Time Predictions in Uber Eats

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Uber Eats

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Agenda

1. ML in Uber Eats
    - Goals & Challenges
    - ML Platform @ Uber
2. How Time Predictions Power Dispatch System
3. Deep Dive in Time Predictions
    - Food Preparation Time Prediction
    - Delivery Time Estimation
    - Travel Time Estimation
4. Q&A

ML in Uber Eats

Agenda

- Goals & Challenges
- ML Platform @ Uber

Our Scale

> 500 Cities

> 220,000
Restaurant Partners

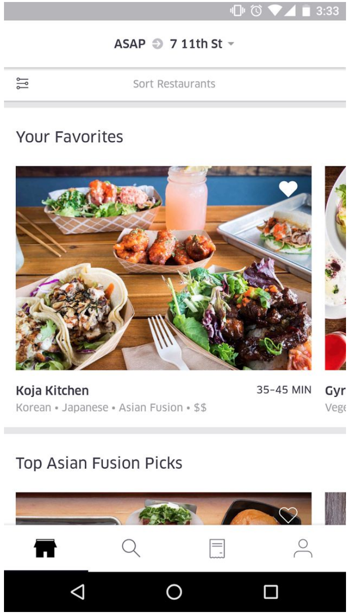
~ 8B
Gross Bookings
for 2018

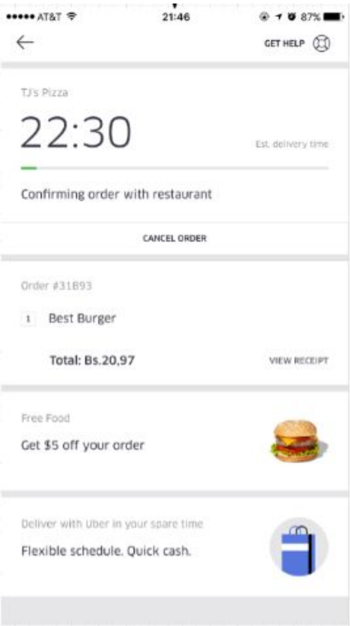
Our Mission

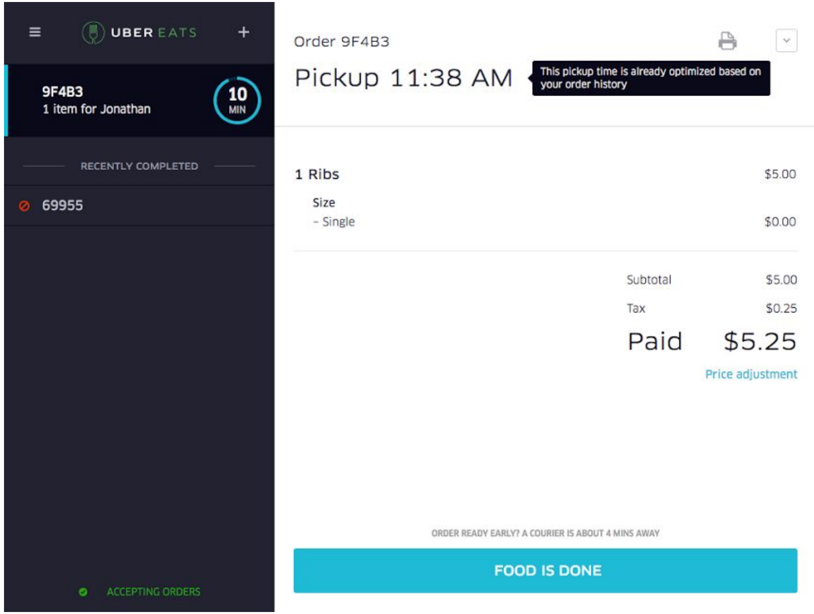
Make eating well **effortless, every day**, for **everyone**.

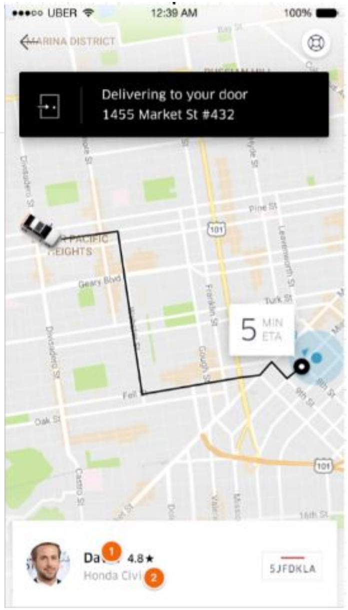
Goals & Challenges

Reliable	Affordable	Effortless
Predicting the Future	Network Efficiency	Food Discovery







