International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Impact Factor (2012): 3.358

A Perceptual Evaluation of Optimization Algorithms and Iterative Method for E-Commerce

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Abstract: ***In the age of digital and network, every high efficiency and high profit activity has to harmonize with internet. The business behaviors and activities always are the precursor for getting high efficiency and high profit. Consequently, each business behavior and activities have to adjust for integrating with internet. Underlay on the internet, business extension and promotion behaviors and activities general are called the Electronic Commerce (E-commerce). The quality of web-based customer service is the capability of a firm's website to provide individual heed and attention. Today scenario personalization has become a vital business problem in various e-commerce applications, ranging from various dynamic web content presentations. In our paper Iterative technique partitions the customer in terms of frankly combining transactional data of various consumers that forms dissimilar customer behavior for each group, and best customers are acquired, by applying approach such as, IE (Iterative Evolution), ID (Iterative Diminution) and II (Iterative Intermingle) algorithm. The excellence of clustering is improved via Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). In this paper these two algorithms are compared and it is found that Iterative technique chorus Particle Swarm Optimization (PSO) is better than the other Ant Colony Optimization (ACO) algorithms. Additionally the results show that the Particle Swarm Optimization (PSO) algorithm outperforms other Ant Colony Optimization (ACO) algorithms methods. Finally quality is superior along with this response time higher and cost wise performance is increased and both accuracy and efficiency.***

Keywords: E-Commerce, Ant Colony Optimization (ACO), Clustering, Preprocessing, Davies-Bouldin's Index, Particle Swarm Optimization (PSO)

1. Introduction

Electronic commerce (or e-commerce) encompasses all business operated by means of computer networks. The telecommunications and computer technologies in recent years have built up computer networks an Indiscernible part of the economic infrastructure. More and more companies are facilitating transactions over web [1]. There has been tremendous competition to objective each and every computer owner who is connected to the Web. Electronic commerce is increasingly famous in today's businesses and is becoming an Indiscernible facet in the online shopping experience. Ecommerce web sites are increasingly introducing personalized features in order to build and retain relationships with customers and enlarging the number of purchases made by each customer [2].

In this paper experimentally identify the dynamics of online service personalization, extraordinarily in the context of online apparel retail settings, and to furnish managerial insight into online retail management. In this paper online service personalization [3] is now in its youngling stages. Personalization appears to be an imperative and arduous challenge for current advertisers. Besides, it is more individualized than objective advertising, which simply divides customers in a market into specific segments. It makes ready to assign an appropriate advertisement to a single web user rather than to a group of individuals. To obtain this goal, personalization systems need to have some information about the user [4]. Numerous web portals create user profiles using information facility during the registration process or ask the user to answer some questions about their precedence. Anyway, this requires a lot of time and endeavor wherein could discourage many users. Except that, users tend to give inappropriate data when there are concerns about their solitude. Furthermore dependable data become out of date with the advancement of online customer's interests.

Presently, there has been much interest in the marketing and data mining communities [5] in learning individual models of customer behavior within the context of one-to-one marketing and personalization in this exemplification the models of customer behavior learn from the data pertaining only to a distinctive customer [6]. These learned individualized models of customer behavior are stored as parts of customer profiles and are subsequently used for recommending, delivering personalized products and services to the customers. In this paper, we have employed iterative techniques. This direct grouping viewpoint, partitions the customer in terms of outright combining transactional data of various customers that forms different customer behavior for each group, and finding the optimal partition of customers by differentiating IE, ID & II Algorithm. The clustering is performed using two algorithms PSO and ACO. It is analyzed that in PSO technique clustering quality is better than other ACO algorithms.

2. Related Works

The clustering is a so-called "unsupervised"analysis that is designed to categorize observations (in this case customer) into a number of different groups ("clusters"), with each being comparatively similar based on their values for a limit of different factors. In each case, some form of inter measure is used to patch up how close jointly or far apart different customers are based on their attributes. There are several flavors of clustering methods depending upon how you

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measure the distance between points within and between clusters [7] and also on how you explore the different groupings.

The procedure continues until there's just one cluster containing all the observations. A so-called dendrogram figure 1 can be produced that shows which clusters are integrated at each step and the associated variance total, allowing us to select the most applicable number of clusters.

