# BAYESIAN STATISTICS 5 pdf

## 1: Frequentist And Bayesian Approaches In Statistics - Probabilistic World

*Bayesian statistics is a theory in the field of statistics based on the Bayesian interpretation of probability where probability expresses a degree of belief in an event, which can change as new information is gathered, rather than a fixed value based upon frequency or propensity.*

Frequentist Statistics[ edit ] Resampling vs. Bayesian Computation[ edit ] Typically, the question one attempts to answer using statistics is that there is a relationship between two variables. To demonstrate that there is a relationship the experimenter must show that when one variable changes the second variable changes and that the amount of change is more than would be likely from mere chance alone. There are two ways to figure the probability of an event. The first is to do a mathematical calculation to determine how often the event can happen. The second is to observe how often the event happens by counting the number of times the event could happen and also counting the number of times the event actually does happen. The use of a mathematical calculation is when a person can say that the chance of the event rolling a one on a six sided die is one in six. The probability is figured by figuring the number of ways the event can happen and divide that number by the total number of possible outcomes. Another example is in a well shuffled deck of cards, what is the probability of the event of drawing a three. The answer is four in fifty two since there are four cards numbered three and there are a total of fifty two cards in a deck. The chance of the event of drawing a card in the suite of diamonds is thirteen in fifty two there are thirteen cards of each of the four suites. The chance the event of drawing the three of diamonds is one in fifty two. Sometimes, the size of the total event space, the number of different possible events, is not known. For instance, a warranty for a coffee maker is a probability statement. The manufacturer calculates that the probability the coffee maker will stop working before the warranty period ends is low. The way such a warranty is calculated involves testing the coffee maker to calculate how long the typical coffee maker continues to function. Then the manufacturer uses this calculation to specify a warranty period for the device. Experiments, Outcomes and Events[ edit ] The easiest way to think of probability is in terms of experiments and their potential outcomes. Many examples can be drawn from everyday experience: On the drive home from work, you can encounter a flat tire, or have an uneventful drive; the outcome of an election can include either a win by candidate A, B, or C, or a runoff.

## 2: Bayesian Statistics: www.enganchecubano.com

*The proceedings of the Valencia International Meeting on Bayesian Statistics (held every four years) provide an overview of this important and highly topical area in theoretical and applied statistics.*

The most straightforward thing you can do is give a detailed description of the sample. You only use these quantities to summarize the sample. But what if you wanted to learn something more general than just the properties of the sample? Inferential statistics Say you wanted to find the average height difference between all adult men and women in the world. Your first idea is to simply measure it directly. The current world population is about 7. Would you measure the individual heights of 4. A more realistic plan is to settle with an estimate of the real difference. Many differences are much too subtle to detect in such direct ways. People have developed many statistical techniques to deal with these complex cases. Parameter estimation In the context of probability distributions, a parameter is some often unknown constant that determines the properties of the distribution. Data prediction For this goal, you usually need to have already estimated certain parameters. You use them to predict future data. Then you can use these values to predict the probability of a randomly chosen female to have a height within a certain range of values. Then, if you randomly pick an adult female from the population, you can expect her to have a height within the range of â€" cm 3 standard deviations from the mean. A model is basically a set of postulates about the process that generates the data. For example, a model can postulate that the height of an adult is determined by factors like: Biological sex Nutrition Physical exercise A statistical model would postulate a specific relationship between these factors and the data to be explained. In short, according to the frequentist definition of probability, only repeatable random events like the result of flipping a coin have probabilities. These probabilities are equal to the long-term frequency of occurrence of the events in question. This is a very important point that you should carefully examine. In contrast, Bayesians view probabilities as a more general concept. For more background on the different definitions of probability, I encourage you to read the post I linked to above. Parameter estimation and data prediction Consider the following example. We want to estimate the average height of adult females. First, we assume that height has a normal distribution. Therefore, the only thing we need to estimate is the mean of the distribution. The frequentist way How would a frequentist approach this problem? Well, they would reason as follows: However, I know that its value is fixed not a random one. The Bayesian way A Bayesian, on the other hand, would reason differently: Their criticism is that there is always a subjective element in assigning them. Data prediction Here, the difference between frequentist and Bayesian approaches is analogous to their difference in parameter estimation. In fact, I encourage you to read it even if you are, due to their very frequent misinterpretation. As usual, you start by collecting sample data from the population. You determine the whole procedure, including the sample size, before collecting any data. Summary In this post, I introduced the distinction between descriptive and inferential statistics and explained the 3 goals of the latter: Parameter estimation Model comparison I ignored the last goal and mostly focused on the first. Bayesian statistics, on the other hand, defines probability distributions over possible values of a parameter which can then be used for other purposes. Finally, I showed that, in the absence of probabilistic treatment of parameters, frequentists handle uncertainty by limiting the long-term error rates, either by comparing the estimated parameter against a null value NHST , or by calculating confidence intervals.

