An Ontology Based Recommendation System for Elderly and Disabled Persons

Ingo Zinnikus[1], Anton Bogdanovich[1], Ralph Schäfer[2]

DFKI GmbH
Stuhlsatzenhausweg 3, 66123 Saarbrücken
{zinnikus, anton, Ralph.Schaefer}@dfki.de

Abstract.

In this paper, we describe the use of a hierarchical ontology representation as a basis for modelling user preferences in the SAID project for elderly and disabled persons. The nodes of the ontology tree are associated with either pre-selected or dynamically found web sites relevant for each topic of the user's interest (in this way web-surfing can be substituted by browsing through the ontology). In order to further reduce the complexity of the tree, we combine this approach with applying a probability based recommendation system which monitors the user's actions and adapts itself according to the observed behaviour. We also show that the resulting ontology tree is compatible with Bayesian networks and discuss limitations and possible extensions.

Keywords: User-adaptivity, user modelling, ontology, SAID.

1 Introduction

In the SAID project, elderly and disabled people get support by a personalised interface which provides among other things access to the web. Since the structure of many web pages is very complex and daunting for elderly people the main goal of an information service is to reduce the complexity of the web pages in a reasonable way. Our approach is based on the assumption that adapting to the user preferences helps to achieve this goal. For this purpose, the following issues have to be addressed:

- How can subject and themes be represented so that interesting recommendations may be given to the user?
- How can the user's action be interpreted in order to estimate her interests?

The paper is structured in the following manner: In Section 2 we describe the context of the SAID project and explain why we decided to use the ontology based approach. To represent the subject and themes, we use an Ontology-tree for supporting a user in selecting interesting themes. This tree is described in Section 3. Section 4 demonstrates how the actions of the user are interpreted to generate individual user profiles. For estimating interests we employ a probability based recommendation system. In Section 5 we show that the user profile is compatible with Bayesian networks (BN) so that the interpretation of the user's actions can be seen as learning task of BNs with given structure. Finally, limitations and extensions of the solution are discussed.

2 Context: Said – Social Aid Interactive Development

The aim of the SAID project is to develop an innovative social assistance infrastructure to provide more efficient social care for elderly persons, improving both services and access. SAID supports a

[1] This work is funded by the European Commission's Information Society Programme (IST), grant No. IST-2000-25024.
[2] This work has been partially supported by the EC through the IST-Programme under contract IST-1999-10688 CAWICOMS (see http://www.cawicoms.org for additional information).

number of services under a Digital TV infrastructure. This involves more efficient social care for the elderly, improved services and availability of new information technologies for a sector of the population for which such developments have been hitherto unavailable.

The project involves three areas of research: novel developments for digital television, the development of intelligent agents (personalised assistants adapted to specific users' characteristics), and new approaches for simplified user interfaces, mobile information access and data management specifically designed for the elderly.

Independent living for the disabled & elderly (D&E) requires development of a suitable environment for that task. The D&E may stay at home in a known environment, close to their relatives and friends. The concept of independent living means improved access to a wide range of information and communication technologies within the home environment by means of the

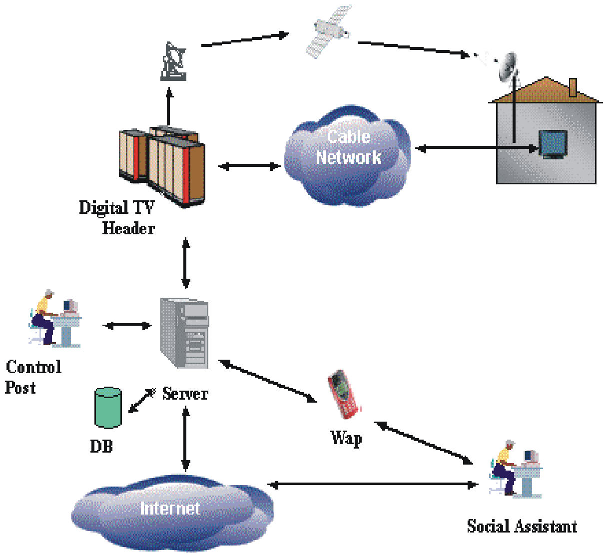

Figure 1: General system design

development of an integrated framework. For the D&E this implies improved access to information, participation in social and community activities, self-satisfying learning, leisure, etc. Support is still provided by human assistance, e.g. social workers, who are enabled to monitor the D&E.

