Data Validation at Scale

Managing Data Quality in Complex Data Pipelines

DB / DC 2023, Munich, Germany

December 05, 2023

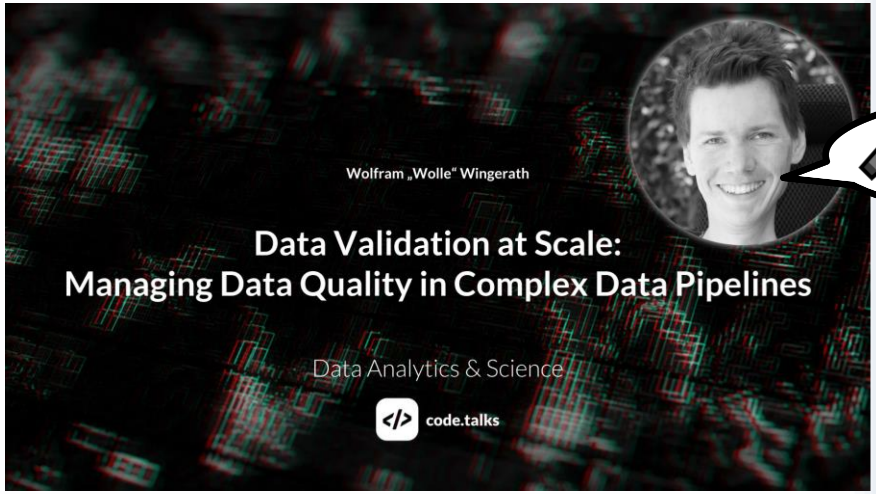
Wolle

Material Available at https://wolle.science

(Direct Link to Slides: https://wolle.science/data-validation)

Data Validation at Scale

Mana



Video of a similar presentation!

Wolfram "Wolle" Wingerath. Data Validation at Scale: Managing Data Quality in Complex Data Pipelines, code.talks (2023)

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I Am Wolle

Research:
- Stream Processing
- Real-Time Databases
- NoSQL & Cloud Systems
- …

Practice:
- Web Caching
- Big Data Analytics
- Anger Management
- …

+

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Carl von Ossietzky
Universität
Oldenburg

Baqend

Talk Outline

1

The Importance of Data Validation

Where is data validation integrated into data science pipelines and what is its impact?

2

Data Quality & Constraints

What dimensions of data quality are there and how can they be ensured?

3

Scalability-Related Challenges

Why is data validation difficult in data-intensive domains?

Running Example: Web Performance Analysis Pipeline

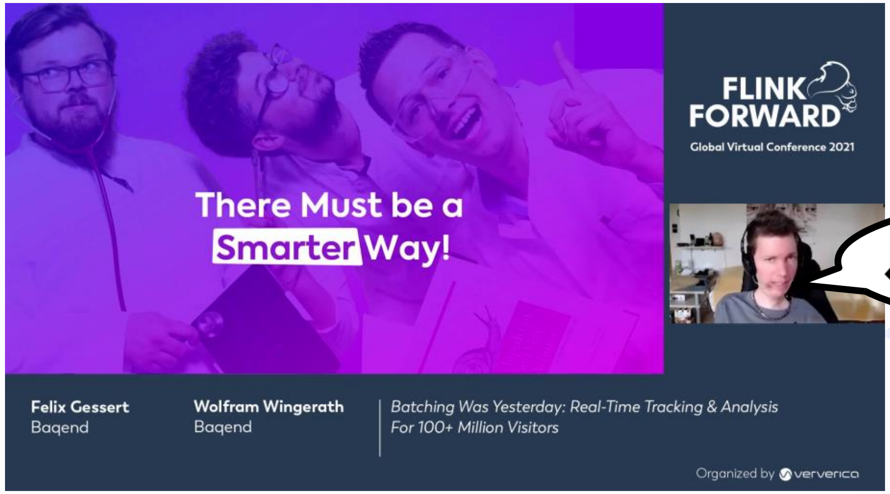
Collection

Ingestion

Analytics

Reporting

Tracking
(RUM)



F. Gessert, W. Wingerath. Batching Was Yesterday: Real-Time Tracking & Analysis For 100+ Million Visitors, Flink Forward (2021)

As presented here at DB/DC '20!

Performance Dashboard

QA Dashboard

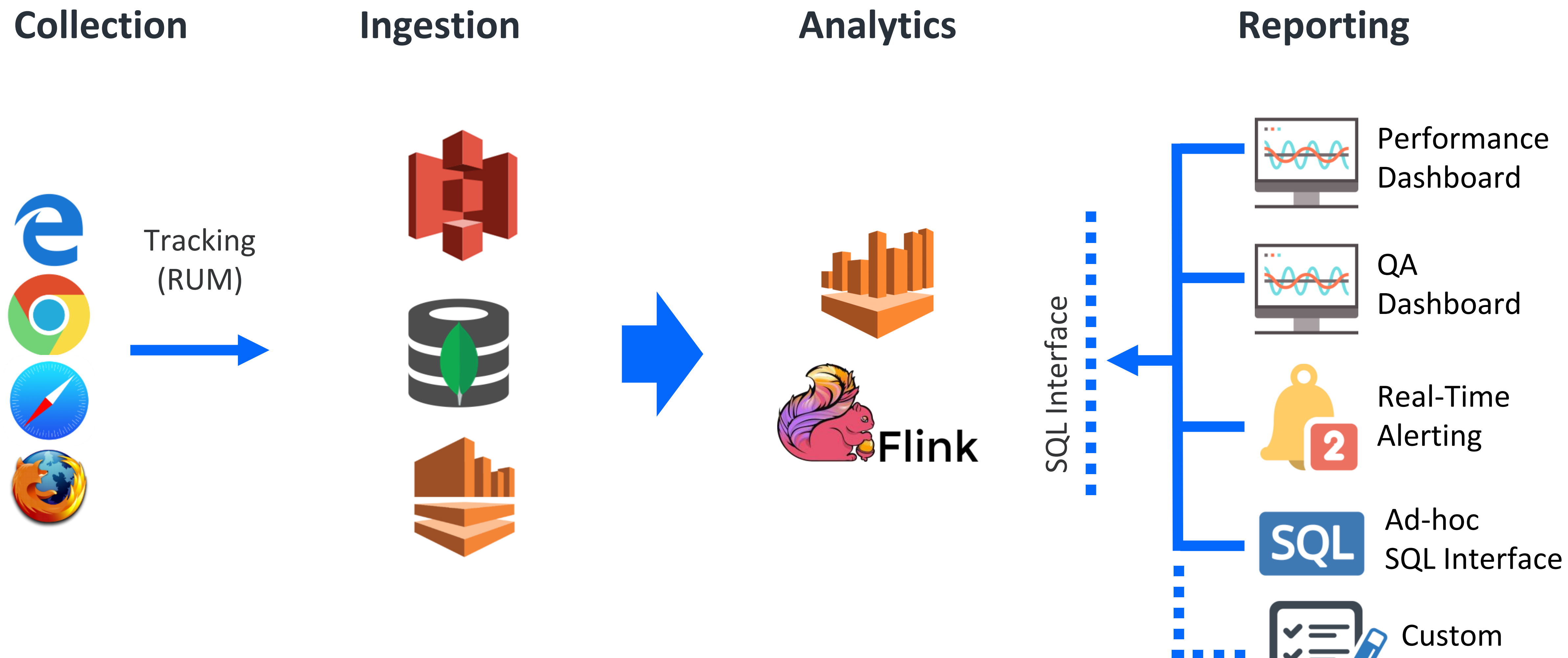
Real-Time Alerting

Ad-hoc SQL Interface

Custom Reporting

W. Wingerath, B. Wollmer, M. Bestehorn, S. Succo, F. Bücklers, J. Domnik, F. Panse, E. Witt, A. Sener, F. Gessert, N. Ritter. Beaconnect: Continuous Web Performance A/B-Testing at Scale, VLDB (2022)

