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USER EVALUATION-DRIVEN RANKING CONCEPT

Zosimov V. V. – Dr. Sc., Professor of the Department of Applied Information Systems, Taras Shevchenko National University of Kyiv, Kyiv, Ukraine.

Bulgakova O. S. – PhD, Associate Professor of the Department of Applied Information Systems, Taras Shevchenko National University of Kyiv, Kyiv, Ukraine.

Perederyi V. I. – Dr. Sc., Professor of the Department of informatics and computer science, Kherson National Technical University, Kherson, Ukraine.

ABSTRACT

Context. The problem of personalizing search engine results, empowering users with search result management tools and developing new ranking models based on user's subjective information needs. The object of the study was to modeling information search results in the Internet based on user ratings.

Objective. The goal of the work is to form unique expert groups for each user, based on calculating the measure of agreement between the current user's opinions and potential experts.

Method. Introducing a novel method for ranking search results based on user ratings, which takes a subjective approach to the ranking process. This approach involves the formation of distinct expert groups tailored to individual users. Experts are selected based on the level of agreement between their opinions and the current user, determined by shared ratings on a specific set of web resources. User selection for the expert group is based on their weight relative to the current user, serving as a measure of agreement.

The proposed methodology offers a fresh approach to forming unique expert groups for each user, utilizing three different strategies depending on the presence of shared ratings on a particular set of web resources between the user and potential experts.

The developed ranking method ensures that each user receives a personalized list of web resources with a distinct order. This is accomplished by incorporating unique ratings from the expert group members associated with each user. Furthermore, each rating contributes to the ranking model of web resources with an individual weight, calculated based on an analysis of their past system activity.

Results. The developed methods have been implemented in software and investigated for complex web data operation in real time.

Conclusions. The conducted experiments have confirmed the effectiveness of the proposed software and recommend its practical use for solving complex web data operation in real time. Prospects for further research may include optimizing software implementations and conducting experimental investigations of the proposed methods on more complex practical tasks of various nature and dimensions

KEYWORDS: information search, ranking, search results, user ratings, expert groups, social profile, inductive algorithms, polynomial neural network, active neurons.

ABBREVIATIONS

ADE is a method of average differences of estimates, method of calculating the expert's weight;

CIDO is a complex Internet data operating system;

GMDH is a group method of data handling;

MIA is a multilayered iterative algorithm;

RIA is a relaxation iterative algorithm;

CIA is a combined iterative algorithm;

MICA is a multilayered iterative-combinational algorithm;

RICA is a relaxation iterative-combinational algorithm;

GIA is a generalized iterative algorithm;

DM is a dialogue mode;

IC is a iterative-combinatorial mode;

MR is a multilayered-relaxative mode;

AM is a arithmetic mean;

WAM is a weighted arithmetic mean;

HM is a harmonic mean;

WHM is a weighted harmonic mean.

NOMENCLATURE

U_0 is a current user, the user for whom the group of experts is formed and for whom the ranking of search results is carried out;

U_i is a first-level potential expert, the user who shares ratings with the current user, but whose level of agreement has not yet been calculated;

$\hat{U}_j$ is a second-level potential expert, the user who does not share ratings with the current user, but shares ratings with a first-level expert;

$\tilde{U}_k$ is a third-level potential expert, the user who does not share ratings with the current user or first-level experts;

$U_{0,\exp}$ is a user's who do not have any common ratings with the current user or with the members of the expert group, as potential experts of the third level;

$X[U_0, \ldots, U_n]$ is a set of all users of the system;

$d(U_0, U_i)$ is a metric on the metric space (X, d);

W is a coefficient of concordance;

n is a number of indicators;

m is a number of experts;

r_{ij} is a rank of the i-th indicator determined by the j-th expert;

d_i is a sum of ranks of the i-th indicator by all experts;

T_i is a number of connections (types of repeated elements) in the evaluations of the i-th expert;

L_i is a number of links (types of repeating elements) in the evaluations of the i-th expert;

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t_L is a number of elements in the L-th link for the i-th expert (the number of repeating elements);

χ^2 is a consistency criterion;

$F(x,\Theta)$ is a distribution law;

$x_{(0)}$ is a lower bound of the domain of definition of a random variable;

$x_{(k)}$ is an upper bound of the domain of definition of a random variable;

H_0 is a tested hypothesis;

$X_{r+1} = (y_1^r,...,y_F^r, x_1,\ldots,x_m)$ is the input matrix for a layer r+1 in GIA, where $x_1,\ldots,x_m$ are the initial arguments and $y_1^r,...,y_F^r$ are the intermediate ones of the layer r;

d_k, $k = 1,2,3$, $d_k = \{0, 1\}$ are elements of the binary structural vector $d = (d_1\, d_2\, d_3)$ where values 1 or 0 mean inclusion or not a relevant argument;

CR is a selection criterion;

AR is a regularity criterion;

R^2 is a coefficient of determination;

K is a number of freedom degrees.

INTRODUCTION

At present, Internet advertising is the most effective way to promote a business. This has led search engines to no longer serve as information retrieval tools but rather transformed them into advertising platforms, where the pages displayed to users are not the most relevant to their informational needs but rather those that have invested more in promotion. Search engines benefit from artificially reducing the quality of organic search results, as contextual advertising appears more appropriate in comparison, even though it is often less relevant to the search query. The fact that search engines are not inclined towards high-quality organic search is evident from the introduction of the “Google SearchWiki” technology in 2009 by the world’s most popular search engine, Google. It allowed users to customize the search results by sorting and removing them. Additionally, a global rating system for web resources was implemented. However, this technology was active for less than six months and was eventually discontinued due to low demand among users. Although it is evident that personalized search results, achieved through the accumulation of large amounts of statistical data and user ratings, will significantly enhance search efficiency in the long run, rendering many contemporary methods of artificial web resource promotion ineffective [1–2].

Search engine ranking algorithms take into account a large number of factors, but the main weight is given to the page rating, which is calculated based on the analysis of the number and quality of external links to the page [3]. Such assessment methods are objective, but they are easy to falsify in the presence of a certain advertising budget, due to the purchase of the necessary number of quality links from external sources [4]. It follows that they are focused on meeting the needs of advertisers, not users.

The development of methods for personalizing search engine results by providing users with search result management tools and the creation of new ranking models based on users’ subjective information needs are therefore crucial tasks.

The object of study is the process of web data operation. The paper discusses an approach to personalize search results by utilizing a ranking model based on expert evaluations, which are considered authoritative for the user. The obtained ranking model is significantly more difficult to falsify as it is based on subjective factors. The ranking model will be unique for each user, making it even more challenging to falsify since it would require replicating each user’s preferences, which is much more complex than acquiring links to one’s website from authoritative sources.

The subject of study is the models and methods of personalizing the ranking of search results.

The ranking algorithms of search engines primarily rely on the page ranking, which is calculated based on the analysis of external links [3]. However, these methods can be easily manipulated through the acquisition of high-quality links [5], prioritizing the needs of advertisers over users.

The purpose of the work is to improve the quality of search output for current user by means of personalization methods in search engine systems, through providing users with search result management tools and developing new ranking models based on subjective user information needs.

1 PROBLEM STATEMENT

The paper considers an approach to personalization of search results through the use of a ranking model based on the assessments of experts whose opinion is authoritative for the user.

To rank data based on expert evaluations, such methods as Kemeny’s median, Kendall’s concordance coefficient, Bord’s method, etc. are used [6–8]. The use of such methods requires the presence of a predetermined group of experts. However, in the real task of ranking search results, the input data is the evaluations of users for whom their status as an expert is not defined. It is obvious that it would not be correct to accept the opinion of all users who rated the web resource as expert. It is also obvious that the assessment and personal data specified during registration are not enough to uniquely identify the user as an objective expert in the subject area. However, these data are sufficient to determine subjective expert groups for each user based on the criterion of closeness of the user’s ratings to the ratings of each of the experts.

The evaluation of service quality is highly subjective. It is also important to consider that the same service can be provided differently to different clients due to various subjective reasons of the provider. Therefore, the application of methods for assessing consensus among experts, such as the coefficient of concordance, may yield results lower than expected values.

