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A Hotel Recommender System using Context-Based Clustering

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Abstract*— The web is one of the largest textual data repositories in the world. There is voluminous data in the digital world. To search for online hotels based on specific requirements of the user is not a very easy job. Ratings and reviews available on different travel websites help to some extent but gives generalized recommendations. A recommender system (RS) which uses reviews is known as content-based and is preferred, to produce a recommendation. Proposed RS maps all requirements of a traveler to features of a hotel and produces person specific recommendation. Phrase-based Recommender System is proposed to reduce efforts and time as compared with a traditional generalized recommender system. The proposed approach makes use of hotel reviews downloaded from TripAdvisor site. The technique initiates with phrase-based feature extraction followed by iterative clustering and ends with feature mapping and exports more relevant recommendations. Betterment of a technique is proved in terms of relevance, accuracy, scalability, and consistency by comparing precision and entropy refinement and corpus size with existing technique.

***Keywords*—phrase, context-based recommendation and clustering, hotel reviews, precision**

I. INTRODUCTION

The current trend in data analysis focuses mainly on adaptive systems and algorithms that process voluminous information and produces personalized recommendations for users. Recommendation systems turned out to be benefited for customers as well as for commercial bodies [1]. It offers services/products in which the user is interested. Recommender systems (RS) facilitate prospective buyers to select any product or service having features matching his or her choice as also considering the popularity amongst other users. [2, 3]. Recommendations can be product or service based, one of the services based recommendations is, hotel RS, where generally reviews are used to export recommendation. Review websites have become an integral part of the online marketplace, often heavily influencing consumer behaviour. If a consumer is traveling to a new or unfamiliar location or even looking for a new type of experience, the internet is usually the first stop for information. Whether a consumer is looking for a restaurant, barber, or hotel, customer reviews can sway a potential customer's opinion before they even step on the premises. Websites like TripAdvisor, where users can leave reviews for hotels, restaurants, and other tourist activities, are commonplace for decision-making and contain ratings on various aspects of the business [4].

Consumer focus has shifted from conventional rating systems to personalized ratings based on individual users and their experiences, giving customers a say in driving future business success

[5]. Tripadvisor survey says that 94% of users use a business with a rating of 4 or higher.

Reviews are unstructured, and it's necessary to impose some matrix to make it machine interpretable. This step allows applying the existing mining algorithms. Generally, document term matrix is used in which rows of the matrix represent documents and terms are placed in columns [6]. Dimension curse can occur due to extracting all terms and in turn, can reduce algorithm efficiency. To avoid dimension curse, frequency occurrence of terms is considered and significant terms are selected. A well-known feature selection technique is known as Term Frequency-Inverse Document Frequency (TF-IDF) [7] overlooks commonly existing terms with respect to the entire set of documents and chooses the significant words/terms based on the frequency of occurrence [8].

Most of the times, customers use various types of adjectives along with nouns and express their emotions in reviews. As a result, phrases play an important role to preserve the context of the review. [9]

That is "fantastic food," excellent service," and so on. TF-IDF ignores the sequencing of terms, but the meaning attached to a term heavily depends on the context and thus depends on the other terms forming the phrase. If the terms present in the phrase get separated, then the context gets lost [10]. Phrase document matrix preserves the context of the documents by extracting frequent phrases as column heads. The word 'Right' appearing in 'Right Hand' and 'Right Answer' carries a different meaning and need to be treated as separate features. Considering phrases as major attributes lead to decrease in dimensions as compared to TF-IDF, which in turn improves cluster quality. There is a need to use dimension reduction techniques which will result in the right groups of text clusters and relevant recommendation.

A phrase based Recommender System is proposed, for mapping requirements user to select the hotel and the features of the hotel. The requirements are to be entered in the form of phrases. ("low budget") .

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The proposed approach uses phrase based clustering. The iterative hierarchical clustering method not only generates compact clusters but also generates a Feature vector for each cluster and a Feature matrix. Recommendations of the hotel are based on phrases present in the review.

Related work and background is presented in the second section. A hotel recommender system is explained in the third section. The fourth section presents the experimental work carried out to prove the efficacy of the system. The paper ends with implications and limitations, followed by a conclusion.

The research is innovative because

1. Context is involved in the process to recommend more relevant hotels than the existing technique.
2. The personalized recommender system reduces time and efforts compared to the traditional generic recommender system.
3. Dimension reduction facilitates the betterment of technique measured in terms of precision and refined entropy and scalability.

