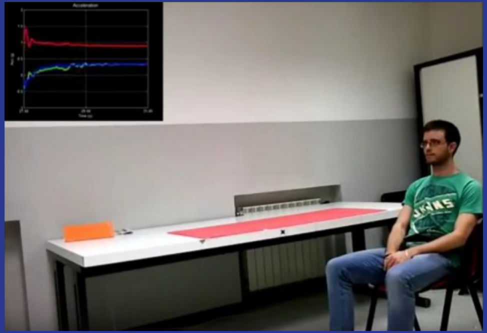
Human Activity Recognition Using Smartphone Dataset

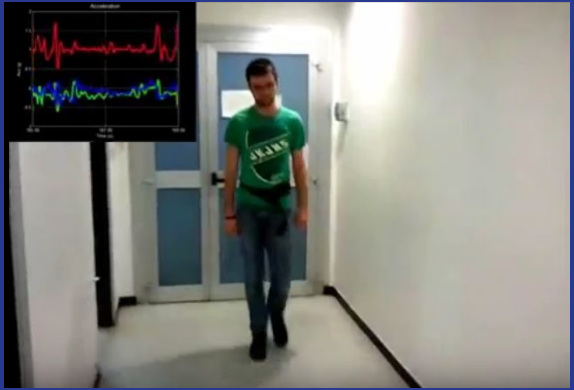
About the Dataset

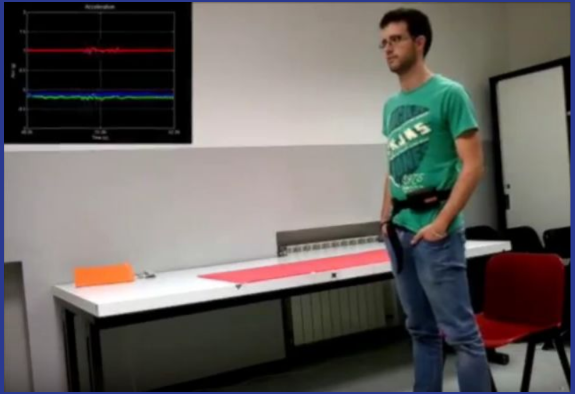
The Human Activity Recognition dataset was built from the recordings of 30 study participants performing activities of daily living while carrying a waist-mounted smartphone with embedded inertial sensors. *The objective is to classify activities into one of the six activities performed.*The experiments 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 on the waist. Using its embedded accelerometer and gyroscope, 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz were captured. 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.

Walking, Walking Upstairs, Walking Downstairs, Sitting, Standing, Laying







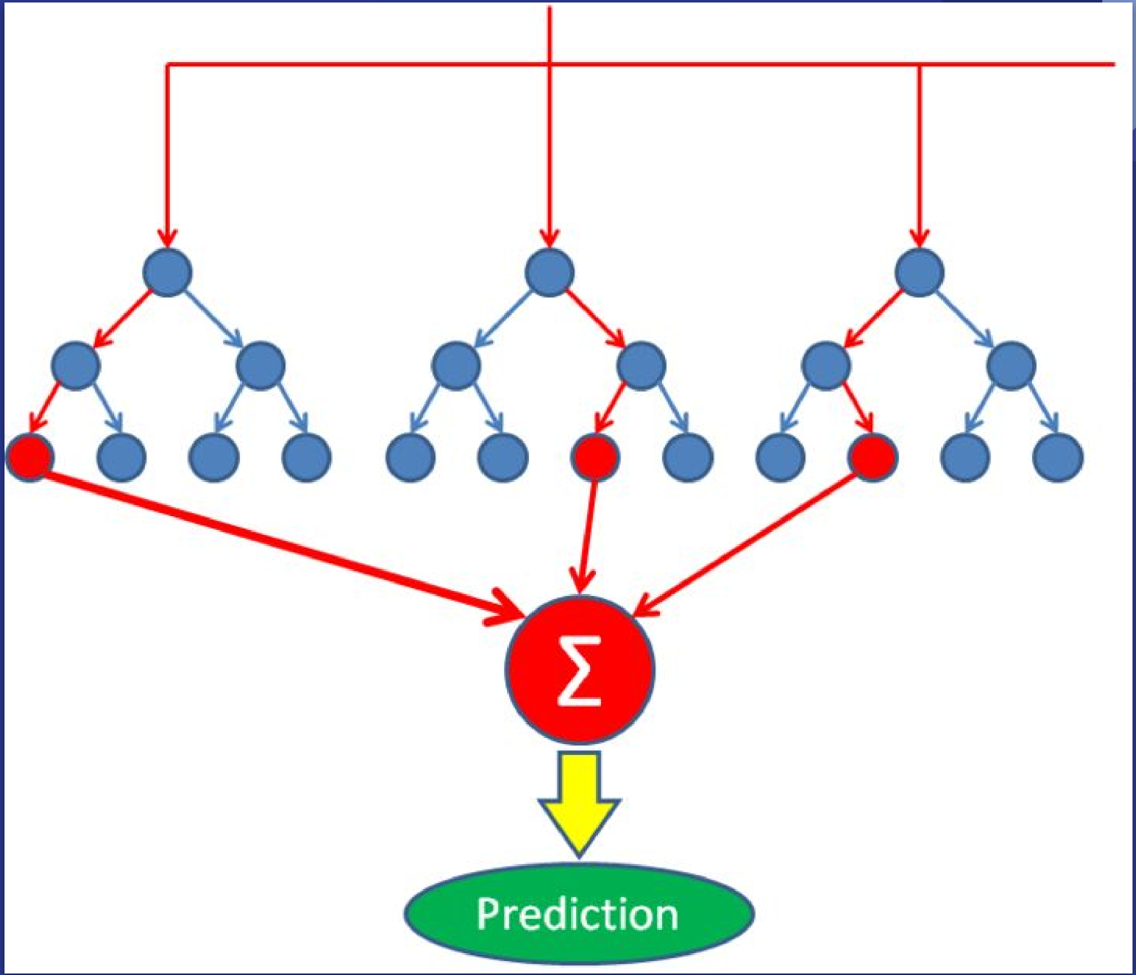
Libraries used :