## 3: Bayesian Statistics Explained in Simple English For Beginners

*While Bayes Rule, the mathematics that underlies Bayesian methods, is applied across all branches of probability and statistics, Bayesian Statistics, the particular use for statistical inference, has always been less well accepted, the Cinderella of statistics.*

But, the more I write the harder it is to find everything! This should make it easier for everyone to learn the basics. I plan to continually update this guide as I add new content. For updates follow willkurt on twitter or subscribe to the email list. If you can work out the chance of flipping a coin and getting 3 heads in a row, then you should be all set. If you do need a refresher the Khan Academy has some great lectures on the topic. There is no need for a background in Statistics. The beauty of Bayesian Statistics is it can be built up from basic probability. What to read to get you excited? This is a great book to get you excited about Bayesian Stats! There are no strong math requirements for this book. If equations still make you a bit nervous this is a great place to build up your enthusiasm to dive in! Recommended posts for getting started! This allows you to use visual learning to build a deep intuition for the theorem. Prior Probabilities allow us to model our beliefs about the world. Ever wonder if your friend is really allergic to gluten? In these posts, we focus on how we can model our beliefs about the world, learn about the beliefs of others and compare hypotheses the Bayesian way! Recommended Posts to get you thinking like a Bayesian! Bayesian Reasoning in The Twilight Zone! That glimmer in his eye is from Bayesian Statistics! Do you believe that a dinner novelty could have mystic powers? How much would it take to convince you? Evidence allows us to very easily interpret the results of our test. No more confusing p-values! Though there is plenty of math, this book is about philosophy. Jaynes is probably the most radical Bayesian there is. A few pages often provide me with food for thought for months. Also, if you need insults to sling at Frequentists this is the place to get them! The catch is that this is a very challenging book. To help guide you through it Aubrey Clayton has put together a very nice set of lectures. In my experience, there are two major benefits to Bayesian statistics over classical statistics: The first is that you very easy model existing information. This can very often lead to better results since the model has more to work with. Additionally, you can account for inherent bias in your analysis. By modeling the subjective parts of analysis, you can better control them. The second is that is no "mystery meat" in your tools. All of Bayesian statistics is built from the basics of probability. Determining whether or not the data comes from a biased coin is the real challenge. Parameter estimation deals with how we fill in these missing probabilities. But quite often prior beliefs are based on hard data. In this post, we see how we can use existing data to develop priors. With data backed priors we can develop much better parameter estimates. Rejection Sampling and Tricky Priors Rejection sampling looks pretty fun! In this post, we learn one of the simpler techniques for working difficult prior probabilities and still getting useful results. Can you derive a classical t-test from scratch? My guess is not without some difficulty. One of the benefits of Bayesian statistics is everything can be built from the basics. It will cover much of the material we have so far and then take you much further. The approach is mathematical, but never too challenging. This book is full of wonderful, practical examples For practical Bayesian statistics, nobody gets me more excited than Andrew Gelman! This is not an easy book to work through but it is an absolute gem. The text is filled with wonderful, real world example that will alway renew your love of Bayesian Statistics. Look out for updates! I plan to continually update this guide as I write relevant posts or come across other amazing books. Please subscribe the to email list or follow me on twitter for updates.

