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Online Product Recommendations based on Diversity and Latent Association Analysis on News and Products

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Integrating news websites with product recommendation can create more benefit and is an important trend of online worlds. The information offered by the websites is becoming even more complicated. Accordingly, it is important for the websites to implement online recommendation methods that can raise the users' click-through rates and loyalty. In this work, we proposed a novel online product recommendation approach for recommending products during news browsing. The proposed method combines online hybrid interest analysis and recommendation diversity. There are cold-start and data sparsity issues on the website. Accordingly, a hybrid of collaborative filtering and content-based approach is used to alleviate the issues. Specifically, latent association analysis is conducted on user browsing news and products to discover the latent associations between products and news. Moreover, a hybrid method is proposed based on Matrix Factorization and Latent Topic Modeling to predict user preferences for products. In addition, online interest analysis is integrated to adjust users' online product interests according to the currently browsing news. Finally, the proposed approach combines recommendation diversity and users' online interests to raise the chance of discovering potential user preferences on products and enhance the click through rate of online product recommendations. Online evaluations are conducted on a news website to evaluate the proposed approach. Our online experimental results indicate that the proposed approach can enhance the click-through rate of online product recommendations.

Keywords: product recommendation, matrix factorization, diversity, latent topic modeling, online recommendation

1. INTRODUCTION

News websites integrating with e-commerce portals are blooming. More and more users acquire news or other specific topics such as travel, makeups and lifestyle information via the Internet information websites, or use e-commerce platforms to purchase goods. Through the website, we can analyze user browsing behavior, consumer trends and consumer preferences, and then combine the data with e-commerce for selling related goods. It can attract more users to increase the traffic flow of the website and conduct e-commerce to make greater profit.

In our work, we mainly investigate online product recommendation methods for new types of online news websites, which integrate e-commerce to provide lifestyle news browsing and merchandise purchasing. With the diversified development, it makes the amount of information provided by information websites increase exponentially. Therefore,

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determining how to recommend relevant products of user interest to users, and enhance user's click-through rate and loyalty comprise a critical issue. Online product recommendation can help users to find products and enhance user loyalty.

Users mainly read news on Lifestyle information platform; relatively speaking, they have few product purchasing records. In other words, they are cold-start users in terms of e-commerce. Currently, researches on product recommendation are based on content-based filtering (CBF), which recommends user similar products according to purchase history [16], Collaborative filtering (CF) or Matrix Factorization (MF) methods which recommend user products according to neighbors whose interests are similar to those of the user [13, 26]. However, most users on Internet information website are cold-start users who have few or even no purchase history. Traditional recommendation methods mostly have poor performance with cold-start users. The Information website enables user behavior, including news reading and product purchasing. General recommendation systems only analyze the history of the recommended target, for example, analyzing the content and history of products when recommending products. The sparsity problem will result in a poor quality recommendation system. Hybrid approaches combine the CF and CBF methods to overcome the cold start and data sparsity issues [8, 43].

In this work, we proposed a novel online product recommendation approach for product recommendation when users are browsing the news. The proposed method combines online hybrid preferences and recommendation diversity analysis. The news articles are content-based, while the products contain the tags, categories and product descriptions, which can also be extracted as term features. Accordingly, a hybrid of collaborative filtering and content-based approach is adopted for product recommendation. Specifically, we use Nonnegative Matrix Factorization (NMF) [21] to proceed with latent association analysis which analyzes the relation between articles and products and finds latent factors. Then according to the relation, we use mutual information [11] to enrich the terms in the product. Moreover, we analyze latent topic vectors of articles and products by using the Latent Dirichlet Allocation (LDA) model [6]. By analyzing news reading history and product browsing history of the user, latent factor and latent topic vector of users can be derived to analyze user product preferences. The method combining NMF and LDA alleviates the cold-start and data sparsity problems and predicts the users' product preferences.

We developed the online product recommendation approach by considering users' current online interests on products when browsing news articles. Online interest analysis is integrated to adjust users' online interest on products according to the news that target user is currently reading. For the investigated online news website, there are cold-start users for product channel and very few product browsing records to analyze user preferences. We consider the diversity of recommended items to mitigate the cold start and data sparsity issues. Diversity is generally defined as the average pairwise dissimilarity between the recommended items [7, 27]. Recommendation diversity helps to raise the chance of discovering potential interests. However, it may result in low accuracy with diverse recommendations. Thus, relevant studies have investigated how to balance the trade-off between diversity and accuracy [4, 7, 14, 22, 27].

We developed the online recommendation approach based on the hybrid of user preferences and diversity of recommendation to enhance users' willingness to purchase products. We calculate the relative diversity scores between the target product and the products in the recommendation list, so that we can generate the recommendation list for each user based on his/her interest and recommendation diversity. We run our product recommendation mechanism online and evaluate the actual performance. Our research verifies the performance by online user's click-through rate (CTR). The evaluation results indicate that our proposed method can improve the CTR for recommending products and mitigate the cold-start problem. The recommendation diversity can enhance the quality of recommending products online for the website, even with very few product purchasing records.

The paper is organized as follows. In Section 2, we discuss the related previous work, after which we present the details of the proposed online product recommendation method in Section 3. Our experimental evaluation is reported in Section 4, and Section 5 summarizes and concludes the paper.

2. RELATED WORK

In this section, we illustrate the related studies, including recommender systems, latent topic modeling, non-negative matrix factorization and recommendation diversity.

2.1 Recommendation Systems

Recommendation systems have been applied in many areas [30, 33, 39, 47], such as products [5, 25, 28, 32, 37], music [2] and articles [31]. The content-based filtering (CBF) approach derives users' interests according to the content of items and conducts recommendations based on user profiles [34]. Items purchased or viewed by users were used to build user profiles. The collaborative filtering (CF) approach makes recommendations by analyzing the relationship between items or users to identify the target user's neighbors who have similar interests [1]. The latent factor methods of CF use matrix factorization to find the latent factors of users and items, and then predict preferences for items by using an inner product of the latent factors [26]. The CBF method is limited in providing recommendations from the interests of similar users, while CF has the drawback of handling the data sparsity and cold start issues. Hybrid approaches combine the CF and CBF methods to overcome the drawbacks of the two methods [8, 43]. Besides, several studies propose online interest analysis methods to provide online recommendations [19, 30, 31].

