

# Lessons Learned Developing and Managing High Volume Apache Spark Pipelines in Production

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#SAISML4

# Over 350,000 connected homes across Europe

Our partners:



Interpolis.



Launched in 2012

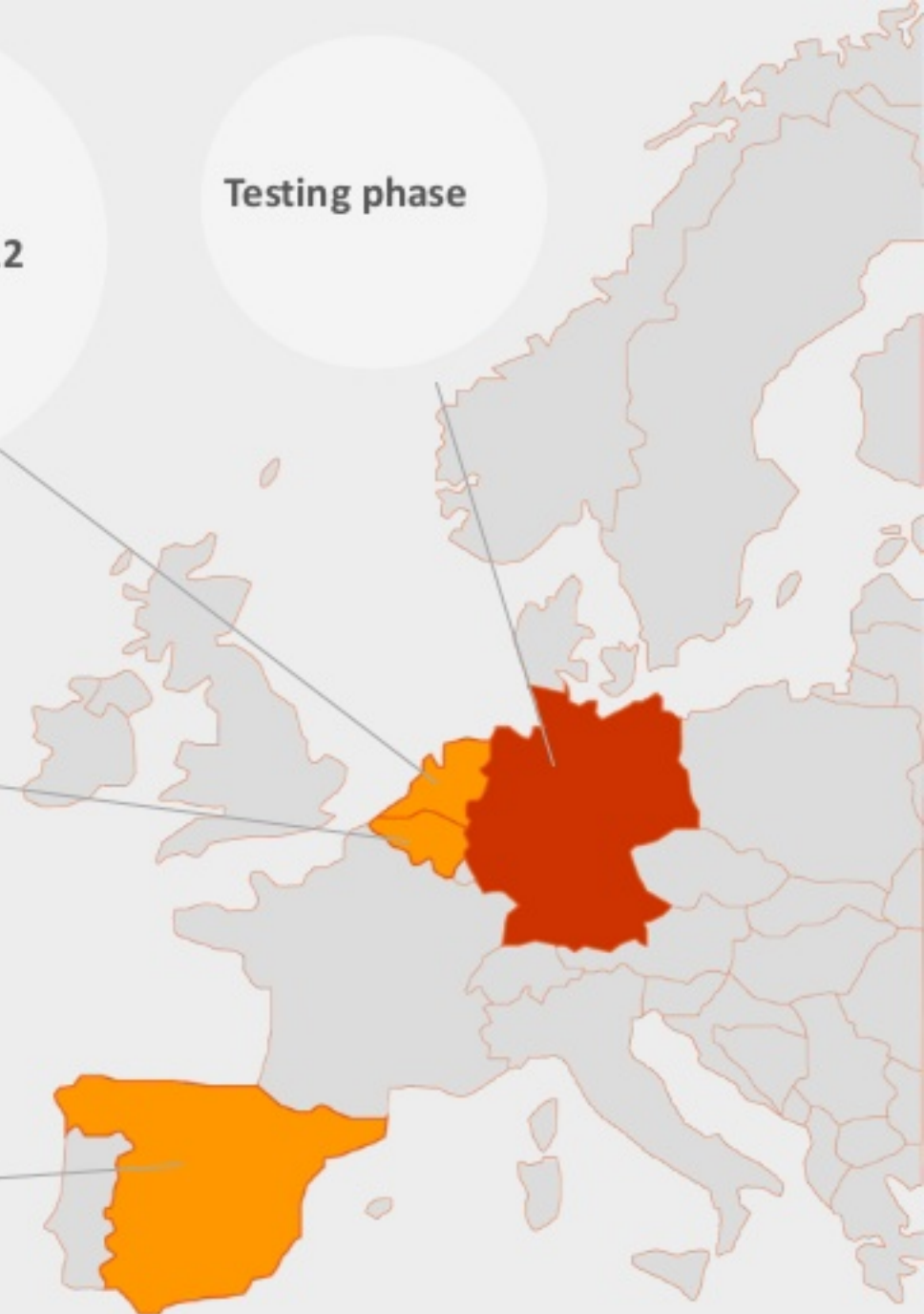
Testing phase

Launched in 2016

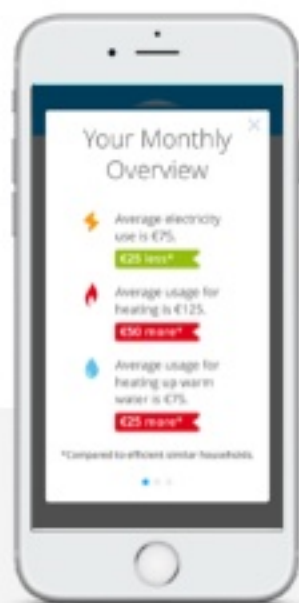
Launched in 2017

Toon available

Toon in testphase



# TOON



ENERGY  
INSIGHTS APP



SMART METER  
DONGLE & APP



SMART THERMOSTAT &  
APP



SECURITY  
PACKAGE & APP

