On Modelling Cognitive Styles of Users in Adaptive Interactive Systems using Artificial Neural Networks

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Abstract: User modelling in interactive Web systems is an essential quality to optimally filter, personalise and adapt their content and functionality to serve the intrinsic needs of individual users. The mechanism for obtaining the user model needs to be intelligent, adaptive and transparent to the user, in the sense that user experience should not be disrupted or compromised. Human factors are extensively employed lately for enriching user models by capturing more intrinsic perceptual characteristics of the users. Accordingly, this paper proposes the use of Artificial Neural Networks (ANNs) for attaining cognitive styles of users in adaptive interactive systems. One of the main benefits is the automatic prediction of cognitive typologies of users by avoiding psychometric tests, which are among the typical ways of constructing user profiles and are particularly time-consuming. Furthermore, ANNs can efficiently model the relationship between cognitive styles and user interaction. The experimental setup and the results obtained show that ANNs are suitable for predicting the cognitive styles ratio of users in respect to their actual cognitive style ratio value.

1 INTRODUCTION

Adaptive interactive systems (Brusilovsky et al., 2007) have become progressively popular since the late 2000s due to the exponential increase of users and availability of digital information, mainly with regards to interactive systems on the World Wide Web. Based on various definitions given to date (Brusilovsky et al., 2007; Perkowitz and Etzioni, 2000; Frias-Martinez et al., 2005) an adaptive interactive system is capable to automatically or semi-automatically adapt its information architecture and functionality to the needs and preferences of its users with the aim to provide a personalised and positive user experience.

Adaptation of the functionality and content in interactive systems heavily depends on successful user modelling. The user model is the representation of static and dynamic information about an individual, and it represents an essential entity for an adaptive interactive system. User models aim to provide or guide adaptation effects in adaptive interactive systems (i.e., the same system can look different and provide diverse functionalities to users with dissimilar user models).

Popular user characteristics considered in user modelling of adaptive interactive systems are the user's knowledge, interests, goals, background, and cognitive styles (Brusilovsky et al., 2007). This work focuses on modelling cognitive style of users, which represents an individually preferred and habitual approach to organising and representing information (Riding, 2001).

Psychometric tools have been primarily used for classifying users to particular cognitive typologies (Brusilovsky et al., 2007), which could be further used to adapt the content and functionality of interactive systems. However, systems that offer personalised content based on cognitive styles heavily depend on the users' willingness to dedicate a considerable amount of time for participating in the user modelling process. Therefore, an imperative need has been identified for intelligent user modelling in adaptive interactive systems to offer automatically personalised content but without requiring any effort on behalf of the user.

In this context, nature-inspired intelligent methodologies such as Artificial Neural Networks (ANNs) could be used as a powerful technique to dynamically and transparently model human behaviour in Web-based applications. ANNs comprise of emerging effective modelling techniques especially in nonlinear conditions and where the development of conventional relations in a particular context becomes impractical and cumbersome. ANNs have been extensively used for user modelling, mainly for classification and recommendation in order to group users with the same characteristics (Frias-Martinez et al., 2005). Accordingly, ANNs could be used to predict the users' cognitive characteristics based on their interactions with the system, something which has not been investigated thoroughly yet, to the best of the authors' knowledge.

To this end, the work presented introduces an intelligent user modelling approach for eliciting the cognitive styles of users based on ANNs, combined with a psychometric measurement that highlights differences in cognitive styles of users as well as interaction data of users within a Web-based environment. In particular, an ANN has been trained based on the cognitive style of users and interaction data with the aim to predict the cognitive style of newly entered users' based on their interaction data. As interaction data we have considered specific metrics of CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) (Von Ahn et al., 2004) since it is a common mechanism used online daily by millions of users (e.g., reCAPTCHA (http://google.com/recaptcha) estimates that over 200 million reCAPTCHAs are completed daily). The main objective of the paper is to investigate whether specific metrics of CAPTCHA mechanisms could be used by an ANN to predict the users' cognitive characteristics. The identification of users having specific cognitive and interaction style/pattern will ultimately help in defining various adaptation mechanisms required to assemble and target a different user interface experience in Web-based environments for various cognitive typologies of users.

