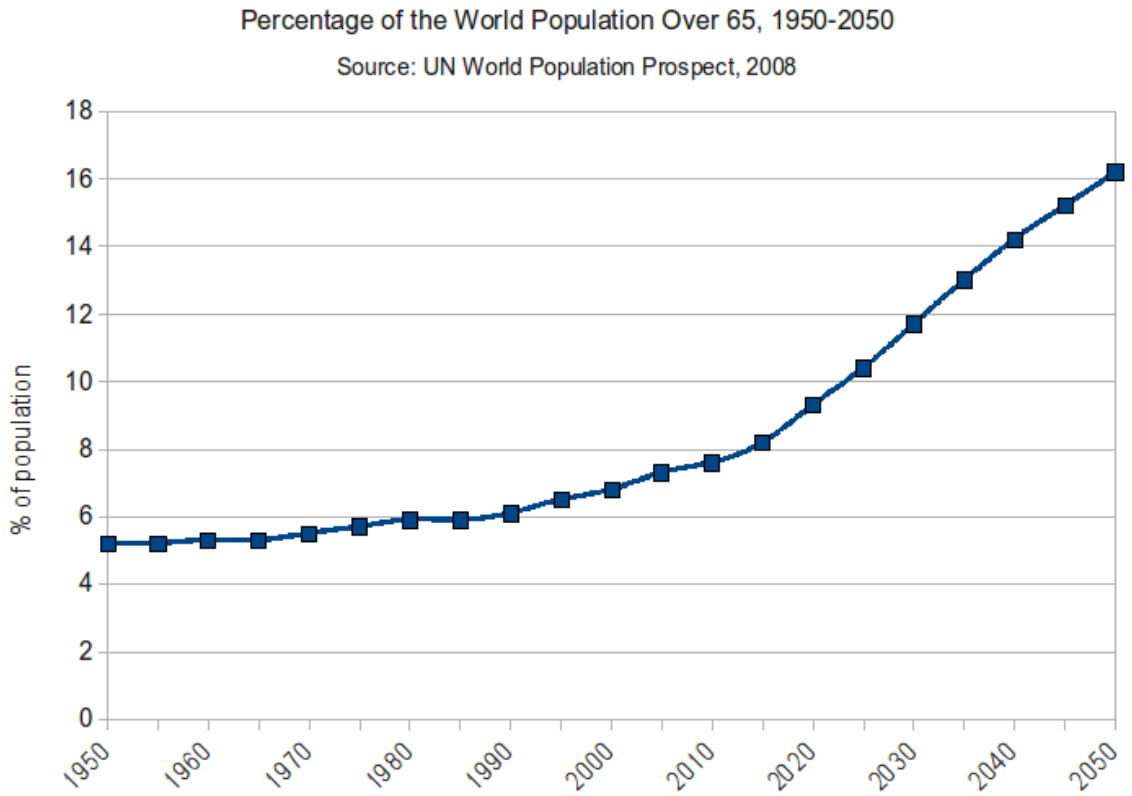
https://comfortcaregivers.com/contact_home_care/

Addressing Challenges in Senior mobility

Research need in mobility solutions for seniors

- Significant portion of market:
  - Seniors (age > 65 yrs) made 12% of all trips, 10% of all miles traveled in 2009 (AARP, 2015)
- Increasing mobility needs:
  - Number of senior transit users increased by 55% from 2001 to 2009, exceeding 1 billion trips (AARP, 2015)
- Aging population (UN, 2008)



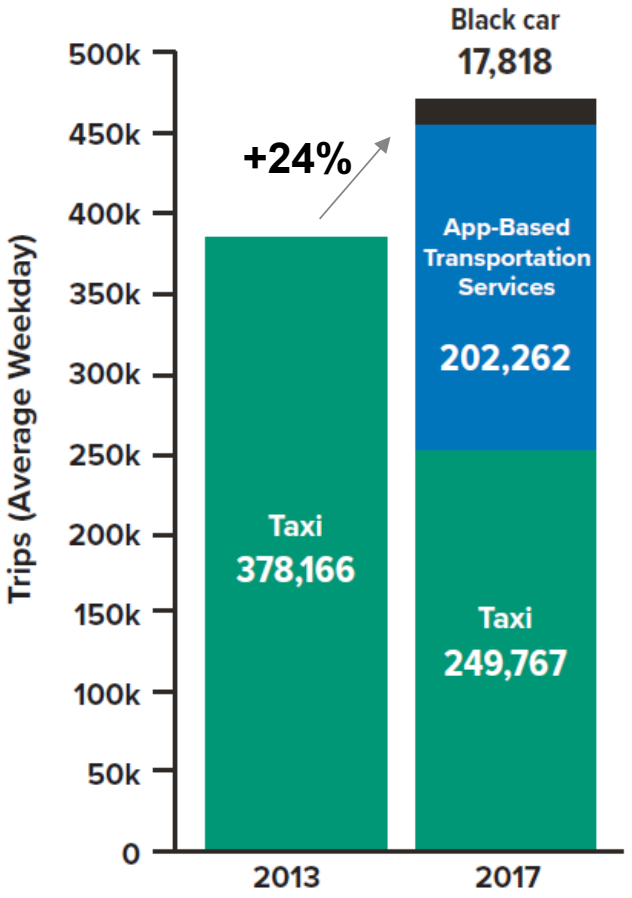
Survey to understand seniors' mobility needs

- Conducted surveys in El Paso, TX (UTEP) and Manhattan, NY (NYU)
- Asked about lifestyle, mobility needs, smartphone usage and etc.
- 458 responses from El Paso and 61 from Manhattan
- Top trip concerns: Travel time/cost, extreme weather and on-time departure and arrival
- Few experiences on paratransit and ridesharing service

Item	El Paso	Manhattan
Smartphone ownership	49%	62%
Taxi usage	5%	44%
Paratransit usage	10%	20%
Ridesharing service usage	5%	13%

Market expands, but seniors don't use them

FIGURE 2. Taxi and FHV Service Trips in the Manhattan CBD, 2013-17



Fix NYC Advisory Panel, 2018

- Top eight smartphone apps (Forbes, 2015) for seniors

1.	Magnifying Glass with Light	Eyesight
2.	Skype	Social
3.	Pillboxie	Medication
4.	MedCoach	
5.	Crosswords Classic	Game
6.	Sudoku	
7.	Luminosity	
8.	Red Panic Button	Emergency

General lack of solutions related to mobility for seniors!