## 4: Free Online Course: Bayesian Statistics from Coursera | Class Central

*This course describes Bayesian statistics, in which one's inferences about parameters or hypotheses are updated as evidence accumulates. You will learn to use Bayes' rule to transform prior probabilities into posterior probabilities, and be introduced to the underlying theory and perspective of.*

High Density Interval HDI Before we actually delve in Bayesian Statistics, let us spend a few minutes understanding Frequentist Statistics, the more popular version of statistics most of us come across and the inherent problems in that. Frequentist Statistics The debate between frequentist and bayesian have haunted beginners for centuries. Infact, generally it is the first school of thought that a person entering into the statistics world comes across. The objective is to estimate the fairness of the coin. Below is a table representing the frequency of heads: We know that probability of getting a head on tossing a fair coin is 0. Difference is the difference between 0. Dependence of the result of an experiment on the number of times the experiment is repeated. Person A may choose to stop tossing a coin when the total count reaches while B stops at  Similarly, intention to stop may change from fixed number of flips to total duration of flipping. In this case too, we are bound to get different p-values. I like p-value depends heavily on the sample size. These three reasons are enough to get you going into thinking about the drawbacks of the frequentist approach and why is there a need for bayesian approach. It provides people the tools to update their beliefs in the evidence of new data. Let me explain it with an example: Suppose, out of all the 4 championship races F1 between Niki Lauda and James hunt , Niki won 3 times while James managed only 1. So, if you were to bet on the winner of next race, who would he be? I bet you would say Niki Lauda. What if you are told that it rained once when James won and once when Niki won and it is definite that it will rain on the next date. So, who would you bet your money on now? By intuition, it is easy to see that chances of winning for James have increased drastically. But the question is: To understand the problem at hand, we need to become familiar with some concepts, first of which is conditional probability explained below. In addition, there are certain pre-requisites: Probability and Basic Statistics: To refresh your basics, you can check out another course by Khan Academy. Probability of an event A given B equals the probability of B and A happening together divided by the probability of B. Assume two partially intersecting sets A and B as shown below. Set A represents one set of events and Set B represents another. We wish to calculate the probability of A given B has already happened. Lets represent the happening of event B by shading it with red. So, the probability of A given B turns out to be: Therefore, we can write the formula for event B given A has already occurred by: Suppose, B be the event of winning of James Hunt. You must be wondering that this formula bears close resemblance to something you might have heard a lot about. Probably, you guessed it right. It looks like Bayes Theorem. This could be understood with the help of the below diagram. Bayesian Inference There is no point in diving into the theoretical aspect of it. Models are the mathematical formulation of the observed events. Parameters are the factors in the models affecting the observed data. The outcome of the events may be denoted by D. It is perfectly okay to believe that coin can have any degree of fairness between 0 and 1. If we knew that coin was fair, this gives the probability of observing the number of heads in a particular number of flips. P D is the evidence. To define our model correctly , we need two mathematical models before hand. Since prior and posterior are both beliefs about the distribution of fairness of coin, intuition tells us that both should have the same mathematical form. Keep this in mind. We will come back to it again. So, there are several functions which support the existence of bayes theorem. Knowing them is important, hence I have explained them in detail. So, we learned that: It is the probability of observing a particular number of heads in a particular number of flips for a given fairness of coin. We can combine the above mathematical definitions into a single definition to represent the probability of both the outcomes. Furthermore, if we are interested in the probability of number of heads z turning up in N number of flips then the probability is given by: Mathematicians have devised methods to mitigate this problem too. It is known as uninformative priors. I would like to inform you beforehand that it is just a misnomer. Every uninformative prior always provides some information event the constant distribution prior. It has some very nice mathematical properties which enable us to model our beliefs about a binomial distribution. Probability density function of beta distribution is of the form: The denominator is there just to ensure that the total probability density function upon integration evaluates to 1.

## 5: Bayesian Statistics: A Beginner's Guide | QuantStart

*Bayesian inference is a method of statistical inference in which Bayes' theorem is used to update the probability for an hypothesis as more evidence or information becomes available. Bayesian inference is an important technique in statistics, and especially in mathematical statistics.*

