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PAPER

Determination of outlier in live-weight performance data of Japanese quails (*Coturnix coturnix japonica*) by Dfbeta and Dfbetas techniques

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Abstract

This study aimed to determine the outlier values in live-weight performance data of Japanese quails. Japanese quails were grown under the same conditions, and, after being divided according to gender, the live weight data of quails up to 56 days of age (7 weeks) was collected. For both male and females, measurements on 50 animals were done, and these values were measured over. For each week measurement, values were separately determined. In order to determine the outlier values in each measurement, DFBETA and DFBETAS criteria were used. In males, females, and in all the flock a high number of outlier values was found. However, more outliers were observed especially in females. Under the same conditions, in spite of the training, the potential environmental effects of the variability in females was originated to react more quickly than in males.

Introduction

In the past, the problem of outliers basically was a subjective matter inquiring which observation(s) are possible outliers. Nowadays, owing to developments in computer technology, it has turned into a matter defining the algorithms to diagnose the observations or observation groups not complying with the general pattern of the relevant data in regression analysis and multi-dimensional datasets. Scientific data generally show normal distribution and most of the statistical analysis methods were developed over the assumption that relevant data has normal distribution.

Therefore, before prospective analyses, data should be subjected to normality tests (Bek and Efe, 1987; Akdeniz, 1998). Evaluation of numerical data obtained after comprehensive scientific work often reveals that one or more of the observations are away from the others. Such observations are called as extreme, irregular, discordant, suspicious observation, surprise, dirty, contaminated, deviate values (outliers), etc. (Çil, 1990; Billor *et al.*, 2000).

Non-normal distribution of datasets, expected to be normally distributed, is mostly due to the existence of outliers. In the present study, the methods used to detect outliers will be investigated. Outliers are defined as the observations far away from the mean values of the dataset. Such values may either be only one or more. These values increase the standard deviation of data, change the pattern of distribution and consequently may lead to data misinterpretations during the statistical analyses (Alpar, 1997). Outliers may be observed because of a recording error, a disruption in production processes, human errors, or may be formed differently from the large portion of the data. They may cause wrong model formations, wrong parameter estimations or erroneous analysis results (Liu *et al.*, 2004).

There are several statistical methods to identify or test whether an observation away from the average is an outlier. Among these methods, some are able to detect only one observation while others are able to detect more than one observation as statistically outliers. Some questions regarding outliers arise: is the detected observation really an outlier? Should the outlier observation be omitted from the dataset? Should it be evaluated separately from the dataset? What are the reasons for it to differ from the general dataset? Is this a natural difference? All these questions should be identified and answered by the researchers and it is impossible to get a distinct judgment because of the subjective nature of the outliers.

Goals of the present study are to use the data observed for quails by DFBETA and DFBETAS methods.

Materials and methods

Experiments were carried out at quail areas of the Poultry Units, Animal Science Departments, Bingöl and Ahi Evran Universities, Bingöl and Kırşehir, Turkey. Japanese quails (*Coturnix coturnix japonica*) were used in the experiments. Live weights were measured twice a week from the hatch-

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ing until the 10th week of age with a digital scale (± 0.01 g). A total of 100 quails (except for initial weight) were used and on each of them 20 measurements were performed. All the measurements were recorded separately. Experiments were carried out in two groups with 5 replications (each replication had 10 quails, *i.e.*, measurements were performed over 50 quails of each group. Experiments were performed in a cage poultry house. Quail grower feed [starter feed containing 23% crude protein (CP) and 3100 kcal/kg metabolizable energy (ME) during the 1st week and grower feed containing 20% CP and 3250 kcal/kg ME during the following 10 weeks] for 0-10 weeks was used and *ad libitum* feeding was provided (Table 1). Nutrient composition of the feed ratios was prepared in accordance with the National Research Council (1994). A total of 100 quails (of which 50 males and 50 females) was selected among simultaneously hatched 150 quails after the 4th week of hatching and wing numbers were installed to chicks after hatching. All these live-weight measurements were used to detect possible outliers. Measurements were evaluated by considering male, female and flock total live weights.

In this study, live-weight data was used to determinate outliers by using DFBETA and

DFBETAS methods (SPSS 16 V package programme was used for determination of outlier values). All throughout the study, measurements were recorded by humans.

DFBETA is used to calculate the changes to be observed in parameters of new regression equation formed after omitting i^{th} observation from the dataset. DFBETA is expressed by the following equation (Belsley *et al.*, 1980):

$$DFBETA = \hat{\beta} - \hat{\beta}_{(i)} = \frac{(X' X)^{-1} X' r_i}{1 - h_i}$$

where, X is the explanatory variable matrix, r the residual vector, i h the i^{th} diagonal member of line matrix, and i x the i^{th} line of matrix X . While the value with higher DFBETA is an indicator of an outlier, DFBETA values calculated from the observations proportionally decrease with increasing number of observations.

