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Data Quality & Verification @ Uber, Netflix & Amazon

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Active Learning

↳ Participation & Discussion

Let's solve it together...

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Sources:

1. https://eng.uber.com/monitoring-data-quality-at-scale/ (2020) ← Uber DQM
2. https://databricks.com/session_na20/an-approach-to-data-quality-for-netflix-personalization-systems (2020)
3. https://www.amazon.science/publications/automating-large-scale-data-quality-verification (2018)

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Scale @ all companies

~ 1 - 10PB

10K - 100K tables

100s of Millions of events

1000's of metrics

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(Q) what platform(s) & techniques would you use to process internet-scale data?

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Data Quality impacts all downstream tasks

↓

Data Analysis

Biz decision-making

ML & DL models

Infra-costs

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Let's map Data Quality to an ML-problem?

Any Suggestions?

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Data Quality

- Time-series of metrics (detect anamolies)
  - KPI
  - utilization
  - Table
    - # rows
    - column-level
      - missing values
      - min; max; unique-values
      - ...

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— Data Anamolies $\mathcal{D} = \{x_i, y_i\}_{i=1}^{n}$

(Q) what techniques can we employ here ?

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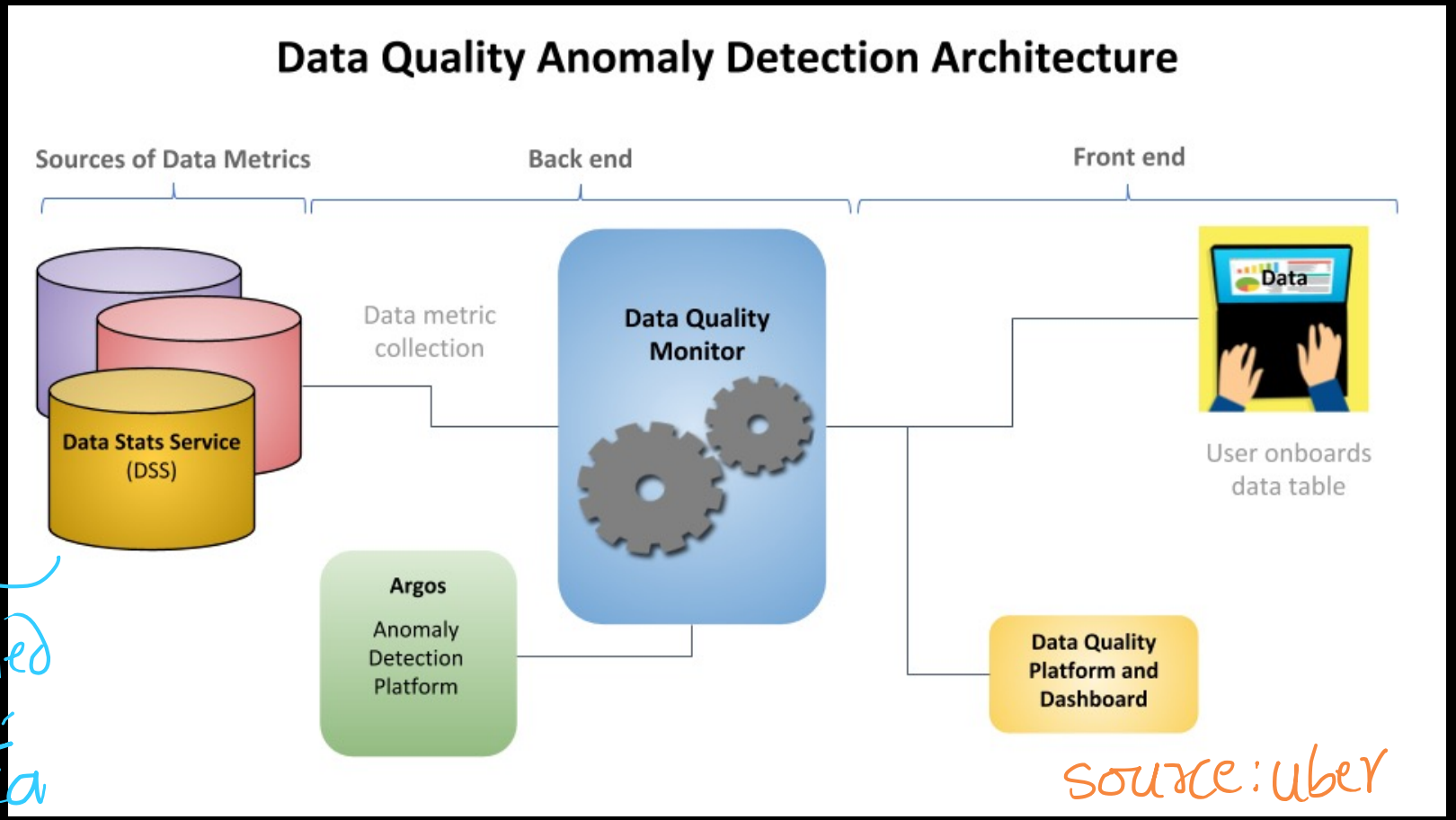
Uber DQM



