

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

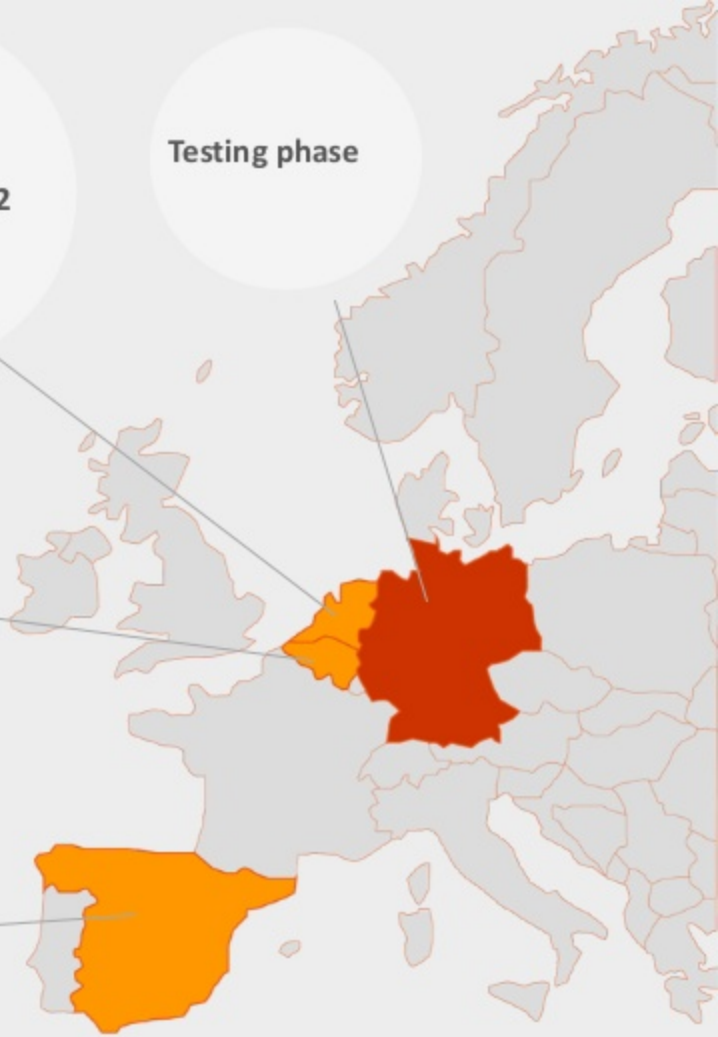
Testing phase

Launched in 2016

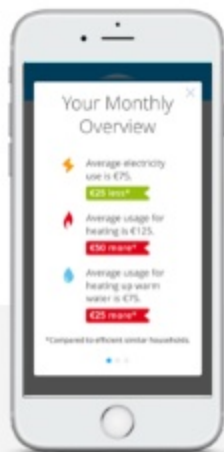
Launched in 2017

Toon available

Toon in testphase



TOON



ENERGY
INSIGHTS APP



SMART METER
DONGLE & APP



SMART THERMOSTAT &
APP



