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Transforming ENERGY

Estimating Travel Energy Consumption Uncertainty Based on Inferred Travel Mode and Sensed Travel Length

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Bridging Transportation Researchers

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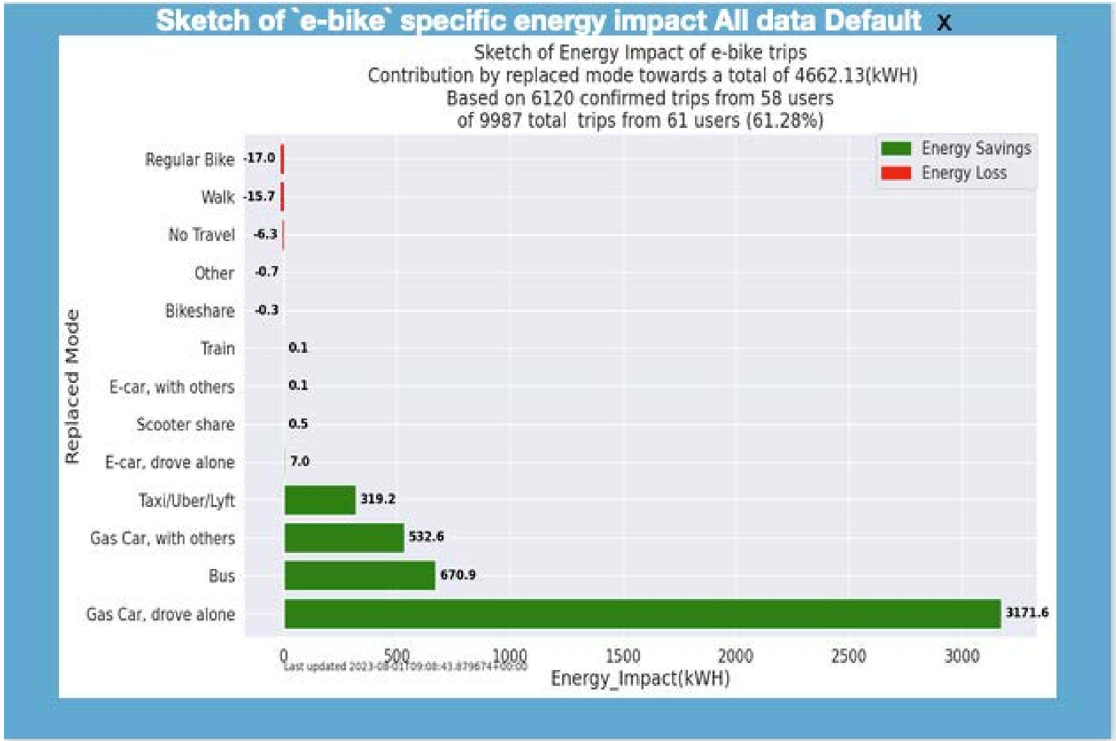
Photo from iStock-627281636

Vehicle Energy Consumption

Vehicle	Energy Impact Score	Greenhouse Gas Emissions (tailpipe)
Compare 	5.0 barrels/yr	10 1 10 Best 151 grams/mile
Compare 	5.4 barrels/yr	9 1 10 Best 162 grams/mile

