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A Multi-Technique Approach for Recommender Systems

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ABSTRACT
Recommender Systems (RSs)are well known for their wide use in e-commerce to predict and recommend products for online users. To enhance the quality of recommendations made by such systems, different recommendation techniques have been developed. A number of hybrid approaches were proposed to minimize the limitations found in single approaches. Hybridization of Content Based Filtering (CBF) and Collaborative Filtering (CF) techniques has been used extensively for the implementation of RSs. The hybrid technique offers a high degree of effectiveness in recommendations, yet it suffers from portfolio effect characterized by data sparsity and cold start problems. Knowledge Based Filtering (KBF) are used to recommend products based on users' preferences, such techniques are prone to the general drawbacks of knowledge based systems. In this paper, a multi-technique approach for recommender systems is proposed. The proposed model integrates CBF, CF, and KBF approaches to give optimal recommendations to online users.

Keywords: Recommender Systems, Content Based, Collaborative Filtering, Knowledge Based, and Portfolio Effect.

1. INTRODUCTION
Obtaining recommendations from trusted sources is a critical component of the natural process of human decision making. With burgeoning consumerism buoyed by the emergence of the web, buyers are being presented with an increasing range of choices while sellers are being faced with the challenge of personalizing their advertisement efforts. Recommender Systems(RSs) have evolved to fulfill the natural dual need of buyers and sellers by automating the generation of recommendations based on data analysis [1].

The large amount of product information in today online stores poses vast challenges to both customers and online businesses in sighting products that best fits their needs. The goal of RSs is to generate meaningful recommendations to a collection of users for items or products that might interest them so as to minimize the time spent while searching [2]. Online businesses are overwhelmed by the volume of data extracted from its users; hence, it is relatively difficult to recommend appropriate products to customers [1].

RSs are a key way to automate mass customization for E-commerce sites [8]. These have become increasingly important feature that maximizes the value of customers to their site and provides exactly the pricing and service adjudged to create the most valuable relationship with the customer, as modern businesses are increasingly focused on the long-term value of customers to the business[4][20].

RS algorithms that use different types of data create the possibility for "subtle personalization", in which the site provides a completely organic personalized experience to the customer. The customer interacts with the site just as he would have before personalization. He does not need to take any explicit actions to inform the site of his interests or desires. The site subtly changes the interface in nearly invisible ways to create a more personal experience for him, without him noticing that anything has changed [17][26]. Other applications of RSs are detailed in [2][3].

Notions of affinity that are used to identify well-matched pairsbetween users and itemsare developed using varying recommender techniques[10]. Collaborative Filtering (CF) and Content Based Filtering (CBF) are the most used techniques in RSs [4]. CFrecommender systems analyze historical interactions while CBF recommendersystems are based on profile attributes. Othersinclude Demographic, Utility-based and Knowledge Based recommender techniques.

Hybrid RSs are designed by combiningone or more techniques so as to provide a more suitable system. This research therefore proposes amodel that integrates Content Based Filtering, Collaborative Filtering, and Knowledge Based Filtering (KBF) concepts. Thus, the proposed model is capable of minimizing the portfolio effect associated with RSs by recommending products for online users irrespective of the users' conversance with the system.

The remaining part of this paper is presented as follows: Section 2 presents the background of study for the research; Section 3 presents the architecture of the proposed model and method adopted by the research, while Section 4 presents the conclusions drawn from the findings.

2.BACKGROUND STUDY
RSs can be described as systems that suggest or recommend products to users while making decisions[11]. RSs acquire user's opinion about certain items and use the information to predict new items that might be of great interest to him [16].In this section, review of literature on CF, CBF, KBF, and Hybrid approaches of RSs and presented.

Collaborative Filtering Recommender System (CFRS) collects users' feedback in the form of item ratings and exploitsthe similarities in the rating behavior so as to make recommendations. Common methods of CFRSincluding *neighborhood-based* and *model-based* are detailed in [5].

Some early successes of CFRS on related domains included the GroupLens system [29]. CFRSs were introduced in the context of the first commercial RS, called Tapestry[9], which was designed to recommend documents drawn from newsgroups to a collection of users. The motivation was to leverage social collaboration so as to prevent users from getting flooded by large volume of documents.

CFRSs perform better in domains where the content associated with items is not much and the content is difficult for computer to analyze. However, challenges faced by CFRSs include data sparsity, first-rater problem, and fraud [2].

Content-Based Recommender System (CBRS) selects items based on the correlation between the content of the items and a user's preferences. CBRS is prevalent in Information Retrieval (IR), where text and multimedia content of documents are used to select documents relevant to user's query [13].