Running Example: Web Performance Analysis Pipeline



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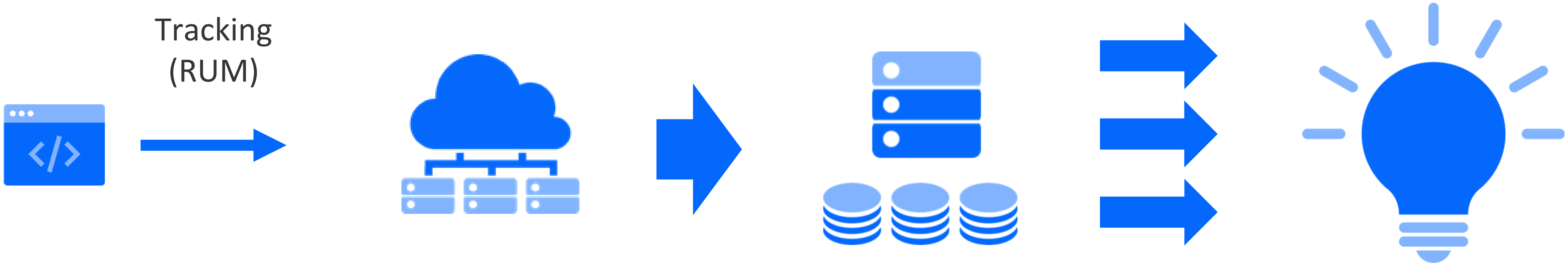

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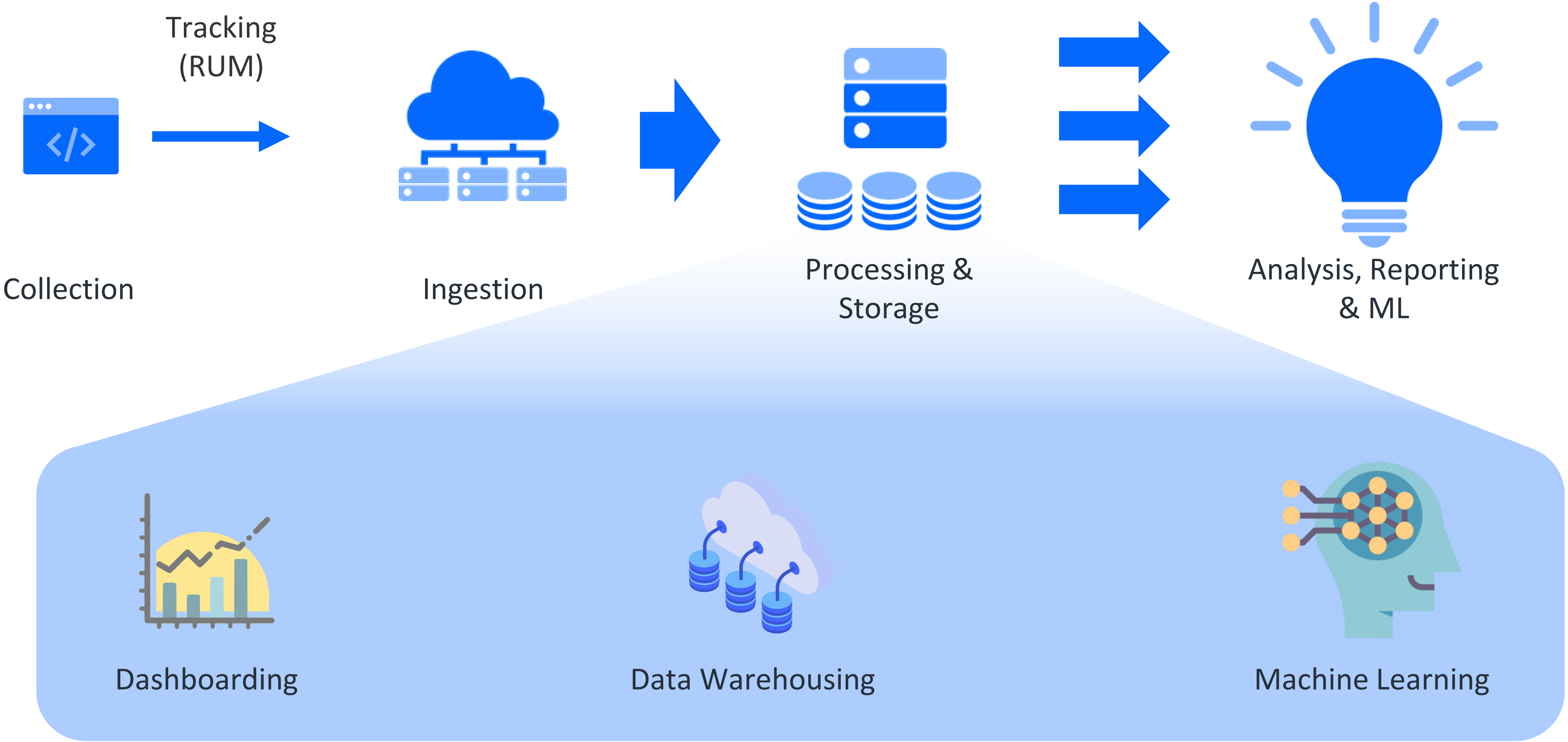
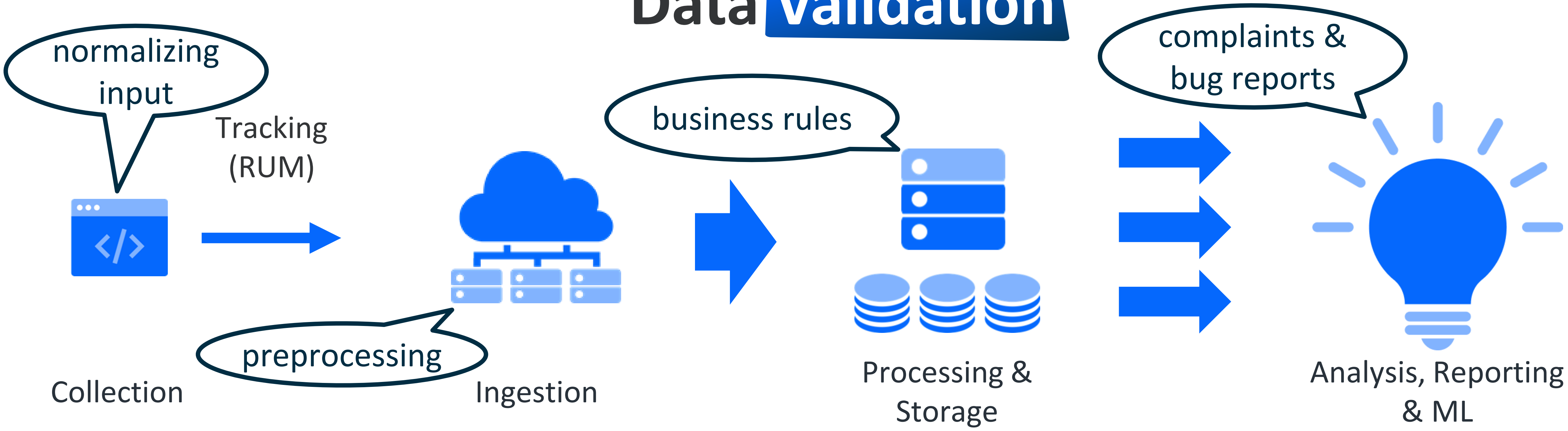
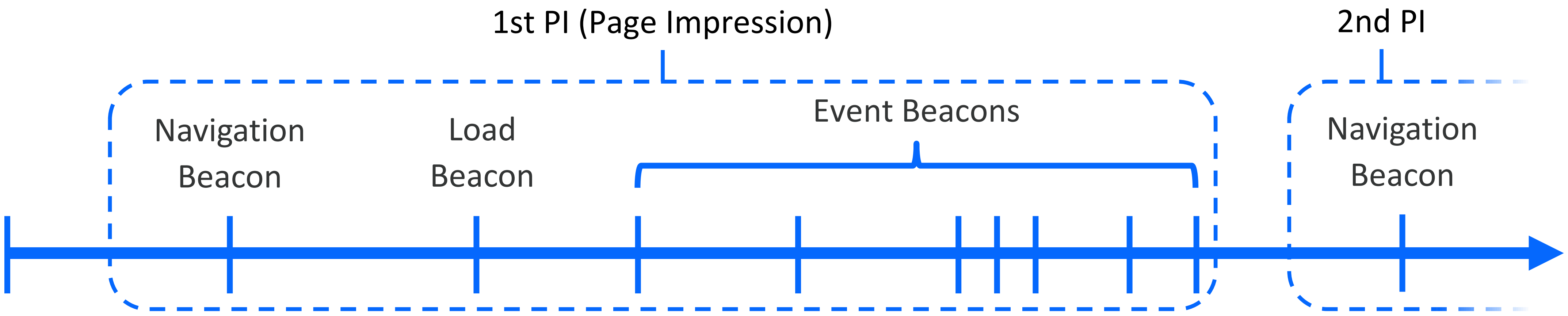


