DATA-DRIVEN HUMAN ACTIVITY RECOGNITION IN SMART ENVIRONMENTS

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Abstract:

Many applications of human activity recognition like healthcare, security *etc.* show how human activity recognition is important in everyday life. In this paper, we compare different machine learning algorithms like Naïve Bayes (NB), One R (1R) rule, Zero R (0R) rule, J 48 trees, Random Forest (RF) and Random Tree (RT) applied on sensor-based human activity recognition in a home environment. We show that Random Forest achieves better performance in terms of correctly classified instances comparing to other algorithms, while application of 0R rules algorithm achieves significantly the worst performance. Additionally, in order to reduce the dimensionality of the algorithm, we applied wrapper method using the same classifier in the attribute selection. It is shown that using the wrapper method the performance of the classification in terms of correctly classified instances is not significantly changed, while it shows much better performance in terms of algorithm complexity. After calculating accuracy of each algorithm, we calculate accuracy for each activity classified by each classifier.

Key words:

activity recognition, machine learning, sensors, classification, wrapper.

1. INTRODUCTION AND THEORETICAL BACKGROUND

The Internet evolved into Internet of Things (IoT), from processors embedded into the computers to processors and sensors embedded almost in every "thing" *i.e.* in any device. IoT, by market segment, can be classified into three broader categories, such as health self-tracking and personal environment monitoring, smart homes/buildings, and transportation/automotive applications (Swan, 2012). Activity recognition is the foundation of these areas as it enables a wide range of computing applications (*e.g.* elder care and health applications). In some papers it is shown that it is possible to detect a large range of activities (Bao *et al*, 2004) (Huynh *et al*, 2007; Lester *et al*, 2006). Since human activities are complex and highly diverse, the goal of activity recognition is to recognize common activities in daily life (Kim *et al*, 2010). However, recognizing complex human activities is still challenging area, especially when dealing with concurrent or interleaved activities.

Activity recognition can be defined as the process that includes (a) adequate sensors to monitor and capture a user's behavior according to environment state change, and (b) system for collecting, storing, processing, and analyzing perceived information, in order to create activity models for

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developing algorithms that will infer activities from sensor data (Chen *et al*, 2012). Activity recognition can be vision-based, sensor-based, data-driven or knowledge-driven.

Vision-based activity recognition uses visual sensing devices (*e.g.* video cameras) that generate video sequences or video digitized data. On the other hand, sensor based activity recognition uses wearable sensors or smart phones (attached to an actor), or dense sensing (attached to objects) that generate time series of state changes or various parameter values that are processed through some probabilistic or statistical analysis methods (Chen *et al*, 2012). With the expansion of mobile computing, wearable sensors receive more attention. Sensor-based are more convenient for smart environments, such as smart homes, smart hospitals, smart buildings, *etc.* In Anguita *et al.* (2012), a system for activity recognition is presented using Smartphone inertial sensors. Since mobile phones are limited in terms of energy and computing power, a novel hardware-friendly approach for multiclass classification is proposed. This method is based on Support Vector Machine and exploits fixed-point arithmetic for computational cost reduction.

Data-driven activity recognition creates user activity models from existing large datasets of user behaviors using data mining and machine learning techniques, and then uses the learnt activity models to infer activities (Gu *et al*, 2011; Okeyo *et al*, 2012). However, it is difficult to apply learnt activity models generally to all people. In Ordonez *et al.* (2012), the use of two machine learning algorithms, Artificial Neural Network and Support Vector Machines, within the framework of Hidden Markov Model, in order to perform activity recognition in a home environment, is described. A knowledge-driven activity recognition construct activity models based on rich prior knowledge. Hybrid approaches combine knowledge-driven and machine learning to formulate activity models (Okeyo *et al*, 2012).

In this paper different classification models applied on sensor-based dataset in home environment are compared. The aim is to identify the algorithm that achieves better performance for sensor-based activity recognition. Since all algorithms analyzed in numerous papers are extremely complex, this paper proposes wrapper methods to reduce the dimensionality of each method.

