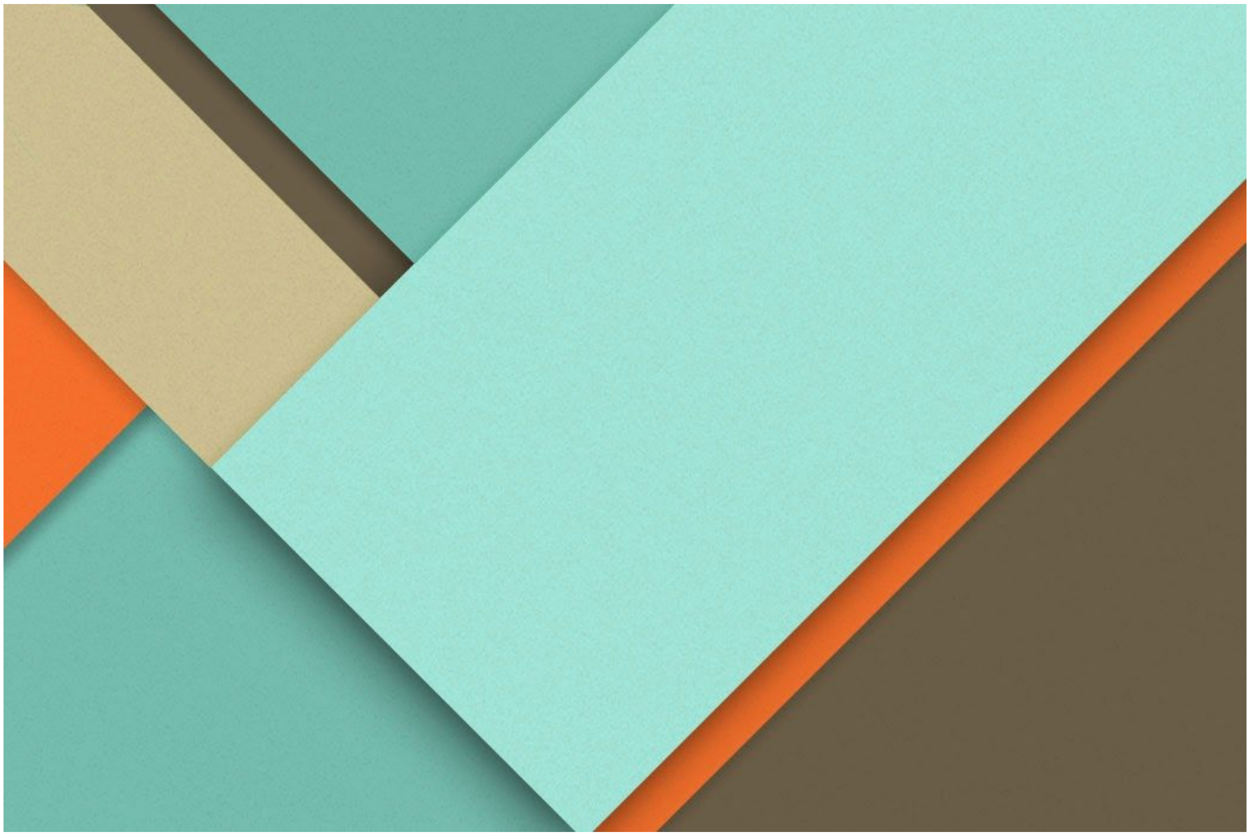

Human Activity Recognition

Udacity Machine Learning Engineer Nanodegree: Capstone Project Proposal

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Domain Background

The problem of automatic identification of physical activities performed by human subjects is referred to as Human Activity Recognition (HAR) [1]. HAR is an attractive area of research due to its application in areas such as smart environments and healthcare [2], especially in the Intellectual and Developmental Disability (I/DD) space where I operate. If embedded inertial sensors such as accelerometers and gyroscopes found in smartphones and smartwatches can be used to predict activities of daily living (ADL), then patients with I/DD can be accurately monitored and a much better service provided. No such system exists for the industry yet. It is my goal to introduce such a mechanism.

Problem Statement

The goal is to use the processed/raw accelerometer and gyroscope sensor data to classify activities into one of the six basic ADL: three static postures (**standing, sitting, lying**) and three dynamic activities (**walking, walking downstairs and walking upstairs**). The data also includes postural transitions that occurs between the static postures. These are: **stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie, and lie-to-stand**. Hence, given a stream of such data, the goal is to accurately classify the activities with a high degree of accuracy for real-life deployment.

