

A Simulation-Based Approach to Compare Policies and Stakeholders' Behaviors for the Ride-Hailing Assignment Problem

Ignacio Erazo¹ Rodrigo de la Fuente²

¹Georgia Institute of Technology

²University of Concepcion

Winter Simulation Conference 2021,
December 16th

Ride-Hailing

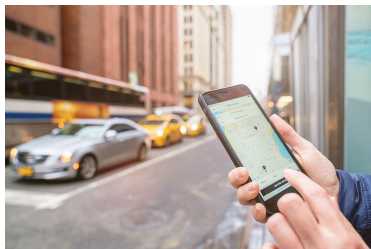
- On-demand transportation system for passengers.

Ride-Hailing

- On-demand transportation system for passengers.
- Origin and destination.
- Use of GPS, integrated payment.
- Customized services offered in an app.

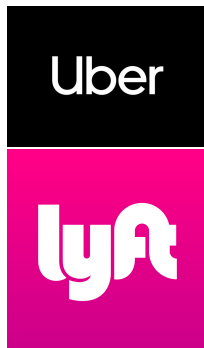
Ride-Hailing

- On-demand transportation system for passengers.
- Origin and destination.
- Use of GPS, integrated payment.
- Customized services offered in an app.



Impact

- Global market of 57 billion USD in (2021).
- Expected market of 108 billion USD (2025).
- 15 million trips per day (Uber, 2019).
- 30 million trips per day (Didi, 2019).
- Uber and Lyft produce up to 14% vehicle miles driven in some states (The Verge).



Literature review

1. **Forecast demand, then balance it with supply:**
(Moreira-Matias et al. 2013), (Miao et al. 2016), (Xu et al. 2020), ...
2. **Assigning vehicles to passengers:**
(Souza et al. 2016) → Assignment problem.
(Lowalekar et al. 2016), (Maciejewski et al. 2016) → Two-stage stochastic optimization.
(Alshamsi et al. 2009), (Glaschenko et al. 2009) → Multi-agent simulations.

Literature review

1. **Forecast demand, then balance it with supply:**
(Moreira-Matias et al. 2013), (Miao et al. 2016), (Xu et al. 2020), ...
2. **Assigning vehicles to passengers:**
(Souza et al. 2016) → Assignment problem.
(Lowalekar et al. 2016), (Maciejewski et al. 2016) → Two-stage stochastic optimization.
(Alshamsi et al. 2009), (Glaschenko et al. 2009) → Multi-agent simulations.
3. **Strategies to optimize performance: drivers' behaviors**
(Hoque et al. 2012) → Data analysis to help drivers find passengers.
(Li et al. 2009), (Henao and Marshall et al. 2019) → Idle time: park or drive?

Goal and Contributions

Goal: Propose different behaviors for drivers while waiting for passengers and compare them with respect to multiple objectives.

Contributions:

Goal and Contributions

Goal: Propose different behaviors for drivers while waiting for passengers and compare them with respect to multiple objectives.

Contributions:

1. We present the most realistic simulation model for this problem, coded on open source code (Python 3.6), available in github.

Goal and Contributions

Goal: Propose different behaviors for drivers while waiting for passengers and compare them with respect to multiple objectives.

Contributions:

1. We present the most realistic simulation model for this problem, coded on open source code (Python 3.6), available in github.
2. We examine the effect of different passengers' arrival conditions on the multiple objectives.

Goal and Contributions

Goal: Propose different behaviors for drivers while waiting for passengers and compare them with respect to multiple objectives.

Contributions:

1. We present the most realistic simulation model for this problem, coded on open source code (Python 3.6), available in github.
2. We examine the effect of different passengers' arrival conditions on the multiple objectives.
3. We compute and present all results for the multiple objectives on a micro-level, which is novel and allows for better insights and helps to construct better policies.

Model Classes

Driver:

Class Attributes:

- Number of drivers
- Distance driven with passengers
- Distance driven to pick-up passengers
- Distance driven idle
- Number of rides rejected by drivers
- Number of "Roaming events"

Instances Attributes:

- Preferences to accept a ride
- List of arrival events
- List of leaving events
- Capacity
- Luxury Status
- Arrival locations
- Next Roaming Event

Passenger:

Class Attributes:

- Number of passengers
- Number of accepted drives
- Number of "non-available drivers for ride"
- Number of drives rejected by passengers

Instances Attributes:

- Arrival location
- Destination
- Waiting time preferences
- Capacity needed
- Luxury requirements

