ACTIVITY RECOGNITION USING DATA FROM WEARABLE SENSORS AND SMART SHOE DEVICES: CLASSIFYING KICK-BOARD AND SKATEBOARD COMMUTING BEHAVIORS

"ANAVEZOUT AR VEVREDEREZH DRE ZIADURIOÙ GANT SENSERIOÙ GOURIZET HA DAOUGEZIOÙ SKAO : RANVELLIÑ AN EMZALC'HOÙ DRE GOMPANIAJ HAG AVAELEREZH."

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Rational (1/2)

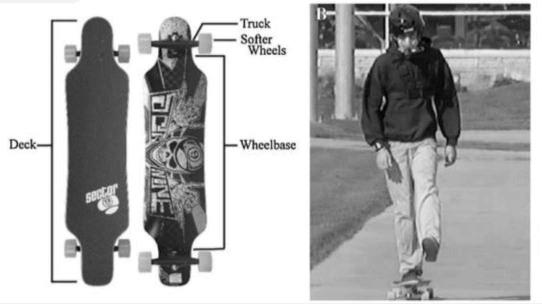
Skateboard study

- Many sociology studies
- Trick recognition [**Groh et al., PMC. 2017**]
- Assessment of Energy expenditure (longboard cruising) [**Board, Brownings, EJAP. 2014**]
- Heart rate response (skatepark) [**Wiles et al., IJES. 2020**]
- Transportation and built environment study [**Fang, Handy, Transportation. 2017**]
  - → **Rising popularity of skateboard for transportation.**

Kickboard (=kick-scooter, nonmotorized scooter)

- **Became a popular transportation mean in the past decade**.
- Recent increase in the number injuries related to the use of kickboard [**Tucket. BMC Public Health, 2022**; **Park et al., J Oral Maxillofac Surg. 2021**]

Taken from Groh et al. (2017), PMC.
10.1016/j.pmcj.2017.05.007

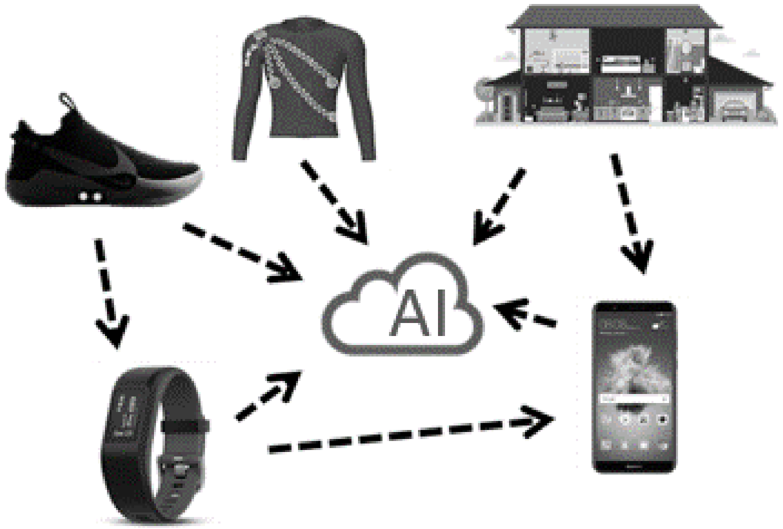


Board, Browning (2014), EJAP.
10.1007/s00421-014-2959-x

→ No study aiming at developing wearable device algorithms able to recognize skateboard and kickboard behaviors and predicting the related energy expenditures.

Because active transportation can be an important contributor to daily PA [**Dinu et al., Sports Med. 2019**], the lack of push-push-glide activity-specific algorithms for wearable activity trackers may lead to misestimations of daily energy expenditure in regular skateboard or kickboard commuters.

Rational (2/2)



An example of interconnected environment where algorithms in the cloud process data from various connected devices, including smart shoes, wearable sensors, and smartphones.

📱🏃 Activity tracker platforms

- Constant evolution (hardware, connectivity, software)
- Contemporary trackers:
  - ➢ Multi-sensing capabilities
  - ➢ Consist in wrist-worn device paired to smartphone
- 5G and IoT technology
  - → Ever more ubiquitous monitoring of our physical behaviors

