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Process of using data analysis Not to be confused with Statistical interference. Part of a series onResearch Research design Ethics Proposal Question Writing Argument Referencing Research strategy Interdisciplinary Multimethodology Qualitative Art-based Quantitative Philosophical schools Antipositivism Constructivism Critical rationalism Empiricism Fallibilism Positivism Postpositivism Pragmatism Realism Critical realism Subtle realism Methodology Action research Art methodology Critical theory Grounded theory Hermeneutics Historiography Human subject research Narrative inquiry Phenomenology Pragmatism Scientific method Methods Analysis Case study Content analysis Descriptive statistics Discourse analysis Ethnography Autoethnography Experiment Field experiment Social experiment Quasi-experiment Field research Historical method Inferential statistics Interviews Mapping Cultural mapping Phenomenography Secondary research Bibliometrics Literature review Meta-analysis Scoping review Systematic review Scientific modelling Simulation Survey Tools and software Argument technology GIS software LIS software Bibliometrics Reference management Science software Qualitative data analysis Simulation Statistics Philosophy portalvte Statistical inference is the process of using data analysis to infer properties of an underlying probability distribution.[1] Inferential statistical analysis infers properties of a population, for example by testing hypotheses and deriving estimates. It is assumed that the observed data set is sampled from a larger population. Inferential statistics can be contrasted with descriptive statistics. Descriptive statistics is solely concerned with properties of the observed data, and it does not rest on the assumption that the data come from a larger population. In machine learning, the term inference is sometimes used instead to mean "make a prediction, by evaluating an already trained model";[2] in this context inferring properties of the model is referred to as training or learning (rather than inference), and using a model for prediction is referred to as inference (instead of prediction); see also predictive inference. Statistical inference makes propositions about a population, using data drawn from the population with some form of sampling. Given a hypothesis about a population, for which we wish to draw inferences, statistical inference consists of (first) selecting a statistical model of the process that generates the data and (second) deducing propositions from the model.[3] Konishi and Kitagawa state "The majority of the problems in statistical inference can be considered to be problems related to statistical modeling".[4] Relatedly, Sir David Cox has said, "How [the] translation from subject-matter problem to statistical model is done is often the most critical part of an analysis".[5] The conclusion of a statistical inference is a statistical proposition.[6] Some common forms of statistical proposition are the following: a point estimate, i.e. a particular value that best approximates some parameter of interest; an interval estimate, e.g. a confidence interval (or set estimate), i.e. an interval constructed using a dataset drawn from a population so that, under repeated sampling of such datasets, such intervals would contain the true parameter value with the probability at the stated confidence level; a credible interval, i.e. a set of values containing, for example, 95% of posterior belief; rejection of a hypothesis;[note 1] clustering or classification of data points into groups. Main articles: Statistical model and Statistical assumptions Any statistical inference requires some assumptions. A statistical model is a set of assumptions concerning the generation of the observed data and similar data. Descriptions of statistical models usually emphasize the role of population quantities of interest, about which we wish to draw inference.[7] Descriptive statistics are typically used as a preliminary step before more formal inferences are drawn.[8] Statisticians distinguish between three levels of modeling assumptions: Fully parametric: The probability distributions describing the data-generation process are assumed to be fully described by a family of probability distributions involving only a finite number of unknown parameters.[7] For example, one may assume that the distribution of population values is truly Normal, with unknown mean and variance, and that datasets are generated by 'simple' random sampling. The family of generalized linear models is a widely used and flexible class of parametric models. Non-parametric: The assumptions made about the process generating the data are much less than in parametric statistics and may be minimal.[9] For example, every continuous probability distribution has a median, which may be estimated using the sample median or the Hodges–Lehmann–Sen estimator, which has good properties when the data arise from simple random sampling. Semi-parametric: This term typically implies assumptions 'in between' fully and non-parametric approaches. For example, one may assume that a population distribution has a finite mean. Furthermore, one may assume that the mean response level in the population depends in a truly linear manner on some covariate (a parametric assumption) but not make any parametric assumption describing the variance around that mean (i.e. about the presence or possible form of any heteroscedasticity). More generally, semi-parametric models can often be separated into 'structural' and 'random variation' components. One component is treated parametrically and the other non-parametrically. The well-known Cox model is a set of semi-parametric assumptions.[citation needed] See also: Statistical model validation The above image shows a histogram assessing the assumption of normality, which can be illustrated through the even spread underneath the bell curve. Whatever level of assumption is made, correctly calibrated inference, in general, requires these assumptions to be correct; i.e. that the data-generating mechanisms really have been correctly specified. Incorrect assumptions of 'simple' random sampling can invalidate statistical inference.[10] More complex semi- and fully parametric assumptions are also cause for concern. For example, incorrectly assuming the Cox model can in some cases lead to faulty conclusions.[11] Incorrect assumptions of Normality in the population also invalidates some forms of regression-based inference.[12] The use of any parametric model is viewed skeptically by most experts in sampling human populations: "most sampling statisticians, when they deal with confidence intervals at all, limit themselves to statements about [estimators] based on very large samples, where the central limit theorem ensures that these [estimators] will have distributions that are nearly normal."[13] In particular, a normal distribution "would be a totally unrealistic and catastrophically unwise assumption to make if we were dealing with any kind of economic population."[13] Here, the central limit theorem states that the distribution of the sample mean "for very large samples" is approximately normally distributed, if the distribution is not heavy-tailed. Main articles: Statistical distance, Asymptotic theory (statistics), and Approximation theory Given the difficulty in specifying exact distributions of sample statistics, many methods have been developed for approximating these. With finite samples, approximation results measure how close a limiting distribution approaches the statistic's sample distribution: For example, with 10,000 independent samples the normal distribution approximates (to two digits of accuracy) the distribution of the sample mean for many population distributions, by the Berry–Esseen theorem.[14] Yet for many practical purposes, the normal approximation provides a good approximation to the sample-mean's distribution when there are 10 (or more) independent samples, according to simulation studies and statisticians' experience.[14] Following Kolmogorov's work in the 1950s, advanced statistics uses approximation theory and functional analysis to quantify the error of approximation. In this approach, the metric geometry of probability distributions is studied; this approach quantifies approximation error with, for example, the Kullback–Leibler divergence, Bregman divergence, and the Hellinger distance.[15][16][17] With indefinitely large samples, limiting results like the central limit theorem describe the sample statistic's limiting distribution if one exists. Limiting results are not statements about finite samples, and indeed are irrelevant to finite samples.[18][19][20] However, the asymptotic theory of limiting distributions is often invoked for work with finite samples. For example, limiting results are often invoked to justify the generalized method of moments and the use of generalized estimating equations, which are popular in econometrics and biostatistics. The magnitude of the difference between the limiting distribution and the true distribution (formally, the 'error' of the approximation) can be assessed using simulation.