Using Collective Intelligence to Generate Trend-based Travel Recommendations

Sabine Schlick, Isabella Eigner and Alex Fechner
Institute of Information Systems, Friedrich-Alexander University, Lange Gasse 20, 90403, Nürnberg, Germany

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Abstract: Trips are multifaceted, complex products which cannot be tested in advance due to their geographical distance. Hence, making a travel decision people often ask others for advice. This leads to an increasing importance of communities. Within communities people share their experiences, which results in new, more extensive knowledge beyond the individual knowledge of each member. The objective of this paper is to use this knowledge by developing an algorithm that automatically generates trend-based travel recommendations. Based on the travel experiences of the community members, interesting travel areas are identified. Five key figures to evaluate these areas according to general criteria and the users' individual preferences are developed. The algorithm allows to generate recommendations for the whole community and not only for highly active members, resulting in a high coverage. A study conducted within an online travel community shows that automatically generated, trend-based trip recommendations are rated better than user-generated recommendations.

1 INTRODUCTION

Trips are multifaceted, complex products that consist of many different components. Due to their geographical distance they cannot be tested in advance (Hwang, Gretzel and Fesenmaier, 2002). When it comes to travel decisions, people are highly motivated to exchange experiences with others. This emphasizes the important role of communities in tourism, as they often provide better support in information search than guidebooks (Prestipino and Schwabe, 2005). Research even shows that recommendations from users are rated better than automatically generated recommendations (Magno and Sable, 2008). Exchanging their experiences within online-communities, people generate new knowledge beyond the knowledge of the individuals (Bächle, 2008). Whereas the members of a travel community have knowledge about single trips they did in the past and can share their experiences, the collected knowledge of all community members is much more extensive. This phenomenon is defined as collective intelligence (Malone, Laubacher and Dellarocas, 2009). By analyzing this knowledge, new, enriched knowledge can be generated (Gruber, 2008). On the downside, the increasing amount of user-generated content leads to an information overload for the users (Jannach, 2011). Recommender systems tackle this problem by suggesting products that fit the individual preferences of the customers (Smyth, 2007). Besides content-based and collaborative filtering, the two classical approaches, demography-based, knowledge-based, utility-based and hybrid methods exist (Burke, 2002). Moreover, other recommender systems are based on social relationships and trust between users (Meo et al., 2011). Overall measures for the quality of recommender systems are the quality of the recommendation (the rating of the users) and the coverage (percentage of users a recommendation can be generated for) (Massa and Avesani, 2007).

The goal of this paper is to use the collective knowledge of a travel community to generate individualized, trend-based travel recommendations. By analyzing the places community members have visited in the past, relevant travel areas are detected. Based on these travel areas, individualized recommendations of trips within these travel areas are generated. We then evaluate if the automatically generated, trend-based recommendations are rated better than the trips recommended by the members of the community while increasing the coverage.

This paper is structured as follows. Chapter 2 gives an overview of related work followed by the

