International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-9 Issue-3 September 2020

Trajectory Based Location Prediction and Enriched Ontological User Profiles for Efficient Website Recommendation

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Abstract: ***The spread over of huge amount of information in the vast area of internet makes difficult for the users to obtain the search items that are relevant to them. The adoption of web usage mining helps to discover the accurate search results that satisfy their requirements. To fulfill their need, it is necessary to know their preferences of search at various contexts. In general, the user profiles are used to determine the taste of the users. The traditional method of user profiling does not provide a complete detail regarding their search. In addition, the search preference of the individuals varies in accordance with time and location. The user profiles do not update the dynamic location changes of the users. The traditional location based recommendation systems suggest the search results based on their location to compensate the dynamic preferences of the users. The drawbacks of the conventional systems are resolved by the Location and User Profile (LUP) based recommendation system. To attain a higher user satisfaction by providing accurate search results, a trajectory based location prediction and enriched ontological user profiles to recommend the appropriate websites to the users is proposed in this paper. In this article, we suggest a novel method for predicting the location of a user's profile using Semantic Trajectory Pattern (STP), based on both the place and semantic features of user trajectories. Our prediction model 's central concept is based on a novel cluster-based prediction approach that evaluates the location of user search data based on the regular activities of related users in the same cluster, calculated by evaluating the typical behavior of users in semantic trajectories. The combination of location information along with enriched ontological user profiles improves the efficiency of the proposed web recommendation system. The experimental results are evaluated using recall, precision and F-measure metrics.***

Keywords: Geographic mining, Ontological user profiles, semantic mining, Trajectory pattern mining, Web usage mining.

I. INTRODUCTION

World Wide Web (WWW) is a place where people get a large amount of information relevant to their search. Due to the rapid growth in the development of internet, the users get an enormous expanse of search results for their query. The search intentions of the users vary from each other based on various strategies. For example in an online shopping search, the preferences and tastes of the users are subjected to change according to their characteristics.

Revised Manuscript Received on August 28, 2020.
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The main objective of the users is to receive a set of URLs to attain the information for which they are searching for.

As the search requirement of individual user has certain variations, it is necessary for the search engines to provide the results to satisfy their needs.

Here comes the necessity of web mining to extract the desired information from a pool of search results. Web mining applies various mining technique to discover the search by understanding the customer behavior (Jagan & Rajagopalan, 2015). Web mining has its classification into three types including web content mining, web structure mining, and web usage mining. The behavior analysis of user plays a vital role in the extraction of relevant websites that fulfills the user's need. The usage patterns and the browsing behavior of the users are utilized in the web usage mining applications to provide accurate search results. Personalization and recommendation system can serve the users by eliminating the irrelevant results produced by the search engine. Personalization is the process of customizing the search results with respect to the behavior patterns and characteristics of the users(Mehtaa, Parekh, Modi, & Solanki,2012). Recommendation systems project the recommended websites based on the personalization. User profiling is one of the best sources for web search personalization. The profiles of the users hold their characteristics from which their preferences can be derived.Since, a single keyword has several synonyms the search results become irrelevant. The traditional user profiling techniques do not consider the search context of the user before generating the search results. This leads to the need of ontology based user profiling to retrieve the results without the direct observation of user patterns. Once the user profiles are annotated with ontology, it facilitates the communication between the users having similar profiles. The reasoning time of the search engine was reduced by combing both the implicit and explicit interests of the users. User profiling is the first and foremost stage of all the personalized web search engines to gather the interests and preferences of the individual users. The accuracy and performance of the recommendation systems rely on the generated user profiles. The user profiling is categorized into two types such as document based user profiling and concept based user profiling. The document based user profiling method collects the click through data of each user to consolidate their search history.

The concept based user profiling constructs the user profiles using the topic of their search by extracting the types of search topics. As the search of individual user has certain variation, the preferences of the same user may vary according to the location. The user profiling alone will not help to get the accurate search results, when the user posts a query from various locations.

Hence, location prediction has a significant part in search personalization and recommendation. The location based recommendation systems suggest the recommendations relevant to the current user location.