Key challenges: Cost and Schedule changes

Access-a-Ride wastes up to $100 million a year, experts say

Uber, more subway elevators and other alternatives would save a bundle on paratransit, budget and transportation groups find

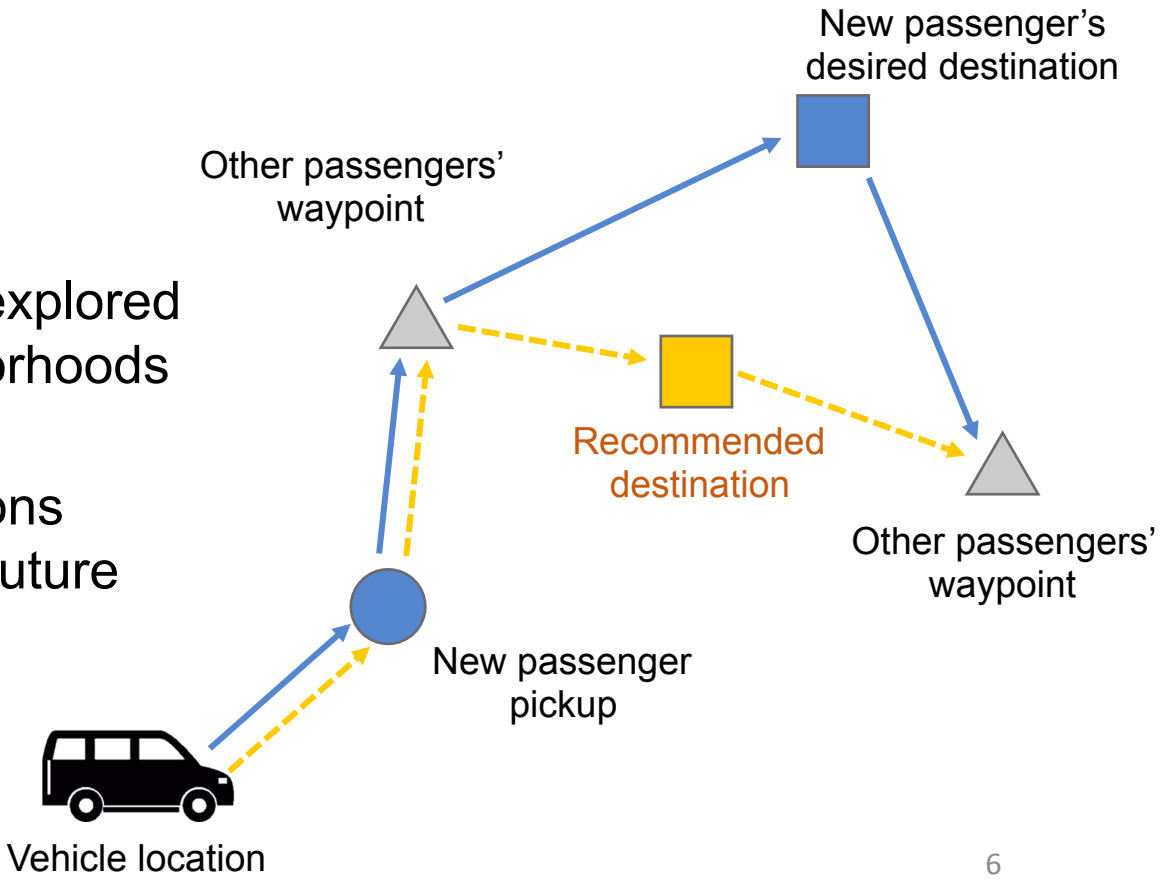
- 144,000 users per year, spent $461M
- Costs of paratransit service in NYC as high as $71/trip in 2015 (source: Crain's New York)

One of the most common ways that a daily paratransit schedule gets disrupted is by passengers with no-shows and late cancellations. No-shows are passengers that simply are not available to ride the paratransit vehicle as scheduled and do not provide any pre-notice of their unavailability. Late cancellations are those passengers that call to cancel their reservation but do so without adequate notice for the transit agency to readjust its daily trip schedules.

- Readjusting daily trip schedules due to no-shows and cancellations (source: CUTR, USF, 2008)

What if MOD can recommend destinations?

- Mobility-on-Demand (MOD) move passengers between OD
- Results of providing alternatives to passengers
  - Recommend alternative options
    : mitigate costs that arise due to unplanned disruptions or schedule cancellations
  - Suggest new destinations
    : provide information to users who have not explored establishments beyond their typical neighborhoods (particularly the elderly)
  - Learn from users' responses about destinations
    : present improved recommendations in the future