Source: www.fueleconomy.gov

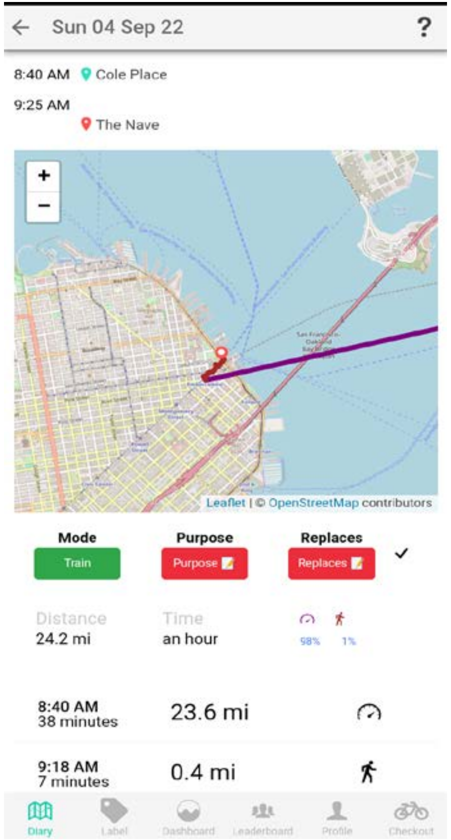
Traveler Energy Consumption



Energy savings when e-bike replaced the modes on the left.
Data collected with OpenPATH in Durham, NC

Smartphone Travel Diaries

- Smartphones can collect travel diaries
  - Carry phone during travel
- Participants get tired of labeling trips
  - Only 38% (94,000) of OpenPATH trips labeled
- Lots of unused information (146,000 trips)
- What if we try to use that information for decisions?
  - Infer travel mode with sensors or past labels



Screenshot from CanBikeCO app

Key Points

- Travel diaries from smartphones can tell you about travel behavior in a region
- Mode inference (machine learning) models can fill in some info that travel monitoring participants leave out
  - Makes data collection easier
- BUT: need to know how well those models perform
- We looked at uncertainty for one metric – energy consumption

Accounting for Uncertainty

- Energy = Energy Intensity * Travel Length = I*L
- For a travel diary or set of trips D:

$$E = \sum_{t \in D} I_t L_t$$

- Need uncertainty in both inputs
- Used ground truth smartphone travel data set (MobilityNet (Shankari et al, 2020))
- Energy Intensity/Mode uncertainty – confusion matrix
  - Can find for any mode classification algorithm
  - Accuracy not enough
- Length uncertainty – relative length error

Accounting for Uncertainty

- Mode: confusion matrix
  - Given predicted mode
  - Mean and variance of energy intensity (I)
- Length: relative length error
  - Given measured length
  - Mean and variance of actual length (L)
- Combine with variance propagation

$$\sigma_E^2 \approx \sigma_I^2 \mu_L^2 + \sigma_L^2 \mu_I^2$$

	Predicted Mode				
Actual Mode		Car	Ebike	Bike	Walk
	Car	7	2	1	0
	Ebike	2	5	3	1
	Bike	1	2	4	1
	Walk	0	1	2	8

Example confusion matrix.
Entries are number of occurrences.
More modes were present in actual

- Convert confusion matrix columns to probability distributions
  - P(actual mode | predicted mode)
- One approach: Divide each entry by the sum of its column
- After that, assign each an energy intensity
  - Based on the Transportation Energy Data Book from Oak Ridge National Laboratory

		Predicted Mode			
		Car	Ebike	Bike	Walk
Actual Mode	Car	0.7	0.2	0.1	0
	Ebike	0.2	0.5	0.3	0.1
	Bike	0.1	0.2	0.4	0.1
	Walk	0	0.1	0.2	0.8

