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How DoorDash leverages AI in its world-class on-demand logistics engine

Raghav Ramesh
DoorDash

DOORDASH

How DoorDash leverages AI in its on-demand Logistics Engine

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May 2018

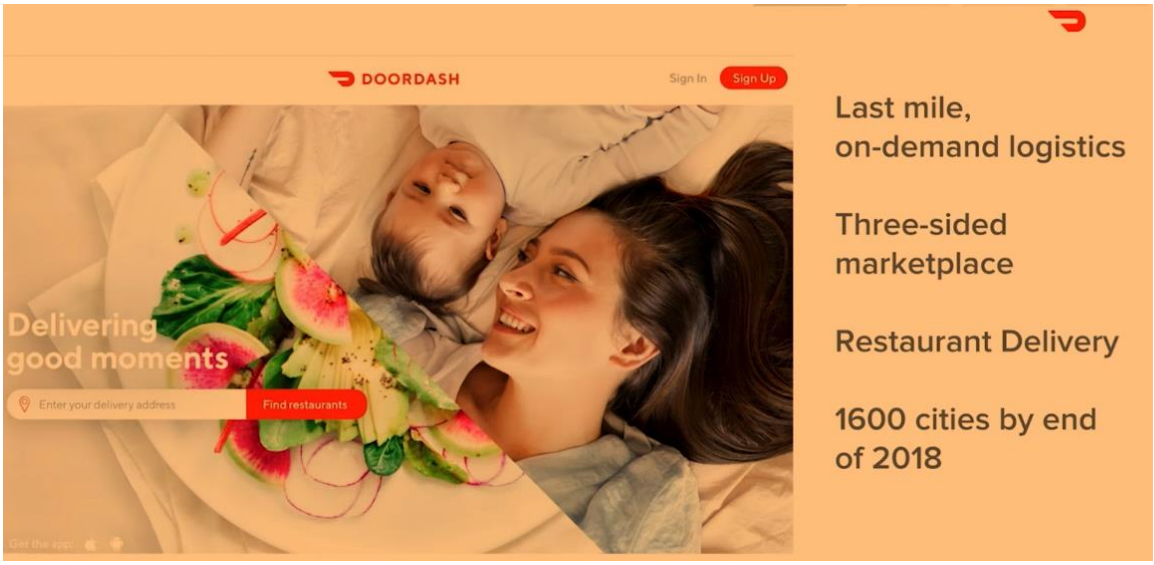
Outline

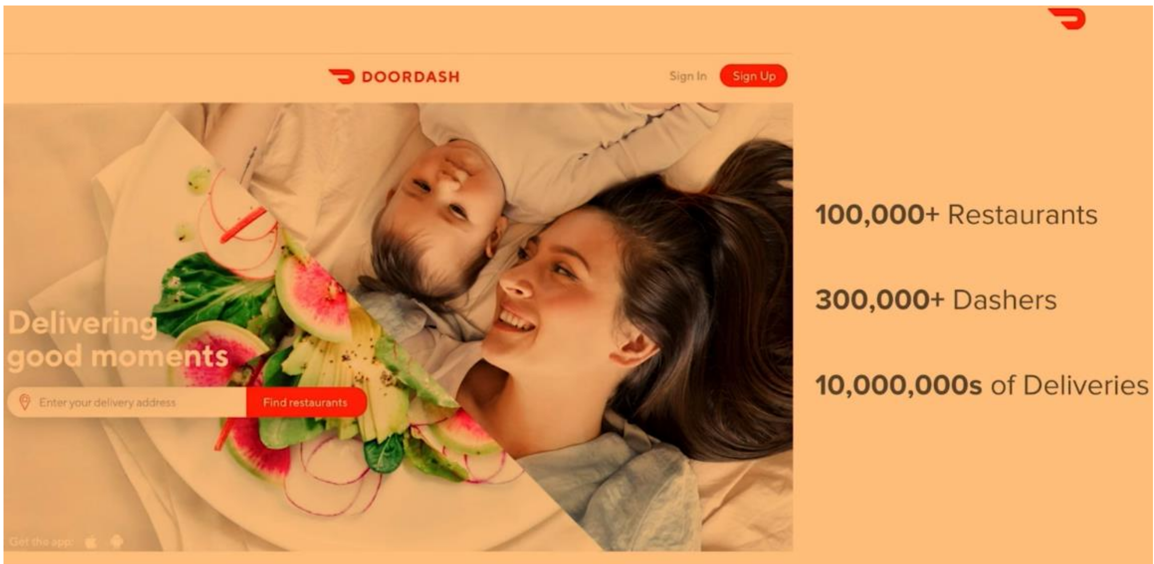
DoorDash Overview

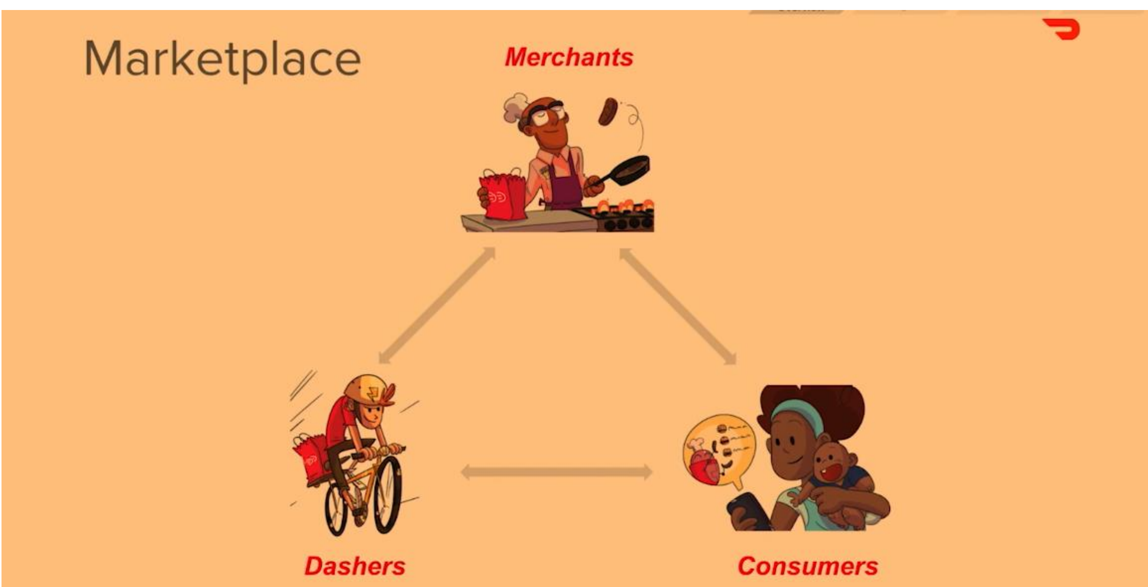
AI in Logistics

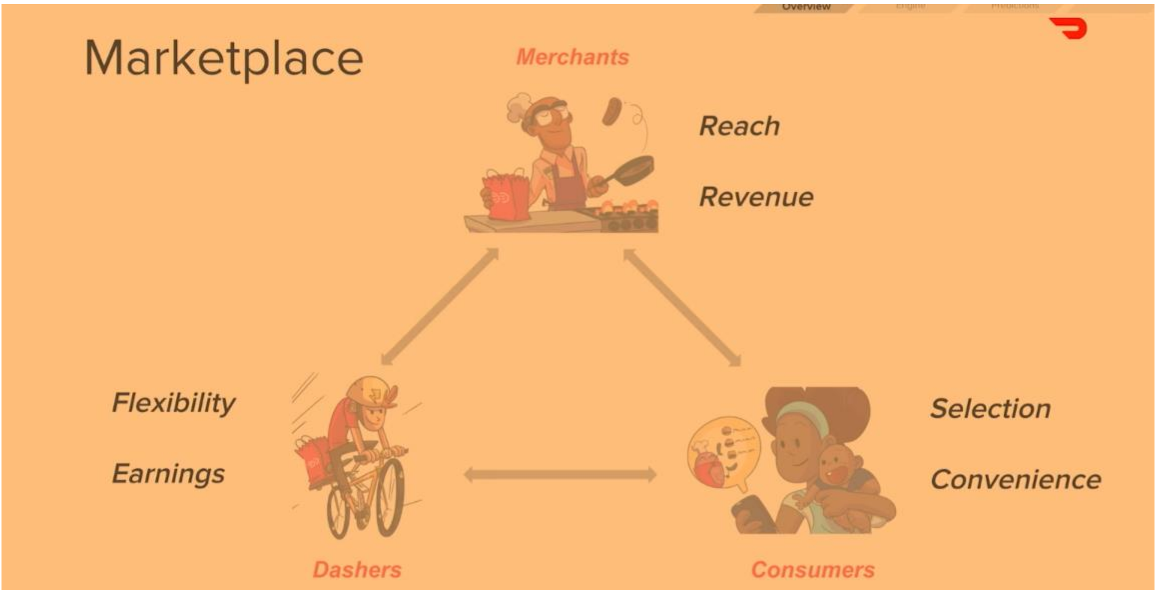
Delivery Time Predictions

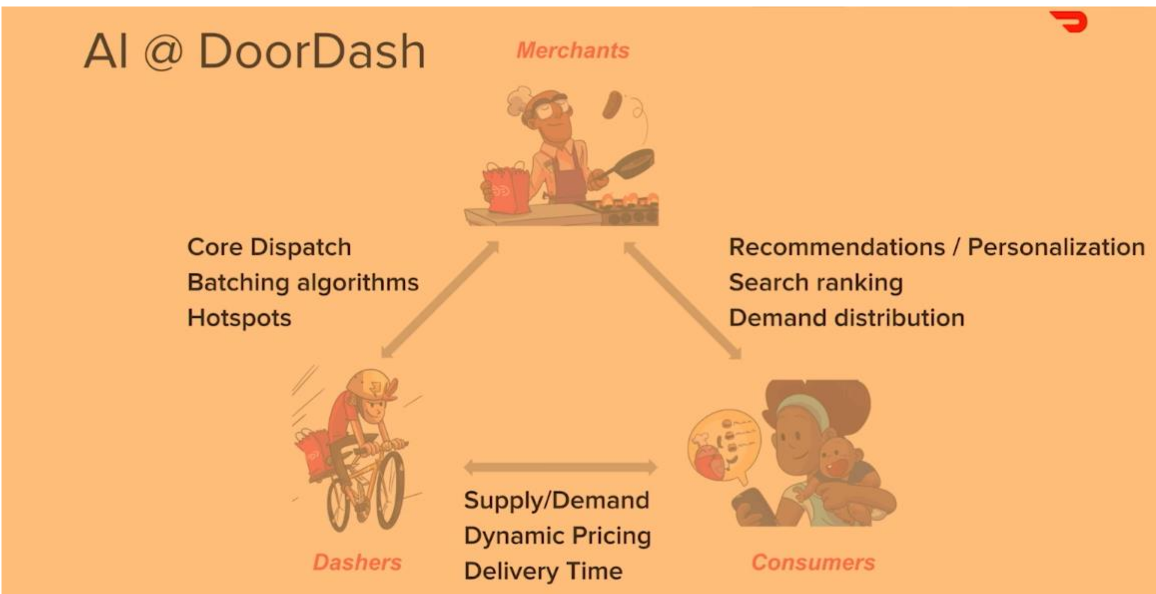
Batching Algorithms

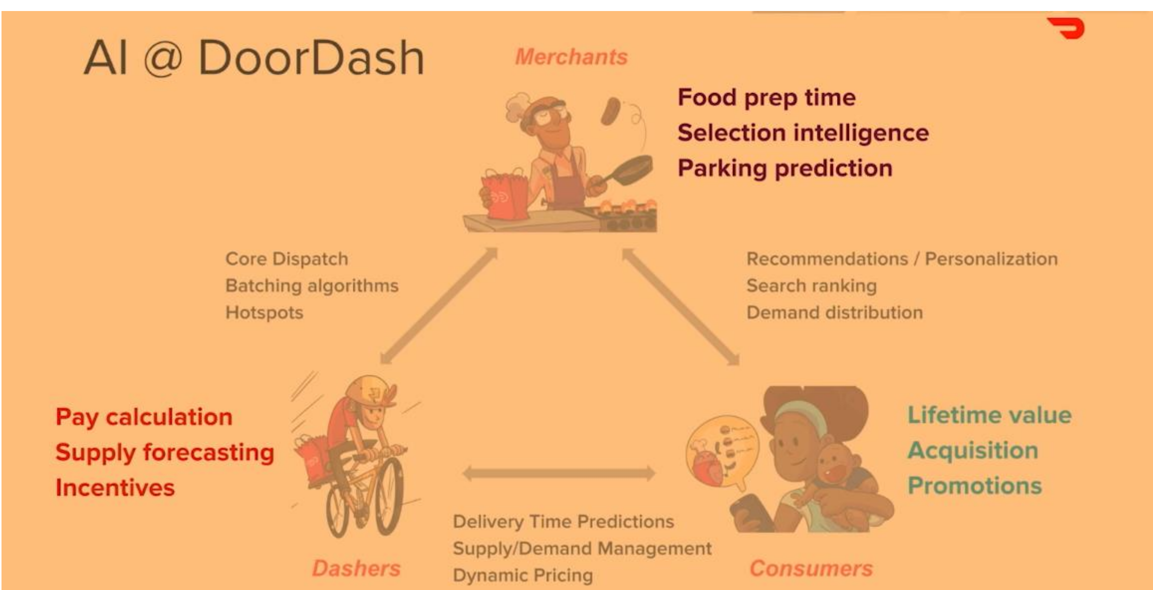

