User Modelling for Live Help Systems: Initial Results

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ABSTRACT

This paper explores the role of user modelling in live help systems for e-commerce web sites. There are several potential benefits with user modelling in this context: 1) Human assistants can use the personal information in the user models to provide the users with efficient support tailored to their personal needs; 2) Assistants can be more comfortable in their supporting role; 3) Consultation resources can be saved, and thus, financial savings can be made for the e-commerce company. A user modelling approach has been implemented and deployed in a real web environment as part of a live help system. Following the deployment we have analysed consultation dialogue logs and answers to a questionnaire for participating assistants. The initial results show that assistants consider user modelling to be helpful and that consultation dialogues can be an important source for user model data collection.

1. INTRODUCTION

It has been shown that customer service has a positive influence on e-commerce. For example, in [9] it is suggested that customer service has a positive effect on user attitudes toward Internet catalogue shopping. Still, the current state of practise in customer service for e-commerce is limited and in need of improvements [7].

In our previous work we have introduced a general model for customer service for web sites [1], now referred to as a model for *live help*. The model features a combination of human assistants and computer-based support. We propose a flexible user interface where users can select how they want to interact with the system. For example, users can choose whether they only want computer-based customer service or if they prefer to chat with human assistants via text chat, voice chat, or other means of interaction. In our model, we also aim at providing personalised customer service by employing user modelling.

There are several potential benefits with user modelling for live help systems. Knowledge about the user can allow a human assistant to provide high quality and personalised support to the individual user [6]. User modelling can also allow human assistants to be more comfortable in their supporting role, simply because the information in the user model can make them feel familiar with the user. Further, user models can make help sessions more efficient and the dialogues smoother, because the assistants do not have to ask the user for the same information over and over. In [4] an example is presented illustrating the potential financial savings to be made for a company employing a kind of live help system, due to the shorter dialogue time: assuming a modest 20 second reduction per help session, a large company can save $1.5M per year, under realistic conditions.

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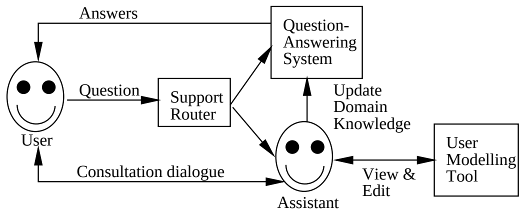

Figure 1: Overview of the live help model

In this project our main aim was to test the technical feasibility of the live help model. To do this we implemented an instance of the full model and deployed it at an existing web site for a three-week period.

The focus of this paper is on the study of the user modelling component that was part of the project. We explore the value and feasibility of user modelling for live help systems. Apart from testing technical feasibility we focus on two main questions: 1) What are the subjective opinions of assistants towards the concept of such a user modelling tool? 2) What kind and amount of user model data can be collected from consultation dialogues, and what are the linguistic characteristics for the dialogues?

2. LIVE HELP SYSTEM

An overview illustration of our live help model is presented in Figure 1. The support router is responsible for deciding whether the user needs computer-based support or support by a human assistant. The computer-based support is a question-answering system. If the support router connects the user to a human assistant they can have a real-time consultation dialogue. A user modelling tool for supporting the assistant is also part of the model.

In our implementation of the model the support router always routes the user through the question-answering system before connecting to a human assistant. The question-answering system is implemented using an information retrieval approach with frequently asked questions (FAQs) [2]. The user modelling component is the focus of this paper and will be further described in the next section.

The user's support process is initiated when the user asks a question in natural language. The question is fed to the automatic question-answering system. FAQ items which closely match are returned as potential answers to the question. If the user indicates that the returned answers are not satisfactory, the support router will connect the user to a human assistant with expertise matching the topic of the question. If all the appropriate assistants are currently busy, the user can choose to wait in a queue. Once an assistant is available the user is connected to that assistant and can proceed with a consultation dialogue via textual chat.

The implemented live help system has been evaluated from the users' point of view in [3]. The findings are very encouraging, particularly when it comes to users' attitudes.

