Intelligent Consumer Technologies

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a.a. 2024/2025

Personalization, recommender, and adaptive systems

Intelligent systems

Topics: Personalization, Recommender Systems, Adaptive Systems

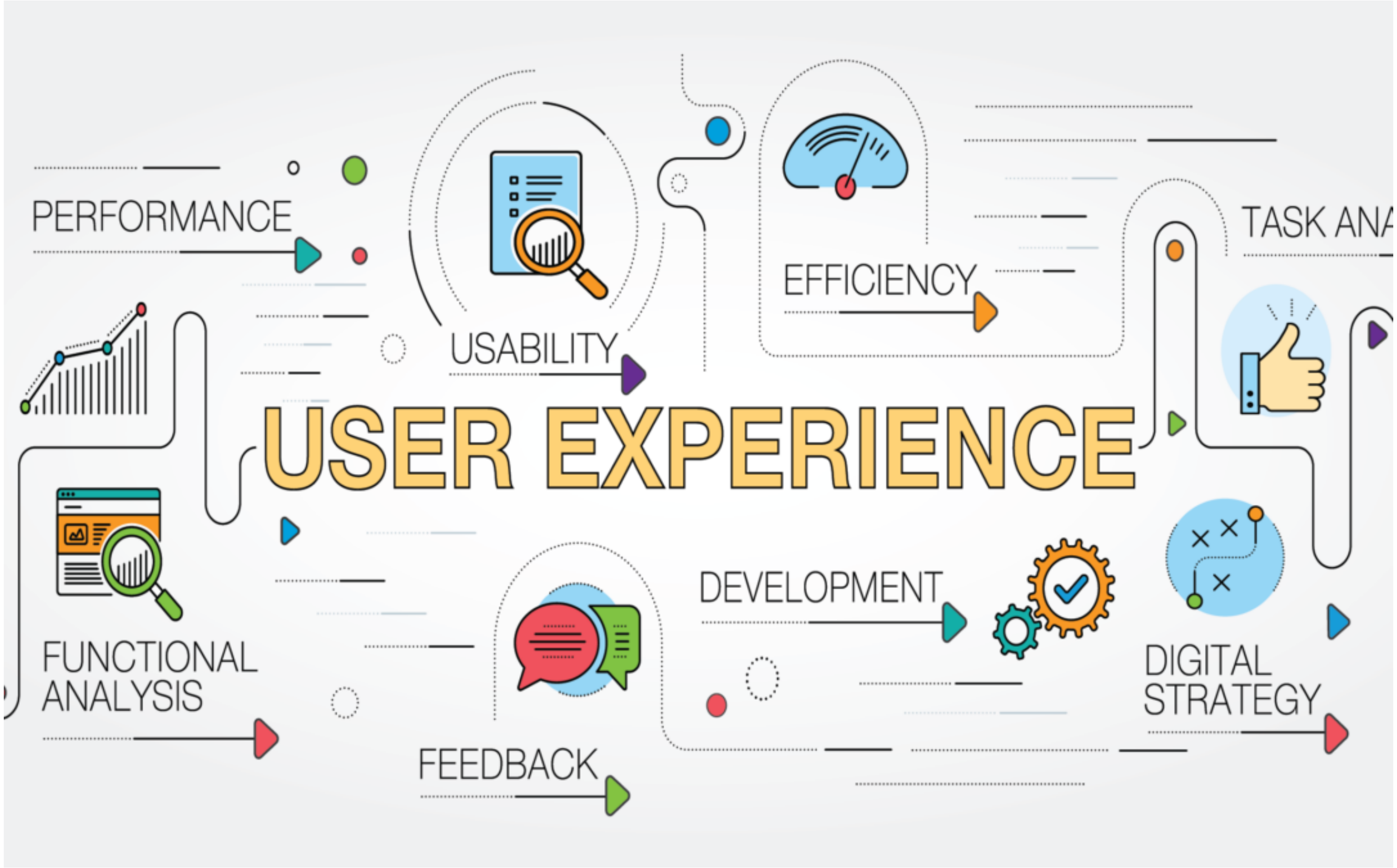
Learning Objectives

- Being able to design personalization on Intelligent Systems
- Being able to understand recommendation mechanisms on Intelligent Systems
- Being able to design adaptive Intelligent Systems

Human-centered technologies

HCI

Human centered technology has its roots in media technology, computer science, and behavioural science.

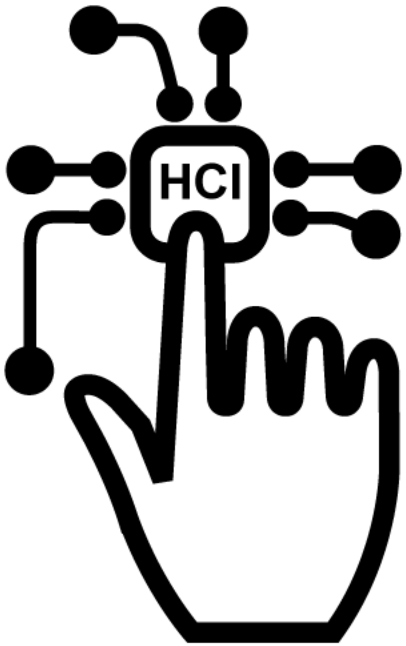


Goals of Human-Computer-Interaction

Main features

Allow users to carry out tasks

- **Safely**
- **Effectively**
- **Efficiently**
- **Enjoyably**



Some of these slides are taken from Chris Shaw Course in Interface Design
http://www.sfu.ca/~shaw/iat334/index.html

Goals of System Engineering

Functionality

- Tasks and sub-tasks to be carried out

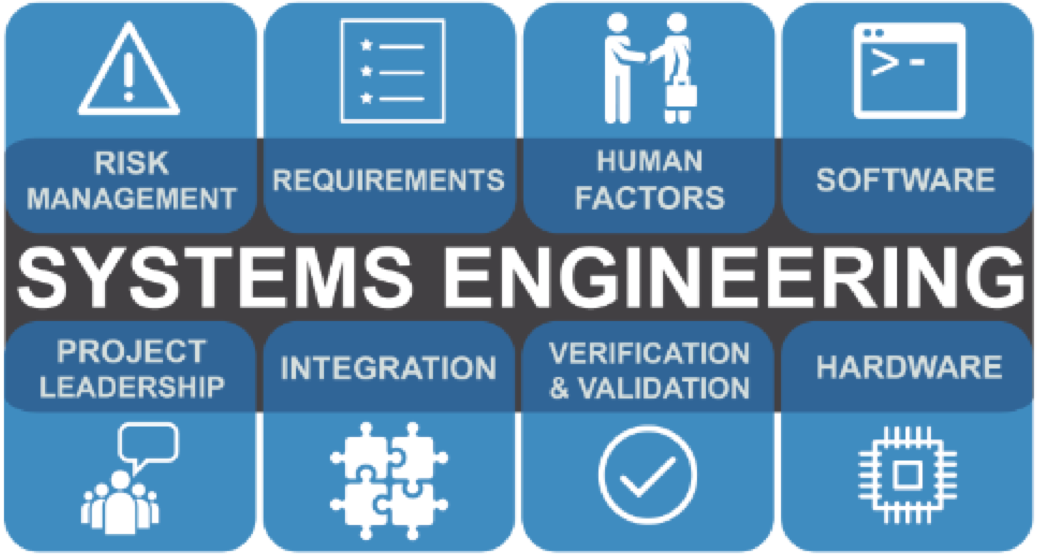
Reliability

- Maintaining trust in the system

Standardization, integration, consistency and portability

Schedules and budgets

- Adhering to timelines and expense
- Human factors principles and testing reduces costs



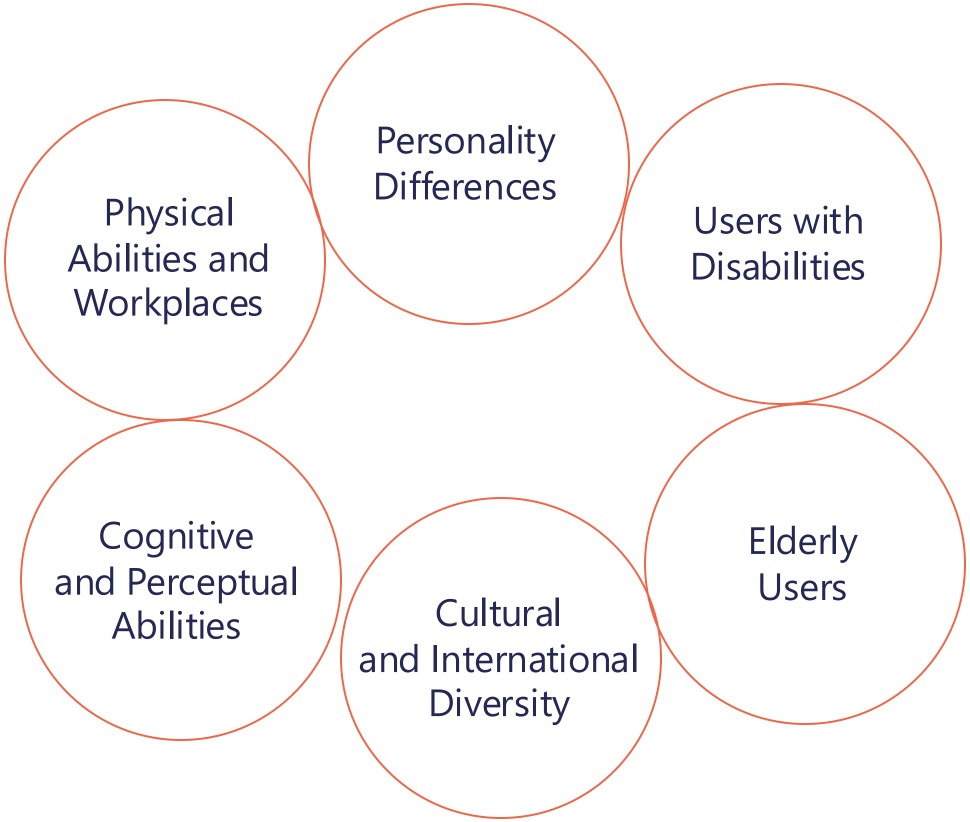
Usability

- Five <u>Measurable</u> Goals of UI Design

- Combination of
  - **Ease of learning**
  - **High speed** of user task performance
  - **Low** user **error rate**
  - Subjective user **satisfaction**
  - **User retention** over time

