The relationship between learning approaches and students' achievements in statistics units in Argentina

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Learning approaches refer to the strategies students adopt in order to learn and why they choose them. A deep strategy is based on a critical analysis of new ideas related to prior knowledge leading to long-term concept retention, which may be used in solving problems in unusual situations. Conversely, a surface approach is characterized by a tacit acceptance of information leading to material rote-learning in an unrelated manner. This strategy leads to short-term material retention. Moreover, students can adopt a strategic approach by focusing their learning mainly on achieving good grades. In this study, we analyzed the relationship between learning approaches in an Introductory Statistics course and the performance obtained at the end of the course and in a test two years later in an Advanced Statistics course. We analyzed the responses given by 91 students to ASSIST (Approaches and Study Skills Inventory for Students). These students were from an Introductory Statistics course at the Agricultural School of the University of Buenos Aires. We estimated scores for each type of strategy based on the respective factors of the confirmatory factor analysis. Student who take an Advanced Statistics course two years later were subjected to a pre-test on the first class in order to evaluate basic statistics knowledge. Higher scores in the deep strategy were related to higher grades obtained both at the end of the Introductory Statistics course and in the pre-test. Conversely, higher scores in the superficial strategy were related to lower grades obtained both at the end of the Introductory Statistics course and in the pre-test. The students who adopted the strategic approach obtained intermediate scores. These results provide evidence for the relationship between learning strategies and learning retention in the short and medium term.
Keywords: ASSIST, basic statistical concepts, factor scores

Introduction

Within the context of uncertainty in which knowledge areas are developing, being unable to make decisions may be particularly costly not only for individuals but for the society at large. In this sense, Statistics as a discipline that deals with the management of information, quantifying the risks of predictions, has been included in most university programs throughout the world as a main curriculum component.

The success of learning Statistics is that the basic knowledge acquired can be maintained over time, beyond completion of the course in order to be used in new situations without the presence of the teacher. In this way, the basic concepts can be transferred to real situations far from the academic realm. The challenge of teaching Statistics at large classes with limited human resources is that students become lifelong learners which is essential at a time when technical knowledge is constantly changing (Hannigan, 2010). Besides, an increasingly large number of students come back to university to take postgraduate courses, thus basic concept retention is vital for students. In this sense, a key concept concerning learning is the strategy adopted by students. Learning strategy approaches have been originally studied by Marton and Saljö (1976a y b), who identified individual differences in learning approaches based on a qualitative learning analysis. They found out that the intentions students have when studying determine learning strategies and learning outcomes in terms of

understanding. According to literature, three different approaches can be identified: deep, surface and strategic (Marton and Saljö, 1976 a y b; Byrne et al., 2010; Ramsden, 1979; Bilgin, 2010).
Students, who adopt the deep approach strategy in order to understand teaching materials, critically interact with given arguments and relate them to prior knowledge, assessing to what extent conclusions may be justified by the evidence presented. Therefore deep approaches may enhance learning retention, transfer, integration and knowledge use, resulting in better quality learning outcomes (Ramsden, 1992). On the other hand, a surface approach strategy is characterized by a lack of the students' personal commitment in the learning process. Students focus on rote-learning without relating concepts. Thus, students adopting surface approach strategies may forget contents in a short time. This strategy brings about a lack of understanding of relevant concepts and low quality learning processes. The strategic approach is oriented to qualification (Biggs, 1987; Bilgin, 2010). In this case, students´ interest relies on test demands. Students use any learning methodology which may increase their academic performance (Watkins, 2000).
Higher education institutions are responsible for developing learning settings enabling deep learning strategies (Kreber, 2003) because they promote sustainable skills (Anderson et al, 2011). If teachers are to find ways of improving their students´ learning experience, they should know how their students learn and the environmental effects on learning approaches. To know how students learn is a requirement to develop strategies to improve learning (Byrne et al, 1999). In this sense, at ICOTS 8 meeting, some Argentine (University of Buenos Aires), Australian (Macquarie University) and Italian (University of Florence) researchers started an intercultural and interdisciplinary project to assess learning strategies adopted by students in Statistics courses at non-mathematical programs (López et al., 2012; Pérez et al., 2012; Bilgin, 2013; Gozlu et al., 2013; López et al., 2013; Primi and Chiesi, 2013; Bilgin et al. 2014). In Argentina, due to the characteristics of the two programs at the University of Buenos Aires analyzed, we were able to obtain information from a cohort of students over time.
The aim of this study is to verify the relationship between the retention of basic statistics concepts and the strategy adopted by the student in two academic programs of the Faculty of Agronomy of the University of Buenos Aires.