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The rankings of web resources in the search results for the current user's query are determined by calculating the weighted harmonic mean of ratings from the expert group. Unique expert groups are formed for each user in the background mode of the CIDO system [9] using three methods based on shared ratings for a specific set of web resources between the user and potential experts. Experts are categorized into three levels for clarity, corresponding to the method of calculating their weight. This categorization is purely logical, and all expert weights at each level hold equal significance during the ranking of search results without requiring additional coefficients.

Expert weight is a measure of agreement between the expert's opinions and the current user, calculated based on the similarity of their ratings for a certain set of web resources. The weight of expert U_i relative to the current user U_0 can be considered as the metric $d(U_0, U_i)$ in the metric space (X, d), where $X[U_0, ..., U_n]$ represents the set of all users in the system

The function d satisfies the identity, symmetry, and triangle axioms, but it cannot be defined for every pair of elements from the set X, as not all users have common ratings. Therefore, in the context of this problem, it is incorrect to use the term metric space. Instead, we will refer to the function $d(U_0, U_i)$ as an analogue of a metric for defining the weight of an expert.

The value of the expert's weight is a number in the interval $d(U_0, U_i)\in[0, \dots, 0.9]$, therefore, not the value itself, but the result of the normalization function is used to determine the qualitative assessment:

$$W(d) = 1 - \left(1.1 \cdot \frac{d(U_0, U_i)}{10}\right).$$

The obtained value is used as an indicator of the expert's weight to further calculate the ranks of web resources.

It is necessary to find measures of consistency of the user's opinions with each of the potential experts, depending on the presence of joint evaluations for some set of web resources.

2 REVIEW OF THE LITERATURE

In [10], a learning-based ranking model is proposed to enhance recommendation systems using implicit user feedback. Adaptive learning is described in [11] to improve content-based recommendation systems. [12] introduces a hybrid ranking model for scientific articles, combining content-based and citation-based approaches. A neural network-based ranking model is presented in [13–14], which can handle incomplete data, making it versatile and user-friendly. However, understanding the principles of neural network operation can be complex. [15] explores the use of BERT (Bidirectional Encoder Representations from Transformers) for search engine ranking, demonstrating high accuracy compared to traditional methods but requiring significant computational resources. [16] proposes a novel ranking approach that employs reinforcement learning to aggregate diverse page ratings, leading to improved accuracy but with associated computational and implementation complexity.

Sentiment analysis methods are discussed in [17], covering rule-based and machine learning-based techniques and their applications in domains like social media monitoring and product review analysis. The integration of recommender systems and sentiment analysis is emphasized for more effective and personalized recommendations.

[18] presents a development aimed at enhancing search relevance within organizations by capturing employee knowledge and expertise. While this approach improves search results, its efficiency in utilizing contextual information may be limited. Considering context and adapting to evolving user requirements are crucial to avoid irrelevant or incomplete results.

Brytsov R. A. addresses this issue in his work [19], proposing a theoretical ranking model based on web resource visit statistics and document viewing time. However, it does not consider user opinions or agreement levels between users and experts. User rating-based methods commonly employed for product ranking in online stores rely solely on the number and values of ratings.

Recent studies demonstrate the potential of neural networks and reinforcement learning in improving search engine ranking accuracy, albeit at the cost of significant computational resources. Information retrieval, as defined in [20], involves searching for unstructured documentary information to satisfy individual and subjective user information needs. Accordingly, search result ranking algorithms should incorporate user-specific subjective factors.

3 MATERIALS AND METHODS

Let's consider the method of average differences of estimates. The direct calculation can be applied when the current user shares ratings with the set of potential experts X for a certain set of web resources. It allows for the calculation of the similarity of ratings separately for each pair of "current user – potential expert", denoted as $d(U_0, U_i)$. User ratings range from 1 to 10, where 10 represent the most acceptable option. The expert weight value is determined as the arithmetic mean of the absolute differences between each pair of user and potential expert ratings:

$$d(U_0, U_i) = \sum_{j=1}^{m} \frac{|U_{0j} - U_{ij}|}{m}. \quad (1)$$

A qualitative assessment of closeness is provided on the Chaddock scale. Candidates with high and very high connectivity strength are selected as experts. To determine the qualitative assessment on the Chaddock scale, the result of a normalization function $W(d)$ is used, rather than the actual value itself.

To justify the choice of this method for calculating the measure of agreement among experts, let's compare its

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effectiveness with the results obtained from calculating Kendall's concordance coefficient for each pair of "current user – potential expert".

The concordance coefficient is a numerical value that serves as a measure of agreement among experts [21]:

$$W = \frac{S}{\frac{1}{12}m^2(n^3-n) - m\sum_{i=1}^{m} T_i}, \quad (2)$$

where

$$S = \sum_{i=1}^{m}\left(\sum_{s=1}^{d} r_{ij} - \bar{r}\right)^2, \quad (3)$$

$$T_i = \frac{1}{12}\sum_{i=1}^{L_i}(t_L^3 - t_L). \quad (4)$$

If there are no associated ranks, then T_i is zero. The significance assessment of the concordance coefficient is determined by the Pearson agreement criterion [22]. This consistency criterion is the most widely used criterion for testing the hypothesis that the studied sample $x_1, x_2, \ldots x_n$, with volume n, belongs to some theoretical distribution law $F(x,\Theta)$.

The hypothesis testing procedure using χ^2-type criteria involves grouping observations. The domain of definition of the random variable is divided into k non-overlapping intervals with boundary points $x_{(0)}, x_{(1)}, x_{(k-1)}, x_k$.

According to the given partition, the number n_i of sample values falling into the i-th interval and the probabilities of falling into the interval $P_i(\theta) = F(x_{(i)},\theta) - F(x_{(i-1)},\theta)$ corresponding to the theoretical law with the distribution function $F(x,\theta)$ are calculated. In addition $n = \sum_{i=1}^{k} n_i$ and $n = \sum_{i=1}^{k} P_i(\theta) = 1$. When testing a simple hypothesis, both the form of the distribution law $F(x,\theta)$ and all its parameters (known scalar or vector parameter θ) are known. The statistics used in the conditions of goodness-of-fit type χ^2 are based on measuring deviations $\frac{n_i}{n}$ from $P_i(\theta)$. The Pearson's goodness-of-fit test statistic χ^2 is defined by the relationship:

$$X_n^2 = n\sum_{i=1}^{k}\frac{\left(\frac{n_i}{n} - P_i(\theta)\right)^2}{P_i(\theta)}. \quad (5)$$

In the case of testing a simple hypothesis within the limits as $n\to\infty$, this statistic follows a χ_r^2 -square distribution with $r=k-1$ degrees of freedom if the tested hypothesis H_0 is true. The probability density function of the χ_r^2 -square distribution, which is a specific case of the gamma distribution, is described by the formula:

$$g(s) = \frac{1}{2^{\frac{r}{2}}\Gamma\left(\frac{r}{2}\right)} s^{\frac{r}{2}-1} e^{\frac{-s}{2}}. \quad (6)$$

The H_0 hypothesis is rejected at large statistics values, when the statistical value calculated from the sample X_n^{2*} is greater than the critical value $\chi^2_{r,\alpha}$, or the achieved significance level (p-value) is less than the specified significance level (given probability of error of the 1st kind) α:

$$P\left(X_n^2 > X_n^{2*}\right) = \frac{1}{2^{\frac{r}{2}}\Gamma\left(\frac{r}{2}\right)}\int_{X_n^{2*}}^{\infty} s^{\frac{r}{2}-1} e^{\frac{-s}{2}} ds. \quad (7)$$

The calculated value χ^2 is compared with the table value for the number of degrees of freedom $K = n-1$ presented in Table 1.

