Multi-Modal Transportation Simulation Framework: A Routing Game Approach

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Contents

1 INPUTS

The following files are required to run the simulation.

`INPUTS/pop_data.csv`
`INPUTS/regions.geojson`
`INPUTS/carta_gtfs.zip`
`INPUTS/gtfs_trips.obj`
`INPUTS/vehs.csv`

The following files are optional.

`INPUTS/background_traffic.obj`

Details for each are given below.

- `INPUTS/pop_data.csv`

  (or similar file) Contains population data for constructing agents in simulation. (Generated by Agrima's code).

- `INPUTS/regions.geojson`

  (or similar file) Contains information about group ondemand regions Details for generating `.geojson` files given in Sec. 5.1. The current file has regions named

  `'full','downtown','south','northeast','southwest,'east27','west27'`

  as illustrated in Fig. 1 in Section 3

- `INPUTS/carta_gtfs.zip`

  Contains stored gtfs feed information for CARTA.

- `INPUTS/gtfs_trips.obj`

  Contains precomputed optimal trips for fixed line CARTA transportion generated using the `RAPTOR` object. Generation detailed in Sec. 8.8.

- `INPUTS/vehs.csv` Contains some census data used by Agrima's input code.

- `INPUTS/background_traffic.obj` (OPTIONAL)

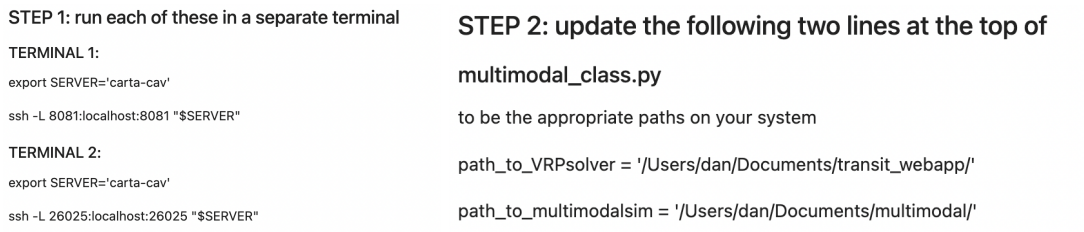
  (or similar file) Contains background traffic information.

2 RUN INSTRUCTIONS

The following is details for running the simulator in the Jupyter notebook `MULTIMODAL_SIM.ipynb`. The code depends on the functions and structures defined in `multimodal_class.py`.

- **PRELIMINARIES**

  The Instructions for connecting with the VRP solver module.



- **Imports**

  The following lines import the appropriate functions and structures.

```
[1]: %load_ext autoreload
     %autoreload 2
     from multimodal_class import *
```

- **Constructing File Names**

  The following constructs the appropriate file names.

CONSTRUCTING FILE NAMES

[9]:
```
max_num_people = 200;
ondemand_cost = 0;
num_iters = 14;
num_drivers_per_group = {'group0':int(7),'group1':int(7),'group2':int(7)}; drivers_per_group = '12n8';
region_assignment = {
    'group0':{'pickup':'south','dropoff':'downtown'},
    'group1':{'pickup':'south','dropoff':'south'},
    'group2':{'pickup':'downtown','dropoff':'downtown'},
}

name = 'case3'

save_fits_file = 'INPUTS/' + name + '.pickle';
load_fits_file = save_fits_file;
save_outputs_folder = 'OUTPUTS/' + name
dashboard_folder = 'DASH/' + name;
csv_file_path = 'INPUTS/pop_data.csv'
geojson_file = 'INPUTS/regions.geojson'; # + str(regions_num) + '.geojson';

print('geojson_file: ',geojson_file)
print('load_fits_file: ',load_fits_file)
print('save_fits_file: ',save_fits_file)
print('save_outputs_folder: ',save_outputs_folder)
print('dashboard_folder: ',dashboard_folder)
```

```
geojson_file:  INPUTS/regions.geojson
load_fits_file:  INPUTS/case3.pickle
save_fits_file:  INPUTS/case3.pickle
save_outputs_folder:  OUTPUTS/case3
dashboard_folder:  DASH/case3
```

- **Initial Parameters Inputs**

INITIAL PARAMETER INPUTS

[10]:
```
params = {'csv_file_path': csv_file_path, #'INPUTS/PRE_micro_0.csv',
          'modes':['drive','walk','gtfs','ondemand'],
          'time_window': [21600,36000], # in seconds. 6 AM to 10 AM
          'bnds':[np.array([-85.3394,  34.9458]), # bottom left
                  np.array([-85.2494,  35.0658])], # top right
          'groups_regions_geojson': geojson_file, #'INPUTS/regions3.geojson',
          'max_num_people':max_num_people,
          # 'groups_regions_pickup_geojson': geojson_pickup_file, #'INPUTS/regions3.geojson',
          # 'groups_regions_dropoff_geojson': geojson_dropoff_file, #'INPUTS/regions3.geojson',
          'num_drivers_per_group': num_drivers_per_group, #{'group0':int(10),'group1':int(4),'group2':int(4)},
          'region_assignment': region_assignment,
          'monetary_costs':{'ondemand':0,'gtfs':1.5},
          # 'background_congestion_file': 'INPUTS/background_traffic1.obj',  # OPTIONAL - LOADS BACKGROUND TRAFFIC
          ############ PRECOMPUTED GTFS DATA ###########
          'load_ondemand_fits': load_fits_file, #'INPUTS/load_file.pickle',
          'save_ondemand_fits': save_fits_file, #'INPUTS/save_file.pickle',
          'gtfs_feed_file': 'INPUTS/carta_gtfs.zip',
          'gtfs_precomputed_file': 'INPUTS/gtfs_trips.obj'}
```

- **Generate Population**

[7]:
```
if not os.path.exists(save_outputs_folder):
    os.mkdir(save_outputs_folder);
    os.mkdir(save_outputs_folder+'/figs');
```

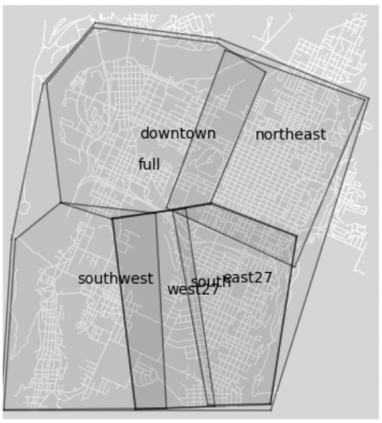
[8]:
```
if False: #not os.path.exists(csv_file_path):
    df = GENERATE_SAMPLE_POPULATION('data/pop/lodes_combinations_upd.parquet',filter_region_path=geojson_file,sample_num = 10000)
    df.to_csv(csv_file_path); #, index_label='tag')'INPUTS/new_pop_data1.csv'
```

- **Initialize Simulation**

[13]:
```
# OPTION-1: FULL ONE-SHOT SETUP
# BLAH = WORLD(params,full_setup = True)
# OPTION-2: STEP-BY-STEP SETUP
WORLD1 = WORLD(params)
WORLD1.initGRAPHSnFEEDS();
WORLD1.initREGIONS();
```

```
monetary cost of drive segment: 0 $
monetary cost of walk segment: 0 $
monetary cost of gtfs segment: 1.5 $
monetary cost of ondemand segment: 0 $
```

[32]:
```
WORLD1.plotREGIONS(figsize=(5,5),includes={'labels':True},
                   specregions=['full','downtown','south','northeast','southwest','west27','east27']);
                   # specregions=['downtown','south','northeast','southwest']); #'west27','east27']);
```



[15]:
```
WORLD1.initNETWORKS();
WORLD1.initCONVERTER();
WORLD1.initSTATS()
WORLD1.initONDEMAND();
WORLD1.initPEOPLE();
WORLD1.initBACKGROUND();
```

```
constructing NETWORK  drive mode...
constructing NETWORK  walk mode...
constructing NETWORK  gtfs mode...
constructing NETWORK  ondemand mode...
adding 7 to group0 ...
adding 7 to group1 ...
```

- **Plot ODs & Group Regions**

•[11]:
```
from multimodal_class import *
WORLD1.plotPRELIMINARIES(include_demand_curves=False,save_file=save_outputs_folder+'/figs/od_regions.png',figsize=(5,5));
```

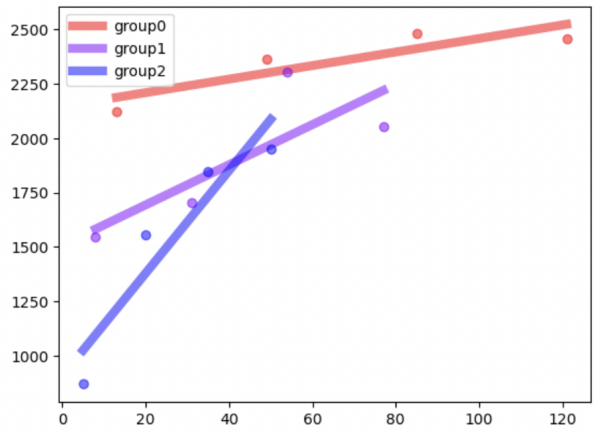
```
OUTPUTS/regionsC_drivers8n8_cost0_people300_iters6/figs/od_regions.png
```

- **Fit Congestion Demand Models**

[12]:
```
from multimodal_class import *
WORLD1.load_fits = False;
# counts = {'num_counts':8,'num_per_count':1}
counts = {'num_counts':4,'num_per_count':1}
WORLD1.fitModels(counts=counts,force_initialize=True);
```

PRELIMINARY DEMAND CURVES (OPTIONAL)

[18]:
```
colors = {'group0':[1,0,0,0.5],'group1':[0.5,0,1,0.5],'group2':[0,0,1,0.5],'group3':[1,0.5,0.,0.5]};
WORLD1.ONDEMAND.plotCongestionModels(colors=colors,save_file=save_outputs_folder+'/figs/demand_curves.pdf')
```



[14]:
```
# WORLD1.save_fits = True; #se; # must be set to True
# WORLD1.save_fits_file = save_fits_file;
# WORLD1.saveFits();
```

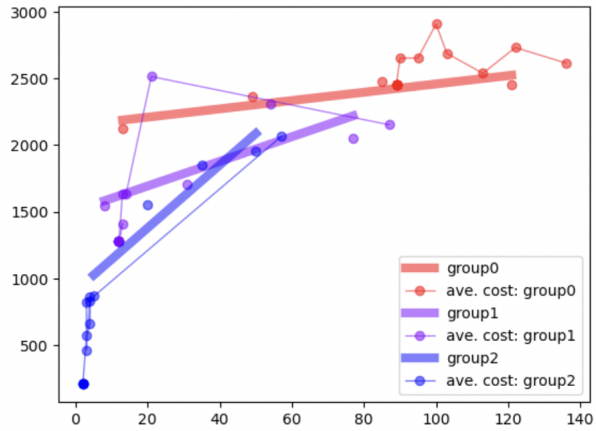
- **Run Simulation**

•[16]:
```
from multimodal_class import *
num_iters = 10;
WORLD1.SIM(num_iters = num_iters, restart = False, constants = ['drive','gtfs','walk']);
WORLD1.initUNCONGESTED()
```

- **Plot Ondemand Convergence**

PLOT DEMAND CONVERGENCE ¶

[22]:
```
colors = {'group0':[1,0,0,0.5],'group1':[0.5,0,1,0.5],'group2':[0,0,1,0.5],'group3':[1,0.5,0.,0.5]};
WORLD1.ONDEMAND.plotCongestionModels(colors=colors,with_converge = True, save_file=save_outputs_folder+'/figs/demand_curves_wconvergence.pdf
```



- **Generate Outputs**

```
•[19]: from multimodal_class import *
WORLD1.generateOutputs(); #randomize=['money','switches']);
mode = 'ondemand'
dfs_to_show = [mode]
WORLD1.printOutputs(show_active=True,dfs_to_show = dfs_to_show,row_count = 100);
WORLD1.saveOutputs(save_outputs_folder,typ='pickle',overwrite=True)
```

- **Generate Dashboard**

```
•[22]: from multimodal_class import *
WORLD1.generateLayers();
WORLD1.plotLAYERS(folder = dashboard_folder,overwrite = True,verbose=False)

WORLD1.DASH = DASHBOARD(WORLD1.dash_folder);
WORLD1.DASH.makeGrid();
WORLD1.DASH.addOutputs(WORLD1.OUTPUTS,use_active=True,filter_for_zeros=True)
WORLD1.DASH.addImages(WORLD1.layers)

WORLD1.DASH.show()
import plotly.io as pio
pio.write_html(WORLD1.DASH.fig, file=dashboard_folder+'/dash.html', auto_open=True)
```

3 EXAMPLES

We now give several examples of case studies run with the simulator.

The first set of case studies focus on how the use of ondemand service changes as a fixed number of drivers are split up among different areas of the downtown Chattanooga. (The population data in these studies can be improved and thus the results improved as well.)

We consider the following regions with names labeled

Figure 1: Labeled group operation regions in Chattanooga

Each ondemand group makes trips back and forth between a pickup region and a dropoff region. We run several case studies comparing different divisions of drivers among ondemand groups

- **CASE 1:**

  - `group0`: pickup = 'downtown'; dropoff = 'south'; num drivers = 8
  - `group1`: pickup = 'south'; dropoff = 'south'; num drivers = 12

- **CASE 2:**
  - `group0`: pickup = 'downtown'; dropoff = 'south'; num drivers = 12
  - `group1`: pickup = 'south'; dropoff = 'south'; num drivers = 8

- **CASE 3:**
  - `group0`: pickup = 'downtown'; dropoff = 'south'; num drivers = 8
  - `group1`: pickup = 'south'; dropoff = 'south'; num drivers = 6
  - `group2`: pickup = 'west27'; dropoff = 'east27'; num drivers = 6

Each simulation is run with 200 agents from 6 AM to 10 AM. The monetary cost of a fixed line transit trip is $1.5 and the ondemand service is taken to be free.

3.1 CASE 1:

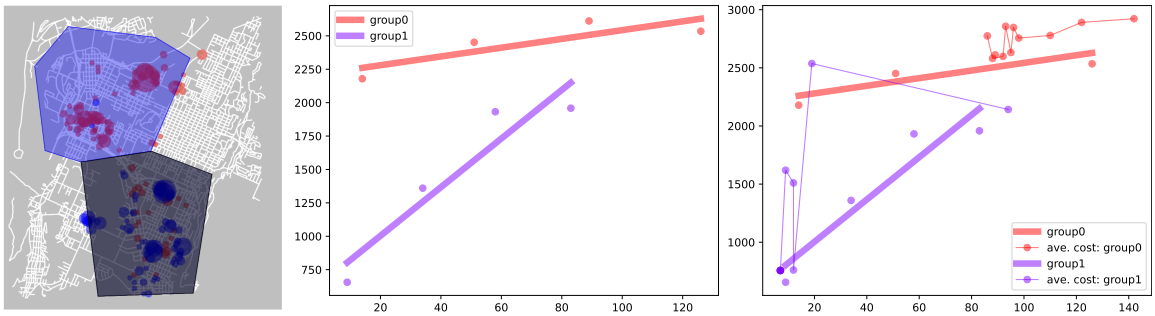
In the first case study we consider two groups of ondemand drivers: one taking passengers back and forth between the `'south'` region and the `'downtown'` region and one taking drivers back and forth in the `'south'` region. We consider 8 drivers between the downtown and south regions and 12 drivers within the south region.