CBRSs are found to be efficient in recommending items by solely exploiting the ratings provided by a certain user inorder to build his profile; it also provides details of recommended items by listing the features that caused an item to be recommended. Cold start,which occurs in CFRSs as a result of new items that are not yet rated,is alleviated in CBRS [15].

The adoption of content based recommendation paradigmspresent several advantages overthe CFstandardswith major considerations on '*User Independence*', '*Transparency'* and '*New Item*' [23][24]. In CBRS, ratings provided by an active user are solely exploited to buildthe user's profile while in CF,ratings from the "nearest neighbors" of the active user are used to build his profile. Transparency is a featureof CBRSwhere by explanations on how recommendations are made is provided; this helps users to decide whether to trust a recommendation or not. Lastly, the cold-start problems resulting from items that were not yet ratedare assuaged in CBRS.

Nonetheless, CBRS have several shortcomings including limited content analysis,over-specialization, and new-user problems [23]. Limited content analysis is as a result of natural limit in the number and types of features that are associated with recommended objects.Over-specialization, known as serendipity, is a situation whereby items previously recommended and rated by users are re-recommended. Lastly, enough ratings have to be collected before CBRS can really understand users' preferences and provide accurate recommendations. In essence, the system cannot provide reliable recommendationsin the availability of few ratings.

Various techniques including the nearest neighbor algorithm [18], association rule mining [25] and neural networks [30] have been used for designing RSs. All the existing techniques have their strengths and weaknesses in the aspect of performance, reliability, agility, and security. Several hybrid approaches where both CF and CBF techniques were combined to leverage theirweaknesses have been proposed. [29] proposed a general framework for *Content-Boosted Collaborative Filtering*; content-based predictions were applied to convert a sparse user ratings matrix into a full ratings matrix and recommendations were provided using a CF method. [27] demonstrated improved results using a content-predictor (TAN-ELR) and unweighted Pearson Collaborative Filtering. Several other hybrid approaches are based on traditional CF, but also maintain a contentbased profile for each user [17].

Several hybrid approaches treat recommendation as a classification task, and incorporate collaborative elements in the task. [26] used*Ripper*, a rule induction system, to learn a function that takes a user and movie and predicts whether the movie will be liked or disliked. The study proposed a hybrid system by creating features such as *comedies liked by user* and *users who liked movies of genre X*, and then recommend movies for the user. In [28], each user-profile is represented by a vector of weighted words derived from positive training examples using the Winnow Algorithm. Predictions are made by applying CF directly to the matrix of user-profiles.

Some hybrid approaches directly combinedcontent and collaborative data under a single probabilistic framework. Hofmann's Aspect Model [32] incorporated a three-way co-occurrence data among users, items, and item content. This generative model assumes that users select latent topics while documents and their content words are generated for the topic. [33] extend this approach and focused recommending items that have not been rated by any user. Other combination methods that have been employed are reported in [14][17][26][28].

Knowledge Based Recommender System (KBRS) attempts to suggest products based on inferences deduced from users' needs and preferences. In some regards, all recommendation techniques could be described as doing some kind of inferences but Knowledge Based (KB) approaches are distinguished by their inherent functional knowledge which is used to reason on how a particular item can serve user's needs [14].

The common portfolio effect associated with both CFRSs and CBRSs can be easily taken care of by KB approach to RSs. Nevertheless, KBRSs are prone to the drawbacks of all KB systems. To make good recommendations, a KBRS must understand the product domain well. It must have knowledge of important features of the product, and be able to access the knowledge base where these important features are stored in an inferable way. Thus, a KBRS requires knowledge engineering with all of its attendant difficulties.

The amalgam of CF and CBF techniques offers a high degree of effectiveness in recommending products to users [12], yet it suffers from *Portfolio Effect*, a yokefellow to both techniques.Therefore, we introduce a multi-technique approach for recommender systems. The proposed architecture integrates Content Based Filtering, Collaborative Filtering, and Knowledge Based Filtering concepts. We believe that the proposed architecture will inherit all the advantages of a CFRS, CBRS, and KBRS but will not suffer from their shortcomings and hence, optimal recommendations will be given to online users irrespective of their conversance with the system.

3. THE PROPOSED MODEL AND METHOD

The study proposes a model using a multi-technique approach forRSs. The architecture of the proposed modelis presented in Figure 1.The components of the architecture, and the processes needed to carry out recommendation tasks are described thereafter.

