Creating and operating ML models from event-based data using a feature engine and a feature store



Davor Bonaci CEO KASKADA





Dr. Charna Parkey VP, Product KASKADA

Taimur Rashid Chief Business Development Officer



ATTENTION CUSTOMERS:

· Bread

Due to high demand these items will be limited to two per customer: · Bath tissue · Paper towels · Hand sanitizers • Gallon milk · Case water Disinfecting wipes THANK YOU

Photo by <u>Wesley Tingey</u> on <u>Unsplash</u>

Delivery Trends - Pandemic

- 30% drop in ordered items being found
- Average customer basket size +>35% month over month
- 500% increase in year over year order volume
- More localized events needed to predict which items will sell out
 - Increase in the number of items needing to be scored
 - Increase in the number of shops needing predictions
 - Noise reduction is critical



ML models can only be as good as the data we give it





Latency is an outage



500

million



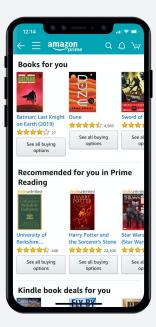
You need native time travel and a low latency, high throughput feature store



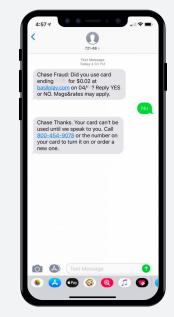
Time travel is hard











Personalization

Amazon: Contributes 35% of revenue



Recommendations

Netflix: +13% in revenue due to savings

Fraud Alerts

FICO: +30% in detection of CNP fraud



The growth in demand for unpredictable event-based data needs is increasing

Ad hoc event-based data requests

Time



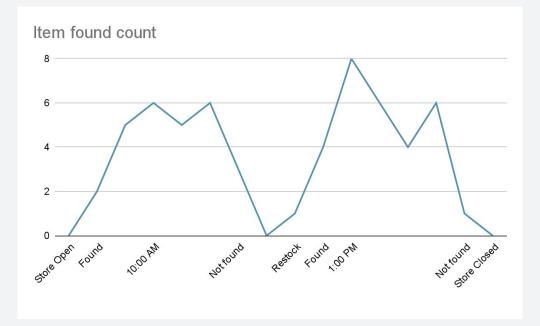


Instant Iteration Requires

- Historical feature value generation to try new features
- Expressive time selection to specify your model context iteratively
- Joining values between different entities, at precise times without leakage
- Shared feature definitions to power live models

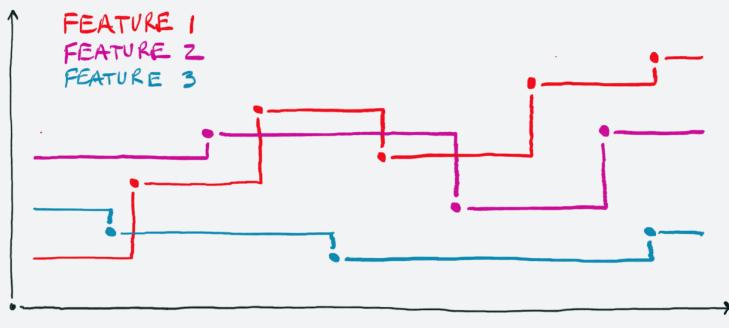


Relative event times are important





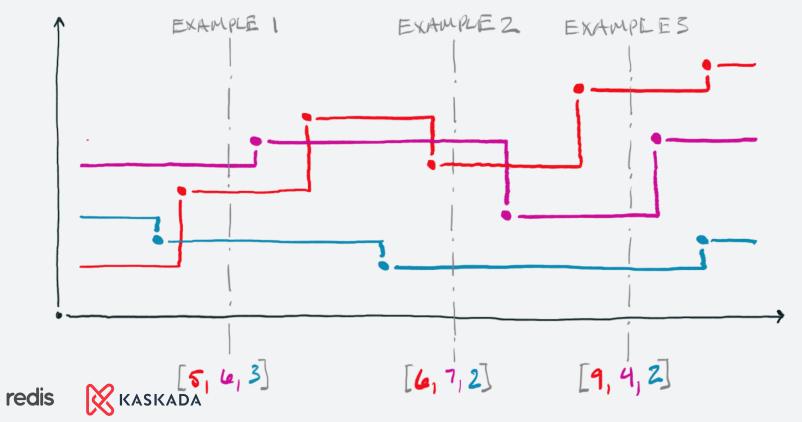
Feature definitions define what to compute



TIME



Time selection defines when to compute



Discrete + continuous time temporal processing

Item Entity Features

- Historical purchase count
- Historical replacement rate
- Historical found rate
- Time since last found
- Expected time to next not found

