REVIEW

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Review of the recommender systems application in cardiology

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Abstract

The article provides a review of the recommender systems application in medical field, cardiology, in particular. The concept of recommender systems is defined, the brief history of the recommender systems development is given. The main types of recommender systems and principles of their construction are presented. The advantages and disadvantages of the recommender system methods application in cardiology are identified. Methods for improving the recommender systems are proposed.

Keywords

Recommender system, Filtering, Collaborative, Content, Hybrid, information retrieval, MRS, PEHC

Imprint

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Topicality of the research

This paper presents a review of the currently available research in the field of big data, namely, software systems, called recommender systems. To date, the processing of big data, in particular, the construction of recommender systems, is one of the most promising areas of informatics development. One of the fastest growing segments of the recommender algorithms application is the segment of medicine and public health. This review is relevant also on this basis. Novelty and fundamental difference of this review is its focus on the implementation of the recommendations in the narrower, but the most important branch of medicine, cardiology.

Introduction

It is not a secret that in recent years the Internet has developed by leaps and bounds: it generates vast amounts of data stored. The average user has to process, analyze and organize the data, and, above all, allocate the necessary information from the mass. Of course, it is very difficult to do, because the necessary information is lost among the large amounts of data. In connection with this, there are tools that can assist the user in finding relevant data. These tools are called recommender systems. Recommender system is a software that analyzes users requests to predict what kind of information will be of interest to a particular user at a particular time. Recommender systems show preference of the content for a particular user based on the information that the user considers relevant or based on the processing of user's data, such as his search queries. Recommender system made significant changes in the interaction with users. Instead of the generation of static data, the system changes, adjusts to the specific user [1]. Recommender systems have the following common characteristics: the system adapts to the individual user; takes into account the current end-user preferences, adjusting to them over time; constantly finds new information and offers it to the user. Due to these properties, sites, based on the use of recommender systems, are attractive to the user. Accordingly, recommender systems are interesting to the owners of the sites themselves, because with their help they increase the attractiveness of the site and its content. Recommender systems have been applied in many areas of human life: search for information, commerce, social networks, medicine, etc.

The main "actors" in any recommender systems are user and item, i.e. the recipient of the recommendations and the recommendation itself, i.e. the object, recommended to the user.

The user is also a source of data about his preferences, on the basis of which the item is selected [2]. In general, the task of the recommender systems can be formulated as the "definition of the object, previously unknown to the user (or not used by him for any length of time), but useful or interesting to him in the current context". The user's preferences can be determined by analyzing his past behavior, i.e. grades given by the user, his preferred items. Also, no less important is the behavior of other users in the system.

History of the recommender systems development

The field of recommender systems are relatively new, but, despite this, conducted have been a lot of research, published numerous papers and scientific articles and developed a large number of algorithms. Recommender systems have been actively studied in the early nineties of the twentieth century, that is, since the first development in the field of collaborative filtering [1-3]. The term "recommender system based on collaborative filtering" was first used by David Goldberg in 1992, in article «Using collaborative filtering to weave an information tapestry» [4] in the process of working on the Tapestry recommender system for Xerox. The basis for the works on the content-based filtering can be considered in [5]. In subsequent years, one of the fundamental works in the field of recommender systems was written, which is also a reference: Recommender Systems Handbook [6]. This book systematizes all the different methods and concepts used in recommender systems, and related to a variety of areas of expertise, such as: data analysis, statistics, probability theory, decision support systems, marketing, and others. The book also addresses practical approaches to the construction of recommendations used in advanced corporations, for example, Amazon, Google, AT & T. Among the most important works devoted to the development of the recommender systems industry manuscript "Recommender Systems: The Textbook" [7] Can be distinguished. It lists the fundamental recommender algorithms and methods to assess their accuracy and speed. The paper details the application of recommender systems in a wide range of application areas: social systems, Internet commerce, search of the necessary information, and many others. In addition, it examines the following technical issues of the recommender systems creation: ensuring reliability and protection of information, correct ranking of results. In 2001 the manuscript was published, in which the recommender systems were first used for the selection of music. In the music recommendations, as well as in other ones, primarily the standard filtering methods are used, i.e., collaborative and content-basedfiltering [8]. But apart from them it is worth paying attention to the study of the hybrid approaches [9] in creating playlists, music social networking and tagging.

