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A secured context-aware tourism recommender system using artificial bee colony and simulated annealing

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Abstract: Context-aware recommender systems have been developed to consider users' preferences in various contextual situations. While designing such systems, one immediate concern, is to preserve the integrity of the recommender and minimise the attack probability of biased users who may indirectly influence the outcome of the system. Several algorithms have been developed to identify malicious users in contextual environments. In this paper, we propose a reputation-controlled fish school (RCFS) algorithm to identify trustable users and utilise them in recommendations. In addition, we propose a recommendation algorithm that replicates the behaviour of social insects using a hybrid artificial bee colony (ABC) and simulated annealing (SA) technique. Finally, we demonstrate that the resulting feedback strategies can increase the effectiveness of the recommenders' decisions.

Keywords: artificial bee colony; ABC; contextual recommender system; fish school algorithm; reputation ratings; simulated annealing; SA; trusted user detection.

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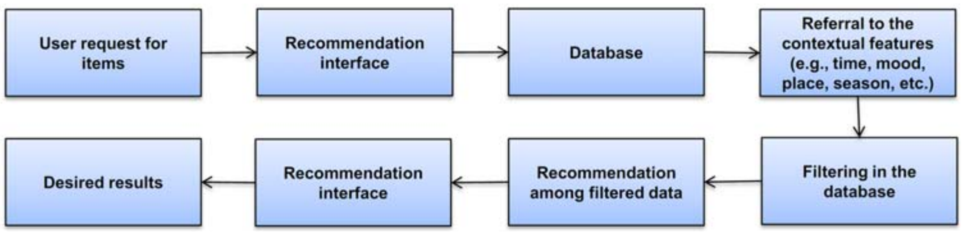
1 Introduction

The existing recommender systems rely on recommending optimal items to individual users. However, they usually do not consider any contextual information, such as the time the user has, the place where the user is or the group of people the user belongs to(e.g., for watching movies or for a long drive or could be simply retuning back home after rigorous office hour). In other words, recommender systems deal with applications having only three types of entities: users, items and set of constraints. The missing context, when providing recommendations could be crucial for the users to make a choice in line with their cognitive, aesthetic and behavioural preferences. For instance, in applications like recommending a vacation package, personalised content on a website or music recommendation depending on the mood of the individuals, the relevance of a contextual recommender system is evident (Su etal., 2010). More specifically, we consider the challenging task of a new tourist, who must gather all possible information before a trip. In the earlier days, people had to rely on manual-based indicative tools (e.g., route map, guide book, informal way of information gathering, etc.) prior to a trip. The immediate shortcomings of these resources (information overload, lack of reality, etc.) could confuse new tourists who could be easily misguided. As a consequence, a personalised dynamic recommendation becomes mandatory for most of the collective tasks.

A recommender system is a software tool, which serves users' needs. The working principle behind a recommender system is to perform filtering operations among an enormous volume of information in the database. Standard filtering techniques include collaborative, content, knowledge and hybrid filtering. Information can also be recommended with respect to specialised users' event occurrences. A recommender oriented towards identifying users' event is known as a context-aware recommender system. For example, a rainy weather context might require songs recommendation suitable for rainy days. A context may have different specifications known as contextual features (mountain, sea, hill, etc.). Contextual computing is one of the tricky tasks and at present it is in demand. The representation of a simple contextual recommender system at work is given in Figure 1.

Figure 1 A contextual recommender system at work (see online version for colours)



One of the difficulties of working in contextual environments is to guarantee the security of the system. Indeed, the system could be intentionally biased towards misconception and, consequently, lead to false recommendation. In order to overcome this limitation, the current paper proposes a novel algorithm to detect suspicious similar profile-based users and learn preferences from similar trusted users. In order to identify the reputed and trusted users; we propose a reputation-controlled fish school (RCFS) algorithm. We also propose a conventional recommendation approach using a hybrid strategy to recommend choices towards the target user.

The remainder of this paper is organised as follows: Section 2 presents the state-of-the-art on context-aware recommender systems. Sections 3 and 4 describe the model proposed in this study. Section 5 discusses our experimental results. Finally, conclusion and future research directions are presented in Section 6.

2 State-of-the-art

In the last few years, context-aware systems have been growing as a popular research area among research communities associated with recommender, information retrieval, machine intelligence, data and web mining. Due to the diversified nature of contextual features context-aware systems also have immense potential practical applications to commercial fields. For example, context-aware recommender systems have been successfully used in industry as devise for product recommendation at Amazon, music recommendation at iTunes, movie recommendation at Netflix, etc. Moreover, researchers have extensively explored context-aware systems in association with contextual variables. In the following paragraph we highlight some of the most recent works related to contextual computing.

The classical results on contexts, contextual computing, contextual applications and classifications have been introduced by Abowd et al. (1999). The importance of contextual features achieving recommendation accuracy has been discussed in (Adomavicius and Tuzhilin, 1999). The article introduced three algorithms: contextual pre-filtering, post-filtering and modelling for inclusion of contextual features. A study on multidimensional user-item rating approach was proposed by (Adomavicius et al., 2005). The work compared multi-dimensional and traditional two dimensional user-item rating in contextual environments.

Apart from the classical approaches, a recent research on context-aware mobile tourism recommenders Meehan et al. (2013) has used contextual factors (temperature, weather, time, sentiment and user preferences). The user rating strategy in contextual mobile recommenders and their effectiveness has been discussed in Baltrunas et al. (2012). The strengths and weaknesses of mobile tourism recommenders have been identified in Schwinger et al. (2008). Kaminskas and Ricci (2011) proposed a location-based contextual tag oriented music recommender. The use of fuzzy utility theory to model uncertain users' context preferences has been studied in Park et al. (2006). Meyers (2007) demonstrated the effect of users' mood-based preferences on *Music Recommender* in his Master's thesis. The use of probabilistic contextual variables for daily activities in mobile music recommender has been introduced in Wang et al. (2012). A music recommender model C2_Music recommendation has been proposed in Lee and Lee (2007). Rho et al. (2009) introduced a music recommender based on mood classification and human emotion prediction. An agent-based contextual recommender that predicts users' preferences has been proposed in Hong et al. (2009). Abbar et al. (2009) developed a contextual recommender to improve recommendation. The performance improvement in contextual recommenders has been studied in this work. Liu and Aberer (2013) discussed asocial recommender to predict missing user-item ratings. Odic et al. (2013) presented an algorithm that helps users to select significant contextual information resulting in high ratings or recommendation.