The paper is organised as follows: In Section 2, we provide related work on adaptive interactive systems that make use of ANNs. In the same section we present the related theoretical background. The experimental setup and data metrics are presented in Section 3. In Section 4, we analyse the experimental results and consequently, we conclude the paper and describe our directions of future work in Section 5.

2 RELATED BACKGROUND

Numerous researchers have attempted to use ANNs in the context of adaptive interactive systems, primarily for classification of users with the same characteristics and creation of user models with the aim to recommend and adapt Web content. For example, Kim et al. (2004) have proposed an ANN-based collaborative filtering method that investigates the possibility of identifying and predicting the correlation between users or items in a Web environment using a Multi-Layer Perceptron (MLP). Chou et al. (2010) aim to identify the users' prior knowledge for specific products in e-commerce applications by analysing their navigation patterns through Web mining and constructing a Back-Propagation Network (BPN) (Wu et al., 2006) that uses a supervised learning method and a feed-forward architecture, in order to predict the users' potential future needs. Magoulas et al. (2001) use ANNs to learn and fine tune rules and/or membership functions from input-output data to be used in a Fuzzy Inference System (FIS). In particular, they have proposed a classification/recommendation system with the aim to plan the learning content of a course according to the student's level of knowledge.

Taking into consideration the abovementioned works, this paper examines the potential of ANNs for predicting users' cognitive characteristics based on their preference and ability in solving CAPTCHA challenges in order to offer an automatic way for capturing their typology and adapting accordingly the content and functionality of interactive systems. The overall benefit of modelling users' cognitive style through an automatic mechanism would be to minimise the effort of users performing specially designed psychometric tests (Brusilovsky et al., 2007) and instead model the users' cognitive styles with a dynamic, and not visible to the users, user modelling mechanism. The proposed method elicits similar groups of users based on their interaction with CAPTCHA mechanisms and investigates how these groups may be related to cognitive styles. To the best of the author's knowledge, this is among the first attempts to study the relation between the cognitive style of users and their interaction data in Web-based systems, apart from sporadic attempts, the first of which utilised a number of clustering techniques to understand human behaviour and perception in relation with cognitive style, expertise and gender differences of digital library users (Frias-Martinez et al., 2007), and a second more recent research attempt which studied the connection between the way people navigating in a museum and electronic encyclopaedia system and the way they preferred to process information cognitively (Antoniou and Lepouras, 2010; Belk et al., 2012).

The rest of this section presents the theoretical background on cognitive styles and ANNs.

2.1 Cognitive Styles

Among the numerous proposed theories of individual styles (e.g., Riding, 2001; Felder and Silverman, 1988; Witkin et al., 1977), the proposed work utilises Riding's Cognitive Style Analysis

(CSA) that classifies users to the cognitive typologies of Verbal-Intermediate-Imager (Riding, 2001). The so called Verbal/Imager dimension refers to how individuals process information. Users that belong to the Verbal class can proportionally process textual and/or auditory content more efficiently than images, whereas users that belong to the Imager class the opposite. Users that belong in between the two end points (i.e., Intermediate) do not differ significantly with regards to information processing. In this regard, we consider that Riding's CSA implications can be mapped on Web environments, since they consist of distinct scales that respond directly to different aspects of the Web space. The CSA implications can provide guidelines in the context of Web design (i.e., selecting how to present visual or verbal content) and is probably one of the most inclusive theories, since it is derived from the common axis of a number of previous theories (Riding and Cheema, 1991).