Table 1 – The percentage points of distribution χ^2

α → / ↓ n	90%	70%	50%	30%
…	…	…	…	…
15	8.547	11.721	14.339	17.322
16	9.312	12.624	15.338	18.418
17	10.085	13.531	16.338	19.511
18	10.865	14.440	17.338	20.601
19	11.651	15.352	18.338	21.689
20	12.443	16.266	19.337	22.775
21	13.240	17.182	20.337	23.858
22	14.041	18.101	21.337	24.939
23	14.848	19.021	22.337	26.018
	10%	**5%**	**1%**	**0,5%**
…	…	…	…	…
15	22.307	24.996	30.578	32.801
16	23.542	26.296	32.000	34.267
17	24.769	27.587	33.409	35.718
18	25.989	28.869	34.805	37.156
19	27.204	**30.144**	36.191	38.582
20	28.412	31.410	37.566	39.997
21	29.615	32.671	38.932	41.401
22	30.813	33.924	40.289	42.796
23	32.007	35.172	41.638	44.181

Let's consider the generalized iterative algorithm.

The GIA approach is employed at the third level to determine the weight of users who lack any shared ratings.

The generalized iterative algorithm encompasses a collection of iterative and iterative-combinatorial algorithms, which are defined by three index sets: DM, IC, MR. Each iterative algorithm is considered a specific instance of the generalized GIA = {DM, IC, MR}. DM can assume three distinct values: 1 – standard automatic mode, 2 – planned automatic mode, 3 – interactive mode.

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IC can be either 1 – iterative or 2 – iterative-combinatorial algorithms. MR has three potential values: 1 – classical multilayered, 2 – relaxative, 3 – combined algorithms [23]. In the case where DM is set to 1, we encounter three standard variations of iterative algorithms: MIA=GIA(1,1,1), RIA=GIA(1,1,2), CIA=GIA(1,1,3), as well as three iterative-combinatorial variants: MICA=GIA(1,2,1); RICA=GIA(1,2,2), CICA=GIA(1,2,3).

Formally, in general case, a layer of the GIA GMDH may be defined as follows, Figure 1 [23]:

1) the input matrix is $X_{r+1} = (y_1^r, ..., y_F^r, x_1, \ldots, x_m)$ for a layer r+1;

2) the operators of the kind:

$$\begin{aligned} y_l^{r+1} &= f(y_i^r, y_j^r),\ l = 1,2,\ldots,C_F^2,\quad i,j = \overline{1,F}, \\ y_l^{r+1} &= f(y_i^r, x_j),\ l = 1,2,\ldots,F_m,\ i = \overline{1,F},\ j = \overline{1,m} \end{aligned} \quad (8)$$

may be applied on the layer r+1 to construct linear, bilinear and quadratic partial descriptions:

$$\begin{aligned} z &= f(u,v) = a_0 + a_1 u + a_2 v; \\ z &= f(u,v) = a_0 + a_1 u + a_2 v + a_3 uv; \\ z &= f(u,v) = a_0 + a_1 u + a_2 v + a_3 uv + a_4 u^2 + a_5 v^2. \end{aligned} \quad (9)$$

3) for any description, the optimal structure is searched by combinatorial optimization; e.g.:

$$f(u,v) = a_0 d_1 + a_1 d_2 u + a_2 d_3 v. \quad (10)$$

Then the best model will be described as $f(u, v, d_{opt})$, where

$$\begin{aligned} d_{opt} &= \arg\min_{l=\overline{1,q}} CR_l,\ q = 2^p - 1, \\ f_{opt}(u,v) &= f(u,v,d_{opt}). \end{aligned} \quad (11)$$

4) the algorithm stops when the condition $CR^r > CR^{r-1}$ is checked.

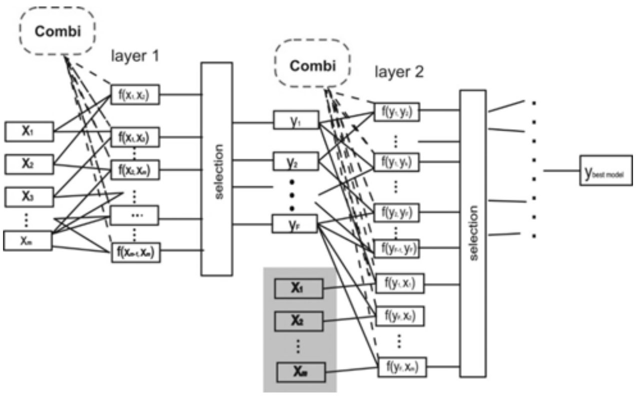

Figure 1 –The generalized architecture of GIA GMDH

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4 EXPERIMENTS

To compare the results of expert agreement calculations using the described methods, a data sample (Table 2) was used, where 20 users evaluated 20 web resources based on the quality of presented information and ease of use. The evaluation scale ranged from 1 to 10, with 10 being the best rating. Expert №0 is the current user, and a group of experts is selected based on their ratings. To facilitate comprehension, the web resources will be denoted by capital Latin letters with a numerical index corresponding to the data sample number, and the users will be represented by numbers.

Table 2 – The fragment of the user evaluations data sample of web resources №1

web resource → ↓ User	A_1	B_1	C_1	D_1	E_1	…	Q_1	R_1	S_1	T_1
0	10	10	8	5	7	…	8	8	3	5
1	10	10	9	6	8	…	8	8	4	4
2	8	8	9	5	6	…	7	7	3	4
3	9	9	9	5	7	…	7	6	3	3
4	10	10	9	7	7	…	9	9	4	3
5	2	7	1	6	7	…	7	2	7	9
6	9	10	7	6	8	…	7	6	4	4
7	7	7	3	9	10	…	5	2	9	9
8	8	8	6	4	7	…	9	7	3	4
9	7	9	8	5	6	…	9	7	4	3
10	7	9	7	4	8	…	9	8	3	4
11	9	10	8	5	7	…	7	9	4	4
12	8	8	9	6	7	…	8	8	3	4
13	8	10	7	6	8	…	3	4	9	10
14	7	7	5	4	8	…	8	9	2	4
15	9	3	9	1	7	…	5	3	7	10
16	4	2	10	3	1	…	4	6	9	7
17	5	2	9	3	2	…	4	4	9	10
18	7	7	10	6	4	…	5	8	6	7
19	7	9	9	8	5	…	6	7	7	9
20	8	7	9	7	4	…	5	8	8	4

Let's consider the calculation of the weight of first-level experts.

For each potential expert paired with user №0, the measure of agreement of opinions was calculated using two methods. The significance evaluation of the concordance coefficient was determined using the Pearson agreement criterion. The tabulated value of the Pearson criterion for k=20–1=19 degrees of freedom and a significance level of α=0.05 is equal to 30.144. If the calculated value χ^2 is greater than or equal to the tabulated value, it is considered that the value of the W criterion is not a random variable, and the obtained results are meaningful and can be used for further research. Otherwise, the value of the W criterion is considered a random variable. The calculation results are presented in Table 3.

The calculated values of the concordance coefficient passed the Pearson criterion test at the given significance level of α=0.05 for only 11 out of 20 potential experts. The values of the concordance coefficient for the remaining 9 users were very small (<30.144).

Additional research on artificially constructed datasets has shown that the coefficient of concordance starts to produce values that do not pass the Pearson criterion test with a specified significance level of α=0.05 when the values according to the method of average differences of estimates (ADE) are less than 0.85. This indicates that the coefficient of concordance cannot accurately determine experts across the entire range of correspondence according to the Chaddock scale.

Table 3 – Measures of agreement between user №0 and each of the potential experts

User	Concordance coefficient		ADE method
	W	χ^2 | reliability (χ^2 >=30.144)	Weight value of the potential expert | Strength of the connection >0.7
1	$W = 0.96$	36.63 | +	0.9285 | +
2	$W = 0.96$	36.42 | +	0.8735 | +
3	$W = 0.94$	35.53 | +	0.9010 | +
4	$W = 0.95$	35.95 | +	0.9120 | +
5	$W = 0.4$	15.40 | –	0.6370 | –
6	$W = 0.97$	36.81 | +	0.9120 | +
7	$W = 0.24$	9.120 | –	0.5765 | –
8	$W = 0.94$	35.79 | +	0.8955 | +
9	$W = 0.94$	35.63 | +	0.8955 | +
10	$W = 0.91$	34.47 | +	0.9010 | +
11	$W = 0.97$	36.80 | +	0.9285 | +
12	$W = 0.95$	36.14 | +	0.9175 | +
13	$W = 0.47$	17.69 | –	0.6975 | –
14	$W = 0.84$	32.08 | +	0.8570 | +
15	$W = 0.39$	14.91 | –	0.6315 | –
16	$W = 0.25$	9.330 | –	0.5600 | –
17	$W = 0.25$	9.360 | –	0.5270 | –
18	$W = 0.64$	24.35 | +	0.7580 | +
19	$W = 0.49$	18.75 | –	0.7195 | +
20	$W = 0.53$	20.19 | –	0.7525 | +

These findings suggest that the coefficient of concordance and similar methods that take a list of rankings as input data cannot be used to solve the problem of expert selection for ranking web resources based on evaluations.

