Using Smartphone Sensors to Encourage Physical Activity

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My Background

UCLA Urban Planning
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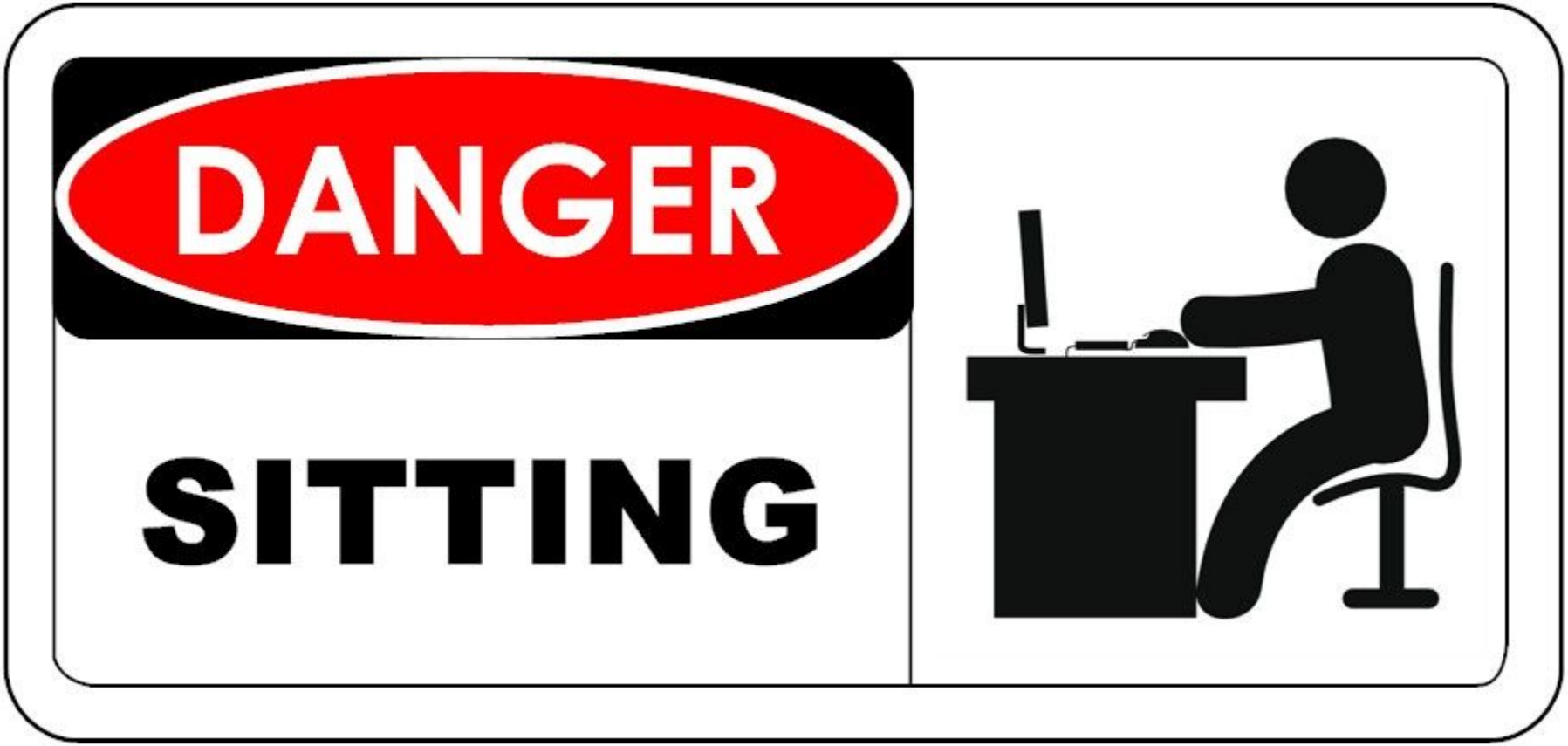
DEPARTMENT OF TRANSPORTATION
UNITED STATES OF AMERICA

One of the most dangerous activities



Annals of Internal Medicine®

ORIGINAL RESEARCH | 3 OCTOBER 2017

Patterns of Sedentary Behavior and Mortality in U.S. Middle-Aged and Older Adults: A National Cohort Study

Keith M. Diaz, PhD; Virginia J. Howard, PhD; Brent Hutto, MSPH; Natalie Colabianchi, PhD; John E. Vena, PhD; Monika M. Safford, MD; Steven N. Blair, PED; Steven P. Hooker, PhD

Article, Author, and Disclosure Information

Abstract

Background: Excessive sedentary time is ubiquitous in Western societies. Previous studies have relied on self-reporting to evaluate the total volume of sedentary time as a prognostic risk factor for mortality and have not examined whether the manner in which sedentary time is accrued (in short or long bouts) carries prognostic relevance.

