

# A Bayesian alternative to null hypothesis significance testing

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## Abstract

Researchers in second language (L2) learning typically regard “statistical significance” as a benchmark of success for an experiment. However, because this statistic indicates nothing more than the probability of data sets occurring given the essentially impossible condition that the null hypothesis is true, it confers little of practical or theoretical importance. Significance is also the source of widespread misinterpretation, including confusion of significance with effect size. Critics of NHST assert that alternative approaches based on Bayes’ theorem are more appropriate for hypothesis testing. This paper provides a non-technical introduction to essential concepts underlying Bayesian statistical inference, including prior probabilities and Bayes factors. Common criticisms of NHST are outlined and possible benefits of Bayesian approaches over NHST are discussed.

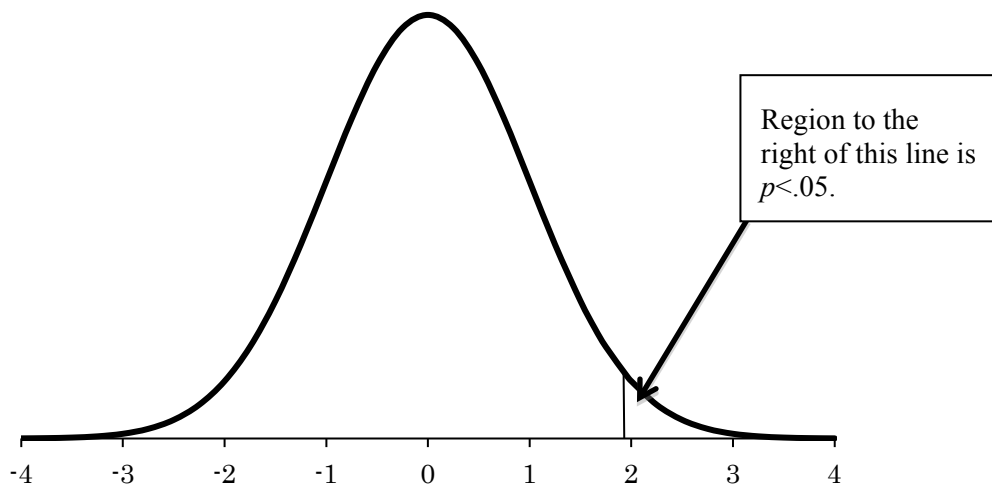
## Introduction

In this article, I provide an overview of Bayesian statistics and contrast it with null hypothesis significance testing (NHST). I also describe criticisms often expressed about NHST (e.g. in Cohen, 1994) and reasons that Bayesian statistics might be a suitable alternative for analyses in second language (L2) learning research. I will also outline concepts important to Bayesian approaches, such as prior probability distributions and Bayes factors.

Perhaps the best way to introduce Bayesian statistics is by way of an example. Research has demonstrated that the motivational variable *interest* has a powerful effect on processes important to reading comprehension (see Hidi & Renninger, 2006, for a review). A researcher wants to learn whether interest influences comprehension in L2 reading in a comparable way as occurs in first language (L1) contexts, so she has a group of 25 students read an interesting and a boring story and take comprehension tests. She checks for differences between the test scores by using a *t* test.

Researchers use *t* tests to compare two groups of data produced under different conditions to determine the probability that no difference exists between them beyond random variation. The hypothesis that no difference exists is called the null hypothesis ( $H_0$ ). Data from a *t* test consists of an independent variable (IV) that is manipulated and a dependent variable (DV) that might be affected by the IV.

The probability (the *p* value) that a *t* statistic of the size produced by the test would occur given that  $H_0$  is correct is calculated. A *p* value of less than .05 would mean that if we were to repeat this test 100 times, a statistic of this size or higher would result by random chance fewer than five times (see Figure 1). In this case the results are considered “significant” and the researcher rejects the null hypothesis.



**Figure 1.** Idealized distribution of scores with threshold  $p=.05$  marked. If the  $t$  statistic falls to the right of this line, the mean difference between  $H_0$  and  $H_1$  is considered statistically significant.

Note that space constraints do not permit detailed discussion in this article of one- and two-tailed tests,  $t$  distributions, degrees of freedom, confidence intervals, effect sizes, or statistical power, but these are also important aspects of NHST. Readers unfamiliar with these concepts are encouraged to read explanations that can be found in many introductory statistics textbooks (e.g. Field, 2009).

