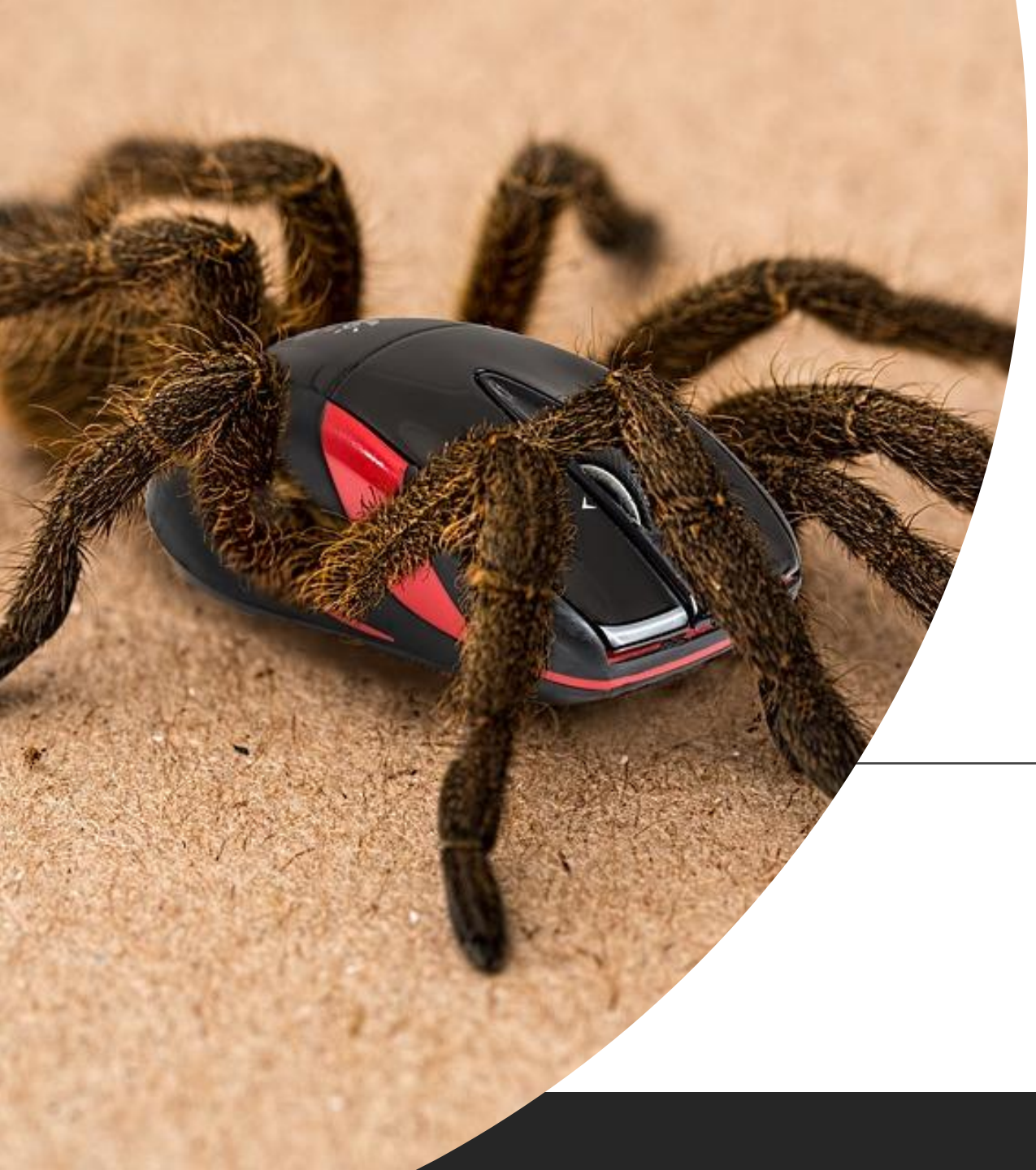


# Developing your inner Spidey Sense

# Anomaly Detection for 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

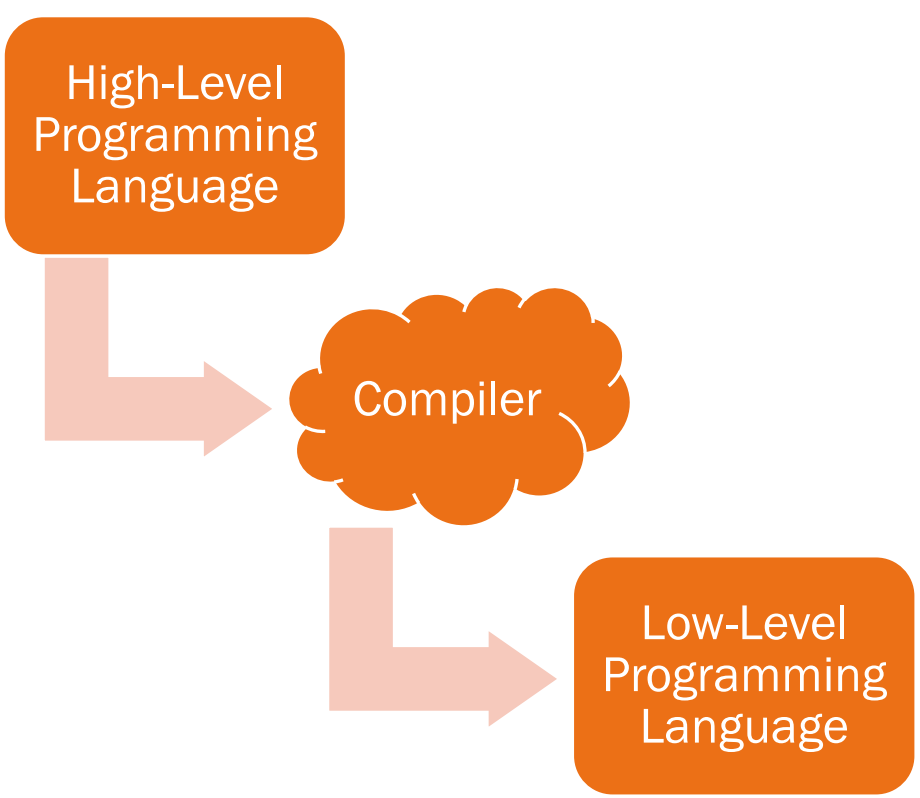
Feeling

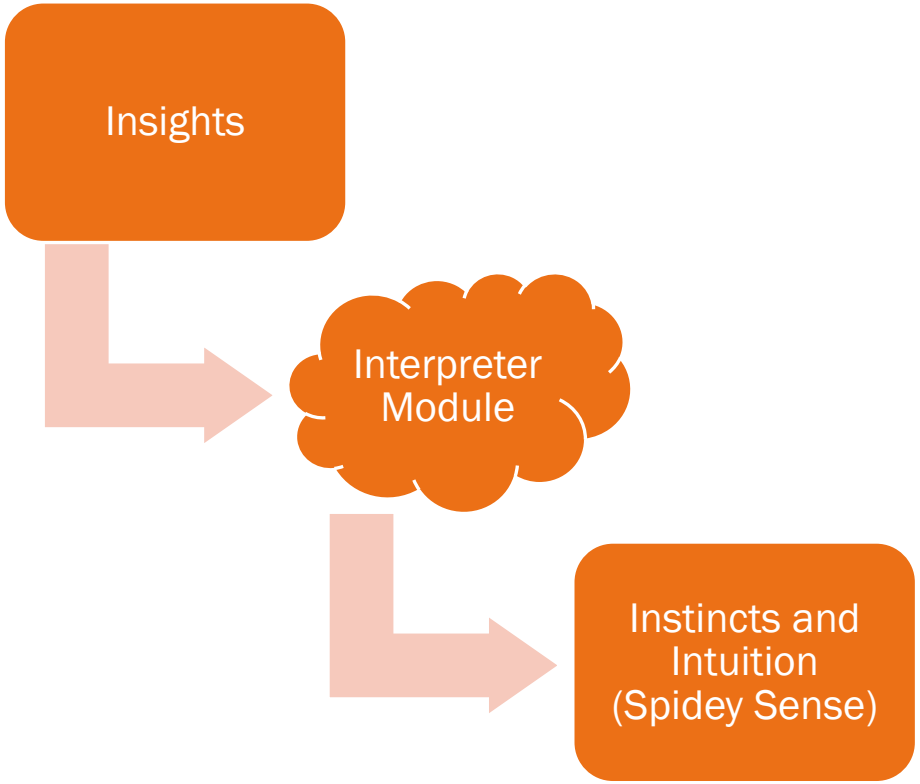
Intuition

Discover Blind Spots

Learning from the past

# 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

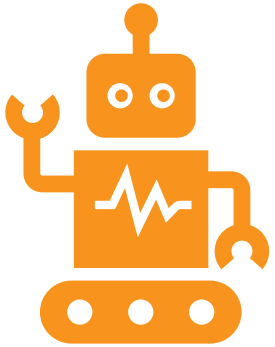
An Outlier



Assumptions:

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

# Causes of Outliers

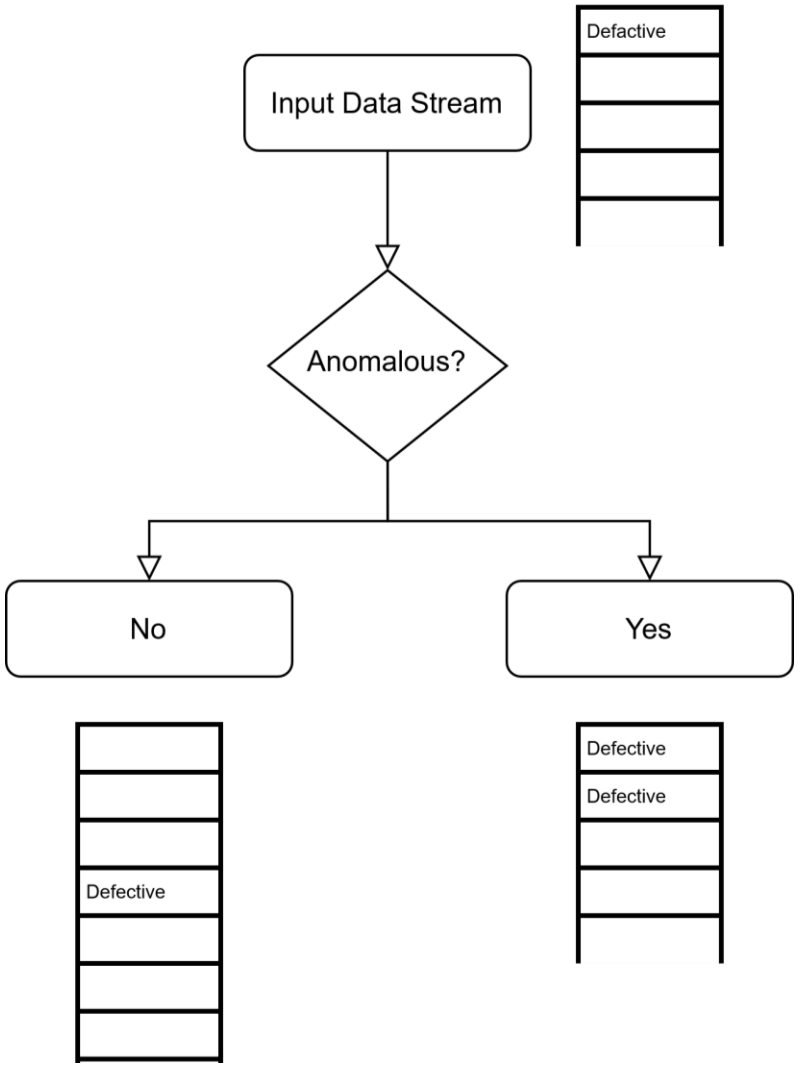


Artificial (Error) / Non-natural

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 few 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



"Experience is the teacher of all things."

Julius Caesar

