Daily Activity Pattern Simulation

Greg Macfarlane

Contents

Lab Task

Construct basic weekday daily activity patterns for Payson's current (2019) population. Your population should have two segments:

- workers
- non-workers

Both population groups should choose between the following daily activity patterns:

- *Mandatory* patterns include one `work` activity and up to one additional after-work activity. The work activity should "occur" on I-15 leaving the region.
- *Non-mandatory* patterns include between one and three `other` activitities. The other activities should occur in Payson or on I-15 leaving the region.
- *Home* patterns include no activities outside the home.

Use MATSim's population and plans libraries to build these plans. You may determine how to locate the households and their activities, but please document how you did this in your memorandum. Run the scenario until you reach a satisfactory level of convergence, and analyze the volumes at the I-15 interchange you are using for your Vissim analysis.

Helps

In class we built a Java class file that will help you construct and write these plans to an `xml.gz` file. You can find an example of this class file here.

There are a few additional inputs you will need to create the plans.

- Population records (and forecasts for 2050 for the future volumes)
- A distribution of points in Payson
- A distribution of daily activity patterns by worker status

Population Records

```
utco2019 <- 585694
utco2050 <- 1396997
growthpct <- (utco2050 - utco2019)/utco2019

payson2019 <- 19892
payson2050 <- payson2019 * growthpct + payson2019
```

According to Google, the 2017 population of Payson was 19,892. Go ahead and use this for your 2019 target. The Kem C. Gardner Policy Institute forecasts that Utah County will grow from 585,694 in 2015 to 1,396,997 by 2050, or 138.52 percent. If we apply the same growth rate to Payson (doubtful, but easy), this would mean 5.e+04 people will live in Payson in 2050.

> Can you think of a better way to get future population in the region under study?

```
young <- c(9.9, 9.7, 9.2, 9.3) # shares of age groups less than 20
old <- c(4.2, 2.3, 0.7) # shares of age groups greater than 65
```

The labor force participation rate for all adults between 20 and 64 in the Provo-Orem metropolitan area is 76.8% ACS. The share of the population that is this age is 54.7%, so the share of the total population that works is 0.420096

Point Distribution in Payson

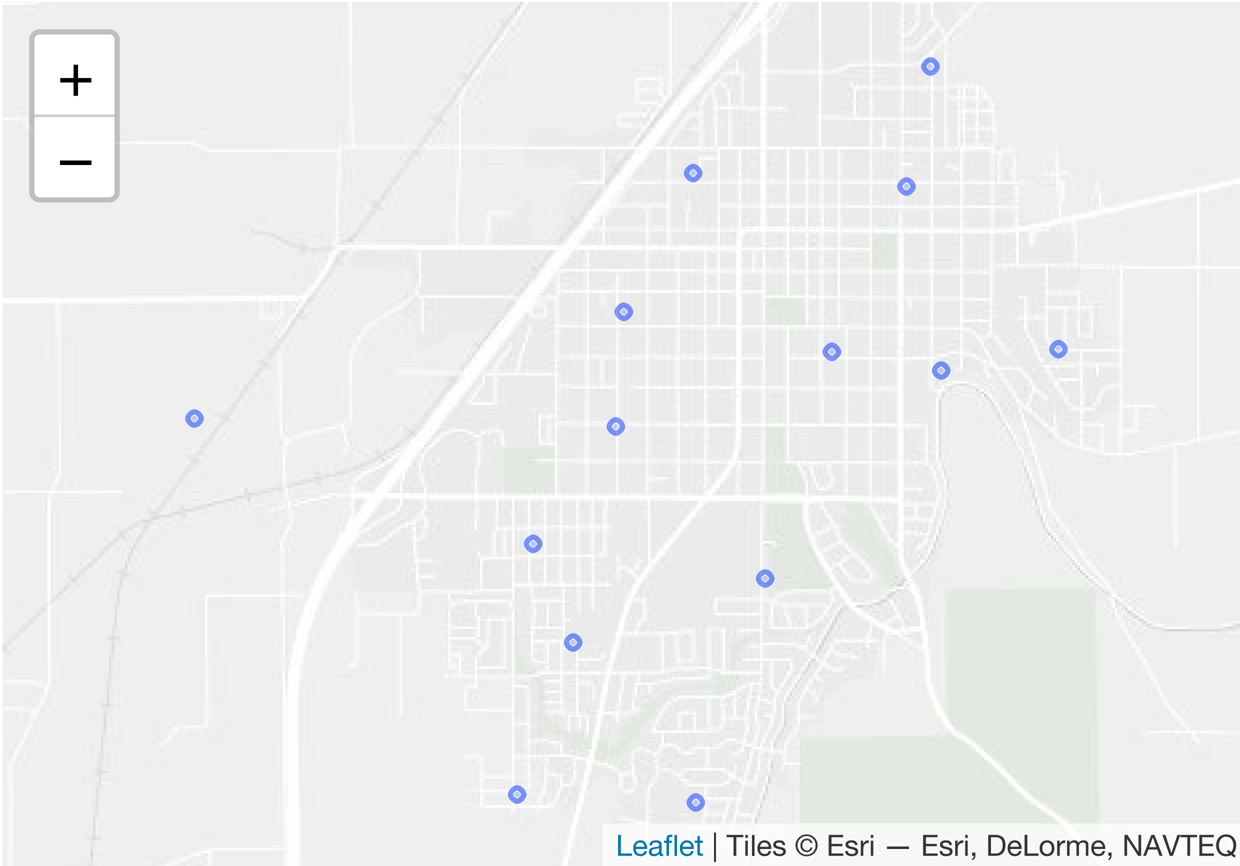
Using OpenStreetMap, we can determine that Payson can be generally described with the following bounding box:

```
LATITUDE  > 40.0135   & LATITUDE  < 40.0680
LONGITUDE > -111.7771 & LONGITUDE < -111.7046
```

