An Improved DEA-DA Approach: Application on Bank Industry

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Abstract
Classifying a set of decision making units (DMUs) is a useful tool which helps the manager to group and name DMUs on the basis of something that they have in common. By doing this manager can understand certain qualities and features which they shares as a class. Classifying is also a way of understanding differences between things. Discriminate Analysis (DA) deals with classifying a DMU into one of several groups and Data envelopment analysis (DEA) is a management science technique for measuring the efficiency score of a set of DMUs. Some approaches have been developed to utilize DEA into DA formulation which are known as DEA-DA methods. In this study, we first overview a two-stage DEA-DA approach and then we show its drawback. Next, we improve the model and illustrate the potential uses with applications to the largest private bank in Iran.

Keywords: Data Envelopment Analysis, Discriminate analysis, Classification, Bank industry.
JEL codes: C6

1. Introduction

Data envelopment Analysis (DEA) is a well-known mathematical quantitative approach for measuring the performance of a set of similar units (DMUs). Since the pioneering work of Charnes et al. (1978), DEA has demonstrated to be an effective technique for measuring the relative efficiency of a set of homogenous DMUs. In managerial applications, DMUs may include banks, department stores and supermarkets, and extend to car makers, hospitals, schools, public libraries and so forth. In engineering, DMUs may take such forms as airplanes or their components such as jet engines. The first two well-known DEA model are called CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes and Cooper). The CCR model is formulated for constant returns to scale (CRS) situation, however Banker et al (1984) extended it to variable returns to scale (VRS) situation. There are various types of DEA models such as, additive, Slacks-Based Measure (SBM) and Russell Measure (RM). More specifically, DEA models usually are looking for an efficient frontier that envelops all DMUs. These models are able to classify all DMUs on the efficient frontier as efficient and other DMUs that are enveloped by the efficient frontier as inefficient. Although DEA models can categorize DMUs into two main groups (efficient and inefficient), they fail to classify units. In categorization process, we are looking for dividing DMUs into groups with the know criteria (perceived similarities). For example, DEA can categorize DMUs based on their efficiency status. Meanwhile, classification process assigns each DMU to one and only one class within a system of mutually exclusive and nonoverlapping classes with unknown criteria.

The classification problem is an important topic in decision making. For example, financial analysts typically evaluate the financial health of firms, and they have to classify the firms accordingly. Discriminate Analysis (DA) uses a group of DMUs, whose memberships are already identified, are used for the measurement of a set of estimates (weights) by minimizing incorrect group classification. The estimations also can be used for predicting group membership of a newly sampled data. The method may be either a statistical technique or a goal programming (GP) technique for classifying an observed data set into one of several groups. Sueyoshi (2006) categorized DA approaches into eight different groups: standard mixed integer programming (MIP), two-stage MIP, logit, probit, Fisher's linear DA, Smith's quadratic DA, neural network (NN) and decision tree (DT).

In view of GP, there are seven types of DA approaches that are called GP-based DA methods: *MMaD* (Minimize Maximum Deviation), *MMiD* (Maximize Minimum Deviation), *MSID* (Minimize Sum of Interior Deviations) and *MSD* (Minimize Sum of Deviations) proposed by Freed and Glover (1981, 1986); *MMO* (Minimize Misclassified Observations) by Banks and Abad (1991), *hybrid model* (minimize external deviations and maximize internal deviations) by Glover (1990) and r*atio model* (maximize the ratio of internal to external deviations) by Retzlaff-Roberts (1996a, b). The computational practicality of MSD makes this approach as the most frequently applied among the others. However, the main disadvantage of these approaches is that they are parametric.

Sueyoshi (1999) incorporated DEA and DA approaches and proposed a non-parametric DEA-DA classification method which is an interesting classification approach because it maintains its discriminant capabilities by incorporating the non-parametric feature of DEA into DA. In the next section, we represent the DEA-DA approach and illustrate it with a numerical example.

