REVISTA BRASILEIRA DE CIÊNCIA & MOVIMENTO
ISSN 0103-1716

An alternative approach to measure effect size

Uma medida alternativa de tamanho de efeito

PANDELO JUNIOR. An alternative approach to measure effect size. **R. bras. Ci. e Mov** 2017;25(4):176-180.

Domingos R. Pandelo Junior[1]

[1]Universidade Federal de São Paulo

RESUMO: The aim of this paper is to present an alternative approach to measure effect size. The model proposed belongs to *r* family.

Key Words: Effect size; p value; Correlation.

RESUMO: O objetivo deste artigo é apresentar uma medida alternativa de cálculo de tamanho de efeito. o modelo proposto pertence a família *r*.

Palavras-chave: Tamanho do efeito; Valor de p; Correlação.

Contato: Domingos Rodrigues Pandelo Junior - pandelo@hotmail.com

Recebido: 29/07/2016
Aceito: 18/09/2017

Introduction

The aim of every researcher is conducting a study in which find robust explanations for their data, thereby generalizing gets easier and your work takes shape. For many years, indeed decades, the main instrument for assessing the robustness of the findings was p value.

The p value was developed by Fischer, in the 20s, and it was never the intention of its creator that it was used as a probability[1]. In fact, if there's one thing he does not measure is likely. If there is interest in measure probability, the correct would be the use of bayesian statistics[2].

Recently, some academic journals, such as Basic and Applied Psychology, banned the use of p value. The American Psychological Association previously does the same[3]. Any article, to be accepted in that publication, must remove any mention of the p value. It was a radical measure, perhaps did not need too much, but given the amount of misuse of the p value may even be interesting to force researchers use statistics as an additional tool and not as a crutch. One point to consider is that there is a difference between statistical significance and practical significance, for example. Another aspect is that the significance level can be brutally changed by the sample size[4]. For a critical analysis of p value, it is worth reading the classic, although recent[5], paper, A Dirty Dozen: Twelve P - Value Misconceptions.

The point is that there are other mechanisms to evaluate the robustness of a finding, in a study. Using the p value can, and should, when used, be supplemented by other tools, such as the confidence interval, effect size measures, or even likely using bayesian statistics.

The intention here is to present an alternative measure of effect size. Several researchers have worked with the development and application of effect size measures. Among them we can mention Jacob Cohen, for whom "the primary product of the research inquiry is one or more measures of effect size, not p values[6]."

Effect size measures are split into two major groups: the *d* family, that asses the differences between groups and the *r* family that measuring the strength of the relationship of variables. For a detailed analysis, and practice of principals effect measures of the two groups is worth seeking[7]. A care that must be taken with the use of effect size measures is not to fall into simplistic generalizations. Cohen[6], with the aim of illustration only, reported that steps *d* to 0.2, 0.5 and 0.8 might be considered small, medium and large effect sizes. As for correlations, *r* values of 0.1, 0.3 and 0.5 could be considered small, medium and large, to an in deep effect size implementations see Kelley[8]. Here it is worth the same observation of p value. Researcher must not just establishing standards, limits, cuts, but look more at the data, the type of sample, our sample size and try to get as much information as possible[4].

The model

The approach that is proposed in this paper is a measure of effect size that belongs to *r* family. Of course the prerequisites for the implementation of this effect size model are the same existing in all other *r* family, but its interpretation is more complete than the simple use of a measure of correlation, as there is an adjustment for standard deviation of the groups.

The effect size measure to be presented can be used to n groups, but its calculation will always be in pairs, as in other correlation models.

The initial step for the calculation of β effect size measure is to find the mean between the two groups. The mean between groups (X) will be the first step. In this paper let's considerer that we have two groups A and B, and suppose that X is the mean between the groups.

For the first variable A, for example, the calculation is made by dividing the covariance between X and A the variance of X. Calculation of effect size (β) for variable B, would be made by the same way, with the specific data B (eq. 1).

$$\beta = \frac{Cov(X, A)}{s_X^2} eq1$$

As the analysis of covariance is less intuitive than correlation, we can substitute the same in the formula shown in the following manner (eq. 2).

$$r = \frac{Cov(X, A)}{DPX.DPA} eq2$$

$$\beta = \frac{r.DPX.DPA}{DPX.DPX} eq3$$

$$\beta = \frac{r.DPA}{DPX} eq4$$

Thus, the β effect size index is a function of correlation between each of variables set multiplied by the standard deviation of the mean of variables and the other variable (A, in this case) divided by the standard deviation between the variables (X), as showed in eq. 3. We can reduce the equation as we can see in eq. 4.