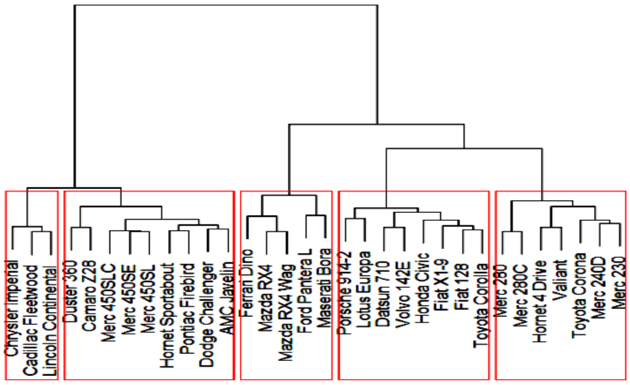

Figure 1: The dendrogram for a hierarchical cluster analysis with five final clusters

There is a subjective element to use these clustering techniques. Following the analysis, we would need to review the data and recognize what the members of each cluster [8] have in usual in a meaningful and practical sense. Similarly, we can investigate that members of distinct groups differ in some obvious and episodic method. This process can help to determine how many segments are needed. The customer base and their transaction histories are placed into similar clusters for the purpose of building preferable models of customer behavior using these clusters. The outstanding issues in personalization such as the degree of personalization, intrusiveness, privacy, scalability, trustworthiness, and usage of various metrics to measure effectiveness of personalization have been formerly pointed out by many researchers, are discussed extensively in the literature. These authors have proposed integration of advanced profiling and matchmaking techniques [9]. For extracting the profiling information the authors have insisted upon certain modeling metrics such as conjunctive rules framing, signatures and sequences. Vice versa adopts this methodology suffers problems in selection of metrics. This may not be well suited for the application at hand also not giving the accurate measurements. In this paper, to chastise the traditional viewpoint for clustering market basket type data, relations among transactions are modeled according to the items eventful in these transactions. However, an individual item might induce dissimilar relations in dissimilar contexts.

By clustering the patterns in the dataset, a clustering of the transactions is inferred and represented this way. Besides customer profiles can be defined as sets of attributes assorted [10] with the sets of rules defining the behavior of the customer sets of sequences such as sequences of Web browsing activities which are concentrated, extremely on and signatures are used to occupying the evolving behavior learned from data streams of transactions [11]. Therefore the personalization approaches developed in the data mining and user-modeling communities include only the task of building good profiles and models of customers, but it does not contemplate apparent grouping methods, also excludes optimal or suboptimal customer segmentation scheme [12], iterative grouping against one to- one and statistics-based segmentation methods are not dissimilar too [13]. In our proposed approach iterative techniques are especially taken and experimentally differentiated with their performance repugnant the statistics- based approaches and one-to-one approaches.

3. The Proposed Systematize Model

3.1 Cluster Analysis of Dataset

The term cluster analysis (first used by Tryon, 1939) encompasses a number of different algorithms and methods for grouping objects of identical kind into respective categories. Cluster analysis is an investigation data analysis tool [14] which aims at sorting dissimilar objects into groups in a way that the degree of association between two objects is maximal if they belong to the same group and minimal otherwise. The cluster analysis can be used to discover structures in data without providing a clarification explication. In other words, cluster analysis is simply discovering structures in data without decode why they exist.

A physical or abstract structure of objects is indicated as patterns. This is specific from others by a collective set of attributes called features [15], which simultaneously represents a pattern. The individuals or variables are classified based on the similarity of the characteristics they possess. It eyesight for abbreviate within-group variance and maximizing between-group variance. The principal substantive thing of data-clustering is to receive an optimal assignment of O objects in one of the C clusters where O is the number of objects and C is the number of clusters. In this paper, we are proposing two algorithms firstly Particle Swarm Optimization (PSO) and secondly Ant Colony Optimization (ACO) is utilized for optimal.

