Active Learning in Electrical Engineering: Measuring the Difference

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Abstract

Engineering Electromagnetics is a challenging junior-level course containing many concepts and formulae, and is a core course in many Electrical Engineering programs. A traditional way to teach this class is via direct instruction, i.e., didactic lecture. The instructor often introduces the concepts and then works examples for the students. While the process of working examples may be helpful to some students, at Texas State University the question arose as to whether or not actively engaging the students would improve their understanding of the material. To address this hypothesis, raw exam scores were examined for a total of four semesters. In the first two semesters of the study only direct instruction was used. The next two semesters used active learning with direct instruction for the first half of the class period, working no examples, and then had students collaboratively solve examples and problems for the second half of the class. Students were strongly encouraged to work together in teams and to discuss the material while the instructor circulated to give guided practice. Solutions became visible 15 minutes before the end of the class period via the learning management system so that students could check their level of understanding. These in-class exercises, in the form of worksheets, were worth one and one-half letter grades. Pre and post course instructional style student knowledge was measured by comparing normalized raw scores on four exams for each semester consisting of three exams and a final. Each exam covered the same topics, for example, the first exam was concerned with transmission lines, the second exam tested for knowledge of electrostatics and magnetostatics, and so forth. While the exams differed from semester to semester by changing values, boundary conditions, or solving for a particular variable, the exams were substantially similar in content, number of questions, and number of concepts tested. While student grades were determined by scaling the exam scores, the extent of their content mastery for purposes of this analysis was performed by comparing normalized raw scores. Subsequent analysis revealed that there was an improvement both in mean raw score and in standard deviation of score. For example, the mean exam raw score before active learning was 55.9% with a standard deviation of 18.6% (62 students) vs. a mean of 66.6% with a standard deviation of 17.6% (62 students) after active learning was implemented. The p-value was <.001 indicating better than 99% confidence. While the standard deviation improved by 1%, the mean increased from 55.9% to 66.6% which is an entire letter grade.

Introduction and Background

Traditional instruction by lecturing in the classroom has been the dominant role in University education for over a millennium [1]. Changes to the instructional method should be considered in order to improve the engineering classroom learning experience. Active learning is an approach developed to improve student learning outcomes, and typically consists of techniques requiring students (as the name implies) to be actively engaged in learning through specially designed activities, followed by reflection upon, often in groups, what they have done [2].

There is considerable literature that addresses the advantages of using hands-on experiences in engineering and STEM curricula [3]-[8]. While Active learning has been shown to increase student performance in STEM classes [9], many still do not implement active learning in the classroom.

Collaborative learning is one form of active learning that can be implemented in the classroom and it has been practiced and studied since the early 1900s. The principles are based on the theories of Bloom's taxonomies, Vygotskian perspectives, Dewey's Hands-on learning [10]-[12]. Their efforts resulted in a focus on student-centered learning.

Can a relatively simple change from a class comprised of all lecture to one with the class period split between lecture and collaboratively solving problems in a group, be sufficient to see gains in student learning, as have other implementations of active learning? This study is an application of active learning through collaborative learning between students in a junior-level electrical engineering course, Engineering Electromagnetics.

Engineering Electromagnetics Course

Electrical engineering undergraduate students typically must complete a Physics course on electricity and magnetism, and many universities additionally require a course in engineering electromagnetics. At Texas State University this course provides a review of the physics of electricity and magnetism then proceeds to emphasize the engineering aspects and applications of electromagnetics for the remainder of the semester. The application of electromagnetics and its impact upon modern society is stressed to students by comparing their current society connectivity and conveniences to the mid-1850's.

As currently taught, this electromagnetics course consists of four modules, each with an associated free-response examination:

1. Transmission lines and matching, and transient effects (6 class periods)
2. A review of electrostatics and electromagnetics (5 class periods)
3. Maxwell's equations, propagation, transmission, reflection and refraction (7 class periods)
4. Waveguides, antennas, satellites, communication links and radar (6 class periods)

Accordingly, the first module is assessed in Exam 1, the second module in Exam 2, the third module in Exam 3, and the fourth module in the Final Exam.

This class met a total of 27 times per semester, and consisted of an 80 minute lecture in which the instructor worked three to five examples. Homework problems were assigned from the textbook, which has remained the same through the eight times in which this instructor has taught this class. The class also included two Python programming assignments. The first was to calculate the input impedance of a transmission line versus distance and the second to calculate the propagation parameters of various materials at a given frequency.

Experiment

After teaching this course for three times, the instructor began to wonder if working examples for the class was perceived by the students as another component of the lecture, i.e., direct instruction, and not active learning. Subsequent reflection showed that the instructor was spending approximately 35 minutes working examples out of the 80 minute class period.

For the next two semesters the lecture component was shortened to 45 minutes after which an in-class worksheet was passed out and students were directed to work collaboratively for the remainder of the class time. Students were not permitted to work by themselves during the active learning period. These worksheets contained most of the examples that the instructor previously used to work for the class. In the remaining 35 minutes of class, the instructor circulated about the classroom offering guided practice in the form of clarification or gentle hints - but did not work the problems.

A total of 24 worksheets were created, one for each lecture. Worksheets were graded as credit / no credit, with credit being awarded if the student put forth reasonable effort. These in-class worksheets were implemented for two long semesters, 15 weeks in calendar duration with a total of 14 weeks of instruction. The electromagnetics class during these semesters had identical schedules, meeting twice per week at the same time of day and on the same days of the week.

A statistical comparison was made between classes conducted in 2017 vs. 2018. The Spring 2017 and Fall 2017 semesters consisted of 80 minute lectures with no active learning. The Spring 2018 and Fall 2018 semesters consisted of 45 minute lectures followed with 35 minutes of collaborative active learning.

