Understanding Travel Demand through Passively-generated Mobile Data: a Python-based Mobility Analysis Workshop

C2SMARTER Student Learning Hub Series

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Acknowledgements

I sincerely appreciate the National Center for Understanding Future Travel Behavior and Demand (TBD) for their ongoing support.

What you will learn today

- Theoretical
  - Basics of travel behavior theory
  - Sources of and issues with large-scale mobility data (and the collection thereof)
  - Introduction to U.S. Census data
  - Some mobility models (i.e., assumptions and limitations)
- Practical
  - Data structures for mobility data
  - Merging with census data
  - Measuring and visualizing mobility quantities (volumes, distances, etc.)
  - Predicting mobility flows with the Gravity model

Note: Some familiarity with coding / object-oriented programming may be beneficial but is not necessary to follow this session.

Overview

Before I start...

Go to this link: https://tinyurl.com/c2smartGit

And hit this button:

Why do we care about travel behavior?

Can help planners/engineers answer questions like:

- Where should we place a new transit station?
- How should we tune our signal timing to optimize traffic flow?
- How do we ensure equitable access to employment opportunities given the distribution of work/housing imbalances?
- To what extent can we predict human migration (i.e., moving to a different state for work, international migration, etc.)?

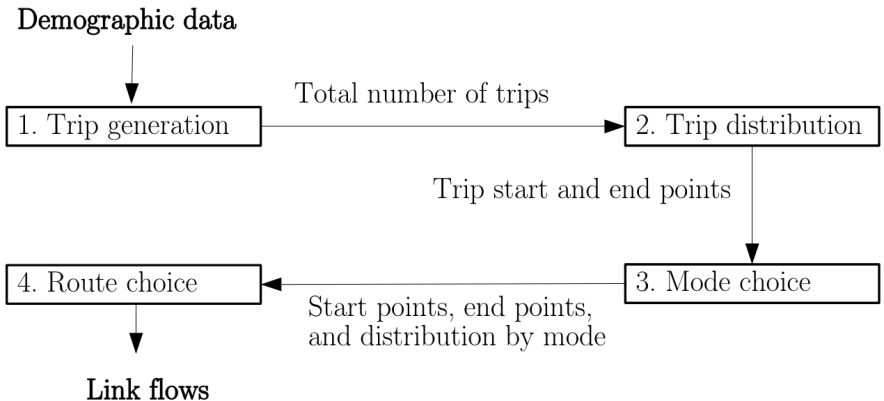
Dimensions of Travel Behavior

- **Who**: The trip maker
- **What**: Trip generation
- **When**: Departure choice, arrival time
- **Where**: Trip distribution, traffic assignment
- **Why**: Trip purpose
- **How**: Mode choice

Influences on Travel Decisions

- Person and household-related attributes
  - Socioeconomics and demographics (McGuckin and Murakami, 1999; Nishii et al., 1988)
  - Attitudes and feelings (Bayarma et al., 2007)
- Built environment
  - Surrounding origin and destination
  - Density, diversity, and design (Cervero and Kockelman, 1997)

The Four-Step Model



Source: (Boyles et al., 2025)

How do we study travel behavior?

We use mobility data, some sources of which include:

- Household travel surveys
- Traffic flow counts (i.e., from loop detectors)
- Public transit sensors
- Call detail records
- **Traces from GPS-equipped devices** ← focus for today

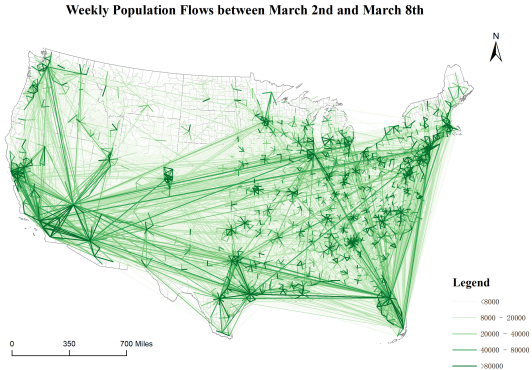
How GPS traces are collected

- Users opt-in to the privacy policies of smartphone apps
- Those apps partner with location data aggregators
- As apps 'ping' the opted-in user's device, GPS data is generated
- Some providers also have access to commercial GPS data (i.e., equipped on long-distance trucks and other commercial vehicles) which tend to be more reliable

Today's Data

Aggregate travel volumes between census block groups (CBGs) for the week of 01/04/2021.

