Recommender system for choosing carer directions by Việt Nam school students

Duc The Tran[1], Evgeny Cherkashin[2,3]
[1] *Institute for Informational Technologies and Data Analysis*,
National Research Irkutsk State Technical University, Irkutsk, Russia
[2] *Laboratory of Complex Informational Systems*,
Matrosov Institute for System Dynamics and Control Theory, Siberian Branch of Russian Academy of Sciences, Irkutsk, Russia
eugeneai@irnok.net
[3] *Chair for Informational Technologies*,
Institute for Mathematics and Information Technologies, Irkutsk State University, Irkutsk, Russia

***Abstract*—The research of the paper is devoted to present of an R&D of a recommender system in carer guidance for Việt Nam middle school students. The system is built on the base of John Holland's six personality types theory and collecting university students' opinions on their study conditions. The RS relates new user (an entrant or a pupil) to a student group and then presents [[top-N]] universities/departments as a recommendation. Techniques of overcoming "cold start" problem and other ones in this domain are considered.**

***Index Terms*—recommender system, cold start, carer guidance, TODO:**

I. Introduction

In the countries with predominantly young population, such as Viet Nam, the demand of young specialists is high. While still a high school student, one have to make a decision about a career. Career choice depends on many factors such as personal interests, academic ability and employment opportunities available after the graduation. Therefore, choosing the right job is not an easy problem. In fact, quite often graduates remain unemployed for a long time or do not work in their specialties mastered in an educational institution. This leads to inefficient use of state funds, their irrational distribution. That's why the choice of an university after receiving a certificate of maturity is very important. Choosing a suitable university results in an increase students' study productively, as they work and practice with enthusiasm. Supporting the decision activities will give a better chance of achieving students' goals in the future.

In Table 1 and 2 we present the result of interest assessment to career guidance and relevance of improving of the guidance system. Tables show that

TABLE I
Interest assessment to the carer guidance in Việt Nam, Hà Tĩnh city

Interest level	Count of votes	Ratio, %
Very interested	218	51.9
Relatively interested	155	36.9
Less interested	36	8.6
No interest	11	2.6
Total	420	100

TABLE II
Questionary results of middle school students on need for improvement of the carer guidance system

Answer option	Quantity	Ration, %
very necessary	272	64.8
necessary	145	34.5
no necessity	3	0.7
Total	420	100

At present, with the development of the Internet, the search for information about universities is sufficiently efficient. However, having a huge amount of information, selecting substantive information is a difficult task. Recommender systems (RS) have emerged as a decision support tool, providing users with the most useful and personalized variants for goods and services. The functioning of RS is based on filtering information with respect to a set of known properties of objects and users. For example, RSs are used to assess the users' preferences for goods and services (songs, films, video clips, books, articles, *etc.*), which have been not previously given ratings by the user trying to make a choice.

RSs are also quite successfully used in many business spheres, such as entertainment: offering songs to listeners (*e.g.*, the LastFM system – www.last.fm), offering films (the Netflix system – www.netflix.com), recommended videos (the YouTube system – www.youtube.com); in education and training (learning resources, books, articles, site addresses), in intelligent systems of teacher assistants (predicting students' learning capabilities). RSs are the field of active IT research since 2007.

Teaching experience of the first author of this paper in secondary school shows the relevance of the problem of choice of a profession. This research, being the results of a master thesis, is dedicated to the development of an RS that allows students (applicants) to receive recommendations when taking career decisions. The aim of the research is development of a RS for supporting students in their carer decision making.

The resulting RS prototype has two options for producing recommendations. The first one is realized on the base of

John Holland theory [**?**], according to which most people have one of six personality types. After determining the type, a set of corresponding universities are produced. The second one is an aggregation of questioning data about concrete universities obtained from students already being taught there. The recommendations, then, are generated by means of collaborative filtration (CF) based on users' profile comparison. Thus, the RS prototype combines two approaches: using expert knowledge and CF.

II. Technique of construction for the RS helping with the carer choice

Recommender systems [1] are decision support information systems designed to assess the user's level of interest in a particular product or service (object) based on available information about user and object. The RS development industry began to actively develop with the emergence of online sales services, and now it is one of the active areas of development of decision support systems, a direction of artificial intelligence, focused primarily on commercial use, as well as on solving problems of increasing the productivity of searching for relevant information. A profession is the object of RS recommendation production. Let us consider the development technique for RS construction from the point of view of solving the standard set problems and challenges.

