

THE MATH BEHIND THE INCIDENT AFTERMATH

(A Practical Guide To Measuring Incident Impacts)

SREcon22 Asia/Pacific

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Overview

Table of Contents

Basics

Incident Impact

- 1.1 Production Environment
- 1.2 Incident Lifecycle
- 1.3 Incident Aftermath
- 1.4 Manual Assessment Challenges

Design

Of System

- 2.1 Requirements
- 2.2 Manual Assessment Process
- 2.3 Key Abstractions
- 2.4 Architecture

Math

Models

- 3.1 6-Week Trimmed Avge. Model
- 3.2 Machine Learning
- 3.3 Implementation Considerations
- 3.4 Models Assessment

Features

& Take-Aways

- 4.1 Key Features
- 4.2 Opportunities & Challenges
- 4.3 Titbits on *How to Setup one?*
- 4.4 Questions

THE BASICS

On Incidents & Its Aftermath

THE BASICS

Production Environment At a Glance

Behind the technology platform of scale

Business in Q3'22

- 5.6 billion transactions
- \$337 billion in total payment volume
- 432 million active accounts
- Connects people and businesses in > 200 markets

Platforms

- On both cloud & on-premises
- Distributed across several availability zones
- Hardware and software components
- 1000s of VMs

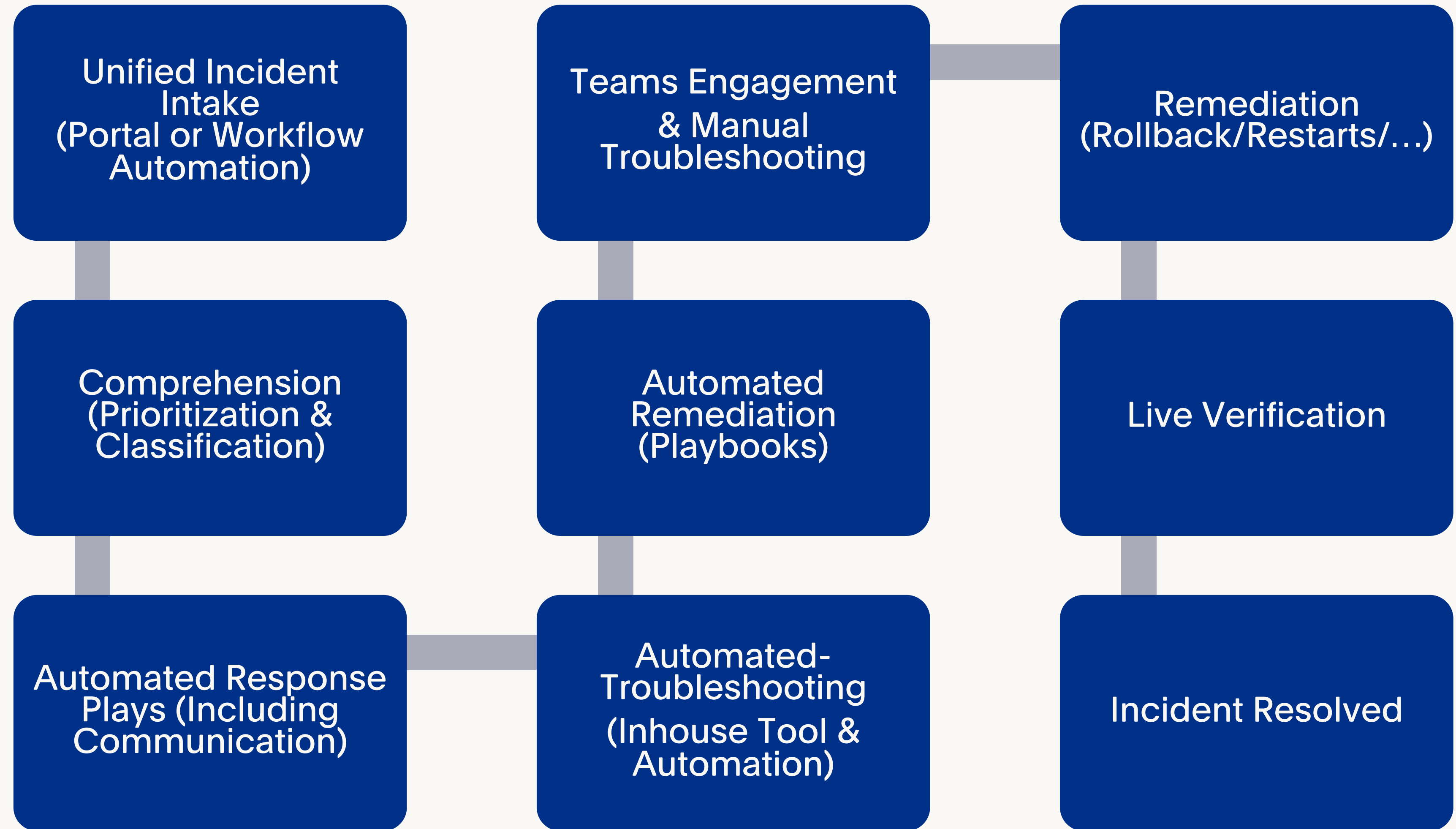
Applications

- Over 3200 applications and services
- Database & data warehouse
- Multiple programming languages
- Web, mobile & API offerings

THE BASICS

Incident Lifecycle

How does an incident transition?



THE BASICS

Incident Aftermath

What is done after an incident?

Incident Timeline

Start Time, Alert Time, Ack Time, Diagnosis Time, Mitigation Time, Impact Duration, Incident End Time.

Impact Assessment

Transaction loss (TPV & Revenue Impact), Availability loss, Segmentation by Customers, Merchants, Products, and Countries.

Notification

Internal and external communication. Regulatory Reporting. Partners, Customers, Merchants, Executives, Status page updates are done.

Root Cause Analysis

Sequence of events. How the process works and what lead to the incident? Caused by change?

Preventive Measures

Any scope for improvements in Detection, Diagnosis, Mitigation, and Recovery? How can we prevent? What lessons are learned (people, processes & technology)?

THE BASICS

Manual Assessment Challenges

Challenges

- Time-consuming (several hours)
- Toil to segment the data by products and countries in the trenches
- Knowledge of the area/domain & Challenges in interpreting data
- Error prone
- Inherent urgency in assessing and moving forward
- Not scalable as we grow

Urgency

On the other hand, we need instant assessment for

- Regulatory reporting (varies from 4 to 72 hours)
- Instant communication for customers/merchants & in PayPal Status site
- To know the loss incurred and segment it for next steps

Some Regulators

- CSSF (Luxembourg/EU)
- APRA (Australia)
- KLFB (Japan)
- NYDFS (U.S.)
- SEC (U.S.)
- BACEN (Brazil)
- HKMA (Hong Kong)
- MAS (Singapore)
- BOT (Thailand)
- CBR (Russia)
- CERT-IN (India)

SYSTEM DESIGN

On Requirements & Architecture

SYSTEM DESIGN Requirements

What are the requirements?

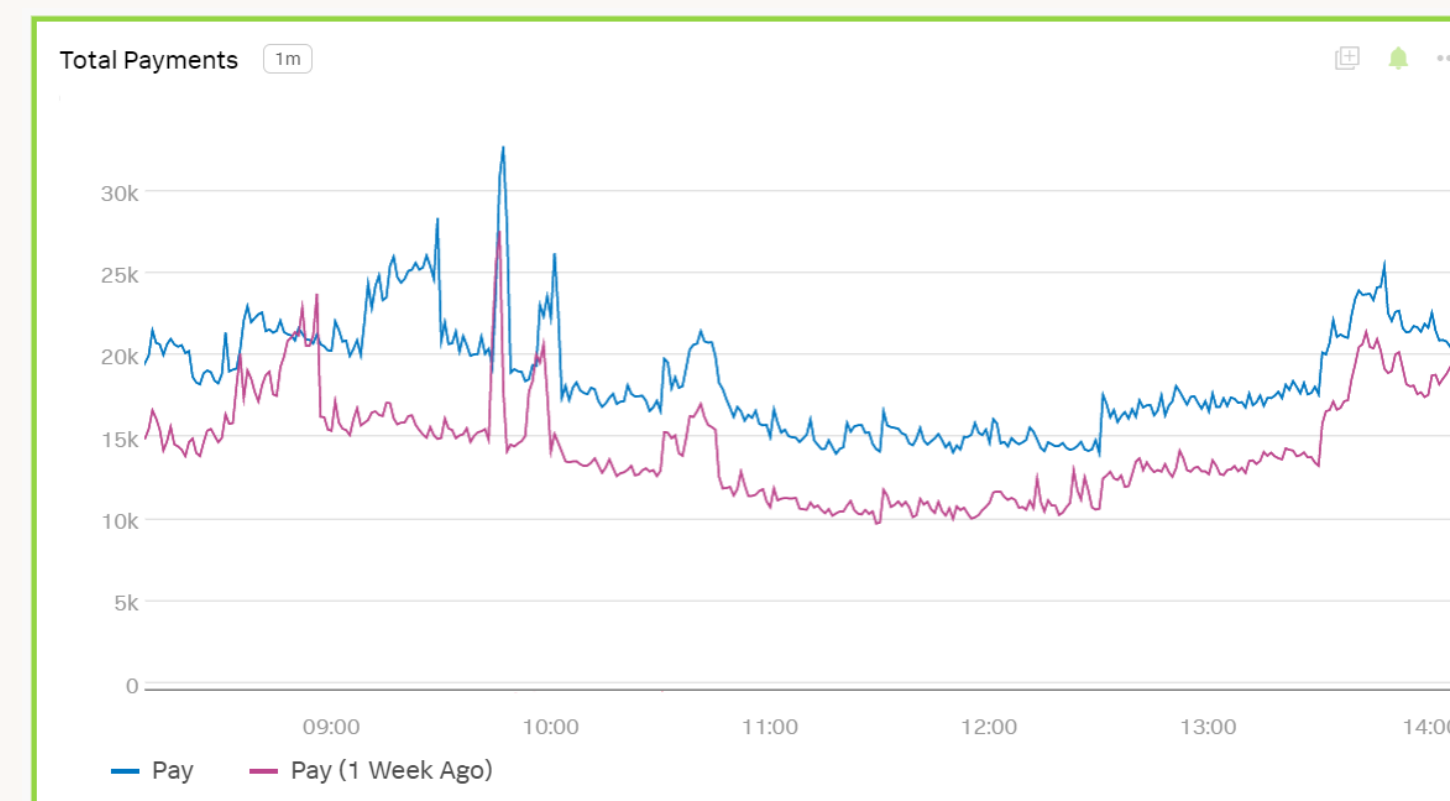
Requirements

- Automate the impact assessment process, i.e., to measure the loss during an incident.

Business Health

- Payment volume is number of payments over a time window (say per minute).
- Total Payment volume is a reliable metric that represents the business health.

