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which are correlated with rdf schemas are used in our application

- Class
- rdfs:subClassOf
- rdf:property
- rdfs:subPropertyOf
- rdfs:domain
- rdfs:range
- Individual

Step 6: Here term weight of the preprocessed user query is used to find out the OWL class with the help of tree object generated in previous step. After this, index for the hierarchy is used.
Step 7: Here indexed classes of the tree is used for fetching the URL which are stored in databases.
Step 8: This step is important for capturing the user evidence factors which are used for the personalization. Such as username, date, time, query, interested links, and session timings.
Step 9: The step refers to user personalization model where previous evidence of the same query entered by the user is checked. Checks for previous evidence for the query by the user.

If system finds the evidence then system fetches the evidence and then sends it to the indexer part. Indexer part is a part where evidence is properly displayed with the existing results. After this user personalization is done where user interests and process queries are used in timely manner. Below is the equation which represents the combined adaptive personalization.

$$P_m(X: Y) = \sum_{j=0}^{k} . \sum_{i=0}^{N} Ul(1)$$

Where X= { i=1,……….N} is the set of URLs used for user personalization.
Where Y= { j=1,……….k} is the set of adaptive queries.
U_l is the User interest URL
Time based adaptation can be represented with the below equation.
$F_t = (t_c- t_l) > T:(Q-U_q)$ (2)

Where t_c is the current time, t_l is the lastly updated time, T is the adaptive time for the user, Q is the set of Queries and U_q is the user query to delete.
The above two equations can be summarized in the following algorithm.

Algorithm: Time based adaptive user personalization
// input: U_l is the interest user interest URL
// N is the number of user personalized URL
//K is the number of user adaptive queries
// t_c is the current time and t_l is the last query updated time
// T is the adaptive time for the user, Q is the set of Queries
// U_q is the user query need to delete.
//output: Q is the set of adaptive user personalized

Function : adaptive User Personalization (U_l,N,K,t_c,t_l,T,Q,U_q)

1. Get the N user interest URLs
2. Update all the URLs U_l into the database
3. **for all** $Q \in [1; k]$ do
4. Get the query Q, date, time and query count and update in database
5. **if** (t_c- t_l)>T then delete query U_q
6. Reset the set Q
7. **return set**

4. Results And Discussions

In our proposed system we evaluate the efficiency of the user personalization systems. Also we checked whether the techniques mentioned by us provide proper results to the user or not. Proposed system creates the ontology of more than 50 keywords of the general news categories like business, sports and health etc. with the respective URLs in the database. Then with the help of adaptive sequences user personalization is given to the user. Experiments shows that, our system gives more efficient results than the other as in our system sessions are increases on specific time interval.

We conducted a survey to know interest degree of the 10 users which captured on five different time intervals. So our survey shows always last interval always has more range over the first one. So this shows that system captures the more interest with the help of adaptive rules.

To show the experimental evaluation of the system we measures the associated user personalized URL and the adaptive interest of the user for the given query. For better understanding of retrieval effectiveness precision and recall parameters are used. And for this purpose again 10 users are considered. As the users personalized details are captured on fixed interval of time, it will get easy to find out the precision and recall.

For more clarity we assign
- A = Expected interest degree.
- B = the number of relevant interest not retrieved, and
- C = the number of irrelevant interest retrieved.

So, Precision = A/ (A+ C)
And Recall = A/ (A+ B)

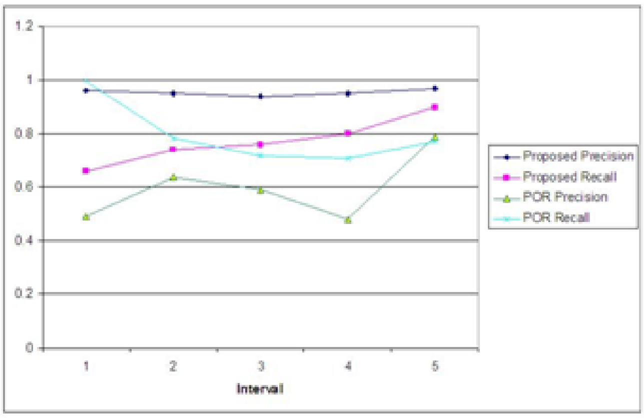

Figure 3: Precision and recall at different interval time for adaptive personalization process

By considering a regular interval of time precision and recall of the system is calculated as shown in figure 3. All the values of the user interests are normalized between 0 to 1.

Graph clearly indicates the difference of proposed model with the user personalization. In partial order manner [13] (POR) .By studying the algorithm we concludes that our system give much better result in terms of precision and recall as interval time is increasing. Whereas POR system has little lesser ratio of precision and recall compare to our system of adaptive personalization through ontology. This indicates our proposed system of adaptive user personalization literally opens many possibilities in enforcing the system of user personalization.

5. Conclusion and Future Scope

Proposed approach of user personalization successfully captures the user interested URLS on the click of the URL. And process this URL for the adaptive personalization theme where URLs are managed till given weight and time parameter. On exceeding these parameters system automatically adopt the new URLs which are searched by the designed ontology based focus search engine for the limited URLs of the news. Adaptive personalization can be enhancing to give more intelligence along with the coordination of the web browser to catch the user interest based on the surfing time on the specific web page.

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