## DATA SERVICES

WASTE CHECKER

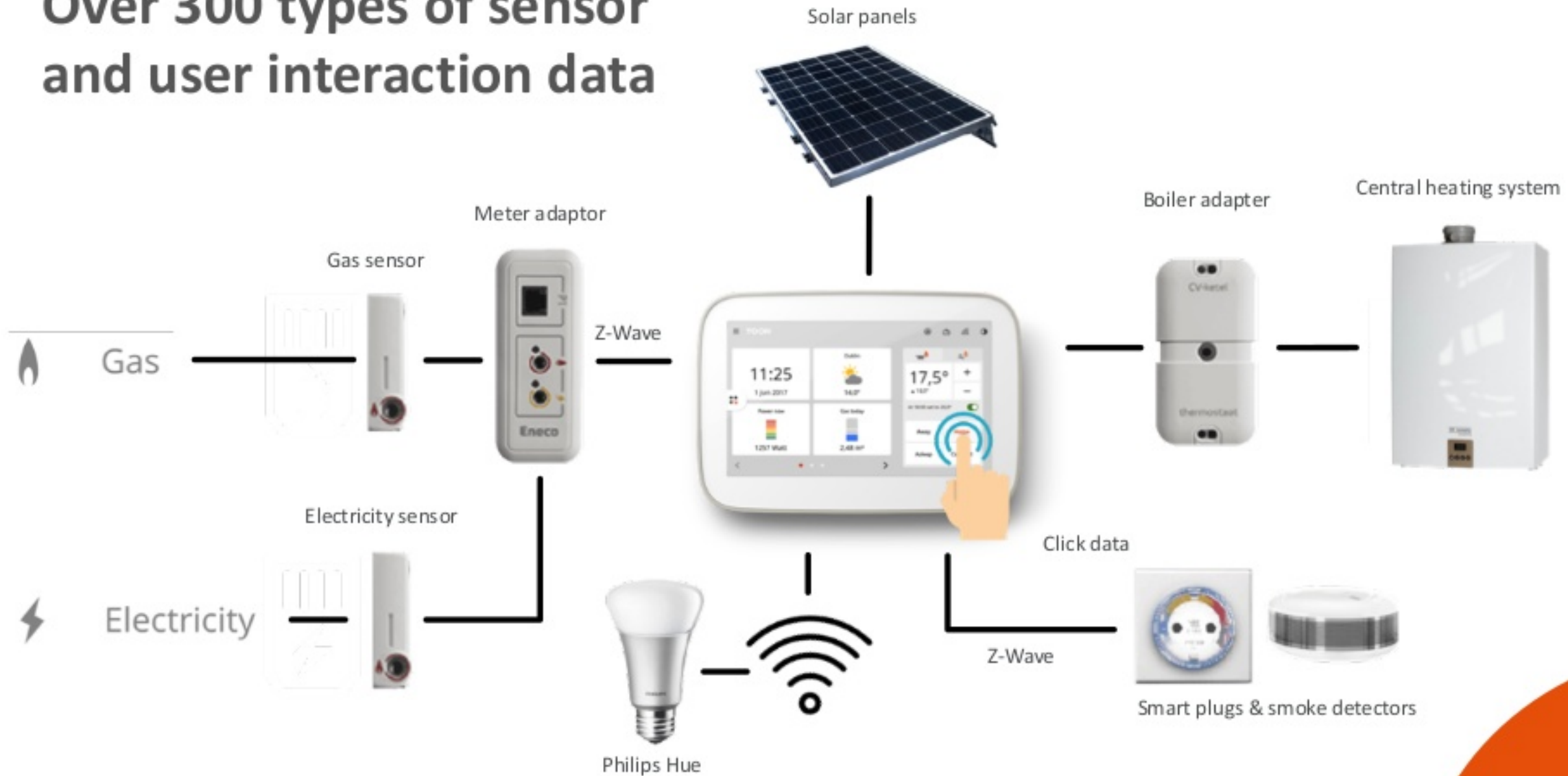
WATER INSIGHT

MONTHLY ENERGY  
INSIGHT

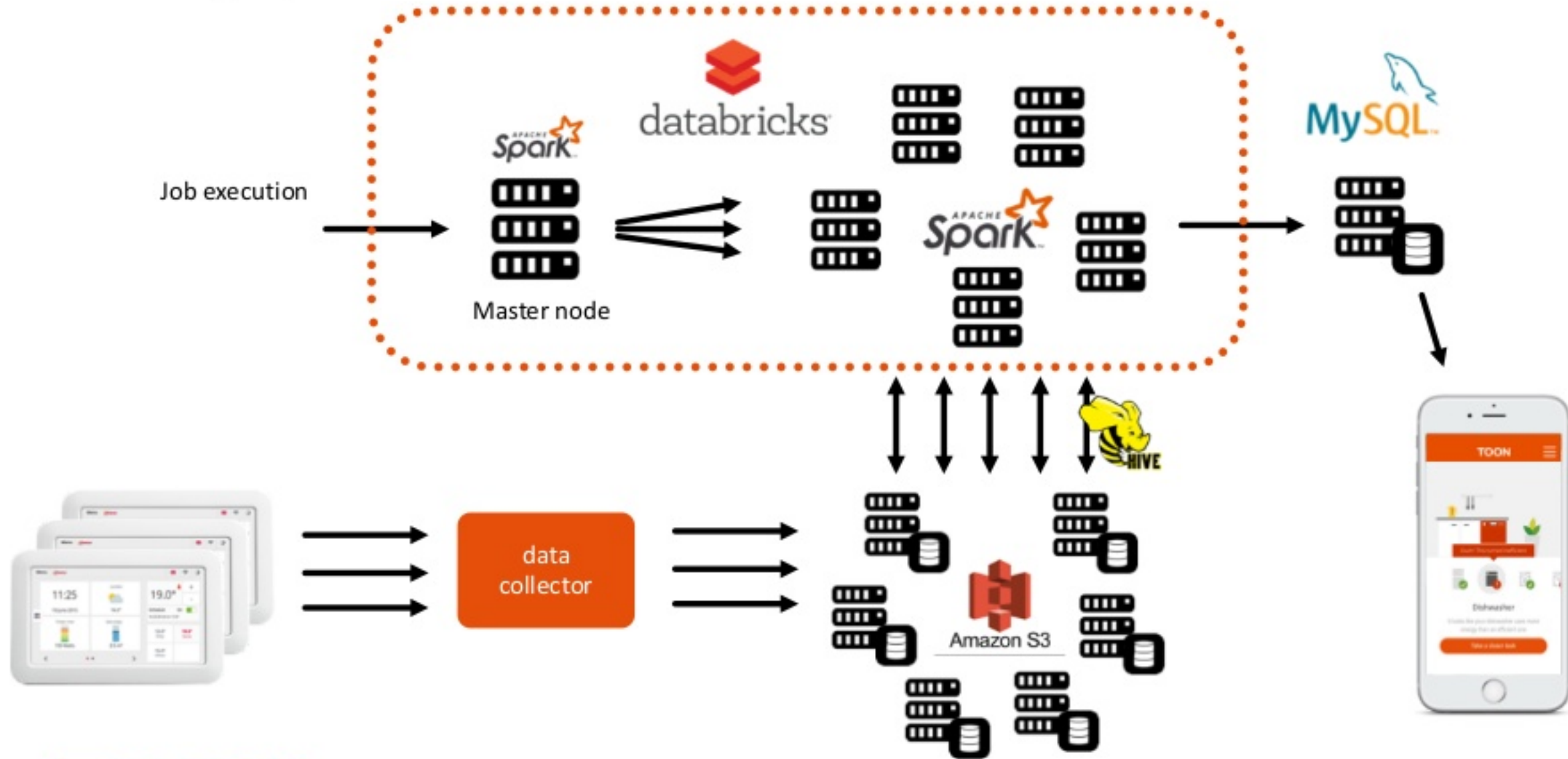
TOON SOLAR

BOILER MONITORING

# Over 300 types of sensor and user interaction data



# Batch pipeline





# USE CASE #1

## Waste Checker



# Energy Waste Checker

*"We don't always notice how much energy we're wasting. Toon can now expose the energy guzzlers in your home."*

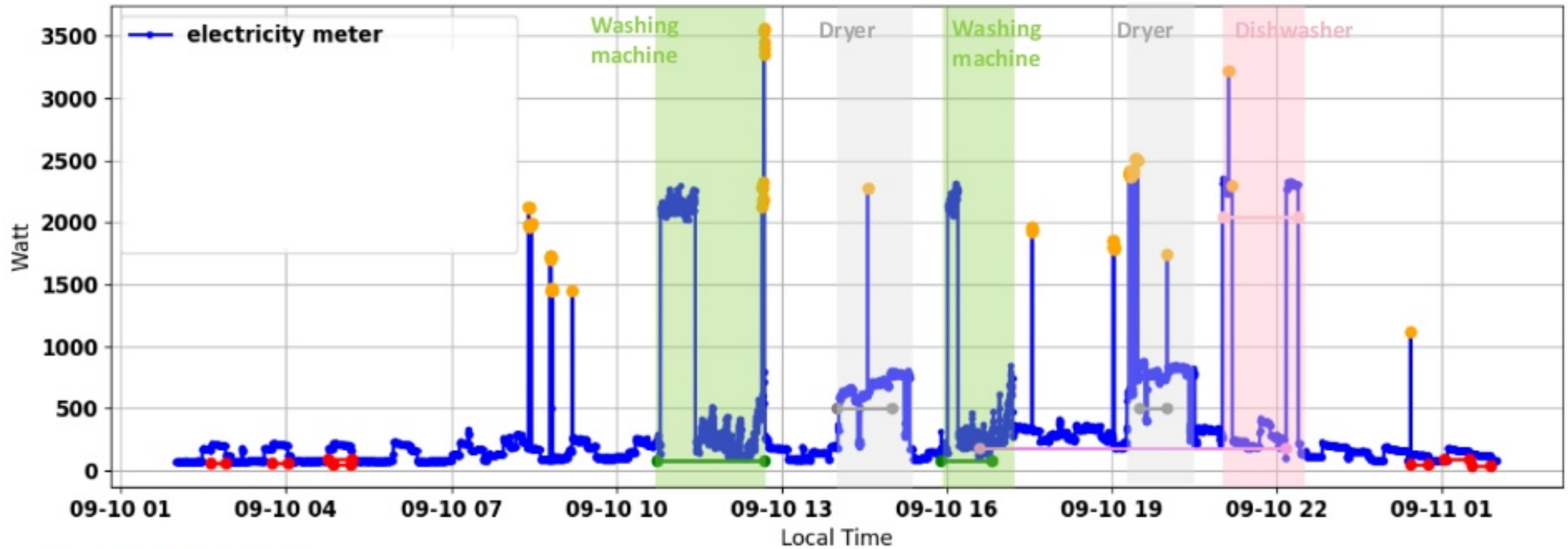
Launched in December 2017 to all  
Eneco Toon users

