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User Profile and Multi-Criteria Decision Making: Personalization of Traveller's Information in Public Transportation

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Abstract

Personalization plays an important role in information systems. It is an effective solution for reducing complexity when searching information. In this way, the user feels like the system was developed for him/her. In this context, personalization can be seen as an optimization problem. To this end, we propose a multi-criteria decision making approach to personalize systems. The proposed approach has been validated by applying it to personalize a system in intelligent transport field.

Keywords: Intelligent Information Systems; Decision Making; Personalization; Multi-criteria; Intelligent Transport Systems;

1. Introduction

Recent advances in information and communication technologies offer the opportunity to access voluminous masses of information using a variety of platforms and supporting different modes of interaction. In fact, personalization plays an important role in information systems. For example in transport field, the main difficulty of traveler is to choose the most adapted itinerary to his/her preferences in a complex multimodal network (integrating several modes of transport: bus, train, etc., multiple transport operators and many criteria: cost, duration, comfort, etc). To this end, our aim is to provide personalized itinerary and to maintain the evolution of user profile.

The remainder of this paper will be structured as follows: section 2 is dedicated to the definition of personalization and user profile. In Section 3, we give an overview of our proposal. Section 4, explains how this approach has been validated by applying it to personalize a system in intelligent transport field. The related work in personalized information system is outlined in Section 5. Finally, we conclude with some future works.

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2. Personalization and User Profile

In the literature, there are several definitions about personalization. For [1], "Personalization is the capability to customize communication based on knowledge preferences and behaviors at the time of interaction". [2] describes personalization as "the dynamic adaptation of the interface to the profile". According to [3], "Personalization is the ability to provide content and services that are tailored to individuals based on knowledge about their preferences and behaviors". [4] considers that personalization is part of adaptation which is the process of modifying systems to work adequately in a given context (see Fig.1).

Fig1. Personalization position [5]

In general, we can say that personalization deals with the adaptation capacity of a system considering some information related to the profile user.

User profile is a set of information describing the user. It contains data referring to user preferences which are an expression that prioritizes the importance of information in a profile or context [6]. These authors consider user profile as a structured data describing the environment of interaction between a user and a system. For [7-8], user profile is an ontology employed in order to have more structured user profile representation. It allows representing knowledge (context and user's preferences) as a set of concepts. For us, user profile is divided into two data types: preferences P_u corresponding to user's interests and history H_u which save the user's request and the system's response.

3. Approach Overview

This section shows how personalization can be seen as an optimization problem. We also show why the size of the corresponding search space makes combinatorial multi-objective optimization process necessary in order to evaluate the generated solutions. We propose to consider the search as a multi-criteria optimization problem instead of a single-criteria one. To this end, we propose a multi-criteria decision making approach to personalize system.

3.1. Multi-criteria decision making overview

In this subsection, we outline different Multi-Criteria Decision Making (MCDM) approaches. We distinguish two main categories as [9]:

- Total Aggregation Methods (TAM): They are based on a unique value function, as an additive utility to compare alternatives [10]. We can mention for example, SMART (Simple Multi-Attribute Rating Technique) [11], TOPSIS (Technique for Order by Similarity to Ideal Solution) [12] and AHP (Analytic Hierarchy Process) [13].
- Partial Aggregation Methods (PAM): also called outranking methods. They are based on pair-wise comparisons on criteria to determine the preferred alternative by accepting incomparability [10]. The well-know methods are PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) [14] and ELECTRE (Elimination and Choice Translating Reality) [15].

Comparing these two categories of methods, we note first that when evaluating a solution "A" using TAM, its weakness over one criterion may be offset by a performance over another. However, when employing PAM, the weakness of a solution “A” compared to solution ”B” prevent that “A outperforms B” even if “A” got the upper hand for the rest of criteria. Second, since treated criteria are heterogeneous, (qualitative and quantitative), we therefore need a standardized scale when employing the TAM. However, when using PAM we don’t need this scale since criteria are treated separately. Finally, TAM is looking for the best solution. Nevertheless, PAM is seeking a trade-off of the evaluation criteria. In this way, our method will be based on partial aggregation methods (ELECTRE) in order to find the optimal itinerary which satisfies the trade-off of evaluation criteria.