# 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

- 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.

## SUPERVISED LEARNING

- 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 Methods

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

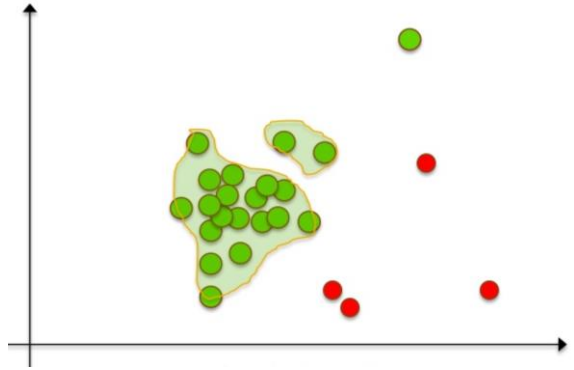
Unsupervised
(e.g. K-Means, Hierarchical Clustering, DBSCAN)

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.



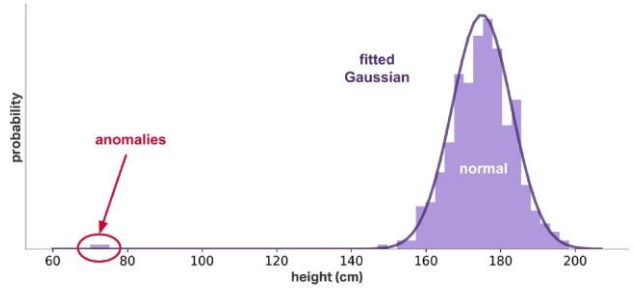
Clustering-Based Anomaly Detection

- *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

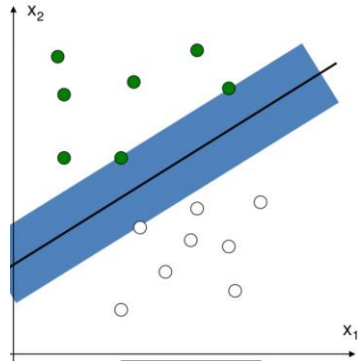
- Gaussian Distribution and given a new data-point,
- Compute the probability of the data-point
- If the probability is below a threshold => outlier or anomalous.