Deep learning methods have been adopted to develop recommendation systems [10, 12, 18, 24, 38, 40, 41, 45, 46]. For example, Convolutional Matrix Factorization (ConvMF) [24] uses different filtering layers of CNN to generate hidden feature vectors, and then combines a PMF scoring matrix to learn the latent factors of users and items. Deep learning techniques have been applied for fashion recommendation [38]. An improved recurrent neural network model based on time window is proposed for product advertising recommendation [46]. Autoencoders are adopted to design recommendation systems for product recommendation [23].

2.2 Information Retrieval and Latent Topic Modeling

Information retrieval (IR) is mainly adopted to process textual content and retrieve descriptive terms of items [35, 36]. The vector space model [36] represents queries and documents as multi-dimensional vectors, which contain terms with weights computed by term frequency and inverse document frequency. Document recommendation techniques usually adopt vector space model to create term vectors, or adopt latent Dirichlet allocation model (LDA) [6] to create latent topic vectors of articles. User vectors are then generated by aggregating the vectors of articles read by users. Recommendation scores are derived according to the similarity between user and document vectors for making recommendations.

A latent topic model derives the relations between the terms and explores latent topics hidden in the corpus. Latent Dirichlet Allocation (LDA) [6] is a generative probabilistic model that processes latent variable analysis in the corpus. Documents are represented as random mixtures over latent topics, and each topic is featured by a distribution over words. An Expectation Maximization (EM) algorithm is used to handle the derivation process. In addition, Griffiths and Steyvers [17] replaced original multinomial distribution with prior probabilistic distribution and used Gibbs sampling to address the coverage speed problem. Among the researches applying LDA, Zahalka, *et al.* [44] proposed an multimodal content-based venue recommendation that used LDA in the text domain, and used a SVM model to learn the interacting user's preferences.

2.3 Non-Negative Matrix Factorization

Matrix Factorization (MF) recommendation [26] is a common latent factor model that belongs to the collaborative filtering (CF) method. Matrix factorization models decompose user-item matrix R and map both users and items into a joint latent factor model of lower dimension, such that user-item preferences are modeled as inner products of latent factors. Non-negative Matrix Factorization (NMF) [29] enforces the constraint that the low-rank factor matrices can have only nonnegative elements. Non-negative matrix factorization (NMF) [20, 21] is adopted for discovering non-negative representations of data, and has shown usefulness in recommendation. Given a matrix $V \in R^{m \times n}$, $V \geq 0$, NMF approximates V as the product of two non-negative matrices, $X \in R^{m \times n}$ and $Y \in R^{m \times n}$, where each column of V is an input vector. NMF uses nonnegative linear combinations to approximate all vectors. Measuring the distance between V and XY results in the minimization problem, as defined in Eq. (1):

$$\min_{X,Y \geq 0} \frac{1}{2} \left\| V - XY \right\|_F^2 + \rho_1 \sum_{i,r} X_{ir} + \rho_2 \sum_{r,j} Y_{rj} \cdot \tag{1}$$

2.4 Recommendation Diversity

Most researches on recommendation systems focus on improving the accuracy of recommendations. Recommendation diversity offers a wider option to users and raises the opportunities to find latent interest [4, 15, 27, 42]. Diversity is generally adopted to measure how different the items are with respect to each other for a set of items. A common definition of diversity is the average pairwise dissimilarity between the recommended items [7]. Nevertheless, aimless random recommendation would lead to decreased accuracy. Therefore related researches investigate into the balance between diversity and accuracy [7, 14]. Recommendation diversity can be divided into individual and aggregate diversity [4, 48]. Individual diversity is measured by calculating the diversity of recommendations for each user. Aggregate diversity is measured by considering the aggregate diversity of recommendations for all users. Most researches are mainly about individual diversity. Ziegler *et al.* [48] proposed intra-list similarity (ILS) which is measured by characteristics of the item to calculate the diversity score of the personal recommendation list. With regard to how to increase diversity, Bradley and Smyth [7] proposed three diversity strategies: bounded random selection, greedy selection, and bounded greedy selection. A mathematical model using multi-objective optimization approaches is proposed to address the combination of accuracy, individual diversity and aggregate diversity in recommendations [9]. A two-sided post-processing approach is proposed to maximize aggregate diversity while minimizing the loss in recommendation accuracy by considering both user and item utilities [15].

3. PROPOSED APPROACH

3.1 Overview

We propose a novel online product recommendation methodology that integrates user preference analysis and diversity analysis based on news/product reading history and online interest analysis, as illustrated in Fig. 1.

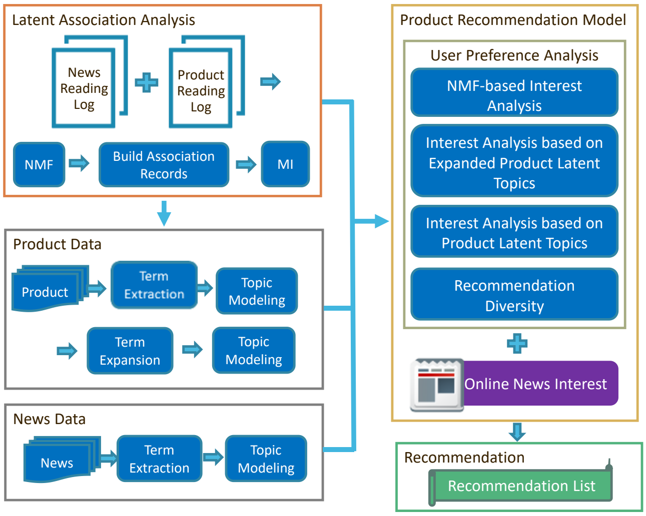

Fig. 1. An overview of the proposed recommendation method.

News are content-based articles. Products also contain descriptive terms. Accordingly, a hybrid interest analysis approach integrating collaborative filtering and content-based approach is adopted to alleviate the problems of data sparsity and cold-start users/products. We adopt and modify the well-known NMF-based (CF-based) and LDA-based (content-based) methods to tackle the problem of recommending products during news browsing. Moreover, a novel online product recommendation method is proposed by integrating hybrid interests and recommendation diversity.

