Computation on User-Side of PMSE using Preferences

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Abstract- The major challenges in Mobile Search are information mismatch, uselessness of the information and overload of information on first page. This has a incredible impact on the relevance of the information search, gathering knowledge and capturing information needs of end users. To improve the effectiveness of information personalization, the generation of user profile must capture more recent interest of user, and should be efficient and accurate. This research focuses on construction of user profiles from the (social networking) twitter tweet data of user for more recent trends followed. User profiles is generated by applying ANN back propagation algorithm. Interest score is assigned to topic ontology and maintained. User interest changes are reflected from his tweets over a period of time. As per the change of user interest, the user profile also changes over time. An experimental setup is designed to evaluate the performance of the proposed computational load sharing of personalized mobile search engine. Top ten relevant documents list are then categorized. Precision and Recall are used as the measures to summarize and match up to the user search results. High precision means that an algorithm returned considerably more relevant results than irrelevant, while high recall means that an algorithm returned most of the relevant results.

Keywords – Precision, Preferences, Recall, Relevance, Search engine, Semantic search, Twitter.

I. INTRODUCTION

The Internet and especially World Wide Web are incredibly popular. Because of the absence of centralized control or authority, statistics about the net lack some degree of certainty. There is no question however, that the Net is enormous in terms of numbers of users, Web sites and Web pages. For instance, an estimate of the minimum number of host machines on the Internet is over 1,028,544,414, (Internet Domain Survey, July 2014). Similarly, India had about 243 million Internet users as of June 2014, according to IAMAI (Internet and Mobile Association of India). There is every reason to believe these numbers with all increase significantly in the next few years, with some analysts suggesting that the Web is doubling in size every 100 to 125 days (Morgan, 1996) .

A. Objective

The objectives of the work are.

• Preserving privacy of the users, it means to shared the computational load of personalized mobile search engine on client-side. • To create the user profile based on Twitter account wall to best represent his interest preferences.

• To rerank the retrieved search links for recent interest of user. • To test the personalized mobile search engine effectiveness measurements of precision and recall.

In most of the search engines the same results are displayed to any user sending the query. Howsoever, different user may be looking for different information, his need may be completely different from the others. This is not accounted in a commercial search engine. So an obvious objective of computational load sharing of personalized mobile search engine is to distinguish between different users and present them with results pertaining to their need and preferences.

B. Assumptions

Terminology used in PMSE

In this report study, specific set of terms are used when referring to PMSE Search. Each query which goes to Google Search is composed of one or more keywords. In response to a query, Google Search returns a page of results [eg. query word "Health"] which is sample of Google Search results for the query "Health". Each page contains ten results (in some cases there may be more or less). Most results contain one link. In this study, the only focus was on primary link in each result and description along with it. In most cases, the link is pointing to a third-party website.

The following assumptions are made in the proposed approach;

• The Proposed system prior requires a active user of twitter account with a smart mobile phone.

• The profile of user for only three preferences (Health, Sports and Entertainment) is created and reranking is done on those preferences.

• The user clicks at least one link from the reranked results.

• The first ten results from google are used to rerank.

II. Literature Survey

To understand the innovation of search engine techniques, it is necessary to examine their history work. The search engine plays an important role for extracting the information. The information can be utilized for different purposes, like business purpose, electronic commerce, marketing like sales and buy product. Because of that purpose, develop the computation load sharing of personalized mobile search engine using artificial neural network. It is helpful to study their history briefly.

A. Personalized mobile search

A Personalized Mobile Search Engine (PMSE) that captures the users preferences in the form of concept by mining their click-through data. The user preferences are organized in an ontology-based, multi facet user profile, which are used to adapt a personalized ranking function for rank adaptation.

Personalization is a way available to the individual for customized products, service, information or information relating to a product or service. It cover user system, customization and adaptive web sites. It is a process used to customize the services based on the individual needs, characteristics or preferences. It is commonly based on the attributes of users. Personalization can be applied to web content or Web applications to reach customers quickly and easily. For example, web search engine is personalized based on the past queries, clicked documents and browsing activities of an individual to target marketing activities. The key requirement is the understanding of users need to tailor the web services to maximize the customer satisfaction. Personal user information must be collected to personalize any web application.