- Publically available here: https://github.com/GeoDS/COVID19USFlows
- Aggregated by SafeGraph

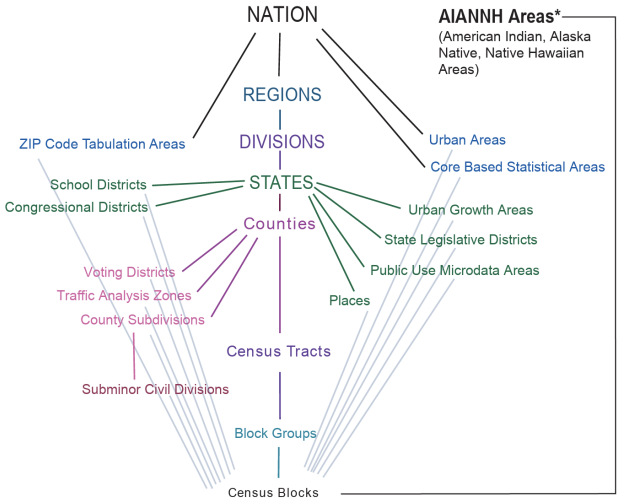


Let's get set up on our code!

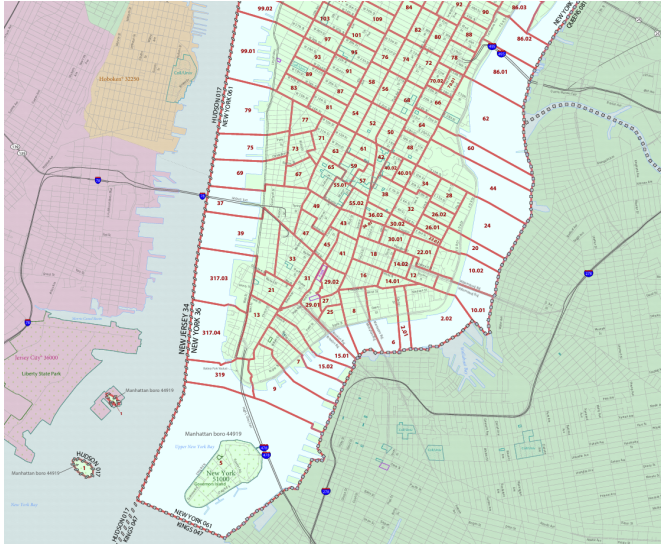
American Community Survey (ACS)

- Conducted every month, every year
- Sent to a sample of addresses (about 3.5 million) in the 50 states, District of Columbia, and Puerto Rico
- Asks about topics not on the 2020 Census, such as education, employment, internet access, and transportation
- Methodology is detailed here.

Census Geography Hierarchy



NYC Census Block Groups



Let's merge ACS data with aggregated mobility data!

Taxonomy of Mobility Models

Individual-level

- Preferential Return (Song et al., 2010)
- Recency (Barbosa et al., 2015)
- Social-based models (De Domenico et al., 2013)
- Other activity-based models (e.g., check out SoundCast!)

