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THE USE OF CLUSTER ANALYSIS FOR BUSINESS GAME PERFORMANCE ANALYSIS

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ABSTRACT

This paper uses cluster analysis as a methodology to enhance the evaluation procedures of business games that are a part of the curriculum in many Business Policy and Strategy courses. The experiment described, implementing cluster analysis, illustrates the effects of methodology in expanding the outcome analysis of business games.

Introduction

Business game evaluation and subsequent student grading are very important components of the business game segment in Business Policy and Strategy Courses. However, often these evaluation procedures have been predetermined and are followed each successive semester. Furthermore, a business school, as long as it uses the same business game, will continue to use the same set of outcome performance criteria.

This paper describes a methodology, cluster analysis that can be used to evaluate the business game as well as analyze the students' performances. An experiment that used the Business Strategy and Policy Game (BUSPOG) of Eldridge and Bates (2) will illustrate the use of cluster analysis for analyzing students performances as well as the significance of different decisions.

BUSPOG has been used in the capstone course in both the graduate MBA and undergraduate program at a large university. The students evaluate strategic scenarios, on a quarterly basis for three years, and then execute a set of interrelated strategic decisions. Figure 1 displays a list of the decisions used in the game.

FIGURE 1 - DECISIONS MADE EACH QUARTER

The simulated competition of BUSPOG requires that the management team for each company make the following set of operating decisions once each quarter of a year. The particular decisions are:

Marketing
1. Selling price for each of the three markets.
2. Advertising budget for each of the three markets.
3. Salespersons hired or discharged in each of the three markets.
4. Product research and development budget for the company.
5. Sales commission for the company

Production
1. Scheduled production work week for the company.
2. Change in the production labor force for the company.
3. Allocation of finished product to the three markets.
4. Process research and development budget for the company.
5. Raw materials ordered for the company.
6. Plant investment budget for the company.

Personnel *
1. Sales salaries for the company.
2. Sales training budget for the company.
3. Production wage rate for the company.
4. Production training budget for the company.
5. Profit sharing for the company.

Finance
1. Bonds sold or redeemed for the company.
2. Bank loan requested for the company.
3. Dividends paid by the company.
4. Stock issues by the company.
5. Long term savings account deposit or withdrawal for the company.

* As the four person student teams has a President role, the duties under Personnel are allocated between marketing, production, and finance as follows: I and 2 went to marketing, 3, and 4 went to production, and 5 went to Finance.

Cluster Analysis Methodology

Cluster analysis uses data matrices whose columns, for the business game, can represent the competing student team companies in an industry and the rows (attributes) are the set of twelve quarterly student decisions, performance outcomes or both combined together. Student team companies are grouped into clusters as a function of the similarity of their quarterly decisions, performance outcomes, or a combination of decisions and performance outcomes.

This paper illustrates three different sets of data matrices. The first set is mentioned in the preceding paragraph. The columns in the second set of data matrices represent the set of the student teams decisions for each of twelve quarters and the attributes are the different student team numbers. The different decisions group into clusters depending on the consistency and similarity within the student teams as they participate in each business quarter. The third data set uses the student teams performance outcomes as the columns and the attributes are the student team numbers. The clusters form, as previously stated, as a result of the both the consistency and similarity within the student teams over the twelve quarters.

There are four basic steps in the cluster analysis process. The first concerns the data sets. Often the scales of measure for the data sets range from one digit to thousands of dollars, percentages, ratios, numbers of people, pounds of weight, and so forth. Thus the cluster analysis methodology, as described by Romesberg (6), provides a procedure, such as the Z score, for standardizing (normalizing) the data to transform it into dimensionless units to remove arbitrary affects.

The second step is computing a resemblance coefficient that measures the degree of similarity among pair student teams, student team decisions or performance outcomes. It is a coefficient that is sensitive to size displacement and shape in the different data attributes, a natural characteristic of the different decisions and performance measures. The “smaller” the value of the resemblance coefficient, the more similar a pair of student teams, decisions or performance outcome measures are. The formula for this resemblance coefficient is the literal distance between two objects (student teams and so forth) when viewed as points in a two-dimensional space formed by two attributes. However, for “n” attributes, the formula is the square root of the sum of the squares of the differences of the values on the “n” attributes.

