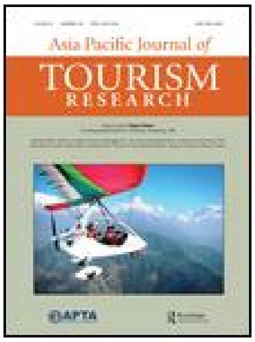

Asia Pacific Journal of Tourism Research

ISSN: 1094-1665 (Print) 1741-6507 (Online) Journal homepage: https://www.tandfonline.com/loi/rapt20

A recommender system based on personal constraints for smart tourism city

Il Young Choi, Young U. Ryu & Jae Kyeong Kim

To cite this article: Il Young Choi, Young U. Ryu & Jae Kyeong Kim (2019): A recommender system based on personal constraints for smart tourism city, Asia Pacific Journal of Tourism Research, DOI: 10.1080/10941665.2019.1592765

To link to this article: https://doi.org/10.1080/10941665.2019.1592765

Published online: 16 Mar 2019.

ASIA PACIFIC JOURNAL OF TOURISM RESEARCH
https://doi.org/10.1080/10941665.2019.1592765

A recommender system based on personal constraints for smart tourism city*

Il Young Choi[a], Young U. Ryu[b] and Jae Kyeong Kim[a]

[a]School of Management, Kyung Hee University, Dongdaemun-gu, Seoul, Korea; [b]School of Management, University of Texas at Dallas, Richardson, TX, USA

ABSTRACT

In a smart tourism ecosystem, travel communication websites play a critical role in choosing destinations and hotels. This research suggests a travel recommender system for automating word-of-mouth (WOM) effects and providing personalized travel-planning services to tourists. Collaborative filtering (CF)-based recommender systems have been extensively employed for personalization services in diverse areas; the basic principle of CF is WOM communication. This research proposes a travel recommender system that helps a tourist build his/her personalized travel plan based on CF and constraint satisfaction filtering. Constraint satisfaction filtering is adopted to profile a tourist's needs and circumstances. For this purpose, this research modifies the existing constraint satisfaction method to an approximate constraint satisfaction filtering method that incorporates indifference intervals into constraints. We build a prototype system and a benchmark system to evaluate the effectiveness, usability, and novelty of the proposed travel recommender system. The experimental results demonstrate a methodology for performing personalized tourist's travel planning and automating WOM communication outperforms the benchmark system.

KEYWORDS

Smart tourism; smart tourism city; recommender system; travel recommender system; travel planning; travel-planning service; travel package; approximate constraint satisfaction; constraint satisfaction; word-of-mouth communication

1. Introduction

Due to the rapid growth of smart tourism technologies, such as cloud computing, big data, Internet of things applications, and social networking services recently, the concept of a smart tourism city emerges as a means to provide value-added services to tourists (Gretzel, Sigala, Xiang, & Koo, 2015; Gretzel, Zhong, & Koo, 2016). A smart tourism city can enhance tourists' experiences by analyzing travel patterns and offering personalized attractions. Consequently, the satisfaction of tourists increases (Lee, Lee, Chung, & Koo, 2018).

In a smart tourism ecosystem, travel community such as TripAdvisor have a critical role not only in choosing tourism destinations (Kim & Canina, 2015; Schuckert, Liu, & Law, 2016) but also as hubs for travel planning (Cox, Burgess, Sellitto, & Buultjens, 2009; Liu, Schuckert, & Law, 2015; Schuckert et al., 2016; Schuckert, Liu, & Law, 2015). Tourists have exchanged travel information, advice, and tips on travel community. With the information and knowledge gotten from travel community, tourists can plan their personalized travels by not only saving efforts, time and money but also gaining more attractive travel options (Litvin, Goldsmith, & Pan, 2008; Rabanser & Ricci, 2005).

However, tourists often make complex decisions and substantially spend their time planning their travels because their travel plans need to consider their destination, flights, hotels, travel packages, and their time and money constraints. Abundant information about travel community websites complicates the decision-making of tourists. To solve these problems and provide tourists with better services, travel recommender systems have been introduced by major travel agencies (e.g. http://www.travelocity.com). Generally, a travel recommender system attempts to offer more

CONTACT Jae Kyeong Kim jaek@khu.ac.kr School of Management, Kyung Hee University, 1 Hoegi-dong, Dongdaemun-gu, Seoul, Korea

*Portions of this paper were previously presented in the 48th Hawaii International Conference on System Sciences, 2015.

customized travel-planning services by analyzing tourists' past travel histories. However, the system has a tendency to imitate a travel agent's role and does not consider the word-of-mouth (WOM) communication effect (Rabanser & Ricci, 2005). WOM communication has an important role in travel decision-making (Baloglu, Pekcan, Chen, & Santos, 2004; Cai, Feng, & Breiter, 2004; Gretzel & Yoo, 2008; Hernández-Méndez, Muñoz-Leiva, & Sánchez-Fernández, 2015; Li, Tung, & Law, 2017; Murphy, Mascardo, & Benckendorff, 2007; Tung & Ritchie, 2011). WOM communication has a positive impact on the destination image and destination choice (Jalilvand, 2017; Jalilvand, Samiei, Dini, & Manzari, 2012; Tham, Croy, & Mair, 2013). Online consumer reviews based on WOM communication have helped consumers to make difficult and complex purchase decisions (Bae & Lee, 2011; Park, Lee, & Han, 2007).

Collaborative filtering (CF) recommends items to target user based on the purchase histories of neighbors who have purchased almost the same items as target users. Thus, CF operates in a manner similar to WOM communication. CF has been utilized as a representative methodology in recommender systems over the last 40 years (Adomavicius & Tuzhilin, 2005; Herlocker, Konstan, & Reidl, 2000; Sarwar et al., 1998). CF and its extended hybrid methodology have been extensively employed for recommending products (books, clothes, and shoes) and contents (movies and music) of almost all areas (Park, Kim, Choi, & Kim, 2012). However, applying existing CF-based recommender systems to travel-planning services, such as selecting traveling destination, hotels, and flights has many drawbacks. The underlying basic principle of CF recommender systems is to determine a target user's preference based on the preference of similar neighbor users (Kim, Kim, & Ryu, 2009). Thus, recommending items based on the past purchase histories of the target user and other users has produced excellent results in the online market, such as movies, booth, music, books, images, online advertisements, and grocery (Choi, Oh, Kim, & Ryu, 2016; Kim, Moon, An, & Choi, 2018; Moon, Kim, & Ryu, 2013; Park et al., 2012). CF-based recommender systems for group users have been well developed (Garcia, Sebastia, & Onaindia, 2011; Kim, Kim, Oh, & Ryu, 2010; Kim, Oh, Gu, & Kim, 2011).

