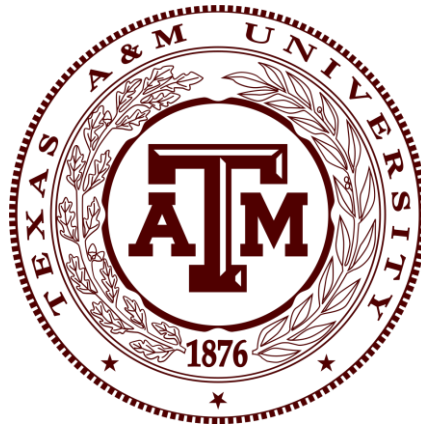


# Explaining an R Package **bayesestdft** to estimate degree of freedoms of the student t-distribution

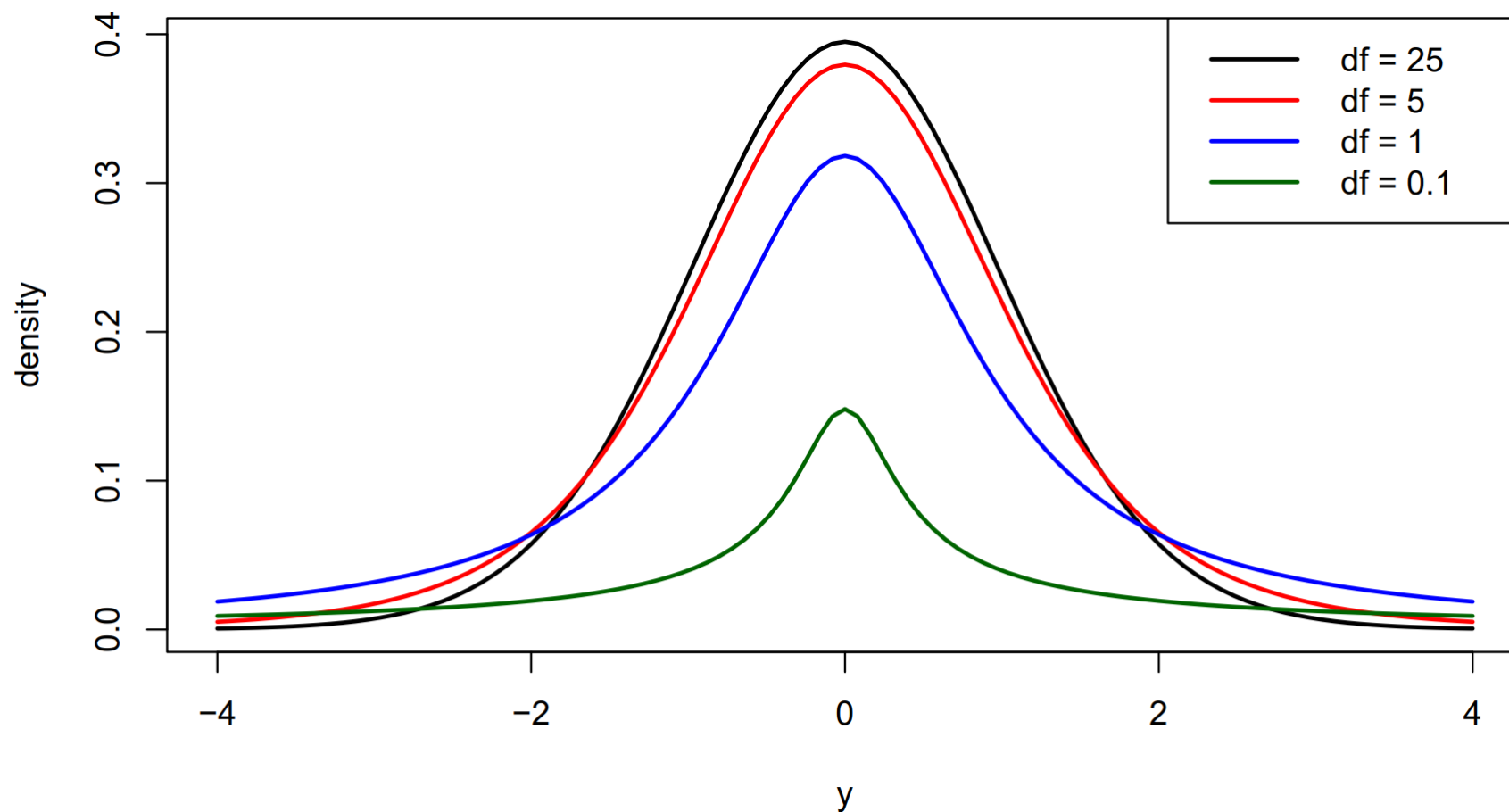


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# Student t-distribution

- Probability density function

$$f(y|\nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \cdot \left(1 + \frac{y^2}{\nu}\right)^{-\frac{\nu+1}{2}}, \quad -\infty < y < \infty$$



# Student t-distribution

- **Probability density function of Student t-distribution:**  $Y \sim t_\nu(y)$ , ( $\nu > 0$ ) :

$$f(y|\nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \cdot \left(1 + \frac{y^2}{\nu}\right)^{-\frac{\nu+1}{2}}, \quad -\infty < y < \infty$$

- **Special case 1:** when  $\nu = 1$ ,  $Y \sim t_{\nu=1}(y) = \text{Cauchy}(y)$

$$f(y|\nu = 1) = \frac{\Gamma\left(\frac{1+1}{2}\right)}{\sqrt{\pi}\Gamma\left(\frac{1}{2}\right)} \cdot (1 + y^2)^{-1} = \frac{1}{\pi(1 + y^2)}, \quad -\infty < y < \infty$$

