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 businessoriented 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 resourceintensive 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 littleknown, 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.

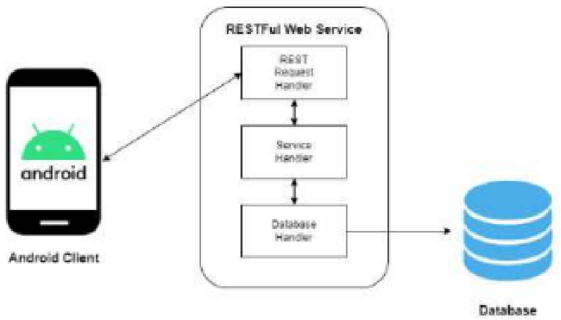

Рис. 1: General scheme of interaction between Android client and database in REST Architecture.

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.

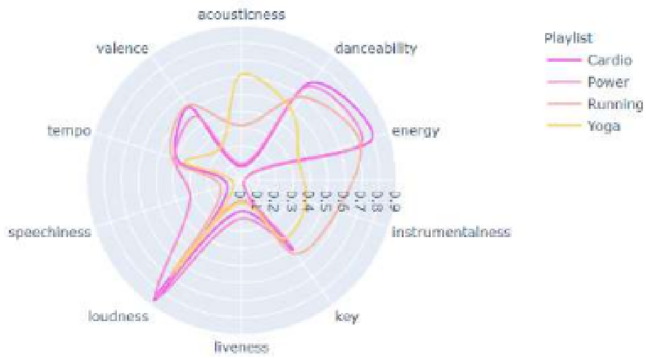

Рис. 2: Example of classification of the musical tracks by recommender system.

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).

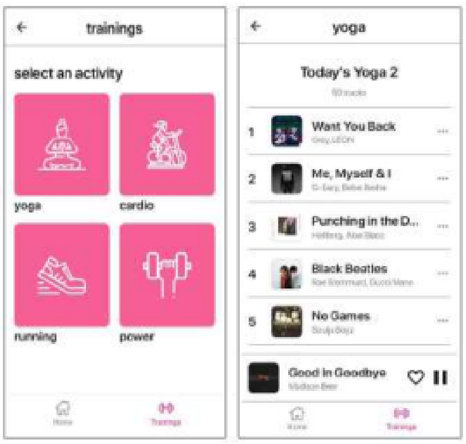

Рис. 3: Interface of the mobile recommender system for choosing musical tracks for different sport trainings.

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.