

Multiwinner Election Mechanisms for Diverse Personalized Bayesian Recommendations for the Tourism Domain

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Abstract

In this work, we employ several multiwinner voting rules from the social choice literature to the personalized recommendations problem. Specifically, we equip with such mechanisms a Bayesian recommender for the tourism domain, allowing for effective personalized recommendations while promoting diverse results with respect to travel-related features. Our system models *both* users and items—i.e., tourist points of interest (POIs)—as *multivariate normal distributions*. We employ a novel, lightweight preference elicitation process, during which the user is presented with and asked to rate a small number of POIs-related images. We then use these ratings to guide a Bayesian updating process of beliefs regarding the user's preferences. Moreover, we study the effectiveness of our approach when we equip our system with some *prior knowledge* regarding the (average) preferences of a specific tourists' type (i.e., tourists of a specific age group), given data collected via questionnaires from actual visitors of a popular tourist resort on a Greek island. Finally, we conduct a systematic experimental evaluation of our approach by applying it on a real-world dataset. Our results (i) highlight the ability of our system to successfully produce personalized recommendations that match the specific interests of a single user; (ii) confirm that the employment of prior knowledge regarding the preferences of tourists, based on their demographics, guides our recommender to avoid the cold-start problem; and (iii) demonstrate that the use of multiwinner mechanisms allows for diverse recommendations with respect to travel-related features, and increased system performance in the case of limited user-system interactions.

Keywords

Bayesian Recommender System, Personalized Recommendations, Social Choice Theory

1. Introduction

Recommender systems in tourism play the key role of digital guides for the various activities that a tourist destination might provide to visitors based on their preferences [1, 2, 3, 4]. Tourism recommenders can be broadly categorized as hotel RSs, restaurant RSs, tourism RSs that are associated with group recommendations, tour planning (or travel packages); and tourist attraction RSs (i.e., points of interests, museums, etc.) [5]. However, in the complex domain of tourism, most of the times the user-items ratings are very sparse compared to other domains (e.g., the movies domain), and as such the employment of classic recommender system approaches, e.g., collaborative filtering techniques, can be a complicated task [6]. Additionally, many tourists

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have limited time when they visit a travel destination, and as such a recommender system should be able to provide efficient recommendations in order to maximize their satisfaction with a light-weight user-system interaction. Finally, visitors commonly use their mobile phones as a tool in order to exploit an unknown destination. As such, the development of recommender systems that use computationally efficient algorithms that can run on the mobile devices of the users is of utmost significance.

Against this background, in this work we introduce a personalized Bayesian recommender system for the tourism domain and evaluate it on a real-world dataset for a tourist destination in Greece—specifically that of Agios Nikolaos, Crete. The dataset was created for the needs of a real-world tour planning recommender system that is currently being developed in collaboration with an e-commerce company and the corresponding municipality. Generally, Bayesian methods are able to provide efficient recommendations and, most importantly, such techniques can be applied for real-time mobile recommendation services [7]. In more detail, real world data on *points of interests (POIs)* and users’ preferences were collected exploiting: (i) information and data provided by the Municipality of Agios Nikolas, Crete; (ii) online sources; and (iii) questionnaires that were filled by tourists. We propose an image-based process to elicit user’s preferences, by efficiently updating system’s beliefs about the user’s interests via a computational efficient Bayesian updating procedure that exploits the priors’ *conjugacy property*. Furthermore, we equip our system with *prior knowledge*, obtained via questionnaires from real-world tourists, and experimentally study its effectiveness.

Our main contribution in this paper, however, is putting forward a novel recommendation mechanism that can be used to increase the *diversity* of the final personalized recommendations (instead of simply “greedily” recommending the POIs so-far-perceived-as-best). Such diversity is important, and contributes to the overall quality of the recommendations—especially when these do not rely on ratings of other tourists/users, but are strictly personalized (in the sense that they are produced given only a few interactions with the user in question, as is the case in our system). Our mechanism is inspired by multiwinner election rules used in social choice theory [8], and which come complete with theoretical guarantees regarding properties satisfied by the set of the election winners (e.g., proportionality of the representation). Specifically, our approach creates a “personalized election” in order to “elect” a set of k “winners” (corresponding to the k final recommendations made to the targeted tourist-user). We study several voting rules and show that such an approach can be useful since it provides *diverse* results with respect to travel related features—e.g., *Culture, History, Cuisine*, and other characteristics that a tourist attraction may provide. For instance, assume that a user has due to various reasons (e.g., could have been pressed with time) rated highly only cultural POIs, when visiting a tourist destination. A mechanism that produces *diverse* final recommendations (i.e., a set of “election winners”), would present to the user POIs that are related to *various* categories, and not just Culture-related ones—a fact that is in fact expected to enhance the tourist experience. As such, our approach can be thought of as aiming to tackle the manifestation of the classic *exploration vs exploitation problem* [9] in this domain. Our experiments confirm that using multiwinner elections leads to improved system performance when the user-system interactions are limited, while the advantage thus provided decreases or evaporates with increased user-system interactions. To the best of our knowledge, this is the first time that such an approach is used in the recommender systems literature.

Finally, we conduct a systematic experimental evaluation of our recommender system by applying it on a real-world dataset of the popular Greek island tourist resort in question. Our results confirm the effectiveness of our approach, and highlight its ability to provide top personalized recommendations with respect to user's preferences and interests.

2. Background and Related Work

In this section, we provide the necessary background for this work. Specifically, we begin by briefly reviewing some recommender systems for individual users in the tourism domain. Finally, we describe some well-known notions of the social choice theory and present several rules for multiwinner-elections.

2.1. Personalized Recommendations

In general, tourism is a domain that contains various items of different types (e.g., leisure POIs, cultural POIs etc.), while it is highly connected with users' preferences and interests. Thus, the development of efficient recommender system approaches is crucial for such a domain. There is a plethora of tourism- or travel-oriented recommenders, potentially classified in different categories, as listed in [5]. Most of those systems recommend POIs that correspond to touristic attractions (e.g., restaurants, hotels, historical sites or museums), that are ideally highly connected with each individual tourist's preferences. Here we brief-review a few representative such systems.