- **Special case 2:** when  $\nu = \infty$ ,  $Y \sim t_{\nu=\infty}(y) \sim N(y|0,1)$

$$f(y|\nu = \infty) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}, \quad -\infty < y < \infty$$

- **Likelihood for  $N$  i.i.d data points  $(y_1, y_2, \dots, y_N)$  from the t-distribution:**

$$L(\nu) = \prod_{i=1}^N t(y_i|\nu) = \prod_{i=1}^N \left( \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \cdot \left(1 + \frac{y_i^2}{\nu}\right)^{-\frac{\nu+1}{2}} \right) = \left( \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \right)^N \prod_{i=1}^N \left(1 + \frac{y_i^2}{\nu}\right)^{-\frac{\nu+1}{2}}$$

# Student t-distribution

By plugging-in  $\eta = \log v$  ( $v = e^\eta$ ), we have

- **Likelihood ratio:**

$$\frac{L(e^\eta)}{L(e^{\eta^{(s)}})} = \frac{\left( \frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta} \pi \Gamma\left(\frac{e^\eta}{2}\right)} \right)^N \cdot \prod_{i=1}^N \left( 1 + \frac{y_i^2}{e^\eta} \right)^{-\frac{e^\eta + 1}{2}}}{\left( \frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}}} \pi \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)} \right)^N \cdot \prod_{i=1}^N \left( 1 + \frac{y_i^2}{e^{\eta^{(s)}}} \right)^{-\frac{e^{\eta^{(s)}} + 1}{2}}}$$

- **Likelihood ratio (log-scaled):**

$$\begin{aligned} \log\left(\frac{L(e^\eta)}{L(e^{\eta^{(s)}})}\right) &= \log\left(\left(\frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta} \pi \Gamma\left(\frac{e^\eta}{2}\right)}\right)^N \cdot \prod_{i=1}^N \left(1 + \frac{y_i^2}{e^\eta}\right)^{-\frac{e^\eta + 1}{2}}\right) - \log\left(\left(\frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}}} \pi \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)}\right)^N \cdot \prod_{i=1}^N \left(1 + \frac{y_i^2}{e^{\eta^{(s)}}}\right)^{-\frac{e^{\eta^{(s)}} + 1}{2}}\right) \\ &= N \cdot \log\left(\frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta} \pi \Gamma\left(\frac{e^\eta}{2}\right)}\right) + \sum_{i=1}^N \log\left(\left(1 + \frac{y_i^2}{e^\eta}\right)^{-\frac{e^\eta + 1}{2}}\right) - \left\{ N \cdot \log\left(\frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}}} \pi \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)}\right) + \sum_{i=1}^N \log\left(\left(1 + \frac{y_i^2}{e^{\eta^{(s)}}}\right)^{-\frac{e^{\eta^{(s)}} + 1}{2}}\right) \right\} \\ &= N \cdot \log\left(\frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta} \pi \Gamma\left(\frac{e^\eta}{2}\right)}\right) - \frac{e^\eta + 1}{2} \sum_{i=1}^N \log\left(1 + \frac{y_i^2}{e^\eta}\right) - \left\{ N \cdot \log\left(\frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}}} \pi \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)}\right) - \frac{e^{\eta^{(s)}} + 1}{2} \sum_{i=1}^N \log\left(1 + \frac{y_i^2}{e^{\eta^{(s)}}}\right) \right\} \\ &= N \cdot \left[ \log\left(\frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta} \pi \Gamma\left(\frac{e^\eta}{2}\right)}\right) - \log\left(\frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}}} \pi \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)}\right) \right] - \left[ \frac{e^\eta + 1}{2} \sum_{i=1}^N \log\left(1 + \frac{y_i^2}{e^\eta}\right) - \frac{e^{\eta^{(s)}} + 1}{2} \sum_{i=1}^N \log\left(1 + \frac{y_i^2}{e^{\eta^{(s)}}}\right) \right] \end{aligned}$$

Independent of data  $(y_1, y_2, \dots, y_N)$

Dependent of data  $(y_1, y_2, \dots, y_N)$

# Student t-distribution

- Numerical Stability:**

The first part of the likelihood ratio (log-scaled) can be made numerically stable by using the final analytic form

These parts take Infinity when  $\eta$  and  $\eta^{(s)}$  take large values due to the nature of the gamma function

$$\begin{aligned}
 & \log \left( \frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta \pi} \Gamma\left(\frac{e^\eta}{2}\right)} \right) - \log \left( \frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}} \pi} \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)} \right) = \\
 & \log \left( \frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta \pi} \Gamma\left(\frac{e^\eta}{2}\right)} \right) - \log \left( \frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}} \pi} \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)} \right) = \\
 & \log \left( \Gamma\left(\frac{e^\eta + 1}{2}\right) \right) - \log \left( \sqrt{e^\eta \pi} \Gamma\left(\frac{e^\eta}{2}\right) \right) - \left\{ \log \left( \Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right) \right) - \log \left( \sqrt{e^{\eta^{(s)}} \pi} \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right) \right) \right\} \\
 & = \log \left( \Gamma\left(\frac{e^\eta + 1}{2}\right) \right) - \log \left( e^{\frac{\eta}{2}} \cdot \pi^{\frac{1}{2}} \cdot \Gamma\left(\frac{e^\eta}{2}\right) \right) - \left\{ \log \left( \Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right) \right) - \log \left( e^{\frac{\eta^{(s)}}{2}} \cdot \pi^{\frac{1}{2}} \cdot \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right) \right) \right\} \\
 & = \log \left( \Gamma\left(\frac{e^\eta + 1}{2}\right) \right) - \left[ \frac{\eta}{2} + \log \pi^{\frac{1}{2}} + \log \left( \Gamma\left(\frac{e^\eta}{2}\right) \right) \right] - \left\{ \log \left( \Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right) \right) - \left[ \frac{\eta^{(s)}}{2} + \log \pi^{\frac{1}{2}} + \log \left( \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right) \right) \right] \right\} \\
 & = \log \left( \Gamma\left(\frac{e^\eta + 1}{2}\right) \right) - \left[ \frac{\eta}{2} + \log \pi^{\frac{1}{2}} + \log \left( \Gamma\left(\frac{e^\eta}{2}\right) \right) \right] - \left\{ \log \left( \Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right) \right) - \left[ \frac{\eta^{(s)}}{2} + \log \pi^{\frac{1}{2}} + \log \left( \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right) \right) \right] \right\}
 \end{aligned}$$

