

Bayesian Statistics

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The Reverend Thomas Bayes, began the objective Bayesian theory, by solving a particular problem

- Suppose X is Binomial (n,p) ; an 'objective' belief would be that each value of X occurs equally often.
- The only prior distribution on p consistent with this is the uniform distribution.
- Along the way, he codified Bayes theorem.
- Alas, he died before the work was finally published in 1763.



REV. T. BAYES

The real inventor of Objective Bayes was Simon Laplace (also a great mathematician, astronomer and civil servant) who wrote *Théorie Analytique des Probabilités* in 1812

- He established the 'central limit theorem' showing that, for large amounts of data, the posterior distribution is asymptotically normal (and the prior does not matter).
- He virtually always utilized a 'constant' prior density (reasons: CLT; parameter choice; robustness).
- He solved very many applications, especially in physical sciences.
- He had numerous methodological developments, e.g., a version of the Fisher exact test.
- Later in his life he invented frequentist statistics.



What's in a name, part I

- It was called *probability theory* until 1838.
- From 1838-1950, it was called *inverse probability*, apparently so named by Augustus de Morgan.
- From 1950 on it was called *Bayesian analysis* (as well as the other names); for why, see Fienberg (2006).



AUGUSTUS DE MORGAN

Brief History of Bayesian Statistics

1764 -1838: called “probability theory”



1838 - 1945: called “inverse probability” (named by Augustus de Morgan)



1945 - : called “Bayesian analysis” (Refer to [Steve Fienberg, 2006](#))

1955 - : Emergence of Bayesian analysis, and development of Bayesian testing and model selection. ↓

Harold Jeffreys: fixed the logical flaw in inverse probability (objective Bayesian analysis)



Bruno de Finetti and others: developed the logically sound subjective Bayes school.

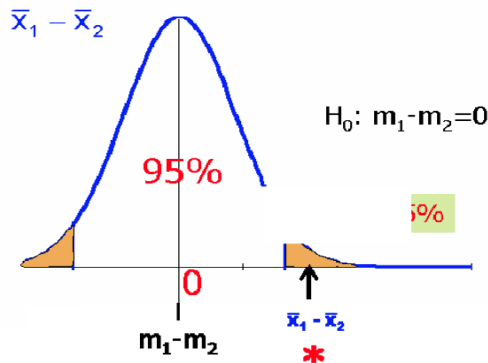
Motivating example

- ▶ Assess whether a selected population for has a higher growth rate than a control population.
- ▶ Classical statistics: the hypothesis to be tested is that there is no difference between the two treatments
- ▶ Before making the experiment, the error of rejecting this hypothesis when it is actually true is fixed at a level of 5%)
- ▶ Repeating the experiment an infinite number of times difference between the averages of these samples ($\bar{x}_1 - \bar{x}_2$)
- ▶ true value of the difference between selected and control populations ($m_1 - m_2$)

Motivation

If our sample lies in the shadow area,

- ▶ There is no difference between treatments, our sample is a **rare** one
- ▶ The treatments are different, and repeating an infinite number of times the experiment, $(\bar{x}_1 - \bar{x}_2)$ will not be distributed around zero but around an unknown value different from zero.



Bases of Bayesian inference

- ▶ Natural to find the most probable value of a parameter based on our data rather than to find which value of this parameter, if it would be the true value, would produce our data with a highest probability.
- ▶ To make probability statements based on our data we need some prior information and it is not clear how to introduce this prior information in our analysis or how to express lack of information using probability statements.
- ▶ Apply Bayes Theorem!