The Study

In the context of the multinational education project on learning strategies, we limit our work to two programs of the University of Buenos Aires, the programs of Agricultural Engineering and Environmental Sciences, Faculty of Agronomy. These two academic programs have the first two years in common. Thus, in the second year of their studies students from both programs attend together an Introductory Statistics course (80 hours course). This course covers topics related to descriptive statistics, probability and random variables, sampling distributions, inference for one and two populations, simple linear regression and categorical data analysis. The performance of student is assessed through continuous evaluation (with assignments that are submitted in every class) and two midterm tests (four or five problem-solving exercises). If students gained 70% or above in the midterm tests, then they pass the course, they do not need to sit a separate final exam. This student condition is known as *Promoción* (P). If the performance during the semester falls below 40%, they fail the unit and they are not allowed to sit the final exam. This condition is known as *Libre* (L). Students with intermediate performances –achievement between 40 and 70%- are required to sit a final, integrated examination, which consists of multiple choice questions. These students are said to be in *Regular* condition (R) (Bilgin et al., 2014). Upon completion of the course, the students are assessed. In the fourth year, only students who approved the Introductory Statistics course, share another compulsory advanced course in statistics, (48 hours course). This course extends knowledge to inference for more than two populations, giving basic knowledge of experimental design and linear models (ANOVA for one and two factors, and multiple linear regression analysis). Figure 1 shows the layout of the courses dynamics. At the end of the second year of study, students of Agricultural Engineering and Environmental Sciences are in similar situations facing Statistics. At the time of attending the Introductory Statistics course, students of both programs had shared all previous courses. Programs differ from second year on. In the fourth year, before taking the advance statistics course, most Environmental Sciences students take Environmental Risk Analysis course. In this course, students learn methods to quantitatively describe and communicate environmental risks using the notions of variability, uncertainty, probability distributions, and some other new concepts.

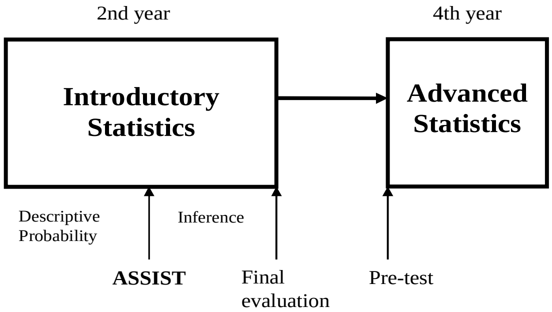

Figure 1: Layout of the course dynamics.