SECURITY
PACKAGE & APP

DATA SERVICES

WASTE CHECKER

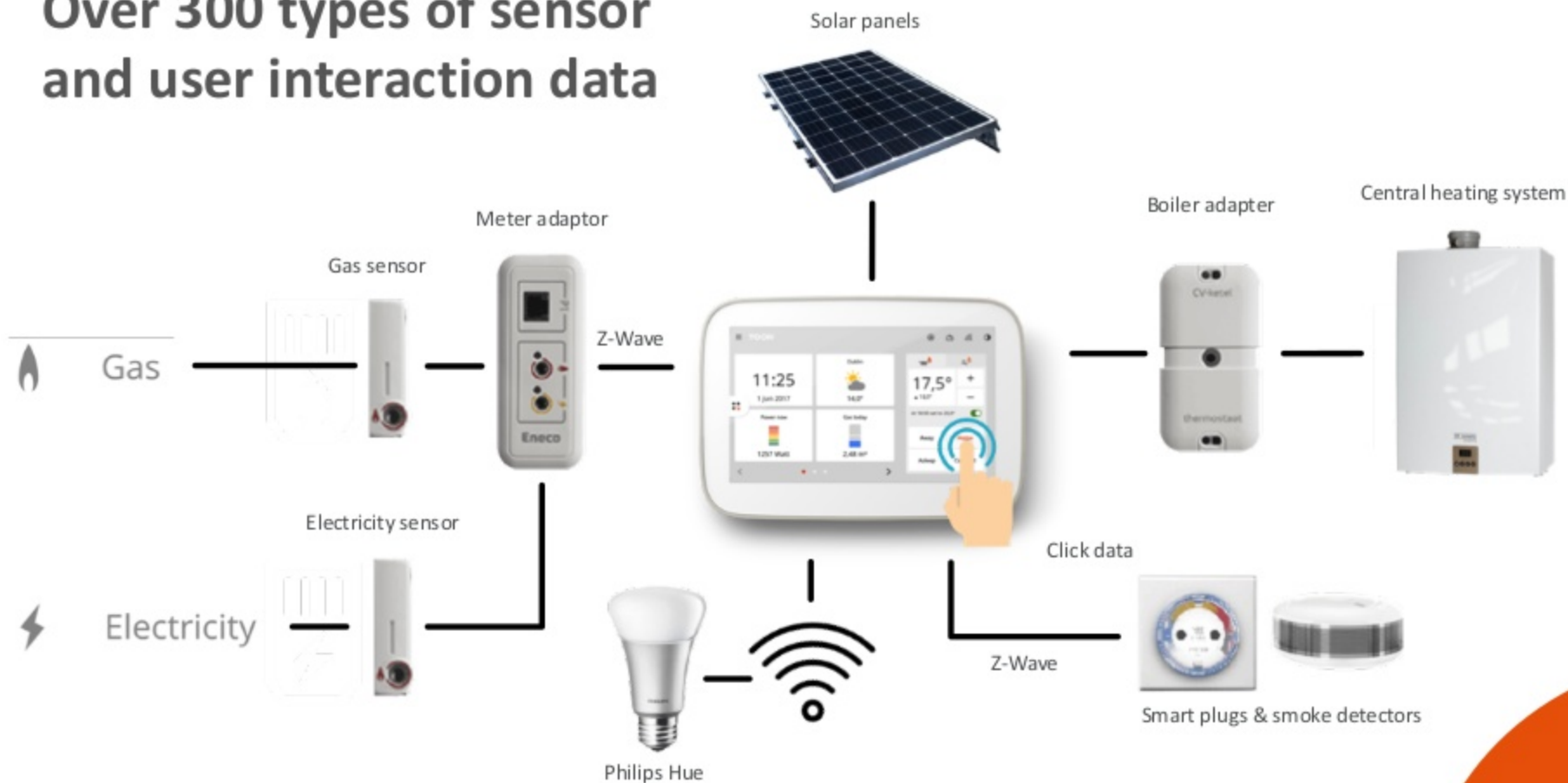
WATER INSIGHT

MONTHLY ENERGY
INSIGHT

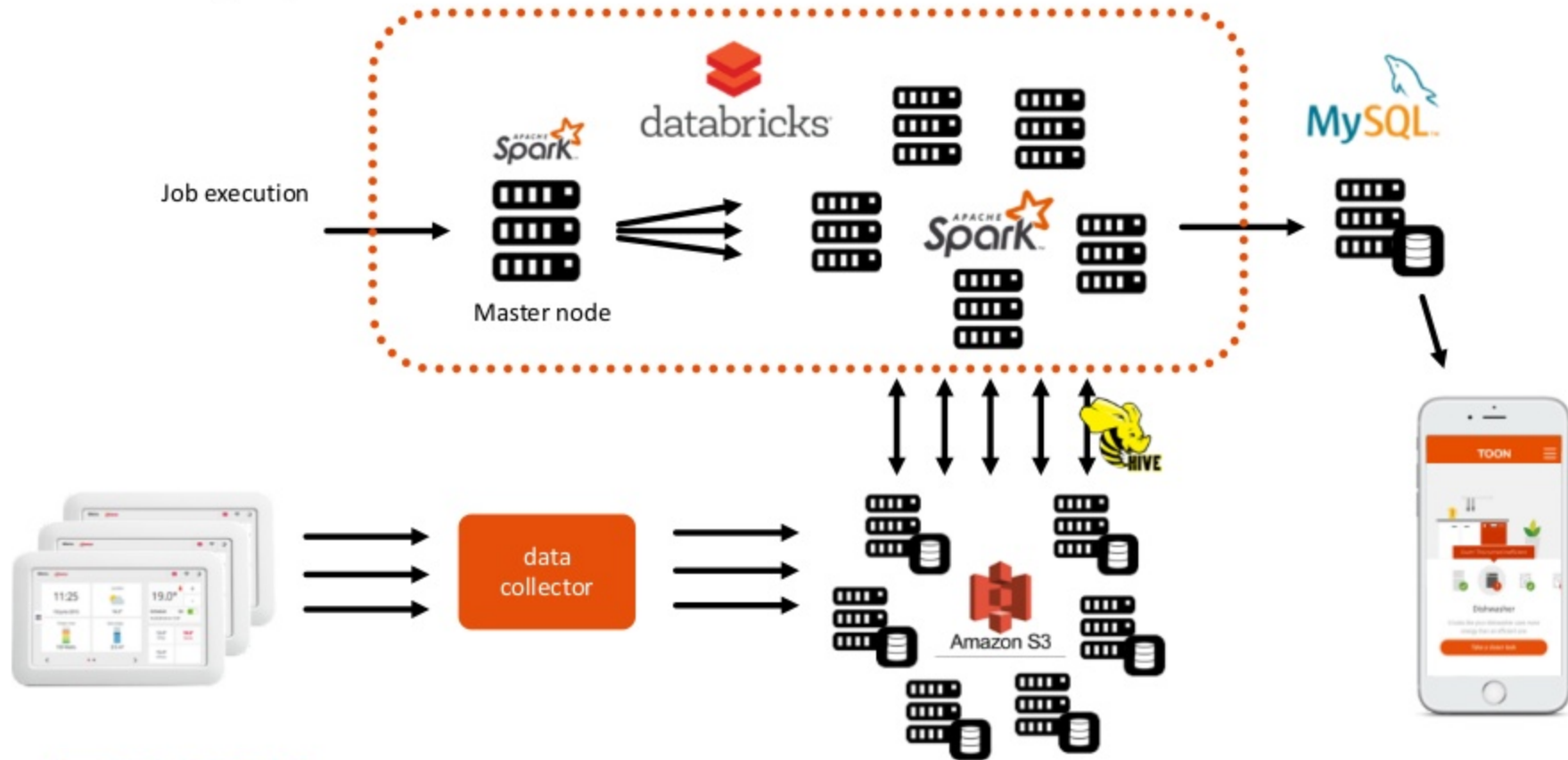
TOON SOLAR

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."

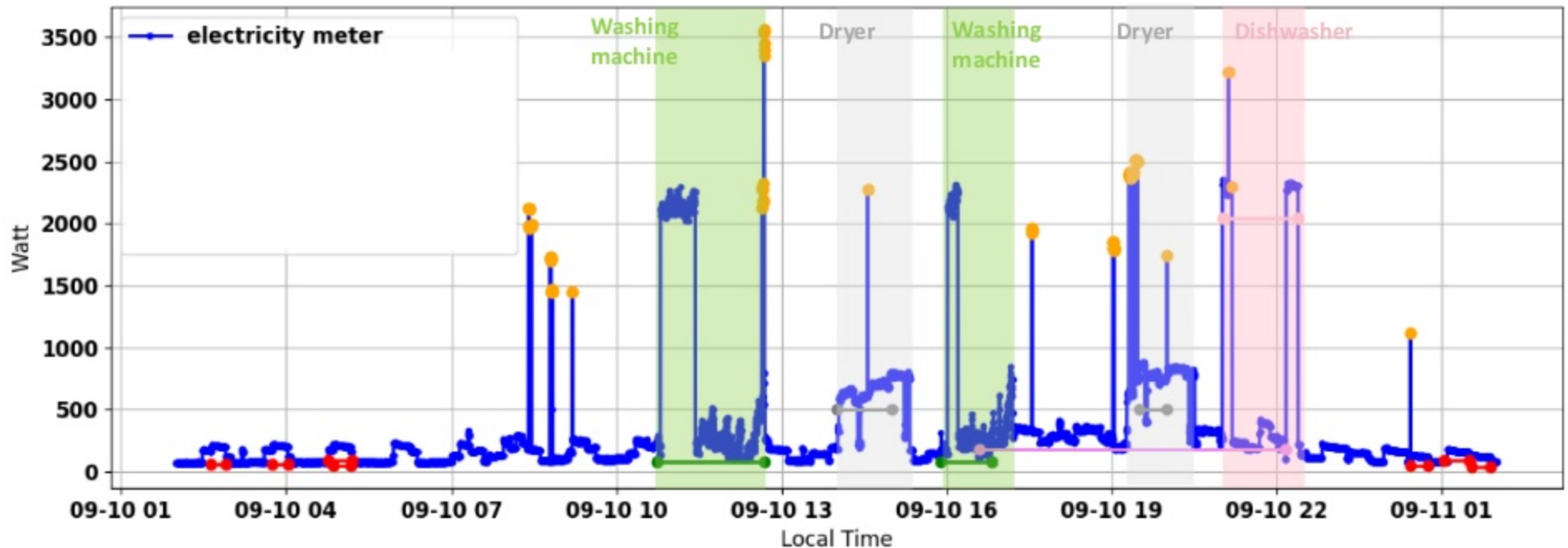
Launched in December 2017 to all
Eneco Toon users

TOON[®]
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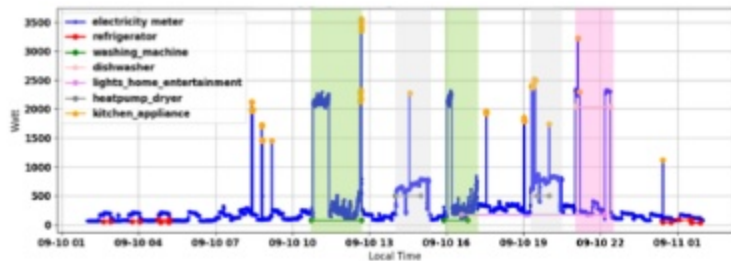
Quby's disaggregation algorithms

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



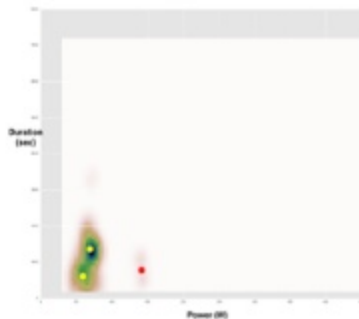
Use case example: Inefficient dishwasher diagnosis

