Adding context to accelerometer data using GPS devices

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Picture by Leif Tuxen

Why do we want to add context to our accelerometer data?

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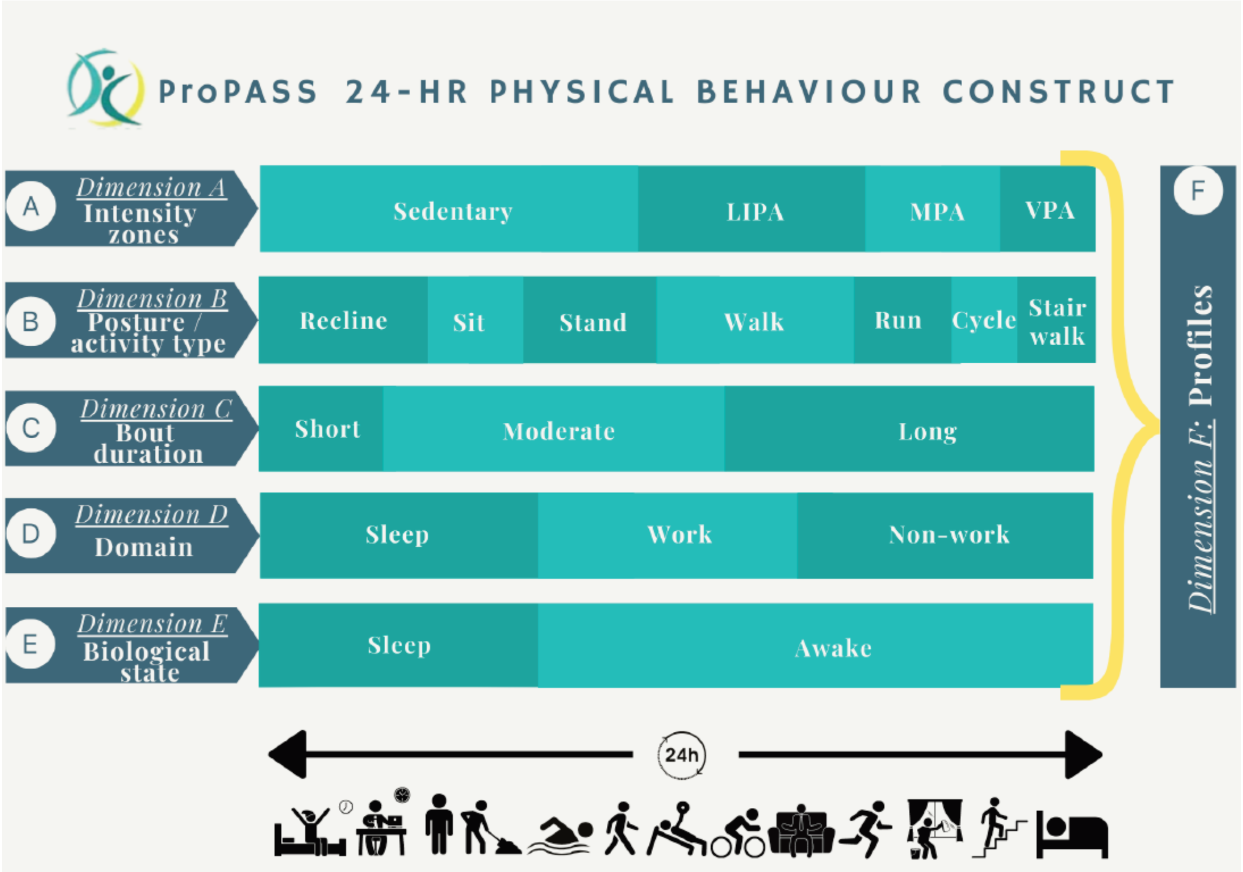
Domains of physical activity



