Bayesian Data Analysis, class 3b

Andrew Gelman

Chapter 3: Introduction to multiparameter models (part 2)

Discussion of homework due beginning of Class 3b

- Theory problem
- Computing problem
- Applied problem

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Theory problem

- Prove that a posterior density is proper by bounding the integral over the range $(\alpha, \beta) \in (-\infty, \infty) \times (-\infty, \infty)$

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Computing problem

- Compute posterior density on a grid

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Applied problem

- Paired experiment on chicken brains
- How does the effect depend on frequency? Is there evidence from the data that the effect is not constant across frequencies?
- Should we use the sham data in the estimates?

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3. Introduction to multiparameter models (part 2)

- Logistic regression
- Computation for a two-parameter model
- Inference for a ratio
- Elementary modeling and computation

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3.7. Example: analysis of a bioassay experiment

Dose, x_i (log g/ml)	Number of animals, n_i	Number of deaths, y_i
−0.86	5	0
−0.30	5	1
−0.05	5	3
0.73	5	5

- Modeling the outcomes:
  - $y_i|\theta_i \sim \text{Binomial}(n_i, \theta_i)$, for $i = 1, \ldots, 4$
  - List all the assumptions in that model
- Prior distribution

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- Prior distribution
  - $\theta_i = \text{logit}^{-1}(\alpha + \beta x_i)$, for $i = 1, \ldots, 4$
  - $p(\alpha, \beta) \propto 1$
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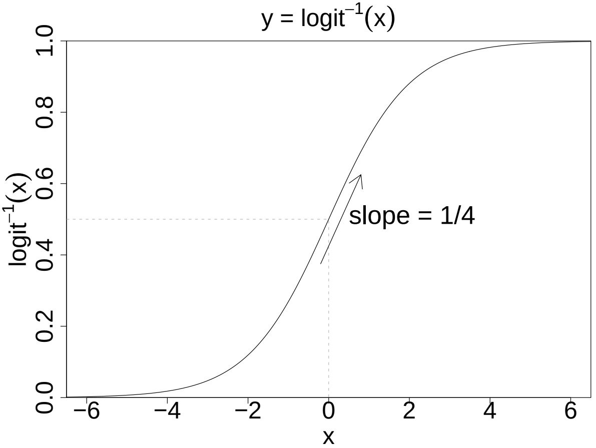
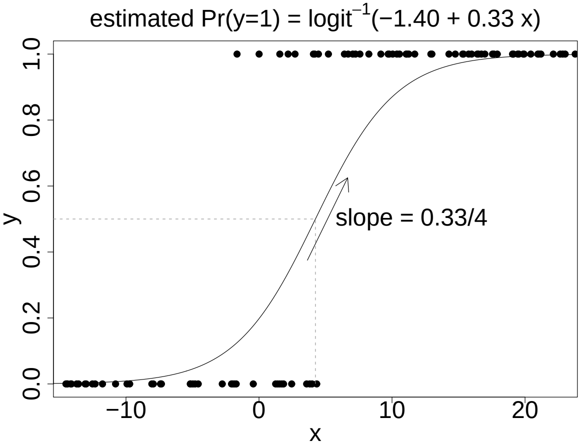
Logistic regression



A clean example



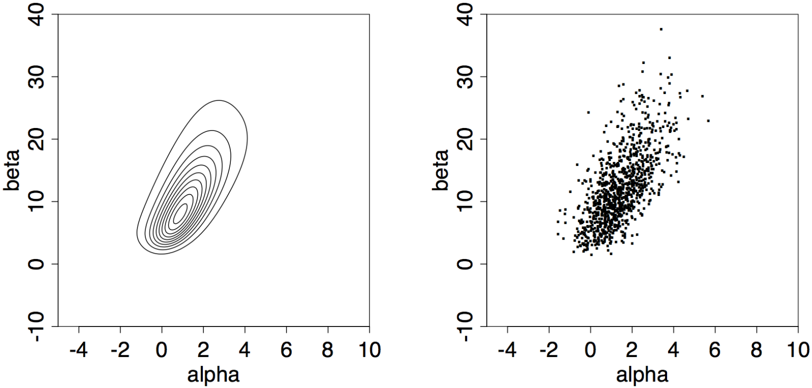
Posterior computation

- Unnormalized posterior density:

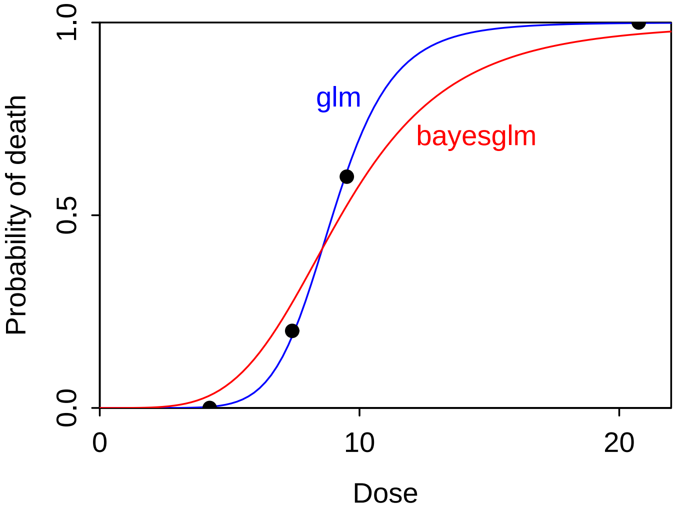
$$
\begin{aligned}
p(\alpha, \beta | y) &\propto p(\alpha, \beta) \prod_{i=1}^{k} p(y_i | \alpha, \beta, n_i, x_i) \\
&= 1 \cdot [\text{logit}^{-1}(\alpha + \beta x_i)]^{y_i} [1 - \text{logit}^{-1}(\alpha + \beta x_i)]^{n_i - y_i}
\end{aligned}
$$

