

Time Predictions in Uber Eats

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QCon New York 2019

Uber Eats

June 2019



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

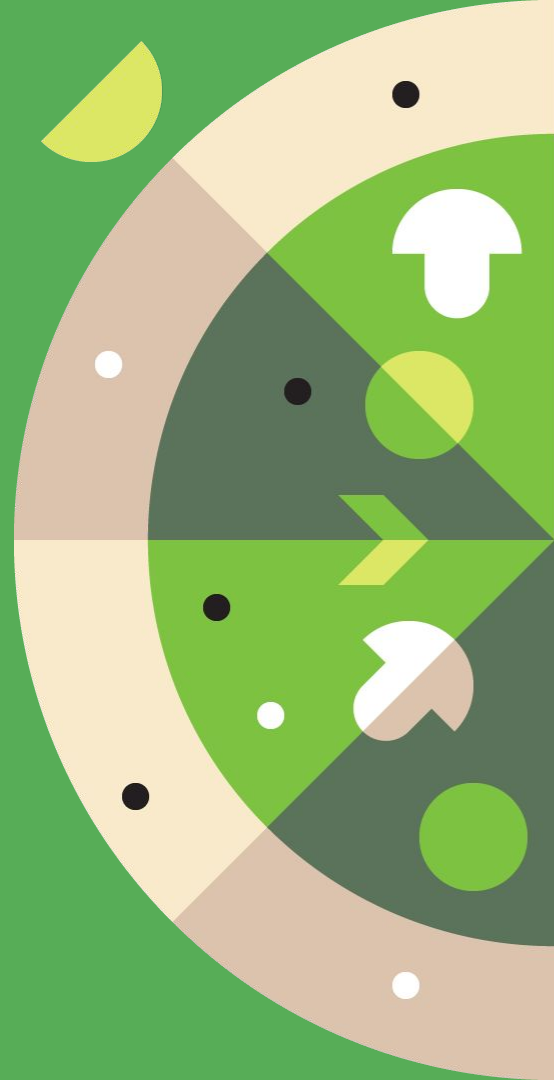
> 500 Cities

> 220,000
Restaurant Partners

~ 8B
Gross Bookings
for 2018

Our Mission

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



Goals & Challenges



Reliable

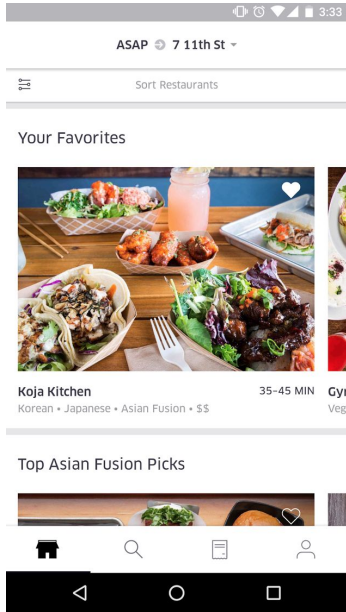
Predicting the Future

Affordable

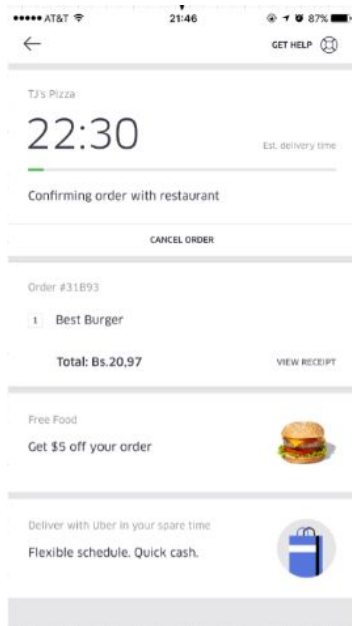
Network Efficiency

Effortless

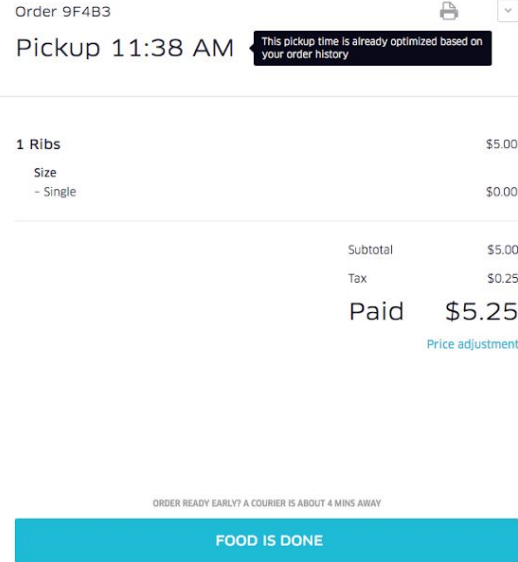
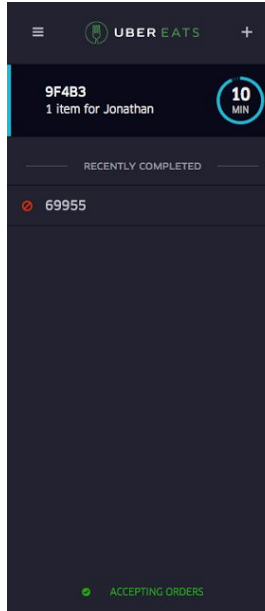
Food Discovery



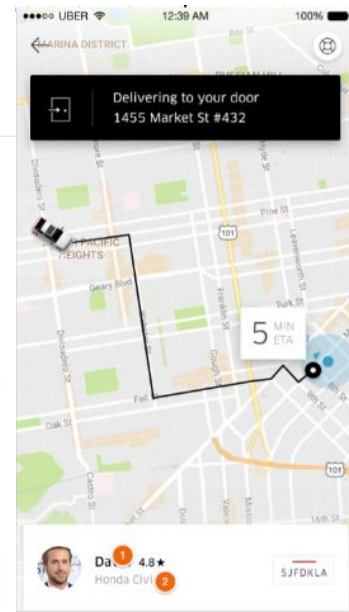
Eyeball ETD prediction



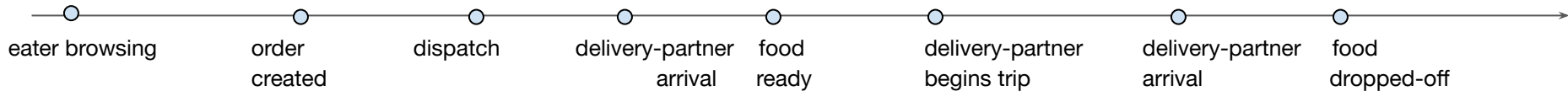
ETD prediction



Prep-time prediction



ETA prediction



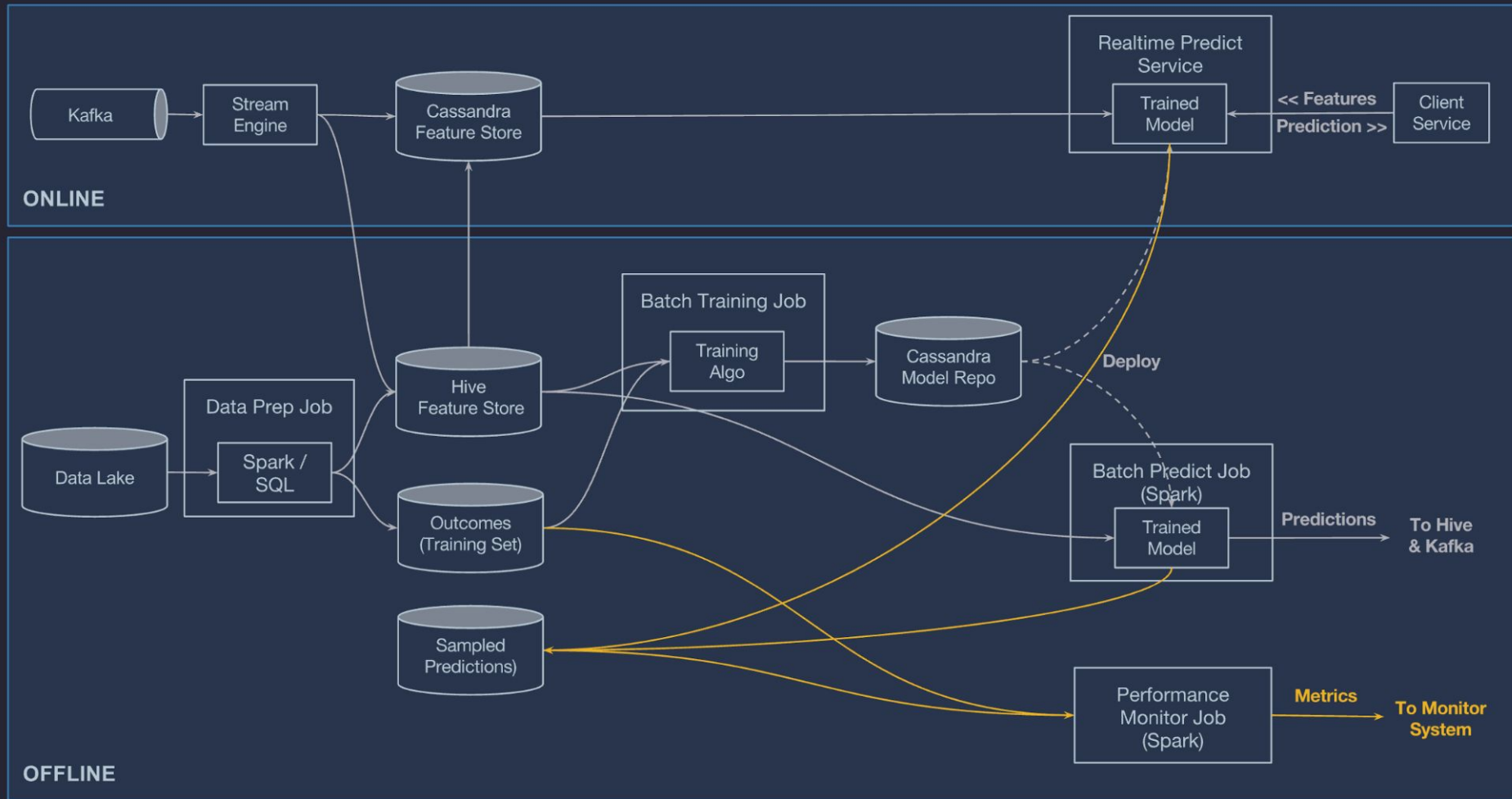
ML Platform @ Uber

GET DATA

TRAIN MODELS

EVAL MODELS

DEPLOY, PREDICT & MONITOR



Feature Report



← 2017-06-02-12-35-47-065-UTC

DEPLOY

RETRAIN



PERFORMANCE

MODEL VIS

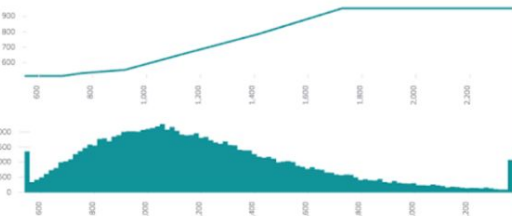
FEATURES

Features

Feature histogram & Partial dependence

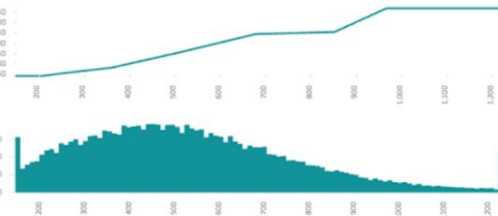
feature_31

importance 0.2362
coeff 85.28
nulls 0
zeros 0
mean 2756
std 2.35e+5
p01 547.6
p99 2360



