Convergence diagnostics for MCMC chains MLPM Summer School 2015

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22 September 2015

To assess convergence is not a trivial task, especially in large-dimensional settings . . .

What can we do?

- Visual inspection: trace-plots, cumulative means plots, etc
- ▶ Statistical tests: e.g. the ones implemented in the coda library

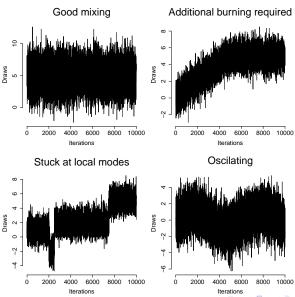
We can also run multiple chains (with different starting values) and check if all chains converge to the same values.

To illustrate convergence diagnostic tools, we create 4 artificial chains

Visual inspection - Traceplots

```
par(mfrow = c(2,2))
plot(Chain1, type = "l", bty = "n", xlab = "Iterations",
    ylab = "Draws", main = expression("Good mixing"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
plot(Chain2, type = "l", bty = "n", xlab = "Iterations",
    ylab = "Draws", main = expression("Additional burning required"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
plot(Chain3, type = "l", bty = "n", xlab = "Iterations",
    ylab = "Draws", main = expression("Stuck at local modes"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
plot(Chain4, type = "l", bty = "n", xlab = "Iterations",
    ylab = "Draws", main = expression("Oscilating"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
```

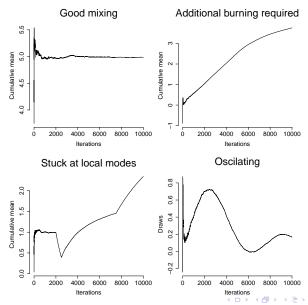
Visual inspection - Traceplots



Visual inspection - Cumulative means plots

```
par(mfrow = c(2,2))
plot(cumsum(Chain1)/1:10000, type = "l", bty = "n",
     xlab = "Iterations", ylab = "Cumulative mean",
     main = expression("Good mixing"),
     cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
plot(cumsum(Chain2)/1:10000, type = "l", bty = "n",
     xlab = "Iterations", ylab = "Cumulative mean",
     main = expression("Additional burning required"),
     cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
plot(cumsum(Chain3)/1:10000, type = "l", bty = "n",
     xlab = "Iterations", ylab = "Cumulative mean",
     main = expression("Stuck at local modes"),
     cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
plot(cumsum(Chain4)/1:10000, type = "l", bty = "n",
     xlab = "Iterations", ylab = "Draws",
     main = expression("Oscilating"),
     cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
```

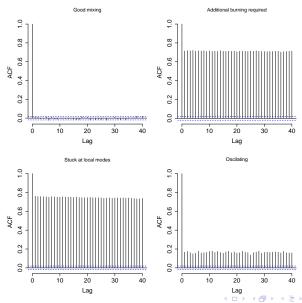
Visual inspection - Cumulative means plots



Visual inspection - Auto-correlation plots

```
par(mfrow = c(2,2))
acf(Chain1, bty = "n",
    main = expression("Good mixing"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
acf(Chain2, bty = "n",
    main = expression("Additional burning required"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
acf(Chain3, bty = "n",
    main = expression("Stuck at local modes"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
acf(Chain4, bty = "n",
    main = expression("Oscilating"),
    cex.main = 2.5, cex.lab = 1.5, cex.axis = 1.5)
```

Visual inspection - Auto-correlation plots



Statistical tests

The R library makes available several statistical test for convergence diagnostics. To load this library use

```
library(coda)
```

To use these tools, a first step is to transform chains into objects of class mcmc.

```
Chain1.mcmc = mcmc(Chain1)
Chain2.mcmc = mcmc(Chain2)
Chain3.mcmc = mcmc(Chain3)
Chain4.mcmc = mcmc(Chain4)
```

Statistical tests - Geweke

Compares the means of two non-overlapping segments of the chain (typically the first 10% and last 50% of draws). It returns a z-score which is adjusted for autocorrelation

```
geweke.diag(Chain1.mcmc)$z

## var1  ## var1
## -0.02164115  ## -57.39918

geweke.diag(Chain3.mcmc)$z

geweke.diag(Chain4.mcmc)$z

## var1  ## var1
## -2.722006  ## 1.416636
```



Statistical tests

Other diagnostics implemented in coda include

- Gelman and Rubin
- Raftery and Lewis
- Heidelberg and Welch

Because of time restrictions, we won't explore all of these today.

NOTE: For better results it is important to combine visual inspection and test-based convergence diagnostics

Each of these convergence diagnostics are designed to assess the convergence of a chain for a single parameter

What to do for high-dimensional models?

Once again, there is no trivial answer. Some ideas:

- Select a random subset of model parameters
- Calculate averages within sets of parameters