DFBETAS it is a statistics method named after the difference in estimated regression coefficients and indicates the change in the j^{th} estimated regression coefficient only by omitting the i^{th} observation (Belsley *et al.*, 1980). DFBETAS statistics is calculated by the following equation:

$$DFBETAS_{j(i)} = \frac{\hat{\beta}_j - \hat{\beta}_{j(i)}}{s_{(i)}\sqrt{C_{jj}}}, \quad i=1,2,\dots,n$$

where, $\hat{\beta}_{j(i)}$ is the j^{th} estimated regression coefficient by omitting the i^{th} observation and $(j+1)^{th}$ diagonal member of $(X' X)^{-1}$ matrix of the regression model including the C_{jj} , β_0 coefficient. The value with higher DFBETAS is

expressed as an outlier. A higher DFBETAS value indicates the impact of the i^{th} observation on the j^{th} parameter. DFBETAS values decrease proportionally to n , with n being the number of observations (observations with $DFBETAS_{ij}>2$ or $DFBETAS_{ij}>2/n$ are expressed as outlier observations). Outliers were determined by standart deviation above 2. Analyses were done by MINITAB V14 statistical programmes. During the investigation for outlier values, genders were separately evaluated, later combined with total flock values. The aim was to find out whether there is any variation between the genders in outlier values.

Results and discussion

The possible detection of outliers depends on several factors, including development in computer processors, number of observations, data contamination, type of contamination and algorithm parameters (Woodruff and Rocke, 1993, 1994). In the present research, three different evaluations were performed: males, females and flock averages. Therefore, results were presented in three groups. The data obtained by DFBETA and DFBETAS methods are provided in Tables 2 and 3. Outlier graphs of DFBETA and DFBETAS are presented in Figures 1 and 2.

Although DFBETA seems to be well masking

Table 1. Composition of quail feeds used in the experiments.

	Starter feed	Grower feed
Ingredients, %		
Corn	48.0	56.0
Wheat	6.0	6.0
Soybean meal	33.0	24.50
Vegetative oil	4.0	4.5
Fish meal	4.0	4.0
Meat-bone meal	2.5	2.5
DCP	0.5	0.5
Limestone	1.0	1.0
Methionine	0.2	0.2
Lysine	0.1	0.1
Salt	0.4	0.4
Vit+min premix	0.3	0.3
Calculated values		
CP, %	23	20
Metabolic energy, kcal/kg	3100	3250

DCP, dicalcium phosphate; CP, crude protein.

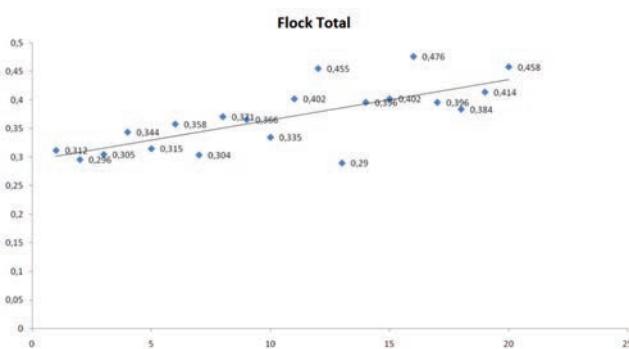


Figure 1. Graph of outliers obtained by DFBETA for flock total.

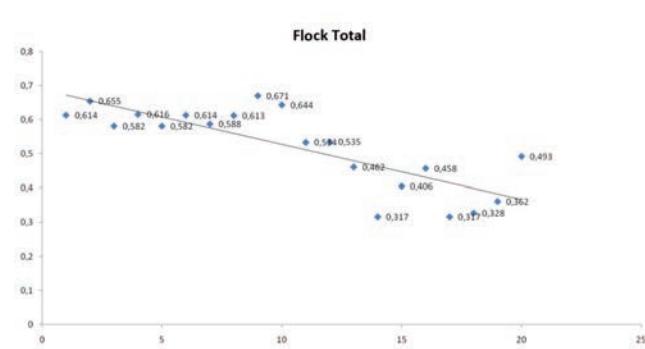


Figure 2. Graph of outliers obtained by DFBETAS for flock total.

in some configurations, it explained much more clean observation as outliers. On the other hand, DFBETAS can be defined as successful against small contamination along direction. Such changes can clearly be seen in Tables 2 and 3. Especially with regard to mean values, variations were observed among male,

female and flock means. The mean values by DFBETA were observed as 0.3359, 0.4323 and 0.3689, respectively for males, females and flock means. The mean values by DFBETAS, on the other hand, were observed as 0.4652, 0.5938 and 0.5195.

