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A Neural Network Model for Interface Preference

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Abstract: This paper develops a model for estimating user's interface preferences based on given user's characteristics, using artificial neural networks. Results from a large scale online survey (n=2658) show that the eighteen user characteristics specified in our study do not suffice to define interface preferences *explicitly,* while they do indicate statistically significant relationships between user characteristics and interface preferences. These survey data are used to establish a level of experience for the neural network model.

This study proposes seventeen questions about interface preferences, and an additional eighteen questions to generate user characteristics. Statistical analyses show that there is a significant relationship between, say, Interface Menu Icons, User Age Class and User Entertainer. Although there are eighteen user characteristics questions, only two user characteristics questions significantly related to Interface Menu Icons. This information is then used to develop a more efficient neural network model. Eliminating irrelevant user characteristics avoids unnecessary calculations and saves CPU time.

The neural network model attempts to estimate the answer of Interface Menu Icons question by the help of the given answers of User Age Class and User Entertainer questions. In this model, all possible answer –options- for the inputs form a node, with w_{01}, …,w_{08} the respective weights of the nodes. The answer of the Interface Menu Icons question can be subsequently estimated.

Using a similar approach, neural network models are developed for each interface preference question, except for Interface Windows question, as this question does not display any significant relationship with any user characteristics. A Microsoft Excel macro is furthermore developed using Visual Basic for Applications (VBA) to implement a "*Gradient Descent Supervised Learning Algorithm*".

The online survey data collected in our research is subsequently used to train neural network models developed for each interface preference question. Each neural network model is tested for alternative learning rate settings. The best learning rate setting based on the input data is then deployed for the learning process (the learning rate with the maximum number of successful estimates over survey data is selected, using a binary search algorithm to find the best learning rate).

Data collected from 2658 participants are used to train sixteen neural network models. Trained neural network models for each interface preference question are then deployed to generate the final user interface. Interface preferences proposed in this study are stated in terms of design decisions to assist user interface designers. Our model assists in identifying possible user interface preferences of a specific user.

Keywords: *Neural networks, interface design, survey research*

INTRODUCTION

McDaniel defines user interfaces as "*Hardware, software (including menus, screen design, keyboard commands, and command language), or both that allows a user to interact with and perform operations on a system, program, or device*" (McDaniel, 1994, IBM dictionary of computing (10th ed.). New York: McGraw-Hill, p. 724). With the advent of Web 2.0, the Internet has become increasingly user-centric, with users enabled to gather or prove information in their own way (O'Reilly, 2005). This development gives further importance to understanding different cultural traits, thinking and cognition styles in designing computer interfaces (Rau et al., 2004). Furthermore, on average, the source code to implement a user interface takes up to 40-90% of the source code for the entire software system (Chalmers, 2003). While software interface design, development and evaluation has been widely researched (Paradowski, 2004; Reed et al., 1999; Kumar et al., 2004; Simpson, 1999; Goldberg and Kotval 1999; Carroll, 1997; Kim, 2001; Agah and Tanie, 2000; Alfaro and Stoelinga, 2004), no definite conclusions have emerged as of yet as to what is good or evil in user interface design (Lif, 1999; Reed et al., 1999; Kumar et al., 2004; Morris and Dillon, 1996; Bailey, 1993; Henninger, 2000; Moussa, 2000; Souza, 2001; Hartson, 1998). This study addresses the latter issue by investigating the relationship between user characteristics and user's interface preferences. Such relationship will shed light on (1) which user characteristics form which user's interface preferences, and (2) how user characteristics affect user's interface preferences. Such insights may lead to improved design and development of user interfaces that better fit users' needs.