And because it allows them to incorporate their knowledge about a problem in a fairly systematic manner. And so here I give you sort of a range of what you can expect to see in Bayesian statistics from your second edition of a traditional book, something that involves computation, some things that involve risk thinking. This book, for example, seems to be one of them. This book is definitely one of them. This one represents sort of a wide, a broad literature on Bayesian statistics, for applications for example, in social sciences. So we do have some experts at MIT in the c-cell. Tamara Broderick for example, is a person who does quite a bit of interesting work on Bayesian parametrics. So before we go into more advanced things, we need to start with what is the Bayesian approach. Actually, often you will see the same method that comes out of both approaches. The first thing, we had data. We observed some data. And we assumed that this data was generated randomly. The reason we did that is because this would allow us to leverage tools from probability. Then we made some assumptions on the data generating process. For example, we assumed they were iid. That was one of the recurring things. Sometimes we assume it was Gaussian. If you wanted to use say, T-test. Maybe we did some nonparametric statistics. We assume it was a smooth function or maybe linear regression function. So those are our modeling. But maybe a small set of distributions that indexed by some small parameters, for example. Or at least remove some of the possibilities. And so for example, this was associated to some parameter of interest, say data or beta in the regression model. Then we had this unknown problem and this unknown thing, a known parameter. And we wanted to find it. We wanted to either estimate it or test it, or maybe find a confidence interval for the subject. In the Bayesian approach, we still assume that we observe some random data. But the generating process is slightly different. But this is actually going to be something that brings us some easiness for us to incorporate what we call prior belief. But often, you actually have prior belief of what this parameter should be. When we, say least squares, we looked over all of the vectors in all of R to the p, including the ones that have coefficients equal to 50 million. Those are things that we might be able to rule out. We might be able to rule out that on a much smaller scale. But maybe you can rule out the fact that almost everybody is turning their head in the same direction, or almost everybody is turning their head to another direction. So we have this prior belief. And this belief is going to play say, hopefully less and less important role as we collect more and more data. But if we have a smaller amount of data, we might want to be able to use this information, rather than just shooting in the dark. And so the idea is to have this prior belief. So belief encompasses basically what you think and how strongly you think about it. So for example, if I have a belief about some parameter theta, maybe my belief is telling me where theta should be and how strongly I believe in it, in the sense that I have a very narrow region where theta could be. The posterior beliefs, as well, you see some data. So this is just an indicator for each of my collected data, whether the person I randomly sample is a woman, I get a one. Now the question is, I sample these people randomly. I do you know their gender. And then we could do some tests. I want to test maybe if p is equal to 0. That sounds like a pretty reasonable thing to test. But we want to also maybe estimate p. But here, this is a case where we definitely prior belief of what p should be. We are pretty confident that p is not going to be 0. We actually believe that we should be extremely close to one half, but maybe not exactly. Maybe this population is not the population in the world. But maybe this is the population of, say some college and we want to understand if this college has half women or not. So I could integrate it in a blunt manner by saying, discard the data and say that p is equal to one half. So how do I do this trade off between adding the data and combining it with this prior knowledge? So if you have five observations, this is just the sixth observation, which will play a role. The Bayesian approach is a tool to one, include mathematically our prior. And our prior belief into statistical procedures. Maybe I have this prior knowledge. And the second goal is going to be to update this prior belief into a posterior belief by using the data. How do I do this? One is where you draw the parameter at random. And two, once you have the parameter, conditionless parameter, you draw your data. Nobody believed this actually is happening, that nature is just rolling dice for us and choosing parameters at random. How would you say, my belief is as follows? So essentially, I have this possible value of p. And then I have 0. If you remember, this sort of looks like the kind of pictures that I made when I had some Gaussian, for example. So in a way, if I were able to tell you all those ranges for all possible values, then I would essentially describe a probability distribution for p. I could have something that looks like this, maybe. It could be like this. Some of them are definitely going to be mathematically more convenient than others. So the idea of using this two layer thing, where we think of the parameter p as being drawn from some distribution, is really just a way for us to capture this information. But the Bayesian approach does as if it was random. And then, just spits out a procedure out of this thought process, this thought experiment. So when you practice Bayesian statistics a lot, you start getting automatisms. You start getting some things that you do without really thinking about it. So here, I can describe my parameter as being theta in general, in some big space parameter of theta. But what spaces did we encounter? Well, we encountered the real line. So in particular, this is the speed in which my parameter that I usually denote by p for Bernoulli lives. And so what I need is to find a distribution on the interval 0, 1 just like this guy. And so the question is, I need to think about distributions that are probably continuous. So the beta distribution has two parameters. So x follows a beta with parameters a and b if it has a density, f of x is equal to x to the a minus 1. Why is that a good thing? But now I have these two parameters and a set of shapes that I can get by tweaking those two parameters is incredible. Because if you think about this, what would it mean if your prior distribution of the interval 0, 1 had this shape? It would mean that, maybe you think that p is here or maybe you think that p is here, or maybe you think that p is here. Which essentially means that you think that p can come from three different phenomena. But if you think.