However, two challenges exist for adapting a travel-planning service in CF-based systems due to the difference between the characteristics of a travel-planning service and books or music. First, a travel-planning service consists of a composite product instead of a single product. A composite product indicates that travel planning includes the simultaneous selection of a destination, hotel, and attraction. Thus, an existing CF-based recommender system is not more useful for a travel-planning service. Second, travel planning is a very complicated process that needs many constraints, such as traveling period, duration, and travel cost. A constraint satisfaction filtering process is needed in existing CF-based recommender systems. This research models the requirements of each tourist as an approximate constraint satisfaction problem. Because the constraint satisfaction method is often too strict, a minor difference may have a role in changing a critical decision (Choi, Kim, & Ryu, 2015; Ryu, 1998). Therefore, this research proposes an approximate constraint satisfaction-based methodology by adopting indifference intervals to derive a flexible and robust result. A tourist's personal requirements are modeled by constraints, and an approximate constraint satisfaction method automates tourists' decision processes for choosing their personalized travel packages to enhance tourists' convenience and satisfaction. In this research, constraint satisfaction is approximated by the following two ways: First, if tourist's constraint for travel planning is not satisfied, the degree or amount of dissatisfaction is used instead of deleting the candidate tourist's package. Second, in the case of multiple constraints, the constraints are ordered according to their important factor, and the satisfying value of a more important factor is used to select a better tourist package.

In this research, we propose a CF-based travel recommender system coupled with an approximate constraint satisfaction process for automating WOM communication and offering personalized travel-planning services. For a web-based travel recommender system, a prototype is developed, and a benchmark system is also developed for comparison with our proposed system. We conduct a survey to evaluate tourists' perceptions of the recommendation results of our prototype system. Our experimental findings are summarized in the results.

2. Literature review

2.1. Travel recommender systems

As the development of economic growth, there has been a cultural and social revolution in the tourism industry. To survive in the escalated competition, travel agencies have provided extensive travel products or services. For example, Travelocity offers more than one million flights, hotels, and packages. However, tourists experience difficulty in looking for the necessary information even though the amount of travel information is substantially increased. Tourists who need information want to receive more smart services when considering their preferences. One of the techniques to solve this problem is to use the travel recommender systems, which help tourists find travel products and services that fulfill their preferences.

Some researchers focus on travel recommender systems to find personalized tourist attractions. Huang and Bian (2009) have proposed an intelligent travel system to estimate a tourist's travel preferences based on a Bayesian network, and prioritize his/her attractions by the analytic hierarchy process (AHP). Yeh and Cheng (2015) have developed an attraction recommender system using a Delphi panel and repertory grid techniques. Other studies have concentrated on offering personalized hotels (Nilashi, bin Ibrahim, Ithnin, & Sarmin, 2015; Schiaffino & Amandi, 2009), flights (Coyle & Cunningham, 2003), destinations (Gavalas, Konstantopoulos, Mastakas, & Pantziou, 2014), and travel packages (Liu et al., 2014; Lorenzi, Bazzan, & Abel, 2007; Lorenzi, Loh, & Abel, 2011) to tourists. However, previous studies overlook the effect of WOM communications in the smart city and tourism industry, which has a critical role in selecting travel destinations (Murphy et al., 2007). According to TotalMedia (2010), 25% of tourists have participated in a social networking site, such as TripAdvisor.com, to seek tourist information. Approximately 50% of US tourists have obtained tourist information by communication with their family, friends, and colleagues. Travel opinion leaders enjoy sharing their experiences with others (Litvin et al., 2008). Therefore, a travel recommender system that incorporates tourists' implicit preferences is needed.

2.2. Collaborative filtering

Collaborative filtering (CF) introduced by Goldberg et al. (1992) has been known to be one of the representative models of recommender systems. CF attempts to automate WOM recommendations received from famil, relatives, friends, colleagues, and other socially related people (Adomavicius & Tuzhilin, 2005; Herlocker et al., 2000; Sarwar et al., 1998). The idea of CF is that a high probability exists that a user will purchase items that were frequently purchased by a set of users with a high degree of similarity among the users, known as neighbors. CF has been introduced as an important method for maintaining a sustainable competitive advantage by Internet leaders such as Amazon (Linden, Smith, & York, 2003), Google (Das, Datar, Garg, & Rajaram, 2007) and Netflix (Bennett & Lanning, 2007). Thus, CF is known to be a commercially successful recommendation technique.

In general, a CF system employs three phases, as shown in Figure 1. The first phase creates a user profile using purchase history data. The second phase forms a set of users, which are known as neighbors, by comparing the degree of similarity among the users. The final phase generates a top-*N* recommendation list of items that the target user is likely to purchase.

However, a CF system poses some issues. The first issue is related to a sparsity problem. Because users purchase a very small portion of a large item set, the recommendation quality of a CF system based on the k-nearest neighbors (kNN) algorithm decreases (Balabanovic & Shoham, 1997; Sarwar, Karypis, Konstan, & Riedl, 2000). The second issue is related to a scalability problem. The kNN algorithm is often very time-consuming because a recommender system addresses the user profile, which consists of millions of users and items. The final issue is related to a new item ramp-up problem. If newly released items do not have any transaction records, a CF system cannot recommend them (Choi et al., 2016). To address these problems, numerous hybrid recommender systems to incorporate content-based filtering, demographic filtering, and other data mining techniques into CF are developed to recommend better items (Balabanovic & Shoham, 1997; Cho, Kim, & Kim, 2002; Kim, Lee, Cho, & Kim, 2004; Melville, Mooney, & Nagarajan, 2002). These hybrid approaches are successful in some applications, but selecting travel products or services that satisfy a tourist's requirements among the recommended products and services remains as the role of the tourist. Thus, to provide acceptable recommendations, travel recommender systems prepare a countermeasure for these drawbacks in the tourism domain.

3. CF-based travel recommendation with approximate constraint satisfaction

3.1. Overall View

Many tourists try to get much travel information as possible by interpersonal communication instead of

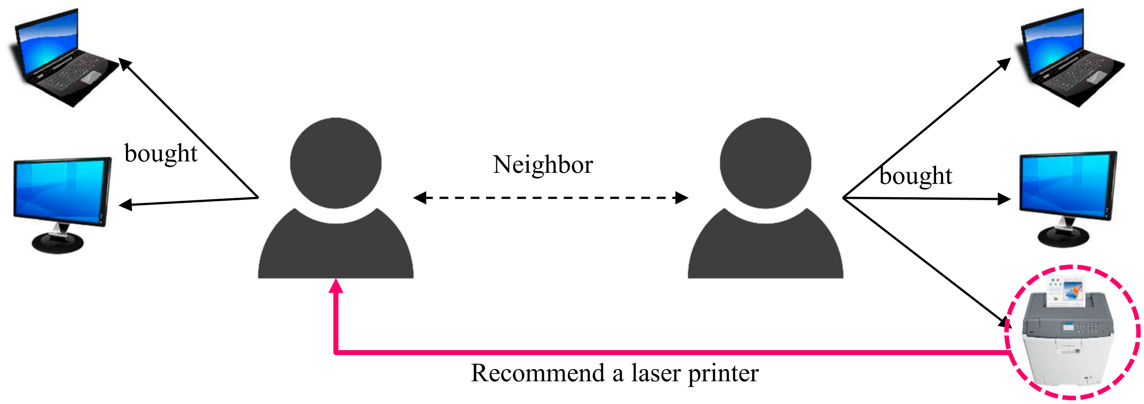

Figure 1. CF procedure.

travel brochures, travel agencies, and social media reviews (Litvin et al., 2008; TotalMedia, 2010). Travel community websites such as TripAdvisor are surrounded by a considerable amount of travel information. As a result, tourists encounter difficulty in choosing travel packages that satisfy their preferences. Information gathering and processing in this way may be time-consuming and the vast amount of information suggested by many commercial travel sites causes confusion and hinders the ability of tourists to make a decision. Therefore, we suggest a CF-based recommendation methodology that involves the automation of WOM communication to create a travel plan that is not easily constructed using other tourists' preferences and satisfies a tourist's implicit preferences using approximate constraint filtering.