# Machine Learning

Support Vector Machine-Based Anomaly Detection

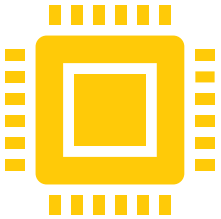
- *OneClassSVM*
- *>100 features, aggressive boundary*
- find a function that is positive for regions with high density of points, and negative for small densities



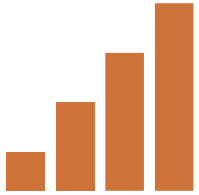

PCA-Based Anomaly Detection

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

# Internet of Things



Increasing Data Volume
(sensors are cheaper)

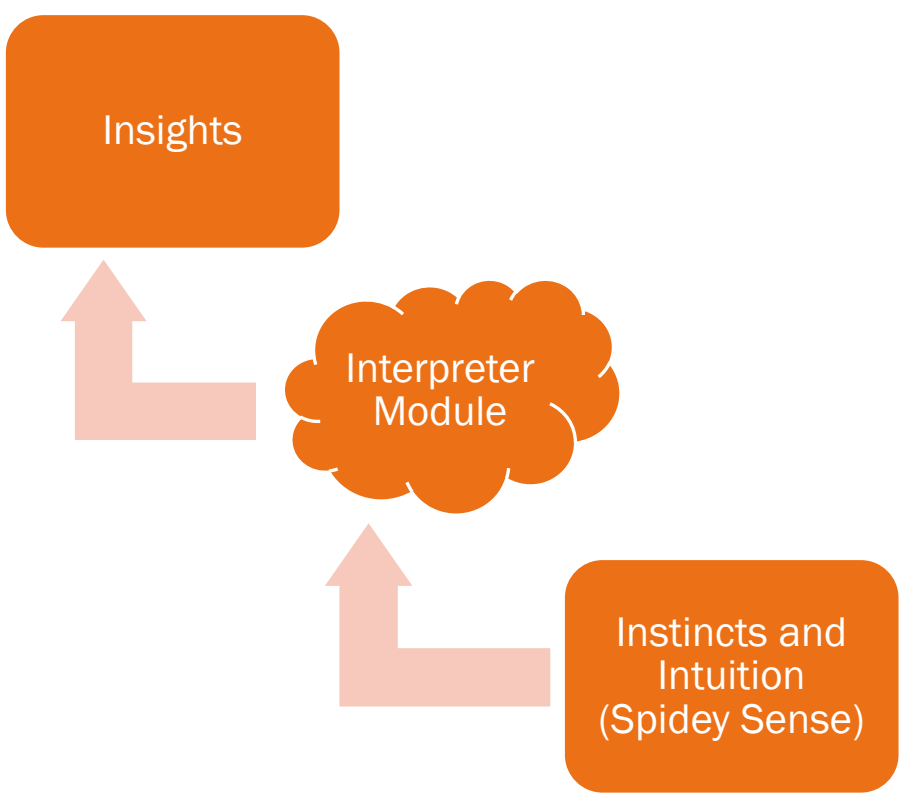


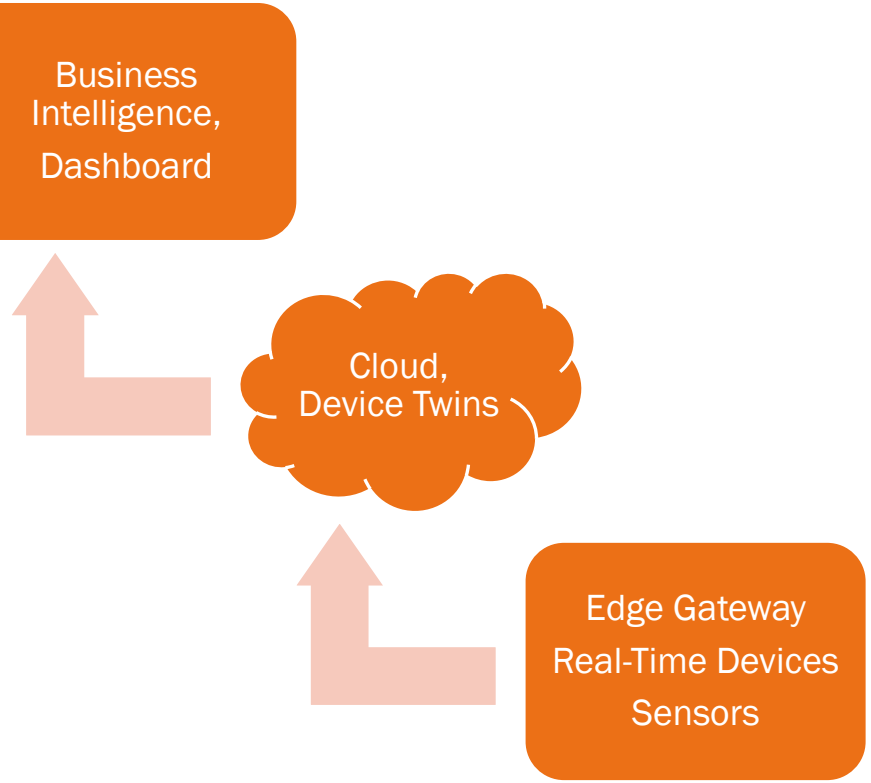
Increased Data Speed
(improved networking)

