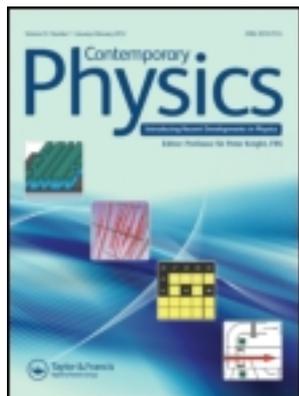


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Bayes and Frequentism: a particle physicist's perspective

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Bayes and Frequentism: a particle physicist's perspective

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In almost every scientific field, an experiment involves collecting data and then analysing it. The analysis stage will often consist in trying to extract some physical parameter and estimating its uncertainty; this is known as Parameter Determination. An example would be the determination of the mass of the top quark, from data collected from high energy proton–proton collisions. A different aim is to choose between two possible hypotheses. For example, are data on the recession speed s of distant galaxies proportional to their distance d , or do they fit better to a model where the expansion of the Universe is accelerating? There are two fundamental approaches to such statistical analyses – Bayesian and Frequentist. This article discusses the way they differ in their approach to probability, and then goes on to consider how this affects the way they deal with Parameter Determination and Hypothesis Testing. The examples are taken from everyday life and from Particle Physics.

Keywords: Bayes; frequentism; meaning of probability; parameter determination; hypothesis testing

1. Introduction

There are two fundamental approaches to statistical analysis, Bayesianism and Frequentism. The Bayesian approach dates back to Reverend Thomas Bayes (Figure 1), whose paper was published posthumously in 1763. The Polish statistician Jerzy Neyman (Figure 1) played a crucial role in the development of frequentist statistics. In the past there have been vigorous discussions about the relative merits of these two methods.

In this article, the fundamental differences between these two approaches will be explained, and illustrated with examples from Physics and from everyday life. We consider them in situations where we are trying to measure a parameter (e.g. the mass of the top quark), or are testing hypotheses (e.g. do we have evidence for the existence of the Higgs boson?).

1.1. Why the fuss?

Given that there are these fundamentally different ways of analysing data, how is it possible that many scientists spend a lifetime measuring all sorts of physical parameters, without being aware of the sharp differences of philosophy between the Bayesian and Frequentist approaches? The answer is that in the simplest of problems the two methods (and others too, like χ^2 or maximum likelihood) can give the identical answer, that the probability that a parameter μ lies in the range μ_l to μ_u is, say, 68%.

By the ‘simplest of problems’, we mean that the measured value m is Gaussian distributed about the true value μ with known variance σ^2 , and that μ can in principle have any value from minus infinity to plus infinity.

However, in many practical problems in Particle Physics, these conditions are not satisfied. The parameter may be restricted in range (masses cannot be negative), and the data distribution may not be Gaussian (counting experiments often follow the Poisson distribution). So there is ample opportunity for the results of Bayesian and Frequentist analyses to differ. The two types of statisticians have often had strong criticisms of each other's approach.

1.2. Probability

The differences between the Bayesians and frequentists start with their interpretation of ‘probability’. Underpinning both of these is the mathematical approach, which is largely due to Russian mathematicians such as Kolmogorov. It is based on axioms (e.g. probability is a number in the range 0 to 1; the sum of the probabilities for something to occur and for it not to occur is 1; etc.). This is very important for manipulating probabilities, but provides little physical intuition about the concept.

For frequentists, the probability p of ‘something’ is defined in terms of a large number N of essentially identical, independent trials: if the specified ‘something’ happens in s of these trials, p is defined as the limit of the

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Figure 1. The Reverend Bayes (left), whose paper on his theorem was published posthumously in 1763; and Jerzy Neyman, a Polish statistician who played a crucial role in the development of the frequentist approach.

ratio s/N , as N tends to infinity. Thus the probability of the sum of the numbers on two rolled dice adding up to 10 can be determined in this way to be $1/12$.

Bayesians attack this definition, as it requires a large number of ‘essentially identical’ trials. They claim that to determine whether the trials are indeed ‘essentially identical’ requires the concept of probability, and hence the definition is circular.

Given that a repeated series of trials is required, frequentists are unable to assign probabilities to single events. Thus, with regard to whether it was raining in Manchester yesterday, there is no way of creating a large number of ‘yesterdays’ in order to determine the probability. Frequentists would say that, even though they might not know, in actual fact it either was raining or it wasn’t, and so this is not a matter for assigning a probability. And the same remains true even if we replace ‘Manchester’ by ‘the Sahara Desert’.

Another example would be the unwillingness of a frequentist to assign a probability to the statement that ‘the first astronaut to set foot on Mars will return to Earth alive’. This does not mean it is an uninteresting question, especially if you have been chosen to be on the first manned-mission to Mars, but then, don’t ask a frequentist to assess the probability.

A different type of example involves physical constants. Frequentists will also not assign probabilities to statements involving the numerical values of physical parameters, e.g. does dark matter constitute more than 25% of the the critical density for our Universe? This again is a situation which cannot be checked by replicated tests. And again, it is either true or false, and not suitable for frequentist probabilities. A similar argument applies to statements about theories: a frequentist will not allow probability assignments as to whether the Higgs boson exists.

Bayesians have a very different approach. For them, probability is a personal assessment of how likely they

think something is to be true. It depends on their own judgement and/or previous knowledge about the situation, and can hence vary from person to person. Thus if I toss a coin, and ask you what is the probability of the result being heads, you are likely to say 50%. But maybe I cheated and looked at the coin, and saw that it was tails, so for me the probability of heads is 0%. Or maybe I just gave it a quick glance, and think (but I am not certain) that it was tails, so I assign a probability of 20% to heads.

Because Bayesians have this personal view of probability, they would be prepared to give numerical estimates for ‘one-off’ situations (e.g. who gets this year’s Nobel Prize?), for parameter values (e.g. fraction of dark matter), or concerning theories (e.g. existence of Higgs boson). Again, these numerical assessments could vary from person to person.

Personal Probabilities

This is a story that I originally heard from the Nobel Prize winner Frank Wilczek in a slightly different context, but it illustrates the way that for Bayesians the assessment of probability can differ from person to person.

A shy postdoc is attending a workshop on the topic of ‘Extra Dimensions’. Each evening, after an intensive day’s work, he goes to the local bar, sits next to an empty chair and orders two glasses of wine, one for himself and the other for the empty chair. By the third evening, the barman’s curiosity cannot be controlled and he asks the postdoc why he always orders the extra glass of wine. ‘I work on the theory of extra dimensions’, explains the postdoc, ‘and it is possible that there are beautiful girls out there in 12 dimensions, and perhaps by quantum mechanical tunnelling they might appear in our three-dimensional world, and perhaps one of them might materialise on this empty chair, and I would be the first person talking to her, and then she might go out with me’. ‘Yes’, says the barman, ‘but there are three very attractive real girls sitting over there on the other side of this bar. Why don’t you go and ask them if they would go out with you?’ ‘There’s no point’, replies the postdoc, ‘that would be very unlikely’.

It sounds as if this is very personal and not conducive to numerical estimates. But Bayesians’ assessment of probability should be consistent with the ‘fair bet’ concept. If a Bayesian believes that a certain statement has a 10% probability of being true, they should be prepared to offer odds of 9 to 1 (or 1 to 9) to

someone who is prepared to bet with them on this being true (or false, respectively). With a poor assessment of the probability, they would be in danger of losing money.

2. Likelihoods, Bayes theorem and priors

We now have a relevant digression into considering likelihood functions, and then introduce Bayes Theorem and Priors, essential ingredients of the Bayesian approach.

2.1. Likelihoods

The likelihood approach is a very powerful one for parameter determination, and is also very much involved in Bayesian and Frequentist methods for this. Likelihood ratios are also used for checking which of two theories provides a better description of the data.

The likelihood function is best illustrated by a simple example. Imagine we are performing a counting experiment for some fairly rare process. For example, we may be interested in the flux μ of cosmic ray showers with energies above 10^{20} electron volts. We have a large detector of known area, and find n_0 high energy showers (e.g. 2) when running the detector for one year. We want to make a statement about the value of the actual flux μ and its uncertainty.

