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Last Chance Statistics for Untenured Professors: An Introduction to the History and Application of Cognitive Psychotherapy to Assumptions Regarding Statistical Hypotheses Testing

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Introduction

The Cognitive Revolution in Statistics: Propitious Hypotheses Testing

Until recently, the average social scientist understood little about the tremendous advances occurring in the nascent branch of statistics known as "propitious hypotheses testing" (PHT). The goal of these new statistical procedures is straightforward: to provide a logical basis for consistent rejection of the null hypotheses (H_o), thereby, at last, maximizing the probability that psychological theory can be grounded in acceptable empirical findings. Furthermore, despite their theoretical complexity, the methods associated with such a lofty task are also intuitively understandable; they simply involve an application of scientific techniques of cognitive psychotherapy to the assumptions underlying inferential statistical procedures.

Like the paradigmatic revolutions caused by other applications of cognitive psychology, in areas as diverse as learning, social psychology, and artificial intelligence, this sweepingly new approach has shattered the very foundations of classical strategies for social research. Although those stodgily trained in the generations of "classical" statistical techniques may find PHT methods extraordinary, the application of cognitive psychotherapy to statistical procedures promises to spawn the most productive period in the young history of social sciences. Prior to a discussion of specific "Last Chance Statistics," as they are popularly known, a brief history of fundamental shifts in paradigms associated with the philosophical development of cognitive modification of empirical findings is necessary, in order that the nonmathematically inclined reader may make most appropriate use of the numerous techniques of auspicious hypotheses inquiry.

A Brief History of the Cognitive Revolution in Statistics

The roots of this cognitive revolution in statistics can be traced to the prevalence of a Kantian model of data analysis (Kant, 1828/1989). It is a little known fact that Kant, after his failure to secure tenure at Leipzig,[1] radically departed in his philosophical thinking from an emphasis on epistemology and morality to one of statistical inference. (During this period he also began writing romance novels.) Similarly, Freud (1928) was a firm believer in the Kantian notion of categorical *verstehen*, a concept he apparently encountered while reading some of Kant's later, more amorous efforts. A strong case

This paper is humbly dedicated to the memory of the late Sir Cyril Burt (1905-1974).

[1]In his classic work "Prologommena to Any Tenure Track" Kant established his famous categorical imperative, "Categorically, it is imperative that results support the hypotheses."

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can be made that Freud, too, was a pioneer in the use of cognitive expectations to maximize the power of qualitative data. The actual term "cognitive statistics" was first popularized by Murray (1938), in response to the the failure of traditional parametric approaches to support the reliability of the Thematic Apperception Test (TAT). Murray sanguinely noted that, "Since the TAT and other thematic material are projective instruments, the experimenter can also project a reliability onto the testing situation, insofar as he *believes and expects the instrument to be reliable*" (emphasis ours).

Unfortunately, Murray was not sufficiently trained in statistical methods and did not capitalize on his fundamentally different conceptual strategy for improving the reliability of projective instruments by allowing the psychometrician, as well as the patient, an innovative degree of projection. Two further separate developments were necessary before the application of cognitive psychotherapeutic techniques could produce the technology of post hoc data manipulation that is so popular today. Contrary to popular sentiment, these paradigm shifts had nothing to do with the academic ethos regarding the necessity of voluminous publications that coincidentally developed during the same period. Instead, they involved a cognitive psychotherapeutic redefinition of two key notions in traditional statistics, *expected value* and *error variance*.

Albert Ellis and the Notion of Expected Values

Reformulation of the concept of expected value fell to Ellis (1962), the famous cognitive psychotherapist. According to classic statistical theory, the expected value is the mean of a sampling distribution, or mathematically:

Given that a Reinmann Stieltjes integral exists such that

$$g(x)\, dF(x)$$

then the expected value of

$$E(x) = \int xf(x)dx$$

Ellis' genius was the use of cognitive therapy to challenge traditional notions of expectation in expected value. According to Ellis, statistical tests are free to deviate around any mean and assume any value the experimenter wishes them to, simply by the experimenter changing his expectations about what the results "should" be. Assumptions of "biased" and "unbiased" population estimators, Ellis claims, reflect the *a priori* cognitive schema of the researcher, and are no more an adequate model of reality than any other particular reality the researcher happens to have embraced (Ellis, 1962). These cognitive distortions can best be remedied by what Ellis calls the ABC model of empirical research: (A) *Always* use the test that supports your hypothesis; (B) *Be* sure to estimate population parameters in line with your hypothesis; and (C) *Correct* error variance for what you need it to be, since such errors are cognitive distortions that interfere with your happiness and publication record. Mathematically, this can be expressed as a simple corollary to the central limit theorem as seen below.

$$E \sum (X) = \text{A Publishable Result}$$

where X is any study, and A Publishable Result is any result that would be accepted by any editor in a refereed journal.

