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決策球模式及其運用

Decision Ball Models and Applications

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Abstract

Many decision-making or choice problems in Marketing incorporate preferences. How to assist decision makers in understanding the decision context and improving inconsistencies in judgments are two important issues in ranking choices. This study develops a decision-making framework based on the screening, ordering, and choosing phases. Two optimization models and a Decision Ball model are proposed to assist decision makers in improving inconsistencies and observing relationships among alternatives. By examining a Decision Ball, a decision maker can observe ranks of and similarities among alternatives, and iteratively adjust preferences and improve inconsistencies thus to achieve a more consistent and informed decision.

Key words: Decision Ball; Ranking; Inconsistency; Decision-making

摘要

在行銷偏好的選擇上有很多的決策擬定跟選擇的問題。如何去幫助決策者瞭解決策問題的內容及改善不一致性是選擇性排序的兩個主要議題。本研究以檢視、排序及選擇等步驟發展了一套決策制定的架構方法，其架構包含有兩個最佳化模型及一個決策球模型。目的在提供使用者改善偏好的不一致性及檢視方案選擇之間的關係。利用決策球，決策者可以看出決策方案之間的相似度及優先順序，並且透過不斷的調整喜好程度來改善決策過中出現的偏好不一致，使得決策者能夠獲得一個更好的決策資訊。

關鍵字：決策球、排序、不一致性、決策擬定

目錄

Part I (Decision Making)

1. Introduction

Many decision-making or choice problems in Marketing incorporate preferences (Liechty et al, 2005; Horsky et al. 2006; Gilbride and Allenby, 2006). Keeney (2002) identified 12 important mistakes frequently made that limit one's ability in making good value judgments, in which "not understanding the decision context" and "failure to use consistency checks in assessing value trade-offs" are two critical mistakes. Hence, how to assist decision makers in understanding the decision context and adjusting inconsistencies in judgments are two important issues in ranking choices.

There is evidence that decision makers' preferences are often influenced by the visual background information (e.g., Simonson and Tversky 1992; Tversky and Simonson, 1993; Seiford and Zhu, 2003). From marketing it is known from consumer choice theories that context impacts the choices consumers make (Seiford and Zhu, 2003). For example, a product may appear attractive against a background of less attractive alternatives and unattractive when compared to more attractive alternatives (Simonson and Tversky, 1992). Visual representations can simplify and aggregate complex information into meaningful pattern, assist people in comprehending their environment, and allow for simultaneous perception of parts as well as a perception of interrelations between parts (Maruyama, 1986; Meyer, 1991; Sullivan, 1998). Hence, how to provide visual aids to help decision makers make a more informed decision is the first issue addressed by this study.

Ranking alternatives incorporating preferences is a popular issue in decision-making. One common format for expressing preferences is to use pairwise comparisons, which forces one to make a direct choice of one object over another when compariing two objects, rather than requiring one to comparing all objects simultaneously (Cook et al., 2005). For example, in sports competitions, such as tennis, football and baseball, pairwise rankings are the typical input (Hochbaum and Levin, 2006). Several methods have been proposed (e.g., Saaty, 1980; Jensen, 1984; Genest and Rivest, 1994) to rank alternatives in pairwise comparisons fashion. However, inconsistencies are not unexpected, as making value judgments is difficult (Keeney, 2002). The ranks different methods yield do not vary much when the decision makers' preferences are consistent. But, if a preference matrix is highly inconsistent, different ranking methods may produce wildly different priorities and rankings. Hence, how to help the decision makers to detect and improve those inconsistencies thus to make a more reliable decision is the second issue addressed here.

Multicriteria decision makers tend to use screening, ordering and choosing phases to find a preference (Brugha, 2004). They tend to make little effort in the first phase as they screen out clearly unwanted alternatives, use somewhat more effort in the second phase as they try to put a preference order on the remaining alternatives, and reach the highest effort in the final phase when making a choice between a few close alternatives.

This study develops a decision-making framework based on these three phases. Preferences in pairwise comparison fashion are adopted in the choosing phase. Two optimization models and a Decision Ball model are proposed to assist decision makers in improving inconsistency and observing relationships among alternatives. By examining Decision Balls, a decision maker can iteratively adjust preferences and improve inconsistencies thus to achieve a more consistent decision. The proposed approach can be extensively applied in Marketing. Possible applications are the selection of promotion plans, decisions regarding product sourcing, choice of marketing channels, evaluation of advertising strategy, research of customer behavior …etc.

The reasons why this study uses a sphere model instead of a traditional 2-dimensional plane or a 3-dimensional cube model are described as follows. A 2-dimensional plane model cannot depict three points that do not obey the triangular inequality (i.e. the total length of any two edges must be larger than the length of the third edge) neither can it display four points that are not on the same plane. For instance, as illustrated in Figure 1, consider three points, Q_1, Q_2, Q_3, where the distance between Q_1Q_2, Q_2Q_3, and Q_1Q_3 are 3, 1, and 6, respectively, as shown in Figure 1(b). It is impossible to show their relationships by three line segments on a 2-dimensional plane, as shown in Figure 1(a). If there are four points, Q_1, Q_2, Q_3, and Q_4, which are not on the same plane, as shown in Figure 1(c), it is impossible to present these four points on a 2-dimensional plane too. In addition, a sphere model is also easier for a decision maker to observe than a 3-dimensional cube model because the former exhibits alternatives on the surface of a sphere rather than inside the cube.

This paper is organized as follows. Section 2 reviews the relevant literature. Section 3 sets the three-phase decision making framework, including the screening, ordering and choosing phases. Section 4 proposes a weight-approximation model and a Decision Ball model to support a decision maker to filter out poor alternatives in the ordering phase. Section 5 develops an optimization model which can assist a decision maker in improving inconsistencies in preferences, and provides three methods to allow a decision maker to iteratively adjust his preferences in the choosing phase. Sections 4 and 5 form the main theoretical part of this paper; therefore, readers only interested in the application of proposed approach can skip these two sections. Section 6 uses an example to demonstrate the whole decision process.

2. Relevant Literature

Several visualization approaches have been developed to provide visual aids to support decision-making process. For instance, Li (1999) used deduction graphs to treat decision problems associated with expanding competence sets. Jank and Kannan (2005) proposed a spatial multinomial model of customer choice to assist firms in understanding how their online customers' preferences and choices vary across geographical markets. Kiang (2001) extended a self-organizing map (SOM) (Kohonen, 1995) network to classify decision groups by neural network techniques. Many studies (Kruskal, 1964; Borg and Groenen, 1997; Cox and Cox, 2000) adopted Multidimensional scaling (MDS), which is widely used in Marketing, to provide a visual representation of similarities among a set of alternatives. For instance, Desarbo and Jedidi (1995) proposed a new MDS method to spatially represent preference intensity collected over consumers' consideration sets. However, most of conventional visualization approaches are incapable of detecting and improving the decision makers' inconsistent preferences. Gower (1977), Genest and Zhang (1996) proposed a powerful graphical tool, the so-called Gower Plot, to detect the inconsistencies in decision maker's preferences on a 2-dimensional plane. Nevertheless, the Gower plots do not provide suggestions about how to improve those inconsistencies either.

A pairwise-comparison ranking problem can be provided with magnitude of the degree of preference, intensity ranking; or in terms of ordinal preferences only, preference ranking. These are sometimes referred to also as cardinal versus ordinal preference (Hochbaum and Levin, 2006). Many studies (Saaty, 1980; Saaty and Vargas, 1984; Hochbaum and Levin, 2006; etc.) use multicriteria decision making approaches to find a consistent ranking at minimum error. However, conventional eigenvalue approaches cannot treat preference matrix with incomplete judgments. And, most of them focus on adjusting cardinal or ordinal inconsistencies instead of adjusting both cardinal and ordinal inconsistencies simultaneously. Li and Ma (2006)(2007) developed goal programming models which can treat incomplete judgments and improve cardinal and ordinal inconsistencies simultaneously. However, the ranks of and similarities among alternatives can be displayed.

This study cannot only improve cardinal and ordinal inconsistencies simultaneously but provide visual aids to decision makers. They can observe ranks of and similarities among alternatives, and iteratively adjust their preferences to achieve a more consistent decision.

3. Setting the Decision-Making Framework

The proposed decision-making framework is illustrated by the screening, ordering, and choosing phases as listed below:

(i) The screening phase: the decision maker tries to screen out clearly unwanted alternatives. The decision maker specifies upper and/or lower bounds of attributes to screen out poor alternatives.

(ii) The ordering phase: the decision maker tries to put a preference order on the remaining alternatives.

- The decision maker roughly specifies partial order of alternatives.
- An optimization model and a Decision Ball model are developed to assist decision maker in calculating and viewing ranks of and similarities among alternatives.
- The decision maker filters out poor alternatives according to the information displayed on the Decision Ball.

(iii) The choosing phase: the decision maker tries to make a final choice among a few alternatives. There are four steps in this phase, including specifying pairwise-comparison preferences, detecting and improving inconsistencies, adjusting preferences, and determining the best alternatives.

- Specifying pairwise-comparison preferences. Decision maker has to make more sophisticated comparisons for the remaining alternatives in this phase. Pairwise-comparison fashion, like analytical hierarchy process (AHP; Saaty, 1980), is adopted here because it is good for choosing phase (Brugha, 2004).
- Detecting and improving inconsistencies. Because inconsistent preferences may result in unreliable rank order, significant inconsistencies should be modified to obtain a more consistent solution. An optimization model is proposed to assist decision maker in detecting and improving inconsistencies. After inconsistencies have been reduced, the ranks of and similarities among alternatives are calculated and displayed on a Decision Ball.
- Adjusting preferences. According to the information displayed on the Decision Ball, the decision maker can iteratively adjust his preferences and see the corresponding changes on the Decision Ball.
- Determining the best alternatives. Decision maker makes the final choice with the assistance of the Decision Ball.

The detailed explanations about the ordering and choosing phases are illustrated in the following two sections.

4. The models for ordering phase

Consider a set of alternatives $\mathbf{A} = \{A_1, A_2, \ldots, A_n\}$ for solving a choice problem, where the decision maker selects m criteria to fulfill. The values of criteria $c_1, \ldots, c_m$ for alternative A_i are expressed as $c_{i,k}$, for $k = 1,\ldots, m$. All criterion values are assumed to be continuous data. Denote C = $[c_{i,k}]_{n\times m}$ as the criterion matrix of the decision problem. Denote $\underline{c_k}$ and $\overline{c_k}$ as the lower and upper bounds of the criterion value of c_k, respectively. The value of $\underline{c_k}$ and $\overline{c_k}$ can be either given by the decision maker directly or calculated by the minimum and maximum raw criterion value of c_k. The score function in this study is assumed to be in an additive form because it is the most commonly used form in practice and more understandable for the decision maker (Belton and Stewart, 2002). Denote S_i as the score value of an alternative A_i. An additive score function of an alternative A_i ($c_{i,1}$, $c_{i,2}$, …, $c_{i,m}$) is defined as below:

$$S_i(\mathbf{w}) = \sum_{k=1}^{m} w_k \frac{c_{i,k} - \underline{c_k}}{\overline{c_k} - \underline{c_k}}, \tag{1}$$

where (i) w_k is the weight of criterion k, $w_k \geq 0,\ \forall k$ and $\sum_{k=1}^{m} w_k = 1$. $\mathbf{w} = (w_1, w_2, ..., w_m)$ is a weight vector, (ii) $0 \leq S_i(\mathbf{w}) \leq 1$. In order to make sure that all weights of criteria and scores of alternatives are positive, a criterion $c_{i,k}$ with cost feature (i.e., a DM likes to keep it as small as possible) is transferred from $c_{i,k}$ to ($\overline{c_k} - c_{i,k}$) in advance.

Following the score function, the dissimilarity function of reflecting the dissimilarity between alternatives A_i and A_j is defined as

$$\delta_{i,j}(\mathbf{w}) = \sum_{k=1}^{m} w_k \frac{|c_{i,k} - c_{j,k}|}{\overline{c_k} - \underline{c_k}}, \tag{2}$$

where $0 \leq \delta_{i,j}(\mathbf{w}) \leq 1$ and $\delta_{i,j}(\mathbf{w}) = \delta_{j,i}(\mathbf{w})$. Clearly, if $c_{i,k} = c_{j,k}$ for all k then $\delta_{i,j}(\mathbf{w}) = 0$.

