Teaching and learning statistics and experimental analysis for environmental science students, through programming activities in R

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Abstract
We present a constructionist approach for the teaching and learning of statistics and experimental analysis for environmental and biological science students, through computational activities based on the R programming environment[4]. These activities, tried out in three institutions in Portugal and Mexico, in 5 postgraduate and 2 undergraduate courses, are hands-on sets of tasks in R script that include programming work and were carried out collaboratively. Results indicate that students enjoyed the course, lost some of their fear of statistics, and may have developed competencies for applying statistical methods and using computational tools, such as R, on their own data.

Keywords Statistics education, experimental analysis, programming, R code, constructionism

1. Introduction

1.1. The need for statistics knowledge in science

Probability knowledge and statistical methods are necessary tools for experimental data analysis in scientific disciplines, such as environmental sciences, and provide methods that assist decision-making in different situations [1]. Thus, statistical education scholars emphasise that students of all levels [2], particularly those being trained as future researchers [3], have an understanding of the basic concepts of experiment design and data collection, management and analysis. Graduate students, particularly, must be able to interpret, communicate and defend their findings using statistical arguments, with good understanding of the methods and language used.

However, probability and statistics are commonly recognised as difficult both to teach and learn. Their inclusion in graduate programs in biology and related sciences have often had unsuccessful results [4], with learners having difficulty in understanding and applying the concepts. A study [3] on training researchers in statistics, showed that many statistics concepts, even basic ones, are often poorly understood and used incorrectly by researchers, and consequently also by their students. Moreover, many students enrol in these courses once they have collected their experimental data, so when they apply analysis techniques, it is often too late to adjust their experimental design.

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1.2. Background: Observed difficulties for the learning of statistics

For the past 10 years, the main author of this paper has been teaching statistics courses, at both undergraduate and post-graduate levels, for environmental science students –mainly at the Sisal Academic Unit of the School of Sciences of the National Autonomous University of Mexico (UNAM) in the post-graduate programs of Marine Science and Limnology, and Biological Sciences; in the undergraduate program of Sustainable Management of Coastal Zones; and in courses held at other institutions abroad (e.g. in Chile and Portugal). Until two years ago, her teaching approach, like that of her colleagues, was a traditional one, and she observed issues such as those described above, in three areas related to: 1) students' aversion to mathematics and statistics; 2) the software that is commonly used in statistics courses in her institution; and 3) the syllabus conception and approach. In general, when students have difficulties understanding the abstract and relatively complex concepts in this area, they become frustrated and convinced of their inability to learn and apply them, leading to rejection and creating a vicious circle.

Some elements that we have identified as playing a role in students' aversion towards learning statistics include: (i) Mathophobia [5] and negativity towards mathematics: In fact, some common statements are "we study biology because it doesn't have much mathematics." (ii) A failure to find meaning for the use of statistics in their field of study (this is particularly the case of undergraduate students in the Sustainable Management of Coastal Zones program). (iii) Some students (such as those in the post-graduate programs in Marine Science and Limnology, or in Biological Sciences) previously have taken a statistics course, and had many difficulties with some complex concepts, such as probability and its interpretation in time ("once an event has passed, its probability no longer makes sense"), ratios and proportions, statistical inference and intrinsic variability.

A second issue relates to the computational tools and software (e.g. Statistica) that are more commonly used for analysing data in Biology and Environmental Sciences: these generally not only do not help but rather hamper the learning of the statistics concepts as well as of the use of the tools. On the one hand, students easily confuse the development of skills for using the software, with the understanding of analysis strategies, their results and their interpretation. On the other, there are problems in that many of the most widely used software are black boxes (e.g. Statistica); or unfriendly and unreliable (e.g. Excel), in that one doesn't really know what is actually happening when a function is applied, and errors are difficult to recognise. Also, these software do not facilitate the construction of graphs, with little user control on how graphs are constructed; this creates a disassociation between the numerical results and the graphical output of an analysis. Thus, both representational registers become harder to understand and interpret, making the graphical exploration of the data difficult to carry out –an exploration that is a fundamental part of any statistical analysis and the basis for the strategic planning of the method to apply. Finally, software like Statistica is commercial and needs a licence; therefore it is only installed in few computers which prevents students from having easy access to the software.