date partitioned

Hive & Vertica

source: uber

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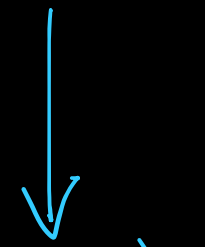
DSS: multi-dimensional time series output



(DQM) → PCA & project to lower-dim

→ Time-series anamoly detection (using forecasting)

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(Q) why do you PCA is helpful here?

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many metrics are highly correlated

↓

eg: trip duration & trip distance

Uber: 90% of variability explained by the top-PC.

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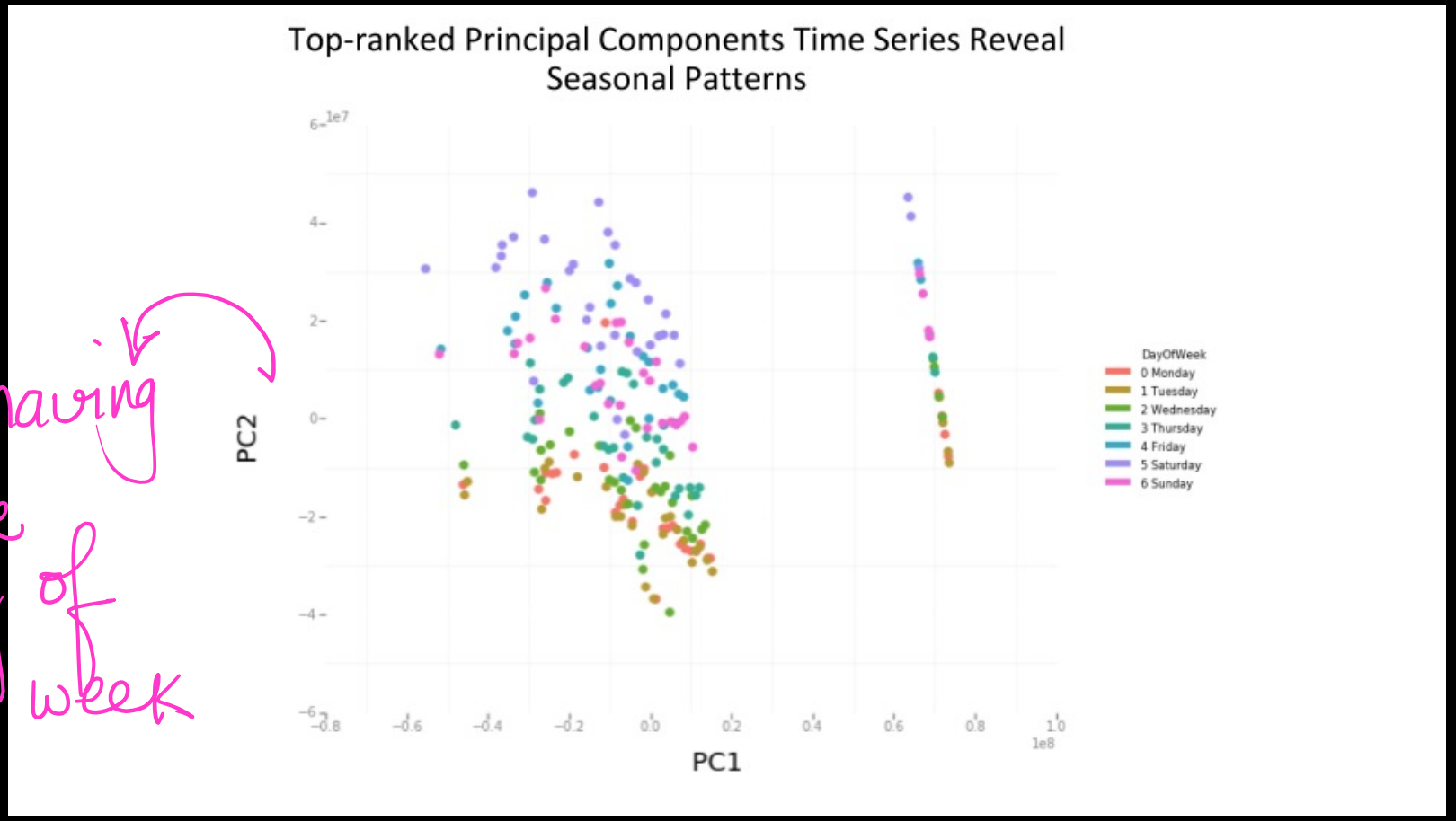
source: uber