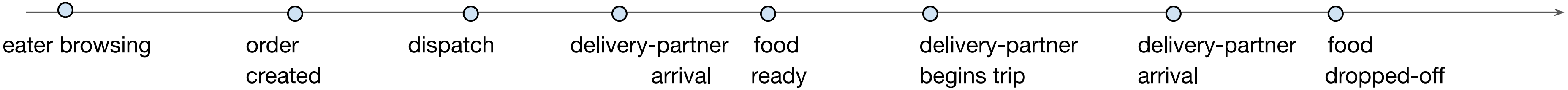


Eyeball ETD prediction

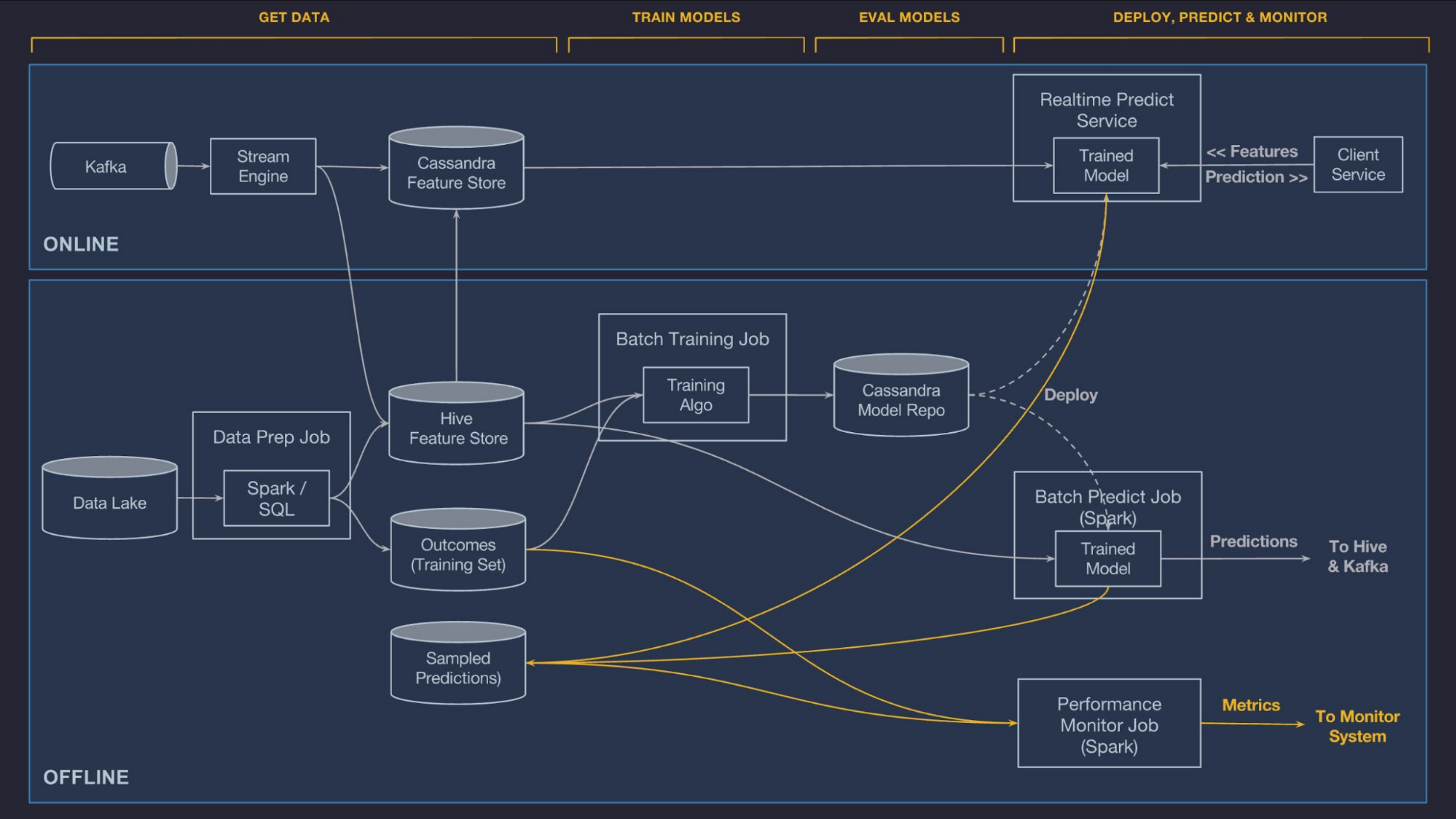
ETD prediction

Prep-time prediction

ETA prediction

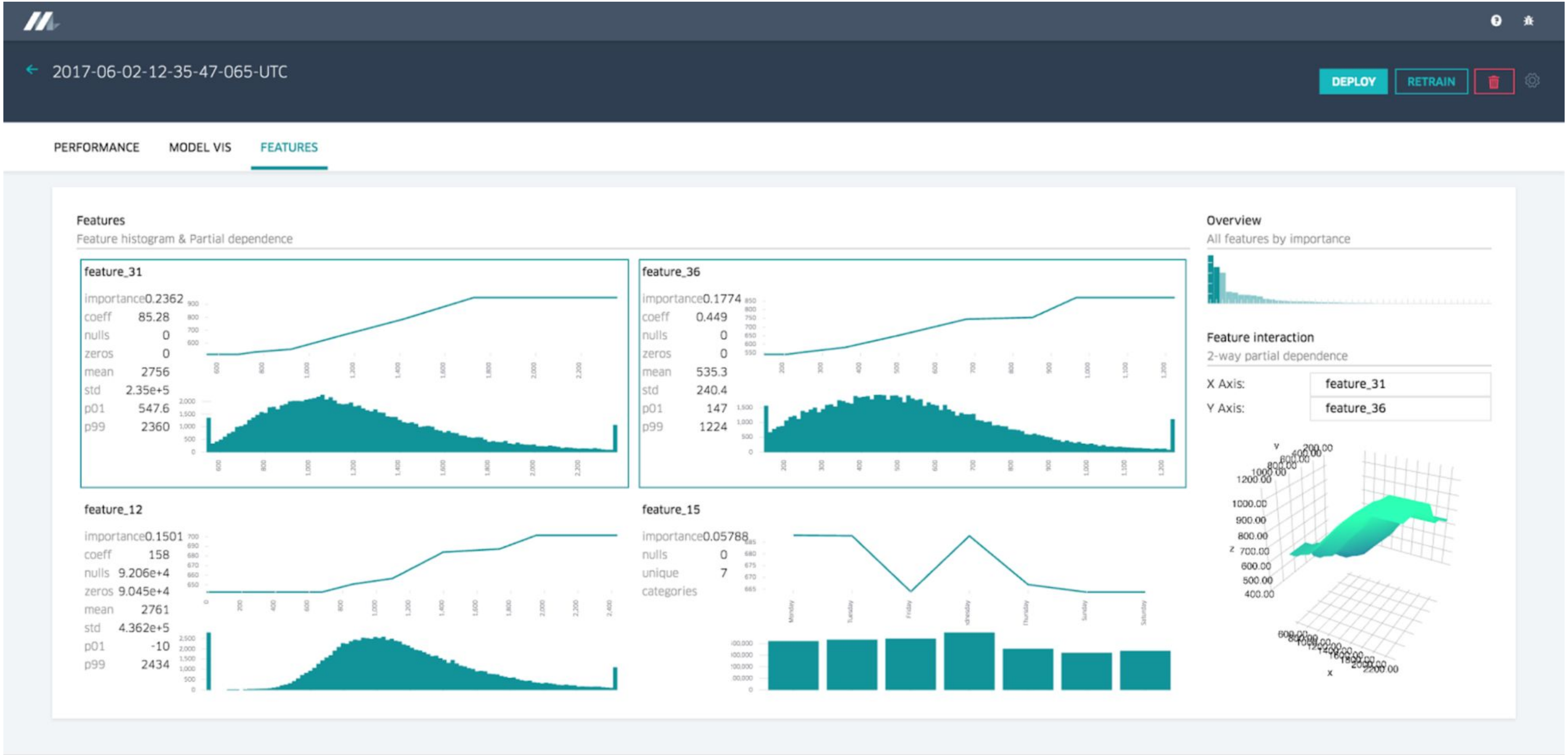


ML Platform @ Uber

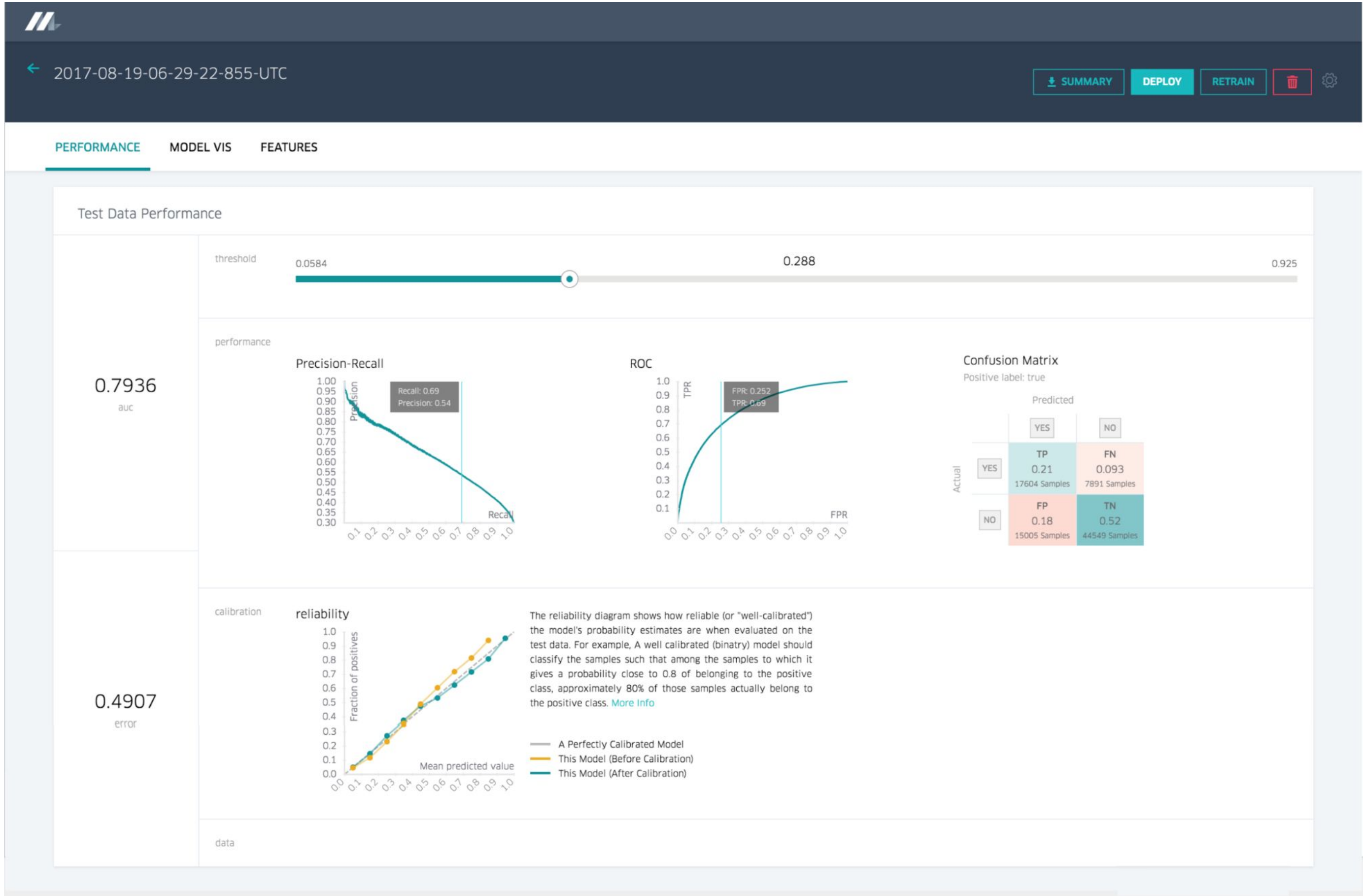


GET DATA
TRAIN MODELS
EVAL MODELS
DEPLOY, PREDICT & MONITOR
ONLINE
Kafka
Stream Engine
Cassandra Feature Store
Realtime Predict Service
Trained Model
<< Features
Prediction >>
Client Service
OFFLINE
Data Lake
Data Prep Job
Spark / SQL
Hive Feature Store
Outcomes (Training Set)
Sampled Predictions)
Batch Training Job
Training Algo
Cassandra Model Repo
Deploy
Batch Predict Job (Spark)
Trained Model
Predictions
To Hive & Kafka
Performance Monitor Job (Spark)
Metrics
To Monitor System

Feature Report



Model Accuracy Report



How Time Predictions Power Dispatch System

Agenda

- Overview of Dispatch System
- Evolution via Time Predictions
    - Dispatch System w/o Time Predictions
    - Dispatch System w/ Time Predictions

Make Demand-Supply Matching Decisions

Challenges

- Solve an NP-Hard problem with a large problem space within seconds
- Improve efficiency without compromising delivery quality
- Eater & Restaurant & Delivery Partner

Eater & Restaurant & Delivery Partner

Eater

- Fast drop-off
- Low delivery fee
- 24/7

Restaurant Partner

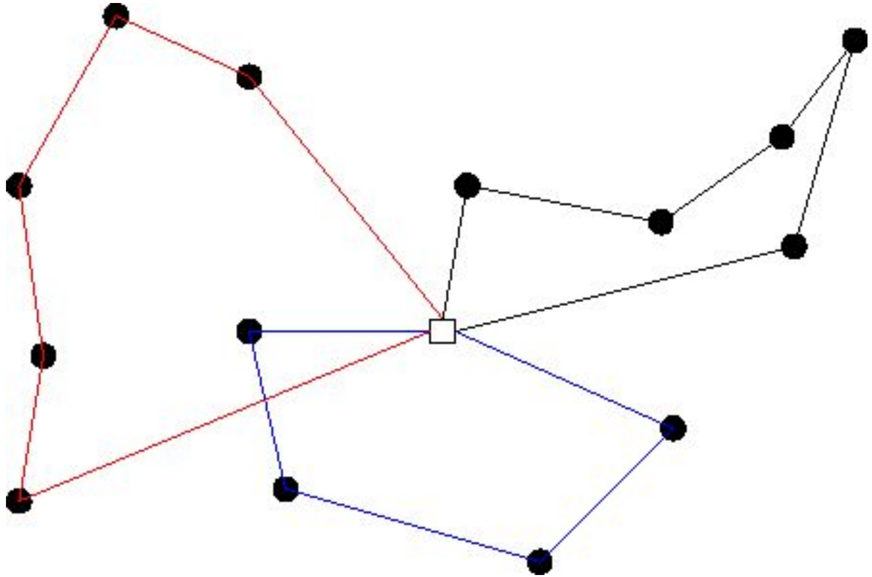
- Short wait time
- Low Unfulfillment

Delivery Partner

- Short wait time
- Smart route planning
- Quick hand-off

Matching Algorithm:

An Augmented Vehicle Routing Problem (VRP)



$$Input(Plans(Supplies, Jobs, Constraints)) \Longrightarrow max \sum_{p \in plans} DOF(p) \Longrightarrow optimal\ plans$$

