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Educational and Scientific Recommender Systems: Designing the Information Channels of the Virtual University*

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In this article we investigate the role of recommender systems and their potential in the educational and scientific environment of a Virtual University. The key idea is to use the information aggregation capabilities of a recommender system to improve the tutoring and consulting services of a Virtual University in an automated way and thus scale tutoring and consulting in a personalized way to a mass audience. We describe the recommender services of myVU, the collection of the personalized services of the Virtual University (VU) of the Vienna University of Economics and Business Administration which are based on observed user behavior and self-assignment of experience which are currently field-tested. We show how the usual mechanism design problems inherent to recommender systems are addressed in this prototype.

INTRODUCTION

UNIVERSITIES worldwide are hard pressed in meeting the challenges of teaching an increasing number of students, supporting life-long learning for larger and larger parts of the population and of dealing with growing student heterogeneity. At the same time they must strive to maintain a competitive and high-level research profile in the face of severe cuts in funding and in the face of global competition in the education market [1]. Recommendations for universities range, for example, from a massive deployment of information and communication technology in universities coupled with a move to a common distance learning and progress monitoring environment which would lead to a world market in learning materials as requested in the famous Dearing report [2] to a radical reorganization of universities based on the separation of labor along the value chain as in the media industry with the appropriate restructuring of the university system as predicted by D. Tsichritzis [3].

Surprisingly, market-related ideas as to the concept of a market as a decentralized coordination mechanism with the price system as information channel [4] or the idea of organizing a *university as a marketplace* [5] are almost absent from the discussion. In this article we focus on the metaphor of a Virtual University as an information market with a recommender system as the market information channel. The fact that state university systems are usually financed from government funds (that is indirectly) should not be an obstacle to such an approach. Even if a direct price system, for example for university courses, is missing, market forces are still operating through means like contractual changes, adaptation of the product quality, and through information channels (e.g. word-of-mouth effects) as F. Hayek already observed [4].

THE POTENTIAL OF RECOMMENDER SYSTEMS IN EDUCATION AND SCIENTIFIC RESEARCH

Suppose you just arrived as an exchange student at the Wirtschaftsuniversität Wien for the first time in your life. Which lectures do you choose for your exchange term? Well, usually you either ask your mentor or you listen to the gossip of your fellow students during lunch at the university's canteen or you refer to the student union's last course evaluation leaflet.

In everyday life this is a common situation: you often have to make choices without sufficient experience of the alternatives. A recommender system assists and augments this social process [6]. 'In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients' [6].

University systems worldwide face the following challenges today:

1. Teaching growing numbers of students with a more or less fixed staff size.
2. Supporting life-long learning for more and more citizens at a socially acceptable cost.

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3. As a consequence teaching increasingly heterogeneous student groups.
4. Dealing with information overload caused by the exponential Internet growth and—what is often overlooked—the increasing number of researchers worldwide. (It is said that 90 percent of all researchers ever live today.)

Because of these trends, today the members of a university, namely teachers, researchers and students, are a time-starved species. Recommender systems in education and scientific research help in meeting the challenges by freeing time. In the following examples we demonstrate the time-saving potential of recommender systems in a university teaching and research environment.

Student/teacher communication

Does modern telecommunication technology address the bottle neck in the communication capabilities of a university teacher? No, even with modern communication technology the number of students a university teacher can tutor and support with recommendations is severely limited by the time needed for each interaction (e.g. meeting, talk, chat, e-mail, phone-call). An educational recommender system, however, addresses this problem by freeing teachers from the more routine recommendations, as for example 'I want to make my own home page. Which book should I read?'

Information overload

Why is the utilization of the Internet in education and research not as high as previously expected, despite the fact that almost everything is available on the Internet? The answer is, because of search cost and time necessary e.g. for a scientific inquiry or for finding, comparing and evaluating instructional material. An educational and scientific recommender system has the potential of substantially reducing these search costs by aggregating and collecting user-experiences of a large group of users.

User heterogeneity

In the university of the future students differ with regard to their background knowledge, their professional experience, their preferred learning styles. Scientists come from different disciplines, have very special and particular interests and previous experience profiles. With an educational and scientific recommender system user heterogeneity can be addressed e.g. by self-assessment of experience as explained below.

