Conditional Preference Learning for Personalized and Context-Aware Journey Planning

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Abstract. Conditional preference networks (CP-nets) have recently emerged as a popular language capable of representing ordinal preference relations in a compact and structured manner. In the literature, CP-nets have been developed for modeling and reasoning in mainly toy-sized combinatorial problems, but rarely tested in real-world applications. Learning preferences expressed by passengers is an important topic in sustainable transportation and can be used to improve existing journey planning systems by providing personalized information to the passengers. Motivated by such needs, this paper studies the effect of using CP-nets in the context of personalized and context-aware journey planning. We present a case study where we learn to predict the journey choices by the passengers based on their historical choices in a multi-modal urban transportation network. The experimental results indicate the benefit of the conditional preference in passengers' modeling in context-aware journey planning.

Keywords: User modeling · Preference learning
Conditional preferences · CP-nets · Personalized journey planning

1 Introduction

Personalized journey planning provides tailored information to the passengers on sustainable transit options through usually web-based journey planner [3]. It seeks to overcome the habitual use of cars, enabling more journeys to be made on bike, foot, or public transport. This is achieved through the provision of personalized information, to increase the passengers' satisfaction using multimodal transit to support a voluntary shift towards more sustainable choices. The planner uses expressed passenger preferences to recommend journeys to the individuals based on his/her circumstances. The power of the individual-based journey planning is that it can often lead to more significant behavior change than a one-solution-fits-all-approach [3].

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Currently, the majority of *'intelligent'* commercial journey planners only have a small set of predefined preferences (e.g., preferred highways or public transit modes) made available for passengers to choose from and rank (Yahoo! trip planner, PTV journey planner, Google Maps) [2]. Although these planners are reliable and offer adequate assistance to passengers, they assume the values of passengers' preferences are independent i.e., the value of one attribute does not influence the passenger's preference on the value of other attributes [12]. This assumption, however, is not sound in real-world journeying. For example, the weather condition may affect the passengers' preferences towards the transportation modes that they are willing to take. This issue could be alleviated by incorporating passengers' preferences and context into the planning process. Here, we refer to the 'context' as the interrelated conditions in which the journey occurs such as departure-time, weather status, the purpose of the journey, companionship, etc. (see Sect. 3). By incorporating context and user preferences, more desirable journey plans can be recommended to the passengers which, by increasing their satisfaction, can motivate them to use multimodal transit.

As an example, suppose we are observing a user's interactions with a particular web-based journey planning system. For instance, we observe that the passenger prefers a train over a bus arriving at *Flinders Street* for one query, and we also observe that for another query, the passenger prefers a train arriving at *Flinders Street* to a bus arriving at *Swanston Street* for a specific destination. An intuitively correct hypothesis that explains her behavior could be that she unconditionally prefers trains over buses, and *Flinders Street* over *Swanston Street*. Such a hypothesis is useful for further predictions. For example, using this hypothesis, we can predict that she will prefer a train to *Flinders Street* over anything else. However, such a hypothesis gives no further information about other preferences, for example, we cannot predict whether she prefers a bus arriving at *Flinders Street* over a train arriving at *Swanston Street* or not. Now assume that in the later observations, we observe that she also prefers a bus arriving at *Swanston Street* over a train arriving at *Swanston Street*. A new possible updated hypothesis could be that she prefers *Flinders Street* over *Swanston Street* when traveling by train and vice versa when traveling with buses. In other words, her preferences over the transportation modes are **conditioned** with her destined street.

In the above scenario, the passenger has used previous travel experiences to learn specific preferences about the journeys and a similar approach can be followed by a computer algorithm. The learning problem underlying this scenario is to extract a preference structure by observing the user's behavior in situations involving a choice among several alternatives. Each alternative can be specified by many attributes, such as the transportation mode, the destination location, the arrival and departure time, etc. in the above example. As a result, the space of possible situations has a combinatorial structure. Furthermore, as we have shown in the example, the preferences induced by the passenger's behavior are intrinsically related to conditional preferential independence, a fundamental notion in multi-attribute decision theory [20]. Indeed, the initial hypothesis is unconditional in the sense that the preference over the values of each attribute is independent of the values of other attributes. By contrast, in the final hypothesis, the passenger's preferences among the transportation modes of the journeys are conditioned by the destined streets.

