A Hybrid Knowledge-based Recommender for Mobility-as-a-Service

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Keywords: Recommender Systems, Mobility-as-a-Service, Knowledge-based, CSP.

Abstract: Mobility as a Service (MaaS) is the integration of various forms of transport services into a single "mobility plan", that can be considered as a bundled set of distinct services/products, bought and used as a single product. The concept of MaaS is gaining an increasingly high interest however, there are still many challenges that have to be dealt with when designing and offering viable MaaS products, including the suggestion of the optimal MaaS plan that matches a user's personal needs. In this paper, we propose a knowledge based recommender system that builds upon constraint programming mechanisms and provides the necessary functions to capture user preferences, exclude MaaS plans which do not match those preferences and infer the similarity of the remaining plans to the user's profile. The final outcome is a filtered and ranked list of MaaS plans which allows the user to select the one that better matches her/his preferences.

1 INTRODUCTION

Mobility as a Service (MaaS) is a new mobility paradigm that aims to provide integrated and seamless access to transport services through one single digital platform. The key concept behind MaaS is to place the user at the core of transport services by offering tailor made mobility solutions according to users' individual needs. In this respect, MaaS users receive customised door-to-door transport services as well as personalised trip planning and integrated payment options (Durand et al., 2018).

MaaS is offered by a new type of mobility operators the "MaaS Operators". These are intermediary companies that make agreements with public and private transport operators on a city, intercity or national level and offer subscriptions to bundles of transport services, termed as "MaaS plans" or mobility products (Kamargianni and Matyas, 2017). Access to the transport services in achieved through mobility apps and related back-end platforms that are maintained by MaaS operators and integrate all the available transport services while providing a single point for MaaS plans selection, route planning and payment.

In a MaaS environment there can be a multitude of MaaS plans with varying characteristics, in order to meet the specific needs of different types of travellers. These plans are derived from combinations of available transport services. For example, MaaS plans can combine and include public transport, taxi, car sharing, bike sharing, car rental and/or other related services such as parking or e-vehicle charging stations.

It is evident that the selection space of MaaS plans for end users increases according to the available transport services, the combinations of which can generate large choice sets with complex structures. Moreover, despite the fact that travellers make use of individual mobility services and are familiar with them, they are not that familiar with the MaaS concept where mobility services are bundled. Consequently, finding a MaaS plan that is aligned to the individual traveller's needs and preferences quickly and accurately is a cognitive task that travellers will not be able to manage easily.

In this paper, we describe a hybrid knowledge-based recommender system that supports travellers' decisions related to the selection of MaaS plans, out of a plethora of available plans that match their preferences and needs. The recommender provides the necessary functions to capture user preferences, exclude plans that do not match those preferences and infer the similarity of the remaining plans to the user's preferences. The final outcome is a filtered and ranked list of MaaS plans. Users are presented with a short list of plans that better match their preferences and select the one they want to use. The proposed approach is hybrid in the sense that it combines two techniques. Firstly it incorporates constraint

Arnaoutaki, K., Magoutas, B., Bothos, E. and Mentzas, G.
A Hybrid Knowledge-based Recommender for Mobility-as-a-Service.
DOI: 10.5220/0007921400950103
In *Proceedings of the 16th International Joint Conference on e-Business and Telecommunications (ICETE 2019)*, pages 95-103
ISBN: 978-989-758-378-0

modelling, where the MaaS package selection problem is represented using constraint programming formalisms. in order to infer a subset of potential MaaS plans from a wider set of available plans. Secondly, a weighted similarity calculation function ranks the remaining MaaS plans, based on their similarity to user preferences. A main advantage of our approach is its ability to adapt to the needs of different MaaS settings by integrating the knowledge and requirements of domain experts as rules of a constraint satisfaction problem.

The remainder of this paper is organized as follows. In Section 2 we discuss the related work. In Section 3 we present our hybrid knowledge based recommender, while in Section 4 we elaborate on the implementation details. Section 5 presents an indicative usage scenario of the proposed approach and finally, Section 6 concludes the paper and provides directions for future work.

2 BACKGROUND AND RELATED WORK

2.1 Background

The problem of suggesting personalized MaaS plans resembles that of generating bundle recommendations which has been mainly addressed by data-driven approaches that rely on the analysis of past user choices (see Section 2.2 for an overview of the related work). However, a data-driven approach in our case would require significant amounts of historical data concerning user's past selections of MaaS plans, which are not available in any newly deployed MaaS solution.

