User Evaluation of Fusion-based Approach for Serendipity-oriented Recommender System

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ABSTRACT

In recent years, studies have focused on the development of recommender systems that consider measures that go beyond simply the accuracy of the system. One such measure, serendipity, is defined as a measure that indicates how the recommender system can find unexpected and useful items for users. We have previously proposed a fusion-based recommender system as a serendipity-oriented recommender system. In this study, we improve upon this system by considering the concept of serendipity. Our system possesses mechanisms that can cause extrinsic and intrinsic accidents, and it enables users to derive some value from such accidents through their sagacity. We consider that such mechanisms are required for the development of the serendipity-oriented recommender system. The key idea of this system is the fusion-based approach, through which the system mixes two user-input items to find new items that have the mixed features. The contributions of this paper are as follows: providing an improved fusion-based recommender system that adopts a fusion-based approach to improve serendipity; practically evaluating the recommender system through user tests using a real book data set from Rakuten Books; and showing the effectiveness of the system compared to recommender systems on websites such as Amazon from the viewpoint of serendipity.

Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]: Information Filtering

General Terms

Experimentation

Keywords

Recommender systems, Serendipity-oriented recommender systems, Serendipity

1. INTRODUCTION

In recent years, several studies have focused on the development of recommender systems that consider measures beyond simply the accuracy of the system, such as the novelty, diversity, and serendipity [1][2]. This is because these studies have found that users are not always satisfied with recommender systems with only high accuracy—they desire for the systems to consider various other viewpoints, too.

In an attempt to satisfy this need, in this study, we focus on the serendipity. Serendipity means "the ability to make unexpected and valuable discoveries by accident." We thus define a serendipitous item as something unexpected and valuable, and we believe that such an item can diversify users' interest regardless of their experiences, thus making their lives richer. This study therefore aims to develop a serendipity-oriented recommender system that provides users with serendipitous items.

First, it is necessary to gain some insight into the original meaning of the word "serendipity." The word "serendipity" originated from a story called "The Three Princes of Serendip" [3], which tells the story of three princes. These princes discovered a series of novel things during the course of various and unexpected events on their journeys, which they attributed to their luck. Horace Walpole, who read this story, stated that "the princes were always making discoveries, by accidents and sagacity," to describe which he coined the word "serendipity," which means "the ability to make unexpected discovery by accidents and sagacity" [4]. In light of Walpole's definition, we believe that a serendipity-oriented recommender system should possess an interface that has mechanisms that output "unexpected discoveries" based on the input of "accidental events" experienced by the users and the sagacity of the users.

In addition, [4] states that accidents are of two types: "extrinsic" and "intrinsic." For example, a well-known serendipitous discovery is that of gravity—it is stated that "Newton had an inspiration of the notion of universal gravitation at the sight of an apple that fell from a tree"[5]. In this event, the apple falling from the tree can be considered an "extrinsic accident," that is, one that occurs regardless of the action of a person. Another example of a serendipitous discovery is that made by Koichi Tanaka, which won him the Nobel Prize in Chemistry in 2002. Although he realized that he had accidentally used glycerin instead of acetone as a sample, he continued his experiments in order to observe the results. This led to him discovering an unknown phenomenon. In this event, the discovery of the unknown phenomenon can be considered an "intrinsic accident," that is, one that results from the action of a person with the positive expectation of something. It is of great importance to derive some value from these accidents. In this light, a person's sagacity plays a crucial role.

The above-described examples suggest that a serendipity-oriented recommender system should have an interface consisting of the following mechanisms:

(a) A mechanism that causes extrinsic accidents.

(b) A mechanism that causes intrinsic accidents.

(c) A mechanism that enables users to derive some value from accidents through their sagacity.

In this study, we have proposed a fusion-based recommender system to satisfy these requirements. The key idea of this system is adopting a fusion-based approach for discovering serendipitous items by mixing two user-input items together. As described at the beginning of this section, we define a serendipitous item as an unexpected and valuable item. Specifically, the following items are relevant to serendipitous items:

- Items that can excite the user's interest for the first time although he/she does not know about them and he/she would not be able to discover them by himself/herself.
- Items that can excite the user's interest for the first time although he/she thought that he/she was not interested in them.
- Items that can attract the user's interest after being displayed by the system.