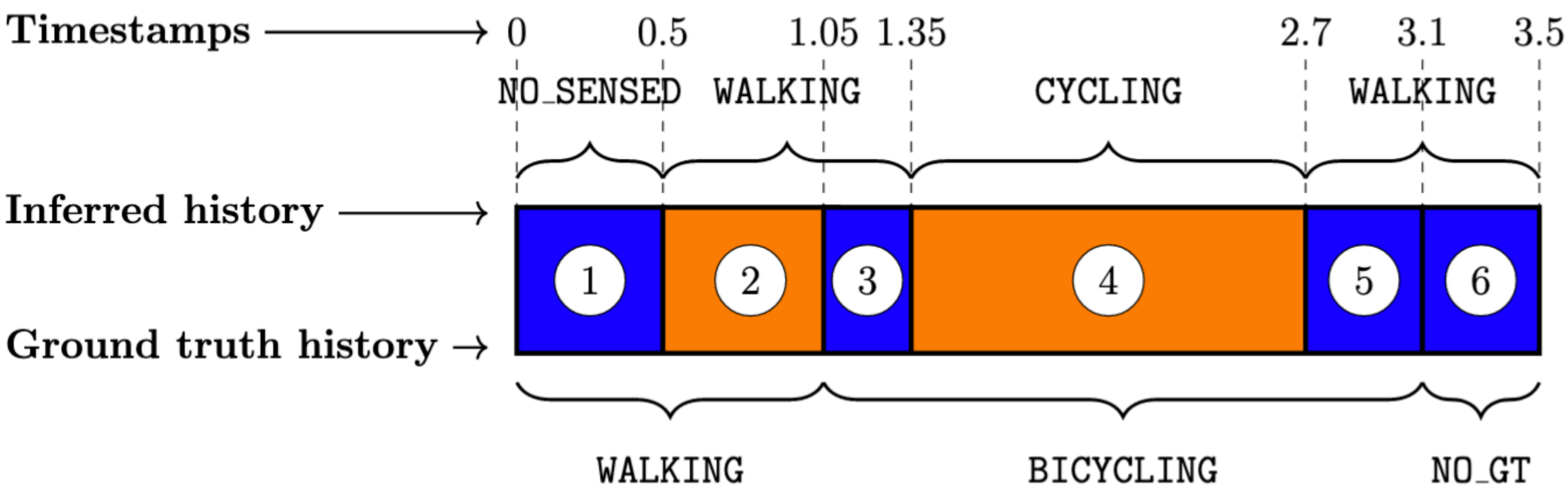
Now a table of mode probabilities in columns

	predict car	predict ebike	predict bike	predict walk
1.512 (car)	0.7	0.2	0.1	0
0.022 (ebike)	0.2	0.5	0.3	0.1
0 (bike and walk)	0.1	0.3	0.6	0.9

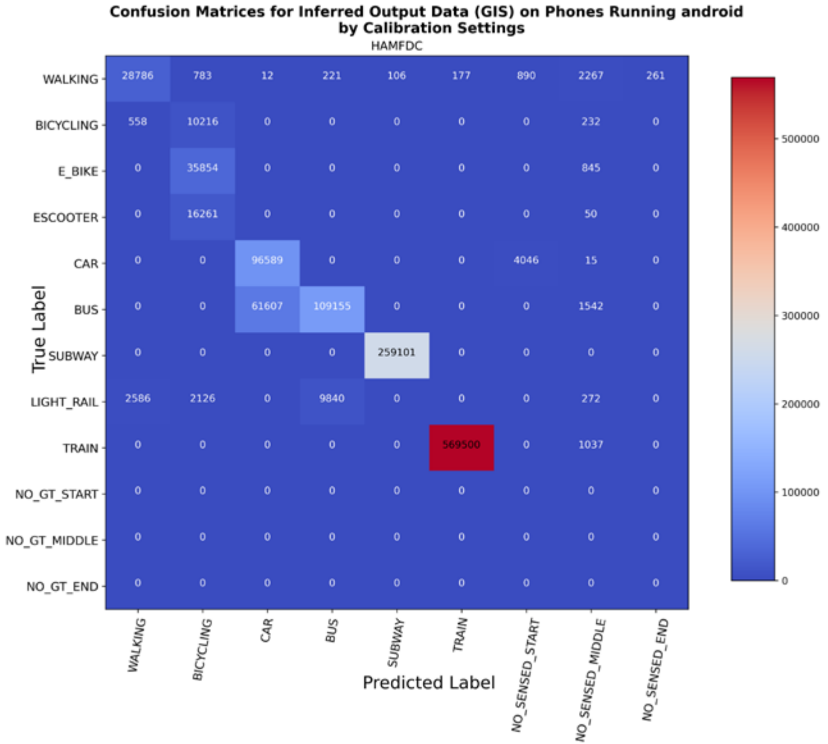
Table of energy intensity (kWH/PMT) probabilities