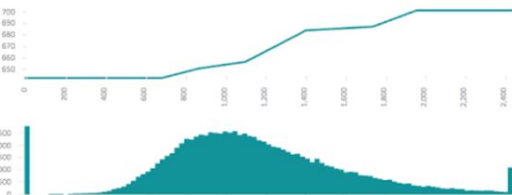
feature_36

importance 0.1774
coeff 0.449
nulls 0
zeros 0
mean 535.3
std 240.4
p01 147
p99 1224



feature_12

importance 0.1501
coeff 158
nulls 9.206e+4
zeros 9.045e+4
mean 2761
std 4.362e+5
p01 -10
p99 2434



feature_15

importance 0.05788
nulls 0
unique 7
categories



Overview

All features by importance



Feature interaction

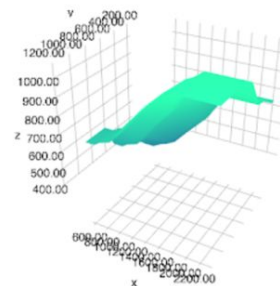
2-way partial dependence

X Axis:

feature_31

Y Axis:

feature_36



Model Accuracy Report



← 2017-08-19-06-29-22-855-UTC

[SUMMARY](#) [DEPLOY](#) [RETRAIN](#) [🗑️](#) [⚙️](#)

[PERFORMANCE](#) [MODEL VIS](#) [FEATURES](#)

Test Data Performance

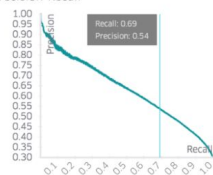
0.7936

AUC

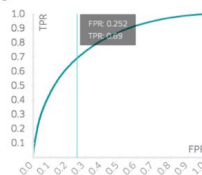


performance

Precision-Recall



ROC



Confusion Matrix

Positive label: true

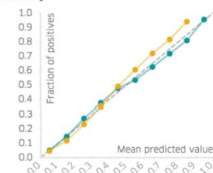
		Predicted	
		YES	NO
Actual	YES	TP 0.21 17604 Samples	FN 0.093 7891 Samples
	NO	FP 0.18 15005 Samples	TN 0.52 44549 Samples

0.4907

error

calibration

reliability



The reliability diagram shows how reliable (or "well-calibrated") the model's probability estimates are when evaluated on the test data. For example, A well calibrated (binary) model should classify the samples such that among the samples to which it gives a probability close to 0.8 of belonging to the positive class, approximately 80% of those samples actually belong to the positive class. [More Info](#)

data

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

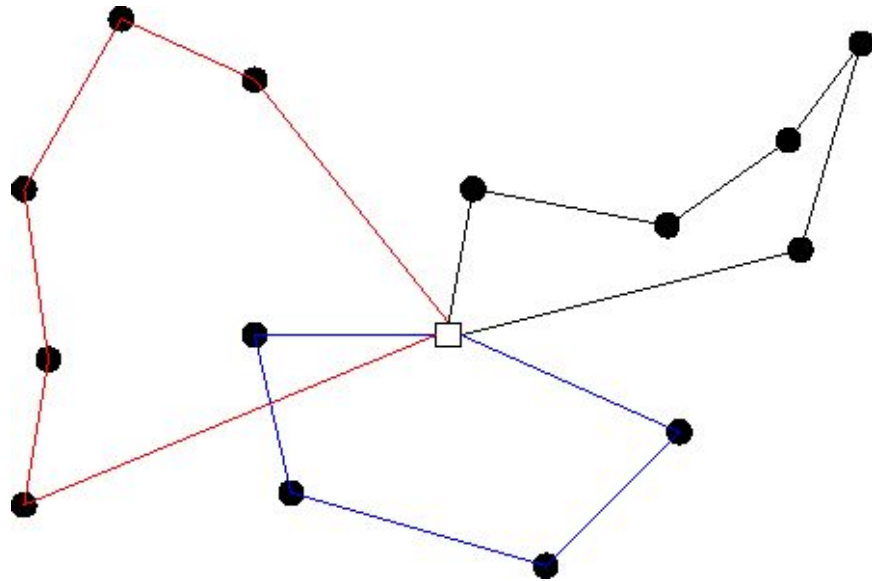


Delivery Partner

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

Matching Algorithm:

An Augmented Vehicle Routing Problem (VRP)



$Input(Plans(Supplies, Jobs, Constraints)) \Rightarrow \max_{p \in plans} \sum DOF(p) \Rightarrow optimal\ plans$

DOF : dispatch objective function

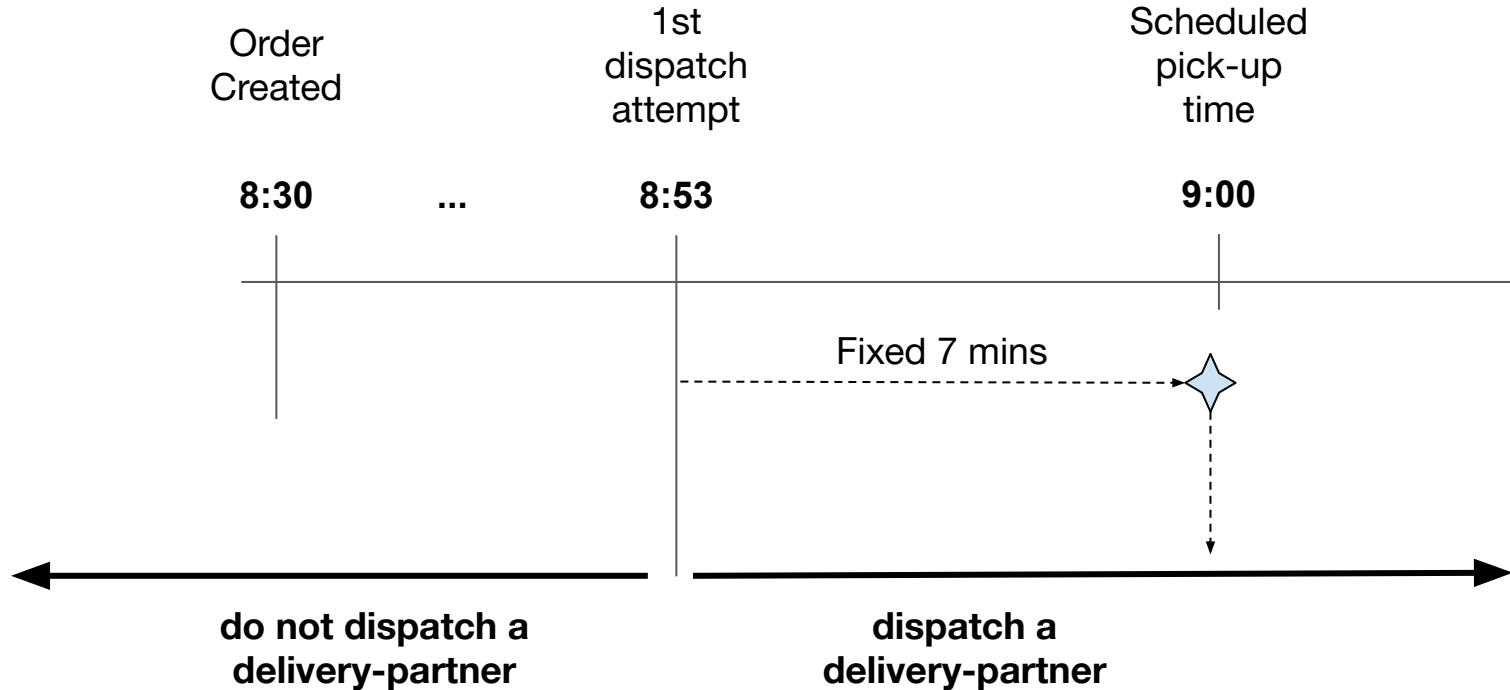
Supply : A courier eligible for job assignments

