Advanced topics in Machine Learning
Lab 7: JAGS, Sampling based methods

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1 MCMC sampling in JAGS

1. **Implementing a simple statistical inference using JAGS.** Assume we've got a set of 1000 data points from a normal distribution with unknown mean and variance. We want to estimate the posteriors of the parameters.

   (a) create a file `example1.bug` which contains a description of the model:

   ```
   model {
         for (i in 1:N) {
            x[i] ~ dnorm(mu, tau)
         }
         mu ~ dnorm(0, .0001) # wide normal prior
         tau <- pow(sigma, -2)
         sigma ~ dunif(0, 100) # wide uniform prior
   }
   ```

   Note that the normal distribution is defined using *precision* $\tau = 1/\sigma^2$ instead of standard deviation.

   (b) Run the model in `R` using the `rjags` package

   ```
   library(rjags)
   library(coda)
   N <- 1000
   x <- rnorm(N, 0, 5) # generating data
   jags <- jags.model('example1.bug', data = list("x" = x, "N" = N),
       n.chains = 1, n.adapt = 100)  # burn-in
   update(jags, n.adapt = 1000) # more burn-in
   s <- coda.samples(jags, c('mu', 'sigma'), 1000, thin=1)
   summary(s)
   ```

   (c) Try different thinning and burn-in parameters. Use the `coda` and `mcmcplots` package to perform diagnostics:

```
library(coda)
plot(s)  # trace plots
autocorr.plot(s)
geweke.diag(s)

library(mcmcplots)
mcmcplot(s, dir = getwd())
denplot(s)
caterplot(s)
```

2. Implement simple linear regression in JAGS. $y \sim N(X\beta, \sigma^2 I)$, where $\beta = (\beta_0, \beta_1)^T$, $X = [1^T, x_1^T]^T$. Find estimates of β and σ.

3. Implement one dimensional logistic regression in JAGS. $y_i \sim Bernoulli(1, p_i)$, where $p_i = \frac{1}{1+exp(-\mu_i)}$, $\mu_i = \beta_0 + \beta_1 x_i$ and $x_i = i$. Find estimates of β.