

SPOTLIGHT ON CURRICULUM:
"WHAT'S ON YOUR STATISTICS SYLLABUS, WHAT'S NOT, AND WHY?"

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United States Conference on the Teaching of Statistics (USCOTS 2005)
Spotlight Session: Curriculum
Designing a suitable statistical curriculum in a mathematics department

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Abstract:

Designing a suitable statistics curriculum in a department of mathematics is a topical issue. A large number of dialogues, conferences and forums have been organized where various experts have discussed this issue extensively. Against the background of faculty interests and training, and the departmental needs, we review the available statistical courses in a mathematics department in an effort to have a strong statistics minor and major degree options.

A Brief Summary

The main purpose of this work is to design a statistics curriculum from a list of available statistics courses; actively taught and stale in a department of mathematics. Our hypothetical case considers a department of mathematics offering up to a masters' degree in mathematics. Although, there are a few number of courses in statistics at the undergraduate and graduate levels, there does not currently exist either a minor or major in statistics. However, efforts are being made to consolidate existing courses, design others if necessary, and design both minor and major degree options. Curriculum development in the academia is a dynamic process, capturing new trends and needs in the society in the areas of teaching, research, development, and services. For example, there is a need to reflect the use of technology in the teaching of statistics (and also in research) into a curriculum that was designed a decade ago in order to adequately handle the current large volumes of data. Experts agreed that curriculum should be revised every five years.

Curriculum Development

We attempt to answer the following questions:

- How do we develop both minor and major statistics degree options from the actively run and abandoned statistics courses that will better serve the need of students, and reflect the current trend and development in the field of statistics?
- If new courses are to be added, what are these courses?

Some References

- Franklin, C., (2000). Are our teachers prepared to provide instruction in statistics at the K – 12 levels? *Mathematics Education Dialogues*, www.nctm.org/dialogues/2000-10/
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- http://www.maa.org/cupm/crafty/focus/cf_statistics.html

Stat 101 Counts as a Math Competency Requirement, or Why We Moved to a 4-Credit Course

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Abstract

Working with non-statistician colleagues has created rewarding challenges as our university moved from a three to a four credit introductory statistics that also doubles as a mathematics competency university requirement. This session will highlight the expanded topics outline as well as the challenges associated with guiding the statistically challenged colleagues.

Like many statisticians teaching at a university whose mission is excellence in undergraduate teaching, we have always taught a basic three credit introductory statistics course which has been a required course by disciplines such as business, allied health, pharmacy, journalism, and nursing as well as mathematics minors. Throughout the years undergraduates who aspired to graduate school in biology, political science, sociology, education, and history usually managed to enroll in this type of course to fulfill a graduate school prerequisite. At the University of Wisconsin-Eau Claire's (enrollment of 10,000) mathematics department we have two statisticians, one probabilist, applied biological mathematician, and several hybrids teaching introductory statistics to over 500 students per semester.

During the 2002-2003 academic year we decided to offer students a wider choice of options for mathematics competency. At that time a four credit college algebra was the mathematics competency choice for various disciplines who also required basic statistics. The move from a three credit to a four credit statistics course required a public relations team to market the idea across campus before proposing the idea to the university curriculum committee. For the entire academic year the team visited various departments, and presented the proposal that offered additional four credit mathematics courses for competency, i.e., finite mathematic, college algebra, earth algebra, calculus I, pre-calculus, mathematical thinking, and elementary statistics. The team solicited the departments for suggestions, but the main focus was to garner support prior to submitting the proposal to the university curriculum committee. By 2003-2004 the mathematics department had campus wide and curriculum support for this proposal. This 2004-2005 academic year we offered all the proposed courses and most importantly the four credit elementary statistics course with an expanded curricula.

The interesting challenge is that although the mathematical methods for the various topics are not difficult, the non-statistician colleagues usually have not had much personal exposure to such topics as analyses involving Chi-Square, regression, and ANOVA and probably little teaching experience related to these topics. So, part of this four credit basic statistics course that doubles as a mathematics competency involves faculty development. This will be a very time consuming enterprise. Many of our colleagues have definite ideas on the mathematical underpinnings but



desire much needed guidance on the pedagogy. Many are reluctant to develop discovery techniques and student oriented group activities. It will be a most interesting 2005-2006 academic year.

Recently, we have had request from incoming students freshmen whether or not Advanced Placement Statistics will count as the elementary statistics course and mathematics competency. Our general guideline has been a score of three or more will count in both cases. As for transfer students we will take into consideration each situation individually and decide accordingly.

Some hidden benefits: many more students may use the four credit elementary statistics course as a competency and receive information that will benefit them in their daily life, as the only college level analytic course where the students will get exposure to different critical thinking exercises. Faculty will need to rethink their method of delivery. On a personal note teaching load will become more uniform across the department (two sections of a statistics course and an upper level course per semester usually means a full teaching load –12 credits.)

The following is the expanded syllabus outline (see italic font for topics included beyond the three credit basic statistics course.) The textbook currently in use is *Statistics & Informed Decisions, 2004*, by Sullivan, Pearson Publishing.

Elementary Statistics Syllabus Outline, 4 credits

A class period is 50 minutes. Semester is fifteen weeks.

An introductory statistics course should emphasize statistical thinking, data, and concepts, while de-emphasizing recipes and computations. In particular, the course should emphasize collecting data appropriately, conducting exploratory data analysis, verifying assumptions, performing appropriate tests and interpreting the results.

Topics (not necessarily in order of presentation)	Approx Number of periods
Data Collection	4
Overview of Data Collection	
Methods of Collection	
Types of Variables	
Sampling	
Basic Vocabulary: Sample, Population	
Simple Random Samples	
Other types of sampling Block Design, Matched Pairs, (Optional) Stratified random sample	
Surveys (Optional)	
Characteristics of a well-designed, well-conducted survey	
Sources of Bias	
Experiments (Optional)	

Characteristics of a well-designed, well-conducted experiment
Treatment, Control Groups, Replication, Blinding, Placebo Effect
Sources of Bias and Confounding

Exploring Data/Descriptive Statistics

Univariate Data

8

Graphs

Types: Stemplot, histogram, boxplot (Optional: dotplot, bar graph, pie chart, cumulative frequency, time series)

Interpretation: Center, Spread, Shape, Outliers (Optional: Misrepresentation of data)

Numerical Description

Measures of Center: mean and median

Measures of Spread: standard deviation and interquartile range

Measures of Position: quartiles, percentiles, z-scores

Five Number Summary vs. Mean/Standard Deviation

Comparison of Data

Back to Back Stemplot, parallel boxplots

Comparing features of distributions (Centers, spreads, shapes, and outliers)

Bivariate Data

7

Graphs

Scatterplot

Interpretation: form, direction, strength, outliers

Numerical Description

Least-Squares Regression line

Coefficients of Correlation and Determination

Optional: Misuses of regression and correlation, causation, residual plots, influential outliers,

Two-way tables for categorical data

Random Variables/Distributions

Probability

3

Basic definition and Properties

Addition Rule for mutually exclusive events

Multiplication Rule for independent events

Optional: general probability rules, conditional probability,
tree diagrams, Bayes Rule

Random Variables

11

Discrete, Continuous

Mean and Standard Deviation of a Random Variable

Optional: Mean and Standard Deviation of Transformed Random Variable

Sampling Distributions

Binomial Distribution

Poisson Distribution

Normal Distribution

Empirical Rule, Normal Probability Plots

Law of Large Numbers, Central Limit Theorem

<u>Statistical Inference</u>	
Confidence Intervals	6
Introduction	
Confidence Level	
Types of Intervals	
For a single mean, σ known	
For a single mean, σ unknown	
For a single proportion	
For two means: independent, dependent samples	
For two proportions	
Hypothesis Testing (p-values approach emphasized)	12
Introduction	
Logic of testing, setting up hypotheses, p-values, 1 and 2 sided tests, concept of Type I and Type II Errors, Concept of Power	
Types of Tests	
For a single mean, σ known	
For a single mean, σ unknown	
For a single proportion	
For two means: independent, dependent samples	
For two proportions	
<i>Chi-Square</i>	4
<i>Goodness of Fit Test</i>	
<i>Association-Contingency Tables</i>	
<i>Independence</i>	
<i>Analysis of Variance</i>	5
<i>Inference about regression model</i>	
<i>One-way ANOVA</i>	

Note about Calculations and Technology:

An introductory statistics course should emphasize statistical thinking, data, and concepts, while de-emphasizing recipes and computations. However, it is necessary to be able to generate the correct values of statistics. Therefore technology should be used to automate calculations, allowing more time to focus on the concepts. In particular, technology should be integrated throughout the course with the following topics, at a minimum, covered using technology:

- Descriptive Statistics on Univariate Data
- Least-Squares Linear Regression on Bivariate Data
- Confidence Intervals and Hypothesis Testing
- Chi-Square*
- One-way Analysis of Variance*

Italic font represents additional topics covered in the four-credit course that are not covered in the three-credit course.

