



influx/days

Advanced usages of flux

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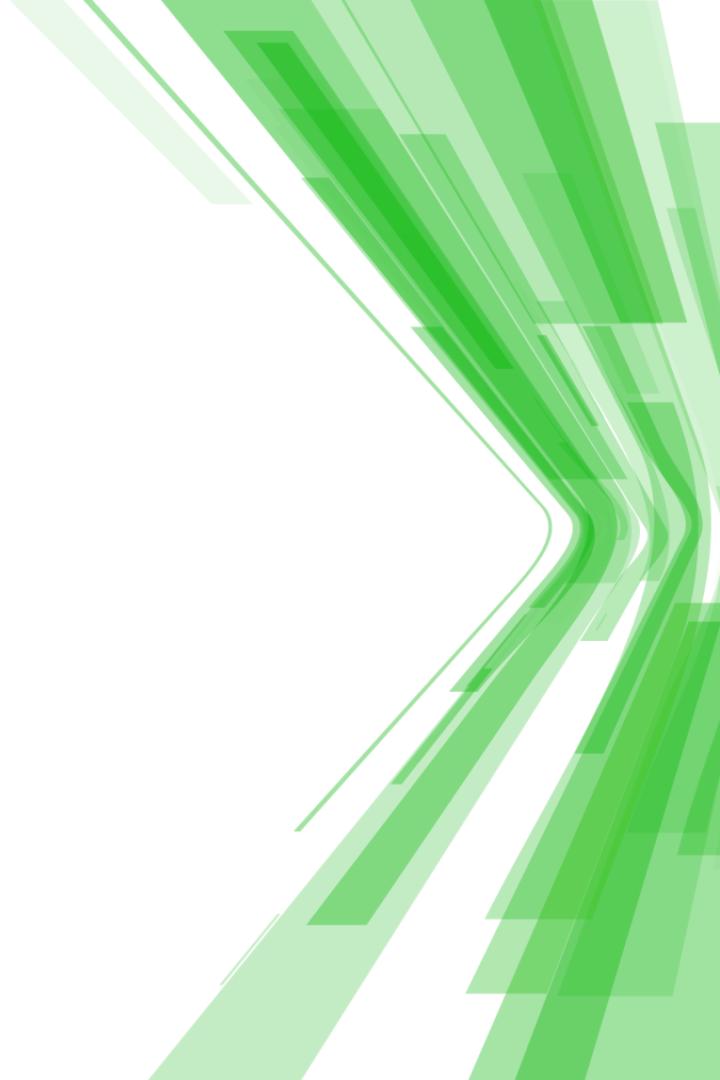
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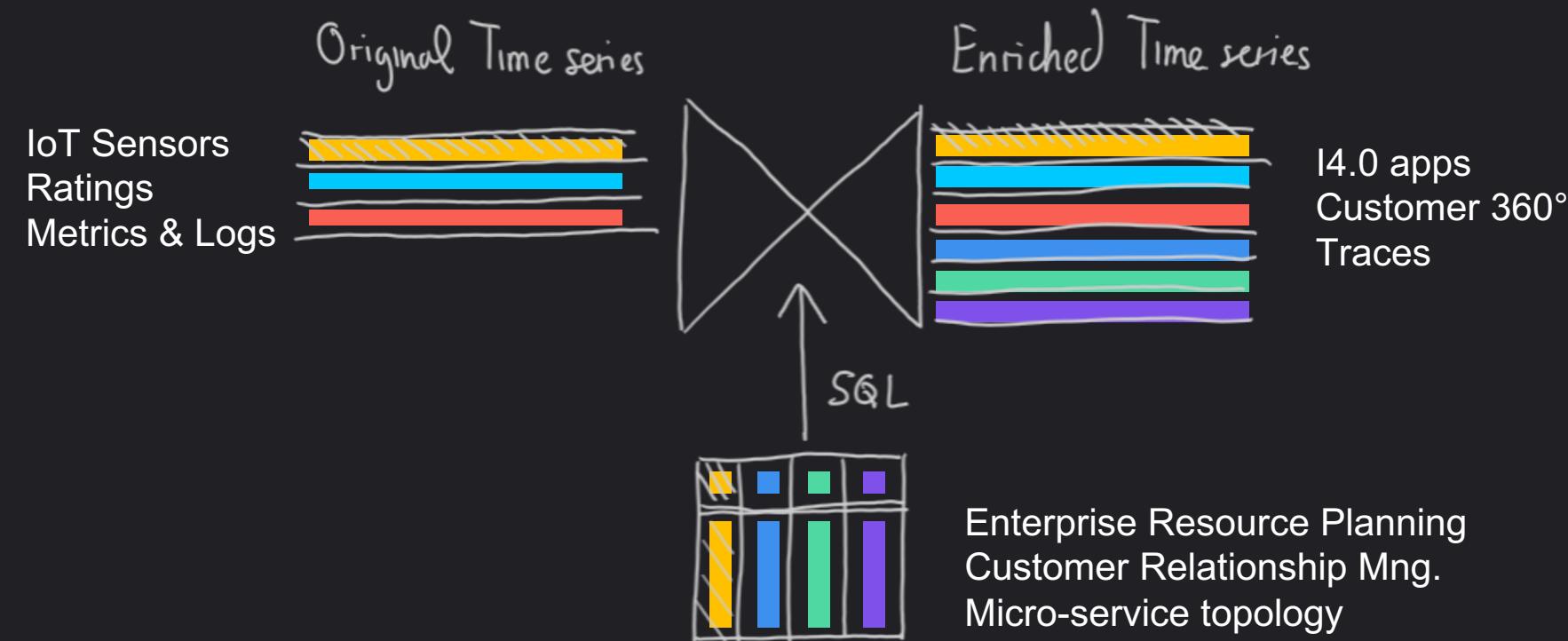
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Time Series Enrichment