Team-building

One of the problems of mass universities is the increasing social isolation of the individual student/teacher/researcher. With their capability to group persons with common interests inferred from common information product (e.g. a course unit) buying/usage patterns, educational and scientific recommender systems offer the chance of improving collaboration by building small learning groups for students or research groups of scientists.

DESIGN SPACE OF RECOMMENDER SYSTEMS

Recommender systems are among the top rated products today: For example, Alexa, a Web-browser plug-in for related links has won PC Magazine's Best of 1998 Award [7]. Another important example is Firefly Network Inc. which was recently acquired by Microsoft, because it is market leader in the personalization and personalized recommender business. Relationship Tech-like recommender systems is regarded by visionaries of the new economy like Kevin Kelly as the key technology for network economies [8]. Several Internet companies have recently introduced recommender systems for information products ranging from recommendations for web-sites (URLs) to recommendations for music, videos, and books (e.g. Amazon.com, http://www.amazon.com). Internet marketing agencies use recommender systems for targeting customers with specific ads (e.g. ActiveAgent Werbenetz, http://www.activeagent.at). Web usage mining and web content mining are active areas of research, see e.g. [9].

Historically recommender systems grew from the information filtering research of the late 80s and early 90s which applied information retrieval techniques for personalized information delivery. Examples of early recommender systems include Tapestry [10], Group Lens [11], Fab [12]. They coined the terms 'collaborative filtering' and 'social filtering', mainly with group-ware applications in mind.

P. Resnick and H. R. Varian [6] classify recommender systems according to the following dimensions:

1. *What is the content of a recommendation?* The content of a recommendation can come in a variety of forms, as e.g. a single bit (1 = recommended, 0 = not recommended), a grade in school, one to five stars (e.g. for hotels), or a simple unstructured text, a reference to an information source in the form of an URL, a bibliographic reference, etc.
2. *Is the recommendation based on user opinions or observed user behavior?* The emphasis here is on the difference between explicit recommendations which reflect the users' opinions or implicitly derived evaluations which are inferred from observed user behavior. Note, that the Internet-based infrastructure of a Virtual University offers a rich environment for gathering implicit indicators, e.g. reading time of users, mining newsgroups, web usage mining,
3. *Is the user anonymous?* In a traditional university setting, either a teacher knows a student or

not. In the environment of a Virtual University, however, anonymity is a matter of degree:
- anonymous single purchase incidents, as e.g. http-transactions in the log of a stateless http-protocol;
- anonymous sessions, e.g. http-server logs with cookies;
- pseudonymous users, that is we know which sessions belong to a single student;
- attributed pseudonyms, that means in addition to a pseudonym, the student has revealed several attributes like sex, age, discipline, experience, interests, profession, etc.;
- fully identified (for exams it is a legal requirement that students are identified by the teacher).

4. *How are recommendations aggregated?* This is the richest area for exploration. Options range from one man/one vote, weighted and discounted voting, personalized weighting to content analysis. In addition, we can vary the level of aggregation to respect user heterogeneity: specific for a person, for a group (cluster) or a segment, or for all users of the system (globally).
5. *How are recommendations used in the system?* For example, as annotation of a course, as label (e.g. a five star label for the highest-rated courses), for ranking a list, for filtering or discarding negatively rated text-books, etc. In addition, recommendations can be used for building adaptive user-interfaces, as e.g. demonstrated by myVU recommender services.

In addition, the choice of a concrete design on this landscape for recommender systems must take the characteristics of the items being evaluated and of the user community of the recommender system into account. For instance, P. Resnick and H. R. Varian recommend to analyze the following questions:

- *What type of item should be evaluated?* For example, newsgroup articles, Web-sites, home pages, e-mail, course units, business games, software, etc.
- *How many items must be evaluated?* In many instances the sheer volume determines the practicability of what kind of recommendations can or should be given.
- *What is the lifetime of an item?* For items with a very short lifetime (e.g. newsgroup articles) the timeliness of recommendations is very important.
- *What is the loss function of the peoples decision of choosing an item or not?* Consider, for example, the risk of reinventing the wheel, because a researcher has missed a relevant article.

