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A STUDY OF THE IMPACT OF THE WEIGHTED RECIPROCAL RANK FUSION METHOD ON THE QUALITY OF RECOMMENDER SYSTEMS

Abstract. Providing high-quality recommendations is an important factor in increasing the level of audience engagement, since under conditions of rapid growth in the volume of available information, a significant part of which is presented in the form of implicit feedback, recommender systems ensure the effective selection and ranking of items according to individual user preferences. CF is one of the most widespread strategies for constructing such systems and generates recommendations based on the analysis of user interactions with similar behaviour patterns, which makes it possible to identify not only obvious but also unexpected potentially relevant items. During the generation of recommendations by different CF algorithms, recommendation lists for each user are produced that differ in the composition and order of items, which is caused by differences in the principles of determining the relevance of items. Since CF algorithms produce distinct recommendation lists for each user, it is appropriate to apply the WRRF method, which ensures the aggregation of rankings generated by algorithms in order to construct a single ranked recommendation list of higher quality. The purpose of this work is to study the influence of the WRRF method on the quality of generation and ranking of recommendation lists obtained as a result of the pairwise combination of CF algorithms through rank aggregation of items. According to the results of the experimental study, it has been established that the use of the WRRF method in the vast majority of cases ensures an improvement in recommendation quality compared with the best algorithm in the corresponding pair. The experimental evaluation was carried out using six CF algorithms on three datasets transformed into the implicit

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feedback format. The obtained results can be used in the development and improvement of industrial recommender systems in order to increase the quality of recommendation ranking without significant complication of their software architecture.

Keywords: weighted reciprocal rank fusion, recommender system, collaborative filtering, implicit feedback.

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ДОСЛІДЖЕННЯ ВПЛИВУ МЕТОДУ ЗВАЖЕНОГО ВЗАЄМНОГО ЗЛИТТЯ РАНГІВ НА ЯКІСТЬ РЕКОМЕНДАЦІЙНИХ СИСТЕМ

Анотація. Надання високоякісних рекомендацій є важливим чинником підвищення рівня залученості аудиторії, оскільки в умовах стрімкого зростання обсягу доступної інформації, значна частина якої представлена у вигляді неявного зворотного зв'язку, рекомендаційні системи забезпечують ефективний відбір і впорядкування об'єктів відповідно до індивідуальних уподобань користувачів. CF є однією з найбільш поширених стратегій побудови таких систем і формує рекомендації на основі аналізу взаємодій користувачів із подібними моделями поведінки, що дає змогу виявляти не лише очевидні, але й неочікувані потенційно релевантні об'єкти. Під час формування рекомендацій різними алгоритмами CF для кожного користувача формуються списки рекомендацій, що відрізняються за складом і порядком об'єктів, що зумовлено відмінностями у принципах визначення релевантності об'єктів. Оскільки різні алгоритми CF формують відмінні списки рекомендацій для кожного користувача, доцільним є застосування методу WRRF, який забезпечує агрегування упорядкувань, сформованих окремими алгоритмами, з метою побудови єдиного впорядкованого списку рекомендацій підвищеної якості. Метою цієї роботи є дослідження впливу методу WRRF на якість формування та впорядкування списків рекомендацій, отриманих у результаті попарного комбінування алгоритмів CF шляхом агрегування рангів об'єктів. За результатами експериментального дослідження встановлено, що використання методу

WRRF у переважній більшості випадків забезпечує підвищення якості рекомендацій порівняно з найкращим алгоритмом у відповідній парі. Експериментальну перевірку проведено з використанням шести алгоритмів CF на трьох наборах даних, перетворених у формат неявного зворотного зв'язку. Отримані результати можуть бути використані під час розроблення та вдосконалення промислових рекомендаційних систем для підвищення якості впорядкування рекомендацій без суттєвого ускладнення їх програмної архітектури.

Ключові слова: зважене взаємне злиття рангів, рекомендаційна система, колаборативна фільтрація, неявний зворотний зв'язок.

Problem Statement. The rapid growth in the volume of digital content and services makes it difficult for users to independently search for and select relevant items. Under such conditions, recommender systems (RS) become a key instrument for the personalised selection and ranking of items, ensuring the presentation of the most appropriate options according to individual user preferences and previous user interactions [1].