Assuming these cosmic rays are falling on Earth at a constant rate, and are independent of each other, if the true rate is μ , the conditional probability $P(n|\mu)$ of obtaining n counts is given by the Poisson distribution as

$$P(n|\mu) = e^{-\mu} \mu^n / n!. \quad (1)$$

Then the likelihood is defined by replacing n in the above formula by the observed value n_0 , i.e.

$$L(\mu|n_0) = e^{-\mu} \mu^{n_0} / n_0! \quad (2)$$

This likelihood is regarded as a function of μ , for the fixed data value n_0 . (For example, if we observe two events, the likelihood is $\mu^2 e^{-\mu}/2$.) It is the probability of observing the data, for different choices of μ . Then the likelihood estimate of a parameter μ is that which maximises the likelihood, i.e. it is the value of μ which maximises the probability of observing the actual data n_0 . (In our case, not surprisingly the likelihood estimate of μ is simply n_0 .) Values of μ for which the likelihood is small are regarded as excluded, and the uncertainty on μ is related to the width of the likelihood distribution.

A Poisson puzzle?

According to the Poisson distribution, if the expected number of observations in a specified time is μ , the probabilities $P(1|\mu)$ and $P(2|\mu)$ are

$$P(1|\mu) = \mu e^{-\mu}, \quad P(2|\mu) = \mu^2 e^{-\mu} / 2.$$

For small μ , these are approximately μ and $\mu^2/2$, respectively. Given the fact that the probability for observing one rare event in the time interval is μ , why is the probability for observing two independent events equal to $\mu^2/2$, rather than simply μ^2 , as perhaps expected from Equation (4)?

It is really important not to confuse the Poisson probability $P(n|\mu)$ with the likelihood function $L(\mu|n_0)$, even though Equations (1) and (2) bear a remarkable similarity.¹ The distinction should be easy in this case: $P(n|\mu)$ is a function of the discrete variable n at fixed μ , while $L(\mu|n_0)$ is a function of the continuous variable μ at fixed n_0 (see Figure 2). Furthermore, $P(n|\mu)$ are real probabilities, while the likelihood $L(\mu|n_0)$ cannot be interpreted as a probability density (it does not transform as expected for a probability density if the parameter is chosen, for example, as $1/\mu$ rather than μ).

2.2. Bayes theorem

If we consider two ‘events’ A and B (in the statistical sense), we can write the probability $P(A \text{ and } B)$ of them both happening as

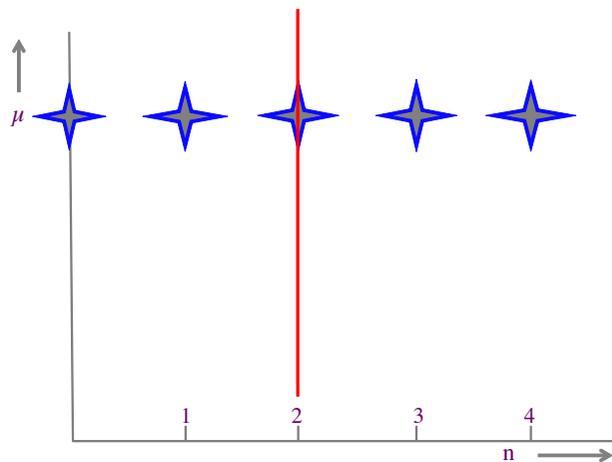


Figure 2. Illustration of the difference between the probability density distribution for the integer variable n and the likelihood function for the continuous parameter μ , for the Poisson distribution (see Equations (1) and (2)). They involve the same function of n and μ , but it is evaluated at fixed μ for the *pdf*, but at fixed n for the likelihood.

$$P(A \text{ and } B) = P(A|B) P(B), \quad (3)$$

where $P(A|B)$ is the conditional probability of A happening, given the fact that B has occurred. An example could be where we select a random day from last year, and A is whether it was snowy in Oslo, and B that it was a December day. Then Bayes Theorem says that the probability of choosing a snowy December day is equal to the probability of it being snowy in December, multiplied by $31/365$ (the probability of a random day being in December). If the probability of A occurring does not depend on whether B has done so, Equation (3) reduces to the better-known result that

$$P(A \text{ and } B) = P(A) P(B), \quad (4)$$

for independent A and B .

Conditional probability

Conditional Probability $P(A|B)$ is the probability of A , given the fact that B has happened. For example, the probability of obtaining a 4 on the throw of a dice is $1/6$; but if we accept only even results, the conditional probability for a 4, given that the number is even, is $1/3$.

Because $P(A \text{ and } B)$ is symmetric in A and B ,

$$P(A \text{ and } B) = P(A|B) P(B) = P(B|A) P(A). \quad (5)$$

Then Bayes Theorem is derived from the second equality above:

$$P(A|B) = P(B|A) P(A)/P(B), \quad (6)$$

i.e. it relates $P(A|B)$ to $P(B|A)$. (See Section 2.4 for examples where these are obviously not equal.)

It should be stressed that Bayes Theorem itself is not controversial, and frequentists are willing to make use of it, provided the various probabilities are genuine frequentist ones. The controversy begins when Bayesians replace A by a theoretical parameter (and B is the observed data). The theorem then states that

$$P(\text{param}|\text{data}) \propto P(\text{data}|\text{param}) \times P(\text{param}), \quad (7)$$

where $P(\text{data}|\text{param})$ is just the likelihood function; $P(\text{param})$ is the Bayesian prior density, and expresses what was known about the parameter before our measurement; and $P(\text{param}|\text{data})$ is the Bayesian posterior probability density for the parameter, and contains the information about the parameter obtained by combining the prior information with that from our measurement.

Bayesian Posteriors

Jim Berger says that he and his wife have professions that are similar, but with a small difference. He is a Bayesian Statistician and she is a fitness trainer. The similarity is that they both aim to optimise posteriors, but while he wants to maximise them, she aims to minimise posteriors.

The frequentist objection to this is that the prior and the posterior both refer to parameter values; while this is allowed for Bayesians, it is strictly forbidden in the frequentist approach. In addition to this, complications are caused by the need to choose a probability density for the prior.

2.3. Bayesian priors

In order to obtain the Bayesian posterior probability distribution from the likelihood function, the latter needs to be multiplied by the Bayesian prior. There are several flavours of Bayesians, who have different motivations for their choice of prior. In this article, we will concentrate on evidence-based priors. So if in our Poisson example of Section 2.1, there was a previous measurement of μ which gave the result 5 ± 1 , the prior might be chosen as a Gaussian in μ , centred on 5 with standard deviation 1 (and probably truncated at zero). Then the posterior, assuming two observed counts, would be

$$P(\mu|n_0 = 2) \propto (\mu^2 e^{-\mu}/2) \times (e^{-(\mu-5)^2/2}/(2\pi)^{1/2}), \quad (8)$$

where the first factor on the right is the likelihood $L(\mu|n_0 = 2)$, and the second is the prior $\pi(\mu)$.

This is all very well when previous data on μ exists. But what if our measurement is ground-breaking, and essentially nothing is previously known about μ ? How do we now choose the prior $\pi(\mu)$? The 'obvious' answer is to choose a prior that is independent of μ (but zero for unphysical negative μ), so as not to favour any particular value of μ . However, do we really believe, as implied by the constant prior, that μ is as likely to be in the range 10^{500} to $10^{500} + 0.5$, as in 0.1 to 0.6?

Another problem is that if we are trying to use a flat prior to express our ignorance about a parameter, it is not clear why we should choose one functional form for the parameter rather than another. For example, if we are aiming to provide a very precise measurement of the mass m of the tau neutrino, should we parametrise our ignorance of its mass by a flat prior in m , m^2 , $\ln(m)$, etc.? Basically priors may be not bad for parametrisation prior knowledge, but are not so good for prior ignorance.

2.4. $P(A|B) \neq P(B|A)$

Bayes Theorem relates the conditional probabilities $P(A|B)$ and $P(B|A)$. People often confuse these two probabilities, and may erroneously think they are the same. Thus journalists or even Laboratory Spokespersons may incorrectly say that there is a 99.9% probability that some particle exists, rather than the correct statement that under the null hypothesis that it does not, the data are very unlikely.

