Leveraging Front End Events for Credit Risk and First Party Fraud Detection

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Background and Motivation

01

Overview of Alternative Data in Risk Models

The Events-Based Model serves as an alternative data source leveraging user activity within the Revolut app to support credit risk assessment and first-party fraud detection. Unlike traditional models that rely solely on static data points, this model captures dynamic behavioral signals leading up to a credit application.

02

Introduction of Event Based Models

Transforms raw app events into behavioral features that reveal user engagement patterns and potential risk signals. Focuses on understanding how users navigate, interact, and make decisions within the app environment.

03

Significance and Impact

Traditional models have limitations in capturing nuanced user behavior and emerging fraud tactics. The Events-Based Model was developed to address these gaps by incorporating behavioral data as a complementary source, ultimately aiming to improve prediction accuracy and reduce risk.

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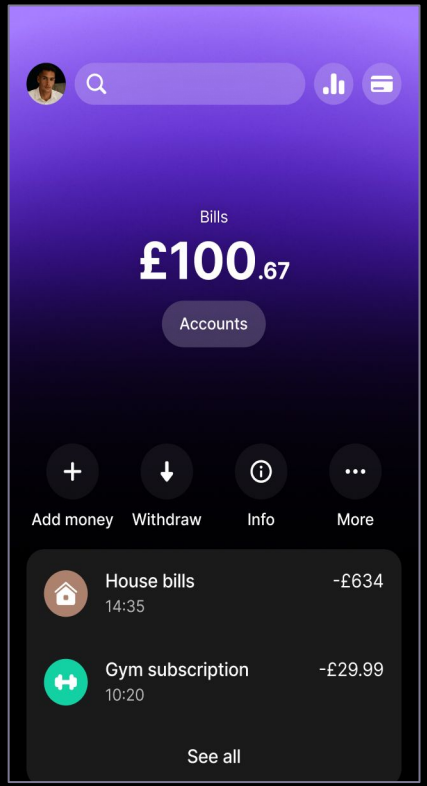
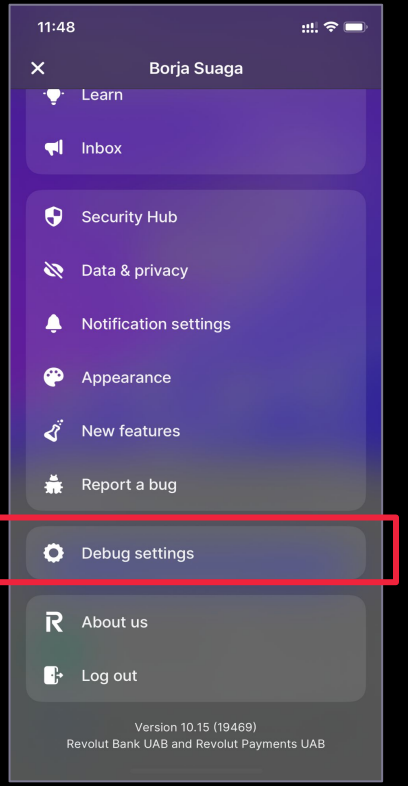
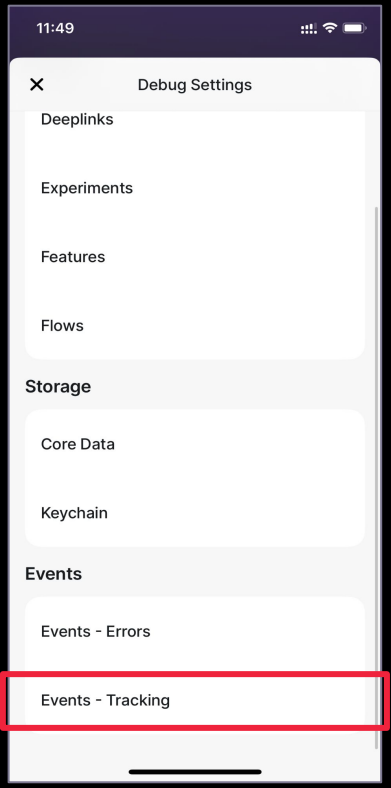
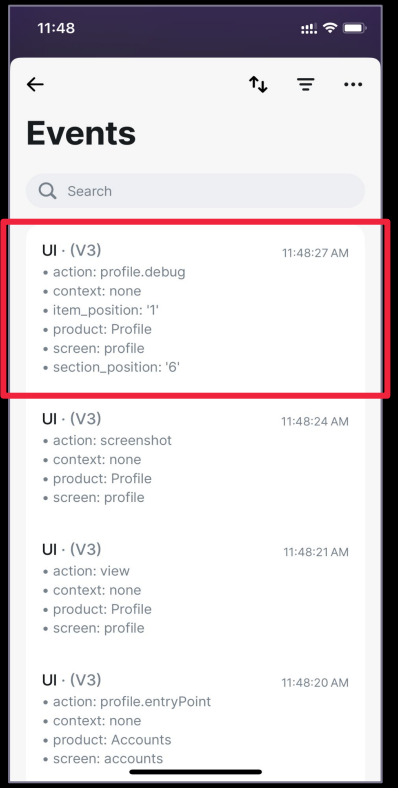
Revolut App Events Raw - How data is stored (Simulator)









