MobilityNet

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Outline

- Motivation and relation to climate change
- Dearth of good quality datasets for mobility
- MobilityNet: privacy preserving, cross platform, ground truthed
  - 1080 hours of multimodal, diverse data
  - 16 sets of travel contexts (e-scooter, bike, walk, etc)

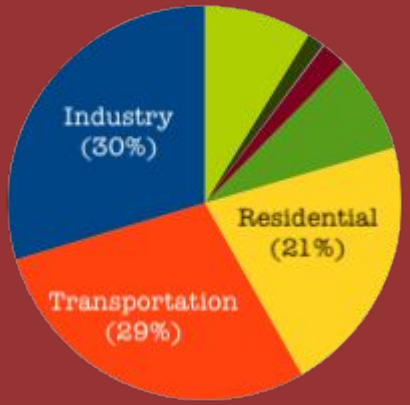
Motivation

Transportation emissions

Photo by **Arthur Ogleznev** from **Pexels**

7.0

GtCO2eq



29%

Contribution worldwide

25%->28%

(1990) (2015)

Increasing trend

Travel behavior is critical

Greenhouse Gas (GHG) reduction strategies:

- Behavior: Avoiding journeys (land-use, tech)
- Behavior: Modal shift
- Engineering: Lowering energy intensity (fuel efficiency)
- Engineering: Reducing fuel intensity (alternative fuels)

New Delhi, near the Yamuna river, in Mar 2018 and Apr 2020,
In India, life under coronavirus brings blue skies and clean air, Washington Post

Public policy stakes example

Plan BayArea 2040 budget

~ $292 Billion

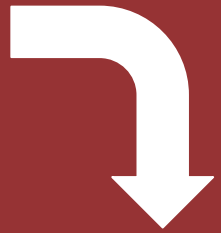
Over

30 years

6 meetings

50 - 300 attendees each

4 lawsuits



Understanding data accuracy is key!

(e.g. census)

Karen Trapenberg Frick (2016) Citizen activism, conservative views & mega planning in a digital era, Planning Theory & Practice, 17:1, 93-118, DOI: 10.1080/14649357.2015.1125520

Limitations of existing datasets

Power vs. accuracy

- Geolife dataset
  - 182 users, 3 years
  - GPS data from dedicated devices
  - 2 sec interval
- SHL challenge
  - Kitchen sink data collection
  - 8 sensors, high frequency
  - Only single user 4 month subset released

Battery icons shape perceptions of time and space and define user identities. City University London. https://phys.org/news/2019-09-battery-icons-perceptions-space-user.html

The study of London commuters found that respondents viewed their daily trip in terms of the time and distance between charging points for mobile technology.

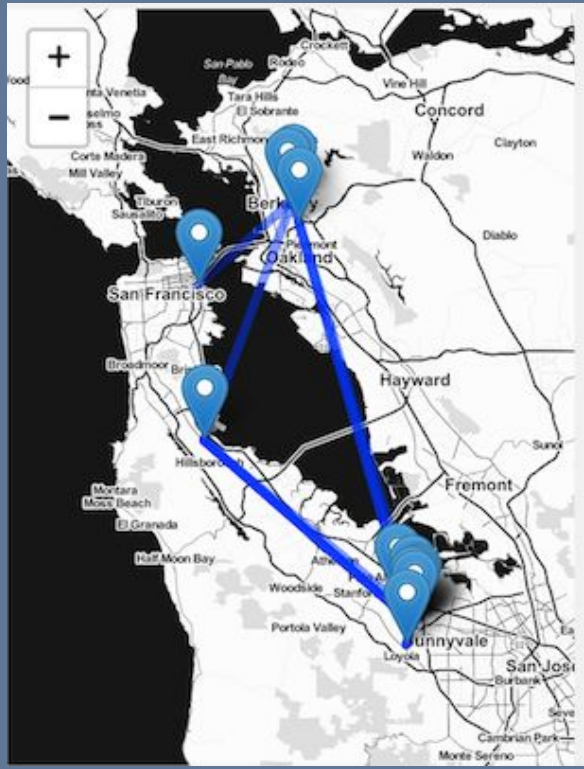
"People no longer think about their destination being 10 km away or 10 stops on the tube. They think about it being 50 per cent of their battery away," said the study's lead author, Dr. Thomas Robinson.