A convincing example of their difference is provided by a database containing just two pieces of information about everyone on Earth: their sex and whether or not they are pregnant. We extract a random person from the database, who turns out to be female. Given that the person is female, the chance of being pregnant is about 3%. We then extract another random person, who turns out to be pregnant. Given the fact that the person is pregnant, the probability that they are female is 100%. i.e.

$$P(\text{pregnant} | \text{female}) \ll P(\text{female} | \text{pregnant}). \quad (9)$$

Similarly, if you select a card randomly from a deck of 52, the probability of it being an ace, if it happens to be a spade, is 1/13; however, the probability of a spade, given that it is an ace, is 1/4.

2.5. A Bayesian example

Imagine that you, a Bayesian, are betting on the results of coin flips. Each time you bet ‘Heads’, and for the first five flips it comes down ‘Tails’. Given that the probability of being wrong five times is 3%, should you suspect it is not a fair coin?

We regard this as a parameter-estimation problem, and want to see whether the probability p_H of ‘Heads’ is consistent with 0.5. The data (no heads in five spins) enables us to calculate the likelihood function, but in order to extract the posterior probability as a function of p_H , we must multiply the likelihood by a prior $\pi(p_H)$. Now if the person betting against us is a complete stranger, we might assign a constant value for p_H in the range 0 to 1; then the posterior is such that $p_H = 0.5$ looks unlikely. On the other hand, if it is our local village priest, we are so convinced that he is honest, we use a delta function at $p_H = 0.5$, and then even if the coin continues to fall down ‘Tails’, we will still believe that it is fair. Thus our conclusion depends very much on which prior we choose.

Given the freedom to select one’s prior, it seems as if Bayesian intervals for a parameter can be very dependent on this choice. But in some cases, the ‘data overwhelms the prior’, and the result becomes very insensitive to the choice of prior. For example, the mass

of the intermediate vector boson (Z^0) was measured at the LEP (Large Electron Positron) Collider at CERN. The result was that the likelihood function was essentially a Gaussian at 91,188 MeV c^{-2} , with a width of 2 MeV c^{-2} . A Bayesian now has to multiply this by the prior probability density for the Z^0 mass. However, any reasonable choice of prior will vary very little over the range of a few parts in 10^5 , and so in this case the posterior is essentially independent of the prior.

3. Parameter determination: Bayesian approach

We illustrate the Bayesian approach using a simple example of the determination of the lifetime of some radioactive material. The probability density p for a decay at time t is given by

$$p(t|\tau) = (1/\tau)e^{-t/\tau}, \quad (10)$$

where τ is the lifetime we want to estimate. We can estimate τ from a set of observed decays at times t_i . To simplify the problem we assume we have only one decay at time t_1 (which will not give us a very accurate estimate of τ).

The likelihood is

$$L(\tau) = (1/\tau)e^{-t_1/\tau}, \quad (11)$$

and we have to multiply this by our choice of prior for τ , to obtain the posterior $p(\tau|t_1) \propto L(\tau) \pi(\tau)$. As usual, there is a choice for $\pi(\tau)$ of an evidence-based prior derived from a previous measurement (in which case our posterior and the resulting range for τ will be based not only on our measurement, but also on the previous one), ignorance, theoretical motivation, etc. Because in many cases the choice of prior is not unique, Bayesian analyses are supposed to present results for several plausible priors, so as to investigate the sensitivity of the result to the choice of prior.

Once the posterior is available, several options are available for determining a range of preferred τ values at some chosen probability level γ , i.e.

$$\int_{\tau_l}^{\tau_u} p(\tau|t_1) d\tau = \gamma. \quad (12)$$

Possibilities include:

- A central range from τ_l to τ_u could be obtained by having probabilities of $(1 - \gamma)/2$ below the range, and $(1 - \gamma)/2$ above it.
- The upper limit τ_{UL} is obtained by setting the limits of integration in Equation (12) from zero to τ_{UL} .

- In a similar manner, a lower limit τ_{LL} is obtained, using integration limits τ_{LL} and infinity.
- The shortest posterior range in τ containing probability γ is also popular, but does not correspond to the shortest range in the decay rate $1/\tau$, or for other reparametrisations of the variable of interest.

4. Parameter determination: Frequentist approach

We now consider the Frequentist approach for the same problem as in the previous section.

The Neyman construction is used to show on a plot of the parameter τ versus the data t the likely values of t for each τ (see Figure 3(a)). This is achieved by using $p(t|\tau)$ of Equation (10) for a given τ to select a region of t such that the integral of $p(t|\tau)$ over this range of t is, say, 68%.² By repeating this procedure for all τ , we obtain the ‘confidence band’. In our example, the edges of the band are defined by the straight lines $t = 0.17\tau$ and $t = 1.8\tau$. Finally we use the actual observed value t_1 to read off the range of τ values (τ_l to τ_u , which are $t_1/1.8$ and $t_1/0.17$, respectively) for which t_1 is a likely observation. For larger values of τ , t_1 is too small to be likely, and similarly for smaller τ , t_1 is too large.

In a more plausible scenario where the data consisted of a set of observed decay times t_i , the data statistic could be the mean of the t_i . Then the confidence band would be narrower than in the figure, and the range of acceptable τ values would be shorter.

An important feature of this construction is that it does not require a prior distribution for τ , thus avoiding the possible ambiguity that that would have introduced.

Another point to note is that the Frequentist approach does not claim that the range τ_l to τ_u is probable. Nor does it make any statement about different values within this range. It is merely that this is the range of τ values for which the observed data is likely (at the chosen confidence level).

Figure 3(b) shows a more interesting example. An experiment aims to measure the temperature T of the fusion reactor at the centre of the sun, by using a month’s running of a solar neutrino detector to estimate the neutrino flux ϕ from the sun. Assuming we know all about fusion processes and convection in the sun, the properties of neutrinos, the performance of our detectors, etc., we can construct at each T a region in ϕ such that there is a 68% probability the experimental result would lie in it. Then we use the actual measured flux ϕ_{obs} to determine the accepted range for T .

4.1. Coverage

For repetitions of an experiment using a particular statistical analysis to determine a range for the parameter of interest, where the data sets differ from each other just by statistical fluctuations, the coverage is the fraction of the parameter’s intervals that contain the true value of the parameter. This can be determined from Monte Carlo simulation, or in some simple cases analytically. Coverage is a property of the statistical technique that is used to construct the intervals, and does not apply to a single measurement.

Techniques for which the coverage is equal to the nominal value (e.g. 68%) for all values of the parameter are said to have exact coverage. If the coverage drops below the nominal value, the method is said to under-cover. Frequentists regard this as bad: if the actual cover-

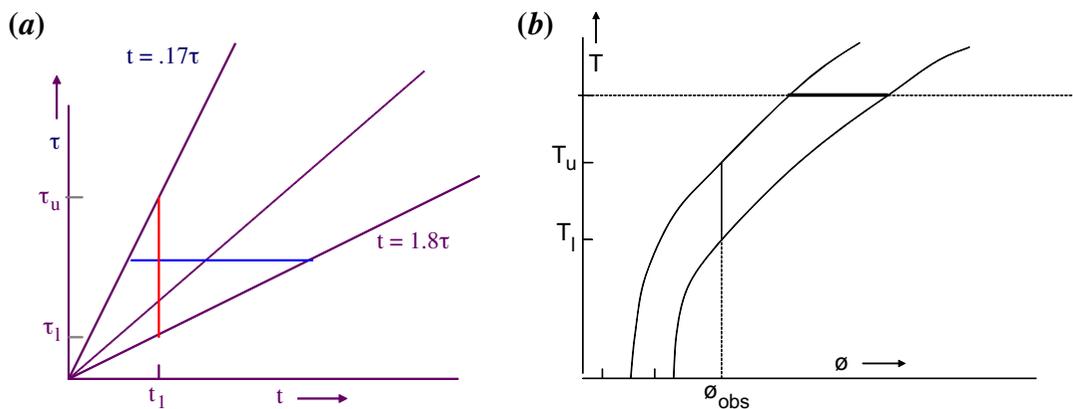


Figure 3. The Neyman construction. (a) For the exponential parameter τ , the central confidence band between the lines $t=0.17\tau$ and $t=1.8\tau$ gives the likely values (at the 68% level) of t for each τ . Then a vertical line at the observed t_1 intersects the edges of the confidence band at τ_l and τ_u , and these define the frequentist range for τ . (b) Here the theory parameter is the temperature T at the centre of the sun, and the data ϕ is the measured flux of solar neutrinos, both in arbitrary units. A measurement of the flux ϕ_{obs} determines a range of temperatures (T_l to T_u) at the sun’s centre.