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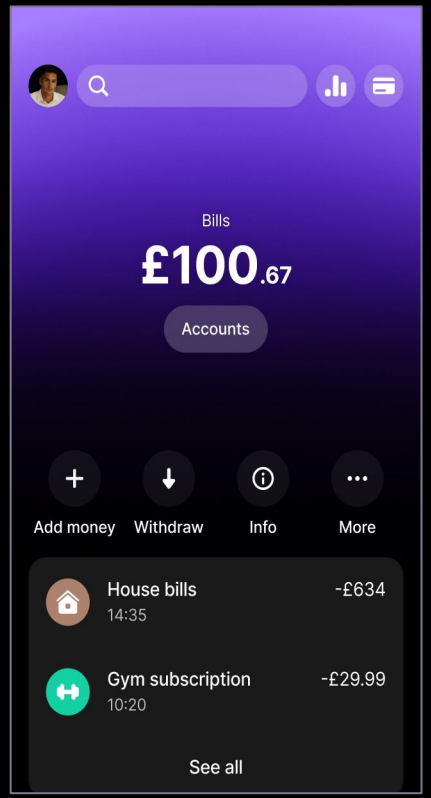
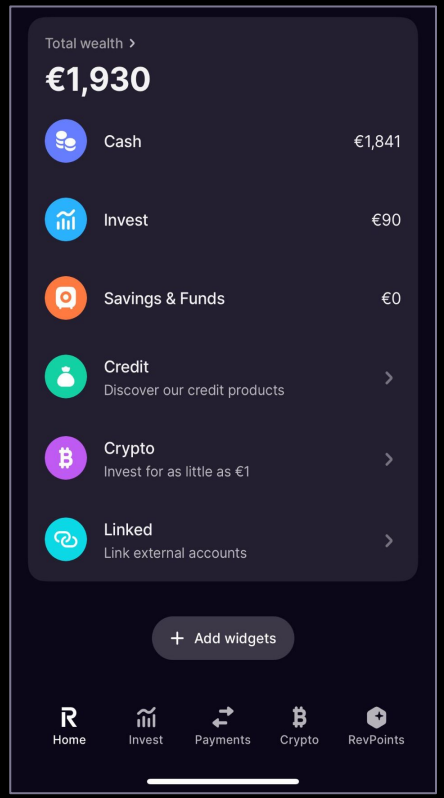
Revolut App Events - Filtering Screens for Model