Chalmers defines the human-computer interface as the point of contact between the computer and the computer user (Chalmers, 2003), which in turn directly affects the performance of this interaction (Puerta, 1998). The term "*usability*" and "*usable user interfaces*" stand for the performance of this interaction. Paradowski defines "*usability*" as "*…capability (in human functional terms) to be used easily and effectively by the specified range of users, given specified training and user support, to fulfill the specified range of tasks, within the specified range of environmental scenarios*" (Paradowski, 2004). Unfortunately, designing "*usable user interfaces*" is a cumbersome and challenging process (Chalmers, 2003). User interface design is a creative process and can not be completely described with a single method (Lif, 1999). People from various backgrounds and cultures may take a different approach to interface design. This difference makes it difficult to construct commonly agreed quality characteristics and specifications for user interfaces (Bailey, 1993). Our study addresses the definition, design, and development of usable user interfaces by looking at the personal attributes of the user.
A number of studies have demonstrated that users' characteristics, cognitive styles and computer experience have an impact on the interaction with user interfaces: Spolsky showed that it is possible to construct a commonly suitable software mental model by observing behaviors of a small group of users (Spolsky, 2001).
Wang stated that numerous studies employ user-centric approaches that include sense-making, cognitive and behavioral structures. The idea behind these studies is to investigate the complex nature of user's information retrieval, and how users' diversities affect interface interaction (Wang, 2000). Kumar et al. claim that it is possible to group users into subcategories according to their demographic information, making it possible for an interface designer to determine user interface features for each demographic subgroup. In their study, Kumar et al., investigate the relationship between users' personal attributes and user interface features (Kumar et al., 2004)

using a survey involving twenty-three participants. Users' demographic information such as age, gender and computer knowledge were shown to impact on user interface interaction. Zajicek focuses on the design of user interfaces for older people, and states that current software design typically produces an artifact which is static and which has no, or very limited, means of adapting to the changing needs of users as their abilities change (Zajicek, 2004). Romitti et al., and Cha et al., note that user interfaces that automatically adapt to each user have better usability than static interfaces (Romitti et al., 1997; Cha et al., 2005). According to Gavrilova, users differ in personal attributes such as age, gender and cognitive style. Gavrilova's study showed that including psychological, physiological and cognitive features into the user model improves human-computer interaction process quality (Gavrilova, 2003). Another study showed that computer knowledge and cognitive styles affect the success of interface usage, and that users' personal characteristics were the most important element for the user interface usability (Kim, 2001). Bailey showed that people from different disciplines have different approaches to interface design. In particular, this study showed that user interfaces designed by ergonomists were more usable than those designed by computer programmers (Bailey, 1993).

The above studies show that users' characteristics, cognitive styles and computer experience have an impact on the interaction with user interfaces, albeit that all these studies used a small sample of participants. This paper conducts a large scale on-line survey to investigate the relationship between user characteristics and users' interface preferences, using user attributes such as age, gender, country, cognitive structures, and computer experience. This information is then used to develop a more efficient neural network model for each interface question. Next, the user characteristics and interface preferences deployed in the survey are elaborated on.

USER CHARACTERISTICS AND INTERFACE PREFERENCES

User characteristics

User characteristics in this study evolved from studies on how design (ie digital vs analog watch) affects how people feel about the environment they are in and the tasks that they carry out in that setting (Selker & Burleson, 2000). In addition, usage styles varying from designer, programmer, data operator, knowledge worker, or entertainer, were based on studies of Gavrilova & Vasilyeva, who found that psychological factors determine the information retrieval, processing and usage, whereas cognitive structures and mental models form physiological factors which in turn determine the senses such as sight, hearing etc., affecting user interface interaction (Gavrilova & Vasilyeva, 2003). Benson and Standing (2000) noted that people who use their left-brain more effectively have a different ability for remembering names, faces, and numbers than people who use their right brain more effectively. This was captured in the survey through questions on "remember faces", "remember names", and "remember numbers". Varying perceptions of the user's mobile phone use was perceived as a potentially important user attribute in predicting user interface requirements, based on the fact that "mobile phones should not simply be conceived as small or inferior versions of desktop applications, but that they enable a host of new services that leverage their contexts for the benefit of the user" (Science Direct Editorial, 2008). According to Benson and Standing (2000), left and right brained people are organized differently, measured through their desktop being organized or untidy. Spolsky (2001) demonstrated that users' habits, such as whether they drive a manual or automatic transmission, affect their user interface perception. According to Sperry (1969), the left hemisphere of the brain is responsible for "Function", while right hemisphere of the brain is responsible for

“Form”, further tested through a visual display turning “clockwise” or “counter clockwise”. McGrenere et al. (2002) take into account users’ interest in the uptake of new features. Demographic attributes included age, gender, and country of residence. This resulted in a total of eighteen questions on user characteristics. All questions have graphical icons to ensure easy understanding of the response categories.