Development of the RSs is aimed at solving the following set of problems [**?**]:

1) Increasing the sales of a product
    - a number of commodities sold,
    - organizing wider range product sales;
2) Increasing user satisfaction and/or loyalty;
3) Better understanding user needs;
4) Better products offers with respect to the user needs;
5) Selection of sets of products for users with a common properties
    - "good" ones, and
    - product groups, having a common usability properties;
6) Mining the classes of products, structuring the RS product domain, and
7) Generate a continuity of recommendations using the classification;
8) Rectifying user profile, *e.g.* with targeted questioning;
9) For the users having no goal to make choice, but searching for an expert opinions,
    - Analysis of other users impact on a choice,
    - Formalizing opinions,
    - Recommending opinions.

In this context, the RS is aimed at solving 4–7-th problems. This set defines the methods of RS proposal generation and algorithms, which have to be implemented. As we can see, the universities and their departments can be distributed on various carer directions by two ways: with the use of expert knowledge, when experts analyze a departments' properties and relate them to a direction, and with use of onions of the students (users who already "consume" a product). In the second case, a good opinion of a user on a department (product) creates or solidifies a corresponding relation. In the same time, a group of students positively characterized a department form a group of "similar" users.

The main problem solved during the R&D is "*cold-start*" *problem*. For RS based on CF, the similarity of user profiles in terms of sets of specified characteristics are performed. Content filtering RS compare products. In both cases, RS cannot generate recommendations if it does not have enough information about users or products. The cold-start problem arises at the first stages of RS functioning and when a new user's behavior had not been observed sufficient time, *i.e.*, the RS have no data about his preferences, or user's profile contains no useful information for a comparison. The same situations arises for a new product, *e.g.* there is no user bought the product, and no responses were given. In this system explicit information collection has been realized for solving cold-start problem in CF, and John Holland's theory was used as initial profile data filling in, including the input data for the Holland's questionary.

The simplest technique for user profile data collection and usage is so called *impersonalized acquisition*. Recommendations are generated for an "average" user related to a nearest group od users. An RS gives top-N products for the group, efficiently ignoring personal preferences. The approach can be developed to support personal data with construction of subgroups of the groups relating them to a set of personal characteristics. This may lead to unwillingness giving personal data of users and impossibility to generate proposals when a user cardinally changes his/her preferences. In this system, as our intention is a detection of a direction of a carer, impersonalized approach seems to give sufficient quality result.

The *scalability problem*. Scalability is a property of software systems to be able to cope with the load prescribed by design, as well as with increased load if additional information–communication and computing resources are available. For a simple RS with several users and products, there is no need to maintain scalability, and algorithms such as "nearest-neighbor" are widely used for assessing interests as the combinatorial space is not large.

Thus, to construct carer choice RS prototype, we have chosen to collect impersonalized data, structure users with respect to their university/department preference and user profiles by means of collaborative filtering, use questionary and expert approach for initial user profile filling in.

III. Preliminary Data Processing

In realty RS, two program agents are implemented, which are executed on an event occurrence. The first one starts by timer of web browser and implements issuing user positive evaluation, if user spends some time viewing a page of a realty object. The second one, located at the server side, is activated if the first one raised event of a positive evaluation. Server agent receives the evaluation and may start recalculation of estimates for recommendations if there are enough computational resources.

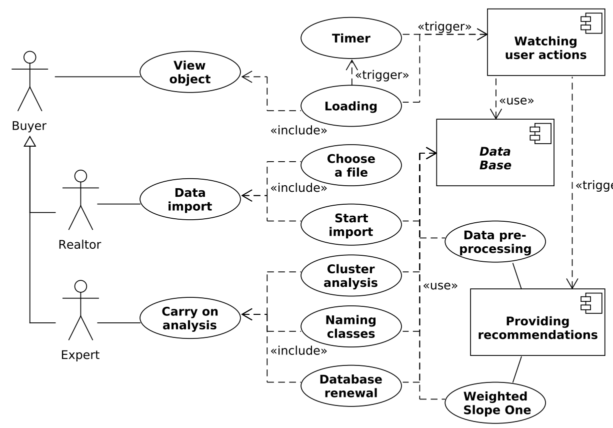

Fig. 1. Use case diagram for real estate RS [TODO: UPDATE to CDT's thesis]

