ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2021. № 1 (15) ISSN 2524-2296 (online)

UDC 004.422, 004.78 DOI: https://doi.org/10.30837/ITSSI.2021.15.059

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IMPLEMENTATION OF A HYBRID METHOD OF SEARCHING FOR CLOSE OBJECTS, TAKING INTO ACCOUNT THE GENERAL AND ACOUSTIC CHARACTERISTICS

The **subject** of research in the article is the methods of finding close objects and technologies of forming recommendations. The **aim** of the article is to develop a recommendation system based on a hybrid method of searching for objects, taking into account both user preferences and audio characteristics of objects. The following **tasks** are solved: analysis of methods and algorithms used in recommendation systems; development of a hybrid method of forming recommendations on the principle of double organization; determination of the main functions and architecture of the system of formation of musical recommendations; testing of calculation algorithms and search methods in the system for analysis of similarity of musical recommendations. The following research **methods** are used: methods of correlation analysis, methods of similarity theory, algorithms of collaborative filtering and content analysis, hybrid methods, methods of analysis of audio characteristics, programming technologies. The following **results** were obtained: A study of collaborative filtering, content-based filtering and hybrid methods. Algorithms and calculation formulas of the considered methods are given. The main audio characteristics of musical compositions are considered. The method of formation of recommendations on the principle of double organization is developed. The main functions of the system of formation of musical recommendations are listed and the diagram of components is formed. An example of calculating the characteristics of user preferences and similarity of musical compositions by audio characteristics is given. **Conclusions**: According to the results of testing the system by three methods, we can conclude that the proposed hybrid method was the most effective among the studied recommendation methods with the lowest standard error rate. In addition, the hybrid method on the principle of double organization solves such problems of existing recommendation methods as excessive similarity of recommendations, potentially small number or no proposals at all by compensating data from one block of data from another.

Keywords: audio characteristics; recommendation system; collaborative filtering; content oriented method.

Introduction

With the receipt of a huge amount of information, it became possible to create models of behavior of certain groups of Internet users, as well as their interests. Recommendation systems facilitate the social process of information exchange and help users to find the most valuable information for them among the large amount of available information (books, articles, web pages, music, etc.) [1]. Recommendation systems have also become key applications in e-commerce, providing suggestions for users to receive the products that best suit their interests, needs and preferences. The recommendation system generates and provides individualized proposals, selects its own settings of many interesting or useful objects from a huge number of possible.

Analysis of existing publications and problem statement

Recommendation systems are designed to form recommendations to consumers regarding the choice of goods and services in the presence of a significant number of alternatives [2, 3]. Such systems use ratings or information about the preferences of other users as input. With the use of machine learning, relationships are formed between the properties of objects and the characteristics of consumers [4, 5].

The scope of such systems is mainly related to the use of e-commerce [6]. Such systems simplify the choice of users who do not have enough knowledge about the characteristics of the objects of interest to them (goods and services) with a wide choice.

In [7] the main types of recommendation systems on the Internet, based on the methods of content and collaborative filtering, are considered. The methods of collecting data about users from web resources, necessary for the formation of recommendations, are considered. Methods of constructing classifiers for content filtering are investigated. There are also ways to calculate the similarity of users or objects in collaborative filtering.

The article [8] proposes an ontological model of an intelligent search and recommendation system focused on functioning in the open environment of the Web, social Web and Semantic Web. The directions of gaining knowledge about users are considered, the expediency of personal testing for creating groups of users with common interests is analyzed, which provides an opportunity for collaborative forecasting of search results evaluations. Methods of replenishment of this model with new knowledge by inductive generalization of experience of interaction of the user with the system providing self-training of search and recommendation system directed on improvement of its work are developed.

During the existence of information technology, many methods have been proposed for the formation of proposals, including content-oriented methods, collaborative methods, knowledge-based methods and more.

The most well-known, popular, accurate and effective methods of forming proposals are such methods as:

- collaborative filtration;
- content-oriented filtering;
- demographic filtering;
- utilitarian filtration;
- filtering based on knowledge base.

A Bayesian preference model is used, which statistically combines several types of information useful for making proposals, such as user preferences and expert

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2021. No. 1 (15)

assessments. They use the methods of the Markov chain and Monte Carlo to conclude on the basis of a sample of parameters from the full conditional distribution of parameters. These models achieved higher performance than pure collaborative filtering.

A promising area is the development of hybrid referral systems that combine the advantages of existing methods of finding similar objects. Therefore, the aim of the article is to develop a recommendation system based on a hybrid method of searching for objects, taking into account both user preferences and audio characteristics of objects.

The following tasks are solved:

1. Analysis of methods and algorithms used in recommendation systems.
2. Development of a hybrid method of forming recommendations on the principle of double organization.
3. Definition of the main functions and architecture of the system of formation of musical recommendations
4. Testing of calculation algorithms and search methods in the system for analysis of similarity of musical recommendations.

Materials and methods

Content-based recommendation systems make suggestions by analyzing the content of information and finding patterns in it [9, 10]. Content-based recommender uses heuristic methods or classification algorithms to make suggestions.