Use R function lgamma functions for the stability of the numerical calculation

# Prior Options in R Package bayesestdft

Priors	R functions in Package bayesestdft	References
$\pi_J(v) \propto \left(\frac{v}{v+3}\right)^{\frac{1}{2}} \cdot \left\{ \psi'\left(\frac{v}{2}\right) - \psi'\left(\frac{v+1}{2}\right) - \frac{2(v+3)}{v(v+1)^2} \right\}^{\frac{1}{2}}$ $\psi(a) = \frac{d \log \Gamma(a)}{da} \text{ and } \psi'(a) = \frac{d\psi(a)}{da} \text{ represent digamma and trigamma functions}$	<b>BayesJeffreys</b>	<ul style="list-style-type: none"> <li>Fonseca, Thaís CO, Marco AR Ferreira, and Helio S. Migon. "Objective Bayesian analysis for the Student-t regression model." <i>Biometrika</i> 95.2 (2008): 325-333.</li> </ul>
$v \sim \pi_E(v) = Ga(\alpha = shape = 1, \beta = rate = 0.1) = Exp(rate = 0.1)$ $\pi_E(v) = \frac{\beta^1}{\Gamma(1)} v^{1-1} \cdot e^{-\beta v} = \beta \cdot e^{-\beta v} = \frac{1}{10} e^{-\frac{v}{10}}$	<b>BayesGA</b>	<ul style="list-style-type: none"> <li>Fernández, Carmen, and Mark FJ Steel. "On Bayesian modeling of fat tails and skewness." <i>Journal of the american statistical association</i> 93.441 (1998): 359-371.</li> </ul>
$v \sim \pi_G(v) = Ga(\alpha = shape = 2, \beta = rate = 0.1)$ $\pi_G(v) = \frac{\beta^\alpha}{\Gamma(\alpha)} v^{\alpha-1} \cdot e^{-\beta v} = \frac{1}{100} v \cdot e^{-v/10}$	<b>BayesGA</b>	<ul style="list-style-type: none"> <li>Juárez, Miguel A., and Mark FJ Steel. "Model-based clustering of non-Gaussian panel data based on skew-t distributions." <i>Journal of Business &amp; Economic Statistics</i> 28.1 (2010): 52-66.</li> <li>Geweke, John. "Bayesian treatment of the independent Student-t linear model." <i>Journal of applied econometrics</i> 8.S1 (1993): S19-S40.</li> </ul>
$v \sim \pi_L(v) = \log N(\mu, \sigma^2)$ $\pi_L(v) = \frac{1}{v\sigma\sqrt{2\pi}} \exp\left(-\frac{(\log v - \mu)^2}{2\sigma^2}\right) = \frac{1}{v\sqrt{2\pi}} \exp\left(-\frac{(\log v - 1)^2}{2}\right)$	<b>BayesLNP</b>	<ul style="list-style-type: none"> <li>Lee, Se Yoon. "The Use of a Log-Normal Prior for the Student t-Distribution." <i>Axioms</i> (2022): 11(9):462.</li> </ul>

# bayesestdft::BayesJeffreys

- **Likelihood:**

$$L(\nu) = p(y_{1:N}|\nu) = \prod_{i=1}^N t(y_i|\nu) = \left( \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \right)^N \prod_{i=1}^N \left( 1 + \frac{y_i^2}{\nu} \right)^{-\frac{\nu+1}{2}}$$

- **Prior:**

$$\nu \sim \pi_J(\nu) \propto \left( \frac{\nu}{\nu+3} \right)^{\frac{1}{2}} \cdot \left\{ \psi'\left(\frac{\nu}{2}\right) - \psi'\left(\frac{\nu+1}{2}\right) - \frac{2(\nu+3)}{\nu(\nu+1)^2} \right\}^{\frac{1}{2}},$$

$\psi(a) = \frac{d \log \Gamma(a)}{da}$  and  $\psi'(a) = \frac{d\psi(a)}{da}$  represent digamma and trigamma functions.

- **Posterior distribution:**

$$\pi(\nu|y_{1:N}) \propto L(\nu) \cdot \pi_J(\nu)$$

- **Target density obtained by change of variable ( $\eta = \log \nu$ ,  $\nu = e^\eta$ ):**

$$\begin{aligned} \pi(\eta|y_{1:N}) &= \pi(\nu|y_{1:N}) \Big|_{\nu=e^\eta} \cdot \left| \frac{d\nu}{d\eta} \right| = \pi(\nu = e^\eta|y_{1:N}) \cdot e^\eta \propto L(e^\eta) \cdot \pi_J(e^\eta) \cdot e^\eta \\ &\propto L(e^\eta) \cdot \left( \frac{e^\eta}{e^\eta+3} \right)^{\frac{1}{2}} \cdot \left\{ \psi'\left(\frac{e^\eta}{2}\right) - \psi'\left(\frac{e^\eta+1}{2}\right) - \frac{2(e^\eta+3)}{e^\eta(e^\eta+1)^2} \right\}^{\frac{1}{2}} \cdot e^\eta \end{aligned}$$

