

# STA 602 Lab 6

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## Exercise 1

Suppose  $U = (U_1, U_2)$  is jointly Gaussian with parameters

$$\begin{aligned}\mu &= (\mu_1, \mu_2) \\ \Sigma &= \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \\ \Lambda &= \Sigma^{-1} = \begin{bmatrix} \Lambda_{11} & \Lambda_{12} \\ \Lambda_{21} & \Lambda_{22} \end{bmatrix}\end{aligned}$$

The conditional is given by the following expression.

$$\begin{aligned}p(U_1|U_2) &= \mathcal{N}(U_1|\mu_{1|2}, \Sigma_{1|2}) \\ \mu_{1|2} &= \mu_1 - \Sigma_{12}\Sigma_{22}^{-1}(U_2 - \mu_2) \\ \Sigma_{1|2} &= \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21} = \Lambda_{11}^{-1}\end{aligned}$$

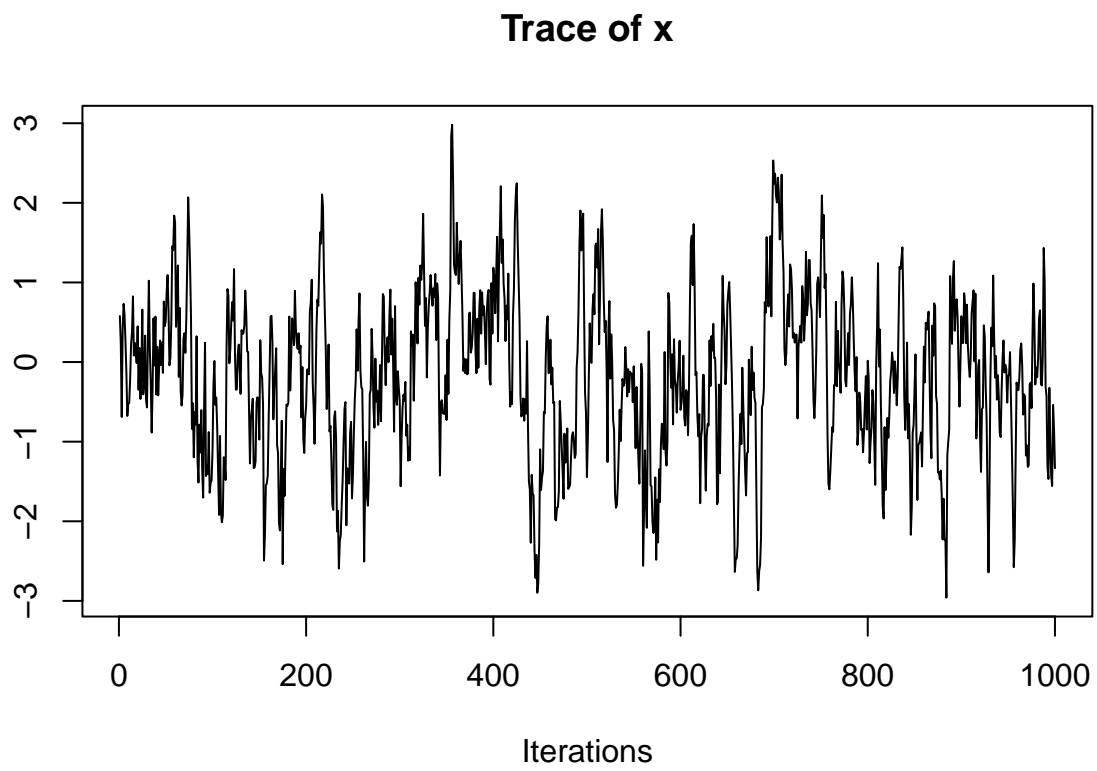
The conditional for  $U_2|U_1$  is just the above equations with flipped signs.

