

BAYESIAN STATISTICS - LECTURE 9

LECTURE 9: HMC, STAN, VARIATIONAL.

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- **Hamiltonian Monte Carlo**
- **Stan**
- **Variational Bayes**

- Assume $\theta = (\theta_1, \dots, \theta_p)$. If p is large, then most of the mass of $p(\theta|\mathbf{y})$ is usually located on some subregion in \mathbb{R}^p with complicated geometry.
- MH: hard to find good proposal distribution $q(\cdot|\theta^{(i-1)})$.
- MH: have to use very small step sizes otherwise too many rejections.
- **Hamiltonian Monte Carlo (HMC)**: **distant proposals** with **high acceptance** probabilities.
- HMC adds an auxiliary **momentum** parameter $\phi = (\phi_1, \dots, \phi_p)$ and samples from $p(\theta, \phi|\mathbf{y}) = p(\theta|\mathbf{y}) p(\phi)$.

- Physics: **Hamiltonian** system $H(\theta, \phi) = U(\theta) + K(\phi)$, where U is the **potential energy** and K is the **kinetic energy**.
- **Hamiltonian Dynamics**

$$\begin{aligned}\frac{d\theta_i}{dt} &= \frac{\partial H}{\partial \phi_i} = \frac{\partial K}{\partial \phi_i}, \\ \frac{d\phi_i}{dt} &= -\frac{\partial H}{\partial \theta_i} = -\frac{\partial U}{\partial \theta_i}\end{aligned}$$

- Think: Hockey puck sliding over a friction-less surface: [illustration](#).
- Use $U(\theta) = -\log[p(\theta)p(\mathbf{y}|\theta)]$.
- Use $\phi \sim N(\mathbf{0}, \mathbf{M})$ and $K(\phi) = -\log[p(\phi)] = \frac{1}{2}\phi^T \mathbf{M}^{-1}\phi + \text{const}$, where M is the mass matrix (often diagonal).
- If we could propose θ in continuous time (spoiler: we can't), the acceptance probability would be one.

■ Hamiltonian Dynamics

$$\begin{aligned}\frac{d\theta_i}{dt} &= [\mathbf{M}^{-1}\phi]_i, \\ \frac{d\phi_i}{dt} &= \frac{\partial \log p(\theta|\mathbf{y})}{\partial \theta_i}\end{aligned}$$

which can be simulated using the **leapfrog algorithm**

$$\begin{aligned}\phi_i\left(t + \frac{\varepsilon}{2}\right) &= \phi_i(t) - \frac{\varepsilon}{2} \frac{\partial \log p(\theta(t)|\mathbf{y})}{\partial \theta_i}, \\ \theta(t + \varepsilon) &= \theta(t) + \varepsilon \mathbf{M}^{-1}\phi(t), \\ \phi_i(t + \varepsilon) &= \phi_i\left(t + \frac{\varepsilon}{2}\right) - \frac{\varepsilon}{2} \frac{\partial \log p(\theta(t)|\mathbf{y})}{\partial \theta_i},\end{aligned}$$

where ε is the step size.

■ Discretization \Rightarrow acceptance probability drops with ε .

THE HAMILTONIAN MONTE CARLO ALGORITHM

■ Initialize $\theta^{(0)}$ and iterate for $i = 1, 2, \dots$

1. Sample the starting **momentum** $\phi_s \sim N(0, \mathbf{M})$
2. Simulate new values for (θ_p, ϕ_p) by iterating the **leapfrog algorithm** L times, starting in $(\theta^{(i-1)}, \phi_s)$.
3. Compute the **acceptance probability**

$$\alpha = \min \left(1, \frac{p(\mathbf{y}|\theta_p)p(\theta_p)}{p(\mathbf{y}|\theta^{(i-1)})p(\theta^{(i-1)})} \frac{p(\phi_p)}{p(\phi_s)} \right)$$

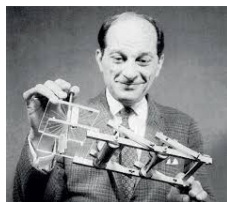
4. With probability α set $\theta^{(i)} = \theta_p$ and $\phi^{(i)} = \phi_p$ otherwise.