DOF : *dispatch objective function*

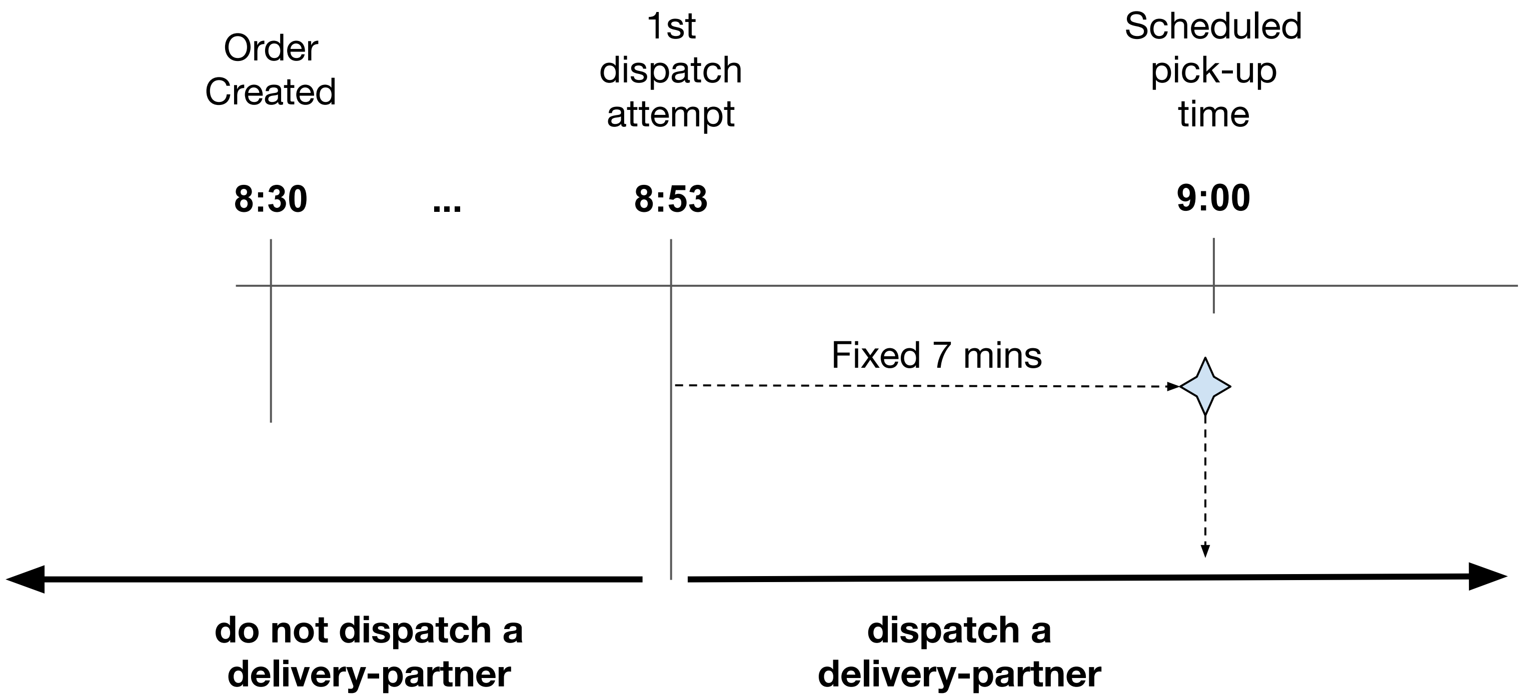
$Supply$: *A courier eligible for job assignments*

Job : *A ordered list of waypoints (pickup, dropoff)*

$Plan$: *a combination of a supply and job(s)*

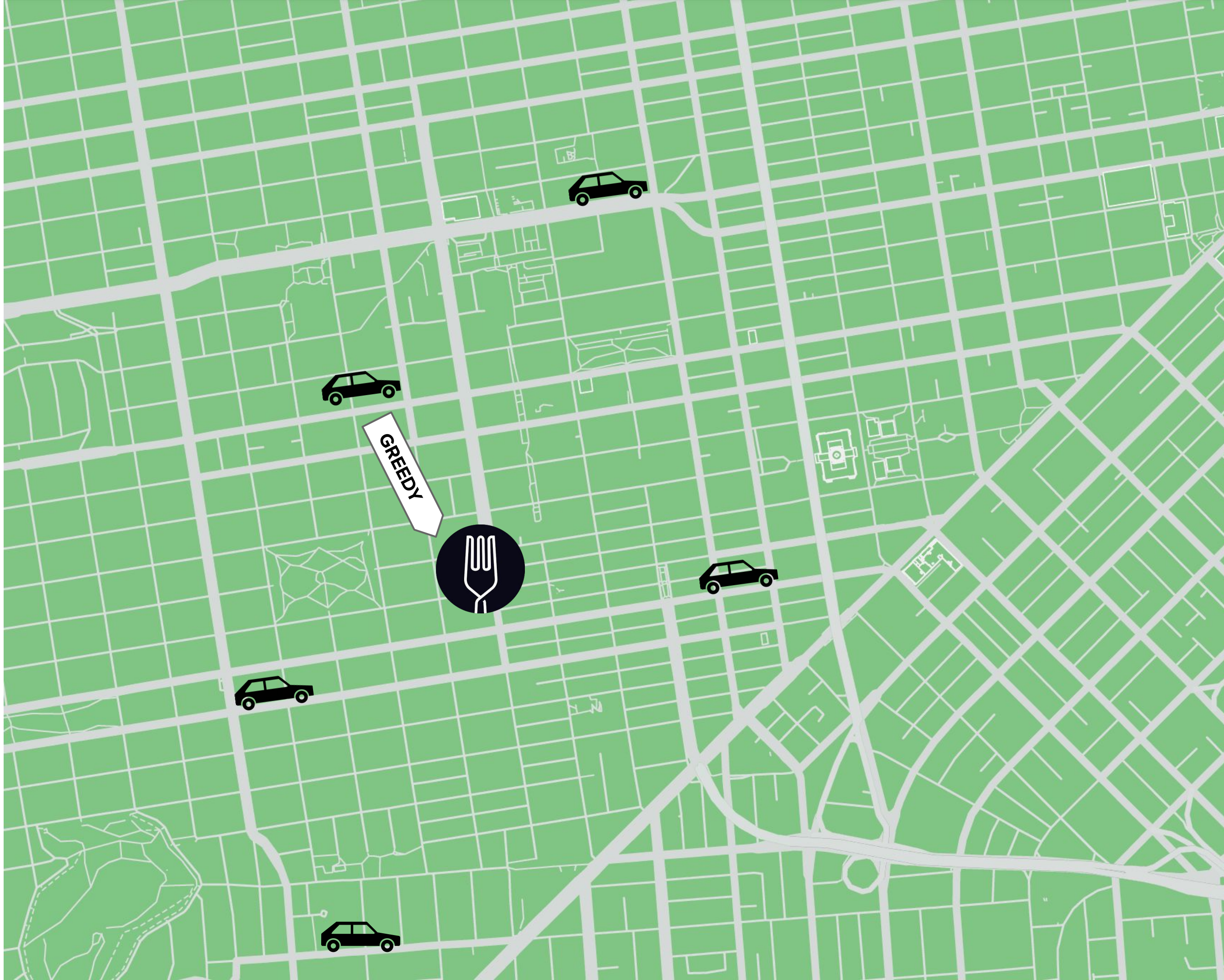
Dispatch System w/o Time Predictions

When to Dispatch?



How to Dispatch? (Greedy)

- Jobs dispatched independently without considering other jobs.



Before...

eater

- Where is my food?

- How much longer do I have to wait?

