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An Efficient Incremental Query Recommendation based Query Ranking Model

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Abstract: To retrieve the information from the web, search area query estimation is selected as an outstanding method depending on the minor query logs. The log data will be developed very quickly, and the existing models should be updated when new data models are developed. In this paper, a new improved query ranking model is implemented to keep the data up to date. The new data is added to the existing model incrementally. The results shows the incremental query ranking model-based techniques are better efficient than the existing query ranking model with better accuracy.

Keywords: Query recommendation, Query ranking model, Incremental query ranking model

1. Introduction

People use Google, Yahoo and other search engines to receive information from the web. It is very difficult to the users to get accurate information [1]. For reducing the burden to the users, the search engines favor with query commendation assistance. Query commendations are generally contrived from drilling query logs [2]. The queries are recommended to the customers based on the previous data they collected. If they shift their interest on the same object, the recommendation decreases. The incrementally updating mechanism is not provided in the existing query recommendation techniques. These models must be re built, by incorporating the new log data [3]. Practically, it is known that the building of existing models is very time consuming. Hence, the query recommendation model must be updated itself based on the past query logs.

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Processing the big data is a big challenge for the existing query models. Commercial search engines receive huge amounts of data daily [4]. This paper implements a new I.Q.R.M. that can increase updates itself compared to the Query Ranking Model (Q.R.M.). In this new I.Q.R.M. the, optimization techniques are added for updating and accelerating the log books. The result shows the I.Q.R.M. is better in updating the query logs.

2. Incremental Query Ranking Model (I.Q.R.M.)

To discuss with the emerging data more strongly, in this paper the Q.R.M. [1] is extended as I.Q.R.M. The problem is defined as below. Suppose estimate that D is an ancient Search Session Group (S.S.G.). Let $Q_D = \{q_1, \dots q_{T_D}\}$ is a person's set D of queries. $\alpha_D = \{\alpha_1, \dots \alpha_{T_D}\}$, $\beta_D = \{\beta_1, \dots \beta_{T_D}\}$, $\gamma_D = \{\gamma_1, \dots \gamma_{T_D}\}$ are the anological perceived, preservious and recommendation stage services of Q_D computed from D [6]. Let a new log data d contain the same queries as in D. The new data d is used to update the S.S.G. group data. As the advancement d of recent search operation is attached to the model S.S.G. D, for computing and updating the $\alpha_{D \cup d}$ that need to estimate only the figure of enquries whose outcomes were find in d. Hence, it very straight forward for updating the data set $\alpha_{D \cup d}$. But it is not easy to enhance the data sets $\beta_{D\cup d}$ and $\gamma_{D\cup d}$ being Q.R.M. utilizes the optimization techniques which hides the updates. Hence in the coming section we are proposing the Incremental gradient method as new optimization technique for reducing the burden on $\beta_{D\cup d}$, $\gamma_{D\cup d}$ in further sections [7].

2.1 Incremental gradient technique

Consider the Q.R.M. objective function as follows (1)

Maximize

$$f(\beta)=\sum_{j=1}^{N}\sum_{i=1}^{M_j}S_{j,i}\log\left(\sigma(\sum_{k=1}^{i}I(C_{j,k}=1)(\mathrm{O}_{j,k}=1).\beta_{j,k})\right)$$

$$+(1-\mathrm{s}_{j,i})\log\left(1-\sigma(\sum_{k=1}^{i}I(C_{j,k}=1)(\mathrm{O}_{j,k}=1).\beta_{j,k})\right)$$

Subjected to $\beta\geq 0$ (1)

Let γ is the level of query service of *Q*, Q.R.M. gets the development complication as succeed (2),

$$f(\gamma)=\sum_{j=1}^{N}\sum_{i=1}^{M_j}\log\left(\frac{I(q_t\in Q^{(j,i-1)}\gamma_t}{\sum q_*\in Q^{(j,i-1)}\gamma_*}+\frac{I(q_t\in Q-Q^{(j,i-1)}\gamma_t}{\sum q_*\in Q-Q^{(j,i-1)}\gamma_*}\right) \quad (2)$$

Subjected to $\gamma\geq 0$

The enhancement gradient technique is used to minimize the objective value, which is made from the summation fundamental actions, such as (3)

Maximize $f(x)=f_1(x_1)+...+f_m(x_m)$ (3)

subjected to $x\in\Re^n$

Where $f_i:\Re^{|x_i|}\rightarrow\Re(i=1,2,...m)$ are the differential original figured problems? For getting the optimized results, use the increasing gradient technique as (4)

$$x(t+1)=\rho_x(X(t)+\alpha(t)\nabla f_{i(t)}(X_{i(t)}) \quad (4)$$

Where t indicates step value of the iteration $\alpha(t)$ is the positive increment in the step size, *X* indicates the values projected with the positive slopes. By the use of this technique, the objective functions of equations (1) and (2) are optimized.

