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A learning ladder toward efficiency: Proposing network-based stepwise benchmark selection ☆

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ABSTRACT

Starting from the knowledge-based view of efficiency improvement, we propose a network-based approach to find the optimal stepwise benchmarking paths toward the efficiency frontier. The approach treats the Data Envelopment Analysis system as a network of teaching and learning firms and calculates the overall shortest paths taking into account both input endowment similarity and the efficiency gap covered in each step. In addition, based on network centrality concepts, the method discriminates between efficient and intermediate units, and highlights possible outliers or specialized units. As a real-world example, the method is applied to a network of Canadian bank branches and practical implications are discussed.

1. Introduction

Efficiency improvement involves technological and organizational changes, and such substantial changes require a carefully oriented inter-organizational knowledge absorbing process [1]. Taking into account that slow learning is a major reason for inefficiency [2], adopting a stepwise benchmarking path not only facilitates the knowledge absorption process but also reduces the risk of failure implied by setting an out-of-reach efficiency target [3,4].

Assuming the Data Envelopment Analysis (DEA) method as a network of units that aim to learn by benchmarking, we propose an application of Social Network Analysis (SNA) in the DEA context to transform the benchmarking information of DEA efficiency measurement into a network of possible efficiency improvements, and calculate the optimal stepwise benchmarking paths.

This paper is grounded on the knowledge-based view of efficiency, which understands efficiency improvement as a learning process [5]. According to the theory of absorptive capacity [6], one firm's ability to learn from another depends on the similarity of the two firms' knowledge base, organizational structures and consumption policies [7]. In a DEA problem, this knowledge overlap and structural relevance can be measured through the similarities in the inputs as well as in the outputs [1,5,8].

Another question also discussed in the paper is the fact that because DEA does not provide stepwise benchmarking paths, it might be risky or not feasible to cover all efficiency gaps in one step [9]. To overcome this problem, several strategies have been proposed to post-process the DEA benchmarking information based on contextual policies in order to provide a reasonable, desirable and feasible stepwise benchmarking path. These procedures can be categorized under the general label of *stepwise benchmarking*.

A recent and relevant trend in the literature [3,4,9,10] uses self-organized map (SOM) input clustering and machine learning techniques to find the optimal path toward efficiency. While some of these techniques provide more appropriate paths than traditional stratification or context-dependent DEA (CD-DEA) methods, some aspects still need improving. First, the existent proposals optimize each step (not the whole path). Using the SNA shortest path makes it possible to optimize the whole path and, when possible, to minimize zigzagging the path toward the efficient frontier. Second, they cannot control the number of steps; the present proposal, by contrast, provides a control parameter and can provide paths with various numbers of steps. Third, clustering based on input similarities reduces the n dimensions input vector data (where n is the number of inputs) into a two dimensional map. Detecting input similarity based on this information—by determining the Euclidean distance of the cluster centers—is not an accurate proxy. In the present paper, this constraint is relaxed and a weighted vector comparison is used to select the most similar Decision Making Units (DMUs) in the path, which seems to be a more realistic and accurate proxy. This comparison indicates

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that a comprehensive model with flexible and comparable policies is still lacking, and SNA has the potential to overcome these shortcomings.

Liu et al. [11] were the first to introduce the novel idea of analyzing DEA problems as a network of efficiency endorsements, and to propose an application of SNA in DEA to obtain a better discrimination in the efficiency ranking of the DMUs. The network structure proposed by Liu et al. [11] is based on lambda values, resulting from a recursive efficiency analysis of the DMUs under study, and discrimination is based on eigenvector centrality of efficient units.

Apart from eigenvector centrality, other powerful SNA concepts can be helpful in efficiency problems, such as proximity, shortest path and alpha centrality. Our proposal combines concepts and methods from SNA and DEA and, for the first time, these concepts are applied in a SNA method with applications such as calculating the optimal benchmarking path, detecting possible outliers, clustering units and highlighting specialized DMUs.

The proposed method has three steps. The first step measures the efficiency scores and results in initial benchmarking peers of DMUs. The DEA type (i.e., radial DEA, hyperbolic DEA, directional distance function—DDF—or slack-based models—SBM) and the possible orientations (input, output or directionally oriented) are exogenous to the method. The second step post-processes the DEA scores and transforms the benchmarking information into a directed and weighted network of all possible efficiency improvement paths. The third step analyzes the resulting network, calculates the optimal benchmarking path, and highlights the potential presence of specialized units as well as the possible outliers.