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

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

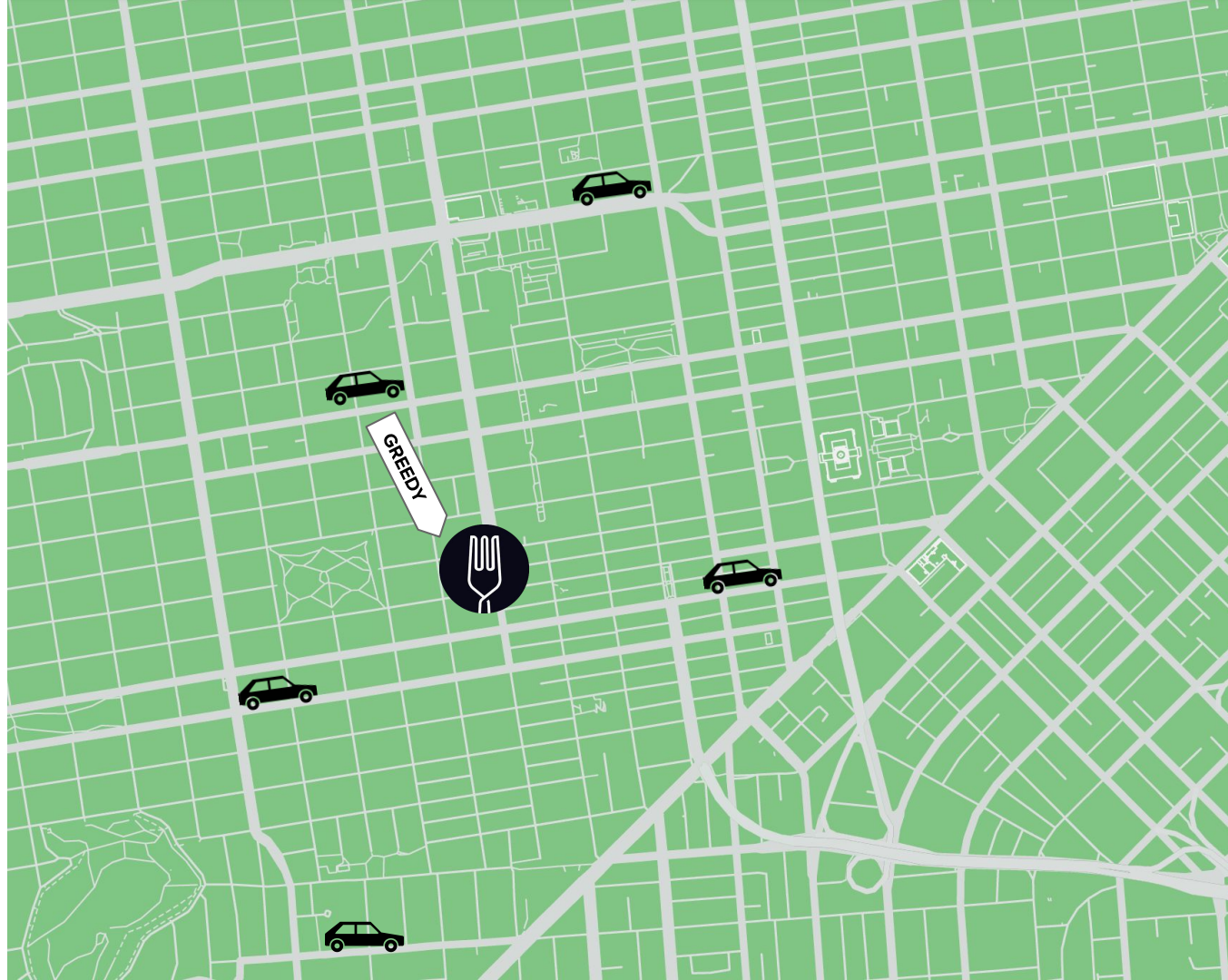
Dispatch System w/o Time Predictions

When to Dispatch?

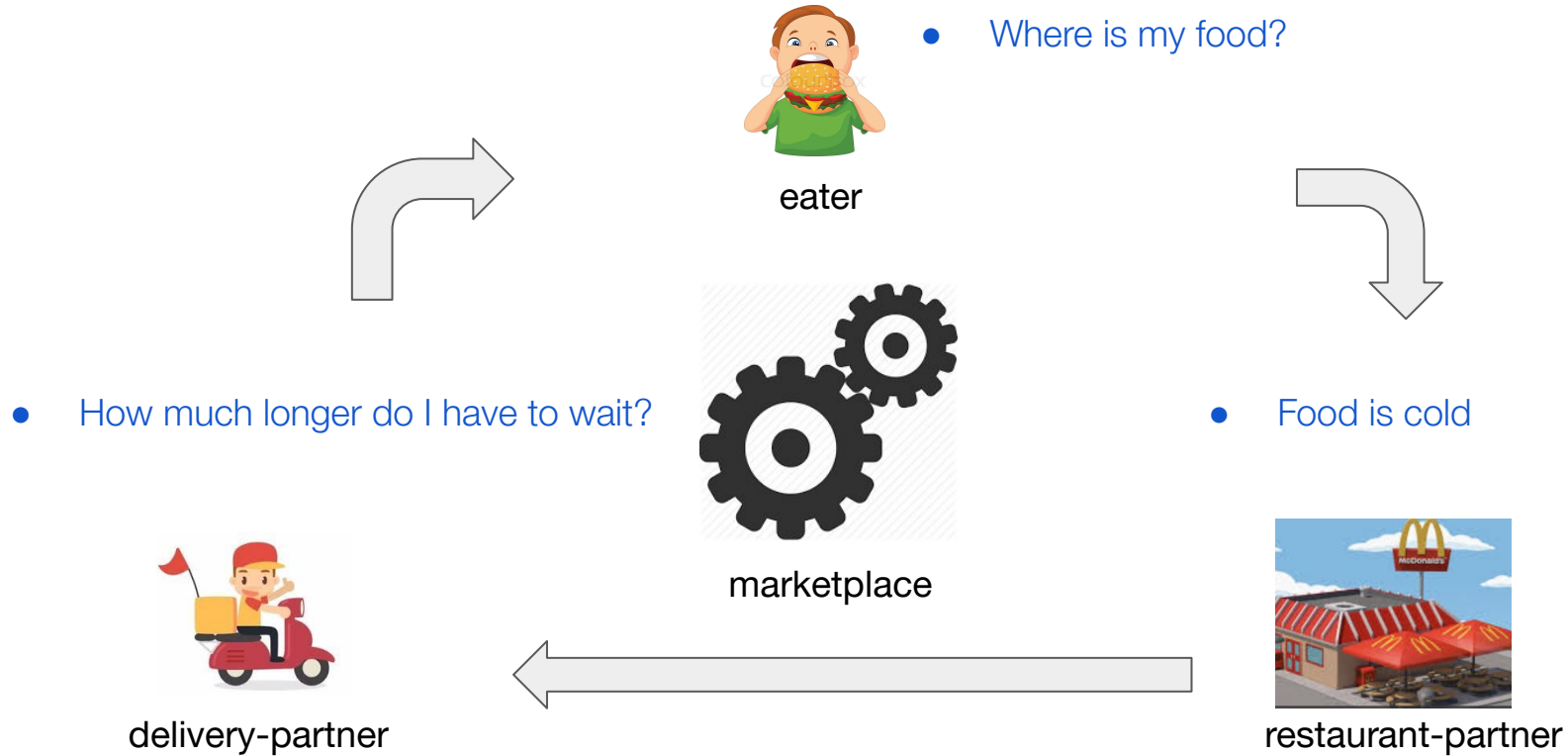


How to Dispatch? (Greedy)

- Jobs dispatched independently without considering other jobs.

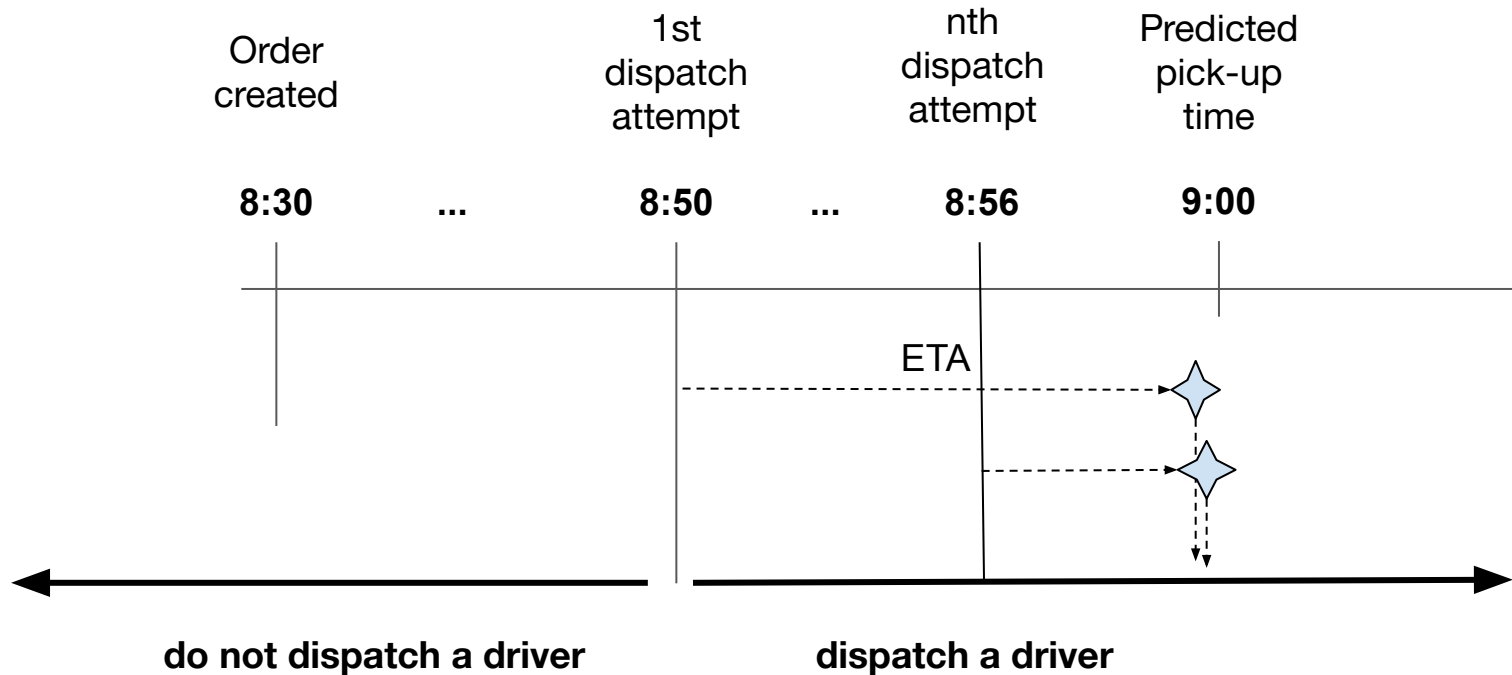


Before...