2.2 Incremental updating of $\beta_{D\cup d}$

In this section earlier we will change the intentional function of equation (1) in to the equation (3). Here *X(i)* denotes the vector β and $f_i(x_i)$ indicates the function of problem components.

$$(1-\mathrm{s}_{j,i})\log\left(1-\sigma(\sum_{k=1}^{i}I(C_{j,k}=1)(\mathrm{O}_{j,k}=1).\beta_{j,k})\right)$$

We will perform various operations such as $\cup$ and $\cap$ on x_i.

2.3 Incremental update of $\gamma_{D\cup d}$

First change the objective value (2) to equation (3). Where xi is the vector, γ and $f_i(x_i)$ are the component functions.

$$\log\left(\frac{I(q_t\in Q^{(j,i-1)}\gamma_t}{\sum q_*\in Q^{(j,i-1)}\gamma_*}+\frac{I(q_t\in Q-Q^{(j,i-1)}\gamma_t}{\sum q_*\in Q-Q^{(j,i-1)}\gamma_*}\right)$$

Because, the above problem value spreads the γ changes, on the total candidate query. We will use the differential increment methods for updating the optimization solution.

3. Results and Discussion

Different experiments are performed for evaluating the strength of the I.Q.R.M. and Q.R.M. methods. They are conducted on a 64 bit, Linux server with 32 G.B. internal storage and 16 Intel Xeon E5620 cores. We experimented on spring 2006 data set for performance evaluation of the both methods. Some symbols are removed and changed all to lower case letters.

3.1 Setting of the parameters

To get a good difference, it set the values of Q.R.M. for good performance, and we set the iterations of both methods to 200 as same. Hear each iteration covers all the variables of the objective business. The merging situation of I.Q.R.M. and Q.R.M. are set to equal as β=10-6 and γ=10-3 and C=0.5 and N=10 in the given step value.

3.2 Performance of I.Q.R.M. with various increments

We ran an experiment on 2000 selected search functions and bundles for strength evaluation of I.Q.R.M. and Q.R.M. These 2000 S.S.G. contains 310007 search sessions and 360850 queries from candidates. We simulated the original application S.S.G. with new search sessions in a given time. We recognized all S.S.G. and separated them into original S.S.G. of *D* and increment S.S.G. of d. these d S.S.G. are assumed as new S.S.G. associated with *D*. The recorded implemented instant of Q.R.M. and I.Q.R.M. on $D \cup d$ and received the average of the implemented value ratios for 2000 S.S.G. The mean performances of I.Q.R.M. and Q.R.M. for various enhancements are recorded in Fig.1. In Fig.1, it will observe that, although the incremental ratio $|D|:|d|$ changes from 1:1 to 40:1, whereas the achievement ratio is reduced from 0.36 to 0.08. The value of decreasing is continuing. The line indicates the acceleration of I.Q.R.M. from side to side among Q.R.M. with increments. If the new I.Q.R.M. is passed down to deal with the given problem operation of (1), for calculating the β attitudes of all candidates' queries, I.Q.R.M. separates all functions into independent functions. The variation of partitions generated by all the candidates' queries by I.Q.R.M. on 2000 S.S.G. is shown in Fig.2. From this figure we can observe that most portions contain up to 4 queries and only a few of them contains more than 5. In the given SSGl, we use *U* to indicate the queries optimized in Ql and O to indicate the queries optimized from starting to old characters and the symbol *I* to finds the people's questions, which are optimized with starting values. First we run the I.Q.R.M. on D of SSGl later we ran the I.Q.R.M. on $D \cup d$. We plotted three values $|U|/|Q_I|$ $|I|/|Q_I|$ for SSGl and calculated the average problems and their standard changes on 2000 S.S.G. These ratios from various incremental changes are depicted in the Fig.3.