We also define a high-serendipity recommender system that can recommend more serendipitous items to users.

By using our proposed fusion-based recommender system, a user can mix two items together in the system interface to create something new from something existing in a manner analogous to mixing colors, ingredients, or sounds. The act of mixing also entails the following:

a) We can intuitively expect mixed results from a combination of inputs. On the other hand, some combinations can yield unexpected results.

b) Because our curiosity may be aroused by the intuitive comprehensibility and unexpectedness of the act of mixing, we might feel like being creative and mixing various combinations of inputs.

Characteristic (a) corresponds to the mechanism that causes intrinsic accidents because unexpected results may be produced by mixing materials together with the expectation of some positive results. Characteristic (b) corresponds to the mechanism that enables us to derive some value from accidents through our sagacity in that we can select valuable inputs from among the given inputs.

Figure 1 shows the interface of the fusion-based recommender system for book recommendation. When the user clicks [Random], [Search], [Popular], and [New] buttons, the system randomly provides the user with corresponding books from the book database. Randomly providing books corresponds to the mechanism that causes extrinsic accidents.

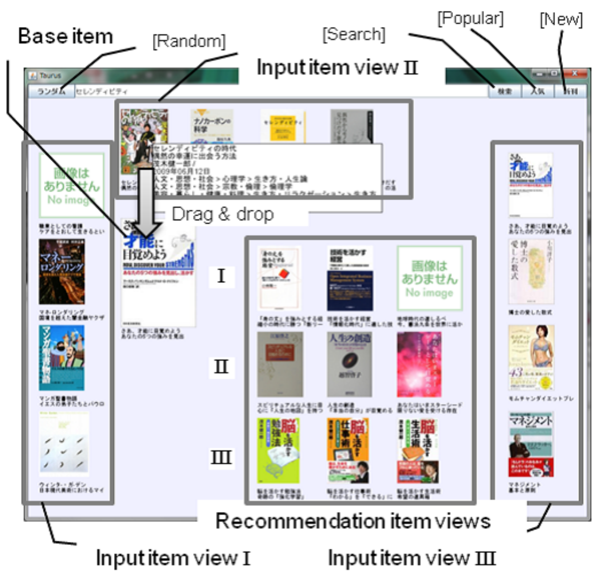

Figure 1: Interface of Fusion-based Recommender System.

The user can also select an interesting book as a material from the displayed books based on his/her sagacity, and then drag-and-drop it into a base book, which is also selected by the user. The system then provides the user with books possessing mixed features of the two books. Although the user can select books to mix with some expectation, some book combinations may yield unexpected results. This may cause intrinsic accidents. The user can repeatedly and creatively use the system to see various mixing results until he/she is satisfied with the results. In this process, serendipitous items are interactively provided to the user.

We have already developed a predecessor to the proposed fusion-based recommender system[6]. In this study, we have improved upon the system interface and internal processing based on the deeper idea of serendipity, and we have evaluated this system from the viewpoint of practical use.

The contributions of this study are as follows:

- developing the improved fusion-based recommender system that adopts a fusion-based approach for improving the serendipity;
- experimentally evaluating the practical usability of the recommender system using a real book data set from Rakuten Books;
- showing the effectiveness of the system compared to recommender systems on websites such as Amazon from the viewpoint of serendipity.

2. RELATED WORK

Herlocker et al. [1] suggested that recommender systems with high accuracy do not always satisfy users. Therefore, they suggested that recommender systems should be evaluated not only by their accuracy but also by various other metrics such as novelty, diversity, and serendipity.

Several studies have already focused on serendipity in the context of recommendation. Ziegler et al. [7][8] suggested that diversifying recommendation lists improves user satisfaction. Toward this end, they proposed topic diversification based on an intra-list similarity metric. Sarwar et al. [9] suggested that serendipity might be improved by removing obvious items from recommendation lists. Berkovsky et al. [10] proposed group-based recipe recommendations. They suggested that recipes loved by a group member are likely to be recommended to others, which may increase serendipity.