DOORDASH
Sign In
Sign Up
Delivering good moments
Enter your delivery address
Find restaurants
Last mile, on-demand logistics
Three-sided marketplace
Restaurant Delivery
1600 cities by end of 2018


DOORDASH
Sign In
Sign Up
Delivering good moments
Enter your delivery address
Find restaurants
100,000+ Restaurants
300,000+ Dashers
10,000,000s of Deliveries


Marketplace
Merchants
Dashers
Consumers


Marketplace
Merchants
Reach
Revenue
Flexibility
Earnings
Selection
Convenience
Dashers
Consumers


AI @ DoorDash
Merchants
Core Dispatch
Batching algorithms
Hotspots
Recommendations / Personalization
Search ranking
Demand distribution
Supply/Demand
Dynamic Pricing
Delivery Time
Dashers
Consumers


AI @ DoorDash
Merchants
Food prep time
Selection intelligence
Parking prediction
Core Dispatch
Batching algorithms
Hotspots
Recommendations / Personalization
Search ranking
Demand distribution
Pay calculation
Supply forecasting
Incentives
Lifetime value
Acquisition
Promotions
Delivery Time Predictions
Supply/Demand Management
Dynamic Pricing
Dashers
Consumers

Logistics Engine

Merchants

Core Dispatch
Batching algorithms
Hotspots

Recommendations / Personalization
Search ranking
Demand distribution

Supply/Demand
Delivery Time
Dynamic Pricing

Dashers

Consumers

Logistics Engine

The AI system that powers DoorDash deliveries

Logistics Engine

Fast and efficient deliveries

On-time delivery to Consumer

Increase marketplace efficiency

Logistics Engine

Balance Supply/Demand

Plan Routes

Dasher/Delivery matching

Optimal Matching

In plain English

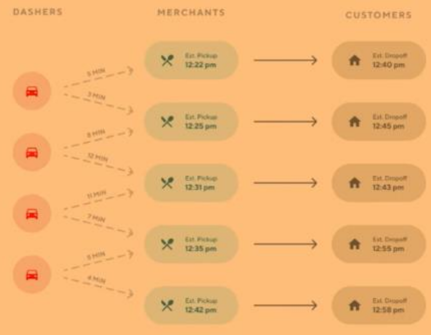
- Pick the best Dasher for a Delivery

In canonical Operations Research

- Vehicle Routing Problem

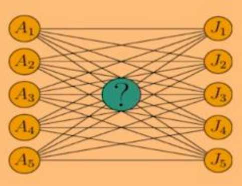
DoorDash specific considerations

- **Real-time** fulfillment
- Optimize supply for future demand
- Decide **when to assign**