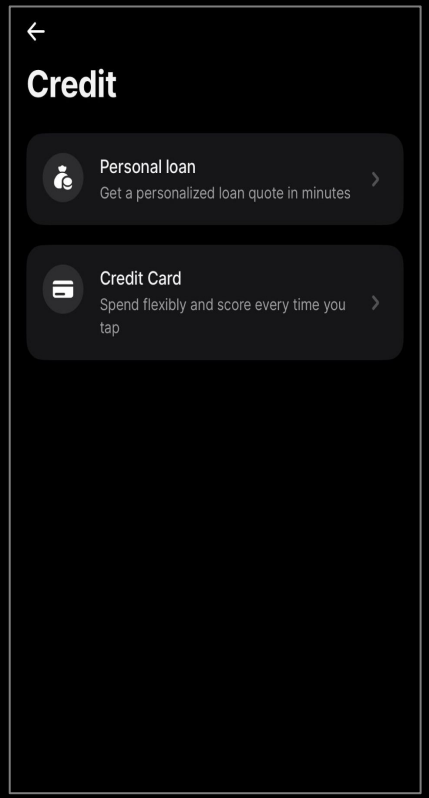
Accounts Screen



Products Screen



Credit Screen



- Only user events from Accounts, Product, and Credit screens were included.
- These events are most relevant for onboarding analysis.
- This approach also ensured the dataset remained manageable in size, avoiding unnecessary data volume.

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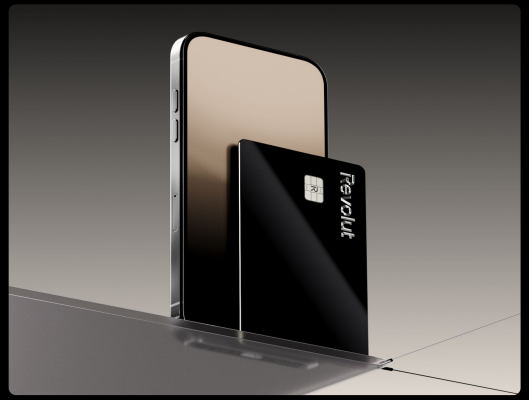
Data Sources and Feature Engineering

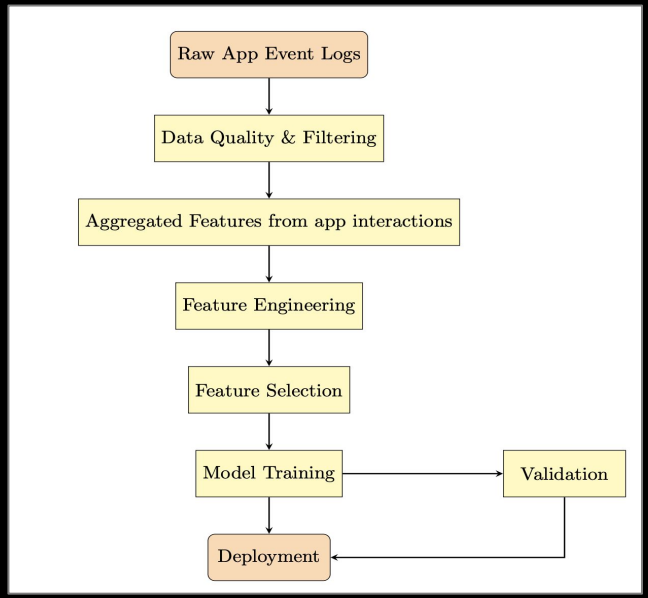


Revolut App Events Data

Data sourced from Revolut app events tracking user interactions up to 45 days before credit application, providing a rich timeline of behavioral data.

Extensive Feature Engineering

Over 250 behavioral variables engineered, including session metrics, device info, interaction patterns, and engagement spikes, to capture nuanced correlations with credit risk.