3. USER MODELLING APPROACH

Information about a user is stored in a predefined attribute hierarchy, in an overlay style. A user's model is displayed for an assistant as soon as a consultation dialogue begins. The assistant can then make use of the information in the model to tailor the consultation to that individual user. No automatic inference is made on the data in the user model, although the assistant is of course free to make inferences as a part of his or her interpretation of the user data. The assistant can also update the model by filling in attribute values based on what is learned from the consultation dialogue with the user. Further, some basic demographic information (age, gender, and country) is automatically inserted in the user model via questions in a registration phase for the live help system (not shown in Figure 1).

We have chosen a simple approach, and there are two reasons for this. First, we look into the general value of this kind of user modelling tool. If we get positive results we can continue to explore technical issues and more advanced designs in a next step. Second, our aim to evaluate the system in a field study requires a simple system that voluntary assistants can take up with minimal instructions and training.

Based on a poll at the web site where we would deploy the system (the site is called Elfwood and is in the art and literature domain), we decided to let the detail level of the attribute hierarchy roughly correspond to the number of questions expected for that attribute category. The user model attribute hierarchy is illustrated in Figure 2. The bracketed numbers in the figure correspond to the number of times that user data occurred in the consultation dialogues. The relevance of these numbers is discussed in section 5.1.

The tool for viewing and editing a user model is shown in Figure 3. Each attribute is displayed as a rectangular button with the attribute name as a label. Attributes without a corresponding value are shown in grey in the figure. An attribute that has been given a value is shown in black, with the actual value written after the attribute name. By clicking on an attribute button, an editor window is brought up, where the assistant can create a value or change an existing value. The value can be chosen from a predefined value set or be created as an arbitrary text string. Textual comments can also be associated to a value. This feature can be used for explaining a given value.

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Personal data (10) - Age (5), Gender, Country (6), Occupation (1), Name (36),
                     Conversation style
Elfwood data (3) - Elfwood member (54), Link to art (41), Link to stories (10)
Art skill (10)
  Art media (2)
    Wet - Ink, Oil paint, Watercolour (2), Acrylics
    Dry - Pencil (7), Coloured pencil (1), Charcoal, Conte, Pastel
    Digital (2) - Adobe Photoshop (8), MetaCreations Painter,
                  Paintshop Pro (2), Graphics tablets (4), 3D programs
  Art objects (6) - Humans (6), Animals, Buildings, Nature
  Art styles (2) - Realism (1), Anime/Manga (7), Impressionist, Art nouveau
  Art techniques (13) - Perspective, Sketching (3), Detail drawing
Writing skill (9)
  Writing styles (1) - Humour, Serious writing, Fantasy (3), Sci-fi (2), Horror
  Writing technical (1) - Grammar, Characters, Setting, Plot, Point of view
Elfwood skill
  Site navigation - Pictures, Stories
  Member functions - Intranet, Tour creation, Picture upload, FARP (creation)
  User functions - Text search, Attribute search, FARP (usage), FantasyHoo
Computer skill (1) - Internet (1), Scanners (3), MS Windows (1), Linux, Unix
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Figure 2: The complete user model attribute hierarchy

