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Poultry Feed Brands Selection Using Profile Analysis

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Abstract: The application of profile analysis in the performances of three brands of poultry feed in a farm was considered. Analysis showed that the profiles were not parallel, implying that the performances of the brands were unequal. Contrasts following profile analysis performed using Scheffe's method showed that the profile of TRAP FEEDS was significantly different from those of the other two brands. Consequently, the highest performing brand was selected.

Key words: Performance analysis, parallel profiles, MANOVA, coincident profiles, level profiles

INTRODUCTION

In poultry farming, the production of high quality (healthy and weighty) birds is always desired, as this boosts the revenue of the poultry farmer. To ensure this, the best of inputs (especially, poultry feeds) has to be used on the birds. This study is set out to show how profile analysis could be carried out and particularly, its application in the selection of poultry feed brands.

Profile analysis, according to Ott (1999), is a specific style of Multivariate Analysis of Variance (MANOVA). It is equivalent to repeated measures MANOVA (Tabacknick and Fidell, 2006), because of its multiple responses taken in sequence on the same subject(s). Usually, the responses are taken over time as in weekly weight measurements to establish growth curves (Littell *et al*., 1998).

THEORY AND PROCEDURE OF PROFILE ANALYSIS

Let X_{ijk}, i = 1, 2, …, g; j = 1, 2, …, n_i; k = 1, 2, …, p, be an observation (a response) in a repeated measures experiment, where, i, j and k stand for treatment group (population), selected subject in the i-th treatment group and observation (response) level, respectively.
Let,

$$X_{ij}^T = [X_{ij1}, X_{ij2}, \ldots, X_{ijp}] \quad (1)$$

denote the response vector for the j-th subject within the i-th treatment group and

$$\bar{X}_i^T = [\bar{X}_{i1}, \bar{X}_{i2}, \ldots, \bar{X}_{ip}] \quad (2)$$

denote the mean response vector for the ith treatment group.

Multivariate Analysis of Variance (MANOVA) is the natural choice for analyzing the type of data in the one-way completely randomized design described in Table 1, since it models the interdependencies among the response variables. However, profile analysis (Repeated Measures MANOVA) is most appropriate.

MANOVA with repeated measures is used when the measure that is repeated (e.g., across time) is a compound formed in the usual MANOVA fashion across multiple dependent variables. Thus, it is different from having multiple repeated measures factors (Tabacknick and Fidell, 2006).

It is worthy of note that certain assumptions and conditions Morrison (2002) and Tabacknick and Fidell

Table 1: Layout of Repeated Measures Design for g-Group Profile Analysis

Treatment group	Experimental unit (Subject)	Observation (Response) level 1	2	...	p
1	1	$[X_{111}$	X_{112}	...	$X_{11p}]$
	2	$[X_{121}$	X_{122}	...	$X_{12p}]$
	⋮	⋮	⋮	⋱	⋮
	n_1	$[X_{1n_11}$	X_{1n_12}	...	$X_{1n_1p}]$
⋮	⋮	Means, $\bar{X}_1^T = [\bar{X}_{11}$	$\bar{X}_{12}$	⋯	$\bar{X}_{1p}]$
i	1	$[X_{i11}$	X_{i12}	...	$X_{i1p}]$
	2	$[X_{i21}$	X_{i22}	...	$X_{i2p}]$
	⋮	⋮	⋮	⋱	⋮
	n_i	$[X_{in_i1}$	X_{in_i2}	...	$X_{in_ip}]$
⋮	⋮	Means, $\bar{X}_i^T = [\bar{X}_{i1}$	$\bar{X}_{i2}$	⋯	$\bar{X}_{ip}]$
g	1	$[X_{g11}$	X_{g12}	...	$X_{g1p}]$
	2	$[X_{g21}$	X_{g22}	...	$X_{g2p}]$
	⋮	⋮	⋮	⋱	⋮
	n_g	$[X_{gn_g1}$	X_{gn_g2}	...	$X_{gn_gp}]$
		Means, $\bar{X}_g^T = [\bar{X}_{g1}$	$\bar{X}_{g2}$	⋯	$\bar{X}_{gp}]$
		Grand means, $\bar{X}^T = [\bar{X}_1$	$\bar{X}_2$	⋯	$\bar{X}_p]$

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(2006) must be met before profile analysis could be carried out on any set of data.

