CAPTURING USER EXPECTATION FOR ACCURATE INFORMATION RETRIEVAL IN PERSONALIZED WEBSITES

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Abstract

CPSS (Cyber Physical Social Systems) provide high quality, proactive and personalized services for humans. Billions of bytes of data are generated every second in CPSS. General search engines are built to serve all users, but they face difficulties in addressing the needs of user. Capturing user expectation has become difficult especially in personalized websites. Here we are using keyword extraction algorithm for effective search, real-time location and relevant feedback algorithm are used to acquire specific information. Implicit feedback based on click-through data analysis is used. To improve the ranking quality we are designing a personalized page rank algorithm.

I. Introduction

Cyber physical and social world includes in CPSSs (Cyber Physical Social Systems), these systems provide accurate results for Personal websites. Cyber systems validates the data and acquire information from the human factors in the daily applications. Wiki, crowd sourcing search engines intensify both data-driven and virtualization methods. Using these cyber physical systems intelligence and knowledge can sorted as fast as light travels. Usage of CPSSs has resulted in the rapid growth of networking sites.

To meet the user expectations on internet, many retrieval techniques have been implemented. As users are familiar to general search engines to gain information from internet through general engines like google, yahoo. But results often contain unnecessary information and unwanted data that is hidden back of a webpage. This lead to time consumption and it is hard to retrieve information more accurately and satisfy user intentions.

We use keyword search technique to reclaim information present in personalized website. This method looks for the queries that are specified by the user. But different users may get information on different aspects when they submit the same query.

Various data mining techniques such as keywords-based, vertical search, multi keywords queries have been extensively employed to retrieve information. Vertical search engines provide certain information, but the information contain some noise data and detailed information is not obtained.

However, the retrieve result contain some amount of unnecessary information and some required information can be hidden back of the webpage. So users need to spend a lot of time to retrieve accurate information. These vertical search engines will not provide satisfactory results to the user.

The main contributions of this paper are summarized as follows:

- we use real-time location strategy
- we use implicit relevant feedback based on click though data analysis
- To improve the ranking quality, we design a personalized page rank algorithm.

II. RELATED WORK

One of the main purpose of CPS (Cyber Physical Systems) is to provide high quality, energetic and personalized services for humans. CPS is supervised by computer based algorithms [1]. Significant enhancement in human living environment is due to rapid advances in information and communication technologies. These information are high dimensional, redundant and noisy, resulting in unrivalled challenges for providing big services in ELEs [2].

CPS are still at their dawning, most recent studies are application-specific and lack of systematic design methodology. To outline future challenges for designing CPS, it introduced latest research improvement on systematic design methodology [3].

Reference [4] presents the outcomes of experiments designed to evaluate the performance of a Real-time Interest Model (RIM) that attempts to identify the dynamic and changing query level interest regarding social media understanding.

This study accord a better understanding of how dwell time can be used as implicit evidence of document usefulness, as well as how contextual factors can help interpret dwell time as an indicator of usefulness. For development of personalized system these findings have both theoretical and practical implications [5].

To enhance the efficiency of information retrieval, researches had put great effort on it. This information retrieval is based on keyword search. Single keyword is considered only in current research work but expanded research work use multiple keyword search is require to process the search request and document return by means of its keyword search [6].
Many of the vertical search results are valid to users in only a short period of time. TSVS (Time Sensitive Vertical Search engine) prototype focused on time critical air force discount information search to investigate the time critical requirements of vertical search and a QTC (Query Triggered Crawling) strategy to solve this problem [7].

The order of top results in a web search can be enhanced by incorporating user behaviour data. The accuracy of web search can be improved by incorporating implicit feedback [8].

User dwell time is used to measure how much time the user needs to search results. Based on browsing activity we derive personalized re-ranking algorithm through mining user dwell time [9].

Reference [10] computes the longest substring of two strings with one mismatch within time and additional apace.

