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Recommendation system development for fashion retail e-commerce

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ABSTRACT

This study presents a real-world collaborative filtering recommendation system implemented in a large Korean fashion company that sells fashion products through both online and offline shopping malls. The company's recommendation environment displays the following unique characteristics: First, the company's online and offline stores sell the same products. Second, fashion products are usually seasonal, so customers' general preference changes according to the time of year. Last, customers usually purchase items to replace previously preferred items or purchase items to complement those already bought. We propose a new system called K-RecSys, which extends the typical item-based collaborative filtering algorithm by reflecting the above domain characteristics. K-RecSys combines online product click data and offline product sale data weighted to reflect the online and offline preferences of customers. It also adopts a preference decay function to reflect changes in preferences over time, and finally recommends substitute and complementary products using product category information. We conducted an A/B test in the actual operating environment to compare K-RecSys with the existing collaborative filtering system implemented with only online data. Our experimental results show that the proposed system is superior in terms of product clicks and sales in the online shopping mall and its substitute recommendations are adopted more frequently than complementary recommendations.

1. Introduction

Recently, e-commerce has become an important channel for many retail businesses. The eMarketer (2017), an e-business marketing company, estimates worldwide retail e-commerce sales will increase from \$2.29 trillion in 2017 to \$4.48 trillion by the end of 2021. In spite of its success, e-commerce has a significant market limitation. While there is staff available to assist customers in offline stores, there is no staff to help buyers in online stores. In order to overcome this limitation, online stores provide various features, for instance, a "search and directory" to assist customers. Although these services can enhance purchase experience, online customers can only take advantage of them if they use them.

Recommendation systems are an innovative solution that overcomes the limitations of e-commerce services. Recommendation systems use customer behavior and information, and product information to identify customer preferences, and proactively suggest products that they are likely to buy. Many studies have been conducted to develop such recommendation systems and many practical systems have been successfully implemented in various businesses (Choi et al., 2012; Koren, 2009a; Linden et al., 2003; Wei et al., 2016).

Recommendation systems used in e-commerce have been developed to reflect unique domain characteristics (Portugal et al., 2015; Schafer et al., 1999; Sivapalan et al., 2014; Wang and Zhang, 2013; Zhao et al., 2015). This study aims to develop a recommendation system for a company – referred to as Company K in the following discussion – that sells fashion products through an online shopping mall as well as through offline shopping outlets. Company K has an average of 5 million members and sells around 40,000 products per year in the online shopping mall. There are around 1.5 million clicks and around 10,000 transactions per month. Company K also operates about 1300 offline stores in Korea and sells around 20,000 products per year.

Company K possesses the following unique operation environment:

(1) When purchasing fashion products, customers buy to replace or supplement their previous purchases, or preferred products.
(2) Demand for fashion products generally decreases over time due to seasonal changes. In general, people buy fashion products appropriate to the current season. Such a pattern

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in purchases is found frequently in fashion items, while purchases of other products like books and music do not display any significant relationship with the changing of the seasons.

(3) Fashion products can be sold in both online and offline stores. Most previous studies focus mainly on online stores. However, online and offline stores usually sell the same fashion products. Usually, customers first decide on potential purchases at online stores and then purchase them online.

Company K has already recognized that recommendation systems are a key success factor for its business and has used a system that employs a conventional item-based collaborative filtering for its online shopping mall. However, Company K wants a new recommendation system to be developed to reflect the fashion industry-specific characteristics discussed above. In the development of this new recommendation system, we address the following recommendation requirements.

First, the recommendation system should reflect the decline in preference for fashion products over time. Previous temporal recommendation studies assume that the intensity of preference decreases as time passes (Campos et al., 2013; Ding and Li, 2005; Ding et al., 2006; Hong et al., 2012; Koren, 2010; Larrain et al., 2015; Lathia et al., 2010; Xu et al., 2016). That is, these studies assume that recent preference-indicating behaviors, such as clicks or purchases for the same product, reflect stronger preferences than older ones. However, this study focuses on the decline in preference for fashion products which occurs over time following their release.