In 2011, during the Introductory Statistics course, students completed the ASSIST questionnaire (Tait et al, 1998) in order to assess their learning strategies after completing Descriptive Statistics and Probability and before Statistical Inference. Two years later, in the Advanced Statistics course, students had to take a seven-item multiple choice test (pre-test) on the first day course to assess basic statistical knowledge (Appendix). One point was given for every correct response, so students could get a total of 0 to 7 points. We were able to relate students' pre-test results with their learning approach scores because students were identified by their national identity document.
ASSIST validation was presented by Perez et al. (2012). Three factors corresponding to the three scales of learning strategies were used. From the confirmatory factor analysis results, scores for the different factors were used to explore variables related to the different strategies (DiStefano et al., 2009).
Homogeneity of results of the two programs was analyzed due to their curriculum differences. The comparison of strategy scores between programs was carried out using Multivariate analysis of variance (MANOVA). Fisher's exact test (Stokes et al., 2000) was used to compare student's performance in the Introductory Statistics course. Comparison of pre-test results between programs was carried out using *t* test. A linear regression model was used to analyze the relationship between pre-test results and strategy adopted by student adjusting by program. Finally, a Biplot from a Principal Component analysis is presented to describe relationships between variables classifying by Introductory Statistics results.

Results

In the Advanced Statistics course, 91 students who had completed ASSIST (31 Environmental Sciences students and 60 Agricultural Engineering students) two years before, also answered the multiple choice pre-test of basic statistical concepts.
No significant differences were found between programs in the factor scores means (Wilk's lambda= 0.98, p-value= 0.5718). Likewise, no differences were detected between programs in the course performance (Table 1).

Table 1: Comparison of student's performance between programs

Introductory Statistics Performance	Program		Total
	Agriculture	Environmental Sciences	
Fail the unit (L)	3 (5%)	1 (3%)	4 (4%)
Final exam required (R)	26 (43%)	13 (42%)	39 (43%)
Pass the unit (P)	31 (52%)	17 (55%)	48 (53%)
Total	60 (100%)	31 (100%)	91 (100%)

Table probability= 0.0698, p-value> 0.999

Two years later, in the Advanced Statistics course, the results of pre-test differed between students of both programs (t test= 4.12, p-value= 0.0001). In general, as shown in Table 2, results of pre-test were poor. Environmental Science students acquired better result, but no student reached seven points.

Table 2: Pre-test results (0 – 7) by program

Program	n	Mean	SD	Min	Max	Median	Q1	Q3
Agriculture Engineering	60	2.35	1.13	0	5	2	2	3
Environmental Sciences	31	3.52	1.52	1	6	4	2	5

A significant linear relation was found between pre-test results and deep strategy adjusting by program (Table 3).

Table 3: Linear regressions between each strategy score and pre-test result adjusting by program

Regression Model	Standarized coefficient	p-value
Surface scores	0.180	0.0719
Program	0.412	<0.0001
Strategic scores	0.117	0.2293
Program	0.397	0.0001
Deep scores	0.227	0.0196
Program	0.431	<0.0001

The differences in pre-test results between both programs can be explained by the characteristics of Environmental Science curriculum. As noted earlier, a great part of students of this program has already taken the Environmental Risk course with an important statistical component. Due to this, we decided to present a biplot for strategy scores and pre-test results only for the Agriculture program with the aim of showing the relationship between the adopted strategy and the retention of basic statistical knowledge (Figure 2).

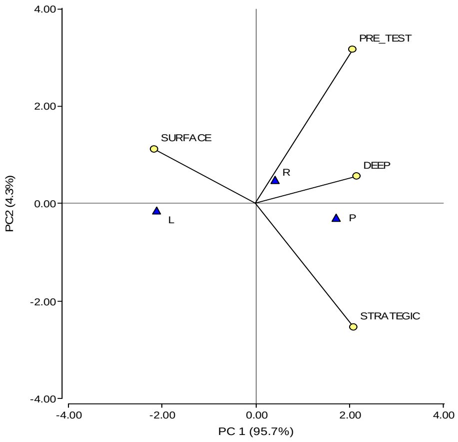

Figure 2: Biplot for strategy scores and pre-test result classifying for Introductory Statistics performance for Agricultural students

The first principal component differentiated the strategic and deep approaches from surface strategy. This component accounted for 95.7% of the variance in the data set. Figure 2 shows that deep and strategic approaches as well as students gaining 70% or above in the midterm (P) are related to higher pre-test results. Conversely, surface strategy appeared highly related to the worse student's performance.