Disaggregation algorithms run on the 10s electricity meter data



Toon determines the “fingerprint” of the appliance through features

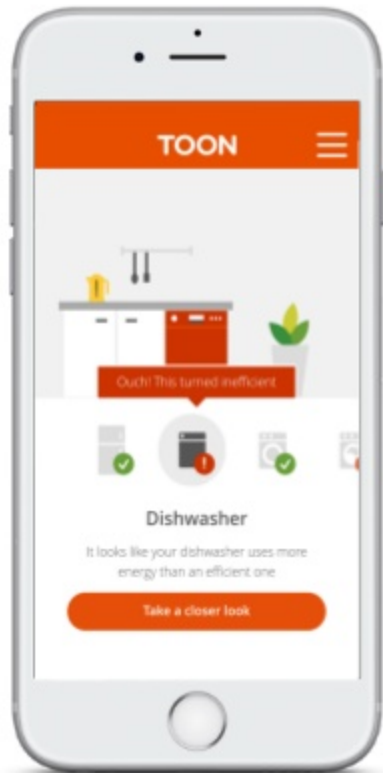
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Compared with industry standards and peers



Translated to personalised advice for the end user



Scale of the Waste checker



Each day we detect over
75,000 dishwasher
cycles

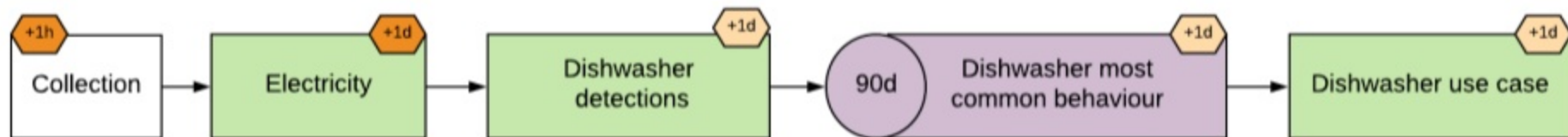
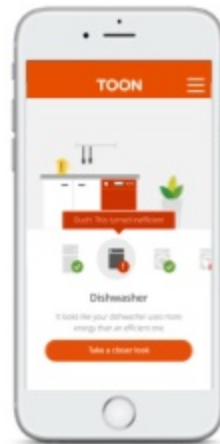
That's
13 years
of dishwashers running
continuously

