Minimum Length of Sensor Data Collection for Robust Mobility Estimation

Zhihang Dong, Yen-Chi Chen, Adrian Dobra

Department of Statistics
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CENTER for STATISTICS and the SOCIAL SCIENCES

Authors

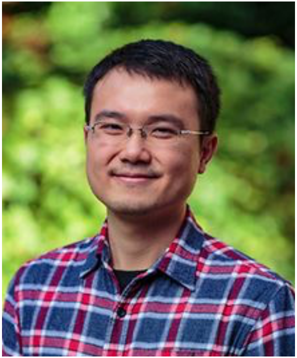

FIGURE – Yen-Chi

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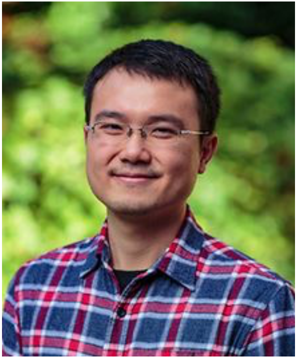

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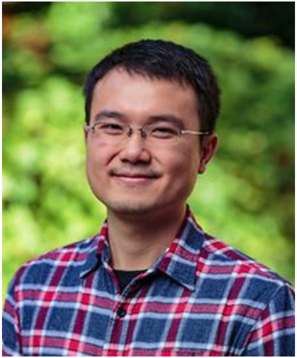

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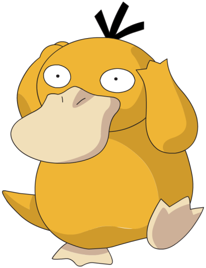

FIGURE – Zhihang (Presenter)

A Fundamental Question

The development of pervasive computing and wearable sensor technology has brought up an exponential growth of data of human activities. With great data comes with great responsibilities... How to handle these data ?

FIGURE – Wearable Sensor Devices (Fitbit)

Current Research

There are many topics studied... Here is a group of topics funded by NIH using censor data...

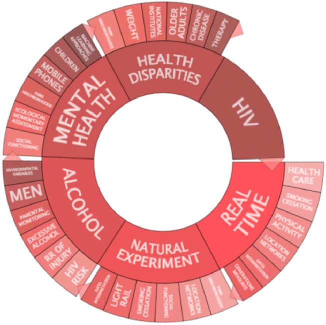

FIGURE – Topics using Sensor Data

A Fundamental Question (2)

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- Stage 5 : *Applications* : Population Health (Zenk et al. 2011, 2012), Public Safety (Graif et al. 2014), Intervention (Free et al. 2013) and Epidemiology (Wu et al. 2010)...

A Fundamental Question (3)

We are concerning Stage 3 with an important question in mind :
What is the minimum amount of time required in order to capture a (moderately) complete picture of human activity ?

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There are several reasons why we should study this problem :

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- Computing burden increased "skyrocketingly" when unnecessarily long time series are considered
- Current health research (and many else) uses an unjustified data collection convention (usually 7 days)[see the figure coming up...]
- There is an absence of a metric to evaluate the coverage (Why do we need a **metric** ?)

Current Practices of Sensor Data Collection

Below is a sample of NIH/non-NIH funded projects with respect to their data collection length, sample size and publication/project funding year. Projects recruit more participants, collect longer data, and are more heavily funded.

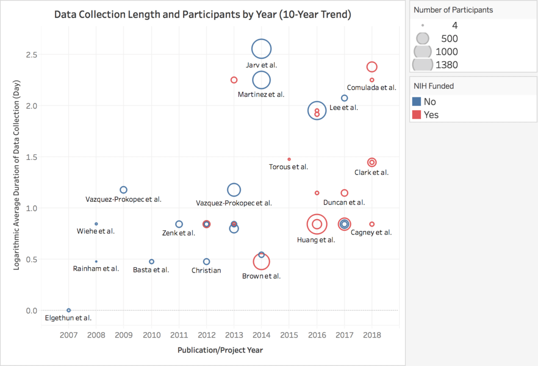

FIGURE – Current Practices of Sensor Data Collection

Notes : $e^{1.5} \approx 4.4$ days, $e^2 \approx 7$ days (1 week), $e^{2.5} \approx 12$ days(roughly two weeks)

Key Aspects to Address

To investigate a complete picture of human activity using censor data, there are some key aspects to consider :

Mobility

The variance, consistency and range of the individual travel behavior in a 'normal' day (not the day you took vacation flight to Sri Lanka).

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The coverage of activity space (amount to the information sample space) we have using this length of data (are they important ? see Block 3).

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To investigate a complete picture of individual activities using censor data, there are some key aspects to consider :

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The variance, consistency and range of the individual travel behavior in a 'normal' day (not the day you took vacation flight to Sri Lanka).