# bayesestdft::BayesJeffreys [Metropolis-Hastings Algorithm]

## [Metropolis-Hastings Algorithm]

**Goal:** Sampling from  $\eta \sim \pi(\eta|y_{1:N})$

$$\propto L(e^\eta) \cdot \pi_J(e^\eta) \cdot e^\eta = \exp(-\gamma(\eta)), \quad \eta \in \mathbf{R}$$

$$\begin{aligned} \gamma(\eta) &= -\log(L(e^\eta)) - \log(\pi_J(e^\eta)) - \eta \\ &= -(\log(L(e^\eta)) + \log(\pi_J(e^\eta)) + \eta) \end{aligned}$$

Specify the step size  $\alpha$

**Input :** current state  $\eta^{(s)}$ .

**Output :** current state  $\eta^{(s+1)}$ .

a. Define a criterion function

$$\alpha(\eta, \eta^{(s)}) = \min \left[ \frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}}, 1 \right] : \mathbf{R} \rightarrow [0,1]$$

b. Choose a threshold  $u \sim U[0,1]$

c. Draw a proposal

$$\eta^* \sim N_1(\eta^{(s)}, 2\delta).$$

d. If  $(u < \alpha(\eta^*, \eta^{(s)})) \{ \eta^{(s+1)} = \eta^* \}$  else  $\{ \eta^{(s+1)} = \eta^{(s)} \}$

• **Posterior ratio:**

$$\frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}} = \frac{\exp(\log(L(e^\eta)) + \log(\pi_J(e^\eta)) + \eta)}{\exp(\log(L(e^{\eta^{(s)}})) + \log(\pi_J(e^{\eta^{(s)}})) + \eta^{(s)})} = \frac{L(e^\eta)}{L(e^{\eta^{(s)}})} \cdot \frac{\pi_J(e^\eta)}{\pi_J(e^{\eta^{(s)}})} \cdot \frac{e^\eta}{e^{\eta^{(s)}}}$$

• **Posterior ratio (log-scaled):**

$$\log \left( \frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}} \right) = \log \left( \frac{L(e^\eta)}{L(e^{\eta^{(s)}})} \right) + \log \left( \frac{\pi_J(e^\eta)}{\pi_J(e^{\eta^{(s)}})} \right) + (\eta - \eta^{(s)})$$

• **Likelihood ratio (log-scaled):**

$$\begin{aligned} \log \left( \frac{L(e^\eta)}{L(e^{\eta^{(s)}})} \right) &= N \cdot \left[ \log \left( \frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta \pi} \Gamma\left(\frac{e^\eta}{2}\right)} \right) - \log \left( \frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}} \pi} \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)} \right) \right] \\ &\quad - \left[ \frac{e^\eta + 1}{2} \sum_{i=1}^N \log \left( 1 + \frac{y_i^2}{e^\eta} \right) - \frac{e^{\eta^{(s)}} + 1}{2} \sum_{i=1}^N \log \left( 1 + \frac{y_i^2}{e^{\eta^{(s)}}} \right) \right] \end{aligned}$$

• **Prior ratio (log-scaled):**

$$\begin{aligned} &\log \left( \frac{\pi_J(e^\eta)}{\pi_J(e^{\eta^{(s)}})} \right) \\ &= \frac{1}{2} \left\{ \log \left( \frac{e^\eta}{e^\eta + 3} \right) - \log \left( \frac{e^{\eta^{(s)}}}{e^{\eta^{(s)}} + 3} \right) \right. \\ &\quad + \log \left( \psi' \left( \frac{e^\eta}{2} \right) - \psi' \left( \frac{e^\eta + 1}{2} \right) - \frac{2(e^\eta + 3)}{e^\eta(e^\eta + 1)^2} \right) \\ &\quad \left. - \log \left( \psi' \left( \frac{e^{\eta^{(s)}}}{2} \right) - \psi' \left( \frac{e^{\eta^{(s)}} + 1}{2} \right) - \frac{2(e^{\eta^{(s)}} + 3)}{e^{\eta^{(s)}}(e^{\eta^{(s)}} + 1)^2} \right) \right\} \end{aligned}$$



# bayesestdft:: BayesJeffreys [Metropolis Adjusted Langevin Algorithm]

## [Metropolis Adjusted Langevin Algorithm]

Goal: Sampling from  $\eta \sim \pi(\eta|y_{1:N})$

$$\propto L(e^\eta) \cdot \pi_J(e^\eta) \cdot e^\eta = \exp(-\gamma(\eta)), \quad \eta \in \mathbf{R}$$

$$\begin{aligned}\gamma(\eta) &= -\log(L(e^\eta)) - \log(\pi_J(e^\eta)) - \eta \\ &= -(\log(L(e^\eta)) + \log(\pi_J(e^\eta)) + \eta)\end{aligned}$$

Specify the step size  $\delta$

**Input** : current state  $\eta^{(s)}$ .

**Output** : current state  $\eta^{(s+1)}$ .

a. Define a criterion function

$$\alpha(\eta, \eta^{(s)}) = \min \left[ \frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}} \cdot \frac{J(\eta^{(s)}|\eta)}{J(\eta|\eta^{(s)})}, 1 \right] : \mathbf{R} \rightarrow [0,1]$$

b. Choose a threshold  $u \sim U[0,1]$

c. Draw a proposal

$$\eta^* \sim N_1(\eta^{(s)} - \delta \cdot \nabla \gamma(\eta^{(s)}), 2\delta).$$

d. If  $(u < \alpha(\eta^*, \eta^{(s)})) \{ \eta^{(s+1)} = \eta^* \}$  else  $\{ \eta^{(s+1)} = \eta^{(s)} \}$

