

MCW Biostatistics Technical Report 63: BART with logGamma errors using a convolution mixture of Normals

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Bayesian Additive Regression Trees (BART) [1] allows one to regress a continuous outcome, y , on a vector of covariates, \mathbf{x} , via an arbitrarily flexible function, f , i.e. $y = f(\mathbf{x}) + \epsilon$ where $\epsilon \sim \mathbf{N}(0, \sigma^2)$. However, suppose ϵ follows some other distribution function, say $G(\epsilon)$, then we can still employ BART provided that $g(\epsilon)$ can be reliably approximated by a mixture of Normals, i.e. $g(\epsilon) \approx \sum_i p_i \mathbf{N}(\mu_i, \sigma_i^2)$ where (p_i, μ_i, σ_i) are known. We extend BART to the situation where ϵ follows the logGamma distribution with distribution function $G_\alpha(y)$ and density function $g_\alpha(y)$.

If x follows the Gamma distribution, then $y = \log x$ follows the logGamma distribution, i.e. $x \sim \mathbf{Gamma}(\alpha, 1)$ where $\alpha > 0$ implies $y \sim \log \mathbf{Gamma}(\alpha, 1)$ and $g_\alpha(y) = \Gamma(\alpha)^{-1} e^{y\alpha - e^y}$.

Fruhworth-Schnatter, Fruhwirth, Held, and Rue (FFHR) [2] show how to reliably approximate the logGamma distribution, $\log \mathbf{Gamma}(\alpha, \beta)$ with a mixture of Normals. However, their method (which we also refer to as FFHR) is not readily applicable to our work since we need $\alpha < 1$ while FFHR requires that $\alpha \geq 1$. Therefore, we extend FFHR to meet our needs with similar high-degree of accuracy so we can approximate any $\log \mathbf{Gamma}(\alpha, \beta)$ routinely via $\log \beta x_\alpha = \log \beta + y_\alpha$ where $\alpha > 0$ and $\beta > 0$.

FFHR employ the Kullback-Leibler divergence [3] to determine the accuracy of the approximation: $\delta_{KL}(\boldsymbol{\theta}_\alpha) = \int_{-10}^6 g_\alpha(y) \log \frac{g_\alpha(y)}{g_\alpha(y; \boldsymbol{\theta}_\alpha)} dy$ where $\boldsymbol{\theta}_\alpha = (\boldsymbol{p}_{y_\alpha}, \boldsymbol{\mu}_{y_\alpha}, \boldsymbol{\sigma}_{y_\alpha})$. Then, they use the Nelder-Mead simplex method [4] to minimize the following objective function: $\Delta_{KL}(\boldsymbol{\theta}_\alpha) = \delta_{KL}(\boldsymbol{\theta}_\alpha) + 10^9 (1 - \sum_i p_{y_\alpha i})^2$ subject to the constraints $0 < p_{y_\alpha i} < 1$ and $0 < \sigma_{y_\alpha i}$.

We adopt the following notation: y_α is a random variable with the same distribution as $\log x_\alpha$ where $x_\alpha \sim \mathbf{Gamma}(\alpha, 1)$. Notice that we can decompose y_α as $y_\alpha = y_{\alpha+1} + w_\alpha$ where $w_\alpha \sim \mathbf{Exp}(\alpha)$ and $y_{\alpha+1} \perp w_\alpha$. This result can be extended to what could be called a ‘‘distributional factorial’’ property of the logGamma distribution: $y_\alpha = y_{\alpha+n} + \sum_{i=1}^n w_{\alpha+i-1}$ where $w_{\alpha+i-1} \stackrel{\text{ind}}{\sim} \mathbf{Exp}(\alpha + i - 1)$ and $y_{\alpha+n} \perp w_{\alpha+i-1}$ for $i = 1, \dots, n$.

Now, let us return to where our interest resides: $\alpha < 1$. We found it difficult to approximate logGamma for $\alpha < 1$ with $\alpha \geq 1$ in one step via $y_\alpha = y_{\alpha+1} + w_\alpha$. However, the approximation with two steps is satisfactory, i.e. substitute $y_{\alpha+1} = y_{\alpha+2} + w_{\alpha+1}$ into $y_\alpha = y_{\alpha+1} + w_\alpha$ which yields $y_\alpha = y_{\alpha+2} + w_{\alpha+1} + w_\alpha$. We

accomplish this by approximating the distribution for each of these 3 terms by their own mixture of Normals the composite of which we call a convolution mixture of Normals.

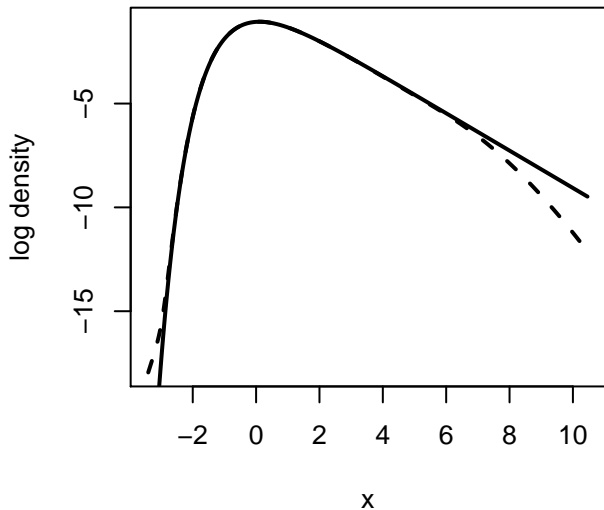
FFHR provide a high-degree of accuracy for approximation at the integers of $\alpha \in \{1, 2, 3, 4\}$ with mixtures of 10 Normals, i.e. $y_\alpha \overset{\text{approx}}{\sim} \sum_{i=1}^{10} p_{y_{\alpha i}} \mathbf{N}(\mu_{y_{\alpha i}}, \sigma_{y_{\alpha i}}^2)$ (note that the FFHR weights, $p_{y_{\alpha i}}$, are identical, $p_{y_{\alpha i}} = p_{y_{\alpha' i}}$, for $\alpha \neq \alpha' \in \{1, 2, 3, 4\}$, however, this will not be the case for our approximations for $\alpha \in (2, 3)$). To create mixtures for non-integer $\alpha \in (2, 3)$, we estimate a starting point via linear interpolation starting with $\alpha = 2.5$ as $0.5\hat{\theta}_2 + 0.5\hat{\theta}_3$. Then we plug this starting point into the subplex algorithm [5] where we minimize $\Delta_{KL}(\theta_{2.5})$ arriving at the solution $\hat{\theta}_{2.5} = \arg \min_{\theta_{2.5}} \Delta_{KL}(\theta_{2.5})$. The subplex algorithm (a variant of the Nelder-Mead simplex method) is more efficient and robust than simplex while retaining the latter's facility with discontinuous objectives. Now, we proceed to fill in the grid of 129 points: $2, 2 + \frac{1}{128}, \dots, 2 + \frac{127}{128}, 3$; i.e. create a linear interpolation starting point $0.5\hat{\theta}_2 + 0.5\hat{\theta}_{2.5}$ to plug into the subplex method arriving at $\hat{\theta}_{2.25}$, etc. Once you reach this grid level, linear interpolation between the grid points provides sufficiently accurate approximations.

Finally, we approximate the distribution of $w \sim \text{Exp}(1)$ by a mixture of 20 Normals. Since the Exponential distribution is restricted to positive values and the Normal distribution is not, we can not employ the Kullback-Leibler divergence. Instead, we rely on integrated squared error: $\delta_{ISE}(\zeta) = \int_0^\infty (g_w(y) - \hat{g}_w(y; \zeta))^2 dy$ and use the objective function $\Delta_{ISE}(\zeta) = \delta_{ISE}(\zeta) + 10^9(1 - \sum_i p_{wi})^2$. Accuracy of approximations achieved can be seen visually in the plots of densities (and log-densities) of $-y$, $y \sim \log \text{Gamma}(\alpha, 1)$ for various choices of α in the range of interest on the next several pages.

References

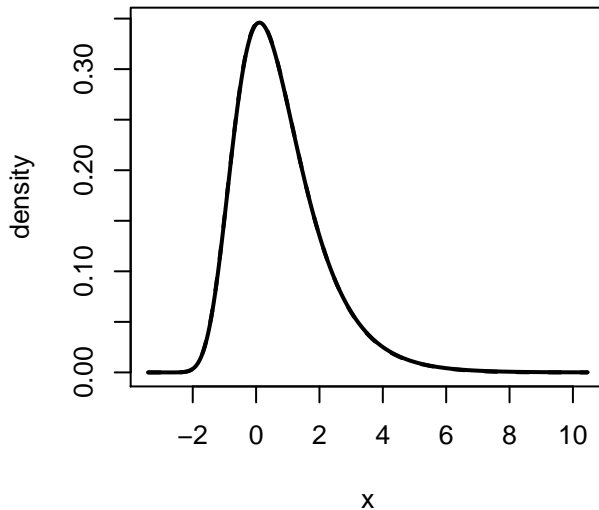
- [1] Hugh A. Chipman, Edward I. George, and Robert E. McCulloch. BART: Bayesian Additive Regression Trees. *The Annals of Applied Statistics*, 4(1):266–298, 2010.
- [2] S. Fruhwirth-Schnatter, R. Fruhwirth, L. Held, and H. Rue. Improved auxiliary mixture sampling for hierarchical models of non-Gaussian data. *Statistics and computing*, 19:479–492, 2009.
- [3] S Kullback and RA Leibler. On information and sufficiency. *Ann Math Stat*, 1951.
- [4] J. A. Nelder and R. Mead. A simplex method for function minimization. *The Computer Journal*, 7:308–13, 1965.
- [5] T Rowan. *Functional Stability Analysis of Numerical Algorithms*. PhD thesis, Department of Computer Sciences, University of Texas at Austin, 1990.

alpha = 0.9



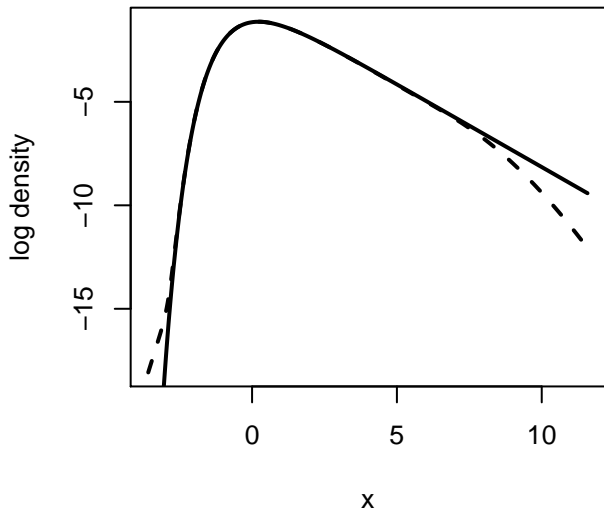
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alpha = 0.9



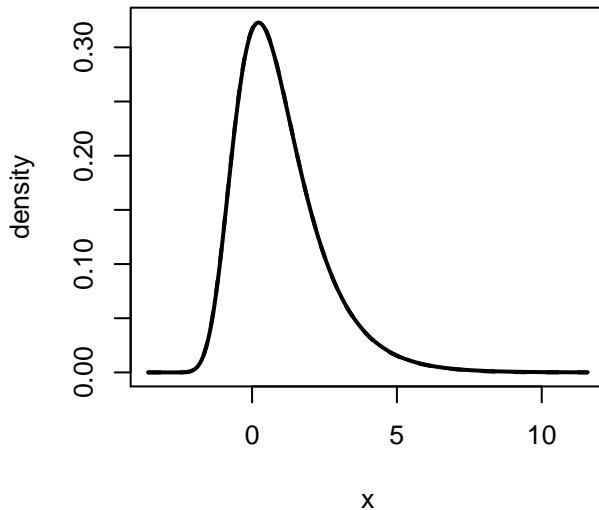
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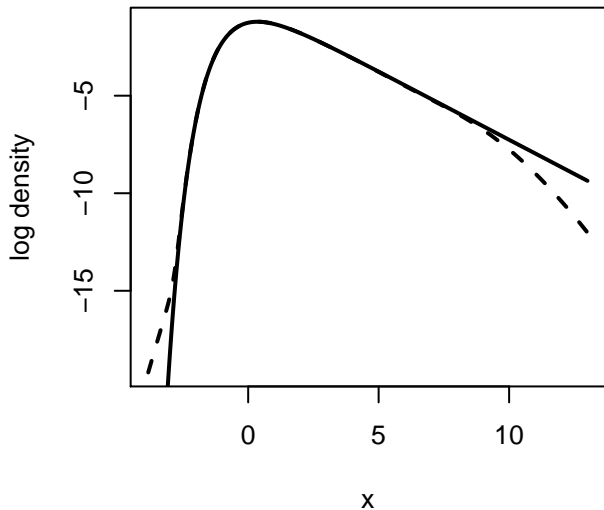
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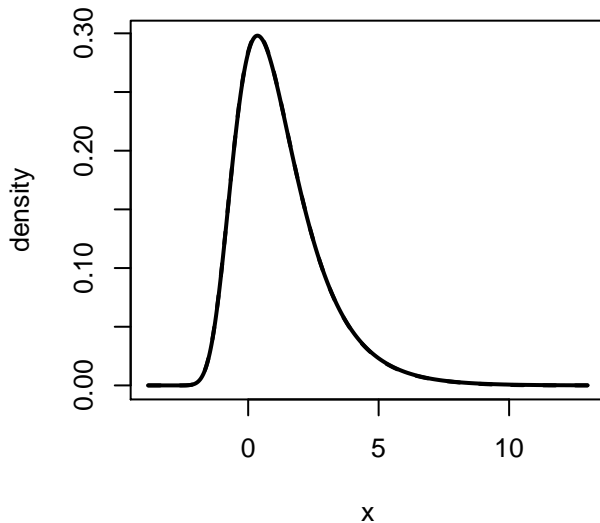
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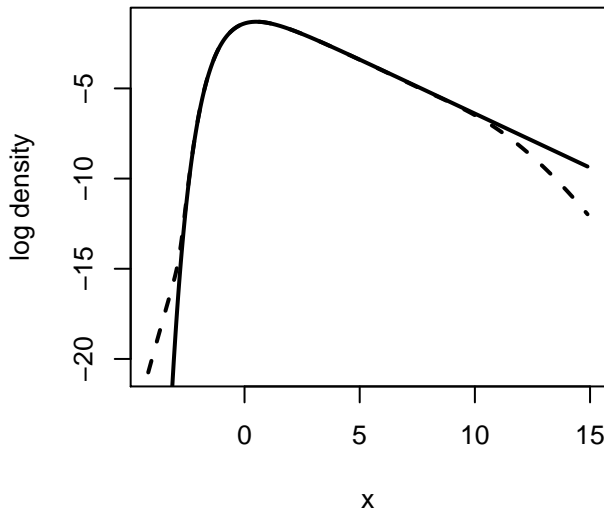
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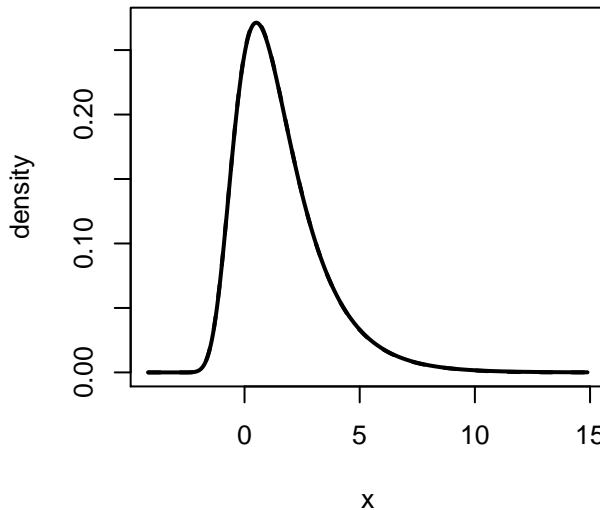
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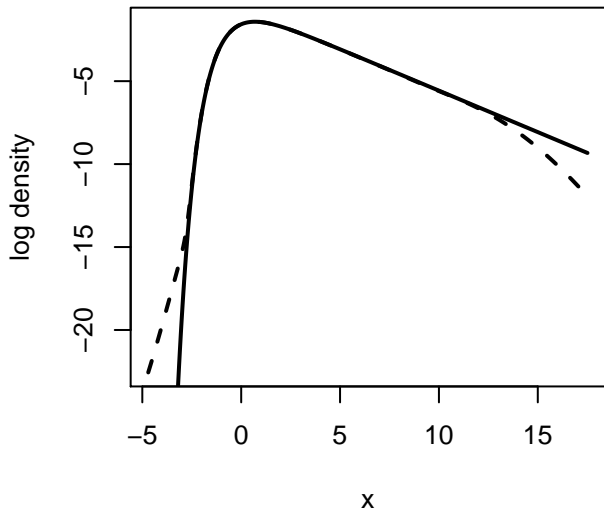
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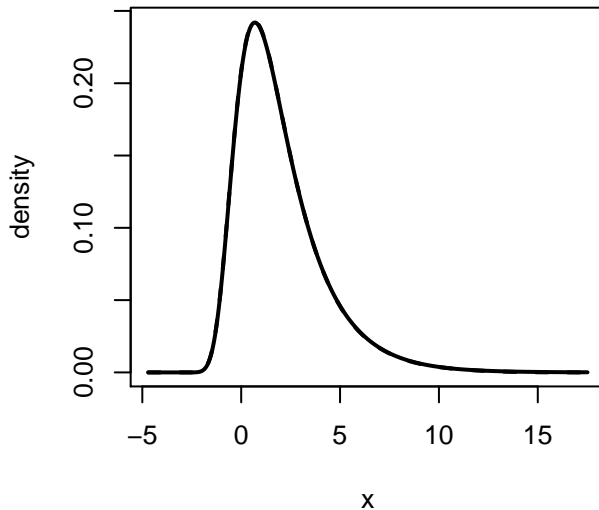
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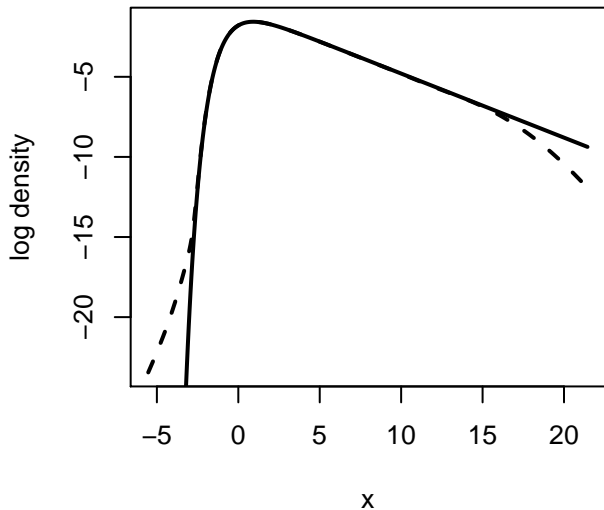
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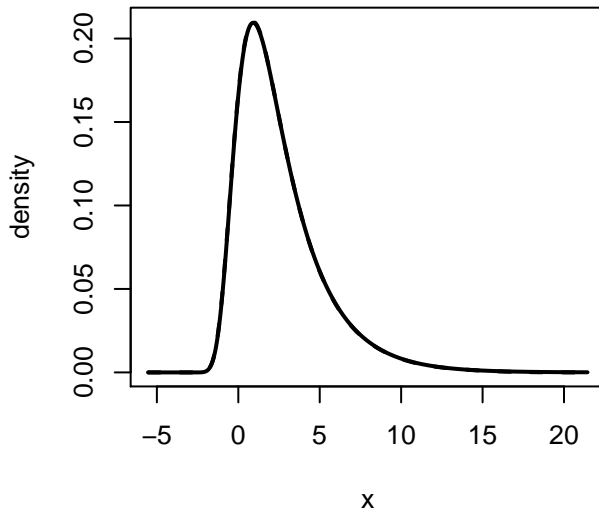
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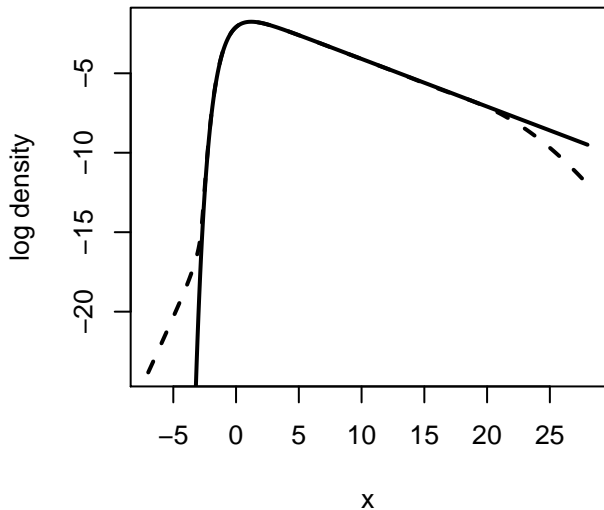
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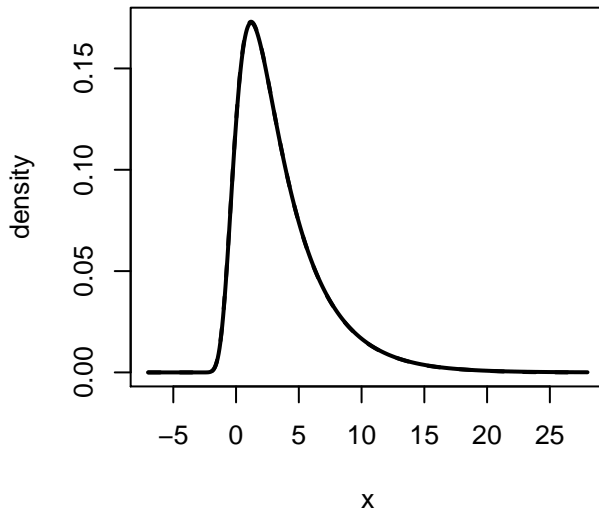
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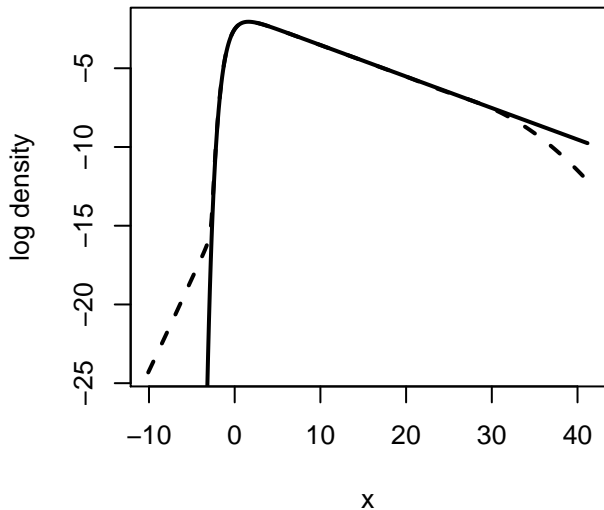
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alpha = 0.3