An extensive overview of tourism recommender system algorithms is provided by Borràs et al. [10]. The authors discuss alternative user interfaces, recommendation techniques and additional services that such system may provide. Sánchez and Bellogín [11] presented a survey of recommender systems that employ Location-Based Social Networks for POIs recommendations, while discussing open challenges for such approaches. A restaurant recommender system for mobile devices introduced by Zeng et al. [12]. Specifically, their approach adopts a user preference model based on the restaurants that the user has already visited in the past, and produce the final recommendations by exploiting the exact location of the user. Kbaier et al. [13] develop a Hybrid recommender system that generates personalized recommendation by combining three different techniques, i.e., collaborative filtering, content-based filtering and the demographic filtering. A personalized tour planner, called eCOMPASS, was proposed by Gavalas et al. [14]. In their work, the system recommended personalized tours, i.e., a route that contains several POIs, by also considering: (i) the weather forecast, and (ii) the possibility that the visitor can use the public transit to move among the POIs. PersTour [4] is another recommendation system that was developed for recommending several POIs to the visitors by considering (i) the popularity of a specific POI; and (ii) the preferences of a specific tourist. Additionally, PersTour modifies the tourist's visiting time for a specific POI, based on how relevant this POI is to her interests. Mishra et al. [15] introduced a recommender system that employs the Sentiment Intensity Analyzer (SIA) in order to find the most appropriate POIs for a specific user by exploring the available reviews of other visitors. In [16] authors introduced a picture-based recommender approach which suggests tourist destinations for a specific individual. Specifically, the user selects any set of pictures which is then used as input to computer vision

models that generate a profile which describes the preferences of the tourist. Massimo and Ricci [1, 17] studied the problem of *next POIs recommendations*, i.e., given a set of POIs that a specific tourist has already visit provide recommendations for the not-yet-visited POIs. Specifically, Inverse Reinforcement Learning (IRL) techniques were employed in order to learn the reward function and the optimal POI selection policy. Finally, Gavalas et al. [18] provide a review of the state-of-the-art techniques for *mobile recommender systems* in the tourism domain.

2.2. Social Choice Theory and Multiwinner Election Rules

Social choice theory is a theoretical framework that applies to various domains such as economics, political science, computer science, etc. In general, social choice theory studies aggregation mechanisms of individual preferences or interests in order to reach a collective choice or decision [8]. The core scenario of collective decision making explored in this field is the election of a single “winner” based on the preferences of several *voters* over a number of *alternatives*. Many single-winner voting rules have been proposed in the literature with most known *plurality*, *Borda count*, *Copeland*, etc. [8]. On another point of view, a different kind of election is that of selecting a k -sized group of candidates, referred to as *committee*, instead of a single winner, i.e., a single alternative. This type of elections are also known as *multiwinner elections* [19] and can be categorized as: (i) Shortlisting, (ii) Diverse Committee and (iii) Proportional Representation mechanisms based on their type and their properties [20]. Intuitively, a Shortlisting mechanisms elects a committee consisting of the alternatives that have the best quality with respect to some feature(s), while a Diverse Committee mechanism elects a “committee” consisting of alternatives that are diverse based on some feature(s). In our, novel for multiwinner elections, application domain, assume users that prefer to go for shopping when they visit a tourist destination. A mechanism that produces a diverse committee as the final recommendations, i.e., the winners, would present to the user POIs that are related to various categories of shopping, i.e., a jewelry shop, a shop for local products, a clothing shop etc. By contrast, the applications of a Shortlisting mechanism may produce recommendations that focus on a specific category of shopping, e.g., only souvenir shops. Finally, a Proportional Representation mechanism selects a committee that captures all the different preferences of the voters proportionally.

We now focus on *approval-based* rules, in which each voter lists the candidates she approves, i.e., the alternatives that she likes. The most common approval-based mechanism is the well-known *Approval Voting*. In more detail, Approval Voting assigns one point to each approval for an alternative and then chooses the alternative with the highest score. As such, in multiwinner elections, Approval Voting elects a committee consisting of k alternatives that the voters approved most frequently [19]. In the case of a single winner, Approval Voting has a number of desirable properties, however it fails to achieve proportional representation in the multiwinner scenario [21]. Notably, an approval-based rule which satisfy strong axioms for election proportionality is the *Proportional Approval voting (PAV)* mechanism. Specifically, under the PAV rule the contribution of each voter to the final score of the committee is determined by how many candidates from the voter’s approval set have been elected [21]. However, Skowron et al. [22] proved that finding winners according to PAV mechanism is NP-hard. As such, the *Rewighted Approval Voting (RAV)*, a greedy variant of PAV has been introduced and can be

considered as a good approximation algorithm for PAV [19]. Formally, RAV is defined as:

Definition 2.1. [19] Consider an election with n voters where the i -th voter approves candidates in the set A_i . RAV starts with an empty committee S and executes k rounds. In each round it adds to S a candidate c with the maximal value of $\sum_{i: c \in A_i} \frac{1}{|S \cap A_i| + 1}$.

Another approval-based rule is the *Bloc* rule; according to *Bloc*, each voter selects her k favourite alternatives and the mechanism elects a committee consisting of the alternatives that were mentioned more frequently [23]. Finally, a well-known non-approval-based rule, the k -*Borda* selects the k alternatives with the highest Borda score [23, 8].

3. Our Approach

In this work we introduce a system that enhances the visitors' experience of a tourist destination by recommending POIs that "match" their interests and preferences. Inspired by the work of Babas et al. [24], we designed a Bayesian recommender system which performs Bayesian updating in order to *learn* user's (which corresponds to tourist's) preferences and provide her with efficient recommendations. Specifically, we model the users and the items (i.e., the POIs of a tourist destination), using a common representation—i.e., multivariate normal distributions over ranges of values, describing the degree that each feature describes a specific user or item. We note that, our system is unaware of every user's *real distribution*, while it is fully informed about each item's distribution. The goal of our agent, i.e., recommender system, is to "predict" the distribution describing a specific user in order to recommend the POIs most appropriate for her, thus increasing her satisfaction.