Knowledge-based recommender systems (RS) help to tackle the absence of data and user feedback, i.e. the so-called cold-start challenge, by combining explicit requirements, stated by the users within a recommendation session, and deep knowledge about the underlying domain for the computation of recommendations (Felfernig et al., 2015).

Our approach relies on the use of constraint programming theory embedded in knowledge-based recommenders, which fits well to the problem of identifying and recommending personalized MaaS plans. More specifically, we consider a Constraint Satisfaction Problem (CSP) that involves finding a value for each one of a set of problem variables where constraints specify that some subsets of values cannot be used together (Freuder and Mackworth, 2006). Following this idea, we considered the task of "MaaS plan selection", where each transport service included in a MaaS Plan can be represented as an option in a constraint satisfaction problem. Under the CSP principles, two discrete phases of the problem solving process are defined: i) the problem is modelled as a set of decision and parameter variables, and ii) a set of constraints are applied on these variables which must satisfy a solution. Decision variables represent the available choices and their potential values coincide with the available decision options. In our case, decision variables are derived from the characteristics of the mobility services which are part of the MaaS plans (such as the available quota of public transport, bike sharing or taxi). The second phase of the process refers to applying a set of constaints in order to find solutions to the problem, so that the values of the decision variables satisfy all the applied constraints. In our case, by applying the constraints, we filter out MaaS plans that do not satisfy the defined constraints.

2.2 Related Work

Generating recommendations and providing personalized suggestions for bundles of products is a problem that has been investigated in domains, such as tourism, telecommunications and e-commerce. An analysis of the types of recommender systems (RS) that can be used for dynamic bundles recommendation of touristic services (e.g. activities, places to stay) is provided by Schumacher and Rey (2011). Zhang et al., (2013) present a hybrid recommendation approach which combines user-based and item-based collaborative filtering techniques with fuzzy set techniques and knowledge-based methods (business rules) and apply it for telecom products and services recommendations. Beheshtian-Ardakani et al., (2018) approach the problem of suggesting product bundles in e-commerce websites from a marketing perspective. They propose a novel model for bundles recommendations by using market segmentation variables and customer loyalty analysis. Customer loyalty is calculated by employing the so-called recency, frequency, and monetary value (RFM) model that considers the recency of the last purchase, the frequency of purchases, and their monetary value (Linoff and Berry, 2011).

Constraint-based recommender systems have been successfully applied in various domains. Felfernig et al. (2006) present CWAdvisor, a domain-independent knowledge-based recommender that assists customers in the product selection process via a personalized conversation. The aforementioned recommender has been successfully applied to support decisions for selecting financial services and electrical equipment. Jannach et al. (2009) introduce a virtual advisor for tourists called “VIBE”. The proposed advisor uses knowledge-based conversational RS technology to provide a personalized way of choosing plans offered by a spa resort from a predefined catalogue, that meet users’ individual requirements. Reiterer et al. (2015) describe a constraint-based recommender that supports households to select the optimal waste disposal strategy that corresponds to their needs. while Murphy et al. (2015) design a constraint-based energy saving recommender system. The proposed system exploits real-world energy use data of appliances, and suggests behaviour changes and optimized appliance usage schedules so that users can reach domestic energy saving goals. Zanker et al. (2010) have approached the composite task of configuring product bundles, namely travel packages combining accommodation and activities services, within the constraint-based framework. Their work concluded in a generic Web configurator, that combines recommendation functionality together with constraint solver principles and results in a range of personalized product bundles, tailored to tourists needs while respecting e-tourism domain restrictions. Their work can be considered as a hybrid paradigm strategy that mixes knowledge-based techniques with collaborative filtering recommendation methods.

3 OUR APPROACH

The proposed recommender system for MaaS plans, relies on state-of-the-art techniques and follows a novel hybrid knowledge based approach that i) encodes the MaaS plans filtering problem as a constraint satisfaction problem (CSP) by leveraging knowledge from domain experts, and ii) uses explicit feedback from users to derive a personalized ranked list of MaaS plans through a similarity function. The proposed approach addresses the cold start problem (Lam et.al, 2008), and can be used to derive recommendations even for newly registered users, for who the system does not have any information regarding their past preferences on the available items.