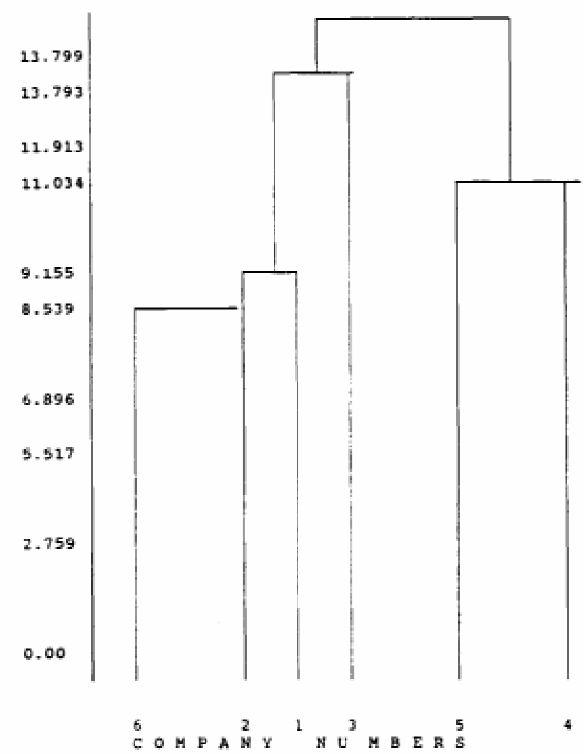
The third step determines the clustering methodology. As Aldendefer and Blashfield (1) point out, the hierarchical agglomerative methods are the most frequently used methodology. They produce a visualization process, called a tree or dendrogram that shows at a glance the degree of similarity between all the pairs of objects (student teams companies and so forth). Gnanadesikan and Kettenring (3) described three hierarchical agglomerative methods. First, single linkage method (SLINK) measures the similarity between two clusters in terms of the most similar resemblance coefficient (maximum value) of objects between the two separate clusters and produces elongated clusters with dendrograms that appear compacted. Second, complete linkage method (CLINK) is the reverse of single linkage and more rigorous. It takes the similarity between two clusters to be the most dissimilar resemblance coefficient (minimum value) of objects spanning two clusters and produces clusters that have highly similar members and extended dendrograms. The last, unweighted pair-group method using arithmetic averages (UMPGA), calculates resemblance coefficients and uses the same criteria for admittance whether a similarity or dissimilarity coefficient is used and produces less distortion in transforming the similarities between objects into a dendrogram. It is a compromise to the extremes of both single and complete linkage, and is the most often method used by researchers as well as in this research.

The fourth and last step in the cluster analysis methodology is the development of the cophenetic correlation coefficient (also know as the Pearson product-moment correlation coefficient). While the dendrogram is a graphical mapping of the resemblance matrix, it is not exactly “like” the data it represents. The cophenetic correlation coefficient gives a partial answer to how well the dendrogram and the resemblance matrix “say the same thing’. The larger the coefficient the less the distortion. Romesberg (6) states that a coefficient near to 0.8 or more says the distortion is not great.

Cluster Analysis Process

At the start of the clustering, each student team, decision, or performance outcome measure is regarded as being in a singleton cluster. The method begins by selecting the pair of student team companies (and so forth) that have the smallest resemblance coefficient and then places these in a single cluster. The distance coefficients are recalculated and placed in a revised and reduced resemblance matrix of the remaining objects (including the cluster with the two objects in it). Each successive resemblance matrix is mapped into a tree called a dendrogram that illustrates the clusters. This process is repeated until all the groups form one cluster. Figure 2 illustrates an example of a dendrogram. The numbers on the left are resemblance coefficients. The degree of grouping of the competing student team companies are illustrated by the incidence of combining related groups at

FIGURE 2 DENDROGRAM FOR SIX COMPANIES



Business Game Experiment

different resemblance coefficients. The lower the point of grouping, the closer the similarity.