Payment Volume



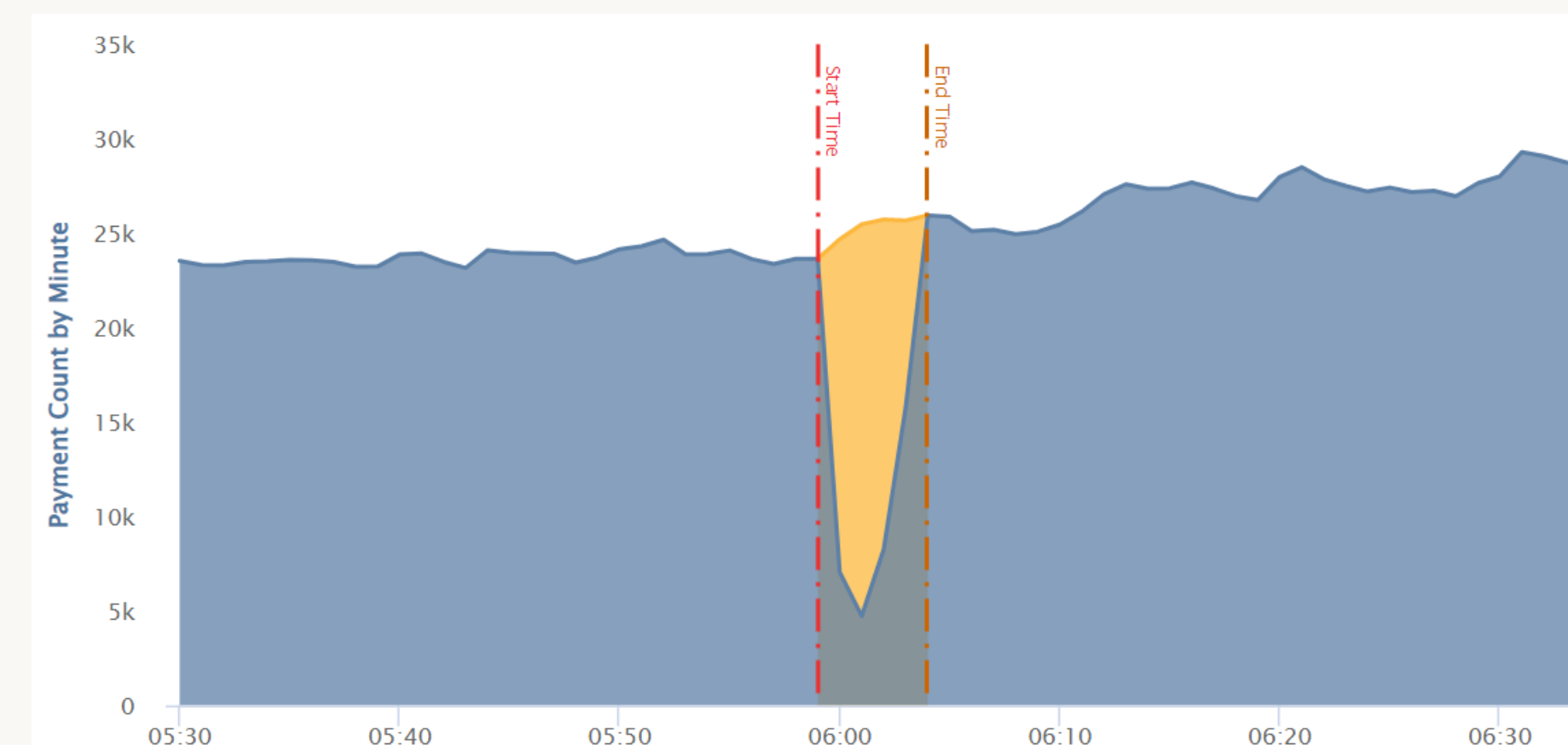
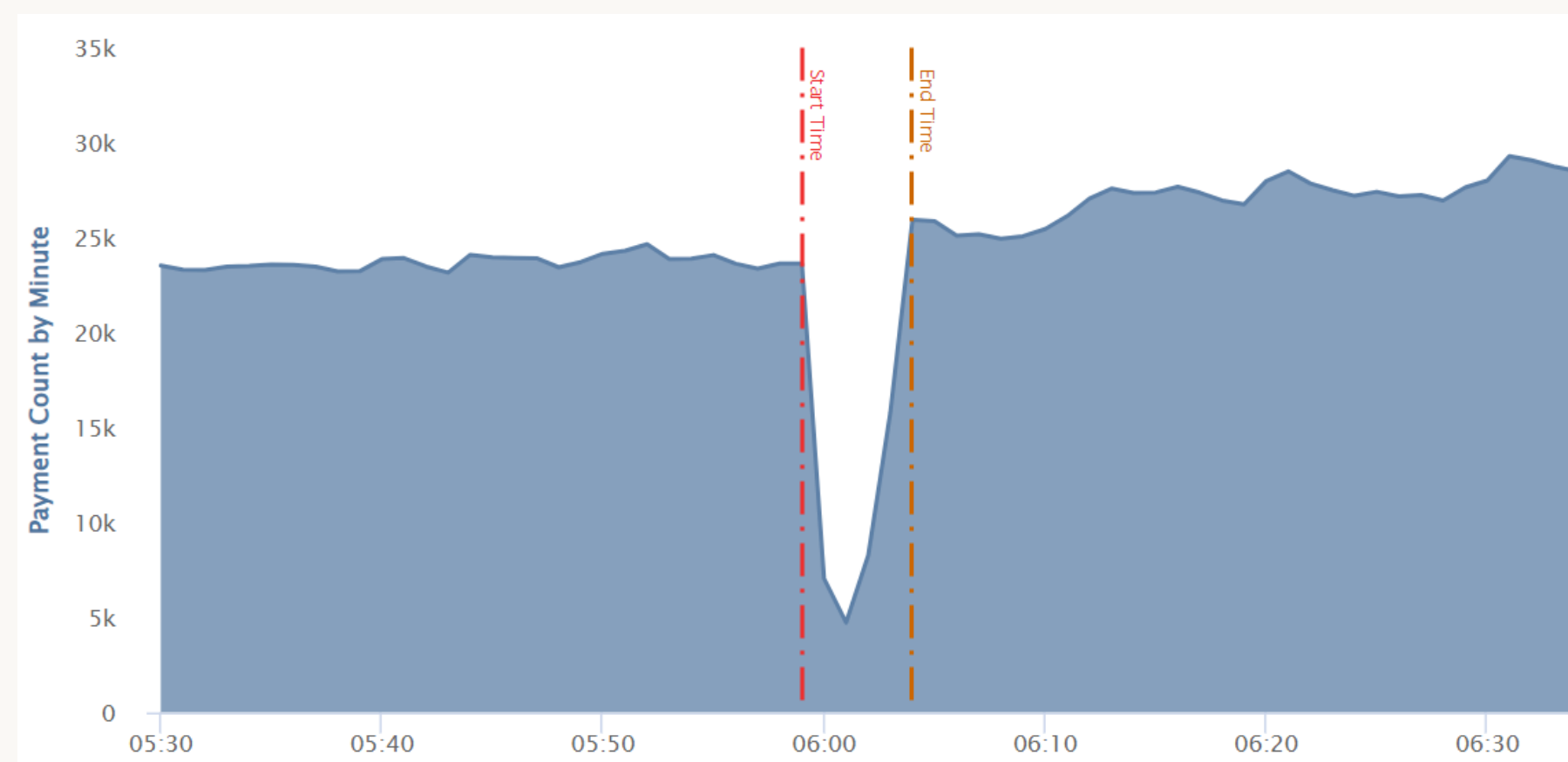
Representational Image

SYSTEM DESIGN

Manual Assessment

How do we measure impacts manually?

STEPS



Representational Images

Step 1 – Determine the impact start & end time.

Step 2 – Choose a statistical model. A simple model is 'x' week average.

Step 3 – Calculate the modeled count for each minute within the window. For e.g., take average of the same minute for the previous 6 weeks.

Step 4 – Impact for a given minute is $\max(0, \text{model payments} - \text{actual payments})$.

Step 5 – Total number of lost transactions is the sum of the impact to each minute in the incident timeframe.

Step 6 – Revenue Impact = Total no. of lost transactions x average revenue per payment (in \$)

SYSTEM DESIGN

Key Abstractions

Evolution of the Architecture

Ad. Requirements

- Key-in start and end times.
- Provision to talk to disparate real-time data sources.
- Visualize the results.
- Scale up and down the modeled counts as needed.
- Record impact (with screenshots) in ticketing system.

Key Abstractions

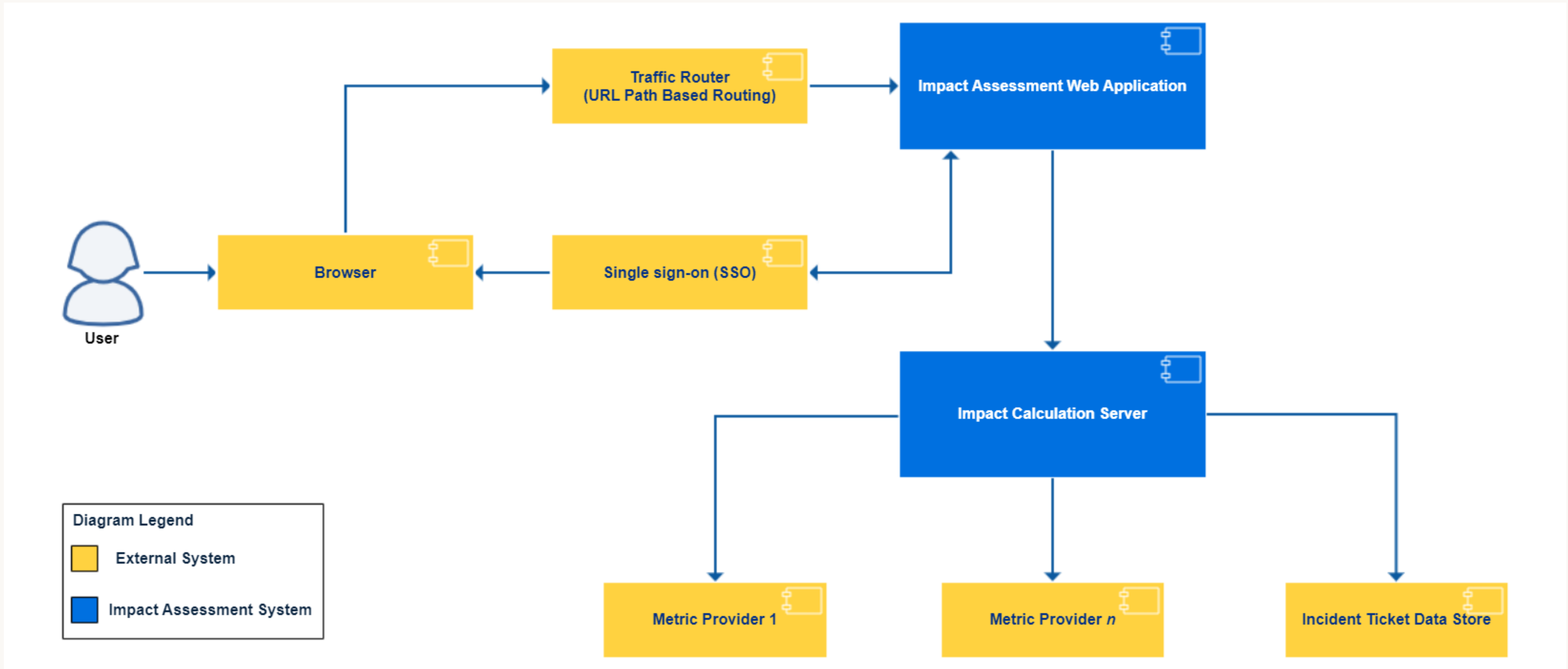
- A front-end web-based user interface application.
- Authentication for the tool using SSO.
- Ability to provide multiple models for consumption.
- A good charting library for data visualizations.
- Visual features to play with the modeled data.