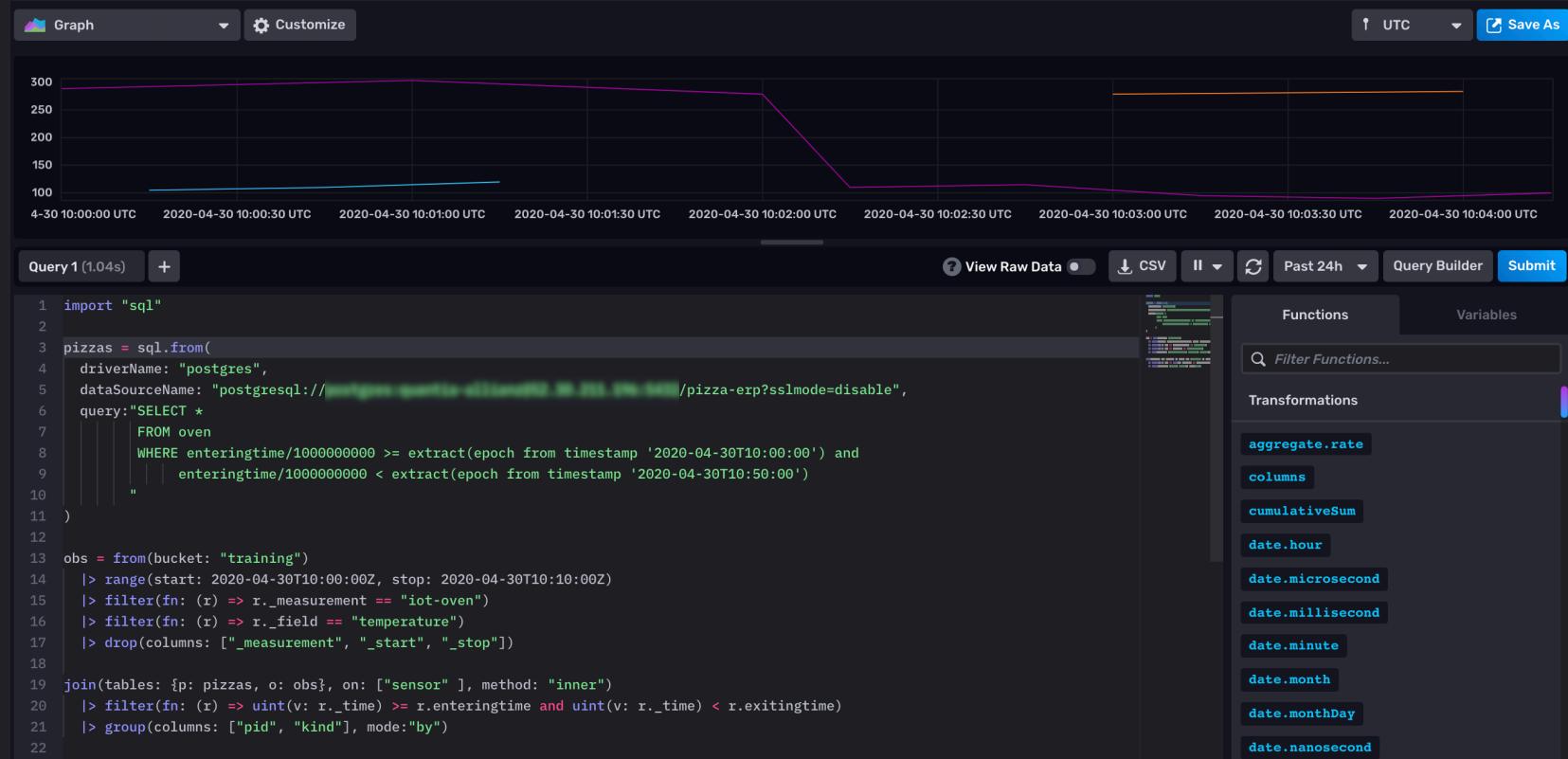
Time Series Enrichment – the intuition



Use case for the Linear Pizza Oven

- Enrich the IoT observations with the ID of the pizza and the kind of pizza contained in the Enterprise Resource Planning RDBMS

Time Series Enrichment in flux

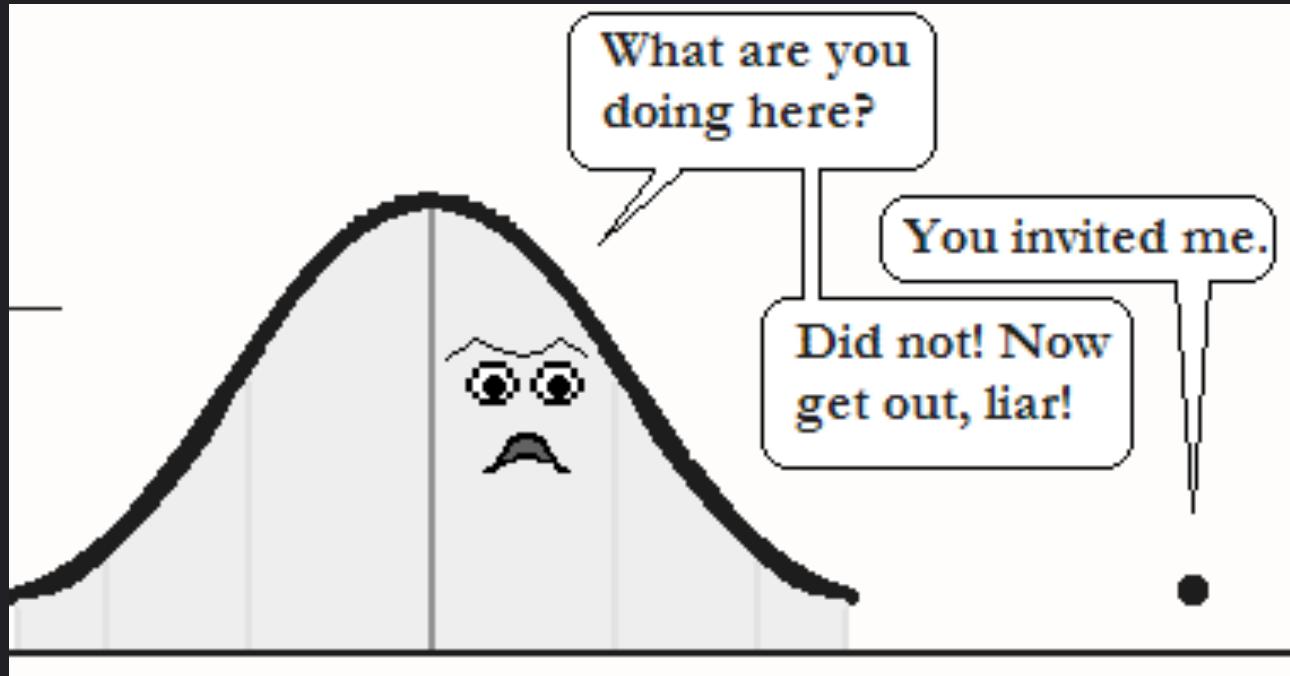


Anomaly Detection

Anomaly Detection

- Anomaly detection is a challenging data analysis task
- Anomalies can represent
 - spurious data to clean out
 - important patterns to detect
- This generality makes anomaly detection a powerful tool used in network security, remote sensing, fault detection, and many other domains