- **Posterior ratio  $\times$  MH Correction:**

$$\frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}} \cdot \frac{J(\eta^{(s)}|\eta)}{J(\eta|\eta^{(s)})} = \frac{\exp(\log(L(e^\eta)) + \log(\pi_J(e^\eta)) + \eta)}{\exp(\log(L(e^{\eta^{(s)}})) + \log(\pi_J(e^{\eta^{(s)}})) + \eta^{(s)})} \cdot \frac{N_1(\eta^{(s)}|\eta - \delta \cdot \nabla_\theta \gamma(\eta), 2\delta)}{N_1(\eta|\eta^{(s)} - \delta \cdot \nabla_\theta \gamma(\eta^{(s)}), 2\delta)}$$

where the proposal density is  $J(\eta'|\eta) = N(\eta'|\eta - \delta \cdot \nabla \gamma(\eta), 2\delta)$

- **Posterior ratio  $\times$  MH Correction (log-scaled):**

$$\begin{aligned}\log \left( \frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}} \cdot \frac{J(\eta^{(s)}|\eta)}{J(\eta|\eta^{(s)})} \right) &= \left[ (\log(L(e^\eta)) + \log(\pi_J(e^\eta)) + \eta) - (\log(L(e^{\eta^{(s)}})) + \log(\pi_J(e^{\eta^{(s)}})) + \eta^{(s)}) \right] \\ &\quad + \log(N_1(\eta^{(s)}|\eta - \delta \cdot \nabla_\theta \gamma(\eta), 2\delta)) - \log(N_1(\eta|\eta^{(s)} - \delta \cdot \nabla_\theta \gamma(\eta^{(s)}), 2\delta))\end{aligned}$$

- **Gradient of negative of log-posterior posterior:**

$$\nabla \gamma(\eta) = \frac{\partial \gamma(\eta)}{\partial \eta} = \frac{\partial}{\partial \eta} \left\{ -(\log(L(e^\eta)) + \log(\pi_J(e^\eta)) + \eta) \right\}$$

Use R package "numDeriv" to obtain the gradient function  $\nabla \gamma(\eta)$

# bayesestdft::BayesGA

- **Likelihood:**

$$L(\nu) = p(y_{1:N}|\nu) = \prod_{i=1}^N t(y_i|\nu) = \left( \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \right)^N \prod_{i=1}^N \left( 1 + \frac{y_i^2}{\nu} \right)^{-\frac{\nu+1}{2}}$$

- **Prior:**

$$\nu \sim \pi_{GA}(\nu) = \frac{\beta^\alpha}{\Gamma(\alpha)} \nu^{\alpha-1} \cdot e^{-\beta\nu}.$$

- **Posterior distribution:**

$$\pi(\nu|y_{1:N}) \propto L(\nu) \cdot \pi_{GA}(\nu)$$

- **Target density obtained by change of variable ( $\eta = \log \nu$  ,  $\nu = e^\eta$ ):**

$$\begin{aligned} \pi(\eta|y_{1:N}) &= \pi(\nu|y_{1:N}) \Big|_{\nu=e^\eta} \cdot \left| \frac{d\nu}{d\eta} \right| = \pi(\nu = e^\eta|y_{1:N}) \cdot e^\eta \propto L(e^\eta) \cdot \pi_{GA}(e^\eta) \cdot e^\eta \\ &= L(e^\eta) \cdot \frac{\beta^\alpha}{\Gamma(\alpha)} e^{\eta(\alpha-1)} \cdot e^{-\beta e^\eta} \cdot e^\eta \propto L(e^\eta) \cdot e^{\eta\alpha - \beta e^\eta} \end{aligned}$$

# bayesestdft::BayesGA [Metropolis-Hastings Algorithm]

## [Metropolis-Hastings Algorithm]

**Goal:** Sampling from  $\eta \sim \pi(\eta|y_{1:N})$

$$\propto L(e^\eta) \cdot \pi_{GA}(e^\eta) \cdot e^\eta = L(e^\eta) \cdot e^{\eta\alpha - \beta e^\eta} = \exp(-\gamma(\eta)), \eta \in \mathbf{R}$$

$$\gamma(\eta) = -\log(L(e^\eta)) - \eta\alpha + \beta e^\eta$$

Specify the step size  $\alpha$

**Input** : current state  $\eta^{(s)}$ .

**Output** : current state  $\eta^{(s+1)}$ .

a. Define a criterion function

$$\alpha(\eta, \eta^{(s)}) = \min \left[ \frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}}, 1 \right] : \mathbf{R} \rightarrow [0,1]$$

b. Choose a threshold  $u \sim U[0,1]$

c. Draw a proposal

$$\eta^* \sim N_1(\eta^{(s)}, 2\delta).$$

d. If (  $u < \alpha(\eta^*, \eta^{(s)})$  )  $\{\eta^{(s+1)} = \eta^*\}$  else  $\{\eta^{(s+1)} = \eta^{(s)}\}$

• **Posterior ratio:**

$$\frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}} = \frac{\exp(\log(L(e^\eta)) + \eta\alpha - \beta e^\eta)}{\exp(\log(L(e^{\eta^{(s)}})) + \eta^{(s)}\alpha - \beta e^{\eta^{(s)}})} = \exp \left( \log \left( \frac{L(e^\eta)}{L(e^{\eta^{(s)}})} \right) + \alpha(\eta - \eta^{(s)}) - \beta(e^\eta - e^{\eta^{(s)}}) \right)$$

