# Engaging Undergraduate Health Science Students in Advanced Statistics

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#### Abstract

Increasing expectations in the Bachelor of Science in Nursing and Athletic Training curriculum has landed sophomore Nursing majors and Athletic Training in a second semester statistics course. This course covers topics such as statistical measures of screening tests, odds ratio and relative risk, ANOVA, non-parametric tests, and multiple regression. The following are share strategies and examples that I have used to increase health science students' interest in statistics.

Key Words: statistics education, undergraduate, health science

### 1. Introduction

The emergence of evidence based practice where practitioners in health related fields use research literature in making decisions about patient care has highlighted the importance of statistics education for undergraduates majoring in health science. A pedagogical challenge exists in motivating students to explore and appreciate the concepts of statistical practice. To bridge the gap between theory and practice, examples with real world applications need to be shared to motivate students in a second semester course in statistics for health science majors.

### 2. Background

In 2014, the American Statistical Association (ASA) published guidelines for the undergraduate curriculum in statistics. The ASA recommends that students entering the work force should have the capacity to "think with data". The key points presented in these guidelines emphasize the importance of students having extensive computing skills, the ability to work with real data, an understanding of design and limitations of the data, and the ability to communicate the results.

For the last two decades, the statistics education community has been actively engaged in reform to improve statistical literacy particularly at the introductory level (Hassad, 2014). Two publications provide an excellent framework for the case study model of teaching. Nolan (2003) found that using case studies motivates students to learn the methodologies and helps students develop skills in statistical thinking. Nolan (2003) uses a case study from data collected in 2000 that examined whether Human Immunodeficiency Virus (HIV) causes Acquired Immune Deficiency Syndrome (AIDS). While this provides an interesting topic in health science, the methodologies used to examine these data are not covered in this second course in statistics. Schafer and Ramsey (2003) used three case studies in their introductory statistics course on obesity and cardiovascular disease, respiratory rates of infants, and an engineering example on insulating fluid that are again not applicable to this second course in statistics. However, these two papers are used as

guidelines for developing the case study curriculum used in this second semester health science statistics courses.

The following examples follow a case study approach so that the student needs to assess the statistical approaches used in literature to truly understand the research results and to be aware of possible limitations in the analysis to determine if further analysis is needed. Often in textbooks, examples and data are presented in the context of the statistical methodology being studied. Textbook examples do not fit the standards of what Grimshaw (2015) defines as authentic data experiences. This eliminates some components of the statistical problem solving process necessary in practice, such as deciding whether the available data addresses the research question or if another method of analysis could be performed. In order to strengthen students' skills in statistical reasoning and data analysis, a better design of the way statistics is taught to undergraduate health science majors is needed. Adding case studies and R computer labs to the curriculum emphasizes the overall practice of statistics meaning "the process of data analysis, the communication of results and the roles of statistics in the accumulation of scientific evidence" (Schafer and Ramsey, 2003).

## 3. Methods

## **3.1 Screening Tests: Measures of Accuracy**

Measures of accuracy in screening tests are important in evidence based practice for health science majors. It is important for students to understand factors that may influence the sensitivity, specificity, positive predictive value and negative predictive value in screening tests. Lopes et al. (2008) published data on screening tests for prenatal diagnosis of chromosomal abnormalities in an unborn child. This article is an enlightening example of how the measures of accuracy change depending on whether screening results are based on sequential or parallel screen from three possible indicators of chromosomal abnormalities.

Students can be given this example directly as an assignment or data could be analyzed in a computer lab. As a homework assignment, the problem can be presented as follows.

### **Example Problem**

Several screening tests are available for prenatal diagnosis of chromosomal abnormalities in an unborn child. In the past, invasive techniques, such as amniocentesis and chorionic villus sampling, were used to detect genetic disorders but presented a risk for miscarriage. More recently, non-invasive techniques are used as an initial screen for chromosomal abnormalities such as trisomy 21 or Down syndrome.

Studies show that advanced maternal age (MA) (MA  $\geq$  35), nuchal translucency (NT) thickness (accumulation of fluid behind the neck of a fetus seen on a sonographic image), and abnormal ductus venosus (DV) flow pattern (results in a fetus with increased NT thickness) are associated with the presence of chromosomal abnormalities.

The following is based on a study that evaluated screening tests or combinations of screening tests based on the three indicators of genetic disorders in the fetus. (Lopes et al., 2008) Here are the results for combining all three tests, a parallel screen.

	Chromosomal Abnormalities**			
Combined NT + DV + MA ≥ 35 years	Present	Not Present	Total	
Positive Screen	12	72	84	
Negative Screen	0	5	5	
Total	12	77	89	

Parallel\* evaluation on NT, nuchal translucency; DV, ductus venosus; MA, maternal age.

\* Parallel evaluation implies that the screen for at least one of the test is positive.

\*\*trisomy 21, trisomy 18, trisomy 22, 47 XXY, chromosomal marker 46 XY inv (9) (gh)

Students are then asked to compute the measures of accuracy for this screening test.