Hijikata et al. [11] and Murakami et al. [2] proposed recommendation methods that predict novelty or unexpectedness. The former study proposed collaborative filtering, which predicts unknown items for a target user based on known/unknown profiles explicitly acquired from the user, and showed that such filtering can improve novelty by providing unknown items to the user. The latter study proposed a method that implicitly predicts unexpectedness based on a user's action history. They introduced a preference model that predicts items the user likes and a habit model that predicts items habitually selected by the user. The method estimates the unexpectedness of recommended items by considering the differences between the models. The disadvantage of these methods is that they need to obtain models or profiles for an individual user. Our proposed system, however, does not have these requirements. It can instantly recommend serendipitous items based on items the user has just selected.

Murakami et al. [2] and Ge et al. [12] introduced measures for evaluating the unexpectedness and serendipity of recommender systems.

The former study assumed that unexpectedness is the distance between the results produced by the system to be evaluated and those produced by primitive prediction methods. Here, primitive methods include recommendation methods based on user profiles or action histories. Based on this notion, they proposed *unexpectedness* for measuring the unexpectedness of recommendation lists and *unexpectedness_r* to take into account the rankings in the lists. The latter study also propose unexpectedness following the notion of the former study.

In our previous study[6], we evaluated our recommender system based on Murakami et al.'s evaluation metrics. However, we did not evaluate the system through tests involving real users to determine its serendipity. In contrast, in this study, we evaluate our proposed fusion-based recommender system through experiments involving real users.

3. FUSION-BASED RECOMMENDER SYSTEM

In this section, we describe our proposed fusion-based recommender system. This system has an interface that consists of the aforementioned mechanisms for recommending serendipitous items (Figure 1).

As shown in Figures 1 , a user selects a base item from items displayed in views and drags-and-drops another material item onto the base item. Then, the system mixes these two items and outputs recommended items that have features of both, which we define as fusion. The user can repeatedly perform fusion by reselecting the base items and researching the material items until he/she obtains acceptable results. During this process, the user may interactively discover serendipitous items.

In Section 3.1, we describe the book database used as the recommendation content in this study. In Section 3.2, we describe the system interface and the user interactions related to the above mechanisms. Finally, in Section 3.3, we show fusion methods as the internal processing of the fusion.

3.1 Book database

In this study, we consider books as the recommendation content; in the future, of course, we intend to apply the system to various contents such as music, movies, and recipes. We collected Japanese book data using Rakuten Books book search API[1] from Rakuten Books[2]. We obtained data for 667,218 books between Dec. 27, 2011, and Feb. 10, 2012.

The book data consists of the attributes of *isbn*, *title*, *sub_title*, *author*, *sales_date*, *item_url*, *review_count*, *review_average*, *books_genre_id*. We created a *book* table consisting of these attributes, in addition to the following tables:

- $book-phrase(\underline{isbn}, \underline{phrase}, idf)$
- $book-author(\underline{isbn}, \underline{author})$
- $book-genre(\underline{isbn}, \underline{genre\_id})$

Here, the $book-phrase$ table contains phrases from *book.title* and *book.sub_title* for each book. In Section 3.1.1, we explain how phrases are extracted. The $book-author$ table contains the authors of each book. The $book-genre$ table contains the genre id of each book. Rakuten Books has 800 genres such as "novels and essays" and "sciences, medical sciences, and technologies," each of which consist of four-level categories. The genre id is a unique id that corresponds to each genre.

3.1.1 Phrase extraction from book data

The system extracts phrases using Chasen[3], a Japanese morphological analyzer, from *book.title* and *book.sub_title* for each book. We heuristically selected "nouns," "verbs," "adjectives," "adverbs," and "unknown words" as target parts of speech. Here, the system extracts also compound words such as "cognitive psychology" that are treated as one phrase.

3.2 System interface

Figure 1 shows the interface of the proposed system, which implements mechanisms (a), (b), and (c) mentioned above.

(a) Mechanism that causes extrinsic accidents.

The system implements [random], [search], [popular], and [new] buttons, which cause extrinsic accidents. When the user clicks each button, the system randomly searches for k corresponding books from the book database. The books are displayed in input item views I, II, and III in Figure 1. Table 1 lists the processes that are called when each button is clicked.