GAISE in Action

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GAISE = Guidelines for Assessment and Instruction in Statistics Education

Basic GAISE Information

- URL: <http://it.stlawu.edu/~rlock/gaise/>
 - College Report
 - K – 12 Report
- College Report endorsed by American Statistical Association
- K – 12 Report seeking endorsement

GAISE Recommendations:

- Emphasize statistical literacy and develop statistical thinking
- Use real data
- Stress conceptual understanding rather than mere knowledge of procedures
- Foster active learning in the classroom
- Use technology for developing conceptual understanding and analyzing data
- Use assessments to improve and evaluate student learning

What it Means to be Statistically Educated

- A list is given in the GAISE report to answer the question, “What it Means to be Statistically Educated”, and I include it in my policy sheet, underneath my 5 goals for the course.
- I use Moore’s Basic Practice of Statistics, 3rd Edition.
- The next set of slides give the objective and the where it is covered in the Basic Practice of Statistics

Students should believe and understand why:

Data beat anecdotes	Not clearly covered
Variability is natural and is also predictable and quantifiable	Chapter 1 Graphs, Chapter 2 Measures of Center & Spread, Chapter 9 Probability, Chapter 10 Sampling Distribution
Random <i>sampling</i> allows results of surveys and experiments to be extended to the population from which the sample was taken	Chapter 7 Sampling, Chapter 8 Experiments
Random assignment in comparative experiments allows cause and effect conclusions to be drawn.	Chapter 8 Experiments

Association is not causation.	Chapter 5 Regression, Chapter 6 Two-way Tables Chapter 8 Experiments
Statistical significance does not necessarily imply practical importance, especially for studies with large sample sizes.	Chapter 15 Inference in Practice
Finding no statistically significant difference or relationship does not necessarily mean there is no difference or no relationship in the population, especially for studies with small sample sizes.	Chapter 15 Inference in Practice

Students should recognize:

Common sources of bias in surveys and experiments.	Chapter 7 Sampling, Chapter 8 Experiments
How to determine the population to which the results of statistical inference can be extended, if any, based on how the data were collected.	Chapter 7 Sampling, Chapter 8 Experiments
How to determine when a cause and effect inference can be drawn from an association, based on how the data were collected (e.g., the design of the study)	Chapter 7 Sampling, Chapter 8 Experiments
That words such as “normal”, “random” and “correlation” have specific meanings in statistics that may differ from common usage.	Chapter 3 Normal Distribution Chapter 4 Scatterplots & Correlation, Chapter 9 Probability

Students should understand the parts of the process through which statistics works to answer questions, namely,

How to obtain or generate data.	Chapter 7 Sampling, Chapter 8 Experiments
How to graph the data as a first step in analyzing data, and how to know when that’s enough to answer the question of interest.	Chapter 1 Graphs, Chapter 4 Scatterplots & Correlation, Chapter 5 Regression, Chapter 6 Two-way Tables
How to interpret numerical summaries and graphical displays of data - both to answer questions and to check conditions (in order to use statistical procedures correctly).	Chapter 1 Graphs, Chapter 2 Measures of Center & Spread Chapter 4 Scatterplots & Correlation, Chapter 5 Regression, Chapter 6 Two-way Tables Chapters 13 – 19 Tests of Significance & CI

How to make appropriate use of statistical inference.	Chapters 13 - 19 Tests of Significance and Confidence Intervals
How to communicate the results of a statistical analysis.	Chapter 1 Graphs, Chapter 5 Regression, Chapter 6 Two-way Tables, Chapters 13 – 19 Tests of significance and Confidence Intervals

Students should understand the basic ideas of statistical inference:

The concept of a sampling distribution and how it applies to making statistical inferences based on samples of data (including the idea of standard error)	Chapter 10 Sampling Distribution Chapters 13 – 19 Tests of Significance and Confidence Intervals
The concept of statistical significance including significance levels and p -values.	Chapters 14 – 19 Tests of Significance and Confidence Intervals
The concept of confidence interval, including the interpretation of confidence level and margin of error.	Chapters 13 – 19 Tests of Significance and Confidence Intervals

Finally, students should know:

How to interpret statistical results in context.	All of the text.
How to critique news stories and journal articles that include statistical information, including identifying what's missing in the presentation and the flaws in the studies or methods used to generate the information.	Not clearly covered, but many of the margin topics relate to media material
When to call for help from a statistician.	Not clearly covered. Added by instructor

Some Uses for GAISE

- Guiding the multiple sections and multiple instructors
 - I have used GAISE to explain to departmental colleagues that *my “weird” teaching ideas* are not strange and are endorsed by a professional organization
 - To set standards across sections
- To set standards across the nation
- To help new instructors of intro. statistics

Using the “Statistically Educated” List

- Guide the instructor throughout the course
- Enable students to look
 - “forward” to what will be covered
 - “backward” to what was covered
- Guide the instructor with assessment
 - Exams and quizzes
 - Assignments
 - Etc.

Assessment

- Collect possible assessment ideas for each of the GAISE “Statistically Educated” objectives at USCOTS during Spotlight Session
- The results will be posted to the following website address after USCOTS
- <http://department.monm.edu/mathcs/Bond/GAISE.htm>
- Idea for the ARTIST website – identify questions with the objectives.

Teaching Statistics---NOT Probability

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INTRODUCTION:

We will compare two ways to present an introductory statistics course, where we define an introductory statistics course to be one for which the only prerequisite is an understanding of high school algebra. There are three broad content areas that generally appear in all such courses: probability, descriptive statistics, and inferential statistics. The difference from course to course is how much time is spent on each of these content areas, and the specific topics that are treated. Both the time spent and the topics can vary greatly from course to course. In this presentation we specifically address the coverage of probability included in an introductory statistics course. We begin by describing two general types of these courses. The first is a course that includes enough coverage of probability topics to merit the title: *An Introduction to Probability and Statistics*. An alternative is a course that has a minimal coverage of probability; we would call this course: *An Introduction to Statistics*. We will conclude with our rationale as to when and why the second course is preferable to the first.

COURSE I: AN INTRODUCTION TO PROBABILITY AND STATISTICS

Courses such as this typically include the following topics from discrete probability: Experiments; sample spaces; events; unions, intersections, and complements of events; mutually exclusive events; conditional probability; independence of events; and the multiplicative and additive rules for finding probabilities. Counting rules with permutations and combinations may also be included, and discrete probability distributions are often covered. Coverage of discrete probability distributions usually includes the binomial distribution, and may include others such as the hypergeometric and Poisson distributions. In addition to these discrete probability topics, most such courses include extensive discussion of the normal distribution, followed by coverage of sampling distributions for statistics like the sample mean and the sample proportion. It is easy to see how instructors might spend as much as, or perhaps even more than, half of the course on these topics.

The descriptive statistics segment of this course will cover both numerical and graphical descriptive methods. The specific methods covered depend on the instructor, but include at minimum the mean, median, variance, standard deviation, and histograms. Some instructors like to discuss the mode, measures of relative standing, bar or pie charts, box-and-whisker plots, stem-and-leaf plots, scatterplots, and correlation.

Finally some basic inferential techniques are discussed. Generally, tests of hypothesis and confidence intervals are both introduced. Depending on the amount of time devoted to probability and descriptive statistics, the inferential statistics segment of the course may be limited to inferences about a population mean, and perhaps a population proportion, using the normal distribution. If time is available, inferences about a population mean using Student's t-distribution may also be covered. There is usually not enough time to consider two sample procedures, or other more advanced statistical methods.

COURSE II: AN INTRODUCTION TO STATISTICS COURSE

This course covers none of the discrete probability topics mentioned in the description of the previous course, beginning instead with a discussion of descriptive statistical methods. As with the first course, exactly which topics are included is at the discretion of the instructor. The normal distribution is then introduced as a way to describe a population with a very specific shape. The notion of a probability arises by considering the percentage or fraction of measurements under some portion of a normal curve.

Sampling distributions are introduced next in the context of describing possible values of sample quantities, namely statistics. Certainly, the sampling distribution of the sample mean is covered, and a discussion of the sampling distribution of the sample proportion would also be an appropriate topic.

Unless descriptive statistics is covered in great detail, it generally takes about 6 weeks of a 15-week semester (40% of the course) to cover this material. This means that the majority of the semester can be devoted to inferential statistics.

We consider the following inferential topics to be essential: Inferences¹ about a population mean using both the z-distribution and the t-distribution, inferences about a population proportion using the z-distribution, and inferences to compare two population means using the t-distribution. The rest of the course can include whatever statistical inferential procedures the instructor finds most valuable or appropriate. Possible candidates include: Inferences to compare two proportions, analysis of variance, chi-squared tests for contingency tables, regression and correlation, and nonparametric tests. It is our experience that there is time to discuss most (all but one in fact!) of these topics.

WHICH COURSE SHOULD I TEACH?

The distinction between these two courses is obvious. The first devotes a significant amount of time to discrete probability, while the second includes none of this material and instead covers many more inferential statistical methods. We believe that you should choose the type of course that best meets your educational or curricular objectives. If you want to introduce your students to probability, descriptive statistics, and inferential statistics, then you should teach the first type of course. However, if your primary goal is to help your students understand the science of statistics, then we think you should teach the second course.

Having taught both types of courses over several years, we have reached the following conclusion: Students do not need to study discrete probability in order to understand inferential statistics. Statistical reasoning hinges on understanding when an observation is very likely or very unlikely, and we find that most students already have an intuitive understanding of these ideas. In fact, for a student taking a single introductory statistics course, time spent on discrete probability only detracts from the student's study of the science of statistics.

If we want our students to have a meaningful understanding of inferential statistics, then they must spend more than three or four weeks studying the topic. In the first type of course we think there are insufficient opportunities to discuss the concepts that are essential to understanding the inference-making process: Type I and Type II errors, the meaning of confidence, p-values, and the rationale behind the testing of hypotheses. It has been our experience that even the brightest students do not really understand these

¹ The word "inferences" in this context is meant to include both tests of hypothesis and confidence intervals.

concepts without repeatedly discussing them in multiple settings. By studying a large variety of statistical techniques, students can continually revisit all of the essential inferential concepts. We believe that this repetition leads to real understanding.