3.2 Pre-processing

Today's real-world databases are highly susceptible to noise, missing, and inconsistent data due to their typically huge size and their likely origin from multiple, varied sources. There are several data preprocessing techniques. Data cleaning can be applied to clean off the noise and correct inconsistencies in data. Data integration harmonizes data from multiple sources into a coherent data store such as a data warehouse. Data deficiency can reduce data size by, for instance, aggregating, eliminating redundant features, or clustering. Data modification may be applied, where data are scaled to fall within a smaller range like 0.10 to 1.20. This can improve the accuracy and efficiency of mining algorithms [16] involving distance measurements. These techniques are not reciprocally exclusive; they may work together. Although real world data tend to be incomplete, noisy and inconsistent. Data cleaning routines endeavor to fill in missing values, smooth out noise while identifying outliers, and correct inconsistencies in the data. Noise is an unsystematic error or variance in a measured variable. Given

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a numeric attribute such as, say, price, how can we smooth out the data to remove the noise? Binning methods smooth a sorted data value by consulting the precincts, values around it. The sorted values are resects into a number of buckets, or bins. Because binning methods, consult the precinct of values, they carry out local smoothing.

The exterior may be detected by clustering, where similar values are organized into clusters. Data can be smoothed by fitting the data to a function, such as with homecoming. Linear regressions involve finding the optimal line to suitable two variables, so that one variable can be used to predict the other [17]. Multiple linear regressions are an extension of linear regression, where more than two attributes are involved and the data are suitable for a multidimensional surface. Using regression to enucleate a mathematical equation to suitable the data helps smooth out the noise. There may be incompatible in the data recorded for some transactions. Some data incompatibility may be corrected manually using external references.

3.3 Iterative Method

The term iterative method mentions to a broad range of techniques that use the successive estimate to instate more accurate solutions to a linear system at each step. The estimation methods for solving system of linear equations makes it [18] possible to instate the values of the root system with the particularize precision as the limit of the sequence of some vectors. This process of constructing such a sequence is known as iteration. The first perspective begins from a single customer and tries to add one customer at a time by inspecting all customers that have not been assigned a cluster yet. This initial perspective is called IE (Iterative Evolution). If a new customer accompanying the group improves the fitness score of the group, then as per IE (Iterative Evolution) it will try to locate the emaciated customer member in order to obtrude from the group for the intention of ameliorating the fitness score of the cluster. Suppose there are set of M customers B_1.., B_m, and their related customer data be C= {C_R (B_1), C_R (B_2)………..C_R (B_m) }. A single prognostic model G on this group of customers C is given by Z = f(Y_1, Y_2, Y_3, ………Y_t) where Z is depending on the transaction and the self sufficient variables Y_1, Y_2, Y_3, ………Y_p ;The fitness function f can be comparatively complex, hence it represents the prognostic power of an licentious prognostic model G trained on all customer data contained in t An instance of construction is a single prognostic model G where the collection of customers C is constituted; Let G is a decision tree built on data C of customers B_1... B_m. For the intention of predicting C_j variable time of purchase, all the transactions and demographic variables are used, except variable C_j as it is the self sufficient variables. The fitness function f of model G can be its prognostic precision on the out of specimen data [19].

The ID (Iterative Diminution) perspective was proposed where the procedures starts with a single group containing all the customers and recapture the feeble performing customer one at a time until no more rearing betterment are possible. The complete effacement is done by ID (Iterative Diminution). All the effacement customers are grouped totally into one remaining group, along with this it tries to detect it using the same procedures. An additional different approach called II (Iterative Intermingle) attempt to find to merge two present customer groups at a time. Next segments containing individual customers, this approach harmonizes two customer snippet snipX and snipY, when the model based on the harmonic data carries out preferable, and harmonize snipX with any other present segments would have resulted in a worse performance than the groupies of both snipX and snipY [20]. Thereby IM attempts to find the best pair of customer groups and merge them simultaneously, resulting in the best merging amalgamation.

3.4 The ANT Colony Optimization

Ant Colony Optimization algorithms are modeled after the foraging behavior of ants because a swarm of cooperating ants can discriminate between sources of food with variable quantity and quality, and between the lengths of the paths to a food source. If the only objective of the ants is finding the closest source [21] of food, then it has been empirically proven that the majority of ants converge to the shortest path. Ant Colony Optimization (ACO) is a paradigm for designing metaheuristic algorithms for combinatorial optimization problems. The first algorithm which can be classified within this framework was presented in 1991 and, since then, many diverse variants of the basic principle have been reported in the literature. The essential trait of ACO algorithms is the combination of a priori information about the structure of a promising solution to a posteriori information about the structure of previously obtained good solutions [22]. Metaheuristic algorithms are algorithms which, in order to escape from local optima, drive some basic heuristic: either a constructive heuristic starting from a null solution and adding elements to build a good complete one, or a local search heuristic starting from a complete solution and iteratively metamorphose some of its elements in order to achieve a better one. The metaheuristic part permits the low-level heuristic to obtain solutions better than those it could have achieved alone, even if iterated. The characteristic of ACO algorithms is their explicit use of elements of antecedent solutions.

