

The development of a laboratory data analysis curriculum for physics
and engineering students.

by

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Abstract

There are notable gaps between formal instruction given to students and the expectations of students with respect to data analysis. In this work, techniques from physics education research are used to design, implement, and evaluate a curriculum module for data analysis in a third and fourth year undergraduate physics laboratory. The results of the study include the deployment of an advanced fitting tool, the establishment of lectures on statistics and data analysis, and a simulated data analysis assignment in which students analyze computer generated data with the techniques and tools they are taught. The effectiveness of the module was evaluated using statistical analysis from a student survey and grade data. The implementation of the curriculum module was met with enthusiasm from the students as evidenced by comments and feedback, but the impact on their grade performance was insignificant. Recommendations of further development to the curriculum module are suggested in light of the findings of this study.

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List of Symbols

Symbol	Description
A	strongly agree survey response
a	somewhat agree survey response
D	strongly disagree survey response
d	somewhat disagree survey response
N	sample size
n	neutral survey response
p	significance probability for hypothesis test
$p(t)$	probability distribution (density) function
$P(t)$	cumulative distribution (density) function
r	Pearson correlation coefficient
s	sample standard deviation
s_x	standard deviation of sample population x
t	Student's t -test statistic
\bar{x}	mean of sample population x
\tilde{x}	median of sample population x
\hat{x}_i	deviation of element from mean of sample population x
x_i	element of sample population x
χ^2	gaussian maximum likelihood metric
μ	population mean

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Chapter 1

Introduction

Quantitative data analysis is a common feature of all scientific disciplines. As a constructivist discipline, science depends on the appropriate analysis of reliable experimental data to reach sound conclusions. Students in the sciences are often called to perform such analyses in laboratories throughout their respective coursework and are evaluated upon their use of tools and judgment. However, there are notable gaps between the formal instruction given to students and the expectations of students with respect to data analysis.

Without formal instruction of data analysis, instructors may unknowingly set an invisible bar for students to reach for. Instructors have a particular expectation in mind for students, but the students may be unaware of it. In the following chapters, techniques from physics education research will be applied to the discipline of quantitative data analysis in order to develop a curriculum module for upper year undergraduate students. The background theory and motivation will be outlined allowing for a discussion of the design and implementation of the curriculum with respect to aspects of the theory. Then, an evaluation methodology will be presented, followed by the presentation of the results of the evaluation and a critical analysis of the design, results, and implications. Finally, the further work on the subject will be described as well as the conclusions of this research study.

Chapter 2

Background theory and motivation

Physics education research is a unique multidisciplinary field. It attempts to combine traditional educational theory and scientific constructivism in a single topic of research. Physics is a unique field in that its academic community shares many common interpretations about the nature of the physical world and its theories have widespread acceptance. In this capacity, physicists share a *community consensus* on the ways of thinking about many features of the physical world [6]. Redish uses classical mechanics and classical thermodynamics as examples of areas of study where the agreement is very strong.

A key consequence of this strong consensus is that physicists believe that there are optimal ways of understanding concepts in physics. This agreement in epistemology has been studied and highlighted in the development of the *Maryland Physics Expectations survey* (MPEX) in which an expert group of American physicists was shown to have 87% agreement on the nature of understanding physics along six different dimensions [7]. The MPEX study has influenced many physics education researchers by encouraging the goal of epistemological sophistication as a key student achievement. Moreover, epistemological development has been suggested as an effective means of improving student performance, and has taken a place in the design and evaluation of physics curricula. The dimensions identified by Redish are shown in Table 2.1.

	Favourable	Unfavourable
Independence	takes responsibility for constructing own understanding	takes what is given by authorities (teacher, text) without evaluation
Coherence	believes physics needs to be considered as a connected, consistent framework	believes physics can be treated as unrelated facts or “pieces”
Concepts	stresses understanding of the underlying ideas and concepts	focuses on memorizing and using formulas
Reality link	believes ideas learned in physics are relevant and useful in a wide variety of real contexts	believes ideas learned in physics have little relation to experiences outside the classroom
Math link	considers mathematics as a convenient way of representing physical phenomena	views the physics and the math as independent with little relationship between them
Effort	makes the effort to use information available and tries to make sense of it	does not attempt to use available information effectively

Table 2.1: Dimensions of student expectations from the MPEX survey.

The consensus on epistemology has helped to shape the goals of physics education research, but there are limitations to the usage of student epistemology as a theoretical framework for physics education. The MPEX study and other studies using the MPEX study as a metric for effectiveness limit their usage to introductory theoretical physics courses [5, 2, 7]. The authors’ common focus is on helping students to understand theoretical concepts and make the assumption that an excellent understanding of concepts implies good problem solving skills. Perhaps as professional physicists, the authors make the assumption that the practical set of problem solving skills necessary for even entry-level physics courses is not trivial. Ehrlich suggests that student epistemology may not be the only explanation for student performance and that other factors such as intrinsic ability should be considered [4]. However, Ehrlich may too hastily conclude that some students simply do not have the ability to do physics. He quotes a student, “. . . hey that course I took with you was great and really made me think, although I only got a C.” And while it may be convenient to label such a student as interested in physics without the required ability, it is possible that the student did not have the tools necessary to solve the examination problems.

Dewey’s theory of education can be roughly interpreted as identifying educational ex-

periences as those which add value and meaning to a variety of different ideas and contexts [3]. Although Dewey's theory is rooted in traditional philosophy, his pragmatic approach to education has value when considering physics education research. Some may worry that a pragmatic view of physics education leads down the slippery slope of a physics education as career training. However, some practical skills are absolutely necessary in order to be a successful physics student. Simple algebraic manipulation and basic calculus are two skill sets that immediately come to mind. So, the teaching of mathematics may be viewed as a form of necessary physics career training. In an experimental physics context, there many more practical skills that must be used to interpret scientific experiments. These can range from the usage of voltmeters and oscilloscopes to the application of statistics to interpret experimental data.

To summarize, the basic educational theory that will be applied throughout this document will be based upon epistemological sophistication and acquisition of practical tools and techniques.

Chapter 3

Design and implementation

In this chapter, the design and implementation of a data analysis curriculum will be presented. An overview of a current curriculum will be discussed followed by a description of the proposed tools and assignments and finally a summary of goals in the context of the theory presented in the previous chapter.

3.1 The advanced physics laboratory

The advanced physics laboratory is an undergraduate experimental physics course offered at the University of Toronto. It is taken by upper year (third and fourth year) undergraduate students in the Physics and Engineering Science programs at the university. The typical enrollment into the course is around fifty to seventy students per semester.

3.1.1 Previous curriculum

The course curriculum is based upon a series of three (3) in-depth laboratory experiments of which students have a degree of choice in selecting. These experiments are usually classic experiments in modern and quantum physics. Examples include calculating particle decay

lifetimes, investigating crystal diffraction patterns, and characterizing the statistical mechanics of macroscopic granular material. In addition, each student is assigned a supervising professor and the aid of a lab demonstrator. Throughout the experiments, the students are required to complete a series of mandatory exercises, but are given the flexibility to pursue other interesting aspects of the experiments and to use a variety of analysis methods. Each student is required to keep a detailed laboratory notebook with their analysis and notes. Each experiment mark is based on a combination of their laboratory technique from informal conversations in the lab, the quality of their analysis presented in their laboratory notebook, and their understanding of the material as indicated by a formal interview with the supervising professor.

In addition to the experiments, the students are required to prepare a formal report of their results of a single experiment, and at the very end of the course, there is an oral examination which is intended to cover all aspects of the experiments performed through the semester. The oral examination is conducted by two of the supervising professors, and one lab demonstrator. The grading scheme for the course is shown in Table 3.1.

Experiment grades	63%
Formal report	17%
Oral examination	20%

Table 3.1: Grading scheme for the advanced physics laboratory for Fall 2005.

Most students in the advanced physics laboratory have had at least two semesters of experimental physics in previous years. The course is a program requirement for Engineering Science students, while it is a technical elective for Physics students.

3.1.2 Existing data analysis curriculum

The previous course curriculum provided no formal data analysis instruction. The students were expected to carry their analysis skills from the first and second year laboratory courses and apply them in the advanced laboratory. However, there is a gap in the material taught between the introductory labs and the advanced labs. The first year labs emphasize con-

ceptual understanding and downplay the statistical and mathematical rigour necessary for a defensible scientific investigation. The second year labs put an emphasis on using various kinds of data acquisition equipment such as oscilloscopes, voltmeters, ammeters, and recording devices. However, the role and estimation of errors in the data analysis is mostly overlooked. Through the first two years, the only formal evaluation of the understanding of error analysis in a laboratory setting is the ERRTEST program. The ERRTEST program is an interactive error analysis quiz that is administered on the computer terminals available in the undergraduate labs. It is short (roughly 15–30 minutes), given relatively small weight (5% course grade), and is unsupervised. It is not uncommon for students to collaborate on multiple tests in order to obtain higher marks.

The physics department also provides the FARADAY fitter as a data analysis tool for undergraduate students. It is a black-box fitter that employs a web interface to fit user-inputted data to polynomial equations. It is also able to calculate χ^2 probabilities and estimate the errors on parameters.

3.2 Proposed course additions

For this research study, some additions to the advanced physics laboratory have been proposed and implemented. They are the deployment of the advanced lab fitter, intended to supercede the FARADAY tool, and the creation of formally taught course material regarding data and error analysis. The additions to the course material include a set of error analysis lectures delivered by one of the supervising professors, and a data analysis assignment. These additions are outlined in more details in the following sections and all associated documentation and source files are included in the appendices. The addition of the data analysis assignment changes the grading scheme for the updated course. The grading scheme for the updated course is shown in Table 3.2.

Experiment grades	60%
Simulated data analysis assignment	5%
Formal report	15%
Oral examination	20%

Table 3.2: Grading scheme for the advanced physics laboratory for Spring 2006 (updated).

3.2.1 The advanced lab fitter

The initial reason for designing the advanced lab fitter was to provide a more powerful fitting tool for students in the advanced physics laboratory. However, there are a number of pedagogical implications of providing a new tool. The advanced lab fitter can be considered with respect to the epistemological framework provided in the previous chapter and additionally (and moreso) as the acquisition of a practical tool and technique.

The advanced lab fitter is built upon a series of MATLAB functions and scripts, and represents a precise implementation of the fitting technique outlined in the data analysis lectures [1]. Since the entire source is provided with the fitter, interested students can examine the operations that the fitter performs to produce its plots unlike previous tools. This open piece of software appeals to the Independence and Concepts dimensions in the epistemological framework. Even though the operation of the fitter is outlined in the lectures, students are provided with the opportunity to learn from a fairly accessible example of a fitter.

The fitter is also sufficiently sophisticated that it is used in some physics research labs at the university. This high level of functionality appeals to the Reality link dimension. The usage in the field identifies the tool as relevant outside of the classroom and gives it a degree of validity. Students benefit from performing analysis which are not artificial, but as justifiable as those performed in academic research.

Finally, the ease of use of the tool appeals to the Effort dimension. This may seem counterintuitive at first. How can providing an easy route encourage increased efforts? The answer can be shown by considering where students place their efforts when performing

an analysis with the fitter. Efforts can be divided between the usage of the tools and the interpretation of the data. If more time and effort is spent simply using the tools, then students will not be able to make effective use of the data. It is easier to “play” with data when the analysis tools are more transparent.

The fitter also clearly fulfills a practical purpose. The fitter provides all the necessarily functionality for parametric analysis and acts as a springboard to apply the techniques taught in the data analysis lectures. It is also a piece of software that can be easily used for any of the analysis tasks in the laboratory exercises and research projects.

3.2.2 Data analysis lectures

The data analysis lectures were delivered during the first weeks of the semester, while the students were engaged in their first experiments. The lectures were also supplemented with a set of notes that explain mathematical derivations in some detail. The purpose of the data analysis lectures were to complement the simulated data analysis assignment and vice versa. A lecture has limited effectiveness, as evaluated through the epistemological dimensions identified in the previous chapter. However where the lecture-based teaching lacks, the analysis assignment excels.

Lecture-based teaching has been shown to at best neutrally affect the independence dimension. The nature of lecture-based teaching lends itself to the mentality of an authority figure dispensing the undisputed truth. It also typically negatively affects the effort dimension as students are passive participants in the exchange, and often have answers spoonfed to them. Although they have limitations, lectures are excellent at improving student epistemologies along the coherence, concepts, and math link dimensions.

The step-by-step derivations and usage of mathematical tools to explain data analysis allow students to see the statistical underpinnings of their analysis. This approach not only helps the Math link dimension, but allows students to grasp the underlying concepts that the statistical analysis are based upon. The explanations also help along the reality

link dimension by educating students how most data fitters used by researchers operate. A skilled instructor will also be able to show how data analysis fits into a systematic approach to experimental physics, thus improving the coherence dimension.

The data analysis lectures also serve to appeal to the different learning styles of the students in the laboratory. While some students may benefit from the practice of crunching numbers in the simulated data analysis assignment, many find that mathematical derivations are the most effective way of assimilating a body of knowledge.