Interface preferences

Functional parameters determine the interaction behavior of the system. These parameters include content and navigation elements. Interactive parameters, on the other hand, determine the performance of the user interface while deployed. Interactive parameters comprise dialogs, menu items, fonts, font sizes, visual elements, navigation status (page number, previous and next page), etc. Service parameters include all the objects participating in the reference and information dialog interface’s functions like stop, help, yes, no buttons. Finally, layout parameters determine the layout of the interface elements, as well as grouping and segmentation. Dialog layout, menu layout, workspace and background color are the main examples of layout parameters (Gavrilova & Vasilyeva, 2003). Kumar et al. (2004) identified the main uses of interface elements as amount of information given, information layout, grouping, use of colors, background color and font color contrast, and effectiveness of navigation elements. Dix et al. (1998) identify interface elements as windows, icons, pointers, menus, buttons, toolbars, palettes and dialogs. Carey (1998), Bass and John (2003) propose guidelines for better representation of error messages, as “Messages are one of the most consistent areas of interface abuse. Users often find messages annoying” Microsoft Press. (1999). Foreground and background color were identified as very important for user interface perception and acceptability (Dix et al., 1998). Alignment of the paragraphs was another dimension identified for content delivery (Chalmers, 2003). While software is processing, it is very common to show some warnings telling the user an operation is in progress (Brewster & King, 2005). Progress bars are prevalent in modern user interfaces. Typically, a linear function is employed such that the progress of the bar is directly proportional to how much work has been completed. However, numerous factors cause progress bars to proceed at non-linear rates. Additionally, humans perceive time in a non-linear way” (Harrison, Amento, Kuznetsov & Bell, 2007). Because a progress indicator only displays information, it is typically not interactive. However, it may be useful to add static text or other information to help communicate the purpose of the progress indicator (Microsoft Press, 1999). For better perception of the forms and the form fields\ filled by the users, label position is important (Penzo, 2006). Some of the interface preference questions are about users’ interface habits, based on earlier studies that demonstrated that users’ interface habits affect users’ interface preferences (Gulliksen, 1996; Spolsky, 2001). Widgets are interface elements assisting users in performing some operations (Swartz & Nardi, 2003). Widgets, with their artificial intelligence, trace user operations and make some proactive actions to help them. This, in turn, makes the use of widgets not acceptable to some users (Swartz & Nardi, 2003). Chalmers indicated that menu icons are very important for some of the users (Chalmers, 2003). Menu is another important interface element, as menu layout impacts on interface usability (Carroll, 1997). Wizards provide a sequential dialog layout, and were shown to offer great advantages for performing some operations (Vanderdonckt & Farenc, 2000). This resulted in a total of seventeen questions on interface preferences. All questions have graphical icons to ensure easy understanding of the response categories.

SURVEY ANALYSIS

This study used seventeen questions to operationalize interface preferences, and an additional eighteen questions to reflect user characteristics. An online survey website (www.fullypersonalinterface.com) was created. After publishing the fullypersonalinterface.com website, invitations were sent to domestic and global online magazines, social networks, blogs and forums, yielding n=2658 usable responses from 120 countries for our analysis. Chi-square tests were used for analyzing the relationship between the nominal scaled variables, grouped as user characteristics questions with interface preference questions. Cramer's V statistics were computed for determining the strength of relationship between variables. A value of zero from Cramer's V statistics indicates no relationship; and a value of one indicates a perfect relationship.

Figure 1 summarizes the relationships found between interface preferences and user characteristics, only displaying elements with Cramer's V value exceeding 0,150 (the elements with Cramer's V value lower than 0,150 are located adjacent to each other).
Some of the interface options such as Interface Warnings: On Form (%92), Interface Forecolor: White (%83), Interface Progress Bars: Progress Bar (%93), Interface Human or Robot Operator: Human (%84), Interface Menu Icons: Important (%88) and Interface Computer Desktop: Organized (%82) seem to dominate. As such, it may be possible to construct globally accepted user interface paradigms based on dominating interface preferences. Figure 1 clearly demonstrates a relationship between users' characteristics and users' interface preferences. Most of the user characteristics such as User Country Class, User Gender, User Age Class, User Designer, User Programmer, User Data Operator, User Knowledge Worker, User Entertainer, User Wrist Watch, User Remember Faces, User Remember Names, User Remember Numbers, User Real Desktop, User Transmission, User Form vs. Function and User New Features show a significant relationship with interface preferences. On the other hand, user characteristics such as User Left Brained or Right Brained and User Mobile Phone show no relation with any interface preferences. These results indicate the importance of taking into account individual user characteristics for designing usable interfaces.

