On-demand public transport is making us mobile*

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1 Introduction

The TLC trip record data[1] reports Yellow and Green taxi and other "for-hire vehicle" trips in New York City. In the earlier years, Yellow and Green taxi records contain time, distance, passenger count, fare, etc., but also location of pickup and dropoff. Based on those data we attempt to answer:

> How many adaptively routed minibuses could meet the same demand?

2 Data preparation

2.1 Taxi trips[2]

We focus henceforth on May 2016 with ∼12M (Yellow) and ∼1.5M (Green) trip records. The ∼11M "for-hire vehicle" records bear no useful details for our purpose. We keep only the trips that begin and end in Manhattan with reported trip distance between 0.1 and 30 miles. We filter out records that lack geo-coordinates. See Fig. 1 for a net summary. code #1

2.2 Road graph[2]

We obtained the road network for Manhattan from the OpenStreetMap Overpass API and #3 filtered for roads plausibly open for public traffic. It is represented as a digraph, i.e. there #4 are one-way roads and the routing $A \to B$ differs from $B \to A$. Edges are broken into bits under 20 m. When modeling individual trips, their reported endpoints are snapped to the nearest grpah node; we ignore ∼10% of records where the discrepancy is over 20 m. The map graphics are from MapBox. #5

*R. Andreev, On-demand public transport is making us mobile, 2021, `http://bit.ly/optimum-2021`

[1] `https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page`

[2] The codes for this section were mostly written in 2019.

2.3 Traffic model

The trip trajectories are not available, only the pickup and dropoff locations (with uncertainty of 10 to 100 m). Leveraging the reported trip duration we infer plausible mean-field travel speeds (see Fig. 2c) throughout the road graph as follows. The speeds on all roads are initialized to 5 m/s. For a sample of trips that start at 6-7 pm the quickest trajectories are estimated. The speed of the road bits participating in those trajectories are adjusted toward the reported trip duration. This is repeated. #6

Henceforth, "quickest" means w.r.t. this traffic model. We are assuming that drivers are not sufficiently incentivised for detours (the credence good asymmetry is not significant).

3 Optimization problem

We are facing a so-called vehicle routing problem with these main attributes:

- Capacitated. There are N vehicles of maximal capacity of C passengers each.
- Time windows. Each passenger has to be picked up within $[-2\,\mathrm{min}, 5\,\mathrm{min}]$ of the recorded pickup time in the trip data (§2.1). Dropoff is accepted until 10 min after the recorded dropoff time. Ignoring a request incurs a penalty to the optimization objective. The vehicles may wait up to 10 min at any location.
- Depot. All vehicles start and finish at a certain location but have enough time to reach anywhere without compromising feasibility.

We use `ortools`[3] to find reasonable solutions computationally (on modest hardware). The optimization objective is the total vehicle travel time, plus about 3 h for each unserviced request. We can roughly assess optimality by allotting more time to the solver.

We focus on a small slice of the trip data at a time, i.e. a few hundred passengers $\times$ 1 h $\times$ a few square km. We compare "customer satisfaction" across fleet sizes and vehicle capacities.

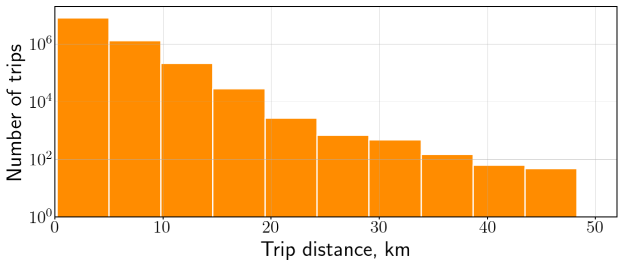
4 Case study #9

4.1 Times Square

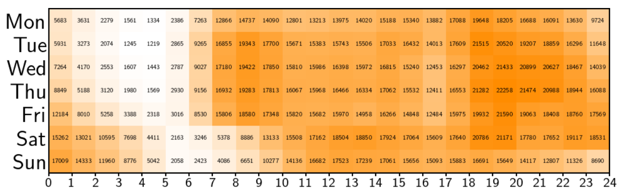
We take the first n single-passenger trips with reported pickup and dropoff within 1 km of Times Square and within 18:00–19:00 on May 1, 2016. Allowing $n = 400$ requests is already a little difficult to optimize (over 1 h $\times$ 2 Gflop/s), so we focus here on

$$n = 100 \text{ requests for } N = 10 \text{ vehicles of capacity } C = 1 \text{ or } C = 8\ .$$

