A Recommender System for Improved Web Usage Mining and Personalization based on Foraging behavior based Swarm Intelligence

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Abstract

Objectives: The core intent of this paper is to propose a dynamic recommender system (i) to endow with an enhanced understanding of the behaviors and interest of online users and (ii) to tumble information overload by providing guidance to the online users. Methods: Foraging behavior based swarm intelligence is motivated from the dynamic social behavior of swarms. It puts forward innate option for modeling dynamic online usage data. In the present work, we mainly concentrate on the innate resemblance between Swarm Intelligence and communal behavior. The proposed WebFrieseBee algorithm is inspired from the foraging behavior of the T. biroiFriese bees and the proposed the proposed BestProphecy-annealing algorithm is used for providing recommendations to users. Findings: The proposed WebFrieseBee is motivated from the dynamic social behavior of swarms. It offers collaborative learning and has decentralized control. Moreover, it also has high exploration ability. That is, it put forward innate option for modeling dynamic online usage data. The proposed BestProphecy-annealing algorithm uses a greedy heuristic approach, for providing recommendations to users by identifying a better neighborhood for agents and gives recommendations based on the preferences of these best neighborhoods. The proposed WebFrieseBee may overcome the data redundancies existing in the repeated use of information which are inappropriate and may provide tradeoff between coverage and precision. Improvements: Our proposed dynamic recommender system surmount the grey sheep problem and new user ramp up problem in many traditional recommender systems. Our proposed dynamic recommender system was compared with Ant clustering approach. The Experimental results shows that our approach offers better quality in terms of coverage, precision and F1 Measure than the traditional Ant clustering approaches. Applications: The recommender system is very effective in increasing the utility of e-commerce by minimizing the user surfing time and overload in servers.

Keywords: Recommender Systems, Software Agents, Stimulated Annealing, Swarm Intelligence, User Profiles, Web Usage Mining

1. Introduction

E-Business has a significant function in modern life since most of the business transactions are done through online. Technology plays a vital role in humanizing the effectiveness of E-business. The quick escalation of the E-business necessitates the improvement of online information management since speedy amplification in the use of WWW. This requires understanding and identifying the steering actions of each user. A user using World Wide Web is in the vein of getting web pages that go well with his needs without soliciting for it. At this juncture, the significance of web personalization/customization by presenting the web pages links based on the preferences of the user according to users past browsing behavior without asking for it, plays a vital role.

The ample data regarding user’s requirements and interests have to be gathered to improve online business. These data have to be analyzed and learned for the creation of user profiles. A user profile divulges concerns, avocations, requirements etc. The competition in E-business is rapidly growing and service from
the opponent is now a clack away for the users. So, it's important to continuously monitor users changing interests and needs. For this, web usage mining is necessary.

Data mining is one of the processes useful for digging out useful information in big data deposits related to web usage. It uses different methods like machine learning, artificial intelligence, statistics and database systems for identifying hidden patterns in big data deposits. Web usage mining is the method of pertaining data mining techniques to web log data to discern significant habitual patterns. It uses the information in server access logs collected in web servers to discover interesting user access patterns.

Swarm intelligence is a strategy that could be used for web usage mining. It gains inspiration from several communities in nature such as fish schools, ant colonies, honey bees and bird flocks. Swarm Intelligence uses intelligent agents to handle copious information. An agent percep from the environment through sensors and it act on the environment through actuators. Intelligent agents can continuously percept the dynamic conditions in the environment; it can perform actions to affect the clauses in the milieu and carry out the reckoning to construe perceptions. The flexibility of the software agents makes it possible to dynamically choose which actions to perform and their sequence in response to the state of its external environment.

The advantages of recommender systems are:
- Boost the amount of items sold: The recommendation system recommends the items that suits user's interest and needs. The recommendation systems give additional set of items other than the items that are purchased without recommendations.
- Vend more assorted items: Recommendations systems allows users to find new items that might be difficult to find without recommendations.
- Amplify the user liking: Recommendation systems give the users with the items that they are interested in. This improves the users can also improve the familiarity with site or application. With a proper human-computer interaction the users will find the items they are interested in. Hence improving user’s enjoyment with the system.
- Enhance user loyalty: Recommendation system can identify the old and new customers. The recommendation system identifies the old customers and treats them valuably. Most of the recommendation systems foretell things based on the user's previous visits and the interactions made. More often a user visits a website, the user model will be more polished and the recommendations will be more productive.
- Improved awareness of what the user wants: The service provider may reuse the knowledge for a number of other purposes such as improving the management of the item's stock or production.