In the ordering phase, a decision maker has to roughly specify partial order of alternatives. If the decision maker prefers A_i to A_j, denoted as $A_i \succ A_j$, score of A_i should be higher than that of A_j ($S_i > S_j$). However, there may be some inconsistent preferences. For instance, a decision maker may specify $A_i \succ A_j$, $A_j \succ A_k$ and $A_k \succ A_i$. A binary variable $t_{i,j}$ is used to record the inconsistent relationship between A_i and A_j: if $A_i \succ A_j$ and $S_i > S_j$, then $t_{i,j}$ =0; otherwise, $t_{i,j}$ = 1. A weight approximation model for ordering phase is developed as follows:

<u>Model 1 (Weight approximation model for ordering phase)</u>

$$\underset{\{w_k\}}{Min} \quad \sum_{i=1}^{n}\sum_{j=1}^{n} t_{i,j}$$

$$s.t. \quad S_i(\mathbf{w}) = \sum_{k=1}^{m} w_k \frac{c_{i,k} - \underline{c_k}}{\overline{c_k} - \underline{c_k}}, \ \forall i, \tag{3}$$

$$\sum_{k=1}^{m} w_k = 1, \tag{4}$$

$$S_i \geq S_j + \varepsilon - Mt_{i,j}, \ \forall A_i \succ A_j, \tag{5}$$

$$\underline{w_k} \leq w_k \leq \overline{w_k}, \ w_k \geq 0, \forall k, \tag{6}$$

$$u_{i,j} \in \{0,1\}, M \text{ is a large value, } \varepsilon \text{ is a tolerable error.} \tag{7}$$

The objective of Model 1 is to minimize the sum of $t_{i,j}$. Expressions (3) and (4) are from the definition of an additive score function (1). Expression (5) indicates that if $A_i \succ A_j$ and $S_i \geq S_j + \varepsilon$, then $t_{i,j}$ =0; otherwise, $t_{i,j}$ = 1, where ε and M are a computational precision and a large value which can be normally set as 10^{-6} and 10^{6}, respectively. Denote $\underline{w_k}$ and $\overline{w_k}$ as the lower and upper bound of w_k, which could be set by the decision maker as in Expression (6). From (1) and (2), the score S_i of alternative A_i and dissimilarity $\delta_{i,j}$ between alternative A_i and A_j can be calculated based on the results of Model 1.

A Decision Ball model is then constructed to display all alternatives A_i in A = {A_1, A_2, …, A_n} on the surface of a hemisphere. A non-metric multidimensional scaling technique is adopted here to provide a visual representation of the dissimilarities among alternatives. The arc length between two alternatives is used to represent the dissimilarity between them, e.g., the larger the difference, the longer the arc length. However, because the arc length is monotonically related to the Euclidean distance between two points and both approximation methods make little difference to the resulting configuration (Cox and Cox, 1991), the Euclidean distance is used here for simplification.

In addition, the alternative with a higher score is designed to be closer to the North Pole so that alternatives will be located on the concentric circles in the order of score from top view. For the purpose of comparison, we define an ideal alternative A_*, where $A_* = A_*(\overline{c_1}, \overline{c_2}, \ldots, \overline{c_m})$ and $S_* = 1$. A_* is designed to be located at the north pole with coordinate (x_*, y_*, z_*) = (0, 1, 0).

The following propositions are deduced:

Proposition 1 The relationship between $\delta_{i,*}(\mathbf{w})$ (the dissimilarity between A_i and A_*)) and $S_i(\mathbf{w})$ is expressed as $\delta_{i,*}(\mathbf{w}) = 1 - S_i(\mathbf{w})$.

<Proof> $\delta_{i,*}(\mathbf{w}) = \sum_{k=1}^{m} w_k \frac{|c_{i,k} - \overline{c_k}|}{\overline{c_k} - \underline{c_k}} = \sum_{k=1}^{m} w_k \frac{(\overline{c_k} - \underline{c_k}) - (c_{i,k} - \underline{c_k})}{\overline{c_k} - \underline{c_k}}$

$$= (\sum_{k=1}^{m} w_k \frac{(\overline{c_k} - \underline{c_k})}{\overline{c_k} - \underline{c_k}} - \sum_{k=1}^{m} w_k \frac{(c_{i,k} - \underline{c_k})}{\overline{c_k} - \underline{c_k}}) = 1 - S_i(\mathbf{w})$$

Denote $d_{i,j}$ as the Euclidean distance between A_i and A_j . Let $d_{i,j} = \sqrt{2}\delta_{i,j}$, such that if $\delta_{i,j}$ = 0 then $d_{i,j}$ = 0 and if $\delta_{i,j}$ = 1 then $d_{i,j} = \sqrt{2}$, where $\sqrt{2}$ is used because the distance between the north pole and equator is $\sqrt{2}$ when radius = 1. Denote the coordinates of an alternative A_i on a ball as (x_i, y_i, z_i). The relationship between y_i and S_i is expressed as

<u>Proposition 2</u> $y_i = 2S_i - S_i^2$.

<Proof> Since $d_{i,*}^2 = (x_i - 0)^2 + (y_i - 1)^2 + (z_i - 0)^2 = 2\delta_{i,*}^2 = 2(1 - S_i)^2$,

it is clear $y_i = 2S_i - S_i^2$. Clearly, if S_i = 1 then y_i = 1; if S_i = 0, then y_i = 0.

Based on the non-metric multidimensional scaling technique, denote $\hat{d}_{i,j}$ as a monotonic transformation of $\delta_{i,j}$ satisfying following condition: if $\delta_{i,j} < \delta_{p,q}$, then $\hat{d}_{i,j} < \hat{d}_{p,q}$. The coordinate (x_i, y_i, z_i) of alternative A_i all i can be calculated by the following Decision Ball model:

Model 2 (A Decision Ball Model)

$$\underset{\{x_i, y_i, z_i\}}{Min} \quad \sum_{i=1}^{n} \sum_{j>i}^{n} (d_{i,j} - \hat{d}_{i,j})^2$$

s.t. $\quad y_i = 2S_i - S_i^2, \ \forall i,$ (8)

$$\hat{d}_{i,j} \le \hat{d}_{p,q} - \varepsilon, \ \forall \delta_{i,j} < \delta_{p,q}, \tag{9}$$

$$d_{i,j}^2 = (x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2, \ \forall i, j, \tag{10}$$

$$x_i^2 + y_i^2 + z_i^2 = 1, \quad \forall i, \tag{11}$$

$-1 \le x_i, z_i \le 1, \ 0 \le y_i \le 1, \ \forall i, \ \varepsilon$ is a tolerable error. (12)

The objective of Model 2 is to minimize the sum of squared differences between $d_{i,j}$ and $\hat{d}_{i,j}$. Expression (8) is from Proposition 2, where the alternative with a higher score is designed to be closer to the North Pole. Expression (9) is the monotonic transformation from $\delta_{i,j}$ to $\hat{d}_{i,j}$ **.**

All alternatives are graphed on the surface of the northern hemisphere (11)(12).

Model 2 is a nonlinear model, which can be solved by some commercialized optimization software, such as Global Solver of Lingo 9.0, to obtain an optimum solution. One restriction of this model is the running time that may considerably increase when the number of alternatives becomes large because the time complexity of Model 2 is n^2. This model has good performance when the number of alternatives less than 10. However, in this case of alternatives more than 10, some classification techniques, like k-means (MacQueen,1967) for instance, can be used to reduce the solving time by dividing alternatives into several groups. The coordinates of group centers are calculated first. Then, these group centers are treated as anchor points. The coordinates of alternatives can be obtained by calculating dissimilarity between alternatives and anchor points. Thus, all alternatives can be displayed on the Decision Ball within tolerable time.

According to the information displayed on the Decision Ball, the decision maker can select better alternatives into the next phase.

5. The models for choosing phase

In this phase, the decision maker has to make more sophisticated comparisons for the remaining alternatives. Pairwise comparisons are adopted here (Brugha, 2004). For some i and j pairs, assume a decision maker can specify $p_{i,j}$, the ratio of the score of A_i to that of A_j, which is expressed as

$$p_{i,j} = \frac{S_i}{S_j} \times e_{i,j}, \tag{13}$$

where S_i is the score of A_i and $e_{i,j}$ is a multiplicative term accounting for inconsistencies, as illustrated in the Analytic Hierarchy Process (AHP) (Saaty, 1980). It is assumed that $p_{i,j} = 1/p_{j,i}$. If the decision maker cannot specify the ratio for a specific pair i and j then $p_{i,j} = \phi$. Denote **P** $=[p_{i,j}]_{n\times n}$ as a $n \times n$ preference matrix. **P** is incomplete if there is any $p_{i,j} = \phi$. **P** is perfectly consistent if $e_{i,j} = 1$ for all i, j (i.e. $p_{i,j} = S_i/S_j$ for all i, j). **P** is ordinally inconsistent (intransitive) if for some $i, j, k \in \{1, 2, 3, \ldots, n\}$ there exists $p_{i,j} > 1$, $p_{j,k} > 1$, but $p_{i,k} < 1$. **P** is cardinally inconsistent if for some $i, j, k \in \{1, 2, 3, \ldots, n\}$ there exists $p_{i,k} \neq p_{i,j} \times p_{j,k}$ (Genest and Zhang, 1996).

If **P** is complete and ordinal consistent, all A_i can be ranked immediately. However, if there is ordinal or highly cardinal inconsistency, these inconsistencies should be improved before ranking because significant inconsistencies may result in unreliable rank order.

An optimization model, developed by a goal-programming optimization technique, is developed to assist decision maker in detecting and improving inconsistencies. In order to reduce the ordinal inconsistency, a binary variable $u_{i,j}$ is used to record if the preference $p_{i,j}$, specified by the decision maker, is suggested to be reversed or not. If $p_{i,j}$ is suggested to be reversed, then $u_{i,j}$ = 1; otherwise, $u_{i,j}$ = 0. A variable $\alpha_{i,j}$, defined as the difference between $p_{i,j}$ and S_i/S_j, is used to indicate the degree of cardinal inconsistency of $p_{i,j}$: the larger the value of $\alpha_{i,j}$, the higher the cardinal inconsistency. The inconsistencies improving model is formulated as below:

Model 3 (Inconsistencies improving model)

$$\underset{\{w_k\}}{\text{Min}} \quad M \times Obj1 + Obj2$$

$$Obj1 = \sum_{i=1}^{n}\sum_{j>i}^{n} u_{i,j}$$

$$Obj2 = \sum_{i=1}^{n}\sum_{j>i}^{n} \alpha_{i,j}$$

s.t. $$\left(\frac{S_i}{S_j} - 1\right) \times (p_{i,j} - 1) + M \times u_{i,j} \geq \varepsilon, \quad \text{for all } i, j \text{ where } p_{i,j} \neq \phi \text{ and } p_{i,j} \neq 1, \tag{14}$$

$$-\left|S_i - S_j\right| + M \times u_{i,j} \geq 0, \quad \text{for all } i,j \text{ where } p_{i,j} = 1, \tag{15}$$

$$\left|\frac{S_i}{S_j} - p_{i,j}\right| \leq \alpha_{i,j}, \ \forall i, j, \tag{16}$$

$$S_i(\mathbf{w}) = \sum_{k=1}^{m} w_k \frac{c_{i,k} - \underline{c_k}}{\overline{c_k} - \underline{c_k}}, \quad \forall i, \tag{17}$$

$$\sum_{k=1}^{m} w_k = 1, \tag{18}$$

$$\underline{w_k} \leq w_k \leq \overline{w_k}, \qquad w_k \geq 0, \forall k, \tag{19}$$

$$u_{i,j} \in \{0,1\}, M \text{ is a large value, } \varepsilon \text{ is a tolerable error.} \tag{20}$$

This model tries to improve ordinal and cardinal inconsistencies simultaneously. The first objective ($Obj1$) is to achieve ordinal consistency by minimizing the number of preferences (i.e., $p_{i,j}$) being reversed. Constraint (14) means: when $p_{i,j} \neq \phi$ and $p_{i,j} \neq 1$, $u_{i,j}$ = 0, if (i)

$(\frac{S_i}{S_j} > 1)$ and $(p_{i,j} > 1)$ or (ii) $(\frac{S_i}{S_j} < 1)$ and $(p_{i,j} < 1)$; and otherwise $u_{i,j}$ = 1. A tolerable positive number ε is used to avoid $\frac{S_i}{S_j} = 1$. Constraint (15) means: when $p_{i,j}$ = 1, if $S_i = S_j$; then $u_{i,j}$ = 0; otherwise $u_{i,j}$ = 1. The second objective (*Obj*2) is to reduce cardinal consistency by minimizing the $\alpha_{i,j}$ values, i.e. to minimize the difference between $\frac{S_i}{S_j}$ and $p_{i,j}$. Since ordinal consistency (*Obj*1) is more important than cardinal consistency (*Obj*2), *Obj*1 is multiplied by a large value *M* in the objective function. Constraints (17) and (18) come from Notation 1. Constraint (19) sets the upper and lower bound of weights. An improved complete preference matrix can be obtained as $P' = [p'_{i,j}]_{n \times n}$, where $p'_{i,j} = \frac{S_i}{S_j}$ if $p_{i,j} = \phi$ or $u_{i,j}$ = 1; otherwise, $p'_{i,j} = p_{i,j}$.

Model 3 is a nonlinear model, which can be converted into the following linear mixed 0-1 program:

$$\min_{\{w_k\}} \quad M \times Obj1 + Obj2$$

$$Obj1 = \sum_{i=1}^{n} \sum_{j>i}^{n} u_{i,j}$$

$$Obj2 = \sum_{i=1}^{n} \sum_{j>i}^{n} \alpha_{i,j}$$

s.t. $$(S_i - S_j) \times (p_{i,j} - 1) + M \times u_{i,j} \geq \varepsilon, \quad \text{for all } i, j \text{ where } p_{i,j} \neq \phi \text{ and } p_{i,j} \neq 1, \tag{21}$$

$$-M \times u_{i,j} \leq S_i - S_j \leq M \times u_{i,j}, \quad \text{for all } i,j \text{ where } p_{i,j} = 1, \tag{22}$$

$$S_j \times p_{i,j} - \alpha_{i,j} \leq S_i \leq S_j \times p_{i,j} + \alpha_{i,j}, \ \forall i, j, \tag{23}$$

(17) ~ (20),

where (21), (22) and (23) are converted from (14), (15) and (16) respectively.