https://www.next-future-mobility.com/

https://www.futurecar.com/

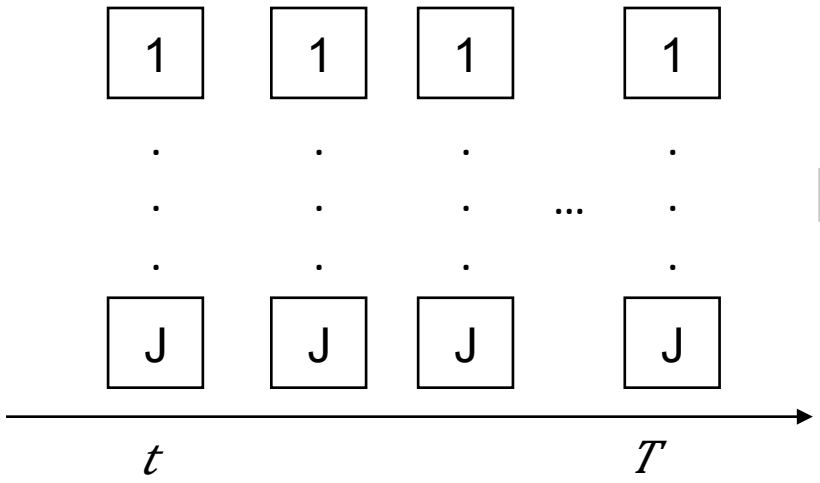
Destination Recommender Systems for MOD

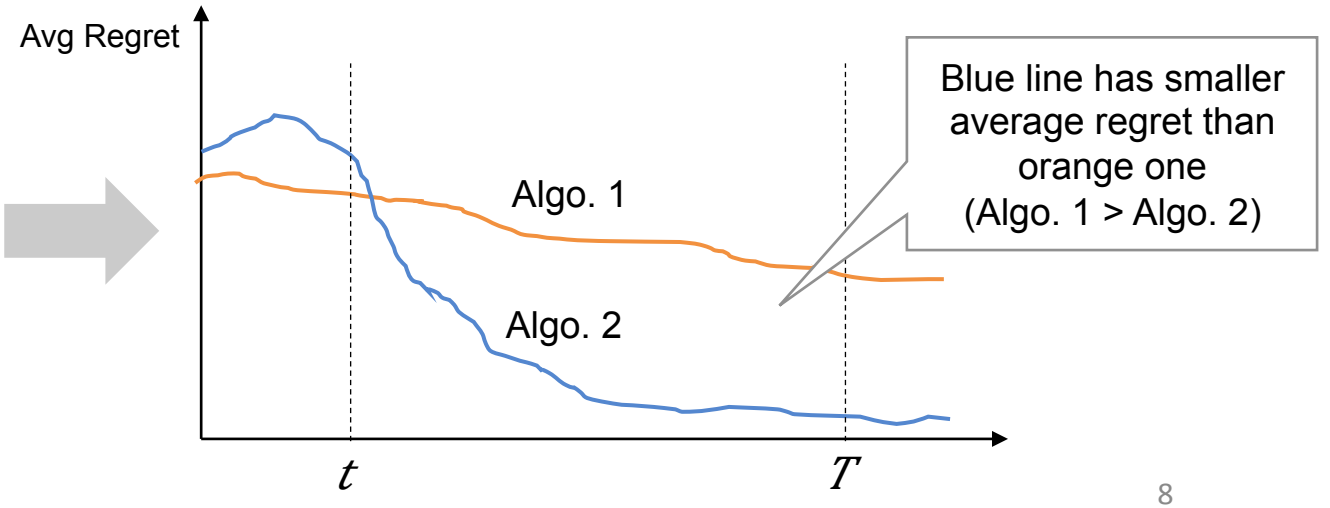
Challenges and solutions

How to recommend destination preferences on an MOD service?

"Recommender systems":

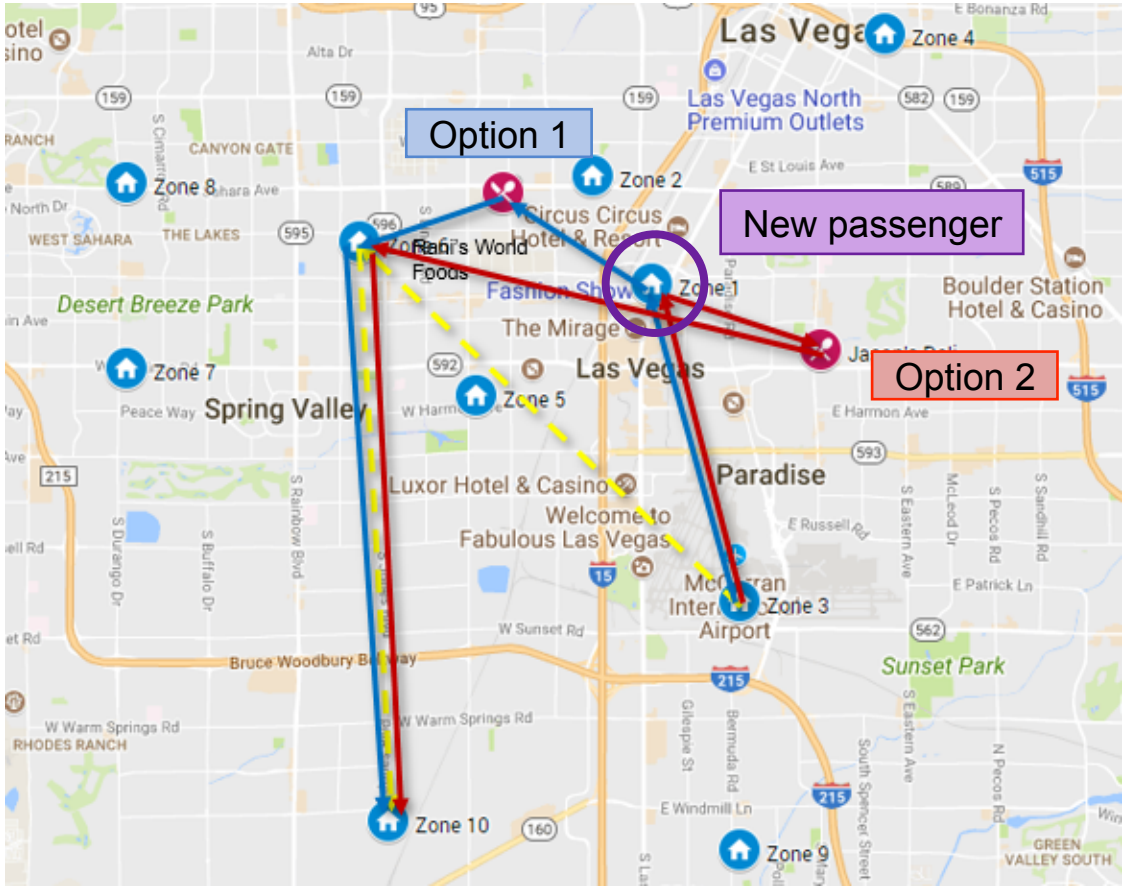
- Use information from prior trials to recommend choices in a current trial
- Famous examples: online services (Amazon, Netflix, Google, …)
- Objective of a choice at trial t out of T trials is to optimize cumulative user service (up to T)





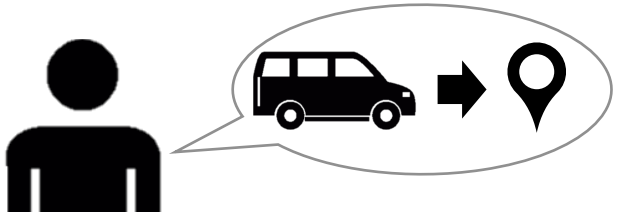
Problems with "routing-constrained" recommender systems

- Alternatives are highly contextual : depends on existing route and new passenger's location
- Fundamental conflict between trying to minimize regret and trying to minimize operating costs and passenger travel costs
- Tour cost change has to be incorporated in the objective of the algorithm



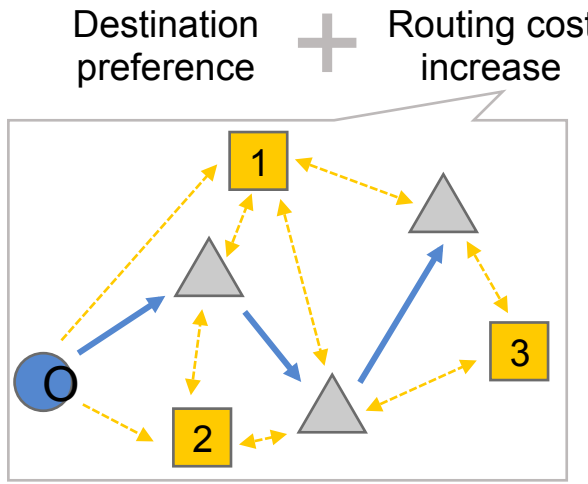
We propose using an "Upper Confidence Bound*" algorithm wherein each trial…