Shopper Features

- Time of day shopping begins
- Day of week shopping begins

Retailer Entity Features

- Historical retailer availability
- Store location
- Restock times
- Store hours

Region Features

• Found rate of parent product category in the region





Photo by Oleksii S on Unsplash

Getting to production is hard for real-time inferencing

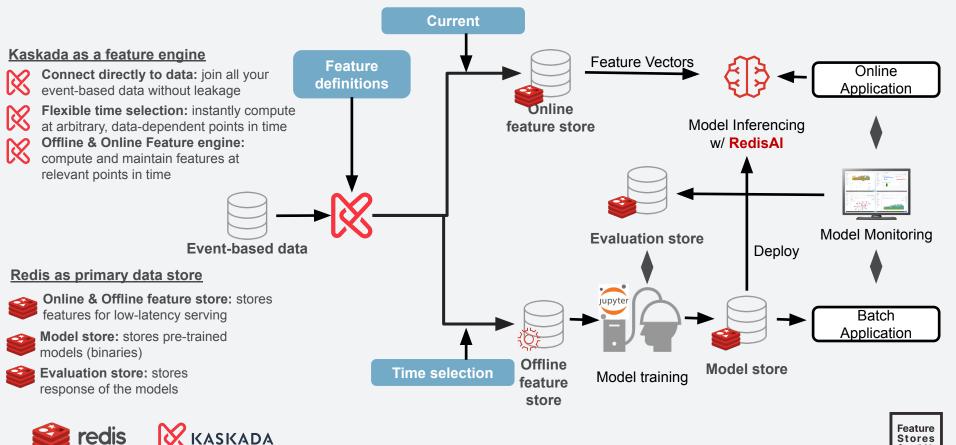
- Over 40% of decision-makers agree their architectures are not good enough to meet the demands of ML
- The high demand for real-time model inferencing (using ML models in production) expose major challenges with accuracy, latency, and reliability in current architectures
- Running ML model inferencing in-database where data is stored solves some of these critical challenges

Forrester Consulting, 2021



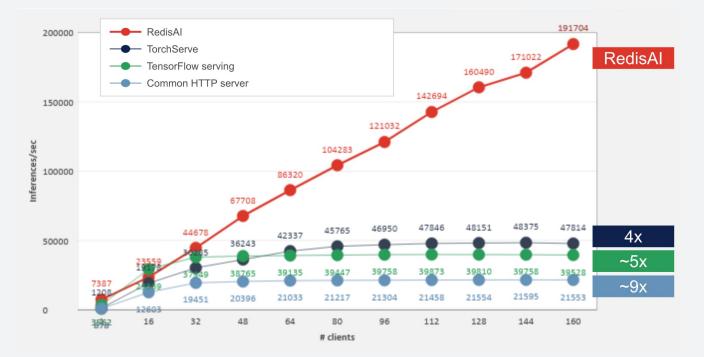
Core ML + AI Computing and Serving for Production Stage

redis



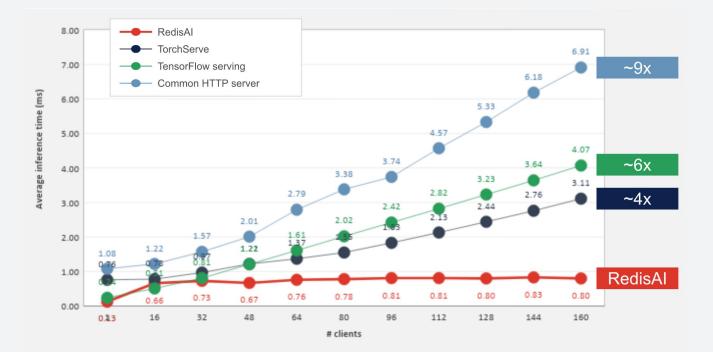
Stores for ML

High throughput required for scoring





Low latency required for serving





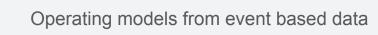
Demo



Summary

Creating models from event based data

- Compute features directly from event based data in order
- Enable iteration by exposing time selection
 + feature definitions in the feature engineering process
- Join values between different entities at precise times historically to prevent leakage
- Instantly compute values at arbitrary data dependent points in time — discrete and continuous



- Eliminate data discrepancies in production via shared feature definitions
- Low latency applications need a feature store to run model inference in database where the data is stored
- Address real-time throughput needs with a high-throughput feature store

Feature

Stores for ML



Thank you!

Do you have any questions?



Davor Bonaci CEO @ Kaskada





Dr. Charna Parkey VP, Product @ Kaskada



Taimur Rashid Chief Business Development Officer @ Redis