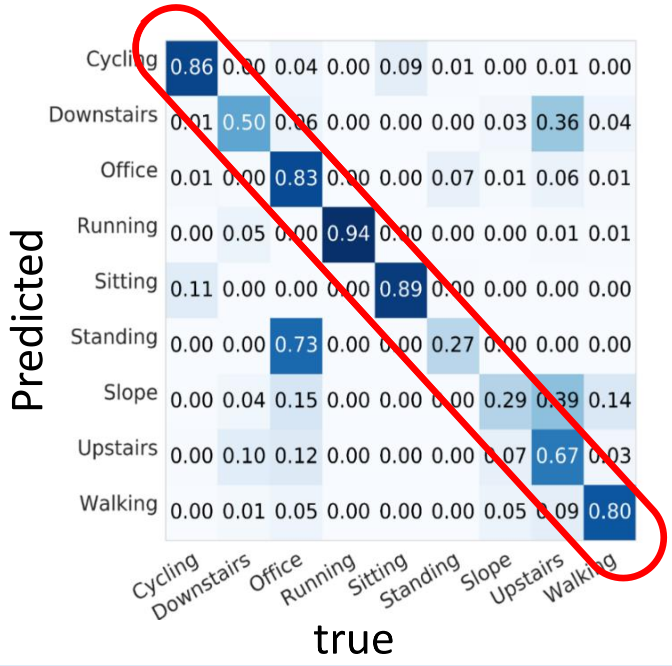
👟 Smart shoe devices

- lower limb contributes significantly to energy expenditure
- Plantar pressure

→ information on the interaction between feet and ground

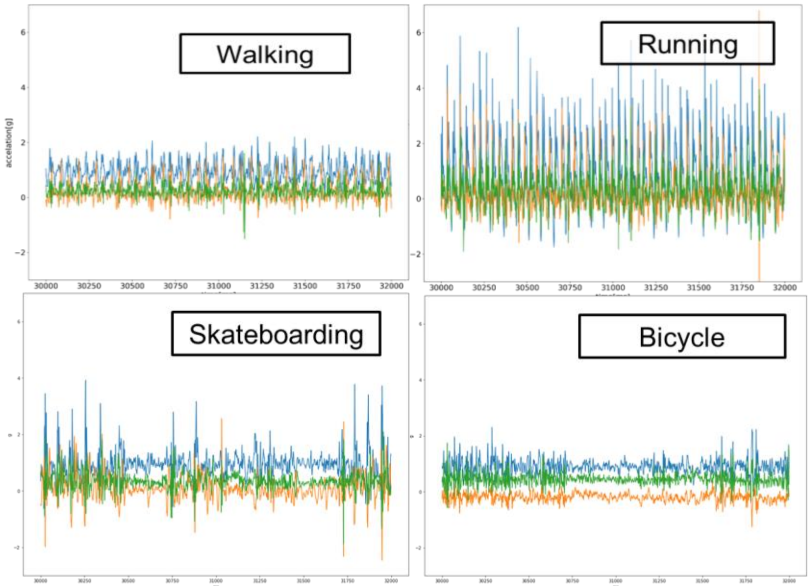
Preliminary studies

Previous **smart shoe** study:



Successful in recognizing a wide range of sedentary and locomotive behaviors (**kickboard and skateboard were not included in the protocol**) [**Ren et al., PeerJ 2020**]

Push-push-glide activity and **accelerometer** sensor:



20-second window 3-axis accelerometer (hip-worn) data for skateboard commuting and 3 other selected locomotive activities

potential signature of push-push-glide activity in the accelerometer sensor signal.

Objective

Testing the feasibility of **recognizing skateboard and kickboard** commuting behaviors **using IMU sensor and/or smart-shoe device data.**

Ultimate goal

→ Supporting more **accurate energy expenditure predictions** related to skateboard and **kickboard commuting behaviors.**

Method

	Mean	SD
Age	33.5	13.9
Height	169.5	11.1
Body weight	63.7	13.4

Heterogenous population of 15 subjects

Subject Number		15
M：F	Male	10
	Female	5
Level	Beginner	5
	Advanced/Expert	9
	Professionnal	1

Stance	Regular	8
	Goofy	5
	Regular Mongo	1
Dominant hand	Right	14
	Left	1
Citizenship		7

IMU

(MMS, METEINLAB, US)

- 3-axis accelerometer
- 3-axis gyro sensor

Smart insole

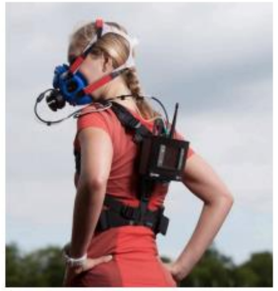
(OpenGO, Moticon, Germany)

- 16 pressure sensors

Gold standard

Indirect calorimetry

(K5, COSMED, Italy)



- Energy expenditure

Heart rate sensor

(HRM-Run, Garmin, US)

- Heart rate

Smart warch

(Polar V2, Polar, Finland)

- GPS

Camera

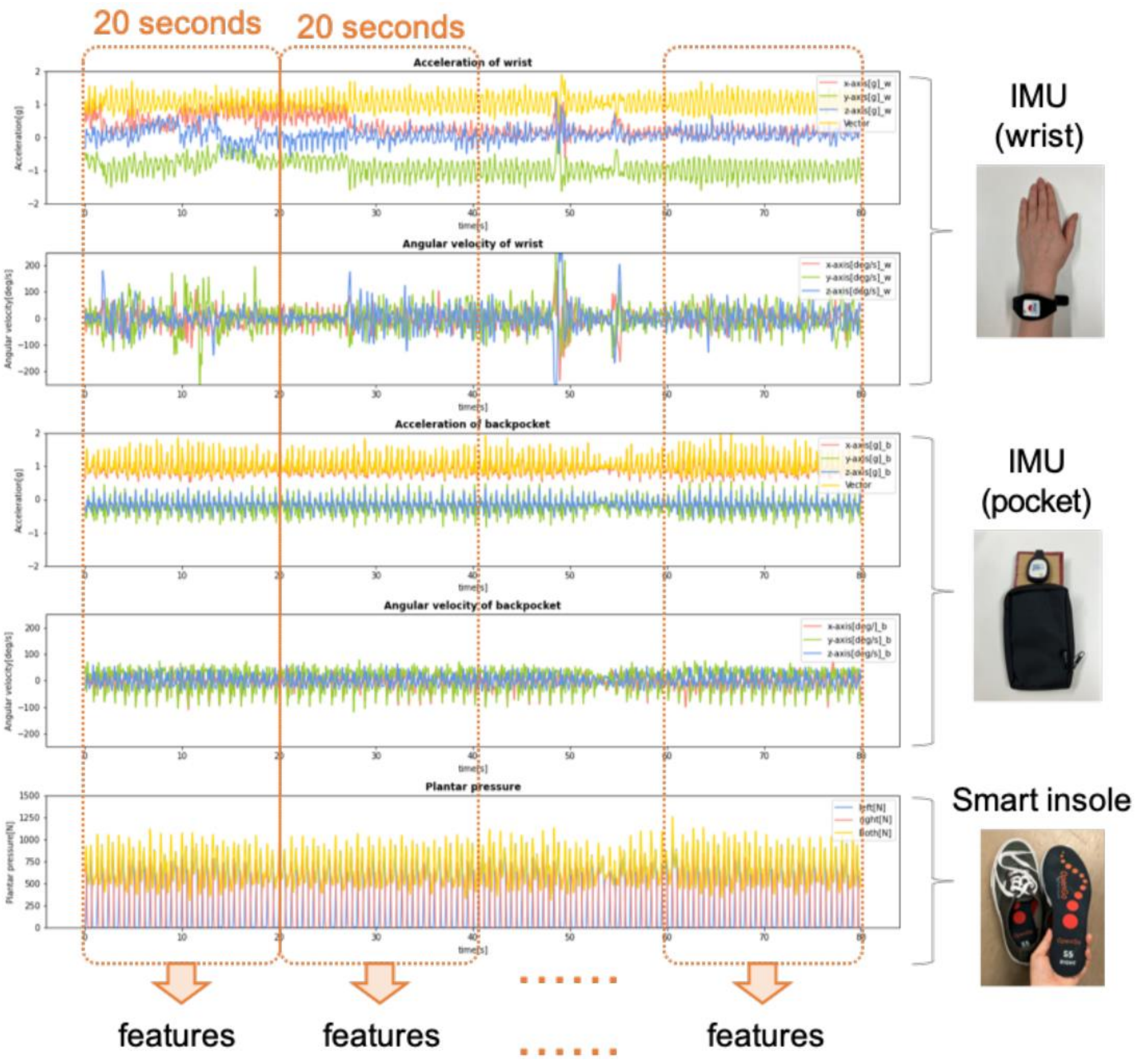
(Garmin, US)