*: Li et al. (2017)



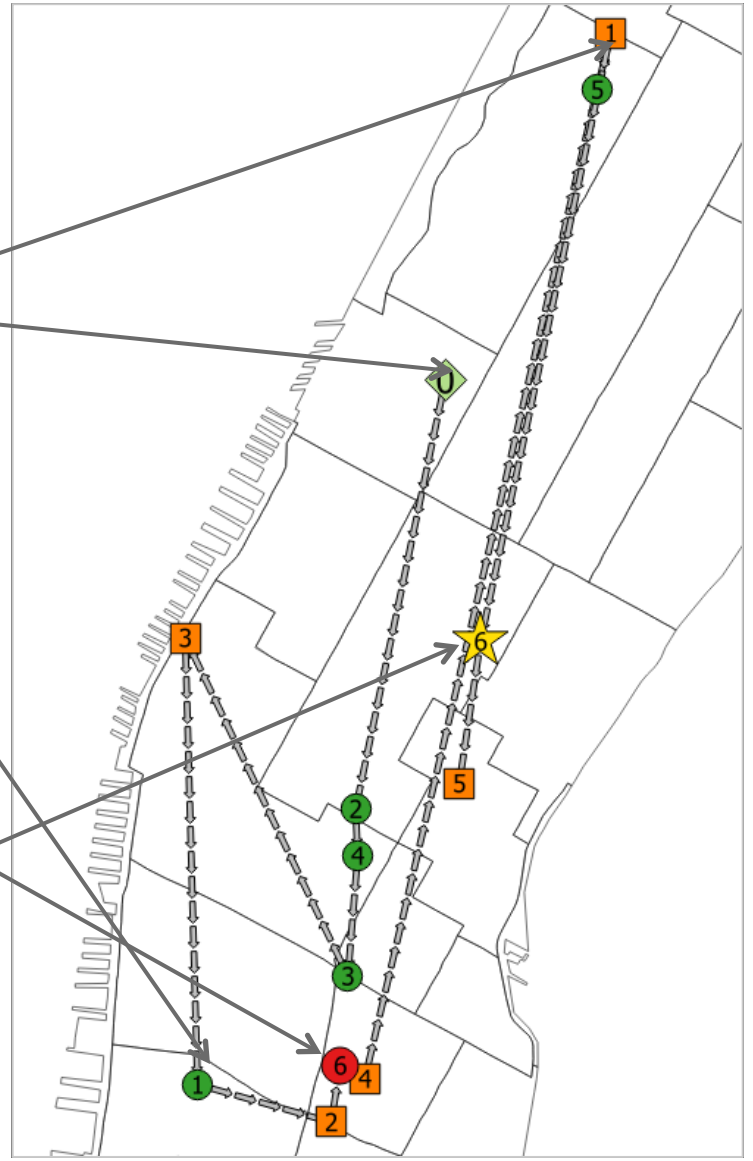
- A new customer at a pickup location initiates the recommender system to suggest a destination
- Destination selection based on mix of current optimization and learning (future optimization)

- Optimization decided by combination of destination preference (e.g. Yelp ratings) and increase in routing cost
- Routing cost decided by an insertion heuristic for traveling salesman problem with pickup and drop-offs (Berbeglia et al., 2010)



Embedded routing function

- Initial vehicle location 0
- Passenger 1's origin 1 and destination 1 : should be connected with precedence
- Consider all possible links among nodes
- Find the shortest route covering all nodes
  - Drop-offs should be located after pickups
  - Vehicle capacity should not be exceeded
- Passenger 6 requests service with destination recommendation
- Recall pool of restaurants and evaluate rating and route cost increase
- Recommend the location with the highest estimated utility
  - If accepted, reroute vehicle to follow modified route



Algorithm "RecMOD"

Route with existing passengers (1) → Insertion of new passenger and alternatives (2) → Analyze features and recommend one of them (3~4) → Observe response and update parameters (5~7)

Input: total trials T, learning period τ, exploration factor α, mean passenger arrival rate λ, vehicle capacity q, degree of congestion γ, mean vehicle speed v, and pool of alternatives $\mathbb{A}$

For $t=1$ to T

1. Given an existing route visiting $2n_t$ points with a subset of k pickups already made, with remaining routing cost w_{0t} obtained from **Algorithm 1**, a new request for destination recommendation comes in

For $\forall s \in \mathbb{A}_t$

2. Construct shortest routes p_{st} and route cost w_{st} visiting $2n_t - k$ points and serving new request from d_t to s using **Algorithm 1**, and calculate $\Delta w_{s,t} = w_{st} - w_{0t}$

3. Add $\Delta w_{s,t}$ to feature vector $\boldsymbol{x_{s,t}}$

End For

If $t \leq \tau$

4-1. Randomly recommend $s_t \in \mathbb{A}_t$

Else If $t > \tau$

4-2. Recommend $s_t = \text{argmax}_{s \in \mathbb{A}_t} (V_{s,t} + \alpha \| \boldsymbol{x_{s,t}} \|_{V_t^{-1}})$, where estimated systematic utility $V_{s,t} = \boldsymbol{\theta}_t \boldsymbol{x_{s,t}}^T$