[3] https://developers.google.com/optimization/routing/vrp

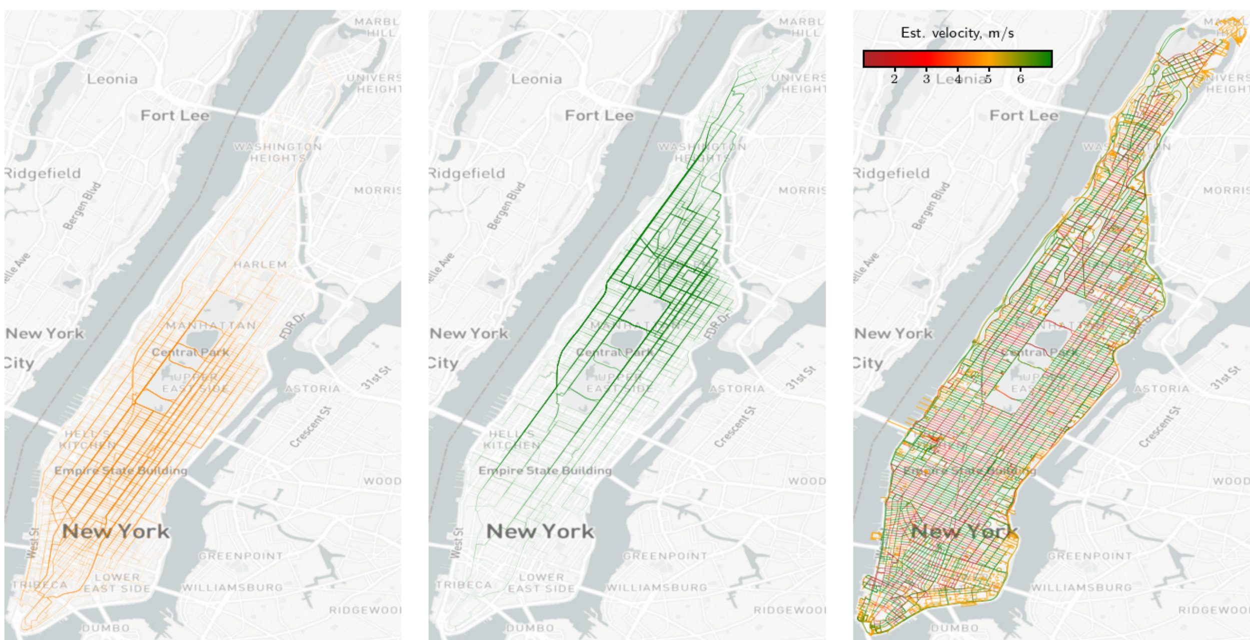


(a) Histogram of the reported trip distance (between 0.1 and 30 miles).



(b) Pickup hour heatmap.

Figure 1: Summary of Yellow (↖) and Green (↗) taxi trips filtered as in §2.1. #2



(a) Sample Yellow taxi trips. (b) Sample Green taxi trips. (c) Inferred mean-field velocity.

Figure 2: A sample of shortest-path trajectories (§2.1/§2.2) and the traffic model from §2.3. #7, #8

The traffic model from §2.3 predicts trip times near Times Square well for 6-7 am but is too optimistic for 6-7 pm (code #10); we use it here nevertheless.

We find that the single-passenger fleet ($C = 1$) can only service about a half of requests, whilst the minibus fleet ($C = 8$) can handle most requests: see Fig. 4. The results for 2 km radius with $N = 20$ vehicles are similar (see code #9 to browse the results).

The minibus fleet runs at about half the capacity on average, see Fig. 5. Since all $n = 100$ pickup requests are from the first 17 min, it would be able to handle more requests per minute when operating over an extended period.

In summary, we estimate that this demand can be serviced by $N \approx 20$ single-passenger taxis; or $N \approx 10$ minibuses of capacity $C \approx 8$ if some excess travel time is tolerated.

4.2 Game-theoretic spin

Consider a passenger (no groups) who chooses between: (A) a single-passenger taxi at cost A that takes the quickest route, or (B) a minibus at cost B that occasionally detours for others. The costs are assumed fixed ($A = 6\,\$$, cf. code #11) since the trips in §4.1 are short.