Wide practical application of recommender systems were not so long ago, at the end of the XX century, and it is connected primarily with the development of the Internet. But the theoretical foundation was developed long before, in the late 40-s - beginning of the 50s, and was based on machine learning. First of all, examined were self-learning algorithms, developed their mathematical foundation and built the models, which are used in recommender systems to this day. In the end of the twentieth century the collaborative filtering has been applied as a solution to deal with the excess of information on the web [10]. Tapestry (experimental postal service) [4] became one of the first systems using this approach: it allows the user to manually create queries based on the opinions or actions of other users. Taking into account the views of other participants, users were able to determine the relevance of such posts for themselves, although, of course, the creation of an additional request took more time and required certain actions from the user. Then, appeared the systems which independently collect relevant opinions and summarize them to make recommendations. For example, in a software component GroupLens [11] this technique was used to identify the materials in Usenet network that might be of interest to a particular user. Users are invited to assess the materials, and the system, in turn, brings them together with grades of other users to provide personalized results. With the development of machine learning and information retrieval, more in-depth study of the problems of interaction between human and machine, recommender systems are becoming increasingly popular. As a result, they have been increasingly applied in music, movies and lots of other products. Recommender systems more and more often appear outside the information technology industry, for example, in trade, as a way of increasing the number of sales.

In the late nineties, commercial recommender systems appeared on the market. Probably the best known of these products developer was the Amazon company [12]. Interest of the user to a particular item was calculated based on purchase history and views of the user, as well as the products viewed by him at a given time . After that, many other commercial companies have started to implement recommender systems, and some companies have even made the implementation of recommender systems its core business. In 2006, the Netflix company launched a competition named Netflix Prize, the purpose of which was to create an algorithm of recommendations that could improve the outcome of the current internal algorithm CineMatch in tests by 10% [13]. It attracted interest in the widespread use of recommender systems and triggered activity, both in academic circles and among commercial developers. The winner was promised 1 million US dollars, that shows the importance of recommender systems for the sphere of information technologies. At the same time, Google has developed its own system of news recommendations, Google News. The system processes the history of clicks made by users, and provides a recommendation for a particular user. In the case of Google News, news stories are regarded as objects of interest, and user clicks as an assignment of a positive rating to the news story. To the collected in such a way grades the collaborative filtering algoritm is appled, and based on the output data, a decision is made to recommend one or another material to a specific user.

The beginning of the 21st century is characterized by explosive growth in popularity of social networks. Naturally, recommender systems have been applied in them. Facebook has first implemented the recommendations of potential social relations algorithms. Such recommendations are somewhat different from the product recommendations: social networking is largely dependent on its growth to increase advertising revenue, so the recommendation of potential friends provide fast growth and network connectivity. This problem is also called a prediction of references in the analysis of network graphs. Therefore, the nature of this type of algorithms is somewhat different from the standard recommendation algorithms, but, in general, the essence remains the same.

Classification of recommender systems

There are three main types of recommender systems: collaborative, content-based, and hybrid systems.

Collaborative filtering primarily analyzes user behavior in the past. Data on rates made by the user to any items, form the basis for collaborative recommender systems. At the same time, the type of rated items does not matter, important is the similarity to user preferences (although some of the characteristics of items can be considered). The method is based on the assumption that users are typically constant in their rates, i.e. if they rated the item in a certain way in the past, they will continue to rate this item as well in the future. Predictions are made individually for each user, while processed are data of multiple users. These predictions show the extent to which the user is interested in the items which have not been rated by him so far [14, 15-20].