Anomaly Detection – the intuition



[image: <https://cerijayne.files.wordpress.com/2011/10/outlierssss.png>]

Considering the distribution of the data point in a time series, anomalous points are **anomalies**, a.k.a. *outliers*

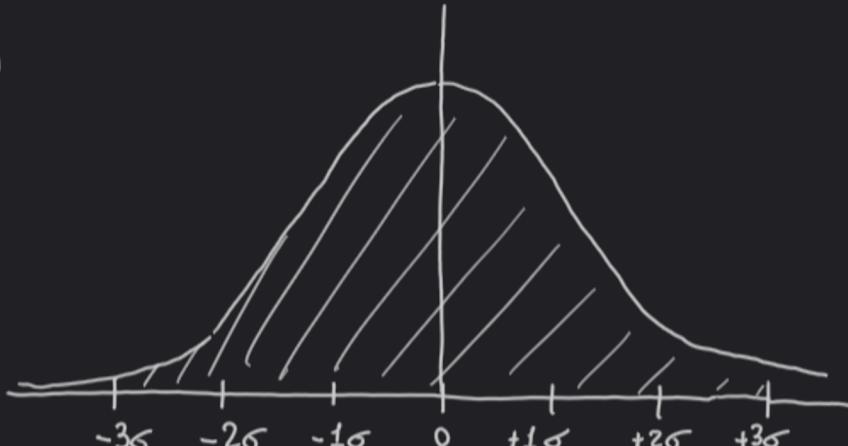
Let's operationalize this intuition using the Z score