When the user moves the mouse cursor over the books displayed in the views, the book information ("title," "sub title," "authors," "publication date," and "genres") are shown in a pop-up window. When the user right-clicks the books, he/she can view detailed information from the site of Rakuten Books through an external browser.

[1] Rakuten Books book search API (in Japanese): http://webservice.rakuten.co.jp/api/booksbooksearch/
[2] Rakuten books (in Japanese): http://books.rakuten.co.jp/book/
[3] Chasen (in Japanese): http://chasen.naist.jp/hiki/ChaSen/

Table 1: Search processing by each button.

Button	Processing	Target view
Random	Searching k books from the book database at random.	Input item view I
Search	Searching k books at random from books whose *title* or *sub_title* includes keywords input in the text box.	Input item view II
New	Searching k books at random from books satisfying $review\_count \times review\_average \geq \theta$.	Input item view III
Popular	Searching k books at random from books saled last one month.	Input item view III

(b) Mechanism that causes intrinsic accidents.

The system implements a fusion mechanism as an interface that causes intrinsic accidents.

The user can select a base item by double-clicking a book from among the books in the input item view or recommendation item view. The base item is considered as the basis when performing fusion.

The user can select a material item from among the books in the same two views. The material item is used for performing fusion with the base item. When the user drags-and-drops the material item onto the base item, fusion of the two items is performed. The system then displays the items outputted by the fusion in the recommendation item view. In Section 3.3, we define three fusion methods. The system displays items outputted by each fusion method in the corresponding recommendation item view I, II, or III.

(c) Mechanism that enables users to derive some value from accidents through their sagacity.

In mechanism (b), the user can select a base item and a material item from among the books deemed interesting in the views. Such intuitive selection of books may correspond to his/her sagacity.

Here, the type of book that can be selected depends on the user. When performing fusion, the user can select items that are suitable for his/her preferences as well as items that are considered interesting.

3.3 Fusion method

As shown in Section 3.2 (b), fusion is performed using the base and the material item when the user drags-and-drops the material item onto the base item. We define the following three methods as fusion methods. In this section, *bookA*, *bookB*, and *book* denote the base item, material item, and recommended item, respectively.

phrase − phrase fusion.

The *phrase − phrase* fusion method searches for a maximum of m books whose *book.title* or *book.sub_title* includes at least one phrase from the phrase list *bookA.phraseList* in *bookA* and at least one phrase from the phrase list *bookB.phraseList* in *bookB*. The searched books are shown in recommendation item view I. Figure 2 (a) shows an example of fusion for *bookA*—"Equation loved by a doctor"—and *bookB*—"Magic for cleaning up giving palpitations of life." In this case, the system displays "Magic doctor" based on "doctor" in *bookA* and "magic" in *bookB*.

phrase − genre fusion.

The *phrase − genre* fusion method searches for a maximum

Figure 2: Example of each fusion method.

of m books whose *book.title* or *book.sub_title* includes at least one phrase from the phrase list *bookA.phraseList* in *bookA* and whose *book.genre_id* corresponds to at least one genre from the genre list *bookB.genre_idList* in *bookB*. The searched books are shown in recommendation item view II. Figure 2 (b) shows an example of the fusion of *bookA*—"Management"—and *bookB*—"Equation loved by a doctor." In this case, the system displays "If a female student who is a manager of high-school baseball team reads 'Management'," whose *book.title* or *book.sub_title* includes "management" and whose *book.genre_id* corresponds to *bookB.genre_id* (i.e., "[novels and essays – Japanese novels]").

phrase − author fusion.

The *phrase − author* fusion method searches for a maximum of m books whose *book.title* or *book.sub_title* includes at least one phrase from the phrase list *bookA.phraseList* in *bookA* and whose *book.author* corresponds to at least one author from the author list *bookB.authorList* in *bookB*. The searched books are shown in recommendation item view III. Figure 2 (c) shows an example of the fusion of *bookA*—"Neuroscience of language"—and *bookB*—"Excitement of science by Kenichiro Mogi." In this case, the system displays "Neuroscience class we want to take the best in the world," whose *book.title* or *book.sub_title* includes "neuroscience" and whose *book.author* corresponds to *bookB.author* (i.e., "[Kenichiro Mogi]").