IKAnalyzer algorithm [11] and some another algorithms which provides ranking for the results which are matched in the search procedure. This approach produces many unwanted results which may lead to massive wastage.

To solve above problem Distributed Hypertext Resource Discovery [12] implements a task of exploring the web in order to find pages of a particular top. Web spiders are created efficiently and solved by reinforcement learning. Reinforcement learning it provides a conformity for measuring the utility of actions that give benefit only in future [13].

Due to increasing size and dynamic content of the web, it is difficult to maintain currency of search engine indices by overtime crawling. One of the main purpose of CPS (Cyber Physical Systems) is to provide high quality, energetic and personalized services for humans. CPS is supervised by computer based algorithms [14].

We use set of page rank vectors to yield more accurate search results. For ordinary keyword search, it computes the topic sensitive PageRank scores for pages satisfying the query using the topic of the query keywords [15].

III. Information Extraction for personalized websites

A. Framework Overview:

The framework of intelligence retrieval and usage of real-time location information to accommodate in retrieving for personalized websites. This system includes four categories in retrieval algorithm.

a) Real-time and web configuration.
b) Keywords extraction.
c) Relevant feedback.
d) Personalized ranking.

In this method, the server will collect some website information into database.so, that server can return appropriate results faster. The overall structure of the intelligence retrieval framework is shown in fig 1.the framework is classified into four steps as shown in fig 1.

a) Real time location and configuration personalized website.
b) Retrieval.
c) Performance optimization.
d) Re-retrieval.

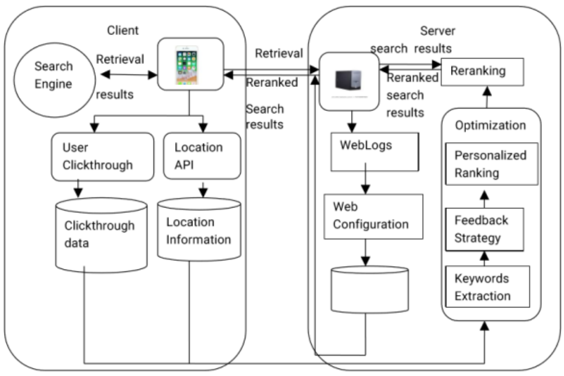

Fig. 1: An overview of intelligent retrieval framework

In the first step, we obtain the users real time location information from location API and uploaded to server. The user can set the retrieval range so, that user can retrieve current location area. The obtained information can be made into long text using keywords extraction algorithms, in order to extract key words.

In the second step, the server obtains the information about the initial websites and calculate the page rank value of the webpages. User can change the list of local websites in the client and upload it to the server. The client then combines the user accordingly to the keywords given for the first time. When the server receives the request, it performs information retrieval on personalized websites, then web log also records the information.

In the next step, the results obtained from the server are not displayed directly to the user. The strategy of click through data is used by client to record user intension and uploaded to the server. The server then process the click through information and page rank value is updated through personalized ranking method.

B. Real-time location and web configuration

Different users have different scenarios and requirements for same query. Substantially, we make use of their location to query results. Both real time location and web configuration are two aspects that intelligence retrieval framework is facing. The overall process of real-time location and web configuration is given below.

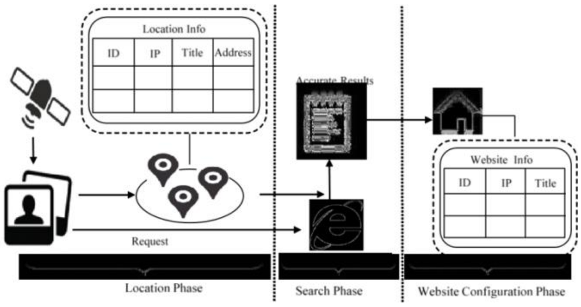

Fig. 2: Process of location and web configuration

The user obtains the information through GPS, using location API .extraction of real-time location includes two main functions. First, we make a note of information that is surrounded by buildings by setting the range parameters such as id, name and location.