Accommodating Human Diversity

Principles of Universal Design



Improving Interfaces

- Know the User!
  - Physical abilities
  - Cognitive abilities
  - Personality differences
  - Skill differences
  - Cultural diversity
  - Motivation
  - Special needs

Improving Interfaces

- Know the User!
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  - Special needs

Enhance UX with Intelligent systems

Definition

Personalization, **recommender systems**, and **adaptive systems** are all related concepts in the field of information technology and **user experience**. They aim to tailor content, services, or experiences to the specific needs, preferences, and behaviors of individual users. Let's explore each of these concepts:

- Personalization
- Recommender Systems
- Adaptive Systems

These concepts are often interconnected, and modern applications frequently use a combination of personalization, recommender systems, and adaptive features to enhance user engagement and satisfaction.

* See **additional materials** on Ferrari, A., Micucci, D., Mobilio, M., & Napoletano, P. (2020). On the personalization of classification models for human activity recognition. IEEE Access, 8, 32066-32079.

Enhance UX with Intelligent systems

Definition

Personalization refers to the process of tailoring products, services, or experiences to meet the individual needs and preferences of users. It involves using data and algorithms to deliver content or recommendations that are relevant to a specific user.

Types:

- Preference personalization
- Adaptation
- Physical personalization
- Gender, age etc. personalization

Example: Smart Speaker may require some samples of the user voice to personalize the UX (e.g. Apple “Siri”).

Enhance UX with Intelligent systems

Definition

Personalized Hey Siri

Personalized "Hey Siri" (PHS) revolves around two methods for user enrollment:

- **Explicit:** a user is asked to say the target trigger phrase a few times, and the on-device speaker recognition system trains a PHS speaker profile from these utterances;
- **Implicit.** a speaker profile is created over a period of time using the utterances spoken by the primary user.

* See **additional materials** on https://machinelearning.apple.com/research/personalized-hey-siri

Enhance UX with Intelligent systems

Definition

Personalized Hey Siri

Personalized "Hey Siri" (PHS) revolves around two methods for user enrollment.

The five explicit enrollment phrases requested from the user are, in order:

1. "Hey Siri"
2. "Hey Siri"
3. "Hey Siri"
4. "Hey Siri, how is the weather today?"
5. "Hey Siri, it's me."

* See **additional materials** on https://machinelearning.apple.com/research/personalized-hey-siri

Enhance UX with Intelligent systems

Definition

Recommender Systems, also known as recommendation systems or engines, are a specific type of personalization technology. These systems analyze user data, such as past behavior, preferences, and interactions, to suggest items or content that the user is likely to find interesting or useful.

Types:

- **Collaborative Filtering:** Recommends items based on the preferences and behavior of users with similar profiles.
- **Content-Based Filtering:** Recommends items based on the features and characteristics of the items themselves and the user's preferences.
- **Hybrid Systems**: Combine collaborative and content-based filtering to improve recommendation accuracy.

Example: Movie recommendations on platforms like Netflix, product recommendations on e-commerce sites.

Enhance UX with Intelligent systems

Definition

Adaptive systems refer to systems that dynamically adjust their behavior or content based on user interactions, feedback, or changing circumstances. They adapt to the evolving needs and preferences of users over time.

Types:

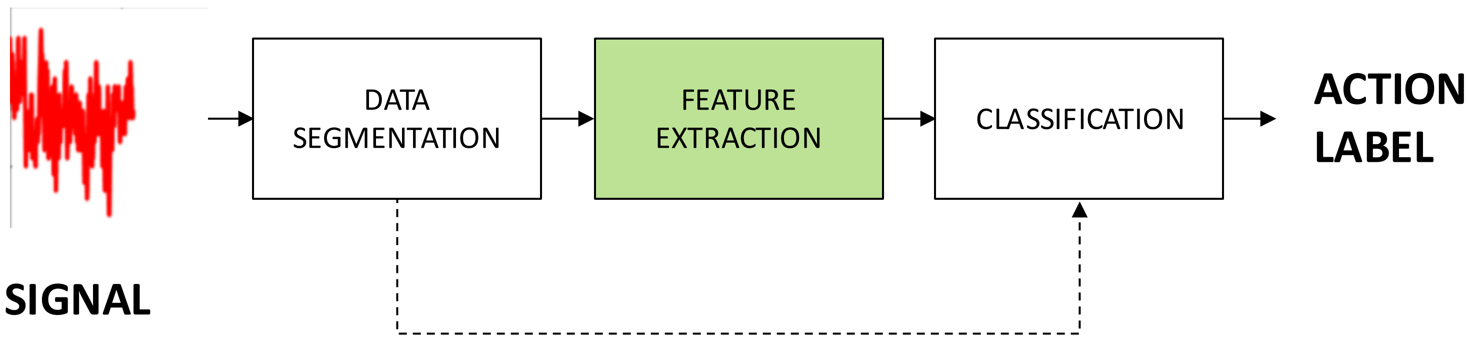
- Mood adaptation
- Sound adaptation
- User feedback adaptation
- ..

Example: An adaptive learning platform that adjusts the difficulty of lessons based on a student's performance, an adaptive user interface that changes its layout based on user behavior.

Personalization, **recommender systems**, and **adaptive systems** are all related concepts in the field of information technology and **user experience**.

Personalization in HAR

CLASSIFICATION PIPELINE



CLASSIFICATION PIPELINE

Feature Extraction (tri-axial or magnitude):

- Raw features
- Traditional Hand-crafted features
- Learned Features

$$(\underbrace{acc_{x_1}, \ acc_{x_2} \ acc_{x_3} \ \ldots \ acc_{x_n}}_{x-dimension\ acceleration} \ \cdots \ \underbrace{acc_{y_1} \ acc_{y_2} \ acc_{y_3} \ \ldots \ acc_{y_n}}_{y-dimension\ acceleration} \ \cdots \ \underbrace{acc_{z_1} \ acc_{z_2} \ acc_{z_3} \ \ldots \ acc_{z_n}}_{z-dimension\ acceleration})$$

Classification:

- Support Vector Machines
- K-Nearest Neighbor (k-NN)
- Etc.