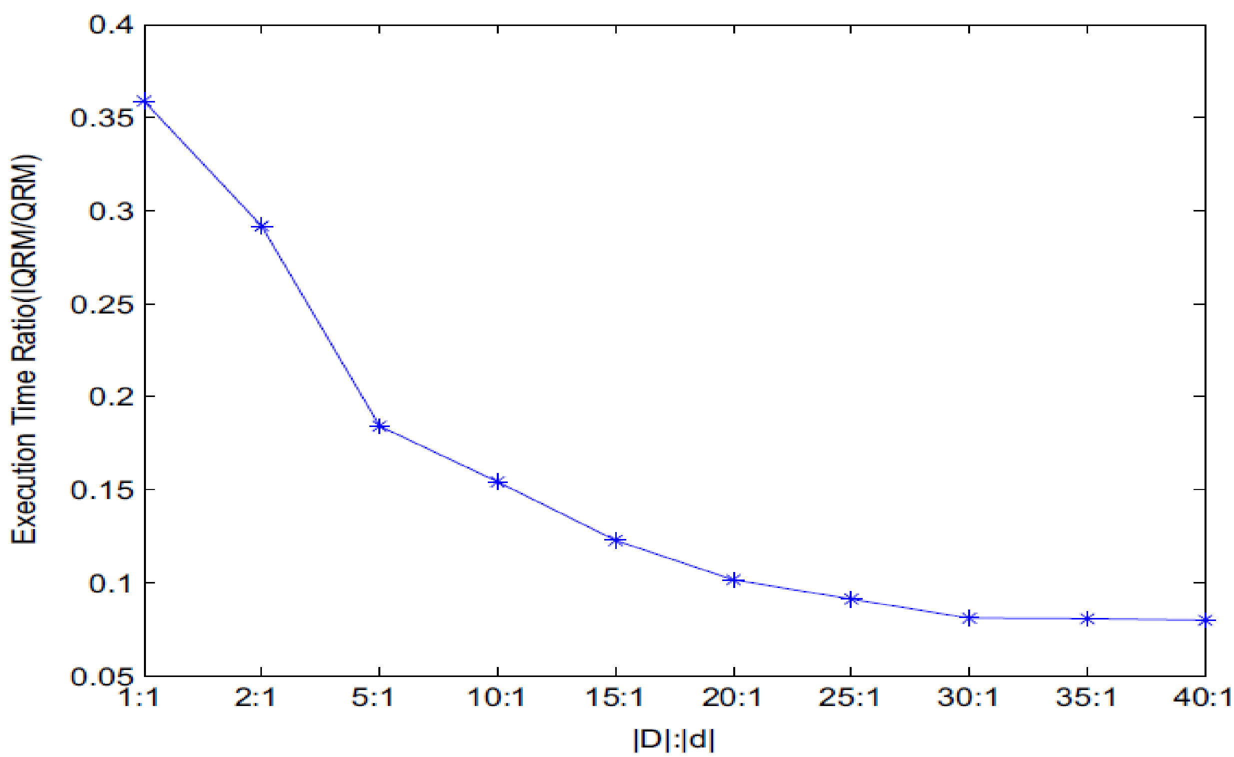

Fig.1. Performance ratio with various increments

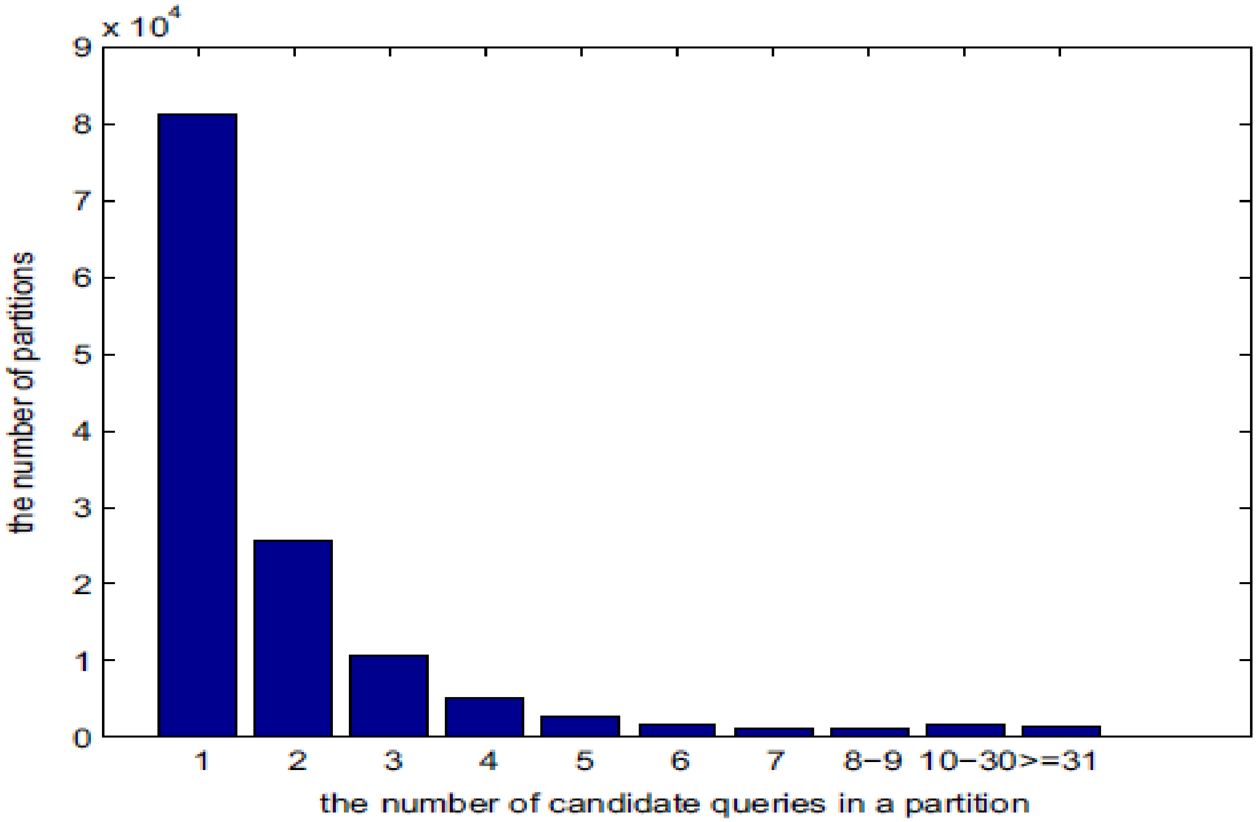

Fig. 2: Distribution of the candidates queries on 2000 S.S.G.