The diversity of recommended items is considered to mitigate the data sparsity and cold-start problems. The proposed approach derives user preferences based on NMF and LDA. Moreover, we developed the online product recommendation approach based on the hybrid of user preferences and diversity of recommendation to enhance users' willingness to browse products. The terms of news and product textual contents are extracted by using Jieba, a Chinese text segmentation module. Due to the rare descriptions of the product, term expansion is adopted to enhance the contents of products by adding news terms to products. We first extract the latent association between products and news by non-negative matrix factorization (NMF). Then term-expansion is carried out to add news terms to products based on the Mutual Information (MI).

For user interest analysis, we analyzed two historical logs: news browsing and product browsing logs. First, we derived a user's latent factor vector and NMF-based user preference based on the latent factors derived from NMF. Second, we used LDA to analyze the latent topics of news/products. Third, expanded latent topic vectors were derived by conducting LDA on news articles and products with term expansion. A user's latent/expanded latent topic vector was generated by analyzing a user's news and product browsing logs. Accordingly, LDA-based user preferences were derived from the latent/expanded latent topic vectors of users and products. Finally, we could integrate NMF-based with LDA-based preference analysis to analyze a user's preferences. The proposed hybrid model combining both the merits of CF-based (NMF) and content-based (LDA) approaches can provide more effective recommendations for cold start products. In addition, users' online interests and recommendation diversity of products were considered. Online interests were analyzed based on the news that the user was currently reading. According to the news a user is reading, we combined the related products of the news with the result of the user's preference analysis. Furthermore, we also designed diverse recommendation lists for each user. We calculated the relative diversity score between the target product and the products in the recommended list. Referencing a user's news reading history and product browsing history, we analyzed the degree of diversity of the user's preferences to generate a recommendation list based on users' interests and recommendation diversity. Finally, the product recommendation score was generated by integrating the user preference and product diversity score.

3.2 Latent Association Analysis between Products and News

Because of very few product purchasing data for the website, it is hard to directly derive users' product interests. Thus, we adopted non-negative matrix factorization (NMF) [21] to derive user preferences and discover latent factors of products and news by finding the latent associations between them. We transferred users' news browsing and product browsing logs to news-products relevance matrix. Let the relevance score $r_{d,p}$ denotes the degree of relevance of news d to product p. The news-product matrix R is created by $r_{d,p}$, which is derived by multiplying the product-news ratio with the popularity of the news, which is one minus the reciprocal of the number of users reading news d. If a user reading news d also browsed product p, we assumed a latent association between them. Hence, the product-news ratio is the number of users who both read news d and browsed product p divided by the number of users reading news d.

By calculating $r_{d,p}$, we built the news-product relevance matrix R, and conducted

NMF [29] to generate the latent factors of news and products by resolving a minimization problem, as defined in Eq. (2). The relevance scores in matrix R can be predicted by a non-negative latent factor matrix $X(x_d)$ of news and non-negative latent factor matrix $Y(y_p)$ of products.

$$\min_{x_d, y_p \geq 0} \left\| r_{d,p} - \hat{r}_{d,p} \right\|^2 + \lambda_x \left\| x_d \right\|^2 + \lambda_y \left\| y_p \right\|^2 ; \hat{r}_{d,p} = x_d^T y_p \tag{2}$$

where λ_x and λ_y are the regularization terms. x_d is used to create the latent factor $\overrightarrow{dlf_d}$ of news d, and y_p is utilized to create the latent factor $\overrightarrow{plf_p}$ of product p. They are utilized to calculate the NMF-based user interest score, as described in Section 3.4.

3.3 Term Expansion for Products

We extracted the terms of products/news article by applying the Chinese text segmentation module, Jieba. Due to the rare descriptions of the product, term expansion is conducted to enhance the product contents. LDA (latent Dirichlet allocation) analysis [6] is conducted on the contents of products to derive k latent topics for each product. Let k be the total number of latent topics. The k-dimensional latent topic vector of each product p is denoted as $\overrightarrow{plf_p}$:$<w_{1,p}, w_{2,p}, \ldots, w_{i,p}, \ldots, w_{k,p}>$ where $w_{i,p}$ is a proportion of topic i in product p. The terms with top-N highest probability were selected to denote each topic. We added the terms that are not in product p's content but describe the most related topic to enrich the content. For each product, the top 20 terms of the most relevant topic were selected to add to the product terms.

Words in news corpus and product corpus may be unrelated. Besides, there are not many words in product corpus. In order to perform LDA analysis on the content of news and product together, we needed to make their contents more related. Hence, we had to find the most related terms from news contents for each product to add in our list. We used Mutual Information [11] to find appropriate news terms to add in the product description. In Section 3.2, we obtained a news-product relevance matrix R. Accordingly, we found the top-30 related news for each product according to the relevance score of each news item to each product. We defined each product and its 30 related articles as a product-news association record, that is, the terms in contents of product and related news appear in the same product-news association record. Then we used Mutual Information (MI) [11] to analyze the correlation between terms in the product corpus and terms in the news term set. According to the calculated MI values, the top-100 relevant news terms were selected and added to expand the term set of each product.

3.4 User Interest Analysis

A hybrid approach, which integrates latent topic modeling – LDA and latent factor modeling – NMF, is proposed to derive user interests on products. Three aspects of user interest scores are derived: NMF-based interest scores (NMFS), product topic-based interest scores (PTS) and expanded product topic-based interest scores (EPTS).