## Exercise 2

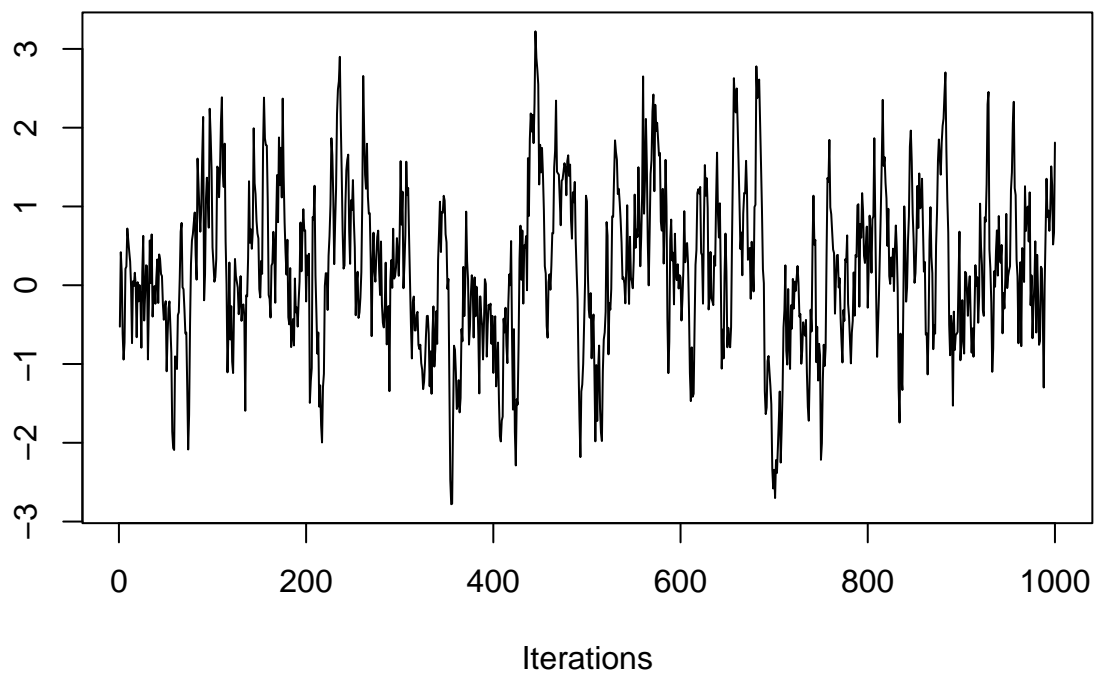
Applying the above formulas, we arrive at the following full conditionals for X, Y, and Z.

$$\begin{aligned}\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} &\sim \mathcal{N}_3 \left[ \theta = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \Sigma = \begin{bmatrix} 1, 0.9, 0.1 \\ 0.9, 1, 0.1 \\ 0.1, 0.1, 1 \end{bmatrix} \right] \\ X|Y, Z &\sim \mathcal{N}(\mu = -0.899Y - 0.01Z, \sigma^2 = 0.1899) \\ Y|X, Z &\sim \mathcal{N}(\mu = -0.899X - 0.01Z, \sigma^2 = 0.1899) \\ Z|X, Y &\sim \mathcal{N}(\mu = -0.0526X - 0.0526Y, \sigma^2 = 0.98947)\end{aligned}$$