For the elderly SAID implements a mixed computer/personal based environment where the individual will be given the opportunity of self care while s/he has the possibility of 24h aid when needed. SAID puts into the hands of the D&E the power of Internet by providing them information that can be automatically filtered or prioritised according to a user profile. The project also aims to provide tools for social assistants (professional carers).

The SAID system comprises the following components, arranged in a star like manner (see Figure 1): a server part, which is responsible for the organization and administration of all the services, and hosting the database, which contains the data of the system components; the client system at the end users' home, equipped with Digital TV including a set top box which provides an interface for the user. The connection between server and the client site is achieved via cable network or satellite. Social assistants supervising and monitoring the clients are connected to a control post responsible for the server activities via mobile phone or via the Internet in order to provide emergency assistance.

For the information service, an agent subsystem is used to provide the web related services. For every user, an agent society acts on behalf of this user. Part of the agent society is the information agent which accesses the web using the user profile and preferences.

Elderly people are often reluctant to use new media because of technophobia. Since the SAID system is intended to be used by this population segment, we decided to avoid the use of web browsers, direct access to search engines (instead, the information service invokes a query on behalf of the user), and are even going to hide the fact that the user accesses the Internet at all. The complexity of web pages with different frames, links and advertisement is hidden and only the content related information is visible for the user. In order to accomplish transparency of the content for the elderly, we encapsulated the knowledge about the web site we use into the project's ontology. Instead of showing a web page, the concepts of the ontology are displayed. Using this approach "web-surfing" will be substituted by browsing through an ontology tree. A further difference of our solution in comparison with e.g. [L95] or [PM97] is that we concentrate on a limited number of web pages where we know or at least assume that the content is interesting and relevant with respect to a specific subject. Finally, since we want to be as unobtrusive as possible we avoid requesting explicit feedback from the user. The system passively monitors the actions of the user and tries to interpret these actions relying on reasonable assumptions (cf. [SPK00]).

3 Ontology

An ontology is usually defined as a set of terms aggregated together with their definitions. This includes also somehow represented inter-concept relations that help to interpret the terms. So the classical view of an ontology is a kind of global knowledge storage (cf. [HJ02]).

The ontology in SAID serves not only as a knowledge storage but also has a functional constituent. It is represented as a hierarchical tree-like structure (so all the relations are of 'is a kind of' type) marked with concept names. The ontology-tree stores also additional information attached to the tree nodes. The information in this case means on the one hand a collection of concept attributes and on the other hand includes the foregoing functional constituent. Thus each of the tree nodes serves as a container for additional data that points to a specific web page and helps to extract only desirable information from it using predefined rules. Let's try to explain it on an example:

Imagine that the ontology consists of e.g. 3 super concepts: Gardening, TV, Wellness, and each of them has a tree of sub-concepts (See Figure 2). Note that e.g. 'Sport' as sub concept of 'TV' does not mean that 'Sport' in general is a sub concept of 'TV' but that sport events on TV are obviously also TV events.