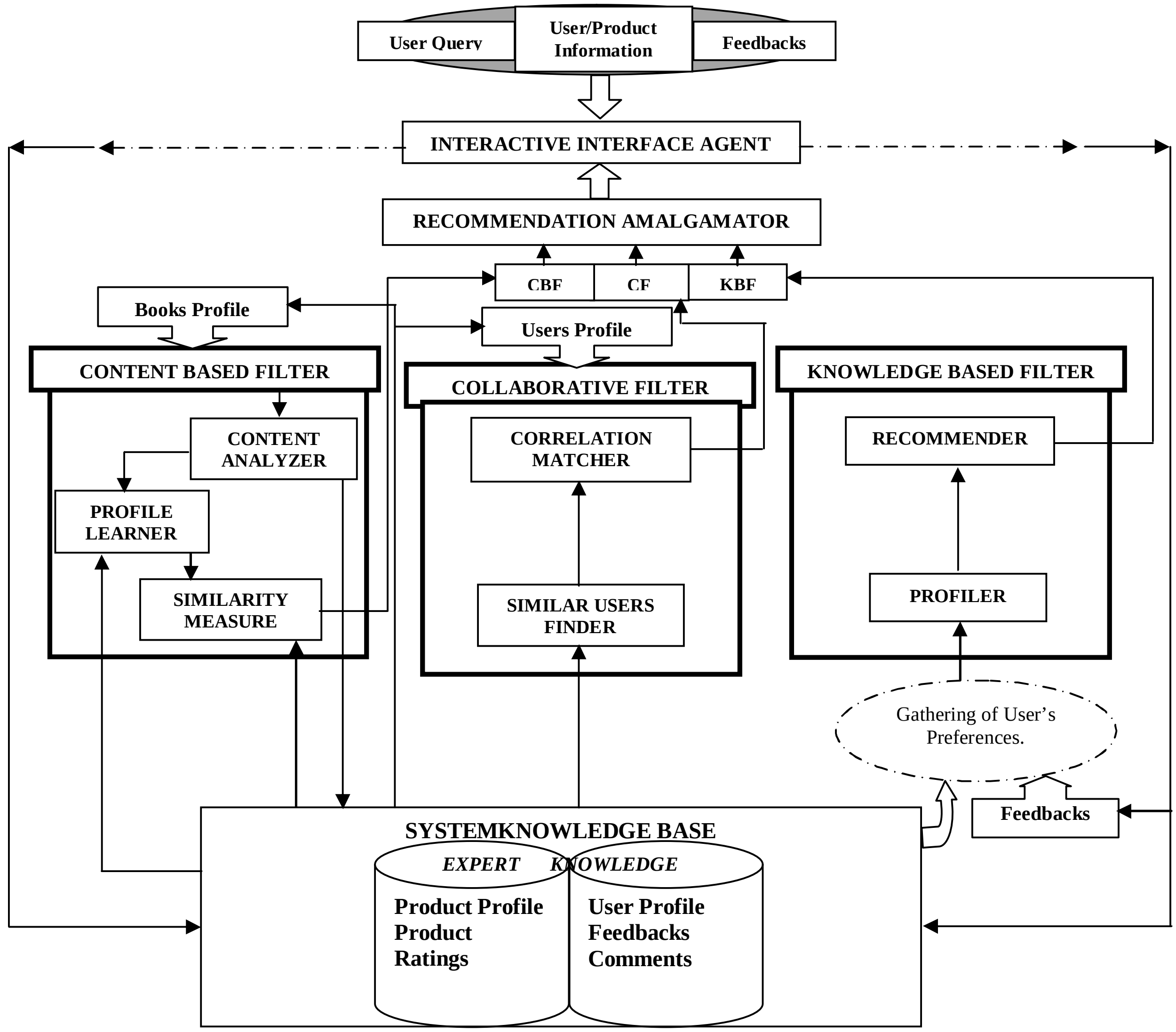

Figure 1: Framework of the Proposed Model

3.1 The Interactive Interface Agent (IIA)

The IIA in the model serves the purpose of a control unit. It acts as an intermediary between the user and the three recommender subsystems. The IIA decides the interaction that takes place in the system at each session, the Content Based Filter and Collaborative Filter may not be useful to a new user until a large number of users, whose interest profiles are known, and a sufficient number of rated items have been stored in the System Knowledge Base (SKB). In such instance, the Knowledge Based Filter performs the major task of products' recommendations. The IIA also enhance the communications that occur between the RS and its users.

