Principles and Experience of Intelligent Decision Support and Recommender Systems Engineering

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***Аннотация*—In the article main principles of engineering of intelligent decision support and recommender systems are considered. Definition and concept of a generalized object are formulated. Technologies of recommender systems engineering and construction are analyzed. Classification of decision support systems is suggested. Experience of decision support and recommender systems engineering is presented.**

***Keywords*—decision support system, recommender system, generalized object, classification, neural networks, algorithmic trading, multi-agent technology**

I. Introduction

Despite existing developments in the area of decision support systems (further — DSS) engineering, these technologies presuppose the adaptation of only individual components of the DSS and do not provide the adaptation of the subject area model. This leads to the use of irrelevant and inaccurate data in the DSS, which negatively affects the efficiency of decision-making in a quickly changing environment. These problems can be solved via adapting subject area models to the conditions of decision-making tasks and well-timed updating of the models with the data, knowledge and precedent (subject) collections necessary for this model. The concept of a generalized object became the base of different DSS with combined intellect engineering and construction. The target of this research is to generalize theoretical and practical experience in the sphere of intelligent decision support and recommender systems construction.

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II. Brief literature review

First theoretical research on decision support systems was made in USA at the Carnegie Institute of Technology in the late 1950s — early 1960s. The first main works on DSS were published in 1978-1980 by P.Keen, M. Scott Morton [1], [2], R. Sprague [3].

Investigations in the sphere of intellectualizing of DSS information technologies are wavy carried out in the world. Moreover, the increase in research activity in time coincides with the periods of development on computing and financial resources (the emergence of personal computers, evolution of the processors, memory capacity, the emergence of a user-friendly interface, the emergence of mobile Internet technologies, etc., with the simultaneous reducing of its prices).

Among the modern works on DSS there are books “Intelligent Decision Support System for IoT-Enabling Technologies: Opportunities, Challenges and Applications” (2024) by ed. S. Sahana [4]; “Intelligent Decision Support Systems for Smart City Applications” (2022) by L. Gaur, V. Agarwal and P. Chatterjee [5]; “Intelligent Decision Support Systems” (2022) by M. Sànchez-Marrè [6]; “Understanding Semantics-Based Decision Support” (2021) by S. Jain [7]; “Intelligent Decision Support Systems: A Complete Guide — 2020 Edition” by G. Blokdyk [8].

The technology of recommender systems gained popularity only in the middle of 1990s. The concept of a recommender system was first used in 1992 in the scientific publication of Xerox, in the same year in the article “Using collaborative filtering to weave an information tapestry” the term “collaborative filtering” was introduced. Subsequently, fundamental works systematizing knowledge on recommender systems were devoted to this area. One of them is “Recommender Systems: The Textbook” [9]: in this book, description, comparison, assessment of the accuracy of basic algorithms for developing recommendations to the user were made, in addition, the field of practical use of such systems is affected. The work “Recommender Systems: The Handbook” [10] deserves special attention. In it the existing variety of methods and concepts of recommender systems was systematized. This source shows how recommender systems can help users in decision-making, planning and procurement processes, illustrates the experience of using these systems in big corporations such as Amazon, Google, Microsoft.

Nowadays the transition to the next-generation computer systems takes place. Intelligent DSS and recommender systems belong to this class of information systems. Such systems should "independently evolve and interact effectively with each other in the collective solution of complex problems" [11]. One of the relevant problems of next-generation computer systems design and development is generalization of formal theory and methodology of their functioning.

III. Definition and the concept of a generalized object

Usually an object O can be represented in the view $O =< Data, Met, Mes >$, where: $Data$ — a set of internal information of the object (data); Met — a set of its own procedures for manipulating the data (methods); Mes — an external interface for interacting with other objects in the subject area (such as a permissible set of event messages outside and inside of the subject area).

However, the need to take into account the development of DSS requires a more general and flexible mechanism for describing and modeling them. Such a mechanism can be built on the base of further generalization of the object-oriented approach and, in particular, of the term "object" in the conceptual model of the subject area.

The term "generalized object" is suggested: $GO =< Data, Met, Model, Knowl, Mes, Link >$, in which models, knowledge and links with the other domain objects are encapsulated in addition to data, methods and messages.

