Expert Systems with Applications 37 (2010) 7880–7887

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Choquet integral-based hierarchical networks for evaluating customer service perceptions on fast food stores

Yi-Chung Hu *, Hsiao-Chi Chen

Department of Business Administration, Chung Yuan Christian University, Chung-Li 32023, Taiwan, ROC

ARTICLE INFO

Keywords:
Interval regression analysis
Interval weight
Choquet integral
Service perception
Key factors

ABSTRACT

It is known that a hierarchical decision structure consisting of multiple criteria can be modeled by a Choquet integral-based hierarchical network. With a given input–output dataset, the degree of importance of each criterion can be directly obtained from the corresponding connection weight after the network has been trained from samples. Since each output value or the synthetic evaluation of an alternative derived from uncertain assessments has its upper and lower bounds, the degree of importance of each criterion should not be unique and can be distributed in a range. In this paper, the range of the degree of importance of each criterion is obtained by three Choquet integral-based hierarchical networks with the pre-specified hierarchical structure: one is a common network constructed by merely minimizing the least squared error, and the others are employed to determine a nonlinear interval regression model. The above three networks are trained with a given input–output dataset using the proposed genetic algorithm-based learning algorithm. Empirical results of evaluating customer service perceptions on fast food stores demonstrate that the proposed method can identify key factors that have stronger effect on service quality perceptions by employing three Choquet integral-based hierarchical networks with the hierarchical structure to determine possible ranges of the degree of importance of respective aspects and attributes.

1. Introduction

A decision problem can be evaluated by a hierarchical structure consisting of diverse criteria. The hierarchy decomposes from the general goal to more specific attributes until a level of manageable decision criteria is met (Meade & Presley, 2002). As depicted in Fig. 1, the given hierarchical structure is usually composed of three decision levels including the objective, the aspects, and the attributes. To obtain the synthetic evaluation of an alternative, the weighted average method (WAM) with the additivity assumption is usually taken into account. In practice, the additive WAM is performed on the objective and each aspect assuming that there is no interaction among the attributes towards the objective attribute (Murofushi & Sugeno, 1989, 1991, 1993; Sugeno, Narukawa, & Murofushi, 1998; Tseng & Yu, 2005). Many well-known scoring methods with additive property, such as the Analytical Hierarchy Process (AHP) (Saaty, 1994), the Delphi method, the eigenvector method, the weighted least square method, the entropy method, SMARTS, SMARTER (Edwards & Barron, 1994), a weight-assessing method with habitual domains (Tzeng, Chen, & Wang, 1998), as well as the linear programming techniques for multi-dimensions of analysis preference (LINMAP), can be employed to find the degree of importance of respective criteria. For the above methods, the sum of degree of importance of respective criteria is assumed to be just one.

Unfortunately, the additivity assumption is not warranted in many real-world problems (Wang, Leung, & Klir, 2005; Wang, Wang, & Klir, 1998). Instead, the fuzzy measure can be employed to describe the interaction among the attributes in a set. Once a nonadditive fuzzy measure is employed to express the importance of relevant attributes towards the objective attribute, the synthetic evaluations of individual alternatives can be obtained by a nonadditive data mining technique, the Choquet integral (Murofushi & Sugeno, 1989, 1991, 1993; Sugeno et al., 1998), rather than the additive techniques such as WAM (Wang et al., 2005). In view of the nonadditive property, the Choquet integral has been widely applied to multiple-criteria decision-making (MCDM) (Chiou & Tzeng, 2002; Chen, Wang, & Tzeng, 2000; Jeng, Chuang, & Su, 2003; Kwak & Pedrycz, 2004; Tzeng, Ou Yang, Lin, & Chen, 2005; Tseng & Yu, 2005; Wang, Leung, et al., 2005; Tsai & Lu, 2006).

In particular, Chiang (1999) introduced the structure of the Choquet integral-based hierarchical network, which can be regarded as a fuzzy neural network, and demonstrated the effectiveness of the network for nonlinear mappings. The advantage of the Choquet integral-based hierarchical network is that, when the synthetic

* Corresponding author. Tel.: +886 3 2655130.
E-mail address: ychu@cycu.edu.tw (Y.-C. Hu).

0957-4174/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2010.04.049

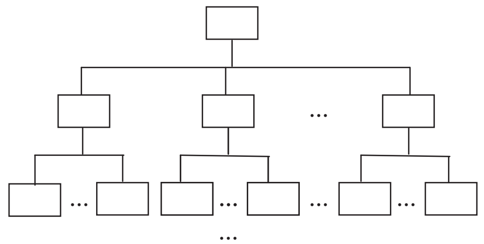

Fig. 1. A hierarchical structure for a decision problem.

evaluation (i.e., output) of each alternative and its performance values (i.e., input) on individual attributes are acquired by the questionnaire, the fuzzy measure values or the degree of importance of each criterion including aspects and attributes can be identified from the corresponding connection weight after the Choquet integral-based hierarchical network has been trained with the input–output dataset. Similar to the back-propagation algorithm for a multi-layer perceptron (Jang, Sun, & Mizutani, 1997), the training performance of the common Choquet integral-based network is merely the least squared error. In particular, the Choquet Integral-based hierarchical Network with the Hierarchical Structure (CINHS) depicted in Fig. 1 is taken into account.

