# Classification of human posture and movement

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**Abstract**

Coming soon...

## 1 Introduction

Human activity classification has wide reaching applications, such as in providing medical assistance to disabled or elderly persons. This project implements several machine learning algorithms to classify human posture and movements. The different activities being classified are:

- Sitting
- Sitting down
- Standing
- Standing up
- Walking

The difference between "Sitting" and "Sitting down" is that the former is the static posture, whereas the latter is the transitional movement from standing to sitting.

### 1.1 Past work

Coming soon...

## 2 Data

### 2.1 Source

The data is made publicly available on UCI's Machine Learning Repository. It can be accessed at: http://groupware.les.inf.puc-rio.br/har#dataset.

### 2.2 Description

The dataset contains the following features

- Age
- Weight
- Body Mass Index
- Height
- x,y,z axis readings from 4 different accelerometers

Table 1: Frequency of each class

| **Class** | **Frequency** |
|---|---|
| Sitting | 50631 |
| Sitting down | 11827 |
| Standing | 47370 |
| Standing up | 12415 |
| Walking | 43390 |

# 3 Features

The features used in our models are the 12 accelerometer readings. Although the original data also contains age, weight, body mass index and height, they are neglected in this preliminary analysis and classification because they are less relevant in determining human movement compared with the 12 accelerometer readings.

# 4 Gaussian Discriminant Analysis

## 4.1 Binary classification

The first model implemented was the GDA model. For each class, 90% of the class's data is used as positive training examples, while 90% from each of the other classes are concatenated to be used as negative training examples.

## 4.2 Multi-class classification

For a testing example, in order to make a prediction into 1 of the 5 classes, the posterior distribution is calculated for each class, and the predicted label is chosen depending on the largest posterior.

That is

$$h_\theta(x) = \arg\max_y p(x|y)p(y)$$

where $y \in \{1, 2, 3, 4, 5\}$.

## 4.3 Results

The confusion matrix of the results is shown below:

| Actual \ Predicted | Sitting | Sitting down | Standing | Standing up | Walking |
|---|---|---|---|---|---|
| Sitting | 3916 | 1126 | 0 | 22 | 0 |
| Sitting down | 0 | 1112 | 63 | 7 | 2 |
| Standing | 0 | 601 | 4136 | 0 | 1 |
| Standing up | 116 | 558 | 454 | 103 | 11 |
| Walking | 0 | 1257 | 900 | 48 | 2135 |

Most of the errors come from predicting "sitting down" and "standing up" These are both two transitional states, depending on the exact instant when the accelerometer readings were taken, they could easily be confused with the state of "sitting" or "standing".

# 5 k-means

## 5.1 Training

The second model implemented is k-means. Although k-means is primarily used in unsupervised learning where there are no labels and we have 5 labels in this classification problem, because that a particular human movement usually requires a harmonious coordination among different parts of the body, accelerometer readings would exhibit clustering properties.
For each class, 5000 data examples are used to train the model, totaling $5000 \times 5 = 25000$ training examples. 30 iterations are conducted to find the cluster centroids.

## 5.2 Model Validation

Although the accelerometer readings would exhibit clustering properties, due to human movements' complexity, the centroids could be close to each other and thus could cause misclassifications. Therefore it is important to validate the clustering. All training examples are now used as testing examples to check if they have been properly classified.
The confusion matrix of the validation is shown below:

| Actual \ Predicted | Sitting | Sitting down | Standing | Standing up | Walking |
|---|---|---|---|---|---|
| Sitting | 5000 | 1883 | 0 | 482 | 286 |
| Sitting down | 0 | 0 | 0 | 0 | 744 |
| Standing | 0 | 1742 | 5000 | 1509 | 3959 |
| Standing up | 0 | 1367 | 0 | 2169 | 7 |
| Walking | 0 | 8 | 0 | 840 | 4 |

It can be seen that the classifications of Sitting and Standing are precise, classifications if sitting down and walking are poor while the classification of Standing up is moderate.

## 5.3 Results

1000 examples in each calss different from the training examples are used to test the model. The confusion matrix of the testing is shown below:

| Actual \ Predicted | Sitting | Sitting down | Standing | Standing up | Walking |
|---|---|---|---|---|---|
| Sitting | 1000 | 73 | 0 | 54 | 27 |
| Sitting down | 0 | 0 | 0 | 2 | 95 |
| Standing | 0 | 340 | 1000 | 26 | 859 |
| Standing up | 0 | 579 | 0 | 253 | 0 |
| Walking | 0 | 8 | 0 | 665 | 19 |

It can be seen that the testing results is similar to the validation results, showing very good classifications of sitting and standing but unsatisfactory classifications of sitting down, standing up and walking. This suggests a relatively poor capability for k-means to distinguish among dynamic movements of humans.

# 6 Next steps

Intuitively, among the 12 accelerometer readings, there are readings that are more relevant to human movement classifications. For examples, these 5 classes of human motions does not involve lateral movements. Thus lateral readings x1, x2, x3 and x4 are actually introduced as noises in the machine leaning perspective. They are also the most probable culprit for causing misclassifications. In the next step, these readings would be carefully scrutinized to determine their influence on the machine learning model and the accuracy of the prediction.