Online Personalization of Cross-Subjects based Activity Recognition Models on Wearable Devices

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1. Motivation

Motivation

Most of the existing works target subject-specific activity recognition

- requires training data for each subject
- is not available immediately
- behavior changes are often not considered

➡ evolving cross-subjects based activity recognition

Idea

1. Build a cross-subjects activity recognition model
   - reduces data collection and training effort
   - is available at hand
   - focus on specific groups of people (child vs. elder)

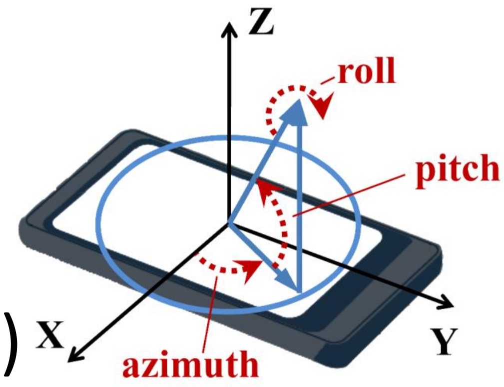
2. Personalize the base model
   - use online learning to avoid retraining or storing all data
   - use active learning to query the user (uncertainty)

2. Data & Features

Data Set

- 15 subjects (8 males / 7 females)
- seven wearable devices / positions
- chest, forearm, head, shin, thigh, upper arm, waist
- acceleration, GPS, gyroscope, light, magnetic field, and sound level
- climbing stairs up/down, jumping, lying, standing, sitting, running, walking
- each subject performed each activity ≈10 minutes

Feature Extraction



Previous experiments have shown …

- time and frequency-based features
- gravity-based features (low-pass filter)
  - derive device orientation (roll, pitch)

… splitting the recorded data into small overlapping segments has been shown to be the best setting.

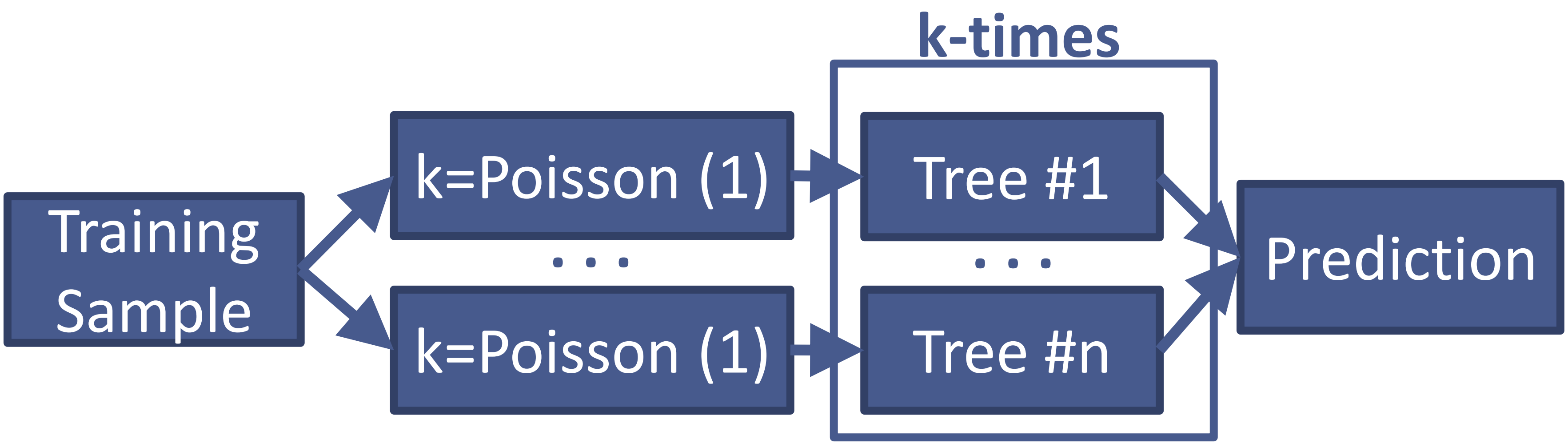
	Methods
Time	Correlation coefficient (Pearson), entropy (Shannon), gravity (roll, pitch), mean, mean absolute deviation, interquartile range (type R-5), kurtosis, median, standard deviation, variance
Frequency	Energy (Fourier, Parseval), entropy (Fourier, Shannon), DC mean (Fourier)