After these four semesters were completed the authors had two, 2-semester data sets: two semesters of 80 minute lectures that included working example problems and with no in-class exercises with a total of 62 students, and two semesters of 45 minute lectures where no example problems were worked and with 35 minute in class exercises, with a total of 62 students.

The question to be answered was: even though the students were receiving less instruction, and example problems were not being worked for them, was the active learning associated with the in-class exercises increasing their retention and mastery of the concepts? Exam scores were selected as the metric for analysis and the hypothesis was that average exam scores should improve after the implementation of active learning.

The types of problems on exams changed very little from one semester to the next, being very similar both in terms of number of problems, concepts, and point values. However, the specifics of the problem were varied, or, problems were inverted. It is relatively easy to vary the problems in this course while leaving the solution techniques unchanged. For example, in a typical free-response problem,

- In Module 1, the load impedance may be changed in the Smith Chart problem. This changes the load admittance, standing wave ratio, reflection coefficient magnitude and phase, distance in wavelengths to the first voltage minimum, and so forth.

- In Module 2, the observation point, and the polarity, magnitude, and location of point charges may be changed for a Coulomb's Law problem. This changes all the associated vectors and the resulting electric field vector as calculated for the observation point.
- In Module 3, the conductivities, relative permittivities, relative permeabilities and angle of incidence at an interface may be changed for a problem concerning reflection and transmission. This changes the reflected power, angle of refraction, wavelength in the materials, propagation velocity, attenuation constant, wavenumber, and so forth.
- In Module 4, antenna gain or directivity, transmitting power or required received power, distance, and operating frequency may be changed when applying the Friis transmission equation. This changes the received power or required transmitting power, or sets an upper limit on distance, or a required gain for the antenna system, and so forth.

As the examples above have illustrated, exams can be very similar in content and point value while containing problems for which the solutions cannot be memorized. Students must know the concepts and process to solve the problems.

Exam problems were assigned point values based upon the amount of work needed for the given problem. For example, identifying the direction of propagation given the time-domain wave equation was worth one point, whereas calculating the electric field vector from multiple point charges in a Coulomb's Law problem was worth 15 points. In all instances, an equation sheet was included with the exam, and the equation sheets were identical for exams given before and after the incorporation of active learning. No graphing or alpha-numeric calculators were permitted at any time and only simple calculators were allowed. Students had to manually do algebra, Calculus-III, cross-products, and other math operations.

All exams were constructed response and were graded with error carry-forward methods. For example, standing wave ratio may be calculated from the reflection coefficient. If the student incorrectly calculated the reflection coefficient, points were deducted commensurate with the nature of their error. Dropping a negative sign or incorrectly copying a number resulted in a loss of one point. Greater errors, such as incorrectly applying the formula for reflection coefficient, resulted in a loss of more points. However, if the student correctly applied the incorrect reflection coefficient to determine a standing wave ratio, he or she received full credit for the standing wave ratio section of the problem.

The raw point scores for every student on all exams was recorded by the instructor. For purposes of assigning grades, a scale based upon the distribution of scores was applied to each exam. Only raw scores are considered for this analysis.

Each exam raw score was normalized to be out of 100% and these values were taken to be the student scores for purposes of analysis. For example, in Spring 2017, Exam 3 had a total of 81 points possible. The highest score that semester for Exam 3 was 70 points corresponding to 70/81 or a normalized score of 86.4%. For this analysis, each score on every exam was normalized in this fashion. If a student did not take the exam no entry was considered, as opposed to recording the zero entered in to the course grade book, as a zero does not reflect the student's performance on the exam.

Preliminary Results

Two analyses were performed and tested for statistical significance. In the first analysis, all normalized raw exam scores before and after active learning was incorporated were aggregated and compared. This was a total of 8 exams, as there were 4 exams each semester. The same was done for the two semesters after active learning was incorporated comprising an aggregation of 8 exams. There was a total of 124 students in this study, 62 student scores considered before active learning was implemented and 62 students afterwards.

Results from Aggregated Data

The aggregated data consisted of using normalized raw scores from all four exams from two semesters, from a total of 124 students, to compare pre-active learning scores to post-active learning scores. Results were interpreted from both statistical data and visual plots.

The statistical data for comparison of the aggregated data are presented in Table 1. The normalized mean raw exam scores increased by about one letter grade, from 55.93% before active learning to 66.64% after active learning. The standard deviation decreased by 1%. The t-test on the aggregated data yielded a p-value of 1.243×10^{-10} which indicates better than 99% confidence that a difference exists between the data sets.

Table 1: Statistical Results of Aggregated Data		
Parameter	**Pre-Active Learning**	**Post-Active Learning**
Normalized Raw Exam Score Mean	55.93%	66.64%
Standard Deviation	18.59%	17.59%
p-value	1.243×10^{-10}	

Two different types of plots were created to illustrate differences between pre-active learning and post-active learning. The first type of plots were histograms with bins that were approximately 7.7% wide. The second plot type was a kernel density estimation calculated in Python to smooth the distribution. The bandwidth was set by using Scott's Rule, which is a feature in Python's statistical analysis capabilities.