The obvious reason for the low percentage of correct results is the specific normalization of input data values in such a method. The rankings provided by experts for each object $S \in \{1..n\}$, where n is the number of objects, are used as input data for calculating the coefficient of concordance. In contrast, in the task of evaluating web resources, evaluations from 1 to 10 are used, regardless of the number of evaluated objects, which leads to a significant increase in the number of identical rankings for values of n far exceeding 10.

Therefore, the proposed method of average differences of estimates (ADE), is the most acceptable for calculating the weight of experts and will be used for further research on ranking methods. Its application requires a large amount of statistical evaluation data and can be effectively applied at the intermediate stages of system development.

Let's consider the calculation of the weight of second-level experts.

Forming expert groups only from users who have common ratings with the current user significantly narrows down the pool of potential experts. To address this issue, a method for calculating the weight of experts in the absence of common ratings with the current user has been proposed. It involves having shared ratings with first-level experts and determines the overall weight of a second-level potential expert relative to the current user $d(U_0, \hat{U}_i)$, taking into account their weight relative to the first-level expert $d(U_i, \hat{U}_j)$ and the weight of the first-level expert relative to the current user $d(U_i, \hat{U}_j)$.

To investigate the potential use of ratings from second-level experts, additional research was conducted. Table 4 presents a fragment of the data illustrating the calculation of the weight of all members in the expert group for dataset №1 in relation to each other.

Since the calculated weights of the experts are the same for both experts relative to each other, the weight table is symmetric about the diagonal. However, it is presented in its complete form for the sake of simplifying the illustration of further calculations. The analysis of the data presented in Table 4 allows the following observations:

– All experts except one have weight values >0.7, which, firstly, allows them to remain in the expert group, and secondly, demonstrates a high level of agreement within the expert group.

– It is evident that the weight of expert №14 relative to expert №19 shows a value below 0.7, because the weight of expert №14 relative to the current user has a value of 0.72 and is in close proximity to the lower boundary of the acceptable weight for participation in the expert group.

– The calculated weights of the experts relative to those who have a weight >0.9 relative to the current user have values close to their weights relative to the current user.

To develop a methodology for considering the weight of second-level experts in ranking, it is necessary to select criteria for evaluating the ratio of weights of second-level experts relative to the current user, expressed through the weight of first-level experts.

Table 5 presents the absolute differences in weights of second-level experts from Table 4 and their weights relative to the current user, which were calculated earlier (Table 3).

In Figure 2 are presented the obtained data.

Figure 3 shows a graph depicting the relationship between the average differences in the weights of second-level experts relative to the weights of first-level experts.

From the graph, it can be observed that the weight deviation significantly increases when the weight of the first-level expert is below 0.8.

Similar calculations based on expert groups from data sets 2 to 4 yield comparable results (Figures 4–9).

The weight of second-level experts relative to the current user is advisable to calculate as the product of the weight of the first-level expert relative to the potential second-level expert, who share common ratings, and the weight of the first-level expert relative to the current user.

$$W\left(d\left(U_0, \hat{U}_j\right)\right) = W\left(d\left(U_i, \hat{U}_j\right)\right) \cdot W\left(d\left(U_0, \hat{U}_i\right)\right).$$

The expert group selects potential second-level experts whose weight relative to the current user is $W\left(d\left(U_0, \hat{U}_j\right)\right) > 0.7$ on the Chaddock scale.

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Table 4 – The fragment of the sample: weights of experts relative to each other

Users	U_0	U_1	U_2	U_3	U_4	U_6	U_{11}	U_{12}	U_{14}	U_{18}	U_{19}	U_{20}
U_0	1	0.9285	0.8735	0.901	0.912	0.912	0.9285	0.9175	0.857	0.758	0.7195	0.7525
U_1	0.9285	1	0.868	0.9065	0.9285	0.8845	0.912	0.901	0.8625	0.7855	0.758	0.802
U_2	0.8735	0.868	1	0.8845	0.8405	0.8735	0.879	0.901	0.8295	0.7855	0.769	0.802
U_3	0.901	0.9065	0.8845	1	0.89	0.879	0.8955	0.8845	0.824	0.769	0.7525	0.7965
U_4	0.912	0.9285	0.8405	0.89	1	0.868	0.9065	0.8845	0.868	0.747	0.7305	0.7745
U_6	0.912	0.8845	0.8735	0.879	0.868	1	0.9285	0.8955	0.824	0.725	0.7085	0.7305
U_{11}	0.9285	0.912	0.879	0.8955	0.9065	0.9285	1	0.901	0.8515	0.7525	0.736	0.769
U_{12}	0.9175	0.901	0.901	0.8845	0.8845	0.8955	0.901	1	0.8735	0.7745	0.725	0.791
U_{14}	0.857	0.8625	0.8295	0.824	0.868	0.824	0.8515	0.8735	1	0.758	0.6865	0.7635
U_{18}	0.758	0.7855	0.7855	0.769	0.747	0.725	0.7525	0.7745	0.758	1	0.8075	0.8405
U_{19}	0.7195	0.758	0.769	0.7525	0.7305	0.7085	0.736	0.725	0.6865	0.8075	1	0.824
U_{20}	0.7525	0.802	0.802	0.7965	0.7745	0.7085	0.758	0.7525	0.769	0.791	0.736	1

Table 5 – The absolute difference values of the weights of second-level experts

Users	U_0	U_1	U_2	U_3	U_4	U_6	U_{11}	U_{12}	U_{14}	U_{18}	U_{19}	U_{20}
U_0	0	0.9285	0.8735	0.901	0.912	0.912	0.9285	0.9175	0.857	0.758	0.7195	0.7525
U_1	0.9285	0	0.0055	0.0055	0.0165	0.0275	0.0165	0.0165	0.0055	0.0275	0.0385	0.0495
U_2	0.8735	0.0605	0	0.0165	0.0715	0.0385	0.0495	0.0165	0.0275	0.0275	0.0495	0.0495
U_3	0.901	0.022	0.011	0	0.022	0.033	0.033	0.033	0.033	0.011	0.033	0.044
U_4	0.912	0	0.033	0.011	0	0.044	0.022	0.033	0.011	0.011	0.011	0.022
U_6	0.912	0.044	0	0.022	0.044	0	0	0.022	0.033	0.033	0.011	0.022
U_{11}	0.9285	0.0165	0.0055	0.0055	0.0055	0.0165	0	0.0165	0.0055	0.0055	0.0165	0.0165
U_{12}	0.9175	0.0275	0.0275	0.0165	0.0275	0.0165	0.0275	0	0.0165	0.0165	0.0055	0.0385
U_{14}	0.857	0.066	0.044	0.077	0.044	0.088	0.077	0.044	0	0	0.033	0.011
U_{18}	0.758	0.143	0.088	0.132	0.165	0.187	0.176	0.143	0.099	0	0.088	0.088
U_{19}	0.7195	0.1705	0.1045	0.1485	0.1815	0.2035	0.1925	0.1925	0.1705	0.0495	0	0.0715
U_{20}	0.7525	0.1265	0.0715	0.1045	0.1375	0.1815	0.1595	0.1265	0.0935	0.0825	0.1045	0