A characteristic feature of many practical applications of recommender systems is the use of implicit feedback, which is formed through user actions (views, clicks, additions to lists, purchases, etc.) [2]. Such data have a significant volume and are almost always available; however, at the same time they are ambiguous, since the fact of interaction does not guarantee an unambiguous positive evaluation, and the absence of interaction does not mean the absence of interest.

One of the widespread approaches to constructing recommender systems based on implicit feedback is collaborative filtering (CF), which uses patterns of joint user behaviour and the similarity of their interactions with items. A variety of algorithms are used to implement CF, which differ in their construction principles, the way of calculating scores, and the generation of ranked recommendation lists [3].

Due to differences in the principles of evaluating the relevance of items, different CF algorithms usually produce different recommendation lists for the same user – both in terms of the composition and the order of items. As a result, the problem of choice arises: which particular algorithm should be considered the most appropriate in a specific case, given that their effectiveness may depend on the characteristics of the data, the level of sparsity, and the nature of user interactions [4].

This uncertainty requires the consistent aggregation of the results of several algorithms in order to obtain a single ranked recommendation list that potentially combines the advantages of different algorithms. One of the practically applicable approaches to solving this problem is the late fusion strategy [5, 6], applied to combine results through rank aggregation, where the final ranking is formed on the basis of the positions of items in the lists obtained by independent algorithms [6].

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At the same time, the application of rank aggregation requires a well-founded selection of the fusion method and its parameters, as well as experimental evaluation of the influence of such combination on recommendation quality. Therefore, the problem is to determine whether weighted reciprocal rank fusion (WRRF) [7] is capable of providing a consistent improvement in the quality of generation and ranking of recommendation lists in CF tasks with implicit feedback compared with the use of individual algorithms.

Analysis of Recent Research and Publications. Modern scientific discourse, reflected in fundamental review papers, focuses on improving the quality of final lists produced by different ranking systems, in particular in RS, which today are one of the key instruments for the personalisation of digital content [2]. Their use contributes to the growth of audience satisfaction due to relevant recommendations [1, 8]. Over the past several years, numerous algorithms have been proposed, in particular based on CF, which is one of the most widespread strategies for constructing such systems [3], intended for the generation of recommendations in the form of ranked recommendation lists.

However, despite many years of research, a universal algorithm that would generate high-quality recommendations has not yet been identified [4]. Moreover, when comparing generated recommendations in the context of a specific user, these algorithms do not produce identical recommendations. For this reason, paper [4] proposes the use of aggregation methods, the purpose of which is to combine rankings generated by separate recommendation algorithms in order to create a new, 'better' ranking. At the same time, as noted in studies [4, 9], a key challenge for such solutions is that individual algorithms produce results on different scoring scales and with different ranking principles, which complicates the direct combination of their results and requires specialised methods.

To solve this problem, modern research proposes the use of rank aggregation methods [10]. Such methods eliminate differences between scoring scales and ranking principles, since they operate not with absolute relevance values but with the positions of items in ranked lists.

Systematic reviews [4, 10] demonstrate that the use of rank aggregation methods makes it possible to combine the results of several systems into a single consistent ranking, which can improve quality compared with individual lists. However, their effectiveness depends on the specific data and systems for which aggregation is performed [10]. Studies in which experiments were conducted with recommendation algorithms on corresponding datasets indicate that rank aggregation methods can be effectively applied in RS, although their performance also varies [4].

The relevance of these methods is confirmed by modern studies, where rank aggregation methods are applied to combine results obtained from different

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information sources. For example, in **multimodal video retrieval systems** [5], the obtained results show [7] that combining information from text, audio, and images using weighted rank aggregation with the WRRF method makes it possible to produce more accurate and consistent final lists.

This confirms that rank aggregation is an effective instrument in tasks where data come from heterogeneous sources and require the unification of scores in order to improve the quality of results.

At present, in the scientific literature [10], studies of rank aggregation methods are mainly focused on different tasks without specific application in RS. Those studies [4] that consider these methods in the context of RS mostly analyse them without specification within CF and within the broader set of rank aggregation methods, without providing a detailed investigation of the method proposed in this paper.

Filling this **gap** through the application of the WRRF method for the pairwise aggregation of the results of CF algorithms that differ in their construction principles, followed by an analysis of the values of quality metrics for the generation and ranking of recommendation lists, constitutes a relevant research task and requires resolution.