Data Validation



- **Goal**: verify that data in the pipeline is in an acceptable state for downstream processing, e.g.
  - External reporting (statistics, visualizations & dashboarding)
  - Internal reporting (debugging, product optimizations)
  - Decision-making (analytics, machine learning)
- Data validation can be integrated **in and between all stages**

Dimensions of Data Quality: Completeness



- There are different **dimensions of data quality**, especially:
  - *Completeness: Do we have all the data we need to assess page load performance?*
  - *Consistency: Does data have a valid format and does it comply with business semantics?*
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  - *Uniqueness: Are duplicate records known and are all unique attributes actually distinct?*

Dimensions of Data Quality: Completeness

Timestamp	Pageload ID	Browser	LCP (Performance)	Session ID	URL
09:05:04.578	37ab08	Edge	"670ms"	123	null
13:26:48.139	9cddf7	Firefox	692 654	456	abc.de/red
13:28:23.857	0b577a	Firefox	0.256	456	abc.de/blue
13:29:17.468	faf55e	Edge	1.598	456	abc.de/sold
20:45:38.941	faf55e	null	null	null	abc.de/sold

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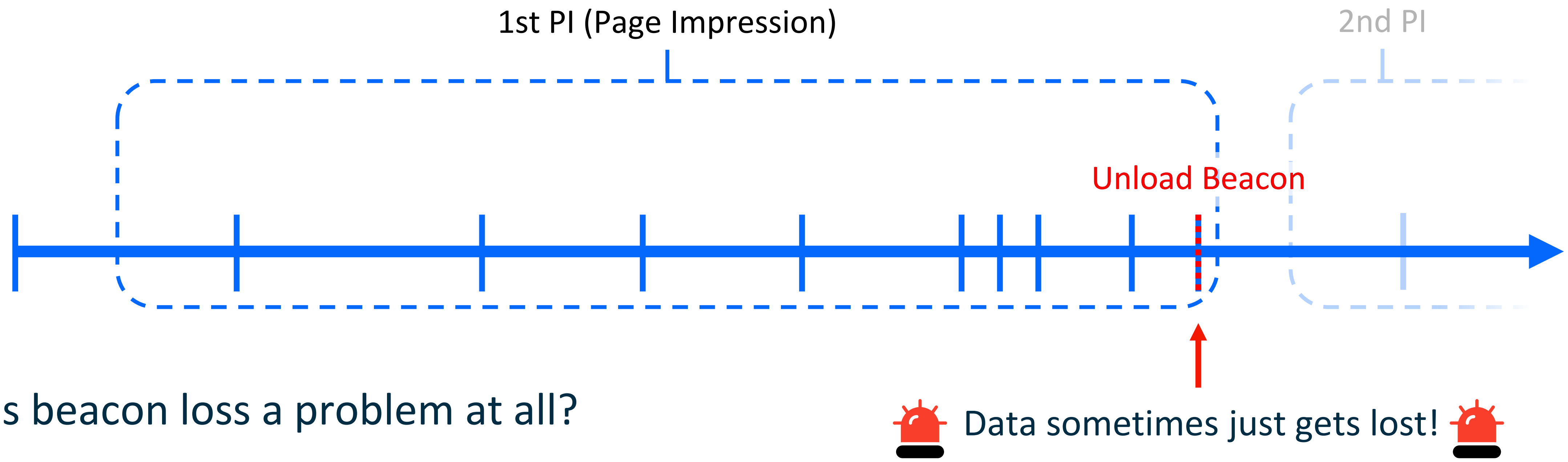
Unload Beacon **Reliability** as an Example Challenge



- Is beacon loss a problem at all?
- **When** is beacon loss a problem?

  → For which beacon types? For which beacon strategies?
- **Where** is beacon loss a problem?

  → For which browsers? For which device types?

Unload Beacon Reliability by Strategy

```
addEventListener("unload", (event) => {
  navigator.sendBeacon(url, JSON.stringify(data));
});
```

```
addEventListener("beforeunload", (event) => {
  navigator.sendBeacon(url, JSON.stringify(data));
});
```

```
addEventListener("pagehide", (event) => {
  navigator.sendBeacon(url, JSON.stringify(data));
});
```

```
addEventListener("visibilitychange", (event) => {
  if (document.visibilityState === 'hidden') {
    navigator.sendBeacon(url, JSON.stringify(data));
  }
});
```

available on all platforms

experimental feature

(only available as origin trial in Chrome)

```
var beacon = new window.PendingPostBeacon(
  url,
  {
    timeout: 60000,
    backgroundTimeout: 0
  });
beacon.setData(JSON.stringify(data));
```

Erik Witt. Unload Beacon Reliability: Benchmarking Strategies for Minimal Data Loss, Speed Kit Tech Blog (2023)

Unload Beacon Reliability by Strategy

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addEventListener("unload", (event) => {
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Available on all platforms

```
addEventListener("befor
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});
```

```
addEventListener("pageh
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});
```

```
addEventListener("visibilityc
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  }
});
```