2. DEA Methodology

DEA is a nonparametric approach for measuring the efficiency score of a set of homogeneous DMUs. Suppose there are *n* DMUs ($\mathrm{DMU}_j \;\; j=1,\ldots,n$) and let input and output data for DMU_j be $\mathbf{x}_j=(x_{1j},\ldots,x_{mj})$ and $\mathbf{y}_j=(\mathrm{y}_{1j},\ldots,\mathrm{y}_{sj})$, respectively. Let $v_i \;\; (i=1,...,m)$ and $u_r \;\; (r=1,...,s)$ be the weights of i^{th} input and r^{th} output, respectively. Mathematically, the efficiency score of DMU_j can be calculated as

$$e_j=\frac{\sum_{r=1}^{s}u_r y_{rj}}{\sum_{i=1}^{m}v_i x_{ij}},\; j=1,...,n.$$

Charnes et al. (1978) proposed the following well-known CCR model to measure the efficiency score of the under evaluation unit, DMU_o ($o\in\{1,\ldots,n\}$):

$$\begin{aligned}
&\max e_o=\sum_{r=1}^{s}u_r y_{ro}\\
&\text{s.t.}\\
&\sum_{i=1}^{m}v_i x_{io}=1\\
&\sum_{r=1}^{s}u_r y_{rj}-\sum_{i=1}^{m}v_i x_{ij}\le 0 \qquad j=1,...,n\\
&u_r\ge 0 \qquad r=1,...,s\\
&v_i\ge 0 \qquad i=1,...,m
\end{aligned} \tag{1}$$

This model must be solved one for each DMU_j to be evaluated. Notice that in this model $v_i^*=0$ indicates that i^{th} input is removed from the efficiency evaluation calculations and might make inaccurate result. In this model, DMU*o* is CCR-efficient if and only if $e^*=1$ and there exists at least one optimal solution $(\mathbf{u}^*,\mathbf{v}^*)$ with $\mathbf{u}^*>0$ and $\mathbf{v}^*>0$. To obtain the positive weights, Carnes et al. (1979) revised their model as follows:

$$\max e_o = \sum_{r=1}^{s} u_r y_{ro}$$
$$\text{s.t.}$$
$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{2}$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad j = 1,\dots,n$$
$$u_r \ge \varepsilon \qquad r = 1,\dots,s$$
$$v_i \ge \varepsilon \qquad i = 1,\dots,m$$

where ε is a non-Archimedean infinitesimal number and must be determined correctly. Amin and Toloo (2004) designed a polynomial time algorithm to find a suitable value for epsilon. In the revised model, DMU*o* is CCR-efficient if and only if $e^* = 1$. As will be seen subsequently, zero weights in DEA-DA approach might lead to incorrect result.

3. DEA-DA approach

Suppose there are *n* DMUs ($\text{DMU}_j \;\; j = 1,\dots,n$) and each DMU$_j$ has *k* independent (inputs and outputs) factors $\mathbf{z}_j = (z_{1j},\dots,z_{kj}) \in R^k$. All DMUs can be classified into either Group1 (G1) or Group 2 (G2). We also suppose $|G_1| = n_1$ and $|G_2| = n_2$ where $n_1 + n_2 = n$. We are looking for a hyperplane $H = \{\mathbf{z} : \; \boldsymbol{\alpha}\mathbf{z} = d\}$ such that

$$\forall j \in G_1, \;\; \mathbf{z}_j \in H^+$$
$$\forall j \in G_2, \;\; \mathbf{z}_j \in H^- \setminus H$$

where $\boldsymbol{\alpha} \in R^k$ is the *normal* or the *gradient* to the hyperplane, *d* is a *threshold value* and $H^+ = \{\mathbf{z} : \; \boldsymbol{\alpha}\mathbf{z} \ge d\}$, $H^- = \{\mathbf{z} : \; \boldsymbol{\alpha}\mathbf{z} \le d\}$ are *half-spaces*. However, the mentioned conditions can be rewritten as bellow

$$\forall j \in G_1, \;\; \mathbf{z}_j \in H^+$$
$$\forall j \in G_2, \;\; \mathbf{z}_j \notin H^+$$

If there is such hyperplane, then all DMUs in G1 and G2 are classified correctly. Otherwise, the classification is incorrect and such situation is called an ‘overlap’. To deal with overlap situation, we have to find some $j \in G_1, \;\; \mathbf{z}_j \notin H^+$ and let $j \in G_2$ and/or find some $j \in G_2, \;\; \mathbf{z}_j \in H^+$ and let $j \in G_1$. Apparently, with these changes all DMUs are classified correctly.