This is a similar version to the slope of the linear equation. In a previous study, Peterson & Brown[9], show the use of beta coefficient in meta-analysis, and it relationship with the *r*. In other areas such as finance, for example, a similar model is used to calculate the risk (variance of returns) of an asset relative to the market[10]. It is therefore, as already mentioned, a relative measure between the variables to be studied (groups) and the average of the groups. The model can be extended for n groups. The great advantage of its use is the intuitive interpretation. For example, if we have an index equal to 1 we will have a situation in which the group in question has an equal reaction to the average between groups. If the index is less than 1 (0,7, for example), the group in question has a reaction rate lower than the average. Finally, if the index is greater than 1, the group in question has a greater reaction than the average. The analysis should be done with two approaches on the one hand the magnitude and on the other, the direction of variation. It is, therefore, a simple metric to work and easy to analyze.

An Example of Application

An example application of the model will be shown below. Let's suppose that we are trying to calculate the performance of an athlete in relation to his competitors. Let us suppose that in X we have the values of the performance of the athlete in question and in Y the value of the average values of the competitors in the modality.

Table 2, in turn, shows the calculation of the performance variance of the athletes (the competitors). As verified in equation 6, after the final calculations, the value will be in 0.140, with the roundings. Thus, the B of the athlete in relation to the average of the competitors will be given, with the application of the proposed formulas, by 1.108 (0.155 / 0.140).

Table 1. Shows the covariance calculation, which in this example will be 0.155.

X_i	Y_i	μ_x	μ_y	$x_i - \mu_i$	$y_i - \mu_i$	$(x_i - \mu)(y_i - \mu_i)$
1,1	2,3	1,3	2,1	-0,2	0,2	-0,04
1,9	2,5	1,3	2,1	0,6	0,4	0,24
0,6	1,5	1,3	2,1	-0,7	-0,6	0,42
1,6	2,1	1,3	2,1	0,3	0,0	0,00
					Total	**0,62**

$$\boxed{\mathrm{Cov}(x,y) = \sigma_{xy} = \frac{\sum_{i=1}^{N}(x_i-\mu_x)(y_i-\mu_y)}{N} \quad \sigma_{xy} = \frac{0{,}62}{4} \quad \sigma_{xy} = 0{,}155}$$

Table 2. Variance

y_i	μ	$(y_i - \mu)$	$(y_i - \mu)^2$
2,3	2,1	0,2	0,04
2,5	2,1	0,4	0,16
1,5	2,1	-0,6	0,36
2,1	2,1	0,0	0,00
Total		**0,0**	**0,56**

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\mu)^2}{N}} \quad \textit{eq 6}$$

Conclusions

As showed, the model is very simple and can be used without need of complex approaches. It's very intuitive and can help us to assess and analyze our data. Of course the model has the limitations and demands that all family *r* measures of effect size have.

References

1. Fisher RA. "Theory of Statistical Estimation", Proceedings of Cambridge Philosophical Society. 1925. 22 v.

2. Stone JV. Bayes' Rule: a Tutorial Introduction to Bayesian Analysis. 2013.

3. American Psychological Association. Publication manual of the American Psychological Association Sixth Edition, Washington: Editorial Staff.; 2010.

4. Cumming G. Understanding The New Statistics: Effect Sizes, Confidence Intervals, and Meta-Analysis. New York: Routledge; 2012.

5. Goodman SN. A dirty dozen: Twelve P-value misconceptions. Seminars in Hematology. 2008; 45: 135-140.

6. Cohen J. Things I have learned (so far). American Psychologist. 1990; 45: 1304-1312.

7. Ellis PD. The Essential Guide to Effect Sizes: Statistical Power, Meta-Analysis, and the Interpretation of Research Results. Cambridge, UK: Cambridge University Press; 2010.

8. Kelley K. Confidence intervals for standardized effect sizes: Theory, application, and implementation. Journal of Statistical Software. 2007; 20(8): 1-24.

9. Peterson RA, Brown SP. On the use of beta coefficients in meta-analysis. J. Appl. Psychology. 2005; 90: 175-181.

10. Sharpe WF. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance. 1964; 19(3): 425-442.