Collaborative Filtering (CF) methods use a user preference database for items to predict additional topics or products that a new user might like [11, 12]. The source information is a list of m users $\{u_1, u_2, ..., u_m\}$ and a list of n elements $\{i_1, i_2, ..., i_n\}$. Each u_i user has a list of elements that he has evaluated or that have been inferred from their behavior. Ratings can be rated both on a quantitative scale and on a qualitative or nominal scale.

Memory-based CF algorithms use user and object databases to generate predictions. Each user is part of a group of people with similar interests. By identifying the so-called neighbors of a new user (or active user), they can make predictions of benefits for new objects.

The following steps are performed in the CF algorithm:

- calculation of similarity or weight $w_{i,j}$ which reflects the correlation between two users or two objects i and j;
- making predictions for the active user on the weighted medium values of all user or object ratings.

To make the top N recommendations, it is necessary to identify N nearest neighbors [13].

Let's look at methods for calculating similarities between users or objects [14]:

1. Similarity based on Pearson's correlation:

$$w_{u,v} = \frac{\Sigma_{i\in I}\ (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\Sigma_{i\in I}\ (r_{u,i} - \bar{r}_u)^2}\sqrt{\Sigma_{i\in I}\ (r_{v,i} - \bar{r}_v)^2}},$$

where $w_{u,v}$ – a measure of similarity between the two users, i, j – objects, u,v – users, $\bar{r}_v$ – medium user rating v, $r_{u,i}$ – rating of user u for the object i.

To calculate the similarity, you can use a limited Pearson correlation, Spearman's rank correlation, Kendall correlation.

Similarity based on the cosine vector. If we have a matrix of features of objects R of dimension $m \times n$, then the similarity between the two elements i and j is defined as the cosine of n-dimensional vectors corresponding to the i-th and j-th columns of the matrix R:

$$w_{i,j} = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\| * \|\vec{j}\|}.$$

Obtaining predictions or recommendations is the most important step in collaborative filtering. The forecast of user rating a for a particular object i is the weighted medium of all ratings for that object:

$$P_{a,i} = \bar{r}_a + \frac{\Sigma_{u\in U}(r_{u,i} - \bar{r}_u) w_{a,u}}{\Sigma_{u\in U}\left|w_{a,u}\right|},$$

where r_a and r_u – medium user ratings a and u for all other rated items, $w_{a,u}$ – the weight of the difference between user a and user u.

The summation occurs for all users $u \in U$ who have rated object i.

For object-based forecasting, the weighted mediums of the prediction estimates $P_{u,i}$ user u for object i are used.

$$P_{u,i} = \frac{\Sigma_{n\in N} r_{u,n} w_{i,n}}{\Sigma_{n\in N}\left|w_{i,n}\right|},$$

where $w_{i,n}$ – the weight of the difference between objects i and n, $r_{u,n}$ – user rating u for object .

The summation occurs for all other estimated objects $n \in N$ by user u.

The algorithms of top-N recommendations allow to determine k most similar objects for each of the other objects as follows [13]:

1) the set of candidates (C) for the recommended objects is determined;
2) combines k most similar objects;
3) objects are selected from the set U, which the user has already evaluated;
4) the similarity between each object from set C and set U is calculated;
5) the resulting set of C objects, sorted in descending order of similarity, will be the recommended list of top-N objects.

Consider a method based on the *factorization of rating matrices*. The essence of this method is to break the matrix of ratings into the product of two matrices - a matrix of hidden user preferences and a matrix of implicit characteristics of the object. For each object, the degree to

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2021. № 1 (15) ISSN 2524-2296 (online)

which it has a particular characteristic can be either positive or negative, as well as for the user, the degree of his interest in the object can be positive if he is interested, or negative if not interested. The rating is represented as a scalar product of two vectors: a vector of hidden user preferences and a vector of implicit characteristics of the object, which shows the general interest of the user in the characteristics of the object.

Each user u, according to this model, must correspond to a vector and ∈ ℝ, the components of which show the extent to which the object has each of the factors. Similarly, each object i corresponds to a similar vector i '∈ ℝ, the components of which show the extent to which the user is close (interesting) objects that have each of the factors. The evaluation of the object by user u is thus represented as a scalar product. The idea of the method is to find the values of vectors and, using known estimates, and then use the found values of these vectors to calculate the predictions of unknown estimates. The main task in building a recommendation system based on the modeling of latent factors is to find the components of vectors and.

In the search for such a breakdown of the rating matrix, the regularized quadratic error is minimized. The minimization is performed either by the stochastic gradient descent method or by the alternative least squares method. In the method of least squares there is a cyclic recalculation of vectors of users and objects, i.e. when fixing vectors of objects, regularization is carried out only on the vectors of users, divided into smaller squares. In the same way regularization of vectors of users on vectors of objects is carried out.