In many practical applications, since available information is often derived from uncertain assessments, real intervals can be employed to represent uncertain and imprecise observations (Hwang, Hong, & Seok, 2006). The interval regression analysis, which provides interval estimation of individual dependent variables, is an important tool for dealing with the uncertain data (Huang, Zhang, & Huang, 1998; Hwang et al., 2006; Jeng et al., 2003). The interval parameters of a linear interval model can be determined by solving a basic linear programming problem of interval regression analysis (Ishibuchi, 1990; Ishibuchi & Nii, 2001; Ishibuchi & Tanaka, 1992). In view of the high capability of multi-layer neural networks as an approximator of nonlinear mappings, Ishibuchi and Tanaka (1992) employed two multi-layer perceptrons (MLPs), and Jeng et al. (2003) proposed using support vector interval regression networks to identify the upper and lower bounds of data interval. This motivates us to employ two CINHSs to determine a nonlinear interval regression model.

In addition, since each output value or the synthetic evaluation of an alternative derived in an uncertain circumstance has its upper and lower bounds, the degree of importance of each criterion should not be unique and can be distributed in a range. In other words, the relative weights should be estimated as intervals because of a decision-maker's uncertainty of judgments involved in real-world decision problems (Entani & Tanaka, 2007; Sugihara, Ishii, & Tanaka, 2004; Wang, Yang, & Xu, 2005). In recent years, many approaches have been proposed to determine interval weights in the analytic hierarchy process (AHP) (e.g., see Entani & Tanaka, 2007; Sugihara et al., 2004; Wang & Elhag, 2007; Wang et al., 2005). There is no doubt that the identification of interval weights is a very important area of research. This also motivates us to identify interval weights in CINHSs.

This paper aims to determine interval weights or possible ranges of the degree of importance of both aspects and attributes on the basis of three CINHSs with pre-specified hierarchical structure: one is a common network constructed merely by the least squared error, and the other two networks identify the upper and lower bounds of data interval. That is, each aspect or attribute has three relative weights. Furthermore, the key criteria can be further identified by inspecting the above ranges of the degree of importance. Learning algorithms of different CINHSs involving a general-purpose optimization technique, genetic algorithm (GA) (Goldberg, 1989), are proposed to automatically determine unknown connection weights from the input–output data.

The rest of this paper is organized as follows. The Choquet integral and the fuzzy measure for hierarchical decisions are presented in Section 2. Section 3 introduces interval regression model. Section 4 describes the proposed GA-based learning algorithms of CINHSs for nonlinear interval model in detail. In Section 5, in order to demonstrate the effectiveness of the proposed method, the above-mentioned three CINHSs are evaluated by a practical decision problem about customer service perceptions on fast food stores in Taiwan. A simple but effective ranking method proposed by Wang et al. (2005) is further employed to compare the interval weights of criteria to identify key factors. The discussion and conclusions are presented in Section 6.

2. Choquet integral-based hierarchical decision

A hierarchy is usually employed to model a decision problem. Since the additive assumption is not realistic in many applications, it is reasonable to use the nonadditive Choquet integral with respect to a fuzzy measure, instead of the most common WAM with respect to a classical additive measure (e.g., the probabilistic measure), as an aggregation tool in the objective and each aspect in Fig. 1. In this section, the identification of the interaction among criteria by a fuzzy measure is presented in Section 3.1. In Section 3.2, the Choquet integral performed in the CINHSs is described.

2.1. Identification of the interaction among attributes

Let X denote a finite set of $\{x_1, x_2, \ldots, x_n\}$. A fuzzy measure $\mu{:}P(X) \to [0, 1]$ is a nonadditive set function that satisfies the following properties (Chen, Chang, & Tzeng, 2002; Sugeno, 1974, 1977; Wang & Klir, 1992):

1. $\mu(\phi) = 0$, $\mu(X) = 1$ (boundary conditions);
2. for $\forall A, B \in P(X)$, if $A \subset B$, then $\mu(A) \leqslant \mu(B)$ (monotonicity),

where $P(X)$ denotes the power set of X. In comparison with the additive measure, the fuzzy measure with the monotonicity assumption considers the interrelation between attributes by expressing importance of relevant attributes towards the objective attribute (Chen et al., 2002; Tseng & Yu, 2005; Tzeng et al., 2005). For instance, $\mu(\{x_i, x_j\})$ represents the combined grade of importance of $\{x_i, x_j\}$. Owing to the nonadditive property of μ, $\mu(\{x_i, x_j\})$ is usually not equal to $\mu(\{x_i\}) + \mu(\{x_j\})$. In particular, if $\mu(\{x_k\}) = 0$, then x_k is viewed as a redundant attribute (Brady, Voorhees, Cronin, & Bourdeau, 2006).

Fuzzy measures can be used with the Choquet integral for aggregating information sources. Among diverse fuzzy measures, the λ-fuzzy measure has been suggested for computing the fuzzy integral for its convenience and feasibility (Kuncheva, 2000; Wang & Wang, 1997). For all A, $B \in P(X)$ with $A \cap B = \phi$, μ is a λ-fuzzy measure satisfying the following property:

$$\mu(A \cup B) = \mu(A) + \mu(B) + \lambda\mu(A)\mu(B), \quad \lambda \in (-1, \infty) \tag{1}$$

where λ is found from $\mu(X) = 1$. The value of μ for any subset A can be obtained by the values of n fuzzy densities (i.e., $\mu(\{x_1\}), \ldots, \mu(\{x_n\})$) as follows:

$$\mu(A) = \frac{1}{\lambda}\left[\prod_{x_k \in A}(1 + \lambda\mu(\{x_k\})) - 1\right] \tag{2}$$

The characteristic of the λ-fuzzy measure is that μ can be uniquely determined by $\mu(\{x_1\}), \ldots, \mu(\{x_n\})$.

The interaction among $x_1, \ldots, x_n$ can be identified by the value of λ,