Volume 6, Issue 5, May 2016 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Electronic Books Recommender System Based on Implicit Feedback Mechanism and Hybrid Methods

Megharani V. Misal, Pramod D. Ganjewar
Department Of Computer Engineering, Savitribai Phule Pune University, Pune, Maharashtra, India

Abstract: Now–a-days recommender systems(RSs) becoming very popular among internet users.RSs provide relevant information to users in time efficient manner by filtering large amount of information on the web.RSs are developed as an information filtering and classification techniques to deal with information overload problem. Most of the present recommender systems find the users interest through explicit feedback mechanisms where user explicitly specifies their interests. Most of the users do not like to rate the contents in the context of electronic books because this approach may affect the user reading and understanding pattern as user has stop reading and rate the contents. To overcome this problem here architecture of electronic book recommender system developed which considers user behavior, reading and understanding pattern. This architecture analyzes and transforms user behavior into explicit rating in an implicit way. Again to improve the performance of RS recommendation engine uses hybrid approaches to improve the quality of recommendations generated by the system. By developing this system as social network of electronic books collaborative learning of digital contents is allowed among all users of the system.

Index Terms*: *Recommender System; Collaborative Learning;

I. INTRODUCTION

With the advancements in technology and growth of internet information available on the web is growing so rapidly which leads to the problem of information overload. To overcome this problem RSs are developed as information filtering and classification techniques.RS filters the large amount of information available on the web and provides relevant information to the users. RSs are used in many applications such as electronic commerce, online social networks (Facebook,You-Tube,LinkedIn etc.).Despite of major popularity and utilization of recommender system still there is a gap in information feedback process of RS.There are two types of feedback mechanisms used by recommender system such as explicit and implicit feedback mechanism. In case of explicit mechanism user assigns a some value to object to evaluate it. While in implicit approach user need not to interact with system to evaluate it. Even though most of the present RSs are based on the explicit feedback there are some limitations of this approach in the context of electronic book. This approach may alter the user reading and understanding pattern as user has to stop reading in between and rate the contents explicitly and now a days most of the people do not like to rate the contents so it becomes impossible to find users interest. In[3][4] some previously proposed approaches some implicit parameters are defined and comparative analysis between the implicit parameters and explicit rating is done. Results of this analysis showed that it is possible to find users interest by analyzing the user behaviour. Here architecture of electronic book recommender system is proposed which considers users behaviour while developing RS to improve the performance of recommendation process .This architecture also allows users collaborative learning of contents among the all registered users.

II. RELATED WORK

RSs are commonly used for the research and commercial purposes since the collaborative filtering(CF) techniques were first introduced [1].RSs use software tools and techniques to filter the large amount of information and remove redundant information from large information base and also help users to find information of their interest in easy and efficient way[5].RSs are employed to deal with information overload on the web as an information recovering and classification technique [6][7][8].Search engines like Google, Amazon have incorporated RSs to generate personalized information[9].RSs are used in various application areas such as commercial or experimental or scientific. For example, Fab: Content based collaborative filtering recommendations [10], Amazon.com recommendation. [11], PHOAKS [12], Hybrid news recommendation techniques [13].RSs are classified into different types [2] according to information used to recommend 1) Collaborative filtering: Which calculate the similarity between the users. And based on user information. Collaborative filtering again divided into two types [1] such as Memory-based and Model-based approaches. Memory-based approach based on similarity between user profiles and item profiles. While Model-based approaches use the hidden users or items characteristics 2) Content-based: Generate recommendations based on contents or characteristics of items that to another user liked in the past.3) Hybrid Approach: It combines the characteristics of both approaches to overcome the limitation of both. The first mechanism used to give user specific recommendation by finding good user-item match over large amount of data is CF. It calculates the similarity between the users called close neighbors for making recommendations. In this technique recommendation quality is directly dependent on the size of dataset used for rating the items. Collaborative filtering is again divided into two sub-types.(1)Memory Based CF: The memory based approaches are also known as neighborhood-based techniques, a similar users are chosen based on similarity between the user profiles, and a weighted combination of their ratings is used to make predictions for this user. (2)Model Based CF : Model based techniques allow recommendation of items by calculating parameters of statistical models for user ratings. Recently matrix factorization and latent analysis techniques are also used in model based approaches. On the basis of empirical study it is shown that model-based approaches outperforms than the memory-based approaches in terms of performance.