Such model of a generalized subject area can be considered as a type of multi-object neural network, if add to the usual method of object interaction by messages the possibility of activating objects (transmission of excitation) through links with weights (priorities) indicating the value of the response threshold level for each object. The value of the response threshold level can change in accordance with the system development stage, solved problems, accumulated statistical experience of problems solving, etc. Interaction between generalized objects can be carried out through messages or changes in the links structure of the generalized object system. This system is separated from their functional part. It can be and represented by a dynamic links list, by changes in the links weights (filtering) and actuation threshold values.

Each generalized object can have several states and go from one state to another depending on the incoming messages that are the result of the activities of other generalized objects. At the same time, the generalized object changes its state when its excitation value exceeds some non-zero threshold of actuation. In general, such subject area model can be considered as a hierarchy of abstractions represented by classes of generalized system, problem and user objects. The status of the subject area actually depends on the status of each generalized object and the message queues at the input and output of these generalized objects. The latter can be considered as a database of facts about events on the base of which it is possible to determine an output machine for interpreting of existing and generating new facts in the process of simulating of modelling system functioning.

Requirements to the multi-agent DSS can be formulated by means of object-oriented classification (enumerations of the object classes involved in solving problems, their properties, relationships and behavior). The main principle of classification is the specification of object classes based on the set of internal properties inherent in class objects. After that, the requirements are sequentially detailed until the multi-agent DSS project is fully described in terms of the basic objects of the used tools.

IV. Recommender systems

In today's world, we can often face the problem of recommending goods and services to users of any site, information system. The modern economic formation involves intense competition in various market niches, which leads to a struggle for each potential buyer among companies. In order to improve their experience of interacting with the company's services, it is beneficial to create personalized collections that will have client response. Previously, for such recommendations list, a set of current actions and the most popular goods was sufficient, but the current situation does not allow such low-cost methods to act. A relatively new technology of recommender systems can be used for buyers' attraction and sales increasing.

The essence of recommender systems approach presupposes the dynamic formation of recommendations personally for each specific client, which, unlike static information, significantly increases probability of coincidence with the real needs of people. Recommender systems take into account all kinds of parameters (purchase history, time and date of registration, region, purchased products, etc.), which allows prediction of the user's wishes as accurately as possible.

Recommender systems have already found their place in many areas: in addition to e-commerce, this kind of technology has been introduced for finding books, films, music, and social media contacts.

The relevance of recommender systems is growing every year. Recommender systems are the programs aimed for the prediction of the user's interest in certain objects and giving them the recommendation for purchase or using the items, which the user probably likes. Such recommendations are personalized and are formed for each user depending on their preferences. Although the technology itself appeared quite recently, its use is considered mandatory for all promising companies.

One of the first to become interested in introducing recommender systems was the largest American e-commerce platform Amazon. Already in the late 1990s, the best minds of the company developed their own algorithms for the so-called collaborative (joint) filtering, which offered recommendations to each client based on the history of their purchases, views, and liked goods. The success of the marketplace forced competitive companies to pay attention to the recommender systems technology. In the rapidly growing segment of social networks business-oriented network LinkedIn also uses recommender system. Its system offers a member of the community the closest to the interests, specialization and experience of the community, company, specialists. To build recommender systems, there are four main types of data filtering [12]:

- collaborative filtering;
- content filtering;
- knowledge-based filtering;
- hybrid filtering.

Often the recommender system technology is based on the principles of collaborative filtering, which analyses the actions of the most similar users with a similar profile. However, other types of filtering are also used in practice.

A. Collaborative filtering

The main principle of the functioning of filtering programs is the assumption that users with the same interests will subsequently have similar preferences. For the effective functioning of the model, not only the previous behavior of the client, its query history, but also the corresponding parameters of the additional cluster of similar users are taken into account. The target of collaborative filtering is to identify a certain number of customers operating with the closest patterns of behavior, and to recommend in further the goods or services liked by this group.

The next method, which in turn is already based on comparing the similarity of objects, is called item-based. Its principle can be formulated as follows: if users who rated two products liked both, then the following users who tried only one product can be offered another.

B. Content filtering

Content filtering is based on the assumption of the constancy of user interests. In other words, based on the client's past activity, it can be argued that in the future he will be interested in similar objects. Content filtering uses the following input data: both a set of users and a set of categories that correspond to users' queries and to the objects, which users like.

