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Culture and E-Learning: Automatic Detection of a Users' Culture from Survey Data

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Abstract

Knowledge about the culture of a user is especially important for the design of e-learning applications. In the experiment reported here, questionnaire data was used to build machine learning models to automatically predict the culture of a user. This work can be applied to automatic culture detection and subsequently to the adaptation of user interfaces in e-learning.

1 Introduction

The identification of relevant features of users has been of great interest in the research on adaptive interfaces (Mandl et al. 2003). One important factor is certainly the culture of a user. The usability of information systems for an international user population can be improved when functions, layout and knowledge structures are optimized for each culture (Del Galdo & Nielsen 1996). The design of internationally used information systems requires the identification of the culture of a user and the subsequent adaptation .

1.1. Culture in the E-Learning context

Learning is an activity heavily influenced by cultural factors as we can see in the great variety of educational systems in the world. As global organizations face an increasing need for continuous training of their employees across national borders, the development of educational software will demand a more and more sophisticated approach to cultural adaptation. The effects of this process need to go beyond general localization strategies focusing merely on visible cultural variables such as colors, currency or date formats. Designing educational multimedia systems for an international audience requires the consideration of at least two central aspects: communication norms and conventions in learning situations (such as general didactical approach, learning objectives, feedback presentation, and the relation and communication between teacher and student established within a particular culture) and culture-bound patterns of knowledge presentation and discourse structures.

The study described in this paper is carried out within the SELIM project (Software Ergonomics for Learning Systems In Multimedia Context) which combines research on multimedia, user-interface usability, and educational theory. Current work in SELIM aims at establishing relations between learning theory and human-computer interaction (HCI) design standards. A model for educational software would be highly desirable for rapid development. In SELIM, learning concepts from theories like behaviorism, cognitivism and constructivism are implemented in prototypes of educational systems, which are tested with regard to their didactic effectiveness and usability (cf. Schudnagis & Womser-Hacker 2002).

The cultural aspects of learning systems were identified as an important factor in this process. Cultural differences need to be considered in learning programs when designing layout, interaction, navigation, content, didactics and learning style preferences. The ultimate goal is the implementation of a user modeling module which will enable the system to adapt to the individual needs and expectations of students from different cultures (cf. Kamentz & Womser-Hacker 2002).

1.2 Culture Identification

In this paper we focus on the automatic identification of the culture of a user which is the basis for adaptation. Machine learning is applied to determine the culture based on questionnaire data. The detection would optimally be based on usage data or explicit declarations of users about their background, however, this approach is not always feasible. Although the findings from this study cannot be applied directly to the automatic adaptation of a learning system to a cultural background, they can be exploited in many ways:

- The results will show whether it is possible at all to identify the culture of a user based on knowledge about his attitude toward information technology and e-learning software or other questionnaire data.

- With the approach presented, the culture of a user can be determined in situations where a questionnaire is filled out but where it would be inappropriate to ask for the culture of the user directly.
- The models derived will support the identification of culturally relevant features. This supports the development of future questionnaires as well as information systems. For example, one of the highest correlations between a question and a culture we found in our study was the correlation between members of the Chinese culture and support for the statement: "When I encounter a problem with the computer, I think I can solve it" This corresponds to the attitude in Asian cultures not to admit problems. For a new questionnaire, dropping this question for Chinese users, may be considered because their answers are culturally biased. If it is not dropped, the results should be exploited during the interpretation of the data. For example, a negative attitude toward the statement by a Chinese user is more significant than for other users.
- This research on automatic detection of culture and the knowledge about the design of questionnaires on learning systems for an international audience will eventually contribute to the construction of user models for adaptive systems. Consider the example above. Asian users might be more reluctant to use a help system because they may think that they might acknowledge a deficit. To admit a problem may contribute to a "loss of face" which Asian cultures try to avoid. As a consequence, the integration of active support elements should to be considered.

The remainder of this paper is organized as follows. Chapter 2 defines the notion of culture for our purposes, chapter 3 describes the SELIM project and shows the data collection for this study. In chapter 4, machine learning methods are briefly introduced. Then the experiments are described and the results are presented and discussed. An outlook in chapter 5 points to further research directions.

2 Culture and Learning

Education and learning are phenomena which differ greatly between cultures. Culture influences many aspects of learning situations, such as the student-teacher-relationship, the content and the presentation mode of teaching materials, or the learning style of an individual.

2.1 Definition of Culture

Understanding a particular culture and the resulting needs in relation to the design of information systems, and especially with regard to educational software, first requires an understanding of culture itself and the factors that contribute to its existence (cf. Del Galdo 1996).

