PRML Course Project Evaluation

Activity Change Detection

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Abstract

This project focuses on building classifiers that accurately identify the activities being performed by individuals using their smartphone sensor data. Using this, we aim to quickly detect the change in the activity of the subject with the best possible accuracy. In this work, we present a comparitive study wherein we compare the performances of machine learning algorithms namely k-Means and Hidden Markov Models with the modern Deep Learning algorithm Long Short Term Memory Networks (LSTM).

Introduction

As more sensors are being built into mobile phones to measure our movements, positioning and orientation, the opportunity to understand this data and make improvements in our daily lives increases greatly. The scope of our project consists of analyzing mobile phone sensor data or any other sensor data which tracks the subject activities, in the context of activity recognition. For this study, we have considered two datasets, namely WISDM dataset which is mined from wireless devices*[1]* and a Pet dataset which is collected from the sensors on pets.

Studying activity recognition offers several benefits and enables many new applications. Mobile health applications that track a user's activities over time can be beneficial for elderly assistance or personal health monitoring. In addition to providing personal support, this research also has connections to various fields of study including medicine, human-computer interaction, and sociology.

Data Visualization

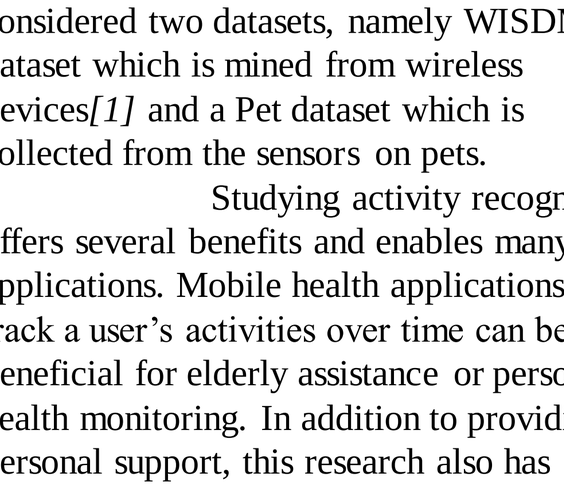


Fig1: This fig shows the accelerometer data for different actions of WISDM dataset.

Block Diagram

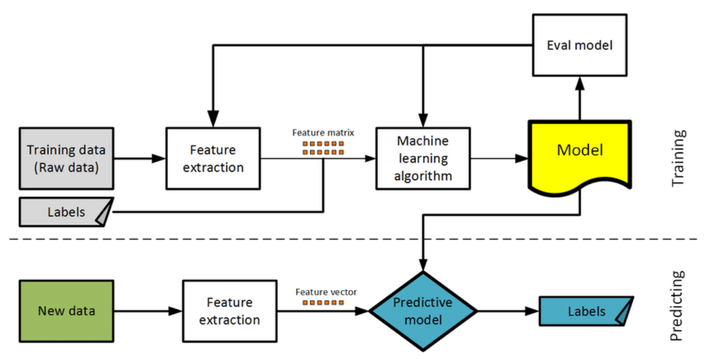
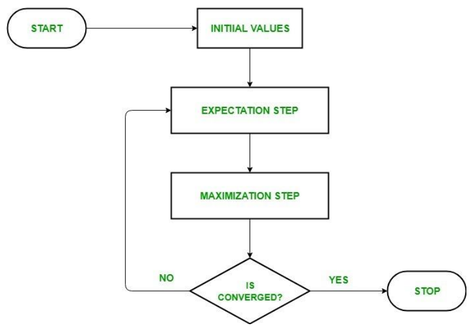


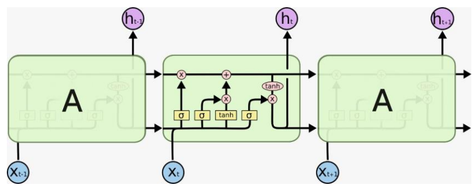
Fig 2. Depiction the training and testing paradigm for the supervised algorithm

Modeling Schemes

1. **K-Means:** Randomly initialized k feature vectors as the cluster centroids. Then, each feature vector is assigned to its closest cluster. Then, we recomputed the cluster centroids as mean of the f.v.s assigned to the respective cluster. The above process is repeated till convergence is observed. During testing, for a given test vector, compute distances and assign it to the closest cluster centroid.
2. **Hidden Markov Model:** For this study, we have implemented a Gaussian-HMM. In this, the states are discrete, i.e. the various activities of the subject. And the emission probabilities of each state are modeled as Gaussian R.V. The estimation of model parameters is done by an iterative Expectation-Maximization algorithm called as Baun-Welch algorithm. Given an observation sequence, the optimal hidden state sequence is calculated by Viterbi algorithm.



3. **LSTM:** Long Short Term Memory Networks are well suited for classifying, processing and making predictions based on time-series data. The LSTM architecture implemented is composed of a cell and 3 regulators called gated: an input gate, an output gate, and a forget gate. For training, data sequences were created using a window of size 200 taken with an overlap of 20. Training is done using an optimization algorithm, combined with back propagation through time to compute the gradients needed during the optimization process. Adam optimization algorithm was implemented to train the model.



Results

- The activity labels of WISDM dataset are: sitting, standing, walking, upstairs, downstairs, and jogging.
- The activity labels for pet data set are: bark, canter, gallop, lay, sit, stand, trot, and walk

Tab1: Table showing the performance of the models used on the WISDM and Pet Data Sets

Model	WISDM Data-Set	Pet Data Set
K-Means	15.79 %	7 %
Gaussian HMM	47.21 %	62.34 %
LSTM	86.91 %	76.10%

Conclusion

In this project, we have implemented 3 models namely, K-means, Gaussian-HMM, LSTM. From the results it can be observed that k-Means was not able to capture the temporal relationships present in data as it used. Further, from the results it is evident that Gaussian HMM was able to capture the temporal relationships in the data and shows a significant improvement in performance over k-Means. Finally, the performance of the LSTM network is better as compared to the performance of HMM model which signifies the importance of long temporal dependencies which are better captured by LSTM networks

Acknowledgement

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References

1. Jennifer R. Kwapisz, Gary M. Weiss and Samuel A. Moore (2010). Activity Recognition using Cell Phone Accelerometers, *Proceedings of the Fourth International Workshop on Knowledge Discovery from Sensor Data (at KDD-10)*, Washington DC.
2. A Binning Approach to Quickest Change Detection with Unknown Post-Change Distribution Tze Siong Lau, Wee Peng Tay, Senior Member, IEEE, and Venugopal V. Veeravalli, Fellow, IEEE
3. Adaptive Sequential Stochastic Optimization. Craig Wilson, Venugopal Veeravalli, Angelia Nedic.