Activity Prediction Using LSTM in Smart Home

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***Abstract*—In the near future, smart home systems will play more and more important role to provide comfortable and safe life to human. Today, we already have some realistic way to monitor the daily life of human and recognize their activities by cameras or wireless sensing technology. However, the current research still faces the challenge to the prediction of human activities. In this paper, we analyse the similarity between human activities of daily living and deep neural networks. Inspired by this, the paper proposes a method to predict human activity by deep learning model and evaluates the performance of the approach with real world data. Compared with the traditional algorithm, our approach reaches higher prediction accuracy. In the future, we will try to improve the prediction accuracy and add more kinds of activities.**

***Index Terms*—Human Activity Recognition, Activity Prediction, Smart Home, Wireless Sensing.**

I. Introduction

Smart home systems that aims at providing inhabitants with intelligent and personalize service become popular these years. Especially to the disabled and elderly people, smart home systems are required to work on their own initiative. Monitoring human activities of daily living(ADL) is considered a key aspect in building such systems. Systems that recognize ADL with hybrid sensor have been proposed and achieve fairly good performance. However, recognizing the past or ongoing activity is not enough for smart home to manage and prepare service. Activity prediction is the next challenge for smart home systems.

There are mainly three kinds of human activity recognition(HAR) systems with different devices: cameras [1], wearable devices [2], and ambient aware sensors [3]. Most of them utilize machine learning methods to build a model to recognize activity from streaming data and gain the activity number. Thus, the activity number is also another kind of streaming data. Inspired by this, this research focuses on building a universal approach to predict human activity in smart home with the log of activity. In this way, the proposed approach can be used in existing smart home systems directly.

The daily life of human differs from each other, while the individual always build their own routine unconsciously. This routine forms the daily life of human and reflects the habit of human. For example, a father will always watch TV after having dinner. It means that the current activity does not happen randomly. The current activity does have relation with the past activity. In this paper, we believe that the current activity is the consequence of not only the last one activity but also last several activities. In the same way, we can predict the next activity based on the current and past activities. To solve such problem, we chose Long Short Term Memory(LSTM) neural networks as a tool to model the relation between activities.

LSTM neural networks are a special kind of recurrent neural networks(RNN), capable of learning long-term dependencies. The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates. Those gates act on the signals they receive, and similar to the neural networks nodes, they block or pass on information based on its strength and import, which they filter with their own sets of weights. Those weights, like the weights that modulate input and hidden states, are adjusted via the recurrent networks learning process. That is, the cells learn when to allow data to enter, leave or be deleted through the iterative process of making guesses, back propagating error, and adjusting weights via gradient descent.

The proposed approach based on LSTM has several advantages. The first is that the approach is general and can be used in different current HAR systems. Since the model only needs the stream data of activity log ignoring how the activity log generated, the approach is universal. The next is that the proposed approach utilize not only the current activity to predict the next activity, but also the past several activities. In this way, the prediction accuracy is higher than the classical machine learning approach.

II. Activity Prediction with LSTM

In this research, we treat human activity prediction as a time sequence predicting problem. We believe the inhabitants act different activities in a relative fixed pattern. For example, there is a user who always goes to watch TV after having dinner according to the activity log. If the user are detected to have dinner currently, then the next activity the user will act is most probably watching TV. Such problem to predict next state based on current state can be solved by classical machine learning method. Nevertheless, the next activity has relation with not only the current activity but also the previous ones. So we introduce deep learning to this problem. RNN perform well on spatial temporal predicting problems, such as location prediction [4]. LSTM networks are a special kind of RNN, which are proved to be more efficient [5]. LSTM networks have the ability to memorize both long and short term knowledge, which tally with human mind.

