Expert Systems with Applications 36 (2009) 11595–11604

Contents lists available at ScienceDirect

Expert Systems with Applications

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

A method of stepwise benchmarking for inefficient DMUs based on the proximity-based target selection

Shaneth A. Estrada [a], Hee Seok Song [b,*], Young Ae Kim [c], Su Hyeon Namn [b], Shin Cheol Kang [b]

[a] Department of Computer Engineering, Hannam University, 133 Ojeong-dong, Daedeok-gu, Daejeon 306-791, Republic of Korea
[b] Department of Management Information Systems, Hannam University, 133 Ojeong-dong, Daedeok-gu, Daejeon 306-791, Republic of Korea
[c] Business School, Korea Advanced Institute of Science and Technology (KAIST), 207-43 Cheongyangri 2-dong, Dongdaemoon-gu, Seoul 130-722, Republic of Korea

ARTICLE INFO

Keywords:
Data Envelopment Analysis
Self-Organizing Map
Reinforcement Learning
Proximity-based target selection
Benchmarking

ABSTRACT

DEA is a useful nonparametric method of measuring the relative efficiency of a DMU and yielding a reference target for an inefficient DMU. However, it is very difficult for inefficient DMUs to be efficient by benchmarking a target DMU which has different input use. Identifying appropriate benchmarks based on the similarity of input endowment makes it easier for an inefficient DMU to imitate its target DMUs. But it is rare to find out a target DMU, which is both the most efficient and similar in input endowments, in real situation. Therefore, it is necessary to provide an optimal path to the most efficient DMU on the frontier through several times of a proximity-based target selection process. We propose a dynamic method of stepwise benchmarking for inefficient DMUs to improve their efficiency gradually.

The empirical study is conducted to compare the performance between the proposed method and the prior methods with a dataset collected from Canadian Bank branches. The comparison result shows that the proposed method is very practical to obtain a gradual improvement for inefficient DMUs while it assures to reach frontier eventually.

1. Introduction

Data Envelopment Analysis (DEA) is a mathematical programming formulation based technique that develops an efficient frontier to provide an estimate of relative efficiency for each decision making unit (DMU) in the problem set (Charnes, Cooper, & Rhodes, 1978). It is built around the concept of evaluating the efficiency of a DMU based on its performance of creating outputs by means of input consumption. A DMU is said to be relatively or Pareto efficient if no other DMU or combination of DMUs can improve one of its outputs without at the same time worsening its any other outputs or increasing at least one of its input levels. DEA can be used to determine whether a DMU is relatively efficient and then to yield a reference target for an inefficient DMU.

However, it is very difficult for inefficient DMUs to be efficient when they have to benchmark a target DMU which has different input use. In real situation, many DMUs are competing with the other DMUs, which have similar input endowments. For example, a small and medium-sized company set a target not within the major company group, but within the small and medium-sized group for its competition. Gonzales and Alvarez (2001) also suggest that when a firm is informed that it is inefficient, a reasonable strategy for its target selection would be to select and benchmark the efficient firm that is most similar to its input use. In this study, we call this strategy a "proximity-based target selection" given the fact that proximity can be measured in terms of input use.

This paper focuses on how to choose practical target DMUs for benchmarking based on the similarity of input use among the DMUs. The simplest proximity-based target selection strategy is to choose the closest DMU in its input use among the DMUs, which are on the frontier (i.e. efficient DMUs). However the selected target DMU still may be different in its input use and hard to be imitated. It is rare to find out a target DMU, which is both the most efficient and similar in input endowments in real situation. Therefore, it is necessary to develop a method, which helps inefficient DMUs improve their efficiency gradually over time and benchmark the most efficient DMU on the frontier eventually. In order to help inefficient DMUs improve their efficiency gradually, it is necessary to provide an optimal path to the most efficient DMU on the frontier through several times of a proximity-based target selection process.

To make this idea operative, a stepwise benchmarking procedure for inefficient DMUs is proposed. To find out similar DMUs in its input use, we use Self-Organizing Map (SOM) which provides neighborhood information through clustering DMUs according to input use. Because this mapping tends to preserve the topological relationships of input data, we can easily find out neighbor DMUs, which have similar input use, on the SOM output map. The gradual

* Corresponding author. Tel.: +82 42 629 8344; fax: +82 42 629 8416.
E-mail address: hssong@hannam.ac.kr (H.S. Song).

0957-4174/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2009.03.035

approach for improving efficiency considers the closest neighbor DMUs in a SOM output map as the next candidate benchmarking DMU set. In finding an optimal path to the frontier, Reinforcement Learning (RL) algorithm is adopted. Through Reinforcement Learning algorithm, each inefficient DMU can learn an optimal path to reach to the frontier.

This paper is organized as follows. Section 2 presents the previous studies for target selection and efficiency improvement. Section 3 introduces the general view of Data Envelopment Analysis, Self-Organizing Map and Reinforcement Learning and Section 4 defines the problem. Section 5 discusses our proposed method and Section 6 explains the details of our empirical study. Finally Section 7 summarizes our work and provides the future works.

2. Literature review

Several studies have been done on efficiency improvement based on DEA. The research objective of the existing work is categorized into three areas; target selection, direction of efficiency improvement, and stepwise improvement.