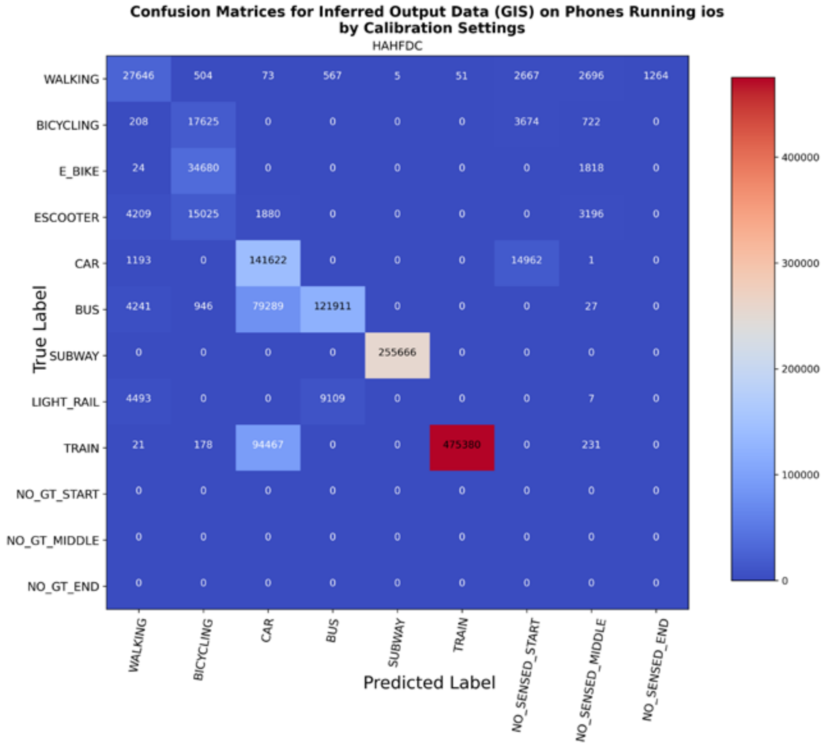
PMT = passenger miles traveled

Align Segments

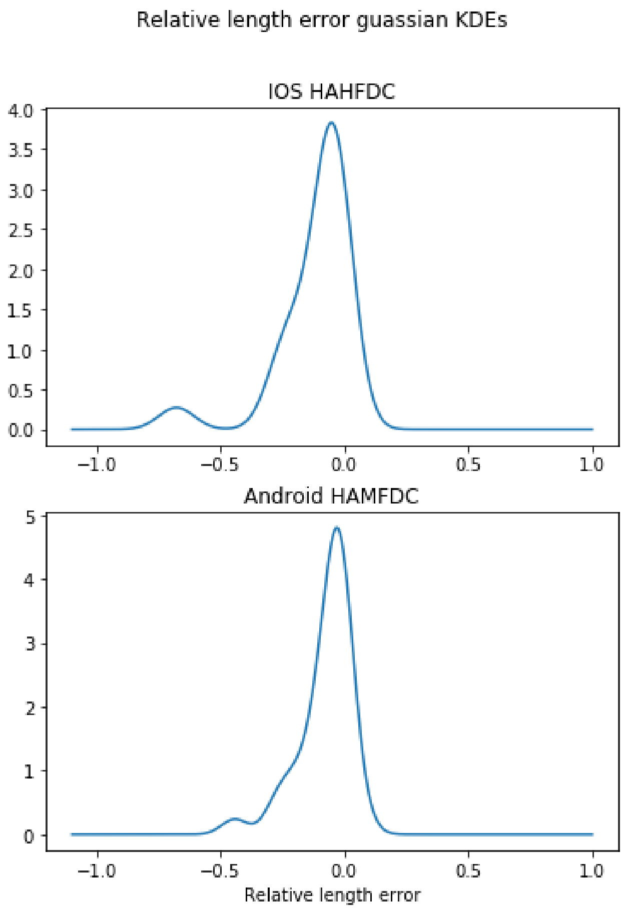


G. Kosmacher and K. Shankari, 2022





- Confusion matrix for phones running Android or iOS for a sensor-based mode inference model. Entries are in meters (found with methods based on G. Kosmacher and K. Shankari).
- HAHFDC and HAMFDC: phone configurations for recording data.
    - HAHFDC: High Accuracy, High Frequency, Duty Cycling
    - HAMFDC: High Accuracy, Medium Frequency, Duty Cycling



$$L_{actual} = L_{measured} * \frac{1}{1+R}$$

- Sampled from relative length error (R) distributions to find mean and variance of actual length given a 1 unit measured length

	$\bar{x}_R$	s_R^2	μ_L MCS	σ_L^2 MCS
android HAMFDC	-0.0776	0.1051	1.1060	0.03214
ios HAHFDC	-0.1397	0.2018	1.2224	0.3305

Acronyms:

- KDE: Kernel Density Estimate
  - Finds a distribution to represent the variation in data