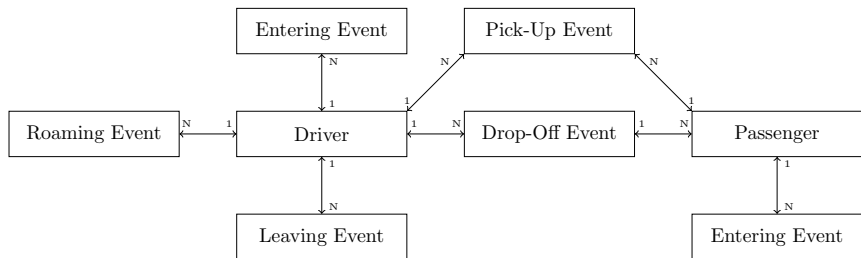
MatchingAlgorithm(Passenger,*AvailableDriversList,RoadNetwork):

```

PossibleDrivers = AvailableDriversList;
Times = GetTimes(Passenger,PossibleDrivers,RoadNetwork)
while length(Times) ≥ 1 do
  Index = argmin(Times)
  SelectedDriver = PossibleDrivers[Index]
  if SelectedDriver.MeetsRequirements == True then
    if SelectedDriver.AcceptsRide == True then
      | return SelectedDriver, Times[Index]
    end
  else
    | Update DriverRejectsRide metric
    | PossibleDrivers.Eliminate(SelectedDriver)
    | Times.Eliminate(Index)
  end
end
end
else
  | Update DriverDoesNotMeetRequirement metric
  | PossibleDrivers.Eliminate(SelectedDriver)
  | Times.Eliminate(Index)
end
end
return "No driver meeting requirements is available"

```

Model Events



Roaming Events

1. **No movement scenario:** After arriving to the system or dropping-off a passenger the driver waits parked in the same location.

Roaming Events

1. **No movement scenario:** After arriving to the system or dropping-off a passenger the driver waits parked in the same location.
2. **Single movement scenario:** After ending an event the driver continues driving to another location looking for passengers.

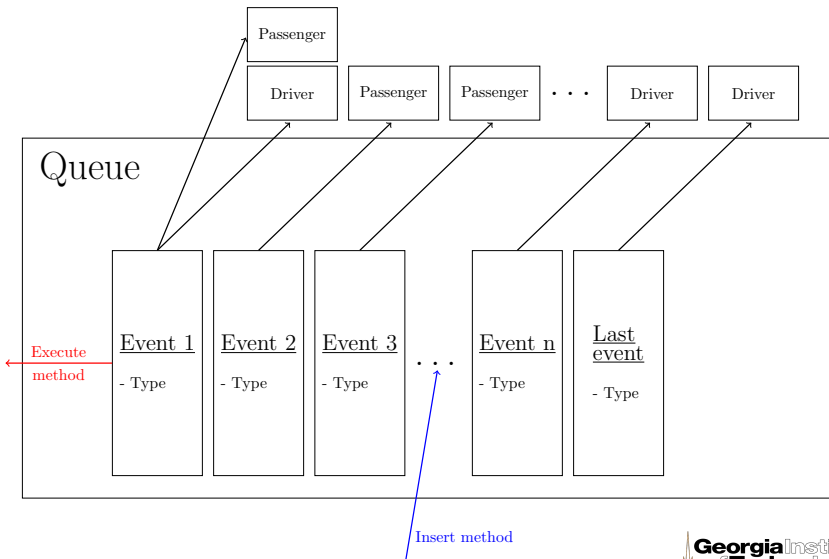
Roaming Events

1. **No movement scenario:** After arriving to the system or dropping-off a passenger the driver waits parked in the same location.
2. **Single movement scenario:** After ending an event the driver continues driving to another location looking for passengers.
3. **Nearest hotspot scenario:** Company gives a list of hotspots, and drivers go to nearest hotspot where they wait.

Roaming Events

1. **No movement scenario:** After arriving to the system or dropping-off a passenger the driver waits parked in the same location.
2. **Single movement scenario:** After ending an event the driver continues driving to another location looking for passengers.
3. **Nearest hotspot scenario:** Company gives a list of hotspots, and drivers go to nearest hotspot where they wait.
4. **Coordinated hotspot scenario:** Company decides where the driver should go among a list of hotspots.