Second, the recommendation system needs to combine both offline customer preference data and online customer preference data. Purchases in offline shopping malls reflect the preferences of offline customers. Therefore, combining offline purchase data with that of online customers can improve the performance of online recommendation. Some researchers emphasize that online and offline information can help predict customer preferences, but have not applied this finding to the development of recommendation systems. (Cheema and Papatla, 2010; Dzyabura et al., 2016). Only a few studies consider the problem of integrating online and offline shopping mall data into recommendation systems (Adomavicius and Tuzhilin, 2001; Cantador et al., 2015; Kim et al., 2016; Nilashi et al., 2014a). The most important reason seems to be that it is difficult to find a domain where it is important to integrate both online and offline preference data. However, fashion products are sold through both online and offline stores and therefore preference data can be collected from these two stores. This study therefore aims to propose a way to combine online and offline preferences for recommending fashion products.

Third, customer purchase intent should be reflected by the recommendation system. When buying a product, the customer chooses an item that can be used with, or an item that replaces something that he or she had previously preferred. In this paper, the former is called a *complementary product*, and the latter is called a *substitute product*. This study proposes a method that recommends complementary products and substitute products separately using product category information.

2. Related work

2.1. Collaborative filtering recommendation systems

Recommendation systems are one of the most important applications in big data analytics and have performed excellently for numerous businesses (Bobadilla et al., 2013; Shi et al., 2014; Su and Khoshgoftaar, 2009). Many online companies, such as Amazon (Linden et al., 2003), Netflix (Koren, 2009a), Google (Das et al., 2007), and Facebook (Shapira et al., 2013), are using recommendation systems as part of their business.

Recommendation systems are broadly categorized into content-based systems and collaborative filtering systems. Content-based systems recommend products which have content similar to products preferred by a customer. Content-based systems use content to build a model for recommendation, but this study does not use this approach. Instead, we use a product content model to improve the collaborative filtering system as discussed below.

On the other hand, collaborative filtering systems are popular in business as well as in research because of their simplicity and its high performance levels (Bobadilla et al., 2013; Shi et al., 2014; Su and Khoshgoftaar, 2009). Collaborative filtering systems are based on customer ratings of products regardless of the availability of product content. Two approaches have been developed for collaborative filtering systems. User-based collaborative filtering systems recommend products which have been chosen most in the past by similar customers (Breese et al., 1998; Herlocker et al., 2004; Konstan et al., 1997; Resnick et al., 1994; Sarwar et al., 2001; Shardanand and Maes, 1995). For any two given customers, their similarity is calculated based on their ratings of products that both have rated. Correlation (Konstan et al., 1997; Shardanand and Maes, 1995) and cosine similarity (Breese et al., 1998; Sarwar et al., 2001) are commonly used as measures of similarity. Default voting, inverse user frequency, case amplification and weighted-majority prediction are employed to aggregate similar users' ratings (Breese et al., 1998; Delgado and Ishii, 1999).

Item-based collaborative filtering systems analyze similarities between products and recommend products that are most similar to products selected by the customer (Shardanand and Maes, 1995). The similarity between products is computed by functions, such as cosine similarity and conditional probability based similarity (Karypis, 2001). The advantage of this approach is that it can precompute similarities between products and can be presented as soon as a customer clicks or buys a product.

A typical collaborative filtering system focuses on a user-item matrix that represents customer clicks or purchases of products in a matrix format. However, recent collaborative filtering systems improve their performance by using additional information related to users and products and information related to the interaction of users and products (Shi et al., 2014).

2.2. Recommendation systems for fashion industry

Recommendation systems have usually been developed for specific domains such as movies, books, music, etc. Several previous studies focus on the unique characteristics of the fashion industry. We classify them into the following three groups.