Secondly, with the help of surrounding information we extract “tittle” and “address” to combine information into a long text. Finally, we obtain the website name of users personalized query.

C. Keyword Extraction Algorithm:

This paper deploys an algorithm for keywords extraction. This algorithm calculates the frequency of each word in the text, which presents at "first line”, “first" and "tail". To calculate the frequency of words emerging in text, first the text should be broken into clauses.

To extract the keywords of the text, a public substring extraction algorithm is used. It depends on the word frequency and word length. The public substring algorithm is shown below in algorithm 1.

Algorithm 1: **Public substring extraction algorithm**

```
Input: str1[], str2[]
Output: pstr []
Int rowLength;
index[rowLength][str1.length()];
int row=0;
for j=0 to str2.len do
  for j=0 to strdd1.len do
     if str2.getChar(j)==str1.getChar(k)
then
        if index[row][k]==-1 then
          index[row][k]=j;
        end
     else if index[row][k]>-1 then
        row++;
        index[row][k]=j;
     end
    end
  end
end
```

This algorithm reduces the time complexity and space complexity. In terms of space complexity, it changes the string traversal method based on traditional LCS (Longest Common Subsequence) algorithm. For instance, let us consider two string lengths as l and m, the space complexity is O(lm) according to LCS algorithm. But the space complexity of the algorithm is O(ln),because we adopt the frequent character(n) as the height of the matrix. The space complexity of the algorithm O(ln) is obviously less than the space complexity of LCS algorithm.

In terms of time complexity, the string traversal based time complexity is still O(lm),but the total running time of the algorithm is reduced to a certain degree because of the reduction in height of the matrix.

D. Relevant Feedback Algorithm:

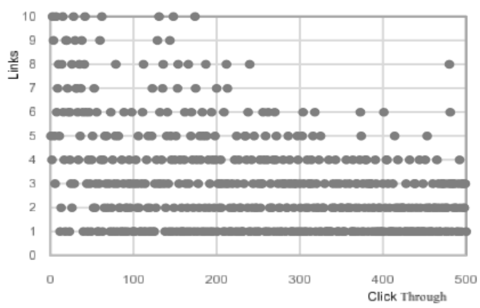

Fig. 3: Distribution information of user click-through

To improve the retrieval performance, the extra overhead of user feedback should be minimized. The distribution information of a user click-through is shown in fig.3.

When users retrieve information from search engines, only the top few retrieval results will attract the attention of the user. Even if they input the same keywords as a retrieval condition, they have different concerns about the target link. Therefore we can obtain a certain value from the information from the users click-through data.to improve the performance of search engines and the user's satisfaction, this paper presents a strategy to obtain user's click-through data via implicit feedback.fig.3.

Definition 2.1 Click Set(CS): Given a query keywords with accessible links and the CS satisfying

CS=(ID,QK,S,T)

- ID is the number of the user's interest group and used to distinguish users in different groups.
- QK is a query keywords, shows the query conditions of the retrieval;
- S denotes a collection of all links returned from the search engine.
- T denotes a collection of all links clicked by the user.

Definition 2.2 Feedback Set(FS):It indicates the relevant feedback information obtained from the click-through data analysis.

FS=(ID,map)

Where map is a relational table which stores relative degrees of correlation between two webpages.

In our strategies, the relevant degree of unclicked link and the link which is in the front is low .If the previous link is clicked and a present link is not clicked, then the relevant degree of that present link is low.