Conditional preference networks, also known as CP-nets, was proposed for handling problems where the preferences are conditioned to one another [4]. CP-nets have received a great deal of attention due to their compact and natural representation of conditional preferences [8,12,17]. Informally, a CP-net is a digraph where nodes represent attributes pointing to a (possibly empty) set of parents, and a set of conditional tables associated with each attribute, expressing the local preference on the values of the attribute given all possible combinations of values of its parents (Fig. 1) (see Sect. 2). The transitive closure of these local preferences is a partial order over the set of alternatives, which can be extended into several total orders. CP-nets and their generalizations are probably the most famous compact representation language for conditional preferences in multi-attribute domains [1]. While many facets of CP-nets have been studied in detail, such as learning of CP-nets, consistency and dominance checking, and optimization (constrained and unconstrained), to the best of our knowledge, there are no works on studying the effect of conditional preference modeling with CP-net in a real-world application. This paper aims to examine the effect of conditional preference modeling in the context-aware journey planning problem.

The objective of this paper is to investigate the effect of conditional preference modeling - using a GA-based CP-net learning methods (CPLGA) proposed in [8] - in personalized journey planning problem and compare it with various conventional preference learning techniques (four derived from the literature namely, RankNet citeburges2005learning, AdaRank [18], OSVM [13] and SVOR [11], and one designed for the problem under investigation called learning preference weight (PWL) [9]) alongside with the performance comparison of three state-of-the-art passive CP-net learning methods presented in [8,14,15] for the personalized journey planning problem.

2 Background on CP-Net

Assume a finite list $V = \{X_1, \ldots, X_n\}$ of attributes, with their associated finite domains $Dom = \{D_1, \ldots, D_n\}$ where n is the number of domain elements. An attribute X_i is a binary attribute if D_i has two elements, which by convention we note x_i, $\bar{x}_i$ [17]. By $\Omega = \times_{X_i \in D} D_i$, we denote the set of all complete alternatives, called *outcomes*.

A *preference relation* is a reflexive and transitive binary relation $\succeq$ over Ω. A *complete preference relation* $\succeq$ *is a preference relation* that is connected, that is, for every $x, y \in \Omega$ we have either $x \succeq y$ or $y \succeq x$. A *strict preference relation* $\succ$ is an irreflexive and transitive (thus asymmetric) binary relation over Ω. A *linear preference relation* is a strict preference relation that is connected. From a preference relation we define a *strict reference relation* in the usual way: $x \succ y$ *iff* $x \succeq y$ and $y \not\succeq x$.

Preferences between outcomes that differ in the value of one attribute only, all other attributes being equal (or *ceteris paribus*) are often easy to assert and to understand. CP-nets [5] are a graphical language for representing such preferences. Informally, a CP-net is composed of a directed graph representing the preferential dependencies between attributes, and a set of conditional preference tables expressing, for each attribute, the local preference on the values of its domain given all possible combinations of values of its parents.

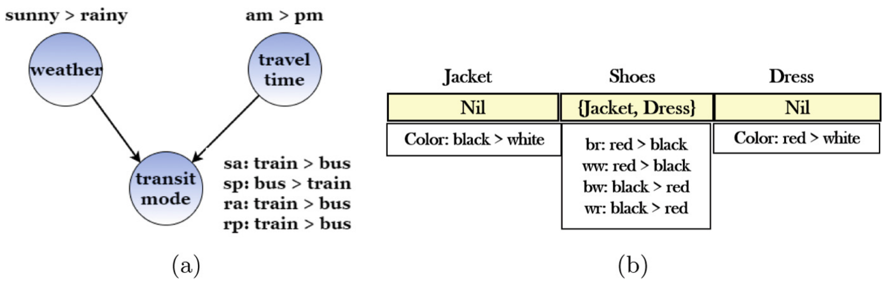


Fig. 1. (a) A simple CP-net N, modeling the passenger preferences. Journeys are defined by three attributes and for this particular passenger the preferences over transit mode is conditioned with the values of time of the journey and weather condition. (b) The equivalent chromosome of the sample CP-net

Definition 1. *Preference: A strict preference relation $\succ_u$ is a partial order on a set of outcomes $O \in \Omega$ defined by a user u. $o_i \succ_u o_j$ indicates that the user strictly prefers o_i over o_j.*

Definition 2. *Conditional Preference Rule (CP-rule): A CP-rule on an attribute X_i is an expression of the form $t : p \succ \overline{p}$, where p is a literal of X_i and t is a term such that $t \in \{V \backslash X_i\}$.*

Such a rule means given that t holds, the value p is preferred to the value $\overline{p}$ for the attribute X_i.