• **Posterior ratio (log-scaled):**

$$\log \left( \frac{e^{-\gamma(\eta)}}{e^{-\gamma(\eta^{(s)})}} \right) = \log \left( \frac{L(e^\eta)}{L(e^{\eta^{(s)}})} \right) + \alpha(\eta - \eta^{(s)}) - \beta(e^\eta - e^{\eta^{(s)}})$$

• **Likelihood ratio (log-scaled):**

$$\log \left( \frac{L(e^\eta)}{L(e^{\eta^{(s)}})} \right) = N \cdot \left[ \log \left( \frac{\Gamma\left(\frac{e^\eta + 1}{2}\right)}{\sqrt{e^\eta \pi} \Gamma\left(\frac{e^\eta}{2}\right)} \right) - \log \left( \frac{\Gamma\left(\frac{e^{\eta^{(s)}} + 1}{2}\right)}{\sqrt{e^{\eta^{(s)}} \pi} \Gamma\left(\frac{e^{\eta^{(s)}}}{2}\right)} \right) \right]$$

$$- \left[ \frac{e^\eta + 1}{2} \sum_{i=1}^N \log \left( 1 + \frac{y_i^2}{e^\eta} \right) - \frac{e^{\eta^{(s)}} + 1}{2} \sum_{i=1}^N \log \left( 1 + \frac{y_i^2}{e^{\eta^{(s)}}} \right) \right]$$

• **Prior ratio:**

$$\alpha(\eta - \eta^{(s)}) - \beta(e^\eta - e^{\eta^{(s)}})$$

# bayesestdft::BayesLNP

- **Likelihood:**

$$L(v) = p(y_{1:N}|v) = \prod_{i=1}^N t(y_i|v) = \left( \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\Gamma\left(\frac{v}{2}\right)} \right)^N \prod_{i=1}^N \left( 1 + \frac{y_i^2}{v} \right)^{-\frac{v+1}{2}}$$

- **Prior:**

$$v \sim \pi_L(v) = \log N(v|\mu, \sigma^2).$$

- **Posterior distribution:**

$$\pi(v|y_{1:N}) \propto L(v) \cdot \pi_L(v)$$

- **Target density obtained by change of variable ( $\eta = \log v$ ,  $v = e^\eta$ ):**

$$\begin{aligned} \pi(\eta|y_{1:N}) &= \pi(v|y_{1:N}) \Big|_{v=e^\eta} \cdot \left| \frac{dv}{d\eta} \right| = \pi(v = e^\eta|y_{1:N}) \cdot e^\eta \propto L(e^\eta) \cdot \pi_L(e^\eta) \cdot e^\eta \\ &\propto L(e^\eta) \cdot \log N(e^\eta|\mu, \sigma^2) \cdot e^\eta = L(e^\eta) \cdot \frac{1}{e^\eta \cdot \sigma\sqrt{2\pi}} \exp\left(-\frac{(\log e^\eta - \mu)^2}{2\sigma^2}\right) \cdot e^\eta \\ &= L(e^\eta) \cdot \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(\eta - \mu)^2}{2\sigma^2}\right) = L(e^\eta) \cdot N(\eta|\mu, \sigma^2) \end{aligned}$$

# bayesestdft::BayesLNP [Elliptical Slice Sampler]

## [Elliptical Slice Sampler]

**Goal:** Sample from the posterior density

$$\pi(\eta|y_{1:N}) \propto L(e^\eta) \cdot N(\eta|\mu, \sigma^2),$$

$$\text{where } L(v) = \left( \frac{\Gamma(\frac{v+1}{2})}{\sqrt{v\pi}\Gamma(\frac{v}{2})} \right)^N \cdot \prod_{i=1}^N \left( 1 + \frac{y_i^2}{v} \right)^{-\frac{v+1}{2}}.$$

**Input:** Current state  $\eta^{(s)}$

**Output:** A new state  $\eta^{(s+1)}$

- Choose an ellipse centered at  $\mu$ :  $\rho \sim N(\mu, \sigma^2)$ .
- Define a criterion function:

$$\alpha(\eta, \eta^{(s)}) = \min \left\{ \frac{L(e^\eta)}{L(e^{\eta^{(s)}})}, 1 \right\} : R \rightarrow [0, 1].$$

- Choose a threshold and fix:

$$u \sim \text{Unif}[0, 1].$$

- Draw an initial proposal  $\eta^*$ :

$$\phi \sim \text{Unif}(-\pi, \pi];$$

$$\eta^* = (\eta^{(s)} - \mu) \cdot \cos \phi + (\rho - \mu) \cdot \sin \phi + \mu.$$

- if (  $u < \alpha(\eta^*, \eta^{(s)})$  )  $\{\eta^{(s+1)} = \eta^*\}$  else {

Define a bracket :  $(\phi_{min}, \phi_{max}] = (-\pi, \pi]$

**while** (  $u \geq \alpha(\eta^*, \eta^{(s)})$  ) {

Shrink the bracket and try a new point:

if (  $\phi > 0$  )  $\phi_{max} = \phi$  else  $\phi_{min} = \phi$

$$\phi \sim \text{Unif}(\phi_{min}, \phi_{max}];$$

$$\eta^* = (\eta^{(s)} - \mu) \cdot \cos \phi + (\rho - \mu) \cdot \sin \phi + \mu.$$

