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Matching and Dynamic Pricing for Ride-Hailing

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New England Statistical Symposium 2018
Ariana Grande concert in Madison Square Garden, 2015:

Source: Hall, Kendrick, and Nosko (2015)
New Year’s Eve in New York City, 2015 (surge pricing outage):

Source: Hall, Kendrick, and Nosko (2015)
Takeaways:

- Intelligent matching and dynamic pricing reduce wasted time
- Novel matching methods could decrease price variability
Outline

1. Ride-Hailing
2. Matching
3. Dynamic Pricing
4. How to Estimate Their Inputs
5. Mitigating Price Variability Through Matching
6. Conclusions
Marketplace @ Uber

- Statisticians, ML scientists, economists, operations researchers...
- developing Uber’s marketplace decision systems...
  - pricing
  - dispatch & carpool matching
- and their inputs:
  - predicted demand and supply
Maps @ Uber

- Base map definition
- Points of interest
- Map search
- Traffic
- Route recommendation and travel time prediction
- Navigation
Maps @ Uber

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Outline

1. Ride-Hailing
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Hyperlrowth

Rapid growth of ride-hailing, through convenience and efficiency:

- Intelligent matching
- Calibrating demand with supply through pricing
Less Wasted Time

More time on trip for drivers:

Lower pickup time for riders:

Source: Cramer and Krueger (2016); Feng, Kong, and Wang (2017)
Matching

How should riders be matched with drivers?

How should carpool riders be matched with each other?
Dynamic Pricing

The price calculation involves a "surge multiple" that is $= 1$ under normal conditions and is $> 1$ when demand $>>$ supply.
Outline

1. Ride-Hailing
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Matching

How should riders be matched with open drivers?

- First-dispatch protocol: immediately dispatch the driver with the shortest pickup time
- \( \Rightarrow \) generally lower pickup times than street-hailing

Source: Feng, Kong, and Wang (2017)
Predicting Travel Time

Matching requires prediction of travel time between two points
Matching

How should riders be matched with open drivers?

- First-dispatch protocol: immediately dispatch the driver with the shortest pickup time

\[ \Rightarrow \text{generally lower pickup times than street-hailing} \]

Source: Feng, Kong, and Wang (2017)
Predicting Travel Time

Matching requires prediction of travel time between two points.
Trip Upgrade

Pickup time can be further reduced with "trip upgrade":

Trip Upgrade video
Matching: Trip Swap
Matching: Trip Swap
Trip Upgrade

Pickup time can be further reduced with "trip upgrade":

▶ Trip Upgrade video
Outline

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3. **Dynamic Pricing**
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Dynamic Pricing

How to calculate the surge multiple?
Dynamic Pricing

Surge is based on supply and demand conditions:

Demand (rider sessions) prediction

Supply (open cars) prediction

Surge multiple
Why isn’t it the usual market equilibrium?

Welfare = Consumer surplus + producer surplus

- Measures "value created" for riders & drivers

The equilibrium price maximizes welfare
Why isn’t it the usual market equilibrium?

Drivers cycle between three states:

- Riders are sensitive to pickup time
- Drivers are sensitive to pickup + open time
Why isn’t it the usual market equilibrium?

The market equilibrium is a price and pickup time for which there is not much wasted time, so drivers and riders participate at high rates.

- Few drivers & riders ⇒ long pickup times
- Many drivers & riders ⇒ short pickup times
Why isn’t it the usual market equilibrium?

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Few drivers & riders ⇒ long pickup times

Many drivers & riders ⇒ short pickup times
Pickup Time Model

Pickup time can be accurately predicted based on open car level:

\[ \text{Average Pickup Time (s)} \]

![Graph showing average pickup time vs. # open cars with a fitted curve](image)

- **Actual** line
- **Fit** line given by \( \frac{\alpha}{O^\beta} \)
Counting Car Minutes

Say we know the rate at which trips are completed $C$ and the average trip time $T$. On average, how many cars will be on-trip?

$$\text{Cars on Trip} = C \times T$$

This is an application of Little's Law!
A Closed Steady-State Supply Model (Single Geo)

Principle of conservation of cars:
- Cars are neither created nor destroyed

\[ N = O + C \cdot T + C \cdot \eta(O) \]

- \( N \): total # of cars
- \( O \): open
- \( C \cdot T \): on-trip
- \( C \cdot \eta(O) \): enroute

- \( T \): Average trip time
- \( C \): Trip completion rate
- \( \eta(O) \): Average pickup time
A Closed Steady-State Supply Model (Single Geo)

Solving for the trip completion rate $C$ in terms of the # of open cars $O$,

$$C = \frac{N - O}{T + \eta(O)}$$

$T$: Average trip time
$N$: Total # cars
$\eta(O)$: Average pickup time

Trip-maximizing open car level

$O^*$

Trip Completion Rate
Pickup time
Danger Zone

Open Cars

1 6 11 16 21 26 31 36 41 46 51 56 61 66 71 76 81 86 91 96

Pickup Time
35

3.0000
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
A Closed Steady-State Supply Model (Single Geo)