- Video

Total: 2-hour experiment

Method

20-second window analysis



Accelerometer sensor [Oxford Wearables Group]:

- Processing of the 3-axis and vector norm time series
  - General statistics
  - Roll, pitch, yaw analysis
  - FFT analysis
  - Cross-correlation analysis

Gyro sensor:

- Processing of the 3-axis
  - Roll, pitch, yew analysis
  - FFT analysis
- Combining gyro sensor and accelerometer information [**push-push-glide activity-specific features**]:
  - Cross-correlation

Plantar pressure [Ren et al., PeerJ 2020]

- Total Force vector data [sum of sensor 1-16] (Moticon Software):
  - General statistics
  - FFT analysis
  - Peak-interval analysis
  - Left and right feet comparative analysis

→ Total of 464 data features

https://github.com/OxWearables/biobankAccelerometerAnalysis
Ren et al., PeerJ 2020

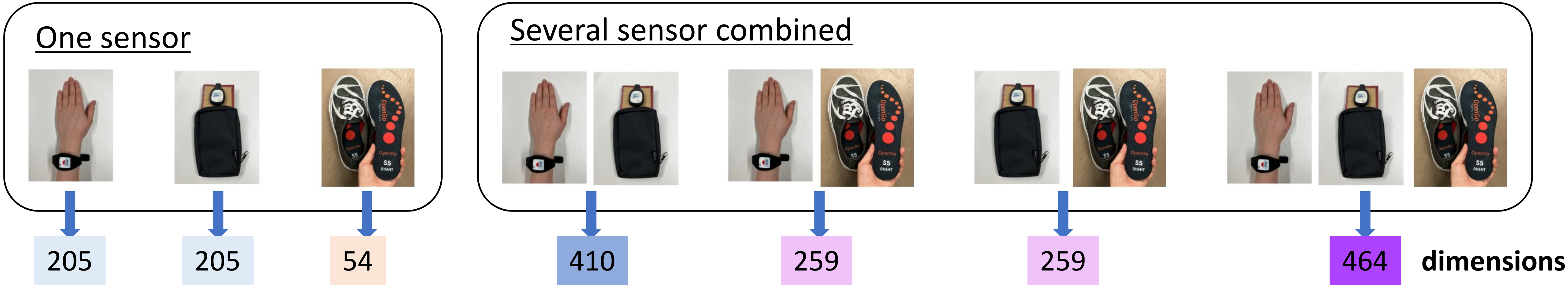
Method

Summary of the data reduction process

Raw data vector shape:

7 activities x 15 subjects x 6 min x 60 sec x 100 Hz sampling rate = 3,780.000 samples (x 8 time series)

3,780,000 samples (100 Hz) / 20-sec windows (windows of 2,000 samples) = 1890 data points



Activity Recognition random forest classifier

[sklearn ensemble.RandomForestClassifier]

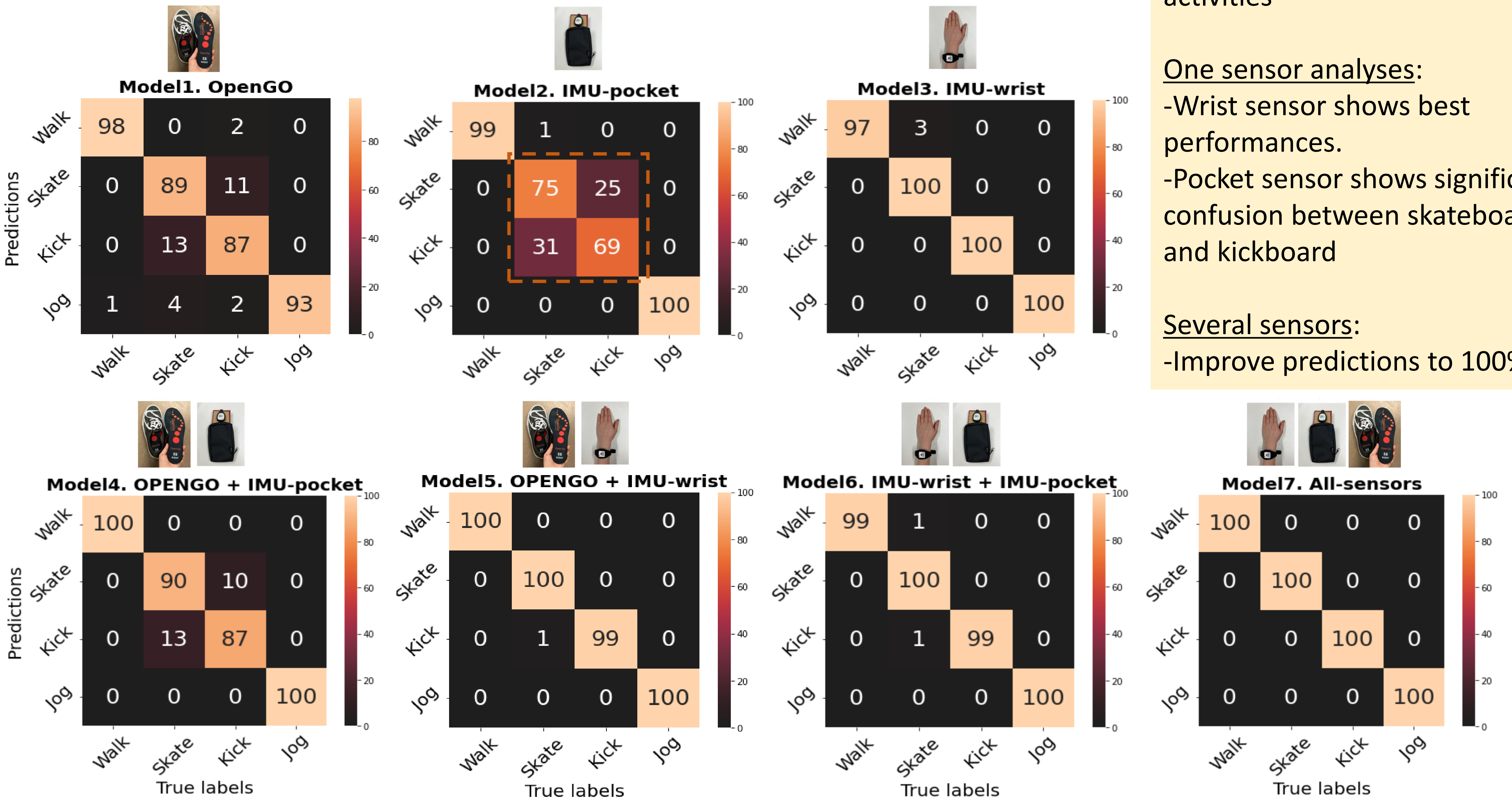
Training-Test split:
- Subject-wise design
- Training: 10 subject / Testing: 5 subjects

