

# Anomaly Detection in Time Series from Scratch

Using statistical analysis

by Ivan Shubin



Booking.com

# Ivan Shubin



## Bio

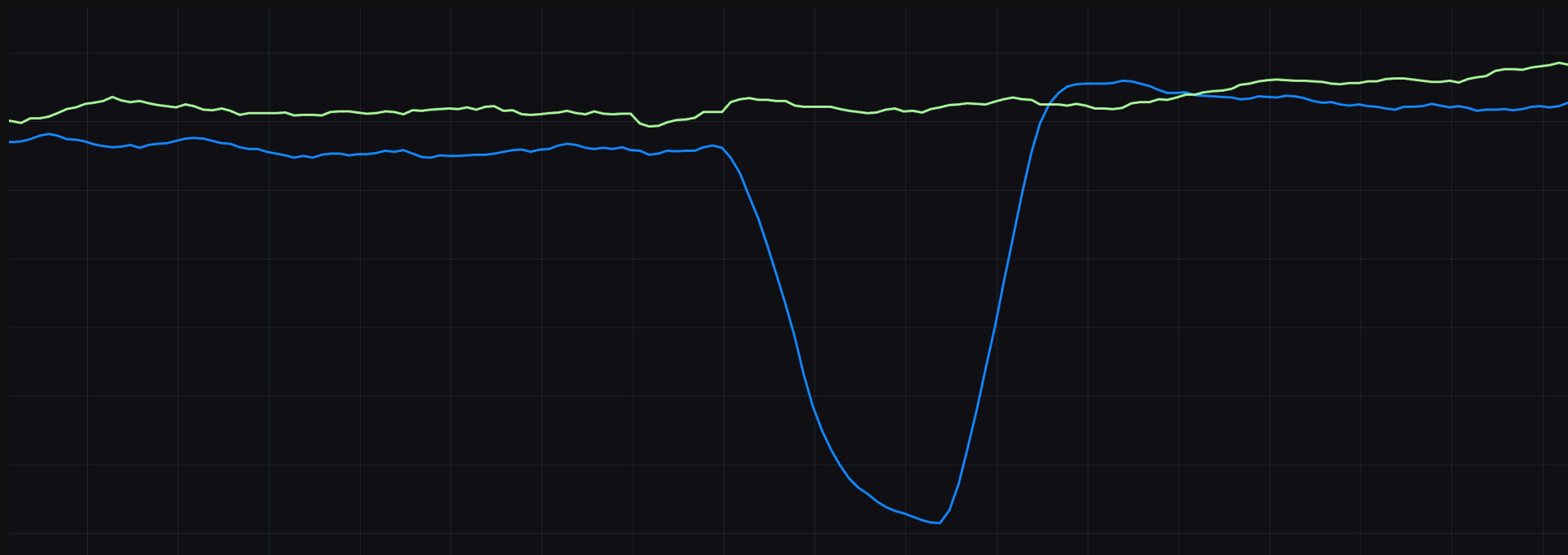
- Booking.com (Senior SRE)
- TomTom (SRE)
- eBay Classifieds Group (SRE, Dev, QA)
- Author of Schemio and Galen Framework

## Links

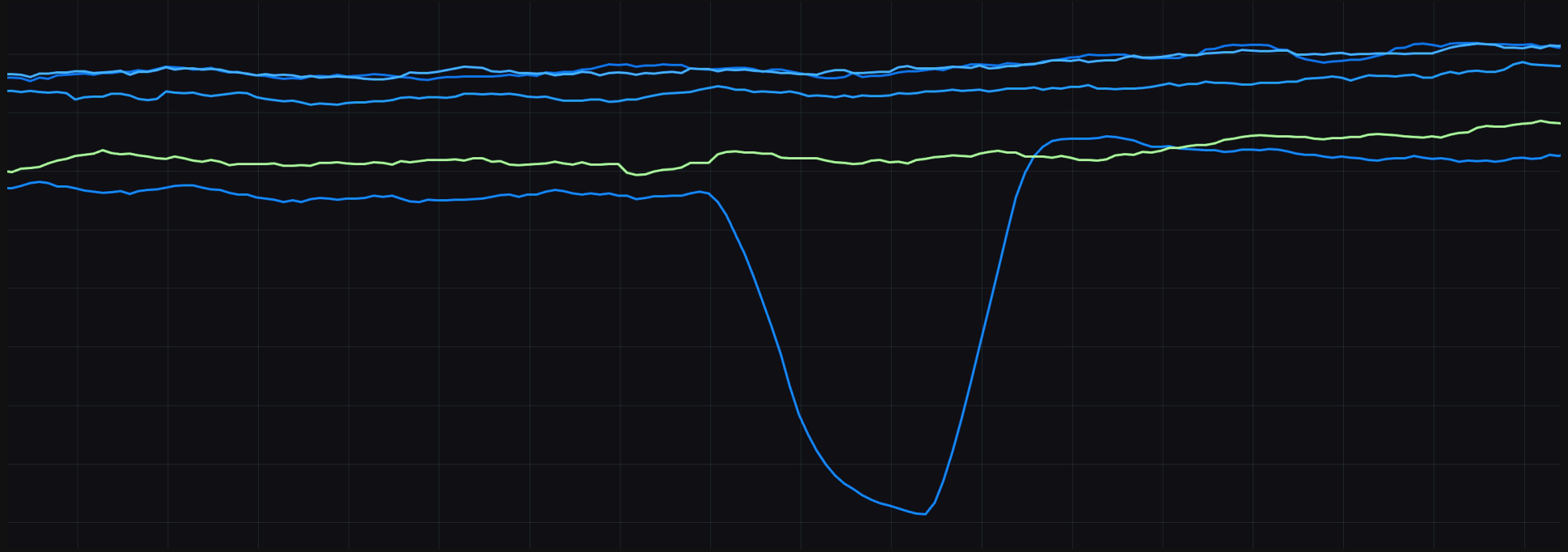
<https://github.com/ishubin>

<https://www.linkedin.com/in/ivan-shubin>

# Simple approach: **Current** vs **Previous week**

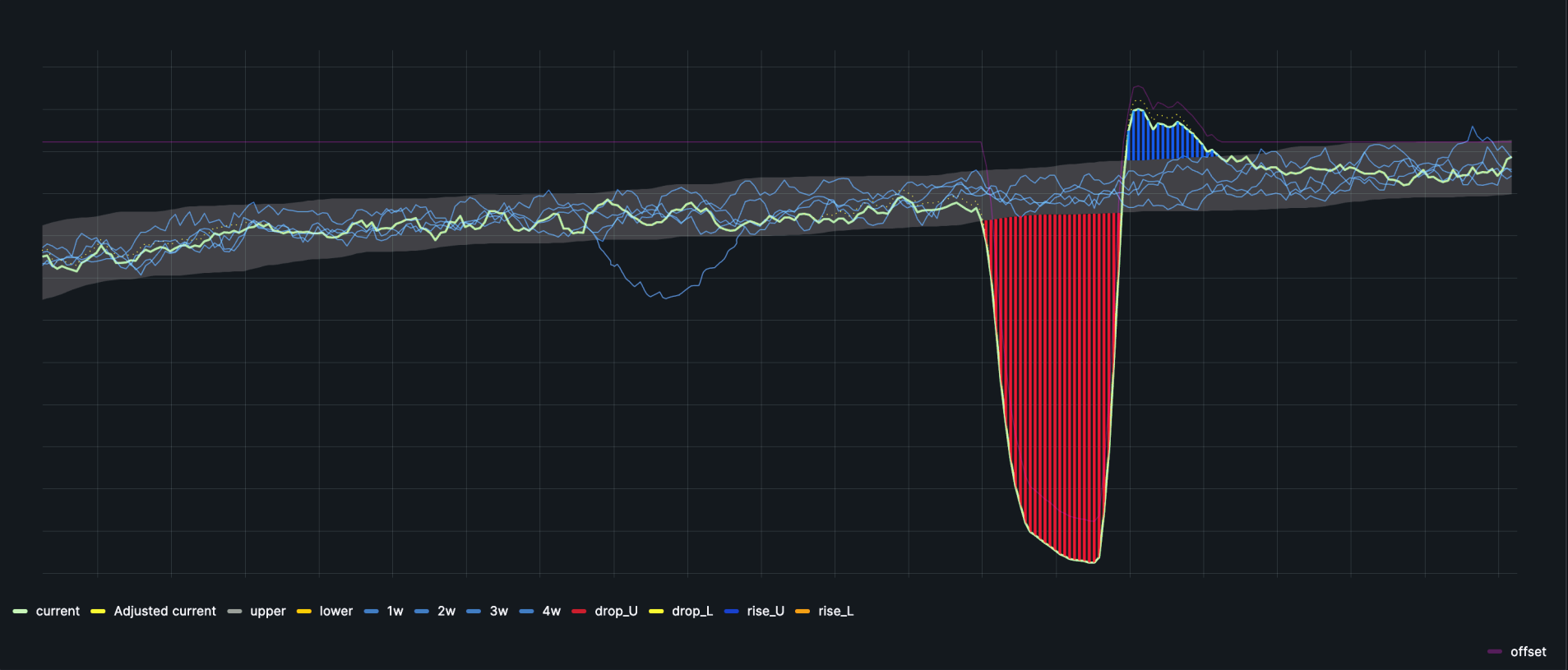


# Simple approach: **Current** vs **Previous week**

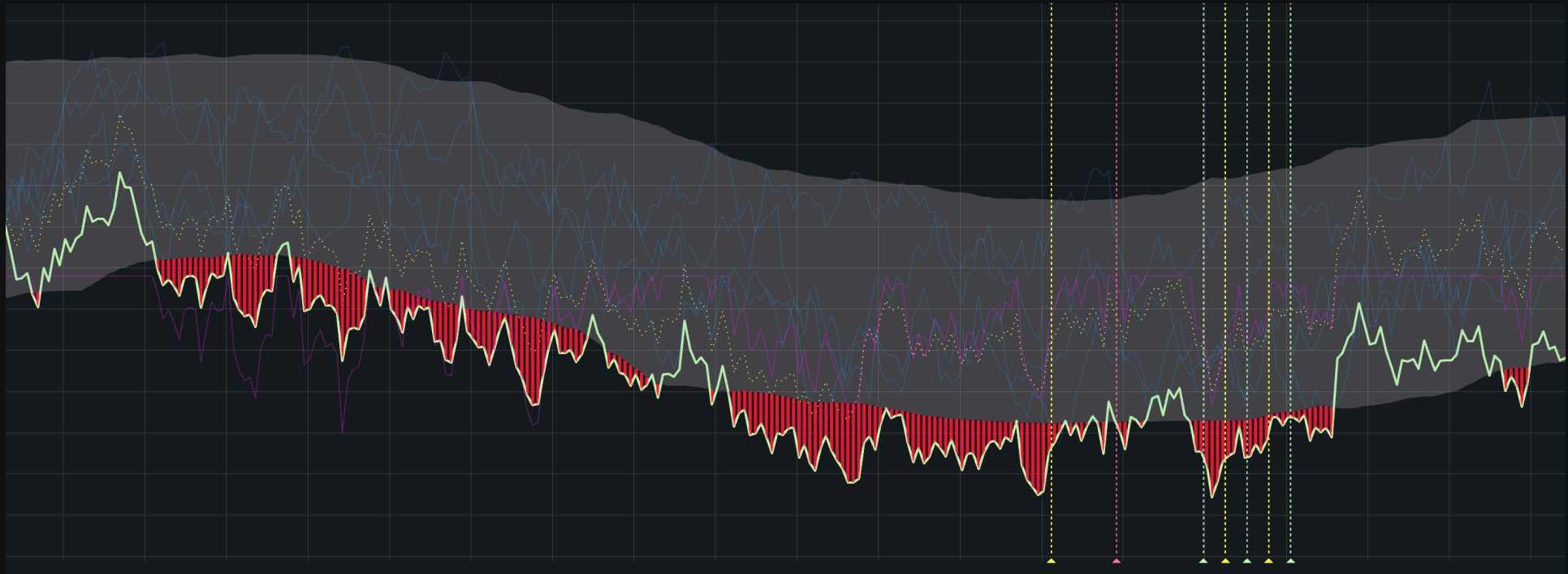




# How it should look like



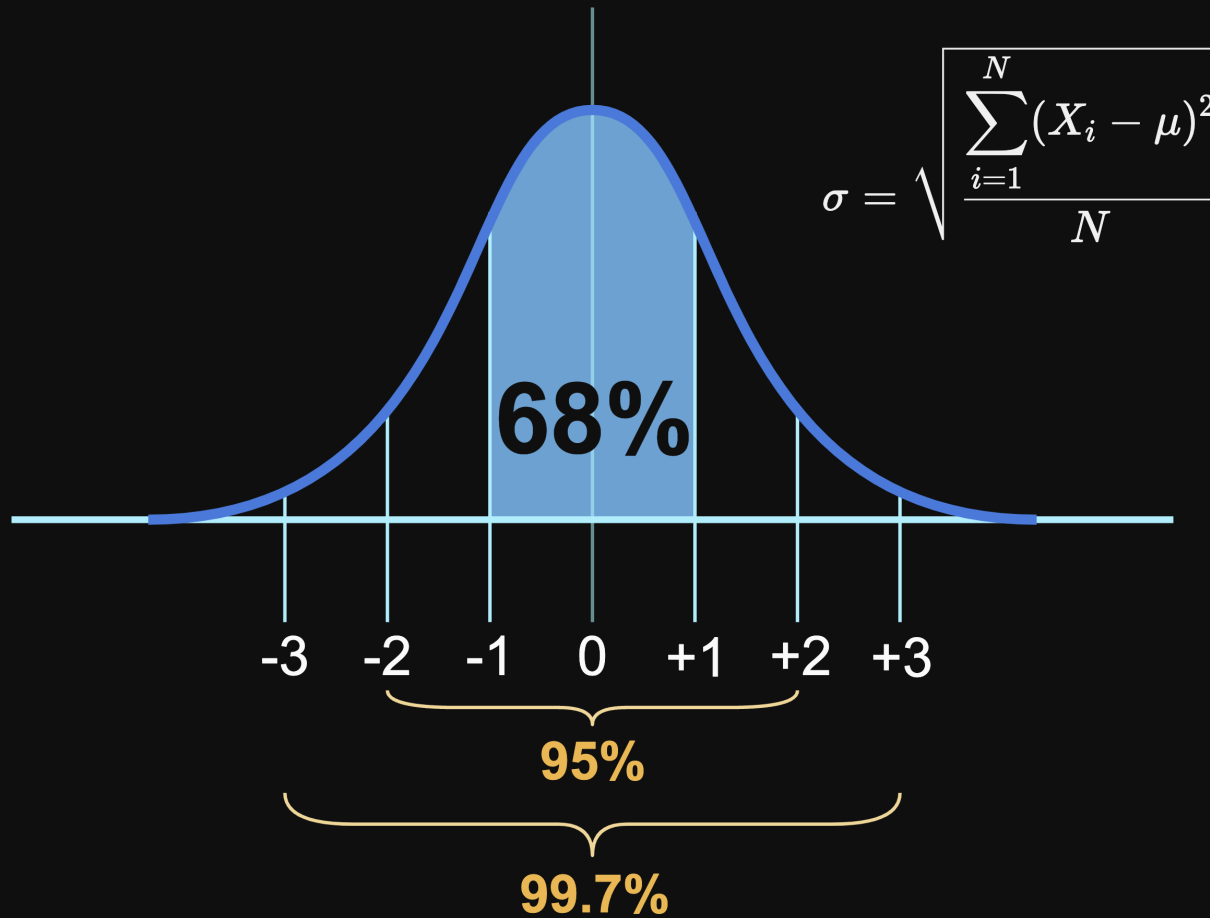
**We wanted to detect "slow burns"**



# Statistics



# Standard deviation



Point  
value

Mean

$$Z \text{ score} = \frac{x - \mu}{\sigma}$$

Standard  
Deviation

z-score

Confidence

0.



50%

1.



84%

1.5



93%

2.



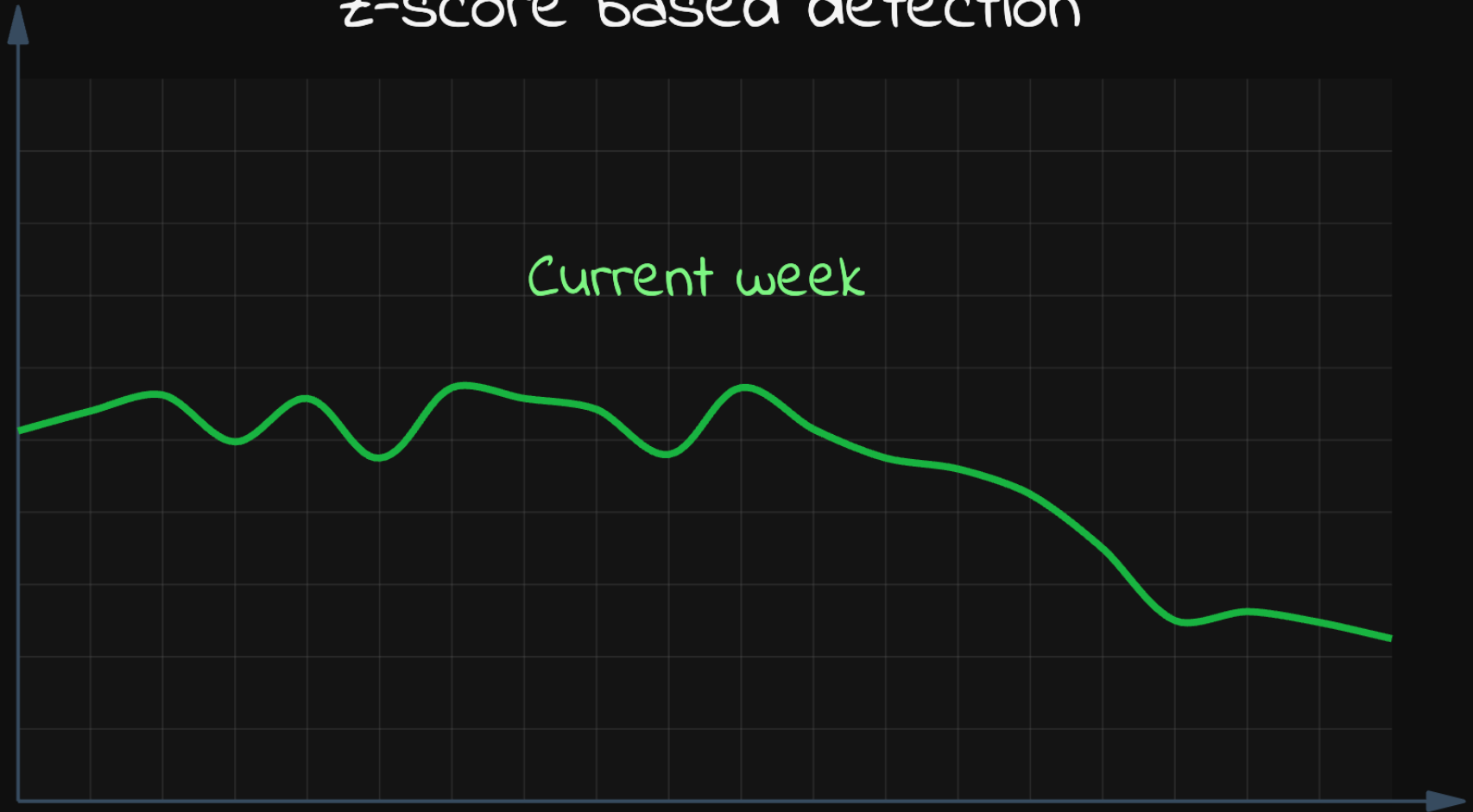
97.7%

3.