End If

5. Observe the user's response where $y_t = 1$ if the user accepts the recommendation and $y_t = 0$ otherwise.

6. Accumulate $\boldsymbol{x_{s,t}}$ and y_t to $\boldsymbol{X_t}$ and $\boldsymbol{Y_t}$

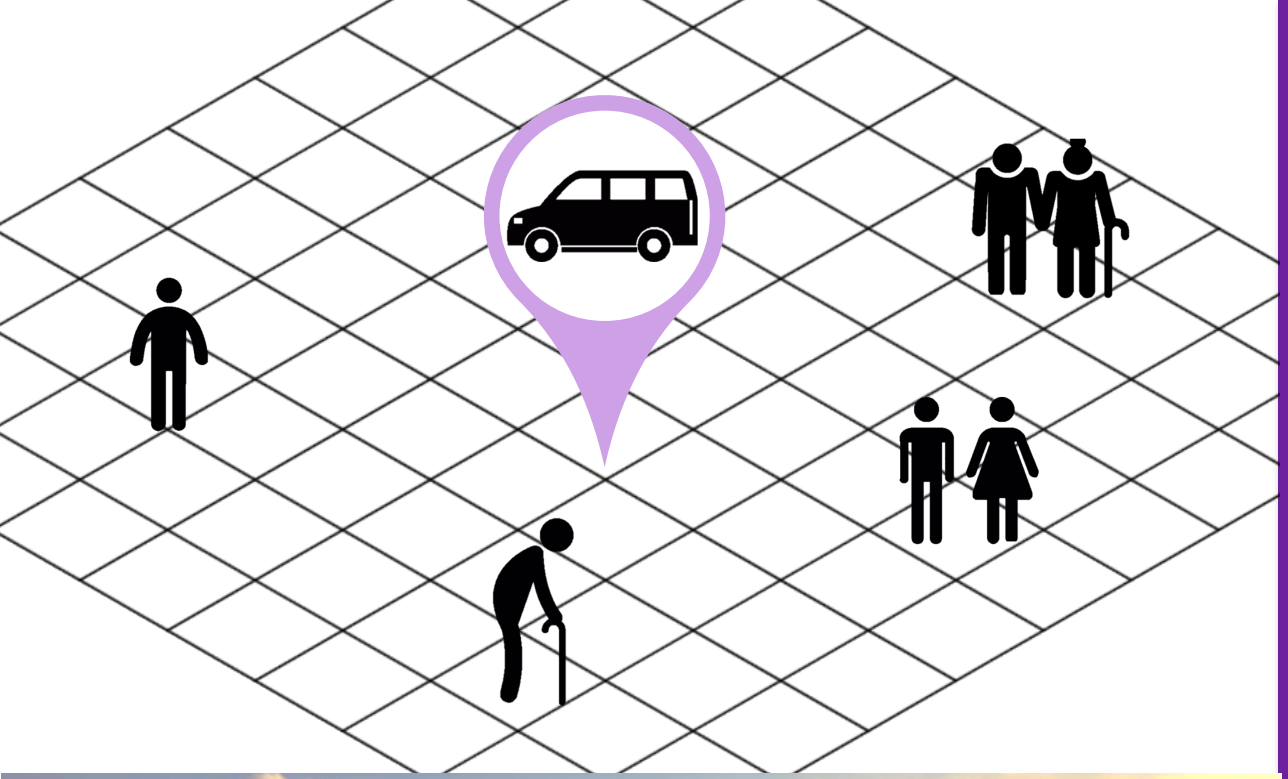
If $t \geq \tau$

7. Solve the equation to obtain the maximum-likelihood estimator $\boldsymbol{\theta_{t+1}}$

$$\sum_{i=1}^{t} (\boldsymbol{Y_i} - \mu(\boldsymbol{\theta X_i})) \boldsymbol{X_i} = 0$$

End If

End for



Simulation Experiment

3 Cases – 2 simple networks and Manhattan

Experiment 1: algorithm verification

- 100 destinations with single shuttle moving in Euclidean distance (avg. speed 10mph and capacity of 4)
- Simulated unobserved utility function for accepting a recommendation:

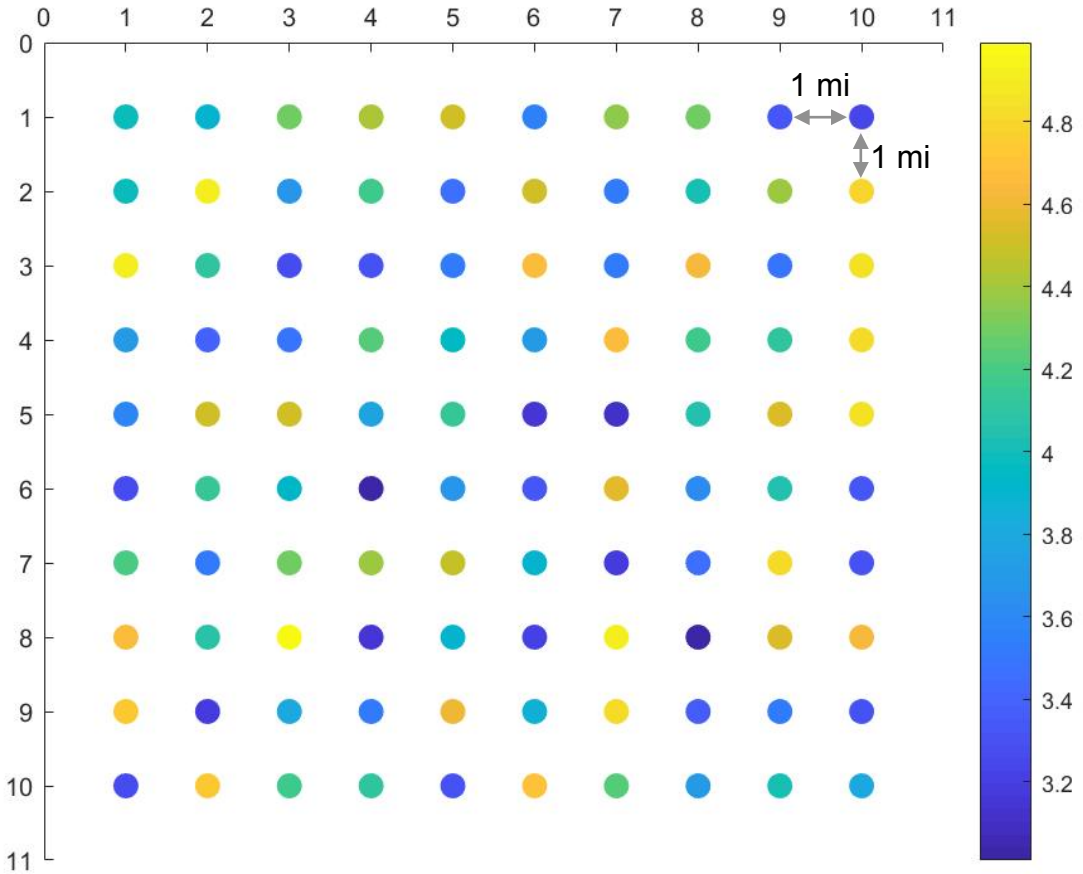
$$U\downarrow ns = -5 + 2 \times RATING\downarrow s - 0.1 \times TTIME\downarrow ns + \varepsilon\downarrow ns$$

where

$RATING\downarrow s$ = destination rating (real value, $3 \leq RATING\downarrow s \leq 5$)