CONCLUSION:

There are many different course designs for an introductory statistics course. We strongly recommend that instructors carefully and thoughtfully consider their objectives for such a course. What do you want your students to learn? If the answer is inferential statistics, then you do not need to teach discrete probability. In this case, we strongly recommend that you try teaching *An Introduction to Statistics Course*, rather than *An Introduction to Probability and Statistics*. By eliminating the discrete probability coverage, there is time for students to gain a deeper understanding of statistical methods. In fact we like to think of this course as a course in applied statistics, which is accessible to even students with a modest mathematical background. *An Introduction to Statistics* gives students the tools to succeed in discipline-specific research courses, promotes critical thinking skills for liberal arts or general education students, and prepares students for responsible citizenship in a data-rich culture.

We would be happy to discuss these ideas with our colleagues. Feel free to contact us via e-mail at:

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Introductory Courses of Statistics for Students of the Economic University: What to Teach and Why?

Jakub Fischer

There are six faculties at the Prague University of Economics, five in Prague and one in Ceske Budejovice, the town in Southern Bohemia. At our department of statistics we organize the learning of Introductory Statistics for all five Prague faculties (Faculty of Finance and Accounting, Faculty of International Relations, Faculty of Business Administration, Faculty of Informatics and Statistics and finally Faculty of Economics and Public Administration). This learning is common and compulsory for all students of the University, so each student has the same statistics. Some other universities in the Czech Republic use the different model – each faculty has their own department of statistics and teaches statistics for their students only. This alternative model has an obvious advantage – learning of statistics could be adjusted for specifics of the branch. On the other hand, in our model student could meet the colleagues from different branches, secondly we save money and teachers (lectures are joint for all students of the University).

We teach statistics in two semesters. In each semester (our semester has 13 or 14 weeks of teaching and 6 weeks for exams) we have 3 hours per week (one two-hour lecture each week and one two-hour exercise every two weeks).

The first course (Probability and Statistics) provides students with basic statistical procedures for data processing from research and from the other areas. This course aims at education in the sphere of descriptive statistics and simple data processing and presentation using tables and graphs, elementary probability calculus, random variable, probability distributions, elements of statistical inference. It includes one-dimensional descriptive statistics, characteristics of numerical variable, simple data processing and presentation, basic operations with events and with their probabilities, random variable, basic probability distributions, sample types, sampling methods, elements of statistical inference, point estimates, confidence interval estimates, statistical hypotheses testing, selected parametric and nonparametric tests and goodness-of-fit tests.

The second compulsory course (Statistical Methods) focuses on knowledge and skills in the sphere of statistical methods of dependence investigations, methods of time series analysis and forecasting and the most commonly used types of index numbers. It includes methods of measuring dependence among numeric and categorical data (regression analysis, correlation analysis, analysis of variance, contingency tables), methods of time series analysis (elementary characteristics of time series, time series models, decomposition of time series, simple models of trend, seasonal adjustment, models with variable parameters – moving averages and exponential smoothing, time series forecasting and analysis of residuals) and finally the index numbers (individual and aggregate index numbers).

These courses are ended by credit tests (each course) and bachelor's examination. Credit tests are based on two written tests and a written homework.

At both courses we use special software. Till this semester we use Statgraphics, which is very good for pedagogical purposes, for the next year we have bought a license of SAS. This software is more robust, but many colleagues are afraid of their complexity and intricacy. There are some opinions, that Microsoft Excel is sufficient for introductory courses. This spread-sheet program has an advantage – it is available for students, they have often an Excel at their PCs at home.

Now we have to solve three topical problems: firstly, we have a little time for exercises. There is very difficult to exercises the lecture (which is two-times longer than the exercise) and show special statistical software. During exercises it is also compulsory to write two tests per semester, so there is no time for exercising themes at the end of the outline (index numbers, which could be very useful for students, maybe more useful than probability). The second problem is caused by joint learning for students from different branches (e. g. informatics and international relations), because they have very different knowledge of exact disciplines, mainly of mathematics. Some students have a basic knowledge of probability from a high school, but at some schools there is no learning of basic combinatorial and probability analysis. The third problem is organizational: each teacher has the exercises for different lecturers (e.g. one person has ten student groups from four lecturers), so there is very difficult issue to make a connection between lecture and exercise.

At some colleges (not universities!) in the Czech Republic there is less time for teaching statistics. They usually teach descriptive statistics, index numbers and economic statistics. It is a question, which approach is better. For university students, for example understanding of probability thinking is necessary.

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Gaining Student Interest in AP Statistics at Your School

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Abstract: Within three years, our secondary statistics program grew from one, difficult to fill class into our most popular elective math course. To generate interest in statistics, I created projects that increase student understanding while promoting the statistics course throughout the campus. Projects and other “promotional” strategies will be discussed.

Author Notes: I believe that every student should take a statistics course at some time in their academic careers; however, it is not always easy to get a statistics course running at the high school level. We hope in this spotlight session to share strategies for beginning a course on your high school campus as well as projects and ideas to strengthen your already existing course.

Strategies to be Discussed:

1. The First Year – Getting Students Involved

- a. Target your intended population
Unlike AP Calculus, students in AP Statistics do not need to be the strongest math students. Students do need to be proficient in Algebra II, but Pre-calculus is not necessary. It is just as important that your students have good English skills as reading and writing have a role in today’s AP Statistics curriculum.
- b. Don’t compete with Calculus
Many students are able to take both Calculus and Statistics – however, the majority of my students are students who do not want, or are unable, to compete in the AP Calculus environment. An AP Statistics program should strengthen your existing mathematics program, not compete with it.
- c. Discuss Math Requirements for University Programs
This is a large draw for enrollment in high school statistics. Have students in lower-level math courses investigate the math requirements needed for careers in which they have an interest. Students are often surprised at how prevalent statistics is on college campuses.
- d. Educate Students about the applications of Statistics
For all of your ‘when are we ever going to use this’ students, statistics is a wonderful course with many practical applications.

2. Once a Program is Running

a. Promote Statistics on Campus

Get the non-statistics students interested in your statistics class by conducting samples on campus, displaying student projects, and bringing in guest speakers. I often have younger students ask me about the course because of projects they've seen around campus.

b. Refine promotional techniques from above

3. Student comments on why they signed up for Statistics will also be shared.

Promotional Projects:

These particular projects are used both to increase student understanding of AP Statistics topics and to generate interest in taking the course to non-statistics students on campus.

An Overview of the Projects:

1. Sampling Project

After studying sampling methods: SRS, cluster, stratified, and systematic, have students design and conduct a sample on campus to answer a question of interest to them. Students begin by selecting their question of interest, their target population, and preferred sampling method. After deciding these, they submit a written sample design detailing the steps they will take to conduct their sample based on their sampling method. Their sample design includes everything from obtaining a list of their population, (if required), and detailing the sampling process to steps they will take to prevent bias and deal with issues of nonresponse. Once approved, students conduct their samples on campus. A week later they submit a poster of their results presented in a creative way that is displayed on campus. Non-statistics students who were randomly selected to participate in these samples will gather to read the results. My statistics students, as well as myself, will often receive follow-up questions about the statistics course and sampling process from non-statistics students as a result of this project.

2. Statistics in Life: Experiment/Sample Analysis

Students scour newspapers and magazines for articles that contain real-life examples of statistical inference. An article may concern a medical study, upcoming election, or other topic in which the results of an experiment or sample have been compiled. Upon selecting an appropriate article, the students then use their knowledge of appropriate statistical procedures to critique the methods used in the article. The project is broken up into parts: students must explain the methods used in this study, discuss the good and "could be improved" aspects, and redesign the original experiment or survey. Students prepare a poster containing a copy of the article with their analysis results. When displayed on campus these posters show practical knowledge the students are gaining from the course.

3. Significance Testing and Confidence Intervals on Campus

This is a natural expansion of the sampling project described above. Revisit the earlier sampling project or have students conduct a new on-campus survey for a question of interest. This time after collecting the data, students will find a confidence interval for

the true mean of the campus population or perform an appropriate significance test for a given claim. I do this project after the students have studied inference procedures with proportions as well as the t- and chi-square distributions. This is a great tool for emphasizing the importance of checking conditions as well as strengthening the students' understanding of when to use which procedure. I find that my students take this project very seriously and over the years I have had students tackle such strong issues as comparing the divorce rate of students' parents to the national divorce rate and testing for a relationship between GPA and number of sports/extracurricular activities. These projects are once again displayed on campus and become a point of conversation to promote interest in the statistics course.

**Handouts for projects as well as grading rubrics will be available at our session table. If you are unable to attend our spotlight session and would like copies, email me at gillespiemath@yahoo.com .

An Overview of the AP Statistics Program

USCOTS
May 20, 2005

Brad Hartlaub
Kenyon College

The Growth Continues!

<u>YEAR</u>	<u>EXAMS</u>	<u>% PASSING</u>
1997	7,500	62.2
1998	15,500	59.7
1999	25,000	57.1
2000	34,118	53.7
2001	41,609	59.7
2002	49,824	56.8
2003	58,230	61.9
2004	65,878	59.8
2005	The latest projection is 77,000!	