1. Numpy
2. Pandas
3. Scikit-learn
4. Matplotlib
5. TensorFlow

Random Forest Classifier

In random forests each tree in the ensemble is built from a sample drawn with replacement from the training set. In addition, when splitting a node during the construction of the tree, the split that is chosen is no longer the best split among all features. Instead, the split that is picked is the best split among a random subset of the features. As a result of this randomness, the bias of the forest usually slightly increases (with respect to the bias of a single non-random tree) but, due to averaging, its variance also decreases, usually more than compensating for the increase in bias, hence yielding an overall better model.

The scikit-learn implementation combines classifiers by averaging their probabilistic prediction, instead of letting each classifier vote for a single class.

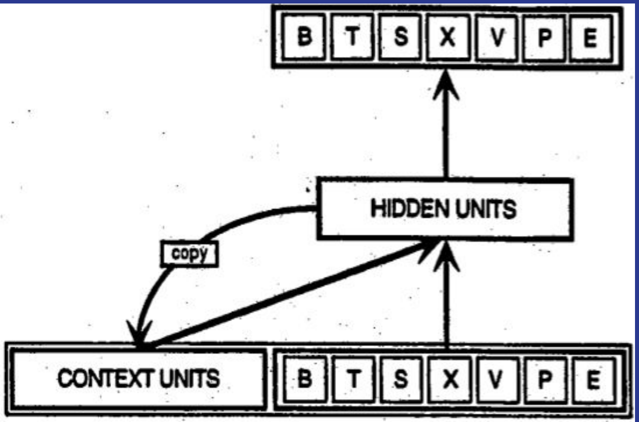

Σ
Prediction

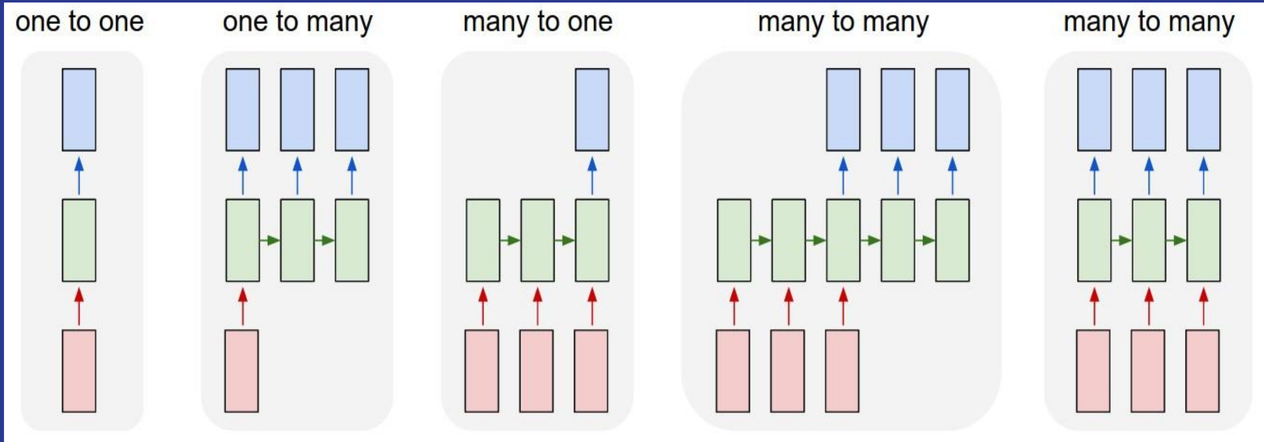
Features of Random Forest

- It is unexcelled in accuracy among current algorithms.
- It runs efficiently on large data bases.
- It can handle thousands of input variables without variable deletion.
- It gives estimates of what variables are important in the classification.
- It generates an internal unbiased estimate of the generalization error as the forest building progresses.
- It has an effective method for estimating missing data and maintains accuracy when a large proportion of the data are missing.
- It has methods for balancing error in class population unbalanced data sets.
- Generated forests can be saved for future use on other data.
- Prototypes are computed that give information about the relation between the variables and the classification.
- It computes proximities between pairs of cases that can be used in clustering, locating outliers, or (by scaling) give interesting views of the data.
- The capabilities of the above can be extended to unlabeled data, leading to unsupervised clustering, data views and outlier detection.
- It offers an experimental method for detecting variable interactions.