3.1. Online Random Forest

Online Random Forest

Considering online mode, the main differences are …

- bagging (generation of subsamples)
  - replace *sample with replacement* with *Poisson(1)*
- growing of the individual trees
  - Select thresholds and features randomly *(Extreme Randomized Forest)*



3.2. Cross-Subjects Activity Recognition

Cross-Subjects Activity Recognition (1/2)

Recognition model relies on labeled data of several people expect target person

→ most common approach: leave-one-out

Problem: Children and elders walk differently

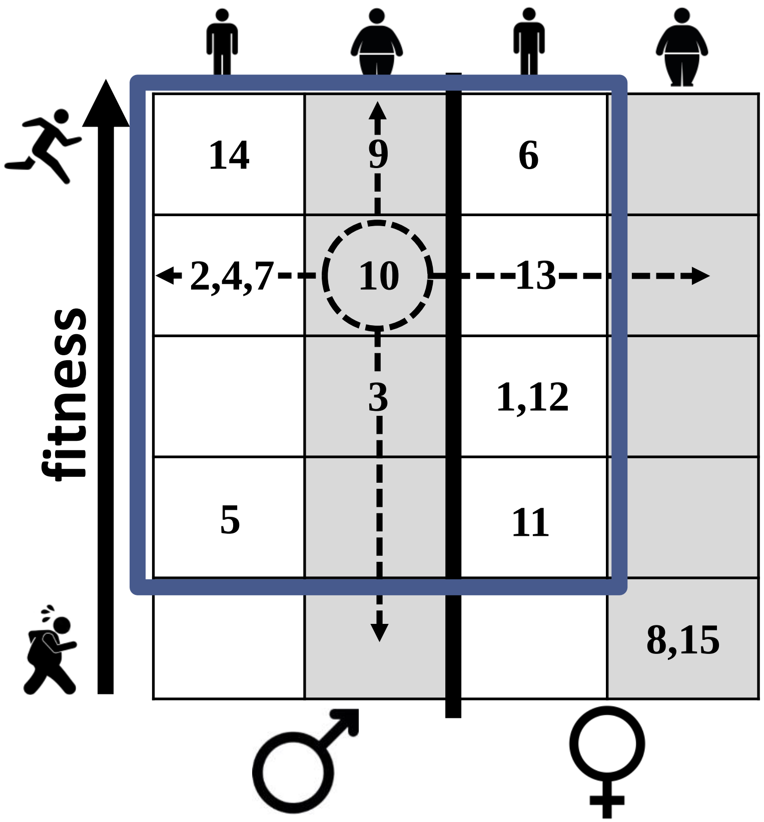
→ Model only covers most dominant behavior across all people

Cross-Subjects Activity Recognition (2/2)