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

# Internet of Broken Things

# Artificial Intelligence of Things



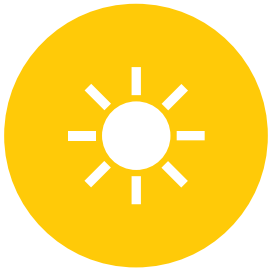



# Time Series Anomaly Types

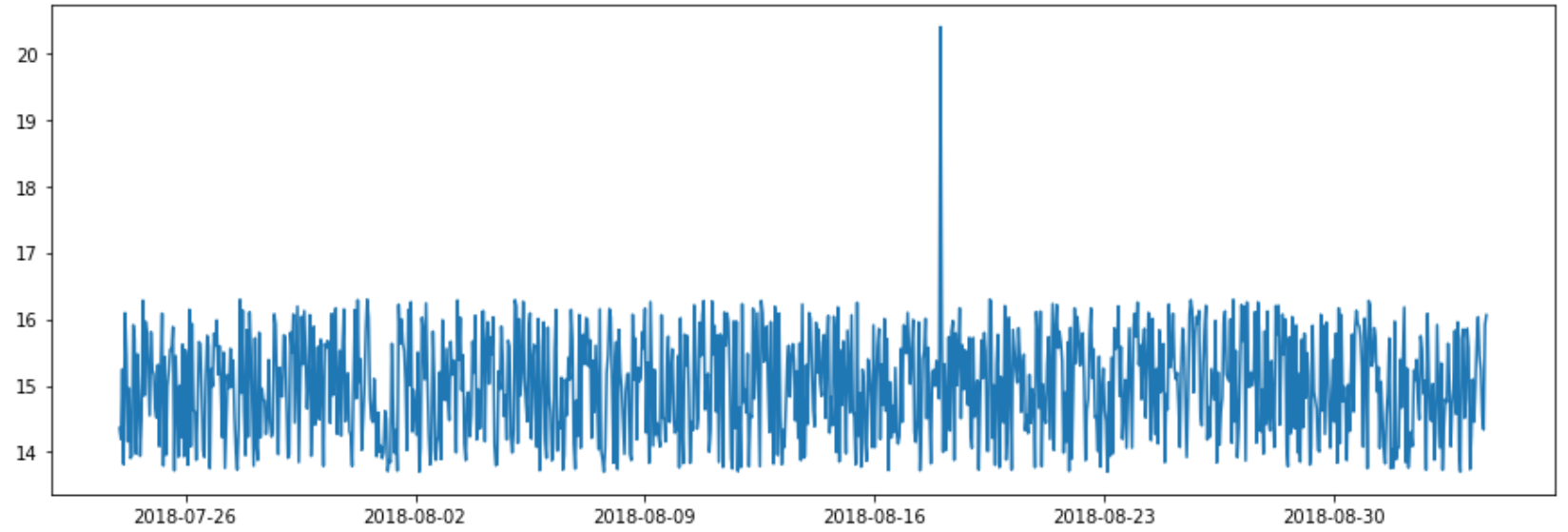
OUTLIER

SPIKE AND LEVEL SHIFT

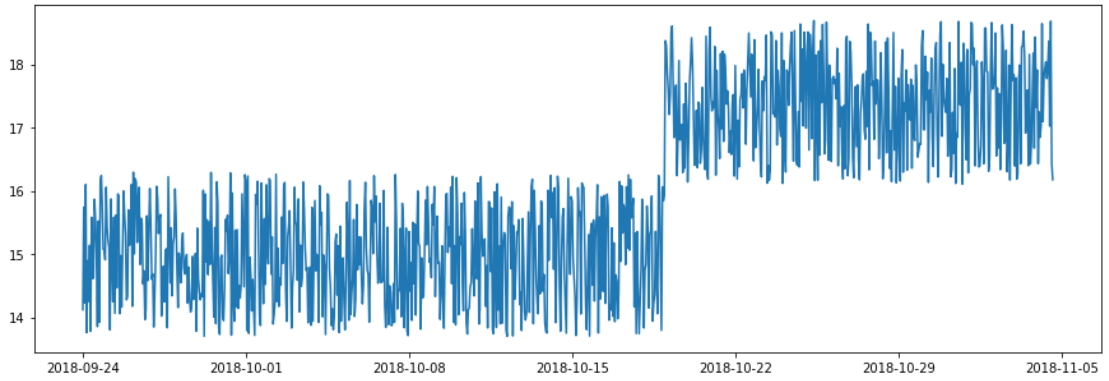
PATTERN CHANGE

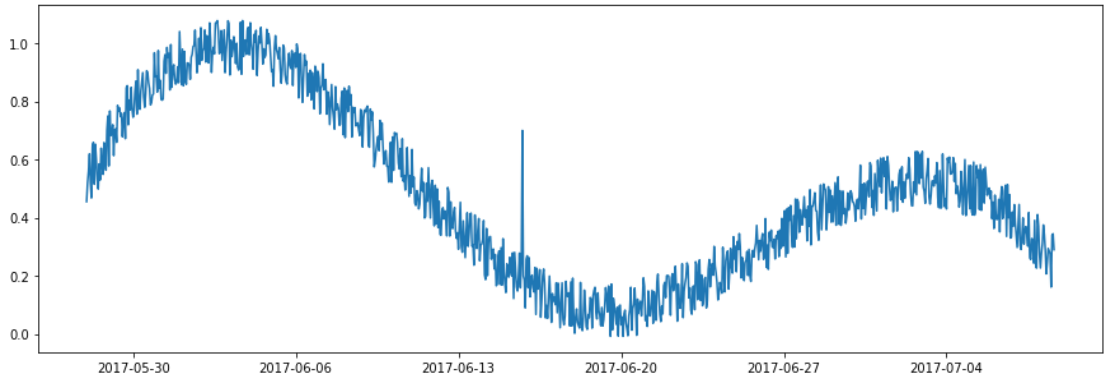


SEASONALITY

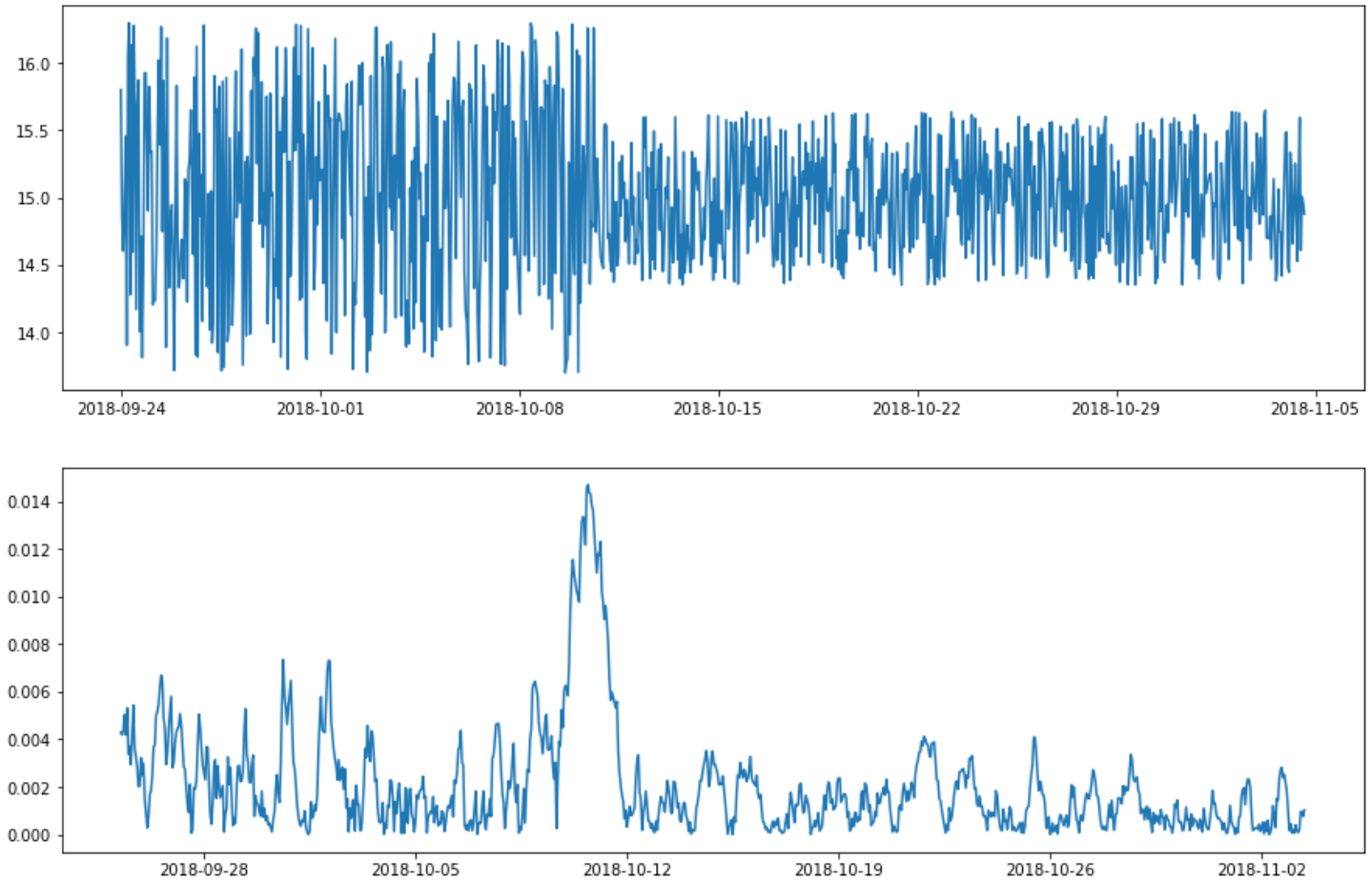

20
19
18
17
16
15
14
2018-07-26
2018-08-02
2018-08-09
2018-08-16
2018-08-23
2018-08-30