After the weight vector, (w_1, w_2, …, w_m), is found, $S_i(\mathbf{w}) = \sum_{k=1}^{m} w_k \frac{c_{i,k} - \underline{c_k}}{\overline{c_k} - \underline{c_k}}$ and $\delta_{i,j}(\mathbf{w}) = \sum_{k=1}^{m} w_k \frac{|c_{i,k} - c_{j,k}|}{\overline{c_k} - \underline{c_k}}$ can be calculated. All alternatives are shown on a Decision Ball by

Model 2.

According to the information visualized on the Decision Ball, the decision maker can iteratively adjust his preferences by the following ways:

(i) Adjusting preference order. Since alternative with a higher score is designed to be closer to the North Pole so that a decision maker can see the rank order by the location of alternative: the higher the latitude, the higher the score. If the decision maker would like to adjust a preference order, from $A_1 \prec A_3$ to $A_1 \succ A_3$ for instance, a constraint $S_1 \geq S_3 + \varepsilon$ will be added into Model 3.

(ii) Adjusting dissimilarity. The distance between two alternatives on a Decision Ball implies the dissimilarity between them: the larger the dissimilarity, the longer the distance. Therefore, if a decision maker observes the Decision Ball and decides to adjust the dissimilarity relationship, from $\delta_{1,3}(\mathbf{w}) < \delta_{1,2}(\mathbf{w})$ to $\delta_{1,3}(\mathbf{w}) > \delta_{1,2}(\mathbf{w})$ for example, a constraint $\delta_{1,3}(\mathbf{w}) > \delta_{1,2}(\mathbf{w})$ (i,e. $\sum_{k=1}^{m} w_k \frac{|c_{1,k} - c_{3,k}|}{\overline{c_k} - \underline{c_k}} \geq \sum_{k=1}^{m} w_k \frac{|c_{1,k} - c_{2,k}|}{\overline{c_k} - \underline{c_k}} + \varepsilon$) will be added into Model 3.

(iii) Adjusting preference matrix. A decision maker can choose to adjust the preference matrix directly. The value of $p_{i,j}$ in Model 3 will be modified according to the change in the preference matrix.

Solving Model 3 yields a new set of weights, and an adjusted Decision Ball will be displayed. The decision maker can iteratively adjust his preferences until he feels no adjustments have to be made. A final choice can be made with the assistance of a resulting Decision Ball.

6. Application to choice data: selection of a store location

Example 1 (*Selection of a store location*)

The choice of a store location has a profound effect on the entire business life of a retail operation. Suppose a manager of a convenience store in Taiwan who needs to select a store location from a list of 43 spots $\mathbf{A} = \{A_1, \ldots, A_{43}\}$. The manager sets four criteria to fulfill: (c_1) sufficient space, (c_2) high population density, (c_3) heavy traffic, and (c_4) low cost. Store size is measured in square feet. The number of people who live within a one-mile radius is used to calculate population density. The average number of vehicle traffic passing the spot per hour is adopted to evaluate the volumes of traffic. Cost is measured by monthly rent. The criteria values of 43 candidate locations are listed in the criterion matrix $\mathbf{C_1}$, as shown in Table 1.

The manager would like to rank choices incorporating his personal preferences. The manager can rank these choices by the following three phases:

Phase 1 – the screening phase

The manager tries to screen out clearly unwanted alternatives by setting upper or lower bound of each criterion. He sets the minimum space required to be 800 square feet, the minimum population density to be 700, the minimal traffic to be 400, and the maximum rental fee to be 5000. That is, $\underline{c_1}$ = 800, $\underline{c_2}$ = 700, $\underline{c_3}$ = 400 and $\overline{c_4}$ = 5000. The values of $\overline{c_1}$, $\overline{c_2}$, $\overline{c_3}$ and $\underline{c_4}$ can be set as the maximum values of c_1, c_2, c_3 and minimum value of c_4, i.e. $\overline{c_1}$ = 1500, $\overline{c_2}$ = 1260, $\overline{c_3}$ =780, and $\underline{c_4}$ = 3100. After filtering out alternatives with criterion values exceeding these boundaries, only 23 choices {A_3, A_4, A_6, A_7, A_8, A_{11}, A_{13}, A_{15}, A_{17}, A_{18}, A_{21}, A_{23}, A_{24}, A_{25}, A_{26}, A_{29}, A_{31}, A_{32}, A_{34}, A_{37}, A_{40}, A_{42}, A_{43}} are remaining for the next phase.

Phase 2 – the ordering phase

The decision maker roughly specifies partial order of alternatives. He specifies $A_3 \succ A_7$, $A_7 \succ A_{37}$, $A_{15} \succ A_8$, $A_{17} \succ A_6$, $A_{31} \succ A_{25}$ and $A_{42} \succ A_{40}$. The minimum weight of each criterion is set as $\underline{w_k}$ = 0.01 for all k by the decision maker. Applying Model 1 to these preference relationships yields w = {w_1, w_2, w_3, w_4} = {0.21, 0.43, 0.01, 0.35}, $t_{15,8}$ =1, and the rest of $t_{i,j}$ = 0. The objective value is 1. The variable $t_{15,8}$ = 1 indicates the preference relationship $A_{15} \succ A_8$ should be reversed. When checking criterion matrix in Table 1, all criterion values of A_8 are better than or equal to those of A_{15} which makes $A_{15} \succ A_8$ impossible; therefore, the relationship between A_{15} and A_8 is reversed.

The score of alternatives can be calculated according to Expression (1), where S_3 = 0.54, S_4 = 0.10, S_6 = 0.33, S_7 = 0.54, S_8 = 0.71, S_{11} = 0.29, S_{13} = 0.59, S_{15} = 0.36, S_{17} = 0.53, S_{18} = 0.31, S_{21} = 0.30, S_{23} = 0.30, S_{24} = 0.45, S_{25} = 0.22, S_{26} = 0.39, S_{29} = 0.23, S_{31} = 0.22, S_{32} = 0.42, S_{34} = 0.46, S_{37} = 0.39, S_{40} = 0.31, S_{42} = 0.34, S_{43} = 0.24. The dissimilarity between alternatives can also be calculated according to Expression (2).

Applying Model 2 to this example yields coordinates of alternatives. The resulting Decision Ball is displayed in Figure 2. Because the alternative with a higher score is designed to be closer to the North Pole, the order of alternatives can be read by the latitudes of alternative: the higher the latitude, the higher the score. The order of top ten alternatives is $A_8 \succ A_{13} \succ A_3 \succ A_7 \succ A_{17} \succ A_{34} \succ A_{24} \succ A_{32} \succ A_{37} \succ A_{26}$. In addition, the distance between two alternatives represents the dissimilarity between them: the longer the distance, the larger the dissimilarity. For instance, the dissimilarity between A_{26} and A_{37} is smaller than that of between A_{37} and A_7.

Based on the information provided on the Decision Ball, assume the decision maker decides to select the top eight alternatives to make more sophisticated comparisons. That is, only

A_8, A_{13}, A_3, A_7, A_{17}, A_{34}, A_{24} and A_{32} are remaining for the next phase.

Phase 3 – the choosing phase

In the choosing phase, the manager uses pairwise comparisons to express preferences among pairs of choices in preference matrix $\mathbf{R_1}$, as listed in Table 2. Because the manager is unable to make comparison among some spots, the relationships $p_{3,34}$, $p_{7,17}$, $p_{8,24}$, $p_{13,34}$ are left blank, which means $\mathbf{R_1}$ is incomplete. The preference matrix $\mathbf{R_1}$ is ordinally inconsistent because there is an intransitive relationship among A_3, A_8 and A_{32}. That is, A_3 is preferred to A_8 ($p_{3,8} > 1$), and A_8 is preferred to A_{32} ($p_{8,32} > 1$); however, A_{32} is preferred to A_3 ($p_{3,32} < 1$). $\mathbf{R_1}$ is also cardinally inconsistent. For instance, there exists $p_{3,8} = 1.6$, $p_{8,13} = 2.5$; but, $p_{3,13} = 2$ ($1.6 \times 2.5 = 4$, that is $p_{3,8} \times p_{8,13} \neq p_{3,13}$).

Applying Model 3 to the example yields $Obj1 = 1$, $Obj2 = 3.91$, $u_{3,8} = 1$ and the rest of $u_{i,j} = 0$, $(w_1, w_2, w_3, w_4) = (0.04, 0.19, 0.06, 0.71)$, $(S_3, S_7, S_8, S_{13}, S_{17}, S_{24}, S_{32}, S_{34}) = (0.55, 0.55, 0.78, 0.27, 0.39, 0.40, 0.74, 0.51)$. The variable $u_{3,8} = 1$ implies that the value of $p_{3,8}$ is suggested to be changed from $p_{3,8} > 1$ to $p_{3,8} < 1$ (i.e. from $A_3 \succ A_8$ to $A_3 \prec A_8$) to improve ordinal inconsistency. The values of unspecified preferences can be computed as $p_{3,34} = \frac{S_3}{S_{34}} = 1.08$, , $p_{7,17}$, $= 1.41$, $p_{8,24} = 1.93$, and $p_{13,34} = 0.76$. The corresponding Decision Ball is shown in Figure 3. The order of alternatives is $A_8 \succ A_{32} \succ A_3 \succ A_7 \succ A_{34} \succ A_{24} \succ A_{17}$.

According to the information observed on the Decision Ball, the decision maker can iteratively adjust his preferences. Suppose he would like to adjust a preference order from $A_7 \succ A_{34}$ to $A_{34} \succ A_7$. A constraint $S_{34} \geq S_7 + \varepsilon$ is added into Model 3. Solving Model 3 yields $Obj1 = 3$, $Obj2 = 3.96$, $u_{3,8} = u_{7,34} = u_{17,24} = 1$ and the rest of $u_{i,j} = 0$, $(w_1, w_2, w_3, w_4) = (0.01, 0.13, 0.17, 0.69)$, $(S_3, S_7, S_8, S_{13}, S_{17}, S_{24}, S_{32}, S_{34}) = (0.53, 0.50, 0.76, 0.27, 0.44, 0.40, 0.71, 0.51)$. In order to satisfy the relationship $A_{34} \succ A_7$, the relationship between A_{17} and A_{24} has to be reversed ($u_{17,24} = 1$). Applying Model 2 to this result yields a new set of coordinates. An adjusted Decision Ball is displayed in Figure 4. On this Decision Ball, the latitude of A_{34} is higher than that of A_7.

By seeing the relationships of alternatives displayed on the Decision Ball in Figure 4, the decision maker would like to adjust some dissimilarity relationships between alternatives. His adjustment is that the dissimilarity between A_3 and A_8 is larger than that of between A_7 and A_8. A constraint $\sum_{k=1}^{m} w_k \frac{|c_{3,k} - c_{8,k}|}{\overline{c_k} - \underline{c_k}} \geq \sum_{k=1}^{m} w_k \frac{|c_{7,k} - c_{8,k}|}{\overline{c_k} - \underline{c_k}} + \varepsilon$ is added into Model 3. Solving Model 3 again yields $Obj1 = 5$, $Obj2 = 4.33$, $u_{3,8} = u_{7,34} = u_{17,24} = u_{3,7} = u_{8,32} = 1$ and the rest of $u_{i,j} = 0$, $(w_1, w_2, w_3, w_4) = (0.01, 0.04, 0.19, 0.76)$, $(S_3, S_7, S_8, S_{13}, S_{17}, S_{24}, S_{32}, S_{34}) = (0.51, 0.53, 0.74, 0.19, 0.39, 0.36, 0.78, 0.53)$. This result shows that in addition to rank reversal of A_3 and A_8, A_7 and A_{34},

A_{17} and A_{24} ($u_{3,8} = u_{7,34} = u_{17,24}$ =1), the relationship between A_3 and A_7, A_8 and A_{32} are suggested to be reversed to satisfy the adjustment of dissimilarity. A corresponding Decision Ball is depicted in **Figure 5.**

Suppose the decision maker stops further adjustment. The decision maker can make a final decision based on the Decision Ball in Figure 5. From the latitude of alternatives, the decision maker can tell the rank of choices as $A_{32} \succ A_8 \succ A_{34} \succ A_7 \succ A_3 \succ A_{17} \succ A_{24} \succ A_{13}$. The best choice is A_{32}. The dissimilarity between alternatives can be read by the distance between them. For instance, the dissimilarity between A_3 and A_{34} is the smallest because the distance between them is the shortest. That is, if A_{32} , A_8 and A_{34} are not available, A_3 as well as A_7 will be a good choice.

It is important to notice that A_3 is more similar to A_{34} than A_7 is but $A_{34} \succ A_7 \succ A_3$. This kind of relationship is possible. For instance, comparing with three alternatives A, B, C with benefit criterion values (5, 5, 5), (4, 4, 6) and (3, 5, 5), given equal weight and $\underline{c_k}$ = 0 and $\overline{c_k}$ =10 for k = 1…3. The scores of three alternatives are S_A = 0.5, S_B = 0.47, and S_C = 0.43. The dissimilarities between alternatives are $\delta_{A,B}$ =0.1, $\delta_{B,C}$ =0.1 and $\delta_{A,C}$ =0.067. It is obvious that $A \succ B \succ C$ but C is more similar to A than B is because $\delta_{A,C} < \delta_{A,B}$.

Example 1 was solved by Global Solver of Lingo 9.0 [20] on a Pentium 4 personal computer. The running time was less than 3 minimums for three phases totally.

