# Video: Activity Recognition on Mobile Phones – Why do we need it and how can it be done?

## 1 Introduction

Mobile phones have become an integral part of our everyday lives. Current models are equipped with a variety of sensors and enough processing power to make activity recognition on the device practicable. Several approaches to smart phone based recognition (e.g. [7, 4–6]) have been published which demonstrate the importance of research in this field. However, certain issues have to be taken into account, ranging from flexibility over extensibility to energy efficiency. The gained context information can be used for various applications. In the video, an example app for the automatic adjustment of the user's phone profiles is presented. Two situations, in which badly set phone profiles lead to embarrassing or even dangerous situations are presented. After a presentation of the inner workings of the ActiServ system, the examples are picked up and it is shown how activity recognition could have helped to prevent the unwanted situations.

## 2 Activity Recognition

Activity recognition on mobile phones has to face several challenges. The activity classification has to be flexible, robust [2], extensible [3], resource gentle [1] and location aware in order to be practicable. A modular architecture is presented, which approaches these challenges. In particular, the video covers two challenges, the flexibility and the extensibility. The term flexibility is presented along a particular challenge, the personalization of activity recognition.

### 2.1 Architecture

In the video, a novel activity recognition architecture which utilizes modular classifiers is presented. As figure 1 shows, the classification is subdivided into several modules of which only one is active at each point in time. This reduces the average processor load to a minimum and therefore limits the power consumption of the recognition. The modular approach also offers flexibility, since the modules can be exchanged and individually adapted or personalized. Modules can be added to a dynamic queue, which makes the activity recognition extensible.

### 2.2 Personalization

Each of the activity recognition modules can be adapted or personalized. This is especially necessary, since the user, the users clothes, the environment, the physical and mental conditions can change. If a service offers pre-trained classifiers, these

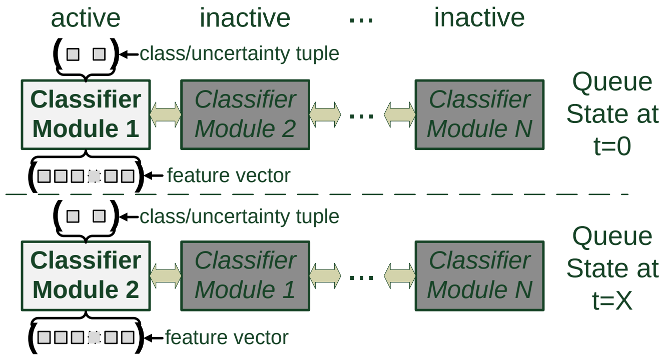


**Fig. 1:** Dynamic queue of classifier modules.

classifiers need to be personalized to the actual user. This is done via a bit vector masking, that specifies the 'active' and 'inactive' dimensions of each rule for one classifier module. Therefore only the user variant modules need to be personalized and not the whole activity recognition process. The bit vector masking is also temporary and does not change the classification capabilities permanently.

### 2.3 Extensibility

Adding the recognition of new activities to a pre-existing system is of importance too, since different users have different recognition needs. If new classifier modules are added to the existing queue, the old ones need to be adapted, so that they recognize transitions to the new classifiers. Through an adaptation technique, in which the dimensions of each rule for each pre-existing classifier module are 'activated' or 'deactivated' through a bit vector masking, transition capabilities improve without changing the classification accuracy. The original classifier module is preserved and can be restored at any time. The optimal combinations of 'active/inactive' rule dimensions is determined by a genetic algorithm.

## 3 ActiServ – A Service Supporting Activity Recognition

One of the key components shown in the video is the service supporting the modular recognition. It offers the capability of personalization and extensibility, which can not be done on the device due to limited resources. Also, due to the various users in the community of the service called ActiServ, the collection of data is reduced to a minimum and a constant improvement of the recognition process can be guaranteed.

