Human Activity Recognition using Time Series Analysis

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In this project, we studied various techniques to classify time series for Human activity recognition including Conditional Random Fields, Hidden Markov Models and Max-Entropy Models.

Introduction

Sensor-based activity recognition integrates the area of sensor networks with novel data mining and machine learning techniques to model a wide range of human activities.

In this project, we were interested in modeling the UCI HAR dataset and comparing various models such as Conditional Random Fields and Markov Models. To model transitions probabilities, we resorted to different techniques such as Gaussian fitting as well as Multi-Layer Perceptrons.

The latter sparked the question of how to find the MLP's most suitable architecture: how many layers? what hidden dimensions to choose? We investigated this issue by implementing a simulated annealing algorithm to find the 'best' architecture.

The Data

The data was collected by a group of 30 individuals who performed 6 activities wearing a smartphone:

- Walking
- Walking Upstairs
- Sitting
- Standing
- Laying
- Walking Downstairs

For each time step, we were given a label and a 561-feature vector with time and frequency domain variables computing from the triaxial acceleration and angular velocity from the sensors

The objective of this project was to be able to classify any given time series into these 6 classes.

The Models

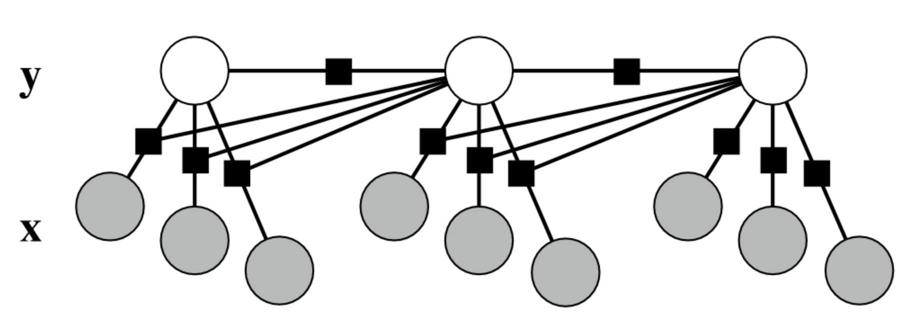
A. Hidden-Markov Models

HMM consists of a discrete-time, discrete-state Markov chain with hidden states s(t) and an observation model p(x(t) | z(t)).
The observations are assumed independent.
The joint distribution of the model is:

$$p(\mathbf{z}_{1:T}, \mathbf{x}_{1:T}) = p(\mathbf{z}_{1:T})p(\mathbf{x}_{1:T}|\mathbf{z}_{1:T}) = \left[p(z_1)\prod_{t=2}^{T} p(z_t|z_{t-1})\right]\left[\prod_{t=1}^{T} p(\mathbf{x}_t|z_t)\right]$$

We focused on two tasks here: **Decoding** (i.e. inferring the most probable states sequence given observations and an HMM) with the Viterbi algorithm and **Training** (i.e. learning the best HMM parameters given an observation sequence and an initial HMM) with the Baum-Welch algorithm.

B. Conditional Random Fields



CRF is a discriminative sequence model and a generalization of HMM. Its optimization space is over all possible sequence labelings:

$$p(\mathbf{y}|\mathbf{x}) = \frac{p(\mathbf{y},\mathbf{x})}{\sum_{\mathbf{y}'} p(\mathbf{y}',\mathbf{x})} = \frac{\exp\left\{\sum_{k=1}^{K} \lambda_k f_k(y_t, y_{t-1}, x_t)\right\}}{\sum_{\mathbf{y}'} \exp\left\{\sum_{k=1}^{K} \lambda_k f_k(y'_t, y'_{t-1}, x_t)\right\}}$$

C. Max-Entropy Markov Models

The objective of the MEMM is to find a distribution over the possible activities using features of the current observation and the previous activity recognized at each time step:

$$P(a_i \mid a_{i-1}, o_i) = \text{softmax}(f(a_{i-1}, o_i))$$

Where $f(a, o)$ is the result yielded by the MLP. An MLP is a model that processes information through a series of interconnected computational nodes, such as linear transformation or activation layer that can propagate information in the network. This allows to skip the feature selection step.