Stevens et al 2020, BMJ Open

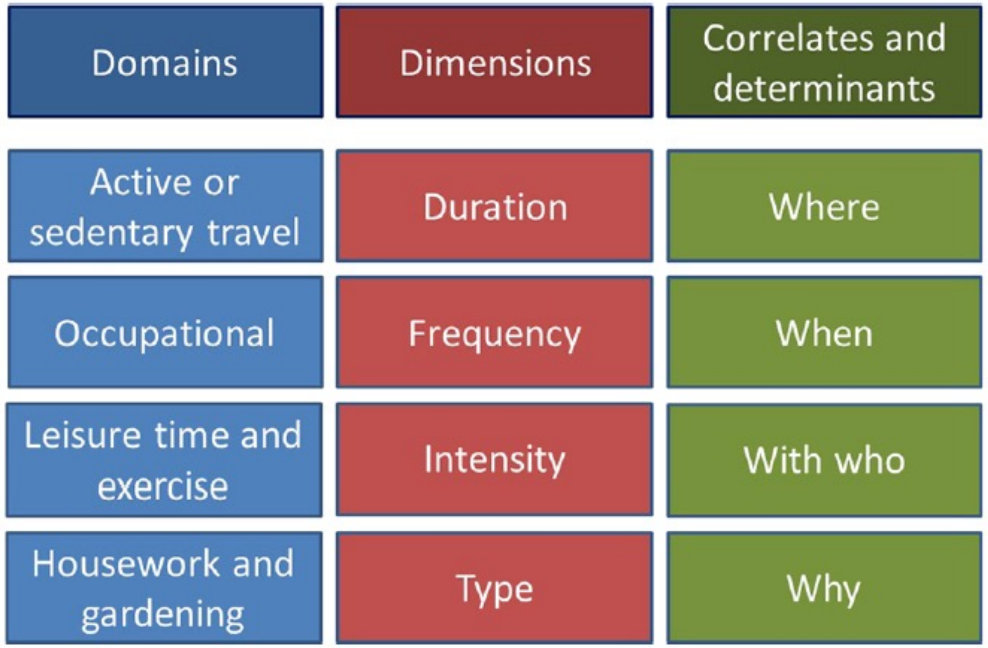
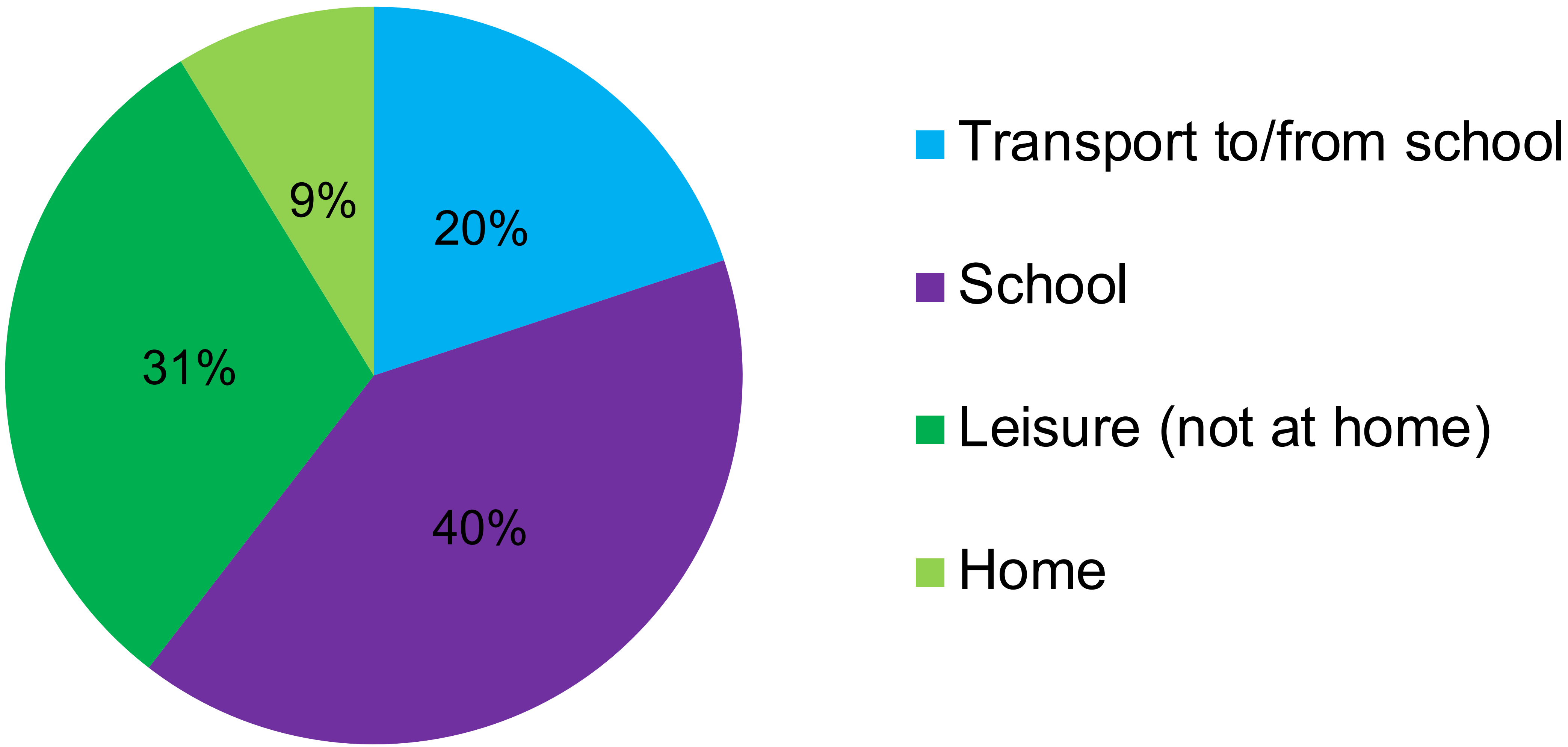


Fig. 1 Domains, dimensions, and correlates and determinants of PA and SB. We use this figure to discuss the different ways these behaviours can be described or characterized. It is not meant to be exhaustive, and some may take issue with how we have used 'determinants'. When considering sedentary behaviour posture may require its own box. Source: PAHRC teaching materials (MSc Physical Activity for Health)

Kelly et al 2016, IJBNPA

The context of children's daily MVPA



Klinker et al 2014, *IJBNPA*

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Conduct adequately-powered prospective observational studies using device-based measures and self-report to examine differences in the health effects of various types and domains of physical activity (leisure-time; occupational; transportation; household; education) and of sedentary behavior (occupational; class or study time; screen time; television viewing).