→ 3003 possible combinations

Forest shape:
- 20-tree forests
- No-depth criterion (each leaf is pure)

Outcome:
- confusion matrix (mean values over all combinations)

Results: activity recognition



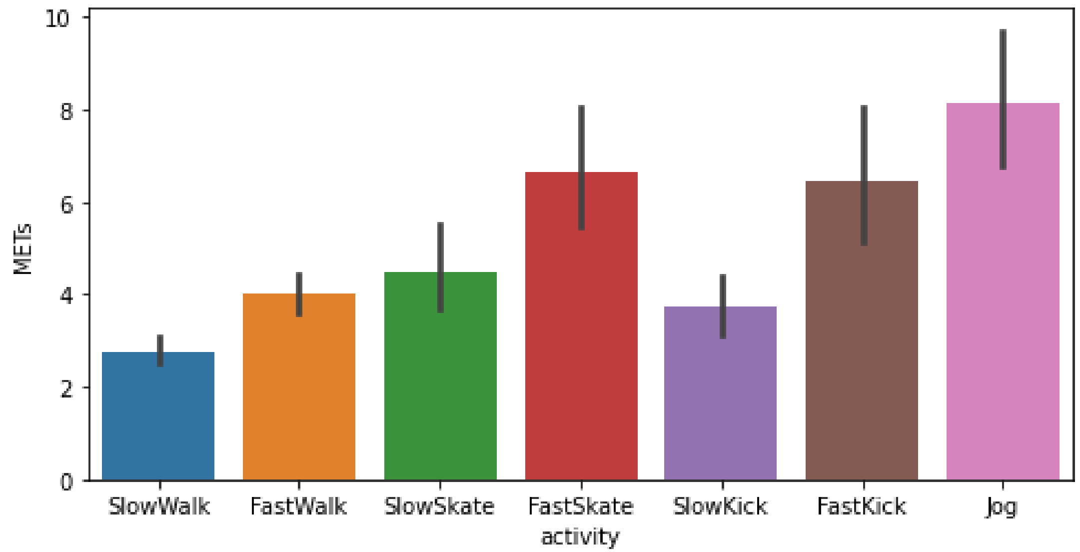
<u>Overall</u>:
-good classification of the activities

<u>One sensor analyses</u>:
-Wrist sensor shows best performances.
-Pocket sensor shows significant confusion between skateboard and kickboard

<u>Several sensors</u>:
-Improve predictions to 100%

Results: energy expenditure (1/2)

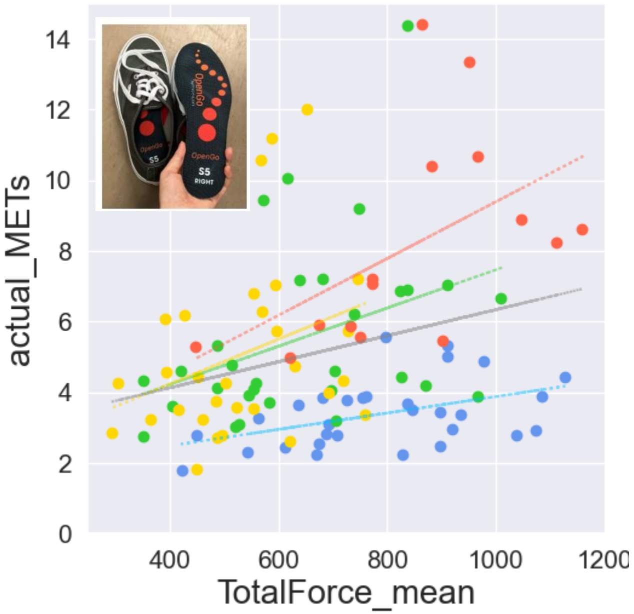
Actual intensities of activities calculated relatively to the resting metabolic rate

