Paper ID: 72

Human Activity Recognition using RNNs

Term Project
Neural Network & Fuzzy Logic (BITS F312)

Yash Bhagat 2017A7PS0063P
Rajeev Singh Naruka 2017A7PS0010P
Dhairya Bhorania 2017A8PS0260P

PROJECT INTRODUCTION

Human activity recognition using smart home sensors is a topic undergoing intense research in the field of ambient assisted living.

The increasingly large amount of data sets calls for machine learning methods.

In this paper, a deep learning models that learns to classify human activities are used.

For this purpose, a Long Short Term Memory (LSTM) Recurrent Neural Network was applied.

ABOUT THE DATASET

OPPORTUNITY Activity Recognition Data Set.

The OPPORTUNITY Dataset for Human Activity Recognition from Wearable, Object, and Ambient Sensors is a dataset devised to benchmark human activity recognition algorithms (classification, automatic data segmentation, sensor fusion, feature extraction, etc).

courtesy of UCI ML repository and ETH, Zurich.

Data Set Characteristics:	Multivariate, Time-Series	**Number of Instances:**	2551	**Area:**	Computer
Attribute Characteristics:	Real	**Number of Attributes:**	242	**Date Donated**	2012-06-09
Associated Tasks:	Classification	**Missing Values?**	Yes	**Number of Web Hits:**	89929

The dataset comprises the readings of motion sensors recorded while users executed typical daily activities:

* Body-worn sensors: 7 inertial measurement units, 12 3D acceleration sensors, 4 3D localization information

* Object sensors: 12 objects with 3D acceleration and 2D rate of turn

* Ambient sensors: 13 switches and 8 3D acceleration sensors

* Recordings: 4 users, 6 runs per users. Of these, 5 are Activity of Daily Living runs characterized by a natural execution of daily activities. The 6th run is a "drill" run, where users execute a scripted sequence of activities.

* Annotations/classes: the activities of the user in the scenario are annotated on different levels: "modes of locomotion" classes; low-level actions relating 13 actions to 23 objects; 17 mid-level gesture classes; and 5 high-level activity classes

Column Description

Column1: Time in Milisecond

Column 1 to 37: Accelerometer around body of subject. unit = milli g

Column 38 to 134: Inertial Measurement Units like   3D acceleration, 3D rate of turn, 3D magnetic field, and orientation of the sensor

Column 135 to 194: Accelerometer on objects. unit = milli g

Column 195 to 207: Reed switch. unit = logical (0/1)

Column 208 to 231: Accelerometer on drawers,doors, etc. unit = milli g

Column 232 to 243: Location tags. unit = millimetres

Labels Description

Label columns:

Column: 244 Locomotion

Column: 245 HL_Activity

Column: 246 LL_Left_Arm

Column: 247 LL_Left_Arm_Object

Column: 248 LL_Right_Arm

Column: 249 LL_Right_Arm_Object

Column: 250 ML_Both_Arms

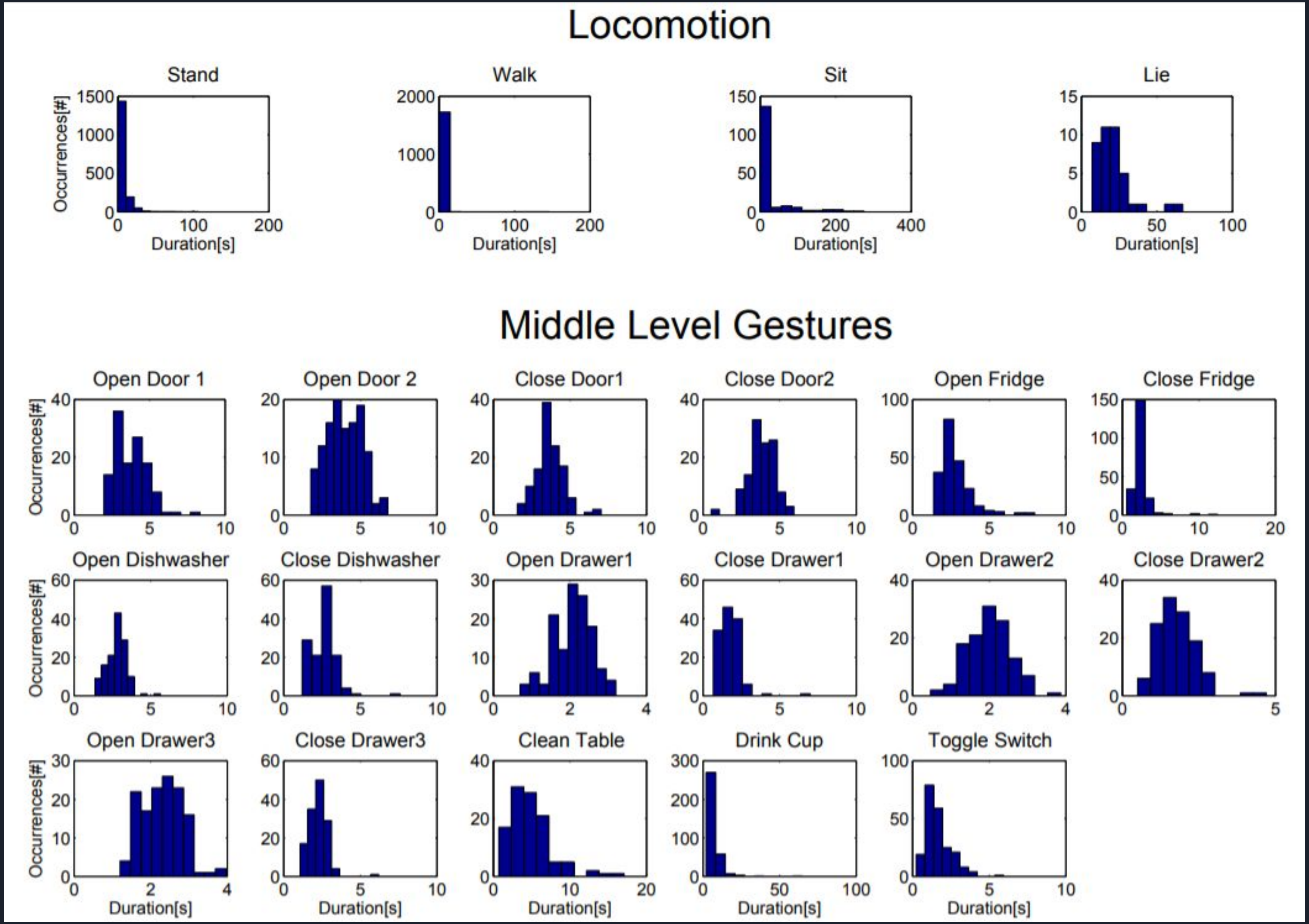
Methodology

We used Long short-term memory (LSTM) for this project which is an artificial recurrent neural network (RNN) architecture.

A common LSTM unit is composed of **a cell, an input gate, an output gate** and **a forget gate**. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell.

LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series.

We have also used GRU (Gated Recurrent Units) also and have drawn a comparison between them.



Locomotion
Stand
Walk
Sit
Lie
Occurrences[#]
Duration[s]
Middle Level Gestures
Open Door 1
Open Door 2
Close Door1
Close Door2
Open Fridge
Close Fridge
Open Dishwasher
Close Dishwasher
Open Drawer1
Close Drawer1
Open Drawer2
Close Drawer2
Open Drawer3
Close Drawer3
Clean Table
Drink Cup
Toggle Switch

Preprocessing the data

1. We used following python libraries during this project: Pandas, Numpy, sklearn, keras, pickle , matplotlib
2. Since data from sensors was continuous, whenever there was NaN encountered, the previous value of sensor was taken to replace it.
3. Next, feature scaling was done because in LSTM, objective functions will not work properly without normalization.
4. After normalization, Labelling was done and label columns were removed before training.
5. Now, we converted data from 2D to 3D for LSTM, where the dimensions of the array are [samples, time steps, features].
6. Saved this preprocessed data in Numpy data format.