For each user, an NMF-based interest score was estimated by using the latent factors of products/news. Let F be the total number of latent factors. The news latent factor of a news d is represented as $\overrightarrow{dlf_d}$:$\langle f_{1,d}, f_{2,d}, \ldots, f_{j,d}, \ldots, f_{F,d}\rangle$. The product latent factor of a product p is represented as $\overrightarrow{plf_p}$:< $f_{1,p}$, $f_{2,p}$, …, $f_{j,p}$, …, $f_{F,p}$>. Many users on the website have not yet purchased or browsed products; this results in difficulty in predicting user preferences for products. To overcome the problem, both the news reading history and product browsing history are used to derive users' interest profiles. The user NMF latent factor vector of a user u is represented as $\overrightarrow{ulf_u}$:< $f_{1,u}$, $f_{2,u}$, …, $f_{j,u}$, …, $f_{F,u}$>, which is calculated by Eq. (3):

$$\overrightarrow{ulf_u} = \alpha \times \frac{1}{|D_u|} \sum_{d \in D_u} \overrightarrow{dlf_d} + (1-\alpha) \times \frac{1}{|P_u|} \sum_{p \in P_u} \overrightarrow{plf_p} \tag{3}$$

where D_u is the set of news articles that user u had read; P_u is the set of products clicked by user u; α is the weight utilized to adjust the importance of news/product latent factor vectors. Then the cosine similarity $sim(\overrightarrow{plf_p})$ between the latent factor vectors $\overrightarrow{ulf_u}$ and $\overrightarrow{plf_p}$ can be computed to acquire a NMF-based interest score $NMFS_{u,p}$ that denotes user u's preference in product p based on NMF analysis.

We conducted LDA analysis on the contents of products to generate the latent topic vectors of products. Let H be the number of latent topics. The latent topic vector of product p is represented as $\overrightarrow{plt_p}$:< $w_{1,p}$, $w_{2,p}$, …, $w_{j,p}$, …, $w_{H,p}$>. The latent topic vector of user u is derived from the products clicked by user u, and is denoted as $\overrightarrow{ult_u}$:< $w_{1,p}$, $w_{2,p}$, …, $w_{j,p}$, …, $w_{H,u}$> , which can be generated as the average of the latent topic vectors of products clicked by user u. Then we calculated the cosine similarity between $\overrightarrow{ult_u}$ and $\overrightarrow{plf_p}$ to get a product topic-based interest score $PTS_{u,p}$ that denotes user u's interest in product p based on the latent topics derived from LDA analysis on product contents.

To alleviate the cold-start problem, term expansion was conducted to enrich the content of the products. After term expansion, we performed an LDA analysis on the contents of news and expanded contents of products. Accordingly, we could derive the K-dimensional expanded latent topic vectors of news d and product p. Let K be the number of latent topics. The expanded latent topic vector of a product is represented as $\overrightarrow{pelt_p}$:< $w_{1,p}$, $w_{2,p}$, …, $w_{j,p}$, …, $w_{K,p}$>. The news latent topic of a news d is represented as $\overrightarrow{delt_d}$:< $w_{1,d}$, $w_{2,d}$, …, $w_{j,d}$, …, $w_{K,d}$>.

The expanded latent topic vector of a user u is denoted as $\overrightarrow{uelt_u}$:< $w_{1,u}$, $w_{2,u}$, …, $w_{j,u}$, …, $w_{K,u}$>, and can be derived from u's clicking products and reading news, as listed in Eq. (4):

$$\overrightarrow{uelt_u} = \beta \times \frac{1}{|D_u|} \sum_{d \in D_u} \overrightarrow{delt_d} + (1-\beta) \times \frac{1}{|P_u|} \sum_{p \in P_u} \overrightarrow{pelt_p}. \tag{4}$$

Where P_u is the set of products that user u had clicked; D_u is the set of news browsed by user u; and β is the weight used to adjust the importance of the expanded latent topics of the news/products. Then, we calculated the cosine similarity between $\overrightarrow{uelt_u}$ and $\overrightarrow{pelt_p}$ to acquire an expanded product topic-based preference score $EPTS_{u,p}$ that denotes user u's interest in product p based on the expanded latent topic vectors derived from LDA analysis on news/expanded product contents.

3.5 Recommendations

3.5.1 User interest scores

A hybrid approach proposed herein to derive the interest scores by combining the

NMF-based (CF-based) and LDA-based (content-based) user interest scores, can provide better user interest prediction. Three parameters w_{nmfs}, w_{epts} and w_{pts}, are utilized to adjust the importance of the normalized interest scores of $NMFS_{u,p}$, $EPTS_{u,p}$ and $PTS_{u,p}$ for deriving the hybrid interest score $HIS_{u,p}$ of use u on product p. The $HIS_{u,p}$ estimation formula is defined as Eq. (5):

$$HIS_{u,p} = w_{nmfs} \times NMFS_{u,p} + w_{epts} \times EPTS_{u,p} + w_{pts} \times PTS_{u,p} \tag{5}$$

where $MFS_{u,p}$ represents the user u's interest in product p based on NMF analysis discussed in Section 3.4; $EPTS_{u,p}$ denotes the user u's interest in product p based on LDA analysis on the expanded product latent topics; $PTS_{u,p}$ is the user u's interest in product p based on LDA analysis on product latent topics.

For each user, we selected 50 products with the top-50 hybrid interest scores (HIS) to generate product candidates based on $HIS_{u,p}$. Moreover, we conduct current preference analysis on the news that target user is currently reading. The current interest score (CIS) is integrated with the HIS to derive the online hybrid interest score (onlineHIS). The target user u's current interest score on product p, $CIS_{d,p}$ was derived according to the similarity between product p and the news d that user u is currently browsing, as defined in Eq. (6). We used w_{elt} and w_{lf} as the weights to combine the results computed by LDA expanded latent topics and NMF latent factors, respectively, where $w_{elt} = w_{epts} / (w_{epts} + w_{nfms})$ and $w_{lf} = w_{nfms} / (w_{epts} + w_{nfms})$. Note that the two values, w_{nmfs} and $w_{epts,}$ are decided by weight of NMFS and EPTS, respectively:

$$CIS_{u,p} = w_{nelt} \times sim(delt_d, pelt_p) + w_{lf} \times sim(dlf_d, plf_p) \tag{6}$$

where d is the news that user u is currently browsing; $sim(i, j)$ is the cosine similarity between vectors i and j. With the $CIS_{d,p}$, we adjusted the interest score of each product in the product candidate set. The online hybrid interest score is derived to obtain a user's current interest on products for reading news online. We adjusted the online interest score of user u on product p, $onlineHIS^t_{u,p}$ based on the hybrid interest score $HIS_{u,p}$ in Eq. (5) and the current online interest score $CIS_{d,p}$ in Eq. (6). The adjustment of $onlineHIS^t_{u,p}$ is expressed as Eq. (7):

