Surprise and Curiosity in A Recommender System

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***Abstract*— The vast amount of online information today has increased the opportunity to discover interesting and useful information. Various recommender systems have been developed to help people discover such information. No matter how accurately the recommender algorithms perform, users' engagement and satisfaction have been complained being less than ideal. In this study, we touched on two human-centered objectives for recommender systems: surprise and curiosity, both of which are believed to play roles in maintaining user engagement and sustain such engagement in the long run. Specifically, we leveraged the concept of surprise and will incorporate it into a recommender system via two approaches. Knowledge-Based approach, in which we assume that statistical co-occurrence likelihood will help to identify surprising recommendations. And Adaptive Knowledge-Based approach, which aims to improve user satisfaction by adaptively incorporating users' real-time feedback into the recommendations. The insights of the research will make researchers and practitioners rethink the objectives of today's recommender systems or more generally information discovery systems as being more human-centered beyond algorithm accuracy.**

***Index Terms*— Users and interactive retrieval, Recommender systems, Human-centered computing User studies**

I. Introduction

Surprise in recommender systems aims to deliver richer information that is outside users' expectation [1]. It is also related to unsought, unintended, and unexpected, but fortunate, discovery and learning experience that happens by accident [2]. On the other hand, curiosity is defined as a strong desire to explore, investigate or learn something; it derives the process of learning and the desire to acquire knowledge and skill [3]. Typically, curiosity is recognized as a prerequisite for surprise, since high coping potential users or curious users can accept more surprising results [4]. In other words, the more the user is curious, the more he/she will be able to recognize and realize the meaning of a happy accident (surprising result) when it occurs.

Recent information retrieval systems lack the ability to promote unexpected exploration and discovery; rather these systems relatively try to reinforce the same limited set of information [5]. In this study, we incorporated the concept of surprise to deliver richer information to the user. To implement the surprise, we propose two computational models: First, Knowledge-Based (KB) and second, Adaptive Knowledge-Based (AKB), to recommend surprising contents with the hope of satisfying users and inspiring their curiosity. Both the KB and AKB approaches will be introduced in more details in section II.

II. Computational Surprise Approaches

Suppose we have a set of articles A, we view each article as "a bag of co-occurring topics", where topics are the labels assigned to an article by experts. Also, suppose that the set of interested topics for user u_i is S_i. On the other hand, suppose we recommend articles on a session basis. Our computational approaches will be presented in the following subsections.

1) Random Surprise (RS) Approach: RS is the simplest approach for incorporating surprise since it relies on a random selection of articles. And it can be used as a baseline to be compared with the other two proposed approaches. For the RS approach proposed in this study, The set of articles recommended for each session is selected randomly from S_i. The steps for the RS approach are depicted in Algorithm 1.

Algorithm 1: RS Algorithm

```
Input: a set S_i of interesting topics for user u_i of size n
Output: a set A_i of recommended articles of size n
for s ← 1 to 2 do
    A_is = NULL;
    for t ← 1 to n do
        A_st ← Random(a') // a' article labeled with
          topic t
        AppendTo(A_is);
```

2) Knowledge-Based Surprise (KB) Approach: In KB approach, the expectation of seeing an article in the corpus is modeled by Pointwise Mutual Information (PMI) measure. PMI is one of the most popular co-occurrence based measures. In which, for two terms (topics) t_i and t_j , $PMI(t_i,t_j)$ is defined as:

$$PMI(t_i,t_j) = log_2 \frac{p(t_i,t_j)}{p(t_i)p(t_j)} \quad (1)$$

Where $p(t_i)$ and $p(t_j)$ are the probabilities that topics t_i and t_j occurs in an article, respectively. While $p(t_i,t_j)$ denotes the probability that t_i and t_j co-occur in the same article. Therefore, PMI is the *log* of the ratio of the observed co-occurrence frequency to the frequency expected under independence. It measures the extent to which the topics occur more than by chance or are independent. The assumption is that if two topics co-occur more than expected under independence there must be some kind of semantic relationship between them, and therefore a lower surprise score. In other words, in Equation 1, the higher the ratio,

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the more likely that both topics t_i and t_j co-occur within a single article in the corpus, and therefore a lower surprise score. While a lower ratio indicates that rare articles labeled by topics t_i and t_j are in the corpus, and therefore a higher surprise score.