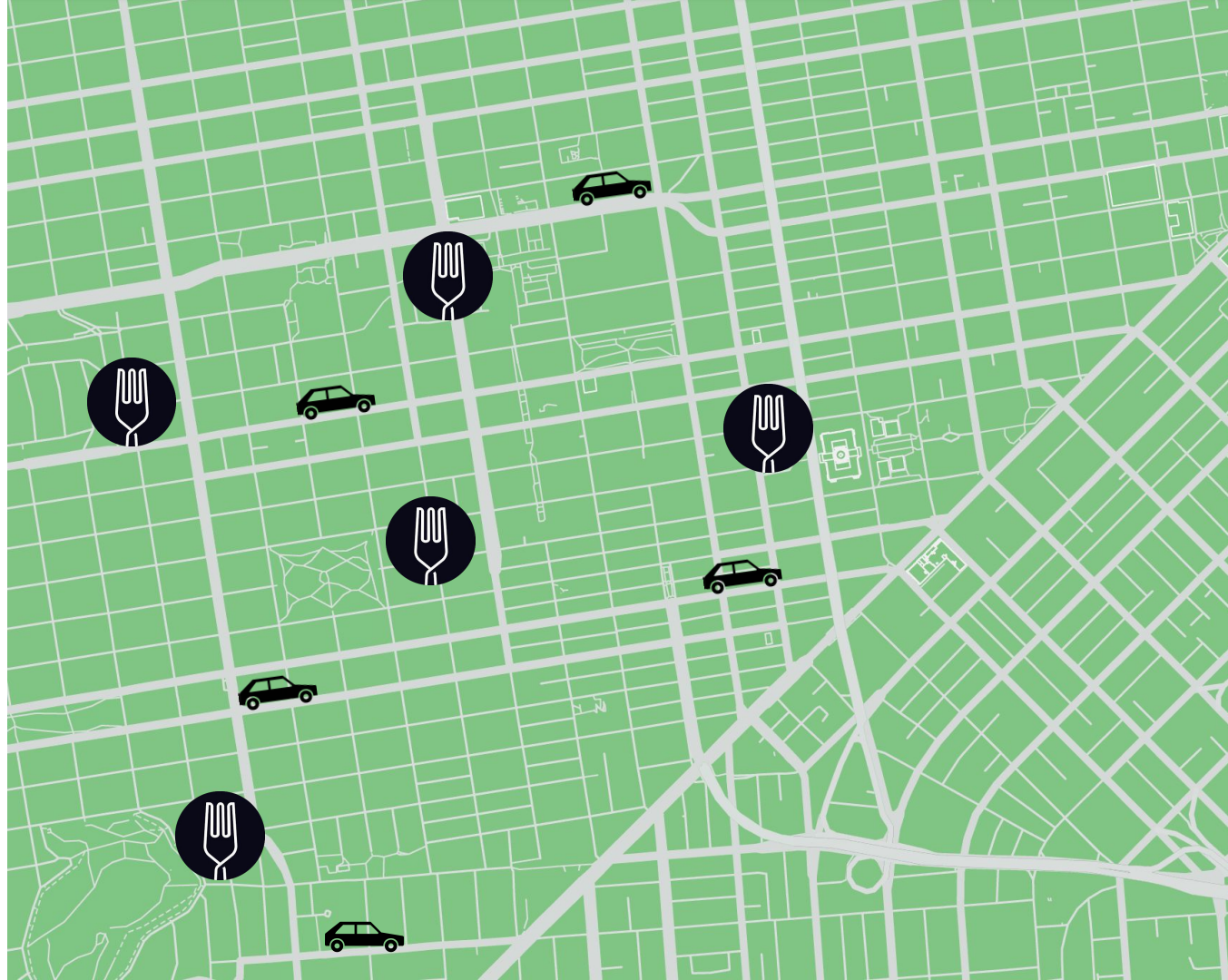
Dispatch System w/ Time Predictions

When to Dispatch?

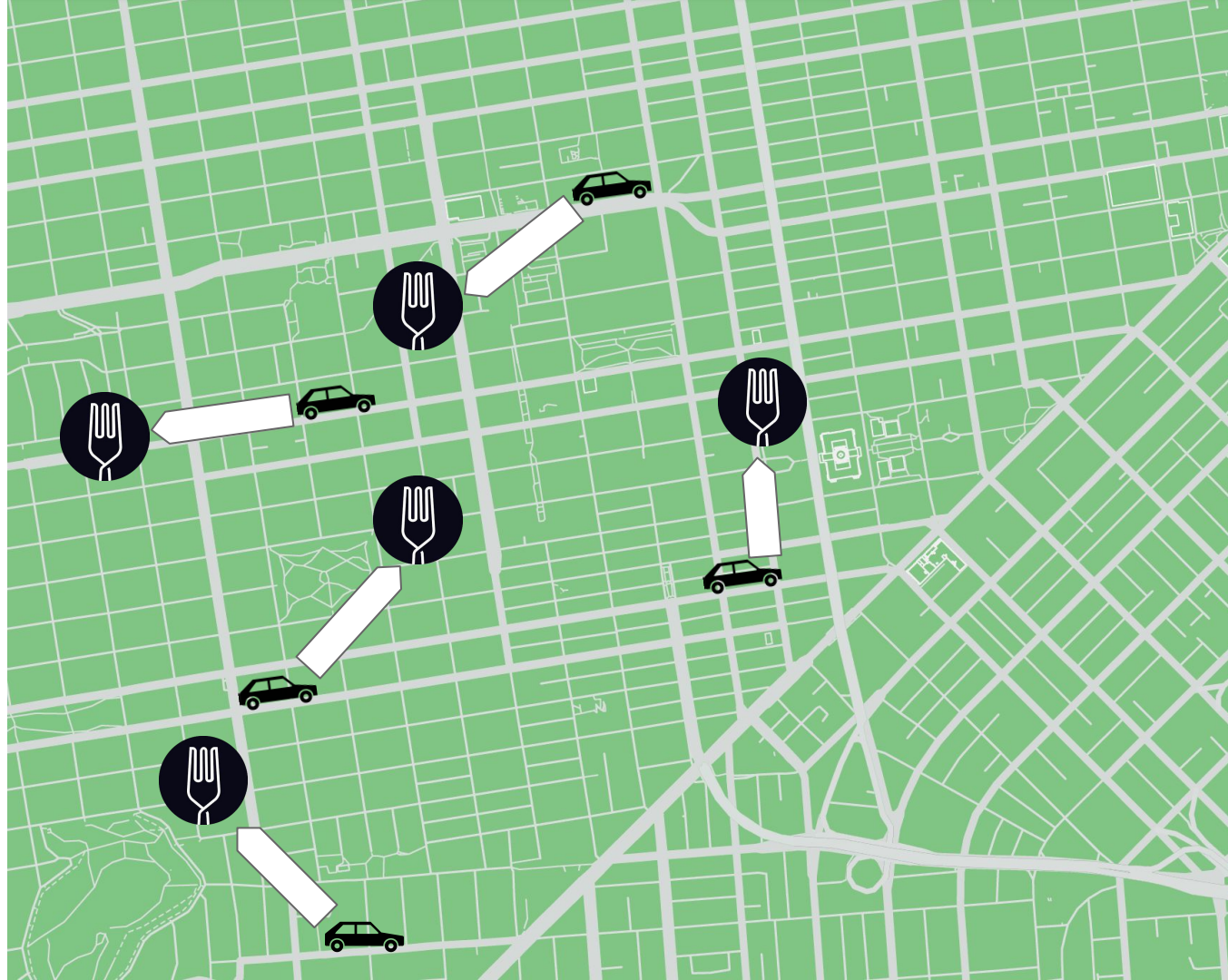


How to Dispatch? (Global)

- 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.