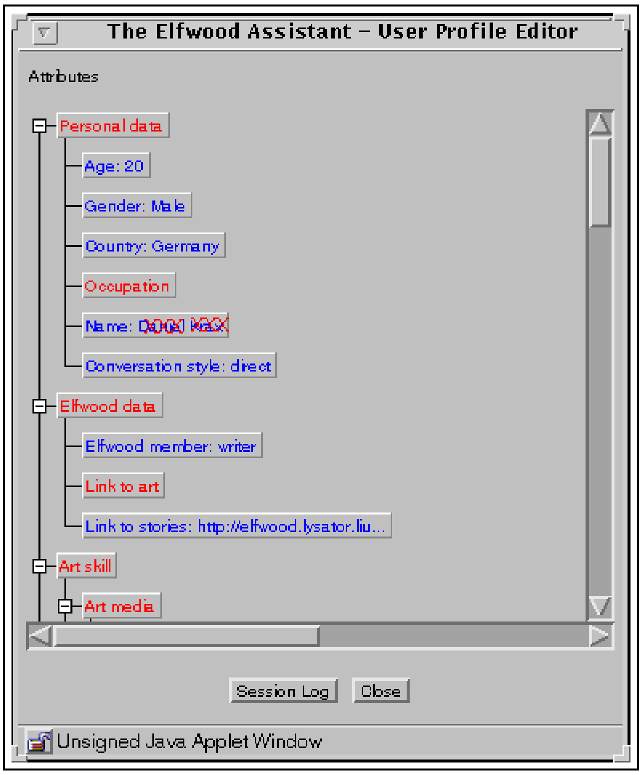

Figure 3: Screen shot from the user model viewer

Kass and Finin [8] analysed user modelling for natural language systems. Several dimensions for categorising user models were discussed. According to these dimensions our approach to user models can be classified as follows. Our models are *individual*, *dynamic*, and intended for *long term* and *descriptive* usage. A *single* user is modelled by a *single* user model. Our user models are mainly intended for *providing help and advice* for the user, and for *providing output to the user*. Further, the information in a user model can be classified into several categories. We model *capabilities* and *knowledge and belief*. We also model what we call personal data, such as name and age of a user.

4. FIELD STUDY

The overall research objective in this project has been to test the technical feasibility of our live help model. Therefore, a field study, where the system is tested in a real environment, is a natural research method. The field study consisted of two parts: system deployment for data collection, and data analysis.

4.1 Environment

The live help system has been attached to an existing web site for a period of three weeks. The site, called Elfwood, is a non-profit site with a focus on art and literature, where amateur artists and writers can exhibit their material. At the time of writing around 9400 artists and 1900 writers exhibit their work in the fantasy and science fiction genre. The artists and writers are members of the site with access to an extranet for updating their own exhibition galleries. A part of the site is devoted to teaching art, and offers a large number of feature articles on different topics.

We mainly supported three types of user tasks: 1) Learning how to create art and literature; 2) Searching for interesting art and literature at Elfwood; 3) Member activities, including the management of each member's exhibition area.

We chose Elfwood as the environment for our study for two reasons. First, we wanted a site with a reasonable number of users and user traffic, and with a user community that would allow the recruitment of suitable assistants. Second, we wanted to test our system in a low risk environment where unexpected system problems would not have large financial consequences.

4.2 Participants

Voluntary assistants participated in the study from their home or work environment. They were recruited some months before the field study began and they were all Elfwood members. In the end 30 persons with proper expertise served as assistants. During the field study, 636 users registered with the system, and 129 of these users worked through the system to have consultation dialogues with assistants.

4.3 Data collection and analysis

4.3.1 *Dialogue analysis*

During the three weeks of the data collection period a total of 175 consultation dialogues took place. We have analysed the dialogue logs in order to answer the following questions. 1) *How much user model data, and what type of data can be collected from help dialogues?* 2) *In what conversational circumstances does the user provide user model data?* 3) *What are the chat language characteristics for the consultation dialogues?*

4.3.2 *Assistant questionnaire*

In order to also get a subjective view from the assistants, we employed a questionnaire. This questionnaire contained items related to various aspects of the user modelling system. All 30 assistants who had participated in the field study received the questionnaire by e-mail just after the data collection period was over. We received 22 answers. Unfortunately, only 14 of these were answered completely, which corresponds to a response rate of roughly 47%.

Circumstance	Occurrences	Average
Q-A	134 (50.8%)	0.77
Vol	67 (25.4%)	0.38
Vol-Back	51 (19.3%)	0.29
Rej-Soln	12 (4.5%)	0.07
All circumstances	264	1.51

Table 1: Conversational circumstances statistics

5. RESULTS

5.1 Dialogue analysis

How much user model data, and what type of data can be collected from help dialogues? We found a total of 264 user statements containing personal information that could be used for user modelling purposes. In this total we do not count information about a user that is out of the scope of the tasks for the live help system. There were 175 consultation dialogues in total, which means that each dialogue revealed on average 1.51 pieces of information about a user. Regarding the type of user model data that can be collected from consultation dialogues we present the distribution over the attribute hierarchy in Figure 2 (on the previous page). The numbers in brackets that appear after some of the attributes correspond to the number of times that related user model data occurred in the dialogues. In some cases user model data did not fit into any of the most specific attributes. Then we placed the data in the least general attribute that fit with the data.

