POLYTECHNIC SCHOOL
DEPARTMENT OF COMPUTER AND INFORMATION TECHNOLOGY ENGINEERS

COMPUTATIONAL INTELLIGENCE

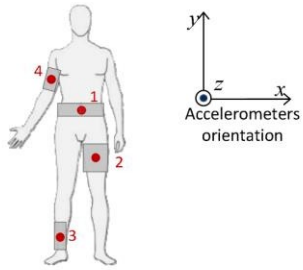
Teachers: S. Lykothanasis, D. Koutsomitropoulos

Academic Year 2022-2023

Laboratory Exercise
Part A

A. Human Activity Recognition Using Neural Networks

Human Activity Recognition (HAR) is a process of interpretation of human movement by computer systems. Activities are recorded with the help of sensors, and the resulting data are analysed and used by various sectors such as health, sports, entertainment, etc. A typical case is the attempt to classify postures-movements of the body into a predefined number of classes. Specifically, in this paper you are given data from four sensors placed on four users for
8 hours in total, and you are asked to implement an implementation that classifies this data into exactly one of the five available classes. The following figure shows the positions of the four sensors (portable accelerometers) on the human body.



In particular, you should consider using a multilevel TND to predict the 5 classes (*sitting-down, standing-up, standing, walking,* and *sitting*) corresponding to each sample. For this purpose, the *PUC -Rio* dataset[1] that collects *165,633* samples will be exploited for training and testing. The integer values from the sensors together with the basic data of the users from which the data were taken and the type of activity (class) are contained in the dataset-HAR-PUC-Rio.csv file.

In detail, each record-line includes the following data: user, gender, age, height, weight, body mass index, (x,y,z) from waist sensor, (x,y,z) from left thigh sensor, (x,y,z) from right ankle sensor, (x,y,z) from upper arm sensor and class. So for example a sample is as follows :

wallace;Man;31;1,71;83;28,4; -24;92;-118;1;92;-128;-12;166;-87;-212;-74;-173;walking

To implement the algorithms you can use any environment, library or programming language you see fit. *MatLab, WEKA, Azure M L Studio, Google Colaboratory, TensorFlow, Keras, SciKit -Learn.*

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1 https://eclass.upatras.gr/modules/document/file.php/CEID1060/dataset -HAR-PUC-Rio.csv

UCI Machine Learning Repository: Wear able Computing: Classification of Body Postures and Movements (PUC-Rio) Data Set

The task in this paper is to build and train an AI that classifies inputs (activities) into 5 different classes.

A1. Data Preprocessing AND Preparation [*20 units*]

<u>*Caution: whatever transformations are applied to the training set data, the same should be applied to the control set data or alternatively reversed before measuring the evaluation metrics below.*</u>

α) *Coding and pre-processing of data:* the dataset contains mainly numerical, but also categorical values (gender, posture). The categorical values, in order to be used in the training of an AI, should be mapped to numerical values. For example, the 5 classes (*sitting-down, standing-up, standing, walking, sitting*) can be replaced by the values (1, 2, 3, 4, 5) in the whole dataset. The values from the sensors, as mentioned, are integer and range in the interval [-617,533]. The range of data values can vary significantly by feature. For this reason, there is a risk of overestimating the contribution of some attribute over others or to polarise the values of some attributes or the resulting weights. Given the specific mapping and the possible need to adjust these values to a different scale (eliminating possible polarisation), the following three methods are presented:

- *C entering:* this method subtracts the average of the values for each characteristic from all the values assigned.
- *Normalization (Normalization or min-max scaling).* we transfer the range of values of an attribute to a new scale e.g. [0,1].
- *Standardization (Standardization or z-score):* with this method we provide the sample with properties such as zero mean and unit variance (Gaussian).