Alexander Pretscher, in [4], proposed to explore ways of incorporating users interests in to the search process to improve the results. The user profiles are structured as a concept hierarchy of 4,400 nodes. These are populated by "watching over a users shoulder" while he is surfing. No explicit feedback is necessary. The obtained profiles are shown to converge and to reflect the actual interests quite well. One possible deployment of these profiles is investigated: re-ranking and filtering search results. The increases in performance are moderate, but they are noticeable and they show that fully automatic creation of large hierarchical user profiles is possible.

Kapil Gorenka, in [3], proposed that the search engines have a deterministic behavior as they return the same search results for all users, who submit the same query at certain time. He suggested to integrating user context and preferences in the retrieve process. He builds an ontological model of user interest on the users mobile devices based on his interaction with web personalization of search engine is achieved by re-ranking search results returned by a (yahoo) search engine. He found the training the document classifier on the right set is important and its results are affected by over and under training, thus is not very reliable.

Samira et al., in [2], She proposed that the current search engine do not consider the context of queries during searching process. She suggested a personalized context dependent web search engine model titled "sama search engine". A comparative study between his model and semantic tree model has shown performance effectiveness of his model over other model. The "sama" uses only synonym and not hypernoymy and hyponymy. Also one needs to consider user preferences to achieve personalized web search engine.

M. Mahalakshmi et al., in [1], Personalized Mobile Search Engine has been developed to display any user desired result or reranked result in accordance with the user given query (UGQ) which includes content and the location of the user. It works efficiently with the help of ontology-based, multi user profile. User preferences are framed based on the clickthrough data, ARM (Association rule mining) and Joachims proposed techniques such as spying technique and novel voting method. Query processing is another important aspect which is been supervised by content ontology agent and location ontology agent, query typed (geo or non-geo) and users location (using GPS) respectively.

Reranked list is prepared after analysing the diversity relevance entropies. Like the web search performance, enhanced PMSE also has appeasing users expectation. Evaluation of Personalized Mobile Search Engine (EPMSE), is a client server model. Client captures the user query, convey the needs of the server and displays the re-ranked result. Server performs the search action and prepares the desired output. EPMSE does meta search on engines such as Google, Yahoo.

Chan, in [8], proposed an approach which is mainly directed on assisting users by tailoring and presenting the profiles to each user. Ontological model observes the user behavior and acknowledges the user needs and preferences. It discovers user interests from the query they have submitted, their frequency and clicked documents. It also constructs the user profiles. Profiles are built with semantic relationship since topic ontology is used to provide these relationships between ontological topics. The major advantage is that it also obtains the negative preferences based on the interest scores.

Strasunskas et al., in [12], Most existing systems employed Spreading Activation algorithm with domain and reference ontology, not with topic ontology. Topic ontology is not used for profiling process. Ontologies are mainly used in the task of information retrieval. Nevertheless, there is no efficient analysis on enhancing ontology facets or search performance.

Wen et al., in [7], presented internet users are not satisfied with the results of existing search engines since they provide irrelevant results for user query. Personalization is not efficient on queries of distinct users. Existing profiling approaches use only strong relationships and others are discarded. Classifiers are also used to categorize the documents based on user search preferences.

Sieg et al., in [6], proposed Interest score weight is assigned to the vectors on the beginning of downloaded and browsed documents in order to obtain the user current interest. Most frequent topics are recommended to the user. It also explains the information of how user preferences or interests are applied to personalize the search results.

Daoud et al., in [5], proposed a personalized search engine is automatically learn the users interest and preferences without any human interference. User preferences are captured using the search or click history relevant to the user interest. This approach improves the search quality and personalization quality. Search provides ranked pages which the user clicks. Personalization improves the quality of the retrieval process and session data is thin to personalize perfectly. Session is a time closest order of actions done by the same user.

