Intuitive Biostatistics

Harvey Motulsky
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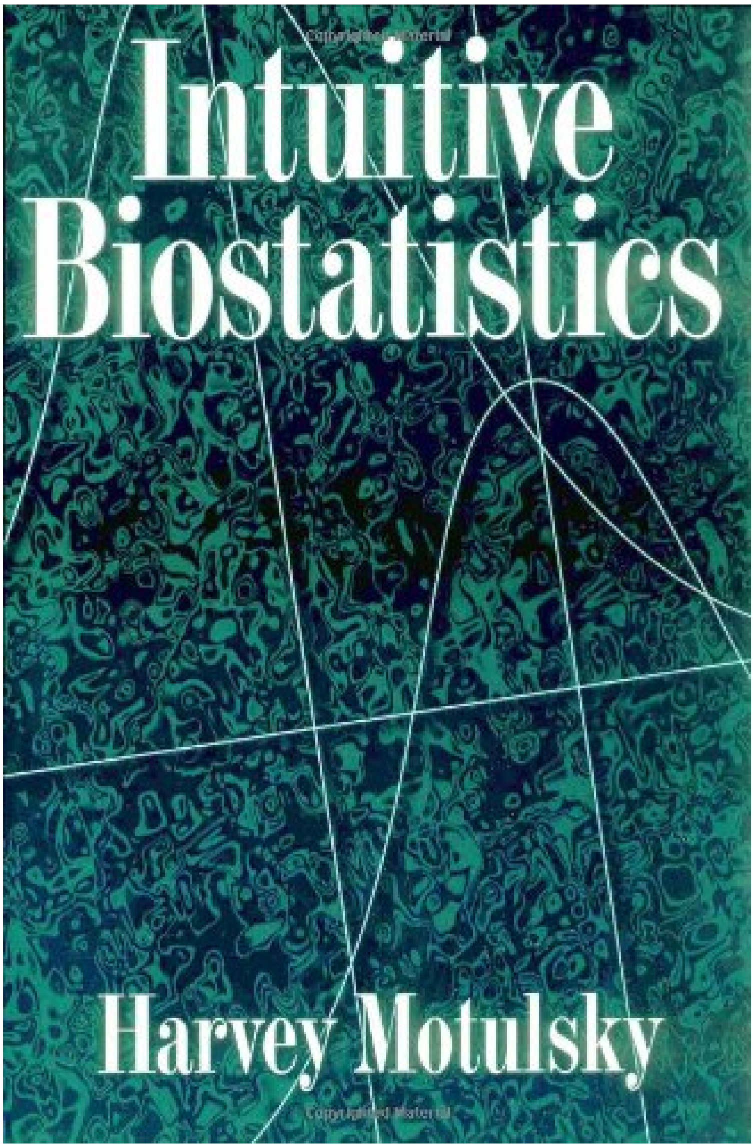

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Harvey Motulsky : Intuitive Biostatistics before purchasing it in order to gage whether or not it would be worth my time, and all praised Intuitive Biostatistics:

0 of 0 people found the following review helpful. I read it over spring break and came back with a much better understanding of p-values and confidence intervalsBy carolynThis book helped me get on my feet in Statistics! I read it over spring break and came back with a much better understanding of p-values and confidence intervals. The textbook used by my class was written by a family of 5 statisticians, and I felt it was too cut-n-dry to understand.

Motulsky explained things more simply. Best $6 I ever spent on Statistics textbooks!0 of 0 people found the following review helpful. An unequivocally insightful approach to biostatisticsBy RVCIntuitive biostatistics is a comprehensive overview of biostatistics. Instead of reading cover to cover, I have used this relatively detailed statistics text to review relevant sections as needed.Motulsky does not include mathematical equations. Rather, he focuses on interpreting statistical concepts, common pitfalls, and challenges the reader to think critically.Highly recommended for clinical, medical, and pharmaceutical professionals responsible for reviewing clinical data. Even for readers confident in their statistics knowledge, this is a great refresher. I have expanded my biostatistics acumen thanks to this book.This text is daily my go-to reference guide.0 of 0 people found the following review helpful. Best general biostatistics text out thereBy Bones McCoyBest general biostatistics text out there. Highly useful in conducting research protocols and doing data analysis without using expensive software.

Designed to provide a nonmathematical introduction to biostatistics for medical and health science students, graduate students in the biological sciences, physicians, and researchers, this text explains statistical principles in non-technical language and focuses on explaining the proper scientific interpretation of statistical tests rather than on the mathematical logic of the tests themselves. Intuitive Biostatistics covers all the topics typically found in an introductory statistics text, but with the emphasis on confidence intervals rather than P values, making it easier for students to understand both. Additionally, it introduces a broad range of topics left out of most other introductory texts but used frequently in biomedical publications, including survival curves. multiple comparisons, sensitivity and specificity of lab tests, Bayesian thinking, lod scores, and logistic, proportional hazards and nonlinear regression. By emphasizing interpretation rather than calculation, this text provides a clear and virtually painless introduction to statistical principles for those students who will need to use statistics constantly in their work. In addition, its practical approach enables readers to understand the statistical results published in biological and medical journals.