To this purpose, our system performs a series of "questions" in order to determine user's preferences by exploiting the data derived by this procedure. Specifically, we employ an image-based user preference elicitation approach, by presenting to the user a set of generic travel-related pictures and noting her "likes" in order to build a user model. Moreover, we equip our system with some prior knowledge regarding the general preferences of a specific type of visitors, i.e., tourists that belong to the same age group. Finally, we design a social choice inspired mechanism that produces diverse personalized recommendations to the user with respect to travel-related features. Specifically, given a specific user we create a "personalized election" based on her inferred model and employ various multiwinner election rules in order to produce diverse personalized recommendations.

3.1. Bayesian Inference

When a new user enters our system, commonly no (prior) information regarding her preferences is provided to our recommender system,¹ i.e., regarding her multivariate normal distribution. As such, we employ the *Normal-Inverse Wishart (NIW)* [25] conjugate priors to model the system's *beliefs* regarding the user's underlying parameters. In general, the NIW distribution is a multivariate four-parameter family of continuous probability distributions that has the

¹We study later the case in which our system is able to exploit prior information regarding a user based on demographics information derived by real tourists via questionnaires.

desired property of *conjugacy* of a multivariate normal distribution with unknown mean and covariance matrix. The use of conjugate priors offers a closed-form for the computation of the posterior distribution, resulting in a computationally efficient Bayesian updating procedure [24]. Specifically, we can update the prior hyperparameters— κ_0 , μ_0 (the mean vector), ν_0 (degrees of freedom), and Ψ_0 (the precision matrix)—using samples drawn from the data to get the posterior ones, as follows:

$$\mu_n = \frac{\kappa_0}{\kappa_0 + n} \cdot \mu_0 + \frac{n}{\kappa_0 + n} \cdot \bar{x} \quad (1)$$

$$\kappa_n = \kappa_0 + n \quad (2)$$

$$\nu_n = \nu_0 + n \quad (3)$$

$$\Psi_n = \Psi_0 + S + \frac{\kappa_0 \cdot n}{\kappa_0 + n} \cdot (\bar{x} - \mu_0) \cdot (\bar{x} - \mu_0)^T \quad (4)$$

$$S = \sum_{i=1}^n (x_i - \bar{x}) \cdot (x_i - \bar{x})^T \quad (5)$$

where \bar{x} is the sample mean, n is the number of the samples, x_i are the samples drawn from the data, S is a scatter matrix. Finally, we can use an *Inverse Wishart* and a *Normal* distribution to derive the *covariance matrix* Σ and the *mean* μ given the updated beliefs, as follows:

$$\Sigma \sim \mathcal{IW}(\Psi_n, \nu_n) \quad (6)$$

$$\mu|\Sigma \sim \mathcal{N}(\mu_n, \Sigma/\kappa_n) \quad (7)$$

3.2. Recommendation Process

First, when a user registers in the system the *preference elicitation* procedure begins. In more detail, the preference elicitation procedure is an iterative process where in each iteration our system presents n alternative *generic images* to the user. We use the term “question” to refer to such a presentation of a set of generic images. These generic images, similar to POIs, are represented as multivariate Gaussians. Each generic image corresponds a specific *type* of POIs, i.e., a restaurant, a monument, a beach etc. We select this picture-based approach to elicit user’s preferences, since there is a great complexity regarding the tourism product [6], and such approaches have been efficiently applied in order to elicit travel-related preferences [26, 27]. We highlight that the set of the generic images and the set of POIs do not share any common element (i.e., there are no items that belong to both lists).

Note that our agent selects which generic images to present to the user based on the available information (represented by the multivariate distribution), regarding her preferences (see Section 3.3). However, when a new user enters the system, most of the times we have no available information about her, so we have to *randomly* pick some generic images in the first iteration, unless our system has some prior knowledge at its disposal (e.g., a prior knowledge regarding the preferences of a specific age group, as we discuss later in Section 4.1.2). In such a case, our recommender is able to exploit the extra knowledge in order to pick the images that will present to the user in the first iteration. Once our algorithm selects the generic images that will present to the user, the user picks the image that is most “attractive” to her, with respect to

her interests, and provides a rating on a 5-level Likert scale, where 5 implies that this image fits her preferences perfectly.

In our approach, similarly to that of [24], we use the *Kullback-Leibler (KL) Divergence* criterion in order to compute the similarity between any item (generic image or POI) and any user based on her preferences and interests. In particular, knowing that both users and items share a common representation—since both are modelled as *multivariate normal distributions*— we can employ the KL-divergence criterion in order to find “how similar” their distributions are. Formally, the KL-divergence between a Gaussian x and a Gaussian y , of dimension D each, is given by:

$$KL(y||x) = \frac{1}{2} \log |S_y^{-1} S_x| + \frac{1}{2} \text{tr}((S_y^{-1} S_x)^{-1}) - \frac{D}{2} + \frac{1}{2} (m_y - m_x)^T S_x^{-1} (m_y - m_x) \quad (8)$$

where S_y, m_y, S_x and m_x are the distributions’ parameters, and $\text{tr}(\cdot)$ is the trace of the corresponding matrix [28]. In principle, a small KL-divergence between a Gaussian x and a Gaussian y means that they are similar, while a large KL-divergence means the distributions are not similar. Thus, in our work we make the natural assumption that the more similar the distributions of a user u and an item i are, the higher the rating (of user u for item i) would be. As such, the (predicted) rating of a user (represented as a Gaussian u) for an item (represented as a Gaussian i) can be defined as:

$$r_{u,i} = M - \frac{KL(u||i)}{M} \quad (9)$$

where M is the maximum rating the user can give to an item, i.e., $M = 5$.