Leung et al., in [10], proposed six concept based user profiling methods that considered both users positive and negative preferences. P Joachims−C, P mJoachims−C, P SpyNB−C, P Click+Joachims−C, P Click+mJoachims−C and P Click+SpyNB−C. In most recent developments, multi- purpose ontology based search process integrates user interests to get better search results. User profiles are ordered as a concept hierarchy and it allows automatic creation of huge structured user profiles.

Nour Salama, in [11], This has ultimately led to the introduction of context aware web search to obtain more adequate results. Proposed a context aware web search system architecture that is based on social networks context. In the query formulation stage has experimented with multiple techniques to see which one yields the best results. The focus on using social context obtained from user social networks to refine search queries. Our initial target is to proposed a system that ultimately demonstrate, the effectiveness of integrating this type of context when conducting mobile search. But doesn't extract all types of social context from the users Facebook profiles and use them for query refinement. Also include all types of queries without any limitations and tackle all different domains as well in mobile web search. Also experiment with different ranking techniques and see whether they have positive impact on the results or not.

Kenneth Wai-Ting et al., in [9] , proposed a personalized mobile search engine that captures the users preferences in the form of concepts by mining their clickthrough data. Due to the importance of location information in mobile search, personalized mobile search engine classifies these concepts into content concepts and location concepts. In addition, users locations (positioned by GPS) are used to supplement the location concepts in personalized mobile search engine. Proposed personalized mobile search engine to extract and learn a user content and location preferences based on the users click-through. Also propose two privacy parameters, minDistance and expRatio, to address privacy issues in personalized mobile search engine by allowing users to control the amount of personal information exposed to the personalized mobile search engine server. The privacy parameters facilitate smooth control of privacy exposure while maintaining good ranking quality. Investigate method to exploit regular travel patterns and query patterns from the GPS and click-through data to further enhance the personalization effectiveness of mobile search engine.

III. PROPOSED APPROACH

The proposed approach constitutes following main steps:

1. Creating the API for the proposed PMSE.

2. Creation of Twitter API.

3. Train the ANN and acquire Preference profile of the user.

4. Re-ranking the search results.

Train the ANN and Generate Preference User Profile

User profile depicts users interests and preferences, these preferences are collected from the users twitter tweets. In user profile consists of a set of categories and for each category, a set of five keywords with weights.

Each category represents a user interest in that category. When the user tweets with the keywords in the twitter, that builds the stronger interest and preference of the user. The weight of a word in a category reflects the significance of the word in representing the users' interest in that category. For example, if the word "Fruit" has a high weight in the category "Health", then the occurrence of the word "Fruit" in tweets of the user has a tendency to indicate that the category "Health" is of interest for the user. An user profile weighted automatically from the users tweets by applying Artificial Neural Network (ANN) as shown in Fig 3.1.

From the twitter account latest tweets are downloaded (which forms the dataset for the ANN), then using one personalization strategy Feed-forward neural network is used to weight the tweets. The data collected from twitter and then used to evaluate to find the preference of user. In detail query re-ranking and evaluation are completed in the following steps:

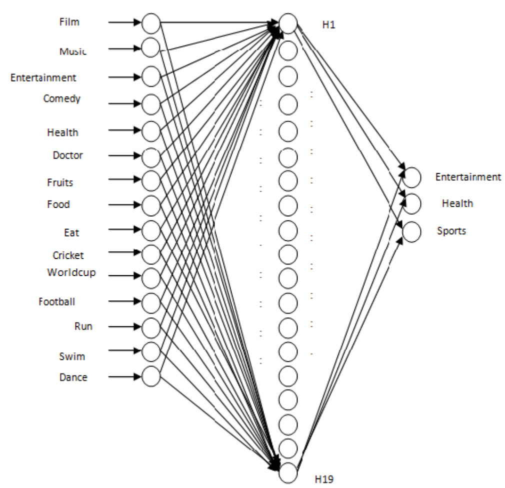

Figure 3.1: Neural Network for PMSE

- Downloading the top 10 search results from Google search engine for testing query.
- Train the ANN over the tweets downloaded. Find the preference in which the user is recently interested.
- Adding the weights for all the neurons the ANN give one of the preferences from Health, Sports and Entertainment.