A. Motivation

The web users are looking for a search engine that fits for all kind of search activities. The representation of client inclinations, seek connection, or the undertaking connection is for the most part non-existent in most web crawlers. Powerful personalization of data access includes two vital difficulties: precisely recognizing the client setting and sorting out the data in a manner that matches the specific setting. Since the obtaining of client interests and inclinations is a vital component in recognizing the client connection, most customized pursuit frameworks utilize a client demonstrating segment. The survey demonstrates that clients frequently begin perusing through pages that are returned by less exact questions which are subjectively simple to develop. Since the clients are hesitant to indicate their hidden expectation and hunt objectives, personalization must seek after systems that influence verifiable data about the client's advantages. The application of ontologies enhanced the route viability and additionally customized Web look and scanning, particularly when joined with the thought of consequently creating semantically advanced preference based client profiles.

There are several challenges in location based recommendation system.

- The location information is not able to produce accurate results without the help of user preferences.
- It is difficult for the location prediction systems to adapt in the dynamically changing environment.
- The process of acquiring the current location of all the users is a crucial task, when there is an enormous amount of population.
- The lack of enriched user profile leads to inaccurate results.
- Managing complexity of the location based personalization system is one of the most challenging issues.

To overcome these issues, this paper proposed a Trajectory based location prediction and enriched ontological user profiles to recommend the appropriate websites to the users. The ontological profiles of the users contain the detailed information of the users and their preferences. The trajectory pattern mining algorithms are applied for identifying the location of users. The location information along with the preference contexts provides personalized search results for the web users.

The remaining sections of the paper are organized as follows. Section II reviews the existing techniques related to ontological user profile generation and location based recommender systems. Section III describes the proposed Location and User Profile (LUP) based web recommendation system. Section IV discusses the performance analysis of the proposed LUP recommendation system. Section V concludes the paper along with the future work.

II. RELATED WORK

This section presents the literature review of the traditional techniques related to user profile and location-aware recommendation systems for website recommendation. A context-aware recommendation system that utilized the location information was proposed to mine the web services. The preferences of the users and their geographical location were considered for providing the required web services. The social network profile of the users was utilized for identifying their search interests and locations were followed using a discrete Hidden Markov Model (HMM). The present user feelings were determined by a decision tree, which was provided as the input for HMM (Savage, Baranski, Chavez, & Höllerer, 2012). A social network based recommendation system, namely, SoCo was introduced to improve the performance of web mining. The context and social network information of the users were combined to produce the search results. The individual users were allowed to rate each item in the website. A user-item matrixwas generated to cluster the items with same ratings. The user similarity was determined using the Pearson correlation coefficient. The missing preferences of the user were detected by factorizing the user-item matrix. Finally, the preferences were mined by combining a social regularization term and matrix factorization concept (X. Liu & Aberer, 2013). A personalized recommendation system was proposed to recommend the websites by mining the geo-tagged information available in social media. The travel experiences and their places of interest were collected from the photos tagged in Flickr. The travel history of the user from one place to another was determined to generate their favorite places of tourism. The suggested system generated better search results regarding the unknown locations (Majid et al., 2013). An intelligent recommendation system was suggested to resolve issues in conventional tourist guide applications. Personalization and content filtering were integrated for decision making purpose in the intelligent recommendation system. The demographic profiling was utilized to estimate the weight and significance of various search items. The information overload due to irrelevant recommendations was reduced to make the users to concentrate more on their preferred search. The Global Positioning System (GPS), Global System for Mobile communication (GSM) and Wireless-Fidelity (Wi-Fi) were used to predict the locations. Fuzzy logic, Artificial Neural Network (ANN) and Principal Component Analysis (PCA) were applied for decision making purposes (Meehan, Lunney, Curran, & McCaughey, 2013). A music recommender system was proposed to satisfy the short term music needs of users.

The context-related information was collected using a probabilistic model to enhance the accuracy of user preference. The daily activities of the users were provided as user context for recommendation. The suggested music recommender system increased the usability of the application (Wang, Rosenblum, & Wang, 2012). A Location-Aware Recommender System (LARS) was proposed to generate accurate recommendations. It considered the spatial and location based information for enhancing the quality of recommendations.