A farraginous optimization problem is a problem defined over a set C = c_1... c_n of basic components. A subset S of components represents a solution of the problem; $F \subseteq 2^C$ is the subset of feasible solutions, thus a solution S is presumable if and only if $S \in F$. A cost function z is defined over the solution domain, z : 2^C => R, the objective being to find a minimum cost feasible solution S* to find S*: $S^* \in F$ and $z(S^*) \leq z(S)$, $\forall S \in F$. An ACO algorithm includes two more mechanisms first trail evaporation and secondly optionally, daemon actions. Trail evaporation decreases all trail values over time, in order to avoid unlimited accumulation of trails over some component. Daemon actions can be used to implement centralized actions which cannot be performed by single ants, such as the invocation of a local optimization procedure, or the update of universal information to be used to decide whether to prejudice the search process from a non-local perspective.

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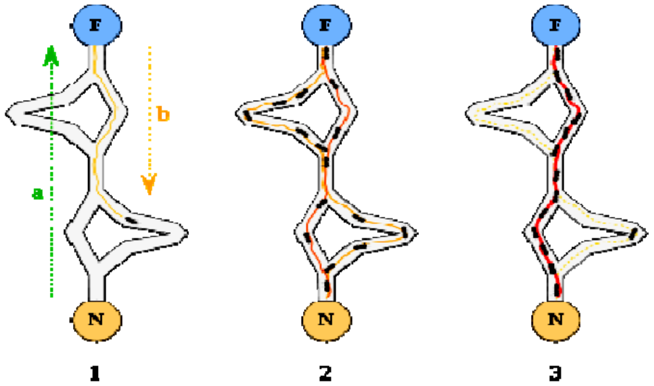

Figure 2: The Architecture diagram for ant colony algorithm

At the core of the ACO algorithm falsehood [23] a loop, where at each iteration, each ant moves from a state ι to another one ψ, corresponding to a more complete partial solution. At each step σ, each ant k computes a set $Ak^{\sigma}(\iota)$ of presumable expansions in its current state, and moves to one of these in probability. The probability distribution is specified as follows. For ant k, the probability $p\iota\psi^k$ of moving from state ι to state ψ depends on the combination of two values, firstly the attractiveness $\eta_{\iota\psi}$ of the move, as computed by some heuristic indicating the a priori desirability of that move. Secondly the trail level $\tau_{\iota\psi}$ of the move, indicating how proficient it has been in the past making that particular move, it represents therefore an a posteriori indication of the desirability of that move.

The trails are updated ordinarily when all ants have completed their solution, increasing or decreasing the level of trails corresponding to moves that were part of good or bad solutions serially. The move probability distribution defines probabilities pιψk to be equal to 0 for all moves which [24] are infeasible or else they are computed by below formula. Where α and β are user defined parameters ($0 \le \alpha,\beta \le 1$).

$$p^k_{\iota\psi} = \begin{cases} \dfrac{\tau^{\alpha}_{\iota\psi} + \eta^{\beta}_{\iota\psi}}{\sum_{(\iota\zeta)\notin tabu_k} \left(\tau^{\alpha}_{\iota\zeta} + \eta^{\beta}_{\iota\zeta}\right)} & \text{if } (\iota\psi) \notin \text{tabu}_k \\ 0 & \text{otherwise} \end{cases}$$

In formula tabu k is the tabu list of ant k, while parameters α and β specify the impact of trail and attractiveness, respectively. Subsequently, each iteration t of the algorithm. When all ants have completed a solution, trails are updated by means of a formula

$$\tau_{\iota\psi}(\tau) = \rho\, \tau_{\iota\psi}(\tau - 1) + \Delta\tau_{\iota\psi}$$

Where $\Delta\tau_{\iota\psi}$ signify the sum of the contributions of all ants that used the move (ιψ) to construct their solution, ρ, $0 \le \rho \le 1$, is a user-defined parameter called evaporation coefficient, and $\Delta\tau_{\iota\psi}$ represents the sum of the contributions of all ant's that used the move (ιψ) to construct their solution [25]. The ant's contributions are proportional to the quality of the solutions achieved, the better solution is, and the higher will be the trail contributions added to the moves it used.

