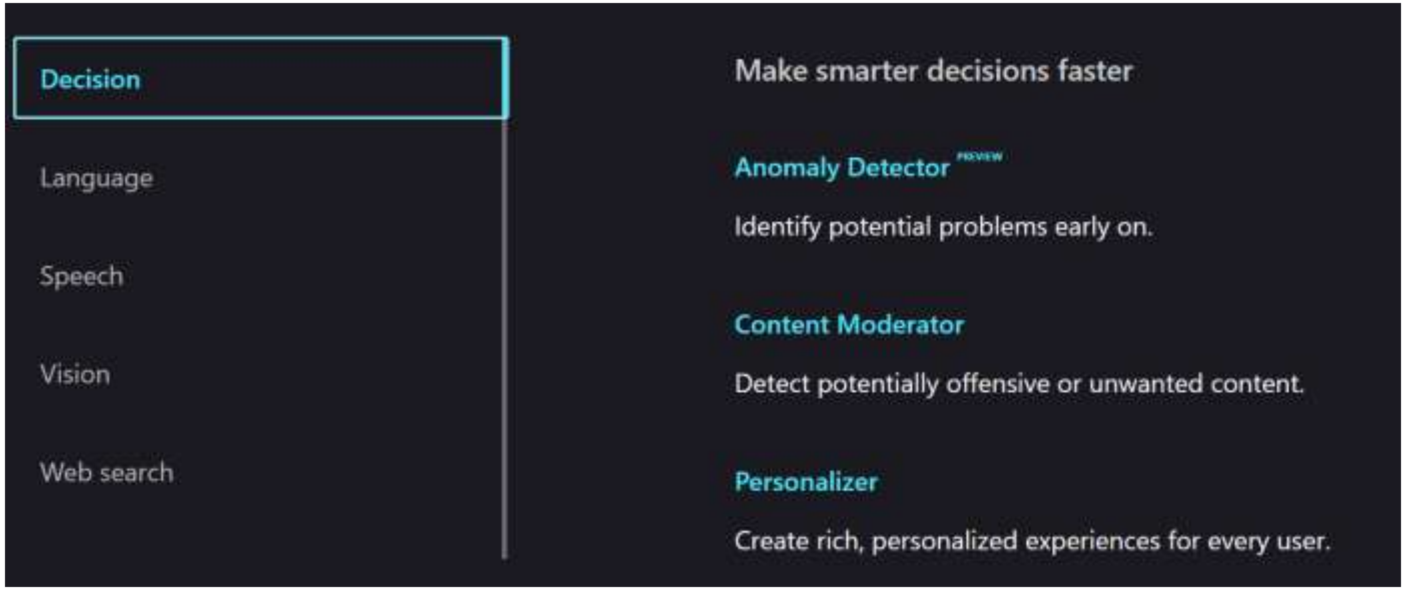

```
WITH AnomalyDetectionStep AS
(
    SELECT
        EVENTENQUEUEDUTCTIME AS time,
        CAST(temperature AS float) AS temp,
        AnomalyDetection_ChangePoint(CAST(temperature AS float), 80, 1200)
        OVER(LIMIT DURATION(minute, 20)) AS ChangePointScores
    FROM input
)
SELECT
    time,
    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

Azure Cognitive Services

- AI for every developer— w/o requirement ML expertise.
- Just an API call



Anomaly Detector Features

Detect anomalies as they occur in real-time.

Detect anomalies as a batch.

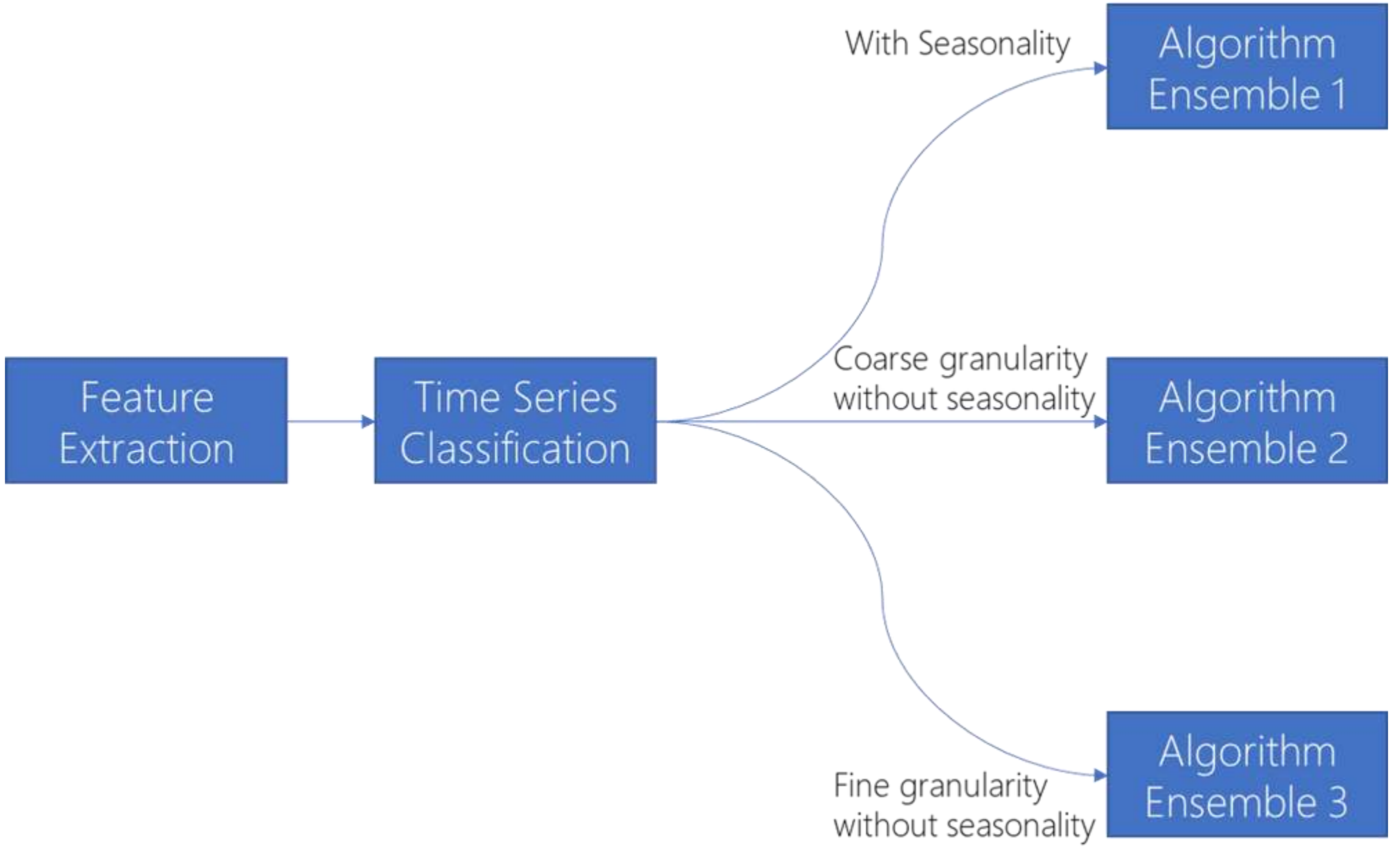
Automatically adapts and learns from new data

Fine Tune Sensitivity

Anomaly Detector Features

- REST API
- No machine learning expertise needed
- Eliminate need for labeled training data
- Automatically identify and apply best-fitting model

Gallery of Algorithms



Fourier Transformation

Extreme Studentized Deviate (ESD)

[STL Decomposition]()

Dynamic Threshold

Z-score detector

[SR-CNN]()

Limitations

Data Granularity – Daily, Hourly, Minutely, Monthly, Weekly, Yearly

Series Data Points – 12 to 8640 entries