**TOON**<sup>®</sup>  
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# Quby's disaggregation algorithms

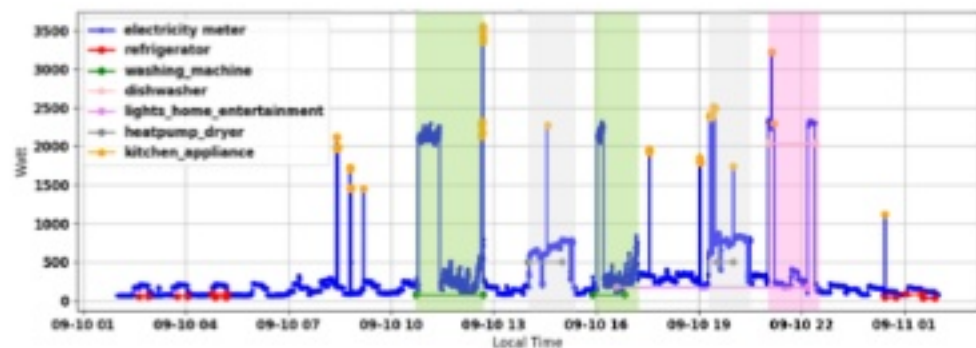
Patent pending algorithms can detect appliances from 10 second resolution electricity meter data



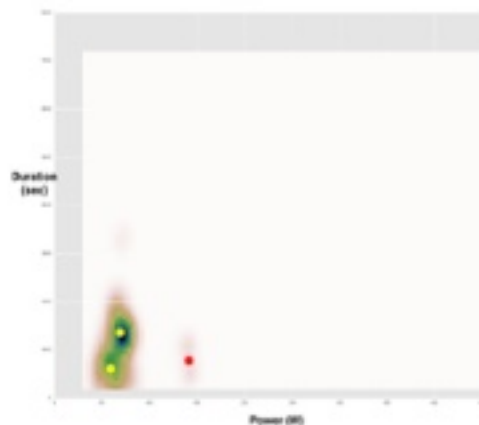


# Use case example: Inefficient dishwasher diagnosis

Disaggregation algorithms run on the 10s electricity meter data



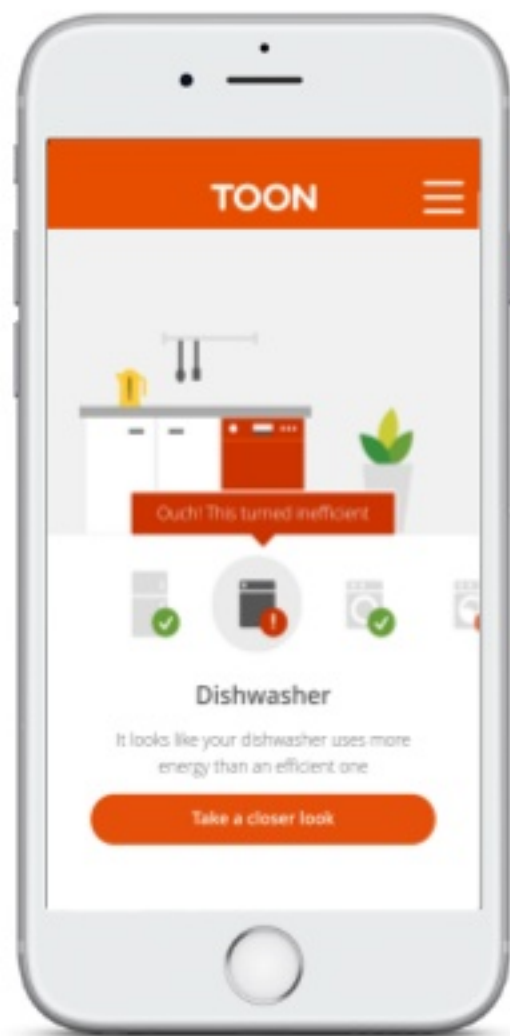
Toon determines the “fingerprint” of the appliance through features



Compared with industry standards and peers



Translated to personalised advice for the end user



## Scale of the Waste checker

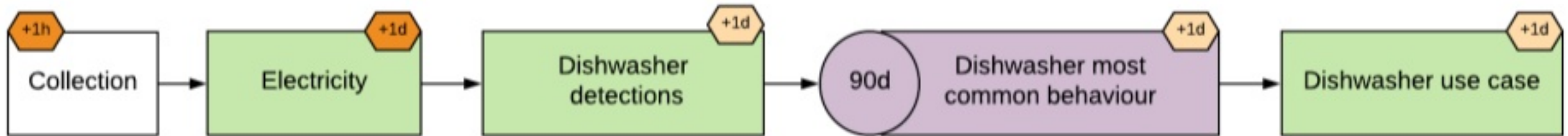
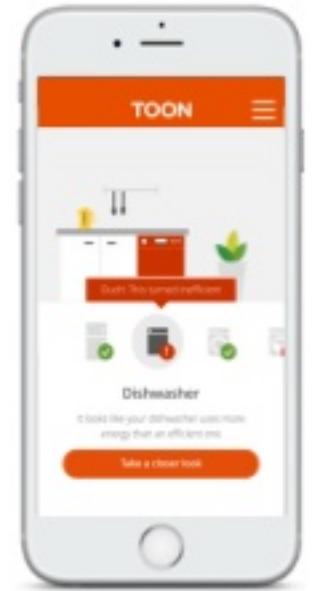


Each day we detect over  
**75,000** dishwasher  
cycles

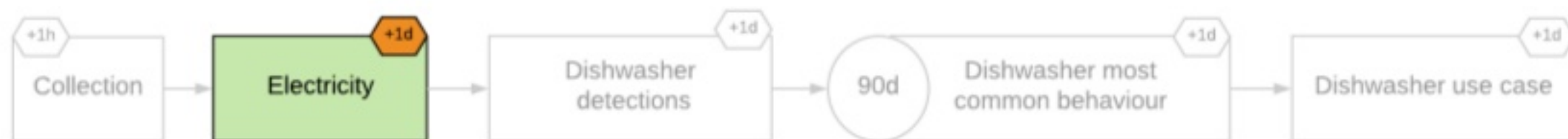
That's  
**13 years**  
of dishwashers running  
continuously