Then, depending on the provided rating our system draws an appropriate number of samples from the distribution of the selected generic image. Specifically, we use the *logistic function* [29] and the rating of the user in order to compute the exact number of samples that will be drawn from the generic image’s distribution. Intuitively, the form of this function fits to our purposes, since a high rating (signifying the user likes a generic image), means that the distributions of the user and the image are similar, and as such a sufficiently large number of samples from the image’s distribution will contribute to construct a good model regarding user’s preferences; while a small rating means that the user does not feel that this image describes her preferences well. Thus, a small number of samples should be drawn since they are not representatives of user’s interests. Once the user enters her rating, our approach performs a *Bayesian updating* in order to produce an updated type of user (i.e., distribution) combining prior knowledge and the new data of this iteration, which corresponds to an user-system interaction. Note that the posterior derived in iteration t will be the prior for iteration $t + 1$, with which our system will choose which generic images to present to the user next (see Section 3.3). That is, the generic images at each iteration are chosen based on the beliefs updated on the previous iteration. This procedure terminates after m iterations. As such, our system estimates the parameters of user’s (μ, Σ) based on the hyperparameters of the NIW distribution (see Section 3.1).

Finally, our greedy version of our system utilizes the estimated parameters of the user in order to produce its final recommendations, by applying the KL divergence—i.e., it greedily recommends the k POIs that are more similar to the tourist’s inferred model. We note that, more user-system interactions, i.e., more m iterations, can provide our system better indications regarding the feature preferences of a specific user resulting a more representative user model.

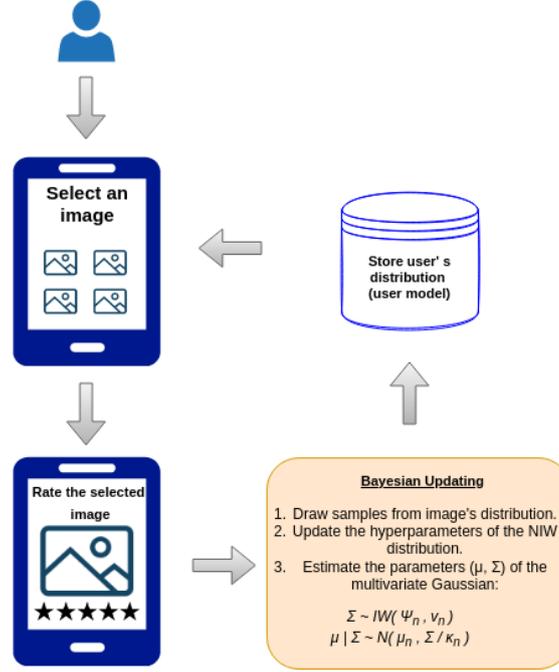


Figure 1: The preference elicitation process and the Bayesian updating.

3.3. Generic Images Selection

One crucial aspect of our recommendation system is the selection of an effective method which decides the items that will be shown to the user at each iteration. The item selection method should handle in an efficient way the *exploration vs exploitation* dilemma in order to increase the performance of our system. In our work we studied three alternative item selection methods, namely: a greedy mechanism based on the KL-divergence, the VPI exploration [24], and the Boltzmann selection. The Boltzmann selection mechanism performed better and as such is the method we detail here. Notably, in the experimental evaluation the results corresponds only to this mechanism.

Intuitively, Boltzmann exploration [30] tells us to pick an action with a probability that is proportional to its average reward. As such, actions with greater average rewards are picked with higher probability. Formally, at each time step t , our agent assigns a selection probability to each item i using the following formula:

$$Pr(i) = \frac{e^{r_{u,i}/T}}{\sum_{j=1}^n e^{r_{u,j}/T}} \quad (10)$$

where $T = c \cdot a^t$, with c be a constant value, $r_{u,i}$ is the quantity computed in Equation 9, and $a < 1$. In this method, the exploration vs exploitation trade-off is controlled via a temperature parameter T that decreases over time to progressively reduce exploration. Specifically, for very small values of T the action with the highest average reward (in our case, the highest predicted

$r_{u,i}$ rating) is more likely to be selected. On the other hand, in initial stages where the value of T is large, the Boltzmann method effectively corresponds to a random policy.

3.4. Generating Personalized Recommendations using Multiwinner Election Mechanisms

As described in Section 3.1, our system *learns* the preferences of a user via a Bayesian inference procedure that “builds” a distribution that describes the user with respect to some travel-related features. Moreover, our recommender greedily recommends the k items that are more similar to the tourist’s inferred distribution based on the KL divergence criterion. However, such an approach can lead to several undesirable properties regarding the final recommendations that the user will receive. For example, let us assume that a tourist during the preference elicitation process chose to give a high rating only to restaurants. In this case, a “greedy” approach will produce recommendations which will only be related to restaurants. Such a property might be desirable in other domains such as movies (e.g., action movies, etc.) but in the tourism domain, a tourist would like to have a variety of different POIs that she could visit in a travel destination, e.g. a restaurant, a monument, a bar, and so on. In other words, in order for the recommender algorithm to be able to provide a multitude of choices to the tourist, it should guarantee that there will be some diversity between its final k recommendations. Moreover, we remind the reader that the computation of the recommendations’ quality is based on the user model constructed so far. However, such a model is constructed using only limited user-system interactions resulting to a rather naive estimation of the actual user model; thus, we conjecture that providing diversity in the final recommendations is helpful. Thus, it is natural to apply a multiwinner voting rule from the social choice theory in order to ensure diverse results with respect to any subset of features. Figure 2 depicts our proposed approach.

In general, given a set of users (or voters), N , and their preferences, multiwinner election mechanisms select a k -sized set of alternatives (i.e., “a committee”). Such mechanisms satisfy specific properties based on their type (see Section 2.2). Given this, we now detail our approach to provide diverse recommendations to a tourist with respect to some travel-related features, instead of greedily selecting the POIs that are more similar to user’s inferred model.