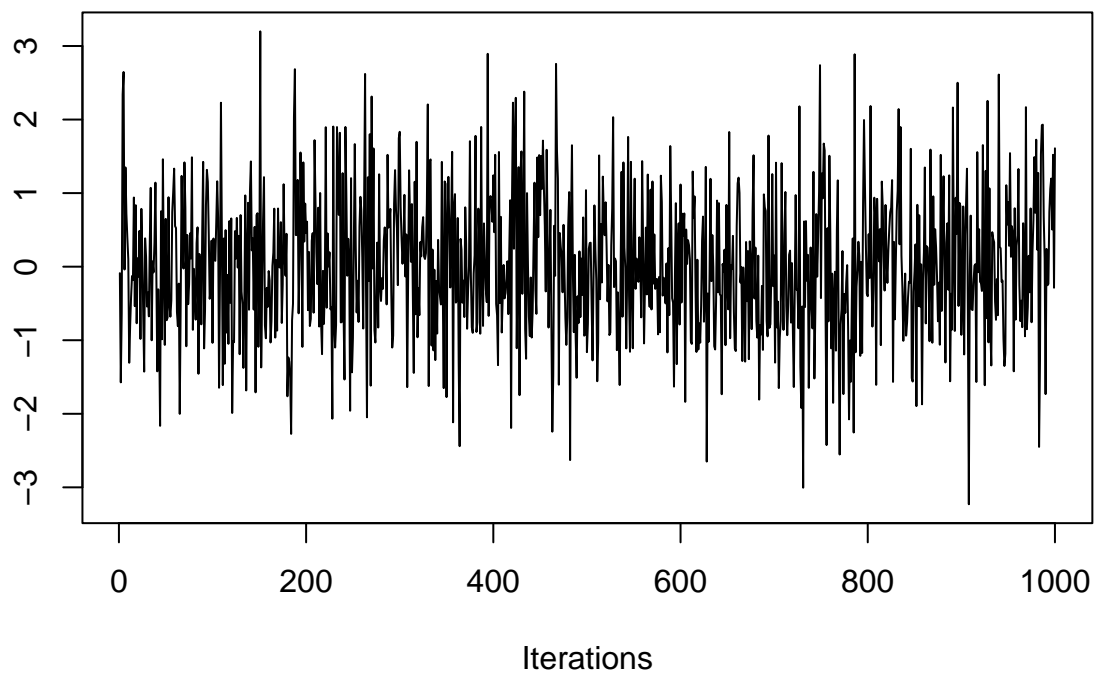
### Exercise 3

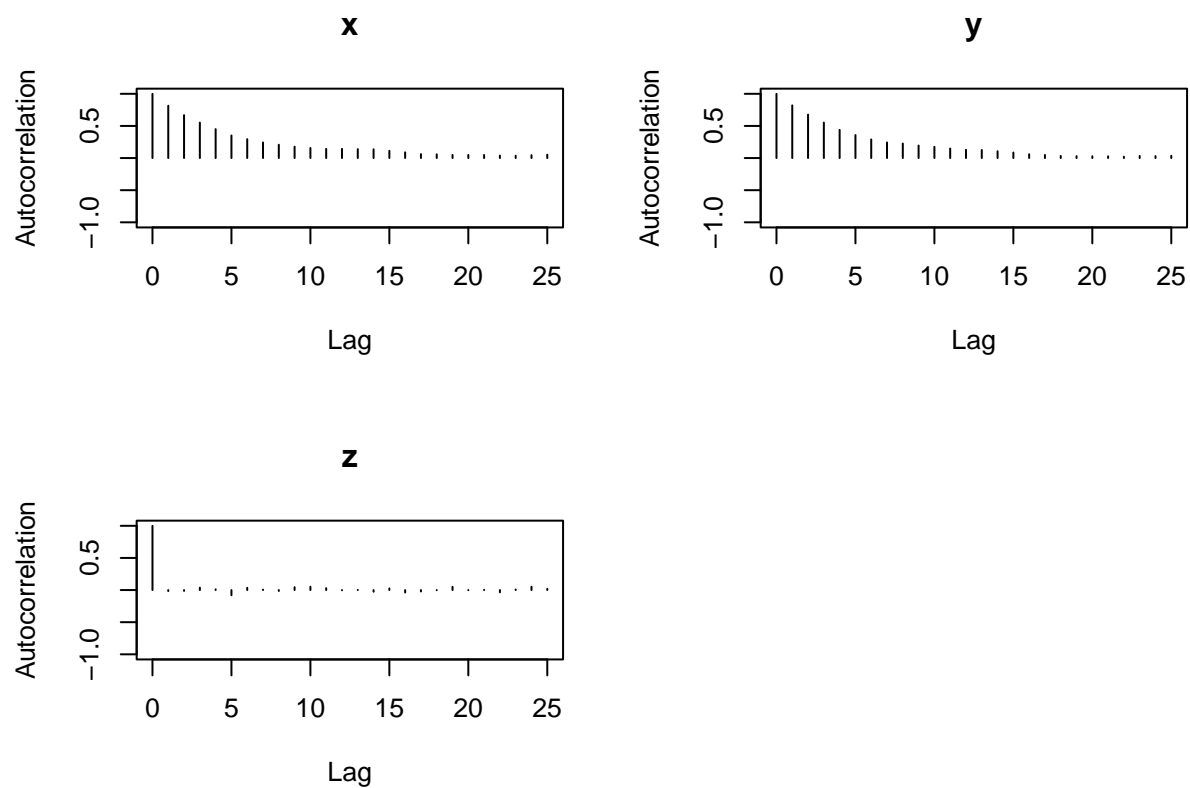


**Trace of y**



**Trace of  $z$**



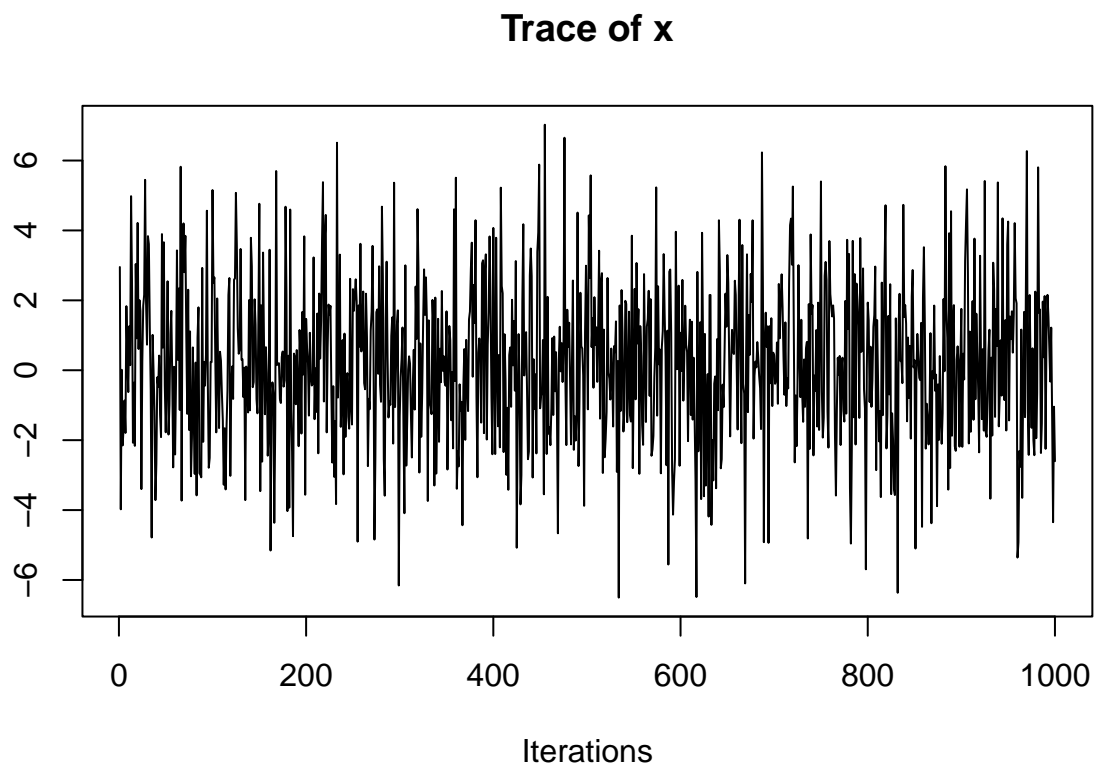


