

1 Optimized Model of Recommendation System for E-Commerce 2 Website

3 Fares Aqlan¹ and Abdullah Alqwbani²

4 ¹ Central South University

5 *Received: 7 December 2013 Accepted: 2 January 2014 Published: 15 January 2014*

6

7 **Abstract**

8 The purpose of this work is to optimize the recommendation system by creating a new model
9 of recommender system with different services in a global e-commerce website. In this model
10 the most effective data sources are integrated to increase the accuracy of recommendations
11 system, which provides the client more intuitive browsing categories interface. The sources
12 used for this model are the user's searching log on the global website, and data referred
13 extracted from search engines, more clicked URLs, highly rated items, and the
14 recommendation algorithms of new users and new items. In additions, user's interests based
15 on locations, and the hot releases items recommended by the admin or shop owner of the
16 e-commerce website according to the website marketing strategy. When the users browse the
17 website, the data sources will automatically combine to incorporate the derived structure and
18 associate items for each category into a new browsing recommendation interface.

19

20 **Index terms**— ecommerce, data mining, recommendation system, clustering algorithm.

21 **1 Introduction**

22 The global systems internet with World Wide Web has revolutionized the human life like nothing before. Since
23 1997, the web has progress into a true economy and a new frontier for business [1]. The WWW became more
24 important as a source for the basic data and a place for trading, which called Electronic Commerce (EC).

25 Electronic commerce includes the use of all kinds of information and communication technology in the
26 business processes among the trade. Moreover, it helps to get a share in the market and improve customer
27 service by creating a Web page and supporting the investors' relations or communicating electronically with
28 customers [2]. Electronic commerce is more than ordering goods from an on-line catalog. It involves all
29 aspects of an organization's electronic interactions with its stakeholders, the people who determine the future of
30 the organization. Such stakeholders include customers, suppliers, government regulators, financial institutions,
31 managers, employees, and the public at large [3].

32 Nowadays many sites have a good business and become well known ecommerce sites, such as ebay.com,
33 Amazon.com, taobao.com and others. Business is evenhanded to the process of shopping on the web site.
34 It becomes the way of shopping in wide field including personal need, house need or business need.

35 Fast growing of Internet technologies presents complicated challenges and opportunities to organizations and
36 guiding them to develop new managerial roles and practices [4]. These explosive developments of the internet
37 and E-commerce technology have led to the daily growth of recommendation systems.

38 Recommendation systems typically suggest commodities (information, items or services) that are of interest
39 to users based on customer demographics, features of items, and/or user preferences (e.g., ratings or purchasing
40 history) [5]. Recommendation services are used by E-commerce websites to suggest items to their consumers.

41 Along with EC areas, the B2B (Business to Business) Recommendation system is being spotlighted as an
42 interesting research area considering its size and the potential impact it has overall. Now various recommender
43 systems are being used in seller-centric E-marketplaces, intermediary-centric E-marketplaces, and buyer-centric
44 E-marketplaces etc [6].

6 A) BASIC ARCHITECTURE OF RECOMMENDER SYSTEM

45 However, in many global e-commerce websites, well-defined recommendation systems are not available;
46 moreover, in some other e-commerce sites, the recommendation systems are too coarse and less intuitive to
47 distinguish properties according users interests, which will lead to very bad user experience [7].

48 To address these problems, in this project we propose building a new model of recommendation system that
49 depends on hierarchical structure for emerging ecommerce products according to users' behavior preference,
50 which can be derived from searching logs and data referred extracted from search engines, highly clicked URLs,
51 top rated items, users interests based on the same area customers, recommendation algorithms for the new items
52 and also the new users. We also create a personalized recommendation strategy managed by the admin of the
53 website.

54 2 II.

55 3 Motivation

56 The E-commerce environment includes all online activities and business operations achieved between multiple
57 parties using electronic techniques.

58 With the huge development of internet and E-commerce websites; when consumers choose their needs of items
59 and commodities, they confront some serious problems of data overloading. Therefore; many website researches
60 and projects have focused on recommendation system development, in order to provide users more individual
61 recommendation services.

62 Recommendation system has become serious business tools used by many of the largest commerce websites,
63 in order to provide the users more effective and efficient way to find their interested products. The recommender
64 systems work like salesman who provides users advices and services to help them find the commodities and items
65 they are interested in. However, with the wide use of recommendation services, many common challenges and
66 problems come out, such as real-time, sparsely of information, cold start problem and recommendation quality.

67 In addition, with the rapid development of web and e-commerce business, a large number of growing user
68 interaction to the application provides a number of very valuable data and information. This interaction forms
69 include users of e-commerce sites click browse, clinch a deal to buy goods online sales and online collection of
70 goods. This increasing interaction behavior leads to the emergence of the information overload problem. In
71 additions, most recommender systems still meet some serious problems and challenges, such as sparsely data,
72 real-time, cold start and the quality of recommendation results ??8].

73 Therefore need a system that provides services which provide solutions to overcome these common problems by
74 using the interactive information to find user interests and preferred orientation with high quality and real-time
75 techniques.

76 The goal of this project is to build a new model of personalized recommender system. We have proposed and
77 applied some data mining ideas and clustering algorithms that optimize the recommendation services on a global
78 E-commerce websites.

79 Our optimized recommender system helps consumers to find their needs and save their efforts and time
80 in complicated operations. For e-commerce sites, our ideal personalized recommendation system will directly
81 increase online sales of commodities brought in, increase the orders-size by turning browsers into buyers.

82 4 III.

83 5 Purposed Recommender System

84 The traditional recommendation technologies have their own advantages and also many shortcoming points [9].
85 So to solve these issues we have build a new model of recommender system which based on hybrid recommendation
86 techniques and combined with data mining clustering technology to overcome the shortcoming points and provide
87 the best recommendation results which meets all kind of users' interests and needs.

88 Our system belongs to a complete personalized recommender system, using data mining combined with hybrid
89 recommendation methods. The new model of recommender system provides more adaptive and scalable services;
90 as it is highly considering the recommendation quality, real-time recommendation, and proposed solutions for
91 problems such as cold start and other issues. In the following we introduce the architecture structure, project
92 algorithms and technologies of our E-commerce recommendation model.

93 6 a) Basic Architecture of Recommender System

94 The tremendous development of the Internet has led millions of companies to set up shop on the Internet and
95 over 100 million consumers are eagerly participating in the global online marketplace [10].

96 From this quick development of e-commerce websites; we start to get destruct with the recommendation systems
97 methods and advantages to meet users' need and interests. The enhancements of this project are designed to
98 meet such needs including the recommendation functions and site features.

99 The recommendation functions are designed to provide the users the ability to discover their real interest ed
100 items with flexibility and high efficiency, which will save users' own efforts and time.

101 Our recommendation system include five parts of functions, first part recommend the items which will be
102 derived from user's searching logs on our website and data referred extracted from search engines, through the
103 searching log and search engines are considered to discover user's attributes and interests.

104 The second part of our model functions include the most rated items; the convenience of this function is to
105 compare products through the multi-products website, which save more time and effort during all customers'
106 visits.

107 The third part of our system propose and apply some algorithms which will recommend the new items of the
108 website, as well as, some algorithm to recommend items for our new users. The advantage of this part is to solve
109 the cold start problem of recommendation system.