Definition 3. *Conditional Preference Table (CPT): $CPT(X_i)$ is a table associated with each attribute that consists of conditional preference rules (CP-rules) $t : p \succ_i \overline{p}$ specifying a linear order on $Dom(X_i)$ where t indicated to the parents of X_i in the dependency graph.*

Definition 4. *Conditional Preference Network (CP-net): A CP-net is a digraph on $V = \{X_1, \ldots, X_n\}$ in which each node is labeled with a CPT. An edge (X_i, X_j) indicates that the preferred value of X_j is conditioned by the value of its parent attribute X_i.*

Definition 5. *Dominance Testing: A dominance testing, defined by a triple (N, o_i, o_j), is a decision of whether o_j is dominated by o_i given the CP-net N and $o_i, o_j \in \Omega$. The answer is in the affirmative if and only if $N \models o_i \succ o_j$.*

Let us explain the properties of a CP-net with an example of the journey planning problem. Figure 1 represents a CP-net model for a particular passenger. Since the graph has three nodes we can infer that each journey is formulated by three attributes namely, weather condition, travel time and transit mode. Please note that one can describe journeys with a different set of attributes. As we can see in the Fig. 1, the CP-net contains three CPTs with six CP-rules (weather and travel time nodes has one rule each and four rules for transit mode node). Using this CP-net, as well as dominance testing, we can infer that the passenger prefers a train leaving in a morning on a sunny day to a bus leaving in the same condition. Formally speaking, a journey with a train dominates a journey with a bus for the traveler on a sunny morning. However, we still need to answer the question *'how can one model a passenger with a CP-net using her historical travel information?'*.

In GLPCA [8], we proposed a GA-based CP-nets learning solver in order to find a CP-net from historical and inconsistent preference examples. Each chromosome is representing a CP-net and the length of each chromosome is set to the number of attributes and is composed of two main parts: $Parent_i$ and CPT_i. $Parent_i$ denotes to the nodes $j \in \{N \backslash i\}$ in the dependency graph which the preference over the value of node i is conditioned on them and CPT_i denotes the conditional preference table associated with node i (Fig. 1(b) represents the equivalent chromosome for the sample CP-net in Fig. 1(a)). Then, we used GA to find an individual that best describes the training preference dataset. The output of the algorithm is then considered as the user's model and is used to predict her future ranking in order to provide personalized information. We refer readers to [8] for detailed information about the algorithm.

3 Multimodal Journey Planning Tool

In our study, we use the journey planner presented in [10] to find multimodal journey plans. This planner computes optimal multi-objective journey plans using a customized NSGAII-based algorithm [7]. Here we considered two criteria to optimize journey plans. The first criterion is the travel time and the second criterion is journey convenience which is a linear combination of the number of transfers, waiting and walking times. We refer the readers to [10] for detailed information about the algorithm.

3.1 Journey Plan Attributes

To apply a CP-net, first, we need an attribute-based representation approach to describe each journey. Based on the knowledge of mobility experts, we divided the journey's attributes into two categories: journey plan attributes and contextual attributes. Regarding journey plan attributes, we identify the following set of attributes to describe each journey:

Travel Time: which denotes to the total time spent to complete the journey.

Modes of Transport: which refers to the utilized transportation modes in the recommended journey.

Personal Energy Expenditure (PEE): which denotes to the PEE of the journeys that contain walking or cycling concerning the weight of the passenger as well as the average speed of the walking/cycling mode using the published energy consumption rates presented in [16].

CO_2 ***Emission:*** which denotes to the CO_2 emissions related to each journey. We utilized unit rates (per kilometer) for each vehicle to calculate the emission of a journey [ABS 2013].

Number of Transfers: which denotes to the number of transfers required to complete the journey.

Monetary Cost: which is the monetary cost associated with each journey [ABS 2013]. When a journey contains multiple public transport, the cost is calculated once in every 2-h time window.

Finally, CP-nets are typically designed to function with categorical data; therefore, we first have to discretize the numeric attributes described above. To do this, we employed a fuzzy-set method [12] that assigns each possible value to one or two predefined categories. In particular, we divide each numerical attribute into five equal intervals: very low, low, normal, high and very high. This method allows for a more accurate discretization by assigning a weight to the categories that are close to the boundaries separating two intervals.

3.2 Contextual Attributes

Based on the knowledge of mobility experts we identified seven contextual factors as relevant in this domain: 2 *user-specific* factors: companionship and reason of the journey, and five *environmental-based* factors namely: time of day, time of the week, weather, temperature, and crowdedness.