The ratings are utilized to increase the system scalability without compromising the recommendation results. LARS was proven as an efficient and scalable recommender system, when compared to the traditional systems (Levandoski, Sarwat, Eldawy, & Mokbel, 2012).
An ontology-based user profile learning method was proposed to study the interests of users. Bayesian networks, ontologies and association rules were used to enrich the user profiles, thereby enhancing the performance of the web service agent (Eyharabide & Amandi, 2012). A personalized web search engine was proposed to narrow down the recommendations based on user's intention. The personalization was performed by combining user profiling and query reformulation. The relevant search results were determined by the analysis of user's search history, which was stored in the web log files. The history based results were sorted and ranked based on their ratings. The link rate and the user value that was derived from the Vector Space Model (VSM) were used to rank the results. The keyword suggestions to attain the preferred search links were also provided (Makvana, Shah, & Shah, 2014). A Location Context-Aware Recommendation System (LCARS) was introduced to perform the web search based on interest and location of the user. A threshold algorithm was applied
to develop query processing technique that enhances the performance of the recommender system. The data sparsity issue in user-item matrix was resolved by combining the location and interest profiles (Yin, Sun, Cui, Hu, & Chen, 2013). A novel activity monitoring system that utilized the Radio Frequency Identification (RFID) was introduced to mine the frequent trajectory patterns. It offered a cost effective solution by eliminating the transceivers and receivers from the system. An array of RF tags was arranged in an order for activity monitoring. The data mining techniques were also incorporated for sequential pattern identification (Y. Liu, Zhao, Chen, Pei, & Han, 2012). A random walk was applied to identify the new locations in a location based recommendation systems in social networks. The behavioral and spatial patterns were used to recommend the locations for the mobile users. The filtering methods were applied to produce the accurate results. The random walks were personalized by combining the user-place graph and the visited locations (Noulas, Scellato, Lathia, & Mascolo,2012).Various location-based recommendation systems in the social networks were survey to bridge the gap between digital data and the social locations. This survey included the data source, methodology and objective of different recommendation systems (Bao, Zheng, Wilkie, & Mokbel, 2015). The matrix factorization was fused with the Point-of-Interest to determine the location of social network users. A multi-center Gaussian model was applied to check the probability of the users' location. The social and the geographical factors were integrated together to frame the factorization matrix. The distance between the locations were utilized for the efficient functioning of the system (Cheng, Yang, King, & Lyu, 2012). The spatio-temporal contexts of the users were predicted using the proposed mobile location prediction method. The locations were determined by the combination of spatial and temporal characteristics that were trained by the smoothing techniques. The experiments were conducted by utilizingthe Nokia Mobile Data Challenge dataset. Totally, nine baseline models were applied to evaluate proposed sophisticated location prediction system. (Gao, Tang, & Liu, 2012). The subsequent locations of the mobile users were identified by the Hidden Markov Model (HMM). In accordance with the characteristics of the users, the location histories were clustered together. Each and every cluster were trained using the HMM model and the model was tested by the GeoLife project (Mathew, Raposo, & Martins, 2012).A cluster based location prediction system, namely, TrajUtiRec was proposed to recommend the items to the user based on their location. The items preferred by the users vary, as their location changes. The users with similar characteristics are clustered together and the high utility item set mining algorithm was applied to determine the highly preferred itemset (Ying et al., 2014). (M.jenifer et al., 2018) paper presents a location-aware collaborative filtering (CF) and association-based clustering approach for web service recommendation. The similarity between users and web services is measured by considering the personalized deviation of QoS of web services and QoS experiences of users. Hence, web service recommendation becomes a really challenging and time-consuming task due to the large search space. To reduce the search space, clustering of the web services into clusters is an efficient approach. The services are clustered based on the semantic similarity and association between them. Our proposed approach recommends services using the generated clusters and services with better QoS values.

III. PROPOSED WORK

This section presents the overall description of the proposed user profile and location based recommendation system. The suggested recommendation system is a combination of trajectory based location prediction and enriched ontological user profiles.

A. Enriched Ontological User Profiles

The context can be defined as the varied intention of users, while they search for different information. The user's context can be determined by the combination of present and the previous activities of the particular user. Commonly, the domain interests of the users are derived from an existing knowledgebase.