Let's get the population-weighted centroids for block groups in Utah that fall inside this bounding box.

```
## pop-weighted block group centroids from Census bureau
url <- "https://www2.census.gov/geo/docs/reference/cenpop2010/blkgrp/CenPop2010_Mean_BG49.txt"
payson_bg <- read_csv(url) %>%
  filter(LATITUDE  > 40.0135, LATITUDE  < 40.0680) %>%
  filter(LONGITUDE > -111.7771, LONGITUDE < -111.7046)
```

```
## Rows: 1690 Columns: 7
## -- Column specification --------------------------------------------------------------------------------
## Delimiter: ","
## chr (2): COUNTYFP, TRACTCE
## dbl (5): STATEFP, BLKGRPCE, POPULATION, LATITUDE, LONGITUDE
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```



Then, let's calculate the mean and standard deviation of these points in the x and y direction. The map following shows 1000 random points with this mean and standard deviation. This method seems to work pretty well, though it's not perfect given that Payson is largely on one side of the freeway. But it'll work for this lab. You might also choose to use a uniform distribution instead.

```
payson_distribution <- payson_bg %>%
  summarise(
    lat = weighted.mean(LATITUDE, w = POPULATION),
    lon = weighted.mean(LONGITUDE, w = POPULATION),
    lat_sd = sqrt(Hmisc::wtd.var(LATITUDE, POPULATION)),
    lon_sd = sqrt(Hmisc::wtd.var(LONGITUDE, POPULATION)),
  )
knitr::kable(payson_distribution, digits = 7)
```

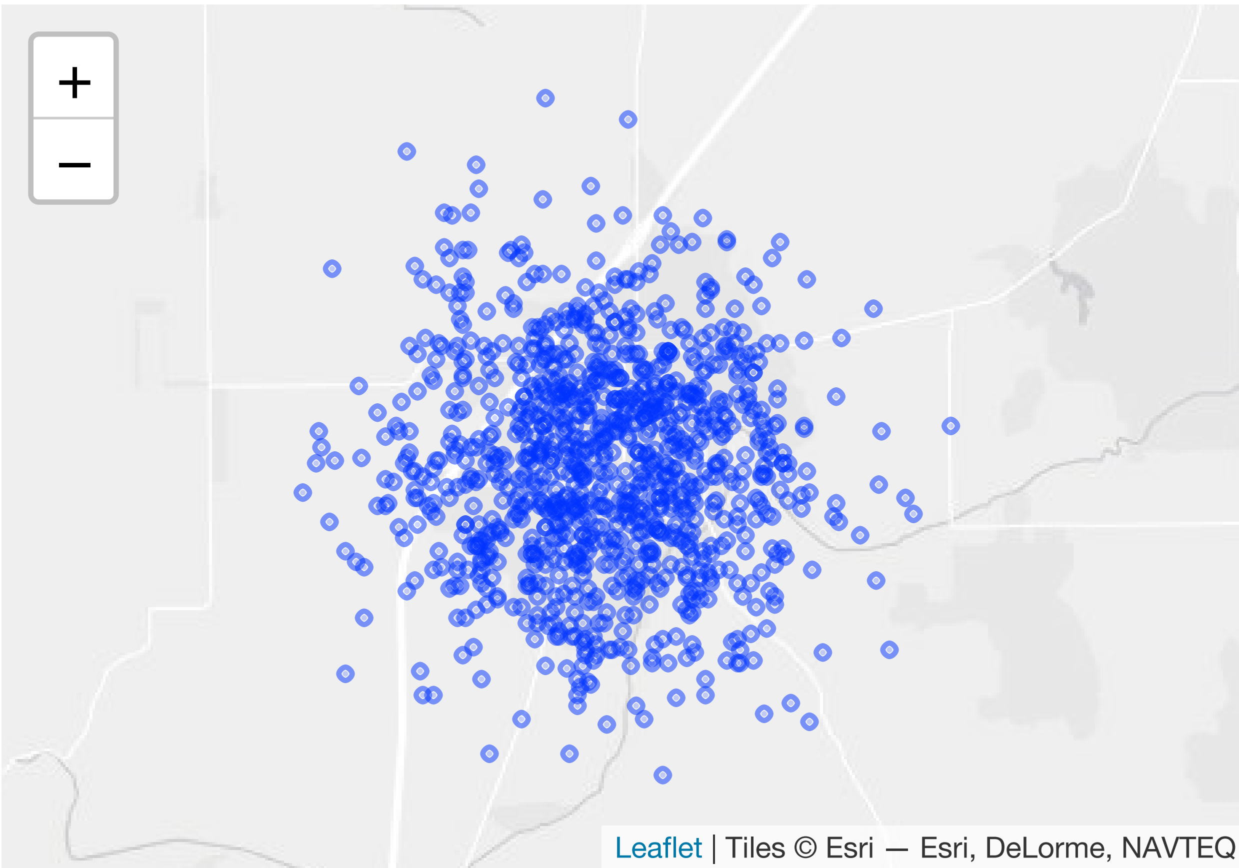
lat	lon	lat_sd	lon_sd
40.03375	-111.7362	0.0105619	0.0135612