$$onlineIS^t_{u,p} = \begin{cases} HIS_{u,p} \times \left(1 + CIS_{d,p}\right), \text{ if } t = 1 \\ onlineIS^{t\text{-}1}_{u,p} \times \left(1 + CIS_{d,p}\right), \text{ if } t > 1 \end{cases} \tag{7}$$

where t denotes the tth recommendation to user u in a day. For the first recommendation, we calculate $onlineHIS^t_{u,p}$ based on $HIS_{u,p}$. For the tth recommendation, we calculate $onlineHIS^t_{u,p}$ based on $onlineHIS^{t\text{-}1}_{up}$ which is the prior result. A user's $onlineHIS$ is adjusted with the news that the user has browsed.

3.5.2 User preference diversity analysis

Recommending diverse products can help to discover users' latent interests and enhance their desire to purchase products. We predict a user's preference diversity by calculating the diversity of the user's news reading history as well as product browsing history, respectively. The news preference diversity of user u, NPD_u, is the average dissimilarity between the news articles that user u had browsed, as shown in Eq. (8). The product preference diversity of user u, PPD_u, is the average dissimilarity between the products which user u had clicked, as defined in Eq. (9). While computing the dissimilarity between the items, we used w_{elt} and w_{lf} as the weights to combine the dissimilarity results which were computed based on the LDA expanded latent topic and NMF latent factor vectors, respectively. $w_{elt} = w_{epts} / (w_{epts} + w_{nfms})$ and $w_{lf} = w_{nfms} / (w_{epts} + w_{nfms})$. Note that the two values, w_{nmfs} and w_{epts}, are decided by weight of NMFS and EPTS, respectively. The values of w_{elt} and w_{lf} are determined according to the best performance of the experiments conducted under various combinations of parameter values in Section 4.2.3.

$$NPD_u = \frac{1}{|D_u| \times (|D_u| - 1)} \sum_{d_1 \in D_u; d_1 \neq d_2} \sum_{d_2 \in D_u} \begin{bmatrix} w_{elt}\left(1 - sim\left(\overrightarrow{delt_{d_1}}, \overrightarrow{delt_{d_2}}\right)\right) + \\ w_{lf}\left(1 - sim\left(\overrightarrow{dlf_{d_1}}, \overrightarrow{dlf_{d_2}}\right)\right) \end{bmatrix} \tag{8}$$

$$PPD_u = \frac{1}{|P_u| \times (|P_u| - 1)} \sum_{p_1 \in P_u; p_1 \neq p_2} \sum_{p_2 \in P_u} \begin{bmatrix} w_{elt}\left(1 - sim\left(\overrightarrow{pelt_{p_1}}, \overrightarrow{pelt_{p_2}}\right)\right) + \\ w_{lf}\left(1 - sim\left(\overrightarrow{plf_{p_1}}, \overrightarrow{plf_{p_2}}\right)\right) \end{bmatrix} \tag{9}$$

where D_u is the set of news articles read by user u; P_u is the set of products which user u had clicked; $sim(i, j)$ is the cosine similarity between vector i and vector j.

The two diversity preferences are combined to derive the user preference diversity of user u UPD_u defined in Eq. (10). The recommender system recommends products when users are browsing news articles. Thus, the product preference diversity PPD_u should account for a larger proportion of a user's preference diversity. If user u is a new user who had not browsed any article, UPD_u is equal to 1 and more diverse products will be recommended:

$$UPD_u = (NPD_u/2)(1 + PPD_u). \tag{10}$$

3.5.3 Recommendation score

The recommendation score is calculated by considering the online hybrid interest scores and diversity scores of products. We used the recommendation score to determine the final recommendation list by choosing the top-5 products from the product candidate set.

We adopted a greedy approach [7] to derive the recommendation list iteratively and calculate the diversity between the newly added product p and the products in user u's recommendation list RL_u. The relative diversity of product p, $RelDiversity_{p,RL_u}$ is defined as Eq. (11):

$$RelDiversity_{p,RL_u} = \frac{1}{|RL_u|} \sum_{i \in RL_u} \left[1 - sim\left(\overrightarrow{pelt_i}, \overrightarrow{pelt_p}\right)\right] \tag{11}$$

where $sim(\overrightarrow{pelt_i}, \overrightarrow{pelt_p})$ is the similarity between the LDA expanded latent topics $\overrightarrow{pelt_i}$ and $\overrightarrow{pelt_p}$.

We developed the online recommendation approach based on the hybrid of user preferences and diversity of recommendation to enhance users' willingness to purchase products. Two alternatives were adopted to combine user interests and recommendation diversity. One uses a fixed weight and the other takes a user's diversity tendency to combine user preferences and recommendation diversity. A user's diversity tendency indicates the degree of diversity of the user's preferences and is derived by analyzing the news reading history and product browsing history. The recommendation score $RS_{u,p}$ of each user u is defined as Eq. (12). We consider the preference diversity of each user and use user preference diversity UPD_u defined in Eq. (10) to control the degree of diversity of the recommendation list. If UPD_u of a user u is high, the proportion of diversity in the recommendation list will become larger, resulting in recommending more diverse products:

$$RS_{u,p} = (1 - UPD_u) \times onlineHIS^t_{u,p} + UPD_u \times RelDiversity_{p,RL_u}. \tag{12}$$

The alternative was to compute a recommendation score $RS_{u,p}$ by utilizing a weighted combination of online hybrid interest scores and diversity scores, as defined in Eq. (13):

$$RS_{u,p} = (1 - \gamma) \times onlineHIS^t_{u,p} + \gamma \times RelDiversity_{p,RL_u}. \tag{13}$$

We adopted a greedy approach to generate the recommendation list iteratively. First, the candidate products, which are selected based on the offline hybrid interest scores derived from Eq. (5), are ordered according to their online hybrid interest scores; the candidate with the highest score is chosen and put into the product recommendation list. During each iteration, we calculate recommendation score $RS_{u,p}$ of each product p in the remaining candidate products, and the candidate with the highest recommendation score is put into the product recommendation list.