First, a number of studies concentrate on assigning fashion products with specific attributes. Quanping (2015) integrates fashion attributes, such as style, color, material, quality, brand and seasonality, into a collaborative filtering recommendation algorithm. Experimental results demonstrate that the collaborative filtering recommendation system which integrates these attributes outperform conventional methods. Nguyen et al. (2014) suggests a fashion recommendation system which exploits implicit feedback such as clicks, wants, purchases to generate implicit user preference scores, together with price, popularity and recentness to modify user preference scores.

Second, some research focuses on recommending a set of products, not individual products. Hu et al. (2015) suggest a functional tensor factorization based recommendation system that suggests a set of fashion products instead of single product. A similar approach which uses one-class collaborative filtering has been suggested (He and McAuley, 2016). Shen et al. (2007) suggest a scenario-oriented fashion recommendation system, focusing on the context of wearing fashion products.

Finally, some research focuses on suggesting products interactively via multimedia systems. Chao et al. (2009) propose a recommendation system used in a smart mirror system that provides virtual fitting in offline shops. Tu and Dong (2010) suggest a multimedia mining based fashion recommendation system which helps customers to find their most suitable fashion products. Tu and Dong combine three different models: a interaction and recommendation model; an evolutionary hierarchical fashion multimedia mining model; and a color tone analysis model in their system.

Our proposed system recommends products based on classification information without considering all product information. Classification information is not generally used to generate a recommendation model, but it is used to distinguish recommended products as substitute or complementary products. The proposed system recommends products based on customer preferences for individual products, but it implicitly considers product groups.

2.3. Expanding item-based recommendation reflecting domain characteristics

2.3.1. Decaying effect of preference

Fashion products are sensitive to seasonal changes. People generally buy products that are appropriate for the season. For example, people buy winter season products during winter time. This implies that product preference decreases over time after fashion products are released. It is beneficial to reflect this seasonal effect when developing a recommendation system for fashion products.

This study adopts the temporal recommendation system approach, which assumes that most recent preference behavior data expresses a higher level of accuracy of customer preference than past behavior. Previous studies demonstrate that collaborative filtering systems based on temporal recommendation algorithms have improved performance (Campos et al., 2013; Ding and Li, 2005; Ding et al., 2006; Hong et al., 2012; Koren, 2010; Larrain et al., 2015; Lathia et al., 2010; Li et al., 2015; Lu and Lee, 2015; Wang et al., 2016; Xu et al., 2016). Ding and Li (2005) suggest an item-based collaborative filtering computing the time weights for different products based on the temporal deviation. They define the decay function as a monotonic decreasing function, which reduces uniformly with time t and the value of the time weight lies in the range (0, 1). Lathia et al.(2009) view the issue as a time-dependent, iterative prediction problem and use temporal information to adjust values by the number of k of neighbors to be in *k-NN* based collaborative filtering. Koren (2009b) uses temporal information to detect changes in the user's preferences in a model-based collaborative filtering implemented by the matrix factorization model. This study builds on the work of Ding and Li and employs a *monotonous decay function* to reflect preference decrease over time.

2.3.2. Combining purchase and click data

This research aims to integrate customers' click data and purchase data in a collaborative filtering system. The multi-criteria recommendation system research (Adomavicius and Kwon, 2007; Jannach et al., 2012; Lee and Teng, 2007; Nilashi et al., 2014a) is similar to our approach, because it views offline customer purchase data as additional ratings. Adomavicius and Kwon (2007) first proposed a multi-criteria recommendation problem, while Lee and Teng (2007) use a skyline query technique to solve the multi-criteria recommendation problem, because they regard the multi-criteria recommendation problem as an optimization problem. Jannach et al. (2012) suggest a support vector regression (SVR) to combine multiple ratings demonstrating that the SVR outperforms single-rating algorithms. Nilashi et al. (2014b) show that combining dimensionality reduction and Neuro-Fuzzy techniques can improve recommendation quality significantly. However, only a few studies directly address the integration of online and offline preferences (Cheema and Papatla, 2010; Dzyabura et al., 2016; Kim et al., 2016). Dzyabura et al. (2016) use offline preferences for predicting online preferences.