For the participants in a recommender system P. Resnick and H. R. Varian identify the following attributes:

- *Who are the producers of a recommendation?*
- *What is the density of recommendations?*
- *Who are the consumers of recommendations?*
- *How fast do consumers' tastes, needs, or experiences change?*

Answers to these questions strongly influence the technical design of a recommender system in education and research. For example, in a mass university, a recommender system matching students with similar study interests is more valuable than in a small research university, where everybody knows everybody.

MECHANISM DESIGN PROBLEMS FOR RECOMMENDER SYSTEMS

Now consider, for example, the effects anonymous recommendations might have on the reputation of a teacher or a researcher. As part of the evaluation of courses which is required by law in Austria, a feedback-box which allows the submission of anonymous suggestions for course improvement was introduced at the Vienna University of Business Administration. In the first version all suggestions were instantly made available to the general public on the Web, before the responsible university teacher had a chance to react. After several cases of abuse by anonymous users, the procedure of operating the feedback-box had to be changed repeatedly (restricted access for university members only, response of teacher required only for non-anonymous suggestions, etc.).

The design of recommender systems poses several interesting and challenging incentive and privacy problems [6] which are also present in an educational and scientific context:

- **Free-riding.** As soon as a user has established a profile of interest, it is easy to free-ride by consuming recommendations provided by others. This may lead to too few evaluations or unrepresentative evaluations or even misleading evaluations. Moreover, even with a recommender system relying exclusively on observed user behavior this problem may still persist as Avery and Zeckhauser [13] demonstrate by showing that the payoffs of the users of a recommender system may resemble the payoffs in the famous Prisoner's Dilemma game.
- **Biased recommendations.** If anyone can provide recommendations, it is tempting for content owners to generate large amounts of positive recommendations and to damage competitors with negative recommendations.
- **Privacy.** The quality of (explicit) recommendations is inversely related to the degree of privacy. Moreover, there is a tension between the desire to gain recognition for good recommendations and the desire to remain anonymous.
- **Credibility.** Recommender systems which are financed by advertisers or have other (hidden) interests in the contents of recommendations

must carefully strive to maintain their credibility with their readers.

- **Positive/negative feedback effects.** A few early positive or negative recommendations may lead to a self-reinforcing feedback loop resulting either in an exponential increase or decrease in the usage of an information product. This implies that success or failure of such a product may depend on the random sequence of the first few recommendations (path-dependency).
- **Economies of scale.** The bigger the set of users of a recommendation system, the larger the expected benefits of each user. That is, if users have the choice between several recommender systems, they will choose the one with more users. If several recommender systems compete in the same market, there is probably only one survivor.

In addition, because of the incentive and privacy problems inherent in recommender systems discussed above, we suggest that the following questions should be analyzed in depth, when designing a recommender mechanism:

1. What is the relation between the owners of items evaluated, operators of the recommender system, producers of recommendations and consumers of recommendations?
2. What kind of incentive/privacy problems can be identified for specific design of a recommender system?
3. What are the risk/threats/benefits for each party involved?
4. What is the payoff function for all parties involved?

MyVU: DESIGN PRINCIPLES, ARCHITECTURE AND RECOMMENDER SERVICES

In this section we describe the recommender services of the Virtual University (VU) and of myVU (http://myvu.wu-wien.ac.at), the collection of personalized services of the Virtual University (http://vu.wu-wien.ac.at) of the Vienna University of Economics and Business Administration. In Table 1 we show where these recommender services are situated in the design space discussed previously.

This section is organized as follows: First, we concentrate on the design principles in order to emphasize the economic ideas and broker system. Then we discuss the high-level architecture of the system. Finally, we present the recommender services which are already operational.

Design principles

The design principles of the VU and myVU recommender services are based on the key ideas presented in the following paragraphs.

- **Information channels.** As discussed in the introduction we treat the Virtual University as information market with a recommender system as information channel.
- **Observed purchase behavior.** We generate recommendations from observed purchase behavior for information products.