$TTIME\downarrow ns$ = routing cost increase (min)

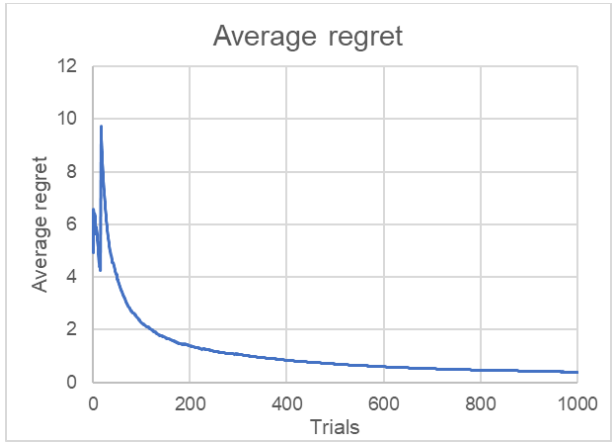
$\varepsilon\downarrow ns$ = unobservable noise



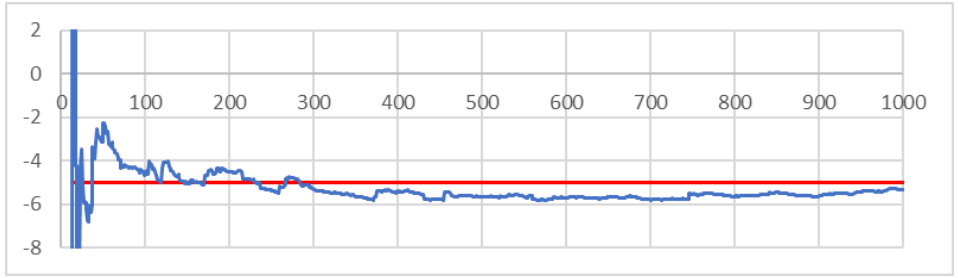
Simulated ratings of 100 destinations (out of 5)

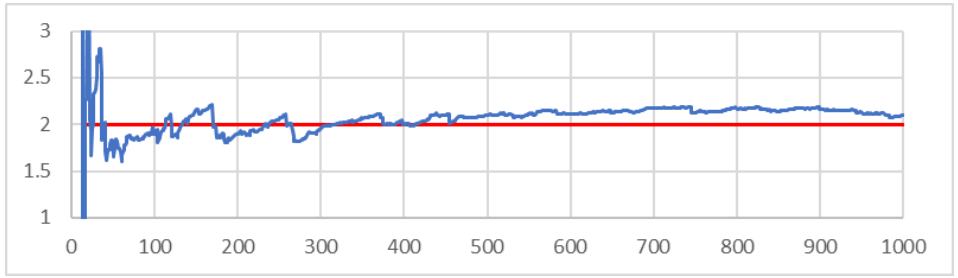
Performance measures and parameter estimation

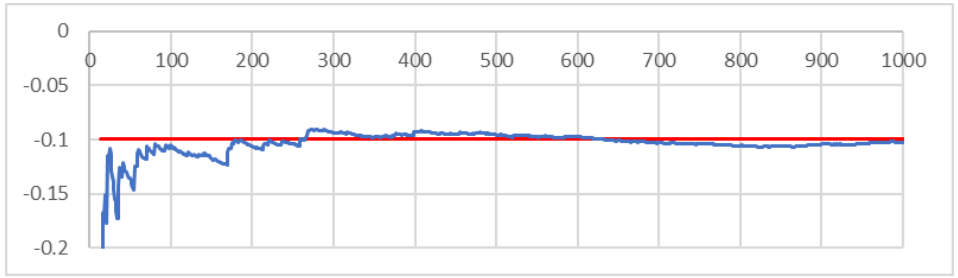
- 1000 simulated trials including a 12-trial learning period



Parameter	True	Learned
Constant	-5	-5.324 (6.5%)
RATING	2	2.095 (4.7%)
TTIME	-0.1	-0.103 (2.7%)