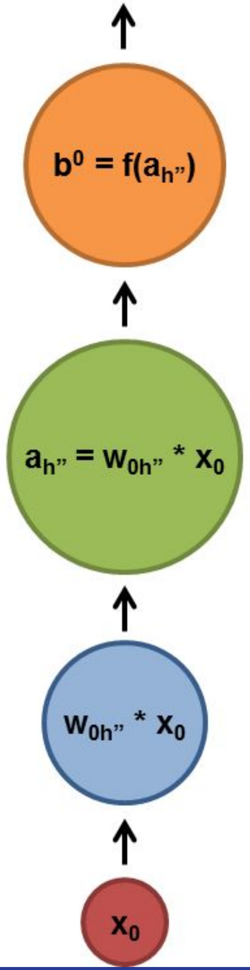
Recurrent Neural Network

An RNN takes many input vectors to process them and output other vectors. It can be roughly pictured like in the image below, imagining each rectangle has a vectorial depth and other special hidden quirks in the image below. In our case, the "many to one" architecture is used: we accept time series of feature vectors (one vector per time step) to convert them to a probability vector at the output for classification.



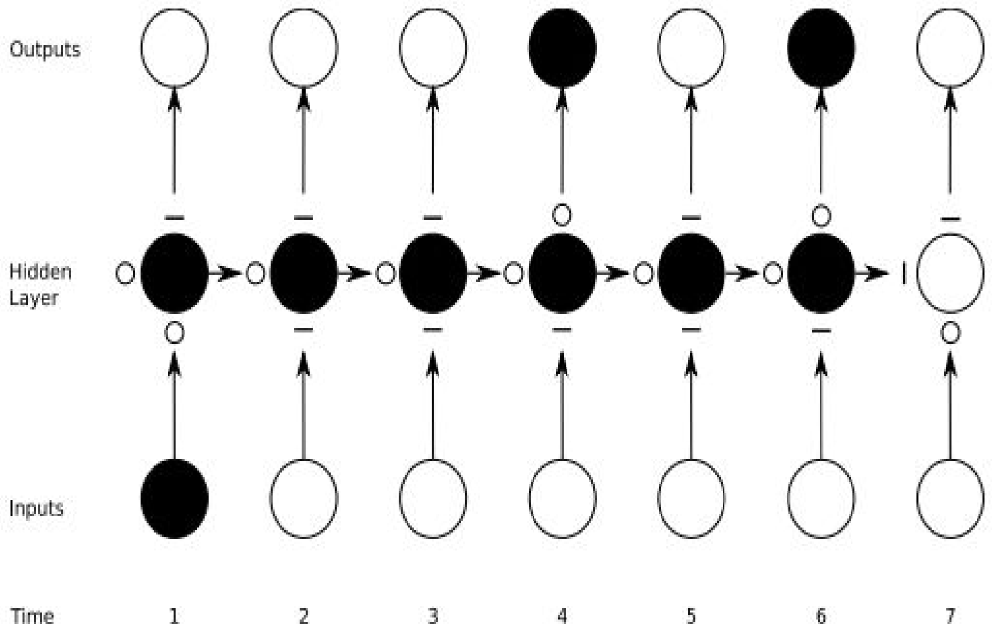


b^0 is fed to next layer



Long Short Term Memory Units (LSTM)

LSTMs help preserve the error that can be backpropagated through time and layers. By maintaining a more constant error, they allow recurrent nets to continue to learn over many time steps (over 1000), thereby opening a channel to link causes and effects remotely. This is one of the central challenges to machine learning and AI, since algorithms are frequently confronted by environments where reward signals are sparse and delayed, such as life itself.



LSTMs contain information outside the normal flow of the recurrent network in a gated cell. Information can be stored in, written to, or read from a cell, much like data in a computer's memory. The cell makes decisions about what to store, and when to allow reads, writes and erasures, via gates that open and close. Unlike the digital storage on computers, however, these gates are analog, implemented with element-wise multiplication by sigmoids, which are all in the range of 0-1. Analog has the advantage over digital of being differentiable, and therefore suitable for backpropagation.

Future Scope

1. Monitoring human activities by gathering real time data through mobile app.
2. Improving the accuracy of the classifier.

Challenges :

1. Large number of features, time series data.
2. It may need to take into account the fact that different subjects have slightly different profiles over activities.

Citations

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.

“Random Decision Forests,” T. Ho (1995).

Andrej Karpathy blog - http://karpathy.github.io/2015/05/21/rnn-effectiveness/