"During interviews respondents discussed how a full battery gauge made them feel positive and as though they could go anywhere or do anything. Anything less than half full, however, induced feelings of profound anxiety and discomfort," he said.

One of the study's respondents described the experience of watching their battery icon throughout the day: "Full would be 'Yeah, ok great', good to go for the day'; 50 per cent I'd be a bit 'Oh God, I had better stop it from updating itself all the time in the background' ... then it would be at 30 per cent and I would be like: 'Now I'm not having fun anymore'," the respondent said.

Privacy

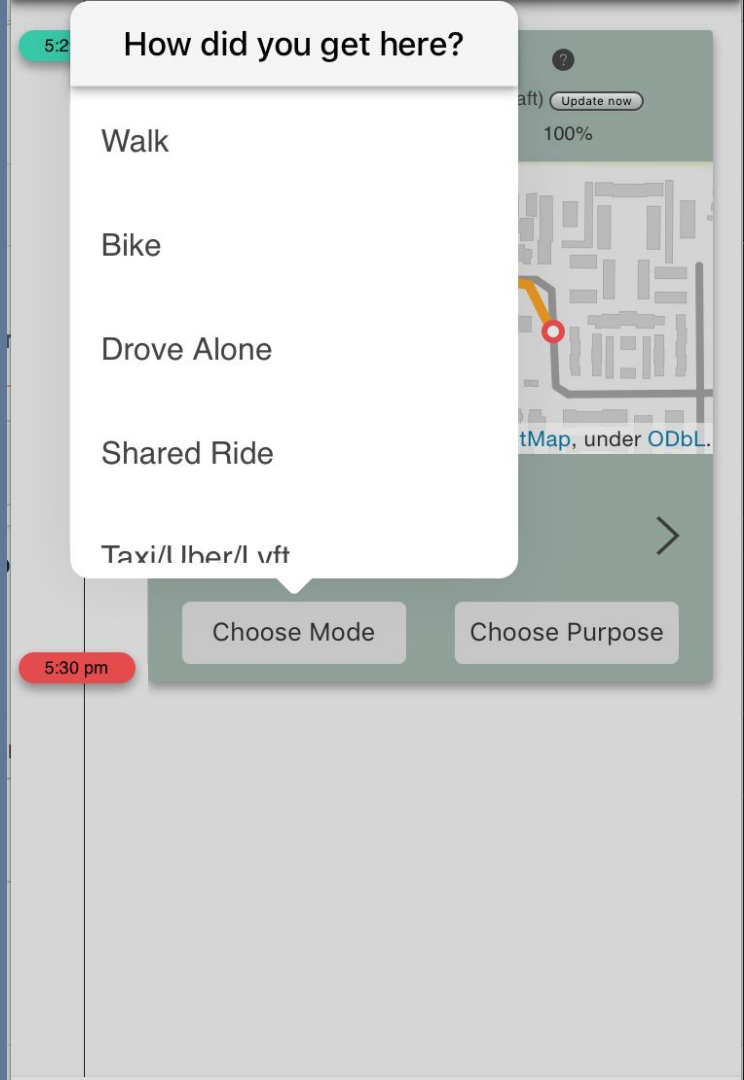
- Location data is inherently privacy sensitive
  - Redacting user name and email is not enough
  - Fuzzing ends is not enough
  - Home + work combination at cell tower granularity
    - unique for more than 50% of users*
- Very little public data
  - Opportunity Activity Recognition Challenge (no GPS)
  - US-Transportation Mode Dataset (no GPS)
  - Multiple mode inference papers (no dataset published)



* Montjoye, Yves-Alexandre de, César A. Hidalgo, Michel Verleysen, and Vincent D. Blondel. 2013. “Unique in the Crowd: The Privacy Bounds of Human Mobility.” *Scientific Reports* 3 (March). https://doi.org/10.1038/srep01376.