3.2 The Content Based Filter

The content based filter is used to recommend similar products by utilizing ratings that were previously specified by an active user, such products are arranged based on the user's rating. The key features of each product (for instance, *keywords* in books) are extracted, using feature extraction techniques, and analyzed by the *Content Analyzer*. The products are represented in a **1xm** vector form, using Keyword Vector Space Model [13]. In the model, products are represented asan m-dimensional vector, where each dimension corresponds to certain features$f_i$of the productp_j.

Letall the products found in the SKB be represented as: $P = (p_1, p_2, p_3, \ldots, p_n)$, each product $p_j$is represented as:

$$p_j = (w_{1,j}, w_{2,j}, \ldots, w_{m,j}) \qquad (1)$$

wherem is the number of features attributed to p_j, and $w_{i,j}$is the weight of feature f_i in p_j . $w_{i,j}$ is determined by using equation 2.

$$w_{i,j} = \begin{cases} 0 & iff_i \nexists p_j \\ kf_i \,.\, log\left(\frac{n}{df_i}\right) & otherwise \end{cases} \qquad (2)$$

where$kf_i$is the number of occurrences of feature$f_i$in p_j, n is the number of products in the SKB, and$df_i$is the number of products in the SKBwheref_i appears at least once.

The *Profile Learner* collects data representing the user's preferences and generalizes it in order to construct the user's profile. All the productsthat were previously rated by the user are retrieved and arrangedbase on the user's ratings. User's rating is an explicit feedbackdenoted by a set of linguistic terms, the linguistic terms are mapped to numerical values which facilitate the calculation of actual values for ratings. Table 1 shows the numeric mappings.

Table 1: Numeric Ratings of Linguistic Term

S/N	Linguistic Term	Ratings
1	Totally dislike	0
2	Moderate dislike	1
3	Neutral	2
4	Moderate like	3
5	Totally like	4

All products stored in the SKB are arranged based on active user's ratings, the top-most rated product p_i is compared toall other products p_j in the SKB so as to observe their *Similarity Measures* as shown in equation 3.

$$sim(p_i, p_j) = \frac{\sum_{j=0}^{n} w_{k,i} \cdot w_{k,j}}{\sqrt{\sum_{j=0}^{n} w_{k,i}^2 \cdot w_{k,j}^2}} \quad (3)$$

The similarity measures are sorted as a*1xM*vector, which represents the recommendations given by the Content Based Filter.This is passed to the *Recommendation Amalgamator.*

3.3 The CollaborativeFilter

The Collaborative Filteridentifies users with similar preferences and uses this information to generate recommendations for the active user. This component of the proposed modelemploysItem-based CF [6] where rather thanmatching similar users, they match a user's rated items to similar items. In practice,this approach leads to faster online systems, and often results in improvedrecommendations [6][36].

The *Similar Users Finder* of the collaborative filter observes the similarities between pairs of products iand j. This is done by computing the weight ($w_{i,j}$)between the paired products iand jusing*Pearson Correlation Coefficient* [22], given by:

$$w_{i,j} = \frac{\sum_{u\in U}(r_{u,i} - \bar{r}_i) \cdot (r_{u,j} - \bar{r}_j)}{\sqrt{\sum_{u\in U}\left(r_{u,i} - \bar{r}_i\right)^2} \cdot \sqrt{\sum_{u\in U}\left(r_{u,j} - \bar{r}_j\right)^2}} \quad (4)$$

whereU is the set of all users that have rated two products i and j, $r_{u,i}$and $r_{u,j}$ are the ratings given by user u to products i and j respectively;$\bar{r}_i$ is the mean rating ofith product by all users.

The rating foran item i by auser a ispredictedin the *Correlation Matcher* using simple weighted averaging technique as we have in equation 5.

$$p_{a,i} = \frac{\sum_{j\in K} r_{a,j} \cdot w_{i,j}}{\sum_{j\in K}|w_{i,j}|} \quad (5)$$

whereK is the neighborhood set of j items rated by a that are most similar to$i$; $p_{a,i}$ is the prediction weightfor a product i by a.

All the products in the SKB are arranged based on their prediction weights. A *1xN*vector of the arranged products is taken as recommendation givenby the Collaborative Filter of the proposed RS. This is alsosent to the *Recommendation Amalgamator*.

3.4 The KnowledgeBased Filter

The Knowledge Based Filter is used to generate recommendations that best matches user's preferences. User's preferences are a set of areas of interest that were indicated by the user.