- **Params:**
  - Agents: 200
  - Time: 6AM -10 AM
  - Ondemand groups:
    - `group0`: pickup = 'downtown'; dropoff = 'south'; num drivers = 8
    - `group1`: pickup = 'south'; dropoff = 'south'; num drivers = 12

- **Results:** `OUTPUTS/case1/*`
  - `OUTPUTS/case1/mode_drive.pickle`: driving mode statistics
  - `OUTPUTS/case1/mode_walk.pickle`: walking mode statistics
  - `OUTPUTS/case1/mode_gtfs.pickle`: fixed line transit statistics
  - `OUTPUTS/case1/mode_ondemand.pickle`: ondemand mode statistics
  - `OUTPUTS/case1/mode_ondemand_driver_runs.pickle`: specific statistics for ondemand driver runs. `OUTPUTS/case1/dash.html`: interactive dashboard

The results are contained in folder `OUTPUTS/case1/`. The pickle files contain the output data for various travel modes on ondemand metrics (see Sec. 6.1 for details/format). `dash.html` contains the html dashboard.

Fig. 2a shows the pickup/dropoff regions and the origin-destination pairs for the agents. Fig. 2b shows the demand curve fits (could be improved by more data points) and Fig. 2also the ondemand costs converging over the course of the simulation.



(a) OD-pairs & group regions (b) Ondemand latency curves (c) Iteration convergence of ondemand latency costs

Figure 2: Dashboard example for example with one region with 20 ondemand drivers.

Fig. 3 contains a screenshot of the dashboard.

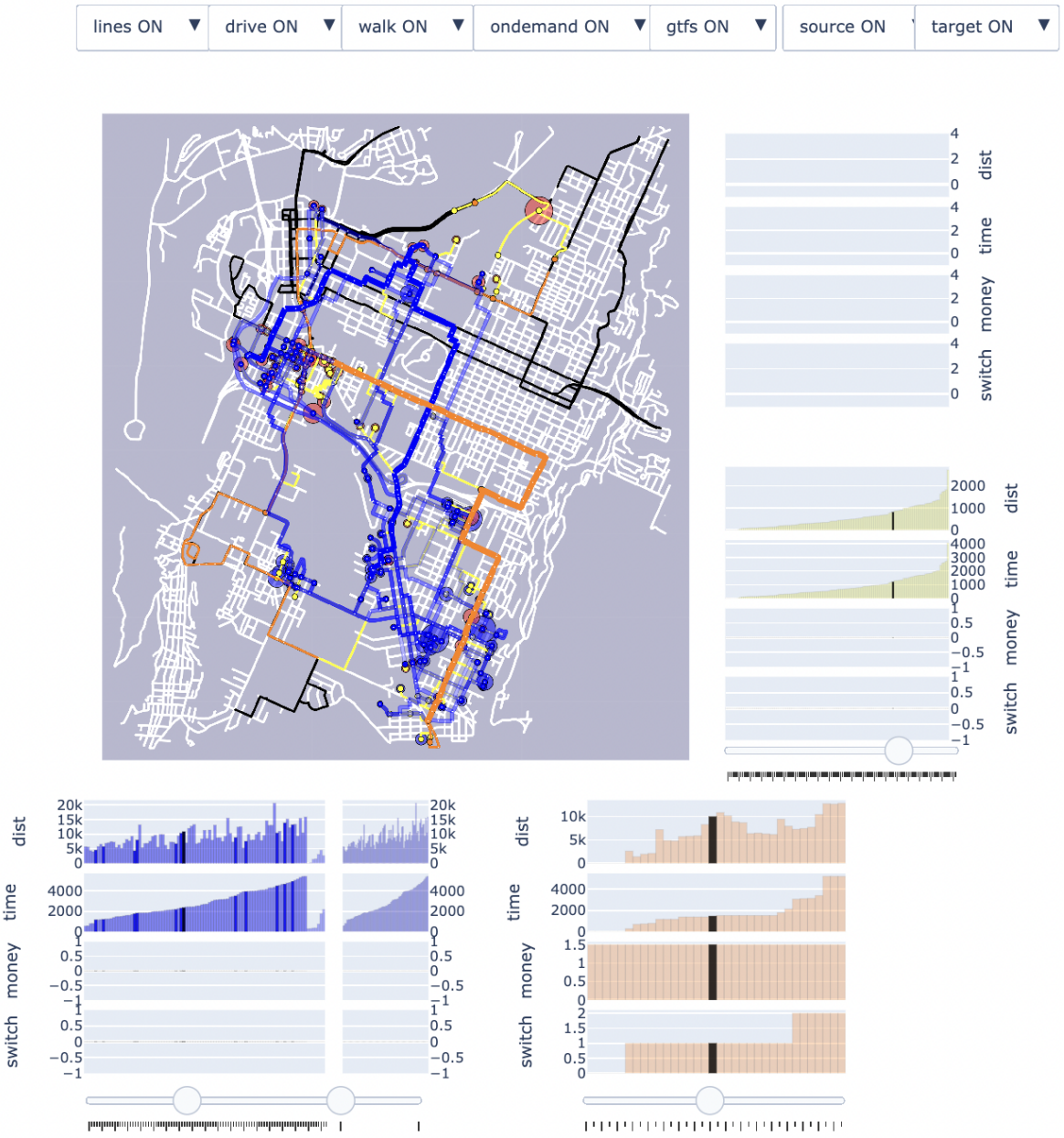


Figure 3: Dashboard example.

3.2 CASE 2:

In the second case study we consider two groups of ondemand drivers: one taking passengers back and forth between the `'south'` region and the `'downtown'` region and one taking drivers back and forth in the `'south'` region. We consider 12 drivers between the downtown and south regions and 8 drivers within the south region.

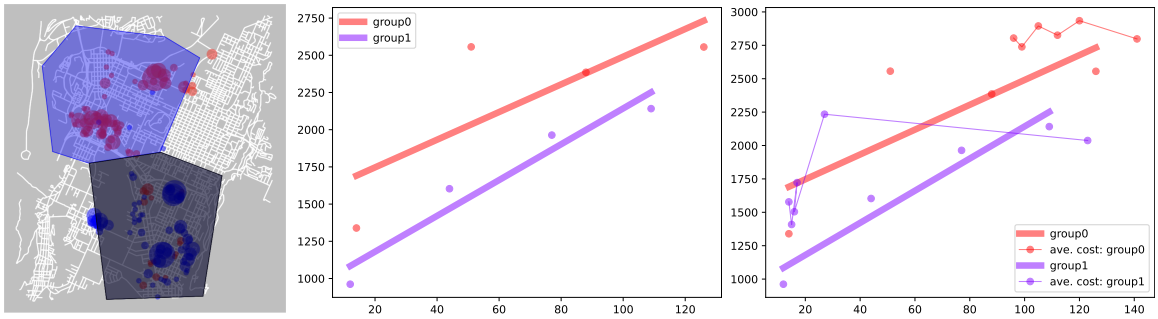
- **Params:**

  - Agents: 200
  - Time: 6AM -10 AM
  - Ondemand groups:
    * `group0`: pickup = 'downtown'; dropoff = 'south'; num drivers = 12
    * `group1`: pickup = 'south'; dropoff = 'south'; num drivers = 8

- **Results:** `OUTPUTS/case2/*`
  - `OUTPUTS/case2/mode_drive.pickle`: driving mode statistics
  - `OUTPUTS/case2/mode_walk.pickle`: walking mode statistics
  - `OUTPUTS/case2/mode_gtfs.pickle`: fixed line transit statistics
  - `OUTPUTS/case2/mode_ondemand.pickle`: ondemand mode statistics
  - `OUTPUTS/case2/mode_ondemand_driver_runs.pickle`: specific statistics for ondemand driver runs. `OUTPUTS/case2/dash.html`: interactive dashboard

The results are contained in folder `OUTPUTS/case2/`. The pickle files contain the output data for various travel modes on ondemand metrics (see Sec. 6.1 for details/format). `dash.html` contains the html dashboard.

Fig. 4a shows the pickup/dropoff regions and the origin-destination pairs for the agents. Fig. 4b shows the demand curve fits (could be improved by more data points) and Fig. 4also the ondemand costs converging over the course of the simulation.



(a) OD-pairs & group regions (b) Ondemand latency curves (c) Iteration convergence of ondemand latency costs

Figure 4: Dashboard example for example with one region with 20 ondemand drivers.

Fig. 5 contains a screenshot of the dashboard.

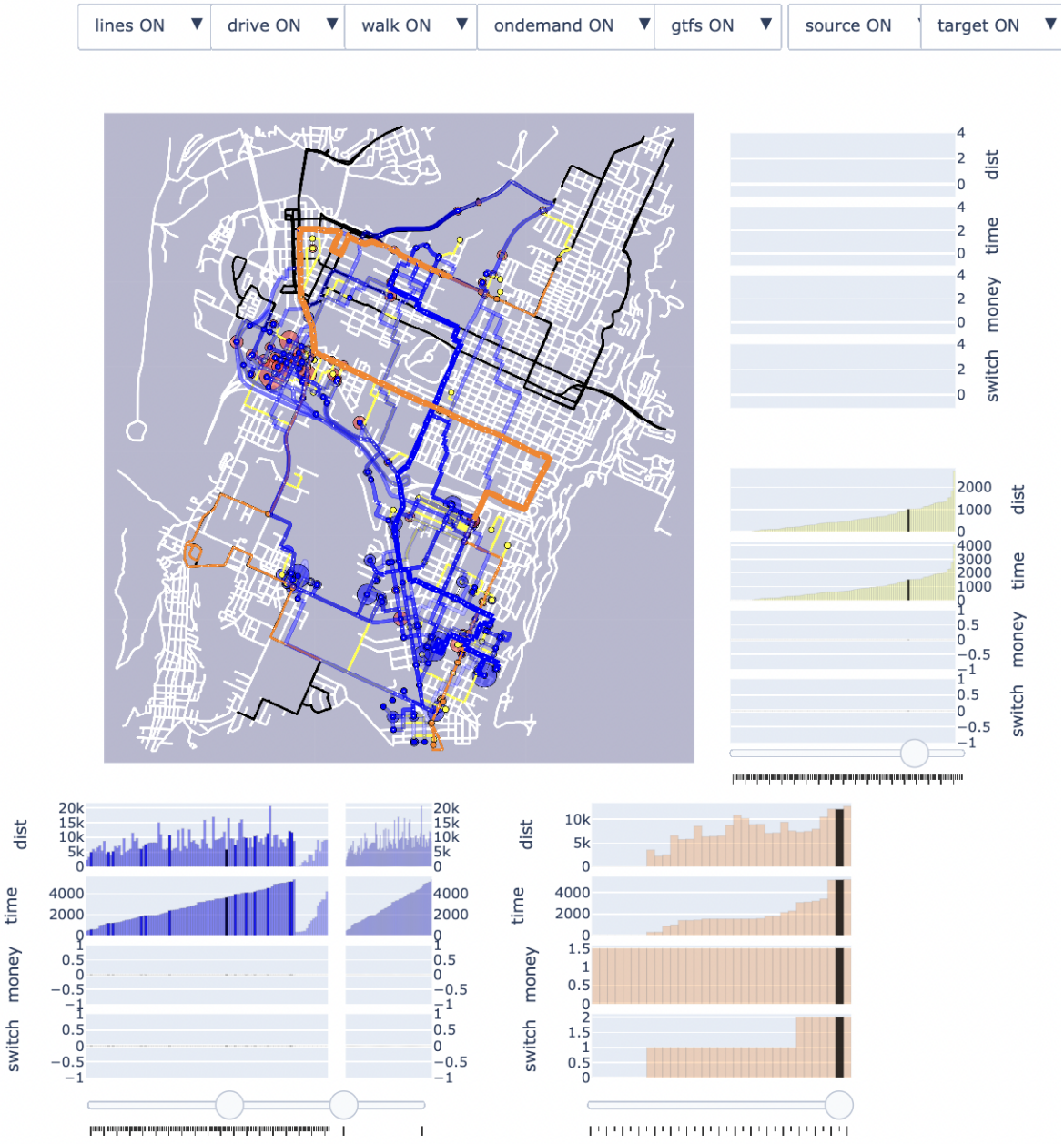


Figure 5: Dashboard example.

3.3 CASE 3:

In the third case study we consider three groups of ondemand drivers: one taking passengers back and forth between the `'south'` region and the `'downtown'` region with 8 drivers, one taking drivers back and forth in the `'south'` region with 6 drivers, and one shuttling drivers back and forth between `west27` and `east27` with 6 drivers.

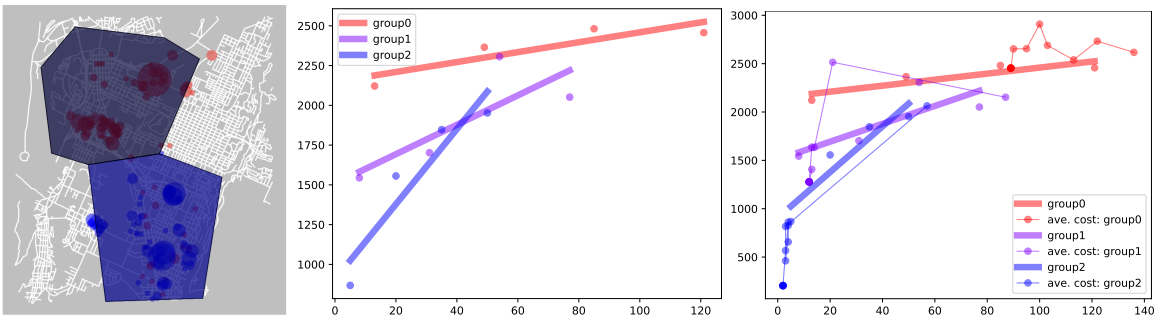
- **Params:**

- Agents: 200
- Time: 6AM -10 AM
- Ondemand groups:
  - `group0`: pickup = 'downtown'; dropoff = 'south'; num drivers = 8
  - `group1`: pickup = 'south'; dropoff = 'south'; num drivers = 6
  - `group2`: pickup = 'west27'; dropoff = 'east27'; num drivers = 6

- **Results:** `OUTPUTS/case3/*`
  - `OUTPUTS/case3/mode_drive.pickle`: driving mode statistics
  - `OUTPUTS/case3/mode_walk.pickle`: walking mode statistics
  - `OUTPUTS/case3/mode_gtfs.pickle`: fixed line transit statistics
  - `OUTPUTS/case3/mode_ondemand.pickle`: ondemand mode statistics
  - `OUTPUTS/case3/mode_ondemand_driver_runs.pickle`: specific statistics for ondemand driver runs. `OUTPUTS/case3/dash.html`: interactive dashboard

The results are contained in folder `OUTPUTS/case3/`. The pickle files contain the output data for various travel modes on ondemand metrics (see Sec. 6.1 for details/format). `dash.html` contains the html dashboard.