behaving like day of week

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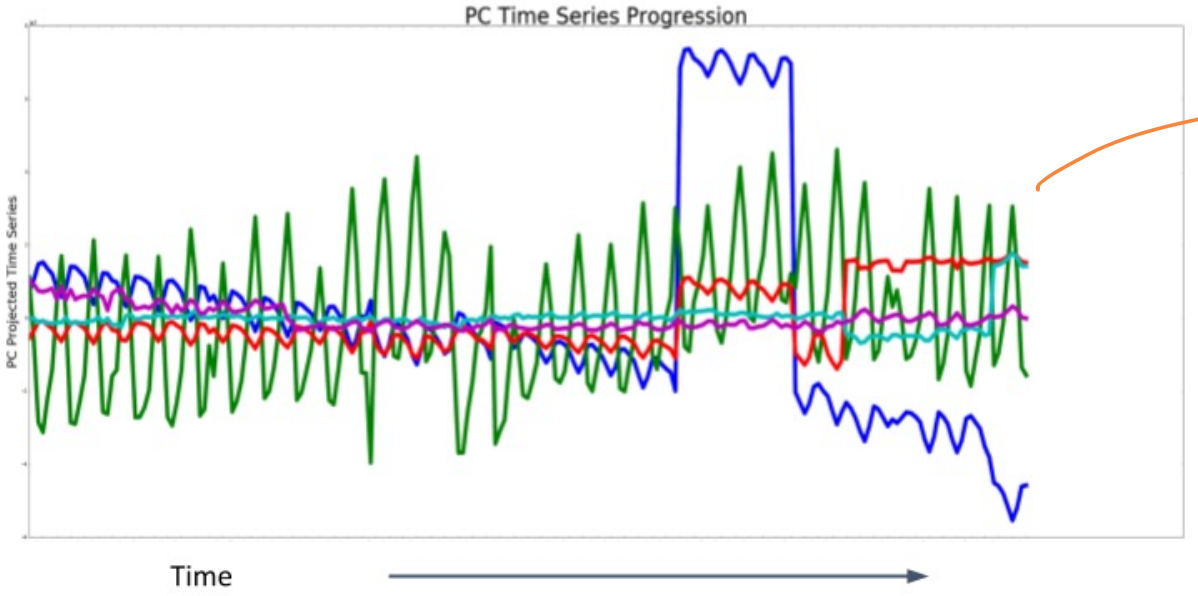
Principal Component Time Series Shows State Changes and Seasonalities



Top 5-PCs across time

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(Q) why not perform time-series anamoly detection on raw metrics ?

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Analyzing top-5 PCs

vs

Analyzing 100's of metrics

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Time-series anamoly detection

- via forecasting
- Holt-winters model
  - exponential moving average
  - Seasonality
  - Trends

https://otexts.com/fpp2/holt-winters.html

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(Q) why exponential smoothing ?

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recent data is given more weightage

↓

fast growing startup with sudden changes

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Seasonality → weekends; evening-hours; holidays ...

Trend → Typically to capture broader growth over time.

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Lesson: Use the 'simplest' model that works.

