Reinforcement Learning Based Online Active Learning for Human Activity Recognition

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ABSTRACT

Online active learning (OAL), i.e., asking a user in a targeted and parsimonious way to provide annotation for activities they are currently engaged in, has been established as a meaningful way for bootstrapping human activity recognition (HAR) systems for real-world deployments. In this paper we extend on the idea of optimizing budgets of user-provided annotations by introducing a reinforcement learning based OAL approach. Our method decides on which data sample a user shall provide a label for using a continuosly updated base classifier and a reward function that takes into account the classifier's confidence in form of its a-posteriori probability. We evaluate our approach on seven benchmark datasets and demonstrate recognition capabilities of the resulting classifiers that are superior to the state-of-the-art and reach the performance of fully supervised baseline systems for half the datasets. The presented approach has the potential to push the boundaries for real-world deployments of HAR systems.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**; • **Computing methodologies** → **Machine learning approaches**.

KEYWORDS

human activity recognition; machine learning; online active learning, reinforcement learning

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1 INTRODUCTION

Human Activity Recognition (HAR) models are essential for many application domains such as daily living [1] and complex health-related scenarios [8–10, 18, 19, 27, 33]. For the predominant supervised learning of HAR models, the training of such systems relies on ground truth labels of data collected from wearable sensors, which is challenging since obtaining (large amounts of) ground truth labels from external annotators is impractical if not impossible. In such cases, the subject engages into the activities and is asked–in time–to provide information about the activities, which can be implemented through an Active Learning approach [24].

An exemplary scenario is the automated assessment of health conditions through body-worn sensing and machine learning based HAR, which would directly involve the patient for providing ground truth annotation. The patient's availability for data labeling is limited compared to the vast amount of data required for training state-of-the-art HAR systems resulting in the problem / task of 'budget constrained annotation' (short: 'budget constraint'), where quotas exist for human-provided annotations.

Online Active Learning follows the active learning paradigm in which an oracle is asked to provide labels for sensor readings that are deemed most informative for building a classifier [12, 13]. In contrast to pool-based active learning, OAL only has access to sensor readings as they are captured in real time by the platform. As such, the fundamental question for OAL approaches is: *How shall the limited budget of human provided annotations be spent when bootstrapping a human activity recognition system?*

Existing online active learning systems leverage classification uncertainty by assuming that data points with higher classification uncertainties are closer to decision boundaries, thus helpful for training underlying HAR models. Some of such OAL methods have been evaluated with wearable-based HAR data streams [25, 26], but they deviate from more realistic HAR scenarios by pre-training models with some data from all classes. Moreover, factors other than classification confidence to data informativeness can be learned, as aforementioned works only consider data informativeness as functions of classification uncertainty. More recent OAL techniques take advantage of Reinforcement Learning (RL) which address the the above issues by taking into account the sequential characteristics of data streams. However, previous works on RL focus largely on pool-based active learning scenarios[2, 14, 28] and those that explore online (stream-based) active learning[32] are yet to be adapted to HAR applications. Thus, in this paper we explore RL methods for online active learning in wearables-based HAR use cases through the following contributions:

(1) We adopt and adapt a reinforcement learning based approach to online active learning for bootstrapping wearables-based human activity recognition systems.
(2) We compare our method to previously proposed approaches of OAL for HAR and demonstrate its effectiveness on seven benchmark datasets.
(3) We discuss the practical implications of our approach for real-world deployments of HAR systems.

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2 RELATED WORK

Online Active Learning (OAL) is one variant of Active Learning (AL), a machine learning approach that automatically determines most informative training samples for which an (human) oracle is asked to provide annotation. Two major categories of Active Learning exist as summarized in what follows.