and over  
**25%** are  
used  
inefficiently

# Example data flow

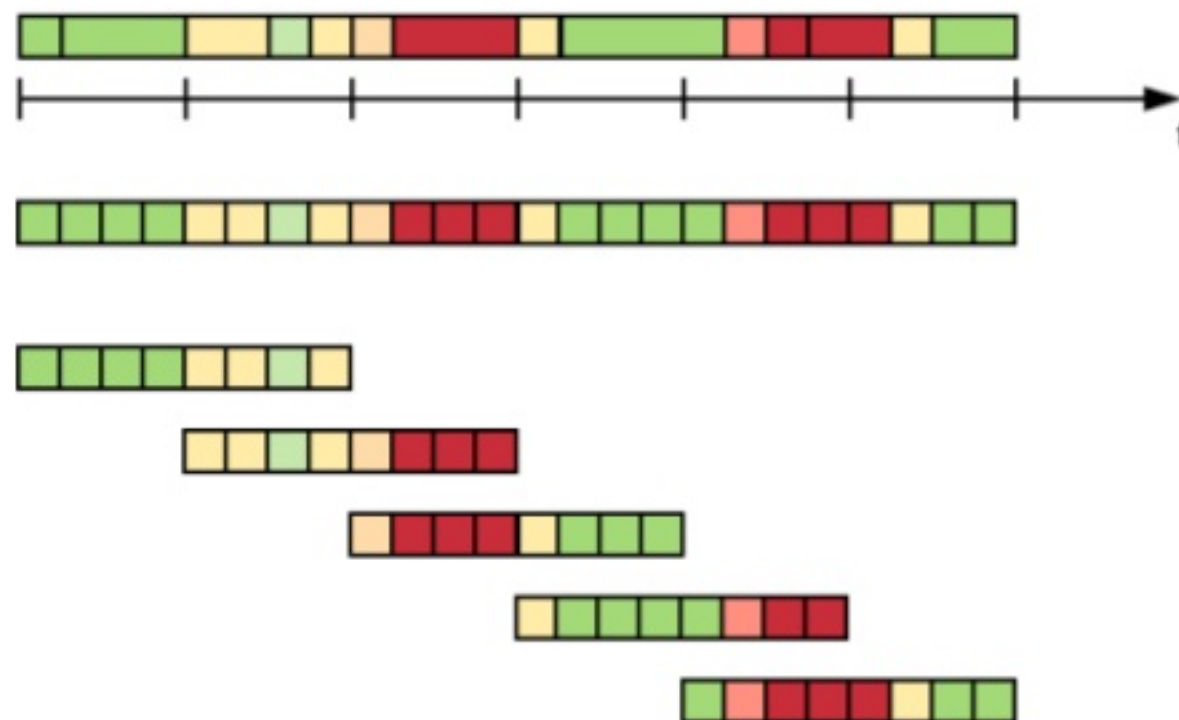


# Example data flow

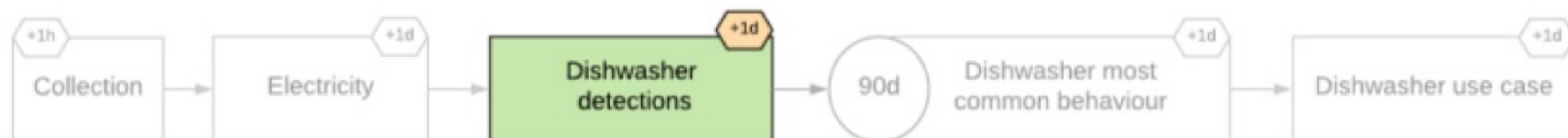


## Getting the data ready

- Extraction & Cleaning
- Resampling
- Vectorization



# Example data flow



## Detecting appliances

- **Signal processing**
- Machine learning  
(One Big model)