To this end, given a specific tourist that is described by a multivariate Gaussian distribution over a set of features, we create a “personalized election” in order to produce our final recommendations. In more detail, given a user u , we exploit her mean vector, μ_u , in order to create a set of voters based on u ’s values over the selected travel-related features, i.e., the values on the μ_u for each (selected) feature. As such, we generate a set of voters, V , that provides proportional representation of user’s preferences over the features, i.e., a feature that has a high score will be represented by more voters than a feature that has a low value for u . Specifically, for any travel-related feature f , with value f_v , we generate $\lceil f_v \cdot 10 \rceil$ voters. Moreover, we make the natural assumptions that any voter that has been generated from feature f : (i) approves an item i , i.e., a POI, that has a value that is greater than 3 on feature f , i.e., $f_i \geq 3$; and (ii) prefers an item i over an item j if and only if i has a greater value than j on feature f , i.e., $f_{i,v} > f_{j,v}$ ². On the other hand the set of alternatives, A , and the set of POIs are identical. Therefore, we can apply

²We note that if $f_{i,v} = f_{j,v}$ we randomly select which item is preferred ($i \succ j$ or $j \succ i$) for each voter independently.

any³ multiwinner rule on this election in order to be able to pick *several* “personalized” winners that also satisfy specific properties (e.g., proportionality of the preferences’ representation) guaranteed by the rule in question, based on the travel-related features and the preferences of the tourist. As such, by not simply “greedily” recommending the so-far-perceived-as-best POIs, the proposed approach provides diverse recommendations. This fact is evident in our experimental results, where we see that using multiwinner elections leads to improved system performance when the user-system interactions are limited—with this advantage decreasing or evaporating with increased user-system interactions.

We also point out that such an approach allows us to provide diverse recommendations with respect to *any selected subset* of travel-related features. In more detail, our approach can maintain such property by creating a “personalized election”, where the voters have been produced *solely* from the selected subset of features following the procedure that has been already described in this section. (Of course, the set of the alternatives remains the same—i.e., it comprises all the available POIs.)

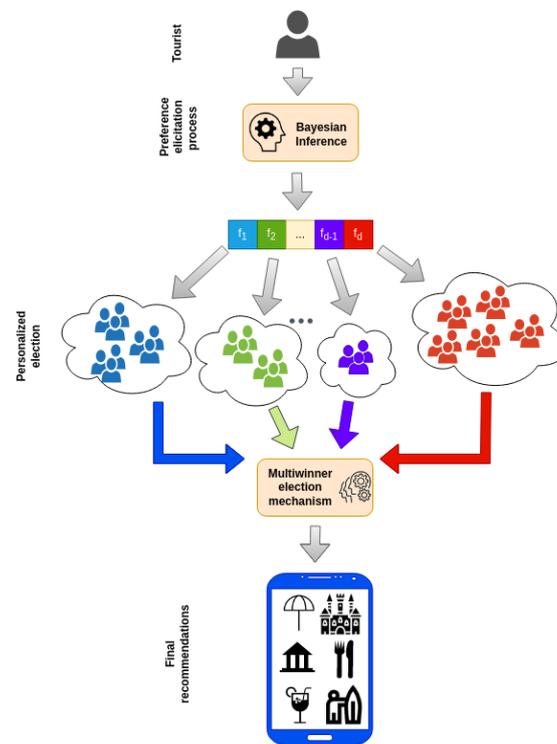


Figure 2: The social choice inspired mechanism for generating the final personalized recommendations.

³In our experiments below, we test several multiwinner election rules—specifically, AV, RAV, *k*-Borda and Bloc (see Section 2.2).

4. Experimental Evaluation

In this section we present a series of experiments to evaluate: (i) the ability of our approach to learn the preferences of a user, and provide high quality recommendation *wrt* her preferences; and (ii) the performance of several multiwinner election mechanisms with respect to the quality of the final recommendations. We use a real-world dataset including 430 POIs of a popular tourist resort on a Greek island. Alongside the available POIs, we used 90 generic images for the preference elicitation process. Note that for this series of experiments we assume that each user, POI, and generic image can be described as a multivariate normal distribution, where $D = 12$. Specifically, we consider the following travel-related features: *Culture, Sun & Sea, History/Archaeology, Adventure/Sports, Affordable Prices, Family-friendly activities & facilities, Rural Tourism, Luxury Accommodation, Nightlife, Gastronomy/Cuisine, General Shopping* and *Shopping Local Products*. We note that the Boltzmann exploration parameters for all series of experiments were set to: $c = 1, \alpha = 0.5$ and $t \leq 3$, with $t_0 = 0$ and $t_{i+1} = t_i + 1$.

4.1. Personalized Recommendations

First we present a series of experiments performed to evaluate the greedy version of our approach for personalized recommendations, using synthetic tourists. In more detail, using preference-related data collected from actual tourists via questionnaires, we generate 500 synthetic tourists for the age groups of 18-25, 26-35, 36-45, 46-55, 56-67 and 67 plus respectively, i.e., 3000 synthetic users in total. The average of the answers (i.e., values in the scale of 1...5 recorded on the questionnaires) of each age group for the 12 features provided by the questionnaires is calculated for each corresponding feature. In order to generate the synthetic users for each age group, we take 500 samples from a multivariate normal distribution, whose mean vector is the average values of the 12 features; the covariance matrix is diagonal and each diagonal element takes a value equal to 1. We run a series of user-system simulations with varying slate size—i.e., number of generic images $n = \{1, 2, 3, 4, 5\}$ that are presented to a user in each question asked, and number of questions $m = \{1, 2, 3, 4, 5\}$ asked. Finally, for each $\langle n, m \rangle$ combination we ran 1000 simulations: in every simulation, we randomly pick a tourist out of our 3000 synthetic users. As an evaluation metric, we compare the real distribution that represents user’s actual preferences with her inferred one—i.e., the distribution that our algorithm constructed via the preference elicitation method (see Section 3.2)—by using Equation 9. In what follows, we denote this resulting “predicted rating” metric by r for short. Notice that had the inferred distribution been *identical* to the real one, this metric’s value would be equal to 5, i.e., the maximum rating that an item can receive by a user.