and over
25% are
used
inefficiently

TOON®

#SAISML4

Example data flow

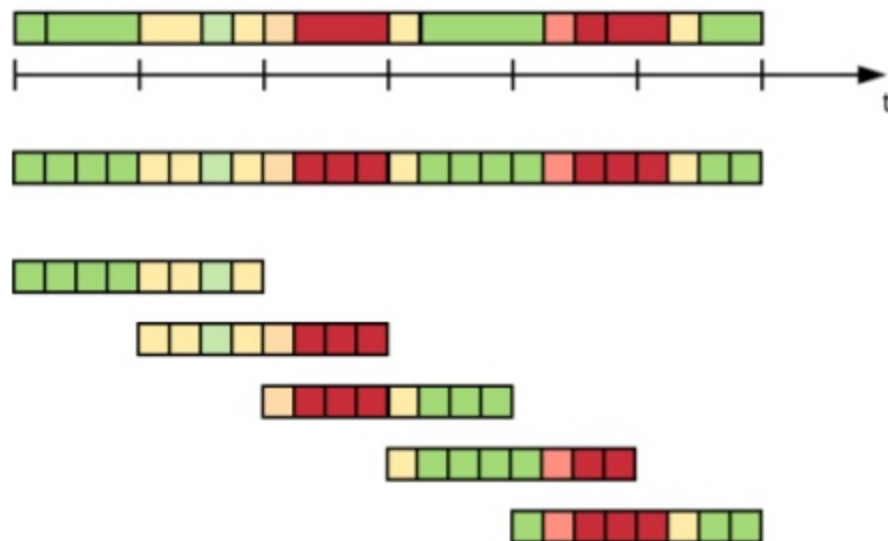


Example data flow

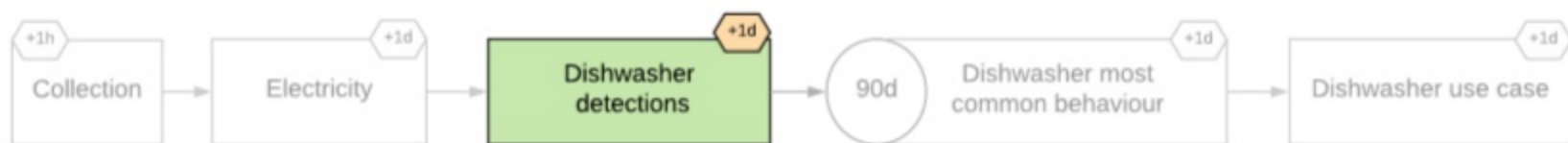


Getting the data ready

- Extraction & Cleaning
- Resampling
- Vectorization



Example data flow

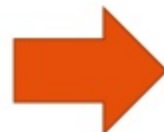


Detecting appliances

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



Vectorized electricity



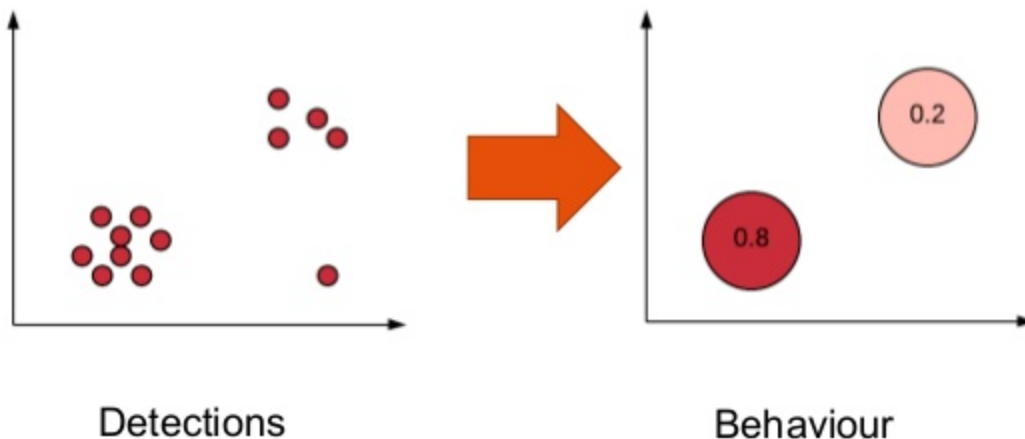
Predictions

Example data flow



Finding user behavior

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

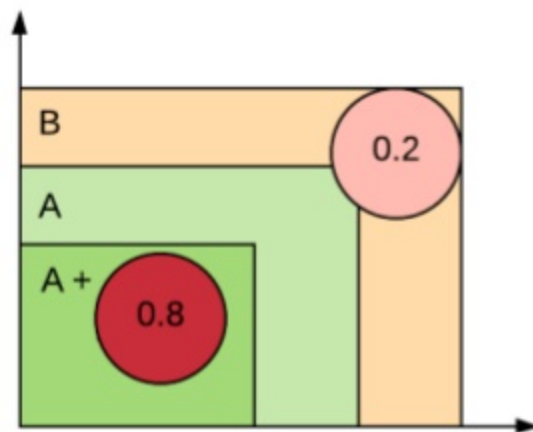


Example data flow

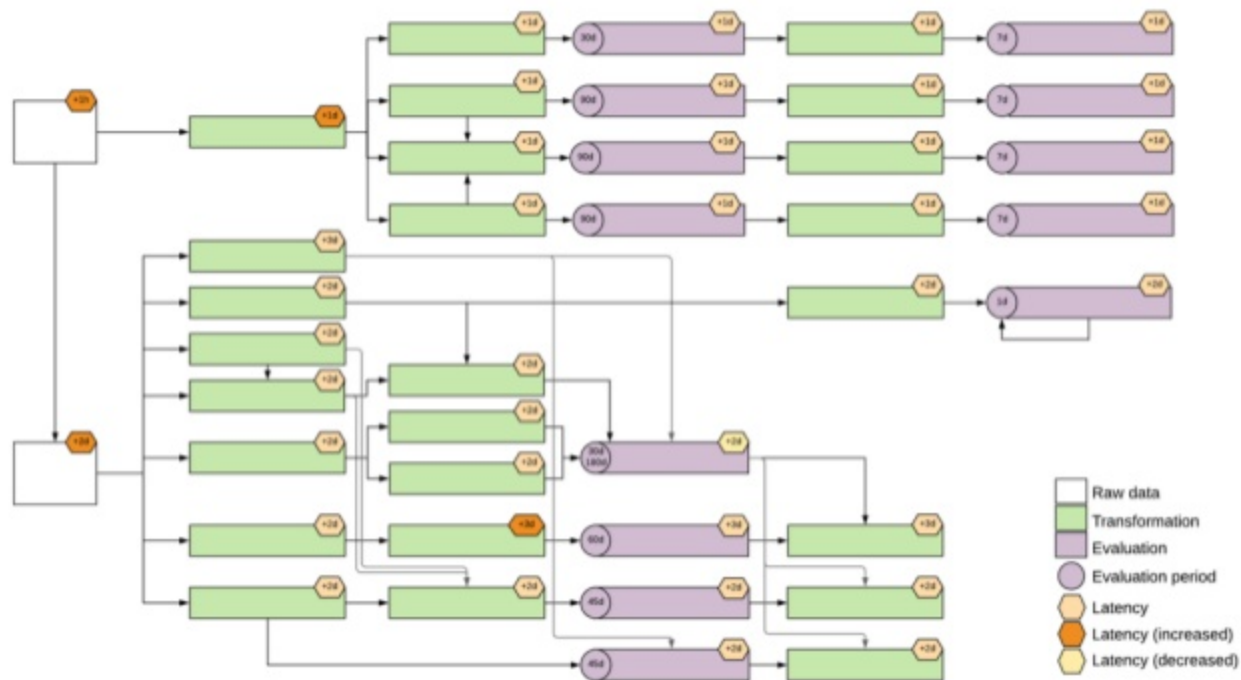


Drawing conclusions

- 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
Run Now / Run Now With Different Parameters						