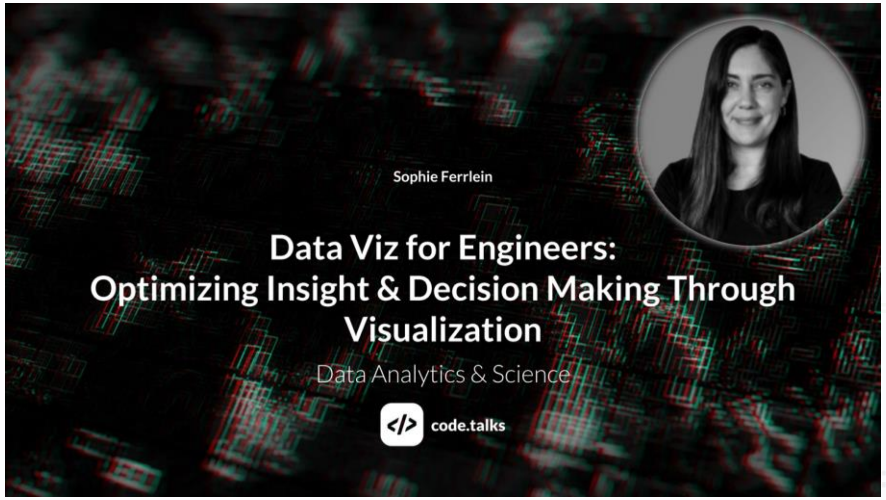

Sophie Ferrlein. Data Viz for Engineers: Optimizing Insight & Decision Making Through Visualization, code.talks (2023)

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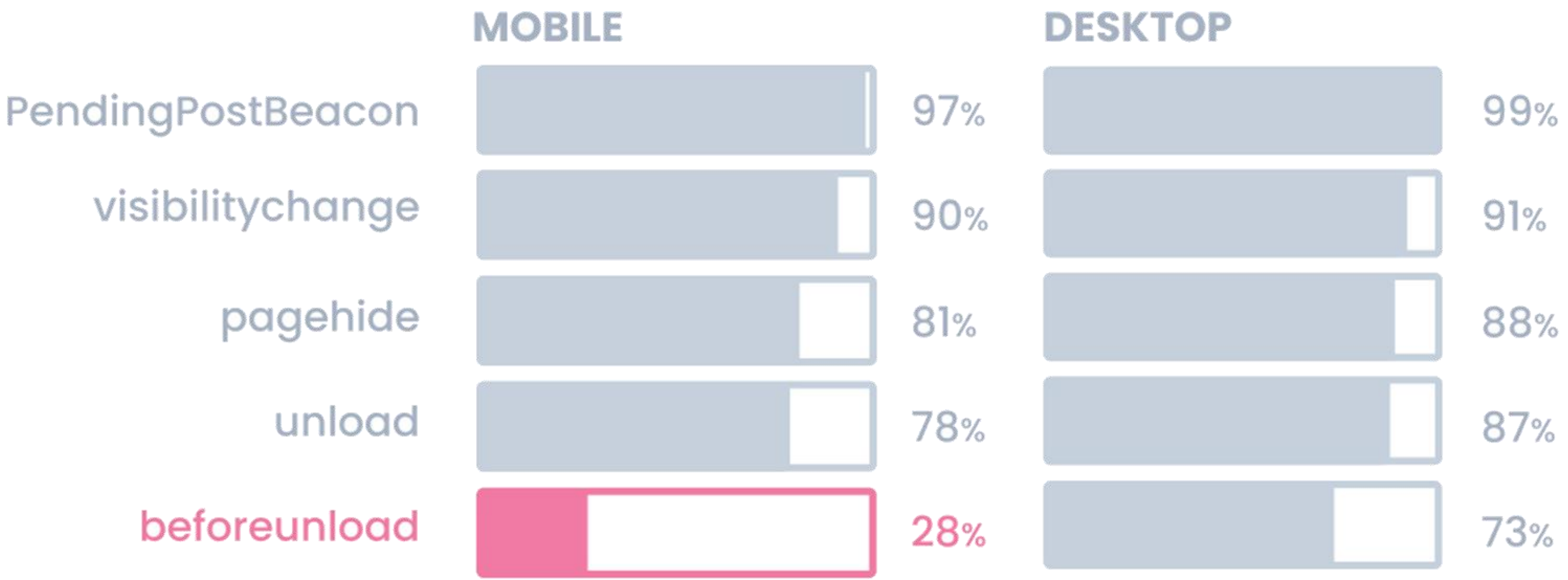
Erik Witt. Unload Beacon Reliability: Benchmarking Strategies for Minimal Data Loss, Speed Kit Tech Blog (2023)

Unload Beacon Reliability by Strategy & Device

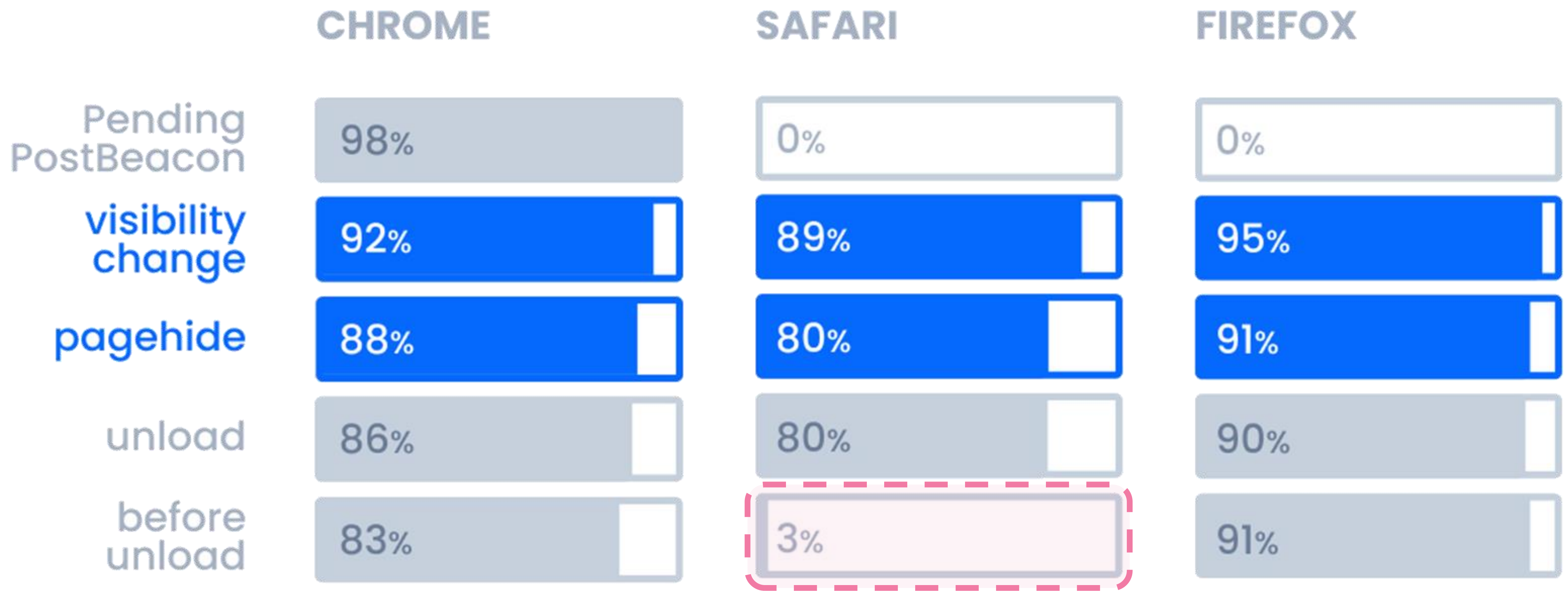


Based on 52 million page views on a globally operating e-commerce site measured by Speed Kits real user-monitoring | August 2023

Desktop data may be overrepresented!