■ **Tuning parameters:** 1. **stepsize** ε , 2. **number of leapfrog iterations** L and 3. **mass matrix** M . **No U-turn.**

- **Stan** is a probabilistic programming language based on HMC.
- Allows for Bayesian inference in many models with automatic implementation of the MCMC sampler.
- Named after Stanislaw Ulam (1909-1984), co-inventor of the Monte Carlo algorithm.
- Written in C++ but can be run from R using the package `rstan`



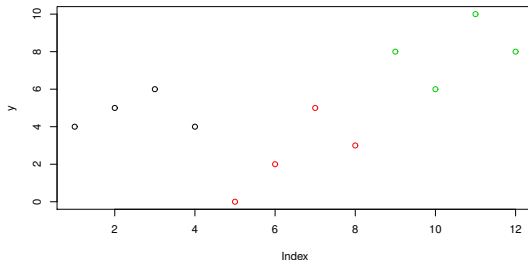
Stan logo



Stanislaw Ulam

STAN - TOY EXAMPLE: THREE PLANTS

- Three plants were observed for four months, measuring the number of flowers



STAN MODEL 1: IID NORMAL

$$y_i \stackrel{iid}{\sim} N(\mu, \sigma^2)$$

```
library(rstan)
y = c(4,5,6,4,0,2,5,3,8,6,10,8)
N = length(y)

StanModel = '
data {
  int<lower=0> N; // Number of observations
  int<lower=0> y[N]; // Number of flowers
}
parameters {
  real mu;
  real<lower=0> sigma2;
}
model {
  mu ~ normal(0,100); // Normal with mean 0, st.dev. 100
  sigma2 ~ scaled_inv_chi_square(1,2); // Scaled-inv-chi2 with nu 1, sigma 2
  for(i in 1:N)
    y[i] ~ normal(mu,sqrt(sigma2));
}'
```

STAN MODEL 2: MULTILEVEL NORMAL

$$y_{i,p} \sim N(\mu_p, \sigma_p^2), \quad \mu_p \sim N(\mu, \sigma^2)$$

```
StanModel = '  
data {  
  int<lower=0> N; // Number of observations  
  int<lower=0> y[N]; // Number of flowers  
  int<lower=0> P; // Number of plants  
}  
transformed data {  
  int<lower=0> M; // Number of months  
  M = N / P;  
}  
parameters {  
  real mu;  
  real<lower=0> sigma2;  
  real mup[P];  
  real sigmap2[P];  
}  
model {  
  mu ~ normal(0,100); // Normal with mean 0, st.dev. 100  
  sigma2 ~ scaled_inv_chi_square(1,2); // Scaled-inv-chi2 with nu 1, sigma 2  
  for(p in 1:P){  
    mup[p] ~ normal(mu,sqrt(sigma2));  
    for(m in 1:M)  
      y[M*(p-1)+m] ~ normal(mup[p],sqrt(sigmap2[p]));  
  }  
}'
```

STAN MODEL 3: MULTILEVEL POISSON

$$y_{i,p} \sim \text{Poisson}(\mu_p), \quad \mu_p \sim \text{logN}(\mu, \sigma^2)$$

```
StanModel = '  
data {  
  int<lower=0> N; // Number of observations  
  int<lower=0> y[N]; // Number of flowers  
  int<lower=0> P; // Number of plants  
}  
transformed data {  
  int<lower=0> M; // Number of months  
  M = N / P;  
}  
parameters {  
  real mu;  
  real<lower=0> sigma2;  
  real mup[P];  
}  
model {  
  mu ~ normal(0,100); // Normal with mean 0, st.dev. 100  
  sigma2 ~ scaled_inv_chi_square(1,2); // Scaled-inv-chi2 with nu 1, sigma 2  
  for(p in 1:P){  
    mup[p] ~ lognormal(mu,sqrt(sigma2)); // Log-normal  
    for(m in 1:M)  
      y[M*(p-1)+m] ~ poisson(mup[p]); // Poisson  
  }  
}'
```

STAN: FIT MODEL AND ANALYZE OUTPUT

```
data = list(N=N, y=y, P=P)
burnin = 1000
niter = 2000
fit = stan(model_code=StanModel,data=data,
           warmup=burnin,iter=niter,chains=4)

# Print the fitted model
print(fit,digits_summary=3)

# Extract posterior samples
postDraws <- extract(fit)

# Do traceplots of the first chain
par(mfrow = c(1,1))
plot(postDraws$mu[1:(niter-burnin)],type="l",ylab="mu",main="Traceplot")

# Do automatic traceplots of all chains
traceplot(fit)

# Bivariate posterior plots
pairs(fit)
```

- [Getting started with RStan](#)
- [RStan vignette](#)
- [Stan Modeling Language User's Guide and Reference Manual](#)
- [Stan Case Studies](#)

