Board 79: Leveraging Learning Styles for Enhanced Student Outcomes: A Study at a New York University

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Leveraging Learning Styles for Enhanced Student Outcomes at USMA

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Abstract

In an era where personalized learning methodologies are increasingly recognized as pivotal in enhancing educational outcomes, our research delves into the realm of student-teacher dynamics through the lens of learning styles, as evaluated by the Silverman-Felder Index of Learning Styles (ILS). This study aims to contribute to the discourse within engineering education by examining the correlation between the alignment of student and instructor learning styles and its impact on student academic performance. The Silverman-Felder ILS, a well-established tool, delineates learning styles across four dimensions: active/reflective, verbal/visual, sensing/intuitive, and sequential/global. We operationalize alignment as the proximity in four-dimensional space between a student's ILS score and that of their instructor. Initial findings based on a cohort of 300 Cadets at the United States Military Academy (USMA), primarily from advanced sections of first-year mathematics courses, reveal a statistically significant correlation between the proximity of student-instructor learning styles and student grades. Building upon this groundwork, our ongoing research, encompassing a broader sample size of 550 Cadets, extends beyond advanced mathematics sections to include the general student population. Preliminary results indicate a 2% increase in final grades among advanced mathematics Cadets (informally called Jedis) when their learning styles closely align with that of their instructor. However, this trend did not hold true for Cadets outside the advanced mathematics sections. Initial findings and chi squared testing showed no statistically significant results in final grades and crude distance of instructor-student pairings. However, when the data was partition (Jedi vs. all), there were statistically significant results congruent with previous research, indicating that sectioning in the Jedi program may enhance student outcomes in STEM heavy programs.

Keywords: learning styles, student sectioning, student performance

Background

In the landscape of higher education, the structure of introductory courses varies widely, ranging from large-scale seminars in public universities to smaller, more intimate classes typical of private institutions. At our university, we prioritize smaller class sizes, capped at 19 Cadets per course, to foster personalized learning experiences. While this approach enhances student engagement and individualized instruction, it necessitates a larger pool of instructors to accommodate the demand. Consequently, the proliferation of instructors teaching the same course introduces variability in teaching methodologies, classroom environments, and instructional approaches.

However, this diversity among teaching personnel presents an opportunity to leverage the range of instructional styles available. By employing the Felder-Silverman Index, which categorizes learning styles into distinct dimensions, we seek to optimize the student learning experience by aligning them with instructors whose teaching styles closely match their individual preferences. Our objective is to develop a systematic approach to group Cadets based on their learning styles and pair them with instructors using a "closest by distance" methodology. This approach aims to maximize compatibility between Cadets and instructors, leading to improved learning outcomes as measured by end-of-term grades. Our research endeavors to explore the efficacy of this tailored student-teacher pairing system within the context of our institution's smaller class sizes and diverse instructional personnel, thereby contributing to the discourse on engineering education and pedagogical optimization.

Literature Review

Numerous studies have delved into learning styles, tracing back to the early 20th century with contributions from pioneering educators like Alfred Binet and Dr. Maria Montessori (Chandler). Over time, an array of frameworks has emerged, offering various perspectives on how Cadets prefer to learn (Mosely). The fundamental premise of learning styles suggests that Cadets possess stable preferences in how they absorb information, and tailoring instruction to these preferences can enhance learning outcomes. This notion has garnered widespread appeal, spawning a market for products, materials, and training aimed at leveraging learning styles to improve teaching.

The popularity of learning styles has led to an astonishing array of over 70 classification systems, each with corresponding educational materials (Coffield). Among these, the Visual/Audio/Reading(Verbal)/Kinesthetic (VARK) model stands out as one of the most prevalent, attracting significant attention even in recent years. However, the VARK framework has faced scrutiny, with headlines questioning its efficacy, such as "The Myth of Learning Styles" from The Atlantic (Khazan, 2018) and "Belief in Learning Styles Myth May Be Detrimental" published by the American Psychological Association in 2019 (Nancekivell). Despite the widespread use of the VARK model, research into its effectiveness has primarily adopted descriptive, correlational, or causal-comparative designs, with only a few experimental studies conducted. Among these studies, only one effectively refuted the efficacy of teaching with the VARK framework (Fauziah).