Some of the limitations of collaborative filtering are as follows:

- Cold Start Problem
- Sparsity
- Item Problem
- Popularity Bias

Content-based methods try to recommend the similar content to particular user based on the contents that was liked by another users in the past. Most content based techniques uses the information retrieval and information filtering methods. Such a systems are mostly based on text documents. It also uses user profiles as well as item profiles. There are certain limitations in content-based approach such as:

- Limited Content Analysis.
- Overspecialization.
- New User Problem.

To remove the drawbacks of both CF and content-based techniques several recommendation systems use hybrid approach. This approach combines the both CF as well as content-based approach to predict recommendations. The recommender systems collect user information by using the feedback techniques. User information is stored in the user profiles which show the users interest which is useful in making recommendations. There are two types of feedback techniques [6] Explicit and Implicit feedback techniques. (1)Explicit feedback: To evaluate the system user assigns some value or rating to some objects or a set of objects by using survey process. Explicit feedback technique is used to explicitly state the interest of user in particular system or object. There are various rating systems are used to rate the con-tents. For example, Amazon online store, Film affinity use the star rating system,(2)Implicit feedback: This process consist of the evaluating the system without the user being aware. In this process information is captured through the users actions that are performed by users on the electronic books. Then by using this information users behavior is analyzed to find the users interest. Nowadays, most of the implemented RSs are based on the explicit ratings. But it is inconvenient as users do not like to rate. Implicit approach does not require any effort from user side therefore it seems an attractive approach.

III. PROPOSED WORK

To make the recommender system more efficient its feedback mechanism need to be improved. Feedback mechanisms which are using explicit feedback can be inconvenient for users those who do not like to rate contents. If users do not rate the contents then it is impossible to make recommendations to users of their interest. Hence, it is necessary to collect users information from his interaction with electronic book in an implicit way. In this way users interest can be easily understood. This makes possible to implement more efficient feedback mechanisms. This paper proposed an architecture which tries to achieve approximations to the solution that is given by using explicit feedback. This architecture allows analysing and transforming user behavior. As shown in Fig.1 proposed architecture implements recommender system for electronic books based on implicit feedback.

Here proposed architectures implementation requires following components:

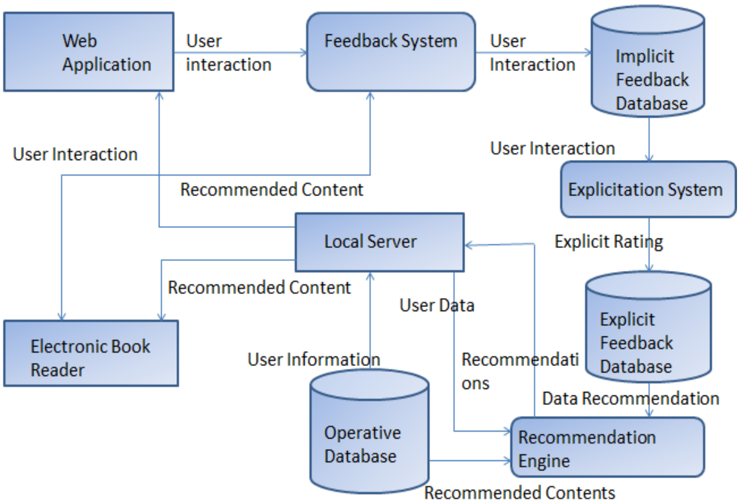

Fig. 1: Electronic Books Recommender Platform

1) User interface:
The goal of this architecture module is to develop a web application which allows users to interact with system. Here in this module role of both user as well as administrator is defined and users are allowed to register themselves to system. This allows all registered users to find and share contents among the electronic book readers community.

2) Electronic book reader:
This module collects information about book and pre-processing is done over collected data. This module also develops electronic book reader interface which will allow users to read the book and perform all implicit actions over the book as mentioned in a Table.1.

3) Feedback System:
This module allows collecting and storing users actions in an implicit way through web services. In this architecture, when a user performs an action from the web, e.g. highlight, remark, add comments, etc., a controller is invoked to perform necessary action.

4) Explicitation system:
Explicitation system performs analysis and conversion of implicit actions performed on the electronic book into explicit values. In order to analyse and evaluate the different users behaviour according to their actions performed on the platform User Interactions Converter Algorithm (UICA) is used. As shown in mathematical model in next section all actions are calculated individually by using different equations and at last final rating for all these action is calculated.