Although this research does not directly address the issue of recommendation, it demonstrates that online information can be used for the prediction of offline preferences. Cheema and Papatla (2010), and Kim et al. (2016), propose friend recommendation using offline information (e.g., place visit history) and online information (e.g., friends' relationship), but our research additionally addresses information related to preference. The recommended method developed in this study is based on the method proposed by Cheema and Papatla (2010) and Dzyabura et al. (2016), who proposed a recommendation system that uses offline sales data to improve the performance of recommendation system developed using online data. In this study, the same products are available in online and offline stores, but online and offline customers are different, and there is no information that can be used to link them to each other. For this reason, our recommendation system builds on item-based collaborative filtering.

2.3.3. Product information

Product information (e.g., category) can provide an additional opportunity for improving recommendation performance (Shi et al., 2014). Moshfeghi et al. (2009) suggests a collaborative filtering system for movie recommendation which uses the underlying semantics of movies as well as user rating. Singh and Gordon (2008) suggest a model based collaborative filtering system for movies, called collected matrix factorization (CFM). They combine the conventional user-item matrix with the matrix containing item information (e.g., a movie genre matrix). CFM reduces the sparsity problem in the conventional user-item matrix and enhances effective latent factors. Similarly, Zhu et al. (2007) suggest a document recommendation system that uses a joint matrix factorization approach. Hong et al. (2012) propose a recommendation system that exploits product taxonomy to capture the user's preferences over products belonging to different category. Hung (2005) advocates a product recommendation system after classifying customers into three addictive categories: item addictive, brand addictive, and hybrid addictive. These studies did not utilize product category information to reflect purchase intentions, but we use product category information in our recommendation system. The proposed system first generates recommended products regardless of these types, and then recommends two set of products using product category information.

3. Method

3.1. Data preparation subprocess

Our system generates a product list, product metadata, purchase history data (offline) and click history data (online). First, the system constructs a *product list* from the online shopping mall database and generates product metadata, which includes a product code (individual and group code), gender type (male, female, unisex), product status (e.g., active and inactive), sale type (e.g., general sale and set sale), product type (clothing, shoes, etc.), and a production year. If any product does not activate metadata, it is excluded from the product list because metadata plays important role in the process. Second, the system constructs a *purchase history dataset* from the offline shopping mall database. Each record contains a customer identifier, a product identifier and the number of days since the product's first release. Finally, the system constructs a *click history dataset* from the web log database. Each record contains a personal computer identifier, a customer identifier, a product identifier and the number of days since release.

When a customer logs on to the shopping mall, the customer identifier becomes the user identifier; otherwise the customer identifier is decided as follows. If a computer has only been used to log onto the shopping mall by a single customer, the computer identifier is also used as the customer identifier. On the other hand, if many customers login into the shopping mall via one computer, the personal computer identifier is used as the customer identifier.

3.2. Time-discounted association score calculation subprocess

Suppose that a dataset consisting of n customers ($C = \{c_1, c_2, \ldots, c_n\}$P) and m products ($P = \{p_1, p_2, \ldots, p_m\}$) is obtained. An n × m customer-product matrix, R, is created based on the customers' ratings on specific products. An element of R,$e_{i,j}$, which represents rating of the ith customer and the jth product, is 0 if the customer does not purchase or click a product, or a *time discounted rating value* if the customer purchases or clicks a product. The *time discounted rating value* of product k is defined as:

$$t_k = 1 - \frac{d_k}{D} \tag{1}$$

where d_k is the number of days after the release of product k, and D is the maximum number of days considered for the life span of product k. Korea has four distinctive seasons and people change fashion products according to season. Once a fashion product is introduced to the market, its popularity usually decreases over the year, and it is generally replaced by a substitute fashion product in the same or similar category in the following year. Domain experts are convinced that the fashion products have varied life cycles. While some products are sold consistently over the year, other products are sold during a specific time period. Products have been clustered by using their monthly sales data with a k-means clustering algorithm. Referring to the clusters, the domain experts set different D for products in the same cluster.