}

$$\eta^{(s+1)} = \eta^*$$

}

- Likelihood ratio:**

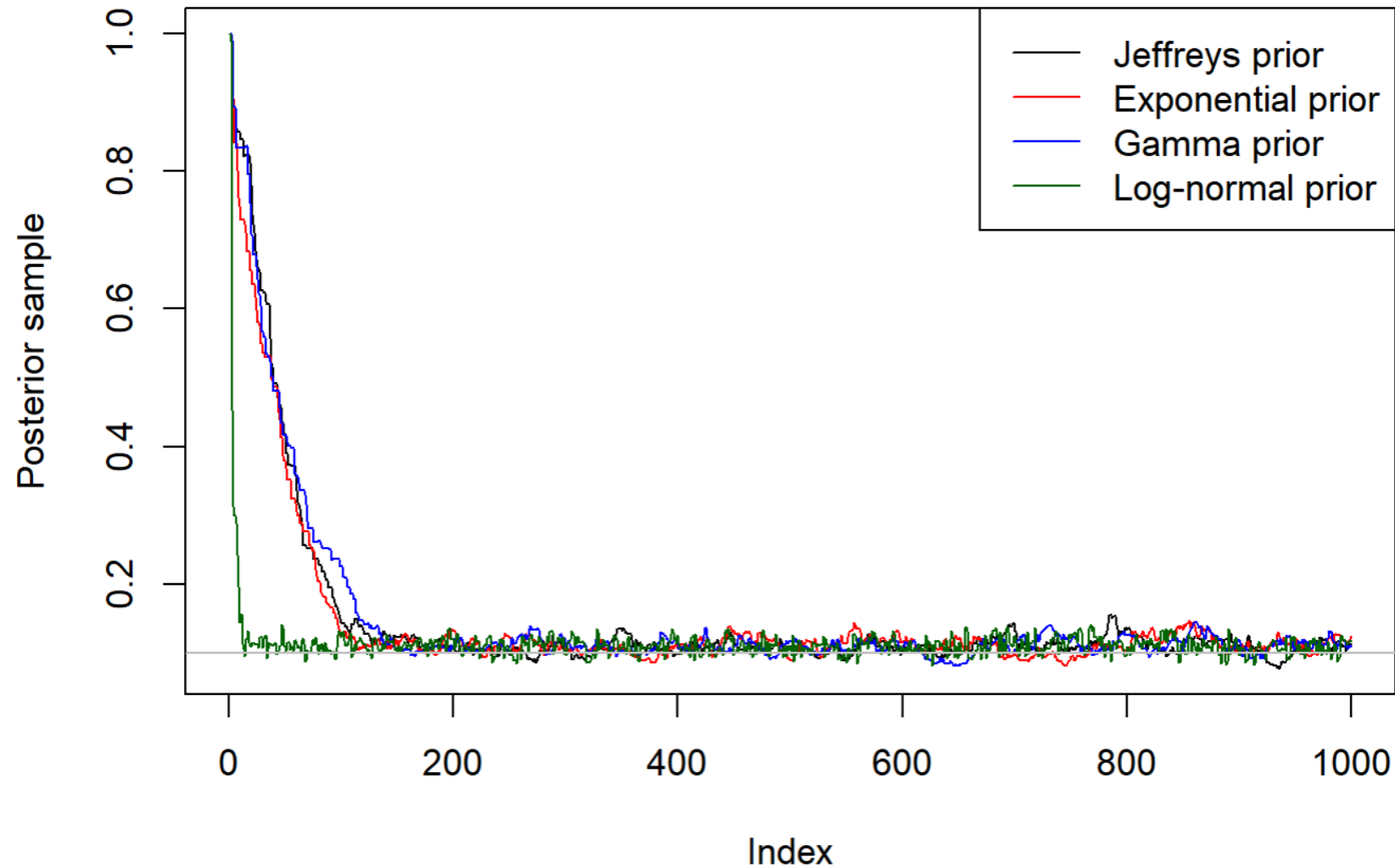
$$\frac{L(e^\eta)}{L(e^{\eta^{(s)}})} = \frac{\left( \frac{\Gamma(\frac{e^\eta + 1}{2})}{\sqrt{e^\eta \pi} \Gamma(\frac{e^\eta}{2})} \right)^N \cdot \prod_{i=1}^N \left( 1 + \frac{y_i^2}{e^\eta} \right)^{-\frac{e^\eta + 1}{2}}}{\left( \frac{\Gamma(\frac{e^{\eta^{(s)}} + 1}{2})}{\sqrt{e^{\eta^{(s)}} \pi} \Gamma(\frac{e^{\eta^{(s)}}}{2})} \right)^N \cdot \prod_{i=1}^N \left( 1 + \frac{y_i^2}{e^{\eta^{(s)}}} \right)^{-\frac{e^{\eta^{(s)}} + 1}{2}}}$$

- Likelihood ratio (log-scaled):**

$$\begin{aligned} \log \left( \frac{L(e^\eta)}{L(e^{\eta^{(s)}})} \right) &= \\ &= N \cdot \left[ \log \left( \frac{\Gamma(\frac{e^\eta + 1}{2})}{\sqrt{e^\eta \pi} \Gamma(\frac{e^\eta}{2})} \right) - \log \left( \frac{\Gamma(\frac{e^{\eta^{(s)}} + 1}{2})}{\sqrt{e^{\eta^{(s)}} \pi} \Gamma(\frac{e^{\eta^{(s)}}}{2})} \right) \right] \\ &\quad - \left[ \frac{e^\eta + 1}{2} \sum_{i=1}^N \log \left( 1 + \frac{y_i^2}{e^\eta} \right) - \frac{e^{\eta^{(s)}} + 1}{2} \sum_{i=1}^N \log \left( 1 + \frac{y_i^2}{e^{\eta^{(s)}}} \right) \right] \end{aligned}$$