Erik Witt. Unload Beacon Reliability: Benchmarking Strategies for Minimal Data Loss, Speed Kit Tech Blog (2023)

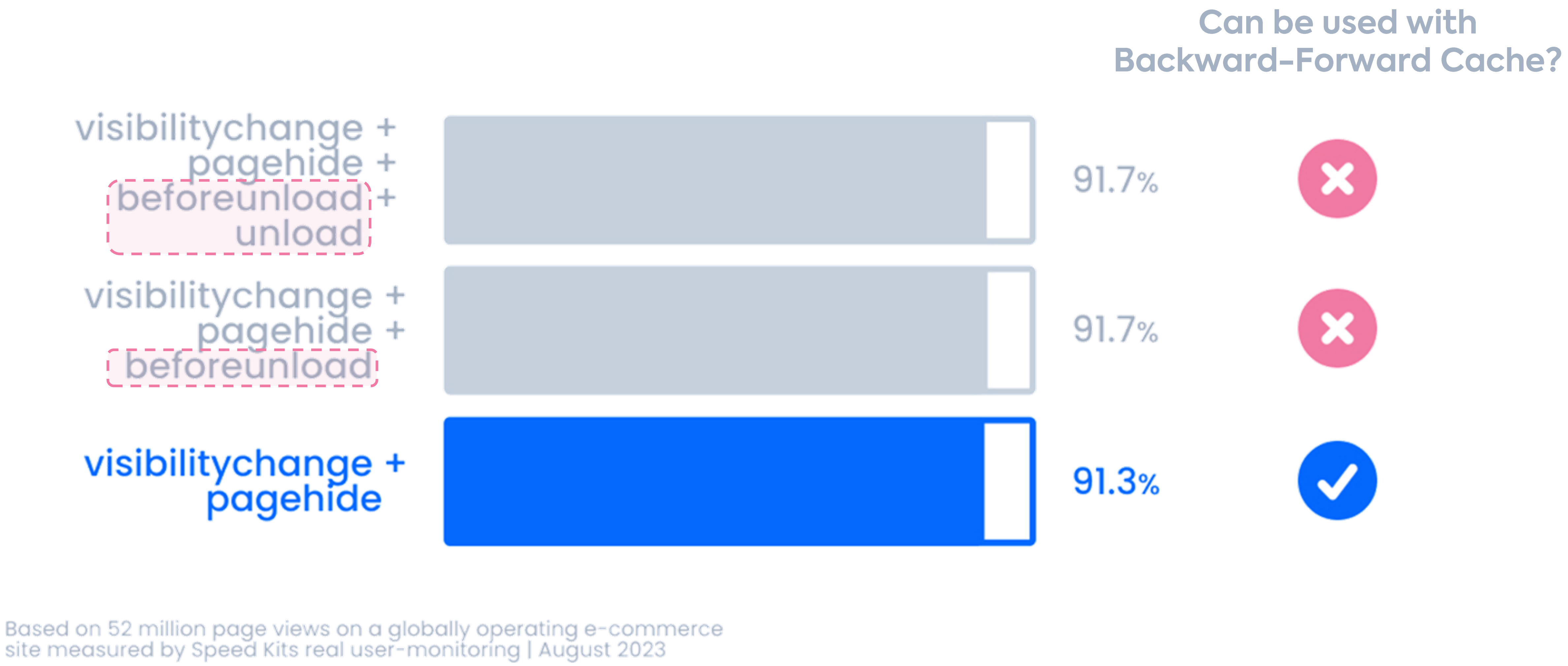
Unload Beacon Reliability by Strategy & Browser



Based on 52 million page views on a globally operating e-commerce site measured by Speed Kits real user-monitoring | August 2023

Erik Witt. Unload Beacon Reliability: Benchmarking Strategies for Minimal Data Loss, Speed Kit Tech Blog (2023)

Unload Beacon Reliability: The Ideal Combo Strategy



Erik Witt. Unload Beacon Reliability: Benchmarking Strategies for Minimal Data Loss, Speed Kit Tech Blog (2023)

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Same browser

Same session

Note: Browser values should be unified for all records in the same session!

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Note: Browser values should be unified for all records in the same session!
→ value may be replaced with majority vote (another reasonable option: replace old values with latest one)

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Note: All values represent milliseconds, but formats differ depending on browser.

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→ values may be converted to integer

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Dimensions of Data Quality: Accuracy

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Note: Despite being in the right format, one value does not represent a reasonable timer value.

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→ broken value may be removed

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Dimensions of Data Quality: Uniqueness

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Note: The ID field should be unique, but two different records share the same value!

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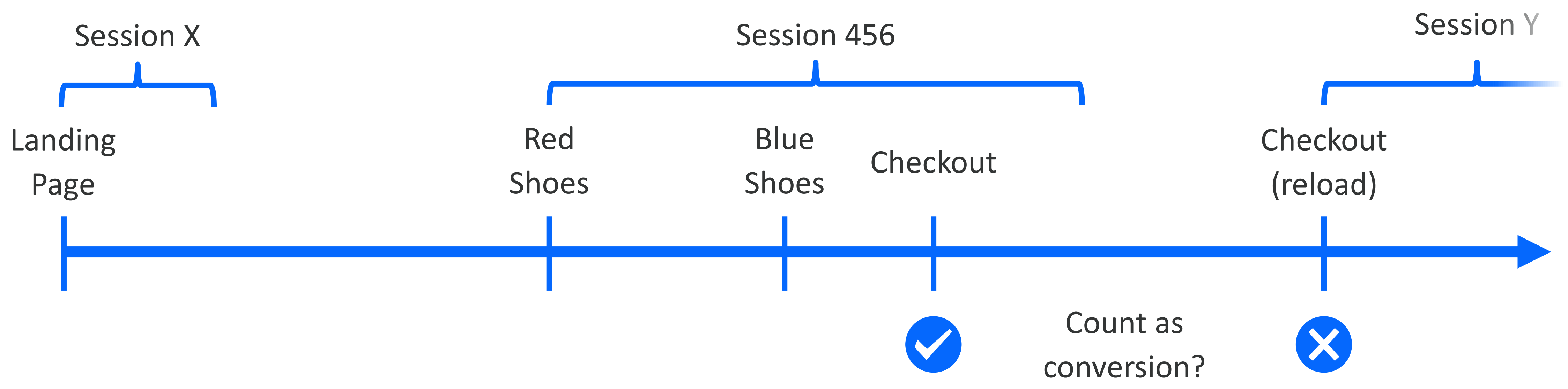

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~~20:45:38.941~~	~~faf55e~~	~~null~~	~~null~~	~~null~~	~~abc.de/sold~~

Note: The ID field should be unique, but two different records share the same value!
→ merge duplicates into a single record

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Maintaining Data Quality With Constraints

- **Constraints** are rules, conditions, or limits that data must adhere to
- **Type Checks** represent expectations on the data format, e.g.
  - *Value range* for numerical data (e.g. [0,MAX_INTEGER) for load timers)
  - *Format or pattern* for string-valued data (e.g. ISO 8601 for timestamps)
  - *Structure* for complex attributes (e.g. required keys for JSON objects)
- **Complex conditions** can further describe complex semantics such as
  - Cross-field or cross-record relationships (e.g. same browser within sessions)
  - Referential integrity between records in different collections
  - Custom constraints for domain semantics

Example: Declarative Constraints With Pandera (1/3)

```
import pandas as pd
import pandera as pa
from pandera import Column, DataFrameSchema, Check

# Define the schema
schema = DataFrameSchema(
    {
        "Timestamp": Column(pa.DateTime),
        "Pageload ID": Column(pa.String,
            Check(lambda x: x.str.len() == 8)),
        "Browser": Column(pa.String,
            Check(lambda x: x.isin(["Chrome", "Edge", "Firefox"]))),
        "LCP": Column(pa.Int,
            Check(lambda x: (x >= 0) & (x <= 600000))),
        "Session ID": Column(pa.Int),
    }
)
```