The knowledge based filter takes example(s)provided by a user as his preference(s) in order to generate an initial user profile. This profile consists of a vector of features which are described by a set of linguistic terms. The knowledge based filter performs two basic processes:*Profiling*and *Recommending.*

In profiling, the system builds user's profile using necessities stated by the user. This is done in two steps:

A. Gathering the Preferred Example from the User

The KBF of the proposedRS starts by defining user's necessities.The user is presented with series of products where hechooses an item as an example; the selected item is used to define the initial profile of the user as follows:

i. Let $p_e$be the product given as example by a useru_e; the product is described in the SKB as an *Utility Vector* given by:$F_e = \{v_1^e, v_2^e, \dots, v_l^e\}$, where $v_k^e$is an assessment for feature v_k of the product p_e ,expressed in terms of S_k.$v_k^e \in S_k$.
ii. The selected example is used to define an initial user profile as:$UP_{e0} = \{up_1^{e_0}, \dots, up_l^{e_0}\}$, where $up_k^{e_0} = v_k^e$.In this initial user profile, the linguistic terms not other than those used in the SKB are used.
iii. Linguistic terms are generated by considering all terms distributed on a 7-term scale as:

$$\{\boldsymbol{s_0}: \boldsymbol{Normal}, \boldsymbol{s_1}: \boldsymbol{Very\ Low}, \boldsymbol{s_2}: \boldsymbol{Low}, \boldsymbol{s_3}: \boldsymbol{Medium}, \boldsymbol{s_4}: \boldsymbol{High}, \boldsymbol{s_5}: \boldsymbol{Very\ High}, \boldsymbol{s_6}: \boldsymbol{Perfect}\}$$

iv. The semantics of the terms are given by fuzzy numbers defined in the interval [0,1]. Linear trapezoidal membership functions are good enough to capture the vagueness of linguistic assessments.Figure 2shows a typical structure of the membership function.

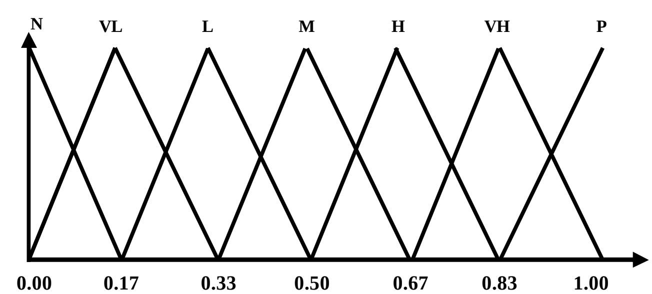

Figure 2: Knowledge Based Linguistic Term Set and its Semantics

B. Casual Modification of Preferences

Following the definition of the initial profile, the linguistic term defined by the domain experts (database's builders) may not be appropriate for the user;therefore the user is allowed to utilize other variables in the linguistic sets that he found more suitable to the product.

For an attribute c_k of a product p_e, the useru_e can assign a new value, $p_k^{e_1}$, expressed in other linguistic term set, S'_k. Therefore, a final user profile$P_e$is obtained as:

$$P_e = \begin{cases} p_k^e = p_k^{e_0}, p_k^{e_0} \in S_k^e = S_k & \text{if } c_k \text{ is not been modified} \\ p_k^e = p_k^{e_1}, p_k^{e_1} \in S_k^e = S'_k & otherwise \end{cases} \quad (6)$$

where $P_e = \{p_1^e, \dots, p_l^e\}$.

In the second phase, the system makes recommendations by observing how close the products are to the final user's profile. This is done by evaluating the similarity between all the products of the SKB and the user's profile following the steps below:

Unification of the linguistic information: Since there is no way to deal directly with information in different linguistic terms, we need to unify the information in a unique domain. In this case, we choose Basic Linguistic Term Set (BLTS),denotedas S_T , as the unification domain. The information will be unified by means of fuzzy sets defined in the BLTS, $F(S_T)$, using the MultigranularTransformation Function (MTF)[19][31]:

Let $A = \{l_0, \dots, l_p\}$ and $S_T = \{s_0, \dots, s_g\}$ be two sets of linguistic terms such that $g \geq p$:the Multigranular transformation proceeds as:

$$\boldsymbol{\tau_{AS_T}}: A \rightarrow F\ (S_T) \quad (7)$$

$$\boldsymbol{\tau_{AS_T}}(\boldsymbol{l_i}) = \left\{ (s_k, \propto_k^i) \middle| k \in \{0, \dots, g\} \right\}, \forall\ l_i \in A \quad (8)$$

$$\propto_{\boldsymbol{k}}^{\boldsymbol{i}} = max_y \min \{\mu_{l_i}(y), \mu_{s_k}(y)\} \quad (9)$$

where τ_{AS_T} is the MTF,$F\ (S_T)$ is the fuzzy sets defined on (S_T); $\mu_{l_i}(y)$ and $\mu_{s_k}(y)$ are membership functions of the fuzzy sets associated to the terms l_i and s_k respectively.