2.2 Artificial Neural Network Models

The use of Artificial Neural Network (ANN) (Haykin, 1999) models in this work was based on the advantage they have in offering automatic computations that may dynamically provide guidelines in adapting the content of interactive systems in a way that is not disruptive to the user. The ANN model has been successfully used across many interdisciplinary areas and extensively in cases of automatically extracting patterns, decisions, or transformations based on human behaviour due to the ability they have to approximate reasoning processes in a model-free manner, i.e., without requiring knowledge of a function or relation a priori (Haykin, 1999).

This work utilises a Multi-layer Perceptron (MLP) model which is a popular and flexible mechanism for the representation of common characteristics of users and for obtaining predictions based on these characteristics. The resulting prediction may ultimately be used for providing personalised content and functionality.

3 EXPERIMENTAL SETUP

3.1 Sampling and Procedure

A total of 93 individuals participated voluntarily in a study carried out within February 2012. All participants were undergraduate students and their age varied from 17 to 20. A Web-based psychometric test, exploiting Riding's CSA (Riding, 2001), was developed that measures the response time of specific statements (i.e., identify whether a statement is true or false) and computes the ratio between the response times for each statement type in order to highlight differences in cognitive style.

Furthermore, one text- and one picture-based CAPTCHA mechanism were developed using available open-source software (Elson et al., 2007; Golle, 2008; Secureimage, 2012). In Figure 1 and Figure 2 we illustrate an example of the text- and picture-based CAPTCHA mechanisms used during the study, respectively. The text-based mechanism produced distorted images of random characters whilst the picture-based mechanism produced pictures. During the experiment participants were asked to reproduce the distorted random characters and to select the appropriate pictures belonging to a specific group (e.g., select pictures that illustrate cats) in order to solve the CAPTCHA challenge. Both CAPTCHAs contained a refresh button that initialised the CAPTCHA with a new sequence of characters or pictures.

Figure 1: Text-based CAPTCHA used in the study.

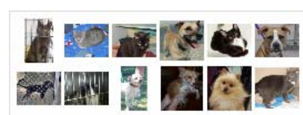

Figure 2: Picture-based CAPTCHA used in the study.

The participants visited a Web-page but before entering the Web-page they were asked to solve a number of CAPTCHA challenges. In addition, the users were first required to choose between the two variations of CAPTCHAs (i.e., text- vs. picture-based) and then solve the preferred CAPTCHA challenge. The same task of choosing between the two CAPTCHA types was repeated 10 times in order to offer the chance to the users to try out the variations of CAPTCHAs offered and also increase the chance of optimum measurements of performance and ability of the users by taking average values of their overall effort in solving the CAPTCHA challenges, rather than taking just one-off measures. After solving the CAPTCHA challenge, the users were redirected to the psychometric test aiming to identify the users' cognitive styles which will be used by the ANN model for verification purposes (i.e., whether the prediction obtained from the ANN model regarding cognitive style ratio is correct).

3.2 Data Metrics' Definition

The following metrics were utilised for monitoring the usage of CAPTCHA in the study.

- *Preference*; how many text- and picture-based CAPTCHAs were solved by each user,
- *Processing Time*; average time (in seconds) required per user to solve a text- and picture-based CAPTCHA,
- *Ability*; how many attempts and how many attempts on average were needed by each user to successfully solve a text- and picture-based CAPTCHA.

Based on the aforementioned metrics, a browser-based logging facility was implemented with JQuery JavaScript Library (http://jquery.com) to collect the CAPTCHA usage/interaction data. The interaction data were used to predict the cognitive ratio of new users (that were not used in the training phase of the algorithms developed) utilising ANNs as explained in the experiments section.

4 EXPERIMENTS AND RESULTS

4.1 Experimental Design

The ANN designed and utilised in this work were implemented in Matlab R2011a (http://www.mathworks.com/products/matlab). As already mentioned, a typical ANN was developed for predicting the cognitive style of users based on their interaction with the experimental environment; a Multi-layer Perceptron (MLP) ANN with one output neuron for calculating the cognitive style ratio. The nodes of the ANN were organised in layers and forming the so-called input-hidden-output layers. At the input layer the aforementioned metrics were used.

