DOWNLOAD PDF UNDERSTANDABLE STATISTICS CONCEPTS AND METHODS 11TH EDITION

Chapter 1 : Editions of Understandable Statistics by Charles Henry Brase

UNDERSTANDABLE STATISTICS: CONCEPTS AND METHODS, Eleventh Edition, is a thorough yet accessible program designed to help you overcome any apprehensions you may have about statistics. The authors provide clear guidance and informal advice while showing you the links between statistics and the world.

In comparison, a data set that has a distribution that is symmetric and bell-shaped, or in particular, an approximate normal distribution, is more restrictive in that 1. Remind students regularly that a z value equals the number of standard deviations from the mean for data values of any distribution approximated by a normal curve. That is, emphasize that the area under any normal curve equals 1 and that the percentage of area under the curve between given values of the random variable equals the probability that the random variable will be between these values. The values in a z table are areas and probability values. Emphasize the differences between population parameters and sample statistics. Point out that when knowledge of the population is unavailable, then knowledge of a corresponding sample statistic must be used to make inferences about the population. Emphasize the main two facts derived from the central limit theorem: Choosing sample sizes greater than 30 is an important point to emphasize in the situation mentioned in part 2 of the central limit theorem above. This commonly accepted convention ensures that the x distribution of part 2 will have an approximate normal distribution regardless of the distribution of the population from which these samples are drawn. Emphasize that the central limit theorem allows us to infer facts about populations from sample means having normal distributions. Emphasize the conditions whereby a binomial probability distribution discussed in Chapter 5 can be approximated by a normal distribution: When a normal distribution is used to approximate a discrete random variable such as the random variable of a binomial probability experiment , the continuity correction is an important concept to emphasize to students. A discussion of this important adjustment can be a good opportunity to compare discrete and continuous random variables. Emphasize that facts about sampling distributions for proportions relating to binomial experiments can be inferred if the same conditions satisfied by a binomial experiment that can be approximated by a normal distribution are satisfied: Emphasize the difference in the continuity correction that must be taken into account in the sampling distribution for proportions and the continuity correction for a normal distribution used to approximate the probability distribution of the discrete random variable in a binomial probability experiment. That is, instead of subtracting 0. And if the mean of a population is considered a constant, then the event that this mean falls in a certain range with known numerical bounds has either probability 1 or probability 0. In other words, we may think of the population from which we are sampling as one of many populationsâ€”a population of populations, if you like. One of these populations has been randomly selected for us to work with, and we are trying to figure out which population it is or at least what its mean is. It might seem so, but in general, the answer is no. How is this possible? To understand this paradox, let us turn from mean finding to a simpler task: Suppose that a sack contains some red marbles and some blue marbles. And suppose that we have a friend who will reach in, draw out a marble, and announce its color while we have our backs turned. And likewise for the red marble. It depends on what we think about the mix of marbles in the bag. Suppose that we think that the bag contains three red marbles and two blue ones. But this is a special case. This story has two morals. First, the probability of a statement is one thing, and the success rate of a procedure that tries to come up with true statements is another. Second, our prior beliefs about the conditions of an experiment are an unavoidable element in our interpretation of any sample data. Let us apply these lessons to the business of finding confidence intervals for population means. Instead, we would have a probability lower than that because we previously thought the mean was outside that range. Thus, under normal circumstances, our exact level of certainty about the confidence interval could not be calculated. So the general point made in the text holds even if we think of a population mean as a variable. The procedure for 12 finding a confidence interval of confidence level c does not, in general, produce a statement about the value of a population mean that has a probability c of being true. Confidence Intervals for p Section 7. Critical Region Method The most popular method of statistical testing is the P-value method. For this reason, the P-value method is emphasized in this book. The P-value method was used extensively by a famous statistician, R. Fisher, and is the most popular method of testing in use today. At the end of Section 8. It was used extensively by statisticians J. In recent years, the use of this method has been declining. The critical region method for hypothesis testing is convenient when distribution tables are available for finding critical values. However, most statistical software and research journal articles give P values rather than critical values. Most fields of study that require statistics want students to be able to use P values. Emphasize that for a fixed, preset level of significance , both methods are logically equivalent. Once again, we run the risk of confusion over the role of probability in our statistical conclusions. The P value is not the same thing as the probability, in light of the data, of the null hypothesis. Instead, the P value is the probability that the data would turn out the way they did, assuming that the null hypothesis is true. Just as with confidence intervals, we have to be careful not to think that we are finding the probability of a given statement when we are in fact doing something else. To illustrate, consider two coins in a sack, one fair and one two-headed. One of these coins is pulled out at random and flipped. It comes up heads. This probability is in fact the P value of the outcome. Now suppose that instead of containing two coins of known character, the sack contains an unknown mixâ€"some fair coins, some two-headed coins, and possibly some two-tailed coins as well. So the P value of the outcome is one thing, and the probability of the null hypothesis is another. The lesson now should be familiar. Without some prior idea about the character of an experiment, either based on a theoretical model or based on previous outcomes, we cannot attach a definite probability to a statement about the experimental setup or its outcome. We normally lack the information needed to calculate probabilities for the null hypothesis and its alternative. What we do instead is to take the null hypothesis as defining a wellunderstood scenario from which we can calculate the likelihoods of various outcomesâ€"the probabilities of various kinds of sample results, given that the null hypothesis is true. By contrast, the alternative hypothesis includes all sorts of scenarios, in some of which for instance two population means are only slightly different, in others of which the two means are far apart, and so on. Unless we have identified the likelihoods of all these possibilities relative to each other and to the null hypothesis, we will not have the background information needed to calculate the probability of the null hypothesis from sample data. Finding the power requires knowing the H 1 distribution. Because we cannot specify the H 1 distribution when we are concerned with things such as diagnosing disease instead of drawing coins from a sack and the like , we normally cannot determine the probability of the null hypothesis in light of the evidence. A Paradox About Hypothesis Tests The way hypothesis tests work leads to a result that at first seems surprising. It sometimes can happen that, at a given level of significance, a one-tailed test leads to rejection of the null hypothesis, whereas a two-tailed test does as the case may be but not justified in not. Apparently, one can be justified in concluding that k or k concluding that k â€"even though the latter conclusion follows from the former! What is going on here? This paradox dissolves when one remembers that a one-tailed test is used only when one has appropriate information. With the null hypothesis H 0: In other words, when a right-tailed test is appropriate, rejecting the null hypothesis means concluding both that k and that k. But when there is no justification for a one-tailed test, one must use a two-tailed test and must have somewhat stronger evidence before concluding that k. Here it may be worth mentioning that for linear regression, the choice matters. The results of a linear regression analysis will differ depending on which variable is chosen as the explanatory variable and which is chosen as the response variable. This is not immediately obvious. But this would be a mistake. The figure below shows the vertical distances from data points to the line of best fit. The line is defined so as to make the sum of the squares of these vertical distances as small as possible. These are the distances whose sum of squares would be minimized if the explanatory and response variables switched roles. With such a switch, the graph would be flipped over, and the horizontal distances would become vertical ones. But the line that minimizes the sum of squares for vertical distances is not, in general, the same line that minimizes the sum of squares for horizontal distances. So there is more than one way, mathematically, to