The question of equality of the population mean response vectors sought in MANOVA which is given by:

$$H_0 : \mu_1 = \mu_2 = ... = \mu_g$$

is divided into several specific possibilities. The question is formulated in a stage-wise fashion:

- Are the profiles parallel?
  Or equivalently: H_{01}: μ_{1k}-$\mu_{1(k-1)}$ = μ_{2k}-$\mu_{2(k-1)}$ = ... = μ_{gk} -$\mu_{g(k-1)}$; k = 2, 3, ..., p
- Assuming the profiles are parallel, are they coincident?
  Or equivalently: H_{02} :μ_{1k} = μ_{2k} = ... = μ_{gk}; k = 1, 2, ..., p
- Assuming the profiles are coincident, are they level? That is, are all means equal to the same constant?
  Or equivalently: H_{03}: μ_{11} = μ_{12} = ... = μ_{1p} = μ_{21} = μ_{22} = ... = μ_{2p} = ... = μ_{g1} =μ_{g2} = ... = μ_{gp}

Before testing the hypothesis of parallelism, it is advisable to make a plot of the means (otherwise known as average profiles).

Test for parallel profiles: This test is achieved by working with the successive differences in the responses. The profiles are parallel if the differences are the same across the treatment groups. Thus, the null hypothesis in stage 1 can be written as:

$$H_{01}: \begin{bmatrix} \mu_{12}-\mu_{11} \\ \mu_{13}-\mu_{12} \\ \vdots \\ \mu_{1p}-\mu_{1(p-1)} \end{bmatrix} = \begin{bmatrix} \mu_{22}-\mu_{21} \\ \mu_{23}-\mu_{22} \\ \vdots \\ \mu_{2p}-\mu_{2(p-1)} \end{bmatrix} = \cdots = \begin{bmatrix} \mu_{g2}-\mu_{g1} \\ \mu_{g3}-\mu_{g2} \\ \vdots \\ \mu_{gp}-\mu_{g(p-1)} \end{bmatrix}$$

or

$$H_{01}: C\mu_1 = C\mu_2 = ... = C\mu_g$$

where, C is contrast matrix given by:

$$\underset{[(p-1)xp]}{C} = \begin{bmatrix} -1 & 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & -1 & 1 \end{bmatrix} \quad (3)$$

For independent samples of sizes, n_1, n_2, ..., n_g from the g-groups, H_{01} can be tested (in the usual one-way MANOVA fashion) by constructing the contrast-transformed observation vectors:

$$CX_{ij}; i = 1, 2, \ldots, g; j = 1, 2, \ldots, n_i$$

having sample mean vectors:

$$C\bar{X}_{ij}; i = 1, 2, \ldots, g$$

and grand mean vector, $C\bar{X}$

There are several different multivariate test statistics available for the test of parallel profile, all of which will generally yield equivalent results. Amongst the four common test statistics-namely Wilks Lambda, Pillai's Trace, Hotelling-Lawley Trace and Roy's Greatest Root; Wilks Lambda (Λ) is the most desirable because it can be converted exactly to an F-statistic (Ott, 1999; Everitt and Dunn, 1991). For details of this conversion and the exact distribution of Λ, see Johnson and Wichern (2001). It also presented a modification of Λ due to Bartlett (1938) for cases where the number of groups is more than three (g>3), as well as when large sample sizes are involved. It is worthy of note here that (p-1) would replace p in the circumstances above.

Employing the Wilks lambda criterion, therefore, H_{01} is rejected at α level if the ratio of generalized variances:

$$\Lambda_1 = \frac{\det W_1}{\det(B_1 + W_1)} \quad (4)$$

is too small, or rather still if its equivalent F-statistic is greater than the critical value. For instance, where (p-1)$\geq$1 and g = 3, the critical region would be:

$$\left(\frac{\sum_{i=1}^{g} n_i - p - 1}{p-1}\right)\left(\frac{1-\sqrt{\Lambda_1}}{\sqrt{\Lambda_1}}\right) > F_{2(p-1),2(\sum n_i - p - 1);\,\alpha} \quad (5)$$

The matrices B_1 and W_1 in Eq. 4 are the treatment (Between) sum of squares and cross products, respectively and residual (Within) sum of squares and cross products for the CX_{ij}'s given as:

$$B_1 = \sum_{i=1}^{g} n_i(C\bar{X}_i - C\bar{X})(C\bar{X}_i - C\bar{X})^T \quad (6)$$

and

$$W_1 = \sum_{i=1}^{g}\sum_{j=1}^{n_i}(CX_{ij} - C\bar{X}_i)(CX_{ij} - C\bar{X}_i)^T \quad (7)$$

If H_{01} is rejected, it would be concluded that at least one of the average profiles is significantly different. Consequently, it would rather be unreasonable to embark on testing the second null hypothesis. Otherwise proceed with the test.