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Part II (Business Schools Ranking)

1. Introduction

Path dependency theory argues that a standard which is first-to-market can become entrenched – this "path dependence" can persist even if it is an inferior standard because of the legacy that this standard has established. This theory was developed from Paul David's description of how the QWERTY layout on the keyboard of typewriters largely became the standard even though it was not necessarily the best layout for a keyboard (David, 1985, 1986). The theory is now widely utilized in the social sciences although it is yet to be significantly employed in management science. This research examines changes in business school rankings over a five year period to examine the impact of path dependency on the rankings of business schools.

The research on business school rankings began to appear in the late 1970s (Hunger and Wheelen, 1980; Schatz, 1993). Since those initial efforts a number of popular rankings of business school have developed such as the Business Week (BW) ranking which began in 1988, Financial Times (FT) in 1995, Economist (Econ) in 1996, Forbes in 1999, and Wall Street Journal in 2000 (Business Week, 2006 and 2009; Financial Times, 2006 and 2009; U.S. News & World Report, 2006, 2007, and 2009; Economist.com, 2009). Numerous schools focus on the rankings and seek to improve themselves in order to move up the rankings. However, path dependency would indicate that the changes the schools are making may not necessarily be changing the school to be better. Instead, path dependency would indicate that the schools are simply changing themselves to be more like the market leaders. Thus, the manner in which someone moves up the rankings would not be to change in some manner that may actually improve education but instead the schools would improve their position the most if they become more like the market leaders.

This research will conduct an initial exploration of this issue using a new clustering method that visualizes business schools based on their rankings at a given point and time. Looking over time it can be observed how clustered schools on a three-dimension ball have changed and evolved over time. This visualization methodology will allow us to see not only if schools change absolute position but their cluster of similar schools.

This initial exploration will allow for the understanding if richer and deeper study of this topic. This research will initially review the path dependency literature relevant to this investigation. We will then examine the literature on business school rankings. Since this research is an early exploration of path dependency and business schools we employ a proposition to guide our examination. From this proposition and our findings we then develop a research agenda on this important topic. This paper will make three significant contributions to the theory. First, theoretically we will conduct path dependency theory with management science. While the theory widely used in other business domains its application in management science has been limited. The ability to contextualize a theory in different settings is an important theoretical contribution as it helps to establishes uses and limits to a theory (Zahra, 2007). In addition, a secondary contribution of the research is that it will help better understand both the rankings of business schools and the change in business education around the world. Finally, this paper introduces a new method to visualize data for managers and researchers decision making.

2. Path Dependency Theory

The path-dependence perspective argues that actors are not free when selecting a social process because former decisions and a given organization's foundation conditions would have an impact on later decisions (Arthur 1989; David 1985). This occurs since as organizations make choices they develop an incentive to stay on the same path as others in the organization or other organizations in the industry. The result is individuals in the firm or more broadly firms in an industry adopt the same choice as market leaders. This leads to individuals or organizations actions reinforcing existing patterns of behavior rather than seeking new alternatives. Thus, individuals or organizations in an industry become locked in a trajectory, no matter whether this is the best choice.

This trajectory is the result of reinforcing feedback loops that are created (Burgelman, 2002). Once a successful path is created then there is a narrowing of the strategic options as organizations assume that there the given path will lead to success (Helfat, 1994). Thus, it can be that other strategic options are in fact excluded from consideration. Schumpeter pointed out that any system designed to be efficient at a point in time will not be efficient over time (Bruton et al., 1994). Thus, pressures on managers to change can come from changes in institutional environment or changes in a market, or both. However, these pressures to break from the existing path and create a new path must be particularly high to generate such change. Unless pressures trigger questions about the exiting path's effectiveness and efficiency organizations will continue along the established path in that industry since there is inertia to resist any change (Garud and Karnøe 2001).

The model of business education we have today can largely be tracked to two complementary studies from 1959: *Higher Education for Business,* financed by the Ford Foundation, and *The Education of American Businessmen,* financed by the Carnegie Corporation. These two reports were triggers that helped to reshape the business education framework to what we have today. However, since this change business schools have not undergone a similar radical change again and instead today appear as a mature industry in which path dependency may exist. Thus, rather than rankings generating new forms of business education, path dependency theory would argue that the rankings serve to enforce the established path since they act to encourage firms to be more like the leading business schools. This research will conduct a preliminary exploration of path dependency in business schools.

3. Business School Rankings

3.1 Initial Business School Ranking Efforts

The first business school ranking appeared in 1977, reported by Carter (Schatz, 1993). For ranking criteria, the Carter Report used the frequency of faculty publications in academic journals, asked the deans of the business schools to vote on the best program, and questioned business school faculty about which schools they thought were the best. In 1979, through collecting opinions from deans at business schools accredited by AACSB and senior personal executives in industry, Hunger and Wheelen (1980) ranked business schools using four criteria: faculty reputation, academic reputation, student quality, and curriculum.

Ball and McCulloch (1984) later conducted a survey using ten criteria (namely, Faculty Quality, Internationalization, Faculty Research, Reputation, Publications, Competence of Graduates, Graduate Placement, Student Quality, Number of Students, and Foreign Study Internships) to rank business schools by collecting 212 questionnaires from 1286 Academy of International Business members. In the same year, Laoria (1984) ranked business schools in New Jersey by sending questionnaires to 83 business schools in New Jersey and 65 corporations that had headquarters in New Jersey. Brecker & Merryman Inc. (1985) ranked American business schools by surveying executives at 134 national companies of the 250 largest industrial and service firms. Since these two initial ranking efforts a wide variety of studies discussing business school rankings appeared.

3.2 Dominant Current Business School Methodology

Although various business school rankings exist, NWR and FT are two of the most popular media. NWR started to rank business schools in 1987. The methodology adopted by NWR is first to standardize collected data under each criterion by weighting the standardized scores, secondly to rescale the scores so that the top school received 100 and others received their percentages of the top scores (U.S. News and World Report, April, 22 2009). Since late 1990s, NWR assessed business schools from three aspects of Quality Assessment (weighted by 0.40), Place Success (weighted by 0.35), and Student Selectivity (weighted by 0.25). As Table 1 displays, under Quality Assessment, there are two criteria named Peer Assessment and Recruiter Assessment; Under Place Success, there are three criteria labeled Mean Starting Salary and Bonus, Employment rate at Graduation, and Employment in 3 Months; Under Student Selectivity, there are three criteria called Mean Undergraduate GPA, Mean GMAT Score, and Acceptance Rate. In 2009, the Peer Assessment Scores for each school come from 381 business school deans via sending the survey to 426 deans, revealing 89.43% of the response rate.

FT conducted business school ranking in 1995. In contrast to other media, FT survey data is audited and provided by one of the world's major accounting firms, KPMG (Financial Times, 2006). In contrast to NWR, the methodology originally set by FT is to rank global business schools and highlight on strong international orientation, high research reputation, alumni satisfaction, and gender diversity on faculty. Accordingly, FT employs 21 criteria and associated weights to rank business schools as shown in Table 2. Noteworthy, where FT Doctoral Rank is rated by number of doctoral graduates taking up a faculty position at one of the top 50 business schools, while FT Research Rank is assessed by faculty publications in 40 international journals, points are accrued by the business school at which the author is presently employed, and adjustment is made for faculty size. Although the FT rankings are mostly global in its scope, its global view may be heavily from European and English-speaking nations. Which may explain why salary-related criteria occupy 40% of the weight, and the research reputation is only evaluated by a selected group of 40 English language journals (10% of the weight). It has argued that due to cultural biases embedded in the ranking methodology, FT rankings are dominated by English-speaking business schools (Financial Times, December 23, 2009).

Insert Tables 1-2 here.

4. Testable Proposition

It was noted before others have observed that the various methods to rank schools largely generate the same set of top schools (Morgeson and Nahrgang, 2008). The greatest variation in the impact in any method is not among the very top schools but in the second and third tier schools. These general observations indicate that path dependency may be driving the rankings of business schools. That is, the top schools are being judged as the model and the various ranking methods are driven not by what may be the best business school but rather the ranking methods seek to reinforce the belief that established top schools are what all schools should look like.

Since this research is an exploratory effort to examine this important effort we will propose a proposition rather than a hypothesis. If support is found for the proposition we will then develop at the end of the paper an agenda for research on this important topic. Therefore, we propose:

> Proposition 1: Path dependency results in those top ranked business schools staying largely the same over time with changes in business schools focused mainly on second and third tier business schools seeking to become more like the leading schools.

5. Methods

5.1 Scoring Business Schools

Tables 1-2 contain the criteria used by NWR and FT. While there similarities in the systems the two do place greater importance on individual variables. That is, one magazine ranking might place more emphasis on certain criteria (goal or mission) while another magazine might choose to emphasize on other area. The aforementioned may help explain why different publications produce different rankings and employ different methodologies to compile their lists. Consequently, the functions used by NWR and FT to assess business schools are formulated as the follows:

NWR Scoring Function

$$s_i = \sum_{i=1}^{I} \sum_{k=1}^{8} (w_k c_{ik}) \qquad (1)$$

FT Scoring Function

$$s_i = \sum_{i=1}^{I} \sum_{k=1}^{21} (w_k c_{ik}) \qquad (2)$$

In (1) and (2), s_i denotes the score of i'th school, I denotes the number of surveyed business schools, w_k represents the weight of k'th criteria, and c_{ik} is the value of k'th criteria of i'th school. Tables 3, 4, and 5 provide the rankings of the various schools over the years examined.

Insert Tables 3-5 Here

5.2 Clustering Business Schools

The proposition argues that other schools will largely move to become more like leading schools. To explore this, we must first cluster schools into groups. Clustering partitions a set of observations into a set of meaningful groups where observations are similar to each other if they belong to the same group while observations are dissimilar to each other if they belong to different groups. Partition-based clustering breaks observations into some pre-specified number of clusters and them evaluate them by pre-defined criteria, hierarchical clustering is to partition observations by creating a hierarchical decomposition tree via either agglomerative or divisive approach, density-based clustering considers clusters as regions and partition observations by judging the density function within a specified neighboring scope, grid-based clustering uses a grid data structure to quantize the data space into a finite number of cells on which clustering is then carried out, and model-based clustering is to partition observations by optimizing the fit between the data and the used model.

However, traditional clustering that partitions observations into two-dimension space with the coordinates of x-axis and y-axis. In this exploratory research our desire is to see a richer and more descriptive understanding of the movement among business schools. Therefore this study will employ a novel clustering algorithm which can cluster schools on a three-dimension space with the coordinates of x-axis, y-axis, and z-axis. Obviously, in one dimension, all observations are clustered very close and not easily to be visualized as shown in Fig. 1(a), meanwhile in two dimension, all clustered observations become more sparse but restricted to deal with linear distance as shown in Fig. 1(b). A three-dimension sphere can depict points with nonlinear relationships as shown in Fig. 1(c) and can deal with the relations of four points which not on the same plane as depicted in Fig. 1(d). Particularly, as here we are focusing on exploratory research we will employ a clustering method that will allow greater visualization of the rankings since it will help us to better understand the potential for path dependency.

Insert Figs 1(a), 1(b), 1(c), and 1(d) here.

Therefore, this study employs the two axes to cluster observations while the third axis is predetermined to interpret the rankings of business schools. Accordingly, rather than simply partitioning observations into clusters, this proposed clustering framework is to partition business schools into the three-dimension space positioning by 3 non-parallel vectors of x-axis, y-axis, and z-axis. That is, this study attempts to not only simply cluster business schools by their homogeneity, but also cluster business schools by considering their "ranking tiers".

As noted, during clustering observations, finding the optimal number of clusters is another challenge work and has been considered as a NP-hard problem (Rinzivillo et al., 2008). Therefore, one of advantages of the proposed algorithm is to directly put the observations on the spheres without pre-determining the number of clusters. The 'trick' this study use to achieve this advantage is that we calculate the dissimilarity coefficients between business schools, and then rescale (re-normalize) these relative differences based on x-axis (latitude) and z-axis (longitude) to reflect their dissimilarity distances while concurrently using y-axis (the vertical middle axis of the sphere) to reflect ranking tiers. In doing so, business schools can view the clustered results on a three-dimension sphere and judge/determine the number of clusters by themselves. Taken the above together, the framework of clustering business schools into three-dimension sphere is based on current rankings.

5.3 Generating dissimilarity matrix

This study employs the attributes with their weights used in NWR and FT as shown in Formula (1) and (2) to calculate the dissimilarity coefficients among business schools. Another reason to do so is that it has long been recognized that not all attributes contribute equally to valuing objects (DeSarbo et al., 1984; Donoghue, 1990; Steinley and Brusco, 2008). Therefore, after using weighting attributers to value business schools, the next important step is to generate the dissimilarity matrix between business schools. To calculate the similarity between schools, the dissimilarity function is formulated below:

$$d_{ij} = \sum_{k=1}^{L} w_k \frac{| c_{i,k} - c_{j,k} |}{\bar{c}_k - \underline{c}_k}, \quad (3)$$

where $c_{i,k}$ denotes the value of the attribute k for school I, $\bar{c}_k$ and $\underline{c}_k$ denote the upper and lower bounds of $c_{i,k}$, L is the number of attributes, w_k are weights for attribute k. Accordingly, if $c_{i,k} = c_{j,k}$ for all *k* then $d_{ij} = 0$, and if $c_{i,k} = \bar{c}_k$ and $c_{i,k} = \underline{c}_k$ then $d_{ij} = 1$. Besides, $0 \le d_{ij} \le 1$ and $d_{ij} = d_{ji}$.

