

Human Activity Recognition (HAR) Explanation Interface

This project aims to provide an Explanation interface (XAI) for Human Activity Recognition (HAR) system based on commercial wearable data.

Context and Motivation

As the name suggests, Human activity recognition (HAR) involves employing machine learning algorithms to recognise physical activities based on data generated by a variety of sensors. In this respect, HAR is an emerging research area, especially ubiquitous for behavioral activity analysis in real-time. Ability to correctly and timely identify activities is deemed useful with several daily use cases ranging from maintaining healthy lifestyle to providing personalized patient rehabilitation or diagnosing an ongoing illness or pre-symptomatic detection of Covid-19, and even for monitoring well-being of employees working in remote areas.

Wearable devices have emerged as tools for measuring detailed physical activity. Moreover, these devices store data for Behaviour in-the-wild (real-life). Therefore, wearables are seen as a potential tool for Behavioral context recognition. This allows us to readily monitor and provide real-time feedback based on activity measurements. Alongside, the ever-advancing machine learning tools can now help us gauge more fine-tuned predictions and deeper interpretations for movement classification at population level. However, dealing with wearable data has some innate challenges, such as small data analysis, distributed data, and also idiosyncratic characteristics like drop in sensor signal or different sensors with varying calibrations.

HAR Dataset

This dataset is from a recent study - [Predicting lying, sitting, walking and running using Apple Watch and Fitbit data \(Fuller et al., 2021\)](#). This study aims to examine whether machine learning models can predict six different movement types from sensor data stored with commercial wearables.

The data set is openly available at [Harvard Dataverse](#). The preprocessed dataset includes 3656 minutes of Apple Watch data and 2608 minutes of Fitbit data,

- Y : Target outcome variables are six activity classes - lying, sitting, walking self-paced, 3 METS, 5 METS, and 7 METS (different intensities of running).
- X : Minute-by-minute heart rate, steps, distance, and calories from two wearables - Apple Watch and Fitbit. Indirect calorimetry used to measure energy expenditure.

Summary of Participants:

- Participants recruited using social media post and word-of-mouth in Canada
- Inclusion Criterion - 18 years and above, completing the Physical Activity Readiness Questionnaire (PAR-Q)
- Sample of 46 participants (26 women) wearing : Apple Watch and Fitbit Charge HR2.
- Participants complete a 65-minute protocol with 40-minutes of total treadmill time and 25-minutes of sitting or lying time.

Also, Participants were not provided with any compensation. All participants provided signed informed consent. Interestingly, Patients or the public were not involved in the design, conduct, or reporting, or dissemination plans of our research.

Interface Goals and Process

Our goal is to create an Explanation interface for analyzing the wearable data. In this respect, we followed three steps,

1. Identify the user
2. Set-up the design goals
3. Actual implementation of the interface

Intended Users - Who is the user ?

Broadly speaking, our users could be direct health-givers and receivers or policy-makers or corporates or health insurance companies or academic researchers or data scientists. However, after brainstorming, we asked ourselves - What are the questions one has. This allowed us to switch our approach from Who the users are to What their needs are.

So, instead of classifying our users from non-users, we propose that anyone who would like to elucidate on the questions below can easily find this Explanation interface useful.

- Can ML techniques be deployed to predict activity class from wearable data ?
- What are the properties of chosen data ?
- What are the performance metrics ?
- Are the predictions fair, reproducible and scalable ?
- How do the outcomes vary for different models ?
- How do the outcomes vary across wearable brands ?
- How do the model perform with reduced features ?
- Which features are deemed useful for the model ?
- What if - features or data are perturbed impacts the resulting model output ?

Feedback : We learnt that we can incorporate the concept of Personas.

Design goals:

After identifying the questions one can answer with the interface, the design goal was to ensure that,

1. Make the necessary information available
2. Access to the information be intuitive - from simple to complex
3. Have a good mix of structure and flexibility to help understand primary questions, but also give a simple way to play with the interface.

With this regard, some of the key decisions that were made,

1. Choose the *right* amount of Content for each section - be it for description or choice of models or visualization. In practice, we left out some other analysis for the Exploratory section.
2. Break the Content into smaller digestible chunks with the help of tabs, subsections, sections and page breaks.
3. For aiding ease of navigation - specific naming conventions, icons, font style and color are chosen. Moreover, to drive navigation decision e.g., explanation tab has two icons
4. For each section, flow of the content hierarchy moves from basic & primary to more detailed & complex. That is, we kept Static analysis - summary statistics, heatmaps on the top. Only later, we introduce user-driven analysis with filtering interactive options. Sidebar was used for information that is available to the user all the time.
5. Since, cognitive load and human fatigue is a function of information display, we took decision such as choice of tab sequence : Interface → Data → HAR (left → right)

Together, the attempt was to present information that is not only available but also easily and consistently accessible. Moreover, the user first learns to depend and trust the interface, and only then apply filtering options for a more independent view.

Challenges during the process:

1. Switching from modeling perspective to integrating user-needs. For us, deciding on the modeling aspects is easier than deciding the interface aspects.
2. Integrating challenges - Technical aspects such as running 4 models simultaneously on the streamlit platform. Other than the technicals, it was about bringing different people working on different sections with individual taste in fonts and writing style to come together. Learning : Decide on a template -> Build on it.
3. Building the interface was an iterative process - revisiting things again to make it more precise. Having specific goals, but how to translate it into design was difficult. For eg, Feedback - that slider markdown is generally used for code and not content.

Link for DEMO - [Human Activity Recognition Interface Overview | Loom](#)