Grading the AP Exam

- Rubrics (scoring standards) are drafted by the Chief Reader
- The Test Development Committee reviews the rubrics and refines the free response questions
- Rubrics are revised and the Test Development Committee reviews the rubrics for a second time (approximately 6 months after the first review)
- The Chief Reader makes final revisions to the draft rubrics for the pre-reading meetings

Pre-Reading Meetings

- Four days before the reading begins question teams composed of high school teachers and college and university professors arrive at the reading site (Lincoln, Nebraska) to begin sample selection
- Student samples are selected from hundreds of exam booklets to form training packets and revisions are made to the draft rubrics
- The leadership team, which consisted of 43 leaders in 2004, conducts practice briefings (training sessions) and final decisions are made on scoring

A Typical Reading Day

- A briefing is held to train the readers on how to score a particular question
 - 240 readers scored approximately 66,000 exams in 2004
 - Each reader scored at least three different questions during the seven day reading
- Readers go to reading rooms and work with a partner on one folder of exams (25 exams in a folder) and then begin scoring other folders
- Two Leaders are in each reading room to answer scoring questions and backread scored exams

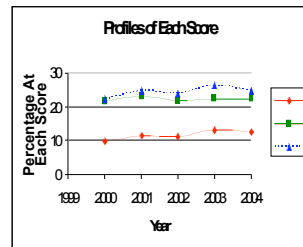
Holistic Grading

- We use a five point scoring system that is probably very different from any system you have ever used to grade papers, projects, or exams:
 - 4 Complete Response
 - 3 Substantial Response
 - 2 Developing Response
 - 1 Minimal Response
 - 0

Grade Setting

- Each student receives a composite score (100 possible points – 50 for multiple choice section and 50 for the free response section)
- Grades are set based on the distribution of the composite scores.
 - 5 – Extremely well qualified
 - 4 – Well qualified
 - 3 – Qualified
 - 2 – Possibly Qualified
 - 1 – No recommendation

Student Performance (over 5 years)



Highlights from 2004 Reading

- Overall performance on the multiple choice questions was better than the previous two years.
- The scores on the free response questions were lower than the previous two years.
- The overall average was down slightly, but very close to the averages in 2002 and 2003.

The Best and Worst of 2004

- The best news is that all six questions showed good discrimination across the entire range of scores.
- The most discouraging news is that students continued to perform poorly on standard problems dealing with statistical inference.

Common Student Errors (2004 Edition)

- Many students provided solutions with no justification or an incomplete justification. Students need to be encouraged to show all of their work and justify their answers.
- Students failed to read the problems carefully and then provided information that was not relevant to the questions that were asked.
- Communication of statistical analyses and concepts continues to be a problem.

College Comparability Study

- College students from selective to highly selective colleges and universities across the country completed free response questions 1, 5, and 6.
- Consider the logistical hurdles that must be dealt with when trying to complete this type of study.
 - Contact time, content of the course, text, quality of students, vocabulary, format of the test, etc.

Institutions Participating in the College Comparability Study

Baylor University
California Polytechnic State University
Columbia University
George Washington University
Oberlin College
Ohio State University
Texas A&M
The College of New Jersey
University of California -Davis
University of Wisconsin -Milwaukee

Results of the College Comparability Study

- AP Statistics students did much better on the exam than college students
 - The averages for the college students on all three free response questions (1, 5, and 6) were substantially below the corresponding averages for the AP students.
 - The multiple choice scores were better for AP students.
- In short, AP students stand out in every comparison that was made with college students.
- This is very encouraging and exciting news, not only for the AP Statistics Program, but for everyone involved with statistics education.

Recommendations for Teachers

- Emphasize conceptual understanding and communication over mechanics.
- Be sure that students are comfortable reading output from statistical software – integrating computer use into your course is preferable.
- Emphasize the importance of **checking** conditions for statistical procedures.
- Ask your students to answer questions in context.

More Suggestions

- Give your students time to discuss and debate their solutions in a group setting.
- Provide as many practical applications and problems as possible. Students need to practice applying the concepts they have learned before they get to the AP Exam.
- Writing assignments are essential for success – communication continues to be an area of weakness for many students.

A Clarification from the AP Statistics Test Development Committee

- Geometric distributions were recently introduced to the AP Statistics Content Outline under the Probability content area.
- On the AP Statistics examination, students will be expected to calculate probabilities for geometric distributions. However, no additional formulas will be provided on the three pages of formulas that are available for reference during the exam administration. (Students will not be expected to know the formulas for the mean and standard deviation of a geometric random variable.)

Professional Development Opportunity

- Please consider getting more involved in the AP Statistics Program by becoming a reader.
- We have been unable to hit our target of 60% college and 40% school readers.
- To complete the online application, just point your web browser to AP Central (apcentral.collegeboard.com)
- A new module on Design and Sampling will soon be available at The College Board Store.

Statistical Modeling in an Introductory Course

Daniel T. Kaplan
Macalester College, Saint Paul, MN 55105
kaplan@macalester.edu

May 6, 2005

We are teaching a novel introductory statistics course that introduces basic statistical concepts in the context of statistical modeling. We believe this helps to increase student motivation, since students can ask complicated, realistic questions of data. It also allows us to provide multivariate analysis techniques that are increasingly demanded in client departments such as economics and biology.

The course is built on some fundamental principles that make statistical modeling accessible to introductory students:

1. Whenever possible, use geometry rather than algebra for derivations. Almost all students have good geometry skills, knowing about angles and lengths and shadows. They all know the pythagorean theorem and understand the geometry of right triangles. All we need to do is get them to generalize these skills to N dimensions.
2. Use simulation and resampling to construct sampling distributions and confidence intervals. Who doesn't understand about shuffling a deck and dealing?
3. Use sophisticated computation routinely. What was a supercomputer 20 years ago is now available at the local mall for \$500, and sophisticated software such as R is free.

The tools provided by an introductory statistics course are not up to the complex questions that students need to answer in fields such as economics, business, or biology. Introductory statistics courses build an impressive theoretical structure to answer a rather simple question: Are these two groups different? Answering this question is important, but it is not the only sort of question our students will need to address. They will need to deal with multiple explanatory variables.

We might use examples of Simpson's paradox to show the importance of considering more than one explanatory variable, but conventionally we don't give students the tools to deal with such situations: just a cautionary tale.

Challenging the Assumptions

At Macalester, we had a chance to challenge some of the assumptions about introductory statistics students.

First, we revised our introductory calculus course so that it covers functions of multiple variables, modeling concepts, and important ideas from linear algebra (projection, linear combinations, subspaces, etc.) This means that the students entering our new introductory statistics course all know about vectors, how to compute angles between vectors, multi-variable polynomial models (out to quadratic order), and so on.

Second, we make available to every student sophisticated computing capability. This isn't so hard with computer prices falling and computers widely available at home. With about one-twentieth of what a year's college education costs, one can nowadays buy a laptop computer and install on it free, but sophisticated statistical software such as R. We then teach every student the basics of using such software: plotting, defining variables, reading in data, defining a function.

With the computer in hand, we are then freed from the need to teach students algorithms. Instead, we can focus on the concepts behind the algorithms, so that students develop the understanding that they need to reason about the statistics rather than being forced to follow the calculations.

Example 1: Multivariate Modeling

Our course has a very heavy emphasis on modeling. Even simple descriptive statistics such as the mean are presented as a kind of model. We don't distinguish between simple regression and multiple regression: all of it is projection of the vector of the response variable onto the subspace spanned by the explanatory variable.

In a conventional introductory statistics course, one might teach simple linear regression by having students draw a line over a scatter plot and indicate the residuals. This is a good exercise for our students too, but we also work through the calculation in a vector-space formalism: plotting the response and explanatory variables (for $N = 2$), finding the orthogonal projection of the response variable onto the model subspace, finding the residuals. These easy geometrical calculations can then be matched up to the computer's calculations. It's also feasible to do graphical calculations with $N = 3$. Once a student sees how the projection works, and sees how the graphical solution can be computed using dot products, etc., it's easy for them to understand how the computer does things

for large N .

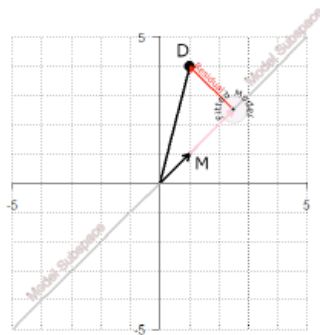


Figure 1. A graphical depiction of fitting the model $M = (1, 1)$ to the data $D = (1, 4)$. Fitting the model means finding the multiplier a to make the length of the residual vector $D - aM$ as small as possible. This particular model corresponds to finding the mean of the values in D . The fitted values, shown as a light-colored vector, are a projection of the data vector onto the model subspace. The residual vector connects the fitted values to the response values.

Example 2: Confidence Intervals

Confidence intervals play a justifiably important role in introductory statistics courses. They emphasize the variability in measurements and how to quantify them; they show why it's helpful to have large N . With the computer, it's natural to teach about sampling distributions by using simulation and resampling. No formulas are necessary. However, some central ideas — the width of the interval depends on the confidence level, the dependence on N — can still easily be expressed and mastered.

With the conceptual apparatus supplied by resampling, theoretical concepts such as power can readily be approached on a practical level. For example, suppose one has a data set that hints at the relationship between two variables, but without reaching statistical significance. If we take the data set as reflecting our alternative hypothesis, it is a straightforward matter to resample from that data set, varying the sample size as necessary to reach a desired p-value. At any given sample size, the number of trials in which the p-value is small enough indicates the power for that sample size.

Similarly, the sampling distribution under the null hypothesis can be generated by resampling an explanatory variable.

Example 3: ANOVA

Just about every student knows the pythagorean theorem and understands the geometry of right triangles. With that, and

the notion of projections, it's straightforward to understand analysis of variance. The computer allows students to do the calculations on large data sets, but students can do the basic calculations themselves with a ruler.

Here is the ANOVA report, using R software:

```
> summary(aov( c(1,4) ~ c(1,1)-1))
              Df Sum Sq Mean Sq F value Pr(>F)
c(1, 1)       1  12.5    12.5  2.7778 0.3440
Residuals     1   4.5     4.5
```

The sum of squares can be estimated graphically just by measuring the length-squared of each vector. For example, the length of the fitted model is about $23/32$ in, and the length of the residual is $7/16$ in. Taking the square of the ratio of lengths gives us the F value.

