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Analytic network process for pattern classification problems using genetic algorithms

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ABSTRACT

The analytic network process (ANP) is a useful technique for multi-attribute decision analysis (MCDA) that employs a network representation to describe interrelationships between diverse attributes. Owing to effectiveness of the ANP in allowing for complex interrelationships between attributes, this paper develops an ANP-based classifier for pattern classification problems with interdependence or independence among attributes. To deal with interdependence, this study employs genetic algorithms (GAs) to automatically determine elements in the supermatrix that are not easily user-specified, to find degrees of importance of respective attributes. Then, with the relative importance for each attribute in the limiting supermatrix, the current work determines the class label of a pattern by its synthetic evaluation. Experimental results obtained by the proposed ANP-based classifier are comparable to those obtained by other fuzzy or non-fuzzy classification methods.

1. Introduction

The popular analytic hierarchy process (AHP) [19–21] employs a uni-directional hierarchy to describe the relationships between decision levels with independent attributes. Compared to traditional AHP, the analytic network process (ANP) developed by Saaty [22] generalizes the AHP to deal with all kinds of dependence and feedback among clusters or components for a decision problem using the supermatrix approach [13]. The ANP replaces hierarchies with networks and uses a network representation to indicate interrelationships between components or elements [12]. A component consisting of various elements may be an aspect, a criterion, or a set of alternatives. For instance, the manager could employ components, such as advertising and quality, to estimate the market share of different stores of providing instant foods. The advertising component may contain many elements such as promotion and creativity. Moreover, advertising and quality could influence each other. The manager could further utilize the degree of importance for each attribute obtained by ANP to compute a synthetic evaluation of each alternative, previously handled by the traditional weighted average method (WAM) [27].

The independence assumption among attributes is not warranted [27], therefore ANP applies to many decision problems. The ANP has gained much attention, owing to its effectiveness in allowing for complex interrelationships between attributes. Several studies explore ANP, including product mix planning of semiconductor fabrication by Chung et al. [2], selecting information system projects by Lee and Kim [9], project management by Meade and Presley [11] and Meade and Sarkis [12], constructing a financial-crisis model by Niemira and Saaty [13], the strategic management for forest management by Wolfslehner et al. [29], reverse logistics operations for end-of-life computers by Ravi et al. [16], evaluating digital video recorder systems by Chang et al. [39], a SWOT analysis by Yüksel and Dağdeviren [40], the transportation-mode selection by

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Tuzkaya and Önüt [41], urban industrial land valuation by Aragonés-Beltrán et al. [42]. Nevertheless, the ANP has not been applied to pattern classification in the literature.

Pattern classification is a multi-attribute decision problem that partitions a pattern space into classes and then assigns an input pattern to one of the classes [7]. A decision-maker can perform input pattern classification by employing the widely-used WAM to derive the synthetic evaluation, and should consider interrelationships between attributes to determine respective attribute weights for the WAM. Although different attributes may influence each other, it is not possible to arbitrarily assume interdependence or independence among attributes for a classification problem. Thus, this paper develops an ANP-based classifier by employing ANP to deal separately with interdependence and independence among attributes. Since obtaining the relative importance of respective attributes is the focus, this paper only accounts for one component containing different attributes. In implementation, this work obtains the relative importance for respective attributes by ANP, and then employs the synthetic evaluation of a pattern, obtained by the WAM with degrees of importance for respective attributes, to determine the corresponding class label. To deal with interdependence, this study determines the elements in the supermatrix by a general-purpose optimization technique, namely GAs [3], thus further obtaining the degree of importance for each attribute from the limiting supermatrix. We incorporates maximizing the number of correctly classified training patterns into the fitness function.

The rest of this paper is organized as follows. Section 2 briefly introduces the ANP. Section 3 presents the GA-based learning algorithms for the proposed ANP-based classifier. Section 4 evaluates classification performance of the proposed method using computer simulations of well-known classification problems, including the appendicitis data, the cancer data, the thyroid data, the Wisconsin breast-cancer data, and the Pima Indian diabetes data. We demonstrate that the proposed classifier performs well compared to other fuzzy or non-fuzzy classification methods. This paper concludes with Section 5.

2. Analytic network process for pattern classification

For a network representation, arrows signify direction of dependence or causal impact [22] and a node represents a component. Inner dependence represents interdependency among elements within a node, while outer dependence denotes interdependency among elements between two nodes. A looped arrow in the component indicates the inner dependence of elements in that component [11]. Let n be the number of attributes for a classification problem. Conceptually, the classifier can be described as a one component system in which n attributes form a network where every attribute interacts or has influence on itself or some or all of the other attributes in the system. Fig. 1 depicts that the possible network representation with only one component named "Attributes" is considered for a pattern classification problem with three attributes, namely x_1, x_2 and x_3 ($n = 3$). That is, three elements are presented in the component. An arc with a two-way or looped arrow indicates the feedback effect. For instance, impact from x_2 and x_3 could influence x_1. Moreover, x_1, x_2 and x_3 could impact on each other. Thus, a looped arrow is created for the component. On the contrary, if there is no inner dependence in the component, then x_1, x_2 and x_3 are assumed to be independent of each other. For this, a looped arrow cannot be created for the component.

In practice, this paper incorporates two different network models into an ANP-based classifier. One model comprises the component with a looped arrow (Type I) and the other comprises the component without a looped arrow (Type II). The reason is that we do not make arbitrary assumption of interdependence or independence among attributes for a classification problem in advance. The main difference between Type I and Type II is that Type I considers interdependency among attributes while Type II does not. The traditional ANP algorithm usually comprises the following four major steps [11]:

Step 1: Model construction and problem structuring
Clearly define the decision problem and give the corresponding network representation.

Step 2: Determine pairwise comparison matrices and priority vectors
Similar to AHP, ANP makes pairwise comparisons of attributes with respect to their relative importance toward their control attribute. The relative importance of each attribute with respect to the control attribute can be further obtained from a pairwise comparison matrix. Pairwise comparisons reflect the relationships between elements within the component. Decision-makers respond to a series of pairwise comparisons where two attributes are compared in terms of how they contribute to their control attribute [12]. Then, a local priority vector can be derived from the pairwise comparison matrix.

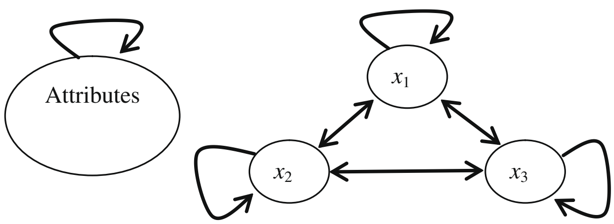

Fig. 1. A network representation with one component comprising three attributes.