Machine learning methods, data mining algorithms can recognize complex models based on training data, and then make intelligent predictions for common CF problems for test data or real data [15]. CF algorithms based on Bayesian models, clustering models, and dependency networks can be used as CF models if user estimates are reliable, and regression models and singular decomposition methods can be used for quantitative estimates.

The Bayesian algorithm assumes that the characteristics are independent, the probability of a certain class of all characteristics can be calculated [16]. For incomplete data, probability calculations and classification are made from observations:

$$\mathrm{class} = \underset{\mathrm{j \in classSet}}{\arg\max}\, \mathrm{p(class_j)} \prod_{\mathrm{o}} \mathrm{P(X_o = x_o \,|\, class_j)},$$

where class – is a set of classes, x_o – characteristics.

Content-based filtering depends on the content of objects represented by certain characteristics [17]. To calculate the similarity between the two products, the objective distance between the elements is considered. When objects are described by numerical attributes, a metric such as Euclidean distance is used:

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2},$$

where x_i and y_i – *i*-th characteristics of objects *x* and *y*.

If the attributes are nominal, the function can be calculated to quantify the distance, assuming a value of 0 when both elements are equal or 1 otherwise:

$$d(x,y) = \omega \sum_{i=1}^{n} \delta(x_i, y_i),$$

where ω and δ – nominal characteristics.

Systems that implement a recommendation approach based on content, analyze a set of objects that have previously been evaluated by the user, and build a profile of user interests based on the characteristics of objects evaluated by the same user. A profile is a structured representation of users' interests adopted to recommend new objects. The recommendation process is mainly to match the attributes of the user profile with the attributes of the content object.

Audio analysis techniques are used to compare audio files. Audio analysis, an area that includes automatic speech recognition (ASR), digital signal processing, and music classification, tagging, and generation, is a developed subdomain of deep learning applications. The products must be described by automatic methods. In the music industry, automatic methods are implemented by algorithms that analyze the parameters

1) low level:
- mel frequency,
- sampling frequency of the audio file,
- spectral width,
- spectral center of the sound frame,
- color of audio, etc.;

2) intermediate level:
- key,
- rhythm,
- harmony,
- intensity,
- structure;

3) high level: for example, analysis of similar guitar solos.

Some of the most common machine learning systems, such as Alexa, Siri and Google Home, are based on models that extract information from audio signals. Sound waves are digitized by sampling from discrete intervals known as sampling rates. Typically, this is 44.1 kHz for CD-quality audio, i.e. 44,100 samples per second.

Each sample represents the amplitude of the wave in a certain time interval, where the depth in bits determines the degree of its detail (fig. 1).

In signal processing, sampling is the conversion of a continuous signal into a series of discrete values. The sound is presented in the form of an audio signal with such parameters as frequency, bandwidth, decibels, etc. A typical audio signal can be expressed as a function of amplitude and time, as in fig. 2.

In addition to these characteristics, a spectrogram is used for comparison - a visual way to represent the signal level in time at different frequencies present in the form of a wave.

From the specified characteristics it is necessary to choose signs which will be used for comparison.

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2021. No. 1 (15)

Spectral (frequency) features are obtained by converting a time signal into a frequency domain using a Fourier transform. These include:

- fundamental frequency,
- frequency components,
- spectral centroid,
- spectral flux,
- spectral density,
- spectral decline, etc.

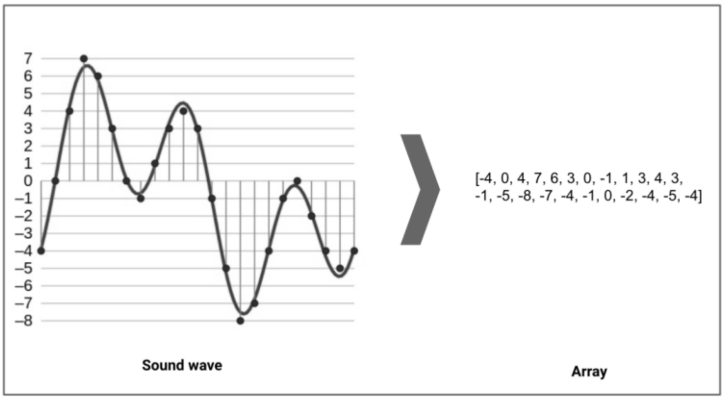

Fig. 1. Example of digital signal processing of samples

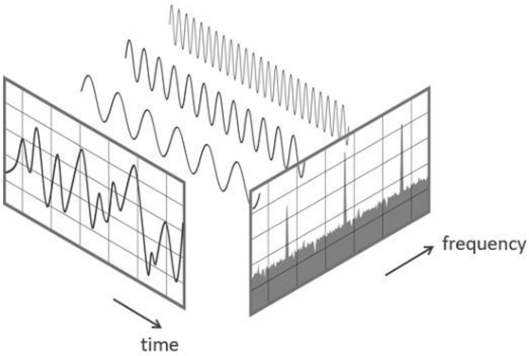

Fig. 2. Representation of sound in the form of an audio signal as a function of amplitude and time

1. The spectral centroid indicates at what frequency the energy of the spectrum is concentrated:

$$f_c = \frac{\Sigma_k S(k) f(k)}{\Sigma_k S(k)},$$

where $S(k)$ is a spectral value of the separation element k, $f(k)$ – frequency of the element k.