ANOVA becomes the basic training ground for hypothesis testing. It is in many ways a more natural training ground than, say, the z -test because it has a simple geometrical interpretation. For example, in the graph below, I seek to know whether the model vector M is significantly associated with the response vector D . The null hypothesis is that M is unrelated to D , that is, that M might be equally likely to point in any direction relative to D . The p-value is the probability that a randomly pointing vector would be more closely aligned with D than M is. This p-value is easily computed as a ratio of angles.

Of course, the point isn't to replace standard regression and ANOVA calculations with graphics, but to develop an intuition about the calculations so that students can successfully use them to reason about complex multi-variable relationships in the systems they are interested in studying.

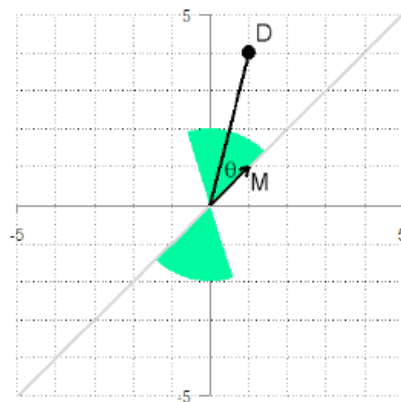


Figure 2. The p-value is the probability of a randomly pointing model vector falling closer to the response vector: that is, anywhere in the two cones shown. The fraction of the circle subtended by these cones is the p-value. In this case, since the model vector is $(1, 1)$ we are effectively testing whether the mean of D is non-zero; the ratio of angles is exactly the same as p-value generated by a one-sample t-test or ANOVA. The angle θ is 31 degrees, giving a p-value of $4 \times 31/360 = 0.344$.

Structure and Freedom Allowed Adjunct Faculty in Teaching Introductory Statistics
S. David Kriska, Mark C. Fulcomer, and Marcia M. Sass

Dimensions of Structure

Syllabus

Unstructured		Highly Structured
Extreme Anchors for the Dimension		
Adjunct choice of topics with constraint of course catalog description		Daily schedule provided to adjunct with a 'stick to the schedule' effort expected
Advantages		
<ul style="list-style-type: none"> • Capitalize on skills and interests of adjunct 		<ul style="list-style-type: none"> • Ensures uniform coverage of topics across instructors
Disadvantages		
<ul style="list-style-type: none"> • Variance across sections 		<ul style="list-style-type: none"> • Adjunct may not teach favorite topics

Textbook

Unstructured		Highly Structured
Extreme Anchors for the Dimension		
Adjunct selects text		Standard text used in all sections
Advantages		
<ul style="list-style-type: none"> • Text is familiar to adjunct 		<ul style="list-style-type: none"> • Consistency for students • Text may be used in sequence of courses
Disadvantages		
<ul style="list-style-type: none"> • Text may be inappropriate for students 		<ul style="list-style-type: none"> • Text may not be familiar to adjunct

Examples Used in Class

Unstructured		Highly Structured
Extreme Anchors for the Dimension		
Adjunct provides own examples		The department provides examples
Advantages		
<ul style="list-style-type: none"> • Adjunct provides examples with real-world appeal • Adjunct has in-depth knowledge of the example 		<ul style="list-style-type: none"> • Consistency across sections
Disadvantages		
<ul style="list-style-type: none"> • Statistical principles have the potential to become complex 		<ul style="list-style-type: none"> • Examples tend to be simple-minded

Grading Scales

Unstructured	Highly Structured
Anchors for the Dimension	
No constraints on adjunct	Median grade or frequency distribution recommended and expected
Advantages	
<ul style="list-style-type: none"> • Adjunct is free to use grades to maximize class involvement 	<ul style="list-style-type: none"> • Expected consistency across sections in grade distribution
Disadvantages	
<ul style="list-style-type: none"> • Adjunct may be too easy and concerns about grade inflation are raised. • Substantial variance across sections 	<ul style="list-style-type: none"> • Adjunct may be overly rigid in applying guidelines.

Evaluation Exercises

Unstructured	Highly Structured
Anchors for the Dimension	
Adjunct develops own tests, homework, and problems	Department provides standardized tests, homework, and projects
Advantages	
<ul style="list-style-type: none"> • Adjunct can develop interesting assignments 	<ul style="list-style-type: none"> • Consistency across sections
Disadvantages	
<ul style="list-style-type: none"> • Substantial variance across sections 	<ul style="list-style-type: none"> • Opportunities for academic misconduct • Adjunct needs to be sure all elements of tests are adequately covered

We would like to hear from you. Consider the dimensions noted above and tell us, “What constitutes ideal structure when employing adjunct faculty?”

**The Advantages and Disadvantages of Incorporating a Project
in the Introductory Applied Statistics Course**
John D. McKenzie, Jr., Babson College, Babson Park, MA 02457

Abstract: There are numerous pluses and a few minuses when one includes a project in Stat 101. This poster session will describe several successfully-used multi-deliverable projects. These illustrate some ways that a project can be effectively managed. Direct and indirect ways to assess each student's project performance will also be given.

Here is an example of one of the multi-deliverable Stat 101 projects that I used in a recent spring semester:

Project Deliverable 1 (PD1)–Proposal

Each team should submit its first project deliverable via e-mail, as an attachment, by 10:00 p.m. on xx, xx February xxxx. Before that time at least one member of each team should consult with the course instructor during an office hour about the project. Your project proposal should be placed in a well-written one-page document suitable for a business client. The document should be named PDlxx, where xx is your team, e.g., PD1A2. Among the items that should be described in your proposal to analyze an industry's websites from a well-designed sample are the following:

- your population of websites and your population frame
- your simple random sampling procedure to obtain at least 40 observations
- your pretested well-designed five-variable list of website characteristics you propose to analyze, that contains at least one categorical variable and at least one numerical continuous variable
- your well-designed plan of attack to obtain the data from your sample of websites
- your best guess at the average value you will obtain for your numerical continuous variable of most interest

Your proposal should also identify your team, e.g., A2, and its members. The maximum amount of credit for PD1 will be 10 points, out of the 100 points for the entire project. No late PD1s will be accepted.

Each member of your team is expected to contribute to the team effort. At the end of the project each member will be given an opportunity to evaluate the contributions of the other members of his or her team.

Project Deliverable 2 (PD2)–Data Collection

Each team should submit its second project deliverable at the beginning of class on xx, xx March xxxx, in a well-labeled pocket binder. Before that time it is recommended that at least one member of each team should consult with the course instructor during an office hour about the project. This deliverable consists of the following five well-designed exhibits:

- a listing of your population frame including its source
- Minitab output showing your simple-random-sample-based procedure
- a detailed explanation of your well-designed plan of attack to obtain the data from your sample of webpages—this explanation should include operational definitions of each of your five webpage characteristics among other procedural details
- your coding scheme for entering your five webpage characteristics into Minitab
- Minitab output showing the retrieval of your Minitab worksheet (MTW) data file that should be called DATAxx, where xx is the name of your team, e.g., DATAB2, an info summary of your file's contents, and a listing of your coded data

Each exhibit should identify your team, e.g., B2, and its members. The maximum amount of credit for PD2 will be 15 points, out of the 100 points for the entire project. No late PD2s will be accepted.

Each member of your team is expected to contribute to the team effort. At the end of the project each member will be given an opportunity to evaluate the contributions of the other members of his or her team.

Project Deliverable 3 (PD3)–Descriptive Statistics

Each team should submit its third project deliverable at the beginning of class on xx, xx April xx, in a well-labeled pocket binder. Before that time it is recommended that at least one member of each team should consult with the course instructor during an office hour about the project. This deliverable consists of the following:



- Minitab output showing the retrieval of your Minitab worksheet (MTW) data file that should be called DATAxx, where xx is the name of your team, e.g., DATAB2, and an info summary of your file's contents, and listing of your coded data
- Well-chosen and well-designed displays (graphs or tables) for each variable immediately followed by a succinct one-paragraph explanation of that variable (Each paragraph should mention relevant summary statistics, e.g., a mean or a proportion, in addition to describing the display. It should also describe the shape of the data based upon both the display and relevant summary statistics.)
- A one-paragraph discussion of how well your team believes it guessed the average value for your numerical variable of interest based upon the above information
- A four-paragraph discussion concerning the approximate normality of your numerical variable of interest. (The first three paragraphs should contrast the actual and theoretical properties; the last paragraph should interpret a constructed BL normal probability plot. All of these paragraphs should reference Minitab exhibits.)

Each folder should identify your team, e.g., B2, and its members. The maximum amount of credit for PD3 will be 35 points, out of the 100 points for the entire project. No late PD3s will be accepted.

Each member of your team is expected to contribute to the team effort. At the end of the project each member will be given an opportunity to evaluate the contributions of the other members of his or her team.

Project Deliverable 4 (PD4)—Inferential Statistics and Report

Each team should submit a copy of its fourth project deliverable and a well-labeled virus-free disk with only a properly-named Minitab worksheet file containing your data for the beginning of class on xx, xx April xx. Before that time it is recommended that at least one member of each team should consult with the course instructor during an office hour (and possibly the Writing Center) about the project.

The new material in this deliverable consists of the possible identification, and possible elimination, of any outliers in your numerical variable of interest, followed by inference on the same variable, even though that variable may not be normally distributed. In particular, your team should construct a two-sided confidence interval for the variable's population mean, using a seven-step procedure, and perform related two-tailed hypothesis tests, using both 10-step procedures. Based upon these exhibits there should be a one-paragraph discussion of how well your team believes it guessed the average value for your numerical variable of interest.