II. BACKGROUND

On-line sales make use of recommender systems; the aim is to suggest the most appropriate and accurate product/services to the user. The necessary information is filtered out from a pool of user and sales data.

Recommending a hotel is not an innovative idea, and it aligns with hotel selection. Conventionally most of the tourists used to get alike recommendations of hotels by measuring their general quality. The priorities of the travelers were not available or partially available. Fortunately, social sites play an important role, to get a better understanding of travelers. The information existing on social sites such as ratings, reviews, social links, and profiles are studied and analyzed. Personalized hotel recommendation becomes possible, with this rich available information share the opinions on hotels. Websites like Yelp and TripAdvisor help travelers to search for specific hotels. Generally, ratings and reviews are used to express views regarding the hotel. Various features of the hotel, such as cleanness, location, and service, are considered while rating the hotel. On TripAdvisor travelers rate a 1-5 star or thumbs for the hotel but travelers receive the same recommendation without personalization, in this recommendation process. For example, a tourist having a limited budget may get the recommendation of the expensive hotel due to its high average rating. It is really difficult to search out the exact set of hotels by only sorting these hotels through available criterion and provide an accurate recommendation from thousands of hotels in a popular destination [5].

Development of text evaluation algorithms for semantic analysis and textual processing is the need of an era. Monetizing the data has resulted in a feedback loop where sites seek to engage users to provide content, such as ratings and reviews but also use it to suggest hotels or restaurants based on the data in those ratings and reviews. This data is used while selling ads and selling favorable placement in the display of the suggestions. This has led to the development of recommender systems and the algorithm and methods that allow them to function.

Travelers' life will be easy if person specific recommendation of the hotel is provided, which comes up with a limited group of hotels and specific to travelers' requirement. The recommendation process can be refined by involving context while clustering hotels based on their features.

In general, content-based filtering and collaborative filtering are two techniques to develop recommender systems.

A. Techniques used by the recommender system

By analyzing ratings or preferences provided by travelers, collaborative filtering methods generate recommendations. One of the accurate CF methods, which is the most popular is Matrix Factorization (MF). Latent factor spaces shared between travelers and hotels are discovered by this approach. To describe the features of hotels and the choice of travelers, latent factors are used. It is a mapping between users' requirement and hotel features.

Content-based Filtering methods uses similarities between the contents of items [11] and produces recommendations. For example, if a movie is an item, then director, actors, type of movie can be extracted as the content of movies. In the perspective of the recommendation of the hotel, reviews may be considered as features of a hotel. Textual reviews should be converted into the matrix format before applying any clustering algorithm. Many text mining [12, 13] methods use TF-IDF approach, to represent documents [14], but it assumes all words are independent while words usually occur in contextual groups or phrases [15, 16]. Table I specifies the significant mile stones in the evolution of context-based hotel recommender system.

Sr. No	Author, year	Techniques and Contributions	Gaps/Future work
1	Chen et al., 2015	contextual opinions are important to consider to process simple texts like posts and tweets from social networking websites, review-based user profile building, and review-based product profile building	combining multiple types of review elements enhancing multi-criteria recommenders, context-aware recommenders, and emotion-based recommenders, realistic evaluation techniques

III. CONTEXT-BASED HOTEL RECOMMENDER SYSTEM

Table I: Contribution of hotel recommender system

2	Lu et al., 2015	CATIS (Context-aware tourism recommender systems) context-aware recommender system, used for recommending tourist accommodation, restaurants and attractions. Context manager to trace location information. The recommendations are generated by combining the user query and the user context information from the application server.	
3	Zisos et al., 2018	hybrid recommender system, multi-criteria analysis, sentiment analysis and filtering methods, using the big volume of data, cold start problem was solved	Development of an online version of the recommendation platform, New recommendation, using similarity metrics
4	Nilashi et al., 2018	A knowledge-based recommendation agent is proposed for tourism websites. CART is developed, discovering the decision rules from the TripAdvisor dataset. Fuzzy-rule based technique for overall rating prediction.	Context can be involved while recommending the hotel
5	Khaleghi et al., 2018	This TF-IDF Vectorization to process review text, collaborative filtering model is used, which is faster to process than the matrix factorization model. Evaluation of the recommender system and predicting how a user would rate the hotel	Accuracy and prediction can be improved

Hotels are a prime candidate for this analysis. There are a wide variety of hotels, from bed and breakfasts to multinational chains, with a lot of segmentation in the market. There is also a large amount of data, even compared to restaurants, which are similarly reviewed. A hotel experience lasts much longer than a dinner at a restaurant, and there are more facets of the experience to review. Rather than just wait for service and food quality, a hotel has a check-in experience, location, room quality, cleanliness, amenities, etc. A large amount of feature-rich data available for hotels is prime for Context-based hotel Recommender System [6].