2. Spectral width - the width of the band of light at half the maximum point (fig. 3).

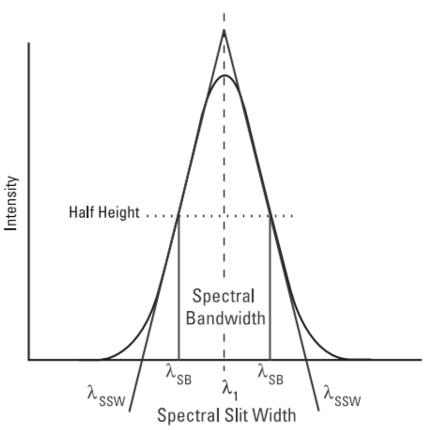

Fig. 3. Graphic representation of spectral width3. Spectral decline is a measure of the waveform expressed by the frequency at which high frequencies fall to zero.

4. Zero cross-section speed - a method of measuring the smoothness of the signal, which is expressed by the number of zero cross-sections within the signal segment.

5. Mel-frequency spectral coefficients (MFSC) are a set of features that describe the common form of the spectral envelope.

6. Chromaticity - is represented by a vector of signs of 12 elements, which indicates the amount of energy of each altitude class {C, C #, D, D #, E,…, B} in the signal.

The quality of the recommendations can be assessed by the following criteria:

- accuracy,
- resistance to attacks,
- dependence on cold start,
- reliability and others.

To measure the accuracy of predicting results, you can use indicators such as:

- medium absolute error (MAE),
- medium standard error (MSE),
- medium error (ME),
- standard deviation (SD).

Medium standard error is calculated by the following formula:

$$MSE = \sqrt{\frac{\sum\limits_{(u,i)\in T} (p_{ui} - r_{ui})^2}{T}},$$

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2021. № 1 (15) ISSN 2524-2296 (online)

where u – user, i – product or object, r – evaluation, p – projected estimate, T – the total number of test estimates.

Method of forming recommendations on the principle of double organization.

In order to avoid the limitations of any system and increase the speed of submission of proposals, combined (hybrid) methods of proposal formation are used. *Hybrid recommendation systems* combine CF with other recommendation methods. Hybrid methods are created by adding characteristics for CF models, adding CF characteristics to content-oriented models, or combining different CF algorithms.

The CF algorithm, supported by the content, uses the Bayesian classifier, and then fills the missing values of the rating matrix with forecasts from the content prediction system to form a matrix of pseudo-ratings. Based on the obtained pseudo-rating matrix, forecasting is performed using a weighted algorithm and Pearson correlation.

The weighted hybrid recommender combines different methods of supply based on the weight calculated by the results of other methods. A linear function with normalized weights can be used as an integration. As a result, you can choose a weighted majority or a weighted average.

The switching hybrid recommender switches between recommendation methods using a number of criteria. Here there is a problem of complexity of parameterization for switching criteria.

There are also mixed hybrid recommenders, cascading hybrid recommenders, meta-level recommendators and others.

The combination of several methods of forming proposals in hybrid methods is as follows:

- monolithic organization, when one of the methods is chosen as the main one, and the others strengthen and support its work;

- parallel organization, in which each of the methods works separately, and then the results of their work are combined according to certain principles;

- pipeline organization, when all methods work sequentially, with the input data for each subsequent method is the output of the previous.

In order for the results of the methods to be the most effective, the principle of double organization is applied and an algorithm is developed that combines the methods of parallel and pipeline organization as follows (fig. 4):

- filtering takes place in two independent working units;

- in one of the blocks the method of collaborative filtering will work first, and at the end of its work the obtained results are processed by the content-oriented method;

- in another block, on the contrary, first the content-oriented filtering works, and then - collaborative filtering;

- after receiving the results from the two blocks, a common list of objects will be displayed as suggestions.

Each of the individual units supports the principle of conveyor organization in its work.