Model Parameters Description

For predicting Locomotion:

- Input Nodes : 133
- Hidden Nodes: 35
- Output Nodes : 5
- Window Size : 32

For predicting High Level Activity:

- Input Nodes : 99
- Hidden Nodes: 30
- Output Nodes : 5
- Window Size : 32

Locomotion Prediction for Subject 1 using LSTM

We predicted locomotion for all the users.

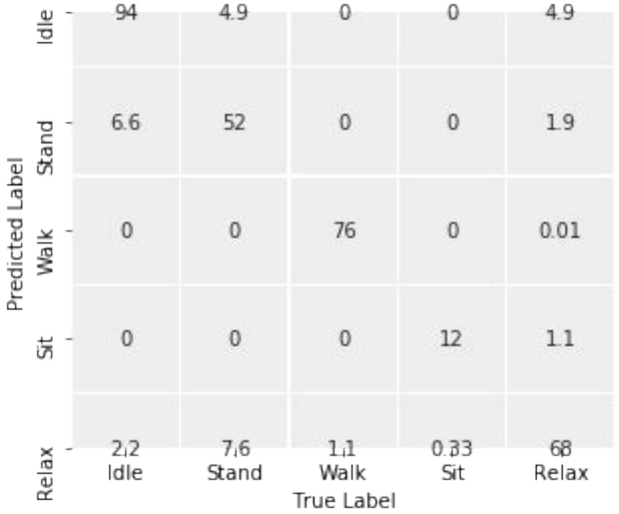
This is confusion matrix of Subject 1, ADL3.

Accuracy score = 0.9078547576787702

F1 score = 0.9080745337361374

Recall score = 0.9078547576787702

Precision score = 0.9089062763306287



Locomotion Prediction for Subject 2 using LSTM

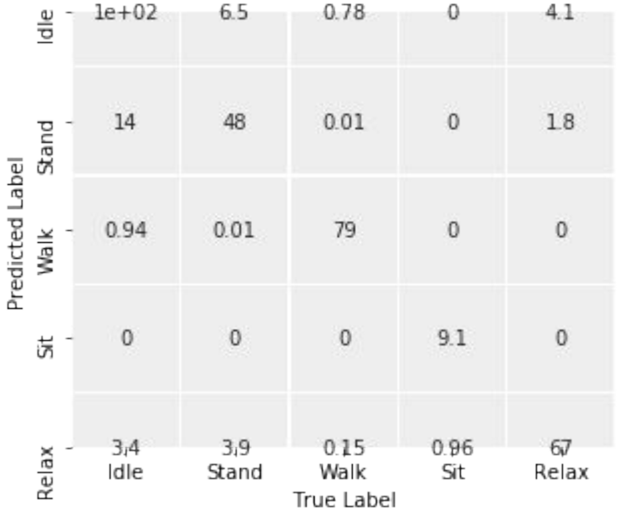
This is confusion matrix of Subject 2, ADL3.

Accuracy score = 0.8940643274853801

F1 score = 0.8933840898664495

Recall score = 0.8940643274853801

Precision score = 0.8939353388384801



Locomotion Prediction for Subject 3 using LSTM

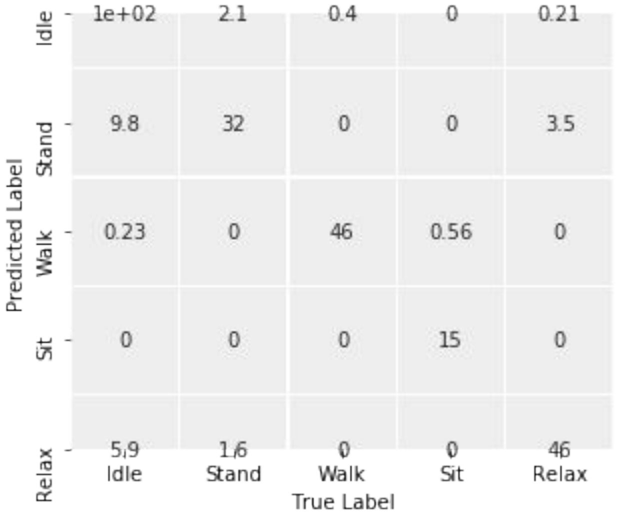
This is confusion matrix of Subject 3, ADL3.