Patterns

- n-tier /multitier architecture.
- Database may not be needed.
- Facade design pattern for multiple data sources.
- Existing popular Languages would work.

SYSTEM DESIGN

Architecture



MATHEMATICAL MODELING

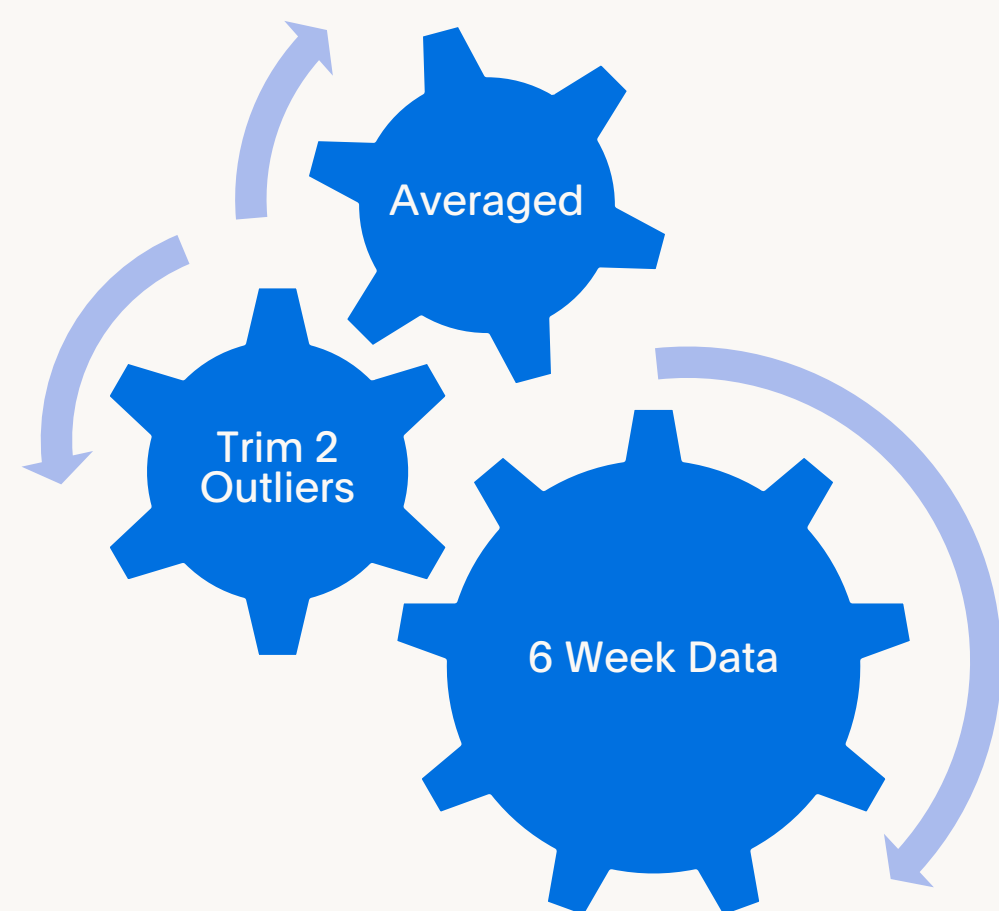
On Statistical & Machine Learning

MATHEMATICAL MODELING

Scaled 6 Week Trimmed Average

How does the 6-week average model work?

Process



Model

1. Get count of the same minute for each of the previous 6 weeks.
2. Remove the highest and lowest value (2 outliers).
3. Calculate the mean of the remaining 4 values.
4. Repeat the process for all the minutes in the window.
5. Scale by a multiplier to align it with the data preceding the incident.

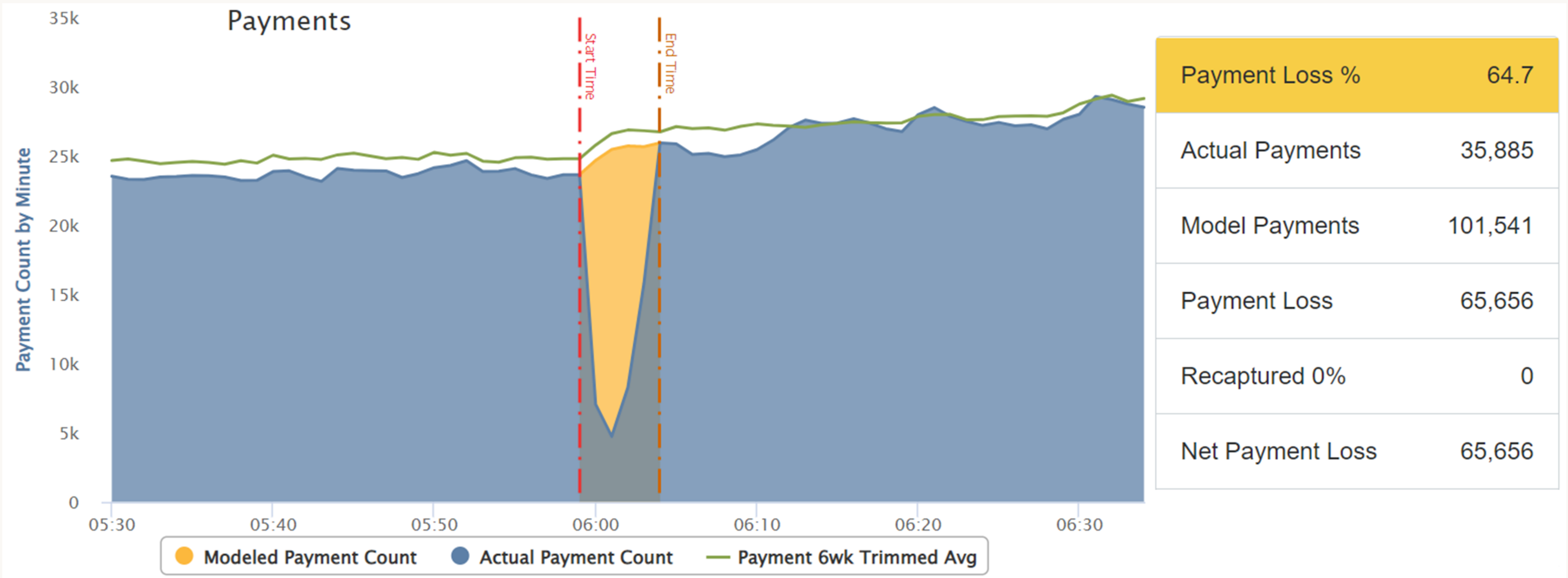
Example

| Description | Incident Time | # Payment | Comment |
|---------------|---------------------|-----------|---------|
| Incident Time | 2022/12/07-10:30:00 | 4 | Actual |
| Week-1 | 2022/11/30-10:30:00 | 7 | |
| Week-2 | 2022/11/23-10:30:00 | 8 | Outlier |
| Week-3 | 2022/11/16-10:30:00 | 7 | |
| Week-4 | 2022/11/09-10:30:00 | 4 | |
| Week-5 | 2022/11/02-10:30:00 | 3 | Outlier |
| Week-6 | 2022/10/26-10:30:00 | 6 | |
| Mean | | 6 | |
| Lost | | 2 | |

MATHEMATICAL MODELING

Scaling of Trimmed Average

How does scaling work?