Each project team should combine this new material with revised material from the previous three deliverables into a well-designed project report. This report should explain how a thorough statistical analysis has been performed on a set of empirically gathered data. It should be a maximum of 10 double-spaced pages, not including a mandatory one-page non-technical executive summary of the statistical investigation. A cover page identifying your team and its members should appear before your executive summary. The report should reference a set of nicely-organized exhibits explaining the entire analysis process. For example, the actual data, along with its source, should be placed in an exhibit. These exhibits may contain computer output that must be professionally prepared. Each exhibit should identify the team and its members. Following the exhibits should be a bibliography identifying any software you have used and any books or articles you have consulted. Each report is to be neat and legible, and clearly written for an audience of managers, not an audience of Ph.D. statisticians. It is required that the report be typed with the use of a word processing package. The entire project report should be done on 11" by 8.5" paper.

The maximum amount of credit for PD4 will be 40 points, out of the 100 points for the entire project. No late PD4s will be accepted.

Each member of your team is expected to contribute to the team effort. Discussion with other individuals is allowed if it is acknowledged. At the end of the project each member will be given an opportunity to evaluate the contributions of the other members of his or her team.

Additional projects, assessment forms, etc. will be available at this session.



Eugenio María de Hostos Community College
of The City University of New York



THE FIRST US CONFERENCE ON TEACHING STATISTICS (USCOTS)

Ohio State University, May 19-21, 2005

A Spotlight Session On

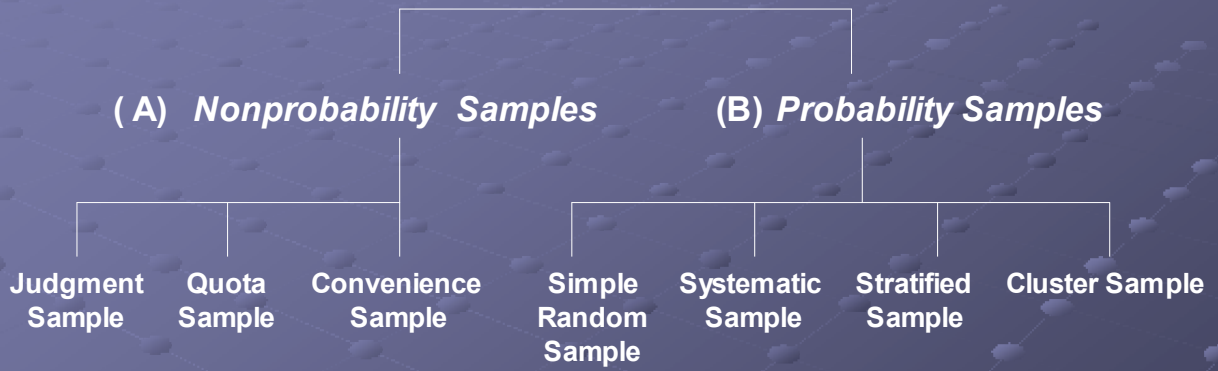
“SAMPLING & SAMPLING TECHNIQUES: ***The WHAT, the WHY, the HOW, and the WHEN to*** ***teach in an INTRODUCTORY STATISTICS COURSE***

ABSTRACT:

This presentation discusses the meaning of sampling, the reasons for sampling, the Central Limit Theorem, and the different sampling techniques. Practical examples are given to make sampling techniques understandable to students of Introductory Statistics courses. With a thorough knowledge of sampling techniques given at the appropriate time, students are equipped with the necessary tools to undertake basic research.

Presenters
Violeta C. Menil, Ph.D.
Olen Dias, Ph.D.

Types of Samples Used



Spotlight Session
What Defines a “Statistically Literate Citizen?”

Assuming that the purpose of liberal arts Stats 101 is to produce statistically literate citizens, lifelong users of statistical concepts, what exactly does that mean? What exactly are the basic statistics concepts that we want our students to master? And once the concepts are defined, how are we to teach them?

Jerry Moreno
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John Carroll University
University Hts. OH 44118
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Questions for Discussion:

1. Are our students learning anything in Stats 101 for lifelong use?

- If “yes,” what is the evidence?
- If “no,” why not?

2. Is Stats 101 preparing students for Stats 102?

- If “yes,” what is the evidence?
- If “no,” why not?

3. Can *STATS 101* satisfy both questions 1 and 2?

- If “yes,” how on earth?
What are the topics of such a course?
Once the topics are defined, how are they to be taught?
- If “no,” what has to be changed if we can offer only one course?
What are the topics of such a course?
Once the topics are defined, how are they to be taught?

To initiate discussion, I am convinced that the answers to both questions 1 and 2, are “No!” Even though our Stats 101 course has been “modernized” (ala D. Moore) over the past 15-plus years by less emphasis on formulas and more on concepts and the use of technology for computation, use of activities, etc., it is my view that students do not leave the course with well-mastered concepts that they will use throughout their lives. One reason is that the course has far too much stuff in it to allow for any sort of true mastery of even *one* concept. For the vast majority of students who take the course, Stats 101 is their sole exposure to statistics. What should be in the course that will enable them to be able to read a

newspaper more intelligently, make personal health inquiries and decisions, understand polls, political, and advertising claims, i.e., to be become better decision-makers throughout their lives?

Draft Suggested Outline of Topics for “Productive Citizens Stats 101:”

I: Graphs/Tables

Good use, bad use (bar, pie, dot, stem, box, hist, line, scatter, time, picto)

II: Probability

Contingency Table

Relative Risk

Odds Ratio

III: Inference (emphasis on two population comparison)

Confidence Interval

p-value

WHAT ARE YOUR TOPICS FOR SUCH A TRULY USEFUL COURSE?

Once the topics have been determined, then “HOW WOULD THE COURSE BE TAUGHT?” can be tackled.

Underlying requirement for the new course:

Stats 101 is a core course at John Carroll University, a liberal arts institution. As such, whatever the new hybrid literacy/methodology course is created, it must satisfy the following criteria:

- Develop quantitative reasoning
- Stress critical thinking and problem-solving
- Stress oral/written expression
- Encourage active learning
- Employ various methodologies to develop knowledge
- Be interdisciplinary
- Be foundational
- Be pedagogically rigorous
- Help students become aware of their own values
- Develop a reflective view of life
- Introduce the ethics of a discipline
- Address state-of-the-art technology
- Encourage the collaborative process of learning
- Create an awareness of current issues

Are We Teaching the Right Things in Introductory Statistics?

Jerry Reiter, Duke University
Handout for USCOTS, May 2005

This handout summarizes some of my thoughts on how we teach introductory statistics. It is meant to stimulate discussion. Please let me know your reactions by sending me an e-mail at jerry@stat.duke.edu.

Some facts about real-world statistical analyses

1. Most surveys are not simple random samples
2. Non-sampling errors (e.g., misinterpretation of questions, incorrect responses, interviewer effects) are a more serious source of inaccuracy than sampling errors.
3. Simple comparisons of means or proportions are rarely adequate in observational studies attempting to estimate causal effects.
4. Most studies have missing data.
5. Best statistical practice incorporates the science of the data in models. This is done by teams of statisticians and substantive researchers.
6. Decisions are made in the context of cost-benefit analyses.
7. New directions in statistics involve simulation and complex modeling.

Some facts about introductory statistics text books (and probably some courses)

1. Most texts spend little time on study design, usually one or two chapters.
2. Most texts spend little time on non-sampling errors, usually a handful of pages.
3. Most texts warn about the dangers of making causal statements from observational studies, but they offer few genuine examples and approaches that deal with potential confounding (e.g., by using matching methods or by modeling).
4. Most inferential problems and examples are about means and percentages, assuming simple random samples. In fact, many texts pretend that data from complex surveys were collected from simple random samples, primarily to illustrate computations with interesting data.
5. Missing data are rarely dealt with in any depth. Usually the problem of missing data is discussed in a handful of pages and then ignored in inferences. For example, often only respondents are used in problems without any discussion of nonresponse issues.
6. Most problems ask students to read a paragraph in which the science underlying the data is glossed over, if explained at all. Often, understanding the science is not needed to solve the problem, since the problem exists primarily for students to practice computations.
7. Most texts rarely get into aspects of simulation and complex modeling.
8. Most texts are organized in chapters that present methods as general tools rather than as examples of modeling specific phenomena.
9. Most texts do not place statistical analyses in the context of decision-making, except for brief discussions of practical versus statistical significance.

My Concern:

What we teach in introductory statistics does not match actual statistical practice.



Possible implications of the mismatch between real-world analyses and teaching

1. Students do not appreciate the importance of study design. For example, when asked to do their own analyses rather than text book problems, many students make causal statements from observational associations based on means or correlations. I believe part of the problem is because these computations are what text books emphasize, without adequate discussion of the issues related to the study design.
2. Students do not consider the problems of missing data (or noncompliance in experiments) in their analyses or when reading about others' analyses. They are following what they've learned to do in text books, which is to ignore the missing data.
3. Students are trained to analyze data they will rarely see in real life, e.g., simple random samples without any missing values or complicated modeling needs. When confronted with situations that don't meet those criteria, they fall back on what they know how to do, which may be irrelevant, inadequate, or even wrong for the question of interest.
4. The mismatch between teaching and practice leads to a perception that statistics is a set of tools rather than a way of thinking. The fun parts of modeling are rarely communicated to students. This weakens students' interest in statistics.
5. Because of the procedural nature of the way the material is presented, students are fixated on properties of the procedures, such as statistical significance, rather than on the practical implications of their results. This fixation is transferred to researchers and policy makers, who sometimes do not consider cost-benefit analyses.

Some thoughts on re-thinking how we teach statistics

Perhaps we need two types of introductory courses. The first course would focus on statistical literacy. We could emphasize study design, non-sampling errors, and decision-making more than we do currently, perhaps dropping some methods of inference. For example, we can drop chi-squared tests and ANOVAs, which are only valid in simple random samples or completely randomized experiments. We don't need to teach all the varieties of hypothesis tests and confidence intervals (e.g., is it really more important to distinguish between z-tests and t-tests as compared to talking more about study design?), which again have limited applicability.