[21] The heuristic application of limiting results to finite samples is common practice in many applications, especially with low-dimensional models with log-concave likelihoods (such as with one-parameter exponential families). Main article: Randomization See also: Random sample and Random assignment For a given dataset that was produced by a randomization design, the randomization distribution of a statistic (under the null-hypothesis) is defined by evaluating the test statistic for all of the plans that could have been generated by the randomization design. In frequentist inference, the randomization allows inferences to be based on the randomization distribution rather than a subjective model, and this is important especially in survey sampling and design of experiments.[22][23] Statistical inference from randomized studies is also more straightforward than many other situations.[24][25][26] In Bayesian inference, randomization is also of importance: in survey sampling, use of sampling without replacement ensures the exchangeability of the sample with the population; in randomized experiments, randomization warrants a missing at random assumption for covariate information.[27] Objective randomization allows properly inductive procedures.[28][29][30][31][32] Many statisticians prefer randomization-based analysis of data that was generated by well-defined randomization procedures.[33] (However, it is true that in fields of science with developed theoretical knowledge and experimental control, randomized experiments may increase the costs of experimentation without improving the quality of inferences.[34][35]) Similarly, results from randomized experiments are recommended by leading statistical authorities as allowing inferences with greater reliability than do observational studies of the same phenomena.[36] However, a good observational study may be better than a bad randomized experiment. The statistical analysis of a randomized experiment may be based on the randomization scheme stated in the experimental protocol and does not need a subjective model.[37][38] However, at any time, some hypotheses cannot be tested using objective statistical models, which accurately describe randomized experiments or random samples. In some cases, such randomized studies are uneconomical or unethical. It is standard practice to refer to a statistical model, e.g., a linear or logistic models, when analyzing data from randomized experiments.[39] However, the randomization scheme guides the choice of a statistical model. It is not possible to choose an appropriate model without knowing the randomization scheme.[23] Seriously misleading results can be obtained analyzing data from randomized experiments while ignoring the experimental protocol; common mistakes include forgetting the blocking used in an experiment and confusing repeated measurements on the same experimental unit with independent replicates of the treatment applied to different experimental units.[40] Model-free techniques provide a complement to model-based methods, which employ reductionist strategies of reality-simplification. The former combine, evolve, ensemble and train algorithms dynamically adapting to the contextual affinities of a process and learning the intrinsic characteristics of the observations.[41][42] For example, model-free simple linear regression is based either on: a random design, where the pairs of observations (X 1 , Y 1) , (X 2 , Y 2) , ⋯ , (X n , Y n) {\displaystyle (X_{1},Y_{1}),(X_{2},Y_{2}),\cdots ,(X_{n},Y_{n})} are independent and identically distributed (iid), or a deterministic design, where the variables X 1 , X 2 , ⋯ , X n {\displaystyle X_{1},X_{2},\cdots ,X_{n}} are deterministic, but the corresponding response variables Y 1 , Y 2 , ⋯ , Y n {\displaystyle Y_{1},Y_{2},\cdots ,Y_{n}} are random and independent with a common conditional distribution, i.e., P (Y j ≤ y | X j = x) = D x (y) {\displaystyle P\left(Y_{j}\leq y|X_{j}=x\right)=D_{x}(y)} , which is independent of the index j {\displaystyle j} . In either case, the model-free randomization inference for features of the common conditional distribution D x (.) {\displaystyle D_{x}(.)} relies on some regularity conditions, e.g. functional smoothness. For instance, model-free randomization inference for the population feature conditional mean, μ (x) = E (Y | X = x) {\displaystyle \mu (x)=E(Y|X=x)} , can be consistently estimated via local averaging or local polynomial fitting, under the assumption that μ (x) {\displaystyle \mu (x)} is smooth. Also, relying on asymptotic normality or resampling, we can construct confidence intervals for the population feature, in this case, the conditional mean, μ (x) {\displaystyle \mu (x)} .[43] Different schools of statistical inference have become established. These schools—or "paradigms"—are not mutually exclusive, and methods that work well under one paradigm often have attractive interpretations under other paradigms. Bandyopadhyay and Forster describe four paradigms: The classical (or frequentist) paradigm, the Bayesian paradigm, the likelihoodist paradigm, and the Akaikean-Information Criterion-based paradigm.[44] Main article: Frequentist inference This paradigm calibrates the plausibility of propositions by considering (notional) repeated sampling of a population distribution to produce datasets similar to the one at hand. By considering the dataset's characteristics under repeated sampling, the frequentist properties of a statistical proposition can be quantified—although in practice this quantification may be challenging. p-value Confidence interval Null hypothesis significance testing One interpretation of frequentist inference (or classical inference) is that it is applicable only in terms of frequency probability; that is, in terms of repeated sampling from a population. However, the approach of Neyman[45] develops these procedures in terms of pre-experiment probabilities. That is, before undertaking an experiment, one decides on a rule for coming to a conclusion such that the probability of being correct is controlled in a suitable way: such a probability need not have a frequentist or repeated sampling interpretation. In contrast, Bayesian inference works in terms of conditional probabilities (i.e. probabilities conditional on the observed data), compared to the marginal (but conditioned on unknown parameters) probabilities used in the frequentist approach. The frequentist procedures of significance testing and confidence intervals can be constructed without regard to utility functions. However, some elements of frequentist statistics, such as statistical decision theory, do incorporate utility functions.[citation needed] In particular, frequentist developments of optimal inference (such as minimum-variance unbiased estimators, or uniformly most powerful testing) make use of loss functions, which play the role of (negative) utility functions. Loss functions need not be explicitly stated for statistical theorists to prove that a statistical procedure has an optimality property.[46] However, loss-functions are often useful for stating optimality properties: for example, median-unbiased estimators are optimal under absolute value loss functions, in that they minimize expected loss, and least squares estimators are optimal under squared error loss functions, in that they minimize expected loss. While statisticians using frequentist inference must choose for themselves the parameters of interest, and the estimators/test statistic to be used, the absence of obviously explicit utilities and prior distributions has helped frequentist procedures to become widely viewed as 'objective'.[47] See also: Bayesian inference The Bayesian calculus describes degrees of belief using the 'language' of probability; beliefs are positive, integrate into one, and obey probability axioms. Bayesian inference uses the available posterior beliefs as the basis for making statistical propositions.[48] There are several different justifications for using the Bayesian approach. Credible interval for interval estimation Bayes factors for model comparison Many informal Bayesian inferences are based on "intuitively reasonable" summaries of the posterior. For example, the posterior mean, median and mode, highest posterior density intervals, and Bayes Factors can all be motivated in this way. While a user's utility function need not be stated for this sort of inference, these summaries do all depend (to some extent) on stated prior beliefs, and are generally viewed as subjective conclusions. (Methods of prior construction which do not require external input have been proposed but not yet fully developed.) Formally, Bayesian inference is calibrated with reference to an explicitly stated utility, or loss function; the 'Bayes rule' is the one which maximizes expected utility, averaged over the posterior uncertainty. Formal Bayesian inference therefore automatically provides optimal decisions in a decision theoretic sense. Given assumptions, data and utility, Bayesian inference can be made for essentially any problem, although not every statistical inference need have a Bayesian interpretation. Analyses which are not formally Bayesian can be (logically) incoherent; a feature of Bayesian procedures which use proper priors (i.e. those integrable to one) is that they are guaranteed to be coherent. Some advocates of Bayesian inference assert that inference must take place in this decision-theoretic framework, and that Bayesian inference should not conclude with the evaluation and summarization of posterior beliefs. Main article: LikelihoodismLikelihood-based inference is a paradigm used to estimate the parameters of a statistical model based on observed data. Likelihoodism approaches statistics by using the likelihood function, denoted as L (x | θ) {\displaystyle