EDITORIAL

The space and risks of statistics in scientific research

Statistics – As it holds the semblance of truth associated to numbers – sounds like an exact tool, having no ambiguity, straight in the validation (or not) of scientific hypothesis and, in fact, it can be a powerful tool for the scientific research. This potential, added to the easy access to computers and eventual decrease of the cost of data processing, has led to a popularization of its use in scientific works.

In an academic writing, the acritical use of statistics favors an environment where the visual impact of charts and the impression that numbers are associated to accuracy; the ignorance of their assumptions and limitations might converge to a text that which is closer to an exercise of rhetoric than one of scientific logic.

Nowadays we have access to computers with statistical packages ready to perform all the calculations we want to at a cost that could be unthinkable 20 years ago. Well, hardware and software make a researcher an expert in statistics as much as a car makes a driver a mechanical engineer.

Statistics does not speak by itself. Its use, a priori, requires delimitation from a bibliographical review and, a posteriori, interpretation of results in relation to the references found. However, pressured either by managers or by need for resources, many researchers lead their experiments without proper knowledge. This question, despite its importance for scientific praxis, goes beyond the scope of this text. Likewise, this text does not intend to provide a detailed explanation about the practical use of statistics, though it aims to warn about the minimal attention for its use. A list of basic prescriptions to the good use of statistics is presented below.

Use of the same set of data to calibrate and validate models

This practice is statistically tantamount to letting the fox guard the chicken coop. Once the model was calibrated from the same set of data used for the calculation of adjustment quality statistics, these will tend to track the original data, providing an overestimated estimation.

The best to do is to use cross-validation procedures that allow you to estimate the degree of accuracy against a new set of data. This technique consists of partitioning data in independent sets to be used, systematically, for calibration or training of models for validation or test. The most used forms of cross-validation are a holdout, k-fold, and leave-one-out.

Non-random, insufficient or inadequate samples for the analyzed hypothesis

In order to manage a data analysis, we start from a sample that, collected adequately and properly, represents the characteristics of a population that finally, but not necessarily in this order, corresponds to the outlined hypotheses and goals. Therefore, a corresponding sampling plan would have the following definitions: Object of study, hypotheses to be tested, sampling units, variables, data collecting tools, sampling procedures, and admitted sampling error.

The definitions above represent only a possibility of arrangement among many possible, but what matters is that it must have an argumentative logic. But what logic? Any logic. The most important is that your articulation must be coherent and useful to science.

Use of inadequate or inefficient procedures

The analyzed hypotheses must correspond exactly to the probing hypotheses of the statistical tests used. You should not select a determined procedure because of its popularity. Meantime, scientists are human beings susceptible to the same biases in the society around them and, thus, they might end up following instituted trends and habitus. Despite the attention and care, some research will be enough to detect articles with inefficient or improper statistical methods even in high impact factor journals.

Na example is the use of a means test for independent samples when the experiment was paired, with the evident loss of discrimination power. Even worse - and still usual - is the use of multiple means tests instead of an analysis of variance follower by a *post-hoc* test. Besides the non-computed raise in the level of significance associated with this practice, we know that the adequate procedure is the classic one, proposed by Sir Ronald Fisher, the father of modern statistical experiment, in 1918, but it remains ignored.

Statistical procedures have assumptions associated with their deduction. These are more than prescriptions; they are the a priori considered in their mathematical inferences. Not to consider them implies walking on a swampy ground, an environment in which we lose the guarantees regarding the significance levels obtained. In this case, you must look for alternative ways, usually non-parametrical, that have lighter assumptions. Nevertheless, it is worth it warning that the relative asymptotic efficiency of those procedures is most of the time lower than 1, what justifies its parsimonious use.

In the same order of thoughts, an exploratory analysis of the failure to meet the assumptions can many times lead to the detection of outliers that could be either deleted, in the case they correspond to collection, processing or typing errors, or still analyzed in order to capture characteristics of the experiment that could be used in its discussion.

Use of statistics software without checking if its standard parameters are adequate

Statistics processing software programs have a priori settings for the procedures. However, those settings not always correspond to the most adequate choice. The access to computers as software give a researcher proficiency in statistics as much as possessing a scalpel makes a physician a surgeon. The use of these tools is important to scientific research, but only with knowledge and parsimony.

Unclosing the curtains

The adequate use of statistics, as well as any other science, requires the mastery of knowledge and subjects. Nevertheless, the pressure to publish and grant degrees as soon as possible, though justified, causes young scientists to access the career without a complete formation and, more often, leads to hasty scientific researches. This results in a series of methodological skips that ends up in an unauthentic semblance that statistics speaks for itself, or that it can be denied where it actually applies.

Attention is not limited to basic knowledge on experimental delineation. In a broader sense, it implies a whole praxis based on evidence. The interdisciplinary nature of science sets up daily challenges that have the following prescriptions to be overcome:

- Increase your proficiency in all the areas regarding the objects of study. This does not mean a deep mastery, which must be reserved to your specificity, but it must be solid enough to widen the horizon of studies and help you communicate with experts of other areas
- Articulate a network of researchers so you can increase possibilities and depths of your study projects
- Review the delimitation and the references for your research projects until your praxis is as simple as possible, but not oversimplified.

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