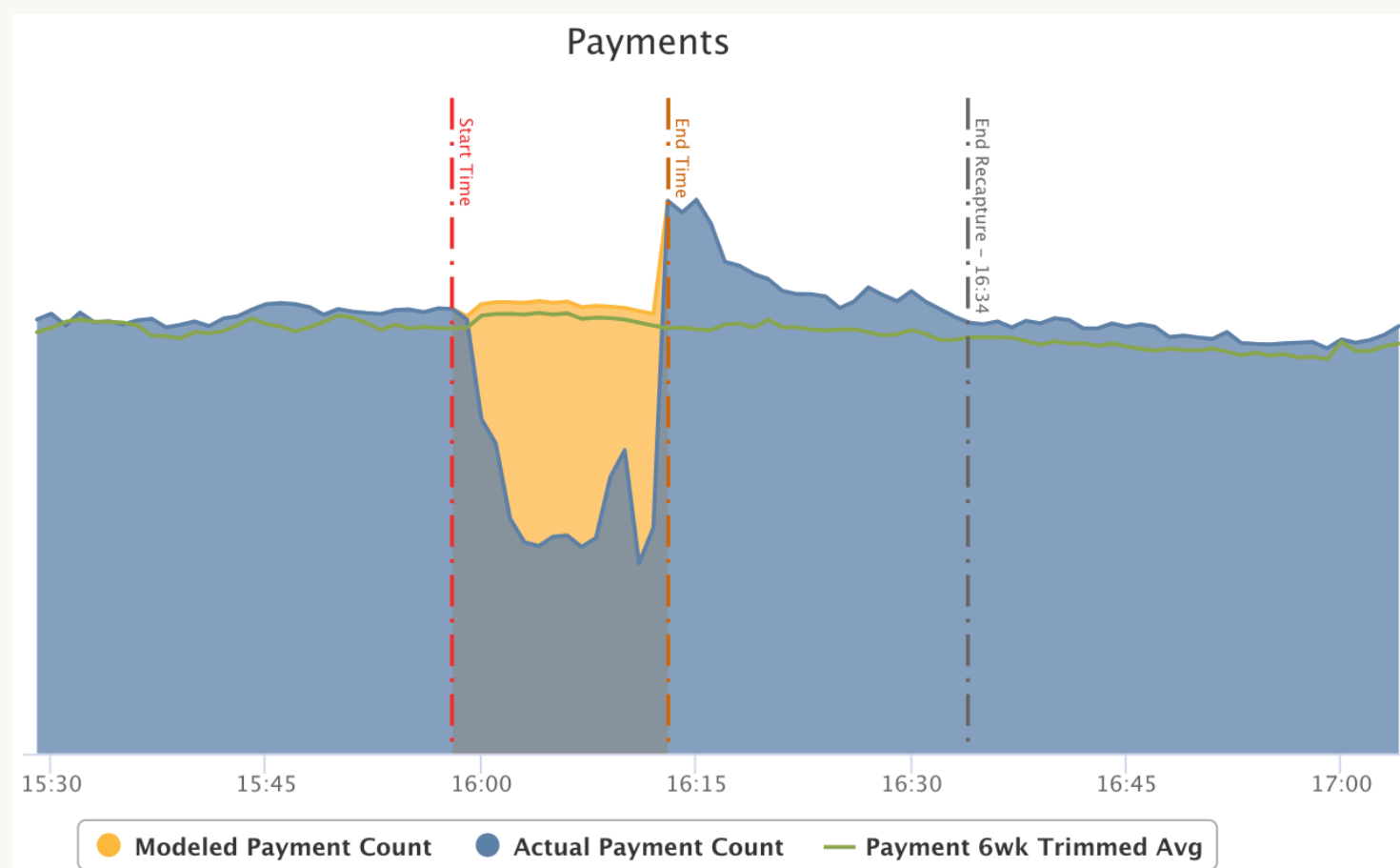
Representational Image

MATHEMATICAL MODELING

Recapture & Manual Scaling

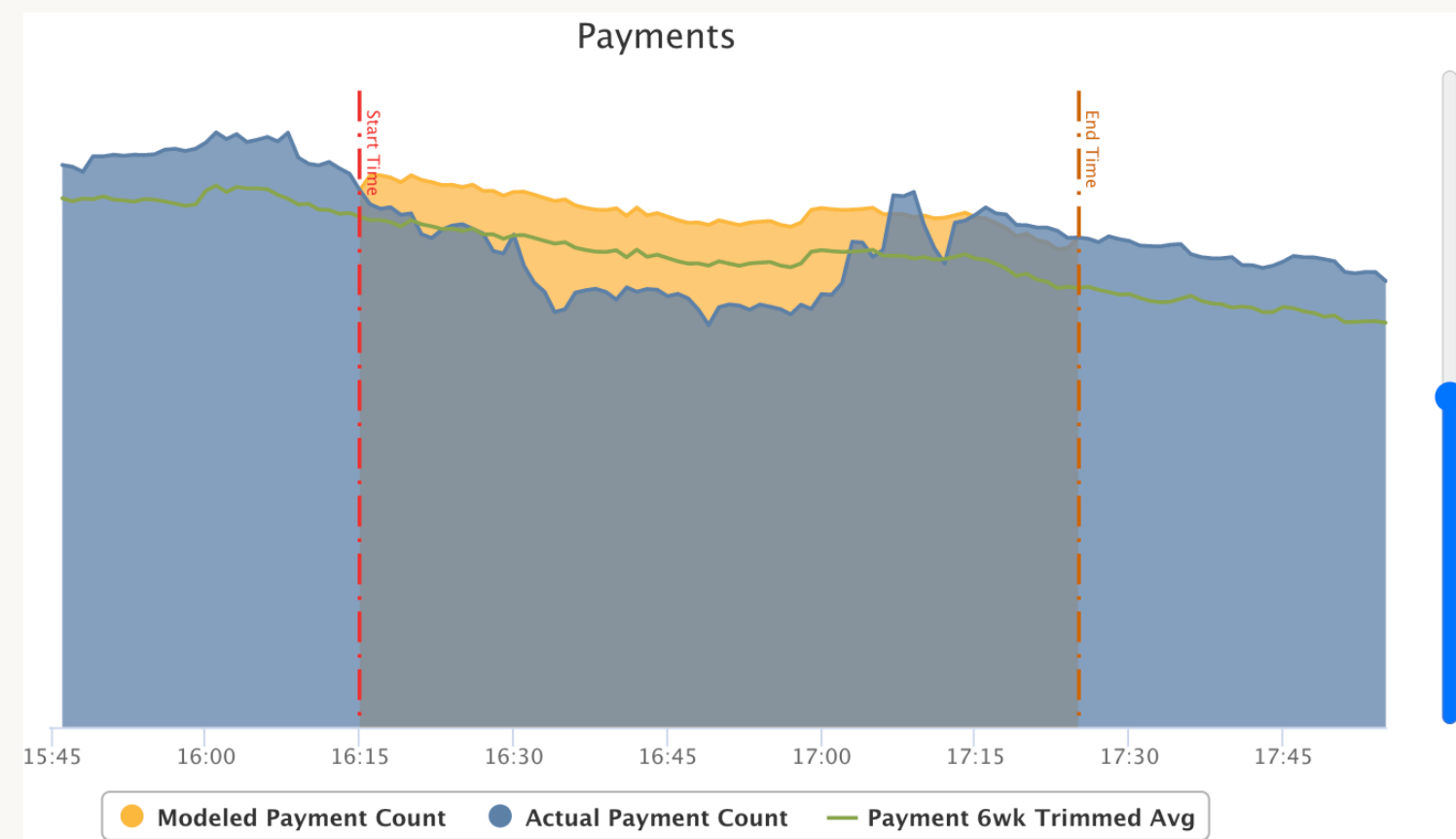
How do we account for recapture & can we adjust scaling?

Recapture



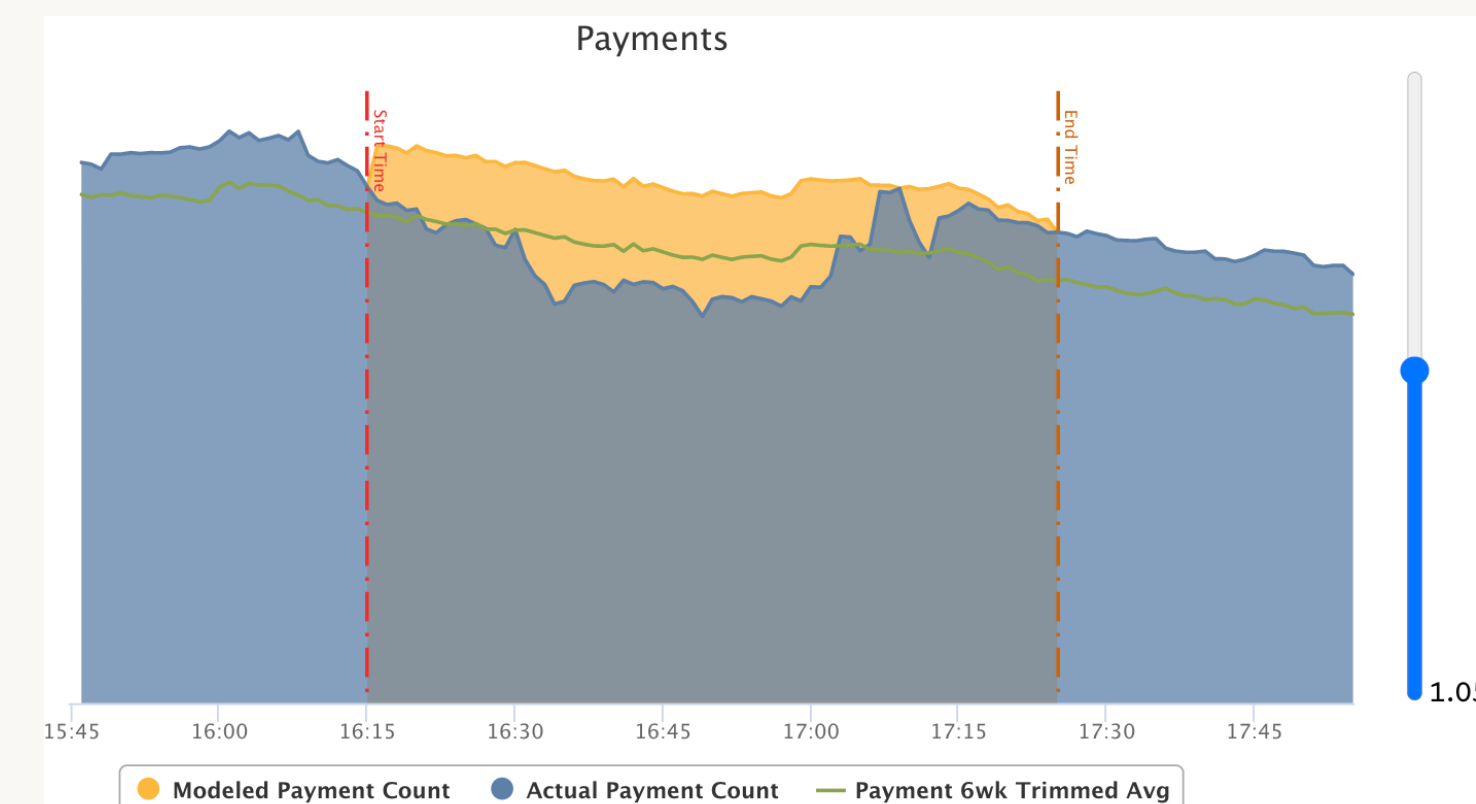
After the incident ends, some failed transactions would be retried. This can be seen as a spike compared to the norm. We discount them from impact.

Default Model @ 1.0



Rarely a model like scaled `6` week trimmed average may not align properly with current trend. This can be observed visually.

Scaled Model @ 1.05



Users can do minor scaling (multiplier) to the model to align it to the current trend. Here the model is scaled by 5% upwards.

MATHEMATICAL MODELING

Formula for 'x' Week Trimmed Average

'X' Week Trimmed Average

$$impact(start_time, end_time) = \sum_{t=start_time}^{t=end_time} \max(expected_value[t] - observed_value[t], 0)$$

$$\begin{aligned} & recaptured(end_time, recapture_end_time) \\ & = \sum_{t=end_time}^{t=recapture_end_time} \max(observed_value[t] - expected_value, 0) \end{aligned}$$

$$\begin{aligned} & net_impact(start_time, end_time, recapture_end_time) \\ & = impact(start_time, end_time) - recaptured(end_time, recapture_end_time) \end{aligned}$$

$$max_value(t) = \max\{observed_value[t - week_to_minutes(w)]: w = 1..x\}$$

$$min_value(t) = \min\{observed_value[t - week_to_minutes(w)]: w = 1..x\}$$

$$sum_of_past_observations(t) = \sum_{w=1}^{w=x} observed_value[t - week_to_minutes(w)]$$

$$\begin{aligned} & expected_value(t) = sum_of_past_observation(t) - max_value(t) - min_value(t) / (x - 2) : x > 2 \\ & expected_series = \{expected_value(t): t = start..end\} \end{aligned}$$

MATHEMATICAL MODELING

Alignment and Scaling

Scaling to align with recent trend

$$padded_start = start - 30$$

$$padded_end = end + 30$$

$$ratio(t) = observed_value(t) / expected_series(t)$$

$$factor = median(\{ratio(t) : t = padded_start .. start\})$$

$$expected_series(padded_start, padded_end) = \{v * factor : v \in expected_series\}$$