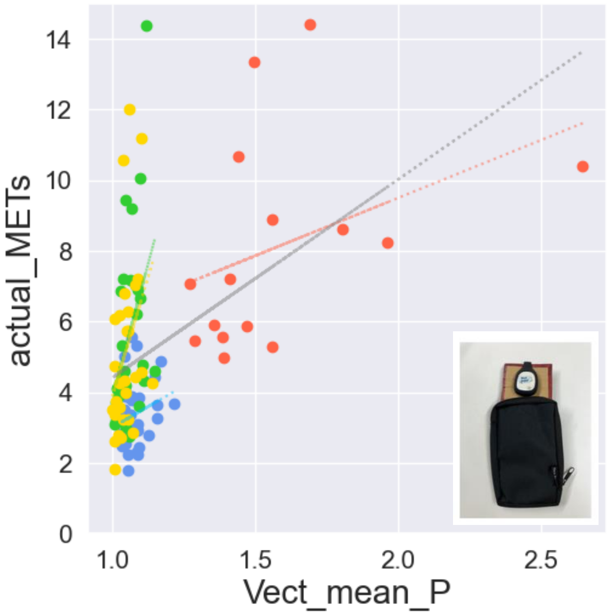


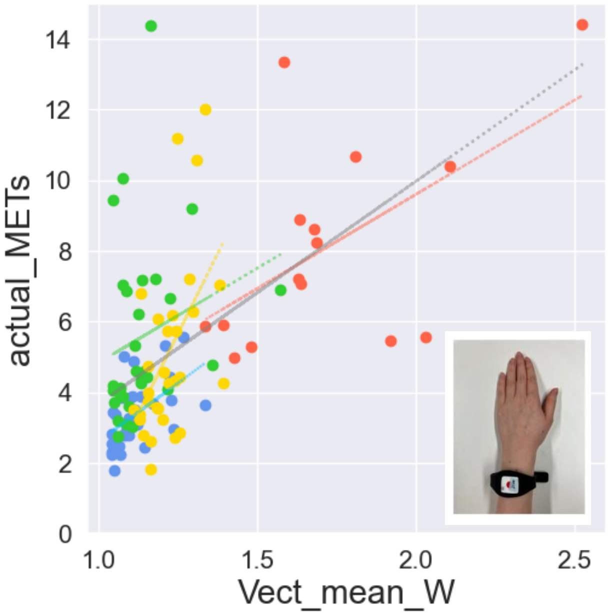
	METs			
	Mean	**SD**	**2011 Compendium of Physical Activities**	
Slow Walk	2.78	0.58	2.8-3.0	walking 2.0-2.5mph, firm surface
FastWalk	4.01	0.86	4.3	walking 3.5mph, brisk, firm surface
SlowSkate	4.51	1.87	5.0	skateboarding, moderate effort
FastSkate	6.64	2.80	6.0	skateboarding, vigrous effort
SlowKick	3.73	1.29	-	
FastKick	6.44	2.78	-	
Jogging	8.13	2.96	7.0-8.0	jogging, general, in place

Results: energy expenditure (2/2)

Walk Skate Kick Run All







Feature: Total Force mean					
model	walk	skate	kick	jog	all
coeff	0.0023	**0.0054**	**0.0064**	0.008	0.0037
R2	0.196	0.143	0.101	0.269	0.077
p-value	0.014	0.04	0.086	0.048	0.004

Feature: Acceleration Vector mean					
model	walk	skate	kick	jog	all
coeff	4.7	**30.2**	**26.9**	3.3	5.6
R2	0.054	0.191	0.135	0.15	0.222
p-value	0.218	0.016	0.046	0.154	<0.001

Feature: Acceleration Vector mean					
model	walk	skate	kick	jog	all
coeff	6.6	5.3	**18.1**	5.3	6.3
R2	0.279	0.053	0.276	0.321	0.333
p-value	0.003	0.223	0.003	0.028	<0.001

More important slope for the skateboard and kickboard activities for some selected feature expressing plantar pressure (smart shoe) or acceleration (IMU pocket, IMU wrist) quantitatively

→ Necessity to perform intraclass regression for accurate predictions of energy expenditure

Conclusions

- Recognizing skateboard and kickboard cruising activities using wearable IMU sensor and or smart shoe devices is feasible.
- The wrist-worn activity tracker device acquiring accelerometer and gyroscope data reach nearly 100% of accuracy in classifying skateboard and kickboard among other typical locomotive activities.
- Push-push-glide activities showed activity-specific relationships between acceleration (IMU sensors) and energy expenditure, and plantar force (smart shoe device) and energy expenditure.

→ Skate board cruising and kickboard is <u>feasible</u> but also <u>crucial</u> to the accurate computation of energy expenditure predictions related to these activities.