SCIENCE

Americans Are Sitting More and We Have Computers to Blame

Research sets out to quantify how much time people spend sitting down; teens are more sedentary than grown-ups

By Brianna Abbott

Updated April 23, 2019 11:22 a.m. ET

Americans are sitting more than ever, and the habit starts young, according to a large study that found computer use in particular has contributed to a more sedentary lifestyle over the past two decades.

Across a range of age groups, average sitting time increased roughly an hour a day from 2007 to 2016, according to the study, which was published Tuesday in JAMA, the Journal of the American Medical Association.

Average

Goal: Physical Activity (PA) Tracker

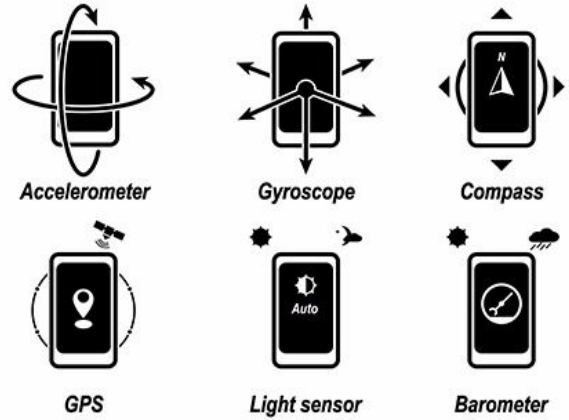
Use smartphone sensors

Sedentary vs. moving

Intensity of PA

Prompt after long period without PA

Measure and track the amount of PA



Constraints

- Recognize PA for new users
- Any phone, any position
- Preserve battery life
- Provide user feedback in real time

RealWorld Data

15 subjects

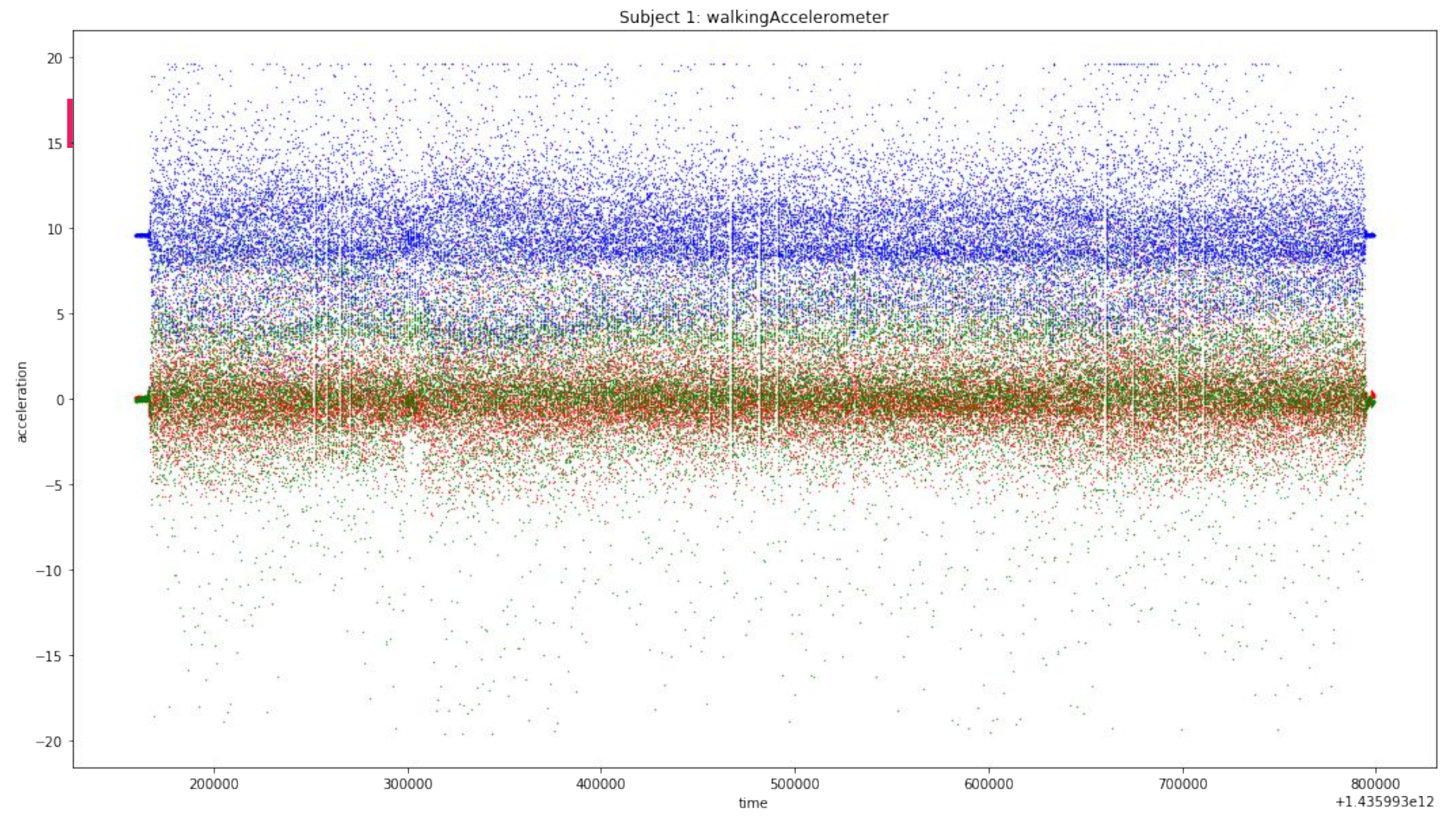
8 activities

Going down stairs, going up stairs, jumping, lying, standing, sitting, running, and walking