Completed in past 60 days

Latest successful run (refreshes automatically)

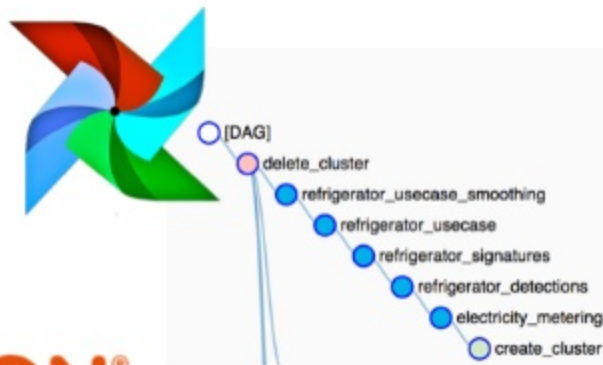
< Previous 20

Next 20 >

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

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>

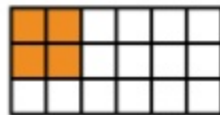
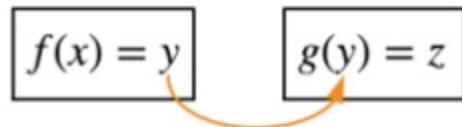
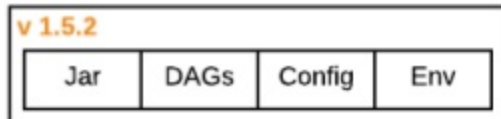