Our researcher performs a  $t$  test on the data (in reality, the data was produced using a random number generator for normal distributions at Wessa, 2008). Table 1 shows the descriptive statistics and the results are provided in Table 2.

**Table 1.** Descriptive Statistics for Boring and Interesting Text Conditions ( $n = 25$ )

Text Group	N	M	SD	SE
Boring	25	10.24	2.13	.43
Interesting	25	10.92	3.76	.75

**Table 2.**  $T$  Test Results for Boring and Interesting Text Conditions

Df	SED	MD	T	p (one-tailed)
24	.489	.68	1.69	.098

*Note:*  $p<.05$ .

As can be seen, the results are insignificant at  $p<.05$ , because .098 is larger than .05. The researcher therefore is inclined not to reject the null hypothesis. A colleague of our researcher, on a lark, does the same experiment with a very similar group of students and adds the scores to the original data. The  $t$  test is performed again, now with an  $n$  size of 50. The new descriptive statistics and  $t$  test results are provided in Tables 3 and 4.

**Table 3. Descriptive Statistics for Boring and Interesting Text Conditions ( $n = 50$ )**

Text Group	N	M	SD	SE
Boring	50	10.24	2.10	.30
Interesting	50	10.92	3.72	.53

**Table 4. T Test Results for Boring and Interesting Text Conditions ( $n = 50$ )**

Df	SED	MD	T	p (one-tailed)
49	.342	.68	1.99	.026*

Note. \* $p < .05$ .

As we can see, the descriptives have changed little, but the results of the  $t$  test are now significant. By convention, these results are now considered publishable, despite the fact that for all practical purposes they are identical to those of the previous experiment. This poses a serious dilemma for our researchers. Should they reject or not reject the null hypothesis? In order to get published, should they favor the second results and pretend those of the original study did not occur? The source of the dilemma lies in the fact that finding significance is reliant on statistical power, which is related to sample size. Such is the relationship between  $N$  size and significance that in the case of a large enough number of cases, finding significance is all but certain, irrespective of an actual experimental effect. This is one of several problems described by critics of NHST.

### Criticism of null hypothesis significance testing

Criticism of NHST can be divided into two categories: 1) weaknesses of NHST as an evaluative tool, and 2) misinterpretations of what NHST results mean.

#### Weaknesses

Problematic qualities of NHST cited by critics include:

- The primacy of significance. Editors of L2 learning academic journals tend to view significance as the mark of success, but using the  $p$  value as a Litmus test for “success” is problematic. As noted, variations of sample size can change the likelihood of finding significance, a characteristic that leads some statisticians to argue that NHST  $p$  values do not qualify as measures of statistical evidence, much less success, because identical  $p$  values do not convey identical levels of evidence when sample sizes differ (Wagenmakers, 2007).
- The primacy of significance thresholds. R.A. Fisher, whose work underpinned the development of the  $p$  value, did not himself regard  $p$  values as rigid cut-off points (Salsburg, 2001). In fact, Fisher’s selection of these benchmarks was at least somewhat arbitrary; he identified  $p$  value thresholds in his book *Statistical Methods for Research Workers* (1925) by providing critical values tables, which were limited to .05, .02, and .01, to “save space” (Field, 2009, p. 51). As Abelson (1997) commented, “Literal insistence on the .05 level is as silly as would be other arbitrarily rigid quality standards for research results, like 30% generality, or more interestingness than three quarters of the existing literature” (p. 14).
- Power issues. Statistical power refers to the probability that a test can detect an effect. Adjustments made in analyses to reduce the chances of incorrectly rejecting  $H_0$  (Type I

errors) or incorrectly failing to reject  $H_0$  (Type II errors), inevitable in a range of NHST-based tests, involve a loss of statistical power.

### **Misconceptions**

Misconceptions persist regarding what NHST in fact measures and what its results mean. Some are outlined below.

