

Rstan Practice

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```
set.seed(1234)
N = 250
K = 3
covariates = replicate(K, rnorm(n=N))
colnames(covariates) = c('X1', 'X2', 'X3')
X = cbind(Intercept=1, covariates)

coefs = c(5, .2, -1.5, .9)
mu = X %*% coefs
sigma = 2
y = rnorm(N, mu, sigma)

modlm = lm(y~., data = data.frame(X[, -1]))
summary(modlm)

##
## Call:
## lm(formula = y ~ ., data = data.frame(X[, -1]))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.6160 -1.2391 -0.0206  1.2228  5.3990
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.9362     0.1236  39.940 < 2e-16 ***
## X1             0.3211     0.1214   2.645  0.00869 **
## X2            -1.2710     0.1173 -10.833 < 2e-16 ***
## X3             0.9885     0.1317   7.508  1.1e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.948 on 246 degrees of freedom
## Multiple R-squared:  0.4139, Adjusted R-squared:  0.4067
## F-statistic:  57.9 on 3 and 246 DF,  p-value: < 2.2e-16
```

Time for Stan.

```
# create the data list object for stan input
dat = list(N = N, K = ncol(X), y=y, X=X)
# create the stan model object using Stan's syntax
stanmodelcode = "
data {
  int<lower=1> N;
  int<lower=1> K;
  matrix[N, K] X;
  vector[N] y;
}
```

```

parameters {
  vector[K] beta;
  real<lower=0> sigma;
}
model {
  vector[N] mu;
  mu = X * beta;
  // priors
  beta ~ normal(0, 10);
  sigma ~ cauchy(0, 5);
  // likelihood
  y ~ normal(mu, sigma);
}
"

```

Run the stan model

```
library(rstan)
```

```

## Loading required package: ggplot2
## Loading required package: StanHeaders
## rstan (Version 2.18.2, GitRev: 2e1f913d3ca3)
## For execution on a local, multicore CPU with excess RAM we recommend calling
## options(mc.cores = parallel::detectCores()).
## To avoid recompilation of unchanged Stan programs, we recommend calling
## rstan_options(auto_write = TRUE)
### run the model and examine results
fit = stan(model_code = stanmodelcode,
           data = dat,
           iter = 5000,
           warmup = 2500,
           thin = 10,
           chains = 4)

##
## SAMPLING FOR MODEL '7b080505fdclab8b066e2ee81db2afab' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 3.5e-05 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0.35 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 5000 [ 0%] (Warmup)
## Chain 1: Iteration:   500 / 5000 [ 10%] (Warmup)
## Chain 1: Iteration:  1000 / 5000 [ 20%] (Warmup)
## Chain 1: Iteration:  1500 / 5000 [ 30%] (Warmup)
## Chain 1: Iteration:  2000 / 5000 [ 40%] (Warmup)
## Chain 1: Iteration:  2500 / 5000 [ 50%] (Warmup)
## Chain 1: Iteration:  2501 / 5000 [ 50%] (Sampling)
## Chain 1: Iteration:  3000 / 5000 [ 60%] (Sampling)
## Chain 1: Iteration:  3500 / 5000 [ 70%] (Sampling)
## Chain 1: Iteration:  4000 / 5000 [ 80%] (Sampling)
## Chain 1: Iteration:  4500 / 5000 [ 90%] (Sampling)

```