Example: Declarative Constraints With Pandera (2/3)

```
# valid data item
good = {
    "Timestamp": [pd.Timestamp("2023-05-10 13:26:48.139")],
    "Pageload ID": ["9cddf7"],
    "Browser": ["Firefox"],
    "LCP": [256],
    "Session ID": [456],
}

# invalid data item
bad = {
    "Timestamp": [pd.Timestamp("2023-05-10 09:05:04.578")],
    "Pageload ID": ["37ab08"],
    "Browser": ["Edge"],
    "LCP": [692654], # timer value out of bounds
    "Session ID": [123],
}
```

Example: Declarative Constraints With Pandera (3/3)

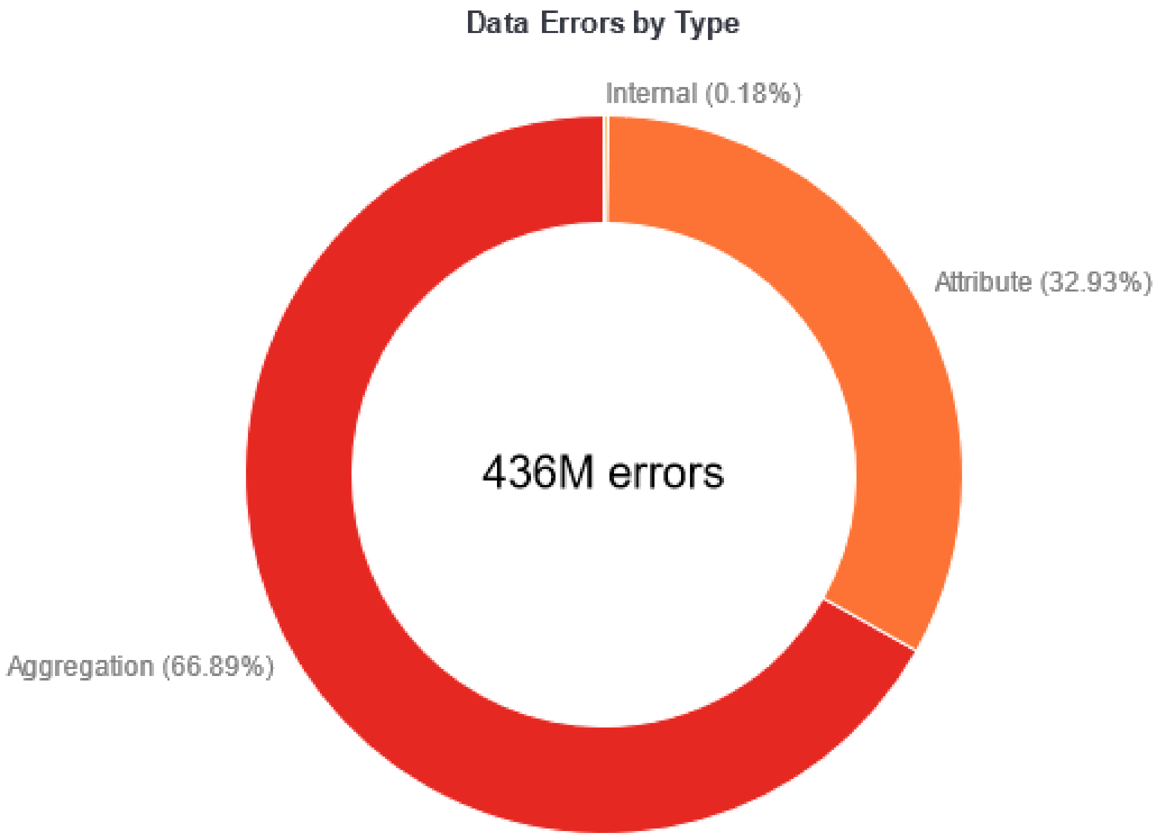
```python
for record in [good, bad]:
    record_id = record['Pageload ID'][0]
    try:
        validated = schema(pd.DataFrame(record))
        print(f"\nValidation passed for record {record_id}!")
    except pa.errors.SchemaError as e:
        print(f"\nValidation FAILED for record {record_id}:")
        print(e)
```

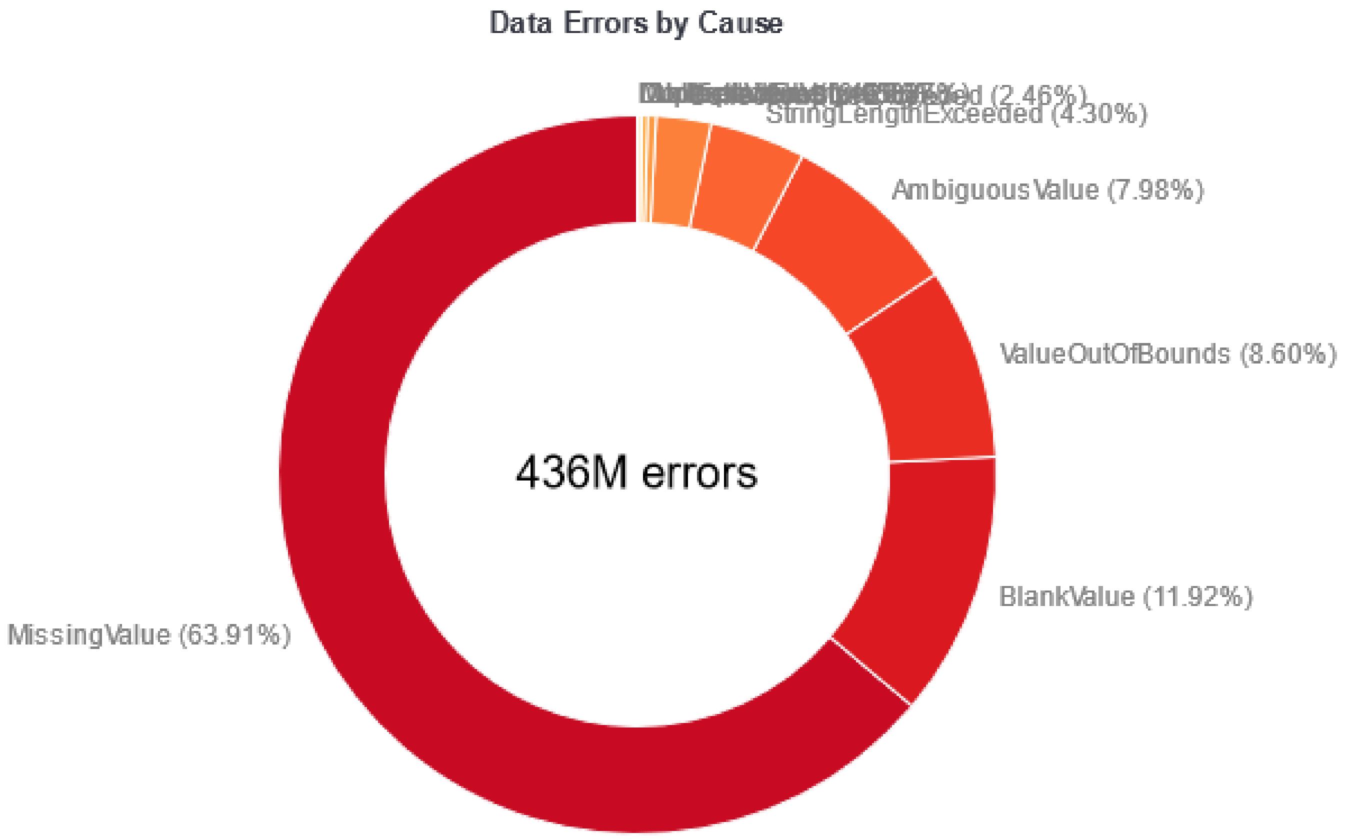
```
Validation passed for record 9cddf7!

Validation FAILED for record 37ab08
<Schema Column(name=LCP, type=DataType(int64))> failed element-wise
validator 0:
<Check <lambda>>
failure cases:
   index  failure_case
0      0        692654
```