- Let $\theta = (\theta_1, \dots, \theta_p)$. Approximate the posterior $p(\theta|y)$ with a (simpler) distribution $q(\theta)$.
- We have already seen: $q(\theta) = N[\tilde{\theta}, J_{\mathbf{y}}^{-1}(\tilde{\theta})]$.
- **Mean field Variational Bayes (VB)**

$$q(\theta) = \prod_{i=1}^p q_i(\theta_i)$$

- **Parametric VB**, where $q_{\lambda}(\theta)$ is a parametric family with parameters λ .
- Find the $q(\theta)$ that **minimizes the Kullback-Leibler distance** between the true posterior p and the approximation q :

$$KL(q, p) = \int q(\theta) \ln \frac{q(\theta)}{p(\theta|y)} d\theta = E_q \left[\ln \frac{q(\theta)}{p(\theta|y)} \right].$$

- Factorization

$$q(\theta) = \prod_{i=1}^p q_i(\theta_i)$$

- **No specific functional forms are assumed** for the $q_i(\theta)$.
- **Optimal densities** can be shown to satisfy:

$$q_i(\theta) \propto \exp(E_{-\theta_i} \ln p(\mathbf{y}, \theta))$$

where $E_{-\theta_i}(\cdot)$ is the expectation with respect to $\prod_{i \neq j} q_j(\theta_j)$.

- **Structured mean field approximation.** Group subset of parameters in tractable blocks. Similar to Gibbs sampling.

MEAN FIELD APPROXIMATION - ALGORITHM

■ Initialize: $q_2^*(\theta_2), \dots, q_M^*(\theta_p)$

■ Repeat until convergence:

$$\begin{aligned} \cdot q_1^*(\theta_1) &\leftarrow \frac{\exp[E_{-\theta_1} \ln p(\mathbf{y}, \theta)]}{\int \exp[E_{-\theta_1} \ln p(\mathbf{y}, \theta)] d\theta_1} \\ \cdot \vdots \\ \cdot q_p^*(\theta_p) &\leftarrow \frac{\exp[E_{-\theta_p} \ln p(\mathbf{y}, \theta)]}{\int \exp[E_{-\theta_p} \ln p(\mathbf{y}, \theta)] d\theta_p} \end{aligned}$$

■ Note: we make no assumptions about parametric form of the $q_i(\theta)$.

■ But the optimal $q_i(\theta)$ often turn out to be parametric (normal, gamma etc).

■ The updates above then boil down to just updating of hyperparameters in the optimal densities.

- **Model:** $X_i | \theta, \sigma^2 \stackrel{iid}{\sim} N(\theta, \sigma^2)$.
- **Prior:** $\theta \sim N(\mu_0, \tau_0^2)$ **independent** of $\sigma^2 \sim \text{Inv} - \chi^2(\nu_0, \sigma_0^2)$.
- **Mean-field approximation:** $q(\theta, \sigma^2) = q_\theta(\theta) \cdot q_{\sigma^2}(\sigma^2)$.
- Optimal densities

$$q_\theta^*(\theta) \propto \exp \left[E_{q(\sigma^2)} \ln p(\theta, \sigma^2, \mathbf{x}) \right]$$
$$q_{\sigma^2}^*(\sigma^2) \propto \exp \left[E_{q(\theta)} \ln p(\theta, \sigma^2, \mathbf{x}) \right]$$

■ Variational density for σ^2

$$\sigma^2 \sim \text{Inv} - \chi^2 (\tilde{\nu}_n, \tilde{\sigma}_n^2)$$

$$\text{where } \tilde{\nu}_n = \nu_0 + n \text{ and } \tilde{\sigma}_n^2 = \frac{\nu_0 \sigma_0^2 + \sum_{i=1}^n (x_i - \tilde{\mu}_n)^2 + n \cdot \tilde{\tau}_n^2}{\nu_0 + n}$$

■ Variational density for θ

$$\theta \sim N (\tilde{\mu}_n, \tilde{\tau}_n^2)$$

where

$$\tilde{\tau}_n^2 = \frac{1}{\frac{n}{\tilde{\sigma}_n^2} + \frac{1}{\tau_0^2}}$$