The proposed methodology is composed of the following two phases in Figure 2. In the first phase, a tourist profile on destinations is created and other tourists (called neighbors) who have had a similar preference for the target tourist' destination, are identified. And then, top-*N* recommended destinations are generated as candidate destinations. In the second phase, travel items (e.g. flight and hotel) in a catalog of the candidate destinations with the target tourist's requirements (e.g. means of transport, types of hotel, and price) are compared. Here, the target tourist's requirements are named as constraints. And then the destination and the best set of items that approximately satisfy the tourist's constraints are recommended to the target tourist.

3.2. Phase 1: CF-Based filtering

The proposed CF-based filtering is divided into three steps. First, a tourist profile indicates a collection of m tourists' preference ratings on n destinations. Thus, the tourist profile is represented in the space vector of m x n matrices, $R = (r_{ij})$, where $i = 1$ to m, $j = 1$ to n, $r_{ij} \in [1, 5]$. Here, m and n are the total number of tourists and the total number of destinations, respectively, and r_{ij} is the tourist ith rating on the jth destination (1 = "very dissatisfied", 5 = "very satisfied").

Second, the similarity is computed to form the neighborhood of a target tourist. The Pearson correlation coefficient is used to compute the similarity among tourists (Kim et al., 2004; Sarwar et al., 2000).

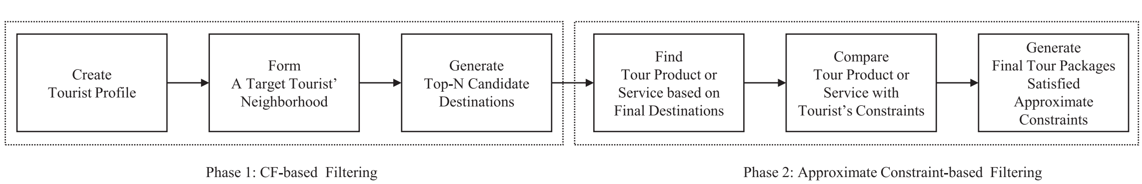

Figure 2 .#Overall procedure.

Last, the *selection likelihood score (SLS)* of the target tourist a on the jth destination is used to generate the top-N candidate destinations. Assume that K_a is the target tourist a's neighbor set; $SLS(a, j)$ is calculated as follows:

$$SLS(a, j) = \frac{\sum_{i \in K_a} r_{ij} \cdot sim(a, i)}{\sum_{i \in K_a} sim(a, i)}, \tag{1}$$

where $sim(a, i)$ indicates the similarity between the target tourist a and his/her neighbor i. The higher is the SLS value, the more likely the target tourist will choose a destination. Therefore, top-N destinations with high SLS values are selected as candidate destinations.

3.3. Phase 2: approximate constraint-based filtering

A typical CF-based travel recommender system suggests destinations by a comparison between the target tourist's profile of destinations and the neighbors' profiles of destinations. Even if tourists travel the same destinations, they may differ with regard to their likes and dislikes of these destinations. Thus, we suggest an additional filtering layer of approximate constraint satisfaction to enable Tourists to have more customized travel-planning services. Tourists may directly provide their needs or constraints, such as budget limits, types of accommodations, and means of transport, that are suitable for their travel products. These tourist constraints are not absolute criteria but rather are expressions of preference. For instance, a small difference (e.g. \$30) in the price may be disregarded but a large difference (e.g. \$130) may be considered to be significant. Tourists may discover that certain constraints (e.g. flight duration) are more important than other constraints (e.g. hotel ratings). We also assume that trade-offs between constraints are not allowed.

Tourists' constraints are then applied to evaluate the candidate destinations that are available in the electronic catalog. The evaluation yields the degree of dissatisfaction between a constraint and an item (i.e. product) in the electronic catalog. For constraint c_i, for tourist i expressed as a relation such as "price ≤ 500" or "flight = American Airlines," the evaluation result $e(c_i, \theta)$ for the electronic catalog item θ is the error function that returns the satisfaction error, i.e. degree of dissatisfaction.

If a constraint contains real numbers (d_1 and d_2), then the error function for the arithmetic constraint is

$$\begin{aligned}
&e(x_i = d_1, \theta) = |\theta - d_1| \\
&e(x_i \leq d_1, \theta) = \max(\theta - d_1, 0) \\
&e(x_i < d_1, \theta) = \max(\theta - d_1 + \varepsilon, 0) \\
&e(x_i \geq d_2, \theta) = \max(d_2 - \theta, 0) \\
&e(x_i > d_2, \theta) = \max(d_2 - \theta + \varepsilon, 0) \\
&e(d_{12} \leq x_i \leq d_1, \theta) = \begin{cases} \theta - d_1 & \text{if } \theta > d_1 \\ d_2 - \theta & \text{if } \theta < d_2 \\ 0 & \text{otherwise,} \end{cases}
\end{aligned} \tag{2}$$

where $\varepsilon > 0$ is an infinitesimally small number.

If the constraint is categorical, the error can be measured in one of the following two ways: First, if categorical values can be converted into scalar values or vectors, such as colors, then the error is calculated as the scalar difference or the vector distance. For instance, destination scenery can be mapped into a vector of affectivity, physical atmosphere, and accessibility values. Second, if categorical values cannot be converted into scalars or vectors, then a categorical constraint is evaluated as a binary constraint. Thus, the evaluation result will be either true (valued 0) or false (valued 1).

Assume that tourist i gives p constraints $\{c_{i,1}, c_{i,2}, \ldots, c_{i,p}\}$ such that constraint $c_{i,s}$ is more important than constraint $c_{i,t}$ for $s < t$, that is, the constraints follow a strict linear order. For the constraint $c_{i,k}$, we define $\succ_{c_{i,k}}$ by items in the electronic catalog:

$$\theta \succ_{c_{i,k}} \theta' \text{ if and only if } e(c_{i,k}, \theta) < e(c_{i,k}, \theta'). \tag{3}$$

We define $\approx_{c_{i,k}}$:

$$\theta \approx_{c_{i,k}} \theta' \text{ if and only if } e(c_{i,k}, \theta) = e(c_{i,k}, \theta'). \tag{4}$$

With (4) and (5), we obtain the binary relation $\succ$ of the preference on items in the electronic catalog:

$$\begin{aligned}\theta \succ \theta' \text{ if and only if for some } c_{i,k},\ \theta \succ_{c_{i,k}} \theta' \\ \text{and for all } c_{i,j} \text{ with } j < k,\ \theta \approx_{c_{i,j}} \theta'.\end{aligned} \tag{5}$$

Tourist i prefers the catalog item θ to the catalog item θ' if and only if (a) the satisfaction error of $c_{i,k}$ for θ is less than that for θ' for some constraint $c_{i,k}$ and (b) for all constraints $c_{i,j}$ that are more important than $c_{i,k}$, the satisfaction error of $c_{i,j}$ for θ is same as that for θ' for some constraint $c_{i,j}$. We also define the $\approx$ of the indifference in the items in the electronic catalog:

$$\theta \approx \theta' \text{ if and only if both } \theta \succ \theta' \text{ and } \theta' \succ \theta \text{ do not hold.} \tag{6}$$

Tourist i is indifferent between θ and θ' if and only if i prefers neither θ nor θ'.