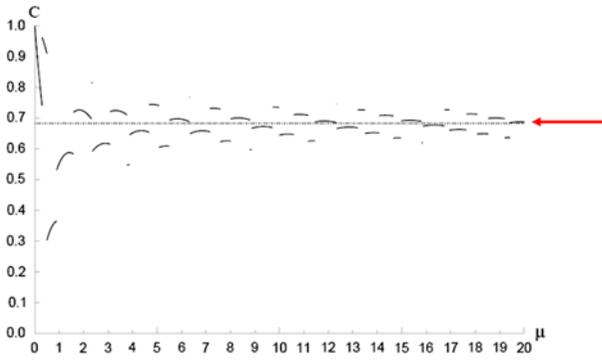


Figure 4. Coverage C for Poisson parameter intervals, as determined by the $\Delta(\ln(L))=0.5$ rule. Repeated trials (all using the same Poisson parameter μ) yield different values of the observation n , each resulting in a range μ_l to μ_u for μ ; then C is the fraction of trials that give ranges which include the value of μ chosen for the trials. The coverage C varies with μ , and has discontinuities because the data n can take on only discrete integer values. For large μ , C seems to approach the expected 0.68.

age for determining the parameter is only 30% rather than the nominal 68%, just quoting the range for the parameter as determined by that method is likely to mislead a reader into believing that your result is more accurate than it really is. Over-coverage does not have this problem, but it suggests that maybe the confidence intervals produced by that method are more conservative (i.e. wider) than they need be.

A particularly important property of the Neyman construction is that the confidence intervals for the parameter have the property of not undercovering. This property is not guaranteed for other techniques (e.g. Bayesian, χ^2 , maximum likelihood, method of moments).

Figure 4 shows the coverage C for the following situation. An experiment is performed to determine the rate μ of some Poisson counting experiment, and n counts are observed. The statistical procedure chosen for determining a 68% range for μ is the likelihood method with the $\Delta(\ln L) = 0.5$ rule to define the ends of the range. In envisaged repetitions of the experiment, n will vary according to a Poisson distribution with mean μ_0 . Then $C(\mu_0)$ is the fraction of the resulting ranges for μ which include μ_0 . The likelihood method does not have the frequentist guarantee of coverage, and indeed large under- and over-coverage occur, especially at low μ [1].

5. Parameter determination: common issues

Here we discuss some issues that are common to both Frequentist and Bayesian approaches.

5.1. Parameters with limited range

Very often a physical parameter has meaning only over a limited range. For example, the square of the mass of the neutrino (m_ν^2) produced in nuclear beta decay cannot be negative, the branching ratio for some particular decay mode of an elementary particle must be between zero and one, etc. Bayesians can incorporate this information by setting the prior for the parameter to zero in the non-physical region. This ensures that the best estimate of a parameter or an upper limit for it are guaranteed to be physical. In contrast, a frequentist upper limit could well turn out to be unphysical, or the range for m_ν^2 could be empty (i.e. there was no physical value of m_ν^2 for which the data was likely); in general Particle Physicists are unhappy with such a situation.

For many years, experiments estimating m_ν^2 had ‘likelihood functions’ that maximised at negative values. Upper limits for m_ν^2 were then usually derived by Bayesian methods.

5.2. Interpretation of $\mu_u \geq \mu \geq \mu_l$

Both Bayesian and Frequentist methods of parameter determination end up with a statement of the form $\mu_u \geq \mu \geq \mu_l$ at some probability level, but their interpretations are very different.

For frequentists, the parameter μ is unknown, but it does have a true value and, as discussed earlier, it is not suitable for probability statements. So the probability refers to the range μ_l to μ_u . If the experiment were to be repeated many times, a series of ranges for μ would be obtained, and the probability refers to what fraction of these ranges contain the true value; this is just the coverage mentioned earlier. Thus frequentists regard the ends of the range as random variables.

For Bayesians, μ_u and μ_l have been determined by the experimental analysis, and are considered fixed; Bayesians do not want to be involved in deciding what would have happened in hypothetical repetitions of the experiment. But they are prepared to treat the unknown physical constant as if it were a random variable, and for them the

Table 1. Interpretations of ‘ $\mu_u \geq \mu \geq \mu_l$ at 68% confidence level’.

	Bayes	Frequentist
What is fixed?	μ_u, μ_l	μ
What is variable?	μ	μ_u, μ_l
What does 68% prob apply to?	Single measurement: percentage of posterior in range	Set of measurements: percentage of ranges $\mu_l \rightarrow \mu_u$ that contain μ

probability refers to the fraction of the Bayesian posterior probability density for μ within the quoted range (see Table 1).

5.3. Dealing with systematics

Very often, in trying to estimate a parameter, some other quantity involved in the analysis is not known exactly, and this can affect the deduced range for the parameter of interest. For example, in the original Reines and Cowan experiment [2] to discover the electron neutrino, a detector sensitive to neutrinos interacting in it was built close to a powerful nuclear reactor. However, there were also background processes which mimic the interactions of the reactor neutrinos. Then the observed number of counts n is likely to be Poisson distributed with mean $b + s$:

$$P(n) = e^{-(b+s)} (b+s)^n / n!, \quad (13)$$

where b is the expected background, and s is the signal rate. If b is precisely known, s is the only unknown parameter, and can be determined essentially as described earlier. But if there is some uncertainty in the expected value of b , this results in a systematic uncertainty in the answer. Statisticians refer to b as a nuisance parameter.

Bayesians tend to treat all parameters (i.e. those of physical interest and nuisance parameters) in a similar manner. Thus, assuming that the background b has been estimated in a subsidiary counting experiment as m_0 while the result of the main measurement of $s + b$ was n_0 , they would start by writing the likelihood for s and b as

$$L(s, b | n_0, m_0) = (e^{-(s+b)} (s+b)^{n_0} / n_0!) \times (e^{-b} b^{m_0} / m_0!). \quad (14)$$

Next this is multiplied by the chosen prior $\pi(s, b)$ for s and b , to give the posterior probability $p(s, b)$ for the parameter of interest s and the nuisance parameter for the background b . Then this is integrated (or ‘marginalised’) over b to give the probability density just for the parameter of interest:

$$p(s) = \int p(s, b) db. \quad (15)$$

Finally the required parameter range is extracted from $p(s)$, e.g. a central 68% range.

In contrast, frequentists start from the probability density $p(n, m | s, b)$ for observing any n and m as

$$p(n, m | s, b) = (e^{-(s+b)} (s+b)^n / n!) \times (e^{-b} b^m / m!). \quad (16)$$

The fully frequentist method consists in performing a Neyman construction to produce a confidence belt for

likely data (n, m) as a function of the parameters (s, b) . In analogy with the simpler problems discussed earlier, the actual data (n_0, m_0) is then used to read off the region in parameter space (s, b) for which the data is likely. If a range just for s is desired, it could be taken as the extrema of the (s, b) region, although this will give rise to overcoverage.

There are also various approximate methods, which are simpler than the full Neyman construction and which tend to produce less overcoverage (but for which the frequentist guarantee of coverage no longer applies). An example is the profile likelihood approach, in which the probability $p(n, m | s, b)$ is replaced by $p_{\text{prof}}(n, m | s, b_{\text{best}}(s))$, where $b_{\text{best}}(s)$ is the value of b which maximises the probability for that value of s ; because $b_{\text{best}}(s)$ is a function of s , the profiled probability depends on the single parameter s , which simplifies the problem.