Challenges

Complexity	Time constraint	Variance
Combinatorial options	Asap delivery	Merchant operations
Delivery constraints	Real-time Consumer demand	Traffic
	Dasher flexibility	Weather



ML meets OR

Operations Research (OR)

- Given deliveries, Dashers, and business goals, determine cost function to use and identify the optimal matching

Machine Learning (ML)

- **Set up the marketplace**
  - Forecast supply and demand
  - Balance
- **Calculate inputs to the cost function**
  - Travel times, Food preparation times
- **Calculate constraints**
  - Variances, Batching estimates
- **Auxiliary**
  - Help with decision on when to assign

Logistics Engine: Summary

Data	Predictions	Optimizations	Actions
Delivery data Location Type Size	Total delivery duration	Cost functions	Dasher assignment
Dasher data Location Capacity	Dasher travel duration	Optimal matching	
Constraints Equipments	Food prep duration	Mixed integer programming	
	Batching quality prediction		
	Can two orders be batched?		

Let's talk predictions

Data	Predictions	Optimizations	Actions
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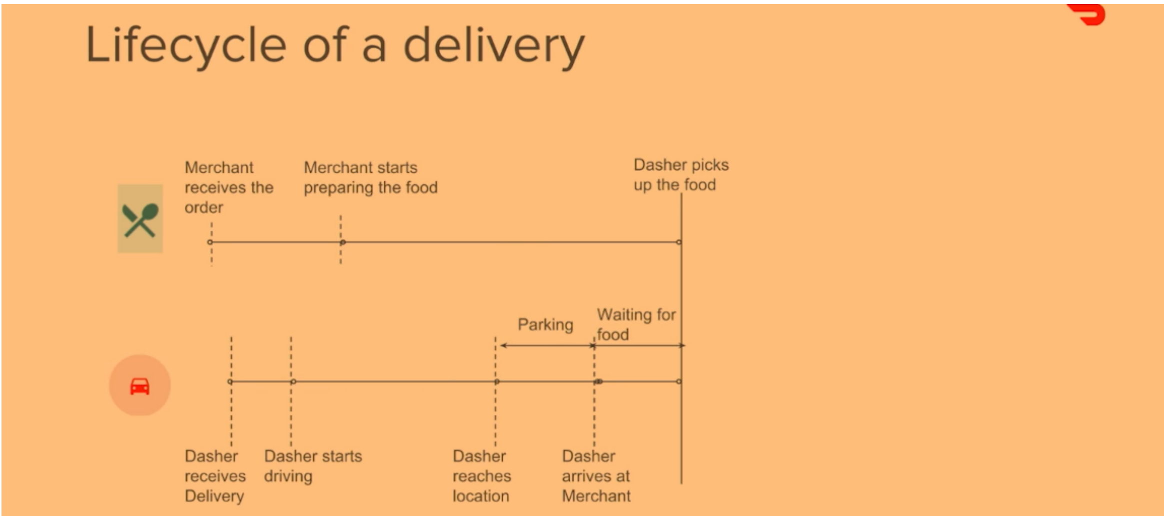
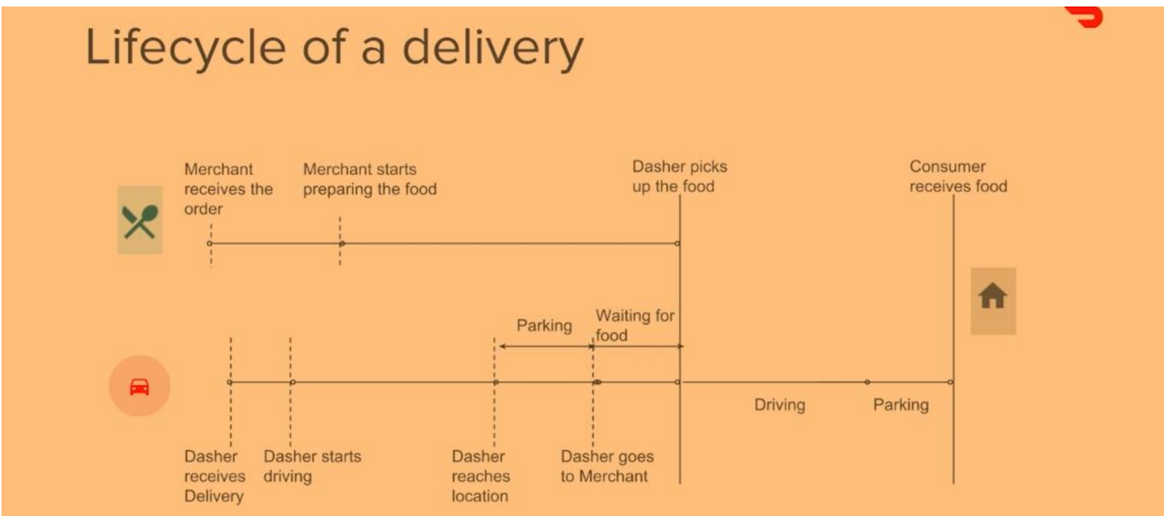
Delivery Time Predictions