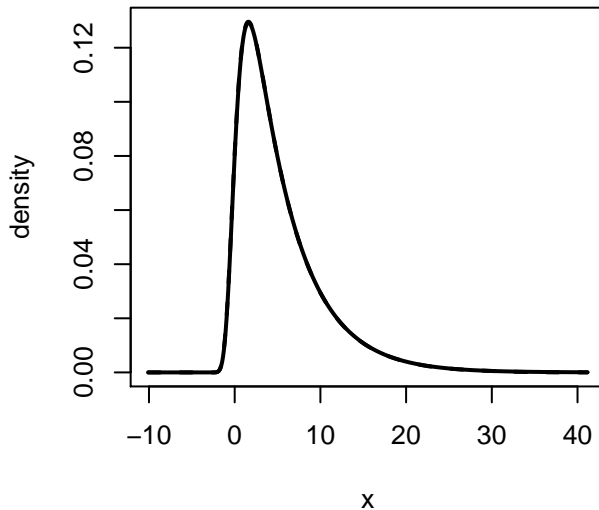
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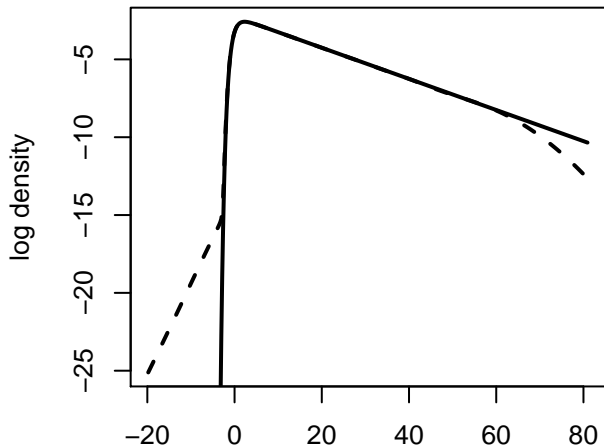
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alpha = 0.2



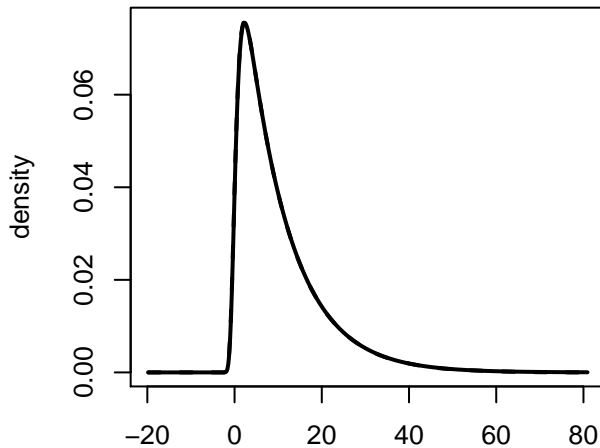
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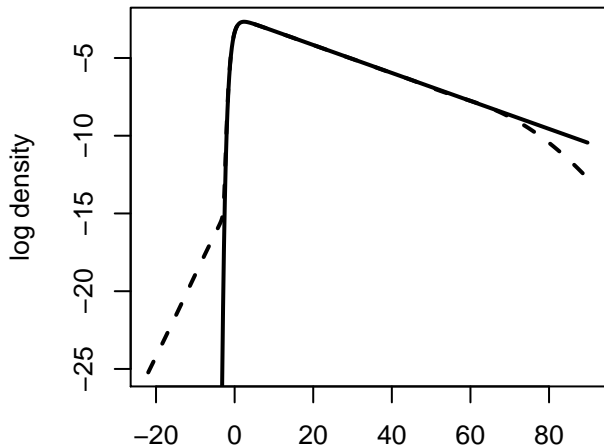
x
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alpha = 0.1



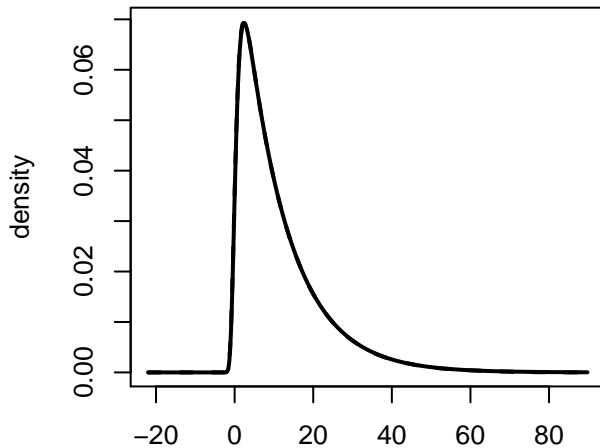
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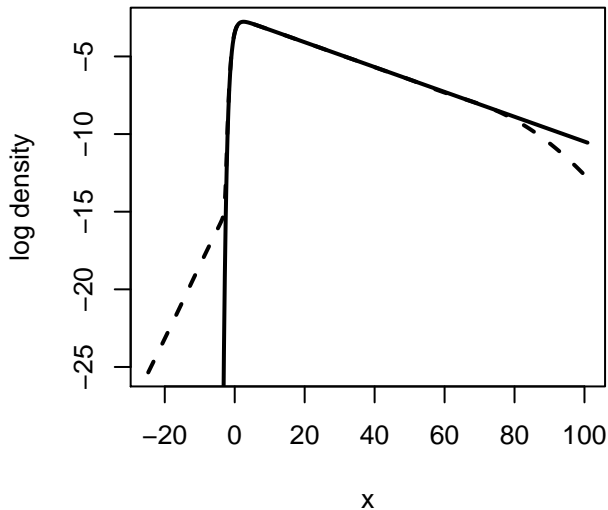
x
KL = 0.00015 on $\mu - 3\text{sd}$ to $\mu + 7\text{sd}$

alpha = 0.09



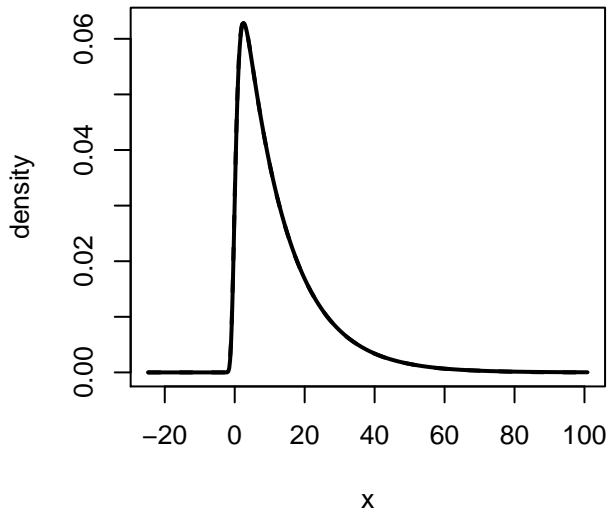
x
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alpha = 0.08



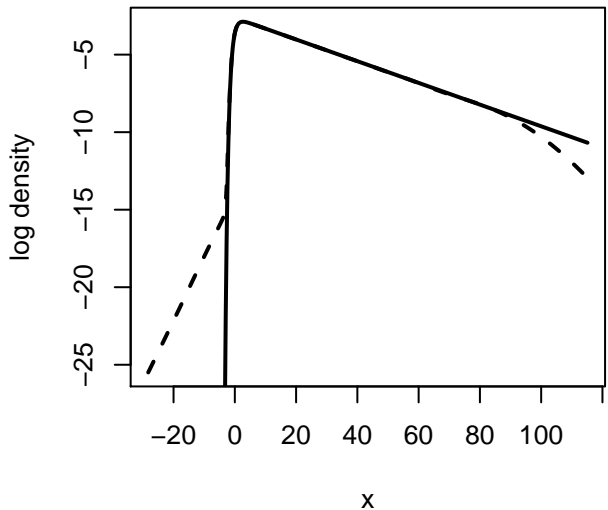
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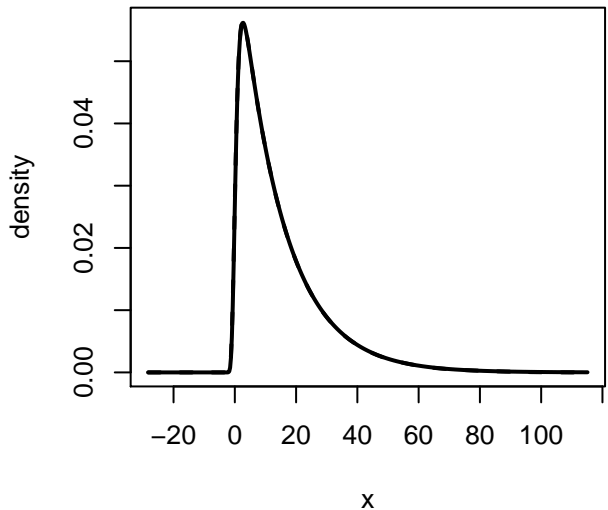
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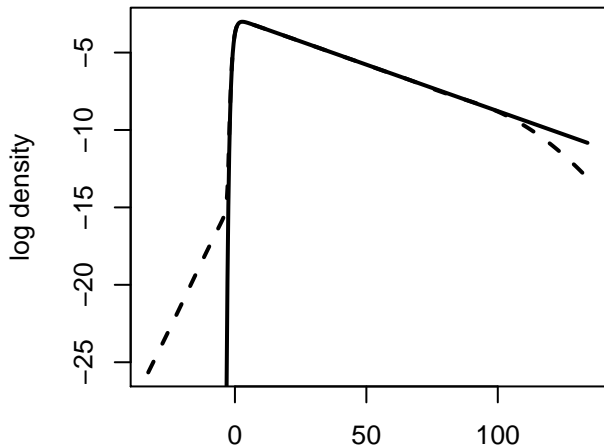
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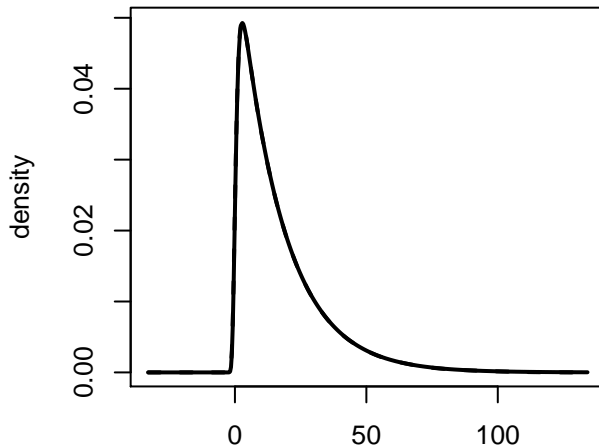
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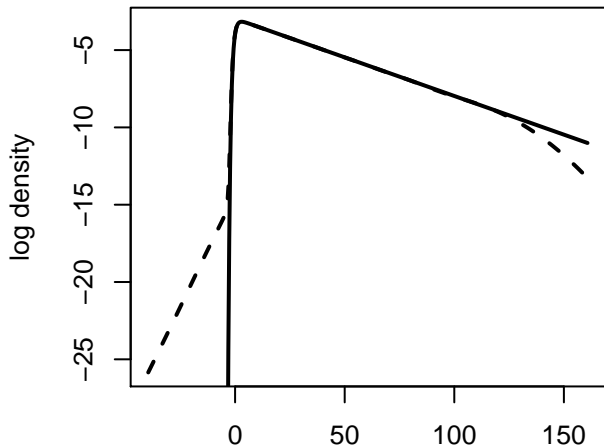
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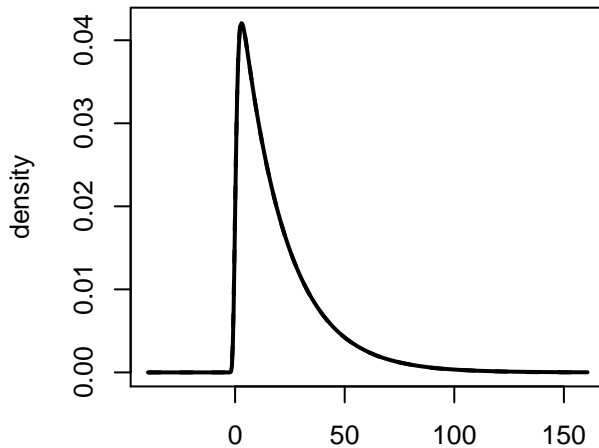
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alpha = 0.05



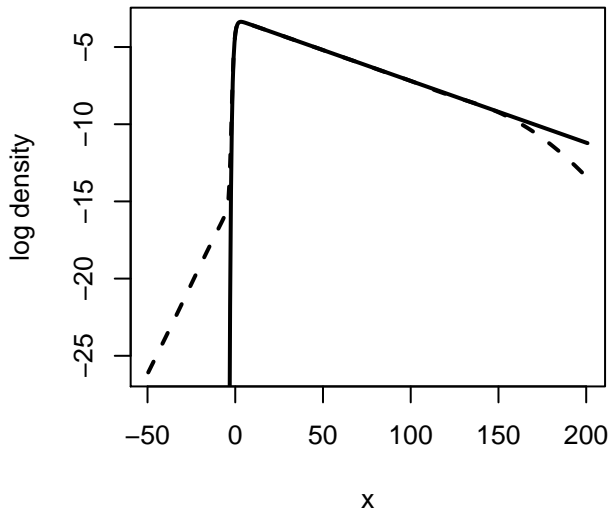
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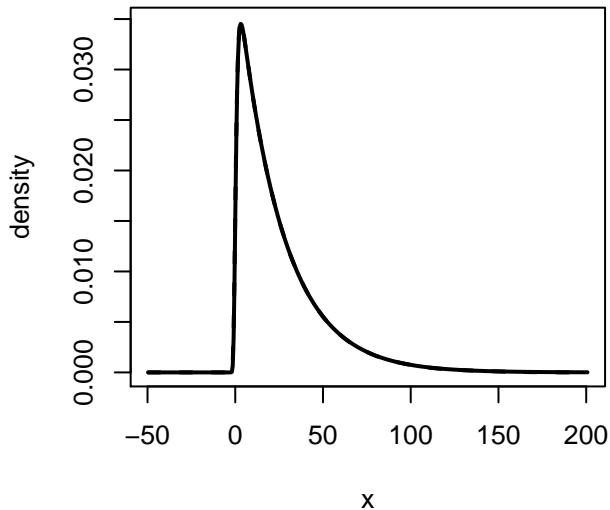
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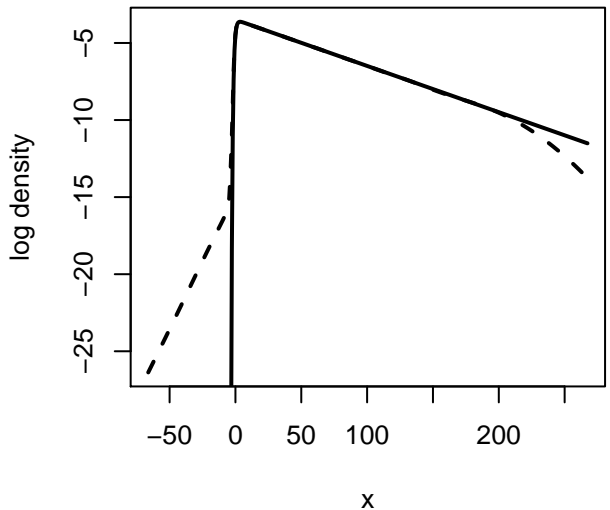
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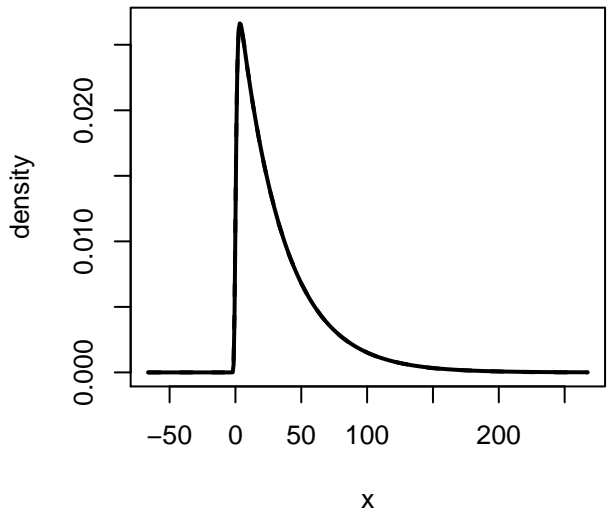
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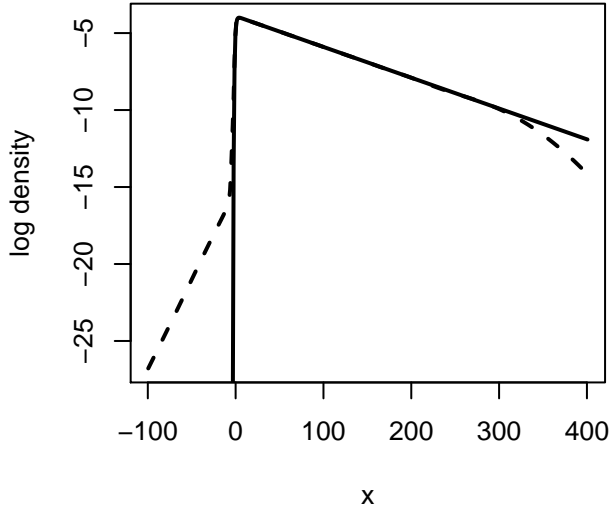
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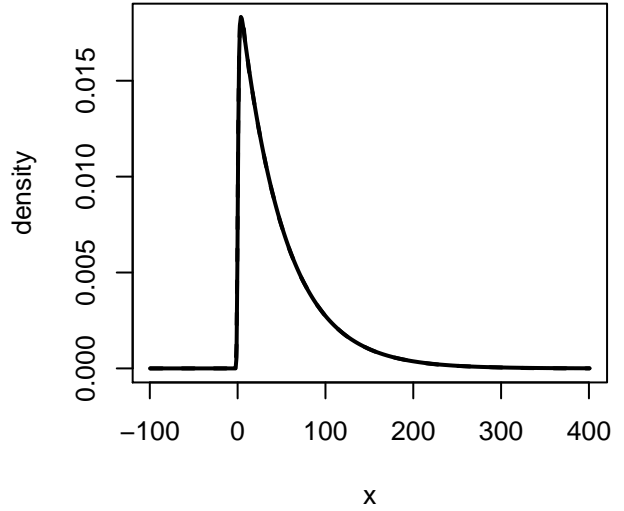
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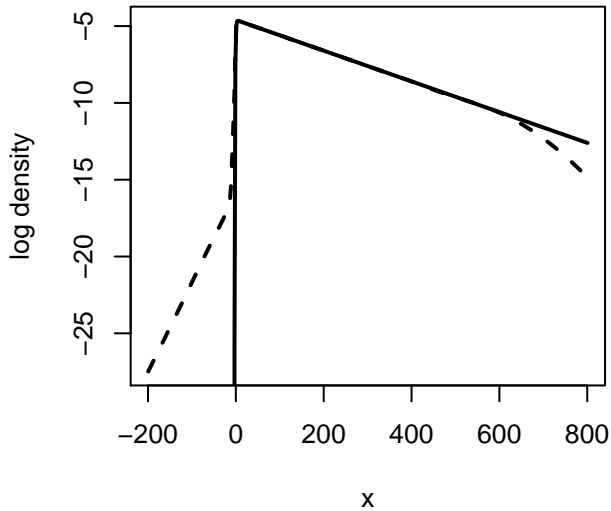
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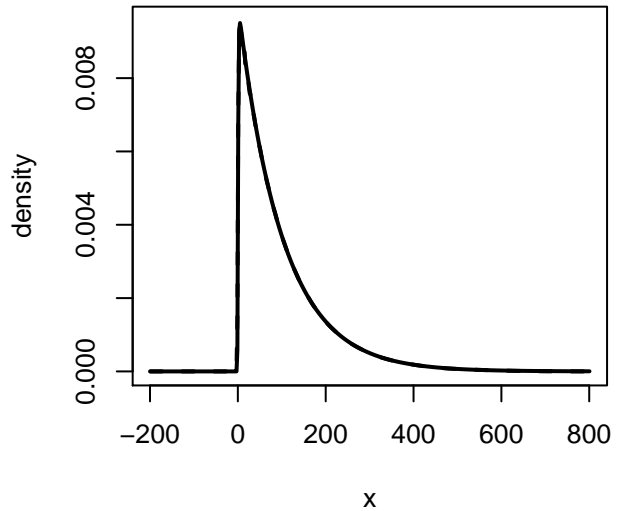
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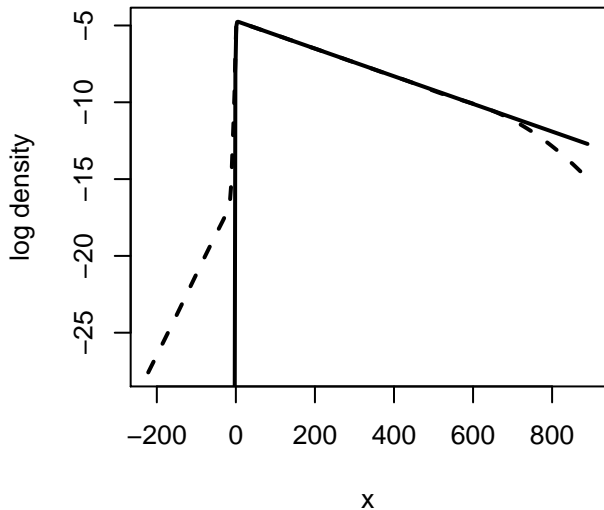
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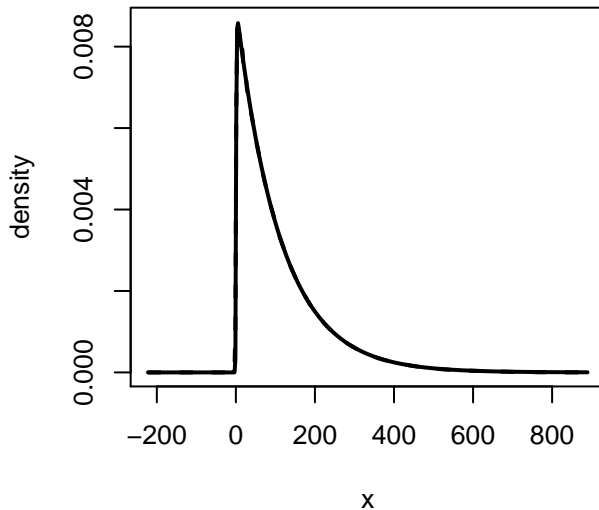
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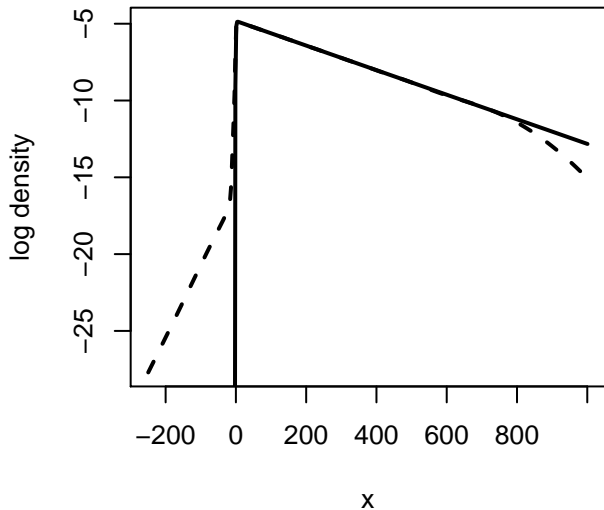
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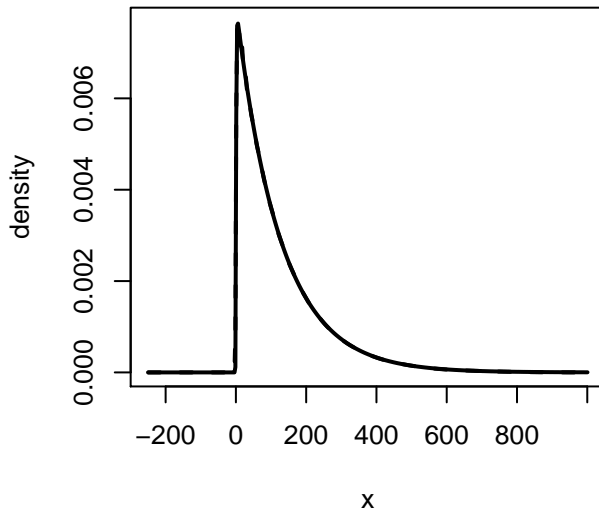
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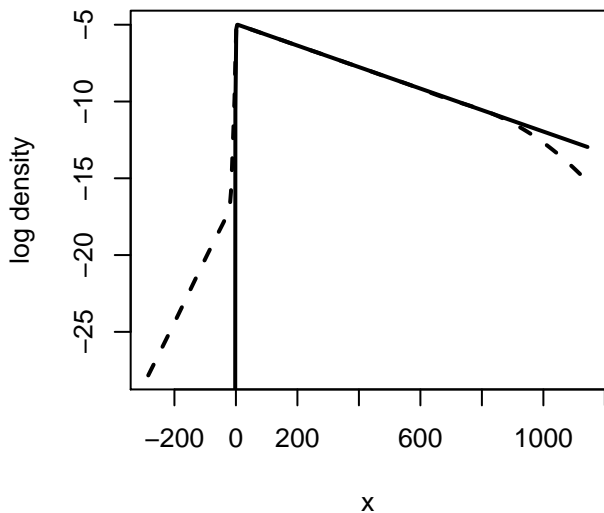
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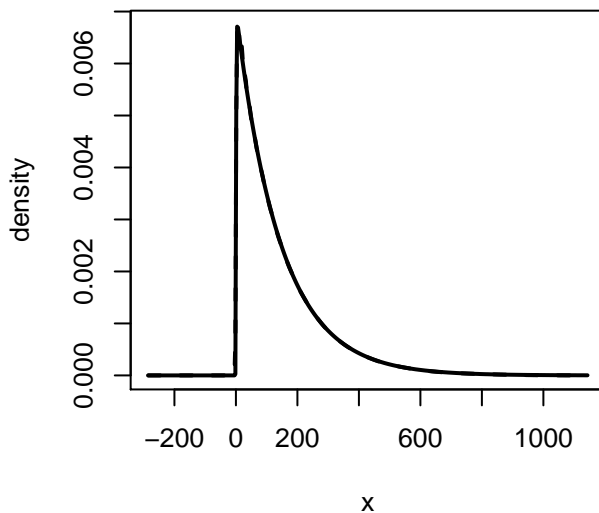
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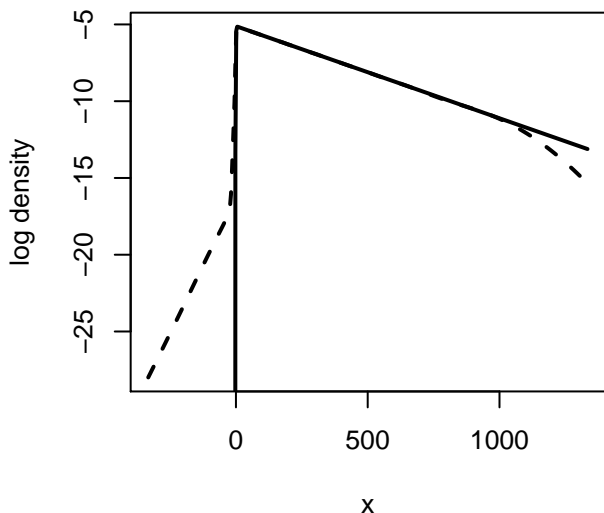
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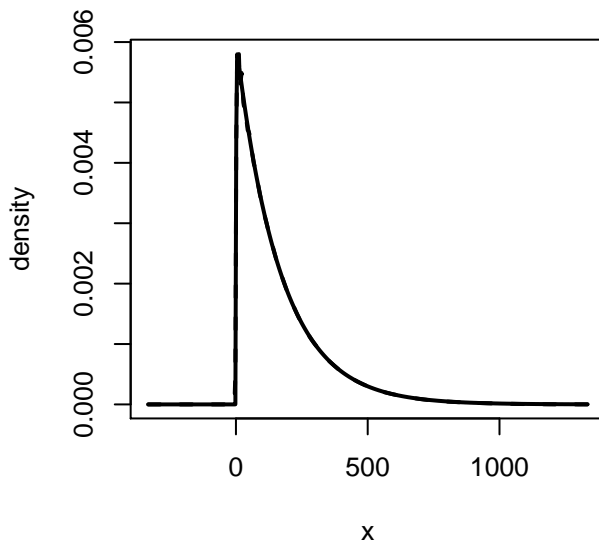
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alpha = 0.006