- MCS: signifies that an estimate came from Monte Carlo Simulation

Variance Propagation

- At first, we summed the variances across trips:
  - $\mathrm{E} =$ variance of energy consumption for all trips
  - $var(E) = \sum_{t \in D} \sigma_t^2$
- However, most program (set of participants) estimates were above 7 standard deviations (sd) from the truth
  - With this, we would be placing more certainty on our estimates than we should

Variance Propagation

A better approach:

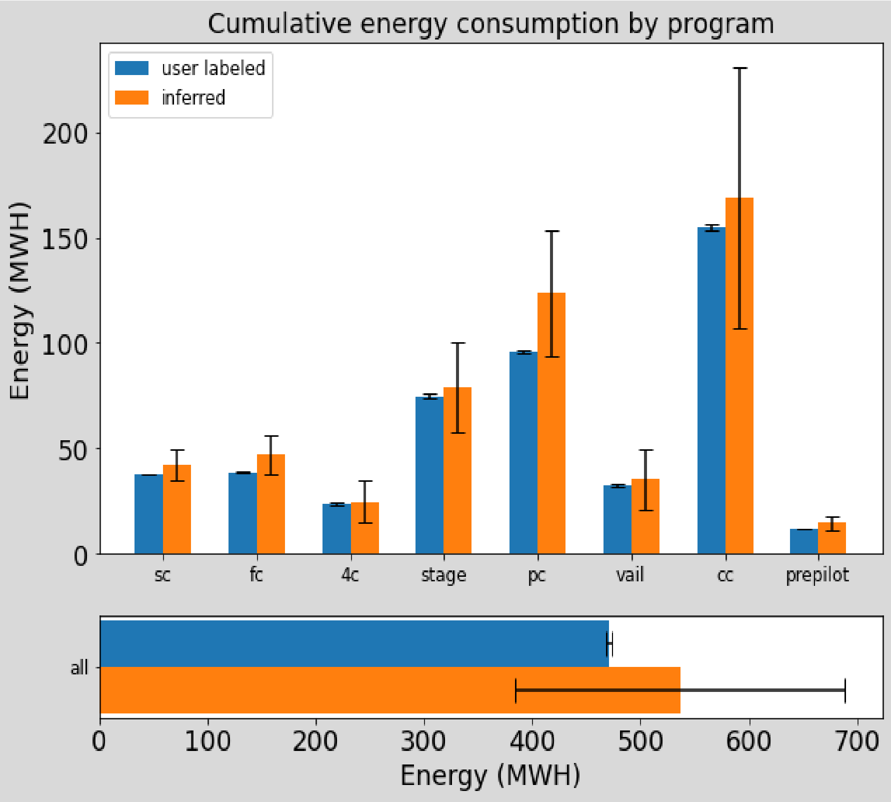
- Group trips together by predicted mode
- Number the modes (m) as {1, 2, …, k}
- I_m, L_m: Intensity for mode m, total travel length where mode m was predicted
- $var(E) = var(\sum_{m=1}^{k} I_m L_m) = \sum_{m=1}^{k} var(I_m L_m)$
  - $var(I_m L_m) \approx \sigma_{I_m}^2 \mu_{L_m}^2 + \sigma_{L_m}^2 \mu_{I_m}^2$
- Considers that predictions are not isolated events
  - Some mistakes might be repeated often