Various other learning styles indices, such as the Kolb Learning Styles, Honey and Mumford's Learning Styles Questionnaire, and Sternburg's Thinking Styles Inventory, have also been proposed, but the literature surrounding them is limited. Some indices lack sufficient research on their efficacy, while others have limited experimental evidence either supporting or refuting their use. Meta-analyses by Pashler et al. in 2009 and Cuevas in 2015 argued that the evidence regarding learning styles overwhelmingly suggests they offer no discernible benefit to student learning. However, proponents argue that much of the criticism directed towards learning styles research stems from misunderstandings of their nature and purpose (Felder), proposing metrics like the Felder-Silverman Index of Learning Styles (ILS) as alternatives (Felder, 2).

Research on the Silverman-Felder ILS, particularly in experimental classroom settings, has been sparse. In 2022, Zillmer and Mussmann conducted a year-long longitudinal study examining the passive effects of student-instructor "closeness" (measured by the four ILS dimensions) on student performance in first-year college mathematics. Their data indicated a statistically significant impact of student-instructor distance on student performance, in line with learning styles theory. Specifically, Cadets whose ILS scores became more similar to their instructors tended to perform better, while those with greater dissimilarity tended to perform worse (Zillmer). This paper aims to replicate and extend the findings of Zillmer and Mussmann's study.

Research Goals

Previous research conducted by Mussmann & Zillmer in 2022 in this area highlighted grade variations among Cadets, specifically within the Jedi population at USMA. These Cadets have a unique background: all have taken a first course in calculus and scored a 4 or 5 in the AP exam or have demonstrated proficiency in calculus skills prior to arriving at the university as deemed by placement exams. Cadets also have the mathematical skills to succeed in a rigorous, differential equations course. In the first iteration of this study, the Cadets in this specific, advanced sections of math were given the Silverman-Felder Index of Learning Styles (ILS) survey as well as their respective instructors for both semesters of their first-year math courses. Their end of term grades from each semester were compared to their distance in R4 to produce a linear regression model for predicting the grade outcome. Our research expands on this initial study, now considering the entirety of the first-semester Cadets in and their respected two-semester math classes.

We are interested in how to posture the engineering Cadets well in their first few semesters in their undergraduate program. In order for undergraduate Cadets to be successful in engineering programs, they need a solid foundation in mathematics. A UK study in 2008 showed that out of 14 factors associated with success of first year engineering Cadets, the top three were related to mathematics (Lee). Additionally, in a more recent study, researchers found that mathematics can be a barrier for completing an engineering degree – Cadets who performed better in mathematics courses tended to perform better in engineering (Tsui). The bulk of our Cadets will not take an engineering course their first year but will take two semesters of appropriate level of mathematics to build a strong math foundation for further engineering sequences. However, not all the engineering Cadets at our university start in the advanced sections of mathematics, which is what previous research focused on. Given previous indications of a positive correlation with the decrease in distance between instructor student pairing and end of term grades for advanced placement mathematics Cadets, we would like to expand that notion and consider alignment between a cadet's Silverman-Felder learning style and their instructor's learning style and overall student grades across all mathematics courses offered to all first-year Cadets at our university. This expanded inquiry allows us to address three research questions:

1. Do we see the same instance of positive grade outcome for Cadets who are more closely aligned with their instructor for the advanced mathematics program?
2. Is there a similar correlation between instructor-student alignment in learning styles and overall student performance across first-year mathematics courses? If so, then...
3. Should we consider how we section our Cadets to assist in their success in their first-year mathematics programs, leading to a solid foundation for their engineering education?

Assumptions

With research comes necessary assumptions to move the research forward. We identified four pivotal assumptions that underpin our research endeavors. Firstly, we posit that participants conscientiously responded to the Silverman-Felder ILS questions, providing accurate insights into their learning preferences and personalities. The Cadets, while offered bonus points as an incentive for survey participation, had no motive to distort their preferences, particularly as the survey outcome did not directly influence their grades. Consequently, we posit that their survey responses faithfully reflect their authentic learning styles.

Secondly, we assert that the Silverman-Felder ILS effectively delineates distinct learning styles, a pivotal assumption given that this constitutes the focal point of our investigation.

Thirdly, we presume that educators structure their teaching methodologies in alignment with their personal learning preferences. For instance, an instructor inclined towards hands-on learning is likely to organize their classroom activities to promote practical engagement with concepts during instructional periods.

Lastly, a crucial assumption in our study is the belief that learning styles remain relatively static in the short term, persisting throughout the observed year. This temporal constancy forms the basis for our longitudinal examination of learning styles.