All possible ants select a cluster number with a probability value for each element of F feature to form its own solution feature F. In pursuance of the data clustering problem, the quality of constructing solution string F is purposeful by the value of the objective function. This target function is outlined as the sum of squared Euclidian distances between each object and the center of related cluster. The value of the optimal solution in memory is updated with the optimal solution value of the present iteration if it has a lower target function value than that of the optimal solution in memory or else the optimal solution in memory is kept. This procedure decode that an iteration of the algorithm is finished. These steps many times iterated by the algorithm until a somewhat number of iterations. The solution is having lowest function value relates the optimal partitioning of target from a given dataset into several groups. In our approach the customer segmentation is done on enforcing ACO.

3.5 Davies-Bouldin's Index

The specimen of data from the dataset is extracted and applied in ACO. Next to the inter distance similarity between the clusters were been evaluated based on the Davies-Bouldin's Index. The Davies-Bouldin (DB) index captures the average similarity of a cluster and its most similar cluster. It is formally defined as

$$DB_p = \max_{q \in C, p \neq q} \frac{S_p + S_q}{M_{pq}}$$

Where S_p is the measure of scatter or intra-cluster similarity for p, and M_{pq} is the measure of dispersion or inter-cluster similarity between clusters p and q [26]. There are many variations of the DB index depending on the definitions of scatter and dispersion. We again use the original suggested definitions, where dispersion is the distance between cluster centroids, i.e., $M_{pq} = d(o_p; o_q)$, and scatter are the average distance of each data point to its cluster centroid,

The computational insolubility of DB is much less burdensome than what was seen when calculating Dunn since inter-cluster distance is defined using cluster centroids, not individual data samples. Thereby, we have exhaustively searched for a score against all q ϵ c.

$$S_p = \frac{1}{|p|} \sum\nolimits_{\forall x_i \in p} d(x_i, o_p)$$

The Collectively smaller DB scores indicate better cluster quality since DB is a ratio of intra-cluster of inter-cluster similarity. Nevertheless, cluster p takes the maximum score for all q ϵ C because the maximum score will identify the cluster most similar to p [27]. If the scatter S_q were equal for all clusters, the most similar cluster would be defined as the nn_p. This is shown in figure 3 where clusters q_i and q_j have the same variance, but the centroid of cluster qi is closest to the centroid of p, making it the most similar to p. Otherwise, if there was a preference between two clusters with centroids equidistant from p, then the cluster with larger dispersion S_q would produce the maximum score.

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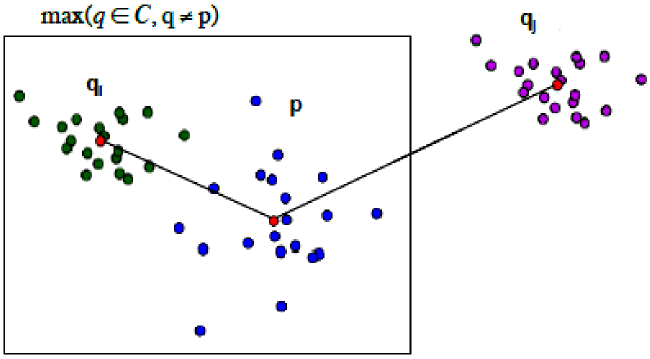

Figure 3: The examples of cluster quality measures

3.6 The PSO Algorithm

Particle Swarm Optimization (PSO) was invented by Kennedy and Eberhart1 in the mid 1990s, while attempting to simulate the choreographed, graceful motion of swarms of birds as part of a socio cognitive study investigating the notion of “collective intelligence”in biological populations [21]. In PSO, a set of randomly generated solutions (initial swarm) propagates in the design space towards the optimal solution over a number of iterations based on a large amount of information about the design space that is assimilated and shared by all members of the swarm [28]. PSO is inspired by the ability of flocks of birds, schools of fish, and herds of animals adapt to their environment, find rich sources of food, and avoid predators by implementing an information sharing perspective consequently, developing an evolutionary advantage.