```

## Chain 1: Iteration: 5000 / 5000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.231078 seconds (Warm-up)
## Chain 1: 0.194629 seconds (Sampling)
## Chain 1: 0.425707 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL '7b080505fdclab8b066e2ee81db2afab' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 3.8e-05 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.38 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration: 1 / 5000 [ 0%] (Warmup)
## Chain 2: Iteration: 500 / 5000 [ 10%] (Warmup)
## Chain 2: Iteration: 1000 / 5000 [ 20%] (Warmup)
## Chain 2: Iteration: 1500 / 5000 [ 30%] (Warmup)
## Chain 2: Iteration: 2000 / 5000 [ 40%] (Warmup)
## Chain 2: Iteration: 2500 / 5000 [ 50%] (Warmup)
## Chain 2: Iteration: 2501 / 5000 [ 50%] (Sampling)
## Chain 2: Iteration: 3000 / 5000 [ 60%] (Sampling)
## Chain 2: Iteration: 3500 / 5000 [ 70%] (Sampling)
## Chain 2: Iteration: 4000 / 5000 [ 80%] (Sampling)
## Chain 2: Iteration: 4500 / 5000 [ 90%] (Sampling)
## Chain 2: Iteration: 5000 / 5000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.177892 seconds (Warm-up)
## Chain 2: 0.329345 seconds (Sampling)
## Chain 2: 0.507237 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL '7b080505fdclab8b066e2ee81db2afab' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 1.3e-05 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0.13 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 5000 [ 0%] (Warmup)
## Chain 3: Iteration: 500 / 5000 [ 10%] (Warmup)
## Chain 3: Iteration: 1000 / 5000 [ 20%] (Warmup)
## Chain 3: Iteration: 1500 / 5000 [ 30%] (Warmup)
## Chain 3: Iteration: 2000 / 5000 [ 40%] (Warmup)
## Chain 3: Iteration: 2500 / 5000 [ 50%] (Warmup)
## Chain 3: Iteration: 2501 / 5000 [ 50%] (Sampling)
## Chain 3: Iteration: 3000 / 5000 [ 60%] (Sampling)
## Chain 3: Iteration: 3500 / 5000 [ 70%] (Sampling)
## Chain 3: Iteration: 4000 / 5000 [ 80%] (Sampling)
## Chain 3: Iteration: 4500 / 5000 [ 90%] (Sampling)
## Chain 3: Iteration: 5000 / 5000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.187076 seconds (Warm-up)
## Chain 3: 0.210964 seconds (Sampling)

```

```

## Chain 3:          0.39804 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL '7b080505fdclab8b066e2ee81db2afab' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 1.3e-05 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0.13 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 5000 [  0%] (Warmup)
## Chain 4: Iteration:   500 / 5000 [ 10%] (Warmup)
## Chain 4: Iteration:  1000 / 5000 [ 20%] (Warmup)
## Chain 4: Iteration:  1500 / 5000 [ 30%] (Warmup)
## Chain 4: Iteration:  2000 / 5000 [ 40%] (Warmup)
## Chain 4: Iteration:  2500 / 5000 [ 50%] (Warmup)
## Chain 4: Iteration:  2501 / 5000 [ 50%] (Sampling)
## Chain 4: Iteration:  3000 / 5000 [ 60%] (Sampling)
## Chain 4: Iteration:  3500 / 5000 [ 70%] (Sampling)
## Chain 4: Iteration:  4000 / 5000 [ 80%] (Sampling)
## Chain 4: Iteration:  4500 / 5000 [ 90%] (Sampling)
## Chain 4: Iteration:  5000 / 5000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.184386 seconds (Warm-up)
## Chain 4:          0.185156 seconds (Sampling)
## Chain 4:          0.369542 seconds (Total)
## Chain 4:

```