4. EXPERIMENTS

In this section, we show the experimental results of user tests of our proposed fusion-based recommender system. We implemented this system using Java and Processing as the evaluation system. In the experiments, we selected books as recommendation contents and created the book database described in Section 3.1 using MySQL.

4.1 Experimental method

Nine subjects (eight males and one female) participated in our study. Their age is from 20 to 23. They had average computer skills and used the Internet regularly (every day/nearly every day). They also used online shopping websites such as Amazon very rarely (a few times so far) or rarely (a few times a month). They read books rarely (a few times a month) or moderately (once to three times a week).

The experimental procedure is as follows:

(1) We explain the recommender system to be used to each subject and provide them with the task "Find three books you want to read on holidays."

(2) Each subject carries out the task using the assigned system (without time limitation).

(3) If the subject finds suitable books, he/she marks them (at most 3 books). We call these books the main recommended books.

(4) If the subject finds books that are not suitable but are interesting, he/she marks them (any number of books). We call these books the sub-recommended books.

(5) The subject finishes the task when he/she finds three main recommended books. However, he/she can finish the task if he/she is satisfied or satiated with even less than three books.

(6) After the task is finished, the subject answers all the questions listed in Table 2 for each recommended book.

(7) The subject performs the same steps for each recommender system.

Section 4.2 discusses the recommender systems used in the experiments. Each subject uses the various recommender systems in a different order to cancel any effect that might otherwise be produced.

Table 2 lists the questions about the recommended books. Here, the subjects answered Q1 using a three-level scale {3:unknown, 2:known but never read, 1:have been ever read}, and Q2 to Q4 using a five-level scale {5:strongly agree, 4:agree, 3:neither agree nor disagree, 2:disagree, 1:strongly disagree}. With regard to "by myself" in Q4, we explained to the subjects that "if you think that you can easily find the book by using existing search engines (e.g., Google, Yahoo!) or by using a genre or keyword search at online/real book stores or libraries by yourself, the book is regarded as 'findable book by myself'."

After all tasks were finished, the subjects answered questions, "this system excited my interest and enabled me to discover somthing new," which is related to serendipity of the recommender systems using the same five-level scale.

4.2 Comparative systems

We choose Amazon[4], a large online store with recommender systems, for comparison with our proposed system.

[4] amazon.co.jp (Japanese site): http://www.amazon.co.jp/

Table 2: Questions for recommended books.

No.	Question
Q1	I did not know this book.
Q2	I have been interested in this book before the system presented it to me.
Q3	This book excited my interest for the first time.
Q4	I think that I could not find this book by myself.

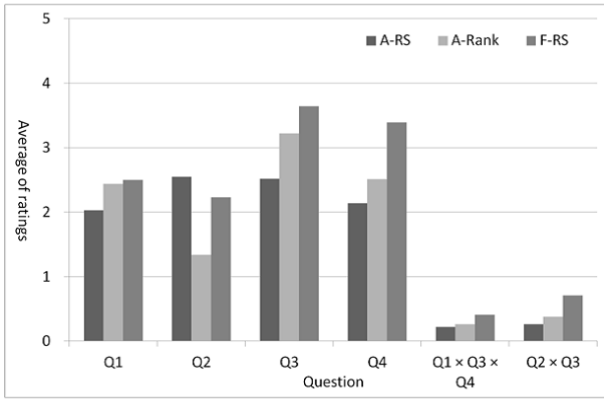

Figure 3: Separate evaluation of sub-recommended book.

We considered two types of systems—Amazon search and recommend (A-RS) and Amazon ranking (A-Rank)—as baseline systems. In this section, we explain the utilization of the baseline systems and the proposed system.

Amazon search and recommend (A-RS).

The subjects are allowed to only use keyword and genre search method on the Amazon site, following which they can use the recommendation list (a list shown under "Customers Who Bought This Item Also Bought"). We encouraged the subjects to refer to the entire recommendation list because toward the end, the list potentially includes unexpected but interesting books. Amazon's recommendation method is implemented by item-based collaborative filtering[13].