## 6: Doing it (making sense of statistics) â€“ 5 â€“ Bayesian statistics | Statistics for HCI

*Bayesian statistics uses the word probability in precisely the same sense in which this word is used in everyday language, as a conditional measure of uncertainty associated with the occurrence of a particular event, given the available information and the accepted assumptions.*

It has become clear to me that many of you are interested in learning about the modern mathematical techniques that underpin not only quantitative finance and algorithmic trading, but also the newly emerging fields of data science and statistical machine learning. Quantitative skills are now in high demand not only in the financial sector but also at consumer technology startups, as well as larger data-driven firms. Hence we are going to expand the topics discussed on QuantStart to include not only modern financial techniques, but also statistical learning as applied to other areas, in order to broaden your career prospects if you are quantitatively focused. In order to begin discussing the modern "bleeding edge" techniques, we must first gain a solid understanding in the underlying mathematics and statistics that underpins these models. One of the key modern areas is that of Bayesian Statistics. We have not yet discussed Bayesian methods in any great detail on the site so far. In the article we will: Bayesian statistics is a particular approach to applying probability to statistical problems. It provides us with mathematical tools to update our beliefs about random events in light of seeing new data or evidence about those events. In particular Bayesian inference interprets probability as a measure of believability or confidence that an individual may possess about the occurance of a particular event. We may have a prior belief about an event, but our beliefs are likely to change when new evidence is brought to light. Bayesian statistics gives us a solid mathematical means of incorporating our prior beliefs, and evidence, to produce new posterior beliefs. Bayesian statistics provides us with mathematical tools to rationally update our subjective beliefs in light of new data or evidence. This is in contrast to another form of statistical inference, known as classical or frequentist statistics, which assumes that probabilities are the frequency of particular random events occuring in a long run of repeated trials. For example, as we roll a fair i. Frequentist statistics assumes that probabilities are the long-run frequency of random events in repeated trials. When carrying out statistical inference, that is, inferring statistical information from probabilistic systems, the two approaches - frequentist and Bayesian - have very different philosophies. Frequentist statistics tries to eliminate uncertainty by providing estimates. Bayesian statistics tries to preserve and refine uncertainty by adjusting individual beliefs in light of new evidence. Frequentist vs Bayesian Examples In order to make clear the distinction between the two differing statistical philosophies, we will consider two examples of probabilistic systems: Coin flips - What is the probability of an unfair coin coming up heads? Election of a particular candidate for UK Prime Minister - What is the probability of seeing an individual candidate winning, who has not stood before? The following table describes the alternative philosophies of the frequentist and Bayesian approaches: Example Bayesian Interpretation Unfair Coin Flip The probability of seeing a head when the unfair coin is flipped is the long-run relative frequency of seeing a head when repeated flips of the coin are carried out. That is, as we carry out more coin flips the number of heads obtained as a proportion of the total flips tends to the "true" or "physical" probability of the coin coming up as heads. In particular the individual running the experiment does not incorporate their own beliefs about the fairness of other coins. Prior to any flips of the coin an individual may believe that the coin is fair. After a few flips the coin continually comes up heads. Thus the prior belief about fairness of the coin is modified to account for the fact that three heads have come up in a row and thus the coin might not be fair. After flips, with heads, the individual believes that the coin is very unlikely to be fair. The posterior belief is heavily modified from the prior belief of a fair coin. Election of Candidate The candidate only ever stands once for this particular election and so we cannot perform "repeated trials". In a frequentist setting we construct "virtual" trials of the election process. The probability of the candidate winning is defined as the relative frequency of the candidate winning in the "virtual" trials as a fraction of all trials. As new data arrives, both beliefs are rationally updated by the Bayesian procedure. A key point is that different intelligent individuals can have different opinions and thus different prior beliefs , since they have differing access to data and ways of interpreting it. However, as both of these individuals come across new data that they both have access to, their potentially differing prior beliefs will lead to posterior