Additional steps (see Harmann, 1968, for proof) demonstrate that this equation is equivalent to the following:

$$\Sigma E \Sigma (X)^{1 \to \infty} = \text{Tenure}$$

This simple formula indicates that a summation of expected value studies that are publishable will eventually lead to permanent employment, usually defined as "tenure."

The Cognitive Rethinking of Error Variance

A separate development in what are now known as "invasive statistics" was a cognitive reformulation of the notion of error variance. In traditional data analysis, a particular result is thought to be "significant" if the probability of its occurrence or relation with another variable exceeds a particular and admittedly arbitrary level, usually .05. To test this, a similar procedure is followed. For example, in testing the hypotheses that two variables significantly differ in their mean values, independent random samples are drawn from the populations to be compared, and the sampling distribution of this ratio of two independent unbiased estimates of population variance is compared to a known distribution.

Unfortunately, there is always the problem of error variance, caused by random fluctuations, data mistakes, lapses in experimenter attention and the like, which may serve to depress the critical comparison of the observed distribution ratio to that of the known distribution. Basically, this means that if you have more within group variance due to extraneous factors (i.e., more junk in the denominator) you are less likely to find significant results than if you had conducted your experiments in a Candide-like, best-of-all-possible worlds. As a result, a serious shortcoming in traditional statistics is that the experimenter is often faced with a set of findings that *may merely have the appearance* of nonsignificance. The experimenter who fails to find between-group differences where they have been expected by a carefully crafted theory often *knows* that inflated error variance is the culprit. But how can he or she prove this to the scientific community?

Since Kant, however, philosophical arguments have suggested that estimates of error variance should be congruent with the experimenter's expectations. This idea was first represented by Hans Vaihinger, whose book "Statistics as If" was published during Freud's day. Vaihinger was a neo-Kantian admirer of Nietzsche who took the spirit of Kant's and Pascal's ethical doctrine to "behave as if a God exists," and developed it into a statistical method. For Vaihinger, all beliefs were fictions. One man's "error" somehow gained the upper hand and convinced the first party that he was wrong. Applying this to statistical principles, error and true variance are simply convenient fictions that enable us to understand the world. Mathematically, then, Vaihinger redefined error variance as

$$\Sigma E = X\ Y\ Z$$

where the arbitrary characters X, Y, and Z equal any value necessary for desired results to be significant. Again, this was later shown to equal the following, by now, familiar equation,

$$E \Sigma (X)^{1 \to \infty} = \text{Tenure!}$$

This powerful line of reasoning has fostered development of a number of techniques to attenuate with-in group differences, based on calculations of what the experimenter expects them to optimally be. These methods will be discussed below.

The Existential Contribution to Statistical Choice

Although less important mathematically to the development of PHT, or "tenurable" statistical techniques, the contribution of other profound thinkers cannot go unnoticed. This is especially true concerning the Existential/Humanists, such as Boss, Binswanger, and Frankl, all of whom have emphasized the role of choice in statistics, and have served to popularize the notion that traditional statistical tests represent an arbitrary constraint on Free Will and Tenure. For example, Victor Frankl has stated with typical existential clarity and relevance that the decision of *what* one chooses to investigate is much more important than what one actually finds, "insofar as serving to illuminate the ineffability of choice over arbitrary and stifling reality" (Frankl, 1949). Recently, this idea has gained some prominence, especially among graduate students experiencing difficulty in completion of their dissertations.

More directly, Binswanger (1946) has discussed the "nauseating arbitrariness of the analysis of variance." In one of the most moving passages in modern statistical theory, he argues:

> I am a man. I live in the world. I can choose to grasp Being in any statistical approach. I can choose an analysis of variance. Or I can choose a less powerful sign test. Who are you, a mere mortal, ultimately not responsible for my life, to tell me which statistic to use? It is my life, my choices, my beliefs, my grappling with the world. I may even choose to disregard the sterile results of inferential assumptions completely, believing instead in my own struggling experience facing the ever present reality of the death that is certain if I do not publish (*Keintenureheit*). Indeed, I may wish, as a man led to the gallows wishes, to utilize my own, subjective, "last chance statistics" (*Lastchanznumerren*).