Hotel recommender systems have been particularly valuable for review sites, as they seek to add value to the user experience to gain market share and to create new revenue streams through deals. Hotels are a prime target for this effort, as there is a large number for most destinations and a lot of differentiation between them. The recommender system should be able to search for suitable hotels for the requested features. The review is written in the form of text, and this type of data is termed as unstructured data. To apply a clustering technique, textual reviews are converted to structured form or also called as vector form. This vector form is termed as a phrase-document matrix (PDM). In PDM, reviews are placed in rows represent and important phrases extracted from hotel reviews occupy columns. Reviews describe the customer's opinion and many times expectations about the hotel. The required features of the users are extracted from reviews. Thus column in the term-document matrix is replaced by phrases which tend to reduce dimension and context involvement. Context based recommender system contributes to knowledge creation and sharing among members in the collaborative environment [17].

IV. EVALUATION OF CLUSTER

Grouping of similar types of objects can be achieved by clustering. In this data mining technique, the proximity of extracted features are used to map cluster features while in document clustering terms act as features. The moment context of the term is brought into the clustering, it becomes more realistic. Cluster quality is measured using F-measure, entropy, precision, and silhouette width to validate the number of clusters [18, 19]. Entropy measures the uniformity or purity of a cluster, and precision directly reflects the performance of clustering. Entropy is used with various pre-processing methods such as a wrapper, filter for feature elimination, reduction and selection.[20,21]

V. EXPERIMENTAL SETUP

In the proposed approach, in the absence of request data reviews act as input dataset and termed as request review. The features are extracted iteratively from this request review. The extracted features are mapped with the requirement of tourists, using extended hierarchical clustering. The most mapped cluster of hotels is identified, which fits the user's requirement. All hotels present in the cluster are recommended to the tourists, which act as the outcome of the experimental setup.

The efficacy of the proposed approach is validated by performing several experiments. The experiments are conducted using different packages available in R programming, e.g., TM, Snowball, StringR, and so on. Available data on the web is used to perform large-scale experiments. The dataset was downloaded from a TripAdvisor website Reviews were pre-processed to get the Phrase document matrix. (PDM). Table II shows the phrase and respective count of phrases occurring throughout the corpus.

Table II: Phrase and its respective count

Phrase	Frequency
excellent food	16
good service	10
attentive staff	9
beautiful view	8

Significant phrases are considered while forming PDM. Significance of phrase is decided using the frequency of phrase. The threshold frequency is considered to select the phrase. For example, in table III, the phrase document matrix gives the number of occurrences of each phrase. By normalizing the values to (0, 1) range, the feature matrix is created. Feature matrix (FM) consists of the feature vector. Thus feature vector for review R1 is {(excellent food), (good service), (beautiful scenery}…}. Feature matrix expressed in a quantified form related to a set of reviews is represented in Table III.

Table III Feature Matrix for 24 reviews

Review	F1=excellent food	F2=good service	..	F20=beautiful view
R1	0.61	0.21	..	0.22
R2	0.92	0.11	..	0
R3	0.34	0.93	..	0.12
..	..	..	..	..
R24	0	0.12	..	0.22

Table IV Reviews and dimensions

Reviews	Features
24	20
49	35
200	50

As the larger set of reviews are processed, the feature set size also increments. Table IV shows that fifteen phrases are added after processing 49 reviews. The table signifies that the total count of significant phrases do not increase exponentially, though there is an increase in dataset size four times that is from 49 to 200. Thus compactness in the dimensions due to the selection of significant phrases is observed.