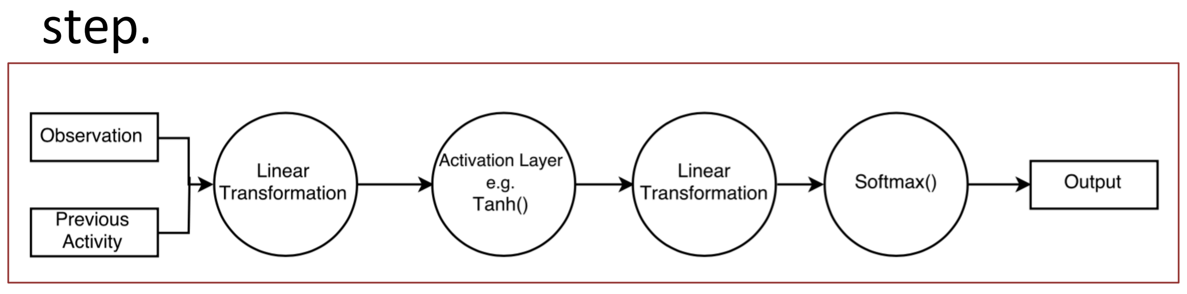


Figure 1. Example of simple MLP architecture

MLP and Simulated Annealing

Choosing the architecture of an neural network is more an art than a science. We developed a simulated annealing algorithm to explore in a more systematic the range of possible architectures. The pseudo code is presented below:

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Preliminary: Choose a "maximal" architecture to prune

1. Select a subset of this architecture as initial architecture and train the model
2. Evaluate the cost C_curr associated with this model
3. Sample a new architecture by perturbing the current one and evaluate the cost C_new after training
4. Accept this new architecture with probability:

   exp(-(C_new-C_curr)/T)

   where T is a 'temperature' parameter that dictates the acceptance rate
5. Repeat (2 - 4) until convergence
```

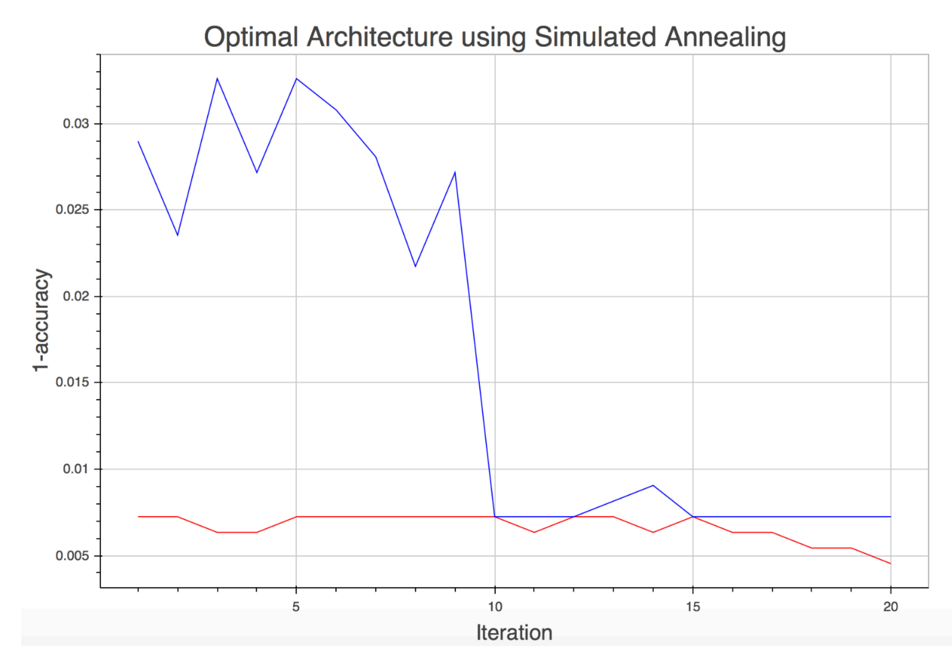

Figure 2. SA for different initial architectures

Experiments and Results

Data was split into a training and testing with a 70-30 ratio. We also held-out 10% of the training data as validation set.

We used Python for the CRF and HMM and Lua for the MEMM

	CRF	HMM	MEMM
Accuracy			92.9%

Table 3. Accuracy on the predicted test sequence

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