The second course (which has no statistics pre-requisite) would be aimed at students potentially interested in research experiences. This course would include modeling exercises and discuss real-world analyses beyond simple means and percentages. I see no reason why we cannot teach introductory students about inference in the context of complex (linear and logistic) regression modeling, about matching methods in observational studies, about analysis of complex surveys, or about ways of dealing with missing data. I suspect such courses would increase the appreciation students have for statistics, give students a stronger foundation for further study, and more closely match statistical practice.

Stat 404: Effective Statistics Communication
Poster Presentation
United States Conference on Teaching Statistics – USCOTS
Columbus OH – May 20, 2005

Mary Ann (Mimi) Ritter
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Background

Many people have recognized the importance for statisticians of developing good communication skills. To teach these skills to their undergraduate majors, the University of Michigan Statistics Department has created Stat 404: Effective Statistics Communication.

Aim

The aim of the course is to give students the opportunity to learn and practice the communication of statistical information to statisticians and non-statisticians both orally and in writing.

Course Description

Stat 404 is a one-semester, two-credit seminar for undergraduate statistics majors and minors. A statistics project class, either sampling or experiments, is a prerequisite. Students write and speak about previous statistics work; there are no new methods taught in the class. This class satisfies the Upper Level Writing Requirement (ULWR) of the University of Michigan's College of Literature, Science and the Arts.

Grades

Grades are based on homework (30%), class participation (30%), and a final project (40%). The final project is a team project to demonstrate mastery of as many of the communication skills as possible. It includes an oral presentation and a written report. The students are asked to focus on content, organization, and execution to produce effective communications.

Course Topics

The major topics covered by the course include

- General principles
- Ethics
- Written reports
- Oral presentations
- Visual aids
- Outlines
- Outline alternatives
- Graphs
- Professional correspondence
- Resumes

Re-writing

Re-writing is encouraged as an important and necessary tool to achieve effective writing. Students are required to re-write one assignment and permitted to re-write any others that they choose in order to improve their grades. In the most recent course every student chose to re-write at least one assignment. There were 55 re-written assignments and 78% (43) of these resulted in better grades.

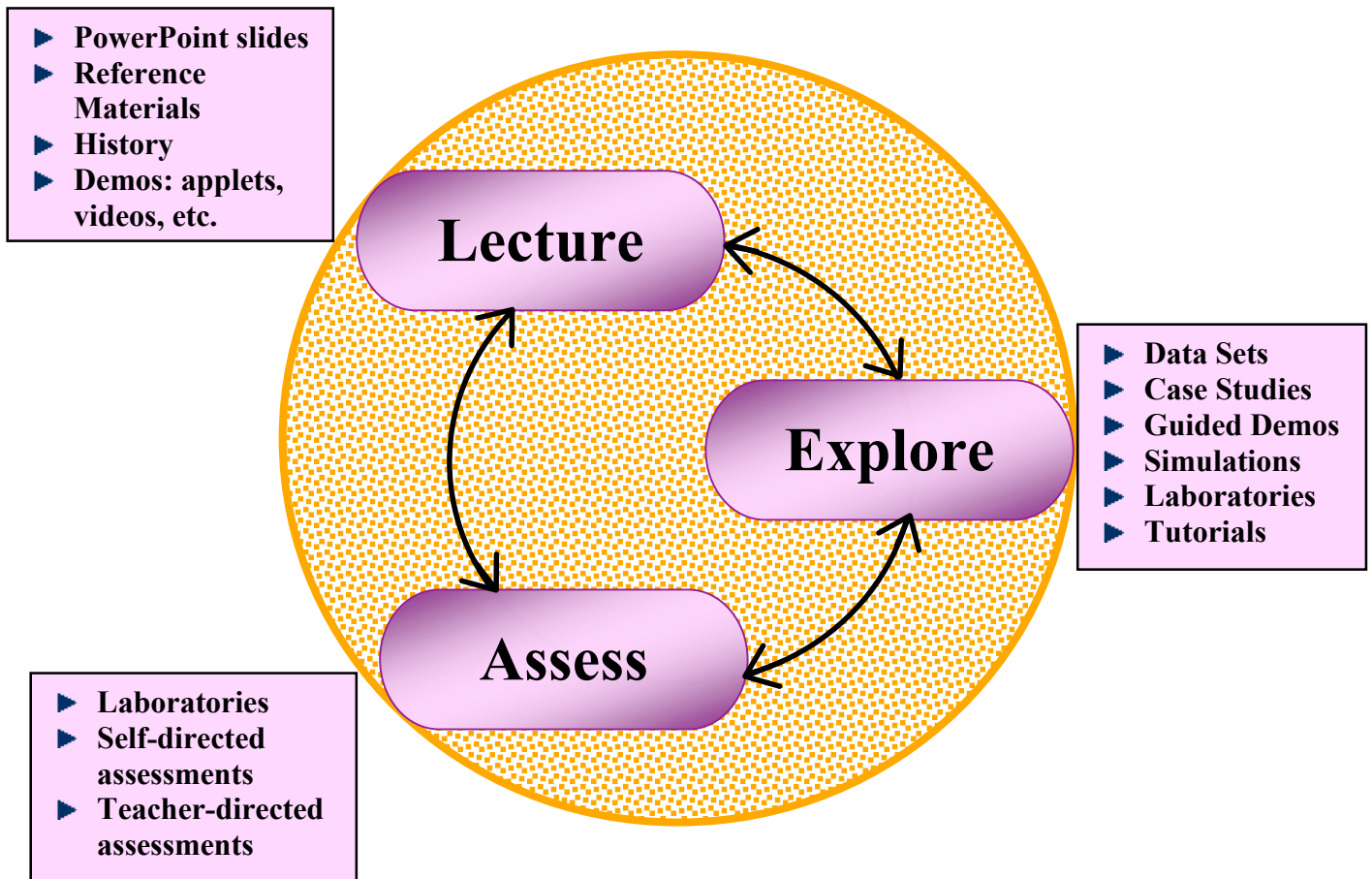
The Instructor

Mary Ann Ritter is an adjunct lecturer in the Statistics Department of the University of Michigan. In addition to teaching Statistics 404, she occasionally lectures about reliability engineering. She has over 20 years experience at General Motors in executive positions in strategic planning, production and engineering. She has an S.M. degree in management from MIT as well as a B.S. in mathematics and an M.S. in statistics from Stanford University.

Utilizing a Digital Library to Teach Undergraduate Statistics US COTS Spotlight on Pedagogy, May 2005

Ginger Holmes Rowell, Scott N. McDaniel, Lisa B. Green
Megan Duffey, Ileah McKee, and Aimee Gorham
Middle Tennessee State University
rowell, smcdanie, and lbgreen@mtsu.edu

CAUSEweb, a new digital library for undergraduate statistics instructors, is a great source for on-line teaching and learning materials. This searchable database of resources includes lecture examples, laboratory activities, datasets, analysis tools, etc. CAUSEweb's resources can be easily integrated into instructional plans for statistics courses.



Searching Hints:

It often helps to search not only by topic, but also by ***type of resource***, ***application area***, or ***object format***. For instance, if you want an applet that simulates the Central Limit Theorem and applies to business, type **applet + simulation + business + central limit theorem** in the search box. (The “+” signs are optional.)

Resource Types: animation, case study, collection, drill and practice, quiz/test, lecture/presentation, reference materials, simulation, sound, tutorial, webpage.

Application Areas: biology, business, psychology, mathematics, etc.

Object Formats: Java applet, audio, video, Flash, etc.

Utilizing a Digital Library to Teach Undergraduate Statistics: An Example

Correlation and Regression

LECTURE

Linear Regression

- Regression relationship = trend + residual scatter

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \text{Err}_r$$
- Trend=best linear fit Line (LS)

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}; \quad \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$
- Scatter = residual (prediction) error $\text{Err} = \text{Obs} - \text{Pred}$

$$\sum_{i=1}^n (y_i - \hat{y}_i)^2 = (y_1 - \hat{y}_1)^2 + (y_2 - \hat{y}_2)^2 + \dots + (y_n - \hat{y}_n)^2$$

Slides like this one from the PowerPoint presentation **Statistical Methods in Biomedical Imaging¹** can be used to save a lecturer the time of creating his or her own.

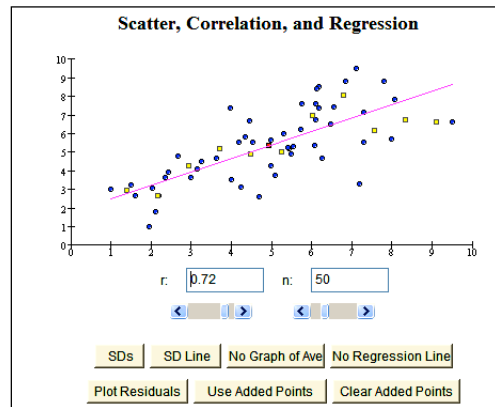
Search Criterion: correlation + regression + lecture/presentation

¹ Ivo Dinov. UCLA STAT 233.

http://www.stat.ucla.edu/~dinov/courses_students.dir/04/Spring/Stat233.dir/STAT233_notes.dir/StatisticalMethods05.pdf

EXPLORE

Applets like this one from **SticiGui Java Tools²** can be used to help students understand correlation and regression. Students can explore changes in the correlation coefficient and the data to see how it affects the regression line.



Search Criterion: correlation + regression + applet + simulation

² Phillip Stark. UC, Berkley. <http://stat-www.berkeley.edu/~stark/Java/Html/Correlation.htm>

ASSES

SELF-ASSESSMENT

Simple Linear Regression

This exercise is designed to test your knowledge of Simple Linear Regression.