Re-ranking framework for PMSE search results

The Preferences are used to re-rank the results using tokenize every text, a personalized score for each web link is used to weight that link and rank the list in descending scores. The simplest kind of neural network of a single layer perceptron network, which consists of a single layer of output nodes is used. The inputs are fed directly to the outputs via a series of weights. In this way it can be consider the simplest kind of feed-forward network. The sum of the product of the weights and the input is calculated in each node. The Re-ranking framework for a new user there are following steps are executed:

- Train the ANN and generate preference profile of the user.
- Re-rank the result using score calculation.

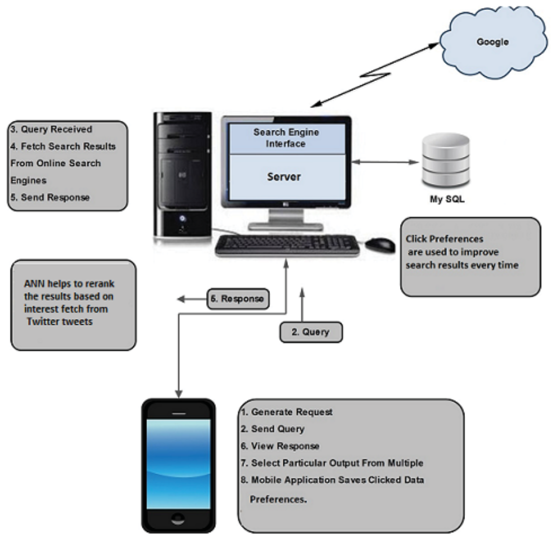

Figure 3.2: Design Architecture of Computation Load Sharing for Search

A. Design Architecture of Computation Load Sharing for PMSE

The design for PMSE is done adopting the search approach which takes one of the commercial search engines, such as Google. To perform a search action for given query. The PMSE user requests a query and submits it, displays the results and collects the time stamp in order to complete the search. The PMSE is made responsible for handling heavy tasks such as to send the requests to a commercial search engine as well as training and reranking of search results before they are returned to the user.

The user profile is created before any search is fired or if once created can be used unless the user thinks he has tweets a lots and his preferences have changed. So there is no need to store the user preference on server, thus preserving privacy of the users. The data user has shared with others over twitter is used to create the preference for search. This has reduced the exposer of user's information to search engine server.

Also as the query passes through personalized search engine and rerank results are displayed in PMSE environment, the server has less chance of knowing which data found useful.

B. Mathematical model

Coefficient of relevancy

Coefficient of relevancy is defined as percentage of information contain in the data. Mathematically, Coefficient of relevancy is defined as:

$Rd = -\log P(Ri) \times 100$ (1)

Where P(Ri) : Probability of rerank link

$P(Ri) = Rank/Total\ Search\ on\ Page \times P(Si)$ (2)

Where P(Si) : Relevant data in content

In this case, $P(Si)=1/10$

As all links are equiprobable for the content of data,

In this case,

$P(Ri) = Rank/10 \times 1/10$

$P(Ri) = Rank/100$

$Rd = [-\log_2 (Rank/100)] \times 100$

In case of "Doctor", "bestdoctor.com" is at 9th rank in net user search engine. But, PMSE Search engine gives the rank 6th to "bestdoctor.com". The information contain in the link is:

$-\log P(Ri) = -\log_2 (6/10\times1/10)$ (3)