7 devices

6 sensors

acceleration, gyroscope, GPS, light, magnetic field, and sound level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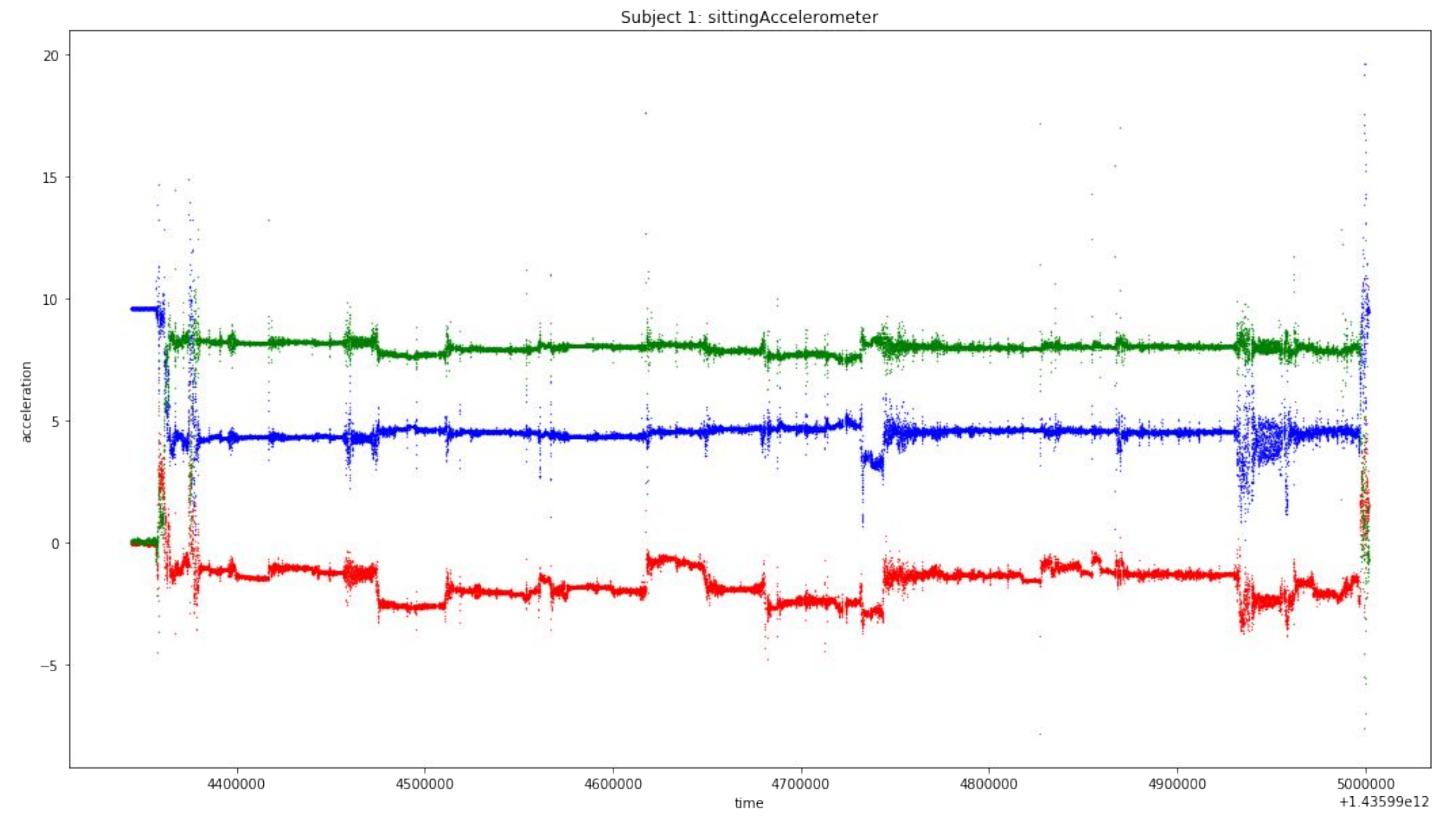
