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Transferable Representation Learning for Human Activity Recognition in Smart Homes

Hao Niu HA-NIU@KDDI-RESEARCH.JP
Kei Yonekawa KE-YONEKAWA@KDDI-RESEARCH.JP
Mori Kurokawa MO-KUROKAWA@KDDI-RESEARCH.JP
Shinya Wada SH-WADA@KDDI-RESEARCH.JP
Kiyohito Yoshihara YOSSHY@KDDI-RESEARCH.JP
KDDI Research, Inc. Japan.

Abstract

Sensor data collected in smart homes are analyzed extensively by machine learning approaches to recognize and support humans' activities. Generally, human activity recognition (HAR) model is constructed independently for different smart homes, due to different floor plans or adopted sensors. However, it is costly and even impossible to acquire labels for each home, which promotes transfer of HAR model among homes. In this work, we propose to learn transferable representations (TRs) of sensors in different homes based on their contextual similarity, and realize the model transfer using the learnt TRs. The effectiveness is evaluated by experiments on CASAS dataset.

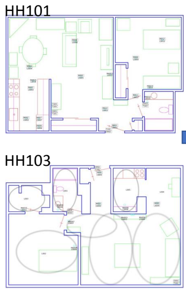
Keywords: Human activity recognition, smart homes, transfer learning, Word2Vec, LSTM

1. Introduction

Human activity recognition (HAR) is important to the applications of smart homes. Different machine learning approaches have been used for HAR, and LSTM is proved to be able to achieve significant recognition performance on the time series sensor data Liciotti et al. (2019). Due to the differences between homes (e.g., different floor plans or adopted sensors), the model built for one home cannot be reused directly for other homes. One solution is to build a model only based on some common sensors which are with the same location and type in different homes. However, such a model cannot deal with the samples in which common sensors are not active. We thus propose to generate transferable representations (TRs) for all the sensors of different homes in a common vector space, based on their contextual similarity (i.e., the similarity of location, type and *co-occurrence*). Then we can build and transfer the HAR model from one home to other homes using TRs. Besides smart homes, our proposed method can be also applied to the model transfer of other smart systems.

2. Methodology and Experimental Results

We use two smart homes in CASAS dataset Cook et al. (2013) to describe our proposed method: HHi (i = 101, 103). Similar to Liciotti et al. (2019), the data of each home i is processed to $\{X_i, Y_i\}$, where X_i is the set of sequences of [sensor ID + action]s and Y_i is the set of labels. Assuming that Y_{101} is not available, the task is to build a HAR model based

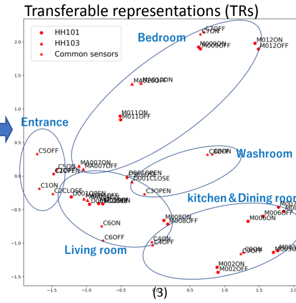


(1)

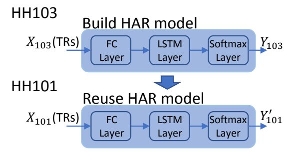
Common sensors

HH101	HH103	
M001	M001	C1
D002	D002	C2
D003	D003	C3
M004	M005	C4
M010	M002	C5
MA013	MA003	C6
MA014	MA009	C7
MA015	MA008	C8
MA016	MA006	C9

(2)



(3)



(4)

Recognition performance comparison (101←103)

	Accuracy	Precision	Recall	f1-score
LSTM	0.69	0.71	0.69	0.67
TRs+LSTM	**0.74**	**0.78**	**0.74**	**0.75**

(5)

f1-score

	LSTM	TRs+LSTM
101←103	0.67	**0.75**
101←105	0.74	**0.86**
103←101	**0.73**	0.68
103←105	**0.72**	0.63
105←101	0.82	**0.92**
105←103	0.78	**0.82**

*i←j means transferring the HAR model from HHj to HHi.

(6)

Figure 1: Description of our proposed method and performance comparisons.

on $\{X_{103}, Y_{103}\}$, and apply it to X_{101}. For a simple description, we only use the door and motion sensors and classify 7 class activities (Leave_Home, Enter_Home, Watch_TV, Cook, Toilet, Dress, Sleep). The common sensors between the two homes based on the location and type are listed in Fig1-(2). Since a sensor usually has several actions (e.g., ON and OFF) which have different contextual meanings, we generate representations for the actions of sensors instead of the sensors themselves.

To generate TRs, we first learn the representations of HH103 using Word2Vec model Singla and Bose (2018), which captures sensors' co-occurrence similarity. Then the vectors of common sensors in HH101 are set to be equal to the vectors of their corresponding common sensors in HH103, and are frozen when performing Word2Vec model on the data of HH101. Fig 1-(3) visualizes the learnt vectors for both HH101 and HH103 based on the vectors' first to second principal components of principal component analysis. We can observe that the sensors with contextual similarity (intuitively the location similarity) are located closely to each other. Then, we can use these representations to transfer/reuse the HAR model between HH101 and HH103. In the above case, we build the model based on $\{X_{103}, Y_{103}\}$, and reuse it on X_{101} to predict Y_{101}. We compare the recognition performance of our proposed method TRs+LSTM with the LSTM model only using common sensors in Fig 1-(5), which confirms the effectiveness of TRs+LSTM. The recognition performance of different transfer patterns between HHi (i = 101, 103, 105) is also given in Fig 1-(6), where only f1-score values are shown due to the space limitation. The proposed method is effective for the HAR of HH101 and HH105 using the model of other homes, but not for HH103. The reason is considered to be that there are less sensors in HH103 and contextual similarity, especially the co-occurrence similarity, cannot be well exploited. In future, we will continue to analyze the HAR model transfer for the homes like HH103, and consider the transfer from multiple labeled smart homes to further improve the recognition performance.

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