Capstone Project

Machine Learning Engineer Nanodegree

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Jan 23th, 2018

Definition

Project Overview

"With the rapid advances in micro electro-mechanical systems (MEMS) technology, the size, weight and cost of commercially available inertial sensors have decreased considerably over the last two decades. A recent application domain of inertial sensing is automatic recognition and monitoring of human activities".

In this project, I created a classifier that recognize daily and sports activities done by a person with the help of signals from inertia sensors dataset.

Problem Statement

"Automatic recognition, representation and analysis of human activities based on video images has had a high impact on security and surveillance, entertainment and personal archiving applications.

Using cameras fixed to the environment (or other ambient intelligence solutions) may be acceptable when activities are confined to certain parts of an indoor environment. If cameras are being used, the environment needs to be well illuminated and almost studio like. However, when activities are performed indoors and outdoors and involve going from place to place (e.g. commuting, shopping, jogging), fixed camera systems are not very practical because acquiring video data is difficult for long-term human motion analysis in such unconstrained environments. Recently, wearable camera systems have been proposed to overcome this problem; however, the other disadvantages of camera systems still exist, such as occlusion effects, the correspondence problem, the high cost of processing and storing images, the need for using multiple camera projections from 3D to 2D, the need for camera calibration and cameras' intrusions on privacy".

Analysis

Data Exploration

Each of the 19 activities is performed by eight subjects (4 female, 4 male, between the ages 20 and 30) for 5 minutes. Total signal duration is 5 minutes for each activity of each subject. The subjects are asked to perform the activities in their own style and were not restricted on how the activities should be performed.

For this reason, there are inter-subject variations in the speeds and amplitudes of some activities. The activities are performed at the Bilkent University Sports Hall, in the Electrical and Electronics Engineering Building, and in a flat outdoor area on campus. Sensor units are calibrated to acquire data at 25 Hz sampling frequency. The 5-min signals are divided into 5-sec segments so that 480(=60x8) signal segments are obtained for each activity.

The 19 activities are:

- Sitting (A1),
- Standing (A2),
- Lying on back and on right side (A3 and A4),
- Ascending and descending stairs (A5 and A6),
- Standing in an elevator still (A7)
- Moving around in an elevator (A8),
- Walking in a parking lot (A9),
- Walking on a treadmill with a speed of 4 km/h (in flat and 15 degree inclined positions) (A10 and A11),
- Running on a treadmill with a speed of 8 km/h (A12),
- Exercising on a stepper (A13),
- Exercising on a cross trainer (A14),
- Cycling on an exercise bike in horizontal and vertical positions (A15 and A16),
- Rowing (A17),
- Jumping (A18),
- Playing basketball (A19).

File structure:

- 19 activities (a) (in the order given above)
- 8 subjects (p)
- 60 segments (s)
- 5 units on torso (T), right arm (RA), left arm (LA), right leg (RL), left leg (LL)
- 9 sensors on each unit (x, y, z accelerometers, x, y, z gyroscopes, x, y, z magnetometers)
- Folders a01, a02, ..., a19 contain data recorded from the 19 activities.
- For each activity, the subfolders p1, p2, ..., p8 contain data from each of the 8 subjects.
- In each subfolder, there are 60 text files s01, s02, ..., s60, one for each segment.
- In each text file, there are 5 units x 9 sensors = 45 columns and 5 sec x 25 Hz = 125 rows.
- Each column contains the 125 samples of data acquired from one of the sensors of one of the units over a period of 5 sec.
- Each row contains data acquired from all of the 45 sensor axes at a particular sampling instant separated by commas.

Dataset download from https://archive.ics.uci.edu/ml/datasets/Daily+and+Sports+Activities

Algorithms and Techniques

“The classification techniques used in daily and sports activity recognition research include threshold-based classification, hierarchical methods, decision trees (DTs), the *k*-nearest neighbor (*k*-NN) method, artificial neural networks (ANNs), support vector machines (SVMs), naive Bayesian (NB) model, Bayesian decision-making (BDM), Gaussian mixture models (GMMs), fuzzy logic and Markov models, among others”.

Benchmark

“BDM provides a correct classification rate of 99.2% with relatively small computational cost and storage requirements. The same rate of 99.2% is achieved with ANN and SVM in WEKA. The average correct classification rates previously reported for BDM using RRSS and 10-fold cross-validation techniques are 99.1 and 99.2%, respectively, whereas these rates drop to 96.5 and 96.6% for NB”.

Methodology

Implementation

First of all to make daily and sport activities dataset ready for machine learning algorithm some techniques of data wrangling including merging is done. Dataset will be divide into training set and test dataset. Feature scaling of data is done. After that using various machine learning algorithm (such as SVM, Decision tree, ANN, Naïve Bayes etc.), accuracy of all models are obtained and some model with highest accuracy are selected and their hyperparameter are tuned to increase accuracy.
It is a case of multiclass classification so strategy is to train a binary classifier for every pair of digits: one to distinguish 0s and 1s, another to distinguish 0s and 2s, another for 1s and 2s, and so on. This is called the one-versus-one (OvO) strategy.

Results

Model Evaluation and Validation

Evaluation is done by Confusion Metrix which is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

It is often convenient to combine precision and recall into a single metric called the F1 score, in particular if you need a simple way to compare two classifiers. The F1 score is the harmonic mean of precision and recall. Whereas the regular mean treats all values equally, the harmonic mean gives much more weight to low values. As a result, the classifier will only get a high F1 score if both recall and precision are high.

References

http://kilyos.ee.bilkent.edu.tr/~billur/publ_list/cj14.pdf

https://en.wikipedia.org

http://www.sciencedirect.com/science/article/pii/S0306457309000259

Hands-On Machine Learning with Scikit-Learn and TensorFlow

Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython

https://archive.ics.uci.edu/ml/datasets/Daily+and+Sports+Activities