Advancing the global physical activity agenda: recommendations for future research by the 2020 WHO physical activity and sedentary behavior guidelines development group

Loretta DiPietro[1*], Salih Saad Al-Ansari[2], Stuart J. H. Biddle[3], Katja Borodulin[4,5], Fiona C. Bull[6,7], Matthew P. Buman[8], Greet Cardon[9], Catherine Carty[10], Jean-Philippe Chaput[11], Sebastien Chastin[12], Roger Chou[13],

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How can we add context to our accelerometer data?

Adding context to accelerometer data using GPS devices

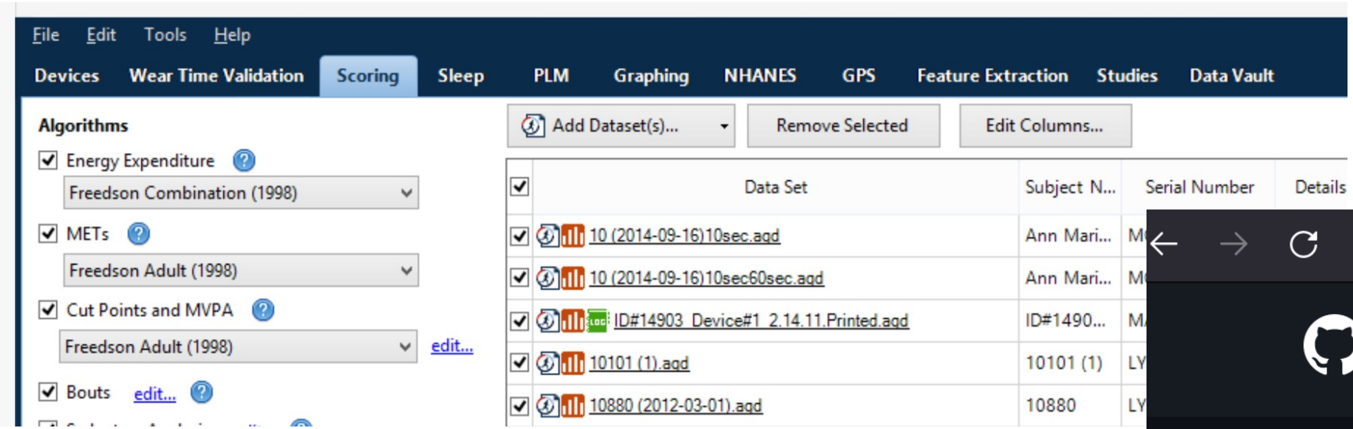
A Framework for Using GPS Data in Physical Activity and Sedentary Behavior Studies

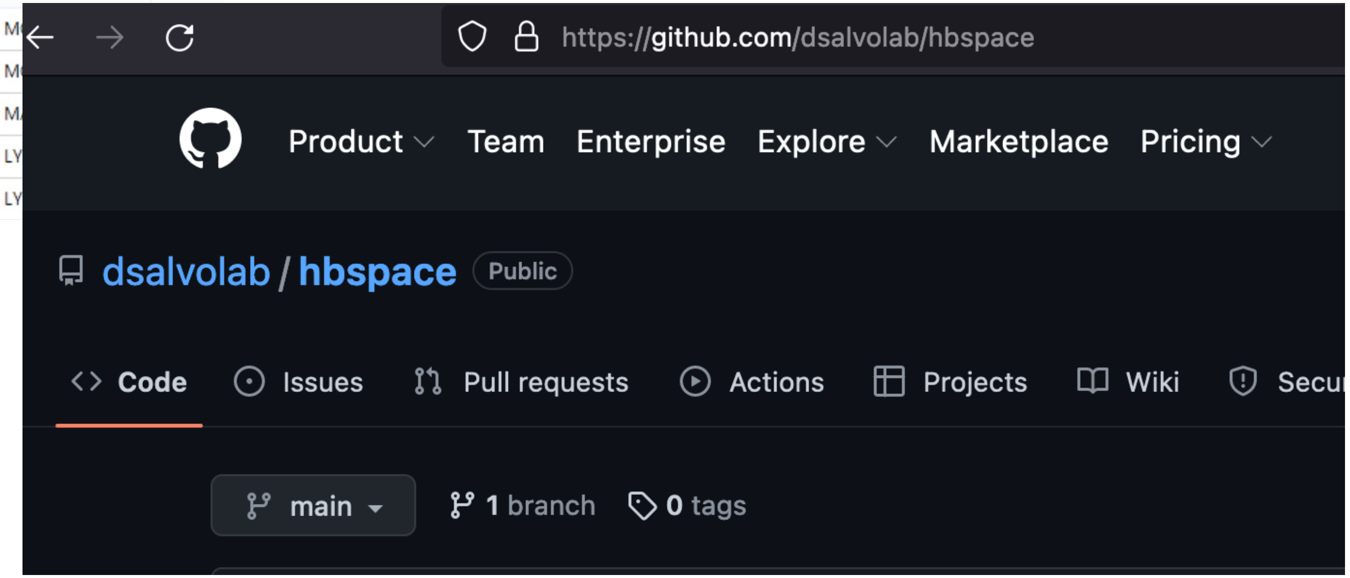
Marta M. Jankowska[1], *Jasper Schipperijn*[2], *and Jacqueline Kerr*[1]

[1]Department of Family and Preventive Medicine, University of California San Diego, La Jolla, CA; and
[2]Department of Sports Science and Clinical Biomechanics, University of Southern Denmark, Odense, Denmark

Jankowska et al. 2015, *Exercise and Sport Sciences Reviews*

How to add GPS data to accelerometer data?