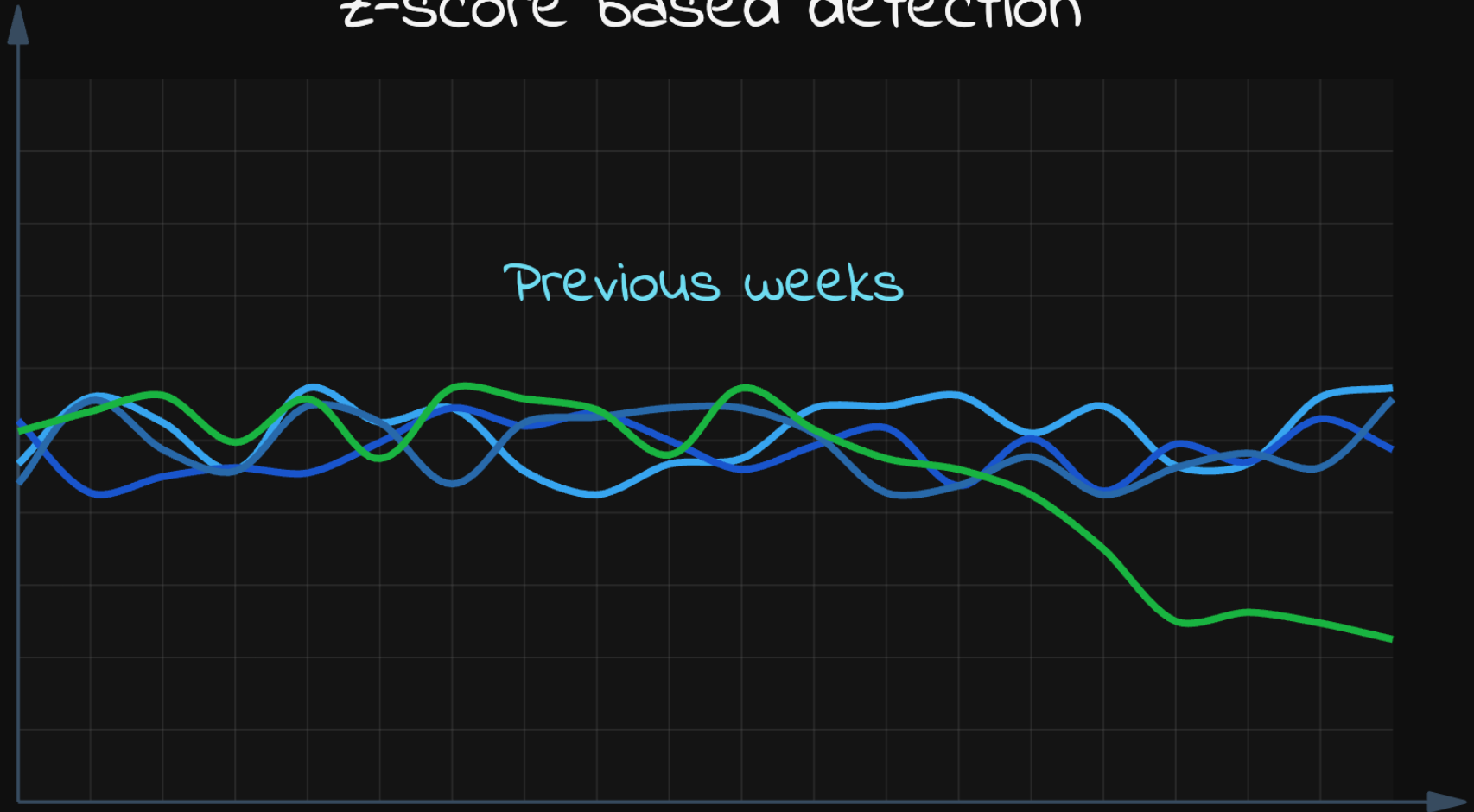


99.87%

# z-score based detection



# z-score based detection





# z-score based detection



# z-score based detection



# z-score based detection

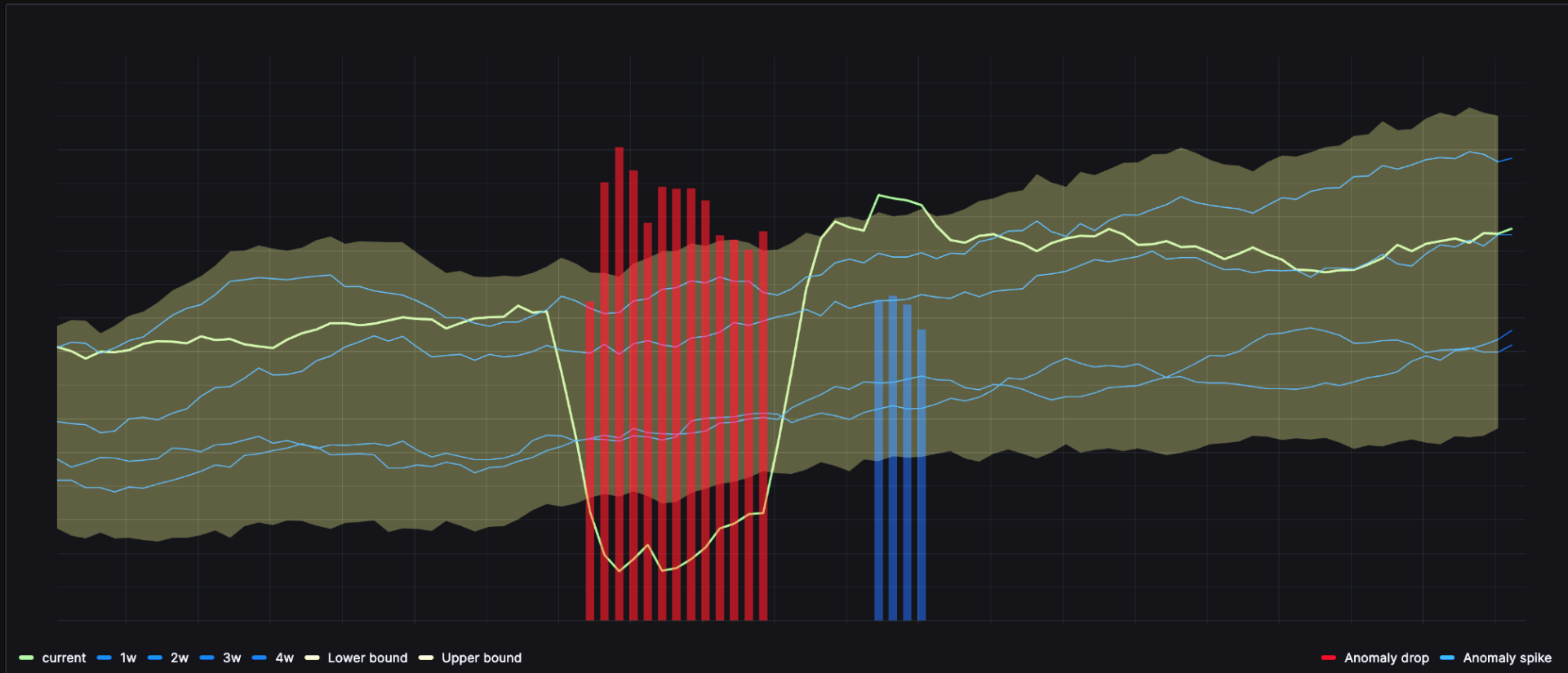


# z-score based detection



**Can we use Graphite itself?**

# Graphite based anomaly detection



## Z-score calculation with Graphite

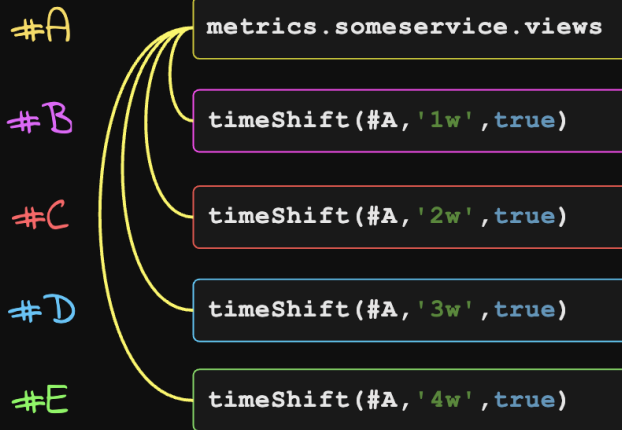
Graphite metric

#A

```
metrics.someservice.views
```

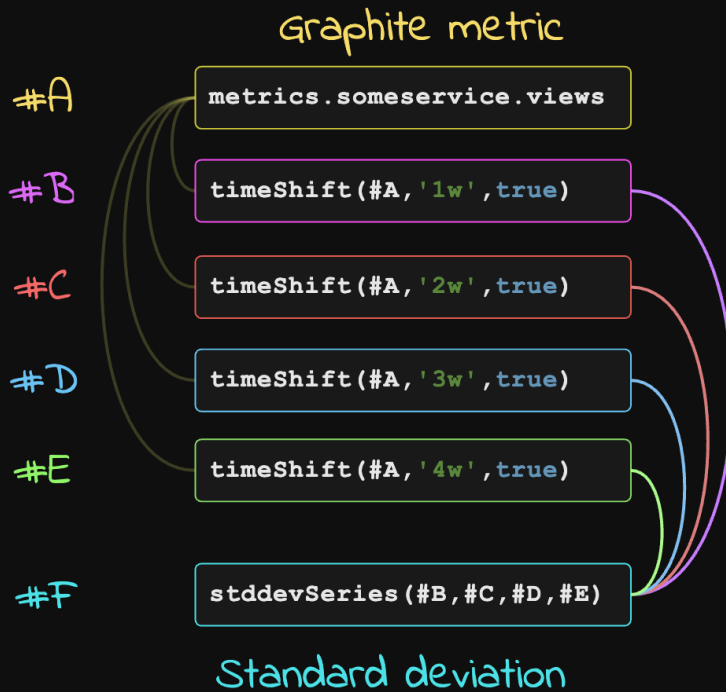
## Z-score calculation with Graphite

### Graphite metric

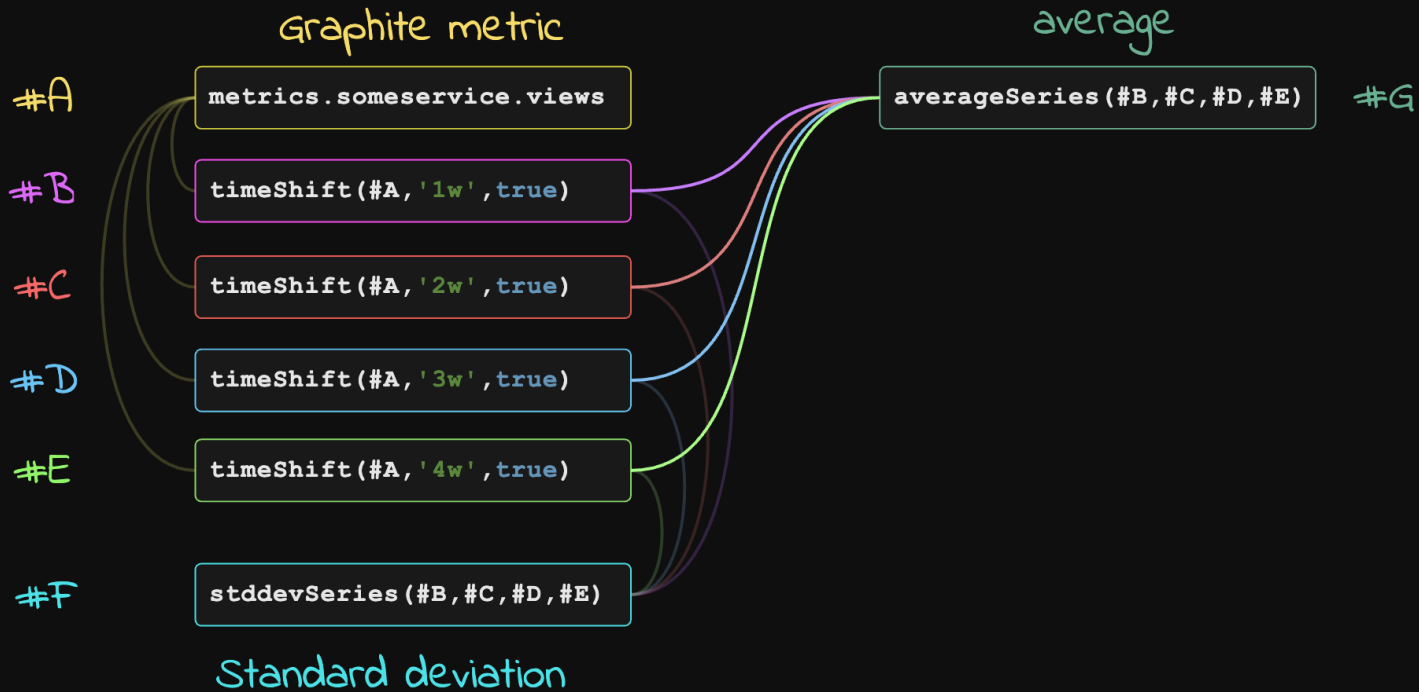




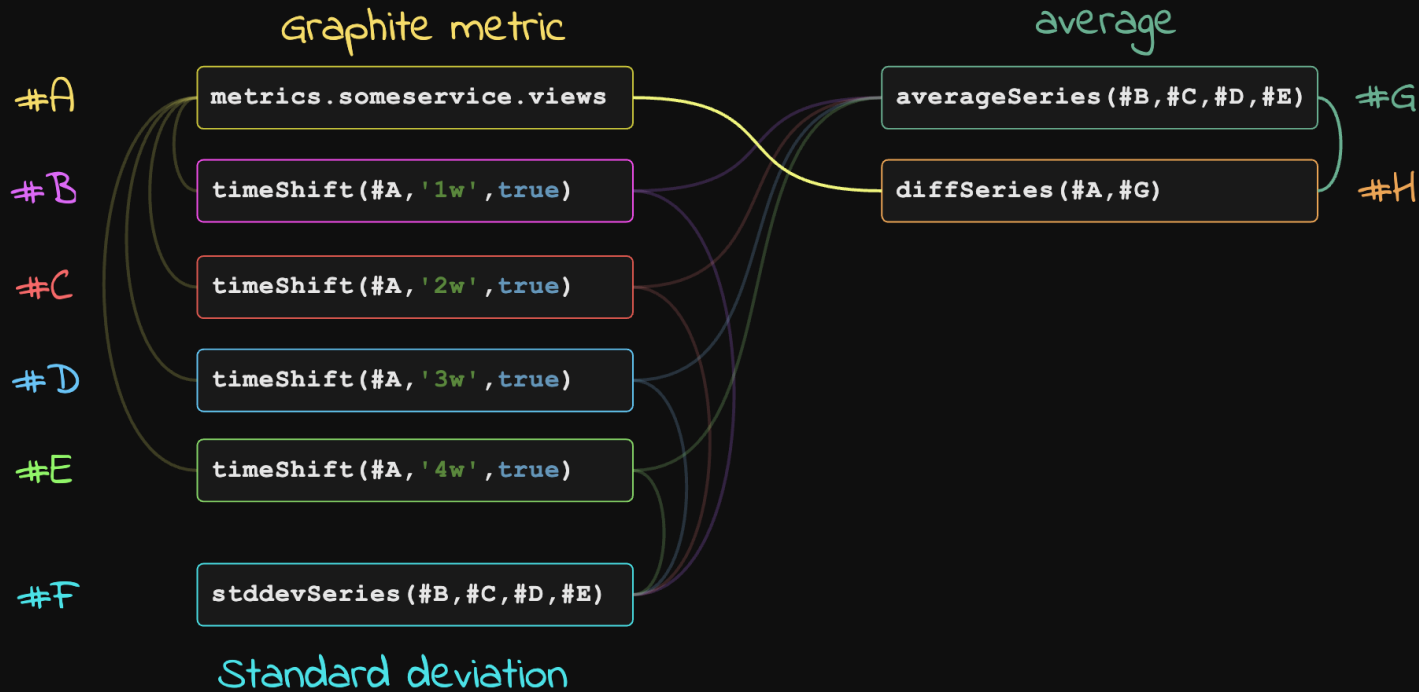
# Z-score calculation with Graphite



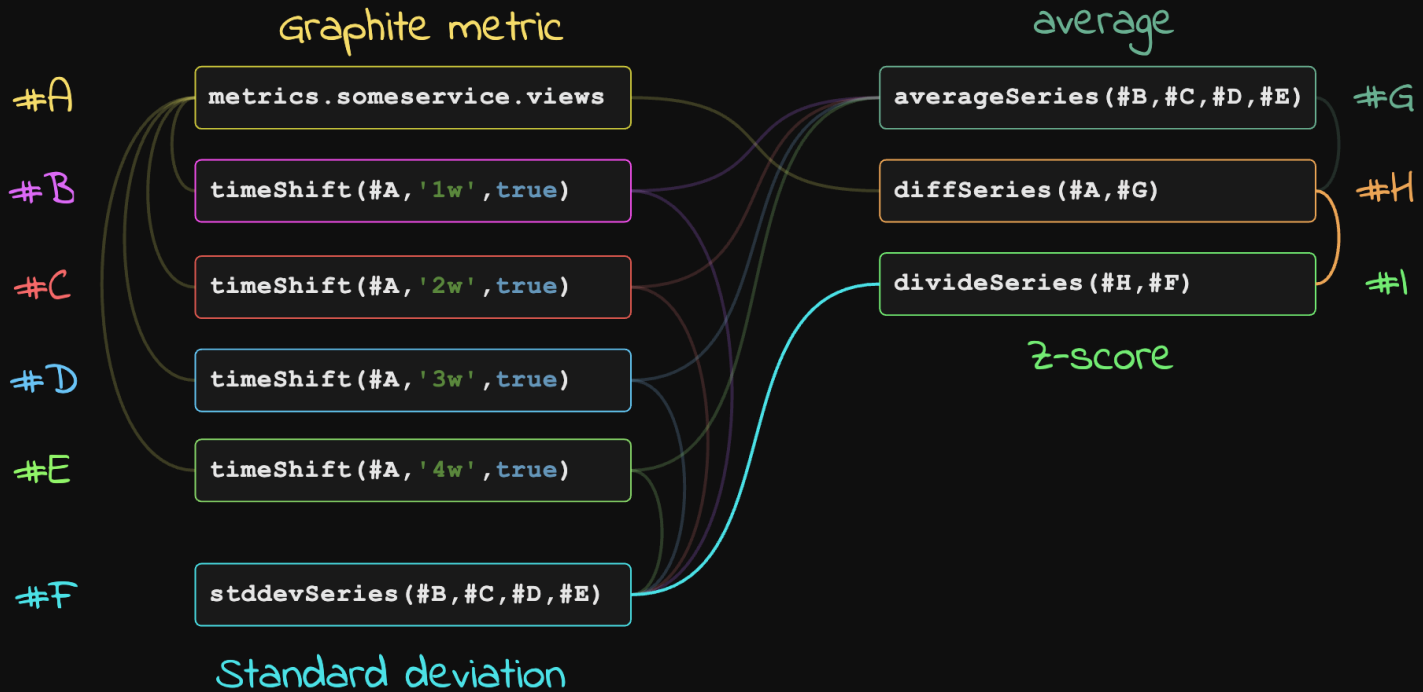
# Z-score calculation with Graphite



# Z-score calculation with Graphite



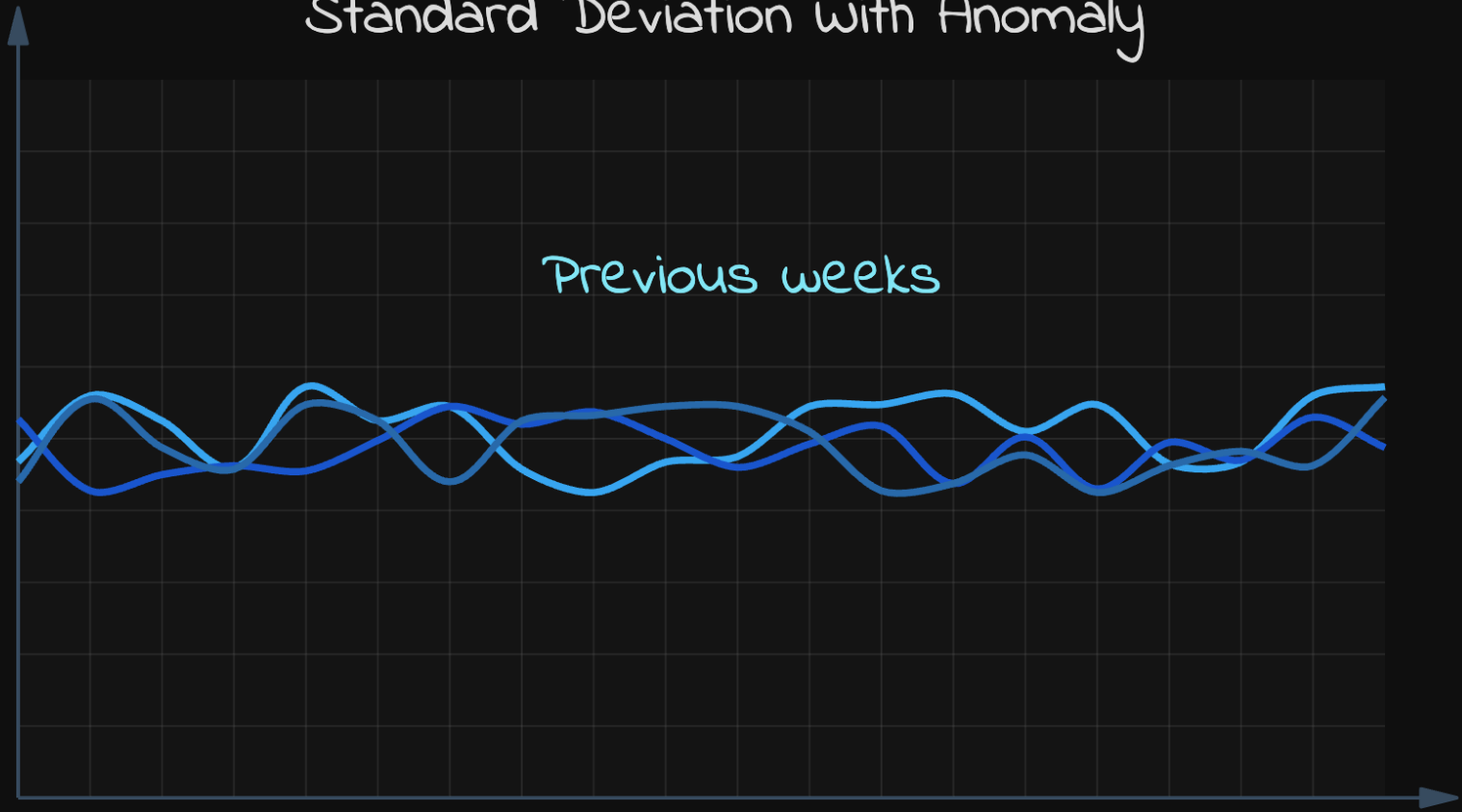
# Z-score calculation with Graphite



# Past incidents distorts the prediction

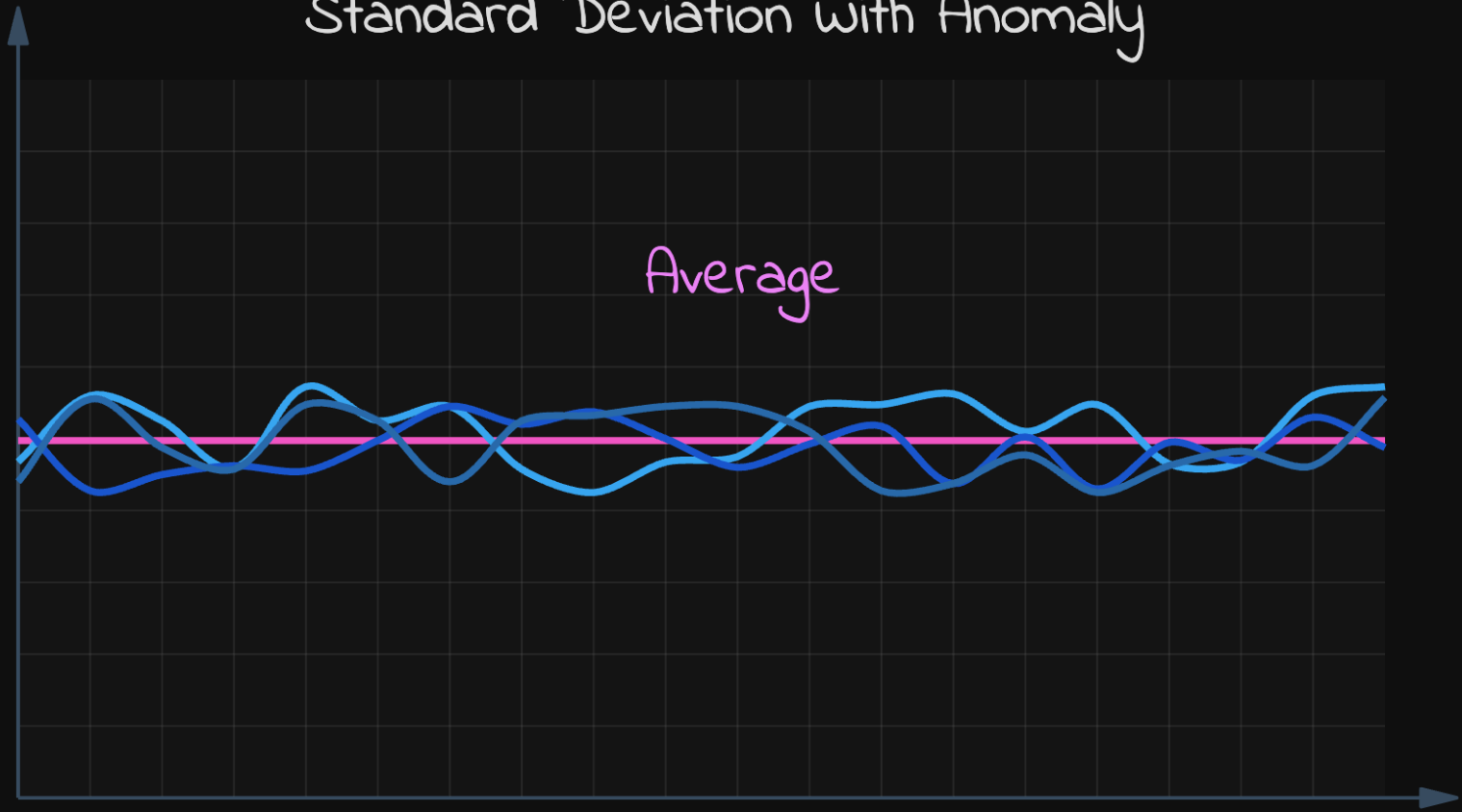


# Standard Deviation with Anomaly



Previous weeks

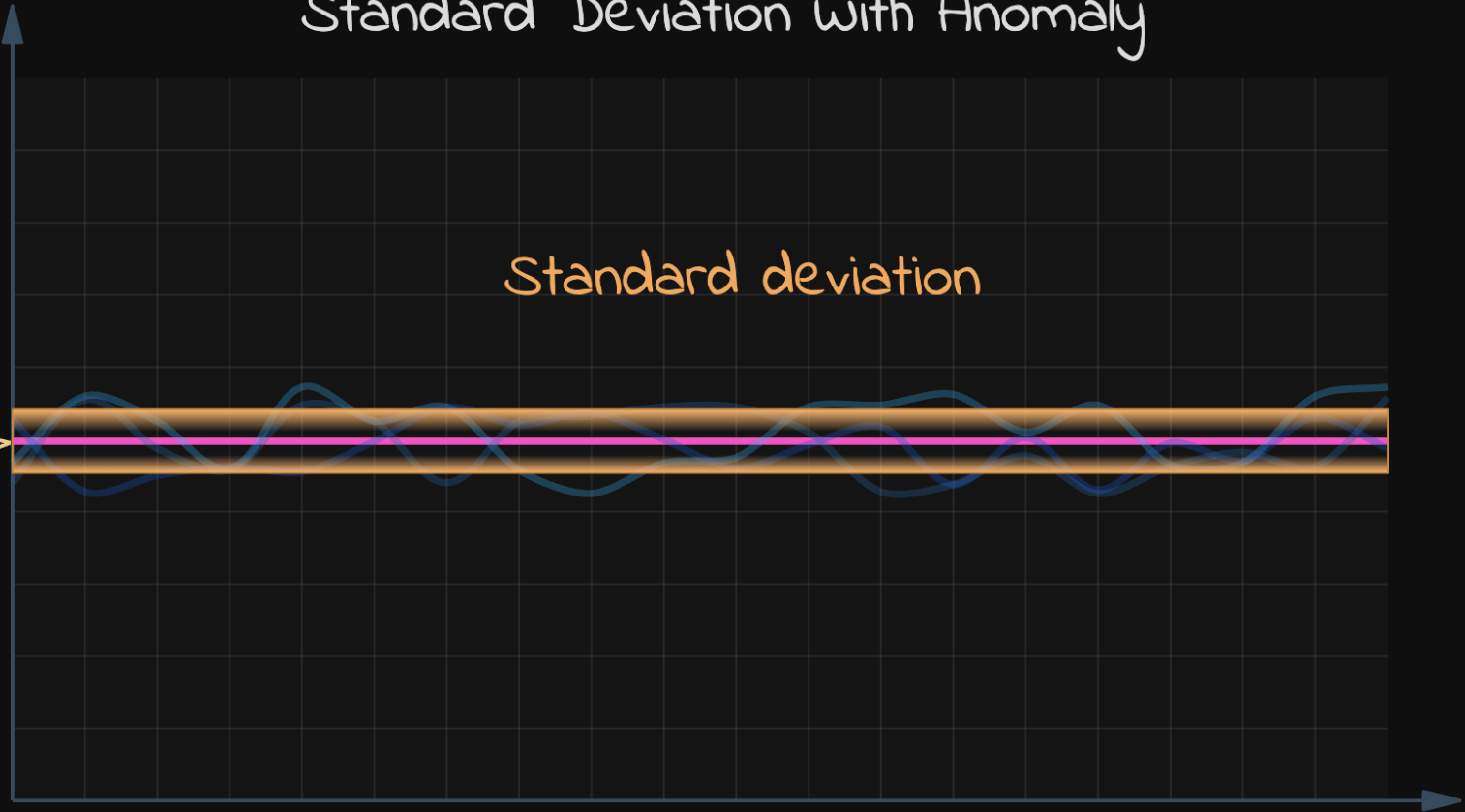
# Standard Deviation with Anomaly



# Standard Deviation with Anomaly

Standard deviation

17.6