3.2.3 The simulated data analysis assignment

The simulated data analysis assignment was conceived to isolate the data analysis portion of the laboratory exercise. In a typical laboratory exercise, a student must worry not only about the validity of the results, but also the quality of the data. If the data is of questionable quality, then an analysis will yield limited information. By generating data of uniform quality, and separating the analysis from the laboratory experiments, students have the ability to focus on performing a well justified analysis.

The assignment provides each student with a unique set of data corresponding to two statistical data analysis problems. The first problem is a spectral analysis, where students are asked to characterize a gaussian peak on a quadratic background with a few parameters. The second problem is an exponential fit to some voltage data. Each data set is generated along with a solution provided by the advanced lab fitter. The course coordinator retains the solution manual, while the students are given numbered assignments each with unique data. The analysis was weighted as shown in Table. 3.2 and was marked by the course coordinator.

The simulated data analysis assignment has value and strength where the lectures are weak, such as the independence and effort dimensions of the epistemology theory. While a systematic approach can be taken to the assignment, there is no single correct approach to answering the questions. This allows students to seek solutions independently, and construct

understanding from their own perspectives. The assignment is also open ended. There are many statistical features of the data that can be analyzed and various tests of significance can be applied to ensure the analysis is valid. The open ended nature of the assignment appeals to the effort dimension, by providing students the opportunity to make the most of a limited amount of data. And since the data is known to fit a model, analyses of greater depth will only assure confidence in the results.

There is also a strong benefit to the Reality link aspect of the theory. Students are expected to produce an analysis at a quality level that is expected of their notebook. So, this serves as a test bed for students to make “free” mistakes without impacting the quality of their work, since small mistakes can lead to great misunderstandings when applied to an entire experimental system. Outside of the six dimensions identified by the MPEX survey, an opportunity to use advanced tools for a data analysis problem is highly practical. The assignment can provide training for data analysis outside of the laboratory, since the tools are used for analysis in academic research.

3.3 Course schedule

Ideally, the data analysis lectures and the simulated data analysis assignment would be given out prior to any of the experiments so that the skills and knowledge gained could be applied to the semester’s work. However, due to the scheduling of the supervising professors, the experiment schedule could not be modified. So, the lectures were provided and the simulated data analysis assignment was distributed during the first experiment period. The data analysis assignment was due shortly after the first experiment deadline.

This schedule also allows for a limited pre/post effect analysis between the first and second experiment. While students may not have had the opportunity to assimilate and apply the skills from the lectures and assignment in their first experiment, they would be able to in their second. The usage of grades and other metrics of student performance are outlined in the next chapter.

Chapter 4

Evaluation methodology

In this chapter, the approaches to evaluate the effectiveness of the curriculum additions are outlined. There are a few basic indicators of effectiveness that have been selected. These indicators are, the student adoption and approval of tools, student perceptions of the value of learning, student performance on the assignment, positive and negative feedback on the assignment and fitter, and correlations of performance to epistemological beliefs.

4.1 Student feedback and survey

In order to identify indicators of effectiveness, a student survey and feedback form was created and distributed to the students after they had attended the data analysis lectures, completed the simulated data analysis assignment, received their grades and got feedback from the course coordinator who graded them. The survey was anonymous, but attached to the assignment identification number so that paired analysis could be conducted. The full text of the survey is available in the appendix.

The survey was sixteen questions long, fourteen of which were questions based on a Likert scaling. That is, students were presented with statements and asked to respond in agreement or disagreement. Each question had five choices, “strongly disagree” (*D*), “some-

what disagree” (d), “neutral” (n), “somewhat agree” (a), and “strongly agree” (A). This kind of scaling method allowed for simple statistical analysis of the data instead of having to establish predefined relationships between question choices for an arbitrary multiple choice survey.

The questions of the survey focused primarily on the previously listed indicators of effectiveness. In addition, there were several questions that were asked in order to verify some assumptions about the expectations of students. For example, the survey asks students their perception of effort expended on the assignment, which was compared to the grades on the assignment.

4.2 Statistical methods

Agreement and disagreement values were assigned to each question response so that a neutral response corresponds to zero and strong responses have twice the weight of weaker ones. Thus, $(D, d, n, a, A) \rightarrow (-2, -1, 0, 1, 2)$ was selected as the mapping for the responses. This mapping allows for simple statistical analysis to be applied.

In this analysis, the key method of evaluating the teaching methodology was statistical methods. The primary statistical tests chosen were the Student’s t -test, and p -tests for various statistics including the Pearson coefficient, the Kolmogorov-Smirnov test, and Wilcoxon signed rank test. A statistically significant result is identified at the 2% level. This means that when comparing two statistical distributions, the test would produce a result at least as extreme as the measured result less than once in fifty experimental runs if they were identical distributions.

4.2.1 Kolmogorov-Smirnov test

The Kolmogorov-Smirnov (K-S) test is used to determine if a set of data obeys a particular statistical distribution. For survey data, one cannot make the assumption that the answers

to the survey follow a normal distribution or Student's t -distribution. The K-S test ensures that an appropriate hypothesis testing method is used for the survey data. To apply the K-S test, the empirical cumulative distribution function is calculated and compared to a theoretical cumulative distribution function. The absolute maximum between the two functions defines a statistic with a particular probability distribution function that will indicate whether the sample data corresponds to the theoretical statistical distribution.

The Kolmogorov-Smirnov test is implemented in MATLAB using the `kstest` function.

4.2.2 Wilcoxon signed rank test

The Wilcoxon signed rank test can be used to identify whether paired observations with an arbitrary probability distribution differ significantly. To apply the Wilcoxon signed rank test, the differences of the paired observations are calculated and ranked. The ranks associated with positive differences are summed to define a statistic. This statistic has a particular probability distribution function that can identify whether there is a significant difference between the paired observations with a given probability.

The Wilcoxon signed rank test is implemented in MATLAB using the `signrank` function.

4.2.3 Student's t -tests

Student's t -distribution is a statistical distribution published by William Gossett in 1908. It describes the probability distribution for random variable t without knowing the population standard deviation of a sample. In the limit of a large sample size, the t -distribution approaches the Gaussian distribution. The random variable t is defined as

$$t = \frac{\bar{x} - \mu}{s} \sqrt{N} \quad (4.1)$$

where \bar{x} is the sample mean, μ is the population mean, N is the sample size, and s is defined as

$$s = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2. \quad (4.2)$$

The t -distribution can be used to identify whether a small sample is statistically significant from a larger population. It can also be used to compare whether the distributions of variables between paired sets of data are significant. For example, if a small group of students are chosen from a larger population, the t -distribution could determine whether a measurable property of those students differs significantly from the population (such as height, weight, or GPA). For paired data an example could be subsequent measurements of a single property of a small group of students after some influence such as measuring body temperature before and after administering caffeine. The t -distribution could tell whether the influence had resulted in a significant difference of that property.

For paired data, the random variable t is defined as

$$t = (\bar{x} - \bar{y}) \sqrt{\frac{N(N-1)}{\sum_{i=1}^N (\hat{x}_i - \hat{y}_i)^2}} \quad (4.3)$$

where \bar{x} and \bar{y} are the sample means for the paired data, N is the sample size, and \hat{x}_i and \hat{y}_i are defined as

$$\hat{x}_i = x_i - \bar{x} \quad \text{and} \quad \hat{y}_i = y_i - \bar{y}. \quad (4.4)$$

Finally, the probability distribution function for Student's t -distribution is given by

$$p(r; t) = \frac{\Gamma(\frac{r+1}{2})}{\sqrt{\pi r} \Gamma(\frac{r}{2}) \left(1 + \frac{t^2}{r}\right)^{\frac{r+1}{2}}} \quad \text{where} \quad r = N - 1 \quad (4.5)$$

and the cumulative distribution function is given by

$$P(r; t) = \frac{1}{2} + \frac{t \Gamma(\frac{r+1}{2}) {}_2F_1\left(\frac{1}{2}, \frac{r+1}{2}; \frac{3}{2}; -\frac{t^2}{r}\right)}{\sqrt{\pi r} \Gamma(\frac{r}{2})} \quad (4.6)$$

where ${}_2F_1(a_1, a_2; b_1; x)$ is the hypergeometric function of index $(p, q) = (2, 1)$.

The Student's t -test is implemented in MATLAB using the `ttest` and `ttest2` functions.

4.2.4 Pearson correlation coefficient

A Pearson correlation coefficient can describe the relationship between two normally distributed properties in a single sample population. The value of the correlation coefficient also describes the effects of selecting portions of the sample population. The correlation coefficient, r is defined as

$$r = \frac{\sum_{i=1}^N (x_i y_i - \bar{x} \bar{y})}{\sqrt{\left(\sum_{i=1}^N (x_i^2 - \bar{x}^2)\right) \left(\sum_{i=1}^N (y_i^2 - \bar{y}^2)\right)}} \quad (4.7)$$

where \bar{x} and \bar{y} are the sample means for the paired data and N is the sample size.

Pearson correlation coefficients also obey a statistical distribution so that correlations can be identified as significant with respect to a population correlation coefficient. The probability distribution function for a correlation coefficient with a known population correlation coefficient is defined as

$$p(\rho, N; r) = \frac{1}{\pi} (N-2) (1-r^2)^{\frac{N-4}{2}} (1-\rho^2)^{\frac{N-1}{2}} \int_0^\infty \frac{dx}{(\cosh(x) - \rho r)^{N-1}} \quad (4.8)$$

where ρ is the population correlation coefficient, N is the sample size, and r is the measured correlation coefficient. For the tests in this study, the test for significance is referenced to perfectly uncorrelated data, i.e. $\rho = 0$. If this condition is applied, the probability distribution function for the correlation coefficient is simplified considerably. The probability distribution function for a Pearson correlation coefficient with population coefficient of 0 is defined as

$$p(N; r) = \frac{1}{\sqrt{\pi}} \frac{\Gamma\left(\frac{r+1}{2}\right)}{\Gamma\left(\frac{r}{2}\right)} (1-r^2)^{\frac{r-2}{2}} \quad (4.9)$$

and the cumulative distribution function is defined as

$$P(N; r) = \frac{1}{\sqrt{\pi}} \frac{\Gamma\left(\frac{N-1}{2}\right)}{\Gamma\left(\frac{N-2}{2}\right)} (1-r^2)^{\frac{N-4}{2}}. \quad (4.10)$$

The Pearson correlation coefficient is implemented in MATLAB using the `corrcoef` function.

Chapter 5

Analysis and results

5.1 Summary of student grades

A summary of the grades for the Spring 2006 semester are shown in Table 5.1. A summary of the grades for the Spring 2005 semester are shown in Table 5.2. The experiments were marked by a variety of supervising professors in both years, while the simulated data analysis assignment was marked only by the course coordinator.

The entire sample of students were divided into four different sample groups for initial analysis. The sample groups were the physics students, the engineering students, the students who chose experiment A in the simulated data analysis assignment, and those who chose experiment B. There were no significant variations between the different samples or between the experiment marks. The grades on the simulated data analysis assignment were slightly higher than those on the experiments, but otherwise there were no significant features of the data.

The experiment grades for the previous year are shown for comparison. The grades for the engineers in spring of 2005 were greater than those of the physics students and statistically significant. The K-S test and Student's t -test reject the hypothesis of identical

Sample	N	Experiment 1			Experiment 2			Sim. Data Analysis		
		\bar{x}	\tilde{x}	s_x	\bar{x}	\tilde{x}	s_x	\bar{x}	\tilde{x}	s_x
physics	11	77.3	81.0	9.5	75.7	75.0	7.0	83.7	80.0	8.0
engineering	37	80.4	83.0	15.5	82.7	84.0	8.2	87.5	90.0	11.6
experiment A	18	77.2	82.0	20.6	79.2	79.0	8.1	84.6	86.5	11.6
experiment B	29	81.2	83.0	8.3	82.2	83.0	8.6	87.9	90.0	10.4
all	47	79.6	83.0	14.3	81.1	82.0	8.4	86.6	90.0	10.9

Table 5.1: Summary of grades for Spring 2006 semester, $N = 47$.

Sample	N	Experiment 1			Experiment 2		
		\bar{x}	\tilde{x}	s_x	\bar{x}	\tilde{x}	s_x
physics	24	72.7	75.0	10.1	70.4	74.5	19.9
engineering	49	82.9	82.0	10.2	82.8	83.0	9.3
all	73	79.7	80.0	11.2	78.9	81.0	14.6

Table 5.2: Summary of grades for Spring 2005 semester, $N = 73$.

mark distribution at less than the 0.1% level, ($p < 0.001$). However, between experiment 1 and 2, there was no significant variation in grade in any sample.