110 The forth part of our new model propose the algorithms which do the recommendation according to the user's
111 interests based on locations, our system collect the interest data of same location users, as different location
112 users have different interests; since each location has its own habits, needs and life traditions. But through this
113 function, the users easily can find the most interested items by his location users on our global website.

114 The last part of our recommendation system model includes the items which can be recommended by the
115 admin or shop owner of the website according to the website marketing strategy.

116 **7 Enhancement**

117 To enhance our new model of recommender system, first we have to enhance the relational database. The enhance
118 operation is divided into two parts: The process model step which focuses on the operation process of database
119 stored data. Second step is the online recommender which analyzes the recommendation type of system, as well
120 as, the recommendation algorithms used and proposed for this project.

121 **8 a) Process Model**

122 The core of recommender system is the recommendation algorithms models, as a different algorithm requires
123 different data, so the system needs to manage the input data to provide a high quality of output results. The
124 main data as shown in logical schemas figure above include: User, Item, and Rating. Due to E-commerce website
125 deals with a huge amount of data which growing rapidly, it makes the algorithms model take a long time, and a
126 big consumption for system resource. That seriously affects the real-time recommendation.

127 As a result, the recommender system using offline process model to output results. And online recommendation
128 model then uses the output results with the system input data to recommend items for the user.

129 The process model based on the incremental updates of input data, so when the new ratings data of users
130 reach a certain limit value, it needs to deal with process model again.

131 **9 ? Data preprocessing**

132 According to different algorithms' required data, the system deals with insert data using input data model.

133 **10 ? Model calculation**

134 The recommender system according to data amount updates, regular operates models, calculates the update
135 data, modify the model output results, to ensure the quality of recommendation.

136 The process model of our recommender system can be displayed as it shown in the following figure 3 The
137 personalized E-commerce recommender system mainly used to recommend items for users based on their interests.
138 The main functions of online recommender are to analyze the recommendation type, and choose the related input
139 and output data of algorithm model, to predict recommendation results, and provide it for users. The main
140 process of online recommender is as shown in the following figure 4: The online recommender uses a real-time
141 recommendation model to provide a high quality recommendation. When a user login the E-commerce website,
142 and browse items, the recommender system reads his/her profile data, user rating data and purchased log to
143 predict interested items, and feedback direct to the user the Top 10 items that user most likely interested in.
144 techniques. Specifically, we use the STC algorithm to analyze the data mining of search engine and search log
145 data. We have also applied neighbor clustering algorithm to complete data mining work as a clustering technique
146 for ratings data. For the classification algorithm, we have applied support vector machine (SVM). We have also
147 proposed some matrixes that determine the users' locations in order to provide recommendation results based on
148 location.

149 In the following, we introduce the project algorithms and its applications technique.

150 **11 i. STC Algorithm**

151 The STC algorithm clustering that has been applied in previous work ??12] is an efficient method of clustering
152 search results, but because it's clustering process only start from the characteristics of the document itself, and
153 it gets the clustering results based on the document attributes. So for our best knowledge, this is not enough for
154 a personalized recommendation system. In this project, we combine the user personal interests' model with on
155 STC algorithm, which improves the STC algorithm strategy.

156 Suffix Tree Clustering (STC) has three logical steps: (1) document "cleaning", (2) identifying base clusters
 157 using a suffix tree, and (3) combining these base clusters into clusters.

158 After the suffix tree construction, each node on the document can be used as a base cluster. So as to reduce
 159 the clusters numbers, we have to combine some base clusters into a big cluster, this process called "Combine
 160 Base Clusters". In order to better implementation of the personalized recommendation, the clusters should be
 161 ordered according to the user's interests.

162 To measure the user interest into any document, we use the following formulas which show the steps of our
 163 recommender system technique using search data identifications:

164 12 Basic Data Construction

165 Using the Google engine to query on a keyword, the results will show many pages which include this keyword
 166 inside its contents. For the search results of Web page, we use the data structure to explain the steps of operation:

167 Struct Step1: Read FileName into memory Step2: remark snippets, if it is "<HEAD>", then proceed operation
 168 onto the head of Web catalog file. Or

169 Step3: remark snippets, if it is "<BODY>", then apply operation onto the body of Web catalog file.

170 Step4: Return CatalogSnippetList;

171 The Web file is semi-structured data, so to facilitate process, we need to structure the data, and clean all the
 172 return results. After the data cleaning operation, we get a list that contain all search results, so we move to next
 173 step, clustering analyze.

174 13 Clustering Analysis

175 The clustering analyze process will return a large number of search engine data, such as catalog snippets, and
 176 then divide it into classes or small clusters. Make the most similar objects into one cluster, and different data
 177 objects into different clusters. By comparing the cluster methods, we decide to use an improved STC algorithm
 178 method as basic clustering algorithm for search data of our personalized recommender system. Specifically, there
 179 are three steps to improve STC algorithm: 1. Create suffix tree structure, so we add each complete cleaned
 180 catalog snippet into the suffix tree. 2. Determine the base clustering.

181 14 Combine the base cluster with clustering results.

182 The improved STC algorithm combines the cluster results with user interest profile data to provide sorted cluster
 183 results.

184 15 Personalized Recommendation Strategy

185 The clustering analyze of search results will provide better clean and sorted information, as the improved STC
 186 algorithm did implement the measurement of similarity on base clustering combined(D D D D) Year 2014 E 1.

187 16 2.

188 3.

189 17 4.

190 with content-based technology, as well as, they process the cluster results as sorted data.

191 These kind of results and techniques help to return users more specific recommendation according to his search
 192 information collected by our algorithms, it also arrange the results as Top N more interested and searched items
 193 to provide it on the recommendation system interface.

194 ii. Neighbor Algorithm

195 The clustering analyze used to divide the stored data of database into significant sub classes. This classification
 196 operation is based on the similarity and difference between data.

197 The algorithm function of neighbor clustering can be constructed as follows:

198 For given finite sample set $\{U\}$, that includes n samples, assign a number C of clusters where?K i,j = 1,2, A,
 199 C?

200 For each model, if the sum of sample's distances to the cluster center achieves the minimum value,

201 The mathematical model of clustering can be given by:min ? ? ?U ? v j ? U?K j C j=1 v j = 1 ? x ij n i=1 ?
 202 x ij n i=1 U

203 Where C is the number of clusters, $v j$ is the mean vector of sample j .

204 So if the model sample i assigned into the centre of cluster j , Then $x_{ij} = 1$; else $x_{ij} = 0$; ? $x_{ij} n i=1$
 205 = 1 means that model sample i only can be assigned into centre of one cluster.

206 The clustering analysis classifies models according to the closeness degree between samples features. The basic
 207 similarity has the following two functions:

208 1. Distance Function Sample uses 13 d of features variables for description; each sample can be seen as a point
 209 in the empty space, using some distances to indicate the similarity between sample points. The closer sample
 210 points, the more similar features they have, and far away distance between different sample points.