The explicit domain knowledge bases are difficult to be updated with current user activities. Hence, in the proposed recommendation system the implicit way of ontological user profile generation is carried out. Figure 1 show the general ontology of the user profiles. The process of mapping the relationship between concepts is termed as ontology. The ontology knowledge base consists of a set of objects and the relationship descriptions of the domain. The ontology is organized in a tree structure, which consists of existing web topics based on user preference.

The proposed recommendation system personalizes the search results by applying the ontology based user contexts. The results obtained due to the processing of a given query are reranked according to the user preference and context. The domain concepts in the ontology are provided with interest scores using the implicit user behavior. The semantic knowledge of the web search engine is obtained from the domain ontology. The ontology based user profiling resolves the cold-start issue in the web recommendation systems. The current behaviors of the users are matched with the predefined ontologies to provide relevant results. The similarity score between the users and the concepts are computed to annotate each concept with a similarity score. The objects in the reference ontology signify the user profiles and all the concepts are provided with an initial score of one. Figure 2 represents the overall flow of enriched ontological user profiles generation (David Martin et.al).

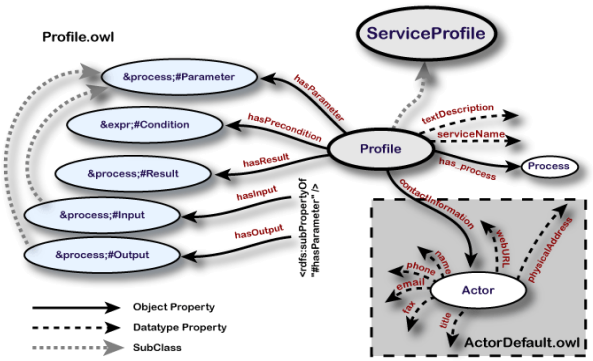

Figure 1 General ontology of a user profile

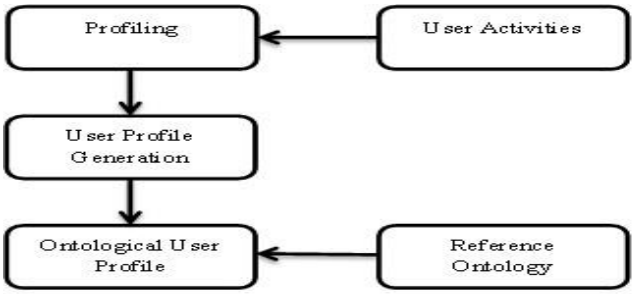

Figure 2 Flow of enriched ontological user profile generation

As the users visits the page, the interest scores of each concept is dynamically updated. The existing concepts in the reference ontology are represented using the web pages as training data. The documents in the training data have a vector and the documents are represented using certain weights. The document vector consists of the weight of all the instances which denoted by $\vec{d} = \{w_1, w_2, \dots w_n\}$. The weights of the documents are estimated using the frequencies of the term and inverse documents.

The documents are grouped based on their sub concepts as follows:

$$D(n) = [\cup_{n' \in S(n)} Docs(n')] \cup \{d_1^n, d_2^n, \dots d_1^n\} \text{ --- (1)}$$

The term vector is estimated as follows:

$$\vec{n} = {[\sum_{d \in Docs(n)} \vec{d}]}/{|Docs(n)|}$$

The interest score of each website is updated in the ontological user profiles. The personalized search results are obtained by reranking the documents in the ontological user profiles. The similarity between the document and the user query is calculated using the cosine similarity measure. The rank score and the interest score are multiplied to find the best matching query.