Following the formula (3), the dissimilarity matrixes among top American business schools are summarized in Tables 6 and 7 for NWR and FT systems, respectively. The value of dissimilarity coefficient between schools represents the degree of dissimilarity. That is, the smaller the value of dissimilarity coefficient, the more similar two business schools are. For example, $d_{12} = 0.4057$ and $d_{23} = 1.2806$ express that the dissimilarity degree between the schools 2 and 3 is triple that between the schools 2 and 1.

Insert Tables 6-7 here

5.4 Rule for allocating objects on three-dimension sphere

To allocate items on the sphere first denote the coordinates of the i'th school as (x_i, y_i, z_i), where $0 \le x_i \le 1$, $0 \le y_i \le 1$, and $0 \le z_i \le 1$. To link the y-axis and the ranking scores, the relationship between y_i and s_i (the score of the i'th school) is computed as $y_i = 2s_i - s_i^2$**.** The reason behind this equation is stated below:

Let $d_{i,j} = \sqrt{2}\delta_{i,j}$, such that if $\delta_{i,j} = 0$ then $d_{i,j} = 0$ and if $\delta_{i,j} = 1$ then $d_{i,j} = \sqrt{2}$, where $\sqrt{2}$ is used because the distance between the north pole and equator is $\sqrt{2}$ when radius = 1. Since $d_{i,*}^2 = (x_i - 0)^2 + (y_i - 0)^2 + (z_i - 1)^2 = 2\delta_{i,*}^2 = 2(1\text{-}s_i)^2$, it is clear that $y_i = 2s_i - s_i^2$.

Accordingly, the rules of allocating objects on spheres are described below.

(i) For three objectives i, j, and k, if the dissimilarity of i and j points is higher than that of i and k points, then the distance of $\widehat{ij}$ arc is larger than that of $\widehat{ik}$ arc. This relationship can be expressed as:

if $d_{ij} > d_{ik}$, then $(x_i\text{-}x_j)^2+(y_i\text{-}y_j)^2+(z_i\text{-}z_j)^2 > (x_i\text{-}x_k)^2+(y_i\text{-}y_k)^2+(z_i\text{-}z_k)^2$

(ii) The relationship between y_i and s_i (the score of the i'th school) is computed as

$y_i=2s_i\text{-}s_i^2$

5.5 Computing coordinates for business schools

Following the above rules, a point in space can be positioned by 3 non-parallel vectors. Therefore, all coordinates for business schools can be generated by the following model:

$$\underset{\{x_i,y_i,z_i\}}{Min} \quad Obj = \sum_{i=1}^{IJ}\sum_{j>i}^{IJ}(q_{ij} - d_{ij})^2 \tag{4}$$

subject to

$$y_i = e^{0.5*(2s_i - s_i^2)}, \quad \forall \ i, j, \tag{5}$$

$$q_{ij}^2 = (x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2, \ \forall i, j, \tag{6}$$

$$x_i^2 + y_i^2 + z_i^2 \le 1, \quad \forall i, \tag{7}$$

$$-1 \le x_i, z_i, y_i \le 1, \quad \forall i, \tag{8}$$

where *Obj* is the objective function intending to minimize the sum of difference between q_{ij} and d_{ij}, IJ represents the number of business schools' relations, $q_{i,j}$ denotes the distance between objects i and j, d_{ij} come from dissimilarity matrix generated by Formula (3), x_i, y_i, and z_i are coordinates of the school i on a sphere, and x-axis is latitude, z-axis is longitude, y-axis is the vertical middle axis of the sphere. Constraint (5) is to specify the relationship between y_i and s_i based on Proposition 1, which provides a scale adjustment for schools' ranking tiers. Constraint (6) is to determine the distance between school i and school j subject to their dissimilarity coefficients d_{ij}, Constraints (7) and (8) aim to ensure that all points must be allocated on the sphere. Notably, the concept of monotonic increasing function is used to scale y value for all schools, and s_i is determined by Formula of (1)-(2).

6. Analysis

The first part of this section is to analyze the current business rankings, while the second part is to analyze clustered business schools on the three-dimension sphere.

6. 1 Analysis of Current Business School Ranking Results

Following Tables 1-2 and Functions (1)-(2) used by NWR and FT, the scores of worldwide business schools can be generated. However, for the purpose of simplifying illustration, this work use top 50 American business schools ranking data during the last five -year period produced by NWR and FT. Since FT ranked worldwide business schools, the rankings listed in the columns of FT are renumbered after removing non-American business schools (as shown in Tables 3 and 5). Accordingly, the scores of top 50 American business schools at 2009, ranking by NWR and FT by their respective ranking function (1) and (2), are displayed in Table 3. What is clear in looking at Table 3 is that there is relative stability in both ranking systems on what are the best schools in 2009 (i.e., 10 of the top 12 schools and 13 of the top 15 are listed in both ranking methods). Tables 4-5 list the ranking of schools across 2005-2008. What is clear is that the schools at the top (i.e., top 12 and top 15) are largely the same. Specifically, 12 of the top 15 schools in 2009 are also in the top 15 schools during 2005-2008 in both FT and NWR.

6. 2 Analysis of Clustered Business Schools

After following algorithm to compute the coordinates of all business schools, business schools are displayed on the three-dimension spheres, as shown in Figs 2-11. In these figures the clustering of the schools can be seen as leading tier in the north semi-sphere, the 2nd tier around the equator, and the 3rd tier in the south semi-sphere. It is reasonable to say that the top schools in different years are quite stable and a path dependency exist in these figures for the lower ranked schools moving up to higher ranked schools. The dissimilarity coefficients employed to cluster schools acts to reinforce the belief that established top schools are what all schools should look like since the current ranking model push schools to become more like those schools. The greatest variation in the impact in any year is among tiers, particularly in NWR system.

Insert Figures 2-11 here

7. Implications and Discussion

Slight changes in criterion selection or weights on criteria, the school ranks are significantly impacted. For example, if the weights of the top half of criterion except for criterion 1 because its weight is zero (which means the criterion 1 not used to assess the schools in FT system) are decreased by 0.01 and the bottom half of the criteria are increased 0.01criterion very different picture can arise. After using Functions (1)-(2) to re-calculate the business schools scores, this work found that approximate 54% of school ranks across 2005-2009 are changed. This phenomenon is similarly occurred in NWR system. However, it is interesting to note that the top 12/15 schools ranking is impacted the least. Thus, the criteria are set in ways that supports these leading schools as dominant powers. The change in the second and third tier standings as the result of such changes in weightings shows that they can have greater stability in their ranking but becoming more like the leaders in multiple dimensions. It is interesting to note that this study also found most schools are clustered in the same groups across years even if their individual ranks have changed. As a result, this phenomenon may lead to that change in ranking place is easier than in ranking tier when few changes occur in the school data, and school clustering is more stable than the school ranking. These two facts together provide support for path dependency view of business schools.

Organizational change covers a wide range of topics but the overlying concern is that it is a "process of continually renewing an organization's direction, structure, and capabilities to serve ever changing needs" (Moran & Brighton, 2001). There are a variety of different models of organizational change that have developed including Luecke's (2003) seven step model, Kottler's (1996) eight step model, and Kanter's (1992) 10 step model of organizational change. The various models of organizational change share the belief that change in organizations is typically the result of triggers. The trigger leads organizations to recognize the need for the change, generate the vision for the change, and to be willing to implement the change. For a firm such a trigger could be a negative profit report. For a business school, such a trigger could be a business school ranking report.

However, the preliminary evidence here is that this is not the case. Instead the rankings act not as triggers other than for schools in the second and third tier to seek to become more like those in the first tier. Thus, business schools are seeking to reinforce an existing model of business education rather than looking for new methods and means to provide business education. As a result the path dependency theory appears to offer a vital insight to business schools.

8. New Research Agenda

The evidence in support of path dependency here provides a rich, but weak test of the presence of path dependency. The analytical method employed here is interesting and provides rich insight but there is now need for a more detailed and quantitative investigation of business education and the role of change in business education. The evidence here is that what has occurred to date is that the leading schools dominance has become more entrenched as a result of the ranking methods used. There is a need subject in greater detail using a much larger and international database, over a longer period of time. For example, it is possible that outside the United States the impact of rankings has been to create a more substantive change. In addition, richer data such as course content, teaching methods, faculty and research features, school environment and mission, and so forth may enrich the clustered meanings.

In addition, the method employed here has the potential to open a rich new set of topics for investigation. The visualization of material is often easier for individuals to learn. The future researches may compare the proposed clustering method with current clustering methods in a wide variety of fields such as psychology, biology, sociology, ecology, marketing, economic, and pattern recognition such as consumer lifestyle.

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Table 1 Eight criteria used by NWR

k	Criteria (c)	Weight (w)
1	Peer Assessment Score	0.25
2	Recruiter Assessment Score	0.15
3	Average Undergraduate GPA	0.075
4	Average GMAT Score	0.1625
5	Acceptance Rate	0.0125
6	Average Starting Salary	0.14
7	Graduate Employment	0.07
8	Employment in 3 Months	0.14

Table 2 Twenty-one criteria used by FT

k	Criteria (c)	Weight (w)
1	Salary Today	0
2	Weighted Salary	0.2
3	Salary Percentage Increase	0.2
4	Value for Money Rank	0.03
5	Career Progress Rank	0.03
6	Aims Achieved	0.03
7	Placement Success Rank	0.02
8	Employment at 3 Months	0.02
9	Alumni Recommendation Rank	0.02
10	Women Faculty	0.02
11	Women Students	0.02
12	Women Board	0.01
13	International Faculty	0.04
14	International Students	0.04
15	International Board	0.02
16	International Mobility Rank	0.06
17	International Experience Rank	0.02
18	Languages	0.02
19	Faculty with Doctorates	0.05
20	FT Doctoral Rank	0.05
21	FT Research Rank	0.10

Table 3 Top American business schools ranked by NWR and FT at 2009

NWR			**FT**		
i	**School Name**	**Rank (Score)**	**i**	**School Name**	**Rank (Score)**
1	Harvard University	1 (0.912)	1	University of Penn	1 (0.765)
2	Stanford University	2 (0.896)	2	Harvard University	2 (0.755)
3	University of Penn	3 (0.834)	3	Columbia University	3 (0.745)
4	Northwestern University	3 (0.834)	4	Stanford University	4 (0.735)
5	MIT	5 (0.814)	5	MIT	5 (0.725)
6	University of Chicago	5 (0.814)	6	NYU	6 (0.715)
7	UC – Berkeley	7 (0.760)	7	University of Chicago	7 (0.663)

8	Dartmouth University	8 (0.746)	8	Dartmouth University	8 (0.638)
9	Columbia University	9 (0.727)	9	Yale University	9 (0.601)
10	Yale University	10 (0.721)	10	Northwestern University	10 (0.560)
11	NYU	11 (0.687)	11	Duke University	11 (0.549)
12	Duke University	12 (0.679)	12	U. of Michigan – Ann Arbor	12 (0.541)
13	U. of Michigan – Ann Arbor	13 (0.626)	13	Emory University	13 (0.531)
14	UCLA	14 (0.625)	14	University of Virginia	14 (0.529)
15	University of Virginia	15 (0.620)	15	UCLA	15 (0.519)
16	Carnegie Mellon University	15 (0.620)	16	UC – Berkeley	16 (0.482)
17	Cormell University	17 (0.615)	17	Cormell University	17 (0.472)
18	U. of Texas – Austin	18 (0.541)	18	Georgetown University	18 (0.462)
19	Georgetown University	19 (0.539)	19	University of Arizona	19 (0.461)
20	U. of North Carolina	20 (0.529)	20	U. of Maryland –College Park	20 (0.443)
21	U. of South California	20 (0.529)	21	U. of North Carolina	21 (0.419)
22	Emory University	22 (0.483)	22	University of Rochester	22 (0.401)
23	Indiana University	22 (0.483)	23	U. of Texas – Austin	23 (0.399)
24	GIT	22 (0.483)	24	Carnegie Mellon University	24 (0.397)
25	Washington U. in St. Louis	22 (0.483)	25	Rice University	25 (0.377)
26	Ohio State University	26 (0.482)	26	University of Pittsburgh	26 (0.374)
27	U. of Washington	26 (0.482)	27	U. of Illinois-Urbana Champaign	27 (0.368)
28	U. of Wisconsin – Madison	28 (0.442)	28	Vanderbilt University	28 (0.352)
29	Arizona State University	29 (0.405)	29	Boston University	29 (0.341)
30	Brigham Young University	29 (0.405)	30	Texas A&M University	30 (0.339)
31	University of Rochester	29 (0.405)	31	Indiana University	31 (0.338)
32	Purdue University	32 (0.401)	32	U. of South California	32 (0.336)
33	Texas A&M University	33 (0.394)	33	Washington U. in St. Louis	33 (0.335)
34	U. of Minnesota – Twin Cities	33 (0.394)	34	University of Florida	34 (0.333)
35	U. of Notre Dame	33 (0.394)	35	Michigan State University	35 (0.331)
36	Vanderbilt University	33 (0.394)	36	University of Iowa	36 (0.329)
37	University of Florida	37 (0.390)	37	Penn State University	37 (0.327)
38	Rice University	38 (0.348)	38	University of Washington	38 (0.323)
39	U. of Illinois – Urbana Champaign	38 (0.348)	39	Thunderbird University	39 (0.318)
40	Michigan State University	40 (0.335)	40	U. of South Carolina	40 (0.317)
41	Penn State University	40 (0.335)	41	Southern Methodist University	41 (0.314)
42	UC–Davis	40 (0.335)	42	U. of Minnesota – Twin Cities	42 (0.313)
43	U. of Maryland –College Park	40 (0.335)	43	UC – Irvine	43 (0.307)
44	Boston College	44 (0.317)	44	Arizona State University	44 (0.302)
45	University of Iowa	44 (0.317)	45	University of Notre Dame	45 (0.292)
46	Boston University	46 (0.306)	46	Purdue University	46 (0.290)
47	Southern Methodist University	47 (0.302)	47	Ohio State University	47 (0.288)
48	Tulane University	48 (0.296)	48	George Washington University	48 (0.285)
49	Babson College	49 (0.215)	49	Wake Forest University	49 (0.284)
50	U. of Texas - Dallas	49 (0.215)	50	Boston College	50 (0.271)