A third issue is that the statistics courses' syllabi do not contemplate this subject as a means to see and understand reality; on the contrary: (i) The approach to the subject matter tends to be separate from the natural world it is meant to analyse. (ii) Little importance is given to statistics in the professional development of the students, apparently conceiving it only as a set of algorithmic skills for using predetermined software tools (akin to learning how to use a machine, without understanding how it works or its different possible uses.) (iii) The courses' approach tends to dissociate the statistics from the scientific environment (e.g. one that includes the scientific method, uses predictive models, formulates potential hypotheses, etc.) (iv) Discussions on the meaning of the error in a statistical inference are superficial (with hardly any assessment on the limitations of a statistically significant statement / the impossibility of rejecting the Null Hypothesis –the paradigm of Bayesian statistics). (v) They miss the opportunity that is provided naturally when going through a statistical procedure, of exercising strategic decision-making for reaching a specific result, which helps develop a sense of awareness of when, how and why certain decisions are made (identifying the moments and motives for choosing a certain path among other possible ones and thus comprehending the arguments that justify that result). (vi) The above issues lead to a further alienation of students from the problem-solving context in which statistical knowledge is applied, making statistical modelling and data analysis a "field of specialists".

1.3. Approach for overcoming the difficulties.

Proposals to solve these difficulties, recommend contextualising the concepts by using concrete examples that include data from real research situations [6], [7], and translating problem statements to (abstract) mathematical formulations in order to create statistical models [6]. Generally, it is recommended that teaching methodologies shift the role of students from passive to active, with emphasis on developing statistical reasoning, rather than a blind application of statistical tests.

Moreover, the use of diagrams in the teaching and learning of statistics has been recognised as important (e.g. [9]). Graphic representations are essential in data organisation and analysis; they are a tool for transnumeration as well as a basic form of statistical reasoning [10]. Also, the construction of knowledge requires being able to change from one representational register to another [11]: for example, when a data list is converted to a histogram, it becomes possible to visualise the mode and perceive the symmetry or asymmetry of the distribution. The correct interpretation of graphs is a research topic in statistics education, and several levels of graphic comprehension have been defined [12]: 1) "read the data" (a direct reading of the graph without interpreting the information it contains; 2) "read inside the data" (an interpretation and integration of the data in the graph); 3) "read further than the data" (predictions and inferences from the data about information not directly reflected in the graph); and 4) "read behind the data" (a critical assessment of the data collection methods, their validity and reliability, as well as the possibilities for extending the conclusions). In this regard, computer technologies can be used for simulating and visualising stochastic phenomena, and in general for statistics education [12], [13], [14].

Some approaches to the use of technology in education in general, draw on constructivist theories of knowledge, and specifically on the constructionist paradigm, which suggests that learning can be facilitated if students can explore ideas and concepts through construction, such as is involved in computer programming activities [15], potentially also providing early access to relatively advanced abstract ideas. In our case, we were inspired by Logo programming activities [16] and experiences, to attempt a constructionism-based teaching and learning approach for statistics topics. In the past couple of years we have been researching how to do this through iterative design. This paper presents this approach and the results of the implementation of computer programming-based activities using the R statistical software, during seven university courses in Portugal and Mexico.

2. A constructionist approach for teaching experiment analysis

2.1. The statistics courses: a new strategy

As mentioned above, the first author of this paper has been teaching statistics courses for over a decade to environmental sciences undergraduate and post-graduate students. These courses focus on giving theoretical and applied knowledge related to experimental design and data analysis, such as given in [17]. They cover various elements of experimental design (e.g. replication, blocking, balance, etc.). They aim to strengthen students' statistic knowledge related to hypothetical-deductive methods, confirmatory techniques using either complex models (with the proper use of experimental controls), or arranged by research data from both social and environmental areas. They include reviews of general linear models (GLM) starting with a single explanatory (categorical) variable, and increasing the complexity up to multivariate models.