If a user clicks a link then the relevant degree of that link higher than the previous unclicked links of the link. The relevant feedback algorithm is shown below in algorithm 2

Algorithm 2: Relevant feedback algorithm

```
Input: CS(ID,Qk,S,T)
Output:FS(ID,map)
for j=1 to n do
 for k=1 to n do
  for 1<=k<j<=n then
      if link(j)∈T&&link(k)   then
         (lj,lk) stored in map;
      end
      else if 1<=j<=n-1 then
             if link(j)∈T&&link(j+1)  ∉ T then
                 (lj,lj+1) stored in map;
             end
      end
      else if j=n then
           If link(j)∈T then
             for k=1 to n do
               (lj,lk) stored in map;
               end
           end
      end
       else if link(j)∈T&&link(k)  ∉ T then
    If num(link(j))>num(link(k)) then
            (lj,lk) is stored in map;
    end
   end
  end
 end
end
```

N is the number of S sets.link(j) represents the j[th] link in the linked collection returned from search engine. The relevant degree of link j is higher than that of link k for the keywords used in this query and the relationship is denoted as (l_j,l_k).The number of clicks of link j is represented as num(link(j)).

E. Personalized PageRank Algorithm:

PageRank algorithm estimates the importance of a website by counting the number and quality of links to a page. But this PageRank algorithm ignores the importance of webpages. This paper includes the user behavior and the relevant acknowledgement information which is obtained through click-through data analysis. A map table is obtained for the relationship of relevant degrees between links.

A vector v is added to improve the PageRank algorithm. If the relevancy of link l_j for the same keywords is greater than link l_k and webpage weight of link l_j is less than link l_k. The modification of the weight which are stored in the database is done using vector v. The calculation is as follows:

$$v[l_i] = \frac{\sum(Rank(l_j)-Rank(l_k))}{2} / N(l_j,l_k) \quad -(1)$$

$$v[l_k] = -v[l_j] \quad -(2)$$

Where

- $Rank(l_j)$ represents the current weight of the link li in the database, and
- $N(l_j,l_k)$ represents the number of relationships in the relevancy table.

To make the vector v perfect, have to analyze and merge the click-through data of different users. The collection process of the modified vector v is represented in formula (3)

$$vold[l_j] = c1\ vold[l_j] + c2\ vnew[l_k] \quad -(3)$$

Where

- $vold[l_j]$ represents the original value of the modified vector for link l_j.
- $vnew[l_k]$ indicates the modified value calculated based on the relevancy of the newly acquired click-through data. Introducing the modified vector v into the traditional PageRank equation, the following formula (4) is obtained:

$$\forall l_j Rankn+1(l_j) = \sum_{lk \in Bl_j} Rank n(l_j)/N_{lk} + v[l_j] \quad -(4)$$

Bl_i represents the collection of all links in, and N_{lj} represents the total number of chain links to the webpage. For formula (4), a variable d is added to control the coefficient of the modified vector q and the traditional PageRank value. The calculation is as follows

$$\forall l_j Rankn+1(l_j) = d*\sum_{lk \in Bl_j} Rank n(lj)/N_{lk} + (1-d)v[l_j] \quad -(5)$$

Formula (4) and formula (5) add the modified vector q to the traditional PageRank. The corresponding formula including the webpage access probability C is as follows:

$$\forall l_j Rankn+1(l_j) = d*[(1-w)+w*\sum_{lk \in Bl_j} Rank(l_j)]/N_{lk} + (1-d)v[l_j] \quad -(6)$$

The calculated PageRank value shows significant differences, because the relevant feedback information provided by users is different and modified vector v value is also different. The Personalized PageRank algorithm is shown below in algorithm 3.

Algorithm 3: Personalized PageRank algorithm
Input: Consider the relation of the link
Consider the relevant feedback information based on click-through data analysis
Output: Personalized PageRank value
While To Calculate the PageRank value do
Step-1: Initially, the PageRankvalue of the webpage have to be calculated
Step-2: Next the feedback vector have to calculated using the formulas (1),(2),(3);
Step-3: Based on the above information Personalized PageRank value is calculated using the formula (6)
end

IV. Experimental Results

1. Keyword Extraction Efficiency:

This experiment analysis explains the accuracy in extraction and time cost for the mentioned keywords extraction algorithm. This experimental setup consists of 1000 data sets which includes keywords and abstract driven from the papers in CNKI (China National Knowledge Infrastructure) platforms.