ActiLife

GPS Correlation

Merge ActiGraph data with compatible GPS files and generate activity intensity heat maps using Google Earth.

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HABITUS

Human **A**ctivity **B**ehavior **I**dentification **T**ool and data **U**nification **S**ystem

A system for data harmonization and analysis of accelerometer and GPS data

HABITUS

Principles

Open source and collaborative

Sharing of algorithms (and training data)

Sharing of workflows and data processing settings

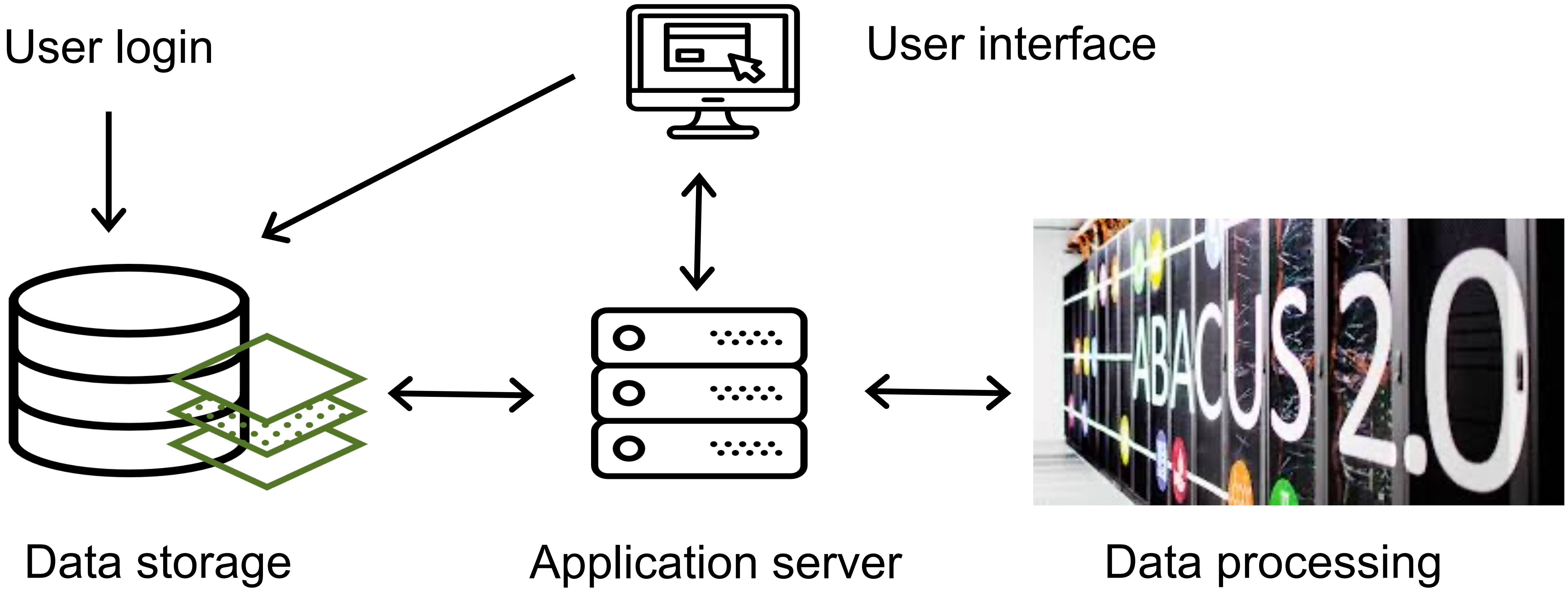
Aims

Make it easier to combine acceleromter and GPS data

Facilitate transparancy of data processing decisions

Offer secure data storage and HPC data processing

HABITUS


User login
User interface
ABACUS 2.0
Data storage
Application server
Data processing

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About

- Secure Platform
- Interactive HPC
- Data Analytics
- Private Cloud
- Share & Collaborate
- Project Management

Getting Started

- Manage Files and Folders
- Share and Mount Locally
- Access Applications

UCloud User Guide¶

Interactive digital research environment built to support the needs of researchers for both computing and data management, throughout all the data life cycle