Ground truth

- Primary focus on travel mode
- Prompted recall (PR): show list of trips for labeling
  - But mode depends on correct segmentation!
  - PR unreliable as ground truth*
    - Certainly wrong 9%
    - Probably wrong additional 10%
- No spatio-temporal ground truth

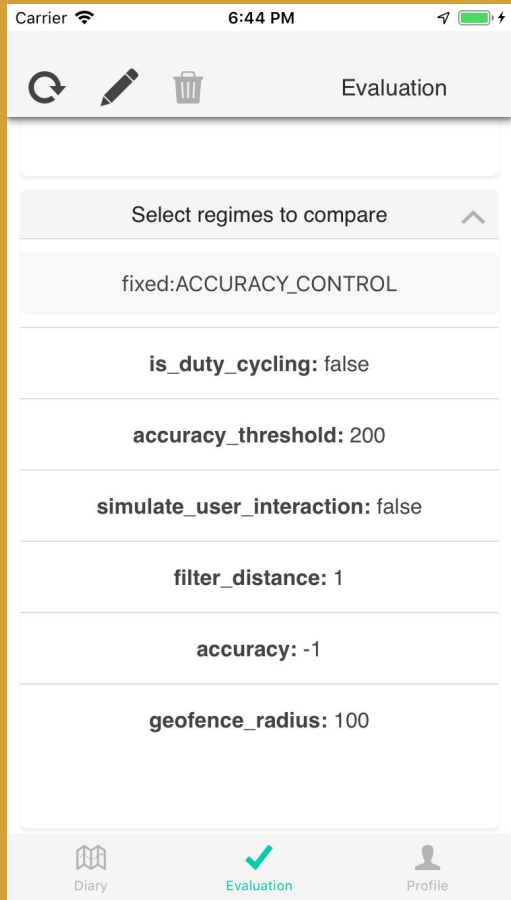


* Peter R. Stopher, Li Shen, Wen Liu, and Asif Ahmed. The Challenge of Obtaining Ground Truth for GPS Processing. *Transportation Research Procedia*, 11:206–217, 2015. ISSN 23521465. doi: 10.1016/j.trpro.2015.12.018

MobilityNet

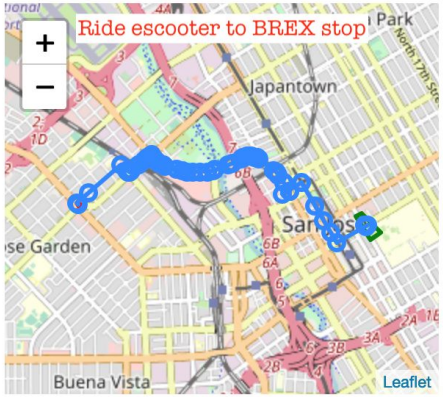
Concepts

- Artificial trips
  - **Uses:** Pre-defined spec with trajectories and modes
  - **Solves:** Privacy and spatial ground truth
- Control phones
  - **Uses:** Multiple phones with auto-configured app
    - accuracy and power controls
  - **Solves:** Power/accuracy tradeoff, temporal ground truth
- Repeated travel
  - **Uses:** Pre-defined spec with travel time and dwell time
  - **Solves:** Context sensitive variation from sensing APIs