Methodology

At the university, all first-year Cadets are required to take a full-year math sequence. Depending on the track (advanced or traditional), a given student will uniformly take a particular course in the fall and in the spring. As instructors in the advanced first year math sequence at the university, we have relatively unfettered access to the average end-of-semester grades for the Cadets in both of the advanced courses. This data was easily merged with their instructor information for each of the two semesters in which they were enrolled in the university's core first-year math sequence. Similarly, we collaborated with peers from across the department to collect and combine end-of-semester summary data and instructor pairings for Cadets not in the advanced math sequence.

To collect the ILS survey data, we again collaborated with instructors across the department and offered an opportunity for Cadets to take the ILS survey with the benefit of earning a modicum of bonus points for the course. We assume that the bonus points did not result in any selection bias for the survey for two reasons. First, the bonus points represented approximately one sixth of one percent of the total points in the course – a number we deem not significant enough to cause bad incentives nor selection bias. Second, we believe that the motivation (however small) to participate would help support our first assumption that the surveys would be taken in good faith. The survey provided us with 44 data points which we scored in-house according to the "ILS Scorecard" provided for proctors of the survey. The data points resulted in a score ranging from –11 to +11 in each of the four dimensions of the learning styles. Many, but not all, of the instructors in the department supported this research by also taking the survey. Instructor participation was not incentivized.

Across advanced and traditional tracks, 550 Cadets and 27 instructors completed the survey. There was an 'underlap' in the number of instructors that completed the survey, relative to the Cadets that completed it (i.e., a given Cadets' first or second semester instructor may not have taken the survey). A student that had an instructor 'underlap' was removed from the data pool because of the inability to compare across the math sequence. These Cadets were still awarded bonus points for participating to the best of their ability. The underlap resulted in 371 cleaned student samples for use. Here, we make an additional fifth assumption that the data from the resulting 371 pairings is an accurate representation of the whole population. These samples were preserved in a full data set (all valid samples from both tracks), a data set for advanced Cadets only (n=203), and a data set for traditional Cadets only (n=168). To conclude cleaning the data, we standardized the grades for each student in each semester to account for any potential differences in one class being "easier" than the other. The standardization method was to subtract the average grade in the course from the student's grade. This resulted in Cadets' grades being distributed approximately normally about zero due to random sampling.

To test the hypothesis, we used the end-of-semester summary statistics, and the ILS survey results to compare "distance" in variety of definitions to determine if there is a statistically significant correlation between the student's learning style and their instructor's learning style. As a result of assumption three above, we suppose that the information that the instructor is attempting to communicate will be more readily received by a student who shares a similar learning style to the instructor. In turn, we define the instructor-student learning style similarity as any of the distances defined below.

We measured distance using three different methods through the $\mathbb{R}^4$ space in which the survey data points exist. We also measured a simple one-dimensional distance using a separate interpretation of the raw survey results. We will first describe the methods used to define (not measure) the distance between survey respondents.

We have coined the initial method of survey response differences as the crude difference. This difference is simply the number of questions answered differently by a given student and the instructor against whom they are being compared. Survey responses were recorded as either a 1 or a 2 in the raw data, thus the algebraic difference between responses on a given question was constrained to be either –1, 0, or +1 and the crude distance could be quickly calculated as the sum of the absolute values of the differences of the questions' raw data. Crude distance ranged from 0 (identical survey responses) to 44 (exactly opposite survey responses). Mathematically, this is represented below where s_i is the i^{th} student survey response and t_i is the i^{th} instructor (teacher) survey response.

$$\text{Crude Distance} = \Sigma_{i=1}^{44} |s_i - t_i|$$

A second (and ultimately more valuable) manner of measuring differences was to use the −11 to +11 scale of each attribute of the survey. This produced a point in $\mathbb{R}^4$ that allowed for measuring distances in each of the three methods alluded to above; that is, the 1-norm, the 2-norm, and the infinity norm. The axes in the $\mathbb{R}^4$ space are each of the learning style dimensions from the survey. That is, the Active-Reflective (AR) dimension, the Sensing-Intuitive (SI) dimension, the Visual-Verbal (VV) dimension, and the Sequential-Global (SG) dimension. The general expression for p-norm calculation is below where v is some vector of dimension n with elements $a_1, a_2, \dots, a_n$.

$$||v||_p = (|a_1|^p + |a_2|^p + \cdots + |a_n|^p)^{\frac{1}{p}}$$

Where p is some real number greater than 1. The infinity norm is represented by

$$||v||_\infty = \lim_{p \to \infty} ||v||^p = \max_{i \epsilon [1,n]} |a_i|$$

For illustrative purposes, we will consider a hypothetical pairing of two Cadets and their instructor in only the $\mathbb{R}^2$ space using the AR and VV axes. The table below contains the hypothetical data for this scenario, which is depicted in the following figure.

