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Project Proposal:

Human Activity Recognition using Smartphones

Domain Background:

Since 1870 a large growth in human life expectancy has been observed in Europe. This growth has expanded in the whole world [1] principally due to the great achievements in health care field. As a result, the proportion of elderly people is rapidly increasing. Aging people in general lives in isolated conditions. In addition to that some of them are not capable to live normally and take advantages from health care facilities services. Building remote monitoring systems for elderly patients who live alone or without permanent caretaking will improve their quality of life. For better decision making these remote monitoring systems needs some regular and trustful information about patients.

The goal of this project is to build a machine learning model and a signal processing pipeline capable of processing signals collected using smart phone inertial sensors (accelerometer and gyroscope) and producing useful datasets will be used as inputs of a machine learning model capable of recognizing some of human daily activities (sitting, walking …) included in the dataset (see datasets and Inputs section) with a low error rate. The signal processing pipeline and the final model could be used as a good source of information about patient's daily activities needed by remote monitoring systems mentioned earlier.

Datasets and Inputs

Dataset used in this project was collected during a set of experiments were carried out with a group of 30 volunteers. They performed a protocol of activities composed of six **basic activities**: three static postures (standing, sitting, lying) and three dynamic activities (walking, walking downstairs and walking upstairs). The experiment also included **postural transitions** that occurred 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. All the participants were wearing a smartphone (Samsung Galaxy S II) on the waist during the experiment execution. We captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz using the embedded accelerometer and gyroscope of the device. The experiments were video-recorded to label the data manually. The sensor signals (accelerometer and gyroscope) of each experiment were stored in folder called **RawData**.

-**'RawData/acc_expXX_userYY.txt'**: The raw triaxial acceleration signal for the experiment number XX and associated to the user number YY. Every row is one acceleration sample (three axis) captured at a frequency of 50Hz. Units used for acceleration are 'g' s (gravity of earth =9.80665 m/sec^2)

- **'RawData/gyro_expXX_userYY.txt'**: The raw triaxial angular speed signal for the experiment number XX and associated to the user number YY. Every row is one angular velocity sample (three axis) captured at a frequency of 50Hz. Units used for angular velocities are radian per second (rad/s)

- **'RawData/labels.txt'**: includes all the activity labels available for the dataset (1 activity label per row). Each row contains the start-end row numbers related a group of log samples located in acc and gyro files. These files can be identified using the exp Id and the user Id existing in that row.

Use of this dataset in publications must be acknowledged by referencing the following publication:

- **[2] 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.**

Problem Statement

Raw triaxial signals cannot be fed directly to machine learning models. A signal processing pipeline should be built to filter noise, extract useful and clean signals splitting them into windows. From each window a vector of features is generated to obtain a classical dataset. The target column will contain activity labels associated to each vector of features(window). Recognizing the activity associated to each vector is a multiclass classification problem. To solve it, I intend to use some supervised learning classifiers (since each vector has an activity ID label) and compare predictions.

Solution Statement

The solution will be predictions of the activity performed [activity Ids from 1 to 12] included in test files. First, I will use median filter to reduce noise from these signals. Then a Fast Fourier Transform will be applied to extract useful frequency components: **body components** and **gravity component**. **Body signals** will be derived in time domain to obtain jerk signals. the magnitude of each triaxial signals will be generated. All useful signals will be sampled in fixed-width sliding windows of 2.56 sec (128 readings/window) [2]. For each window a Fast Fourier transform will be applied some time domain signals to obtain signals in frequency domain. From each window, a vector of features was obtained by calculating variables from the time and frequency domain signals. Each vector is row in the final datasets.

For training models, I will compare **Logistic Regression classifier** and **Decision Tree classifiers** since this is a classification problem. Finally, I will select the best model for this problem and fine its hyper-parameters to get the best accuracy.

Benchmark Model

For this problem, the benchmark model will be gaussian **Naive Bayes Classifier(GaussianNB)**. I will try beat its accuracy with algorithms mentioned earlier.

Evaluation Metrics

Prediction results are evaluated in general using **accuracy**: the number of samples correctly predicted divided by the total number of samples in each dataset. I will use the confusion matrix adapted to multiclass problems to obtain details about each model's performance on each type of activity.

Project Design

After Importing all logfiles. I will first visualize some acceleration and gyroscope signals recorded while users were performing some activities using the labels file to understand the nature of data I am dealing with. Then I will start building the signal processing pipe line by defining and applying functions related to each step mentioned in the solution statement. The windowing step has two types of windowing functions. the first type (type I) will sample useful signals related to basic activities only. The second type (type II) of windowing will sample all useful signals. Choosing the activity Id related to each window differ on the type of windowing. Each type of windows will be stored in a different dictionary. The rest steps in signal processing pipeline are the same for both types of windows. Finally, the resulted datasets are:

- Dataset type I: Concerns basic activities only.
- Dataset type II: Concerns basic activities and postural transitions mentioned earlier.

Since all features are real numbers a feature scaling is needed to standardize all columns. Rows considered as Outliers will be detected using a threshold which is an integer number: the number of features considered as outliers in a row. Outliers will be deleted before generating the train and test files for both datasets.

To train models, I plan to choose 3 models one as benchmark model, the two others will be used to beat the benchmark results. Using cross-validation I can find which model performs best and then use that one, tweak relative parameters for both datasets.

I expect to spend 70% of time on signal processing and data cleaning and 30% of the time on training models and tweaking parameters. The final accuracy will be calculated against the test files generated during the data processing part.

References:

[1] life expectancy _ James Riley for data 1990 and earlier: https://ourworldindata.org/grapher/life-expectancy-globally-since-1770.

[2] https://www.elen.ucl.ac.be/Proceedings/esann/esannpdf/es2013-84.pdf