211 So the distance function can be displayed using the following formula: For non-negative conditions,
212 $\delta ???"\delta ???"(??, ??) \geq 0$; $\delta ???"\delta ???"(??, ??) = 0$; and for Symmetry we have $\delta ???"\delta ???"(??, ??) = \delta ???"\delta ???"(??, ??)$;
213 which meet the triangle inequality $\delta ???"\delta ???"(??, ??) + \delta ???"\delta ???"(??, ??) \geq \delta ???"\delta ???"(??, ??)$.

214 2. Distance measurement method using Euclidean distance: $\delta ???"\delta ???"(??, ??) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$
215 $\sqrt{\sum_{i=1}^n (x_i - y_i)^2} = \sqrt{\sum_{i=1}^n (x_i^2 - 2x_i y_i + y_i^2)}$

216 Where $\bar{x} = (\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n)$ and $\bar{y} = (\bar{y}_1, \bar{y}_2, \dots, \bar{y}_n)$ are two
217 n-dimensional data objects.

218 If each attribute of data is given a weight, then the weighted Euclidean distance is expressed as: $\delta ???"\delta ???"(??, ??) = \sqrt{\sum_{i=1}^n (w_i x_i - w_i y_i)^2}$

219 . Similarity coefficient: The two sample points are more similar, the similarity coefficient is closer to 1; and the
220 similarity coefficient is closer to 0 when two sample points are more different. Phase angle cybermetrics: Using
221 vector of included Angle cosine formula to measure the angle's similarity degree between samples $\cos(\theta) = \frac{\bar{x} \cdot \bar{y}}{\|\bar{x}\| \|\bar{y}\|}$
222 and $\theta = \arccos(\frac{\bar{x} \cdot \bar{y}}{\|\bar{x}\| \|\bar{y}\|})$. The angle cosine formula is: $\cos(\theta) = \frac{\bar{x} \cdot \bar{y}}{\|\bar{x}\| \|\bar{y}\|}$
223 $\cos(\theta) = \frac{\sum_{i=1}^n x_i y_i}{\sqrt{\sum_{i=1}^n x_i^2} \sqrt{\sum_{i=1}^n y_i^2}}$

224 Pearson correlation coefficient:

225 The correlation coefficient of sample i and sample j is as the following: $\rho_{ij} = \frac{\sum_{k=1}^n (x_{ik} - \bar{x}_i)(x_{jk} - \bar{x}_j)}{\sqrt{\sum_{k=1}^n (x_{ik} - \bar{x}_i)^2} \sqrt{\sum_{k=1}^n (x_{jk} - \bar{x}_j)^2}}$

226 18 ??

227 Where \bar{x} is mean value, $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$, and $\rho_{ij} = 1$ if $x_i = x_j$

228 iii. Support Vector Machine (SVM)

229 The support vector machine is used to classify data; this task is called machine learning [13]. For given data
230 points which belong to one or more classes, we use SVM to decide which new data point will contain the class.

231 Suppose x_1, x_2, \dots, x_n , where $x_i \in \mathbb{R}^d$, $i = 1, \dots, n$ are d -dimensional training samples. The corresponding
232 mark of each sample is y_1, y_2, \dots, y_n , where $y_i \in \{-1, 1\}$, and $i = 1, \dots, n$ indicating the class to which the
233 vector belongs.

234 For linear SVM, the hyperplane $w \cdot x + b$ will classify the training samples, then $w \cdot x + b \geq 0$
235 $\delta ???"\delta ???"(w \cdot x + b) = 1$ if $x_i \in \{1, -1\}$

236 This can be rewritten as: $\sum_{i=1}^n y_i (w \cdot x_i + b) = 1$

237 So according to the theory, hyperplane can classify the samples, and also maximize the distance between the
238 classes. In the following figure, we have three hyperplane (H_1, H_2, H_3), we can see that H_1 does not separate
239 the classes. H_2 does, but only with a small margin. H_3 separates them with the maximum margin. The following
240 figure 5 shows the maximum margin hyperplane: problem. This optimization problem has been solved by the
241 saddle point given by (Christopher, 1998): $\max_{w, b} \min_{a} \sum_{i=1}^n \max_{y_i \in \{-1, 1\}} (y_i (w \cdot x_i + b) - a_i)$

242 Where a_i is Lagrangian multiplier. According to above saddle point, we have: $w = \sum_{i=1}^n a_i y_i x_i$
243 Which declare that only a few a_i will be bigger than 0, x_i is the support vector that lie on the margin and
244 satisfy condition $y_i (w \cdot x_i + b) = 1$.

245 So by substitute the above formula, we get the following points which show that SVM reduces to the following
246 optimization problem: Maximize $\sum_{i=1}^n a_i$ we get: $\max_{w, b} \sum_{i=1}^n a_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n a_i a_j y_i y_j (x_i \cdot x_j)$

247 And to the constraint from the minimization: $\sum_{i=1}^n a_i = 1$, $a_i \geq 0$.
248 So w can be computed by: $w = \sum_{i=1}^n a_i y_i x_i$, $a_i \geq 0$ Where y_i is the support vector.

249 As well as, in the hyperplane function, for constant C , it can be displayed as the following: $C = \frac{1}{2} \|w\|^2$
250 $\max_{w, b} \min_{a} \sum_{i=1}^n \max_{y_i \in \{-1, 1\}} (y_i (w \cdot x_i + b) - a_i)$

251 Where $x^* \in \{1, -1\}$ declare that belongs to first class of support vector, and $x^* \in \{1, -1\}$ declare that belongs to the
252 second class of support vector.

253 According to above, we get the function of the best classification hyperplane as follows: $f(x) = \text{sgn}(\sum_{i=1}^n a_i y_i x_i + b)$,
254 x_i is the support vector, a_i is Lagrangian multiplier, and b is constant.

255 Above we have described the training samples classification by using linear SVM, also the support vector and
256 the basic principles of best hyperplane. But if the training samples cannot be classified by linear SVM, then the
257 above principles will be useless. In this situation, we use soft margin to solve problems, soft margin will choose
258 a hyperplane that classify samples as cleanly as possible.

259 For non-negative slack variables $\xi_i \geq 0$, $i = 1, \dots, n$, so the function becomes: $\min_{w, b} \sum_{i=1}^n \xi_i$
260 $\text{subject to } y_i (w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0$

261 Then by using Lagrangian multiplier, the optimization problem can be computed by: For, $\max_{w, b} \sum_{i=1}^n a_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n a_i a_j y_i y_j (x_i \cdot x_j)$

262 $\text{subject to } \sum_{i=1}^n a_i = 1, a_i \geq 0$ By minimization we get: $\min_{w, b} \sum_{i=1}^n \xi_i$

263 $\text{subject to } y_i (w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0$ Where $i = 1, \dots, n$, $T > 0$ is a constant.

273 **19 iv. User's Location Matrix and Algorithms**

274 There have been some previous works into geolocation technology and software which determine the user's
275 geographic details including country, city, ZIP code, and so on.

276 The user's location information is effective for recommendation system to provide more specific recommenda-
277 tion results according to the user location interest and preference identification. Since our recommender system
278 builds a preference or interest profile for each user enter our website, so our recommender system will use the
279 user's interest profile to create session-interest matrix to indicate the user's interest based on user's location.