The purpose of this article is to study the influence of the WRRF method on the quality of generation and ranking of recommendation lists obtained through the pairwise combination of different CF algorithms by means of rank aggregation of items.

To achieve this purpose, it is necessary to solve the following tasks.

1. Formalise the WRRF method in the context of rank aggregation of items from a set of recommendation lists that differ in the composition and order of items.

2. Determine a sufficient number of recommendation candidates in recommendation lists for the correct application of the WRRF method based on the late fusion strategy of results through rank aggregation under conditions of limited length of base recommendation lists of CF algorithms.

3. Determine the optimal values of weight coefficients of CF algorithms and the constant k in the WRRF method that ensure the maximum quality of generation and ranking of the aggregated recommendation list.

4. Conduct experiments and analyse the influence of the application of the WRRF method on recommendation quality by evaluating the relative improvement of the values of quality metrics compared with the best base algorithms in the corresponding (selected) pairs.

The object of the study is the process of generation and ranking of recommendations in CF RS based on implicit feedback.

The subject of the study is the WRRF method in tasks of rank aggregation of CF recommendation algorithms for implicit feedback.

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Presentation of the main material. In RS, the objects of ranking are recommendation items obtained from N different algorithms, and aggregation is performed separately for each user.

The mathematical formulation of the problem is as follows.

Let U be the set of users, I the set of recommendation items, $L_j(u)$ the ranked recommendation list produced by the j-th algorithm for user $u \in U$, where $L_j(u) \subseteq I$. Each list $L_j(u)$ defines the ranking of items in decreasing order of their predicted relevance according to the j-th algorithm.

For each item $i \in I$, the rank $r_j(u,i)$ is defined, which corresponds to the position of item i in the recommendation list $L_j(u)$ if $i \in L_j(u)$. To account for the possibility that an item may be absent from the recommendation list, an indicator function of item presence is introduced (1); this modification distinguishes the WRRF method proposed in this article from the method presented in [7]:

(2)

$$\mathbb{I}\left(i \in L_j(u)\right) = \begin{cases} 1, i \in L_j(u), \\ 0, i \notin L_j(u). \end{cases} \quad (1)$$

The classical Reciprocal Rank Fusion (RRF) method [7] assumes an equal contribution of each list to the final result, which does not take into account possible differences in the recommendation quality of the algorithms. To generalize the method, weight coefficients $w_j \in \mathbb{R}$ are introduced, which determine the degree of influence of each recommendation list on the final result, and the weight coefficients satisfy the normalization condition:

(3)

$$\sum_{j=1}^{N} w_j = 1, w_j \geq 0. \quad (2)$$

Taking into account the introduced notation, the WRRF method defines the aggregated relevance score of item $i \in I$ for user $u \in U$ (Figure 1) by the formula (3):

(4)

$$WRRF(u,i) = \sum_{j=1}^{N} \frac{w_j}{k + r_j(u,i)} \mathbb{I}\left(i \in L_j(u)\right). \quad (3)$$

This formula is a generalization of the classical RRF method for RS tasks.