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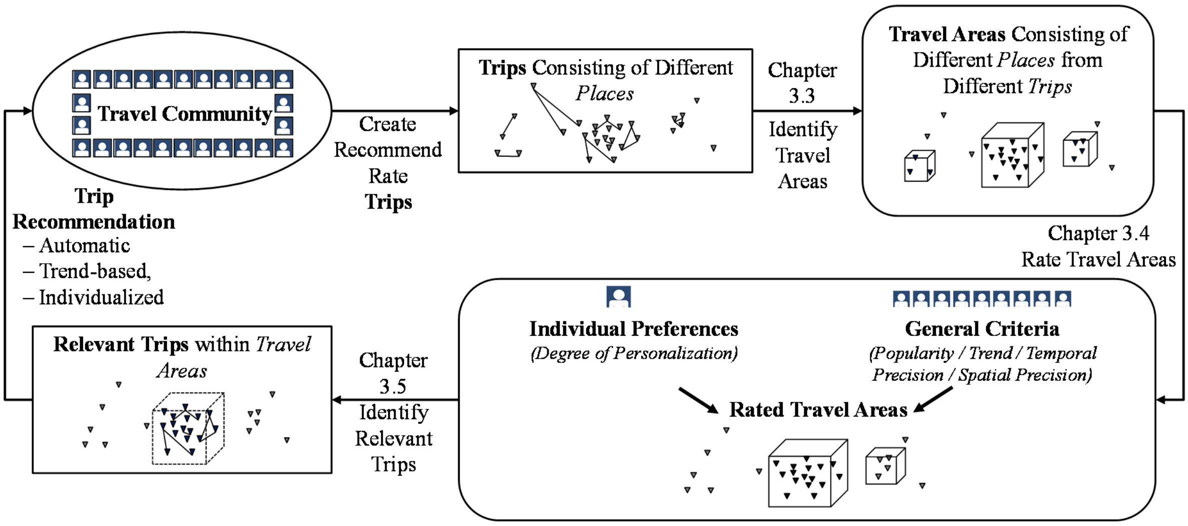

Figure 1: Approach.

method development and the single steps of the algorithm (chapter 3). Chapter 4 deals with the study to evaluate the trend-based recommendations. Chapter 5 summarizes the findings, outlines limitations, and gives suggestions for future research.

2 RELATED WORK

Many recommender systems either integrate user preferences or spatio-temporal trends in the recommendation process. Wallace et al. (2004) and Ricci et al. (2006) use product bundles and travel plans of other users to generate recommendations, whereas Gruber (2008) and Frers (2010) integrate user knowledge about travel destinations. While the focus of these systems lies on the matching of user preferences and trip characteristics, spatio-temporal factors are only considered as trip characteristics.

In contrast, others focus on spatial and temporal aspects as an influencing factor for their recommendations. The hybrid system of Sebastia et al. (2009) not only bundles places, but orders them chronologically. Others also consider temporal factors to analyze the availability of single points of interest (Tung and Soo, 2004). While Baraglia et al. (2012) only use spatial data to find suitable travel routes, Monreale et al. (2009) additionally extract the spent time within user trajectories to find common paths. Yoon et al. (2012) also utilize user trajectories to group single places to interesting travel regions, but disregard the temporal development of the popularity.

Existing approaches show the high relevance of spatio-temporal data for travel recommendations. However, the detection of both spatio-temporal trends in combination with further personalization is not considered yet. By exploiting this gap, our new approach enables users with low activity within the community and thus limited information to also receive valuable recommendations. Personalized recommendations for active community members can also be improved by considering general travel trends for more diversified suggestions.

3 METHOD DEVELOPMENT

3.1 Approach

To develop an algorithm to automatically generate trend-based recommendations, this research follows the design science paradigm (Hevner et al., 2004).

Figure 1 gives an overview on the developed approach. Starting point is a travel platform that enables users to create trips consisting of individual places. The trips as well as the single places comprise a number of attributes, e.g. the location type. Within this travel community, users share and rate their travel experiences or recommend trips to other users. According to the theory of collective intelligence (Malone, Laubacher and Dellarocas, 2009), new knowledge that is more extensive than that of the single community members, emerges. By analyzing this collective knowledge, new, enriched knowledge about travel trends and user preferences can be gained. First, the places users visited in the past are analyzed to identify relevant travel areas. As a next step, criteria to rate these travel areas are developed.

General criteria as well as the fit of a travel area to the individual user preferences are taken into account. Afterwards, relevant trips for the individual users within these travel areas are identified and recommended to the community members. To evaluate the findings, user ratings for the automatically generated recommendations are compared to user-generated recommendations.