# Standard Deviation with Anomaly

Lets pretend we had an incident 1 week ago

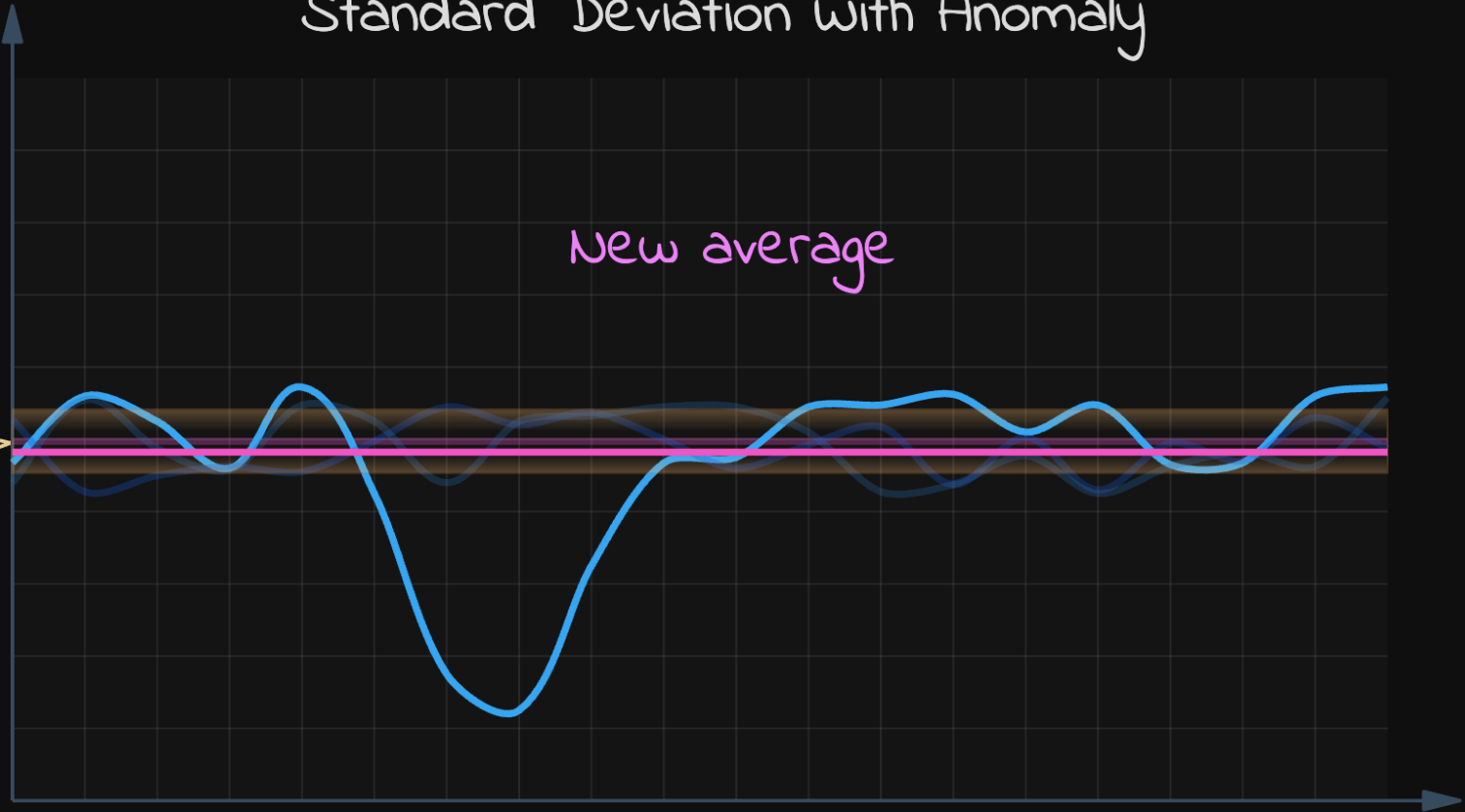
17.6



# Standard Deviation with Anomaly

New average

17.6

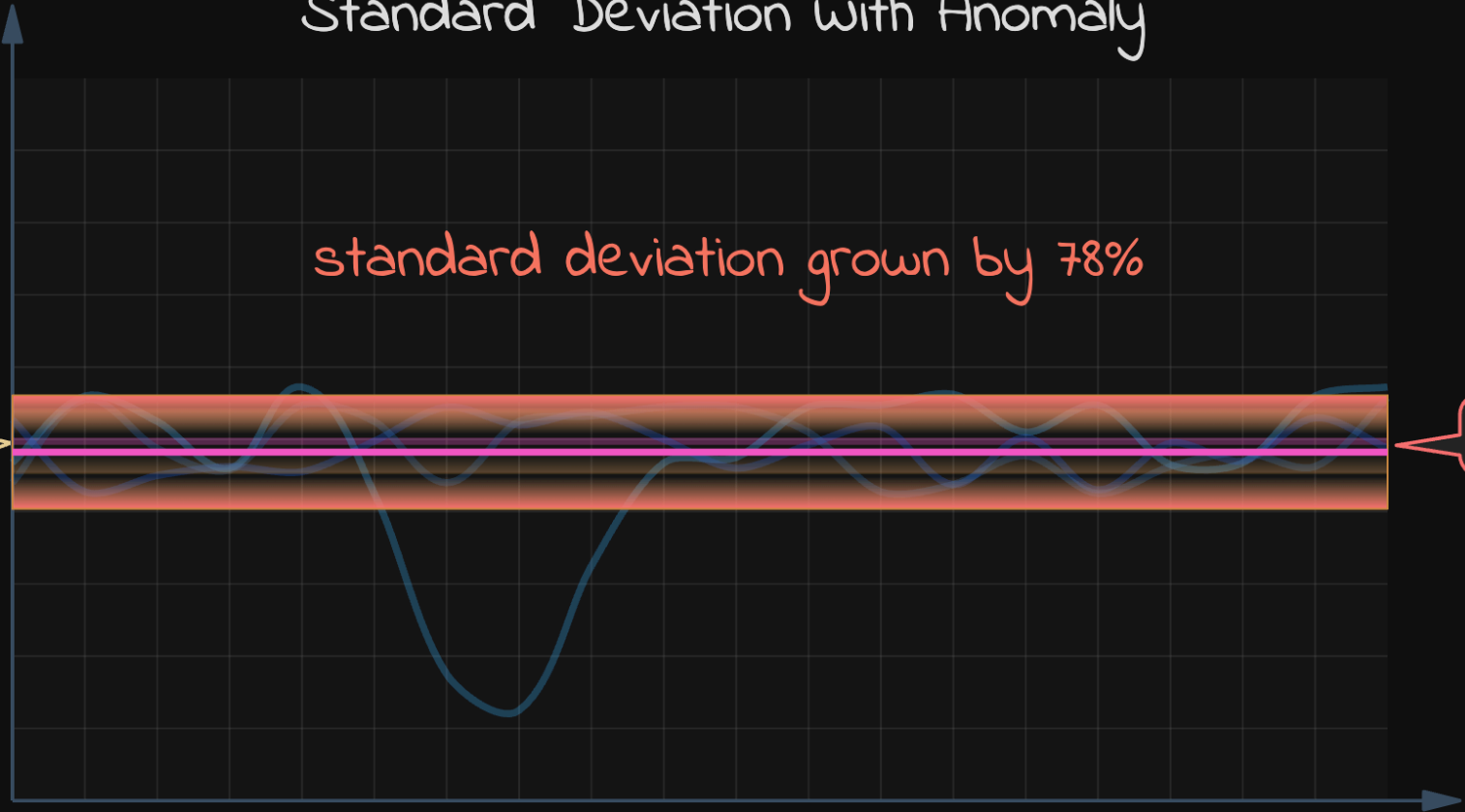


# Standard Deviation with Anomaly

standard deviation grown by 78%

17.6

31.4



# Median absolute deviation

Point  
value

Median

$$MAD = \frac{\sum_{i=1}^N |x_i - \mu|}{N}$$

Number of  
observations

Standard Deviation

Original = 17.6  
incident = 31.4

Median Absolute Deviation

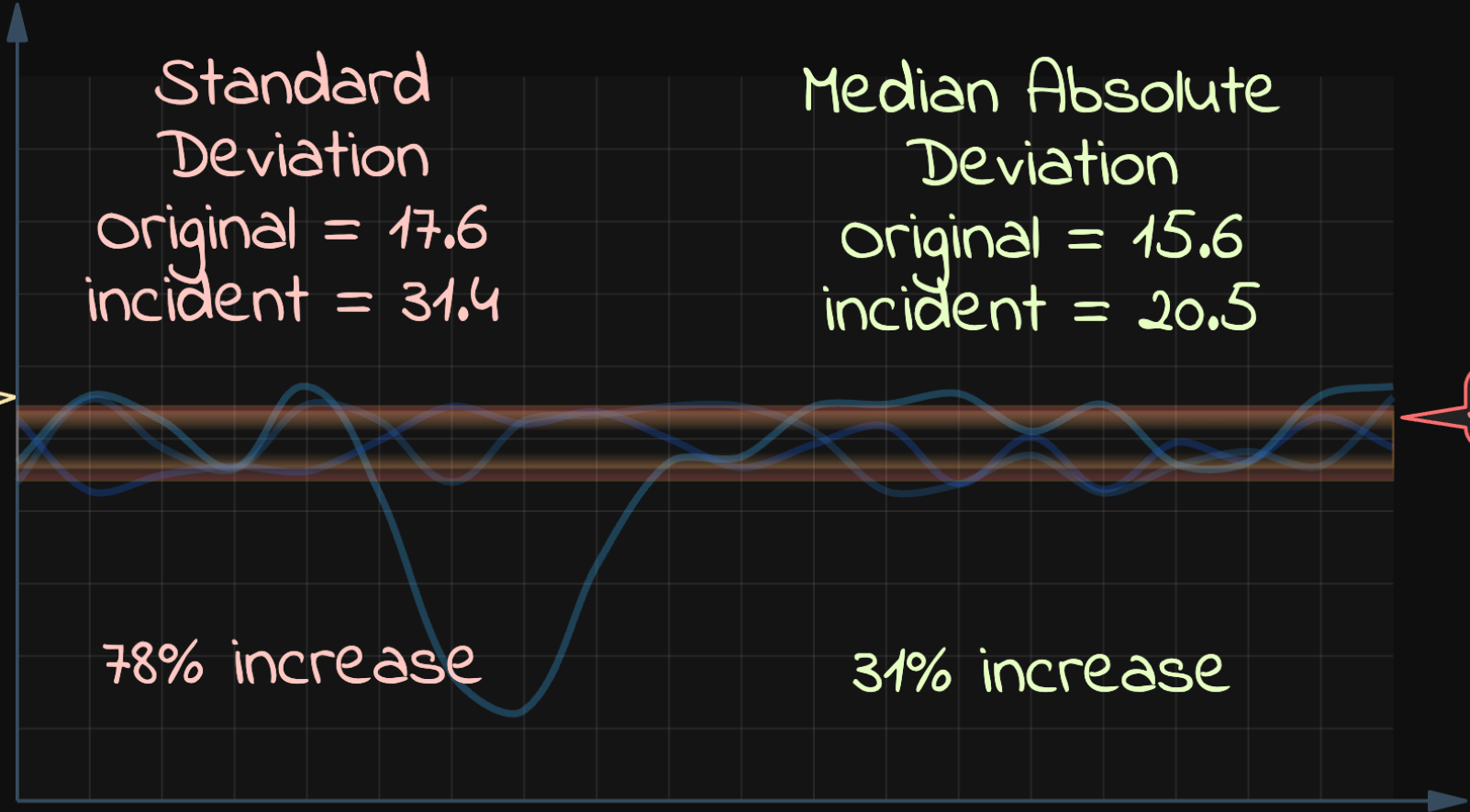
Original = 15.6  
incident = 20.5

15.6

20.5

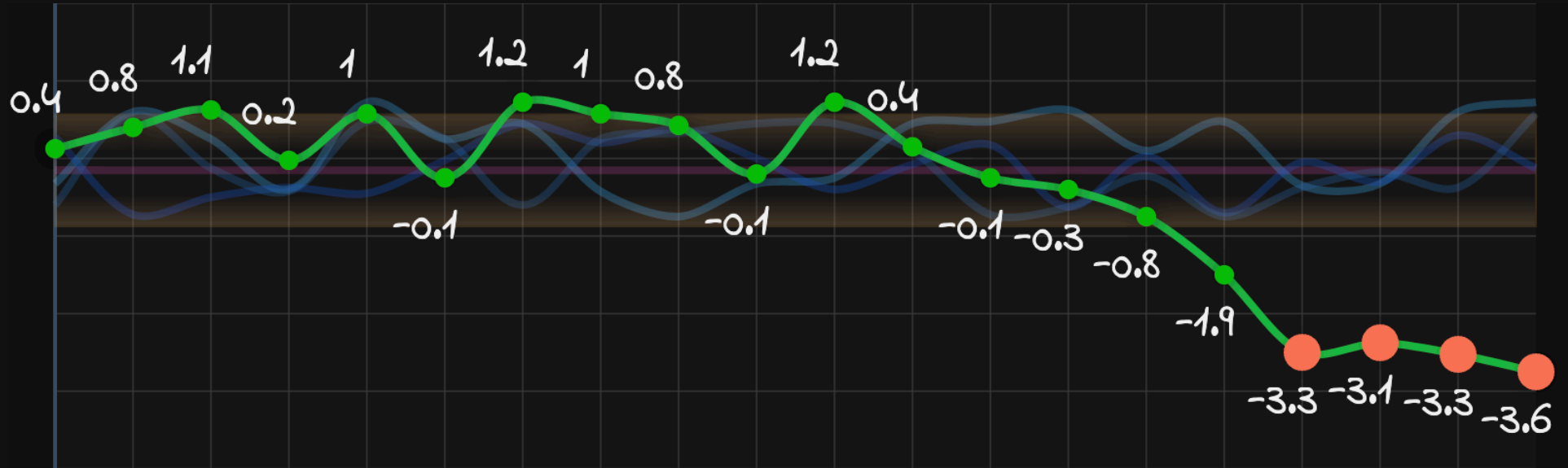
78% increase

31% increase

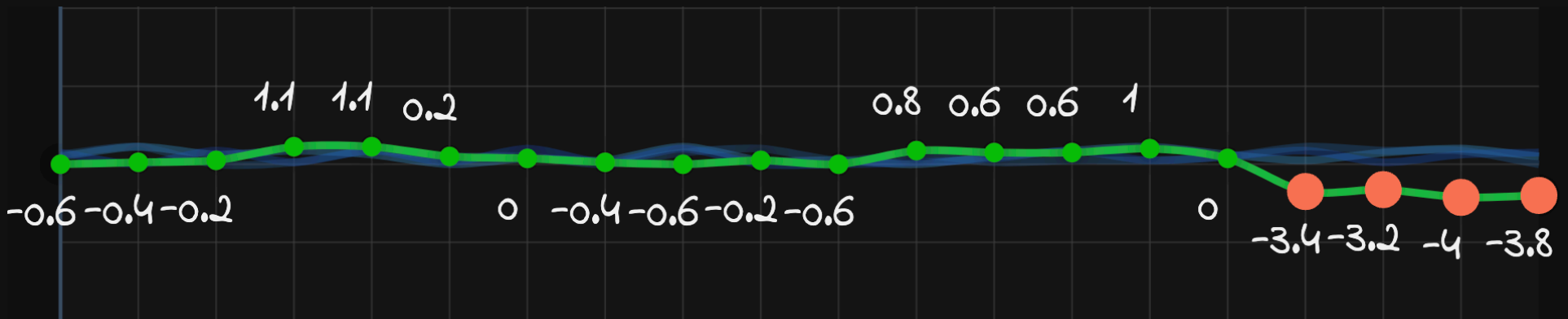
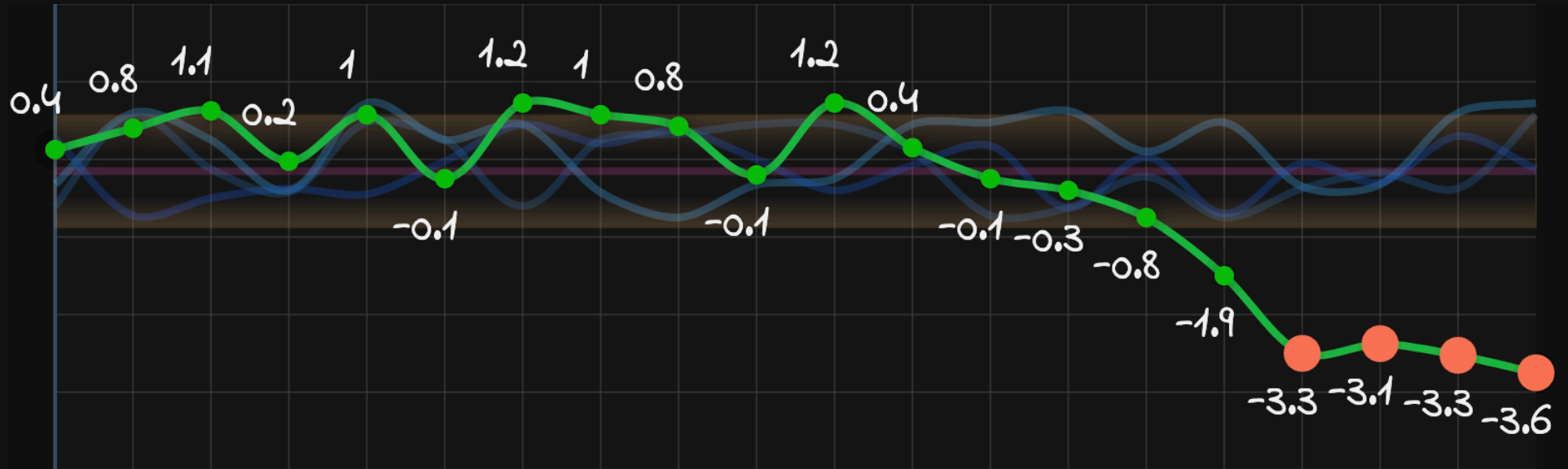


# Z-score drawbacks

# Too sensitive in smaller deviations



# Too sensitive in smaller deviations



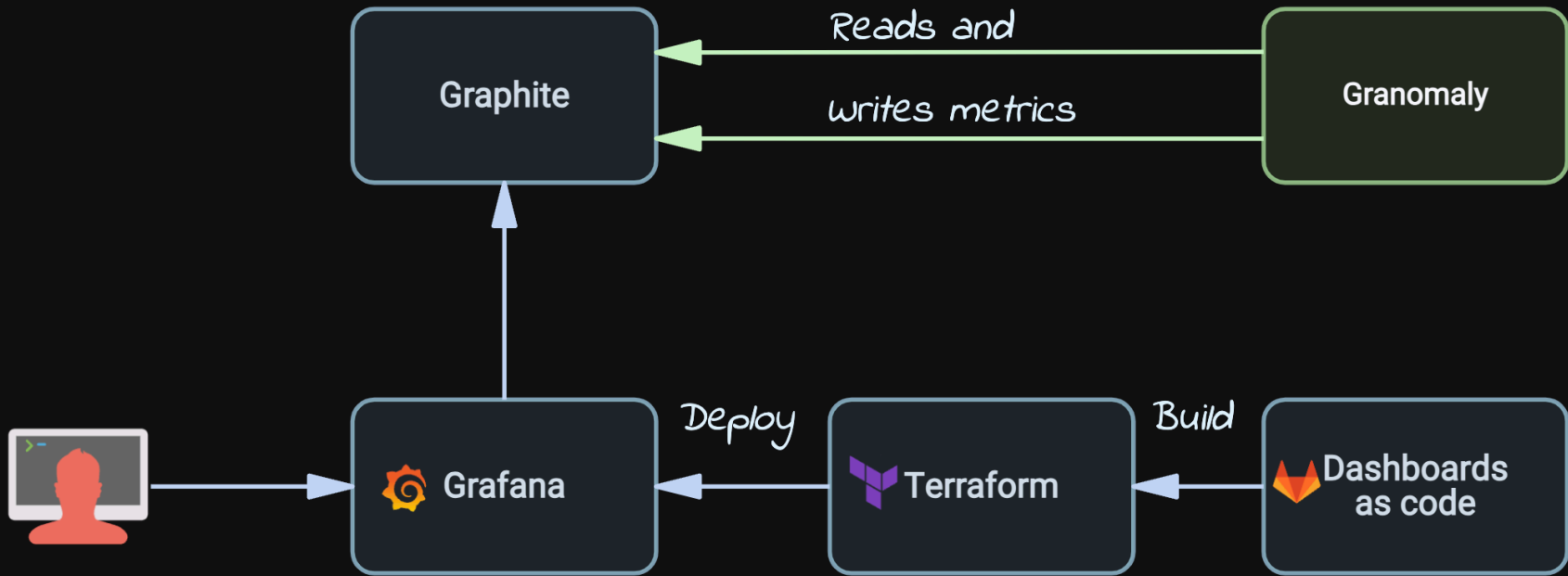


# Granomaly

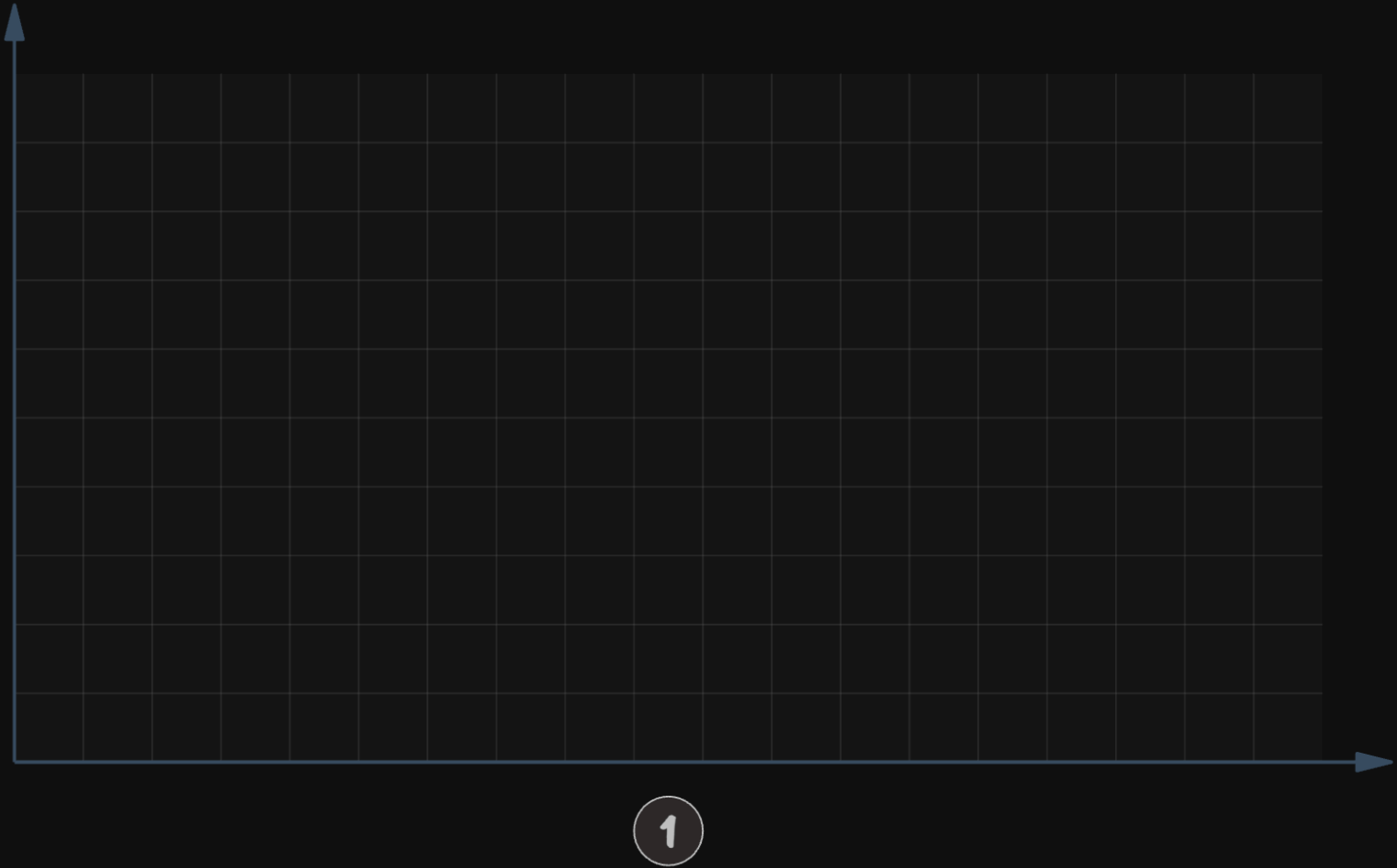
## Building our own service

- Use Graphite as a source
- Detect “slow burning” events and short outages
- Exclude past anomalies from the data samples
- Flexible tuning in Grafana
- Configure holidays, events and time of a day corrections