In the past two years, we have developed a new teaching strategy for those courses (see section 2.3) that includes a series of computer-based activities. So far, as detailed in Table 1, we have applied those activities in altogether seven courses at undergraduate and post-graduate levels in three institutions: at the Sisal unit in Mexico; at the Portuguese Institute of the Sea and the Atmosphere (IPMA), in Lisbon, Portugal; and at the Interdisciplinary Centre for Research in Marine and Environmental Sciences (CIIMAR), in Porto, Portugal.

<table>
<tr><th>Courses (and codename)
Undergraduate</th><th>Main topics</th><th>Duration (hours) & period</th><th>Place & year</th><th>Participants</th><th>P. No.</th><th>Activities</th></tr>
<tr><td>"Probability and Statistics" (Prob&Stats)</td><td>Basic probability theory; distribution of random variables; statistical inference; simple hypothesis testing.</td><td>112 (16 weeks)</td><td>Sisal, 2013</td><td>2nd year UG students in Coastal Zone Management studies</td><td>18</td><td>1-13</td></tr>
<tr><td>"Experimental planning and analysis" * (ExpPlann)</td><td>ANOVA; linear regression</td><td>112 (16 weeks)</td><td>Sisal; 2014</td><td>2nd year UG students in Coastal Zone Management studies</td><td>19</td><td>(1-4 review) 14-23</td></tr>
<tr><td>Postgraduate</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>"Univariate statistics" (UV-IPMA)</td><td>Probability distribution of random variables; statistical inference and hypothesis testing; linear regression</td><td>30 (1 week)</td><td>IPMA, Lisbon; 2012</td><td>Postgraduate (4); postdoctoral (4); researchers (6) in Marine Biology and Environmental Science</td><td>14</td><td rowspan="4">1-5; 7; 9-11; 14-23</td></tr>
<tr><td>"Univariate statistics" (UV-CIIMAR)</td><td>Probability distribution of random variables; statistical inference and hypothesis testing; linear regression</td><td>40 (1 week)</td><td>CIIMAR, Porto; 2013</td><td>Postgraduate (12), and postdoctoral (7) in Marine Biology and Environmental Science</td><td>19</td></tr>
<tr><td>"Experimental design and data analysis" (EDDA 2013)</td><td>Probability distribution of random variables; statistical inference and hypothesis testing; ANOVA; linear and multiple regression</td><td>80 (2 weeks)</td><td>Sisal, 2013</td><td>Postgraduate (14) in Marine Biology and Limnology</td><td>14</td></tr>
<tr><td>"Experimental design and data analysis" (EDDA 2014)</td><td>Probability distribution of random variables; statistical inference and hypothesis testing; ANOVA; linear and multiple regression</td><td>80 (2 weeks)</td><td>Sisal, 2014</td><td>Postgraduate (18) in Marine Biology and Limnology</td><td>18</td></tr>
<tr><td>"Introduction to Multivariate Statistics" * (IMV)</td><td>Measures of association; ordination techniques; multivariate GLM</td><td>40 (1 week)</td><td>Sisal, 2014</td><td>Postgraduate (22) in Marine Biology and Limnology</td><td>22</td><td>(1-4 review) 25-34</td></tr>
<tr><td colspan="7">* Follows the previous course.
Sisal: Sisal Academic Unit, National Autonomous University of Mexico (UAS-UNAM), Sisal, Mexico.
IPMA: Portuguese Institute of the Sea and the Atmosphere, Lisbon, Portugal.
CIIMAR: Interdisciplinary Centre for Research in Marine and Environmental Sciences, Porto, Portugal</td></tr>
</table>

Table 1: Statistics courses, duration and participants with corresponding R-based activities.

Each of those courses has as general aims for students to: understand how to carry out and apply the theoretical and experimental design, and develop criteria for selecting tools and types of tests in a research approach; learn to use the basic concepts of experimental design that help to build a statistical model to be used in a research study; and apply statistical computing software (in this case, the programming language R –see below) to carry out the calculations related to the experimental design of experiments, and learn how to interpret the results given by the software. The new courses include theoretical and practical components, so that students can correctly apply the concepts to problems related to their subject of study. To do this, students need to develop familiarity with the programming language R (R-Project) and its libraries by learning simple programming commands for the analysis of variability. They have to learn to draw and interpret graphs (i.e. visualise the models) to assist in exploratory data analysis, and how graphs can complement the numerical representations of quantitative results.