- ▶ A, B are 2 events

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

- ▶ Interested in assessing effect of a drug on growth rate of a rabbit population
- ▶ Selected group of rabbits and a control group in which growth rate has been measured.
- ▶ S : Effect of the drug the selected group, C : Effect of the control group, Interested in assessing $(S - C)$.
- ▶ Want to find the probabilities of all possible values of $(S - C)$ according to the information provided by our data.
- ▶ This can be expressed as $P(S - C | y)$

- ▶ The posterior distribution

$$P(S - C | y) = \frac{P(y | S - C)P(S - C)}{P(y)}$$

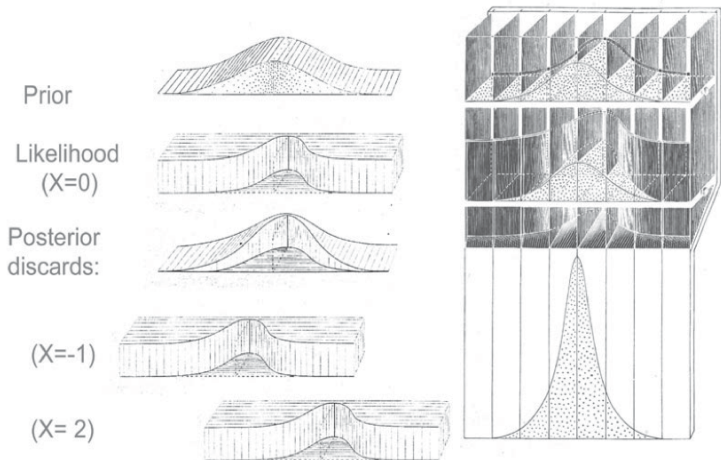
- ▶ $P(y | S - C)$: distribution of the data for given value of the unknown, often known or assumed to be known from reasonable hypotheses.
- ▶ $P(S - C)$: Prior probability of the difference between selected and control group independent of data.
- ▶ $P(y)$: the probability of the sample.

Summarizing Bayesian inference: The general set-up

- ▶ General set up: $y_i \sim f(y | \theta), \theta \sim \Pi(\theta)$ &
- ▶ Obtain posterior distribution $\Pi(\theta | y_1, \dots, y_n)$ as

$$\Pi(\theta | y_1, \dots, y_n) = \frac{\prod_{i=1}^n f(y_i | \theta) \Pi(\theta)}{\int_{\theta} \prod_{i=1}^n f(y_i | \theta) \Pi(\theta)}$$

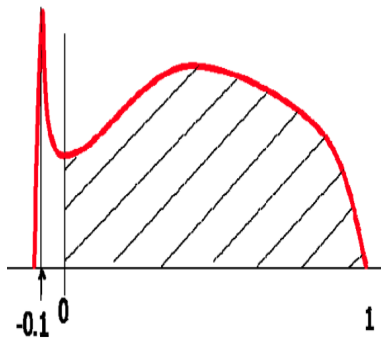
1877 Algorithm: Normal Prior-Posterior

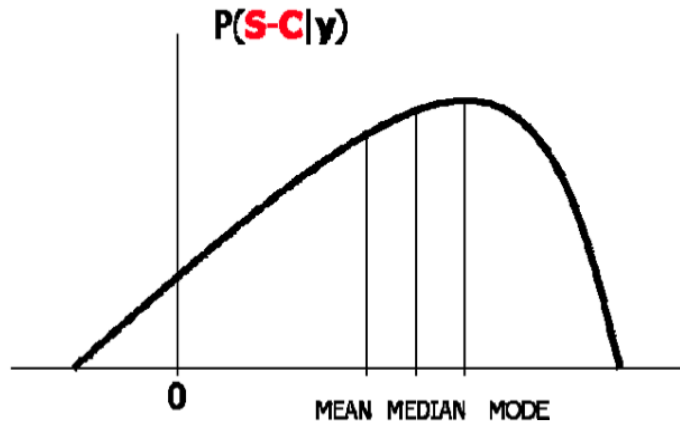


- ▶ Measure of Discrepancy - $R = E_{\theta, y_1, \dots, y_n} L(\hat{\theta}(y_1, \dots, y_n), \theta)$
 1. Posterior mean: minimizes R with squared error L
 2. Posterior median: minimizes R with L as absolute deviation
 3. Posterior mode minimizes R with L as the $0 - 1$ loss.