Companionship: which is a binary attribute indicating that the passenger is alone or not.

Reason of the Journey: which specifies the purpose of the journey including, *going to work*, *going back home* and *site seeing*.

Time of Day: which can be either *early morning*, *morning*, *afternoon*, *evening* and *night*.

Time of the Week: which is a binary value distinguishing between *weekends* and *week-days*.

Weather: which indicate the expected weather of a particular journey including, *sunny*, *rainy* and *windy*.

Temperature: which is a multivalued attribute consisting of *very cold*, *cold*, *normal*, *hot* and *very hot*.

Crowdedness: which denotes to the expected crowdedness of a particular public transit mode and can range from *quiet*, *natural* and *crowded*.

4 Algorithms' Evaluation

4.1 Experimental Setup

We have conducted experiments on real data collected from the transportation network of the City of Melbourne, to evaluate the effectiveness of the conditional preference modeling in the context-aware journey planning domain. For the road, bike and foot transportation network the OpenStreetMap[1] data has been used. Regarding public transit network, we used the GTFS[2] data, consisting of several information such as stop locations, routes, and timetable. A total of 34617 locations considered including 31259 bus stops, 1763 tram stations, 218 train stations, and 44 rental bike stations were included in the network. For the multi-modal network, all pairs of nodes, within *0.25* km radius, are connected by walking legs. Cycling legs are only available between two bike stations within the distance of two hours. The speed of walking and cycling legs is *5* km/h and *12* km/h respectively.

To carry out the experiment, we first had to collect a data-set of user ratings for a variety of journey plans. For each user, a set of 200 random queries, including random origin, destination and departure time, are created. By default, a set of contextual conditions was randomly picked for each query. In response to each query, the journey planner generated five to seven alternative journey plans combining different modes of transportation. Each plan was followed by a detailed explanation of characteristics of the journey plan and Users were asked to analyze and rank them from 'best' to 'worst' taking into consideration the 'active' contextual situation. This experiment lasted four weeks, and we collected a total of 5,218 orders given by 45 users to 31,350 journey plans in 8,710 queries. The participants comprised of 55% women and 45% men living in Melbourne (Australia) at the time of the experiment. Each user, on average, provided 115 rankings.

Besides, a common problem that arises when dealing with human subjects is the possibility of noise or inconsistent information [8]. Therefore, to test the robustness of the results, we also evaluated the behavior of preference learning methods under noisy conditions. To add order noise into the data set, we swapped the rankings of two randomly selected pairs of adjacent journeys in the original sample orders. The noise level could be controlled by changing the number of times that the swapping happens. Finally, We generated three data-set with 0.1%, 1% and 10% of noise, respectively.

Various types of distance metrics have been proposed in the literature to compute the distance between two orders, O_1 and O_2, composed of the same sets of solutions, i.e., $X(O_1) = X(O_2)$. In this paper, we use the widely-used Spearman's rank correlation coefficient (ρ) [17], which is a non-parametric measure of correlation between two variables and is defined as:

[1] http://www.openstreetmap.com.

[2] The General Transit Feed Specification (GTFS) data which defines a common format for public transportation schedules and associated geographic information. For more information, please visit http://www.transitwiki.org.

$$\rho = 1 - \frac{6d_s(O_1, O_2)}{L^3 - L}, \tag{1}$$

where L is the length of orders and $d_s(O_1, O_2)$ is the sum of the squared differences between ranks O_1 and O_2.

Finally, in all the experiments, we used the CPLGA with the configuration setup described in Table 1. The parameters of CPLGA are set following our experience in practice. We have chosen a non-parametric test, Wilcoxon Signed Rank Test [6] as the statistical significant testing. The test is performed at the 5% significance level.

Table 1. CPLGA setup used in experiments

Selection mechanism	Ranked bias
	Bias = 1.2
Nr. of parents	Nr. of attributes
Cross-over rate	0.8
Mutation rate	0.4
Pool size	200
Maximum number of evaluation	20000
Results average over	30

4.2 Result Analysis

Table 2 shows the means of ρ for the CP-net based preference learning algorithm with the learning-to-rank methods, namely RankNet [5], AdaRank [18], OSVM [13], SVOR [11] and PWL [9], different sample size and noise levels. These methods are the most popular methods for learning-to-rank in recent years and can perform reasonably well under noisy training samples. The experiment shows that CP-net based ranking significantly outperformed all the learning-to-rank methods at different noise levels and different training sizes. This is due to the fact that learning-to-rank methods do not take into account the conditional dependency of the attributes. However, our further experiments reveal that there exists a dependency between passengers' preferences that the conventional learning-to-rank methods tend to overlook.