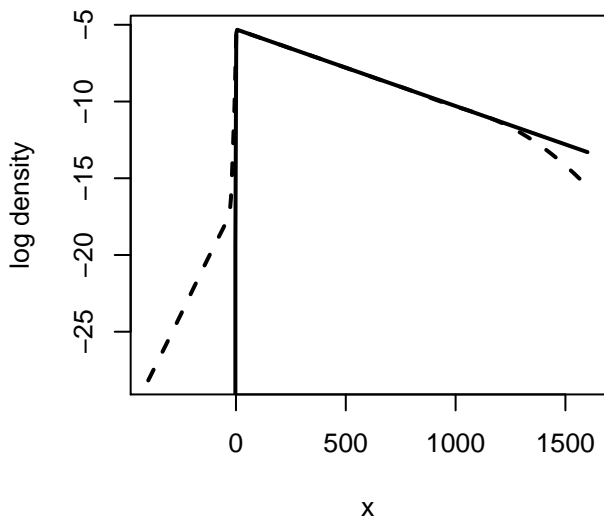
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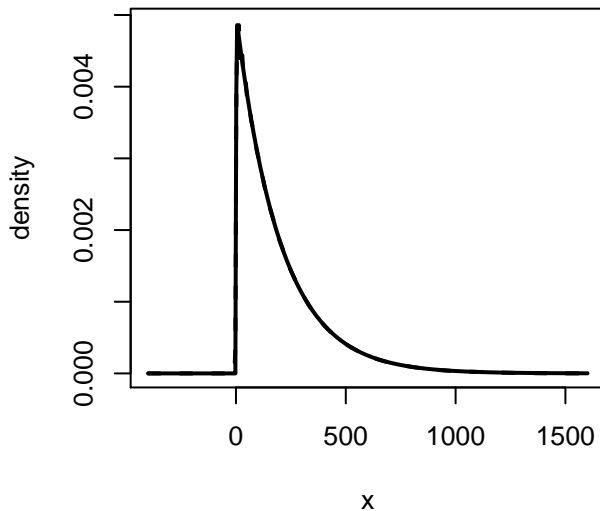
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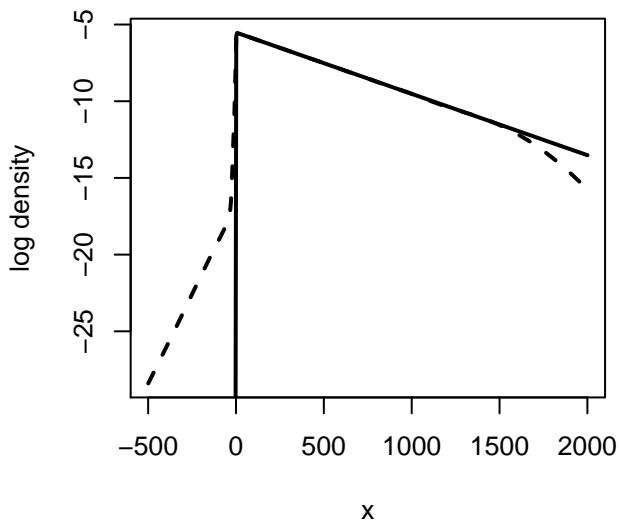
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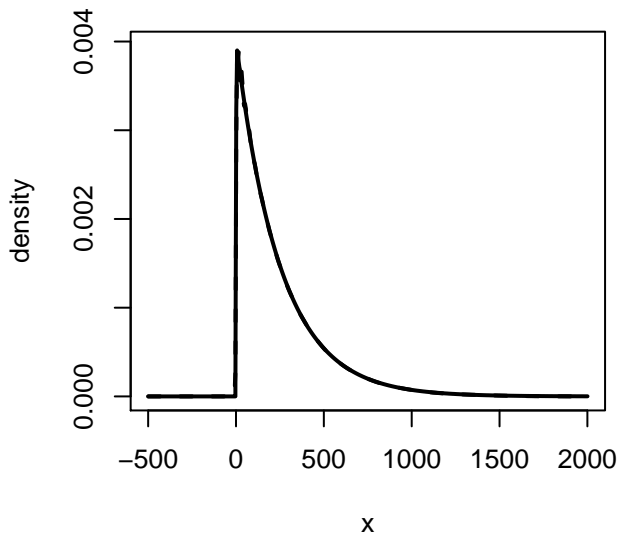
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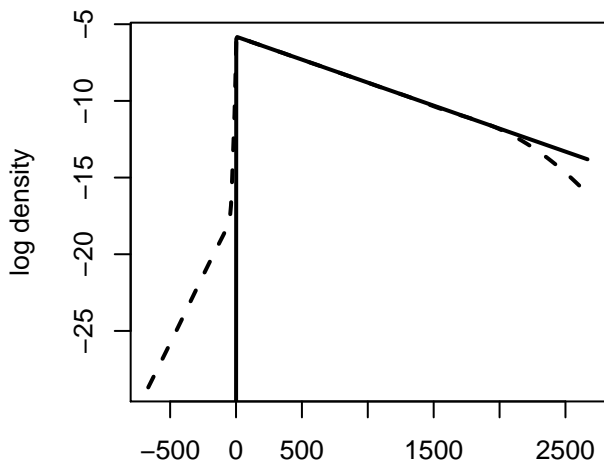
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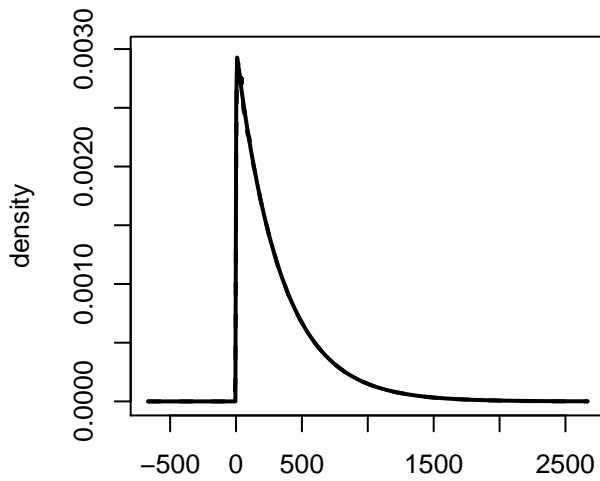
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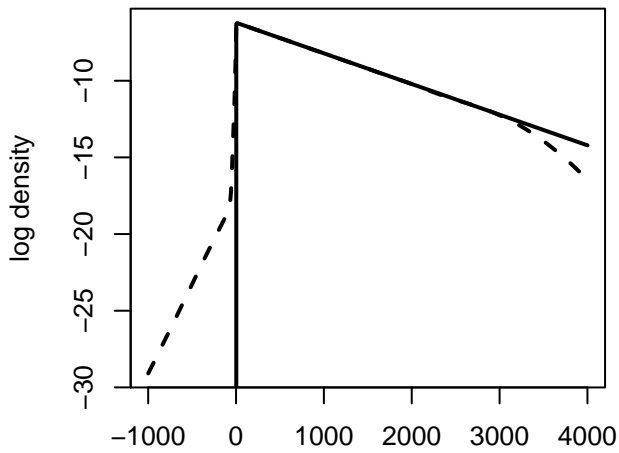
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alpha = 0.003



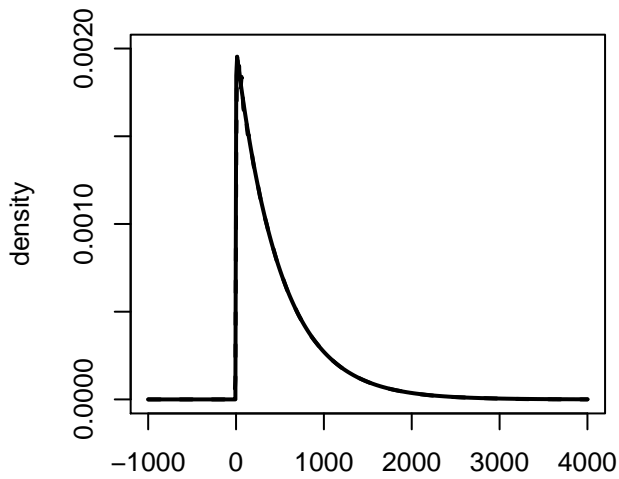
KL = 0.00516 on $\mu-3\text{sd}$ to $\mu+7\text{sd}$

alpha = 0.002



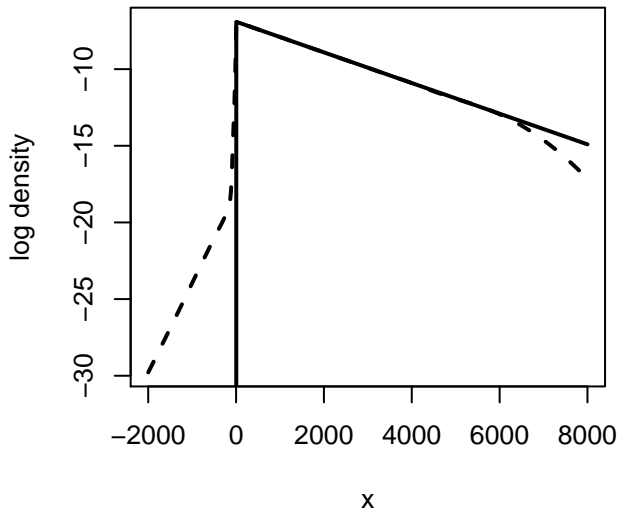
KL = NaN on $\mu-3\text{sd}$ to $\mu+7\text{sd}$

alpha = 0.002



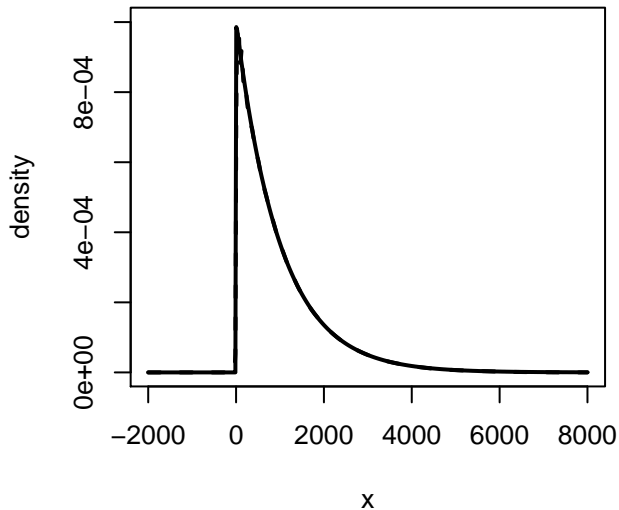
KL = NaN on $\mu-3\text{sd}$ to $\mu+7\text{sd}$

alpha = 0.001



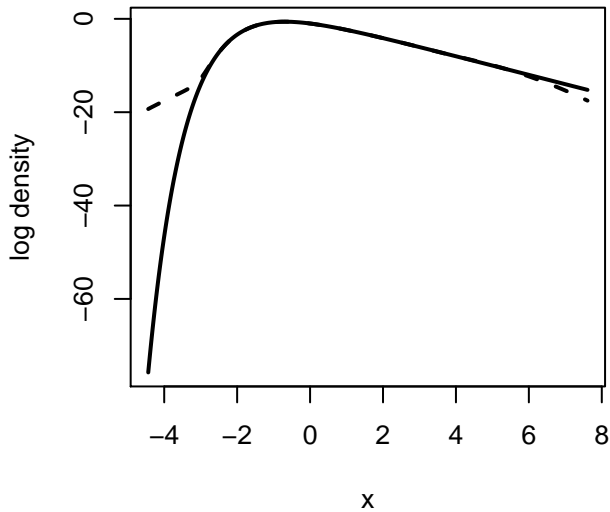
KL = NaN on $\mu - 3\text{sd}$ to $\mu + 7\text{sd}$