Figure 1 provides an overview of the proposed approach. Since different combinations of offerings and MaaS plans may be available in a city depending on the available transport services and business environment, we have designed a *MaaS plan configurator* tool that allows MaaS operators to define and configure the MaaS plans to be offered.

Our knowledge-based approach exploits a recommender *knowledge base* that contains explicit rules (*MaaS constraints*) about how to relate user requirements (*customer variables*) with MaaS product features (*product variables*). Such rules are defined by knowledge engineers with knowledge of the field, while user requirements are acquired through questions incorporated into a graphical *knowledge acquisition user interface* (see Figure 4 for an indicative example).

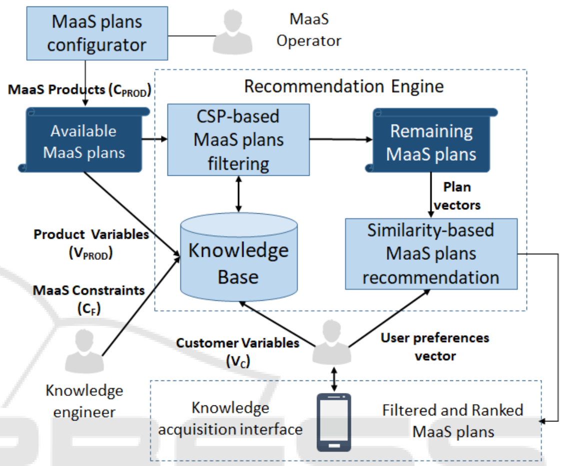

Figure 1: Overview of our knowledge-based CSP and similarity-based MaaS plans recommender.

The MaaS product selection problem is formulated as a Constraint Satisfaction Problem (CSP), with the goal of limiting the size of the space that must be searched in order to identify the plans to present to the user among those available. The CSP is integrated into a *recommender engine*, where the solution objective is to derive a list of preferred MaaS plans by filtering out plans not satisfying the constraints. The list of remaining MaaS plans is further processed using a weighted similarity function which sorts the results in a ranked list of plans which are aligned with user preferences. In the case that no matching product is found as a solution to the CSP, the similarity-based approach is applied to all available products to rank them based on their similarity to the user profile, under user-provided budget constraints.

3.1 MaaS Knowledge Base and CSP-based MaaS Plans Filtering

The knowledge base of a constraint-based recommender system can be described through two sets of variables (V_C, V_{PROD}) and two different sets of constraints (C_F, C_{PROD}) (Felfernig et al., 2015). These variables and constraints are the vital elements of a constraint satisfaction problem (Tsang, 1993). A solution for a constraint satisfaction problem consists of concrete instantiations of the variables such that all the specified constraints are fulfilled. In correspondence to the Recommender Knowledge Base, under the CSP formalisms stated above, we define the various components of the knowledge base that was developed as the basis for CSP-based MaaS plans filtering as follows:

MaaS Customer Variables V_C, refer to each user's individual properties. In the domain of MaaS, the frequency of public transport usage is an example for a customer variable and *public transport usage=Every day* represents a concrete customer requirement, indicating a daily use of public transportation services. The most important customer variables along with the questions used to derive them are the following:

- Driving license; derived through the question "Do you hold a full driving license?"
- Public Transport usage; derived through the question "how often do you use public transport?"
- Fare reductions; derived through the question "Are you eligible for any public transport travel fare reductions?"
- CarSharing usage; derived through the question "How often do you use car sharing?"
- Taxi usage; derived through the question "How often do you use Taxi services?"
- BikeSharing usage; derived through the question "How often do you cycle?"

MaaS Product Variables V_{PROD}, refer to the various attributes of a MaaS plan, including its id, price and the quota per transport mode that is available within the period the plan is valid for (e.g. a month). Examples include the number of taxi, bike sharing and/or car sharing trips included in the plan, as well as number of days a Public Transport service can be used.

MaaS Products C_{PROD}, refer to the allowed instantiations of product properties, which define the set of available MaaS plans. Indicative examples of MaaS plans are presented in Table 1, illustrating product properties' values (e.g.PT,Taxi etc) within monthly scale.