The basic PSO algorithm consists of three steps, namely, generating particles’ positions and velocities, velocity update, and finally, position update. Here, a particle refers to a point in the design space that changes its position from one move to another based on velocity updates [29]. The first positions, X_k^i, and velocities, V_k^i, of the initial swarm of particles are randomly generated using upper and lower bounds on the design variable values, $\mathbf{x}_{min}$ and $\mathbf{x}_{max}$, as expressed in below equations. The positions and velocities are given in a vector format with the superscript and subscript denoting the i^{th} particle at time k. The rand is a uniformly distributed random variable that can take any value between 0 and 1. This initialization process allows the swarm particles to be randomly distributed across the design space.

$$\mathbf{x}_0^i = \mathbf{x}_{min} + rand(\mathbf{x}_{max} - \mathbf{x}_{min})$$

$$\mathbf{v}_0^i = \frac{\mathbf{x}_{min} + rand(\mathbf{x}_{max} - \mathbf{x}_{min})}{\Delta t} = \frac{\text{position}}{\text{time}}$$

The second step is to update the velocities of all particles at time k +1 using the particles objective or fitness values which are functions of the particles current positions in the design space at time k. The fitness function value of a particle [30] determines which particle has the best global value in the current swarm, P_k^g, and also determines the best position of each particle over time p^i in current and all previous moves. The velocity update formula uses these two pieces of information for each particle in the swarm along with the effect of current motion, V_k^i, to provide a search direction, V_{k+1}^i, for the next iteration [31]. The velocity update formula includes some random parameters, related by the uniformly distributed variables rand to ensure good coverage of the design space and avoid entrapment in local optima. The three values that effect the new search direction, namely current motion, particle own memory and swarm influence are unified via a summation perspective with three weight factors, namely, inertia factor w self confidence factor, c_1, and swarm confidence factor, c_2 serially.

$$\underbrace{\mathbf{v}_{k+1}^i}_{\text{velocity of particle } i \text{ at time } k+1} = \underbrace{w}_{\substack{\text{inertia factor}\\ \text{range: 0.4 to 1.4}}}\underbrace{\mathbf{v}_k^i}_{\substack{\text{current}\\ \text{motion}}} + \underbrace{c_1}_{\substack{\text{self confidence}\\ \text{range: 1.5 to 2}}}\, rand \underbrace{\frac{(\mathbf{p}^i - \mathbf{x}_k^i)}{\Delta t}}_{\substack{\text{particle memory}\\ \text{influence}}} + \underbrace{c_2}_{\substack{\text{swarm confidence}\\ \text{range: 2 to 2.5}}}\, rand \underbrace{\frac{(\mathbf{p}_k^g - \mathbf{x}_k^i)}{\Delta t}}_{\text{swarm influence}}$$

The original PSO algorithm1 uses the values of 1, 2 and 2 for w, c_1, and c_2 respectively, and suggests upper and lower bounds on these values as shown in above. However, the research presented in this paper found out that setting the three weight factors w, c_1, and c_2 at 0.5, 1.5, and 1.5 serially provides the best convergence rate [32] for all test problems considered. Further combinations of values usually lead to much slower convergence or sometimes non-convergence at all. The tuning of the PSO algorithm weight factors is a topic that warrants proper investigation, but is outside the scope of this work. The weight factors use the values of 0.5, 1.5 and 1.5 for w, c_1, and c_2 respectively. Position update is the last step in each iteration. The position of each particle is updated using its velocity vector as shown in below and depicted in figure 4.

$$\mathbf{x}_{k+1}^i = \mathbf{x}_k^i + \mathbf{v}_{k+1}^i \Delta t$$

The three steps of velocity update, position update, and fitness calculations are repeated until a desired convergence criterion is met. The hold-back criteria are that the maximum change in best fitness should be smaller than the specified tolerance for a specified number of moves S. The S is specified as ten moves and ε are specified as 10^{-5} for all test problems.