Accuracy score = 0.9092748735244519

F1 score = 0.9068413721373243

Recall score = 0.9092748735244519

Precision score = 0.9112229299941746



Locomotion Prediction for Subject 4 using LSTM

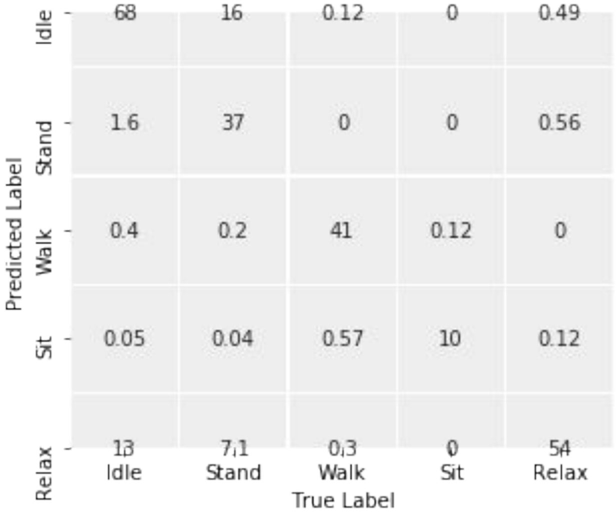
This is confusion matrix of Subject 4, ADL3.