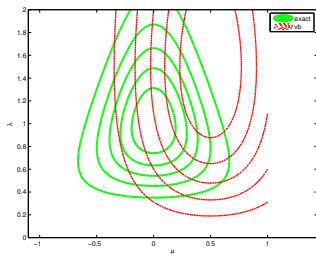
$$\tilde{\mu}_n = \tilde{W}\bar{X} + (1 - \tilde{W})\mu_0,$$

where

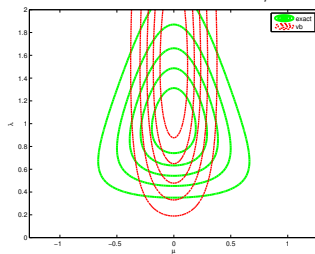
$$\tilde{W} = \frac{\frac{n}{\tilde{\sigma}_n^2}}{\frac{n}{\tilde{\sigma}_n^2} + \frac{1}{\tau_0^2}}$$

NORMAL EXAMPLE FROM MURPHY ($\lambda = 1/\sigma^2$)

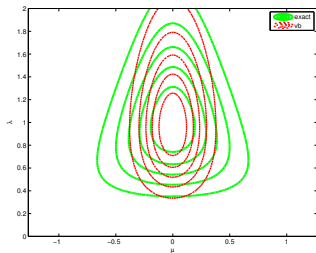
Initial values



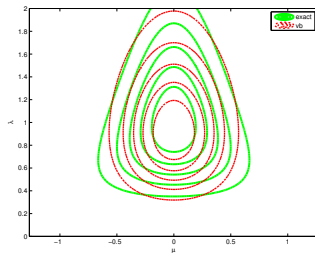
After updating q_μ



After updating q_{σ^2}



At convergence



■ **Model:**

$$\Pr(y_i = 1 | \mathbf{x}_i) = \Phi(\mathbf{x}_i^T \beta)$$

■ **Prior:** $\beta \sim N(\mathbf{0}, \Sigma_\beta)$. For example: $\Sigma_\beta = \tau^2 I$.

■ **Latent variable formulation** with $\mathbf{u} = (u_1, \dots, u_n)'$

$$\mathbf{u} | \beta \sim N(\mathbf{X}\beta, \mathbf{1})$$

and

$$y_i = \begin{cases} 0 & \text{if } u_i \leq 0 \\ 1 & \text{if } u_i > 0 \end{cases}$$

■ Factorized **variational approximation**

$$q(\mathbf{u}, \beta) = q_{\mathbf{u}}(\mathbf{u})q_{\beta}(\beta)$$

■ VB posterior

$$\beta \sim N \left(\tilde{\mu}_\beta, \left(\mathbf{X}^T \mathbf{X} + \Sigma_\beta^{-1} \right)^{-1} \right)$$

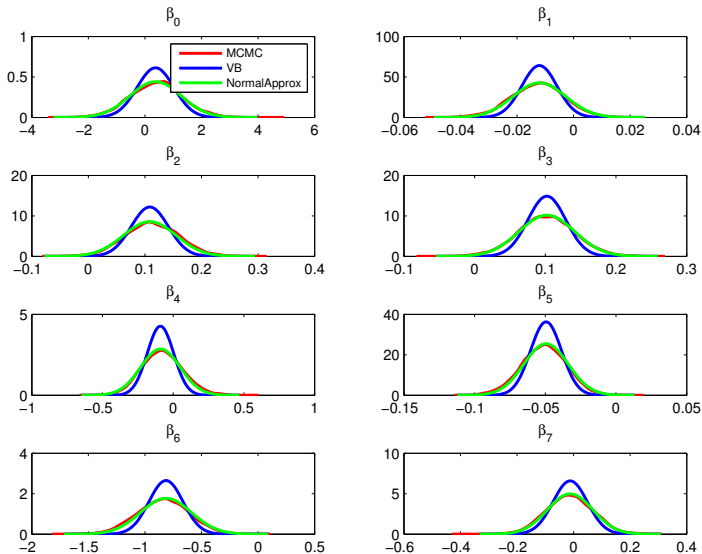
where

$$\tilde{\mu}_\beta = \left(\mathbf{X}^T \mathbf{X} + \Sigma_\beta^{-1} \right)^{-1} \mathbf{X}^T \tilde{\mu}_\mathbf{u}$$

and

$$\tilde{\mu}_\mathbf{u} = \mathbf{X} \tilde{\mu}_\beta + \frac{\phi(\mathbf{X} \tilde{\mu}_\beta)}{\Phi(\mathbf{X} \tilde{\mu}_\beta)^{\mathbf{y}} [\Phi(\mathbf{X} \tilde{\mu}_\beta) - \mathbf{1}_n]^{\mathbf{1}_n - \mathbf{y}}}.$$

PROBIT EXAMPLE (N=200 OBSERVATIONS)



PROBIT EXAMPLE