Verbert et al. (2012) discussed an intelligent approach to improve *technology enhanced learning* under contextual environment. In addition, their work identified and critically evaluated recent significant works in contextual recommendation. Wang et al. (2015) proposed an efficient collaborative filtering algorithm for similar users. The algorithm deploys entropy-driven model to compute users' similarities and Manhattan distance-based model to perform rating and recommendation. Wu et al. (2015) conceived a graph-based approach to perform improved contextual recommendation. Moreover, they proposed a novel probabilistic method to execute the filtering process. Majid et al. (2013) proposed a contextual tourism recommendation algorithm using social media data. Their experiment revealed significant improvement in recommendation compared to traditional techniques. Castro et al. (2015) introduced a strategy to generate high consensus among members to reveal actual item ratings. Similar to Castro's work, Yu (2015) proposed a multiplicative intuitionistic fuzzy algorithm to predict preference to group of users. Liu (2009) developed an algorithm to incorporate social information in to recommender providing effective results compared to traditional collaborative filtering. Shi et al. (2013) presented an effective movie recommender based on user mood using joint matrix factorisation method. Liu (2009) discussed an effective method to rank items reducing the searching time. A contextual query-based recommendation technique has been proposed by Levandoski et al. (2013). Dutta and Kumaravel (2015) designed a method to incorporate contextual information which increases the recommender performance. Bedi and Agarwal (2012) proposed a recommender *aspect-oriented trust-based mobile recommender system* (AOTMRS). The recommender schema considers user location and dynamics of the recommender agents. Friedrich and Zanker (2011) proposed a schema capable of performing justifiable recommendation.

One specific aspect worries the researchers that is maintaining the privacy in contextual computing. Pingley et al. (2009) proposed a various-size-grid Hilbert curve mapping approach to maintain privacy in a contextual recommender. Feng et al. (2012) introduced a reputation strategy to detect suspicious users in social recommender. Götz and Nath (2011) discussed a greedy strategy for preserving the privacy. Chakraborty et al. (2014) proposed an effective rule-based strategy to maintain privacy in mobile recommender. Neisse et al. (2006) discussed the challenges to maintain the privacy in a recommender. Mobasher et al. (2007) presented an algorithm to detect suspicious users who intentionally disrupt recommendation process. Bedi and Sharma (2012) presented an effective bio-inspired optimisation *ant colony* algorithm to identify trusted users using large scale datasets. Gunduz (2003) discussed usefulness of user clicks and navigations towards efficient recommendation in his doctoral thesis.

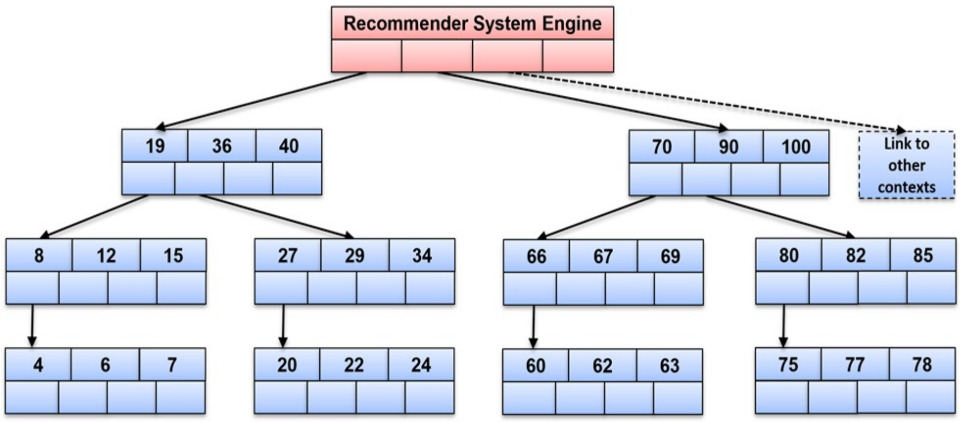
3 A secure RCFS system

One of the difficult tasks of a recommender (conventional or contextual) is maintaining security aspects during the filtering process. From the viewpoint of a contextual tourism recommender, for instance, the aim is to identify intruders that may access in the form of legitimate users. Applying their own voting or recommendations strategies, the intruders interrupt the recommendation process promoting less popular locations or reducing the repute of famous locations. As a consequence, new users may not be provided with a 'secure evaluation', when they use the recommender system. To overcome this difficulty, we follow a statistical approach known as *reputation rating* (Jøsang and Ismail, 2002).

Reputation systems use reputation ratings to derive a user reputation score. The reputation scores from users are combined to compute an aggregated feedback. Each user computes two such feedback values (positive and negative) for others. In other words, our idea is to construct a contextual recommender similar in structure to a B-tree hierarchy. A node represents a context and its children represent the specialised features. The degree of the tree represents the number of users associated with system. Each entry of a node represents a number of clicks by a user at a time snap. A new user or tourist initially interacts with the leaf nodes.

The reputation score is a dynamic parameter which changes over time taking into account user activities. To model reputation transitions, we have designed a RCFS algorithm. In relation to the present problem, fish school algorithm keeps track and computes neighbour or similar user reputations. This operation is performed in subsequent levels of the tree corresponding to the target or new user need. The pictorial representation of the proposed recommender is given in Figure 2.

Figure 2 Contextual recommender systems (as a four-way B-tree) and user clicks in a timesnap (see online version for colours)



3.1 Reputation technique

The objective of the current paper is to construct a reputation-based tourism recommender framework to measure how much a potential user can be trusted before taking his recommendations or ratings in account. The successful identification of reputed users requires the formulation of some parameters which are presented below. These parameters are finally fed into the system. The *degree of impact of a user u* on a contextual feature following from the i^{th} context, (G_{iu}), can be denoted as follows:

$$(G_{iu}) = \frac{(O_{iu} + f_{iu}) - (j_{iu} + v_{iu} + e_{iu})}{n_d} \tag{1}$$

where O_{iu} is the number of useful user u clicks resulting in recommendation, higher rating etc. f_{iu} is the number of user u clicks performing interesting promotional operations, j_{iu} is the number of user u clicks resulting in opposite opinion from communities, v_{iu} is the number of user u clicks performing obstruction operations, e_{iu} is the number of user u clicks resulting in non-interesting operations and n_d is the number of user u clicks over the period d.