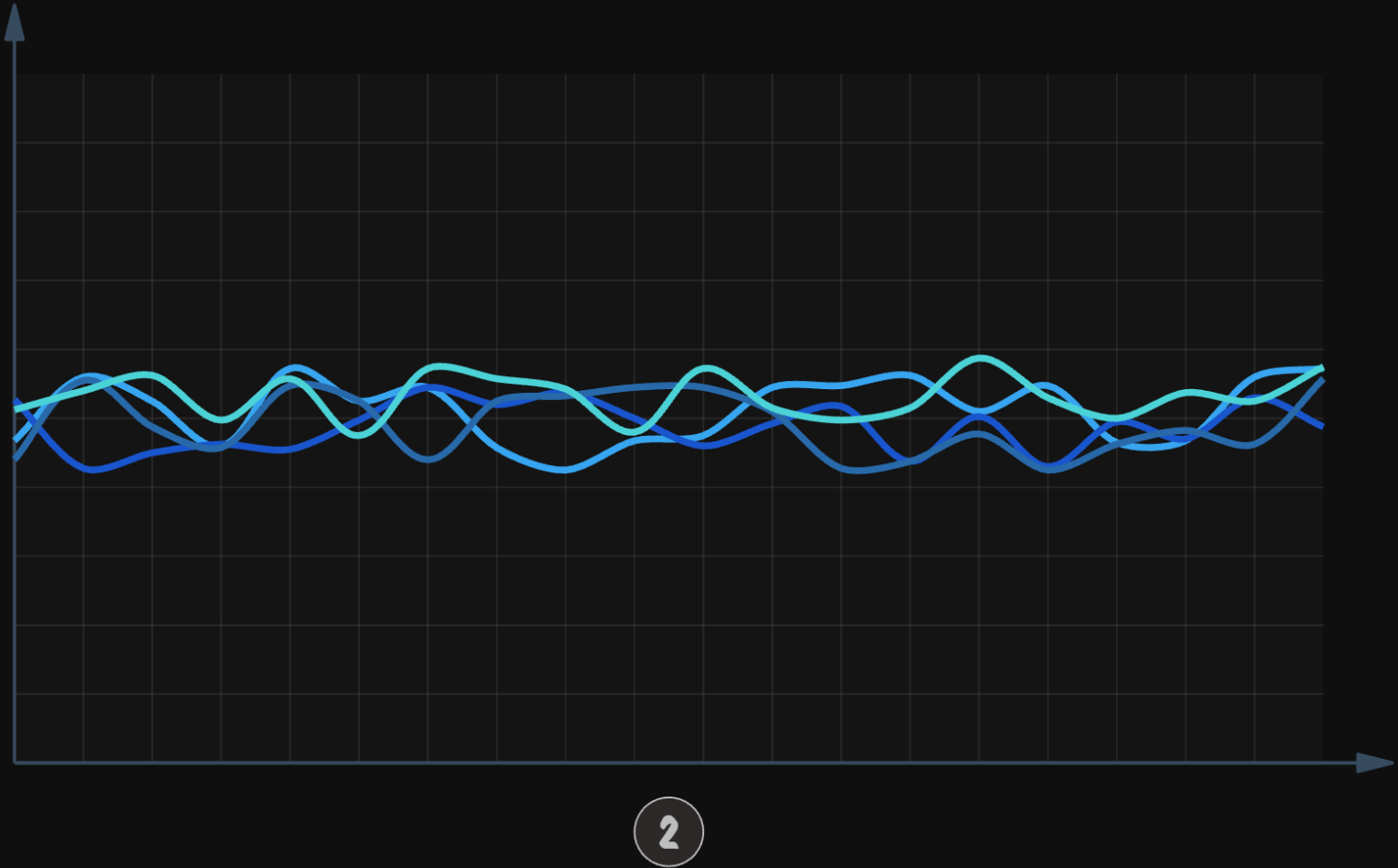
# Granomaly



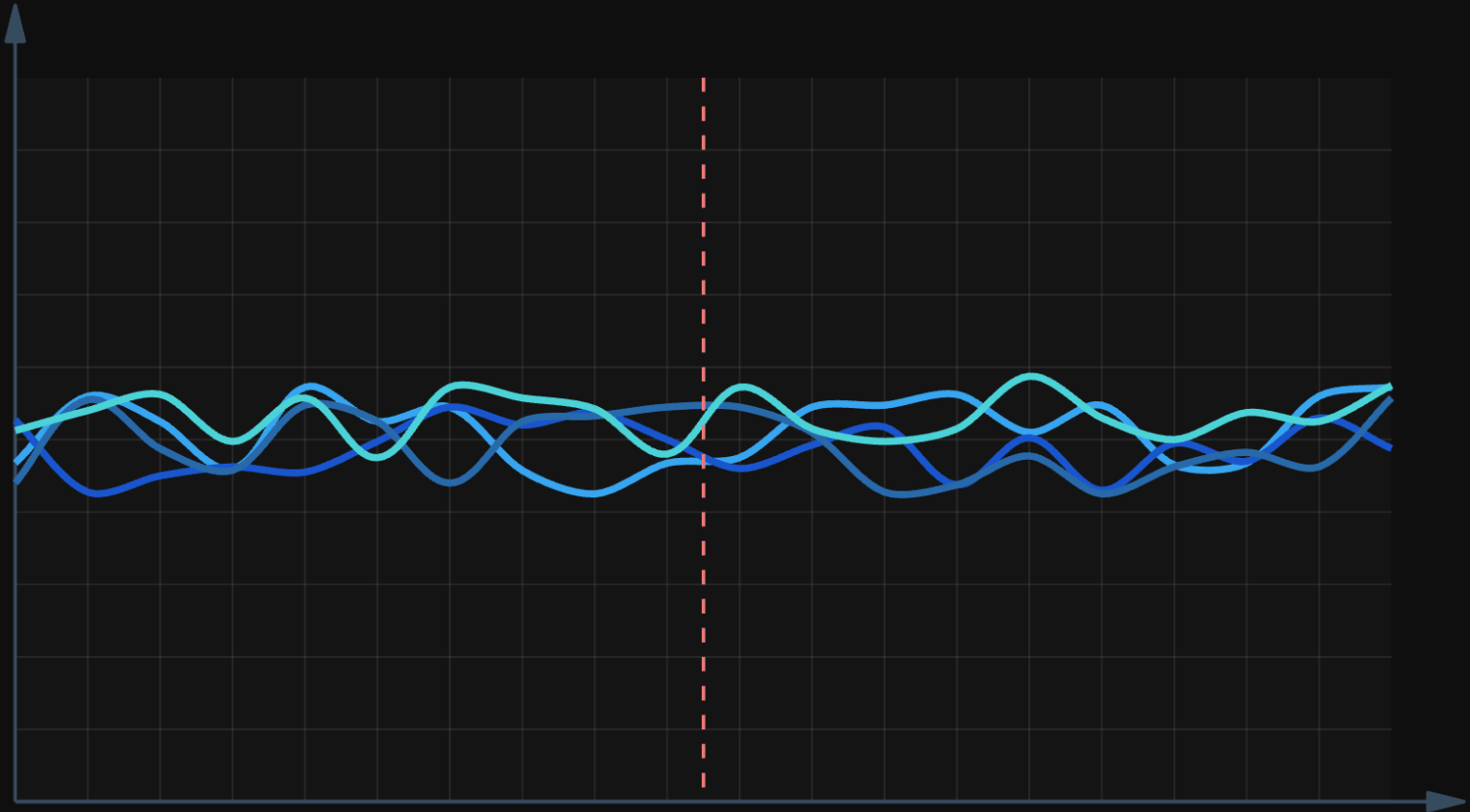
# How Granomaly works



# How Granomaly works



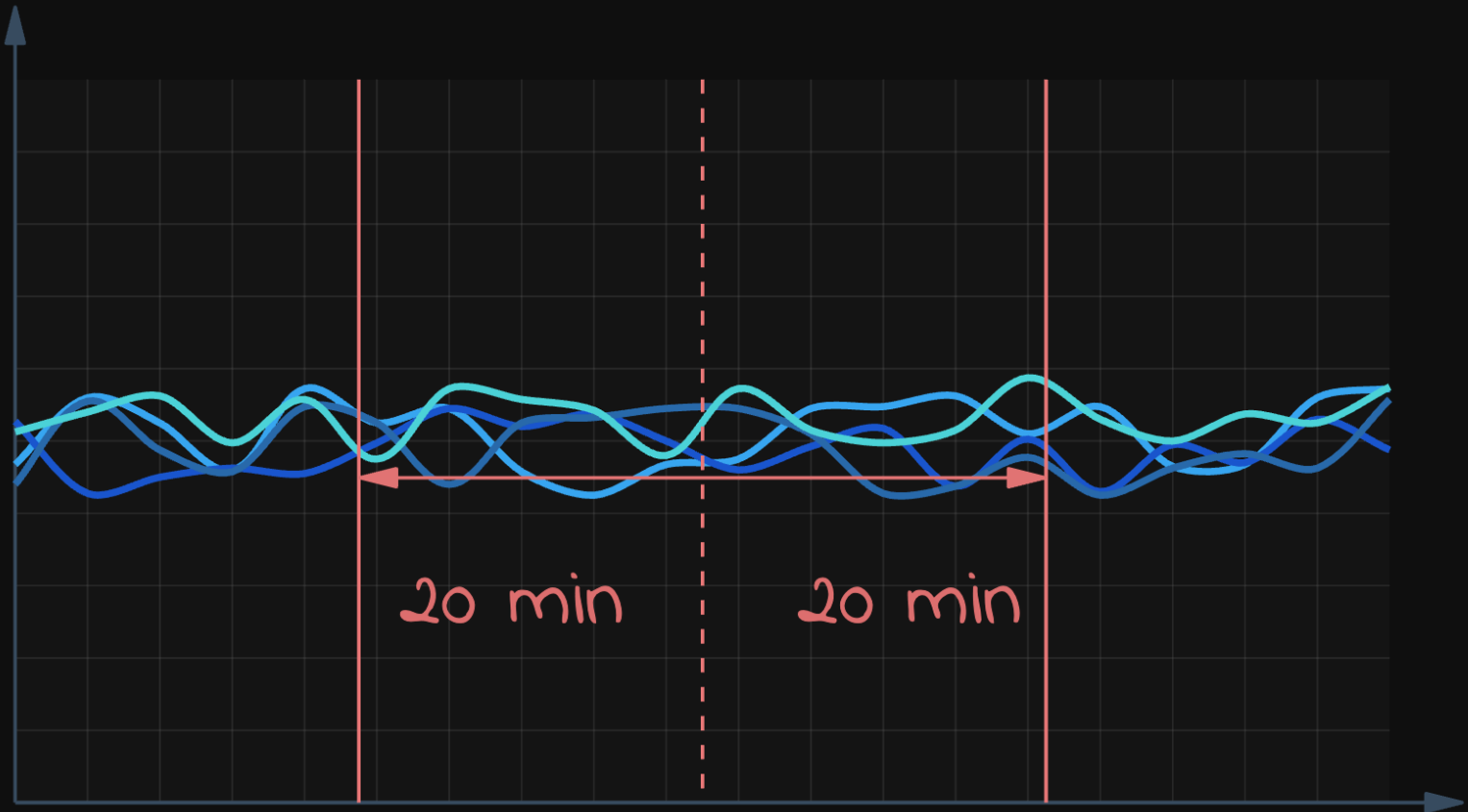
# How Granomaly works



window = 40 min

3

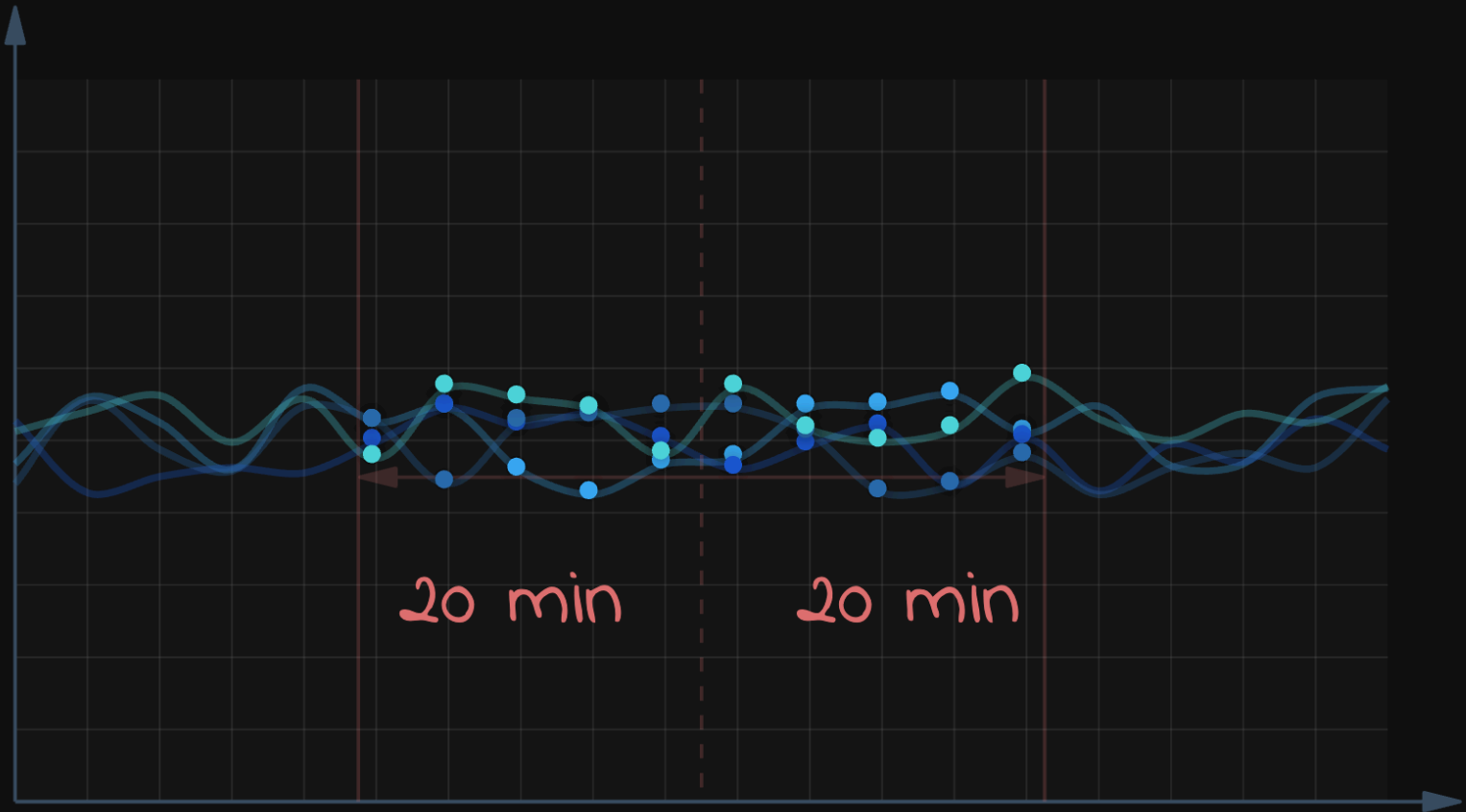
# How Granomaly works



window = 40 min

4

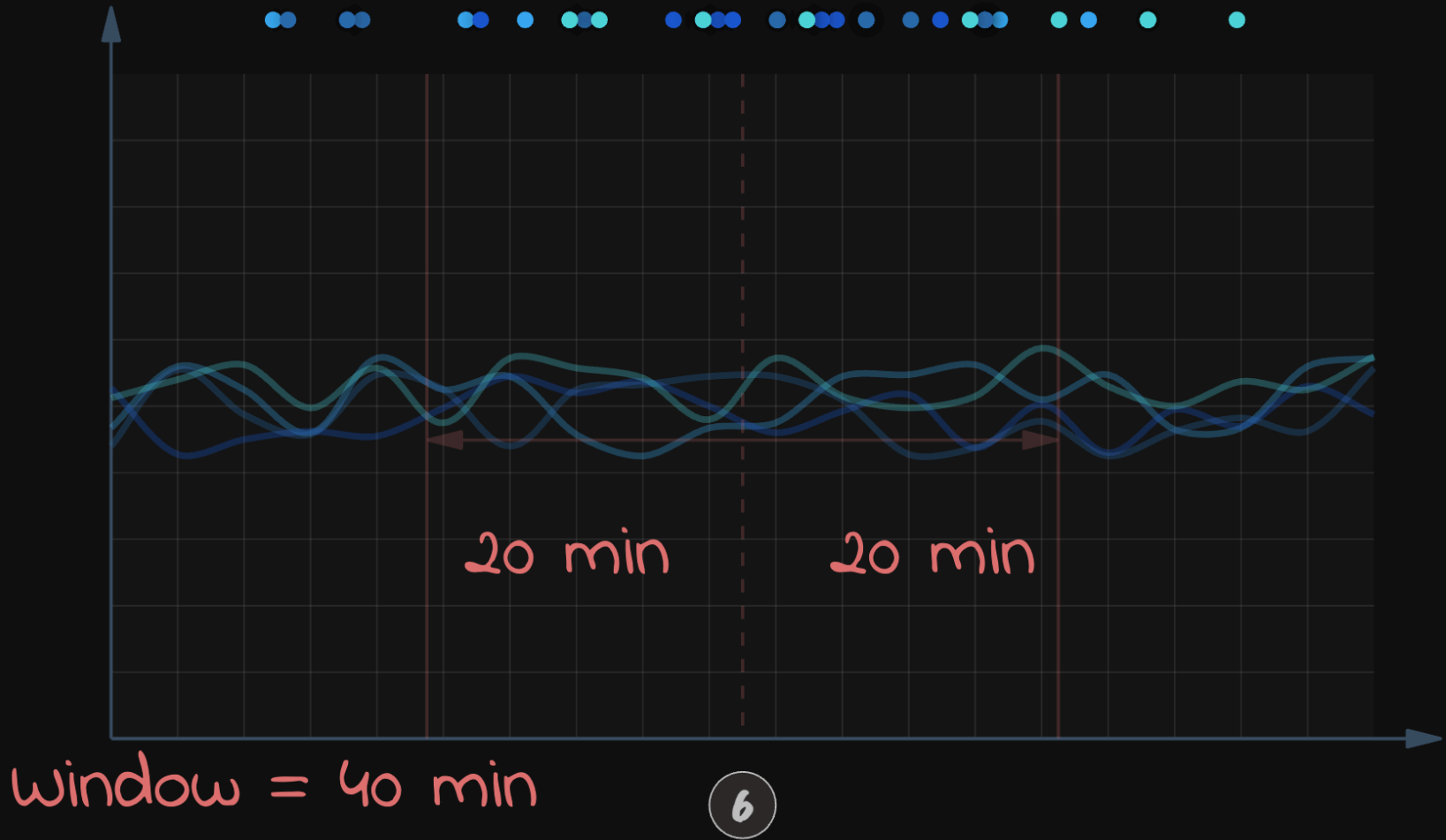
# How Granomaly works



window = 40 min

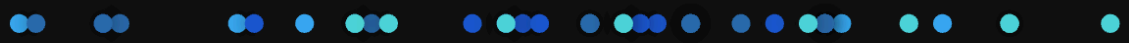
5

# How Granomaly works

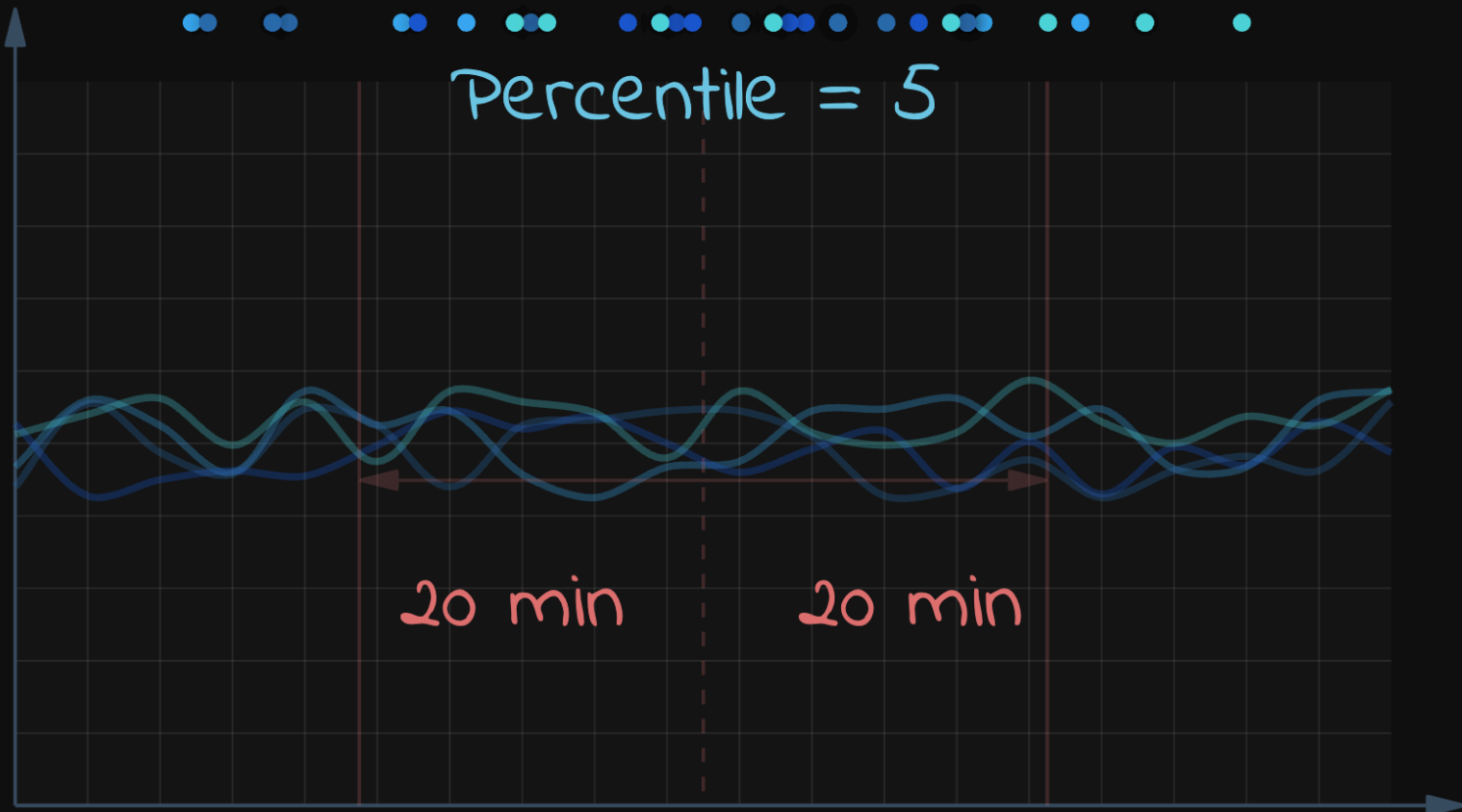




# How Granomaly works



Percentile = 5



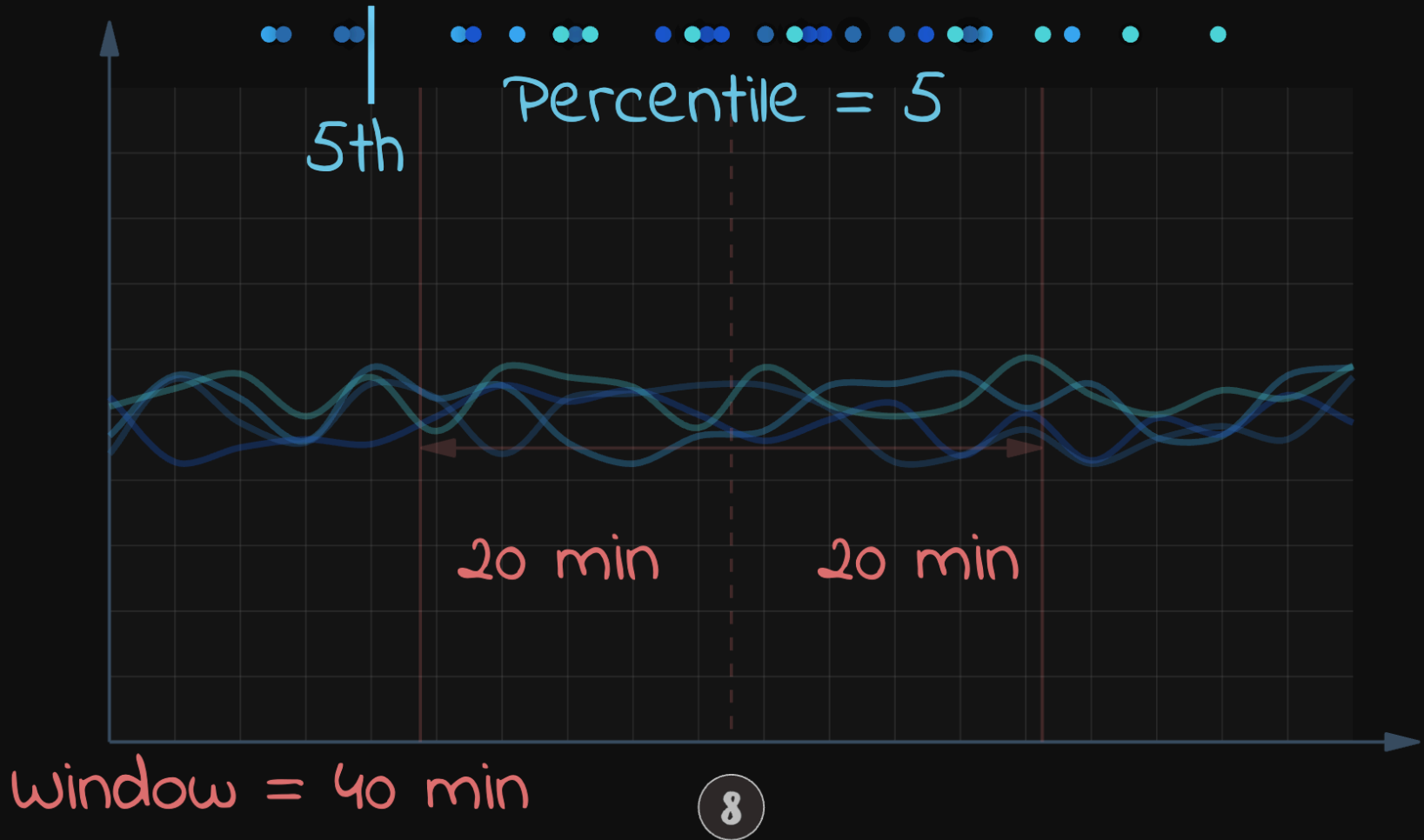
20 min

20 min

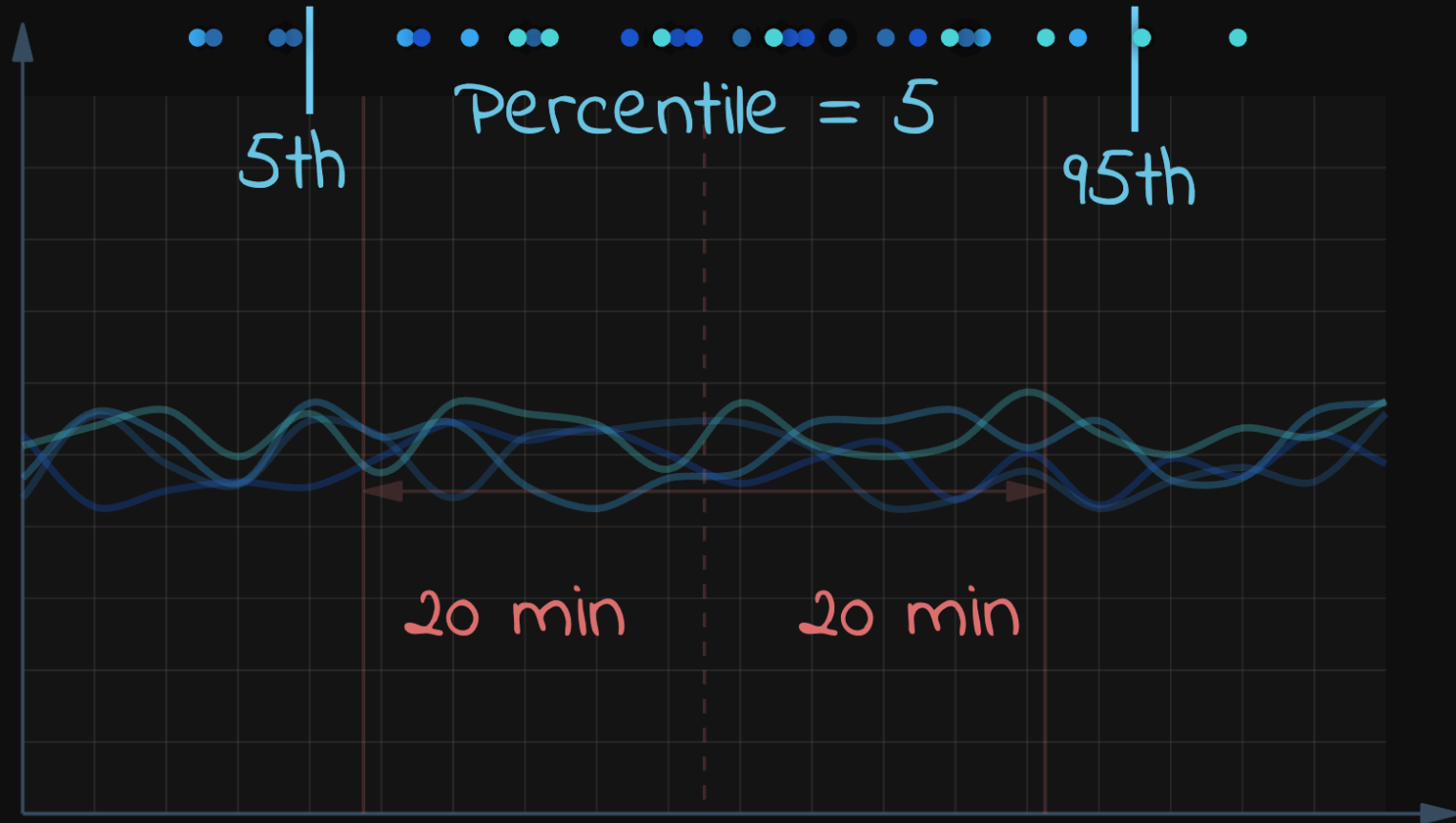
window = 40 min

7

# How Granomaly works



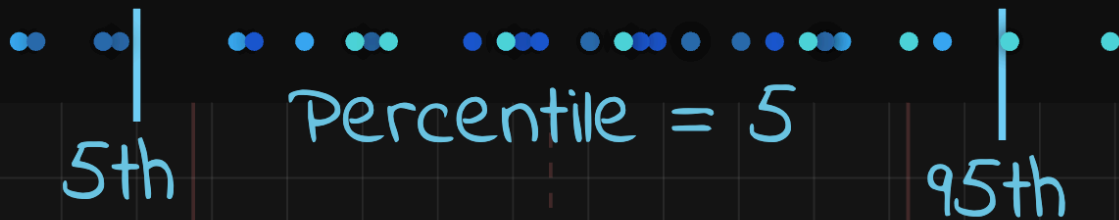