3.2. ELECTRE methods

The ELECTRE method is one of the multi-criteria decision making methods. In our case, the objective is to find responses that have a compromise of the different criteria. The set of candidate solutions corresponds to a set of request’s responses (R).

Multi-criteria decision making approaches consist in associating a weight to each criteria’s function. These weighs represent the relative importance of the criterion in optimization problem. In our problem, the criteria don’t have the same importance. Weights correspond to the importance of every user’s preference.

Multi-criteria decision making methods guide decision makers obtaining a value assessment of alternatives with regard to a number of diverse and conflicting criteria in order to conclude what is the most preferred alternative.

Similar to ELECTRE I, when evaluating solutions, we have to sort them out according to different criteria. For example, a traveler chooses an itinerary among others, basing on a certain criteria of selection (cost, distance, trip duration, etc.).

3.3. Proposed approach

3.3.1. User profile

In this sub-section, we describe our proposal user modeling. In fact, in the same user modeling defined by [4], we propose to divide the user profile M_u into two data types: preferences P_u and history H_u.

$$M_u = P_u \cup H_u$$

The history saves the queries of users and theirs selected answers:

$$H_u = \{(Q_1, s_1), (Q_2, s_2), .., (Q_n, s_n)\}$$

Where:

- Q_j: the query performed by the user;
- S_j: the preferred solution (itinerary) selected by the user in response to the query Q_j.

The user preferences are implicitly acquired by the system based on his/her historical choices:

$$P_u = \{(p_1, w_1), (p_2, w_2), \dots , (p_n, w_n)\}$$

Where:

- p_i: the user’s preference (Criteria).
- w_i: the weight associated to the preference p_i which represents the importance of the user for the criteria $_i$.

To ensure learning system, we recalculate the weight of the user's preference basing on the formula (1).

$$W_i = \frac{\mathrm{Mark}(S_{sj}, Cr_i)}{\sum_{i=1}^{n} \mathrm{Mark}(S_{sj}, Cr_i)} \tag{1}$$

Where:
- Ssj: the preferred solution selected by the user.
- $\mathrm{Mark}(S_{sj}, Cr_i)$: The selected solution mark according to the criterion Cr_i.

Thus, the final criterion weight is the average of the calculated weight in the different user sessions (see formula (2)).

$$\text{Weight } (\mathrm{Cr_i}) = \frac{\sum W_i}{n} \quad (2)$$

Where:
- n: number of user queries.

This learning process maintains the scalability of the user's preferences, without requiring him to intervene and express their needs.

3.3.2. Personalization multi-criteria method

In a multimodal transport network, the user finds difficulty to choose itinerary according to the multitude of itineraries and the variety of evaluation criteria that are conflictual and compensatory (cost, comfort, time, security, correspondence, etc.). In this context, we propose Multi-criteria Personalization Method (MPM) based on ELECTRE I which ensures the choice of the preferred itinerary relative to the user needs. Our goal is not to find the best solution, but the one that can achieve a compromise between the different compensatory criteria. Our proposed method is composed of six phases: 1) Determining the performance ratings, 2) Comparison between couple of solutions, 3) Convert relations between solutions into numerical values, 4) Ascertainment of concordance and discordance, 5) Post-filtering of solutions and depict a decision graph and 6) Rank actions (solutions). Fig2. shows the general structure of our approach.