Data pipeline

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Key Behavioral Metrics in Events Model

Session Metrics	Analyzes session durations, timing, and intervals to assess user engagement and consistency.
Device and Locale Information	Tracks device and locale usage, stability, and anomalies to contextualize user environment and detect unusual behavior.
Interaction Metrics	Analyzes user interactions, screen visits, and action patterns to understand navigation behavior and user intent.
Credit Actions & Screen Metrics	Analyzes average time intervals between credit-related actions and behavioral consistency ratios to identify patterns in credit application
Spike and Engagement Metrics	Identifies activity spikes, gauges magnitude and timing of these spikes, overall user engagement during spikes
Velocity Metrics	Identifies rate at which user performs actions on the screen and clusters actions to identify high or low user activity phases
Cancellation Metrics	Total application cancellations and average time-to-cancellation to capture indecision tendencies
Questionnaire Engagement	Proportion of time focused on form completion for credit as an indicator of user attention

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Model Development and Training Approach

Data Source

Raw events data for Revolut Facilities and Repeated applications till 45 days prior to application date

Risk Targets Defined

Two targets:
First Party Fraud - (90DPD@4MOB),
Early Risk (30DPD@3MOB) for short-term repayment risk.

Feature Selection

Automated Feature Selection using a combination of Forward Elimination, Correlation Analysis and LightGBM Feature Importance

Model Training

LightGBM model is used to train the model on the final selected features. Benchmarking of the model performance is done by also training a Logistic Regression Model

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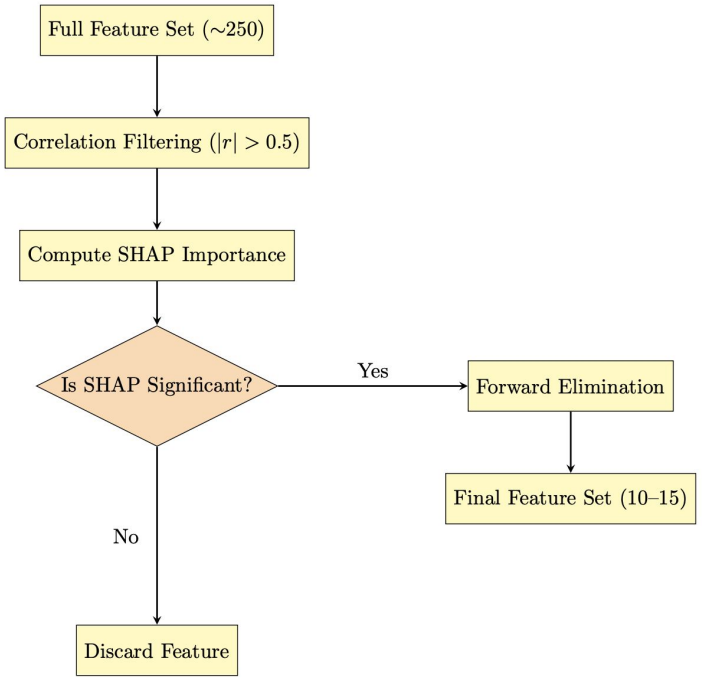
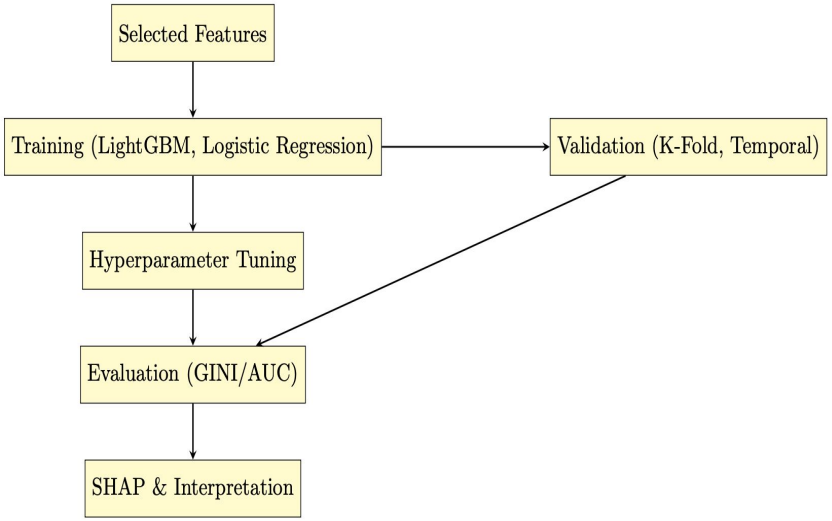
Model Architecture



Feature selection workflow



Model development and validation workflow.