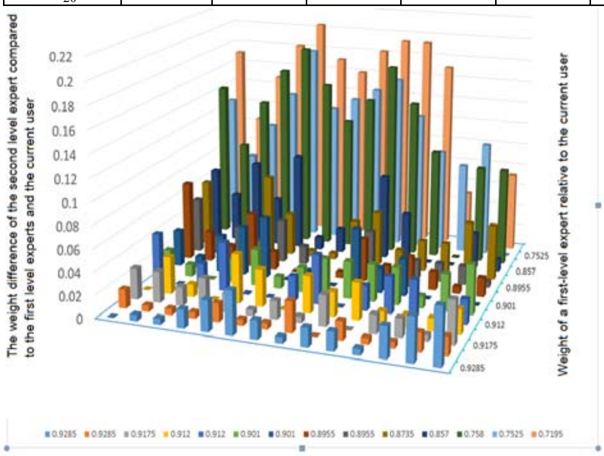

Figure 2 – The weight difference of second-level users

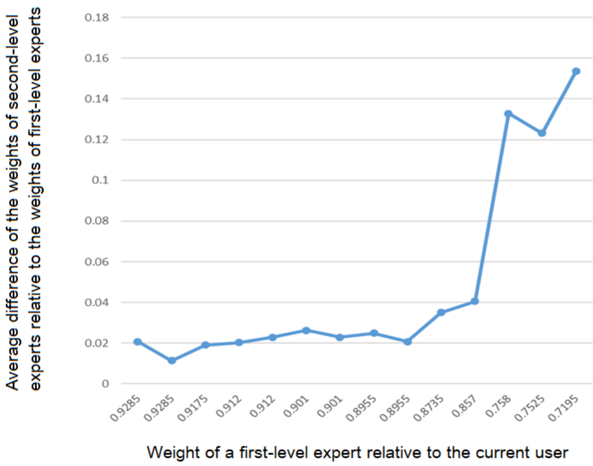

Figure 3 – The dependence of the average difference in weight of a second-level user on the weight of a first-level expert

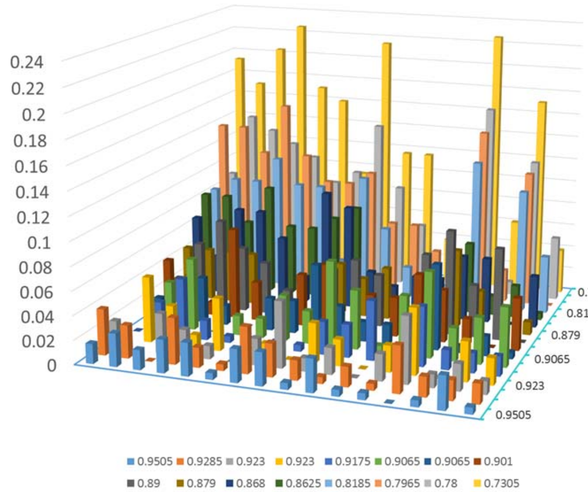

Figure 4 – The weight difference of second-level users for data set №2

Let's consider the calculation of the weight of users who do not have common ratings.

The indirect approach is suitable when there are limited or no shared ratings. It utilizes a model that calculates the weight of potential experts based on their individual social profiles. The most accurate results are obtained by analyzing the experts' previous activities. However, in the system's initial implementation phase and before accumulating a substantial rating database, situations may arise where there is insufficient data to apply this method. Accumulating a sufficient rating database means having a significant number of shared ratings to form expert groups for the majority of system users. Therefore, to ensure the system's proper functioning in its early stages, a method was developed to determine the weight of users with no shared ratings at all.

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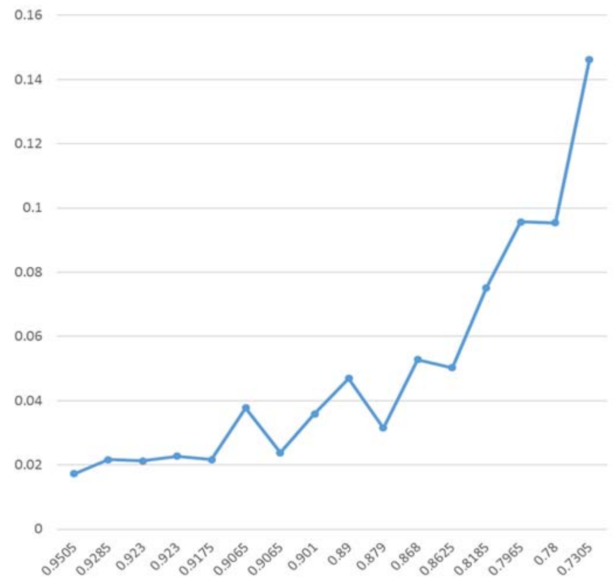

Figure 5 – The dependence between the average weight difference of second-level users and the weight of first-level experts in dataset №2

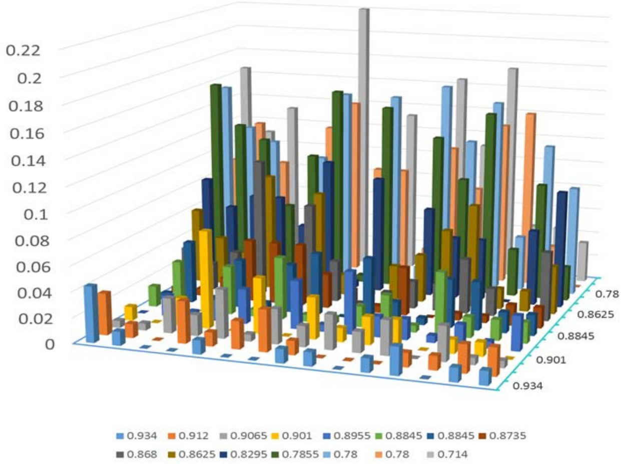

Figure 6 – The weight difference of second-level users for data set №3

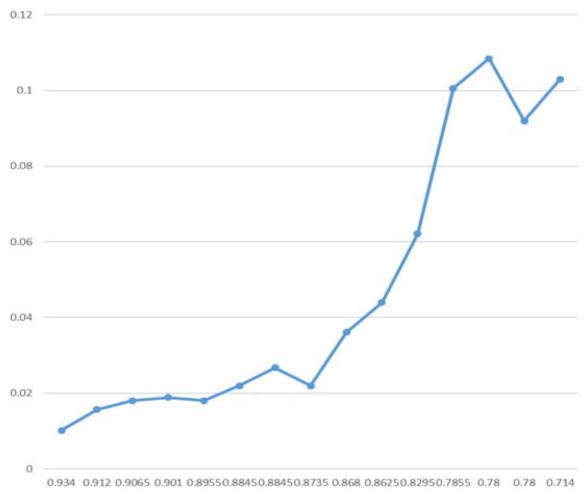

Figure 7 – The dependence between the average weight difference of second-level users and the weight of first-level experts in dataset №3

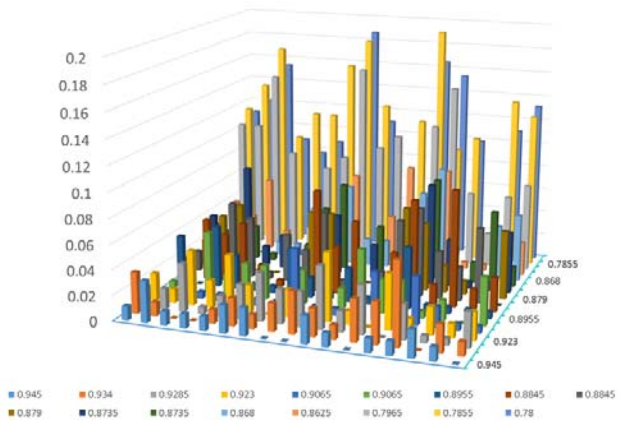

Figure 8 – The weight difference of second-level users for data set №4

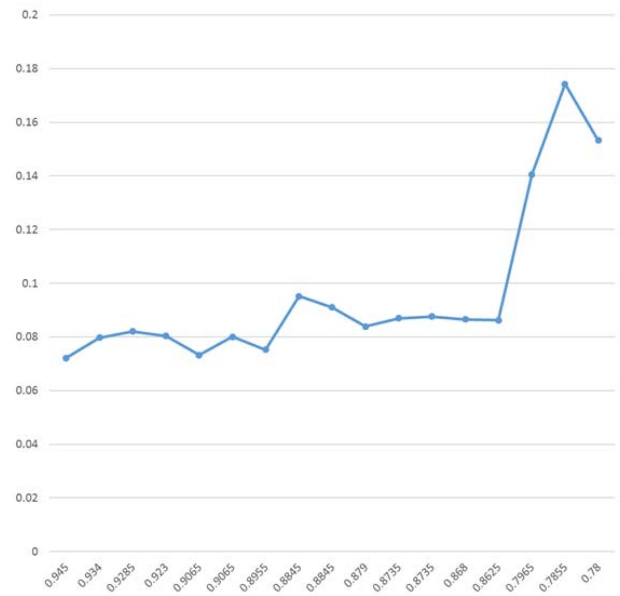

Figure 9 – The dependence between the average weight difference of second-level users and the weight of first-level experts in dataset №4

A user's social profile is formed based on the information they provide during system registration [24]. Taking into account global and domestic experience in conducting psychological research [25–27], a set of socio-personal factors that may influence the formation of a user's opinion was selected. Based on the research results, the factors found to be informative in building the model for determining the weight of potential experts will be included as mandatory fields in the system's registration form.