→ easy to interpret

↳ do NOT need DL everywhere

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Table-level scores

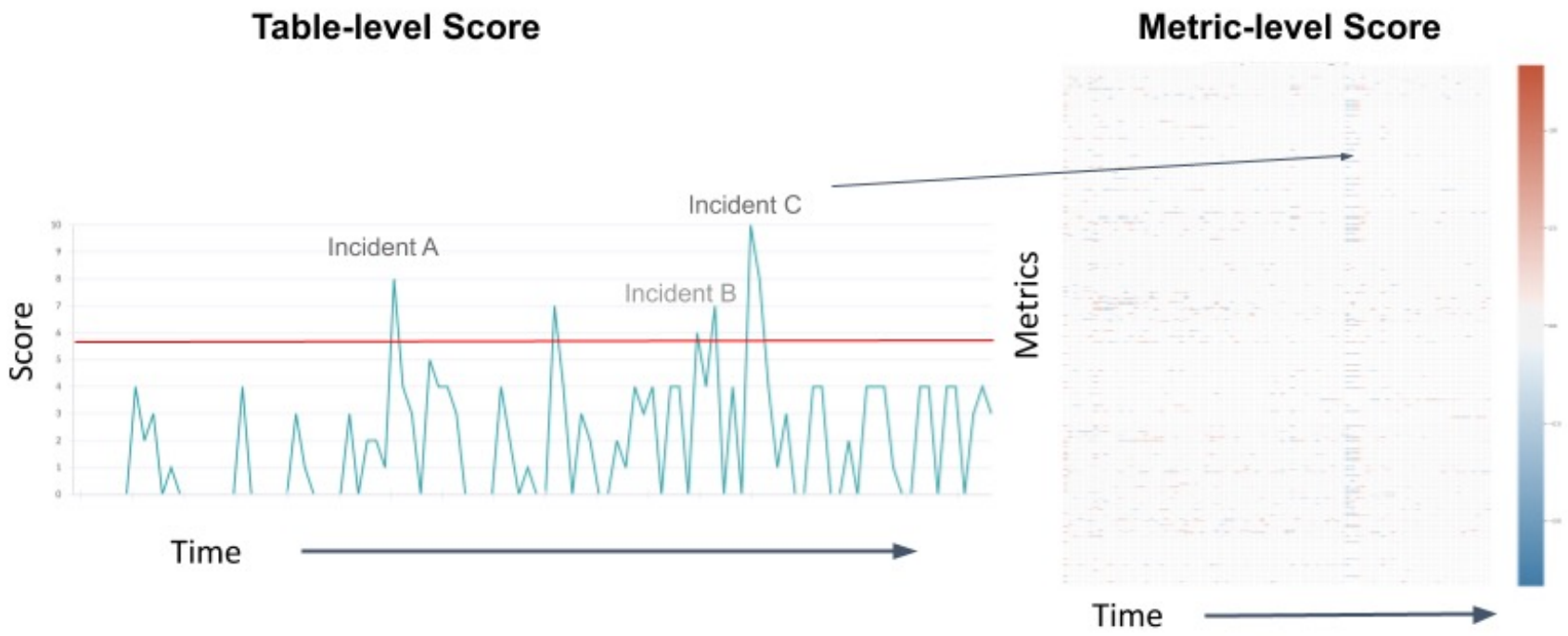
↳ Time-series of data in a table

→ using top PC's with equal weightage

→ anomaly detection

source: Uber

Anomaly Capture with Table and Metric-Level Scores



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DQM: Pyspark & Hive

↳ (what better platform than this?)

Vertica (Columnar NoSQL database)

Figure 5. One of our next steps towards making alerts more intelligent is leveraging data table lineage information. In fact, we have observed strong correlation between data table quality and lineage as the clustering of table-level quality scores over time can reconstruct table ancestry. This is validated in practice as we see related tables have common root causes when they degrade in data quality.

Source : Uber

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Source: Netflix.com

Source ↓

https://databricks.com/session_na20/an-approach-to-data-quality-for-netflix-personalization-systems

(slides & video)

Source: Netflix.com

Netflix PI Historical Fact Store

- Manages more than 10PB of data
- Manages hundreds of attributes
- More than 1 Billion rows flow through the ETL pipelines per day
- This data is used by several machine learned models and algorithms that enable Personalization