This paper is organized in three parts. The first part describes seven machine learning methods and their comparative advantages for the activity recognition problem. The second part describes datasets with selected activities and type of sensors. The third part presents the results of experiment and compares the performance between selected methods.

2. CLASSIFICATION MODELS DESCRIPTION

To represent and recognize the activities based on the optimal features, six different machine learning algorithms like NB, 1R, 0R, J 48 trees, RF and RT were applied to sensor-based data in terms of CCI and number of attributes were selected by a wrapper method.

Naive Bayes Model

Since all of the attributes contribute equally and independently to the decision, we can apply Naive Bayes (NB) method explained by John *et al.* (1995). Probability of event *H* with given evidence *E* is presented as

$$P_r(H|E) = \frac{P_r(E|H)P_r(H)}{P_r(E)} \tag{1}$$

Where $P_r(H)$ presents Prior probability and $P_r(H|E)$ presents Posterior probability of event *H*. In our model, *H* presents a user activity that we want to identify, and evidence *E* presents an instance in our dataset. Evidence splits into independent parts

$$P_r(E|H) = P_r(E_1|H)P_r(E_2|H)...P_r(E_n|H) \tag{2}$$

Where particular evidences, or attributes E_1, E_2...E_n, are statistically independent.

One R rule Model

This method is explained by Holt (1993). This method, the same as NB Model, relies on Frequency Table (Kohavi, 1995). It is based on using the minimum-error attribute for prediction, discretizing numeric attributes.

Zero R rule Model

The same as NB Model, 0R model is based on Frequency Table. This is the simplest classification method which relies on the target and ignores the predictors. It predicts the mean (for a numeric class) or the mode (for a nominal class) constructing a frequency table and selecting its most frequent value.

J 48 Trees Model

J48 model is one of the Decision Trees models, a hierarchical data structure based on conquer strategy. This classification model is explained by Quinlan (1993). The idea is to select which attribute to divide on at the root node, and then create a branch for each possible attribute value. Then, in order to make the selection, the procedure is recursively repeated for each branch, selecting an attribute at each node, using only instances that reach that node. The objective is to get the smallest tree, and top-down tree induction methods use different approaches. The most used approach to produce pure nodes is an information theory-based approach founded by Claude Shannon (1948).

Random Forest

Since the combination of classification models increases the classification accuracy, Random Forest (RF) model is proposed (Breiman, 2001). It works as a large collection of forest of the correlated random decision trees.

Random Tree Model

This model is based on constructing a tree that considers K randomly chosen attributes at each node. A Random Tree (RT) model is explained by Aldous in 1991. RT model associated with random graphs is also explained by Aldous in 1990.

Wrapper-based Approach

In order to decrease data dimensionality, it will be interesting to select the most effective features from our feature vector. In Kohavi *et al.* (1997), Wrapper method for feature selection is described. The flowchart of wrapper-based approach in this paper is presented in Figure 1.

This method is based on the evaluation of the attribute sets by using a learning scheme. Cross validation is used in order to estimate the accuracy of the learning scheme for a set of attributes. In order to compare performance with and without subset extraction and find a subset, the evaluator will use the same classifier as in training set.

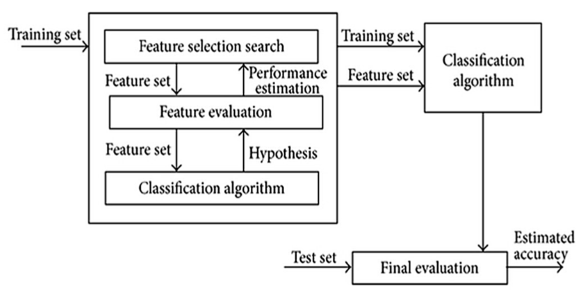

Figure 1. Flowchart of wrapper-based approach to feature subset selection (Kohavi et at, 1997)

3. DATA SETS DESCRIPTION

In order to validate this testing, we use 407 instances from Ordonez A dataset generated by Kasteren (2013). This dataset comprises activities of daily living (ADL) performed by a user in home environment. Datasets were generated by a set of simple state-change sensors. The wireless sensor network (WSN) was measuring passive infrared sensors to detect motion, reed switches for opening or closing of doors or cupboards, and float sensors for measuring the toilet being flushed.