Table 1. Features of VU and myVU recommender services

	VU	myVU
Content?	URL to Web-site	URL to Web-site
User opinions or behavior?	User behavior	User behavior, self-assessment of experience
Anonymous?	Yes, session data	Pseudonyms
Aggregation Method?	ABC-analysis, market basket analysis	Context-specific market basket analysis based on self-assessment of experience, analysis of purchase history
Use?	Ranked lists, labeling of lists, ranked market basket lists	In addition: group specific market baskets and profiles of related information product groups, personal favorites (web-sites or groups)

In Fig. 1 we show a sketch of the VU broker system.

Broker systems

Whenever the user follows an external link from the Virtual University broker to an information product (course, course unit, article, bibliography, management game, quiz, etc.) we consider this as a purchase incident. Use of internal links in the broker system indicates user preferences for broker services. Note, that information products

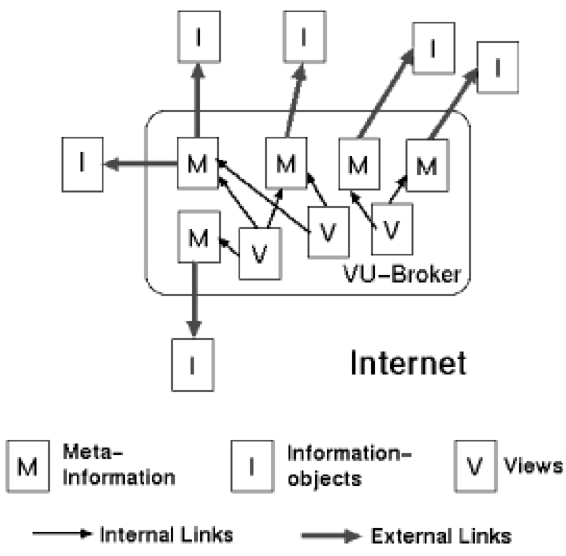

Fig. 1. VU-Broker.

in the Virtual University have a rich meta-data description which may also include categorization by several classification schemes. This corresponds to the product category structure used in the retailing industry. Depending on the degree of anonymity of the user we transfer several popular analysis methods of the retailing industry into a scientific and educational setting.

In the simplest case, anonymous users with http-transaction log data only, purchase frequencies for information products and information product groups are analyzed and used for displaying frequency-ranked product lists and for labeling hot-selling products based on their class in an ABC-analysis. Even this admittedly simple use of information strongly influences the choice behavior of users in online environments as shown by empirical evidence surveyed by L. Introna and H. Nissenbaum [14].

The user of the Virtual University 'buys' several information products during a single session. Such market-baskets which are extracted by analyzing user sessions are aggregated and used for example to analyze cross-product purchase behavior.

What is the motivation to base a recommender system on market-basket analysis? As S. Bellmann *et al.* [15] put it, observed consumer behavior is the single most important information for predicting future purchases, online as well as offline. For example, they reported that for a recent Internet survey of the GVU (Georgia Tech Graphics, Visualization Usability Center) demographic data alone explained only 1.2 percent of all online purchases. Every transaction tells a story. Market-basket analysis in retail stores show a cross-selling potential of up to 70 percent which waits to be tapped [16].

A market-basket contains all information products which a user has visited (= bought) during a session. From market-baskets we can easily compute for each information product the conditional probability distribution of buying an other information product offered by the broker, if this information product has been bought. This constitutes the documented collective purchasing behavior of all customers.

If market baskets additionally are labeled with the pseudo-identity of a buyer, we have the whole purchase history available for analysis. The purchase history is a requirement for using stochastic models of consumer behavior [17]. Even rather short purchase histories have considerable value in improving the effectiveness of target marketing as shown by Rossi *et al.* [18]. We expect similar results in the educational and scientific environment of a Virtual University too, but we do not yet have empirical evidence, because at the time of writing this article, myVU which makes use of this information has been in use for just 3 weeks. Furthermore, purchase histories can be exploited for generating fully personalized user interfaces and thus support heterogeneous user groups as demonstrated e.g. by the 'Favorite Entries' and 'Favorite Categories' services of myVU discussed below.