The Normal Distribution

probability
Values

Standard Deviations
from the Mean

Cumulative %



Z Score

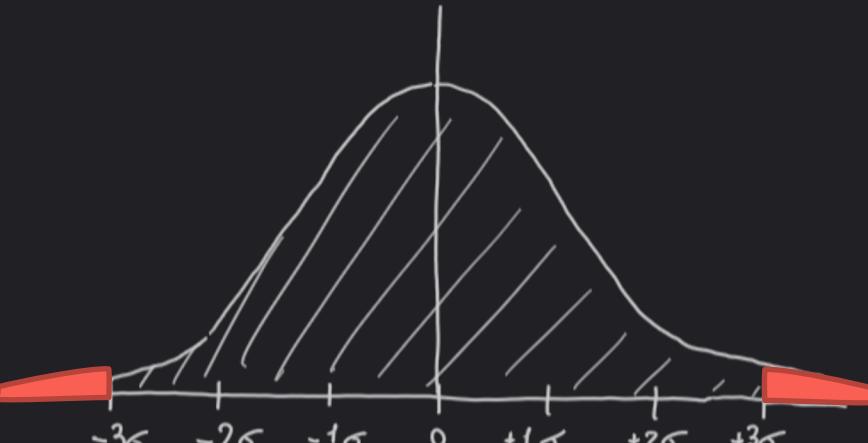
-3 -2 -1 0 +1 +2 +3

Z score

$$Z = \frac{X - \mu}{\sigma}$$

Let's operationalize this intuition using the Z score

The Normal Distribution



probability
Values

Standard Deviations from the Mean

Cumulative %

Z Score

-3 -2 -1 0 +1 +2 +3

Z score

$$Z = \frac{X - \mu}{\sigma}$$

Anomaly

$Abs(z) > 3$

0.2% of data

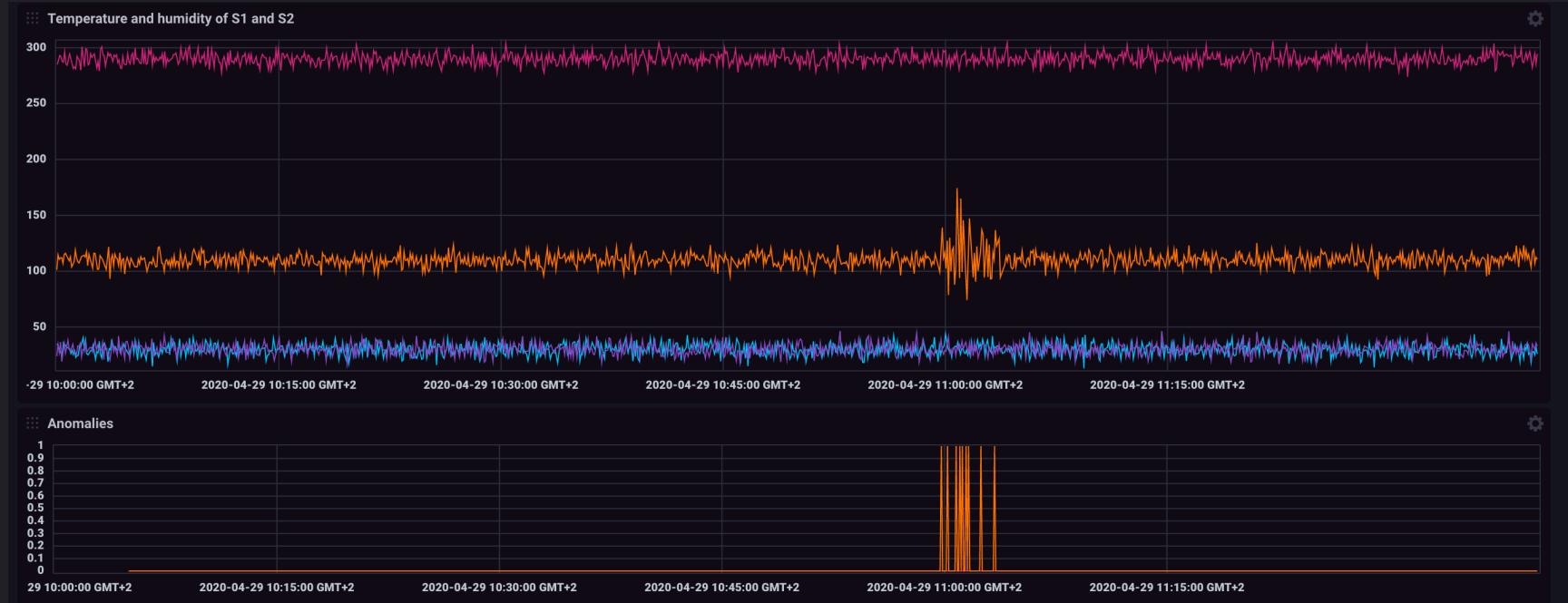
Use case for the Linear Pizza Oven

- Detect if a failures of the temperature controller of the mozzarella melting area
 - Correct behavior: $110 \pm 10 \text{ C}^\circ$
 - Anomalous: ?

Use case for the Linear Pizza Oven

- Detect if a failures of the temperature controller of the mozzarella melting area
 - Correct behavior: $110 \pm 10 \text{ C}^\circ$
 - Anomalous: let's compute the z-score where
 - the Mean is computed with `aggregateWindow(every: 5m, fn: mean)`
 - the StdDev is computed with `aggregateWindow(every: 5m, fn: stddev)`
 - the Z score is computed **joining** the times-series of all observations with the one of the Mean and the one the StdDev

Use case for the Linear Pizza Oven – data viz



Use case for the Linear Pizza Oven – solution 1/3

```
movingAvg = from(bucket: "training")  
|> range(start: v.timeRangeStart, stop: v.timeRangeStop)  
|> aggregateWindow(every: 5m, fn: mean, createEmpty: false)  
|> filter(fn: (r) => r._stop != r._time)  
|> drop(columns: ["_start", "_stop", "_measurement"])  
|> rename(columns: {_value: "avg"})
```