Sample	AR Score	VV Score
Instructor	5	4
Student 1	1	4
Student 2	1	1

Table 1 – Hypothetical Data for Figure 1

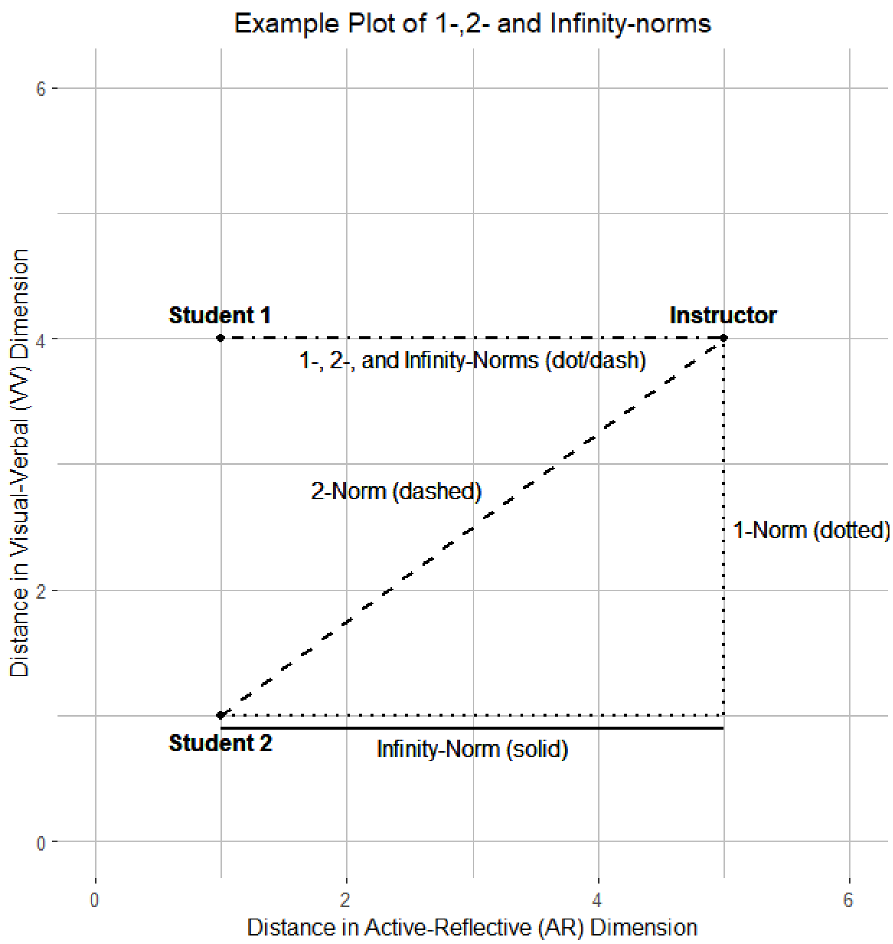

Figure 1: Hypothetical Depiction of 1-, 2-, and Infinity Norms

We selected these three norms for use because they provide a distinct perspective on the distance between points, particularly in higher dimension spaces. The 1-norm, sometimes called the Manhattan or taxicab distance, reflects the distance between points that results from only moving in along paths that are parallel to the axes that form the space. To its credit, this method "weights" each dimension equally, but does not give a picture of whether the distance is equally balanced in both (all) dimensions, or if there is a great distance in one dimension and only relatively small distances in the remaining dimensions. The 2-norm, sometimes called the Euclidean distance, is the straight-line distance and gives us an idea of the "direct" distance between points. The infinity-norm will measure the longest distance on any axis between the two points, which will give insight into any dimensions that have an outsized influence on the student's course outcome during the analysis.