- The meaning of significance. It is tempting to conclude that statistical significance indicates that the null hypothesis is false and the alternate hypothesis is true, but this is not correct. The finding of significance really means nothing more than the researcher is inclined to reject the null hypothesis based on a low probability (defined by a somewhat arbitrarily chosen threshold) that the data at hand would occur randomly in many recursions of it. Significance does not mean the null hypothesis is formally invalid. Rejecting  $H_0$  does not prove  $H_1$ , but instead merely offers an indirect and rather flimsy indicator of support for it.
- The meaning of lack of significance. Because NHST purports to test the hypothesis that the null hypothesis is true, one might well be inclined to infer that an “insignificant” finding means just that: the null hypothesis is true. In fact, situations where mean differences are literally zero virtually never occur in the real world.
- Substitution of a conditional probability for its inverse. The notion that the probability of certain data given that  $H_0$  is true, that is,  $P(D|H_0)$ , is equivalent to the probability that  $H_0$  is true given certain data, or  $P(H_0|D)$ , is intuitively appealing, but the difference between these two becomes clear when contemplating the probability of having a runny nose given the condition of having the flu versus having the flu given the condition of having a runny nose; one can have a runny nose for many reasons besides the flu.
- The idea that “significance” means “importance”. Significance does not refer to the magnitude of an experimental effect. Reporting effect sizes in published studies would help clarify this misunderstanding, but few L2 researchers do so.

While the issues outlined above might create obstacles to rigorous hypothesis construction and testing, critics of NHST assert that a solution to many of these problems lies in Bayesian statistics.

### **Bayesian statistics**

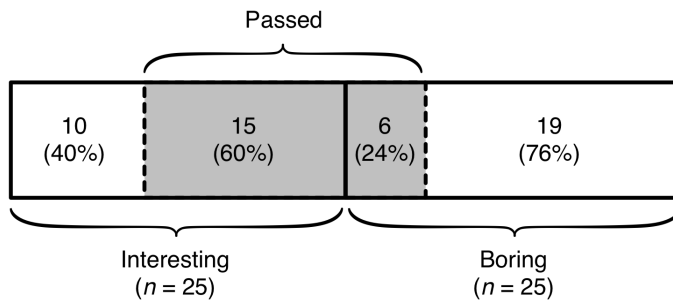
Bayesian statistical approaches are drawn from the work of 18th century mathematician Thomas Bayes. Bayesian and classical statistical approaches differ crucially in two areas. The first relates to how analyses are interpreted. Frequentist approaches like NHST produce  $p$  values that estimate the likelihood that the data would occur given that the null hypothesis is true. Rather than stating a “cut point” after which one hypothesis is chosen over another, Bayesian analyses result in probability values that are used to compare the relative support for one hypothesis over another. In short, frequentists seek significance and Bayesians seek probability support for a hypothesis. The second area where the two kinds of approaches differ is the formal use of prior information. Frequentists ignore what was previously known about the experimental condition when conducting a new experiment, but incorporating this prior information into future analyses is an essential part of Bayesian approaches. Prior information is incorporated by using the feature which most distinguishes Bayesian statistics, the *prior probability*.

Thomas Bayes's solution to a problem of "inverse probability" (e.g., estimating the unknown likelihood of an event happening given the known likelihood of a certain condition) contained a description of the formula which has come to be known as Bayes' theorem. As noted, a distinctive feature of the formula is the prior probability (the *prior*). In a basic application of Bayes' formula, the multiplied product of the prior and the probability of data given a certain parameter is divided by the probability of the parameter defining the sample space to produce a *posterior probability* (the *posterior*):

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

where A is the parameter under investigation and B is the data.

Let us make our introduction to Bayes less abstract with a simple example (adapted from Bonilla, 2011; for another non-technical example of Bayes' formula, see Yudkowsky, 2003). The data used in the first *t* test could be categorized as individuals who passed and failed the comprehension test. If we consider test scores of 12 (60%) or higher as "pass" and those below as "fail," then 6 of 25 students (24%) passed the test in the boring text condition, and 15 of 25 students (60%) passed in the interesting text condition. To understand how Bayes' formula works, it is useful to concentrate on how the *Interest* condition relates to the *Pass* scores (see Figure 2).



**Figure 2.** Interesting and boring text conditions divided into passed (shaded areas) and failed (unshaded areas) results on comprehension tests.

The rectangle on the left indicates the Interesting condition, the rectangle on the right the boring condition. The shaded areas indicate the proportions of students in each condition that passed the test. The shaded rectangle to the left of the center dividing line represents the intersect of students who found the text interesting *and* passed the test; it is denoted as  $Int \cap Pass$ , which can be read as "*Int* and *Pass* happen together". Likewise, the shaded portion of the "Boring" condition indicates the intersect of students who found the text boring with those who passed the test ( $Bor \cap Pass$ ).