2.2. The R programming environment

In recent years, R (the *R Project for Statistical Computing*[5]) has been used as a pedagogical tool for the analysis of various kinds of quantitative data. We chose R because it is a programming environment which favours a constructionist approach, but also because it allows to have control and transparency, in contrast to Statistica or Excel.

R, as a software environment as well as an object-oriented programming language [18], includes the handling of objects and their representations. It is an expression language where executable representations can be run through a set of intuitive and relatively simple commands, using a repeatable and consistent syntax with inputs to functions written between parentheses, in the common mathematical function style. R includes primitive functions and libraries of pre-defined commands. When R is opened, some libraries are automatically loaded. But one can create a library for one's own purposes and create new commands that are submitted to the R Development Core Team for approval and saved and shareable in the repositories of the R-project server (called CRAN). Elementary commands consist of expressions or assignments. New objects created in R can be variables, arrays of numbers, character strings, functions, or more general structures built from such components. Values can be assigned to objects by using the '<-' operator or, alternatively, the '=' operator. Using the R console, one can directly run commands, or scripts (programs) created in an editor.

Although R provides its own editor, there are many external editors with added functionalities. We prefer the Crimson Editor (http://www.crimsoneditor.com) which, for example, allows us to colour code the different objects (blue for functions, green for comments, black for operators, etc – see Figure 1). Colour coding (syntax highlight) is important for several reasons, among which is the opportunity for students to add their comments to their code files (either those provided by us, or those they create themselves).

One of R's strengths is the ability to produce plots and graphs of varying degrees of complexity (see Figure 2). This facilitates the interaction and coordination between representational registers [10], thereby promoting the disclosure of new information and the construction of conceptual links in the learner at each step of an exploratory activity.

[5] R (http://www.R-project.org) is a cross-platform free software environment (distributed under the GNU Licence) for statistical computing and graphics, created by Ross Ihaka and Robert Gentleman in 1996. It is considered a dialect of AT & T Bell Laboratories' S language [19]. Its development and distribution are carried out by several statisticians known as the "R Development Core Team" [18].

```
# 5. Otro tipo de representación para una distribución es el comando 'boxplots'. Aplícalo a los datos anteriores.
boxplot(sam1)
boxplot(sam2)
# ¿Cómo podrías obtener dos diagramas de caja en una misma gráfica?.
boxplot(sam1, sam2)
# Utilizando la ayuda de esta función en R, descubre lo que representan los bigotes, la caja y
# la linea de en medio de la caja.
?boxplot
?boxplot.stats
Los bordes de la caja son el 1er y 3er cuartil (cuando n es par, pero no si es non).
Los bigotes son +/-1.58 * IQR/sqrt(n).
Chambers et al., 1983

# 6. ¿A partir de la información que has obtenido de los datos hasta ahora, ¿podrias asegurar que las distribuciones
# anteriores son normales? Si tu respuesta es negativa, ¿qué información te hace falta?
Parecen normales a simple vista, pero no puedo estar seguro.

# 7. Vamos a asumir que las muestras anteriores provienen de una distribución normal. ¿Cómo calcularías la probabilidad
# de que un caballito de la localidad 1 mida 39 mm de LT? Calcula también la de un caballito de la localidad 2 y compara.
# Pista: recuera la función 'dnorm').
dnorm(39,mean(sam1),sd(sam1))
dnorm(39,mean(sam2),sd(sam2))
```

Figure 1: Excerpt of an activity on Poisson distributions (in this case using data from seahorses morphology) that involves diverse constructions of graphs