L(x|\theta)} , quantifies the probability of observing the given data x {\displaystyle x} , assuming a specific set of parameter values θ {\displaystyle \theta } . In likelihood-based inference, the goal is to find the set of parameter values that maximizes the likelihood function, or equivalently, maximizes the probability of observing the given data. The process of likelihood-based inference usually involves the following steps: Formulating the statistical model: A statistical model is defined based on the problem at hand, specifying the distributional assumptions and the relationship between the observed data and the unknown parameters. The model can be simple, such as a normal distribution with known variance, or complex, such as a hierarchical model with multiple levels of random effects. Constructing the likelihood function: Given the statistical model, the likelihood function is constructed by evaluating the joint probability density or mass function of the observed data as a function of the unknown parameters. This function represents the probability of observing the data for different values of the parameters. Maximizing the likelihood function: The next step is to find the set of parameter values that maximizes the likelihood function. This can be achieved using optimization techniques such as numerical optimization algorithms. The estimated parameter values, often denoted as y ¯ {\displaystyle {\bar {y}}} , are the maximum likelihood estimates (MLEs). Assessing uncertainty: Once the MLEs are obtained, it is crucial to quantify the uncertainty associated with the parameter estimates. This can be done by calculating standard errors, confidence intervals, or conducting hypothesis tests based on asymptotic theory or simulation techniques such as bootstrapping. Model checking: After obtaining the parameter estimates and assessing their uncertainty, it is important to assess the adequacy of the statistical model. This involves checking the assumptions made in the model and evaluating the fit of the model to the data using goodness-of-fit tests, residual analysis, or graphical diagnostics. Inference and interpretation: Finally, based on the estimated parameters and model assessment, statistical inference can be performed. This involves drawing conclusions about the population parameters, making predictions, or testing hypotheses based on the estimated model. Main article: Akaike information criterion This section needs expansion. You can help by adding to it. (November 2017) The Akaike information criterion (AIC) is an estimator of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection. AIC is founded on information theory: it offers an estimate of the relative information lost when a given model is used to represent the process that generated the data. (In doing so, it deals with the trade-off between the goodness of fit of the model and the simplicity of the model.) Main article: Minimum description length The minimum description length (MDL) principle has been developed from ideas in information theory[49] and the theory of Kolmogorov complexity.[50] The (MDL) principle selects statistical models that maximally compress the data; inference proceeds without assuming counterfactual or non-falsifiable "data-generating mechanisms" or probability models for the data, as might be done in frequentist or Bayesian approaches. However, if a "data generating mechanism" does exist in reality, then according to Shannon's source coding theorem it provides the MDL description of the data, on average and asymptotically.[51] In minimizing description length (or descriptive complexity), MDL estimation is similar to maximum likelihood estimation and maximum a posteriori estimation (using maximum-entropy Bayesian priors). However, MDL avoids assuming that the underlying probability model is known; the MDL principle can also be applied without assumptions that e.g. the data arose from independent sampling.[51][52] The MDL principle has been applied in communication-coding theory in information theory, in linear regression,[52] and in data mining.[50] The evaluation of MDL-based inferential procedures often uses techniques or criteria from computational complexity theory.[53] Main article: Fiducial inference Fiducial inference was an approach to statistical inference based on fiducial probability, also known as a "fiducial distribution". In subsequent work, this approach has been called ill-defined, extremely limited in applicability, and even fallacious.[54][55] However this argument is the same as that which shows[56] that a so-called confidence distribution is not a valid probability distribution and, since this has not invalidated the application of confidence intervals, it does not necessarily invalidate conclusions drawn from fiducial arguments. An attempt was made to reinterpret the early work of Fisher's fiducial argument as a special case of an inference theory using upper and lower probabilities.[57] Developing ideas of Fisher and of Pitman from 1938 to 1939,[58] George A. Barnard developed "structural inference" or "pivotal inference",[59] an approach using invariant probabilities on group families. Barnard reformulated the arguments behind fiducial inference on a restricted class of models on which "fiducial" procedures would be well-defined and useful. Donald A. S. Fraser developed a general theory for structural inference[60] based on group theory and applied this to linear models.[61] The theory formulated by Fraser has close links to decision theory and Bayesian statistics and can provide optimal frequentist decision rules if they exist.[62] The topics below are usually included in the area of statistical inference. Statistical assumptions Statistical decision theory Estimation theory Statistical hypothesis testing Revising opinions in statistics Design of experiments, the analysis of variance, and regression Survey sampling Summarizing statistical data Predictive inference is an approach to statistical inference that emphasizes the prediction of future observations based on past observations. Initially, predictive inference was based on observable parameters and it was the main purpose of studying probability,[citation needed] but it fell out of favor in the 20th century due to a new parametric approach pioneered by Bruno de Finetti. The approach modeled phenomena as a physical system observed with error (e.g., celestial mechanics). De Finetti's idea of exchangeability—that future observations should behave like past observations—came to the attention of the English-speaking world with the 1974 translation from French of his 1937 paper,[63] and has since been propounded by such statisticians as Seymour Geisser.[64] Algorithmic inference Induction (philosophy) Informal inferential reasoning Information field theory Population proportion Philosophy of statistics Prediction interval Predictive analytics Predictive modelling Stylometry ^ According to Peirce, acceptance means that inquiry on this question ceases for the time being. In science, all scientific theories are revisable. ^ Upton, G., Cook, I. (2008) Oxford Dictionary of Statistics, OUP. ISBN 978-0-19-954145-4. ^ "TensorFlow Lite inference". 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(page 188) ^ Pfanzagl (1994) : "By taking a limit theorem as being approximately true for large sample sizes, we commit an error the size of which is unknown. [. . .] Realistic information about the remaining errors may be obtained by simulations." (page ix) ^ Neyman, J.(1934) "On the two different aspects of the representative method: The method of stratified sampling and the method of purposive selection", Journal of the Royal Statistical Society, 97 (4), 557–625 JSTOR 2342192 ^ a b Hinkelmann and Kempthorne(2008) [page needed] ^ ASA Guidelines for the first course in statistics for non-statisticians. (available at the ASA website) ^ David A. Freedman et alia's Statistics. ^ Moore et al. (2015). ^ Gelman A. et al. (2013). Bayesian Data Analysis (Chapman & Hall). ^ Peirce (1877-1878) ^ Peirce (1883) ^ Freedman, Pisani & Purves 1978. ^ David A. Freedman Statistical Models. ^ Rao, C.R. (1997) Statistics and Truth: Putting Chance to Work, World Scientific. 