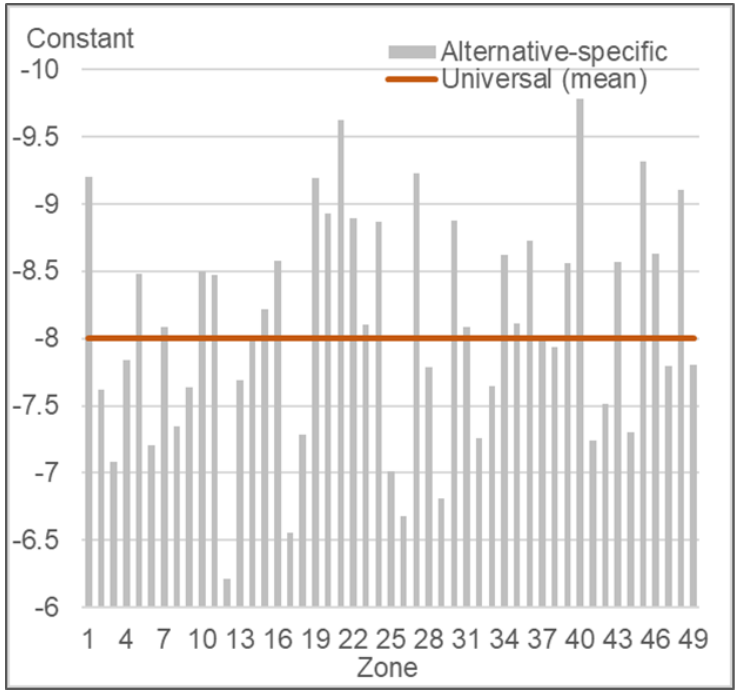


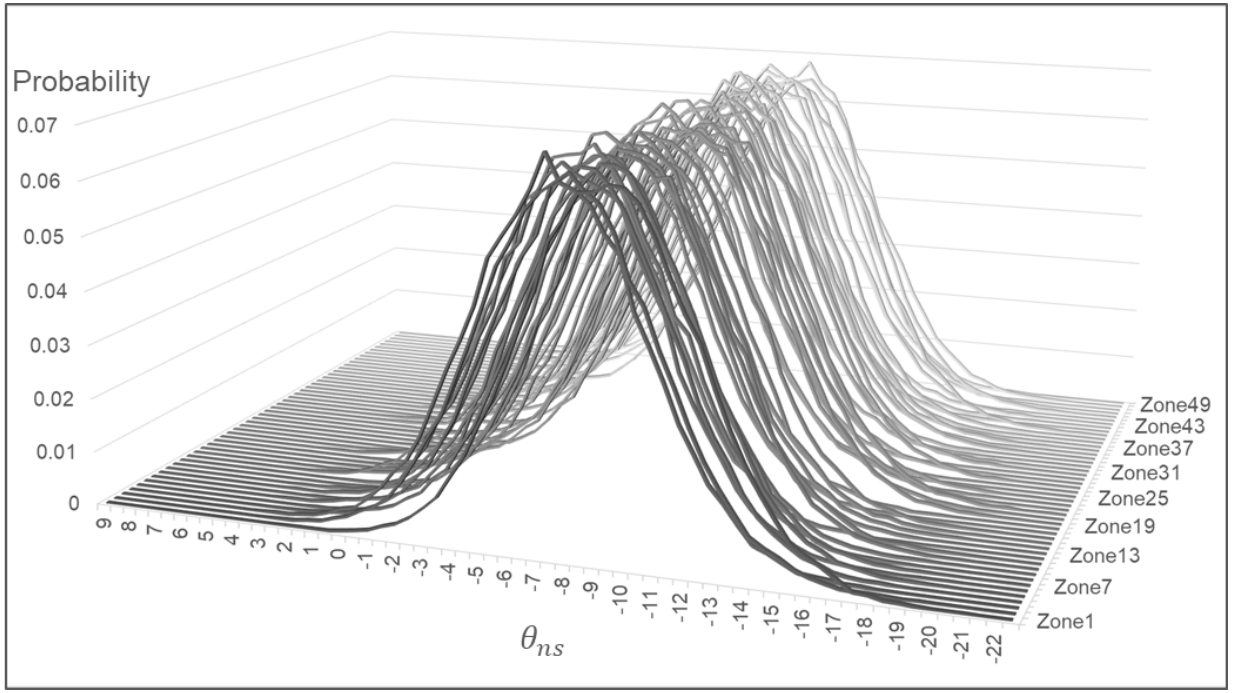




Experiment 2: comparison with other schemes

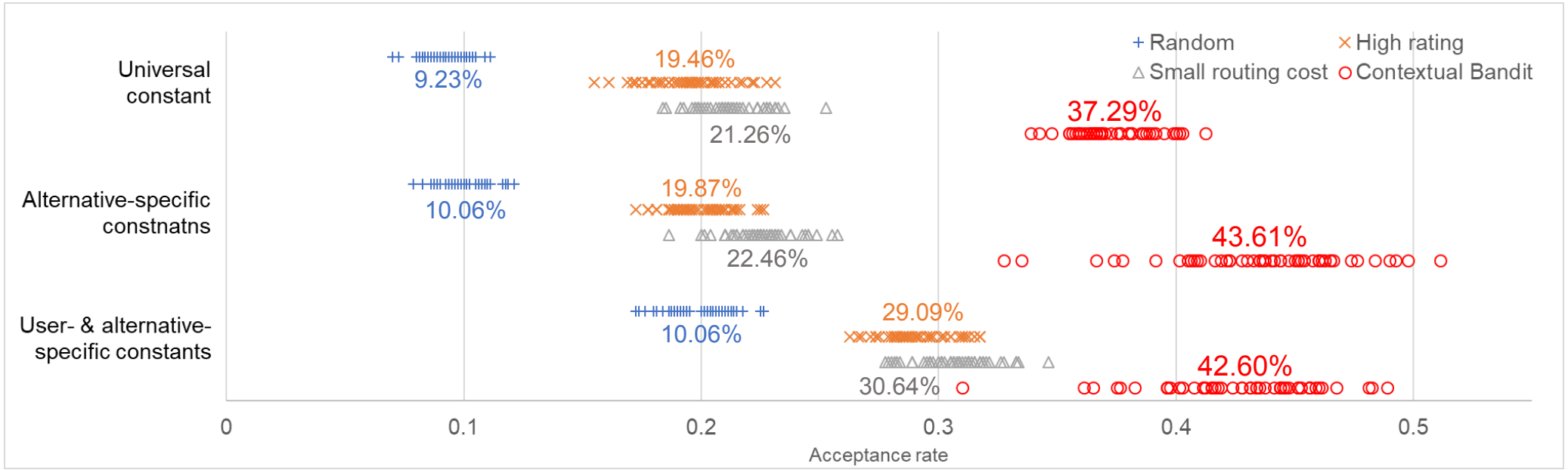
- 7×7 grid with 49 zones, 2000 trials per simulation
- 3 different constant setting
  - Universally constant ($\theta\downarrow 0$) / Alternative-specific ($\theta\downarrow s$) / User- and alternative-specific





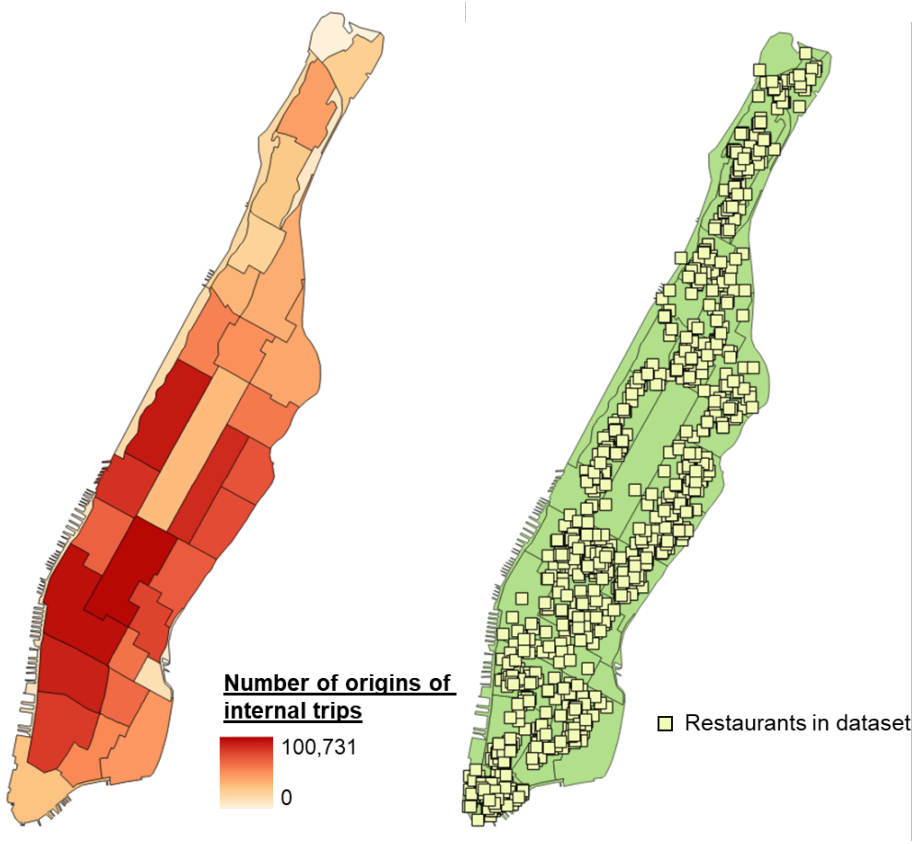
How does the acceptance rate change?