280 To create the aforementioned session-interest matrix, we need to process the following three steps: ? Session-IP
281 Scope Matrix The system generates all users' session IP address from user session data identification. Then our
282 Support Vector Machine (SVM) will classify all IP addresses in some classes according to the first two segments
283 of session-IP scope list. By creating this matrix, we use value 1 for each session user location in the matrix, so
284 each row contains only one value as 1 and others take 0. ? IP scope-Interest matrix We create this matrix, in
285 which the columns represent users' interests based on aforementioned user profile data, and its rows represent
286 the same IP addresses of session-IP scope matrix created in step 1. The IP scopeinterest matrix indicates the
287 highest interest of website users according to their behavior and experiences on our E-commerce website. To
288 fill the matrix, we use 0 and 1 numbers to make its rows and columns represent user session and his interest
289 value. ? Session-Interest matrix In this part, we create session-interest matrix by multiply the previous obtained
290 matrixes in step 1 (Session-IP scope matrix) and step 2 (IP scope-Interest matrix). The following steps show the
291 method of creating this matrix: } }; According to these steps, we have used values 0 or 1 to fill the elements of
292 session-interest matrix, the output information is a referer matrix based on user's location and his/her interest
293 profile data. Since every customer who visit our website has an IP address, but not all users have interest profile
294 such as new users who do not have any rated information or purchased data. So to solve this issue, we have
295 process the classification and clustering algorithms on two matrixes, one for users who do not have interest profile.
296 For such users, we use the data integration based on similar users coming from the same location. The system
297 generates the interest items for users who have similar IP addresses with our current user.

298 For this process, we use k-mean clustering algorithm to generate identification data based on clusters of same
299 location users according to the classification on session-IP scope list.

300 **20 v. Algorithms Integration**

301 The recommendations based on STC algorithm, user profile, neighbor clustering, IP session matrix and support
302 vector machine (SVM) will combine the item's features with user preference. These algorithms will also divide
303 the items according to difference features and catalogs. Then summarize the user's preference value on these
304 different features with measuring their interest into item's lists, until we get the user preference model. According
305 to user's different interest, we use the userprofile data with STC algorithm to measure user's interest by ordering
306 clustering based on their interest model data. This process will integrate the search engine data and user search
307 behavior on our website, in order to generate their interest's information and build an interest model for each
308 user.

309 For user preference model, we use neighbor clustering, which generate the users who have similar preference
310 level into different features of items. These users became neighbors, to provide real-time recommendation. In
311 addition, combining with contentbased recommendation technology can promote the recommendation of new
312 items.

313 So considering adjust and analyze the user information; when making recommendation, and choosing a nearest
314 neighbor; it will help to make the user similarity comparison results as weighted to provide a high quality
315 recommendation. The project will uniformly process the user's information, in order to facilitate the comparison.

316 By combining the neighbor clustering algorithm of content-based technology, we get the clusters units, and
317 then compare the users of each cluster unit to get the similar users. So the hybrid recommendation by combined
318 user information is recommended on the basis of content recommendation technology.

319 For the classification results of support vector machine (SVM), it helps to predict the user's nearest neighbor,
320 and proceed a weighted adjustment operation, to further improve the quality of recommendation. Year 2014

321 **21 E**

322 In the E-commerce business, a user buy items not only related to item's features or preference; as the user's basic
323 information (age, occupation, location,? etc) have also a certain relevance.

324 Because of the reliable results of prediction recommendation based on demographic information for limited
325 data volume; so after the classification operation by support vector machine, we get the similarity degree between
326 users according to the comparison results of users' information. These similarity degrees are used as weighted
327 values for predictive ratings process.

328 We also have used IP session matrix with support vector machine (SVM) to classify and divide the users
329 according to their locations, and use the identification data based on location to provide user a useful and helpful
330 recommendation including the most interested items by same location users.

331 V.

332 22 Implementation a) Identification Based on Search Data

333 The following steps show our recommender system technique using search data identifications: i. Update User-
334 Interest Profile

335 The user interest profiles are automatically generated based on the type of content viewed by the user. A
336 system generates user interest profiles by monitoring and analyzing a user's access to a variety of hierarchical
337 levels within a set of structured data.

338 User's interest is constantly changing, so the update of user interest profile based on user interests must be
339 considered. The retrieve information of user input as the sources information for user interest profile updating
340 process. ii. Improve STC Algorithm

341 The STC algorithm clustering that has been discussed above is an efficient method of clustering search
342 results, but because it's clustering process only start from the characteristics of the document itself, and it
343 gets the clustering results based on the document attributes. So for our best knowledge, this is not enough for
344 a personalized recommendation system. In this project, we combine the user personal interests' model with on
345 STC algorithm, which improves the STC algorithm strategy.

346 In order to better implementation of the personalized recommendation, the clusters should be ordered according
347 to the user's interests. To measure the user interest into any document, we use the following formula:

348 $Score(c_i) = \sum_{j=1}^M w_j$

349 Where $\sum_{j=1}^M w_j$ is the occurrences number of keyword j into i document c_i for user interests model.
350 w_j is the weight of j .

351 To combine base clusters we use Single-Pass algorithm which has a better timeliness compared with Single-Link
352 algorithm.

353 The basic process of Single-Pass process is as follows:

354 1. Assign the $i=1$ cluster $j=1$. For $i=2$ to N do (a) Calculate similarity S_{ij} between i and j and $S_{ij} > S_{ik}$ for all k . (b) Find the cluster j with largest similarity S_{ij} between i and cluster j . (c) If $S_{ij} > threshold$, then assign i to cluster j and recalculate cluster representative for j , else create a new cluster for i .

355 Cluster representative status such as if the cluster is represented by its centroid.

356 Here, use the user interest degree to measure the similarity of different documents, $similarityS_{ij}$. And use the Score value average of document cluster as the cluster centroid. The process steps are as follows: Traverse each base cluster queue, and convert base cluster into one document; Measure the Score value of each document;

357 Use Single-Pass cluster algorithm to combine all the original base clusters of the same document cluster; order the results according to centroid value;

358 By comparing the results of user interest's measurement, the Single-Pass algorithm we have used in this project to combine base clusters did improve the algorithm efficiently compared with Single-Link algorithm used by previous works. As an implementation result for the above algorithms on search engine data and search information on our E-commerce website, we could check all the info we need via the management system as we see in following figure 6 items ? ETC 1 1 1 ? 0 2 0 0 ? 1 ? ? ? ? K 1 0 ? 0 (D D D D D D D)

359 Year 2014

370 23 E

371 24 By combining the ratings table and items features table, we 372 get the following table:

373 According to the data analyze of search data, our recommender system generates all the information need to
374 recommend items based on search engine data, query keywords and clicked URLs on the website.

375 25 Identification Based on Rated Items

376 Recommendation system can be defined as a program that predicts a user's preferences using information about
377 the user, other users and the items in the system.

