A PUBLIC DOMAIN DATASET FOR REAL-LIFE HUMAN ACTIVITY RECOGNITION USING SMARTPHONE SENSORS

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MOTIVATION

- Nowadays everyone has a fitness tracker, be it a watch, a band, a ring, or simply a smartphone in the pocket.
- How all of the above mentioned devices detect and identify all the types of movement is a challenge many companies are currently undertaking.
- Simple access to accelerometer, gyroscope, GPS and magnetometer is enough to detect many types of physical activity, and even estimate calories used.

OVERVIEW

- This paper and model intends to be able to identify actions based on data acquired from smartphone sensors.
- The sensors present in this devices have usually a high degree of accuracy and performance, in a small package.
- There are two main challenges, The data space, temporality, and quantity the devices produce, and lack of a mapping between device data and subject behaviour.
- Most studies use the device stuck at a body part, making the data very dependant on smartphone location. This study makes the subjects use their devices normally, thus providing and using a more realistic dataset.

PROBLEM DESCRIPTION / TECHNICAL DETAILS

- Data acquired using custom app. Acquired over two sets of a month and a week each.
- 4 activities were considered: Inactive, Active, Walking, Driving
- Data acquired comes from 4 sensors: accelerometer, magnetometer, gyroscope and GPS
- Data from the accelerometer gets pre-processed into linear acceleration.
- Data from accelerometer and magnetometer pass through a low-pass filter to avoid noise, and the gyroscope passes through a high-pass filter to remove gyro-drift.
- Data frequency is inconsistent across sensors

PROBLEM DESCRIPTION / TECHNICAL DETAILS

Activity	Accelerometer Hz.	Gyroscope Hz.	Magnetometer Hz.	GPS Hz.
Inactive	11.00 ±16.38	4.66 ±0.74	7.91 ±11.72	0.13 ±0.35
Active	32.55 ±24.80	4.46 ±1.44	9.13 ±13.64	0.06 ±0.23
Walking	31.24 ±27.47	6.24 ±11.86	8.16 ±12.05	0.06 ±0.23
Driving	51.16 ±31.59	4.66 ±2.42	17.00 ±20.01	0.04 ±0.20

Activity	Time Recorded (s)	Number of Recordings	Number of Samples	Percentage of Data
Inactive	292,213	147	7,064,757	24.25%
Active	178,806	99	8,918,021	30.62%
Walking	98,071	200	4,541,130	15.59%
Driving	112,226	128	8,602,902	29.54%
Overall	681,316	574	29,126,810	100%

DATA PREPARATION

- A sliding window of 20s was chosen, with overlap of 19s.
- GPS changes higher than a certain threshold are eliminated.
- Data with bad timestamps are eliminated.
- The first and last five seconds of each recording are eliminated, giving the user time to put and take the phone from the pocket.
- Recordings with no GPS data gets deleted.
- Mean, variance, median, absolute deviation, maximum, minimum and interquartile range were calculated and fed to the model.

MODELS OVERVIEW

- **SVM**

Is a supervised machine learning model that uses classification algorithms for two-group classification problems. SVM looks for the hyperplane that maximizes the margins between the two classes.

- **Linear**
  - Computes the dot product of the input data.
  - The linear was selected to have a basis for comparison.

- **Polynomial**
  - Computes the dot product of the input data and adds a coefficient to the power of the degree.
  - The polynomial was selected to have a basis for comparison.
- **RBF**
  - Measures the distance between a point in the input space and the origin. It is defined as the Euclidean distance between the point and the origin, raised to a power.
  - RBF kernel is one of the most used ones in the literature.

HYPERPARAMETERS TUNED

- Hyperparameters tuned to improve the performance:
  - **C**: Controls the trade-off between the margin and the misclassification error.
  - **Kernel**: Function that transforms the input data into a higher-dimensional space, where it becomes possible to find a hyperplane that can separate the data points into different classes.
  - **Gamma**: Directly affects the curve of the hyperplane, making it softer or more accentuated, depending on the patterns that are introduced into the model.
  - **Degree**: It controls the degree of the polynomial function used to transform the data.

BEST CONFIGURATION AND ARCHITECTURE OF THE NETWORK

- In this process, a stratified 10-fold cross-validation is used to have 10 sets with presumably the same number of patterns for each class.
- The f1-score is used as the evaluation metric, since it is less influenced by class imbalances and more closely linked to the correct classification of each pattern.
- A grid search is used to tune the hyperparameters of the SVM, including the kernel (polynomial, RBF, or linear), the C parameter, the gamma parameter (for the RBF and polynomial kernels), and the degree parameter (for the polynomial kernel).
- The best combination of hyperparameters is chosen for each fold based on the results of grid search, and the resulting model is tested.

OUR PLAN OF THE EXPERIMENTAL STUDY

- Use SVM model and tune C and kernel hyperparameters.
- Use decision tree and random forest in order to experiment with other models. In the case of the decision tree, we tuned the Maximum depth and criterion hyperparameters and in the case of the random forest, we tuned the maximum depth and number of trees parameters.
- In order to obtain the values of the hyperparameters, candidate values based on previous notebooks and the paper were used.