As discussed earlier, the purpose of CP-net is to provide a conditional model to represent the user preferences. Therefore, during the experiments, we modeled each user with a CP-net based on his/her rating data-set, i.e., a total number of 45 CP-nets were obtained. Figure 2 illustrates the dependencies between journey attributes and contextual attributes among all 45 learned CP-nets. The number in a circle represents the number of CP-nets that the two attributes were conditioned to each other. For example, we observed that for 27 passengers, the value of transportation mode was dependent on the expected weather condition of the journey. In other words, for 27 passengers, the learned model indicates

Table 2. Comparing the conditional preference learning with conventional learning to rank methods for different training sizes.

$\|S\|$	200				500				1000			
Noise level	0	0.01	0.05	0.1	0	0.01	0.05	0.1	0	0.01	0.05	0.1
Method	ρ											
AdaRank	0.7453	0.7458	0.7352	0.7140	0.7642	0.7799	0.7614	0.7397	0.7895	0.7917	0.7743	0.7527
RankNet	0.6663	0.6642	0.6438	0.6242	0.7031	0.6833	0.6768	0.6493	0.7376	0.7165	0.7046	0.6765
OSVM	0.7305	0.7123	0.6653	0.6276	0.7866	0.7622	0.7201	0.6383	0.8257	0.7881	0.7281	0.6476
SVOR	0.7360	0.6965	0.6569	0.6363	0.7718	0.7704	0.6754	0.6271	0.8063	0.7704	0.6883	0.6435
PWL	0.7260	0.7246	0.7149	0.7002	0.7864	0.7751	0.7592	0.7520	0.8119	0.8031	0.7808	0.7717
CPLGA	**0.8435**	**0.8432**	**0.8215**	**0.8090**	**0.8817**	**0.8769**	**0.8530**	**0.8433**	**0.9285**	**0.9019**	**0.8946**	**0.8775**

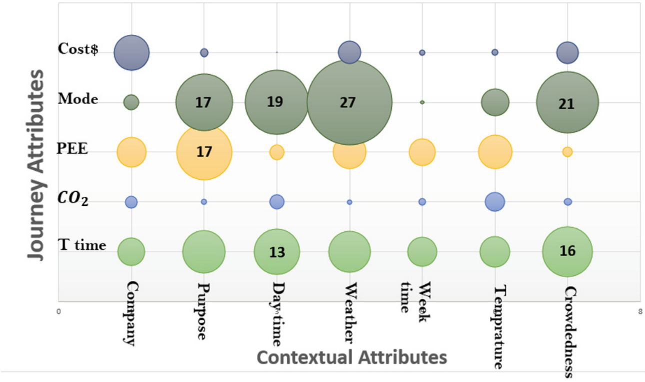
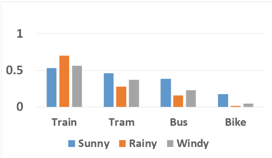


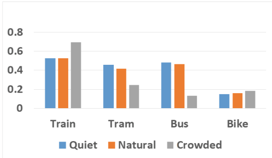
Fig. 2. The conditional dependency between contextual and journey attributes. The numbers in the circles denote the number of CP-nets that the values of two attributes are dependent on each other.

that their preferences among the transportation modes used in the journey are conditioned on the weather status. We also observed that almost half of the participants have a conditioned preference over the transportation modes based on the expected crowdedness of the transportation network. Latent information such as this, which is ignored by the majority of popular learning-to-rank methods, can be precious when one wants to predict the passengers' behavior. We believe that this information was the main reason of why CP-net based preference learning method outperformed all conventional ones. However, we first need to prove that the learned CP-net are concordant with the actual passengers' behavior. To achieve this, we conduct another experiment to reveal that whether the actual behavior of passengers matched with our learned CP-nets. For the sake of brevity, in this paper, we only present the two highest conditioned attributes, namely (weather and mode) and (crowdedness and mode).

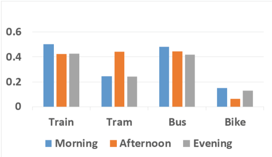
Figure 3 presents the average percentage of transportation mode against four different attributes namely, crowdedness, day-time, purpose and weather condition. In Fig. 3(a) we show the average percentage of transportation modes for



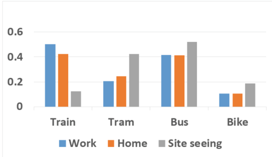
(a) Weather (27 passengers from Fig. 2).