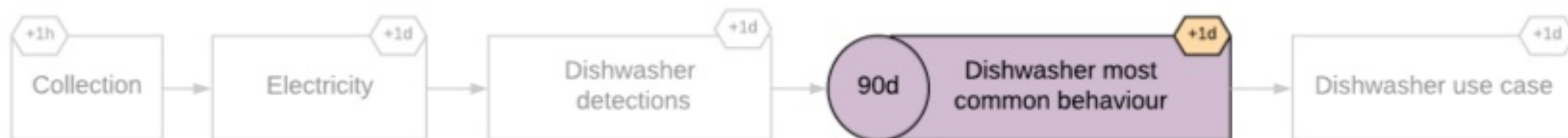
Vectorized electricity



Predictions

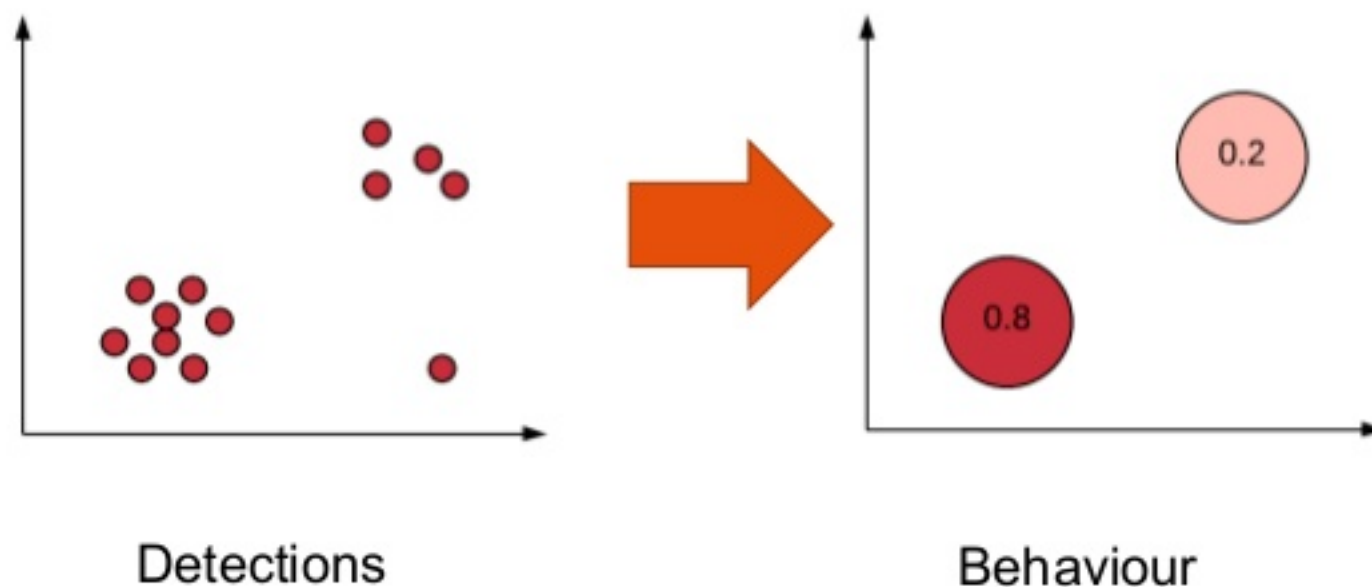


# Example data flow

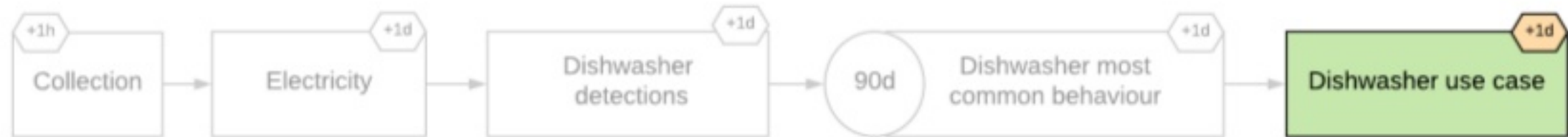


## Finding user behavior

- Clustering per user
- Many, many, **many** (small) models

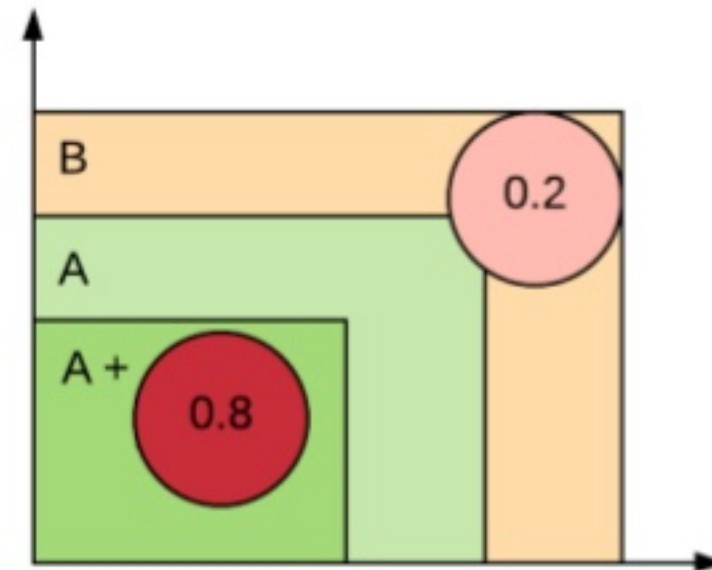


# Example data flow

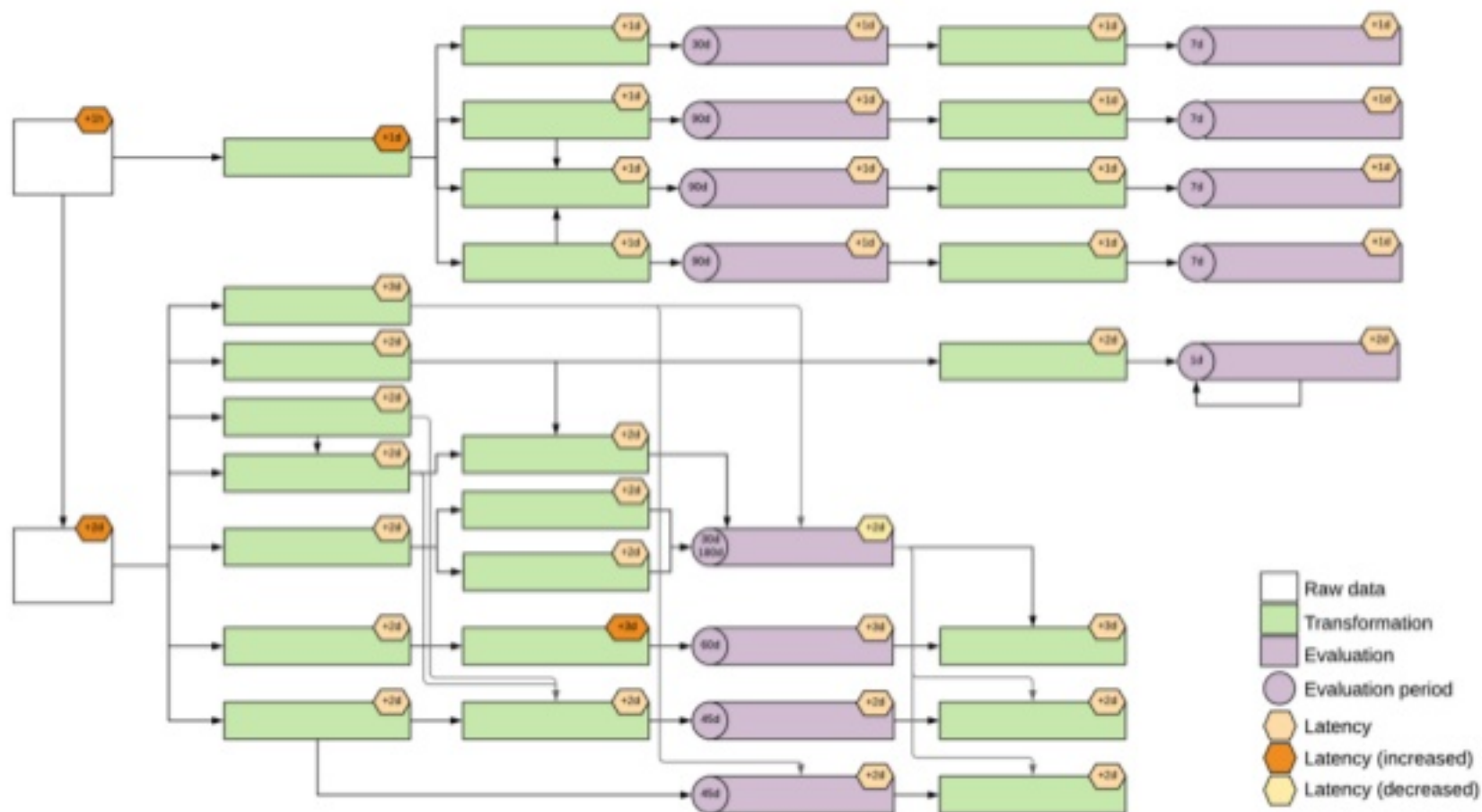


## Drawing conclusions

- Comparing to other users
- Comparing to industry standards



# The Data Pipeline



# Managing jobs (Option 1)

- Databricks Jobs & Notebook Workflows

<https://databricks.com/blog/2016/08/30/notebook-workflows-the-easiest-way-to-implement-apache-spark-pipelines.html>

## Active runs

Run	Run ID	Start Time	Launched	Duration	Spark	Status
<a href="#">Run Now / Run Now With Different Parameters</a>						

## Completed in past 60 days

[Latest successful run \(refreshes automatically\)](#)

< Previous 20

[Next 20 >](#)

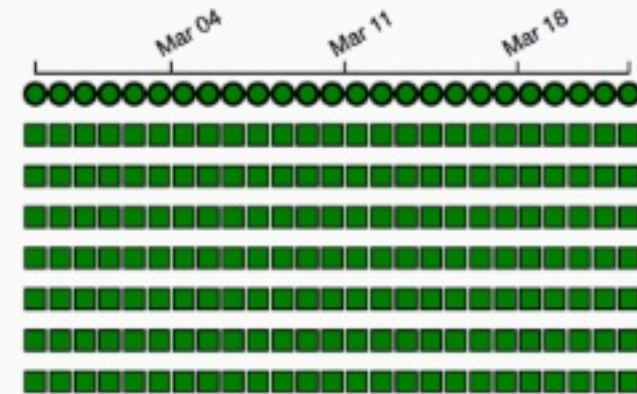
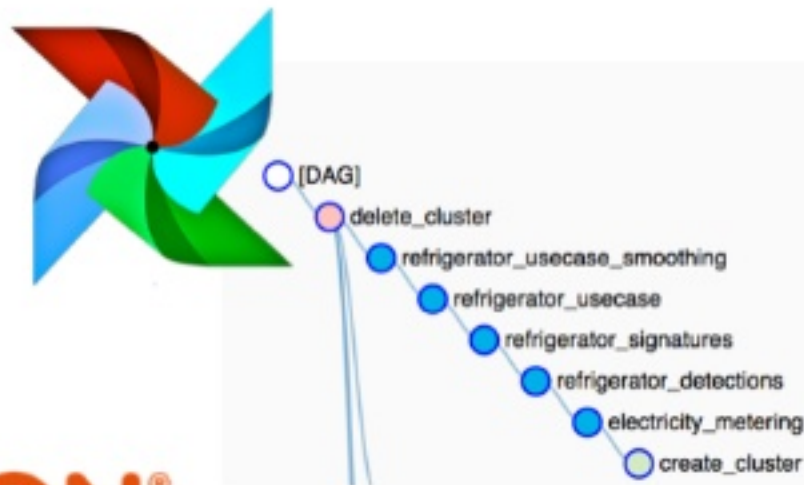
Run	Run ID	Start Time	Launched	Duration	Spark	Status	
<a href="#">Run 206</a>	114438	2018-09-28 11:21:46 CEST	Manually	47m 57s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Succeeded	✕
<a href="#">Run 205</a>	114350	2018-09-28 04:00:00 CEST	By scheduler	3m 26s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Failed	✕
<a href="#">Run 204</a>	114109	2018-09-27 04:00:00 CEST	By scheduler	44m 54s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Succeeded	✕
<a href="#">Run 203</a>	113874	2018-09-26 04:00:01 CEST	By scheduler	46m 27s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Succeeded	✕
<a href="#">Run 202</a>	113635	2018-09-25 04:00:00 CEST	By scheduler	46m 35s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Succeeded	✕
<a href="#">Run 201</a>	113370	2018-09-24 04:00:00 CEST	By scheduler	46m 31s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Succeeded	✕
<a href="#">Run 200</a>	113132	2018-09-23 04:00:00 CEST	By scheduler	45m 22s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Succeeded	✕
<a href="#">Run 199</a>	112893	2018-09-22 04:00:00 CEST	By scheduler	45m 45s	<a href="#">Spark UI</a> / <a href="#">Logs</a> / <a href="#">Metrics</a>	Succeeded	✕