An evaluation study of factors affecting the user interest was discussed in. One of the solutions to address the issues related to such website usage is web personalization. It provides the recommender systems that will give suggestions that will be probably liked by the user. These recommender systems avoid unnecessary crawling over the web by the user to search and to get what he wants. They use web usage mining methods to ascertain significant usage patterns as of web data and to tailor a web page for an end user. That is, they provide recommendations that will be possibly similar to the user preferences. The main confronts related by the online usage data is its high dimensionality and dynamic nature. Many research works have been done on such recommender systems. Fab adaptive content based recommendation systems gives web page recommendation service to users based on the recommendations of other users and also by analyzing their content. Automated collaborative filtering (ACF) system predicts a person's interest for an item by using that person's recorded interest with the recorded interest of a community of like-minded people. Nevertheless, they overlook the dynamic scenery of data. Even though FlockRecom is a well-known recommender system, it also fails to manage the dynamic nature of incoming data. These recommender systems suffer from over specialization problem. That is, they provide less variety in recommendations. Moreover, in these systems the qualities of recommendations are affected by number of users. That is, they fail to handle scalability property.

Clustering is one of the effective approaches used in e-bussiness. It could be used for web personalization also. The most popular swarm intelligence clustering algorithms like ant clustering, particle swarm clustering and flocks of agent based clustering are also used for web usage mining purpose. Ant Clustering groups web usage sessions using chemical recognition systems in artificial ants. AntClust algorithm gains inspiration from ant’s ability to differentiate between the nest mates and outsiders using the exchange of some chemicals. AntClust compute the similarity between the objects and group the
input web user sessions that represents the number of hits per page into clusters.

Binary Particle Swarm Optimization (BPSO)\textsuperscript{13} is biclustering clustering approach for grouping web Usage Data. It discovers totally most favorable bicluster from the web usage data. These biclusters have relationships between online end users and web pages. It gives a high volume of coherence between users and web pages. These are useful for the E-business applications and targeted marketing. Daiet al.\textsuperscript{14} introduced an efficient particle swarm chaos optimization mining algorithm based on chaos optimization (PS.COMA) and particle swarm optimization by using feedback model. This provides users a listing of best-matching web pages for user.

Incremental DBSCAN\textsuperscript{15} has two parameters epsilon and minimum points. Initially it begins with a random starting point. All the points within epsilon distance are considered as the neighborhood. But the amount of points in the vicinity is more than the minimum points, and then a cluster is formed. The starting points and neighbors be appended towards this cluster and then the beginning point is blotched as visited. All these process were done recursively by the algorithm. If the number of neighbors is less than minimum points, then it marked as noise. This approach can handle the clusters that come into sight and fade. But this approach does not lump the information points that vary during moment in time. Incremental SOM\textsuperscript{16} is an unsupervised learning technique. Self-organizing map use the concept of self-organizing neural networks. It uses a competitive learning technique. In incremental SOM neural nodes are added incrementally to a new stimuli or data points. The substantial position of neurons is not influenced by the incremental discovering method. The pose vector and the load vector are the similarity of the neuron, not its physical location. Incremental SOM can handle only emerging clusters. It fails to handle disappearing clusters and visualization. Moreover, it fails to hold the dynamic temperament of online usage data. This concept drift\textsuperscript{17} leads to mine dynamic clusters.

The techniques disc used above could not deal with the dynamic chattels of web usage data. Moreover, there is a decrease in quality measure in terms of F1 Measure as the number of user’s increases. That is, they fail to address scalability issue. In these methods, we observed those standard deviations, cluster errors and the amount of iterations required before convergence is high. Another problem with these techniques is that they do not use redundant data repeatedly. Hence, the effective methods to address the data redundancy in the web usage data and to accomplish with dynamic character of web data are necessary to be developed.