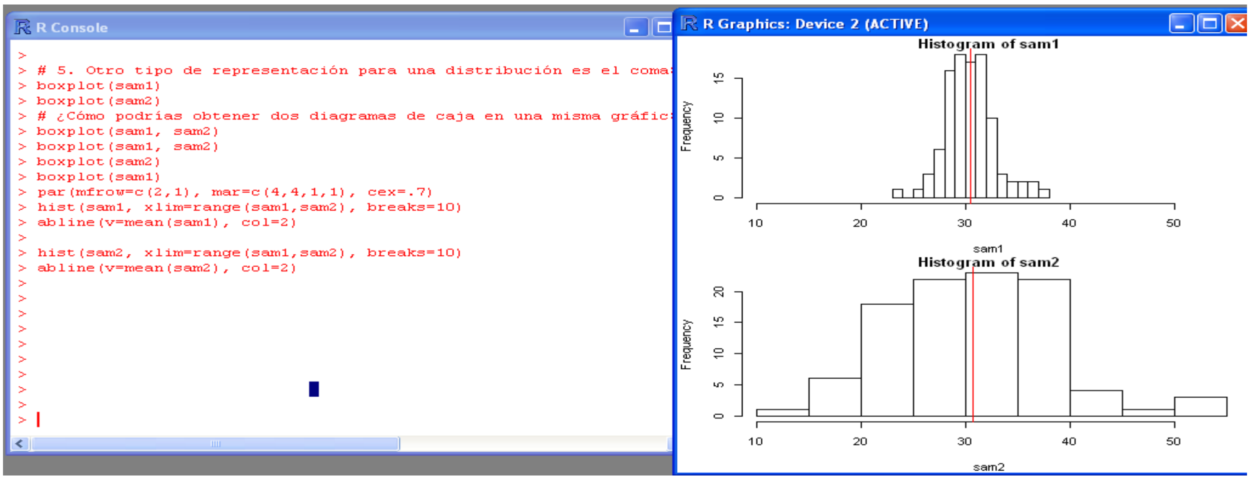

Figure 2: Construction of plots (in this case histograms from the activity in Figure 1) using the R console.

The use and programming of R, like that of any other programming language, requires initiative in order to look for different strategies that reach the same result; it encourages experimentation which leads students to lose their fear of failure; different strategies can be compared and analysed; it involves memory and understanding of previously learned commands in order to apply them in new problems. All of these factors invite students to reflect on how they think about a determined problem and on their approach, giving them an active and responsible role in their own learning.

Due to all of the above, R is a versatile tool for the application of statistical tools in biology. Moreover, since computational instructions can have direct correspondence with the behaviour of the phenomena – with an analogy between the mathematical model (equations) and what is written in R, e.g. Xijk = Ai + Bj + ABij is expressed in R as

Response ~factor(A) + factor(B) + factor(A):factor(B)

– they have further potential of facilitating the understanding of the statistical concepts involved.

2.3. The sequence of activities and their design rationale

In our proposal, all the activities for teaching statistical reasoning were thus designed to be carried out using R. Using the hypothetical-deductive method, we have used multiple variables models to teach theoretical and applied experimental design. So far we have designed 34 computational activities, using an iterative approach in which we have revised and redesigned the activities according to the experiences and results of implementing them in each successive course. The activities were written using the Crimson Editor (but can be opened in other editors); they are "worksheets" in R-code with instructions or guidelines, examples, programming tasks, questions for reflection, comments, and also commented solutions to the activities which were made available to students at the end of each session.

These activities were designed using the following criteria: (i) Simple texts with short and clear explanations of the concepts presented. (ii) Include realistic but simple examples that facilitate the presentation and contextualization of concepts. (iii) Involve the construction and interpretation of plots and diagrams whenever possible. (iv) Are exercises involving the simulation of data (with random components) after a numerical or graphical result has been given. (v) The exercises are supplemented by comments and questions that invite to reflection and assist in the assimilation of new ideas. (vi) The questions are short and can immediately be tested through trial and error so that they can promote learning through feedback and self-corrections. (vii) Elements found in both numerical and graphical outputs, relate to concepts learned and used earlier. (viii) "Hints" are provided to invite students to venture into executing a new commands. (ix) Clear indications are given for finding information related to the problem at hand, both among the R-packages and other published documentation.