Consider the usefulness of the above methods for this problem and apply them to the training data, if appropriate. [15]

b) *Cross-validation:* make sure you separate your data into training and control sets, so that you use 5-fold CV for all experiments. Make sure that each fold is balanced in terms of the number of samples in each class. [5]

A2. Choice OF architecture [*50 units*]

Regarding the topology of the TNDs for training with the back-propagation algorithm, you will use TNDs with *a hidden layer* and experiment with the number of hidden nodes. To train the network, initially use a learning rate *h* = 0.001.

α) Training and evaluation of your models can be done using *Cross-Entropy* (CE), Mean *Square Error* (MSE), and Accuracy[2]. Explain in simple terms what is the relevance of the above metrics for this problem. Which one is preferable for training (loss)? [5]

b) How many neurons will you need at the output level, given the requirement of multiclass classification? [5]

[2] This is the percentage of correct predictions from the network. If $\hat{y}_i$ is the desired class for sample *i* and y is the class provided by the network, then accuracy $(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} 1(\hat{y}_i = y_i)$

c) Choose an appropriate activation function for the hidden nodes and document your choice. [5]

d) Which activation function will you use for the output level? Sigmoid, linear, Softmax or some other? [5]

e) Experiment with 3 different values for the number of neurons in the hidden layer and complete the table below. Empirically appropriate values for the number of hidden nodes are in the interval [O, $I+O$] (*I number of inputs, O number of outputs, H number of nodes in the hidden layer).* Include graphs of convergence (M.O.) per training cycle. State your conclusions about (i) the number of hidden nodes, (ii) the choice of the cost function, and (iii) the convergence speed with respect to the training epochs. [15]

Number of neurons in the hidden layer	**CE loss**	**MSE**	**Acc**
$THE_1 = O$			
$_1 = (I+O)/2$			
$THE_1 = I+O$			

f) Finishing criterion. Select and document an appropriate training termination criterion each time (for each fold). Can the early stopping technique be used? [5]

Attention: in all experiments you will use 5-fold cross validation (5-fold CV).

A3. Changes in training rate AND momentum constant [15 *units*]
Choosing the topology that gives the best result based on the previous
query, perform an optimization of the training rate hyperparameters η and momentum constant m using CV and complete the table below. Include the graphs of convergence (M.O.) with respect to the training cycles that will be needed. Document theoretically why $m < 1$.

η	**m**	**C E loss**	**MSE**	**Acc**
0.001	0.2			
0.001	0.6			
0.05	0.6			
0.1	0.6			

Briefly state the conclusions drawn from the 4 experiments.

A4. Normalisation [*15 units*]
One method to avoid overfitting the network and improve its generalization ability is regularization of the weight vector. Explain which regularization method ($L\ 1$ or $L\ 2$) is preferable for this problem. Then apply it and retrain your network, as derived from A3, by evaluating different values for the coefficient *r.*

i) $r = 0.1$ (ii) $r = 0.5$ (iii) $r = 0.9$
Complete the table below for each of the above cases using a 5-fold CV. Include graphs of convergence (M.O.) by training cycle.

Coefficient *r*	**C E loss**	**MSE**	**Acc**
0.1			
0.5			
0.9			

Formulate your conclusions about the effect of the method on the generalizability of the network.

A 5. Deep Neural Network *[optional question - 10 bonus points]*

Try adding more than one hidden layer to the network (up to 3). Experiment with the number of nodes, as you did in A2. Describe a logic for stacking the hidden layers (is it good to have the same number of nodes? Decreasing? Increasing?). Report CE, MSE and Acc for your experiments with 5-fold CV and state your conclusions about adding hidden layers.

Deliverables

Your report should contain a detailed commentary of your experiments, as well as a full record of your results and conclusions, by sub-question. Also, you should include at the beginning of your report a link to the code you have used (in a file sharing service or code repo).

Don't forget to fill in your details at the top of the 1ης page.

Evaluation

The answer to questions A and B carries 20% weight in the final course grade (the total of both parts of the paper carries 40% weight). The Bonus grade (10%) is added to the above 40%.

Comments

1. The report, in electronic form, must be posted in e-class by Monday, 24/4/2023, at 23:59.
2. For any clarification/question you can use the relevant forum in the eclass of the course.