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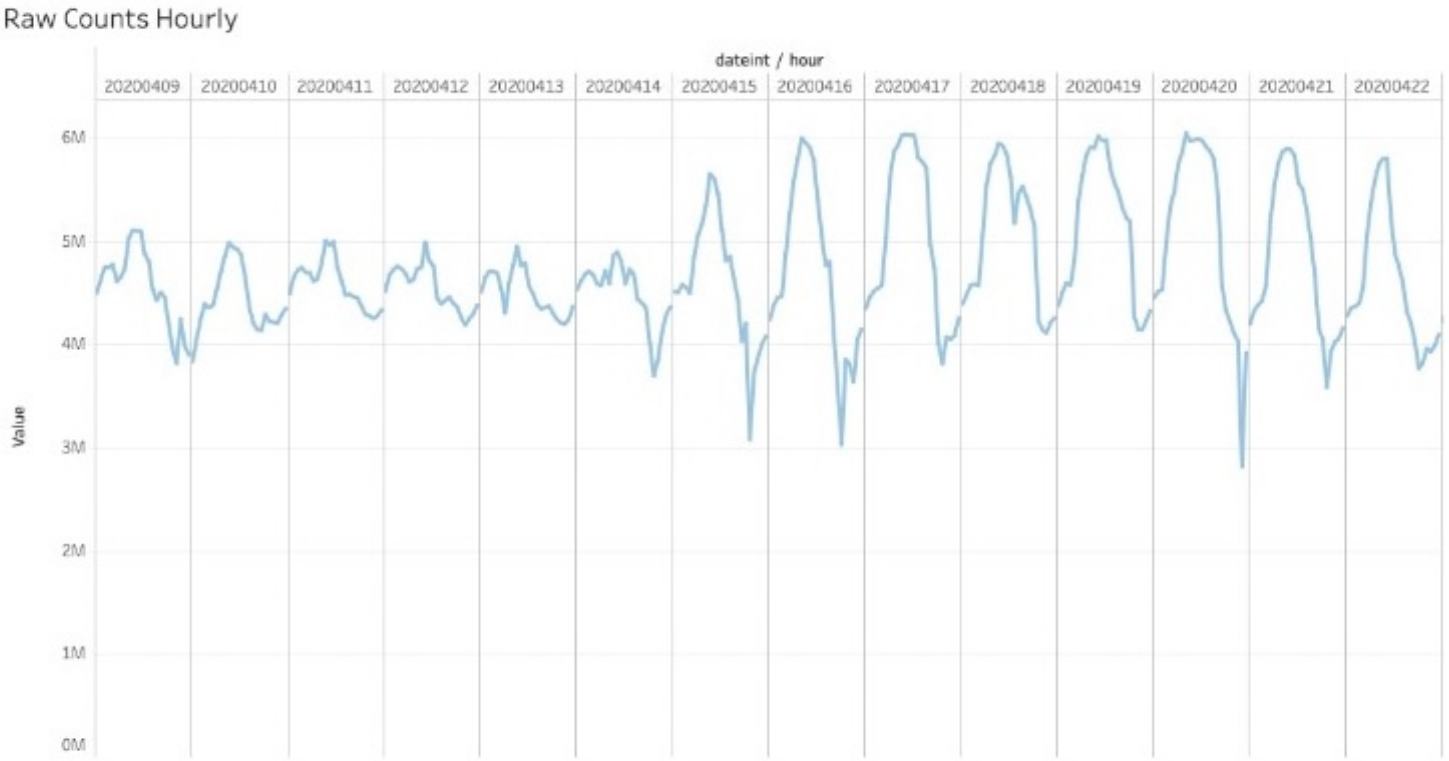
Bad Data Example 1: Drift