Data analysis focused on two main statistical methods. The first was a simple linear regression in which we generated models both within and between the semesters using the standardized semester averages and the Cadets' crude distances with their instructors. The second was a chi-squared test. The chi-squared test was conducted on 15 different combinations of the dimensions from the learning style survey. For example, we compared 1-norm, 2-norm, and infinity-norm distance using only the AR dimension, using the only SI dimension, etc. Then we calculated the same norms using only the AR and SI, the AR and VV, and the AR and SG dimensions. This combinatorics continued for each possible combination of the learning style dimensions. Full exploration of the combinatorics and their impacts can be seen in Tables 1-3A in Appendix A. Each column of the tables show which combination of learning style dimensions were considered for the chi-squared test. In the encoding in the tables, the AR dimension is used if the column contains a 1. There is similar encoding for SI as 2, VV as 3, and SG as 4. Both the regression and the chi-squared tests were conducted with the null hypothesis that there is not a statistical impact of the distances on the student's outcome in the course and a confidence level of 95%.

We did not conduct a rigorous factor analysis for two reasons. First was that we believe we have fathomed each of the meaningful combinations of the predictors in Tables 1 – 3A. We believed that adding any loading factors onto the analysis may have appeared as trying to manipulate the data to support the hypothesis. Second, we believe that we have accounted for much of any unobserved factor dominance by considering the infinity norm because of the way that it effectively only measures the maximum dimensional distance. To explore that idea, the infinity norm was tested for each combination of the predictors.

Results

The linear regressions of the crude distance did not show any significant correlation between the Cadets and their scores across semesters. Interestingly, we found minor correlation between the student outcome and proximity to their instructor ***within*** the second semester, but not in the first (F-statistic of 0.02136). We refrain from making any conjectures about the implications of the correlation within the second semester as we believe that any conclusions toward that end would be purely speculative.

The chi-squared test also initially did not prove to be fruitful for finding statistically significant correlations between student outcomes and instructor proximity on the full data set on any p-norm. We then ran the analysis again on the partitioned data set (advanced and traditional Cadets) and found that there is a statistically significant correlation between instructor difference and student outcome in exclusively the advanced math courses. This correlation was true across all three p-norms for the advanced Cadets, but not necessarily on the same combinations of the learning style dimensions. See summarized statistically significant outcomes in Table 2 below. Note that two of the rows had two statistically significant dimensional combinations, and so both are reported. The more significant value will be marked with an asterisk. Full summary of chi-squared results can be seen in Appendix A.

p-norm	Dimension Combination	F-statistic
1-norm	AR, SI, VV, SG	0.047667
2-norm	AR, VV	0.0440259*
2-norm	AR, VV, SG	0.0472679
Inf-norm	AR, VV	0.0447372
Inf-norm	AR, VV, SG	0.0444211*

Table 2 – Summarized Data of Statistically Significant Results from Advanced Track Cadets

Conclusions

While interpretation of the results may lead into discussions of psychology beyond the scope of the qualifications of the research team, we do have hypotheses about the cause for discrepancy between the advanced and traditional track Cadets. One possible explanation for the significance that exists in the advanced track but not in the traditional track could be the additional noise that is introduced by Cadets who elected to stay in the traditional track despite showing either transcripts or aptitude that could have seen them in the advanced track. This noise would manifest in Cadets who are predisposed to performing well in the course despite any proximity or lack thereof to their instructors. There also tends to be a higher concentration of Division I athletes in the traditional track which may cause a large discrepancy in the amount of time that a student-athlete has available to dedicate to their studies in a given semester. In other words, it stands to reason that a student-athlete's grade may be better in their off-season regardless of their proximity to their instructor simply because of the extra time they can dedicate to their studies.

Another possible explanation for the difference in significance is the different pedagogical uniformity between the advanced track and the traditional track. The research team makes no assertions as to which method is "correct" or "better," but we do note that there is less top-down direction in how instructors ought to deliver material in the advanced sections. The supposition is that this allows for the advanced track instructors to express the material in a manner more aligned with their learning style than the instructors in the traditional track that are more homogenized in the manner that they deliver the material, which in turn may make student-instructor proximity effects more pronounced in the advanced track and more muted in the traditional track.