We aim to build a model that considers physical characteristics

Rely only on specific people …

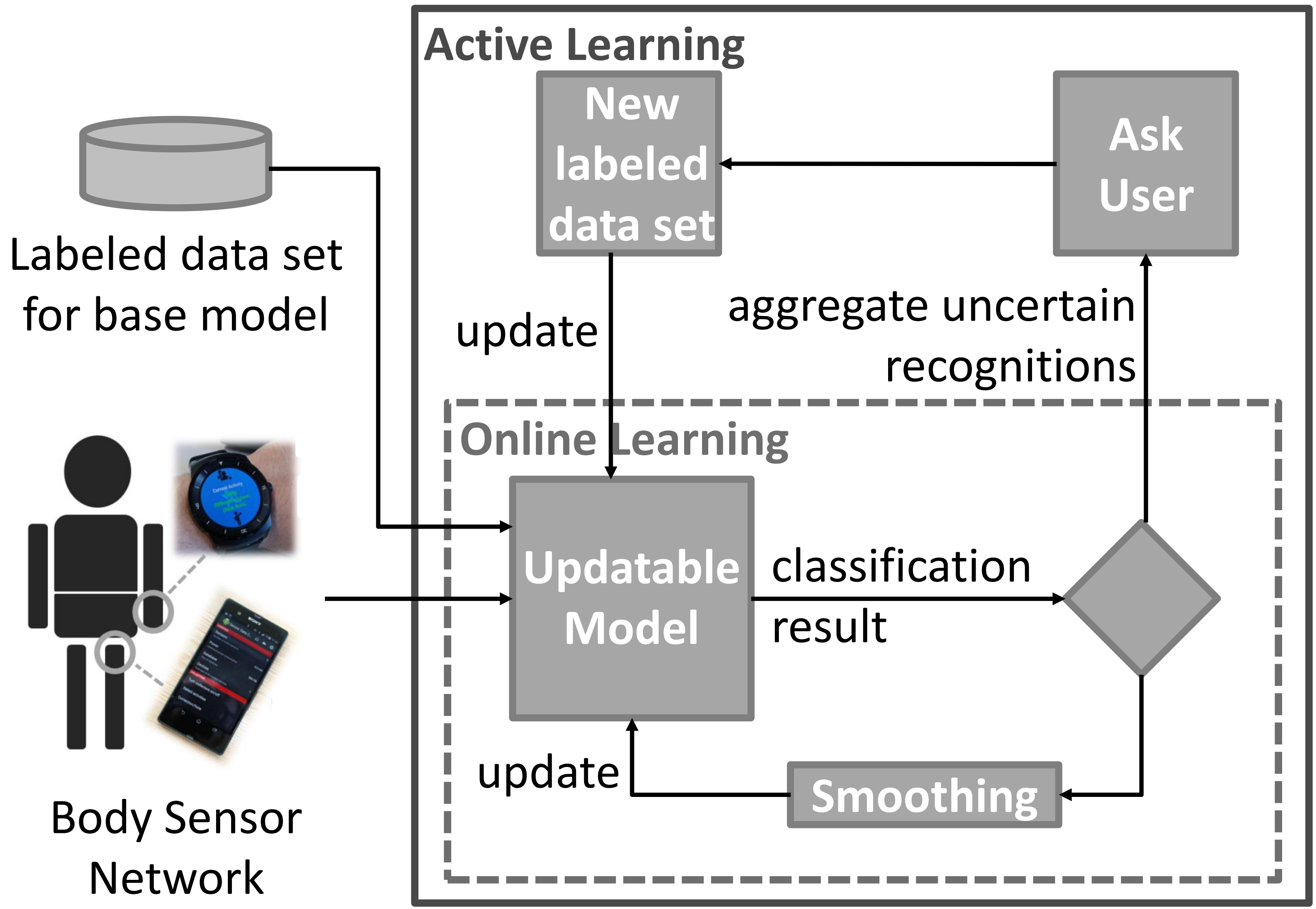
- … same/similar gender and physique (walking)
- … similar fitness level (running)



We follow a group-based approach …

3.3. Personalization: Online and Active Learning

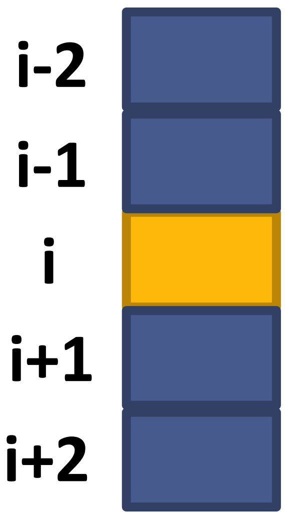
Personalization: Online and Active Learning

