Tourist Attraction Recommendation Service: An Approach, Architecture and Case Study

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Keywords: Recommendation System, Tourism, Context-awareness, Collaborative Filtering, Point-of-interest, Knowledge, Ontology.

Abstract: The paper proposes a complex multi-model approach to recommendation systems design in the domain of tourist information support. Specifically, it proposes to construct a recommendation system as a composition of loosely coupled modules, implementing both personalized and non-personalized methods of recommendations and a coordination module responsible for adaptation of the whole system to the specific tourist and situation context.

1 INTRODUCTION

Tourism has become one of the largest and fastest-growing economic sectors in the world. Despite occasional shocks, it has shown virtually uninterrupted growth. International tourist arrivals have increased from 527 million in 1995 to 1133 million in 2014. International tourism receipts earned by destinations worldwide have surged from US$ 415 billion in 1995 to US$ 1245 billion in 2014 (World Tourism Organization, 2015). Moreover, the number of international tourist arrivals worldwide is expected to increase by an average of 3.3% a year over the period 2010 to 2030 (*ibid*.).

At the same time, there are some structural and behavioral changes in tourism highly connected to the development of Internet and Information Technologies. The increasing use of ICTs in tourism services allows tourists to take a more active role in the production of tourism products, being no longer satisfied with standardized products. The "postmodern tourist"' with differentiated life-styles, individual motives and specific interests demands products tailored accordingly to stated preferences (Berka, T. and Plößnig, M., 2004).

All that makes the problem of tourists' information support more actual than ever. Therefore, information (and search) services of all kinds that can help in collecting information about the trip being planned and provide tourist with information needed during the trip are becoming more and more popular. One of the functions typically provided by those services is recommendation of attractions based on tourist's preferences and current conditions (weather, transport, etc.).

Systems intended to mitigate a choice problem leveraging (implicit or explicit) subjective preferences received a name of "recommendation systems". The variety of techniques to build, deploy and assess this kind of systems separated into a specific research area in the mid-90s of XX century.

Approaches to build recommendation systems are usually classified according to the kind of input data that is used for recommendations. Most popular are two of them (Adomavicius G. and Tuzhilin A., 2005): collaborative filtering and content-based. In the former one the only information that is available are ratings that users assigns to objects. In the latter, input information is formed by structured representation of items and a vector of user's ratings. There are several more approaches: demographic recommendation systems, knowledge-based recommendation systems, social-based recommendation systems, but they are less used.

Dependence on a specific type of information causes limitations in applying each of recommendation techniques. For example, collaborative filtering cannot be used when the number of ratings is small, but just after start of any recommendation system the set of ratings is usually empty, hence the so called "cold start" problem.

Smirnov, A., Ponomarev, A. and Kashevnik, A.
Tourist Attraction Recommendation Service: An Approach, Architecture and Case Study.
In *Proceedings of the 18th International Conference on Enterprise Information Systems (ICEIS 2016) - Volume 2*, pages 251-261
ISBN: 978-989-758-187-8

Similarly, the structured representation of items needed for content-based methods might be available for one regions (in tourist recommender systems) and be missing for others.

This paper proposes multi-model approach, which prescribes creation of a family of recommendation modules, based on various principles and relying on different types of input information. Coordination of the modules and composing an aggregate recommendations list, taking into account current situation, is performed by a coordination module. Employed basic models range from knowledge-based fuzzy rules to collaborative filtering and coordination module leverages fuzzy inference to evaluate each basic model in the current context.

There is a prototype implementation of the recommendation service, functioning as a part of tourist information support system «TAIS – Mobile Tourist Guide" (Smirnov et al., 2014).

2 RECOMMENDATION SYSTEMS IN TOURIST INFORMATION SUPPORT

Key premises to employ recommendation systems in some domain are, first, abundance of choice complicating decision-making, and second, significant subjectivism in decision-making. Tourist in an unfamiliar environment (city, country) frequently face both of the premises: abundance of attractions to visit and uncertainty in which of them to visit to gain most positive experience from the stay. This explains the attention that is paid to tourist information support in recommendation systems community. Besides, social sciences research reveals the importance of decision support systems in tourism, caused by large number of aspects that need to be paid attention to: tourist mobility, high risk and uncertainty in unfamiliar environment, distributed nature of information sources and several other factors (Gretzel, 2011).

Main directions and achievements in tourist recommendation systems design are summarized in review papers (Kabassi, 2010) (systems before fall 2009) and (Borràs et al., 2014) (2008-2014). These studies reveal that nowadays in tourist recommendation systems all modern recommendation techniques are used. Collaborative filtering, content-based and demographic ones are the most widely employed.