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Source: Netflix.com

Bad Data Example 2: Drastic changes

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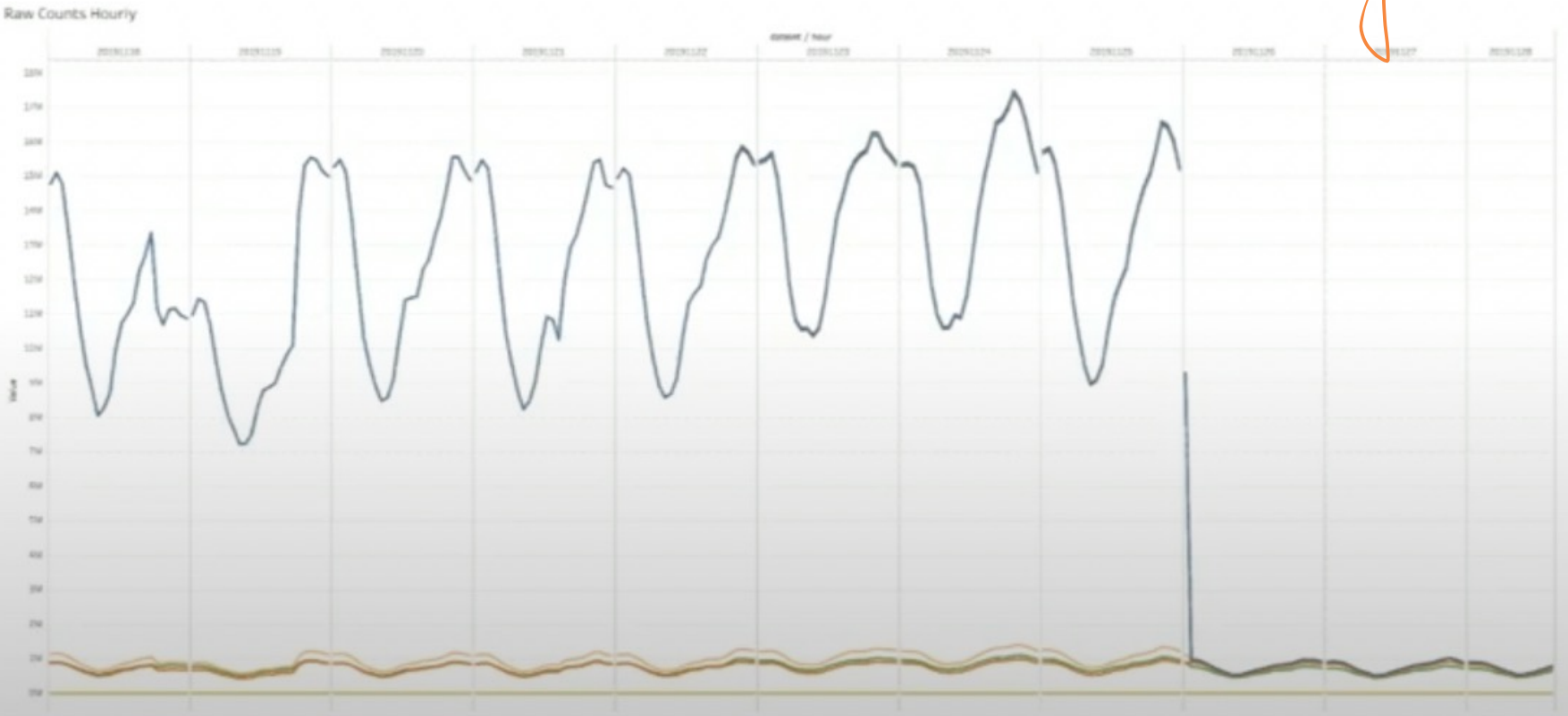
Very important but often ignored

Bad Data Example 3: Under Utilization



Source: Netflix.com

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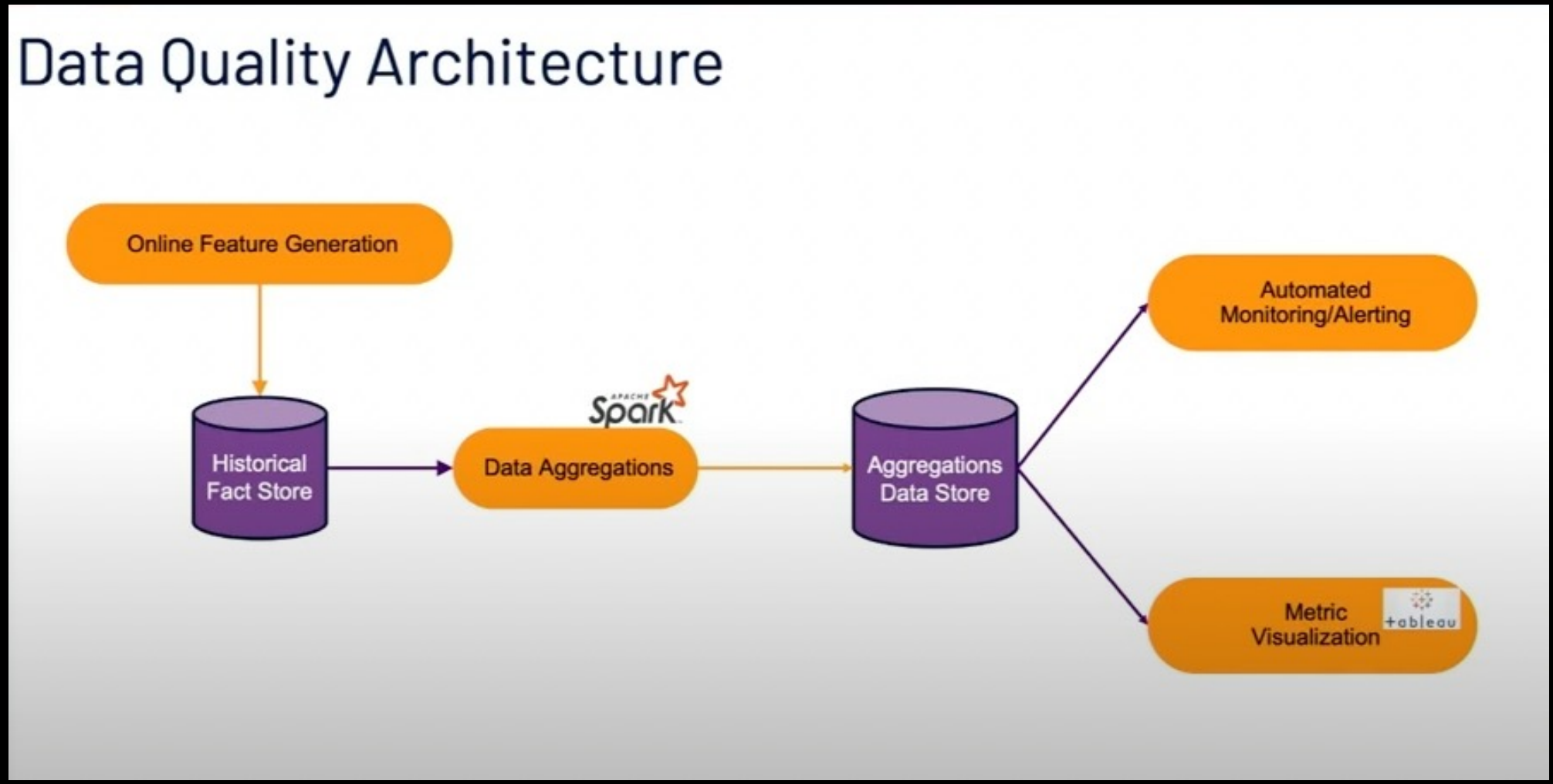
Source: Netflix.com



