



Inference of User Demographics and Habits from Seemingly Benign Smartphone Sensors



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Introduction

Smartphone permissions systems control access to private user data. [1,2]



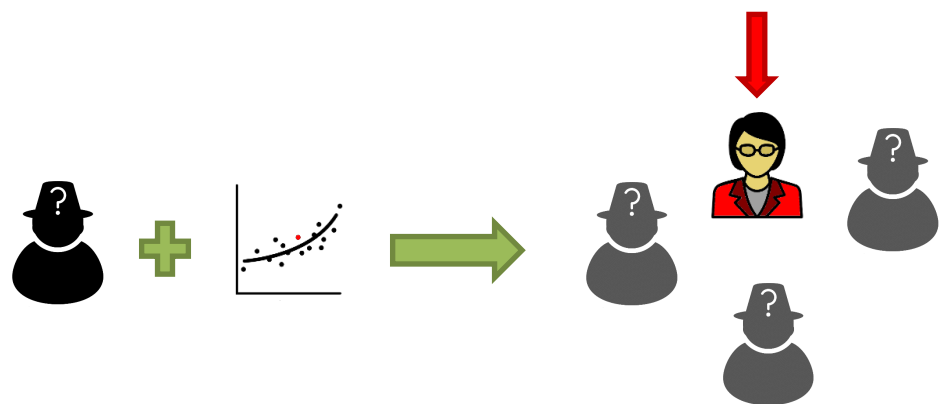
Non-GPS sensors are not restricted.



The ad-tech industry builds individual profiles to better target ads [4] We explore methods to infer private data from these “benign” sensors.

Objectives

Research Question: Are sensor readings correlated with user traits? Is it sufficient for machine learning?



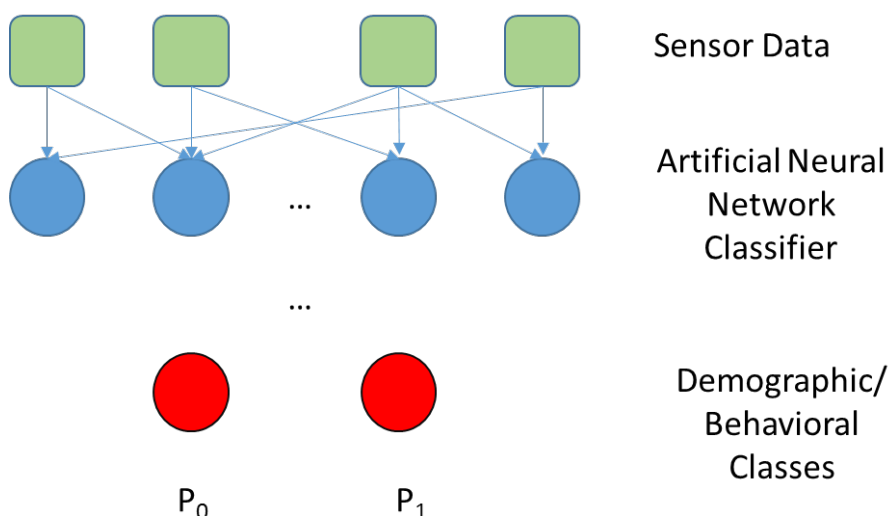
Gender	Weight	Fitness Habits
Income level	Height	Work Schedule

Methodology

Data Collection:

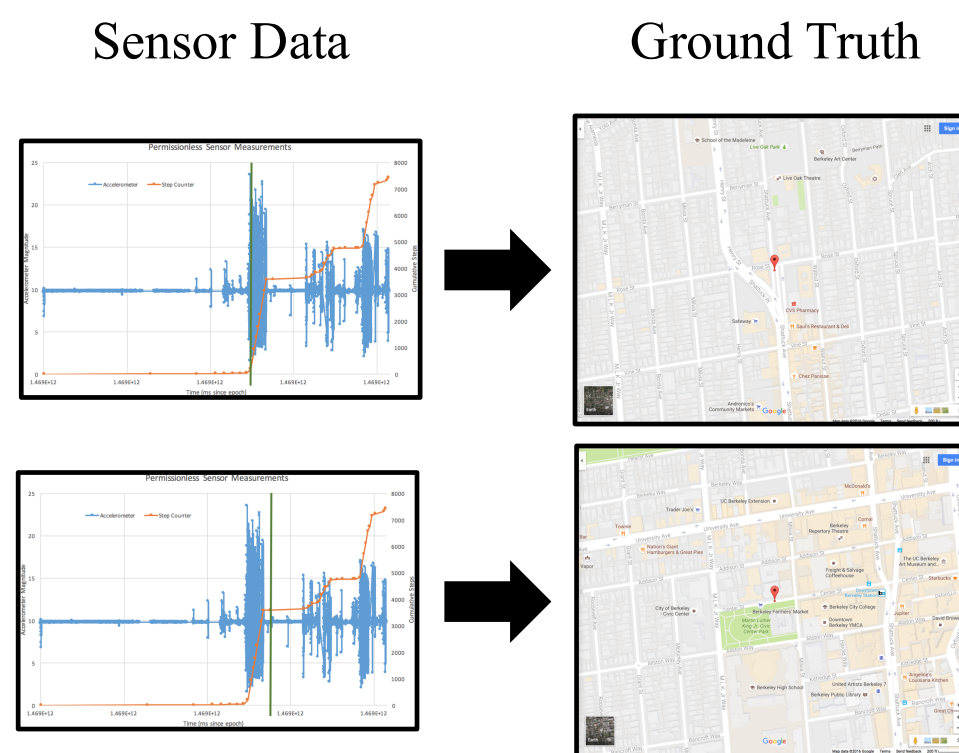
Population: MTURK, 1-week observation period, N = 100