3.2 Data Set

User-generated content is used to identify travel areas and to provide the recommendations. On the travel platform users create trips consisting of one or more places they have visited by tagging the single places on a map. The geo-coordinates are assigned automatically. Users add some characteristics from a predefined selection to the trips and places. Characteristics of trips are the date (from-to), the travel style (e.g. couple), and the travel type (e.g. cruise). Characteristics of the places are the location type (e.g. beach), the transportation (e.g. by car), the activities (e.g. swimming), and the costs (in Euro).

3.3 Identify Travel Areas

Based on the places users create on the travel platform, travel areas, defined as an accumulation of places, have to be identified. Neither the spatio-temporal location nor their extent is known in advance. The spatial extent of a travel area is e.g. a certain city or region. Besides the spatial extent, the temporal extent plays an important role. A skiing region in the Alps can be popular in winter, but is also visited in summer for hiking activities. The skiing region in winter might be smaller than the hiking region in summer, but might have more visitors. Therefore, two travel areas have to be identified. Using the user-generated content the algorithm is able to detect the relevant spatial and temporal extent for each travel area. To find travel areas, places that are nearby in spatial and temporal respect have to be detected. Figure 2 shows places (triangles), trips (bundles of places), and two accumulations of places (boxes) that define travel areas (left hand side). Based on this accumulation of places, the position and the extent of a travel area can be detected. The position is defined by the spatial (longitude and latitude) and the temporal (time) position (right hand side). The extent is determined by the spatial and the temporal distance between the position and the places with the highest spatial and temporal distance.

To identify travel areas, the "Density–Based Spatial Clustering of Applications with Noise (DBSCAN)" algorithm is applied (Ester et al., 1996). This algorithm allows to identify clusters even if neither the number of clusters nor their extent and shape is known. If the distance of two objects is below a certain threshold ε, these objects are neighbors. Objects (places) are assigned to a cluster (travel area) if they have a minimal number of dense neighbors or if they are dense to an object that has a minimal number of dense neighbors, otherwise they are noise. Since the DBSCAN only uses one threshold for clustering, the algorithm has to be adapted in a similar way as proposed by Birant and Kut (2007). They adapted the DBSCAN to cluster objects in spatial, temporal and non-spatial respect. To detect travel areas, only spatial and temporal aspects are relevant. Therefore, two thresholds are taken into account, a spatial threshold ε_s and a temporal threshold ε_s, that amount to the spatio-temporal threshold $\vec{\varepsilon}_{st} = (\varepsilon_s, \varepsilon_t)$. An object is only assigned to a cluster, if the spatial and the temporal distances are lower than the spatial and the temporal thresholds. Two places $(\vec{p}_1, \vec{p}_2)$ are neighbors if their spatial and temporal distances $\vec{d}_{st}$ are smaller than the given spatio-temporal threshold:

$$\vec{d}_{st}\,(\vec{p}_1, \vec{p}_2) \leq \vec{\varepsilon}_{st} \tag{1}$$

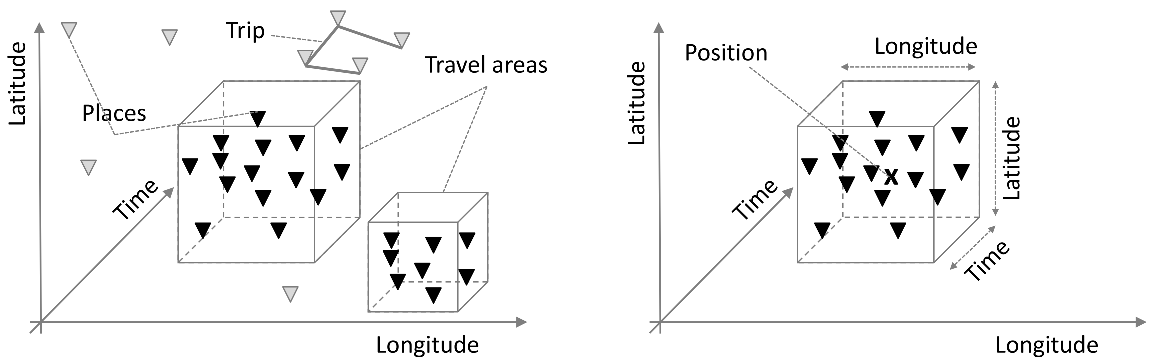

Figure 2: Places, trips, and spatio-temporal travel areas.