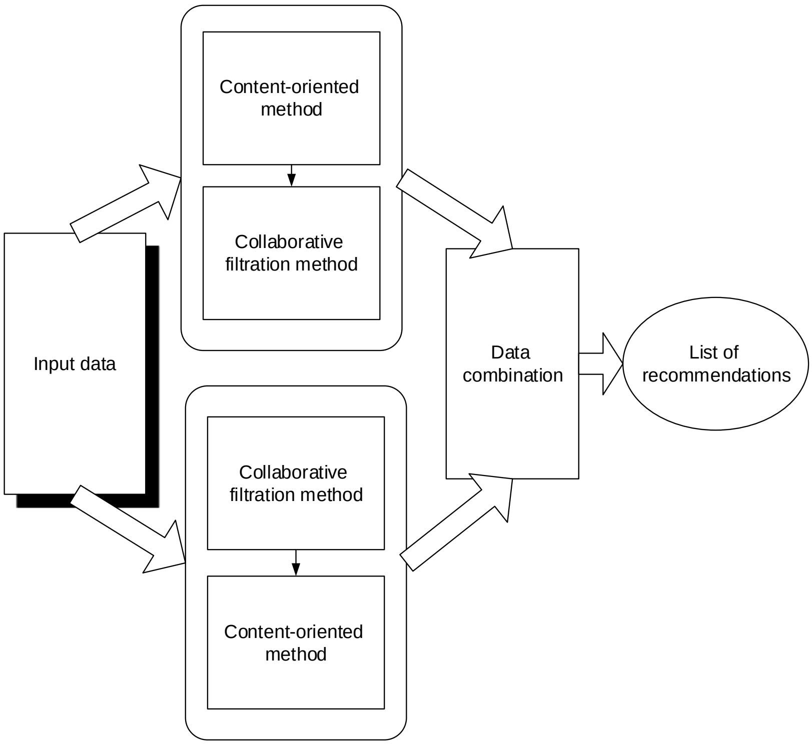

Fig. 4. Hybrid method of forming proposals based on double organization

The developed hybrid method combines the approaches of parallel and pipeline organization. Conveyor cascade organization of recommendation methods in each of the individual units allows to obtain more accurate proposals at the output. The first method in the chain is responsible for creating rough estimates for candidate products, as well as for eliminating products without grades. The second method adjusts the results of the evaluations of the first method and organizes them, creating a final list of proposals. Each of the blocks is

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2021. No. 1 (15)

given a weighting factor, which is calculated and changed during the analysis of the results of previous proposals. Initially, the coefficients of both blocks are 0.5. If after receiving the offers the user gave a rating that is different from the forecast, then when recommending this object to other users, the weight will increase, which will allow you to refine the rating.

The main functions and architecture of the system of formation of musical recommendations

The music recommendation system is a standalone web application that allows users to receive suggestions for favorite items based on their music profile.

The main *functions* of the system:

- formation of a musical profile;
- creating lists of personal musical preferences;
- integration with music resources (Last.fm, Spotify);
- generating a list of music offers;
- the ability to listen to and purchase recommended songs;
- search for information about songs and their performers.

Creating a music user profile is one of the main functions of a web application. A music profile is a user's listening history, that is, a list of names of music tracks and their artists that have been registered as listened to. The user can integrate with other existing music resources by downloading a listening history and adding this information to their profile. This information then becomes available to anyone and can be obtained via http-requests through a special API. In this way you can get a more complete picture of the various user preferences.

Two lists of personal preferences are created for each user: favorite music tracks and those you don't like ("favorites" and "blacklist"). Suggestions will be generated primarily for songs that have been added to the favorites list, and will be ignored primarily similar to those included in the "black" list.

In the component diagram shown in fig. 5, you can see the central position of the web server, which makes requests via the http protocol to open APIs of remote resources, such as iTunes, Last.fm, Spotify, SoundCloud, YouTube. The user will use the web interface in the browser to provide commands in the form of requests to the web server, which in turn will execute them and return the result to the browser, which will show it to the user.