```

# summary
print(fit, pars = c('beta', 'sigma'), digits = 3, probs = c(.025, .5, .975))

```

```

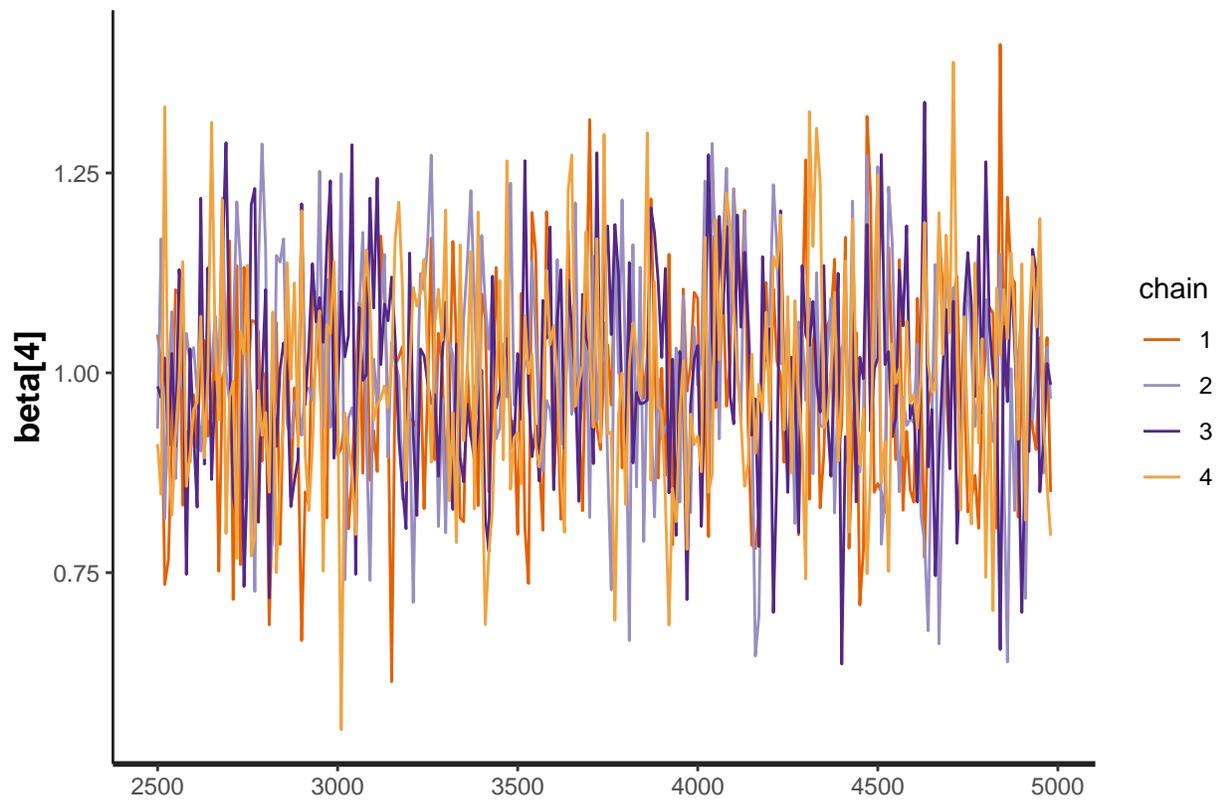
## Inference for Stan model: 7b080505fdclab8b066e2ee81db2afab.
## 4 chains, each with iter=5000; warmup=2500; thin=10;
## post-warmup draws per chain=250, total post-warmup draws=1000.
##
##          mean se_mean   sd  2.5%   50%  97.5% n_eff  Rhat
## beta[1]  4.941   0.004 0.126  4.697  4.943  5.197  1191 0.998
## beta[2]  0.322   0.004 0.120  0.101  0.324  0.574  1032 0.998
## beta[3] -1.269   0.004 0.117 -1.496 -1.272 -1.047   855 0.998
## beta[4]  0.991   0.004 0.134  0.728  0.988  1.258   976 1.002
## sigma    1.954   0.003 0.089  1.787  1.949  2.136   965 0.998
##
## Samples were drawn using NUTS(diag_e) at Wed Mar  6 20:50:44 2019.
## For each parameter, n_eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor on split chains (at
## convergence, Rhat=1).

```