The MTFs:τ_{S_k} and $\tau_{S_T}$are used to unify the final user's profile and products of the SKB fuzzily described in the BLTS. For instance, an assessment of the user profile, $p_k^e \in S_k^e$, and an assessment,$v_k^j \in S_k$, of a product a_j, are transformed into a fuzzy sets$p_k'^e$ and $v_k'^j$ respectively.The fuzzy sets are described by a tuple of membership degrees given by equations 10 and 11 respectively:

$$p_k'^e = (\propto_{k0}^e, \dots, \propto_{kg}^e) \quad (10)$$

$$v_k'^j = (\propto_{k0}^j, \dots, \propto_{kg}^j) \quad (11)$$

Calculation of the similarity between the user profile and the items:Once all information is expressed in the same domain, the system will look for all products that are closer to the user's necessities. This is done by calculating the similarities between the final user's profile, P_e , and each producta_j, of the SKB using the equation 12.

$$d_j = d(P_e, a_j) \quad (12)$$

This is simplified as:

$$d_j = \frac{1}{l} \sum_{k=1}^{l} w_i\ .\ sim(p_k'^e, v_k'^j) \quad (13)$$

where w_i represents the importance of each attribute and $\sum_1^n w_i = 1$. $sim()$computes the similarity between the values P_e and a_j, using measures based on the Central Value (CV) of fuzzy values[9]as follows:

Giving a fuzzy set $b' = (\propto_1, \dots, \propto_g)$ defined on $S = \{s_h\} \propto_1 \forall h = 0, \dots, g$, we obtain the CV as:

$$cv = \frac{\sum_{h=0}^{g} idx(s_h) \propto_h}{\sum_{h=0}^{g} \propto_h} \quad (14)$$

where $idx(s_h) = h$ and represents the central position or centreof gravity of the information contained in the fuzzyset b'. The range of this central value is the closedinterval $[0, g]$

Let cv_1 and cv_1 be the central values of fuzzy setsb'_1andb'_2respectively, the similarity between them is calculated as:

$$sim(b'_1, b'_2) = 1 - \left| \frac{cv_1 - cv_2}{g} \right| \quad (15)$$

The final result of this phase is a similarity vector $D = (d_1, \dots, d_g)$in which the system keeps the similarity between user profile $P_e$and all items in the database.

Recommendation: The system will rank the products according to their similarity values,with the best ones (those with the greater scores) at the top of the list.

3.5 Recommendation Amalgamator

The recommendation amalgamatormerges the results of the three subsystems and produces a single result. This is done by sorting products in the three vectors using their unique Id, and computing the average value of each product as shown in equation 16.The result is stored as an ordered list whose ordering is used to recommend the top-N products that passes a set threshold test.

$$RA_{w_p} = \frac{\sum_{i=1}^{n} w_i}{n} \quad (16)$$

where RA_{w_p} is weight ascribed to a product p by the recommendation amalgamator, w_i is the weight of p from ith sub-recommender, and n is the number of sub-recommenders that participate in the recommendation process.

Let $V = (v_1, \dots, v_n)$ represents the unique vector for the products, r the maximum number of products to be recommended and $h$the threshold to be reached. Then, the recommendation to the user is given by the recommendation vector (P_A) where the first element is the topmost recommended product, the second element is the second closest product, and so on.

$$P_A = \left(a_{q(1)}, \dots, a_{q(n)}\right) \quad (17)$$

Finally, it queries the product database of the SKB for the attributes (characteristics) of these n selected products, and returns these items together with their attributes to the IIA as output. These items and their attributes are presented to the user by the IIA.

3.6 The System Knowledge Base

A Knowledge Base is an advanced form of database system where data resides [34].The SKB of the proposed model stores both structured and unstructured knowledge about the problem domain and serves as a repository for operational data that are to be processed. Structured knowledge includes the profile of products that are to be recommended, user profile, feedbacks and comments of users; structured knowledge are stored in a relational database model as proposed in [35]. Unstructured knowledge includes the experts' knowledge used in recommending products,the unstructured knowledge are represented using fuzzy logic concepts [11]. FL is basically aimed at providing approximate reasoning [21].