Between 6-7 am and 6-7 pm, the number of requests doubles (Fig. 1b) while trip speeds near Times Square are nearly 3× lower (code #10 and #12). We postulate a causal link and assume the traffic model of §2.3 when all passengers take (B); assume 1/3 the speeds when all passengers take (A); and interpolate linearly inbetween.

We take the $n = 100$ requests from §4.1 and split them randomly into a that take (A) and b that take (B). For simplicity, we keep the minibus fleet at $N = 10$ regardless of a/b. Some of (B) remain unserviced by the minibus fleet and count as (A).

We assume passengers convert excess travel time to dollars. As a proxy for this, we approximate the 2019 income[4] by the log-normal distribution with $\mu = 11$ and $\sigma = 0.7$ (code #13); a passenger's income is drawn from this log-normal; division by $52 \times 5 \times 8$h gives their hour-to-dollar conversion factor c. #14

For each condition a/b we compute the expected excess travel time e for (B) passengers. Comparing A vs. $B + (e \times c)$ for each c from the income distribution gives a ratio $\bar{a}/\bar{b}$ of those who actually prefer (A) to those who prefer (B).

This model predicts these equilibria (Fig. 6b):

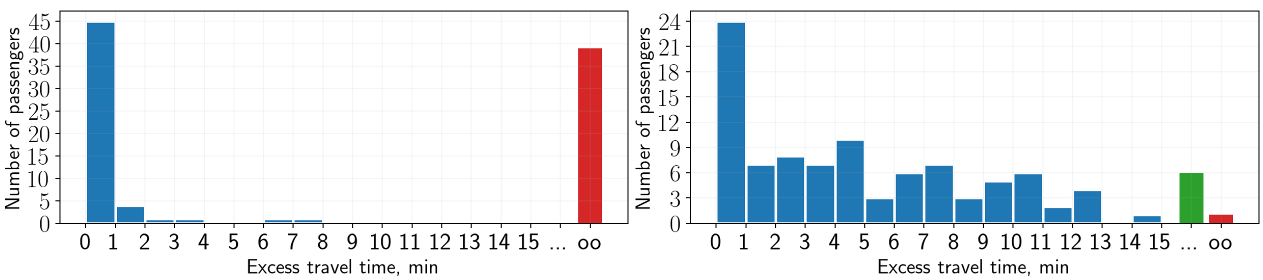
- **50-60%** would take the minibus if $A = B + 3\,\$$; and
- **80-90%** if $A = B + 6\,\$$.

[4] https://data.census.gov/cedsci/table?g=1600000US3651000&tid=ACSST5Y2019.S2001

(a) Vehicle capacity $C = 1$.

(b) Vehicle capacity $C = 8$.

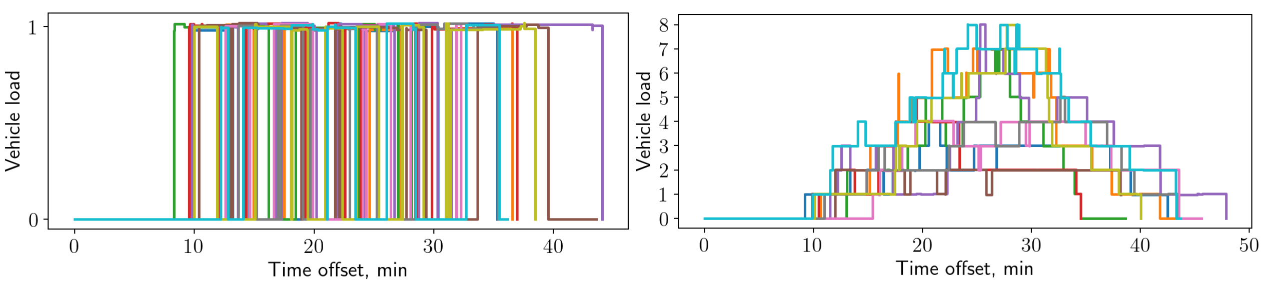
Figure 3: Passenger trajectories colored by excess travel time w.r.t. the quickest route ($n = 100$ requests for $N = 10$ vehicles). Empty red circles are unserviced pickup requests. Cf. §4.1.