The constraint satisfaction at the right-hand side of (3) and (4) is often too strict. For instance, assume that a tourist has a price constraint of \$1,500 or less and that travel products θ_1, θ_2, and θ_3 are priced at \$1,510, \$1,511, and \$1,600, respectively. Although θ_1 is less expensive than θ_2 such that $e(\text{price} \leq \$1{,}500, \theta_1) > e(\text{price} \leq \$1{,}500, \theta_2)$, the tourist may be indifferent between θ_1 and θ_2 when only prices are considered (due to the difference of only \$1). However, the tourist may consider the prices of θ_1 and θ_3 to be significantly different. To relax this strictness in the constraint evaluation, we adopt the concept of the indifference interval (Luce, 1956). Therefore, we have a relaxed version of (3):

$$\theta \succ_{c_{i,k}} \theta' \text{ if and only if } e(c_{i,k}, \theta') - e(c_{i,k}, \theta) > \delta_{i,k}, \tag{3'}$$

where $\delta_{i,k} \geq 0$ is i's indifference interval for the constraint $c_{i,k}$, that is, θ is recommended if and only if the satisfaction error of $c_{i,k}$ for θ' is *significantly* greater than that for θ. Similarly, i is indifferent between θ and θ' in the evaluation with constraint $c_{i,k}$ if and only if the satisfaction error of $c_{i,k}$ for θ and θ' is sufficiently similar. Thus, we have a relaxed version of (4):

$$\theta \approx_{c_{i,k}} \theta' \text{ if and only if } |e(c_{i,k}, \theta) - e(c_{i,k}, \theta')| \leq \delta_{i,k}. \tag{4'}$$

The destinations selected in Phase 1 are evaluated by (2) and re-ranked by (5) and (6), that is, the approximate constraint satisfaction method of (2), (5), and (6) filters the CF-method's results and changes their rankings.

A key issue in approximate constraint satisfaction is the selection of indifference intervals in (3′) and (4′) for constraints. They can be experimentally determined if sufficient data are available, that is, optimal indifference intervals can be obtained by cross-validation of recommendation experiments. If these data are not available, professional travel agents may help determine them.

4. An Illustrative example

To understand the proposed method, a simple example is presented in this section. Assume that the tourist T_1 is collecting travel information from an online travel agency for planning a vacation in Europe or North America. However, he/she has trouble organizing his/her itinerary due to the large number of destinations, hotels, and attractions and numerous concerns, as shown in Table 3.

We consider the recommendation process for tourist T_1. Assume that eight tourists, ten destinations, a combined total of 22 flights, a combined total of 21 hotels, and a combined total of 21 activities exist for all destinations (refer to Tables A1, A2, A3, and A4 in the Appendix). We assume that tourists' rated the 10 visited destinations as shown in Table A5 in the Appendix.

4.1. Phase 1: CF-Based filtering

Given the tourist profile, CF-based filtering requires the following two steps. In the first step, we apply the Pearson-*r* correlation coefficient to identify the neighbors of the target tourist. For the target tourist T_1, the similarity between T_1 and the other neighbors are shown in Table 1. If two neighbors exist, then the neighbors of T_1 are T_2 and T_6, who are highly similar to T_1.

The *SLS* value is computed with the destinations rated by neighbors of T_1 to generate candidate destinations (refer to Table 2). Assume that two candidate destinations exist. The following two destinations are selected as the candidate destinations: *Mad* (*Madrid*) and *New* (*New York*).

4.2. Phase 2: approximate constraint-based filtering

Assume that the target tourist T_1 regards the constraints listed in Table 3 as important. In addition, assume that the most important constraint of T_1 is the airfare and a difference of \$200 is not sufficient for discriminating among flights.

For generating the recommendation set, we compute the satisfaction error e for the constraint

Table 1. Similarity value.

	T_2	T_3	T_4	T_5	T_6	T_7	T_8
T_1	0.32	−0.63	0.06	−0.09	0.41	−0.16	0.02

Table 2. SLS.

Los	Mad	New
1.75	3.00	2.25

Table 3. Constraints for target tourist T_1.

No	Constraint	Indifference Interval
1	The airfare is \$900 or less	\$200
2	An one stop flight	None
3	The hotel price is \$150 or less	\$10
4	A 4.0-star hotel or above	None
5.	Desired activities include events and shows	None
6	The activity price is \$100 or less	\$10
7	The activity location is within 10 Km of the recommended hotel	1 Km

and the set of candidate recommendations. First, we have e(flight price ≤ \$900, *F_Mad001*) = 580, e(flight price ≤ \$900, *F_Mad002*) = 154, e(flight price ≤ \$900, *F_Mad003*) = 50, e(flight price ≤ \$900, *F_ New001*) = 930, e(flight price ≤ \$900, *F_ New002*) = 470, and e (flight price ≤ \$900, *F_New003*) = 190 for the flight.

We exclude only *F_Mad001, F_New001*, and *F_New002* from the set of candidate recommendations because the price difference of \$200 is not sufficient for discriminating among flights. Second, we perform an analysis according to the target tourist's second constraint among the remaining flights. Third, the satisfaction errors for the second constraint are expressed as follows: e(number of stops per flight = 1, *F_Mad002*) = 0, e(number of stops per flight = 1, *F_Mad003*) = 1 and e(number of stops per flight = 0, *F_New003*) = 1. Accordingly, we recommend *F_Mad002* to the target tourist T_1.

For hotels, we have e(hotel price ≤ \$150, *H_Mad001*) = 0, e(hotel price ≤ \$150, *H_Mad002*) = 40, and e(hotel price ≤ \$150, *H_Mad003*) = 16. We only exclude *H_Mad002* from the candidate recommendation set because the price difference of \$20 is not sufficiently significant to discriminate the hotel. We have e(hotel star rating ≥ 4.0, *H_Mad001*) = 0 and e (hotel star rating ≥ 4.0, *H_Mad003*) = 1. Thus, we only select H_*Mad001* (*Hilton Madrid Airport*).

For activities, we only include *A_ Mad001* and *A_Mad002* as the candidate recommendation set because they satisfy the target tourist's fifth constraints. We have e(activity price ≤ \$100, *A_Mad001*) = 0 and e(activity price ≤ \$100, *A_Mad002*) = 7. We also include *A_Mad001* and *A_Mad002* as the candidate recommendation set because the satisfaction error of *A_Mad001* and the satisfaction error of *A_Mad002* are less than \$10. The target tourist's seventh constraint is compared with the candidate recommendation set. Consequently, we only exclude *A_Mad002* from the candidate recommendation set because the location of *A_Mad002* is far from the recommended hotel H_*Mad001* (*Hilton Madrid Airport*).

Thus, we recommend the {destination = *Mad* (*Madrid*), flight = *F_Mad002* (*Turkish Airlines*), hotel = *H_Mad001* (*Hilton Madrid Airport*), and activity (events and shows) = *A_Mad001* (*Flamenco Show at Café de Chinitas*)} to the target tourist T_1.