To build the model for calculating the weight of experts, a set of subjective features x_m was selected, which can directly or indirectly influence the visitor's rating. Social profiles of users (U_0 – U_{60}) who participated in previous experiments were used as input data. Since their weight relative to the user U_0 has already been calculated based on the data samples of ratings №1–4, the same expert groups presented in tables 2–5 were used to construct the model.

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It is necessary to construct a model of the influence of socio-personal factors of Internet users on the degree of consensus between the potential expert of the third level $U_{0,exp}$ and the current user.

The sample contains n = 20 observation points and is divided into two parts: 2/3 of the points for the training sample A and 1/3 of the points for the validation sample B: n_A = 14, n_B = 6.

The accuracy of the obtained models was assessed using the coefficient of determination R^2.

The GIA algorithm is used at the third level to determine the weight of users who have no shared ratings at all [28–29].

The aggregated results of the modeling are presented in Table 6.

From Table 6, it can be observed that the best modeling results were obtained using the GIA. The GIA allows for the utilization of the mathematical model itself, which is more convenient for this particular task, as the obtained model serves as an intermediate step in solving the given problem within a limited time frame. Furthermore, as evident from the obtained dependency (GIA model), only 6 out of the 11 variables are significant. Detailed results for the GIA are presented in Table 7 and Figures 10–12.

Figure 10 show that the generalized algorithm reaches a minimum on the 7th layer.

Based on the above, a general conclusion can be drawn: the modeling results indicate that the best model was found using the generalized iterative algorithm, which incorporates all previous iterative structures.

Table 6 – Summarized results of modeling by GMDH algorithms

Algo-rithm	R^2, %	True monomials											Number of re-dundant mono-mials
		x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	
Iterative algorithms with linear partial model description													
MIA	42.2	+	+	+		+	+	+	+	+			3
RIA	17.70			+									10
CIA	55.14	+	+	+		+	+	+	+	+	+		2
Iterative algorithms with quadratic partial model description													
MIA	56.25			+		+	+	+	+	+			5
RIA	54.25					+		+		+			8
CIA	77.17			+		+		+					8
MICA	71.80	+		+		+	+	+	+		+		4
RICA	54.25					+		+		+			8
GIA	80.27	+	+			+		+	+				6

Table 7 – GIA results

№	Data set	y (real)	$\hat{y}$ (model)	Error
1		1	0.904	0.096
2	*A (training)*	0.9285	0.895	0.033
3		0.8735	0.752	0.122
4		0.901	0.882	0.019
5		0.912	0.810	0.102
6		0.637	0.628	0.009
7		0.912	0.865	0.047
8		0.5765	0.637	–0.061
9		0.8955	0.818	0.077
10		0.8955	0.961	–0.066
11		0.901	0.911	–0.010
12		0.9285	0.886	0.042
13		0.9175	0.928	–0.010
14		0.6975	0.737	–0.040
15		0.857	0.856	0.001
16		0.6315	0.730	–0.098
17		0.56	0.680	–0.120
18	*B (testing)*	0.527	0.574	–0.047
19		0.758	0.788	–0.030
20		0.7195	0.814	–0.094
21		0.7525	0.750	0.003
		R^2, %	80.27%	

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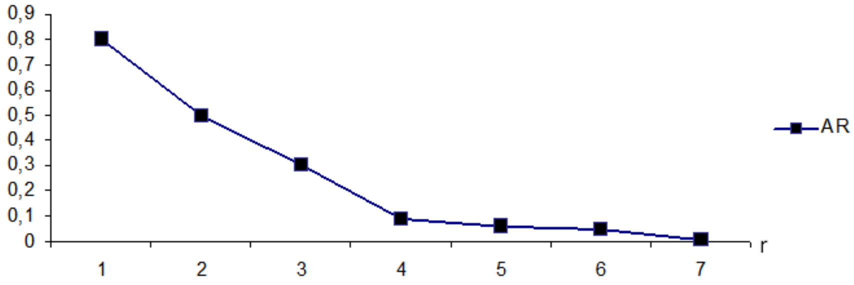

Figure 10 – The value of the evaluation criterion (*AR* criterion) by layers

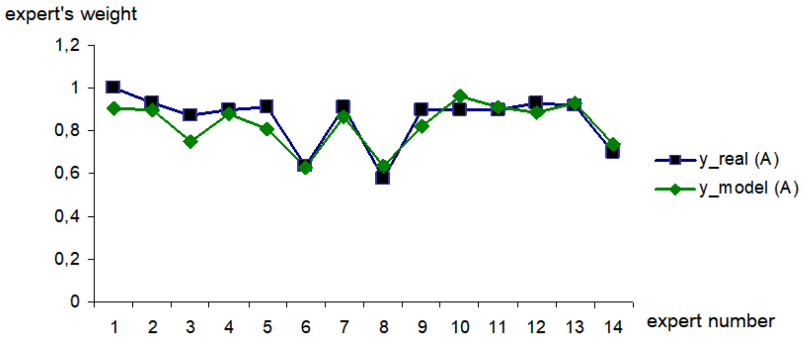

Figure 11 – The values of true and model results on sample *A*

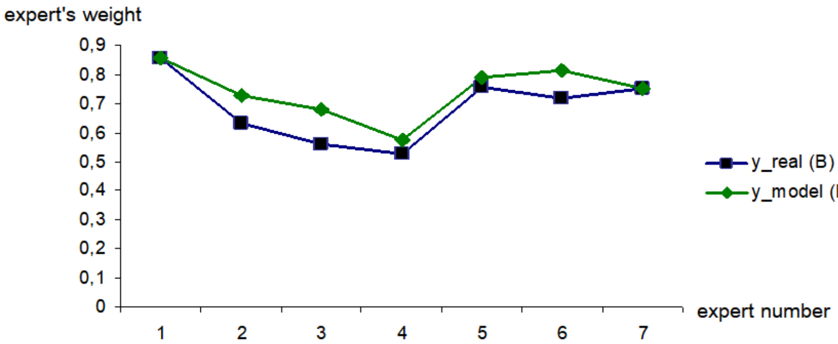

Figure 12 – The values of true and model results on sample *B*

5 RESULTS

The paper explores the challenge of ranking search engine results using google.com.ua as a case study. Initially, this task may seem formidable due to the vast number of results, often reaching hundreds of thousands or even millions. However, a closer examination of search engine algorithms reveals that the computational complexity is significantly lower [27]. In practice, the user's accessible search results are much fewer than what the system claims during query execution. Consequently, the ranking process effectively focuses on analyzing only a few hundred results, requiring minimal computational power.

To assess the effectiveness and accuracy of the aforementioned ranking methods based on user ratings, four experiments were conducted. Each experiment formed a distinct data sample, consisting of 20 users rating 20 web resources based on information quality and usability. A total of 60 users participated across the four samples, with some users rating web resources in multiple samples. Consistent numbering was employed for the same users across all experiments, ensuring User №1, for instance, remained consistent. Additionally, each experiment incorporated a combination of previous experts and new users, allowing for tracking the weight values of the same experts across different data samples.

Let's consider the determining the weight of experts by the ADE method.