5.2 Student grades

Student grades reflect the instructor's judgment of obtaining the goals of the assignment. The grades for the simulated data assignment were quite high, and not distributed normally. A plot of the histogram is shown in Fig. 5.1. The sample is size relatively small at $N = 47$ with a mean grade of 86.6% and standard deviation of 10.9%. The sample is skewed to the high end with a significant number of students obtaining 100%. 38 of 47 students received a grade of A- or better ($> 80\%$). If based solely on the judgment of the instructor, these grades suggest that a large proportion of students are performing acceptable data analysis.

The grade on the simulated data assignment should also be reflected in the experiment grades. The assignment would be called into question if there was not a strong positive correlation between the two due to self-consistency of the assignments. A scatter plot of the average experiment grade (less one outlier due to zero experiment mark) versus simulated data assignment grade is shown in Fig. 5.2. The correlation is moderately strong at $r = 0.41$

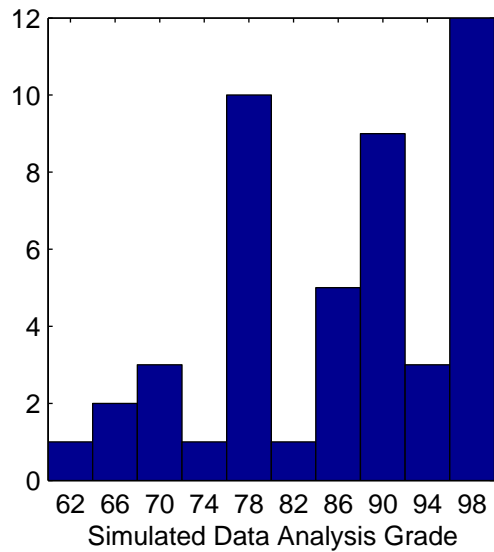


Figure 5.1: Histogram of Simulated Data Assignment Grades, $N = 47$. Bin label indicates centre grade for a bin width of 4%.

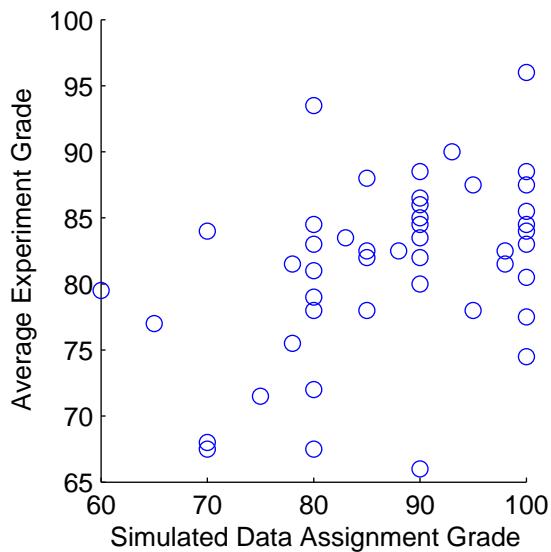


Figure 5.2: Scatter plot of Average Experiment Grade versus Simulated Data Assignment Grade, $N = 46$. Correlation coefficient of $r = 0.41$ corresponding to $p = 0.0044$.

and highly significant ($p = 0.0044$). This suggests that 41% of the change in experiment grade due to selection of population is associated with a change in the simulated data assignment grade.

The mean grades between the first and second experiment reject the null hypothesis of

identical mean at the 81% level, and thus is likely to have the same mean. The probability distribution functions of the first and second experiments are indistinguishable using the Kolomogorov-Smirnov test ($p = 0.62$), and the two are indistinguishable using Student's t -test ($p = 0.99$) and using the Wilcoxon signed rank test ($p = 0.91$). The difference between the first and second experiment has an insignificant correlation coefficient with the simulated data analysis assignment mark ($r = -0.12$, $p = 0.42$). This suggests that the simulated data analysis assignment has had no impact on experiment grade performance. However, this does not take into account the fluctuations in the experiment marks due to changes in workload during the term. If the previous year shows a statistically significant drop in experiment marks from first to second, then the simulated data analysis assignment may aid to maintain grades.

The grades of students in the Spring 2005 semester as shown in Table 5.2 indicate that there was no significant change in the experiment grades between the first and second experiment. This leads to the conclusion that the simulated data analysis assignment did not have a significant impact on the experiment grades. However, data analysis makes up only a fraction of the experiment grade ($\sim 30\%$), the effect may not be measurable with such a small sample size.

5.3 Summary of survey results

A total of 37 students completed the research survey. With the mapping, $(D, d, n, a, A) \rightarrow (-2, -1, 0, 1, 2)$, for agreement and disagreement, a test rejecting the hypothesis of zero mean indicates significant agreement or disagreement to a survey question. Table 5.3 summarizes the application of a variety of statistical tests and the resulting significance levels for rejecting the null hypothesis. The null hypothesis for the K-S test is that the distribution of answers is gaussian. The null hypothesis for the Wilcoxon signed rank test is that the distribution has a mean of zero (neutral). The null hypothesis for the Student's t -test is also that the distribution has a mean of zero.

Question	K-S test	Wilcoxon signed rank test	Student's t -test	Mean
2	0.0018	0.97	–	0.00
3	0.0018	$5.7 \cdot 10^{-7}$	–	1.16
4	0.019	$8.7 \cdot 10^{-5}$	–	0.89
5	0.17	0.72	0.74	0.05
6	0.12	0.21	0.21	0.24
7	0.014	0.84	–	-0.03
8	0.0035	$3.6 \cdot 10^{-5}$	–	0.95
9	0.0042	0.0017	–	0.64
10	0.0046	0.76	–	-0.03
11	0.0074	0.039	–	-0.41
12	0.066	0.11	0.12	0.32
13	0.042	$8.2 \cdot 10^{-5}$	–	-0.86
14	0.0095	$8.9 \cdot 10^{-7}$	–	-1.19
15	0.0028	$3.6 \cdot 10^{-7}$	–	-1.41

Table 5.3: Summary of statistical tests applied to survey responses, $N = 37$.

From the statistical analysis, questions 3, 4, 8, 9, 13, 14, and 15 are significant at the 2% level ($p < 0.02$). These responses indicate that there was agreement on the value and applicability of the data analysis lectures, the improvement and ease of use of the advanced lab fitter, and experimental physics epistemology. These responses will be analyzed in greater detail in the following sections.

5.4 Student perception of value

Questions 3–6 in the survey are intended to gauge student perceptions of the educational value of the data analysis lectures and the simulated data analysis assignment. Question 3 directly asks whether the data analysis lectures were valuable by stressing the acquisition of techniques and concepts. A histogram of the agreement and disagreement with the survey question is shown in Fig. 5.3.

The student perceptions of the data analysis lectures were very positive. Most students agreed with the statement in question 3, implying that the data analysis lectures were valuable. The results for question 3 are not normally distributed as indicated by the K-S test ($p = 0.0018$) and indicate a highly significant positive value (agreement) using the

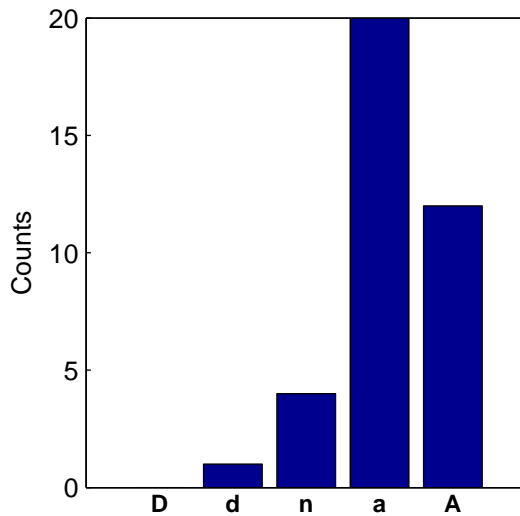


Figure 5.3: Question 3 histogram: *I learned many new concepts and techniques from the data analysis lectures.* agree/disagree = 32/1, $N = 37$.

Wilcoxon signed rank test ($p = 5.7 \cdot 10^{-7}$).

Question 4 determines whether students applied what they learned from the data analysis lectures in their own laboratory work. It is clear from the histogram that most students agreed with the statement in question 4. The distribution is not normal indicated by the K-S test ($p = 0.020$), but highly significant as indicated by the Wilcoxon signed rank test ($p = 8.7 \cdot 10^{-5}$). The survey results from question 4 are plotted against question 3 in a two dimensional histogram. A correlation coefficient of the agreements was calculated, but not found to be significant ($p = 0.24$). However, those who disagreed to the usage of the data analysis material agreed to the value of the data analysis lectures. The histogram of question 4 responses is shown in Fig. 5.4 and the two dimensional histogram of question 4 versus question 3 is shown in Fig. 5.5.

Question 5 asks whether students learned new techniques and concepts from the simulated data analysis assignment. On this question, student responses are fairly divided. The distribution of responses are normal indicated by the K-S test ($p = 0.17$) and the agreement or disagreement in this question is not statistically significant indicated by Student's t -test ($p = 0.74$). This is an expected result, since the purpose of the simulated data analysis

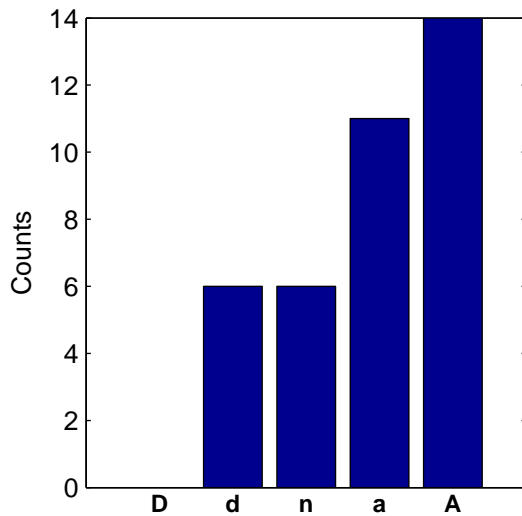


Figure 5.4: Question 4 histogram: *I applied the concepts and techniques taught in the data analysis lectures in my own laboratory work.* agree/disagree = 25/6, $N = 37$.

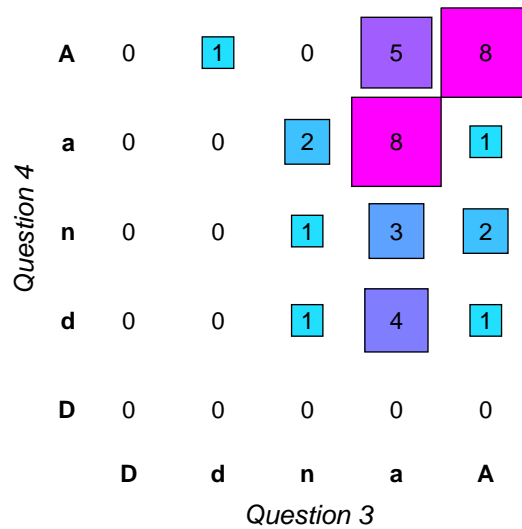


Figure 5.5: Question 4 vs. Question 3 histogram. Correlation coefficient, $r = 0.20$, $p = 0.24$, $N = 37$.

assignment was to allow for the application of existing knowledge. The null result in this case indicated that students were well prepared for the simulated data analysis assignment since they did not need to learn many new content or techniques. When first-time advanced physics laboratory students are selected from the sample, the agree/disagree ratio changes to 8/4, but it is not statistically significant due to the small sample size. The histogram of

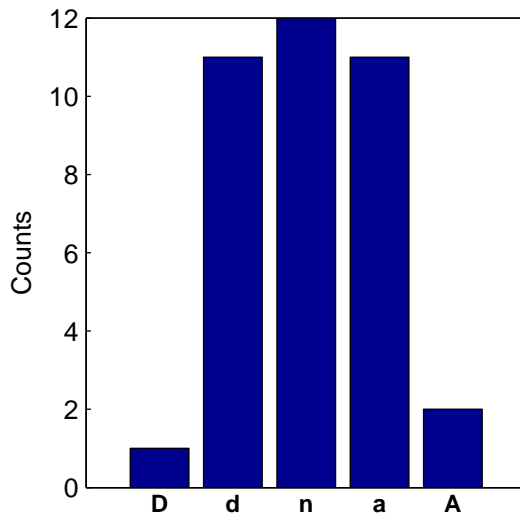


Figure 5.6: Question 5 histogram: *I learned many new concepts and techniques from the Simulated Data Analysis project.* agree/disagree = 13/12, $N = 37$.

question 5 responses is shown in Fig. 5.6

Question 6 asks students to compare the value of the data analysis lectures to the simulated data analysis assignment. The student responses are also fairly divided, the distribution is normal indicated by the K-S test ($p = 0.12$), and the mean is not statistically significant indicated by Student's t -test ($p = 0.21$) and the Wilcoxon signed rank test ($p = 0.21$). This indicates that students found the data analysis lectures and simulated data analysis assignment to be fairly equally valuable.

5.5 Student adoption rate and approval of tools

The student adoption rate of the provided tools is an indicator of the effectiveness of the curriculum. Questions 8–11 in the survey indicate the usage and approval of the advanced lab fitter.