Table 4 Top American business schools ranked by NWR during 2005-2008

2005		2006		2007		2008	
I	**School Name**	**i**	**School Name**	**i**	**School Name**	**i**	**School Name**
1	Harvard	1	Harvard	1	Harvard	1	Harvard
2	Stanford	2	Stanford	2	Stanford	2	Stanford
3	U. of Penn	3	U. of Penn	3	U. of Penn	3	U. of Penn
4	MIT	4	MIT	4	MIT	4	MIT
5	Northwestern	5	Northwestern	5	Northwestern	5	Northwestern
6	Dartmouth	6	Chicago	6	Chicago	6	Chicago
7	UC – Berkeley	7	Columbia	7	Dartmouth	7	Dartmouth
8	Chicago	8	UC – Berkeley	8	UC – Berkeley	8	UC – Berkeley
9	Columbia	9	Dartmouth	9	Columbia	9	Columbia
10	Michigan (Ann Arbor)	10	UCLA	10	NYU	10	NYU
11	Duke	11	Duke	11	Michigan (Ann Arbor)	11	UCLA
12	UCLA	12	Michigan (Ann Arbor)	12	Duke	12	Michigan (Ann Arbor)
13	NYU	13	NYU	13	Virginia	13	Yale
14	Virginia	14	Virginia	14	Cormell	14	Cormell
15	Cornel	15	Yale	15	Yale	15	Duke
16	Yale	16	Carnegie Mellon	16	UCLA	16	Virginia
17	Carnegie Mellon	17	Cornel	17	Carnegie Mellon	17	Carnegie Mellon
18	Emory	18	Emory	18	North Carolina	18	Texas (Austin)
19	Texas (Austin)	19	Texas (Austin)	19	Texas (Austin)	19	North Carolina
20	U. of Washington	20	North Carolina	20	Emory	20	Indiana
21	Ohio State	21	Purdue	21	USC	21	USC
22	North Carolina	22	Ohio State	22	Ohio State	22	Arizona State
23	Purdue	23	Indiana	23	Purdue	23	Georgetown
24	Minnesota	24	Michigan State	24	Indiana	24	Emory
25	Rochester	25	Minnesota	25	Georgetown	25	Rochester
26	USC	26	Rochester	26	GIT	26	Washington
27	Georgetown	27	Washington	27	Maryland	27	Ohio State
28	Indiana	28	U. of Illinois – UC	28	Minnesota	28	Minnesota
29	U. of Illinois – UC	29	USC	29	Michigan State	29	Brigham Young
30	Maryland	30	U. of Washington	30	Texas A&M	30	GIT
31	Arizona State	31	Texas A&M	31	U. of Washington	31	Texas A&M
32	GIT	32	Notre Dame	32	Wisconsin (Madison)	32	Wisconsin (Madison)
33	Michigan State	33	Wisconsin (Madison)	33	Washington	33	Purdue
34	Texas A&M	34	Arizona State	34	Penn State	34	Boston College
35	Notre Dame	35	Brigham Young	35	Vanderbilt	35	Florida
36	Washington	36	Georgetown	36	Rochester	36	Notre Dame
37	Penn State	37	GIT	37	Florida	37	Washington
38	U. of Iowa	38	Penn State	38	U. of Illinois – UC	38	U. of Illinois – UC
39	Wisconsin (Madison)	39	UC-Irvine	39	Boston College	39	Maryland
40	Brigham Young	40	Maryland	40	Notre Dame	40	Boston U.
41	U. of Arizona	41	Boston College	41	Arizona State	41	Michigan State
42	UC–Davis	42	SMU	42	Babson College	42	Penn State
43	Florida	43	Florida	43	Boston U.	43	Rice
44	Wake Forest	44	Boston U.	44	Brigham Young	44	SMU
45	Tulane	45	Rice	45	Tulane	45	UC–Davis
46	Georgia	46	UC–Davis	46	UC–Davis	46	UC–Irvine
47	Vanderbilt	47	Georgia	47	Georgia	47	Vanderbilt

48	Boston U.	48	Pittsburgh	48	Rice	48	Babson College
49	Rice	49	Babson College	49	Wake Forest	49	Georgia
50	UC-Irvine	50	Tulane	50	U. of Iowa	50	U. of Iowa

Table 5 Top American business schools ranked by FT during 2005-2008

2005		2006		2007		2008	
I	**School Name**	**i**	**School Name**	**i**	**School Name**	**i**	**School Name**
1	Harvard	1	U. of Penn	1	U. of Penn	1	U. of Penn
2	U. of Penn	2	Harvard	2	Columbia	2	Columbia
3	Columbia	3	Stanford	3	Harvard	3	Stanford
4	Stanford	4	Columbia	4	Stanford	4	Harvard
5	Chicago	5	Chicago	5	Chicago	5	MIT
6	Dartmouth	6	NYU	6	NYU	6	Chicago
7	NYU	7	Dartmouth	7	Dartmouth	7	NYU
8	Yale	8	MIT	8	Yale	8	Dartmouth
9	Northwestern	9	Yale	9	MIT	9	Yale
10	MIT	10	Michigan (Ann Arbor)	10	UCLA	10	Northwestern
11	UC – Berkeley	11	UC – Berkeley	11	Northwestern	11	UCLA
12	Michigan (Ann Arbor)	12	Northwestern	12	Michigan (Ann Arbor)	12	Emory
13	North Carolina	13	UCLA	13	Duke	13	Michigan (Ann Arbor)
14	Duke	14	Virginia	14	UC – Berkeley	14	Duke
15	Virgina	15	Duke	15	Virginia	15	UC – Berkeley
16	Cornell	16	North Carolina	16	Cornel	16	Virginia
17	UCLA	17	Michigan State	17	Maryland	17	Cornell
18	Emory	18	U. of Iowa	18	North Carolina	18	Maryland
19	Rochester	19	Cornel	19	Emory	19	Georgetown
20	Maryland	20	Georgetown	20	Georgetown	20	North Carolina
21	Vanderbilt	21	Maryland	21	Arizona	21	Washington
22	Carnegie Mellon	22	U. of Illinois – UC	22	Michigan State	22	Rochester
23	Georgetown	23	Rochester	23	U. of Illinois – UC	23	Carnegie Mellon
24	U. of Iowa	24	Carnegie Mellon	24	Rochester	24	Michigan State
25	USC	25	Emory	25	Carnegie Mellon	25	U. of Iowa
26	Notre Dame	26	Penn State	26	Penn State	26	USC
27	Boston U.	27	Brigham Young	27	U. of Iowa	27	Arizona
28	Rice	28	Boston U.	28	Minnesota	28	Penn State
29	U. of Illinois – UC	29	William & Marry	29	Rice	29	UC–Davis
30	Brigham Young	30	Washington	30	Purdue	30	South Carolina
31	Case Western Reserve	31	Thunderbird	31	UC–Irvine	31	Indiana
32	Michigan State	32	USC	32	Boston College	32	Texas A&M
33	Minnesota	33	Georgia	33	SMU	33	TSGM
34	Penn State	34	Boston College	34	Arizona State	34	Purdue
35	Texas (Austin)	35	Minnesota	35	Brigham Young	35	Rice
36	Virginia Tech	36	Notre Dame	36	Washington	36	Florida
37	SMU	37	Vanderbilt	37	Vanderbilt	37	U. of Illinois – UC
38	Arizona	38	Washington	38	Boston U.	38	UC–Irvine
39	Babson College	39	Texas (Austin)	39	Texas (Austin)	39	Washington
40	UC–Irvine	40	Case Western Reserve	40	Indiana	40	Boston College
41	Arizona State	41	Rice	41	Notre Dame	41	William & Marry
42	Thunderbird	42	Temple	42	Babson College	42	George Washington
43	Washington	43	Wake Forest	43	George Washington	43	Texas (Austin)

44	Pittsburgh	44	Arizona State	44	USC	44	Vanderbilt
45	Tulane	45	Ohio State	45	South Carolina	45	Notre Dame
46	Wake Forest	46	SMU	46	UC–Davis	46	Tulane
47	William & Marry	47	George Washington	47	William & Marry	47	Georgia
48	Temple	48	Babson College	48	Case Western Reserve	48	Brigham Young
49	UC-Davis	49	Purdue	49	Georgia	49	Babson College
50	USC	50	UC-Davis	50	Pittsburgh	50	Boston U.

Table 6 Part of Dissimilarity Matrix for NWR system during 2005-2009

2009									
j \ i	**1**	**2**	**3**	**4**	**5**	**……………………………**	**48**	**49**	**50**
1	0	0.4057	1.0422	1.0397	1.161	…………………………	4.9677	5.8671	4.9055
2		**0**	**1.2806**	1.0392	1.0339	………………………………	4.9402	5.7397	4.8549
3			0	0.7497	0.8085	………………………………	4..1853	5.1116	4.7286
4				0	0.4864	………………………………	4.4917	4.8274	4.5617
5					0	………………………………	4.4917	4.8274	4.2056
:						………			
:						…………			
:						…………			
48						…………	0	2.5350	2.7588
49								0	2.8362
50									0
2008									
						:			
						:			
						:			
						:			
2005									
j \ i	**1**	**2**	**3**	**4**	**5**	**……………………………**	**48**	**49**	**50**
1	0	0.6178	0.5980	0.9962	0.9689	…………………………	4.7967	5.2368	4.7827
2		0	0.6058	0.8752	0.6119	………………………………	4.4901	4.9302	4.4761
3			0	0.7633	0.7053	………………………………	4.4743	4.8303	4.3762
4				0	0.4166	………………………………	3.8594	4.2994	3.8453
5					0	………………………………	3.8782	4.3183	3.8642
:						………			
:						…………			
:						…………			
48						…………	0	1.1956	1.3522
49								0	1.2469
50									0

Table 7 Part of Dissimilarity Matrix for FT system during 2005-2009

j \ i	1	2	3	4	5	……………………………….	48	49	50
2009									
1	0	1.2634	0.5916	1.0485	1.01515	…………………………	4.0586	3.2893	4.4148
2		0	1.4986	0.9894	1.0083	………………………………	3.0525	3.0689	3.3939
3			0	1.1883	1.0447	……………………………	4.1171	3.1954	4.2062
4				0	0.7743	……………………………	3.8776	3.3433	3.9667
5					0	………………………………	3.5909	3.2435	3.5868
:						………			
:						…………			
:						…………			
48						………	0	1.5766	1.6221
49								0	1.6007
50									0
2008									
						:			
						:			
						:			
						:			
2005									
1	0	0.7210	0.8373	0.6636	0.8621	…………………………	3.5098	2.1536	3.1677
		0	0.6996	0.8667	0.7729	………………………………	3.1105	2.6743	3.1474
			0	0.9266	0.7149	……………………………	3.2102	2.4720	3.0444
				0	0.8638	……………………………	3.7849	2.6407	2.9007
					0	……………………………	3.3558	2.7601	3.1105
						………			
						…………			
						…………			
						…………	0	1.6267	1.4216
								0	1.7370
									0

Fig. 1(a)

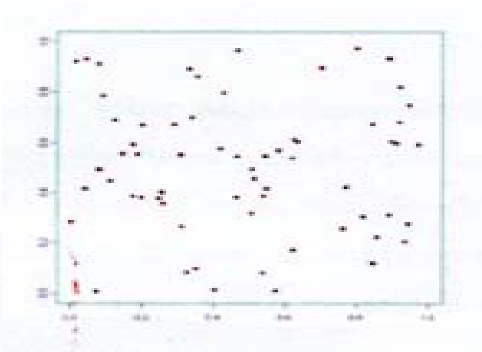

Fig. 1(b)

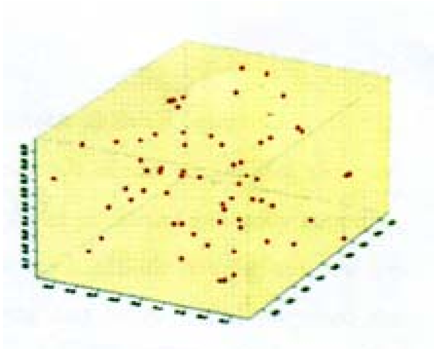

Fig. 1(c)

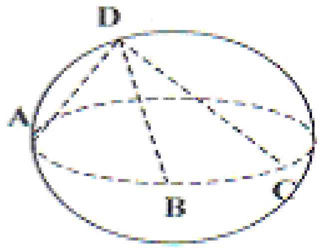

Fig. 1(d)

