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A Case-based Reasoning System with Two-dimensional Reduction Techniques for Classification of Leisure Constraints

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Abstract. Chiu et al. recently published an article entitled “Developing a case-based reasoning system of leisure constraints” in volume 10 of the Information Technology Journal. In this article, they applied the case-based reasoning technology to predicting the type of leisure constraints that visitors encounter to assist leisure services providers in negotiation of the constraints. Unfortunately, the inference relies on all instances in the database and features of these instances (or cases). Inaccurate results may be obtained if the instances or features are not representative. A plan of simultaneously selecting representative instances and features through GA optimized training with random combinations of instances or features is proposed and expected to improve the performance of the existing system.

Keywords: Case-based reasoning, leisure constraints, negotiation, genetic algorithms.

1. Introduction

Leisure constraints are various limitations and difficulties that may affect people’s participation in and satisfaction with leisure activities [1]. Crawford & Godbey [2] and Jackson & Dunn [3] have identified three types of leisure constraints, including intrapersonal constraints, interpersonal constraints, and structural constraints. Intrapersonal constraints refer to leisure preferences derived from personal beliefs, habits, and experiences. Interpersonal constraints arise when co-participation of some companions, such as family members, peers or friends, in certain leisure activities is required. Structural constraints are most common leisure constraints in modern days. They are caused by external or irresistible conditions, such as seasonal and climatic factors, leisure resources, facilities, time, and money.

Although leisure constraints affect one’s perception and decision-making with respect to leisure activities, one’s practical participation in leisure activities still depends on the results of his or her negotiation of the constraints. Leisure participation occurs only when one can overcome intrapersonal, interpersonal or structural constraints ([2], [4]). According to Jackson et al. [5], strategies used for negotiating leisure constraints vary from one person to another. Basically, these strategies can be classified into “behavioral strategies” and “cognitive strategies”. Behavioral strategies are to resolve constraints through change of attitude, preference or behavior and reduction of psychological inadaptability. They are intended to reduce obstruction by making substantive changes in one’s leisure behavior. Cognitive strategies are mainly based on cognitive dissonance reduction. For instance, people perceive less constraints to leisure if the incentives for participation can be improved, costs of participation reduced or the rewards for participation increased. To be succinct, all leisure constraints can be overcome through negotiation. One considers leisure participation when he or she can overcome intrapersonal constraints and feel motivated to participate in certain activities. With such motivation, one will further manage to overcome other external difficulties and limitations. His or her practical leisure participation or continuance will finally occur after all the requirements for leisure participation are met.

It is generally believed that demographic variables (such as gender, age, occupation, social status, and income) and family life cycle have direct or indirect effects on one’s leisure participation and are also key determinants of the type of leisure constraints that one may experience (e.g., [5]–[8]). Besides, all types of leisure constraints can be negotiated using behavioral and/or cognitive strategies. Hence, if we can predict the type of leisure constraints that visitors may encounter, we can adopt effective negotiation strategies to help them overcome the constraints and have higher behavioral intention for leisure participation.

Chiu et al. [9] applied the case-based reasoning technique (CBR) to develop a case repository-based leisure constraints inference system, in which the type of leisure constraints that visitors encounter can be predicted to help leisure service providers in negotiation of the constraints and strategic marketing. CBR is one of the techniques of artificial intelligence. Like human reasoning mechanisms, it searches for solutions to current problems from past similar cases or experiences. It can solve non-structured and complicated problems and has the instant update capability, which is to instantly adjust certain conditions of past cases to meet the needs in the new problem. Featuring high efficiency in inferring solutions to new problems from past problems and high applicability, CBR has been extensively studied in the artificial intelligence area and applied in many other areas, including business, manufacturing, marketing, and medical diagnosis (e.g., [10], [11]).

Chiu et al. [9] pioneered in application of CBR to leisure research, in an attempt to predict the type of leisure constraints that low-participation visitors (new cases) may encounter. In applications of CBR, comparison of past instances stored in the database is usually required, and this process may drag down the performance of the inference system if the case database is too huge. This paper thus proposes a system that relies on genetic algorithms (GA) to simultaneously select representative instances and features to improve the performance of the inference system.

2. Definition, types, and negotiation of leisure constraints

2.1. Definition

The term "leisure constraints" first appeared in 1960s in a national recreation survey conducted by the Outdoor Recreation Resources Review Commission (ORRRC). In early leisure research, researchers discussed primarily about "barriers" to leisure. Such barriers are mainly caused by lack of interest and belong to only one of many types of leisure constraints. Hence, early barrier research could only investigate whether one would still continue a certain leisure activity under influence of the internal or the external environment. Some later researchers introduced the term "constraints", defining leisure constraints as any factors that may inhibit one's ability to participate in leisure activities, to spend more time in doing so, to take advantage of leisure services or to achieve a desired level of satisfaction. The introduction of this term also increased the scope and depth of later leisure research [5].