The method of collaborative filtering, in turn, can be divided into 2 submethods (approaches):
1. user-based, i.e., "based on the neighborhood"
2. item-based, i.e., "model-based"

The user-based approach historically is the first and still used in most systems. When using the user-based for an individual user selected is the group of users similar to him. In the selection of recommendations for a given user taken into account is a combination of weights and rates made by the group of users. To do this, each user of the group is assigned a weight in view of the similarity of his rates with the rates of active user. Users whose rates are as close as possible to the active user ones, are combined into one group called neighbor. Taking into accout the rates of these neighbors performed is the prediction of active user's rates and on this basis the system generates recommendation [15-20].

item-based measures parameters of statistical models for users' rates. To construct these models different methods are used, the most common of which are the following: clustering, Bayesian networks, latent semantic model, Markov decision process, and others. The models are developed using data mining, machine learning algorithms to find patterns based on the training data [15-20].

Item-based approach gives more relevant results, as deeply analyze factors that explain the observed rates. Better than in user-based processed are sparse matrix, that contributes to the scalability of large data sets. But, at the same time, there is a possibility of loss useful information loss in connection with the reduction of models .

The main problem of collaborative filtering is the so-called problem of "cold start", i.e. the virtual absence of data on new sites or users [15-20]. New items or users are a big problem for recommender systems. A high entry threshold is necessary, without knowing anything about the user's interests, the recommendations are virtually useless. To some extent this problem can be solved by using a content-based approach, which is known to use attributes instead of rates. In addition to the "cold start" problem, we can also note the problem of the recommender system inability to distinguish similar items with different names. The same items having different names are called synonymous. Most modern systems are not able to discover the hidden connections between synonymous items. Interesting can also be the problem of “white raven". "White ravens" are users who have diverse tastes, their opinions do not always coincide with the majority of others. Accordingly, it is impossible to recommend anything. But it should be noted that the problems of these people come from real life, so it would not be entirely correct to call it a problem of recommender systems. The advantage of collaborative filtering is a theoretical accuracy.

In content-based filtering the profiles of users and items are created. User profiles may include demographic information or answers to a specific set of questions. [14] Profiles of items can include the names of genres, actor names, artist names, etc., depending on the type of item. Items similar to those that the user has already used, are recommended to the user. Similarity is estimated on the basis of the items' content. The main problems of these systems are the strong dependence on the subject area, as well as the fact that the usefulness of recommendations is limited. Advantage of this approach is that it can recommend to even unfamiliar users, thereby bringing them into service, it is possible to recommend the items that have not yet been evaluated by anyone. Disadvantage is a lower accuracy.

Hybrid systems, as the name implies, combines both filterings, increasing the efficiency (and complexity) of recommender systems. Combining the results of the previous two types of filtering with a high probability can improve prediction accuracy [15-20]. In addition, hybrid systems can partially solve the problem of the so-called "cold start" inherent in collaborative filtering. The hybrid approach first weighs the results according to the principles of the content filtering, and then, as soon as sufficient data on the analyzed user obtained, shifts the weights toward the collaborative filtering.

Knowledge-based recommender systems

In addition to the recommender systems, appeared at the dawn of the artificial intelligence development, i.e., content-basd and collaborative, currently there are many systems that use in their work several different principles. Example of such systems may be a so-called "recommendations based on knowledge". The data in them are not descriptive evaluations but deeper relationships. Knowledge-based, in some formal features, can be attributed to the content-based approach, but according to the existing classifications it is still referred to a separate class. In the knowledge-based recommendations considered are only the common characteristics of items, but deeper dependency are based on.

Information processed by "recommendations based on knowledge", can be divided into: (a) rules (metrics) of similarity and (b) the items of interest. The system recommends items based on the user desires. User formulates his preferences in terms of the element properties, which, in turn, are presented in terms of rules (restrictions). A detailed review of decision-making mechanisms that can be used in filters of this kind are described in [21].