# Outlier

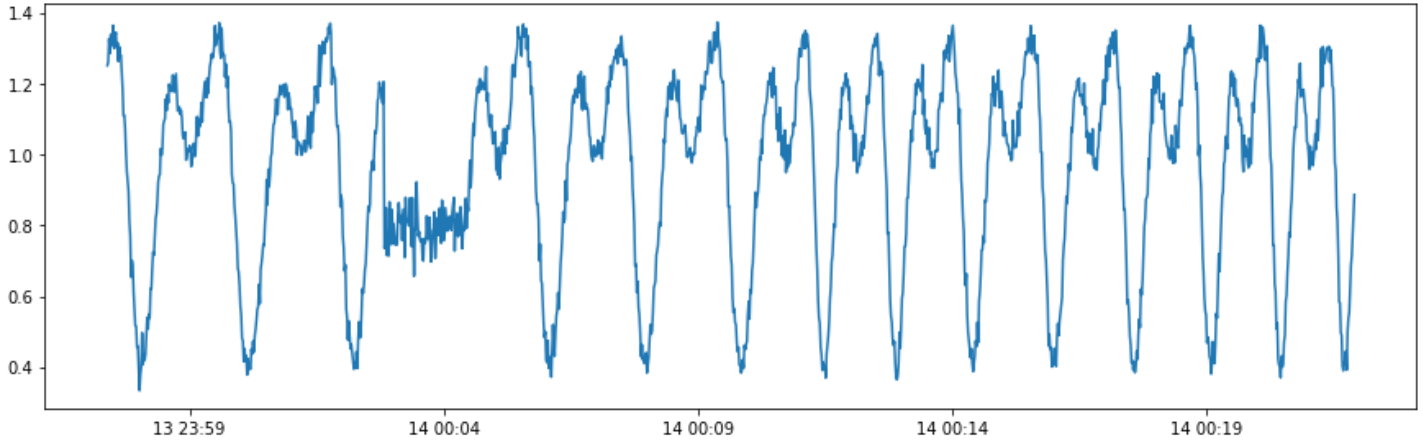


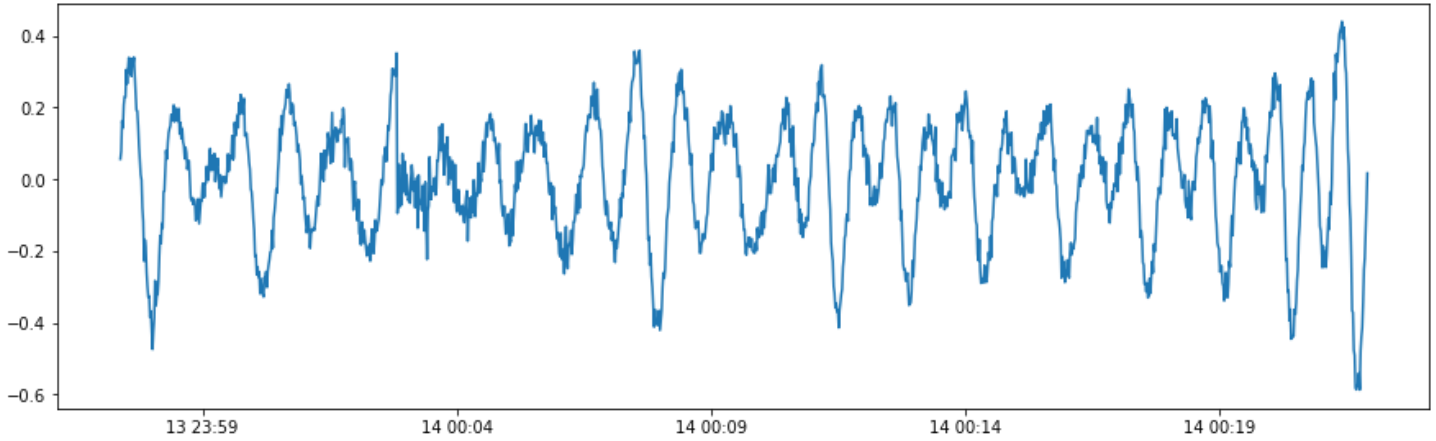




# Spike and Level Shift




# 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

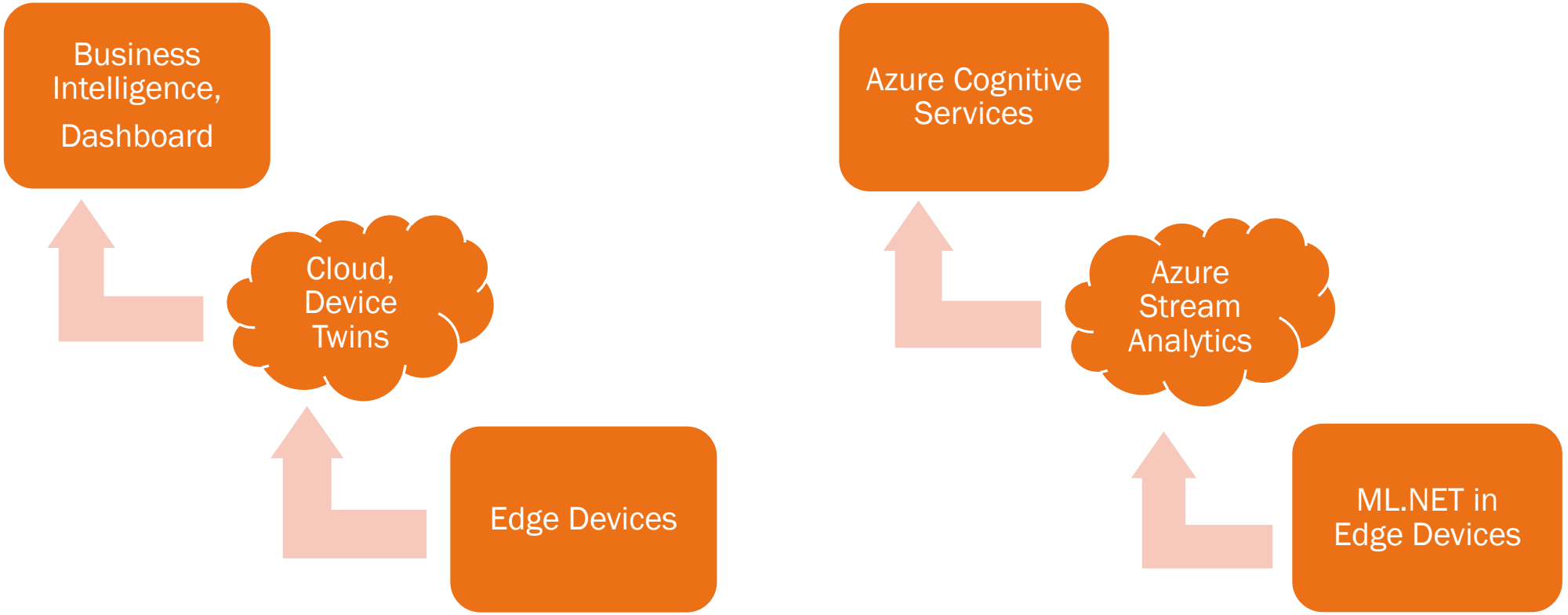
## Spikes

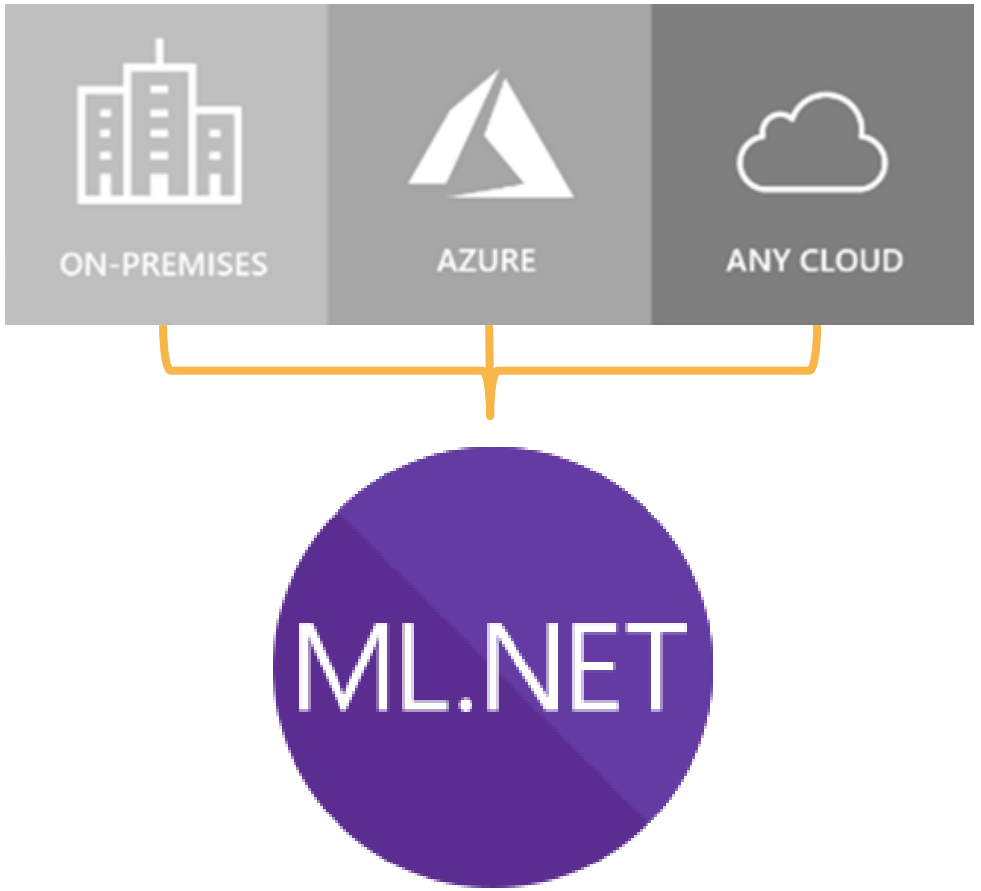
- temporary bursts of anomalous behavior in the system.

## Change points

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

# Anomaly Detection in IoT






**An open source and cross-platform machine learning framework for .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 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 1.5.1 – Time Series