Test for coincident profiles: The second null hypothesis investigates whether the profiles are superimposed on one another or rather identical. Under the condition of parallel profiles will be coincident only if the total heights:

$$\sum_{k=1}^{p}\mu_{1k} = 1^T\mu_1, \sum_{k=1}^{p}\mu_{2k} = 1^T\mu_2, \ldots, \sum_{k=1}^{p}\mu_{gk} = 1^T\mu_g$$

are equal (Johnson and Wichern, 1992). Therefore, the null hypothesis at this stage can be written in the equivalent form:

$$H_{02}: 1^T\mu_1 = 1^T\mu_2 = \ldots = 1^T\mu_g$$

Where:

$$\underset{(1xp)}{1^T} = 1,1,\ldots,1 \quad (8)$$

Hence, the test is univariate, based on the univariate observations:

$$1^T X_{ij},\ i = 1, 2, \ldots, g;\ j = 1, 2, \ldots, n_i$$

Invariably, this is equivalent to performing a one-way ANOVA on the subject totals. Timm (1975) stated that the univariate and multivariate tests are equivalent, assuming parallelism. Nevertheless, the multivariate test approach is preferable since the data have already been arranged in a multivariate configuration for the first test.

Employing the Wilks lambda criterion, H_{02} is rejected at α level if the ratio of generalized variances:

$$\Lambda_2 = \frac{\det W_2}{\det(B_2 + W_2)} \quad (9)$$

is too small, or rather still if its equivalent F-statistic is greater than the critical value. Generally, the critical region for the null hypothesis of coincident profiles is given by:

$$\left(\frac{\sum_{i=1}^{g} n_i - g}{g-1}\right)\left(\frac{1-\Lambda_2}{\Lambda_2}\right) > F_{(g-1),(\sum_{i=1}^{g} n_i - g);\,\alpha} \quad (10)$$

unless where a modification of Λ_2 due to Bartlett is, however, sought.

The matrices B_2 and W_2 in Eq. 9 are, respectively given as:

$$B_2 = \sum_{i=1}^{g} n_i\left(1^T\bar{X}_i - 1^T\bar{X}\right)\left(1^T\bar{X}_i - 1^T\bar{X}\right)^T \quad (11)$$

and

$$W_2 = \sum_{i=1}^{g}\sum_{j=1}^{n_i}\left(1^T\bar{X}_{ij} - 1^T\bar{X}_i\right)\left(1^T\bar{X}_{ij} - 1^T\bar{X}_i\right)^T \quad (12)$$

If H_{02} is rejected, it would be concluded that the profiles were not identical and embarking on testing the third null hypothesis would rather be unreasonable. Otherwise, proceed with the test.

Test for level profiles: The third null hypothesis investigates whether all variables have the same mean, so that the common profile is level. That is, $\mu_1 = \mu_2 = \ldots = \mu_p$.

A simple way to approach this problem is to again take successive differences, as was done in the first test. If the profile is indeed level, then the (p-1) differences should be zero. Thus, the null hypothesis at this stage can be written as:

$$H_{03} = C\mu = 0$$

where, C is as given by Eq. 3 and μ (the common mean vector) is estimated by $\bar{X}$ (the sample grand mean vector).