Sueyoshi (1999) suggested a two stages DEA-DA approach for predicting group membership. Suppose DMUs are classified into two groups: G1 and G2. The first stage verifies whether or not all DMUs are correctly classified whereas the second stage deals with overlap situation.

3.1 First stage

The following model is proposed to classify and identify the overlap:

$$
\begin{aligned}
s_1^* = \min \quad & \sum_{j\in G_1} s_{1j}^+ + \sum_{j\in G_2} s_{2j}^- \\
\text{s.t.} \quad & \sum_{i=1}^{k} \alpha_i z_{ij} + s_{1j}^+ - s_{1j}^- = d, \qquad j\in G_1 \\
& \sum_{i=1}^{k} \beta_i z_{ij} + s_{2j}^+ - s_{2j}^- = d-\eta, \qquad j\in G_2 \\
& \sum_{i=1}^{k} \alpha_i = 1 \\
& \sum_{i=1}^{k} \beta_i = 1 \\
& \text{all slacks} \ge 0, \quad \alpha_i \ge 0, \quad \beta_i \ge 0 \\
& d : \text{unrestricted}
\end{aligned} \tag{3}
$$

where η is a parameter for imposing a gap between two groups. Slacks, s_{1j}^+ and s_{2j}^- represent deviations for G_1 and G_2, respectively. More precisely, s_{1j}^+ indicates how much $\boldsymbol{\alpha}\mathbf{z} = \sum_{i=1}^{k} \alpha_i z_{ij}$ is separated from the threshold score d and similarly s_{2j}^- shows how much $\boldsymbol{\beta}\mathbf{z} = \sum_{i=1}^{k} \beta_i z_{ij}$ is separated from $d-\eta$. Hence, this model minimizes two types of incorrect classification: DMUs in G1 are classified in G_2 and DMUs in G_2 are classified in G_1. The two normalization constraints $\sum_{i=1}^{k} \alpha_i = 1,\ \sum_{i=1}^{k} \beta_i = 1$ are added to avoid a trivial solution $\alpha_i = \beta_i = 0$.

Note that in this model we are looking for the following two hyperplanes

$$
\begin{aligned}
H_1 &= \{\mathbf{z}:\ \boldsymbol{\alpha}\mathbf{z} = d\} \\
H_2 &= \{\mathbf{z}:\ \boldsymbol{\beta}\mathbf{z} = d-\eta\}
\end{aligned}
$$

such that $\forall j \in G_1,\ \mathbf{z}_j \in H_1^+\ \&\ \forall j \in G_2,\ \mathbf{z}_j \in H_2^-$.

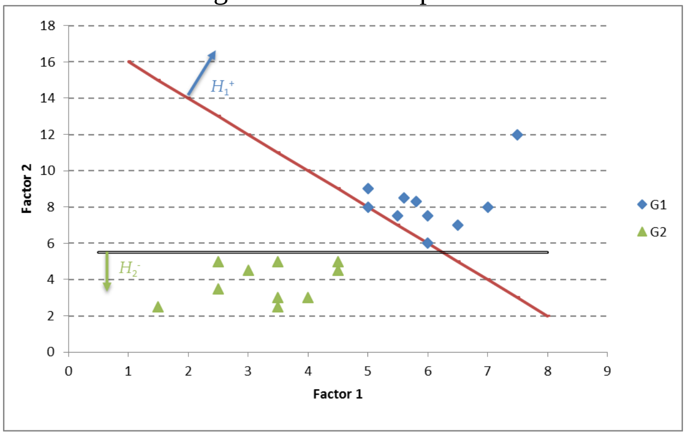
Suppose this model is solved and the optimal solution is at hand. The overlap of DMU_o can be identified by the following criteria:

1. If $\boldsymbol{\alpha}^*\mathbf{z}_o - d^* \ge 0$ and $\boldsymbol{\beta}^*\mathbf{z}_o - d^* \ge 0$, then no overlap exists and $\mathbf{z}_o \in G_1$.
2. If $\boldsymbol{\alpha}^*\mathbf{z}_o - d^* < 0$ and $\boldsymbol{\beta}^*\mathbf{z}_o - d^* < 0$, then no overlap exists and $\mathbf{z}_o \in G_2$.
3. If ($\boldsymbol{\alpha}^*\mathbf{z}_o - d^* > 0\ \&\ \boldsymbol{\beta}^*\mathbf{z}_o - d^* \le 0$ or $\boldsymbol{\alpha}^*\mathbf{z}_o - d^* \le 0\ \&\ \boldsymbol{\beta}^*\mathbf{z}_o - d^* > 0$), then there is an overlap and $\mathbf{z}_o \in G_1 \cap G_2$.

