INTRODUCING COMPUTER-AGE STATISTICAL METHODOLOGIES THROUGH INTERACTIVE WEB APPS: EXPERIMENTAL EVIDENCE FROM A FILIPINO CLASSROOM

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Novel computational methods of statistics have largely relied on algorithmic approaches and high-level abstractions that students below the graduate level may struggle to grasp. Following successful implementations of teaching complex statistics through interactive applications, we develop one for motivating and exploring the popular K-Means Clustering Algorithm. This paper presents the results of an experiment in a Philippine secondary school classroom. Comparing between-group improvements in their performance on a short test reveals only weak evidence that an interactive approach might work better than a static one. However, within-group performance shows students understood the assigned topic significantly better after using the web app. Feedback collected from the students also show that students found the interactive version more helpful than a standard module with static visuals.

INTRODUCTION

The following paper is our addition towards a growing body of literature on the advantages and potential challenges of using interactive web apps in the classroom. In the past two decades alone, there have been a significant number of contributions towards this end (see for instance, Forbes et al., 2018 and Demirhan et al., 2018, both contributions to ICOTS10). Rossman and Chance (2004, para. 1) aptly observed this as a "reform movement" in statistics education.

The advent of powerful and accessible computing in the twenty-first century has ushered in new possibilities for the field of statistics. However, this has led to stagnancy in terms of students' learning of concepts and theory at the secondary and tertiary levels. Although great strides have been made within fields such as Bayesian Inference and Nonparametric Modeling, students are left stranded with "Stat 101" types of materials, most of which now hardly even count towards the actual statistical rigor called for in practice (Tintle et al., 2013).

Demirhan et al. (2018) gave a successful demonstration of teaching Bayesian statistics through interactive web apps. Not only have these web apps been proven useful in the classroom setting, but their effectiveness for self-teaching may also be invaluable considering recent challenges brought by the COVID-19 pandemic. As schools and universities around the world begin to explore hybrid learning setups in preparation for similarly disruptive phenomena (Skulmowski & Rey, 2020), active learning approaches such as this may soon become part and parcel of standard curricula around the world.

The present paper demonstrates the potential usefulness of adopting interactive web applications as a means of presenting modern methods and use-cases in statistics and data science. We choose, specifically, to teach the K-Means Clustering Algorithm in a limited case study. The potential gains of this interactive approach is measured empirically through an experimental test in a Filipino classroom of secondary-level students. The subsequent section goes into more detail regarding the design of the material, followed by a brief presentation of the results of the experiment. We also dedicate a penultimate section after this to discuss the students' feedback regarding their experience of learning from using the web application.

DESIGNING THE MATERIAL

A web app that includes a modular introduction and demonstration of Lloyd's Algorithm for K-Means Clustering was designed for this study. In consideration of the students' level of foundational knowledge in geometry and statistics, the module focuses more on providing a conceptual understanding of the algorithm, primarily through visualizations, leaving behind much of the mathematical justification and theory.

For instance, on the subject of initializing the algorithm using a random assignment of centroid coordinates, Figure 1 shows how a typical (static) module might show graphs with different locations for the centroids with accompanying text. Our interactive version, in Figure 2, replaces the static graphs

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with a single applet, allowing the student to experiment with different starting locations of the centroids, and visualizing how each observation in the data changes membership accordingly.