TABLE III
COMPARING FEATURES AND THEIR WEIGHT COEFFICIENTS

Attribute	Calculation technique	v_k, %	Formula
`string Name`	not used		
`ILocation Location`	equality	10	(1)
`string Address`	–"–	10	
`float Price`	relative difference	25	(2)
`CurrencyEnum …`	not used		
`float Area`	relative difference	35	(2)
`AreaUnits AreaUnit`	not used		
`string ImageURL`	–"–		
`string URL`	–"–		
`int Rooms`	relative difference	100	(2)
`int RoomsOffered`	–"–	100	(2)
`int Floor`	–"–	30	(2)
`int FloorTotal`	–"–	10	(2)
`BuildingEnum …`	equality	30	(1)
`IBuilding …`	–"–	30	(1)
`PropertyEnum …`	–"–	30	(1)
`CategoryEnum …`	–"–	100	(1)
`string Description`	not used		
`string GUID`	–"–		

All data are stored in a database, which structure is represented as objects in Fig. 2. The central entity is `IOffer`, representing the offer of a realty object. The information on an object, which is independent of an offer, is stored as `IObject`-object. The object structure corresponds to standard Yandex and Google form of real estate representation.

The real estate domain specifics is the total availability of data for realty objects, so the import function provides the whole body of information on objects by importing it from other sites.

A. Classification of realty objects

Comparison of the object is done in a vector space according to the features presented in Table III.

In the table, with (1) and (2) we denote the following formulas:

$$d_k(i,j) = \begin{cases} 0, & \text{if} \quad a_i = a_j, \\ 1, & \text{if} \quad a_i \neq a_j, \end{cases} \tag{1}$$

$$d_k(i,j) = \frac{|a_i^k - a_j^k|}{a_i^k + a_j^k}, \quad a_i^k + a_j^k > 0. \tag{2}$$

The aggregate assessment is made with formula:

$$d(i,j) = \frac{\sum_{k=1}^{m} |v_k \cdot d_k(i,j)|}{\sum_{k=1}^{m} v_k}, \qquad 0 \leqslant d_{i,j} \leqslant 1,$$

where v_k is a weight of k-th attribute value in the table.

In order to create a taxonomy, expert user must run the hierarchical clustering function supplying the number N of general clusters to figure out. After the function finishes, expert will see the numbers of top N clusters with number of their objects. Next step is naming the clusters. Expert enters the subsets and reviews the objects, forming an image of the common properties of the objects. After naming the image in the first interface, expert changes name of cluster from a number to the name. This is to be done for each $\overline{0, N-1}$ cluster. If expert cannot form a concrete image of the class, them we recommend repeat the procedure with larger number of clusters.

Some clusters can gain the same name, and after renaming, clusters with the same name are joined. Hierarchical clustering allows us to make experiments with data without recalculation of the taxonomies. Before running clustering function, expert can restrict the set of objects to be examined, *e.g.* by 200 objects, so we can use even agglomerative hierarchical clustering.

The following classes are presented on Irkutsk region real estate market: two-room flats, one-or-two-room flats (comfort class realty), one-room flats, dachas, houses, rooms, commercial space, a garage, and elite realty (flats with three and more rooms).

User interests are acquired as follows. New user is suggested a set of objects from all the classes of realty. Watching users activities, which objects he/she is viewing, the systems gains initial interest, and then specifies the class of objects to view at following steps. Each object observed by user during long time considered to be of interest, the positive evaluation is added to database. Recommended objects are shown in a list located at the bottom of the interface window. The set of suggested objects is restricted by 20 items.

IV. RECOMMENDATIONS GENERATION

V. WEB APPLICATIONS

Both RS use MVC [17], [18] architecture in construction of user interface. Realty RS is based on `Nancy` ASP.NET framework, where for each URL template a lambda function is related, having supported parameters of the Request objects. At the beginning of each function we restore `session` object, and at the end, the Response object is created by applying a context model and a view object to a template. As template engine SharpTAL is used, an implementation of Zope page template (ZPT) with Template attribute language (TAL). This implementation follows traditions of C#, namely, compiling its content into objects at the phase of project compilation.