Queue



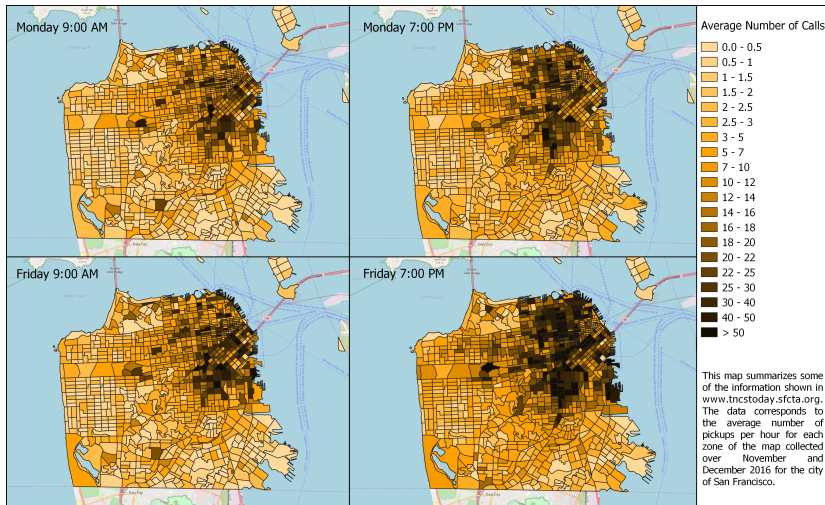
San Francisco Area

- Top 5 most-populous area in US.
- By the end of 2016 more than 5,700 drivers in peak-hours.
- More than 570,000 miles everyday, more than 170,000 drives, 15% of intra-SF trips (SFCTA 2017)
- Causing 55% average speed decline in the city (Marshall 2018)

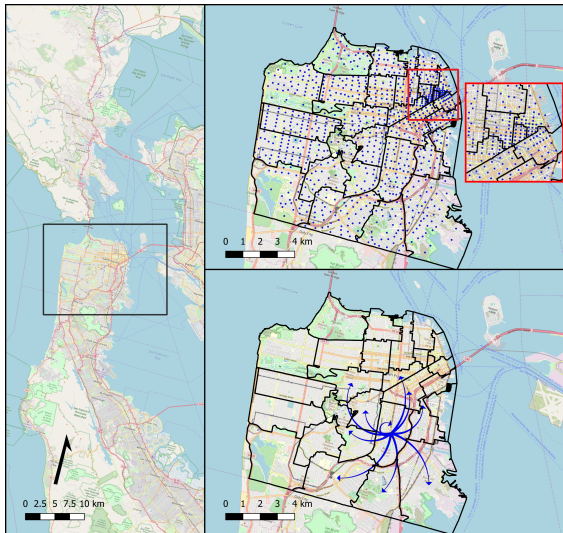
San Francisco Area

- Top 5 most-populous area in US.
- By the end of 2016 more than 5,700 drivers in peak-hours.
- More than 570,000 miles everyday, more than 170,000 drives, 15% of intra-SF trips (SFCTA 2017)
- Causing 55% average speed decline in the city (Marshall 2018)
- QGIS for road network.
- 11,372 nodes and 31,428 edges.
- 70x70 meters digital elevation model.
- Speed according to edge classification and adjusted by slope (Verma et al. 2017).
- Shortest path algorithm is based on the network.

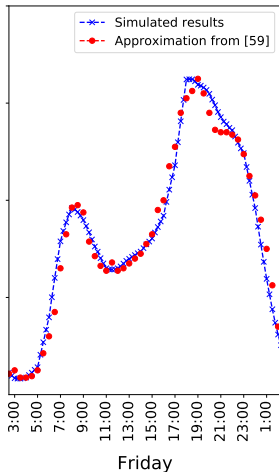
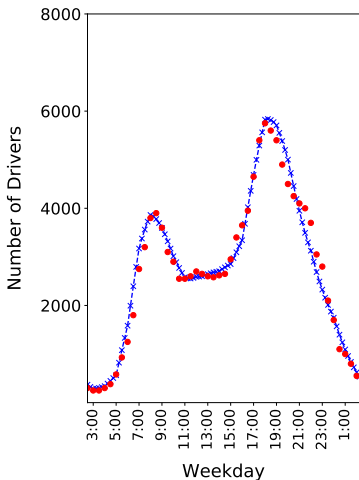
Passengers (SFCTA 2017)



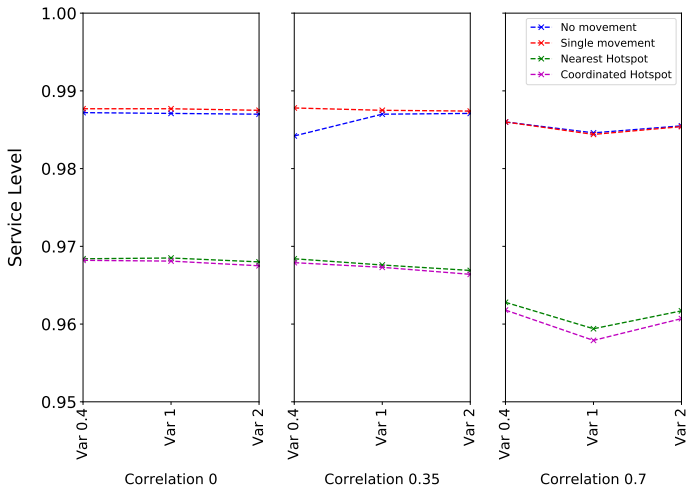
Drivers (Piorkowski et al. 2009)