Business Game Experiment

During three simulated year of the business game (BUSPOG), twenty separate and interrelated decisions made prior to each quarter of the business game and eight performance outcome measures were used as the attribute data for the first cluster analysis. The performance outcome measures chosen are a range of those consistently used by the game administrator for evaluating the performance of student teams. For this experiment, the two data sets, decisions and performance measures, are analyzed both separately and then combined together. Figure 3 lists the decisions and performance measures selected for the first cluster analysis.

FIGURE 3 DECISIONS AND PERFORMANCE MEASURES

DECISIONS	PERFORMANCE MEASURES
Product Price	Percentage Market Share
Advertising Budget	Productivity
Product R&D Budget	Quick Ratio
Salesmen Commission	Profit on Sales Ratio
Process R&D Budget	Stock Price
Sales Training Budget	Earnings per Share
Production Wage Rate	Bank Loan/Interest Rate
Profit Sharing Percentage	Price Earning (PE) ratio
Production Training Budget	
Labor Force Size Change	
Production Work Week	
Raw Material Purchased	
Number of Salespersons	
Salesperson Salary	
Bank Loans Requested	
Bonds Sold or Redeemed	
New Stock Issued	
Long term Investment Deposit or Withdrawal	
Dividends Paid	
Plant and Equipment Investment	

The number of clusters needed for analysis in this experiment determines where to cut the dendrogram, which originally displays a single cluster. The choice is either a matter of judgement, if the classification is for a special purpose, or determined by measurements taken from the dendrogram for general-purpose classifications. The first method, used for this experiment, may seem to be an unscientific way of proceeding, but informed subjective judgements do play a crucial role in all research. Figures 4a, b, and c illustrate the cluster membership of the student team companies numbered 1, 2, 3, 4, 5, and 6 for the decisions, performance measures, and combined data during the twelve business quarters for the three simulated years. The order of the numbers across the rows, from left to right, reflects the degree of their similarity and approximate distance from each other.

FIGURE 4 - CLUSTER MEMBERSHIP

(a) Operating Decisions - Clusters

QTR	Cluster1	Cluster2	Cluster3	Correlation
1	6,2,1	3	5,4	0.8810 *
2	5,4,2	6,1	3	0.6910
3	5,1,6,3	2	4	0.8401 *
4	2,4	5,1	6,3	0.6161
5	5,1	2,3	4,6	0.7056
6	2,4	5,1	6,3	0.6455
7	2,3,5,1	4	6	0.7734 *
8	1,4,5,2,3	6	*	0.9198 *
9	2,4,1	5,3	6	0.7270 *
10	2,3	1,4,5	6	0.8581 *
11	1,2,3	5	4,6	0.8342 *
12	2,3,5,4	6	1	0.6167

* signifies concordance between resemblance matrix and dendrogram

(b) Performance Outcome Variables - Clusters

Qtr	Cluster1	Cluster2	Cluster3	Correlation
1	2,5,1,6,3	4	*	0.8886 *
2	2,4,5	1,6	3	0.7954 *
3	2,4,5	1,6	3	0.6850
4	4,5	1,2	3,6	0.5939
5	1,2,5	3,6	4	0.8046 *
6	2,5,6,3	4	1	0.6369
7	2,6,3	1,5,4	*	0.5800
8	1,5,4	2,6,3	*	0.6615
9	2,5,4,3	6	1	0.7922 *
10	2,4,3	5,6	1	0.8368 *
11	2,3,5,4	6	1	0.8781 *
12	2,3,4	1,5,6	*	0.6864

Qtr	Cluster1	Cluster2	Cluster3	Correlation
1	1,6,5,2,3	4	*	0.8597 *
2	4,5,2	1,6,3	*	0.8144 *
3	1,5,2,4	3,6	*	0.6078
4	1,6,5,2,3	4	*	0.7419 *
5	1,5,2,3,6	4	*	0.7349 *
6	2,5,4,1	3,6	*	0.6432
7	2,3,6	1,5,4	*	0.5559
8	2,3,6	1,4,5	*	0.6604
9	2,3,5,4	1	6	0.6840
10	2,3,5,4,1	6	*	0.7466 *
11	2,3,5,1,4	6	*	0.8541 *
12	2,3,4	1,5,6	*	.6778

Each cluster represents those student teams that are most similar in the different attributes such as decisions or performance outcomes. Cluster 1 represent the student teams that are the most similar during successive business quarters, while cluster 2 and cluster 3 contain student team companies that are least similar to each other.