What is the probability that a student passed the test if he read the interesting text? In conditional probability notation, this is signified by  $P(Pass | Int)$ , which is read, "the probability of the event of a student's passing given the event that the student read the interesting text". We can think of this as the answer to the question, "how much of the *Interesting* rectangle is accounted for by the shaded *Passed* area?" The answer is already given as 60%.

This is not what the researcher really wants to know, however. The researcher is interested not in the probability of passing given that the text is interesting, but in the probability of the text being interesting given that the student passed. This is represented by  $P(Int | Pass)$ , which means, "the

probability the text was interesting given that the test was passed”. We can easily calculate this information from Bayes’ formula as follows:

$$P(Int|Pass) = \frac{P(Pass|Int)P(Int)}{P(Pass)}$$

The values in the numerator are already known—the probability a student passed given that he thought the text was interesting is 0.60:

$$P(Pass|Int) = .60$$

and the probability that the student found the text interesting is 0.50, as half the scores came from the interesting condition:

$$P(Int) = .50$$

The shaded *Pass* area has two parts: (A) the section contributed by the *Int* condition, and (B) the section contributed by the non-*Int* (boring) condition. To calculate  $P(Pass)$ , these two parts are added.

In calculating (A), we are asking, “how much of the *Pass* area is made up of passing scores in the context of the *Interest* rectangle? The probability of a passing score within the *Interest* rectangle,  $P(Pass | Int)$ , is .60. To find out how much of this probability contributes to the *Pass* area, we simply multiply it by  $P(Int)$ , which is the probability of the student finding the text interesting, or 50%:

$$.60 \times .50 = .30.$$

Likewise, in calculating (B), we are asking “how much of the *Pass* area is comprised of passing scores in the context of the *Boring* condition?” Mathematically, this is  $P(Pass | B) \times P(B)$ . We know that 24% of the students who read the boring text passed the test and that 50% of the scores came from this condition. Therefore, (B) is calculated:

$$.24 \times .50 = .12.$$

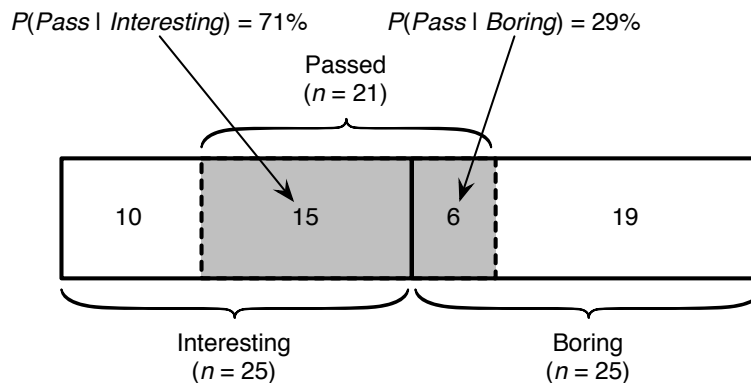
The denominator in Bayes formula,  $P(Pass)$ , then, is:

$$.30 + .12 = .42.$$

Plugging our values into Bayes’ formula, we obtain:

$$P(Int|Pass) = \frac{.30}{.42} = .71$$

Therefore, if we randomly draw a student with a passing test score from this group, there is a 71% chance that he read the interesting text. If we were to calculate  $P(B | Pass)$  using Bayes formula, we would obtain the remaining percentage of this region, that is, 29%. Of course, since probability of a given space must add up to 1, we could also simply subtract .71 from 1 to derive .29. We can now add these probabilities to the previous diagram:



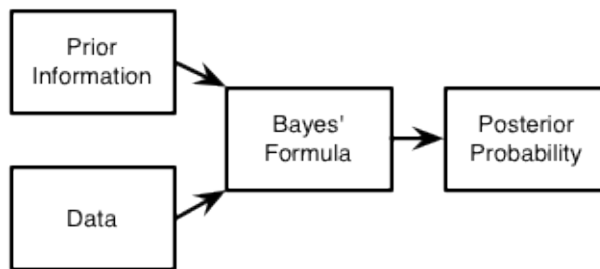
**Figure 3. Bayes formula provides probabilities of passing conditions.**

Although in this simple example the difference between pass and fail percentages is stark; however, it should be noted that the results are not always so obvious. If far more students found the texts boring than interesting, it is possible that a student that passed will *still* have a higher likelihood of having thought his book was boring, even if a much higher proportion of students who thought the texts were interesting passed. Bayes' rule adjusts for differences in sample sizes between conditions when calculating these probabilities.