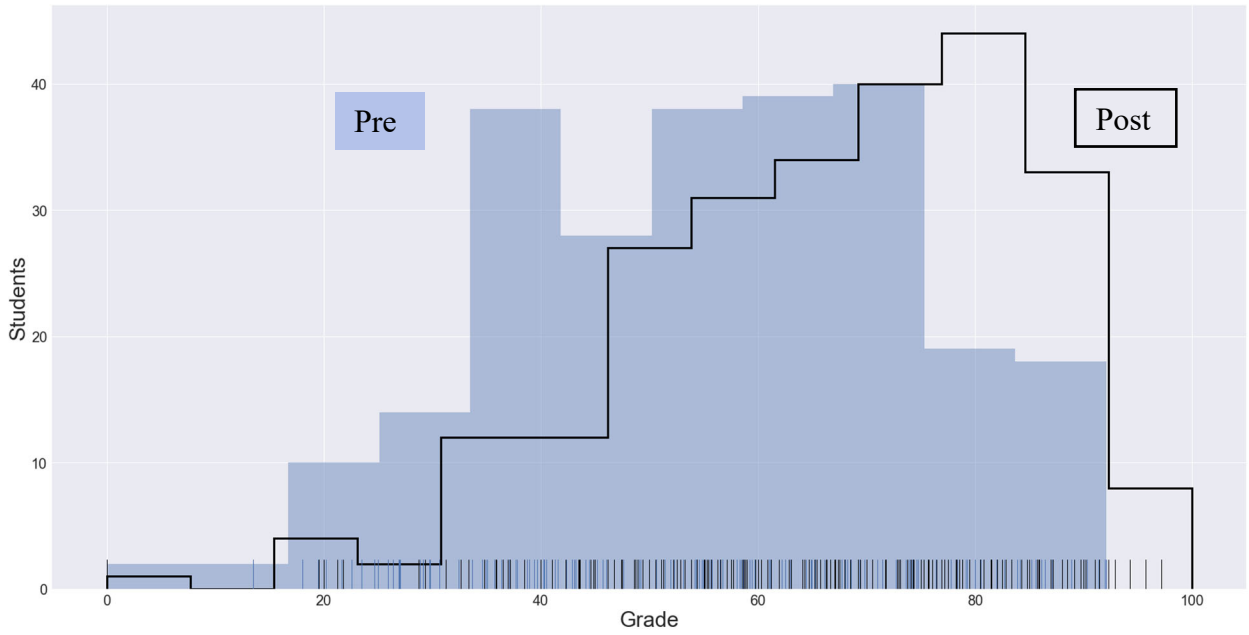

Figure 1: Histogram plot of aggregated exam scores, with eight exams of pre-active learning and eight exams of post-active learning. Number of students in each group was 62 for a total of 124 students in the study. The solid blue is the frequency plot for the pre-active learning group, and the solid outline is for the post-active learning group. The trend towards higher raw exam scores is seen by the outline plot shift to the right.

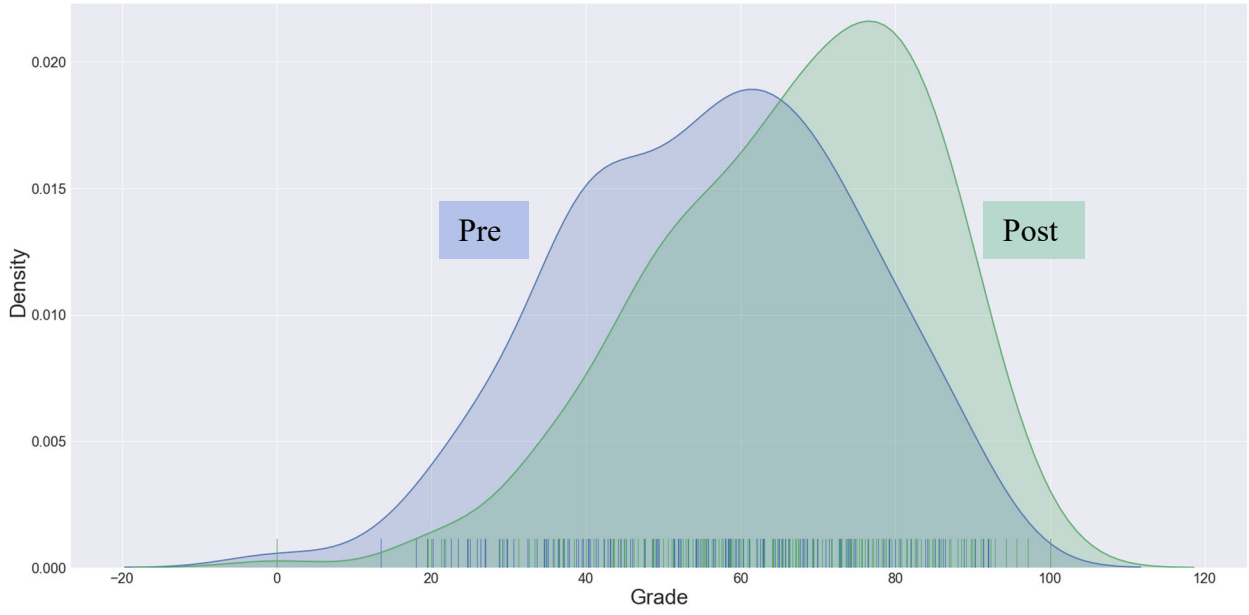

Figure 2: Kernel density estimation plot of aggregated exam scores, with eight exams pre-active learning and eight exams post-active learning. Number of students in each group was 62. The solid blue is the frequency plot for the pre-active learning group, and the solid green is for the post-active learning group. The trend towards higher raw exam scores may be seen by the shift in score distribution to the right.

Results From Comparison of Individual Exams

In the preceding section, normalized raw exam scores from all four semester examinations were combined to compare student performance of two semesters without active learning to two semesters with active learning. In this analysis a similar comparison is made but between each of the four exams. In each case, the normalized raw exam scores for a given exam were combined in order to compare pre- to post-active learning student performance.