2.2. Types of leisure constraints

Although leisure constraints vary depending on leisure type and participants, they are conceptually similar in many aspects. Many taxonomies of leisure constraints have thus been proposed. Early studies classified leisure constraints into internal constraints and external constraints. Internal constraints can be caused by factors including personal health and fitness, motivation, perceived importance of leisure, satisfaction of personal needs, pressure, personal capabilities, knowledge, interest, and convenience of the leisure activities. External constraints can be caused by factors including lack of time or money, geographical distance, and lack of facilities (e.g., [12], [13]). Crawford & Godbey [2] focused on barriers to family leisure, including those experienced by family members or spouses and associated with family life-cycle. They identified three types of leisure constraints, including intrapersonal constraints, interpersonal constraints, and structural constraints. Intrapersonal constraints refer to leisure preferences derived from personal beliefs, habits, and experiences. Personality, attitude, emotion, religion, subjective values, and past experience of leisure activities can all become intrapersonal constraints. Interpersonal constraints arise when co-participation of companions, such as family members, peers or friends, in certain leisure activities is required. For instance, one may have lower intention to participate in certain leisure activities if he or she is unable to find a partner. Structural constraints are most frequently seen leisure activities in modern days. They are caused by external or irresistible conditions, such as seasonal and climatic factors, leisure resources, facilities, time, and money.

2.3. Negotiation of leisure constraints

In 1990s, some scholars pointed out that there are interactions among different types of constraints and proposed that individuals tend to negotiate perceived constraints to facilitate their leisure participation. Kay & Jackson [14] investigated the influence of socioeconomic characteristics and leisure constraints on leisure participation. Their findings suggested that in the presence of financial constraints, 60% would reduce their participation, 23% would manage to overcome the constraints using various strategies, such as saving money, seeking for other activities that cost less or reducing expenditure for other aspects, and 11% would decide not to participate; in the presence of time constraints, 71% would reduce leisure participation in all possible ways, and 29% would save their time for other activities (daily activities or work activities) to make leisure participation possible. Jackson et al. [5] proposed that people adopt different negotiation strategies depending on the leisure constraints they experience. Basically, these negotiation strategies can be classified into behavioral and cognitive strategies. Behavioral strategies are to eliminate constraining factors and reduce psychological inadaptability by changing one's attitude, preference or behavior. Cognitive strategies are mainly based on cognitive dissonance reduction. Activities featuring lower incentives, higher costs or less rewards will be devalued. Negotiation strategies can also be divided into time management, skill acquisition, interpersonal coordination, and financial resources [6]. To sum up, people have different perceptions of leisure constraints. In order to motivate or facilitate leisure participation, negotiation strategies that are suited for the targeted participants and activity should be adopted.

3. Case-based reasoning

3.1. Traditional CBR

Case-based reasoning (CBR) was proposed by Schank & Abelson [15] in 1977. It is a problem-solving technique that relies on artificial intelligence. It solves new problems based on the solutions to similar past problems. CBR has two tenets of nature: (1) similar problems have similar solutions; (2) the same type of problems tend to recur. A CBR system will automatically store the solution to each problem it has solved for machine and human learning. Through this process, it is enabled to quickly cope with the same or a similar type of problems in the future [16]. In general, CBR relies on past experiences stored in a case database for solving new problems. When confronted with a new problem, users only need to input known features of the problem, and the CBR system will automatically search for most similar cases in the database and offer a suggested solution to the problem. After the new problem is solved, the final solution to the new problem will also be retained in the repository for future use. Through this process, knowledge can be updated and repeatedly used.

3.2. CBR with 2-dimensional reduction

The main drawback of CBR is that the inference relies on all instances in the database and features of these instances. Inaccurate results may be obtained if the instances or features of the instances are not representative. To address the above issue, several techniques have been proposed, including Instance Selection and Feature Selection. "Instance Selection" is to select more representative instances from the database for case indexing and retrieval. This method can avoid inference error caused by extreme instances [17]. "Feature Selection" is to select critical features from numerous features of the existing instances to enhance the case indexing or retrieval efficiency [18]. Both of the above selection methods are one-dimensional reduction techniques. They do not fully take into account the potential noise between instances or features and may cause reduced inference performance. In recent years, some scholars have proposed two-dimensional reduction techniques (e.g., [19], [20]), which integrate instance selection and feature selection to simultaneously delete instances and features that are not considered from the case database.

4. Genetic algorithms

Genetic algorithms(GAs) are global search and optimization techniques motivated by the process of natural selection in the biological system [21]. The primary distinguishing features of GAs include an encoding, a fitness function, a selection mechanism, a crossover mechanism, a mutation mechanism, and a culling mechanism. The algorithm for GAs can be formulated according to the following steps: (1)

Randomly generate an initial solution set (population) of N individuals and evaluate each solution (individual) by a fitness function. Usually an individual is represented as a numerical string. (2) If the termination condition is not met, repeatedly do {Select parents from population for crossover, generate offspring, mutate some of the numbers, merge mutants and offspring into population, cull some members of the population. (3) Stop and return the best fitted solution.