Profile likelihood

In many situations, the probability of observing a particular set of data d depends not only on a parameter of physical interest ϕ (e.g. the mass of the Higgs boson), but also on some other so-called nuisance parameters ν (e.g. a scale factor for correcting jet energies as measured in the detector). Then the likelihood $L(\phi, \nu | d)$ is a function of both sets of parameters ϕ and ν . In order to draw conclusions about ϕ , it is often helpful to consider the **profile** likelihood $L_{\text{prof}}(\phi, \nu_{\text{max}}(\phi) | d)$, where for each value of ϕ , the nuisance parameters are chosen to maximise the full likelihood $L(\phi, \nu | d)$, i.e. ν_{max} varies with ϕ . However, L_{prof} now is a function just of ϕ but not of the nuisance parameters ν , thereby simplifying the problem of making inferences about the parameter of interest ϕ , at the cost of losing some of the properties of the likelihood function.

Rather than maximising L with respect to ν , Bayesian methods tend to **marginalise**, i.e. integrate the likelihood with respect to ν , usually after using priors for ν to convert L into a posterior probability distribution for ϕ .

For the case where L is a multi-dimensional Gaussian distribution such as $L \propto \exp\{-(a\phi^2 + 2b\phi\nu + c\nu^2)\}$, marginalisation over ν or profiling with respect to it will give the same functional form for the modified likelihoods.

Reference [3] contains a longer discussion of systematics, while Demortier [4] deals with ways of incorporating systematics in both parameter determination and hypothesis testing.

6. Hypothesis testing

Possibly more interesting than Parameter Determination is Hypothesis Testing. Here the issue is to decide which of two (or more) competing theories provides a better fit to some data. For example, was data collected at the Large Hadron Collider at CERN in the first half of 2012 more consistent with what is known as the Standard Model (SM) of Particle Physics without anything new, or with the production of the Higgs boson in addition to the known SM processes? (See Figure 5.)

In Particle Physics, for reasons to be explained below, it is much more common to use a Frequentist method to decide. In other fields, Bayesian approaches tend to be favoured. We discuss Bayesian methods briefly in Section 7.

6.1. Frequentist approach

The first task is to choose some data statistic t which will help distinguish between the hypotheses. In the simple case of a counting experiment, where the data consists just of the number of accumulated counts n_0 for a given amount of running time, it could simply be n_0 . Then in most cases new physics would manifest itself in a larger number of counts when the expected rate is $s + b$, than if there were just background; here s and b are the expected signal and background rates, respectively.

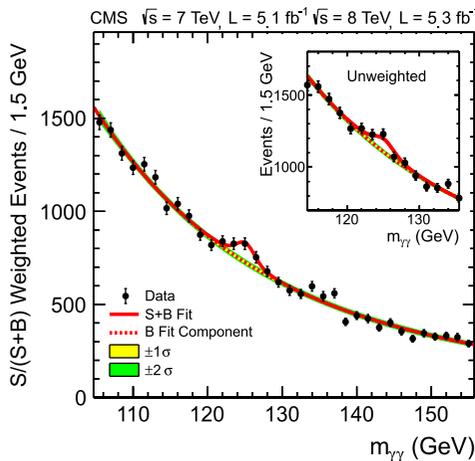


Figure 5. The observed distribution in the CMS experiment for the effective mass $m_{\gamma\gamma}$ of pairs of γ s produced in high energy proton–proton collisions at CERN’s LHC. If the Higgs boson exists and decays to a pair of γ s, it could result in a peak centred on the mass of the Higgs. Otherwise, the expected distribution is expected to be smooth. In the main plot, the events are weighted according to their quality; the inset shows unweighted events. The apparent peak around 125 GeV is part of the evidence for the existence of a new particle, whose properties seem consistent with those expected for a Higgs boson.

In more complicated cases, the data could consist of one or more histograms or multi-dimensional distributions. Then usually t is chosen as a likelihood ratio for the data, assuming the two hypotheses:

$$t = L_1(H_1|d)/L_0(H_0|d), \quad (17)$$

where L_1 is the likelihood for H_1 (the hypothesis of signal+background), given the data, while L_0 is for the background only hypothesis H_0 , given the same data. When the hypotheses are completely specified without any free parameters, they are known as ‘simple hypotheses’ and the above formulation is satisfactory. Then the Neyman–Pearson lemma [5] says that if we choose H_0 based on the likelihood ratio being below some suitably defined cut-off, this will guarantee that we will achieve the lowest rate for ‘Errors of the Second Kind’ (i.e. incorrectly selecting H_0 when H_1 is true), for a given rate for ‘Errors of the First Kind’ (i.e. rejecting H_0 when it is true).

If, however, one or more of the hypotheses involves free parameters (‘composite hypotheses’), the Neyman–Pearson lemma does not apply. Nevertheless a form of the likelihood ratio, such as the ratio of profile likelihoods, is often used as a method that may well be nearly optimal.

6.2. p -values

For the null hypothesis H_0 , the expected distribution of our test statistic t is $f_0(t)$. Then for a given observed value t_{obs} , the p -value is the fractional area in the tail of $f_0(t)$ for t greater than or equal to t_{obs} . For definiteness we consider the single-sided upper tail (assuming that the alternative hypothesis yields larger values of t), but lower or two-sided tails could be appropriate in other cases.

A small p -value means that the data are not very consistent with the hypothesis. Apart from the possibility that the cause of the discrepancy is new physics, it could be due to an unlikely statistical fluctuation, an incorrect implementation of the hypothesis being tested, an inaccurate allowance for detector effects, etc.

As more and more data are acquired, it is possible that a small (and perhaps not physically significant) deviation from the tested null hypothesis could result in the p_0 becoming small as the data become sensitive to the small deviation. For example, a set of particle decays may be expected to have an exponential decay, but there might be a small background characterised by decays at very short times, and which is not allowed for in the analysis. A small amount of data might be insensitive to this background, whereas a large amount of data might give a very small p -value for a test of exponential decay,

even though the background is fairly insignificant. With enough data, we may be able to include physically motivated corrections to our naive H_0 . The possibility of a statistically significant but physically unimportant deviation has been mentioned by Cox [6].

It is extremely important to realise that a p -value is the probability of observing data like that observed or more extreme, assuming the hypothesis is correct. It is **not** the probability of the hypothesis being true, given the data. These are not the same – see Section 2.4.

Many of the negative comments about p -values are based on the ease of misinterpreting them. Thus it is possible to find statements that of all experiments quoting p -values below 5%, and which thus reject H_0 , many more than 5% are wrong (i.e. H_0 is actually true). In fact, the expected fraction of these experiments for which H_0 is true depends on other factors, and could take on any value between zero and unity, without invalidating the p -value calculation.

6.3. p -values for two hypotheses

With two hypotheses H_0 and H_1 , we can define a p -value for each of them. We adopt the convention that H_1 results in larger values for the statistic t than does H_0 . Then p_0 is defined as the **upper** tail of $f_0(t)$, the probability density function (*pdf*) for observing a measured value t when H_0 is true. It is conventional to define p_1 by the area in the **lower** tail of $f_1(t)$ (i.e. towards the H_0 distribution) – see Figure 6(b), which shows the probability densities for obtaining a value t of a data statistic, for hypotheses H_0 and H_1 . For a specific value t_{obs} , the p -values p_0 and p_1 correspond to the tail areas above t_{obs} for the H_0 *pdf*, and below t_{obs} for H_1 , respectively.³ Then t_{crit} is the critical value of t such that its p_0 value is equal to a pre-set level α for rejecting the null hypothesis.

The p_1 -value when $t = t_{\text{crit}}$ is denoted by β , and the power of the test is $1 - \beta$. The power is the probability that we successfully reject the null hypothesis, assuming that the alternative is true. We expect the power to increase as the signal strength in H_1 becomes stronger, and the *pdf*'s for H_0 and H_1 become more separated.

Depending on the separation of the two *pdf*'s and on the value of the data statistic t , several situations are now possible (see Table 2):

- p_1 is small, but p_0 acceptable. Then we accept H_0 and reject H_1 , i.e. we exclude the alternative hypothesis.
- p_0 is very small, and p_1 acceptable. Then we accept H_1 and reject H_0 . This corresponds to claiming a discovery.