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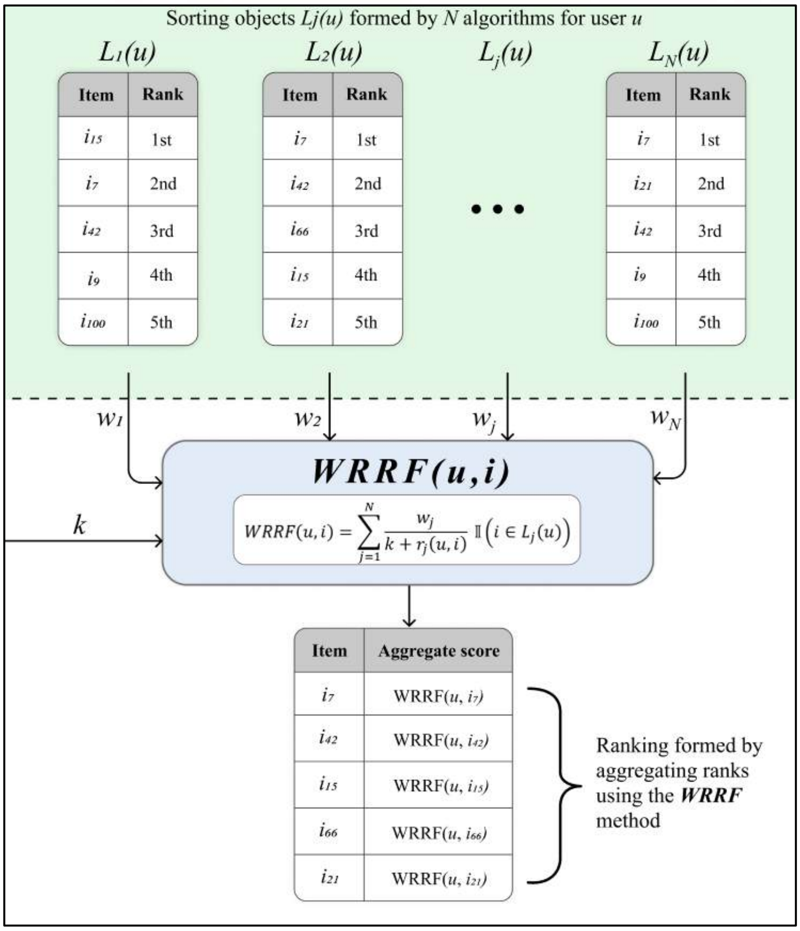

Fig. 1. Graphical representation of rank aggregation of rankings using the WRRF method

The final ranking of items for user $u \in U$ is determined on the basis of the aggregated relevance score $WRRF(u,i)$. Let $r^*(u,i)$ be the rank of item $i \in I$ in the final aggregated recommendation list for user u, where $r^*(u,i) \in \mathbb{N}$ and a smaller value corresponds to a higher position in the list. Then the final ranking is determined by ordering items in descending order of the function $WRRF(u,i)$ according to formula (4):

(5) $$r^*(u,i) = rank^{\downarrow}_{i \in I} WRRF(u,i), \quad (4)$$

where $rank^{\downarrow}$ is the sorting operator in descending order of the argument value.

Accordingly, the final recommendation list for user u is formed as an ordered set of items I, ranked according to the values $r^*(u,i)$.

Since this work considers pairwise aggregation of the results of recommendation algorithms, the general formula (3) for the case of two ranked recommendation lists can be applied with the following notation.

Let $L_1(u)$ and $L_2(u)$ be recommendation lists produced by the first and the second algorithms for user $u \in U$, respectively, and $w_1 \in \mathbb{R}$, $0 \le w_1 \le 1$ be the

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weight coefficient of the first algorithm, which determines the degree of its influence on the final result.

To ensure the weight normalisation condition, the complementary weight coefficient of the second algorithm $w_2 \in \mathbb{R}$ is introduced according to formula (5):

(6) $$w_2 = 1 - w_1, \qquad (5)$$

where w_2 is the residual contribution of the second algorithm to the final aggregated score.

Taking into account the introduced notation, the aggregated relevance score of item $i \in I$ for user $u \in U$ in the case of pairwise aggregation of two recommendation lists is calculated according to formula (6):

(7) $$WRRF_{1,2}(u,i) = \frac{w_1}{k + r_1(u,i)} \mathbb{I}\big(i \in L_1(u)\big) + \frac{w_2}{k + r_2(u,i)} \mathbb{I}\big(i \in L_2(u)\big). \qquad (6)$$

The final ranking of items for user $u \in U$ in the case of pairwise aggregation is determined analogously to formula (4), however instead of $WRRF(u,i)$ the value $WRRF_{1,2}(u,i)$ defined by formula (6) is used.

According to the late fusion strategy of results through rank aggregation, the WRRF method forms the final list based on the positions of items in the input recommendation lists $L_j(u)$.

However, when base lists of length K are generated, the recommendation lists produced by different CF algorithms may differ significantly in composition, which leads to insufficient overlap between lists and consequently limits the number of items for which rank aggregation is informative. This complicates the correct application of the WRRF method when the final list is evaluated only at the top-K positions, while the input lists have the same length.

To eliminate this problem, in this work an extended set of recommendation candidates is used by increasing the length of the input lists compared with the length of the evaluated final list.