The degree of impact of a user u on the i^{th} context (H_{iu}) can be determined as follows:

$$H_{iu} = \begin{cases} \dfrac{(O_{iu} + f_{iu}) - (j_{iu} + v_{iu} + e_{iu})}{n_d} + G_{iu}, & \text{if a single contexual feature is used by } u \\ \dfrac{(O_{iu} + f_{iu}) - (j_{iu} + v_{iu} + e_{iu})}{n_d} + (\text{Number of interactions}) \cdot (\text{Average of } G_{iu}\text{'s}), & \text{if multiple interacting features are used by } u \end{cases} \quad (2)$$

The degree of impact of a user u on the eventual entity (K_u) can be determined as:

$$K_u = \underset{i}{Max}\{H_{iu}\} \quad (3)$$

Computing a final user reputation is a twofold process:

1 computing the reputation ratings from individual's perspectives

2 combining the reputations to derive a resultant reputation score.

Mathematically, the reputation rating about a user u by a user (users) x is denoted as:

$$Reputation_u^x = \frac{r_u^x - s_u^x}{r_u^x + s_u^x + 2} \quad (4)$$

where r_u^x and s_u^x is the positive and negative feedback about u by x respectively.

In our problem, r_u^x can be determined as follows:

$$r_u^x = \left\lfloor \frac{z \times A}{y} \right\rfloor \quad (5)$$

where z is the number of helpful interactions, A is the number of ratings greater than a threshold signifying a higher rating and y is the number of required services, while, s_u^x can be determined as follows:

$$s_u^x = \left\lfloor \frac{B}{y} \right\rfloor \quad (6)$$

where B is the number of ratings less than a positive threshold.

Moreover, the following parameters are useful for finding the recommendation level of a reputed user similar to the new user.

$$\psi = \frac{Average\ number\ of\ recommendations\ by\ new\ users}{Average\ number\ of\ recommendations\ by\ all\ users\ of\ the\ contexts\ or\ features} \quad (7)$$

$$\mu = \frac{Number\ of\ recommendations\ by\ new\ users}{Number\ of\ recommendations\ by\ all\ users\ of\ the\ feature} \quad (8)$$

$$\chi = \frac{Number\ of\ levels\ of\ the\ hierarchy\ forwards\ the\ preference\ of\ user\ u}{Number\ of\ levels\ of\ the\ hierarchy\ used\ by\ user\ u} \tag{9}$$

$$\begin{aligned} u_{CF} &= User\ relevance\ or\ similarity\ using\ collaborative\ filtering \\ &= \frac{\left(\varepsilon/\xi\right)\times \upsilon}{Abs\left(\sigma_1 - \sigma_2\right)} \end{aligned} \tag{10}$$

where ε is the number of common traits between a user and the target user, υ is the number of similar rating values, ξ is the profile features and $Abs(\sigma_1 - \sigma_2)$ denotes the absolute rating difference.

$$\begin{aligned} u_{CCF} &= User\ relevance\ u\sin g\ contextual\ collaborative\ filtering \\ &= \frac{Max_{context} P\left(Feature_1 \wedge Feature_2 \vee Feature_3 \middle| context\right)}{u_{CF}} \end{aligned} \tag{11}$$

where the probabilistic term signifies conditional probability of selecting contextual features provided a context is selected, *context* denotes the generic context among those under considerations.

3.2 Fish school search

Fish school search is an intelligent optimisation technique (Filho et al., 2008). FSS is based on collective behaviour of the fishes for food searching in the aquarium. The movements of fishes are controlled by four operators: individual movement, feeding, collective instinctive movement and collective volatile movement operators. Initially, it is assumed that all fishes are positioned randomly in the aquarium and their weight $W_i(0)$ is initialised to 1. All the reputation controlled operators are defined through the following sub-sections.

3.2.1 Individual movement operator

The movement of a fish in different instances is tracked using the individual movement operator. A fish moves to a new region evaluating the amount of food. The quality of a food source is measured in terms of the Fitness value. Thus, current location of a fish is given by the following:

$$x_i(t+1) = x_i(t) + rand(-1, 1) \times step_{ind}(t) \tag{12}$$

where $x_i(t)$ is the current position of a fish at time instant, *rand*() is a random value function between [–1, 1] and $Step_{ind}$ denotes the individual step size of a fish. Mathematically, an updated $Step_{ind}$ is obtained using equation (13) below, where $Step_{ind\ initial}$ and $Step_{ind\ final}$ are the initial and final individual steps, respectively, and *Iterations* denotes the total number of occurrence of the phenomenon.

$$Step_{ind}(t+1) = Step_{ind}(t) - \frac{Step_{ind\ initial} - Step_{ind\ final}}{Iterations} \tag{13}$$

The fitness difference between the current and new location of a fish, Δf_i, and the corresponding displacement, Δx_i, are computed using (14) and (15).

$$\Delta f_i = f\left(x_i(t+1)\right) - f\left(x_i(t)\right) \tag{14}$$

$$\Delta x_i = x_i(t+1) - x_i(t) \tag{15}$$

In our problem, we need to define two fitness functions: one assigning a fitness value to each context node, given by:

$$F_{context\ node} = \frac{\sum_{u=1}^{\lambda} \gamma_u}{(\alpha - \lambda) \times \beta} \tag{16}$$

and one assigning a fitness value to each neighbour, given by:

$$f_u = \frac{\gamma_u}{\beta_u} \tag{17}$$

In equations (16) and (17), γ_u is the average ratings of the neighbours of the target user u of a context assigned by non-λ's, λ is the number of neighbours, α is the number of users of the context and β is the average degree of impact of users in that context.