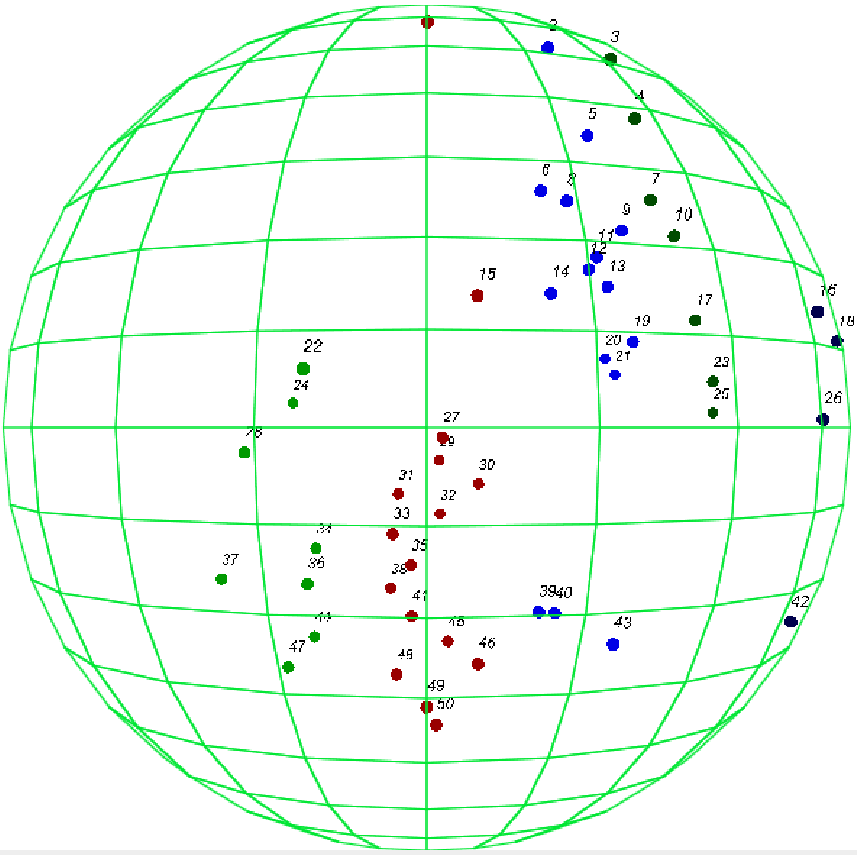

Figure 2. Clustered schools ranked by NWR in 2005

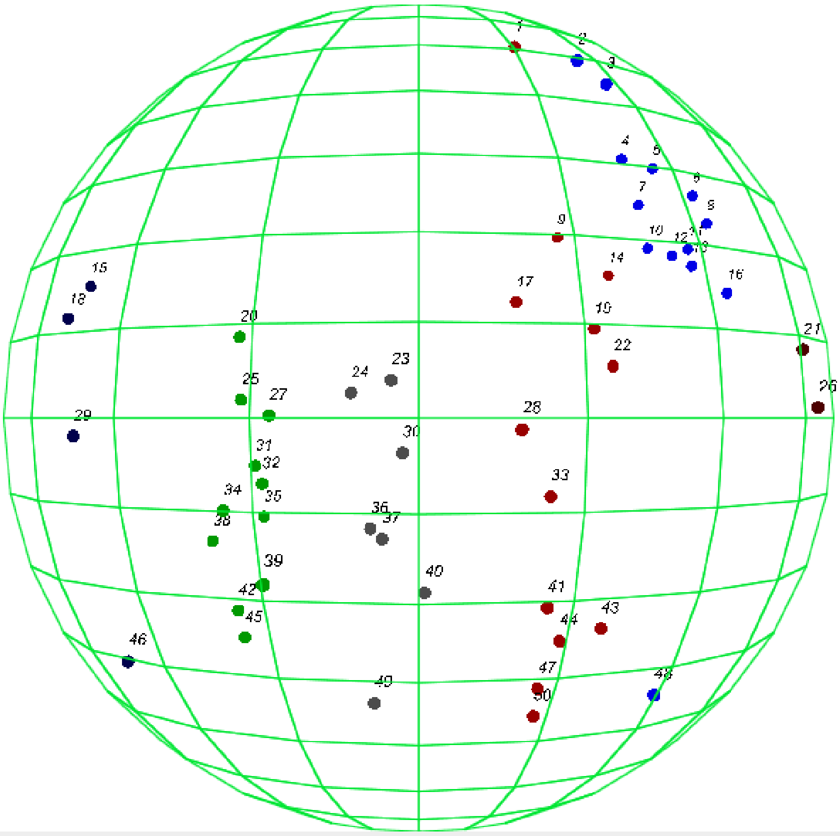

Figure 3. Clustered schools ranked by NWR in 2006

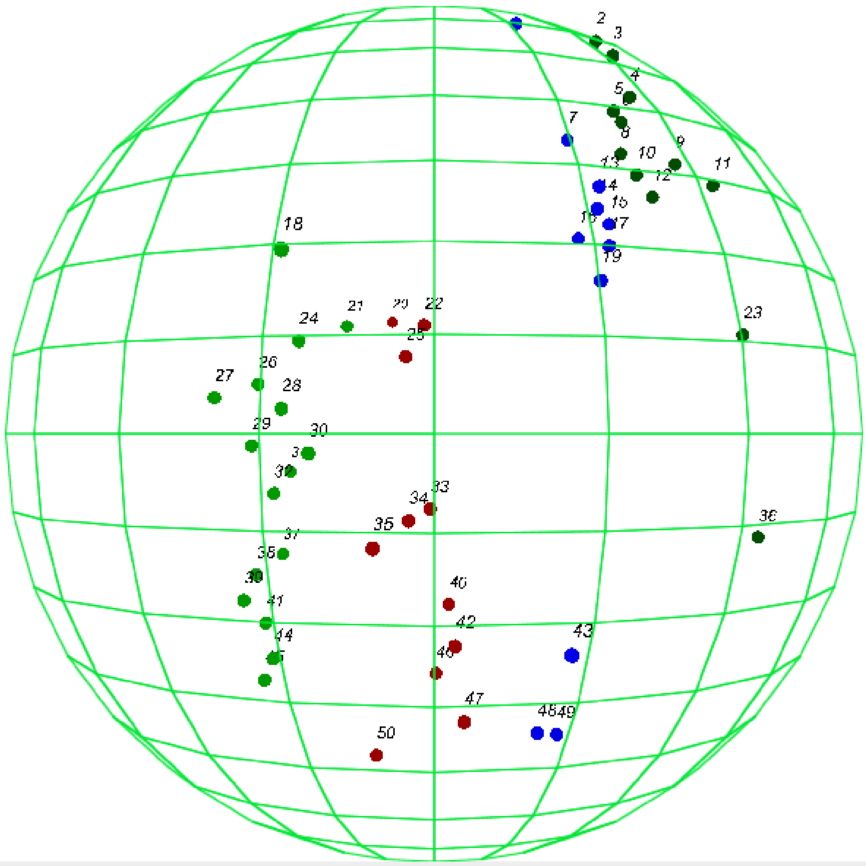

Figure 4. Clustered schools ranked by NWR in 2007

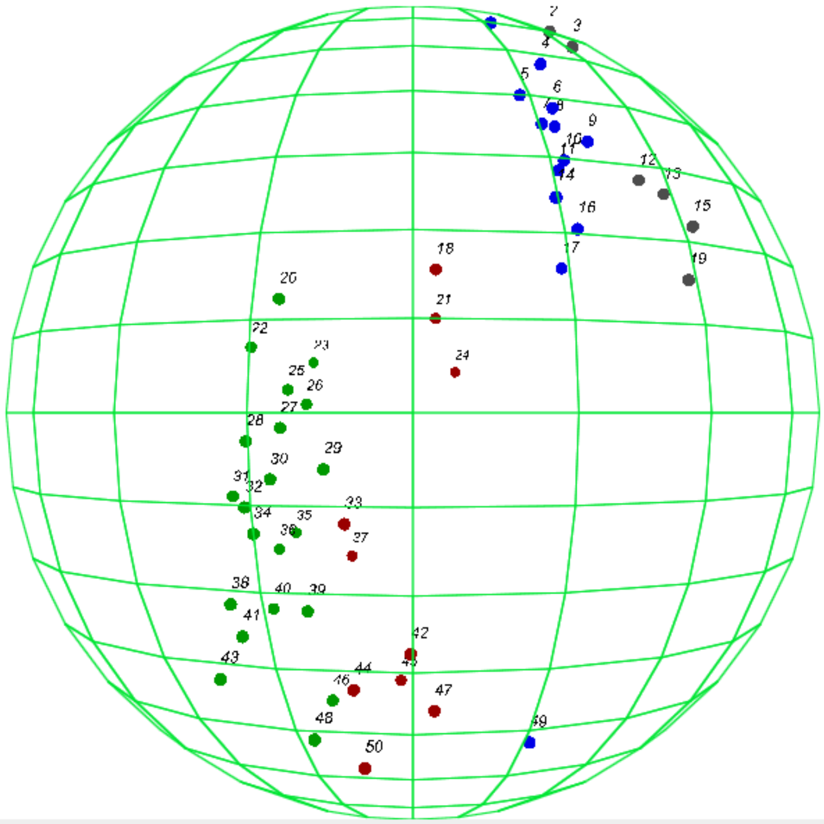

Figure 5. Clustered schools ranked by NWR in 2008

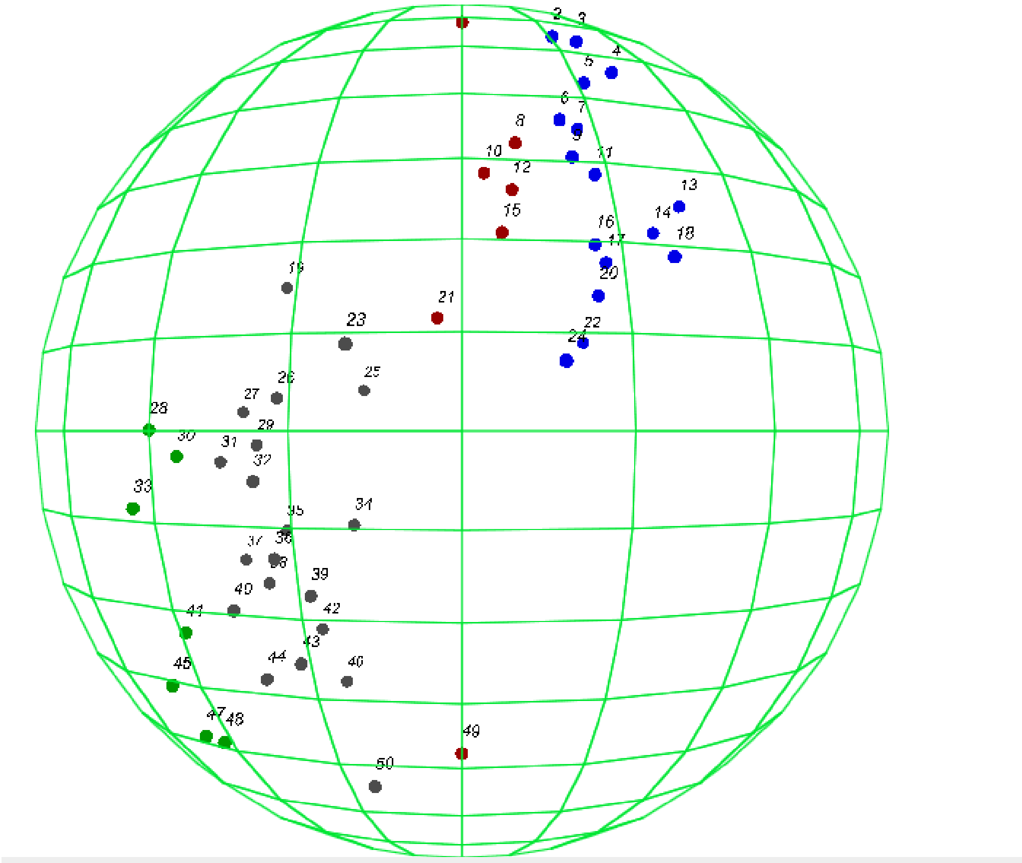

Figure 6. Clustered schools ranked by NWR in 2009

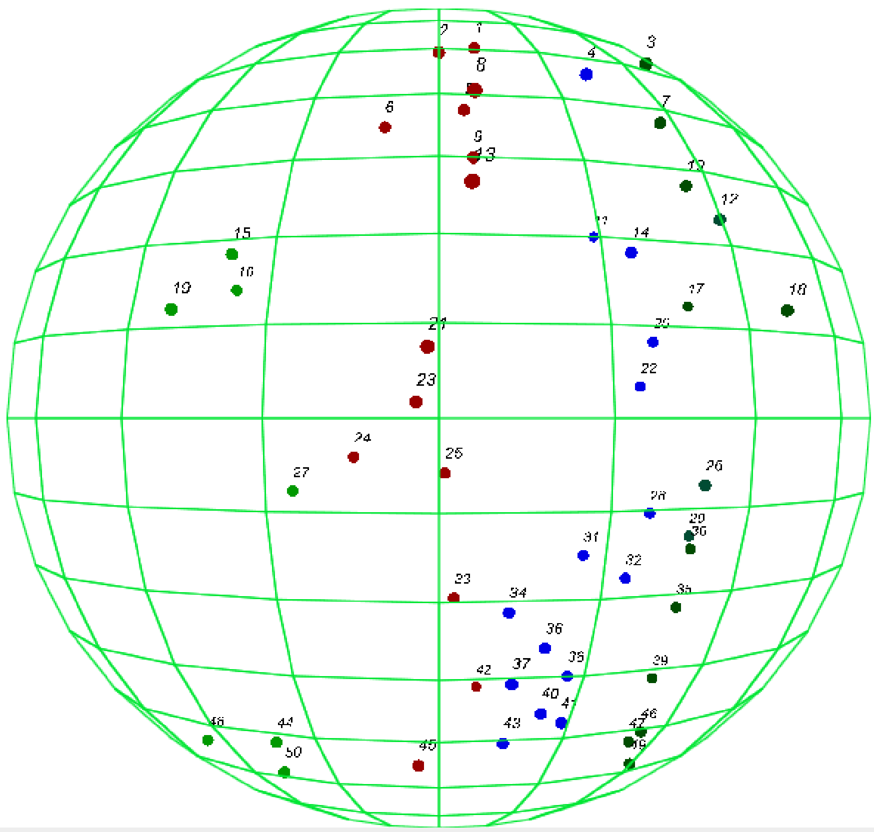

Figure 7. The clustered Top 50 business schools ranked by FT in 2005

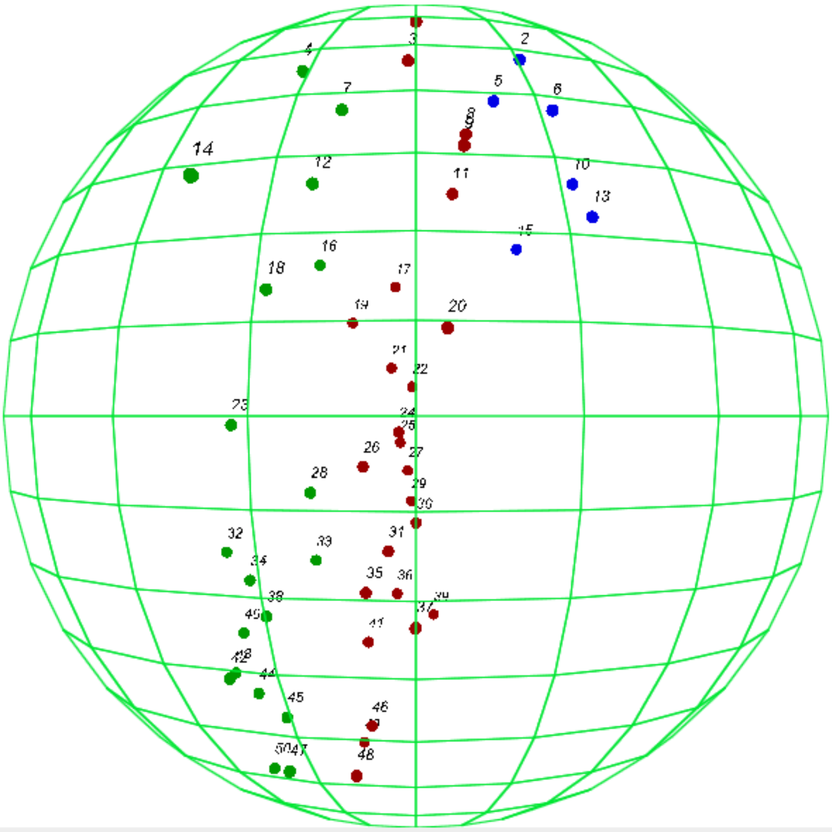

Figure 8. The clustered Top 50 business schools ranked by FT in 2006

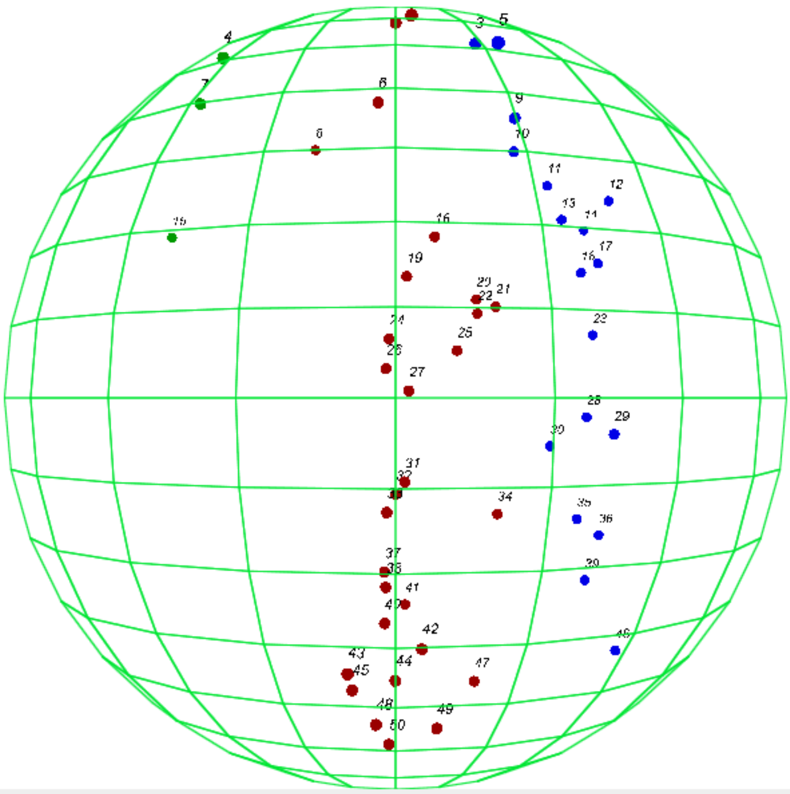

Figure 9. The clustered Top 50 business schools ranked by FT in 2007

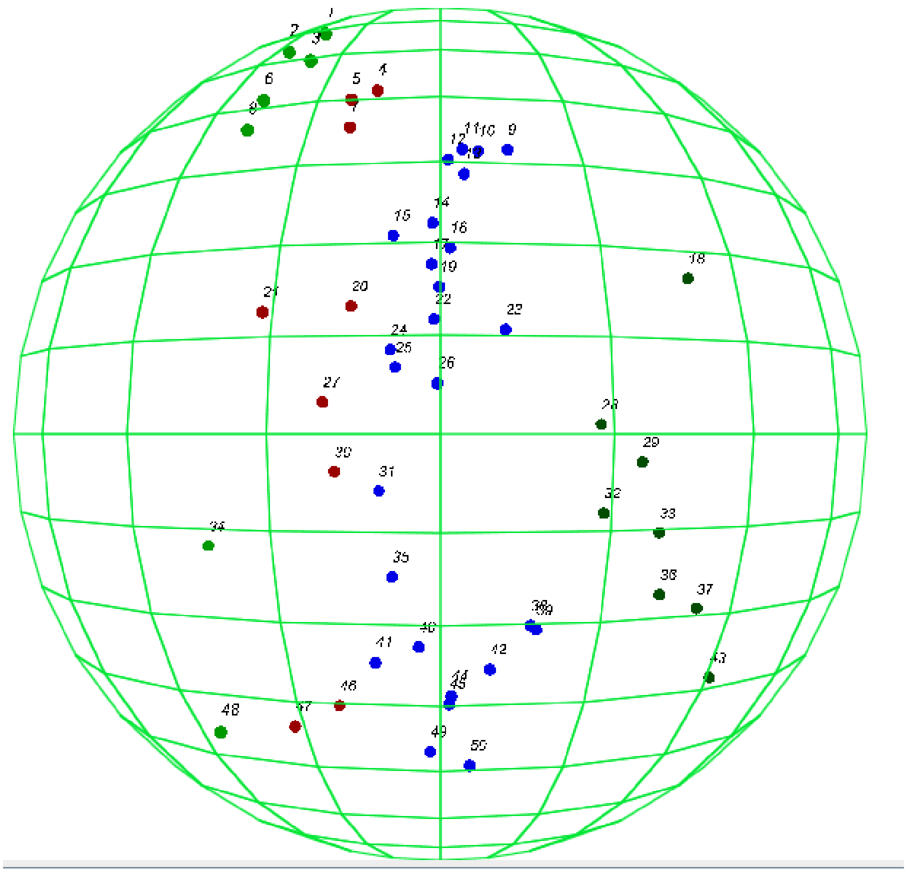

Figure 10. The clustered Top 50 business schools ranked by FT in 2008

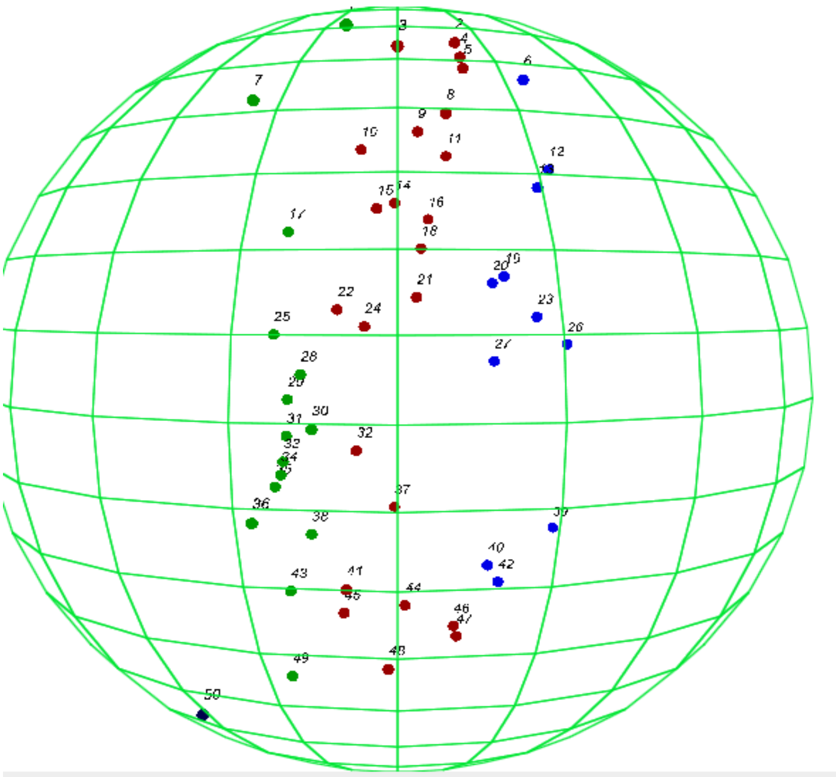

Figure 11. The clustered Top 50 business schools ranked by FT in 2009

計畫成果自評

1. 本研究主要分為 Parts I and II。在 Part I 中主要討探一般性決策議題，在最佳化方法的輔助下提供合理的最佳解。Part II 主要分析並研究全世界學校排名績效問題及其脈絡的追尋，進一步提供學校體制的調校，以有效提昇排名的績效。

2. 本研究的目的在發展一決策球理論以應用在決策最佳化問題上。此一理論已具體達成在大問題的實驗結果上並獲得証實。

3. 本研究主要成果已收錄於國際知名期刊如下：

   (i) Han-Lin Li and Li-Ching Ma. 2008. Visualizing Decision Processes on Sphere based on the Even Swap Concept. Decision Support System, 45(2), 354-367.

   (ii) Li-Ching Ma and Han-Lin Li. 2011. Using Gower Plots and Decision Balls to rank alternatives involving inconsistent preferences. Decision Support System 51, 712-719.

   (iii) Han-Lin Li, Chian-Son Yu and Garry Bruton. 2011. Analyzing Business School Rankings and Cluster Ranking Business Schools. Decision Support System, revision.