In past, many research works have been done in recommender systems. But, most of the traditional recommender systems cannot handle the dynamic nature of online usage data. Moreover, the traditional recommender systems give limited recommendations. In traditional recommender systems the number of iterations before convergence is high and also the quality of recommendations reduces with the increase in the number of users. The traditional recommender system also cannot balance the quality measures such as coverage and precision.

2. Materials and Methods

As discussed in previous session, most of the traditional clustering techniques in web usage mining like ant clustering\textsuperscript{11}, particle swarm clustering\textsuperscript{12}, incremental clustering techniques\textsuperscript{12,18}, do not deal with redundant data. In these traditional clustering techniques, standard deviations and cluster errors are high due to data redundancies. Moreover, due to data redundancies, traditional clustering methods failed in dealing with providing tradeoff between coverage and precision. Hence, the effective methods to address the data redundancy in the web usage data and to accomplish with the dynamic nature of usage data are necessary to be developed. For granting an enhanced realization the online users along with their behavior or interests, we need to overcome the data redundancies occurring in traditional clustering approaches. This necessitates the need for cluster optimization. For this purpose, we propose a swarm intelligence based recommender system namely WebFrieseBee approach gaining inspiration from the T. Biroifriese bees foraging behavior.

The process of identifying appealing web usage prototypes by applying data mining methods to web log data is known as web usage data. It includes the following stages such as (i) preprocessing of web log data (ii) prototype invention using data mining methods (iii) post processing and (iv) To follow embryonic user silhouettes.

2.1 Datasets and Preprocessing

The data used are listed in Table 1.
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Table 1. Dataset used

| Dataset id | No. of items | No. of attributes | No. of Clusters | Content |
|------------|--------------|-------------------|----------------|---------|
| Web Log Data | 1700 sessions | 350 urls. | NA | IP address, Url Viewed, access time |
| Jester | 1000 users | 100 jokes | NA | Ratings ranging from -10 to +10 |

The Web log data is preprocessed to identify the user sessions. The D dimensional binary feature vector $Vec_i$ is predetermined with the following property:

$$Vec_i = \{1, \text{proviso user } i \text{ visits URL } j \text{ or else }, 0 \}$$

For Jester dataset, the ratings ranges from -10 to +10 is normalized to scale between 0 and 1.

2.2 Proposed SYSTEM

For instance, T. BiroiFriese bees, stingless bees select food by considering distance of the food source from the hive, direction of the food source, and height of the food source from the ground. This fact is used in our WebFrieseBee approach. It may eliminate redundant items. It offers collaborative learning and has decentralized control. Moreover, it also has high exploration ability. Figure 1 depicts the steps involved in proposed recommender system.

![Figure 1. Steps involved in proposed recommender system.](image)

Here, the cosine measure given in equation (1).

$$C = \frac{V_i \cdot V_j}{\|V_i\| \|V_j\|}$$

Algorithm 1: WebFrieseBee

Notations Used: $U(i)$: the ith user session, $\eta_k$: group of user sessions allocated to kth cluster.

Notations Used:

$C_n$: cluster n
$E_n$: Cluster representative
$U_{in}$: ith member of nth cluster
$D(A_i, A_j)$: Distance between ith and jth agents
$\sigma_k^2$: Mean Squared error of kth cluster

Input: dataset d
Output: mined Clusters $p<n$, Visualization of clusters

1. Map every user to agent $k$
2. Assign agent $A_m$ to $C_k$
3. Repeat
4. If ($D(A_m, A_n)$ $\sum_{k \in C_k} Dist_k^2 < \text{dthand } \sigma_k^2 < \text{oth2}$)
5. $\sigma_k^2 = \frac{\sum_{k \in C_k} Dist_k^2}{|C_k|}$
6. // Where $\sigma_k^2$
7. Assign $An$ to $C_k$
8. Else
9. Assign $An$ to $C_{k+1}$

Repeat
10. Generate User Profiles by discovering the items, which are accessed more than item_count_threshold during the entire sessions of that cluster
11. Until no more clusters are to be processed
12. Run BestProphecy-annealing algorithm

End
where, \( V_i \cdot V_j = \sum_{k=1}^{n} v_{ik}^2 v_{jk}^2 \) is used to calculate similarity between agents.

