Machine Learning

CLASSYFIRES

April 30, 2017

Abstract

Human Activity Recognition using Smartphone accelerometer and gyroscope data

1 Introduction

We had to classify six tasks: Stand, sit, walk, bike, stairs-up and stairs-down sing the gyroscope and accelerometer readings of an individual using a smart phone. The dataset that we used for the project contains the accelerometer and gyroscope readings in the x, y and z direction sampled at an interval of 100 Hz.The activities were carried out by 9 users on 4 smart phone models,namely Nexus4, Samsung S3, Samsung Gold and Samsung S3 mini.We tried various classification techniques like Neural Networks, Random Forest classification and finally LSTM and GRU. We did this separately for gyroscope and accelerometer data and finally run it on the merged data as well.

2 Procedure

2.1 Data processing

In general, data produced by sensors generate a large number of data. We had initially partitioned the dataset into 13 partitions for readability purposes which was then processed by taking out samples at the rate of 10Hz. We had initially mapped discrete values to users, Modes and Devices and then applied Neural Networks to this data which was obviously wrong as we hadn't come across One Hot Encoding at that stage. But once we read about it, we applied the same on our data for all the non-integer entries. Also for most of the models, we just dropped the User column as it did not seem to have much affect on the result. We kept the data separately for both gyroscope and accelerometer and merged them as and when required in the code to get better results.

2.2 Classification

We had initially used Neural Networks for classification but it did not make much sense to use just plain Neural Nets as the data which we were dealing with was time-series data. So we switched over to use Recurrent Neural Networks. We have used LSTM(Long Short-Term Memory) and GRU(Gated Recurrent Unit), which is a RNN architecture for classification. The library which we used was Keras for implementing the same.

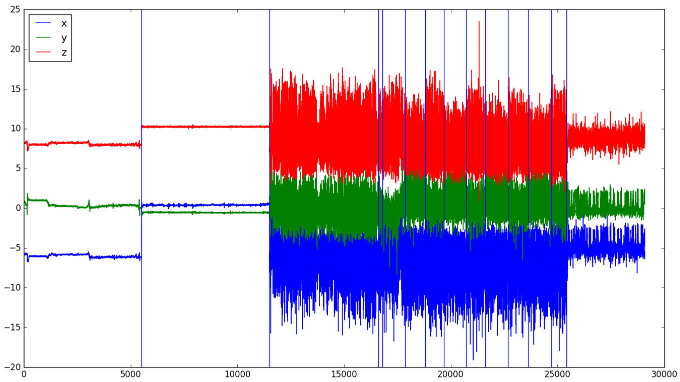
2.3 Training and Cross validation

We have used first 75% of the data for training and the next 25% is used as the test data. For training we varied the number of neurons in a layer, the number of hidden layers,batch size, number of epochs, loss function and activation function. We tried sigmoid, ReLu and softmax as activation functions.We also applied Normalisation on the x, y and z co-ordinates of the data.

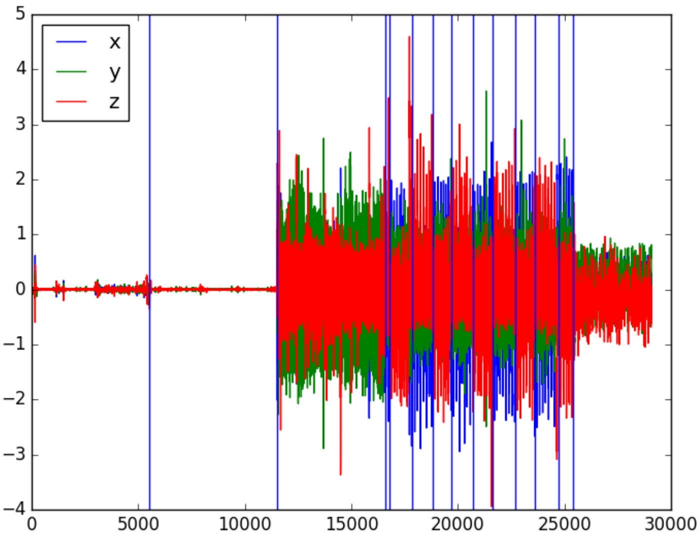
3 Results and Interpretation

3.1 Model Accuracy

Both the gyroscope as well as the accelerometer data independently gave results with accuracy upto 80%. The merged data however, gave an astonishing accuracy of more than 87%. The percentage accuracy on trained as well as test data are shown in the following figures while varying the number of epochs.The best result was obtained for sigmoid activation function and a batch size of 128, when number of epochs equaled 3, being 87.34%.