3.2.2 Feeding operator

The weight of a fish increases after successful food searching. The present weight is calculated using(18):

$$W_i(t+1) = W_i(t) + \frac{\Delta f_i}{\max(\Delta f)} \tag{18}$$

where $w_i(t)$ is the weight of a fish i at the time instant t, Δf_i is the fitness difference between the current and new location of a fish i and $\max(\Delta f) = \max_i\{\Delta f_i\}$. A parameter W_{scale} is used to restrict the maximum weight of a fish. The weight of a fish belongs between 1 and W_{scale} while i initial weight is assumed to be $W_{scale}/2$.

3.2.3 Collective instinctive movement operator

As a consequence of successful individual movement, some fishes attract others. Thus, the resulting direction of all fishes can be formalised using (19), where N denotes the population size. Finally, the updated position of each fish is given by (20):

$$I(t) = \frac{\sum_{i=1}^{N} \Delta x_i \times \Delta f_i}{\sum_{i=1}^{N} \Delta f_i} \tag{19}$$

$$x_i(t+1) = x_i(t) + I(t) \tag{20}$$

3.2.4 Collective volatile movement operator

After a successful food searching the radius of the school should contract, i.e., drift inwards with respect to the barycenter (centre of gravity) of the school. Otherwise, school dilatation would occur. The barycenter considers current position and weight of the fishes and it is obtained using (21). The contraction and dilation are performed using (22) and (23), respectively.

$$B(t) = \frac{\sum_{i=1}^{N} x_i(t) \times W_i(t)}{\sum_{i=1}^{N} W_i(t)} \tag{21}$$

$$x_i(t+1) = x_i(t) - Step_{vol}\ rand(0,1)\ \frac{[x_i(t) - B(t)]}{D(x_i(t), B(t))} \tag{22}$$

$$x_i(t+1) = x_i(t) + Step_{vol}\ rand(0,1)\ \frac{[x_i(t) - B(t)]}{D(x_i(t), B(t))} \tag{23}$$

where *D*(.) is a function that returns Euclidean distance between the barycenter and the current fish position. $Step_{vol}$ is used to direct fish displacements from or to the barycenter. $Step_{vol}$ is expressed as percentage of search space range exploration and is controlled by $Step_{vol\ \max}$ and $Step_{vol\ \min}$. Usually, $Step_{vol}$ is assumed to be twice $Step_{ind}$. $Step_{vol}$ decreases linearly from $Step_{vol\ \max}$ to $Step_{vol\ \min}$ in successive iterations. Table 1 describes the analogy between contextual recommender system and fish school parameters helpful in finding the reputed users and Appendix A presents the proposed RCFSS algorithm.

Table 1 Analogy between contextual recommender and Fish school parameters

Sl	*Fish school parameters*	*Contextual recommender parameters*
1	Fish	New user
2	$X_i(t)$	Current reputation rating of a user similar to the target user
3	$W_i(t)$	Current recommendations of a user similar to the target user
4	$Step_{ind}(t)$	Degree of impact of a user
5	$Step_{ind\ initial}$ and $Step_i$	Maximum allowable degree of impact of a user in the initial (i.e., after the root node) and final level (i.e., in the leaf nodes)
6	*Iterations*	Tree levels
7	Δf_i	Fitness difference between two contexts
8	Δx_i	User reputation difference at the current and previous instant
9	$I(t)$	Desired fitness of a similar user in a new context or feature
10	$B(t)$	Desired recommendations of a similar user in a new context or feature

4 Recommendation using ABC

One advantage of a recommender system is that it performs suggestions according to user need. In other words, it displays the top recommendations. In addition to, the system reveals recent top rated items that influence decision-making. In this section, we propose a novel hotel recommendation strategy using a hybrid artificial bee colony (ABC) and simulated annealing (SA) technique. The ABC algorithm imitates the behaviour of social bees in search of food while SA mimics the melting process of solids in a heat bath. Both of these are efficient approaches for solving optimisation problems. In view of the given problem, the SA algorithm tracks users' visiting in durations whereas the ABC algorithm generates the recommendation.

4.1 Brief overview of ABC

The ABC algorithm was proposed by Karaboga (2005). ABC is a swarm-based optimisation technique which follows the principle of self-organisation. The algorithm is based on the movements of artificial bees in search for food. The quality of each food source depends on the amount of nectar on it. The hive consists of three types of bees: onlooker, employed, and scout. Scouts are responsible in searching of the food locations. Employed bees inspect the quality of the Nectar in a food source. Finally, onlooker bees decide a food source based on the greedy selection policy. In recent years, ABC algorithm has been successfully applied in diverse research domains.

4.2 Brief overview of SA

SA was proposed by Kirkpatrick et al. (1983). SA is motivated by the phenomenon known as 'annealing', that is, the melting of solids in a heat bath beyond their melting point. Subsequently, the cooling of the liquid is performed until the lower energy-based ground state is achieved. The structure of the well-formed crystals depends on the rate of cooling. If the cooling is performed slowly then perfect crystals are formed. Otherwise, crystals will contain imperfect states and results in quenching.

4.3 Proposed hybrid approach

Table 2 describes the analogy between recommender and the ABC and SA parameters.

Consider N hotels, h_i, $i = 1,\dots,N$. The objective function in terms of hotel recommendation is described below. The goal is to maximise the recommendation value of each hotel in a fixed period of time.