In order to find candidate products for recommendation, a measure, called *association score*, is computed on the basis of cosine similarity. Let v be a product purchased or clicked by the customer and let u be one of the candidate products for recommendation. Each customer's purchase or click vectors $\vec{v}$ and $\vec{u}$ are the vth and uth columns of R. The cosine similarity between these two vectors is defined as

$$\mathrm{sim}(\mathrm{v},\mathrm{u}) = \cos(\vec{v},\vec{u}) = \frac{\vec{v}\vec{u}}{||\vec{v}||_2||\vec{u}||_2} \tag{2}$$

where '·' denotes the vector dot-product operation. If both products are purchased or clicked together by each customer, the cosine similarity between them is high; otherwise it is low (Karypis, 2001). This approach eliminates frequently clicked or purchased products being recommended to the customers.

Since the recommendation system recommends for a given product, vector $\vec{v}$ is the same for all recommending products. Therefore, after removing the left part of denominator of the cosine similarity from the Eq. (1), a measure, called *association score*, is defined as

$$\mathrm{association}(\mathrm{v},\mathrm{u}) = \frac{\vec{v}\vec{u}}{||\vec{u}||_2} \tag{3}$$

For product v, the click association score, $\mathrm{association}(\mathrm{v},\mathrm{u})_{click}$, is calculated using the online shopping mall dataset, and the purchase association score, $\mathrm{association}(\mathrm{v},\mathrm{u})_{purchase}$, is calculated using the offline shopping mall dataset. The combined measure, called the *recommendation score,* is defined as

$$\mathrm{rec}(\mathrm{v},\mathrm{u}) = \mathrm{association}(\mathrm{v},\mathrm{u})_{click} + w \cdot \mathrm{association}(\mathrm{v},\mathrm{u})_{purchase} \tag{4}$$

where w is a weight for association score of purchase. The weight w is chosen by conducting simulated recommendations using historical data.

3.3. Recommendation generation subprocess

For a product x in I ($x \in I$), the recommendation system generates two sets of top-N candidate recommendations – one as a substitute and the other for complementary recommendations. First, the recommendation system calculates recommendation scores between product x and all other products in I using the recommendation score calculation method discussed above. Then, the recommendation system generates a set of top-N substitute recommendation products by choosing the N most recommendable products in the same category with product x based on recommendation scores. Finally, the recommendation system generates a set of top-N complementary recommendation products by choosing the k most recommendable products, which are not in the same category as product x based on recommendation scores. Product code, product group code, product type code and gender type are used as category information. Whenever a customer clicks a specific product on the online shopping mall, both the substitute and complementary top-N recommendation products are displayed to the customer.

4. Implementation

A recommendation system, called K-RecSys, was developed using ORACLE PL/SQL. The system runs on IBM Flex 240 (CPU 16 core (8 core *2), RAM 196 GB, HDD 1.2 T). The overall system architecture of K-RecSys is illustrated in Fig. 1.

Raw data are collected from the offline shop management system and online shopping mall system. Offline purchase history data spanning one year before the recommendation process begins is collected from the Enterprise Data Warehouse (EDW). Online click history data spanning two months before the recommendation process begins is collected from Web Log, and product metadata data are collected from the Product Metadata Repository. BIGCRM stores purchase history data, click history data and product metadata. For each product, K-RecSys generates substitute and complementary recommendation product sets and stores them as Recommendation Data. Finally, the recommendation products are copied into the repository of the company's shopping mall system, called Recommendation Repository.

The recommendation workflow is managed by Informatica Workflow Manager. Informatica executes the recommendation server data entry process, runs the recommendation engine, and updates the recommendation list. Every day the Informatica Workflow Manager executes the recommendation process, which takes about two and half hours to complete. We also run the existing system for comparison. Its implementation is based on conventional item-based collaborative filtering using only online click data. Basically its recommendation process is similar to our proposed collaborative filtering system. However, it differs from K-RecSys. First, the system only considers click data for training. However, K-RecSys considers online click data as well as offline purchase data. Second, the system does not consider the decrease of preference over time, while K-RecSys regards it as part of the model. Finally, the system does not consider product data for