The statistical data are presented in Table 2. As before there are 62 students in the Pre group and 62 students in the Post group, for a total of 124 students in the study. Analysis shows that the mean normalized raw exam score improved for all but the first exam. Exam 1 showed the least improvement and also had a p-value of 0.490 which indicates low confidence that a difference exists between the data set. Analysis of the other three exams shows a marked improvement of approximately 13% - a bit more than one letter grade - with p-values indicating greater than 99% confidence that a difference exists in the data sets.

Table 2:Statistical Results of Individual Exam Performance

	Exam 1		**Exam 2**		**Exam 3**		**Exam 4**	
	Pre	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
Normalized Raw Exam Score Mean	63.77%	66.19%	52.36%	66.83%	59.37%	72.10%	48.11%	61.43%
Standard Deviation	19.23%	17.56%	15.22%	16.84%	16.08%	15.60%	19.33%	18.58%
p-value	0.490		2.144×10^{-6}		2.001×10^{-5}		1.706×10^{-4}	

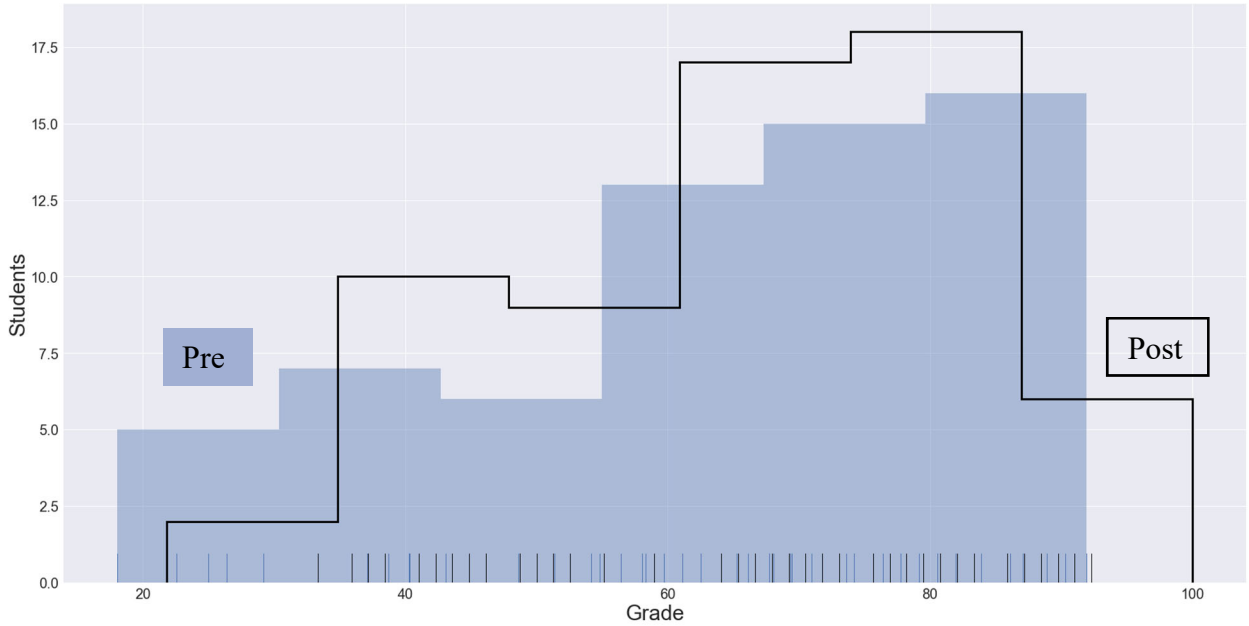

Figure 3: Histogram plot of Exam 1 scores, with two semesters pre-active learning and two semesters post-active learning. Number of students in each group was 62. The solid blue is the frequency plot for the pre-active learning group, and the outline is for the post-active learning group. Any improvement is not clearly visible in this plot and this is supported by the statistical analysis captured in Table 2, where the difference in mean score is small and the p-value is large at 0.490.