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Source: Netflix.com

Aggregations

Date (DD/MM/YYYY)	Number Of Null Plays	Median Play Duration (seconds)	99th Percentile Play Duration (seconds)
1/1/2020	3	360	450
1/2/2020	20	270	780
1/3/2020	1	150	570

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Source: Netflix.com

Automated Monitoring:

↳ distribution - matching of attributes

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(Q) Any suggestions ?

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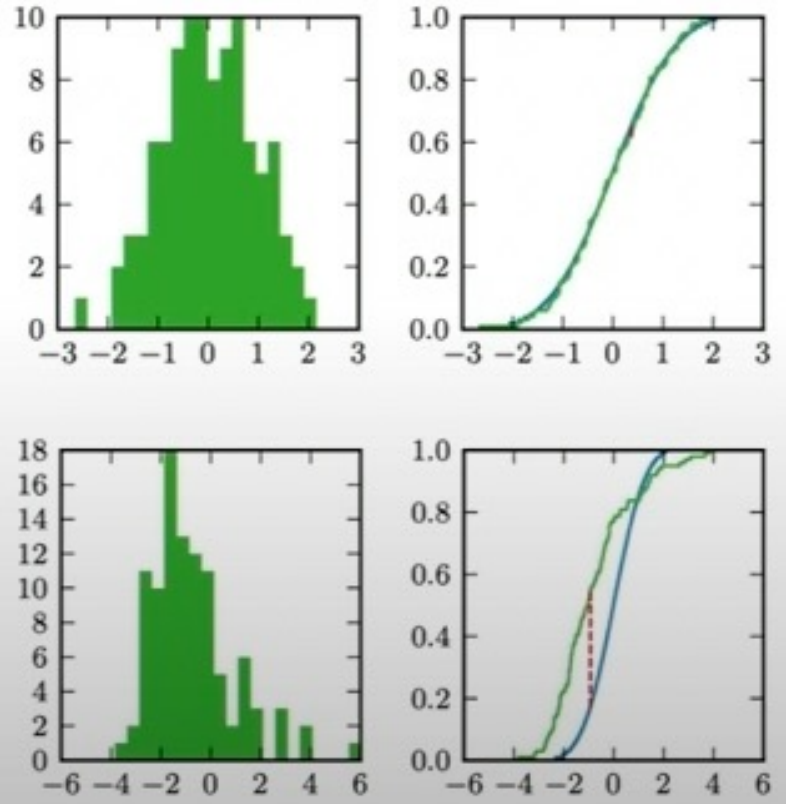
Source: Netflix.com