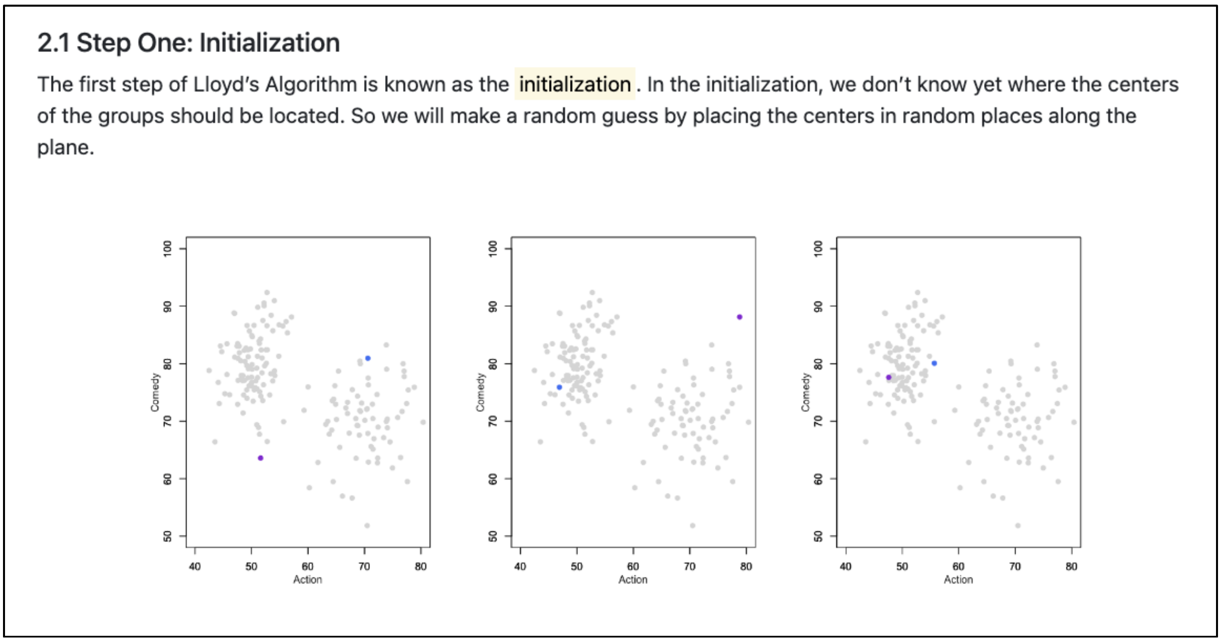

Figure 1. A sample screenshot of the web app, following a more conventional style of presentation

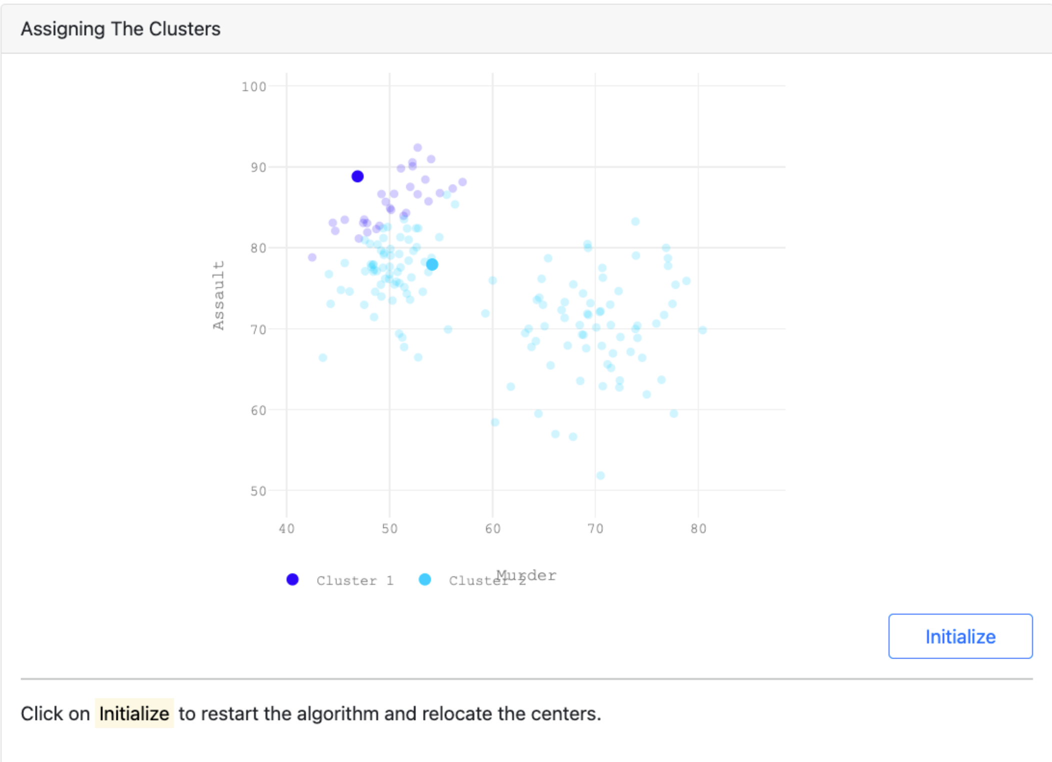

Figure 2. A sample screenshot of the same web app, making use of interactive visualizations

To aid comparison between how students performed in each type of module design, we created two analogous modules carrying mostly the same material and structure, with the only difference being whether the module takes on a more static (such as the approach displayed in Figure 1) or interactive (Figure 2) approach. In subsequent discussions, we refer to the students assigned to the static material as the control group and those assigned to the interactive material as the treatment group. The website produced a simple randomized block design described in Montgomery (2013).

A pilot study was conducted on a classroom of 11th grade students at the Tandang Sora Integrated School in Caloocan City. Before either group of students began the module, a fifteen-item pre-test was administered (also through the website) to gauge any prior knowledge they might have regarding the topic. A post-test of similar length and coverage was administered at the end, and afterwards their feedback on the web app was collected through another online form. Because the web app was designed only to cover one topic, the total duration spanned by the field work was quite short: students were oriented with the web app in one day and completed three modular activities, plus the pre-test, post-test, and student feedback within two school weeks.

Code for the applet may be found on Github (https://github.com/dominicdayta/kmeans-learn).

RESULTS OF EVALUATIONS

Of 20 students slated to participate in the study, 19 were able to successfully access and complete the modules. Figure 3 visualizes the results within each group in a series of boxplots, comparing their performance based on scores on the overall test (left), on the algorithmic subset of questions (middle), and on the definitional subset of questions (right). It can be seen from these plots that the Treatment group saw improvements in terms of higher average scores and narrower variability between the pre-test and the post-test. Improvement in scores were also observed in the Control group, but at wider spreads than their peers in the Treatment group.