Table 1: Indicative examples of MaaS Plans.

Id	V_{PROD}	Value
1	Public_transport	30 days
	Taxi	4 trips
	Bike_Sharing	Unlimited[1]
	Car_Sharing	Unlimited
	Price	90 euros
2	Public_transport	15 days
	Taxi	2 trips
	Price	60 euros

MaaS Constraints C_F, refer to the relationship between Customer and product variables, with the former constraining the values of the latter. Indicative examples of MaaS constraints are provided in Table 2, following an object-oriented annotation language. For example, C_{F1} denotes that MaaS plans which include car sharing are filtered out for users that do not possess a driving license.

Table 2: Indicative MaaS constraints.

Id	C_F
CF_1	If user.driving license='No' then MaaS product. CarSharing='0'
CF_2	If user.Public Transport usage ='Every day' then MaaS product. Public Transport='30' days
CF_3	If user.Fare Reductions = 'Yes' then MaaS product. Id='50'or '51' or '52' (special discounted MaaSPlans)
CF_4	If user.CarSharing usage =' Every day' MaaS product. CarSharing ='Unlimited' trips

Given the user preferences (V_C) provided through the aforementioned questions which are embedded in a knowledge acquisition interface, the MaaS product definitions (C_{PROD}) and the MaaS constraints (C_F), one or more solutions for the constraint satisfaction problem are provided by a CSP solver. The solutions consist of concrete instantiations of the product variables such that all the specified constraints are fulfilled, and correspond to specific MaaS plans that are tailored to the user preferences.

3.2 Similarity-based Plans Ranking

As already mentioned, our approach includes the calculation of a weighted similarity between a user and MaaS plans, in the direction of ranking the MaaS products that satisfy the constraints (i.e. the output of CSP-based MaaS plans filtering process), on the basis of user preferences for the various modes of transport included in the MaaS plan. Many similarity mechanisms have emerged in Case Based Reasoning

[1] Unlimited corresponds to the Large quantity

(CBR) and data mining research as well as other areas of data analysis. Most of them assess similarity based on feature-value descriptions of cases (e.g. items, users etc.) using similarity metrics that use these feature values. We adopt such an approach that follows the so-called intentional concept description strategy, according to which a concept is defined in terms of its attributes (e.g. a monthly MaaS plan has public transportation, taxi, bike sharing and car sharing usage quotas). This notion of a feature-value representation is underpinned by the idea of a space with cases (e.g. MaaS plans) located relative to each other in this space (Tummas and Ricci, 2009). Similarly, users are represented as a set of feature-value pairs with features representing their preferences for the different modes of transport included in the MaaS plans, in order to allow the calculation of similarity between a user and an item, i.e. a MaaS plan.

Each feature in the representation space is considered to have a different contribution to measuring similarity, i.e. each feature is given a different weight in the user-item similarity calculation. This is because there may be a variance in the importance of each feature for similarity computations, depending on the willingness of each user to include the respective mode in his/her MaaS plan. The higher the willingness to include a mode, the bigger the weight of the respective feature will be. For example, in case a user is more willing to include taxi than bike sharing in a MaaS plan, the taxi feature will be given a bigger weight than the bike sharing one.

The vector representing a user in the X-dimensional feature space (with X denoting the number of distinct modes included in MaaS plans), is instantiated based on user responses to the questions about the frequency of public transport, taxi, bike sharing, and car sharing usage, as described in section 3.1. For example, a value of 0 is given to the taxi feature of the user vector, in case the user replies in the relative question, that s/he never uses a taxi service, while a value of 30 taxi rides is given if the user replies in the same question that h/she is using a taxi service “Every day”. The values for other possible responses will vary between these two extremes.. The values for the other features of the user vector are calculated in a similar manner.