Initially, the data were normalised and then they were randomly split into three subsets, the training, the validation and the testing subset consisting of 60%, 20% and 20% of the original data samples. The inputs were inserted in the computational neurons and the output (cognitive typology) was compared with the desired output (actual cognitive typology measured using the psychometric test). The predictive power of the ANN was measured on the testing subset, the validation subset was used as a pseudo-test set in order to evaluate the quality of the network during training and the training subset was used for obtaining the optimal network model.

The weights were adjusted using a gradient (steepest descent) algorithm until the desired output is achieved; this process is called the training of the network. Various architectures were evaluated in order to find the optimal one, which comprise of single hidden layer ANN with varying number of hidden nodes (i.e., nodes in the internal layer or Number of Hidden Nodes (NHN)). Specifically, the varying number of internal neurons examined varied from 6 to 16, with step size equal to 1, in order to identify the optimum performing networks. An early stopping of the training process was also performed to stop training when the validation error was increased.

In addition, the following parameters were selected as they did not demonstrate any instability in the training process of the networks: The algorithm used for training was the Levenberg-Marquardt (trainlm) backpropagation algorithm (Rumelhart et al., 1986) which is usually very efficient, but it requires a lot of memory to run. The maximum number of epochs was set to 100 and the performance was evaluated using the *MSE* with reg performance function, which takes the weight sum of two factors the mean squared error and the mean squared weight and bias values.

Finally, a cross validation process was followed (namely holdout cross validation (Weiss and Kulikowski, 1991)) to ensure the generalisation of the model on larger datasets, which is necessary to be performed especially in cases of small datasets.

4.2 Results and Discussion

Initially, a statistical analysis of the metrics showed that most users irrespective of their cognitive typology preferred to solve the picture-based CAPTCHAs. This preference may be interpreted by taking into consideration that the majority of Web application providers utilise text-based CAPTCHA, and thus, users wanted to try out the different CAPTCHA type (i.e., the picture-based CAPTCHA) out of curiosity and due to the attractiveness images have over text. In addition, this preference seemed to have affected the observations obtained based on the processing time and ability metrics of the users, since an indirect relation between the CAPTCHA metrics was observed.

Therefore, the model-free ANN method was utilised next to investigate the existence of patterns among users' cognitive typologies preference, performance and ability in solving CAPTCHA challenges. The ANN offered an automatic way for predicting the typology of users and adapting accordingly the content and functionality of interactive systems.

The results of the ANNs employed are explained in this section. The best performance of the ANN (with *MSE*=0.01) was obtained at the 8th experimental repetition and at the 9th epoch. The results for the training, validation and testing sets of this network are presented in Table 1 for the performance metrics of *Mean Magnitude of Relative Error* (*MMRE*), *Mean Absolute Error* (*MAE*), *Mean Z Error Ratio* (*MZ*), *Median Magnitude of Relative Error* (*MdMRE*), *Mean Absolute Error* (*MdAE*) and *Mean Z Error Ratio* (*MdZ*). The performance metrics are calculated based on the local measures (described in equations (1)-(3) in Table 2) by using their means and medians respectively.

Figure 3 shows a comparison of the actual cognitive style ratio of the samples used during the testing phase compared to the predicted ratio obtained from the ANN model with architecture 8-13-1.

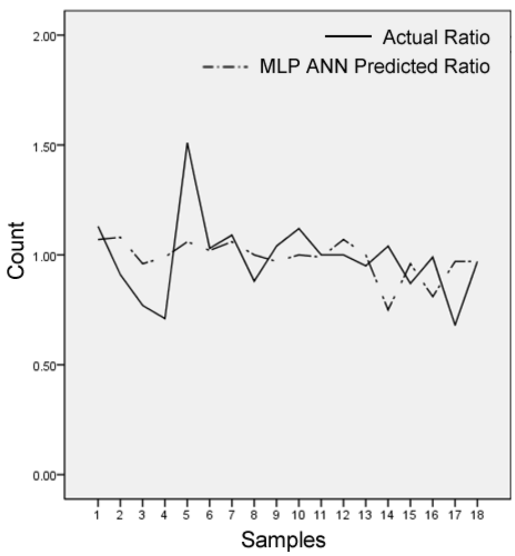

Figure 3: Actual vs. Predicted Cognitive Style Ratio of ANN 8-13-1 during testing phase