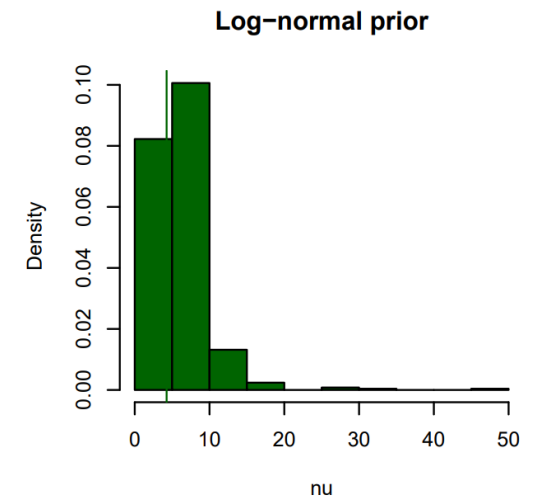
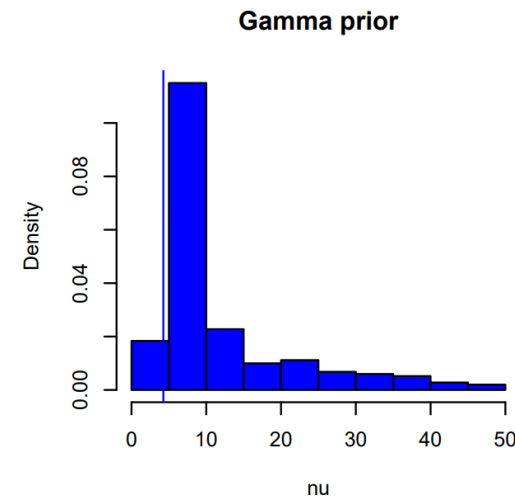
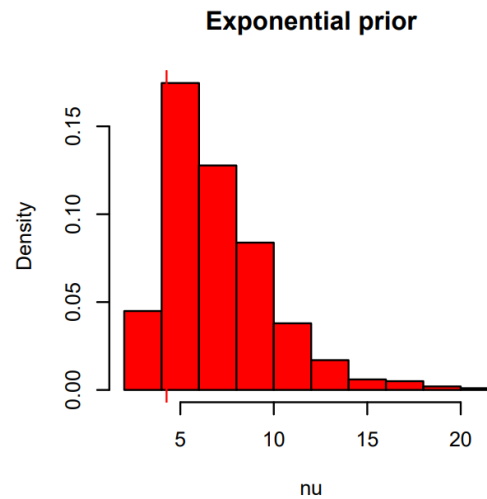
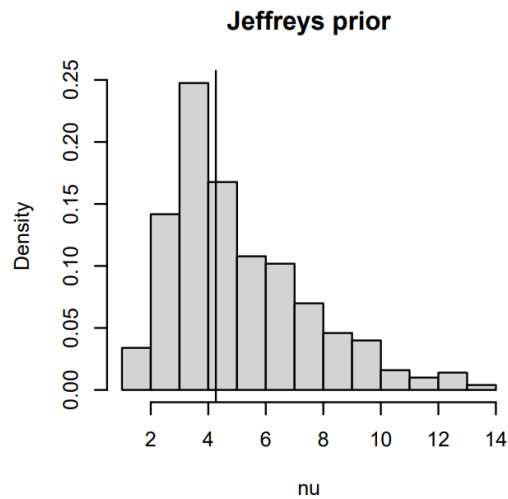
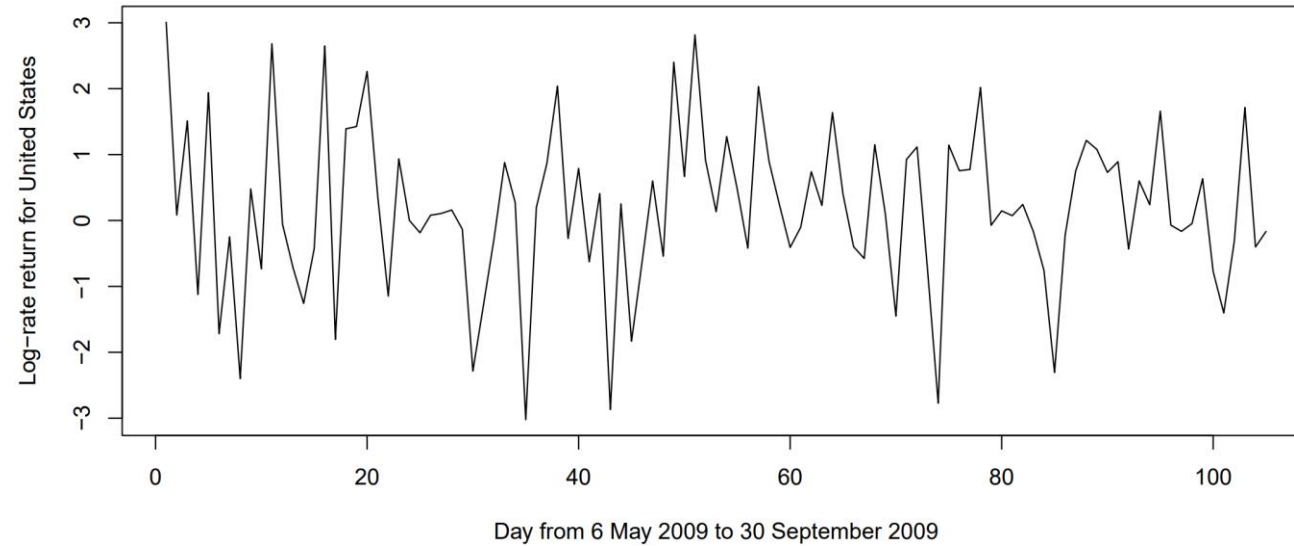
# DEMO 1: comparison of the trace plots

Observations are 100 number of samples drawn from Student t-distribution with  $df = 0.1$



# DEMO 2: financial data analysis

Observations are 105 number of samples of the daily log-rate return for US from 6 May 2009 to 30 September 2009



# References

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