Fig. 6a shows the pickup/dropoff regions and the origin-destination pairs for the agents. Fig. 6b shows the demand curve fits (could be improved by more data points) and Fig. 6also the ondemand costs converging over the course of the simulation.



(a) OD-pairs & group regions (b) Ondemand latency curves (c) Iteration convergence of ondemand latency costs

Figure 6: Dashboard example for example with one region with 20 ondemand drivers.

Fig. 7 contains a screenshot of the dashboard.

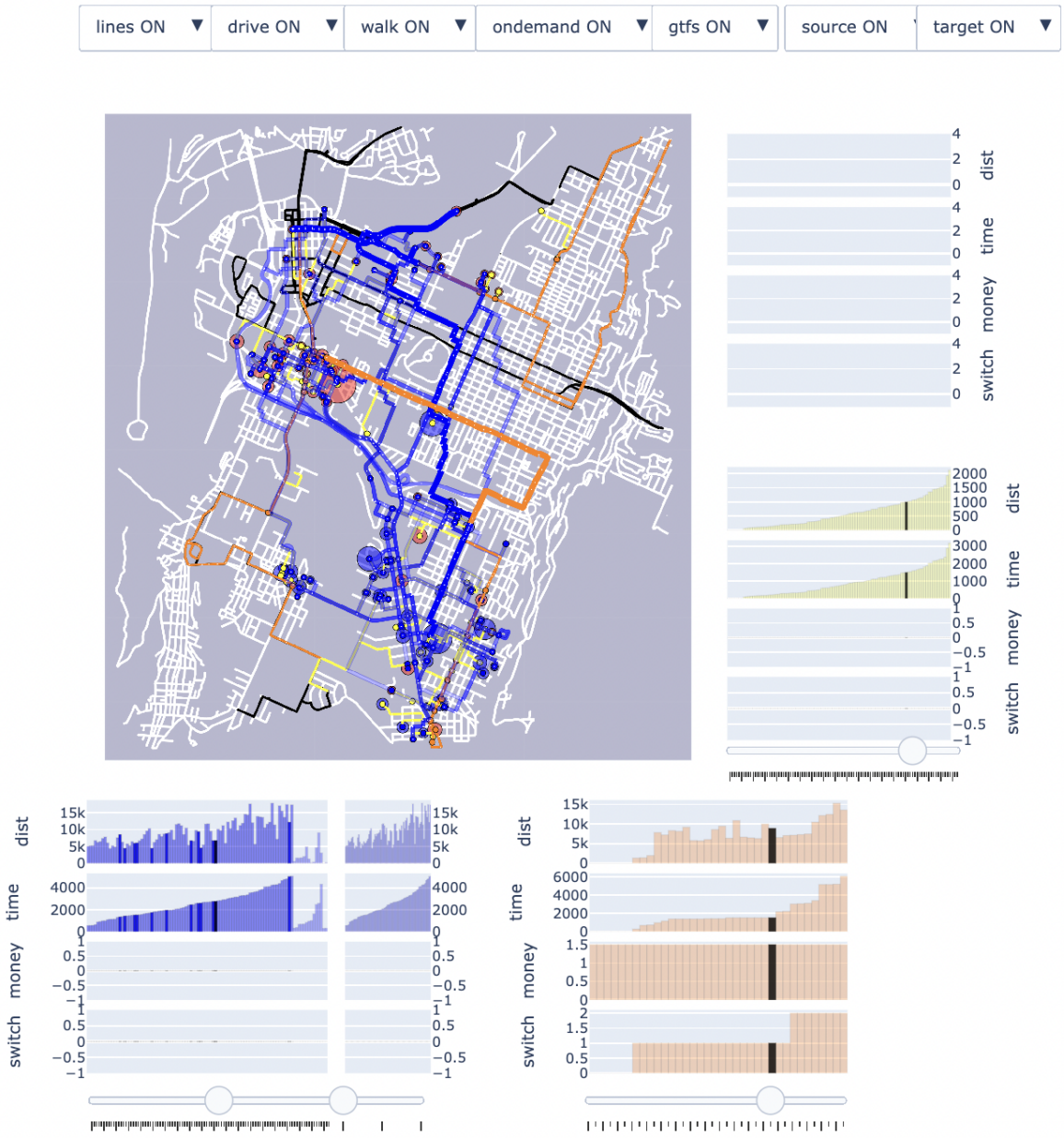


Figure 7: Dashboard example for example.

4 METHODOLOGY

4.1 Travel Time Costs

At each iteration of the simulation, an estimate of travel time is kept based on current congestion in the network. For the driving network this estimate is kept for each edge/street; for the ondemand network this estimate is kept for each ondemand group. (The travel times for fixed line and walking are currently taken to

be independent of congestion.) At each iteration, the travel times are updated based on a dual formulation of classical routing games. This update procedure is detailed here and implemented by the `NETWORK` objects in the function `NETWORK.UPDATE`.

4.1.1 Routing Game Formulation - Primal

In a classical multi-commodity routing game, agents are modeled as a continuous population mass that spreads out over various routes in a network. We give a brief exposition here; more details can be found in [1] and the many references there in.

To formulate a routing game optimization problem we consider a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with nodes $\mathcal{V}$ and edges $\mathcal{E}$. We can write the node-edge incidence matrix of the graph as $E \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{E}|}$.

The routing game optimization problem can be formulated as follows

$$\min_{x_{ij}} \quad \sum_e \int_0^{x_e} \ell_e(u)\, du \tag{1a}$$

$$\text{s.t.} \quad x = \sum_{ij} x_{ij}, \quad Ex_{ij} = S_{ij}m_{ij}, \quad x_{ij} \geq 0 \quad \forall i, j \tag{1b}$$

Here the indices ij refer to different origin-destination pairs; $x_{ij} \in \mathbb{R}^{|\mathcal{E}|}$ is vector of mass flows on each graph edge from the population traveling from i to j and $x \in \mathbb{R}^{|\mathcal{E}|}$ is a vector of the total mass flows on each edge (from all populations combined). m_{ij} is the total population mass traveling from i to j. S_{ij} is a source-sink vector indicating the origin and destination node. By conservation of mass (under some basic assumptions like the graph is simply connected) the constraint $Ex_{ij} = S_{ij}m_{ij}$ ensures that x_{ij} represents the mass traveling from i to j on each edge. Each function $\ell_e(x_e)$ is a latency function that gives the travel time on edge e when population mass $x_e \in \mathbb{R}_+$ is traveling on that edge. $\ell_e(\cdot)$ is usually a positive, increasing function of it's argument in order to encode congestion. The objective function ensures that the effective edge cost for an infinitesimal mass agent in the simulation are the latencies functions at the current level congestion. This is ensured by the KKT conditions of the optimization problem. Specifically at optimal, stationarity with respect to x_{ij} is given by

$$\ell(x)^\top - v_{ij}^\top E - \mu_{ij}^\top = 0 \tag{2}$$

where $\ell : x \mapsto \mathbb{R}^{|\mathcal{E}|}$ is vector of all the individual latency functions on each edge, $v_{ij} \in \mathbb{R}^{|\mathcal{V}|}$ is a dual variable associated with the incidence matrix constraint that encodes the optimal cost-to-go information for population ij, and $\mu_{ij} \in \mathbb{R}_+^{|\mathcal{E}|}$ is the dual variable associated with the positivity constraint that encodes the inefficiency of traveling on a particular edge. By complementary slackness, we also have that $\mu_{ij}^\top x_{ij} = 0$, ie. no mass in the optimal vector x_{ij} is on an inefficient edge. This KKT condition can also be used as a certificate for testing the optimality of any particular route. For an indicator vector $\xi \in \mathbb{R}^{|\mathcal{E}|}$ that encodes a path from i to j, we have that $E\xi = S_{ij}$. We can then multiply ξ by 2 to get that

$$\ell(x)^\top \xi = v_{ij}^\top E\xi + \mu_{ij}^\top \xi = v_{ij}^\top S_{ij} + \mu_{ij}^\top \xi$$

Here $\ell(x)^\top \xi$ is the cost (travel time) of route ξ; $v_{ij}^\top S_{ij}$ is the optimal travel cost from i to j (which is the same for all routes); $\mu_{ij}^\top \xi > 0$ is the inefficiency of route ξ. If ξ only uses edges that have strictly positive mass in x_{ij}, then $\mu_{ij}^\top \xi = 0$ and ξ is an efficient route.

The routing game optimization problem can be updated to include a variable demand function as well that details how the population mass between each origin and destination varies as the price of travel varies. Specific we can update Eq. 1.

$$\min_{x_{ij}, m_{ij}} \quad \sum_e \int_0^{x_e} \ell_e(u)\, du - \sum_{ij} \int_0^{m_{ij}} d_{ij}(u) du \tag{3a}$$

$$\text{s.t.} \quad x = \sum_{ij} x_{ij}, \quad Ex_{ij} = S_{ij}m_{ij}, \quad x_{ij} \geq 0 \quad \forall i, j \tag{3b}$$

Now the mass traveling between each orign and destination pair i, j denoted m_{ij} is a variable and $d_{ij}(m_{ij})$ is an invertible demand function that relates the travel time from i to j to the amount of mass m_{ij} that will choose to take that route. It is somewhat more intuitive to consider the inverse of this function d_{ij}^{-1}. If the travel time from i to j is given by $v_{ij}^\top S_{ij}$ then

$$m_{ij} = d_{ij}^{-1}\left(v_{ij}^\top S_{ij}\right)$$

is the amount of mass of mass that will make the trip at that travel cost. In general, d_{ij}^{-1} will be a decreasing function of the cost, ie. as the travel cost increases, less population will choose to travel. Making m_{ij} a variable and adding the new integral term in Eq. 3a changes the stationarity conditions (2) to

$$\ell(x)^\top - v_{ij}^\top E - \mu_{ij}^\top = 0, \qquad d_{ij}(m_{ij}) = v_{ij}^\top S_{ij} \tag{4}$$

which ensures that m_{ij} is consistent with the demand function at optimum.

4.1.2 Routing Game Formulation - Dual

The dual form of problem (3) can be written as

$$\min_{c,\lambda_{ij},v_{ij},\mu_{ij}} \quad v_{ij}^\top S_{ij} - \sum_e \int_{\ell_e(0)}^{c_e} \ell_e^{-1}(u)\ du \tag{5a}$$

$$\text{s.t.} \quad c^\top = v_{ij}^\top E + \mu_{ij}^\top, \quad \mu_{ij} \geq 0, \quad \forall ij \tag{5b}$$

Here $c \in \mathbb{R}^{|\mathcal{E}|}$ is a new variable that represents the estimated travel time on each edge. $\lambda_{ij} \in \mathbb{R}$ is the travel time on each route. The dual problem can be interpreted as solving for the cost variable information $c, \lambda_{ij}, v_{ij}, \mu_{ij}$ as opposed to the mass flow information. The constraints in (6b) implement the Bellman equation on the graph for each origin destination pair for cost variables c. The objective function makes sure that at optimum, the edge costs c_e are consistent with the mass flow on that edge.

If we want to include the variable demand formulation, the dual problem becomes

$$\min_{c,\lambda_{ij},v_{ij},\mu_{ij}} \sum_{ij} \int_{d_{ij}(0)}^{\lambda_{ij}} d_{ij}^{-1}(u)\ du - \sum_e \int_{\ell_e(0)}^{c_e} \ell_e^{-1}(u)\ du \tag{6a}$$

$$\text{s.t.} \quad c^\top = v_{ij}^\top E + \mu_{ij}^\top, \quad \lambda_{ij} = v_{ij}^\top S_{ij}, \quad \mu_{ij} \geq 0, \quad \forall ij \tag{6b}$$

Here λ_{ij} represents the optimal travel time from i to j. Note the changes to the objective function as well.

4.1.3 Dual Algorithm: Driving Edge Cost Updates

There many algorithms for solving these type of problems (see [1]). We make use of a particular subgradient algorithm for the dual problem updating the estimated edge costs $c \in \mathbb{R}^{|\mathcal{E}|}$ and $\lambda_{ij} \in \mathbb{R}$ for each i, j. (We follow the derivations given in [1] in Sec. 2.3.3 "Further Properties of Equilibrium Soltuions"(p.44) and Sec. 4.3.7 "Dual Algorithms" (p.141).)

To define this algorithm, we first give several intermediate variables. First, for a specific cost vector $c \in \mathbb{R}^{|\mathcal{E}|}$, let $\hat{x}(c) \in \mathbb{R}_+^{|\mathcal{E}|}$ define the predicted flow given by the inverses of the latency functions.

$$\hat{x}_e(c_e) = \begin{cases} \ell_e^{-1}(c_e), & c_e \geq \ell_e(0) \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

(Note that $\hat{x}$ is an intermediate estimate of the flow vector and may not be consistent with the graph structure.) Next, for each origin-destination pair, using any shortest path algorithm such as Dijkstra or

A^*-search, we can compute an optimal shortest path and denote it by an indicator vector $\xi_{ij}(c) \in \mathbb{R}^{|\mathcal{E}|}$. Let the total travel time along this shortest path be given by $\lambda_{ij}(c)$ and the resultant expected mass demand given by

$$\hat{d}_{ij}(c) = \begin{cases} d_{ij}^{-1}(\lambda_{ij}(c)), & \lambda_{ij}(c) \geq d_{ij}(0) \\ d_{ij}(0), & \text{otherwise} \end{cases}$$

The subgradient update at iteration k for $c \in \mathbb{R}^{|\mathcal{E}|}$ can be written as

$$c_e^{(k+1)} = \max\left\{\ell_e(0), c_e^{(k)} + \alpha_k \partial c_e, \right\} = \begin{cases} c_e^{(k)} + \alpha_k \partial c_e, & c_e^{(k)} + \alpha_k \partial c_e \geq \ell_e(0) \\ \ell_e(0), & \text{otherwise} \end{cases}$$

where the subgradient is given by

$$\partial c_e = \left[\sum_{ij} \hat{d}_{ij}\big(c^{(k)}\big)\big[\xi_{ij}\big(c^{(k)}\big)\big]_e\right] - \hat{x}_e$$

and $\lambda_{ij}(c^{(k)})$ is the shortest path cost given the current edge cost estimates $c^{(k)}$. α_k is a stepsize condition that we choose to satisfy the divergent series condition

$$\lim_{k\to\infty} \alpha_k = 0, \qquad \sum_{k=1}^{\infty} \alpha_k = +\infty, \qquad \sum_{k=1}^{\infty} \alpha_k^2 < +\infty. \tag{8}$$

Again, this gradient update is implemented by the `NETWORK` objects in the function `NETWORK.UPDATE`.

4.1.4 Determining Driving Latency Functions

The above optimization problem is dependent on the latency functions $\ell_e(x_e)$. We compute these separately for each edge based on geographic features of each street including street length, speed limit, number of lanes, etc. We use a cubic model given in [1] (Sec. Link Performance Functions, p. 20) for the travel time on edge e for driving modes and a constant travel time for walking modes with no substantial congestion.

$$\ell_e(x_e) = t_e^0\Big(1 + 0.15\big(\tfrac{x_e}{c_e}\big)^{m_e}\Big) \qquad \text{links with congestion (driving)}$$
$$\ell_e(x_e) = t_e^0 \qquad \text{links with no congestion (walking)}$$

where the latency parameters and their computation are given here.