From the results obtained we observe that the proposed ANN model is suitable for recognising the cognitive type of users that did not participate in the training of the model (i.e., this can be observed in the prediction evaluation results of the Test set in Table 1). Observing the rest ANN models constructed we conclude that they present a robust method to distinguish Verbal/Imagers and Intermediates users. This observation is obvious from the results of Table 3 which show on average the performances of various ANN architectures (varying the Number of Hidden Neurons (NHN)) during the testing phase.

The main result obtained from this work is that ANN models can be effectively trained, even with using just a small sample of users, and may reach to very accurate predictions of the cognitive ratio of users that have not participated in the training and construction process of the models. This proposes that utilising only CAPTCHA-related metrics the probability of reaching to accurate approximations of the cognitive styles of users is quite high.

Table 1: MLP ANN 8 -13-1 Performance Results

Set	MMRE	MdMRE	MAE	MdAE	MZ	MdZ
Train	0.087	0.056	0.084	0.059	1.024	1.023
Val	0.135	0.095	0.127	0.091	1.053	1.045
Test	0.144	0.102	0.135	0.130	1.032	1.002

Table 2: Local Performance Metrics

$MRE_i = \frac{\lvert Y_{Ai} - Y_{Ei} \rvert}{Y_{Ai}}$	(1)
$AE_i = \lvert Y_{Ai} - Y_{Ei} \rvert$	(2)
$Z_i = \frac{Y_{Ei}}{Y_{Ai}}$	(3)

Table 3: Cross Validation Testing Performance Results of MLP ANN

NHN	M MRE	Md MRE	MAE	Md AE	MZ	MdZ
8	0.180	0.153	0.173	0.147	1.071	1.046
9	0.160	0.128	0.152	0.130	1.061	1.027
10	0.166	0.137	0.155	0.141	1.096	1.073
11	0.141	0.102	0.135	0.102	1.032	1.002
12	0.176	0.136	0.164	0.140	1.087	1.046
13	0.143	0.113	0.135	0.110	1.049	1.024
14	0.141	0.111	0.133	0.112	1.053	1.025
15	0.135	0.108	0.130	0.109	1.023	1.002
16	0.190	0.172	0.183	0.166	1.074	1.036

5 CONCLUSIONS

The purpose of this paper was to present results of an experimental setup, in order to increase our understanding on automatically attaining cognitive styles based on specific Web interaction data of users. Specific data metrics of CAPTCHA mechanisms have been proposed and utilised by an Artificial Neural Network (ANN), with the aim to predict the users' cognitive style.

The experimental process of the ANN yielded very promising results for the sample examined. In particular, the results obtained with ANNs for predicting the cognitive styles ratio of individuals were particularly successful in respect to their real cognitive style ratio value. This indicates that techniques such as ANNs are suitable for predicting users' cognitive typology using their interaction data with CAPTCHA-related challenges.

The practicality and significance of this work is that the suggested ways of capturing intrinsic characteristics of users, like cognitive styles, and their analysis through intelligent techniques may be more effective and less time and effort consuming than traditional instruments since they might optimise the user modelling process. However, in order to build a cohesive user model psychometric tests are not yet to be replaced since this study is still in its very early stages.

The meaning of the relation between cognitive styles and interaction data needs to be further examined to reach to a more cohesive user model and effectively guide adaptation in interactive systems. Future work includes further experimentation for investigating these relations and further employing fuzzy algorithms or other Artificial Intelligence (AI) methods to determine the degree of adaptation based on user profiles and the correlations obtained by ANN models such as the ones used in this work.

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