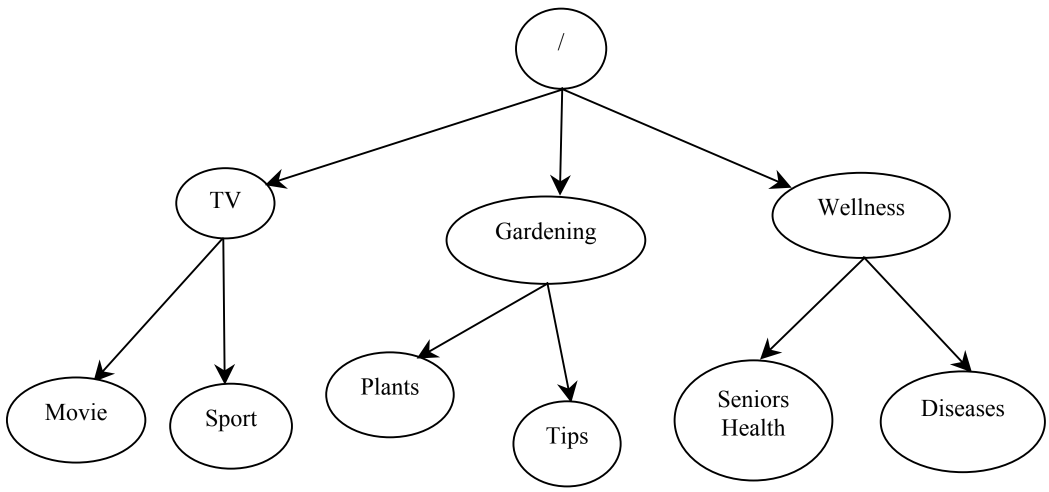

Figure 2: Simple Ontology

Such an ontology tree will be used in our system for helping elderly people to find useful information related to the desired topic (tree node) and for guiding them to this topic by moving down the ontology. Almost all the information will be extracted from the World Wide Web.

Imagine that a user wants to look for Sport programs available on TV. We can find this information using the /TV/Sport node. First when the user starts to work with the system there will be 3 possible ways to proceed: “TV”, “Gardening”, “Wellness”. The user selects “TV” and receives the list of its sub nodes. As the next step, when “Sport” is selected, the URL related to “Sport” will be accessed and the content of the web page will be filtered using rules. The rules are written in a form of normal regular expressions and are used for information extraction by our subsystem called “AEP”. The result of the filtering operation in this case is a plain text. Plain text can be easily displayed on a digital TV screen and will contain only useful information without any advertisement or other “Spam” data.

The concepts of the ontology represent one or more web pages which provide the ‘real’ content (e.g. the sending date and the channel of a TV programme). Most of the web sites we use are preselected and categorised in advance, excepting the case when a search engine is used. Since we have to be aware that the structure of sites in the world wide web and the content of the pages are rapidly changing, there should be a possibility to edit the extraction rules for each concept of the ontology without modifying the program code. For this purpose the utility called *OntologyConfigurator* has been created. This simple program can be used by social assistants in case when the web-site that is related with an ontology node has been removed or changed its structure. The utility allows to see the ontology tree as a simple graphical tree component and allows adding/removing/renaming a node or editing the information related with it.

4 Interpretation of the User's Actions

As it was described in the previous subsection, the ontology tree is used to guide users to interesting information. Browsing through the ontology might be still complex for elderly people when the tree comprises several levels of concepts. User preferences and interests of a specific user help to further restrict the space of concepts. Thus, only those concepts, in which the user has shown interest before, will be displayed by default. However it is still possible to get the complete list of concepts of a current tree level. Furthermore, recommendations based on preferences allow the user to skip several menu iterations and jump immediately to a leaf node. The basic question then is how to adapt to the user preferences.

Learning of user’s interests is done by statistical evaluation of previous user behavior. Since the tree is more a general representation of topics of interest than a representation of a specific user’s preferences the ontology of concepts is complemented by weightings which represent user related preferences.

The main sources of information about the ‘real’ interests are a questionnaire, which is filled out before the user starts to work with the SAID system, as well as her/his use of the information service. The decisions of the user can be traced and stored in an individual copy of the ontology tree. The obvious way to trace the previous actions of the user is to count the number of times s/he selected a specific concept when the information service was entered. The concepts in the hierarchy are associated with information about how many times the user chose to get more details about each concept. Together with the total number of times the information service was used, we can easily calculate the probability for a given concept by dividing the number of acceptances through the number of total uses of the information service. In this way the probability distribution for a specific user can be calculated.

Of course, this interpretation of the user’s actions can be questioned. A user might be just playing around with the system. Therefore, the first assumption is that s/he will regularly use the information service. Another assumption is that the user is to some degree ‘earnest’ and really interested in the concepts s/he selects. Since the users have accepted to join the SAID community and know that they are using the SAID system, both assumptions are reasonable.

Another problem is that selecting a concept out of a menu does not imply real interest in this topic unless the user proceeds to select further sub-concepts until reaching a leaf node. Even then it could be argued that the fact of reaching the leaf doesn’t imply that s/he is interested in the information displayed (in the case of a leaf, the information is an HTML document modified for the Digital TV).