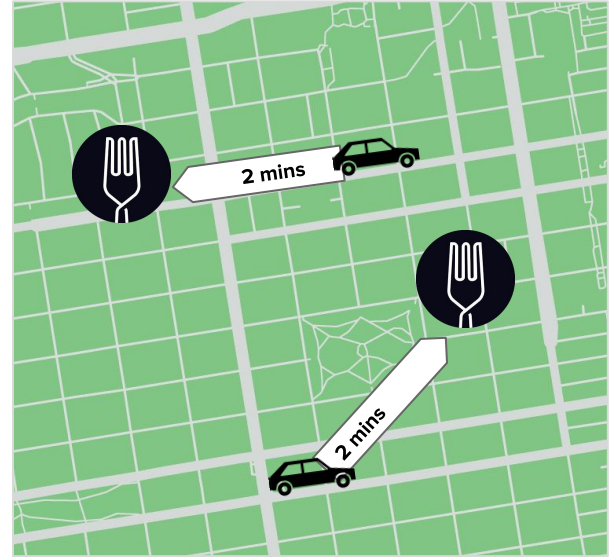


Greedy

1 MIN +

5 MIN

6 MIN

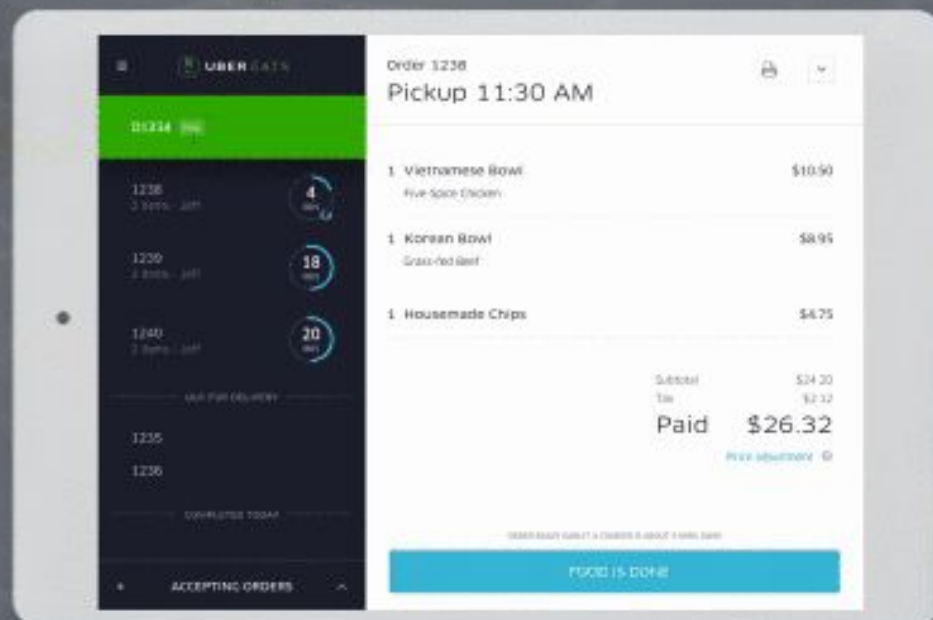


Global

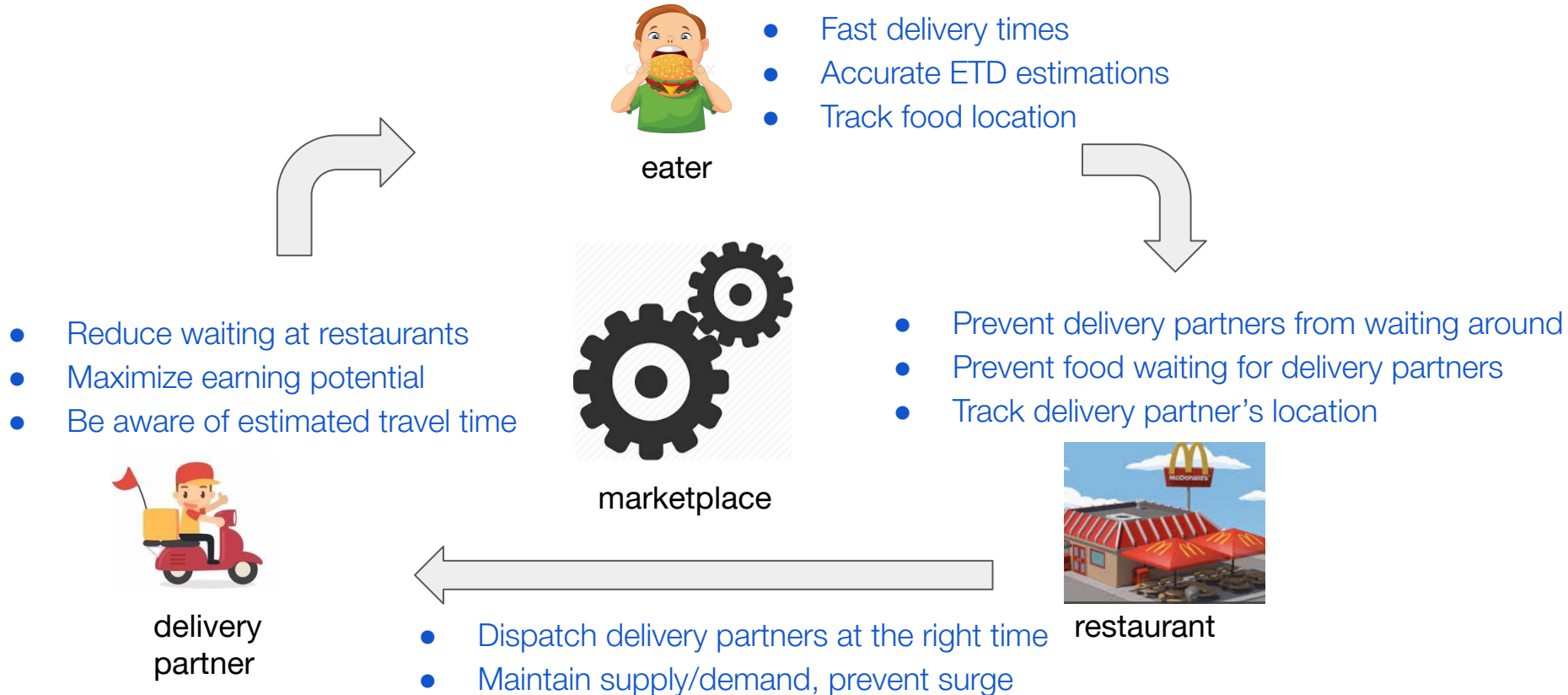
2 MIN +

2 MIN

4 MIN



After...



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

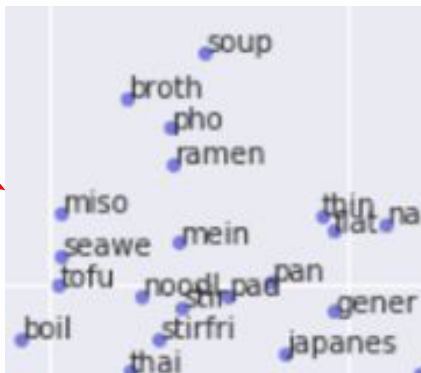
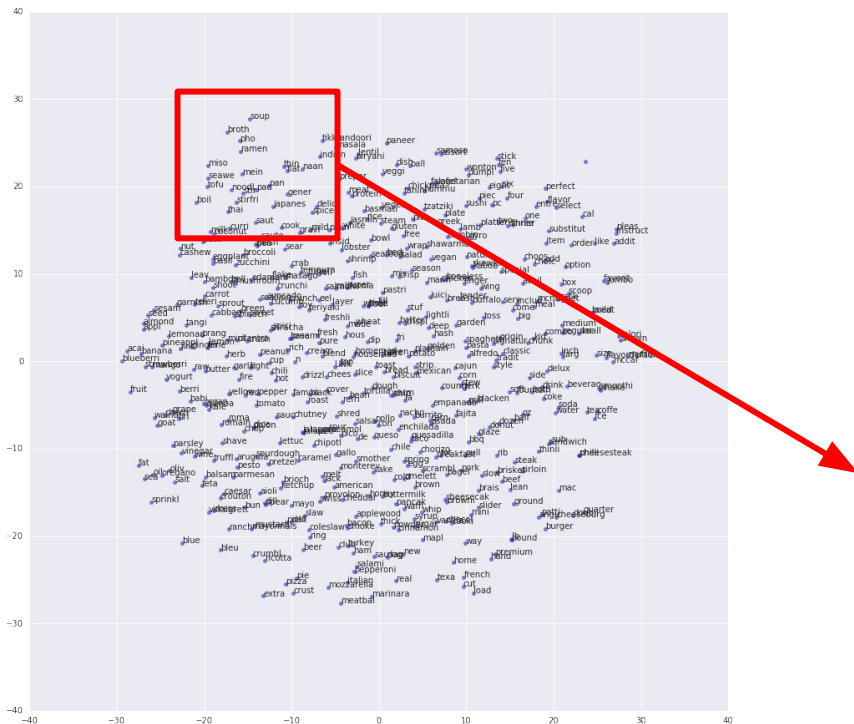
How Did We Use ML to Solve the Problem?

- 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



Miss Saigon

Recommended

Appetizers

Vietnamese Soup

Vermicelli Noodle

Recommended

Pho Tai Mem Soup

Rice noodle with filet mignon rare beef...

\$12.50

Goi Cuon (2 pcs)

Shrimp, pork, and vegetable rolled in rice paper (your choice of shrimp, shri...

\$6.10

Pho Tai Soup

Rice noodle with medium rare beef.

\$11.00

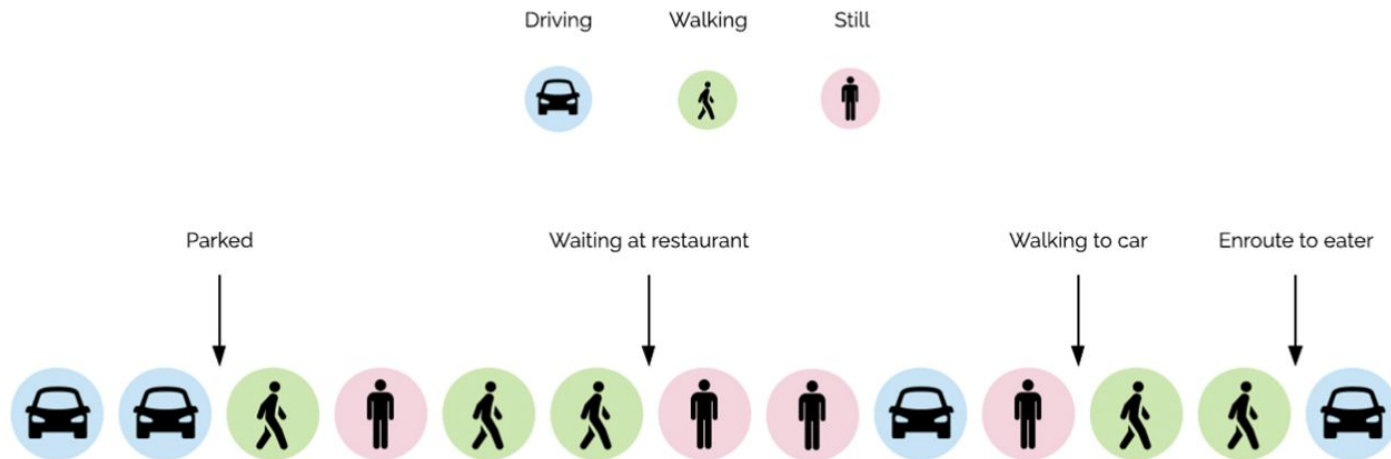
Pho Tai Bo Vien Soup

Rice noodle with medium rare beef and beef balls.