Population-level

- Gravity Model (Zipf, 1946)
- DNN-based Models (Wu et al., 2024; Rong et al., 2024)
- Tensor decomposition-based (Li et al., 2023)
- Other data-driven models (Ma et al., 2020)

The Gravity Model

Draws inspiration from Newton's law of gravitational attraction, positing that the flow between two locations is:

- Proportional to the "masses" of the origin and destination (typically population size)
- Inversely proportional to the distance between them

It has the general form:

$$T_{ij} = K \frac{m_i^{\alpha} m_j^{\beta}}{d_{ij}^{\gamma}} \tag{1}$$

where T_{ij} is the flow from origin i to destination j, m_i and m_j are the populations of the origin and destination, d_{ij} is the distance between the origin and destination, and K, α, β, and γ are parameters to be estimated.

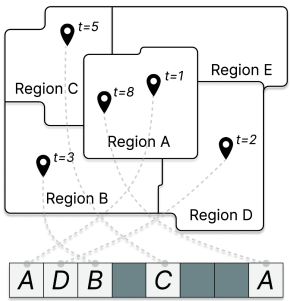
Gravity Model - Parameter Estimation

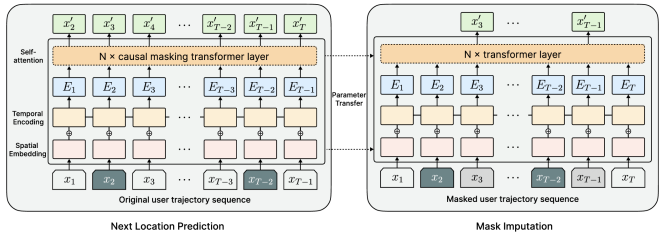
The parameters α, β, and γ are typically estimated from observed flow data. One common approach is to transform the equation into its logarithmic form:

$$\log(T_{ij}) = \log(K) + \alpha \log(m_i) + \beta \log(m_j) - \gamma \log(d_{ij}) \tag{2}$$

This enables the use of Maximum Likelihood Estimation (MLE) to find optimal parameter values that best explain observed flows.

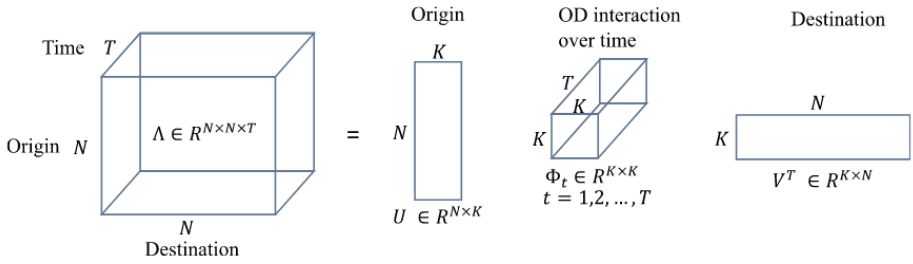
DNN-based Models





Source: (Wu et al., 2024)

Tensor Decomposition-based



Source: (Li et al., 2023)

Model Evaluation

Common Part of Commuters (CPC)

Measures the overlap between predicted and observed flows

$$CPC = \frac{\sum_{i,j} \min(T_{ij}, \hat{T}_{ij})}{\sum_{i,j} T_{ij}} \tag{3}$$

where $\hat{T}_{ij}$ is the predicted flow from zone i to zone j.

- CPC ranges from 0 to 1
- 1 means perfect prediction (all flows match)
- 0 means no overlap between predicted and observed
- Represents the fraction of correctly predicted trips

Model Evaluation

Root Mean Square Error (RMSE)

Quantifies the absolute difference between predicted and observed flows

$$RMSE = \sqrt{\frac{1}{n}\sum_{i,j}(T_{ij} - \hat{T}_{ij})^2} \tag{4}$$

where n is the total number of origin-destination pairs.