5) Database systems:
This module consist of database systems required for electronic book readers platform.
Implicit Feedback Database: Stores all the information resulting from users actions with the application.
Explicit Feedback Database: Stores data obtained from explicitation system.
Operational Database: Stores operative data from the web applications as well as stores the data generated by recommender engine.

6) Recommendation engine:
Here, recommender system is implemented by using any suitable algorithm of information filtering. There are various methods of information filtering such as collaborative filtering, content-based filtering. These two methods have some limitations so the hybrid approach is used to overcome the limitations of both. In this system both collaborative and content based methods are combined to make recommendations by using explicit rating generated by UICA algorithm by analysing user behaviour.

Table. 1:List of user actions performed on electronic books

Id	Name	Type	Weight	Scope
A1	Explicit rating	Explicit		Individual
A_2	Reading time of a content	Implicit	0.1	Social
A_3	Adding a note to a content	Implicit	0.1	Social
A_4	Adding comments to contents	Implicit	0.1	Social
A_5	Recommending a content	Implicit	0.1	Individual
A_6	Adding a content to collection	Implicit	0.1	Individual
A7	Adding a content to the favorites list	Implicit	0.1	Individual
A_8	Rejecting a recom-mended contents	Implicit	0.1	Individual
A9	Removing a content from the favorites list	Implicit	0.1	Individual
A10	Removing a content from the collection	Implicit	0.1	Individual

IV. MATHEMATICAL MODEL

Final rating for actions performed on the electronic book can be calculated by using UICA.UICA calculates value for each action separately. As shown in Table.1 Id represents each action uniquely. Name is the name of action. Type is type of action shows whether it is implicit or explicit. Weight is level of importance in relation to other actions. Scope shows that actions value is calculated by considering other users behaviour on the platform.

Calculation of final rating of a content
Final rating for a jth content for an ith user is calculated by calculating each action separately and assigned W weight to it as follows1:

FR(i,j) = Action1 if Action1>1
I if Action1=0

FR(i , j) is a final rating
I is a Implicit action rating value
Action1 is a explicit rating
Calculation of implicit action rating

I = $\sum_{k=2}^{n}(Wk + Wr)$Action$_k$+Action$_k$ /N+1

I is a Implicit action value.
W_k is the weight assigned to the actions.
k is the sub-index that identifies actions.
N is the amount of actions.

Calculation of rating for each action

- **Action1**:Explicit rating
  Action1(i,j) = Value
  Value is explicit rating value given by i-th user to j-th content.
- **Action2**: Reading time of content
  Action2 (i,j) = $\sum_{k=1}^{n} RTk(i,j)$/n
  Action2(i,j) is reading time of i-th user on j-th content.
  RTk is normalized value for reading time of k-th chapter of j-th Content.
  $RTt_k(i,j) = \frac{RTt_k(i,j)}{SVal(TTtk(i,j))} * (L_{sup} - L_{inf}) + L_{inf}$ If $RTt_k(i,j)>0$
  0 If $RTt_k(i,j)<=0$
  L_{sup} is superior limit on value of RT_k
  L_{inf} is inferior limit on value of RT_k
  $RTt_k(i,j)$ is total amount of time spend.
  $RTt_k = \sum_{k=1}^{n} t(i,j)$
  t is time spend on reading.
  n is different reading times.
  $RTTt_k$ ={RTt_k (1,1), RTt_k (2,1), …. RTt_k (n,1)}
  SVal($RTTt_k$ (i,j) is maximum or average or median reading time of $RTTt_k$.
- **Action3**:Adding notes to content.
- **Action4**:Adding comments to a Contents.
- **Action5**:Recommending the contents.
  Action3,Action4,Action5 can be calculated through an equation similar to Action2.
- **Action6**: Adding content to collection.
  Action6(i,j) = L_{sup} if a=1
  0 if a=0
  a is state of content adding to users collection.
  a=1 if content added to collection.
  a=0 if contents are not added to collection.
- **Action7**:Adding contents to favorites list.
  Contents can be added to users favorites list by using similar equation of action Action6.
- **Action8**:Rejecting recommended contents.
  Action8(i,j) = L_{inf} if r=1
  0 if r=0
  r is state of rejecting the recommended contents.
  r=1 if contents are rejected.
  r=0 if contents are not rejected.
- **Action9**:Removing the content from favorites list.
  Action9(i,j) = L_{inf} if r=1 and Action2(i.j) <= 0
  T if r=1 and Action2(i,j) > 0
  0 if r=0
  r is state of removing the contents.

r=1 if Contents are removed.
r=0 if Contents are not removed.
T is value intersection of values of Action2 and Action3.