Fundamental Challenge: Scalability

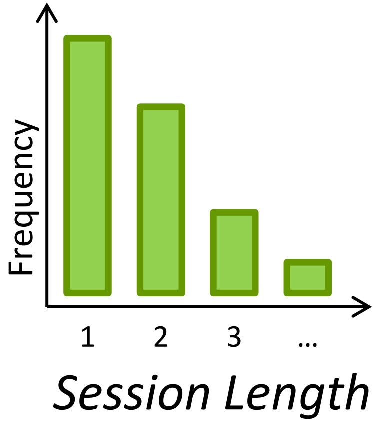
One Month in Data Errors at Baqend: April 2023





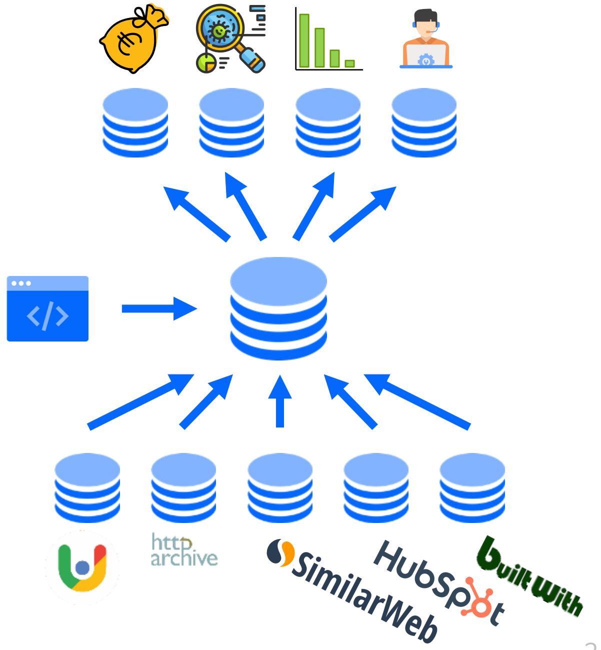
Challenging at Scale: Complexity

Timestamp	Pageload ID	Browser	LCP (Performance)	Session ID	URL	…	Session Length	Conversion
09:05:04.578	37ab08	Edge	**670**	123	null	…	1	0
13:26:48.139	9cddf7	Firefox	**null**	456	abc.de/red	…		
13:28:23.857	0b577a	Firefox	**256**	456	abc.de/blue	…	3	1
13:29:17.468	faf55e	**Firefox**	**1598**	456	abc.de/sold	…		
~~**20:45:38.941**~~	~~**faf55e**~~	~~**null**~~	~~**null**~~	~~**null**~~	~~**abc.de/sold**~~	…		

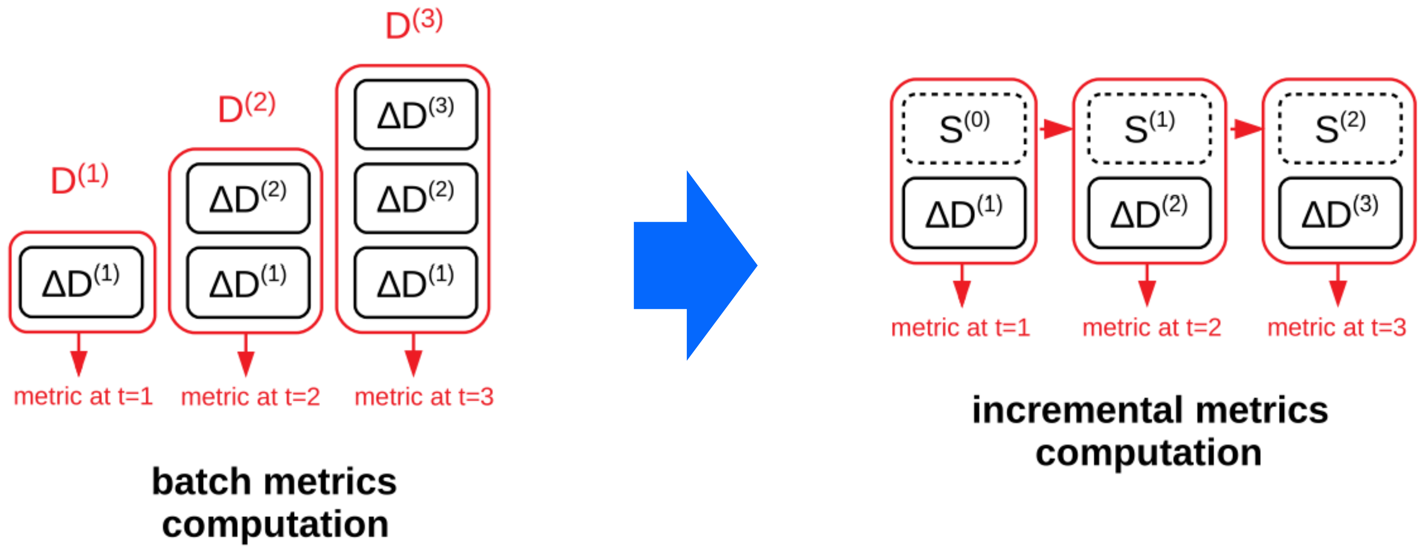


- Manual constraint definition is often infeasible, because of …
  - … inherent data complexity (often <u>hundreds</u> of attributes)
  - … aggregation, derived storage, and evolving schemas
  - … a plethora of other data stores to integrate!

→ **Automation** is necessary!



Challenging at Scale: Continuity



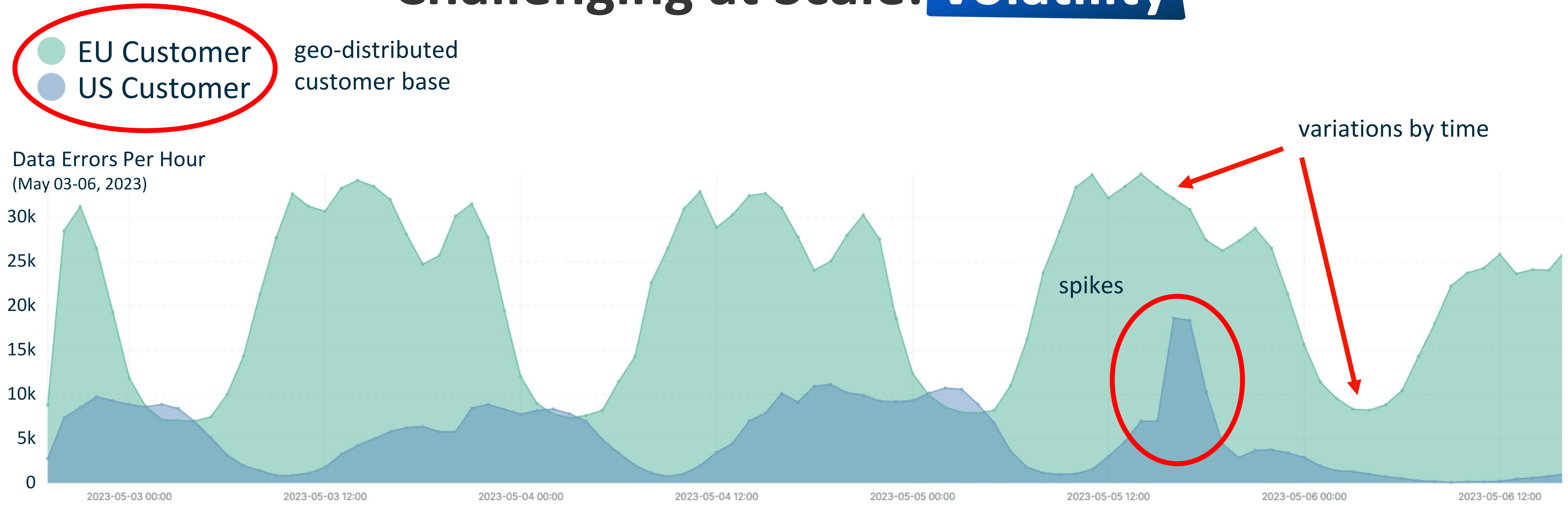
- Computing validation metrics from scratch periodically can be infeasible, because of …
  - … strict timing requirements
  - … efficiency or cost reasons
  - … data privacy reasons