$$scale(series, factor) = \{v * factor : v \in series\}$$

$$scaled_expected_series = scale(expected_series, factor)$$

$$revenu_loss = net_impact * avg_revenue_per_txn$$

MATHEMATICAL MODELING

Employing Machine Learning

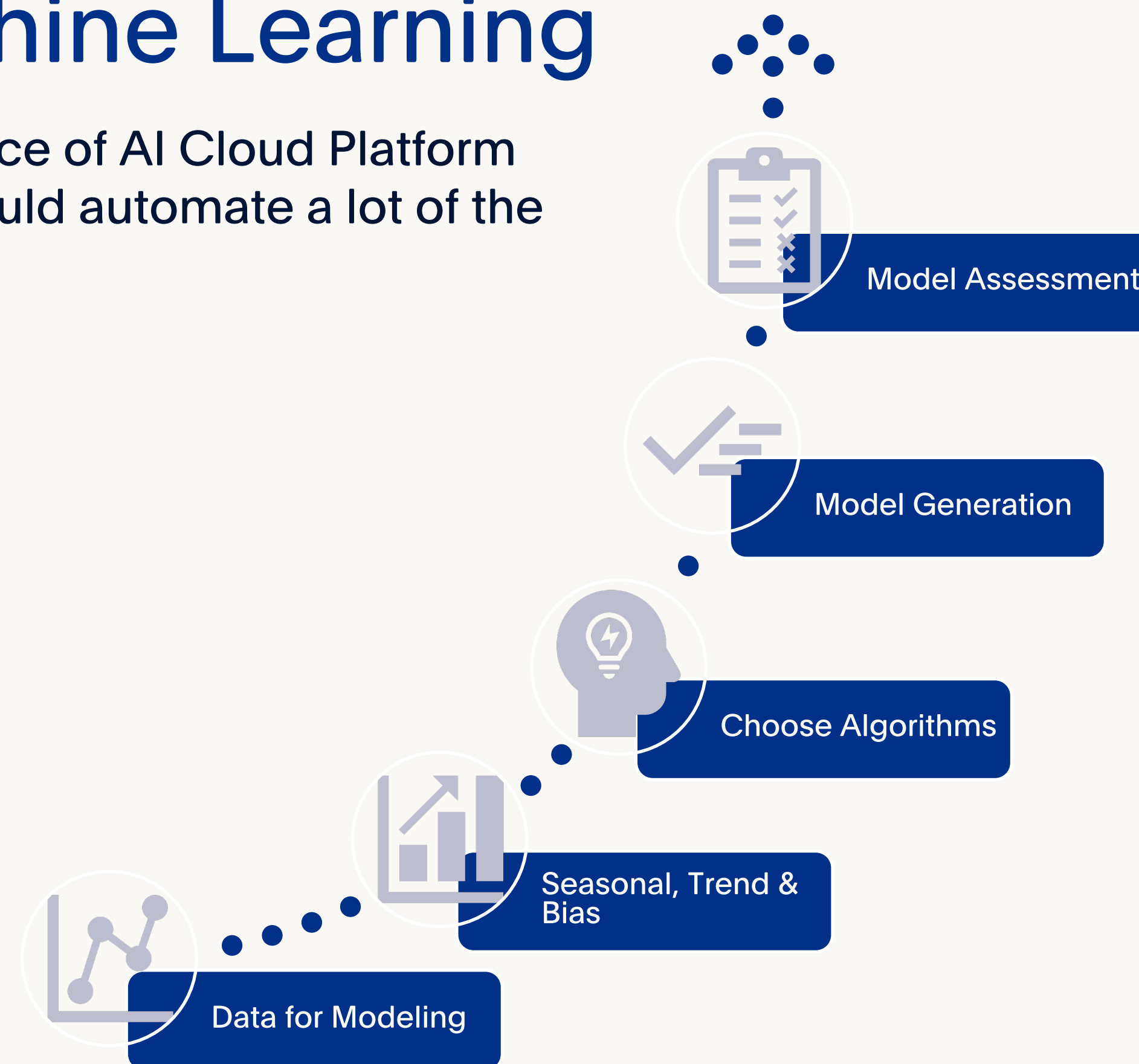
Forecasting

Distilled from ~180 Models on Time Series Forecasting:

- ARIMA & Variants
- LightGBM
- Linear/Polynomial Regression
- LSTM
- NBEATS
- Exponential Smoothing (ETS) Algorithm
- The Theta Model
- Transformer Architectures

Machine Learning

Emergence of AI Cloud Platform which could automate a lot of the steps



MATHEMATICAL MODELING

Implementation Considerations

How do we develop a good model?

Near Real-time Data

As we need to provide the impact data in near real-time, we may have to ensure that the source data is available.

Understanding Datasets

Seasonal, Trend & Bias. Univariate/multivariate data. Stationary and non-stationary data. Highly correlated or not.

Dataset for Training

Test and train the models on nonimpact data.

Many Models

Tried with many models iteratively and with many possible use cases (test data).

Integration

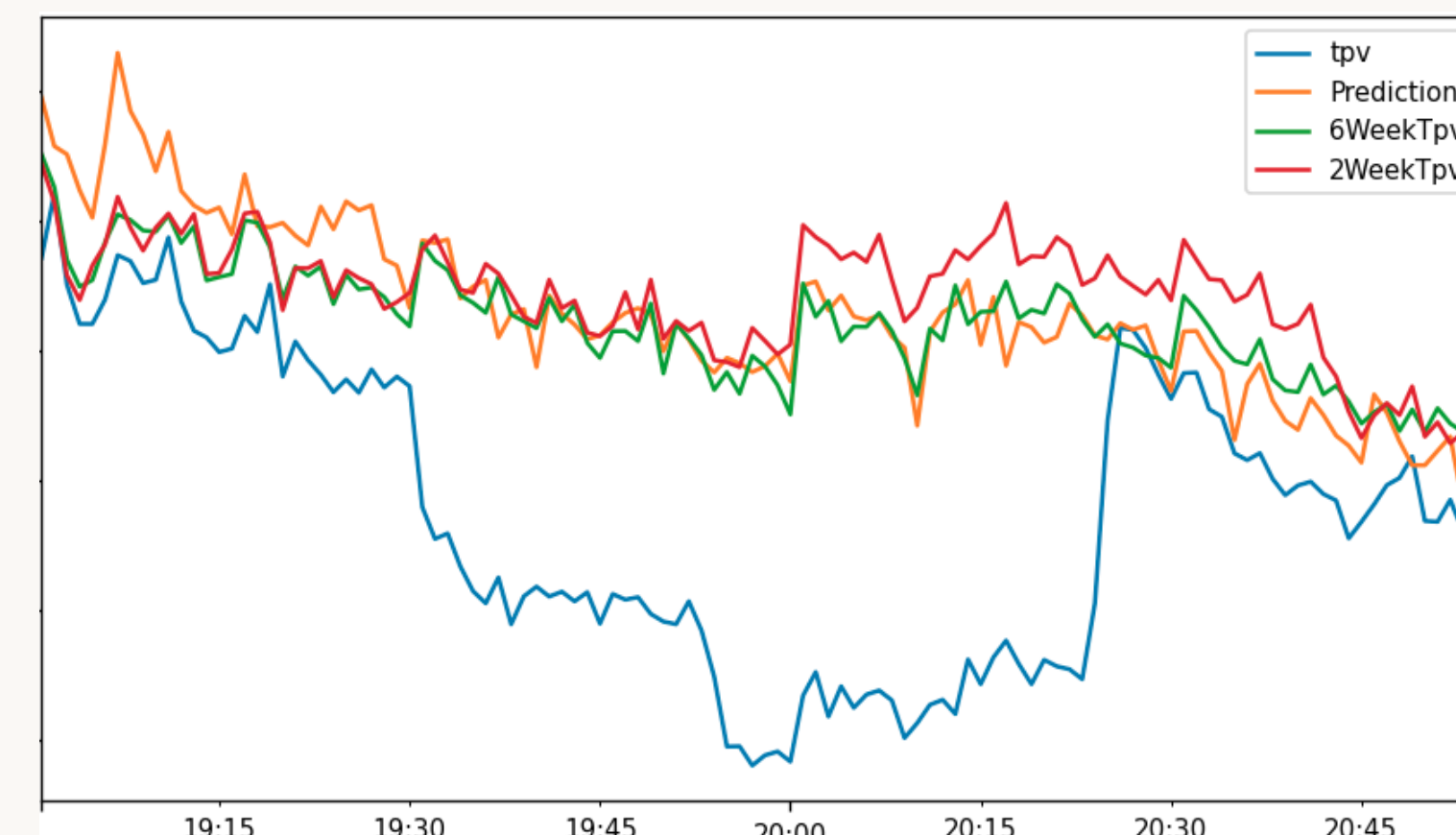
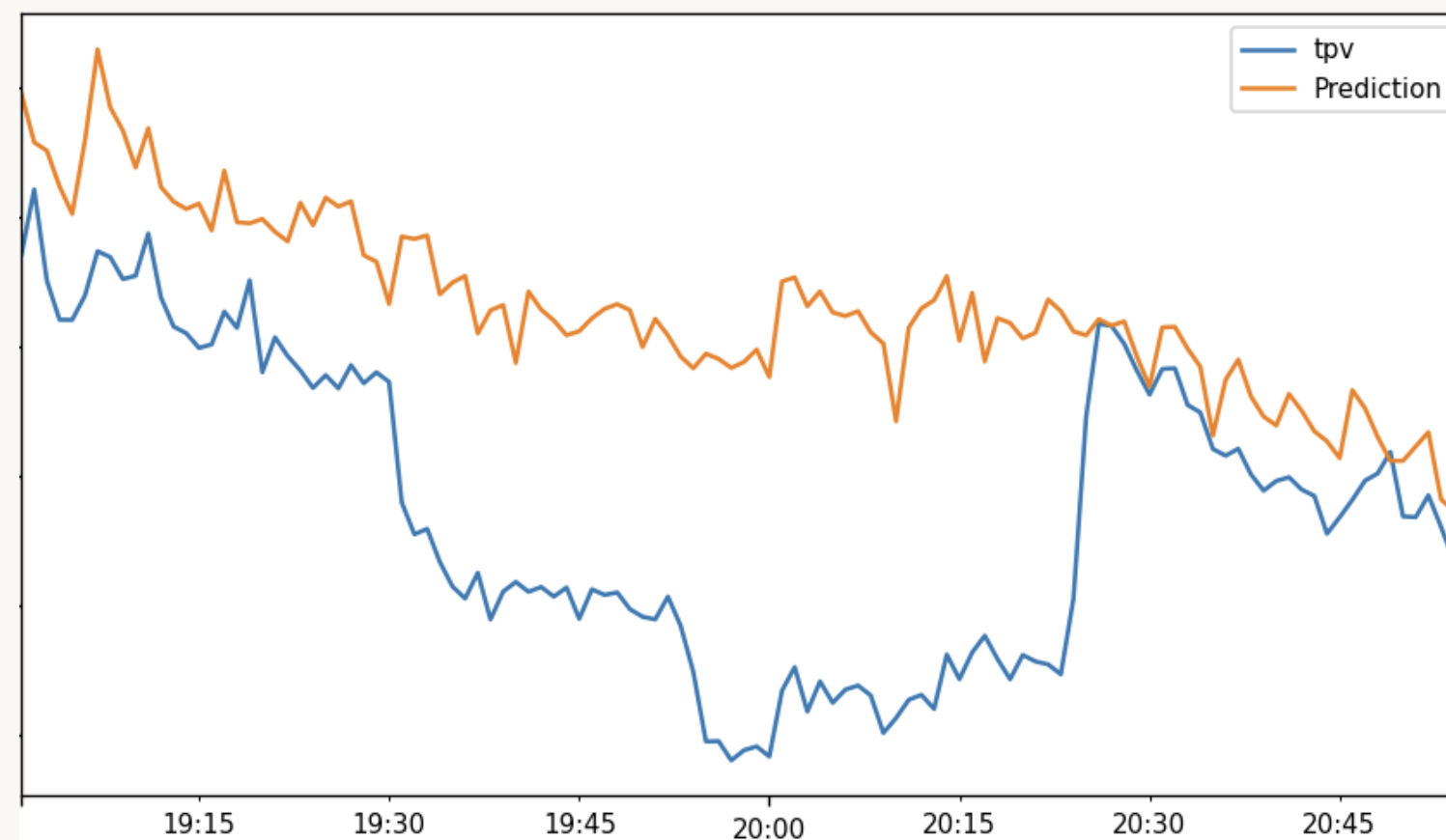
How are we going to integrate the model?

MATHEMATICAL MODELING

ARIMA IN ACTION

ARIMA

How did ARIMA model work?



- ARIMA and variants (ARMA, Seasonal ARIMA).
- ARIMA (3,0,2) fared well compared to others.
- Autoregressive integrated moving average.
- The model performed well but the challenge is to train and utilize it in real-time.
- Also, a lot of preprocessing is required.

MATHEMATICAL MODELING

H2O Driverless AI

Automated Machine Learning – Experiment Result

How do we build models using H2O Driverless AI?