beliefs that will begin converging towards each other, under the rational updating procedure of Bayesian inference. In the Bayesian framework an individual would apply a probability of 0 when they have no confidence in an event occuring, while they would apply a probability of 1 when they are absolutely certain of an event occuring. If they assign a probability between 0 and 1 allows weighted confidence in other potential outcomes. An example question in this vein might be "What is the probability of rain occuring given that there are clouds in the sky? Or in the language of the example above: The probability of rain given that we have seen clouds is equal to the probability of rain and clouds occuring together, relative to the probability of seeing clouds at all. We can actually write: So that by substituting the defintion of conditional probability we get: This is a very natural way to think about probabilistic events. As more and more evidence is accumulated our prior beliefs are steadily "washed out" by any new data. Consider a rather nonsensical prior belief that the Moon is going to collide with the Earth. For every night that passes, the application of Bayesian inference will tend to correct our prior belief to a posterior belief that the Moon is less and less likely to collide with the Earth, since it remains in orbit. In order to demonstrate a concrete numerical example of Bayesian inference it is necessary to introduce some new notation. Firstly, we need to consider the concept of parameters and models. The model is the actual means of encoding this flip mathematically. In this instance, the coin flip can be modelled as a Bernoulli trial. Bernoulli Trial A Bernoulli trial is a random experiment with only two outcomes, usually labelled as "success" or "failure", in which the probability of the success is exactly the same every time the trial is carried out. However, if you consider it for a moment, we are actually interested in the alternative question - "What is the probability that the coin is fair or unfair , given that I have seen a particular sequence of heads and tails? So how do we get between these two probabilities? Our prior view on the probability of how fair the coin is. After seeing 4 heads out of 8 flips, say, this is our updated view on the fairness of the coin. If we knew the coin was fair, this tells us the probability of seeing a number of heads in a particular number of flips. The entire goal of Bayesian inference is to provide us with a rational and mathematically sound procedure for incorporating our prior beliefs, with any evidence at hand, in order to produce an updated posterior belief. What makes it such a valuable technique is that posterior beliefs can themselves be used as prior beliefs under the generation of new data. Coin-Flipping Example In this example we are going to consider multiple coin-flips of a coin with unknown fairness. We will use Bayesian inference to update our beliefs on the fairness of the coin as more data i. At the start we have no prior belief on the fairness of the coin, that is, we can say that any level of fairness is equally likely. We will use a uniform distribution as a means of characterising our prior belief that we are unsure about the fairness. We are going to use a Bayesian updating procedure to go from our prior beliefs to posterior beliefs as we observe new coin flips. This is carried out using a particularly mathematically succinct procedure using conjugate priors. It will however provide us with the means of explaining how the coin flip example is carried out in practice. The uniform distribution is actually a more specific case of another probability distribution, known as a Beta distribution. Conveniently, under the binomial model, if we use a Beta distribution for our prior beliefs it leads to a Beta distribution for our posterior beliefs. This is an extremely useful mathematical result, as Beta distributions are quite flexible in modelling beliefs. At this stage, it just allows us to easily create some visualisations below that emphasises the Bayesian procedure! In the following figure we can see 6 particular points at which we have carried out a number of Bernoulli trials coin flips. In the first sub-plot we have carried out no trials and hence our probability density function in this case our prior density is the uniform distribution. The next panel shows 2 trials carried out and they both come up heads. Our Bayesian procedure using the conjugate Beta distributions now allows us to update to a posterior density. Notice how the weight of the density is now shifted to the right hand side of the chart. This indicates that our prior belief of equal likelihood of fairness of the coin, coupled with 2 new data points, leads us to believe that the coin is more likely to be unfair biased towards heads than it is tails. The following two panels show 10 and 20 trials respectively. Notice that even though we have seen 2 tails in 10 trials we are still of the belief that the coin is likely to be unfair and biased towards heads. After 20 trials, we have seen a few more tails appear. Hence we are now starting to believe that the coin is possibly fair. Bayesian update procedure using the Beta-Binomial