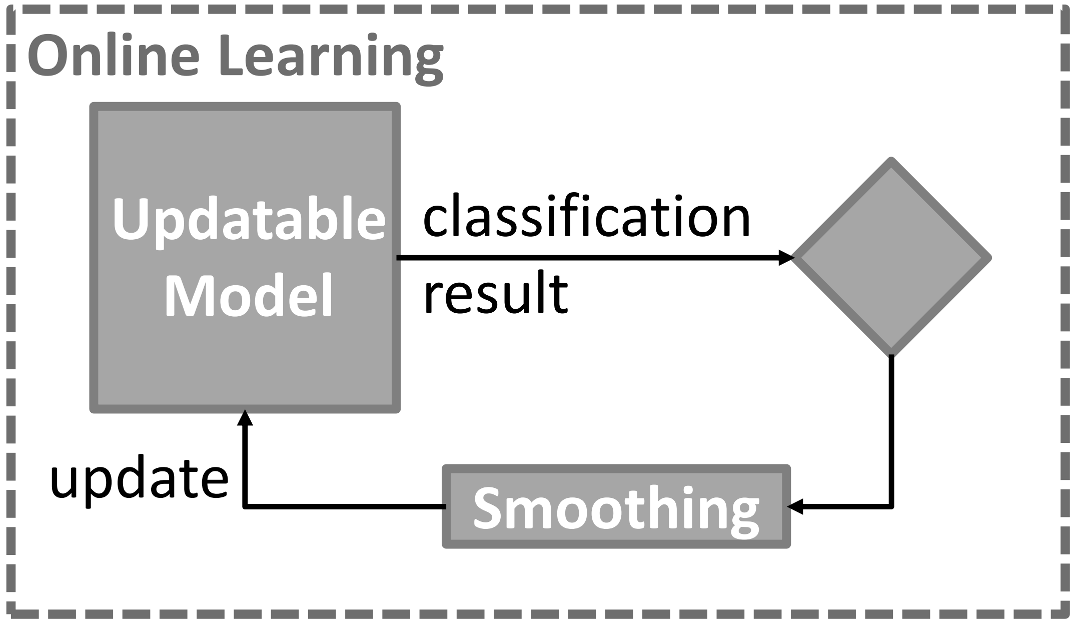


Personalization: Online and Active Learning

Smoothing adjusts the classification result of a single window if it is surrounded by another activity

- adjusted window is used to update the model
- focuses on minor classification errors

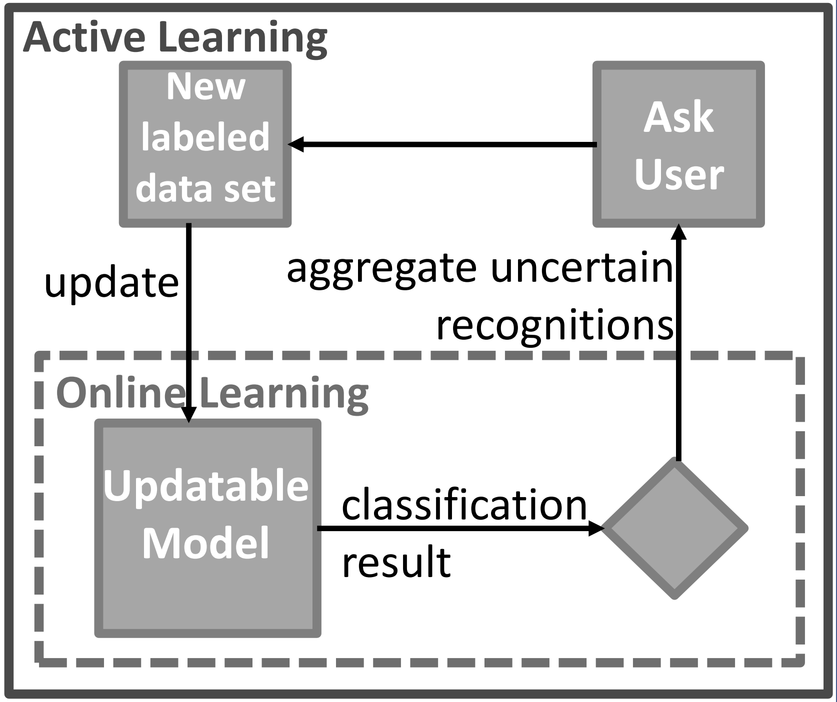




Personalization: Online and Active Learning

User-Feedback queries the user regarding uncertain classification results

- infeasible to ask for a specific window (1 sec)
  - specified a duration of uncertainty
  - query result is a new data set
- focuses on major classification errors



4. Results

Cross-Subject Activity Recognition

Inspecting the individual activities …

- static and dynamic perform comparable (~78%)
- walking and climbing stairs have the lowest rates

Class	Randomly	Leave-one-out	Our approach
stairs up	0.62	0.66	**0.69**
stairs down	0.63	0.67	**0.69**
jumping	0.79	**0.88**	0.87
lying	0.81	0.83	**0.86**
standing	0.71	0.73	**0.79**
sitting	0.59	0.63	**0.68**
running	0.88	0.90	**0.96**
walking	0.60	0.67	**0.70**
avg.	0.69	0.74	**0.78**

Personalization (1/3)

Using online and active learning …

- online vs. offline learning → lower recognition rate
- user-feedback → walking, stairs are mostly resolved
- smoothing → minor errors decrease rapidly

	Base	+ Smoothing	+ User-Feedback	+ Both
static	0.76	0.76	0.79	0.79
dynamic	0.76	0.80	0.86	0.87
w. avg.	**0.76**	**0.78**	**0.83**	**0.84**

Personalization (2/3)

Focusing on interesting combinations …

- offline mode: phone and (watch 69% or glasses 72%)