- Compared 4 different recommendation criteria
  - Random / Highest rating / Smallest route cost increase / RecMOD
  - 50 simulations for each case



Experiment 3: Application to real data

- Consider a scenario in Manhattan with a single shuttle
  - Passenger locations
    - Randomly generated on Manhattan Island following distribution of internal trip origins
    - Around 1000 points generated
  - Recommendable establishments
    - Restaurants in Yelp dataset searched in Nov 2018
    - Including ratings in discrete level and coordinates
    - 100 of them randomly selected as a pool



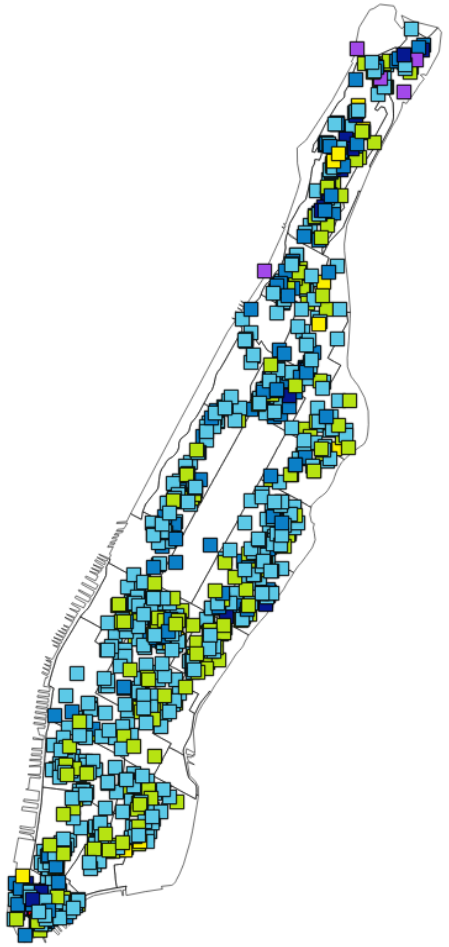
OBJECTIVE: generate different runs under random routing constraint settings (capacity, congestion, degree of exploration) to evaluate elasticity of acceptance rate to these attributes

Simulation settings

- Used the same utility function assumed
$U\downarrow ns = \theta\downarrow ns + 2 \times RATING\downarrow s - 6 \times TTIME\downarrow ns + \varepsilon\downarrow dn$

  where
  $RATING\downarrow s$ = destination rating (0.5-interval rating)
  $TTIME\downarrow ns$ = routing cost increase (hr)
  $\varepsilon\downarrow ns$ = unobservable noise

- Vehicle speed: 10km/h (6.25mph)
- Learning for 100 trials out of 1000
- 200 simulations with varying parameters
- Vehicle capacity: integer of [4, 8]
- Passenger arrival rate: integer of [1, 5]
- Travel time conversion factor (min/km)
  : real number of [0.1, 0.15]
- Exploration factor (α): $0.5 k\downarrow 1$, $k\downarrow 1 \in [1,10]$



Rating	Count	Percent
1.5	1	0.1%
2.0	2	0.2%
2.5	11	1.1%
3.0	32	3.2%
3.5	157	15.5%
4.0	585	57.8%
4.5	208	20.6%
5.0	16	1.6%
Sum	1,012	100.0%

5-point Yelp ratings of sampled restaurants

How does the relation between acceptance rate and parameters look like?

- 200 simulations with different parameter settings
- Linear regression conducted
  - Dependent variable: acceptance rate
  - Independent variables
    - Exploration factor
    - Passenger arrival rate
    - Vehicle capacity
    - Travel time per distance
  - Adjusted R^2 : 0.4452

Parameter	Coefficient	Standard error	*t*-stat	Elasticity
Intercept	**0.8585**	**0.0349**	**24.5659**	**-**
Exploration factor	0.0035	0.0026	1.3736	0.0128
Passenger arrival rate	**0.0271**	**0.0023**	**11.8365**	**0.0997**
Vehicle capacity	0.0013	0.0025	0.5048	0.0093
Travel time per distance	**-1.1778**	**0.2308**	**-5.1038**	**-0.1811**

- How to increase acceptance rate
  - More passengers in the system, faster vehicle speed (or less congested)

Summary and next steps

- MOD with destination recommender system can help improving seniors' mobility, dealing with challenges of cost and schedule changes
- Not likely other present recommender systems, destination recommender system requires to incorporate vehicle routing constraints
- RecMOD algorithm yields better performance measures than other recommendation schemes and estimates parameters adequately
- Demand level and actual vehicle travel speed are significant factors for acceptance rate
- Next steps:
  - Incorporate destination recommender system in UTEP's "Urban Connector" app and test
  - Incorporate personal attributes via Singular Value Decomposition
  - Consider alternative contextual bandit learning in other mobility contexts (like route design)
- Prototype recommender system: https://github.com/BUILTNYU/recommender-system

References / acknowledgements / contact

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C2SMART
CONNECTED CITIES WITH SMART TRANSPORTATION

USDOT Tier 1 University Transportation Center

Consortium members

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Research area: 9 of 12 vision elements identified by USDOT

Resilient, Secure & Smart Transportation Infrastructure

VISION ELEMENT #3 Intelligent Sensor-Based Infrastructure

VISION ELEMENT #8 SmartGrid, Roadway, Electrification & EVs

VISION ELEMENT #11 Low-cost, Efficient, Secure & Resilient ICT

Urban Analytics for Smart Cities

VISION ELEMENT #5 Urban Analytics

VISION ELEMENT #12 Smart Land Use

Urban Mobility & Connected Citizens

VISION ELEMENT #1 Urban Automation

VISION ELEMENT #2 Connected Vehicles

VISION ELEMENT #4 User Focused Mobility Services & Choices

VISION ELEMENT #6 Connected Delivery & Logistics

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https://streeteasy.com/blog/brooklyn-bridge/

Thank you!

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