Use case for the Linear Pizza Oven – solution 2/3

```
movingStddev = from(bucket: "training")  
|> range(start: v.timeRangeStart, stop: v.timeRangeStop)  
|> aggregateWindow(every: 5m, fn: mean, createEmpty: false)  
|> filter(fn: (r) => r._stop != r._time)  
|> drop(columns: ["_start", "_stop", "_measurement"])  
|> rename(columns: {_value: "stddev"})  
  
join1 = join(tables: {all: movingAvg, avg: movingStddev},  
            on: ["_time", "sensor", "_field"])
```

Use case for the Linear Pizza Oven – solution 3/3

```
allData = from(bucket: "training")
|> range(start: v.timeRangeStart, stop: v.timeRangeStop)
|> drop(columns: ["_start", "_stop", "_measurement"])

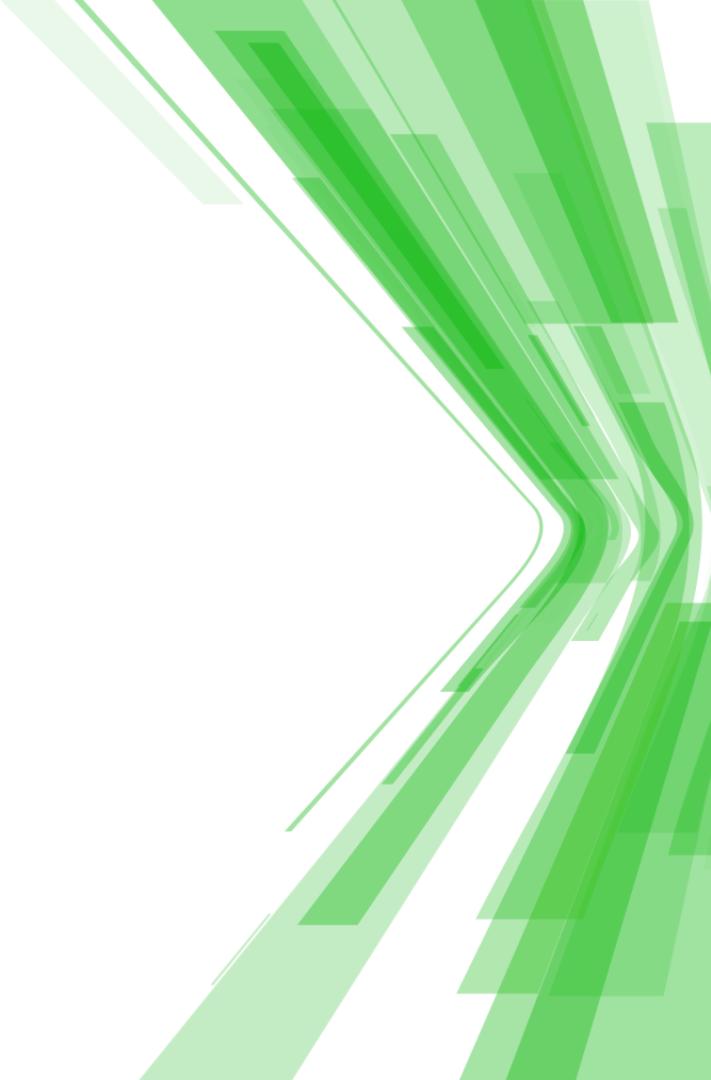
join(tables: {all: allData, j: join1}, on: ["sensor", "_field"])
|> filter(fn: (r) => uint(v: r._time_all)-uint(v: r._time_j) > 0)
|> filter(fn: (r) => uint(v: r._time_all)-uint(v: r._time_j) <=
           (5*60*1000000000))
|> map(fn: (r) => ({ r with zscore:
           if math.abs(x: (r._value - r.avg)/r.stddev)>3 then 1 else 0} ))
```

A Network Security example

- Finding anomalies in the number of times users inserts a wrong password when they log into a system
 - Refuse the access to a user that inserts the right password at the first time if she gets in average the right password after 3 attempts
- Much more effective than any rule based approach