Typically, the work for target selection includes models that enhance DEA flexibility in estimating targets for relatively inefficient DMUs. In the study of Thanassoulis and Dyson (1989), they developed a DEA model that set targets for DMUs. They point out that it would be desirable to take not only the nature of the controllability of their inputs and outputs but also of the priorities of improving individual inputs and outputs into account.

The work for direction of efficiency improvement is able to determine how an inefficient DMU can be improved. The studies of Kao (1994), Talluri, Huq, and Pinney (1997), Bogetoft and Hougaard (1999), and Gonzales and Alvarez (2001) are included in this category. Kao (1994) developed a modified BCC (1984) model by substituting nonlinear terms in the ratio formulation and modifying bounds constraints through which all inefficiencies could be eliminated and from there it could improve. Talluri et al. (1997) developed a model that uses a cross-efficiency matrix to identify periods of best cell operating practices which aid management in cell process improvement. Bogetoft and Hougaard (1999) introduced the potential improvement index. That efficiency index will guide the selection of reference plans. Gonzales and Alvarez (2001) developed a model based on the input-contraction method that computes the sum of input contractions required to reach the efficient subset of the production frontier.

The work for the final category provides a stepwise path for improving the efficiency of each inefficient DMU. These are studies of Alirezaee and Afsharian (2007) and Hong et al. (1999). Alirezaee and Afsharian (2007) proposed the layer measurement model that provides the strategy for moving toward a better layer. However, it lacks information on how to choose the reference DMU on each layer. Hong, Ha, Shin, Park, and Kim (1999) developed a method that generates rules for classifying new DMUs into each tier and measures the degree of affecting the efficiencies of the DMUs. They also proposed a stepwise path for improving the efficiency of each inefficient DMU. However, it does not guarantee to reach to the frontier eventually because inefficient DMUs can be improved just within its same cluster. Therefore, we propose a method for the gradual improvement of inefficient DMUs which considers alternative paths to move to the frontier.

3. Research background

3.1. DEA

Data Envelopment Analysis (DEA) is a linear-programming methodology which evaluates the relative efficiency of decision making units (DMU). Calculating the ratio of weighted inputs and outputs produces a single measure of productivity. The units that have a ratio of 1 are referred to as efficient DMU. Otherwise, it is inefficient (Cooper, Seiford, & Tone, 2006).

DEA became a powerful tool in evaluating the performance of DMUs because of several reasons. It has the capability of evaluating DMUs without using any predefined function. It offers multiple advantages in the form of several models and orientations. It is flexible so that researchers have applied it into various applications (Herrero & Salmeron, 2005; Hong et al., 1999; Kao & Hung, 2008).

Aside from these studies, it is interesting to know the advantage of DEA for benchmarking (Donthu, Hershberger, & Osmonbekov, 2005; Fuchs & Zach, 2004; Homburg, 2000; Seol, Choi, Park, & Park, 2007). Benchmarking is defined as "a continuous, systematic process for evaluating the products, services, and work process of organizations that are recognized as representing best practices for the purpose of organizational improvement" (Spendolini, 1992). It is achieved by using the DMUs on the frontier as role models. An inefficient DMU can choose efficient DMUs on the frontier that operate within its scope. Hence, an inefficient DMU can have different sets of role models. In this study, it is important to find benchmark targets in order to get some ideas about how a DMU could improve its process.

3.2. Self-Organizing Map (SOM)

A SOM (Kohonen, 1995; Rousset, Guinot, & Maillet, 2006; Simula, Vasara, Vesanto, & Helminen, 1999) is a sophisticated unsupervised clustering algorithm in terms of the visualization of its clustering results. It clusters high-dimensional data points into groups and represents the relationships between the clusters onto a map that consists of a regular grid of processing units called "neurons". Each neuron is represented by an n-dimensional weight vector, where n is equal to the dimension of the input features. The weight vector of each neuron is updated during iterative training with input data points.

The SOM tends to preserve the topological relationship of the input data points so similar input data points are mapped onto nearby output map units. This topology-preserving property of SOM facilitates the ability to implement proximity-based target selection strategy in this paper (Kohonen, 2001; Smith, 2002).

3.3. Reinforcement Learning

Reinforcement Learning (Mitchell, 1997; Sutton & Barto, 1998) is characterized by goal-directed learning from trial-and-error

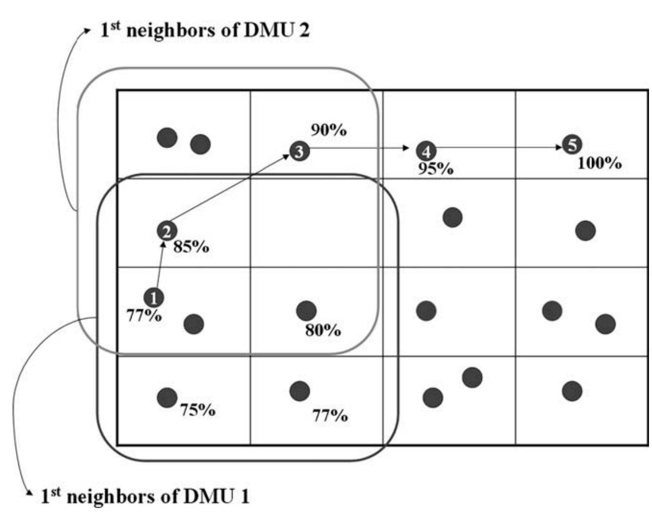

Fig. 1. An example of the path finding for an inefficient DMU.