(b) Crowdedness (21 passengers from Fig. 2)



(c) Day-time (19 passengers from Fig. 2)



(d) Purpose (17 passengers from Fig. 2)

Fig. 3. The conditional dependency between transit mode and four highly conditioned variables extracted from the true ratings of the passengers.

the first ranked journey for the 27 passengers presented in Fig. 2 based on the learned CP-nets for these passengers, we expected that the transportation mode was conditioned to the weather status. Figure 3(a) shows the actual behavior of these passengers when they rated the actual recommended journeys. In here we assumed that, for each query, they would choose their highest ranked journey. As shown in Fig. 3(a), there is a clear correlation between the used transportation mode and the weather status which demonstrates that the learned CP-net is concordant with the actual behavior of the passengers. For example, we observed that when raining, the usage of trains was increased as these passengers preferred trains more over other means of transportation. We also observed that the usage of buses dropped dramatically in raining condition. It could be since, for buses and trams, the possibility of delays increases in raining weather and passengers – who gained this knowledge through experience – try to avoid it by leaning towards trains which are more robust against variations in weather conditions. Although, this information may seem trivial, but note that these explicit dependencies are being ignored by the conventional learning-to-rank methods. Needless to say, such information is beneficial when the system wants to predict passengers' preferences to recommend personalized journeys to them.

Figure 3(b) demonstrates the same results for the relation between expected crowdedness of the transportation network and the passengers' preferences among different modes of transportation. As we stated before, in 21 out of 47 learned CP-net, the value of transportation mode is conditioned with the value of expected crowdedness. Again, we observed that there is a clear correlation between the two attributes in actual passengers' behaviors. For example, we observed an increase in train usage in crowded situations. One explanation could be that the passengers prefer to avoid traffic jams, in case of buses, or limited space, in case of trams. We also observed an increase of bicycle usage when the transportation network is crowded. This could be because, in the City of Melbourne passengers are only allowed to bring their bikes onto the trains, but prohibited for other means of transportation, so some passengers are willing to take some part of the journey with bikes during rush hours.

To have a fair comparison, we also compare CPLGA [8] against two CP-net learning algorithms proposed in [14,15]. Similar to CPLGA, these methods learn CP-nets passively from inconsistent examples. We observed that CPLGA algorithm significantly performs better than the other two. Regarding [15] it is because this algorithm starts with a hypothesis and then performs a local search to optimize that hypothesis, making the algorithm prone to getting stuck in local optima for larger problems. Another issue is the sample size. Note that for larger problems (i.e., more than ten attributes) these algorithms need a large training set to prove their hypothesis. We also tested the robustness of these methods in noisy condition by adding 1% to 20% of noise to the data-set. We observed that all methods which have handled the noisy data and could find similar preference graphs as the noise-free setting; however, we again observed a significant gap between CPLGA model and the other algorithms concerning their performance (Table 3).

Table 3. Comparison between the three state-of-the-art passive CP-net learning methods on real data with different noise level.

$\|S\|$	ρ	0	0.01	0.05	0.1	0.2
	Method	Sample agreement				
500	[15]	0.5533	0.5564	0.4756	0.4213	0.2712
	[14]	0.5117	0.5107	0.4819	0.4665	0.2301
	CPLGA	**0.9212**	**0.9230**	**0.9195**	**0.8400**	**0.7512**
1000	[15]	0.5812	0.5601	0.5139	0.4201	0.3320
	[14]	0.5210	0.5109	0.4939	0.4339	0.3134
	CPLGA	**0.9309**	**0.9101**	**0.9152**	**0.8754**	**0.7713**

5 Conclusions

In this paper, we discussed the effect of conditional preference learning in the domain of context-aware journey planning problem. To this aim, we have proposed a context-aware journey recommendation test-bed and we have implemented and evaluated the CP-net based preference learning algorithm and compared it with five state-of-the-art PL strategies and two similar CP-net learning approaches. Our experiment results have concluded that there exists the latent conditional information in the user preferences and this information can be very useful when one wants to predict the passengers' behavior in the urban transportation network.

Our future work is to further improve the performance of the conditional preference learning methods. We also want to investigate the effectiveness of the conditional preference learning strategies when applied during the construction of the journey plans. We believe that in this way the preference model can have a major impact on quality of the recommended journeys and also help to speed up the plan generation process by reduction of the search space.

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