The spatial and the temporal distance have to be calculated separately. Spatial places $\vec{p}$ are described by their geographical coordinates, the latitude θ, the longitude φ and the constant radius of the earth R, $\vec{p} = (R, \theta, \varphi)$ (Nitschke, 2014). A spatio-temporal place is additionally defined by its point of time t, $\vec{p} = (R, \theta, \varphi, t)$. The spatio-temporal distance is calculated by the vector over the spatial distance d_s and the temporal distance d_t:

$$\overrightarrow{d_{st}}(p_{st_1}, p_{st_2}) = \begin{pmatrix} d_s\,(p_{st_1}, p_{st_2}) \\ d_t\,(p_{st_1}, p_{st_2}) \end{pmatrix} \quad (2)$$

To calculate small spatial distances between two places the Haversine formula (Sinnott, 1984) is considered to be very suitable (Montavont and Noel, 2006). As travel areas consist of a number of close places, the distances thus are by definition small. The temporal distance is calculated by the difference between two points of time t_1 and t_2. Applying the cluster algorithm, spatio-temporal accumulations of places are detected. Knowing the places of a certain travel area, the position $\vec{c}_{st}$ is calculated. It is defined by the temporal and the spatial center. The temporal center t_m is computed, which requires the arithmetic mean of the points in time. To identify the spatial center, the geographical coordinates first have to be converted into Cartesian coordinates. After calculating their arithmetic mean they are transformed back into geographical coordinates (Nitschke, 2014). Subsequently, the spatio-temporal extent $\vec{e}_{st} = (e_s, e_t)$ is calculated. The spatial extent e_s is the geographical distance $d_{emax}\,(\vec{c}_{st}, \vec{p}_{smax})$ between the position $\vec{c}_{st}$ of the travel area and the place within this travel area that has the highest distance to the position $\vec{p}_{smax}$. Analogously, the place $\vec{p}_{tmax}$ that has the highest temporal distance to the position of a travel area is used to compute the temporal extent $d_{tmax}\,(\vec{c}_{st}, \vec{p}_{tmax})$. In conclusion, a travel area can be described by its position and its spatial and temporal extent $ta = (\vec{c}_{st}, e_s, e_t)$.

3.4 Rate Travel Areas

After the identification of travel areas in general, five key figures to rate these travel areas are developed. Four of these key figures (*popularity*, *trend*, *spatial precision* and *temporal precision*) are general criteria and used for the whole community. To consider individual preferences of the single users, a fifth key figure (*degree of personalization*) is introduced.

3.4.1 General Criteria

Popularity: The popularity is measured by the number of visitors. The more users visit places in a certain travel area the higher is the *popularity* of that travel area:

$$\begin{aligned} &Popularity \\ &= Number\ of\ visitors\ in\ a\ travel\ area \end{aligned} \quad (3)$$

Trend: Using only the number of visitors in a certain area is not sufficient. Travel areas that have a high number of visitors might be identified as relevant areas, even if the number of visitors is strongly decreasing over time. Besides, upcoming relevant trend areas might not be recognized. Therefore, a second key figure is introduced to observe the popularity of the travel areas over time.