- **Extraction Accuracy:**

The length of text carries major role in keywords extraction accuracy. In this experiment single text is texted for 12 times

The accuracy is measured by the similarity between the actual data and outputs of the algorithms. Thus keyword extraction accuracy can be given as

$$accuracy = 1/n \sum_{j=1}^{n} sim(j) \quad -(7)$$

Where

- n is the total number of keywords extraction outputs.
- sim(j) represents the similarity of number j with the range $0 \leq sim(j) \geq 1$

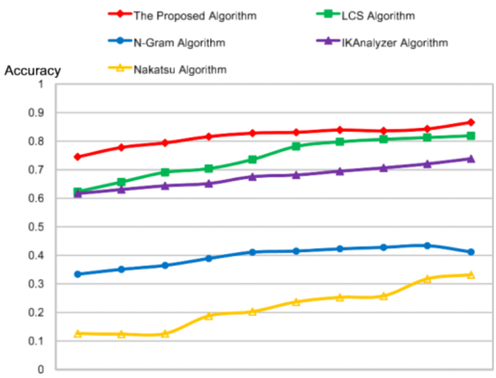

Fig. 4: Relation between keywords extraction accuracy and text length

From fig (4), the extraction of algorithm accuracy is higher than the traditional sub sharing algorithm. The keyword Extraction algorithm does not exceed the limit of words (or) phrase length. While enhancing key words, meaningless phrases are avoided. It also matches the theme of text and word frequency.

- **Time Cost:**

  Both length and quantity of keywords influence the execution time of algorithm. The time increases with the increase in length and text quantity.

  From fig (5), The LCS algorithm and Keyword Extraction algorithm are having same time. Complexity, as the two algorithms extract substrings from the phrases of text.

  Algorithm achieves less space complexity as high frequency texts are included. The time consumed for scanning an array is very low. The time complexity of system is loss when compared to LCS algorithm. The key words extraction time is high for nakatsu because of its complexity.

  The procedure of extracting key words in N-gram is simple. The time complexity is less due to one words segmentation is performed. Both N-gram LEVEL IKANALYZER have same process, thus time complexity is high for IKANALYZER.

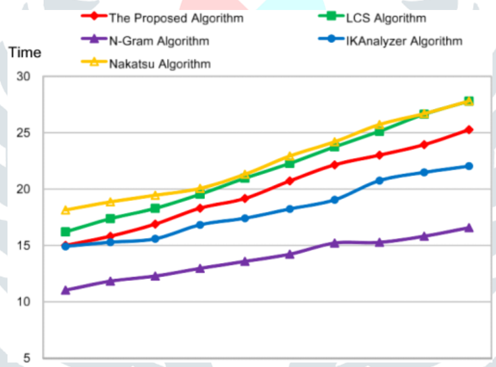

Fig. 5: Relation between keywords extraction time and text length

2. Relevant Feedback Extraction Strategy Efficiency

The second experiment tests the relationship between web page results and query keywords according to the strategy for extracting relevant comments based on analysis of click data. In the simulation experiment, we set 20 static links in the Android client and 10 links per page. We first set the initial tuple (ID, Map) in the database. Then, click on links 1, 5, 20 links in sequence, and click once for each link. Partial data is displayed in the table of the map in the table1.

Table 1. The results of partial data in map

no.	results in map
1	(l_5,l_2)
2	(l_5,l_3)
3	(l_5, l_4)

From table 1, link 5 is before links 2, 3 and 4, which were not clicked; thus, the relevant degree between the links and the query keywords is less than link 5.

Then press five links 1, 6, 8, 11, and 15, respectively, after trimming the map table, and clicking each link once. Partial data is displayed in the map table in Table 2. From Table 3, we found that the link that was not clicked or behind the clicked link is low. In addition, Link 15 is higher than all other links clicked because it was the last clicked link. Results are consistent with the strategy phenomenon.