B. Trajectory Based Location Prediction

The ontological user profiles are generated and now it is necessary to predict the geographical location of the users. The geographical locations of the users are determined using the trajectory pattern mining technique. The sequential, temporal and periodic patterns can be used to identify the location of the users. The spatiotemporal trajectories have the place and time of visit of a particular location by the user. The trajectory construction is carried out after the time and place analysis. The start time and finish time of the user at an exact location is predicted. The duration of staying at a location is recorded in the document as $d \in \{T_1, T_2, \dots T_n\}$. The patterns are then extracted as follows:

- Clustering
- Score computation
- finalizing the patterns based on score

The time period is utilized for grouping the trajectories that have similar patterns. The clustering involves centroid computation and counter initialization. The centroid of the cluster is compared with the threshold value to assign an ID to each transaction. Figure 3 shows the overall flow of location prediction. The search interest of users at various places is determined by the geographic and demographic features. The demographic features are defined in the ontological user profiles, which includes gender, age, place of work, search interests, home location of the user, etc. The search topics of the users at new places can also be easily identified. The activities of the users enhance the accuracy of user's location. The process of location prediction involves three steps such as data preprocessing, semantic mining and geographic mining. The location sequences are identified by data preprocessing step, semantic behaviors are extracted by semantic mining step, whereas the geographical behaviors are gathered from geographical mining. The probability of the location is estimated using a scoring function. While computing the probability, the geographical and semantic information are not taken into account. For optimal path selection, the geographic and semantic scores become essential.

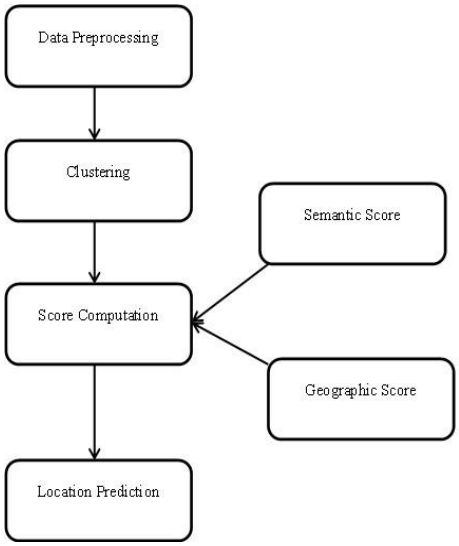

Figure 3 Overall flow of the location prediction in LUP

C. Data Preprocessing

Initially, the location, where the users halt for a certain amount of time is located.The amount of time the user stays in a particular location is identified by finding the time difference between entry time and exit time. The stay time is compared with the time threshold specified by the user. If the stay time is lesser than the threshold, the locations are piggy backed to form a location sequence.

D. Semantic mining

The semantic mining contains the ontologies at the core layer of semantic web, which denotes the random environment. The conceptualization of the shared information is explicitly framed in the ontology structure of the websites. The concepts involved are formalized in terms of hierarchical relations. It also specifies the relationship between one or more concepts available in the ontological structures. The ontologies in the sematic web are formulated using Web Ontology Language (OWL) and Resource Description Framework (RDF). The instances in the ontologies are described in an understandable format, whereas the metadata is available in machine readable form. The process of extracting the ontology from a particular website is a crucial task. The structure of the ontology can be learned using some of the machine learning techniques. Several ontologies are combined to generate a multi-domain specific ontology that is more helpful in the extraction of specific information regarding the search preferences of the users. Mapping and merging are the two main operations that take place in the formation of ontological structure. The process of relating the concepts available in a particular ontology with the concepts of remaining ontologies is termed as ontology mapping. The process of combining the concepts of an ontology with one or more ontologies is termed as ontology merging. These operations produce the semantic details of the user search in various domains with respect to the individual's interest. It is necessary to automate the process of information extraction for the construction of semantic web because the manual markups done by the users are not updated in the existing structure. The accuracy of mining the websites based on user preference can be enhanced using the semantic mining approaches. The clustering of relevant webpages is done based on the data derived from preprocessing. The ontologies are utilized for preprocessing the input data, in which the relevant features are selected and grouped together. The user search is customized by combining the concepts in the hierarchy of ontologies and several search decisions. The semantics are generated from the ontological user profiles that contain the search preferences of each and every user. Once stay locations are identified, these sequences are used to mine the semantic patterns. The semantic labels were assigned for the location sequences collected from the preprocessing step. The decision making process becomes simple by the utilization of semantic behaviors. The locations are organized into a tree structure to make the prediction process easier. The Semantic Trajectory Pattern (STP) tree is constructed to represent the locations in a precise manner. The STP tree suffers from the sharp boundary problems, which in turn leads to location inaccuracy. Hence, a space partition approach is incorporated with the STP tree to predict the location. The working process of semantic mining is shown in Figure 4(Josh Jia-Ching Ying et al).