The challenge is to identify a certain travel area in different time periods, e.g. years, because travel areas will not have the exact same position and extent each period as new places might be added or others disregarded. Therefore, travel areas that are equivalent to each other in different time periods are identified by using the similarity of their positions and their extents. The higher the similarity, the higher the probability that two travel areas are equivalent. The initial requirement for two travel areas to have a similar position is to be adjacent. In other words, the distance between the positions of two areas has to be equal or lower than the sum of their extents. Hence, a flexibly adaptable threshold is introduced, that is dependent on the extent of the travel areas. With travel areas that have a small extent, like a small festival, the threshold is lower than the one for travel areas with a larger spatial and temporal extent, e.g. a hiking area. If the distance of the positions is lower than this threshold, the travel areas are equivalent. The threshold is defined by the spatio-temporal extent of the considered travel area $\vec{e}_{st}\,(\overrightarrow{ta_c})$ and the potentially equivalent travel area $\vec{e}_{st}\,(\overrightarrow{ta_p})$:

$$Threshold = \left(\vec{\mathrm{e}}_{\mathrm{st}}(\overrightarrow{\mathrm{ta}}_{\mathrm{p}}) + \vec{\mathrm{e}}_{\mathrm{st}}\,(\overrightarrow{\mathrm{ta}}_{\mathrm{c}})\right) \quad (4)$$

All potentially equivalent travel areas $\overrightarrow{ta_p}$ that have a lower distance to the considered travel area $\overrightarrow{ta_c}$ than the individual threshold, are so called candidates $\overrightarrow{ta_{ca}}$. Figure 3 illustrates on the left hand side travel areas with different extents. On the right hand side, overlapping travel areas are shown. The distance between the positions a and b is smaller than the threshold: they overlap. The distance between b and c and a and c is higher than the threshold. They are not overlapping or adjacent.

After generating a list of candidates for each travel area, the extent of a travel area is taken into account. The more similar the extent of the considered travel area $\overrightarrow{ta_c}$ and a candidate $\overrightarrow{ta_{ca}}$, the higher the

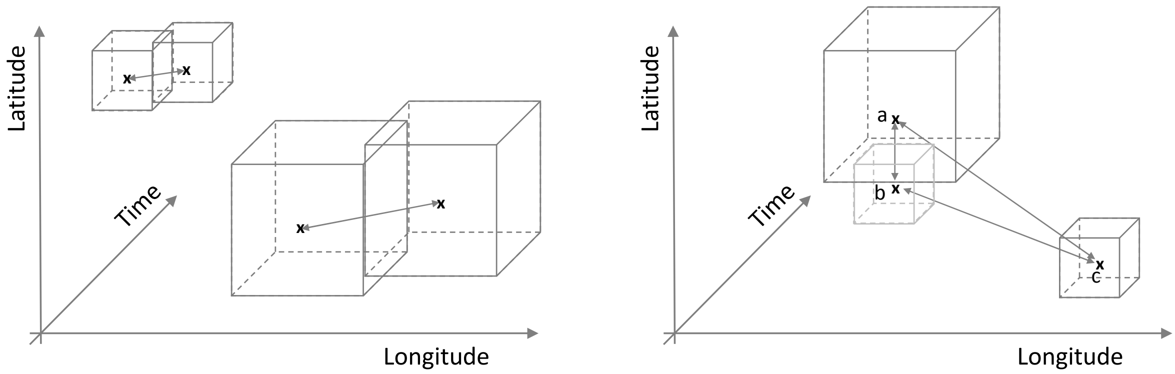

Figure 3: Using the position of travel areas to identify equivalent travel areas.

probability that they represent the same travel area in different time periods. Therefore, the Euclidian distance between the extent of the considered travel area $\vec{e}_{st_c}$ and the candidate $\vec{e}_{st_{ca}}$ is used. The candidate with the lowest distance is identified as the equivalent travel area to the considered travel area.