It is worth noting that we may not have originally thought to partition the Cadets between the advanced and traditional tracks had this research not been a continuation of Zillmer and Mussman from 2022. Their original research considered only the advanced math track and produced results that also indicated that there is a statistically significant correlation between ILS student-teacher proximity. Specifically, by using a linear regression, they found an expected improvement of approximately 2% when using the AR, VV combination of the infinity norm. When we found that our results did not agree with the results from the previous research, we attempted to more closely replicate the methods by partitioning our data into the traditional and advanced tracks. Again, we do believe this partitioning to be valuable for the unquantified pedagogical differences and the supposed latent noise mentioned above.

Using linear regression on the same infinity norm measurement and the same AR, VV combination of learning style dimensions, we find a small negative regression coefficient of -0.0011. In the previous research, Zillmer and Mussmann estimated the practical impacts of their findings by magnifying this regression coefficient with a move from "less similar" to "more similar" using the quartiles of their distance. Their research indicated a more pronounced difference between the 75th percentile and the 25th percentile of 18 units of distance, while our current research only indicates a change of 6 units of distance. Thus, compared to the approximately 2% change in student outcome that Zillmer and Mussmann predict as a potential impact, our current research indicates a less impressive

0.66% increase in a student's final grade. Regression coefficients are available in Tables 3A and the plots showing standardized grade change overlaid distributions by quadrant.

Overall, we find that two years of consistent data indicates that there is reason to believe that learning styles may have a minor impact over a prolonged period of time. We acknowledge that at most institutions there are fewer options or instructors than at our institution where a given 1st year math course can have up to 10 different concurrent instructors. Because of this luxury, the opportunity to place Cadets into a particular instructor's course are readily available and the cost is negligible. Acknowledging that this is not a universal truth, although statistically significant, it is hard to justify the outcomes as practically significant.

Further Work

In the future, our primary goal is to expand this research to include other departments. At USMA, there are similar first year sequences for History and English/literature in which we would like to test our hypothesis. Additionally, we would like to include a qualitative assessment of the instructors' information delivery styles as a supplement to the survey to assess if there is a subjective element to learning style proximity as well as the observed quantitative impact on the Cadets' grades. Finally, we would like to conduct a longitudinal study that looked at the performance of the engineering Cadets in their engineering classes with respect to their performance in their first-year mathematics courses. This could provide the justification for sectioning our Cadets prior to taking their first-year courses in the math department based on their ILS.

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Appendix A – Important Graphics

Figure 1A – Plot of Expected Standardized Grade Change as a Function of Infinity-Norm Distance for Advanced Cadets