As depicted in Fig.1, this is a spread LSTM networks. X_0 to X_t in this paper represent the activity log, and h_0 to h_t

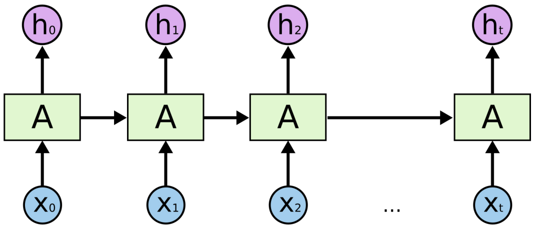

Fig. 1. Activity sequence and RNNs model.

represent the prediction result which is the next activity. We can see that when the time stamp is t, the input of the model is the current activity X_t and the past knowledge remembered from $t-1$ to $t-n$. It means the model can predict the next activity using not only the current activity but also the past several activities. This just accord with our assumption that the activity does not happen randomly and the motivation of next activity is what the human have done.

In the process of prediction, we first need to adjust clean the original data. We treat the same activity that repeats in a short time as pseudo record and merge them together. And we delete some false record which does not meet the common sense, such as having breakfast at night. Then, we do normalization to make the data can be used to train the LSTMs model. To evaluate our LSTM-based solution, we conduct the experiment on open source dataset. The dataset generated by Kasteren [6] includes 10 ADLs performed by the users on a daily basis in their own house. The dataset is divided into two parts: the first 70% is for training and the last 30% is for testing.

III. Experiment and Evaluation

TABLE I
THE HYPERPARAMETERS AND CORRESPONDING PREDICTION ACCURACY.

Timestep	Neurons	Epochs	Train accuracy(%)	Test accuracy(%)
1	16	10000	38.96	54.55
1	32	10000	38.96	54.55
1	64	10000	38.96	54.55
1	128	10000	38.96	54.55
2	16	10000	49.88	58.14
2	32	10000	50.37	58.14
2	64	10000	50.37	55.81
2	128	10000	49.88	62.79
3	16	10000	60.79	64.29
3	32	10000	62.78	61.90
3	64	10000	63.28	64.29
3	128	10000	60.79	61.90
4	16	10000	77.67	60.98
4	32	10000	79.65	56.10
4	64	10000	79.65	53.66
4	128	10000	76.43	51.22
5	16	10000	88.83	45.00
5	32	10000	91.81	47.50
5	64	10000	91.81	50.00
5	128	10000	87.80	50.00

In the experiment, we build a typical LSTM model on TensorFlow-GPU with Keras as the high level API. The training epoch is set to 10000 to make sure the model is well trained. The loss is set ascategorical crossentropy, and the optimizer is adam. Also the prediction result contains two activities which have higher possibility than others. And we adjust the hyperparameters to reach the top performance.

We find that the test accuracy reaches to the top while the timestep equals to 3, as shown in Table.I. This means the LSTM model can utilize the past 3 activities to predict the next activity and get the highest accuracy, which accords with our assumption. And even when the model uses past 5 activities to predict, the train accuracy can reach over 90%. The test accuracy does not rise accordingly, because of overfitting.

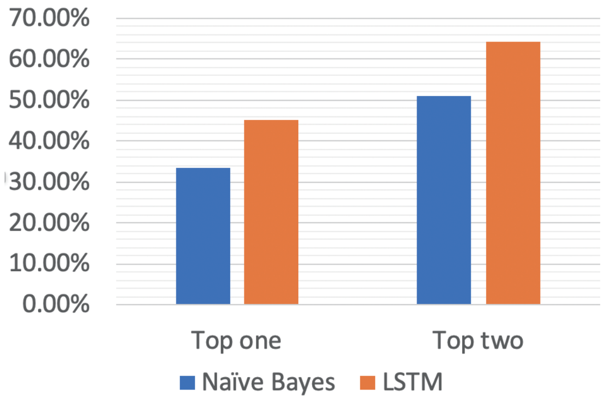

Fig. 2. Accuracy of Naive Bayes and LSTM solution.

We also compare our model with the classical Naive Bayes method as shown in Fig. 2. Because the Naive Bayes method only use the current one activity to predict next activity. We can see that our solution get much higher accuracy than Naive Bayes. The top two prediction accuracy reaches to 65% which is acceptable.

IV. Conclusion

This research proposes a universal LSTM-based solution to predict ADLs in smart home and achieves acceptable performance. Compared with classical method, our approach can utilize more knowledge so that it gets higher accuracy. The experiment shows the single layer LSTMs suffer from overfitting. In the future, we need to extend to use multiple layers LSTMs to improve the accuracy.

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