Loss functions

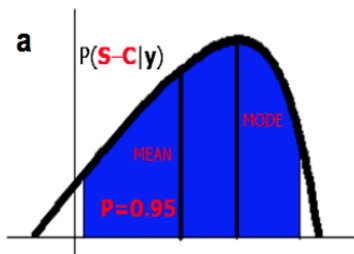
- ▶ **Mean:** 2-fold inconvenience: penalizes high errors, this risk function is not invariant to transformations
- ▶ **Mode:** signifies the most probable value, easier to calculate in the pre-MCMC era - may not be representative
- ▶ **Median:** true value has a 50% of probability of being higher or lower than the median. Attractive loss - invariant to one-to-one transformations



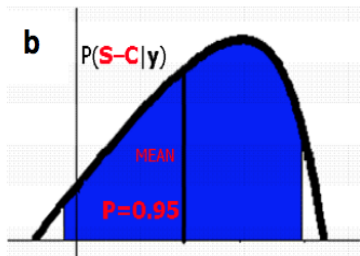


- ▶ **Confidence interval:** How often the interval contains the parameter if the samples are generated according to the truth
- ▶ **Bayesian credible intervals:** Given the data, want to construct interval that encloses 95% of the posterior probability of the parameter
- ▶ $P(\theta \in [L(y), U(y)] | y) = 0.95$
- ▶ Can find the shortest interval with a 95% credible interval (called the **Highest posterior density interval at 95%**).

Highest posterior density credible interval



Shortest interval with $P=0.95$



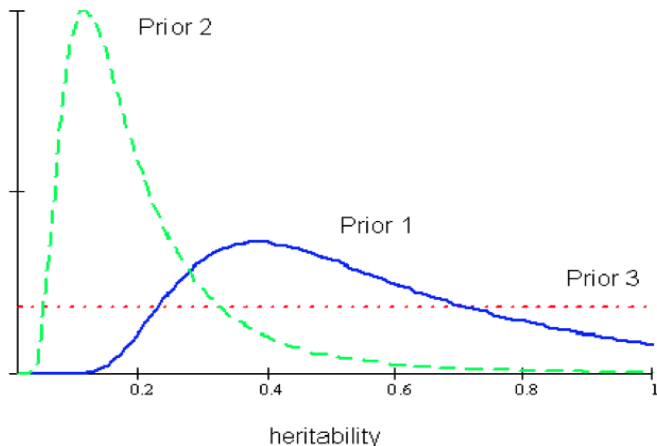
Symmetric interval with $P=0.95$

Example 1: Binomial-Beta model

- ▶ $X \sim \text{Bin}(n, p), p \sim \text{Beta}(a, b)$
- ▶ $p \mid X \sim \text{Beta}(a + X, n - X + b)$

How to choose a and b , Vague / No prior information

- ▶ Toss a coin n times - want to estimate the probability of head
- ▶ Three states of beliefs were tested
- ▶ **Prior 3** called objective or non-informative by Bayesian statisticians



Posterior mean for the Beta-Binomial problem

- ▶ Posterior mean:

$$\begin{aligned} E(p | X) &= \frac{a + X}{a + b + n} \\ &= \frac{X}{n} \frac{n}{\alpha + \beta + n} + \frac{a}{a + b} \frac{a + b}{a + b + n} \end{aligned}$$

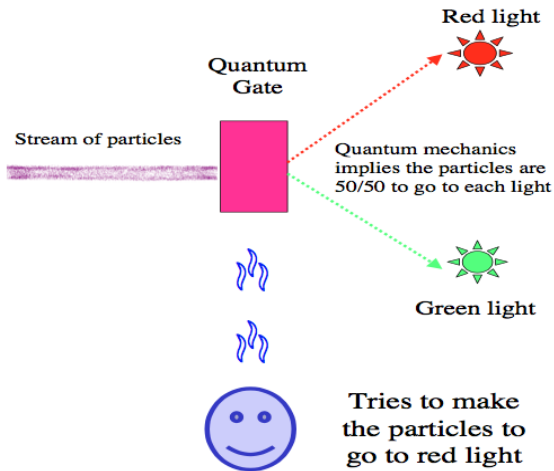
Posterior mean for the Normal-Normal model