Let K_{ext} be the number of items in the extended set of recommendation candidates for further aggregation, K be the number of items in the final list used for quality evaluation, B be the number of additional recommendations. Then the relationship between these quantities can be defined as:

(8) $$K_{ext} = K + B. \qquad (7)$$

Increasing K_{ext} ensures the inclusion of a larger number of potentially relevant items in the candidate set and increases the probability of their presence in different lists $L_j(u)$, which creates the necessary conditions for correct rank aggregation using the WRRF method under conditions of limited length of base recommendation lists.

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The quality of the final ranking produced by the WRRF method is determined not only by the ranks of items in the input lists but also by the values of the method parameters. In particular, the weight coefficients w_1 and w_2 in formula (6) of pairwise aggregation determine the relative contribution of each of the two algorithms to the final aggregated score, while the constant k reduces the influence of the absolute value of the rank on the final result. Therefore, in order to obtain the maximum quality of the aggregated recommendation list, it is necessary to select such values of w_1 and k that are optimal for each specific pair of CF algorithms and for a particular dataset.

In this work, the optimal values of the weight coefficient of the first algorithm, w_1, and the constant k were determined separately for each pair of algorithms using exhaustive search on a regular parameter grid (Grid search) [11]. Let w_1^* and k^* be the optimal values of the corresponding parameters. Then the parameter tuning task is formalised as the problem of maximising the value of the Normalized Discounted Cumulative Gain (nDCG) [12] for the final top-*K* list according to formula (8):

(9) $$(w_1^*, k^*) = \arg\max_{w_1,k} nDCG@K(w_1, k). \quad (8)$$

The search was performed over discrete sets of parameter values:$w_1 \in \{0{,}1;\ 0{,}2;\ \dots;\ 0{,}9\}$ and $k \in \{10, 20, \dots, 100\}$. For each pair of algorithms, the configuration (w_1^*, k^*) that provided the maximum value of $nDCG@K$ was selected, after which the corresponding parameters were used to construct the final aggregated recommendation list.

Experiments and analysis of results.

Pairwise rank aggregation was performed for the following recommendation algorithms: Alternating Least Squares (ALS) [13] in the configuration for implicit feedback, Bayesian Personalized Ranking (BPR) [13], Bidirectional Variational Autoencoder (BiVAE) [13], Light Graph Convolutional Network (LightGCN) [13], Neural Collaborative Filtering (NCF), and Smart Adaptive Recommendations (SAR) [13]. Such a selection is due to the need to consider algorithms that differ in their construction principles [14], which are used in real RS. The implementation of the algorithms was carried out using the open-source Microsoft Recommenders library for the Python programming language [13].

Testing was conducted on the MovieLens 100K dataset [15], as well as on two subsets of datasets from the Amazon Reviews'23 collection, namely Video Games and Movies and TV [16]. In all datasets, each record is represented as an ordered quadruple consisting of a user identifier, an item identifier, a rating value, and an interaction timestamp. The data subsets were constructed through **data unification** (mapping field names to a unified attribute schema), **filtering of invalid records** (removal of entries with missing attribute values) and **duplicate records** (repeated

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entries with identical combinations of user identifier, item identifier, and timestamp), as well as the application of ***k*-core** filtering [17] with a minimum number of user and item interactions, which ensured the extraction of stable subsets of interactions, namely Video Games 15-core and Movies and TV 25-core. All datasets were transformed into the implicit feedback format through rating binarisation using a threshold value [18]. In particular, rating values were transformed according to the following rule:

(10)
$$\tilde{r}_{ui} = \begin{cases} 1, & r_{ui} \geq 4, \\ 0, & r_{ui} < 4 \end{cases} \quad (9)$$

where r_{ui} is the original rating provided by user u for item i; $\tilde{r}_{ui}$ is the binarized value of implicit interaction used in the experiments.

The threshold value was selected given that, in the chosen datasets, ratings are given on a five-point scale in the range from 1 to 5, which forms an ordered set of integer values $\{1, 2, 3, 4, 5\}$, where the value 3 is its median and is interpreted as a neutral evaluation, while the value 4 was selected as the threshold for separating a positive signal from a neutral or negative one.