When every second is worth a million dollars

Delivery time predictions

- 10+ time point predictions for every delivery
- Capture each part of the delivery process
- Critical component of Logistics system


Lifecycle of a delivery
Merchant receives the order
Merchant starts preparing the food
Dasher picks up the food
Parking
Waiting for food
Dasher receives Delivery
Dasher starts driving
Dasher reaches location
Dasher arrives at Merchant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Consumer receives food
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Waiting for food
Driving
Parking
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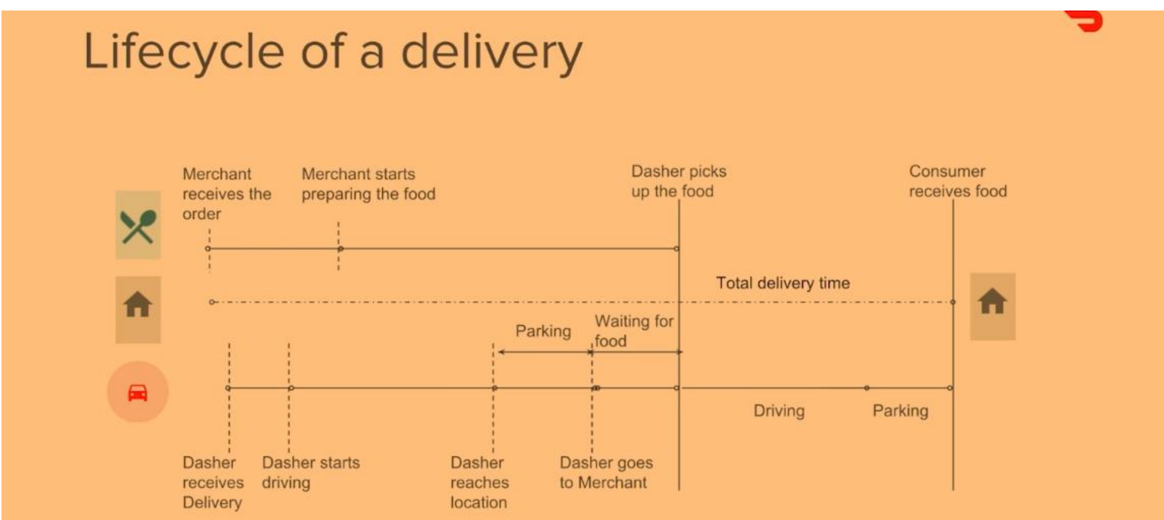
Dasher starts driving
Dasher reaches location
Dasher goes to Merchant


Lifecycle of a delivery
Merchant receives the order
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Consumer receives food
Total delivery time
Parking
Waiting for food
Driving
Parking
Dasher receives Delivery
Dasher starts driving
Dasher reaches location
Dasher goes to Merchant

Total delivery time

Overview

Goal	Inputs	Constraints
Provide ETA to Consumer	Order details	Fast, Scalable
Set constraints for the optimizer	Market conditions	Works for new markets

Directly impacts Consumer conversion and retention

Initial Model

Model

Gradient Boosted Decision Trees (LightGBM)

Target: Total Delivery Time

Evaluation

Historical data for training

Validate on latest data

Evaluate on RMSE

Features

Order Features

Subtotal

Cuisine

Type and price of items

Type of order - group, catering, etc.