Activity Space

The coverage of activity space (amount to the information sample space) given the available spatial data points (are they important ? see Block 3).

Exposure

The spatio-temporal information of these data points : the length of stay, the contingency of "hotspots", etc...

Data

We will be able to address all of them using our data.
The data come from the MDC, a big data Challenge based on Lausanne, Switzerland :

- People : 185 participants participated the study with the length up to two years. Records sent to server every few seconds (or more) from their mobile devices.

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- Data : Demographic (very limited) ; Phone GPS data, Wi-Fi Scans, accelerometer (sum up to about 50 million unique location points).
- Management : Expansion up to 400 GB via Spark, a resilient distributed dataset (RDD), a read-only multiset of data items distributed over a cluster of machines.

Research Questions Boiled Down

Given those data, there are several research questions we want to address :

- Q1 : (Mobility) Is there a general suggestion of when does a person's mobility pattern "converges" ?

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- – Q2 and Q3 also serve as a verification of our answers to Q1.

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Given the mean speed of person i 's travel behavior up to time t_i as $\mu(t_i)$, and the total observation time for this individual i as T_i, the last crossing time $\tilde{t}_i$ for this person i is the time s.t. the mean speed up to this time never exits the region within a tolerance bound of δ :

$$\arg\max \tilde{t}_i := \{\max t_i \mid \mu(\hat{t}_i) \in (\mu(T_i) \pm \delta\mu(T_i)) \ \forall \ t_i \leq \hat{t}_i \leq T_i\}$$

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Notes : Mean Speed by time t : $\mu(t) = \frac{\sum \Delta d}{\sum \Delta t}$

Example

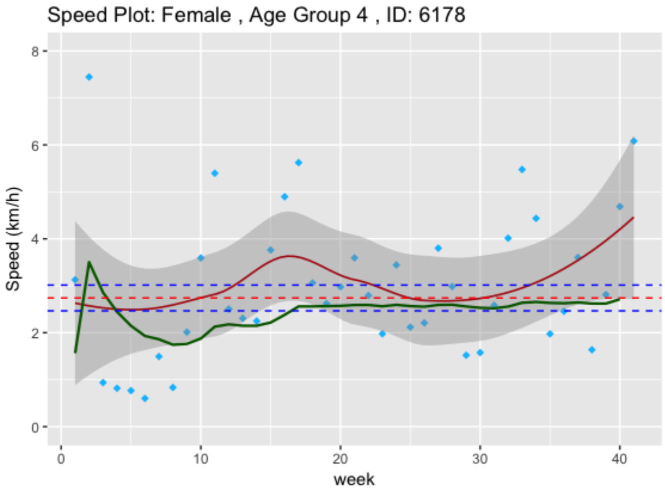

FIGURE – An Example of Convergence

Distribution

Here is the distribution of the 185 participants w.r.t. to their last crossing time using 10% tolerance.

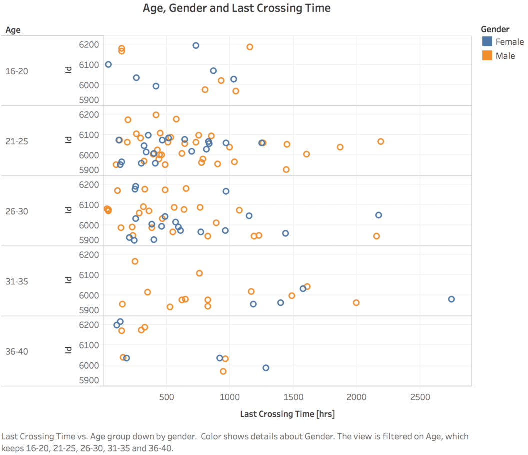

FIGURE – LCT w.r.t. Age/Gender Group

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Can we see this outcome as reliable ?

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No ! There is a list of hazards :

- Outliers (Again, you fly to Sri Lanka)
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To deal with this, we use a rebuilder (a.k.a. 'build-a-new-week') algorithm.