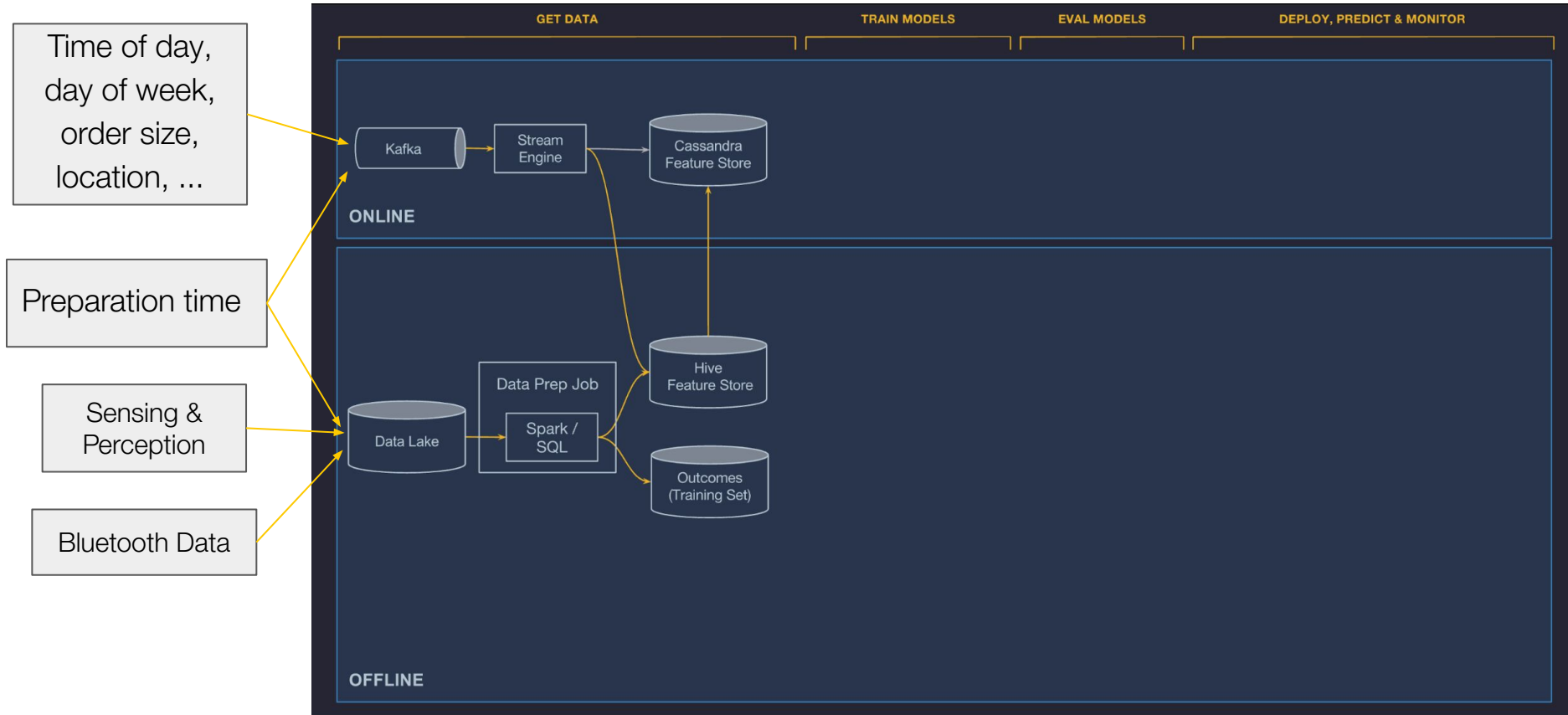
Sensor Signals



Conditional Random Field Model



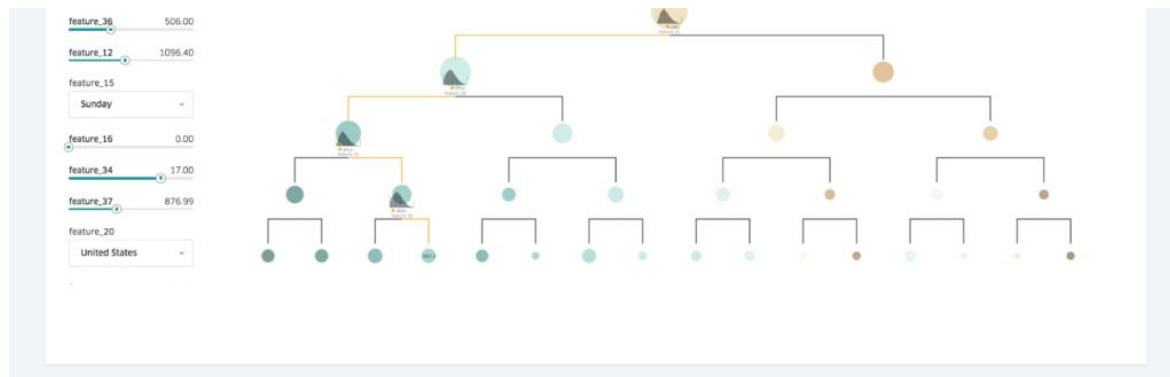
Feature Engineering (Cont'd) - Data Pipeline



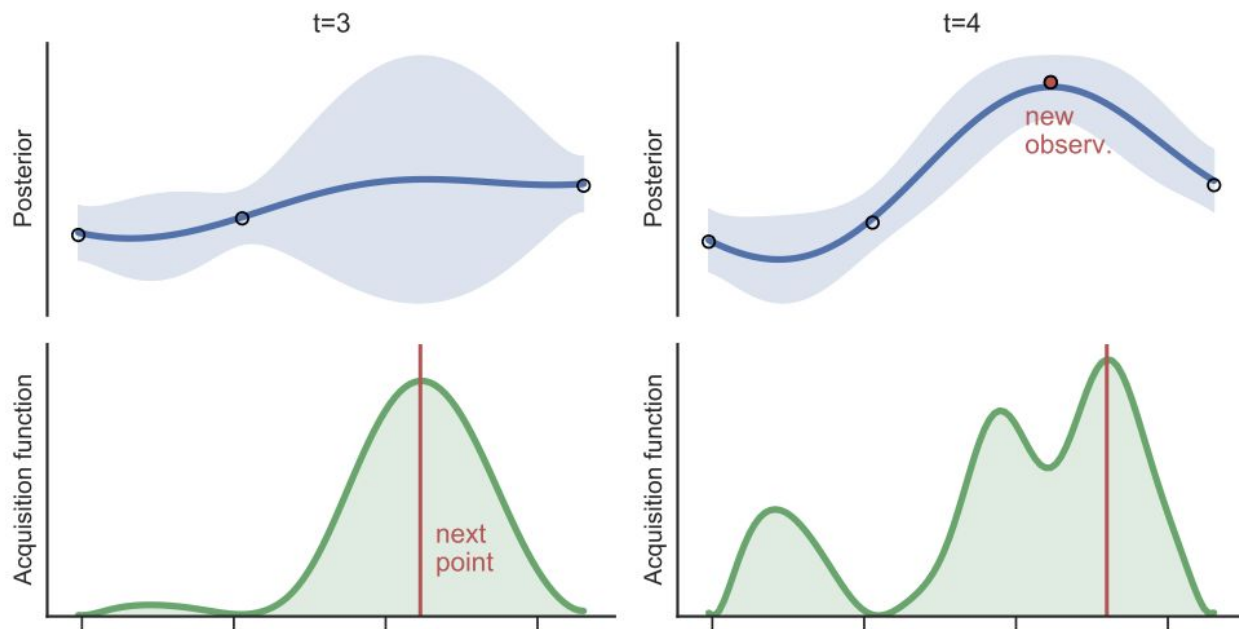
Data preparation pipelines push data into the Feature Store tables and training data repositories.

ML Model

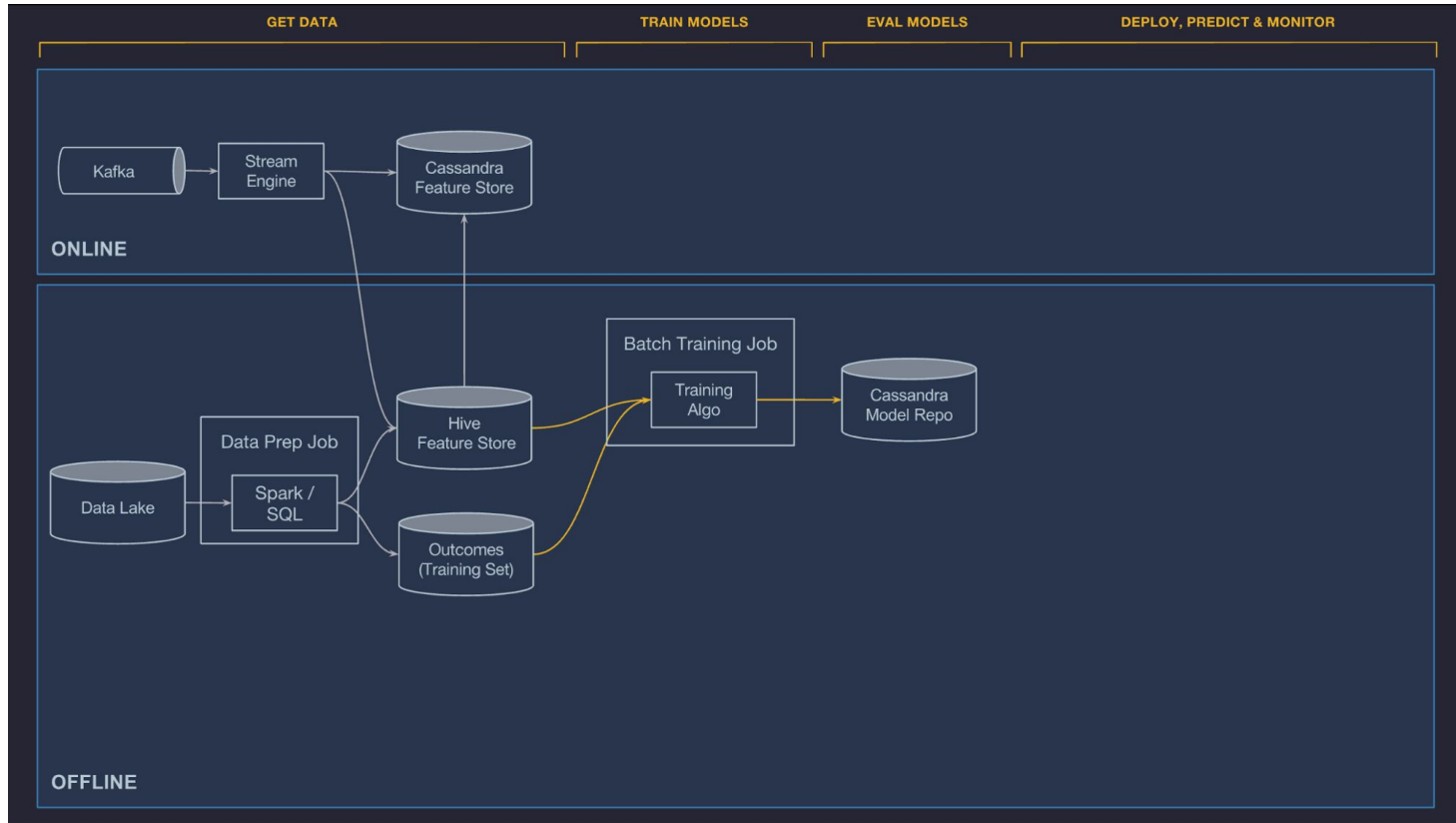
- Model: Gradient boosting decision trees (XGBoost)
- Historical features
- Realtime (Contextual)s features
- Near real-time features