A. hierarchical clustering

In iterative feature extraction, the hierarchical agglomerative approach is extended by using significant phrases. Hierarchical agglomerative clustering algorithm facilitates the clustering at several levels of hierarchy. The features present at the lowest level of the hierarchy are iteratively extracted and added to the existing feature set at the topmost level. The entropy at each iteration is calculated, which improves with add-on features and the documents get assigned to the most relevant clusters. The process continues till stable entropy is obtained, that is entropy value does not change significantly. Steps of Hierarchical approach with synset grouping are shown in Fig. 1

1. Getting a repository of documents.
2. Pre-process the documents/ skillset (stemming, stop words removal, correct misspelled words)
3. Extract terms from documents/ skillset(feature vector)
4. Identify all phrases with their frequency
5. Consider the phrases having higher or equal count than the threshold
6. Formulate the phrase document matrix and feature matrix
7. Apply cosine similarity and a hierarchical clustering algorithm to get document clusters
8. Calculate Entropy to validate cluster quality
9. Extracting features of clusters at the lowermost level
10. Extending the feature set by adding cluster-specific features
11. Repeating 3-6 till entropy stabilizes

Fig. 1 Steps in hierarchical clustering

The cosine similarity matrix is input for the hierarchical clustering. The output of the hierarchical clustering presented in the form of the dendrogram. At the lowermost level of the hierarchy, the features are extracted in the next iteration. These extracted features act as add on features for the topmost level of the dendrogram. On this refined add-on features, the process is repeated. To decide the number of iterations, the cluster entropy is used. The algorithm converges, after a specific number of iterations and entropy becomes stable. Different values of entropy in Table V shows the stable entropy between the third and fourth iterations.

Table V Entropy readings for 200 reviews

Iteration	Entropy
1	0.76
2	0.86
3	0.92
4	0.93

V VALIDATING THE EFFICACY OF THE SYNSET BASED APPROACH

A dataset of 93 reviews was used belonging to 3 different sets of the hotel. These sets were formulated based on specific features of the hotel that is hotels near to the airport, providing excellent food and so on. Clustering was used on this dataset to form four clusters after using different methods for constructing a document matrix. Table 5 shows cluster-wise documents for different methods. Actual column specifies the grouping based on the expert's knowledge. The representative example showing a cluster-wise number of reviews obtained by executing the proposed algorithm, and simple TF-IDF is presented in Table VI. It clearly shows that several reviews by proposed method closely match the actuals, in comparison with that of TF-IDF.

Table VI Cluster-wise occurrence of documents using different methods

Cluster	Actual	Proposed	TF-IDF
1	20	17	25
2	30	28	33
3	25	28	22
4	18	20	13

To show the efficacy of a phrase-based approach over simple TF-IDF that is commonly used, Table VII presents the comparison of precision values.

Precision is the fraction of relevant reviews among the retrieved reviews. A measure of relevance is represented by precision. [22]

More precision indicates good recommendation, which is observed in the proposed method. The performance of the proposed method remains consistent even for the large dataset.

Fig.2 shows the dendrogram of 39 reviews in which each cluster represents its specific properties of hotels.

Table VII Comparison of precision values on different dataset size

Reviews	Precision	
	TF-IDF	Proposed
20	0.78	0.92
39	0.71	0.91
93	0.61	0.89
200	0.62	0.85
500	0.61	0.88

Table VIII: Cluster feature matrix representing associated phrases

Cluster	near airport	disciplined staff		fantastic food
C1	1	0.81	..	0.61
C2	0.88	0.77	..	0.12
C3	0	0.11	..	0.23
C4	0.81	0.91	..	0.11

Table IX : Request review and its features

Review	Great stay	Sweet serenity	..	Business purpose	Good location
NR1	0.12	0.34	..	0.23	0.32
NR2	0.12	0.45	..	0.23	0.65
..	..	..	..	..	..
NR24	1	0.72	..	0.06	0.89
NR25	0.25	0.11	..	1	0.32