When designing data pipelines

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

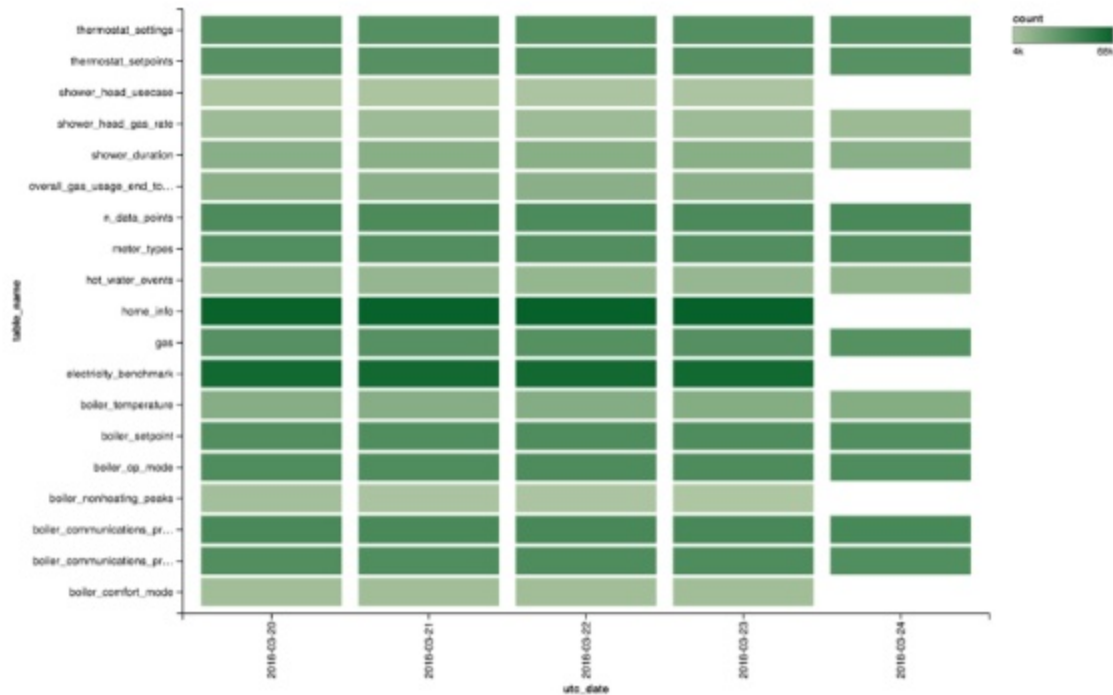
$$f(x) = y$$

Always



Monitoring

- Live dashboards with aggregated data



Monitoring and Validation

- Daily email to Quby's VIP employees

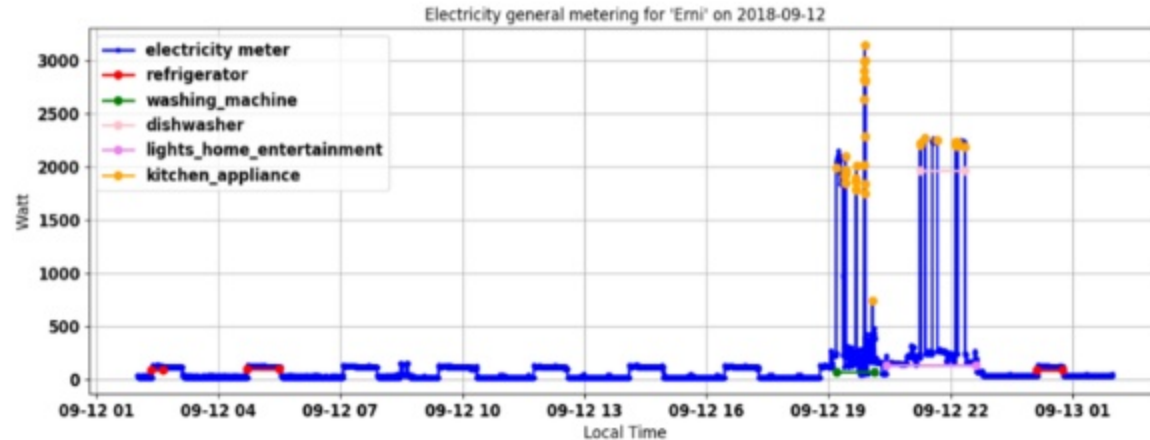
☆ Kaustav Basu

Inbox - Exchange 13 September 2018 at 09:33

K

Energy Breakdown

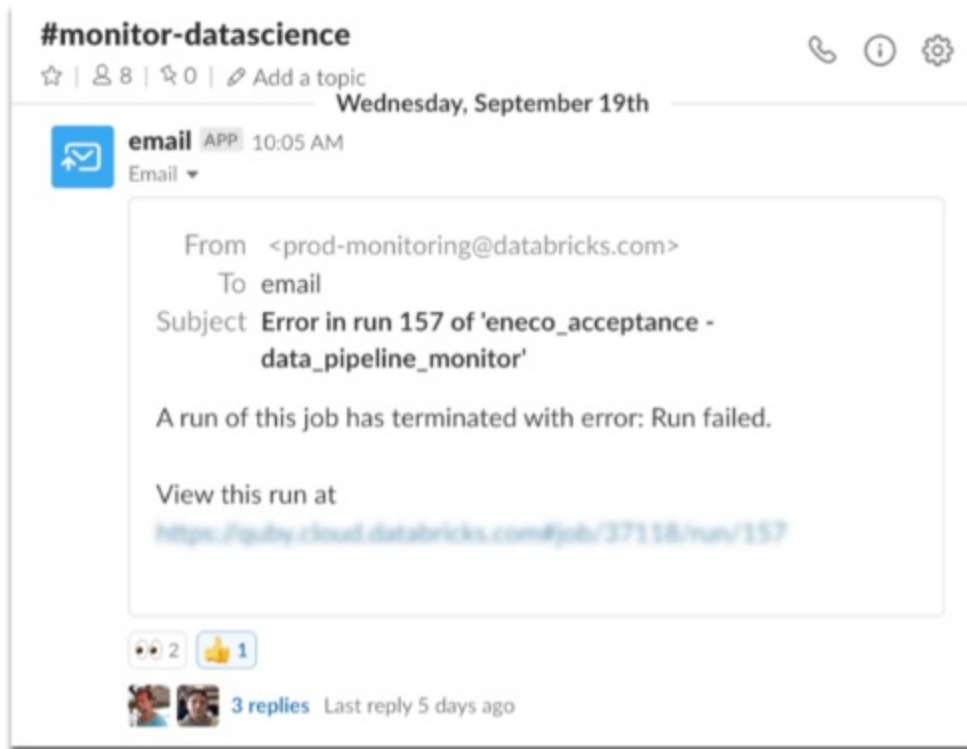
To: erni.durdevic@quby.com



Alerting

Alerting (via Email / Slack)