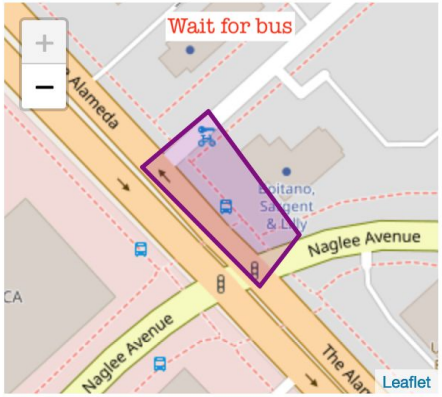


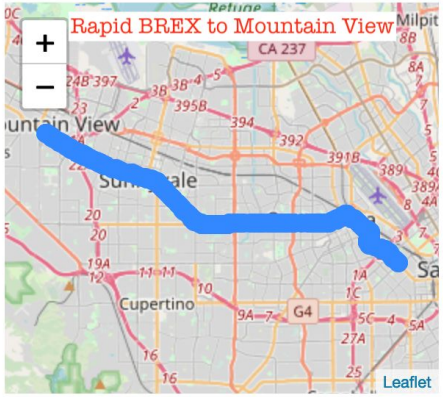
Sample spec


Walk from library to escooter location
Leaflet

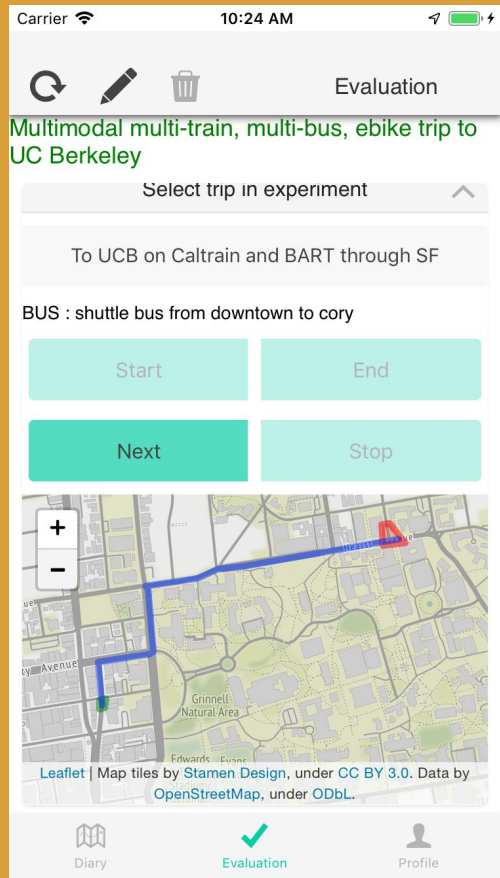

Ride escooter to BREX stop
Japantown
Buena Vista
Leaflet


Park escooter and walk to BREX stop
Naglee Avenue
Leaflet


Wait for bus
Naglee Avenue
Leaflet


Rapid BREX to Mountain View
CA 237
Cupertino
Leaflet


Walk to Mountain View Library
Leaflet


Carrier
10:24 AM
Evaluation
Multimodal multi-train, multi-bus, ebike trip to UC Berkeley
Select trip in experiment
To UCB on Caltrain and BART through SF
BUS : shuttle bus from downtown to cory
Start
End
Next
Stop
Leaflet | Map tiles by Stamen Design, under CC BY 3.0. Data by OpenStreetMap, under ODbL.
Diary
Evaluation
Profile

Data characteristics

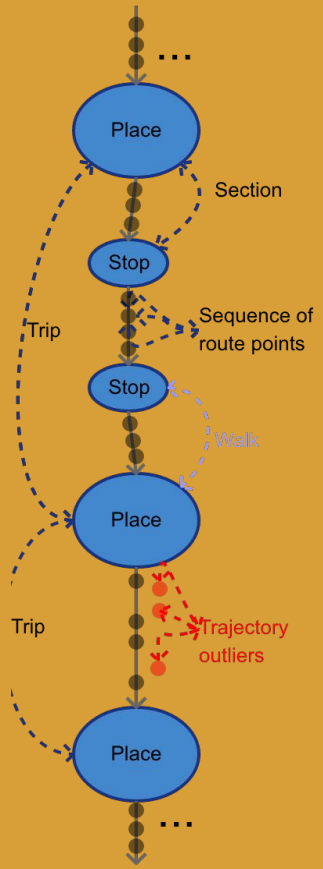
- Trip characteristics
  - ~3x dwell time vs mean travel time
  - Travel between public locations to preserve privacy
- Transfer Between Modes
  - Detecting mode transfer is hard
  - MobilityNet contains many different mode transitions
- Large and multimodal
  - Over 1080 hours across 16 different travel contexts!
  - Similar modes done in different contexts

Data sources

- Primarily from *Virtual Sensors*
  - Closed source APIs provided by phone OS
- Fused Location
  - GPS/WiFi/Cellular (ts, lat lon, accuracy, speed)
- Motion Activity
  - Accelerometer/gyroscope/barometer (ts, confidence, type)
- Trip Transition Events
  - Virtual and custom platform duty cycling events (exit geofence, stop moving, tracking stop)
- Battery