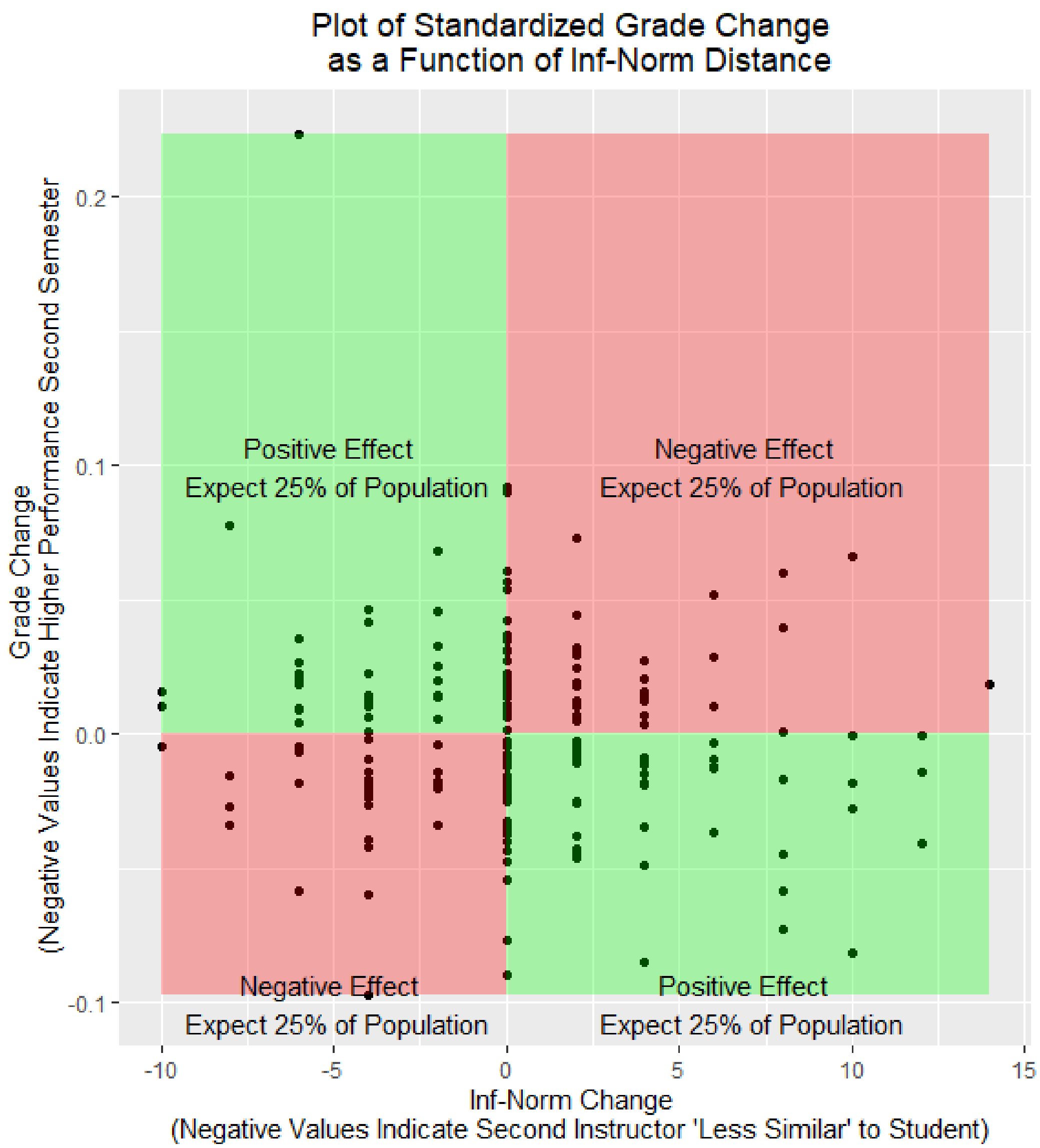
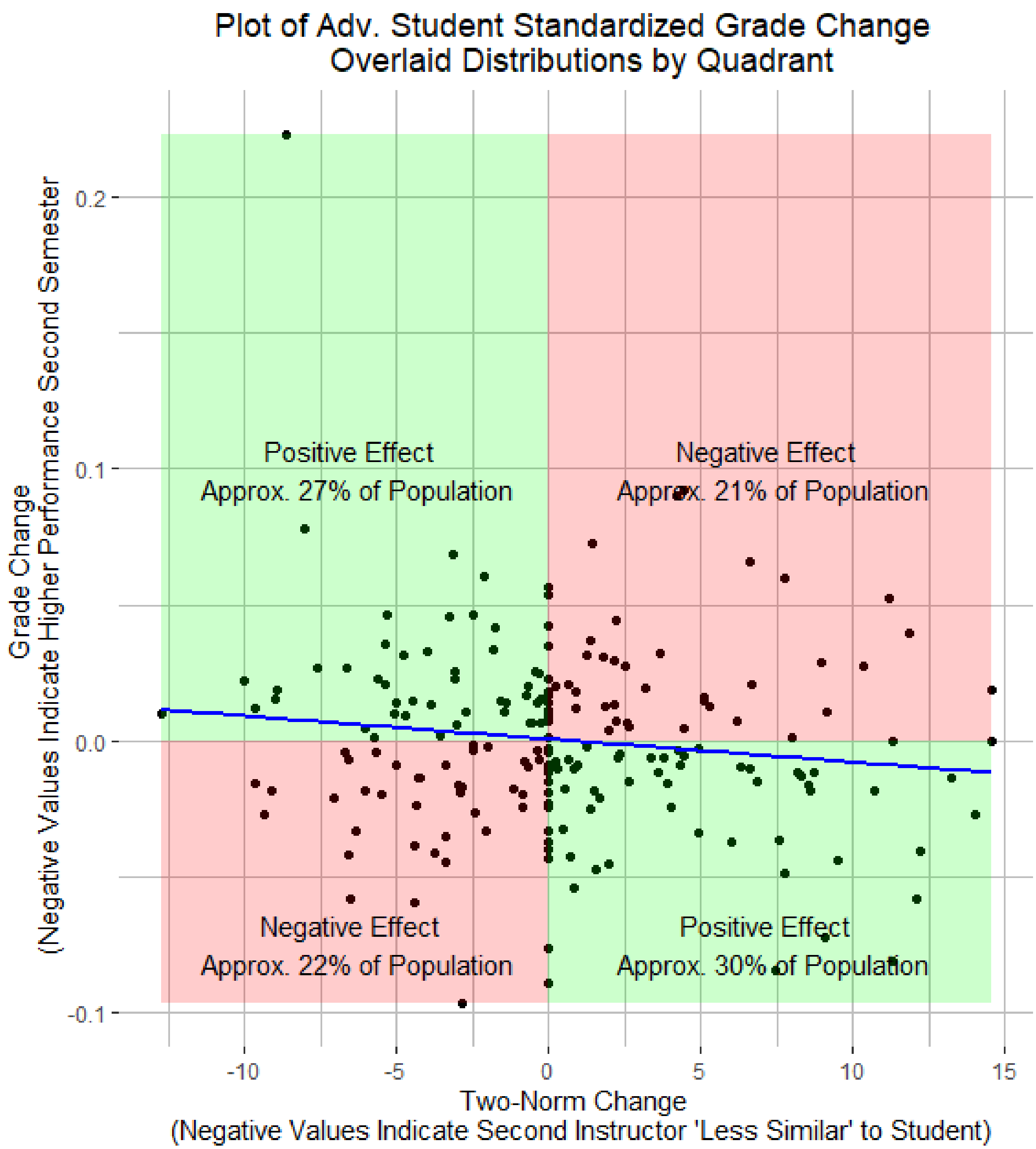