Hybrid recommender systems, in turn, can be divided into mixed-type, cascade and context.

Mixed-type strategy

The basis for a mixed-type hybrid model is a presentation of recommendations in a single integrated view. Data obtained as a result of other types of filtering, are assigned a certain weight. For example, an item that was the highest rated in the collaborative filtering, obtains 100 points, an item best estimated in the content-based filtering, obtains 50 points, etc.

Cascade strategy

According to the name, this method is characterized by cyclical way of building recommendations. The initial iteration is the algorithm, that is a gross filter, and all subsequent operations more and more refine results.

Context strategy

The main, characteristic of all existing recommender systems, mechanism of work is to develop recommendations based solely on the previously recorded ratings and user preferences. [22] This mechanism has been used for a long time and therefore it is considered that it has developed all of its computing capacity, i.e. it is impossible to increase the effectiveness of recommendations using only this mechanism. There appears a need to use new data to make recommendations. Context can play a role of these new data.

Context is a data representing a characteristic of the situation in which the user is located and in which

the evaluation of the item occurs. In general, the context can be divided into 2 following types:
- context in which the user preferences are fixed;
- context in which the recommendation is formed;

Context can also be divided into the following types:
- time, location, type of user activity, weather, light and the like, i.e., physical context;
- presence of others and their roles, social context;
- specifications of the instrument, with the help of which access to the information is supported, i.e. device context;
- nature of the user, his experience, cognitive abilities, i.e. modal context.

Of course, all this makes sense only if the information listed above has a major impact on the selection of an item, carried out by the user.

Practical experience of the context recommendations application shows that the most valuable is the information about the current user, behavior of users in general, properties of recommended products and context of the current user interest [1-3].

Based on the experience obtained by many developers, we can conclude that the context application in recommendations is a promising direction.

The application of context can get rid of the problems typical to many recommender systems, especially collaborative ones: cold start (context allows to characterize a new user based on his psychological and national data, mood and professional affiliation), unusual user problems (taking into account individual characteristics makes it possible to personalize the recommendations in the best way), triviality of recommendations, "filter bubble" (the context allows us not to be limited by user's last points of view). However, in the context systems, the problem of resource-intensive computations due to the large amount of data to be processed remains, and even increases.

Recommender systems in cardiology

Over the past few decades, number of medical data (test results, patient health records, treatment plans, and others) has reached enormous volumes. Consequently, the amount of information available for decision-making on patient treatment, increased significantly, but the problem is that this information is presented on various websites and resources and to gather it together is quite difficult. As a solution now proposed is the creation of personal electronic health cards (PEHC), which would be stored on a single resource, and would be available to both the patient and health care provider.

Moreover, recommender systems start being used in the medical field more often. These systems are used both by doctors and patients. The system allows doctors to speed up and simplify the process of diagnostics, the patient is able to get a preliminary consultation. Ricci et al. allocated the recommendation systems used in medicine, in a separate group, and called it "medical recommender system (MRS)»[6]. The MRS item is not confidential, scientifically proven, not tied to a particular patient medical information. MRS receives and processes data from PEHC of each particular user and on the basis of them builds the recommendations. Both the physician and patient get access to the MRS.

MRS are designed to provide the user with high quality relevant content. To achieve a high level of relevance a broader context should be considered. MRS takes into account the complex relationship between health concepts, decipher acronyms and interpret codes of medical classifications, adapts information to understand by an ordinary patient. Such systems are able to reduce the effect of information overload at the end user.

MRS determines the information needs of a particular user by analyzing PEHC records, user's search queries or by tracing the history of user views. To obtain highly relevant recommendations many computing methods are used. First of all, information retrieval (IR).

Information retrieval is the process of searching unstructured information, which satisfies information needs [23,24].

Term "information retrieval" was first introduced by Kelvin Muersom in 1948 in his doctoral dissertation, published and used in the literature since 1950.