Model Thus it can be seen that Bayesian inference gives us a rational procedure to go from an uncertain situation with limited information to a more certain situation with significant amounts of data. In the next article we will discuss the notion of conjugate priors in more depth, which heavily simplify the mathematics of carrying out Bayesian inference in this example. For each new set of data, we update our current prior belief to be a new posterior. This is carried out using what is known as the Beta-Binomial model. It will be the subject of a later article!

## 7: ELI5: Bayesian Statistics : statistics

*Bayesian statistics is one of my favorite topics on this blog. But, the more I write the harder it is to find everything! I've decided to build this guide the organize these posts.*

Doing it making sense of statistics â€” 5 â€” Bayesian statistics Posted on by alan Bayesian reasoning allows one to make strong statements about the probability of things based on evidence. This can be used for internal algorithms, for example, to make adaptive or intelligent interfaces, and also for a form of statistical reasoning that can be used as an alternative to traditional hypothesis testing. However, to do this you need to be able to quantify in a robust and defensible manner what are the expected prior probabilities of different hypothesis before an experiment. This has potential dangers of confirmation bias, simply finding the results you thought of before you start, but when there are solid grounds for those estimates it is precise and powerful. Crucially it is important to remember that Bayesian statistics is ultimately about quantified belief, not probability. It is common knowledge that all Martians have antennae just watch a sci-fi B-movie. However, humans rarely do. You decide to conduct a small experiment. There are two hypotheses: H0 â€” there are no Martians in the High Street H1 â€” the Martians have landed You go out into the High Street and the first person you meet has antennae. Should you call the Men in Black? You pull a coin out of your pocket, toss it 10 times and it is a head every time. The chances of this given it is a fair coin is just 1 in ; do you assume that the coin is fixed or that it is just a fluke? Instead imagine it is not a coin from your pocket, but a coin from a stall-holder at a street market doing a gambling game â€” the coin lands heads 10 times in a row, do you trust it? Now imagine it is a usability test and ten users were asked to compare your new system that you have spent many weeks perfecting with the previous system. All ten users said they prefer the new system â€¦ what do you think about that? Clearly in day-to-day reasoning we take into account our prior beliefs and use that alongside the evidence from the observations we have made. Bayesian reasoning tries to quantify this. You turn that vague feeling that it is unlikely you will meet a Martian, or unlikely the coin is biased, into solid numbers â€” a probability. We know we are unlikely to meet a Martiona, but how unlikely. Now, just as in the previous scenario, you go out into the High Street and the first person you meet has antennae. You combine this information, including the conditional probabilities given the person is Martian or human, to end up with a revised posterior probability of each: The answer you get does depend on the prior. You might have started out with even less belief in the possibility of Martians landing, perhaps 1 in a billion, in which case even after seeing the antennae, you would still think it a million times more likely the person is human, but that is different from the initial thousand to one posterior. So, returning once again to the job of statistics diagram, Bayesian inference is doing the same thing as other forms of statistics, taking the sample, or measurement of the real world, which includes many random effects, and then turning this back to learn things about the real world. The difference in Bayesian inference is that it also asks for a precise prior probability, what you would have thought was likely to be true of the real world before you saw the evidence of the sample measurements. The process is very mathematically sound and gives a far more precise answer than traditional statistics, but does depend on you being able to provide that initial precise prior. This is very important, if you do not have strong grounds for the prior, as is often the case in Bayesian statistics, you are dealing with quantified belief set in the language of probability, not probabilities themselves.. We are particularly interested in the use of Bayesian methods as an alternative way to do statistics for experiments, surveys and studies. However, Bayesian inference can also be very successfully used within an application to make adaptive or intelligent user interfaces. This is partly because in this example there is a clear prior probability distribution and the meaning of the posterior is also clear. This will hopefully solidify the concepts of Bayesian techniques before looking at the slightly more complex case of Bayesian statistical inference. This is the front page of the Isle of Tiree website. Imagine we have gathered extensive data on use by different groups, perhaps by an experiment or perhaps based on real usage data. Cleary different users access the site in different ways, so perhaps we would like to customise the site in some way for different types of users. Consider visitors to the site. On average 20 of these will be surfers and 80 non-surfers. Of the 80 non-surfers,  For visitors who made different first choices and hence lower chance of being a surfer , we might present the site differently. This is precisely the kind of reasoning that is often used by advertisers to target marketing and by shopping sites to help make suggestions. Note here that the prior distribution is given by solid data as is the likelihood:

## 8: Bayesian inference - Wikipedia

*Thus in the Bayesian interpretation a probability is a summary of an individual's opinion.A key point is that different (intelligent) individuals can have different opinions (and thus different prior beliefs), since they have differing access to data and ways of interpreting it.*

## 9: A Guide to Bayesian Statistics â€” Count Bayesie

*ticians think Bayesian statistics is the right way to do things, and non-Bayesian methods are best thought of as either approximations (sometimes very good ones!) or alternative methods that are only to be used when the Bayesian solution would be too hard to calculate.*

# BAYESIAN STATISTICS 5 pdf

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