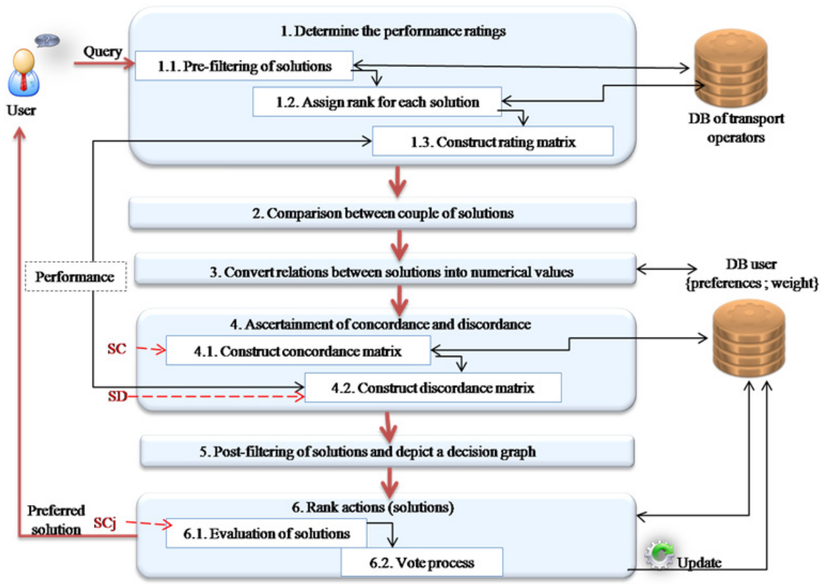

Fig. 2. MPM architecture

Phase1: Determine the performance ratings

This phase is composed of three steps:

1) *Pre-filtering of solutions*: it's based on the parameters of user's query in order to reduce the search space. This step takes as inputs the parameters of query, and generates as output a set of pertinent solutions. For example, let's consider a request R and a set of solutions of this request S_j (j= {1,…,n}; n is the number of possible solutions for the request R).

2) *Assign rank for solutions*: at this level, the system assigns a rank ($Rank_{ij}$) to each solution j according to each criterion i. When evaluating solutions, we have to sort them out according to different criteria.

3) *Construct rating matrix*: in this step, the system assigns a performance to each solution S_j according to each criterion Cr_i based on the ranks. This performance is given by the formula (3).

$$\mathrm{Mark}\left(S_{sj}, Cr_i\right) = \frac{1}{Rank_{ij}} * \delta \tag{3}$$

Where δ is a constant of normalization

Phase 2: Comparison between couple of solutions

In this phase, the actions are compared pair-wise in order to build an outranking relation using the following sets:

- $j^+(s_i, s_k) = \left\{ j \in F \middle| g_j(s_i) > g_j(s_k) \right\}$: it's the set of criteria for which the solution s_i is preferred to solution s_k
- $j^=(s_i, s_k) = \left\{ j \in F \middle| g_j(s_i) = g_j(s_k) \right\}$: it's the set of criteria for which the solution s_i have the same preference compared to the solution s_k.
- $j^-(s_i, s_k) = \left\{ j \in F \middle| g_j(s_i) < g_j(s_k) \right\}$: it's the set of criteria for which the solution s_i is less preferred than the solution s_k.

Thus, the output is a set of indices representing the criteria which satisfy the relations defined for each pair of solutions.

Phase 3: Convert relations between solutions into numerical values

At this level, the aim is to convert different sets obtained after the solutions pairs comparison (S_i, S_k) into values. These values will be represented in a matrix of dimension N×N (N is the number of solutions). For each set, we determine the sum of weights of the criteria belonging to each category as follows:

- $P^+ (s_i, s_k) = \sum_j P_j$ where $j \in j^+(s_i, s_k)$: it's the sum of criteria weights w_{ui} belonging to the set $j^+(s_i, s_k)$.
- $P^= (s_i, s_k) = \sum_j P_j$ where $j \in j^=(s_i, s_k)$: it's the sum of criteria weights w_{ui} belonging to the set $j^=(s_i, s_k)$.
- $P^- (s_i, s_k) = \sum_j P_j$ where $j \in j^-(s_i, s_k)$: it's the sum of criteria weights w_{ui} belonging to the set $j^-(s_i, s_k)$.

We note that:

$P(s_i,s_k)=P^+(s_i,s_k)+P^=(s_i,s_k)+P^-(s_i,s_k)$.

