Sensor Based Activity Recognition

Deep Learning approach to classify human activity

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| Created on: | 16/11/2022 |
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| FHNW Data Science/ | HS22 |

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# Introduction

Human Activity Recognition (HAR) is the identification of one or more human physical activities using sensor data. Wearables such as Apple/ Garmin smart watches uses built-in sensors to counts number of steps or kms travelled. Smartphones too have multiple build-in sensors, which can be used to detect events or gather data about human activities. There are wide range of applications where these sensors come into play such as IoT topics, smart Home, Find your Phone etc.

Using classical Machine Learning (ML) algorithms such as decision tree & Deep Learning (DL) algorithms such as Convolutional Neural Network(CNN), it is possible to train models to classify an activity.

Classification task is one of the standard ML tasks, which is about mapping a class label to a given item. In this challenge, the task in hand is to assign an activity (*class label*) based on input sensor signal (*item*). It is multi-class classification problem as the target class has four labels: Walking, Running, Cycling, and sitting.

The goal is to train models based on different ML algorithms as well as deep learning and compare their performance based on prediction accuracy.

* Which variables are key in classifying an activity? (feature importance)
* What effect does a specific data transformation has on the performance of ML algorithms?
* Does performance of ML algorithms vary by using different aggregation approaches on data points?
* Which aggregation on data points makes more sense?

# Methodology

## Data collection

Raw data was collected using iOS App ‘SensorLog’ [[1]](#_References) by user 1 & Android App ‘AndroSensor’ [[2]](#_References) by user 2, with frequency of 100 Hz i.e. 100 data points recorded per second. Each user logged four activities of 20 minutes duration each: Walking, Running, Cycling and sitting (idle). Each activity was logged with mobile device in left pant pocket and with device screen either towards body or away from body or device upside down or device upright. Raw data was saved in csv format. The meta-data on each of these raw csv files was documented for reference later. See [Fig 1 in Appendix](#_Appendix).

As two different apps were used to log data, different sensors are used (which are dependent on the physical device of the user) and the resulting raw data from different apps has different set of variables/features. An overview is available in Table 1:

|  |  |  |
| --- | --- | --- |
|  | **SensorLog App** | **AndroSensor App** |
| **User** | User 1 | User 2 |
| **Device** | iPhone | Android |
| **# of variables** | ~71 variables | ~31 variables |
| **Duration** | 20 mins | 20 mins |

Table 1: Overview on Apps used to log raw data

## Data Exploration

A simple experiment was done at the beginning in which one user performed a single activity and logged it using both apps at the same time i.e. iPhone and Android device at the same time in the pant pocket while going for a walk. The results from these two apps was then compared and underlying characteristics pro sensor such as units, magnitude, coordinates were compared. Based on this experiment, it was observed that certain sensor data from Android app needs to be transformed to align it with same sensor data from iPhone app. Details on these transformations is captured in table 2.

|  |  |  |  |
| --- | --- | --- | --- |
| **Sensor** | **SensorLog (iPhone)** | **AndroSensor (Android)** | **Transformation** |
| Accelerometer | Measures in G i.e. value of 1 G corresponds to earth’s gravity of 9.8 | Measures in unit | Accelerometer & Gravity sensor data for AndroSensor transformed to G by dividing by -9.80665 |
| Gravity | Measures in *G* | Measures in unit |
| Orientation | Measured in unit *rad* | Measures in unit *degree* | AndroSensor data transformed to unit rad & flipped by dividing by -60 |

Table 2: Overview of data transformations

Explorative data analysis was performed on raw data for each activity and user.

Observations:

* Each app logs different sensor data in

## Data handling

Each activity [log](#_Terminology) using SensorLog/AndroSensor generated a Comma Separated value (CSV) file. Each row of this file represents one data point with a timestamp. Each file includes data from different sensors such as accelerometer, magnetometer, gyroscope and orientation sensors for each axis (X, Y & Z).

GPS data such as latitude, longitude and altitude were not considered since Android App didn’t always log it properly.