"I like this book much, I will be "beta-testing" it on my upper-level undergraduate biostatistics class. It fills a great need for my students."--Harriette Phelps, University of D.C."This splendid book meets a major need in public health, medicine, and biomedical research training--a user-friendly biostatistics text for non-mathematicians."--Gilbert S. Omenn, Executive Vice President for Medical Affairs at the University of Michigan"Motulsky has written a very readable and delightful account of how statistics are used in biology and medicine...He focuses on clinical studies and covers a broad range of topics, including...such specialized areas as survival analysis, Bayesian inference, and logistic regression." --Quarterly of Biology"The unique aspect of the book, which makes it different from other biostatistics books, is its approach to the content...His goal is to help the reader interpret medical literature rather than analyze a set of data....I higly recommend this book for those needing a non-mathematical, explanatory introduction to biostatistics. It is well-written and provides wonderful clinical examples and biostatistical content...An excellent resource book for medical students and housestaff who are struggling along with the concepts; and for those of you who were wondering, it was surprisingly easy to read."--Joseph Chu, MD, MPH, University of Washington in Teaching and Learning MedicineAbout the AuthorHarvey Motulsky is at University of California at San Diego.Excerpt. Reprinted by permission. All rights reserved.CHOOSING BETWEEN PARAMETRIC AND NONPARAMETRIC TESTS (Excerpted from Chapter 37) Choosing the right test to compare measurements is a bit tricky, as you must choose between two families of tests: parametric and nonparametric. Many -statistical tests are based upon the assumption that the data are sampled from a Gaussian distribution. These tests are referred to as parametric tests. Commonly used parametric tests are listed in the first column of the table and include the t test and analysis of variance. Tests that do not make assumptions about the population distribution are referred to as nonparametric- tests. You've already learned a bit about nonparametric tests in previous chapters. All commonly used nonparametric tests rank the outcome variable from low to high and then analyze the ranks. These tests are listed in the second column of the table and include the Wilcoxon, Mann-Whitney test, and Kruskal-Wallis tests. These tests are also called distribution-free tests. THE EASY CASES Choosing between parametric and nonparametric tests is sometimes easy. You should definitely choose a parametric test if you are sure that your data are sampled from a population that follows a Gaussian distribution (at least approximately). You should definitely select a nonparametric test in three situations: 1. The outcome is a rank or a score and the population is clearly not Gaussian. Examples include class ranking of students, the Apgar score for the health of newborn babies (measured on a scale of 0 to IO and where all scores are integers), the visual analogue score for pain (measured on a continuous scale where 0 is no pain and 10 is unbearable pain), and the star scale commonly used by movie and restaurant critics (* is OK, ***** is fantastic). 2. Some values are "off the scale," that is, too high or too low to measure. Even if the population is Gaussian, it is impossible to analyze such data with a parametric test since you don't know all of the values. Using a nonparametric test wi! th these data is simple. Assign values too low to measure an arbitrary very low value and assign values too high to measure an arbitrary very high value. Then perform a nonparametric test. Since the nonparametric test only knows about the relative ranks of the values, it won't matter that you didn't know all the values exactly. 3. The data are measurements and you are sure that the population is not distributed in a Gaussian manner. If the data are not sampled from a Gaussian distribution, consider whether you can transformed the values to make the distribution become Gaussian. For example, you might take the logarithm or reciprocal of all values. There are often biological or chemical reasons (as well as statistical ones) for performing a particular transform. THE HARD CASES It is not always easy to decide whether a sample comes from a Gaussian population. Consider these points: If you collect many data points (over a hundred or so), you can look at the distribution of data and it will be fairly obvious whether the distribution is approximately bell shaped. A formal statistical test (Kolmogorov-Smirnoff test, not explained in this book) can be used to test whether the distribution of the data differs significantly from a Gaussian distribution. With few data points, it is difficult to tell whether the data are Gaussian by inspection, and the formal test has little power to discriminate between Gaussian and non-Gaussian distributions. You should look at previous data as well. Remember, what matters is the distribution of the overall population, not the distribution of your sample. In deciding whether a population is Gaussian, look at all available data, not just data in the current experiment. Consider the source of scatter. When the scatter comes from the sum of numerous sources (with no one source contributing most of the scatter), you expect to find a roughly Gaussian distribution. When in doubt, some people choose a parametric test (because they aren't sure the Gaussian assumption is ! violated), and others choose a nonparametric test (because they aren't sure the Gaussian assumption is met). DOES IT MATTER? Does it matter whether you choose a parametric or nonparametric test? The answer depends on sample size. There are four cases to think about: 1. Large sample. What happens when you use a parametric test with data from a nongaussian population? The central limit theorem (discussed in Chapter 5) ensures that parametric tests work well with large samples even if the population is non-Gaussian. In other words, parametric tests are robust to deviations from Gaussian distributions, so long as the samples are large. The snag is that it is impossible to say how large is large enough, as it depends on the nature of the particular non-Gaussian distribution. Unless the population distribution is really weird, you are probably safe choosing a parametric test when there are at least two dozen data points in each group. 2. Large sample. What happens when you use a nonparametric test with data from a Gaussian population? Nonparametric tests work well with large samples from Gaussian populations. The P values tend to be a bit too large, but the discrepancy is small. In other words, nonparametric tests are only slightly less powerful than parametric tests with large samples. 3. Small samples. What happens when you use a parametric test with data from nongaussian populations? You can't rely on the central limit theorem, so the P value may be inaccurate. 4. Small samples. When you use a nonparametric test with data from a Gaussian population, the P values tend to be too high. The nonparametric tests lack statistical power with small samples. Thus, large data sets present no problems. It is usually easy to tell if the data come from a Gaussian population, but it doesn't really matter because the nonparametric tests are so powerful and the parametric tests are so robust. Small data sets present a dilemma. It is difficult to tell if the data come from a Gaussian population, but it matt! ers a lot. The nonparametric tests are not powerful and the parametric tests are not robust.