Table 2 Analogy between recommender and ABC and SA parameters

Sl	*ABC parameters*	*Hotel recommender parameters*	*SA parameters*
1	Hive	Users	--------
2	Onlooker bee	Customer with maximum recommendation	--------
3	Employed bee	A customer similar to the onlooker having higher ratings or likings	--------
4	Scout bee	New user	--------
5	x_i^j	Hotel rating	--------
6	$x_{\max}^j$	Maximum allowable rating	--------
7	$x_{\min}^j$	Minimum allowable rating	--------
8	j	Pivotal parameters e.g., rooms, facilities, services etc.	Molecular positions
9	$fitness_i$	$\frac{\text{Aggregate rating of the employed bee in the duration}}{\text{Number of visits of a employed bee in a duration}}$	--------
10	--------	Objective function value	Energy
11	--------	Budget	Temperature
12	--------	Feasible solution	State
13	--------	Decrement of budget by a factor	ϑ
14	--------	Subset of the pivotal parameters	Quenching

4.3.1 *Objective function*

$$Max \quad Y_i = \sum_{u=1}^{U_i} \sum_{g_u=1}^{V_{iu}} \left(\delta_{iu} \times \rho_{ig_u}\right) + \left(\kappa_{ig_u} + \omega_{ig_u}\right) \quad \text{for} \quad i = 1, \ldots, N \tag{24}$$

where U_i is the total of users who visit the hotel h_i in the fixed interval of time, V_{iu} is the total number of visit paid by the u^{th} user to the hotel h_i, δ_{iu} is the significance of hotel h_i to the u^{th} user, ρ_{ig_u} is the number of recommendations during the g_u^{th} visit of u^{th} user, κ_{ig_u} is the duration of the g_u^{th} visit of the u^{th} user and ω_{ig_u} is the number of advance bookings.

Subject to:

1 $\frac{\text{Number of features available to the hotel } h_i}{\text{Number of preferred features by } u} \geq \text{Threshold}$

2 Average rating of $h_i \geq$ Threshold

3 $\frac{(\text{Number of recent positive reviews to } h_i) \times (\text{Number of recommendations to } h_i)}{\text{Number of recent reviews to the hotel } h_i} \geq \text{Threshold}$

4 Probability of offering pivotal parameters during the $g_u{}^{th}$ visit $= 1$

5 $\frac{\text{Aggregate overall rating}_{iu}}{V_{iu}} \approx \text{Constant}$

6 $0 \leq \delta_{iu} \leq 1$

4.3.2 Feasible solution

$$\sum_{\text{Feature}=1}^{\text{Required Features in } g_u th \text{ visit}} P(\text{Availability of the Feature}) \times \text{Feature Recommendation}$$

The optimal searching of the objective function value requires the computation of other parameters which are presented below:

$$q_i = \frac{\text{(Seasonal visits-Non-seasonal visits)}}{\text{(Changes in visits in between consecutive discount period)}}$$

$$v_i = \text{Number of voting's to the hotel } h_i$$

$$R'_{ij} = \left[3 \times P\left(R_{kj}\right)\right] + \left[R_{ij} + \varphi_{ij}\left(R_{ij} - R_{kj}\right)\right] + \left[\sum_{Scout\ bees} P\left(\varsigma^{scout}{}_k\right) \times \tau^{scout}{}_k\right] \tag{25}$$

where R'_{ij} is the feedback of h_i, $P(R_{kj})$ are the probability of performing rating k by three types of bees, $P(\varsigma_k^{scout})$is the probability of a scout to become regular visitor, τ_k^{scout} is the number of waggle dances, j is the number of dimensions and φ_{ij} belongs between [–1, 1].

The proposed ABC algorithm here is described in Appendix B.

5 Experimental results

The Irish Trip-Advisor dataset has been used to perform validations for the algorithm. The dataset consists of 29,799 reviews of 21,851 unique peoples. The reviews were collected from September2007 to September 2009 considering every hotel from all areas of Ireland. User activities also needed to be evaluated for computing the reputations. Thus, AOL query dataset has been considered.

Table 3 A record from the Trip-Advisor dataset

Author	*Number of reader*	*Number of helpful*	*Overall hotel rating*	*Value*	*Rooms*	*Location*	*Cleanliness*	*Check in/front desk*	*Services*	*Business services*	$x_i(t)$
Trinzeon	2	2	5	4	4	4	5	5	5	5	0.24

The values in Table 3 show different contextual factors of the context hotel considering a specific location collected from the Trip-Advisor dataset.

Table 4 Results of the individual movement operation (G_{iu}= $Step_{ind}(t)$)

Contextual feature	$Step_{ind}(t)$	$[x_i(t)]$	*rand()*	n_d	$x_i(t + 1)$
None	0	0	0.5	15	0
Travel, maps and weather	–0.2	0.24	0.5	15	0.14
Food and drink	0.3	0.24	0.5	15	0.39
Country and places	0.4	0.24	0.5	15	0.44

The results in Table 4 show a prediction of the reputation values using values from the above mentioned dataset and the specified AOL dataset. The results reveal that user reputation increments with proper operations. The variation of reputation in time considering user operations is shown in Figure 3.

Figure 3 Reputation of a user according to the degree of impact (see online version for colours)

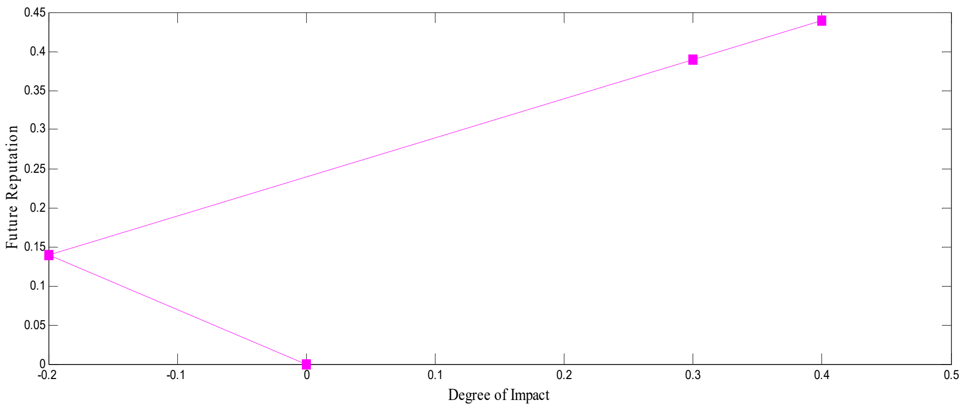


Table 5 Results of the collective instinctive movement operation

Reputation measured by user	$x_i(t – 1)$	$x_i(t)$	(Δf_i)	*I(t)*	$[x_i(t + 1)]$
1	3	4	1	0.5	4.5
2	3	4	1	0.5	4.5
3	4	4	1	0.5	4.5
4	4	4	1	0.5	4.5