- ▶ $Y_1, \dots, Y_n \sim N(\mu, 1), \mu \sim N(\mu_0, 1)$
- ▶ $\mu \mid Y_1, \dots, Y_n \sim N\left(\frac{n\bar{X} + \mu_0}{n+1}, \frac{1}{n+1}\right)$
- ▶ Posterior mean for $\mu = \frac{n\bar{X} + \mu_0}{n+1}$.
- ▶ Posterior mean = $\text{MLE} * \frac{(\text{precision of MLE})}{(\text{precision of MLE} + \text{prior precision})} +$
 $\text{prior mean} * \frac{(\text{prior precision})}{(\text{precision of MLE} + \text{prior precision})}$
- ▶ **Conjugate prior:** Posterior distribution has the same family as the prior distribution

Bayesian testing: Some Anomalies

- ▶ Psychokinesis Example
- ▶ Does a subject possess *Psychokinesis*?
- ▶ Schmidt, Jahn and Radin (1987) used electronic and quantum-mechanical random event generators with visual feedback; the subject with alleged psychokinetic ability tries to “influence” the generator.

Some Anomalies: Psychokinesis Example



- ▶ Each “particle” is a Bernoulli trial (red = 1, green = 0), θ = probability of “1”
- ▶ $n = 104,490,000$ trials
- ▶ $X = \#$ successes
- ▶ $X \sim \text{Binomial}(n, \theta)$, $x = 52,263,470$ is the actual observation.
- ▶ To test $H_0 : \theta = 1/2$ (subject has no influence) versus $H_1 : \theta \neq 1/2$ (subject has influence)
- ▶ P-value = $P_{\theta=1/2}(|X - n/2| > |x - n/2|) \approx 0.0003$.
- ▶ Is there strong evidence against H_0 (i.e., strong evidence that the subject influences the particles) ?

- ▶ Prior distribution for hypothesis: $P(H_i)$ = prior probability that H_i is true, $i = 0, 1$;
- ▶ On $H_1 : \theta \neq 1/2$, let $\pi(\theta)$ be the prior density for θ .
- ▶ Subjective Bayes: choose the $P(H_i)$ and $\pi(\theta)$ based on personal beliefs.
- ▶ Objective (or default) Bayes: choose $P(H_0) = P(H_1) = 0.5$, $\pi(\theta) = 1$ on $0 < \theta < 1$.

Posterior probability of hypotheses:

$$\begin{aligned} P(H_0 | x) &= \text{probability that } H_0 \text{ true, given data, } x \\ &= \frac{f(x | \theta = 1/2)P(H_0)}{f(x | \theta = 1/2)P(H_0) + Pr(H_1) \int f(x | \theta)\pi(\theta)d\theta}. \end{aligned}$$

For the objective prior,

$$P(H_0 | x = 52,263,470) \approx 0.92$$

(recall, p-value $\approx .0003$) Posterior density on $H_1 : \theta \neq 1/2$ is

$$\pi(\theta | x, H_1) \propto \pi(\theta)f(x | \theta) \propto 1 \times \theta^x(1 - \theta)^{n-x},$$

which is $\text{Be}(\theta | 52263470, 52226530)$.