5. Experiments

To perform experiments, a prototype web-based recommender system is developed for the planning travel service shown in Figure 3. To evaluate the proposed prototype system, we developed a benchmark recommender system that resembles a popular online travel booking system. We also surveyed the tourists' perceptions of the recommendation results.

5.1. Data collection

To evaluate the proposed prototype system, 100 undergraduate students at the K university in Korea participated in the experiments. We assigned 50 students to use the prototype system and the remaining 50 students to use the benchmark system. We collected the data over a period of one and a half months and received survey results from 49 students for the prototype recommender system and 50 students for the benchmark recommender system.

The data collection was performed in three steps. We selected 15 popular destinations in the U.S and Canada and 12 popular destinations in Europe that students visited. First, students rated the preferences of the destinations (among 27 destinations), which they visited on a five-point scale (5 = "very satisfied", 4 = "satisfied", 3 = "neither", 2 = "dissatisfied", and 1 = "very dissatisfied"). Second, students input their constraints related to flight, hotel, car, and attraction into the prototype recommender system. Students determined the indifference interval values for the prototype recommender system with the help of two professional travel agents. Last, each student offered travel package recommendations. Here, information about flights, hotels, cars, and attractions was

Figure 3. Travel recommender system.

Table 4. Number of information usages for recommendation.

Continent	Nation	Destination	Flight	Hotel	Car	Attraction
North America	2	15	57	375	90	418
Europe	9	12	54	383	71	269
Total	11	27	111	758	161	687

extracted from the existing popular online booking system, as shown in Table 4.

5.2. Evaluation metrics

Metrics such as the mean absolute error (*MAE*), root mean square error (*RMSE*), recall, precision, or *F*1 value have been employed to evaluate the accuracy of recommender systems in many studies (Good et al., 1999; Herlocker et al., 2000; Herlocker, Konstan, Terveen, & Reidl, 2004; Kim et al., 2009; Sarwar et al., 2000). However, these metrics cannot be utilized because travel recommender systems suggest composite items, such as a tour package-typed recommendations; Thus, existing metrics that measure a single item only is not more useful. Instead, we evaluated the effectiveness, usability, and novelty of the prototype travel recommender system on five-point scales (5 = "strongly agree", 4 = "agree", 3 = "undecided, 2 = "disagree", and 1 = "strongly disagree"), as shown in Table 5 (Ngai & Wat, 2003; Pu, Chen, & Hu, 2011).

A travel recommender system does not provide students with new information when they are already interested in the recommended information. However, if additional novel and detailed travel information is provided to students, they will more likely find information that they may not have discovered.

Table 5. Evaluation metrics.

Metrics	Items	
Effectiveness	EFF1	The recommended destination reflects what I want.
	EFF2	Although the recommended destination is exactly what I want, I gained a new insight in selecting the destinations.
	EFF3	The recommended tour package suits my needs.
	EFF4	The recommended tour package reflects what I want.
Usability	USA1	System is easy to use.
	USA2	System is user friendly.
	USA3	Screen display is well designed.
	USA4	Response time in the system is acceptable.
	USA5	System interface is easy to understand.
	USA6	The questions included in the system are relevant to determining the most suitable tour package.
Novelty	NOV1	The items (destination, flight, car, or attraction) recommended to me are novel and interesting.
	NOV2	System helps me discover new items (destination, flight, car, or attraction).
	NOV3	I could find new items (destination, flight, car, or attraction) through the system.

Table 6. Mean responses to the system evaluation by users.

Items	Prototype System Mean Rating	Prototype System S.D.	Benchmark System Mean Rating	Benchmark System S.D.
(On effectiveness of the system)				
EFF1	4.0	1.3	4.3	1.0
EFF2	3.9	1.3	3.9	1.0
EFF3	4.0	1.3	4.1	0.9
EFF4	3.9	1.2	3.9	1.1
(On usability of the system)				
USA1	4.0	1.1	3.8	1.0
USA2	3.9	1.2	3.6	1.0
USA3	4.0	1.2	3.5	1.1
USA4	4.2	1.1	4.2	0.8
USA5	4.0	1.2	4.1	1.0
USA6	3.9	1.2	3.6	1.1
USA7	4.0	1.2	3.7	0.9
(On usability of the system)				
USA1	4.0	1.0	3.7	0.9
USA2	4.0	1.1	3.4	1.0
USA3	4.0	1.1	3.6	0.8

Table 7. Exploratory factor analysis.

Metrics	Items	Loading	Eigenvalue	Cronbach's α
Effectiveness	EFF1	0.863	3.551	0.913
	EFF2	0.770		
	EFF3	0.789		
	EFF4	0.825		
Usability	USA1	0.801	4.570	0.926
	USA2	0.845		
	USA3	0.855		
	USA4	0.653		
	USA5	0.713		
	USA6	0.707		
	USA7	0.719		
Novelty	NOV1	0.860	2.449	0.869
	NOV2	0.893		
	NOV3	0.911		

5.3. Experimental results and discussions

Our experiments were performed to compare the relative effectiveness, usability, and novelty of the prototype recommender system with those of the benchmark recommender system. The results of the survey are presented in Table 6. Students rated at least 3.9 points for the effectiveness, usability, and novelty of the prototype recommender system. The effectiveness, usability, and novelty score of the benchmark recommender system were at least 3.4 points.

By the simple descriptive statistics, we cannot determine a significant difference between the prototype recommender systems and the benchmark recommender system. For a more detailed analysis, we performed an exploratory factor analysis (EFA) and a paired t-test. First, the EFA was performed to investigate the unidimensionality of items by the principal component with a varimax rotation, factor loadings greater than 0.4 and an eigenvalue greater than 1.0. We use Cronbach's alpha to assess the reliability of items. The Cronbach alpha estimated for effectiveness, usability, and novelty was 0.913, 0.926 and 0.869, respectively (refer to Table 7.).

Second, we conducted a paired t-test to determine whether the mean rating of effectiveness, usability, and novelty for the prototype system differ from those for the benchmark system. Table 8 shows the results of the paired t-tests.

First, no significant difference between the effectiveness of the prototype recommender system and that of the benchmark recommender system was observed at a 0.05 level of significance. Recommendations of the current prototype recommender system are as effective as those of existing benchmark recommender systems, i.e. travel agencies. However, as use of the proposed prototype system increases, the prototype recommender system is expected to be more effective than travel agencies over time. The performance of the prototype recommender system will increase as the system is updated by learning student preferences, with the exception of travel agencies.

Second, no difference was observed between the usability of the prototype recommender system and that of the benchmark recommender system at a 0.05 level of significance. This result was not our expected one. Generally, one of the goals of the travel recommender system is to solve the complexity of establishing travel plans (Lorenzi et al., 2007; Rabanser & Ricci, 2005; Schiaffino & Amandi, 2009). Therefore, students may consider that the prototype recommender system is easier to use than the benchmark recommender system if information about flights, hotels, rental cars, and attractions in the benchmark recommender system is represented with details similar to current travel agencies.

Last, a significant difference in the mean ratings of novelty between the prototype system and the benchmark system. This result indicates that the proposed system provides novel destinations, flights, hotels, or attractions and accidental discovery regardless of the students' expectations. This finding also indicates that tourists can take serendipitous travel opportunities to enjoy inexperienced destinations, hotels, or attractions if they use the proposed system. Serendipity tourists can save more time on

Table 8. Paired *t*-test.