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Subject 1: runningAccelerometer
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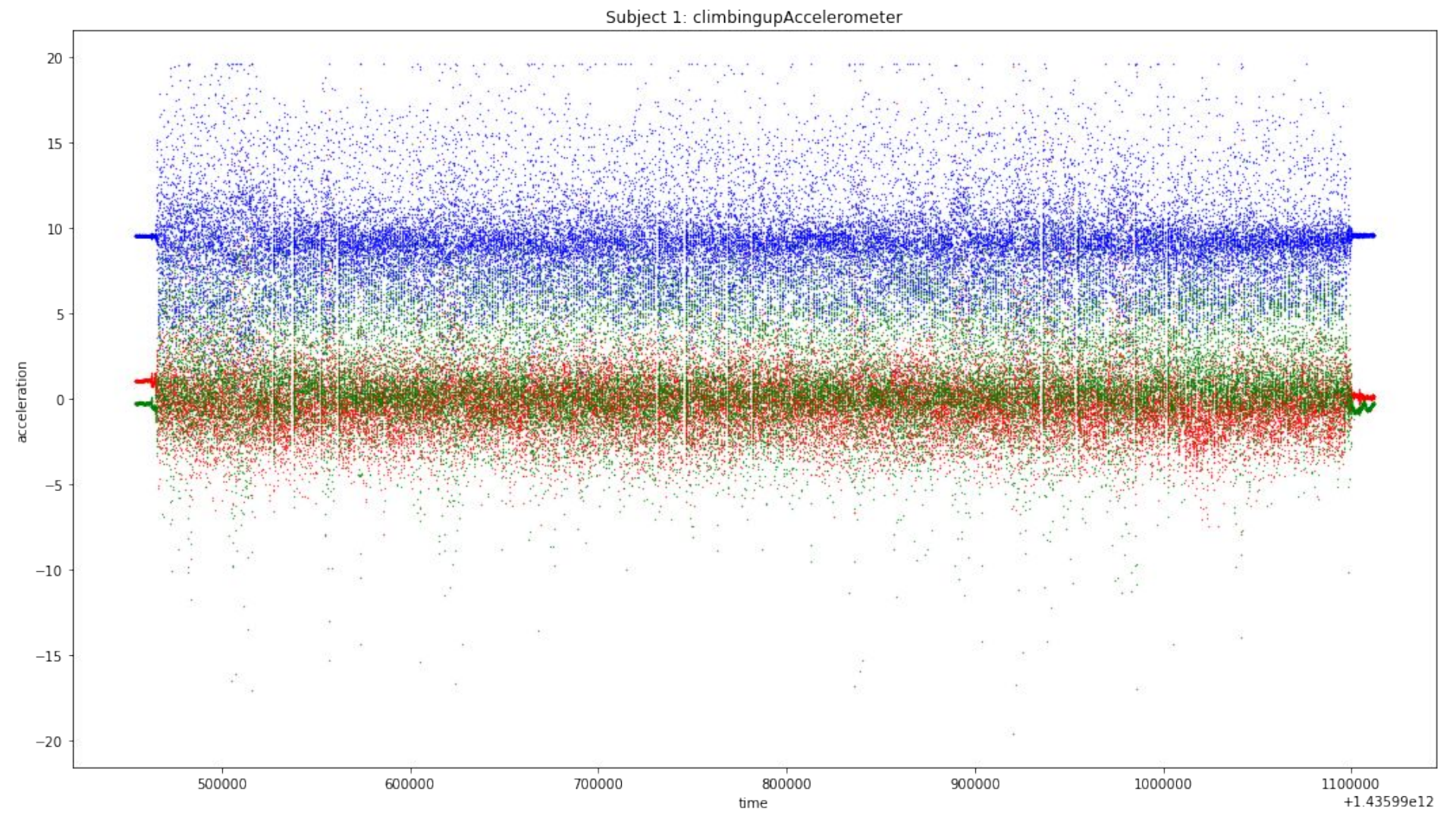