Question 8 asks students whether the advanced lab fitter was an improvement over previously employed tools, specifically FARADAY. Not all students had an opportunity to

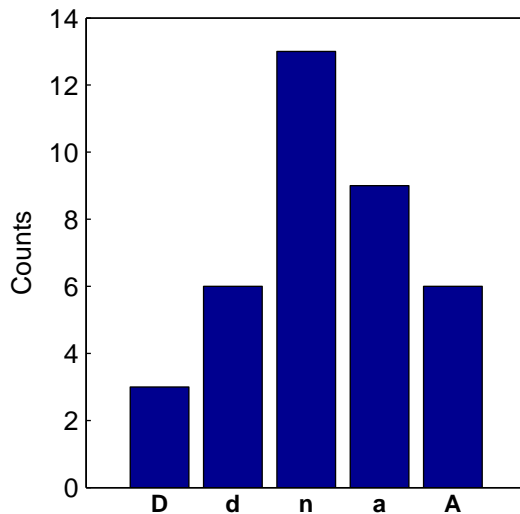


Figure 5.7: Question 6 histogram: *Attending the data analysis lectures was more valuable than doing the Simulated Data Analysis project.* agree/disagree = 15/9, $N = 37$.

use the advanced lab fitter since it was only provided as a recommended tool. However, the responses from this question were mostly in agreement, not distributed normally (K-S test $p = 0.0035$), and highly significant (Wilcoxon signed rank test $p = 3.6 \cdot 10^{-5}$) with a high mean of 0.95. The histogram of question 8 responses is shown in Fig. 5.8. If the responses of students who did not use the advanced lab fitter are discarded, the mean of question 8 increases to 1.24 with similar significance statistics.

Question 9 asks whether the advanced lab fitter was easy to use without comparison. The responses were also in agreement, not distributed normally (K-S test $p = 0.0042$), and highly significant (Wilcoxon signed rank test $p = 0.0017$) with a mean of 0.65. If the responses of students who did not use the advanced lab fitter are discarded, the mean of question 9 increases to 0.83 with similar significance. The histogram of question 9 responses is shown in Fig. 5.19. The ease of use of the advanced lab fitter was highly correlated to the approval rating of the fitter. The two-dimensional histogram of question 9 responses versus question 8 responses is shown in Fig. 5.10.

A number of students commented that they were not provided with adequate background with the MATLAB environment. This may explain the noticeably split distribu-

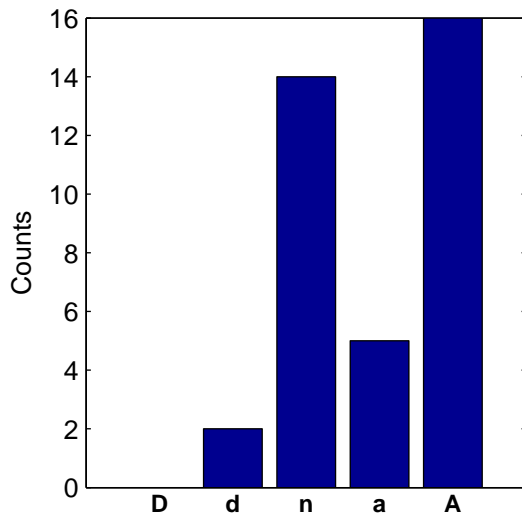


Figure 5.8: Question 8 histogram: *The data analysis tool provided for the project (Advanced Lab Fitter) was an improvement over FARADAY and existing tools.* agree/disagree = 21/2, $N = 37$.

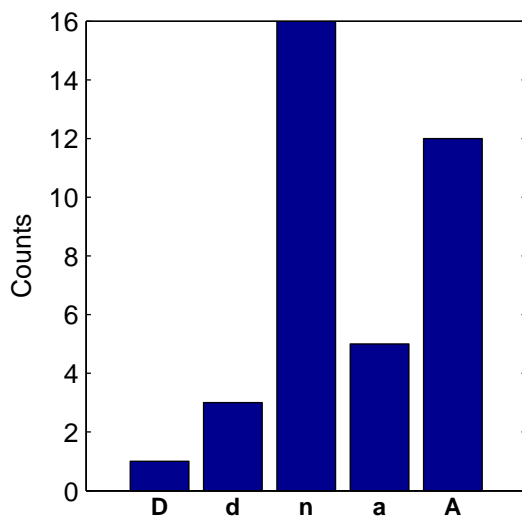


Figure 5.9: Question 9 histogram: *The Advanced Lab Fitter was easy to use.* agree/disagree = 17/4, $N = 37$.

tions of responses for both questions 8 and 9. Nearly all students who strongly agreed with one of question 8 or 9, strongly agreed with the other. Students with some experience with MATLAB found that the analysis tools were easier to use and powerful.

Question 10 asks whether students switched to using the advanced lab fitter for their

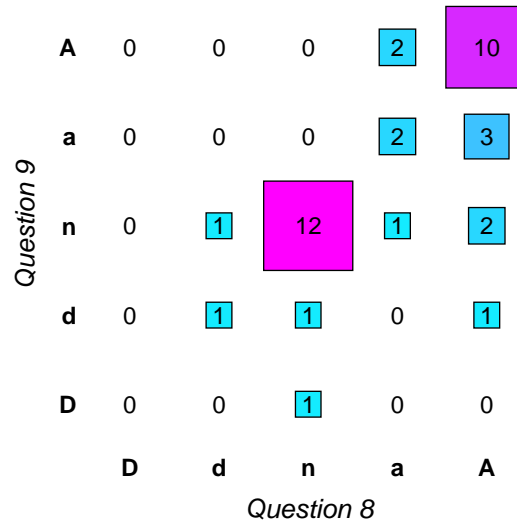


Figure 5.10: Question 9 vs. Question 8 histogram. Correlation coefficient, $r = 0.69$, $p = 2.3 \cdot 10^{-6}$, $N = 37$.

data analysis. The responses were divided, not normally distributed (F-S test $p = 0.0046$), and not differing from neutral significantly (Wilcoxon sign rank test $p = 0.76$). A majority of students did not opt to switch to using the advanced lab fitter, but there are significant correlations relating the adoption of the advanced lab fitter with perceived ease of use, improvement over FARADAY, and ability to explain operation.

5.6 Survey correlations

Significant correlations in the survey data do not identify causality, but show associations between subsets of the sample population. For example given a population with characteristics x and y and correlation r between the two, a sample population of $\bar{x} = \mu_x + \sigma_x$ is expected to have the property of $\bar{y} = \mu_y + r\sigma_y$. The correlations can also help to identify a more detailed investigation into the relationship between two characteristics of the population, such as identifying the causal relationship.

Question 2 asks whether the student was comfortable and confident in their skills of data analysis prior to entering the course. Confidence in ability prior to the course had

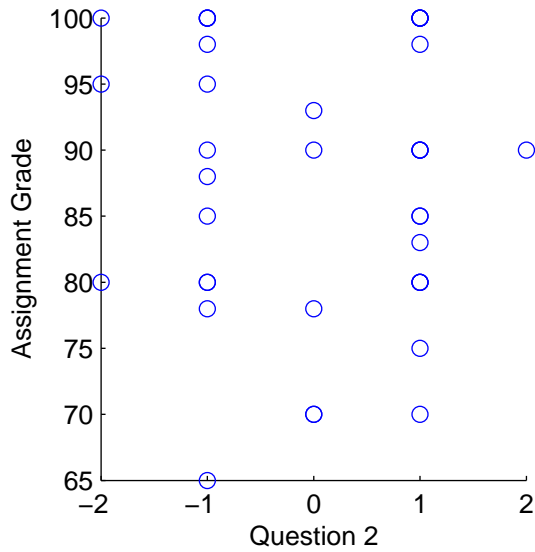


Figure 5.11: Assignment Grade vs. Question 2 scatter plot. Correlation coefficient, $r = -0.06$, $p = 0.74$, $N = 37$.

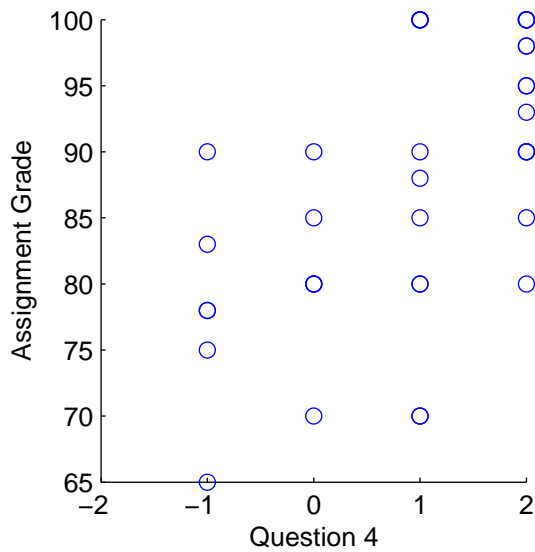


Figure 5.12: Assignment Grade vs. Question 4 scatter plot. Correlation coefficient, $r = 0.59$, $p = 1.2 \cdot 10^{-4}$, $N = 37$.

no bearing on any survey question at all, and interestingly, no association with grades. It was expected that students who were confident in their abilities may have felt they learned less, or may have received higher grades, but neither of these correlations were detected. A scatter plot of question 2 responses versus assignment grade is shown in Fig. 5.11.

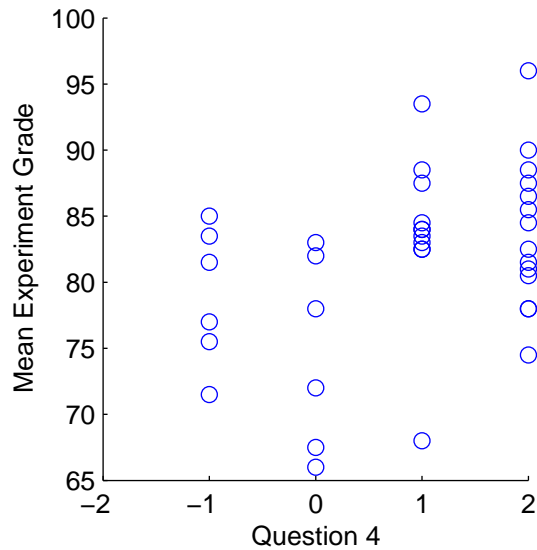


Figure 5.13: Mean Experiment Grade vs. Question 4 scatter plot. Correlation coefficient, $r = 0.39, p = 0.017, N = 37$.

Question 4 asks whether the student applied the concepts and techniques taught in the data analysis lectures in their own laboratory work. The response on this question is notable because it is correlated with the largest number of other survey questions, and it is moderately correlated with the assignment and both experiment grades. These results are interesting because the question of application appears to have the greatest effect on the grades of the student. The adjacent questions both ask whether the student has learned many new things from the lectures and assignment, but neither of the responses of the adjacent questions appear to be related to the grades. The scatter plots and statistics are shown in Fig. 5.12 and Fig. 5.13.

These results suggest that the application of concepts is an indicator of student performance. It also suggests that identifying an application for usage of a concept or technique is an effective way of improving student performance. The application of concepts was also found to be highly correlated to approval of the advanced lab fitter, and ease of use. These correlations will be examined in further paragraphs.

Question 7 asks whether the student expended a considerable effort to complete the simulated data analysis assignment. Ideally, an assignment should be designed so that

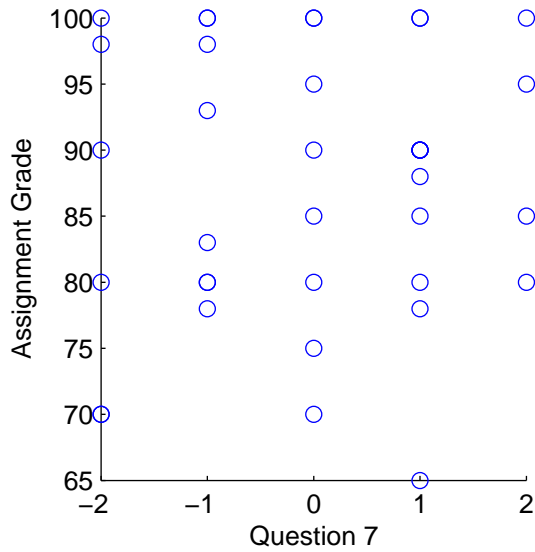


Figure 5.14: Assignment Grade vs. Question 7 scatter plot. Correlation coefficient, $r = 0.07$, $p = 0.66$, $N = 37$.