378 According to our database figure 2, we can see three tables for this section, which are users table, items table
379 and ratings table. The rating table data explain the items rated by users and ratings degree, the following table
380 shows the process of the rating: a) 0 ? 4 User 1 5 0 1 ? 1 User 2 1 1 0 ? 2 ? ? ? ? ? User N K 1 0 ? 1

381 Table 3 shows the rating value of each item and the user who rated the item. As the above info show the user
382 rating and items features, but it doesn't reflect the user interest into different features of items. So we need to
383 convert the user ratings of the items, make each rating value declare the interest degree of each feature, and then
384 explain the user interest into different features of items, as shown in the following steps: ? Initialize relatively
385 matrix of user preference Create user preference matrix CP, the matrix row include eachuser, the column show the
386 Eigen's, and the values on the matrix: This algorithm can be used to recommend the new items of E-commerce
387 website, although the new items don't have ratings or ordered information's, but the features of new items can
388 be used to compare and find the most similar items on our product catalog, then find the interested users on it,
389 and recommend the new items to them.CP ij ($i = 1, 2, A, N, j = 1, 2, A, M$)

390 First, for the new items features, we create a feature matrix called TestItem form, as a new item to follow up
 391 the types, in the form of 0-1.

392 Second, preferences match of relative users: After the classification of relative preference on behalf of the matrix
 393 itemAvg & TestItem, we measure the D-value E, which is integrity, the greater we got, declare the new item
 394 classification belongs to the user preference or interests. Then select the classification user to do recommendation.
 395 One of the cold start problems is new users who have not any interesting data or purchased items log. So to do
 396 the recommendation for these new users, we use the following method which uses the information of users to find
 397 their similar neighbors in order to give them high quality recommendation contents.

398 We compute a feature weight. Each feature weight is calculated separately for each user. ? Users Input Data:
 399 as we can see on the database figure 2 , the new users data can be called newuser, and the original users data
 400 called UserInfo. ? Feature Weight Calculation, For each user, we assign a weight to each feature in a feature set
 401 based on the particular user's past behavior.

402 26 Comparison between new user and original user

403 For new users, because we don't have any ratings information or either purchased data, so we can't recommend
 404 items according to user interests or content based classification. So we use the new user's data to compare and
 405 find the similarity with other original users, and then according to the similarity degree do a prediction rating
 406 for the new user. The similarity degree between users can be calculated according to the following formula:?? ??
 407 = |?????????????? ?? ? ??????????????δ ???"?? ?? | max ?? ? min ??

408 This formula declares the similarity between users info on the term t.

409 27 Weight Calculation

410 Considering all user information terms, according to different extent a , calculate the comprehensive weights of
 411 similarity degree between on behalf of the user as the following: The user location identification data based on
 412 the input of two clustered matrixes, which are session-IP scope matrix and Interest Scope matrix, as well as, the
 413 user session vector. $W = ? a i 3 i=1 S i$, of which ? a i

414 The output is a list of recommended items for the user based on his location identification, that represented
 415 by session-interest clustered matrix.

416 When the user views our website, the recommender system algorithms based on location will process the
 417 following steps to recommend a list of interest items: First, the system construct session-IP scope matrix for the
 418 current user, to determine the location that user belongs to. The matrix row is filled by value 1 for each session
 419 user location in the matrix, so each row contains only one value as 1 and others take 0. Second, the system create
 420 IP scope-interest matrix, the columns values used to represent the user interest and preference according to his
 421 profile data, and its rows represent the same IP addresses of session-IP scope matrix; Since it has one row, so it's
 422 also called the user's location vector.

423 Third, by multiply the two clustered matrixes, we get a new matrix called session-interest matrix, which used
 424 to indicate the user location and interest data. Then according to matrix values, the system recommends items
 425 for user depend on his location.

426 Fourth, the user visit our site and he may has an interest profile or not, so considering this point, we use
 427 k-mean classification algorithm to find the closest neighbor for user, and recommend items for user based on his
 428 neighbor interest. The classification algorithm (KNN) calculates the similarities between users to provide the
 429 current user a list of most interest items by his same location users.

430 According to algorithm calculation, the more much value is gotten, the more similarity of user profile for
 431 our current user session. The recommendation weight for current user session is obtained, and the more much
 432 weighted value is obtained, the more prioritization of interest items to recommend user. The implementation
 433 results of recommendation matrix based on location give us clear information for user's location and a whole
 434 picture about their visits log to our website. The following figures 9 and 10 show the results via management
 435 system of our application

436 The recommender system generates the location address of users according to stored data by the visits overview
 437 of system. The relational database provide a detailed address including city, province and country for each user
 438 browse our website. The following figure 10 indicates the traffic trends of users via management system: e)
 439 Prediction Accuracy Evaluation ? Prediction accuracy of rating methods

440 28 Mean Absolute Error

441 MAE is a quantity used to measure how close predictions are to the eventual outcomes, it measures the error
 442 between new user's predication ratings and the ratings data of real original users. The smaller value of MAE
 443 outcome, the better quality of recommendation system we got.

444 29 ?????? =

445 ? ? (?????????????????? ? ??????????????????????) ?? ?? =1 ?? ??=1 ?? ?? * ?? Where Testrate is user rating
 446 matrix, TestResult is user's predication rating matrix, N is the number of users, and K as the rating terms
 447 number.

448 30 Conclusions

449 The goal of this work is to enhance and optimize the recommendation system of E-commerce website by providing
450 a new developed and useful model of recommender system. Our system provides some new functions to solve
451 the main serious problems and challenges exist in the current recommendation systems. It provides functions
452 that meet the user and consumer expectations and needs, taking the full consideration of online recommendation
453 system development from the following points: 1. Enhancing recommendation results based on search engine,
454 search data and clicked URLs. Our system use some clustering algorithms to generate and enhance the user search
455 experience in order to build a user interest and preference profile. 2. Enhancing the rating functions by proposing
456 some clustering methods to enhance the functions of rated items which will generate these data as sources to
457 provide a high quality of recommendation results. 3. Proposing solutions for current recommendation system,
458 such as cold start problem. Our system proposed and applied some algorithms which provide solutions for new
459 items and new users recommendation. To measure the recommendation quality standard of the system, there
460 are many methods to use; such as Precision vs. Recall, Clicks, Click through rate and direct user feedback...etc
461 [14]. Here we use two main methods to test the quality and accuracy of recommendation algorithms.

462 4. Proposing a new function for recommendation system, as our system build a new interface which provide
463 recommendation results according to the data identification based on user's location. ASP.NET is used as a
464 programming language to build this project, and ORACLE is used as a database engine. By the extra services
465 that our E-commerce application site renders; it will be more flexible and efficiency to use comparing with other
similar internet (B2B) sites.