DOWNLOAD PDF UNDERSTANDABLE STATISTICS CONCEPTS AND METHODS 11TH EDITION

define the line of best fit for a set of paired data. This raises a question: What is the proper way to define the line of best fit? Let us turn this question around. Under what circumstances is a best fit based on vertical distances the right way to go? Well, intuitively, the distance from a data point to the line of best fit represents some sort of deviation from the ideal value. We can conceptualize this most easily in terms of measurement error. If we treat the error as a strictly vertical distance, then we are saying that in each data pair, the second value is possibly off, but the first value is exactly correct. In other words, the least-squares method with vertical distances assumes that the first value in each data pair is measured with essentially perfect accuracy, whereas the second is measured only imperfectly. An illustration shows how these assumptions can be realistic. Suppose that we are measuring the explosive force generated by the ignition of varying amounts of gunpowder. The weight of the gunpowder is the explanatory variable, and the force of the resulting explosion is the response variable. We then would have an experiment with a good deal of error in the response variable measurement 15 but for, practical purposes, no error in the explanatory variable measurement. This would all be perfectly in accord with the vertical-distance criterion for finding the line of best fit by the least-squares method. But now consider a different version of the gunpowder experiment. This time we have a highly refined means of measuring explosive force some sort of electronic device, let us say , and at the same time we have only a very crude means of measuring gunpowder mass perhaps a rusty pan balance.

Chapter 2 : Understandable statistics 11th edition brase solutions manual by Sommerville22 - Issuu

Understandable Statistics: Concepts and Methods, 11th edition, is a thorough yet accessible program designed to help readers overcome their apprehensions about statistics. The authors provide clear guidance and informal advice while showing the links between statistics and the world.

Chapter 3 : Understandable Statistics () :: Homework Help and Answers :: Slader

UNDERSTANDABLE STATISTICS: CONCEPTS AND METHODS, Eleventh Edition, is a thorough yet accessible program designed to help readers overcome their apprehensions about statistics. The authors provide clear guidance and informal advice while showing the links between statistics and the world.

Chapter 4 : Understandable Statistics - Charles Henry Brase, Corrinne Pellillo Brase - Google Books

UNDERSTANDABLE STATISTICS: CONCEPTS AND METHODS is a thorough yet accessible program designed to help students overcome their apprehensions about statistics. The authors provide clear guidance and informal advice while showing students the links between statistics and the world.

Chapter 5 : Understandable Statistics Brase: Books | eBay

Understandable Statistics 11th Edition is a teaming up between CENGAGE Learning and distinguished authors Charles Henry Brase and Corrinne Pellillo Brase. University students will have access to pages of information on business & economics which skillfully contains a breadth of pertinent topics.