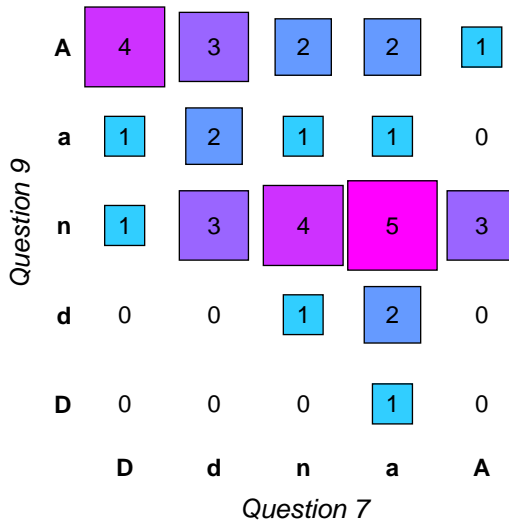


Figure 5.15: Question 9 vs. Question 7 histogram. Correlation coefficient, $r = -0.39$, $p = 0.015$, $N = 37$.

applying greater effort should result in a higher grade. This does not imply that all students who put in a certain level of effort should get an identical grade, but that for an individual student, increased effort should result in acknowledgement of work done. With these ideals in mind, one would expect a mild correlation between assignment grade and effort, but instead, there is no measurable correlation between effort and assignment grade as shown

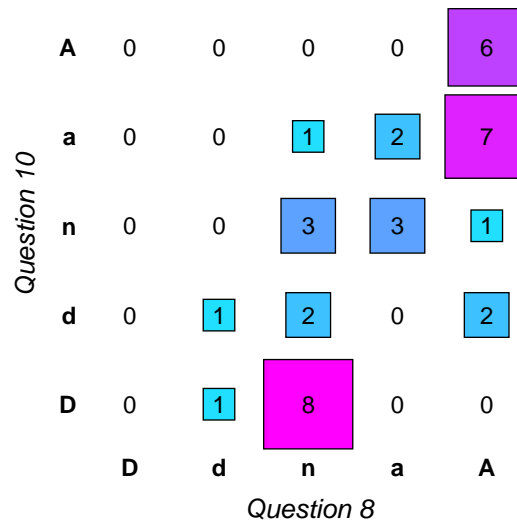


Figure 5.16: Question 10 vs. Question 8 histogram. Correlation coefficient, $r = 0.75$, $p = 9.4 \cdot 10^{-8}$, $N = 37$.

in Fig. 5.14. This could possibly be explained by the partial adoption of the advanced lab fitter amongst students. However, there is the expected negative correlation between expended effort and ease of use of the fitter. This negative correlation is shown in Fig. 5.15.

Question 8 asks whether the student believes that the advanced lab fitter is an improvement over the FARADAY fitter. The strongest correlation from the entire survey is between this question, the approval of the advanced lab fitter, and the adoption of the fitter (question 10), which was expected. This correlation is shown in Fig. 5.16

Question 11 asks whether the student can explain how the advanced lab fitter works at a high level. These responses were correlated with adoption, which was also expected. A more interesting correlation was that ability to explain the fitter operation was negatively correlated with the desire for a textbook. This correlation suggests that students who were unable to explain the operation did not learn well from lecture or example, but are most comfortable with textbook instruction. This negative correlation is shown in Fig. 5.17

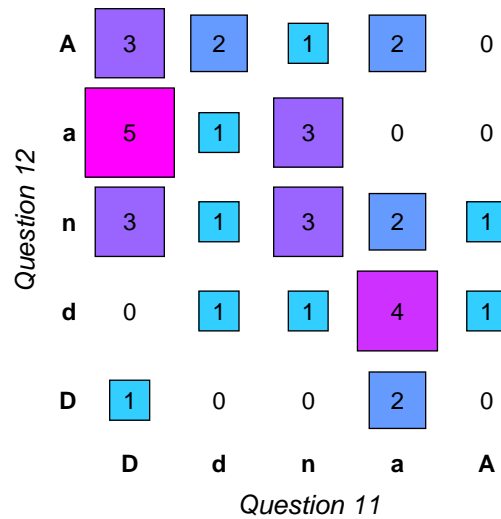


Figure 5.17: Question 12 vs. Question 11 histogram. Correlation coefficient, $r = -0.38$, $p = 0.019$, $N = 37$.

5.7 Student epistemology

Ideally, questions of student epistemology should be asked before and after a course of study. In this case, a survey was only administered once, so the only information that can be weaned is whether students have favourable or unfavourable epistemological beliefs, and whether a contrary belief may affect their performance in the course. The questions on student epistemology had very consistent results. For both questions 14 and 15, the results were highly significant, and in considerable disagreement with the statements, which is the favourable response. Disagreement to the statements of question 14 and 15 indicate that physics is a fundamentally experiment science and that empirical evidence is the only source of knowledge, regardless of the appeal of a theory. There were no significant correlations between the responses to question 14 and 15 and other questions or grades.

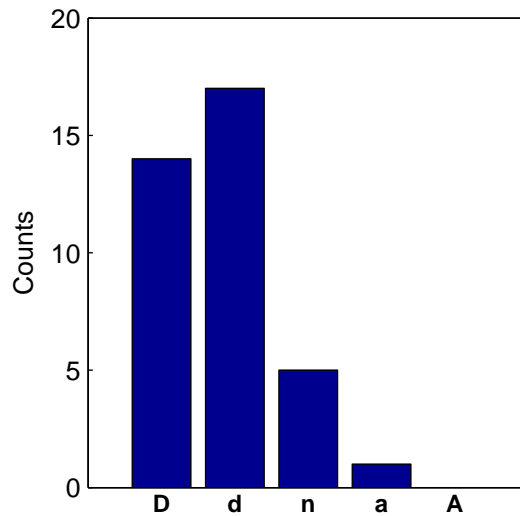


Figure 5.18: Question 14 histogram: *Experiments are performed to verify existing theories, not to discover new theories.* agree/disagree = 1/31, $N = 37$.

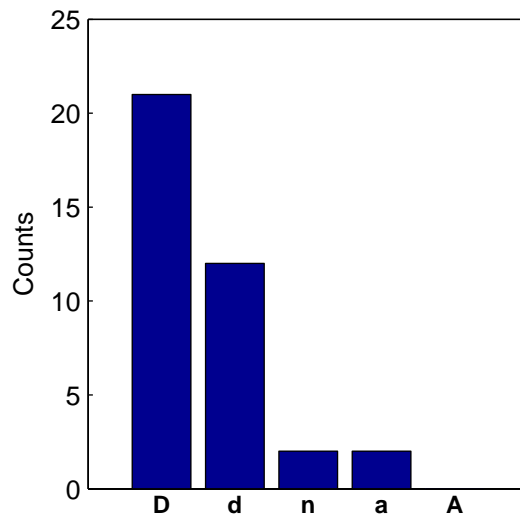


Figure 5.19: Question 15 histogram: *If the data set doesn't agree with theory after careful analysis, the experiment must be flawed.* agree/disagree = 2/33, $N = 37$.

5.8 Student positive or negative feedback

The contents of the comments and suggestions boxes on the back of the survey forms were all read and interpreted as either “critical”, “neutral”, or “supportive”. Critical comments include complaints and other negative comments, neutral comments included observations

	critical	neutral	supportive
data analysis lectures	3	17	17
simulated data analysis assignment	5	27	5
advanced lab fitter	4	25	8

Table 5.4: Summary of student comments and suggestions from survey forms, $N = 37$.

about the features without making suggestion or criticism and blank responses, supportive comments included suggestions for features and positive comments. The results are summarized in Table 5.4.

The data analysis lectures were generally praised and enjoyed. A common comment throughout surveys was the desire for typed notes because some people had difficulty reading the handwritten notes that Professor Thywissen had provided. The simulated data analysis assignment didn't generate many positive or negative reactions. A common comment with regard to the analysis assignment was that students felt that it was overload to be done in parallel with the first experiment. Some students also suggested that it was useful, but would prefer to have it done on a different schedule. The advanced lab fitter also generated mixed reaction. To some students, the interface and usage was intuitive, but others indicated that the learning curve was too steep. A common suggestion was to provide a MATLAB tutorial either in writing or integrated into the data analysis lectures.

Chapter 6

Conclusions

The addition of a data analysis component to the advanced physics laboratory has been beneficial and has helped to address a gap in content that laboratory students lack. However, there are limitations to the impact of the proposed and implemented set of curriculum additions.

The data analysis lectures were generally well received. Students strongly agreed that the data analysis lectures were valuable, and had mostly supportive and positive comments about its implementation. The application of this material was found to have significant value to the performance of students. All grades, including the simulated data analysis assignment and the two experiment grades were moderately correlated with students' degree of application of the lecture material.

The simulated data analysis assignment met a mixed reaction. Based on survey responses, students felt that it was equally valuable, but had additional criticisms of its implementation. It is valuable because it reinforces the application of lecture material in a fairly realistic example. However, the assignment was not found to have significant impact on student performance nor any correlation to student performance, other than assignment grade to experiment grade. This suggests that while the assignment may be useful in theory, in practice it ended up being somewhat cumbersome.

A positive outcome from the assignment of the simulated data analysis assignment was the adoption of the advanced lab fitter. Students who used the fitter were able to complete the simulated data assignment with ease, and many students who used the advanced lab fitter in their assignment continued to use it in their laboratory work. The simulated data analysis assignment could be used as a tutorial exercise for the advanced lab fitter, since the solutions are generated using the same code. Overall, the introduction of formal data analysis instruction had a positive outcome, although not yielding considerable improvement in student performance.

Recommendations for revisions to the data analysis curriculum are outlined in the next chapter.

Chapter 7

Further work

7.1 Additional changes to curriculum

The results of this study have suggested that the value of the simulated data analysis assignment is limited. However, as a springboard to using the MATLAB-based advanced lab fitter, it has proved to be useful. The simulated data analysis assignment could be given as a tutorial for the advanced lab fitter by making its usage mandatory. A short MATLAB tutorial and fitter walkthrough could be provided with the assignments to encourage students to use the tool.

The data analysis lectures could be expanded to cover a greater number of topics and made separate from the experiments. The idea of separating the data analysis component from the experimental work entirely by reserving the first week of the semester has been brought up in discussions with the course coordinator. This suggestion would facilitate expanded lectures and additional tutorial on the usage of the data analysis environment.

7.2 Continuing analysis of curriculum effectiveness

If the data analysis lectures and simulated data analysis assignment are made permanent parts of the advanced physics laboratory, then there must be continued analysis on the effectiveness of the curriculum. In particular, questions of student perceptions of value, adoption rate, approval of tools, and changes in grade performance should be examined in the longer term.

7.3 Fitter improvements and supplemental material

Student suggestions have been useful for identifying possible expansions of functionality for future versions of the tool. Relatively simple additions to the tool-set could include a 3-D surface fitting toolkit, which can actually run on the existing fitting engine with changes only to the metric wrapper functions.

MATLAB remains an environment with a steep learning curve. However, its ubiquity in scientific and engineering research warrants its instruction. In addition, the availability of a better tool begs its usage. The addition of a MATLAB tutorial and fitter walkthrough to the simulated data assignment would greatly reduce the pain of learning how to use MATLAB. The installation of the fitter on the Nortel lab computers using the student accounts proved to be quite tricky. Pre-installation could also minimize headaches. A side benefit of moving to a single fitting solution is that students will have more opportunity to help each other within the lab. With a cornucopia of different data analysis tools and packages, each person has the responsibility of learning and maintaining their own tools. However, with a environment and tool, students will be able to assist each other with their analyses.

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Appendix A

Advanced Lab Fitter

A.1 Functional description

The following material has been adapted from the Advanced Lab Fitter manual.

A.1.1 Introduction and Principles of Operation

The fitter operates in MATLAB and has a graphical user interface to shield the user from the tedium of handling command line options. The fitter works under the principle that a set of measurements should be organized by variable. So, if we take a set of measurements of temperature and voltage, the voltage measurements can be given a name, say `volt` and the temperature measurement can be given a name, say `temp`. This is opposed to an analysis system that works under the principle that measurements should be organized by data point.

Every set of data must be represented in the workspace as an $N \times 2$ matrix. By convention, the first column is *always* the measurement and the second column is always the uncertainty. This is consistent with the idea that a measurement is not meaningful without an uncertainty. Another note is that to be able to fit or plot two variables, they must have the same number of rows.

So, suppose we perform an experiment and collect 3 data points of temperature and voltage, $(280 \pm 1 \text{ K}, -0.45 \pm 0.03 \text{ mV})$, $(290 \pm 1 \text{ K}, 0.04 \pm 0.06 \text{ mV})$, and $(300 \pm 1 \text{ K}, 0.66 \pm 0.07 \text{ mV})$.

These data should be defined in your workspace with two matrices,

$$\text{temp} = \begin{pmatrix} 280 & 1 \\ 290 & 1 \\ 300 & 1 \end{pmatrix} \text{ and } \text{volt} = \begin{pmatrix} -0.45 & 0.03 \\ 0.04 & 0.06 \\ 0.66 & 0.07 \end{pmatrix}$$

The software is broken into two parts that work independently. There is the *Data Preview and Browser* and the *Fitting Tool*. The Data Preview and Browser is executed with the command `databrowser`. The Fitting Tool is executed with the command `fitter(x,y)`, where `x` and `y` are the data corresponding to the `x` and `y` axes respectively.