However, it is a well-examined fact that the time someone spends on a web site is a significant evidence for her/his interest in this document ([CLW+01], [KMM97]). Hence, the time spent for a document is monitored by the SAID system and taken into account when the user's action is interpreted. Only if the time (compared to the length of the document, although time is more significant, cf. [PG 99]) is reasonably higher than a specified threshold, the action is counted as acceptance or implicit expression of interest in this topic. Also, when the time exceeds a certain threshold (e.g. 20 minutes), the action is interpreted as not countable, since the user is then probably doing something else.

5 Compatibility with Bayesian Networks

In this section we will compare our approach with an alternative: The use of Bayesian networks. A *Bayesian network* (BN) is a kind of a probabilistic network (see [Pearl88]) represented as directed acyclic graph. The *nodes* of this graph represent random variables, which consist of a set of mutually exclusive and exhaustive propositions called *hypotheses*. For each of these hypotheses, the probability of being true is maintained. All these probabilities together are called a *probability distribution,* also named the *belief of a node*. The dependencies between the propositions are represented by the *links* between nodes. A *conditional probability table* (CPT) expresses such a dependency.

For the root nodes, a priori probabilities must be defined. The belief of a node that is not a root node can be predicted on the basis of the parent nodes' beliefs. Observed evidence will be interpreted and used to update the beliefs of the nodes in the network. This process is called *solving the network*. Its detailed description can be found in [Pearl88].

A BN in our domain would look like the one depicted in Figure 4. The structure of the network is defined in advance. For learning BNs with given structure, one has to count the occurrences of the events (see [RN95]).

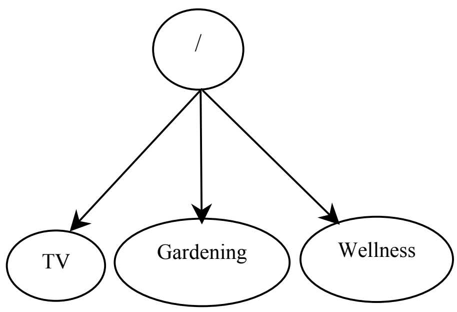

Figure 3: Fragment of a Bayesian network

Actually, we do not employ Bayesian networks, but in the following, we will show that our approach is consistent with the use of BNs.

The frequencies of the user's selection of a concept allow to adopt a Bayesian approach to model the preferences, make recommendations and adapt to the observed behaviour. According to the rule for conditional probabilities,

$$P(A|B)= \frac{P(A,B)}{P(B)}$$

e.g. the probability for selecting the item "Movie" under the condition that "TV" was selected can be calculated in the following way:

$$P(Movie|TV)= \frac{P(Movie, TV)}{P(TV)}$$

Now, since we have the subsumption relation between “TV” and “Movie”, we know that every movie event is also a TV event. Hence we have P(Movie,TV)=P(Movie) and

$$P(\text{Movie}|\text{TV}) = \frac{P(\text{Movie})}{P(\text{TV})}$$

We can now use the frequencies to calculate the conditional probability for P(Movie|TV) and obtain a simple instance of a Bayesian net. This view is also compatible with an alternative view of the process: By using the frequencies, we could learn the conditional probabilities of a Bayesian network with given structure.

The advantage in comparison to a full-fledged Bayesian net is that it is possible to use an algorithm especially tailored to calculate the conditional probabilities for the tree nodes.

Recommendations can now be made in a straightforward manner. When a certain concept is selected, sub-concepts (and even sub-concepts further down the tree) with a conditional probability exceeding a certain threshold are presented automatically. This reflects the previous interests shown by a user and eases the search for new information.