Specifically, the 50 products are ordered according to their $onlineHIS^t_{u,p}$ and the first product to be selected is always the one with the highest online hybrid interest scores. Second, given that we are going to recommend five products for each user, there are four iterations to generate the recommendation list. During each iteration, we calculated $RS_{u,p}$ of each product p from the remaining products one by one. Then, the candidate with the highest $RS_{u,p}$ was chosen and put into the product recommendation list.

On the other hand, for new users who have no records on the website, we cannot analyze their offline hybrid interest score. So, we compute the current interest score (CIS), that is, the cosine similarity between the news which the target user is reading online and each product according to Eq. (6). Then, we choose the top-20 products with the highest *CIS* as the candidates and use Eq. (12) to compute the recommendation score by using *CIS* as the interest score. We use the similar greedy selection to generate the recommendation list. Therefore, for new users, we recommend five products that are related to the current news, and each one has the highest $RS_{u,p}$ with respect to each iteration.

4. EXPERIMENT AND EVALUATION

4.1 Experiment Setup

We collected a dataset from a news website which is called NIUSNEWS (http://www.

niusnews.com/). It not only offers lifestyle news but also sells creative products with the target customers of NIUSNEWS being mainly young females. The news data set contains news and browsing logs taken over a period of eleven months. Moreover, the product data set contains descriptions of products and user browsing logs taken over a period of four months. The experiments include offline parameter evaluations and online recommendation.

For conducting the offline experiments, the product data set was divided into 60% for training set and 40% for testing set. The training set of offline experiment is composed of 5332 news items, 1029 products, and 35127 users. The testing set of the offline experiment is the log data over a three weeks period. There are various parameters in our proposed method. The offline testing experiment aimed to decide the best parameter values for the proposed method, including the latent topic number/weight in LDA, the latent factor number/weight in NMF and the weight combination discussed in section 3.5.1. We sought the best parameter values in offline experiments, and those parameter values are fixed and used to implement our online recommendation system. We implemented our proposed approach in a news website to conduct online recommendations and evaluations. The online experiment was carried out over a period of nine days. The online evaluations consisted of 1102 users and 1011 products.

To evaluate the recommendation quality of the proposed methods, the precision, recall and F1-measure metrics [3] were used as the measurements in the offline experiments. For online recommendations, the recommendation quality is evaluated based on the click-through rate (CTR), which is the frequency of clicking a recommended product divided by the number of recommendations, as defined in Eq. (14).

$$CTR = \frac{number\ of\ clicks\ on\ recommendations}{number\ of\ recommendations} \tag{14}$$

We adopt and modify the well-known NMF-based (CF-based) and LDA-based (CBF-based) methods to tackle the problem of recommending products during news browsing. The NMF-based method is a representative CF-based baseline method and is adopted by considering news/product latent factor vectors. The LDA-based method a representative CBF-based baseline method and is adopted based on product/expanded-product latent topics. The HI method combines NMF-based and LDA-based methods and is a modified baseline approach for recommending products during news browsing.

To tackle the problem of recommending products online during news browsing, we propose a novel online product recommendation approach by integrating hybrid online interests and recommendation diversity. In the experiment, our proposed product recommendation methods, including URD-ONHI and WRD-ONHI, were evaluated with the baseline HI and several alternatives. ONHI and URD-HI are the modified versions of our proposed approach. ONHI does not consider recommendation diversity, while URD-HI integrates the analysis of user preference diversity and hybrid interest without considering an online interest analysis. The compared methods are described as follows:

- **Hybrid Interest Analysis (HI):** HI is a hybrid recommendation approach that derives the recommendation scores by combining the NMF-based (CF-based) and LDA-based (CBF-based) user preference scores. LDA and NMF are well-known representative baseline recommendation methods for CBF-based and CF-based recommendation methods, respectively. The HI method is a modified baseline approach for recommending products during news browsing by integrating CBF and CF to alleviate the cold-start and data sparsity issues. The HI method does not consider an online interest analysis.

- **Online Hybrid Interest Analysis (ONHI):** Recommendation is generated by considering the hybrid interest and online interest analysis; this adjusts the user's online preference score on target product based on the similarity between the product and the currently browsing news. The ONHI method does not consider recommendation diversity.
- **User Recommendation Diversity and Hybrid Interest Analysis (URD-HI):** Recommendation is generated by integrating the analysis of user preference diversity and hybrid interest without considering an online interest analysis.
- **User Recommendation Diversity and Online Hybrid Interest Analysis (URD-ON HI):** Recommendation is generated by integrating the analysis of user preference diversity and online hybrid interest, as discussed in Sections 3.4 and 3.5.
- **Weighted Recommendation Diversity and Online Hybrid Interest Analysis (WRD-ONHI):** Recommendation is generated by a weighted combination of recommendation diversity and online hybrid interest. γ is set as 0.8 for every user.

4.2 Evaluation of Parameters

4.2.1 Determining the parameters in NMF-based interest analysis

We needed to decide the number of latent factors F for non-negative matrix factorization, and the weight α to combine the user's news and product browsing latent factor vectors. We set the regularization terms λ_x and λ_y as 0.002. Recommendation results based on a different number of factors are compared. To decide the best value for α, we adjusted the value of α by an increment of 0.1 systematically. The results are shown in Table 1. We can observe that the highest average $F1$ value occurs when the number of latent factors F = 140 and α = 0.7-0.9. Accordingly, we set F = 140 and α = 0.7 in the rest of the experiments.

Table 1. The evaluation scores based on a different number of latent factors and α.