The purpose of this type of recommender systems is to build such a variety of items that are closest to the favorite categories of the current user. The main task of this methodology is to search for objects potentially close to the interests of users among a set of objects not yet viewed by the client. This search is based on finding the similarity of objects with the user's interests known to the system. The absence of the need to revealing large user groups to ensure the functionality of the method is one of the main advantages of content filtering. This method also avoids the problem of "cold start", because each object has attributes that will be analyzed in future. This type of filtering often make combination with collaborative filtering.

C. Knowledge-based filtering

The most resource-intensive approach is to develop knowledge-based recommender systems. The main source of information is not the user assessment of objects or their metadata, but the rules and conditions developed by experts and expert systems for forming recommendations. Some researchers consider content filtering as a special case of the knowledge-based filtering, however, due to the wide prevalence, most prefer to classify it as a separate type. For the functioning of this kind of recommender systems, it is necessary to distinguish many expert rules, similarity metrics and user interest objects. For practical application of a given rules set, it is necessary to define user's interests and preferences in terms of the subject area.

The knowledge-based approach requires deep understanding of the technical features of the product, creation of user scenarios, inclusive restrictions and rules. Undoubtedly, the use of knowledge-based systems improves the quality of the recommendations being formed, since user requests find the most accurate response from recommendation algorithms among all methodologies. In addition, this method will be indispensable in those areas of commerce where the number of regular customers is relatively small. Of course, the development of such systems is extremely time-consuming in terms of time and resources. To improve the accuracy of functioning, it is necessary to involve relevant specialists in the field of data collection and processing, building the necessary models and user behavior. Also, such systems require additional interaction from the client with the system, which can lead to the outflow of some part of the target audience, moreover, the collected data cannot always be correctly interpreted by software.

D. Hybrid filtering

The last type of recommender systems, hybrid, as the name suggests, is a synthesis of two or three above-mentioned methodologies. The use of hybrid recommender systems increases the efficiency, performance and accuracy of algorithms, and compensate their lacks. For example, the most used combinations are:

- combining collaborative and content filtering approaches (with different weights);
- using some content-based filtering properties in collaborative filtering algorithms;
- partial using of knowledge-based filtering rules in recommender systems based on content filtering;
- building a separate model corresponding to business needs and subject area terms, combining rules of all three types.

There is no unified algorithm for the functioning of hybrid systems, which allows researchers to apply a wide range of modern methodologies to create unique models. It was the hybrid type that became the basis of recommender systems in large companies to ensure better personalized interaction of users with their services.

Let's take a closer look at two of the most popular methods of recommender systems – collaborative filtering and content filtering. Algorithms of these types of filtering can be classified into three main categories:

- anamnestic methods, or methods based on the analysis of available estimates (memory-based filtering), are a family of algorithms that are based on statistical methods, the purpose of which is to search for the nearest group of users to the analyzed user; this approach is similar to the closest neighbors method, and recommendations are formed as a result of calculating a similarity measure based on a matrix of estimates of the users in the database; the main representative of memory-based algorithms is the used-based and item-based weighting of estimations;
- model-based filtering, in which a descriptive model of user and object assessments is preliminary formed, and priority relationships between them are distinguished; the main complexity of this method is its preliminary stage, where resource-intensive training of the model takes place; different approaches can be used to building such a model: cluster analysis methods, Markov decision process (MDP), singular value decomposition (SVD), latent semantic analysis (LSA), principle component analysis (PCA), etc.;
- hybrid methods, which suppose synthesis of several approaches to achieve a better result; for example, collaborative filtering systems can take advantage of a relatively easy-to-interpret anamnestic method with the efficiency and performance of model-based methods, the purpose of which is to increase the speed of recommender system work.

Problems of development of recommender systems may include following situations:

- sparseness of data, which means that due to a huge number of data the matrix "object-user" in system's database becomes difficult to processing that complicates overall algorithm's work;
- scalability, which means that traditional data processing algorithms may not cope with the growing flow of new customers and the goods they evaluate; for example, it can be extremely difficult to perform operations on matrices illustrating information about tens of millions of users and hundreds of thousands of objects, especially because the requirement for modern recommender system is an instant response to customer requests from all over the world;
- "cold start", which arises in the case of new customers and goods emergence, because the absence of the information about the previous user interaction; this problem can be partially solved by the use of content/knowledge analysis or so-called "average"user;
- the lack of unified names of analyzed objects (especially in users' queries) may have negative influence on the efficiency of joint filtering methods; recommender systems do not have the ability to define a hidden speech association, which can lead to the including of the same objects to different classes; for example, an algorithm will not be able to find the coincidence of the "toys for children" and "children's toys" queries;
- fraud, for example, companies interested in the profitable sale of their own products can artificially underestimate the goods of their competitors and wind up a positive rating of their products, that will lead to the recommendation of the products of firms using such frauds;
- market diversity, which allows users to explore the vast expanses of marketplaces in better products search, and such consumer boom does not always correlate with the work of some methods of collaborative filtering, for example, purely based on the rating and success of sales of goods that do not take into account the possibility of promoting little-known, new goods, which can adversely affect the diversity of the market and will lead to the survival of only the largest market players to whom the main user attention has already been focused;
- presence of the clients at the market, whose opinion is strikingly different from the majority; for such users, algorithms may not find unique like-minded people suitable for users, it can reduce the quality of their personalized recommendations.

V. Experience of DSS and recommender systems engineering

There are several main results in DSS engineering have been received by the authors:

- methods of efficiency assessment of the rule and model bases in DSS have been elaborated, which include the following coefficients: rule base certainty, rule base coverage, rating class efficiency and rating efficiency; formulae for calculation of these coefficients are deducted with the using of the rough sets theory [13];
- theoretical and practical approaches of DSS engineering for stock markets have been developed, which include the technology of the liquidity evaluation [14], the technology of algorithmic trading by means of 5-component oscillator [15], the technology of securities prices prediction with the use of the neural network [16];
- the concept of algorithmic marketing and machine learning in relation to the marketing activity, which

is based on decision trees and ABC-analysis and allows reducing time necessary for market big data processing [17];
- the methodology of multi-agent DSS design and developing, which includes approach to the modelling of representation of knowledge about the subject area on the base of the concept of generalized objects [18];
- adaptation of the technology of DSS engineering to recommender systems design, which will be considered below.

Example of the recommender system was realized for the purpose of the choice of musical tracks for different sport training. The initial data for analysis are the most popular audio sets for a specific training session (playlists of reputable sports publications, well-known fitness instructors and trainers, popular music editions).

For the study 4 types of sports training were used:
- yoga, aimed at achieving internal harmony and tranquility;
- cardio training, including a set of intensive exercises that increases the heart rate;
- running, aimed at increasing endurance;
- power exercises that contribute to an increase in muscle strength.

Client-server representational state transfer architecture (REST) is used for the integration of the recommender system with the mobile applications [19]. General scheme of interaction between Android client and database in REST architecture is represented in Fig. 1. The main requirements to this client-server architecture are the following: the server cannot store client information between requests, that’s why interface should be unified.

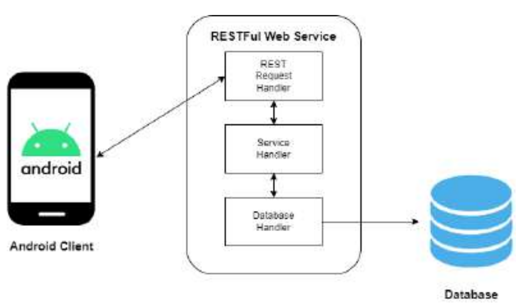

Рис. 1. General scheme of interaction between Android client and database in REST Architecture.

Due to creation of music track pattern for each sport training it is necessary to create a big data set on the base of expert data. A large number of listeners (at least 15,000 people) will serve as an indicator of quality. As a result, a set of 20 playlists was formed for each class, totaling more than 1000 unique tracks, on the base of which the desired average was calculated. Then, unique playlist identifiers are read from the generated files in order to eventually process each composition from the audio selection and sequentially extract all the properties of the tracks from it. To form the desired patterns, the function of calculating the average value of the set of components was used.

As a result, 10 average indices represented in Fig. 2 have been calculated: acousticness, valence, danceability, energy, instrumentalness, key, liveness, loudness, speechiness, tempo.

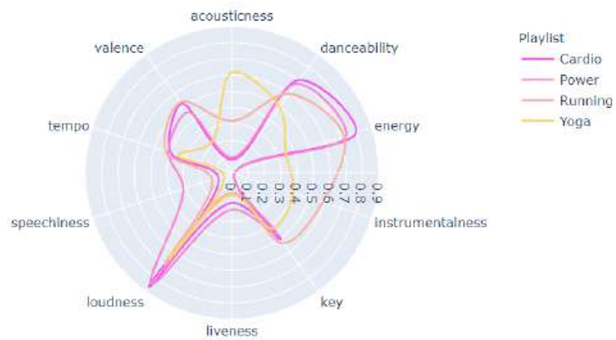

Рис. 2. Example of classification of the musical tracks by recommender system.