# How Granomaly works



# How Granomaly works

180

240

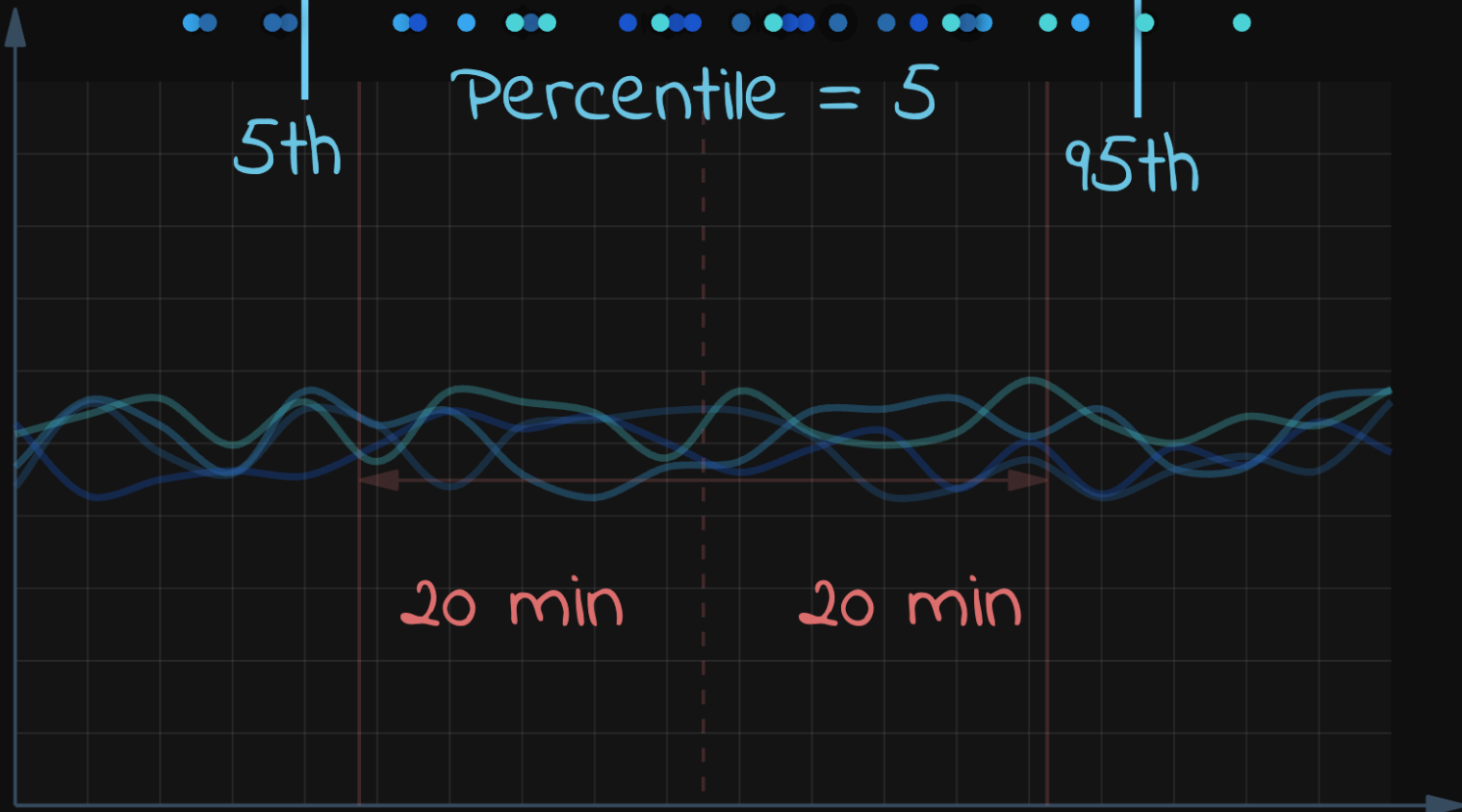


20 min

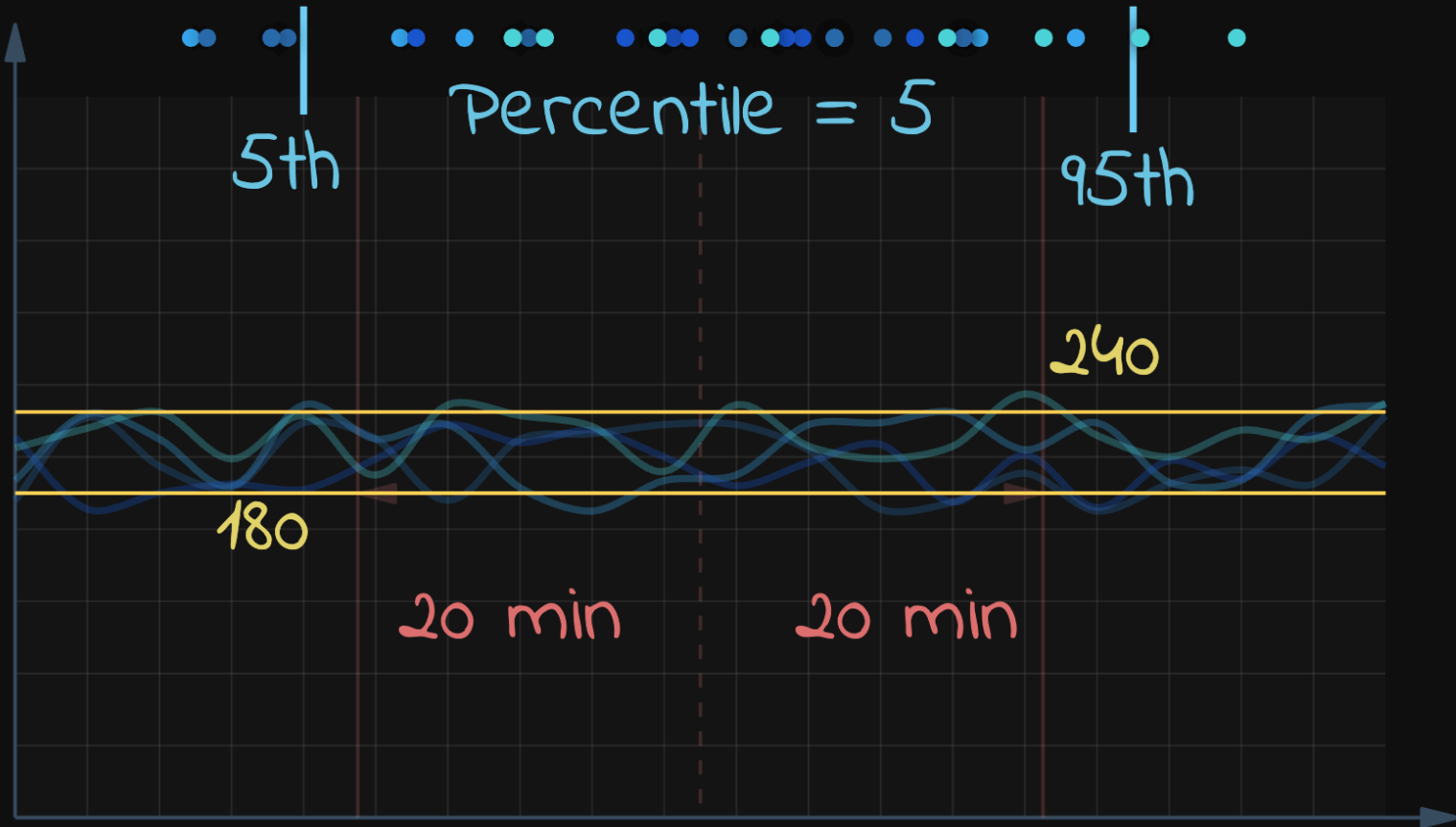
20 min

window = 40 min

10



# How Granomaly works



window = 40 min



# Boundaries for last 24 hours



# Granomaly Simulation

## Config

Exclude outliers  On  Off

Target

Weeks

Window

Percentile

Expand (%)

Until

Duration

Submit

## Distortion

Simulate anomalies  On  Off

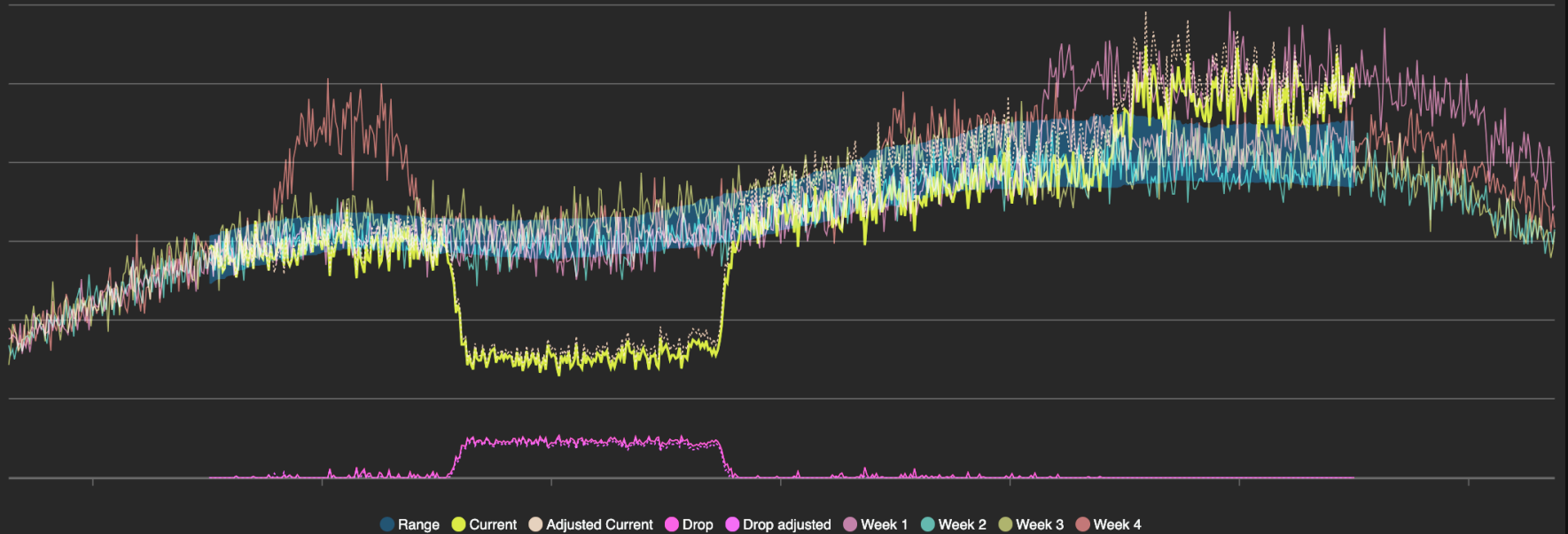
Seed

Frequency

Power

Max length

## Anomaly simulation

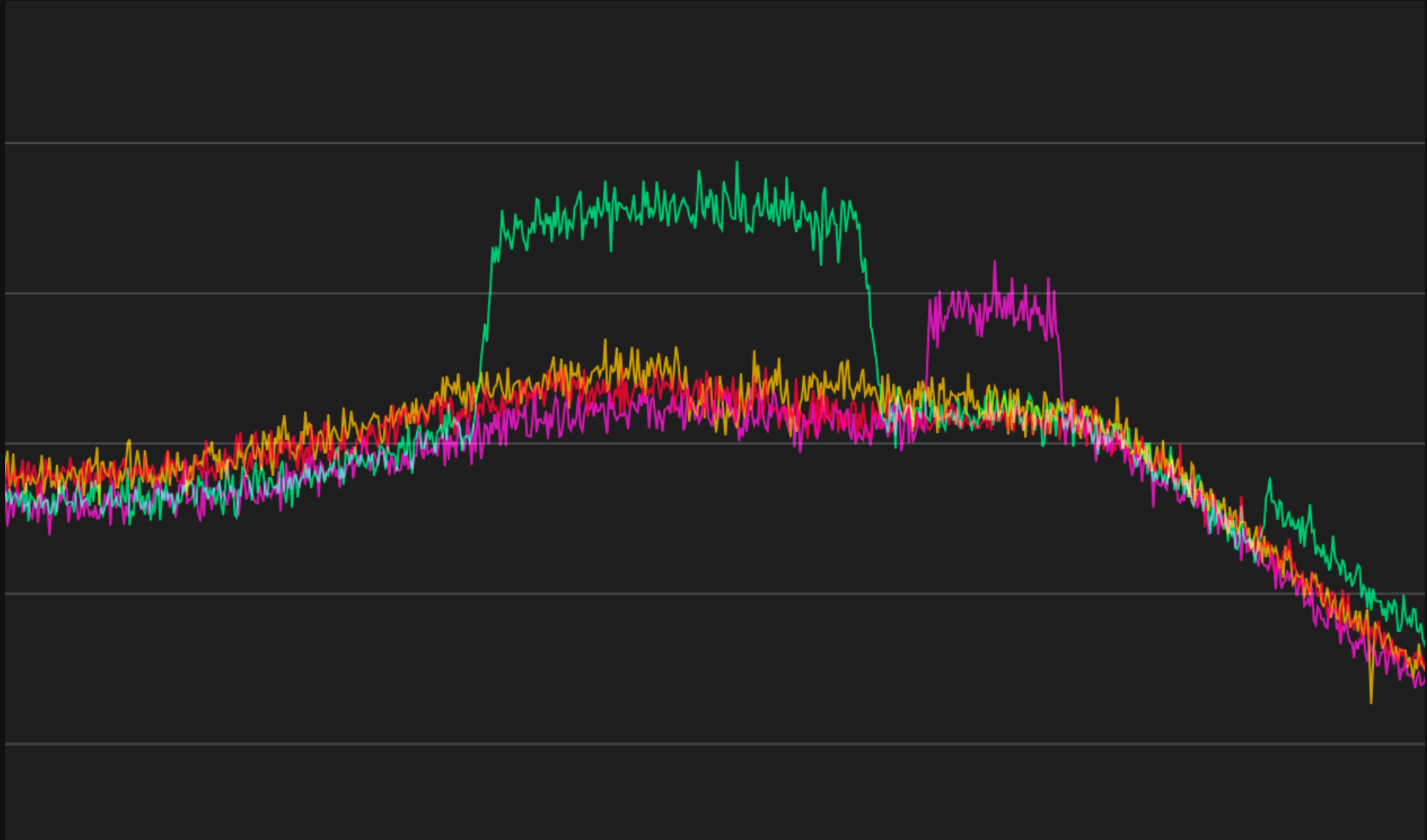


# Running into some problems on the way

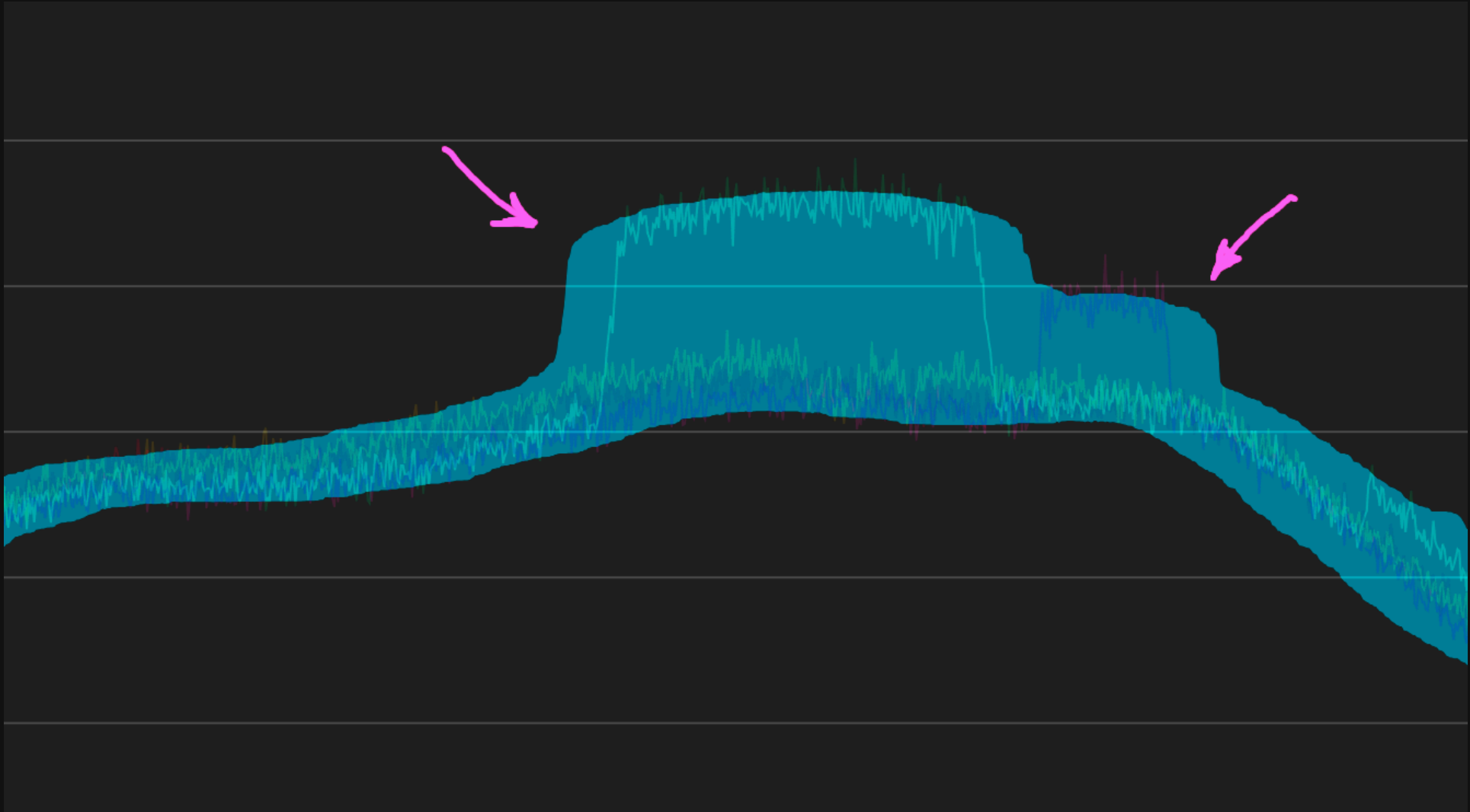
- Past incidents
- Daylight Savings Time
- Incidents while overperforming
- Correcting for known events
- Query complexity