- **Self-assessment of experience.** We support user heterogeneity by self-assessment of experience with respect to a discipline or topic. Users are offered the opportunity to rate themselves according to their own experience in a discipline or with a topic they are interested in as beginners (novices), average, advanced or expert users. We do not have to figure out what experience e.g. a student has in a specific discipline, because he reveals his experience by self-assessment. A student has a strong incentive for revealing his true experience, because this maximizes the value of information product recommended to him. On the other hand, automatic monitoring of the learning progress or detecting to e.g. too ambitious self-assessments of students is possible (although not yet implemented), because the true experience level of a student is reflected in the information products he selects. Self-assessment of experience improves market-basket analysis by allowing to detect purchase profiles with a context-dependent experience dimension. Economists call this principle *self-selection* [19] and it is at the heart of designing product-lines in a profit maximizing way. The key is to identify dimensions of an information product which differentiate customers and to offer different versions of the information product which emphasize these differences.
- **Evolution.** Evolutionary algorithms are based on the interplay of a fitness-biased selection operator (survival-of-the-fittest) and of a random mutation operator. The survival-of-the-fittest selection operator is responsible for the exploitation of information expressed in the sample population. A search algorithm which uses only such a selection operator would quickly converge to a population containing only multiple copies of the best solution from the initial sample. The role of the mutation operator is the exploration of information. A mutation operator explores the neighborhoods of solution candidates by drawing trials from such a neighborhood. John H. Holland showed that a balance between the exploitation and exploration of information is required in order to obtain evolutionary algorithms with efficient search behavior [20]. Several features of recommender systems as, for example, ranked lists and labeling of recommended items influence the choice behavior of users similar to a fitness-biased selection operator, that is a recommender system functions in the same way as an interactive evolutionary algorithm based on fitness-biased selection only. This has raised considerable concern that users of recommender systems tend to reduce their information exploration efforts over time and rely on a narrow collection of information sources. We address this concern with the help of mutation operators

for generating random lists or for selecting random items for stimulating the curiosity of users.

- **Scalability.** Recommender services in a virtual university must support a large population of users. Real-time monitoring of user behavior, aggregation of recommendations and on-the-fly generation of user interfaces are computationally expensive and hard to distribute. To make the system easy to distribute and more scalable, we adopt the strategy of reducing real-time requirements as much as possible by weakening consistency requirements accordingly. More specifically, this implies that only logging of user behavior and explicit user interactions (where the user expects to see the result of his action immediately) are processed in real-time. The process of aggregating recommendations and the adaptation of user interfaces are processed for each recommender service by an agency in the background at regular intervals. The reason that this is a workable compromise is that, at least within one user-session, repeated changes of the user interface are perceived by most users as irritating, because these changes require a continuous reorientation of the user and thus may increase his search time. Parts of the user interface are precompiled, parts are incrementally compiled and memorized. In principle, this allows a coarse-grained distribution of agents for each recommender service and each step in the process.

Architecture

The architecture of the system follows from the design principles explained above. Figure 2 shows the generic pattern of an agency of loosely coupled collaborating agents which is common to the recommender services in VU and myVU. The agency consists of three types of agents, namely observation agents, aggregation agents, and recommendation agents.

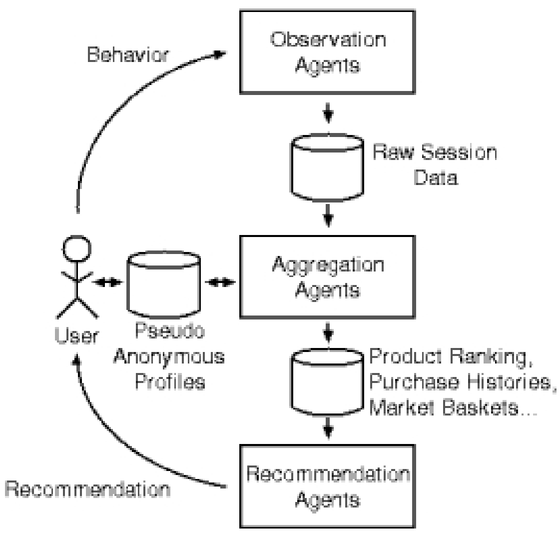

Fig. 2. MyVU architecture.