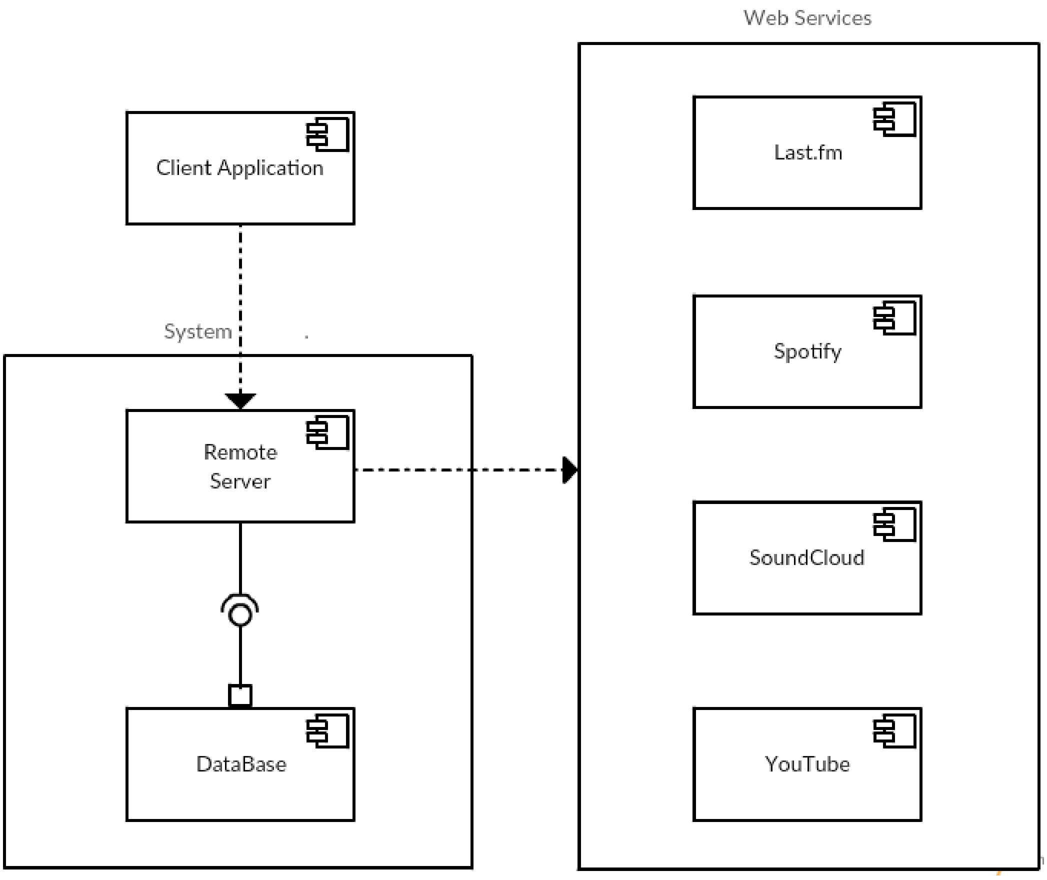

Fig. 5. Component diagram

In order for the collaboration filtering method to give a correct result, it is necessary to have a large amount of data on the preferences of the user of the recommendation system, as well as all users who have common advantages with the data. But at the beginning of the system it takes some time for the database to acquire the size necessary for the correct operation of the system. This phenomenon is called a cold start or a problem of a new user or a new object [18]. The required coverage can be defined as the percentage of products that the algorithm can offer. The problem of reduced coverage occurs when the number of user ratings is very small compared to the large number of

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2021. № 1 (15) ISSN 2524-2296 (online)

objects in the system, and the referral system cannot generate offers for them. Another problem is the phenomenon of neighboring transitivity in databases with a small amount of information, in which users cannot be identified as "similar to each other" if they do not have a score for the same objects.

Thus, to ensure the operation of content-oriented methods, you must first have a database with a description of the products, information about which will be used to provide proposals. It is advisable not to collect product descriptions yourself, but to use a ready-made complete data set. The most complete description of the characteristics of world music songs is contained in the database of the Spotify service, while also having free access via the Spotify Web API.

It should be noted that different methods of generating proposals have different means of using input data then generating output. For example, collaborative filtering techniques will generate user ratings and tastes, interests, and preferences when listening to music when generating suggestions, while content-oriented methods will form a set of data-like songs.

Analysis of user preferences and similarity of musical compositions by audio characteristics. System testing.

Here's an example of measuring the similarity of three different users' queries for different genres of music using Pearson's correlation.

We received user ratings for nine music genres. Each user rated the genres on a scale of 1 to 5, where the most favorite genres have a rating of 5 and the least attractive - 1, respectively.

Having three users, the system is three pairs to calculate the Pearson correlation coefficients. Connections between traits can be strong (close) and weak, they are assessed on the Chaddock scale, where:

$0.1 < r_{xy} < 0.3$ – weak connection;

$0.3 < r_{xy} < 0.5$ – moderate connection;

$0.5 < r_{xy} < 0.7$ – noticeable connection;

$0.7 < r_{xy} < 0.9$ – strong connection.

$0.9 < r_{xy} < 1$ – very strong connection.

Below is table 1 with ratings of genres by three users.

Table 1. *User ratings of different genres*

Genres	User 1	User 2	User 3
Pop	4	5	5
Chanson	2	3	3
Country	4	3	3
Opera	5	5	2
Rock	1	1	4
Jazz	5	3	2
Folk	3	3	1
Hip-Hop	5	5	5
Symphonic	2	1	1

When comparing the ratings of users 1 and 2, the Pearson correlation coefficient 0.8005 was obtained. On the Chaddock scale, this is a strong connection. A comparison of 1 and 3 user ratings showed a score of 0.1318, which is a weak link. Comparison between users 2 and 3 gives a moderate factor - 0.4278.

Thus, if user 1 needs recommendations, he needs to consider the preferences of user 2. User 2 must listen first to user 1 and secondly to user 3.

An example of calculations of audio characteristics of three compositions is given. The Euclidean distance is calculated on the basis of the spectral centroid. Each data set for an individual composition will consist of 12 elements, the value of which is measured in the range between 0 and 1 (table 2). The closer to 1, the higher the frequency of concentration of energy in the spectrum. For example, the closer the ratio is to 1, the more likely it is that the audio contains a large number of loud vocalist sounds or musical instruments. Each element of the array is the average value of the spectral centroids for a duration of 15-20 seconds.