The weight values of potential experts relative to user №0 for data sample №1 were calculated using the ADE method. The results are presented in Table 8.

Based on the results presented in the table, an expert group is formed for User №0. It includes users who have a calculated weight value greater than 0.7 according to the Cheddock scale.

Expert numbers: 1–4, 6, 8–12, 14, 18–20.

A new data sample is created for the ranking of web resources, which includes evaluations only from the experts (Table 9).

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Table 8 – The weight values of potential experts relative to User №0 for data sample №1

User	User weight	Selected to the expert group
1	0.9285	+
2	0.8735	+
3	0.9010	+
4	0.9120	+
5	0.6370	–
6	0.9120	+
7	0.5765	–
8	0.8955	+
9	0.8955	+
10	0.9010	+
11	0.9285	+
12	0.9175	+
13	0.6975	–
14	0.8570	+
15	0.6315	–
16	0.5600	–
17	0.5270	–
18	0.7580	+
19	0.7195	+
20	0.7525	+

Table 9 – The fragment of the expert group evaluations

web resource → ↓ User	A_1	B_1	C_1	D_1	E_1	…	Q_1	R_1	S_1	T_1
0	10	10	8	5	7	…	8	8	3	5
1	10	10	9	6	8	…	8	8	4	4
2	8	8	9	5	6	…	7	7	3	4
3	9	9	9	5	7	…	7	6	3	3
4	10	10	9	7	7	…	9	9	4	3
6	9	10	7	6	8	…	7	6	4	4
8	8	8	6	4	7	…	9	7	3	4
9	7	9	8	5	6	…	9	7	4	3
10	7	9	7	4	8	…	9	8	3	4
11	9	10	8	5	7	…	7	9	4	4
12	8	8	9	6	7	…	8	8	3	4
14	7	7	5	4	8	…	8	9	2	4
18	7	7	10	6	4	…	5	8	6	7
19	7	9	9	8	5	…	6	7	7	9
20	8	7	9	7	4	…	5	8	8	4

Prior to commencing the ranking process using the selected methods, it is essential to acquire a reference ranking as a basis for comparison. Merely sorting the web resources based on User №0's ratings in descending order yields only approximate outcomes. This approach solely arranges clusters of web resources with identical ratings in descending order in Table 10. The precise order of web resources within each cluster remains unknown. Hence, to establish the reference ranking, User №0 manually assigned a rank ranging from 1 to 20 to each web resource, with 1 denoting the highest rank (Table 10). The reference ranking for the current user was created manually.

Let's consider the ranking of web resources by the method of average points.

Traditionally, the application of the average method involves the use of the arithmetic mean for value calculation. In this work, the following methods were used to calculate the averages: AM, WAM, HM, WHM.

Weighted modifications of the arithmetic mean and harmonic mean allow for the calculation of new rankings of web resources, taking into account the experts' weights. The calculation results of the web resource rankings using the average methods are presented in Table 11.

Table 10 – The reference ranking for the current user

The number of the web resource in the data set	Sort by decreasing rating	Manual ranking of the current user
1	A_1	B_1
2	B_1	A_1
3	I_1	K_1
4	J_1	J_1
5	K_1	I_1
6	C_1	C_1
7	H_1	R_1
8	Q_1	Q_1
9	R_1	H_1
10	E_1	E_1
11	L_1	L_1
12	G_1	G_1
13	M_1	N_1
14	N_1	M_1
15	D_1	D_1
16	T_1	T_1
17	F_1	F_1
18	O_1	O_1
19	P_1	S_1
20	S_1	P_1

Table 11 – The results of the web resource rankings using the average methods

Web resource	The rank of the web resource, calculated by methods:			
	AM	WAM	HM	WHM
A_1	8.142857	8.186422	8.158281	8.107372
B_1	8.642857	8.692747	8.699647	8.561141
C_1	8.142857	8.11233	8.101196	8.119847
D_1	5.571429	5.527025	5.614922	5.502869
E_1	6.571429	6.656235	6.639741	6.538092
F_1	5.214286	5.182274	5.272789	5.196464
G_1	5.571429	5.538319	5.598789	5.574416
H_1	7.428571	7.402497	7.459537	7.392929
I_1	7.857143	7.937367	7.836755	7.877952
J_1	8.071429	8.128224	8.07852	8.063776
K_1	8.142857	8.204493	8.148353	8.135257
L_1	6.428571	6.480204	6.459537	6.412008
M_1	6.857143	6.776984	6.810695	6.901067
N_1	6.071429	6.035609	5.976346	6.173482
O_1	3.928571	3.863192	3.928512	3.910907
P_1	4.357143	4.248973	4.402527	4.271915
Q_1	7.428571	7.505052	7.482288	7.391828
R_1	7.642857	7.643954	7.669863	7.644797
S_1	4.142857	4.045014	4.114847	4.126818
T_1	4.357143	4.268852	4.427347	4.288059

The ranking outcomes are displayed in Table 12. To evaluate the efficiency of the proposed techniques in computing average scores, the mean deviation from the reference ranking is utilized. This metric is obtained by averaging the differences in positions among the web resources.

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Table 12 – The results of ranking

The reference ranking	ranking by methods				Position deviation by:			
	AM	WAM	HM	WHM	AM	WAM	HM	WHM
B_1	B_1	B_1	B_1	B_1	0	0	0	0
A_1	A_1	K_1	A_1	A_1	0	1	0	0
K_1	C_1	A_1	K_1	K_1	3	1	0	0
J_1	K_1	J_1	J_1	J_1	1	0	0	0
I_1	J_1	C_1	C_1	C_1	1	1	1	1
C_1	I_1	I_1	I_1	I_1	1	1	1	1
R_1	R_1	R_1	R_1	R_1	0	0	0	0
Q_1	H_1	Q_1	H_1	Q_1	1	0	1	0
H_1	Q_1	H_1	Q_1	H_1	1	0	1	0
E_1	M_1	M_1	M_1	M_1	4	4	4	4
L_1	E_1	E_1	E_1	E_1	1	1	1	1
G_1	L_1	L_1	L_1	L_1	1	1	1	1
N_1	N_1	N_1	N_1	N_1	0	0	0	0
M_1	D_1	G_1	D_1	D_1	1	2	1	1
D_1	G_1	D_1	G_1	G_1	3	0	3	3
T_1	F_1	F_1	F_1	F_1	1	1	1	1
F_1	P_1	T_1	T_1	T_1	3	1	1	1
O_1	T_1	P_1	P_1	P_1	2	2	2	2
S_1	S_1	S_1	S_1	S_1	0	0	0	0
P_1	O_1	O_1	O_1	O_1	2	2	2	2
The sum of deviations:					26	18	20	18
Average deviation value:					1.3	0,9	1	0,9

From the Table 12, it can be seen that the methods of WAM and WHM have the smallest error, indicating the relevance of considering the weight of experts when calculating the ranking of web resources.

To justify the feasibility and effectiveness of using ratings only from users who have a strong connection with the current user in the ranking process, additional calculations were performed to determine the rankings of web resources using ratings from all users in data set №1.

Below is a comparative table of the final rankings of web resources calculated based on the ratings from two groups of users, Table 13:

– Expert group.

– All users from Sample № 1.

Ranking based on the ratings of all users compared to ranking based on the ratings of a predefined expert group produces significantly worse results.

The results presented in Tables 11–13 prove the effectiveness of taking into account the weight of experts when calculating the ranks of web resources and justify the need to filter out users with low indicators of the degree of agreement of opinions relative to the current user. Experiments № 2, 3, 4 were conducted according to the same method. Therefore, their description is not given.