Last Chance Statistics: A Primer of Techniques

Having suggested a firm philosophical basis for development of an alternative paradigm to classical inferential statistics, it is now time to highlight but a few of the many recent developments in this burgeoning field of applied and "results-friendly" data analysis. The current popularity of the cognitive PHT, or so-called "last chance statistics," is evidenced by the large number of computer programs commercially available to assist the user with the procedures commonly known as Post Hoc data manipulation. Such programs include SPPS (Statistics for the Publish or Perish Scientist), BPDQ (Better Publish Damn Quick), and ASS (Adjustments for Social Statistics). Deserving historical note is the early effort "Many Tabs," a program that generated large numbers of correlation coefficients between current restaurant bills and dissertation data, and resulted in some of the most important doctoral theses of the previous generation.

The interested reader is urged to consult Crook and Shambles' (1979) *Quasi-statistic Tests: Post Hoc Manipulation of the Dependent Variable* for a full discussion of the underlying mathematics involved in many of these promising and exhilarating methods of maximizing the probability of H_1. Below are synopses of some of the most popular "last chance statistics," which despite their controversy should prove quite popular for untenured faculty, students struggling with theses, individuals interested in securing grant support, and Republicans documenting the positive effects of trickle-down theory on domestic poverty.

Last Chance Tests Reducing Unexpected Bias

In classical statistics, it can be shown that the expected value of the sample mean is the population mean. This value is called an *unbiased estimate* of a population, because, in the long run, it will equal the population parameter. This handy fact makes all sorts of inferences about broad populations possible from sampling of small portions, and furthermore, allows us to state our degree of certainty in our results mathematically.

As in traditional statistics, the Last Chance Tests assume that unless the sampling mean is equivalent to the expected population value, the sampling mean is also clearly a biased statistic. However, as we have seen, according to cognitive theory of statistical expectancies, the population mean can be thought—quite literally—to be whatever value the experimenter wishes. Therefore, when the experimenter changes his or her cognitive expectancies, he or she is also changing the degree of unbiasness in the sample statistic. Consequently, a perfectly unbiased (in traditional statistics) sample mean may be tremendously biased for the cognitive statistician.

This dreadful condition occurs frequently when the actual data collected is not sufficiently robust to withstand the realities superimposed by the researcher to support the researcher's hypotheses. In this situation, application of traditional statistical tests will almost always be insensitive to the cognitive determinants operating to unconstrain results. This statistical artifact is often known as the problem of "inelastic" or "vanillaed" (compared with "fudged") data. However, since our sample estimate is in fact biased, (i.e., it will not equal what the experimenter expects in the long run) procedures are available for reducing partiality of this number. Among the most popular and simple statistical procedures of this class is the Unbiased Means Elimination Test (Haize, 1971). This procedure relies nicely on Ellis' notion of expectation. Since the population parameter has been "expected" by the experimenter, the Unbiased Means Elimination Test is a procedure to transform the data into the expected sample values that the researcher "has in mind."[2] This is done most often by simply throwing out values that are not in line with the predicted hypothesis. The computer package GLUM (Generally Limit Unmarketable Material) is especially useful for finding experimental values that are not in the expectancy range and removing them with a pseudo-random algorithm.

Another procedure in this class is the Students post hoc *t* (Wino, 1981). It is simple in its brilliance. Variables that might differ between two groups are examined with a *t* test. Differences that are significant are published. Those that are not can become "unexpected, biased estimators," and consequently ignored. Mathematically, this procedure is rather simple.

$$E(X) = \text{WHOOPIE!!!}$$

This method is very popular with people who do field research, for obvious reasons, especially if they are grant funded.

A useful version of this test, where homogeneity of variance is not assured in the different groups, allows the experimenter to *estimate* an error term, based on his or her expected values, as well as past experiences. For example, an experimenter can rationally set the error term to what it *should have been* if he or she had adequate funding, sufficient lab space, a decent graduate assistant, or a spouse that did not snore. This "estimated unbiased mean" is then used as an appropriate pooled variance, much as the more traditional pooled-variance *t* test. Often the results produce a massive reduction in Type II error.

[2]A sensible point was made by Carl Sagan: One should always remember that since the arrows of time can point either forward or backward, the experimenter may simply choose to work backwards, i.e., if the results don't fit your cognitive set, change your cognitive set (read: hypothesis) to fit the data. Since Einstein was allowed to conduct his "thought" experiments, then why can't untenured professors say, "Gee, I thought it was okay to remove outliers."