marketplace

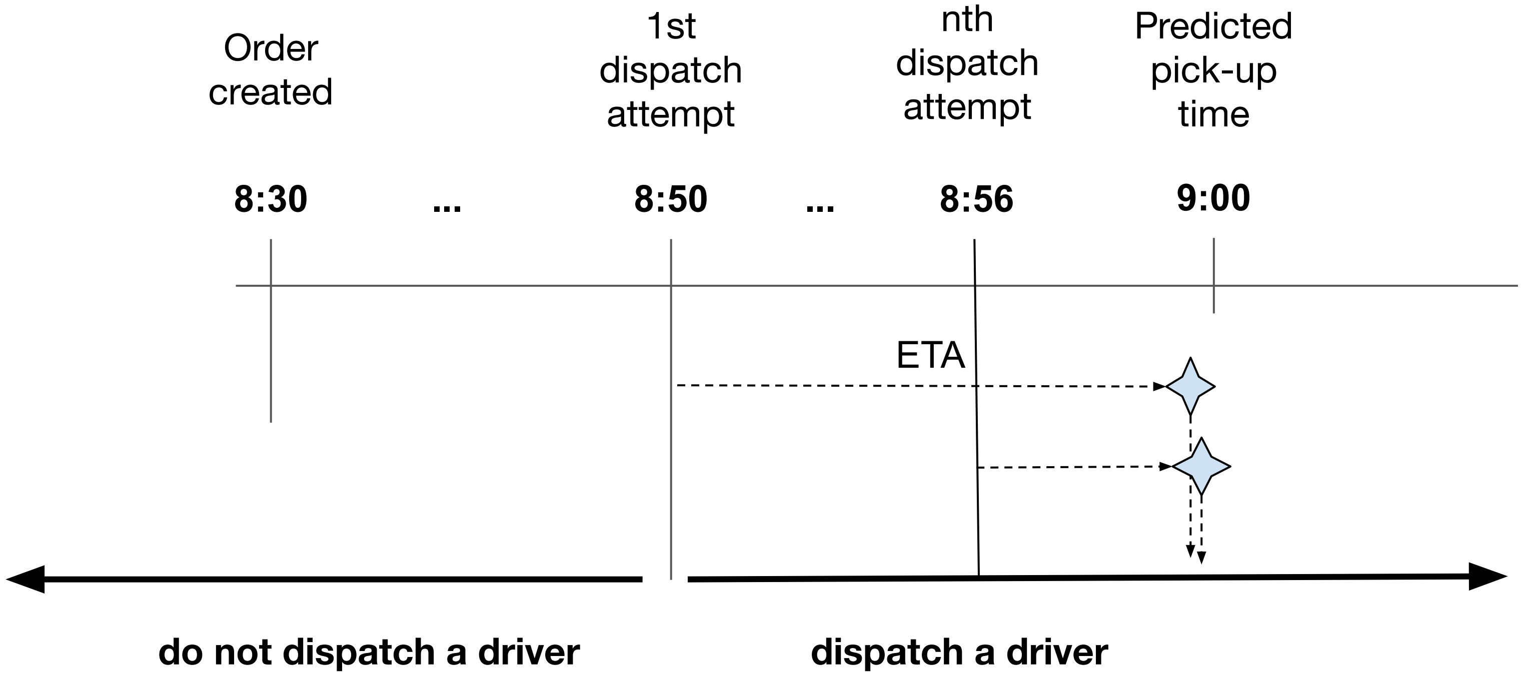
- Food is cold

delivery-partner

restaurant-partner

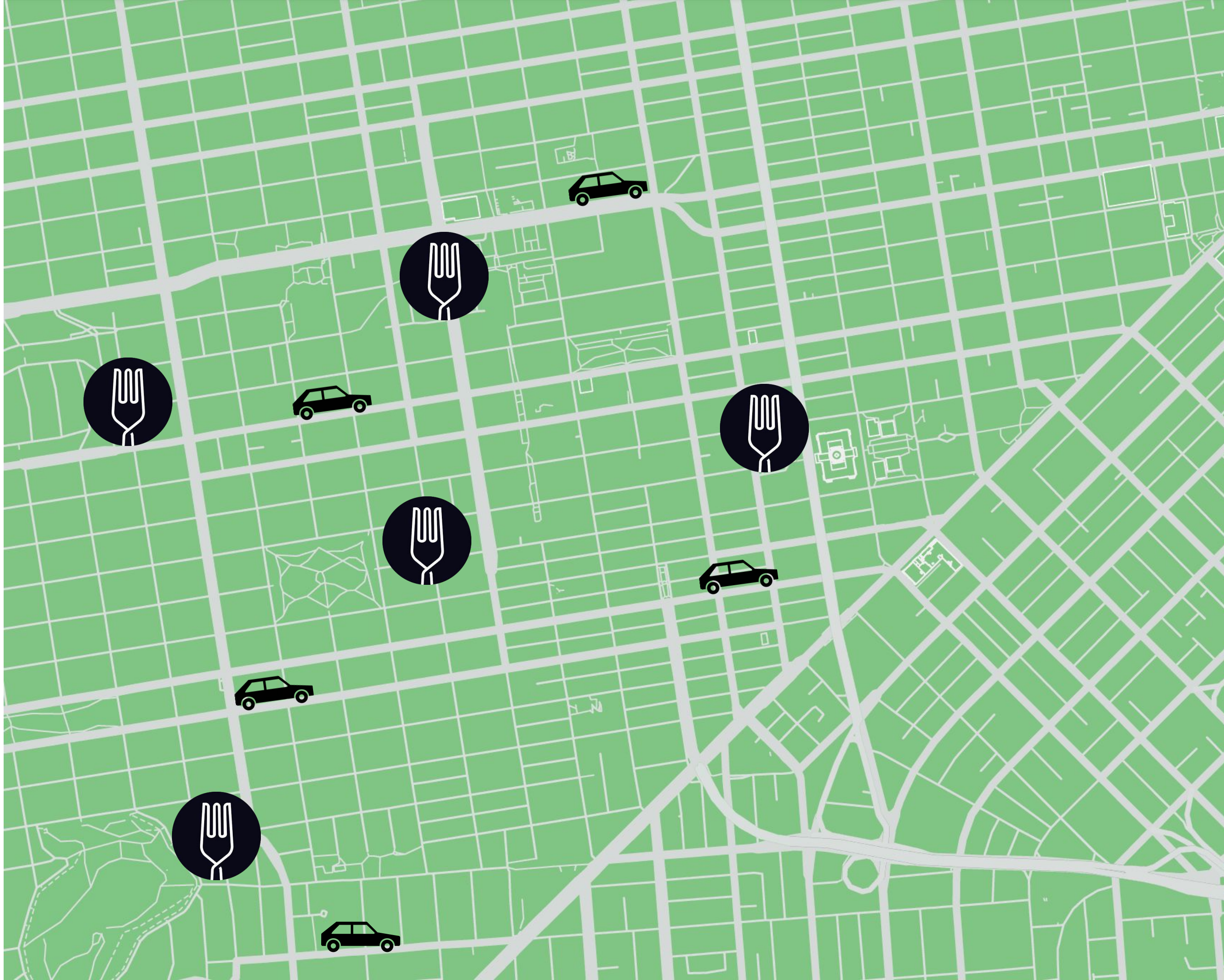
Dispatch System w/ Time Predictions

When to Dispatch?

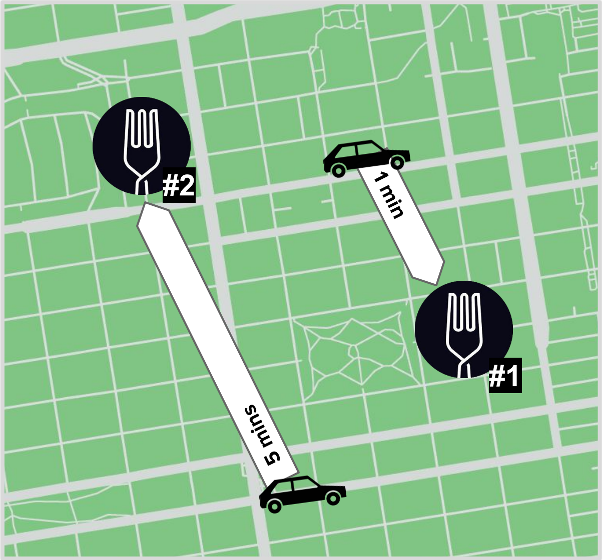


How to Dispatch? (Global)

- All jobs and supplies are considered at the same time.



- Then we solve the entire set of jobs and supplies as a single global optimization problem.

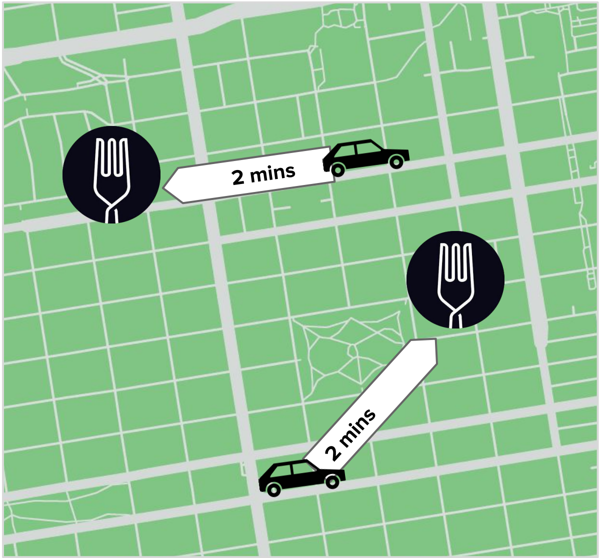


Greedy

1 MIN +

5 MIN

6 MIN

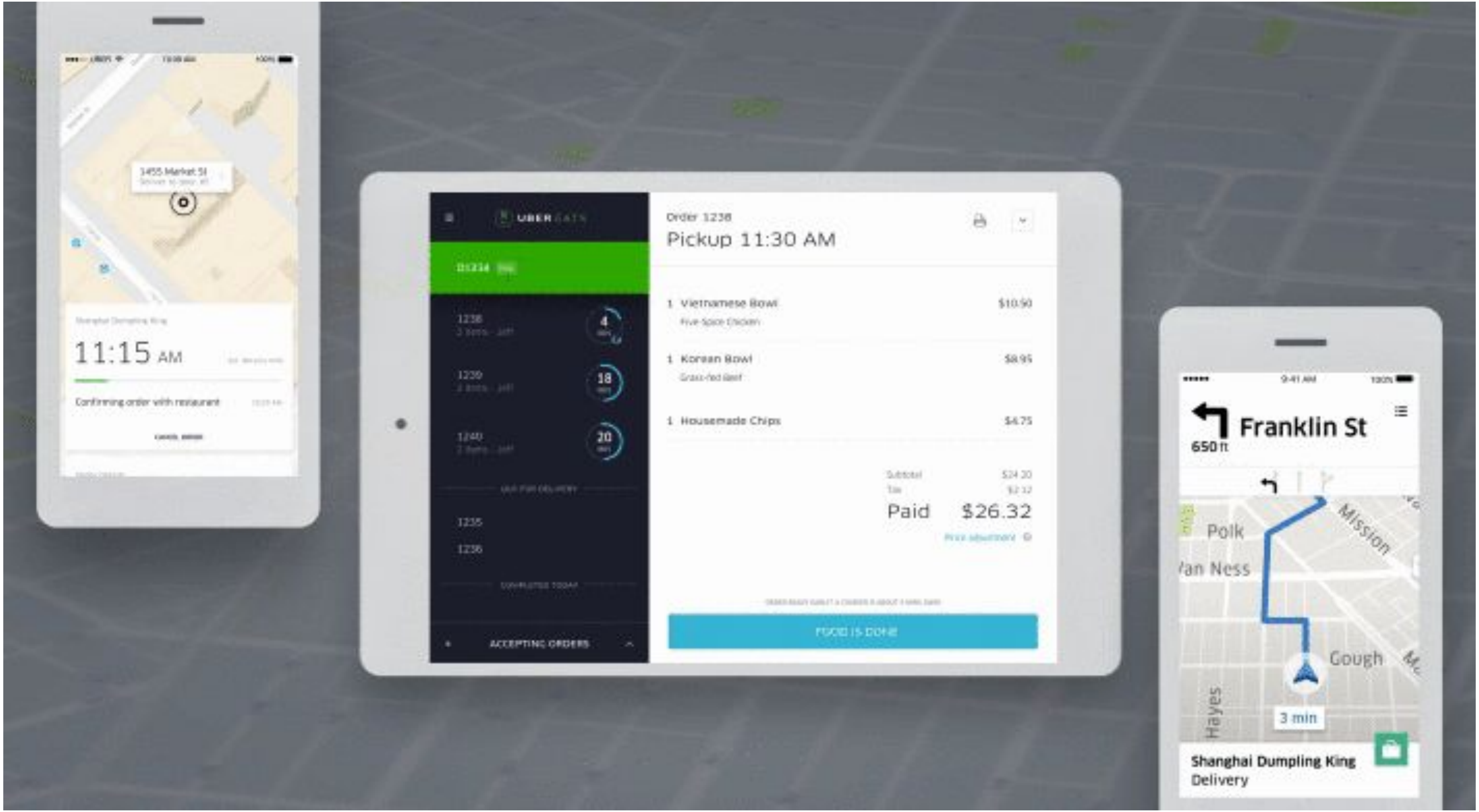


Global

2 MIN +

2 MIN

4 MIN


1455 Market St
11:15 AM
Confirming order with restaurant
UBER EATS
1238
4
1239
18
1240
20
1235
1236
ACCEPTING ORDERS
Order 1238
Pickup 11:30 AM
1 Vietnamese Bowl
$10.50
1 Korean Bowl
$8.95
1 Housemade Chips
$4.75
Paid
$26.32
FOOD IS DONE
Franklin St
650 ft
Polk
Mission
Gough
Hayes
3 min
Shanghai Dumpling King
Delivery

After...

eater

- Fast delivery times
- Accurate ETD estimations
- Track food location

marketplace

- Prevent delivery partners from waiting around
- Prevent food waiting for delivery partners
- Track delivery partner’s location

restaurant

- Dispatch delivery partners at the right time
- Maintain supply/demand, prevent surge

- Reduce waiting at restaurants
- Maximize earning potential
- Be aware of estimated travel time

delivery partner

Deep Dive in Time Predictions

Agenda

- Food Preparation Time Prediction
- Delivery Time Estimation
- Travel Time Estimation

Food Preparation Time Prediction

Why is Predicting Food Prep-time Difficult?