< H2O.ai Experiment **bamosiba**
PROJECTS DATASETS AUTOVIZ EXPERIMENTS DIAGNOSTICS MLI DEPLOYMENTS RESOURCES USER

DRIVERLESS AI 1.9.1.2 – AI TO DO AI
Current User – ASSISTANT

EXPERIMENT SETUP

DISPLAY NAME: **bamosiba**

TRAINING DATASET: **payment_train_4.csv**

ROWS: **89K** COLUMNS: **2** DROPPED COLUMNS: **0**

VALIDATION DATASET: **--** TEST DATASET: **Yes** (payment_test.csv)

TARGET COLUMN: **payment_co...** FOLD COLUMN: **--** WEIGHT COLUMN: **--**

TIME COLUMN: **time** TIME GROUPS COLUMNS: **time** FORECAST HORIZON: **30K minutes**

| TYPE | COUNT | MEAN | STDEV |
|------|-------|-----------|----------|
| int | 89280 | 20627.201 | 4860.658 |

STATUS: COMPLETE

- DEPLOY (LOCAL & CLOUD)
- INTERPRET THIS MODEL
- DIAGNOSE MODEL ON NEW DATASET...
- MODEL ACTIONS
- DOWNLOAD PREDICTIONS
- DOWNLOAD PYTHON SCORING PIPELINE
- DOWNLOAD MOJO SCORING PIPELINE
- VISUALIZE SCORING PIPELINE (EXPERIMENTAL)
- DOWNLOAD SUMMARY & LOGS
- DOWNLOAD AUTODOC

TRAINING SETTINGS

7 ACCURACY | 7 TIME | 6 INTERPRETABILITY | MAPE SCORER

REGRESSION | REPRODUCIBLE | GPUS DISABLED

EXPERT SETTINGS

CPU / MEMORY | Insights Scores Notifications Log Trace

CPU

MEM

ITERATION DATA - VALIDATION

▲ MAPE 5.8105 +/- 0.0000

VARIABLE IMPORTANCE

| | |
|---------------------------|------|
| 0_Date:time-get_hour | 1.00 |
| 0_Date:time-get_day | 0.09 |
| 0_Date:time-get_weekday | 0.08 |
| 0_Date:time-get_dayofyear | 0.07 |
| 0_Date:time-get_minute | 0.03 |
| 7_TargetLag:time.29760 | 0.03 |
| 7_TargetLag:time.29761 | 0.02 |
| 5_Cat:time | 0.02 |
| 7_TargetLag:time.29763 | 0.01 |
| 7_TargetLag:time.29762 | 0.01 |
| 7_TargetLag:time.29774 | 0.01 |
| 0_Date:time-get_week | 0.01 |
| 7_TargetLag:time.29773 | 0.01 |
| 7_TargetLag:time.29772 | 0.00 |

RESIDUALS | ACTUAL VS PREDICTED | SUMMARY

Experiment: **bamosiba** (cb4dd06e-1d88-11ec-82d3-0a58c0fe1434)

Version: 1.9.1.2, 2021-09-24 16:25
Settings: 7/7/6, seed=1035278047, GPUs disabled
Train data: payment_train_4.csv (89280, 2)
Validation data: N/A
Test data: [Test] (52201, 1)
Target column: payment_count (regression, log-transformed)

System specs: Docker/Linux, 15 GB, 80 CPU cores, 0/0 GPU
Max memory usage: 1.14 GB, 0 GB GPU

Recipe: AutoDL (67 iterations, 8 individuals)
Validation scheme: time-based, 2 internal holdouts
Feature engineering: 509 features scored (23 selected)
Timing: MOJO latency: 0.15047 millis (15.8MB)
Data preparation: 11 seconds
Shift/Leakage detection: 0 seconds
Model and feature tuning: 4 minutes 56 seconds (67 of 82 models trained)
Feature evolution: 34 minutes 16 seconds (392 of 1216 models trained)
Final pipeline training: 1 minute 41 seconds (1 model trained)
Python / MOJO scorer building: 1 minute 6 seconds / 27 seconds

Validation score: MAPE = 20.18749 (constant preds of 1.876e+04)
Validation score: MAPE = 8.597274 +/- 0.5937867 (baseline)
Validation score: MAPE = 5.810538 +/- 4.768372e-07 (final pipeline)
Test score: MAPE = 6.287551 +/- 4.768372e-07 (final pipeline)

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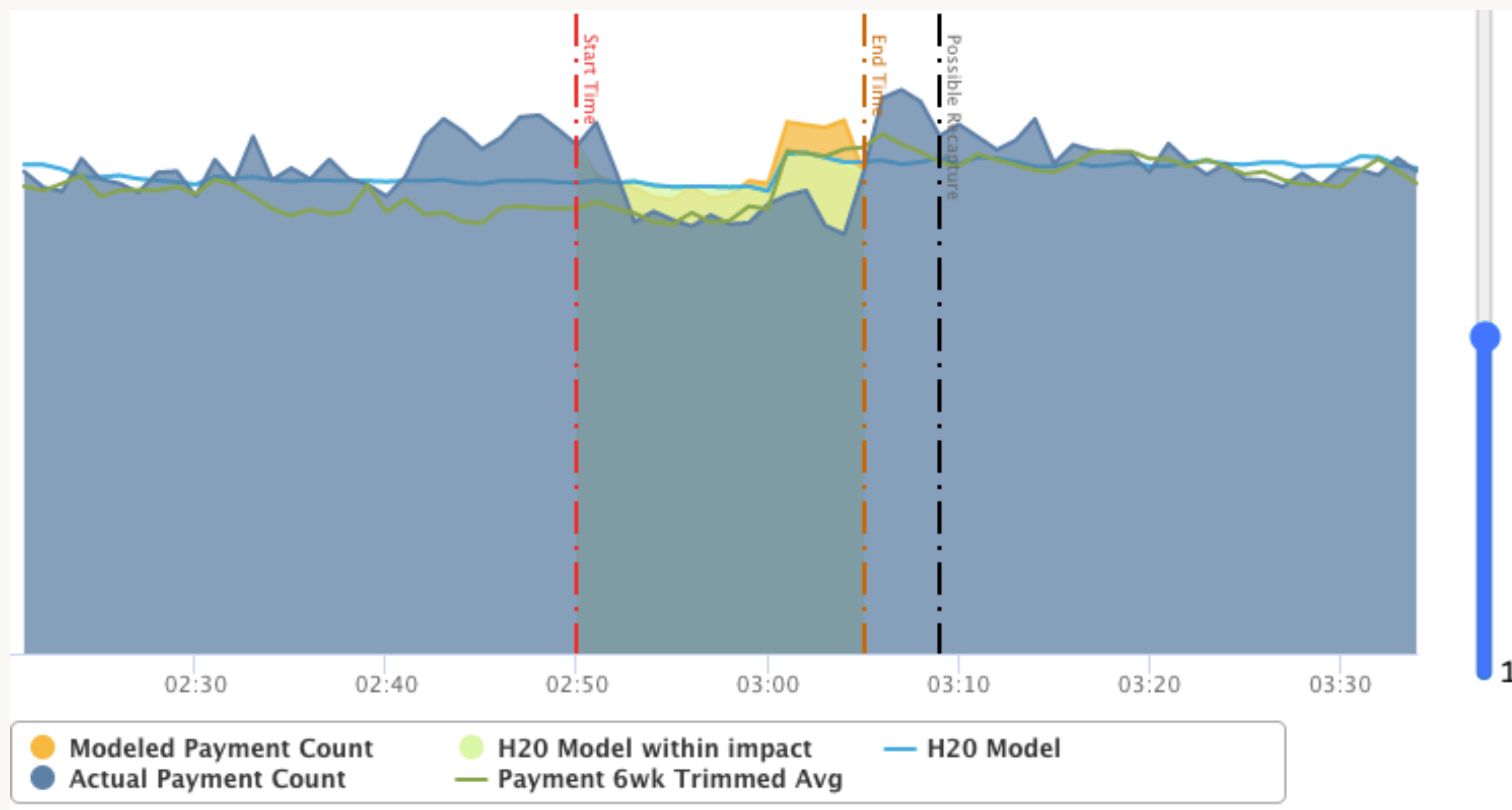
MATHEMATICAL MODELING

LightGBM Performance

H2O (LightGBM) model still lags six-week trimmed average model. In forecast horizon even for first two days we see a significant difference.

How did the LightGBM model perform?

For long intervals six-week trimmed average model performs better but only by a slight margin of 1-2 %.



FEATURES & TAKE-AWAYS

On Capabilities & Take-aways

FEATURES & TAKE-AWAYS

Availability

Availability

- To measure the availability loss during an incident (in addition to payment volume loss).
- Measured in count of requests or time.
- Formulae - $\text{uptime} / (\text{uptime} + \text{downtime})$, or $\text{successful requests} / (\text{successful requests} + \text{failed requests})$.
- Reported in a percentage like 99.9% or 99.999%.

Measured through FCI

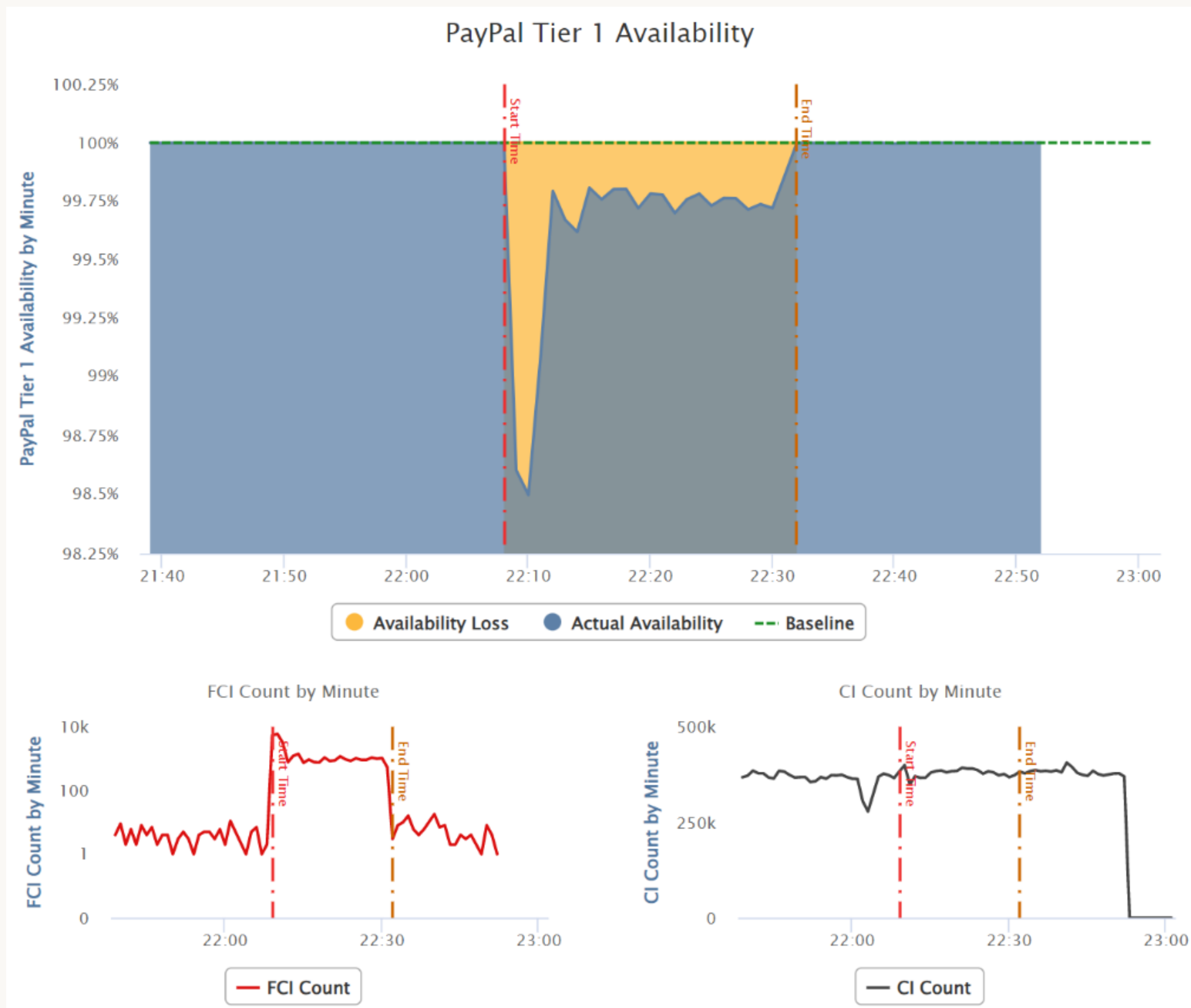
- Failed Customer Interactions (FCI) - Number/percentage of intended actions that a Customer* is unable to complete using functionality offered by PayPal and allowed by PayPal policies.
- Customer* - Consumers, Merchants/Partners, anyone consuming the results of an interaction
- Functionalities are broken down into a set of interactions and the failures of these interactions are what we are going to measure.
- PayPal Availability mostly trends above $\geq 99.99\%$