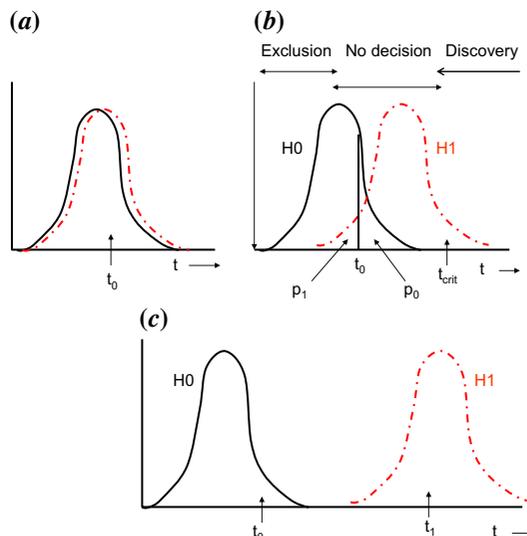


Figure 6. Expected distributions for a statistic t for H_0 =background only (solid curves) and for H_1 =background plus signal (dashed curves). In (a), the signal strength is very weak, and it is impossible to choose between H_0 and H_1 . As shown in (b), which is for moderate signal strength, p_0 is the probability according to H_0 of t being equal to or larger than the observed t_0 . To claim a discovery, p_0 should be smaller than some pre-set level α , usually taken to correspond to 5σ ; t_{crit} is the minimum value of t for this to be so. Similarly p_1 is the probability according to H_1 for $t \leq t_0$. The exclusion region corresponds to t_0 in the 5% lower tail of H_1 . In (b) there is an intermediate ‘No decision’ region. In (c) the signal strength is so large that there is no ambiguity in choosing between the hypotheses. In order to protect against a downward fluctuation in a situation like (a) resulting in an exclusion of H_1 when the curves are essentially identical, CL_s is defined as $p_1/(1 - p_0)$.

- Both p_0 and p_1 are acceptable. The data are compatible with both hypotheses, and we are unable to choose between them.
- Both p_0 and p_1 are small. The choice of decision is not obvious, but basically both hypotheses should be rejected.

5 σ discovery, 95% exclusion

Searches for new phenomena in Particle Physics typically choose the ‘Standard Model’ as the null hypothesis H_0 , and a specific form of New Physics as H_1 . The exclusion level for H_1 is usually set at 5%, whereas that for rejecting H_0 (and perhaps claiming the discovery of New Physics) is usually ‘5 σ ’, i.e. $p_0 \leq 3 \times 10^{-7}$.

Some (not very convincing) reasons for the stringent criterion for rejecting H_0 include:

- The past history of false discovery claims at 3σ and 4σ levels.
- The possibility that systematic effects have been underestimated.
- The Look Elsewhere Effect (see Section 6.5).
- Subliminal Bayesian reasoning that the Standard Model is intrinsically more likely to be true than some specific speculation about New Physics.
- The embarrassment of having to withdraw a spectacular but incorrect claim of discovering New Physics.

In contrast, incorrect exclusion of New Physics is not regarded as so dramatic, and so the weaker criterion of 5% is used. As Glen Cowan has remarked, ‘If you are looking for your car keys and are 95% sure they are not in the kitchen, it’s a good idea to start looking somewhere else’ [7].

Figure 7(a) illustrates the (p_0, p_1) plot for defining various decision regions.

6.4. *p*-values or likelihoods?

Rather than calculating *p*-values for the various hypotheses, we could use their likelihoods L_0 and L_1 . While *p*-values use tail areas beyond the observed statistic, the likelihood is simply the height of the *pdf* at t_{obs} . We return to likelihood ratios in Section 7.

As mentioned in Section 6.1, the Neyman–Pearson lemma provides the best way of choosing between two simple hypotheses, but even when one or both hypotheses contain free parameters, the likelihood ratio may well be a suitable statistic for summarising the data and for helping choose between the hypotheses. In general, it will be necessary to generate the expected distributions of the likelihood ratio according to the hypotheses H_0 and H_1 , in order to make some deduction based on the observed likelihood ratio; for composite hypotheses there are of course the complications caused by the nuisance parameters. The decision process may well be based on the *p*-values p_0 and p_1 for the two hypotheses (see Figure 7). In that case, the procedure can be regarded as

either a likelihood ratio approach, with the *p*-values simply providing a calibration for the value of the likelihood ratio; or as a *p*-value method, with the likelihood ratio merely being a convenient statistic.

6.5. Look elsewhere effect

If you are playing cards, and in your hand of 13 cards you observe that you have four queens, you might think that that is very unusual. Indeed the probability of a random set of 13 cards containing four queens is 0.0026. However, since you decided that ‘four queens’ was unusual only after you looked at your cards, you might have been equally surprised by four kings; or four jacks; or ace, two, three, four of the same suit; etc. Taking these into account, the probability of a surprising hand of cards similar to what we had is going to be a fair bit larger than 0.0026.

A similar effect explains why a seemingly improbable event in our everyday life (e.g. a chance meeting with someone we had been thinking about recently) may in fact be much more likely, if we have not decided at the beginning of the day that this specific event would be a real coincidence if it happened.

Often in High Energy Physics, we are looking for some new phenomenon. Thus we may be searching for a new particle, whose mass is not pre-defined, in a histogram such as that of Figure 5. When we observe an enhancement, we can calculate the *p*-value (the chance of observing a statistical fluctuation at least as big as the one in our data, assuming that no such particle in fact exists), at the observed mass. But this of course underestimates the chance of having a fluctuation anywhere in our mass distribution, which we might mistakenly ascribe to a new particle. We thus need to calculate the probability of observing an effect at least as impressive as ours, anywhere in our mass distribution. In Particle Physics, this dilution of the significance is known as the Look Elsewhere Effect (LEE).

Similar considerations are relevant for searches in other fields. Thus claims for discoveries of gravitational waves would need to calculate the chance of a statistical fluctuation mimicking the observed effect not only at the observed time, frequency and signal structure, but anywhere in the whole dynamic range of these variables for which a real signal is possible.

Of course, specifying where exactly ‘Elsewhere’ is, is fraught with ambiguities. Thus for the above example of

Table 2. Choosing between two hypotheses, based on p_0 and p_1 .

p_0	p_1	Result	If H_0 true	If H_1 true
Very small	O.K.	Discovery	Error of 1st kind	Correct choice
O.K.	Small	Exclude H_1	Correct choice	Error of 2nd kind
O.K.	O.K.	Make no choice	Loss of efficiency	Loss of efficiency
Very small	Small	?	?	?