The Dutch anthropologist Geert Hofstede defines culture as learned patterns of ”thinking, feeling, and potential acting” that form the mental program or the ”software of the mind” (Hofstede 1997, p. 4) of an individual. This particular ”software” affects our way of thinking and our learning behavior. Cross-culturalists such as Fons Trompenaars argue that culture consists of several layers and illustrates that idea by using the metaphor of an onion: the most visible outer layers are easier to access than the hidden inner core, which is difficult to identify. Designing educational multimedia systems for an international target group requires not only localization of the visible elements on the surface such as colors or units of measurement but also the core values that ”make or break the learning experience” (Marinetti 2000)

2.2 Hofstede’s Cultural Dimensions

Cultures are often classified in accordance to their relative positions on a number of polar scales which cultural anthropology commonly calls cultural dimensions. The position of a culture on those scales is determined by the dominant value orientations, the ”preferred or socially desired states” (Beneke 2001:3) that make up its uniqueness.

In an extensive survey among over 116,000 employees of a large multinational corporation Hofstede (1997) defined four dimensions of culture. These international variables are of special importance in the context of educational system design as they allow to understand cultural differences in knowledge presentation, discourse structures, the didactical approach, and the navigational structure – those parts of a learning application that have a decisive influence on learning experiences and results:

1. **Power distance** measures the extent to which subordinates (employees, students) respond to power and authority (managers, teachers) and how they expect and accept unequal power distribution.
2. **Individualism vs. Collectivism**: these value orientations refer to the ties among individuals in a society.
3. **Uncertainty avoidance** describes the extent to which individuals feel threatened by uncertain or unknown situations.
4. **Masculinity vs. Femininity**: these two extreme values of this dimension focus on the differences between the social roles attributed to men and women and the expected behavior of the two sexes.

Differences related to the cultural dimensions influence the structure of learning situations, the learning process, the content and presentation mode of teaching materials and the relation and communication between teacher and student as well as among students. In his research, Hofstede investigated the relationship between learning behavior and culture and found cultural differences in characteristics of the educational process and the instructional practices respectively (cf. Hofstede 1986).

2.3 Cultural differences in academic style and learning behavior

As there is a need for radical localization which goes deeper and explores cultural differences below the surface (cf. Hoft 1995), cultural variables such as academic styles, discourse conventions, and learning styles that affect the way learners think, feel, and act in learning situations require consideration as well. These cultural variations mainly arise from cultural value systems, which have a significant influence on a culture's educational system.

Galtung (1981) has argued for culture-bound variables in the intellectual styles of different countries. He contrasts four intellectual styles based on his experience in working with scholars from different cultural backgrounds. For Galtung, intellectual style means basic models of thought and behavior shown principally by intellectuals. He distinguishes between ”saxonic”, ”teutonic”, ”gallic”, and ”nipponic” academic style. The main aspects of Galtung's analysis concern paradigm analysis, descriptions, theory formation, and commentary on other intellectuals. Despite the clear allusions of the chosen designation, Galtung stresses in his essay that these styles are not to be identified directly with patterns of behavior and thought in specific countries; e.g. the teutonic style is at home not only in Germany but also in the whole of Eastern Europe, the influence of the gallic style covers the whole Latin range of countries, i.e. Spain, Italy, South America. The saxonic style is very strong on the production of hypotheses and weak on theory formation and paradigm analysis. On the contrary, the teutonic and the gallic styles emphasize theory formation and paradigm analysis, but are weak on theses, with the gallic style stressing the significance of the elegance of expression. The nipponic style stands out for a nonlinear, circular thought pattern and argumentation structure.

Clyne's (1991) contrastive analysis of written discourse also proved that different conventions in composing written discourse do exist in different cultures. Clyne studied the role of culture in discourse by comparing English and German essay writing and found several areas of cultural differences in discourse structures and writing styles such as linearity vs. digressiveness, form orientation vs. content orientation, data integration, or the use of advance organizers. These conventions need to be observed when composing teaching materials and developing educational software for an international audience.

We believe that the range of cultural factors that need to be considered when designing educational software also includes learning styles and preferences, which vary from culture to culture. The culturally specific educational environment in which students learn to acquire knowledge (i.e. learn how to learn) strongly affects their personal learning style and therefore the acceptance and effectiveness of the used educational software.

3 Data Collection

The project SELIM develops a deeper understanding between usability issues and learning theory. One component needs to be a user modeling component targeted at the multicultural users. In order to gather the necessary knowledge, several methods are applied. Before designing prototypes for user tests, educational software developed by authors with different cultural backgrounds (i.e. educational programs on CD-ROM and on the internet) is evaluated and students from different cultures are asked to complete questionnaires on their learning styles and their attitudes toward information technology. This investigation is aimed at identifying design principles for different cultures concerning layout, navigational structure, content presentation and the didactic approach of e-learning software. In our study, we used the data form the questionnaires to automatically detect the culture of a user.