(a) Vehicle capacity $C = 1$.

(b) Vehicle capacity $C = 8$.

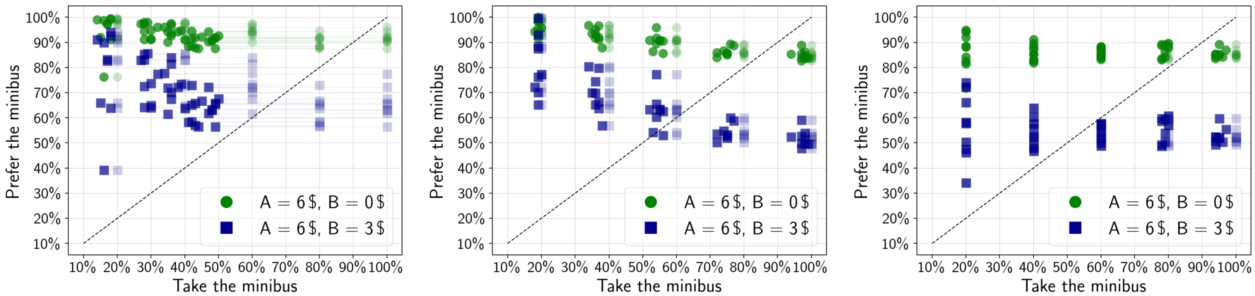
Figure 4: Histogram of excess travel time w.r.t. the quickest route ($n = 100$ requests for $N = 10$ vehicles). The last bar shows unserviced requests. See §4.1.



(a) Vehicle capacity $C = 1$.

(b) Vehicle capacity $C = 8$.

Figure 5: Load of each vehicle over time ($n = 100$ requests for $N = 10$ vehicles). The time begins at ∼17:50 when the fleet is released from the fictitious depot at Times Square. See §4.1.



(a) Bad traffic conditions. (b) Traffic depends on a/b. (c) Good traffic conditions.

Figure 6: Results of §4.2. Faint: the imposed fraction of minibus takers; solid: effective fraction without the unserviced minibus requests.

5 Conclusions

We asked whether taxis could be replaced by a smaller fleet of adaptively routed minibuses. In bad traffic conditions the minibuses do not circulate quickly enough (Fig. 6a). However, if we extrapolate "taxi" to include other point-to-point rides, including Uber/Lyft, and postulate that this will improve traffic (from 6 pm closer to that of 6 am), our model predicts that, depending on the cost differential, 50% to 90% of trips could be covered by the minibus fleet (Fig. 6b). This seems plausible, given the relative success of ride pooling/sharing UberPool and Lyft Line (typically no more than 3 concurrent passengers). Of course, better traffic conditions might invite additional traffic, spoiling the effect.

We pretended here that the demand and the traffic conditions are known in advance, whereas some 10 min in advance would be more realistic. Meanwhile, the density of requests in space and time is quite high. Thus, we believe the results remain informative.

Tradeoffs other than travel time might influence the demand, such as crowd-aversion and the flexibility with pickup and dropoff times. These could be modeled as willingness-to-pay profiles (set up by the customer or inferred by the provider); or perhaps different travel standards that depend on the current traffic could be auctioned off in near-real time.

6 Appendix

6.1 List of codes

	page	https://github.com/numpde/optimum/blob/main/ ...
#1	p.1	code/data/20210610-NYCTLC/a_download.py
#2	p.3	code/data/20210610-NYCTLC/e_explore.py
#3	p.1	code/data/20210611-OSM/a_osm_download.py
#4	p.1	code/data/20210611-OSM/c_road_graph.py
#5	p.1	code/helpers/opt_maps/maps.py
#6	p.2	code/model/20210613-GraphWithLag/b_train.py
#7	p.3	code/data/20210611-OSM/e_explore.py
#8	p.3	code/model/20210613-GraphWithLag/b_train.py
#9	p.2	code/work/20210616-OPT1
#10	p.4	code/model/20210613-GraphWithLag/c_triptime_times_square
#11	p.4	code/data/20210610-NYCTLC/e_explore/trip_fare_vs_distance
#12	p.4	code/data/20210610-NYCTLC/e_explore/trip_speeds_times_square
#13	p.4	code/data/20210621-Income
#14	p.4	code/work/20210616-OPT1/d_postprocess.py

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