¹ ²

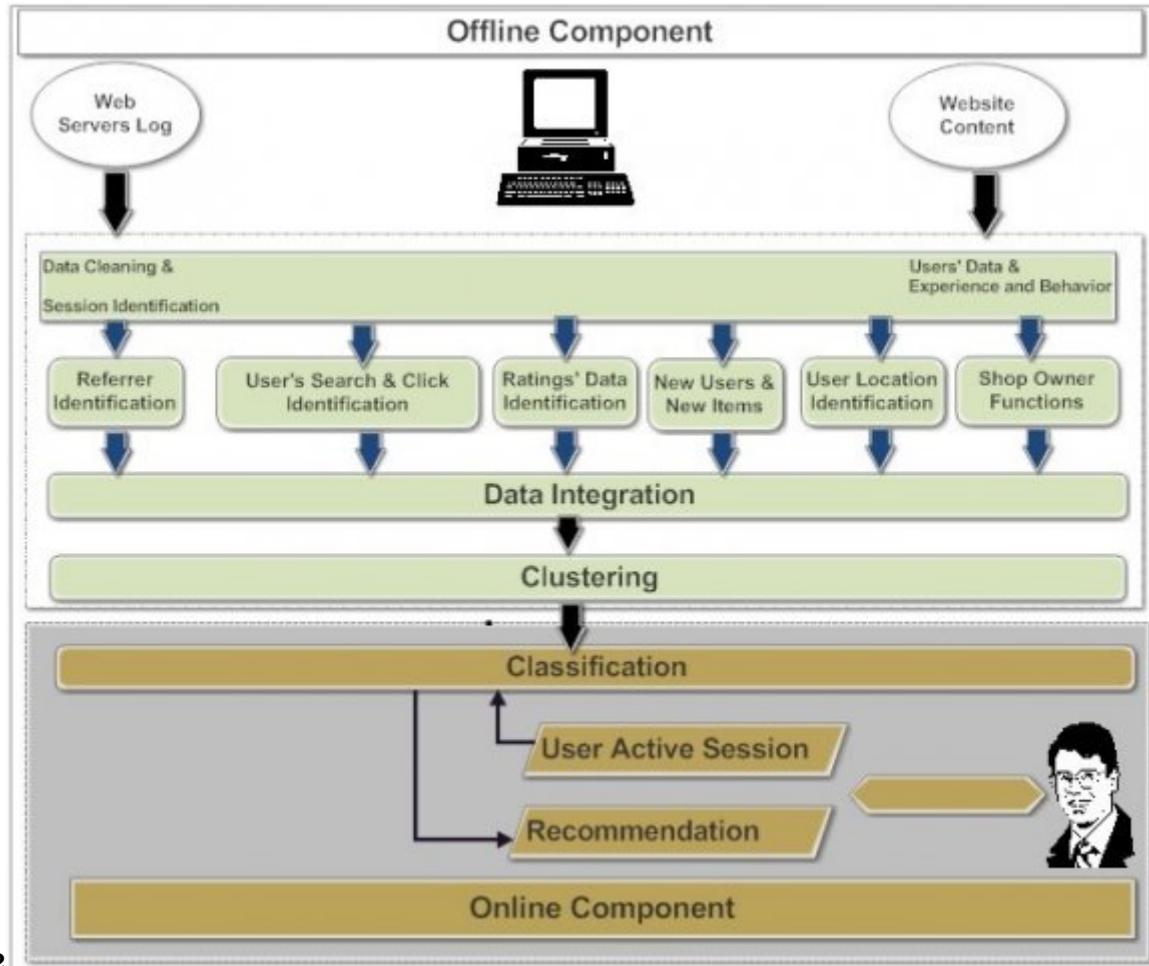


Figure 1: Figure 1 :

466

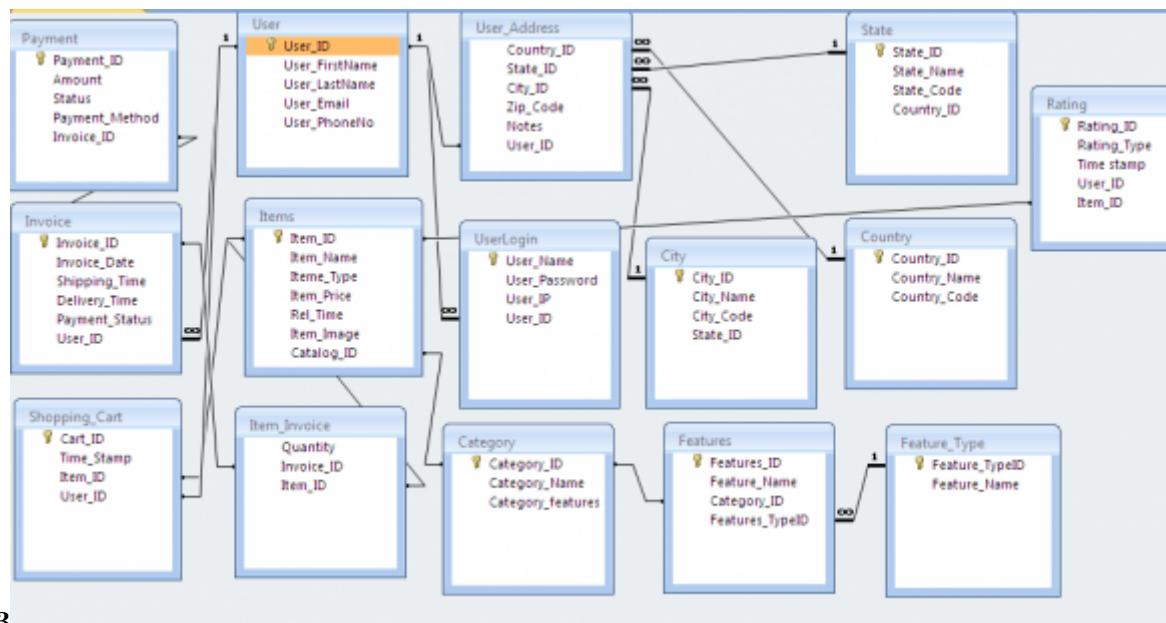
¹© 2014 Global Journals Inc. (US)

²© 2014 Global Journals Inc. (US) Global Journal of Computer Science and Technology



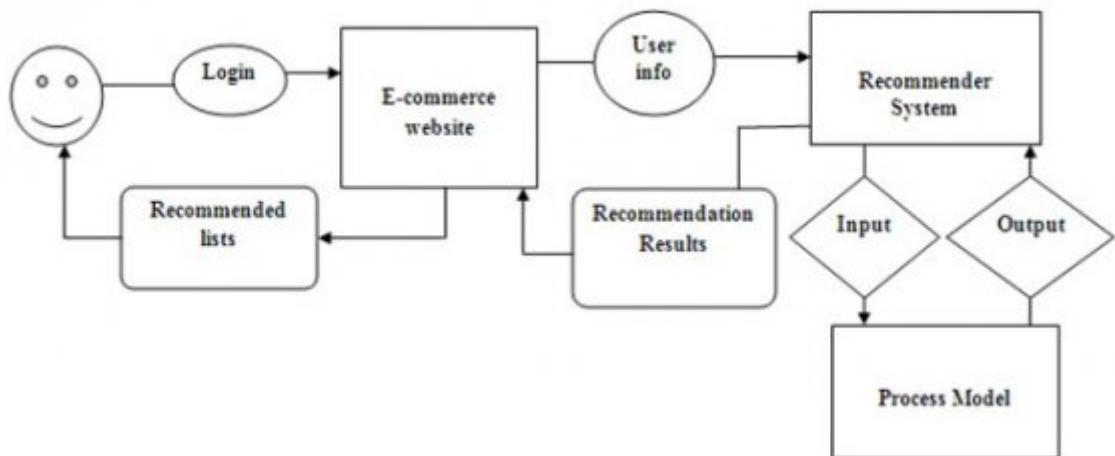
2

Figure 2: Figure 2 :



3

Figure 3: Figure 3 :



4

Figure 4: Figure 4 :