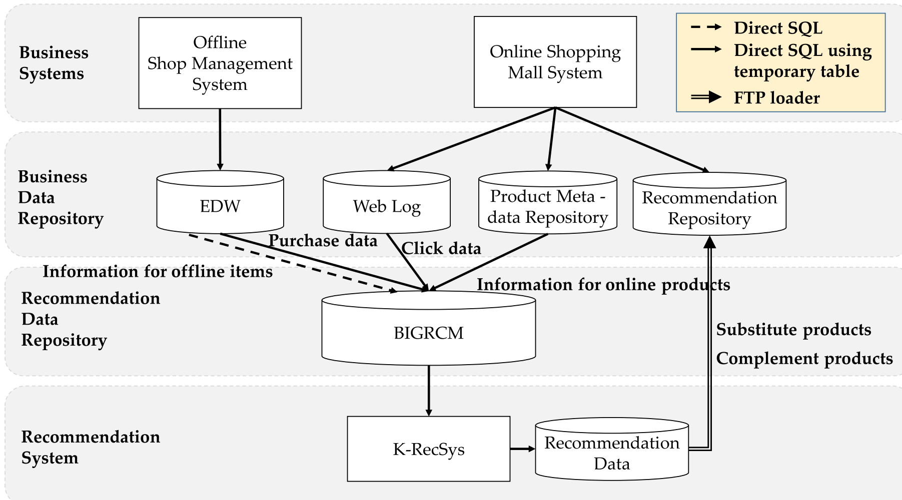

Fig. 1. K-RecSys Architecture.

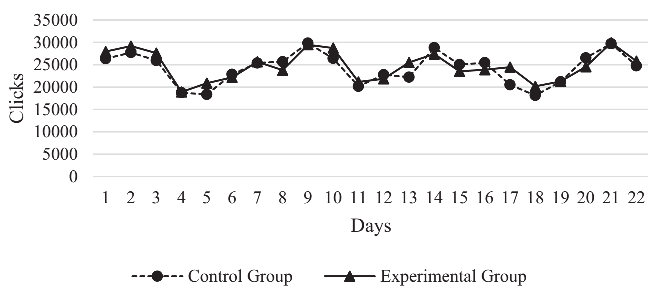

Fig. 2. Daily Clicks by User Group.

generating recommendation; however, K-RecSys suggests two sets of recommendation by considering product category.

5. Experimental design

For the experiment, K-RecSys was implemented into Company K's shopping mall in addition to the existing system. Then, the A / B test was conducted over three weeks (May 20, 2015–June 1, 2015) to compare the performance of K-RecSys with the existing recommendation system. In the following discussion, customers who are recommended by the existing system are referred to as the *control group*, and those who are recommended by K-RecSys are referred to as the *experimental group*.

The experiment was conducted as follows. Each day the current recommendation system and K-RecSys generated a set of recommendations for each product. The customer was able to view product information by browsing product categories or by searching products. When a customer viewed details of a product from the product list, the online shopping mall system randomly displayed eight recommendations generated by one of the recommendation systems. In addition, the customer could request additional products – up to 40 products in total – by clicking on the sliding menu. K-RecSys suggested 20 substitute and 20 complementary products respectively, whilst the existing system recommended 40 products without discrimination. If a customer clicked on, or purchased a product from the recommended products, this was recorded for further analysis. Finally, we analyzed the impact of different recommendation systems on clicks and purchases, and analyzed the impact of substitute and complementary recommendations on the customer's clicks and purchases.

6. Results

6.1. Click results

A total of 1,076,394 clicks occurred during the experimental period in the online shopping mall. From amongst this number, the control group clicked 532,598, which is 49.5% of all clicks, and the experimental group clicked 543,796, or 50.5% of all clicks. Fig. 2 illustrates daily click trends during the experimental period and Table 1 statistically displays the daily clicks by the two user groups.