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# Managing jobs (Option 2)

- Airflow DAGs  
<https://airflow.apache.org/>
- Must read:
  - ETL principles: <https://gtoonstra.github.io/etl-with-airflow/principles.html>
  - Gotcha's: <https://gtoonstra.github.io/etl-with-airflow/gotchas.html>



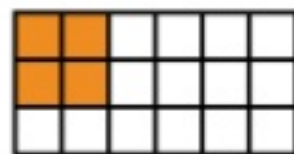
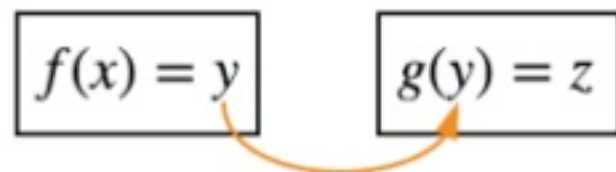
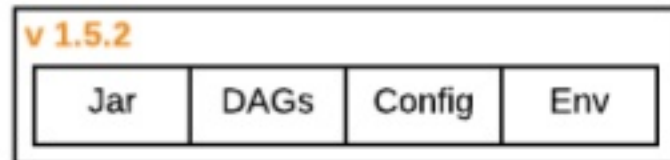


# When designing data pipelines

- Enforce idempotent constraints
- Enforce reproducibility
- Let data transformations be chainable
- Leverage partitioning and data locality