4. 本研究協助與訓練博士班研究生論文寫作

   (i) Ko, Y. C., "Inducing dynamic rules of nations' competitiveness from 2001-2005 MCI-WCY", PhD dissertation, National Chiao Tung University, 2009.

   (ii) Huang, Y.H., "A logarithmic method and its applications", Ph.D. dissertation, National Chiao Tung University, 2011.

出國報告心得（出國類別：研習）

會議主題：2010 Asia Summer Institute in Behavioral Economics

出國成果報告書

計畫編號	NSC 97-2221-E-009-104-MY3	執行單位	交大資管所
出國人員	黃曜輝(博士生)	出國日期	99 年 7 月 26 日至 99 年 8 月 6 日，共 12 日
出國地點	Singapore-NUS	出國經費	國科會

一、目的：

With my advisor Prof. Li, I try to enhance the algorithm of branch-and-bound and let the bound of problems be as tight as possible. Therefore, the resolving time can be accelerated and the solutions will be guaranteed to reach optimum.

For this summer institute in behavior economics, I got

1. Some behavioral economics models have been used in different areas (i.e., price reactions for the marketing and forecasting). In my study, I try to enhance the whole model to reach global optimum with approximate algorithm.
2. Clearly defining an optimal method for solving management science problems such as behavior economics, psychology, social preference and risk management.
3. Finally, develop and formulate strong models for the management science problem and solve it by proposed algorithm to reach the global optimal solution.

二、預期成果

1. 提升學生的能見度
2. 獲取不同的應用議題
3. 尋合適合的研究夥伴
4. 與各國著名學者互動，掌握研究發展趨勢。

二、行程

1. 開會時間：99 年 7 月 26-99 年 8 月 6
2. 開會地點：Singapore-國立新加坡大學

三、心得

1. 參與國際重要學術會議研討，不僅可提升我國的能見度，亦能增加本校的知名度、更能提昇博士生的競爭力。
2. 參與各國學者互動的機會，增加研究主題的靈感並能掌握國際研究趨勢。
3. 參與國際重要學術會議有助於推動跨國合作研究計畫。
4. 最後，學生正積極發展幾何規劃方法之應用性議題，利用最佳化技術對管理的解析，學生藉這次的參與的機會，多方面嘗試結合最佳化方法，以期許能夠全方法解決管理性的議題。