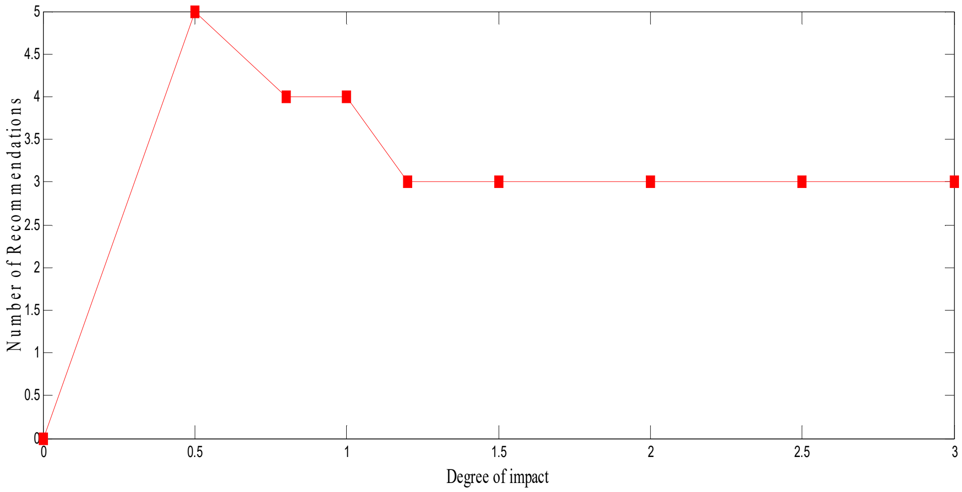
Table 6 Results of the collective volitive movement operation

Reputation measured by user	$[x_i(t)]$	$[w_i(t)]$	*B(t)*	$Step_{vol}$ = $2{*}Step_{ind}(t)$	*rand()*	$[x_i(t + 1)]$
1	5	9	4.7	1.8	0.5	4.7
2	5	9	4.7	1.8	0.5	4.7
3	5	10	4.7	1.8	0.5	4.7
4	4	8	4.7	1.8	0.5	4.7

Tables 5 and 6 forecast the future user reputation using the collective instinctive and collective volitive methods. The computation considers extreme values of the variables (reputation scale-5, recommendation scale-10). As the result demonstrates, collective volitive operator finds the most appropriate and reputed user among all similar contexts or features.

The relation between the degree of impact of a user and the resultant recommendation is shown in Figure 4.

Figure 4 Recommendations of a user according to the degree of impact (see online version for colours)



The relation between the fitness of a context and the degree of impact of the neighbours is shown in Figure 5. The figure reveals that the fitness is proportional to the proper operations of the neighbours.

A comparison between our reputation scheme and a similar work based on trust values of the neighbours 'TidalTrust' algorithm (Golbeck, 2006) is shown in Table 7. The result shows that our algorithm performs better than the TidalTrust algorithm.

Figure 5 Fitness of a context according to the degree of impact of neighbours (see online version for colours)

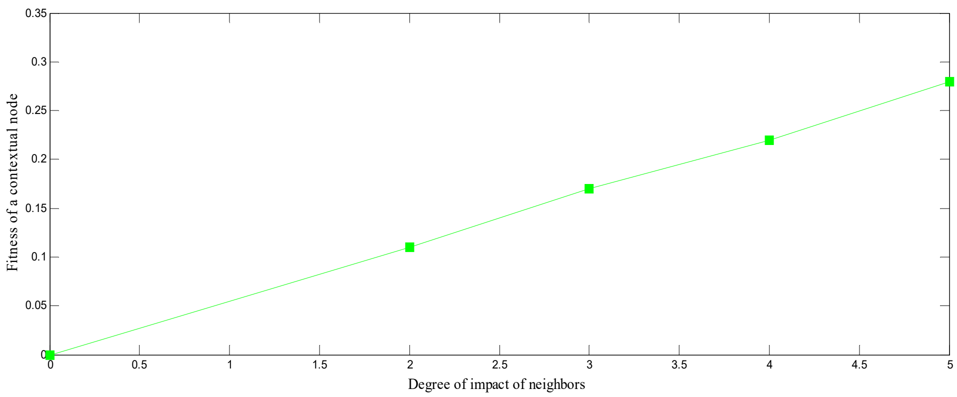


Table 7 Comparison of the results (trust or reputation threshold = 4.0)

Reputation of a user using fish school strategy	*Trust value of neighbours (T_{sj})*			*Trust value of the target user by neighbours (T_{ji})*			*Trust value of the target user by new user's (T_{si})*
5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
5.0	4.9	4.9	4.9	5.0	5.0	5.0	5.0
5.0	5.0	5.0	5.0	4.8	5.0	5.0	4.9
5.0	5.0	4.9	5.0	5.0	4.9	4.8	4.9

6 Conclusions and future research directions

The paper explores different features of existing recommendation systems and proposes a novel feedback strategy for tourism recommendation. The proposed solution is partially unconventional, and here the prime objective is to find out an optimal or near optimal selection for recommendation advice to the other contemporary users. The proposed model also provides additional level of identifying trusted and reputed users, whose feedback can be propagated strategically for next subsequent levels of recommendation. This feature could enhance the trust and reputation of recommender system and reliability of the system also should be upgraded accordingly. Several interesting observations have been made during the implementation of the model based on popular recommenders. The difference of selection and recommendation level demonstrates the relevance of the proposed schema for recommendation. If more non-deterministic features could be added up, then the recommender system will need more adaptive algorithm for achieving better ratings. The proposed research shows a few limitations when handling big and dynamic set of data produced as a result of user-item interactions, recommendation performs optimally when it is tested on relatively small dataset, but it may become slightly unsuitable on very large dataset. *Case-based reasoning (CBR)* could solve the problem of following the similar users more efficiently. Considering the practical importance of recommender and the popularity of social network applications, more hybrid form of recommendation strategies could be required in the next level of the application. In particular, the deployment of suitable machine learning algorithm from context could enhance the ability of recommendations in future applications.

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References

Abbar, S., Bouzeghoub, M. and Lopez, S. (2009) 'Context aware recommender systems: a service oriented approach', *Proceedings of the Third International Workshop on Personalized Access, Profile Management and Context Awareness in Databases*, pp.1–6.