Activities are of two types: 1) Activities to introduce the basics of R functioning, to be carried out in the first course sessions. These are activities 1- 4 called BasicR (on respective topics of general introduction, object manipulation, import/export, and plots). 2) Activities on different topics corresponding to the contents of the different statistics courses. In Table 1, the activities corresponding to each course are given (e.g. activities 5-6 deal with frequency distributions; activities 7-9 on binomial, Poisson, and normal distributions respectively; activities 14-16 on ANOVA and comparisons between means; activity 20 on linear regression; and activities 25-34, which are for the Introduction to Multivariate Statistics course, include topics such as matrices and Eigen analysis). Activities may or may not be carried out in strict sequence, depending on the contents and needs of each course. Instructions within each activity have different purposes depending on the theoretical contents and the moment in which they were introduced during the course. We follow a general sequence starting with instructions to present an R command and explore the output, either graphical or numerical. These are followed by instructions to further discover new arguments within a particular R command, inviting students to modify or add features to the output by identifying the specific form the command should take in each case. Finding new arguments is often encouraged (done by searching the integrated R documentation, the internet or other literature; or if a command is not found try to create it through programming). Instructions then direct students to reflect on theoretical aspects related to the concepts being revised. At this point, instructions guide students to search for alternative ways of obtaining similar results, comparing the different outputs to alternative commands. Particularly difficult parts include hints to remind students of previous or new commands that may assist them in finding the solution. At this stage, instructions frequently involve applying commands to different data sets (that can be directly imported from other sources, such as those stored in Excel) and subsequently comparing numerical and graphical outputs. Questions regarding various aspects of the output promote reflection on the contrasting nature of the data sets and lead to identify the procedures that can best represent them. Activities in relatively advanced stages of the course almost always begin with the presentation of a statistical problem together with data sets that either have a real basis (modified to suit the objectives of the activities), or are entirely simulated.

The construction and understanding of statistical models is facilitated by the construction of objects (Figure 2) to represent each model. These objects can then be explored through commands that output different types of numerical summaries. Students need to identify specific items in these summaries, relate them to graphical representations of the data and interpret them in the context of the problem. In addition, they also need to see the relation between the numerical output and the mathematical formulae given in previous theory sessions. Instructions are frequently included to predict what a change in the argument of a command would produce, and compare the actual results with the predictions. In this way, students are permanently asked to move back and forth through the rationale underlying the analysis of the data. Towards the end of some activities, students are often invited to suggest changes in the datasets in order to obtain a different result in the analysis. With this practice the aim is to illustratively reveal the close relationship between "what the data is", "what data look like" and "what the statistical result portray".

3. Implementation and some results

Activities are designed to be carried out by groups of 2-3 students and moderated by an instructor. The final aim is for students to be able to produce their own statistical models or modify those given (depending on the complexity of the activity) and fully explore their results and interpretations. As shown in Table 1, we have taught the courses in two modalities: as semester-long courses for undergraduate students; and in intensive 1-2 week courses for postgraduate students. The latter have proven to be a good opportunity for these students, who are frequently in urgent need of understanding statistical techniques, to analyse their data and get started with the analysis of their own data. In undergraduate level, the implementation of the collaborative work has been difficult, since there is more passivity, and one has to make it compulsory for students to talk to their peers; in addition, though they are supposed to work in teams, each student works on his/her individual laptops and teams are inconsistent. In contrast, at post-graduate level, there is a more playful, though intensive, atmosphere, and there are even improvised competitions between teams. However, in the post-graduate course, because they were intensive, at least a third of the students in each of the courses expressed that they would have wanted more time, because –in the words of an IPMA course student– time was "not enough to learn and 'play' with R."

For the assessment of the courses, we used, besides field in-class observations, two questionnaires for students to evaluate them (a questionnaire designed by ourselves and, in the last year, a predesigned one from the Ministry of Education); informal interviews; and looked at possible learning, through the commented and modified "worksheets" (the R script activities) that students turn in, and the tendencies in mean achievement (though we are working on developing better techniques for assessing the learning benefits of our approach). In any case, the data obtained so far has helped us with the iterative design of the activities for adjusting them. Details of the assessment instruments are beyond the scope of this paper, but we give an overview of some results here.