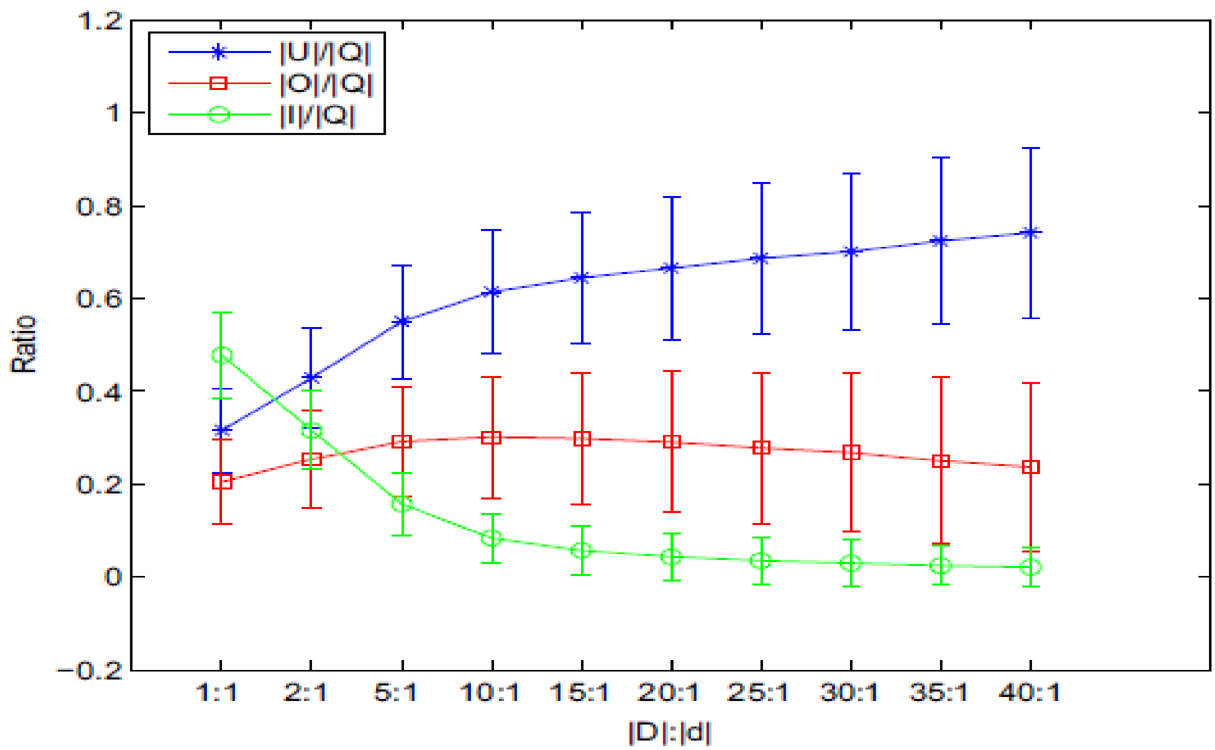

Fig.3: Ratio of un-optimized queries, person queries which are minimized starting with old figures, optimized people queries starting with initial values with various changes.