In general, the results obtained by DFBETA

were not found to be as successful as the results obtained by DFBETAS. DFBETA detected less outliers. With regard to males, the value was 0.3359 for DFBETA and 0.4652 for DFBETAS. For females, the value was 0.4323 for DFBETA and 0.5938 for DFBETAS. Again, DFBETA values were lower than DFBETAS values. With regard to flock means, the value was 0.3689 for DFBETA and 0.5195 for DFBETAS, this case being again similar to the others. On the other hand, more efficient algorithms (Billor *et al.*, 2000, 2007), not requiring to include the entire sub-datasets, may yield better results with the simulations than the other methods. Since the entire possible sub-sets are not searched through, they may be unsuccessful in detecting outliers of some cases. Thus, the problem here is initially a technological one. In large samplings and large dimensions (multiple regression), the high-speed processes able to pull all the possible sub-sets and analyse them separately may overcome such a problem. Yet, this is not sufficient to solve the technical dimension of outlier detection. In such cases, the question will remain as a subjective problem. In large samplings, values can reveal deviation from mean. This is a misinterpretation (Alpar, 1997), and if there is a misinterpretation, outliers will not be determined (Liu *et al.*, 2004).

The outliers obtained by DFBETA can be expressed as follows: there were no outliers detected for males. The 13th observation was detected as outlier for females and the 11th observation was detected as an outlier for flock mean.

The outliers obtained by DFBETAS can be expressed as follows: the 5th, 18th and 19th observations were detected as outliers for males; the 18th observation was detected as an outlier for females and 14th and 17th observations were detected as outliers for flock mean.

Conclusions

Outlier observations have been the subject matter of various researches for years. Initially, outliers have been tried to be detected among single-dimension data, then the detection levels moved up to multi-dimensional data and computers together with efficient algorithms have made the detections of such outliers easier. The methods developed to detect only a single observation may yield reliable results for datasets with more than one outlier only if they were applied for the entire sub-datasets. However, such brute-force approaches working like Gentleman and Wilk (1975)

Table 2. Values obtained by DFBETA for males, females and flock totals.

Measurement order	Male	Female	Flock total
0	0.304	0.310	0.306
1	0.314	0.319	0.312
2	0.321	0.421	0.296
3	0.298	0.398	0.305
4	0.286	0.418	0.344
5	0.301	0.471	0.315
6	0.375	0.308	0.358
7	0.345	0.355	0.304
8	0.312	0.392	0.371
9	0.351	0.465	0.366
10	0.327	0.408	0.335
11	0.296	0.506	0.402
12	0.315	0.471	0.455
13	0.344	0.518	0.290
14	0.386	0.415	0.396
15	0.412	0.470	0.402
16	0.395	0.396	0.476
17	0.351	0.405	0.396
18	0.296	0.508	0.384
19	0.288	0.496	0.414
20	0.405	0.507	0.458

Fifty animals were weighed 20 times for each measurement. The average of measurements is obtained from all the animals.

Table 3. Values obtained by DFBETAS for males, females and flock totals.

Measurement order	Male	Female	Flock total
0	0.513	0.698	0.601
1	0.536	0.712	0.614
2	0.612	0.695	0.655
3	0.458	0.784	0.582
4	0.514	0.741	0.616
5	0.682	0.656	0.582
6	0.601	0.584	0.614
7	0.517	0.703	0.588
8	0.544	0.657	0.613
9	0.538	0.790	0.671
10	0.609	0.786	0.644
11	0.647	0.412	0.534
12	0.598	0.512	0.535
13	0.451	0.465	0.462
14	0.318	0.711	0.317
15	0.296	0.416	0.406
16	0.317	0.507	0.458
17	0.286	0.613	0.317
18	0.258	0.304	0.328
19	0.216	0.412	0.362
20	0.307	0.416	0.493

Fifty animals were weighed 20 times for each measurement. The average of measurements is obtained from all the animals.

algorithm are not able to work out with large data masses with increasing number of observations.

The observations somehow detected as outliers should not be detected just to omit them and start the analysis over the clean data. Sometimes, outliers with their deviations may provide significant information and in some cases they may be a separate research subject matter instead of the remaining portion of the data. On the other hand, while deciding the outlying of an observation, type of analysis should also be taken into consideration. An observation, seeming to be an outlier in multi-variable datasets, may not be an outlier in regression analysis. Therefore, outlying does not necessarily mean just an absolute deviation from the general data. With regard to outlier detection, DFBETAS yielded more outliers than DFBETA. A decision should be made between two methods based on the sensitivity of the research work. If a researcher wishes to improve the sensitivity of the works, DFBETAS may be recommended, otherwise DFBETA may be used. By the study outlier values of each gender were estimated then total flock values were estimated. Results revealed that outlier

values differed between genders. Hence, this differences should be taken into account before planning such measurement and genders should be measured separately.

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