Bayes Factor: An objective alternative to choosing $P(H_0) = P(H_1) = 1$ is to report the

$$\begin{aligned}\text{Bayes factor} &= \frac{\text{likelihood of observed data under } H_0}{\text{'average' likelihood of observed data under } H_1} \\ &= \frac{f(x | \theta = 1/2)}{\int_0^1 f(x | \theta) \pi(\theta) d\theta} \approx 12.\end{aligned}$$

$$\frac{P(H_0 | x)}{P(H_1 | x)} = \frac{P(H_0)}{P(H_1)} \times BF_{01}$$

Posterior odds = Prior odds \times Bayes factor (BF_{01})

so BF_{01} is often thought of as “the odds of H_0 to H_1 provided by the data”.

Clash between p-values and Bayes answers

- ▶ In the example, p-value is **.0003**, but
- ▶ The objective posterior probability of the null is **0.92**; (Bayes factor gives **12 to 1** odds in favor of the null).
- ▶ Was the prior on θ inappropriate? (Few would say it was unfair to give H_0 prior probability of **1/2**.)
- ▶ But it was a neutral, objective prior.
- ▶ Any prior produces Bayes factors orders of magnitude larger than the p-value.

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AIDS MILESTONE

New path for HIV vaccine

Some in study protected from infection, but trial raises more questions

By Karen Kaplan
and Thomas H. Maugh II
Los Angeles Times

Hours after HIV researchers announced the achievement of a milestone that had eluded them for a quarter of a century, reality began

to set in: Tangible progress could take another decade.

A Thai and American team announced early Thursday in Bangkok that they had found a combination of vaccines providing modest protection against infection with the virus that causes AIDS, unleashing excitement worldwide. The idea of a vaccine to prevent infection with the human immunodeficiency virus, HIV, had long been

frustrating and fruitless.

But by Thursday afternoon, initial euphoria gave way to a more sober assessment. There is still a very long way to go before reaching the goal of producing a vaccine that reliably shields people from HIV.

Some researchers questioned whether the apparent 31 percent reduction in infections was a sta-

See **VACCINE**, Page 14



A researcher during the Thai phase III HIV Vaccine Trial, also known as RV 144, tests the "prime-boost" combination of two vaccines.

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- ▶ *Alvac* had shown no effect, *Aidsvax* had shown no effect
- ▶ Question: Would *Alvac* as a primer and *Aidsvax* as a booster work?
- ▶ The Study: Conducted in Thailand with 16,395 individuals from the general (not high-risk) population:
 - ▶ 71 HIV cases reported in the 8198 individuals receiving placebos
 - ▶ 51 HIV cases reported in the 8197 individuals receiving the treatment

The test that was likely performed:

- ▶ Let p_1 and p_2 denote the probability of HIV in the placebo and treatment populations, respectively.
- ▶ Test $H_0 : p_1 = p_2$ versus $H_1 : p_1 > p_2$ (vaccines were not live, so $p_1 < p_2$ can probably be ignored)
- ▶ Normal approximation okay, so

$$z = \frac{\hat{p}_1 - \hat{p}_2}{\sigma_{\hat{p}_1 - \hat{p}_2}} = \frac{0.00866 - 0.00622}{0.00134} = 1.82.$$

is approximately $N(\theta, 1)$, where $\theta = (p_1 - p_2)/(0.00134)$.

- ▶ We thus test $H_0 : \theta = 0$ versus $H_1 : \theta > 0$, based on z .
- ▶ Observed $z = 1.82$, so the (one-sided) p-value is **0.034**.

- ▶ Prior distribution: $P(H_i)$ = prior probability that H_i is true, $i = 0, 1$.
- ▶ On $H_1 : \theta > 0$, let $\pi(\theta)$ be the prior density for θ .
- ▶ Objective (or default) Bayes: choose $P(H_0) = P(H_1) = 1/2$
- ▶ $\pi(\theta) = \text{Uniform}(0, 6.46)$, which arises from assigning: uniform for p_2 on $0 < p_2 < p_1$, and plug in for p_1 .
- ▶ For the objective prior, $P(H_0 | z = 1.82) \approx 0.47$, whereas one-sided p-value is 0.034.