Discussion

Students of two programs at the Faculty of Agronomy showed similar results both in their performance and in the statistical learning strategies in the second year course program which is attended jointly by both student groups. At the end of the second year of study, students of Agriculture Engineering and Environmental Sciences were in similar situations as regards Statistics. At the time of attending the Introductory Statistics course, students of both programs had shared all previous courses. In the two years between the two statistical courses, Introductory and Advanced, the situation was not the same for Agricultural Engineering and Environmental Sciences.

In the fourth year, before taking the Advanced Statistics course, most Environmental Sciences students take the Environmental Risk Analysis course. In this course, students learn methods to quantitatively describe and communicate environmental risks using notions of variability, uncertainty, probability distributions, and some other new concepts. Due to this fact, we considered that Environmental Science students could give us confounding results in the relationship between basic statistical knowledge retention and the strategy adopted.

Students having higher scores in the deep scale were able to get higher scores in basic knowledge test two years later, having better knowledge retention.

Exploratory graphical analysis applied only to Agricultural program, showed a strong relationship between deep and strategic approaches, better performance in Introductory Statistics and higher pre-test results. Conversely, surface strategy appeared related with students who failed the course.

In achieving statistical long term knowledge, it seems that students of Environmental Sciences have been favored in comparison with peers of Agricultural Engineering.

Having started with similar results in terms of the strategies adopted in the Introductory Statistics course, Environmental Science students scored higher on the test two years later. This leads us to think that a possible guideline for achieving better results is the relationship between teachers of different courses that may include some intervention of teachers of Statistics. The challenge is not only to stimulate students interest in Statistics leading to adopt a deep approach strategy but to incentive teachers from other fields to use statistics in different areas to have a learning continuum throughout the different programs.

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APPENDIX

PRE-TEST

ID:________________ When did you take Introductory Statistics course? Year: _______

Introductory Statistics result:
- P
- R
- L

Before coming to class, did you review basic statistical concepts learned in Introductory Statistics ?
- No
- A little
- Deeply

Answer the following questions. There is only one correct response for each question.
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1. Which of the following is NOT a central tendency measure?

a. Median	O	c. Interquartile range	O
b. Mode	O	d. Mean	O

2. Let X be a random continuous variable with expected value μ and variance σ².
2.1 What is μ?

a. The most probable value of X	O	c. Value that leaves half of the values of X below	O
b. The average of all possible realizations of X	O	d. The average of a sample of n realizations of X	O

2.2 What is σ²?

a. The expected value of the squared difference between X and μ	O	c. The expected value of the difference between X and μ	O
b. The average of the squared differences between X and the sample mean	O	d. The sum of the squared differences between the different values of X and μ	O

3. An estimator is a random variable. We say that an estimator is "unbiased" if:

Its variance is minimun	O	The sample mean is equal to the population mean	O
The squared deviations are zero	O	Its expected value is equal to the parameter that it estimates	O

4. In order to generate a confidence interval for a parameter, we need to know

All population data	O	The expected value of the determination coefficient	O
The probability distribution of the parameter estimator	O	The population mean and variance	O

5. Before selecting a sample for hypothesis testing, the probability of rejecting the null hypothesis, which is actually true:

It is unknown	O	It is fixed by the investigator	O
It is equal to 1-α	O	The probability is lower the more data we have	O

6. Consider the pollution of water table in croplands in Santiago del Estero. A student hypothesizes that leaching of nitrates does not vary linearly with soil temperature. To test it, he got a set of data and performed a linear regression analysis. What mistake can he make if he rejects his initial null hypothesis?

Incorrectly rejecting that the expected leaching of nitrates varies with temperature	O	No error, the test is conclusive and significant	O
Incorrectly accepting that the expected leaching of nitrates does not vary with temperature	O	Incorrectly accepting that the expected leaching of nitrates varies with temperature	O

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