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Wikiversity has learning resources about Statistical inference Statistical Inference – lecture on the MIT OpenCourseWare platform Statistical Inference – lecture by the National Programme on Technology Enhanced Learning An online, Bayesian (MCMC) demo/calculator is available at causaScientia Portal: Mathematics Retrieved from " This module introduces our study of inference. Before we begin Linking Probability to Statistical Inference, let's look at how the remainder of the course relates to the Big Picture of Statistics. Recall that we start a statistical investigation with a research question. The investigation proceeds with the following steps: Produce Data: Determine what to measure, then collect the data. ← Types of Statistical Studies and Producing Data Explore the Data: Analyze and summarize the data. ← Summarizing Data Graphically and Numerically, Examining Relationships: Quantitative Data, Nonlinear Models, Relationships in Categorical Data with Intro to Probability Draw a Conclusion: Use the data, probability, and statistical inference to draw a conclusion about the population. ← Relationships in Categorical Data with Intro to Probability, Probability and Probability Distributions, Linking Probability to Statistical Inference, Inference for One Proportion, Inference for Two Proportions, Inference for Means, Chi-Square Tests In the Big Picture of Statistics, we are about to start the last step: Inference. We use data from a sample to "infer" something about the population in this and the upcoming modules. Inference is based on probability. At the end of April 2005, ABC News and the Washington Post conducted a poll to determine the percentage of U.S. adults who support the death penalty. Research question: What percentage of U.S. adults support the death penalty? Steps in the statistical investigation: Produce Data: Determine what to measure, then collect the data.The poll selected 1,082 U.S. adults at random. Each adult answered this question: "Do you favor or oppose the death penalty for a person convicted of murder?" Explore the Data: Analyze and summarize the data.In the sample, 65% favored the death penalty. Draw a Conclusion: Use the data, probability, and statistical inference to draw a conclusion about the population. Our goal is to determine the percentage of the U.S. adult population that support the death penalty. We know that different samples give different results. What are the chances that a sample reflects the opinions of the population within 3%? Probability describes the likelihood that a sample is this accurate, so we can say with 95% confidence that between 62% and 68% of the population favor the death penalty. We illustrated the Big Picture of Statistics with an example about an inference made from survey data. From a random sample of U.S. adults, we estimated the percentage of all U.S. adults who support the death penalty. We saw that probability describes the likelihood that an estimate is within 3% of the true percentage with this opinion in the population. For this example, there is a 95% chance that a random sample is within 3% of the true population percentage. Because random samples vary, inference always involves uncertainty. This uncertainty is captured by probability statements that are part of our conclusions. We emphasize this point in the following example where we look more closely at the process of statistical investigation with a real court case. Our goal is to identify arguments that use statistical inference to draw a conclusion as well as arguments that do not use inference. How can a prosecutor use data to detect cheating? The details of this case appeared in Chance magazine in 1991. The Case: During an exam at a university in Florida in 1984, the proctor suspected that one student, whom we will call Student C, was copying answers from another student, whom we will call Student A. The proctor accused Student C of cheating, and the case went to the university's supreme court. The Evidence: At the trial, the prosecution introduced evidence based on data. Here is the evidence: On the 16 questions missed by both Student A and Student C, 13 of the answers were the same. The Argument: The prosecutor used the data to draw an inference based on probability. He asked the question: Could 13 out of 16 matches be due to chance? He argued that a match of 13 out of 16 by chance alone was very unlikely. The probability of this occurring is very small. So there had to be another explanation besides chance, and the prosecutor said the explanation was cheating. Based on this evidence, Student C was found guilty of academic dishonesty. The Role of Random Chance: To decide if we agree with this argument, we need to understand if chance might explain this result. We need to determine if it would be unusual to get 13 matches on 16 questions by chance alone. To determine if 13 out of 16 is unusual, we have to look at what happens in the long run if students just guess on 16 multiple choice questions. Let's assume that each question had four options: a, b, c, or d. We use a computer program to randomly assign answers to each question, which mimics what happens when someone randomly guesses. Using software to imitate chance behavior is called simulation. Here you see a representation of answers from Student A and Student C as well as three randomly generated answer sets for the 16 questions missed by both Student A and Student C. We highlighted matches with Student A's answers in green. Notice that Student C has 13 answers that match Student A's answers: As a proportion, this is 13 ÷ 16 = 0.8125. It means that about 81% of the time, Student C's answers matched Student A's answers on questions that they both missed. For the random answers generated by "guessing," we see the proportion of matches differs: Set 1 has 6 matches with Student A: 6 ÷ 16 = 0.375 as a proportion, or about 38%. Set 2 has 3 matches with Student A: 3 ÷ 16 = 0.1875 as a proportion, or about 19%. Set 3 has 5 matches with Student A: 5 ÷ 16 = 0.3125 as a proportion, or about 31%. The proportion of matches in the randomly generated answers vary quite a bit, from 0.1875 to 0.3125. But none are close to the proportion of matches seen in Student C's paper, 0.8175. The proportion of matches for the three sets of results from the random guesses are graphed in the following figure. The blue line is the proportion of matches for Student C. Now we repeat the simulation of random sets of answers on the 16 questions, each time determining the proportion of matches to the wrong answers on Student A's paper. On the left is a dotplot for 100 random sets of answers. Each dot represents a set of 16 answers generated by random guessing. On the right is a histogram of 1,025 random sets of answers, which shows the long-run pattern. Analysis: In the histogram, we see that typical results fall between about 0.1 and 0.4. More specifically, if a student randomly guessed on these 16 questions, it would not be surprising to see from 2 to 6 matches with Student A's wrong answers. Translated into proportions, this is 2 ÷ 16 = 0.125 to 6 ÷ 16 = 0.375. Is Student C unusual? Yes. Notice that no randomly generated set of answers comes close to the proportion of matches on Student C's exam. A proportion of 0.8125 would be very unusual if guessing, so we conclude that Student C was not guessing. Conclusion: The prosecution argued that a match of 13 out of 16 wrong answers (a proportion of 0.8125) was unusual and could not be explained by random chance. Our simulation agrees with this observation. When we created answer sets by randomly guessing, we never saw more than 9 matches out of 16, which is a proportion of 0.5625. We agree with the prosecution that there has to be another explanation besides chance. However, could there be another explanation besides cheating? Yes. If you don't know the answer to a question on an exam, you rarely guess at random. It is more likely that you will make an educated guess. Some wrong answers might be more logical than others. This could also explain the large proportion of matches on wrong answers between the two students. So this evidence is not convincing evidence that Student C cheated, but we know that he did not just guess. Student C appealed his case. A second trial was held. This time the prosecution made a different argument using data. This argument did not use statistical inference. The prosecution created a new measurement. They compared every student's paper to Student A's paper. For the 40-multiple choice questions on the test, they counted the number of matches to Student A's paper and divided by 40. This new measurement was also a proportion. Analysis: There were 88 students. Here are the results: Each dot represents a student who took the exam. A dot with a proportion of 0.6 means that 60% of this student's answers matched Student A's answers. Note: Student A is included in the data. Of course, Student A is the dot with the proportion of 40 out of 40 = 1.0 This makes sense because all of Student A's answers matched Student A. (This does not mean that Student A did well on the exam.) We see that many of the proportions fall between between 0.40 (which is 16 matches out of 40) and 0.60 (which is 24 matches out of 40). So it is not surprising if between 40% and 60% of a student's answers matched Student A's answers. Student C had 32 matches out of 40, which is a proportion of 0.80. (This does not mean that Student C made an 80% on the exam. It means that 80% of Student C's answers matched Student A's answers.) Student C is once again an unusual data point. Conclusion: This time it is harder to argue that Student C is not cheating. When we compared him to the rest of the class, his paper had an unusually high number of matches with Student A's answers. This data together with the proctor's testimony is fairly convincing evidence for the prosecution's claim that Student C cheated by copying from Student A's paper. (Source: Phillip J. Boland and Michael Proschan, "The Use of Statistical Evidence in Allegations of Exam Cheating," Chance 3(3):10-14, 1991.) What's the Main Point? Statistical inference always involves an argument based on probability. In this court case, the prosecution used two different types of arguments to provide evidence of cheating. The first argument is an example of statistical inference because it is based on probability. We set up a simulation to reflect an assumption that the prosecutor made. The assumption is that answer sets come from random guessing. We simulated over a thousand answer sets with randomly chosen answers to investigate the long-run behavior of simulated answer sets. We then compared Student C to the distribution of randomly generated answer sets. Student C was unusual. We concluded that