Since the criteria is based on the sign of $\boldsymbol{\alpha}^*\mathbf{z}_o - d^*$ and $\boldsymbol{\beta}^*\mathbf{z}_o - d^*$, they are called α-estimate and β-estimate, respectively.

We utilize the following figure to illustrate this approach. Consider we have 20 DMUs with 2 independent factors and also the DM classified these units into two groups. Figure 1 exhibits a situation that no overlap exists.

Figure 1: No overlap exist



Source: author's calculations.

As can be seen in Figure 1, the correct group classification can be determined by model (3) however, this model fails to deal with overlap situation. In this case, we must resort to the second stage.

3.2 Second stage

Sueyoshi (1999) formulated the following model to deal with overlap:

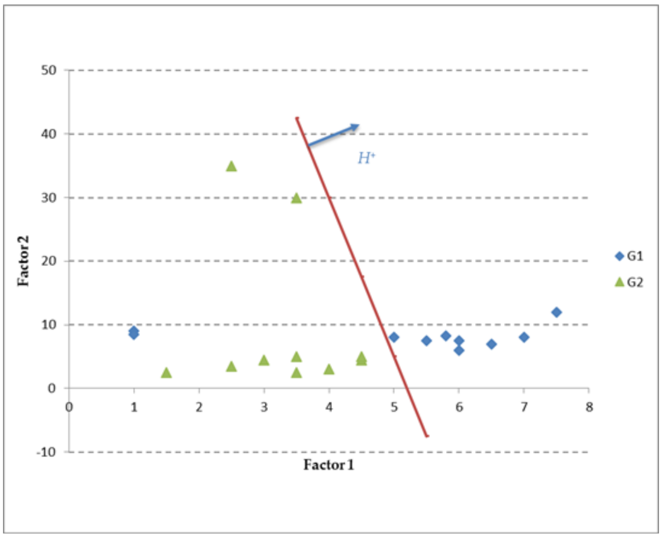
$$\begin{aligned} & s_2^* = \min \quad \sum_{j \in G_1} s_{1j}^+ + \sum_{j \in G_2} s_{2j}^- \\ & \text{s.t.} \quad \sum_{i=1}^{k} \alpha_i z_{ij} + s_{1j}^+ - s_{1j}^- = d, \qquad j \in G_1 \\ & \qquad \sum_{i=1}^{k} \alpha_i z_{ij} + s_{2j}^+ - s_{2j}^- = d - \eta, \qquad j \in G_2 \\ & \qquad \sum_{i=1}^{k} \alpha_i = 1 \\ & \qquad \text{all slacks} \geq 0, \quad \alpha_i \geq 0 \\ & \qquad d : \text{unrestricted} \end{aligned} \tag{4}$$

Suppose this model is solved. As Sueyoshi (1999) explained, with the following conditions all units in $G_1 \cap G_2$ can be classified into either G_1 or G_2:

$$\text{If } \sum_{i=1}^{k} \alpha_i^* z_{ij} \geq d^*, \ j \in G_1 \cap G_2, \text{ then } j \in G_1; \text{ otherwise } j \in G_2.$$

The following figure illustrates this situation

Figure 2: Overlap exist



Source: author's calculations

4. Case study

This section classifies a real data set of the largest private bank in Iran that are previously utilized in Toloo (2013). The bank has approximately 3150 branches in different cities in Iran with 127 branches in one of the northern provinces, Gilan. Table 1 exhibits the data set involving 20 branches of the capital of Gilan. Based on DM, there are six important factors for classification: employees, assets, cost, the number of transactions, deposits and loans.