Information retrieval is a process of identifying a set of documents in all those that satisfy a predetermined search condition (query) or contain the necessary data. In most cases, the information retrieval includes wording, determination of information sources, retrieval of information from these sources, and final stage, acquaintance with information received and evaluation of the results.

The retrieval methods are the following: address, semantic, documentary and factual.

Classical taskof information retrieval is a search for documents that satisfy the request, within a static document collection. But the list of tasks is constantly expanding and currently includes classification issues, filtering and clustering of documents, architecture design of search engines, information retrieval, querying, and others. [25-31]

For MRS, as well as for all recommender systems, advances in IR are essential . The use of IR allows obtaining relevant recommendations. The recommendation is based on PEHC which contain text documents, such as medical certificates, doctor's orders, and others. These text documents serve as queries in IR. Capabilities of IR in query values matching can be applied to the problem of selection of the relevant recommendations in MRS.

It is believed that the collaborative filtering is not suitable for MRS because of the need to keep medical secret. You can challenge this statement, citing the fact that the user information is being processed by not a person but a machine. But to explain this to an ordinary user concerned about his data security is not easy. However, due to the fact that user data is processed during a single session, it is easier to hack a system based on collaborative filtering. Therefore, many researchers believe the content-based filtering is more appropriate for MRS. Content-based filtering can also partially solve the problem of "cold start".

Examples of working MRS are user-oriented web portals of medical information, offering the possibility of making a diagnosis based on symptoms. However, for unprofessionals, in these systems there is a risk of information overload. Moreover, it is difficult to provide relevant results in the system "when the user does not know exactly what he wants." Besides, in case when users of such web portals have an account, which displays PEHC, MRS gives much more accurate results [25-31].

Fernandez-Luque, Karlsen and Vognild [32] identified the MRS possibilities as an educational resource for people leading a healthy lifestyle. They proposed the use of so-called program-assistant which allows scanning medical scientific content provided in a variety of social networks.

Hu H, Elkus A, Kerschberg L. [33] described the system that allows extracting suitable for users with a specific disease information from Internet. The system gives the patient the ability to search relevant content. The authors emphasize that MRS in this case can be viewed as a "medical information storage". The paper also notes the capability of connection to social networks user profiles to improve the recommendations.

Rivero-Rodriguez et al. [34] developed a system that enriches the social network content (YouTube videos, etc.) with materials from medical sources, e.g. Medline Plus. Such an approach contributed to the improvement of such ontologies as a SNOMED-CT. However, the authors acknowledge the need for more accurate meta-data to improve the quality of recommendations.

Other systems are focused on the prevention of disease by sending recommendations to users on mobile gadgets. In practice, this means that people who suffer, for example, diabetes, or nicotine dependence, receive daily personalized advice on dieting and receive medication. Ghorai et al. [35] presented the MRS that helps smokers to quit this addiction. In this case, the system simulates the recommendations based on user behavior data.

In general, many MRS are primarily intended to provide the end user with respect to the recommendations on his health. Based on analysis of the patient's history, the MRS sends to the PEHC user interface the data most appropriate for a particular patient, and of greatest interest to him [36-46]. The following data are most often in PEHC:

1. The detailed medical data about the user (for example,, current treatment, further treatment plan, surgical reports, medical certificates, etc.)
2. The terms collected by PEHC based on the user's search (for example, "the symptoms of myocardial infarction", "flu treatment", etc.)
3. The user behavior statistics (for example, visits to a certain web page, article ratings, etc.)

To obtain the most relevant recommendations MRS processes all of the above data, but paragraph 1 deserves special attention as it is based on information received from health care professionals.

When integrating MRS and PEHC the following requirements should be fulfilled:

1. The system should be able to interpret the following data:

(A) imprecise terms (for example,"hepatitis" instead of "chronic viral hepatitis"),
(B) colloquial expressions (for example , "period" instead of "menstruation"),
(C) inaccurately written expression (e.g., "diaetes" instead of "diabetes").