The semantic score is calculated as

$$semantic\ score = \alpha \times (location_0) \rightarrow (location_1)$$

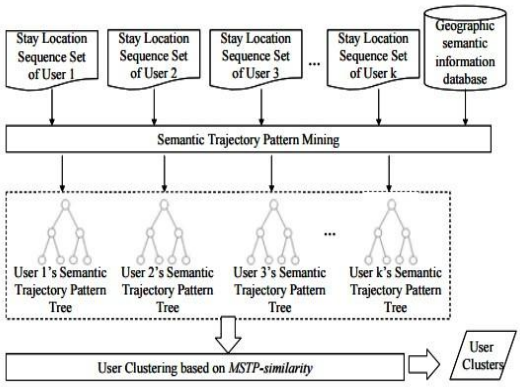

Figure 4 Working of Semantic mining

Steps for Semantic Mining

Input: A semantic trajectory pattern set STP-Set
Output: A semantic trajectory pattern tree STP-Tree
1 root ⇐ CreateNode(∅,∅,∅)
2 foreach semantic trajectory pattern STP in STP-Set do
3 node ⇐ root
4 foreach semantic S in STP do
5 if ∃ a child nc of node s.t. S ⊆ nc.semantic then
6 node ⇐ nc
7 if S is the last element in STP then
8 node.support = STP.support
9 end
10 else
11 child ⇐ CreateNode(S, STP.support ,∅)
12 node.appendChild(child)
13 node ⇐ child
14 end
15 end
16 end
17 return root

E. Geographic Mining

The patterns mined by the semantic mining are not enough to personalize the user preferences. Hence, geographic mining is applied to identify the exact locations of the users to provide them the desired search results. The characteristics of the users do not provide the exact user preferences. In order to resolve the problem of data insufficiency, the semantic clusters are derived for further β processing. The location pattern is discovered based on the current location of the user. If the derived location sequence is very long, the efficiency of the result decreases. The patterns that start from the stay location are predicted by considering the current location as the prefix. Figure 5((Josh Jia-Ching Ying et al) represents the work flow of geographic mining.

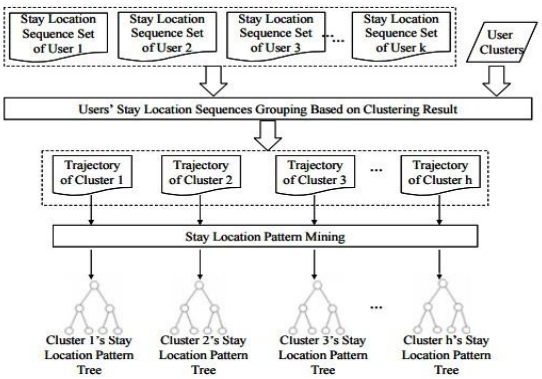

Figure 5 Working of Geographic Mining

Steps in Geographic score mining

Input: A stay location pattern tree SLP-Tree A stay location sequence S Discount parameter α
Output: A set of candidate path along with GeographicScore
1 CandidateSet ⇐ ∅
2 for k ⇐ 1 to |S|
3 node ⇐ SLP-Tree.root
4 Candidate.Sequence ⇐ ∅
5 Candidate.Score ⇐ 0
6 for j ⇐k to |S|
7 if ∃ a child nc of node s.t. Sj=nc.location then
8 node ⇐ nc
9 Candidate.Sequence.append (nc.location)
10 Candidate.Score ⇐ Candidate.Score +
11 (α|S|-j × node.support)
12 end
13 end
14 if j=|S| and Candidate.Score>0 then
15 CandidateSet.add(Candidate)
16 end
17 end
18 return CandidateSet

The user's present location is also added to the existing location sequence and this process expands the sequence of stay location length. The possible subsequences of the locations are determined by the partial matching approach. The outdated locations, recently visited locations and the matching paths are identified using the geographical scores. The geographical scores are estimated as follows:

$$Geographic\ score(A,B) = \sum_{i=1}^{|A|}\sum_{j=k}^{|B|} \alpha^{|B|-j} \times mScore(A_i, B_j)$$

Where,

$$mScore(A_i, B_j) = \begin{cases} A_i.support, & if\ A_i\ and\ B_j\ match \\ 0, & otherwise \end{cases}$$

α represents the exponential decay.