The overall cluster membership of the student team companies for the decision variables implies that some of the student teams exhibit experiential learning, described by Kolb (5), as they group together. Student teams 2, 3, and 4 are mainly in the first cluster; teams 1,5, and 6 fluctuate between clusters 2 and 3. Thus, possibly teams 2, 3, and 4 are “learning” from each other’s decisions. The clustering patterns, that mainly evolve after the first year, indicate some consistency in the decision choices of the competing student teams as they determine their final strategy choices.

The performance outcomes, as well as the combined data are similar. There is congruence between the clustering of the student teams for performance measure outcomes and those of the combined data as both annex the lone objects. Student teams 2, 3, and 4 in one cluster and teams 1, 5, and 6 in the other cluster imply the final performance of these two groupings of the student team companies.

All the clusters that evolve in the three data sets of student teams develop some specific patterns as the management game progresses. This is exemplified in the clustering of all three data sets, independent of the separation into specific cluster groups, as seen in Figure 5. These illustrations display similarities during the twelve quarters. The combined data of decisions and performance outcomes and the decisions are the same twice; the combined data matches the performance outcomes six times; and all three data sets are similar three times, quarters 2, 5, and 8.

FIGURE 5 COMPARATIVE CLUSTERING

Quarter	Combined Data	Performance Outcomes	Decisions
1	162354*	241634	621354*
2	452163*	245163*	542613*
3	152436*	245163*	516324
4	165234	451236	245163
5	152364*	125364*	512346*
6	254136*	256341	245163*
7	236154*	263154*	235146
8	236145*	154236*	145236*
·9	235416	254361	241536
10	235416	243561	231456
11	235146*	235461*	123546
12	234156*	234156*	235461

* similar clustering

These decisions clusters imply that the group decision teams "learn" from their own previously made decisions and thus consistently make the same decisions. How the student teams that cluster together for decision making directly affect the isolated performance outcomes clusters is less obvious. Nevertheless, the decision data combined with the performance outcome clusters follow a pattern that matches their performance improvements.

The second and third data sets, described on the second page, use the decision variables and performance outcomes listed below:

Decision Variables	Performance Outcomes
1. Product price Market Share	1. Percentage
2. Advertising Budget	2. Productivity
3. Product R&D Budget	3. Quick Ratio
4. Salesman Commission Ratio	4. Profit on Sales
5. Process R&D Budget	5. Stock Price
6. Salesperson Salaries share	6. Earnings per
7. Production Training Budget Interest Rate	7. Bank Loan and
8. Production Wage Rate (PE) Ratio	8. Price Earning
9. Sales Training Budget	
10. Profit Sharing Percentage	
11. Long Term Investment	
12. Dividends Paid	
13. Plant & Equipment Budget	
14. Number of Salesman	
15. Production Work Week	

Figure 6 illustrates the cluster membership of the decision variables implemented by the competing student teams and their resulting performance outcomes for the twelve simulated quarters.

FIGURE 6 - CLUSTER MEMBERSHIP

(a) Decision Clusters of the Competing Student Teams

QTR	Cluster1	Cluster2	Clust 3	Corr
1	7,2,1,3,5,9,6,12	11	13	.9586
2	3,5,1,6,12,13	11	*	.9841
3	7,2,3,5,1,9,6,12	11	13`	.9689
4	7,1,3,9,2,5	6,12,13	11	.9713
5	15,7,1,3,5,2,9	6,12	13,11	.9537
6	1,2,15,9,5,3,2,6	13	11	.9886
7	15,1,7,3,5,2,9	6,12	13,11	.9711
8	7,8,15,1,3,9,12,2,5	11,6	13	.9290
9	1,3,5,9,2,12	6,11	13	.9387
10	15,1,3,9,2,12,5,6	13	11	.9433
11	7,15,12,5,3,4,1,2,6,9	13	11	.9520
12	15,7,1,3,9,5,11	12,13	6	.9530

The numbers in the clusters represent the numbered decisions or the performance outcomes.