Table 1: The data set and given group

DMUs	Factors						Group
	Employees	Assets	Costs	Transactions	Deposits	Loans	
1	11	1753	10020	5214	72149	57537	G_1
2	17	2604	11440	5343	89781	51114	G_1
3	7	1155	8427	5145	42654	52485	G_2
4	12	1899	11816	3249	97812	67298	G_1
5	14	2215	12426	6706	77031	43487	G_1
6	14	2357	9907	6259	75923	41442	G_1
7	9	1370	10365	3652	47763	43262	G_2
8	5	829	5283	3913	45732	14237	G_2
9	6	985	11061	3566	55222	41062	G_2
10	6	1023	5856	4559	53323	37418	G_2
11	8	1311	8745	4441	69734	57883	G_2
12	9	1536	7326	5031	49153	47139	G_2
13	8	1367	8326	5053	92365	55543	G_1
14	7	1193	6525	4762	64235	22347	G_2
15	9	1359	8158	6876	89104	45717	G_1
16	7	1111	11135	4307	42012	73925	G_2

17	7	1182	6920	5331	69360	27246	G_2
18	7	1069	5864	4004	51438	26531	G_2
19	6	992	5039	2342	39948	20223	G_2
20	7	1180	8378	4238	154284	43928	G_2

Source: Toloo (2013)

We solve the model (3) for that data set in Table (1) and the following optimal solution obtains:

$$d^* = 1536$$

$$\alpha_1^* = 0.979,\ \alpha_5^* = 0.021, \beta_2^* = 1$$

Table (2) shows α-estimate and β-estimate related to this optimal solution. As it can be extracted from this table, there are three overlaps for DMU_{13}, DMU_{15} and DMU_{20}. The optimal solution of the model (2) give us

$$d^* = 10430.524,\ \alpha_3^* = 0.1133, \alpha_4^* = 0.782, \alpha_5^* = 0.208, \alpha_6^* = 0.637\ .$$

Table 2: Two-stage DEA-DA in case of overlap

DMUs	Stage 1			Stage 2	
	α-estimate	β-estimate	Prediction	α-estimate	Prediction
1	0.000	216.990	G_1		G_1
2	378.617	1067.990	G_1		G_1
3	-627.445	-381.010	G_2		G_2
4	543.499	362.990	G_1		G_1
5	106.143	678.990	G_1		G_1
6	82.720	820.990	G_1		G_1
7	-517.482	-166.010	G_2		G_2
8	-564.333	-707.010	G_2		G_2
9	-362.734	-551.010	G_2		G_2
10	-402.879	-513.010	G_2		G_2
11	-53.990	-225.010	G_2		G_2
12	-488.097	-0.010	G_2		G_2
13	424.433	-169.010	Overlap	84.217	G_1
14	-171.219	-343.010	G_2		G_2
15	356.474	-177.010	Overlap	794.773	G_1
16	-641.017	-425.010	G_2		G_2
17	-62.875	-354.010	G_2		G_2
18	-441.750	-467.010	G_2		G_2

19	-685.629	-544.010	G_2		G_2
20	1732.433	-356.010	Overlap	-0.010	G_2

Source: author's calculations

It seems the proposed approach by Sueyoshi (1999) classifies the data of bank, as follows:

G1: DMU1, DMU2, DMU4, DMU5, DMU6, DUM13, DMU15.

G2: DMU3, DMU7-DMU12, DMU14, DMU17-DMU20.

Now, let us double-check the obtained result. The last column of table (1), given group, is exactly the same as the last column of Table (2), prediction by DEA-DA approach, which illustrates a drawback in this approach: based on the obtained result of the stage 1 model, there is overlap in the data set whereas the group of any observation is not changed in the stage 2 did not change. If the status of all units be the same, then definitely the overlap is still exists. Obviously, this is a drawback and in the next section, we capture it and revise the DEA-DA approach.