Getting Started
Tutorial videos

Platform Overview
Navigate, launch jobs, share & collaborate

Supported Apps
Apps catalogue

https://docs.cloud.sdu.dk/

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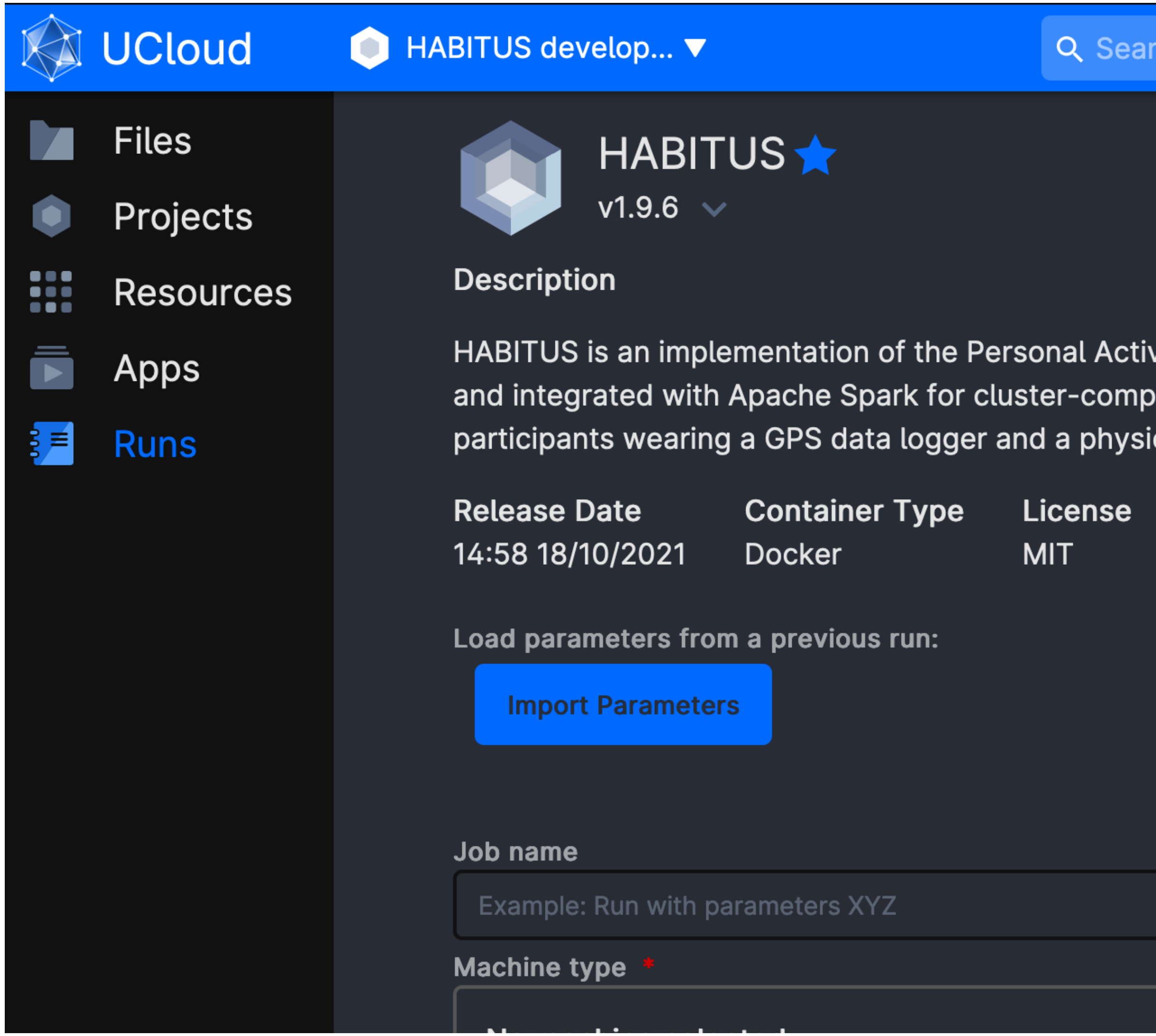
Application server

Applications run in a container

Processing is scalable, 1 core per person (>14,000 cores available)

Packages and libraries written in R or python can be easily integrated



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Build on existing open source software

GGIR

R package for accelerometry

Dr Vincent van Hees, Consultant, www.accelting.com

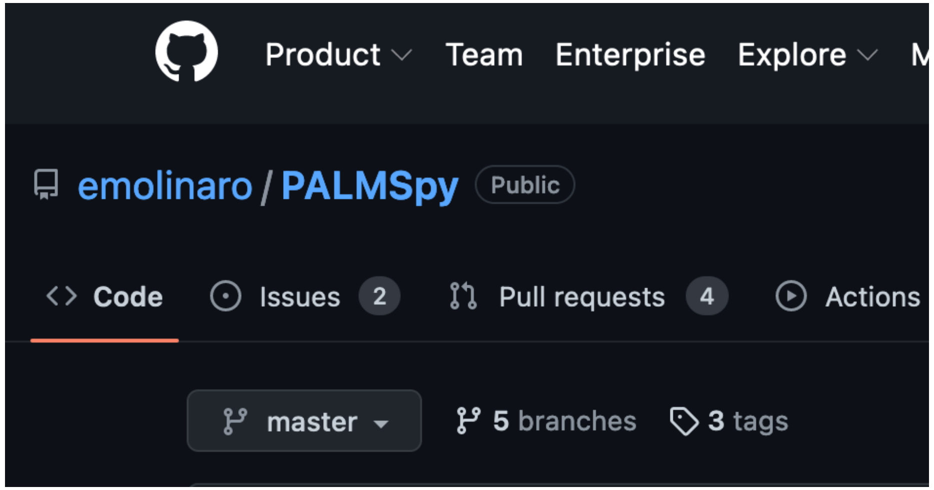
PALMSplus for R

repo status Active | Package version 0.1.0 | Last change 2018-01-12

Overview

palmsplusr is an extension to the *Personal Activity Location Measurement System* (PALMS). This R package provides a customisable platform to combine PALMS data with other sources of information (e.g., shapefiles or csv files). This enables physical activity researchers to answer higher-level questions, such as:

Dr Tom Stewart, Auckland University of Technology



activityCounts

Calculate ActiLife counts from raw acceleration data

Dr Ruben Brondeel et al, Sciensano

Dr Emiliano Molinaro, University of Southern Denmark

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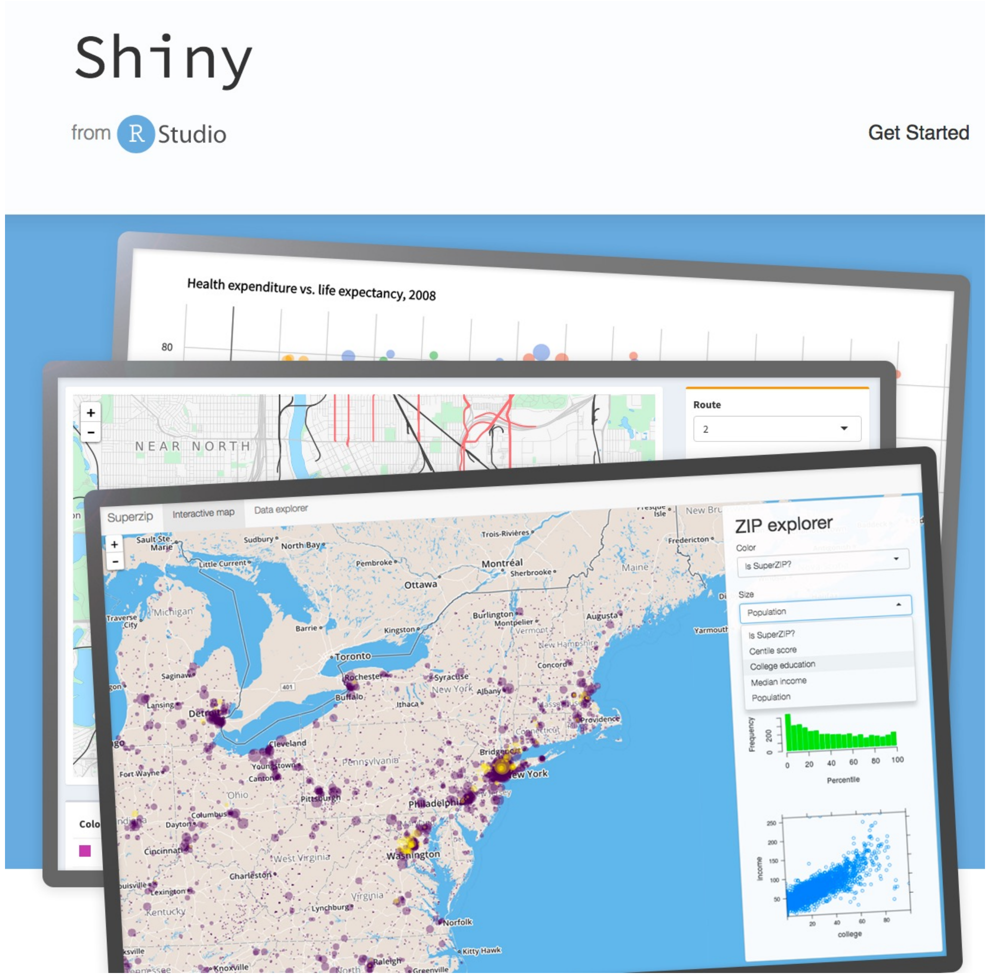
User interface

Shiny for Rstudio
Easy to use interface
Limited number of processing options
Visualisation of output data

Developed by Vincent van Hees



What does HABITUS do?

Match & merge accelerometer and GPS data based on time-stamp
Remove the worst GPS errors (excessive speed and changes in altitude)
Categorize activity counts (sedentary, light, moderate, vigorous)
Identify bouts of MVPA
Identify bouts of sedentary time

Identify trips and tripmode (walking, bicycling, vehicle)

Aggregate data into user-defined domains

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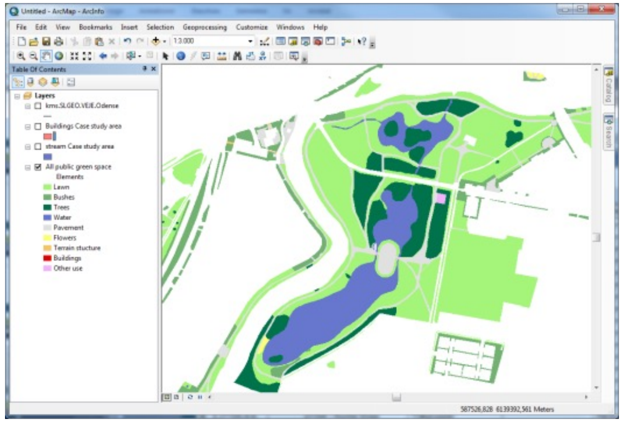
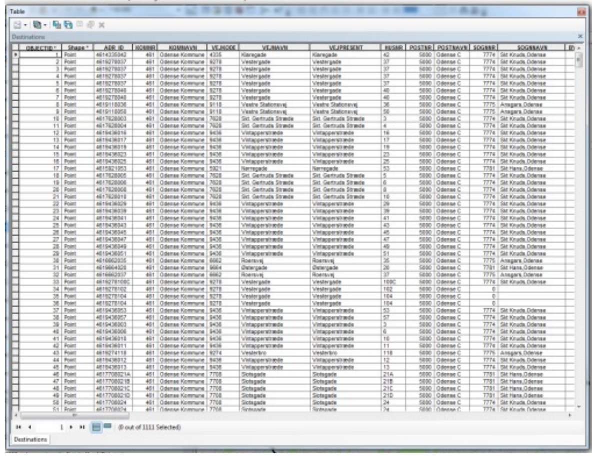
Aggregate data into user-defined domains