- **Action10**: Removing the contents from collection
  This actions value can be calculated from similar equation used by action Action9.

V. EVALUATION

Recommender systems can be evaluated in many different ways .One of the most commonly used approach to evaluate RS is to get user feedback on the recommendations provided by the user .However this approach is expensive and inconvenient as user has to again interact with the system. RS can have many possible objectives therefore the task of evaluation becomes difficult .There are various parameters through which system can be evaluated in different ways. Most commonly used parameters are predictive accuracy metrics, classification accuracy metrics etc.In this paper to evaluate proposed RS performance metrics used are precision and recall .In this context, precision is the Precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved.
Precision can be calculated as follows:

Precision = Relevant recommendations/Total Recommendations.
Recall can be calculated as follows:

Recall = Relevant recommendations / Total Relevant Recommendations.
In proposed system recommendations are generated by using hybrid methods for each user. Therefore for each user precision and recall for given recommendations can be calculated.

- **Comparing precision of electronic book RS for CF and hybrid approach**

For experiment purpose each user perform no of actions on the book .By using UICA rating is calculated. Recommendations are provided by system based on the rating generated by UICA .Recommendations made by using CF approaches still have some limitations .Therefore hybrid approach is used by combing the collaborative filtering and content-based methods. Therefore comparison graph is plotted for both CF and hybrid approach. Graph for electronic book RS is plotted based on the values of precision for each user of the system based on both CF as well as hybrid approach.

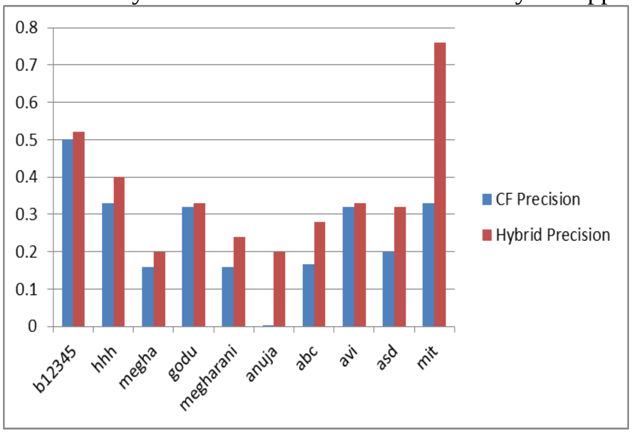

Fig 2. Comparative analysis of precision for CF and hybrid techniques

- **Comparing recall of electronic book RS for CF and hybrid approach**

As shown in above graph. Graph for recall is plotted for both electronic book RS based on CF and hybrid approach. This shows how many recommendations are relevant among the all retrieved relevant recommendations. Graph for electronic book RS is plotted based on the values of recall for each user of the system based on both CF as well as hybrid approach**.**

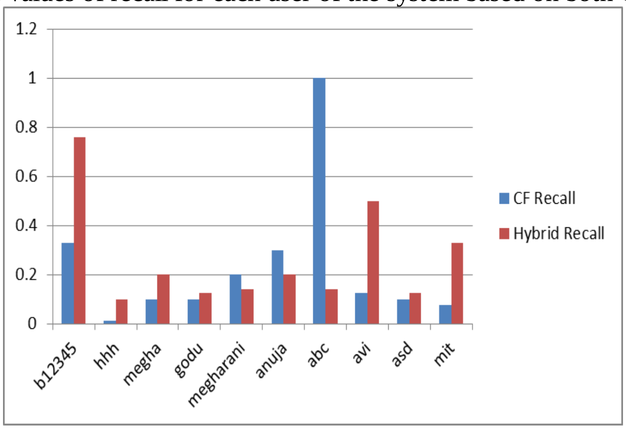

Fig 3. Comparative analysis of recall for CF and hybrid techniques

- **Comparing electronic book RS for CF and hybrid approach in terms of precision and recall.**

As shown in graph values of both precision and recall for hybrid RS are higher than the CF based RS.