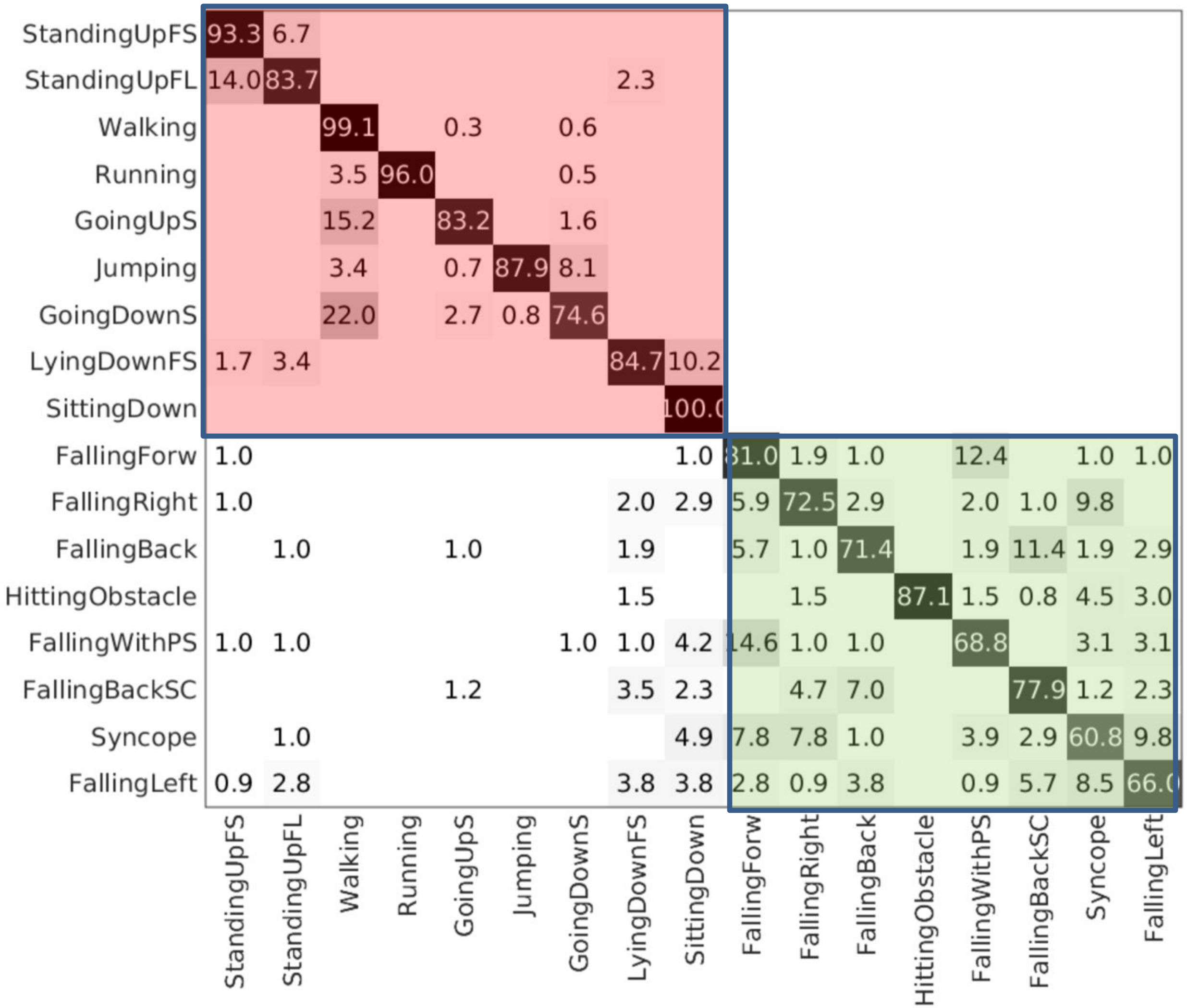
Metrics

- Macro average accuracy (TruePositives/Positives) in case of imbalanced datatets

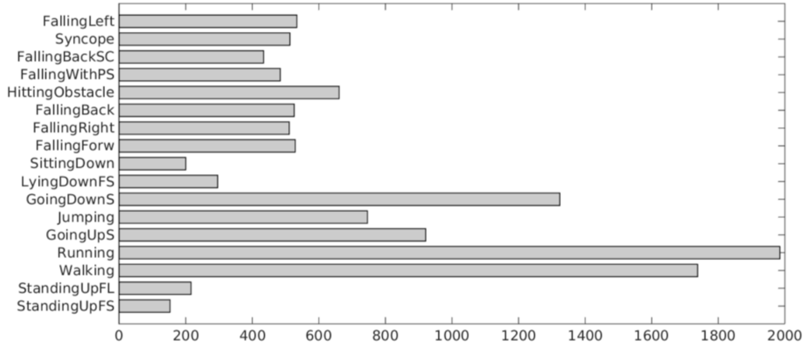
$$MAA = \frac{1}{|E|}\sum_{a=1}^{|E|} Acc_a = \frac{1}{|E|}\sum_{a=1}^{|E|} \frac{TP_a}{NP_a}$$

CLASSIFICATION PIPELINE

Confusion Matrix on classification of UniMiB-SHAR dataset



UNIMIB-SHAR



5-fold

	Raw Data				Magnitude			
Data	KNN	SVM	ANN	RF	KNN	SVM	ANN	RF
AF-17	**82.86**	78.75	56.06	81.48	65.30	65.71	41.95	**65.96**
AF-2	97.78	**98.71**	98.57	98.09	95.56	**97.42**	96.71	95.74
A-9	87.77	81.62	72.13	**88.41**	77.37	**78.94**	62.81	75.14
F-8	**78.55**	75.63	55.07	78.27	53.31	56.34	37.66	**57.26**

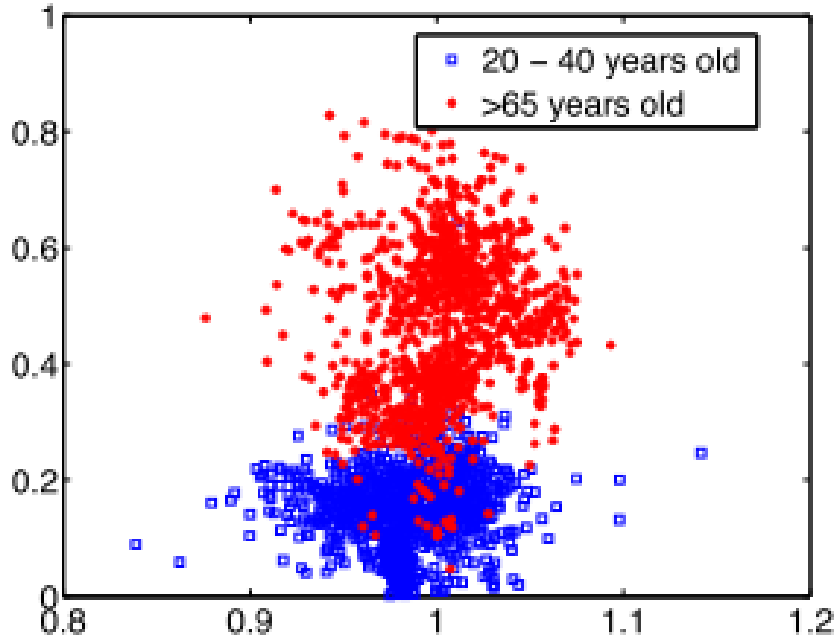
Leave-One-Subject-Out

	Raw Data				Magnitude			
Data	KNN	SVM	ANN	RF	KNN	SVM	ANN	RF
AF-17	52.14	55.15	48.00	**56.53**	52.14	55.09	48.00	**56.58**
AF-2	92.90	**97.57**	95.41	97.02	92.90	**97.57**	96.07	97.05
A-9	63.79	63.32	63.63	**73.17**	63.79	63.36	63.63	**72.67**
F-8	43.66	**48.84**	38.50	45.88	43.66	**49.35**	38.50	45.26

We need PERSONALIZATION !!

Personalization models

- Whatever the type of sensor, the actions performed by human beings have a strong subjective characteristic that is related to different factors, such as **age**, **gender**, **weight**, **height**, **physical abilities**, and **lifestyle**.
- Personalization models have been studied to take into account these subjective factors and it has been demonstrated that using these models, the accuracy of machine learning algorithms can be improved.



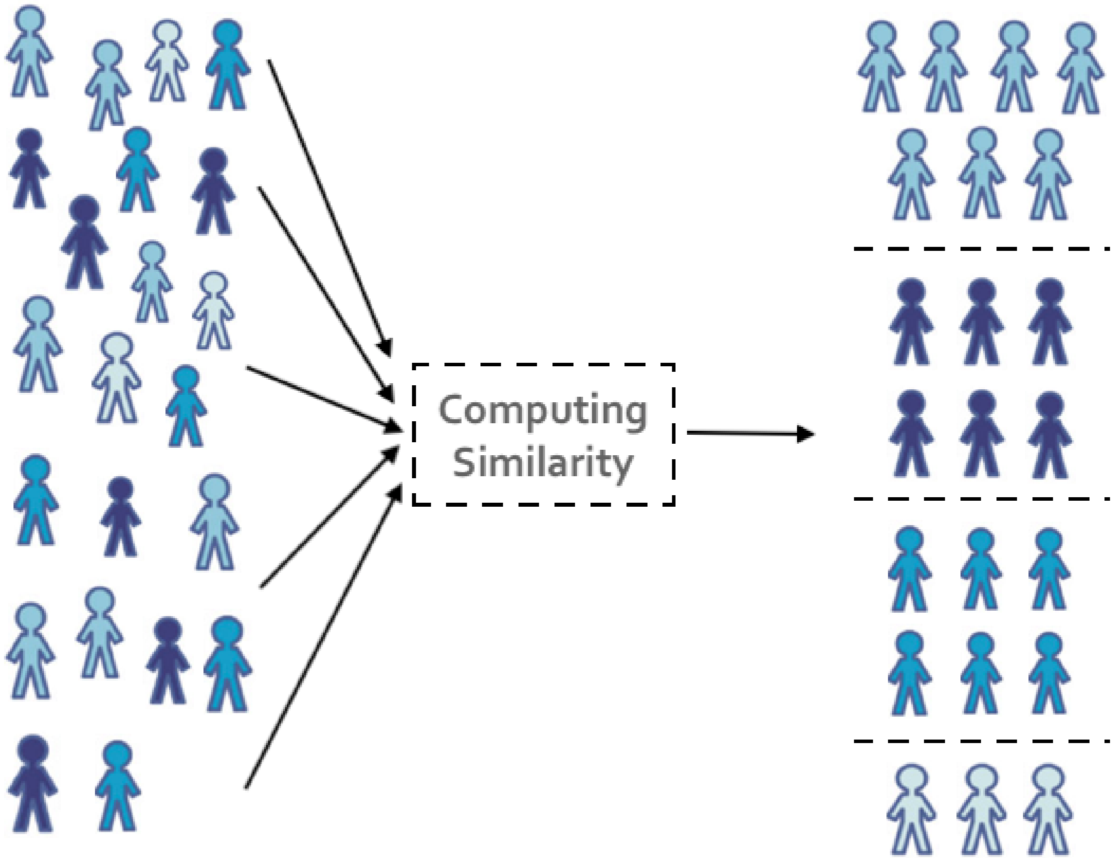
Human Activity Recognition (HAR)