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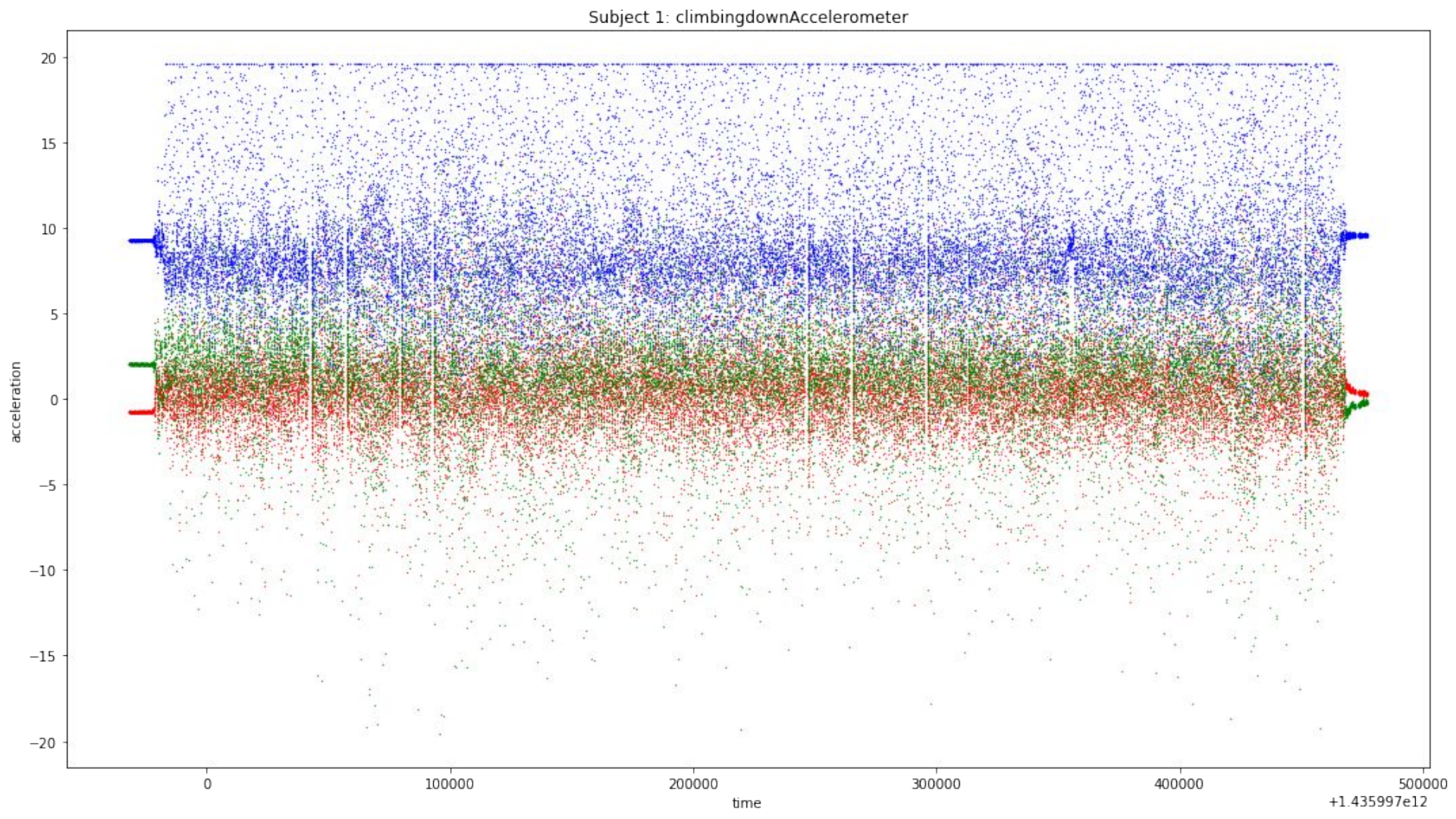
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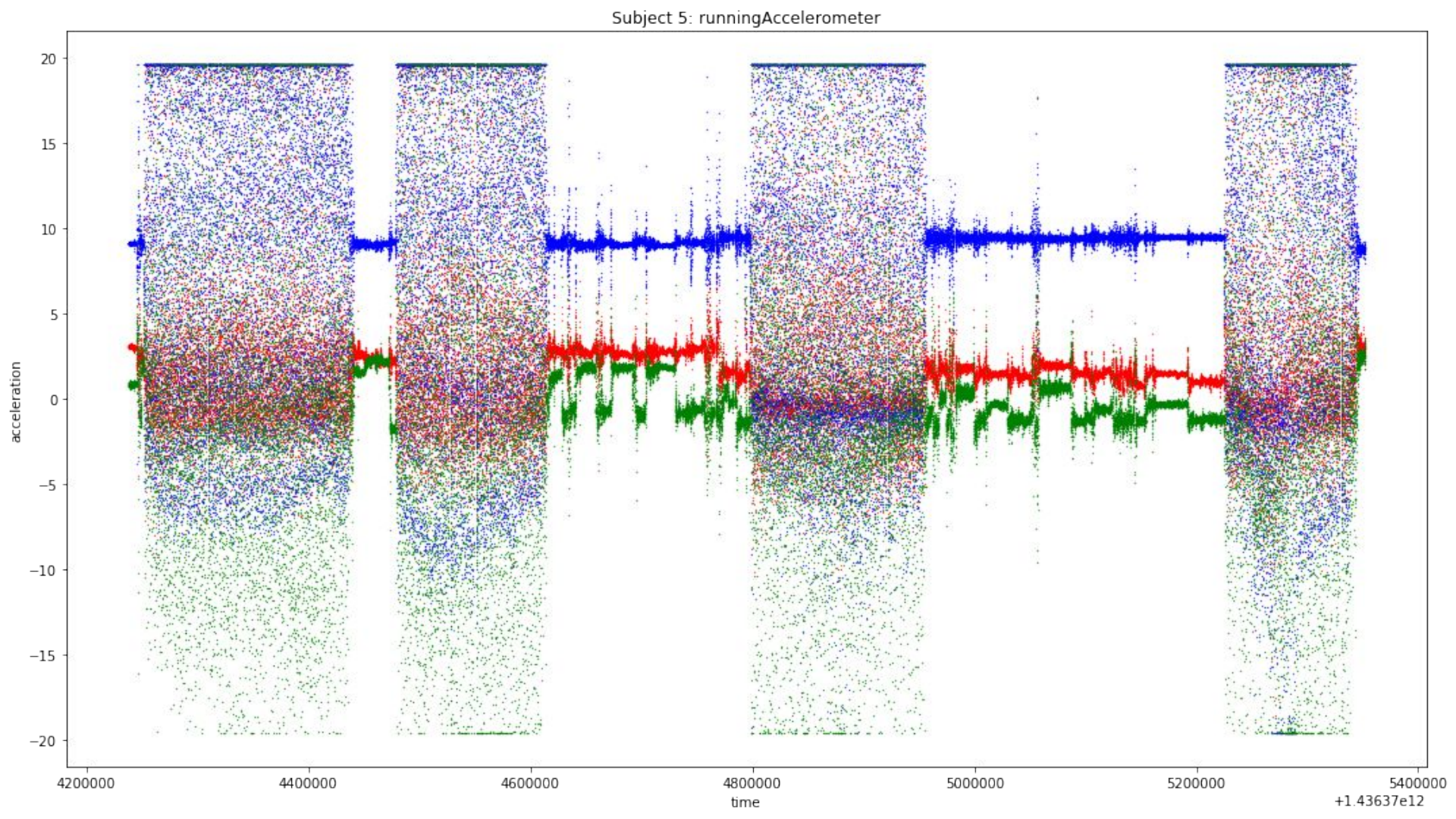