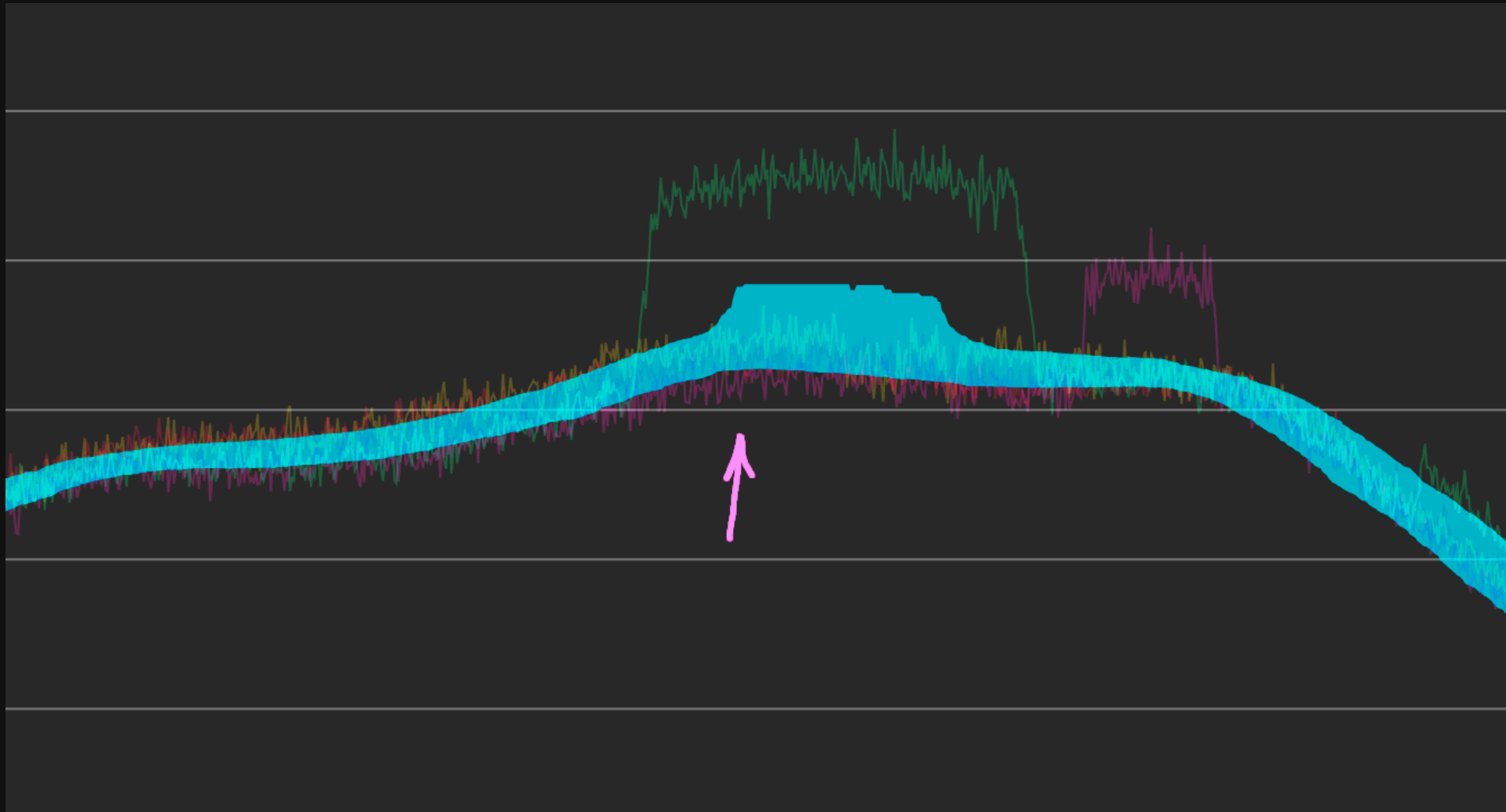
# Problem #1: Past incidents



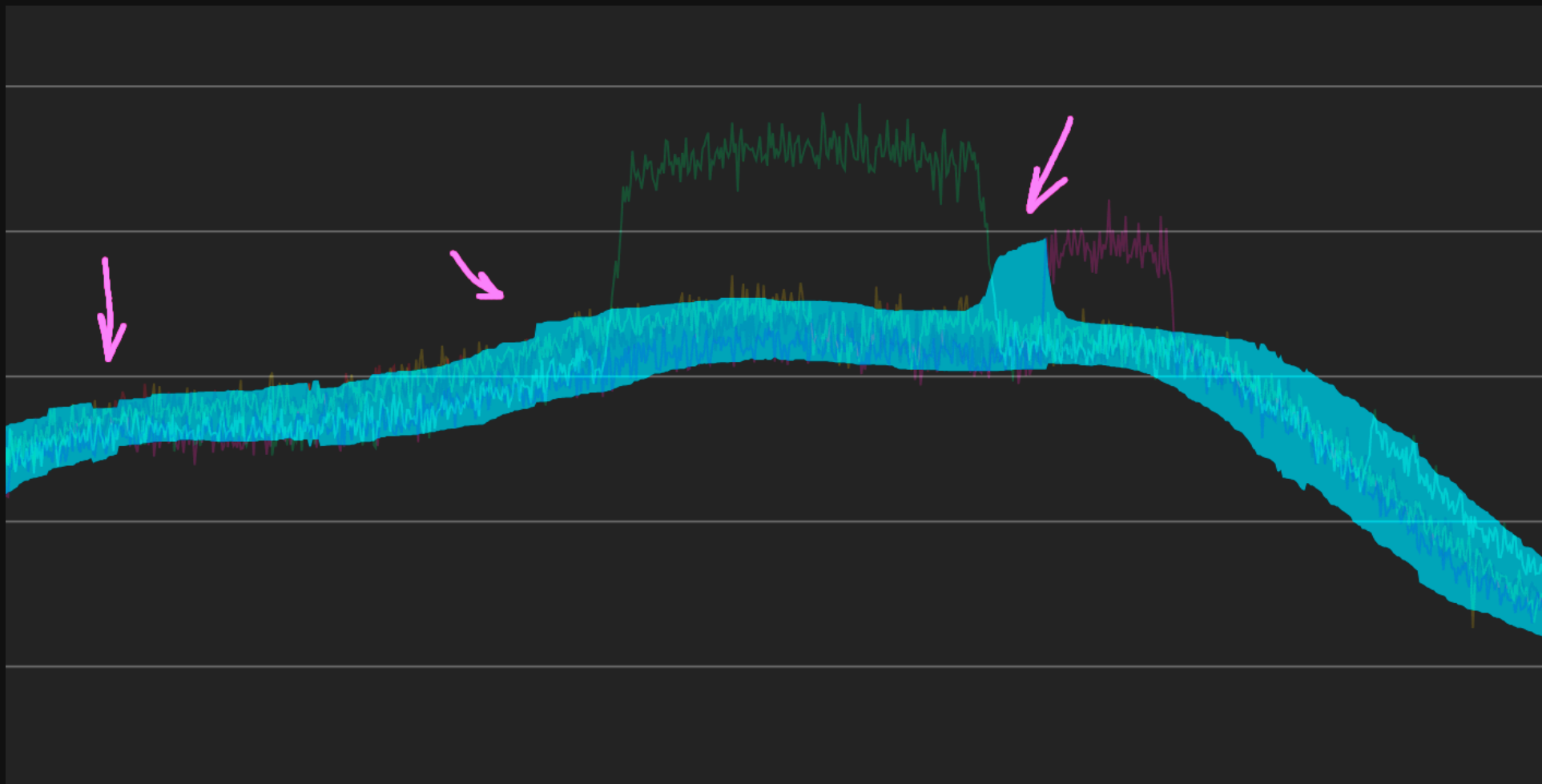
# Using 5th percentile



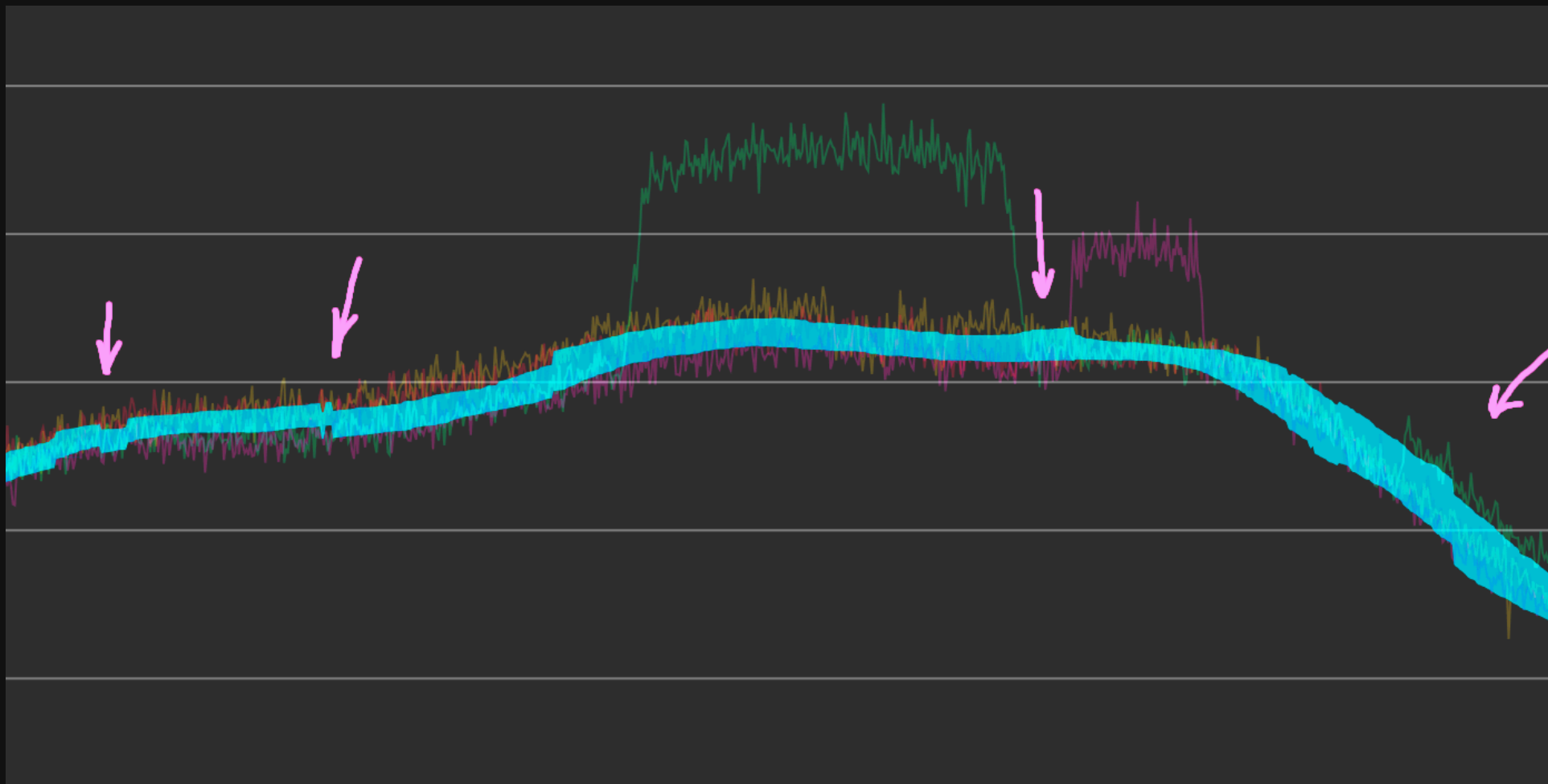
# 25th percentile



# Least stddev based exclusion (5th percentile)



# Least stddev based exclusion (25th percentile)



# Single outlier

Raw data

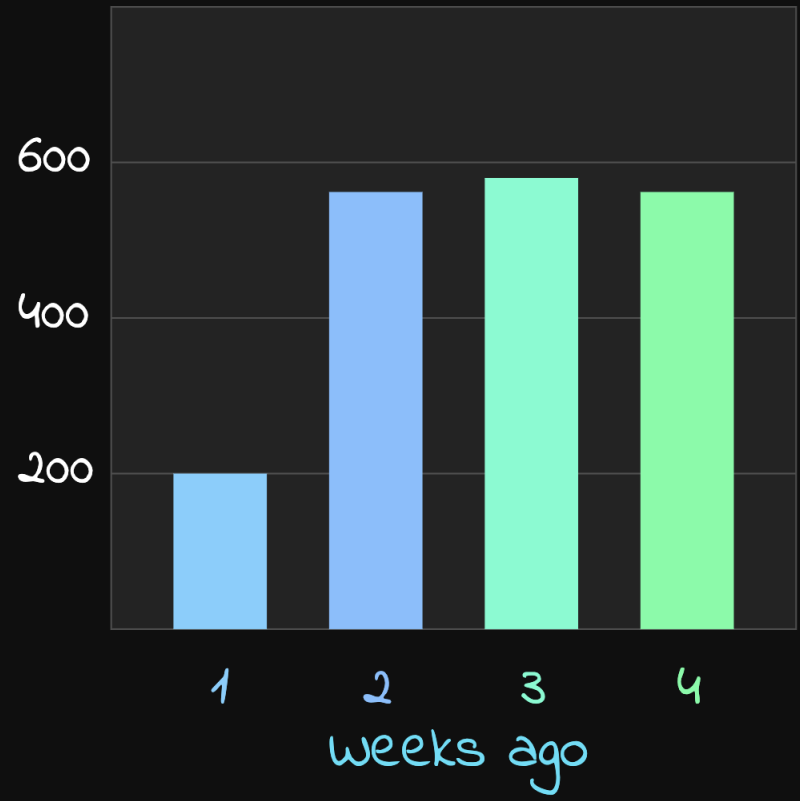


Absolute z-score

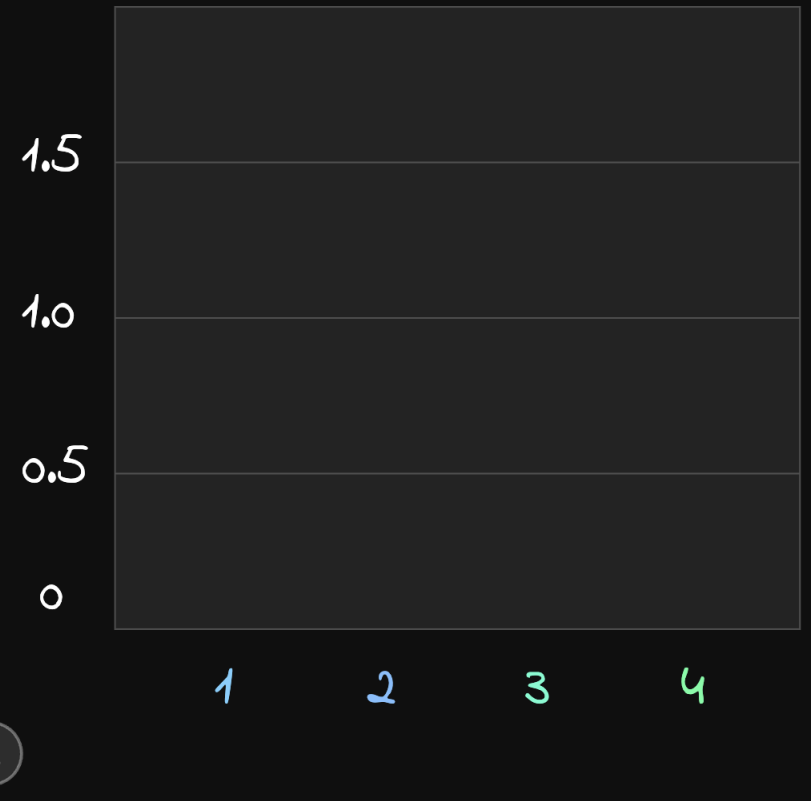


# Single outlier

Raw data



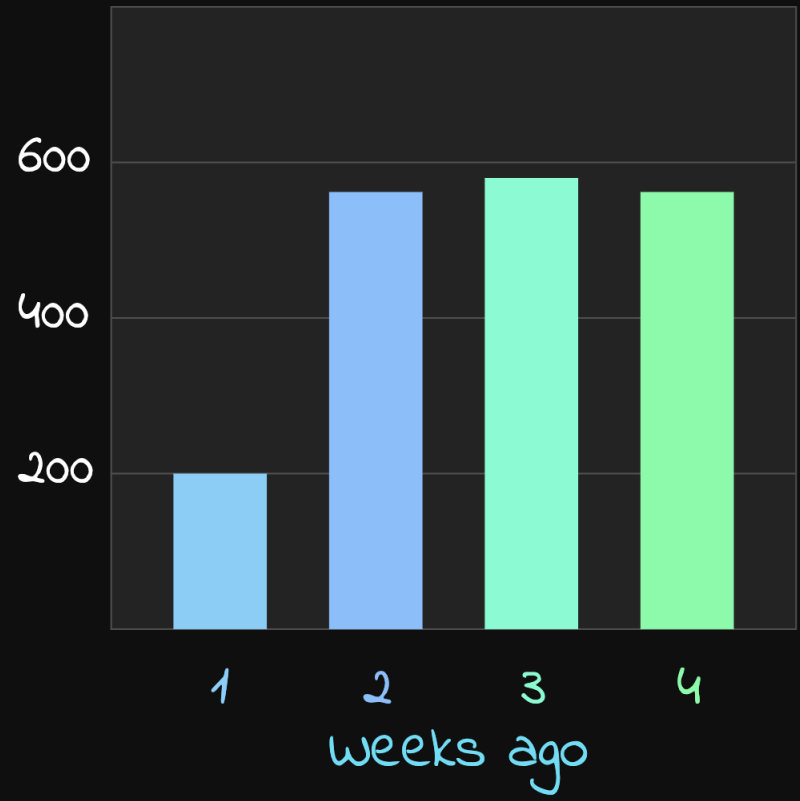
Absolute z-score



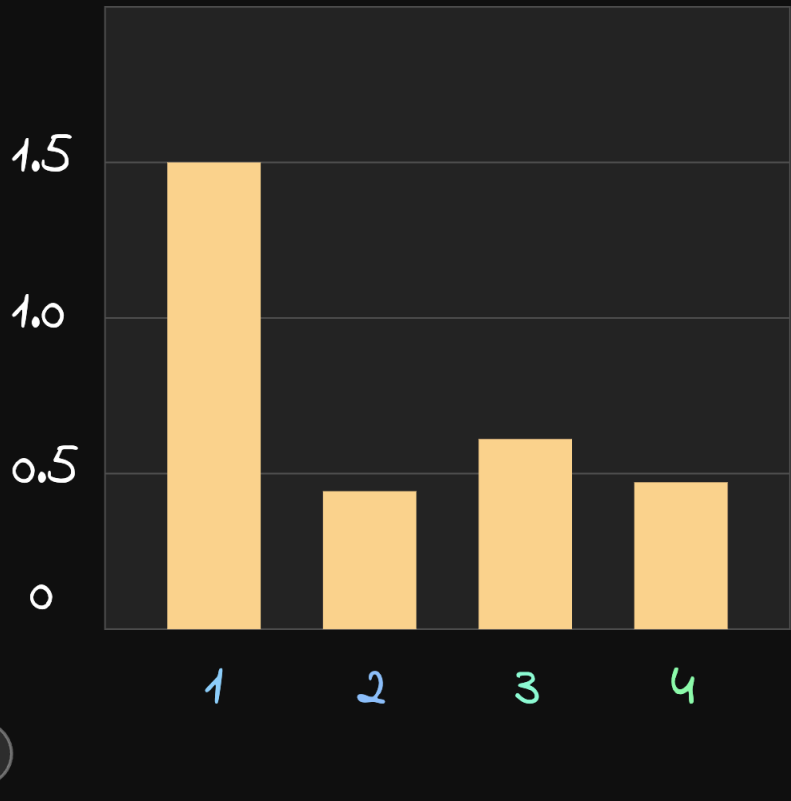
2

# Single outlier

Raw data



Absolute z-score

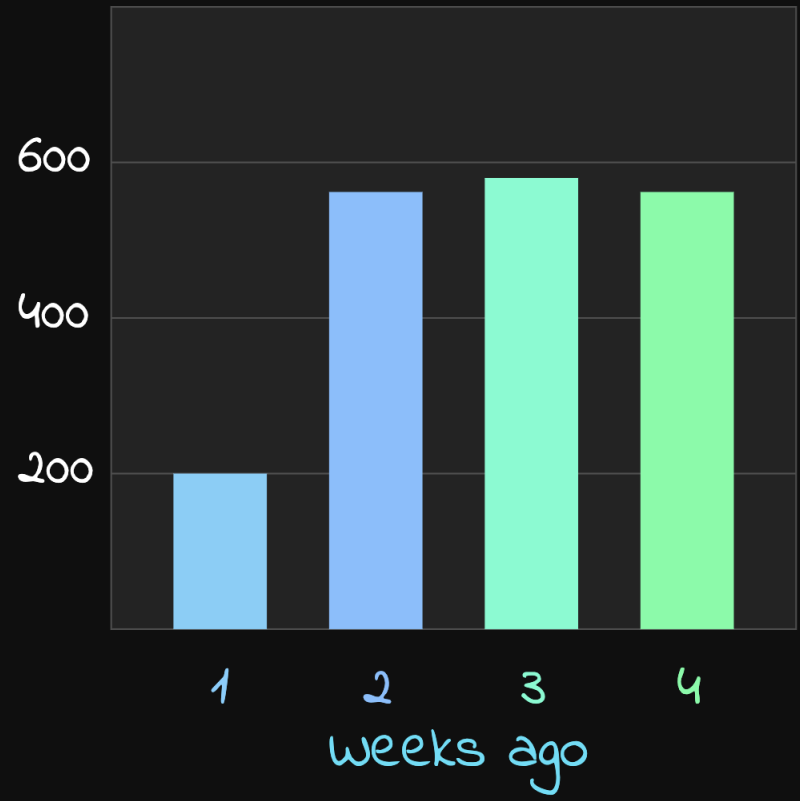


3

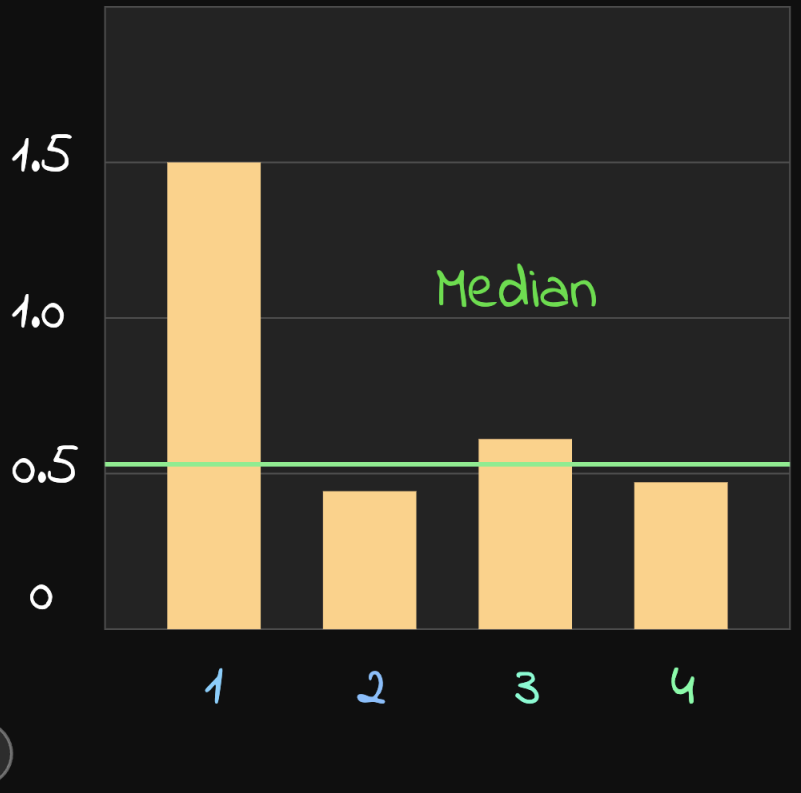


# Single outlier

Raw data



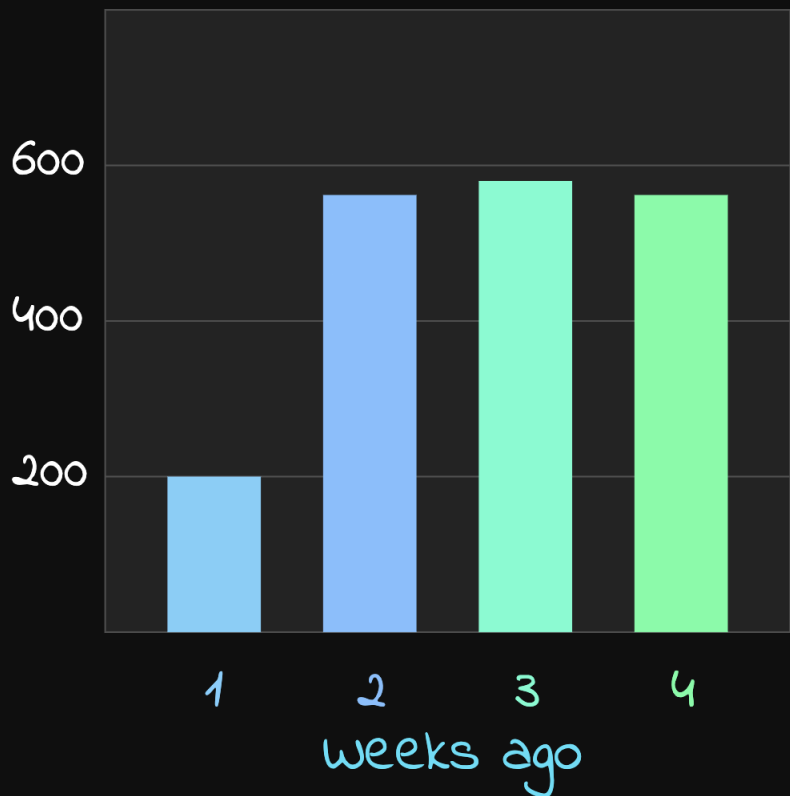
Absolute z-score



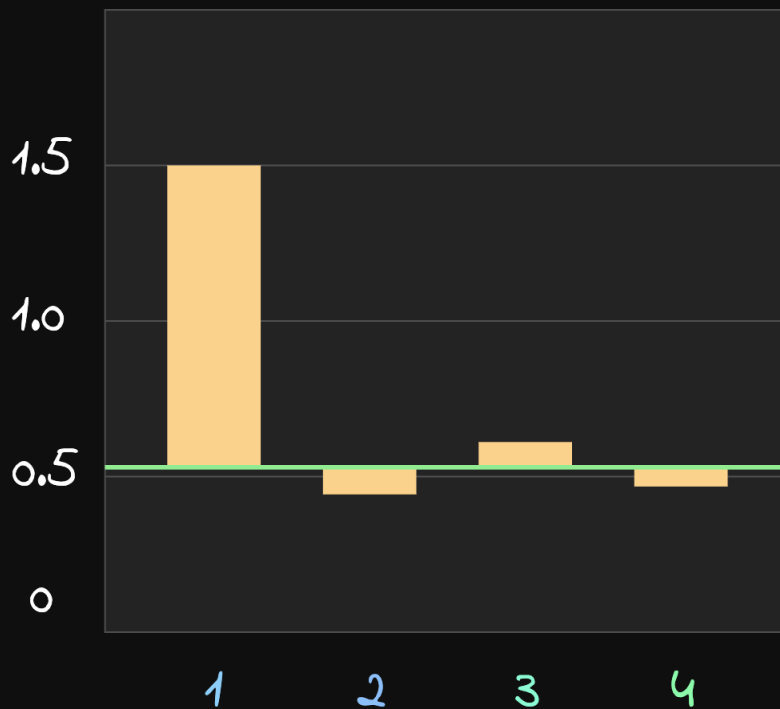
4

# Single outlier

Raw data



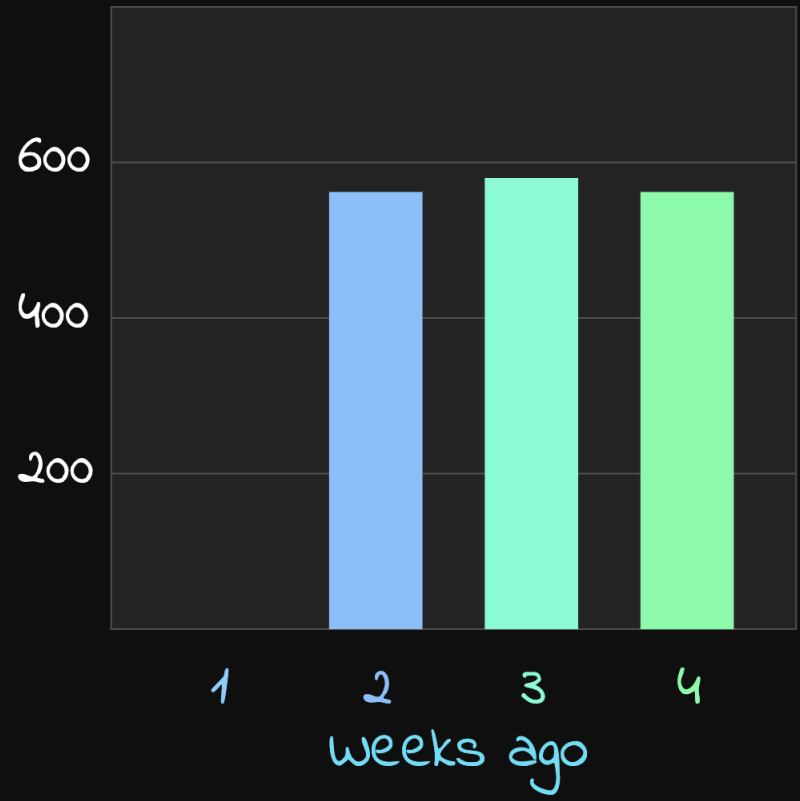
Absolute z-score



5

# Single outlier

Raw data

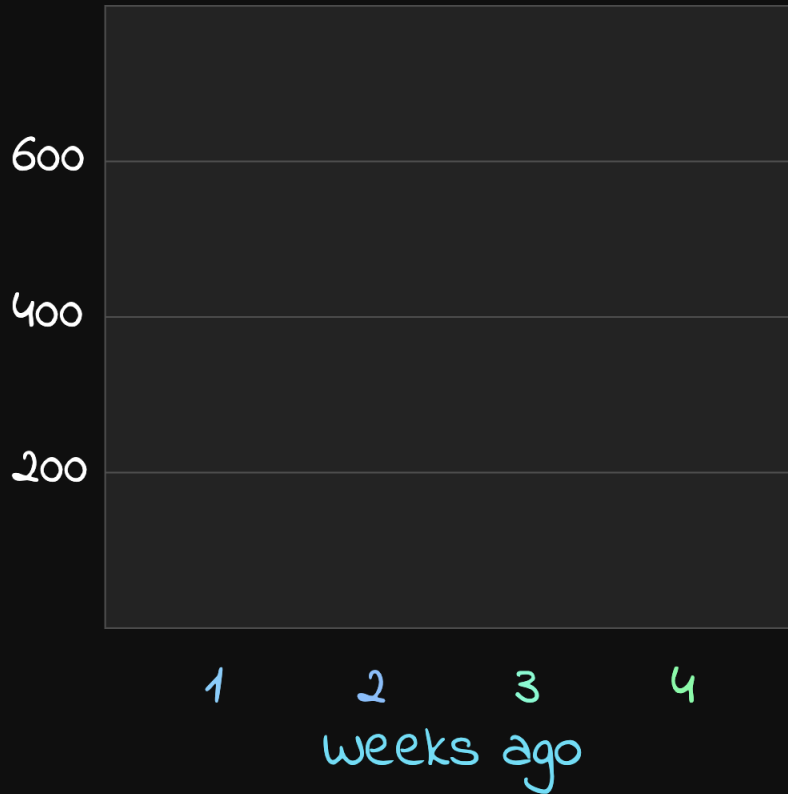


Absolute z-score

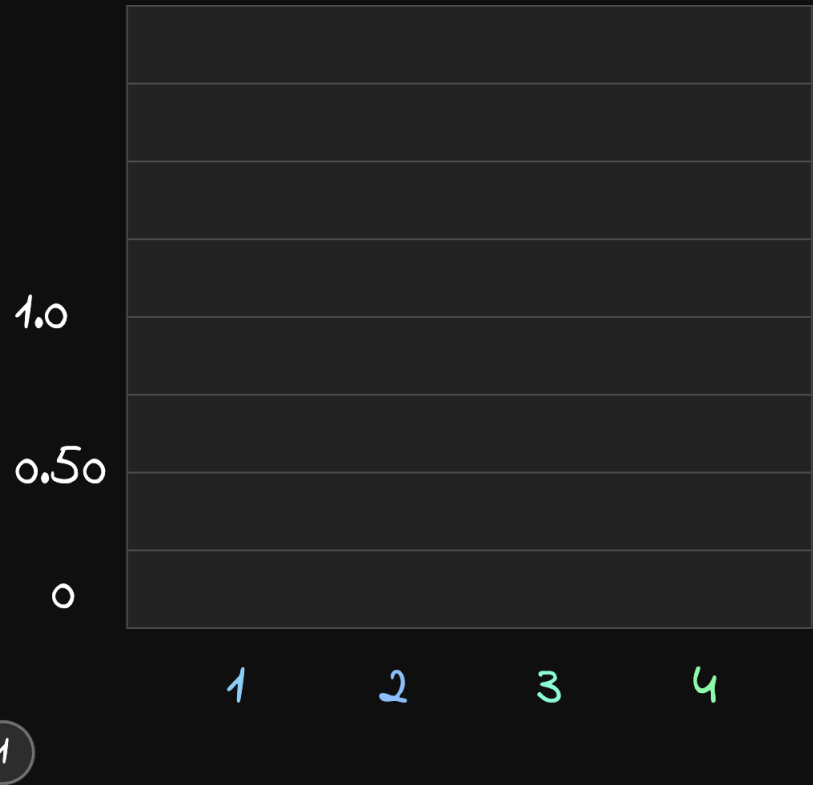


No outliers

Raw data

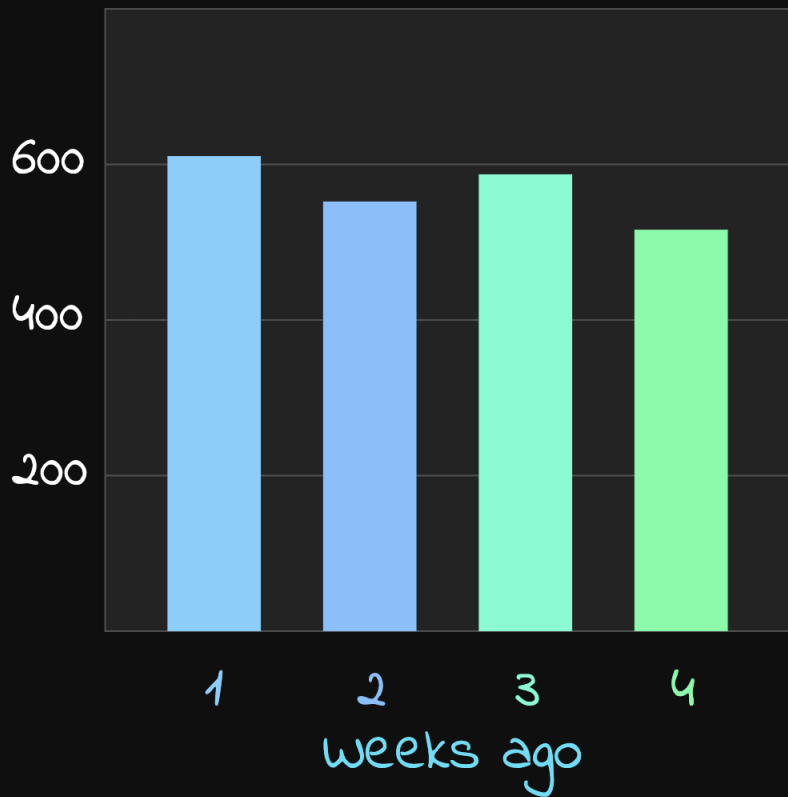


Absolute z-score

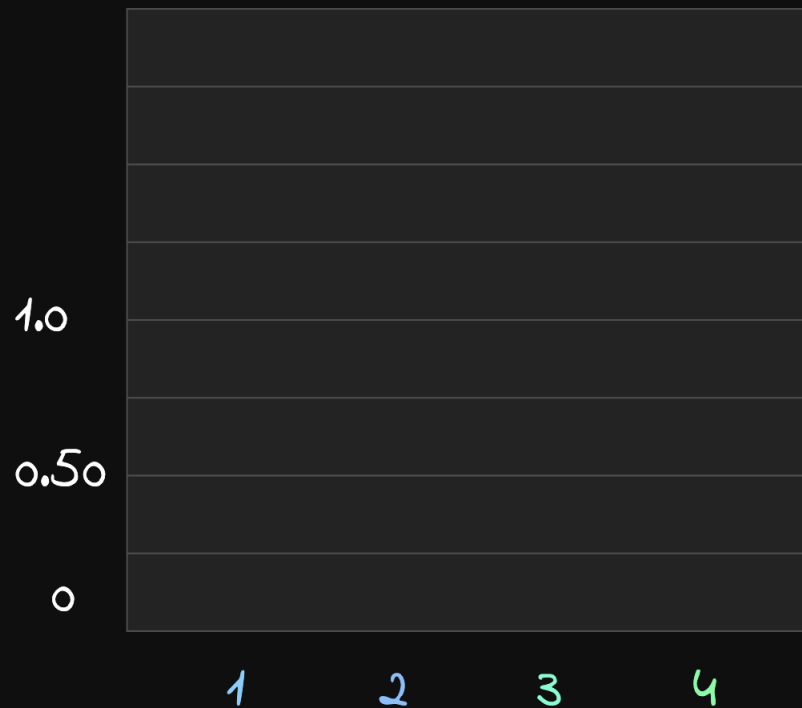


No outliers

Raw data



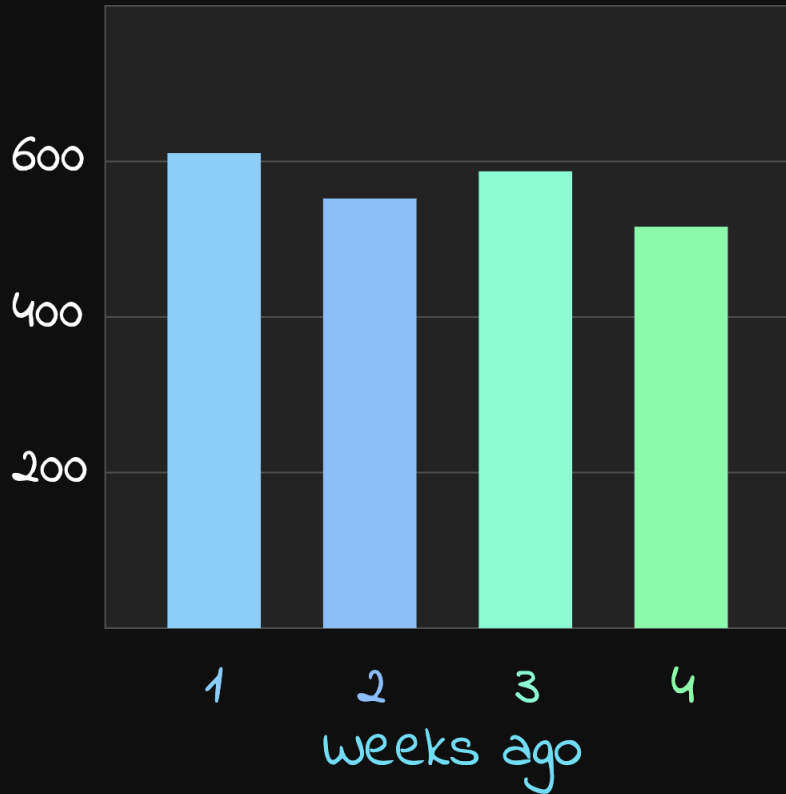
Absolute z-score



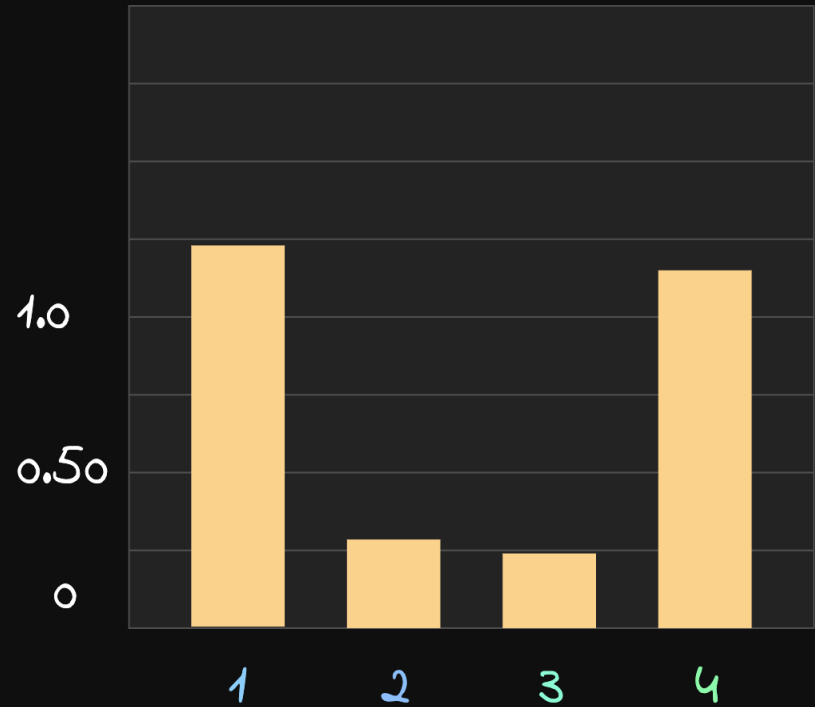
2

No outliers

Raw data



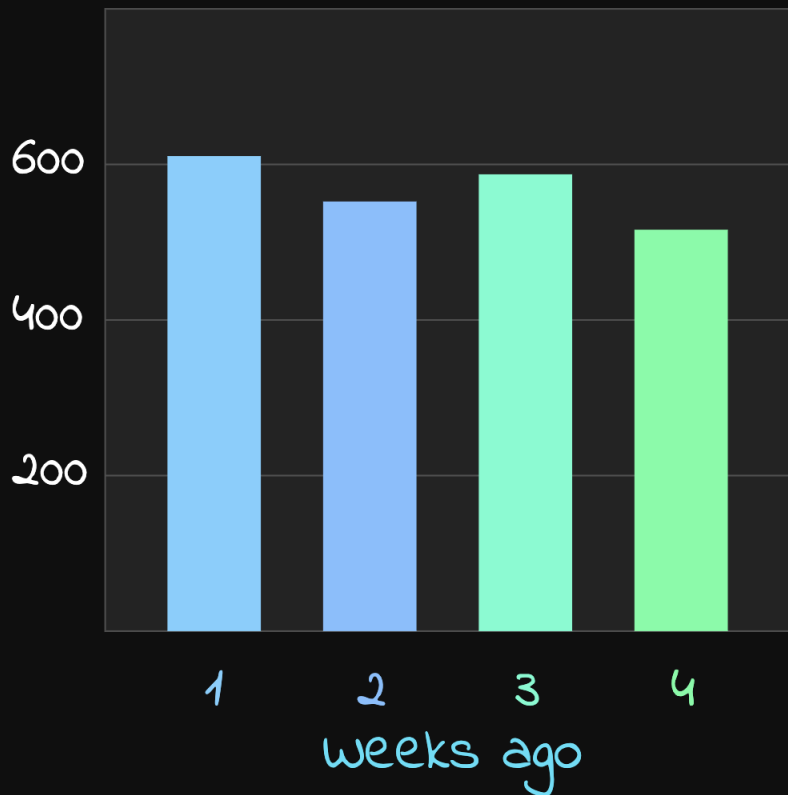
Absolute z-score



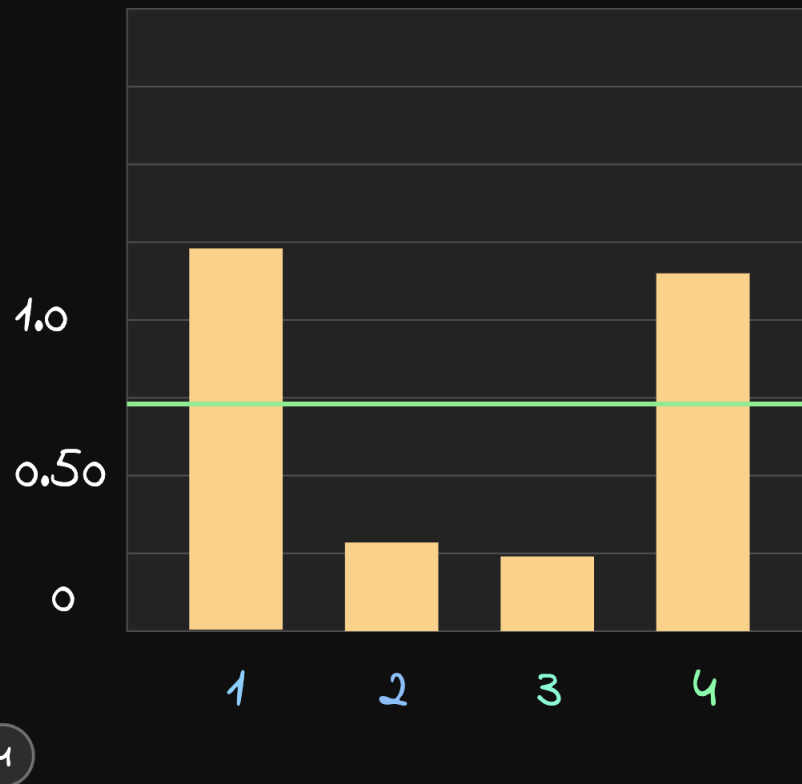
3

No outliers

Raw data

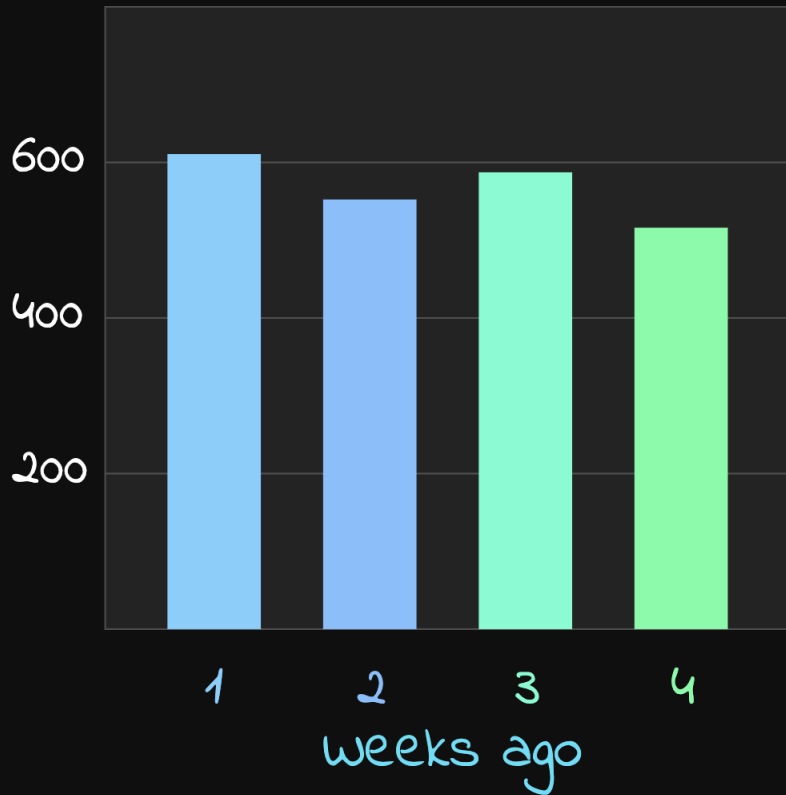


Absolute z-score

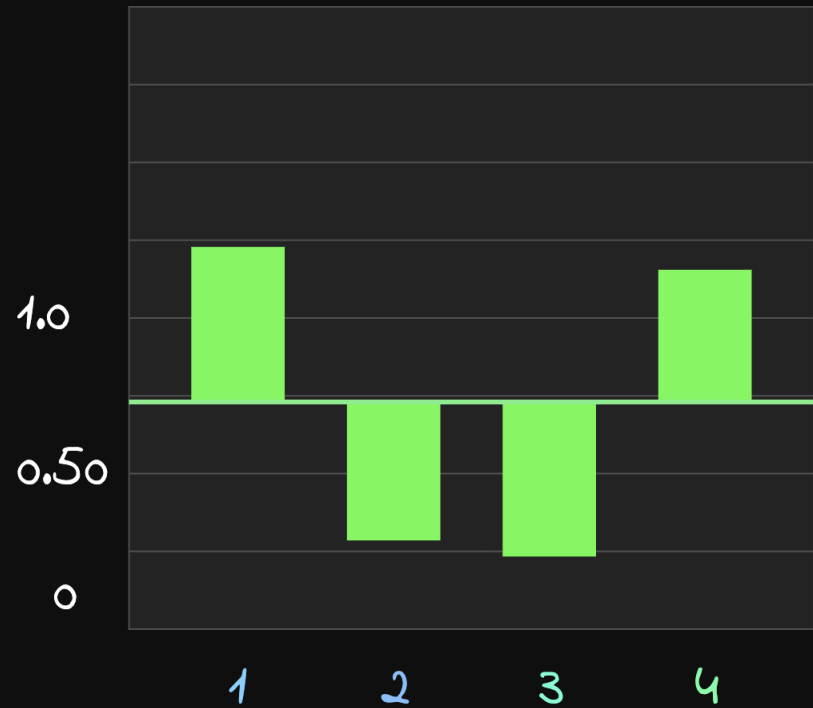


No outliers

Raw data



Absolute z-score

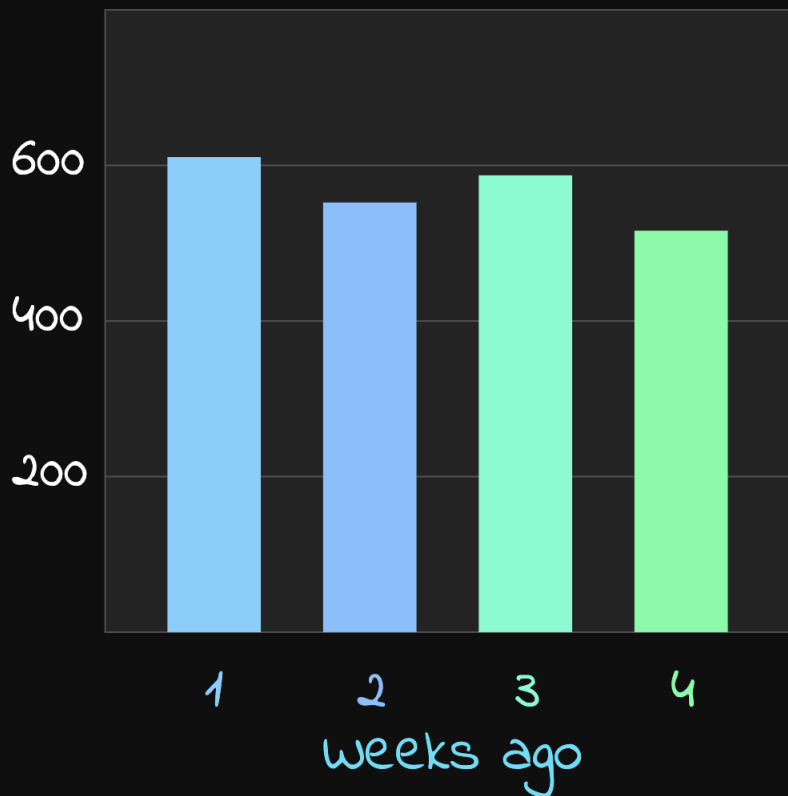


5

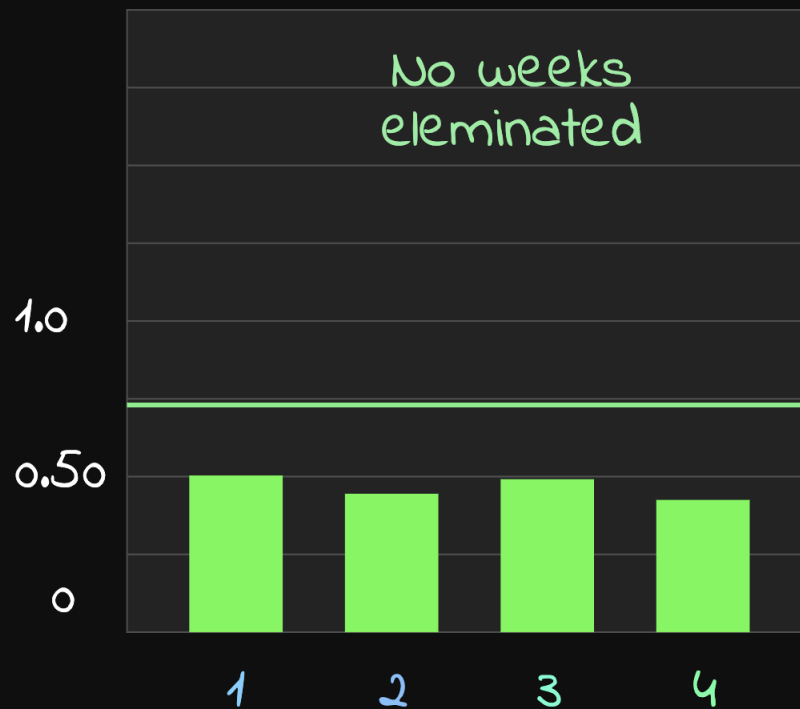


No outliers

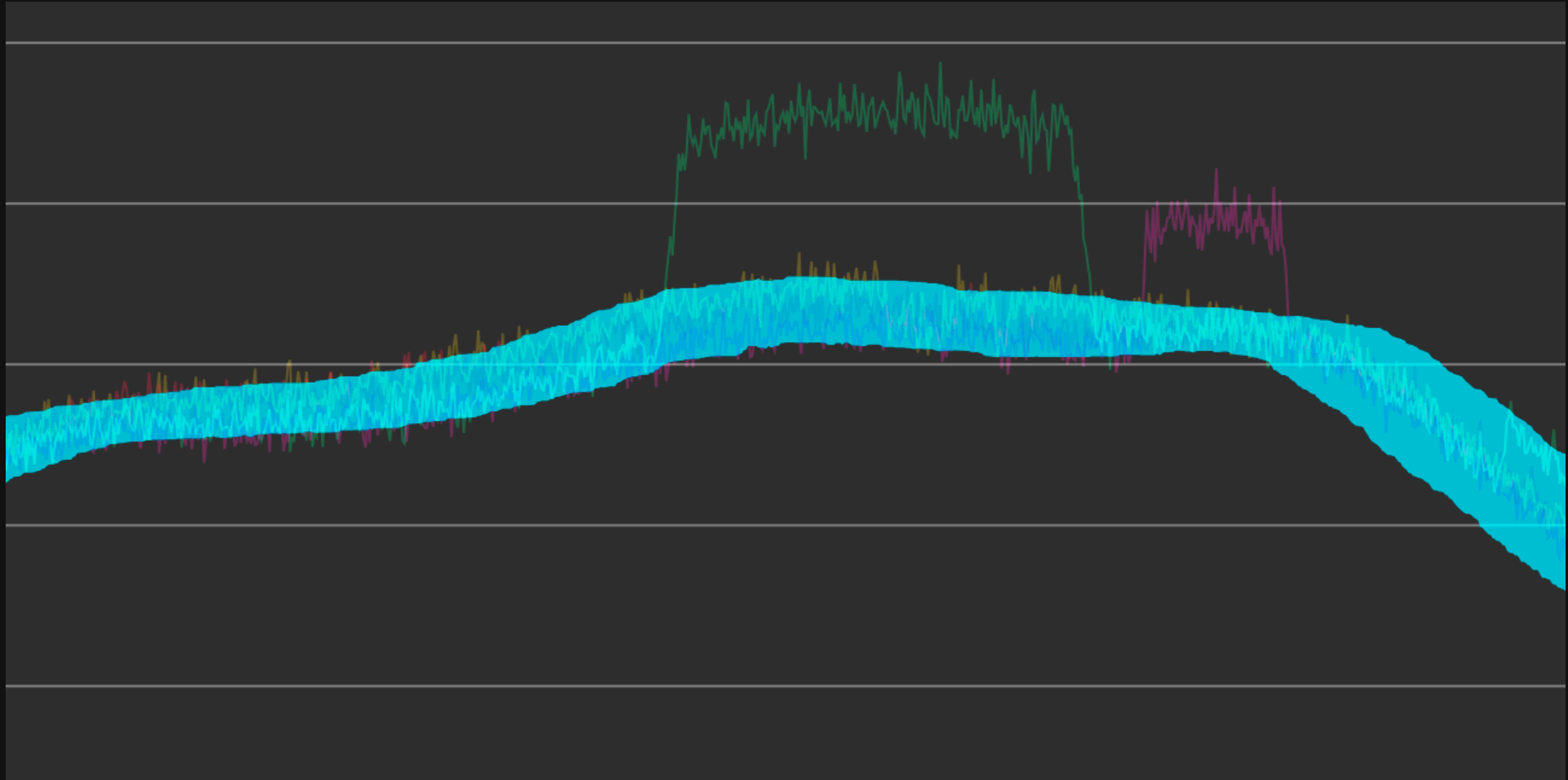
Raw data



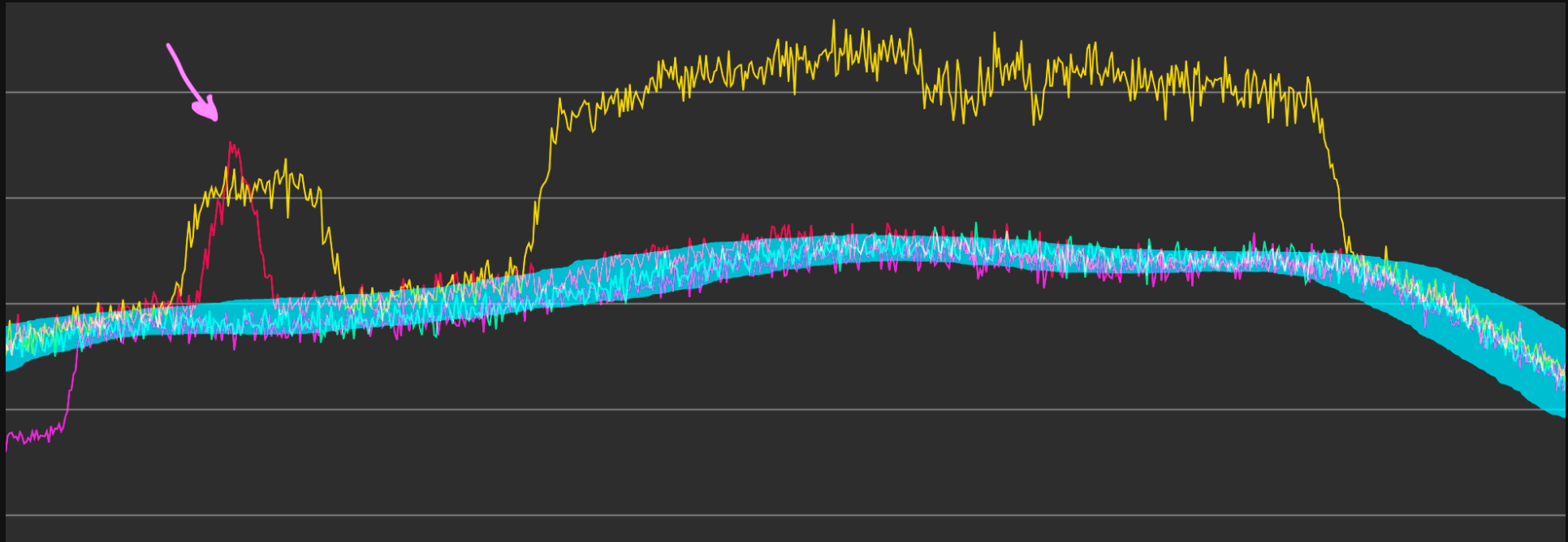
Absolute z-score



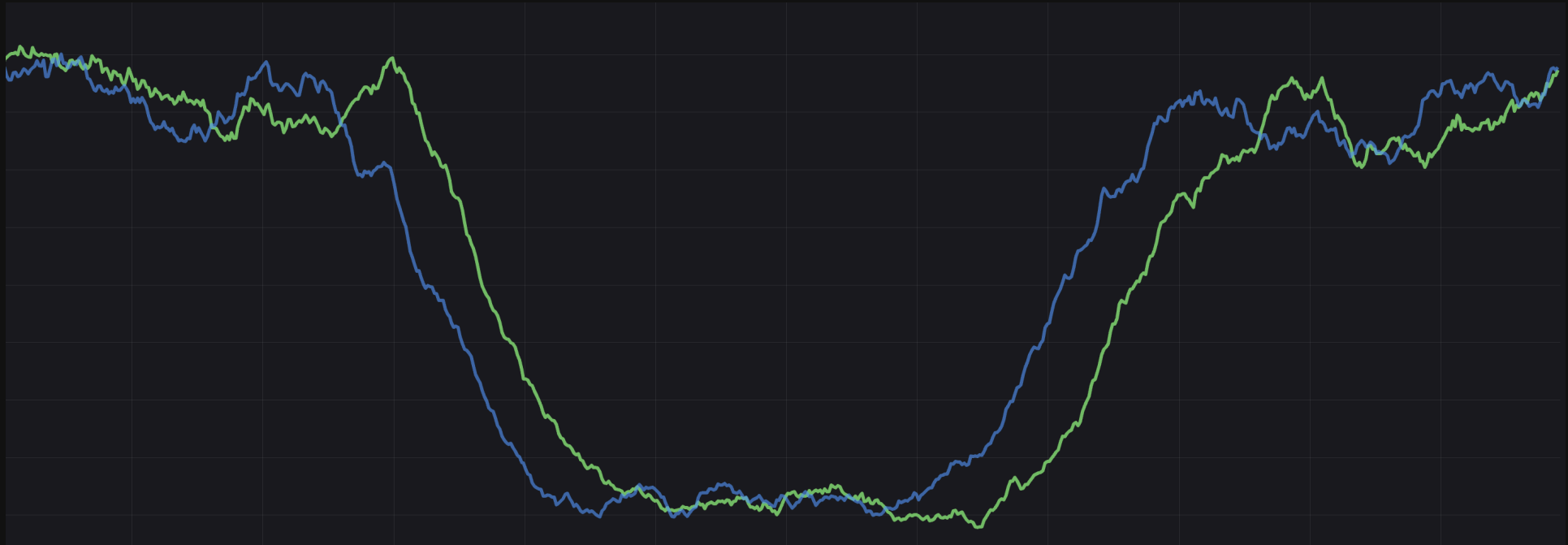
# Result with 5th percentile



# Overlapping incidents



# Problem #2: DST



# Problem #2: DST

```
func sameTimeWeeksAgo(currentTime time.Time, weeksAgo int) time.Time {
    t := currentTime.Add(-time.Duration(weeksAgo*minutesInWeek) * time.Minute)