State of the art in the field of inertial sensors

Dataset	Year	ADLs	Falls	Nr. of Subjects	Gender Female	Gender Male	Age (Years)	Height (cm)	Weight (Kg)
DMPSBFD [24]	2015	yes	yes	5	-	-	-	-	-
Gravity [23]	2016	yes	yes	2	-	-	26–32 29 ± 4.2	170–185 178 ± 10.6	63–80 71.5 ± 12
MobiFall [11]	2014	yes	yes	24	7	17	22–47 27 ± 5	160–189 175 ± 7	50–103 76.4 ± 14.5
MobiAct [25]	2016	yes	yes	57	15	42	20–47 25 ± 4	160–193 175 ± 4	50–120 76.6 ± 14.4
RealWorld (HAR) [26]	2016	yes	no	16	7	8	16–62 32 ± 12	163–183 173 ± 7	48–95 74.1 ± 13.3
Shoaib PA [27]	2013	yes	no	4	0	4	25–30 -	-	-
Shoaib SA [28]	2014	yes	no	10	0	10	25–30 -	-	-
tFall [29]	2013	yes	yes	10	7	3	20–42 31 ± 9	161–184 173 ± 1	54–98 69.2 ± 13.1
UCI HAR [30]	2012	yes	no	30	-	-	19–48 -	-	-
UCI HAPT [31]	2015	yes	no	30	-	-	19–48 -	-	-
UCI UIWADS [32]	2013	yes	no	22	-	-	- -	-	-
UMA Fall [33]	2016	yes	yes	17	6	11	14–55 27 ± 10	155–195 172 ± 9	50–93 69.9 ± 12.3
WISDM [34]	2012	yes	no	29	-	-	-	-	-
UniMiB SHAR	2016	yes	yes	30	24	6	18–60 27 ± 11	160–190 169 ± 7	50–82 64.4 ± 9.7

Personalization models

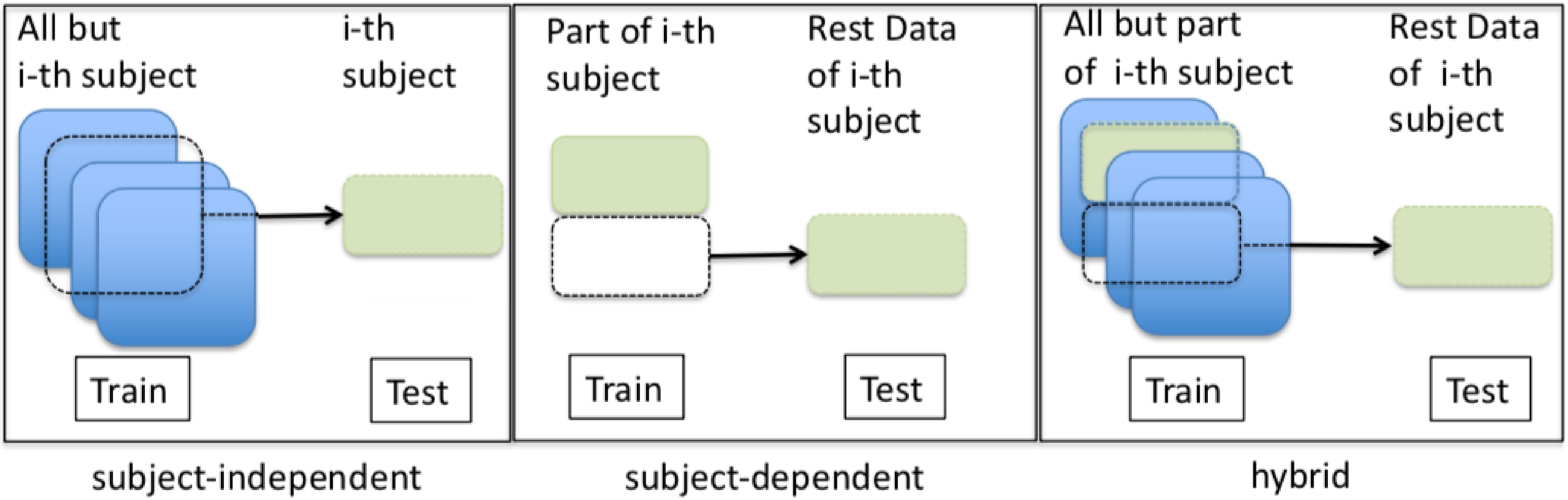
- Based on **physical**, **lifestyle** and **signal similarity**



N. D. Lane, Y. Xu, H. Lu, S. Hu, T. Choudhury, A. T. Campbell, and F. Zhao, "Enabling large-scale human activity inference on smartphones using community similarity networks (csn)," in Proceedings of the 13th international conference on Ubiquitous computing, pp. 355–364, ACM, 2011.

Personalization models

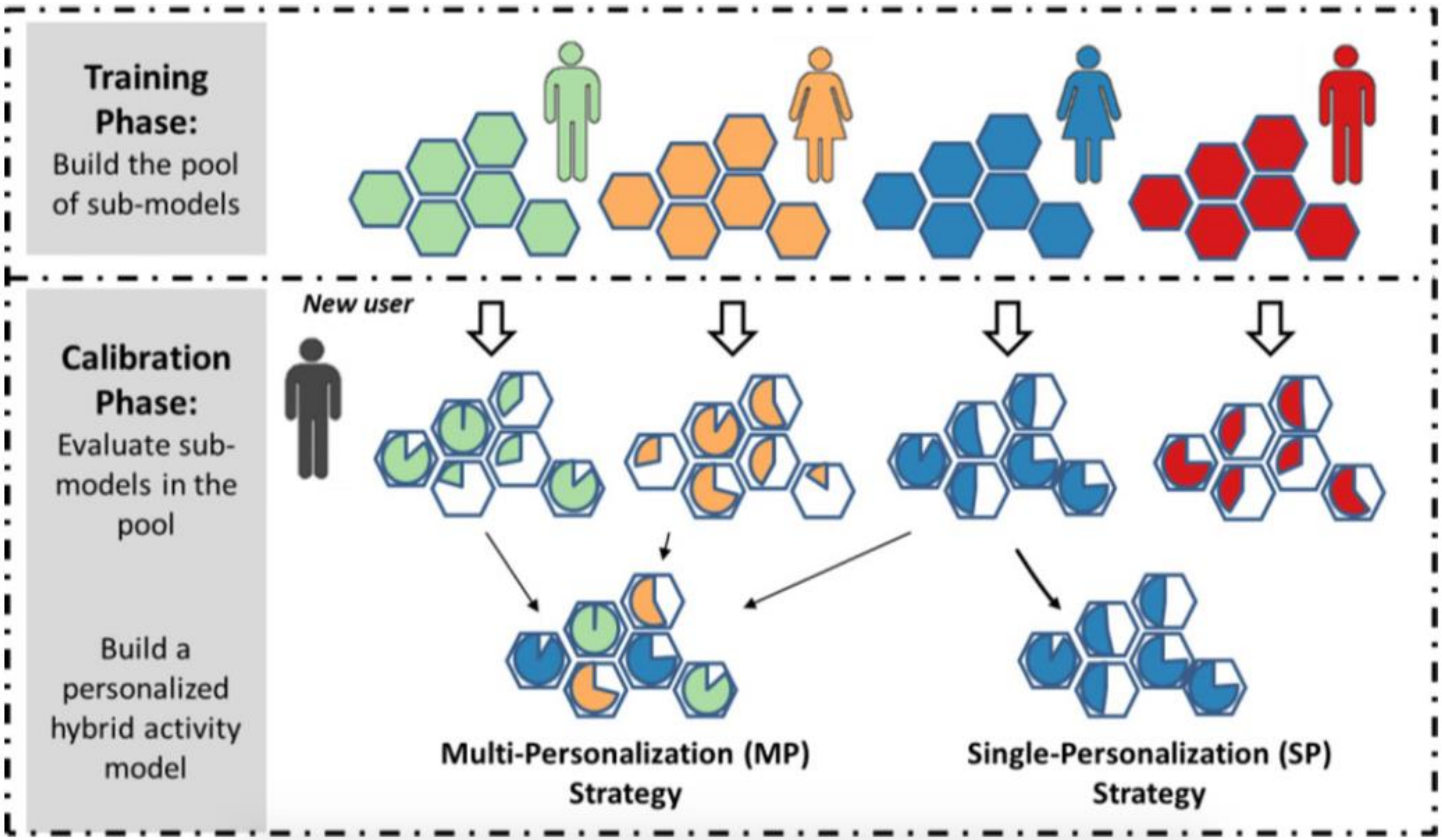
- Kwapisz at al. compared subject-dependent and subject- independent approaches, called respectively *personal* and *impersonal models*, and introduce a new model: the *hybrid model*.



J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," ACM SigKDD Explorations Newsletter, vol. 12, no. 2, pp. 74–82, 2011.