Abowd, G.D., Dey, A.K., Brown, P.J., Davies, N., Smith, M. and Steggles, P. (1999) 'Towards a better understanding of context and context awareness', *Proceedings of the 1st International Symposium on Handheld and Ubiquitous Computing*, pp.304–307.

Adomavicius, G. and Tuzhilin, A. (1999) *Context Aware Recommender Systems*, pp.217–253, Springer Science Business Media.

Adomavicius, G., Sankaranarayanan, R., Sen, S. and Tuzhilin, A. (2005) 'Incorporating contextual information in recommender systems using a multidimensional approach', *ACM Transactions on Information Systems*, Vol. 23, No. 1, pp.103–145.

Baltrunas, L., Ludwig, B., Peer, S. and Ricci, F. (2012) 'Context relevance assessment and exploitation in mobile recommender systems', *Personal and Ubiquitous Computing*, Vol. 16, No. 5.

Bedi, P. and Agarwal, S.K. (2012) 'Aspect-oriented trust based mobile recommender system', *International Journal of Computer Information Systems and Industrial Management Applications*, Vol. 5, No. 1, pp.354–364.

Bedi, P. and Sharma, R. (2012) 'Trust based recommender system using ant colony for trust computation', *Expert Systems with Applications*, Vol. 39, No. 1, pp.1183–1190.

Castro, J., Quesada, F.J., Palomares, I. and Martínez, L. (2015) 'A consensus-driven group recommender system', *International Journal of Intelligent Systems*, Vol. 30, No. 8, pp.887–906.

Chakraborty, S., Shen, C., Raghavan, K.R., Shoukry, Y., Millar, M. and Srivastava, M. (2014) 'IpShield: a framework for enforcing context-aware privacy', *Proceedings of the 11th USENIX Symposium on Networked Systems Design and Implementation*, pp.143–156.

Dutta, P. and Kumaravel, A. (2015) 'Semantic analysis of context attributes for recommender system using ontology', *International Journal of Computer Science and Technology*, Vol. 6, No. 1, pp.81–87.

Feng, Q., Liu, L. and Dai, Y. (2012) 'Vulnerabilities and countermeasures in context aware social rating services', *ACM Transactions on Internet Technology*, Vol. 11, No. 3, pp.1–11.

Filho, C.J.A.B., Neto, F.B.L., Lins, A.J.C.C., Nascimento, A.I.S. and Lima, M.P. (2008) 'A novel search algorithm based on fish school behavior', *Proceedings of the IEEE international Conference on Systems, Man, and Cybernetics*, pp.2646–2651, 12–15 October, IEEE, Singapore.

Friedrich, G. and Zanker, M. (2011) 'A taxonomy for generating explanations in recommender systems', *AI Magazine*,Vol. 32, No. 3, pp.90–98.

Golbeck, J. (2006) 'Generating predictive movie recommendations from trust in social networks', *Proceedings of the 4th International Conference on Trust Management*, pp.93–104, Springer Berlin Heidelbergm Pisa, Italy.

Götz, M. and Nath, S. (2011) *Privacy-Aware Personalization for Mobile Advertising*, Microsoft Research Technical Report MSR-TR-2011-92.

Gunduz, S. (2003) *Recommendation Models for Web Users: User Interest Model and Click Stream Tree*, Unpublished Doctoral Thesis, Istanbul Technical University.

Hong, J., Suh, E., Kim, J. and Kim, S.Y. (2009) 'Context aware system for proactive personalized service based on context history', *Expert Systems with Applications*, Vol. 36, No. 4, pp.7448–7457.

Jøsang, A. and Ismail, R. (2002) 'The beta reputation system', *Proceedings of the 15th Bled Electronic Commerce Conference*, pp.41–55.

Kaminskas, M. and Ricci, F. (2011) 'Location-adapted music recommendation using tags', in Konstan, J.A., Conejo, R., Marzo, J.L. and Oliver, N. (Eds.): *User Modeling, Adaption and Personalization*, pp.183–194, Springer Berlin Heidelberg, Girona, Spain.

Karaboga, D. (2005) *An Idea Based on Honey Bee Swarm for Numerical Optimization*, Tech. Rep. TR06, pp.51–60.

Kirkpatrick, S., Gelatt Jr., C.D. and Vecchi, M.P. (1983) 'Optimization by simulated annealing', *Science*, Vol. 220, No. 4598, pp.671–680.

Lee, J.S. and Lee, J.C. (2007) 'Context awareness by case-based reasoning in a music recommendation system', *Proceedings of the Fourth international conference on Ubiquitous Computing Systems*, pp.45–58.

Levandoski, L., Eldawy, A., Mokbel, M.F. and Khalefa, M. (2013) 'Flexible and extensible preference evaluation in database systems', *ACM Transactions on Database Systems*, Vol. 38, No. 3.

Liu, F. and Lee, H.J. (2010) 'Use of social network information to enhance collaborative filtering performance', *Expert Systems with Applications*, Vol. 37, No. 7, pp.4772–4778 [online] http://dx.doi.org/10.1016/j.eswa.2009.12.061.

Liu, T.Y. (2009) 'Learning to rank for information retrieval', *Foundations and Trends in Information Retrieval*, Vol. 3, No. 3, pp.225–331.

Liu, X. and Aberer, K. (2013) 'A social network aided context aware recommender system', *Proceedings of the 22nd International Conference on World Wide Web*, pp.781–802.

Majid, A., Chen, L., Chen, G., Mirza, H.T., Hussain, I. &Woodward, J. (2013) A context-aware personalized travel recommendation system based on geotagged social media data mining', *International Journal of Geographical Information Science*, Vol. 27, No. 4, pp.662–684.

Meehan, K., Lunney, T., Curran, K. and McCaughey, A. (2013) 'Context aware intelligent recommendation system for tourism', *Proceedings of the IEEE International Conference on Pervasive Computing and Communication*, pp.328–331.

Meyers, O. (2007) *A Mood Based Music Classification and Exploration System*, Unpublished Master's Thesis, Massachusetts Institute of Technology [online] http://hdl.handle.net/1721.1/39337.