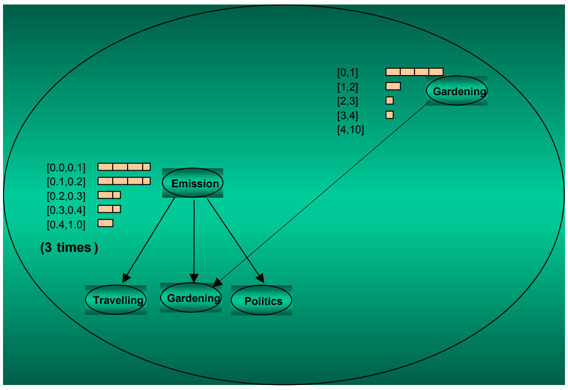

Figure 4: Integrated Bayesian net

6 Restricting and Extending the Network

In the case described above, where the scenarios are TV, Gardening and Wellness, it is not reasonable to treat the complete tree as a Bayesian Net. The TV sub-tree is not independent of other scenarios, since there could be TV programmes about a specific gardening topic. TV is a media – it can transmit contents of other categories. A solution is to treat every sub-trees with independent concepts as a separate instance of a Bayesian net. The preferences for a specific user then consist of an ontology tree, where a number of distinct sub-trees are Bayesian nets which represent the individual interests of this user.

The next step to integrate the sub-trees again into one Bayesian net is to draw crossing links between identical concepts in different sub-trees. If e.g. a TV programme is about roses and “rose” is a concept in the “Gardening” sub-tree, a link is drawn between the sub-trees to integrate this concept into the local Bayesian net (see Figure 4). This means that when the probability for the TV programme is calculated, also the probability for “roses” is taken into account. The drawback of this solution is that we cannot take advantage of the subsumption relation anymore while calculating the conditional probability. Instead, the extended network is a full-blown Bayesian net where already established algorithms can be used to calculate the probabilities.

7 Conclusion

In this paper we described a way to model user preferences for domains where a hierarchical structure of knowledge representation is feasible. In the SAID project, for disabled and elderly persons we provide agent-based information services for selected topics represented in an ontology tree. In order to help the user browsing through the ontology tree the actions of the user are monitored and, based on the observed behaviour, conditional probabilities are calculated in order to predict the interests of a specific user. The approach is compatible with Bayesian networks. When sub-trees of the ontology are not independent of each other, sub-trees are restricted and later on extended by integrating identical or synonymous concepts from other sub-trees.

References

[CLW+01] Claypool, M., Le, P., Waseda, M. and Brown, D. (2001). *Implicit Interest Indicators*. In Proceedings of ACM Intelligent User Interfaces Conference (IUI'01), Santa Fe, New Mexico, pp. 33-40.

[HJ02] Holsapple, C.W., Joshi, K.D. (2002). *A collaborative approach to ontology design.* In Communications of the ACM, 45(2), pp. 42-47.

[KMM+97] Konstan, J.A., Miller, B.N., Maltz, D., Herlocker, J.L., Gordon, L.R. and Riedl, J. (1997). *GroupLens: Applying Collaborative Filtering to Usenet*. Communications of ACM, Volume: 40, No. 3, March 1997, pp. 77-87.

[L95] Liebermann, H.(1995). *Letizia:An agent that assists web browsing.* In Proceedings of the International Joint Conference on Artificial Intelligence, Montreal, pp. 924-929.

[JSS+95] Jameson, A., Schäfer, R., Simons, J. and Weis. T. (1995). *Adaptive provision of evaluation-oriented information: Tasks and techniques*. In C.S. Mellish (ed.), Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence, pp. 1886 – 1893.

[PML01] Parent, S., Mobasher, B., and Lytinen, S. (2001). *An Adaptive Agent for Web Exploration Based of Concept Hierarchies*, to appear in Proceedings of the 9th International Conference on Human Computer Interaction, New Orleans.

[PM97] Pazzani, M., Billsus, D. (1997). *Learning and Revising User Profiles: The Identification of Interesting Web Sites.* In Machine Learning 27(3), pp. 313-331.

[Pearl88] Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference.* Morgan Kaufmann, San Mateo, CA.

[PG99] Pretschner, A., Gauch, S., (1999). *Ontology Based Personalized Search*. In Proceedings of 11th IEEE International Conference on Tools with Artificial Intelligence, pp. 391-398.

[RN95] Russell, S.J., Norvig P. (1995). *Artificial intelligence: A modern approach. Englewood Cliffs, NJ:* Prentice Hall.

[SPK00] Schwab, I., Pohl, W. and Koychev, I. (2000). *Learning to recommend from positive evidence*. In Proceedings of the International Conference on Intelligent User Interfaces, New Orleans, pp. 241-247.

[WE86] Winterfeld, D. von, Edwards, W. (1986). *Decision Analysis and Behavioral Research*. Cambridge, England: Cambridge University Press.