Personalization models

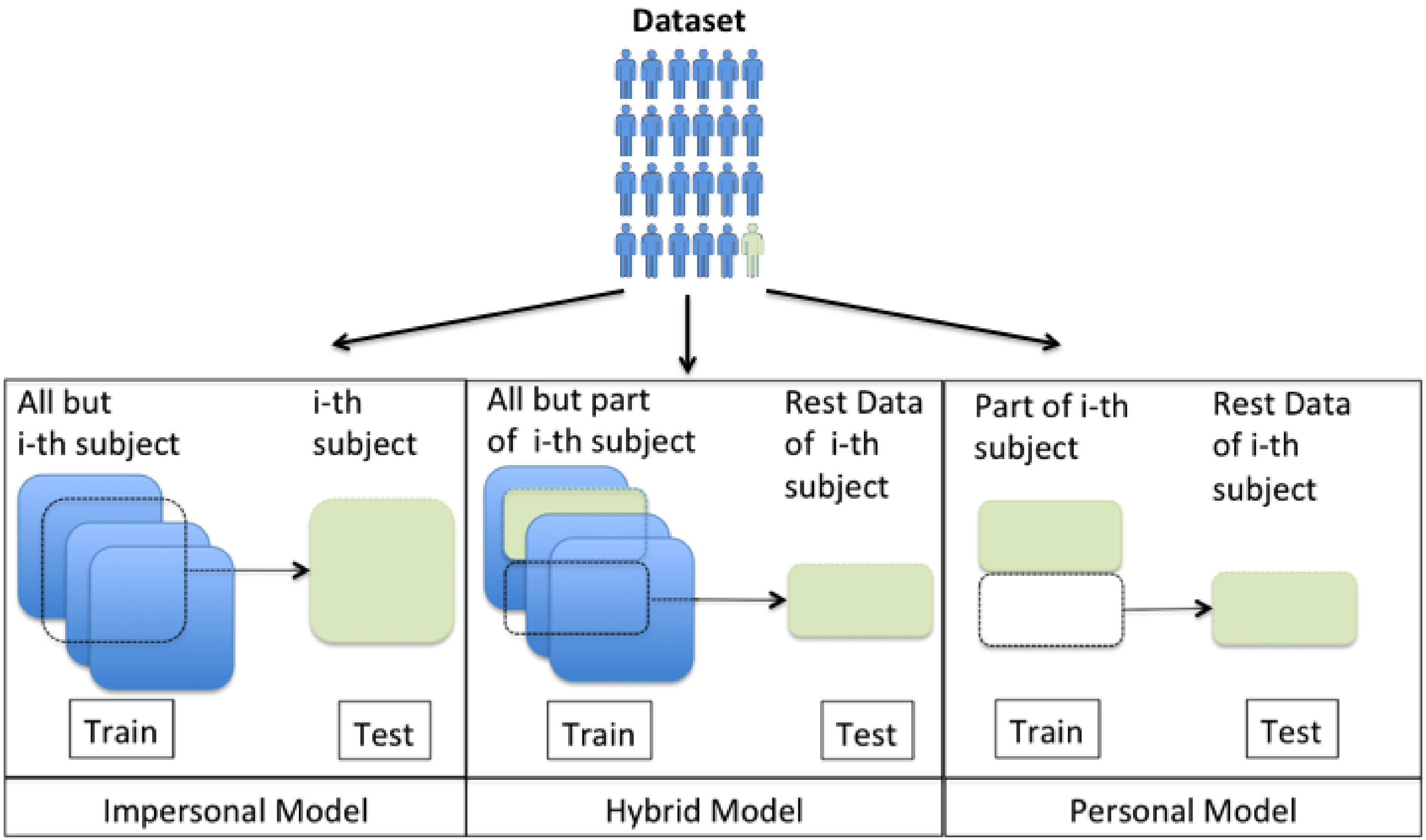
- Classifier-based Personalization



J.-H. Hong, J. Ramos, A.K. Dey, Toward Personalized Activity Recognition Systems With a Semipopulation Approach, IEEE transactions on Human-Machine Systems, Vol.46, n.1, 2016.

Personalization models

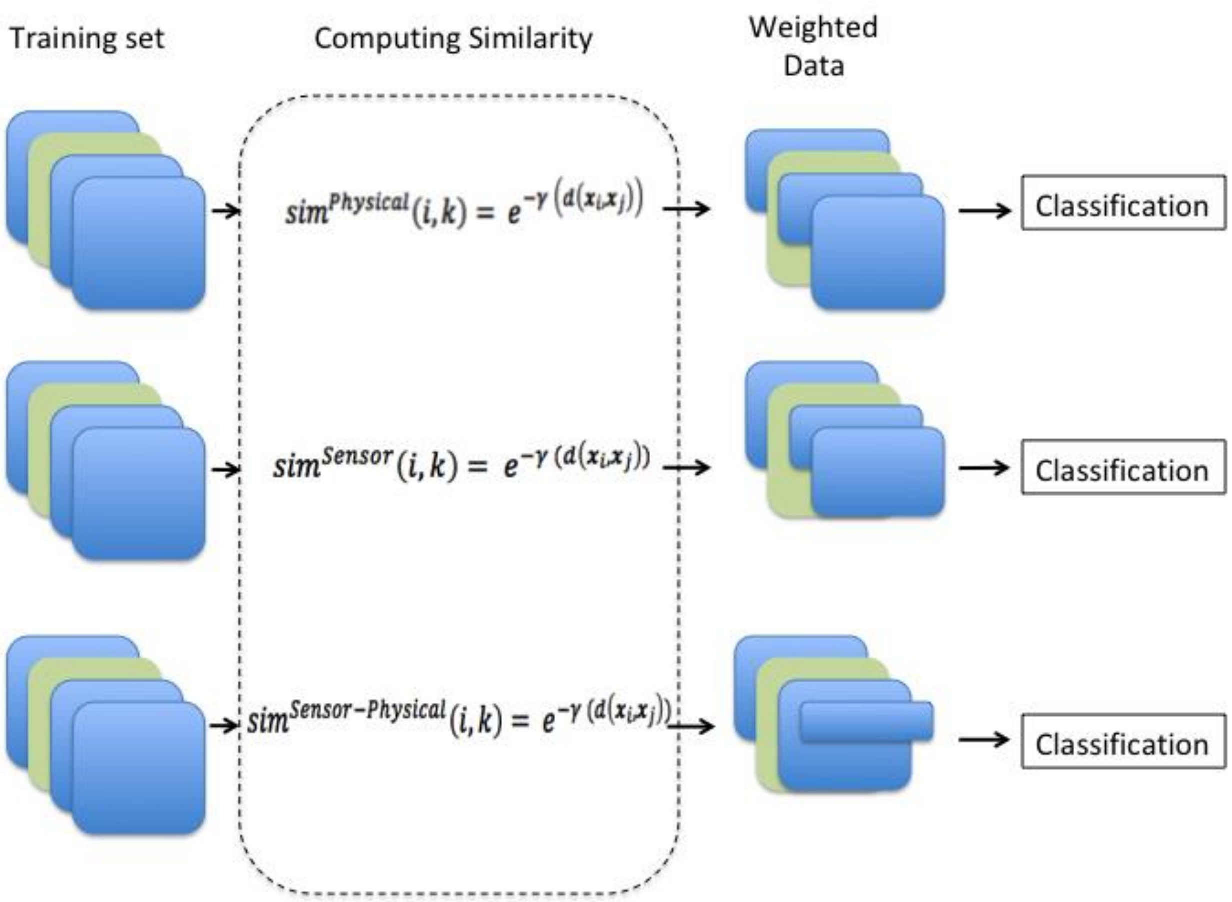
- Data-based Personalization



G.M. Weiss, J.W. Lockhart. The impact of personalization on smartphone-based activity recognition. Proceedings of the Activity Context Representation Workshop. Toronto, Canada, 2012.

Personalization models

- Community similarity networks: physical, lifestyle and signal similarity



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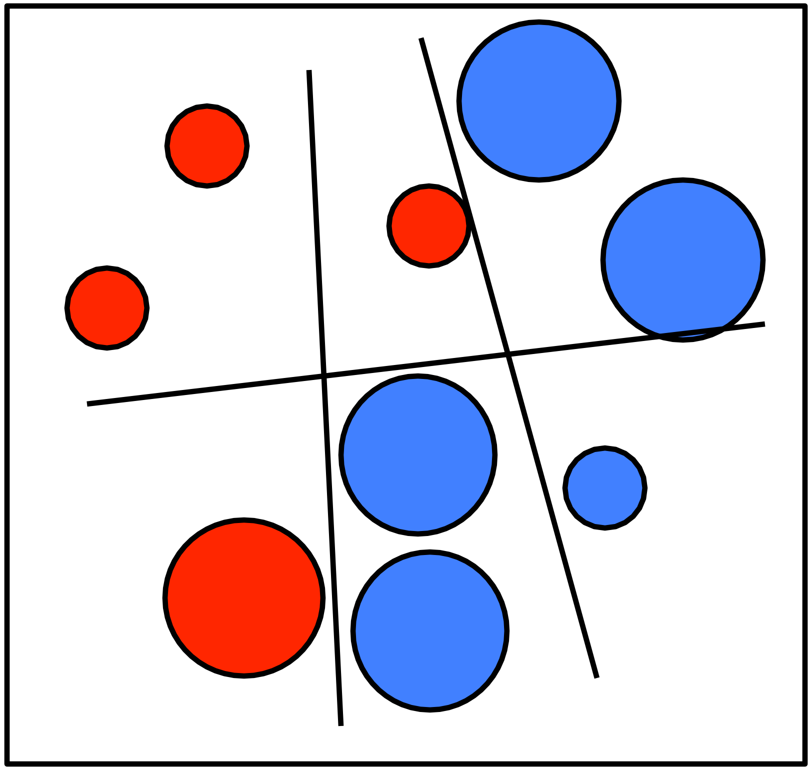
Boosting at work

Final classifier is a combination of weak classifiers



Personalization

Personalization models

Each subject *i* can be described with a feature vector

$$\mathbf{g}_i = \{g_1, \ldots, g_K\}$$

Similarity between two subjects *i* and *j* is defined as follows

$$\mathrm{sim}(i, j) = e^{-\gamma d(i,j)}$$

d is the Euclidean distance between the feature vector of two subjects

$$d(i, j) = \sqrt{\sum_{k=1}^{K} (g_{k,i} - g_{k,j})^2}$$

* See **additional materials** on Ferrari, A., Micucci, D., Mobilio, M., & Napoletano, P. (2020). On the personalization of classification models for human activity recognition. IEEE Access, 8, 32066-32079.