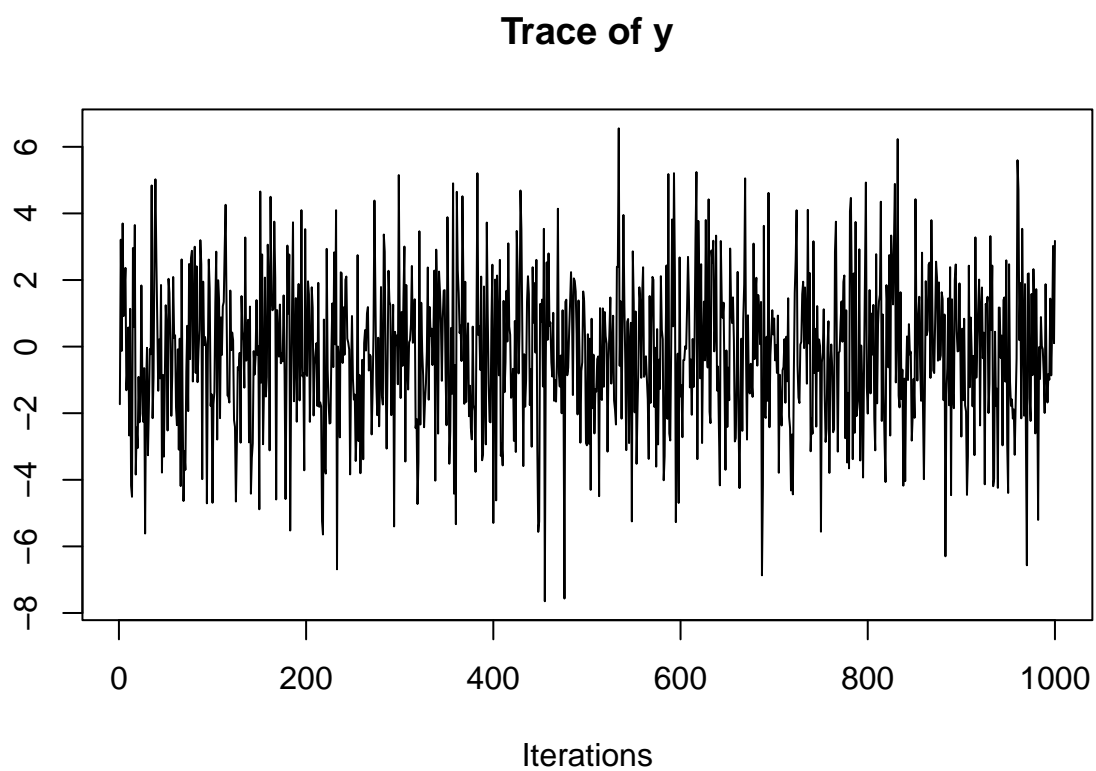
#### Exercise 4

$$X, Y|Z \sim \mathcal{N}\left(\mu = \begin{bmatrix} -0.1Z \\ -0.1Z \end{bmatrix}, \sigma^2 = \begin{bmatrix} 