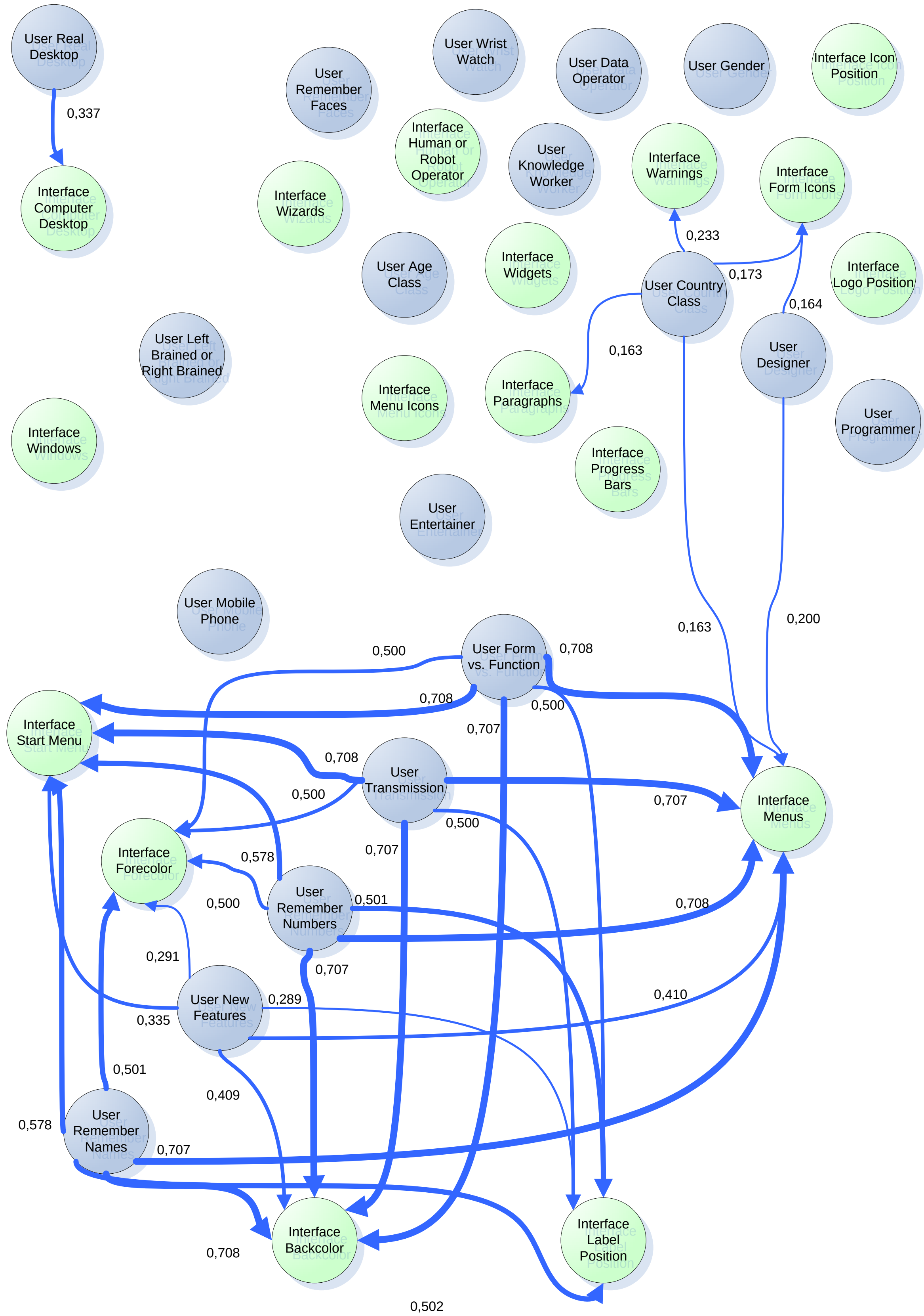


Figure 1: user characteristics-interface preference relationships

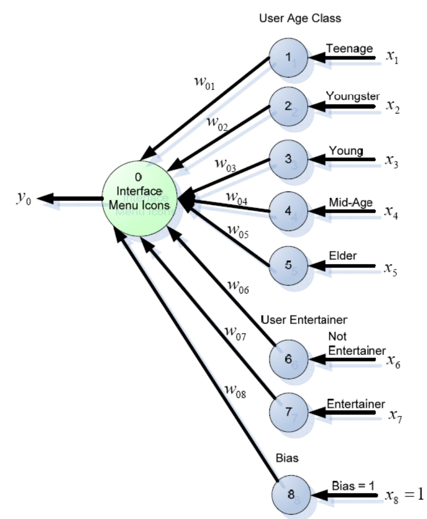
Determination of the relationship between user characteristics and interface characteristics facilitates better user interfaces for the target audience. In order to assess the strength of such relationships, the Cramer's V statistic is used, showing a significant relationship between Interface Menu Icons, User Age Class and User Entertainer, with the remaining sixteen user characteristics not showing any siginificant relationship with Interface Menu Icons. While these results indicate statistically significant relationships between some user characteristics and interface preferences, they do not suffice to define interface preferences *explicitly***.** The next step is development of a neural network model that employs user characteristics as input to estimate user preferences for the interface.

The neural network model

Figure 2 shows an artificial neural network model for an interface preference.

As mentioned earlier, User Age Class and User Entertainer are taken as inputs to the model and Interface Menu Icon preferences as output. In another words, the neural network model attempts to estimate the answer of Interface Menu Icons question based on responses to User Age Class and User Entertainer questions. In this model, all possible answer –options- for the inputs form an input node, with $w_{01}, \ldots, w_{08}$ the respective weights of the nodes. The answer of the Interface Menu Icons question can be subsequently estimated as follows:

$$y_0 = w_{01}x_1 + w_{02}x_2 + w_{03}x_3 + w_{04}x_4 + w_{05}x_5 + w_{06}x_6 + w_{07}x_7 + w_{08}x_8 \quad (1)$$



In equation (1):
y_0, output of the model, denotes the estimated answer of the Interface Menu Icons question.

w_{0i}, relative strengths (weights) of the nodes, denotes the weights of the user characteristics, i=1,…8.

x_i, inputs of the model, denotes values of user characteristics options, i= 1, .., 8 and x_i =0,1 with x_8 = 1.

Figure 2: Neural network mode for user Preference

Using a similar approach, neural network models are developed for each interface preference question, except for the Interface Windows question, as this question does not display any significant relationship with any user characteristics.