4.1.1. No prior knowledge employed

Table 1 illustrates the results of the “greedy” approach on a first set of experiments that does not exploit any prior knowledge regarding the user—i.e., the system does not have any information regarding the user’s age group, but uses an uninformative prior (i.e., one with a mean vector that contains in each dimension a value of 1, and a diagonal covariance matrix where each diagonal element takes a value equal to 2). Note that the presented results are average values

	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$m = 1$	2.6	2.85	3.02	3.12	3.24
$m = 2$	2.74	3.06	3.24	3.39	3.5
$m = 3$	2.81	3.15	3.4	3.54	3.67
$m = 4$	2.86	3.23	3.5	3.67	3.82
$m = 5$	2.9	3.36	3.61	3.78	3.92

Table 1

The r results using uninformative priors (no prior knowledge exploited).

over 1000 simulations for each $\langle n, m \rangle$ combination setting tested. We can see that for n fixed across different settings, the r metric achieved by our algorithm increases as the number of questions, i.e., m , increases. Such a result is expected, since when the system makes more questions to a user, more information regarding her preferences is revealed, and as such our approach builds a better model with respect to the user’s preferences. Also, for a fixed number of m questions, we observe that as n (i.e., the number of alternative pictures shown per question) increases, the r achieved increases as well. This is due to the fact that when the system provides more options to a user, then a picture that best captures her preferences is easier to be found. Thus, by increasing the number of options n , our system is able to build a better user model, since it exploits better quality information regarding user interests.

Following that, we used another metric that captures the effectiveness of our approach based on the *quality* of the recommended POIs. Specifically, for each individual that interacts with the system, we use her “real” distribution in order to create the list l_{real} , which contains the *top-N* POIs for this specific user (i.e., given a user u , the N POIs from the dataset that score the highest $r_{u,i}$ scores). At the same time, we use the inferred model for this user (i.e., the distribution that our system created via the preference elicitation procedure), in order to create the list l_{inf} , which contains the *top-20* POIs for the inferred user. Thus, we can measure the similarity between the lists l_{real} and l_{inf} by finding the *common elements*, i.e., POIs, that these two lists share: that is, we count how many of the (real) user’s *top-N* items coincide with ones in the recommended, given the inferred user model, *top-20* list of items. For this set of experiments we set $N = \{20, 43, 86\}$. Note that, the “top-20” corresponds to only the 4.5% of our dataset. Similarly, the “top-43” constitutes only the 10% of our dataset, while “top-86” the 20%.

Table 2 shows the average of 1000 simulations for each combination of $\langle n, m \rangle$. As seen, for a given n (or a given m), the percentage of common elements that lists l_{real} and l_{inf} share, is rising as m (or n) rises. This is natural, since for larger n (or m) our system collects more information regarding user’s preferences and as such is able to provide better recommendations. Indicatively, in settings with $n=5, m=5$ our agent recommends POIs with 38.82% of them being among the best 20 POIs of each user. Accordingly, 57.81% of them being among the best 43 POIs and 75.19% of them being among the best 86 POIs of each user. Thus, after only a small number of interactions with each user, our approach is able to provide recommendations that match the user interests to a large extent.

4.1.2. Employing prior knowledge

Here, we study the scenario in which our system has at its disposal some prior knowledge regarding general user types preferences. Specifically, we construct some age-related priors—i.e.,

		$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$m = 1$	<i>top</i> - 20	13.75%	17.9%	21.52%	24.11%	27.3%
	<i>top</i> - 43	25%	32.66%	35.91%	40.92%	43.08%
	<i>top</i> - 86	38.43%	47.49%	54.43%	55.95%	59.53%
$m = 2$	<i>top</i> - 20	13.86%	21.17%	23.94%	27.15%	30.32%
	<i>top</i> - 43	25.27%	32.78%	41.19%	44.67%	47.33%
	<i>top</i> - 86	38.49%	49.37%	54.93%	60.73%	65.37%
$m = 3$	<i>top</i> - 20	14.06%	21.94%	27.5%	30.29%	35%
	<i>top</i> - 43	25.58%	34.67%	42.94%	46.79%	52%
	<i>top</i> - 86	38.63%	53.92%	59.94%	65.89%	70.41%
$m = 4$	<i>top</i> - 20	14.31%	23.3%	29.28%	33.36%	36.16%
	<i>top</i> - 43	27.01%	36.52%	43.66%	51.63%	55.78%
	<i>top</i> - 86	42.09%	54.15%	63.48%	69.67%	72.67%
$m = 5$	<i>top</i> - 20	14.48%	23.46%	30.37%	35.74%	38.82%
	<i>top</i> - 43	28.56%	37.92%	47.4%	53.58%	57.81%
	<i>top</i> - 86	42.73%	56.14%	65.44%	72.08%	75.19%

Table 2

Similarity of l_{real} and l_{mf} for “top-20”, “top-43” and “top-86” (uninformative priors).

prior distributions regarding the general preferences of tourists that belong to the same age group, by exploiting data collected via questionnaires from actual visitors. These priors are constructed in the exact same way as the ones from which we draw the synthetic users from, with the only difference being that we insert higher uncertainty, i.e. the diagonal covariance matrix elements have a value equal to 2. In this scenario, we study the performance of our recommender for each age group and we compare it with the case where no such extra information is available to us. For each age group, we generated 1000 users via the process already described in the beginning of this section, along with their corresponding priors.

Tables 3, 4, 5 and 6 depicts the average results over 1000 simulations for the age group of 18-25, 26-35, 36-45, 46-55, 56-67 and 67 plus. In more detail, Tables 3 and 5 capture the performance of our approach for each age group when no prior information is available. Again, we use the r metric in order to evaluate the inference of our system and the number of recommended POIs that belongs to the “top-20” of the user. Tables 4 and 6 present our corresponding results when our system knows the user’s age group and can thus exploit its prior knowledge regarding this age group’s preferences. First, we notice that with such prior knowledge in its disposal, our recommender significantly and consistently outperforms the version that has no prior knowledge available.

Moreover, the system is then able to provide high-scoring recommendations with only limited interaction among the user and the system, i.e. when the values of n and m are small, vastly outperforming the uninformed version. However, as the n and m values increase, the margins between the performance of the two versions decrease. Such a result is expected since the prior knowledge gives insights to our system regarding the user’s preferences.