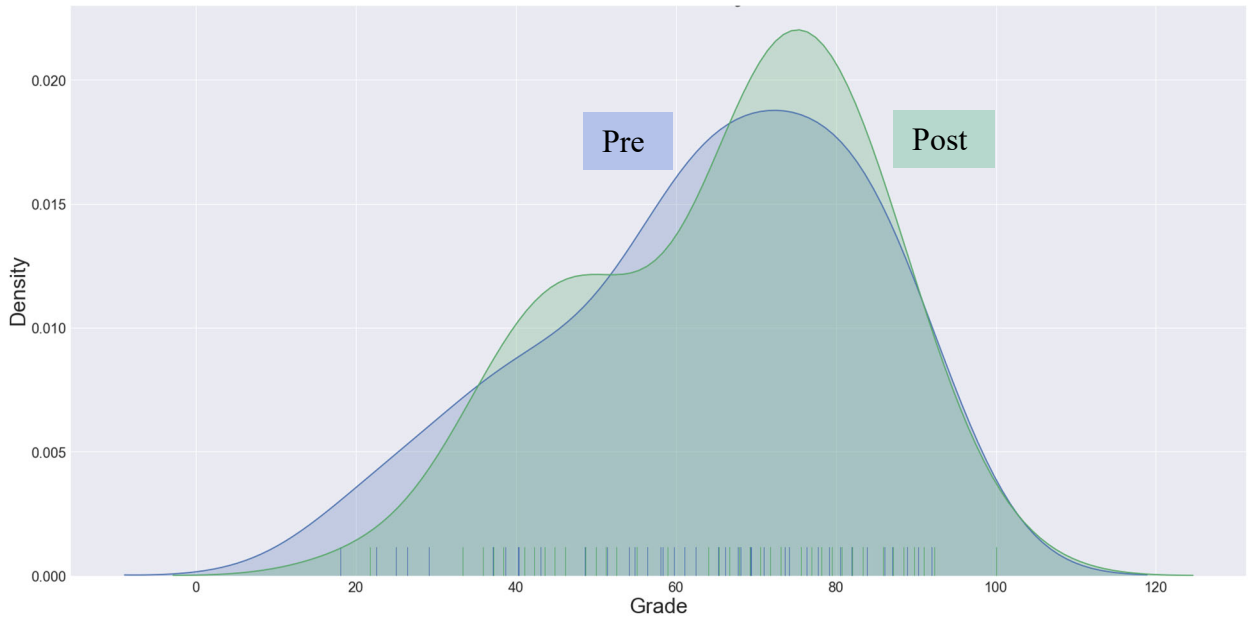

Figure 4: Kernel density estimation plot of Exam 1 scores, with two semesters pre-active learning and two semesters post-active learning. Number of students in each group was 62. The solid blue represents the kernel density estimation of the pre-active learning group, and the solid green the post-active learning group. As with the histogram of Exam 1 shown in Figure 3, a distinct improvement is not visible nor is one supported by the p-value.

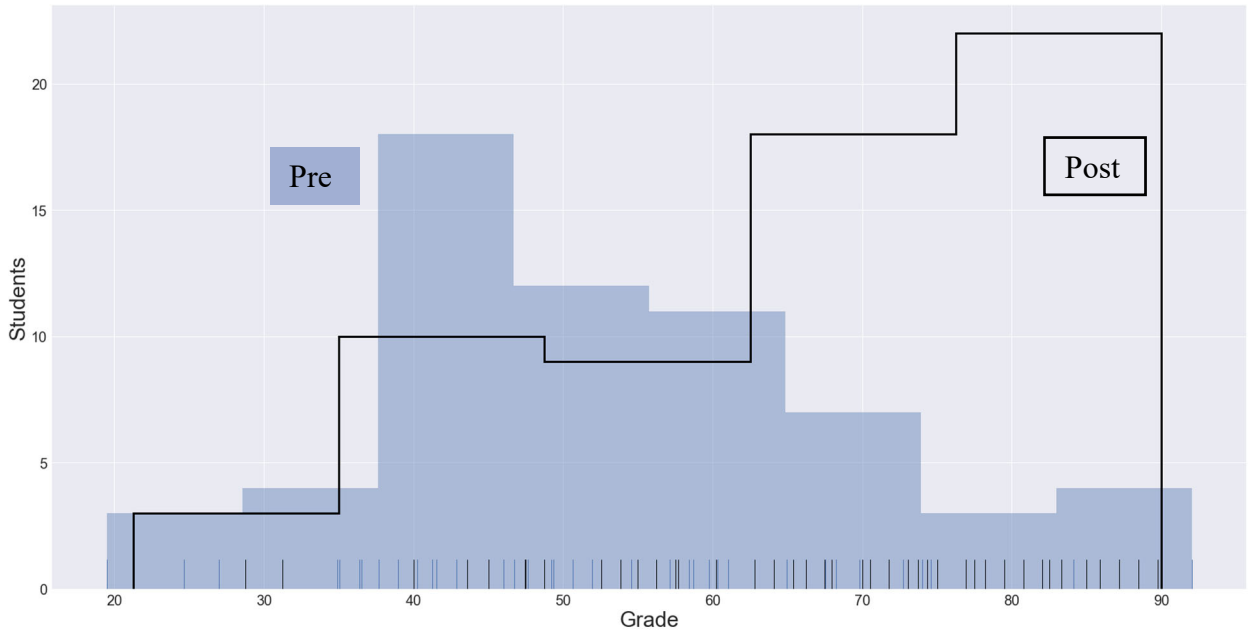

Figure 5: Histogram plot of Exam 2 scores, with two semesters pre-active learning and two semesters post-active learning. Number of students in each group was 62. The solid blue is the frequency plot for the pre-active learning group, and the outline is for the post-active learning group. The trend towards higher raw exam scores may be seen by the outline plot shift to the right.