There is also another branch of research that may be relevant to tourist recommendation system community. It is media stream analysis, employed e.g. for point-of-interest (POI) detection (see, e.g., Han and Lee, 2015). In some sense, this technique can be interpreted as an "open form" of collaborative filtering. Openness here means that this technique does not implement functionality of user's feedback collection typically present in recommendation systems; instead, it relies on some external feedback source, namely, social media event stream. A common idea of this kind of systems is that geo-tagged images are interpreted as some signs that a user who posted them enjoyed the place or view. Additional analysis can help make further inference, e.g., Han and Lee (2015) try to distinguish images made by tourists (which are mostly relevant for making recommendations to tourists) from images made by local population by analysing attributes of the image poster's account in Flickr (the primary media event stream for that system). In (Crandall et al., 2009) city attractions are visualized based on the analysis of images from photo sharing service. In (Marcus et al., 2011) methods are proposed to detect actual events taking place in city based on the Twitter stream. Photo2Trip system (Lu et al., 2010; Yin et al., 2010) makes step further; based on the analysis of sequences of geo-tagged photos from public photo sharing sites, Photo2trip identifies and recommends typical tourist trips.

To the best of authors' knowledge, there are no systems trying to integrate "classical" recommendation approaches (e.g., content-based, collaborative filtering) with emerging "open form" non-personalized recommendation techniques based on the social media event stream analysis.

3 MULTI-MODEL APPROACH FOR RECOMMENDATION SYSTEMS DESIGN

As it was noted earlier, there is a set of well-known approaches to make recommendations. Main criterion for distinguishing between them is the kind of information used in the respective approach. Each existing approach inevitably bears some advantages and disadvantages. In the recommendation systems research specific consequences of disadvantages have received metaphorical (usually) names: "cold start problem", "grey sheep problem". The former one refers to impossibility of a recommendation system that is based solely on historical data, to make recommendations to new users (without any historical data associated with them) or recommend new items (not rated by any user yet). The latter one refers to difficulties in dealing with non-typical users. These problems on a higher level are consequences of incompleteness of input data and assumptions that are immanent to recommendation systems.

As each of the "pure" approaches to making recommendations is based on its own set of input data, it is natural to compensate paucity of information of one type (more difficult to obtain) by information of some other type, leveraging several "pure" approaches simultaneously. This is how hybrid recommendation systems work. Hybridization may touch different levels of the system. For example, one of the most popular forms of hybridization is "collaboration via content" (Blanco-Fernández et al., 2008), which is based on collaborative filtering, but similarity measure between users is modified in such a way that it considers not only ratings, but also similarity of some semantic attributes of users. "Collaboration via content" is an example of "deep" hybridization as it transforms the algorithm of one of "pure" approaches, adding to it some new information. An example of "shallow" hybridization is an ensemble of recommendation systems that work independently with their results merged.

In this paper, recommendation system is built by similar "shallow" hybridization. The system includes several independent modules, each of them implementing one recommendation algorithm (mostly, "pure" ones, as they are more tried-and-tested). Along with recommendation modules, the system includes coordination module that merges recommendations generated by "pure" algorithms, using knowledge about their strong and weak sides and current situation. For example, if there are not so many ratings in the database, then recommendations of collaborative filtering module will likely be regarded as not reliable. Advantage of this modular construction is the simplicity of adding new recommendation modules – it requires mapping its input specification on the information model of the system and (in some cases) modifying the coordination module. Coordination module is intentionally designed as configurable.

Recommendation service provides POI recommendations on two levels: non-personalized and personalized. Personalized recommendations are usually preferable, but their generation requires information about user-item interactions. If this information is not available, the service falls back to non-personalized recommendations, that requires only aggregate information about item popularity, For example, if there is no information about users' preferences, then upon trip to St. Petersburg it is only possible to recommend popular tourist locations like Hermitage museum, Peter and Paul fortress, or St. Isaac's Cathedral, and these recommendations can be made only on the basis of the statistics of visiting. If, however, the user stated in her profile that she is interested in engineering, and it is known that she visited Centre Pompidou during her trip to Paris and enjoyed it, then it is possible to recommend Central Railway Museum, Central Museum of Communications, or Erarta Museum of Contemporary Art.

However, on both levels POI recommendation may, and usually should be context-aware. In the non-personalized recommendations level context-awareness stands for using a stratified and time-bound data for making recommendations. Non-context-aware non-personalized recommendations would be based on overall visiting statistics (actually, for all time). The simplest form of context-awareness in this case, would be making recommendations on yearly statistics data, which would help to identify and recommend places that are most popular now recently. The more elaborate form is making stratified samples, attributing visitors to days of week, months of year, country of origin etc. On the other hand, non-context-aware personalized recommendations are well-known classical collaborative filtering in the space of solely user-item ratings, or content-based methods matching users to some features of items. Context-awareness would usually mean attributing each rating set by the user to some kind of external conditions and limiting ratings used for recommendations to those, which are attributed to similar conditions.