alpha = 0.001

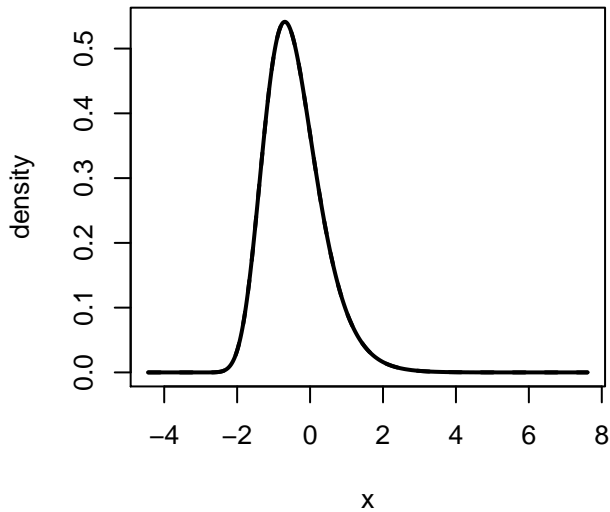


KL = NaN on $\mu - 3\text{sd}$ to $\mu + 7\text{sd}$

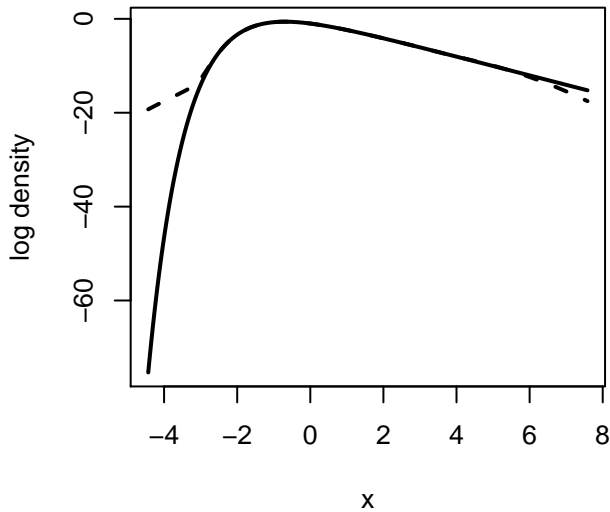
alpha = 2



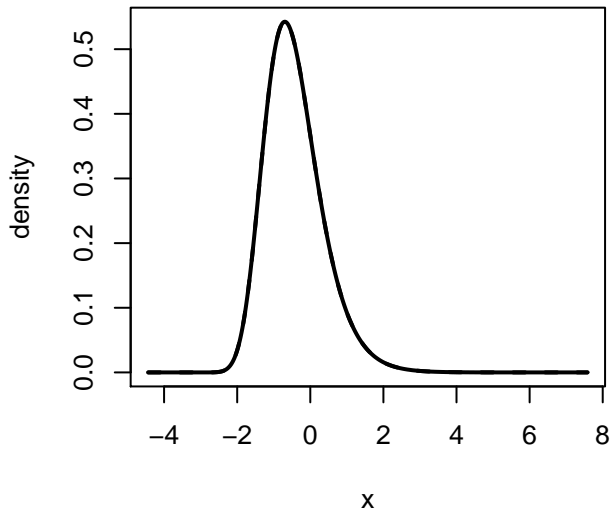
alpha = 2



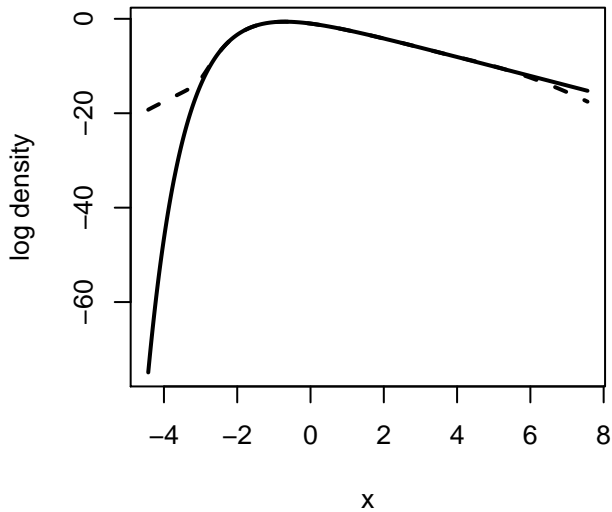
alpha = 2.0078125



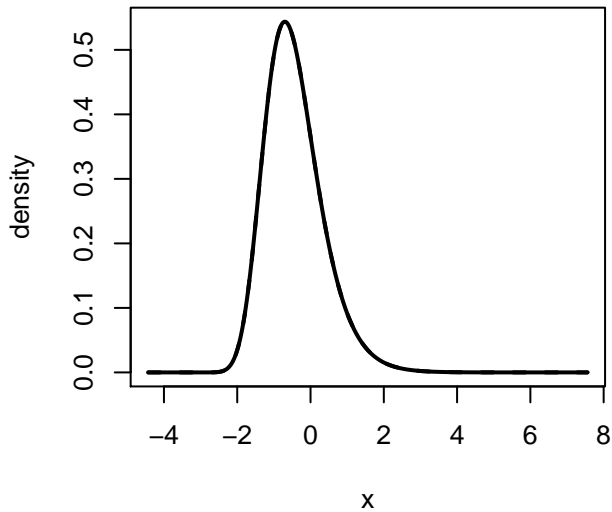
alpha = 2.0078125



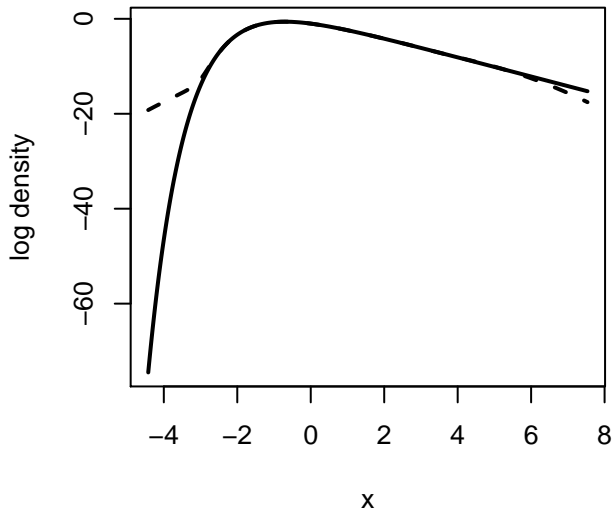
alpha = 2.015625



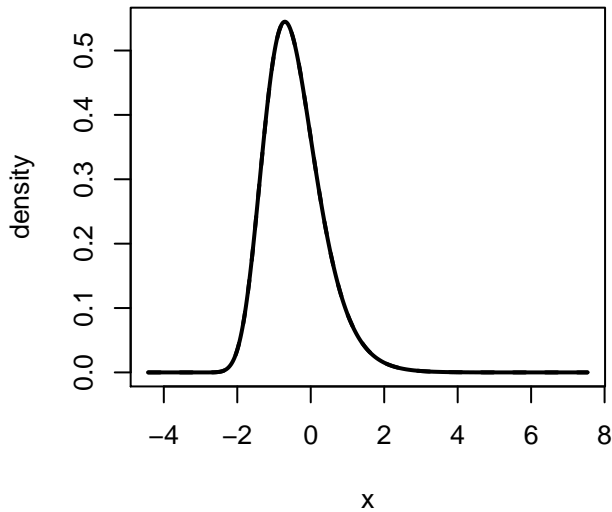
alpha = 2.015625



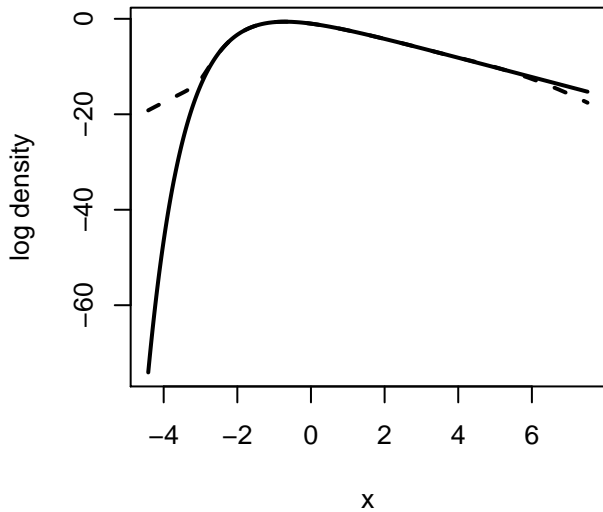
alpha = 2.0234375



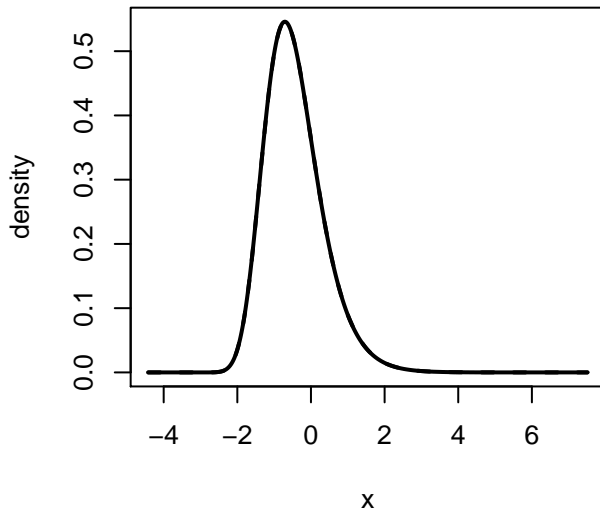
alpha = 2.0234375



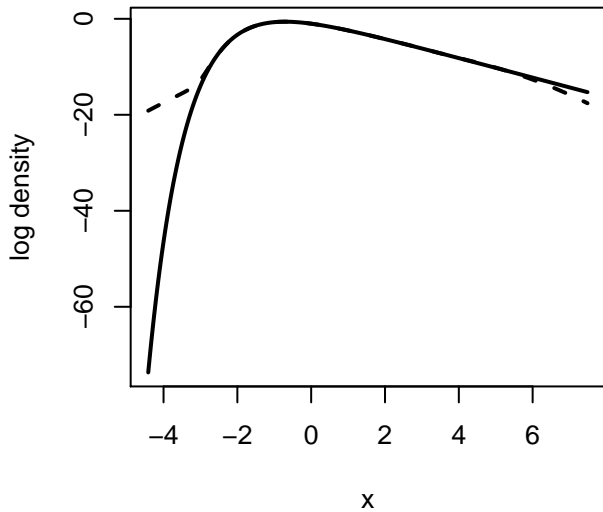
alpha = 2.03125



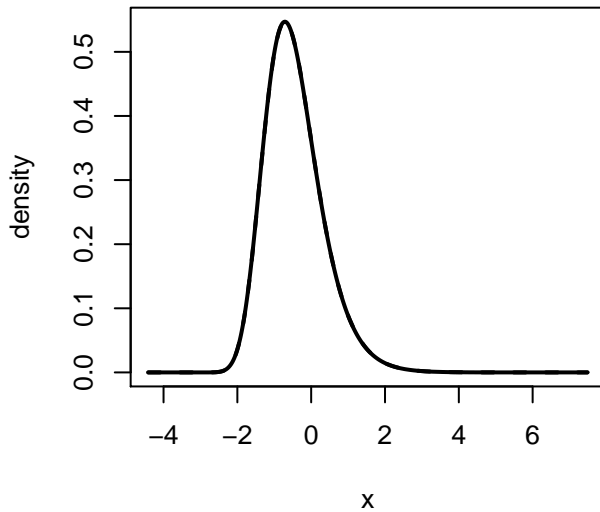
alpha = 2.03125



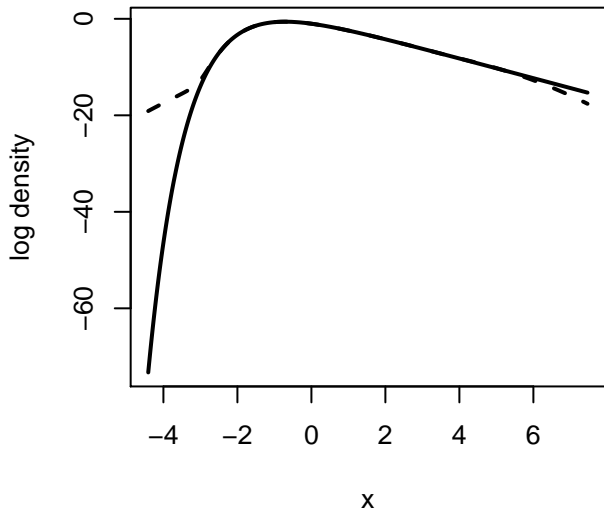
alpha = 2.0390625



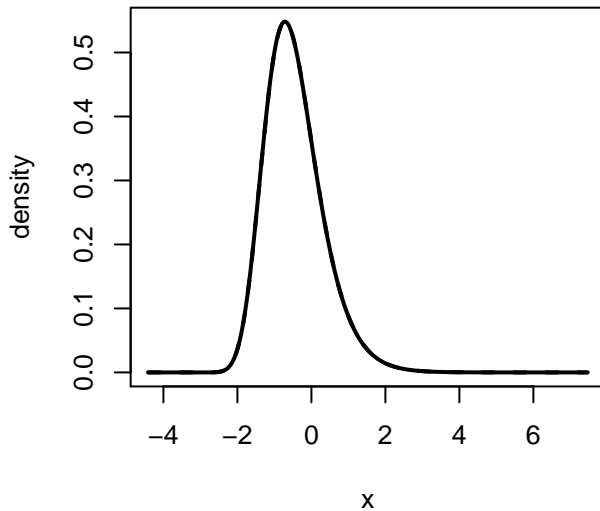
alpha = 2.0390625



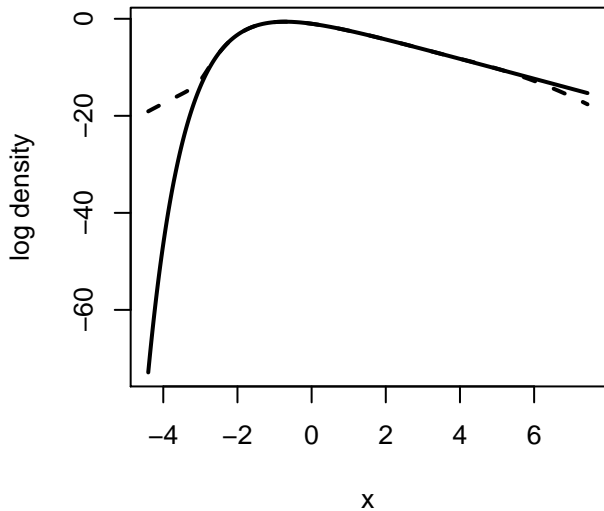
alpha = 2.046875



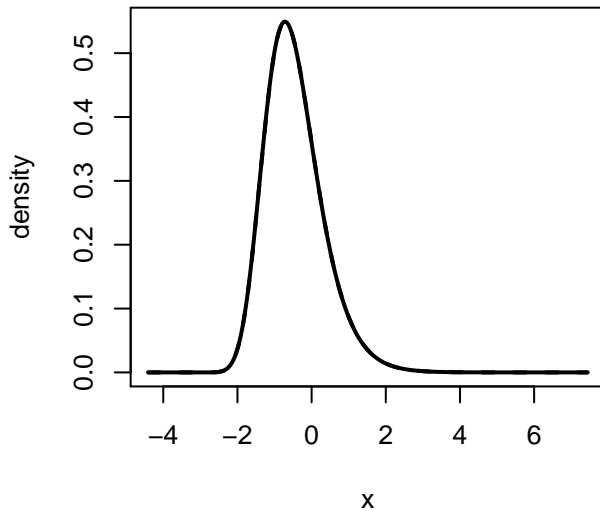
alpha = 2.046875



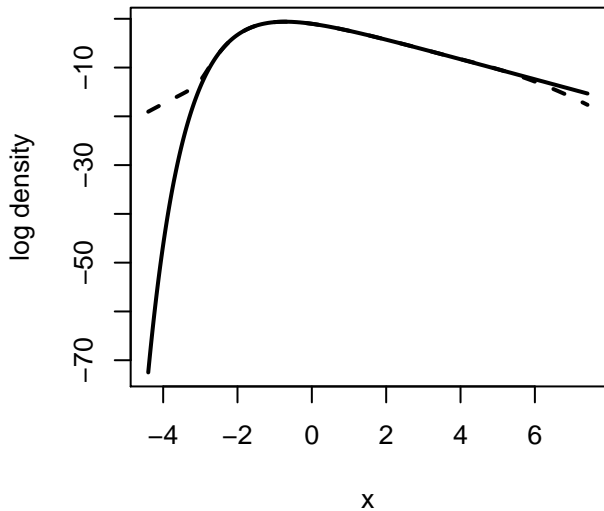
alpha = 2.0546875



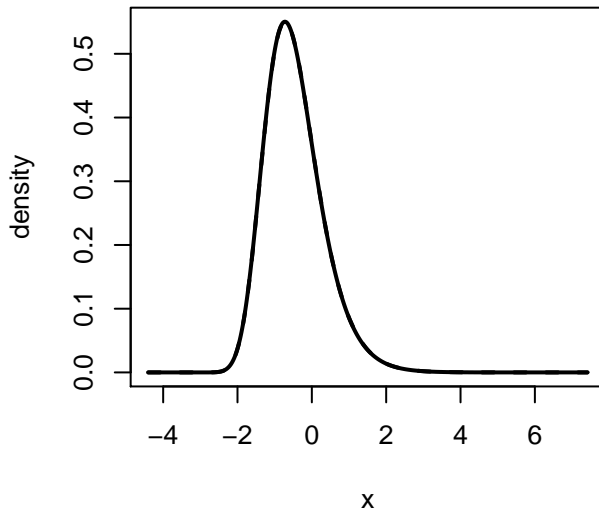
alpha = 2.0546875



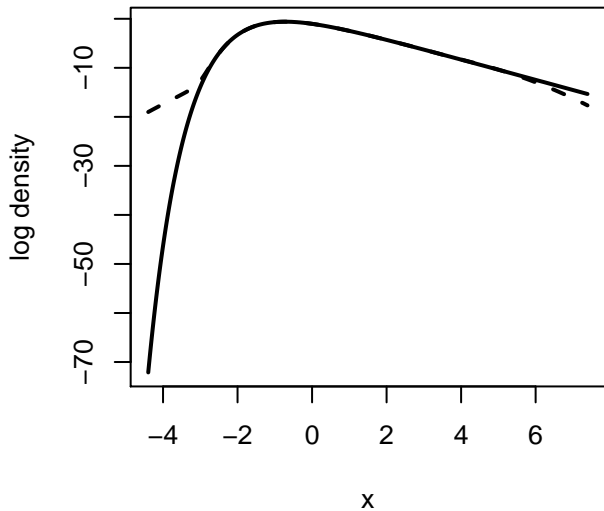
alpha = 2.0625



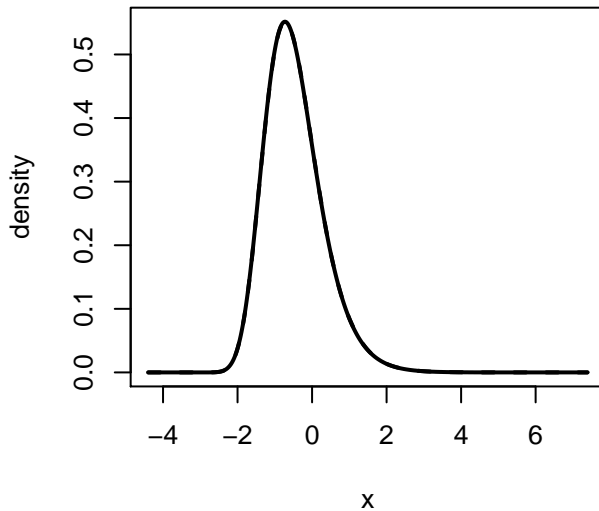
alpha = 2.0625



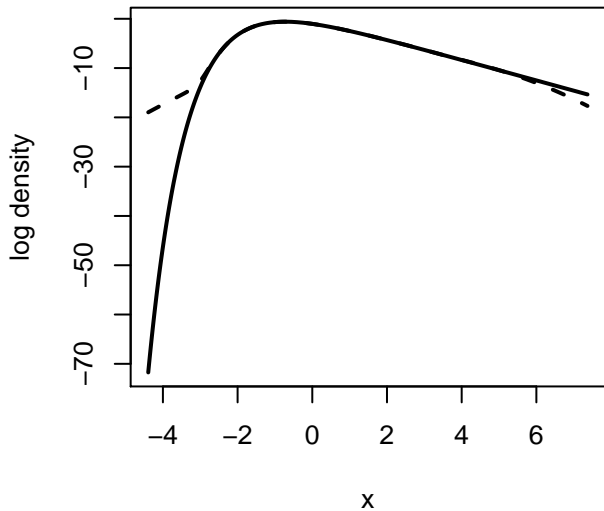
alpha = 2.0703125



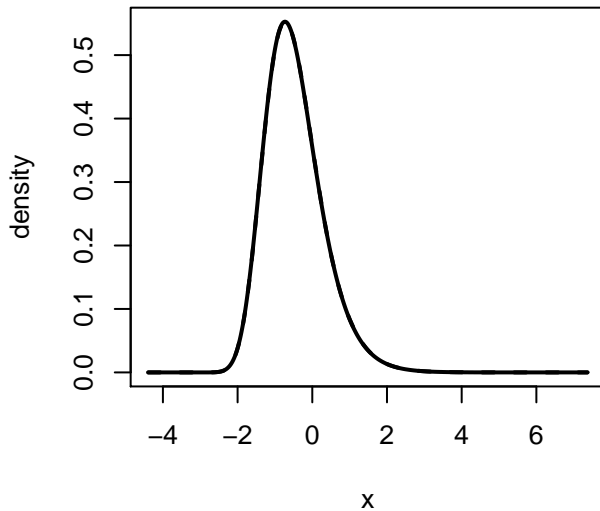
alpha = 2.0703125



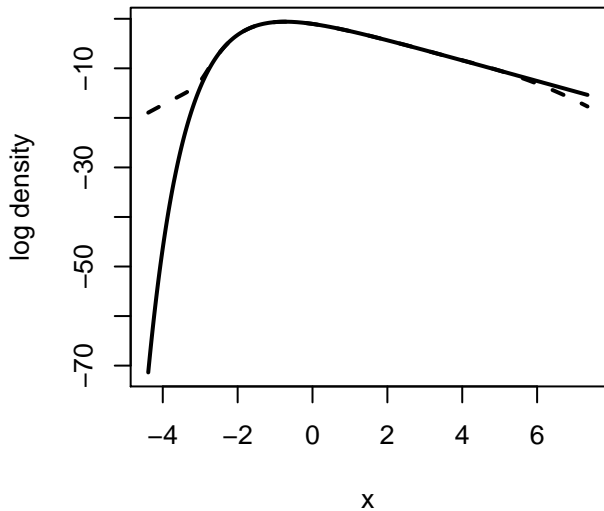
alpha = 2.078125



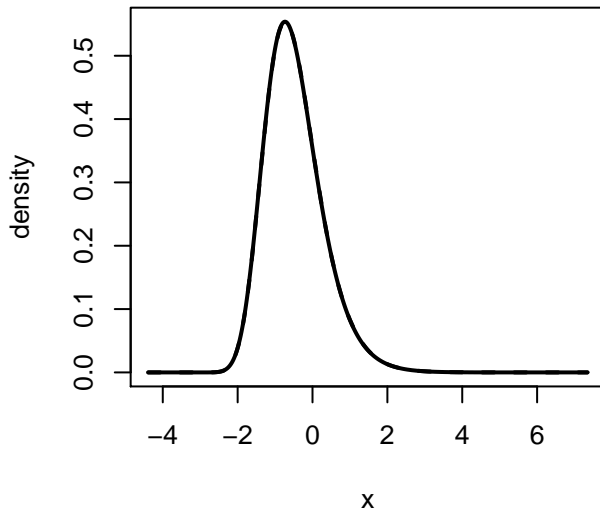
alpha = 2.078125