The item vectors are instantiated for each MaaS plan based on the values of the features of MaaS Product Variables, i.e. the quota per transport mode that is available within the period the plan is valid for (e.g. a month), as described in section 3.1. After the user and MaaS plans vectors have been instantiated for a specific user and a specific list of MaaS plans (the output of the CSP-based filtering), all vectors are normalised and the weighted similarity formula given below is applied to calculate the similarity between the user preferences and all MaaS plans of the list.

$$Similarity(T,S) = 1 - \sqrt{\sum_{i=1}^{F} w_i (T_i - S_i)^2}$$

where F is the number of attributes (i.e. features) in each vector (in our case equals the number of distinct modes included in MaaS plans; four indicatively for Public Transport, Taxi, BikeSharing and CarSharing modes), *i* is an individual feature from 1 to F, w_i is the weight of feature *i* (derived from a likert scale question that follows below) and$T$ and S are the two input vectors for which similarity should be calculated (i.e. a user and a specific MaaS plan vectors), Typically, the weights sum to 1 and are non-negative. The weights are derived from user’s response to the following question:

“Please define your willingness to include the following modes of transport in your new MaaS Plan:”

- Public Transport
- Taxi
- Bike Sharing
- Car Sharing

given within a likert-scale 1-5, with 1 indicating “Very much” and 5 “Totally not” option. This question is also embedded in the knowledge acquisition graphical interface depicted in Figure 1. The calculated similarities between the user and the MaaS plans of the list are used to rank the latter and present them to the user in a tabular form in descending order, i.e. the first plan is the most similar to the user preferences and the last one the least similar.

4 IMPLEMENTATION

For the implementation of the MaaS plans Recommender we followed a three-tier architecture as illustrated in Figure 2. The data tier consists of three data sources already discussed in previous sections, namely the user profile data, the MaaS plans data and the list of domain constraints. The user profile data contain users’ individual preferences. These are acquired when a user interacts with the MaaS app, and the corresponding MaaS plan selection screen, through a set of questions as described in Section 3.1. The MaaS plans data refer to a list of available MaaS products, which are configured by the MaaS operator and form the search space of the recommendation engine. Both the user profile data and the MaaS plans data are stored in a no-SQL MongoDB database whereas the list of domain constraints is generated and stored in the filesystem as a data file in .mzn extension, that corresponds to the MiniZinc model files. The business logic layer integrates a CSP library based on the MiniZinc [2] open-source constraint problem solving software and a modular similarity calculation component which provides the means to infer the similarity of each plan to the user's profile and preferences. For the implementation of the RS we used the Meteor web application framework which is built on top of NodeJS and the Javascript programming language. Node.js packages and modules were used in order to deploy the MiniZinc CSP solver within the Meteor JavaScript platform.

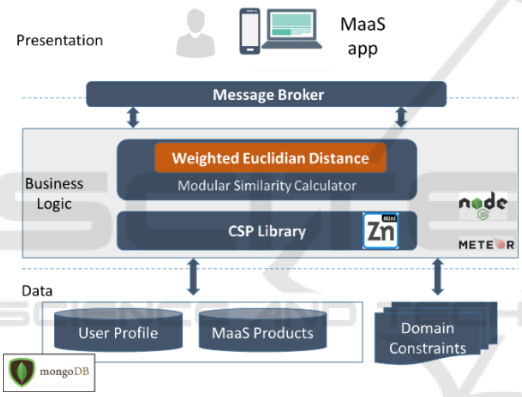

Figure 2: MaaS plans recommender system architecture.

5 USAGE SCENARIO

Figure 3 depicts the MaaS plans recommendation process, including all the steps from setting the user requirements to the recommendation of the final list of MaaS plans, while highlighting the user-recommendation engine interactions. Notable here is the fact that the User Profile record is editable, meaning that knowledge acquisition from the user side is performed once and stored in system's db with a unique user id, while it is updated every time the user states different preferences within other MaaS plans selection efforts.

First, the user opens the MaaS Plans selection screen and a dialog box-wizard appears asking him/her to answer a set of questions used for eliciting user requirements. An indicative view of the interface showing the questions asked to the user is provided in Figure 4. This set of questions is used to build the user's profile database. The answers are linked to the MaaS Customer variables defined in Section 3.1. For instance, the answer to the question "Do you hold a driving license?", is used to set the customer variable "driving_license" as either yes or no (1 or 0). In a similar manner, all the customer variables are set in line with the answers to the questions.