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

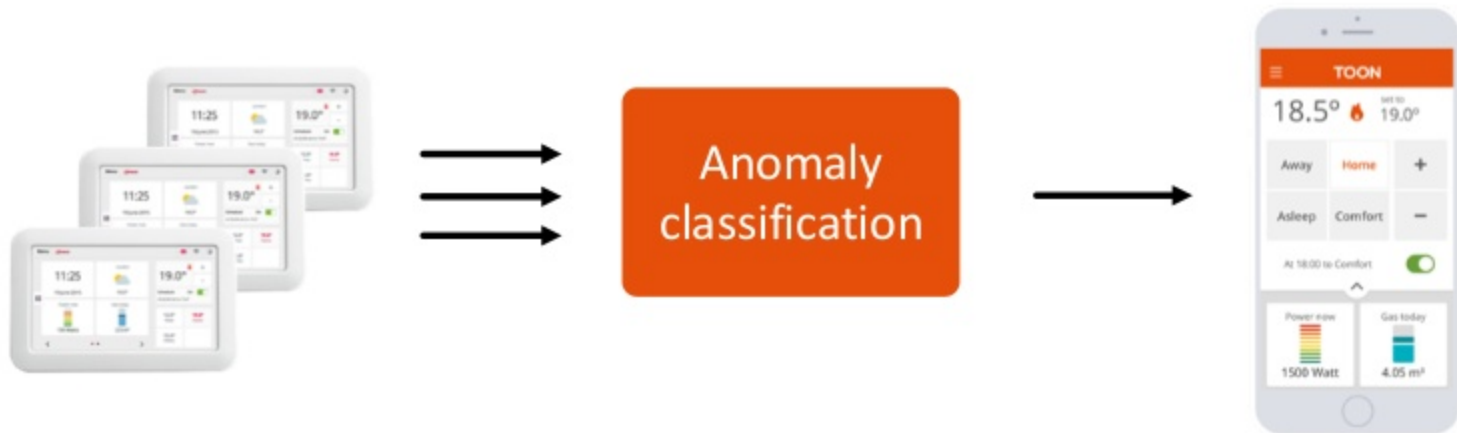


USE CASE #2

Detecting anomalies in heating systems



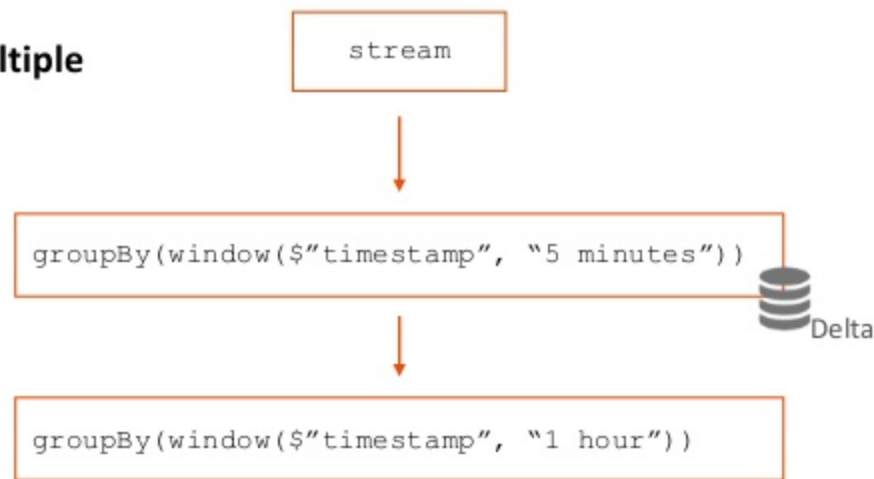
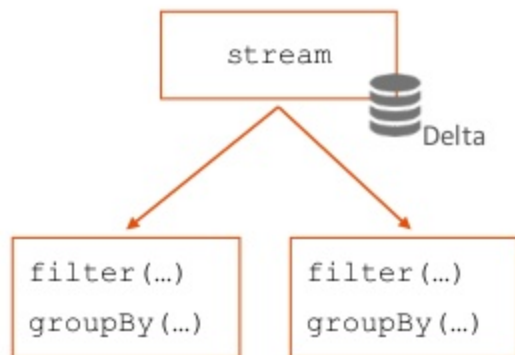
Structured Streaming



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

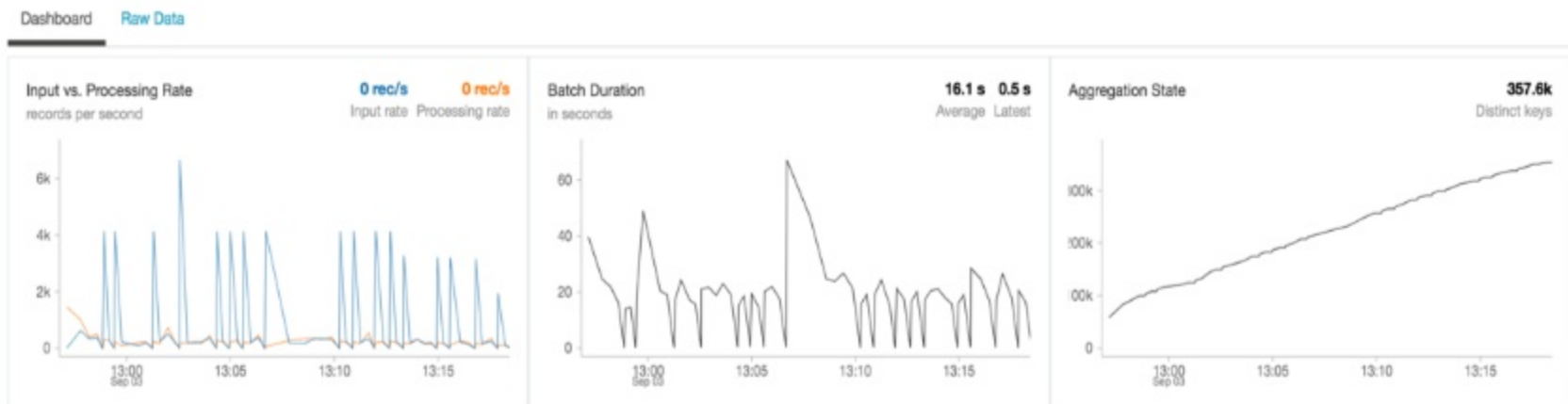
Compute **non time-based window** operations

- 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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