A.1.2 Data Preview and Browser

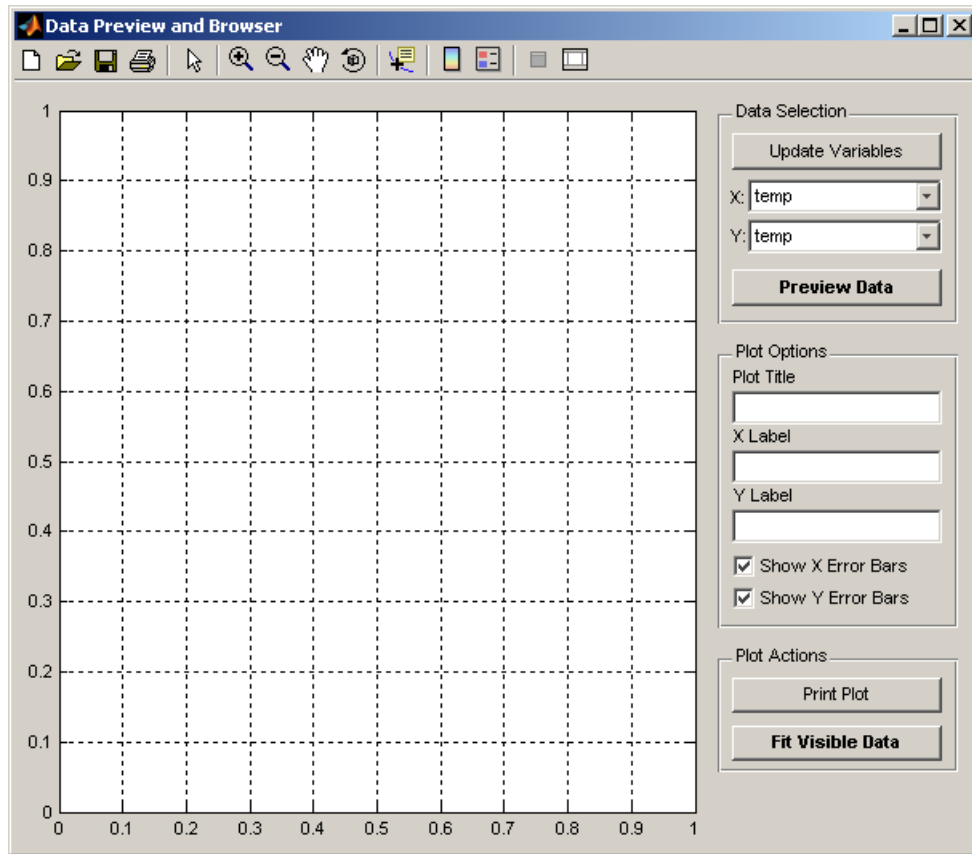


Figure A.1: The Data Preview and Browser.

Upon running the command `databrowser`, you are presented with the interface shown in Fig. A.1. There is one large pair of plot axes, three panels of buttons and edit boxes, and a toolbar at the top of the window.

The *Data Selection* panel allows you to select data from your workspace and using the drop-down menus and plot them against each other using the *Preview Data* button.

The *Plot Options* panel allows you to change the appearance of the plot. You can add labels to the axes and a title using the edit boxes and show or hide the error bars with the check boxes. You will need to use the *Preview Data* button to show changes in error bar visibility.

The *Plot Actions* panel allows you to print or fit the data on the plot. To print a

formatted plot which will fit nicely into a standard black lab book, click the *Print Plot* button. Do not use the print button in the toolbar. You must have a preview of your data visible to print. To fit all of the data points that are visible within the limits of the preview plot, click the *Fit Visible Data* button and an instance of the *Fitting Tool* will be opened with the visible data.

Data can be selected for fitting by changing the view of the data. This can be accomplished by using the *zoom* and *pan* tools from the toolbar. The *zoom in* tool is activated by clicking on the button with the positive magnifying glass. The *zoom out* tool is activated by clicking the button with the negative magnifying glass. *pan* tool is activated by clicking the button with the white hand. All tools can be deactivated by clicking on their respective buttons a second time (they toggle). They are used by clicking and dragging on the plot.

A sample of a labeled preview plot is shown in Fig. A.2.

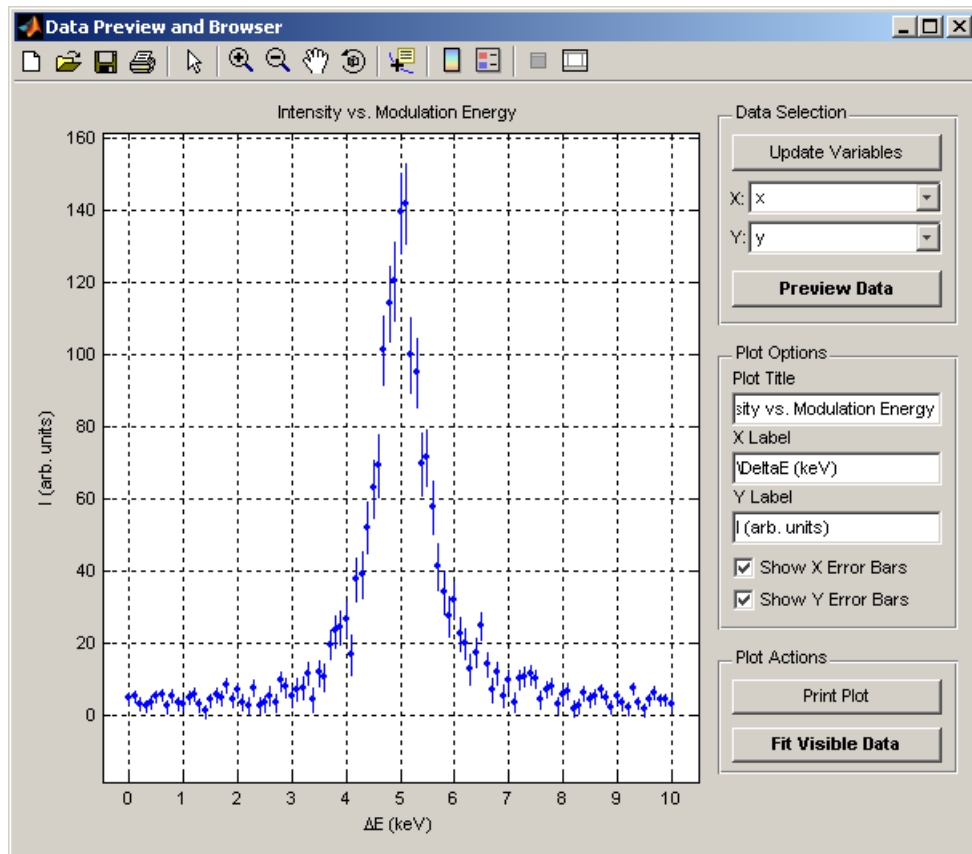


Figure A.2: Sample labelled data preview.

A.1.3 Fitting Tool

Upon running the command `fitter(x,y)` or clicking the *Fit Visible Data* button in the Data Preview and Browser, you are presented with the interface shown in Fig. A.3. There are two pairs of plot axes, three panels of buttons and edit boxes, and a toolbar at the top

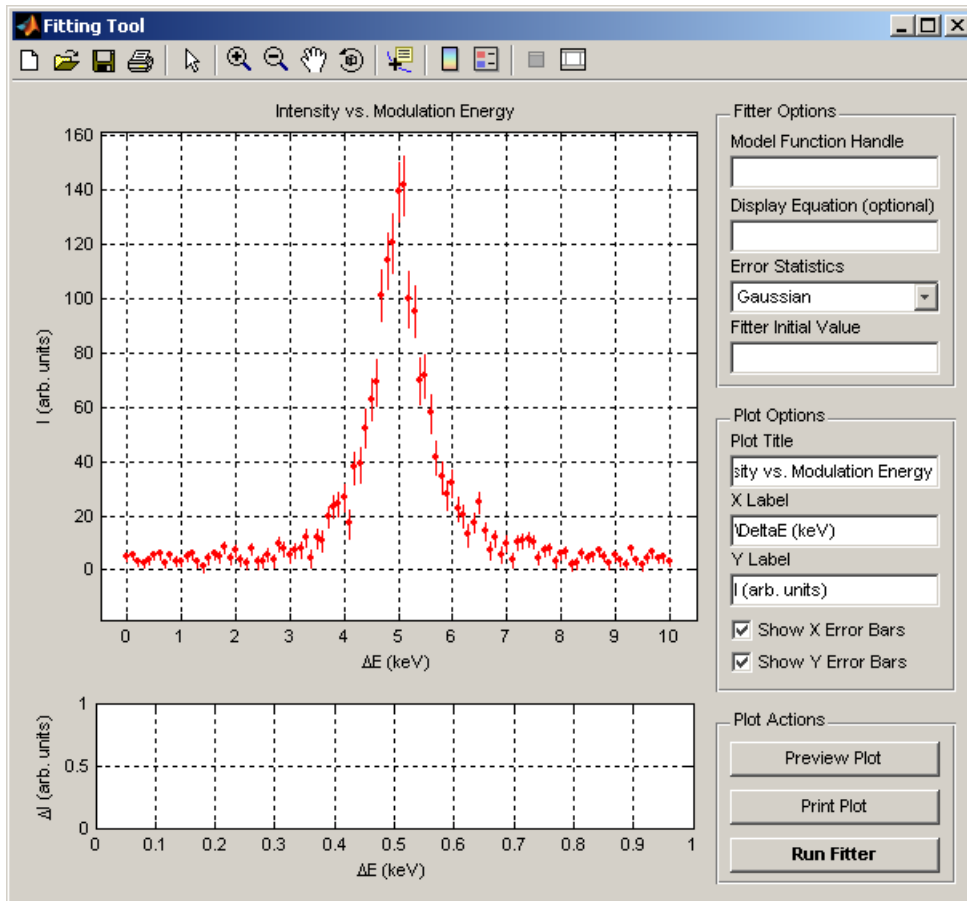


Figure A.3: The Fitting Tool.

of the window.

The large top axes displays a plot of the data, the fit curve, and whatever plot annotation is generated. The smaller bottom axes displays a plot of the fit residuals if they are available. Upon opening the Fitting Tool, there are no residuals since no fit has been attempted.

The *Fitter Options* panel allows you to change the important parameters of the fitter. The *Model Function Handle* edit box requires the name of the model you wish to fit. Each function is specified by a unique string such as “linear” or “quadratic”. A whole library of functions is available. The *Display Equation* edit box can be filled with a \LaTeX equation such as “ $y = a_1 + a_2 x$ ” which is displayed on the plot as an annotation after a fit has been made. This field is optional. The *Error Statistics* popup menu allow you to select the kind of probability distribution function that best describes the uncertainties in all the data points. The options are Gaussian, Poisson, Lorentzian, and None (blind least squares). The *Fitter Initial Value* edit box contains a series of numbers that tells the fitter where in parameter space to start its search. The input corresponds to an initial value of parameter vector \mathbf{A} specified by a list of numbers separated by either spaces or commas with the i^{th} number corresponding to a_i .

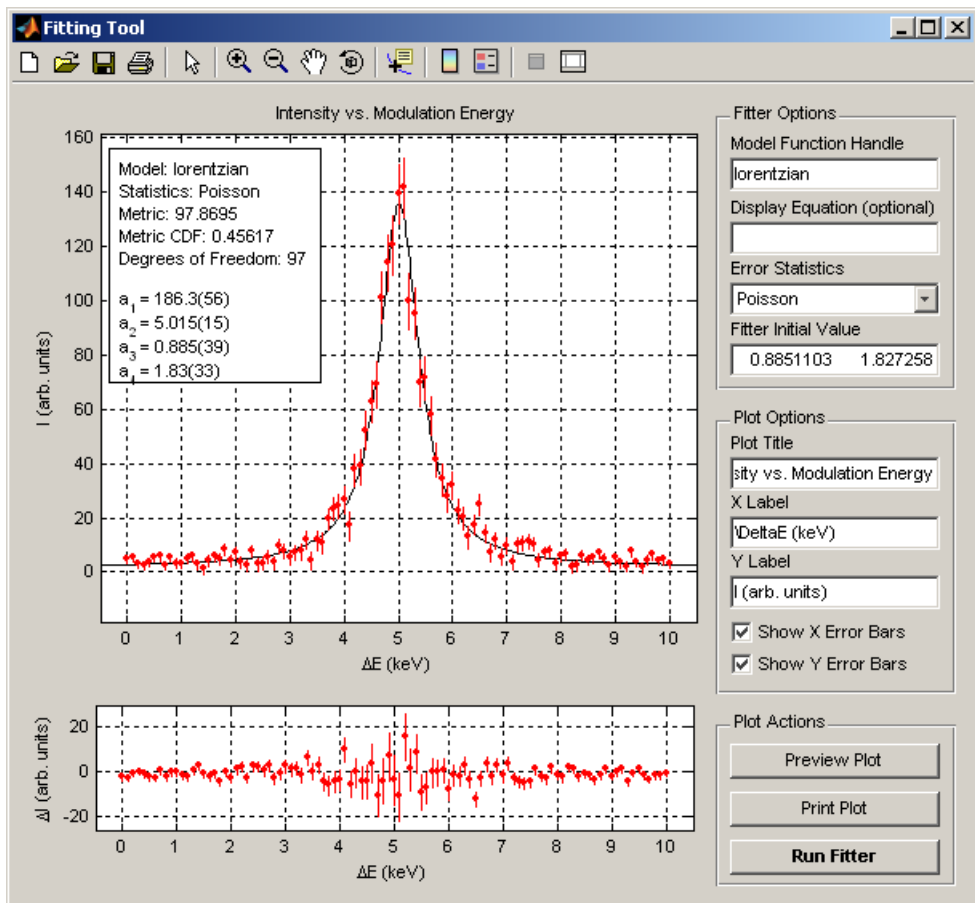


Figure A.4: Successful fit using the Fitting Tool.