Based on the previous assumptions, we can calculate the PMI between all possible pair of topics in our corpus. Then, suppose we have a user u_i, and the set of interesting topics for this user is $S_i = t_{i_1}, t_{i_2}, t_{i_3}, ..., t_{i_n}$, where n is the number of topics selected by the user. Therefore, for each topic $t_{i_j} \in S_i$, we create an ordered list l_i of all topics (that co-occur with t_{i_j}) based on the PMI measure with the topic t_{i_j} from highest to lowest PMI values. Then, we partition l_i into ten groups of topics $l_i = l_{i_1}, l_{i_2}, l_{i_3}, ..., l_{i_{10}}$. Each group l_{i_k} includes a proportion of 10% from topics in l_i. In other words, the size of each group $l_{i_k} \in l_i$ equals to $0.1 * sizeof(l_i)$. Given this, l_{i_1} includes the topics with the lowest bottom 10% surprise scores, and $l_{i_{10}}$ includes the topics with the highest surprise score. In addition to this, for each article a_m in our corpus that have a set of topics S_{a_m}, we generate a feature f_{a_m} of most representative topic pair (topic pair with the highest surprise score) using Equation 2. The steps for the KB approach are depicted in Algorithm 2.

$$f_{a_m} = \max(SS_{ij}) \tag{2}$$

Where SS_{ij} is the surprise score that topics i and j co-occur in an article, and $i, j \in S_{a_m}$.

Algorithm 2: KB Algorithm

```
Input: a set S_i of interesting topics for user u_i of size n
Output: a set A_i of recommended articles of size n
for s ← 1 to 10 do
    A_is = NULL;
    for t ← 1 to n do
        L ← increasing ordered list of topics based on
          SS with t
        l_s ← 0.1 * s * L;
        A_st ← article with max(f_a_tt') value (t' ∈ l_s) ;
        AppendTo(A_is);
```

3) Adaptive Knowledge-Based Surprise (AKB) Approach: Suppose we have a recommended article a_k based on the user's u_i selected topic t_{i_j} in a session s_k. Also, suppose that a_k is labeled by the set of topics S_{a_k}. If a_k do not receive u_i's interest, then further recommendations of articles labeled with topics in S_{a_k} based on KB method may result in losing user's attention. AKB method is developed to overcome the problem of over-presentation of non-interesting or non-useful articles to u_i. AKB method is similar to KB method but it incorporates user's ratings as the implicit real-time feedback. Each topic in $S_{a_k} - t_{i_j}$ (the set of topics in S_{a_k} except the user's selected topic) is penalized (removed) from future recommendations if it receives lower rating from user u_i.

Both KB and AKB recommend articles based on the surprise score of these articles' topics with the user selected topics as discussed before in section II-.2. The only difference between KB and AKB is the topic selection: KB selects topics with high surprise score with the user selected topics. However, AKB uses the same selection approach, but it removes topics that are not interested for u_i during previous sessions. During the first sessions where user feedback (rating) is little, chances are KB and AKB are the same. The steps for the KB approach are depicted in Algorithm 3.

Algorithm 3: AKB Algorithm

```
Input: a set S_i of interesting topics for user u_i of size n
Output: a set A_i of recommended articles of size n
for s ← 1 to 10 do
    A_is = NULL;
    for t ← 1 to n do
        L ← increasing ordered list of topics based on
          SS with t
        for t' ∈ L do
            if interest[t'] < threshold then
                L' = L − t';
        l_s ← 0.1 * s * L';
        A_st ← article with max(f_a_tt') value (t' ∈ l_s) ;
        AppendTo(A_is);
```

III. Discussion and Conclusion

In this paper, we proposed two models of computational surprise. These models aim to recommend an unexpected (surprising) contents to users to inspire their curiosity to know more. To evaluate our proposed model, We will develop a recommender system using the two models of surprise. On the other hand, a user study will be conducted to measure various aspects, including, (i) Users' preference change before and after using the recommender system, (ii) The effect of user's curiosity on accepting surprising contents, and (iii) Users' curiosity change before and after using the recommender system.

References

[1] I. Kotsogiannis, E. Zheleva, and A. Machanavajjhala, "Directed edge recommender system," in *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, pp. 525–533, ACM, 2017.

[2] W. Jones, "Transforming technologies to manage our information: The future of personal information management, part ii," *Synthesis Lectures on Information Concepts, Retrieval, and Services*, vol. 5, no. 4, pp. 1–179, 2013.

[3] J. Litman, "Curiosity and the pleasures of learning: Wanting and liking new information," *Cognition & emotion*, vol. 19, no. 6, pp. 793–814, 2005.

[4] T. B. Kashdan and P. J. Silvia, "Curiosity and interest: The benefits of thriving on novelty and challenge," *Oxford handbook of positive psychology*, vol. 2, pp. 367–374, 2009.

[5] J. Burkell, A. Quan-Haase, and V. L. Rubin, "Promoting serendipity online: recommendations for tool design," in *Proceedings of the 2012 iConference*, pp. 525–526, ACM, 2012.