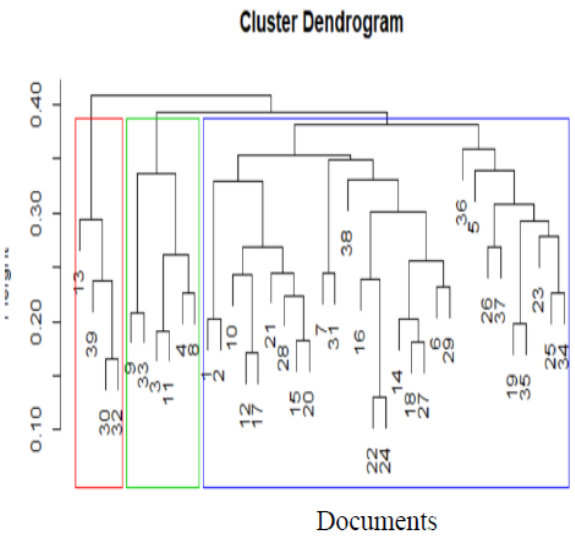

Figure 2: Dendrogram of 39 reviews

VI. EXTRACTING FEATURES OF REQUEST FOR A HOTEL RECOMMENDATION

The expectations of user can be collected through reviews of hotels to which tourists have given the highest rating. Review written for the particular hotel represents that hotel and all reviews of the same hotel are clustered. The features extracted from these reviews denote user requirements to select a hotel. Iterative feature extraction can be applied to form clusters where each cluster represents the hotel properties, and the feature matrix of these hotel properties is obtained. Table VIII shows the cluster feature matrix where each cluster represents the features of a hotel. In cluster 3, for 'near airport' feature, the value is zero, which indicates the absence of a particular phrase that is not present in any of the documents which are in cluster 3. In cluster 1, feature weights of synset groups are more than 0.5, which specifies more degree of significance. Reviews which act as expectations of users, also u action process to generate the feature x for such reviews is shown in Table IX. NR1 is newly arrived review, and features are represented in the form of phrases and their weights, for example, one of the phrases NR1 is {('near airport')} having feature weight as 0.32.

Table x Cosine similarity matrix showing new request assignment to the cluster

Request review	C1(near airport)	C2(business purpose)	C3(good location)	C4(affordable amenities)
NR1	0.32	**0.92**	0.23	0.19
NR2	0.11	0.31	**0.87**	0.76
NR3	0	0	0.21	**0.99**
NR4	0.11	0	0	0.22
NR5	0.23	0.15	**0.99**	0.58
NR6	0.96	0.37	0.28	0
..	..	..	..	..
NR25	0.11	0.13	0.86	0.51

vi. Recommending based on skillset mapping

The preferences or requirement of users is considered as features extracted from reviews. These features or user requirements are related to hotel properties. For example, review of tourist representing NR25 likes to choose a hotel for business purpose, as phrase weight "business purpose" is 1. To select the correct hotel that would fully satisfy the tourists' need to have a mapping process, which is defined in Fig. 3

1. Identify feature vector(term set) for each request review and cluster of reviews using iterative feature extraction
2. Find cosine similarity between the cluster feature vector and the request feature vector
3. The reviews with above-threshold similarity will form recommended hotels for required hotel features

Figure 3: Steps in the mapping process

The cosine similarity measure is calculated to establish the proximity of request review to the cluster, which is shown in Table X. Table XI shows the reviews' clusters and associated phrases. The hotels present in the mapping cluster are recommended to the tourists. The requirement mentioned in newly arrived request review NR1 is mapping to the cluster 2. So hotels present in the second cluster are recommended for that tourist who wishes to book a hotel for business purpose.

Table XI: Clusters with the feature set and request review allocation

Cluster	Phrases	Request review allocated
1	time bound, less distance,..	NR6
2	Conference hall, commercial task, ..	NR1
3	Nice stay, airy room, ..	NR2, NR5, NR25
4	Cheap rate, low price,.	NR3

VII. CONCLUSION

The paper presents a hotel recommender system to not only reduce efforts and time but also to come up with more relevant hotel recommendation than traditional generalized recommender system. Context of the user requirement is involved while recommending hotels, as the proposed approach considers phrases instead of terms.

Improvement in precision, entropy and scalability prove betterment of the approach. The most important prerequisite for this approach is the phrase based feature extraction, iterative semantic clustering, and semantic mapping. The available standard dataset of reviews has been used. In the future, a tool incorporating the proposed approach with the user-friendly interface needs to be designed and implemented.