$= -\log_2 (100/6)$

$= -\log_{10} [(100/6) /(-\log_{10} 2)]$

$= 4.0588$bits

Now, coefficient of relevancy is,

$Rd = -\log P(Ri) \times 100$

$= 405.88$bits

Rank Correlation Coefficient:
Spearman's rank correlation coefficient:
$\rho = 1 - [(6\Sigma d^2 i) / (n(n^2 - 1))]$ (4)
Where di : are differences in ranks
This coefficient correlates two ranking. In our case, we wish to check whether reranking of URL is necessary or not. If rank coefficient correlation between rank or URL given by web search engine and ranks of URL after reranking by personalize search engine is less than 0.5 then, obviously rerank URL give more relevant. Find one rank correlation coefficient. In case of "Health",
Search Query = "Doctor"
Spearman rank correlation coefficient,
$\rho = 1 - [(6\Sigma d^2 i) /(n(n^2 - 1))]$
$\rho = 1 - [(6(77)) /(10(10^2 - 1))] = 1 - 0.46666$
$\rho = 0.533 \cong 0.5$

Table 3.1: Correlation Coefficient of Doctor Query

Link No	Google Links	Rerank Links No	di	di^2
1	https://en.wikipedia.org/wiki/Doctor	1	0	0
2	http://www.thedoctorstv.com/	2	0	0
3	http://en.wikipedia.org/?title=Physician	3	0	0
4	http://www.doctorswithoutborders.org/	8	-4	16
5	https://en.wikipedia.org/wiki/TheDoctor	5	0	0
6	http://www.bestdoctors.com/	9	-3	9
7	http://www.imdb.com/title/tt0101746/	10	-3	9
8	https://en.wikipedia.org/wiki/DoctorWho	3	5	25
9	http://www.bbcamerica.com/shows/doctorwho	6	3	9
10	https://www.youtube.com/user/doctorwho	7	3	9
Sum				Σ=77

This rerank results are more relevant than web search engine ranking.
Search Query=Food

Table 3.2: Correlation Coefficient of Food Query

Link No	Google Links	Rerank Links No	di	di^2
1	http://www.foodnetwork.com/	1	0	0
2	https://en.wikipedia.org/wiki/Food	5	-3	9
3	http://www.food.com/	3	0	0
4	http://www.sciencedirect.com/science/journal	7	-3	9
5	http://www.fda.gov/Food/	9	-4	16
6	https://www.yahoo.com/food/	10	-4	16
7	https://www.reddit.com/r/food/	4	3	9
8	http://www.wholefoodsmarket.com/	8	0	0
9	http://food-la.com/	2	7	49
10	http://www.buzzfeed.com/food	6	4	16
Sum				Σ=124

And for the search query food the Correlation Coefficient comes to be $\rho = 0.2484 < 0.5$ which are more relevant than web search engine ranking.

C. Algorithm

The most common neural network model is the MLP (Multilayer Perceptron). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The MLP and many other neural networks learn using an algorithm called back propagation. With back propagation input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and error is computed. This error is then feedback (back propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training".

Algorithm 1 Artificial Neural Network (back-propagation)
1: START
2: DEFINE max iterations, learning rate
3: DEFINE layers of neurons, neurons in each layer, error
4: Fill input features //it normalize the tweet and provide input to training.
5: Fill output features //normalize output parameter for interest domain
6: (eg. 0-sport, 1-health and 2-entertainment etc.)
7: for all iterations I from 0 to MAX apply training { //for each neuron in every layer
8: error(A)=out(A)(1-out(A))(Target(A)-out(A)) //calculate errors of output neuron.

```
error(B)=out(B)(1-out(B))(Target(B)-out(B))          //change output layer weight.
W(A)=W(A)+error(A)
W(B)=W(B)+error(B)                                   //calculate(back-propagate) hidden layer error
error(A)=out(A)(1-out(A))(W(A)+out(A))
error(B)=out(B)(1-out(B))(W(B)+out(B))               // Change hidden layer weight.
W(A)=W(A)+ in(A)
W(B)=W(B)+ in(B) }
END
```

A feed forward neural network is an artificial neural network where connections between the units do not form a cycle. This is different from recurrent neural networks. The feed forward neural network is first and simplest type of artificial neural network devised.

Algorithm 2 Score calculation to Re-Rank Links

The score calculation is done by using re-ranking algorithm which is presented here.