Student C was not randomly guessing. The second argument is an example of exploratory data analysis with no statistical inference. The prosecutor designed a measurement and collected data from every student in the class. He compared Student C's measurement to the measurements of the other students. Probability did not have a role in this analysis. Probability statements require a random event and a look at long-run behavior of random events, so this is not an example of statistical inference. The court case illustrates how we can view statistical inference as an argument based on probability. Here we briefly connect the probability argument with the vocabulary and ideas from the module Probability and Probability Distribution. Recall the following important points about probability that we learned in that module: Probability is a measure of how likely an event is to occur. We can make probability statements only about random events. Random here means that the outcome is uncertain in the short run but has a predictable pattern in the long run. How does the logic of the probability argument in the court case relate to Probability and Probability Distribution? To understand the probability argument in the original court case, we used a computer simulation to analyze the long-run pattern that emerges if students randomly guess on multiple-choice questions. Our variable was Proportion of matches with Student A's wrong answers on 16 questions. We graphed the distribution of a large number of proportions from the random answer sets to see the pattern. Using the vocabulary of Probability and Probability Distribution, the proportion of matches is a random variable. In the short run, we do not know the proportion of matches that will occur in a random answer set, but in the long run, we see a pattern in the distribution of these proportions. This distribution of proportions is treated as a probability model. From it we can see how much variability to expect in matches from random answer sets. We can also identify unusual values. From the pattern in this distribution, we can say it is very unlikely that Student C guessed. How does this logic relate to the Big Picture? This logic is similar to the logic of inference that we explore in future modules, where we randomly select samples from a population. We continue to use computer simulation throughout these modules to analyze the long-run pattern that emerges in measurements from random samples. We create probability models that tell us how much variability to expect in random samples. We also use these models to identify unusual measurements. From the patterns, we use data to make judgments about the population. In this way, our conclusions about a population are based on probability. Probability and Probability Distribution included a long discussion of probability models that are normal curves. Under certain conditions, the long-run behavior of measurements from random samples can be modeled with a normal curve (or a similar curve), we see in this module and in Inference for One Proportion, Inference for Two Proportions, and Inference for Means. In each module, we ask the question, When can we use a normal model? Once we know these conditions, we can use what we learned in the previous module to make probability-based decisions about population values. Here we add these ideas to the Big Picture to show how probability connects to inference. Note that we highlighted two types of inference in the diagram: Estimate a population value. Test a claim about the population value. We end our introduction to inference with a look at research questions that illustrate these two types of inference. We also connect these examples to the types of inference we learn about in upcoming modules. Research Questions That Involve Inference Type of Question Examples Variable Type Unit Make an estimate about the population What proportion of all U.S. adults support the death penalty? Categorical variable Inference for One Proportion What is the average number of hours that community college students work each week? Quantitative variable Inference for Means Test a claim about the population Do the majority of community college students qualify for federal student loans? Categorical variable Inference for One Proportion Has the average birth weight in a town decreased from 3,500 grams? Quantitative variable Inference for Means Compare two populations Are teenage girls more likely to suffer from depression than teenage boys? Categorical variable Inference for Two Proportions In community colleges do female students have a higher average GPA than male students? Quantitative variable Inference for Means Note: Each research question relates to either a categorical variable or a quantitative variable. In this course, three criteria determine the inference procedure we use: The type of variable. The type of inference (estimate a population value or test a claim about a population value). The number of populations involved. Contribute! Did you have an idea for improving this content? We'd love your input. Improve this pageLearn More Statistical inference is the process of using data analysis to infer properties of an underlying distribution of a population. It is a branch of statistics that deals with making inferences about a population based on data from a sample. Statistical inference is based on probability theory and probability distributions. It involves making assumptions about the population and the sample, and using statistical models to analyze the data. In this article, we will be discussing it in detail.Statistical inference is the process of drawing conclusions or making predictions about a population based on data collected from a sample of that population. It involves using statistical methods to analyze sample data and make inferences or predictions about parameters or characteristics of the entire population from which the sample was drawn.Consider a scenario where you are presented with a bag which is too big to effectively count each bean by individual shape and colours. The bag is filled with differently shaped beans and different colors of the same. The task entails determining the proportion of red-coloured beans without spending much effort and time. This is how statistical inference works in this context.You simply pick a random small sample using a handful and then calculate the proportion of the red beans. In this case, you would have picked a small subset, your handful of beans to create an inference on a much larger population, that is the entire bag of beans.Branches of Statistical InferenceThere are two main branches of statistical inference:Parameter EstimationHypothesis TestingParameter EstimationParameter estimation is another primary goal of statistical inference. Parameters are capable of being deduced; they are quantified traits or properties related to the population you are studying. Some instances comprise the population mean, population variance, and so on-the-list. Imagine measuring each person in a town to realize the mean. This is a daunting if not an impossible task. Thus, most of the time, we use estimates.There are two broad methods of parameter estimation:Point EstimationInterval EstimationHypothesis TestingHypothesis testing is used to make decisions or draw conclusions about a population based on sample data. It involves formulating a hypothesis about the population parameter, collecting sample data, and then using statistical methods to determine whether the data provide enough evidence to reject or fail to reject the hypothesis.Statistical Inference MethodsThere are various methods of statistical inference, some of these methods are:Parametric MethodsNon-parametric MethodsBayesian MethodsLet's discuss these methods in detail as follows:Parametric MethodsIn this scenario, the parametric statistical methods will assume that the data is drawn from a population characterized by a probability distribution. It is mainly believed that they follow a normal distribution thus can allow one to make guesses about the populace in question . For example, the t-tests and ANOVA are parametric tests that give accurate results with the assumption that the data ought to beExample: A psychologist may ask himself if there is a measurable difference, on average, between the IQ scores of women and men. To test his theory, he draws samples from each group and assumes they are both normally distributed. He can opt for a parametric test such as t-test and assess if the mean disparity is statistically significant.Non-Parametric MethodsThese are less assumptive and more flexible analysis methods when dealing with data out of normal distribution. They are also used to conduct data analysis when one is uncertain about meeting the assumption for parametric methods and when one have less or inadequate data . Some of the non-parametric tests include Wilcoxon signed-rank test and Kruskal-Wallis test among others.Example: A biologist has collected data on plant health in an ordinal variable but since it is only a small sample and normal assumption is not met, the biologist can use Kruskal-Wallis testing.Bayesian MethodsBayesian statistics is distinct from conventional methods in that it includes prior knowledge and beliefs. It determines the various potential probabilities of a hypothesis being genuine in the light of current and previous knowledge. Thus, it allows updating the likelihood of beliefs with new data.Example: consider a situation where a doctor is