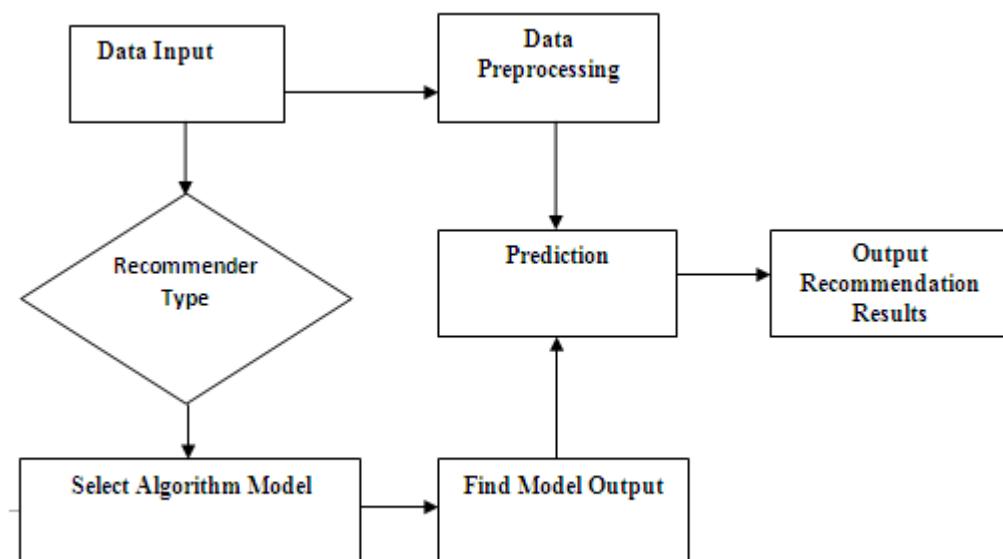


Figure 5:

5

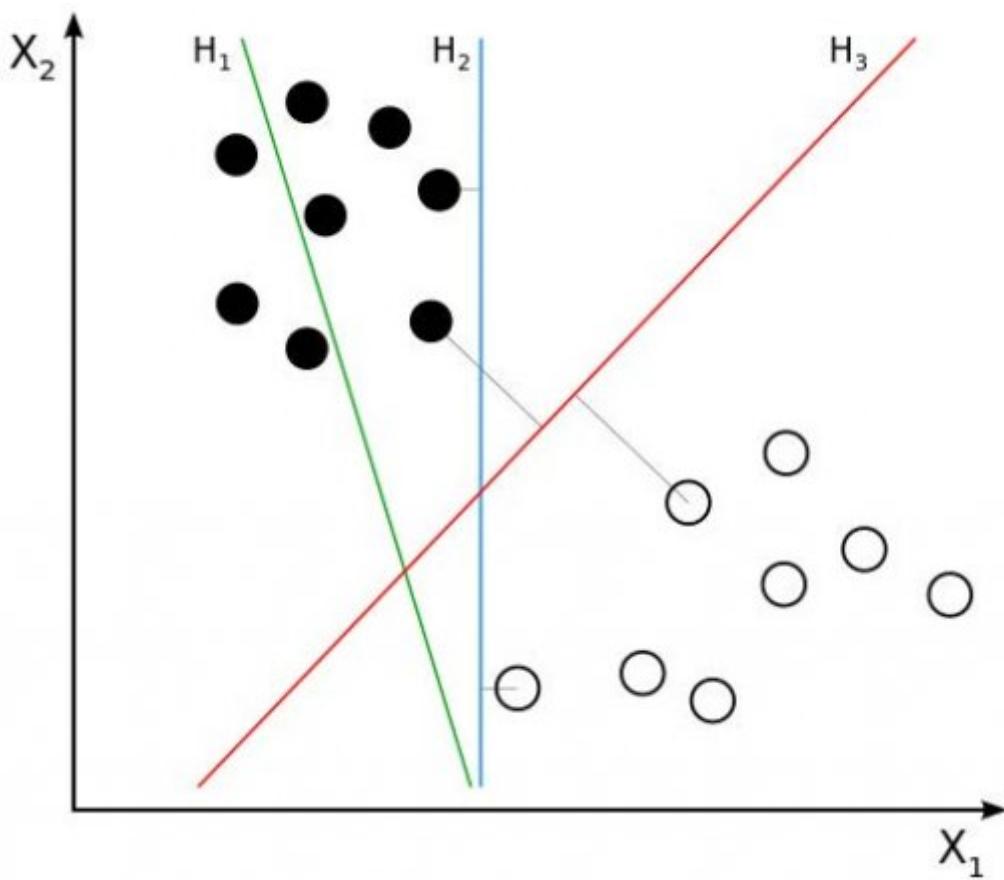


Figure 6: Figure 5 :

ξ_i

Figure 7:

$6\xi_i$

Figure 8: :Figure 6 :

$7\xi_i$

Figure 9: ?Figure 7 :