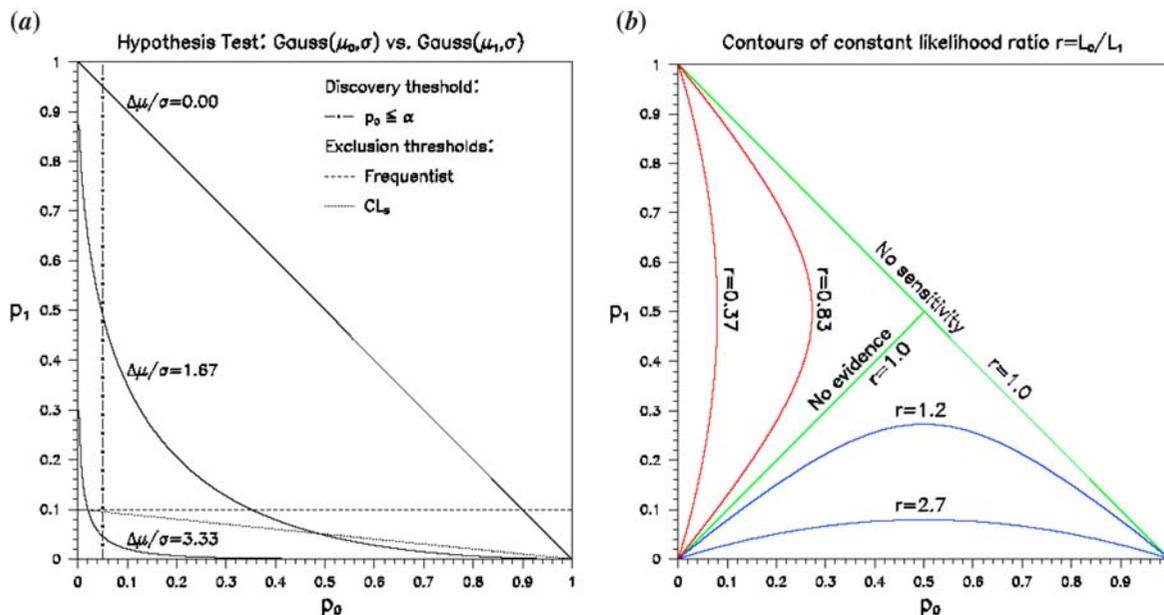


Figure 7. Plots of p_0 against p_1 for comparing a data statistic t with two hypotheses H_0 and H_1 , whose expected $pdfs$ for t are assumed to be two Gaussians of peak separation $\Delta\mu$, and of equal width σ (see Figure 6). (a) For a pair of $pdfs$ with a given separation, the allowed values of (p_0, p_1) lie on a curve or straight line (shown solid in the diagram). As the separation $\Delta\mu$ increases, the curves approach the p_0 and p_1 axes. Rejection of H_0 is for p_0 less than, say, 3×10^{-7} ; here it is shown as 0.05 for ease of visualisation. Similarly exclusion of H_1 is shown as $p_1 < 0.1$. Thus the (p_0, p_1) square is divided into four regions: the largest rectangle is when there is no decision, the long one above the p_0 -axis is for exclusion of H_1 , the high one beside the p_1 -axis is for rejection of H_0 , and the smallest rectangle is when the data lie between the two $pdfs$. For $\Delta\mu = 3.33$, there are no values of (p_0, p_1) in the ‘no decision’ region. In the CL_s procedure, rejection of H_1 is when the statistic t is such that (p_0, p_1) lies below the diagonal dotted straight line. (b) Contours of constant likelihood ratio $r = L_0/L_1$ for Gaussian $pdfs$. The upper right region is inaccessible; the diagonal line from $(0,1)$ to $(1,0)$ corresponds to the $pdfs$ lying on top of each other, i.e. no sensitivity. The diagonal through the origin is when t_{obs} is mid-way between the two $pdfs$. With larger separation of the Gaussian $pdfs$ and for constant p_0 the likelihood ratio increases.

searching for a new particle, Figure 5 is relevant for the possibility of it decaying to two photons, but other decay modes could be possible, and hence could be relevant to the LEE. Similarly, maybe the particle we are considering cannot be produced enough at high masses for us to have the chance of detecting it, so the whole mass range is not relevant for the LEE. The conclusion is that when p -values are corrected for the LEE, it is important to specify exactly what has been taken into account.

6.6. CL_s

The CL_s method [8,9] was introduced in the LEP experiments at CERN in searches for new particles. When evidence for such a particle is not found, the traditional Frequentist approach is to exclude its production if p_1 is smaller than some pre-set level γ , which in Particle Physics is typically set at 5%. However, there is then a 5% probability that H_1 could be excluded, even if the experiment was such that the H_0 and H_1 $pdfs$ lay on top of each other, i.e. there was no sensitivity to the production of the new phenomenon. To protect against this, the decision to exclude H_1 is based on $p_1/(1-p_0)$, known as CL_s .⁴ It is thus the ratio of the left hand tails of the $pdfs$

for H_1 and H_0 . Figure 7(a) shows a (p_0, p_1) region for which H_1 is excluded by CL_s . The fact that it is clearly smaller than for the standard frequentist exclusion region is the price one has to pay for the protection it provides against excluding H_1 when an experiment has no sensitivity to it. We regard it as conservative frequentist.

It is interesting that the CL_s exclusion line in Figure 7(a) for the case of two Gaussians is identical to that obtained by a Bayesian procedure for determining the upper limit on μ_1 when the latter is restricted to positive values, and with a uniform prior for μ_1 . In a similar manner, the standard frequentist procedure agrees with the Bayesian upper limit when the restriction of μ_1 being positive is removed.

In principle, similar protection against discovery claims when the experiment has no sensitivity could be employed, but it is deemed not to be necessary because of the different levels used for discovery and for exclusion of H_1 (typically 3×10^{-7} and 0.05, respectively).

6.7. When neither H_0 or H_1 is true

It may well be that neither H_0 nor H_1 is true. With no more information available, it is of course impossible to say what we expect for the distribution of our test statistic t .

On the plot of Figure 7(a), our data may fall in the small rectangle next to the origin.

It is certainly not true that a small value for p_0 implies that H_1 is correct, although for small enough p_0 , ruling out H_0 is a possibility.

7. Bayesian methods

The Bayesian approach is more naturally suited to making statements about what we believe about two (or more) hypotheses in the light of our data. This contrasts with Goodness of Fit, which involves considering other possible data outcomes, but focuses on just one hypothesis.

All Bayesian methods involve the likelihood function, possibly modified to take into account nuisance parameters. For Hypothesis Testing, some form of a ratio of (modified) likelihoods is usually involved. For simple hypotheses, this is just $L_0(H_0)/L_1(H_1)$, where $L_i(H_i) = p(x|H_i)$, the probability (density) for observing data x for the hypothesis H_i . The issue is going to be how nuisance parameters⁵ v are dealt with for non-simple hypotheses. For the likelihood approach (as opposed to the Bayesian one, which also requires priors), it is usual to profile them, i.e. the profile likelihood is $L_i(H_i|v_{\text{best}})$, where v_{best} is the set of parameters which maximise L . In Particle Physics, the profile likelihood approach is a popular method for incorporating systematics in parameter determination problems.

The complications of applying Bayesian methods to model selection in practice are due to the choices for appropriate priors. This is particularly so for those parameters which occur in the alternative hypothesis H_1 but not in the null H_0 .

Loredo [10] and Trotta [11] have provided reviews of the application of Bayesian techniques in Astrophysics and Cosmology, where their use is more common than in Particle Physics.

7.1. Bayesian posterior probabilities

When there are no nuisance parameters involved, the ratio of the posterior probabilities for H_i is $p_{\text{post}}(H_0|x)/p_{\text{post}}(H_1|x)$, where

$$p_{\text{post}}(H_i|x) \propto L_i(H_i) \pi_i, \quad (18)$$

and π_i is the assigned prior probability for hypothesis i . For example, the hypothesis of there being a Higgs boson of mass 110 GeV might well be assigned a small prior, in view of the exclusion limits from LEP.

With nuisance parameters, the posterior probabilities become

$$p_{\text{post}}(H_i|x) \propto \int L_i(H_i|v) \pi_i(v) \pi_i \, dv, \quad (19)$$

where π_i is the prior probability for hypothesis i and $\pi_i(v)$ is the joint prior for its nuisance parameters, i.e. we now have **integrated** over the nuisance parameters. This contrasts with the likelihood method, where **maximisation** with respect to them is more usual. Even with $\pi_i(v)$ being a constant, integration and maximisation can select different regions of parameter space. An example of this would be a likelihood function that has a large narrow spike at small v , and a broad but lower enhancement at large v .

In relation to all Bayesian methods, it is to be emphasised that the choice of a constant prior, especially for multi-dimensional v , is by no means obvious (compare Section 2.3). Very often, there are several possible choices of variable for the nuisance parameters, with none of them being obviously more natural or appropriate than the others. Thus a point in two-dimensional space could be written as Cartesian (x, y) or polar (r, θ) ; constant priors in the two sets of variables are different. Similarly in fitting data by a straight line $y = a + b x$, using a seemingly innocuous flat prior for $b = \tan \theta$ results in angles θ in the range 0° to 89° have the same prior probability as those in the range 89° to 89.5° .

It should be realised that the results for Hypothesis Testing are more sensitive to the choice of prior than in parameter determination. Thus in parameter determination, sometimes a prior is used which is constant over a wide range of v , and zero outside it. The resulting range for the parameter, as deduced from its posterior, may well be insensitive to the range used, provided it includes the region where the likelihood $L(v)$ is significant. For comparing hypotheses, however, there can be parameters which occur in one hypothesis but not the other. (An example of this is where H_1 corresponds to a smooth background plus a peak, while H_0 is just smooth background.) The widths of such priors affect their normalisation, and hence also the Bayes factor (see next section) directly.