REFERENCES

1. Rafi, M. & Shaikh, M. (2013). An improved semantic similarity measure for document clustering based on topic maps. Cornell University Library.
2. Jashki, M., Makki, M., Bagheri, E., & Ghorbani, A. (2009). An iterative hybrid filter-wrapper approach to feature selection for document clustering. Proceedings of the 22nd Canadian Conference on Advances in
3. Nilashi, M., Ibrahim, O., Yadegaridehkordi, E., Samad, S., Akbari, E., & Alizadeh, A. (2018). Travelers decision making using online review in social network sites: A case on TripAdvisor. Journal of computational science, 28, 168-179.
4. Huang, C., Tian, Y., Zhou, Z., Ling, C. X., & Huang, T. (2006, December). Keyphrase extraction using semantic networks structure analysis. In Data Mining, 2006. ICDM'06. Sixth International Conference on (pp. 275-284). IEEE.
5. Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.37
6. Liu, J., Ren, X., Shang, J., Cassidy, T., Voss, C. R., & Han, J. (2016, April). Representing Documents via Latent Keyphrase Inference. ACM Proceedings of the 25th International Conference on World Wide Web (pp. 1057-1067). International World Wide Web Conferences Steering Committee
7. Cambria, E., Poria, S., Bisio, F., Bajpai, R., &Chaturvedi, I. (2015). The CLSA model: a novel framework for concept-level sentiment analysis. In Computational Linguistics and Intelligent Text Processing (pp. 3-22). Springer International Publishing
8. Feldman, R., & Sanger, J. (2007). The text mining handbook: advanced approaches in analyzing unstructured data
9. Lops, P., De Gemmis, M. and Semeraro, G., 2011. Content-based recommender systems: State of the art and trends. In Recommender systems handbook (pp. 73-105). Springer US.
10. Zesch T., Gurevych I. Approximate Matching for Evaluating Keyphrase Extraction. International Conference RANLP2009. – Borovets, Bulgaria, 2009. – pp. 484–489.
11. Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: a survey. Decision Support Systems, 74, 12-32.
12. Wu, Yutong, et al. "Mining Topical Relevant Patterns for Multi-document Summarization." 2015 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT).Vol. 3.IEEE, 2015.)
13. Marujo, L., Ribeiro, R., de Matos, D. M., Neto, J. P., Gershman, A., &Carbonell, J. (2015). Extending a single-document summarizer to multi-document: a hierarchical approach.arXiv preprint arXiv:1507.02907)
14. Koster, C. H., &Beney, J. G. (2009, November). Phrase-based document categorization revisited. In Proceedings of the 2nd international workshop on Patent information retrieval (pp. 49-56).ACM
15. Khaleghi, Ryan, Kevin Cannon, and Raghuram Srinivas. "A Comparative Evaluation of Recommender Systems for Hotel Reviews." SMU Data Science Review 1, no. 4 (2018):
16. Zisos, I., Matsatsinis, N., & Tsotsolas, N. (2018, June). A Hybrid Multi-Criteria Hotel Recommender System Using Online Ratings and Reviews. In 7th International Symposium and 29th National Conference on Operational Research The contribution of Operational Research, new technologies and innovation in agriculture and tourism (p. 1).
17. Dong, Ruihai, Michael P. O'Mahony, Markus Schaal, Kevin McCarthy, and Barry Smyth. (2013)"Sentimental product recommendation." In Proceedings of the 7th ACM conference on Recommender systems, pp. 411-414. ACM, 20
18. Esparza, Sandra Garcia, Michael P. O'Mahony, and Barry Smyth.(2011) "Effective product recommendation using the real- time web." In Research and Development in Intelligent Systems XXVII, pp. 5-18. Springer London, .
19. Chen, L., Chen, G., & Wang, F. (2015). Recommender systems based on user reviews: the state of the art. User Modeling and User-Adapted Interaction, 25(2), 99-154.
20. Mahmoud Sammour and Zulaiha Othman,"An Agglomerative Hierarchical Clustering with Various Distance Measurements for Ground Level Ozone Clustering in Putrajaya, Malaysia," International Journal on Advanced Science, Engineering and Information Technology, vol. 6, no. 6, pp. 1127-1133, 2016. [Online]. Available: http://dx.doi.org/10.18517/ijaseit.6.6.1482.
21. Tawfiq A. Al-asadi,Ahmed J. Obaid,Rahmat Hidayat and Azizul Azhar Ramli,"A Survey on Web Mining Techniques and Applications," International Journal on Advanced Science, Engineering and Information Technology, vol. 7, no. 4, pp. 1178-1184, 2017. [Online]. Available: http://dx.doi.org/10.18517/ijaseit.7.4.2803.
22. Yanling Li and Sokchoo Ng,"Timeliness of Materials on Reading Recommendation System," International Journal on Advanced Science, Engineering and Information Technology, vol. 8, no. 1, pp. 178-184, 2018. [Online]. Available: http://dx.doi.org/10.18517/ijaseit.8.1.4024.