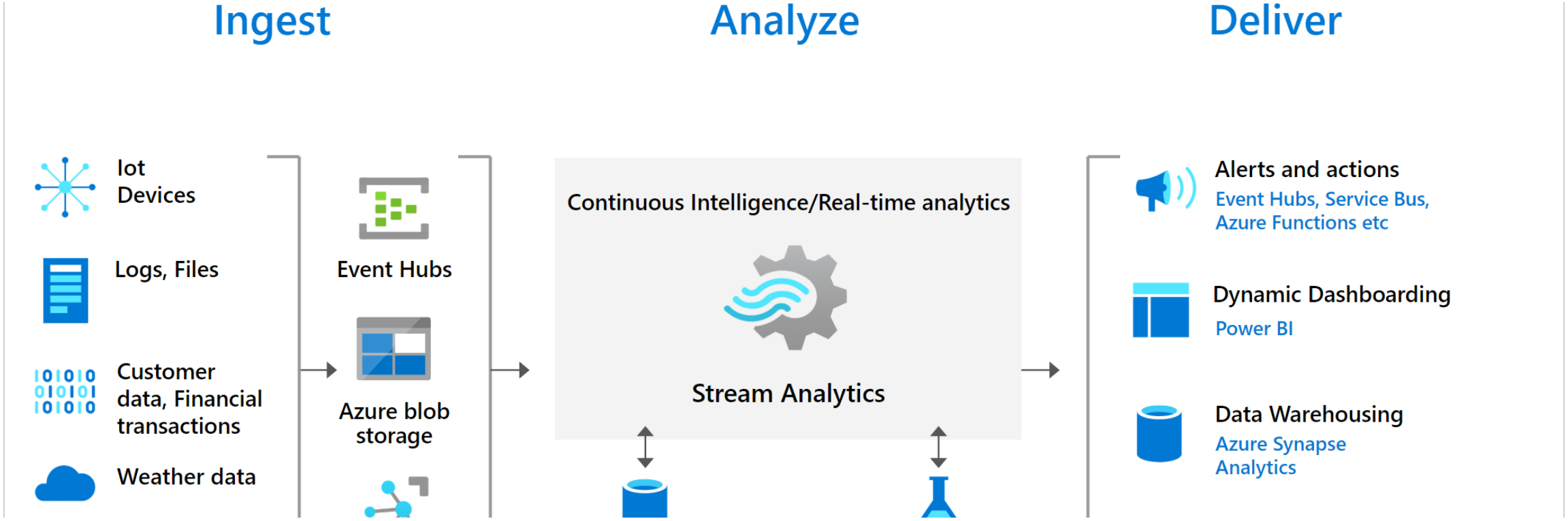
Detecting seasonality in time series

Removing seasonality from time series prior to anomaly detection

Threshold for root cause analysis

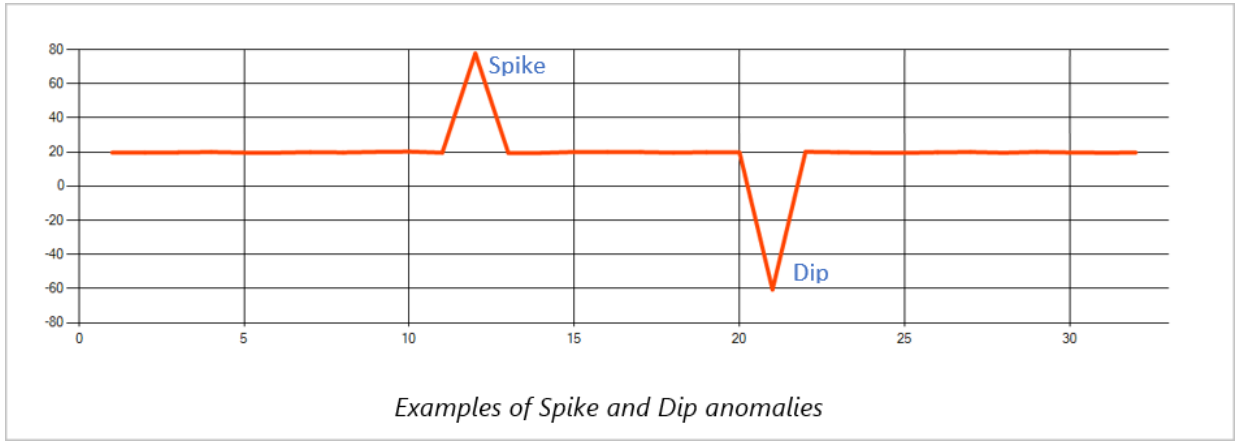
RCA for anomaly detection can now return multiple dimensions