Assumptions

- Mode error and length error independent
- Ignore energy model specification error
  - We are applying an average intensity to the entire trip
- No error in user’s mode labels
- Error in MobilityNet applies to other geographies
- Assume an underlying mode prevalence (chances of each mode)
- Equal chances of drove alone and shared ride (sensing model does not distinguish these)

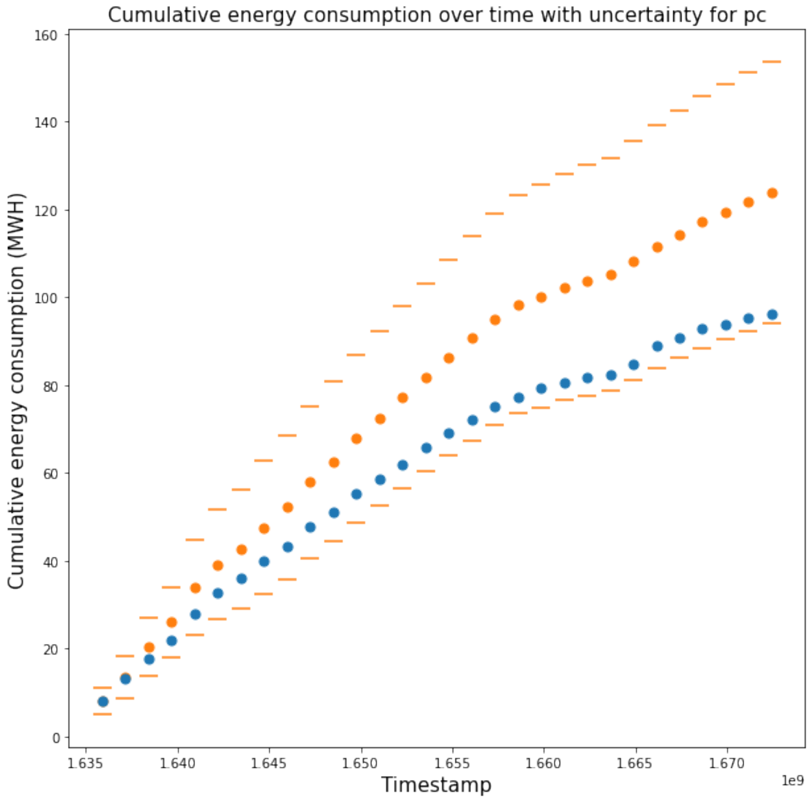
Results

- Benchmark on CanBikeCO
  - Low-income participants given electric bicycles
  - 1.5 years of data
  - Overall energy consumption error: 8% (bottom bars)
    - 13% if basing estimates on sections
  - Each program within 1 estimated standard deviation
  - At the user level: 82% within 2 estimated standard deviations

