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Electronic Books Recommender System Based On Implicit Feedback Mechanism

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Abstract - **In recent years recommender systems (RSs) has gained popularity to solve the problem of web information overload and redundancy. Recommendation system helps users in finding the contents of their interest with minimum efforts. Even though most of the systems use explicit rating to recommend the content of users interest. When reading the electronic books performance of user gets affected because each time user has to stop reading and rate the contents explicitly. To overcome such a problem this paper considers user behavior, preferences and reading background while building recommender system by using collaborative learning implicit approach. In this way recommender system can help users in finding contents of their interest by using implicit rating based on the previous knowledge available. The main goal of this paper is to design and implement architecture that implements a recommender system for electronic books which is based on implicit actions performed by users on books**.

Index Terms**:** Recommender System; Collaborative Learning;

I. INTRODUCTION

RSs become very popular after publishing the first paper on collaborative filtering(CF) in the mid of 1990s [1].RSs are used in various application areas such as Electronic Commerce, Online Social Networks (Facebook, You-Tube, LinkedIn etc). Due to the popularity of RSs leads to problem of information overload on the web. RSs are mainly designed to handle information overload and provide personalized recommendation of contents and services to users across the internet. In spite of major popularity and utilization of RSs there is scope of improvement in feedback mechanism of recommender systems. This paper proposes an approach that considers user behaviour in considered contents to make more accurate recommendations. As stated in [3] even though explicit ratings are commonly used still there are some limitations of all these techniques in case of electronic books. These techniques can make difference in users reading and understanding habits specifically for those users who do not like to rate contents explicitly. In [4] several implicit actions that are performed on electronic books are defined and comparative analysis was performed on the impact of these

results of this analysis conclude that users interest can be determined through the analysis and transformation of user action or behaviour. This paper proposed an architecture that implements algorithm which transforms user actions performed on electronic books into explicit rating. This approach improves performance of feedback process of RS by using implicit feedback mechanism. To handle the problem of information overload it is necessary to use recommender system which improves users satisfaction and experience while searching the contents over the web. As well as by analyzing user behaviour over the social network of electronic book allows users collaborative learning.

II. RELATED WORK

RSs become an important research area since the collaborative filtering was first introduced [1].RSs use software tools and techniques that 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 .RSs filter the large amount of information over the web and present users valuable information[6][7][8].Search engines like google, amazon have incorporated RSs into their systems to generate personalized information[9].RSs are widely used in many application areas for various purposes 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 in-formation used to recommend 1) Collaborative filtering: Which calculate the similarity between the users. Collaborative filtering again has two types [1] such as Memory based and Model based approach. Memory-based approach based on similarity between user pro-files and item profiles. While Model-based approach use the hidden users or items characteristics 2) Content-based: Generate recommendations based contents that to another user liked in the past.3) Hybrid Approach: It combine 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 upon 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 approach is 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 approach. On the basis of empirical study it is shown that model-based approach outperforms than the memory-based approach 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 were liked by another user in the past. Most content based techniques use 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 Problems

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. Which makes possible to implement more efficient feedback mechanism.This paper proposed an architecture which try to achieve approximation to the solution that is given by using explicit feedback. This architecture allows to analyze and transform 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:

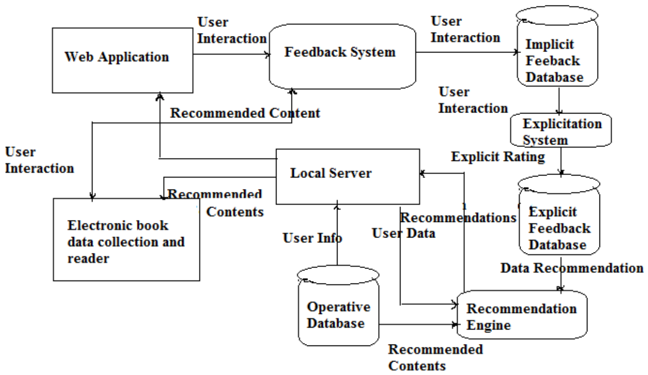

Fig. 1: Electronic Books Recommender Platform

1) **User interface**: The goal of this architecture module is to develop an web application which allows users to interact with system. Here in this module roles of both user as well as administrator are 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 data collection and reader:** This module collects information about book and preprocessing is done over collected data.This module also develop electronic book reader interface which will allow users to read the contents of the system as well as perform all implicit actions 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 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.

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.

Recommendation engine use any suitable algorithm to implement recommender system.RS will generate ratings based on the explicit rating.

Id	Name	Type	Weight	Scope
A_1	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
A_7	Adding a content to the favorites list	Implicit	0.1	Individual
A_8	Rejecting a recom-mended contents	Implicit	0.1	Individual
A_9	Removin g a content from the favorites list	Implicit	0.1	Individual
A_{10}	Removin g a content from the collection	Implicit	0.1	Individual

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

IV. Mathematical Model

Final rating for actions performed on the electronic book can be calculated by using UICA.UICA calculate 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:

$$FR(i,j) = \begin{cases} Action1 & \text{if } Action1>1 \\ I & \text{if } Action1=0 \end{cases}$$

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.

$$RTt_k(i,j) = \begin{cases} \dfrac{RTt_k(i,j)}{SVal(TTtk(i,j))} * (L_{sup} - L_{inf}) + L_{inf} & \text{If } RTt_k(i,j)>0 \\ 0 & \text{If } RTt_k(i,j)<=0 \end{cases}$$

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.

$$RTTt_k = \{RTt_k(1,1), RTt_k(2,1), \ldots RTt_k(n,1)\}$$

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. CONCLUSION

This paper presents recommender system for electronic book which uses implicit feedback mechanism based on the user behaviour to overcome the limitations of explicit feedback mechanism. Design of architecture for electronic book reader platform based on user behaviour will also allow collaborative learning of the contents among the electronic book readers community.

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