Having identified equivalent travel areas, the development of the number of visitors can be observed. Therefor the linear regression is applied to measure if the number of visitors (dependent variable) is increasing (positive algebraic sign) or decreasing (negative algebraic sign) over multiple time periods (y_i) (independent variable). The value of the regression coefficient expresses the strength of the connectivity. Referring to (Bortz and Schuster, 2010), the second key figure (*trend*) is calculated as follows:

$$Trend = \frac{\sum_{i=1}^{c}(y_i - \overline{y})\,(Popularity - \overline{Popularity})}{\sum_{i=1}^{c}(y_i - \overline{y})^2} \quad (5)$$

Spatial and Temporal Precision: The next two key figures concentrate on the characteristics of these travel areas. The number of places within a travel area and the number of their assigned characteristics is different for all areas. To overcome this issue, a weight for each characteristic $wc_{ta_v m}$ is calculated for all travel areas. The more often a characteristic occurs in a certain travel area, the higher the importance of this characteristic. The weight for a characteristic is the occurrence frequency divided by the number of places in a certain travel area. Travel areas that have a big local and global extent, but a low number of places, may be described worse by their characteristics than small travel areas with a high number of places. The *spatial* and the *temporal precision* thus describe the accuracy of the assignment of the characteristic attributes. They are calculated by the popularity divided by the spatial and the temporal extent, respectively:

$$Precision_s = \frac{Popularity}{e_s}$$
$$Precision_t = \frac{Popularity}{e_t} \quad (6)$$

3.4.2 Individual Preferences

Degree of Personalization: So far, travel areas can be rated by general criteria. However, users differ in their preferences (Zins and Grabler, 2006). By considering individual preferences in addition to general criteria, customized recommendations can be given to each user. As users are assumed to like what they liked in the past (Adomavicius and Tuzhilin, 2005), trips and places they created and rated well are used to identify their preferred trip characteristics. These characteristics may include attributes describing the entire trip (e.g. travel type) or specific details of the single places (e.g. activities).

Users that highly favor a certain characteristic will have visited many places containing this characteristic. The more often it can be found in the places a user visited, the more relevant this attribute is for the considered user. Analogously to the weights for the travel areas, weights of the preferred attributes of a user $wc_{u_p m}$ are calculated, by dividing the occurrence frequency of the attributes by the number of places visited by the user. By calculating the Euclidian distance between the weight of the describing attributes of a travel area and the weight of the preferences of the user the *degree of personalization* can be determined. This key figure states to which degree a considered travel area fits the preferences of a user. The lower the value of the key figure, the better the travel area fits:

$$Degree\ of\ Personalization = \sqrt{\sum_{m=0}^{x}\left(wc_{ta_v m} - wc_{u_p m}\right)^2} \quad (7)$$

3.4.3 Apply Key Figures

All in all, five key figures to evaluate travel areas are developed, the *popularity*, the *trend*, the *spatial precision*, the *temporal precision*, and the *degree of personalization*. Whereas the first four key figures are the same for all users, the last one has to be calculated for each user separately. Applying the key figures, all travel areas have to be evaluated in comparison to each other. First all travel areas are ranked within the single key figures. The travel areas with the best value is ranked with one, the second best with two and so on. Afterwards, an overall rating is calculated. Therefore the single ranks of the key figures (k_g) for each travel area are summed up and divided by the number of key figures. To change the influence of a single key figure, a weight (w_{k_g}) is introduced:

$$Rating(ta) = \frac{\sum_{g=1}^{l} k_g * w_{k_g}}{Number\ of\ Key\ Figures} \tag{8}$$

Table 1 gives an example for different values (V) for the five key figures and the assigned rank (R). While travel area ta_0 has the highest *popularity* with 990 visitors, the *trend* is higher for travel area ta_1. If two travel areas have the same value for a certain key figure, e. g. travel area ta_1 and $ta_{(f-1)}$ for the key figure *temporal precision*, both are assigned to the lower rank. After calculating the rating, travel area ta_1 with a value of 1.8 is identified as the most relevant travel area, followed by travel area ta_0 (all key figures are weighted with one). The rating for the trips can also be generated if not all key figures are available. This way, the algorithm can also be applied if, due to the low activity of a new user, the degree of personalization cannot be calculated.