All together, 74 students from 14 countries completed the questionnaire. They came from Germany, China, France, Belgium, Countries of the Former Soviet Union (Russia, Ukraine, Belorussia, Kazakhstan), Spain, Latin America (Peru, Bolivia), Cameroon, Great Britain and Ireland.

For the draft of the first section of the questionnaire Kolb's classification of the **L**earning **S**tyle **I**nventory was chosen (cf. 1984). This self-description test is based on the experiential learning model which illustrates the learning process as a four-stage cycle composed of four learning abilities: concrete experience, reflective observation, active experimentation and abstract conceptualization. The LSI measures the relative emphasis on the four learning modes along the two dimensions allowing the identification of four types of learning styles: Converger (Pragmatist), Diverger (Reflector), Accomodator (Activist) and Assimilator (Theorist). If the learner's preference for one of these styles is influenced by cultural factors then it is interesting to find out which of the characteristics of the four learning styles can be attributed to the culturally biased learning behavior of subjects from different cultures.

The second part of the questioning provided data which are in the focus of our analysis presented in this paper. This section of the questionnaire involved questions on access to computers:

- computer literacy
- previous experiences with computing classes
- attitudes toward information technology
- computer and internet usage behavior (e.g. use of applications, handling of problem situations, topics of interest on the WWW)
- preferences concerning the design and functionality of educational software (e.g. types of exercises, user guidance, degree of user control)

In addition control variables like age, gender, mother tongue and questions on other demographic data were provided.

The identification of the characteristic learning styles and approaches to computers and learning software of users with different cultural backgrounds provides information about the features an educational system should offer in order to meet the individual needs of the learner, e.g. assessment methods, type, composition and structure of content, and the degree of interaction. Therefore, it serves as additional empirical material with regard to the development of a user modeling component.

4 Learning of Cultural Background

The questionnaire data was collected and in the following step, we built models which are able to predict the culture of a user from his answers in the questionnaire. This task may be accomplished by traditional statistical models as well as by machine learning algorithms as they are applied in data mining.

The data available for our study is not sufficient for generalizations yet. However, the results hint that machine learning can be applied in the domain of culture and information technology.

4.1 Machine Learning

Machine learning attempts to build models based on data when the domain is too complex or dynamic for humans to formulate rules which explain and model the data collected. Machine learning can be seen as essential part of data mining which includes collecting and pre-processing data, building a model, evaluate and apply it. "Any algorithm that enumerates patterns from, or fits models to, data is a data mining algorithm" (Fayyad 1997:5).
Many important data mining algorithms are focused on inductive learning or classification. The properties of objects which belong to different classes are fed into an algorithm which tries to find either rules or numerical models for the underlying and unknown membership functions. After successfully learning a model the system can classify new objects into their proper class (Mitchell 1997).

A machine learning model may be represented in various ways. Rule-based algorithms extract if-then-rules which can be interpreted and read by humans. Other algorithms like support vector machines create mathematically complex models which cannot be interpreted by humans. They are capable of modeling non-linear relationships between the properties of each learning instance.

Machine learning results and the quality of models need to be evaluated. The predictive value of a model depends largely on the requirements of the domain and the application. In most cases, the number of correctly predicted class memberships gives a good measure. However, the set for the test needs to be selected carefully in order get general results. An evaluation on the basis of the same set from which the model was derived only hints whether the classification problem can be learned at all and how complex it is. Such an evaluation on the training set needs to be supplemented with an evaluation with an independent test set. Splitting the data in a training set for model creation and a test set for evaluation may still bias the final result. Therefore, it is common practice to build several models and evaluate them based on different splits of the data.

4.2 Data Preparation

Some of the questions asked in the questionnaire were seleced for our study. The selection criteria included relevance for our analysis as well as pragmatic factors like number of individuals available for each culture and the number of individuals who answered the questions. After this pre-processing phase, 62 features were chosen.

The questionnaire has not been filled out by a very large number of individuals. On the other side, many different cultures were represented in the data set. In order to improve the possibilities for the generation of a successful machine learning model we aggregated some of the cultures mainly based on pragmatic reasons. For example, one class for students from Russia and other countries which were part of the former Soviet Union. Although we were aware of the cultural differences we took that approach trying to minimize the information loss by combining sufficiently similar cultures. Our data set consisted of five classes representing five culture groups which can be seen in table 3.

4.3 Statistical Analysis

Correlations between all features from the questionnaire between all cultures were calculated. Most values were rather low and between –0.1 and 0.1. No absolute correlation value was higher than 0.5. For the combinations in the following table the correlation rose above 0.3.

Table 1: Examples for positive correlations

Question	**Answer**	**Culture**
What are desirable activities in a learning software	Drill and Practice	Cameroon
	Yes and No Questions	France
What topics in the internet are of special interest for you?	Nature and environment	Ireland
	Travel and vacation	Spain
	Economics	China
What do you do first when you encounter a problem with the computer?	I try to solve the problem	Germany
	I think I can solve the problem myself	China

It is remarkable that even such a simple analysis reveals interesting facts and that the findings correlate to knowledge about cultures. This analysis shows relationships between answers and a culture. In addition, more complex relationships combining several features or answers are of interest.