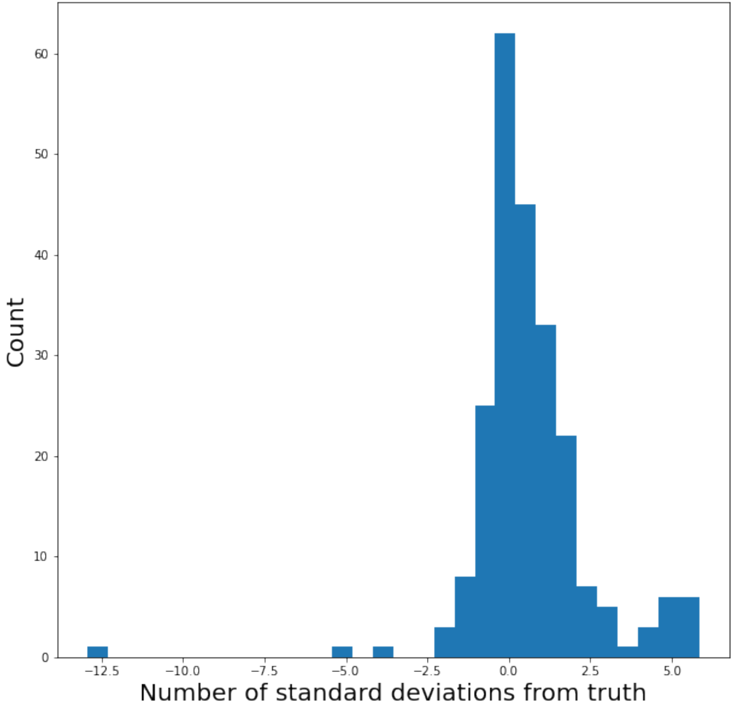


Results

- Cumulative energy consumption over time for Pueblo County (PC)
- PC was the program with the largest error
- Blue: energy based on user labels
- Orange dots: energy based on sensed labels
- Orange dashes: 1 standard deviation from the estimated energy consumption
- Data points are in 30-day increments



Results

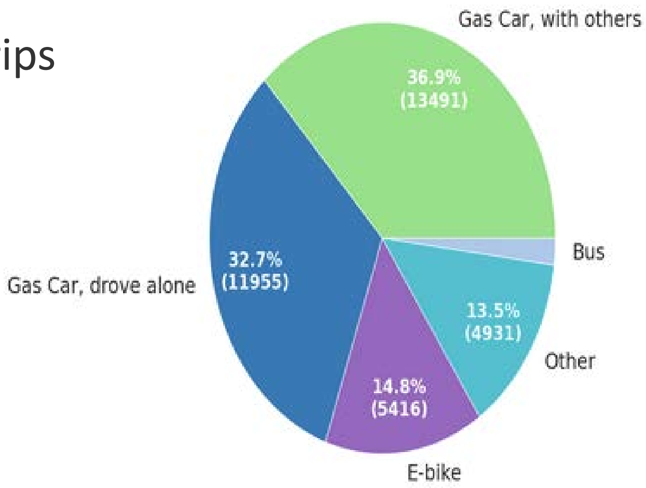


Histogram of user level number of standard deviations from the truth for cumulative energy consumption

Relevance and Future Work

- Inferred labels → Less labeling burden
    - Makes long term studies more viable
- Bias less toward people with free time to label their trips
- Local travel understanding
- Behavior models - better representation in travel demand forecasting

- Estimate mode share, energy/carbon impact, trip purpose share
- Apply methods to other mode inference models
    - e.g., learn from users' past labels
- Make better models (e.g., include route map matching to better distinguish bus and car)
    - → narrow the error bars



Trip miles by mode collected with OpenPATH in Durham, NC

Data Availability

TSDC

Spatial Data ›

An application is required to access latitude and longitude spatial data from transportation studies and surveys.

Transportation Secure Data Center: www.nrel.gov/tsdc

References

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2. G. Kosmacher and K. Shankari. *Evaluating the Interplay between Trajectory Segmentation and Mode Inference Errors*. Transportation Research Record (to appear)

Q&A

www.nrel.gov

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