5. The CBR system proposed by Chiu et al.

GAs Based on the theory of CBR, Chiu et al. [9] constructed a cased-based reasoning system of leisure constraints in four steps: Step 1. Case representation: Use individual characteristics (including demographic variables and family life-cycle) and leisure constraint type (including intrapersonal, interpersonal, structural, and no constraint) as features to represent each selected case of leisure constraint. Step 2. Case indexing: Classify all the cases by features or attributes to facilitate fast search and retrieval of cases. Step 3. Case retrieval: With all the cases indexed, the CBR system can compare a new case to old ones stored in the case database and retrieve the most similar case. The case database consists of three case sets, including reference cases, test cases, and hold-out cases. Reference cases are used for inference in CBR, while test cases or hold-out cases are viewed as new cases to be input in the CBR system. When a new test case is input in the system, the system will represent the leisure constraints encountered and begin the reasoning process. Based on the index of cases, the system computes the Euclidean distance between the new case and each reference case using function (1) to find the closest reference case, and from which the solution to the new case can be derived. Step 4. Case adaptation: Store the latest and suitable cases in the case database to achieve self-learning of the system.

6. The proposed plan

To enhance the inference performance of the system, we integrated GA into the above CBR system for instance selection and feature selection. The proposed plan consists of six steps as follows:

Step 1. Design the structure of chromosomes: To search for optimal combinations of cases and features, all available combinations of cases and features are encoded on chromosomes in a binary string where 0 denotes “unselected” and 1 denotes “selected”.

Step 2. Generate the initial population: Before executing the GA, an initial population comprising n chromosomes should be generated first. The bit values on each chromosome are randomly generated and each of which denotes a possible solution (to initial feature and solution selection). Given a total of a features and b instances, each chromosome can be represented by $(a+b)$ bits, and each generation has n chromosomes. Through evolution of each generation, a better solution can be progressively obtained.

Step 3. Compute the fitness of each chromosome: To compute the fitness of each chromosome, all types of past leisure constraint cases are divided into three groups, including reference cases, test cases, and hold-out cases. Reference cases are used for inference in CBR, while test cases or hold-out cases are viewed as new cases to be input into the CBR system. Generally, reference cases account for the majority of past cases.

For any chromosome i $(i=1,2,\cdots,n)$, the set of reference cases and the set of training cases are selected according to the chromosome, and some cases or case features will be deleted. Assume that R_i and T_i respectively denote the modified set of reference cases and set of test cases. The fitness of chromosome i can be computed via the following steps: (Step 3.1) Infer the expected outcome (EO) of each test case: For each test case k, we apply the afore-mentioned 1NN voting method to select, from the case database R_i, similar cases to infer the group to which the test case belongs (called EO_k). Similarity between any two cases can be measured using Euclidean distance. (Step 3.2) Compute the fitness of chromosome i $(i=1,2,\cdots,n)$:The fitness of chromosome i can be computed using the following function:

$$\mathrm{f}(chromosom\,i)=\sum_{k=1}^{M} hit_k(R_i,T_i)/M \tag{1}$$

where M denotes the number of test cases T_i; hit_k indicates whether the expected outcome (EO_k) of the case k matches the actual outcome (AO_k). If $EO_k = AO_k$, $hit_k(R_i,T_i)$=1; otherwise, $hit_k(R_i,T_i)$=0. This value will be constantly updated during the evolution. In addition, it is also viewed as an indicator of chromosome quality in subsequent genetic evolution. Better chromosomes are more likely to be selected for crossover.

Step 4. Apply genetic operators to derive a new generation: After a new generation is formed, the max fitness value used for the previous generation may be changed. As mentioned earlier, the genetic operators including chromosome selection, crossover, and mutation are used to generate new chromosomes. The selection operator determines whether a chromosome should be kept or eliminated depending on the fitness index. Chromosomes with a higher fitness value are more likely to survive. As to the other two operators, probability of crossover or mutation should be defined in advance.

Step 5. Repeat Step 3 and Step 4 until the stopping rule is met. The hold-out cases can be finally used to further verify the accuracy of CBR classification based on the cases and features selected in the above steps.

7. Conclusions

Understanding people's perceptions of leisure constraints is essential for leisure services providers to set up appropriate marketing strategies that can facilitate negotiation of leisure constraints and increase motivation for leisure participation. In this paper, we proposed a CBR system with two-dimensional reduction techniques to effectively predict the leisure constraints experienced by non-participants. Presumably, the proposed system should outperform traditional CBR systems in terms of inference performance and accuracy. In the future, we will use a wider array of cases from different leisure areas to empirically validate the performance and effectiveness of the proposed system.

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