## Model training

<to be added>

[summary of different experiments which were run]

|  |  |  |  |
| --- | --- | --- | --- |
| Nr | Model | Model complexity |  |
| 1 | Logistic regression |  |  |
| 2 | Decision Tree |  |  |
| 3 | Random Forest |  |  |

# Results

[atleast 2 models and their comparison based on ]

* Model complexity
* How long do we let model run
* Model accuracy on test data

# Conclusion

# Appendix

### About Sensors

Terminology about main device sensors is introduced below:

|  |  |
| --- | --- |
| **Yaw** , **pitch** and **roll** refer to the rotation of the device in three axes. [[6]](#_References) | figure 1  *Source: Springer* |
| **Accelerometer**: measures the linear acceleration of the device on X, Y & Z axis as G-force values. On iPhone, a value of 1.0 represents a load of approximately 1-gravity (Earth’s gravity = 9.8 m per seconds). While in motion, the figures represent the acceleration due to gravity, plus the acceleration of the device itself relative to its rest frame.  X corresponds to roll, Y to pitch and Z to whether the device is front side up or front side down. | The iPhone accelerometer axes  Accelerometer axes  *Source: O’Reilly* |
| **Gyroscope**: measures the rate at which a device rotates around a spatial axis in radians per second. Rotation value may be positive or negative depending on the direction of the rotation. | Gyroscopes measure the rotation rate around the x, y, and z axes  *Source: Apple developer doc* |
| **Magnetometer**: measures the earth’s magnetic field relative to the device in micro Tesla. In the absence of any strong local fields, these measurements will be of the ambient magnetic field of the Earth, allowing the device to determine its “heading” with respect to the geomagnetic North pole. Combing the heading (yaw) information returned by the device with the roll and pitch information returned by the accelerometer helps determine the true orientation of the device in real time. | Using the magnetometer (a.k.a. the digital compass) in the iPhone 3GS you can determine the heading (yaw) of the device  *Source: O’Reilly* |

### Meta-Data for raw data (csv files):

Table

Description automatically generated

Figure 1: Meta-data on raw data

### Raw sensor data

Below sensor data for activity ‘running’ is plotted and compared for both users

|  |
| --- |
| Graphical user interface, chart  Description automatically generated  Chart  Description automatically generated  Chart  Description automatically generated  Chart  Description automatically generated |

Below sensor data for activity ‘walking is plotted and compared for both users :

|  |
| --- |
| Graphical user interface, chart  Description automatically generated  Chart  Description automatically generated  Chart  Description automatically generated  Chart  Description automatically generated with medium confidence |

Below sensor data for activity ‘cycling’ is plotted and compared for both users :

|  |
| --- |
|  |

Below sensor data for activity ‘sitting’ is plotted and compared for both users :

|  |
| --- |
|  |

### Transformations

The AndroSensor data for following sensors was transformed in order to bring it to same units as iPhone sensor data:

* Accelerometer (divided by -9.80665) -> from unit to G
* Gravity (divided by -9.80665) -> from unit to G
* Orientation (divided by -60) -> from unit deg to rad

### References

[1] SensorLog [iOS App](https://apps.apple.com/us/app/sensorlog/id388014573)

[2] AndroSensor [Android App](https://play.google.com/store/apps/details?id=com.fivasim.androsensor&hl=en&gl=US)

[3] Research paper : Amari Vaughn, Paul Biocco, Yang Liz, Mohd Anwar, 2018 Activity Detection and Analysis Using Smartphone Sensor

[4] Time-series resampling and moving windows: [Link](https://coderzcolumn.com/tutorials/data-science/time-series-resampling-and-moving-window-functions)

[5] iPhone [accelerometer](https://developer.apple.com/documentation/coremotion/getting_raw_accelerometer_events), [Gyroscope](https://developer.apple.com/documentation/coremotion/getting_raw_gyroscope_events), [Magnetometer](https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjS8ovx-4r8AhUG_7sIHQQJBgQQFnoECA0QAQ&url=https%3A%2F%2Fwww.oreilly.com%2Flibrary%2Fview%2Fbasic-sensors-in%2F9781449309480%2Fch05.html&usg=AOvVaw1MiMxMTmxCF2Kp9GP8d7im)

[6] Yaw, pitch and roll : [Link](https://learn.microsoft.com/en-us/previous-versions/windows/desktop/bb281738%28v=vs.85%29) & [Springer](https://link.springer.com/article/10.3758/s13428-020-01404-5/figures/1)

[7]

### List of Abbreviations

|  |  |
| --- | --- |
| ML | Machine Learning |
| DL | Deep Learning |
| CNN | Convolutional Neural Network |
| RNN | Recurrent Neural Network |
| HAR | Human Activity Recognition |
| LSTM | Long Short-Term Memory |
| CSV | Comma separated value |

### Terminology

|  |  |
| --- | --- |
| Log | Log is referred as an activity over 20 minutes => 1 csv file |
| Variable/feature |  |
|  |  |