- Lower RMSE == better performance
- Sensitive to large errors due to the squared term
- Same unit as flow data, making interpretation straightforward
- Emphasizes absolute errors, which might overemphasize high-flow connections
- For mobility data, often calculated on log-transformed flows to reduce the impact of extreme values

More Resources

- Additional details on LBS data: BigData4Mobility.github.io
- Data Science for Mobility (DSM) Summer School organized by Luca Pappalardo → notebooks here.
- UW Geospatial Data Analysis Course (hosted entirely open-source!)
  - For a more comprehensive treatment of GeoPandas, check out Modules 3, 4, and 6.
- Excellent review of mobility models: *Human mobility: Models and applications*

Our Work

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Connect with me!

- I'm interested in solving long-range transportation planning problems using large-scale machine learning (ML).
- My personal website is here: https://ekinugurel.github.io/
- LinkedIn: linkedin.com/in/ekin-ugurel
- Google Scholar

The End

Please take this anonymous feedback survey to help me make this presentation better

https://tinyurl.com/c2smart

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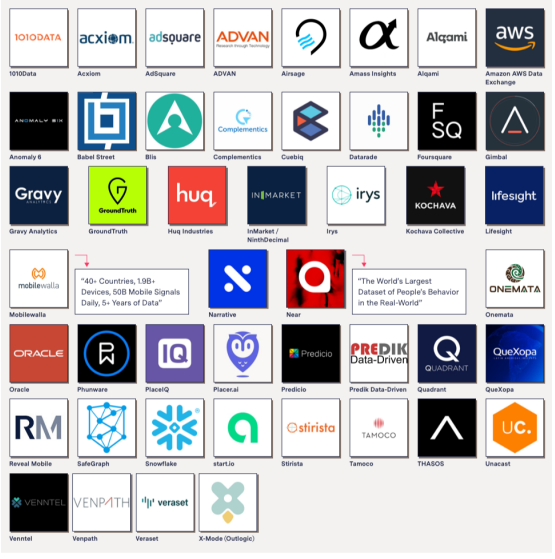
The Mobility Data Landscape



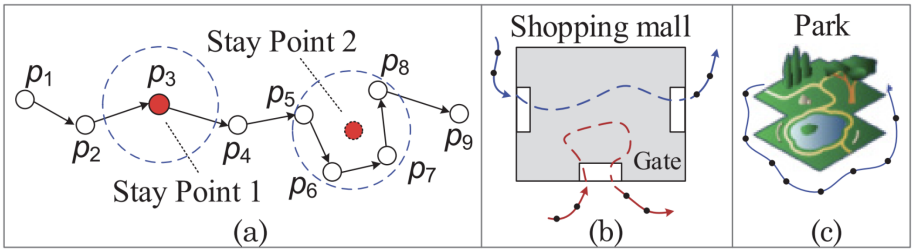
Source: The Markup

Issues in GPS-based data collection / use

- Sparsity
  - Peaks and valleys of observation frequency (Ban et al., 2018)
  - 'Urban canyons' & enclosed structures
  - 'Cold start problem'
- Privacy
  - Sensitive information (e.g., one's home and work locations) is easily inferred from high granularity GPS data (De Montjoye et al., 2013)
  - Anonymization and aggregation methods are needed to protect user privacy
- Bias
  - Self-selection bias prevents representativeness (Li et al., 2024)
  - Observed data may distort real-world patterns

Stay Point Detection

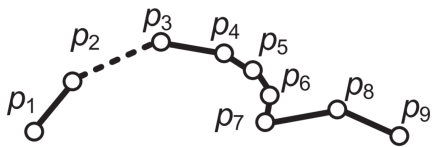
Activity locations where people stay for a period of time.



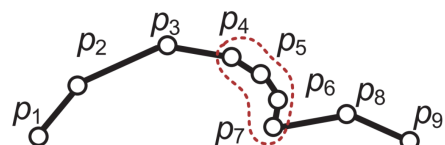
Source: (Zheng, 2015)

Trajectory Segmentation

A trajectory is split into two or more sub- trajectories, with several techniques:



time-interval



stay-point

Source: (Zheng, 2015)