Personalization models

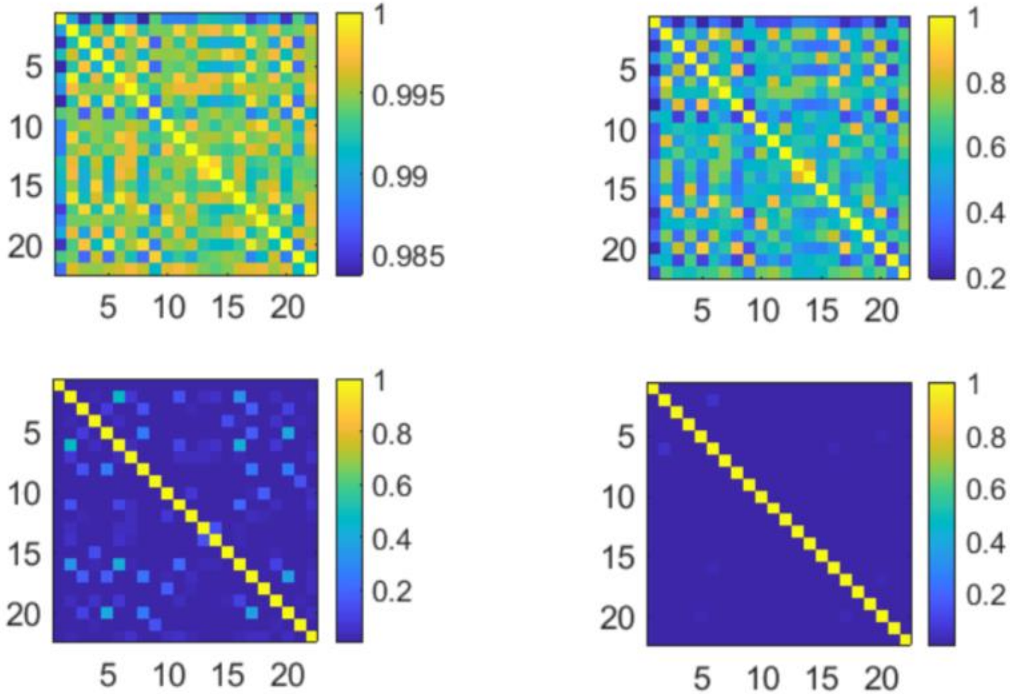
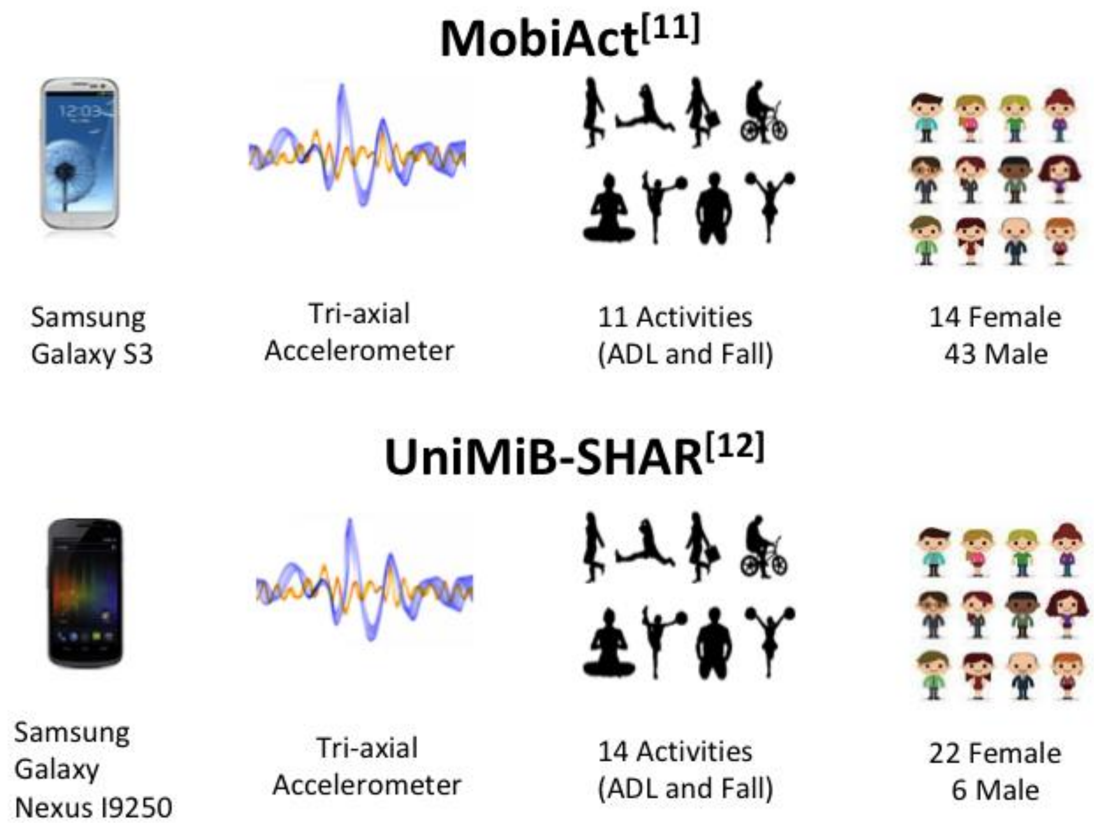


FIGURE 2: Physical Similarity Matrix for different values of $\gamma = 0.01,\ 1,\ 10,\ 40$ (clock-wise order).

Personalization models



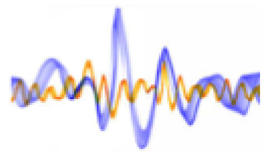
[11] G. Vavoulas, C. Chatzaki, T. Malliotakis, M. Pediaditis, and M. Tsiknakis, The MobiAct Dataset: Recognition of Activities of Daily Living using Smartphones, Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and E-Health (Ict4awe), pp. 143-151, 2016.
[12] D. Micucci M. Mobilio, P. Napoletano, UniMiB SHAR: A Dataset for Human Activity Recognition Using Acceleration Data from Smartphones, IEEE Sens. Lett. 2016, 2, 15-18.
[13] M. Malekzadeh, R.G. Clegg, A. Cavallaro, H. Haddadi, Protecting Sensory Data against Sensitive Inferences. In W-P2DS'18: 1st Workshop on Privacy by Design in Distributed Systems, April 23–26, 2018, Porto, Portugal. ACM, New York, NY, USA, 6 pages

Personalization models

Experiments on three publicily available datasets:

Motion Sense[13]

Samsung S5
LG G4



Tri-axial
Accelerometer

6 Activities
(ADL and Fall)

9 Female
13 Male

Dataset	Sex Male	Sex Female	Age (years)	Weight (kg)	Height (cm)
UniMiB-SHAR	6	22	18-60	50-82	160-190
			27 ± 11	$64.4 \pm 9,7$	169 ± 7
MobiAct	43	14	20-47	50-120	158-193
			25.19 ± 4.45	76.8 ± 14.16	175.73 ± 7.77
Motion Sense	13	9	18-46	48-102	161-190
			28.8 ± 5.46	72.12 ± 16.21	174.2 ± 8.9

TABLE 2: Statistics of subjects physical characteristics

[11] G. Vavoulas, C. Chatzaki, T. Malliotakis, M. Pediaditis, and M. Tsiknakis, The MobiAct Dataset: Recognition of Activities of Daily Living using Smartphones, Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and E-Health (Ict4awe), pp. 143-151, 2016.
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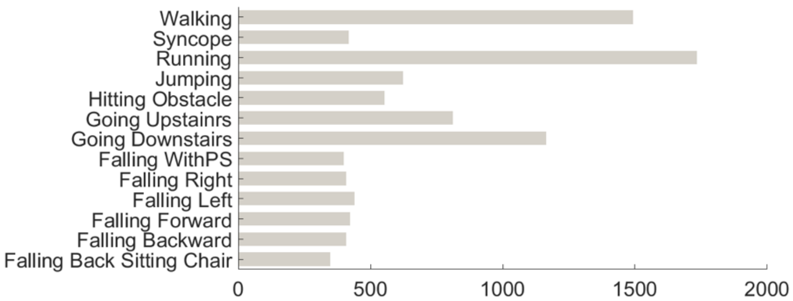
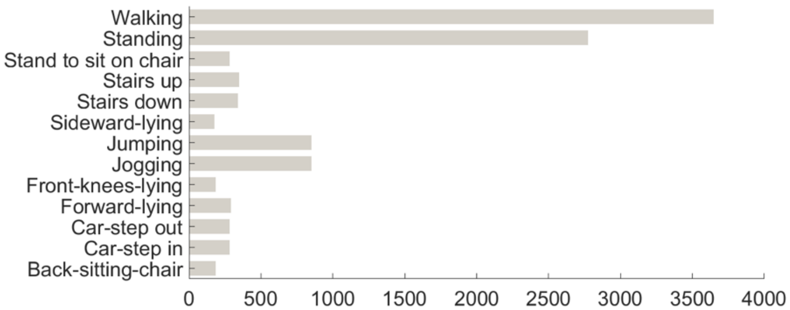
Personalization models