Hyperparameter tuning

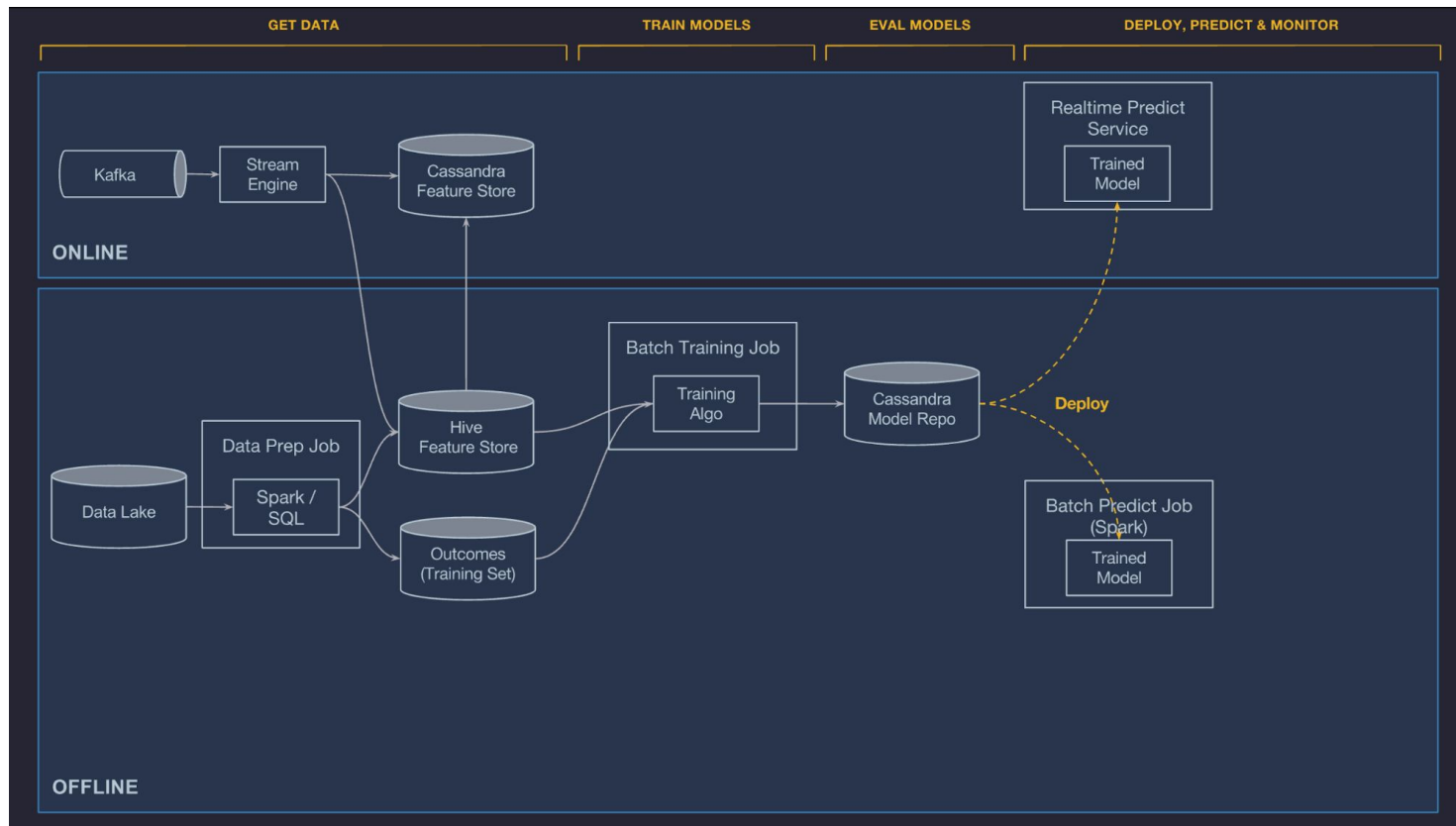


Model Training

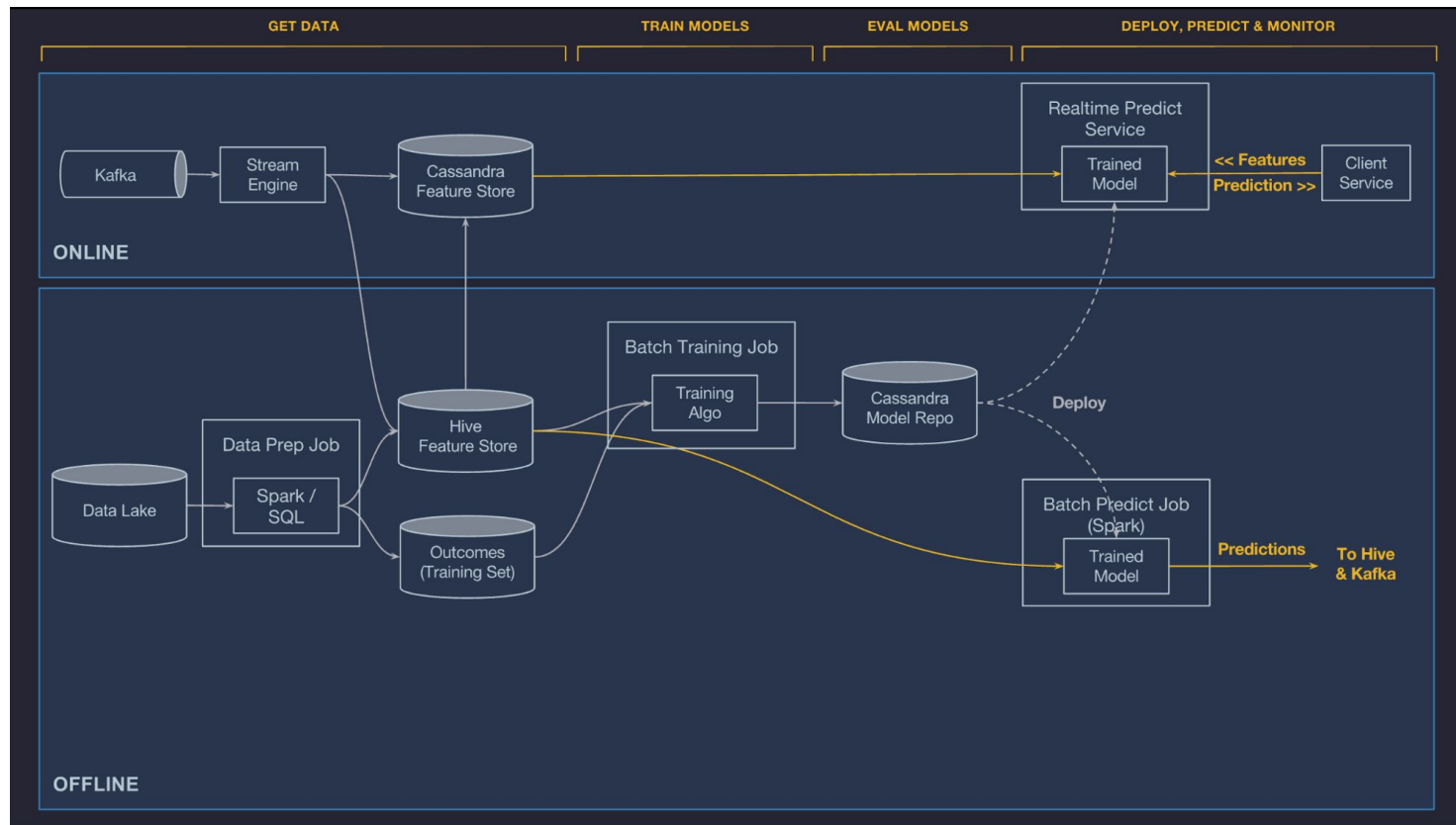


Model training jobs use Feature Store and training data repository data sets to train models and then push them to the model repository.

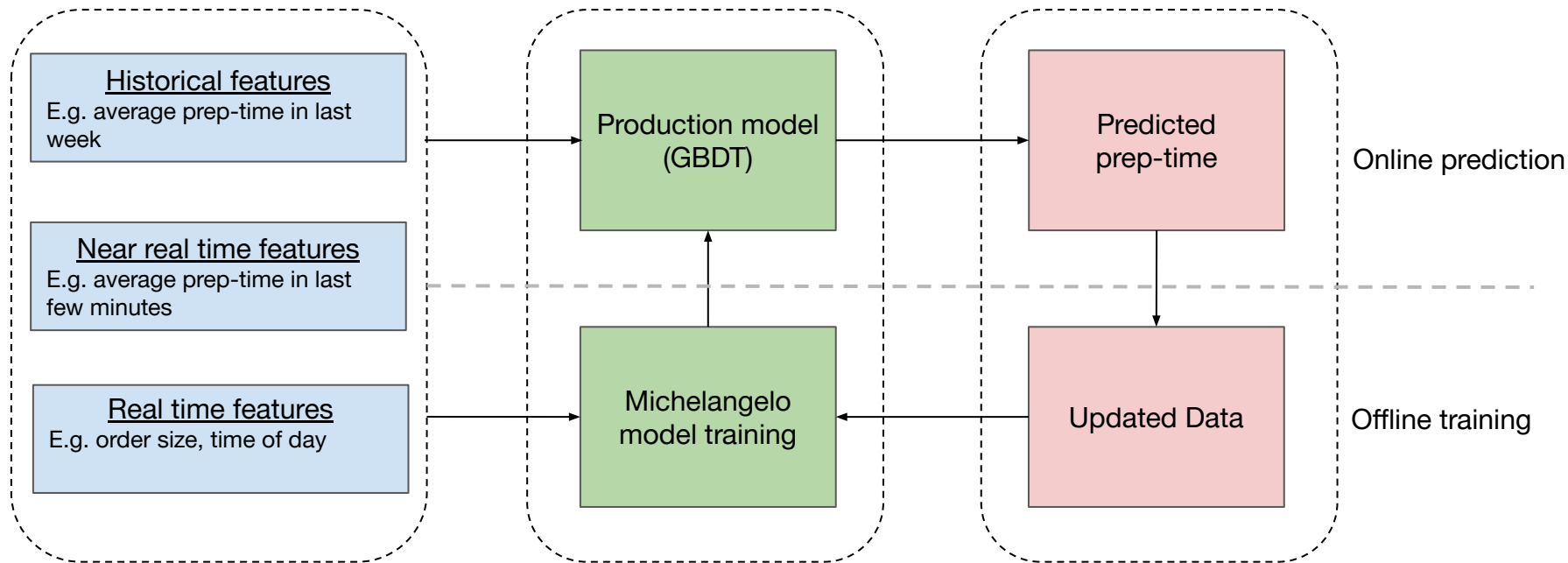
Model Training (Cont'd) - Model Deployment