Employing Wilks Lambda criterion, as before, H_{03} is rejected at α level if the ratio of generalized variances:

$$\Lambda_3 = \frac{\det W_3}{\det(B_3 + W_3)} \quad (13)$$

is too small, or rather still if its equivalent F-statistic is greater than the critical value. Generally, the critical region for the null hypothesis of level profiles is given by Ott (1999) as:

$$\left(\frac{\sum_{i=1}^{g} n_i - (p-1)}{p-1}\right)\left(\frac{1-\Lambda_3}{\Lambda_3}\right) > F_{(p-1),(\sum_{i=1}^{g} n_i - (p-1));\,\alpha} \quad (14)$$

The matrix W_3 in Eq. 13 is the same as W_1 in Eq. 7, while under H_{03} the between sum of squares and cross-products for the CX_{ij}'s is:

$$B_3 = \sum_{i=1}^{g} n_i\left(C\bar{X}_i\right)\left(C\bar{X}_i\right)^T \text{[given that } C\hat{\mu} = C\bar{X} = 0; \text{under } H_{03}] \quad (15)$$

If H_{03} is rejected, the conclusion thus becomes that all the means are not equal to the same constant. Otherwise, the profiles are level.

Contrasts following profile analysis: The major description of result in profile analysis, especially whenever the parallelism or levels hypothesis is rejected, is typically the plot of average profiles. However, when there are more than two levels of significant effects in profile analysis (in MANOVA, generally), it is often desirable to perform contrasts (example, Dunnett's, Tukey, Bonferroni, or Scheffe') to pinpoint sources of variability (Tabacknick and Fidell, 2006).

MATERIALS AND METHODS

A practical example is presented on the application of profile analysis in analyzing the performances of three brands of poultry feed with a view to selecting the best brand.

Data collection and description: The data for this study were collected from the Planning, Research and Statistics Unit of Talented Royal Apex Project (TRAP), Owerri, Imo State of Nigeria. The data were the outcome of an experiment conducted to study the resultant weight-yields of poultry birds upon consumption of three brands of poultry feed in Ndubuisi Farms (a subsidiary of TRAP), with a view to comparing a locally-produced brand of poultry feed by TRAP (branded TRAP FEEDS) with two other brands (GUINEA FEEDS and TOP FEEDS).

Thirty day-old male turkey broilers were randomly selected from a batch of fifty-with common features-and put in three different poultry houses (ten in each). The birds were properly identified (by numbers) and weighed (in grammes). TOP, GUINEA and TRAP FEEDS were equitably administered to the birds in poultry houses 1, 2 and 3, respectively, for the eight-week period. Also, conventional feeding and health programmes obtainable in poultry farming were strictly observed.

Analysis: The data were analyzed by employing the profile analysis procedure outlined earlier. First, as tradition demands, the data were checked and it is sufficient to say that all the assumptions of profile analysis were satisfied. Although there were less than 20 birds in each of the treatment groups (purposely done to avoid over-crowding in the poultry houses), with equal sample sizes ($n_1 = n_2 = n_3$) and $n_1>p$; i = 1, 2 and 3, the multivariate normality assumption is not likely to be violated. Besides, profile analysis is as robust to violation of multivariate normality assumption as other forms of MANOVA (Tabacknick and Fidell, 2006).

A plot of the average profiles for the weight-yields of the birds in the three treatment groups is constructed (Fig. 1) and then followed by the test for parallel profiles.

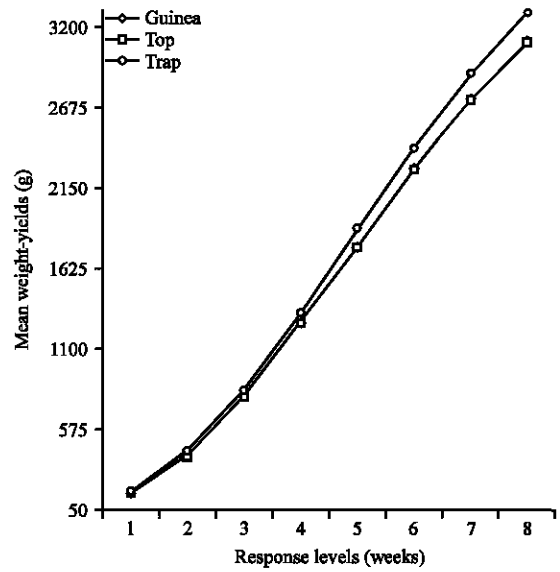

Fig. 1: Average profiles of week-specific weights poultry birde for three brands of feeds