	Mean Rating		S.D			
Metrics	Prototype System	Benchmark System	Prototype System	Benchmark System	*t*-value	*p*-value
Effectiveness	4.0	4.1	1.2	0.8	−.464	0.664
Usability	4.0	3.8	1.0	0.8	1.121	0.265
Novelty	4.0	3.5	0.9	0.8	2.743	0.007

travel planning and information collection about destinations, hotels, or attractions instead of following a structured itinerary (Huang et al., 2014). Therefore, the novelty can generated perceived usefulness of the proposed system. The novelty can increase the sales diversity by changing tourists' preferences on destinations, hotels, or attractions (Aggarwal, 2016; Pu et al., 2011).

6. Conclusions

For the enhancement of tourists' experiences, smart tourism cities can offer personalized travel-planning service by analyzing traveling patterns of tourists and learning their results to increase the satisfaction of tourists. For this purpose of smart tourism cities, learning travel patterns, such as tourists' preferences, time, and budget, and offering personalized attractions, such as shopping, events, and shows, are critical. Travel recommender systems are designed for the implementation of smart tourism cities. However, existing travel planning systems cannot support the automation of WOM communication. They only imitate the role of human travel agents. This research suggests a CF-based travel recommender system for a personalized travel-planning service to enhance the tourists' experience. The suggested recommender system analyzes tourists' preferences and offers personalized destinations, flights, hotels, and attractions. The basic methodology of the proposed travel recommender system is to combine CF with approximate constraint satisfaction for the personalized recommendations. CF is applied to recommend a destination and approximate constraint satisfaction is applied to recommend flight, hotel, and attraction packages. Therefore, the proposed system supports the automation of WOM communication and a personalized travel-planning service.

This finding implies that the proposed methodology can assist tourists in finding destinations, hotels, or attractions that are suitable to their preferences. Consequently, tourists' experiences will be reinforced and their satisfaction will be increased. Second, tourists can save time on travel planning, and travel agencies can benefit from increasing the sales diversity by providing serendipitous travel opportunities, which will motivate voluntary participation and improve the health of the smart tourism ecosystem. Third, existing CF-based recommender systems generally recommend items in a single domain only; thus, the simultaneous recommendation of multi items (for example, hotels, flight, and attractions). However, the suggested travel recommender system combined with approximate constraint satisfaction simultaneously provides destination, hotels, flight, and attraction. This study suggested a clue or a heuristic methodology to expand the application of CF-based recommender systems.

However, we are able to derive only limited conclusions on our research by the evaluation with a small subject set. Conducting experiments using a large number of samples will be a promising future research area. Another limitation is the process of eliciting tourists' constraints. In this prototype system, tourists supply their constraints by themselves, but this process is not easy for tourists. We are currently designing algorithms to facilitate or automate the elicitation process of tourist's constraints. Other methodologies that simultaneously recommend multiple items in a different domain is a promising research area related to the travel recommender system.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge & Data Engineering*, *17*(6), 734–749.

Aggarwal, C. C. (2016). *Recommender systems*. (pp. 1–28). Cham: Springer International Publishing.

Bae, S., & Lee, T. (2011). Product type and consumers' perception of online consumer reviews. *Electronic Markets*, *21*(4), 255–266.

Balabanovic, M., & Shoham, Y. (1997). Fab: Content-based collaborative recommendation. *Communications of the ACM*, *40*(3), 66–72.

Baloglu, S., Pekcan, A., Chen, S. L., & Santos, J. (2004). The relationship between destination performance, overall satisfaction, and behavioral intention for distinct segments. *Journal of Quality Assurance in Hospitality & Tourism*, *4*(3-4), 149–165.

Bennett, J., & Lanning, S. (2007, August). The netflix prize. In *Proceedings of KDD cup and workshop* (Vol. 2007, p. 35).

Cai, L. A., Feng, R., & Breiter, D. (2004). Tourist purchase decision involvement and information preferences. *Journal of Vacation Marketing*, *10*(2), 138–148.

Cho, Y. H., Kim, J. K., & Kim, S. H. (2002). A personalized recommender system based on web usage mining and decision tree induction. *Expert Systems With Applications*, *23*(3), 329–342.

Choi, I. Y., Kim, J. K., & Ryu, Y. U. (2015, January). A two-tiered recommender system for tourism product recommendations. In 2015 *48th Hawaii International Conference on System Sciences*. 3354–3363.

Choi, I. Y., Oh, M. G., Kim, J. K., & Ryu, Y. U. (2016). Collaborative filtering with facial expressions for online video recommendation. *International Journal of Information Management*, *36*(3), 397–402.

Cox, C., Burgess, S., Sellitto, C., & Buultjens, J. (2009). The role of user-generated content in tourists' travel planning behavior. *Journal of Hospitality Marketing & Management*, *18*(8), 743–764.

Coyle, L., & Cunningham, P. (2003). Exploiting re-ranking information in a case-based personal travel assistant. In *Proceedings of the 5th International Conference on Case-based Reasoning*.

Das, A. S., Datar, M., Garg, A., & Rajaram, S. (2007, May). Google news personalization: scalable online collaborative filtering. In *Proceedings of the 16th international conference on World Wide Web* (pp. 271–280). ACM.

Garcia, I., Sebastia, L., & Onaindia, E. (2011). On the design of individual and group recommender systems for tourism. *Expert Systems with Applications*, *38*(6), 7683–7692.

Gavalas, D., Konstantopoulos, C., Mastakas, K., & Pantziou, G. (2014). Mobile recommender systems in tourism. *Journal of Network and Computer Applications*, *39*, 319–333.

Goldberg, D., Nichols, D., Oki, B. M., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. *Communications of the ACM*, *35*(12), 61–71.

Good, N., Schafer, B., Konstan, J., Borchers, A., Sarwar, B., Herlocker, J., & Riedl, J. (1999). Combining collaborative filtering with personal agents for better recommendations. In *Proceedings of the AAAI'99 conference*. (pp. 439–446).

Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: Foundations and developments. *Electronic Markets*, *25*(3), 179–188.

Gretzel, U., & Yoo, K. (2008). Use and impact of online travel reviews. *Information and Communication Technologies in Tourism*, *2008*, 35–46.

Gretzel, U., Zhong, L., & Koo, C. (2016). Application of smart tourism to cities. *International Journal of Tourism Cities*, *2*(2).

Herlocker, J. L., Konstan, J. A., & Reidl, J. (2000). Explaining collaborative filtering recommendations. In *Proceedings of the 2000 Conference on Computer Supported Cooperative Work*. (pp. 241–250).

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Reidl, J. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS)*, *22*(1), 5–53.

Hernández-Méndez, J., Muñoz-Leiva, F., & Sánchez-Fernández, J. (2015). The influence of e-word-of-mouth on travel decision-making: Consumer profiles. *Current Issues in Tourism*, *18*(11), 1001–1021.

Huang, Y., & Bian, L. (2009). A Bayesian network and analytic hierarchy process based personalized recommendations for tourist attractions over the internet. *Expert Systems with Applications*, *36*(1), 933–943.