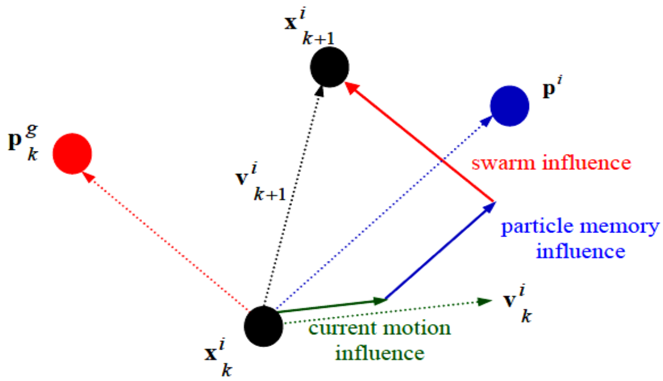

Figure 4: The Depiction of the velocity and position updates in Particle Swarm Optimization

The performance of PSO is depending upon the weight value, the larger the value of greater the global search

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capability [33], smaller the value of w greater the local search capability. Initially, every particle adjusts its position using certain characteristics such as the current positions, the current velocities.

$$\left| f\left(\mathbf{p}_k^g\right) - f\left(\mathbf{p}_{k-q}^g\right) \right| \leq \varepsilon \quad q = 1,2,..S$$

4. Experimental Results

We have processed our experiments, gathering Alexa data which is a standard dataset. Alexa Internet Inc. is a California based subsidiary company of Amazon.com which provides commercial web traffic data. Founded as an independent company in 1996, Alexa was acquired by Amazon in 1999. Its toolbar collects data on browsing behavior and transmits it to the Alexa website, where it is stored and analyzed, forming the basis for the company's web traffic reporting. According to its website, as of 2014, Alexa provides traffic data, global rankings and other information on 30 million websites, and its website is visited by over 6 million people monthly. At the beginning the data is predisposed from the data set. Whenever extracting, the data is noisy, containing missing values, subsequently the missing data are replaced with the mean squared error of that specific feature. So long as pre-processing the data is subjected to go by the three suboptimal iterative segmentation perspectives. The demographic features are Domain Name, Purchase Price, Customer Name, Day, Customer city, Customer State etc. But those features are termed as valued features. An example of II (Iterative Intermingle) is purchase range is provided to merge the customers for which was resulted as the quite highest in purchase price and this is illustrated represented in figure 5.

Thereupon the clustering results acquired from PSO exposed in figure 6. Based on purchase prize the clusters are segregated having high, low, very low, very high extents. An example for a very low cluster is portrayed in figure 6 as per the PSO algorithm for which the clustering transcendence was observed as -0.04 and that the three values are acquired on this cluster centroid. Moreover, as per the ACO algorithm the clustering quality was observed as 0.1971. In addition, in the case of ACO the very low clustering criterion is mined for the feature purchase price. It was experiential that the five values are acquired on this cluster centroid. This is delivered empirically in figure 7.

$$M = \sum_{p=1}^{N} \frac{1}{|\mathrm{b}_p|} \sum y \varepsilon \mathrm{b}_p e(y, \mu_p)$$

Where $|\mathrm{b}_p|$ is the number of data points in cluster p the value of M will be small if the data points in each cluster are close. To investigate this clustering transcendence is represented in figure 8.