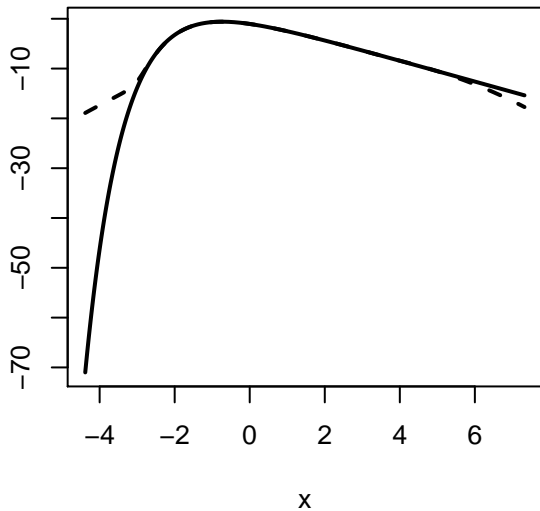
alpha = 2.0859375



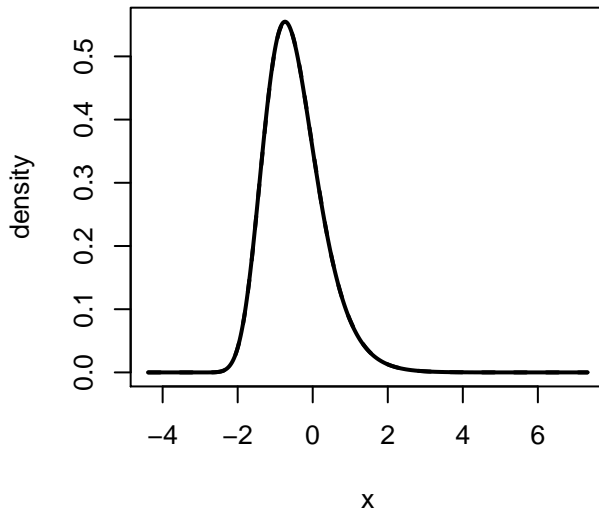
alpha = 2.0859375



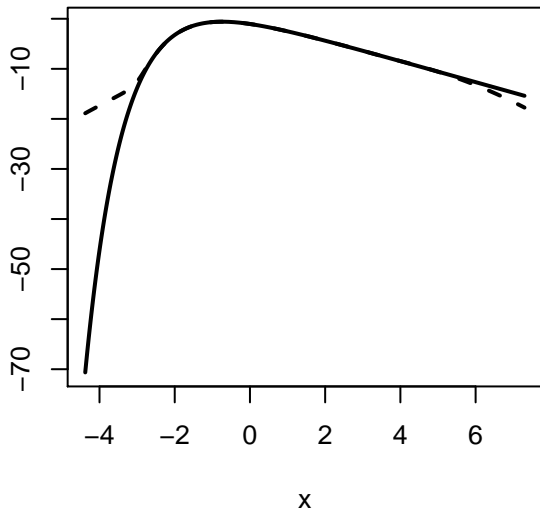
alpha = 2.09375



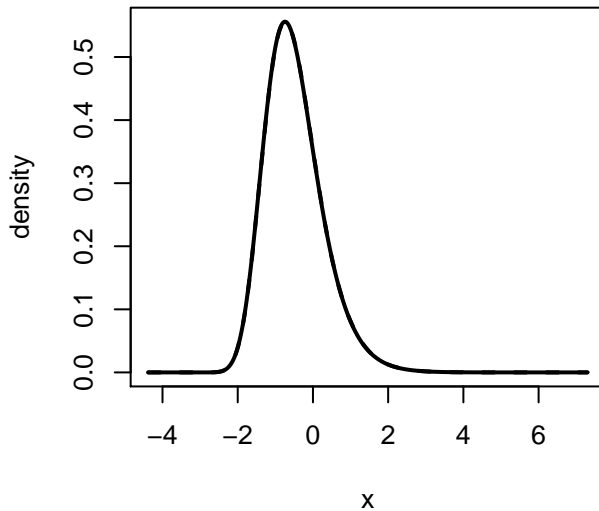
alpha = 2.09375



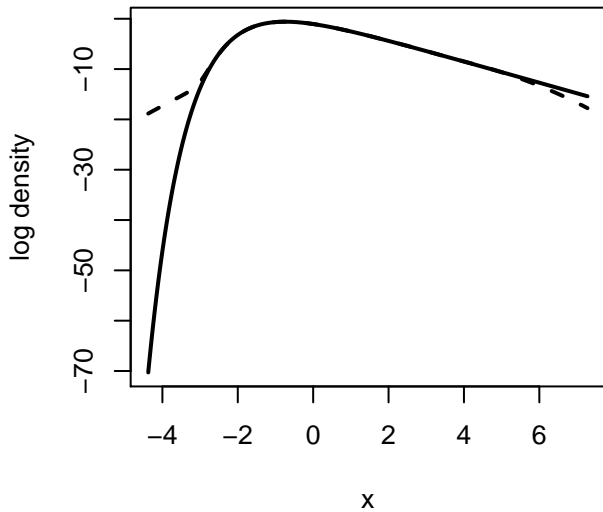
alpha = 2.1015625



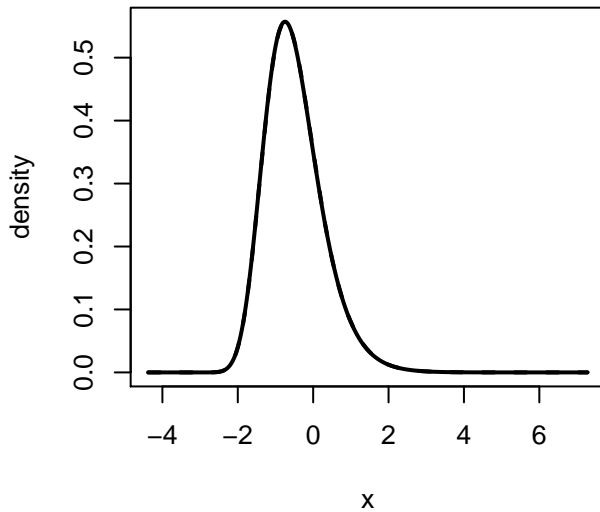
alpha = 2.1015625



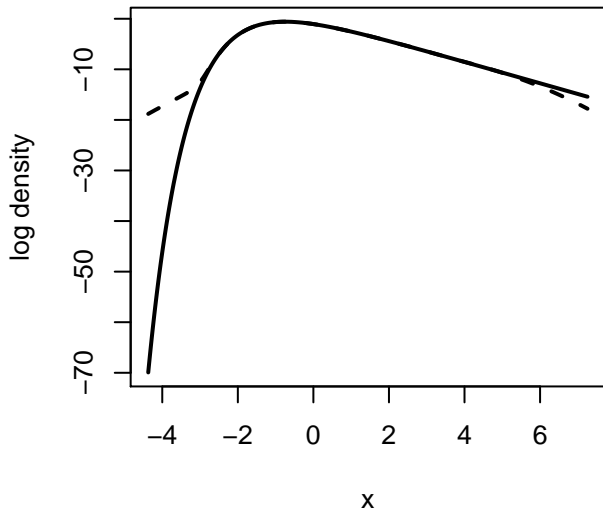
alpha = 2.109375



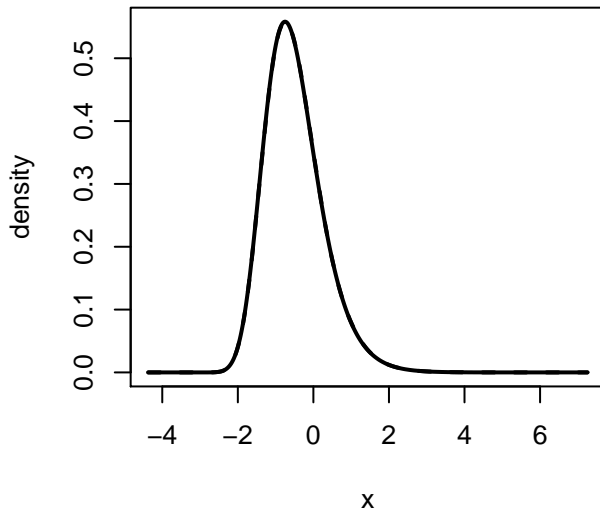
alpha = 2.109375



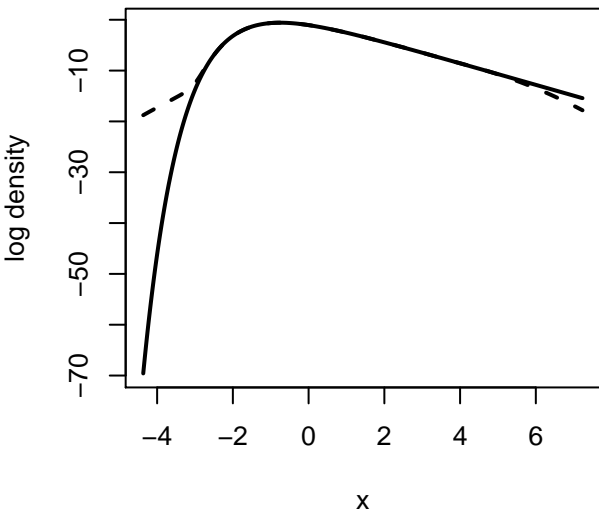
alpha = 2.1171875



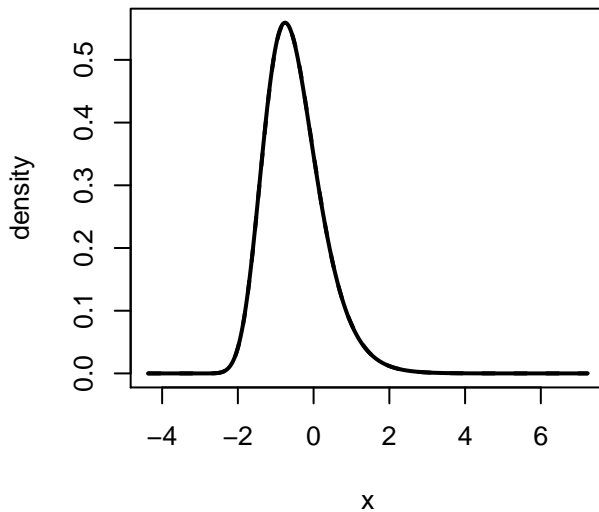
alpha = 2.1171875



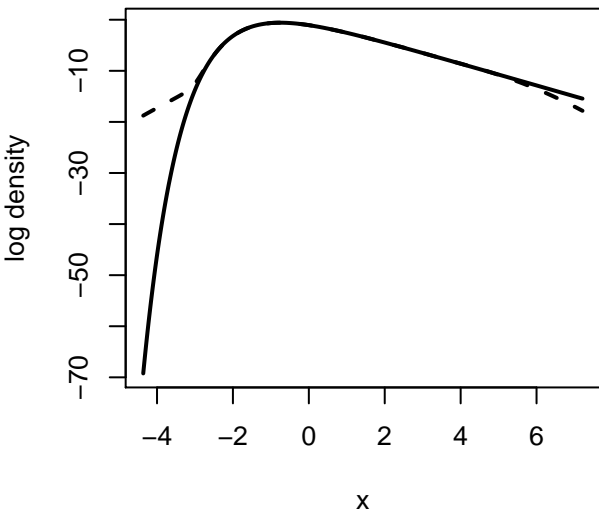
alpha = 2.125



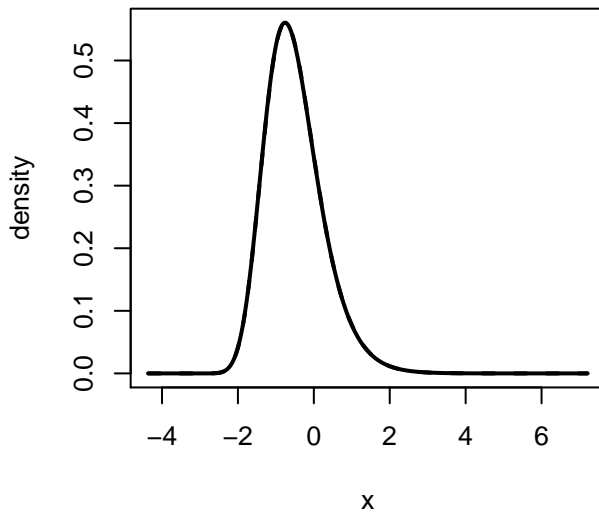
alpha = 2.125



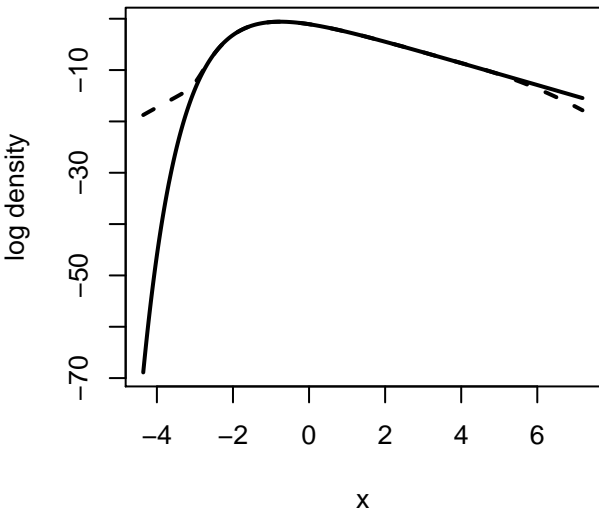
alpha = 2.1328125



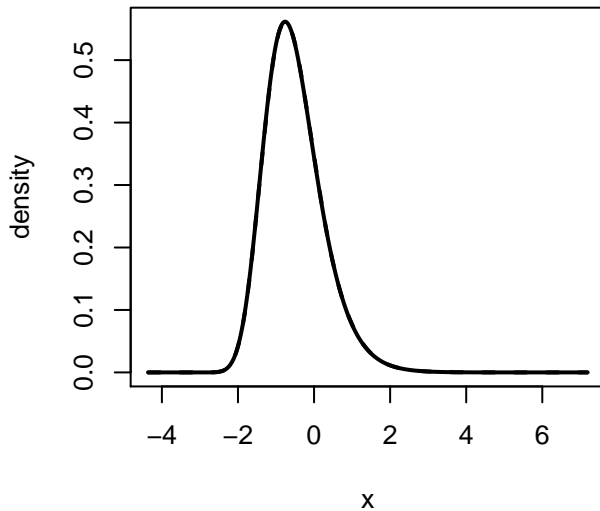
alpha = 2.1328125



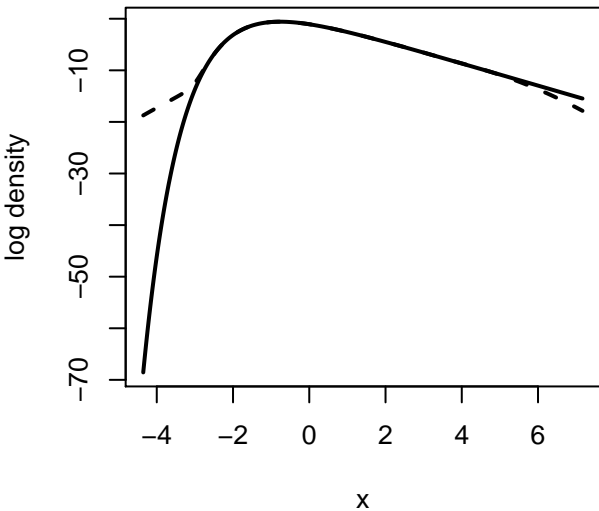
alpha = 2.140625



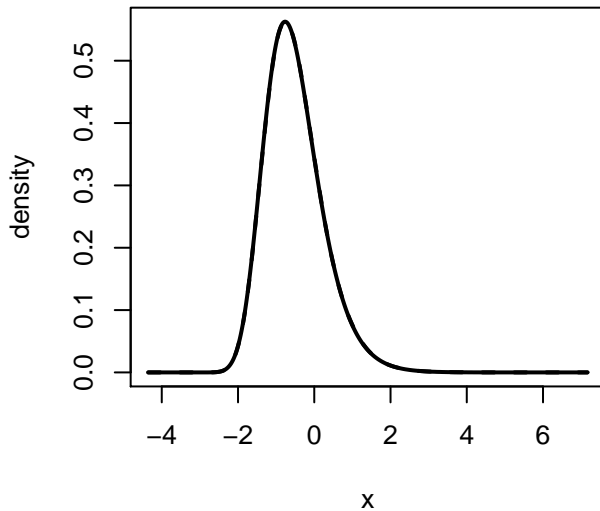
alpha = 2.140625



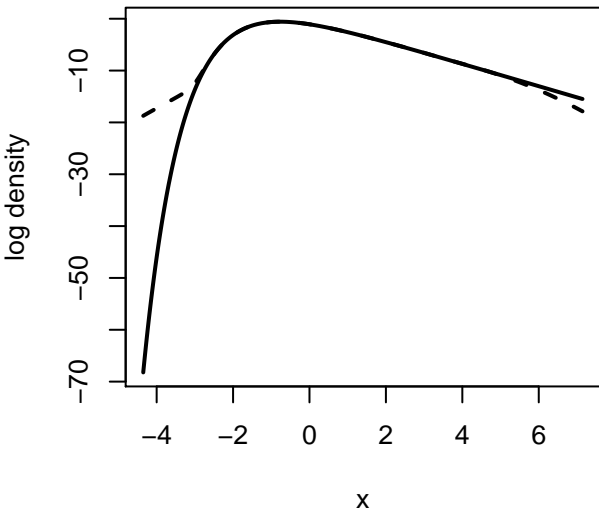
alpha = 2.1484375



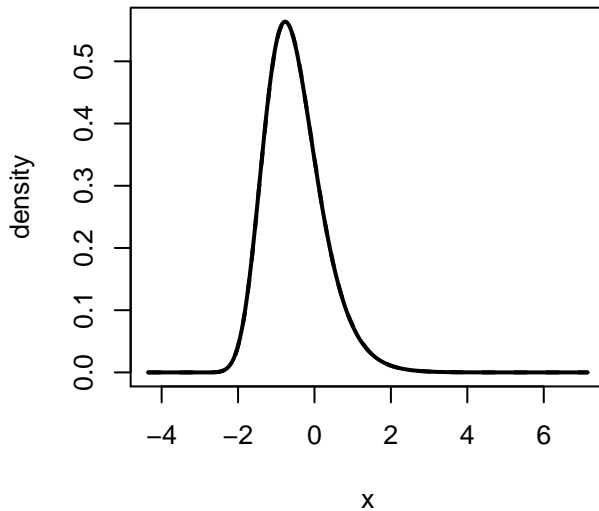
alpha = 2.1484375



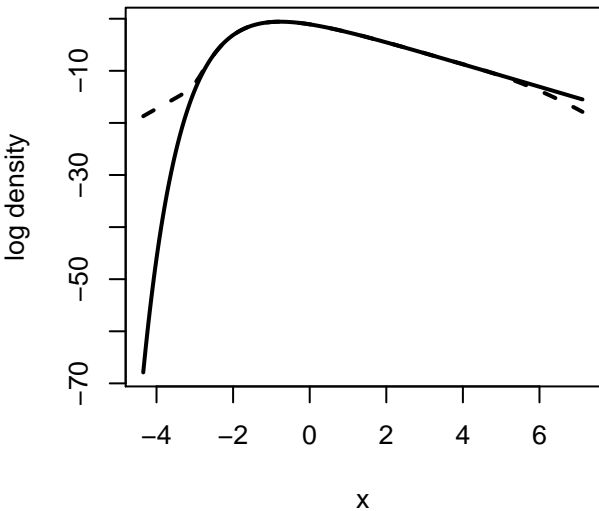
alpha = 2.15625



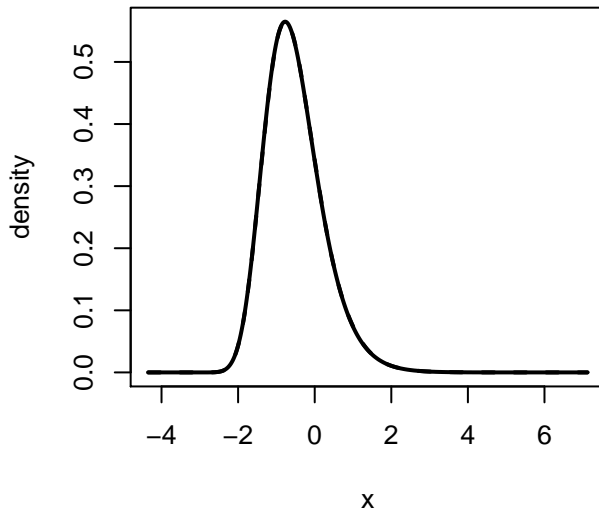
alpha = 2.15625



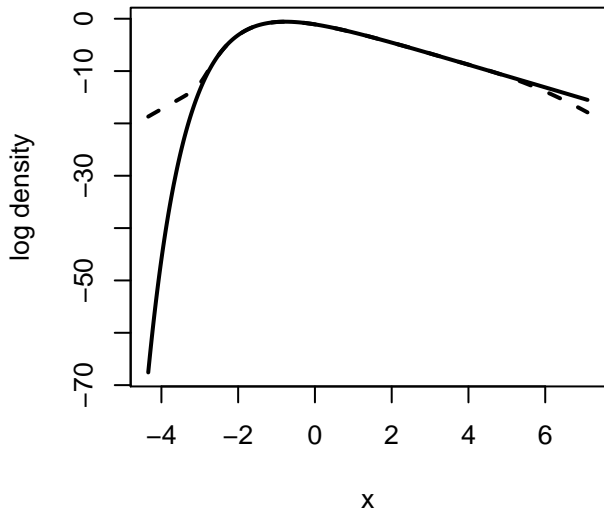
alpha = 2.1640625



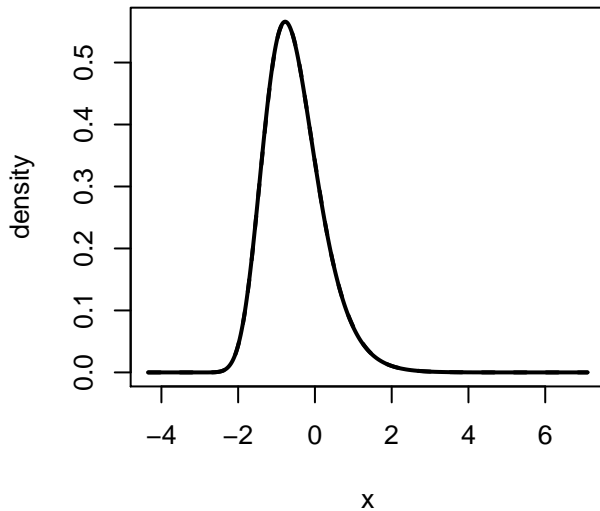
alpha = 2.1640625



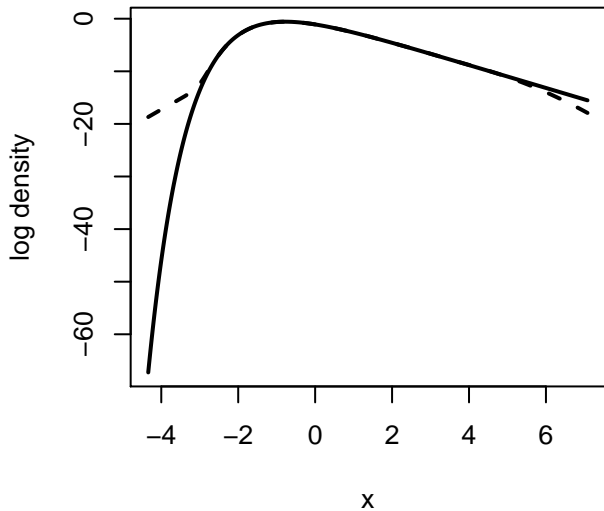
alpha = 2.171875



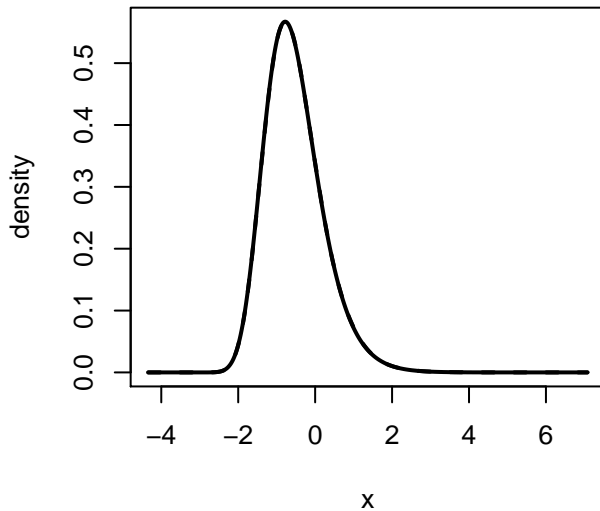