4. CONCLUSION

Hybrid approaches combine, basically, two recommender techniques in order to improve the recommendation performance, and as well tackle with the shortcomings of single approaches. Data sparsity and cold start effects are major challenges faced by CFRSs and CBRSs; KBRSs require knowledge engineering in order to make good recommendations and such systems are also prone to the drawbacks of all KB systems. Therefore, the common hybrid techniques for recommender system are not free from defects of inaccuracy. In this paper, a multi-technique approach that ensures the optimality of recommendations made by recommender systems is proposed.

The approaches considered are Content Based Filtering (CBF), Collaborative-Filtering (CF), and Knowledge Based Filtering. CBF and CF are the most widely used approaches. Knowledge Based Filtering (KBF) is integrated to minimize the effects of data sparsity and cold start in existing RSs built on CBF-CF hybrid approaches.

However, KBRSs have gotten relatively little research with minimal support for multi-criteria rating, which requires users making judgments base on several factors. There is also the limitation in nearest neighbour based computing and scalability problem since computation time grows rapidly with the number of users and products.

Lastly, this paper has only presented a model whose efficiency and effectiveness should be validated via real life experimental settings or simulations. We, therefore, recommend its practical study in future studies.

REFERENCES

1. L. Huang, L. Dai, Y. Wei, M. Huang. **A Personalized Recommendation System Based on Multi-agent**, In Proceedings of the 2nd International Conference on Studies in Computational Intelligence, 2010.
2. P. Melville and V. Sindhwani. **Recommender Systems**. IBM T.J. Watson Research Center, Yorktown Heights, NY 10598, 2005.
3. A. Ansari, S. Essegaier, R. Kohli. **Internet Recommendation Systems**, Journal of Marketing Research. vol. 37, issue 3, pp. 363-375, 2000.
4. D. Peppers, M. Rogers. **The One to One Future: Building Relationships One Customer at a Time**, Bantam Doubleday Dell Publishing, 1997.
5. A. Popescul, L. Ungar, M. Pennock,S. Lawrence.**Probabilistic Models for Unified Collaborative and Content-Based Recommendation in Sparse-DataEnvironments**, In Proceedings of the Seventeenth Conference on Uncertainity in Artificial Intelligence, 2001.
6. G. Linden, B. Smith, and J. York. **Amazon Recommendations: Item to Item Collaborative Filtering**, IEEE Internet Computing, Vol. 71, pp. 76–80, 2003
7. J. Schafer, J.Konstan, and J.Riedl.**Recommender Systems in E-Commerce**, GroupLens Research Project, Department of Computer Science and Engineering, University of Minnesota, 2008
8. R. Burke. **Knowledge-based Recommender Systems**, Encyclopedia of Library and Information Systems, pp. 32-69, 2000.
9. E. Herrera-Viedma, F. Mata, L. Mart´ınez, F Chiclana, and L.G. P´erez. **Measurements of Consensus in Multigranular Linguistic Group Decision Making**,Modeling Decisions for Artificial Intelligence, Proceedings Lecture Notes in Computer Science, vol 31, pp.194–204, 2004
10. I. Soboroff and C. Nicholas, **Combining Content and Collaboration in Text Filtering**, in the Proceedings of the IJCAI'99 Workshop on Machine Learning in Information Filtering, pp. 86–91, 1999
11. B. A. Ojokoh, M. O. Omisore, O. W. Samuel, and T. O.Ogunniyi.**A Fuzzy Logic Based Personalized Recommender System for Laptop Computers**, International Journal of Computer Science and Information Technology & Security, Vol. 2, No.5, pp. 1008-1015, 2012
12. B. Towleand C. Quinn.**Knowledge Based Recommender Systems Using Explicit User Models,** In Knowledge-Based Electronic Markets, Papers from the AAAI Workshop, AAAI Technical Report WS-00-04, Menlo Park, CA AAAI Press pp. 74-77, 2000
13. R.Meteren and M.Someren. **Using Content-Based Filtering for Recommendation**, NetlinQ Group, Gerard Brandtstraat, 1054 JK, Amsterdam, The Netherlands, pp. 26-28, 1998
14. R. Burke.**Hybrid Recommender Systems: Survey and Experiments**, Department of Information Systems and Decision Sciences, California State University, Fullerton, 2009.
15. G.Semeraro.**Content-Based Recommender Systems: Problems, Challenges and Research Directions**, Workshop on Intelligent Techniques for Web Personalization and Recommender Systems, Department of Computer Science, University of Bari Aldo Moro, Big Island of Hawaii, 2010.
16. P. Resnick, and H. Varian.**Recommender Systems**, Communications of the ACM, Vol. 40, Issue 3, pp. 56-58, 1997
17. M.Balabanovic and Y.Shoham. **Fab: Content-Based, Collaborative Recommendation**, Communications of the ACM, 403: pp. 66-72, 1997
18. J. Herlocker, J. Konstan, L. Terveen, and J. Riedl. **Evaluating Collaborative Filtering Recommender Systems**, ACM Transactions on Information Systems. Vol. 22, Issue 1, pp. 50-54, 2004