Huang, W. J., Norman, W. C., Hallo, J. C., Mcgehee, N. G., Mcgee, J., & Goetcheus, C. L. (2014). Serendipity and independent travel. *Tourism Recreation Research*, *39*(2), 169–183.

Jalilvand, M. R. (2017). Word-of-mouth vs. Mass media: Their contributions to destination image formation. *Anatolia*, *28*(2), 151–162.

Jalilvand, M. R., Samiei, N., Dini, B., & Manzari, P. Y. (2012). Examining the structural relationships of electronic word of mouth, destination image, tourist attitude toward destination and travel intention: An integrated approach. *Journal of Destination Marketing & Management*, *1*(1-2), 134–143.

Kim, J. Y., & Canina, L. (2015). An analysis of smart tourism system satisfaction scores: The role of priced versus average quality. *Computers in Human Behavior*, *50*, 610–617.

Kim, J. K., Kim, H. K., Oh, H. Y., & Ryu, Y. U. (2010). A group recommendation system for online communities. *International Journal of Information Management*, *30*(3), 212–219.

Kim, H. K., Kim, J. K., & Ryu, Y. U. (2009). Personalized recommendation over a user network for ubiquitous shopping. *IEEE Transactions on Services Computing*, *2*(2), 140–151.

Kim, C., Lee, J., Cho, Y., & Kim, D. (2004). VISCORS: A visual contents recommender system on the mobile web. *IEEE Intelligent Systems*, *19*(6), 32–39.

Kim, J. K., Moon, H. S., An, B. J., & Choi, I. Y. (2018). A grocery recommendation for off-line shoppers. *Online Information Review*, *42*(4), 468–481.

Kim, H. K., Oh, H. Y., Gu, J. C., & Kim, J. K. (2011). Commenders: A recommendation procedure for online book communities. *Electronic Commerce Research and Applications*, *10*(5), 501–509.

Lee, H., Lee, J., Chung, N., & Koo, C. (2018). Tourists' happiness: Are there smart tourism technology effects? *Asia Pacific Journal of Tourism Research*, *23*(5), 486–501.

Li, N., Tung, V., & Law, R. (2017). A fuzzy comprehensive evaluation algorithm for analyzing electronic word-of-mouth. *Asia Pacific Journal of Tourism Research*, *22*(6), 592–603.

Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing*, *7*(1), 76–80.

Litvin, S. W., Goldsmith, R., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468.

Liu, Q., Chen, E., Xiong, H., Ge, Y., Li, Z., & Wu, X. (2014). A cocktail approach for travel package recommendation. *IEEE Transactions on Knowledge and Data Engineering*, *26*(2), 278–293.

Liu, X., Schuckert, M., & Law, R. (2015). Can response management benefit hotels? Evidence from Hong Kong hotels. *Journal of Travel & Tourism Marketing*, *32*(8), 1069–1080.

Lorenzi, F., Bazzan, A. L. C., & Abel, M. (2007). Truth maintenance task negotiation in multi agent recommender system for tourism. In *Proceedings of the AAAI Workshop on Intelligent Techniques for Web Personalization and Recommender Systems in E-Commerce (AAAI 2007)*. (pp. 122–125).

Lorenzi, F., Loh, S., & Abel, M. (2011, August). PersonalTour: A recommender system for travel packages. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2011 IEEE/WIC/ACM International Conference on* (Vol. 2, pp. 333–336). IEEE.

Luce, R. D. (1956). Semiorders and a theory of utility discrimination. *Econometrica*, *24*(2), 178–191.

Melville, P., Mooney, R. J., & Nagarajan, R. (2002). Content-boosted collaborative filtering for improved recommendations, In *Proceedings of the Eighteenth National Conference on Artificial Intelligence (AAAI 02)*. (pp. 187–192).

Moon, H. S., Kim, J. K., & Ryu, Y. U. (2013). A sequence-based filtering method for exhibition booth visit recommendations. *International Journal of Information Management*, *33*(4), 620–626.

Murphy, L., Mascardo, G., & Benckendorff, P. (2007). Exploring word-of-mouth influences on travel decisions: Friends and relatives vs. Other travellers. *International Journal of Consumer Studies*, *31*(5), 517–527.

Ngai, E. W. T., & Wat, F. K. T. (2003). Design and development of a fuzzy expert system for hotel selection. *Omega*, *31*(4), 275–286.

Nilashi, M., bin Ibrahim, O., Ithnin, N., & Sarmin, N. H. (2015). A multi-criteria collaborative filtering recommender system for the tourism domain using Expectation Maximization (EM) and PCA–ANFIS. *Electronic Commerce Research and Applications*, *14*(6), 542–562.

Park, D. H., Kim, H. K., Choi, I. Y., & Kim, J. K. (2012). A literature review and classification of recommender systems research. *Expert Systems with Applications*, *39*(11), 10059–10072.

Park, D. H., Lee, J. M., & Han, I. G. (2007). The effects of on-line consumer reviews on consumer: The moderating role of involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148.

Pu, P., Chen, L., & Hu, R. (2011, October). A user-centric evaluation framework for recommender systems. In *Proceedings of the fifth ACM conference on Recommender systems* (pp. 157–164). ACM.

Rabanser, U., & Ricci, F. (2005). Recommendation systems: Do they have a viable business model in e-tourism. *In Conference of the International Federation for IT & Travel and Tourism*, 160–171.

Ryu, Y. U. (1998). Approximate constraint satisfaction over a constraint hierarchy. In *Proceedings of the 31st Hawaii International Conference on System Science*. 5, 134–141.

Sarwar, B., Karypis, G., Konstan, J. A., & Riedl, J. (2000). Analysis of recommendation algorithms for e-commerce. In *Proceedings of ACM E-commerce 2000 conference*. 158–167.

Sarwar, B. M., Konstan, J. A., Borchers, A., Herlocker, J., Miller, B., & Riedl, J. (1998, November). Using filtering agents to improve prediction quality in the grouplens research collaborative filtering system. In *Proceedings of the 1998 ACM conference on Computer supported cooperative work* (pp. 345–354). ACM.

Schiaffino, S., & Amandi, A. (2009). Building an expert travel agent as a software agent. *Expert Systems with Applications*, *36*(2), 1291–1299.

Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and tourism online reviews: Recent trends and future directions. *Journal of Travel & Tourism Marketing*, *32*(5), 608–621.

Schuckert, M., Liu, X., & Law, R. (2016). Insights into suspicious online ratings: Direct evidence from TripAdvisor. *Asia Pacific Journal of Tourism Research*, *21*(3), 259–272.

Tham, A., Croy, G., & Mair, J. (2013). Social media in destination choice: Distinctive electronic word-of-mouth dimensions. *Journal of Travel & Tourism Marketing*, *30*(1-2), 144–155.

TotalMedia. (2010). Social travel. Accessed online (www.totalmedia.co.uk) on April 25, 2012

Tung, V. W. S., & Ritchie, J. B. (2011). Exploring the essence of memorable tourism experiences. *Annals of Tourism Research*, *38*(4), 1367–1386.

Yeh, D. Y., & Cheng, C. H. (2015). Recommendation system for popular tourist attractions in Taiwan using Delphi panel and repertory grid techniques. *Tourism Management*, *46*, 164–176.