The average score is estimated by the following equation:

$$Score = \beta \times Geographic\ score + (1-\beta) \times Semantic\ score$$

Where, β lies between 0 and 1.

IV. RESULTS AND DISCUSSION

This section analyzes the performance analysis of the proposed LUP recommendationsystem. The existing recommendation systems including non-clustering recommendation system and semen predict recommendation system. The metrics used for evaluation are as follows:

- Precision
- Recall
- F-Measure

A. Precision

Precision is the ratio of the number of relevant websites in the retrieved list to the total number of retrieved websites. It is measured in terms of percentage (%). It is also termed as positive predictive value. It is the proportion of relevantly retrieved websites for a given search query. For an efficient web recommendation system, the value of precision should be high. The high precision can satisfy the user requirements by retrieving the most relevant queries.

$$Precision = \frac{|(retrieved\ websites) \cap (relevant\ websites)|}{|retrieved\ websites|}$$

Figure 3 and Table 1shows the comparison of the proposed and existing recommendation systems in terms of precision. The precision values are plotted against the minimum support. The proposed LUP system attained high precision, when compared to the semen predict and the non-clustering recommendation system due to the combination of location and demographic information.

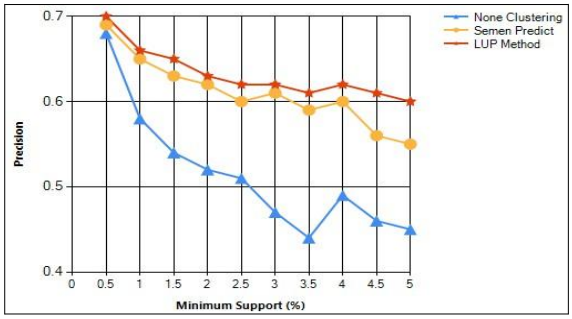

Figure 3 Precision analysis of the LUP, semen predict and non-clustering website recommendation system

Table 1 Precision analysis of the LUP, semen predict and non-clustering website recommendation system

Minimum Support (%)	None Clustering	Semen Clustering	LUP Method
0.5	0.68	0.69	0.7
1	0.58	0.66	0.67

1.5	0.54	0.64	0.65
2	0.52	0.62	0.63
2.5	0.51	0.6	0.62
3	0.48	0.61	0.62
3.5	0.45	0.59	0.61
4	0.59	0.6	0.62
4.5	0.47	0.58	0.61
5	0.46	0.57	0.6

B. Recall

Recall can be defined as the ratio of the number of relevant websites to the total number of relevant websites. It is used to measure the success ratio of to retrieve all the relevant websites. It is measured in terms of percentage (%). The recall must be high to attain a higher level of user satisfaction. It is also termed as sensitivity in classification.

$$Recall = \frac{|(retrieved\ websites) \cap (relevant\ websites)|}{|relevant\ websites|}$$

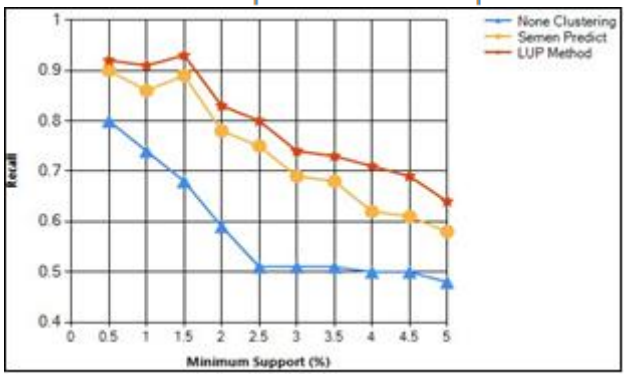

Figure 4 Recall comparison of the proposed LUP system and the existing semen predict and non-clustering system

Table 2 Recall comparison of the proposed LUP system and the existing semen predict and non-clustering system