```
n_people <- 1000
lat <- rnorm(n_people, mean = payson_distribution$lat, sd = payson_distribution$lat_sd)
lon <- rnorm(n_people, mean = payson_distribution$lon, sd = payson_distribution$lon_sd)

payson_houses <- tibble(id = 1:n_people) %>%
  mutate(
    lat = lat, lon = lon
```

```
  ) %>%
  sf::st_as_sf(coords = c("lon", "lat"), crs = 4326)


leaflet(payson_houses) %>%
  addProviderTiles(providers$Esri.WorldGrayCanvas) %>%
  addCircleMarkers(radius = 1)
```



Daily Activity Pattern Distribution

We processed the 2017 National Household Travel Survey for metropolitan areas between 1 and 3 Million people to determine the daily activity patterns for the following two person types:

- `workers`: People with a full or part-time job
- `non-workers`: everyone else

It might be debatable whether Payson behaves more like the metropolitan region it is a part of, or if it behaves like a small and isolated city. But dismissing this quibble for the moment, the DAP distribution for these two person groups is given in the table below.

Person Type	Home	Mandatory	Non-Mandatory
non-worker	0.2294942	0.1654482	0.6050576

Person Type	Home	Mandatory	Non-Mandatory
worker	0.0829301	0.6316277	0.2854422

The definition of these patterns in the context of our simulation is as follows:

- *Mandatory* patterns include one `work` activity and up to one additional after-work activity
- *Non-mandatory* patterns include between one and three `other` activitities
- *Home* patterns include no activities outside the home.