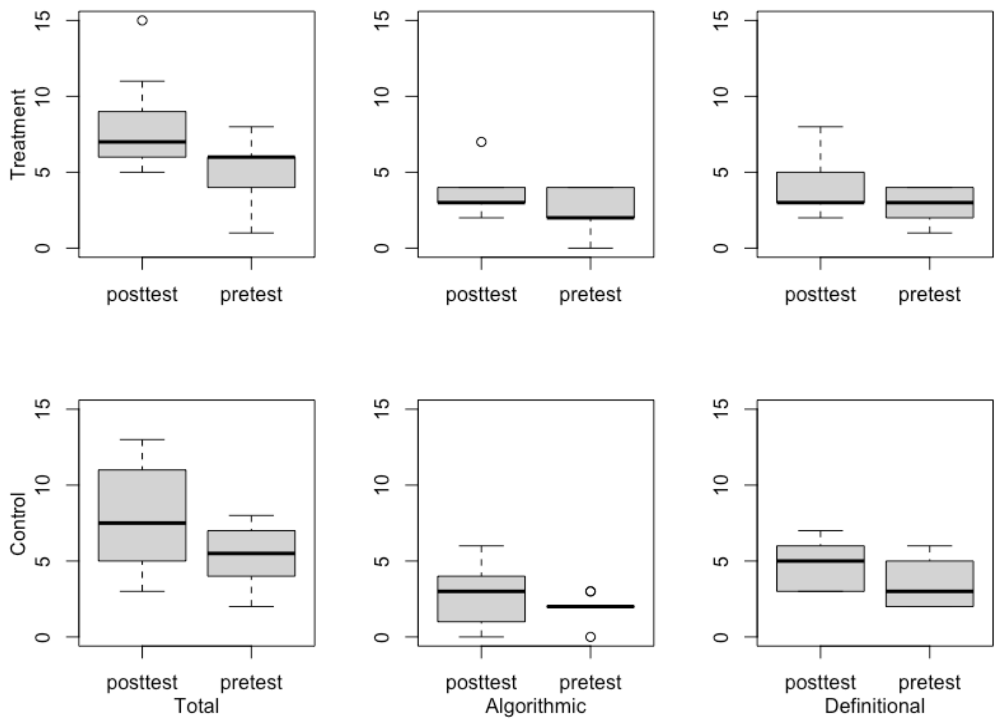

Figure 3. Boxplots of within-group performances in the post-test and pretest; vertical axis scale indicates scores on equivalent fifteen-item pre-test and post-tests

Using a paired t-test within the Control group, the change in overall test scores from the pre-test average of 5.5 to the post-test average of 7.8 can only be concluded as significant in a borderline case ($t(9) = 1.769$, $p = 0.1106$). Improvement within the Control group, however, was much more conclusive, moving from a pre-test average of 5.2 to a post-test average of 7.9 ($t(8) = 2.177$, $p = 0.06112$). We note that the post-test average in the Treatment group is not too far from the post-test average in the Control group, and for this reason a corresponding independent samples t-test fails to return a significant result ($t(16.748) = 0.059$, $p = 0.9536$). Modeling post-test scores against groups with pre-test performance as covariate in an ANCOVA model returns similarly inconclusive results (MSE for groups at 0.037 against 11.374 for residuals, $p = 0.955$).

Analysis on the experimental data reveals little evidence to conclude that students in the Treatment group improved more on their post-test scores. However, it remains evident both from these test results and the boxplots in Figure 3 that the improvement in the Treatment group is best observed in score improvement at a lower spread.

FEEDBACK FROM STUDENTS

Although results from the experimental data leave much to be desired, the students' feedback towards the materials gives us an idea of where the benefit of the interactive web app lies. These responses are summarized in Table 1. Asked to rate (in an ascending scale) their level of understanding of the overall lesson presented in the modules, 20% of the students in the Treatment group and 20% in the Control group reported the highest rating in the scale. However, when asked to rate the usefulness of the visualizations towards their progress with the material, only 20% of the students in the Control group gave the highest rating. On the other hand, 80% of the students in the Treatment group reported the highest rating.

Table 1. Cross-tabulations of responses from the Treatment and Control groups in the feedback form. Ratings are generally 1 = Lowest to 4 = Highest

	Understanding, %		Usefulness, %		Appropriateness, %	
	Treatment (n = 9)	*Control (n = 10)*	*Treatment (n = 9)*	*Control (n = 10)*	*Treatment (n= 9)*	*Control (n = 10)*
4	20	20	80	20	50	40
3	40	50	20	80	30	60
2	40	30	0	0	10	0
1	0	0	0	0	10	0

CONCLUSION

We have demonstrated that web app use has improved the variability at which a classroom progresses in a lesson by fostering an engaging and active learning environment. We have shown that the highly technical nature of modern statistics and data science may not necessarily be a hindrance towards student understanding so long as they are communicated and visualized in a manner that invite student exploration and interaction.

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