Table 2. *The value of the audio characteristics of the compositions*

No.	"Highway to Hell"	"Back in Black"	"Billie Jean"
1	0.854411946129	0.842525219898	0.309617027413
2	0.604124786151	0.561826888508	0.257490051780
3	0.593634078776	0.508715259692	0.384942835571
4	0.495885413963	0.443531142139	0.393766280475
5	0.266307830936	0.296733836002	0.340499471454
6	0.261472105188	0.250213568176	0.284685235124
7	0.506387076327	0.488540873206	0.490791264466
8	0.464453565511	0.360508747659	0.513048089201
9	0.665798573683	0.575435243185	0.569896183990
10	0.542968988766	0.361005878554	0.508417866340
11	0.580444285770	0.678378718617	0.519187529821
12	0.445219373624	0.409036786173	0.490379584500

The following valuesof Euclidean distance are obtained:

- between the songs "Highway to Hell" and "Back in Black" 0.2761;

- between "Highway to Hell" and "Billie Jean" 0.7041;

- between "Back in Black" and "Billie Jean" 0.6888.

The greater the Euclidean distance characteristics between the two tracks, the less similar they are. That is, if the algorithm will determine the most similar song to the track "Back in Black", then in the first place in the priority of recommendations will be "Highway to Hell".

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) *Innovative technologies and scientific solutions for industries. 2021. No. 1 (15)*

For verification, spectrograms of compositions were constructed, on which you can visually see the difference between "Highway to Hell" and "Billie Jean", which confirms the results of calculations (fig. 6, fig. 7).

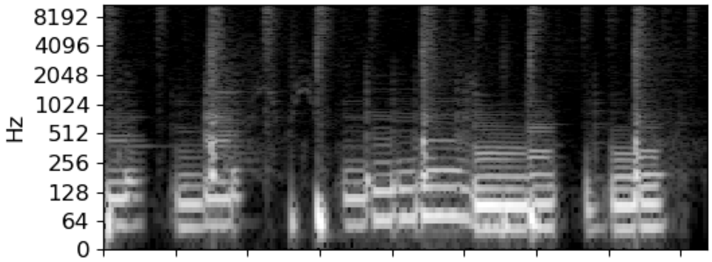

Fig. 6. "Highway to Hell" Spectrogram

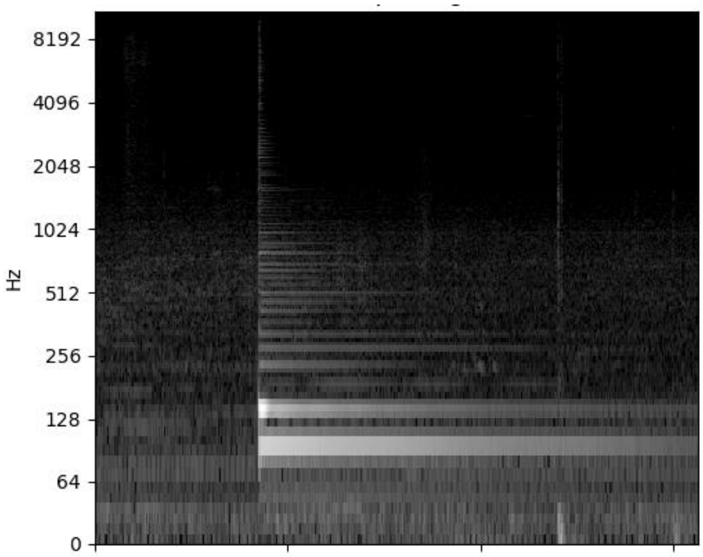

Fig. 7. "Billie Jean" Spectrogram

The system was tested based on the Spotify database, where, according to the statistical website Expanded Ramblings, as of 2020, about 100 million users have been registered and about 30 million music tracks have been added. As the results of the analysis showed, when using 10% or 1% of the data, the results did not change, so all experiments were conducted on 1%, i.e. on 100 thousand users, 30 thousand tracks and 2 million ratings.

Using test data, the process of forming proposals for test users was carried out by two methods sequentially. The method of collaborative filtering by calculating the root mean square error using test data, received an accuracy estimate of 1.48 and worked for about 13 minutes. The content-based method received an accuracy estimate of 1.39 when working for 10 minutes. The hybrid method on the principle of double organization received an estimate of accuracy of 1.37 with a duration of 22 minutes.

Conclusions

The article investigated collaborative filtering, content-based filtering and hybrid methods. Algorithms and calculation formulas of the specified methods are resulted. The main audio characteristics of musical compositions are considered.

The method of formation of recommendations on the principle of double organization is developed.

The main functions of the system of formation of musical recommendations are determined and the diagram of components is formed.

An example of calculating the characteristics of user preferences and similarity of musical compositions by audio characteristics is given.

According to the results of testing the system by three methods, we can conclude that the proposed hybrid method is worse than others in speed by about one and a half times. However, this method proved to be the most effective among the studied recommendation methods with the lowest value of the root mean square error. In addition, the hybrid method on the principle of dual organization solves such problems of existing recommendation methods as excessive similarity of recommendations, potentially small number or no proposals at all by compensating data from one block of data from another.