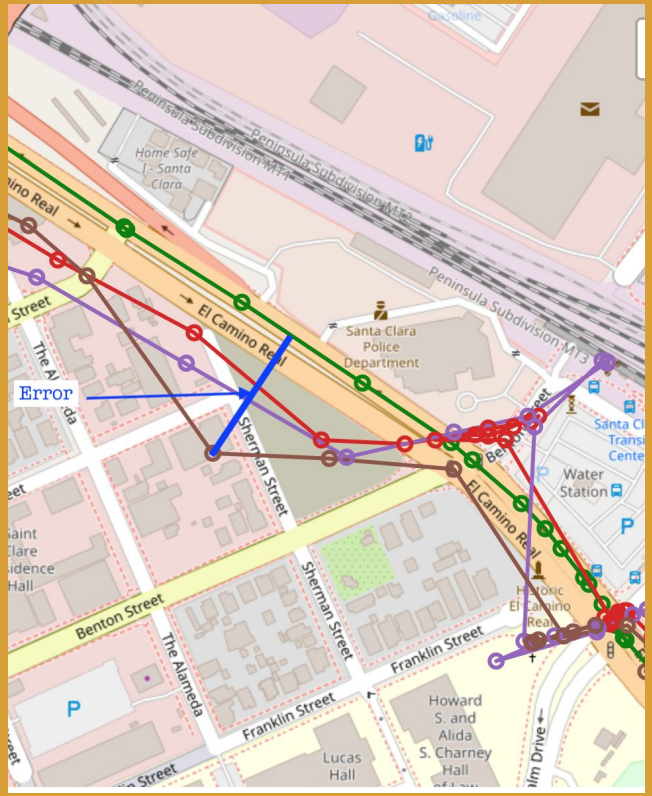
Mobility Diary

- Sensed data ⟶ Mobility Diary
  - Raw data -> trip/section trajectories w/ transport modes
- Construction
  - Trip Segmentation
    - Data will have gaps
  - Section Segmentation
    - Travel by one mode
  - Trajectory Filtering
    - Erroneous data can be common
  - Mode Inference
    - Hard to distinguish some modes from others



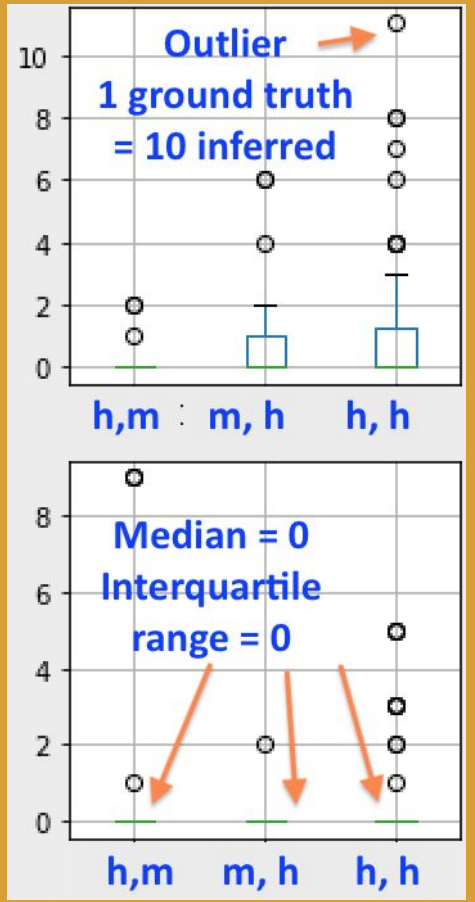
Metrics

- Trip and section segmentation
  - Difference in count
  - Difference in start and end timestamps
- Trajectory outlier detection
  - Spatial: Δ (point, ground truth trajectory)
  - Spatio-temporal: Δ (point, reference trajectory)
- Mode classification
  - Segmentation dependency ↔ % matching
  - Force segmentation ↔ F1 score?
- Battery drain



Baseline results

metric	goal	android h, h	android m, h	android h, m	iOS h, h	iOS m, h	iOS h, m
battery drain (%)	low	42	30	10	10	2	10
trajectory error (m)	low	6	5	10	6	15	3
Δ trip count	low	0	0	0	0	0.5	1
Δ section count	low	0	0	0	0	0	0
Δ trip start (min)	low	4	5	5	5	5	4
Δ trip end (min)	low	5	30	5	2	1	0
Δ section start (min)	low	2	0	3	1	0.5	2
Δ section end (min)	low	0	1	0	3	5	2
Mode match ratio	high	1	1	0.99	0.9	0.8	0.9



Conclusion

- Accurate travel behavior
  - Critical for long-term mitigation of transportation GHG
- Lack of public datasets
- MobilityNet: 1040 hours of cross-platform data
  - http://mobility-net.org/ / https://github.com/MobilityNet/
- Call to action
  - Classic challenges on the public dataset
  - Data collection from other locations for a larger public dataset
  - Hybrid challenges, run winning algorithms on large private data