In general, almost all of the students in the different courses expressed their appreciation for the course, rating it very high and many as excellent: "one of the best courses I've attended"; "it is a model of an intensive course" (EDDA 2014 course participants - CPs); with many requesting a continuation. It was also telling that during the intensive courses, students wanted to go overtime instead of going home, even though they had spent most of the day in the course. They particularly appreciated the practical activities (combined with theory – although a few wanted more theory): "it allows us to learn by practice, something very unusual in stats courses" (IPMA CP); also the comments inside the scripts, their usefulness, and the sample solutions given at the end. Many students commented on how they were surprised by the potentiality and versatility of R as a tool to analyse data: "[R] has really surprised me because of the different possibilities of application that it has" (CIIMAR CP); "it opened our horizon with respect to the variety of things [R] does" (EDDA

2014 CP); "[R's] possibilities are infinite, the only restriction being the knowledge a user has about the different commands and libraries" (EDDA 2013 CP). Moreover, most felt they were now capable of using it on their own, for their own data, either creating new scripts or modifying pre-programmed scripts to suit their needs: "I have all the scripts, which I can re-apply or modify according to my data" (IPMA CP).

Initially, there were slow learning curves, with many students (particularly undergraduate ones) frightened by the idea of programming, but eventually "getting the hang of it." Some comments in this regard were: "I thought R would be very difficult, but as we started using it, it seemed quite intuitive" (EDDA 2013 CP); "the way it was introduced allowed a relatively easy utilization of the language" (CIIMAR CP). One participant, from the EDDA 2014 course, even wrote his evaluation playfully in R-like syntax. Participants from the CIIMAR course who already had some previous knowledge of R, expressed the following: "I found this a much easier way of learning the language;" "I had already worked with R, but only with the execution of previously written scripts; in this course I learned more about the meaning of commands and the fundamentals of statistics;" "[This course] helped us understand what the commands behind the software are really doing." One participant from that course also said that, although the concepts are not easy, the way they were presented helped "understand the mathematical formulae behind statistical tests."

Most students became actively involved in the courses with many expressing how much fun they had: "I really enjoy that with these programs you can play with them while you learn about all its applications;" "on top of everything, I had had lots of fun" and even the challenge: "I liked the way it gradually got more complicated with time" (CIIMAR CPs). Many also appreciated the classroom dynamics that included teamwork and group discussions: "The course dynamics allows interaction between instruction and learning by the whole of the group, and we could discuss our ideas and help each other" (IPMA CP); "the work in small groups encouraged the discussion of concepts and different ways of writing the R code [which] in turn, made it easier to remember commands" CIIMAR CP); "I really enjoyed the atmosphere [of] teamwork" (EDDA 2014 CP). More importantly, they showed understanding of the topics through their participations in classroom discussions, as well as in the commented R files they turned in. For example, we observed that students were able to compare different solutions, and understand what happens if they get different answers, and that graph interpretation was easier when students did the programming themselves: they learnt to analyse the output of data and relate it to the input and to the graphs. Students also realised that mistakes were not a problem in R, because the feedback of the environment tells them if there is a mistake or they get some illogical answer; this promoted reflexion on what went wrong (the value of debugging, already talked about long ago by Papert [5]), which contrasts with software such as Statistica or Excel where students either don't know what to do, or they don't even realise a mistake was made. Another finding was that some mediocre students became better or more dedicated students in these courses.

We end with an illustrative anecdote: A few weeks after the end of 2013 EDDA course, a Honduran student from that course, told us that he had been "infected" with R, and that now he wanted only R. He explained that he had been compelled to use multivariate techniques on his data and had investigated, on his own, commands dealing with these techniques; he had then written his own scripts to analyse his data and was very excited to have been able to do this by himself.

Based on the above results, we can thus claim that the objectives of our approach (of learning by doing and constructing with R) have been met, since most students have been able to overcome their fear of statistics and develop a basic proficiency in both the understanding of statistical concepts as well as in the use of R that allows them to be more self-sufficient in the application of statistics with R to their own data and needs. Our research continues and we carry on reconsidering the approach and redesigning our activities.

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