investigating a new treatment and has the prior belief about the success rate of the treatment. Upon conducting a new clinical trial, the doctor uses Bayesian method to update his "prior belief" with the data from the new trials to estimate the true success rate of the treatment.Statistical Inference TechniquesSome of the common techniques for statistical inference are:Hypothesis TestingConfidence IntervalsRegression AnalysisLet's discuss these in detail as follows:Hypothesis TestingOne of the central parts of statistical analysis is hypothesis testing which assumes an inference or withstand any conclusions concerning the element from the sample data. Hypothesis testing may be defined as a structured technique that includes formulating two opposing hypotheses, an alpha level, test statistic computation, and a decision based on the obtained outcomes. Two types of hypotheses can be distinguished: a null hypothesis to signify no significant difference and an alternative hypothesis H1 or Ha to express a significant effect or difference.Example: If a car manufacturing company makes a claim that their new car model gives a mileage of not less than 25miles/gallon. Then an independent agency collects data for a sample of these cars and performs a hypothesis test. The null hypothesis would be that the car does give a mileage of not less than 25miles/gallon and they would test against the alternative hypothesis that it doesn't. The sample data would then be used to either fail to reject or reject the null hypothesis.Confidence Intervals (CI)Another statistical concept that involves confidence intervals is determining a range of possible values where the population parameter can be, given a certain confidence percentage – usually 95%. In simpler terms, CI's provide an estimate of the population value and the level of uncertainty that comes with it.Example: A study on health records could show that 95% CI for average blood pressure is 120-130 . In other words, there is a 95% chance that the average blood pressure of all population is in the values between 120 and 130.Regression AnalysisMultiple regression refers to the relationship between more than two variables. Linear regression, at its most basic level, examines how a dependent variable Y varies with an independent variable X. The regression equation, Y = a + bX + e, a + bX + e, which is the best fit line through the data points quantifies this variation.Example: Consider a situation in which one is curious about one's advertisement on sales and is presented with it. Ultimately, it may influence questionnaire allocation as well as lead staff to feel disgruntled or upset and dissatisfied. In several regression conditions, regression analysis allows for the quantification of these two effects as well. Specifically, Y is the predicted outcoming factor while X1, X2, and X3 are the observed variables used to anticipate it.Applications of Statistical InferenceStatistical inference has a wide range of applications across various fields. Here are some common applications:Clinical Trials: In medical research, statistical inference is used to analyze clinical trial data to determine the effectiveness of new treatments or interventions. Researchers use statistical methods to compare treatment groups, assess the significance of results, and make inferences about the broader population of patients.Quality Control: In manufacturing and industrial settings, statistical inference is used to monitor and improve product quality. Techniques such as hypothesis testing and control charts are employed to make inferences about the consistency and reliability of production processes based on sample data.Market Research: In business and marketing, statistical inference is used to analyze consumer behavior, conduct surveys, and make predictions about market trends. Businesses use techniques such as regression analysis and hypothesis testing to draw conclusions about customer preferences, demand for products, and effectiveness of marketing strategies.Economics and Finance: In economics and finance, statistical inference is used to analyze economic data, forecast trends, and make decisions about investments and financial markets. Techniques such as time series analysis, regression modeling, and Monte Carlo simulations are commonly used to make inferences about economic indicators, asset prices, and risk management.ConclusionIn summary, statistical inference serves as an important concept which helps us data-driven decision-making. It enables researchers to extrapolate insights from limited sample data to broader populations. Through methods such as estimation and hypothesis testing, statisticians can derive meaningful conclusions and quantify uncertainties inherent in their analyses. Statistical inference is the process of using data analysis to infer properties of an underlying distribution of a population. It is a branch of statistics that deals with making inferences about a population based on data from a sample. Statistical inference is based on probability theory and probability distributions. 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Researchers use statistical methods to compare treatment groups, assess the significance of results, and make inferences about the broader population of patients.Quality Control: In manufacturing and industrial settings, statistical inference is used to monitor and improve product quality. Techniques such as hypothesis testing and control charts are employed to make inferences about the consistency and reliability of production processes based on sample data.Market Research: In business and marketing, statistical inference is used to analyze consumer behavior, conduct surveys, and make predictions about market trends. Businesses use techniques such as regression analysis and hypothesis testing to draw conclusions about customer preferences, demand for products, and effectiveness of marketing strategies.Economics and Finance: In economics and finance, statistical inference is used to analyze economic data, forecast trends, and make decisions about investments and financial markets. Techniques such as time series analysis, regression modeling, and Monte Carlo simulations are commonly used to make inferences about economic indicators, asset prices, and risk management.ConclusionIn summary, statistical inference serves as an important concept which helps us data-driven decision-making. It enables researchers to extrapolate insights from limited sample data to broader populations. Through methods such as estimation and hypothesis testing, statisticians can derive meaningful conclusions and quantify uncertainties inherent in their analyses. Attribution-ShareAlike CC BY-SA Learn more about reviews. Reviewed by Swetank Mohan, Lecturer 1, The University of Texas Rio Grande Valley on 12/16/24 The textbook covers a wide range of topics in statistical inference, from foundational probability concepts through Bayesian concepts. read more Reviewed by Swetank Mohan, Lecturer 1, The University of Texas Rio Grande Valley on 12/16/24 Comprehensiveness rating: 5 see less The textbook covers a wide range of topics in statistical inference, from foundational probability concepts through Bayesian concepts. Content Accuracy rating: 5 Overall, the content for now appear accurate and grounded in standard statistical theory and practice. Relevance/Longevity rating: 5 The material might be relevant for students and practitioners of statistics. Clarity rating: 5 The writing is generally accessible, with step-by-step explanations Consistency rating: 5 The text maintains a consistent tone and approach throughout. Modularity rating: 5 The text is well-structured into chapters. Organization/Structure/Flow rating: 5 Chapters flow logically from basic probability concepts to inference techniques Interface rating: 5 the textbook's interface is clear, with readable fonts, good spacing, and functional navigation tools like a table of contents Grammatical Errors rating: 5 Grammar is largely correct Cultural Relevance rating: 5 language is culturally neutral and inclusive Comments This textbook strikes a nice balance between theoretical rigor and approachable teaching style Reviewed by Kenese Io, PhD candidate, Colorado State University on 11/30/20 The book illustrates a very pragmatic approach with little theoretical application. I would recommend this text to anyone who is teaching applied stats at an early level. read more Reviewed by Kenese Io, PhD candidate, Colorado State University on 11/30/20 Comprehensiveness rating: 4 see less The book illustrates a very pragmatic approach with little theoretical application. I would recommend this text to anyone who is teaching applied stats at an early level. Content Accuracy rating: 5 The book is accurate with a number of very helpful examples for new researchers. The examples provide examples of code for students to use and draw from as they execute their own examples. They also provide examples with commonly used datasets which is very helpful for some students who may be working on their final projects as an undergraduate or homework assignments as a first year graduate student. Relevance/Longevity rating: 5 The book is problem or problem set oriented which will allow the book to maintain its longevity. The examples offer analysis of old data but this is very helpful as instructors can assign similar problem sets with new datasets while the students have an excellent tool to rely on. Clarity rating: 4 The book is generally