➡ improved significantly, especially walking

	Watch & Phone			Glasses & Phone		
Class	**Precision**	**Recall**	**F_1**	**Precision**	**Recall**	**F_1**
static	0.75	0.73	0.73	0.80	0.80	0.80
dynamic	0.87	0.85	0.86	0.88	0.87	0.87
w. avg.	**0.81**	**0.80**	**0.80**	**0.84**	**0.84**	**0.84**

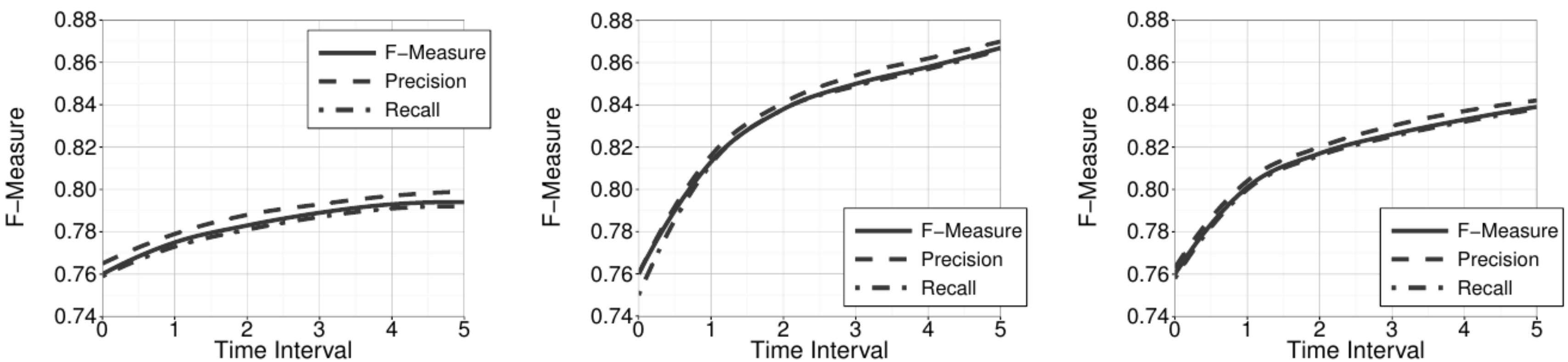
Personalization (3/3)

Personalization is a continuous process …

- especially dynamic activities improve significantly
- most improvement in the first two time intervals