19. L.Mart´ınez, M.Barranco, L.P´erez, M.Espinilla.**A Knowledge Based RS with Multigranular Linguistic Information**, International Journal of Computational Intelligence Systems, Vol.1, No. 3, 225-236, 2008
20. B. J. Pine, D. Peppers, and M. Rogers.**Do You Want To Keep Your Customers Forever**, Harvard Business School Review, 19952: pp. 103-114, 1995
21. L. A. Zadeh. Fuzzy Sets, **Information and Control**, Vol. 8, pp. 338-353, 1965
22. P.Resnick, N.Iacovou, M.Sushak, P. Bergstrom, and J.Reidl.**Grouplens: An Open Architecture For Collaborative Filtering Of Netnews**, In ACM Proceedings of 1994 Computer Supported Cooperative Work Conference, New York, 1994
23. P. Lops, M. Gemmis, G. Semeraro.**Content-Based Recommender Systems: State of the Art and Trends**, Department of Computer Science, University of Bari, Bari Italy, 2010.
24. P. Kantor, F. Ricci, L. Rokach and B. Shapira, **Recommender Systems Handbook, A Complete Guide for Research Scientists and Practitioners**, pp 73-105, 2010.
25. A. Demiriz. **Enhancing Product Recommender Systems on Sparse Binary Data**, Data Mining and Knowledge Discovery, Vol. 9 pp. 147–170, 2004
26. C. Basu, H. Hirsh, and W. Cohen.**Recommendation as Classification: Using Social and Content-Based Information in Recommendation**, In Proceedings of the Fifteenth National Conference on Artificial Intelligence AAAI-98, pp 714–720, 1998.
27. S. Xiaoyuan, R. Greiner, T..Khoshgoftaar, and X. Zhu.**Hybrid Collaborative Filtering Algorithms Using a Mixture of Experts**. In Web Intelligence, pages 645–649, 2007.
28. M. J. Pazzani.**A Framework For Collaborative, Content-Based and Demographic Filtering**, Artificial Intelligence Review, 135-6:393–408, 1999.
29. P. Melville, R. J. Mooney, and R. Nagarajan. **Content Boosted Collaborative Filtering for Improved Recommendations**, In Proceedings of the Eighteenth National Conference on Artificial Intelligence AAAI- 02, pages 187–192, 2002
30. S. V. Chang Chien, and T. C. Lu, **Mining Association Rules Procedure To Support On-Line Recommendation By Customers And Products Fragmentation**, Expert Systems with Applications, 20 2001, 325-335, 2001
31. F. Herrera, E. Herrera-Viedma, and L. Mart´ınez. **A Fusion Approach For Managing Multi-Granularity Linguistic Term Sets In Decision Making**. Fuzzy Sets and Systems, Vol. 114, pp. 43–58, 2000.
32. T. Hofmann, Probabilistic Latent Semantic Analysis, In Proceedings of Uncertainty in Artificial Intelligence UAI, 1999
33. A. I. Schein, A.Popescul, L. H. Ungar, and D. M. Pennock, **Methods and Metrics for Cold-Start Recommendations**, In SIGIR '02: Proceedings of the 25th annual international ACM SIGIR conference on Research and development in information retrieval, New York, NY, USA, 2002. ACM, pages 253–260, 2002.
34. M. OOmisore and O. W. Samuel, **Design of Internet Model for Court Case Citation**, Journal of Communication and Computer, "In Press".
35. E. F. Codd.**Relational Model of Data for Large Shared Data Banks**, Communication of ACM, Vol. 13, No. 6 pp. 377-87, 1970.
36. B.Sarwar, G.Karypis, J.Konstan, and J.Reidl, **Item-based collaborative filtering recommendation algorithms**. In WWW '01: Proceedings of the 10th international conference on World Wide Web, Communications of the ACM, pp. 285-295, New York, NY, USA, 2001

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