FEATURES & TAKE-AWAYS

Availability Measurement

MEASURING FCI LOSS FOR A WINDOW

Sample Availability Loss



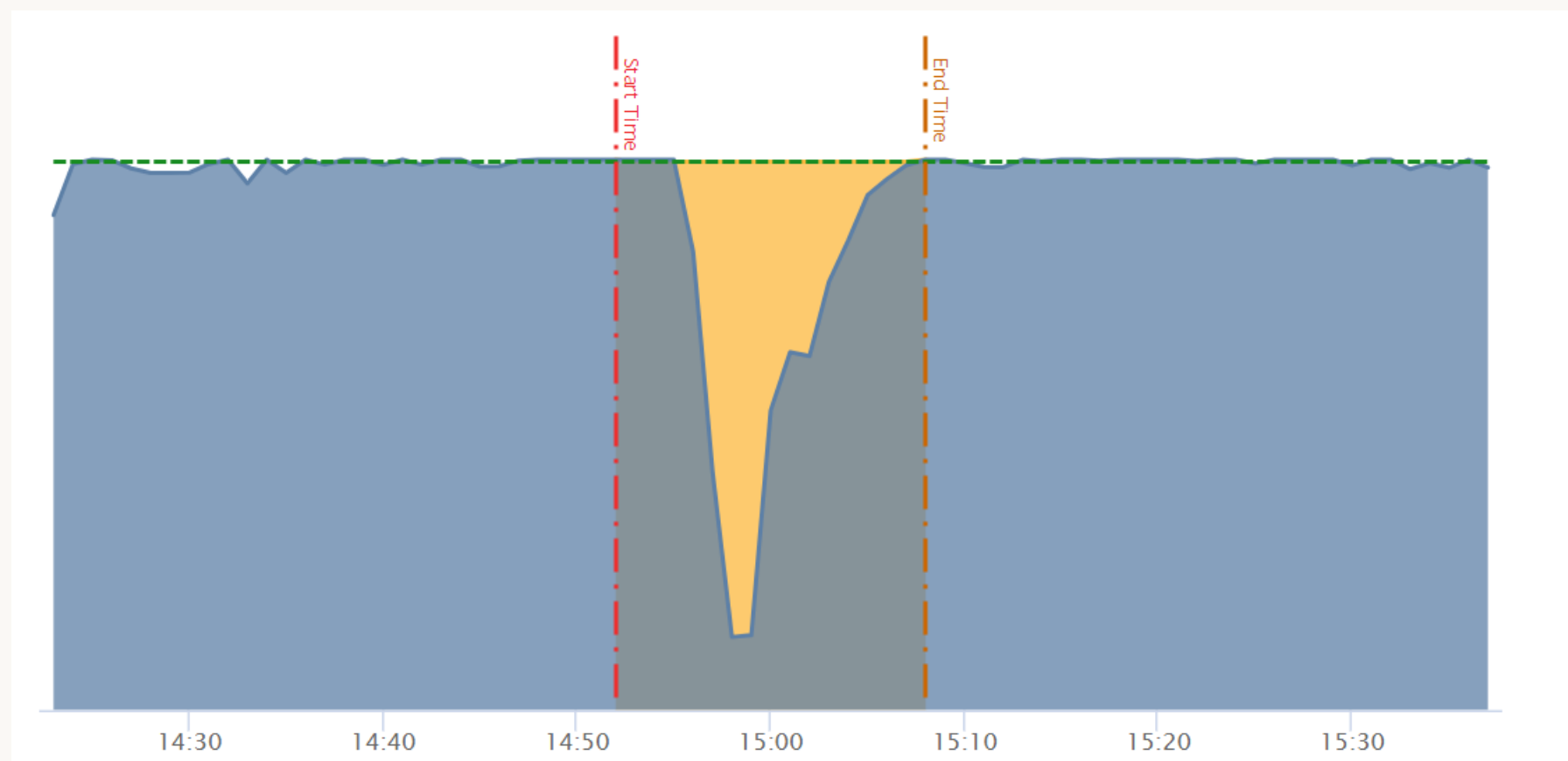
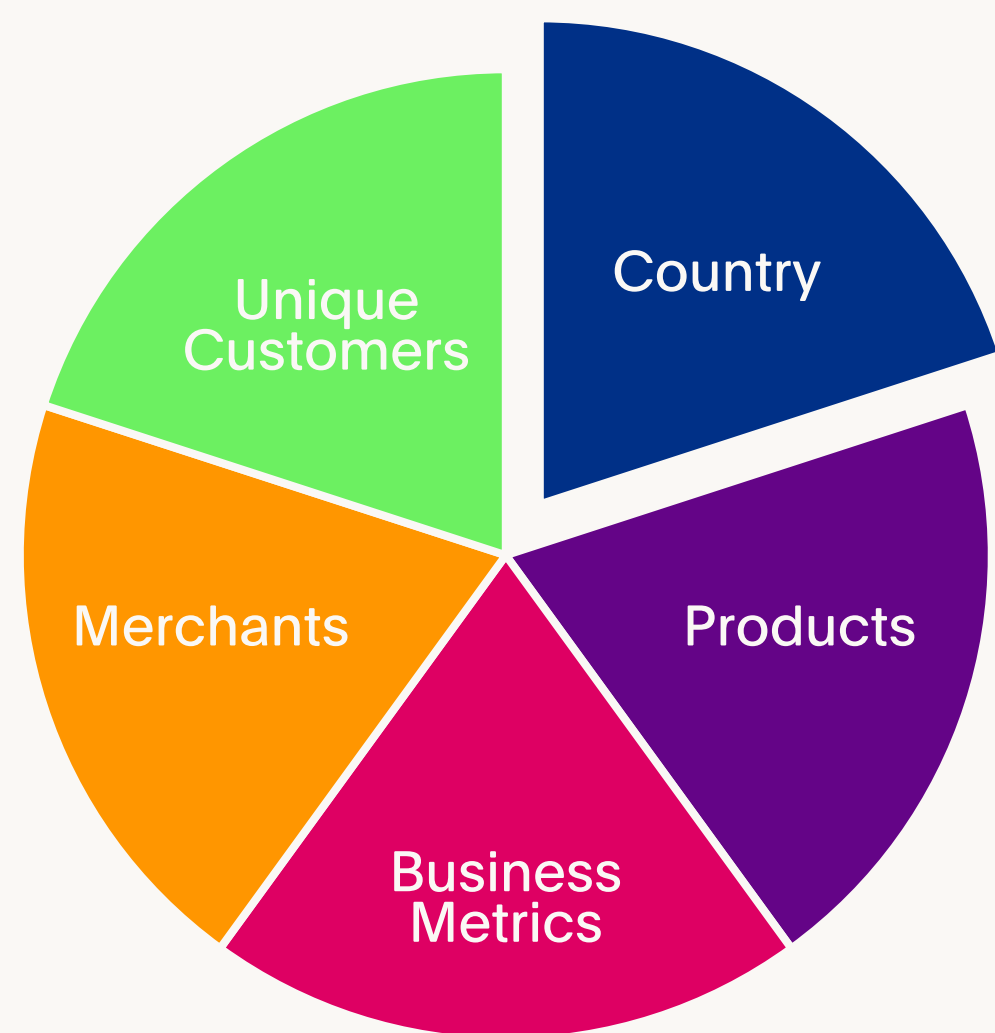
| | |
|-------------------|---------------|
| Baseline | 99.9990% |
| Availability | 99.6171% |
| FCIs | 33,322 |
| Missed CIs | 0 |
| FCI Impact | 33,322 |

Representational Image

FEATURES & TAKE-AWAYS

Segmentation

IMPACT BY COUNTRY



| Country ↕ | Impact ↕ | % Of Impact ↕ |
|----------------|----------|---------------|
| United Kingdom | 352 | 30 |
| Germany | 313 | 27 |
| France | 143 | 12 |
| Italy | 82 | 7 |

Representational Image

- Segmentation by Country and Merchant are available.
- Segmentation computation using Machine Learning has been challenging when limited data is available.

FEATURES & TAKEAWAYS

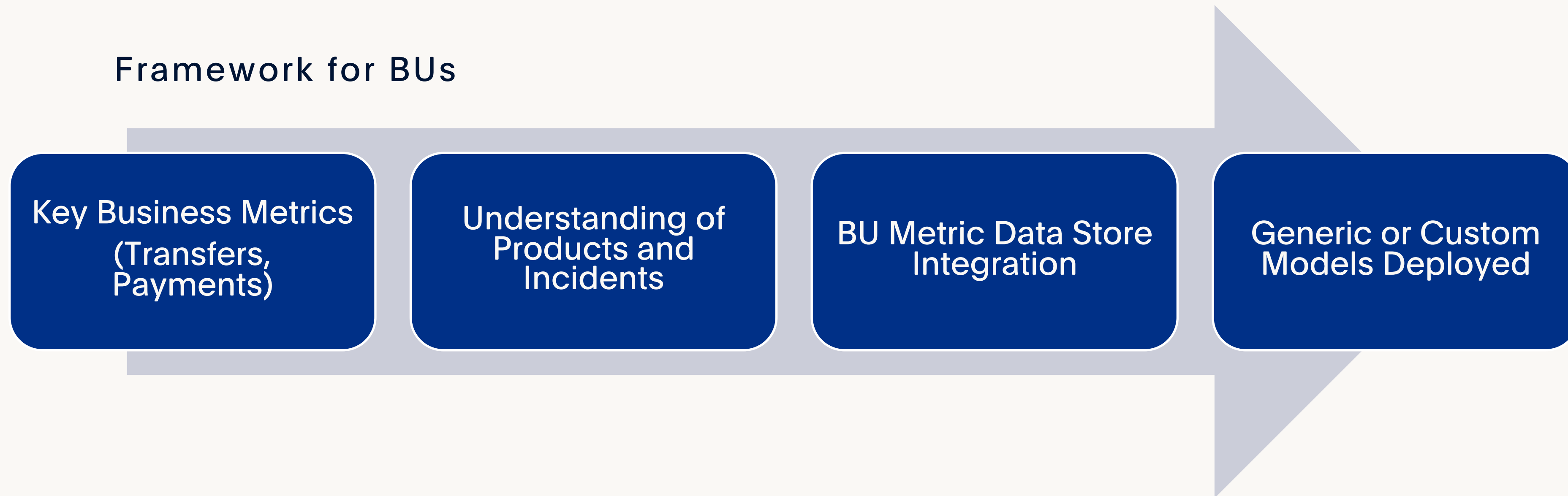
IMPACT FOR XOOM & BRAINTREE

BU Expansion

Xoom and Braintree



Framework for BUs



FEATURES & TAKEAWAYS

Opportunities

What's the road ahead?