# ML.NET DEMO




# Azure Stream Analytics

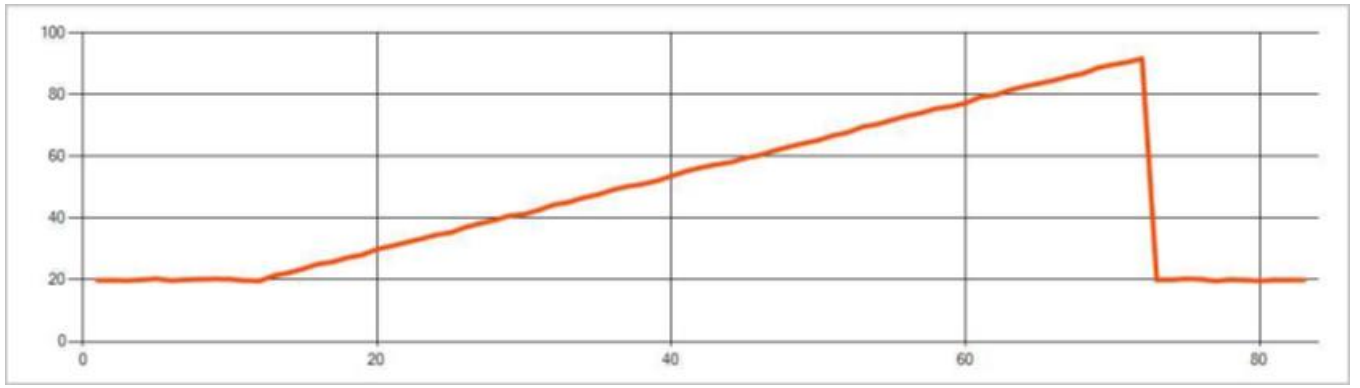
# Spike and Dips




*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



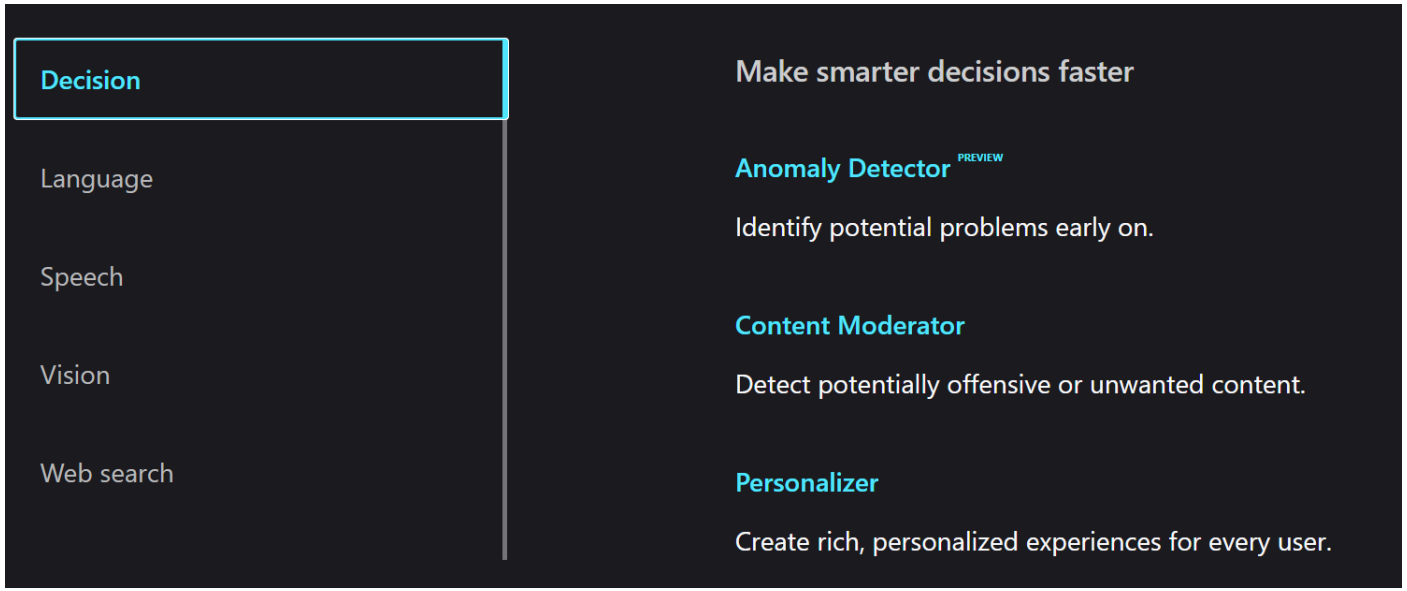

```
WITH AnomalyDetectionStep AS
(
    SELECT
        EVENTENQUEUEDUTCTIME AS time,
        CAST(temperature AS float) AS temp,
        AnomalyDetection_ChangePoint(CAST(temperature AS float), 80, 1200)
        OVER(LIMIT DURATION(minute, 20)) AS ChangePointScores
    FROM input
)
SELECT
    time,
 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



# Azure Streaming Analytics DEMO

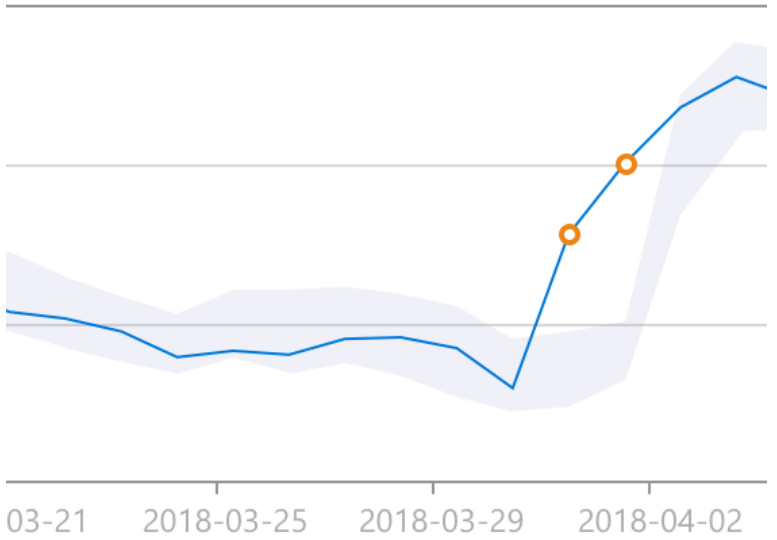