alpha = 2.171875



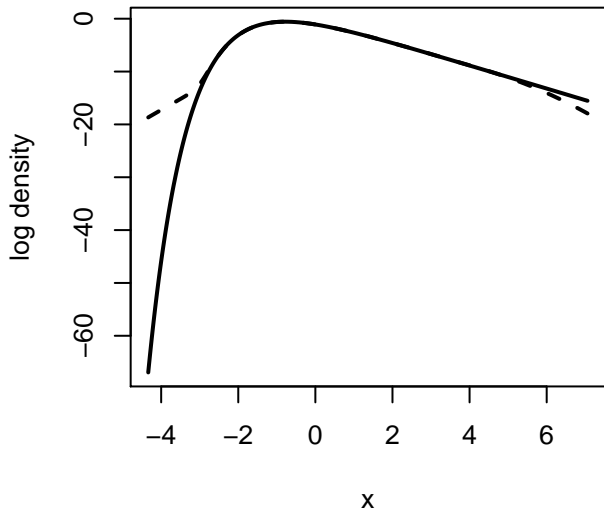
alpha = 2.1796875



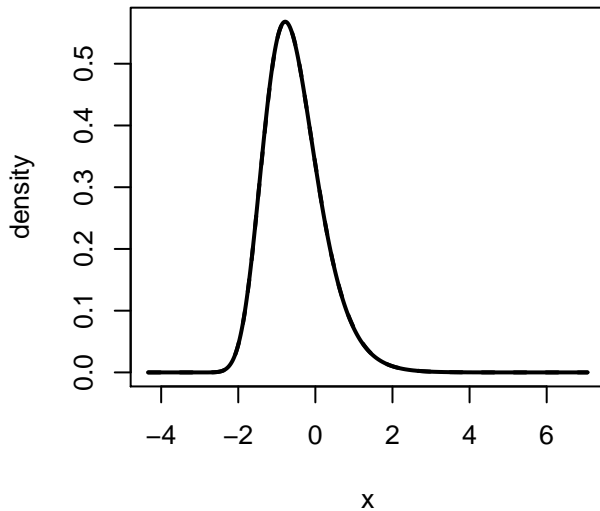
alpha = 2.1796875



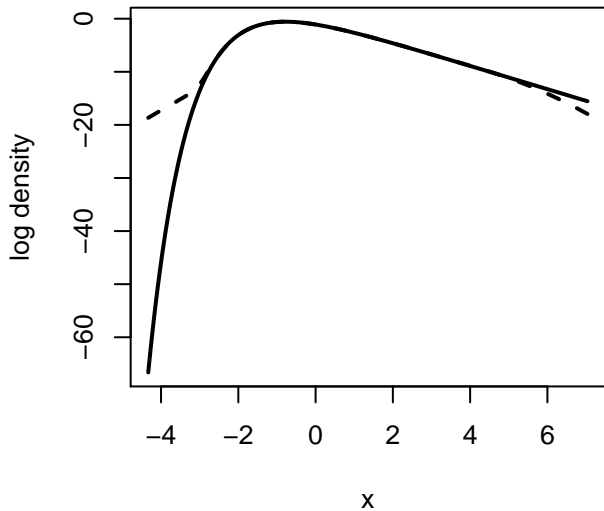
alpha = 2.1875



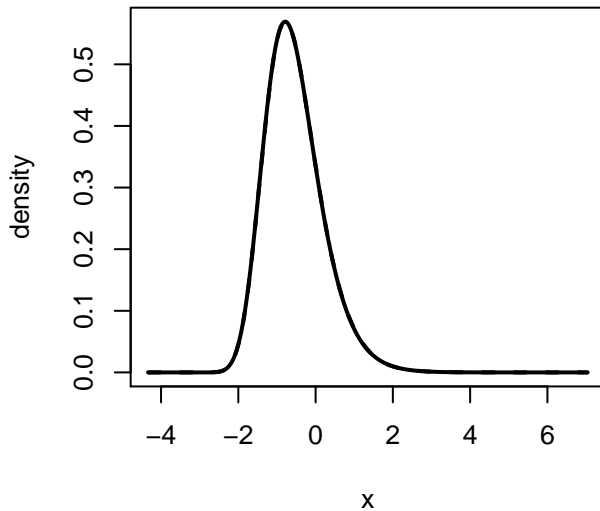
alpha = 2.1875



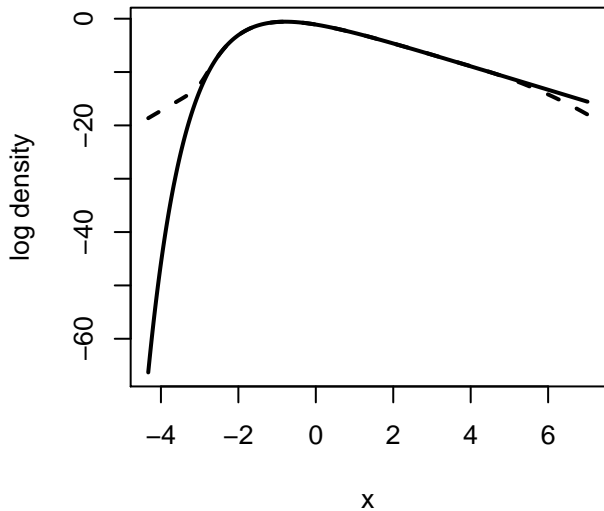
alpha = 2.1953125



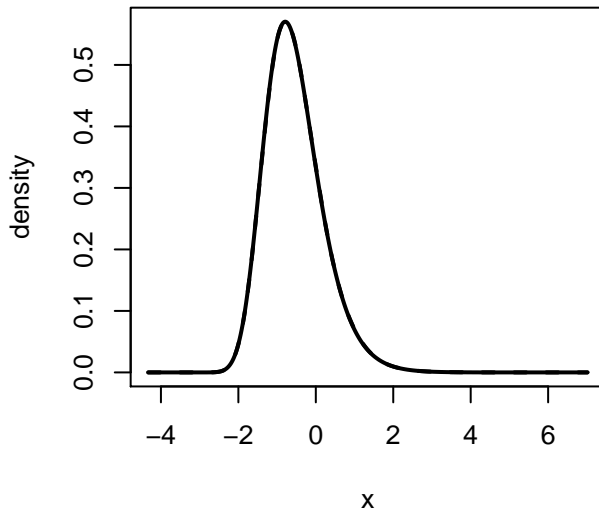
alpha = 2.1953125



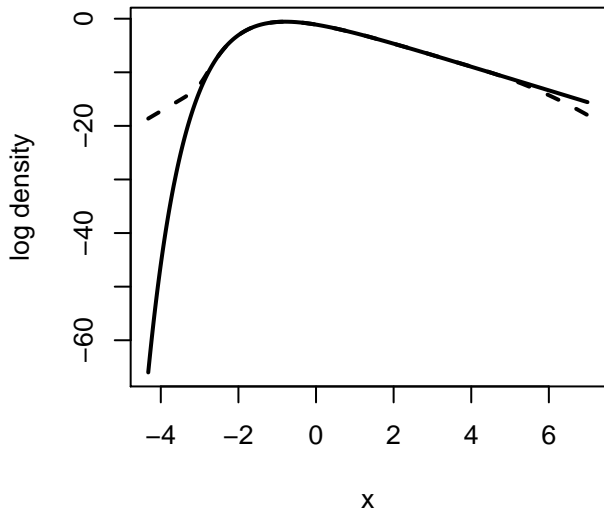
alpha = 2.203125



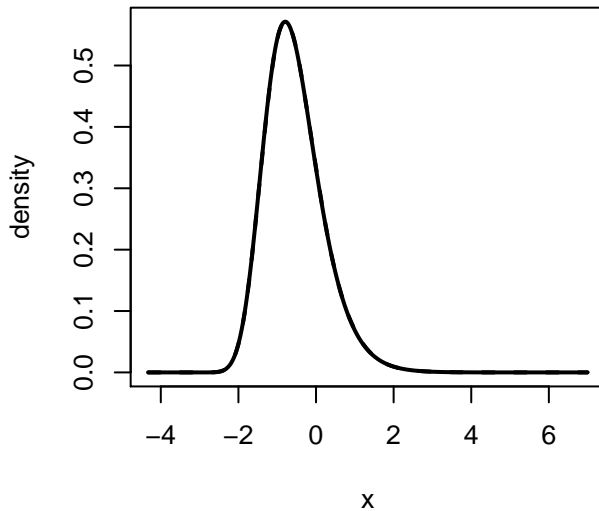
alpha = 2.203125



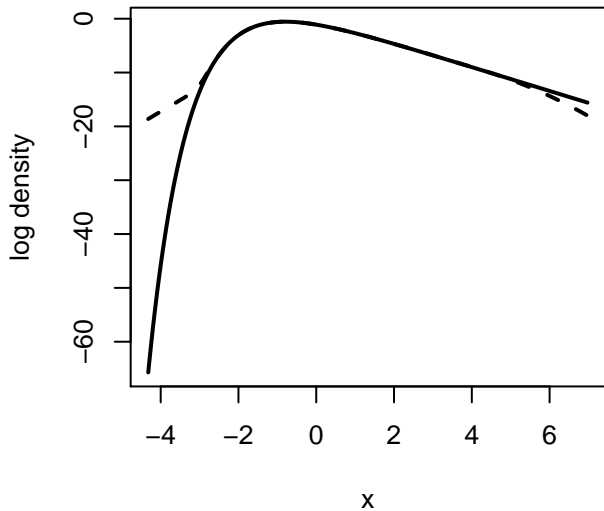
alpha = 2.2109375



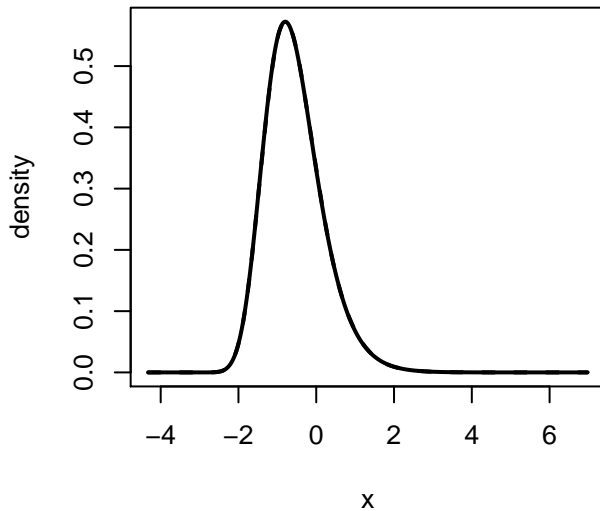
alpha = 2.2109375



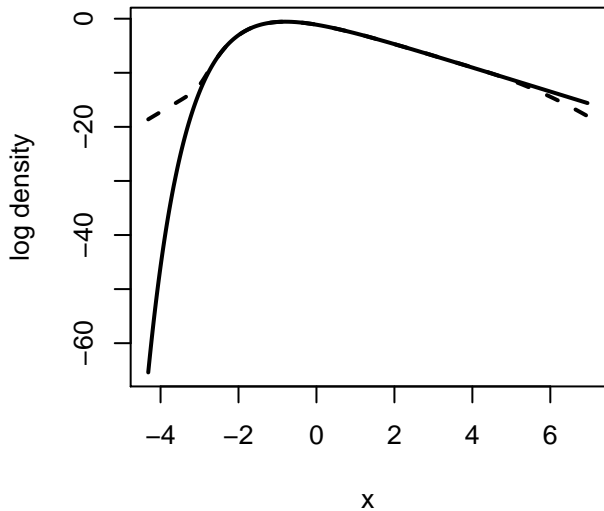
alpha = 2.21875



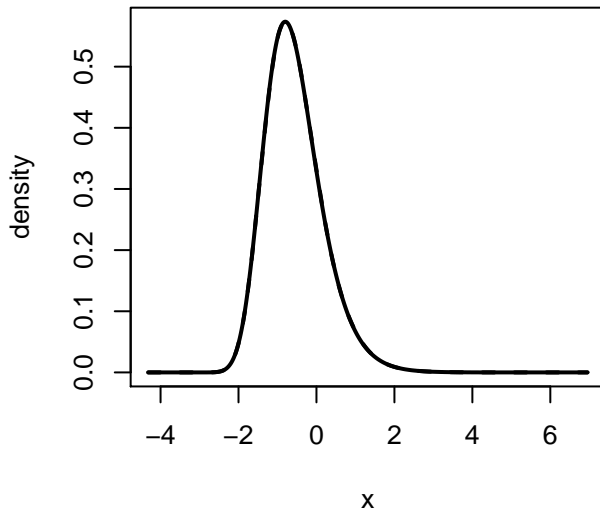
alpha = 2.21875



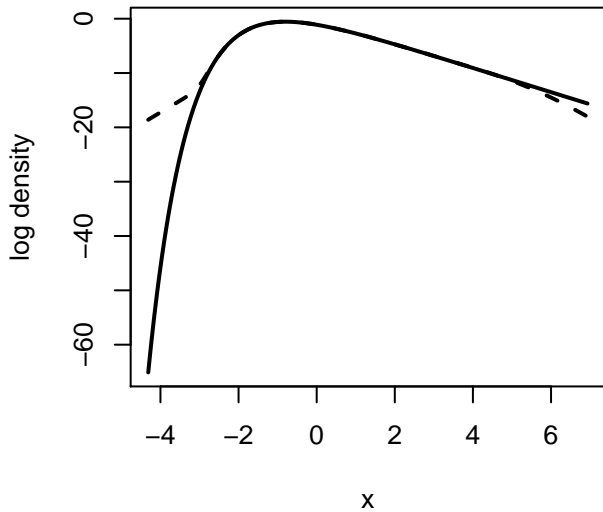
alpha = 2.2265625



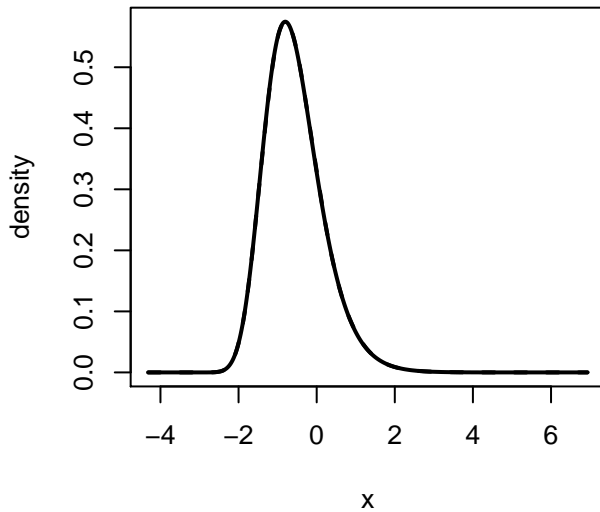
alpha = 2.2265625



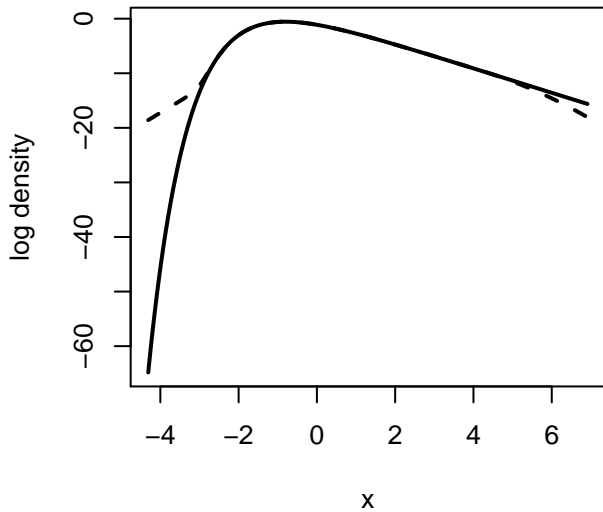
alpha = 2.234375



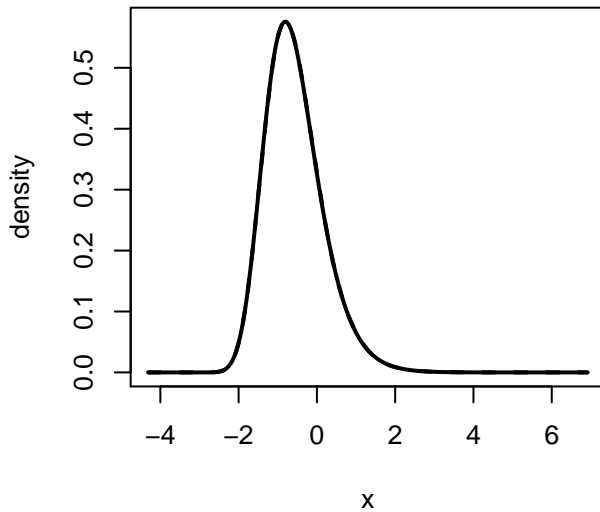
alpha = 2.234375



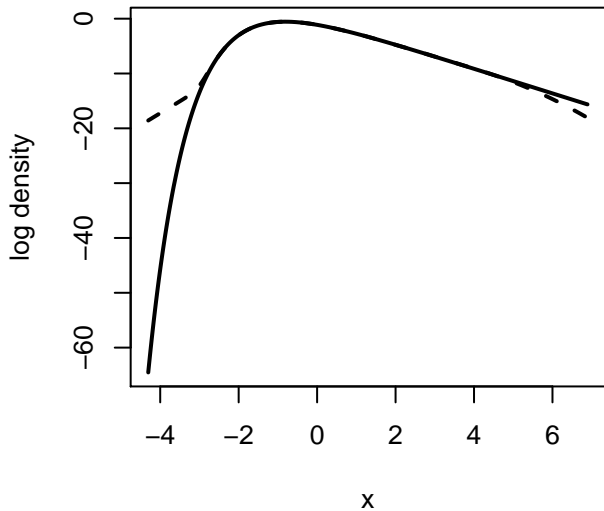
alpha = 2.2421875



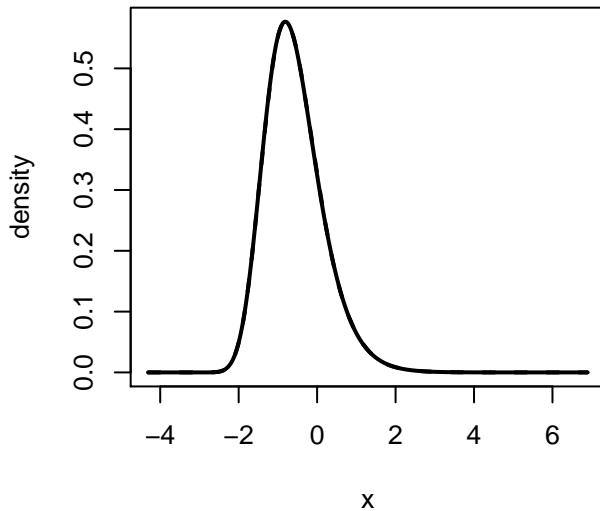
alpha = 2.2421875



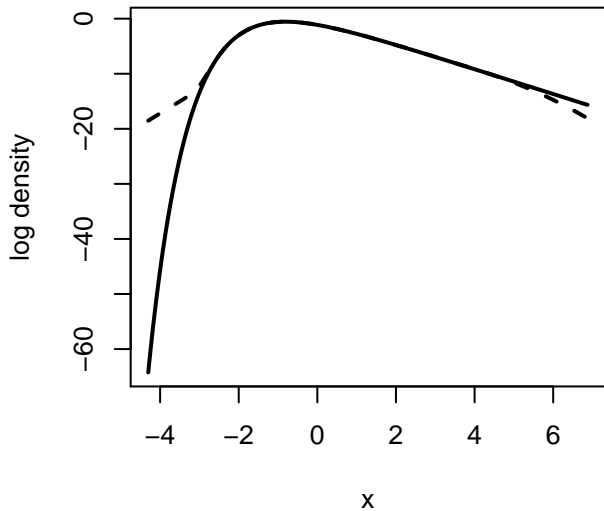
alpha = 2.25



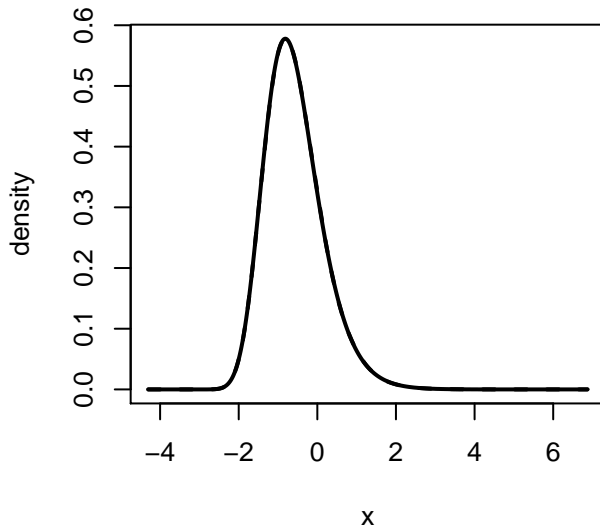
alpha = 2.25



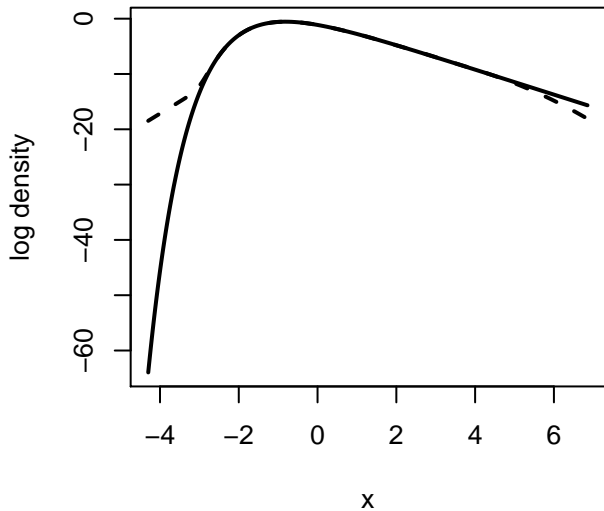
alpha = 2.2578125



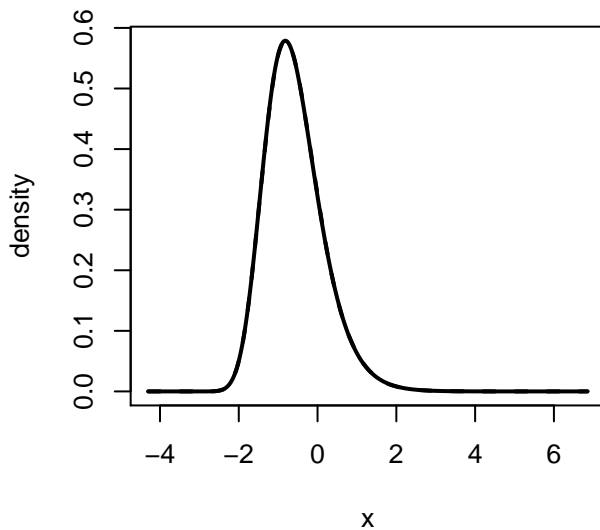
alpha = 2.2578125



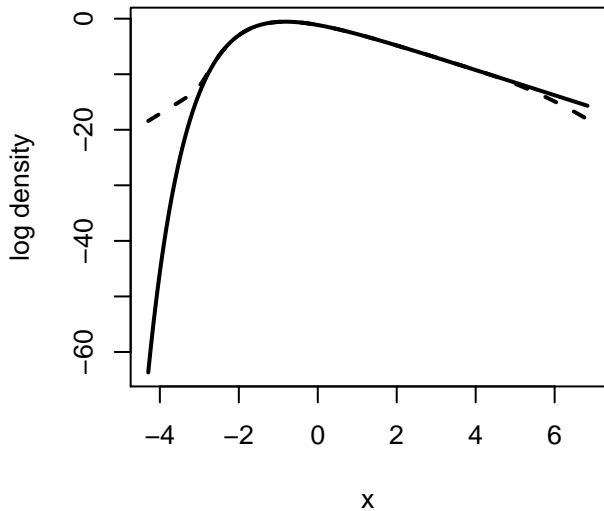
alpha = 2.265625



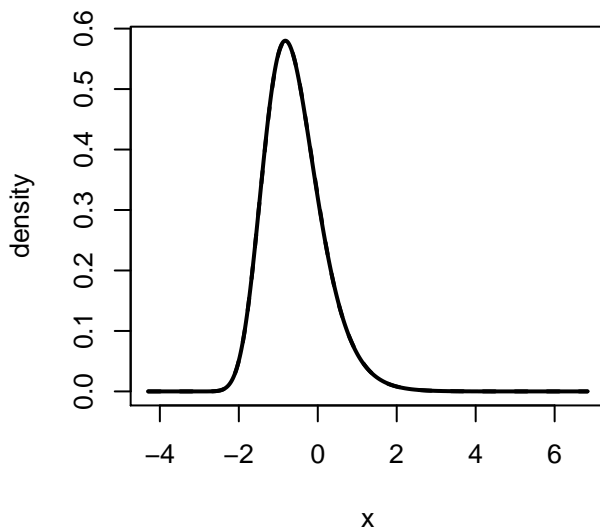