- **Observation agents** observe the behavior of the user and produce raw transaction logs. In the current implementation observation agents are realized by two mechanisms: the standard http-transaction logging of a http-server combined with session cookies and the recording of actual purchase incidents in the VU and myVU broker systems. Pseudo-anonymity is achieved with an additional myVU cookie containing a pseudo-identity with which an anonymous purchase history of a user can be established over several sessions.
- **Aggregation agents** analyze the raw transaction logs produced by the observation agents. The myVU specific aggregation agents have access to user-specific, pseudo-anonymous experience profiles which allow for a group-specific analysis. Typical results of aggregation agents are product frequency rankings, ABC-analysis of products (products in class A account for typically the first 60 percent of purchases, products in class B for the next 30 percent and products in class C for the rest), market baskets, the conditional probability distribution of cross-selling, purchase histories at various aggregation levels (e.g. individual, experience group, etc.).
- **Recommendation agents** convert the intermediate statistics generated by aggregation agents into recommendations. In the current VU and myVU environment, recommendations come in the form of labels, ranked lists, navigation structures, and statistics.
- **Users** receive recommendations in various forms, may incrementally reveal their discipline specific experience by self-assessment and produce traces of their 'buying behavior' by using the VU and myVU systems.

The advantage of this architecture is that it is scalable and that it can be incrementally improved as more sophisticated recommender services are developed.

Recommender services

The recommender system of the VU provides several classes of services. The classes differ in the degree of privacy, and the level of aggregation for clustering. In the following we present our services ranging from services that work with preserving total anonymity to fully personalized services.

In the VU the following recommender services are currently available:

- Information product lists ranked by purchase frequency or by score (a simple measure of relevance).
- Labeling of information products like 'HOT' for class A products.
- Bar charts indicating the relative purchase frequency to the best-selling product.
- 'Others also use' provides for each information

product a list of other products sorted by the conditional probability of a cross-selling incident.

This service works well for very specific research areas due to self-selection, i.e. by searching for information about this subject a student or a researcher identifies himself as a potential member of the group interested in this subject. For general recommendations in an educational context (e.g. which marketing lecture should I attend?) this system, due to the lack of information about the user's experience in this discipline, is only of limited use.

In Fig. 3 we show a screen dump with examples of these services. The screen shot shows a list of references to educational material for artificial intelligence available on the Web. The list is ranked by purchase frequency. Next we describe the recommendations available for the first list item, with the title 'Agent (definition and links from Webopedia'), in Fig. 3. It is labeled 'HOT' indicating that it is a class A product. The bar chart below indicates that it reaches 40 percent of the sales of the best-seller. Finally, 'Others also use', the last element for this item, is a link to cross-selling products shown in Fig. 4. The second reference in Fig. 4 leads directly to a lecture on intelligent Internet agents. This service helps students to find highly relevant material for a topic. A teacher can analyze which other information products are used by his students.

In the near future we plan a variant of this service which can be used for automatically generating link collections specifically for a lecture.

All of these anonymous services assume a fully homogenous user group in terms of knowledge, learning style, interest, etc. However, for modern universities this assumption is highly unrealistic and it is restricting the benefits of students and researchers. The personalized recommender services of myVU address this problem. Note, however, that myVU is still a prototype under rapid development.

In Fig. 5 we show the main page of the myVU prototype.

The following recommender services are available at the moment:

- '*Favorite entries*' are a list of a user's most frequently used information products. For each product the 'Others also use' service described above is available. In addition, a group-specific recommender service based on self-assessment of experience is offered. This service is only available if the user has revealed his experience level previously. 'Experts also use from this category', for example, shows an expert user (who is expert in a specific discipline) the list of information products most frequently