Merchant details

Real time features

# of orders

# of total Dashers

Traffic, Travel estimates

Time of day - lunch / dinner

Day of week - weekend / holiday

Historical aggregates

Past X weeks average delivery times for
- Store
- City
- Market
- Time of day

Similarly
- average parking times
- variance in historical times

Limitations

- Minimizing mean squared error makes sure we are right on average.
- But, it is more important to deliver by the estimated delivery time, not just be correct on average

What we have

$$Actual\ Delivery\ Time\ =\ Estimated\ Delivery\ Time\ +\ Error$$

What we want

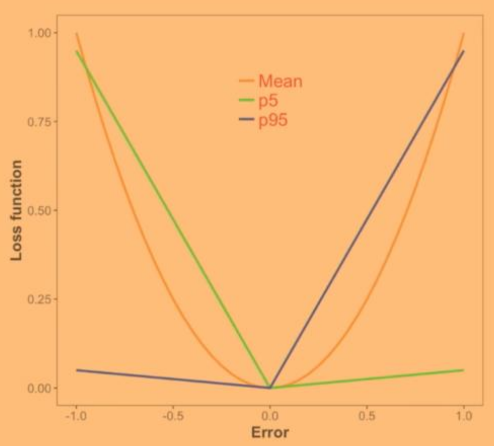
$$Prob\ (Actual\ Delivery\ Time\ >\ Estimated\ Delivery\ Time)\ <\ X\%$$

Quantile Regression

- Modeling technique to generate **prediction intervals**
- Instead of Mean Squared Error, the **Loss function** used is:

$$L(y,\ F(x))\ =\ h_q(\ y\ -F(x))$$

$where$
$h_q(z)\ = z\ *\ (q\ -\ I_{z<0})$
$q\ is\ the\ percentile\ value\ to\ use$
$I\ is\ the\ indicator\ function$



Quantile Regression Model

- Choosing two q values (say 0.05, 0.95) gives you a **prediction interval** where 90% predictions would lie
- Model evaluated using **% predictions within the interval** and average estimated value
- ***Ideal value of q*** identified through experiments to optimize retention

Low estimated value
High lateness

High estimated value
Low lateness

Lower quantile

Higher quantile

Extensions

- Geographical ensembling
  - Market specific model for larger markets
- Use of Embeddings
  - Store
  - Market
  - Time of day
- Near real time aggregates

Let's talk predictions

Batching algorithms

Doing more with less

Context

What is batching?

- One Dasher working on more than one delivery simultaneously

Why is it important?

- Increases marketplace efficiency
- Help manage supply demand spikes

On-time delivery to Consumer

Increase marketplace efficiency

Challenges

Orders emerge on the fly

Batching deliveries is easier if orders are all pre-scheduled and have a delivery window

Scale

Optimization system can not exhaustively match all pairs of deliveries

Food Quality

5 extra minutes due to batching could mean a burger is no longer hot

Interdependence

Multiple deliveries being dependent on each other increases variance further

Batching Quality Model

Route of Normal Delivery

- *Pickup_1, Dropoff_1*

Route of a Batched Delivery

- *Pickup_1, Pickup_2, Dropoff_1, Dropoff_2*

Model Intuition

- Any delay in *Pickup_2* affects *Dropoff_1*
- We should not batch if the probability of delay is high

Model Details

Problem Type

- Classification

Target

- Boolean: Actual Pickup time > Estimated pickup time

Evaluation Metric

- PR-AUC

Use in optimization system

- Two approaches
  - Used as constraints
  - Use in cost function

Takeaways

- Machine learning helps **efficiently solve** traditional Operations Research problems
- Particularly important in **real-time, high variance** environments like DoorDash
- **Quantile Regression** is an effective technique to generate prediction intervals

The Future

Automated menu processing

Price optimization

Self Driving

Product placements

DoorDash Drive

Robotics

Demand shaping

Dispatch for new verticals

Support experience

Marketing

Fraud prevention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