Algorithm: Reranking

```
DEFINE interest domain, score
START        //get all domain specific keywords
for all results from google
DEFINE single result=list<all results>
DEFINE list<words>=SPLIT single result
score=score calculation {}
END loop     //now rerank results according to score
for START to all score-1
for START+1 to all score
DEFINE score1, score2
CHECK score2 > score1
Define temp
temp=score1
score1=score2
score2=temp
END start+1
END start    //finally reranked results are in score
```

In this network, the information moves in only one direction, forward from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycle or loops in the network.

IV. Result and Discussion

The proposed methodology for PMSE can prove to retrieve relevant and re-rank the most relevant at the top of search result according to the users profile. The interest is build from the most recent tweets (social network profile).

A. *Performance Metrics*

A performance metrics determines a behavior and performance of output values. From the users point of view, most people would generally agree to the prescription that a retrieval system should behave as "retrieve as many relevant items as possible and as few non-relevant items as possible in response to a request query". A document or a link is judged by the user to be of interest, it is relevant. Otherwise it is non-relevant. Roughly speaking, the former criterion corresponds to the concept of recall and the latter one pertains to the notion of precision.

Precision and Recall of Personalized Search Engine

Recall and precision are often conflicting goals in the sense that if one wants to see more relevant items (i.e. to increase recall level), usually more nonrelevant ones are also retrieved (i.e. precision decreases). Recall and precision are measured after the system determines an reranking on the documents links in its results in response to a user query[13]. This reranking represents the system judgment of how well each link relates to the user need. On the basis of this judgment, the system can be said to retrieve links that receive sufficiently high ranks.

Recall is defined as the ratio of the number of relevant documents that are retrieved to the total number of relevant documents. Precision is the number of relevant documents retrieved divided by the number of retrieved documents. In particular, a recall-precision graph is often used as a combined evaluation measure of retrieval systems. Such a graph, given an arbitrary recall point tells us the corresponding precision value.

B. Experimental Results

The experimental results are shown using re-ranking algorithm and Score calculation to re-rank Links. The results are tabulated and presented to determine the difference between Google and PMSE Re-ranking with precision and recall.

Table 4.1 to 4.3 shows the results for queries searched by three users with three distinct preferences. The User01 has preference in health field at the instant of firing the query. The User02 has preference in sport field at the instant of firing the query and the User03 has preference in entertainment field at the instant of firing the query. User Profile parameters are extracted from users twitter account.

Table 4.1: Experimental Results for User01 with Health as Preference

User 01 Queries	Total Link	No. of Results Re-ranked	No. of Relevant Results	Precision	Recall	Time for Re-ranking (m-sec)
Health	10	7	5	0.7143	0.6250	30
Doctor	10	7	4	0.5714	0.5714	9
Fruits	10	8	7	0.8750	0.7778	16
Food	10	7	5	0.7143	0.6250	16
Eat	10	9	7	0.7778	0.8750	26

In simple terms, high precision means that an algorithm returned substantially more relevant results than irrelevant, while high recall means that an algorithm returned most of the relevant results.

Table 4.2: Experimental Results for User02 with Sport as Preference

User 02 Queries	Total Link	No. of Results Re-ranked	No. of Relevant Results	Precision	Recall	Time for Re-ranking (m-sec)
Cricket	10	4	3	0.7500	0.3333	23
Worldcup	10	1	1	1.0000	0.1000	25
Football	10	2	2	1.0000	0.2000	21
Run	10	2	1	0.5000	0.1111	12
Swim	10	4	2	0.5000	0.2500	31

As an example, in an information retrieval scenario, the instances are link or documents and the task is to return a set of relevant links or documents given a search query or term are equivalently, to assign each link or document to one of two categories, “relevant” and “not relevant”. Here the “relevant” links or documents are simply those that belong to the “relevant” category.

Recall is defined as the number of relevant documents retrieved by a search divided by the total number of existing relevant documents, while precision is defined as the number of relevant documents retrieved by a search divided by the total number of documents retrieved by that search[13].