The *Plot Options* panel allows you to change the appearance of the plot with the same options as the Data Preview and Browser.

The *Plot Actions* panel allows you to preview fits, print plots, and execute the fitter. The *Preview Fit* button will calculate and display a curve generated from the fitter initial values. It will also calculate the residuals to the data points and the metric with the given parameters. This feature is useful in finding a good initial value for the fitter or to manually perform a fit. The *Print Plot* button will generate a nicely formatted plot, which will fit nicely into a black lab notebook. Do not use the print button in the toolbar since it will print the panels and buttons, which are unpleasant. The *Run Fitter* button will execute the fitting routine with the data that has been provided through the user interface. While fitting, the action buttons will be grayed out and disabled. The buttons are enabled once the fitter is complete. If there is an error, the fitter will try its best to recover and tell you what went wrong.

A sample of a successful fit using the Fitting Tool is shown in Fig. A.4.

A.2 Issues and limitations

The previous section outlines the full functionality of the advanced lab fitter for MATLAB R14 and above. For the advanced physics lab, a “light” version had to be written to run on the older MATLAB R12 installed on the Nortel Lab computers. It uses the same fitting engine that is shown in the following source code section. However, it does not have the “Data Preview and Browser” tool. Instead, the variables are loaded manually into the “Fitting Tool”, which has the same functionality as the MATLAB R14 version.

A.3 Basic fitter code

Listing A.1: physfitter.m—Main fitter function.

```
1 function [residuals,A,covmat,corrmat,dof,met,metcdf] = physfitter(fun,xdat,ydat,
2     initval,fitopts)
3 % [residuals,A,covmat,corrmat,dof,met,metcdf] = physfitter(fun,xdat,ydat,initval,
4     fitopts)
5 %
6 % Run a general fitting routine to minimize a metric for given data and
7 % statistics. Options specified through fitopts structure.
8 %
9 % Rotating incoming matrices so that they are columns of data
10 if size(xdat,2) > size(xdat,1)
11     xdat = xdat';
12 end
13 if size(ydat,2) > size(ydat,1)
14     ydat = ydat';
15 end
16 % Extract data from packed matrices
17 xdata = xdat(:,1);
18 xerror = xdat(:,2);
19 ydata = ydat(:,1);
20 yerror = ydat(:,2);
21 % Determine appropriate metric based on statistics
22 switch getfield(fitopts,'Statistics');
23     case 'Gaussian'
24         metric = @gaussian_metric;
25     case 'Poisson'
26         metric = @poisson_metric;
27     case 'Lorentzian'
28         metric = @lorentzian_metric;
29     otherwise
30         metric = @lsq_metric;
31 end
32 % Set optimization options
33 lsqopts = optimset('LargeScale','off','Display','notify','MaxFunEvals',2000,'MaxIter',
34     ,1000,'TolX',1e-12,'TolFun',1e-12);
35 % Run initial roughing fit by minimizing metric
36 error = yerror;
37 %warning off MATLAB:nearlySingularMatrix;
38 [x,resnorm,residual,exitflag,output,lambda,jacobian] = lsqnonlin(metric,initval
39     ,[],[],lsqopts,xdata,ydata,error,fun);
40 % Iteratively find best chi2 with xerror introduced
41 options = optimset('LargeScale','off','Display','off','MaxFunEvals',10000,'MaxIter',
42     ,2000,'TolX',1e-9,'TolFun',1e-9);
```

```

43 for i = 1:5
44     % Calculate approximate derivatives from roughing fit parameters
45     smallx = (max(xdata) - min(xdata)) / 1e12;
46     dydx = (feval(fun,x,xdata+smallx) - feval(fun,x,xdata-smallx)) / (2*smallx);
47
48     % Adjust uncertainties by introducing xerror and run fit again
49     error = sqrt((xerror.*dydx).^2+yerror.^2);
50     [x,resnorm,residual,exitflag,output,lambda,jacobian] = lsqnonlin(metric,initval
51         ,[],[],lsqopts,xdata,ydata,error,fun);;
51 end
52
53 % Calculate residuals
54 residuals = feval(fun,x,xdata) - ydata;
55
56 % Save fit parameters
57 A = x';
58
59 % Calculate metric
60 met = feval(metric,x,xdata,ydata,error,fun);
61 met = sum(met.^2);
62
63 % Determine degrees of freedom and chi2 cumulative distribution function.
64 dof = size(jacobian,1) - size(jacobian,2);
65 metcdf = 1 - chi2cdf(met,dof);
66
67 % Calculate errors in parameters
68 alpha = jacobian'*jacobian;
69 covmat = inv(alpha);
70 A(:,2) = sqrt(diag(covmat));
71 corrmatrix = covmat ./ (A(:,2)*A(:,2)');
72
73 % Output fitting summary
74 for i = 1:size(A,1)
75     disp(['a_',num2str(i),'_=',formaterror(A(i,1),A(i,2))]);
76 end
77 disp(sprintf('met_=%f',met));
78 disp(sprintf('metcdf_=%0.3f',metcdf));
79 disp(sprintf('dof_=%d',dof));

```

Listing A.2: gaussian_metric.m—Gaussian statistics likelihood metric function.

```

1 function met = gaussian_metric(param,xdata,ydata,uncert,fun);
2 % Gaussian Metric Function
3 % Resulting vector is minimized in squared magnitude
4 err = feval(fun,param,xdata) - ydata;
5 met = err .* uncert.^(-1);

```

Listing A.3: poisson_metric.m—Poisson statistics likelihood metric function.

```

1 function met = poisson_metric(param,xdata,ydata,uncert,fun);
2 % Poisson Metric Function
3 % Resulting vector is minimized in squared magnitude
4 fitdata = feval(fun,param,xdata);
5 % ydata should be strictly positive, but fitdata may not be, so taking
6 % absolute value.
7 err = 2*abs(ydata - fitdata.*log(abs(ydata)) + gammaln(abs(fitdata + 1))) + 2*log(1./
8     sqrt(2*pi*ydata) + ydata.^(-3/2)/60);
9 met = sqrt(err);

```

Listing A.4: lorentzian_metric.m—Lorentzian statistics likelihood metric function.

```

1 function met = lorentzian_metric(param,xdata,ydata,uncert,fun);
2 % Lorentzian Metric Function
3 % Resulting vector is minimized in squared magnitude
4 err = -2*log((uncert/2).^2 ./ ((feval(fun,param,xdata) - ydata).^2 + (uncert/2).^2));
5 met = sqrt(err);

```

Listing A.5: lsq_metric.m—Least squares likelihood metric function.

```

1 function met = lsq_metric(param,xdata,ydata,uncert,fun);
2 % Least-Squares Metric Function
3 % Resulting vector is minimized in squared magnitude
4 met = feval(fun,param,xdata) - ydata;

```

Listing A.6: formaterror.m—Error formatting routine for display.

```

1 function S = formaterror(val,err)
2 % Outputs a string formatted so that x.xxxxxx(yy) \cdot 10^{exp} represents
3 % the quantity given
4
5 if val ~= 0
6     valmag = floor(log10(abs(val)));
7 else
8     valmag = 0;
9 end
10
11 if err ~= 0
12     errmag = floor(log10(abs(err)));
13     errstr = round(err * 10^(1-errmag));
14     errstr = num2str(errstr);
15 else
16     % Format val without any error
17     if abs(valmag) < 3
18         S = num2str(val);
19     else
20         val = val * 10^(-valmag);
21         S = [num2str(val), '\cdot 10^{', num2str(valmag), '}'];
22     end
23     return;
24 end
25
26 if valmag > errmag
27     highmag = valmag;
28 else
29     highmag = errmag;
30 end
31
32 % Format nicely unless the error magnitude is significantly larger than
33 % value
34 if ((abs(highmag) < 3) & (errmag - valmag < 2))
35     % Format val without exponent
36     decimals = 1-errmag;
37     if decimals < 0
38         decimals = 0;
39     end
40     formatstring = ['%', num2str(valmag-(errmag)+2), '.', num2str(decimals), 'f'];
41     valstr = num2str(val,formatstring);
42     S = [valstr, '(', errstr, ')'];
43 else
44     % Format val with exponent
45     valmag = valmag - highmag;
46     errmag = errmag - highmag;
47     decimals = 1-errmag;
48     if decimals < 0
49         decimals = 0;
50     end
51     formatstring = ['%', num2str(valmag-(errmag)+2), '.', num2str(decimals), 'f'];
52     val = val * 10^(-highmag);
53     valstr = num2str(val,formatstring);
54     S = [valstr, '(', errstr, ')', '\cdot 10^{', num2str(highmag), '}'];
55 end

```

Listing A.7: myfitmodel.m—Sample fitting function (custom definition).

```
1 function y = myfitmodel(a,x)
2 y = a(1) * x.^2 .* sin(a(2)*x) + a(3);
```

Appendix B

Simulated Data Analysis Assignment

B.1 Functional description

The simulated data analysis assignment is a data analysis exercise with dynamically generated data with artificial random noise. A series of MATLAB functions generate data with random error magnitude and descriptive parameters. This data is then fitted using the advanced lab fitter and the results are appended as L^AT_EX source to the end of template files for the assignments. The solutions are appended to a separate solution L^AT_EX source file. The raw data is also output to tab separated text files for distribution to students.

The L^AT_EX source files are compiled using a batch script employing dvipdfm to convert the .dvi files into PDFs. Adobe Acrobat Standard is used to concatenate the PDF files into a single document so that it can be printed without opening separate documents. Each separate PDF is kept for distribution to students.

The process is essentially automated. To generate the source files, run the command `makeassign(x)` within the source working directory where x is an integer that defines the number of assignments to be created. Once the source files are generated, run the `makepdfs.bat` MS-DOS batch file to compile the L^AT_EX sources and convert the .dvi files to PDFs. Finally, distribute the data files and assignment files to students either electronically through the web or email, or on paper by printing out the high quality PDF files.

B.2 Generator source code

Listing B.1: `makeassign.m`—Main assignment generating function.

```
1 function y = makeassign(qty);  
2 % Creates a assignments with quantities defined by the qty vector (length  
3 % 3).  
4
```

```

5 | % Close all dangling file pointers
6 | fclose('all');
7 |
8 | % Open the solutions file in append mode and set up the initial parts
9 | copyfile('templates/solution.tex','files/solution.tex');
10 | fsol = fopen('files/solution.tex','a');
11 |
12 | fprintf(fsol,'\\section*{Experiment A: Gaussian Peak with Background}\n\n');
13 | fprintf(fsol,'$$y = a_1 e^{-\frac{(x-a_2)^2}{2a_3^2}} + a_4 + a_5(x-a_2) + a_6(x-a_2)^2$$\n');
14 | fprintf(fsol,'Centre energy given by parameter $a_2$, total particles given by $20\sqrt{2\pi}a_1a_3$.\n\n');
15 | for i = 1:qty(1)
16 |     gentempA(fsol,i);
17 | end
18 |
19 | fprintf(fsol,'\\section*{Experiment B: Polynomial Calibration}\n\n');
20 | fprintf(fsol,'$$y = a_1 \left[ \exp\left(\frac{x}{a_2}\right) - 1 \right] + a_3$$\n');
21 | fprintf(fsol,'Magnetic field constant given by parameter $a_2$, electric field constant given by $a_1/r_{\text{disk}}$, \n\n');
22 | for i = 1:qty(1)
23 |     gentempB(fsol,i);
24 | end
25 |
26 | fprintf(fsol,'\\end{document}\n');
27 | fclose('all');

```

Listing B.2: randrange.m—Random number generator with uniform distribution over range.

```

1 | function R = randrange(lo,hi);
2 | % R = randrange(lo,hi)
3 | % Returns a uniformly distributed number within the given range.
4 | %
5 |
6 | R = lo+(hi-lo)*rand(1);