Thank you

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21K11335

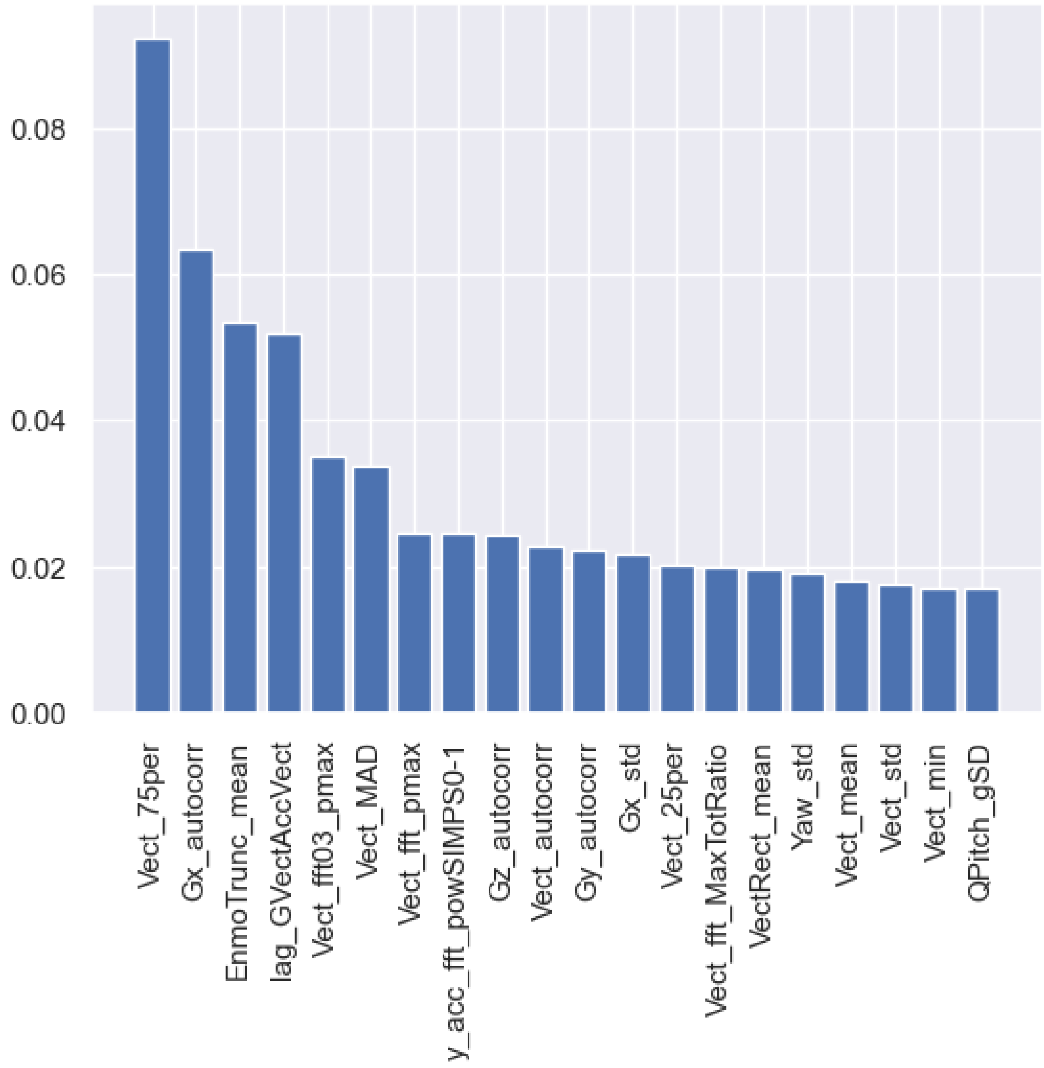
HIGH SKATEBOARDS

Hitomi Hatori, MSc.
activity recognition,
smartshoes, IMU sensor
(this presentation)

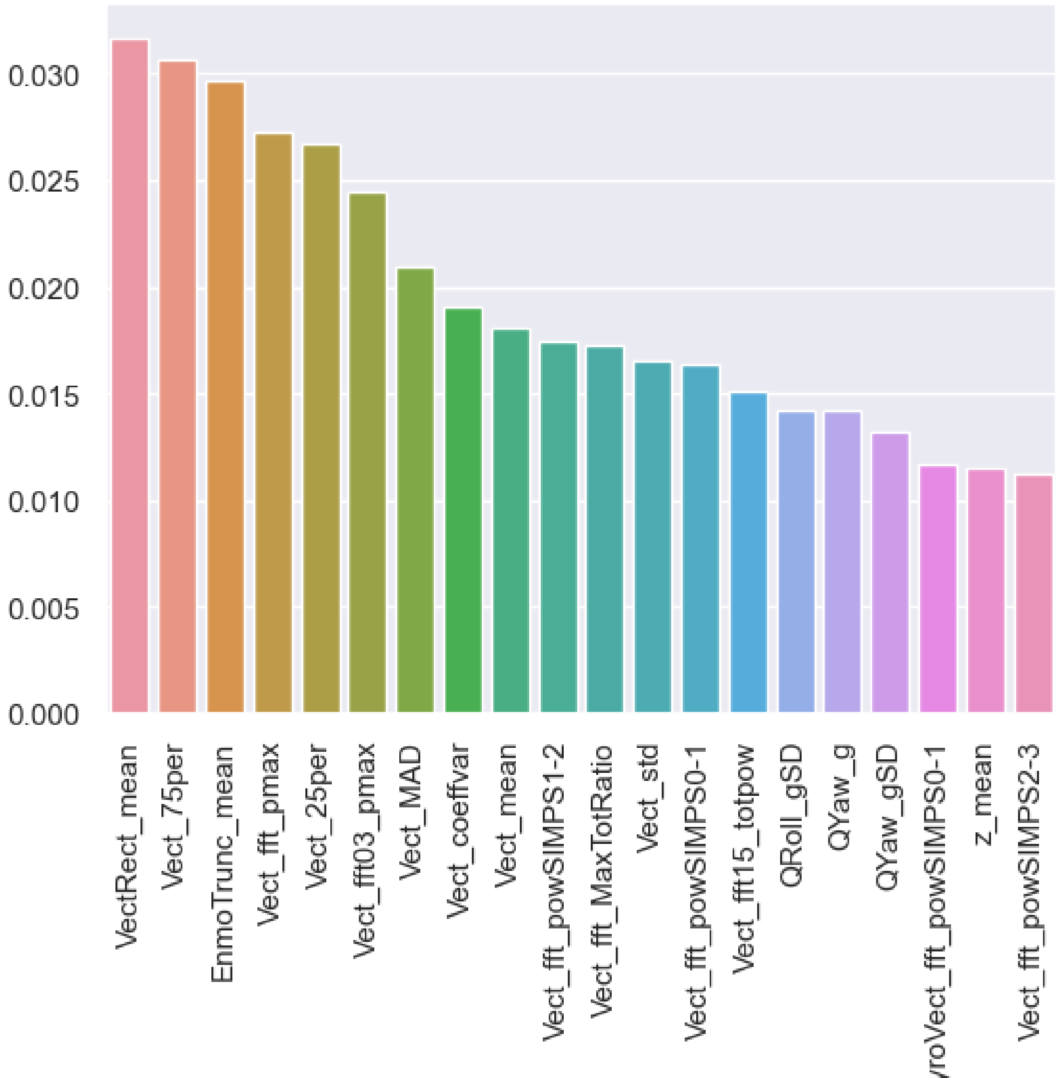
Yuki Nakajima, MSc.
Smart-home and energy
expenditure prediction
(poster presentation)

Walking, upstairs, downstairs, running, bicycle, sitting, standing, skateboarding, kickboarding