Of course, given the way the generic age-related priors are constructed and the fact that the corresponding synthetic users’ distributions are closely related to the priors, these results have to be taken with a grain of salt. However, they do show that high-quality priors can indeed be exploited by our system. Moreover, the experiment provides further insights to the method’s behaviour, given the following interesting observation: Notice that, with prior knowledge available, there are cases where the performance of our approach in terms of recommendations made using KL-divergence, drops with more questions asked or images displayed (cf. Table 6).

	Age Group	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$m = 1$	18 – 25	2.64	2.95	3.17	3.29	3.39
	26 – 35	2.82	3.13	3.24	3.39	3.46
	36 – 45	2.93	3.27	3.43	3.54	3.64
	46 – 55	2.98	3.25	3.44	3.53	3.6
	56 – 67	2.72	2.95	3.14	3.26	3.36
	67+	2.49	2.68	2.83	2.95	3.06
$m = 2$	18 – 25	2.81	3.15	3.4	3.54	3.68
	26 – 35	2.97	3.3	3.49	3.65	3.73
	36 – 45	3.1	3.44	3.64	3.78	3.87
	46 – 55	3.19	3.44	3.64	3.75	3.83
	56 – 67	2.88	3.17	3.36	3.49	3.58
	67+	2.69	2.9	3.08	3.09	3.31
$m = 3$	18 – 25	2.85	3.3	3.57	3.74	3.9
	26 – 35	3.03	3.43	3.71	3.82	3.89
	36 – 45	3.13	3.57	3.81	3.96	4.06
	46 – 55	3.21	3.57	3.79	3.92	3.99
	56 – 67	2.93	3.3	3.52	3.66	3.81
	67+	2.71	3.01	3.22	3.38	3.51

Table 3
Performance with no available prior knowledge (r metric).

	Age Group	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$m = 1$	18 – 25	4.11	4.12	4.13	4.13	4.13
	26 – 35	3.94	3.98	3.99	4	4.01
	36 – 45	4.04	4.1	4.12	4.13	4.14
	46 – 55	3.94	4	4.01	4.02	4.02
	56 – 67	3.97	4	3.98	3.98	3.98
	67+	3.68	3.71	3.72	3.74	3.73
$m = 2$	18 – 25	4.21	4.15	4.16	4.18	4.19
	26 – 35	3.84	3.93	3.96	4.06	4.07
	36 – 45	4.03	4.14	4.15	4.18	4.21
	46 – 55	3.86	4.05	4.07	4.06	4.13
	56 – 67	3.95	3.96	3.97	3.99	3.99
	67+	3.78	3.79	3.77	3.76	3.77
$m = 3$	18 – 25	4.19	4.2	4.17	4.2	4.21
	26 – 35	3.75	3.97	4	4.09	4.11
	36 – 45	3.97	4.18	4.19	4.22	4.25
	46 – 55	3.87	4.07	4.1	4.1	4.12
	56 – 67	3.9	3.96	3.97	3.98	4.01
	67+	3.75	3.78	3.78	3.76	3.78

Table 4
Performance with available prior knowledge (r metric).

	Age Group	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$m = 1$	18 – 25	15.01%	20.21%	23.95%	26.45%	27.5%
	26 – 35	12.71%	18.56%	21.56%	23.45%	25.06%
	36 – 45	16.64%	23.01%	26.54%	30.32%	31.31%
	46 – 55	14.78%	21.02%	24.28%	26.39%	28.76%
	56 – 67	13.99%	18.81%	22.84%	26.23%	27.9%
	67+	14.8%	17.95%	20.82%	23.75%	25.75%
$m = 2$	18 – 25	14.76%	20.38%	25.9%	29.12%	32.17%
	26 – 35	12.76%	20.27%	23.4%	27.4%	28.34%
	36 – 45	17.55%	25%	29.8%	35.29%	36.76%
	46 – 55	16.78%	22.59%	29.14%	30.64%	33.35%
	56 – 67	15.53%	21.32%	25.64%	28.51%	30.5%
	67+	17.9%	19.64%	23.93%	24.05%	28.4%
$m = 3$	18 – 25	14.9%	23.97%	28.53%	31.47%	35.18%
	26 – 35	12.8%	21.49%	27.34%	29.15%	30.86%
	36 – 45	17.18%	27.96%	34.41%	39.09%	41.28%
	46 – 55	16.79%	25.65%	29.98%	32.9%	36.99%
	56 – 67	14.46%	22.93%	28.49%	31.56%	35.6%
	67+	15.32%	21.08%	25.37%	28.08%	32.16%

Table 5
Performance with no available prior knowledge (Similarity of l_{real} and l_{inf} for “top-20”).

	Age Group	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$m = 1$	18 – 25	45.86%	45.06%	45.1%	46.62%	46.68%
	26 – 35	29.38%	32.03%	30.9%	34.83%	34.54%
	36 – 45	48.52%	53.03%	52.36%	49.44%	50.3%
	46 – 55	41.15%	36.68%	39.32%	39.42%	40.43%
	56 – 67	44%	43.78%	42.96%	43.15%	42.72%
	67+	41.53%	42.84%	43.09%	43.94%	43.43%
$m = 2$	18 – 25	42.4%	37.05%	38%	38.68%	38.51%
	26 – 35	21.62%	25.1%	30.87%	40.14%	37.26%
	36 – 45	47.74%	50.4%	47.86%	49.95%	48.95%
	46 – 55	27.19%	36.33%	38.9%	38.07%	41.75%
	56 – 67	31.02%	34.51%	40.23%	39.43%	44.23%
	67+	33.27%	39.75%	39.6%	44.64%	44.14%
$m = 3$	18 – 25	37.25%	34.71%	35.2%	37.02%	38.25%
	26 – 35	19.28%	30.45%	32.77%	37.65%	36.63%
	36 – 45	46.86%	49.83%	47.89%	48.97%	49.83%
	46 – 55	27.2%	39.98%	43.74%	41.08%	41.19%
	56 – 67	30.72%	39.96%	41.44%	41.2%	45.31%
	67+	33.95%	41.82%	42.09%	45.14%	45.64%

Table 6
Performance with available prior knowledge (Similarity of l_{real} and l_{inf} for “top-20”).