Advanced Time Series Analytics



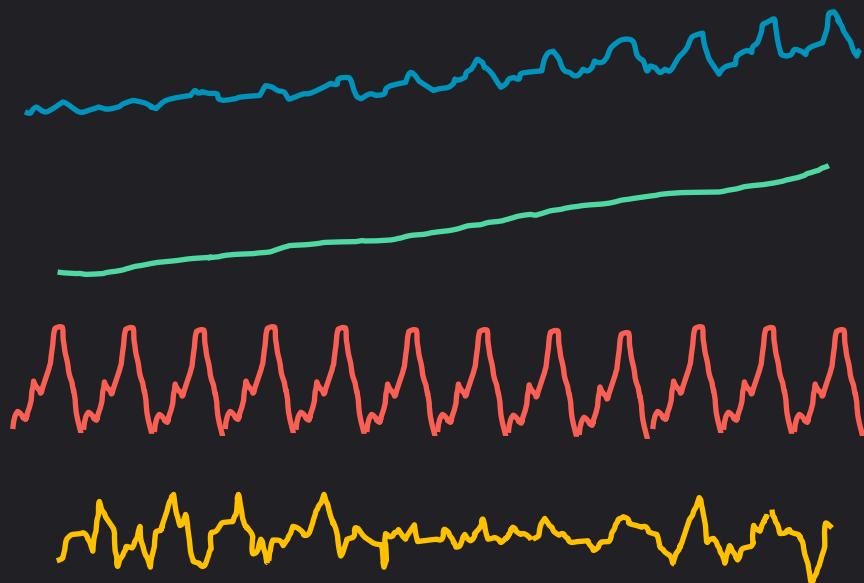
Holt-Winter's method

Given a **time series**

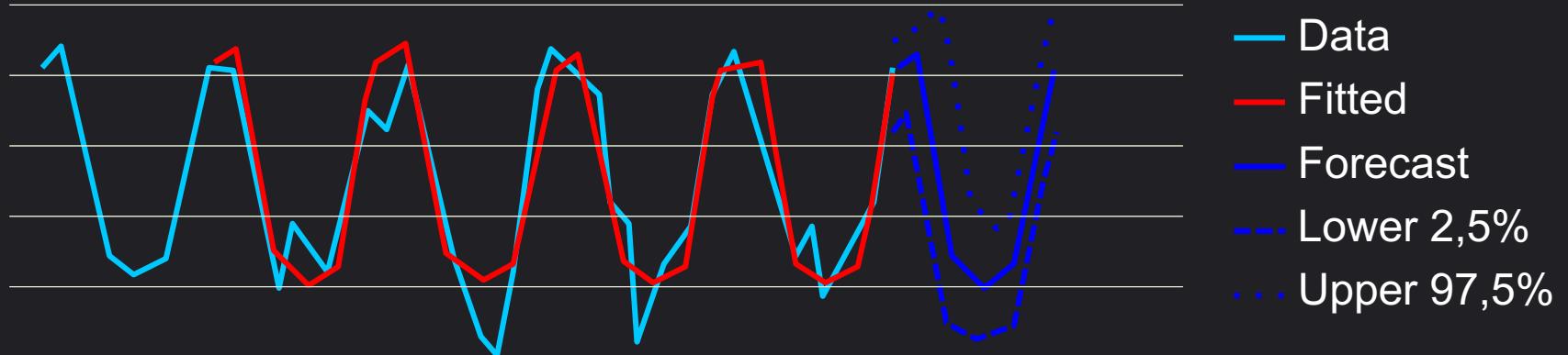
It is often possible to extract

- a **trend**: a long term variation of the time series.
- a **seasonality**: a short term recurring pattern

What is left is call **residual**



Forecasting with Holt-Winter's method



Holt-Winter's in Flux



Holt-Winter's in Flux

```
from(bucket: "training")
|> range(start: v.timeRangeStart, stop: v.timeRangeStop)
|> filter(fn: (r) => r._measurement == "fill_level")
|> filter(fn: (r) => r._field == "value")
|> filter(fn: (r) => r.tank == "B2")
|> aggregateWindow(every: 1m, fn: first)
|> holtWinters(n: 10, seasonality: 8, interval: 1m)
```

What (else) can I do with Flux?

What (else) can I do with flux?

- Map/Reduce
- Derivative, Difference, Integral
- Histograms
- Regular expression matching
- String functions
- Go Math library parity
- Quantile
- Conditional Expressions
- Cross-measurement calculations
- Conditional expressions
- Sorting
- Data Generation
- In-language test assertions
- ...
- And more every day!



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