The user profiles are created by displaying the most frequent items in the sessions of that cluster. By optimizing the clusters using the proposed algorithm, the redundant items were removed from the input clusters. This increased the quality of clusters. The new optimized clusters were also visualized. The output clusters generated by the proposed method were well separated. That is, the members of a cluster were more similar and the similarity of an element of a cluster with the elements of the other clusters was also reduced. In the visualization panel, we may observe that the elements of a cluster lie closer to each other and the clusters generated are also well separated.

The proposed BestProphecy-annealing algorithm gains inspiration from the stimulated annealing concept to identify better neighborhood. It identifies best neighboring solution to agents using a greedy heuristics approach. The liking of the finest neighborhood was used to provide recommendations to end users thereby overcoming the new user ramp up problem and grey sheep problem in many other traditional recommender systems.

### 3. Experimental Results

The proposed recommender system was experimented by standard datasets. In algorithm 1, \( dth = 0.15 \) and \( \sigma k2 = 0.006 \). In algorithm 2, to get better neighboring agents the rate of \( \gamma \) is decremented gradually. Here \( r = 0.96 \) and \( \text{TempLength} = 0.005 \). Trial and error approach was used to select values. It was executed using JADE (java agent development environment). Visualization of agents was done using a 2D visualization pane.
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The quality of the generated user profiles were evaluated in terms of precision, coverage and F1 Measure. These are defined as follows:

- **Precision**\(^{24}\): Every abridge profiles items that are corrector embraced in the novel input data.

\[
\text{Precision}_{ij} = \frac{\beta_j \bigcap_{\gamma_i}}{\gamma_i} \quad (2)
\]

- **Coverage/Recall**\(^{22}, 23\): A précis profile's items that were complete matched up to the summarized data.

\[
\text{Coverage}_{ij} = \frac{\beta_j \bigcap_{\gamma_i}}{\beta_j} \quad (3)
\]

where, \(\beta_j\) is a précis of entered sessions and \(\gamma_i\) symbolizes exposed heap profile \(^{15}\).

- **F1 Measure**\(^{21}\): It gives the measure of steadiness of Precision and coverage. Higher values for F1 Measure gives better quality of results.

\[
F1_{ij} = \frac{2(\text{coverage}_{ij} \cdot \text{precision}_{ij})}{\text{coverage}_{ij} + \text{precision}_{ij}} \quad (4)
\]

The proposed recommender system was compared with traditional Ant Clustering.

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**Algorithm 2: BestProphecy- annealing algorithm**

Notations used:
- \(G(X)\) = agents in addition with their position on the visualization pane
- TempLength = temperature span
- \(G(X)\) *= agents in addition with their restructured location on the visualization plane
- \(U\alpha_i\) = ith agent on the visualization panel
- \(\text{Loc}(U\alpha_i)\) = Location of agent on the visualization pane
- \(n\) = Overall agents on the visualization pane.

Input: Extracted P dynamic clusters
Output: Recommendations to users.

**Repeat**

For each agent \(U\alpha_j\) do

   Locate the cluster \(K\) to which \(U\alpha_j\) is a member.
   \[G(x) = \{\text{neighboring agents of } U\alpha_j \text{ in cluster K within distance dtop}\}\]

**Generate an initial solution** \(G(X)_0 \in G(X)\),

\(G(X)* = G(x)_0\)

Assign \(T=1\)

**Repeat**

Repeat

Identify agent \(A\alpha_j\) neighboring \(G(X)*\)

Let \(\Delta=\)

// where

If \(\Psi<0\)

\(G(X)* = \{A\alpha_j, \text{Loc (} A\alpha_j\}\}\)

Else

If random (0, 1) \(< e^{\Delta/T}\) then

\(G(X)* = \{A\alpha_j, \text{Loc (} A\alpha_j\}\}\)

End if

augment i by one.

Until \(T=\text{TempLength}\)

\(T=r*T \quad //\text{reduce temperature}\)

until stopping condition \(\Psi(G(X)*) = \{\text{recurrently favored items by each agents in } G(x)\}\}

Propose the common items preferred by the majority in \(\Psi(G(X)*)\) to user u represented by \(U\alpha_j\)

End For

Until there is no more agents to be processed

End
3.1 Experimental Results on Jester Dataset

Next, the proposed algorithms were tested on Jester dataset. As discussed previously, the jester dataset contains the ratings of different users on different jokes. Figure 2 shows the 2D visualization of the initial dataset.