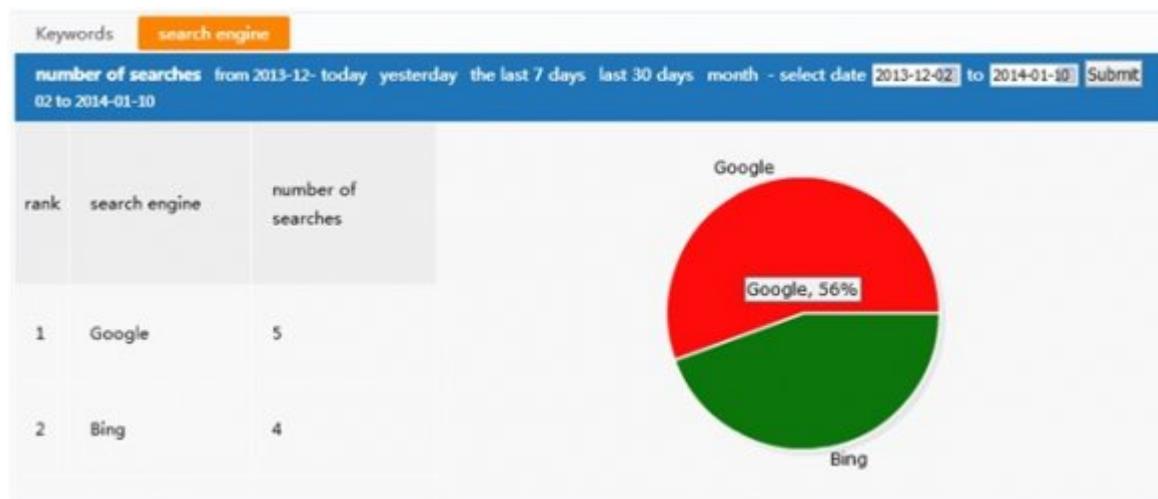
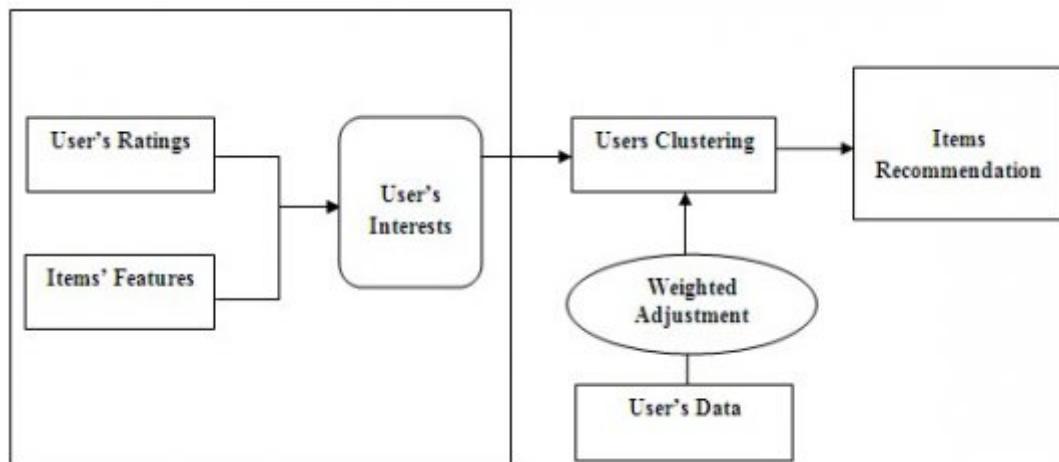
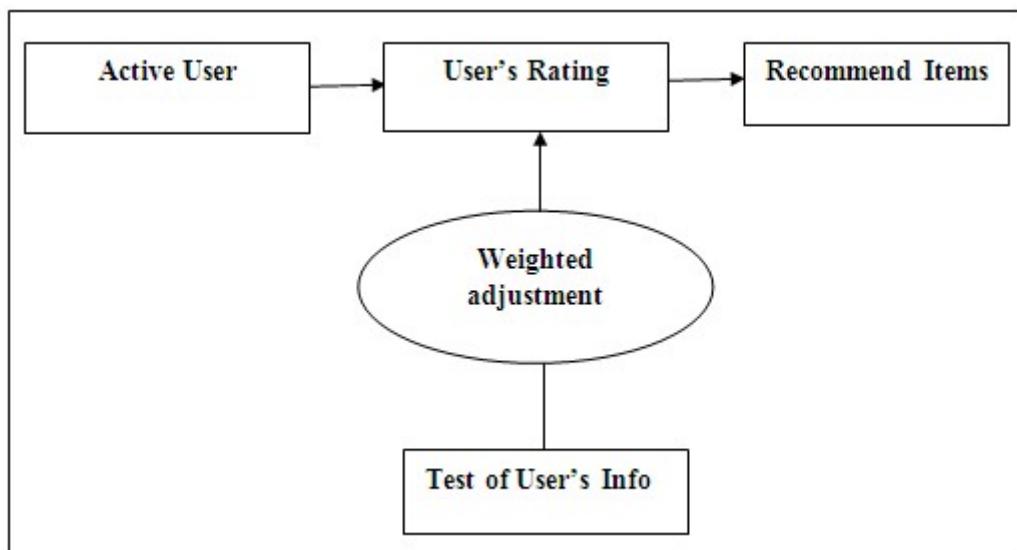


Figure 10:



8

Figure 11: Figure 8 :



9

Figure 12: Figure 9 :

Visits Overview					view all
	PV	unique visitors	IP	per capita Views	
today	1	1	1	1.00	
yesterday	22	8	8	2.75	
average daily	31	6	6		

2

Figure 13: 2 .



10

Figure 14: Figure 10 :

The profile update algorithm is as follows:

Input : search query, user interest ?? ?? Output: User interest ?? ?? Method:

Step1: Extract keywords from search query;

Step2: Define Constant c, 0 ? ?? ? 1 ?? ? ;

Step3:

For (Keyword L of query)

{

if (keyword L in group{?? 1 , continue;

}

Else

{

extract node (?? ?? , ?? ?? =min{?? ?? | 1 ? ?? ? ??});

if (c>?? ??)(L,c)? (?? ?? , ?? ??) else continue;

}

}

step4: ?? ?? units;

Step5: Return ?? ?? ;

Figure 15:

1

UserID	ItemID	Rating
User 1	1	5
User 2	2	4
User 3	3	2
?	?	?
User N	K	I

Every item has its own features; the items table data declares the features of items such as item ID, title,

price, item type and so on. The following table shows items Eigen's data:

Figure 16: Table 1 :

2

ItemID Home goods Technology

Figure 17: Table 2 :

3

User ID	Item ID	Home goods	Technology items	?	Rating
User 1	1	1	1	?	5
User 1	2	0			

Figure 18: Table 3 :

Figure 19:

467 [Wei et al.] , A Survey Of Recommendation Systems In Electronic Commerce Chih-Ping Wei , Michael J Shaw
468 , Robert F Easley .

469 [Hyndman and Koehler ()] *Another look at measures of forecast accuracy*, R Hyndman , A Koehler . 2005.

470 [Content-based Recommender Systems: State of the Art and Trends Pasquale Lops, Marco de Gemmis and Giovanni Semeraro]
471 *Content-based Recommender Systems: State of the Art and Trends Pasquale Lops, Marco de Gemmis and*
472 *Giovanni Semeraro,*

473 [Nikhilesh Dholakia, Ruby Roy Dholakia, Detlev Zwick, and Martin Laub (ed.)] *Electronic Commerce and the*
474 *Transformation of Marketing*, Nikhilesh Dholakia, Ruby Roy Dholakia, Detlev Zwick, and Martin Laub (ed.)

475 [Christopher ()] 'Great Britain: Financial Times / Prentice Hall. 12. Web Document Clustering: A Feasibility
476 Demonstration Oren Zamir and Oren Etzioni Department of'. Martin Christopher . WA 98195-2350 U.S.A.
477 *Logistics and Supply Chain Management: Strategies for Reducing Cost and Improving Service*, 1998. Computer
478 Science and Engineering University of Washington Seattle (2nd edition)

479 [Fui-Hoon Nah and Davis (2002)] *HCI Research Issues In E-Commerce*, Fiona Fui-Hoon Nah , S Davis . March
480 2002. p. 98.

481 [Bian et al.] *Optimizing User Exploring Experience in Emerging E-Commerce Products* Xiubo Geng, Xin Fan,
482 Jiang Bian , Xin Li , Zhaohui Zheng .

483 [Cortes and Vapnik ()] 'Support-vector networks'. C Cortes , V Vapnik . 10.1007/BF00994018. *Machine Learning*
484 1995. 20 (3) p. 273.

485 [Pitt et al. (2002)] 'The Internet And The Birth Of Real Consumer Power'. Leyland F Pitt , Pierre Berthon ,
486 Richard T Watson , George M Zinkhan . *Business Horizons*, July-August(2002. p. .

487 [Today Need of e-Commerce Management to e-Skill Trainings Rashad Yazdanifard and Adnis Zargar] *Today*
488 *Need of e-Commerce Management to e-Skill Trainings Rashad Yazdanifard and Adnis Zargar,*

489 [Turban et al.] E Turban , J K Lee , D King , M Chung . *Electronic Commerce: A Managerial Perspective*,

490 [Watson et al. ()] Richard T Watson , Pierre Berthon , F Leyland , George M Pitt , Zinkhan . *Electronic*
491 *Commerce: The Strategic Perspective. Global Text*, 2008.