3.1 Non-personalized Recommendations

For non-personalized recommendations that are most actual in the paucity of preferences data, the TAIS's attractions recommendation service leverages the publicly available geo-tagged stream of events (photos and tweets). As it was discussed earlier, non-personalized recommendations are based on visiting statistics data. There are three potential sources of these data: a) the data can be collected by the tourist application itself (TAIS in this case); b) the data can be queried for from be local authorities or POI administration; c) the data can be mined from the global stream of public data. The source (a) is the most convenient as the data can be collected with all the needed context attributes and in the most appropriate form and granularity, however, it requires a huge number of users and cannot be employed by a newly created application. The source (b) relies on the communication with external entities (local authorities and museums administration) and is very laborious. It can be appropriate for a local application, e.g. St. Petersburg local city guide, but hardly can be implemented for a global recommendation service that should work in every location worldwide. Moreover, it is not suitable for recommending architectural POIs, publicly available observation places, as there might be no administration to collect visiting statistics. With all the drawbacks of (a) and (b) for making a globally active POI recommendation service, the option (c) becomes viable. With the dissemination of camera and GPS-equipped mobile devices, widening mobile internet coverage and the forming of new information processing habits, publicly available stream of geo-tagged events is becoming more and more affluent. There are many scientific publications showing various ways of leveraging this live source of human activity: from events and opinion detection to, a more relevant to the topic of this paper, POI detection and recommendation. However, this stream obviously bear some bias that must be taken into account. E.g., it is produced by active users of social networks and owners of modern smart-phones. Target users of mobile tourist guide are obviously a subset of smart-phone owners, but actually not necessarily are active users of social networks, so there still is a chance of biased inference.

In the working prototype of the recommendation service Flickr is used as a source of geo-tagged photos. Each geo-tagged photo is interpreted as an evidence that some user has visited certain geographical location. In contrast with classical recommendation systems, making photo doesn't express explicitly user's attitude to the object in the frame. So, not necessarily making photo is equivalent to marking the place with "like" or setting it a good rating. However, as the research on geo-tagged social media reveals, geo-tags are concentrated around attractive landmarks and can be used to detect them.

As TAIS application is targeted on the support of tourists during trip, it is important to differentiate between photos that are likely to be done during trip from those that are done, for example, at the work, after work and even during weekend by local population. In this work the approach described in (Han and Lee, 2015) is adopted. It is based on the analysis of Flickr user's profile, specifically its location attribute. This attribute value designates a location that is perceived as home for a user. Therefore, all the photos that are not associated (taken farther than 30km) with this location are considered to be done on trip and are processed by the procedure of popular tourist places detection.

Therefore, a context of a photo for the non-personalized recommendation includes:

- date and local time when photo was taken with derivate values;

- photo poster's home location.

As it was discussed earlier, photo poster's home location is used to select relevant photos, whereas date and time are used to build spatio-temporal map of location popularity.

All the area is split on rectangles approximately 100x100 meters (10^{-4} degrees latitude and variable range in longitude, depending on the latitude), then the number of tourist photos in each rectangle is counted, taking into consideration local time the photo was taken and its derivative attributes: day of week, time of day and season. This number is attributed to all POIs that are located in the rectangle.

One impediment caused by the way Flickr API is organized, is that it is relatively easy to estimate the number of photos in the area, but getting the attributes (shot time, date and precise location, poster's home location) of all the photos is impractically slow due to the number of API calls required. To solve this problem, sampling technique is used.

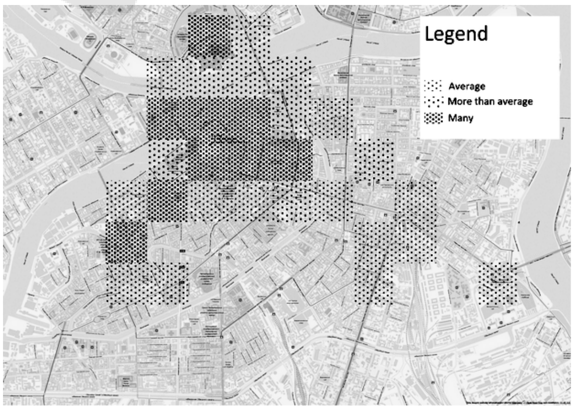

Figure 1: Example statistics on the number of photos made by Flickr users in St.Petersburg in 2015.

3.2 Personalized Recommendations

Personalized recommendations account for user's preferences and potentially are more accurate, however, they demand more information. Particularly, user preferences should be defined in some form. In the proposed service personalized recommendations are represented by context-aware collaborative filtering.