5. The revised DEA-DA approach

It should be noticed that from the optimal solution of stage 1 it is evident that to calculate α-estimates the factors assets, cost, number of transactions and loans are ignored and also to evaluate β-estimates only assets is considered. Also in stage two, employee and assets are removed from calculations. As it was mentioned before, similar to DEA models, in DEA-DA approach all factors have to be considered and hence the value of *α* and *β* variables must be positive. Toward this end, we propose the following two-stage models:

Stage 1

$$
\begin{aligned}
s_1^* = \min \quad & \sum_{j\in G_1} s_{1j}^+ + \sum_{j\in G_2} s_{2j}^- \\
\text{s.t.} \quad & \sum_{i=1}^{k} \alpha_i z_{ij} + s_{1j}^+ - s_{1j}^- = d, \qquad j \in G_1 \\
& \sum_{i=1}^{k} \beta_i z_{ij} + s_{2j}^+ - s_{2j}^- = d - \eta, \qquad j \in G_2 \\
& \sum_{i=1}^{k} \alpha_i = 1 \\
& \sum_{i=1}^{k} \beta_i = 1 \\
& \text{all slacks} \geq 0, \quad \alpha_i \geq \varepsilon, \quad \beta_i \geq \varepsilon \\
& d : \text{unrestricted}
\end{aligned}
$$

Stage 2

$$
\begin{aligned}
s_2^* = \min \quad & \sum_{j\in G_1} s_{1j}^+ + \sum_{j\in G_2} s_{2j}^- \\
\text{s.t.} \quad & \sum_{i=1}^{k} \alpha_i z_{ij} + s_{1j}^+ - s_{1j}^- = d, \qquad j \in G_1 \\
& \sum_{i=1}^{k} \alpha_i z_{ij} + s_{2j}^+ - s_{2j}^- = d - \eta, \qquad j \in G_2 \\
& \sum_{i=1}^{k} \alpha_i = 1 \\
& \text{all slacks} \geq 0, \quad \alpha_i \geq \varepsilon \\
& d : \text{unrestricted}
\end{aligned}
$$

where $0 < \varepsilon < \frac{1}{k}$ is a positive number to forestall weights from being zero.

The following table shows the new results that obtained from our new proposed model with $\varepsilon = 0.01$.

Table 3: The revised Two-stage DEA-DA in case of overlap

DMUs	Stage 1			Stage 2	
	α-estimate	β-estimate	Prediction	α-estimate	Prediction
1	12.739	-114.700	Overlap	376.000	G_1

2	585.765	821.390	G_1		G_1
3	-1080.654	-1044.930	G_2		G_2
4	995.542	376.560	G_1		G_1
5	86.878	271.530	G_1		G_1
6	0.000	345.240	G_1		G_1
7	-988.347	-877.350	G_2		G_2
8	-1405.919	-1750.110	G_2		G_2
9	-753.792	-1184.440	G_2		G_2
10	-897.423	-1245.890	G_2		G_2
11	-94.712	-575.800	G_2		G_2
12	-916.609	-683.580	G_2		G_2
13	664.375	-317.760	Overlap	1627.000	G_1
14	-660.696	-1117.250	G_2		G_2
15	471.117	-439.670	Overlap	1585.250	G_1
16	-870.121	-860.050	G_2		G_2
17	-425.538	-1017.820	G_2		G_2
18	-1075.346	-1335.370	G_2		G_2
19	-1561.004	-1611.380	G_2		G_2
20	2671.892	-0.010	Overlap	5332.250	G_1

Source: author's calculations

As it can be seen from Table (3), DMU_{20} must be classified in G_1. If one puts DMU_{20} into G_1 and resolve the improved stage 1 model, it can be found that there is not overlap in the data set (as we expected).

Now, suppose we wish to predict the group membership of a new branch with the following data set:

Employee: 10
Assets: 1277
Cost: 11701
The number of transactions: 3833
Deposits: 98910
Loans: 38438

The DM can predict the group membership of the new branch by the optimal solution of the improved approach. The α-estimate for the new branch is equal to 741.42 and subsequently the new branch belongs to G_1.

6. Conclusion

In this paper, a mathematical approach for classifying DMUs in DEA-DA was considered. This approach involves two stages for classification and predict the membership: stage 1 identifies the overlap (if exists) and stage 2 deals with overlap situation. We illustrated that zero weighs in these models might lead to an incorrect result and to tackle this issue we put a positive lower bound to the weights. To show the applicability and accuracy of the improved approach, we used 20 branches of Saderat Bank, whose memberships are determined by the bank, and measured a set of normalized weights by minimizing incorrect group classification. We also utilized the estimated weights to predict group membership of a new branch (DMU_{21}).

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