In what conversational circumstances does the user provide user model data? We found no pieces of information given by a user that did not fit into the set of conversational circumstances described in [5][1]. This indicates that they are fairly complete. Statistics from the conversational circumstance analysis is summarised in Table 1. Note that more than 50% of the user data comes from a question by an assistant. This indicates that assistants have an important role to play in user model data collection.

What are the chat language characteristics for the consultation dialogues? We observed that the dialogue language is notably informal. The answer to a question or the rejection of a solution can reach the recipient right away or several lines later, with a "gap" of unrelated text in between. Another striking aspect of the dialogues is that they are generally full of misspelled words, grammar mistakes and incomplete sentences. These results have implications for automatic information extraction of user model data.

5.2 Assistant questionnaire

In Table 2 we present results from the rating statements in the assistant questionnaire. Through ranking statements, we learned that the most useful attributes were the Personal data attributes, the Elfwood data attributes, and the Art skill attributes. The Personal data attributes were useful in the sense that the assistants could know the user's name and thus have a more personal dialogue.

[1]A user provides personal information as: an answer to a question (Q-A), voluntarily (Vol), voluntarily as background information (Vol-Back), or as reason for rejecting a solution (Rej-Soln).

Statement	Mean	Dev.
In general the user models were (no help=1, helpful=10)	6.93	2.95
The amount of time available to view user model data during a help session was (on average) (too limited=1, enough=10)	7.79	2.91
How did the value of a user model change as more data was added to it? (less helpful=1, more helpful=10)	8.29	2.09
The number of times that a user model gave me wrong assumptions about a user were (few=1, many=10)	1.57	0.85
Extracting information from a help conversation for insertion in the user model was (hard=1, easy=10)	5.79	2.94

Table 2: Questionnaire results about the user modelling system

An additional source of user information available at Elfwood was the members' own display of art and literature. Two Elfwood data attributes in the user models represented links to such user info. Links to a user's art or literature proved very valuable for the assistants as it gave a concrete indication of the user's art or writing skill.

It is important to analyse how the user modelling system was helpful to the assistants. Five assistants said that user modelling helped them tailor the help to the individual needs of the user. Another assistant said that the user model data made the dialogues smoother. Yet another assistant said that reviewing the user model reminded her to ask the user questions that were helpful.

6. LIMITATIONS

A main limitation of our study is that the data collection period only lasted for three weeks. Consequently, the number of users who used the system more than once was limited. Only 26 out of the 129 users used the system more than once, and only a small number of users had updated information in their user model. Thus, some of the assistants only got to assist first-time users with empty user models (except for the Age, Country, and Gender attributes). They gave low scores on the question about the helpfulness of user models, stating that the models never contained any helpful information. Disregarding the scores from these three assistants and recomputing the mean and standard deviation for the corresponding questionnaire statement, we get a mean of 8.27 and standard deviation of 1.35 instead. This gives a stronger indication of the potential helpfulness of user modelling for assistants.

In summary, these limitations mean that we must consider our initial results as indications and not as proofs. A natural further step would be to use controlled experiments to statistically test the value of user modelling, both for users and for assistants.

7. RELATED WORK

To our knowledge there is limited prior research on user modelling in this context. One exception is the paper by Fridgen and colleagues [6]. They argue for the importance of customer models in the financial services industry, and discuss different categories of user information that should be modelled. The paper thus complements our work in a nice way.

Work has been done on user modelling in automated dialogue systems [5, 8, 10]. For automated dialogue systems, data about a user's short term goals can be highly relevant in order to interpret the user's question. In contrast, for a live help system it is not important to model this data since the human assistant can interpret the user's question, using his or her human intelligence and domain knowledge. For live help systems, it is most important to model data about the user that is valid over several help sessions. Such data includes the user's preferences, knowledge, and beliefs, as well as personal data.

8. CONCLUSIONS

We conclude by considering the two initial questions raised in the introduction. First, the questionnaire results showed that the assistants in fact considered user modelling to be helpful for assisting users. Second, the dialogue analysis showed that much important user information of various kinds can be gained through such dialogues. We also identified requirements for automatic extraction of user data.

Live help systems are here to stay. The initial questions we have considered in this paper represent merely the beginning of one branch of research on live help systems!

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