Minimum Support (%)	None Clustering	Semen Clustering	LUP Method
0.5	0.8	0.9	0.91
1	0.72	0.88	0.9
1.5	0.69	0.9	0.93
2	0.6	0.79	0.82
2.5	0.51	0.75	0.8
3	0.51	0.7	0.75
3.5	0.51	0.69	0.74
4	0.5	0.62	0.7
4.5	0.5	0.61	0.69
5	0.49	0.59	0.63

Figure 4 and Table 2 illustrates the recall plots of the proposed LUP and the existing semen predict and non-clustering recommendation systems. The graph in Figure 4 shows that the proposed LUP system achieved higher recall than the existing recommendation systems.

C. F-Measure

F-measure is obtained by the combination of recall and precision, which means that the value of F-measure depends on the value of recall and precision. It is the ratio of twice the product of precision and recall to the sum of precision and recall. It is also termed as F-score that is used to evaluate the overall performance of the recommendation system. It is also measured in terms of percentage (%).

$$F - measure = \frac{2.Precision.Recall}{Precision + Recall}$$

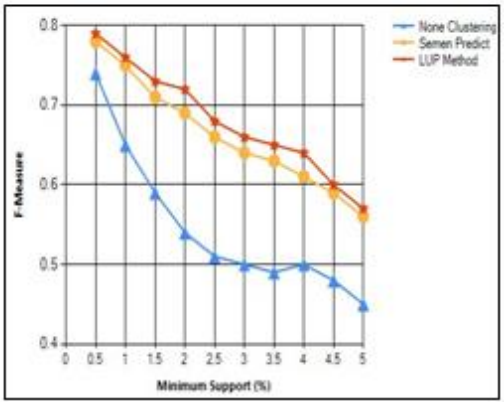

Figure 5 F-measure graph of LUP, semen predict and non-clustering recommendation system

Table 3 F-measure graph of LUP, semen predict and non-clustering recommendation system

Minimum Support (%)	None Clustering	Semen Clustering	LUP Method
0.5	0.73	0.77	0.78
1	0.64	0.75	0.74
1.5	0.69	0.71	0.73
2	0.53	0.69	0.72
2.5	0.51	0.68	0.67
3	0.5	0.65	0.64
3.5	0.49	0.62	0.63
4	0.5	0.61	0.624
4.5	0.48	0.59	0.6
5	0.45	0.56	0.57

The comparison of LUP system and the existing systems are plotted in Figure 5 and Table 3. As the value of recall and precision of the proposed LUP system is high, the F-measure value is also high. Thus, it is understood that the overall performance of the proposed LUP web recommendation system is efficient.

V.CONCLUSION

Personalization and recommendation systems are the vital requirements of web mining to generate the desired results to the search query of the users. The users get satisfied with the search engine, if it produces a list of relevant recommendation to them. In this paper, a Location and User Profile (LUP) based web recommendation system is proposed to satisfy the uses' search requirements. The ontology based user profiling is adopted for the generation of enriched user profiles. The demographic user information is derived from the ontological user profiles. It's really important to retain unique user details and their preferences as a profile for each recommender program.

Developing new learning mechanisms to analyze a user's interactions with the system, and their ability to convert it to user preference, can make recommendation system more dynamic in making suggestions. As the use of location and ontologies can be used as a LUP solution to represent the needs of the user in the semantic way, this solution can address difficulties in the lack of flexibility of the texts. Numerous recommender systems already use the location information, which can be followed by the use of data from device sensors such as RFID signals, weather temperature, and health metrics / signals. Initially, recommender programs concentrated on validation processes to make suggestions more reliable. While designing effective recommendation models, position and ontology knowledge are now integrated with the various factors-influenced data. Further, the accuracy of website retrieval was improved using the location of the users. The location is predicted using trajectory based pattern mining. Initially, the user profiles are preprocessed and clustered based on similarity. Then, the semantic and geographic scores are computed using to get the average score, which in turn is used for location prediction. The proposed LUP system is compared with the existing semen predict and non-clustering recommendation system. The overall performance of the LUP system is improved due to the high value of recall, precision and F-measure.

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