(b) Performance Outcomes of the Student Teams

QTR	Clust 1	Clust 2	Clust 3	Corr
1	2,6,5,7,4,1,3	8	*	.9075
2	2,6	4,8,5,7	1,3	.6500
3	2,6	5,7,4	3,8,1	.6677
4	2,6	4,5,7	1,3,8	.5971
5	2,6,4,5,3,7,1,	8	*	.9923
6	2,6,4,5,3,7,1	8	*	.9755
7	2,6,4,5	1,3,7	8	.9646
8	2,6,5,4	1,3,7	8	.9786
9	2,6,5,1,3,7	4	8	.9876
10	2,6,5,1,3,7	4	8	.9746
11	2,6,5,1,7,3	4	8	.9815
12	2,6,5,1,7,3	4	8	.9464

The clusters in figure 6 (a) illustrate the decisions that the student teams make for each business quarter. The decision numbers 7, 15, 1, 3,9,5 in cluster I are the most similar and are less similar to each other from cluster 2 to 3. Figure 6 (b) clusters are the performance outcomes for the successive business quarters. Herein, performance outcome 2,6,5,1,7,3 in cluster 1 are the most similar and those in cluster 2 and 3 are less similar to each other. The cluster the ture 6 (a), the cluster membership of the decisions and figure 6 (b), the performance outcomes were almost always similar during the simulated 12 quarters emphasizing consistency and significance within each of the student teams. In contrast, figures 4(a), (b), and (c) display less consistent cluster membership between the student team companies as they exercise their decision making in the competive business arena.

The decision variables in figure 6 (a) in the first cluster are product price, advertising budget, product and process R&D budgets, salesman salary, production wage rate, sales training budgets, and production work week. The second cluster is either the salesman salary, long-term investments, and dividends paid or the long-term investments. The thirst cluster is consistently the plant and equipment budget. This analysis shows that the first cluster of decisions made by the student team players are more significant and have specific interrelationships such as price, advertising, R&D budgets. The plant and equipment budget decision is the least significant or consistent decision of these student teams. Other decisions such as dividends paid, long-term investments, profit sharing, and the number of salesmen are either not important or consistent decisions.

The performance outcomes in figure 6 (b), displayed in the first cluster, are predominantly productivity, earnings per share, stock price, percent market share, bank loan interest rate, and the quick ratio. The second cluster contains profit on sales ratio and during a few quarters includes the quick ratio and bank loan interest rate. The third cluster is the PE ratio. The performance analysis also exhibits specific outcomes that have definite interdependencies. The importance of product price, advertising, Process and Product R&D and the other decisions in the first cluster made by the student teams seem to influence the performance outcomes of productivity, earnings per share, stock price, and market share. The PE ratio is less influenced by their decision choices.

Summary and Conclusions

As an addition to a traditional business game analysis, this cluster analysis methodology offers a unique perspective to the classification, evaluation, and grading task. The first cluster membership analysis displays the student teams' decision making and how if effects their performance outcomes. The second and third cluster memberships emphasize the significant and consistent decisions of each student team and their impact on performance outcomes. However, this methodology does not attempt to substitute for the game administrator's experience and judgement.

In this paper, cluster analysis was described and illustrated using an actual game simulation. For the experiment described, the cluster analysis outcomes did support the game administrator's evaluation of the student teams business game performance. In addition, the methodology illustrated the overall performance of the student teams as well as the experiential learning phenomena and its impact upon the final game performance outcomes.

Cluster analysis, as applied to a clustering membership of the decision variables and performance outcomes illustrates the importance and consistency of different decisions as the students play the game and the influence of these decisions on the performance outcomes. During this game experiment, the specific administrator of this game relied on a different order of importance for the performance outcomes than those shown in the cluster membership of figure 6 (b). Other game administrators might choose still a different ordered sets of performance outcomes. Therefore cluster analysis, in its impersonal presentation, can add to a game administrators' understanding of the students' business game simulation experience.

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