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3.2.1 Context-aware Collaborative Filtering

One of the promising directions to improve the predictive quality of recommendation systems in general (and collaborative filtering systems among them) is context-awareness (Adomavicius et al., 2011). The context describes conditions in which the user rates an object or asks for recommendations.

In the proposed tourist attraction information service the following context attributes are distinguished:

a) time;

b) company in which the user visited the attraction (alone, with a friend or with the family);

c) weather (sunny, rainy, etc).

Values are assigned to these attributes in mostly automated fashion. For example, the user opens the attraction evaluation screen being near to that particular attraction (according to the mobile device's GPS sensor). In this case the time attribute is filled in with the current time and current weather is queried from the context service. However, there is also a possibility to set the values of context attributes manually in the evaluation screen of the mobile application. It is convenient, for example, if a user wants to rate the attractions seen during the day upon returning to the hotel in the evening. To facilitate deferred evaluation the proposed system tracks attractions the user visits and shows unrated visited attractions in a special screen. The user does not have to assign values to each context attribute. If a context attribute is not given a value, it is assumed to have value "any".

There are three general approaches to take context into account in recommendation systems (Adomavicius et al., 2011): (a) contextual pre-filtering; (b) contextual post-filtering; (c) contextual modelling.

The advantage of the contextual pre-filtering and post-filtering approaches is that they are compatible with classical (not context-aware) recommendation algorithms. The context awareness in these approaches comes true by transformation of either input or output of the classical recommendation algorithm. In the contextual pre-filtering approach, the rating data that is not related to the context is filtered out before applying the recommendation algorithm. On the other hand, in the contextual post-filtering approach the resulting list of recommendations is ordered or filtered taking into account context values.

In the contextual pre-filtering approach all the ratings that are irrelevant to the context discarded from the rating matrix before the recommendation algorithm is applied. For example, if in some attraction recommendation service the context includes weather conditions, then making recommendations in a rainy day should not use ratings assigned in sunny days. This approach aggravates the important problem inherent to collaborative filtering systems – rating matrix sparsity. The main goal pursued by contextual pre-filtering methods is to take into account the context, but not let rating matrix to become too sparse.

In the proposed system the context generalization method (Adomavicius et al., 2005) (one of the contextual pre-filtering methods) is used for taking context into account. In this method, the rating matrix is filtered not only by exact values of context attributes, but also by its possible generalizations. To use this method the context model has to support context generalization. In most general form, it means that at least one context attribute must be defined on a set with a strict partial order relation of generalization ($\rightarrow$). Let A be a set of attribute values and a_i, $a_j \in A$. Then notation $a_i \rightarrow a_j$ means that value a_j is a generalization of a_i. A context is usually represented by m attributes. Let $c = (c_1, \ldots, c_m)$ and $c' = (c'_1, \ldots, c'_m)$ are two contexts. We define c' as a generalization of c ($c \rightarrow c'$), iff there exists at least one $i \in \{1,..,m\}$, such that $c_i \rightarrow c'_i$. We call context c incompatible with c', iff neither $c \rightarrow c'$ nor $c = c'$. In most cases, the generalization relation forms some kind of a hierarchy (or multiple hierarchies).

In the proposed system, the context generalization is enabled by following:

a) The set of Time attribute values includes not only exact date and time values but also "any" value and aggregate values for each season, day type (working day or weekend) and time of day (morning, afternoon, evening). The generalization relation is defined naturally.

b) The set of Company attribute values includes values "alone", "with friends", "with family" and "any". "Any" value is defined to be a generalization of any other value.

c) The set of Weather attribute values includes values "sunny", "rainy", "cloudy", "snowy" and "any". "Any" value like in (b) is defined to be a generalization of any other value.

For example, the exact context could be (Time: "July 31, 2013 17:30"; Company: "with family"; Weather: "sunny"). This context can be generalized to (Time: "summer"; Company: "with family"; Weather: "sunny") or even to (Time: "summer"; Company: "any"; Weather: "any").

It is obvious that a context can be generalized in several ways and directions. In systems with many attributes and many levels of granularity of attributes, enumerating all possible context generalizations is a problem and various heuristics are used for picking appropriate generalizations (Adomavicius et al., 2005). In the proposed system, there are not so many possible generalizations, so all of them are enumerated through implicit directed graph traversal procedure. The nodes of this graph are attribute values and the arcs are generalization relations.