### 3.1 Service Components

Activity Classification Module Set (ACMS): The ACMS is the collection of classification modules which are running on the user's mobile phone at a given time. Global Trainer Service (GTS): The GTS is the key component which trains new Activity ACMSs. The GTS frequently checks the database for new user activity data sets or for combinations of user data which have not been used. When data is found, the GTS creates a new

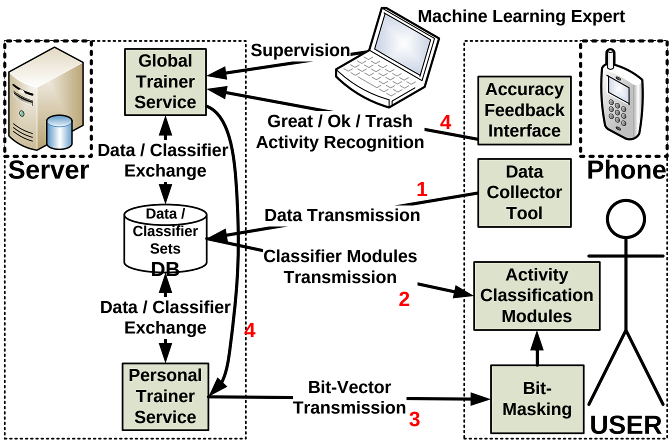


**Fig. 2:** ActiServ service architecture.

ACMS using the new data combination. Through the GTS, the database is constantly filled with new ACMSs, where badly performing ACMSs are replaced to ensure that the database always consists of the best performing ACMSs. Personal Trainer Service (PTS): The PTS selects which modules are delivered to the user device. The decision is made based on the performance of the classifiers over the annotated data collected by the user. The PTS is also responsible for personalizing the classifier modules. Data/Classifier Set Database: This unit is the central storage for the global ACMSs and user data. Bit-Masking: The bit-masking provides a means for personalizing an ACMS without destroying its original activity recognition capabilities. Data Collector Tool (DCT): The DCT on the mobile phone collects annotated activity data. Users select the activity they want to perform and then carry out the activity. Accuracy Feedback Interface (AFI): With the AFI, the users can give feedback to the GTS/PTS as to whether their activity recognition is working. This feedback is not used for personalization per se, as the personalization process is done using the bit-mask, but rather could be used to change the training process in general. However, this is not currently implemented.

### 3.2 Service Workflow

After downloading ActiServ to the phone, the user needs to collect a small amount of initial data. Each of the activities available in the drop down list of the DCT is carried out for 1-2 minutes. After this is done, the data is transmitted (step 1 Fig.2) to the ActiServ server. At this point, the interaction between the user and the service is completed and will only be re-initiated over the AFI if necessary. On the server, the PTS selects the best performing ACMS from the database and transmits the set to the user device (step 2 Fig.2). This step has nearly no delay, since only a search over the pre-existing ACMSs must be done and no training is performed. The transmitted ACMS can now run on the users phone and recognize activities with an initial accuracy. Meanwhile the PTS trains the personalization of the ACMS currently running. This process takes time (depending on efficiency and complexity about 1 hour), but since an ACMS is already running on the user's phone, the delay is not directly recognizable. The personalization data, which is just a bit-vector, is transmitted to the phone in step 3 (Fig.2). On the phone, the bit-masking component personalizes the ACMS. This can be done during runtime in between classifications. Now the phone should have reasonable activity recognition rates, but the process runs further on the ActiServ server. The GTS constantly trains new combinations of ACMSs, in which the new user's data is included as well. Over time, an ACMS is present in the database which has been trained on the data from the new user and can be transmitted to the user's phone (recognition rates can rise to above 97%). This new ACMS can be personalized again via the PTS and therefore be further improved. The user can also optionally give feedback to the system via the AFI (step 4 Fig.2).

## 4 Conclusion

The video as well as this paper present a novel modular architecture, which approaches various challenges in conjunction with activity recognition on mobile devices. These are the need for flexibility, extensibility, robustness and energy efficiency. As an example app, the gained context information is used for the automatic adjustment of phone profiles. For this, two situations in which a badly set phone profiles can lead to embarrassing or even dangerous situations are presented first. After that, the video shows the inner workings of ActiServ system. The video concludes by showing how activity recognition could have helped to prevent the undesired scenarios.

## References


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