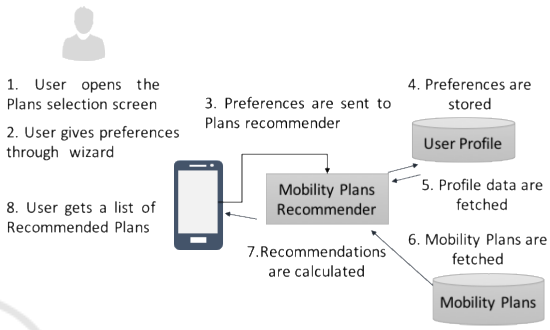

Figure 3: Overview of plans recommendation process.

Moreover, the preconfigured list of MaaS Plans is also stored in the database. Both user profile data and MaaS plans are fetched by the Mobility Plans Recommender where the recommendations are calculated using the CSP and similarity-based mechanism. In the following, we provide an example of MaaS plans recommended by our approach for a particular user and list of available MaaS plans.

A MaaS operator has configured a number of MaaS plans by following the "McDonald's self-customization strategy", which allows the provision of small, medium and large quantities of offerings per mobility service, with each one of the aforementioned levels corresponding to specific quotas of e.g. bike sharing rides or days that Public Transport (PT) can be used. In our example, we consider that the configured plans contain all the combinations of four mobility services as follows: a PT service that can be used for 5 (small), 15 (medium), or 30 (large) days per month, a Taxi service with values of 3 (small), 7 (medium) and 12 (large) rides per month, a BikeSharing service with values of 3(small), 6 (medium), or Unlimited (large) hours per month and a CarSharing service with values of 3 (small), 6 (medium) and Unlimited (large) hours per month. Note that the aforementioned MaaS plans configuration is based on a real case followed by the MaaS service operated by Hannoversche

[2] https://www.minizinc.org/

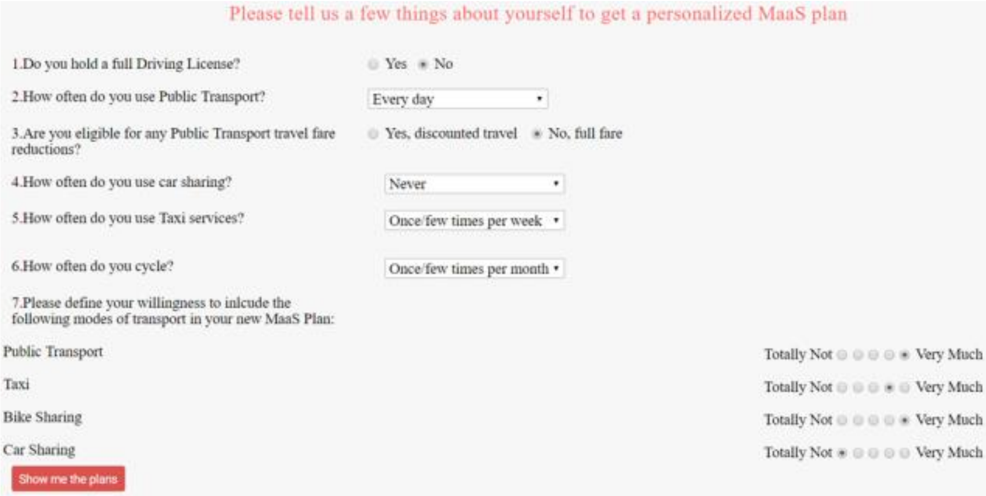

Figure 4: The MaaS plans recommender knowledge acquisition Graphical User Interface (GUI).

Verkehrsbetriebe Aktiengesellschaft, the public transportation company in Hannover, that is considered a pioneer in MaaS (Röhrleef, 2018). The above mobility services combinations result in 120 different MaaS Plans.

In our example scenario, a MaaS traveller with no driving license, who uses frequently public transport and has a friendly attitude towards Bike Sharing schemes, is interested in purchasing one of the above mentioned pre-configured MaaS plans. An instance of user preferences for MaaS as captured by his/her responses to the corresponding list of questions is depicted in Figure 4. The relevant Customer Variables' instances are the following:

- User. Driving license= "No"
- User. Public Transport usage= "Every Day"
- User. Fare reductions= "No"
- User. CarSharing usage= "Never"
- User. Taxi usage= "Once/few times per week"
- User. BikeSharing usage= "Once/few times per month"

The aforementioned customer variables instantiations, along with the MaaS constraints and the pre-configured MaaS plans are used by our CSP mechanism to identify the MaaS plans matching the user preferences. In our example scenario, a list of MaaS plans satisfying the constraints were given by the CSP, but for reasons of simplicity only four are depicted in Table 3, and will further be processed by the similarity mechanism (Table 4).