- t_e^0 - **uncongested travel time on edge:** we compute this as

  $$t_e^0 = \frac{\text{street length (meters)}}{\text{speed limit (meters/second)}}$$

  with default speed limit taken to be 20.1 meters per second (45 mph) for driving modes (and 0.67 meters per second (1.5 mph) for walking modes).

- c_e - **edge capacity:** the quantity of edge flow where traffic stops. we compute this as

  $$c_e = \text{lane capacity } \times \text{num. of lanes}$$

  We take lane capacity to be 0.5278 vehicles per second per lane (1900 vehicles/hr/lane) with the default number of lanes being 1 for streets with lane number not listed in open street map.

- m_e - **degree factor:** Factor that determines the degree of the polynomial latency function. We take $m_e = 3.$, ie. a cubic latency function, for driving modes

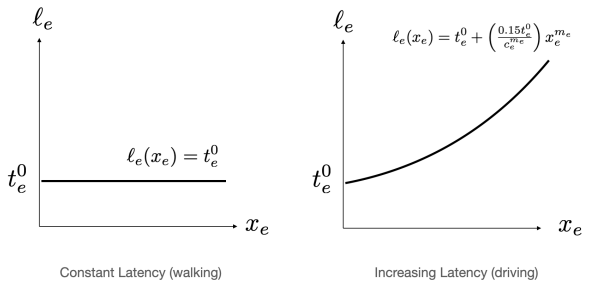


Figure 8: Graphical representation of latency functions

4.2 Ondemand Cost Estimation

Inspired by the routing game formulation in the section, we employ a similar dual cost update scheme to find the equilibrium travel time costs for ondemand groups. Similar to the way the edge latency functions $\ell_e(x_e)$ estimate the travel time on an edge given traffic flow x_e, we fit latency functions $L_g(m_g)$ that give the approximate travel time for each group dependent on the total population that is using the ondemand service. The form of $L_g(m_g)$ is similar to $\ell_e(x_e)$, an increasing function of it's argument, ie. as more population mass uses the ondemand service in a particular group, the average travel time for the group will be higher.

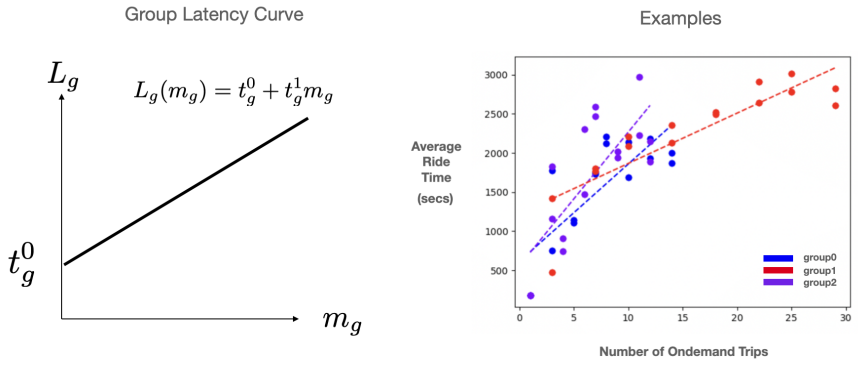


Figure 9: Graphical representation of estimated latencies for ondemand groups

Note that the group latency functions must be fit from data since the actual travel terms are determined by a vehicle routing solver and is significantly more complicated than the travel time based on traffic flow on a street.

4.2.1 Fitting Ondemand Latency Curves

The ondemand latency functions are estimated empirically from data using the VRP solver. For an ondemand group with a given geographic region and a list of potential passengers, random groups of different numbers of those customers are selected and routes are planned for them in order to determine the approximate travel time for an average passenger in the group as a function of how many other passengers are also using it. The current model fits a simple linear group latency function but more complicated curves could easily be implemented and used. The following lines call the ondemand latency fitting functions in the Jupyter notebook.

```
[12]: from multimodal_class import *
      WORLD1.load_fits = False;
      # counts = {'num_counts':8,'num_per_count':1}
      counts = {'num_counts':4,'num_per_count':1}
      WORLD1.fitModels(counts=counts,force_initialize=True);
```

Figure 10: Jupyter notebook lines for fitting ondemand curves

The variables `counts['num_counts']` gives the number of counts of passengers to fit travel times for. The trip counts are selected linearly between 0.1×total possible number of passengers and 0.9×total number. For example, if a group has a maximum possible 100 passengers and `counts['num_counts']=8` then we fit the demand curve by computing optimal group travel time for `[10,20,30,40,50,60,70,80,90]` number of passengers. The individual passengers for each of these counts are randomly selected from the full 100 passengers. Different random groups of passengers will clearly give different group travel times. To get a better fit, we include the variable `counts['num_per_count']` which determines how many different samples should be taken for each count of passengers. For the examples in Fig. 10, `counts['num_per_count']=2`. A more sophisticated approach would be to order the passengers in the group by when they would switch over from their other travel options and then select the first number of passengers for each count. For example, for a count of 30 passengers, the first 30 passengers would be chosen.

4.2.2 Dual Algorithm: Ondemand Group Cost Updates

The travel cost estimate is updated using a rule similar to the driving time edge update. For each group g, we keep track of an estimate of the group travel time $c_g \in \mathbb{R}_+$. From the latency function fit in the previous section for each group, for a specific travel time c_g we can compute the expected population mass that will use the ondemand group

$$\hat{m}_g(c_g) = \begin{cases} L_g^{-1}(c_g), & c_g \geq L_g(0) \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

At each iteration of the simulation, comparing the group travel cost c_g with the other travel options passengers in the group will generate a number of passengers that select the ondemand group m_g. We then use a subgradient style update the estimated group cost.

$$c_g^{(k+1)} = \max\left\{L_g(0), c_g^{(k)} + \alpha_k \partial c_g, \right\} = \begin{cases} c_g^{(k)} + \alpha_k \partial c_g, & c_g^{(k)} + \alpha_k \partial c_g \geq L_g(0) \\ L_g(0), & \text{otherwise} \end{cases}$$

where the subgradient is given by

$$\partial c_g = m_g - \hat{m}_g(c_g)$$

where, again, α_k is a step-size condition satisfying the conditions 8.

Note, that it is important that the cost updates slowly so that the population is able to converge, rather than bouncing around as it would if the cost was updated drastically.

4.3 Trip Cost Computation

The overall cost of a trip segment is a combination of travel time (as estimated in using the methods in Sec. 4.1) and other factors. Right now, the code considers the following cost factors

travel time	monetary cost	number of mode switches	conveniences

Each agent has a cost weighting for each factor as well. We include details of how each cost factor and agent's weights are determined here.

- **Travel Time:** Travel time is estimated using the computations detailed in Sec. 4.1
- **Monetary Cost:** Monetary cost can be adjusted in the simulation. Driving costs are currently taken to be based on price of gas for trip. (Parking prices could easily be added as well.) Price per ondemand trip can be adjusted in simulation as well. Agent weights placed on monetary cost can be computed relative to median income information for demographic regions.
- **Switches:** This factor includes the number of mode switches + the number of switches on a fixed line. For example, switches= 5 for a trip that includes walking to the fixed line transit, making two bus transfers, and then taking ondemand from the end of the fixed line. The switching cost for a single trip segment is initially taken to be 1. If the segment is a fixed line segment, the number of bus transfers is added as well. ToDo: add a model for weight agent's put in cost on number of switches.
- **Convenience:** (not used at the moment) This is an abstract category that can be added to include other factors.

The overall cost for a particular trip segment is determined using a weighted cost function

$$\Big(\text{Cost}\Big)^{\text{seg}}_{\text{agent}} = \sum_{\text{factor}} \Big(\text{Weight}\Big)^{\text{factor}}_{\text{agent}} \Big(\text{Cost}\Big)^{\text{seg}}_{\text{factor}}$$

The overall trip cost is given by summing up the costs of each trip segments.

$$\Big(\text{Cost}\Big)^{\text{trip}}_{\text{agent}} = \sum_{\text{seg}} \Big(\text{Cost}\Big)^{\text{seg}}_{\text{agent}} = \sum_{\text{seg}} \sum_{\text{factor}} \Big(\text{Weight}\Big)^{\text{factor}}_{\text{agent}} \Big(\text{Cost}\Big)^{\text{seg}}_{\text{factor}}$$

4.4 Trip/Route Planning

Individual trips consisting of multiple mode segments are planned using a dynamic programming formulation. For each trip, potential start and stop nodes for each segment are encoded in a `TRIP` object (see Sec. 8.4.1 for details).

4.4.1 Dynamic programming between trip segments

The code supports a dynamic programming framework that computes the optimal start and stop nodes for each segment (along with optimal routes for each segment) as illustrated in Fig. 11.

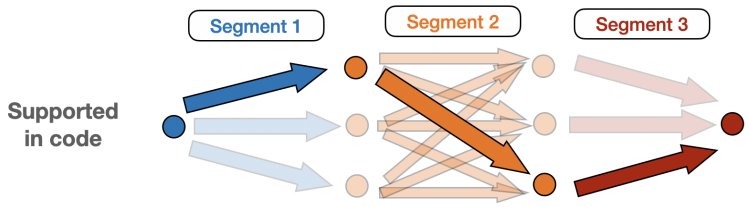


Figure 11: Dynamic programming computation of trip costs.

Currently, all trip segments are only constructed with one start and one stop node for each segment as illustrated in 12.

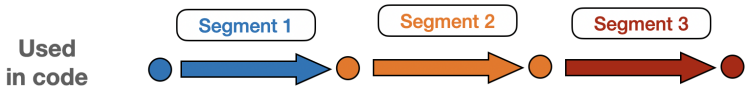


Figure 12: Simple trip segment structure used in code currently

(Adding more start and stop nodes for each trip segment may provide a significant increase in computation time.)

4.4.2 Shortest Path via Dijkstra/A* search - modes: drive, walk

Shortest path planning for driving (and walking) modes are implemented using Dijkstra/A* search using built in functions in NetworkX/OSMNX [2]. The edges weights for shortest path computations are given by the current estimate of the travel costs on each edge based on the current picture of congestion. These edge costs are updated using the dual descent framework detailed in Sec. 4.1.1. At the moment, this congestion model is only implemented for the driving mode and the walking travel times are taken to be fixed (congestion free).

4.4.3 RAPTOR implementation - modes: gtfs

Route planning for fixed line transit is done using the RAPTOR algorithm [3] which plans routes that respect timed-switches between transit lines. Our implementation was based on the discussion and code provided by Kuan Butts [4] with modifications. Our current RAPTOR module is not real time and thus must be precomputed for a given time interval and thus currently does not model congestion of any kind on fixed line transit. Updating the code to run a real-time version could be a significant improvement to the simulation engine.

4.4.4 VRP solver - modes: ondemand

ToDo: add details of VRP solver from Mike's code.

5 GENERATING INPUTS

5.1 Generating Group Bounding Regions

The geographic boundary regions for each group can be generated using the external url geojson.io. These regions can be convenient input by hand using at the url `geojson.io`. The input interface is pictured in the figure below. After drawing input regions (using the toolbar options on the right), the data can be saved as a GeoJSON using the "Save" option in the top left as shown.

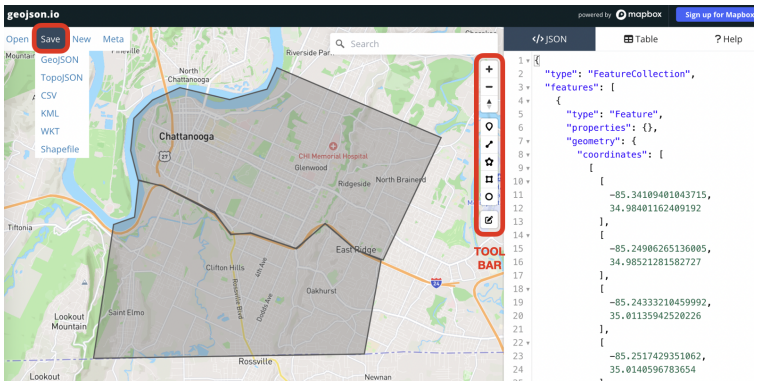


Figure 13: Input interface from geojson.io

Each region should be named as well for reference later as detailed here. Click on the region; input a `name` field on the left and select a specific name for the region, for example, `downtown`; and click save.

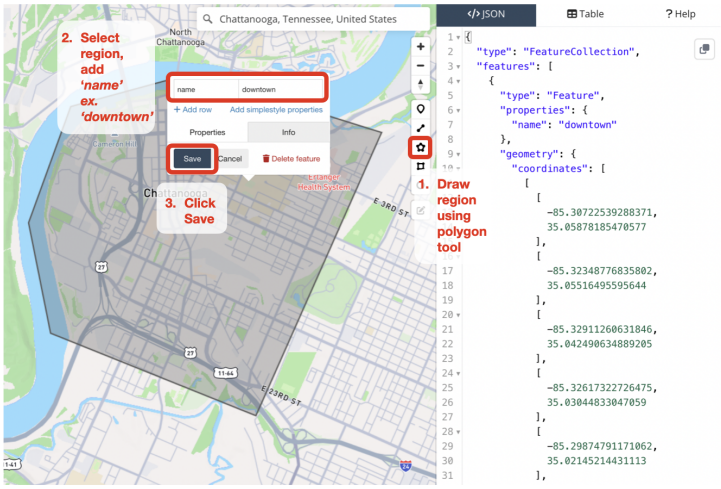


Figure 14: Naming regions in geojson.io

From the `.geojson` file, they can be loaded in to the appropriate format using the custom function `generate_polygons` where the `.geojson` file is stored in `regions.geojson`.

```
polygons = generate_polygons('from_geojson',path='regions.geojson')
```

5.2 Generating Population Data

(Needs to be written based on Agrima's code.)

5.3 Generating Group & Driver Run Data

Needs to be updated to be more user friendly. Currently implemented by functions

`WORLD.createGroupsDF`
`WORLD.createDriversDF`

6 OUTPUT FORMATS

6.1 Simulation Data

Output info from the simulation is stored in a dict of data frames in `WORLD.OUTPUTS`.

6.1.1 By mode

For `mode` in `'drive'`, `'walk'`, `'gtfs'`, and `'ondemand'`, `WORLD.OUTPUTS['by_mode'][mode]` contains a dataframe with data for each mode. Each row corresponds to an individual trip segments. The columns are shown here.