We attribute this behaviour to the fact that apparently our age-related prior is of a very high quality (indeed, it is very similar to the synthetic user’s distribution), and is thus able to capture the preferences of a user to a very large extent—i.e., it describes her interests for every travel-related feature that we have used in our approach. By contrast, when the preference elicitation process kicks in, we present generic images that cannot but represent a very specific type of POIs (e.g., a beach, a restaurant etc.). Thus, when the visitor selects and rates a picture, the samples that will be drawn in order to perform the Bayesian updating of the user’s model will help improve beliefs only for specific features, causing a small drop in recommendations’ quality. Notice that this is despite the fact that performance *wrt.* the r -metric consistently increases with questions asked and images displayed.

	Rule	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$m = 1$	Greedy	14.07%	19.83%	22.29%	24.42%	26.44%
	AV	22.36%	26.15%	27.76%	28.7%	29.63%
	RAV	22.75%	24.53%	25.78%	26.12%	26.65%
	Bloc	19.13%	23.48%	24.66%	23.73%	25.64%
	k-Borda	21.59%	24.88%	25.65%	26.66%	27.61%
$m = 2$	Greedy	15.34%	20.56%	24.39%	27.86%	30.31%
	AV	22.97%	26.24%	28.21%	29.93%	30.85%
	RAV	23.25%	24.99%	25.67%	26.6%	27.2%
	Bloc	20.83%	21.93%	23.68%	26.11%	25.57%
	k-Borda	22.08%	25.49%	25.89%	27.37%	28.97%
$m = 3$	Greedy	15.05%	22%	26.92%	30%	34.17%
	AV	22.81%	26.03%	28.62%	29.94%	31.59%
	RAV	23.26%	24.82%	25.85%	26.84%	27.56%
	Bloc	19.91%	22.64%	24.84%	26.76%	28.86%
	k-Borda	21.23%	24.54%	27.16%	28.6%	28.83%

Table 7
Performance of aggregation mechanisms with no available prior knowledge (Similarity of l_{real} and l_{inf} for “top-20”).

4.1.3. Multiwinner elections for personalized recommendations

Here we evaluate our social choice-inspired mechanism for generating our final recommendations to a tourist. To this end, we created 1000 synthetic tourists following the exact same procedure already described earlier (see Section 4.1), and applied the following well-known aggregation strategies: (i) Approval Voting (AV), (ii) Reweighted Approval Voting (RAV), (iii) Bloc, and (iv) k -Borda. We chose to evaluate our approach by measuring the similarity between the lists l_{real} and l_{inf} for the *top-20* POIs of each user.

Table 7 illustrates the results of our approach on this set of experiments. Note that the presented results are the average values over 1000 simulations of experiments for each (n, m) combination. First, we observe that when the values of n and m are small (i.e. 1 or 2), the greedy approach usually ranks lower in terms of similarity score among most multiwinner election mechanisms methods—while for $n = 1$ and $n = 2$ *all* multiwinner election mechanisms perform better than “greedy” with respect to our metric. These performance results are natural, since for smaller n and m we collect limited information regarding the interests of the user. As a result, our inferred model does not describe the user preferences very accurately. Thus, the selection of the POIs based on the model inferred so far—given only the very limited information provided by the user—is not the optimal policy. On the other hand, the employment of multiwinner election mechanisms allows us to move beyond this suboptimal greedy approach, while it still exploits our inferred model (see Section 3.4). However, as n and m increase, and our system is able to collect more information regarding the interests of the tourist, we notice that the *greedy* performs better than most of the voting rules, but its advantage is in most cases not significant—in contrast to what was the case for low n and m values, where the advantage of the social choice-inspired methods was broad. Additionally, the employment of the voting rules results to a diverse “elected committee”, corresponding to diverse final recommendations with respect to the travel-related features. Thus, we see that such mechanisms can help us (i) achieve better performance regarding the quality of our recommendations when the user-system interaction is limited; and (ii) produce various POIs of different types, by simply paying a small quality penalty compared to the performance of the greedy approach.

Finally, we notice that when $n = 1$ the RAV rule performs better with respect to our evaluation metric, showing that a proportional representation of the travel-related features (our “voters”), is a rational choice when limited information is in our disposal. As the user-system interaction increase, and more information regarding her interests is available to our system, the AV approach achieves the highest performance.

5. Conclusions and Future Work

In this paper, we designed a personalized Bayesian recommender system for the tourism domain. Our system employs several well-known multiwinner voting rules on a “personalized election” generated by the user’s inferred model in order to produce the final recommendations. It models both tourists and POIs as multivariate normal distributions and learns the preferences via a lightweight picture-based elicitation process that guides a Bayesian updating process. Moreover, we equipped our system with prior knowledge exploited via questionnaires from real tourists, and studied the effectiveness of our approach. Finally, we conducted a systematic experimental evaluation of our approach using a real-world dataset of a tourist destination. Our results (i) confirm that our approach is able to accurately model the users and thus to provide effective personalized recommendations; and (ii) demonstrate that the use of multiwinner mechanisms for personalized recommendations allows for diverse recommendations in terms of travel-related attributes, which are nevertheless of high quality and clearly outperform the simple “greedy” Bayesian approach when information provided by the users is limited (and thus our confidence in the inferred user model is low).

In future work, we intend to further evaluate our approach in scenarios in which different types of prior knowledge is available—i.e., when we have and can exploit information regarding the general preferences of a type of visitors not only based on the age group that they belong to, but also their cultural background, their gender, etc. We are currently working on the extension of our proposed system in order to provide group recommendations, since usually people choose to travel with company. Specifically, in ongoing work we study the properties of several multiwinner election mechanisms for the group recommendation problem with respect to well known fairness metrics (i.e., the *m-PROPORTIONALITY* and the *m-ENVY-FREENESS* fairness metrics [31] ones). Finally, we intend to test our approach with actual tourists, via incorporating our recommendation techniques in different versions of a real-world mobile application for tours planning which is currently under development.

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