- 1) True restaurant prep-time is unknown!
  - Example: We need to infer true prep-time in a retrospective manner based *on restaurants and delivery partners' signals*.

- 2) Prediction with limited signals
  - Example: The busyness in the actual restaurant is unknown

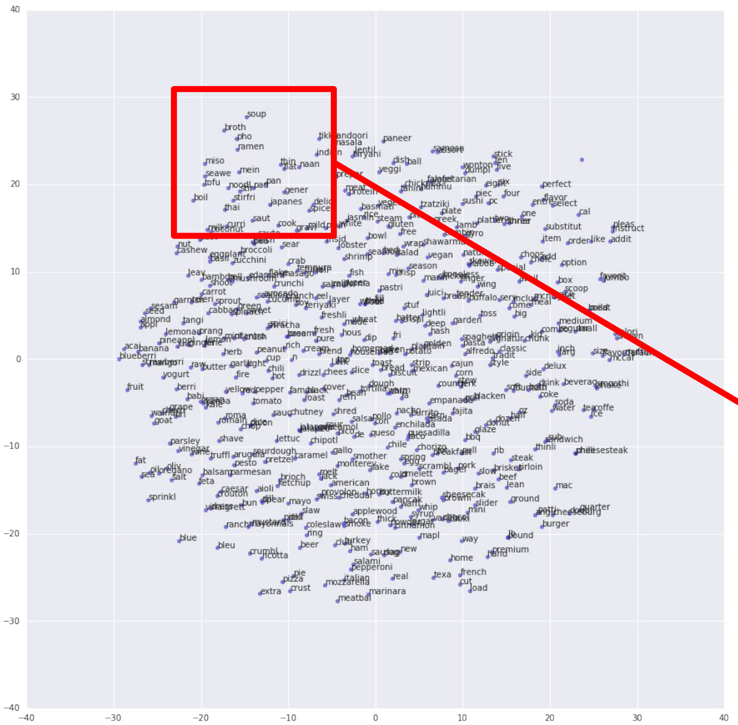
How Did We Use ML to Solve the Problem?

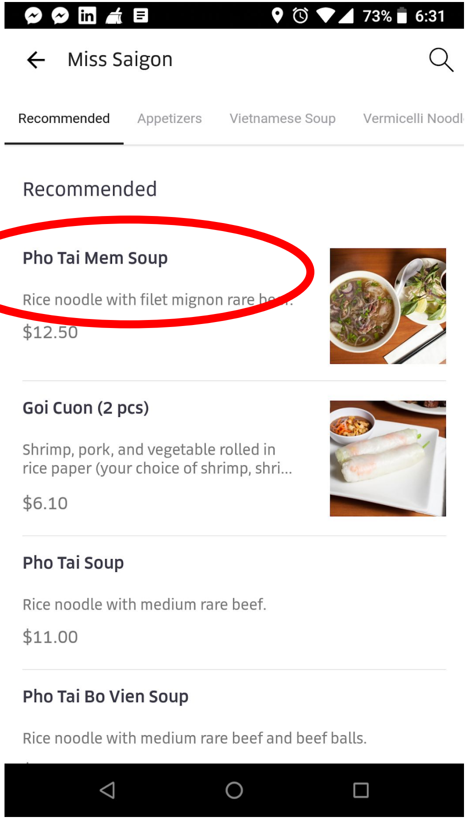
- Feature engineering
- ML Model
- Feedback Loop

Feature Engineering

- Historical features
  - Avg prep-time for 1 week, ...
- Real-time (Contextual) features
  - Time of day, day of week, order size, location, ...
- Near real-time features
  - Avg prep-time for last 10 mins, ...

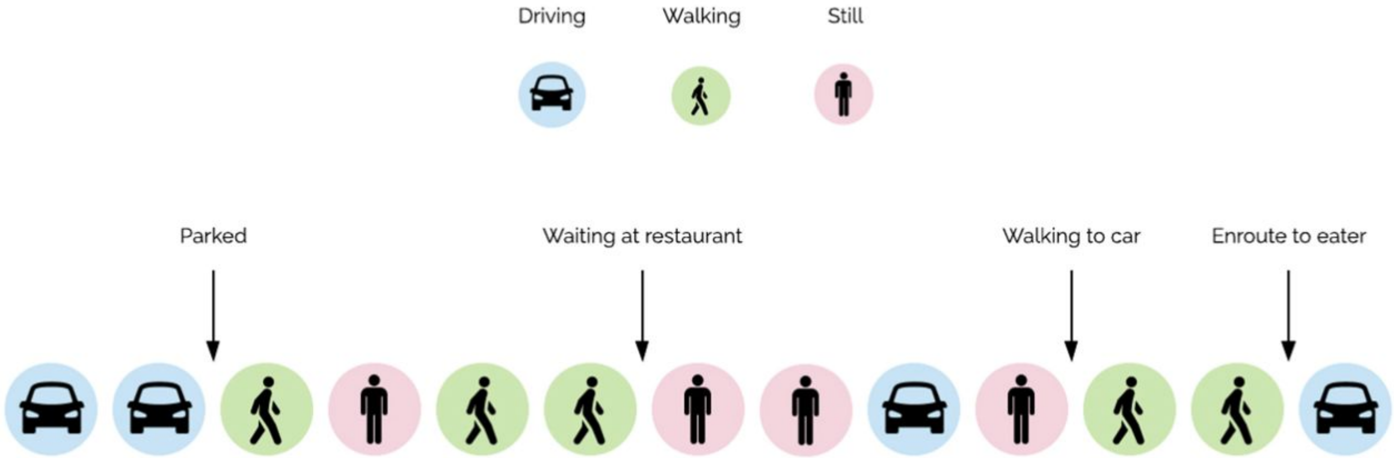
Representation Learning



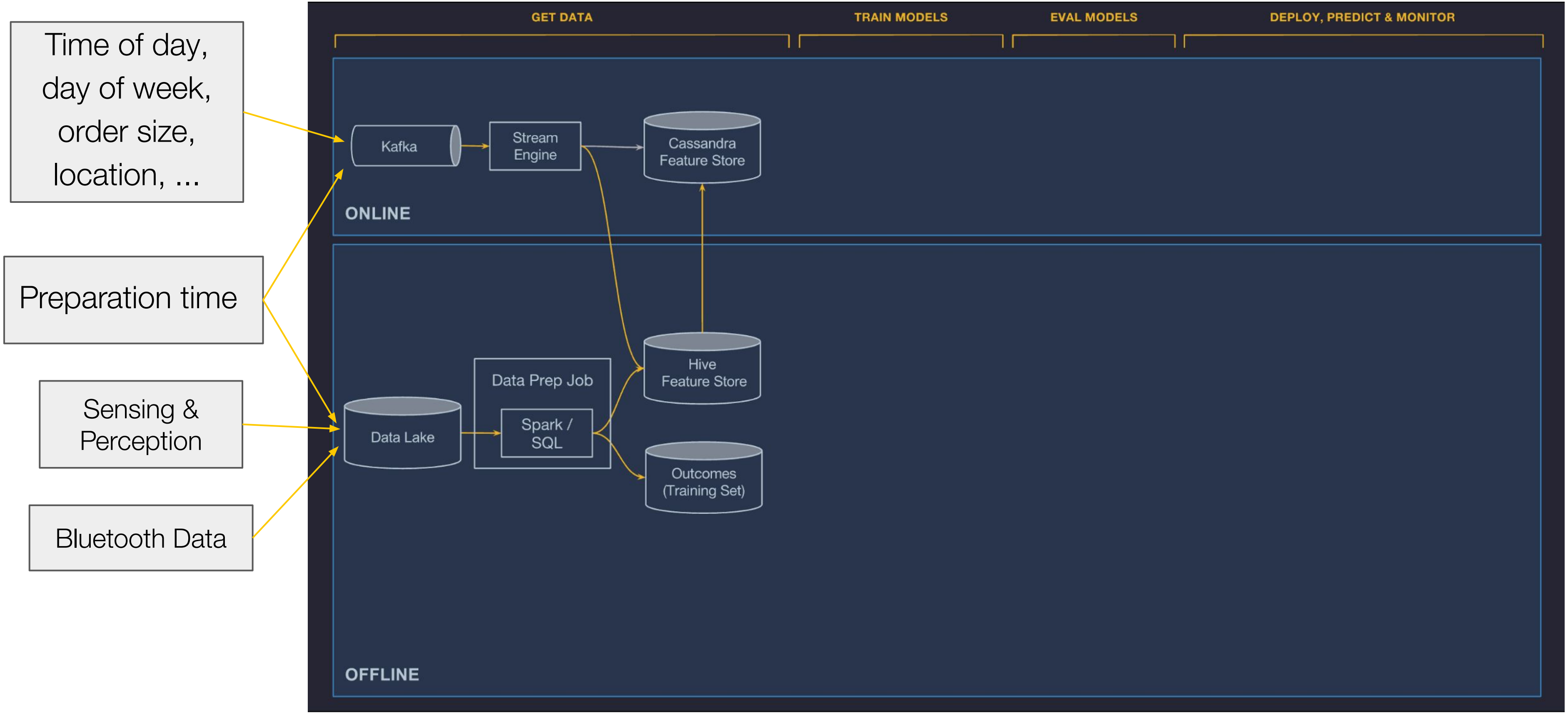


Sensor Signals

Conditional Random Field Model



Feature Engineering (Cont'd) - Data Pipeline

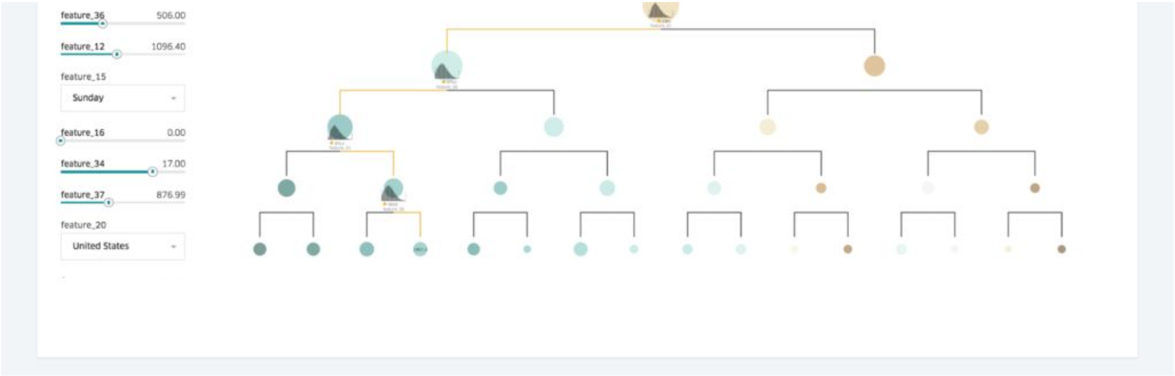


Data preparation pipelines push data into the Feature Store tables and training data repositories.