A user rates attractions on a five-point scale (1 – bad, 5 – excellent). The rating obtained from the user (raw rating) is normalized to reduce individual bias in assessment: some users tend to put relatively high ratings to all attractions, others in contrary tend to put relatively low ratings. Normalized rating $\widetilde{r}_{uj}$ given by user u to attraction j is defined by formula:

$$\widetilde{r}_{uj} = r_{uj} - \frac{1}{|K_u|+1}\left(3 + \sum_{k \in K_u} r_{uk}\right),$$

here, r_{uj} is raw rating of the attraction j given by user u, and K_u is a set of all attractions rated by user u. The idea of normalization is to shift from user-oriented five-point scale to calculations-oriented zero-centered scale. The sign of the normalized rating corresponds to general attitude of the user (whether it is positive or negative) and the absolute value of the rating corresponds to the strength of that attitude. The straightforward way to normalize ratings is to subtract scale average (i.e. "3") from each rating. It would work nice if users normally used all the range of five-point scale. However, most users in fact rate items using some subset of the scale, e.g., only "3", "4" and "5". In this case subtracting scale average would result in non-negative normalized ratings missing the fact that the user definitely likes items he/her rated "5" and probably doesn't like items rated "3". Hence, the normalization procedure should capture not only the scale characteristics but also the observed usage of this scale. Therefore, a popular method of normalization is subtracting average user rating from all his/her ratings. This method works well in most cases but have some subtle drawback which turns out when there are only a few ratings. For example, when the user rated only two items – both with "5" – then normalization over the average user rating would turn these ratings into zeroes. I.e. a priori notion of five-point scale with "5" as the best mark is lost in favor of adaptation to the observed usage of this scale. To alleviate this drawback in the proposed system we use slightly modified version of the normalization over the average user rating. During the normalization we add one fake rating of "3" (scale average) to the set of user ratings having a purpose to stick other ratings to the original notion of the scale. This modification is significant when there are a few ratings (in the example above two "5" ratings become positive) but its contribution to the normalized ratings vanishes as the number of users' ratings grows.

Attraction rating estimation for a given user is performed in two steps:

1) a group of users with ratings similar to the given user's is determined;

2) rating of attraction is estimated based on ratings of this attraction assigned by users of the group.

While building the list of recommendations, several possible generalizations of the context is used. For each context generalization ratings received in contexts incompatible with this generalization are not taken in to account.

User group is determined by k-Nearest Neighbours method (kNN). The similarity between users u and v is calculated as a cosine measure between normalized ratings vectors of users according to the following formula:

$$s_{uv} = \frac{\sum_{i \in I_{uv}} \widetilde{r}_{ui}\widetilde{r}_{vi}}{\sqrt{\sum_{i \in I_{uv}} \widetilde{r}_{ui}^{\,2}}\sqrt{\sum_{i \in I_{uv}} \widetilde{r}_{vi}^{\,2}}}.$$

Here I_{uv} is a set of attractions rated by both users u and v.

Attraction rating estimation for the user is based on ratings of that attraction assigned by other users of the group with respect to their similarity to the user. It is calculated as a weighted average of normalized ratings among group members:

$$r_{uj}^{*} = \frac{\sum_{v \in G} \tilde{r}_{vj} s_{uv}}{\sum_{v \in G} |s_{uv}|},$$

here G is the group of the user.

3.2.2 Context-aware Knowledge-based Recommendations

This recommendations module uses the attractions data extracted from open internet services, tourist type and context data. It is driven by a knowledge base connecting tourist properties, attraction properties and context parameters. The advantage of this approach is that this module does not require ratings history and therefore, it can be used immediately after recommendation service deployment.

Problems of tourist industry development have received much attention in the scientific literature. From the point of this paper, the most valuable are attempts to build a tourist typology and link different types of tourists to their preferred types of activities during trip. One of the first papers proposing a typology like that was (Cohen, 1972), with 4 types of tourists. Later, other typologies either for all the variety of tourists (Wickens, 2002; Gibson and Yiannakis, 2002), or for some subset of them were proposed (Mehmetoglu, 2007; McKercher and Du Curos, 2003).

The knowledge-based recommendation module uses typologies, proposed in (Gibson and Yiannakis, 2002; McKercher and Du Curos, 2003), as Gibson and Yiannakis (2002) propose a typology with a greater differentiation (15 roles), which allows to specify preferences of each role more precisely. McKercher and Du Curos (2003) propose a cultural tourist typology, and cultural tourism is one of the focuses of this paper.

To fill the knowledge base the results of several scientific publications (Pearce and Packer, 2013; Hannam et al., 2014; Park et el., 2012) were used linking types of tourists and their preferred activities.

Fuzzy logic is used to represent the properties of the tourist and of the situation. It is caused by the fact that crisp classifications rarely can be applied to cultural objects or people (Gibson and Yiannakis, 2002).

Linguistic variable is defined by a tuple (x, T, U, G, M), where x is a name of the variable, T – term-set, each element of which (a term) is represented as a fuzzy set on the universe U; G – syntactical rules of new terms construction, often in the form of a grammar; M – semantic rules, defining membership functions of fuzzy sets in T.