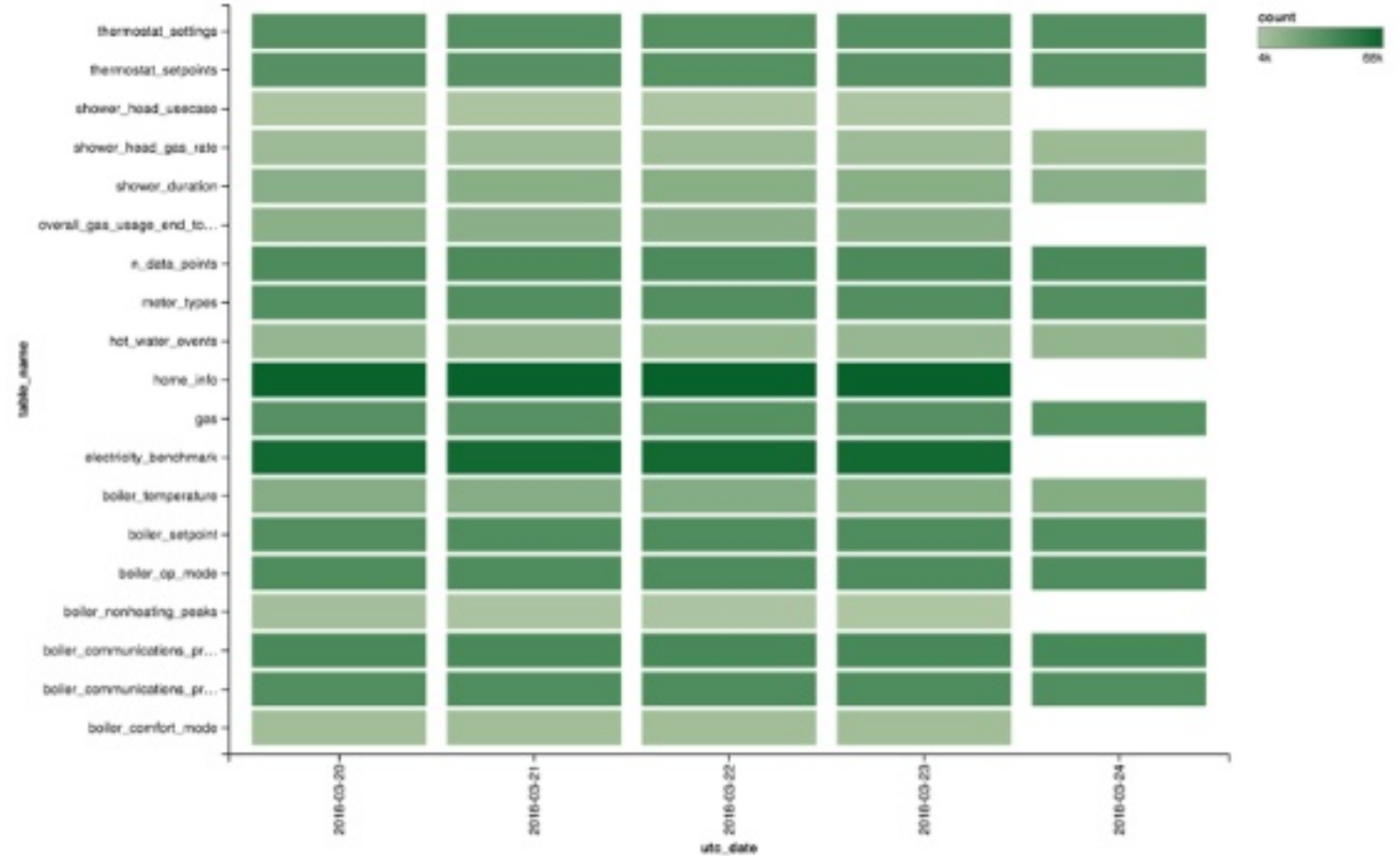
$$f(x) = y$$

Always



# Monitoring

- Live dashboards with aggregated data



# Monitoring and Validation

- Daily email to Quby's VIP employees

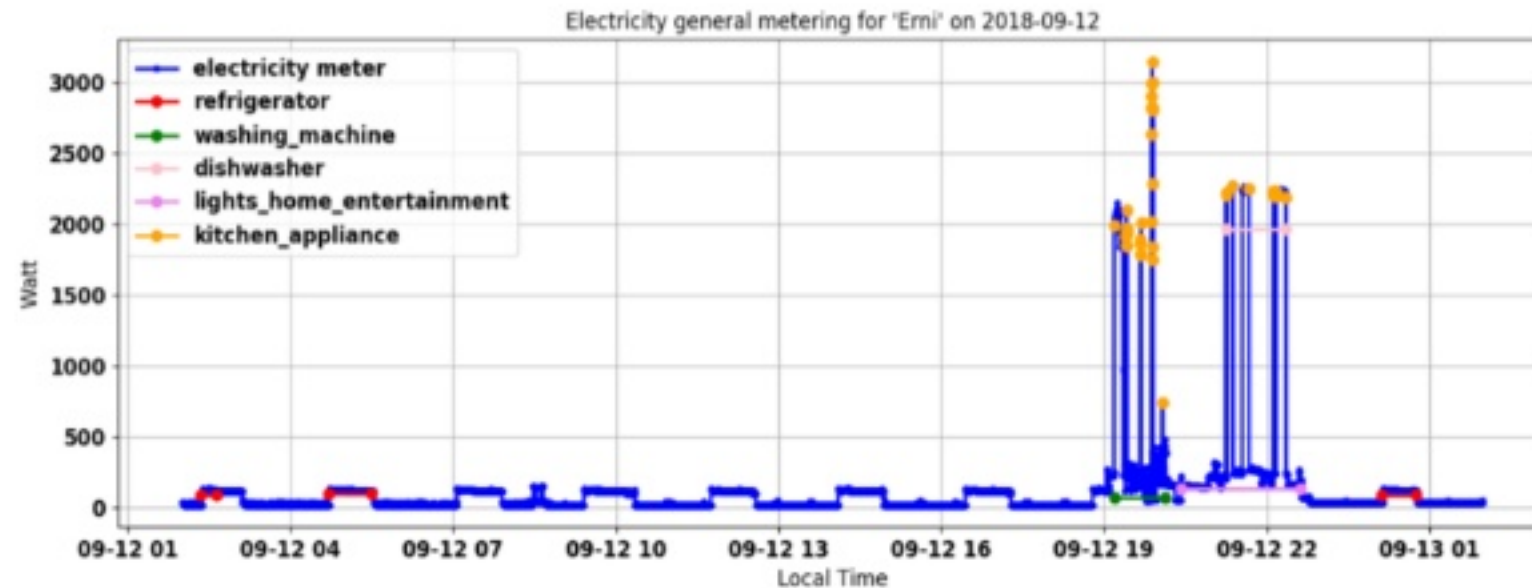
☆ Kaustav Basu @

Inbox - Exchange 13 September 2018 at 09:33

K

Energy Breakdown

To: erni.durdevic@quby.com



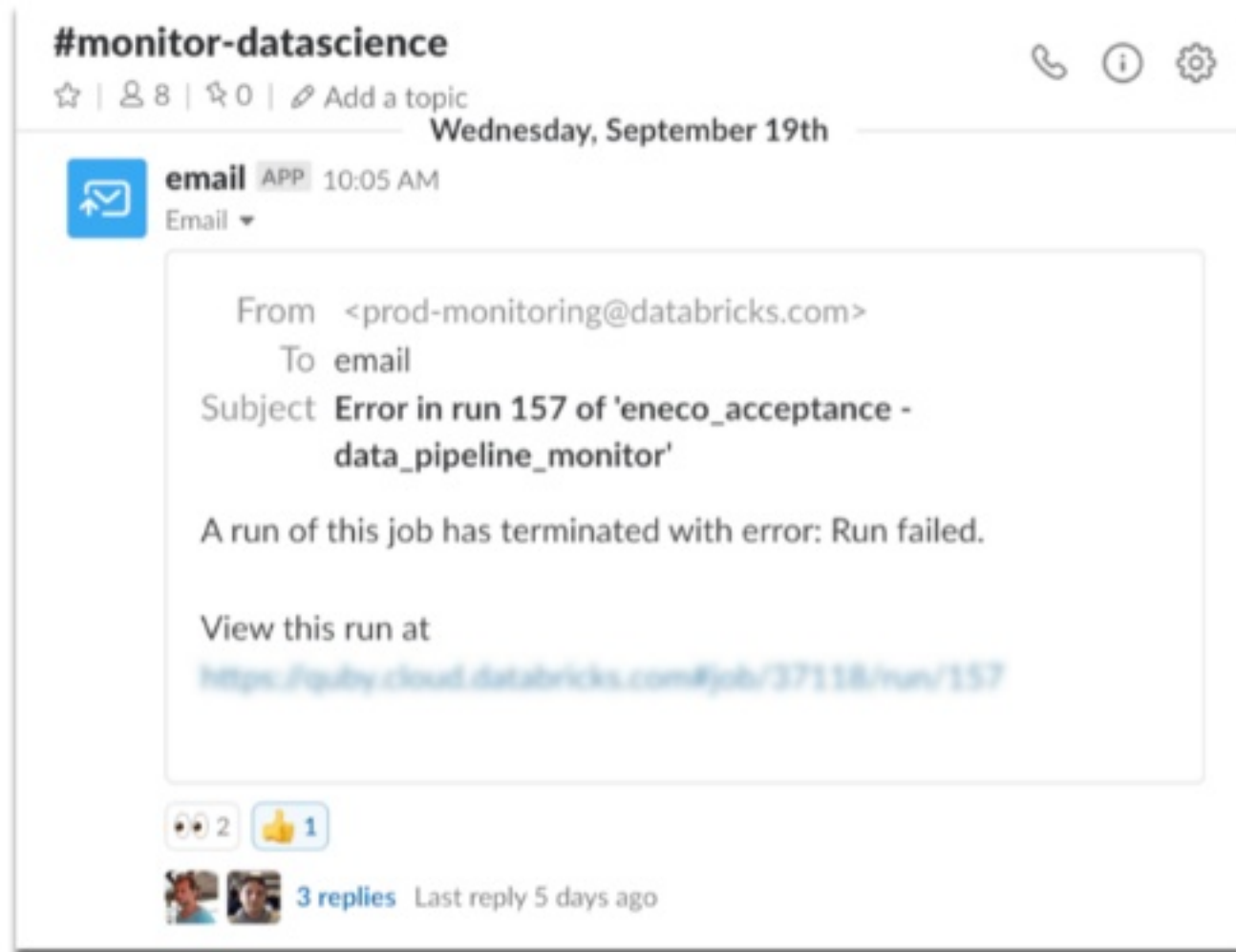
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# Alerting