Preprocess, segment, and classify



Preliminary Results

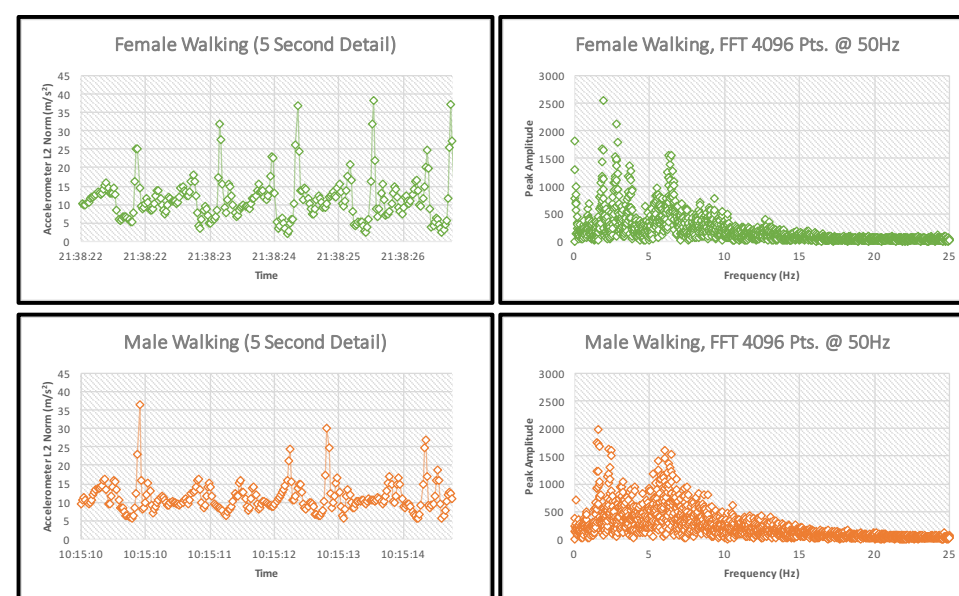
Intuition on Sensor Measurements



- Motion sensor activity correlates with one another (e.g., step counter activity reflected in accelerometer)
- Sensor activity + times could indicate habits, changes in location, etc.

Walking Motion and Gender

- Intuition: Men and women store their phones differently when walking (e.g., side pocket vs. back pocket vs. hand bag)
- Intuition: Different storage will have distinct motion characteristics



- Step counter data used to condition accelerometer readings to walking
- Limited analysis shows possible distinguishable features in time and frequency domains
- Needs broader investigation and sensitivity analysis

Conclusion

Key Takeaways

- Sensors can correlate with one another under various activities
- Conditioned on events, inferences about the user can be made
- Needs further investigation to determine generalizability

Questions For Further Analysis

- For gender inference using walking motion, how stable are the features within genders and across different walking sessions?
- What are the best ways to preprocess, segment, and formulate features from rich sensor data for demographic classification?
- Are there systemic differences in handset sensor hardware that can bias data and resulting inferences? Can those be leveraged?

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5. Y. Michalevsky, A. Schulman, G. A. Veerapandian, D. Boneh, and G. Nakibly. Powerspy: Location tracking using mobile device power analysis. In Proceedings of the Twelfth Workshop on Mobile Computing Systems & Applications, HotMobile '12, pages 9:1–9:6, New York, NY, USA, 2012. ACM.
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