All the linguistic variables in the recommendation module can be divided into three groups:

1) Variables that describe a tourist type, according to (Gibson and Yiannakis, 2002; McKercher and Du Curos, 2003). Their names are synthesized as prefix "*Type_*" followed by a type abbreviation (e.g., *Type_SNL* corresponds to "Sun Lover" type from Gibson and Yiannakis (2002)). Term-set for all these variables is a set T = {"Definitely true", "Likely true", "Likely not true", "Definitely not true"}, and a universe – $U = [0; 1]$.

2) Variable *Weather*, describing the weather in fuzzy linguistic terms.

3) Output variable *Recommend*, having term-set {"Definitely recommend", "Recommend", "Neither recommend or not", "Not recommend", "Definitely not recommend"}.

The recommendations are formed by a set of fuzzy rules involving statements with linguistic variables and crisp predicates using Mamdani-type inference (Mamdani, 1974). For example:

IF (*Type_EDT* **IS** "Definitely true" **OR**
Type_PCT **IS** "Definitely true") **AND**
ObjectType **IS** Museum **AND**
FreeTime > 2 hours
THEN
Recommend **IS** "Definitely recommend"

3.3 Coordination Module

The goal of the coordination module is to merge results obtained by various recommendation modules based on their expected trustworthiness (which is related to the availability of the information crucial for the algorithm implemented by that particular module). Major criteria taken into account by the coordination module are:

- collaborative filtering module requires significant amount of user-item ratings;
- to receive recommendations with the help of collaborative filtering module , a user should express her preferences by making several ratings;
- non-personalized recommendations module can function only in the areas where social media stream is fairly intensive.

Therefore, each recommendation module has its own restrictions, and the coordination module assigns a degree of belief to each of the modules, based on evaluating these restrictions. Coordination module is also based on fuzzy inference. Linguistic variables used in its knowledge base can be divided into 4 groups:

1) User characteristics (a number of ratings set by the user, the number of user's "neighbours" in the collaborative filtering module).

2) Ratings database characteristics (RMSE – Root mean squared error, expected error of rating prediction by collaborative filtering module).

3) Context characteristics (photos in the region).

4) Output variable Belief.

Rule example:

IF *RatingsByUser* **IS** “Many” **AND**
NeighborsOfUser **IS** “Many” **AND**
RMSE **IS NOT** “High”
THEN
Belief **IS** “High”

Degree of belief to the recommendations provided by a module is obtained by applying rules to the module and defuzzification of the output variable. After that, recommendations provided by each of the modules are weighted according to the degree of belief, ranked, and shown to the user. Overall architecture of the recommendation service is shown in Figure 2.

4 TAIS – MOBILE TOURIST GUIDE

TAIS is a mobile travel guide application based on Smart-M3 platform (Honkola et al., 2010) implementing a smart space concept. That allows to significantly simplify further development of the system, to add information sources and services, and to make the system highly scalable. The key idea of this platform is that the formed smart space is device, domain, and vendor independent. Smart-M3 assumes that devices and software entities can publish their embedded information for other devices and software entities through simple, shared information brokers. Platform is open source and accessible for download at Sourceforge.

Implementation of TAIS application has been developed using Java KPI library. Mobile clients have been implemented using Android Java Development Kit. The application consists of a set of services (Smirnov et al., 2014) that interact with each other for providing the tourist recommendations about attraction that is better to see around. There are client application, attraction information service, recommendation service(described earlier in this paper), region context service, ridesharing service (Smirnov et al., 2012), and public transport service.

The main application screen is shown in Figure 3, left screenshot. The tourist can see images extracted from accessible internet sources around,