### *Prior probabilities*

The simple example above might be useful for illustrating the basic dimensions of Bayes theorem, but it elides over some important points, chiefly to do with the assignment of the prior probability. Unlike classical statistics, Bayesian approaches enable researchers to include relevant prior information in formal experimentation. If previous research indicates one outcome is more likely than another, a Bayesian can integrate this information into his hypothesis formation and testing (Figure 3). The revised probability resulting from the new experiment can then influence the selection of priors used in subsequent investigations to further refine probability estimations in support of one hypothesis or other. The prior probability is a summary of a researcher's belief about the outcome of a given experiment.

In the example above, for simplicity, the prior,  $P(I)$ , was given as a known value and as a simple mean, but in a normal Bayesian analysis, the prior would be designated based on personal belief of the researcher. This personal belief could be drawn from previous research, or even just the researcher's conjecture. Since Bayesians, unlike frequentists, regard unknown values under investigation as random variables (that is, variables that manifest as values with certain probabilities), the conjectured outcomes for these values, expressed by the prior, take the form of probability distributions, indicated concretely by parameters like mean, standard deviation, and range. If prior information is lacking, the researcher can use a prior that expresses a high degree of uncertainty. High uncertainty can be related by designating a prior with a large standard deviation and by maximizing the range (Klugkist & Mulder, 2008). When probability distributions are used in Bayesian procedures, the calculations become much more complicated than those of our example. They are accomplished using calculus and sophisticated algorithms (such as Markov Chain Monte Carlo) that require a computer to generate. The good news is that software for using these procedures is available.



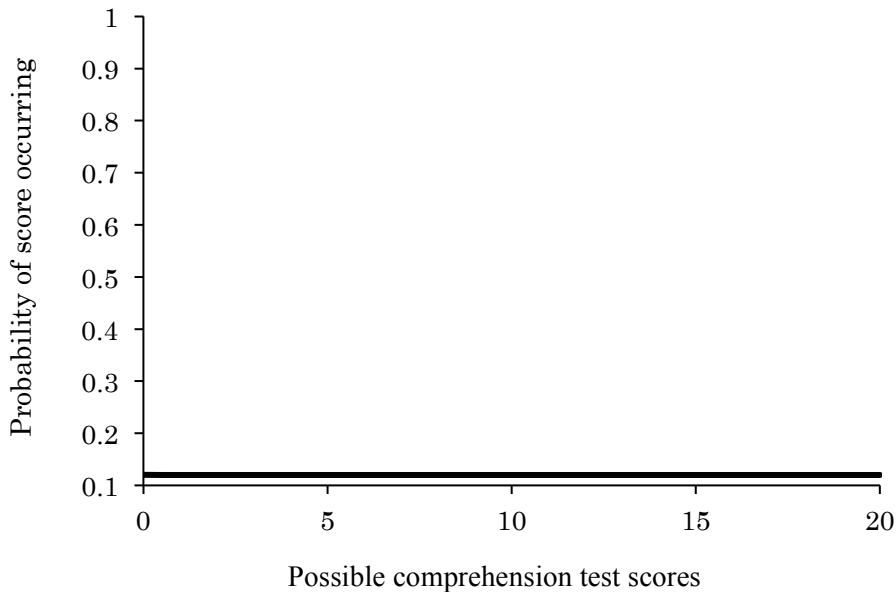
**Figure 4. Bayesian approaches combine prior information, in the form of a prior probability, to produce an updated view of phenomena, in the form of a posterior probability (adapted from Stevens, 2009).**

### Why use a prior?

To understand why Bayesians incorporate prior information into statistical inference, it is helpful to understand the quite different perceptions frequentists and Bayesians have of probability and the different goals the two kinds of researchers have in hypothesis testing. For frequentists, probability is the likelihood that a certain unknown (and ultimately unknowable) value lies within a distribution of values drawn from many samplings of a population, with the goal of analyses being to estimate whether sampled data would occur less than five percent of the time ( $p < 0.05$ ) given the null hypothesis is true. For Bayesians, probability is conceived as a degree of personal belief which can be refined by confrontation with real-world evidence. In Bayesian statistics, the goal is to modify a given state of knowledge about a phenomenon by connecting it to data; to do so without concretely representing the state of knowledge would be impossible. This existing state of knowledge is represented using the prior. Moreover, because the prior summarizes researcher belief about experimental outcomes, it can also be considered an expression of a hypothesis, a prediction subject to modification given new information collected during the new experiment.