JSON

```json
{
    "granularity": "daily",
    "series": [
      {
        "timestamp": "2018-03-01T00:00:00Z",
        "value": 32858923
      },
      {
        "timestamp": "2018-03-02T00:00:00Z",
        "value": 29615278
      },
    ]
}
```

JSON

```json
{
     "granularity" : "minutely",
     "customInterval" : 5
}
```

Calling the Anomaly Detector API

Client SDK

C#, Python, Node

REST API

Any language supporting HTTP calls

Anomaly Detector Demo

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

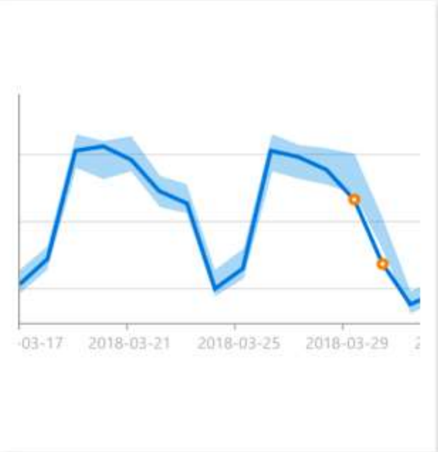
https://docs.microsoft.com/en-us/azure/cognitive-services/anomaly-detector/tutorials/anomaly-detection-streaming-databricks

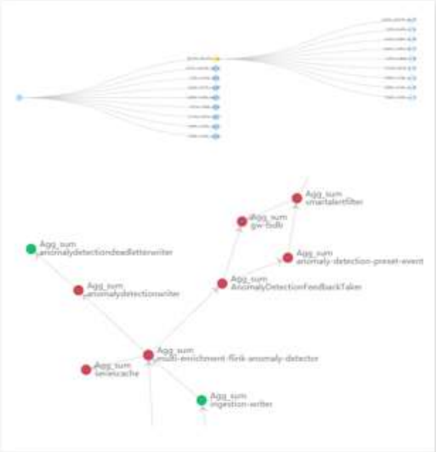
Metrics Advisor

- Part of Azure Cognitive Services
- Performs data monitoring, anomaly detection in time series data
- Automates applying models
- Analyzes multi-dimensional data from multiple data sources
- Identify and correlate anomalies
- Configure and fine-tune the anomaly detection model
- 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





The best superpower you can give to your 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