Nonrandomness in Observations I

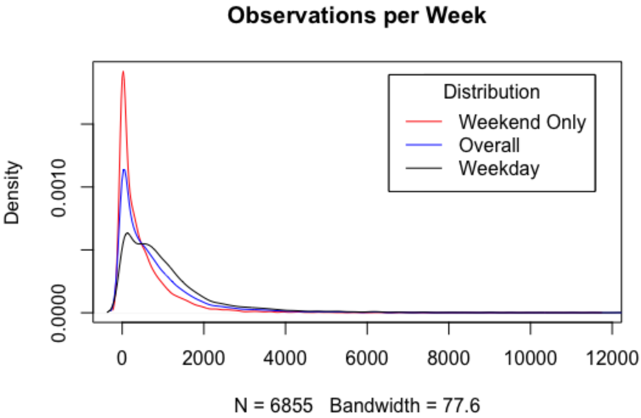

FIGURE – KDE on Weekday vs. Weekend

Nonrandomness in Observations II

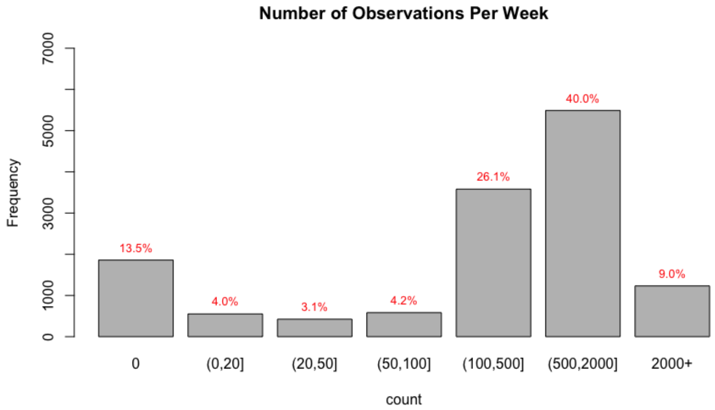

FIGURE – Bar Plot of Observations on Different Day-of-Week

'Build a new week' algorithm

By essence, we consider simulating a person's new week by also considering the 'hour-of-day' and 'day-of-week' variety, because they are not necessarily distributed evenly.

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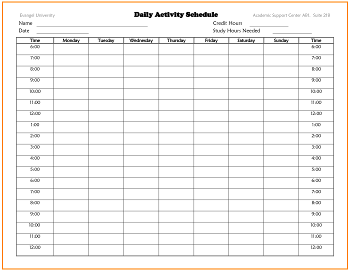
We sample with replacement from 'travel itineraries' created by a person's travel behaviors on Monday, until it filled up the three-hour block (e.g. 6AM-9AM). Then, we repeat this for Tuesday, Wednesday, ... Sunday.


Evangel University

Daily Activity Schedule

Academic Support Center AB1, Suite 218

Name ____________ Credit Hours ____________

Date ____________ Study Hours Needed ____________

Time	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Time
6:00								6:00
7:00								7:00
8:00								8:00
9:00								9:00
10:00								10:00
11:00								11:00
12:00								12:00
1:00								1:00
2:00								2:00
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Does Gender Play a Big Role Here ?

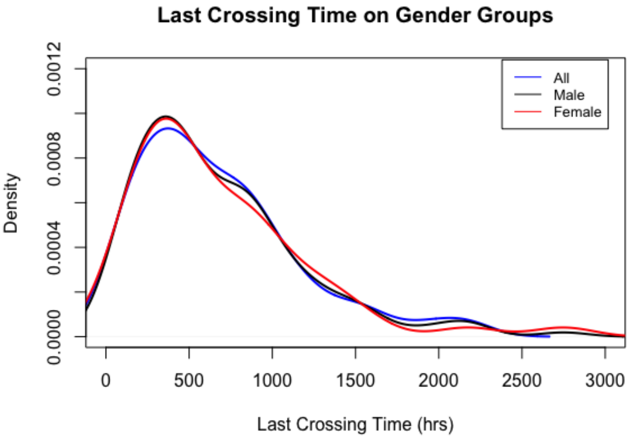

FIGURE – LCT By Gender After Algorithm

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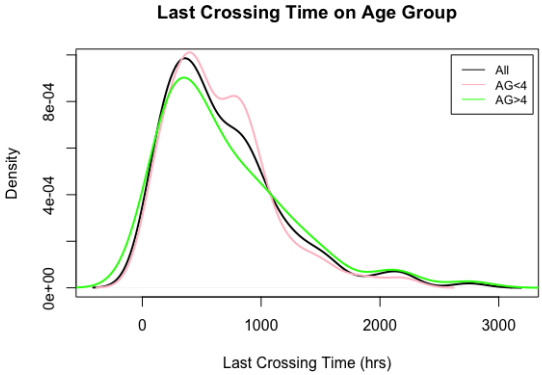

FIGURE – LCT By Age After Algorithm

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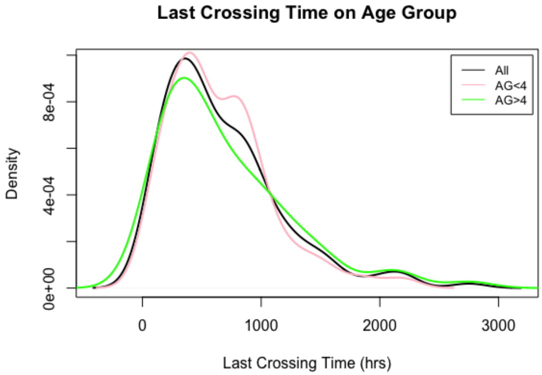

FIGURE – LCT By Age After Algorithm

More specified age group shows weak differences.