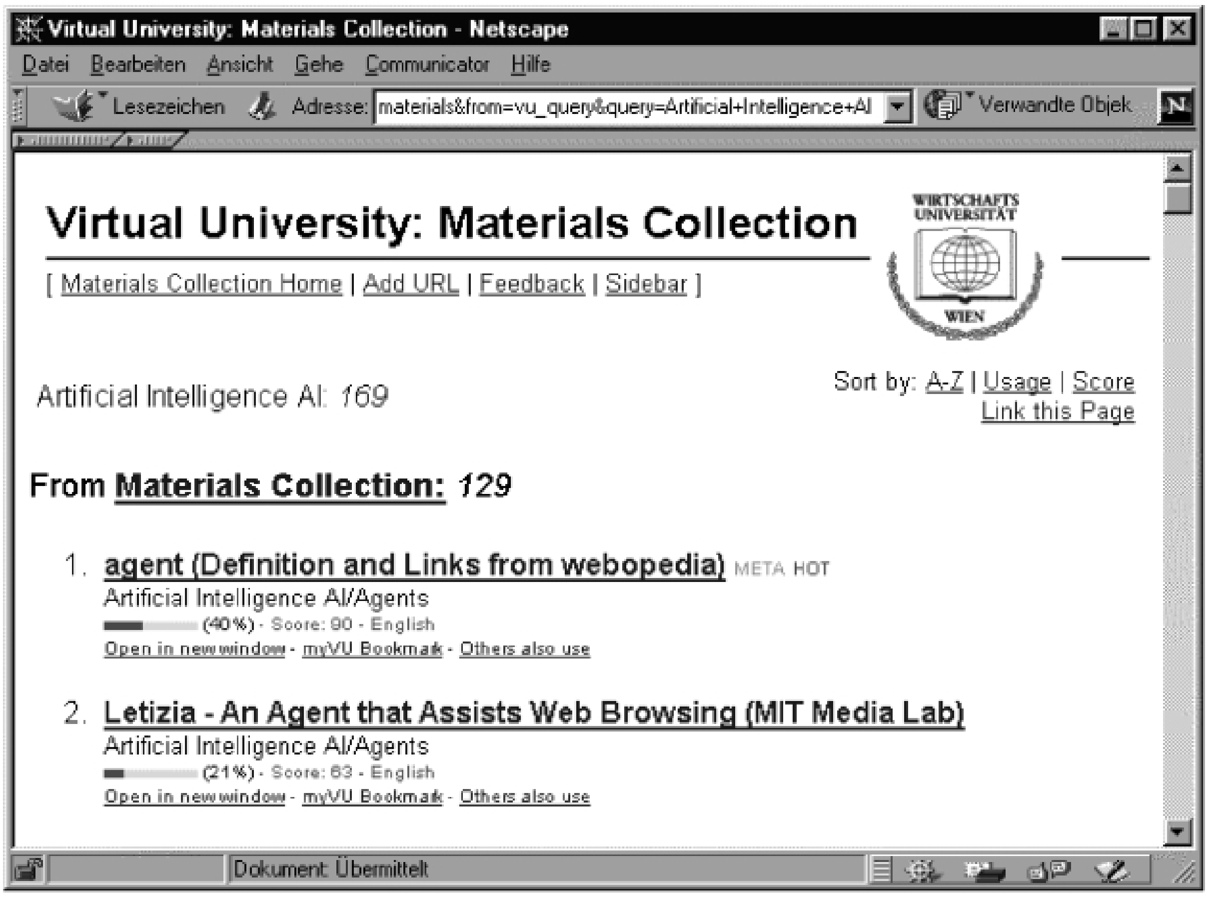

Fig. 3. Examples for VU recommender services.

Fig. 4. Example for 'Others also use'.

used by other experts in the same discipline. At the top of the list under the heading 'Discover VU!', a randomly selected information product, is prominently displayed. The purpose of this service is to increase the curiosity of the user and to promote the exploration of the VU.

- '*Discover entries*' is a list of several randomly selected products from the VU to encourage explorative behavior of students.
- '*Favorite categories*' are a list of a user's most frequently used product categories. In the virtual university all products are classified with respect

Fig. 5. Personalized services of myVU.

to a hierarchical classification scheme. 'Others also use' for categories is similar to 'Others also use' for entries described above. It is based on the conditional probability distribution that a user buys a product from one category also buys a product from another category in the same session. The service displays the list of categories sorted with decreasing probability that he also buys a product from these categories. 'Experts also use from this category' is the same service as presented for entries. However, users are offered an additional access path starting from a category.
- '*Discover categories*' is a list of several randomly selected categories from the VU with the aim of probing the structure of the VU's hierarchical classification schemes.