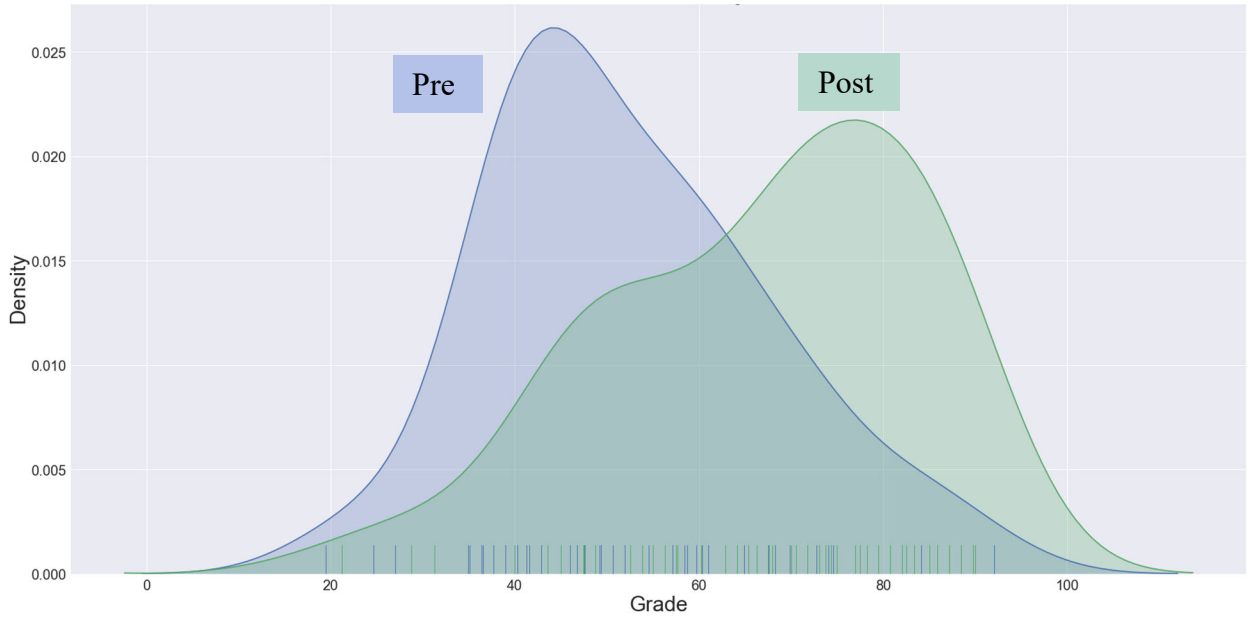

Figure 6: Kernel density estimation plot of Exam 2 scores, with two semesters pre-active learning and two semesters post-active learning. Number of students in each group was 62. The solid blue represents the kernel density estimation of the pre-active learning group, and the solid green the post-active learning group. As with the histogram of Exam 2 shown in Figure 5, a distinct improvement in scores is in evidence. The mean increased from 52.36% to 66.83% with a p-value of 2.144×10^{-6}, indicating high confidence in the validity of the comparison.

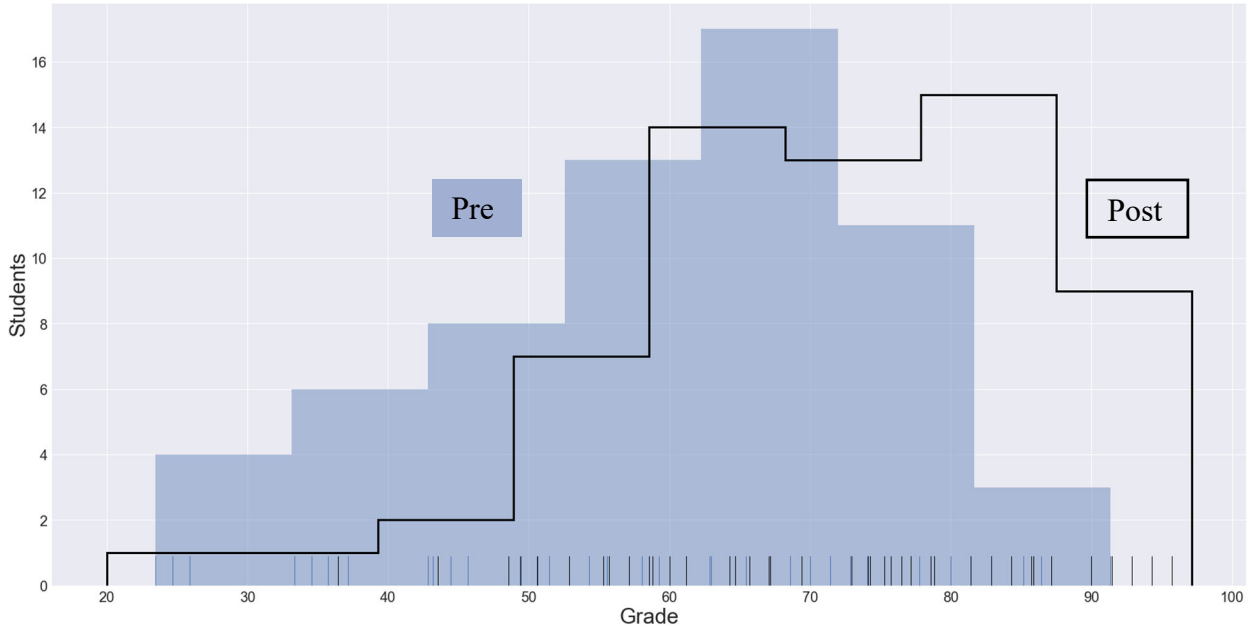

Figure 7: Histogram plot of Exam 3 scores, with two semesters pre-active learning and two semesters post-active learning. Number of students in each group was 62. The solid blue is the frequency plot for the pre-active learning group, and the outline is for the post-active learning group. The trend towards higher raw exam scores may be seen by the outline plot shift to the right.