➡ first iteration +4%, five iterations +8%

➡ number of windows with a low confidence value decrease with each iteration

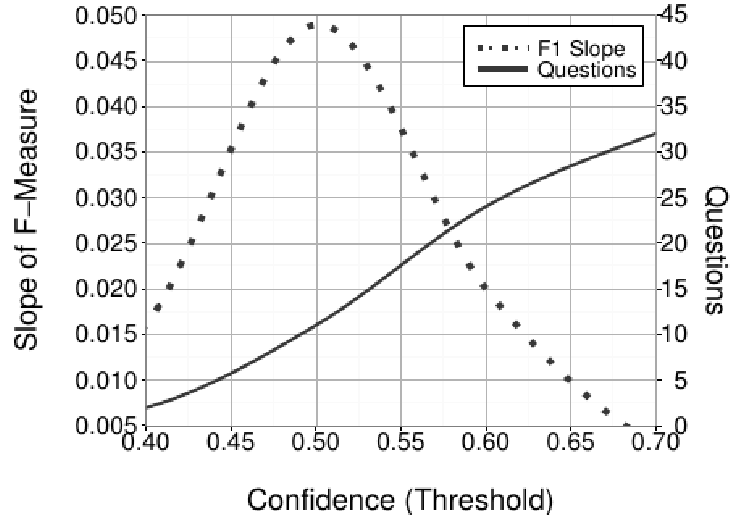


(a) Static activities (b) Dynamic activities (c) All activities

Parameter

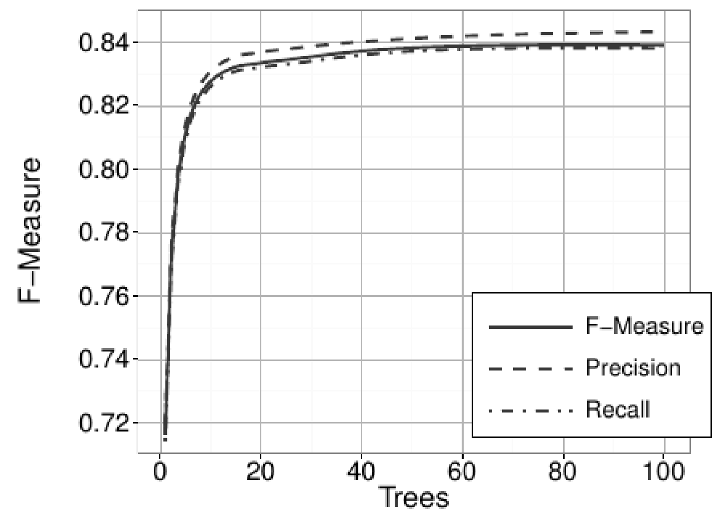
Considering different confidence thresholds …

- *turning point → t=0.5*
- *10 questions → +8%*



Considering a different number of trees…

- *10 trees vs. 100 trees*
- *a smaller forest is more feasible concerning wearable devices*



5. Conclusion and Future Work

Conclusion

Our results show that …

- … physical characteristics allow to build promising cross-subjects models (78%)
- … personalized model achieves a recognition rate of 84%, for dynamic activities even 87%
- … personalization is significantly less effort than creating a labeled data set (10 questions)

➡ personalized cross-subjects based models are feasible (online and active learning)

Future Work

- *Data Set*

  We got access to a large data set (~150 people), including vital parameter.

- *User Acceptance (Scenario)*

  error rate, emotional condition, environment

- *HAR vs. ADL*

  physical activities are often insufficient

Thank you for your attention :)

Cross-Subject Activity Recognition

We trained a single classifier for each subject …

- our group-based approach performs better
- at least a four-sensor setup is necessary

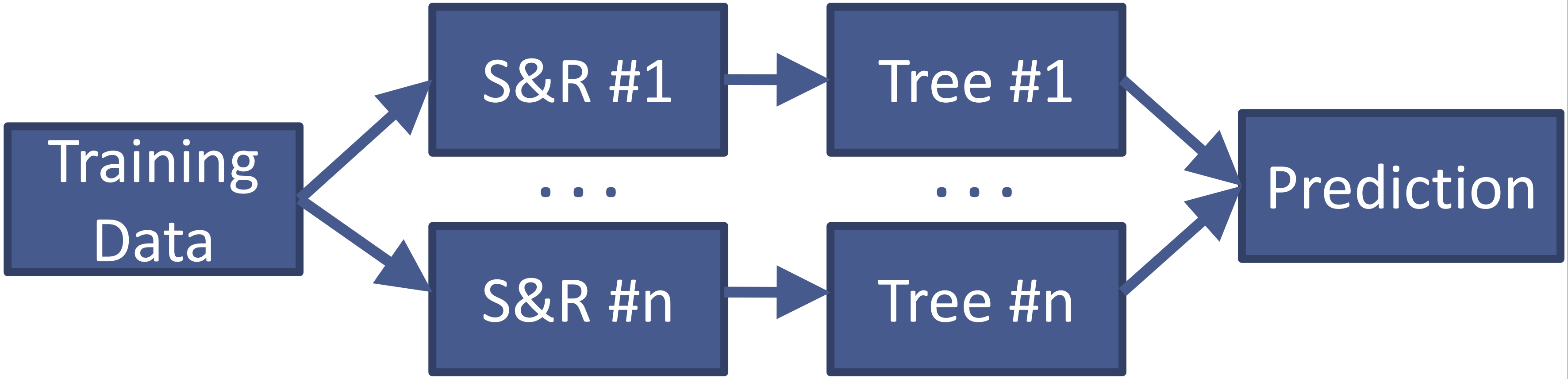
→ not feasible in a real world scenario

	1	2	3	4	5	6
Randomly	0.61	0.69	0.75	0.77	0.79	0.80
Leave-one-out	0.65	0.74	0.79	0.82	0.83	0.85
Our Method	**0.68**	**0.78**	**0.82**	**0.85**	**0.87**	**0.88**

Offline Random Forest

Considering offline mode, typically …

- … for each tree *sample with replacement* is applied
- … at each node features are selected at random
- … a quality measure is used to determine best split
- … after a split samples are propagated to child nodes
- … majority vote over the individual results is applied



Personalization: Online and Active Learning

Online learning enables …

- … to delete already seen/processed data/records
- … to adapt a model to new behavior
- … to weight new information higher (unlearn)

Active learning enables …

- … to gather the most informative unlabeled data