To make this clearer, let's look at another example. Our first researcher, devastated by her  $t$  test debacle, throws away her data. A second researcher, a Bayesian, discovers her data while rooting through the trash bin. He decides to analyze it using a Bayesian approach.

Our Bayesian researcher considers some choices for a prior. In the absence of much prior information or a defined hypothesis, he might choose a prior that indicates only that a range exists in scores, from 0 to 20, with each score having equal probability of occurring. The X-axis of the uniform prior (Figure 4) shows the range of comprehension test scores from zero to 20, and the Y-axis shows the probability of those scores according to the prior. This kind of uniform, approximately objective, prior conveys much uncertainty and provides little information, so the data will dominate the calculation of the posterior probability.

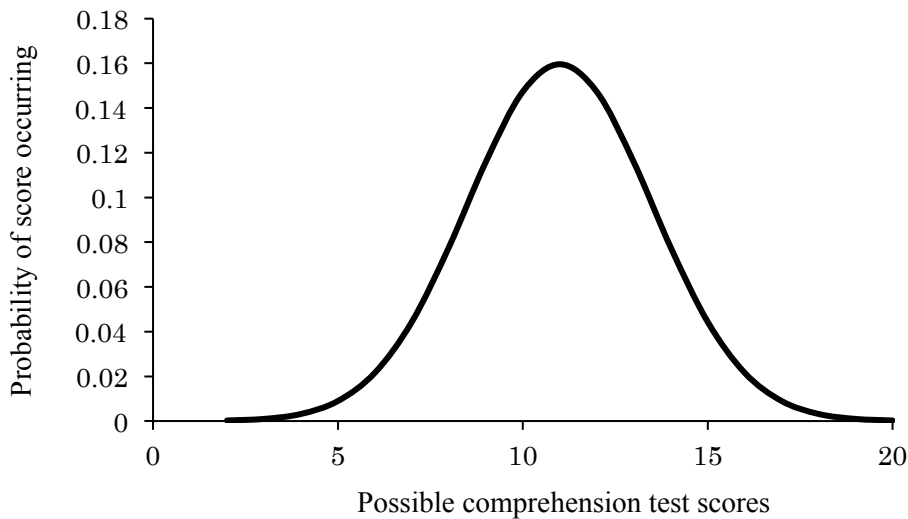


**Figure 4. Uniform prior where each score on the comprehension test has an equal probability of occurring. While this prior would be approximately objective, it would also likely be an unrealistic representation of the data.**

Our researcher might view a uniform prior as unrealistic, since data are unlikely to be flatly distributed. Also, while the results of the scavenged  $t$  tests were contradictory in terms of significance, they do suggest a modest degree of variance attributable to the interesting text condition. Our researcher gleans further in a literature review that related (fictional) studies indicate that interest contributes about 5% to increases in text comprehension. He could assign a prior with a mean score 5% higher than would occur by chance (i.e. one point higher than a mean of 10) with a standard deviation of 5. The standard deviation for a normal distribution can be estimated by dividing the highest extreme of the range of scores, in this case 20, by four. Figure 5 shows the distribution of this subjective prior.

The X-axis shows the range of comprehension scores, and the Y-axis shows the probability of the scores occurring. For example, a score of 11 (the mean) would have a probability of approximately .16 or 16% of occurring whereas a score of 5 would have about .01 or 1% chance of occurring. Using this subjective prior would involve the meeting of the hypothesized outcome represented by the prior (interest influences comprehension positively by a predicted amount, with a predicted degree of dispersion) with the data. The probabilities predicted by this prior would be somewhat higher than those predicted to occur by chance, so while this prior is subjective, it is also quite conservative.

Our Bayesian decides to use the more informative prior to test his hypothesis. To aid in the calculations, and to compare the relative support of his hypothesis with that of the null, he uses a *Bayes factor*.



**Figure 5.** Prior with a normal distribution and a mean of 11. This somewhat subjective prior would reflect a hypothesized distribution based on previous research.

### *Bayes factors*

In a Bayesian version of a  $t$  test, the probability of  $H_0$  and its alternative are compared to produce a statistic called a Bayes factor (BF). Put simply, the BF is a ratio that compares the likelihood of one model over another, thereby showing the relative support for the researcher's hypothesis versus another hypothesis (which may or may not be the null).