In Figure 2, an agent is assigned for every user. The placement of agents on the 2D X-Y visualization pane was done either randomly or based on realm knowledge.

Figure 3 illustrates the 2D visualization of the generated cluster following WebFrieseBee approach.

Tables 2 show the intra and inter cluster similarity measures of clusters formed through different approaches. Standard deviations are shown in brackets.

As of Table 2, we may examine that WebFrieseBee approach offers more similarity among the members of the cluster when compared to Ant clustering approach. Moreover, a low value for inter cluster similarity point out that the members of different clusters are well separated. That is, WebFrieseBee approach offers optimized clusters.

The quality of the proposed recommender system (WB) is compared with traditional Ant clustering (GC). Figure 4 shows the quality measure comparison in terms of precision.

From Figure 4, we may observe that the user profiles generated by the WebFrieseBee approaches contain true data items resulting in optimized clusters. That is, optimized clusters removes redundant or uninterested data items. Figure 5 shows the quality comparison in terms of coverage.

From Figure 5, we may observe that coverage is higher for WebFrieseBee approach when compared to the Ant clustering approach. That is, cluster optimization results in the generation of optimized clusters with user profiles.
as much as similar to the input data. Figure 6 shows the comparison in terms of F1 Measure.

![Figure 6. Comparison of Ant clustering algorithm (GC) and WebFrieseBee algorithm (WB) for Jester dataset in terms of F1 measure.](image)

From Figure 6, we may observe that the F1 Measure is higher for WebFrieseBee approach than the genetic clustering approach. That is, cluster optimization results in removing redundant or uninterested data items thereby improving the quality of generated user profiles. Moreover, WebFrieseBee approach offers a better balancing of coverage and precision. That is, interestingness measure is higher for WebFrieseBee approach than the ant clustering approach.

From the Figure 4 to Figure 6, we may observe that WebFrieseBee (WB) approach gives better precision, coverage and F1 Measure than Ant clustering (GC) approach.

From the above discussions, we may observe that WebFrieseBee approach gives better precision, coverage and F1 Measure than traditional ant clustering approach. An improved F1 Measure shows that our approach provides a better tradeoff between precision and coverage. Moreover, an improved F1 measure serves as a better creation of user profiles which in turn means less cluster error. That is, by eliminating data redundancies using WebFrieseBee approach, we get better quality clusters, which in turn, create better user profiles.

### 3.2 Experimental Results on Web Log Dataset

The experimental results for Web Log dataset is discussed under. Figure 7 shows the initial 2D Visualization of the dataset.

![Figure 7. 2D Visualization of the Initial position of agents for Web Log dataset.](image)

In Figure 7, the dataset was randomly distributed over the space.

Figure 8 shows the visualization of the clusters obtained after applying WebFrieseBee algorithm on Web log dataset.

![Figure 8. 2D Visualization of the clusters of agents after applying WebFrieseBee algorithm for Web Log dataset.](image)

The quality of the clusters before after applying the optimization technique was compared using two similarity measures namely intra and inter cluster similarities. Intra cluster similarity deals with the likeness between the elements of the same clusters and the Inter cluster similarity deals with the likeness between the elements of different clusters. For superior quality clustering the intra cluster similarity assessments should be higher than the inter cluster similarity assessments. Tables 3 show the intra and inter cluster similarity measures for Ant clustering algorithm and the proposed WebFrieseBee algorithm. Standard deviations are given away in brackets.
Table 3. Comparison of quality of clusters formed by Ant clustering algorithm and WebFrieseBee algorithm for Web Log dataset

| Ant clustering algorithm       | WebFrieseBee Algorithm       |
|-------------------------------|-------------------------------|
| Intra cluster similarity      | Intra cluster similarity      |
| Inter cluster similarity      | Inter cluster similarity      |
| run                           | run                           |
| 0.47(0.012)                  | 0.51(0.007)                  |
| 0.022(0.002)                 | 0.013(0.001)                 |
| 0.46(0.015)                  | 0.50(0.015)                  |
| 0.027(0.004)                 | 0.016(0.003)                 |

From Table 3, we may observe that compared to Ant clustering algorithm, WebFrieseBee approach results in better clustering outputs. After grouping the input sessions into clusters, the session categories were summarized in terms of user profiles. It captured the relevance of a particular URL in a session belonging to that cluster. Table 4 shows the sample user profiles generated after applying ant clustering approach.