Mobasher, B., Burke, R., Bhaumik, R. and Williams, C. (2007) 'Toward trustworthy recommender systems: an analysis of attack models and algorithm robustness', *ACM Transactions on Internet Technology*, Vol. 7, No. 4, pp.23–60.

Neisse, R., Wegdam, M. and Sinderen, M.V. (2006) 'A distributed context aware trust management architecture', *Proceedings of the 4th International Conference on Pervasive Computing*.

Odić, A., Tkalčič, M., Tasič, J.F. and Košir, A. (2013) 'Predicting and detecting the relevant contextual information in a movie-recommender system', *Interacting with Computers*, Vol. 25, No. 1, pp.74–90.

Park, H., Yoo, J. and Cho, S. (2006) 'Context aware music recommendation system using fuzzy Bayesian networks with utility theory', *Proceedings of the 3rd International Conference on Fuzzy Systems and Knowledge Discovery*, pp.970–979.

Pingley, A., Yu, W., Zhang, N., Fu, X., Lowell, U. and Zhao, W. (2009) 'CAP: a context aware privacy protection system for location-based services', *Proceedings of the29th IEEE International Conference on Distributed Computing Systems*, pp.49–57, 22–26 June, IEEE, Montreal, QC.

Rho, S., Han, B.J. and Hwang, E. (2009) 'SVR based music mood classification and context based music recommendation', *Proceedings of the 17th ACM international conference on Multimedia*, pp.713–716, ACM, New York, USA.

Schwinger, W., Grun, C., Proll, B., Retschitzegger, W. and Schauerhuber, A. (2008) 'Context awareness in mobile tourism guides', in *Handbook of Research on Mobile Multimedia*, pp.298–314.

Shi, Y., Larson, M. and Hanjalic, A. (2013) 'Mining contextual movie similarity with matrix factorization for context-aware recommendation', *ACM Transactions on Intelligent Systems and Technology*, Vol. 4, No. 1, pp.1–19.

Su, J.H., Ye, H.H., Yu, P.S. and Tseng, V.S. (2010) 'Music recommendation using content and context information mining', *IEEE Intelligent Systems*, Vol. 25, No. 1, pp.16–26.

Verbert, K., Manouselis, N., Ochoa, X. and Wolpers, M. (2012) 'Context-aware recommender systems for learning: a survey and future challenges', *IEEE Transactions on Learning Technologies*, Vol. 5, No. 4, pp.318–335.

Wang, W., Zhang, G. and Lu, J. (2015) 'Collaborative filtering with entropy-driven user similarity in recommender systems', *International Journal of Intelligent Systems*, Vol. 30, No. 8, pp.854–870.

Wang, X., Rosenblum, D. and Wang, Y. (2012) 'Context aware mobile music recommendation for daily activities', *Proceedings of the 20th ACM International Conference on Multimedia*, pp.99–108, ACM, New York, USA.

Wu, H., Yue, K., Liu, X., Pei, Y. and Li, B. (2015) 'Context-aware recommendation via graph-based contextual modeling and post-filtering', *International Journal of Distributed Sensor Networks*, Article ID 613612.

Yu, D. (2015) 'Group decision making under interval-valued multiplicative intuitionistic fuzzy environment based on archimedean t-Conorm and t-Norm', *International Journal of Intelligent Systems*, Vol. 30, No. 5, pp.590–616.

Appendix A

RCFSS algorithm

Initialization: User clicks, Contexts and corresponding contextual features

begin

for level = depth to 1 do//participation of the target user in different levels

for preferred contextual feature = 1 to con_feature do

//a preferred contextual feature of target user

while (Fitness difference between a contextual feature node of two hotels > 1) do

Choose the new node using heuristic strategy of the fish

Select s similar users from the node using standard similarity coefficient

for similar user = 1 to s do

if (Change of f_u in successive instants = FALSE and G_{iu} > Threshold) then

Compute $x_i(t + 1)$ and $w_i(t + 1)$ using (12) and (18)

Compute ψ and µ using (7)and(8)

Update individual and node fitness

break

else

The user has performed malicious operations

end if

end for

if ($B(t)$ = TRUE and ($\mu > \psi$)) then

Update $x_i(t + 1)$ using (22)

else if ($I(t)$ = TRUE and recommendation < $B(t)$ = TRUE) then
Update $x_i(t+1)$ using (20)
else
Update $x_i(t+1)$ of $B(t)$ using (23)
Compute I(t) using(19)
end if
if ($x_i(t)$'s$_{\text{average}}$ = maximum among similar users) then
The user is reputed and appropriate for the new users
else
end while
end if
end for
end for
for reputed user = 1 torepu_user do
Compute $\chi_{\text{repu\_user}}$
end for
if ($\chi_{\text{repu\_user}}$=maximum) then //comparing references between target user and reputed users
The user is trusted
end if
end begin

Appendix B

ABC algorithm

Initialization: Recommendation set S_i = {}, Top rated hotels R_i = {}, Number of times employed bee memorize a hotel rating K_i = {}, Bee_cycle = 1, Solution $Sol = Sol_0$, Temperature $T = T_{max}$
begin
while (Bee_cycle≤Duration) do
//generating the recommendation list for duration
If (v_i >> Threshold and q_i < 0 and availability = TRUE) then
repeat
repeat
A neighbor solution Sol′ is generated and compute difference of the energies
$\Delta E = f(\text{Sol}') - f(\text{Sol})$
if($\Delta E \leq 0$) then
Accept the solution and SetSol = Sol′
else
Reject the neighbor solution
end if

until (iterations in a temperature)
if (Y_i > Threshold) then
Insert the corresponding hotel in S_i
else
Do not insert in S_i
Update the current temperature as $T = \vartheta T$
end if
until ($T \leq T_{min}$)
Compute L = $fitness_{(average)}$ of S_i
else if ($v_i \geq$ Threshold = TRUE and availability = TRUE)
repeat
Scouts bees identifies a rating using food source generation rule
Ratings are inserted in R_i
Employed bees fly to R_i and choose using (25)
Update K_i
until (visits of a scout)
else
break
end if
for i = 1 to selected ratings do
if ($K_i \geq L$) then
Inset the selected hotel in S_i and display
else
Display S_i and R_i
end if
end while
end begin