Column	Description
seg_id	Segment id
mode	Mode tag
trips_ids	list of trips that use segment
active	True/False: is segment active
start_node	start node (in mode network)
end_node	end node (in mode network)
start_loc	start location
end_loc	end location
people	people using trip segment
distance	length of segment (meters)
travel_time	travel-time of segment (secs)
money	monetary cost segment ($)
switches	num of switches

Column	Description
uncongested_distance	distance with no congestion
uncongested_travel_time	travel-time w/no congestion (secs)
group_id*	group id
run_id*	driver run id
pickup_time_start*	start of pickup window
pickup_time_end*	end of pickup window
dropoff_time_start*	start of dropoff window
dropoff_time_end*	end of dropoff window
pickup_time_scheduled*	scheduled pickup time
dropoff_time_scheduled*	scheduled dropoff time
pickup_time*	actual pickup time
dropoff_time*	actual dropoff time
num_passengers*	num of passengers in veh.
line_id**	bus line id
bus_trip_id**	spec. bus trip id

*: only included for ondemand mode. **: only included for gtfs mode.

6.1.2 Ondemand data

WORLD.OUTPUTS['ondemand'] contains a dataframe with extra data about the ondemand mode. Each row corresponds to a specific driver run within a specific group. The columns are given here.

Column	Description
run_id	driver run id
group_id	group id
VMT	vehicle miles traveled
PMT	personel miles traveled
VMT/PMT	ratio of VMT to PMT
VTT	vehicle travel time
PTT	average personel travel time
VTT/PTT	ratio of VTT to PTT
distance	distance of driver route
travel_time	travel time of driver route
money	monetary cost for ea. passenger
total_passengers	total passengers in run
ave_num_passengers	ave. num of passengers at any time in run
max_num_passengers	max num of passengers at any time during run

6.2 Dashboard

Fig. 15 shows the dashboard layout with various controls and images labeled. The sliders change which specific trip segments are highlighted on the map and in the bar charts that show the cost information. The ondemand metrics are broken down by group as well and displayed in the small side plot. (ToDo: Add side plot display for specific fixed transit lines/trips as well.)

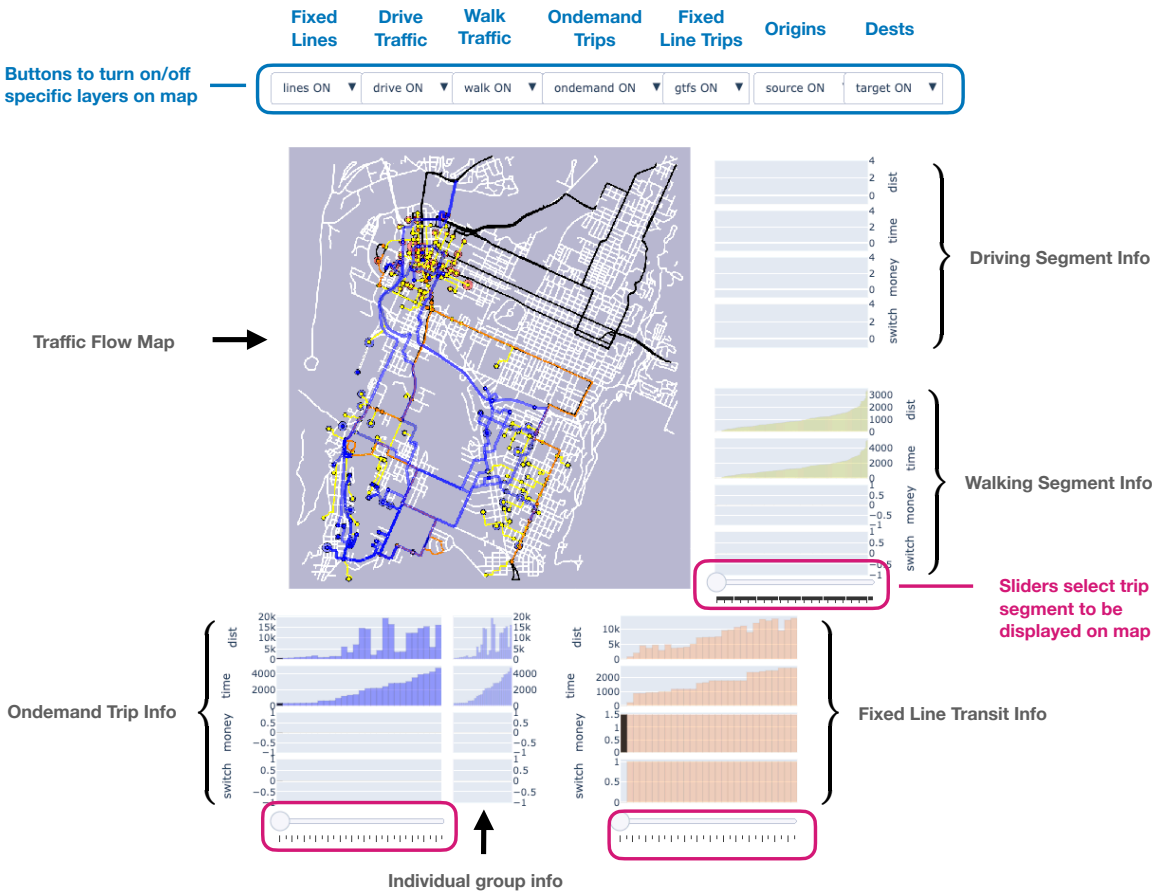


Figure 15: Details of dashboard setup.

7 SIMULATOR OVERVIEW

In this section, we detail the software architecture for the simulator. In the following subsections, we detail the various objects their attributes and functions. A brief overview of each object and its position in the architecture is given here. An overview of the steps in running each simulation iteration are given in Section ??.

7.1 Simulation Object

Figure 20 gives an overview of the main simulation object. More details are given in Section **??**. The `NETWORKS` objects contain details of each mode network including trip segments in use by agents and traffic on each mode (details in Sec. 8.3). The `GRAPHS` and `FEED` objects contains OSMNX graphs and gtfs feed information. The `PERSON` objects in the `PEOPLE` dict contain information for each agent in the simulation (details in Sec. 8.4). The `ONDEMAND` object and `GROUP` objects inside contain information about the ondemand microtransit mode (details in Sec. 8.5 and 8.5.1). The `CONVERTER` converts between nodes in different mode networks (details in Sec. 8.6).

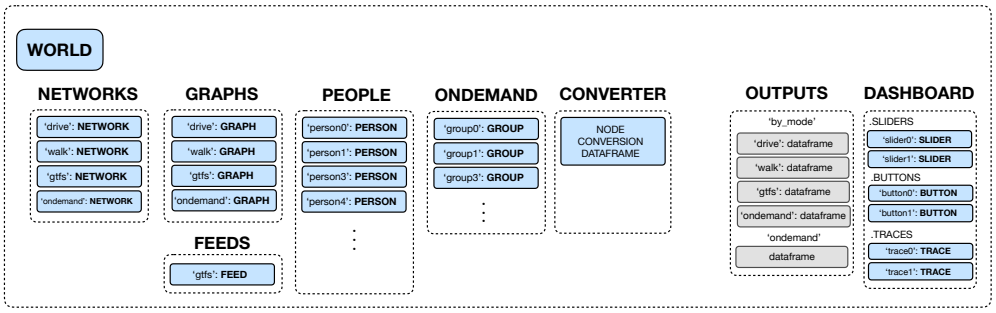


Figure 16: Overview of simulation architecture

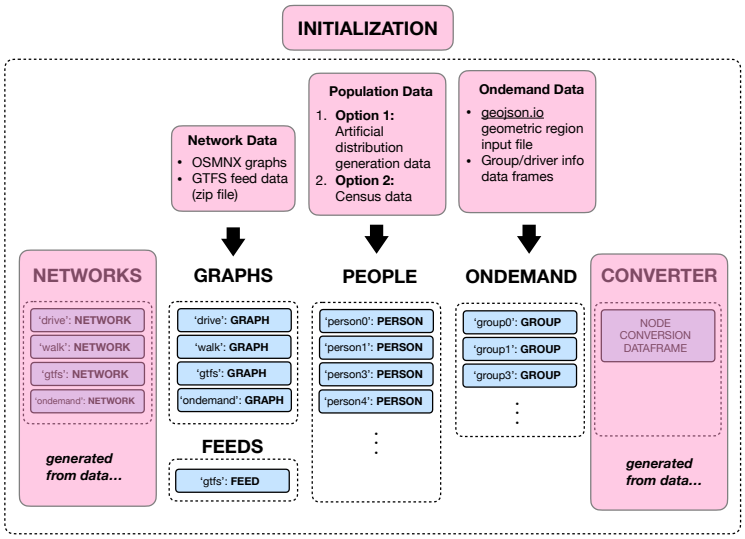


Figure 17: Overview of simulation architecture

7.2 Initialization Steps

An overview of the initialization steps for the simulation are given in Fig. 17. The `GRAPH` and `FEED` are initialized from OSMNX graph structures and gtfs feed (loaded in a zip file). Population data can be generated artifically or generated from census data (details in Sec. 5.2). The ondemand data information is loaded from a `.geojson` file generated from `geojson.io` (details in Sec. 5.1) and from dataframes that contain group and driver run information (details in Sec. 5.3).

The `NETWORK` and `CONVERTER` objects are generated in the initialization. The individual agents (`PERSON` objects) are generated from the population data, initial potential routes are generated, appropriate nodes are added to the node `CONVERTER`, and agents are assigned to the appropriate ondemand group.

7.3 Fitting Ondemand Latency Curves

After the populations are generated and agents are assigned to the appropriate ondemand group, demand curves must be fit for each ondemand group in order to estimate the groups travel time based on the number of users requesting rides during the simulation process. This is done by the function

```
WORLD.fitModels(counts ={'num_counts':10,'num_per_count':4})
```

which in turn calls the functions

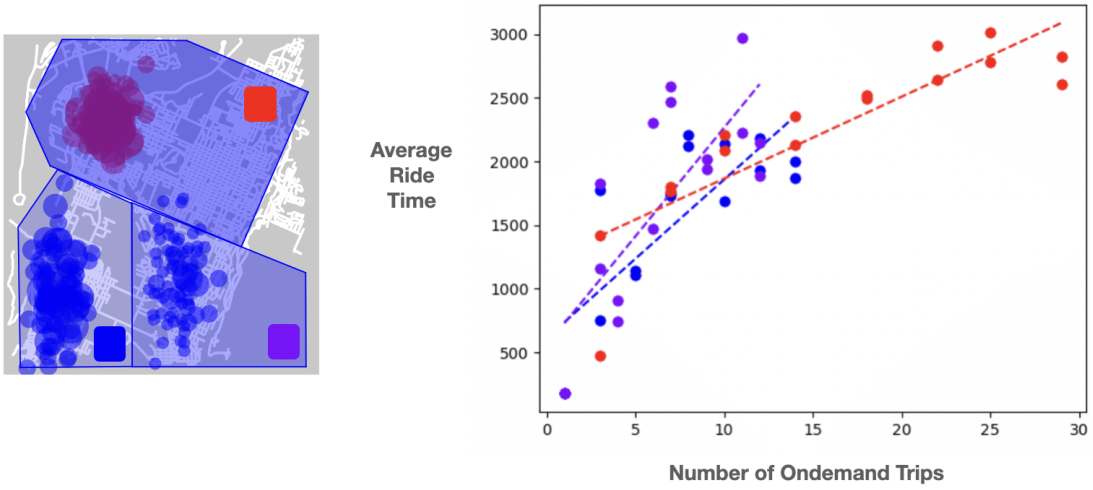


Figure 18: Curve fitting examples

`ONDEMAND.generateCongestionModels`
`GROUP.generateCongestionModel`

In order to fit the demand curve for each group, the VRP solver is called for different numbers of possible agents within the group region at random. The number of agents to plan trips for is chosen at regular intervals over the total possible number of trips. The number of intervals is determined by the input `counts['num_counts']`. The number of random samples to take at each specific number of trips is determined by the input `counts['num_per_count']`. The demand curves are fit using a simple linear model. (This could fairly easily be updated to use a higher order curve.) We give an example of the fitting curves for three ondemand regions in Fig. 18. In this example, the inputs are `counts={'num_counts':8,'num_per_count':2}`.

7.4 Main Simulation Loop

The main simulation loop is detailed in Fig. 19. In each iteration loop, the first step is to update the optimal routes and costs for all the trip segments in each `NETWORK` object. For the ondemand network the `ONDEMAND` object is called to update the optimal VRP solutions for each driving group. This step requires a call to the VRP routing package (details in Sec **??**).

8 ARCHITECTURE DETAILS

This section contains details of each of the objects in the software architecture. We start with a summary of the objects listed below.

SUMMARY

- **WORLD**: Overall simulator object.
- **GRAPH**: NetworkX graph objects that detail the road network for specific transportation modes.
- **FEED**: GTFS feed information for fixed line mode.

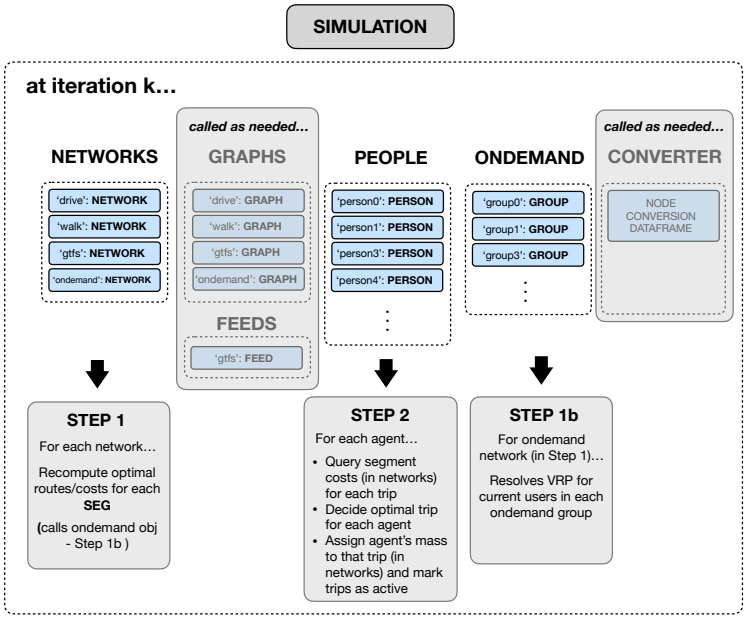


Figure 19: Overview of simulation architecture

- **NETWORK**: Contains information about traffic flow and individual trip segments for a specific transportation mode. Recomputes optimal routes for each segment at each iteration.
  - **SEG**: Contains information about optimal routes between origin and destination nodes within a particular transportation mode.
- **PERSON**: Preference and choice information for a specific agent in the population including preferences for each cost component, origin and destination nodes, possible trips to choose from, and current optimal trip choice and optimal routes.
  - **TRIP**: Contains information about segment combinations that form a single trip origin to destination. May include segments from multiple transportation networks.
- **ONDEMAND**: Contains information specific to the ondemand transportation mode.
  - **GROUP**: Contains information for ondemand transportation group including number of vehicles and other parameters, current driver run assignments, etc.
  - **RUN**: Contains information about specific driver runs for vehicles within an ondemand group.
- **CONVERTER**: Dataframe that converts node tags between different transportation modes.
- **DASHBOARD**: Object that generates and controls the visualization dashboard from data
  - **TRACE** Object that controls a trace on a plot in the dashboard.
  - **SLIDER** Object that controls a slider control on dashboard.
  - **BUTTON** Object that controls a button control on dashboard.
- **RAPTOR**: Class that implements RAPTOR algorithm to solve for shortest path with transfers within a fixed-line transportation network given a GTFS feed. (currently run offline).