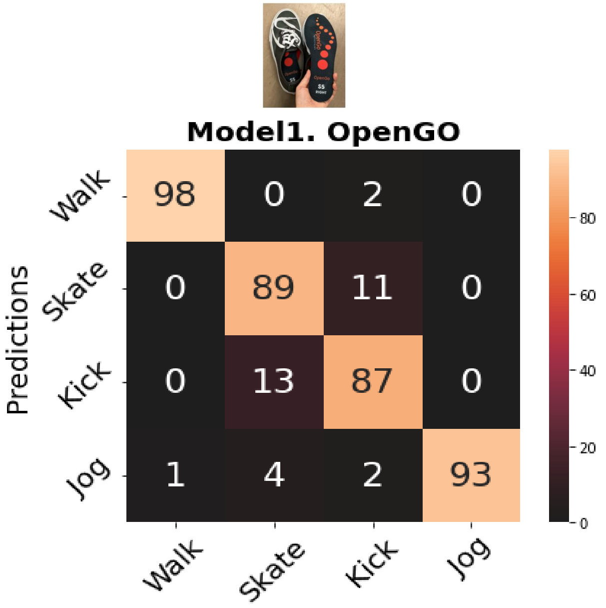
1 vs Rest

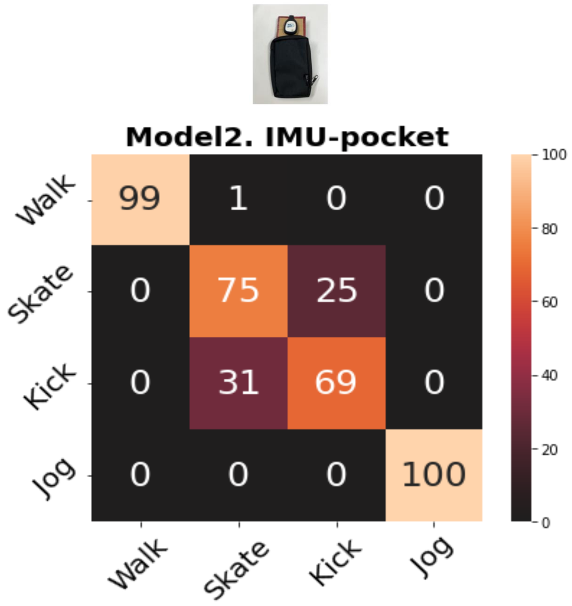


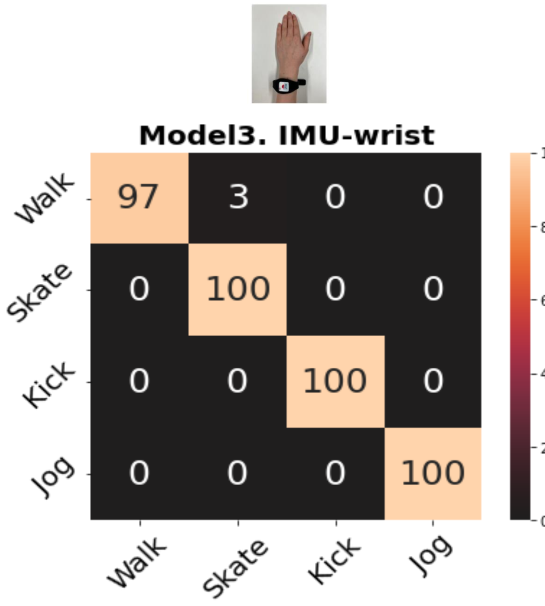
All

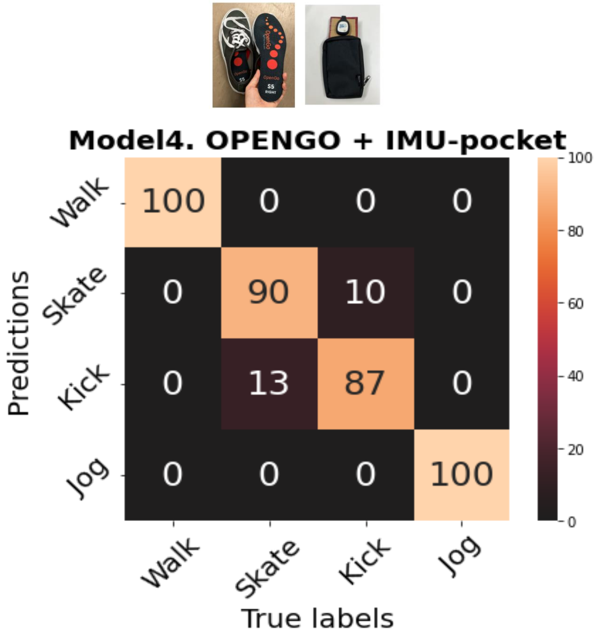


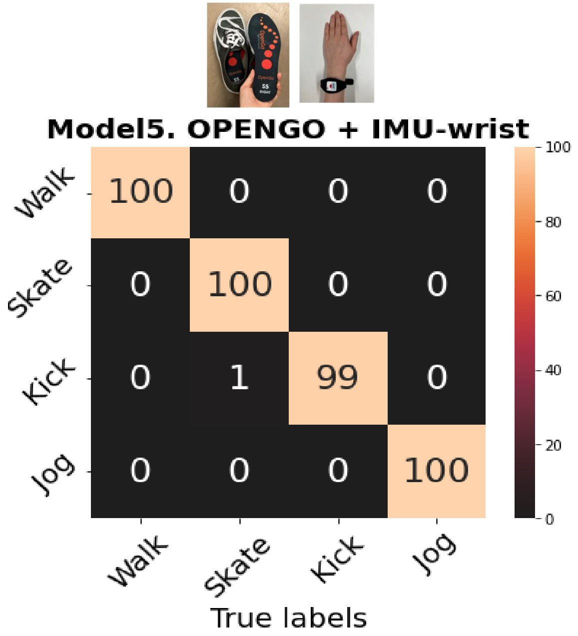
		Scores	
Model	Sensor combination	balanced-train	balanced-test
1	OpenGO	1.000	0.917
2	IMU-pocket	1.000	0.858
3	IMU-wrist	1.000	0.991
4	OpenGO + IMU-pocket	1.000	0.943
5	OpenGO + IMU-wrist	1.000	0.997
6	IMU-wrist + IMU-pocket	1.000	0.994
7	All sensors	1.000	0.998