After that, a stratified split of the data by users was performed in a 75:25 ratio into training and test sets, ensuring that each user retained interactions in both parts. This made it possible to avoid the absence of users in the training set and ensured the possibility of generating personalised recommendations for all users. The training set was used to train the models, while the test set was used to evaluate recommendation quality on interactions that were not used during model training.

As a result, for the studied algorithms on these three datasets, the values of quality metrics for the generation and ranking of recommendation lists were calculated on the test set (Figure 2): mean average precision (MAP) [12], nDCG, precision [12], and recall [12], computed for the first 10 positions of the recommendation list ($K = 10$).

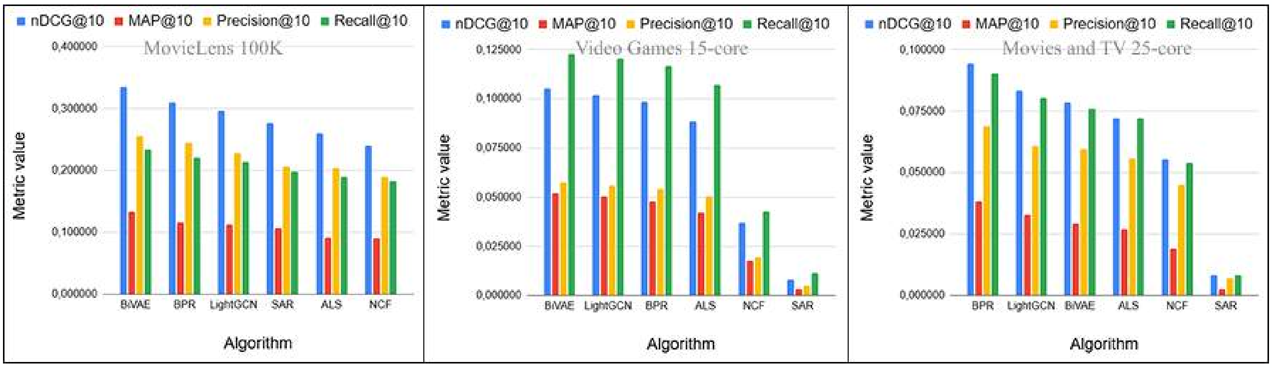

Fig. 2. Values of quality metrics for the selected algorithms

Next, an exhaustive enumeration of fifteen pairwise combinations of algorithms was performed on the three datasets. For each combination, the values of

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quality metrics were measured on the test set (Figure 3), also computed for the first ten positions of the recommendation list. To ensure a sufficient number of recommendation candidates, the number of additional recommendations was set to two hundred ($B = 200$).

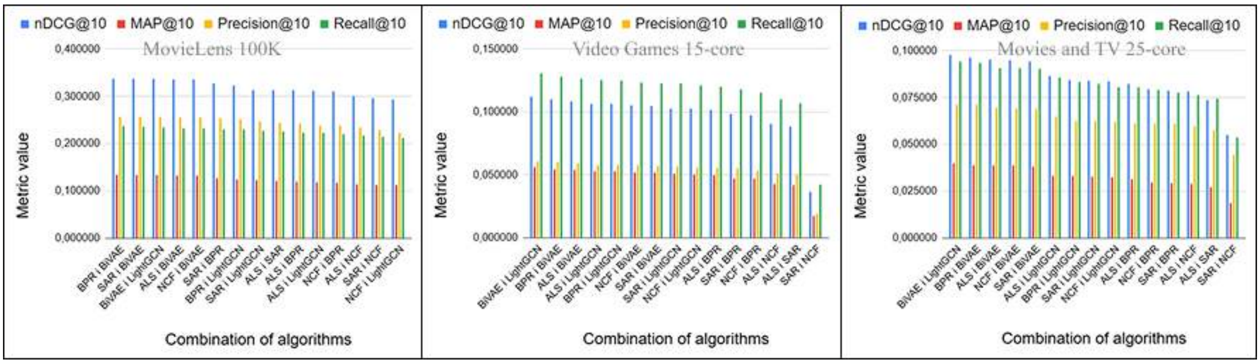

Fig. 3. Values of quality metrics for algorithm combinations

To evaluate the effectiveness of the proposed method, the relative deviation of the values of quality metrics of individual algorithms from the value of the best algorithm in each pair was used, which characterises the improvement (or deterioration) of the results, according to formula (10):

$$\Delta M_{\%} = \left(\frac{M^{WRRF}}{\max\left(M^{(1)}, M^{(2)}\right)} - 1 \right) \cdot 100\%, \qquad (10)$$

where M^{WRRF} is the value of the corresponding quality metric for the aggregated recommendation list produced by the WRRF method; $M^{(1)}$ and $M^{(2)}$ are the values of this metric for the first and the second algorithms compared in the pair, respectively.