In the following sections, we detail each object.

WORLD

Attributes

Field	Value	Description
NETWORKS	dict	dict of **NETWORK** objects
GRAPHS	dict	dict of OSMNX **GRAPH** objects
RGRAPHS	dict	dict of OSMNX (reversed) **GRAPH** objects
FEEDS	dict	dict of stored gtfs feed info
ONDEMAND	obj	**ONDEMAND** object
PEOPLE	dict	dict of **PERSON** objects
grpsDF		dataframe with ondemand group info
driversDF		dataframe with ondemand driver info
DELIVERYDF		
OUT		(preloaded population information)
PRE		(preloaded population information)
NODES		(preloaded population information)
LOCS		(preloaded population information)
SIZES		(preloaded population information)
VEHS		(preloaded population information)
PRELOADS		(preloaded population information)

Field	Value	Description
factors	list	list of cost factors to consider
modes	list	list of modes in simulation
verbose	bool	True/False: to print status during sim
start_time	datetime	start time for sim
end_time	datetime	end time for sim
monetary_costs	dict	monetary cost info for each mode
all_trip_ids	list	list of all possible trip ids
full_region	list	geo polygon - full simulation region
group_polygons	dict	dict of polygons for each region per group
group_polygon_data	dict	dict of polygons for each region per group
SEG_TYPES	list	list of possible trip segments
bnds		geographic bounds for simulation region
load_fits	bool	True/False: to load ondemand curve polynomials
save_fits	bool	True/False: to save ondemand curve polynomials
gtfs_feed_file	str	name of gtfs feed .zip file
gtfs_precomputed_file	str	file with precomputed information from **RAPTOR** object
groups_regions_geojson	str	.geojson file containing region about ondemand groups
preloads_file	str	(optional) file for loading any background traffic info

Functions

Function	Description
__init__	Initializes simulation. (If full_setup = True, also calls the other * functions)
initGRAPHSnFEEDS*	Initializes **GRAPH** and **FEED** objects from OSMNX data and gtfs feed file
initNETWORKS*	Initializes **NETWORK** objects
initCONVERTER*	Initializes **CONVERTER** object
initSTATS*	Loads population states (Interface with Agrima's code)
initONDEMAND*	Initializes **ONDEMAND** object
initPEOPLE*	Initializes **PERSON** objects for each agent (stats for indiv agents loaded in initSTATS
initBACKGROUND*	(Optional) Loads any background traffic info in self.preloads_file
initUNCONGESTED	Computes costs for trips without congestion (for comparison purposes)
createGroupsDF	Creates data frame with ondemand group information
createDriversDF	Creates data frame with ondemand driver run information
plotPRELIMINARIES	Plot initial population information - geographic region, origins and destinations, etc.
add_base_edge_masse	adds background traffic to edges if loaded initBackground

Function	Description
fitModels	Fit ondemand congestion curves (calls ONDEMAND function)
saveFits	(Optional) saves ondemand curve information
loadFits	(Optional) loads precomputed ondemand curve information
graphFromFeed	construct NetworkX graph from gtfs feed
trimGraph	cut down graph based on geographic region
SIM	run main simulation loop
makeDashboard	construct dashboard
generateLayers	generate layers for dashboard plots
plotLayer	plot a layer and save image for dashboard
plotLayers	plot all layers and save as images for dashboard plots
generate_graph_presets	(generate plotting presets for dashboard)
generateOutputs	generate dataframes with output data
printOutputs	display outputs in notebook
saveOutputs	save output data frames in pickle file
LOAD	load precomputed simulation data (may not work)
SAVE	save simulation data

Figure 20: Overview of simulation architecture

8.1 WORLD Object

The simulator is run in a `WORLD` object whose overall structure is summarized in Fig. 20.

WORLD: function descriptions

- **WORLD.__init__:**

  Initializes the overall WORLD simulation object. If the `full_setup = True`, then also calls the `WORLD.init*` functions given below. If `full_setup = False`, the other initialization functions must be called separately.

- **WORLD.initGRAPHSnFEEDS:**

  Loads graphs (from OSMNX) and feed (from `.zip` file). Computes Networkx graph from gtfs feed and also computes reverse graphs (for later computation). Calls `WORLD.trimGraph` to cut graphs down to lie within inside geographic bounding region. Also computes a combined graph from all networks together stored in `WORLD.GRAPHS['all']`.

- **WORLD.initNETWORKS:**

  Initializes `NETWORK` objects for each mode.

- **WORLD.initCONVERTER:**

  Initializes `CONVERTER` object for node conversation between modes.

- **WORLD.initSTATS:**

  (Should be updated to be more user friendly.) Catch all function that loads in precomputed population statistics information, generates some ondemand information using `WORLD.createGroupsDF` and `WORLD.createDriversDF`, and adjusts some population information.

- **WORLD.initONDEMAND:**

  Initializes `ONDEMAND` object.

- **WORLD.initPEOPLE:**

  Initializes all agents (`PERSON` objects) in simulation.

- **WORLD.initBACKGROUND:**

  Loads background traffic and adds it to the appropriate edges in the graph.

- **WORLD.initUNCONGESTED:**

  Computes cost of trips without congestion for comparison purposes. Uncongested trips for `ondemand` mode are the same as driving trips.

- **WORLD.createGroupsDF:**

  (Should be updated to be more user friendly.) Creates dataframes with group information.

- **WORLD.createDriversDF:**

  (Should be updated to be more user friendly.) Creates dataframes with driver run information

- **WORLD.plotPRELIMINARIES:**

  Plots preliminary setup of simulation. Particularly, origin-destination pairs and group geographic regions.

- **WORLD.fitModels:**

  Loads congestion curves (if precomputed in `WORLD.load_fits`) file. If not, calls `ONDEMAND.generateCongestionModels` to fit demand curves for each group.

- **WORLD.saveFits:**

  Saves ondemand congestion curve data.

- **WORLD.loadFits:**

  Loads ondemand congestion curve data if specificed in `WORLD.load_fits` file.

- **WORLD.graphFromFeed:**

  Generates a NetworkX graph from a gtfs feed. Used for plotting, etc.

- **WORLD.trimGraph:**

  Cuts graph down to be within geographic bounding box.

- **WORLD.SIM:**

  Runs main simulation loop for simulation. If input `restart=True`, then the simulation iteration number in `WORLD.main['iter']` is reset to 0. (Otherwise, the simulation continues from the current iteration.) The parameter `WORLD.main['alpha']` contains the iteration update step for updating the cost variables for each network step. (For more details, see Sec. **??**).

- **WORLD.LOAD:**

  (Doesn't work at the moment.) Loads previous simulation run.

- **WORLD.SAVE:**

  (Doesn't work at the moment.) Saves full current simulation run.

- **WORLD.makeDashboard:**

  Construct `DASHBOARD` object.

- **WORLD.generateLayers:**

  Generates image layer information for `DASHBOARD` visualizer. Layer image passed to `WORLD.plotLAYERS`, `WORLD.plotLayer` for plotting.

- **WORLD.plotLayer:**

  Plots individual image layer for `DASHBOARD`.

- **WORLD.plotLAYERS:**

  Plots image layers for `DASHBOARD`. Images are stored in folder `WORLD.dash_folder`.

- **WORLD.generateOutputs:**

  Generate output dataframes. `WORLD.OUTPUTS` is a dict with key tags `['by_mode','ondemand']`. For mode in `['drive','walk','gtfs','ondemand']`, `WORLD.OUTPUTS['by_mode'][mode]` is dataframe with simulation statistics about the specific mode. Each row gives information about a specific trip segment. `WORLD.OUTPUTS['ondemand']` is a dataframe with more statistics specific to the ondemand mode. More details are given in Sec. 6.1

- **WORLD.printOutputs:**

  Prints dataframe outputs to the screen. `dfs_to_show` gives the specific modes to show. If `'groups'` contained in `dfs_to_show`, prints `WORLD.OUTPUTS['ondemand']`. `row_count` gives the number of rows to print.

- **WORLD.saveOutputs:**

  Saves dataframe outputs to input `filename`.

- **WORLD.generate_graph_presets:**

- **WORLD.generate_polygons:**

- **WORLD.add_base_edge_masses:**

8.2 GRAPH & FEED Objects

The `GRAPH` objects are Open Street Map NetworkX graph objects that store transportation grid information for each mode. For the `drive`,`walk`, and `ondemand` modes the NetworkX object is used for shortest path computations. For the `gtfs` mode, the NetworkX object is generated from the a GTFS feed with custom function `load_feed_as_graph` and is primarily used to facilitate plotting. For the fixed line transite mode, a `FEED` object is loaded from a standard GTFS feed.

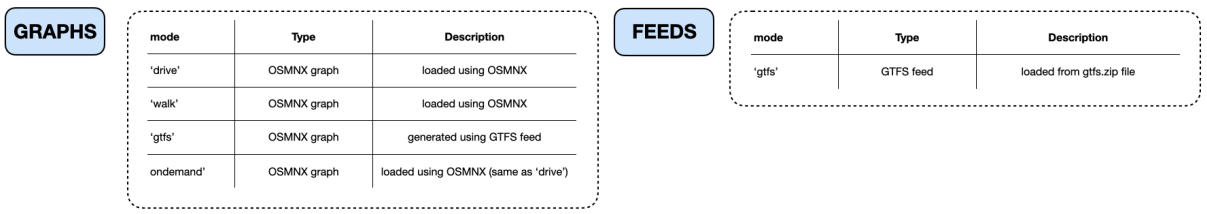


Figure 21: GRAPH and FEED objects

8.3 NETWORK Objects

Each `NETWORK` object contains information about potential trip segments within a specific transportation mode. The primary attribute of the `NETWORK` object is a dictionary, `segs`, which contains `SEG` objects with information about the current optimal route between a start node and end node within the mode network. The keys are a tuples with the form `(start_node,end_node)`. The `UPDATE` function recomputes the optimal routes for each active segment within the mode network. The other attributes and functions are detailed in Fig. 22

NETWORK

Attributes

Field	Value	Description & Details
mode	str	network mode from ['drive','walk','gtfs','ondemand']
GRAPH	NetworkxG	graph for network
segs	dict	**SEG** objects - keys have form (start, end)
edge_masses	dict	history of edge masses on each edge - edge keys
edge_costs	dict	history of costs on each edge - edge keys
current_edge_masses	dict	current mass on each edge - edge keys
current_edge_costs	dict	current cost on each edge - edge keys
edge_cost_poly	dict	poly cost func on each edge - edge key: [a0,a1,a2,...]
people	tag	list of agents using network
active_segs	list	list of active seg tags

Field	Value	Description
precompute*	dict	gtfs data (preloaded)
booking_ids**	list	list of booking ids
time_matrix**	np.array	time matrix for ondemand trips
expected_cost**	list	history of expected costs for ondemand
current_expected_cost**	float	current expected

* gtfs only
** ondemand only

Functions

Function	Description
__init__	generates network structures
UPDATE	updates shortest paths and optimal cost info for each **SEG** in **NETWORK**
createEdgeCosts	generate edge cost functions (based on geography edge information from OSMNX graphs)
createEdgeDists	compute distances on each edge in the network
removeMassFromEdges	removes all mass from edges in the network - for each simulation iteration
addSegMassToEdges	add population mass for a trip segment to appropriate edges in the network.
computeUncongestedEdgeCosts	Setting edge costs for specified graph to the uncontested edge costs
computeUncongestedSegCosts	compute uncontested segment costs for comparison purposes

Figure 22: NETWORK object

NETWORK: function descriptions

- **NETWORK.__init__:** Initializes the NETWORK object. Computes the distances along each edge in the network and generates the latency functions on each edge. For the gtfs mode, loads the precomputed gtfs data and travel times.
- **NETWORK.UPDATE:** For each edge in the network, updates the current estimate of travel time based on the previous travel time and current edge mass usage (see Section **??**) for details. After the edge costs are updated, recomputes the optimal routes and costs for each segment in the network.
- **NETWORK.createEdgeDists:** Computes the distances along each edge in the network.
- **NETWORK.createEdgeCosts** Generates the latency function polynomials each edge in the network. Polynomials of the form $p(x) = a_0 + a_1 x + a_2 x^2 + \dots$ stored as a list of the form `[a0,a1,a2,\dots]`
- **NETWORK.removeMassEdges:**

  Removes the current mass on each edge in the network.
- **NETWORK.addSegMassToEdges:**
  Adds population mass to each edge in a particular trip segment in the network.

- **NETWORK.computeUncongestedEdgeCosts:**
  Computes uncongested edge travel times for each edge in the network.
- **NETWORK.computeUncongestedTripCosts**
  Computes optimal travel time for each segment without congestion (used for comparison purposes and metrics.)

8.3.1 SEG Objects

The `SEG` object is detailed in Fig. 23. The attributes contain information about the start and end node for the segment, the current population mass using the, the trip and agent ids that use the segment, the current costs for each factor, and the current optimal path. Segments in the ondemand network contain additional information about pickup and dropoff times as well as booking id and the ondemand group the segment is assigned to among other things. The functions for each segment compute the optimal path between the start and end node. The `planDijkstraSeg` uses the implementation of shortest path computations using Djikstra for NetworkX objects given the current congestion on the network. The `planGTFSSeg` uses the (precomputed) implementation of RAPTOR for shortest path computation with timed transfers.

SEG: function descriptions

- **SEG.__init__:**
  Initializes trip segment within a network and computes an initial optimal route and travel cost.
- **SEG.planSeg:**
  Plans routes for the segment. Calls either `SEG.planDijkstraSeg` or `SEG.planGTFSSeg` depending on the type of network.
- **SEG.planDijkstraSeg:**
  Plans shortest paths through the network using implementations of Dijkstra from NetworkX. Used for `'drive'` or `'walk'` modes.
- **SEG.planGTFSSeg:**
  Plans shortest paths for transit segments using a precomputed implementation of RAPTOR. Used for `'gtfs'` mode.
- **SEG.pathCost:**
  Computes the cost of a particular path through a given graph.
- **SEG.create_chains:** (only for gtfs) - generates a list of stops (in order) for a fixed line trip.
- **SEG.list_inbetween_stops:** (only for gtfs) - lists all stops (used or not) along a fixed line trip
- **SEG.gtfs_to_transit_nodesNedges:** (only for gtfs) - constructs nodes and edges in NetworkX graph for fixed line trip

8.4 PERSON Object

The `PERSON` object contains information about an agent in the network and is responsible for updating that agent's choice based on the lowest cost of each trip. The attributes and functions are detailed in Fig. 24 The main attribute `trips` is a dictionary of `TRIP` objects (detailed below) that each detail a possible trip the agent could take from their origin to destination. Each trips consist of several connected segments each possibly using a different transportation mode. The keys are tuples of the order of the mode combinations, for example `('ondemand','gtfs','walk')` for a trip that takes ondemand to a fixed line transit stop, takes fixed line to a node close to the destination, and then walks from the final transit node to the destination. Right now the simulator supports the following mode combinations.