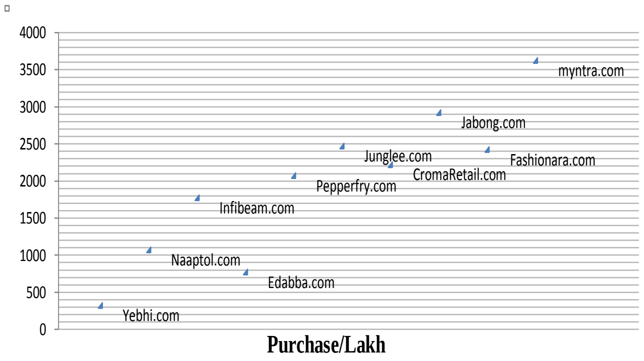

Figure 5: The Merging process data

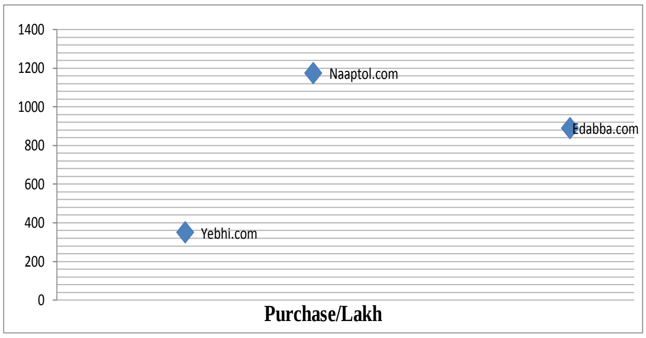

Figure 6: Particle Swarm Optimization based low cluster

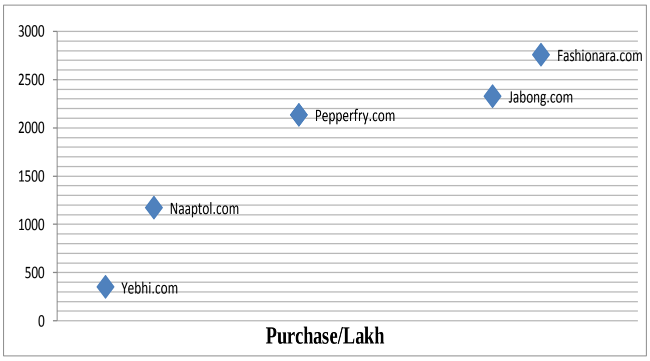

Figure 7: Ant Colony Optimization based low cluster

The graph is plotted between the number of transactions and the quality got in percentage. For 900 data transactions the clustering transcendence observed was 54% for PSO, 48% for ACO. Figure 9 exemplifies the optimized cost acquired in the two approaches. The cost calculated was anxious on memory and processing time. For same 900 data transactions optimized cost based on clustering transcendence precision observed was 45% for PSO, 48% for ACO.

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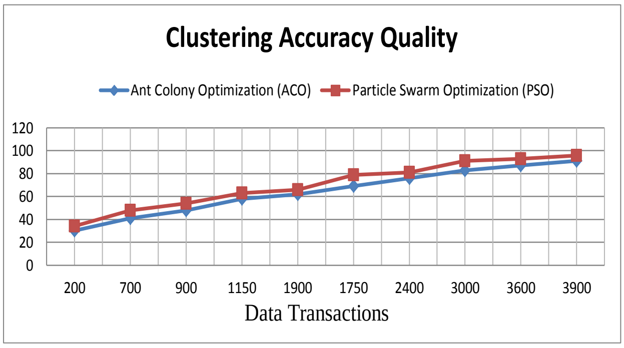

Figure 8: Clustering Accuracy Quality based on PSO and ACO

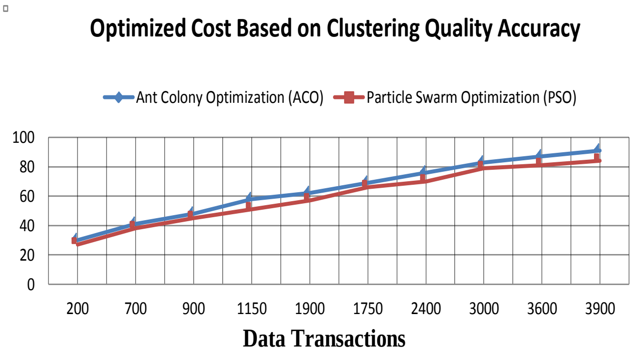

Figure 9: Optimized cost based on clustering quality accuracy in PSO and ACO

5. Conclusion

E-commerce encompasses all business operated by means of computer networks. The telecommunications and computer technologies in nowadays have made computer networks an essential part of the economic infrastructure. More and more companies are facilitating transactions over the web. E-commerce confers several benefits to the consumers in the form of availability of goods at lower cost, wider choice and saves time. Today scenario people can buy goods with a click of a mouse button without moving out of their house or office. Ecommerce web sites are increasingly introducing personalized features in order to build and retain connection with customers and raise the number of purchases made by each customer. In this paper, we have explored some optimization algorithms approaches such as PSO and ACO. At the beginning iterative approaches partitions the customers on harmonizing transaction data of sundry customers and building a single model of customer behavior on this harmonize data. Nevertheless optimizing data compassed is fetched into the clustering algorithms towards the goal of benefit optimized personalization. In this paper, we are propone two algorithms, Particle Swarm Optimization (PSO) algorithm exemplifies good performance in terms of clustering accuracy and cost wise performance is increased than the other Ant Colony Optimization (ACO) algorithms. Our result is 900 data transactions the clustering quality observed was 54% and 48% higher than that of PSO and ACO respectively. The experimental results reveal that the proposed Particle Swarm Optimization (PSO) algorithms are useful and can be used in real world systems.

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