Factor number	Parameter	Precision	Recall	F1-score
130	(α= 0.1)	0.02962	0.09447	0.04097
	(α= 0.3)	0.03209	0.09623	0.04303
	(α= 0.5)	0.03456	0.09800	0.04509
	(α= 0.7)	0.03456	0.09800	0.04509
	(α= 0.9)	0.03456	0.09800	0.04509
140	(α= 0.1)	0.03209	0.10611	0.04467
	(α= 0.3)	0.03209	0.10611	0.04467
	(α= 0.5)	0.03456	0.10787	0.04673
	(α= 0.7)	**0.03456**	**0.10787**	**0.04673**
	(α= 0.9)	0.03456	0.10787	0.04673
150	(α= 0.1)	0.02962	0.09376	0.04056
	(α= 0.3)	0.02716	0.08142	0.03644
	(α= 0.5)	0.03209	0.09553	0.04262
	(α= 0.7)	0.03209	0.09553	0.04262
	(α= 0.9)	0.03209	0.09553	0.04262

4.2.2 Determining the parameters in LDA-based interest analysis

We generate users' latent topics based on the latent topics of the products that users had clicked so we needed to decide the appropriate number of latent topics H for LDA modeling as discussed in Section 3.4. Our experiment result shows that the F-1 value reaches the highest value when the number of latent topics H = 150 for LDA-based user preference derived from product latent topics. To derive users' interests on products based on the LDA analysis of the expanded product terms, we needed to determine the latent topic number K and weight β, as discussed in Section 3.4. We evaluated the parameter values based on the F1-scores of various combinations of K and β. From the performance results, as shown in Table 2, we can observe that the highest F1 value occurs when the latent topic number K = 180 and β = 0.2.

Table 2. The evaluation scores based on a different number of topics K and β.

Topic number	parameter	Precision	Recall	F1-score
170	(β = 0.0)	0.00987	0.04320	0.01587
	(β = 0.2)	0.01481	0.05238	0.02016
	(β = 0.5)	0.00987	0.03827	0.01399
	(β = 0.9)	0.00987	0.03827	0.01399
180	(β = 0.0)	0.00987	0.04320	0.01587
	(β = 0.2)	**0.01481**	**0.05679**	**0.02163**
	(β = 0.5)	0.01481	0.05679	0.02163
	(β = 0.9)	0.00740	0.02592	0.00987
190	(β = 0.0)	0.00493	0.02469	0.00823
	(β = 0.2)	0.00740	0.03703	0.01234
	(β = 0.5)	0.00493	0.02469	0.00823
	(β = 0.9)	0.00493	0.02469	0.00823

4.2.3 Determining the parameters for the hybrid interest score

A hybrid approach – Hybrid Interest Analysis method is proposed for recommending products during news browsing by adopting and modifying the well-known NMF-based (CF-based) and LDA-based (CBA-based) methods. The proposed approach derives the interest scores by combining the NMF-based interest scores (*NMFS*), product topic-based interest scores (*PTS*) and expanded product topic-based interest scores (*EPTS*). The product topic-based interest score *PTS* is derived based on the LDA analysis on product contents. Term expansion is conducted to enrich the content of the products. The expanded product topic-based preference score is derived based on the LDA analysis on news/expanded product contents with term expansion. Three parameters w_{nmfs}, w_{epts} and w_{pts}, are utilized to adjust the importance of the normalized interest scores of *NMFS*, *EPTS* and *PTS* for deriving the hybrid interest score HIS. The three parameters represent the influence on three dimensions of target user's interest. In this experiment, we set the latent factor number F as 140, α as 0.7, topic number H as 150, β as 0.2, and K as 180. Then, different combinations of parameters w_{nmfs}, w_{epts} and w_{pts} were compared for the proposed hybrid method. The results of the combinations of parameter values are shown in Fig. 2; they indicate that the parameter combinations with a high value of w_{nmfs} can achieve better recommendation results.

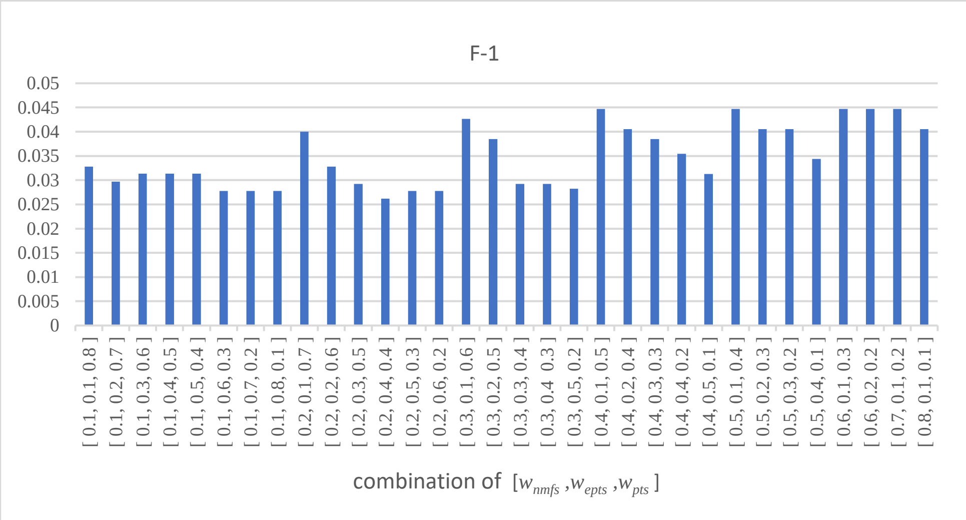

Fig. 2. The F1 score based on overall combinations of parameters $[w_{nmfs}, w_{epts}, w_{pts}]$.

The latent factors that influence the product preferences hidden in the historical data are detected by means of a matrix factorization modeling. The experiment result shows that the best performance can be achieved when $w_{nmfs} = 0.6$, $w_{epts} = 0.1$ and $w_{pts} = 0.3$. w_{epts} is the weight of *EPTS*, which is the interest score derived from the LDA analysis on news/expanded product contents with term expansion. The result shows that integrating *EPTS* based on term expansion (by setting $w_{epts} = 0.1$) can help improve the recommendation quality.

4.3 Online Experimental Results

Conducting on-line experiments in a real website (https://www.niusnews.com/) should be cautiously to avoid losing and disturbing users. Such limitations restrict the number of methods that can be compared on-line. We implemented the recommendation methods on the website to carry out online product recommendations. We compared the proposed online recommendation approaches (URD-ONHI and WRD-ONHI) with the three approaches: consideration of the recommendation diversity and hybrid interest analysis (URD-HI), consideration of the online hybrid interest analysis (ONHI), and consideration of the hybrid interest analysis (HI).