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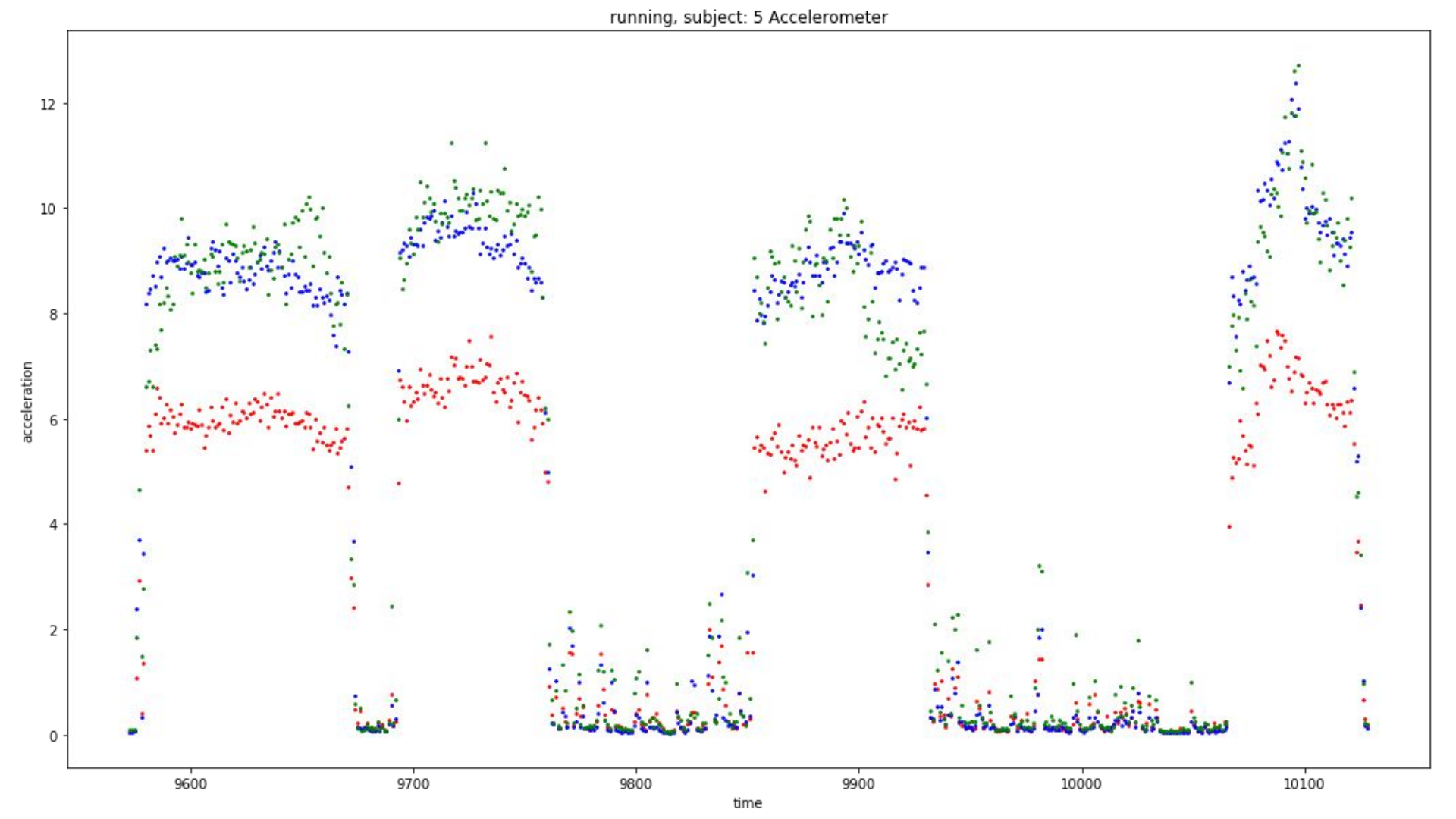
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9800
9900
10000
10100