3.5 Identify Relevant Trips

In a last step, interesting trips within the relevant travel areas are identified. Thus trips are rated depending on the rating of the travel areas their places belong to. If a place is associated with several travel areas, the rating of all these travel areas is assigned to the place. The rating of a trip is calculated by the sum of the ratings of travel areas the single places are allocated to, divided by the number of travel areas the places are assigned to.

$$Rating\ (trip) = \frac{\sum_{v=0}^{f} Rating(ta_v)}{Number\ of\ Travel\ Areas} \tag{9}$$

Table 2 summarizes the steps of the algorithm, the applied methods as well as the flexibly adaptable measures and the respective output.

4 EVALUATION

Within two weeks in 2013, a study is conducted, where 60 participants are asked to create, rate and recommend trips to each other on a travel platform. Combined with already existing trips that were created by other community members before the evaluation study, 3,927 trips are available on the platform. Altogether, the trips are made up of 4,817 places. Based on this data, the developed recommendation algorithm is applied. The temporal threshold (ε_t) is set to 150 days and the spatial threshold (ε_s) to one kilometer. The minimal number of neighbors (MinPts) is set to two. Assuming an equivalent importance of the single key figures, their weighting is set as follows: the spatial and the temporal precision is set to 0.5, the popularity and the trend to 1. The only factor considering the personal preferences, the degree of personalization, is weighted with three to balance the impact of general and individual criteria on the recommendations.

Besides these automatically generated recommendations, users recommend trips to each other manually. Community members have to rate the received recommendations using stars (1=very bad - 5=very good) to determine the fit with their actual preferences. Altogether the participants rate 298 trip recommendations, of which 198 (66%) come from other users, 100 (34%) are generated automatically using the developed algorithm. In general, automatically generated, trend-based

Table 1: Calculating the rating of travel areas.

Travel Area	Popularity		Trend		Spatial Precision		Temporal Precision		Degree of Personalization		Rating(ta)
	V	*R*	*V*	*R*	*V*	*R*	*V*	*R*	*V*	*R*	
ta_0	990	1	0.6	2	0.2	4	0.1	4	0.1	1	(1+2+4+4+1):5=2.4
ta_1	878	2	0.7	1	0.5	2	0.4	2	0.25	2	(2+1+2+2+2):5=1.8
…	…		…		…		…		…		…
$ta_{(f-1)}$	450	3	0.4	3	0.8	1	0.4	2	0.89	4	(3+3+1+2+4):5=2.6
ta_f	89	4	-0.3	4	0.3	3	0.2	3	0.7	3	(4+4+3+3+3):5=3.4

Table 2: Recommending trips based on interesting travel areas – overview.

Steps	Method	Flexibly adaptable	Output
Identify travel areas	Spatio-temporal clustering	Spatial threshold (ε_s) Temporal threshold (ε_t) Minimal number of dense neighbors (MinPts)	Accumulations of places = Travel areas
Rate travel areas by general and individual criteria	Ranking all travel areas according to the key figures (popularity, trend, spatial precision, temporal precision and personalization)	Weightings for the single key figures (w_{k_u})	Travel areas rated by their relevance for an average user and for individual users
Identify relevant trips within fitting travel areas	Using the rating of the travel areas trips have places in to evaluate single trips		Single trips within these travel areas

recommendations receive better ratings (3.85 ± 1.29) than recommendations by users (3.02 ± 1.14). To avoid coincidental results, a t-test (Bortz and Schuster, 2010) is executed using two independent samples. It results in the rejection of the related null hypothesis ("There is no difference between the rating of user-generated and automatically generated recommendations") with a significance level of $p < 0.01$. There is a highly significant difference between the means of the two samples. Therefore it can be proven that the system is able to generate travel recommendations that are qualitatively better than user-generated recommendations.

To evaluate different parameter weightings and to compare the new algorithm to traditional recommendation methods a second study with 51 participants is conducted in 2015. These participants create 131 new trips. All in all 827 trips consisting out of 1,325 places are available on the platform. Four settings are chosen for evaluation: In the first setting the popularity as well as the trend are set to 1/6, the spatial and the temporal precision to 1/12. The degree of personalization has the highest influence and is set to 1/2. In the second setting the popularity and the trend are set to 1/3 and the spatial as well as the temporal precision to 1/6. To analyze the relevance of the degree of personalization, the parameter is set to 0 to compare the results with setting one. Thus the recommendations are only based on travel trends.