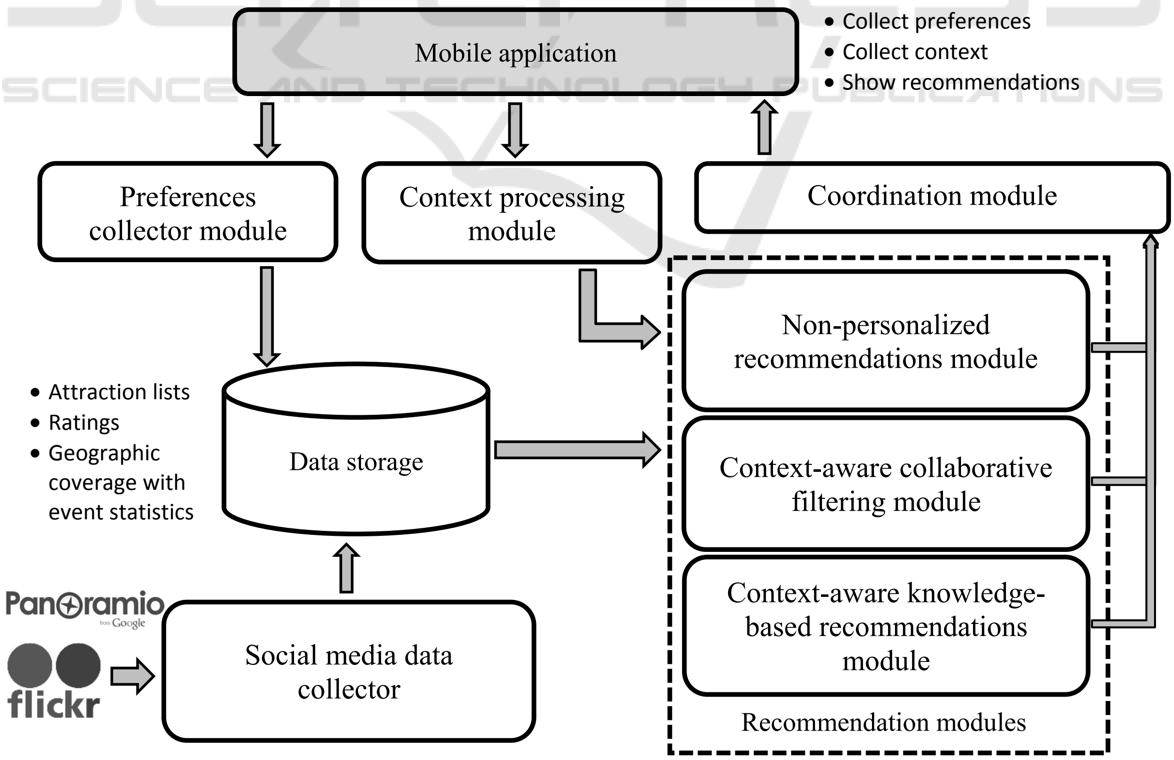

Figure 2: Recommendation service architecture.

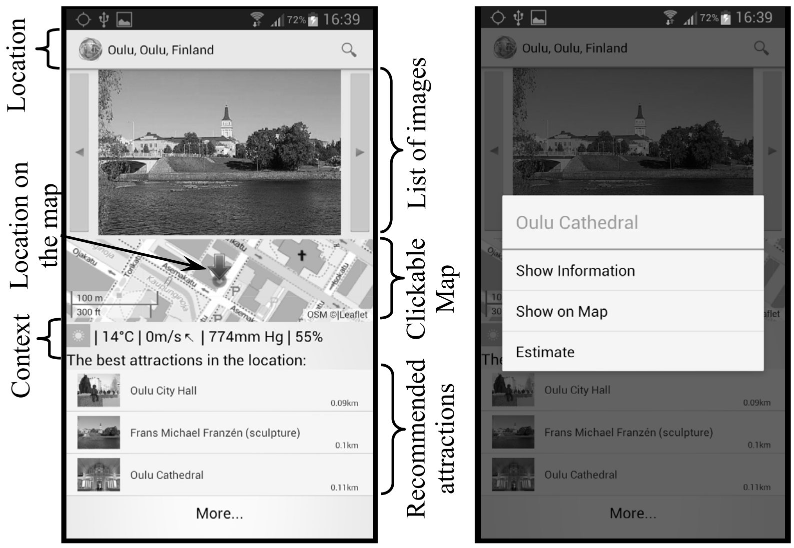

Figure 3: Tourist guide screenshots: main screen, context menu with actions.

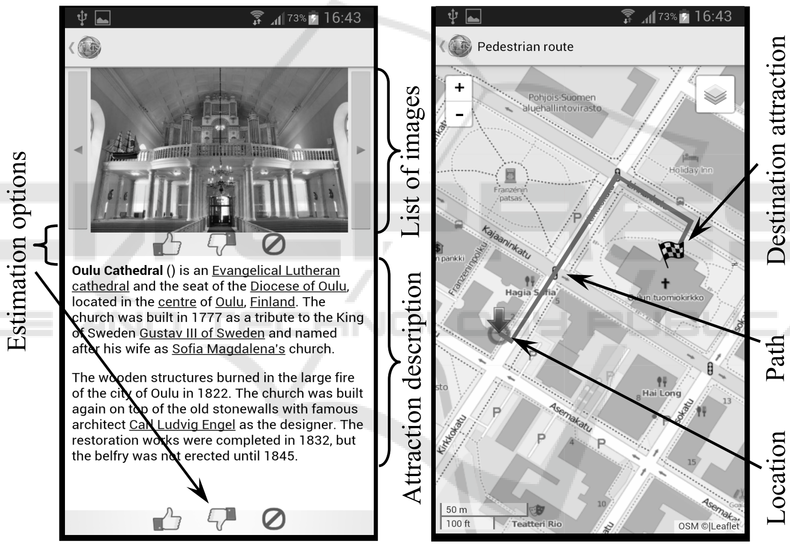

Figure 4: Tourist guide screenshots: attraction details and route to the attraction.

clickable map with his/her location, context situation (weather), and the best attractions around ranked by the recommendation service. When the tourist click to an attraction the following context menu is opened (see Figure 3, right screenshot). The tourist can see detailed information about the chosen attraction (Figure 4, left screenshot), browse attraction reaching path that is proposed by the system route to an attraction (Figure 4, right screenshot), and/or estimate it (Figure 5, left screenshot).