Figure 2A – Plot of Actual Standardized Grade Change as a Function of Two-Norm Distance for Advanced Cadets



Tables 3A – Summarized Outputs for Chi-Squared Test of Various Axis Combinations and p-Norms for Advanced Cadets

p=0	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
1	1	2	3	4	1	1	1	2	2	3	1	2	3	4	1
2	0	0	0	0	2	3	4	3	4	4	2	3	4	1	2
3	0	0	0	0	0	0	0	0	0	0	3	4	1	2	3
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
Rsq	0.0143	0.0021	0.0059	0.0019	0.0084	0.0199	0.0132	0.0101	0.0011	0.0120	0.0135	0.0094	0.0200	0.0082	0.0152
Coeffs	-0.0009	-0.0004	-0.0006	-0.0003	-0.0007	-0.0011	-0.0008	-0.0008	-0.0002	-0.0008	-0.0010	-0.0007	-0.0011	-0.0007	-0.0010
F-stat	0.0898	0.5180	0.2742	0.5370	0.1921	0.0447	0.1026	0.1534	0.6456	0.1204	0.0990	0.1697	0.0444	0.1991	0.0797

p=1	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
1	1	2	3	4	1	1	1	2	2	3	1	2	3	4	1
2	0	0	0	0	2	3	4	3	4	4	2	3	4	1	2
3	0	0	0	0	0	0	0	0	0	0	3	4	1	2	3
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
Rsq	0.0143	0.0021	0.0059	0.0019	0.0138	0.0178	0.0136	0.0068	0.0040	0.0071	0.0174	0.0087	0.0188	0.0150	0.0194
Coeffs	-0.0009	-0.0004	-0.0006	-0.0003	-0.0006	-0.0007	-0.0006	-0.0005	-0.0003	-0.0004	-0.0006	-0.0004	-0.0006	-0.0005	-0.0005
F-stat	0.0898	0.5180	0.2742	0.5370	0.0947	0.0579	0.0972	0.2421	0.3724	0.2335	0.0610	0.1868	0.0509	0.0816	0.0477

p=2	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
1	1	2	3	4	1	1	1	2	2	3	1	2	3	4	1
2	0	0	0	0	2	3	4	3	4	4	2	3	4	1	2
3	0	0	0	0	0	0	0	0	0	0	3	4	1	2	3
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
Rsq	0.0143	0.0021	0.0059	0.0019	0.0116	0.0200	0.0130	0.0072	0.0019	0.0097	0.0164	0.0071	0.0194	0.0110	0.0160
Coeffs	-0.0009	-0.0004	-0.0006	-0.0003	-0.0008	-0.0010	-0.0008	-0.0006	-0.0003	-0.0007	-0.0009	-0.0006	-0.0009	-0.0007	-0.0008
F-stat	0.0898	0.5180	0.2742	0.5370	0.1268	0.0440	0.1055	0.2295	0.5339	0.1620	0.0689	0.2306	0.0473	0.1362	0.0717
						AR, VV							AR, VV, SG		Full