According to the Fig. 2 and Table 1, there is no significant difference in daily clicks between two user groups. This is because the two user groups not only click on products by recommendation, but also click on products in other ways (e.g., search). Therefore, we must compare how many of these clicks are caused by recommendations. We evaluated the number of clicks by recommendation with the total clicks in order to analyze which system provided better recommendations. For the control group, 5.8% of all clicks were generated from recommendations, while for experimental groups 9.9% of all clicks were generated from recommendations. Fig. 3 illustrates the percentage of clicks over all clicks due to recommendations on a daily basis, and indicates that the performance of K-RecSys is consistently better than the existing system. This proves that the recommendation of K-RecSys is superior to the existing system. From the results of this experiment, it can be concluded that the recommendations of K-RecSys are better than those of the existing system.

K-RecSys suggests both substitute and complementary recommendations to users. Interestingly, experimental results confirm that clicks from substitute recommendations are more likely to be accepted than those from the complementary regimen. On average, 77.2% of the experimental group clicks came from substitute recommendations, while 22.8% came from complementary recommendations. Fig. 4 demonstrates the daily click ratios between the two types of recommendations. The results illustrate that substitute recommendations are consistently clicked more often than complementary recommendations.

6.2. Purchase results

Clicks may not directly lead to purchase decisions. Therefore, it was a matter of interest to investigate the impact of the system on real purchases. A total of 7476 purchases occurred at the online

Table 1
Statistics of Daily Clicks by User Group.

	Average	Deviation	Min	Max
Control Group	24,209	3570	18,125	29,838
Experimental Group	24,718	3281	18,906	29,921
Total	48,927	6637	37,669	59,634

Table 2
Statistics of Daily Purchases by User Group.

	Average	Deviation	Min	Max
Control Group	169.6	47.8	99	294
Experimental Group	170.2	48.1	87	261
Total	339.8	93.1	193	555

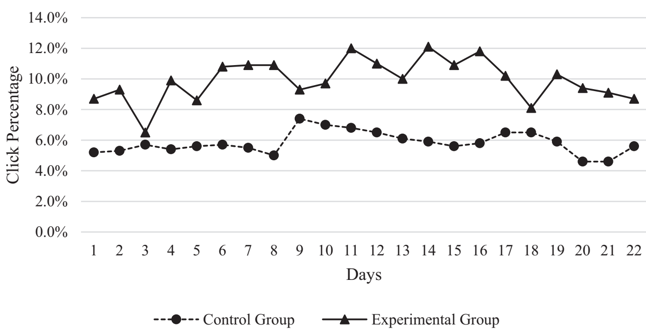

Fig. 3. Daily Clicks by User Group.

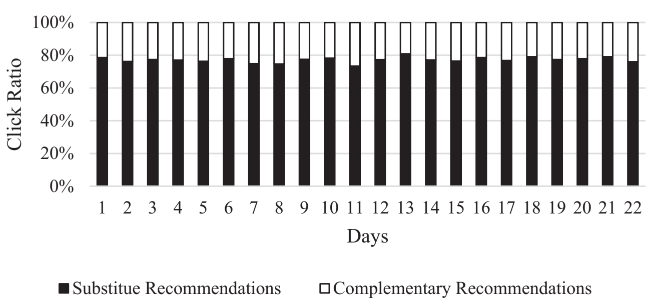

Fig. 4. Daily Click Ratio by Recommendation Type.

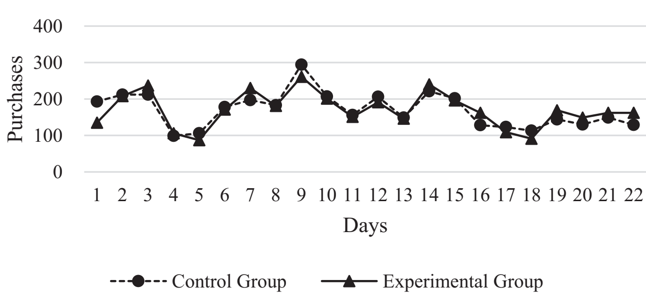

Fig. 5. Daily Purchases by User Group.