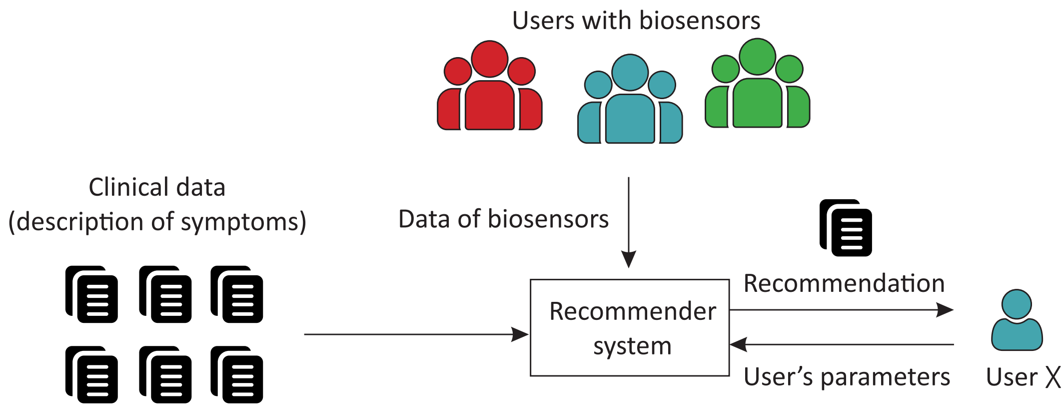

Fig.1. Medical recommender system performance pattern

2. The system should be able to understand professional terms used by doctors.
3. User's data confidentiality must be guaranteed by the MRS developers and owners. Even PEHC administrators should not have access to data containing patient confidentiality.

Despite significant progress in the development of recommender systems, MRS had not yet become a part of everyday life. Many issues remain open. The MRS interface should be clear to both medical professionals and ordinary users of any age [36-46].

Among other things, a big problem is information security, especially preservation of medical confidentiality. The problem of integration of MRS and PEHC is still unsolved because of existing shortcomings in the field of security. Integration with PEHC is necessary because the information on patient available in PEHC can solve the problem of "cold start", i.e. absence of input data. Improving the quality of recommendations will help to motivate users to update data in PEHC. And, in turn, the actual PEHC data contribute to the relevance of recommendations. There also exists a problem consisting in the fact that the MRS has to choose among the PEHC entries just the entries responsible for the current state of patient's health. Entries, which reflect the past diseases of the user, may no longer be relevant. MRS must be able to separate chronic diseases, e.g., diabetes, from diseases manifesting for a short period, e.g., seasonal colds.

An example of practical application of recommender systems in cardiology is a developed by Southampton University (UK) and the University of Islamabad IoS application [47]. The app is able to make a diagnosis and recommend appropriate treatment, diet and daily routine, by processing the data obtained from the biosensors located on the patient's body. Application data is collected from millions of patients wearing biosensors. The collected data is processed by a hybrid recommender system. As a result, by comparing the obtained data with the known symptoms of cardiovascular disease, a diagnosis is made. The diagnosis is compared with the treatment algorithms existing in the base. After that, the system encourages the patient to undergo a certain course of treatment, a diet and other recommendations (Figure 1).

Conclusion

The concept of recommender systems is defined herein, the brief history of the recommender systems development is given. The main types of recommender systems and principles of their construction are presented. The article provides a detailed review of the recommender systems application in medical field, cardiology, in particular. Methods of recommender systems construction are given, advantages and disadvantages of the methods are provided. Efforts to improve applicable in cardiology recommender systems may be extended by improving the basic algorithm, the construction of other models of recommender systems, such as hybrid ones, processing larger arrays of additional data.

Statement on ethical issues

Research involving people and/or animals is in full compliance with current national and international ethical standards.

Conflict of interest

None declared.

Author contributions

The authors read the ICMJE criteria for authorship and approved the final manuscript.

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