Merged acc + GPS data





At home? Yes → Home domain

No ↓

At work? Yes → Work domain

No ↓

In transport? Yes → Transport domain

No ↓

'Other' domain

Transport domain ↓

Other trips | Commuting

Active | Passive

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Example of domains that can be created

Day

Home

Work/school

Transport

Other

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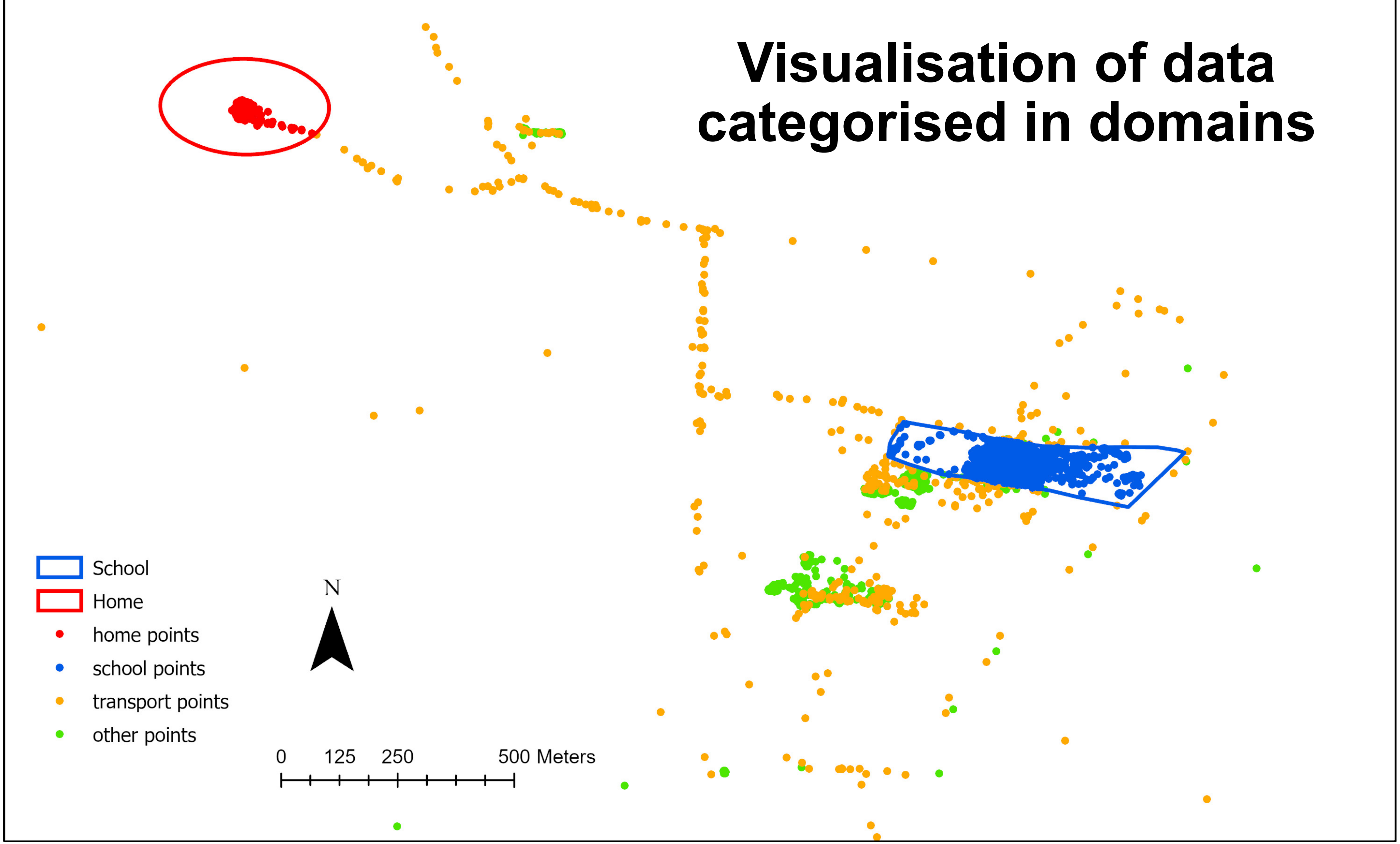
Visualisation of data categorised in domains



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Variables created per domain, per day

Time spent in a domain (duration)

Weartime

Time sedentary (SED)