- Different ways to write the R function:
  - ```
    post <- function (a,b,y,n,x){
    prod((invlogit(a+b*x))^y*(1-invlogit(a+b*x))^(n-y))}
    ```
  - ```
    post <- function (a,b,y,n,x){
    prod (dbinom (y, n, invlogit(a+b*x)))}
    ```
  - ```
    log_post <- function (a,b,y,n,x){
    sum (dbinom (y, n, invlogit(a+b*x), log.p=TRUE))}
    ```
- Contour plot (need crude estimate)
- Posterior simulation on grid
    ```

Contour plot and posterior simulation

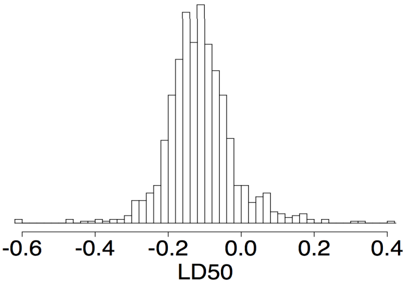


Bayesian estimates given noninformative and weakly informative priors



Inference for LD50

- A qoi!
- Lethal dose 50%: $p = 0.5$, so $\text{logit}^{-1}(\alpha + \beta x) = 0.5$, that is $x = -\alpha/\beta$
- From posterior simulations of (α, β), get simulations of LD50 $= -\alpha/\beta$:



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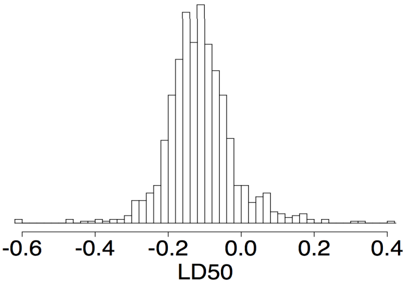

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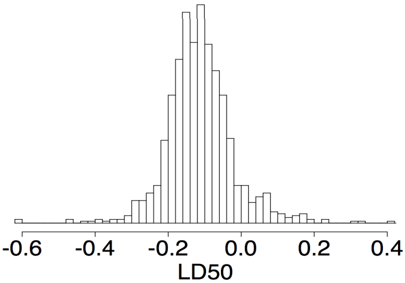

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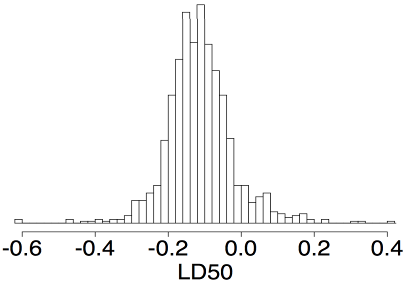

But LD50 is not such a great qoi

- LD50 $= -\alpha/\beta$
- The x-value where the probability curve crosses 50%
- What if β is near 0?
- What is β could be positive or negative?
- The model breaks down

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Difficulties with ratios where the denominator can be positive or negative

- LD50
- Ratio of regression coefficients
- Incremental cost-effectiveness ratio
- Instrumental variables
- Fieller-Creasy problem

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Ratio of regression coefficients

The quote:

> *"Economic freedom is almost 50 times more effective than democracy in restraining nations from going to war. . . . . When measures of both economic freedom and democracy are included in a statistical study, economic freedom is about 50 times more effective than democracy in diminishing violent conflict. The impact of economic freedom on whether states fight or have a military dispute is highly significant while democracy is not a statistically significant predictor of conflict."*

Table 2.1: Effect of Economic Freedom on Militarized Interstate Disputes (MIDs)

Variable	Coefficient	(Standard Error)
Economic Freedom	-0.567^{**}	(0.179)
Capabilities	2.777	(8.491)
Population	$2.08 \times 10^{-6*}$	(8.18×10^{-7})
Major Power?	0.853	(1.133)
Democracy Score	-0.011	(0.065)
Defense Pact?	-0.628	(0.482)
GDP per Capita	8.01×10^{-6}	(8.04×10^{-5})
Trade Openness	1.57×10^{-7}	(1.50×10^{-6})
_spline1	$6.08 \times 10^{-4**}$	(2.32×10^{-4})
_spline2	$-4.53 \times 10^{-4*}$	(1.76×10^{-4})
_spline3	$1.19 \times 10^{-4*}$	(4.87×10^{-5})
Intercept	-0.381	(1.210)
N	2519	
Log-likelihood	-161.719	
$X^2_{(11)}$	160.564	
Significance levels:	†: 10% *: 5%	**: 1%

- "Economic freedom is about 50 times more effective than democracy in diminishing violent conflict"?

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Incremental cost-effectiveness ratio

- Compare two medical treatments:
  - Old treatment has cost C_1 and efficacy E_1
  - New treatment has cost C_2 and efficacy E_2
- Incremental cost-effectiveness ratio, $\frac{C_2 - C_1}{E_2 - E_1}$
- Estimated ratio, $\frac{\widehat{C}_2 - \widehat{C}_1}{\widehat{E}_2 - \widehat{E}_1}$
- Now throw in some posterior uncertainty
- Four quadrants

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Instrumental variables

- Instrument I, intermediate outcome z, ultimate outcome y
- Instrumental variables estimate: $\frac{\text{coef of regression of } y \text{ on } I}{\text{coef of regression of } z \text{ on } I}$
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Fieller-Creasy problem

- $x_1, \ldots, x_n \sim \mathrm{N}(\theta_x, \sigma^2)$, $y_1, \ldots, y_n \sim \mathrm{N}(\theta_y, \sigma^2)$
- Goal: inference about θ_y/θ_x
- Notoriously difficult to get an interval estimate with clsoe to 95% (or any specified) coverage
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The folk theorem and the Pinocchio principle

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- The Pinocchio Principle: A model that is created solely for computational reasons can take on a life of its own

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3.8. Elementary modeling and computation

- Write the likelihood
- Set down a weakly-informative prior density
- Write the unnormalized posterior density as an R function
- Lay out a grid based on crude estimate and standard error
- Posterior simulations
- Qoi's and predictions

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- Marginal and conditional inference, $\phi|y$ and $\theta|\phi, y$
- Standard conjugate families
- Direct computation
- Interpretation of qoi's

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Summary of Chapter 3

- Work with the joint distribution
- Marginal and conditional inference, $\phi|y$ and $\theta|\phi, y$
- Standard conjugate families
- Direct computation
- Interpretation of qoi's

Homework due beginning of class 4b

- All assignments are at http://www.stat.columbia.edu/~gelman/bda.course/homeworks.pdf
  - Theory problem: normal appxoximation to a simple posterior density
  - Computing problem: simulate data and then fit the model
  - Applied problem: set the joint prior distribution for two hyperparameters

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