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Received 20.01.2021

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ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2021. No. 1 (15)

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РЕАЛІЗАЦІЯ ГІБРИДНОГО МЕТОДУ ПОШУКУ БЛИЗЬКИХ ОБ’ЄКТІВ З УРАХУВАННЯМ ЗАГАЛЬНИХ ТА АКУСТИЧНИХ ХАРАКТЕРИСТИК

Предметом дослідження в статті є методи пошуку близьких об’єктів та технології формування рекомендацій. **Метою** статті є розробка рекомендаційної системи на основі гібридного методу пошуку об’єктів з урахуванням як переваг користувачів, так і аудіохарактеристик об’єктів. Вирішуються наступні **завдання:** аналіз методів та алгоритмів, що застосовуються в рекомендаційних системах; розробка гібридного методу формування рекомендацій за принципом подвійної організації; визначення основних функцій та архітектури системи формування музичних рекомендацій; тестування розрахункових алгоритмів та методів пошуку в системі для аналізу схожості музичних рекомендацій. Використовуються такі **методи** дослідження: методи кореляційного аналізу, методи теорії подібності, алгоритми колаборативної фільтрації та аналізу контенту, гібридні методи, методи аналізу аудіохарактеристик, технології програмування. Отримано наступні **результати**: Проведено дослідження методів колаборативної фільтрації, фільтрації на основі контенту та гібридних методів. Приведені алгоритми та розрахункові формули розглянутих методів. Розглянуті основні аудіохарактеристики музичних композицій. Розроблено метод формування рекомендацій за принципом подвійної організації. Перелічено основні функції системи формування музичних рекомендацій та сформовано діаграму компонентів. Приведено приклад обчислювання характеристик вподобань користувачів та схожості музичних композицій за аудіохарактеристиками. **Висновки**: За результатами тестування роботи системи трьома методами можна зробити висновок, що запропонований гібридний метод виявився найбільш ефективним серед досліджених рекомендаційних методів при найменшому показнику середньоквадратичної помилки. Крім того, гібридний метод за принципом подвійної організації вирішує такі проблеми існуючих рекомендаційних методів, як надмірна подібність рекомендацій, потенційно мала кількість або відсутність пропозицій взагалі за рахунок компенсації даних з одного блоку даними з іншого.

Ключові слова: аудіохарактеристики; рекомендаційна система; колаборативна фільтрація; контент орієнтований метод.

РЕАЛИЗАЦИЯ ГИБРИДНОГО МЕТОДА ПОИСКА БЛИЗКИХ ОБЪЕКТОВ С УЧЕТОМ ОБЩИХ И АКУСТИЧЕСКИХ ХАРАКТЕРИСТИК

Предметом исследования в статье являются методы поиска близких объектов и технологии формирования рекомендаций. **Цель** статьи – разработка рекомендательной системы на основе гибридного метода поиска объектов с учетом как предпочтений пользователей, так и аудиохарактеристик объектов. Решаются следующие **задачи**: анализ методов и алгоритмов, применяемых в рекомендационных системах; разработка гибридного метода формирования рекомендаций по принципу двойной организации; определение основных функций и архитектуры системы формирования музыкальных рекомендаций; тестирование расчетных алгоритмов и методов поиска в системе для анализа сходства музыкальных рекомендаций. Используются такие **методы** исследования: методы корреляционного анализа, методы теории подобия, алгоритмы колаборативной фильтрации и анализа контента, гибридные методы, методы анализа аудиохарактеристик, технологии программирования. Получены следующие **результаты**: Проведено исследование методов колаборативной фильтрации, фильтрации на основе контента и гибридных методов. Приведены алгоритмы и расчетные формулы рассмотренных методов. Рассмотрены основные аудиохарактеристики музыкальных композиций. Разработан метод формирования рекомендаций по принципу двойной организации. Перечислены основные функции системы формирования музыкальных рекомендаций и сформирована диаграмма компонентов. Приведен пример вычисления характеристик предпочтений пользователей и сходства аудиохарактеристик музыкальных композиций. **Выводы**: По результатам тестирования работы системы тремя методами можно сделать вывод, что предложенный гибридный метод оказался наиболее эффективным среди исследованных рекомендационных методов при наименьшем значении среднеквадратичной ошибки. Кроме того, гибридный метод по принципу двойной организации решает такие проблемы существующих рекомендационных методов, как чрезмерное сходство рекомендаций, потенциально малое количество или отсутствие предложений вообще за счет компенсации данных из одного блока данным другим.

Ключевые слова: аудиохарактеристики; рекомендационная система; колаборативная фильтрация; контент ориентированный метод.

Бібліографічні описи / Bibliographic descriptions

Малєєва О. В., Єсіпов В. В., Артюх Р. В., Косенко В. В. Реалізація гібридного методу пошуку близьких об’єктів з урахуванням загальних та акустичних характеристик. *Сучасний стан наукових досліджень та технологій в промисловості*. 2021. № 1 (15). С. 59–68. DOI: https://doi.org/10.30837/ITSSI.2021.15.059

Malyeyeva, O., Yesipov, V., Artiukh, R., Kosenko, V. (2021), "Implementation of a hybrid method of searching for close objects, taking into account the general and acoustic characteristics", *Innovative Technologies and Scientific Solutions for Industries,* No. 1 (15), P. 59–68. DOI: https://doi.org/10.30837/ITSSI.2021.15.059