The HI method combining the well-known NMF-based (CF-based) and LDA-based (content-based) methods is adopted to alleviate the issues of data sparsity and cold-start users/products. The NMF-based method is adopted by considering news/product latent factor vectors, while the LDA-based method is adopted based on product/expanded-product latent topics. The HI method is a modified baseline approach for recommending products during news browsing.

The experimental results are shown in Fig. 3. The results show that our proposed online product recommendation methods URD-ONHI and WRD-ONHI, which combine online hybrid interest analysis and recommendation diversity, can achieve a higher recommendation quality (CTR) than by using other methods. The modified baseline – HI integrates NMF-based (CF-based) and LDA-based (content-based) methods to alleviate the cold-start and data sparsity issues. However, the HI method still did not perform well because of lacking enough historical data to derive users' product preferences. The CTR of ONHI (Online Hybrid Interest Analysis), which considered target user's current news interests, is higher than the HI. Therefore, the consideration of users' current online news interests is important for recommending products online. The CTR of URDHI (User Recommendation Diversity and Hybrid Interest Analysis) is also higher than the HI, implying that considering recommendation diversity can improve CTR. Moreover, the website has cold start and data sparsity issues for recommending products. Accordingly, The CTR can be enhanced by integrating the analysis of hybrid interest, online interest and recommendation diversity.

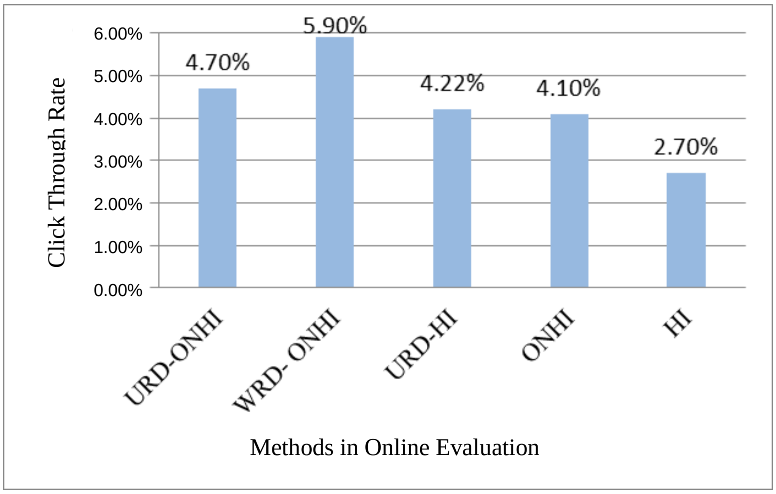

Fig. 3. The Click-Through Rate of the methods compared in online evaluation.

Interestingly, the proposed methods, URD-ONHI and WRD-ONHI, which integrate ONHI and diversity analysis, can perform better than the ONHI and HI methods without diversity analysis. The result indicates that recommendation diversity helps to explore the latent interests of users and enhance the CTR for the news website. For cold-start users, considering recommendation diversity can recommend more diverse products and raise the opportunity of recommending potential interested products.

Our proposed method adopts two strategies to integrate online hybrid interest analysis and diversity analysis: URD-ONHI and WRD-ONHI. The URD-ONHI method combines user preference diversity and online hybrid interests, while the WRD-ONHI method uses a weighted combination of recommendation diversity and online hybrid interests. The result shows that WRD-ONHI can achieve the highest recommendation quality (CTR). The WRD-ONHI method sets the weight of diversity as 0.8 and has a higher CTR than the

URD-ONHI method which adopts user preference diversity analysis. The average user preference diversity of URD-ONHI is 0.4. The reason is that the user preference diversity analysis may not be very effective because there are very few product clicking records for an analysis of the diversity of user preferences. Moreover, most of the products on the investigated website belong to creative and novel types of products, so users may prefer to see more diverse products. Accordingly, the WRD-ONHI method with a diversity weight of 0.8 performs better than the URD-ONHI method with an average diversity weight 0.4. Recommending more diverse products can enhance the CTR of online product recommendations. The online experiment results show that a consideration of hybrid interest, online interest and recommendation diversity can improve online product recommendation.

5. CONCLUSIONS

In this work, we have proposed a novel online product recommendation method based on the analysis of online hybrid interest and recommendation diversity. Online product recommendation is conducted for browsing news. An analysis of latent association between news and products is conducted for term expansion of products by adding related news terms to the products. Moreover, the proposed hybrid interest analysis approach derives user preferences by combining the NMF-based (CF-based) and LDA-based (content-based) user preferences. The proposed approach further adopts an online interest analysis to adjust and obtain users' online product interests more accurately, based on the currently browsing news. The proposed product recommendation model not only considers user's preferences but also takes recommendation diversity into consideration; this approach can increase the chance of identifying potential user interests on products and, consequently, improve the click through rate of online product recommendations.

Our proposed approach was evaluated on a news website – NiusNews. Our online evaluation shows that our proposed approach can alleviate the cold-start issue and enhance the click-through rate of online product recommendations. In our online experiment, the results show that the combination of hybrid online interests and recommendation diversity can achieve the highest CTR of online product recommendation. Consideration of the online interest analysis can give better results than the method that does not take into account the target user's current news interests. Accordingly, the consideration of user's current news interests is important for recommending products online. The results also imply that recommendation diversity is beneficial to discover users' latent interests and enhance the CTR of online product recommendation for a news website. With the proposed novel online product recommendation approach, the news website can enhance the exposure of products and further increase the number of users for purchasing and clicking the products.

Website users often show a keen interest in popular news articles and products. With sufficient product click data, the recommendation quality can be further improved by recommending popular products. Moreover, our current implementation only takes into account login users. It is the anonymous user who contributes to most of the page viewings of websites. Thus, a significant challenge is to perform online product recommendations for anonymous users based on the effectiveness and the efficiency of analyzing user preferences and system performance. Future work is to inspect the issues of analyzing online user preferences and recommendation diversity for anonymous users.

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