You should not attempt this set of exercises until you have completed *Workbook 6 of Biometry: Statistics for Ecology and Natural Resource Management*.

Note that recalling information in an integrative way is the key to deep learning. Avoid the temptation to look at the reminders until you have made a serious attempt at answering the questions.

The Basics

1) The Correlation Coefficient is a measure of

- How well one variable can be predicted from another
- The causal relationship between two variables
- The degree to which two variables vary together
- A measure of the percentage variation in one variable that can be explained by the other
- A measure of linearity

2) Which of the following can simple linear regression NOT be used for

- To establish a relationship that can be used to predict one variable from the other
- To establish causality between a predictor variable and a response variable

Using self-tests like this one from **Biometry: Statistics for Ecology³**, students can submit their answers and get immediate feedback in terms of a grade as well as questions or topics which need improvement.

Search Criterion: regression + quiz/test

³ Arthur Georges. University of Canberra. <http://aerg.canberra.edu.au/envirostats/bm/selftest.htm>

Log-Log Plots

Paul Schuette, Meredith College

Many elementary statistics courses now cover linear regression. A natural extension of linear regression includes simple data transformations. Logarithmic transformations are natural to consider in this context. If one can obtain the relationship $\log(y) = a \log(x) + b$, it follows that $y = 10^b x^a = Ax^a$. Thus, there is a basic relationship between log-log plots and power distributions.

Historically, Pareto (1895) was the first to observe this relationship in conjunction with his investigations into the distribution of wealth. Students may investigate more recent data at <http://www.forbes.com/lists/>. A plot of rank versus wealth for the top 75 wealthiest individuals yields:

Scatter Plot

Scatter Plot

$$\log\text{worth} = -0.511\log\text{rank} + 1.77; r^2 = 0.96$$

It may be noted that for the log-log plot $r \approx -0.98$, showing a rather strong linear relationship. In fact, Pareto thought he had discovered a law of economics, analogous to the laws of physics.

Auerbach (1913) and Lotka (1924) observed similar relationships for cities. Using Census data (<http://www.census.gov/statab/www/>), a log-log plot of rank versus population for 75 cities shows

Scatter Plot

$$\log\text{pop} = -0.728\log\text{rank} + 6.75; r^2 = 0.99$$

Once again, a strong linear relationship ($r \approx -0.9926$), may be observed.

Amazingly enough, one can see a similar picture using word frequencies from James Joyce's *Ulysses*. In linguistics, this is known as Zipf's Law.

Scatter Plot

$$\log \text{freq} = -1.02 \log \text{rank} + 4.47; r^2 = 1.00$$

Finally, one can even show that such relationships hold for scholarly productivity (Lotka, 1926). Jerry Grossman's Edös Number Page <http://www.oakland.edu/enp/papers.html> contains information about the number of papers per mathematician. If we consider those who have written 39 or fewer papers indexed in Mathematical Reviews, we obtain

Scatter Plot

$$\log \text{authors} = -1.54 \log \text{paper} + 5.26; r^2 = 1.00$$

Other examples may be found in biology (area/species relationships), insurance, economics, libraries (Bradford's Law), and the popularity of web pages. Many have speculated that some general phenomena can explain these distributions, but Bruce Hill and others have shown that with the right hypotheses, limit theorems can be proven.

Managing Service Learning Projects in Statistics Courses

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A Definition of Service Learning

“Service learning is a form of experiential education where students participate in activities that integrate community needs with well-designed learning opportunities.”

Barbara Jacoby
“Foundations and Principles of Service-Learning,” *Service-Learning in Today's Higher Education*, 1996.

Service Learning in Statistics Courses at IUP

Step 1: I contacted the county Human Services Commission and asked to speak at one of their meetings. I described the possibility of having students in my classes work on statistical projects for agencies in the community.

Step 2: Two agencies contacted me for assistance. One was an addiction recovery center and the other was a counseling center. Both clients sent representatives to visit my classes. One project involved redesigning a survey and the other involved analyzing a large database.

Step 3: Working in groups, students in my classes over two semesters worked on these projects and prepared reports for the clients. The projects replaced my standard assignments using real but known datasets.

Obstacles

Some of the obstacles my students and I encountered included:

1. Obtaining specific research questions and objectives from the clients.
2. Obtaining relevant information from the clients in a timely manner.
3. Completing the work in within the time constraints of a semester schedule.
4. Distributing the work load equitably among the students and groups in the class.

Cross-Disciplinary Service Learning Teaching Circle at IUP

Colleagues from the IUP Culinary Academy, Psychology Department, and Hospitality Management Department have been meeting approximately monthly for the past two years to share ideas, identify common themes and problems, and to discuss research to assess the efficacy of service learning opportunities on student academic success.

We presented a panel discussion at the “Wings to the Future” conference at Penn State-Altoona in April 2005, and plan to present at the Lilly Conference on College Teaching in Oxford, Ohio in November 2005.

Resources

1. “Statistics as a Service Subject in First Level Courses,” Session at the Sixth International Conference on Teaching Statistics (ICOTS 6), South Africa, 2002.

Beth Chance, Organizer and Chair.

- “Community-Based Learning: Motivating Encounters With Real-World Statistics,” Trisha Thorne and Rob Root
- “Elementary Statistics International Travel Lab Component,” Robert A. Leslie
- “Enriching Introductory Statistics Courses Through Community Awareness,” Jon E. Anderson and Engin A. Sungur
- “Statistical Consulting With Undergraduates - A Community Outreach Approach,” Brian Jersky

2. “Service Learning in Undergraduate and Graduate Statistics Education,” Invited Papers Session sponsored by the American Statistical Association (ASA) Section on Statistical Education at the 2005 Joint Statistical Meetings (JSM 2005), Minneapolis, MN, August 9, 2005.

Thomas H. Short, Organizer and Chair

- “Service Learning through a Student-Run Consulting Program,” Nilupa S. Gunaratna, Craig A. Johnson, and John R. Stevens
- “Community Service Learning in Statistics: Course Design and Assessment,” Debra L. Hydorn
- “Service Learning with Undergraduates,” Brian Jersky
- KB Boomer, Discussant

Do the Right Test! A Nonparametric Approach

Brian E. Smith
McGill University

Presented at the USCOTS conference
Columbus, Ohio
May 19 – 21, 2005

Abstract:

For my second course in Statistics I emphasize the importance of non-parametric tests. I try to impress on my students the dangers of "doing the wrong" test and tie this in with the importance of goodness of fit tests for a normal distribution. Examples of non-parametric tests will be provided.

Suppose that in a test for the equality of two populations (means or medians) we have obtained the following differences in a sample of 14 paired differences:

-7, 34, -85, 140, 175, 180, 150, 99, 65, -36, 18, -8, 3, 1

When we run a sign test on these data we obtain the following results (Minitab output):

Sign Test for Median: Difference

Sign test of median = 0.00000 versus not = 0.00000

	N	Below	Equal	Above	P	Median
Difference	14	4	0	10	0.1796	26.0

We see that, at the 0.05 level of significance, we cannot reject the hypothesis $H_0: \eta_1 = \eta_2$ (p-value = 0.1796).

The Wilcoxon test yields the following results:

Wilcoxon Signed Rank Test: Difference

Test of median = 0.000000 versus median not = 0.000000

	N	for	Wilcoxon	Estimated	
	N	Test	Statistic	P	Median
Difference	14	14	82.0	0.069	50.00

Once again we cannot reject $H_0: \eta_1 = \eta_2$ at the 0.05 level of significance, but we see that the Wilcoxon test statistics of 82 is approaching significance with a p-value = 0.069.

Finally, when we apply the paired sample t-test we get:

One-Sample T: Difference

Test of $\mu = 0$ vs not = 0

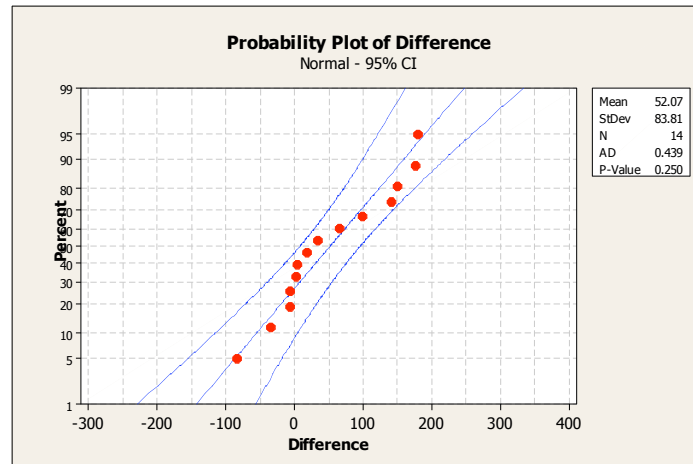
Variable	N	Mean	StDev	SE Mean	95% CI	T	P
Difference	14	52.0714	83.8107	22.3993	(3.6806, 100.4623)	2.32	0.037

In this case we see that the p-value is 0.037 so that we can conclude that there is a significant difference between the population means. We also note the 95% confidence interval is between 3.68 and 100.46, so that the interval does not contain 0.

In this problem it is critical to know which test is the right one, since they yield different conclusions!

To perform the t-test we need to assume a normal distribution. Do the data support this assumption?

The normal probability plot below indicates that the population of differences may be assumed to be normal.



Therefore we are justified in using the paired samples t-test and we can conclude that there is a significant difference between the population means. Note that if we had performed the wrong test (either the sign test or the Wilcoxon signed rank test) we would not have rejected the null hypothesis of no difference, because of the lack of power associated with these tests.

We conclude that in general it is preferable to perform parametric tests, and we should only resort to nonparametric tests in those cases where the underlying distributions are not normal, as demonstrated by performing tests for normality (goodness of fit, normal probability plots, etc.)