Phase 4: Ascertainment of concordance and discordance

At this level, the concordance and discordance indices have to be calculated for each pair of actions.

1) Construct the concordance matrix: the concordance test allows the decision maker to verify if action a1 is at least as good as an action a2. It's calculated basis on formula (4).

$$C_{ik} = \frac{P^+ (s_i, s_k) + P^= (s_i, s_k)}{P(s_i, s_k)} \tag{4}$$

The variation field of C_{ik} is $0 \leq C_{ik} \leq 1$. We denote the set of concordance as:

$$j(s_i,s_k)=j^+(s_i,s_k) \cup j^=(s_i,s_k)$$

2) Construct discordance matrix: it expresses the confident degree at which there is consistent with the hypothesis "a1 outperforms a2". The variation field of D_{ik} is $0 \leq C_{ik} \leq 1$. The employed formula is as in (5).

$$D_{ik}=\begin{cases} 0 & \text{if } j^-(s_i,s_k)=\emptyset \\ \frac{1}{\delta_j}\max\left(g_j(s_k)-g_j(s_i)\right) \text{ where } j \in j^-(s_i,s_k) & \text{, Else} \end{cases} \tag{5}$$

With:

- δ_j: The maximal difference between the higher level and the lower level of the measurement scale evaluation of solutions via criteria.
- $\max\left(g_j(s_k)-g_j(s_i)\right)$: The maximal difference between the solution performances via discordant criteria (for which s_k outperforms s_i)

We denote the set of discordance as: $j^-(s_i, s_k)$

Phase 5: Post-filtering of solution and depict a decision graph

In this phase, the outranking relations are evaluated. To have a reliable outranking relation, we must have as in (6).

$$\left.\begin{matrix} C_{ik} \geq c \\ D_{ik} \leq d \end{matrix}\right\} \leftrightarrow s_i \; S \; s_k \tag{6}$$

Where:

- c: concordance threshold. It's the threshold above which the hypothesis "s_i Outperforms s_k" is valid.
- d: discordance threshold. It's the threshold above which the hypothesis "s_i Outperforms s_k" is no longer valid.

This phase allows extracting from the candidate solutions, the preferred ones. Then, we construct the decision graph to distinguish which action is preferable, incomparable or indifferent

Phase 6: Rank of Actions (Solutions)

The aim of this phase is to rank the actions basing on the user's preferences (decision criteria). This phase is composed into two steps:

1) Evaluation of solutions: the solutions are divided into two subsets: the Preferred Solutions set (PS) and the Not Preferred Solutions set (NPS). This classification is made according to a threshold relative to each criterion SC_j. This threshold is the performances average of the solutions (S_j) according to each criterion (Cr_i) as in (7).

$$Sc_i = \frac{\sum_{i=1}^{n} \text{Mark}(s_j, cr_i)}{n} \tag{7}$$

Where: n is the number of candidate solutions

Thus, for each criterion, if $\text{Mark}(s_j, cr_i) \geq Sc_i$ then S_j is assigned to the subset PS else, S_j is assigned to the subset NPS.

2) The vote process: In this step, we proceed to a series of distillation to classify solutions. In this sorting process, the aim is to adopt majority vote between criteria. The criterion with the higher weight asks other criteria to vote for elimination of less preferred solutions (line 4). Every criterion examines the set of NPS solutions. If a solution appears in this set, it will vote for its suppression from SS. will calculate for each solution of NPS the parameters O_j and N_j (line 7 and 8). O_j represents the sum of criteria weights related to the criteria that improve the elimination of the solution S_i. N_j represents the sum of criteria weights related to criteria that are confirms against its elimination. If This O_j is superior to N_j, the solution will be eliminated from the set SS (line 9 and 10). Then the Classified solution set contains the preferred ones (line 14).