Distribution Checks – Statistical Test

Kolmogorov-Smirnov statistical test[1]

$$F_n(a) = \frac{1}{n} \sum_i \mathbb{I}(x_i < a)$$

$$D_n = \max_x |F_n^1(x) - F_n^2(x)|$$



[1]Source: MIT 6.S085

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Source: Netflix.com

Audits

```
from pyspark.sql import SQLContext
import AuditRunner, Audit

df = SQLContext.sql('SELECT * FROM ml.aggregations WHERE dateint = 20200303')

# Audit Pseudo code
auditRunner = AuditRunner().add(
    Audit (df,  'num_null_plays',      { 'upper_bound': 10 },              { 'alert': 'pager' } ),
    Audit (df,  'num_null_plays',      { 'normal_distribution': True },    { 'alert': 'dev_notification' } ),
    Audit (df,  'avg_play_duration',   { 'query_anomaly_detection': 'rad' }, { 'alert': 'dev_notification' } )
    # ...
)
```

Thresholds

distribution matching

Robust Anamoly Detcn

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Netflix RAD:

https://netflixtechblog.com/rad-outlier-detection-on-big-data-d6b0494371cc

↳ Robust PCA (repeatedly calculate SVD and apply thresholds)

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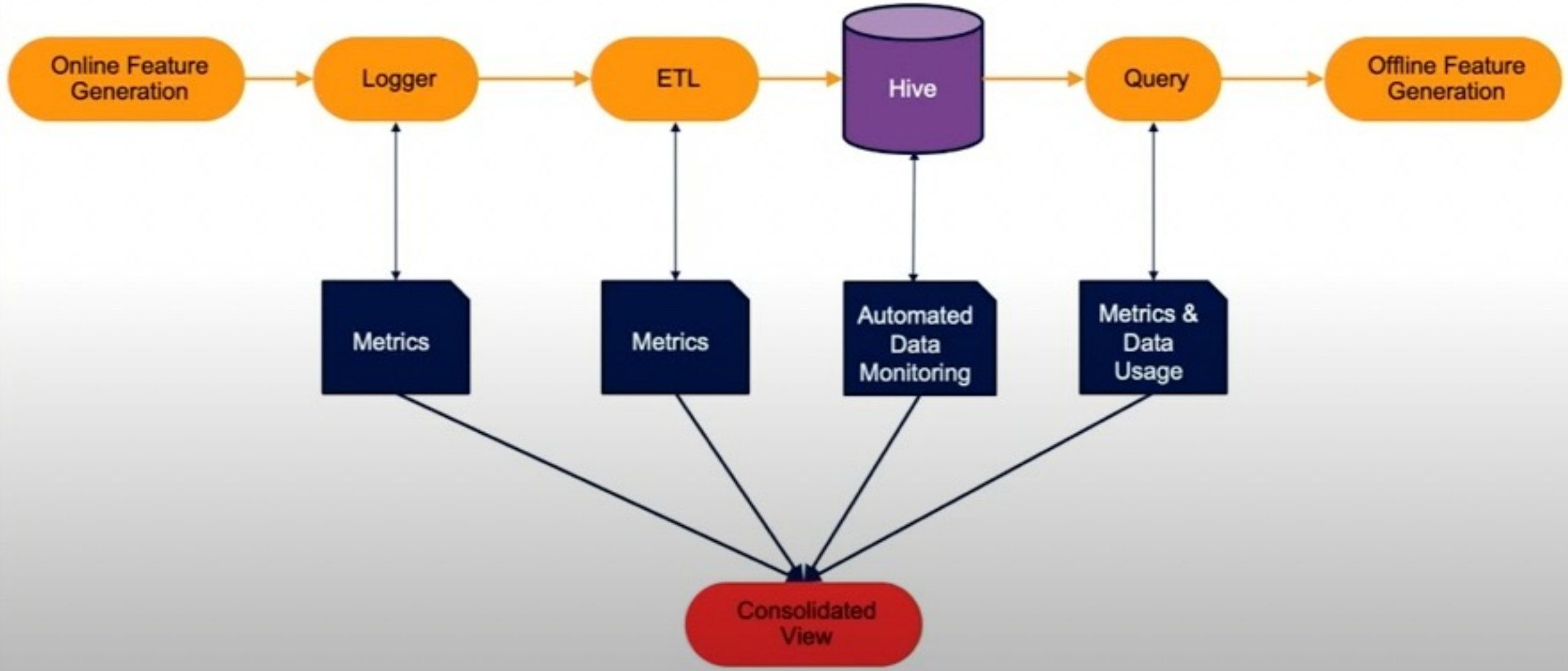
Source: Netflix.com

Plain old visualizations

Data Quality Checkpoints



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Next Session : Amazon's Data Quality System