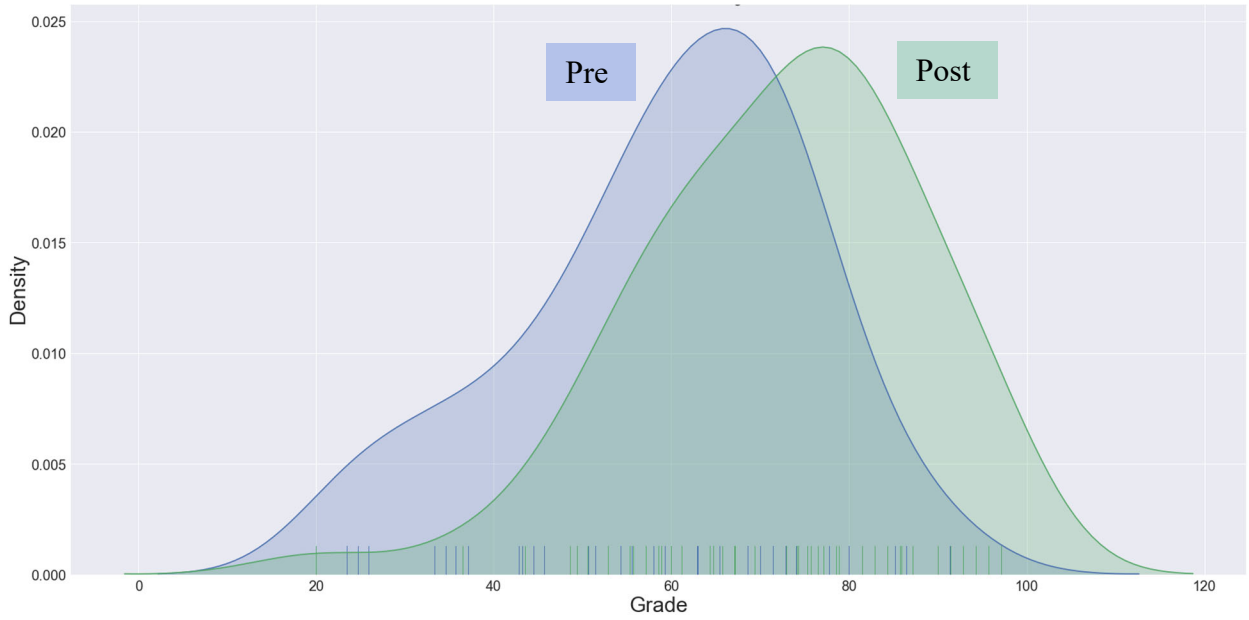

Figure 8: Kernel density estimation plot of Exam 3 scores, with two semesters of pre-active learning and two semesters of post-active learning. Number of students in each group was 62. The solid blue represents the kernel density estimation of the pre-active learning group, and the solid green the post-active learning group. As with the histogram of Exam 3 shown in Figure 7, an improvement in scores is evident by the shift of the post-active learning scores towards higher values. The mean increased from 59.37% to 72.10% with a p-value of 2.001×10^{-5}, indicating high confidence in the validity of the comparison.

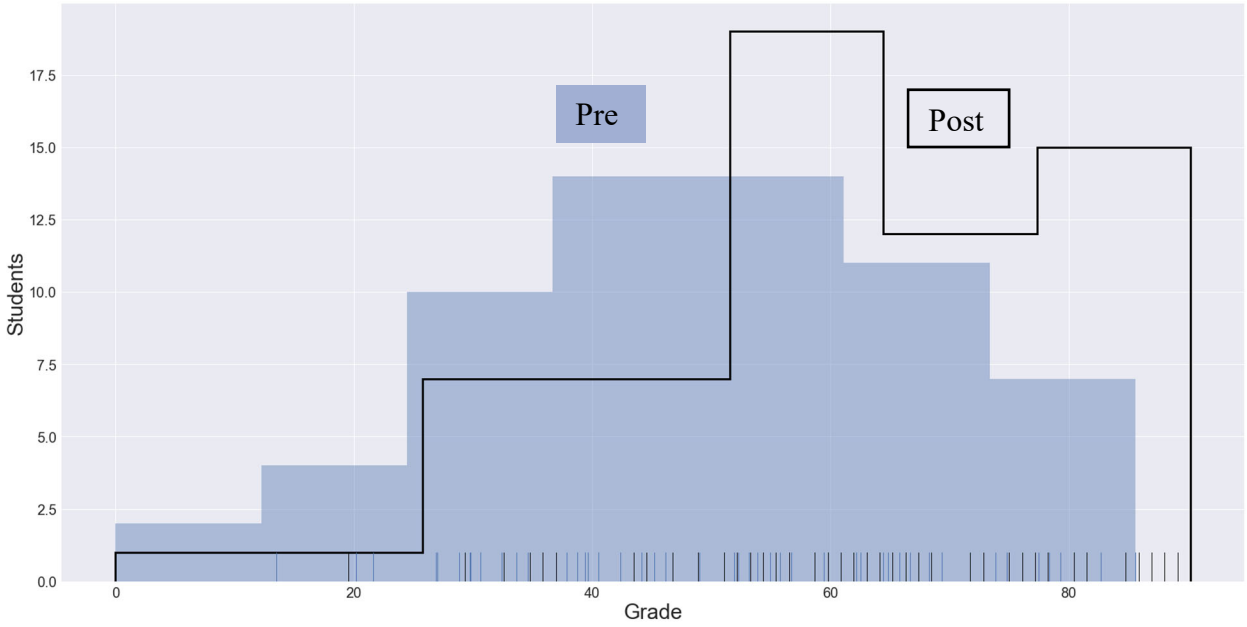

Figure 9: Histogram plot of Exam 4 scores, with two semesters pre-active learning and two semesters post-active learning. Number of students in each group was 62. The solid blue is the frequency plot for the pre-active learning group, and the outline is for the post-active learning group.