Experiments on three publicily available datasets

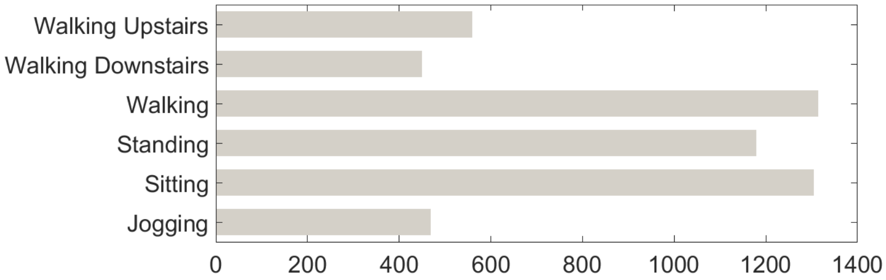
UNIMIB-SHAR



MOBIACT



MOTION-SENSE



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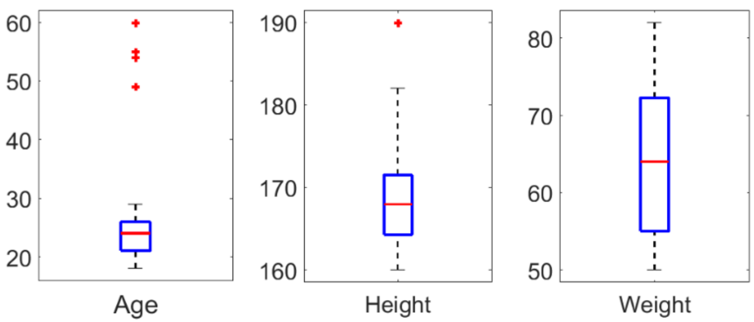
Personalization models

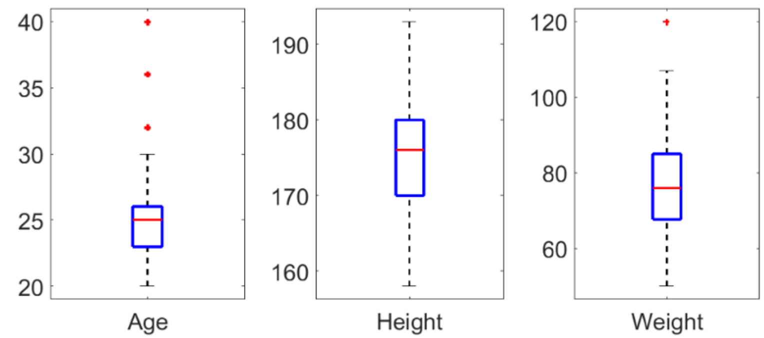
Experiments on three publicily available datasets

UNIMIB-SHAR



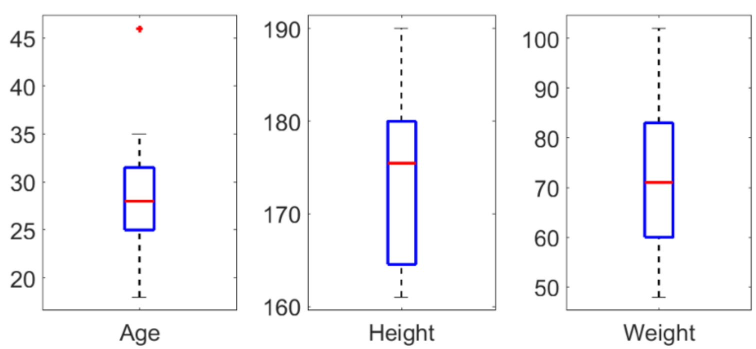
(a)

MOBIACT



(b)

MOTION-SENSE



(c)

Personalization models

Experiments on three publicily available datasets and using the Adaboost classifier which is a more flexible because it combines different weak classifiers,

	UniMiB-SHAR	MobiAct	Motion Sense	AVG
subject-dependent	84.79	45.57	43.55	57.97

	UniMiB-SHAR Δ max % $\sim$ 24	**MobiAct** Δ max % $\sim$ 7	**Motion Sense** Δ max % $\sim$ 4	**AVG** Δ max % $\sim$ 14
subject-independent	56.80	81.29	72.48	70.19
Hybrid	61.66	83.73	73.82	73.07
subject-independent- Physical Similarity	57.39	81.62	72.45	70.49
subject-independent- Sensor Similarity	57.00	82.45	74.03	71.16
subject-independent- Physical Sensor Similarity	56.93	82.64	73.85	71.14
hybrid- Physical Similarity	**85.44**	89.43	77.76	84.21
hybrid- Sensor Similarity	84.71	90.76	**78.06**	**85.51**
hybrid- Physical Sensor Similarity	84.87	**90.90**	77.86	84.53

	no-similarity	similarity	Δ%
Person-dependent	57.97	-	-
Person-independent	70.19	70.93	0.74
Hybrid	73.07	84.42	11.35

Personalization models

Experiments on three publicily available datasets and using the Adaboost classifier + different types of features and classifiers

Layer name	**Shape**
conv1	$\{1{\times}3\} \times n$
conv2_n	$\{1{\times}3 \times f_{maps}\} \times n$
conv3_n	$\{1{\times}3 \times 2f_{maps}\} \times n$
conv4_n	$\{1{\times}3 \times 4f_{maps}\} \times n$
avg_pool_x	$1{\times}32$
fully conn.	$(1 \times 4f_{maps}) \times 15$
softmax	$1{\times}15$

CNN as feature extractor

	AdaBoost+HC Δ max % $\sim$ 14	**AdaBoost+CNN** Δ max % $\sim$ 30	**SVM+CNN** –	**AVG** Δ max % $\sim$ 24
subject-dependent	57.97	62.32	86.01	68.76
subject-independent	70.19	60.61	60.60	63.80
hybrid	73.07	72.36	70.23	71.89
subject-independent- Similarity	70.93	61.67	-	66.30
hybrid- Similarity	**84.75**	**90.03**	-	**87.39**

Comparison with DL

Deep learning seems to provide better performance with respect to both personalized deep learning and machine- learning models

Table 5 Experimental results—accuracy of personalized deep learning (PDL), personalized machine learning (PML), traditional deep learning (DL), and traditional machine learning (ML)

Dataset	Model	PDL	PML	DL	ML
MobiAct	SI-no sim	–	–	88.92	81.29
	SI-phy	86.08	81.62		
	SI-sen	80.14	83.45		
	SI-phy+sen	79.68	82.64		
	Hyb-no sim	–	–	92.62	83.73
	Hyb-phy	81.04	89.43		
	Hyb-sen	81.40	90.76		
	Hyb-phy+sen	88.17	90.90		
Average		82.75	86.46	**90.77**	82.51
UniMiB SHAR	SI-no sim	-	-	58.88	56.80
	SI-phy	35.42	57.39		
	SI-sen	42.83	57.00		
	SI-phy+sen	42.66	56.93		
	Hyb-no sim	–	–	69.72	61.66
	Hyb-phy	45.82	85.44		
	Hyb-sen	47.26	84.71		
	Hyb-phy+sen	46.77	84.87		
Average		43.46	**71.05**	64.30	59.23
Motion Sense	SI-no sim	–	–	81.03	72.48
	SI-phy	78.02	72.45		
	SI-sen	78.8	74.03		
	SI-phy+sen	79.00	73.85		
	Hyb-no sim	-	-	85.75	73.82
	Hyb-phy	80.17	77.76		
	Hyb-sen	80.38	78.06		
	Hyb-phy+sen	80.41	77.86		
Average		79.46	75.66	**83.39**	73.15
Total average		68.56	77.73	**79.49**	71.63

Table 5 Experimental results—accuracy of personalized deep learning (PDL), personalized machine learning (PML), traditional deep learning (DL), and traditional machine learning (ML)

Values in bold correspond on average to the best accuracy obtained when varying the technique both with respect to individual datasets (rows Average) and to all the datasets (Total average row)

Personalization in HAR

- Generally, the recognition of human activities is carried out using the so called ***user-independent recognition models***.

- User-independent models struggle to generalize 1) to new users and 2) to changes in the way a pre-existing user performs an activity due to the ***inter-subject variability*** and ***intra-subject variability***

- These factors make a constantly updated ***personal recognition model*** the ideal solution that can be obtained by training the **subject-independent** model with the data of the new user (*inter-variability*) and keeping the personal model constantly updated with new data for the existing user (*intra-variability*).

Personalization in HAR

- **Deep learning** techniques have proven to be more efficient than traditional ones in classifying ADLs

- A very interesting approach is that of Siirtola et al. that exploits ***incremental learning*** to generate a personalized model without requiring data from the target user.

- The aim of this work is to experiment the effectiveness of an approach that combines **incremental learning** and **deep learning** techniques.

Methods

- Incremental Learning is a technique where a model learns new information progressively without forgetting previously acquired knowledge.

Materials

- **Anguita**: includes 3-axial linear acceleration, 3-axial angular velocity, and gyroscope sensor data of 11 ADLs recorded with Samsung Galaxy S II (30 subjects)
- **Shoabib**: includes 3-axial acceleration, gyroscope, magnetometer, and linear acceleration sensor data of 7 ADLs recorded with Samsung Galaxy S II (10 subjects)
- **Siirtola**: includes 3-axial acceleration sensor data of 5 ADLs recorded with Nokia N8 smartphones. The activities have been performed by 8 volunteers.