ML Model

- Model: Gradient boosting decision trees (XGBoost)

- Historical features
- Realtime (Contextual)s features
- Near real-time features



Hyperparameter tuning

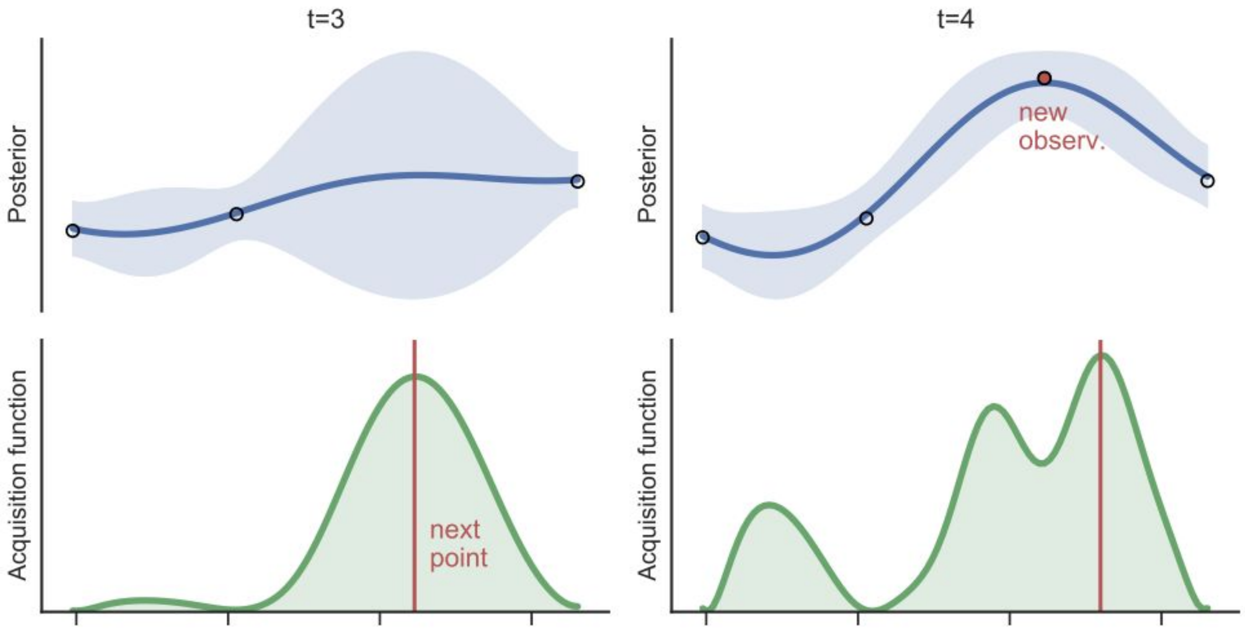
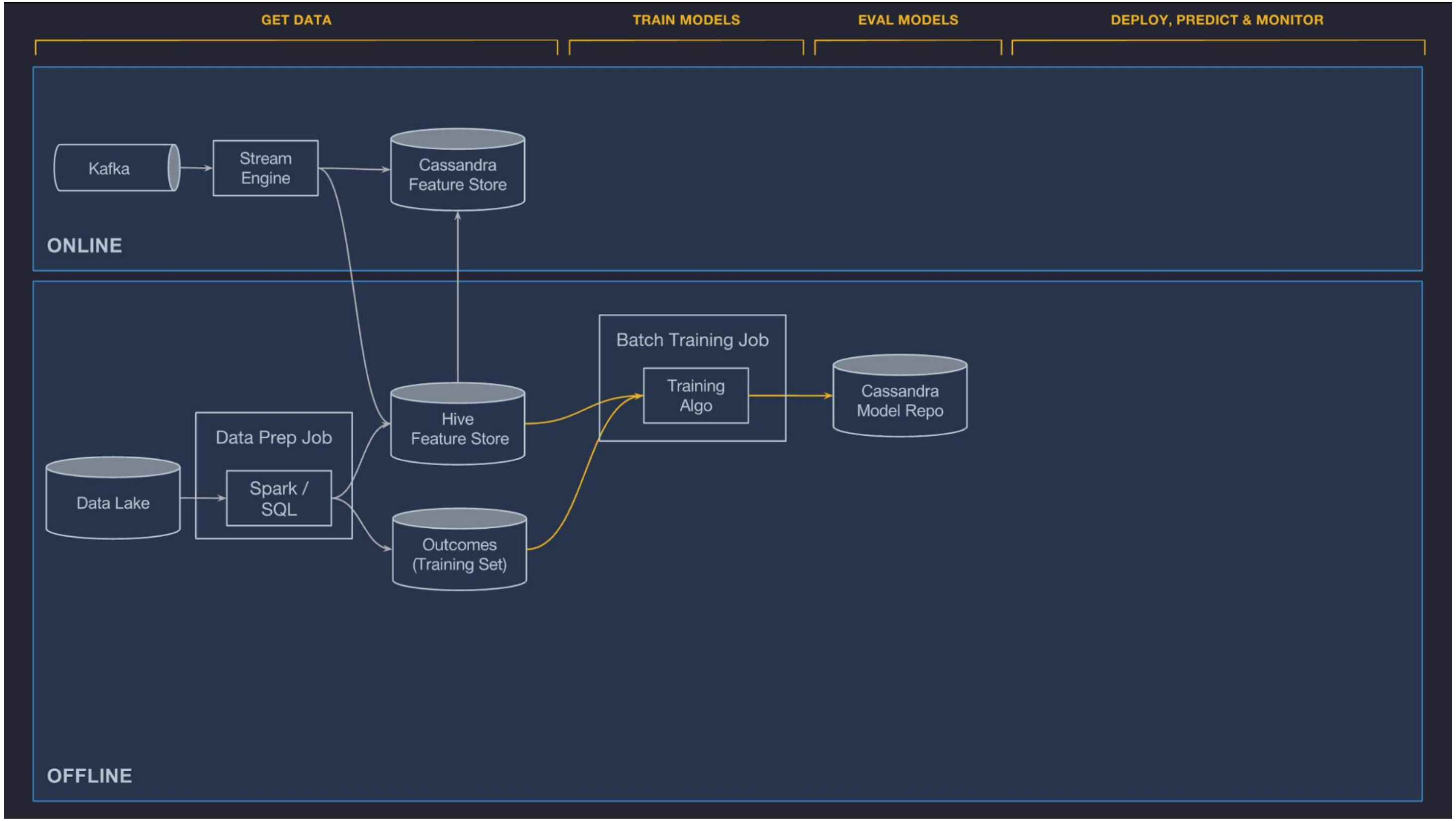


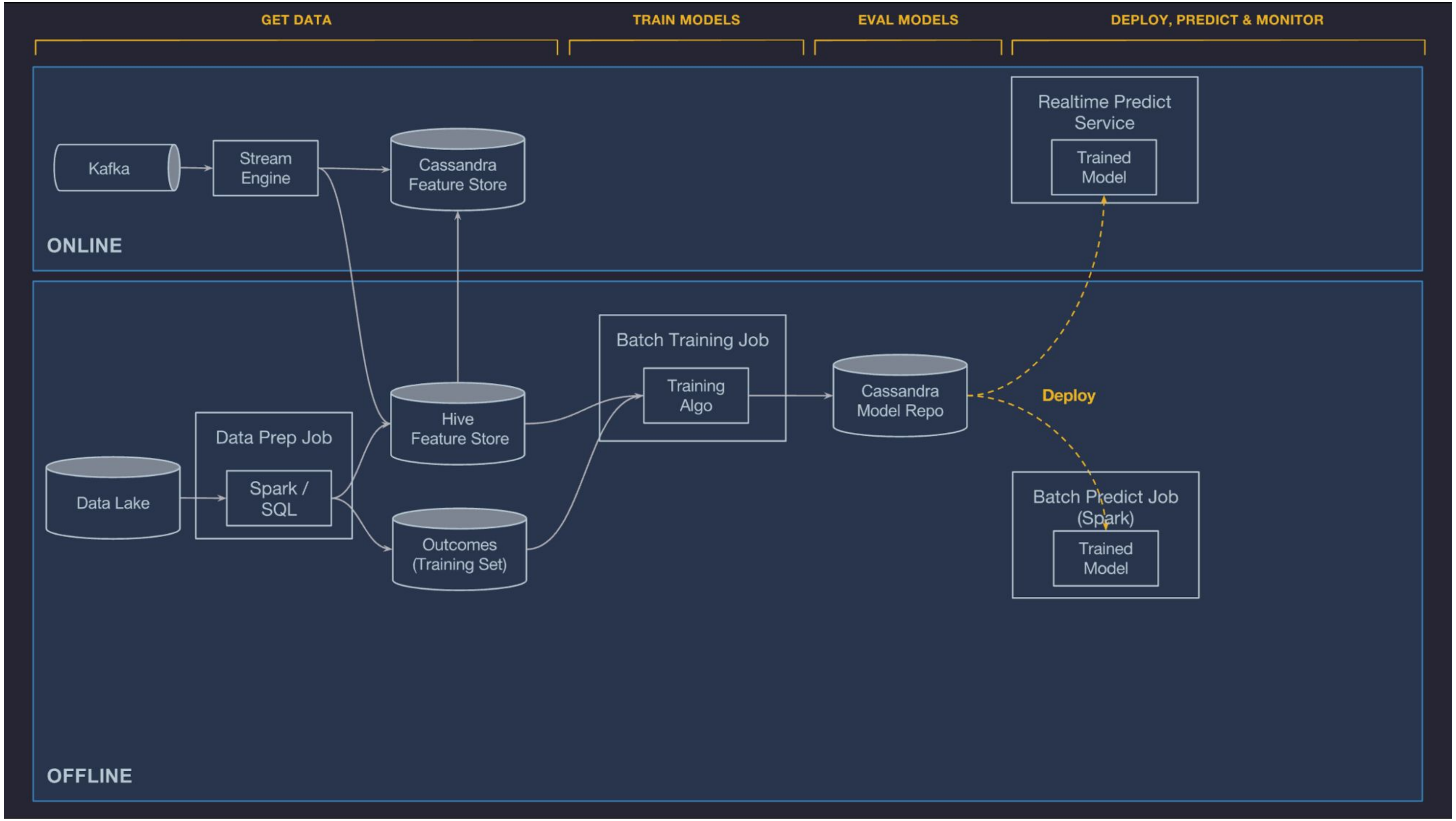
Image source: www.nature.com/articles/nature14541