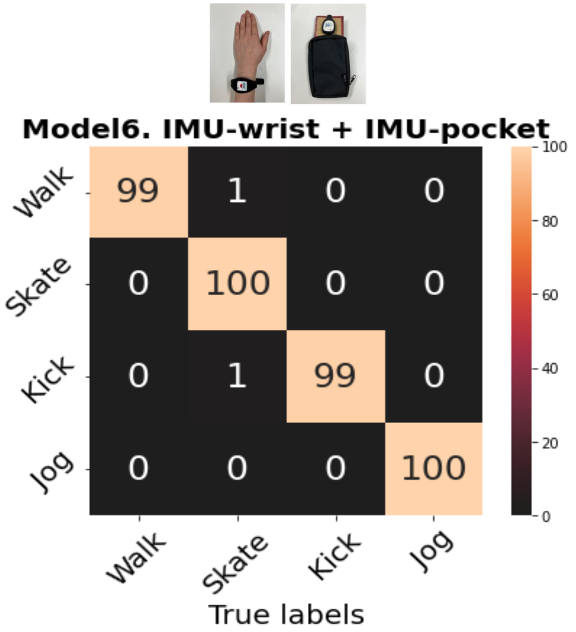












Preliminary studies

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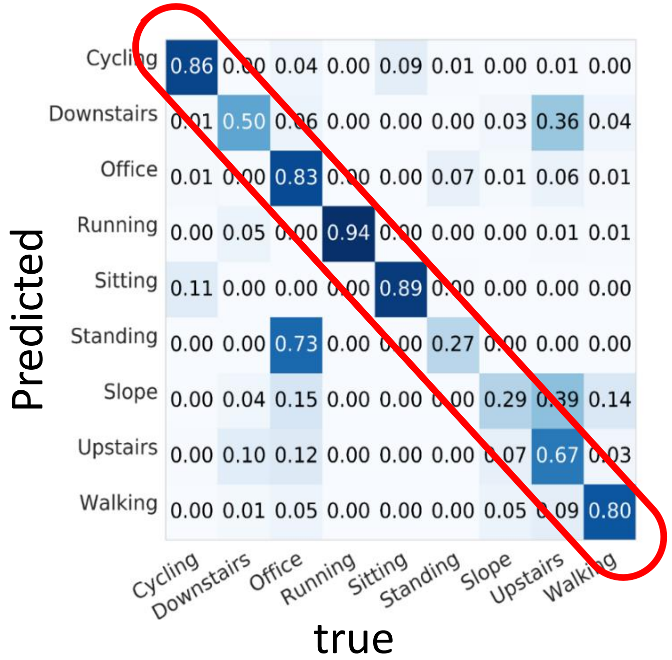

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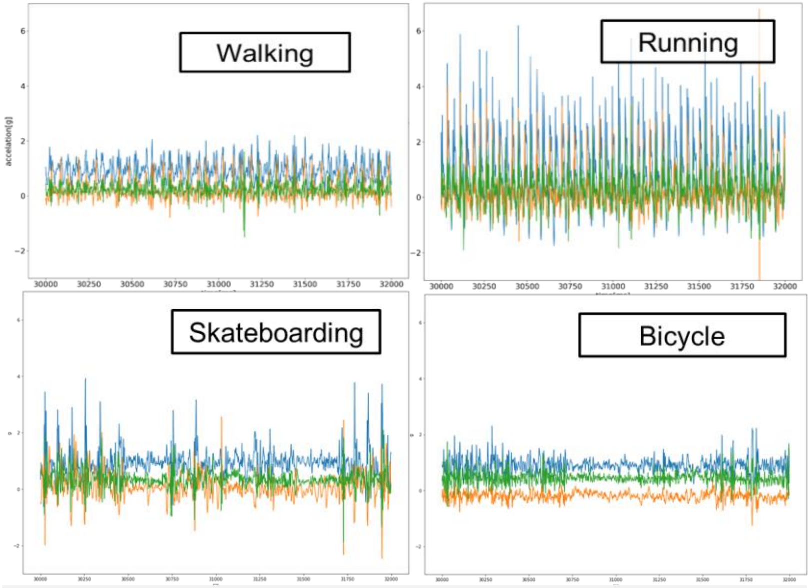

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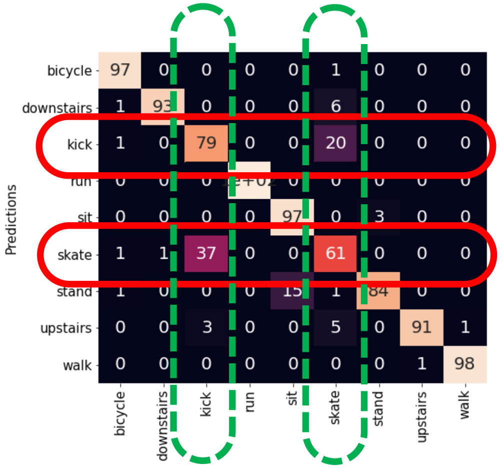
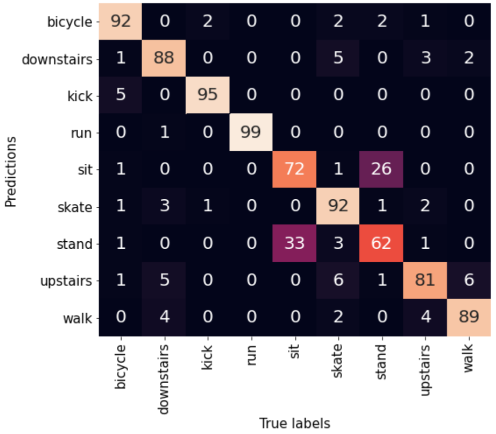
Recognizing skateboard and kickboard using **IMU sensor** data:





The wrist sensor is confused between skateboard and kickboard activities.

- **No energy expenditure data**
- Does **smart shoe devices** help improving the recognition of skateboard and kickboard activities?