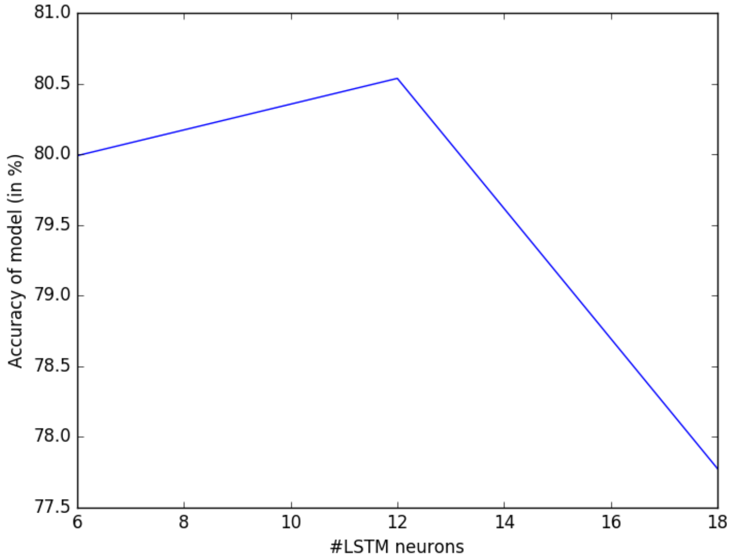


(a) Accelerometer data visualization for a single user.

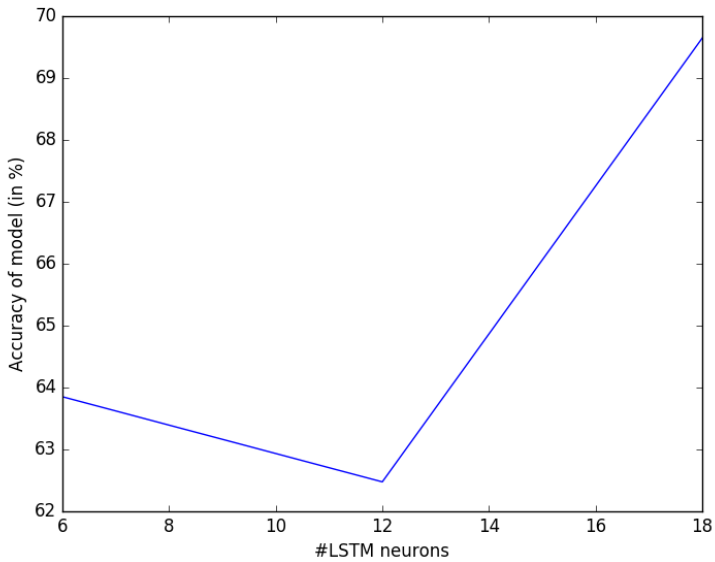


(b) Gyroscope data visualization for a single user.

Figure 1: Visualization for a single user(Blue line represents transition to another activity).



(a) Accelerometer data.



(b) Gyroscope data.

3.2 Observations

On combining the accelerometer and gyroscope datasets, due to increase in features, the model had more parameters to work with and achieved higher training and test accuracy.

We see that smaller the batch size, higher was the accuracy. There was not much change on the accuracy on changing the activation function. LSTM and

GRU gave almost the same accuracy. Among all the loss functions, 'binary-crossentropy' gave much better results.

4 Conclusion

We successfully managed to classify the actions of humans based on sensor data of gyroscope and accelerometer of a smart-phone accurately up to a great extent and produced satisfying results using several Machine Learning techniques. But there still remains a lot of scope for improvement. Some of the major improvements which can be done is removing sensor biases and doing a sophisticated feature extraction.

4.1 Comparison with other models

Comparing our LSTM model with the research paper mentioned in the first bullet of the references, the accuracy of their model was 95% and our model achieved an accuracy of 85% . However when we used a well preprocessed dataset(4th reference) we were also able to achieve 90+% accuracy, which shows us the importance of preprocessing the dataset and feature extraction.

5 References

- Allan Stisen, Henrik Blunck, Sourav Bhattacharya, Thor Siiger Prentow, Mikkel Baun Kjærgaard, Anind Dey, Tobias Sonne, and Mads Møller Jensen "Smart Devices are Different: Assessing and Mitigating Mobile Sensing Heterogeneities for Activity Recognition" In Proc. 13th ACM Conference on Embedded Networked Sensor Systems (SenSys 2015), Seoul, Korea, 2015.
- Using Machine Learning on Sensor Data (Journal of Computing and Information Technology - CIT 18, 2010, 4, 341–347 doi:10.2498/cit.1001913)
- https://archive.ics.uci.edu/ml/datasets/Heterogeneity+Activity+Recognition
- https://archive.ics.uci.edu/ml/datasets/Smartphone-Based+Recognition+of+Human+Activities+and+Postural+Transitions

6 Contribution

- Data processing: Aniket.
- Model Architecture: Purav, Abhishek, Aniket.
- Implementation of Neural Network(Pre-Midsem): Aniket.
- Implementation of LSTM: Abhishek(major part), Purav, Aniket.
- Report making: Aniket, Abhishek.
- Presentation making: Purav