5.266, -4.734 \\ -4.734, 5.266 \end{bmatrix}\right)$$

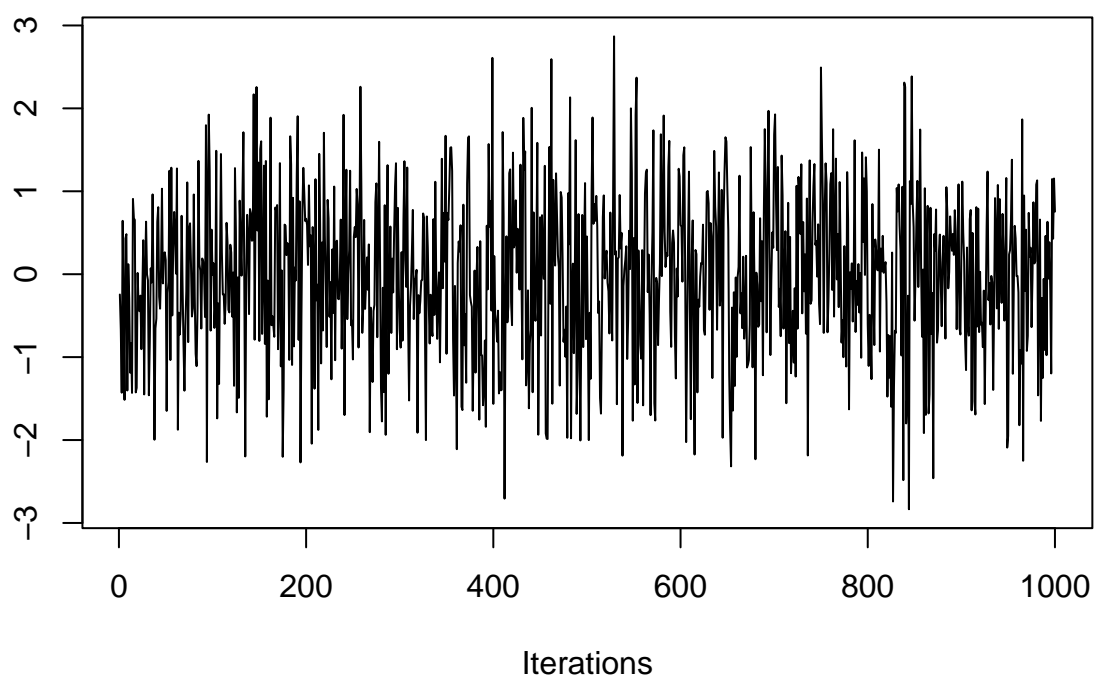
$$Z|X, Y \sim \mathcal{N}(\mu = -0.0526X - 0.0526Y, \sigma^2 = 0.98947)$$