Model Training (Cont'd) - Make Predictions



ML Model with Feedback Loop

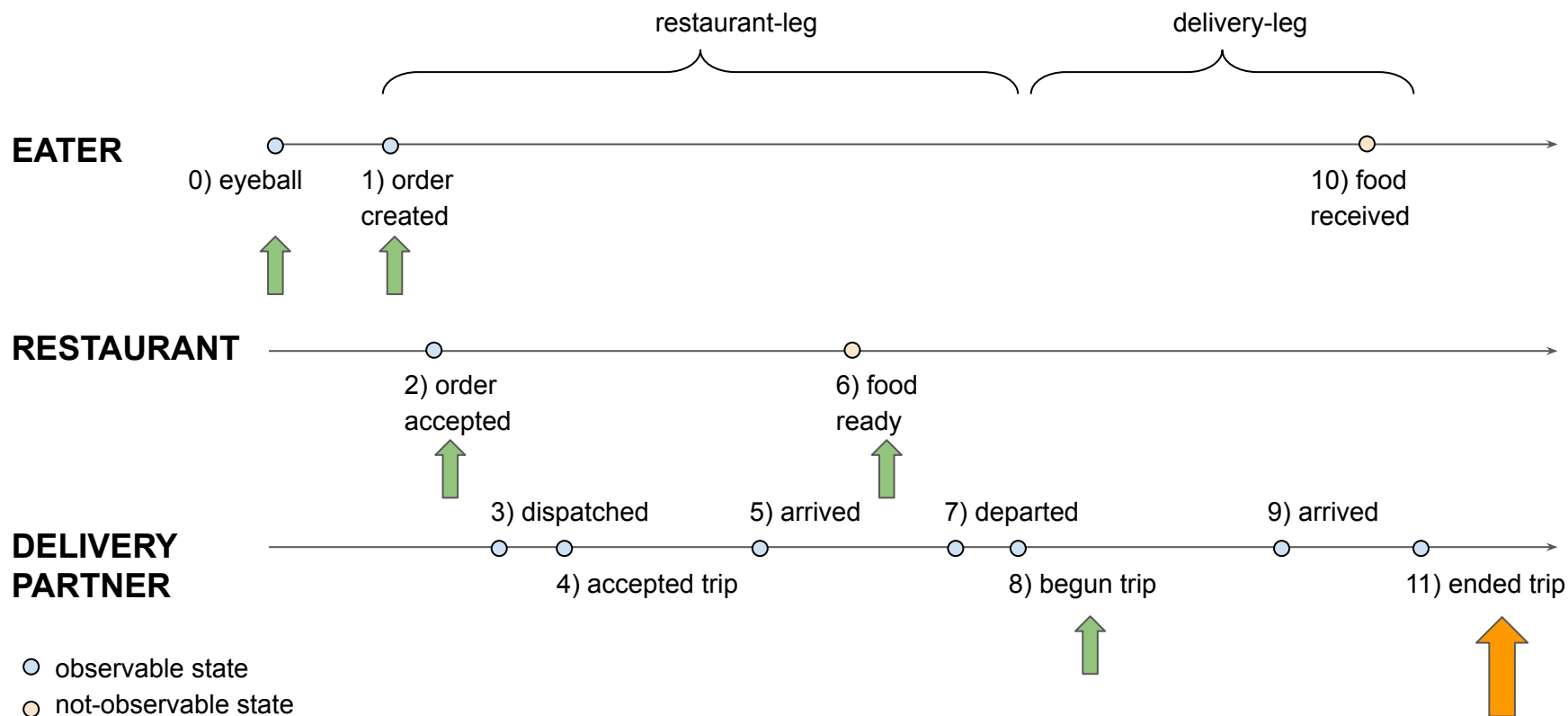


Future Improvements

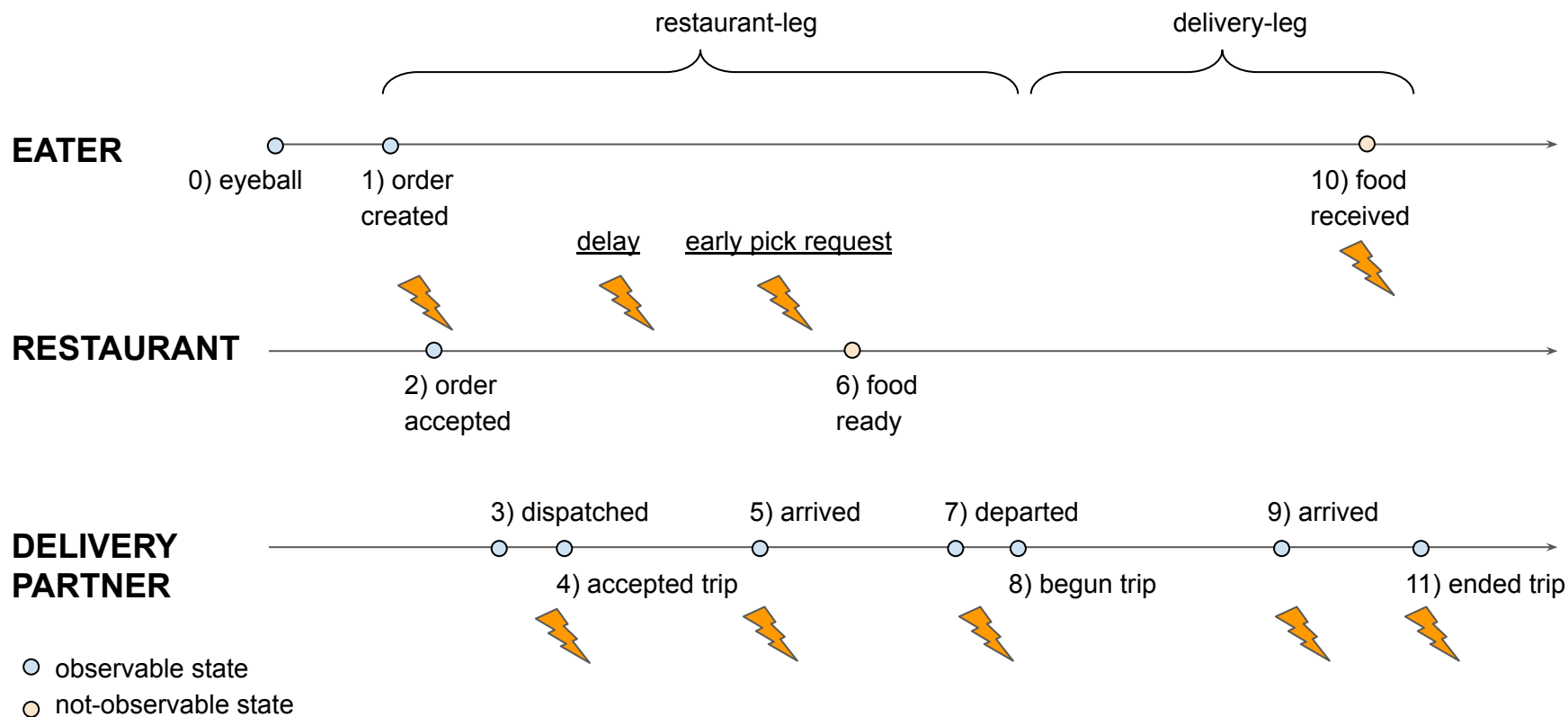
- Ground truth exploration
 - Experiment in restaurants
 - ...
- Improving ML model
 - Feature engineering
 - Exploration of places, weather, and event data
 - Model partitioning
 - ...
 - Leverage ensemble learning (stacking)
 - Collaboration with AI Labs on more deep learning models

Delivery Time Estimation

Eater-facing ETD



Why is predicting ETD difficult?

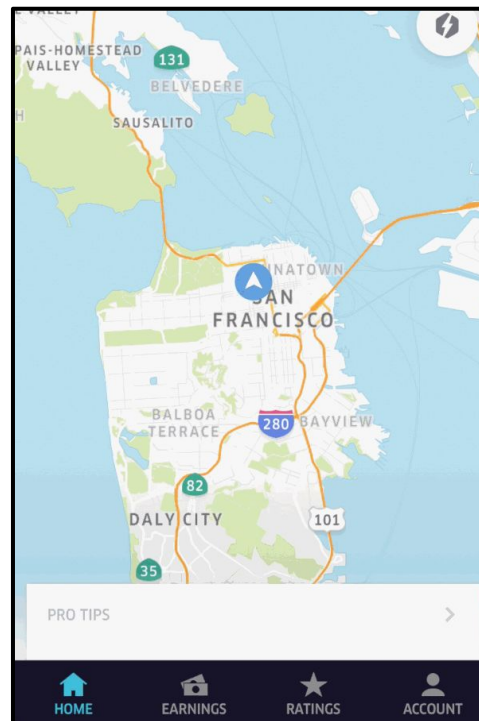
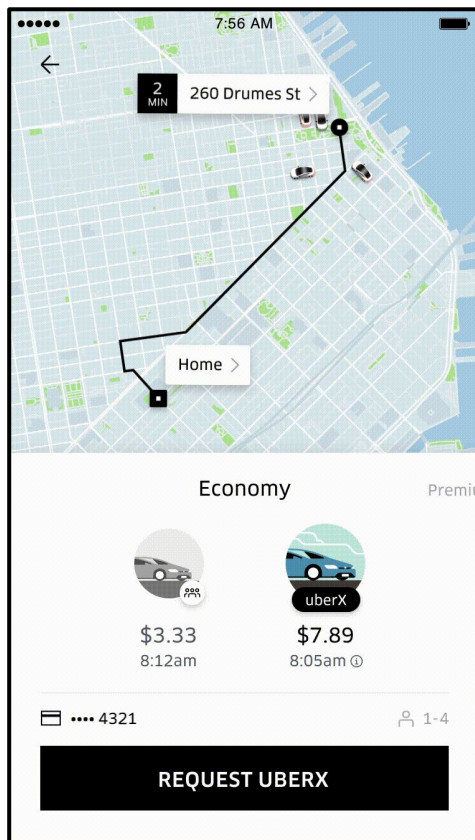


Travel Time Estimation



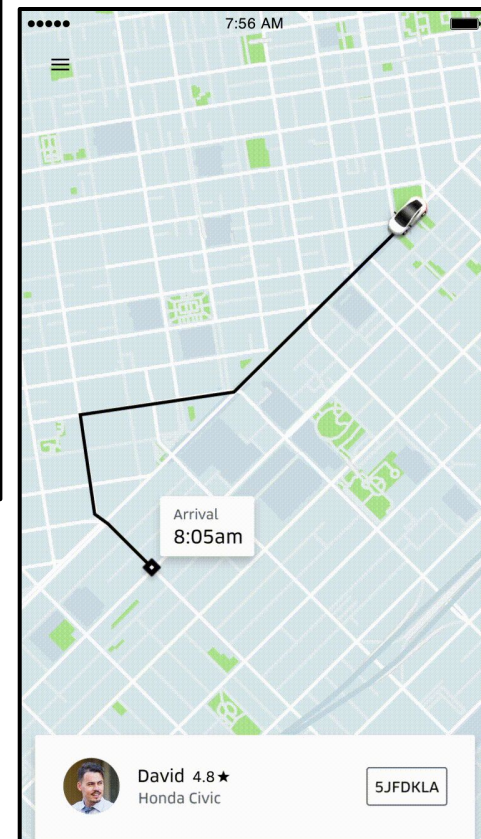
Rider

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

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