This process is based on the following majority-vote algorithm:

Input
RS: Rejected Solution
SS: Set of Solution generated by phase 5)
Crj: Decision criteria
n: number of criteria
Output
Classified solutions [1..card (SS)]
Begin
1: RS← {Ø}
2: CS← {Ø}
3: **While** [(j≠n) and (RS≠SS)]
4: Important-Cr←Crj
5: A←NPS(Crj)-(RSUCS)
6: **For** Sj ∈ A Do
7: Oj ← $\sum_j$ W(Cr_j)
8: Nj← $\sum_j$ W(Cr_j)
9: **IF** Oj> Nj **Then**
10: RS←RS ∪ S_i //The solution is rejected
11: **End If**
12: **End For**
13: j←j+1
14: Classified solutions [i]←SS-RS
15: CS ←CS U Classified solutions [i]
16: SS←SS- Classified solutions [i]
17: i← i+1
18: **End While**
End

4. Validation

Personalized information, related to traveling and mobility of passengers using transport networks, represents an important potential and is object of many research and development perspectives. In fact, communication technologies are developing rapidly the sector of Intelligent Transport Systems (ITS) and one can suggest numerous innovative mobility personalized services. The traveler hopes to have at his/her disposal only some information, just what he/she is directly interested in. So, Personalized Information Systems (PIS) should provide the user with the needed information taking into account his/her preferences. Indeed, the traveler can have access to reliable, multi-modal and personalized information. Before travelling, he/she needs to know the itineraries, time-tables and tariffs. During the travel, the traveler needs to be informed about the impediments and the appropriate means put at his/her disposal in case of accidents. In our work, the proposed application consists in searching itinerary from a given point "A" to a given point "B" in a multimodal network basing on a certain criteria of selection (cost, distance, trip duration, and walk.). The evaluation of our approach is based on two parameters: Precision and Recall. Precision defines how accurate the system is, and recall indicates how thorough it is in finding valuable information [16]. Precision is the ratio between the number of user-Relevant Itineraries that the System proposes to him/her (RIS) and the set of Retrieved Itineraries by the system (RI).

$$\text{Precision}=\frac{\text{RIS}}{\text{RI}}$$

Recall is the ratio between the RIS and the set of Prejudged user-Relevant Itineraries (PRI).

$$\text{Recall}=\frac{\text{RIS}}{\text{PRI}}$$

We consider a community of ten users (students) where a sample is represented in the folowing. Travel details are extracted from the web portal *www.transilien.com*. Every user performs six requests (queries). For each query, the traveler estimates their preferred itineraries. Then we cite the retrieved solution by the system as well as relative precision and recall values. Next we define the selected solution and new preferences weights calculated based on the proposed learning process. All this data are collected in Table1.

Table 1. Evaluation results

	Estimated pertinent itineraries	Retrieved solution	Precision	Recall	Selected solution	New weights			
						Duration	Walk	Connection	Tariff
Q1	I_6, I_5, I_{10}, I_9	1)I_9; 2)I_4, I_5; 3)I_8,	2/4=0.5	2/4=0.5	I_9	0.1345	0.1515	0.355	0.355
Q2	I_4, I_8, I_9	1)I_8 ; I_9; 2)I_1; I_4, I_7; 3) I_{10}	0.5	1	I_8	0.0883	0.267	0.273	0.369
Q3	I_1, I_{17}, I_{16}, I_{18}	1)I_{17};I_{16} ,2)I_4	0.66	0.5	I_{17}	0.071	0.323	0.231	0.374
Q4	I_4, I_6, I_9	1)I_4 ; 2)I_6,I_1,I_7; 3)I_9	0.6	1	I_6	0.07	0.21	0.22	0.5
Q5	I_1, I_2, I_6 ,I_7	1)I_6 ; 2)I_{10} ,3)I_1, 4)I_2	0.75	0.75	I_6	0.0975	0.1675	0.36	0.375
Q6	I_4, I_5	1)I_5	1	0.5	I_5	0.08	0.15	0.38	0.39

Fig 3 presents the evolution graph of precision and recall.