SEG

Attributes

Field	Value	Description
seg_id	str	segment id tag, form = (start node, end node)
mode	str	mode of segment
mass	float	population mass using segment
source	node	source node in mode graph
target	node	target node in mode graph
factors	list	list of cost factors
active	bool	segment active or not
trip_ids	list	trip ids that use this segment
people	list	agents that use this segment
costs	dict	costs of each factor
path	list	history of optimal paths
current_path		current optimal path

Field	Value	Description
booking_id*		booking id for ondemand
group*		assigned ondemand group
run_id*		current run id within ondemand group
typ*		
pickup_time_window_start*	float	time: start of pickup window
pickup_time_window_end*	float	time end of pickup window
dropoff_time_window_start*	float	time: start of drop-off window
dropoff_time_window_end*	float	time: end of drop-off window
pickup_time_scheduled*	float	scheduled pickup time
dropoff_time_scheduled*	float	scheduled drop-off time
num_passengers*	int	number of other passengers in ondemand vehicle
pickup_node_id*	node	node id for pickup node
dropoff_node_id*	node	node id for drop-off node
am*	int	number of ambulatory agents using segment
wc*	int	number of wheelchair agents using segment
delivery_history*		
delivery*		

Functions

Function	Description
__init__	initialize SEG within a network
planSeg	compute optimal cost of segment, uses planDijkstraSeg & planGTFSSeg
planDijkstraSeg	computes the optimal cost for segment where Dijkstra (shortest path) is required
planGTFSSeg	computes the optimal cost for segment where RAPTOR is required. Uses precomputed data
pathCost	compute cost along a path
create_chains*	*only for gtfs - generates a list of stops in order for a fixed line trip
list_inbetween_stops*	*only for gtfs - list all stops (used or not) along a fixed line trip
gtfs_to_transit_nodesNedges*	*only for gtfs - constructs nodes and edges in NetworkX graph for fixed line trip

Figure 23: SEG object

- `('drive',)`
- `('walk',)`
- `('ondemand',)`
- `('walk','gtfs','walk')`
- `('walk','gtfs','ondemand')`
- `('ondemand','gtfs','walk')`
- `('ondemand','gtfs','ondemand')`

The `weights` contains the weights the agent puts on each factor for the trip. The `UPDATE` function queries the current cost of each trip and picks the optimal trip for that agent at the current iteration. More details on the object functions are given below.

PERSON function descriptions

- **PERSON.__init__:**
  Initialize information for each agent in the simulation. Loads pre-generated preference data from `PRE` object for individual agent. For each trip available to the agent, computes the start and stop nodes for each segment and generates the `TRIP` object. Currently, only allows one start and one stop node per segment. (This could be expanded to include more potential start and stop nodes for each segment at the cost of simulation complexity.) Each new start and stop node is added to the node `CONVERTER` object for later use. For ondemand modes, ondemand delivery groups are also selected using `ONDEMAND.selectDeliveryGroup` given the start and stop node for the ondemand segment.

PERSON

Attributes

Field	Value	Description & Details
person_id	str	person id tag
mass	float	Population mass
costs	list	costs for each trip option
weights	list	**WEIGHTS** dicts
logit_version	string	logit function to use in computing costs
trips	dict	dict of **TRIP** objects detailing trips (tags are mode
trips_to_conside	list	list of all possible mode sequences - SEE BELOW
opts	list	list of mode sequences to consider
current_choice	tag	current mode sequence choice
current_cost	float	current cost of travel
cost_traj	list	history of travel cost info for agent
choice_traj		current optimal path

trips_to_consider: *possible mode sequences…*

('drive'), ('walk'), ('ondemand')

('walk','gtfs','walk'), ('walk','gtfs','ondemand') ('ondemand','gtfs','walk') ('ondemand','gtfs','ondemand')

Field	Value	Description
am	int	Number of ambulatory passengers for ondemand
wc	int	Number of wheelchair passengers for ondemand
delivery_grps	string	Possible ondemand group tags
delivery_grp_initial	string	Ondemand group for initial segment
delivery_grp_final	string	Ondemand group for final segment
booking_id*	int/string	Booking id number
pickup_node_id	int	Pickup node id number (used for VRP)
dropoff_node_id	Int	Drop-off node id number (used for VRP)
pickup_time_window_star	time	Earliest pickup time (in seconds)
pickup_time_window_end	time	Latest pickup time (in seconds)
dropoff_time_window_sta	time	Earliest drop-off time (in seconds)
dropoff_time_window_en	time	Latest drop-off time (in seconds)

Functions

Function	Description
__init__	generates agent parameters, computes agents start and end nodes for each segment of each trip including closest applicable fixed transit lines and applicable ondemand delivery groups. Also adds appropriate nodes to the node CONVERTER.
UPDATE	Queries cost of each trip option for the agent and deciding which is the optimal.

Figure 24: PERSON object

- **PERSON.UPDATE:**
  The `UPDATE` function loops through each trip option that an agent can take, runs the `queryTrip` function to determine the cost of trip, chooses the optimal trip and assigns the agent's population mass to the trip in the appropriate networks and assigns those segments in the appropriate network as active. There is an option, `takeall`, which assigns the population mass to every possible trip rather than just the optimal one in order to show all trips an agent can take.

8.4.1 TRIP Object

The `TRIP` object contains details about a specific trip an agent can take. Details are given in Fig. **??**. The `structure` attribute contains a list of `TRIP_SEG` dicts, one for each segment in the trip. The structure of the dict for each segment is illustrated here, containing details for that trip segment, specifically possible start and end nodes for that segment.

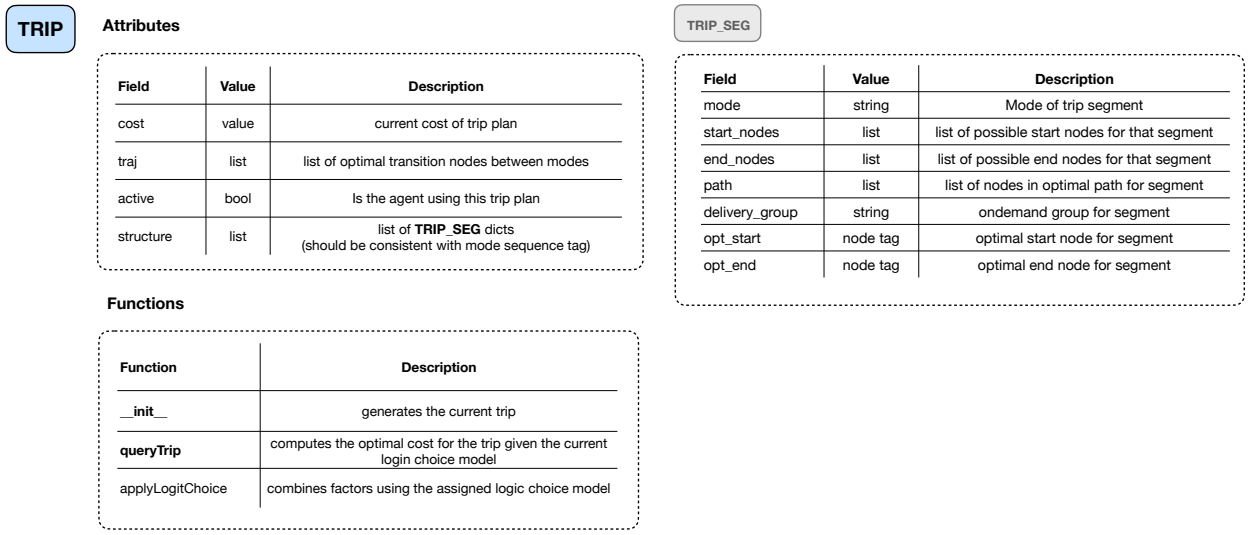


Figure 25: TRIP segment details object

The main function `queryTrip` computes the current cost of each trip. Note this function assumes that the segment information for each component of the trip have been updated in the corresponding network.

- **TRIP.__init__:**
  Generates the `TRIP` object given the mode sequence and start and stop nodes for each segment.
- **TRIP.queryTrip:**
  Queries the cost of each segment in the trip. (If at the time of the query, the segment does not exist in the appropriate transportation network it is generated.) The main loop, loops through each segment in the `structure` attribute in reverse order starting with the final segment and proceeding backwards. For each segment the optimal cost of traveling between each start and end node for that segment is computed using all factors, agents weighting preferences and a logit choice function. (At the moment segments, only contain one start and stop node.) The optimal cost as well as the optimal start and stop nodes for each segment are computed using a dynamic programming style calculation as illustrated here in Fig. 11.
- **TRIP.applyLogitChoice:**
  Computes weighted combination of costs for logit choice model.

8.5 ONDEMAND object

The `ONDEMAND` object contains information specific to the ondemand transportation mode. The main attribute `groups` is a dictionary of `GROUP` objects that have information for each group of ondemand drivers.

ONDEMAND

Attributes

Field	Value	Description
groups	dict	dict of **GROUP** objects
grpsDF	dataframe	dataframe with group information
group_polygons	dict	dict of polygon regions for each group
driversDF	dataframe	dataframe with driver run information
num_groups	int	number of groups
booking_ids	list	list of booking ids
fit	dict	polynomial curve information for ondemand curves for groups

Functions

Function	Description
__init__	initializer **ONDEMAND** object
selectDeliveryGroup	assign ondemand passenger to a particular ondemand group
generateCongestionModels	generate congestion models for each of the ondemand groups
plotCongestionModels	plot congestion curves

Figure 26: Details of GROUP object

ONDEMAND function descriptions

- **ONDEMAND.__init__**
  Generates the `ONDEMAND` object and generates each ondemand `GROUP` from the group data contained in `DELIVERYDF`. `DELIVERYDF['grps']` is a dataframe containing information about the ondemand groups. For a particular group with tag, for example, `'group0'`, `DELIVERYDF['drivers']]['group0']` contains information about the driver runs for that particular group. The `RUN` objects for each driver run are generated in the `GROUP` object.

- **ONDEMAND.selectDeliveryGroup**
  Assigns ondemand trip segments (defined by start and stop nodes) to a specific ondemand group. In general, assumes that there is only one ondemand gropu that will accommodate that trip segment, ie. assumes that the groups have been split up by geographic region. Each group is defined by a pickup area and a dropoff area denoted by polygons defined in the columns `['pickup_polygon']` and `['dropoff_polygon']` of the `ONDEMAND.grpsDF` dataframe. Currently a rider is assigned to an ondemand group if either pickup and dropoff node are in either the pickup or dropoff areas. (The denotation of "pickup" or "dropoff" is arbitrary.) This could be adjusted to allow pickups in only the pickup area, etc. if desired.

- **ONDEMAND.generateCongestionModels:**
  Generates the ondemand congestion for each group assuming that all possible rides have been assigned to the appropriate groups. Calls the function `GROUP.generateCongestionModel` for each group separately.

- **ONDEMAND.plotCongestionModels:**
  Plots the approximated demand curve for each congestion model for each group.

8.5.1 GROUP object

The `GROUP` object contains information about a group of ondemand drivers

GROUP

Attributes

Field	Value	Description
group	str	group id tag
group_ind	int	number of group
date	datetime	date and time of simulation
loc	tuple	(lat,lon) location of group depot
depot	OSMNX node	(lat,lon) location of depot node
depot_node	OSMNX node	depot node in ondemand network
polygon	np.array	pickup + drop-off region for group
pickup_polygon	np.array	pickup region for group
dropoff_polygon	np.array	drop-off region for group
total_num_groups	int	total number of groups
polygon_color	tuple	color for plotting group region
fit	list	

Field	Value	Description
booking_ids	list	list of booking ids for group trips
time_matrix	np.array	
actual_num_segs	int	current number of ondemand group segs
expected_cost	list	list - history of expected costs for group
current_expected_cost	float	current expected cost for group (based on demand curve)
actual_average_cost	float	actual average cost for riders in group
driver_runs		
runs		list of **RUN** objects with driver run info
driversDF		dataframes with driver information
PDF		current payload data frame
MDF		current manifest data frame
current_PDF		current payload data frame
current_MDF		current manifest data frame

Functions

Function	Description
__init__	Initialize group object
generateCongestionModel	fit demand curve for group given region and possible passengers
payloadDF	construct dataframe from payload information
manifestDF	construct dataframe from manifest information
updateTravelTimeMatrix	update travel time matrix for active trips based on current traffic

Function	Description
constructPayload	construct payload input for VRP solver
routeFromStops	construct full route from node stops
routesFromManifest	construct routes thru network from stops in manifest
singleRoutesFromManifest	construct individual routes from stops in manifest
assignCostsFromManifest	assign costs to agents using ondemand from manifest

Figure 27: Details of GROUP object

GROUP function descriptions

- **GROUP.__ init__:**

  Generates `GROUP` object. Driver run information loaded in through the dataframe `driversDF`. `RUN` objects for each driver run are also created.

  GROUP.generateCongestionModel:

  Generates congestion demand curve for ondemand group. Should be run after all rider trips have been assigned. `counts` variable contains information about how many test cases to run to determine congestion model. `counts['num_counts']` is the total number of sample groups to compute travel time for. `possible_trips` is the full list of possible rides that the ondemand group could be responsible for. Rider counts for sample rider groups are chosen at intervals between $0.1\times$ number of total possible rides and $0.9\times$ number of total possible rides using the lines

```
num_pts = counts['num_counts'];
num_per_count = counts['num_per_count'];
num_trips = len(possible_trips);
sample_counts = np.linspace(0.1*num_trips,0.9*(num_trips-1),num_pts)
```

  For each `count` in `sample_counts`, `count` samples are chosen from possible trips and the average travel time is computed using the VRP solver. For each `count`, this sampling and travel time computation is repeated `counts['num_per_count']` times.

  The resulting rider counts and travel times are used to fit a demand curve for the group as illustrated in Fig. 28 where the horizontal-axis is the number of rides in each sample and the vertical axis is the

average time in seconds. These curves are used in the simulation to estimate the expected travel time given the rider demand.