Instances were described by description, sensor event (feature) and ADL (label). Features were recorded using a WAN and data were labelled manually (UCI, 2013). Nine different ADLs, included as labels, were considered: “Leaving”, “Toileting”, “Showering”, “Grooming”, “Sleeping”, “Breakfast”, “Lunch”, “Snack”, and “Spare time”.

Table I shows the number of separate instances per activity in the dataset. Table II, Table III and Table IV show attributes that are considered for this test as location, place and sensor type, respectively.

N_0	Label	Count
1	Sleeping	15
2	Toileting	19
3	Grooming	111
4	Showering	14
5	Breakfast	70
6	Spare_Time/TV	80
7	Leaving	31
8	Lunch	49
9	Snack	18

Table I. Activities count

N_0	Label	Count
1	Bed	15
2	Cabinet	15
3	Basin	70
4	Toilet	45
5	Shower	14
6	Fridge	56
7	Cupboard	34
8	Toaster	14
9	Cooktop	13
10	Microwave	20
11	Seat	80
12	Maindoor	31

Table II. Location of sensors count

N_0	Label	Count
1	Bedroom	15
2	Bathroom	144
3	Kitchen	137
4	Living	80
5	Entrance	31

Table III. Place count

N_0	Label	Count
1	Pressure	95
2	Magnetic	136
3	PIR	97
4	Flush	45
5	Electric	34

Table IV. Type of sensors count

4. EXPERIMENTS AND RESULTS

This experiment was performed using WEKA (Waikato Environment for Knowledge Analysis) tool, developed at the University of Waikato in New Zealand. This software contains large spectrum of tools such as: data pre-processing, classification, regression, clustering, association rules, and visualization. The purpose of this paper is to compare six different machine learning algorithms like NB, 1R, 0R, J 48 trees, RF and RT applied on sensor-based human activity recognition in a home environment in terms of correctly classified instances (CCI) and number of attributes (NA) selected by a wrapper method. After calculating accuracy of each algorithm, it is important to calculate accuracy for each activity classified by each classifier.

In the first part of experiment, we compare classifiers in terms of CCI applied on the entire data set, that has 4 attributes. In the second part of the experiment, we used wrapper method in order to reduce the dimensionality of data. The results are provided with a 10-fold cross-validation.

	Classifier					
	NB	1R	0R	J48	RF	RT
CCI in original data set (%)	78,1	77,8	27,3	76,6	79,6	77,9
CCI with wrapper (%)	77,1	77,9	27,3	76,9	76,6	77,9
NA with wrapper	3	1	0	3	1	1

Table V. Clasiffiers comparison

	Metric		
	P	R	ROC
Sleeping	1	1	1
Toileting	0	0	0,854
Grooming	0,854	1	0,968
Showering	1	1	1
Breakfast	0,681	0,457	0,926
Spare_Time/TV	1	1	1
Leaving	1	1	1
Lunch	0,389	0,714	0,885
Snack	0	0	0,915

Table VI. Deatailed accuracy by class- NB

	Metric		
	P	R	ROC
Sleeping	1	1	1
Toileting	0	0	0,5
Grooming	0,854	1	0,968
Showering	1	1	1
Breakfast	0,597	0,614	0,764
Spare_Time/TV	1	1	1
Leaving	1	1	1
Lunch	0,354	0,469	0,676
Snack	0	0	0,5

Table VII. Deatailed accuracy by class -1R

	Metric		
	P	R	ROC
Sleeping	0	0	0,415
Toileting	0	0	0,474
Grooming	0,273	1	0,492
Showering	0	0	0,41
Breakfast	0	0	0,497
Spare_Time/TV	0	0	0,497
Leaving	0	0	0,482
Lunch	0	0	0,489
Snack	0	0	0,451