alpha = 2.265625



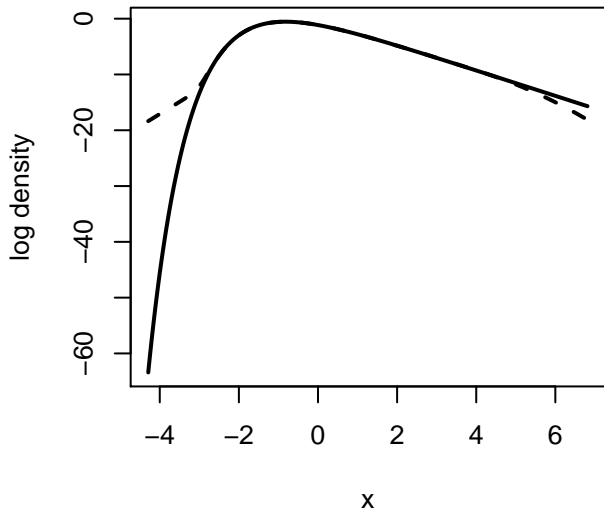
alpha = 2.2734375



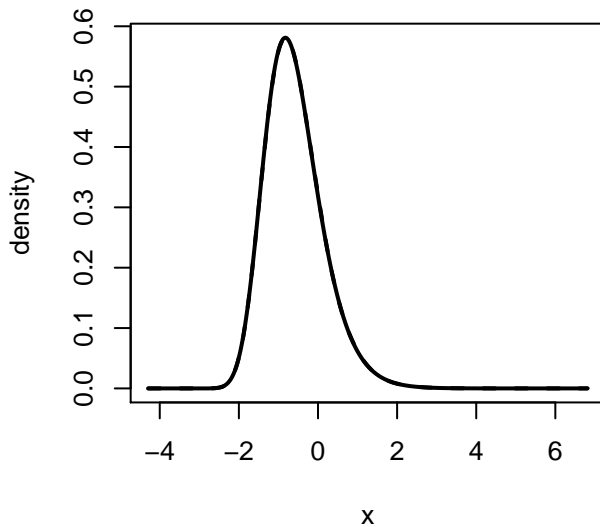
alpha = 2.2734375



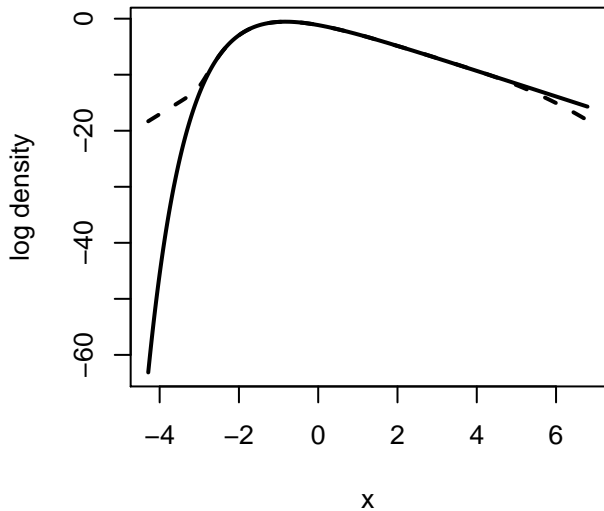
alpha = 2.28125



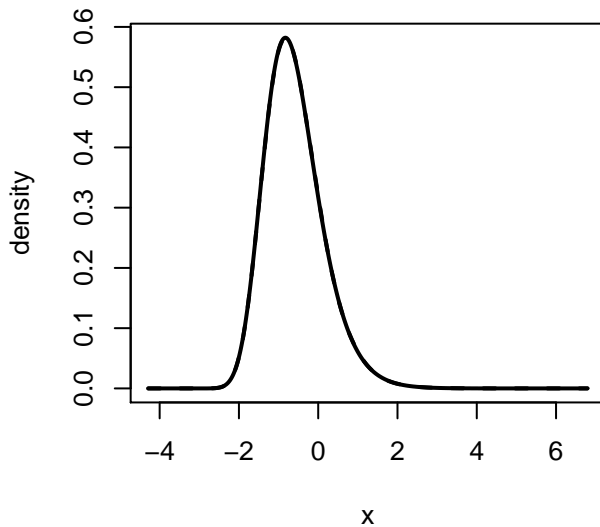
alpha = 2.28125



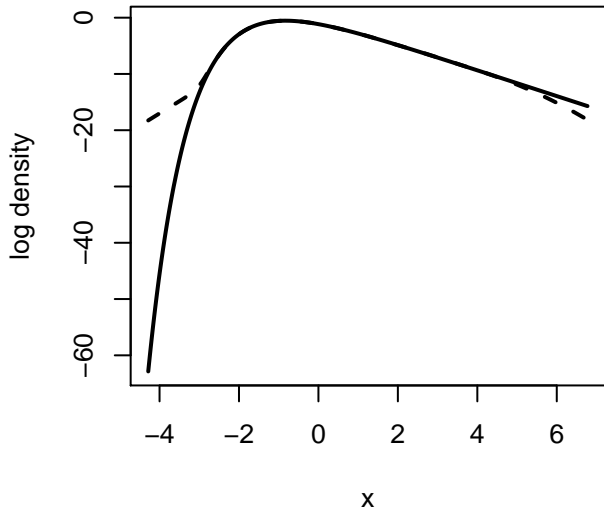
alpha = 2.2890625



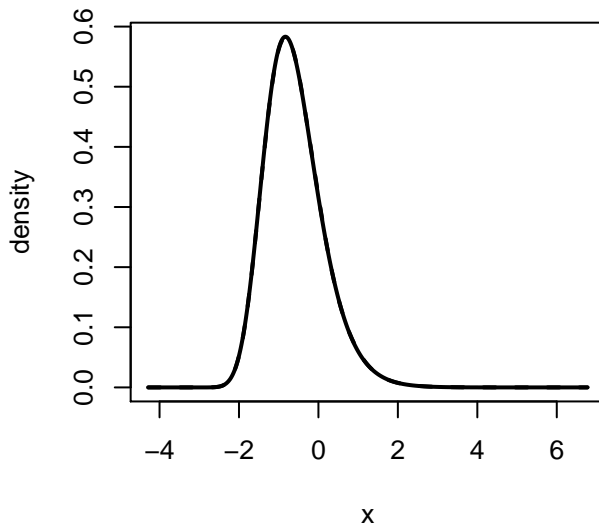
alpha = 2.2890625



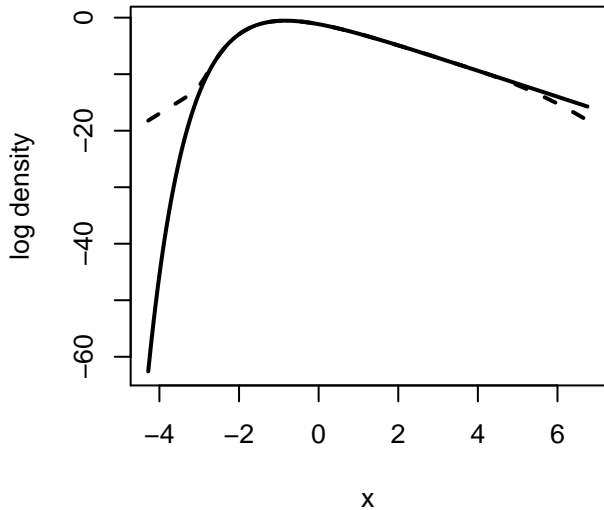
alpha = 2.296875



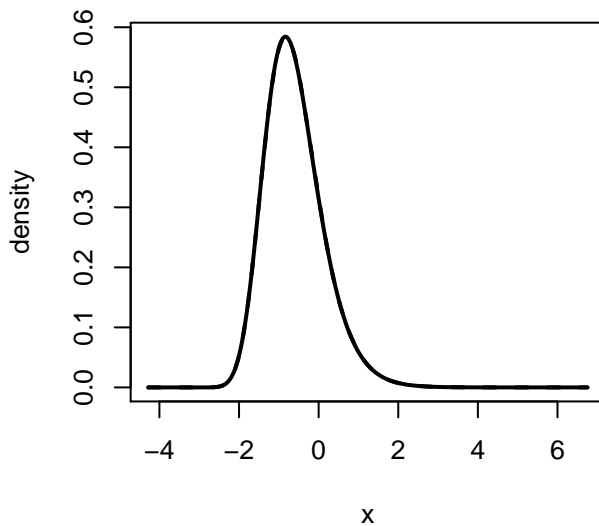
alpha = 2.296875



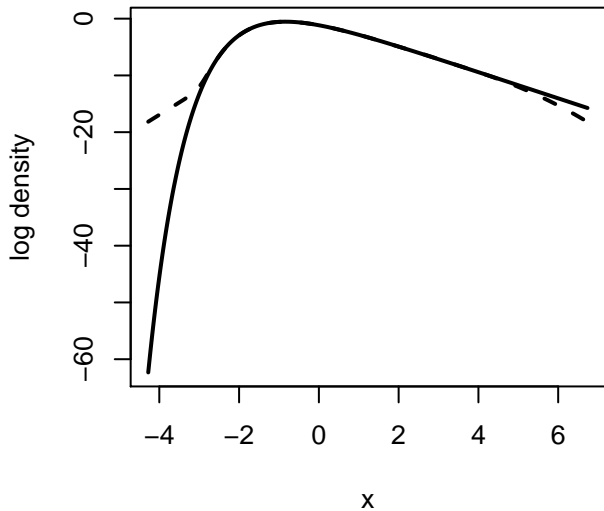
alpha = 2.3046875



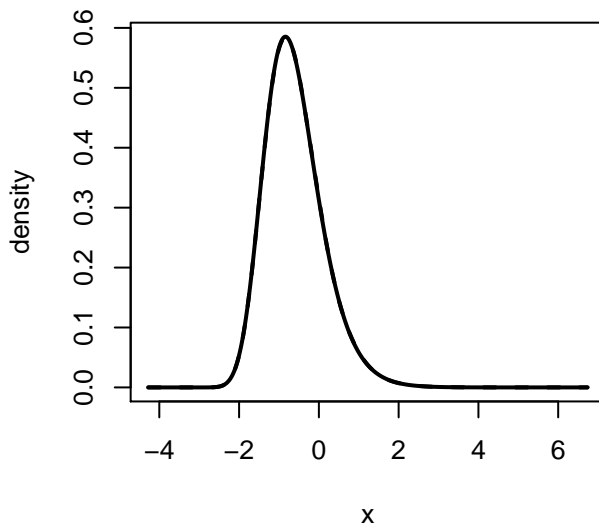
alpha = 2.3046875



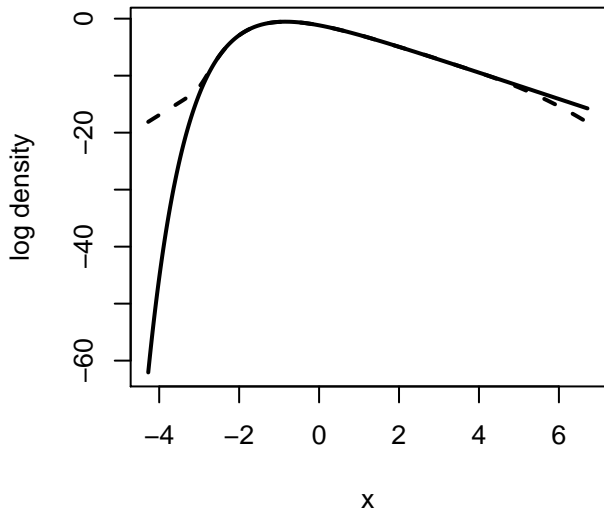
alpha = 2.3125



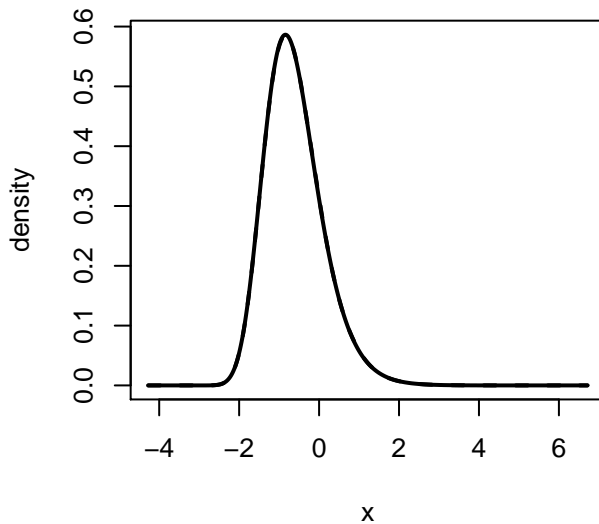
alpha = 2.3125



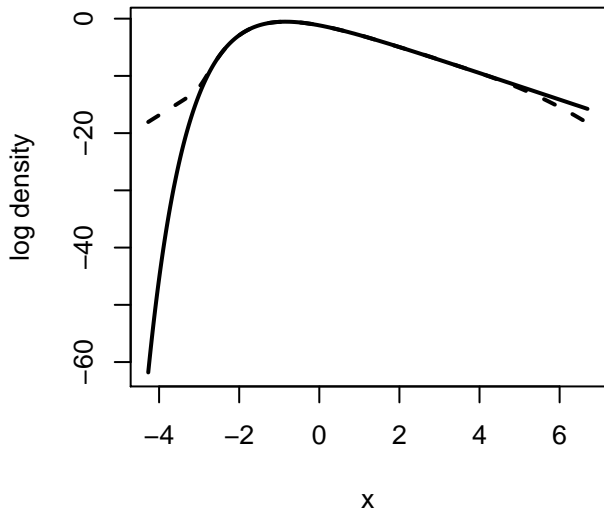
alpha = 2.3203125



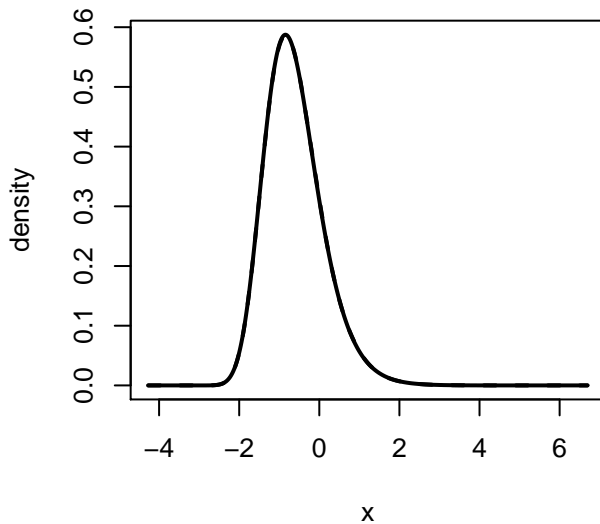
alpha = 2.3203125



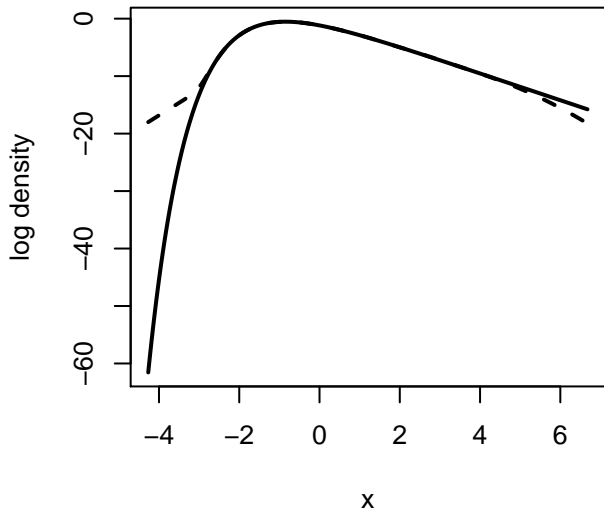
alpha = 2.328125



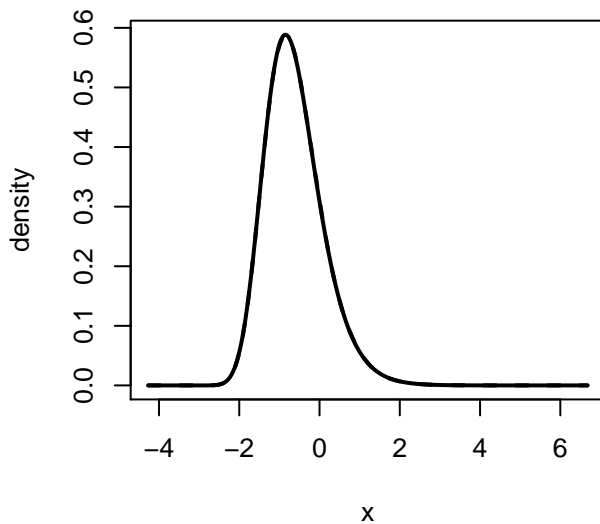
alpha = 2.328125



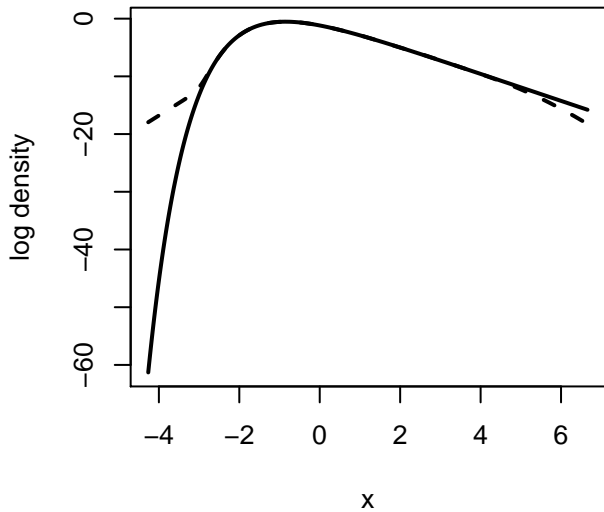
alpha = 2.3359375



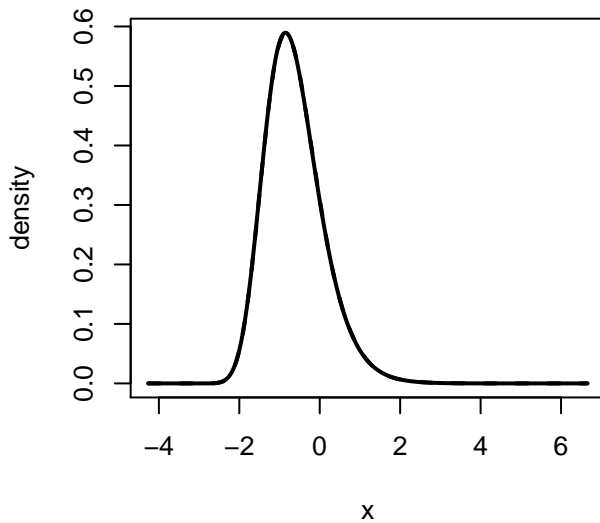
alpha = 2.3359375



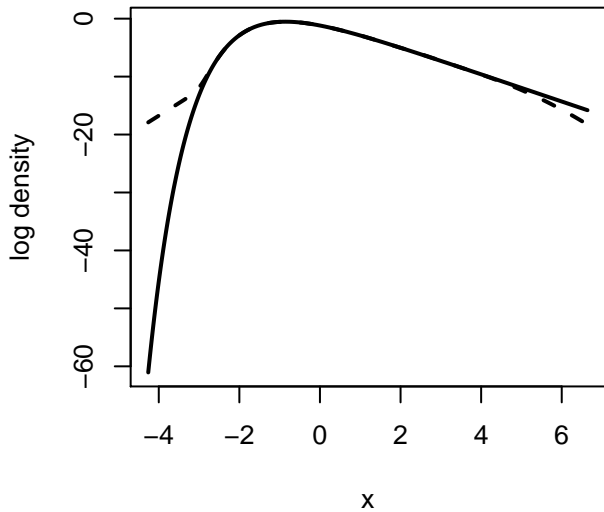
alpha = 2.34375



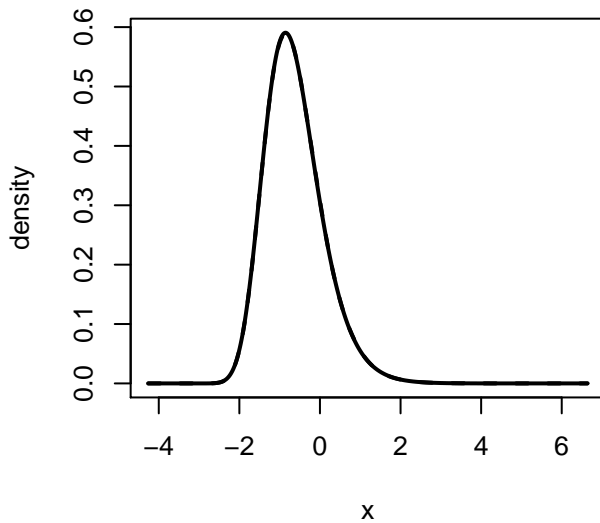
alpha = 2.34375



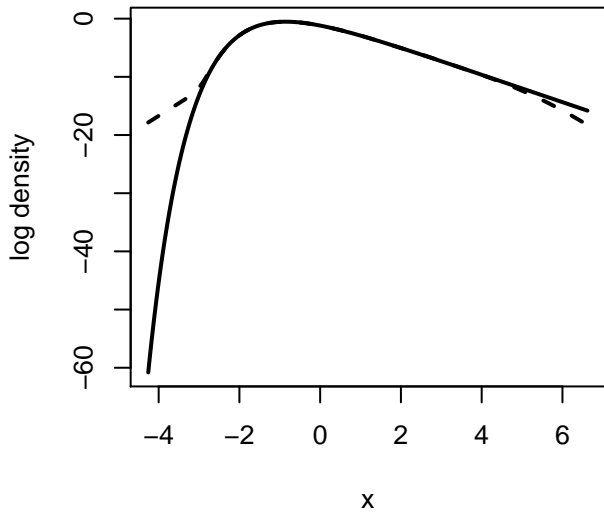
alpha = 2.3515625



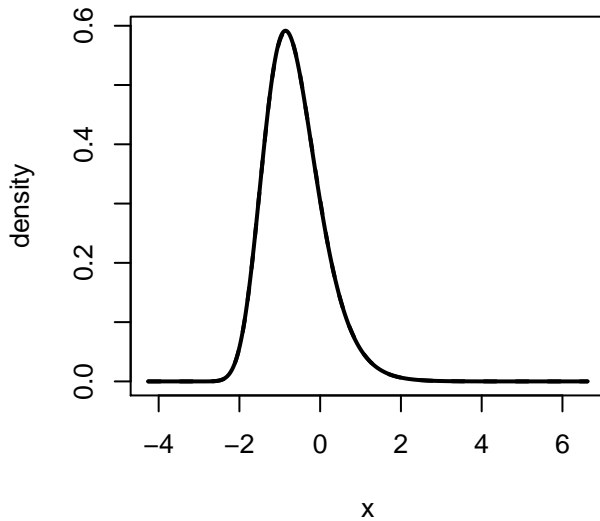
alpha = 2.3515625



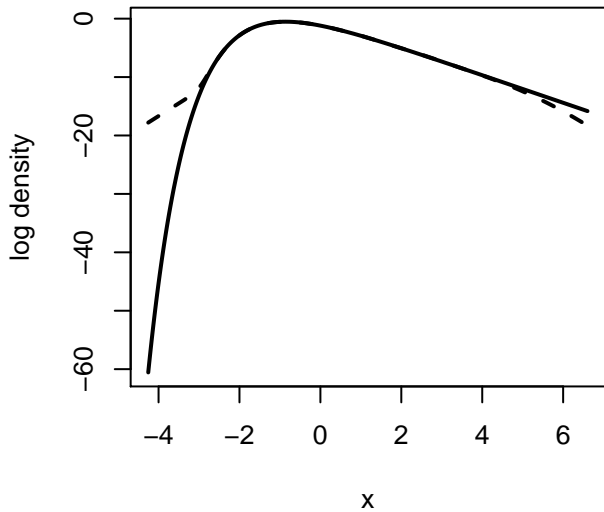
alpha = 2.359375