Data Preparation

- Samples of 100 observations (2 sec)
  - Mean, Standard Deviation, Range
- Filter mislabeled data

Recode into 3 PA Classes

Sedentary (standing, sitting, lying)

Light-Moderate PA (walking, going up stairs, going down stairs)

Vigorous PA (running, jumping)

Train / Validate / Holdout

Modeling Data - 10 subjects

- Training - 7 subjects
- Validation - 3 subjects

Holdout Data - 5 subjects

- Not seen by model

Modeling Approach

18 features: 2 sensors (acc, gyr) x 3 dimensions (x,y,z) x 3 metrics (mean, sd, range)

Logistic regression accuracy:

- Training: 100%
- Validation: 97%

Also tried: K-Nearest Neighbors, Naive Bayes, various types of Decision Trees, Support Vector Machine, XGBoost

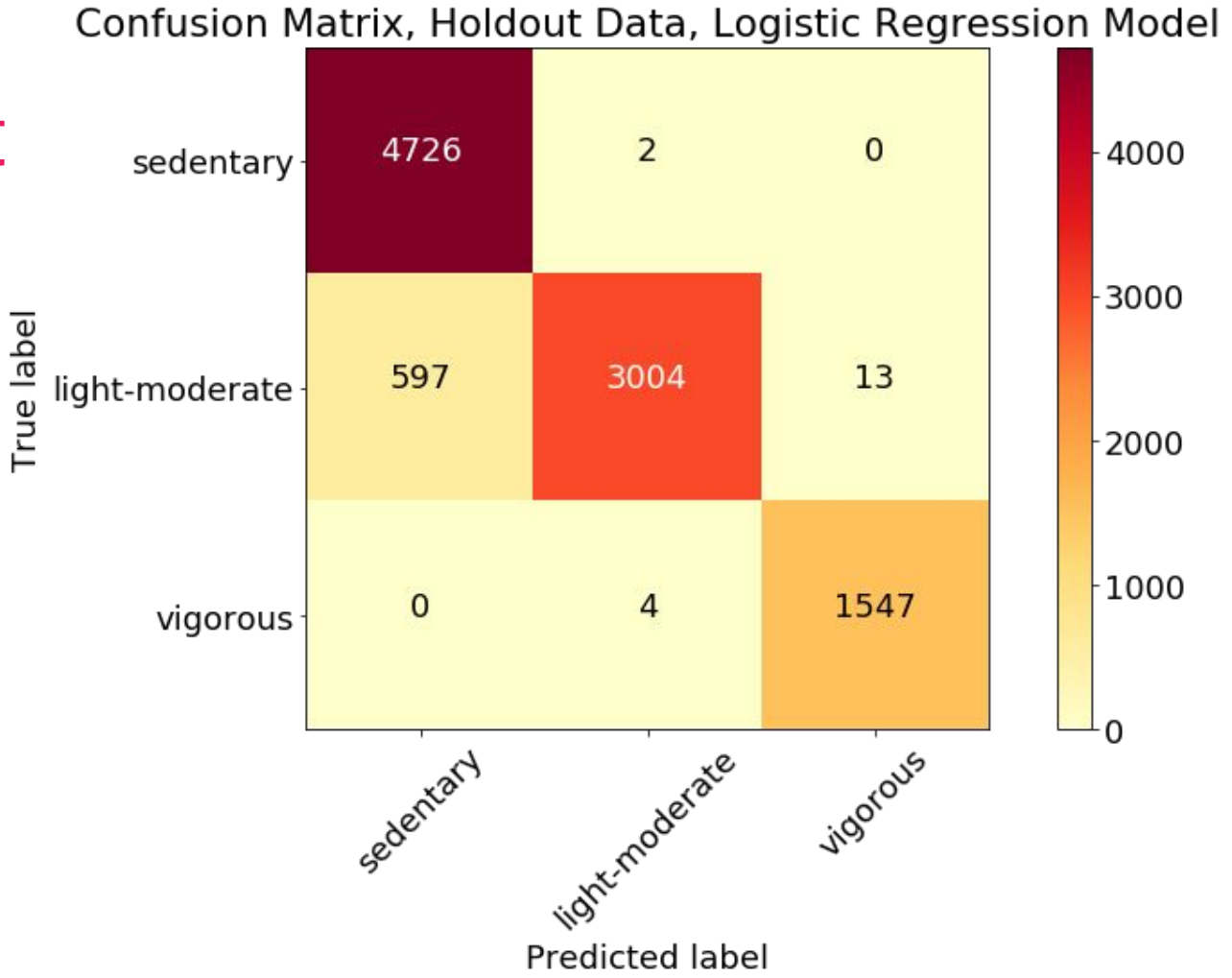
None had better results than LR

LR Test on Holdout