Interpretation of the BF is straightforward. For example, a BF of 4 for  $H_1$  versus  $H_0$  indicates support for  $H_1$  is 4 times that of  $H_0$ . A BF of .5 provides two times the support for  $H_0$  than for  $H_1$  (Klugkist, 2008). Bayes factors between .3 and 3 do not provide much evidence to differentiate the two hypotheses (Jeffreys, 1939, 1998).

In order to run the necessary calculations, the researcher uses an online Bayes factor calculator, provided at the following link (Dienes, 2008):

[http://www.lifesci.sussex.ac.uk/home/Zoltan\\_Dienes/inference/bayes\\_factor.swf](http://www.lifesci.sussex.ac.uk/home/Zoltan_Dienes/inference/bayes_factor.swf)

The calculator provides a limited range of priors templates for calculating a simple BF for a Bayesian " $t$  test" that shows the relative support for the null hypothesis, as manifested by a population value with a mean of 0, and a hypothesis, as expressed by the mean differences and distributions assigned by the researcher (For supporting explanation, see Dienes, 2011).

Some simple modifications to our researcher's data are required to use the calculator. Our researcher chooses a normal distribution option and enters a mean difference of 5% with a range of 1% to 10% and a standard deviation of 2.5. With the  $t$  test data ( $n = 50$ ), the BF produced is .45. This indicates slightly more support for the null versus the interest hypothesis. This contrasts with the finding of statistical significance in the second  $t$  test, and that our researcher's interpretation of the BF involves neither rejecting nor failing to reject the null, but instead making inferences based on the comparative likelihoods of  $H_0$  and  $H_1$ .

Given this result, the researcher would be inclined to align his confidence somewhat away from the findings of other research in L1-based contexts. He might give careful consideration to the special characteristics of L2 readers and design future studies to explore in a more nuanced way potential effects of interest on reading comprehension. In the service of using accumulated experiences to update and refine knowledge, the results of a Bayesian analysis are used to contribute to new hypotheses and to shape the priors assigned in future studies. Note that this kind of statistical reasoning is essentially different from that of many researchers interpreting the results of a NHST. In the case of the example  $t$  tests, our first researcher either rejects the null hypothesis (with the higher  $n$  size) or does not reject the null hypothesis (with the lower  $n$  size), and then draws only peripherally related conclusions.

### **Bayesian benefits**

Several qualities of Bayesian statistics might render them useful in L2 learning research, including:

- Flexibility. Bayesian approaches permit direct comparisons between multiple hypotheses by incorporating inequality constraints; null hypothesis-based comparisons of multiple hypotheses require secondary procedures, such as post hoc tests, which can result in reduced statistical power and can yield mutually inconsistent results.
- Protection against fallacious “significance”. Power and  $N$  sizes are not irrelevant to Bayesian approaches, but, unlike NHST, high numbers of cases do not inevitably result in something akin to “significance.” Instead, in a Bayesian  $t$  test where the null is approximately correct, higher  $N$  sizes drive the BF toward zero (Dienes, 2011).
- Validity: Bayesian methods directly address questions researchers are trying to answer. Unlike frequentists, who test “‘nothing is going on’ versus ‘something is going on but I don’t know what’” (Boelen & Hoijtink, 2008, p. 10), Bayesians ask, “what is the chance my hypothesis is true given the evidence?”
- Possible: A variety of Bayesian software packages are available, some reasonably user-friendly. For example, the Bayesian Inequality and Equality Model Selection (BIEMS) program (Mulder, Hoijtink, & de Leeuw, 2012; Mulder, Hoijtink, & Klugkist, 2010; Mulder, Klugkist, van de Schoot, Meeus, Selfhout, & Hoijtink, 2009) is available for free and has a Windows user interface. For a thoroughgoing description of available software packages for Bayesian approaches, see Hoijtink, (2012).
- Objective: Perhaps the most pervasive criticism of Bayesian approaches relates to the prior, which entails, it is believed, a subjective and therefore biased decision by the researcher. However, vague or uninformative priors can be assigned which are approximately objective.

### **Conclusion**

Researchers in L2 learning use NHST almost exclusively. However, many researchers are unfamiliar with the limitations of NHST and unaware that alternative procedures, such as those related to Bayes’ theorem, exist. Despite the growing wealth of explanatory materials and availability of software by which even non-statisticians can avail themselves to Bayesian statistical methods, to date, no researcher to my knowledge has attempted to use these potentially advantageous procedures in research focused on L2 learning.

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