Accuracy score = 0.8361752988047809

F1 score = 0.8400106080628537

Recall score = 0.8361752988047809

Precision score = 0.8665501987545591



High-Level Activity Prediction for Subject 1 using LSTM

0 - HL_Activity - Relaxing

1 - HL_Activity - Coffee time

2 - HL_Activity - Early morning

3 - HL_Activity - Cleanup

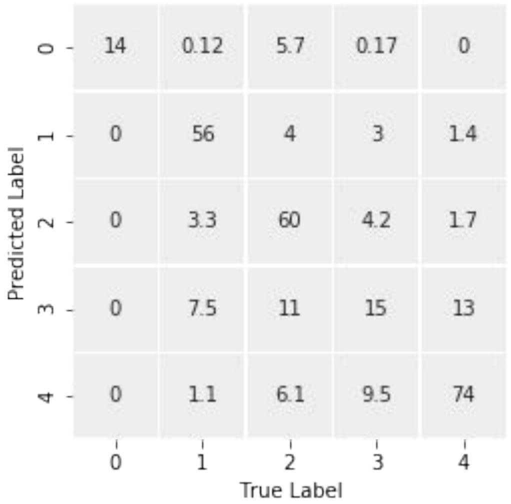
4 - HL_Activity - Sandwich time

Accuracy score = 0.7523408077946309

F1 score = 0.7424607522685885

Recall score = 0.7523408077946309

Precision score = 0.7455713128970118



High-Level Activity Prediction for Subject 2 using LSTM

0 - HL_Activity - Relaxing

1 - HL_Activity - Coffee time

2 - HL_Activity - Early morning

3 - HL_Activity - Cleanup

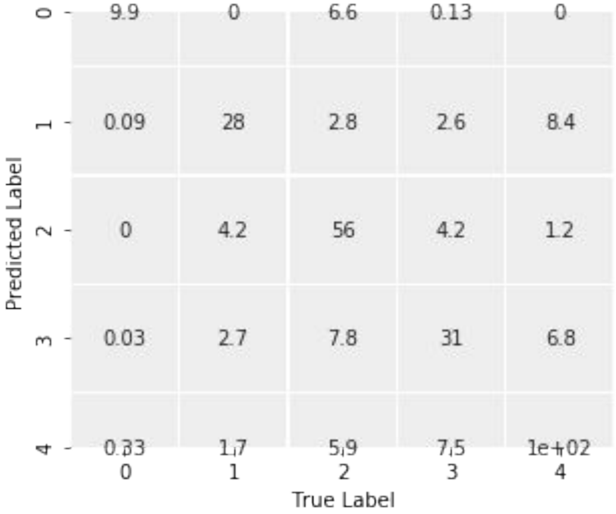
4 - HL_Activity - Sandwich time

Accuracy score = 0.7832818400274631

F1 score = 0.7815344340088767

Recall score = 0.7832818400274631

Precision score = 0.7888172552421614



GRU-units based prediction for Subject 1 locomotion

0 - HL_Activity - Relaxing

1 - HL_Activity - Coffee time

2 - HL_Activity - Early morning

3 - HL_Activity - Cleanup

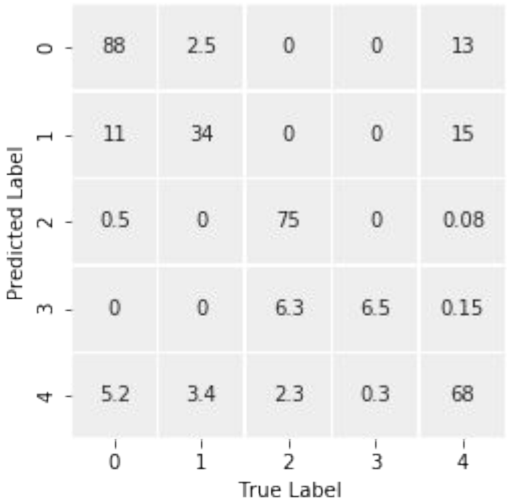
4 - HL_Activity - Sandwich time

Accuracy score = 0.8187479317710057

F1 score = 0.8124637617944473

Recall score = 0.8187479317710057

Precision score = 0.8271011883334703



GRU-units based prediction for Subject 2 High-level activity

0 - HL_Activity - Relaxing

1 - HL_Activity - Coffee time

2 - HL_Activity - Early morning

3 - HL_Activity - Cleanup

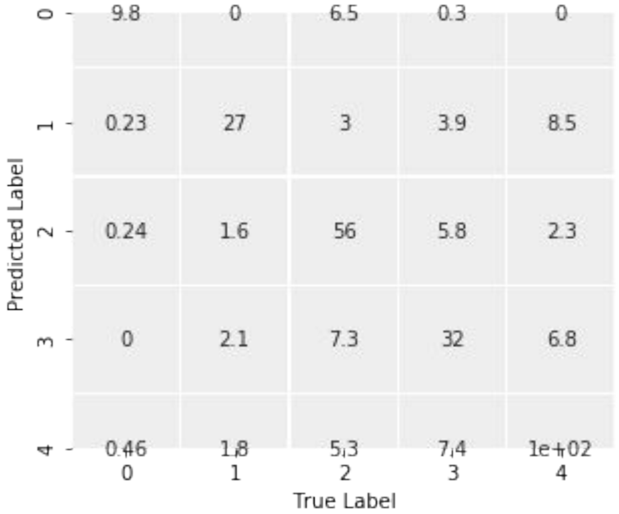
4 - HL_Activity - Sandwich time

Accuracy score = 0.7821489872983178

F1 score = 0.7802625951412586

Recall score = 0.7821489872983178

Precision score = 0.7890066373025654



GRU vs. LSTM

Prediction of Locomotion for subject 1

Accuracy score = 0.81874

F1 score = 0.81246

Recall score = 0.81874

Precision score = 0.82710

Accuracy score = 0.90785

F1 score = 0.90807

Recall score = 0.90785

Precision score = 0.90890

GRU vs. LSTM

Prediction of High-level Activity for subject 2

Accuracy score = 0.78214	Accuracy score = 0.78328
F1 score = 0.78026	F1 score = 0.78153
Recall score = 0.78214	Recall score = 0.78328
Precision score = 0.78900	Precision score = 0.78881