Pool-Based Active Learning: In this scenario, a pool of unlabelled data is available at all time (during training). A model can thus make query decisions utilizing knowledge about high-level compositions of global data [2, 14, 15, 22, 28, 36]. This is not applicable to more constrained HAR applications, since segments of sensor data arrive following temporal sequences, and a model needs to make instant query decisions without knowing data points that arrive in the future. For deep-learning based HAR approaches, training losses are typically jointly optimized for cross-entropy from labelled instances and for entropy from unlabeled data instances. As such, existing active deep-learning active learning approaches [16, 17] are necessarily pool-based for they limit batch sizes, number of activities, and require that all unseen labels are available.

Online (Stream-Based) Active Learning: A model receives a stream of data following a temporal sequence, and a query decision is made at each data arrival. When deciding to annotate, the OAL system retrains its underlying HAR model by adding the current data point with its label to the train set. This resembles real-life HAR applications, and is thus the focus of this paper.

To address the *budget constraint problem*, the OAL literature examines two dimensions: *i)* budget size; and *ii)* budget spending strategies. Previous results show that HAR performance increases with budget size due to more available training data [24]. Recent models treat query decisions as probabilistic events, treating querying probability as functions of classification confidence or accuracy on predicting the label of the given data point[20, 30]. Such models are also adapted to HAR-specific scenarios[25].

Though such models yield promising performance, they either rely on models pre-trained with at least some samples from all target classes, or their simulation environments assume reappearance of activities even if some are initially excluded given low starting querying probability. Unfortunately, neither assumptions hold in realistic HAR applications, since models cannot be realistically aware of the activity classes coming in the future. Nevertheless, previous attempts worked with such assumptions due to a lack of consideration into the context drift problem: given unpredictable behaviors of data streams, decisions based on previous assumptions about data streams become unreliable. Thus, a robust OAL system should start off empty and ought to annotate data of the first activity class in the stream with a moderate probability, therefore requiring more complex relationship to be learned between querying probability and classification confidence.

In response, more recent, generic OAL models introduce randomness into query selection and leverage Reinforcement Learning (RL). Instead of calculating querying probability from every step, RL approaches initialize querying probability with a fixed value and update the value by treating querying decisions as policies and defining functions of classification confidence / accuracy as reward functions, thus adapting contextual changes in data streams in real time[32]. While promising in general, RL inspired OAL approaches have not yet found their way into HAR scenarios. This paper is the first that explores the effectiveness of reinforcement learning based online active learning for effective bootstrapping of human activity recognition systems based on wearables.

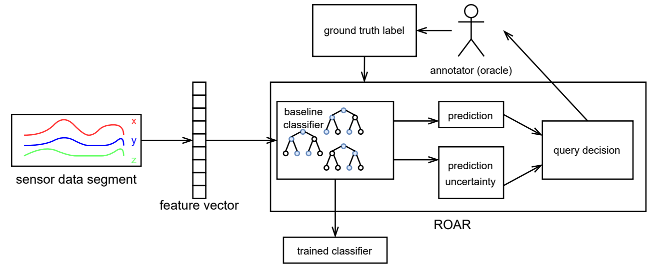


Figure 1: System Overview for ROAR: Reinforcement Learning Based Online Active Learning System for HAR.

3 ROAR: RL-BASED ONLINE ACTIVE LEARNING FOR ACTIVITY RECOGNITION

Given RL’s robustness to context drift as well as the low querying probability at the first class in stream-based scenarios, we introduce ROAR – an RL based OAL framework specific to wearable sensor based HAR applications. In this paper we introduce Reinforcement Learning into online active learning for HAR, which exploits the sequential nature of HAR data streams to make intelligent query decisions. Fig. 1 gives an overview of the system. Sensor data streams are segmented through a standard sliding window procedure that aggregates 5 seconds of consecutive sensor readings into an analysis frame [6]. For each analysis frame, a set of standard features is computed, which is fed into the ROAR system. ROAR contains a baseline classifier that is continuously updated as the system observes more sample data and receives ground truth annotation for them from the human annotator (see below). The baseline classifier assigns a class label and a classification confidence score to each processed window of sensor readings according to the classes that are known to the system at the time of analysis (online processing). The baseline classifier is initialized as empty, i.e., no class models present at the beginning. When ROAR is completed, the baseline classifier is output as the trained final HAR classifier.

