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UNIVERSITY OF CONNECTICUT

Bayesian Computation

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CAS Antitrust Notice

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General differences between Bayesian and Frequntist statistics

- Frequentist
  - Parameters are fixed but unknown
  - Probability based on repeated samples (sampling distribution)
  - Uses asymptotic approximations
- Bayesian
  - Parameters are random variables
  - Subjective prior combined with data
  - No asymptotic approximations

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Confidence Intervals

- What you have to say: “We are 95% confident that the population mean is between X and Y” (frequentist)
- What you want to say: “There is a 95% probability that the population mean is between X and Y” (Bayesian)

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Hypothesis Testing

- P-value: "Given the null hypothesis is true, the p-value is the probability that you obtain a sample statistic as extreme or more extreme than the observed statistic." (frequentist)
- What you want to find: "What is the probability that my null hypothesis is true?" (Bayesian)

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Any other reasons I should use Bayesian methods?

- Ability to incorporate expert opinion and prior knowledge in a structured way.
- Ability to easily find any quantities of interest (e.g. 95% interval for the mean or variance of a gamma distributed loss)
- Easier to set up and estimate complicated models

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Why doesn't everyone learn Bayesian statistics first?

- Thomas Bayes died in 1761
- Bayes' Theorem: $\Pr(\theta|Y) = \frac{\Pr(Y|\theta)\Pr(\theta)}{\Pr(Y)}$
- Seems simple enough, but the difficulty lies in the denominator, $\Pr(Y)$
- $P(Y) = \int_{\Theta} \Pr(Y|\theta)\Pr(\theta)\,d\theta$
- There are many examples where this integral can be solved analytically

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Why doesn't everyone learn Bayesian statistics first?

- But that is only using one parameter, with two

$$\int_{\Theta_1}\int_{\Theta_2} \Pr(Y|\theta_1,\theta_2)\Pr(\theta_1,\theta_2)\,d\theta_2\,d\theta_1$$

- Or more generally . . .

$$\int_{\Theta_1}\cdots\int_{\Theta_k} \Pr(Y|\theta_1,\dots,\theta_k)\Pr(\theta_1,\dots,\theta_k)\,d\theta_k\cdots d\theta_1$$

- No matter how much you love math, you are not going to solve this analytically (outside of a few restrictive examples).

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Why doesn't everyone learn Bayesian statistics first?

- To estimate $\Pr(Y)$ numerically requires:
  - Methodology (MCMC, much work in late 1980s through 1990s)
  - Computing power
- That is why frequentist statistics were preferred in essentially every practical application before 1990.
- That is a lot of history to fight against.

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Bayesian Computing

- Now there are various pieces of software which make writing and fitting Bayesian models much simpler.
  - WinBUGS
  - JAGS
  - STAN
- Go ahead and try it. I think you will like it.

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What about the subjectivity?

- "Bayesian methods are not scientific because of the subjective prior. Frequentist methods remove that bias."
- Let me respond to that assertion with an example
  - Suppose in 12 independent tosses of a coin, I observe 9 heads.
  - I wish to test the following hypotheses
    - $H_o: \theta = 0.5$
    - $H_a: \theta > 0.5$
  - θ is the true probability of a head.

Source: Lindley, D. V. and Phillips, L. D. (1976) Inference for a Bernoulli Process (a Bayesian view). *Amer. Statist.*, ***30***, *112-119*

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What about the subjectivity?

Knowing only that information, there are two possible sampling distributions.

1. Binomial, $n = 12$ fixed beforehand

$$L_1(\theta) = \binom{n}{x}\theta^x(1-\theta)^{n-x} = \binom{12}{9}\theta^9(1-\theta)^3$$

2. Negative binomial, flip until third tail

$$L_2(\theta) = \binom{r+x-1}{x}\theta^x(1-\theta)^r = \binom{11}{9}\theta^9(1-\theta)^3$$

Source: Lindley, D. V. and Phillips, L. D. (1976) Inference for a Bernoulli Process (a Bayesian view). *Amer. Statist.*, ***30***, *112-119*

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What about the subjectivity?

And our sample will give two different p-values

1. Binomial

$$\alpha_1 = \Pr_{\theta=0.5}(X \geq 9) = \sum_{j=9}^{12} \binom{12}{j} \theta^j (1-\theta)^{12-j} = 0.075 > 0.05$$

2. Negative binomial

$$\alpha_1 = \Pr_{\theta=0.5}(X \geq 9) = \sum_{j=9}^{\infty} \binom{2+j}{j} \theta^j (1-\theta)^3 = 0.0325 < 0.05$$

Source: Lindley, D. V. and Phillips, L. D. (1976) Inference for a Bernoulli Process (a Bayesian view). *Amer. Statist.*, ***30**, 112-119*

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What about the subjectivity?

- Only the results should be relevant, not how the experiment is monitored
- This goes back to the definition of the p-value, "observations more extreme" are unobserved.
- Not only is there subjectivity in frequentist statistics as well, it gives inferential weight to unobserved samples

Source: Lindley, D. V. and Phillips, L. D. (1976) Inference for a Bernoulli Process (a Bayesian view). *Amer. Statist.*, ***30**, 112-119*

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Should we always use Bayesian Methods?

- I want to say "YES!!"
- But no, Bayesian methods
  – are more computationally intensive (sometimes impossibly)
  – require tests for prior sensitivity/robustness
  – Difficult to confirm Markov Chain convergence

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What else is in the chapter?

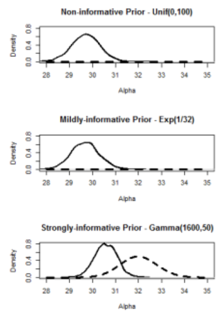
- Basic Computational Methods
  – Gibbs
  – Metropolis-Hastings
  – Convergence metrics
- Prior Distributions
  – Prior elicitation
  – Noninformative priors
  – Prior sensitivity
- R and WinBUGS code for examples
- Many references for how to use Bayesian methods in a wide variety of actuarial applications

Prior Sensitivity Example

Auto Claim Severity Data

$y \sim \text{Gamma}(\alpha, \beta)$
$\beta \sim \text{Unif}(0, 1000)$

Prior distributions:
$\alpha \sim \text{Unif}(0, 1000)$
$\alpha \sim \text{Exp}(1/32)$
$\alpha \sim \text{Gamma}(1600, 50)$



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