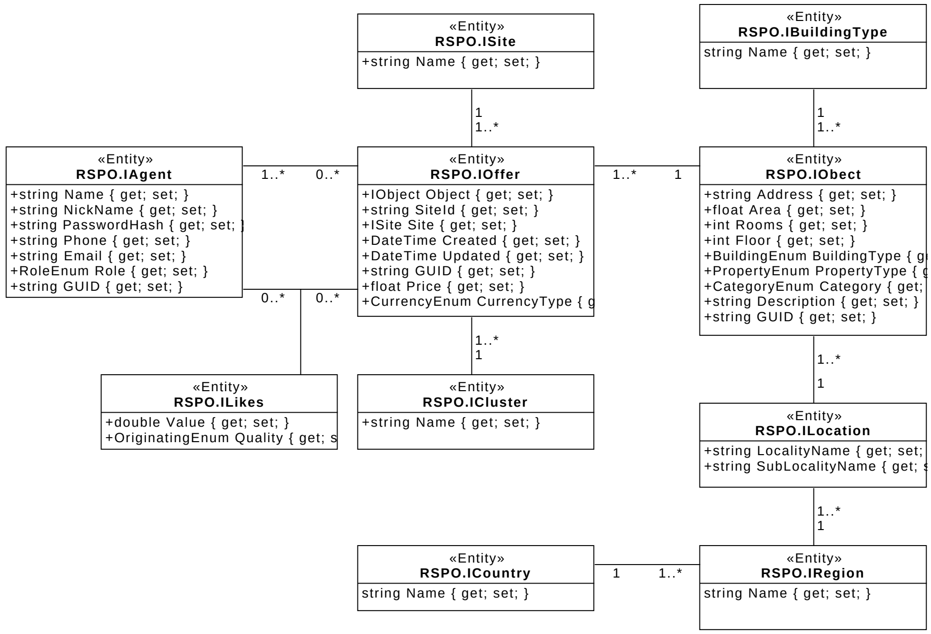

Fig. 2. Class diagram for real estate RS

As for each web template engine, ZPT uses `model`, `view`, which implements *controller* functions as well, and `template` to generate HTML content. Model is referred as `context` of a view, which function is simplification of the access to context by template, and transforming user actions into model change upon `POST` query. For using global application and other data, as context we pass in a general case `application`, `appview`, `user` and `message` objects. User defines the currently authenticated user, and message contains text to show in a view, announcing an event happening in the RS, *e.g.* the fact that a record is successfully stored in the database.

ZPT and TAL technologies were chosen as they give a very powerful tool for HTML tree structure manipulation including usage of named and parametrized macros, attributes subtrees, defined in one-page template, and multiply used in other ones, as well as the technology tries not to extend XHTML syntax with new entities for implementation of element replacement functions.

VI. Related Works

There are many research groups and commercial firms dealing with developing RS technologies for various domains. We will consider related domains and other interesting cases.

In [19] a case-based reasoning RS for real estate market is presented. Its goal is to find a similar instance in the database of existing cases, describing the cases for the user. The obtained relations are used in followed collaborative filtration and content filtering. In theoretical research [20] the users are divided on sellers and buyers. Sellers “advertise” their realty by highlighting the important features by their opinion. So the sellers play expert roles for forming data for content filtration. Research [21] showed that usage of Internet does not influence significantly on the time efficiency, flexibility and satisfaction criteria of the search for a flat to buy. There are no statistical difference between 2009 and 2011, since in 2011 88% of buyers used Internet just as the main source of information. Authors created RS with case based reasoning utilizing an ontology model.

In [21] authors highlight three key features which significantly affects the decision: location, housing unit properties and price. Final decision is made after evaluation of the environment, such as distances to shops, kindergartens, schools. This can be accounted reducing the additional data to the value of the feature of housing unit properties using ontology. The environment constraint is entered by user: user draws a circle around the preferable location, which should contain interested services and realty.

Paper [22] considers a complex logistic problem of organization of a process of real estate control, involving various people group in changing business environment. The main aim is to develop a model, where the groups will be maximally satisfied in a rational micro and macro environment. The efficiency of the realty utilization is evaluated with criteria of market, ownership, renewal prices, capacity, number of operations to be done while ownership transferring, safety, comfort, the time of physical and technical exploitations, *etc*. The software functions shift from “the most economically efficient control of the property” to multicriterial choice, raising computation efficiency.

For recent RS dealing with student’s problem of choice the following papers were observed. In [23] an RS is constructed for helping entrants to choose an education direction (expressed as sets of corresponding high schools) according to his/her grades in GCE (General certificate of education), gained competing prizes, physical activity, and hobby. Three methods of content filtration were implemented: by distances between vector characteristics, axiomatic method of Pareto-set contraction, and analysis of hierarchies. Authors figured out coefficients relating study directions to the features of user using series of experimental assessments controlled by experts.

In [24], a problem of learning outcomes assessment of higher education students is considered. A course RS on the base students' graduate attributes, which describe their developing values, is proposed. RS rates improvement after each course and suggests new courses by a collaborative filtering algorithm in order to improve student's average competence profile. Students are presented as long vectors of courses they already taken with the corresponding grades. Similarity is calculated with a variation of angle cosine of the vectors. The recommendations are the prediction of the grades for the new courses. Similar by the problem statement paper [25], where RS predicts course learning trajectory patterns, the students is suggested elective curses. Source data for collaborative filtering are existing learning trajectories acquired from senior students in the image and likeliness one student advices younger one. Students and courses are divided on clusters. For each student cluster (a group), mean values are calculated. RS algorithms are based on combination of collaborative filtering and fuzzy-like rule based system, which defines process of production of a decision. The article has a good reviews of related works and three classical approaches basics.