To provide the group-specific services based on user discipline-experience profiles myVU supports incremental self-assessment of experience for categories which the user has visited in a previous session. In the current implementation, profiles can be displayed and edited. The display of a user's recommender profile constitutes a rudimentary, alternate user interface with considerable potential for future improvements as, for example, discipline specific learning, progress, monitoring and consulting.

In addition, myVU provides authentication for other distributed services such as the university's digital library and personalized services for example bookmarks or a newswire.

MyVU: ADRESSING THE MECHANISM DESIGN PROBLEMS FOR MARKET INFORMATION CHANNELS

In this section we will discuss how the mechanism design problems are addressed in the myVU system.

- **Free-riding.** All recommender services presented in this article are based on observed user behavior. Use of the VU or myVU system automatically generates raw data. For more than 50 percent of the information products in the VU anonymous recommendations exist after 6 months of use. (On February 18, 2000 for 4184 information products of a total of 7875 in the VU recommendations were available.) This seems to indicate that for unobtrusive recommender services like the VU the argument of Avery and Zeckhauser [13] does not apply. The myVU recommender services work on a tit-for-tat basis. Group-specific recommender services are only available after self-assessment of experience.
- **Biased recommendations.** Behavior-based recommender systems like VU and myVU make it impossible to damage competitors with negative recommendations. Generating positive recommendations is still possible, e.g. by repeatedly visiting the same product with the intent of improving ranking and labeling. However, doing this requires time and, because of the adaptive behavior of the system it must be done repeatedly. To make biasing of information harder, we plan to analyze the repeat-buying behavior of users.
- **Privacy.** Pseudonyms are used for all personalized services to protect the privacy of myVU users. We use a pseudonymous user profile to store self-assessment information, and the same pseudonym is used to attribute sessions to users.
- **Credibility.** VU and myVU are financed by research grants and is a project of the Vienna University of Economics and Business Administration.
- **Positive/negative feedback effects.** We address positive and negative feedback effects in myVU with the mutation operators behind the various 'Discover VU!' services which are copied from evolutionary algorithms. An analysis of the effects of these services is not yet available. In the VU setting, positive feedback effects are caused by frequency ranked lists and for products carrying a 'HOT' label. Both types of recommendations slow down or even prevent new products from being used. To reduce this problem we introduced the 'NEW' marking and present these products always on top of ranked lists. In addition we intend to integrate 'Discover VU!' like services into the VU system.
- **Economies of scale.** Growth is an important success factor. To promote the VU and myVU systems we frequently publish in internal newsletters for students and lecturers as well as in mass media (1997: 4 publications, 1998: 9 publications and 1999: 27 publications), we integrate our services into the university's information systems, we offer tutorials and introductions, and we run E-mail campaigns. We cooperate with an increasing number of the organizational units and research projects of the university.

FUTURE RESEARCH

Informal initial user responses to the system, especially by students, have been very favorable. However, an in-depth study of user acceptance and a field experiment are scheduled for the summer term 2000. Several interdisciplinary research and development projects are on our agenda:

- Discipline-specific learning progress monitoring and consulting.
- 'Purchase profile' identification and analysis (e.g. what bundle of information products supports the author of a research article, etc.).
- User interest profiles and demographic data.

- Analysis of the proper adaptation rate of user interfaces.
- Analysis of the impact of recommender services on user behavior.
- Analysis of the dynamic development of a recommender system (models of diffusion processes, prediction of critical mass and phase-shifts, non-stationarity, detection of change, etc.).
- Visualization of the preference neighborhood of information products.
- Construction of user, task or group-specific portals from aggregated cross-buying analysis for categories of information products.

LINKS

The reader is welcome to visit the Virtual University of the Vienna University of Economics and Business Administration at http://vu.wu-wien.ac.at and try the myVU personalized services at http://myvu.wu-wien.ac.at

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