Principle of conservation of cars:
- Cars are neither created nor destroyed

\[
N \overset{\text{total # cars}}{=} O \overset{\text{open}}{=} C \cdot T \overset{\text{on-trip}}{=} C \cdot \eta(O) \overset{\text{enroute}}{=}
\]

- \(T\): Average trip time
- \(C\): Trip completion rate
- \(\eta(O)\): Average pickup time
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Solving for the trip completion rate $C$ in terms of the # of open cars $O$,

$$C = \frac{N - O}{T + \eta(O)}$$

$T$: Average trip time  
$N$: Total # cars  
$\eta(O)$: Average pickup time
What Happened to Prices?

Need models for demand/supply response to price/time. E.g. # of requested trips:

\[ D(p, \eta) = \lambda r(p) g(\eta) \]

\( \lambda \): arrival rate of demand (rider sessions)
\( r(p) \): Rate of request at price \( p \)
\( g(\eta) \): Rate of request at pickup time \( \eta \)

![Diagram 1: Rate of request vs Surge Multiple](chart1.png)
![Diagram 2: Rate of request vs Pickup Time](chart2.png)
What Happened to Prices?

In equilibrium trip supply must equal trip demand:

\[ D(p, \eta) = \frac{N - O}{T + \eta(O)} \]

The total \# of cars \( N \) depends on earnings, which are a function of \( p \) and the \# of trips.

Solving these equations yields the pickup time \( \eta \) and trip completion rate associated with each \( p \).

Source: Castillo, Knoopfie, and Weyl (2016)
Dynamic Pricing

Welfare is a measure of value created for riders and drivers.

When price is below a threshold, welfare drops precipitously:
- pickup time rises; time on-trip drops
- few rides are created

Source: Castillo, Knopfle, and Weyl (2016)
Dynamic Pricing

The threshold changes over time as demand and supply conditions change.

The welfare-maximizing fixed price is almost as high as the max across time of the welfare-maximizing dynamic price.

⇒ When dynamic pricing is disallowed, welfare & trips are reduced.

Source: Castillo, Knopfle, and Weyl (2016)
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Demand Forecasting

Recall the demand model

$$D(p, \eta) = \lambda r(p) g(\eta)$$

Pricing requires prediction of \( \lambda \), the rider session arrival rate, by geo and time

Source: Daulton, Raman, Kindt
Demand Forecasting

Can use random forests with discretized latitude/longitude/time:

Source: Daulton, Raman, Kindl
Predicting Travel Time

Matching requires prediction of travel time between two points
Travel Time Prediction

Prediction is done based on location data from trips
Travel Time Prediction

Step 1. Process location data from trips by estimating the route taken & time on each segment
Travel Time Prediction

Step 2. Aggregate travel times on individual road segments

4 road segments in Seattle, evening rush hour:

Source: Woodard et al. 2017
Travel Time Prediction

Step 3. Model the road segment travel time

Outcome: segment travel time

Predictors:
- Historical avg travel time for this time of week
- Last 15 minutes avg travel time on the segment
- Weather
- Holiday
- ...
Travel Time Prediction

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4 road segments in Seattle, evening rush hour:

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...
Travel Time Prediction

Step 4. Predict the travel time on each road segment
Travel Time Prediction

Step 5. Compute fastest path based on predicted travel times
Travel Time Prediction

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Travel Time Prediction

Step 5. Compute fastest path based on predicted travel times
Travel Time Prediction

Step 6. Sum the travel times across the segments of the route
Travel Time Prediction

Step 7. Adjust for bias: drivers don’t always take the fastest path
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Dynamic Rider Waiting

- Idea: Choose a "waiting window" $\phi$, that can depend on supply/demand conditions.

- When a rider requests, consider all open drivers and all on-trip drivers within $\phi$ minutes of completing the trip.

- Dispatch the driver who minimizes the pickup time from either current location (if open) or dropoff location (for on-trip).
Dynamic Rider Waiting

- Can dynamically & jointly determine the waiting window and the dynamic price
- Trades off waiting time & price for riders
- Similar idea to the rider walking and waiting used in Uber’s Express POOL
Dynamic Rider Waiting

SF downtown:

![Graph showing optimal dynamic waiting time under dynamic surge multipliers compared to static surge multipliers over the course of a day.](image)
Alleviates "Danger Zone"
Reduces Price Variability
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Takeaways

- Growth of ride-hailing is facilitated by data-driven matching and pricing
- Intelligent matching & dynamic pricing reduce wasted time
- Matching & pricing require forecasts of demand, supply, and travel time
- Novel matching algorithms could decrease price variability
- Need econ, stats, ML, optimization