Table 2. The results of partial data in map

no.	results in map
1	(l_1, l_2)
2	(l_6, l_7)
3	(l_8, l_9)
4	(l_{11}, l_{12})
5	(l_{15}, l_{16})
6	(l_{15}, l_1)
7	(l_{15}, l_6)
8	(l_{15}, l_8)
9	(l_{15}, l_{11})

Press the link 1 five times, connect 3 times twice and connect 9 times seven times after clearing the map table again. Table 3 shows partial data in the mapping table. Table 3 shows that the higher the click on the link, the greater the correlation. Results are consistent with the strategy phenomenon.

Table 3. The results of partial data in map

no.	results in map
1	(l_1, l_3)
2	(l_9, l1)
3	(l_9, l_3)

3. Personalized ranking performance

The third experiment tests the performance of the custom ranking method. We first write 10 simple HTML files as test web pages, and these webpages contain the same web structure, the same as the initial page rank value. For the same keywords, different similarity values will be given for each of the 10 web pages. We click on 10 webpages multiple times, where the number of clicks varies, and the page rank and page rank rankings are analyzed and analyzed.

PageRank values for Web pages are stored first. The PageRank value is only related to the web page's webpage structure because there is no click-through process for the user. A total of 100 clicks are distributed over 10 Web pages on different web pages. The current PageRank value is displayed in Table 4.

Table 4. The status of personalized PageRank value

webpage no.	clicks	initial PageRank value	personalized PageRank value
1	14	2.37E-2	2.96E-2
2	18	2.37E-2	3.12E-2
3	9	2.37E-2	2.76E-2
4	21	2.37E-2	3.24E-2
5	2	2.37E-2	2.30E-2
6	3	2.37E-2	2.31E-2
7	6	2.37E-2	2.39E-2
8	26	2.37E-2	3.38E-2
9	0	2.37E-2	2.17E-2
10	1	2.37E-2	2.17E-2

In Table 4, more clicks result in a greater increase in the value of your PageRank. At the same time, page rank values do not fluctuate with fewer clicks. The custom PageRank value is associated with a web page that is not clicked in return.

We increase the number of clicks to 300 pages per 10 pages and record the change in the value of the PPC after each click. In Figure 7, we randomly extract the PageRank value for three pages. In Figure 7, when a webpage is clicked, the value of the webpage's personal page rank will be particularly high; otherwise, it will be reduced or remain essentially unchanged. Even if you do not click on the web pages at the back of the loopback list, the PageRank value will not change; however, if some links are not clicked before clicking the click web page, the PageRank value will be reduced because the webpage is not of interest the user.

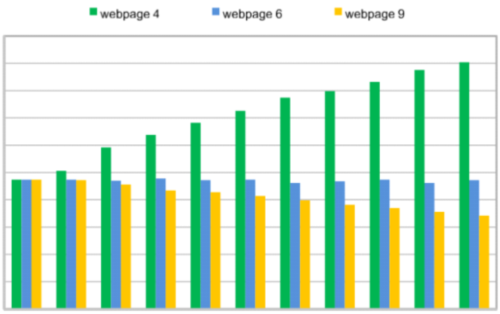

Fig. 6: PageRank value of webpages with different numbers of clicks

V. Conclusions and future Scope

In this paper, we deployed an intelligent retrieval framework with real-time location in CPSSs to resolve the ambiguities of general search engines. We first provide an intelligent retrieval model for one field with a real-time site. Second, to improve the results of the retrieval, the paper deployed a strategy for implied link responses based on the analysis of click data, which obtains the relationship between the terms of the user query and the results of the retrieval. Finally, the paper designs a custom PageRank algorithm, including modified parameters, to improve the quality of the retrieval results by using relevant comments from other users in the interest group.

We have conducted several experiments to evaluate the performance of the framework. Experimental comparisons show that the framework achieves superior recovery performance with minimal effort and provides a superior user experience.

The framework provides an efficient, real-time, personalized approach to CPSSs. Although we have demonstrated the efficiency and effectiveness of the framework, in the future we will focus on conducting thorough investigations into several improvements to the compatibility and feasibility of the framework.

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