```

Listing B.3: gentempA.m—Content generating function for experiment A.

```

1 | function y = gentempA(fsol,index);
2 | % Generate template file for A
3 |
4 | fitopts.Statistics = 'Gaussian';
5 | acode = sprintf('%02d',index);
6 | filename = sprintf('files/assign%02d.tex',index);
7 |
8 | ftemp = fopen('templates/templateA.tex','r');
9 | fout = fopen(filename,'w');
10 |
11 | % Write out template with tags replaced
12 | while feof(ftemp) == 0
13 |     strtemp = fgetl(ftemp);
14 |     strtemp = strrep(strtemp,'$ASSIGNMENT_CODE',acode);
15 |     fprintf(fout,'%s\n',strtemp);
16 | end
17 |
18 | fclose(ftemp);
19 |
20 | % Generate data for assignments
21 | % Need to specify background, energy, and width
22 | Bg0 = randrange(100,1000);
23 | Bg1 = randrange(-100,100);
24 | Bg2 = randrange(-100,100);
25 | Emean = randrange(1,10);
26 | Esigma = randrange(0.05,0.25);
27 | Rate = randrange(200,1000);

```



```

28 \begin{document}
29
30 \maketitle
31 \markright{Simulated Data Analysis Project \#\$ASSIGNMENT_CODE}
32 \pagestyle{myheadings} % immediately after to get rid of first page number
33
34 Please choose one of the following two simulated experiments to analyze:
35
36 \begin{description}
37 \item{\hspace{0.5in}\textbf{Experiment A:}} Gamma Ray Spectrum of a Gaussian Peak on
    a Smooth Background, OR
38 \item{\hspace{0.5in}\textbf{Experiment B:}} Dependence of Voltage of an Applied
    Magnetic Field.
39 \end{description}
40
41 This document and the included data can be found on the web at:\\
42 \texttt{http://www.physics.utoronto.ca/~{}phy326/simdata/assign\$ASSIGNMENT_CODE.pdf}
    \\
43 \texttt{http://www.physics.utoronto.ca/~{}phy326/simdata/dataA\$ASSIGNMENT_CODE.txt}
    \\
44 \texttt{http://www.physics.utoronto.ca/~{}phy326/simdata/dataB\$ASSIGNMENT_CODE.txt}
45
46 \section*{Experiment A}
47
48 \subsection*{Experiment and Theory}
49
50 We believe we may have discovered a new particle, which we have dubbed the
51 \emph{Harlow-on}. The \emph{Harlow-on} decays to gamma rays via  $\rightarrow \gamma$ .
52 In our experiment, we have collided pairs of particles to produce \emph{Harlow-ons}
    at rest
53 which quickly decay to two gamma rays, as well as other background events. Both
    gamma rays are
54 collected in a calibrated calorimeter which yields the total energy for each event.
    Each event
55 contributes one count to a histogram bin corresponding to an energy range. The bins
    in our
56 histogram are 0.050 GeV wide and we specify the centre energy. The energy spectrum
57 of the \emph{Harlow-on} is predicted to have a gaussian shape as shown in Eq.~(\ref{
    eq:gauss}).
58 \begin{equation}
59 \label{eq:gauss}
60 C(E) = A \exp\left(\frac{-(E - E_0)^2}{2 \sigma^2}\right)
61 \end{equation}
62  $C(E)$  is the count rate at energy,  $E$ , and  $A$ ,  $E_0$  and  $\sigma$  are constants.
    This
63 peak is superimposed upon a
64 background which can be assumed to be smooth over the energy range you are
    investigating.
65
66 \subsection*{Your Task}
67
68 You must analyze the simulated data and provide the following in a short report \emph{
    no longer
69 than two pages} excluding figures and graphs.
70 \begin{enumerate}
71 \item{Estimates of the \emph{Harlow-on} energy and the total number of \emph{Harlow-
    on} events observed.
72 Please include estimates of uncertainties on these measurements.}
73 \item{Description of your analysis method including any graphs, figures, or fits.}
74 \item{If you use a fit, the  $\chi^2$  or other metric of ‘goodness of fit’..}
75 \item{A short paragraph discussing systematic effects and possible solutions to
    reduce or account
76 for them.}
77 \end{enumerate}
78
79 \subsection*{Recorded Data}

```



```

16 the effect, which is captured by Eq.~(\ref{eq:exp}).
17 \begin{equation}
18 \label{eq:exp}
19 V(B) = A \left[ \exp\left(\frac{B}{B_c}\right) - 1 \right] \approx \frac{A}{B_c} B +
    \frac{A}{2B_c^2} B^2 + O(B^3)
20 \end{equation}
21  $V(B)$  is the measured voltage at a selected magnetic field,  $B$ .  $A$  and  $B_c$  are
    two constants which characterize
22 the phenomenon. There also may be a constant voltage offset which must be determined
    from the data.
23
24 \subsection*{Your Task}
25
26 You must analyze the simulated data and provide the following in a short report \emph{
    no longer
27 than two pages} excluding figures and graphs.
28 \begin{enumerate}
29 \item{Estimates of the magnetic field constant  $B_c$  and electric field constant  $E_c$ 
    =  $A/r_{\text{disk}}$ .}
30 Please include estimates of uncertainties on these measurements.}
31 \item{Description of your analysis method including any graphs, figures, or fits.}
32 \item{If you use a fit, the  $\chi^2$  or other metric of ‘goodness of fit’.}
33 \item{A short paragraph discussing systematic effects and possible solutions to
    reduce or account
34 for them.}
35 \end{enumerate}
36
37 \subsection*{Recorded Data}
38
39 Note: Errors are given in standard notation, which includes a bracket at the end.
    This signifies
40 that the least significant digits are uncertain by the quantity in brackets. So, as
    an example,
41  $123.4(56) = 123.4 \pm 5.6$ .

```

Listing B.9: makepdfs.bat—MS-DOS batch file for processing L^AT_EX output.

```

1 @echo off
2 rem makepdfs.bat
3 rem Creates PDFs from source TeX and EPS files and deletes logs and auxiliary
4 rem files once complete.
5 rem
6
7 echo Compiling all LaTeX files...
8 for %%x in (*.tex) do call C:\MiKTeX\Main\miktex\bin\latex.exe -quiet %%x
9 rem Repeat command again to ensure that all references are done correctly
10
11 echo Resolving references in LaTeX files...
12 for %%x in (*.tex) do call C:\MiKTeX\Main\miktex\bin\latex.exe -quiet %%x
13
14 echo Converting DVI files to PDF...
15 for %%x in (*.dvi) do call C:\MiKTeX\Main\miktex\bin\dvipdfm.exe -p letter %%x
16
17 echo Cleaning up logs and auxiliary files...
18 for %%x in (*.log) do call del %%x
19 for %%x in (*.aux) do call del %%x
20 for %%x in (*.dvi) do call del %%x

```

Appendix C

Student survey

C.1 Survey questions

0. Have you taken an Advanced Physics Laboratory course in the past? *No, Yes—less than one year ago, Yes—one year ago, Yes—two years ago, Yes—more than two years ago*
1. What data analysis tools do you use most often? (Check all the apply) *FARADAY, Microsoft Excel, MATLAB, Mathematica, Other*
2. I was comfortable and confident in my skills of data analysis prior to entering this course. *D, d, n, a, A*
3. I learned many new concepts and techniques from the data analysis lectures. *D, d, n, a, A*
4. I applied the concepts and techniques taught in the data analysis lectures in my own laboratory work. *D, d, n, a, A*
5. I learned many new concepts and techniques from the Simulated Data Analysis project. *D, d, n, a, A*
6. Attending the data analysis lectures was more valuable than doing the Simulated Data Analysis project. *D, d, n, a, A*
7. I expended a considerable effort to complete the Simulated Data Analysis project. *D, d, n, a, A*
8. The data analysis tool provided for the project (Advanced Lab Fitter) was an improvement over FARADAY and existing tools. *D, d, n, a, A*
9. The Advanced Lab Fitter was easy to use. *D, d, n, a, A*
10. I now use the Advanced Lab Fitter for most of my data analysis. *D, d, n, a, A*
11. I can explain how the Advanced Lab Fitter works at a high level. *D, d, n, a, A*

12. Learning about data analysis would be easier if there was a textbook provided.
D, d, n, a, A
13. Simulated data should be analyzed differently than experimental data recorded in the laboratory. *D, d, n, a, A*
14. Experiments are performed to verify existing theories, not to discover new theories.
D, d, n, a, A
15. If the data set doesn't agree with theory after careful analysis, the experiment must be flawed. *D, d, n, a, A*

C.2 Survey results

	No	Yes, < 1 year	Yes, = 1 year	Yes, = 2 years	Yes, > 2 years
Question 0	17	16	4	0	0

Table C.1: Response to question 0, $N = 37$.

	FARADAY	Microsoft Excel	MATLAB	Mathematica	Other
Question 1	21	20	21	3	7

Table C.2: Response to question 1, $N = 37$.

	<i>D</i>	<i>d</i>	<i>n</i>	<i>a</i>	<i>A</i>
Question 2	3	12	5	16	1
Question 3	0	1	4	20	12
Question 4	0	6	6	11	14
Question 5	1	11	12	11	2
Question 6	3	6	13	9	6
Question 7	6	8	8	11	4
Question 8	0	2	14	5	16
Question 9	1	3	16	5	12
Question 10	9	5	7	10	6
Question 11	12	5	8	10	2
Question 12	3	7	10	9	8
Question 13	13	10	10	4	0
Question 14	14	17	5	1	0
Question 15	21	12	2	2	0

Table C.3: Summary of responses, $N = 37$.

C.3 Notable student comments and suggestions

data analysis lectures All alone, the material was really dry and hard to learn from. I

would leave proofs and derivations to a textbook and use the lectures to focus on the application of the treated techniques.

data analysis lectures What data analysis lectures? Please take me seriously when I urge that there should be some kind of undergraduate course like “Statistics for Experimental Physicists.” A few lab lectures is not enough. I have had to use electives and free time to learn *any* basic stats.

data analysis lectures It was great to see where the equations I’ve used in previous labs come from, but more importantly their limitations and situations in which they don’t apply. I found the first lecture a little slow, and its likely that some very basic statistics knowledge can be assumed of 3rd and 4th year students. It might be good to mention non-gaussian statistics since it is relevant to some of the labs.

data analysis lectures Maybe include the use of advanced lab fitter as part of the lectures.

data analysis lectures They were pretty much as good as can be. Haven’t had a chance to apply them yet (such has been the nature of my exp. this semester), but they filled a huge gap between what we know coming in and what we are apparently supposed to know. Finally, chi-squared makes sense.

data analysis lectures The lectures were very thorough, but too short. Perhaps more lectures that explain the concepts indepth would be better. Other than that, the lecturer Prof. J. Thywissen was very good at explaining the concepts with example. I learn a LOT I didn’t know previously.

data analysis lectures If not too much effort, typed notes would be nice. Excellent, helpful otherwise.

simulated data analysis assignment It was quite straight forward and simple. This is good since it should not be (and wasn’t a major part of the course).

simulated data analysis assignment Make the lectures end at least a week before it’s due so there is enough time to use the techniques learned.

simulated data analysis assignment To focused “chugging” numbers, not actual analysis.

simulated data analysis assignment A great exercise to refamiliarize techniques.

simulated data analysis assignment I don’t think it’s particularly useful, especially in the middle of your lab work—there isn’t much time to spend on it anyways, plus it’s too late to apply what you’ve learned (if anything).

simulated data analysis assignment I think, overall the project was useful. At least in my case I have learned a few new things and used them in my own labs. It s a good idea to have Data Analysis Project first thing in the course such that students can use the material on data analysis in all of their labs. Also at the beginning of semester there is a lot of free time, so students would be more inclined to do the assignment.

simulated data analysis assignment Provide a sample solution to each of the two types of questions afterwards so we can see what was done incorrectly.

simulated data analysis assignment I think it may have been too easy—not many factors to consider. Our labs require much more complex analysis.

simulated data analysis assignment I did not like it. Deciphering the theory took awhile, and the workload for this course is too high as it is. The time could be better spent I think.

advanced lab fitter This touches on the data analysis project as well. Make the assignment in two parts: a) A more complicated analysis with necessary fitting equations provided. b) Simpler raw data that requires the student to decide how to fit it. This would be much closer to lab reality. Though hard to find the right way to put it in a project. Is it possible to expand it (the Fitter) to 3-dimensions? This would allow for some interesting modelling.

advanced lab fitter Add more post fitting analysis tools like in the MATLAB curve fitting toolbox. This includes extrapolation and integration tools. Also, make it easier to enter data sets, like a setting for a constant error instead of a vector.

advanced lab fitter The fitter is the best program I've used, ever!! So easy to use. My only concern is that the fit equations are predefined. Maybe an option that allows us to input our own equations would be nice → kind of like the program Kaleida Graph. Other than that, it is amazing!! I use it for a lot of my other courses and labs now.

advanced lab fitter I downloaded the fitter and got MATLAB. However, did not end up using the fitter for 2 reasons. 1) No clear instruction for starting up. 2) Quite intimidating to the new user. Maybe adding a step by step fit procedure to the manual showing how a fit is done would be useful.