In information retrieval and classification, precision is the fraction of retrieved instances that are relevant, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance. So, precision is ’how useful the search results are’, and recall is ’how complete the results are’. Precision can be seen as a measure of exactness or quality, whereas recall is a measure of completeness or quantity.

Precision = [(relevant documents) ∩ (retrieved documents)] /(retrieved documents) (5)

Recall = [(relevant documents) ∩ (retrieved documents)] / (relevant documents) (6)

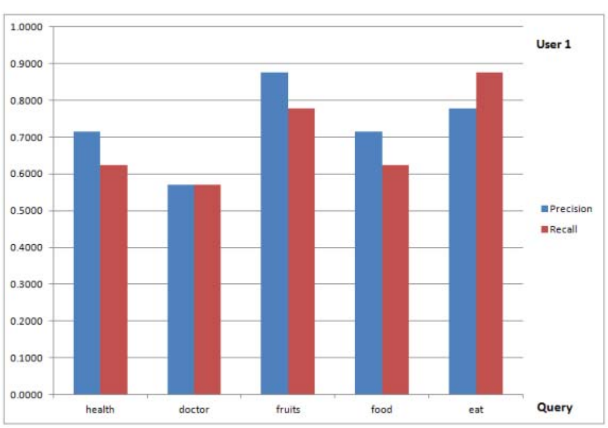

Figure 4.1: User 01 Precision and Recall

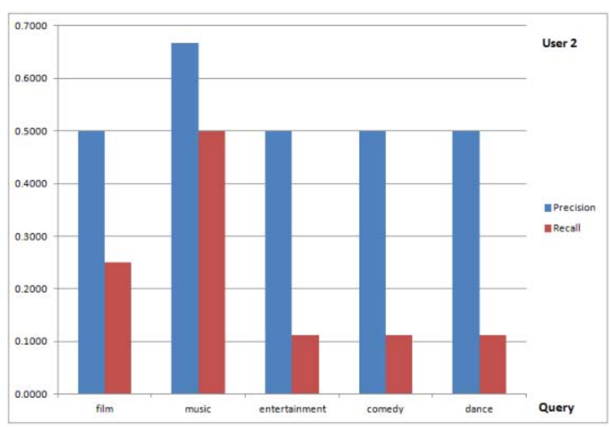

Figure 4.2: User 02 Precision and Recall

The Fig 4.1 & 4.2 shows result for User 01,02 respectively.

For PMSE, a perfect precision score of 1.0 means that every result retrieved by a search was relevant (but says nothing about whether all relevant documents were retrieved) whereas a perfect recall score of 1.0 means that all relevant documents were retrieved by the search (but says nothing about how many irrelevant documents were also retrieved).

C. Discussion

From the evaluations of Table 4.1, Table 4.2 along with Fig 4.1, 4.2 it is revealed that proposed PMSE approach is capable of giving more relevant results. The time taken showed that a very small fraction of time is required to show reranked results to the user. This proves that without spending much time, a personalized result can be presented.

The computation load for reranking is shared by user which gives high levels of precision (0.5 and above) and moderate recall levels calculated using Equations (5) and (6).

V.CONCLUSION

Contribution of computation load sharing personalized mobile search engine provides a novel proposition of keeping the personal information intact and producing personalized reranked search result. The PMSE shows rerank results based on user profile, so as to met the specific requirements. It also proves that when computation load is shared on user side on expense of time taken by normal web search engine, PMSE provides the user with relevant results. Back propagation algorithm, a vital tool of ANN was used effectively to extract the users interest in form of health, sports and entertainment from their tweets. In case of query word ”Football” rank correlation coefficient was 0.4061 which shows that the reranked URL links are more relevant than the links given by normal web search engine. The average precision and recall values were found as 0.6713 and 0.3701 respectively when the user profile is used.A precision score of 0.6713 means that every result retrieved by a search was relevant to the user. Thats why the personalization of mobile search engine is useful for internet user. By keeping the user information on user side privacy was kept in-tact. Computational load was taken on user side which shows delay by a fraction of second in result display, which may be taken as trade off for personalization.

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