# Azure Cognitive Services

- 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



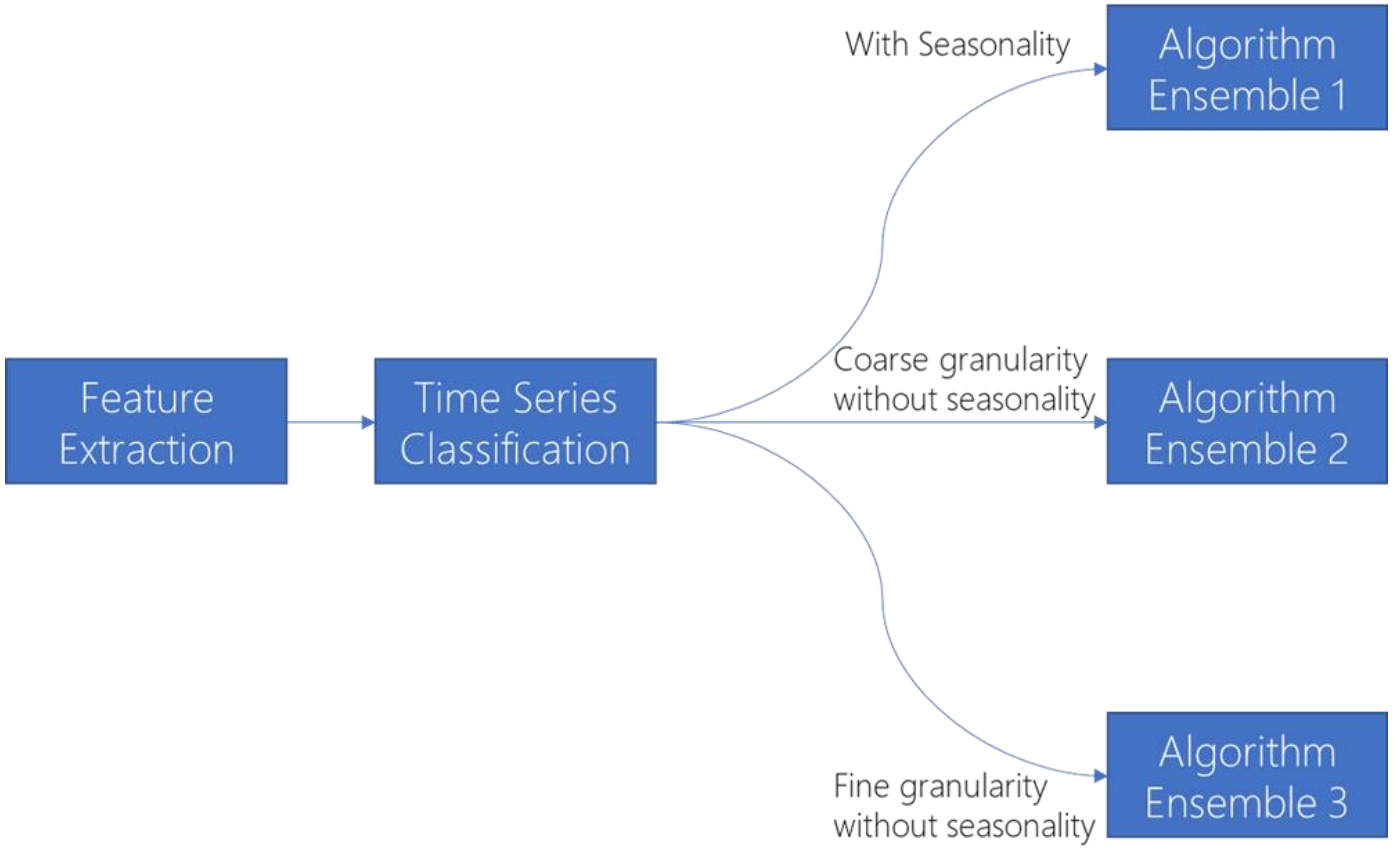
# Anomaly Detector Features

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

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

# 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 protection is early detection

https://bit.ly/spideysense-anomaly

# About Me

## Ron Dagdag


- Lead Software Engineer / AI Edge Specialist
- 4th year Microsoft MVP awardee
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  www.linkedin.com/in/rondagdag/
- Feedback appreciated, help improve my presentation skills