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**Date:** 9/11/25

**Paper Title:** Bayesian Analysis for Social Science Research

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**Year Published:** 2023

**Open questions for discussion in class:**

- How do researchers decide on an appropriate prior distribution when there isn't much prior knowledge?
- When should a social scientist prefer a Bayesian approach over a frequentist one? (I am assuming there are some cases where one is preferred over the other).
- In what ways can Bayesian results be misinterpreted by policymakers or non-experts?
- The political survey case study noted that "unexpected political changes" likely influenced the model's predictive accuracy. So how robust are Bayesian models (which incorporate existing knowledge) to sudden unmodeled/unforeseen shifts in real world social behavior/trends?

**The topic areas covered by the paper are:**

- conjugate and non-conjugate modeling
- hierarchical modeling
- Bayesian computation
- goodness of fit
- model testing
- case studies that use Bayesian methods in social science such as politics, and education testing scenarios.

**The previous approaches to this problem were:**

Frequentist methods used previously in statistical data analysis; Frequentist methods are becoming unreliable when data do not correspond to a random sample or when uncertainty does not arise from repeated sampling. Also, this method can be imprecise when it is used on small datasets.

**Outline the basic new approach or approaches to this problem:**

Use Bayesian approach that considers the parameters as a random variable with prior distributions and not a fixed, unknown quantity.

1. Use prior beliefs (external information).
2. Once data is observed, update the prior beliefs using Bayes' Theorem to get a posterior distribution (which describes the updated state of knowledge about the parameter given the data)
3. For complex models conduct Bayesian computation via Monte Carlo simulation to approximate posterior distributions when exact solutions are not possible. This involves using Markov Chain Monte Carlo (MCMC) algorithms (like the Gibbs sampler, Metropolis-Hastings, and Hamiltonian Monte Carlo) to generate random samples from the posterior distribution

4. Evaluate models for goodness of fit using posterior predictive distribution and test statistics. For model comparison, information criteria like the Deviance Information Criterion (DIC) and Watanabe-Akaike Criterion (WAIC) are used
5. Apply Bayesian hierarchical models to account for variation at multiple levels (individual, group, regional)

**Critical assumptions made include:**

- parameters are random variables (so prior beliefs can be used)
- The choice of prior distributions accurately represents background knowledge (or is at least not misleading)
- MCMC algorithms will eventually converge to the true posterior distribution as the number of iterations grows (if it runs long enough)
- For Monte Carlo approximations, it is assumed that a sufficiently large number of samples can be drawn from the posterior distribution to get a desired level of precision in estimates
- Models assumes correct specific distribution
  - o assuming a Poisson distribution for count data
  - o assuming multinomial distribution for count data in categorical outcomes
  - o assuming normal distribution for continuous variables in linear regression
- Data collected is representative enough to justify inference

**The performance of the techniques discussed in the paper was measured in what manner:**

- Posterior predictive checks (“goodness of fit”): compare replicated data generated by the model with observed data.
- Credible intervals: Bayesian analog to confidence intervals (95%), used to summarize uncertainty in estimates.
- Model comparison metrics: DIC and WAIC to compare predictive performance of different models (lower value = higher predictive accuracy).
- Convergence checks for MCMC sampling: make sure that simulated chains properly approximate the posterior distribution.

**What background techniques are used in the paper that you are not familiar with:**

- Markov Chain Monte Carlo (MCMC) methods (like Gibbs sampler and Hamiltonian MC) that is used to generate samples from complex posterior distribution when mathematical models are too complex to work with.
- Information criteria like DIC and WAIC
- Conjugacy concept in statistics
- improper priors, objective priors, Bayes factors

**The following terms were defined:**

- Bayesian inference: Inductive learning through Bayes’ Theorem.
- Frequentist approach assumes parameter as a fixed but unknown quantity, and any estimate of it constitutes a random variable since it depends on repeated random sampling.
- Bayesian approach assumes parameter as a random variable so that any estimate of it is fixed and constitutes a realization of such a random quantity.

- Prior distribution
- Posterior distribution
- Non-informative prior: prior distribution where all the possible parameter values have the same density.
- Conjugate prior
- Monte Carlo principle: states that any characteristic of a random variable can be approximated well by generating random samples from its probability distribution
- Markov chain
- Ergodic chain
- Gibbs sampler
- Markov property
- Metropolis-Hastings algorithm
- Metropolis algorithm
- Posterior predictive distribution used for external validation tests by generating hypothetical replicas of the data.
- Posterior predictive p-value (ppp) is probability that the replicated data is more extreme than the observed data
- Deviance Information Criterion (DIC)
- Watanabe-Akaike Criterion (WAIC)
- lppd: posterior predictive distribution in logarithmic scale (summarizes the predictive ability of the model fitted to the data)
- Multinomial distribution
- Dirichlet distribution
- Gamma distribution
- Inverse Gamma distribution
- Normal distribution
- Multivariate Normal distribution
- Inverse Wishart distribution

**I rate and justify the value of this paper as:**

8/10. It clearly & simply introduces both the theory (Bayes vs frequentist, priors, posteriors) and the practice methods (MCMC, hierarchical models, model checking). The case studies are useful for seeing Bayesian methods applied to real social science problems. But I found it a bit mathematically heavy in some parts which made it challenging without prior statistics background.