Table 4. Sample user profiles generated after applying Ant clustering algorithm for Web Log dataset

| URL frequency | URL                  |
|---------------|----------------------|
| 0.31          | #98/courses/cse215   |
| 0.30          | #98/courses/cse215/slides.html |
| 0.28          | #98/courses/cse215/notes.html |
| 0.25          | #98/courses/cse215/assignments |
| 0.24          | #98/courses/cse215/quiz.html |
| 0.23          | #98/courses/cse456   |
| 0.22          | #98/courses/cse301   |
| 0.17          | #98/courses/cse301/slides.html |
| 0.14          | #98/courses/cse301/internals.html |
| 0.13          | #98/courses/cse215/assignments/assign1.html |
| 0.12          | #98/courses/cse215/assignments/assign2.html |
| 0.11          | #98/courses/cse215/assignments/format.html |
| 0.11          | #98/courses/cse456/notes.html |
| 0.10          | #98/courses/cse215/project.html |

The most relevant URLs in a user profile were accessed in a session belonging to the $i$th cluster. Table 5 shows the user profiles generated after applying WebFrieseBee approach.

Table 5. Sample user profiles generated after applying WebFrieseBee algorithm for Web Log dataset

| URL frequency | URL                  |
|---------------|----------------------|
| 0.35          | #98/courses/cse215   |
| 0.34          | #98/courses/cse215/slides.html |
| 0.33          | #98/courses/cse215/assignments |
| 0.32          | #98/courses/cse215/project.html |
| 0.3           | #98/courses/cse215/notes.html |
| 0.28          | #98/courses/cse215/quiz.html |
| 0.25          | #98/courses/cse456   |
| 0.22          | #98/courses/cse456/notes.html |

The qualities of the results of applying various algorithms were evaluated using precision, coverage and F1 Measure. Precision symbolizes the fraction of mined items that are significant. Coverage symbolizes the fraction of mined items known to be relevant. F1 Measure shows the interestingness measure. It indicates the harmonizing of recall and precision. Figure 8 shows the comparison in terms of precision for the Ant clustering (GC) and the WebFrieseBee (WB) approaches for web usage data. Here, y axis represents the quality measure in terms of precision and x axis represents the iteration number.

Figure 9. Comparison of Ant clustering algorithm and WebFrieseBee algorithm for Web Log dataset in terms of precision.

From Figure 9, we may observe that precision is higher for WebFrieseBee approach when compared to Ant clustering approach. That is, cluster optimization using the WebFrieseBee approach identifies the user profiles more accurately than the genetic clustering approach. Also, as the number of iteration increases, precision also increases. Figure 10 shows the quality measure in terms of coverage for the web usage data.
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From Figure 10, we may observe that coverage is higher for WebFrieseBee approach than the Ant clustering approach. This indicates that the mined user profiles generated by the WebFrieseBee approach more completely summarize input user sessions. Figure 11 shows the quality measure in terms of F1 Measure for the web usage data.

From Figure 11, we may observe that the F1 Measure is higher for WebFrieseBee approach than the Ant clustering approach. That is, cluster optimization results in better balancing of coverage and precision and user profiles generated increases users interestingness and satisfaction.

4. Conclusion

This paper proposed a WebFrieseBee approach for dynamic cluster optimization and for providing recommendations to users. The proposed BestProphecy-annealing algorithm identifies better neighborhood for agents to give most efficient recommendations to users. It overcomes most of the challenges in traditional recommender systems.

The Bestprophecy-annealing algorithm can overcome the new user ramp up problem and grey sheep problem in many other traditional recommender systems. The Proposed approach supports tumbling information overload problem by understanding the dynamic behaviors, interests and habits of users. The experimental results show that the higher values for precision, coverage and F1 measure authenticate these specifics.