A sequential screen was used (indication of all three conditions) and results in different values for the measures of accuracy. Here are the results:

Sequential\* evaluation on NT, nuchal translucency; DV, ductus venosus; MA, maternal age.

Chromosomal Abnormalities\*\*

Combined NT + DV + MA <u>&gt;</u> 35 years	Present	Not Present	Total
Positive Screen	1	1	2
Negative Screen	11	76	87
Total	12	77	89

\* Sequential evaluation implies that all three screens are positive. \*\*trisomy 21. trisomy 18. trisomy 22, 47 XXY, chromosomal marker 46 XY inv (9) (gh)

Students are then asked to compute the measures of accuracy for this screening test

This example provides an opportunity to compare the sensitivity and specificity for the parallel and sequential screen. The students can compare each screening method and discuss the pros and cons of each with respect to the measures of accuracy.

#### **Computer Lab**

Using simulated data based on the findings of Lopes et al. (2008), a R computer lab can be created. The R package epiR (Stevenson et al., 2015) is a straightforward tool to use in the analysis of screening tests. A lab only requires students to read in the data, use the and/or functions to assign the value of the screening test, create a two-way table, load the package epiR, and use the function epi.test() to get the sensitivity, specificity, PPV and NPV. This serves as a relatively gentle introduction to R.

### **3.2** Relationship between Two Categorical Variables

In this course, relative risk and odds ratio are covered prior to the chi-square test. Once the chi-square test is covered, the follow-up analysis is computing relative risk with a confidence interval. Barat et al., (2011) have an illustrative example with data examining patients' completion of the Gardasil vaccine. Using epiR (Stevenson et al., 2015), these data can be examined pairwise using relative risk and odds ratio or looked at in its entirety using the chi-square test.

Another example of interest to Athletic Training student is data presented by Beynnon et al., (2014) to determine the risk factors for first-time noncontact anterior cruciate ligament (ACL) injuries for athletes.

#### **Example Problem**

Anterior cruciate ligament (ACL) injuries are disabling rendering athletes unable to participate and are associated with the early onset of posttraumatic osteoarthritis (Beynnon et al., 2014). To determine the risk for first-time noncontact ACL injuries for athletes, an investigation was performed at The

McClure Musculoskeletal Research Center, Department of Orthopedics and Rehabilitation at the University of Vermont's College of Medicine to determine how ACL injuries sustained during athletic events are influenced by level of competition (college or HS), type of sport (soccer, basketball, lacrosse, field hockey, football, rugby, volleyball) and the participant's sex.

The article has a table with counts based on the gender, level of athlete and the sport of the athlete. These data can be simulated to be used for analysis in R. Students can learn how to get a subset of the data and use the epi.2by2 function from the epi.R package to compute relative risk and odds ratio between several levels of the variables. The chisq.test function in R can be used to do a chi-square test for any of the variables. **4. Conclusions** 

These two examples are a way to bridge what students may encounter in an evidence based practice course with the material learned in an upper level statistics course. The journal articles are interesting and not too technical for a second year health science student. The programming in R required is not too technical and gives students a glimpse at the practice of statistics.

For code or data, please feel free to contact Darlene Olsen, dolsen1@norwich.edu.

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## References

American Statistical Association Undergraduate Guidelines Workgroup (2014). 2014 *curriculum guidelines for undergraduate programs in statistical science*. Alexandria, VA: American Statistical Association. <u>http://www.amstat.org/education/curriculumguidelines.cfm</u>

Barat, Wrigth, and Chou, (2011). "Examining Potential Predictors for Completion of the Gardasil Vaccine Sequence Based on Data Gathered at Clinics of Johns Hopkins Medical Institutions", *Journal of Statistics Education*, Volume 19, Number 1 (2011)

Grimshaw, S. (2015) A Framework for Infusing Authentic Data Experiences Within Statistics Courses. *The American Statistician* 69:4, 307-314.

Hassad, R.A. (2009). Reform-oriented teaching of introductory statistics in the health, social and behavioral sciences: Historical context and rationale. *International Journal of Social Sciences*, 4(2).

Hassad, R. A. (2014). The status of reform in statistics education: A focus on the introductory course. Retrieved from http://iase-web.org/icots/9/proceedings/pdfs/ICOTS9\_C196\_HASSAD.pdf

Lopes, A. C. V., Pimentel, K., Toralles, M. B. P., Almeida, A. D. M., Lopes, L. V., Araújo Júnior, E., ... & Moron, A. F. (2008). Study of nuchal translucency, ductus venosus, nasal bone and maternal age for detection of fetal chromosomal disorders in a high-risk population. *Radiologia Brasileira*, *41*(2), 93-97.

Nolan, D. (2003). Case Studies in the Mathematical Statistics Course. *Lecture Notesmonograph Series*, 40, 165–176.

R Core Team. (2015). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. <u>http://www.R-project.org/</u>.

Schafer, D. and Ramsey, F. (2003). Teaching the Craft of Data Analysis. *Journal of Statistics Education*, 11(1)

Stevenson M, et al. (2015) epiR: Tools for the Analysis of Epidemiological Data. R package v0.9-62. http://CRAN.R-project.org/package=epiR.