ASSIGNMENT 1. *Human Activities Recognition*

A PREPRINT

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1 Dataset

Human Activity Recognition database built from the recordings of 30 subjects performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors. [1]

The experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed six activities:

- WALKING
- WALKING_UPSTAIRS
- WALKING_DOWNSTAIRS
- SITTING
- STANDING
- LAYING

wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, we captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments have been video-recorded to label the data manually. The obtained dataset has been randomly partitioned into two sets, where 70% of the volunteers was selected for generating the training data and 30% the test data.

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. The gravitational force is assumed to have only low frequency components, therefore a filter with 0.3 Hz cutoff frequency was used. From each window, a vector of features was obtained by calculating variables from the time and frequency domain.

The complete description of the dataset is provided in the dataset files.

2 Models

During the course of the assignment we were applying and comparing three classifiers: Logistic Regression [LR], Support Vector Machine [SVM] and Stochastic Gradient Descent [SGD] that were provided by the Scikit-Learn scikit-learn library. During the lectures and the labs we extensively covered the fundamentals and foundations of the LR and SVM models and briefly covered SGD.

2.1 Logistic Regression

Our Logistic Regression Classifier was initialized with the following settings:

- L2 (Ridge) regularization
- LBFGS solver - a memory limited version of BFGS
- Maximium number of iterations to converge = 500. Scikit-Learn's LR classifier implementation required 10-20 times to be run and *not converge* before it finally converged

Cross Validation Parameters Search

- Multiclass parameter was to be chosen from 'ovr' and 'multinomial'

2.2 Stochastic Gradient Descent

Stochastic Gradient Descent Classifier was initialized with the following settings:

- Maximium number of iterations to converge = 1000. This model, unlike LR, had not problems converging on the very first iteration.
- Tolerance = 0.001, meaning that when $error_n - error_{n+1} < 0.001$ the algorithm will stop.

Cross Validation Parameters Search

- L1 vs L2 regularization

2.3 Support Vector Machine

Support Vectort Classifier was initialized with the following settings:

- Gamma (γ) = 'scale', meaning that $\gamma = \frac{1}{n_{features} * \sigma_x^2}$

Cross Validation Parameters Search

- Kernel to be either 'linear' or 'polynomial'

3 Results

3.1 Confusion Matrices

Every confusion matrix shows that the models performed best on classifying 'LAYING' class. But apart from Confusion Matrices stands Classification Reports that could provide addition insights on the results.

- SGD accuracy: 95.894 time: 55.482 s
- LR accuracy: **96.098** time: 100.141 s
- SVM accuracy: 95.792 time: **55.387** s

$time = start - end$ where $start$ is the snapshot before $evaluate\_model(...)$ is called and end is respectively after.

$y \setminus \hat{y}$	walking	walking upstairs	walking downstairs	sitting	standing	laying
walking	0.96774194	0.02217742	0.01008065	0	0	0
walking upstairs	0.01061571	0.98938429	0	0	0	0
walking downstairs	0.0047619	0.0547619	0.94047619	0	0	0
sitting	0	0.00814664	0	0.92260692	0.06924644	0
standing	0	0	0	0.06954887	0.93045113	0
laying	0	0	0	0	0	1

Table 1: Confusion Matrix: SGD

$y \setminus \hat{y}$	walking	walking upstairs	walking downstairs	sitting	standing	laying
walking	0.99395161	0.	0.00604839	0.	0.	0.
walking upstairs	0.05307856	0.9447983	0.00212314	0.	0.	0.
walking downstairs	0.00714286	0.02857143	0.96428571	0.	0.	0.
sitting	0.	0.00610998	0.	0.87983707	0.11405295	0.
standing	0.0018797	0.	0.	0.02067669	0.97744361	0.
laying	0.	0.	0.	0.	0.	1.

Table 2: Confusion Matri: Logistic Regression

$y \setminus \hat{y}$	walking	walking upstairs	walking downstairs	sitting	standing	laying
walking	0.9858871	0.00806452	0.00604839	0.0	0.0	0.0
walking upstairs	0.04883227	0.94904459	0.00212314	0.0	0.0	0.0
walking downstairs	0.01666667	0.04285714	0.94047619	0.0	0.0	0.0
sitting	0.0	0.00407332	0.0	0.89409369	0.10183299	0.0
standing	0.0	0.0	0.0	0.03007519	0.96992481	0.0
laying	0.0	0.0	0.0	0.0	0.0	1.0

Table 3: Confusion Matri: SVM

3.2 Classification Reports

Given Scikit-Learn's classification report I deduce that precision and recall are feasible to calculate in multiclass examples since F1-score doesn't show the full picture - it is agnostic to the weights of the classes, which may be important. Given that, I suppose, that in the case of recognizing human activities we may prefer to use a model that would show highest performance on a target class. For example, the product that utilizes our model may not care when person walks or lays but targets to detect the moment when a user stands to count activity and the number of hours staying during the day as Apple Watch does.

	precision	recall	f1-score	support
walking	0.986	0.968	0.977	496
walking upstairs	0.925	0.989	0.956	471
walking downstairs	0.988	0.940	0.963	420
sitting	0.924	0.923	0.924	491
standing	0.936	0.930	0.933	532
laying	1.0	1.0	1.0	537
accuracy			0.959	2947
macro avg	0.960	0.958	0.959	2947
weighted avg	0.960	0.959	0.959	2947

Table 4: Classification Report: SGD

	precision	recall	f1-score	support
walking	0.944	0.994	0.969	496
walking upstairs	0.967	0.945	0.956	471
walking downstairs	0.990	0.964	0.977	420
sitting	0.975	0.880	0.925	491
standing	0.903	0.977	0.939	532
laying	1.000	1.000	1.000	537
accuracy			**0.961**	2947
macro avg	0.963	0.960	0.961	2947
weighted avg	0.962	0.961	0.961	2947

Table 5: Classification Report: Logistic Regression

	precision	recall	f1-score	support
walking	0.942	0.986	0.964	496
walking upstairs	0.949	0.949	0.949	471
walking downstairs	0.990	0.940	0.965	420
sitting	0.965	0.894	0.928	491
standing	0.912	0.970	0.940	532
laying	1.000	1.000	1.000	537
accuracy			0.958	2947
macro avg	0.960	0.957	0.958	2947
weighted avg	0.959	0.958	0.958	2947

Table 6: Classification Report: SVM

References

[1] Dheeru Dua and Casey Graff. UCI machine learning repository, 2017.