## Exercise 5

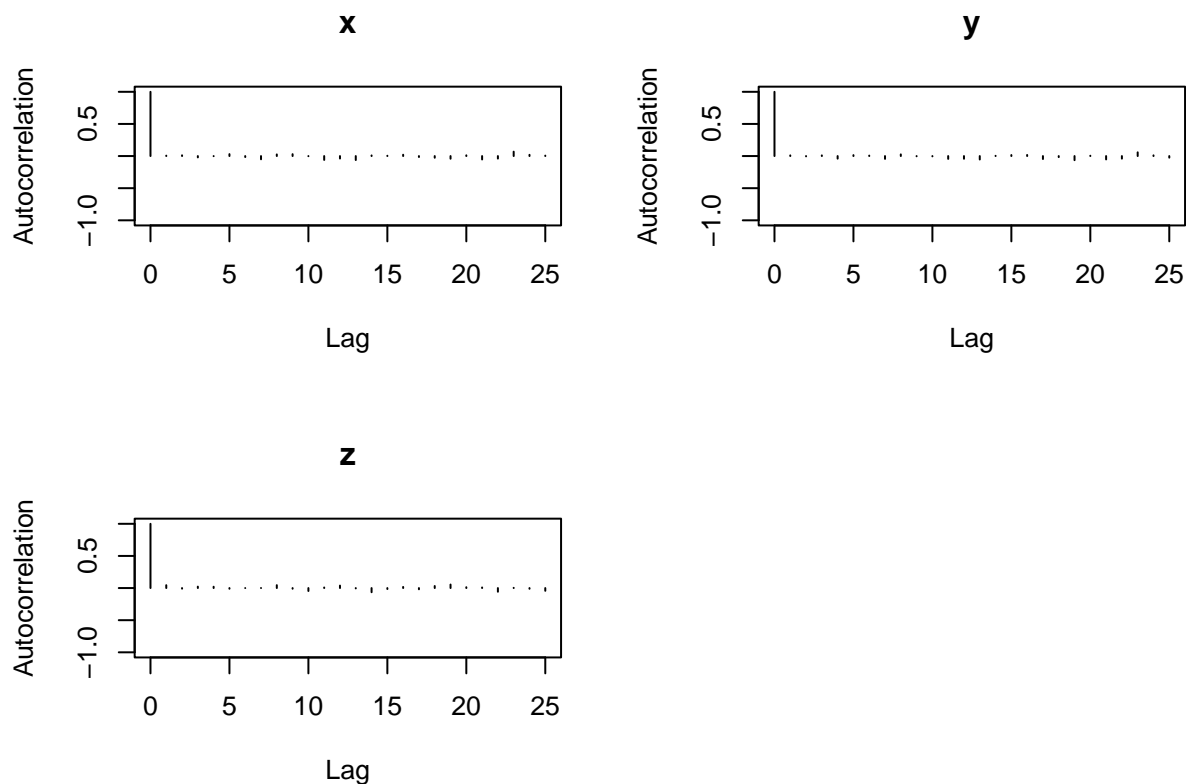




**Trace of  $z$**







## Exercise 6

With a high correlation between  $X$  and  $Y$ , we see that if we use the Gibbs Sampler on each full conditional, we get a sticky chain. The result was the first example that we saw a high autocorrelation among  $X$  and  $Y$  samples. After we use block updates on  $X$  and  $Y$  together, the chain we obtained suddenly gets much better, and the autocorrelation also disappears. The high correlation between  $X$  and  $Y$  limits the sampler's exploration ability, making it less efficient. Treating it as a block speeds up because the relationship between  $Z$  covers a much wider area.

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