    _, cOffset := currentTime.Zone()
    _, tOffset := t.Zone()
    diff := cOffset - tOffset
    return t.Add(time.Duration(diff) * time.Second)
}
```

# Problem #2: DST

- Not all countries have DST
- Some users do not adapt instantly to new time

# Problem #3: Overperforming



# Problem #3: Overperforming

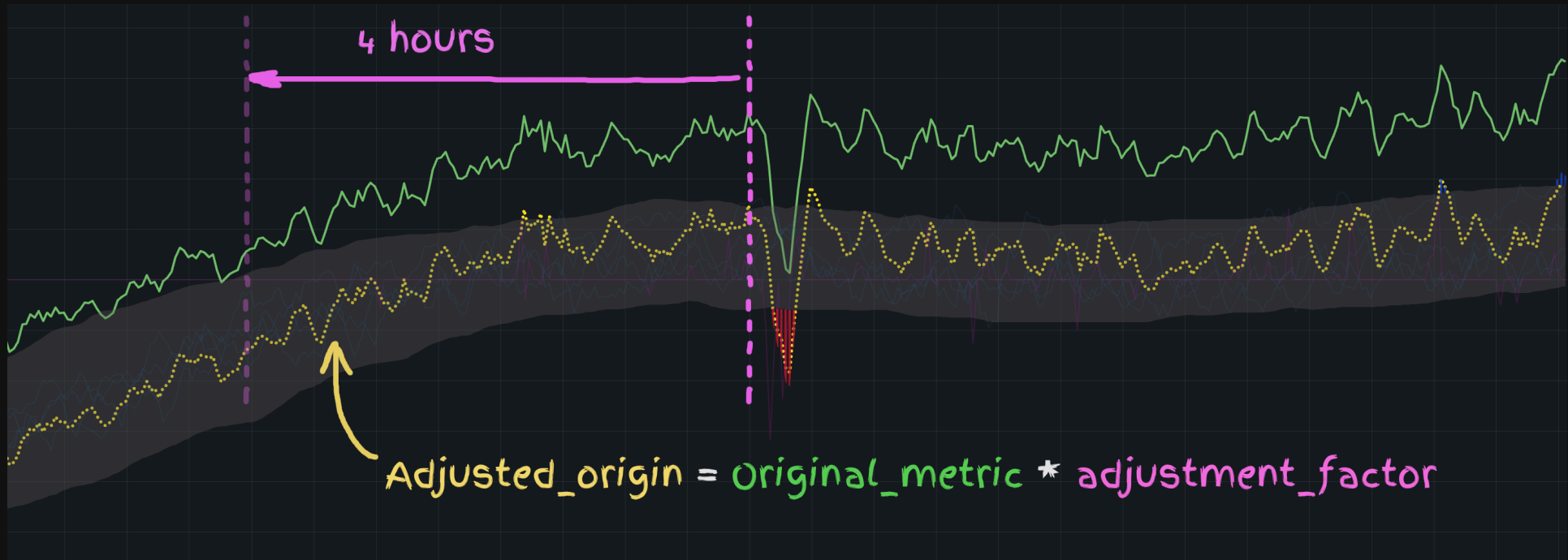




# Problem #3: Overperforming



# Problem #3: Overperforming



# Problem #4: Known events

```
corrections:  
  nightly:  
    baseline: 0  
    daily:  
      - constant: 6  
        ranges:  
          - ['00:00', '09:00']  
  
  weekends:  
    baseline: 0  
    weekly:  
      - constant: 10  
        days: ['Saturday', 'Sunday']  
  
  holidays:  
    baseline: 0  
    calendar:  
      - name: 'Ascension Day'  
        constant: 10  
        ranges:  
          - ['2023-05-18 00:00', '2023-05-18 23:59']
```



# Problem #5: Complexity

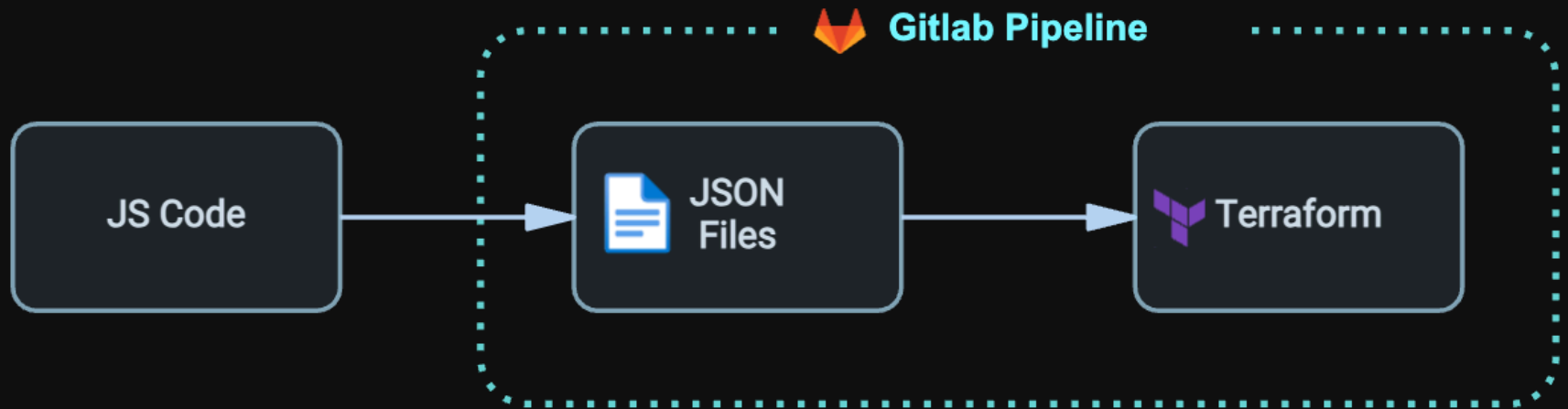
▼ P (Graphite Prod)



```
alias(sumSeries(minSeries(transformNull(removeAboveValue(diffSeries(movingAverage
(sum(some.example.metric.count), '$smoothing'),
multiplySeries(movingAverage(some.example.metric.percentiles.$percentile.lower,
'$smoothing'), offset(scale(movingAverage(some.example.metric.correction,
'$smoothing'), -0.01), 1))), 0), 0),
transformNull(removeAboveValue(diffSeries(multiplySeries(movingAverage(sum(some.e
xample.metric.count), '$smoothing'),
movingAverage(some.example.metric.origin_adjustment.scale, '$smoothing'))),
multiplySeries(movingAverage(some.example.metric.percentiles.$percentile.lower,
'$smoothing'), offset(scale(movingAverage(some.example.metric.correction,
'$smoothing'), -0.01), 1))), 0), 0)),
transformNull(removeBelowValue(diffSeries(movingAverage(sum(some.example.metric.c
ount), '$smoothing'),
multiplySeries(movingAverage(some.example.metric.percentiles.$percentile.upper,
'$smoothing'), offset(scale(movingAverage(some.example.metric.correction,
'$smoothing'), 0.01), 1))), 0), 0)), 'offset')
```



# Dashboards as code



```
class QueryBuilder {
  constructor(target) {
    this.target = target;
  }
  groupByNodes(operator, ...indices) {
