Performance Modelling of the Computational Hardware: A Statistical Approach

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Abstract—**This paper proposes and uses multivariate methods as a tool to evaluate performances of the hardware of microcomputers using their performance data, speed and price. The evaluation is done by classifying the PCs into different categories in terms of their performances. In order to form these categories, the cluster analysis and discriminant analysis methods are used in sequence. The former groups the PCs into "equivalent" classes and the later constructs a function for classification, called discriminant function, based on "equivalent" classes. Elementary statistical mesasures are also associated to extract some descriptive results as a part of the analyses. The performance of proposed method is demonstrated with data from 173 models of different PC brands. The discriminant function obtained is shown to classify PCs according to their performances with high probability of correct classification, namely 94.8%.**

Index Terms—**Cluster analysis, Discriminant analysis, Personal computers, Performance**.

I. INTRODUCTION

Every year the number of personal computer (PC) owners is increasing at an extremely high rate. In addition to the newcomers, current users are changing their hardware and software to improve the performance of their PCs or they are replacing their PCs with newer models that have better features. Thus there is a very large annual increase in the buyers' market of PC hardware and software. Similar increases are also observed on the supply side. Every year many new PC brands and new models of older brands are introduced into the market. For the last few decades there have been so many different brands, models, versions, with a wide variation in prices in the market that it has always been a difficult task to decide on a PC whose performance and price meet buyers' needs and expectations best. Same is also true for the software market.

Many PC magazines have been well aware of the problem and printing results of various benchmark tests they perform on new hardware and software. The trouble is, the test results are not too informative for users and the users may not know the implication of a high or low score for their purposes. Even for those who have some understanding of the meaning of these tests, it is still difficult to assess the implications of all of the tests taken together. They may understand each test and assess the performance of a given PC model on each of the tests reported, one at a time. However, it is extremely difficult to assess the performance of a given PC on all tests simultaneously.

In this study, the use of appropriate multivariate statistical techniques have been proposed and demonstrated for performance modelling and analysis of microcomputers' hardware. More specifically, the cluster analysis and discriminant analysis have been used to create some tools to assist the decision makers in their decisions to choose the most suitable PC for their needs.

Although two studies have been found in the literature where multivariate techniques have been used on benchmark data, their purposes were different than this paper. The first study is for the evaluation of microcomputer statistical programs and gives the users standardized data to check their programs [1], whereas the second one tries to demonstrate how some multivariate statistical models may lead to a better analysis and comprehension phenomena in the field of computer science [2].

II. BENCHMARK TESTS

In a benchmark test, different components of the hardware of a PC or different software that serve the same or similar purpose are subjected to a known workload. The performance of these components or software against this workload are measured in terms of unit time needed to compute the same task. The purpose of these measurements is to compare different systems in terms of their measured performance. If there is a new hardware or software, it can also be subjected to the same benchmark test, to compare it with the ones that were tested before.

There are many benchmark tests on the computational hardware and software. This study is limited to only some of the benchmark tests on the hardware components, price and speed. The hardware tests together with the abbreviations we will use are given below. Their definitions may be found in various articles and dictionary of computer terms (see for example [3], [4], [5], [6] and [7]).

1. FLOAT: Floating point calculation without a coprocessor.
2. MEMORY: Conventional memory.
3. SMALL: File access for small records.
4. LARGE: File access for large records.

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5. BIOS: BIOS disk seek.
6. D-SCREEN: Direct to screen.
7. VIDEO-YES: Video BIOS routine with scrolling.
8. VIDEO-NO: Video BIOS routine without scrolling.

All of these tests measure performance in seconds, except BIOS disk seek, which is measured in milliseconds. In addition to the above performance measures, our data include,

9. SPEED: The speed of the computer measured in megahertz.
10. PRICE: The suggested retail price of the computer in US Dollars.

The data on these variables were collected either from representatives/brochures of different brands or from different magazines. The brand names are not introduced in order not to blaim or not to give credit to any of the available PC brands and/or models in the market today. This will also not contradict the adopted purpose of the paper since our aim is to propose a tool and demonstrate its effectiveness for the assessment of hardware performance of PCs in general.

The main objective for most statistical analyses is to make generalizations based on random samples, about the characteristics of the populations from which these samples are drawn. Although it is not explicitly stated, for the purpose of illustration we will assume that the data we have is a random sample of all PC types.