Table VIII. Deatailed accuracy by class- 0R

	Metric		
	P	R	ROC
Sleeping	1	1	1
Toileting	0	0	0,849
Grooming	0,854	1	0,966
Showering	1	1	1
Breakfast	0,51	0,714	0,9
Spare_Time/TV	1	1	1
Leaving	1	1	1
Lunch	0,282	0,224	0,874
Snack	0	0	0,894

Table IX. Deatailed accuracy by class -J48

	Metric		
	P	R	ROC
Sleeping	1	1	1
Toileting	0	0	0,85
Grooming	0,854	1	0,966
Showering	1	1	1
Breakfast	0,662	0,614	0,927
Spare_Time/TV	1	1	1
Leaving	1	1	1
Lunch	0,417	0,612	0,886
Snack	0	0	0,916

Table X. Deatailed accuracy by class -RF

	Metric		
	P	R	ROC
Sleeping	1	1	1
Toileting	0	0	0,849
Grooming	0,854	1	0,966
Showering	1	1	1
Breakfast	0,597	0,614	0,925
Spare_Time/TV	1	1	1
Leaving	1	1	1
Lunch	0,354	0,404	0,883
Snack	0	0	0,915

Table XI. Deatailed accuracy by class -RT

According to Table V, we can conclude that in the case when we use the entire data set, RF algorithm achieves better performance in terms of CCI comparing to other algorithms, while application of Zero R rules algorithm achieves significantly the worst performance. On the other hand, when wrapper approach is applied, RT has better performance in terms of CCI comparing to RT, while 1R achieves higher CCI comparing to NB. Observing data dimensionality, NB and J48 show higher complexity than other algorithms.

In Table V-Table XI, detailed accuracy for each activity, for each classifier used in this paper is presented. Precision (P) is calculated as proportion of instances that are correctly classified divided by the total instances classified as that class. While Recall (R) is calculated as a ratio of the proportion of instances classified as a given class and the actual total in that class.

Receiver operating characteristics (ROC) graphs are very useful for classifiers comparison in machine learning and data mining research (Fawcett, 2005).

According to table VI, activities such as: "Leaving", "Sleeping", and "Spare time" have the best performance, while "Breakfast", and "Lunch" show the worst performance when NB classifier is applied.

In table VII is demonstrated that activities such as: "Sleeping", "Leaving", "Showering", and "Spare time" have best performance in terms of P, R and ROC when 1 R classifier is applied, while activities such as "Toileting" and "Snack" result in significantly worst performance.

Table VIII shows that when 0R classifier is applied, the best performance shows activity "Grooming". However, it still has very low precision of 0,273.

According to table IX, activities such as: "Leaving", "Sleeping", "Spare time" and "Showering" have the best performance, while activities such as "Breakfast", "Lunch" and "Snack", whose recognition requires magnetic sensors activation, show the worst performance when J48 classifier is applied.

In tables X and XI accuracy by class when RF and RT classifier is applied is shown respectively. They show similar result where "Sleeping", "Showering", "Spare time" and "Leaving" result in best performance, while "Snack" and "Lunch" activities have very low P and R.

5. CONCLUSION AND FUTURE WORK

According to the results obtained, we can see that order in performance of applied classifiers in terms of CCI is different when wrapper method is applied. In case when we use the entire data set for the purpose of human activity recognition, RF classifier shows the best performance, while in case when wrapper approach is applied, RT shows the best performance compared to other classifiers used in this paper.

Additionally, it is shown that is possible to improve the system performance in the human activity recognition problems, using the wrapper method for reducing the dimensionality of the data. In further research, it would be interesting to compare those classifiers on all five data sets described by Kasteren (2013) as: “KasterenA”, “KasterenB”, “KasterenC”, “OrdonezA” and “OrdonezB”.

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