clear but given that it is problem oriented some of the theoretical background is scarce and leaves a bit to be desired. Nevertheless the examples really allow for an immersive experience. Consistency rating: 5 The book does a great job of following a clear formula of historical background/ brief theoretical walkthrough/ long examples that force you engage critically with the assignment. Modularity rating: 5 The book is very easy to assign as the text quickly jumps to examples of matlab code that will draw students to engage with it. I can imagine students constantly flipping between their own code and the text to help simplify analysis or execute their code. Organization/Structure/Flow rating: 4 The book is organized relatively well. I would have liked to see a few of the later chapters earlier likt the common tests for statistical significance but it generally goes from broader to more narrow perspectives. Interface rating: 5 The graphs and code examples are laid out well and the text works great in acrobat reader. Grammatical Errors rating: 5 No errors Cultural Relevance rating: 4 The text does not offer any critical analysis here but this is due to maintaining general examples. I think an instructor could easily assign more critical assignments that rely on the intuition laid out in the book. Reviewed by Jimmy Chen, Assistant Professor, Bucknell University on 1/26/19 As far as Statistical Inference goes, the author has done a great job covering the essential topics. The breadth and the depth of the content are are well balanced. I believe this book can be a great supplemental material for any statistics or... read more Reviewed by Jimmy Chen, Assistant Professor, Bucknell University on 1/26/19 Comprehensiveness rating: 5 see less As far as Statistical Inference goes, the author has done a great job covering the essential topics. The breadth and the depth of the content are are well balanced. I believe this book can be a great supplemental material for any statistics or probability course. Students would have no problems studying this book themselves because the author has explained concepts clearly and provided ample examples. Content Accuracy rating: 5 I think the content is fine. Examples, illustration, and computer codes are all very helpful for the readers to understand the content. Relevance/Longevity rating: 5 The relevance of the book is great. Most supporting examples would be easily relatable to most students. Most statistics or probability concepts discussed in the book are timeless. Detailed computer codes make it easy for verification. Clarity rating: 5 The author has explained concepts very well. The flow of the text and examples are great and thoughtful, make it very easy to flow. Consistency rating: 5 The consistency of the text is great. Modularity rating: 5 The modularity of the text is great. I could easily adopt the entire book or use only certain sections of the book for my teaching. Organization/Structure/Flow rating: 5 The topics in the text are presented in a logical, clear fashion. Interface rating: 5 The layout of the text are clear and easily readable. Imagines, charts, and tables are clear and concise. Very easy to follow. Grammatical Errors rating: 5 The text contains no grammatical errors. Cultural Relevance rating: 5 The text is not culturally insensitive or offensive in any way. Reviewed by Adam Molnar, Assistant Professor, Oklahoma State University on 5/21/18 This book is not a comprehensive introduction to elementary statistics, or even statistical inference, as the author Brian Blais deliberately chose not to cover all topics of statistical inference. For example, the term matched pairs never... read more Reviewed by Adam Molnar, Assistant Professor, Oklahoma State University on 5/21/18 Comprehensiveness rating: 2 see less This book is not a comprehensive introduction to elementary statistics, or even statistical inference, as the author Brian Blais deliberately chose not to cover all topics of statistical inference. For example, the term matched pairs never appears; neither do Type I or Type II error. The Student's t distribution gets much less attention than in almost every other book; the author offers a rarely used standard-deviation change (page 153) as a way to keep things Gaussian. The author justifies the reduced topic set by calling typical "traditional" approaches flawed in the first pages of text, the Proposal. Instead, Blais tries to develop statistical inference from logic, in a way that might be called Bayesian inference. Other books have taken this approach, more than just Donald Berry's book mentioned on page 32. [For more references, see the ICOTS6 paper by James Albert at] None of those books are open-resource, though; an accurate, comprehensive textbook would have potential. This PDF does not contain that desired textbook, however. As mentioned below under accuracy, clarity, and structure, there are too many missing elements, including the lack of an index. As I read, this PDF felt more like a augmented set of lecture notes than a textbook which stands without instructor support. It's not good enough. (For more on this decision, see the other comments at the end.) Content Accuracy rating: 2 The only non-troubling number of errors in a textbook is zero, but this book has many more than that. In the version I read from the Minnesota-hosted website, my error list includes not defining quartiles from the left (page 129), using ICR instead of IQR (page 133), misstating the 68-95-99 rule as 65-95-99 (page 134), flipping numbers in the combination of the binomial formula (page 232), repeating Figure C-2 as Figure C-1 (page 230), and titling section 2.6 "Monte Hall" instead of "Monty Hall". Infuriatingly, several of these mistakes are correct elsewhere in the book - Monty Hall in section 5.4, the binomial formula in the main text, and 68-95-99 on page 142. I'm also annoyed that some datasets have poor source citations, such as not indicating Fisher's iris data on page 165 and calling something "student measurements during a physics lab" on page 173. Relevance/Longevity rating: 4 Because there are so many gaps, including full support for computer presentation, it would be easy to update completed sections as needed, such as when Python becomes less popular. Clarity rating: 2 Quality of the prose is fine, but many jargon terms are not well defined. Students learning a subject need clear definitions, but they don't appear. In my notes, I see exclusive (page 36), conditioning (page 40), complement (used on page 40 but never appears in the text), posterior (page 54), correlation (page 55), uniform distribution (page 122), and Greek letters for which the reference to a help table appears on page 140, but Greek letters have appeared earlier. Additionally, several important terms receive insufficient or unusual definitions, including labeling summary description of data as inference (page 34), mutually exclusive (page 36) versus independence (page 43), and plus/minus (page 146, as this definition of +/- applies in lab bench science but not social sciences). I appreciate that the author is trying to avoid calculus with "area under the curve" on page 127, but there's not enough written for a non-calculus student to understand how these probabilities are calculated. To really understand posterior computation, a magical computer and a few graphs aren't good enough. Consistency rating: 5 Internal consistency to Bayesian inference is quite strong; many of the examples repeat the steps of Bayes' Recipe. This is not a concern. Modularity rating: 3 The book needs to be read in linear order, like most statistics books, but that's not necessarily a negative thing. Dr. Blais is trying to take the reader through a structured development of Bayesian inference, which has a single path. There are a few digressions, such as fallacies about probability reasoning, but the book generally maintains a single path from chapters 1 to at least 7. Most sections are less than 10 pages and don't involve lots of self-references. Although I rated reorganization possibility as low, due to the near-impossibility of realigning the argument, I consider it harsh to penalize the book for this. Organization/Structure/Flow rating: 2 There isn't enough structure for a textbook; this feels more like a set of augmented lecture notes that a book for guided study. I mentioned poor definitions under "Clarity", so let me add other topics here. The most frustrating structural problem for me is the presentation of the fundamental idea of Bayesian inference, posterior proportional to prior * likelihood. The word prior first appears on page 48, but receives no clear definition until a side-note on page 97. The word posterior first appears on page 53. Despite this, the fundamental equation is never written with all three words in the correct places until page 154. That's way, way too late. The three key terms should have been defined around page 50 and drilled throughout all the sections. The computer exercises also have terrible structure. The first section with computer exercises, section 2.9 on page 72, begins with code. The reader has no idea about the language, package, or purpose of these weird words in boxes. The explanation about Python appears as Appendix A, after all the exercises. It would not have taken much to explain Python and the purpose of the computer exercises in Chapter 1 or 2, but it didn't happen. A classroom instructor could explain this in class, but the Open Resource