III. SOME PRELIMINARY ANALYSES

Some preliminary analyses on the data revealed that there were not extreme observations or outliers, i.e. most of the observations are within reasonable bounds. The only exception to this are the measurements on SMALL and LARGE where out of 262 observations, there are 16 and 17 observations respectively, that are outside three standard deviations of their means.

A close inspection of the data also shows that the distributions of LARGE and PRICE are almost symmetric, whereas the distribution of BIOS has no special pattern. The SPEED is skewed to the left and all the other variables are skewed to the right. These indicate that there is no clear cut and easily seen way of differentiating the PCs, indicating the need for multivariate analyses.

The number of PCs that will be used in multivariate analysis is 173 (excluding 89 PCs that have missing and/or extreme observations on one or more variables).

IV. CLUSTER ANALYSIS

Cluster analysis is a technique that uses more than one variable (say p) on the sample or population of say n objects. Then the problem is to group these objects into mutually exclusive classes, or clusters, so that "similar" objects are in the same cluster, i.e. grouping is done on the basis of similarities (or dissimilarities). Thus the basic objective of cluster analysis is to discover natural groupings of the objects under study.

In this study, Cluster analyses techniques were applied on the data, explained above, to group the 173 PCs according to the similarities in benchmark tests, speed and price.

Using average linkage method [8] which is a hierarchical cluster analysis, seven clusters were obtained at the first level. Then in the second level these were combined into four clusters. The third level ended with three clusters and level four had only two clusters. We are interested in finding as few clusters as possible, to make the decision process easy. We note that in the two cluster case, large number of PCs (146) are in one cluster and only 27 are in the other cluster. Therefore using three clusters may lead to a better classification. In order to avoid confusion with the cluster numbers, we will call these three clusters as Cluster I, Cluster II and Cluster III.

The mean performance of the brands and models in the three clusters are given in Table-1. In assessing these means, we should note that for all eight variables, smaller values are better since the unit used is the time spent and the smalller the mean, the faster is the PC. Of course, PCs with higher SPEED and lower PRICE are preferable.

Table-1 The Means of the Variables in Three Clusters

Variables	Clust. I	Clust. II	Clust. III
FLOAT	4.73	3.55	3.56
MEMORY	0.43	0.35	0.35
SMALL	57.52	53.95	52.82
LARGE	5.47	5.22	5.10
BIOS	18.65	15.76	16.54
D-SCREEN	2.38	2.32	2.61
VIDEO-NO	1.53	0.88	1.89
VIDEO-YES	2.33	1.63	2.28
SPEED	25.53	26.16	28.11
PRICE	3311	5750	8370
Total No. Of PCs	109	37	27

In table 1, we observe that Cluster I has higher means for variables FLOAT, MEMORY, LARGE and BIOS and Cluster II has higher means for variables SMALL, D-SCREEN, VIDEO-NO and VIDEO-YES. Furthermore, the means of variables VIDEO-NO and D-SCREEN in Cluster I are between the respective means of Clusters II and III. For the remaining benchmark tests the means of Cluster I are higher than the means of the other two clusters. These findings seem to indicate that Cluster I may be considered as the set of PCs with "poor" performance sold at lower prices.

For Clusters II and III, the means for FLOAT are very close, the means for MEMORY are equal. However, for BIOS, D-SCREEN, VIDEO-NO and VIDEO-YES, the means are lower in Cluster II whereas the means for SMALL and LARGE are lower in cluster III. The SPEED for cluster III is the highest. Therefore it can be concluded that Cluster III should be considered to be better if SMALL, LARGE and SPEED are the most importand performance criteria for some reason. On the other hand if better performance in BIOS, D-SCREEN, VIDEO-NO and VIDEO-YES are preferred then Cluster II should be recommended.

To summarize, classifying the 173 PCs into three clusters seem to indicate a reasonable way of defining "equivalent" categories of PCs. Thus if a PC with high calculation power and sufficient memory characteristics is required then either Cluster II or Cluster III could be considered, whereas someone interested in having a PC with high speed and powerful file processing fuctions should look for it in Cluster III. Finally, if a software such as DBMS or information processing which needs fast information retrieval and fast movement of screen is required, then a PC from Cluster II is recommended. These observations are summarized in Table-2.

Table-2 Cluster to Choose According to the Characteristics Needed by the User

Purpose or Characteristics	Cluster(s) to Search
High calculating power and sufficient memory	II, III
High speed and good file processing characteristics	III
Fast information retrieval or fast screen movement	II
Low price, low performance	I

V. DISCRIMINANT ANALYSIS

The problem addressed by the discriminant analysis is how one may assign a new object into one of m populations (m>1), given that a set of measurements on p variables for that object. This analysis yields a function, called the discriminant function, which is used for the assignement.