In the third and fourth setting traditional recommendation methods are tested and evaluated. In setting three, a content-based approach relying on similar items (Adomavicius and Tuzhilin, 2005), thus trips that are similar to a user's past trips, is used for recommendations. Setting four follows a social recommender approach, thus the trips of friends are used for recommendations. Social recommender systems are a special type of collaborative filtering that utilize the similarity of users for recommendations (Adomavicius and Tuzhilin, 2005). The similarity of users can be identified by analyzing their relationship (Meo et al., 2011). Therefore the trip preferences of the participants' friends in the community are used to identify relevant trips for the individual users. Trips that are similar to trips of friends are identified and recommended to the participants.

All in all 41 participants generate trips and it is possible to provide recommendations based on setting 1 and 3. 36 of the participants rate the received recommendations. 30 participants become friends with other users and recommendations based on setting 4 are possible. All of them rate the received recommendations. As travel trends can be identified without active participation of the single users, recommendations based on setting 2 can be generated for the entire study group. 37 participants also rate the recommendations. Moreover 48 participants receive recommendations by other community members and 37 rate these recommendations. The 30 participants that occur in all groups are used for analysis. They rate the recommendations as follows: setting 1 is rated with 3.948 (± 0.578), setting 2 with 3.877 (± 0.614), setting 3 with 3.972 (± 0,650), and setting 4 with 4.009 (± 0.645). The recommendations they received by other users are rated with 3.313 (± 1.17).

To identify statistically relevant findings a paired t-test (Bortz and Schuster, 2010) is conducted. The related null hypothesis is as follows: "There is no difference between the rating of user-generated recommendations and the four settings of automatically generated recommendations". There is a statistically significant difference between all automatically generated recommendations and the rating for the recommendations by the participants. With a significance level of $p < 0.05$ all automatically generated recommendations are rated better than user-generated recommendations. Within the automatically generated recommendations there is only one statically significant difference between setting 2 and setting 4. Recommendations based on the taste of the friends of a user are rated better than recommendations only based on travel trends with a significance level of $p < 0.05$. Nevertheless, recommendations only based on travel trends can be generated for all users thus reducing cold start problems for new or inactive members. Recommendations based on the taste of friends can only be generated if a user becomes friends with other users on the platform, thus reducing the coverage of recommendations to only socially active users.

5 CONCLUSIONS

In this paper, an algorithm to generate trend-based individualized travel recommendations is developed. The algorithm identifies travel areas based on user-generated trips consisting of different places. Five key figures are developed to rate these travel areas based on general and individual criteria. General criteria are the popularity of a travel area, the trend and the spatial and temporal precision. The degree of personalization allows to rate the travel areas based on individual preferences for each single user. The weights for these criteria are flexibly adaptable. It is also possible to generate recommendations for users that did not take part in the community actively and for whom it is therefore not possible to compute a degree of personalization yet. This way, general recommendations can be generated for all community members resulting in full coverage. To evaluate the quality of the recommendations two studies are conducted. Findings show that automatically generated trend-based recommendations are evaluated significantly better. Currently the algorithm only uses the similarity of trips and travel areas to calculate the degree of personalization. Besides this kind of content-based approach, future research concentrates on analyzing different measures to calculate the degree of personalization (e.g. collaborative approaches). Moreover, although the set values for the thresholds and weightings already lead to good results, further settings have to be evaluated. Within the single key figures other methods for calculation should be considered in further studies. For clustering travel areas, e.g. hierarchical clustering and geodesic k-means should be tested. To adjust for seasonal and transient variations, polynomial regression should also be considered for estimating the popularity of an area.

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