Appendix

Table A1. Travel Database: Destinations.

Destination_ID	Destination	Destination_ID	Destination
Ber	Berlin	*Mon*	Montreal
Chi	Chicago	*New*	New York
Lon	London	*Par*	Paris
Los	Los Angeles	*Rom*	Rome
Mad	Madrid	*Tor*	Toronto

Table A2. Travel database: flights.

Flight_ID	Destination	Flight	Stopover	Price
F_ Ber001	Berlin	Lufthansa Airline	Nonstop	$1,325
F_ Ber002	Berlin	Finnair	1 stop (via Helsinki)	$1,036
F_ Chi001	Chicago	Delta Air Lines	Nonstop	$1,132
F_Chi002	Chicago	Asiana Airlines	1+ stop (via Seattle)	$932
F_Lon001	London	British Airways	Nonstop	$2,503
F_Lon002	London	Air China	1 stop (via Beijing)	$1,818
F_Los001	Los Angeles	United Airlines	Nonstop	$1,110
F_Los002	Los Angeles	Japan Airlines	1 stop (via Osaka)	$947
F_Mad001	Madrid	Iberia Airlines	Nonstop	$1,480
F_Mad002	Madrid	Turkish Airlines	1 stop (via Istanbul)	$1,054
F_Mad003	Madrid	Korean Air	2+ stop (via Dubai and Rome)	$950
F_Mon001	Montreal	Air Canada	Nonstop	$1,715
F_Mon002	Montreal	Air Canada	1 stop (via Toronto)	$1,498
F_New001	New York	American Airlines	Nonstop	$1,830
F_New002	New York	United Airlines	1 stop (via San Francisco)	$1,370
F_New003	New York	Delta Air Lines	2+ stop (via Tokyo and Los Angeles)	$1,090
F_Par001	Paris	Air France	Nonstop	$1,457
F_Par002	Paris	Korean Air	1 stop (via Rome)	$1,234
F_Rom001	Rome	Alitalia	Nonstop	$1,683
F_Rom002	Rome	Asiana Airlines	1 stop (via Amsterdam)	$1,450
F_Tor001	Toronto	Air Canada	Nonstop	$2,350
F_Tor002	Toronto	Korean Air	1 stop (via Vancouver)	$1,910

Table A3. Travel database: hotels.

Hotel_ID	Destination	Hotel	Rating	Price
H_ Ber001	Berlin	SO/ Berlin Das Stue	5.0	$254
H_ Ber002	Berlin	Hotel Berlin	4.5	$199
H_ Chi001	Chicago	Holiday Inn Chicago Mart Plaza River North	3.0	$150
F_Chi002	Chicago	Hilton Chicago Ohare Airport	4.0	$174
H_Lon001	London	Park Plaza Westminster Bridge London	4.0	$330
H_Lon002	London	Days Hotel London Waterloo	3.0	$125
H_Los001	Los Angeles	Millennium Biltmore Hotel Los Angeles	3.5	$330
H_Los002	Los Angeles	Hilton Los Angeles Airport	4.0	$157
H_Mad001	Madrid	Hilton Madrid Airport	4.0	$130
H_Mad002	Madrid	Melia Madrid Princesa	5.0	$190
H_Mad003	Madrid	Hotel Regente	3.0	$166
H_Mon001	Montreal	Hyatt Regency Montreal	4.0	$140
F_Mon002	Montreal	Quality Hotel Midtown	3.0	$85
H_New001	New York	Intercontinental New York Barclay	4.0	$203
H_New002	New York	The Hotel Edison	3.0	$180
H_Par001	Paris	Villa Pantheon	4.0	$121
H_Par002	Paris	Eiffel Rive Gauche	3.0	$102
H_Rom001	Rome	Una Hotel Roma	4.0	$185
H_Rom002	Rome	IQ Hotel Roma	4.0	$169
H_Tor001	Toronto	Hilton Toronto	4.0	$157
H_Tor002	Toronto	Comfort Hotel Downtown	3.0	$125

Table A4. Travel database: activities.

Activity_ID	Destination	Activity Class	Activity Name	Price	Hotel within 10 Km from here
A_ Ber001	Berlin	Events and Shows	Friedrichstadt-Palast VIVID Grand Show	$46.00	SO/ Berlin Das Stue
A_ Ber002	Berlin	Tours and Sightseeing	Berlin Hop-On Hop-Off Bus Tou	$25.00	Hotel Berlin
A_ Chi001	Chicago	Shopping and Fashion	Loop Interior Architecture & Pedway Walking Tour	$28.00	Holiday Inn Chicago Mart Plaza River North
A_Chi002	Chicago	Events and Shows	Tommy Gun's Garage Dinner Show	$67.00	Hilton Chicago Ohare Airport
A_Lon001	London	Arts and Culture	The Household Cavalry Museum	$9.07	Park Plaza Westminster Bridge London
A_Lon002	London	Events and Shows	Sister Act	$93.87	Days Hotel London Waterloo
A_Los001	Los Angeles	Events and Shows	Medieval Times Dinner & Tournament	$63.00	Millennium Biltmore Hotel Los Angeles
A_Los002	Los Angeles	Tours and Sightseeing	Hollywood Sign & Griffith Park Hiking Tour	$39.00	Hilton Los Angeles Airport
A_Mad001	Madrid	Events and Shows	Flamenco Show at Café de Chinitas	$48.00	Hilton Madrid Airport
A_Mad002	Madrid	Events and Shows	Anastasia The Musical	$107.00	Melia Madrid Princesa
A_Mad003	Madrid	Tours and Sightseeing	Day Tour of Toledo & Segovia with Alcazar Entrance	$79.00	Hotel Regente
A_Mon001	Montreal	Arts and Culture	Montreal Art Gallery	$17.18	Hyatt Regency Montreal
A_Mon002	Montreal	Air and Land Adventures	Montreal Bicycle Tour	$66.2	Quality Hotel Midtown
A_New001	New York	Events and Shows	Mamma Mia!	$96.5	Intercontinental New York Barclay
A_New002	New York	Events and Shows	The Lion King	$108.5	The Hotel Edison
A_Par001	Paris	Events and Shows	Crazy Horse Cabaret Show	$127.98	Villa Pantheon
A_Par002	Paris	Theme Parks	Disneyland® Paris Tickets	$62	Eiffel Rive Gauche
A_Rom001	Rome	Arts and Culture	Papal Audience	$38.66	Una Hotel Roma
A_Rom002	Rome	Tours and Sightseeing	Rome in One Day Tour	$141.16	IQ Hotel Roma
A_Tor001	Toronto	Events and Shows	Jersey Boys	$75.34	Hilton Toronto
A_Tor002	Toronto	Events and Shows	The Second City	$23.4	Comfort Hotel Downtown

Table A5. User profile.

	Ber	Chi	Lon	Los	Mad	Mon	New	Par	Rom	Tor
T_1	1	3	1						2	2
T_2		4		4	3				2	1
T_3	2		3	2		2	3	4		
T_4	2	3	4	1	4	5				3
T_5	3			3				4	4	
T_6		5			3		4			4
T_7	2		2	4		4		2	5	
T_8	3	4			6	3	5			4

Note: The figure in each cell indicates the tourist's rating based on how much they liked the destination (5 = highest, 1 = lowest).