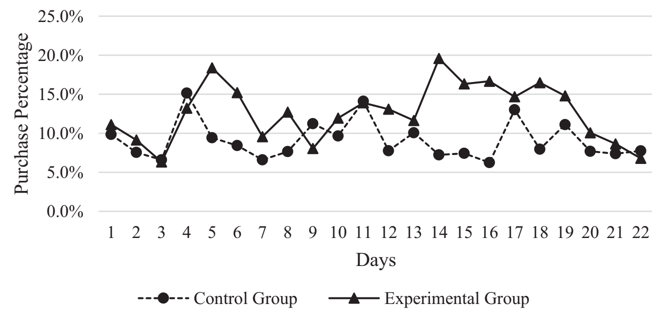

Fig. 6. Daily Purchase Percentage by User Group.

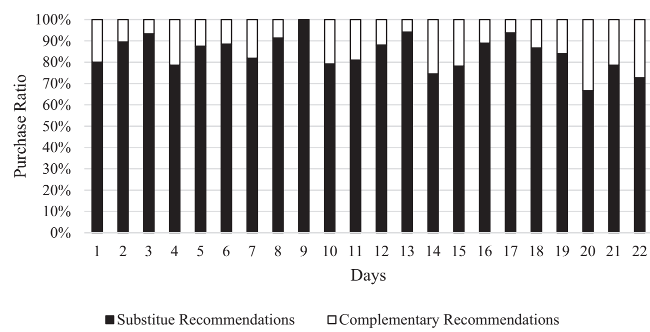

Fig. 7. Purchase Ratio by Recommendation Type.

shopping mall during the experiment period. Among them, the control group purchased 3731 times, which is 49.9% of all purchases, and the experimental group purchased 3745 times, which is 50.1% of all purchases. Fig. 5 illustrates daily purchases trends during the experimental period and Table 2 shows statistics of daily purchases by two user groups.

As displayed in figure and table, there is no significant difference in daily purchases between two user groups. This is because the two user groups purchase products not only by recommendation, but by other modes (e.g., search). We also compared the percentages of products purchased from the recommended products by the users of the control group and experiment group.

Overall, the percentage of purchases which occur as a result of the recommendations of the experimental group is slightly higher than that of the control group. The rate of purchasing through the recommendation of the experimental group is 12.3%, while that of the control group is only 8.9%. Interestingly, the ratios of products purchased through the recommendations of the two groups are greater than the ratios that the two groups clicked through the recommendations. However, the daily purchasing ratios show that the differences between the two groups are not consistent during the experimental period (see Fig. 6).

The experimental results also show that substitute product recommendation is more effective than complementary product recommendation. On average, 84.4% of purchases were from substitute recommendation products, and 15.6% from purchases of complementary recommendation products. The ratios of substitute recommendation products in purchases is greater than those in clicks. However, as shown in Fig. 7, this result was not consistent over the experiment period.

7. Conclusion

In this study, we proposed a new method of recommending fashion products to customers by extending the existing collaborative filtering method to reflect the characteristics of fashion products. First, we considered the fact that fashion products are sold online and offline, and preferences for fashion products also appear online and offline by using online click data and offline purchase data to generate recommendations. Second, customer preference for fashion products generally tends to decrease over time. To reflect this fact in the recommendation method, we have proposed a decay function that decreases the intensity of preference over time. Finally, the product which the customer wishes to purchase is a product that replaces or supplements the product that the customer preferred before. We have used product information to make recommendations that reflect this purchase intention. We developed a new recommendation system to reflect these approaches.

To verify the performance of this system, we applied it to an actual online shopping mall. In the experiment, we compared the performance of the recommendation of the new system with that of a typical collaborative filtering system. Our experimental results show that the proposed system generates better performance than the typical collaborative filtering system in terms of click and purchase. Furthermore, the results of this experiment showed that substitute recommendations are consistently better than complementary recommendations for clicks and purchases. Despite these results, these experiments are limited in that they cannot explain the effects of the use of online and offline data and the effects of preference decline over time.

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