Project doesn't provide an instructor with every book. Like the other things mentioned, the structure around computing is insufficient. Interface rating: 5 I had no problems navigating through the chapters. Images look fine as well. Grammatical Errors rating: 5 Grammar and spelling are good. I only spotted one typographical error, "posterier" on page 131, and very few awkward sentences. Cultural Relevance rating: 4 This is a US-centered book, since it refers to the "standard deck" of playing cards on page 36 as the US deck; other places like Germany have different suits. The book also uses "heads" and "tails" for coins, while other countries such as Mexico use different terms. I wouldn't call this a major problem, however; the pictures and diagrams make the coins and cards pretty clear. There aren't many examples involving people, so there's little scope for ethnicities and backgrounds. Comments On Brian Blais's webpage for the book, referenced only in Appendix A for some reason, he claims that this book is targeted to the typical Statistics 101 college student. It is NOT. Typical college students need much more support than what this book offers - better structure, better scaffolding, more worked examples, support for computing. What percentage of all college students would pick up Python given the contents presented here? My prior estimate would be 5%. Maybe students at Bryant university, where Pre-Calculus is the lowest math course offered, have a higher Python rate, but the bottom 20% of my students at Oklahoma State struggle with order of operations and using the combinations formula. They would need massive support, and Oklahoma State enrolls above-average college students. This book does not have massive support - or much at all. This makes me sad, because I've argued that we should teach hypothesis testing through credible intervals because I think students will understand the logic better than the frequentist philosophical approach. In 2014, I wrote a guest blog post [on teaching Bayes' Rule. I would value a thorough book that might work for truly typical students, but for the students in my everyone, this won't work. 1 Introduction to Probability 2 Applications of Probability 3 Random Sequences and Visualization 4 Introduction to Model Comparison 5 Applications of Model Comparison 6 Introduction to Parameter Estimation 7 Priors, Likelihoods, and Posteriors 8 Common Statistical Significance Tests 9 Applications of Parameter Estimation and Inference 10 Multi-parameter Models 11 Introduction to MCMC 12 Concluding Thoughts BibliographyAppendix A: Computational AnalysisAppendix B: Notation and StandardsAppendix C: Common Distributions and Their PropertiesAppendix D: Tables This is a new approach to an introductory statistical inference textbook, motivated by probability theory as logic. It is targeted to the typical Statistics 101 college student, and covers the topics typically covered in the first semester of such a course. It is freely available under the Creative Commons License, and includes a software library in Python for making some of the calculations and visualizations easier. Brian Blais professor of Science and Technology, Bryant University and a research professor at the Institute for Brain and Neural Systems, Brown University. Submit ancillary resource Suggest an edit to this book record This course provides an elementary introduction to probability and statistics with applications. Topics include basic combinatorics, random variables, probability distributions, Bayesian inference, hypothesis testing, confidence intervals, and linear regression. These same course materials, including interactive … This course provides an elementary introduction to probability and statistics with applications. Topics include basic combinatorics, random variables, probability distributions, Bayesian inference, hypothesis testing, confidence intervals, and linear regression. These same course materials, including interactive components (online reading questions and problem checkers) are available on MIT's Open Learning Library, which is free to use. You have the option to enroll and track your progress, or you can view and use the materials without enrolling. assignment_turned_in Problem Sets with Solutions grading Exams with Solutions assignment_turned_in Activity Assignments with Examples Supplemental Exam Materials co_present Instructor Insights Statistics is a branch of Mathematics, that deals with the collection, analysis, interpretation, and the presentation of the numerical data. In other words, it is defined as the collection of quantitative data. The main purpose of Statistics is to make an accurate conclusion using a limited sample about a greater population. Types of Statistics Statistics can be classified into two different categories. The two different types of Statistics are: Descriptive Statistics Inferential Statistics In Statistics, descriptive statistics describe the data, whereas inferential statistics help you make predictions from the data. In inferential statistics, the data are taken from the sample and allows you to generalize the population. In general, inference means "guess", which means making inference about something. So, statistical inference means, making inference about the population. To take a conclusion about the population, it uses various statistical analysis techniques. In this article, one of the types of statistics called inferential statistics is explained in detail. Now, you are going to learn the proper definition of statistical inference, types, solutions, and examples. Statistical Inference Definition Statistical inference is the process of analysing the result and making conclusions from data subject to random variation. It is also called inferential statistics. Hypothesis testing and confidence intervals are the applications of the statistical inference. Statistical inference is a method of making decisions about the parameters of a population, based on random sampling. It helps to assess the relationship between the dependent and independent variables. The purpose of statistical inference to estimate the uncertainty or sample to sample variation. It allows us to provide a probable range of values for the true values of something in the population. The components used for making statistical inference are: Sample Size Variability in the sample Size of the observed differences Types of Statistical Inference There are different types of statistical inferences that are extensively used for making conclusions. They are: One sample hypothesis testing Confidence Interval Pearson Correlation Bi-variate regression Multi-variate regression Chi-square statistics and contingency table ANOVA or T-test Statistical Inference Procedure The procedure involved in inferential statistics are: Begin with a theory Create a research hypothesis Operationalize the variables Recognize the population to which the study results should apply Formulate a null hypothesis for this population Accumulate a sample from the population and continue the study Conduct statistical tests to see if the collected sample properties are adequately different from what would be expected under the null hypothesis to be able to reject the null hypothesis Statistical Inference Solution Statistical inference solutions produce efficient use of statistical data relating to groups of individuals or trials. It deals with all characters, including the collection, investigation and analysis of data and organizing the collected data. By statistical inference solution, people can acquire knowledge after starting their work in diverse fields. Some statistical inference solution facts are: It is a common way to assume that the observed sample is of independent observations from a population type like Poisson or normal Statistical inference solution is used to evaluate the parameter(s) of the expected model like normal mean or binomial proportion Importance of Statistical Inference Inferential Statistics is important to examine the data properly. To make an accurate conclusion, proper data analysis is important to interpret the research results. It is majorly used in the future prediction for various observations in different fields. It helps us to make inference about the data. The statistical inference has a wide range of application in different fields, such as: Business Analysis Artificial Intelligence Financial Analysis Fraud Detection Machine Learning Share Market Pharmaceutical Sector Statistical Inference Examples An example of statistical inference is given below. Question: From the shuffled pack of cards, a card is drawn. This trial is repeated for 400 times, and the suits are given below: Suit Spade Clubs Hearts Diamonds No.of times drawn 90 100 120 90 While a card is tried at random, then what is the probability of getting a Diamond cards Black cards Except for spade Solution: By statistical inference solution, Total number of events = 400 i.e.,90+100+120+90=400 (1) The probability of getting diamond cards: Number of trials in which diamond card is drawn = 90 Therefore, P(diamond card) = 90/400 = 0.225 (2) The probability of getting black cards: Number of trials in which black card showed up = 90+100 =190 Therefore, P(black card) = 190/400 = 0.475 (3) Except for spade Number of trials other than spade showed up = 90+100+120 =310 Therefore, P(except spade) = 310/400 = 0.775 Stay tuned with BYJU'S – The Learning App for more Maths-related concepts and download the app for more personalized videos.