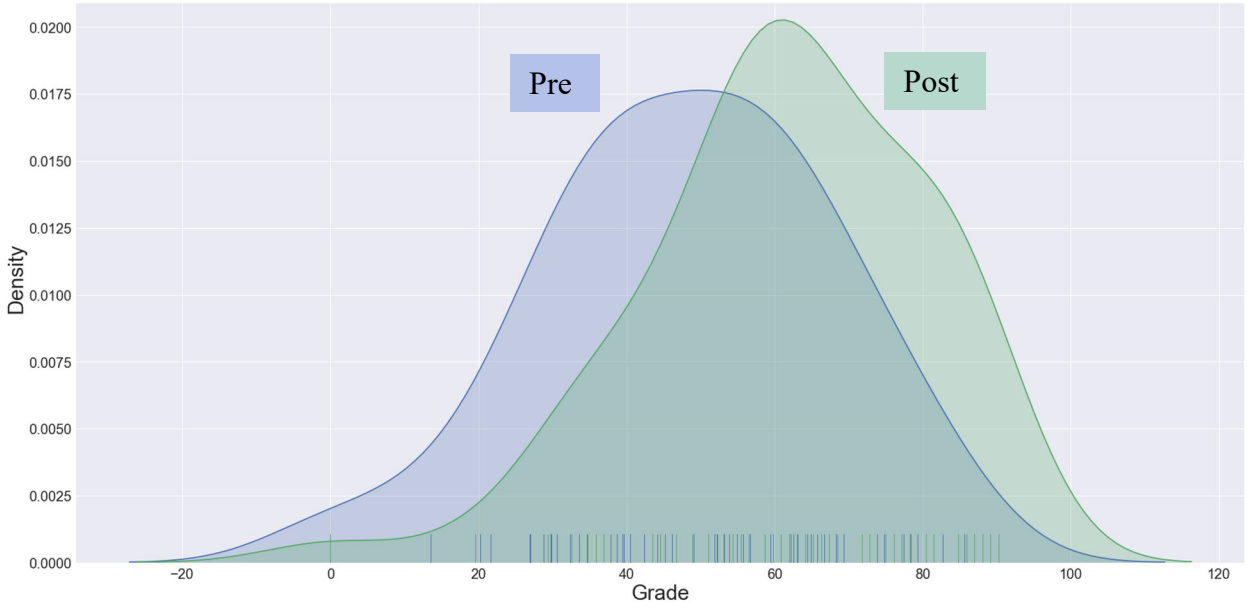

Figure 10: Kernel density estimation plot of Exam 4 scores, with two semesters of pre-active learning and two semesters of post-active learning. Number of students in each group was 62. The solid blue represents the kernel density estimation of the pre-active learning group, and the solid green the post-active learning group. As with the histogram of Exam 4 shown in Figure 9, an improvement in scores is evident by the shift of the post-active learning scores towards higher values. The mean increased from 48.11% to 61.43% with a p-value of 1.706×10^{-4}, indicating high confidence in the validity of the comparison.

Lessons Learned and Conclusions

Results of the statistical analysis support the conclusion that an improvement in normalized raw exam scores and standard deviation occurred when the class was structured to incorporate active learning. These results are supported for the aggregated data and for three of the four exams. The first exam did not show a statistically significant difference in student performance. At this time it is unknown as to why no improvement was seen on Exam 1. It may be possible that since it is the first exam and it is administered relatively early in the class (week 4), the students are not quite sure what to expect from the instructor with regards to assessment.

Exam 2 has traditionally produced the lowest scores of all four exams, as it is a review of Electricity & Magnetism, i.e., Physics-II, and it is more theory-based than applied. Mean scores improved by 14.5% - nearly one and one-half letter grades - although the standard deviation increased by about 1.5%. This improvement alone had a significant impact on semester grades when compared to previous semesters.

In order to determine if raw exam score improvement might have been due to an increased diligence in student homework, aggregated scores were analyzed. During the course of this study, thirteen problem sets were assigned each semester, consisting of one set per week excluding breaks. The number of problem sets, and number of total problems, remained the same in each of the four semesters analyzed for this study.

Table 3: Comparison of Average Homework Scores

	Aggregate Homework Score Averages
Pre-Active Learning	79.34%
Post-Active Learning	71.53%

This data shows that on average students scored lower on their homework during the semesters when active learning was incorporated. Examination of the scores revealed that the lower average score of 71.53% was due to an increased percentage of students not submitting homework assignments. No further statistical analysis was performed since the data did not suggest that exam scores had improved in the post-active learning semesters due to increased focus on homework. The course instructor had other observations that are not quantifiable but are worth mentioning. An increase in student learning and energy level was observed once the class realized that lectures would only be 45 minutes in duration, and that students would be free to talk with each other for the remaining 35 minutes. A natural rhythm developed, consisting of more focused student focus during the lecture period followed by hard work and focus during the active learning exercises.

The course instructor also interacted more with the students in the process of circulating about to check progress and answering questions. This seemed to improve the teacher-student relationship, which has been shown to improve learning outcomes [13].

It was also considered that raw exam scores may have improved during the post-active learning semesters due to the availability of a greater number of old examinations. Each semester a set of

old exams was posted in the learning management system as a study aid. While it is true that the set of old exams grew larger with time, it is worth noting that the structure and length of the exams did not change. As noted in the **Experiment** section, subtle changes in impedances, structure alignment with coordinate systems, and other parameters can dramatically change the numerical results of the exam problems.

Other factors may have contributed to an improvement in test scores after active learning was implemented:

- Since the lecture was decreased from 80 minutes to 45 minutes, students may have been less fatigued and thus better able to focus on example problems.
- During the active learning period students worked at their own pace rather than tracking the pace of the lecture. It is possible that this altered pace reached more learners.
- During the active learning period students discussed the problems with each other. It is possible that stronger students mentored weaker students, and by speaking their language (more so than the instructor who is older), and in a manner perhaps less intimidating than their instructor, they were able to better clarify or explain the examples.
- Since more interaction and communication occurred between instructor and student during periods of active learning, it may be possible that this enhanced communication homogenizes the knowledge and skill sets of the students.
- It is possible that students who had very poor performance were more positively affected than higher-performing students, giving rise to a greater increase of the overall metric.
- A different classroom was used each of the four semesters, varying from a teaching lab that seated 24 to a lecture room that seated 50 to an amphitheatre that seated 100.
- A difference in the cohorts may have existed. Course preparation, GPA, physics and math proficiency, and other academic factors were not considered for purposes of this analysis.
- The in-class worksheets may have improved attendance which could have had a positive effect.

Statistical analysis supports that an improvement in student performance was seen regardless of the underlying causes. As a result of this improvement, which was visible to the course instructor in the very first semester of active learning through the incorporation of collaborative learning, the instructor has modified all assigned content-based courses to follow this same pattern. This has included Electronics-I, Signals & Systems, and Linear Control Systems. Active learning through collaborative learning was incorporated in these three courses the first time they were taught so there is no pre- vs. post- data for purposes of further analysis.

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