Table 3: Maas Plans Derived by the CSP Mechanism.

Plan id	Public Tran.	Taxi	Bike Sharing	Car Sharing	Price
1	30	7	3	0	30
2	30	12	3	0	40
3	30	7	6	0	35
4	30	12	6	0	45

Note that in the example scenario, the CSP-based filtering resulted in MaaS plans with no car sharing (i.e. the CarSharing product variable values have been set to zero) since the user has no driving license and therefore is not allowed to drive. Moreover, the plans derived from CSP-based filtering have large quantities of public transport offerings, since the particular user stated his preference for a daily use of that mode of transport. Similarly, the user stated preference about a low frequency of bike sharing use, resulted in MaaS plans with small and medium quantities of bike sharing offerings. In the opposite direction, the user's frequent needs for taxi are covered through medium and large quantities of taxi offerings. Note that the price values per product have been calculated based on basic assumptions regarding the pricing policy of each Mobility provider included in the MaaS schema.

Thereafter, the weighted similarity function described in Section 3.2 is applied on the plans derived by the CSP mechanism. The weights' values for each attribute of the example will be set to

- w_{PT} =1/(1+2+1+5)=0.11
- w_{TX} =2/(1+2+1+5)=0.22
- w_{BS} =1/(1+2+1+5)=0.11
- w_{CS} =5/(1+2+1+5)=0.56

The calculated similarities are used to rank the four plans as depicted in Table 4. The plans are presented to the user in a tabular form in descending order, i.e.

the first plan is the most similar to the user preferences and the last one the least similar.

Table 4: The ranked list of MaaS plans based on the weighted similarity to the user's preferences.

Plan id	Weighted similarity to the user's preferences
1	0.9969
2	0.9967
4	0.9897
3	0.9896

It should be noted that the user can set the maximum price s/he is willing to pay for a MaaS plan through a slider widget embedded in the plans selection screen. MaaS plans with a higher price than the user-provided maximum are filtered out, while the rest are passed to the MaaS recommender system for CSP and similarity-based filtering. The user choice about the maximum MaaS price can be changed at any time in the context of a single session. Each time the user choice changes, the recommender is triggered to recommend a subset of plans out of those that have a lower price than the maximum. Finally, the user chooses one of the suggested plans for the given budgetary constraints and preferences.

6 CONCLUSIONS

In this paper, we presented a hybrid knowledge-based recommender system for users of the Mobility as a Service (MaaS) mobility paradigm. MaaS aims to provide integrated and seamless access to transport services through one single digital platform. In a MaaS environment there can be a multitude of MaaS plans, that include combinations of transport services, in order to meet the specific needs of different types of travellers. Our recommender supports travellers' decisions related to the selection of MaaS plans by combining Constraint Satisfaction Problem solving and weighted similarity mechanisms in order to compute a personalized ranked list of MaaS plans aligned to the preferences of travellers who are about to use them.

To the best of our knowledge the proposed hybrid recommender constitutes the first attempt for personalizing the MaaS plans selection process while the knowledge-based approach tackles the cold start problem which refers to the lack of data for deriving user needs and preferences. However, the approach relies on knowledge engineers who need to define the set of rules for filtering the MaaS plans. Such engineers may not always be available whereas the knowledge acquisition process can become complicated when many rules need to be defined. In order to mitigate the above limitations, we plan to explore combinations of our approach with data-driven ones. More specifically, by analysing user mobility data, such as GPS tracks, we could automatically infer user needs and preferences for specific transport services, as well as understand how these change in time. Such information can be used to automatically modify the suggestions when user needs and preferences change, and overcome the knowledge acquisition challenge.

As part of our next steps, we are in the process of evaluating our proposed approach and system in real life conditions where travellers from the cities of Manchester, Budapest and Luxemburg will be using a MaaS app integrating our knowledge-based MaaS plans recommender. Our aim is to test our approach and measure the effectiveness and benefits of MaaS plans suggestions to travellers.

ACKNOWLEDGEMENTS

Research reported in this paper has received funding by the H2020 EC project MaaS4EU (GA no. 723176).

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