Table 13 – Comparative table of rankings of web resources calculated based on ratings from two groups of users

Reference ranking	Expert group				All users			
	AM	WAM	HM	WHM	AM	WAM	HM	WHM
B_1	B_1	B_1	B_1	B_1	C_1	J_1	I_I	I_I
A_1	A_1	K_1	A_1	A_1	I_1	I_1	M_1	J_1
K_1	C_1	A_1	K_1	K_1	B_1	C_1	J_1	K_1
J_1	K_1	J_1	J_1	J_1	K_1	K_1	K_1	M_1
I_1	J_1	C_1	C_1	C_1	A_1	A_1	A_1	A_1
C_1	I_1	I_1	I_1	I_1	M_1	M_1	Q_1	B_1
R_1	R_1	R_1	R_1	R_1	Q_1	Q_1	B_1	Q_1
Q_1	H_1	Q_1	H_1	Q_1	J_1	B_1	N_1	C_1
H_1	Q_1	H_1	Q_1	H_1	N_1	R_1	C_1	N_1
E_1	M_1	M_1	M_1	M_1	R_1	N_1	F_1	R_1
L_1	E_1	E_1	E_1	E_1	E_1	E_1	H_1	H_1
G_1	L_1	L_1	L_1	L_1	H_1	H_1	R_1	F_1
N_1	N_1	N_1	N_1	N_1	F_1	F_1	G_1	E_1
M_1	D_1	G_1	D_1	D_1	T_1	L_1	T_1	G_1
D_1	G_1	D_1	G_1	G_1	L_1	G_1	E_1	L_1
T_1	F_1	F_1	F_1	F_1	G_1	P_1	L_1	T_1
F_1	P_1	T_1	T_1	T_1	P_1	D_1	P_1	D_1
O_1	T_1	P_1	P_1	P_1	S_1	T_1	S_1	P_1
S_1	S_1	S_1	S_1	S_1	D_1	S_1	D_1	S_1
P_1	O_1	O_1	O_1	O_1	O_1	O_1	O_1	O_1
The sum of deviations	26	18	20	18	62	58	74	56
Average deviation value	1.3	0,9	1	0,9	3.1	2.9	3.7	2.8

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Table 14 presents the summarized results of the conducted experiments. The last row of the table shows the count of instances where each method yielded the best ranking results. If more than one method achieved the best results during the experiment, all of them are considered the best.

Table 14 – The summary results of experiments

Experiment number	The method of calculating values by the method of average points			
	AM	WAM	HM	WHM
№1 The sum of deviations	26	18	20	18
Average value of deviation:	1.3	0,9	1	0,9
№2 The sum of deviations	32	28	32	24
Average value of deviation:	1.6	1.4	1.6	1.2
№3 The sum of deviations	32	30	24	22
Average value of deviation:	1.6	1.5	1.2	1.1
№4 The sum of deviations	22	22	20	20
Average value of deviation:	1.1	1.1	1	1
Best results	0	1	1	4

From the table 13, it can be seen that during the four experiments, the method of average scores calculated based on weighted harmonic mean showed the smallest deviation from the reference ranking. Based on these results, this approach will be used in the development of the meta-search engine.

6 DISCUSSION

The proposed methodology for forming unique expert groups for each user involves three approaches depending on the presence of shared ratings between the current user and potential experts:

1. When there are shared ratings between potential experts and the current user, the weight is calculated using the ADE method, which includes:

– calculating the average differences of estimates;

– applying a normalization function to scale the data from 0 to 0.99.

– selecting users who have a strong connection with the current user based on the Cheddock scale (values > 0.7).

Research has shown that the ADE method is more effective in solving research tasks and provides significantly better results compared to the Kendall's concordance method and similar approaches.

2. When there are no shared ratings with the current user but there are shared ratings between potential second-level experts and first-level experts, the weight of second-level experts relative to the current user is calculated as the product of the weight of the first-level expert relative to the potential second-level expert with shared ratings and the weight of the first-level expert relative to the current user.

3. When there are no shared ratings at all, the expert group is formed based on a model constructed from the user's social profile using inductive algorithms.

To calculate the rankings of web resources in search result ranking, the methods of average ratings were considered. However, the classical form of the average ratings method does not yield high results and does not take into account the weight of experts. The results of conducted experiments have shown that the best ranking results are achieved using the method of weighted average ratings, specifically using the weighted harmonic mean where the weights are based on the experts' expertise.

Comparative analysis of inductive modeling methods showed that GIA provides the most accurate results. The task involved building a model that captures the relationship between the measure of agreement of opinions and the socio-personal factors of users, which is why the neural network approach was not applied for comparison, as it does not allow obtaining such a model. The best model for calculating the weight of third-level potential experts relative to the current user was found using a generalized iterative algorithm that incorporates all previous iteration structures.

The described methodology of constructing a personalized model for ranking web resources based on user ratings has demonstrated high effectiveness, indicating the promising development of this direction.

CONCLUSIONS

The urgent problem of enhancing search efficiency, an approach to search result management based on user's subjective information needs is employed.

The scientific novelty of obtained results is introducing scientific novelty through a search result ranking method that generates a unique order of web resources for individual users. This is accomplished by leveraging ratings from user-specific expert groups and incorporating each rating with a distinct weight into the model for calculating final rankings. The weight is determined based on an analysis of the web resources' previous activities within the system.

The practical significance of obtained results is that the software that implements the proposed methods, along with conducting experiments to examine their properties. The experimental outcomes support the recommendation of the proposed methods for practical use, while also identifying effective conditions for their application.

Prospects for further research are to involve the exploration of building ranking models that incorporate a multitude of factors, similar to contemporary search systems.

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РАНЖУВАННЯ ДАНИХ НА ОСНОВІ КОРИСТУВАЦЬКИХ РЕЙТИНГІВ

Зосімов В. В. – д-р техн. наук, професор кафедри прикладних інформаційних технологій Київського університету імені Тараса Шевченка, Київ, Україна.

Булгакова О. С. – канд. техн. наук, доцент кафедри прикладних інформаційних технологій Київського університету імені Тараса Шевченка, Київ, Україна.

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Передерій В. І. – д-р техн. наук, професор кафедри інформатики та комп'ютерних наук Херсонського національного технічного університету, Херсон, Україна.

АНОТАЦІЯ

Актуальність. Розглянуто проблема персоналізації результатів роботи пошукових систем шляхом надання користувачу інструментів управління пошуковою видачею, а також розробки нових моделей ранжування, заснованих на суб'єктивних інформаційних потребах користувача. Об'єктом дослідження є моделювання результатів пошуку інформації в мережі Інтернет на основі користувацьких оцінок.

Мета роботи – формування унікальних для кожного користувача експертних груп, заснованого на розрахунку міри узгодженості думок поточного користувача з потенційними експертами.

Метод. Запропонований новий підхід до ранжування результатів пошуку на основі оцінок користувачів. Основною відмінністю даного методу є суб'єктивний підхід до процесу ранжування. Такий ефект досягається за рахунок попереднього формування експертних груп, унікальних для кожного користувача. Експерти відбираються за мірою узгодженості думок з поточним користувачем, що розраховується на основі спільних оцінок для деякої множини веб-ресурсів. Відбір користувачів до експертної групи відбувається на основі його ваги відносно поточного користувача, що є мірою узгодженості їх думок.

Запропонована нова методика формування унікальних для кожного користувача експертних груп, що передбачає три підходи в залежності від наявності спільних оцінок для деякої множини веб-ресурсів між поточним користувачем та потенційними експертами.

Розроблений метод ранжування результатів пошуку видає для кожного користувача список веб-ресурсів, що має свій унікальний порядок елементів. Такий ефект досягається за рахунок використання оцінок членів експертної групи, що є унікальною для кожного користувача, а також за рахунок того, що кожна оцінка входить до моделі розрахунку кінцевих рангів веб-ресурсів зі своєю унікальною вагою, розрахованою на основі аналізу їх попередньої діяльності в системі.

Результати. Розроблені методи реалізовано в програмному забезпеченні та досліджено для вирішення задач оперування даними в мережі Інтернет.

Висновки. Проведені експерименти підтвердили працездатність запропонованого програмного забезпечення та дозволяють рекомендувати його для використання на практиці для вирішення задач оперування даними в мережі Інтернет. Перспективи подальших досліджень можуть включати оптимізацію програмних реалізацій, а також експериментальне дослідження запропонованих методів на більш складних практичних задачах різної природи та розмірності.

КЛЮЧОВІ СЛОВА: пошук інформації, ранжування, результати пошуку, оцінки користувачів, експертні групи, соціальний профіль, індуктивні алгоритми, поліноміальна нейронна мережа, активні нейрони.

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