Take-Home Message

1. We found weak variation on stability of mobility across age/gender groups.

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Sensor Length (Days)	1	3	7	**14**	21	30
LCT Observed	8%	19%	**45%**	**83%**	90%	94%

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LCT Observed	8%	19%	**45%**	**83%**	90%	94%

3. Generally, researchers should not adopt a 'golden standard' of how many days of sensor data researchers should collect without context. We have a general recommendation of 14 days versus the 7-day convention for most health research.

From KDE to Density Ranking Algorithm (I)

(Part adapted from Chen (2017) CS&SS talk)

Given a collection of points, a common statistical approach is to estimate the probability density function (PDF). Based on the estimated density function, we can then compare these datasets. A popular and simple approach called the kernel density estimation (KDE), which is calculated as belows :

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Problems ?

The KDE cannot detect intricate structures inside the GPS data because the underlying PDF does not exist, hence our probability distribution function is singular.

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The density ranking (Chen 2016 ; Chen and Dobra 2017) is a transformed quantity/function from the KDE. The main idea is that, instead of using the density value, we focus on the ranking of it.

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To compare multiple density rankings from multiple datasets, a simple approach is to overlap level plots. For a density ranking $\hat{\alpha}$, let

$$\hat{A}_\gamma = \{x : \hat{\alpha}(x) \geq 1 - \gamma\}$$

be the (upper) level set, hence compare the density ranking of each individual by overlapping their level sets at different levels.

From KDE to Density Ranking Algorithm (III)
(Part adapted from Chen (2017) CS&SS talk)

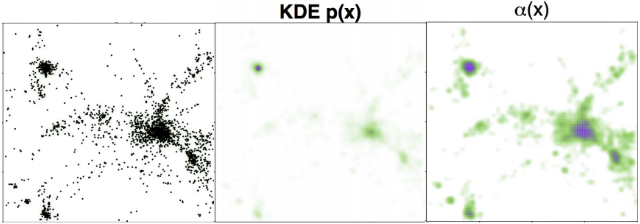

FIGURE – KDE vs Density Ranking

From KDE to Density Ranking Algorithm (IV)
(Part adapted from Chen (2017) CS&SS talk)

As a summary, density ranking methods :

- Density ranking $\hat{\alpha}(x)$ can be viewed as an estimator to certain characteristics of the underlying population distribution ; It also converges to $\alpha(x)$ in topological sense ;

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- The population density ranking to a singular measure can be generalized by the concept of the *Hausdorff (geometric) density*
- To verify our recommendation in Part 3, we examine the coverage by hierarchical clustering, and found our recommendation improved on coverage by over 60% compared to the ones with right truncation at Day 7.

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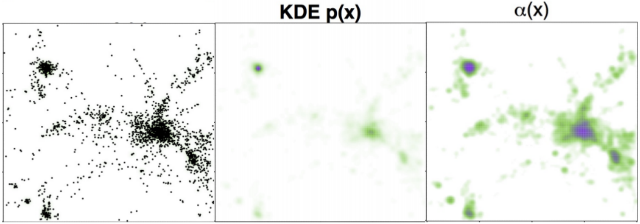

FIGURE – KDE vs Density Ranking

Coming Soon : seq2seq model

For predictive models on coverage, we can use a deep learning method called seq2seq model, for which we draw a multi-layer sequence-to-sequence network with LSTM cells and attention mechanism in the decoder looks like this.

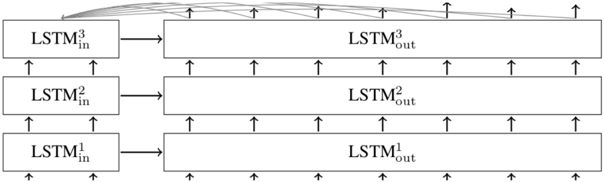

FIGURE – seq2seq models

Future Work

Our work is the first empirical attempt to explore the relationship between the length of sensor data collection per individual and its effect on the size of "information set' (sample) we have, as well as its implications on the application of health research. In the future, our work will consider :

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- The choice of δ for 'convergence' may be better defined.
- – is $\delta = 0.1$ a good tolerance bound ?

Future Work

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- Our experiments are limited by the number of participants. How do we collect such data from a more diverse group of people ?

Thank you !

We thank Prof. Kyle Crowder from Dept. of Sociology at the University of Washington with initial comments on how this work could apply to ongoing research questions in demography.