Model Training

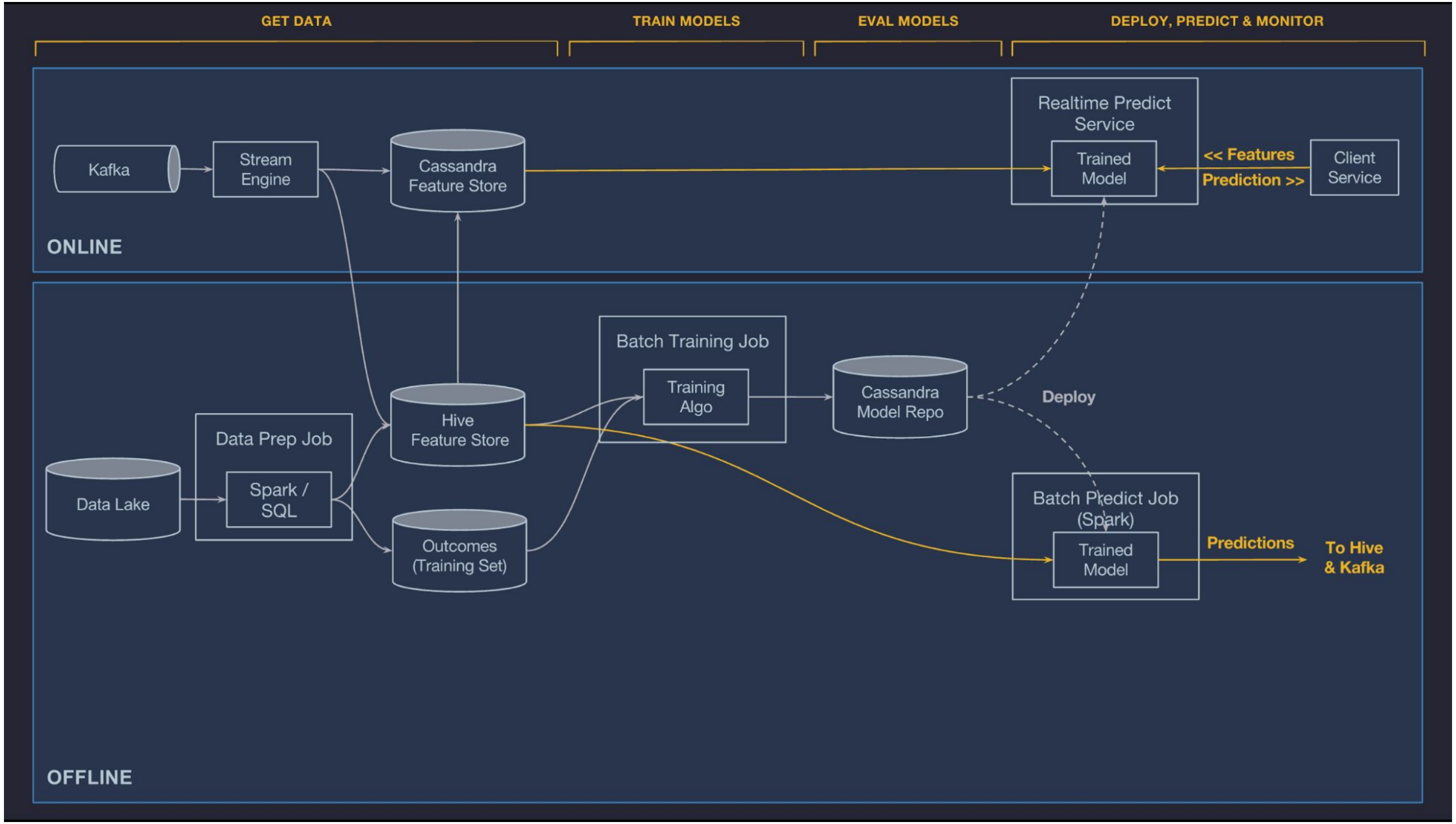


Model training jobs use Feature Store and training data repository data sets to train models and then push them to the model repository.

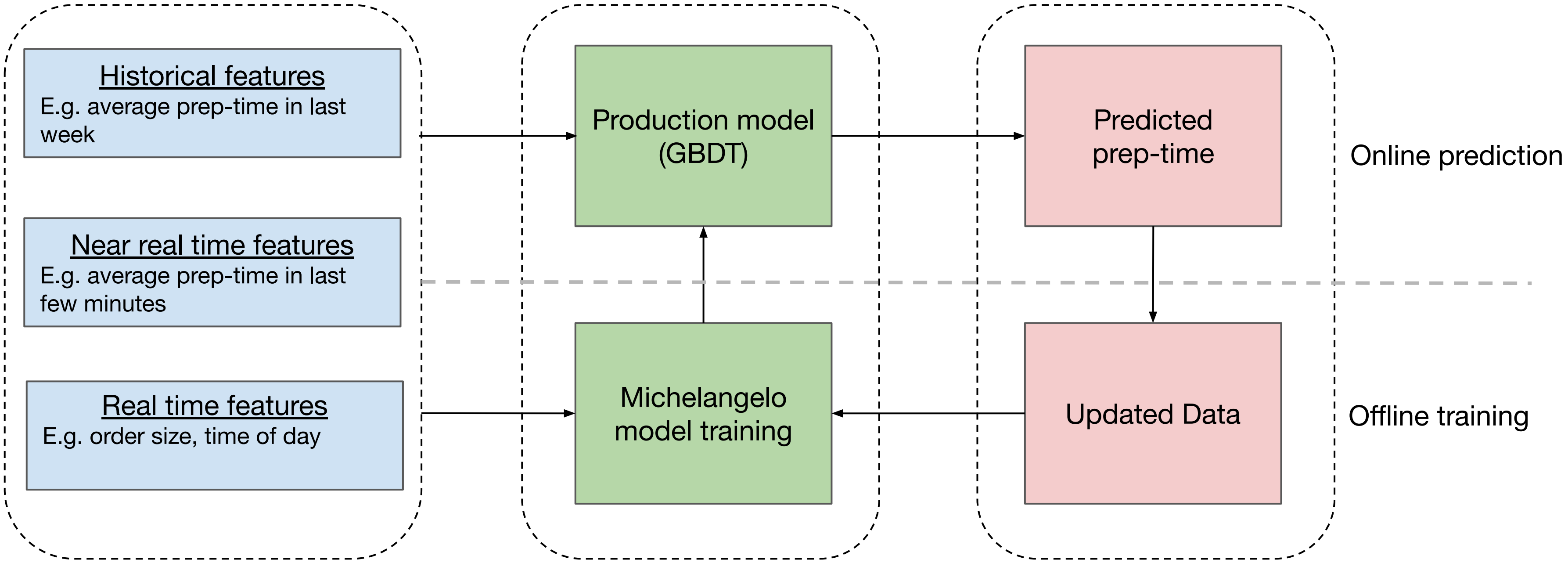
Model Training (Cont'd) - Model Deployment