Detailed information about attraction contains a list of images that is associated with this attraction and it description. This information is extracted by the attraction information service from different internet sources (e.g., Wikipedia, Wikivoyage, and Panoramio are currently used).

The tourist has possibility to rate images using the following options: “like image”, “dislike image”, “this image is not applicable” to the attraction (see Figure 4, left screenshot). Based on these ratings the recommendation service will re-order images for this or another tourist next time.

The tourist can browse the attraction reaching path by choosing “Show on the map” item in context menu (see Figure 4, right screenshot). The routing service that is responsible for path finding uses OpenStreetMap-based web mapping service (Teslya, 2014). Routing service provides the tourist possibility to build pedestrian path, find fellow travelers who go to the same direction (Smirnov et al., 2012), and find public transport to reach chosen attraction.

Tourist can browse information about the best attractions around presented by the mobile tourist guide in the main screen and click button "More" to see more attractions (see left screenshot in Figure 5). The tourist can estimate if an attraction is interesting or not by looking through the names and thumbnail images. If he/she would like to get more information, it is possible to open description window (Figure 4, left screenshot). Tourist guide also calculates distance to every attraction (see Figure 5, left screenshot).

The tourist can rate an attraction if he/she likes or dislikes it (see Figure 5, right screenshot). For this purposes he/she specify the context (company and weather) and assign rating using five stars scale.

Pressing "menu" button allows to search information for worldwide attractions by choosing another area (country, region, and city) and to access the settings page of the mobile tourist guide application. In the status bar, the tourist can search for attractions worldwide.

5 CONCLUSIONS

The paper proposes multi-model approach for recommendation services for tourist domain, which aims on dealing with paucity of input information for recommendations. Its main idea is to create a family of recommending modules, based on various principles and requiring different input. To merge and reconcile results obtained from these modules, a special coordination module is introduced. It is designed to be highly configurable and uses declarative knowledge representation.

The proposed approach is implemented in the recommendation service of "TAIS – Mobile Tourist Guide" system, developed under the EU program for cross-border e-tourism framework in Oulu Region and the Republic of Karelia (Development of Cross-Border e-Tourism Framework for the Program Region – Smart e-Tourism (European Community – Karelia ENPI CBC 2007-2013 Program, 2012-2014 – project KA322)).

Further work is aimed on implementation of new recommendation modules and fine-tuning the knowledge base of the coordination module, based on the actual usage data.

ACKNOWLEDGEMENTS

The research was partially supported by grants # 14-07-00345, # 15-07-08092, # 16-07-00463 of the Russian Foundation for Basic Research and project 213 (program I.5P) of the Presidium of the Russian Academy of Sciences. This work was also partially financially supported by the Government of the Russian Federation, Grant 074-U01.

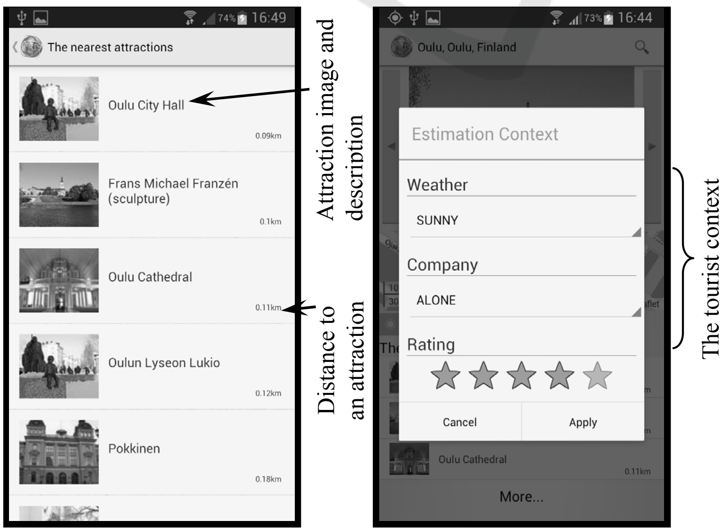

Figure 5: Tourist guide screenshots: all attractions around and estimation attraction interface.

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