5. References

1. Kim S-S, You Y-Y, Kim S-H, Lee SK. Research direction of constructive e-business consulting for SMEs and Medium-Sized Enterprises (SMEs): Focusing on e-commerce business. Indian Journal of Science and Technology. 2015 Apr; 8(S7).DOI:10.17485/ijst/2015/v8iS7/71290.
2. Nasraoui O, Krishnapuram R, Frigui H, Joshi A. Extracting web user profiles using relational competitive fuzzy clustering. International Journal of Artificial Intelligence Tools. 2000; 9(4):509–26.
3. Saka E, Nasraoui O. Improvements in flock-based collaborative clustering algorithms. Computational Intelligence, Collaboration, Fusion and Emergence. 2009:639–72
4. Wooldridge M. An introduction to multi agent systems. Wiley; 2002.
5. Weiss G. Multi agent systems: A modern approach to distributed artificial intelligence. MIT Press; 2013.
6. Aljumah A, Kouchay SA. Global ranking, web visibility and accessibility of quranic websites - An evaluation study. 2015. Indian Journal of Science and Technology2015 Nov; 8(30).DOI:10.17485/ijst/2015/v8i1/76715.
7. Balabanovic M. An adaptive web page recommendation service. First International Conference on Autonomous Agents, New York; 1997. p. 378–85.
8. Herlocker JL, Konstan JA, Riedl J. Explaining collaborative filtering recommendations. ACM Conference on Computer Supported Cooperative Work, Philadelphia; 2000. p. 241–50.
9. Saka E, Nasraoui O. A recommender system based on the collaborative behavior of bird flocks. CollaborateCom; 2010. p. 1–10.
10. Gayathri S, Metilda MM, Babu SS. A shared nearest neighbour density based clustering approach on a proclus method to cluster high dimensional data. Indian Journal of Science and Technology. 2015 Sep; 8(22).DOI:10.17485/ijst/2015/v8i22/79131.
11. Labroche N, Monmarche N, Venturini G. AntClust: Ant Clustering and web usage mining. Proceedings of GECCO; 2003. p. 25–36.
12. Kennedy J, Eberhart R. Particle swarm optimization. IEEE International Conference on Neural Networks. 1995;4:1942–8.
13. Rathipriya R, Thangavel K, Bagyamani J. Binary particle swarm optimization based bi-clustering of web usage data. International Journal of Computer Applications. 2011; 25(2).

14. DaiL, Wang W, Shu W. An efficient web usage mining approach using chaos optimization and particle swarm optimization algorithm based on optimal feedback model. Mathematical Problems in Engineering; 2013.

15. Ester M, Kriegel HP, Wimmer M, Xiaowei Xu. Incremental clustering for mining in a data warehousing environment. 24th International Conference on Very Large Data Bases; 1998.p. 323–33.

16. Benabdeslem K, Bennani. An incremental SOM for web navigation patterns clustering. 26th International Conference on Information Technology Interfaces; 2004.p. 209–13.

17. Cooley R, Mobasher B, Srivastava J. Web mining: Information and pattern discovery on the world wide web. Ninth IEEE International Conference Tools with AI (ICTAI ’97); 1997.p. 558–67.

18. Chen Z, Meng QC. An incremental clustering algorithm based on swarm intelligence theory. International Conference on Machine Learning and Cybernetics; 2004.p. 1768–72.

19. Cooley R, Mobasher B, Srivastava J. Web mining: Information and pattern discovery on the world wide web. Ninth IEEE International Conference Tools with AI (ICTAI ’97); 1997.p. 558–67.

20. Nasraoui O, Krishnapuram R, Joshi A. Mining web access logs using a relational clustering algorithm based on a robust estimator. Eighth International World Wide Web Conference (WWW ’99); 1999.p. 40–41.

21. Web Server Log files. Karunya University, Coimbatore, Tamil Nadu, India.

22. Available from: http://eigentaste.berkeley.edu/dataset/.

23. Ciar RR, Bonto LS, Bayer MHP, Rabajante JF, Lubag SP, Fajardo AC, Cervanvia CR. Foraging behavior of singles bees TeragonulabiroiFries: Distance, direction and height of preferred food source, Cornell University library; 2013.

24. Fisher D. Knowledge acquisition via incremental conceptual clustering. Machine Learning. 1987;2(2):139–72.

25. Murphy RR. Introduction to AI robotics. The MIT Press; 2000.