Model Training (Cont'd) - Make Predictions



ML Model with Feedback Loop

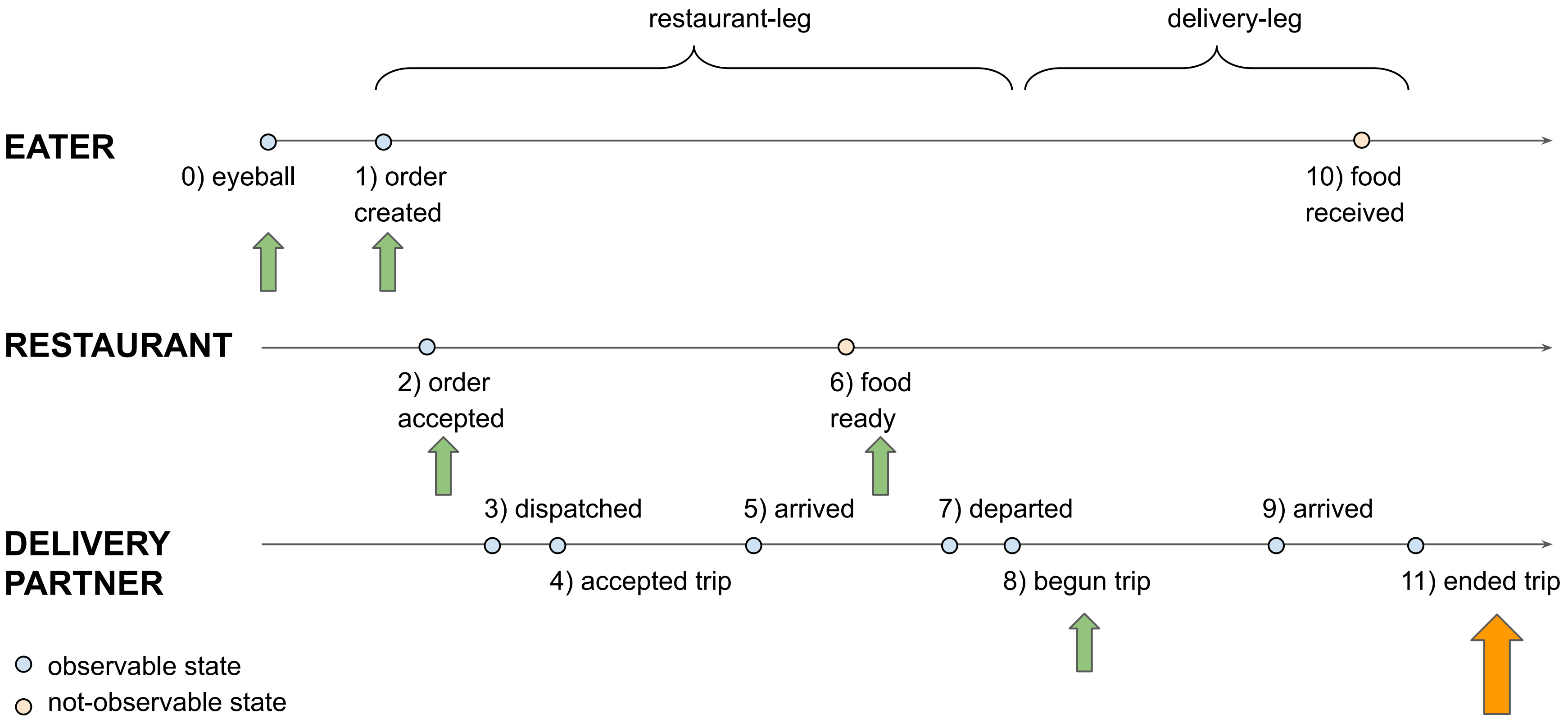


Future Improvements

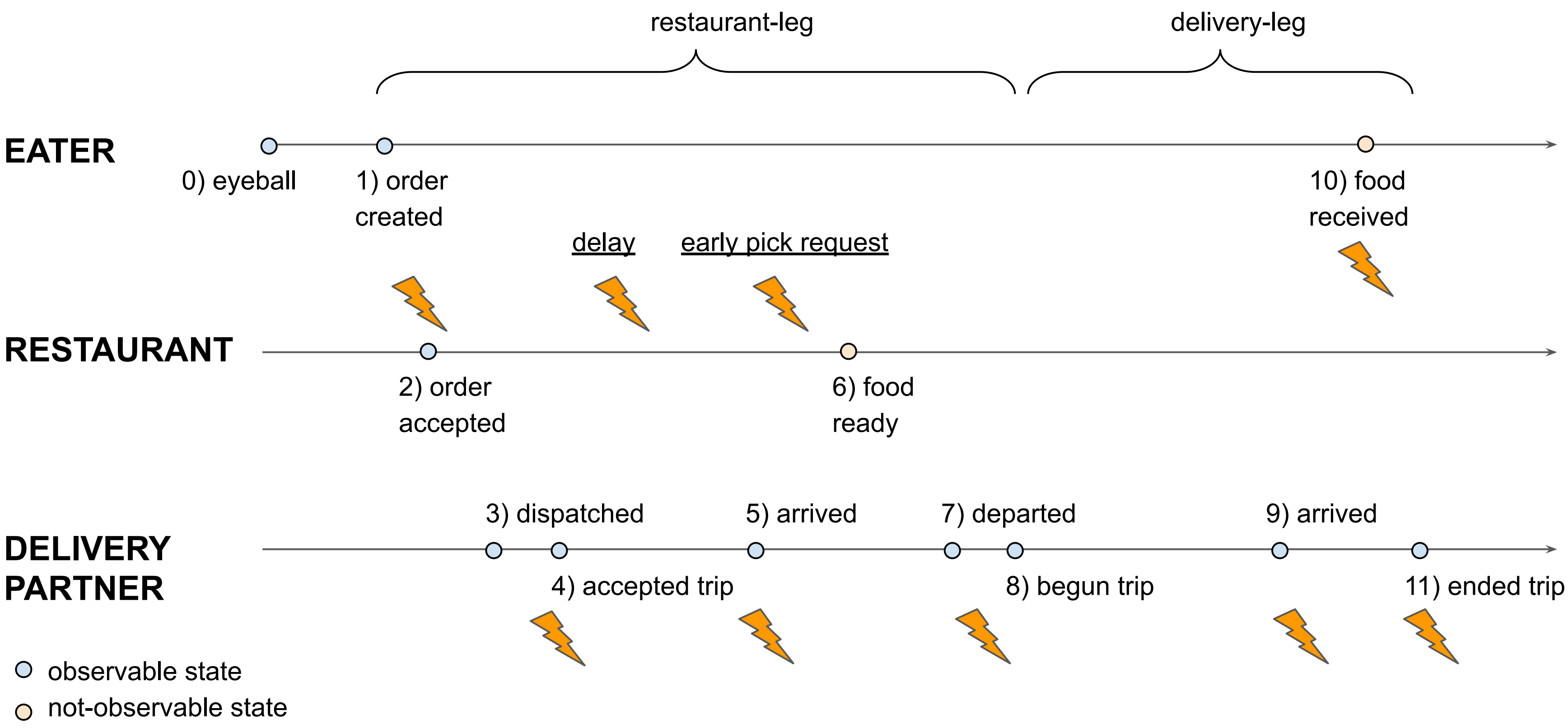
- Ground truth exploration
  - Experiment in restaurants
  - ...
- Improving ML model
  - Feature engineering
    - Exploration of places, weather, and event data
    - Model partitioning
    - ...
  - Leverage ensemble learning (stacking)
  - Collaboration with AI Labs on more deep learning models

Delivery Time Estimation

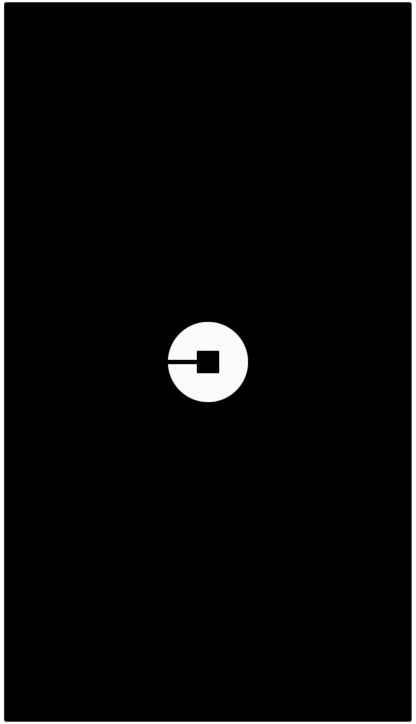
Eater-facing ETD



Why is predicting ETD difficult?

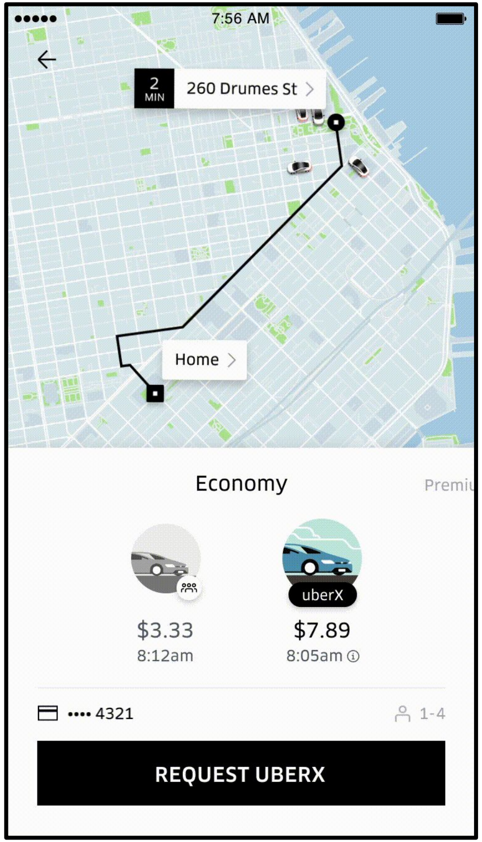


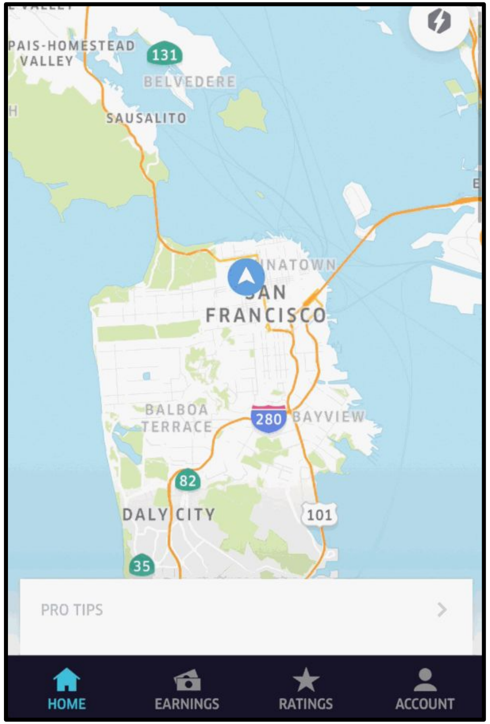
Travel Time Estimation



Rider

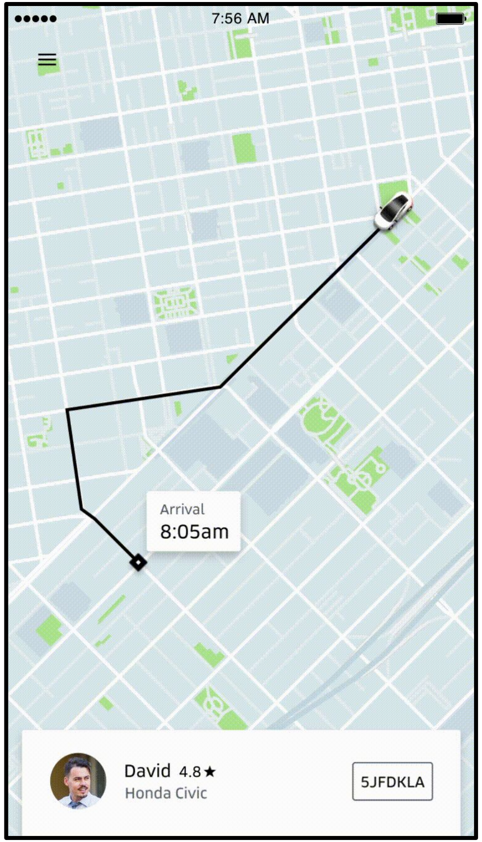
Rider - Request Ride





Driver

Rider - On Trip



Credits

Teams @ Uber

Special thanks to:

- Engineers
- Data Scientists
- Product managers
- Product Ops
- Data Analysts

THANK YOU

Q & A

Uber