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Features

Top Features in Events Model for First Party Fraud Detection

Median Time Between Sessions	The median interval between consecutive user sessions captures user engagement consistency and is the most influential feature, accounting for 45% of model importance.
Peak Action Velocity	The highest peak of user action speed across sessions reflects bursts of activity, indicating impulsiveness or urgency
Morning Session Frequency	Total number of sessions initiated in the morning
Total Critical Actions	The total count of critical actions (e.g., clicking on credit related product) performed by a user.
Average Unique Screens Visited	The average number of unique screens visited per product
Total Cancellations	The total number of times a user has canceled an action (e.g., canceled an application,)

Features

Top Features in Events Model for Credit Risk Assessment

Median Time Between Sessions

The median time gap between consecutive user sessions.

Morning Session Count

The total number of sessions a user has initiated in the morning

Unique Screens

Features such as the average number of unique screens visited per product and min no of unique screens per product

Median Session Duration

Median duration of all user sessions

Interaction Frequency

Average number of actions and critical actions performed by the user, ratio of static to dynamic actions

Action Velocity

Average rate at which the user navigates through the credit related screens

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Performance

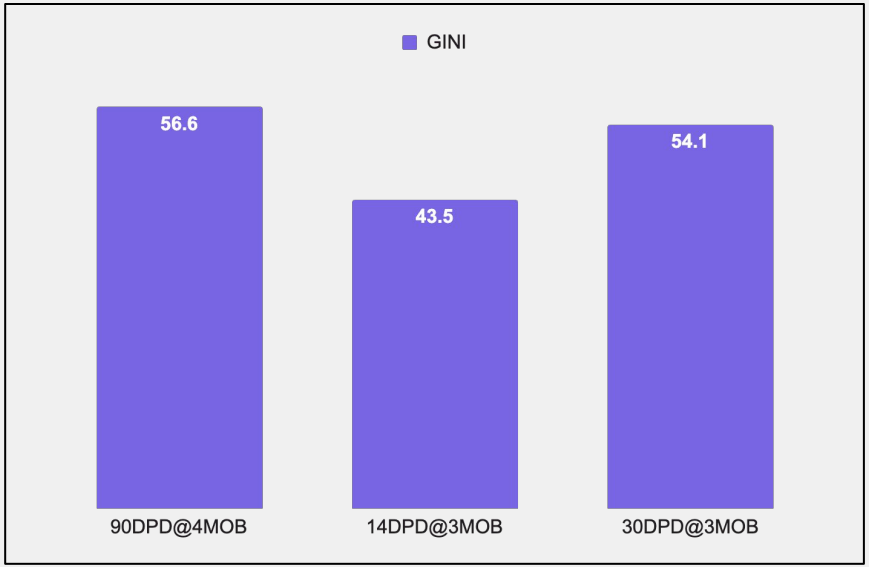
Model Performance Overview

56.6%
GINI (90DPD@4MOB)

43.5%
GINI (14DPD@3MOB)

54.1%
GINI (30DPD@3MOB)

Model GINI Scores for different targets



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Value Addition

Benefits and Value Addition of Events Model

Enhanced Predictive Accuracy

Incorporates over 250 behavioral features derived from app events, capturing nuanced user actions that improve credit risk discrimination beyond traditional data sources.

Comprehensive Behavioral Profiling

Profiles user engagement patterns such as session frequency, critical actions, and navigation flows to reveal subtle risk signals and user intent.

Integration with Local Models

Model scores serve as valuable inputs to local acquisition models, enabling tailored risk assessment and quantifiable GP impact for specific markets and products.

Actionable Insights for Teams

Provides deep insights into user app behavior that data science and credit teams can leverage to refine acquisition strategies and enhance fraud detection capabilities.

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