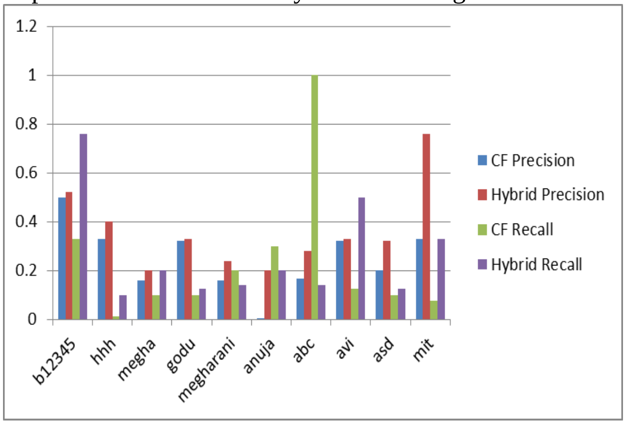

Fig 3. Comparative analysis of precision and recall for CF and hybrid techniques

VI. CONCLUSION

Proposed system will improve the performance of recommender process by using implicit feedback mechanism based on the user behaviour and hybrid methods for recommendation purpose. By implementing recommender system with hybrid approach system will give more relevant recommendations than existing system in terms of precision and recall. This approach will also allow collaborative learning of the contents among the electronic book readers community.

REFERENCES

[1] Adomavicius, G., Tuzhilin,"Toward the next generation of recommender systems: A survey of the state-of-the-artand possible extensions," IEEE Trans. Knowl. Data Eng.,17(6), 734749,2005.

[2] Adomavicius, G., Sankaranarayanan, R., Sen, S., Tuzhilin, A.,"Incorporating contextual information in recommender systems using a multidimensional approac.," Transactions on Information Systems (TOIS), 23(1), 103145,2005.

[3] Claypool, M., Brown, D., Le, P., Waseda, M., "Inferring user interest, "IEEE Internet Computing, 5(6), 3239,2001. Nuez-Valdz, E. R., Cueva Lovelle, J. M., Sanjun Martnez, O., Garca-Daz, V., ordoez de Pablos, P., Montenegro Marn, C. E.,Implicit feedback techniques on recommender systems applied to electronic books., Computers in Human Behavior,2012.

[4] Nuez-Valdz, E. R., Cueva Lovelle, J. M., Sanjun Martnez, O., Garca-Daz, V., ordoez de Pablos, P., Montenegro Marn, C. E.,"Implicit feedback techniques on recommender systems applied to electronic books,"Computers in Human Behavior,2012.

[5] Zhang, Z.-K., Zhou, T., Zhang, Y.C.,"Tag-aware recommender systems: A state-of-the- art survey," Journal of Computer Science and Technology, 26(5), 767777,2011.

[6] Noor, S., Martinez, K., "Using social data as context for making recommendations: An ontology based approach," In Proceedings of the 1st workshop on context, information and ontologies (pp. 7:17:8). New York, NY, USA: ACM,2009.

[7] ODonovan, J., Smyth, B.,"Trust in recommender systems," In Proceedings of the 10th international conference on intelligent user interfaces (pp. 167174). New York, NY, USA: ACM,2005.

[8] Taghipour, N., Kardan, A.," A hybrid web recommender system based on Qlearning," In Proceedings of the 2008 ACM symposium on applied computing (pp. 11641168). New York, NY, USA: ACM,2008.

[9] Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I., et al.,"Context-aware recommender systems for learning: A survey and future challenges," IEEE Trans- actions on Learning Technologies, 6(1), 2007.

[10] Balabanovic , M., Shoham, Y., "Fab: Content-based, collaborative recommendation," Communications of the ACM, 40(3), 6672,1997.

[11] Linden, G., Smith, B., York, J.,"Amazon.com recommendations: Item-toitem collaborative filtering," Internet Computing, IEEE, 7, 7680,2003.

[12] Terveen, L., Hill, W., Amento, B., McDonald, D., Creter, J.,"PHOAKS: A system for sharing recommendations," Communications of the ACM, 40(3), 5962,1997.

[13] Montes-Garca, A., lvarez-Rodrguez, J. M., Labra- Gayo, J. E., Martnez-Merino, M. "Towards a journalistbased news recommendation system: The Wesomender approach," Expert Systems with Applications, 40(17), 67356741,2013.