In the present paper, a path toward the efficiency frontier is considered *optimal* when the unit under evaluation is a relatively good performer, or there are some better intermediate performers with relatively similar input endowments in the middle, promoting the learning process and lowering the risk of failure. Based on this definition, the path shown in Fig. 1 part (III) is a *non-optimal* path, and the one shown in Fig. 1 part (IV) is an *optimal* path. Setting two intermediate efficiency improvement targets not only facilitates the learning process but also indicates that the benchmark is feasible in practical terms.

Despite their shared origin, the method proposed by Liu et al. [11] and our proposal are different. First, as shown in Fig. 1 part I, the nodes in the method proposed by Liu et al. [11] are DMUs and the links between the nodes are the efficiency endorsements directed toward the efficient peers. In the current paper, the nodes are DMUs but the links are not only toward efficient units but also toward any better performer unit (Fig. 1 part II). In this way, the model will include all possible efficiency improvements that are paramount for calculating optimal paths.

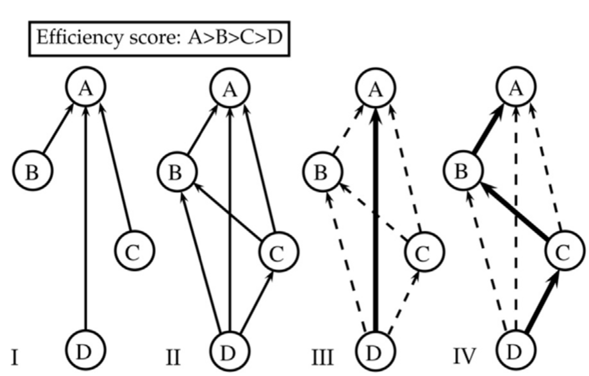

Fig. 1. Illustrative benchmarking paths. (I) DEA benchmarking information. (II) All possible efficiency improvement. (III) Normal benchmarking. (IV) Network-based stepwise benchmarking (optimal path).

The second difference concerns the network construction method. The links in the method proposed by Liu et al. [11] are weighted by summing the lambda values obtained from a recursive DEA efficiency analysis of all possible input/output combinations. This method implies defining several DEA programs with just a partial description of the existing technology, which is difficult to accept, as only a carefully selected dataset with completely substitutable inputs and outputs would be acceptable. Hence, in order to preserve the definition of the technology, in our proposal we avoid using partial technologies.

Finally, considering that it is relatively easier to introduce sophisticated functions of costs and risks as link weights in an SNA network than in a DEA program, our proposal calculates a function of input similarities and benchmarking risks to weight the links. In contrast, the method proposed by Liu et al. [11] does not take into account the input similarities or the efficiency gaps. As a proxy for input similarities, our model calculates the Euclidean distance of normalized inputs, taking advantage of the unit invariant property of inputs in constant return to scale (CRS) and variable return to scale (VRS) [13]. In a similar way, the efficiency gap between the DMUs at the start and end of a link is used as a proxy to benchmark risk of failure. To bonus more appropriate intermediate better performing DMUs, an exponential value of the above-mentioned proxies is taken. It is also possible to introduce a fixed cost to each benchmarking step and a matrix of substitution rates for the inputs.

The rest of paper is organized as follows. Section 2 provides an overview of the previous studies in stepwise efficiency improvement and network-based DEA. Section 3 presents our proposal and revises the application issues. Section 4 provides details of an empirical application evaluating the relative efficiencies of 79 Canadian bank branches and the results are discussed. Finally, Section 5 summarizes the work, states the practical implications and suggests directions for future research.

2. Literature review

2.1. DEA and stepwise efficiency improvement (SEI)

The need for efficiency improvement (EI) is emphasized in the efficiency literature [3,4,9,14]. Scholars mention different but relatively convergent logics and reasons for efficiency improvement, including the learning process, handling data heterogeneity due to size, facilitating efficiency gap removal and dealing with different evaluation contexts.

There are five trends in stepwise efficiency improvement (SEI) methods. Among those, CD-DEA and efficiency improvement path are the most relevant to the present paper. The CD-DEA trend started with Seiford and Zhu [15] and became popular after the improvements made by Seiford and Zhu [16]. Other scholars have extended the CD-DEA method and combined it with other DEA concepts, for example SBM, assurance regions (AR), super and cross efficiency. Although this branch of the literature deals with overall stepwise efficiency improvement, it does not provide a specific path or road-map for inefficient units to remove inefficiency.

The most relevant precedent to the present paper is the efficiency improvement path, which began with the paper by Hong et al. [14] and includes methods that aim to introduce an optimal path toward efficiency. Lozano and Villa [17] and Lozano and Villa [18] provide a sequence of gradual intermediate targets toward efficiency where the targets are not observed units. In contrast, all other papers in this stream calculate an optimal path utilizing the information from observed DMUs. Also, Lozano and Villa [17] and Lozano and Villa [18] only use DEA methods while the other