Datasets and Input

The dataset is the Smartphone-Based Recognition of Human Activities and Postural Transitions Data Set [3]. It was built from the recordings of 30 study participants within the age bracket of 19 to 48 years performing ADL while carrying a waist-mounted smartphone (Samsung Galaxy S II) with embedded inertial sensors. The dataset consists of 10299 samples with 561 attributes. The sensor signals (accelerometer and gyroscope) were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter into body acceleration and gravity. 70% of the volunteers were selected for generating the training set and 30% for the test set. For each record in the dataset the following is provided:

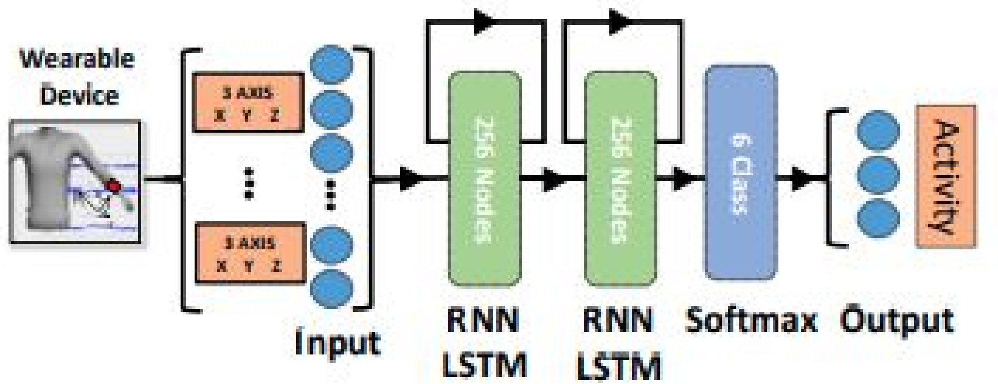
I. Triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration.
II. Triaxial Angular velocity from the gyroscope.

III. A 561-feature vector with time and frequency domain variables.
IV. Its activity label.
V. An identifier of the subject who carried out the experiment.

Solution Statement

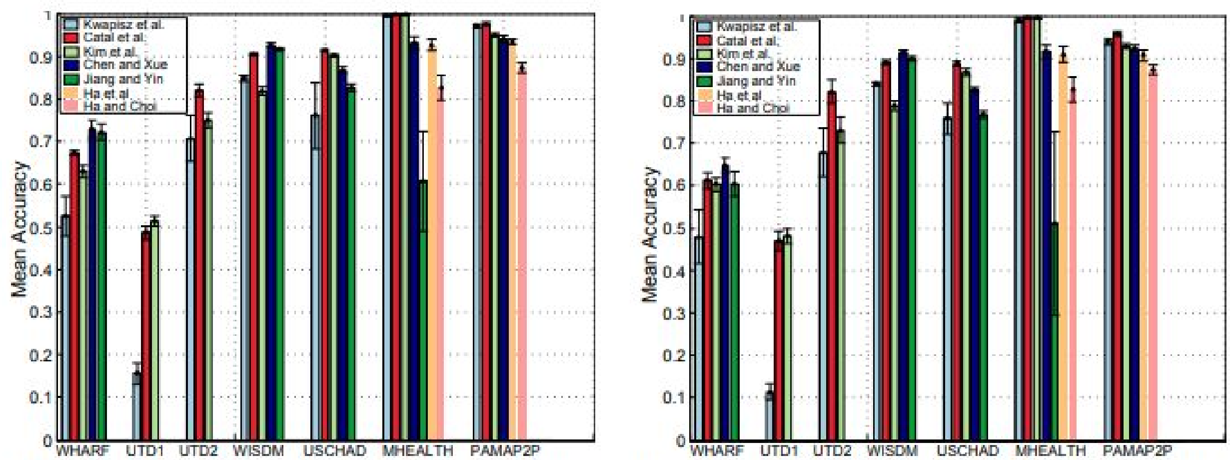
The goal is to develop a state-of-the-art HAR classifier. In the past, CNNs have been used since they have the advantage of being translationally invariant. However, instead of making a classification on a sample of data, I want to learn the underlying trend in these sensor readings. This is because my target audience (I/DD patients) are likely to be very different psychologically and in movement from a fully healthy human being. Hence, I plan on using a RNN since it usually performs better in capturing trends in time-series data.

Fig 1: A possible RNN model [4].



Benchmark Model

Fig 2: Mean Accuracy of different sampling techniques [2].



(a) Results using the semi-non-overlapping-window and cross validation (SNCV) combination.

(b) Results using the full-non-ovelapping-window and cross validation (FNCV) combination.

The diagram shows accuracies obtained on different datasets using different sampling and validation strategies. It is clear that at least 95% accuracy is a realistic target and that is what I am aiming for.

Evaluation Metrics

A simple accuracy measure is sufficient for this task.

Accuracy = (TP + TN) / (TP + FP + FN + TN)

Project Design

I. Load and analyze the training data for feature dependence.

II. Manually extract features or apply PCA. Retain components that preserve 80% of the data variance.

III. Divide the dataset into sequences of length128.

IV. Train a baseline LSTM model.

V. Tune hyperparameters and retrain .

VI. Test accuracy on the test data.

References

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3. Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. A Public Domain Dataset for Human Activity Recognition Using Smartphones. 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013. Bruges, Belgium 24-26 April 2013.
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