In addition, ROAR contains an RL-based active learning back-end that effectively facilitates the online active learning procedure for obtaining ground truth annotation from a human annotator when required, i.e., when the classification confidence of the baseline classifier is below a threshold. In what follows, we describe the details of the components of ROAR.

Baseline classifier: The baseline classifier is trained to complete HAR classification tasks. In ROAR, it also informs query decision by supplying classification predictions and prediction uncertainties for incoming (windows of) sensor data. Owing to the limited size of the training data determined by the budget size, we utilize a baseline classifier that does not require large amounts of data to train. Since our main focus here is to provide a novel active learning approach, a Random Forest Classifier [5] suffices the needs in our application because it not only allows models to start off empty with no information about future classes, but it is also robust to imbalanced training data, suitable for data influx for HAR of unpredictable nature.

Query decision: The fundamental budget constraint problem lies within making querying decisions, in other words, when to ask the human annotator ("oracle") to provide a label for a data point.

The overarching RL method regards each data arrival event as a state, and querying decisions as the actions.Additionally, the RL module models the policy as a threshold for classification confidence, below which a data shall be labelled. Furthermore, the RL method needs to address concept drift, i.e., those changes in the underlying data distribution that could render a learned pattern useless, and in this case, the learned policy. We therefore embrace a certain randomness to making query decisions, meaning that we randomly decide to label certain data even though our baseline model decide not to do so.

The query-decision-making process, as adopted from [32] can be modeled as follows. First, as shown in Algorithm 1, ROAR accepts an incoming feature vector $\mathbf{x}$ and makes a prediction y_{pred} with its corresponding confidence y_{conf} using classifier C. A random number p is then generated from a uniform distribution within $[0, 1]$ to handle concept drift. If p is less than a small fixed threshold ϵ, we

Algorithm 1 ROAR Query Decision

```
procedure ROAR(x, ε, η, θ, p⁺, p⁻, C)
    y_conf ← predictConfidence(C, x)
    y_pred ← predict(C, x)
    p ← U_[0,1]                          ▷ draw a random value from [0, 1]
    if p < ε or y_conf < θ then
        y ← askOracle(x)
    end if
    if y_conf < θ then
        C ← retrain(C, x, y)
        r ← getReward(y_pred, y, p⁺, p⁻)
        θ ← min(θ(1 + η × (1 − 2^(r/p⁻))), 1)      ▷ update policy
    end if
end procedure

function getReward(y_pred, y, p⁺, p⁻)
    if y_pred = y then
        return p⁻
    else
        return p⁺
    end if
end function
```

ask the oracle for label y regardless of the policy, thus solving the context drift problem by leveraging randomness. Alternatively, if p is greater than ϵ and the policy decides that the ground truth label should be queried ($y_{pred} < \theta$), we know $\mathbf{x}$ belongs to a previously under-explored feature space, and therefore should be queried to retrain classifier C. We shall then obtain a reward such that if it is negative then C already predicts $\mathbf{x}$ accurately and positive otherwise, and update policy value θ by a function of learning rate η and reward r. We compare our proposed approach to OAL, wherein a data point is queried only when $y_{pred} < \theta$.

Hyper-Parameters: We further optimize the hyper-parameters towards our HAR scenarios. For complex activity recognition problems, especially those that contain non-periodic activities, we set the magnitude of p^+ (0.5) to be significantly lower than that of p^- (2) with a high ϵ (0.05) because encountering useful data would be more common than encountering useless data due to the data-consuming nature of training for difficult tasks. Alternatively, we set p^+ (1) lower than p^- (2) for easy, periodic tasks since only a few representative data would suffice to train the base-line model. Moreover, we set θ to higher values (0.9) when expecting fewer incoming activity classes, and we set a low ϵ (0.02) due to common occurrences of non-useful, repetitive data.