4.4 Learning Models

The machine learning experiments were carried out with the WEKA[1] package (Waikato Environment for Knowledge Analysis). WEKA is open source software in JAVA which implements a wide range of learning algorithms (Witten & Frank 2000). Linear Models as well as non linear models reach excellent performance when the training is evaluated on the basis of our training data. Interestingly, support vector machines model the membership of all individuals to their culture perfectly. On the contrary, the linear Naive Bayes classifier cannot create a perfect model. As a consequence, non linear models should be considered for applications of this approach.

When using a ten-fold cross validation for evaluation, ten percent of the data is left out during training and used for testing. This process is repeated ten times such that each training case is used for testing once. For ten-fold cross validation the performance drops significantly, however, the quality of the predictions is satisfying. In this case, a performance of around 50% is far better than guessing, because the classification problem consists of five classes.

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[1] http://www.cs.waikato.ac.nz/ml/weka

Table 2: Overall quality of the learning models

Evaluation Method	**Learning Algorithm**	**Correctly Classified Instances**	**Incorrectly Classified Instances (in %)**	**Root m. squared error (in %)**
Evaluation on training data	Support Vector Machine	100.0	0	0
	Naive Bayes	84.9	15.1	0.21
Ten fold cross validation	Support Vector Machine	50.7	49.3	0.44
	Naive Bayes	50.7	49.3	0.41
	JRIP	50.7	49.3	0.38
	Bagging (Naive Bayes)	54.8	45.2	0.38

There is no quality difference for the first three models in table 2 evaluated with ten-fold cross validation. Bagging is a so called committee machine which combines several individual classifiers. It achieves a slightly better performance.

Table 3: Performance for individual classes (F-Measure)

Evaluation Method	**Learning Algorithm**	EU	HIS-PANIC	AFR	CHI-NA	RUSS
Evaluation on training data	Support Vector Machine	0.865	0.824	0.833	0.8181	0.857
	Naive Bayes	1	1	1	1	1
Ten fold cross validation	Support Vector Machine	0.641	0.5	0	0.381	0.348
	Naive Bayes	0.644	0.571	0	0.25	0.286
	JRIP	0.667	0	0	0.125	0.4
	Bagging (Naive Bayes)	0.704	0.222	0	0.167	0

When considering the performance for one class C, a classifier can err in two ways. Firstly, an individual may be assigned to this class C although he belongs to another. Secondly, an individual may be assigned to another class although he belongs to class C. Consequently, there are different measures for these two error cases. We chose a combined measure, the F-measure, to express the overall quality of the predictions for each class in table 3. Table 3 shows that different models predict differently well for different cultures. As a consequence, different learning algorithms may be chosen depending on the cultures most important in a specific e-learning context.

Table 4: Ranking of most important attributes (answers in the questionnaire)

What topics in the internet are of special interest for you? Education and Knowledge
I am a computer freak
Using computers is an interesting spare time activity
What topics in the internet are of special interest for you? Shopping
What topics in the internet are of special interest for you? Politics
What topics in the internet are of special interest for you? Economics and Finance
What topics in the internet are of special interest for you? Geography
Computers are a useful tool and necessary in the work place.
What are desirable activities in a learning software? Assignment activities
What are desirable activities in a learning software? Fill-in text
What are desirable activities in a learning software? Entering free text
What are desirable activities in a learning software? Multiple choice

4.5 Analysis of the Models

Another method for analyzing the questionnaire data is the selection of the most important factors. From a machine learning perspective, the attribute contributing most information for the prediction of a class membership is the most relevant or significant. Such an analysis is helpful for the optimal design of future questionnaires. We used the following two methods from WEKA to automatically identify the most distinctive attributes for the membership to a culture from the questionnaire: Chi-squared ranking filter and Information gain ranking filter. Both resulted in the same ranking. The most important attributes found are presented in table 4.

5 Outlook

The analysis presented here can serve as a methodological model for similar analysis of questionnaires of culturally heterogeneous user populations. Generally, research on international and cultural aspects of information systems should be more strongly directed toward the inclusion of cultural dimensions. For our study, we intend to replace the classes for the learning problem. Instead of training merely culture names we will try to assign the cultural dimension values of the different cultures to the individuals. This would also lead to a more distributed learning problem. The information about the class membership would not be isolated in one value but distributed over several dimensions like power distance or uncertainty avoidance. Further research should also consider automatic clustering algorithms. Users can be assigned to automatically constructed clusters and these can be compared to the real culture of the user. That way, similarities between cultures relevant for information and especially learning systems may be identified and quantified.

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