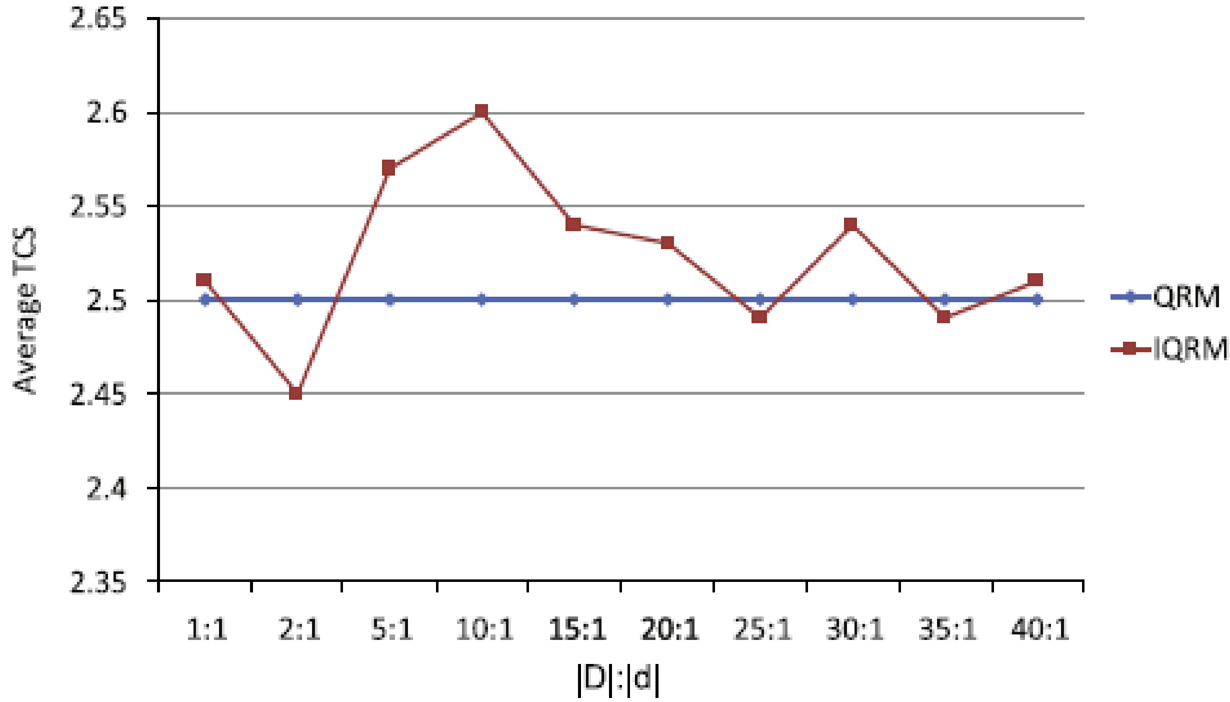

Fig.4: Performance of I.Q.R.M. and Q.R.M. over query utility area

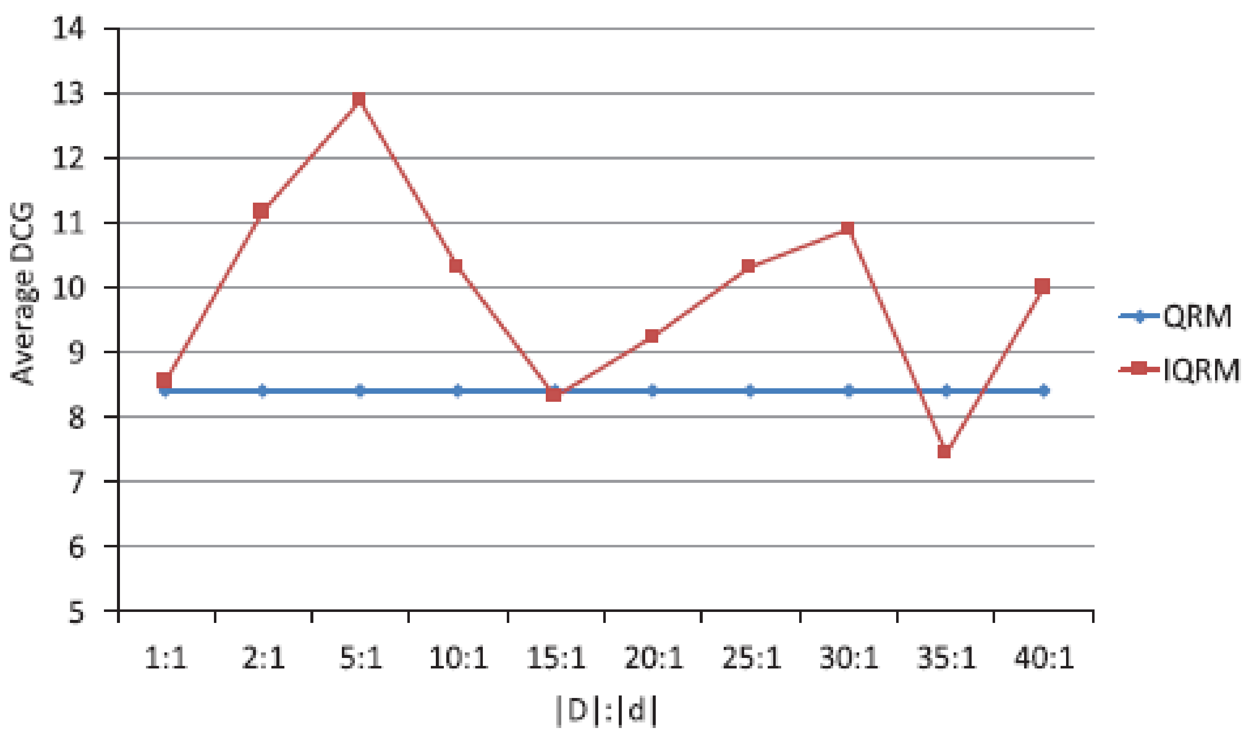

Fig.5: Performance of I.Q.R.M. and Q.R.M. on document utility area

Fig.3 shows that the blue channel indicates the candidates minimized recommendations, the red channel shows the candidate queries optimized with old figures and the green shows the candidate queries started with initial values. The vertical bar shows the fundamental changes. When the change $|D|:|d|$ changes from 1:1 to 40:1, the blue colour values varies with 0.3 to 0.75 and the incremental recommendation is preceded. Even for small increments the result shows good improvements. When the blue channel increases, the red channel increases from 0.2 to 0.3 and decreases to 0.2. This indicates that the recommendations are minimized with old figures and they become constant at 20% with various changes. The green line decreases when the ratio $|D|:|d|$ increases, indicating that the low valued increments d shows optimized results starting from initial values. Threes are three reasons for better performance of I.Q.R.M. over Q.R.M. The strength of I.Q.R.M. is evaluated over Q.R.M. in utility area and document utility area and their effectiveness is depicted in the Fig. 4 and Fig.5.

4. Conclusion

To get the information up to date, a new I.Q.R.M. is presented in this paper. On evaluating the query log, when updated with I.Q.R.M., it uses the last time information of I.Q.R.M. to reduce the computation. The results show the I.Q.R.M. is highly strong compared to Q.R.M. on evaluating the query log. However they are suffering with redundant utility level. Further work is recommended to recognize the clicked URLs region and optimize the reductions in the suggested data.

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Conflict of Interest

The authors declare no conflict of interest

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