    return new QueryBuilder(`groupByNodes(${this.target}, '${operator}', ${indices.join(',')})`);
  }

  sum() {
    return new QueryBuilder(`sum(${this.target})`);
  }

  movingAverage(period) {
    return new QueryBuilder(`movingAverage(${this.target}, '${period}')`);
  }

  divideSeries(otherSeries) {
    return new QueryBuilder(`divideSeries(${this.target}, ${otherSeries})`);
  }

  multiplySeries(otherSeries) {
    return new QueryBuilder(`multiplySeries(${this.target}, ${otherSeries})`);
  }

  maxSeries(...series) {
```

```
const rise = query(current.build())
    .diffSeries(upper.build())
    .removeBelowValue(0)
    .transformNull(0);

const drop = query(current.build())
    .diffSeries(lower.build())
    .removeAboveValue(0)
    .transformNull(0);

const dropAdjusted = query(adjustedCurrent.build())
    .diffSeries(lower.build())
    .removeAboveValue(0)
    .transformNull(0);

const finalDrop      = drop.minSeries(dropAdjusted.build());
const offset         = finalDrop.sumSeries(rise.build());
const slowBurnOffset = drop.sumSeries(rise.build());
```

```
const rise = query(current.build())
    .diffSeries(upper.build())
    .removeBelowValue(0)
    .transformNull(0);

const drop = query(current.build())
    .diffSeries(lower.build())
    .removeAboveValue(0)
    .transformNull(0);

const dropAdjusted = query(adjustedCurrent.build())
    .diffSeries(lower.build())
    .removeAboveValue(0)
    .transformNull(0);

const finalDrop      = drop.minSeries(dropAdjusted.build());
const offset         = finalDrop.sumSeries(rise.build());
const slowBurnOffset = drop.sumSeries(rise.build());
```

⌵ L (Graphite Prod)



Series some example metric select metric



Functions movingAverage(5min) diffSeries(#K) removeBelowValue(0) transformNull(0) alias(drop\_U) +



# Understanding the anomaly



Breakdown by Regions, Devices, Order/Users types, Marketing channels etc.

# Recap

- Basic statistics works for detecting anomalies
- User driven metric is better for anomaly detection
- Median absolute deviation vs Standard Deviation
- Grafana can be used for complex calculations
- Understanding anomaly is harder than detecting it.

**Thank you!**