```

# visualize
stan_trace(fit, pars = c('beta[4]'))

```

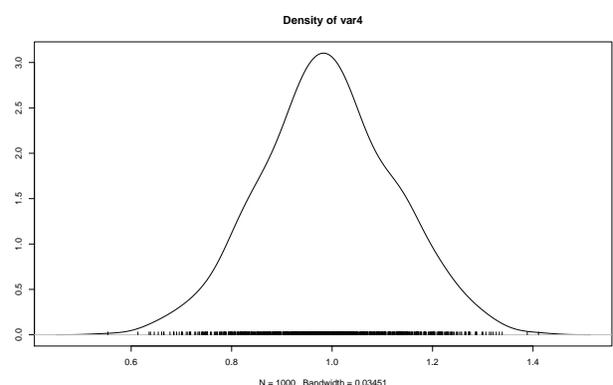
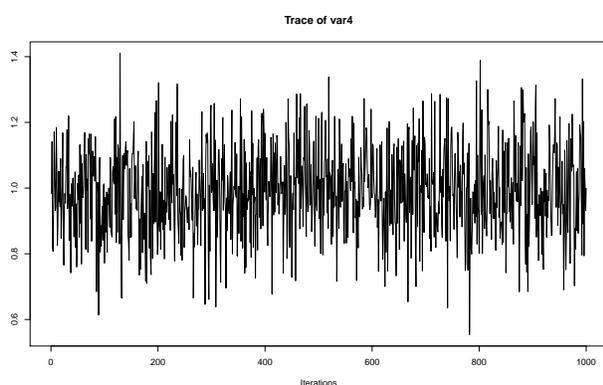
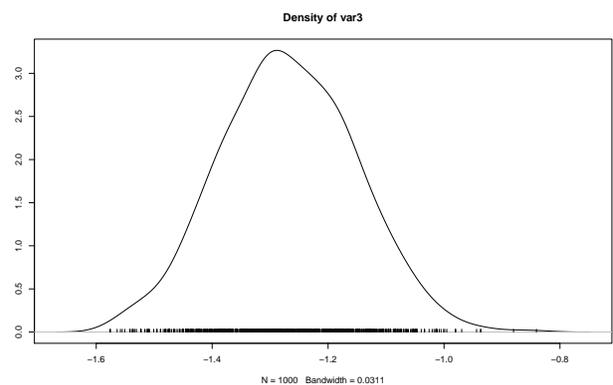
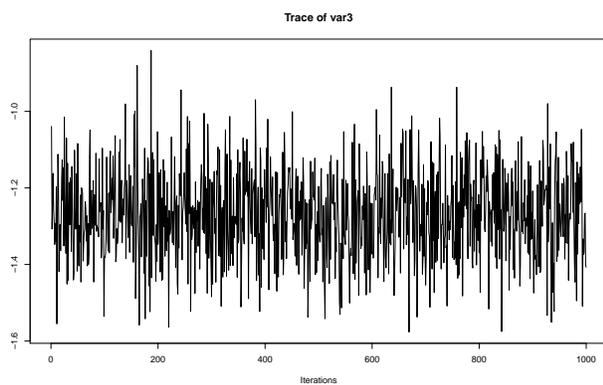
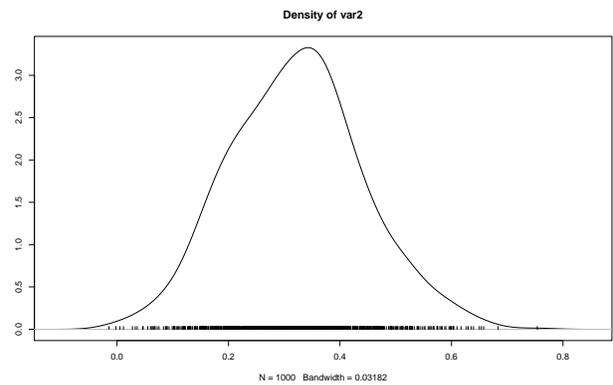
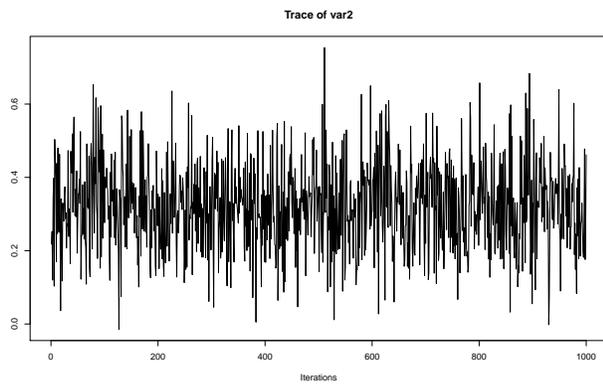
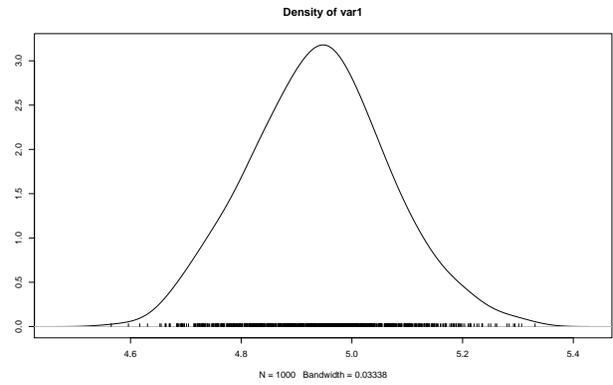
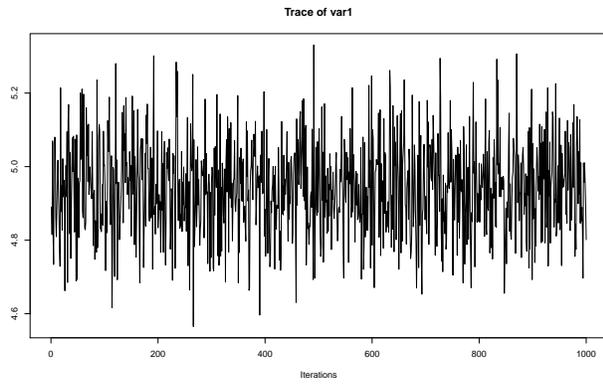


Diagnostics with coda package:

```
library(coda)
```

```
##  
## Attaching package: 'coda'  
## The following object is masked from 'package:rstan':  
##  
## traceplot
```

```
betas = extract(fit, pars='beta')$beta  
betas.mcmc = as.mcmc(betas)  
plot(betas.mcmc)
```



Reference

Rstan: Regression Models