Modified Bonferroni Adjustments

One of our favorite types of tests is the family of procedures known as the Modified Bonferroni Adjustments (MBAs—also very popular with individuals with this degree). In traditional classical statistics, Bonferroni adjusted *alpha* levels are considered *procedure-wise* to prevent inflation of the possibility of Type I error, or the possibility that the theory is not true but that the results are significant by chance. For example, if during one procedure, 20 experiments are performed, then the *alpha* level in a Bonferroni adjustment would be divided by the number of experiments (in this case .05/20, or .0025) to prevent multiple tests causing chance results.

However, as cognitive psychotherapists would tell us, this procedure "catastrophizes" or expects the worse. Why not be more optimistic? Why not maximize the chance that the theory is true? You're going to have statistical imprecision somewhere, and cognitive therapy, along with a heavy dose of existentialism, suggests you choose what is to your advantage. The popular method for this is the Modified Bonferroni procedures, tests which adjust *alpha* levels to maximize the chance that the merely arbitrary model of reality suggested by data may be found to coincide with the reality of adequate theory and expectation.

One procedure, the so-called Turkey's Honestly Insignificant Difference Test, multiplies the *alpha* level by the number of tests employed. In other words, if the experimenter tests 20 hypotheses, the accepted *alpha* level for any of them is 1.0, or any finding at all. The reader is cautioned regarding this method, as its mathematical assumptions are not well developed.

A more desirable approach adjusts the *alpha* levels according to the number of hypotheses that are *expected* to be significant. Since hypotheses would not be tested unless there was a belief that at least some of them were significant, this seems to be a reasonable procedure. Why else would the experimenter have gone to the trouble? If the experimenter tests six hypotheses and thinks three will be significant, he or she can set the *alpha* level at .15, or 3 X .05. Obviously, in this case, individuals who do multi-hypothetical research are not penalized as they might be under traditional statistical procedures. A further advantage is that it can be mathematically shown that the researcher does not even need to perform *any* experiments whatsoever, as long as he or she expects enough hypotheses to be significant. The tremendous savings in cost implied with this technique add to its attractiveness.

The logic behind this method can also be utilized with a traditional analysis of variance, or ANOVA. One popular procedure is known as the *Shiftless F* test, or simply, an *Adjusted F*. Procedurally, it is accomplished by dividing the bottom term in the analysis of variance by a constant term. When this latter, more conservative procedure is employed, it is referred to as a *Fixed Reduction Analysis Under the Denominator* (FRAUD) *F* test and usually lacks the power of other invasive statistics.[3]

Finally, the researcher may choose the Bonferroni Ordinary Significance Test. This statistical procedure is intuitively appealing and elegant in its design. Kerk (1984) discussed the rationale:

> This test simply allows the experimenter to adjust his/her alpha level for ordinary day-to-day levels of significance. Is .05, or 1 chance in 20, an unreasonable criterion? How often during a day do *you* demand such a proof? Would you cheat on your spouse or run a red light if the chances were 1 in 20 that you would be caught? How about 1 in 5? Come on folks, let's introduce some reality into our statistics...

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[3]As Steven Gould (1988) has noted, "If Heisenberg was allowed to be uncertain about his data and then allowed to plead relative as opposed to absolute reality (and, in fact be awarded the 1932 Nobel), then it is entirely feasible that the untenured professor could be equally justified in post hoc uncertainty about his own results."

To perform this test, the experimenter simply chooses whatever *alpha* level will be proof enough for him or her. Current debate in the literature is attempting to clarify whether this choice can be legitimately made *post hoc* or not. However, if the *alpha* level is sufficiently high *a priori* (i.e., unity), this concern is irrelevant. Mathematically, this can be expressed as:

$$E(X) = \frac{\text{Don't Worry}}{\text{Be Happy}}$$

where *alpha* = 1.00, and X is the result of any laboratory finding.

Conclusion

The new techniques of the cognitive statistical revolution are just being developed. With this in mind, it should be recognized that the next few years in the social sciences will produce some of the most interesting and democratic findings our discipline has seen. Theory has frequently suffered at the hands of the outrageous demands of data. The untenured professor is now statistically equipped to boldly declare this liberating message: When theory and data collide, God help the data. Clearly, however, urgent work (and increased funding) is needed to develop solutions to determine who indeed will qualify for college tenure once these methods of propitious hypotheses testing become more commonplace and academic publications become more numerous.[4]

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[4]Already, a number of intriguing methods have been suggested to solve this impending crisis. These include random assignment of tenure track employment throughout the population through some sort of lottery system, perhaps as a consolation prize (California Lottery Commission, 1989), or the use of meta-analyses to promote untenured professors with the biggest "effect size" associated with their statistical findings. This procedure has been advocated by the sociobiologists (Wilson, 1982).