The results of the performed calculations of the relative deviations of quality metrics are presented in Figure 4.

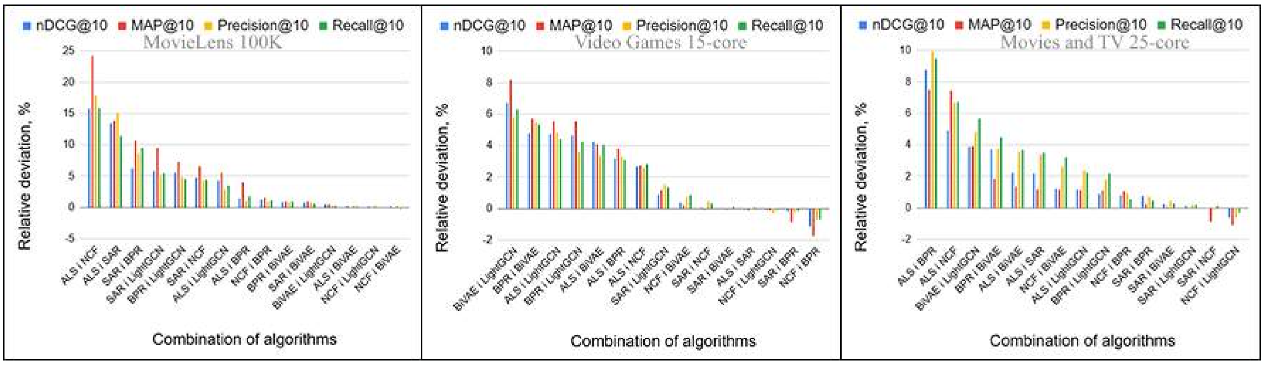

Fig. 4. Relative deviation of quality metric values for combinations of algorithm pairs

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For the MovieLens 100K dataset, the maximum increase in relative deviation according to the nDCG metric is 15.74% for the pair ALS and NCF (MAP +24.21%, Precision +15.12%, Recall +9.50%), while a positive relative deviation according to the nDCG metric is observed for all 15 pairs of algorithms. For the Amazon Reviews'23 Video Games 15-core dataset, a positive relative deviation in nDCG is recorded for 11 out of 15 pairs, with the maximum value of 6.75% for BiVAE and LightGCN (MAP +8.18%, Precision +5.79%, Recall +6.31%). For the Amazon Reviews'23 Movies and TV 25-core dataset, improvement in the nDCG value is observed in 13 out of 15 pairs, with the maximum value of 8.79% for ALS and NCF (MAP +7.44%, Precision +9.96%, Recall +9.47%). In the last two datasets, isolated negative relative deviations of nDCG, MAP, Precision, and Recall are observed, but they are small.

Conclusions. This work investigates the application of the weighted reciprocal rank fusion method WRRF for pairwise aggregation of the results of collaborative filtering algorithms in RS with implicit feedback. The experimental results showed that the use of WRRF in the vast majority of cases (70%–100%) improved the quality of recommendation generation and ranking compared with the best collaborative filtering algorithms in the studied pairs. This confirms the usefulness of the proposed method as an effective means of improving final recommendation lists.

The practical significance of the obtained results is that the WRRF method can be used to combine the results of different CF algorithms within industrial RS without significantly complicating their architecture. Such an approach creates the possibility of improving recommendation quality by combining the advantages of individual algorithms, in particular their ability to identify different types of patterns in data, provide different balances between precision and recall of recommendations, and rank relevant items differently.

The prospects for further research lie in extending the proposed approach to the aggregation of the results of more than two CF algorithms, studying the effectiveness of multi-level fusion, in which not only the primary recommendation lists of base algorithms but also previously aggregated lists may be aggregated, as well as in the comparative analysis of WRRF with other rank aggregation methods [10] in RS using CF.

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