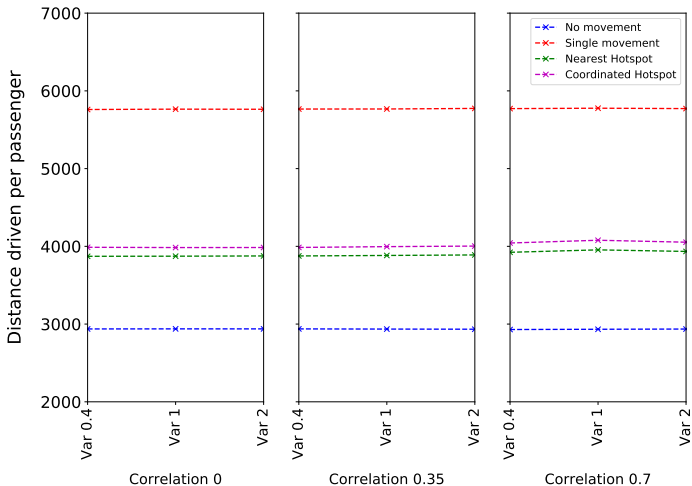
Drivers (SFCTA 2017)



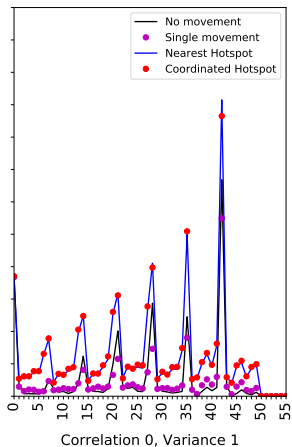
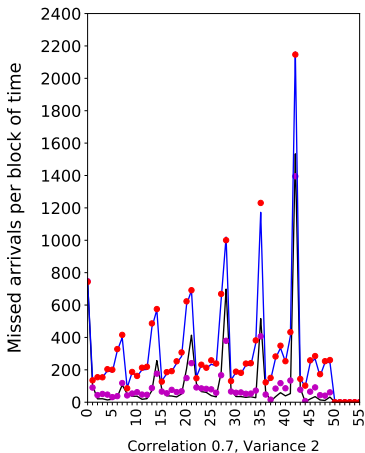
Overall Service Level

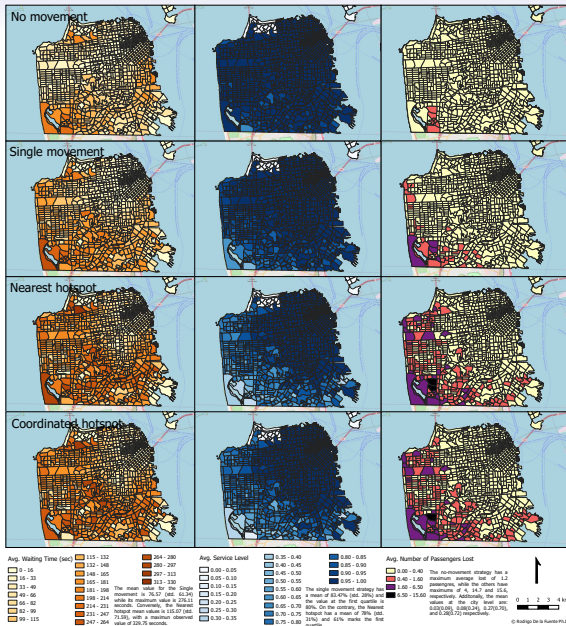


Distance Driven



Chaotic Conditions Effect





Discussion

- No movement saves at least 11M USD per year and 57M of CO_2 per year in SF versus Single movement.
- No movement is very hard to implement now, needs extensive parking (up to 39,000 sq. meters).
- Nearest Hotspot saves 7.9M USD and 38M of CO_2 .
- A need of interaction and mutual agreement between stakeholders. Investments are also needed.
- Spatial discrepancies should be addressed by introducing incentives/new transportation options.

Conclusions and Future Work

- Proposed realistic simulation model that can be used under multiple conditions.
- Framework allows the comparison of different drivers' behaviors while waiting for riders, and also to evaluate the impact in different areas of the city and periods of time.
- Huge benefits can be obtained if the behaviors are optimized.

Conclusions and Future Work

- Proposed realistic simulation model that can be used under multiple conditions.
- Framework allows the comparison of different drivers' behaviors while waiting for riders, and also to evaluate the impact in different areas of the city and periods of time.
- Huge benefits can be obtained if the behaviors are optimized.
- Different matching algorithms → dynamic reallocation.
- How to better select the hotspots?
- Pricing incentives and their effects.