To estimate the coefficients of discriminant function, we use m random samples of objects of sizes n_1, n_2, ... n_m from the m different populations and observe the values for the p random variables X_1, X_2, ...,X_p for each of the m samples. The most commonly used type of discriminant function is linear.

A. Discriminant Model With all Variables

In this paper we have assumed that the three clusters defined in section 4 form the three different populations of PCs. The sample of observations from these three populations (assumed to be random) are then used to define a linear discriminant function in terms of the ten variables of this study.

The three clusters found in section 4 were used in computing the coefficients of the discriminant function. The following model can be used for allocating a new PC into one of the three groups:

D_ALL = + (0.7565)FLOAT
+(0.0107)BIOS +(1.2165)PRICE
- (0.4275)MEMORY -(0.0262) SMALL -(0.2746) LARGE
-(0.1638)D-SCREEN -(0.1673)VIDEO-NO -(0.1075)VIDEO-YES
-(0.3700)SPEED.

As seen in the above estimates of the coefficients, the change in PRICE will affect the discriminant score more than the other variables since it has the highest coefficient. On the other hand, BIOS has the smallest coefficient (in absolute value) and hence a unit change in BIOS will have little influence on the discriminant score.

The above discriminant function helps us to allocate a given PC into one of the three clusters. For this purpose, information on its PRICE, SPEED and results of the benchmark tests are obtained and put into the above function to obtain a discriminant score for that PC. Then this score is used for the allocation of the PC into one of the three clusters as follows.

Usually, the midpoints are used for the allocation. The midpoints are the averages of the cluster means of the discriminant scores. The mean discriminant score for Cluster I is -1.86, for Cluster II it is 1.60 and for cluster III it is 5.30. Thus, to decide between Clusters I and II, the midpoint of -0.13 (which is theaverage of the cluster means -1.86 and 1.60) can be used. Similarly, to decide between Clusters II and III, the midpoint 3.45 is used. Since the means of clusters I and III are too far, there is no need to choose between these clusters. Thus if the discriminant score of a PC is less than -0.13, it is allocated to Cluster I, if it is greater than -0.13 but less than 3.45, then the PC belongs to Cluster II. If the score is greater than 3.45 then the PC belongs to Cluster III.

By using the above procedure, we have allocated each of the 173 PCs into one of the three clusters, resulting in 94.8% correct classification. Such a performance is highly satisfactory. Thus, if we are given a new PC with the required information on its characteristics, we can easily allocate it into one of the three clusters with a probabilty of 0.948 of correct classification and only 0.052 probability of misclassification.

B. Discriminant Model Without the Prices

We note in the three discriminant functions given above that the estimated coefficients of the variable PRICE is quite high relative to the other variables indicating that PRICE is a variable with high discriminating power. This is of course expected. However, it is also known that there are usually large differences between the actual purchase price of any PC and the suggested retail price used in the analysis. Furthermore, the prices of PCs change a lot over time. Thus one should not put too much emphasis on the price. For these reasons we have repeated the analyses using only the benchmark data and PC types.

Initial classification yielded 31 different clusters. These were then grouped into three clusters at the sevent stage of clustering. In this way we obtained: One group (with 13 PCs) that has high performance, another group (with 9 PCs) with low performance, the remaining 151 PCs were in the third group with intermediate performance.

Due to small number of PCs in the first two groups, we decided not to continue with further analyses.

VI. CONCLUSION

This paper introduces the use of selected multivariate methods as a tool to evaluate microcomputers in terms of their performance data namely benchmark test results, speed and price.

Analyses are based on eight benchmark tests, together with two additional variables SPEED and PRICE of 173 different brands and models of PCs. The developed discriminant function is capable of classifying most of the PCs correctly since the probability of misclassification has been found to be 0.052.

With this approach, the decision maker may limit his/her search for a PC by specifying his/her need and the characteristics of the PC. Using these characteristics as input, the discriminant function obtained may then be used to find the class in which the search should be carried out, thus limiting the search only to PCs of "equivalent" nature.

The proposed approach can be extended to cover other multivariate methods for more detailed analyses and can also be used for software evaluation and should be applied with the assistance of a professional in computer hardware who has some background in statistics.

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