After forming a pattern sample for each of the classes, it is necessary to select a set of tracks that are most similar to the pattern (200 songs are selected in the application). The search for songs is carried out from a large external data set, the storage of which is organized in a .csv file.

For example, the program uses a file with 32880 unique compositions, where, in addition to a unique identifier, genre, the name and listing of the artists participating in the recording of the song, the extracted audio properties are presented. The playlist downloaded as a result of the operation of the HTTP library is displayed as interactive buttons, clicking on which leads to the playback of the corresponding song (Fig. 3).

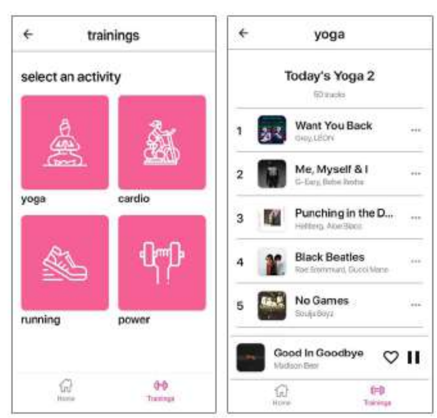

Рис. 3. Interface of the mobile recommender system for choosing musical tracks for different sport trainings.

The recommender system also has own media player, where it is possible to pause/continue playing a song, turn on the next/previous composition; and mix and loop modes are available.

VI. Classification of decision support systems

DSS can be classified into 9 different classes in accordance with the used information data, models and knowledge. In table 1 structure formulae for each class of DSS are represented [20].

Таблица I
DSS classification

DSS structure formula	Information for decision making	Used data, models and knowledge
=objects + information + information collection tools	all which exists	all factual data about subject area
=alternatives + data + links	all which can be useful	actual data
=alternatives + criteria + criteria's values	all which is necessary (from that which exist)	relevant (selected) data
=data + models	all which can be formalized (modelled)	formalized data (actual models)
=models + rules criteria's estimations	all which must be modelled	relevant models
=rules of alternatives' estimation + alternatives' rating	any variants	results of decision variant modelling (actual knowledge)
=rules of alternatives' choice + set of acceptable alternatives	all the best (from that which exist)	relevant (generalized) knowledge
=problem situations + set of their decisions examples in the form of subject collections	all useful (about what formalized information exists)	formalized knowledge about existing experience (precedent base)
=inference system + best alternative	best (possible) variant	decision on the base of digital intellectualizing

This classification allows creating a more efficient enterprise business model. This is achieved mainly due to the rational management of automation systems for physical operations of production and related business processes, integrated into united information space in accordance with the key subsystems of the Industry 4.0 concept (Product Lifecycle Management, Big Data, SMART Factory, cyber-physical systems, Internet of Things, interoperability).

VII. Conclusion

In this research the experience of intelligent decision support and recommender systems construction is systematized. The concept of generalized object is formulated for DSS engineering. Principles of recommender systems are systematized, and include possible types of data filtering. Their advantages and disadvantages are analyzed. An example of recommender systems for musical tracks choice for the different sport trainings is presented. Classification of DSS and their structure formulae in accordance with the used information data, models and knowledge are suggested. The use of these results made possible to reduce the time for creating models by an order of magnitude. Also suggested principles of DSS and recommender systems design make the systems more transparent, and the results are more justified and explainable. Received experience can be used in development of next-generation intelligent DSS.

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ПРИНЦИПЫ И ОПЫТ ПРОЕКТИРОВАНИЯ ИНТЕЛЛЕКТУАЛЬНЫХ СИСТЕМ ПОДДЕРЖКИ ПРИНЯТИЯ РЕШЕНИЙ И РЕКОМЕНДАТЕЛЬНЫХ СИСТЕМ

Железко Б. А., Синявская О. А.

В статье рассмотрены основные принципы проектирования интеллектуальных систем поддержки принятия решений (СППР) и рекомендательных систем. Сформулированы определение и концепция обобщенного объекта. Проанализированы технологии проектирования и разработки рекомендательных систем. Предложена классификация СППР. Представлен опыт проектирования СППР и рекомендательных систем.

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