A Microsoft Excel macro was furthermore developed using Visual Basic for Applications (VBA) to implement a "*Gradient Descent Supervised Learning Algorithm*" (Turban 1995). According to Turban, the supervised learning algorithm stands for a set of data with known inputs and known or desired outputs. The difference between desired and actual output is then used to calculate corrections to the weights of the nodes. Gradient descent refers to the condition where the learning curve has the steepest trajectory for error reduction (largest marginal error reduction).

The online survey data collected in our research is subsequently used to train neural network models developed for each interface preference question. Each neural network model is tested for alternative learning rate settings. The best learning rate setting based on the input data is then deployed for the learning process (the learning rate with the maximum number of successful estimates over survey data is selected, using a binary search algorithm to find the best learning rate). Data collected from 2658 participants in the earlier survey are used to train a total of sixteen neural network models, one for each interface preference question, which are subsequently deployed to generate the final user interface. The models are then tested on responses of 10 participants that were not among the training set, yielding a success rate of 76.25% (or an average of 12.2 out of 16 correctly predicted interface preferences).

CONCLUSIONS

A model was developed to estimate user's interface preferences based on given user's characteristics, using artificial neural networks. Results from a large scale online survey (n=2648) are used to establish a level of experience for the neural network model. This study proposed seventeen questions about interface preferences, and an additional eighteen questions to generate user characteristics, of which only two significantly related to Interface Menu Icons. This information was then used to develop a more efficient neural network model. Using a similar approach, neural network models were developed for each interface preference question, and the online survey data used to train the neural network models. Trained neural network models for each interface preference question were then deployed to generate the final user interface. Testing on responses of participants that were not among the training set yielded a 76.25% success rate of correctly predicting user interface preferences.

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