Work [26] has the similar aim to develop RS for advising students new courses, but is focusing on description of courses, taking advantage of natural language processing over course documents to acquire descriptions. Feature descriptions contain formal course data (name, structure, lecturer) and a placement in a keyword appearance frequency space. Existing student data, represented as grades of the courses he/she already got, related to the course data. The resulting recommendations are represented as top-5 new courses, where student will gain the best grades. This is a simplistic direct approach and, by authors opinion, gives good results; some measurement supporting the opinion were carried on.

Interesting research has been done in [27], where the problem of overcoming the cold start problem in recommending genres and music compositions, as well as movies. The authors developed the RS "EZSurf" automating the process of web surfing and content filtering using a user profile on the social network "VKontakte", as well as API services `last.fm` and TheMovieDB, to obtain information about similarity of the objects. This approach greatly simplifies storage of RS data, since it does not require the designing own system of classifications. In [28], a problem of choosing top–N objects, with higher evaluations of user interest, in content filtration. Authors proposed RS model based on fuzzy sets, RS quality assessment technique, and a corresponding algorithm. The models have been tested on `last.fm` data.

In a comprehensive RS review dealing with text (scientific) document relevance grading [3], authors noted that more than half (55%, 34 of 62) RS were based on content filtration. Collaborative filtration was used only in 18% (11 of 62) cases. Stereotype based and hybrid methods are also presented. Authors concluded that 81% in of cases modeling user does not produce significant results in comparison to explicit indication the set of keywords. The papers were described by keywords and, less frequently, N–grams included in the text, as well as metadata such as authors and references. Most popular recommending model is based on vector space approach. User interest modeling is implemented with graphs, where vertices are the papers, and arcs are their relationships, and topic lists assigned to user by machine learning. The topics are organized in hierarchical catalogs using ACM classifiers. In the RS which used collaborative filtration, the explicit ratings was not collected at all as users were too lazy to supply a rating to a paper he/she looked through. Implicit ratings were obtained by measuring the number of pages user read, document user interaction (loading, editing), co–loadings, co-view and co-citing by users of one group.

The collaborative filtration is currently more popular as it reflects practical experience: most of RS R&D have to solve "cold start" problem of initial lack of information on objects and users, as well as have adaptation to user group interest transformations due to modern trends.

VII. Discussion

The realty RS was tested by a number of human being fictitious buyers, none of them mentioned misbehavior of the system like spontaneous transitions from one class to another, or supplying empty sets of recommendations.

The overview of the presented experience shows that C# .NET and MONO technologies and used techniques are well suitable for construction RS of various kind, fulfilling the following typical requirements:

1) working in "cold start" conditions;
2) do not require user to register and authorize while implicit gathering information needed for recommendation generation;
3) testing systems are to be done in a local conditions to be able to check the results comparing with existing "natural" data;
4) using open-source technologies, modules and libraries.

The obtained real estate RS implementation as well as the second project do not take advantage of the nowadays methods of R&D development, which corresponds to current traditions. Most attention is paid to preliminary data processing and obtaining minimal valuable product (MVP).

VIII. Conclusion

We presented results of two master degree projects in the field of recommender system (RS) development in real estate and university entrants' study direction decision-making. The first one is finished, and the second one is on a half way. Both systems have similar design, but rely on different RS technique: the realty RS is based on collaborative filtration, the entrants' one is based on content filtering. Both systems use object-oriented representation of application entities, which are persistent as well.

Solutions of “cold start” problem for both domains has been considered. They are based on creating taxonomies of objects by cluster analysis and partial transition to consider classes as objects of users’ interests. In the entrant RS we also created taxonomies of users according their subscriptions in a social network.

The RS are implemented as MVC web applications for users, the administrative and expert user interfaces are implemented as window applications in entrant RS. This simplifies user role model: web users must register, administrator runs form application at workstation and is not required to register. Testing the finalized RS showed stable work when used by human users.

The described technique could be developed further by adaptation the standard directions such as:

- development or adaptation of ontology of domain to extend search capabilities especially in students’ courses domain;
- case based reasoning for the same domain;
- predictive modeling of attribute values for realty;
- providing geospacial data of infrastructural service organizations in the environment, *e.g.* schools, kindergartens and shops.

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