Bayesian Computation

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Class 4, 28 Sept 2011
Review of homework 4

Skills:

1. Write the joint posterior density (up to a multiplicative constant)
2. Program two-dimensional Metropolis jumps
3. Program the accept/reject rule
4. Tune the parameters of your algorithm
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Optimization of Gibbs and Metropolis algorithms

- Conclusion of presentation by Wei Wang, Ph.D. student in statistics
- You can interrupt and discuss . . .
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- Binomial model for #deaths given #rats
- Logistic model for Pr(death)
- Prior distribution for the logistic regression coefficients
- Discuss extensions to the model
- Steps 2, 3, 4, 5 are straightforward
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Tuning the algorithm

- Shape of jumping kernel
- Scale of jumping kernel
- Objective function to optimize
- Trying different tuning parameters
- Stochastic optimization
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For next week’s class

- Homework 5 due 5pm Tues
- All course material is at http://www.stat.columbia.edu/~gelman/bayescomputation
- Next class:
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