NUMBER OF SEGMENTS AND CLASSES FOR EACH DATASET

Dataset	segment size	# segments	# per user	# classes
Anguita	150x4	9,712	$\sim$ 324	11
Shoaib	150x4	41,930	4,193	7
Siirtola	120x4	6,921	$\sim$ 865	5

Methods

- The **incremental learning** procedure consists in three phases: *(1) data preparation*, *(2) model generation*, and *(3) personalization:*

  - ***Data preparation*****:** the subjects, except subject x, are used to train the base model in the *model generation* phase. The subject x is used in the *personalization* phase to adapt the model trained in the previous phase.
  - The ***model generation*** phase consists of obtaining an initial model from all the samples of the dataset except those from the user x. This model is called *user-independent model*.
  - For the ***personalization*** phase we experimented three different approaches: *non-supervised approach*, *semi-supervised*, and *supervised*

- **Proposed CNNS:** *Residual Network (ResNet) , Simplified CNN*
- We compared deep learning with a previous method based on Learn++ with hand-crafted features

Methods

- *Non-supervised approach*, *semi-supervised*, and *supervised*

Methods

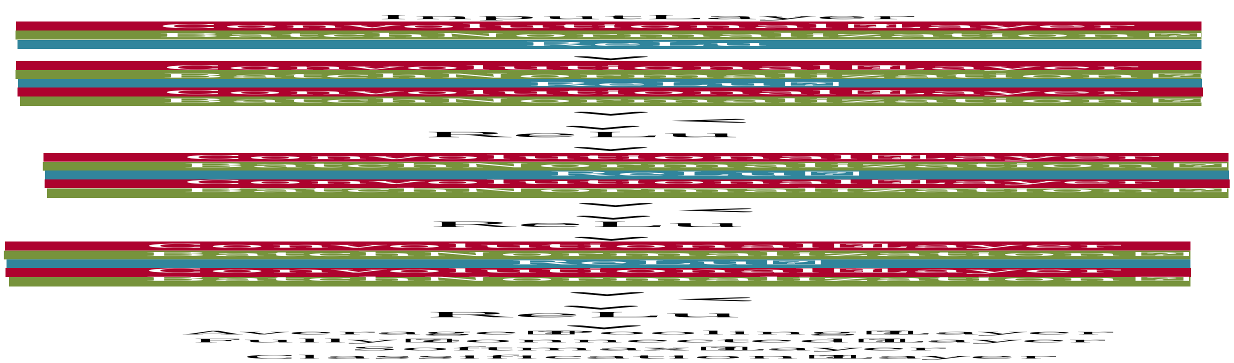
- Learn++ algorithm with the classification and regression tree (CART)
- The Learn++ algorithm is based on ensemble of classifiers. It was inspired by the AdaBoost (adaptive boosting) algorithm developed to improve the classification performance of weak classifiers.
- Learn++ generates an ensemble of weak classifiers, which are trained with different distributions of training samples. These classifiers are combined with a weighted majority algorithm to obtain the final classification result.
- Therefore, to achieve incremental learning new classifiers are trained with new samples and combined to adapt the classification on new data.

https://github.com/gditzler/IncrementalLearning

Methods

- S-CNN + ResNet

Fig. 1. Architecture of S-CNN.



Results

Performance is measured in terms of **macro average accuracy**

AVERAGE OF THE MACRO AVERAGE ACCURACY OF ALL USERS WHATEVER IS THE METHOD ADOPTED WITH AND WITHOUT THE DATA AUGMENTATION PROCEDURE PROPOSED. BEST RESULTS ARE REPORTED IN BOLD.

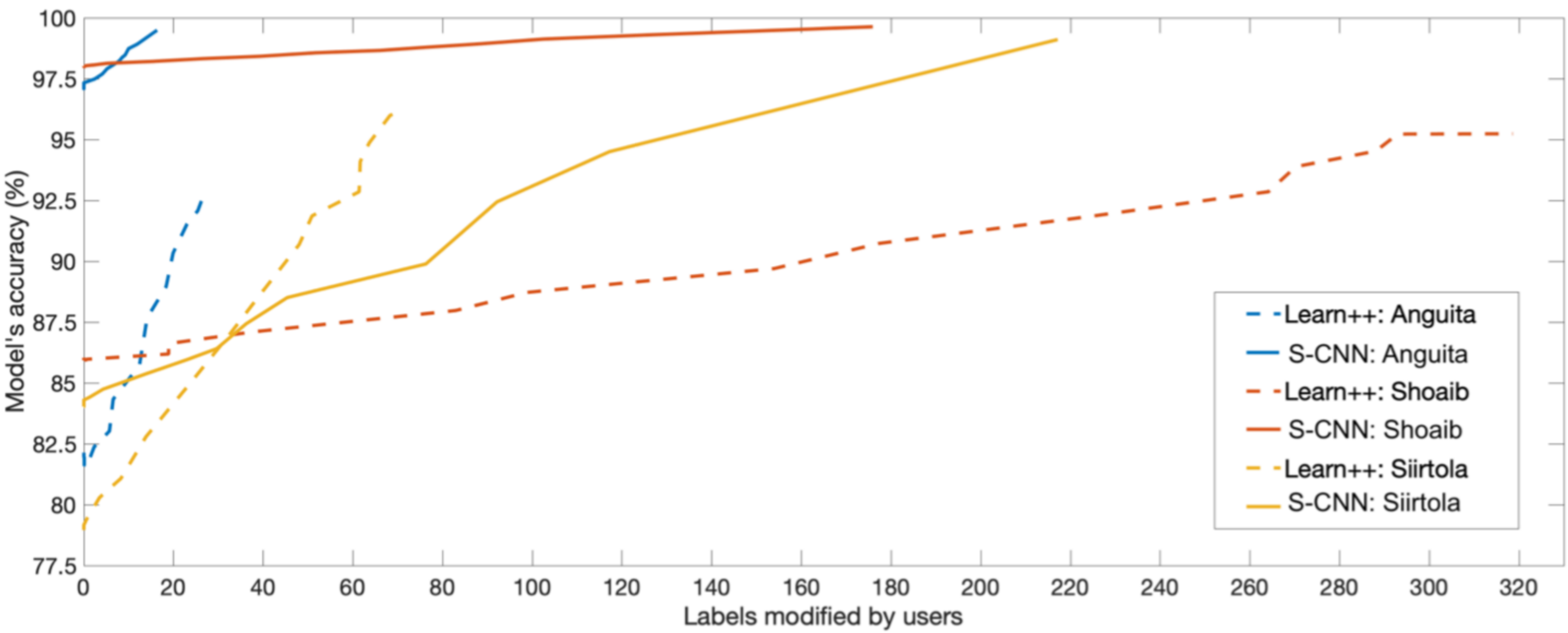
Augmentation	User-Independent	Non-Supervised	Semi-Supervised	Supervised
no	89.10 (± 7.56)	89.41 (± 7.76)	94.78 (± 5.95)	98.01 (± 1.98)
yes	**90.32** (± **6.24**)	**90.73** (± **6.24**)	**96.98** (± **3.46**)	**99.53** (± **0.88**)

MACRO AVERAGE ACCURACY OF ALL USERS: LEARN++ VS RESNET AND S-CNN. FOR EACH MODEL (USER INDEPENDENT, NON SUPERVISED, SEMI-SUPERVISED AND SUPERVISED), THE BOLD FONT REPRESENTS THE BEST METHOD.

Dataset / Method	User-Independent	Non-Supervised	Semi-Supervised	Supervised
Anguita / Learn++	85.60 (± 7.74)	86.72 (± 7.81)	96.89 (± 4.52)	99.53 (± 0.61)
Shoaib / Learn++	86.79 (± 4.10)	87.95 (± 4.06)	97.71 (± 1.91)	99.02 (± 0.48)
Siirtola / Learn++	75.84 (± 17.51)	76.24 (± 17.53)	95.59 (± 6.08)	97.66 (± 5.73)
Mean	82.74 (± 9.78)	83.64 (± 9.80)	96.73 (± 4.17)	98.74 (± 2.27)
Anguita / ResNet	97.30 (± 2.53)	97.33 (± 2.67)	98.78 (± 2.13)	99.81 (± 0.53)
Shoaib / ResNet	98.45 (± 0.76)	98.52 (± 0.76)	99.07 (± 0.56)	99.96 (± 0.05)
Siirtola / ResNet	86.67 (± 9.41)	87.31 (± 9.25)	92.72 (± 7.31)	99.94 (± 0.04)
Mean	**94.14** (± **4.23**)	**94.39** (± **4.23**)	96.86 (± 3.33)	99.90 (± 0.21)
Anguita / S-CNN	97.49 (± 2.75)	97.61 (± 2.79)	99.06 (± 1.87)	99.99 (± 0.27)
Shoaib / S-CNN	98.32 (± 0.78)	98.37 (± 0.83)	99.22 (± 0.64)	99.93 (± 0.05)
Siirtola / S-CNN	86.54 (± 10.61)	86.50 (± 10.48)	93.74 (± 6.11)	99.90 (± 0.12)
Mean	94.09 (± 4.71)	94.16 (± 4.70)	**97.34** (± **2.87**)	**99.94** (± **0.15**)

Results

Learn++ algorithm and S-CNN comparison in semi-supervised cases. The plot shows the trend of classifiers' accuracy in relation to the number of labels adjusted by a user.



QUESTIONS?