Testing for parallel profiles: We have the hypothesis of parallelism as:

$$H_{01} : C\mu_1 = C\mu_2 = C\mu_3$$

By using Eq. 6

$$B_1 = \begin{pmatrix} 2615.4 & & & & & & \\ 580.5 & 148.2 & & & & & \\ 3787.5 & 807.5 & 5541.8 & & & & \\ 7803.9 & 1701.7 & 11353.2 & 23333.4 & & & \\ 1490.7 & 346.2 & 2132.5 & 4423.9 & 861.8 & & \\ 4445.7 & 989.5 & 6433.4 & 13260.8 & 2536.1 & 7557.3 & \\ 2287.8 & 516.4 & 3298.4 & 6812.8 & 1310.8 & 3890.1 & 2005.1 \end{pmatrix}$$

and Eq. 7

$$W_1 = \begin{pmatrix} 441.4 & & & & & & \\ -179.1 & 259.0 & & & & & \\ 351.1 & 127.3 & 2604.2 & & & & \\ 73.1 & -126.7 & -377.0 & 422.9 & & & \\ 49.4 & 198.1 & 2809.7 & -563.9 & 4385.4 & & \\ -0.4 & 32.4 & 150.6 & -70.2 & 417.0 & 159.2 & \\ -16.2 & 4.4 & 91.2 & -57.2 & 93.4 & -17.8 & 136.8 \end{pmatrix}$$

Equation 4 yields Λ_1 = 2.733E-3 (using MATLAB 6.0), while with p = 8 and g = 3, Eq. 5 yields:

$$F_{\text{equivalent}} (= 54.39) > F_{14,42;0.05} (= 1.94)$$

Consequently, H_{01} is rejected at the 5% level of significance.

RESULTS AND DISCUSSION

The result of the analysis showed that the profiles were not parallel and this caused the other two hypotheses (H_{02} and H_{03}) contingent on the tenability of H_{01}, not to be tested. In other words, significant differences existed amongst the profiles of the three treatment groups.

For profile analysis, the major description of results is typically a plot of profiles. Figure 1 showed that the average profile for TRAP FEEDS (Group 3) was well above the other two groups and this implied that its average performance was the highest regarding the resultant weekly weight-yields of the birds upon consumption.

Furthermore, contrasts performed by the method of Scheffe´ showed that there was no significant difference between the profiles of TOP and GUINEA FEEDS while the profile of TRAP FEEDS was significantly different from those of TOP and GUINEA FEEDS.

Consequently, TRAP FEEDS was selected as the best brand of poultry feed amongst the three brands used in the farm.

CONCLUSION

In this study, we have presented the procedure of carrying out profile analysis-the most appropriate statistical method for analyzing repeated measures data. We have also demonstrated the application of profile analysis in analyzing the performances of three brands of poultry feed, to know whether they are equal. The analyses showed that the profiles were not parallel (that is, statistically significant differences exist in the average performances of the feeds). The average profile of TRAP FEEDS was found to be well above those of the other two brands of feed, which implied highest performance. Hence, TRAP FEEDS was selected as the best brand of poultry feed for the birds in the farm.

REFERENCES

Bartlett, M.S., 1938. Further aspects of the theory of multiple regressions. Proc. Camb. Phil. Soc., 34: 33-33.

Everitt, B.S. and G. Dunn, 2001. Applied Multivariate Data Analysis. 2nd Edn., Edward Arnold, London, ISBN-10: 0340741228.

Johnson, R.A. and D.W. Wichern, 2001. Applied Multivariate Statistical Analysis. 5th Edn., Prentice Hall Inc., New Jersey, ISBN-10: 0130925535.

Littell, R.C., P.R. Henry and C.B. Ammerman, 1998. Statistical analysis of repeated measures data using SAS procedures. J. Anim. Sci., 76: 1216-1231.

Morrison, D.F., 2002. Multivariate Statistical Methods. 4th Edn., Brooks, Cole, Montery, California, ISBN-10: 053487780.

Ott, P., 1999. MANOVA: Profile analysis-an example using SAS. biometrics information. Pamphlet #60. http://www.for.gov.bc.ca/hre/biopamph/pamp60.pdf.

Tabacknick, B.G. and L.S. Fidell, 2006. Using Multivariate Statistics. 5th Edn., Prentice-Hall Inc., New Jersey, ISBN-10: 0205465250.

Timm, N.H., 1975. Multivariate Analysis with Applications in Education and Psychology. 1st Edn., Brooks, Cole, Montery, California, ISBN-13: 9780818500961.