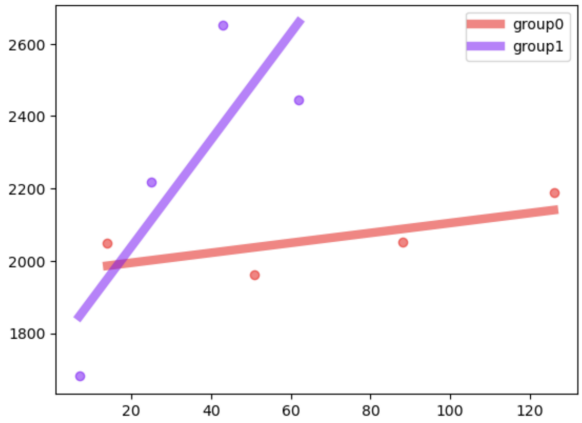


Figure 28: Sample demand curves

- **GROUP.updateTravelTimeMatrix:**
  Updates the travel time matrix for the group for computation in the VRP solver. Uses the `'drive'` mode graph so as to take into account the current traffic conditions.
- **GROUP.constructPayload:**
  Constructs payload to pass to the VRP solver for current active riders in the group. VRP solver is called using the function

  ```
  manifests = optimizer.offline_solver(payload)
  ```

- **GROUP.payloadDF:**
  Constructs a dataframe to store the payload information.

  ```
  PDF = GROUP.payloadDF(payload,GRAPHS,include_drive_nodes = True);
  ```

- **GROUP.manifestDF:**
  Constructs a dataframe with the manifest information from the VRP solver.

  ```
  MDF = GROUP.manifestDF(manifests,PDF)
  ```

- **GROUP.routeFromStops:**
  Constructs a full driving route from (the ordered list of nodes from) the manifest generated by the VRP solver. **GROUP.singleRoutesFromManifest:**
  Generates routes for driver runs in manifest generated by VRP solver. Used in `GROUP.assignCostsFromManifest` to assign costs to agents taking ondemand within group.
- **GROUP.assignCostsFromManifest:**
  Give a manifest from the VRP solver, computes the costs for each ondemand segment taken by an agent and updates the cost information in that segment in `NETWORK.segs`. This step is important so that individiuals can simply query the appropriate segment in `NETWORK.segs` to get their cost information for using ondemand for a segment of their trip.

RUN

Attributes

Field	Value	Description
run_id	str	run id tag
date	date	date of simulation
start_time	datetime	start time of run
end_time	datetime	end time of run
am_capacity	int	max num of ambulatory passengers
wc_capacity	int	max num of wheelchair passengers
group	str	group id of run
group_ind	int	number of group
booking_ids	list	list of booking ids for run
loc	tuple	group location
depot	node	depot node for group
depot_node	node	depot node for group
expected_cost	list	list of expected costs for run
current_expected_cost	float	current expected cost for un
actual_average_cost	float	actual average costs for
costs	dict	−−
total_passengers	int	max number of passengers during run
max_num_passengers	int	max number of passengers during run
ave_num_passengers	float	ave num of passengers at any time

Field	Value	Description
DF	list	
VMT	list	history of vehicle miles traveled
PMT	list	history of ave. personal miles traveled
VMTbyPMT	list	history of ratio of VMT to PMT
current_VMT	float	current vehicle miles traveled
current_PMT	float	current ave. personal miles traveled
current_VMTbyPMT	float	current ratio of VMT to PMT
VTT	list	history of vehicle travel time
PTT	list	history of ave. personal travel time
VTTbyPTT	list	history of ratio of VTT to PTT
current_VTT	float	current vehicle travel time
current_PTT	float	current ave. personal travel time
current_VTTbyPTT	float	current ratio of VTT to PTT

Figure 29: Details of RUN object

- **GROUP.routesFromManifest:**
  Generates all routes for each driver run in the manifest generated by the VRP solver. (Only used in sorting data and plotting after the fact.)

8.5.2 RUN object

The `RUN` object contains information about a specific driver run within a group. It does not contain any specific functions.

8.6 CONVERTER object

The `CONVERTER` object converts node tags between the different network modes. `CONVERTER.NDF` is a data frame with columns for each mode with a graph and/or a gtfs feed. In the current setup, we have the following columns: `['drive','walk','gtfs','feed_gtfs','ondemand']`. Each row of this dataframe represents a separate node with id tag in each graph or feed given by the value in the appropriate column. `CONVERTER.NINDS` is a dictionary (of dictionaries). For each `mode`, `CONVERTER.NINDS[mode]` is a dictionary with keys given by nodes in that mode network. `CONVERTER.NINDS[mode][node]` then gives the appropriate (row) index for that node in `CONVERTER.NDF`. The indices for `CONVERTER.NDF` have the form `'node0'`,`'node1'`,etc. We can then do the following to convert between nodes in different mode networks. For example suppose, we want to convert a node with tag `node_tag1` from the `mode1` to `mode2`. We can use the following commands.

```
index = self.NIND[mode1][node_tag1]; # this returns the index of the appropriate row self.NDF
node_tag2 =self.NDF.loc[index][mode2]; # this returns the new node tag in the mode2 network
```

CONVERTER function descriptions

- **CONVERTER.__init__:**
  Sets up converter object to convert between nodes in different networks.

CONVERTER

Attributes

Field	Value	Description
NDF	dataframe	dataframe with node conversion info - each contains all the tags (in ea. network) for a node
NINDS	dict	dict for locating the appropriate row in NDF for a node tag from a specific network.

Functions

Function	Description
__init__	
convertNode	convert node label between two networks
findClosestNode	find the closest node in a particular network given a node in another
addNodesByType	
addNodeToConverter	add a node to the node converter, finding closets nodes in other

Figure 30: Details of CONVERTER object

- **CONVERTER.convertNode:**
  Converts between node tags in two different mode networks. (Details in the explanation above)
- **CONVERTER.findClosestNode:**
  When a new node is added to the node converter, this function finds the closest node within each network. (At the moment there is no check to make sure the nodes are less than some maximum distance from each other. This should be fixed.)
- **CONVERTER.addNodesByType:**
  This function adds many precomputed nodes to the node converter including all the stop nodes on the transit lines and origin and destination nodes for each agent in the population.
- **CONVERTER.addNodeToConverter:**
  Adds a new node to the node converter if it is not there already.

8.7 DASHBOARD

The `DASHBOARD` object gives a visual display of the simulation results, including a graphical display of the routes on a transportation map and also various cost metrics for the given routes.

Plotly (Python) for interactive static html: The code is built on the interactive plotting libraries `plotly` and `plotly.express` [5] and particularly their ability to print interactive plots to static `.html` webpages. (see https://plotly.com/python/) We specificially did not use any of any `DASH` functionality so that the dashboard can easily be displayed as a static html webpage.

DASHBOARD

Attributes

Field	Value	Description
folder	str	folder for dashboard files
DATAINDS	dict	indices of traces, figs, buttons, etc in the dashboard data
SLIDERS	dict	dict of **SLIDER** objects
BUTTONS	dict	dict of **BUTTON** objects
TRACES	dict	dict of **TRACE** objects
slider_names	list	names of slider objects
button_names	list	names of button objects
button_display_names	list	display names for buttons
factors	list	factors to plot
pltgrps		(stores subplot locations)
subplots		(stores subplots)

Field	Value	Description
imgpad	list	padding
slider_grid_locs	list	grid location of sliders
slider_hpads	list	horizontal padding - sliders
slider_vpads	list	vertical padding - sliders
slider_grid_lengths	list	slider lengths - in grid units
slider_lengths	list	slider lengths
button_lengths	list	button lengths
button_locs	list	location of buttons
button_hpads	list	horizontal padding of buttons

Field	Value	Description
colors	dict	color infö for plotting layers
edgecolors	dict	edge color info for plotting layers
opacities	dict	opacities for plotting layers
width	int	width of dashboard
height	int	height of dashboard
numx	int	num of columns
numy	int	num of rows
row_heights	list	row heights
col_widths	list	column widths

Functions

Function	Description
__init__	initialize dashboard object
makeGrid	make grid of subplots - core of dashboard construction
addSliders	add sliders to dashboard
addButtons	add buttons to dashboard
sortingData	sort data for constructing traces on dashboard and generating outputs
connectControls	connect controls (sliders, buttons, etc) to dashboard
addTraces	add traces to the different plots on the dashboard
addOutputs	construct output dataframes from sorted data
show	display dashboard

Figure 31: Details of DASHBOARD object

DASHBOARD function descriptions

- **DASHBOARD.__init__:**
  Sets up dashboard object for visualization and display.
- **DASHBOARD.makeGrid:**
  Generates grid structure for dashboard
- **DASHBOARD.show:** Generates dashboard. Updates axes. Adds sliders, buttons, and traces and connects controllers.
- **DASHBOARD.addTraces:**
  Adds traces to dashboard.
- **DASHBOARD.addSliders:**
  Adds sliders to the dashboard.
- **DASHBOARD.addButtons:** Adds buttons to the dashboard.
- **DASHBOARD.addOutputs:**
  Generates outputs.
- **DASHBOARD.sortingData:**
  Sorts data for presentation on the dashboard.
- **DASHBOARD.connectControls:**
  Connects controls (after generation)

8.7.1 TRACE

The `TRACE` object stores information for each plot and image in the dashboard figures. The current software supports three types of traces `'bar'`,`'box'`, and `'image'` traces.

- `'bar'`: Traces on bar charts
- `'box'`: traces on box plots.
- `'image'`: Images on image plots.

TRACE

Attributes

Field	Value	Description
fig	figure	figure to show trace on
image	image	image data (for images)
x	dict	x data for trace (for plots)
y	dict	y data for trace (for plots)
sliders	dict	sliders that control trace
buttons		buttons that control trace
loc	list	grid loc of TRACE
dataind	list	index of trace data within the figure
filename	list	filename for loaded traces

Field	Value	Description
color	tuple	rgb color value for trace
linecolor	tuple	rgb color value for trace
opacity	float	alpha value for trace
typ	str	type of trace .. opts: 'bar','box','image'
init_visible	bool	initial visibility of trace
bar_width	float	width for bar charts

Functions

Function	Description
__init__	initialize trace object
add	adds trace to the given plot on the dashboard

Figure 32: Details of TRACE object

- **TRACE.__init__:**
  Initializes a trace object.
- **TRACE.add:**
  Adds the trace object to the appropriate figure.

8.7.2 SLIDER

SLIDER

Attributes

Field	Value	Description
loc	tuple	grid loc of slider
xanchor	str	horizontal anchor for slider
yanchor	str	vertical anchor for slider
active	bool	slider active or not
length	float	length of slider
pad	dict	dict of padding information

Field	Value	Description
currentvalue	int	current slider value
steps	list	info for each step of slider
datainds	list	ref indices in figure data for traces referenced in the slider
turnoninds	list	which positions turn on which traces
num_steps	int	num of steps for sliders

Functions

Function	Description
__init__	initialize slider for dashboard
addTrace	adds trace to the **SLIDER**
addSteps	add information for a particular step of the slider

Figure 33: Details of SLIDER object

- **SLIDER.__init__:**
  Initializes slider object for dashboard
- **SLIDER.addTrace:**

  Adds trace to slider. `dataind` is the reference index for the trace in the figure data. `turnoninds` is the indices of the positions of the slider where the trace is turned on. Can be more than one index if the trace turns on at more than one slider position.
- **SLIDER.addSteps:**

  Sets up information for each step of the slider.

8.7.3 BUTTON

- **BUTTON.__init__:**
  Initialize `BUTTON` object.
- **BUTTON.addTrace:**
  Add data index from trace to the button.
- **BUTTON.add:**
  Generate button object that toggles traces added to the button.

BUTTON

Attributes

Field	Value	Description
name	str	identifier tag for button
display_name	str	name to display near button
typ	str	type of button
loc	tuple	grid location for buton
xanchor	str	anchor values for button
yanchor	str	anchor values for button

Field	Value	Description
currentvalue	tuple	current value of button
datainds	float	datainds associated with button
active	bool	whether the button is active
direction	str	direction of button
pad	dict	dict of pad values for button

Functions

Function	Description
__init__	initialize button object
addTrace	add trace to button
add	construct button for dashboard

Figure 34: Details of BUTTON object

8.8 RAPTOR object

Separate Notebook: `MULTIMODAL_RAPTOR.ipynb`

The `RAPTOR` object is run from a separate notebook and used to precompute the optimal timed transfer paths through the fixed line network for predetermined number of possible transfers. Run times are given in the notebook and a print out is shown in Fig. 35

RAPTOR

Attributes

Field	Value	Description
gtfs_file	str	filename for gtfs .zip file - ex. 'carta_gtfs.zip'
save_file	str	filename for file to save computed RAPTOR trips to - ex. 'gtfs_trips_NEW.obj'
feed	gtfs feed	loaded gtfs feed
transfer_limit	int	num of allowed transfers that passengers can make
add_footpath_transfers	bool	True/False - does routing consider foot transfers

Functions

Function	Description
__init__	initializes RAPTOR object - loads gtfs feed from .zip file
calculateGTFStrips	wrapper function - calls raptor_shortest_path
raptor_shortest_path	**main function -** runs RAPTOR calculations from each stop
get_trip_ids_for_stop	
get_trip_profile	
stop_times_for_kth_trip	
compute_footpath_transfers	computes possible foot transfers between stops (run once initially)
get_trip_lists	(not used at the moment)
SAVE	saves RAPTOR to RAPTOR.save_file

Figure 36: Details of RAPTOR object

RECOMPUTE GTFS FEED

for 868 stops in CARTA transit

Run times: (roughly 1 hour per transfer all`owed)

- 2 transfers = 2 hrs, 3 transfers = 3 hrs, 4 transfers = 3.85 hrs, 5 transfers = 4.85 hrs, 6 transfers = 6 hrs...

[*]:
```
recompute = True;
params = {}
params['gtfs_file'] = 'INPUTS/carta_gtfs.zip';
params['save_file'] = 'data/gtfs/gtfs_trips3.obj'
params['transfer_limit'] = 3; #default if not specified here is 1.
params['add_footpath_transfers'] = True; # default if not specified her is False;
if recompute:
    RAPTOR1 = RAPTOR(params)
    RAPTOR1.calculateGTFStrips(); # SOLVED =
```

```
preparing to implement raptor for... 868 bus stops
time to compute foot transfers:  14.67206883430481
stop number:  0
time to add stop is... 12.489600896835327
stop number:  1
time to add stop is... 12.301872253417969
stop number:  2
time to add stop is... 12.262991189956665
stop number:  3
time to add stop is... 12.290733814239502
stop number:  4
time to add stop is... 12.308046817779541
stop number:  5
time to add stop is... 12.208059787750244
```

SAVING PRECOMPUTED GTFS...

[*]:
```
saveraptor = False;
if saveraptor:
    RAPTOR1.SAVE();
```

Figure 35: Details of RAPTOR object

RAPTOR function descriptions

- **RAPTOR.__init__:** Initializes RAPTOR object - loads gtfs feed from .zip file
- **RAPTOR.calculateGTFStrips:** Main wrapper function - initially computes possible foot transfers and then calls `RAPTOR.raptor_shortest_path` which runs the main computation.
- **RAPTOR.raptor_shortest_path:**

  Main function - runs RAPTOR calculations from each stop. Number of potential transfers is given by `RAPTOR.transfer_limit`.
- **RAPTOR.SAVE:** Saves computed trip info to RAPTOR.save_file
- **RAPTOR.get_trip_ids_for_stops:**
- **RAPTOR.get_trip_profile:**
- **RAPTOR.stop_times_for_kth_trip:**
- **RAPTOR.compute_footpath_transfers:**

  Computes possible foot transfers between stops. Run once initially by `RAPTOR.calculateGTFStrips`.

References

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[3] D. Delling, T. Pajor, and R. F. Werneck, "Round-based public transit routing," *Transportation Science*, vol. 49, no. 3, pp. 591–604, 2015.

[4] K. Butts, "RAPTOR transit routing algorithm basics — kuanbutts.com," https://kuanbutts.com/2020/09/12/raptor-simple-example/, [Accessed 28-05-2024].

[5] "Plotly — plotly.com," https://plotly.com/python/, [Accessed 28-05-2024].