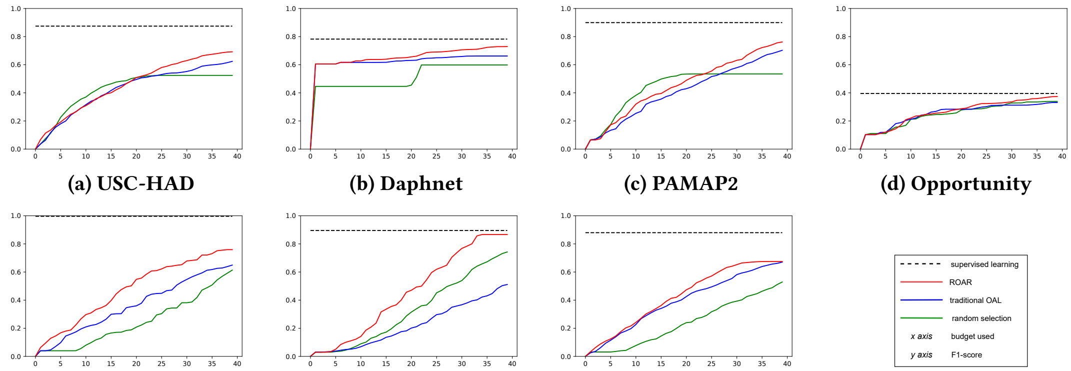
4 EXPERIMENTAL EVALUATION

We aim at examining ROAR's effectiveness in realistic HAR scenarios. To this end, we evaluate ROAR on benchmark datasets in the field: Opportunity [11], PAMAP2 [29], SKODA [31], USC-HAD [35], Daphnet Gait [23], MHealth [3], and WARD [34]. In line with previous work [24, 25, 32], we focus on classifying target activities only, and we only use accelerometry data collected from the arm.

Data Stream Simulation: Given that our focus is on *online* active learning, we process the datasets as streams of sensor data:

(1) For each subject from a given dataset, we apply standard 4:1 random train-test split for each activity, and concatenate training data in activity-after-activity fashion without shuffling the sequential order of the stream. This split is commonly encountered in the machine learning literature [17]. However, in our work, the training data size is determined by a fixed budget size drawn from the training data.
(2) We apply 5-second sliding windows to the sensor data streams with 2.5-second overlaps. This choice of window size ensures that we capture longer context beneficial for non-periodic activities (i.e., Opportunity). Also, the state of the art OAL procedure makes use of this specific window size, which we retain to provide for a consistent comparison. For each window, we pick the most frequent activity label as the ground-truth label of that window and utilize data pre-processing outlined in the previous section to obtain a 9-dimensional feature vector (mean, standard deviation of x, y, z axis respectively and covariance of each pair combinations) [25], which are then fed into the ROAR backend.
(3) We train the initial baseline classifier with the first feature vector from the stream, and we let ROAR process one feature vector at a time until all training data are seen or the budget limit (40) has achieved.
(4) For comparison, we repeat the procedure for traditional OAL and random selection (the budget-spending strategy that randomly asks for annotations with fixed probability), and thus adopt the budget size used in the literature

Results: As shown in the above procedures, the (macro-) F1-score of the baseline classifier against the test set of the corresponding subject is recorded when an annotation is obtained to retrain the classifier. This produces a learning curve for each subject across a given dataset, and we then average learning curves across subjects for this dataset – shown in Fig. 2. Tab. 1 summarizes the final classification results achieved when the annotation budgets were exhausted for model training given the various budget spending strategies: *i)* Random: randomly decides whether to query for annotation on each data point by a fixed probability *ii)* OAL: models probability to query for annotation on each data point by a function



(a) USC-HAD **(b) Daphnet** **(c) PAMAP2** **(d) Opportunity**

(e) Skoda **(f) MHealth** **(g) WARD**

Figure 2: Experimental evaluation on seven benchmark datasets with F1-score averaging learning curve over all subjects.

Table 1: Overview of recognition results. Models are trained using variants of ground truth provision: Baseline (fully supervised); Random (randomized query decision); OAL (Online Active Learning from [25]; ROAR (our method).