Tested on 5 subjects not previously used

Accelerometer only

94% accuracy



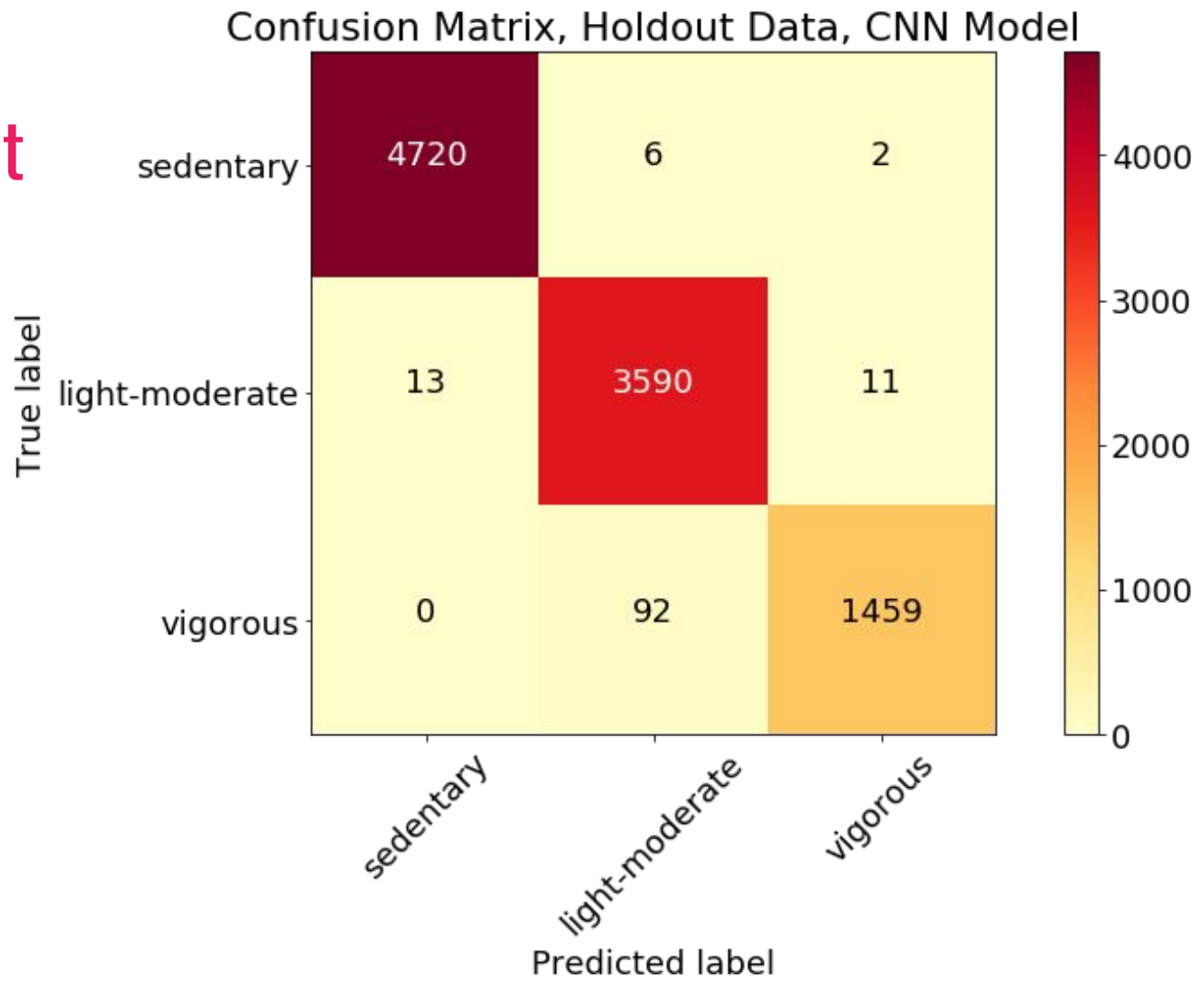
Neural Network Model

- **Raw sensor data** as array of 100 obs x 6 features (2 sensors x 3D)
- **2 Recurrent layers** to handle the time dimension using Gated Recurrent Unit (GRU)
- **2 Convolutional layers** to learn important features, prevent overfitting, and reduce number of parameters
- **Batch normalization** layer to further reduce overfitting

NN Test on Holdout

Accelerometer & gyroscope data.

99% accuracy



Takeaways and Next Steps

- **Simplify** the problem to match use case
- **Validate** on previously unseen subjects
- **Simple hand-crafted features** with LR regression produces good results
- **Neural network** has even better results
- **Test** with lower sampling rate
- **Expand** model to other data