→ **Incremental computation** can be the only option!

W. Wingerath, B. Wollmer, M. Bestehorn, S. Succo, F. Bücklers, J. Domnik, F. Panse, E. Witt, A. Sener, F. Gessert, N. Ritter. Beaconnect: Continuous Web Performance A/B-Testing at Scale, VLDB (2022)

Sebastian Schelter, Dustin Lange, Philipp Schmidt, Meltem Celikel, Felix Biessmann: Automating Large-Scale Data Quality Verification, VLDB 2018.

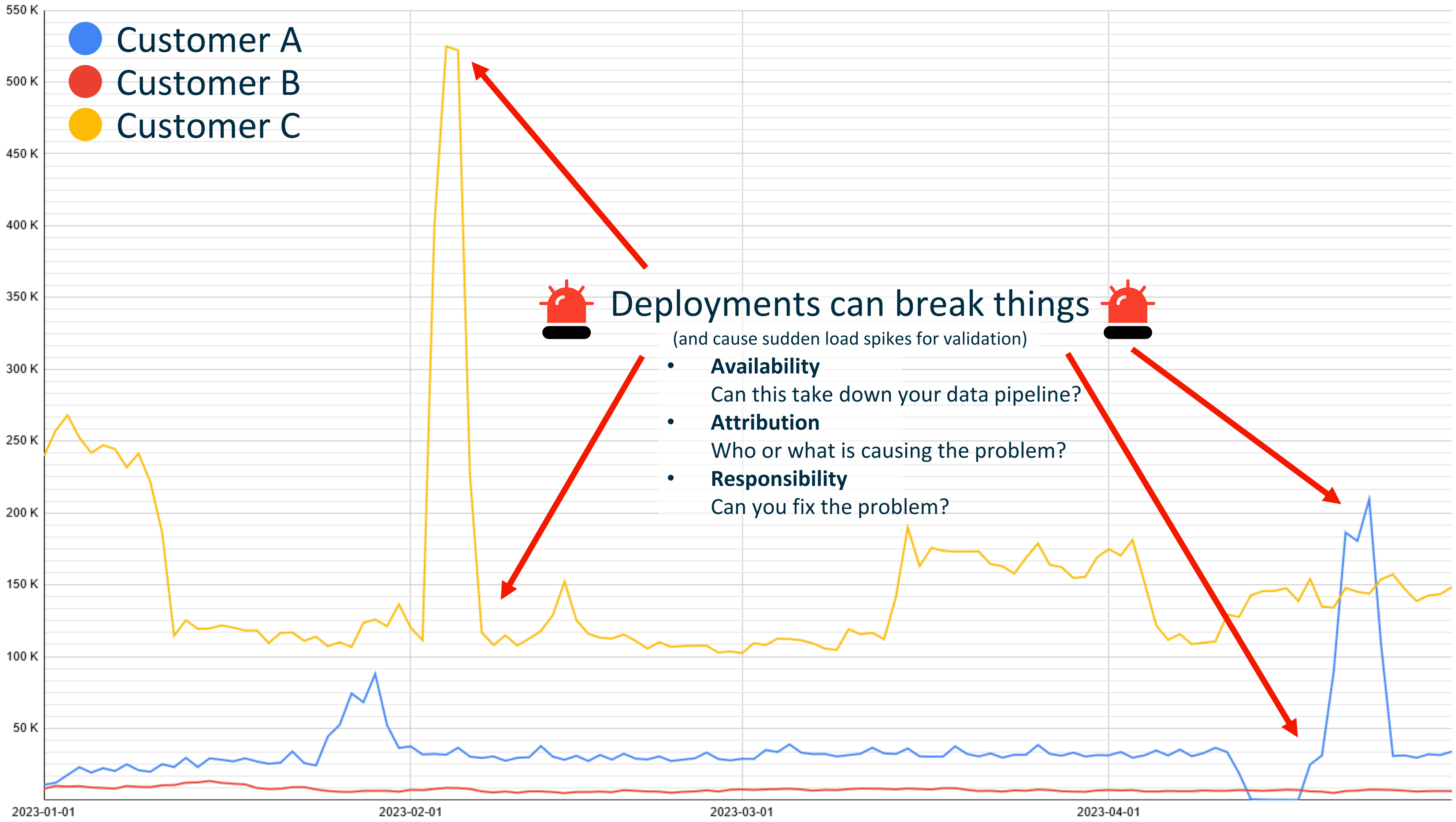
Challenging at Scale: Volatility



- Specifying generalized constraints can be difficult in large deployments, because of …
  - … temporal fluctuations (e.g. throughout the day, on black Friday, or during holidays)
  - … multi-tenancy (e.g. different data patterns by customer timezone or domain)

→ **Elasticity & Multi-Tenancy** requirements can be challenging!

Challenging at Scale: „Continility“ (Continuity + Volatility)



Deployments can break things

(and cause sudden load spikes for validation)

- **Availability**
  Can this take down your data pipeline?
- **Attribution**
  Who or what is causing the problem?
- **Responsibility**
  Can you fix the problem?

So How Do You Handle All This?

- **Advanced Techniques**
  - Inferring constraints
  - Adapting to schema changes
  - Incremental computation of complex measures
- **Tooling & Frameworks**
  - Validation libraries such as Great Expectations, Pandera, TFDV, or Deequ
  - Preprocessing and validation with Apache Spark and Apache Flink
- **Further Challenges**
  - Handling distribution (validation per partitioning, avoiding skew, ...)
  - Efficiency and performance (load distribution, approximation, ...)
  - Operational challenges (anomaly detection, fixing, load shedding, ...)

Data Validation at Scale: Summary

- **Data Quality** can be measured along dimensions such as completeness, consistency, accuracy, and uniqueness
- **Constraints** specify expectations about the data and can be used to enforce them
- **Data Validation** is the process of ensuring high data quality for processes like analysis, modeling, and decision-making
- Data Validation **Challenges at Scale** include
  - *Complexity*: schemas are often too complex to define constraints manually
  - *Volatility*: data varies throughout the day, by season, or by customer
  - *Continuity*: incremental processing is required when computation from scratch is infeasible

Thanks! Questions ?

Material Available at https://wolle.science