Dataset	Random (F1-score)	OAL (F1-score)	ROAR (F1-score)	Baseline (F1-score)
USC-HAD	0.52 ± 0.17	0.62 ± 0.13	0.69 ± 0.12	0.87 ± 0.10
Daphnet	0.60 ± 0.21	0.66 ± 0.22	0.73 ± 0.20	0.78 ± 0.17
PAMAP2	0.54 ± 0.11	0.70 ± 0.12	0.76 ± 0.07	0.90 ± 0.05
Opportunity	0.34 ± 0.11	0.33 ± 0.06	0.37 ± 0.10	0.40 ± 0.11
Skoda	0.61 ± 0.05	0.65 ± 0.01	0.76 ± 0.01	0.98 ± 0.01
MHealth	0.74 ± 0.07	0.51 ± 0.04	0.87 ± 0.08	0.90 ± 0.06
WARD	0.53 ± 0.11	0.67 ± 0.13	0.68 ± 0.12	0.88 ± 0.11

of classification uncertainty of that data point, in the absence of access to the entire dataset, to select the most informative samples (pool-based AL) *iii)* ROAR: our method. We also contrast the results to the fully supervised baseline models (no budget constraints).

It can be observed that, upon budget exhaustion, ROAR outperforms both active learning alternatives (Random and OAL) with higher performance stability (lower standard deviation on most datasets), leading to better HAR performance in realistic deployment scenarios. We can also see that for about half of the datasets our method leads to recognition results that are comparable to the fully supervised baselines, while for the others the difference remains substantial. Notably, none of the other active learning methods come close to those supervised baselines.

The learning curves (Fig. 2) indicate that although random selection and traditional OAL may boost baseline classifier performance faster at the beginning, ROAR’s advantage becomes more significant when more labels are obtained. Across the board, ROAR leads, quickly, to classifiers with superior performance compared to the state-of-the-art in online active learning.

5 DISCUSSION

Our results show that ROAR outperforms traditional OAL methods in general. Still, whether ROAR can achieve performance comparable to supervised-learning depends on the tasks’ difficulties and budget sizes. For instance, Fig. 2b shows that base-line model accuracy increases quickly in an easy binary classification scenario, and 2f shows that ROAR can achieve classification accuracy close to that of fully supervised learning when budget size is large compared to the size of the dataset. On the contrary, 2e achieves low accuracy compared to supervised learning at budget exhaustion because budget size is minimal compared to the size of the dataset, thus unable to represent the full data space. As such, hyper-parameters need to be tuned carefully by leveraging assumptions about data streams – if such assumptions are available. In this work, we assume full access to ground truth labels offered by benchmark datasets, since the training and testing procedure is conducted in a simulation of users always providing accurate labels. Also, although label querying still imposes labeling burden to users as much as previous approaches, ROAR addresses user annoyance by intelligently querying for important data points with a fixed budget. We also assume that queries are labeled instantly, to make comparisons across OAL and ROAR consistent for the evaluation criteria, and will consider effects of delayed response in future work. Future extensions of ROAR could improve complex use cases by leveraging the sequential characteristics of activities using RL [4, 21] and integrate with interactive annotation tools [7]. To conclude, the utility of RL for multi-modal HAR tasks requires further investigation [8, 10].

6 CONCLUSION

Obtaining ground truth annotation for the development of wearables-based human activity recognition systems is hard. One way to tackle this problem is to ask the wearer to provide labels on activities they engage in, in a targeted way, e.g., through online active learning (OAL) methods. In this paper we extended the idea of OAL for HAR through utilizing a reinforcement learning approach.

We experimentally evaluated our approach on seven HAR benchmark datasets through which we emulate a typical online annotation and active learning scenario. For the same budget sizes across different approaches, ROAR provides a more intelligent way to query for data points and thus leads to better performance scores, indicating the effectiveness of RL-based annotation budget spending strategy. For half the cases our results even get close to fully supervised baselines.

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