Superpose

multiple models



Track Model

use for learning



Calculate &

post automatically



Suggest

incident window



Expand to

Other BUs like

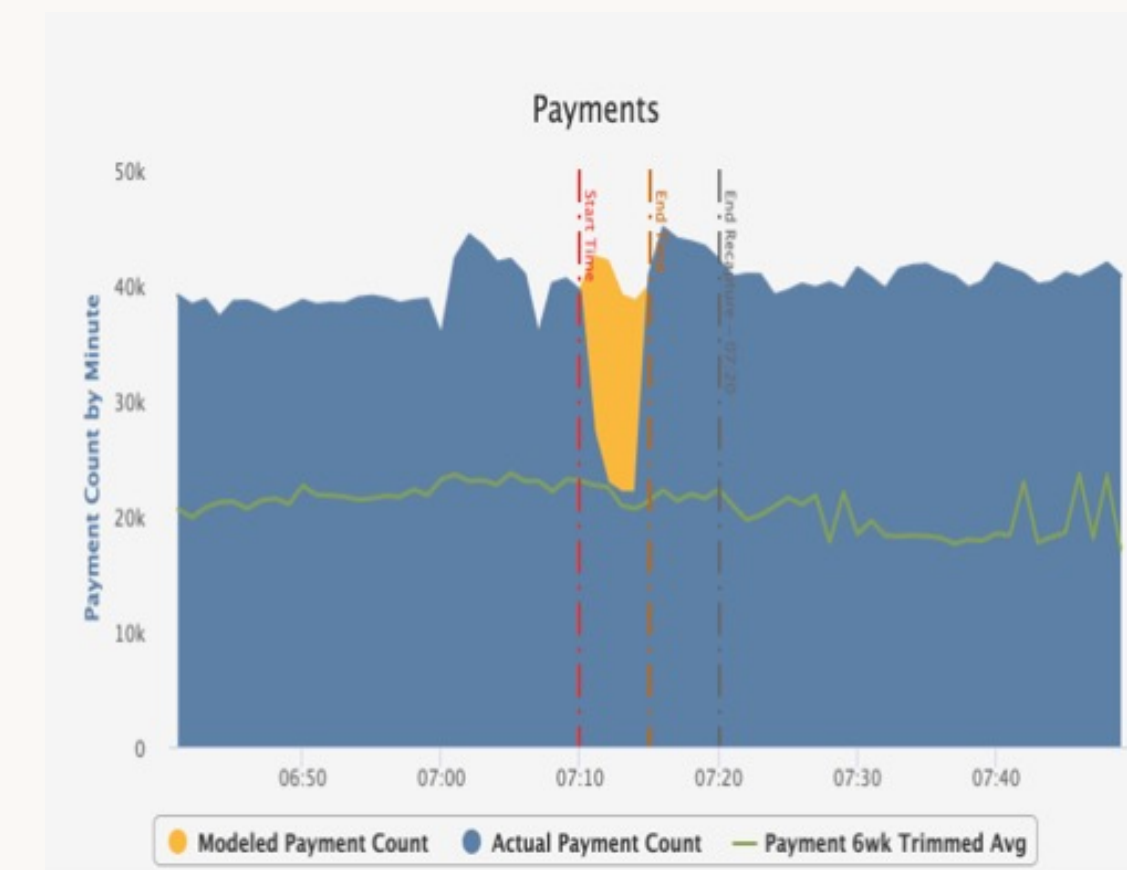
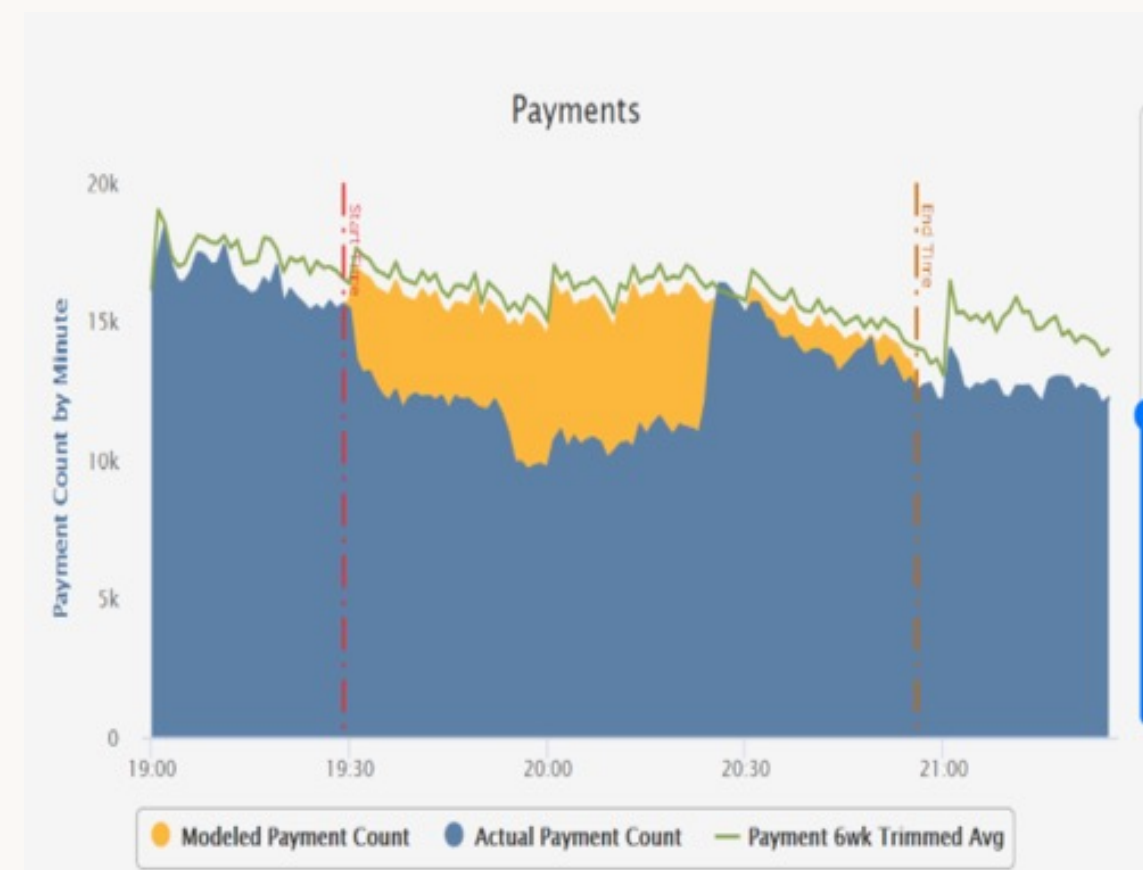
venmo

FEATURES & TAKEAWAYS

MULTIPLIER USAGE & RECAPTURE END TIME

Auto-suggestions

Can the tool suggest me automatically?



Representational Images

Can the tool auto-suggest the following?

- To use multipliers (as in the left diagram)?
- To re-capture end time (as in the right diagram)?
- Drop in Customer Interactions (CI) count?

FEATURES & TAKEAWAYS

Top Challenges

What challenges do we have?

Heavy Reliance on User

Tool relies heavily on the user for providing impact window, to apply visual reasoning etc.

Testing

Testing in general with a variety of use cases for modeling and segmentation.

Modeling

Machine Learning Modeling for segmentation and other use cases with very little data has been challenging.

Building Intelligence

We found that building auto-suggestions for CI drop, incident window suggestions is challenging.

Approximation

Data is aggregated at minute level. If the current window suffers high volume despite taking an impact, model can't find it correctly. Take rate across products may vary.

FEATURES & TAKEAWAYS

How to Start Building?

What are the considerations?

BUSINESS METRICS



- What are the key business metrics?
- Is it granular enough for segmentation?

DATA SOURCES



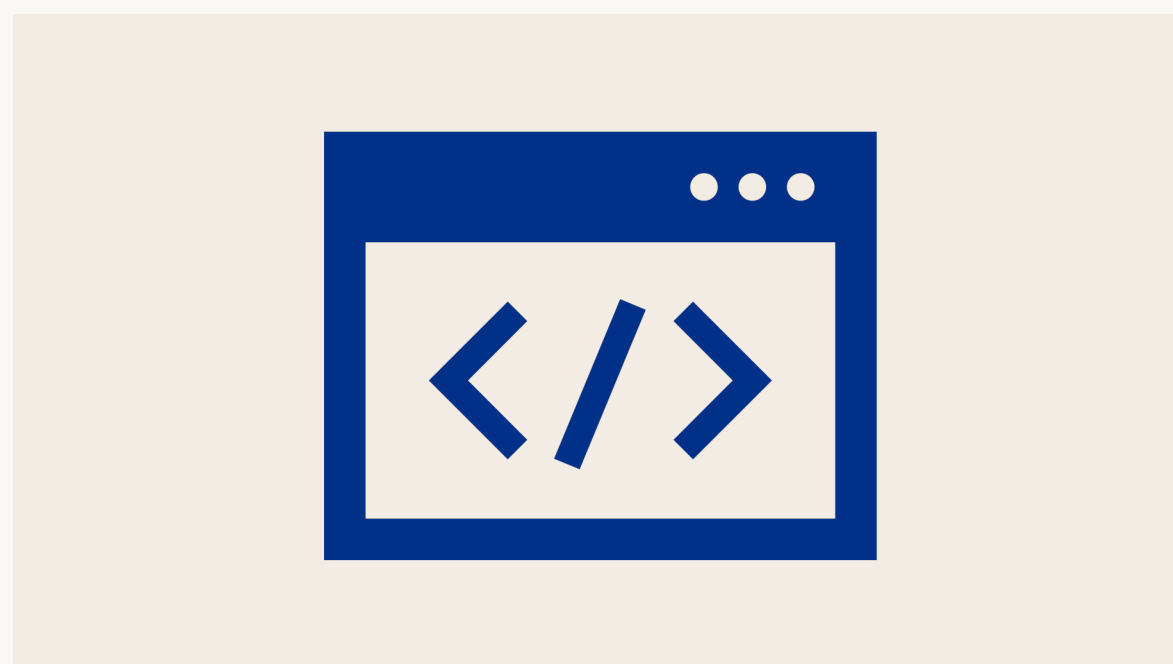
- Is your use case real-time?
- How would you access?

MANUAL ASSESSMENT



- How do you assess manually?
- Do we need to change the process?

MODELLING



- Do you understand dataset?
- What model would you use?

TEST & REMODELLING



- How do you test for various use cases?
- Is it consistent? Need remodeling?

INTEGRATION



- How do you integrate and run?
- Is your product working well?

Questions



Thank You