Amazon ranking (A-Rank).

The subjects are allowed to only refer to the ranking of "Best Sellers" and "New Releases." They are also allowed to refer to the ranking in each category.

Fusion-based recommender system (F-RS).

We explained the system interface, described in Section 3.2, and how it is used to the subjects in advance. However, we did not explain the details of the internal processing of the fusion method, described in Section 3.3, because we would like to observe whether the subjects can gradually understand the same through trial and error.

Here, we used $k = 4, \theta = 1000$, and $m = 3$, as mentioned in Section 3.2 and Section 3.3.

4.3 Results

4.3.1 Evaluation of sub-recommended books

We analyzed what type of books were marked as sub-recommended books. Figure 3 shows the overall results of the subjects' ratings for Q1–Q4 from Table 2 about sub-recommended books. The figure shows the averages of the ratings for each recommender system.

As described in Section 1, the first definition of serendipitous items is "items that can excite the user's interest for the first time although he/she does not know about them and he/she would not be able to discover them by himself/herself." From this viewpoint, we evaluated the systems based on not only the discoverability but also whether the recommended items excited the users' interest. Therefore, from the viewpoint of serendipity, we analyzed how many items that satisfied the conditions of books that "Q1: I did not know this book," "Q4: I think that I could not find this book by myself," and "Q3: This book excited my interest for the first time" could be found by each system. If the rating of a book for Q1 $= 3$, Q4 ≥ 4, and Q3 ≥ 4, we assign it a score of "1," otherwise we assign a score of "0." Figure 3 shows the averages. We found significant differences between the average of F-RS and those of A-RS and A-Rank by a t-test with a significance level of 5%.

The second definition of serendipitous items is "items that can excite the user's interest for the first time although he/she thought that he/she was not interested in them." From this viewpoint, we analyzed how many items that satisfied the conditions of books that "Q2: I have not been interested in this book" and "Q3: This book excited my interest for the first time" could be found by each system. If the rating of a book for Q2 ≤ 2 and Q3 ≥ 4, we assign it a score of "1," otherwise we assign a score of "0." Figure 3 shows the averages. We found significant differences between the average of F-RS and that of A-RS by a t-test with a significance level of 1%. In addition, we found significant differences between the average of F-RS and that of A-Rank with a significance level of 5%.

Although A-RS recommends books related to the browsed book through item-based collaborative filtering, there is little possibility of the recommended book being largely against the user's interest because of its high accuracy. Meanwhile, because A-Rank recommends popular books, the user may already know the recommended books if they belong to genres the user is interested in. On the other hand, the fusion-based recommender system can recommend books that are occasionally against the user's interest depending on the selection of the material item. This is why the system showed high discoverability, although this involves some risks. In addition, because the recommended books are still relevant to the base item, the user may be interested in them. This is why the fusion-based recommender system was superior from the viewpoint of serendipity.

4.3.2 Evaluation of systems

We focus on the question about serendipity, "this system excited my interest and enabled me to discover something new." The average of the subjects' ratings were 3.00 for A-RS, 2.67 for A-Rank, and 4.22 for F-RS. From this viewpoint, the proposed system significantly outperformed A-RS and A-Rank with a significance level of 5%. This result indicates that the proposed system can provide serendipitous items related to "items that can attract the user's interest after being displayed by the system," which is one of the definitions of serendipitous items.

5. CONCLUSION

In this study, we improved upon our fusion-based recommender system based on the deeper idea of serendipity. This system possesses mechanisms that cause extrinsic and intrinsic accidents and enables users to derive some value from accidents through their sagacity. The key idea of the system is the fusion-based approach, through which the system mixes two user-input items to find new items that have the mixed features.

We experimentally evaluated the fusion-based recommender system through user tests using a real book data set from Rakuten Books. The experimental results showed the effectiveness of this system compared with the recommender systems used on the Amazon website from the viewpoint of serendipity. We would like to enhance its interfaces and make the fusion methods more intuitive and understandable for the users.

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