Time in LPA

Time in MPA

Time in VPA

Time in MVPA

Average CPM

Example output data – day level

identifier	dte	dow	day_duration	day_weartime	day_lpa	day_mvpa	day_sed	day_cpm
GR012BE	13/06/2017	2	7200	4155	0	0	4155	0.644
GR012BE	14/06/2017	3	86400	11955	2790	15	9150	0.742
GR012BE	15/06/2017	4	86400	47310	9165	0	38145	0.652
GR012BE	16/06/2017	5	86400	21120	2865	15	18240	0.499
GR012BE	17/06/2017	6	86400	21750	5250	0	16500	0.753
GR012BE	18/06/2017	7	86400	4545	0	0	4545	0.095
GR012BE	19/06/2017	1	86400	28875	5175	105	23595	0.604
GR012BE	20/06/2017	2	86400	23310	3540	30	19740	0.522
GR012BE	21/06/2017	3	86400	12225	1455	0	10770	0.323

Trip level output

HABITUS identifies trips an classifies them as walking, cycling or vehicle → not a perfect classification, but acceptable

We further process trips to:

- create multi-modal trips
- identify home-school and school-home trips
- create output files as table and as Shape file for GIS

Next steps – HABITUS 2.0

We are testing the new version at moment

Workshop at ICAMPAM in a few weeks

Next steps - adding domain classification to the next generation of devices/systems

We hope to build on SurPASS

Activity type data in domains

Non-count accelerometer metrics

https://sens.dk/

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Next steps – combine accelerometer and GPS in machine learning

frontiers in
PUBLIC HEALTH

METHODS ARTICLE
published: 22 April 2014
doi: 10.3389/fpubh.2014.00036

Identifying active travel behaviors in challenging environments using GPS, accelerometers, and machine learning algorithms

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Background: Active travel is an important area in physical activity research, but objective measurement of active travel is still difficult. Automated methods to measure travel behaviors will improve research in this area. In this paper, we present a supervised machine learning method for transportation mode prediction from global positioning system (GPS) and accelerometer data.

Methods: We collected a dataset of about 150 h of GPS and accelerometer data from two research assistants following a protocol of prescribed trips consisting of five activities: bicycling, riding in a vehicle, walking, sitting, and standing. We extracted 49 features from 1-min windows of this data. We compared the performance of several machine learning algorithms and chose a random forest algorithm to classify the transportation mode. We used a moving average output filter to smooth the output predictions over time.

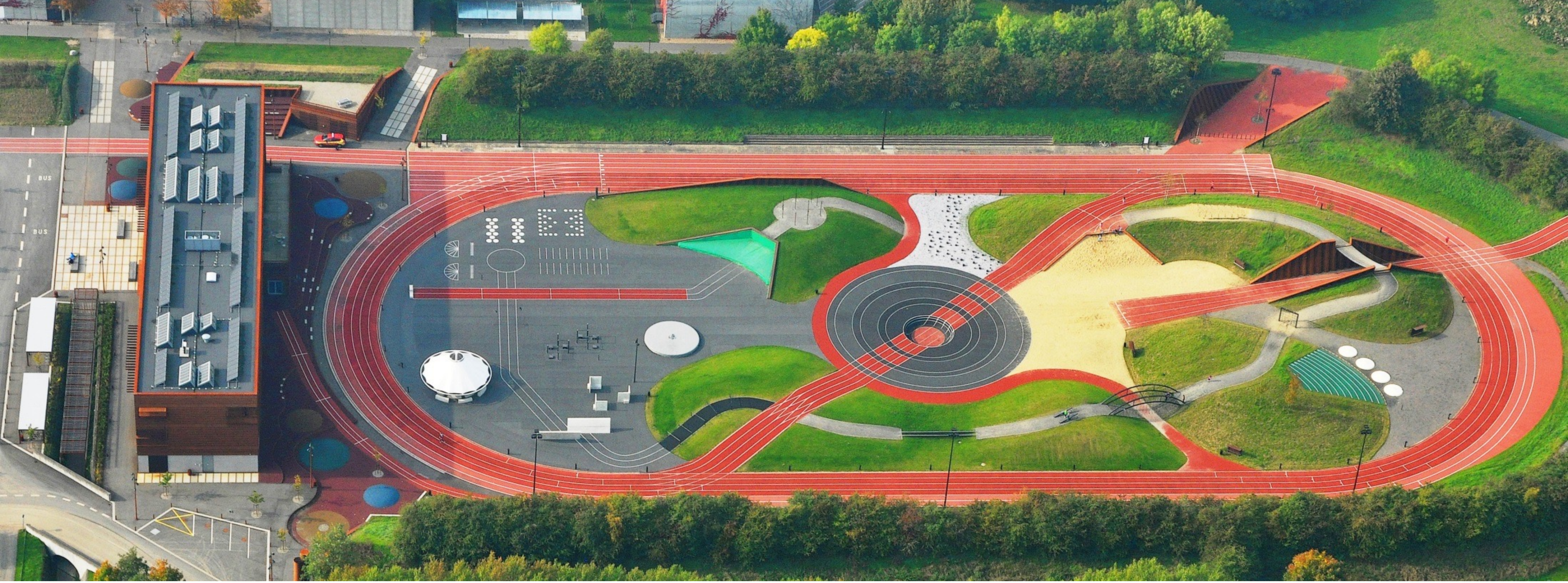
Summing up

Adding context to accelerometer data is important and needed in many studies

Combining GPS and accelerometer makes it possible to create devise-measured domain-specific physical activity measures

More collaboration in the further development of tools and analyses would be useful

Novel tools and devices will make it easier



Thank you!

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