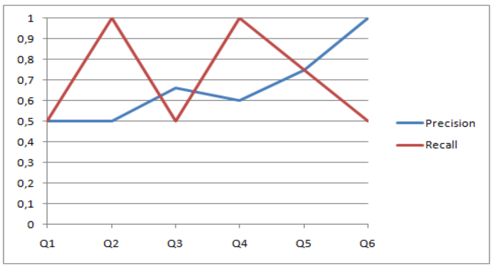

Fig 3. Precision and recall evolution

Fig.3 shows that the users request number affects the system prediction. In fact, when a request number increases, the precision increases. This may be explained by the fact that when the user performs a certain number of requests, the system starts to learn better the user' preferences and to retrieve only pertinent solutions. On the other hand, the recall value is variable according to user' queries. It means that MPM is not able to retrieve all the pertinent solutions. Nevertheless, generally, the majority of relevant solution is retrieved (recall>0.5). This may be explained by the variation of discordance and concordance values. In order to improve the MPM's recall, we propose to define two functions to calculate dynamically concordance and discordance thresholds. These functions depend on the number of concurrent alternatives. In addition, it will be interesting to construct the user profile basing on ontology approach in order to take into account heterogeneous concepts. Finally, since we have tested our approach only in the transport context, it would be also interesting to generalize the approach with other fields of application (e-learning, logistics, etc).

5. Related Works

Several studies have recently focused on systems personalization using different techniques. We may mention first GRecOC (Group Recommender for Online Communities) [17] is a book recommender system for online communities. The system aims to improve satisfaction of users with similar interests. The approach works in two phases. The first one uses a classic Collaborative Filtering method to build a group profile, by merging the profiles of its members. Each group's nearest neighbors are found and a "candidate recommendation set" is formed by selecting the top-n items, the second phase evaluates the relevance of the books in the candidate recommendation to achieve satisfaction of each member. Items not preferred by any member are eliminated and a list of books is recommended to the group. A similar work was proposed in Web personae [18] is a system that interacts in an off-line mode with web application. It is composed of a constructor and an identifier. The constructor progressively sets the user model which is a list of profiles corresponding to user preferences given from the web interactions. The identifier finds out the user profile which is related to the system current use. It is based on collaborative filtering to provide personalized information. These works are classified as social methods that recommend personalized information for a current user basing on the preferences of others users. In our approach, we propose an automatic learning method which collects implicitly information. Our objective is to analyze the user background (history) in order to update his/her preferences. For example, when a user chooses an itinerary among others, his/her choice is based on a certain criteria of selection.

Some other aggregation methods have been also proposed for the regulation of public transportation systems. We can mention those of [19 - 20]. In regulation process, the aim is to optimize the regularity criterion which corresponds to minimize the total waiting time of the passengers at the network stops. The mono-criterion problem is obtained by aggregating the different criteria's functions to optimize into only one linear function. In fact, the most commonly used aggregation when multiple criteria are replaced by an overall objective function is based on the weighted sum.

[21] presents a tourism recommender system called Traveler that suggests package holidays and tours to customers. This tourism recommendation system is based on association rules. Traveler uses many criteria for evaluating the package and tours, for instance: destination, price, means of transport, transport company, accommodation, type of room single, double, suite and duration. To our best knowledge, our proposal is the first work that uses multi-criteria decision making methods to personalize information according to conflicting criteria.

6. Conclusion

PIS is a field in rapid development. The aim of such system is to provide the user with relevant information that takes into account the context when using the system basing on the user preference learning. Today, these systems are indispensable to those who want to retrieve appropriate information with less effort at anytime and anywhere. Lately, personalized systems have been gaining interest in transport field to assist users with their travel itineraries. For example, traveler search for information about itineraries details, make online air-ticket bookings, online room reservations, etc. Personalization is an effective solution for reducing complexity when searching information. But the personalization of such systems is difficult and objects of very few propositions and studies in the literature. In this paper, we present the problem statement. Then, we give an overview of our proposal. After that, we explain how this approach has been validated by applying it to personalize a system in intelligent transport field. Finally, we conclude with some future works.

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