## Alerting (via Email / Slack)

- If anything goes wrong
- If an independent monitoring job detects missing data



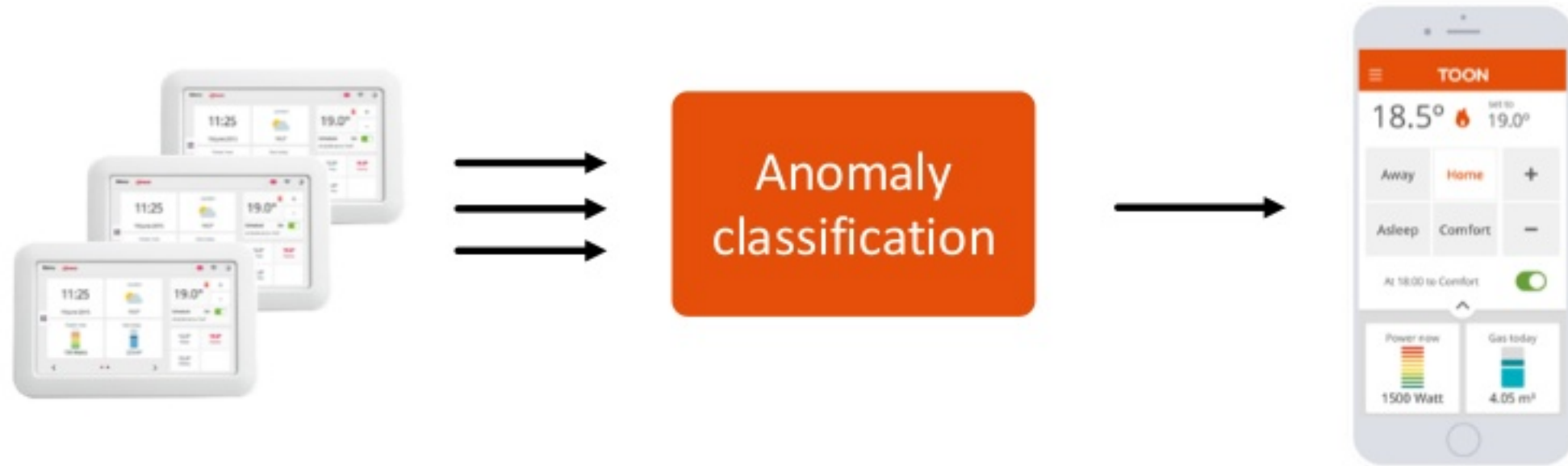
## USE CASE #2

# Detecting anomalies in heating systems





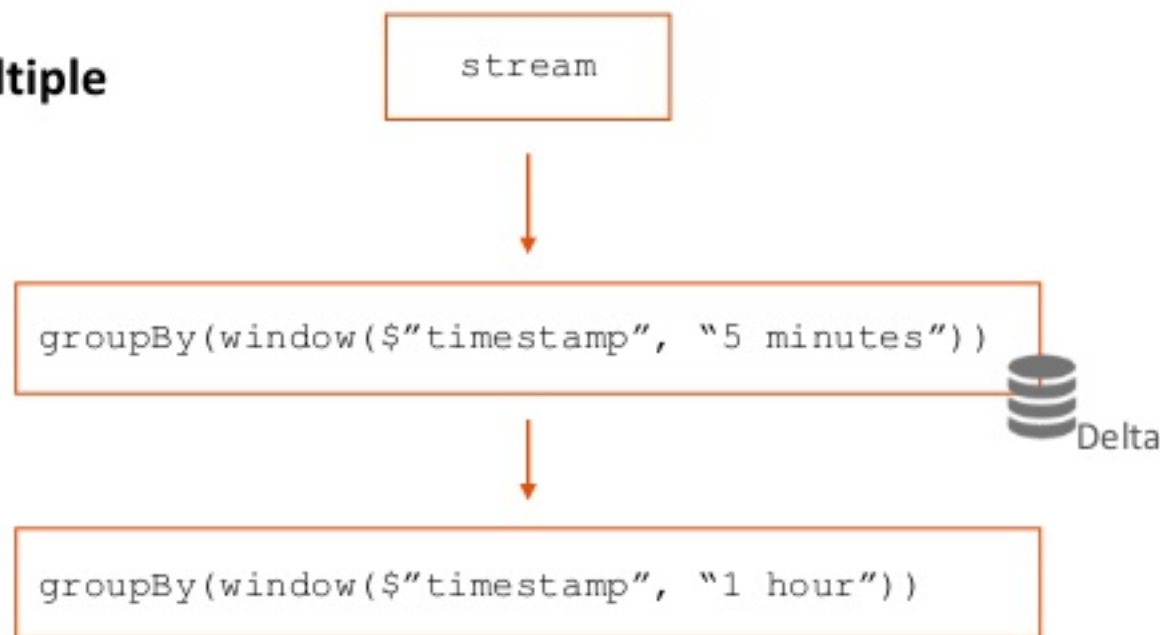
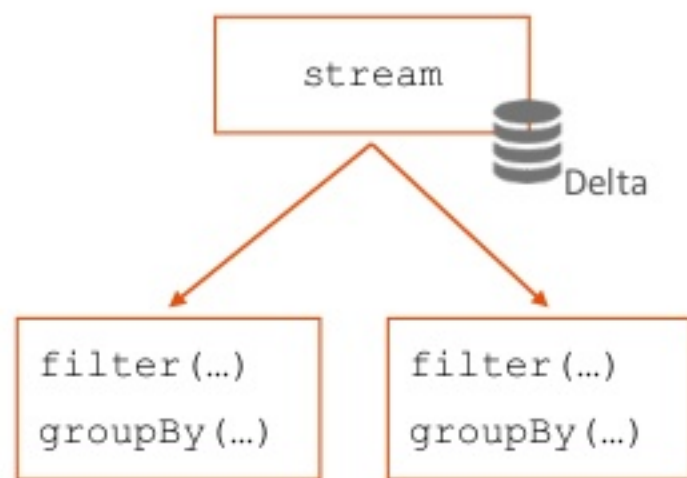
# Structured Streaming



# Multiple Streaming aggregations

When working with streams in spark it is not possible to do **multiple aggregations** on the same stream

- E.g. Forking a stream in multiple streams
- E.g. Do consecutive aggregations



## Work around

Output the aggregations on a sink and read it back in Spark (E.g. Kafka, Kinesis, Delta tables)

# Non time-based windows on streams

- When working with streams in spark it is not possible to compute **non time-based window** operations
  - E.g. Compute the derivative of a signal

## Our solution

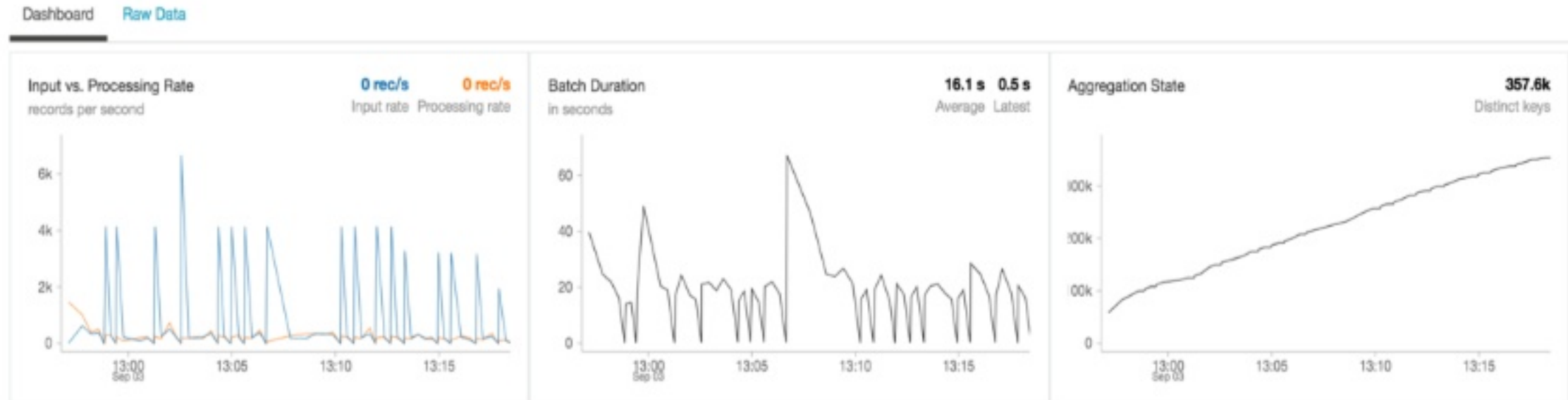
Compute **non time-based window** operations

- Use (Flat) mapGroupWithState (Beware: no ordering guarantee)
- Inside a time-based window by collecting a list of Struct(Timestamp, Value)

timestamp	lag(timestamp)
2018-10-04 14:00:00	
2018-10-04 15:00:00	2018-10-04 14:00:00
2018-10-04 16:00:00	2018-10-04 15:00:00

# Stream to stream joins

- When doing **stream to stream joins**, keep an eye on the distinct key count on aggregation state



# Streaming in production

- Structured Streaming in Production checklist
  - Setup recovery of queries from failure
    - Configure Checkpointing
    - Query restart
  - Configure Spark scheduler pool for efficiency
  - Optimize performance of stateful streaming queries
  - Configure multiple watermark policy

Reference: <https://docs.databricks.com/spark/latest/structured-streaming/production.html>





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