On the other hand, in searches for a new particle of unknown mass, the Bayesian probability for the particle existing will depend on the range of the prior used for the particle's mass – the wider the range, the lower the normalisation and hence the lower the probability.⁶

At least qualitatively, this resembles the effect of the LEE in the Frequentist approach, where the significance of a peak in a mass spectrum is diluted if the search extends over a wide mass range (see Section 6.5).

7.2. Bayes factor

For each hypothesis we define $R_i = p_{\text{post}}/\pi$, where p_{post} and π are respectively the posterior and prior probabilities for hypothesis i . Thus R is just the ratio of posterior and prior probabilities. Then the Bayes factor for the two

hypotheses H_0 and H_1 is $B_{01} = R_0/R_1$. If the two hypotheses are both simple, then this is just the likelihood ratio. If either is composite, the relevant integrals are required for p_{post} . A small value of B_{01} favours H_1 .

Demortier [12] has drawn attention to the fact that it can be useful to calculate the **minimum** Bayes factor [13]. This is defined as above, but with the extra nuisance parameters of H_1 set at values that minimise B_{01} , i.e. they are as favourable as possible for H_1 . If even this value of B_{01} suggests that H_1 is not to be preferred, then it is a waste of time to investigate further since any choice of priors for the extra parameters cannot make B_{01} smaller.

7.3. Other Bayesian methods

The Bayesian approach can be used in conjunction with Decision Theory, in order to provide a procedure for choosing between two hypotheses. In addition to any priors, a cost function has to be defined, which assigns a numerical ‘cost’ for each combination of the true hypothesis (H_0 or H_1), and the possible decisions – see Table 3. The decision procedure is designed to minimise the expected cost, as determined by the cost function and the expected distribution of posterior probabilities for H_0 and H_1 .

Because of the problems of assigning realistic costs, and the use of priors in determining the posteriors for the hypotheses, there is little or no usage of this approach in Particle Physics searches for New Physics.

Table 3. Cost function. Typically the cost A assigned to a false discovery claim would be larger than B , the cost for a failure to discover. There is zero cost for making a correct decision.

	H_0 true	H_1 true
Accept H_0	Correct choice. Cost=0	Failure to discover. Cost= B
Reject H_0	False discovery claim. Cost= A	Correct choice. Cost=0

Table 4. Comparison of Bayes and Frequentist approaches.

	Bayes	Frequentist
Basis of method	Bayes theorem \rightarrow posterior probability distribution	Uses <i>pdf</i> for data, for fixed parameter values
Meaning of probability	Degree of belief	Frequentist definition
Probability for parameters	Yes	No, no, no
Needs prior	Yes	No
Choice of interval	Central, upper limit, shortest, ...	Choice of ordering rule
Data used	Only the data you have	Also other possible data
Needs ensemble of possible experiments	No	Yes (but often not explicit)
Obeys the likelihood principle	Yes	No
Unphysical/empty ranges possible?	Excluded by prior	Can occur
Final statement	Posterior prob dist	Param values for which data is likely
Do param ranges cover?	Regarded as unimportant	Built in
Include systematics	Integrate over prior	Extend dimensionality of frequentist construction

Other Bayesian methods such as AIC, BIC, ... (Akaike Information Criterion, Bayesian Information Criterion, ...) aim to provide approximations to the Bayes factor, but which are easier to calculate. Given the powerful computational facilities available nowadays, these methods are likely to decrease in general usage. Again there is little or no experience of using them in Particle Physics applications.

7.4. Why p is not equal to the likelihood ratio

There is sometimes discussion of why a likelihood ratio approach (or the Bayes factor, if there are nuisance parameters) can give a very different numerical answer to a p -value calculation. A reason some agreement might be expected is that they are both addressing the question of whether there is evidence in the data for new physics.

In fact they measure very different things. Thus p_0 simply measures the consistency with the null hypothesis, without any regard to the degree of agreement with the alternative, while the likelihood ratio takes the alternative into account. There is thus no reason to expect them to bear any particular relationship to each other. This can be illustrated by contour plots of constant values of the likelihood ratio $r = L_0/L_1$ on a p_0 versus p_1 plot (see Figure 7(b)). The figure is constructed by assuming that the *pdfs* for the two hypotheses H_0 and H_1 are given by Gaussian distributions, both of unit width. Then at constant p_0 , it is seen that the likelihood ratio can take a range of values, corresponding to the

Gaussians having different separations. Thus with the Gaussian for H_0 's *pdf* centred at zero, a measured value of 5.0 yields a p_0 -value of 3×10^{-7} , regardless of the position of the H_1 Gaussian. Such a small p -value is usually taken as sufficient to reject H_0 . As the centre of the H_1 Gaussian starts at $\mu_1 = 0$, the two Gaussian *pdfs* are identical, and $r = 1$. With increasing μ_1 , p_0 of course remains constant, but r at first decreases to a minimum when $\mu_1 = 5$, but then increases through unity when $\mu_1 = 10$ (i.e. the data is midway between the *pdf* peaks), and then keeps on rising with further increases of the separation of the *pdfs*. At that stage, the data are more in agreement with H_0 than with H_1 , despite the small value of p_0 .

8. Conclusion

We have seen how Bayesians and frequentists differ fundamentally in the way they consider probability. This then affects the way they approach the topics of parameter determination, and of choosing between two hypotheses. Table 4 provides a summary of the differences between the two approaches.

A cynic's view of the two techniques is provided by the quotation:

Bayesians address the question everyone is interested in by using assumptions no-one believes, while Frequentists use impeccable logic to deal with an issue of no interest to anyone.

However, it is not necessary to be so negative, and for physics analyses at the CERN's LHC, the aim is, at least for determining parameters and setting upper limits in searches for various new phenomena, to use both approaches; similar answers would strengthen confidence in the results, while differences suggest the need to understand them in terms of the somewhat different questions that the two approaches are asking.

It thus seems that the old war between the two methodologies is subsiding, and that they can hopefully live together in fruitful cooperation.

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Notes

1. The '!' symbol in Equations (1) and (2) not only expresses surprise ('Wow! These equations look very similar), but it also denotes the factorial.
2. This definition does not provide a unique range. The one we show has a probability of 16% on either side of the selected

region, which is then known as a central interval. An alternative would be to have the whole of the 32% on the left hand side of the confidence interval; this would be useful for producing upper limits on τ .

3. If t is a discrete variable, such as a number of events, then 'above' is replaced by 'greater than or equal to', and correspondingly for 'below'.
4. This stands for 'confidence level of signal', but it is a poor notation, as *CLs* is in fact a ratio of p -values, which is itself not even a p -value, let alone a confidence level.
5. For the purpose of model comparison, any parameters are considered as nuisance parameters, even if they are physically meaningful, e.g. the parameters of a straight line fit, the mass of the Higgs boson, etc.
6. This is an example of Occam's Razor, whereby a simpler hypothesis may be favoured over a more complex one.

Notes on contributor

After completing his doctorate, Louis Lyons spent six months working in the Alvarez group at Berkeley, where statistical techniques relevant for analysing data in Particle Physics were being used and understood. On his return to Oxford, he suggested that it would be a good idea to have lectures on these topics for graduate students. The head of the Oxford Nuclear Physics group thought this was a good idea, and told Louis to give the lectures.

Louis' next mistake was to think that it would be easy to turn the course's lecture notes into a book. This took several years to complete, but eventually appeared as *Statistics for Nuclear and Particle Physicists*, published by Cambridge University Press. His other books are *All You Wanted To Know About Mathematics But Were Afraid To Ask*, and *A Practical Guide To Data Analysis*, also published by Cambridge University Press.

He maintained his interest in these issues, and in 2000 initiated a Workshop at CERN on 'Confidence Limits'. This turned out to be the first in the PHYSTAT series of Workshops and Conferences. Further details can be found at the website of the most recent of these meetings: <http://indico.cern.ch/conferenceDisplay.py?confId=107747>. Louis was the first Chair of the CDF Collaboration's Statistics Committee, and is also a member of the corresponding committee for the CMS experiment at CERN. He has lectured on statistical issues in the accelerator centres at CERN, Fermilab, Brookhaven, Argonne, TRIUMF, KEK (Japan) and Frascati, as well as at numerous Universities worldwide and at Summer Schools.

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