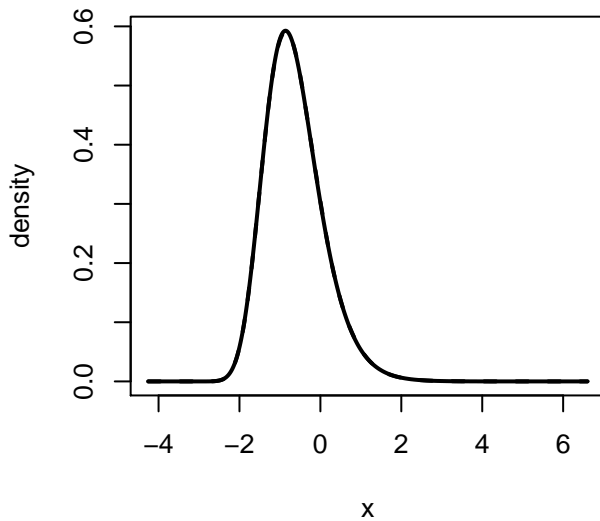
alpha = 2.359375



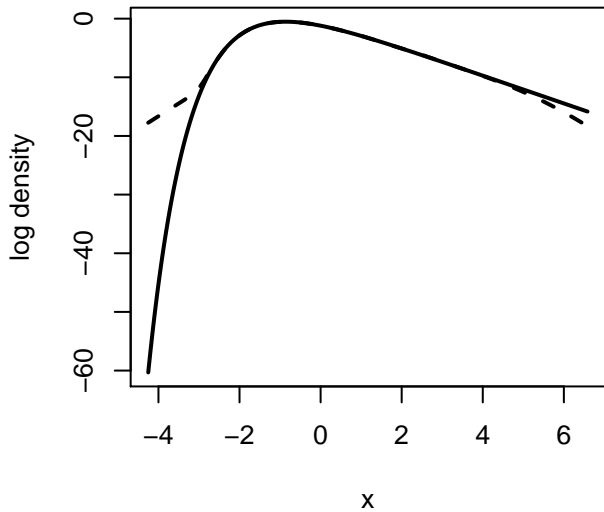
alpha = 2.3671875



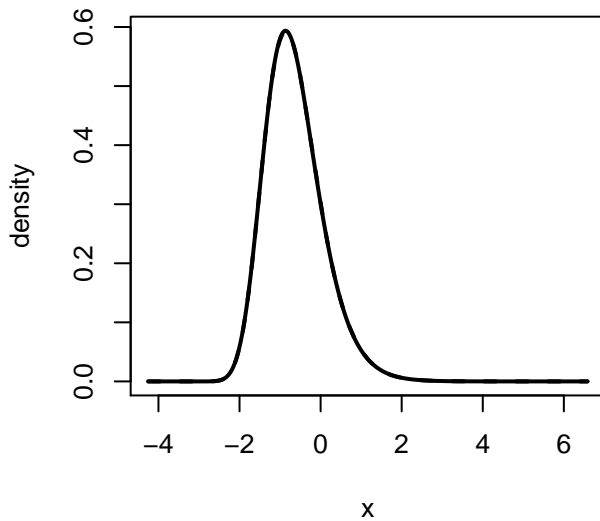
alpha = 2.3671875



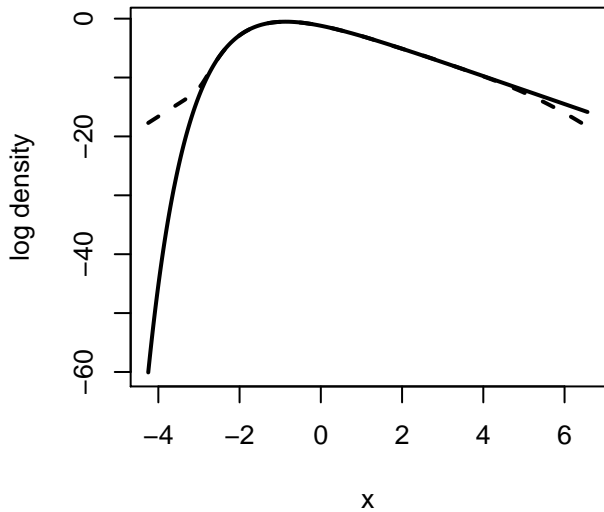
alpha = 2.375



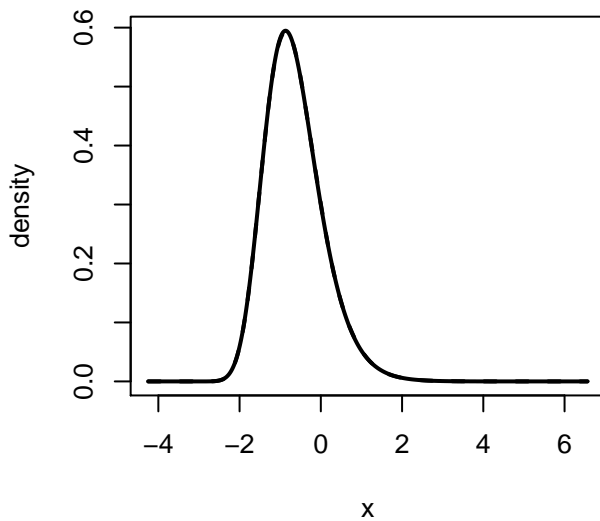
alpha = 2.375



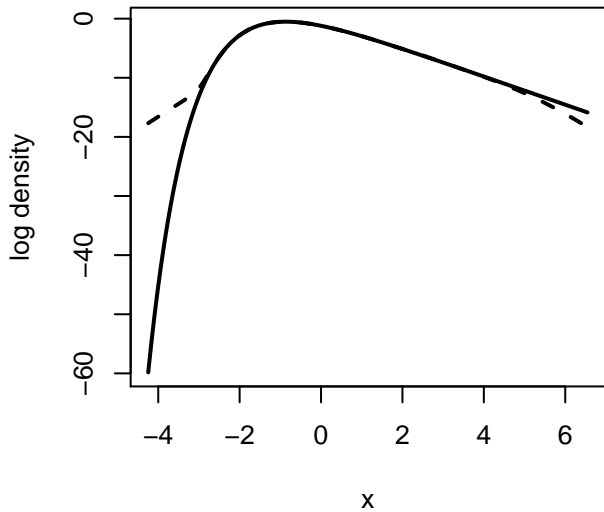
alpha = 2.3828125



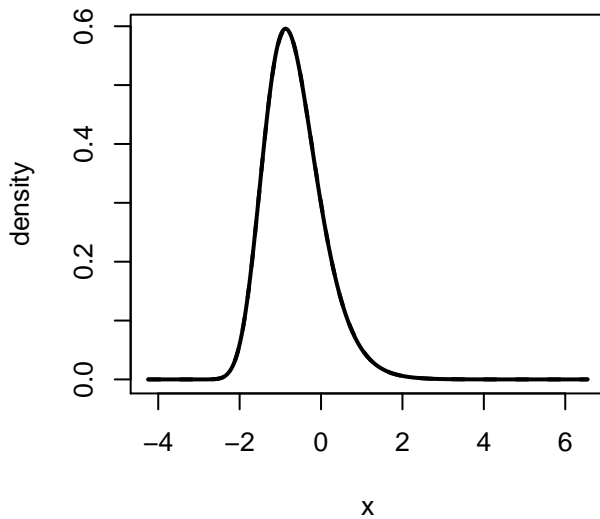
alpha = 2.3828125



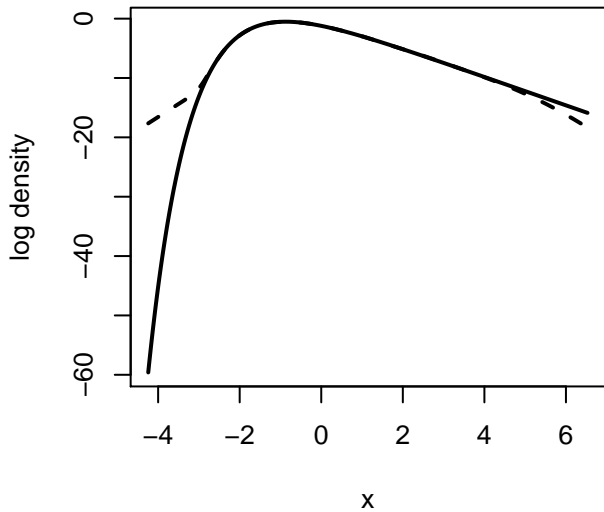
alpha = 2.390625



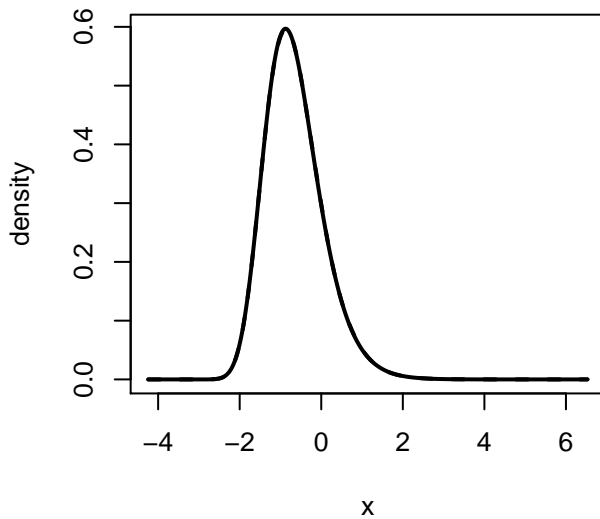
alpha = 2.390625



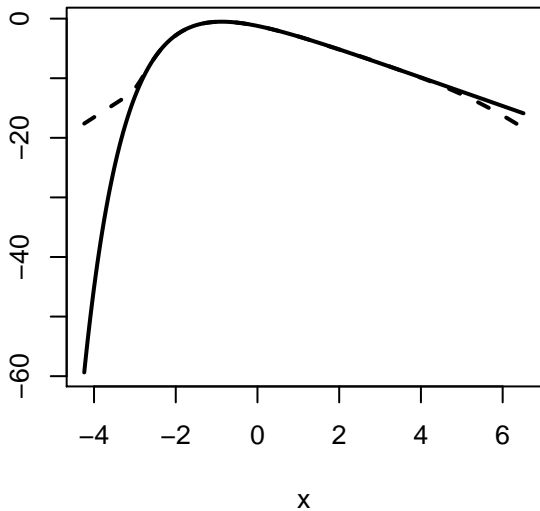
alpha = 2.3984375



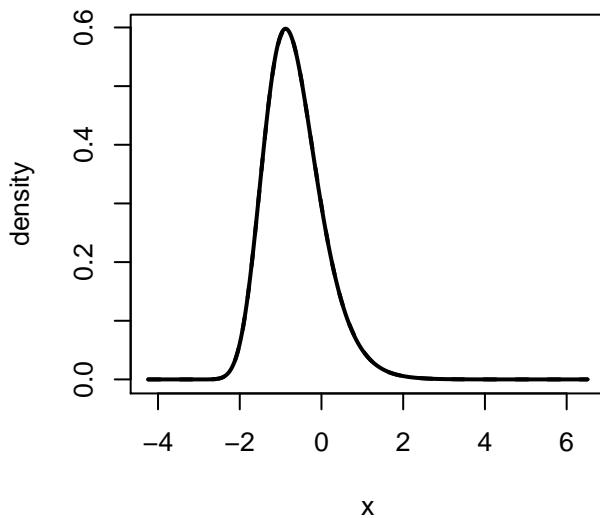
alpha = 2.3984375



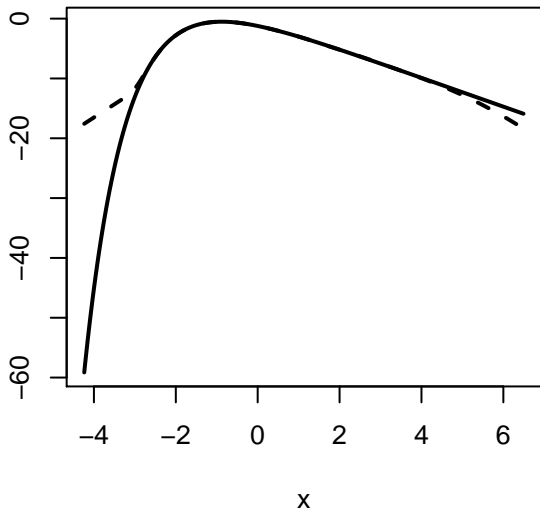
alpha = 2.40625



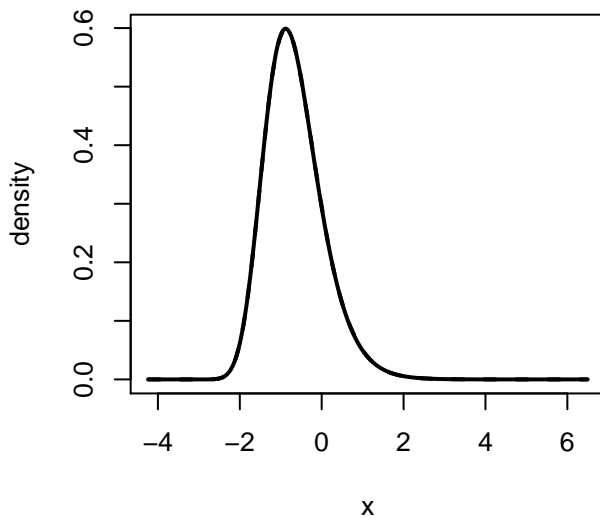
alpha = 2.40625



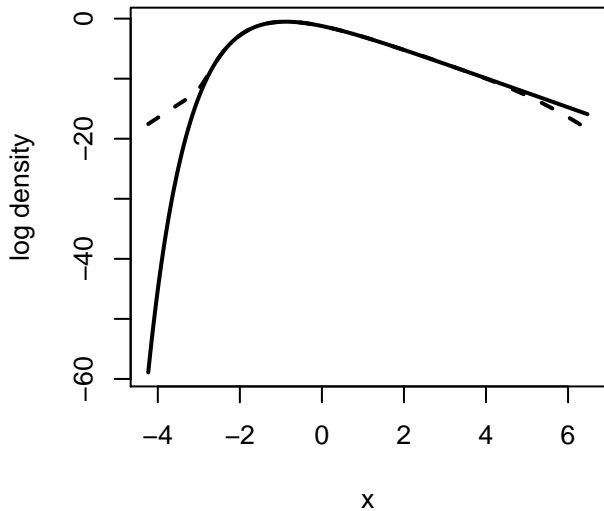
alpha = 2.4140625



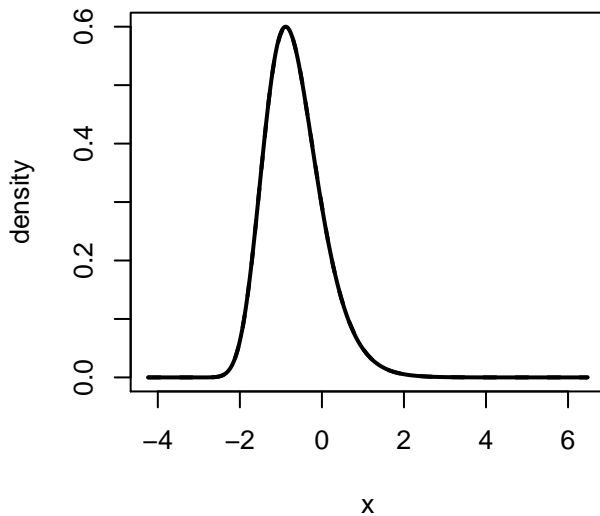
alpha = 2.4140625



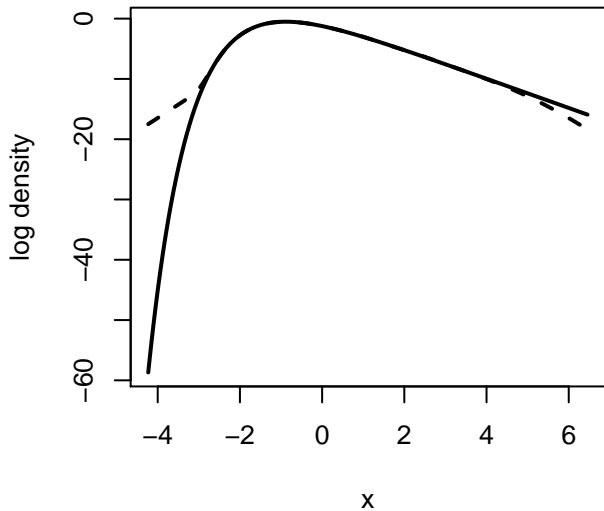
alpha = 2.421875



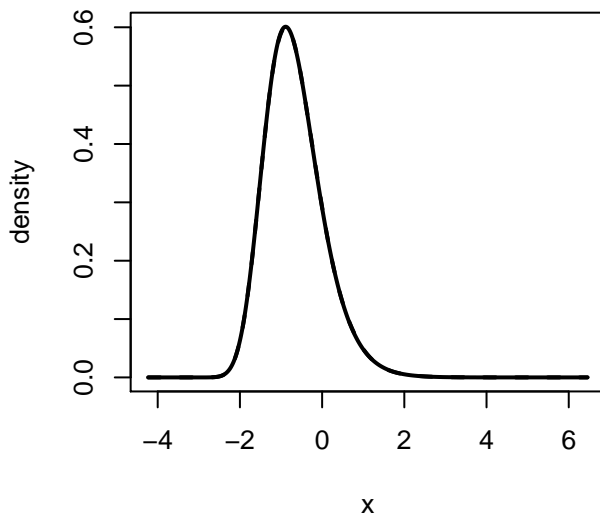
alpha = 2.421875



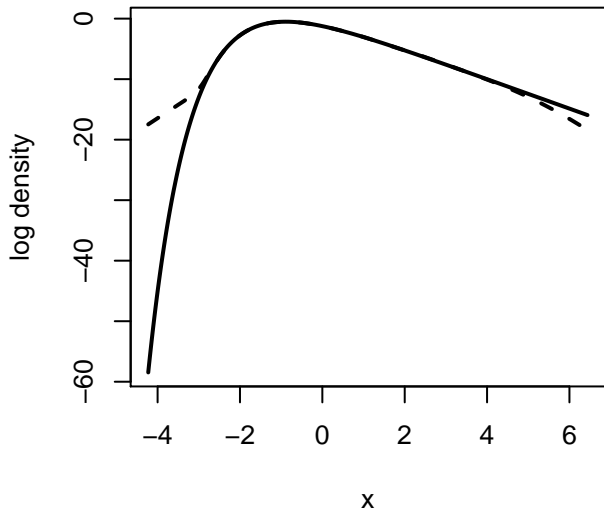
alpha = 2.4296875



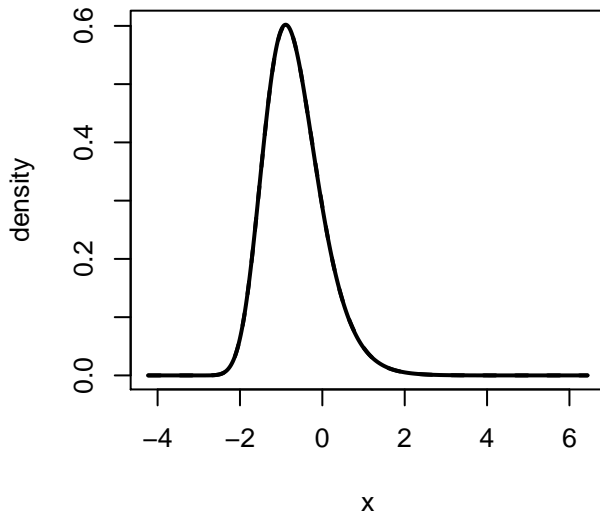
alpha = 2.4296875



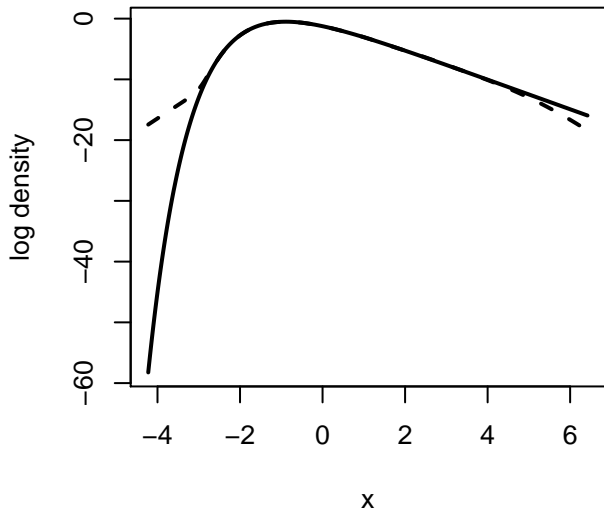
alpha = 2.4375



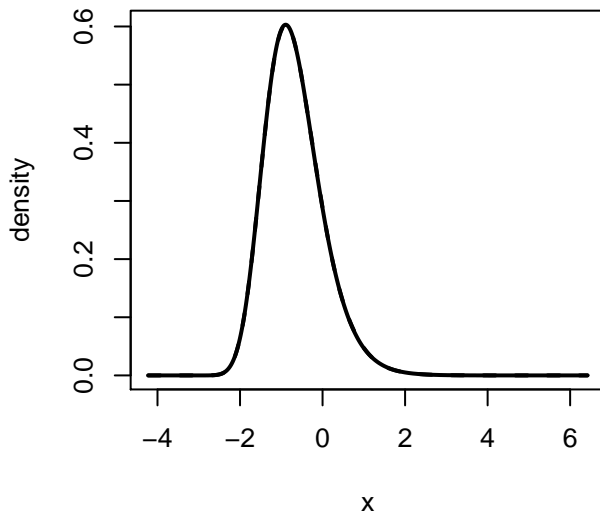
alpha = 2.4375



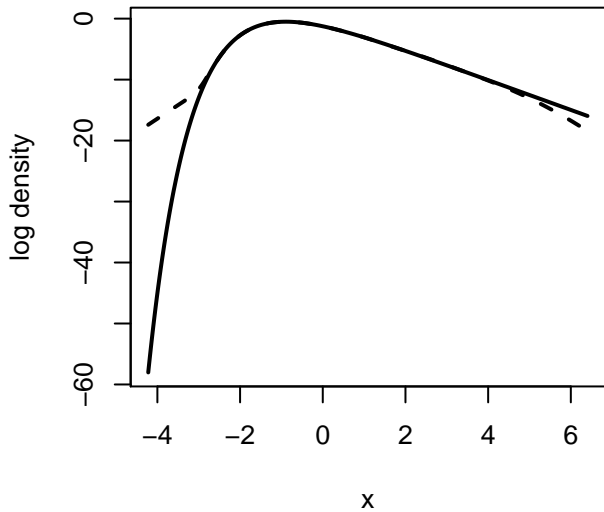
alpha = 2.4453125



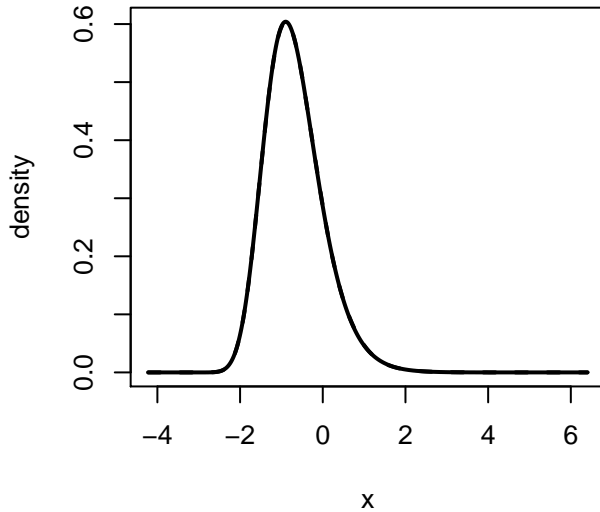
alpha = 2.4453125



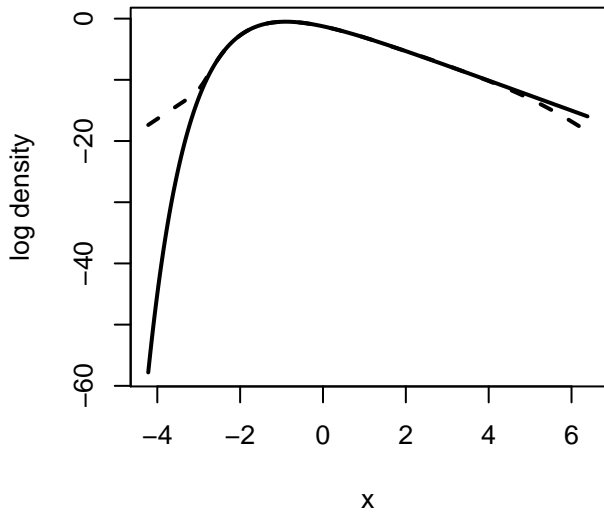
alpha = 2.453125



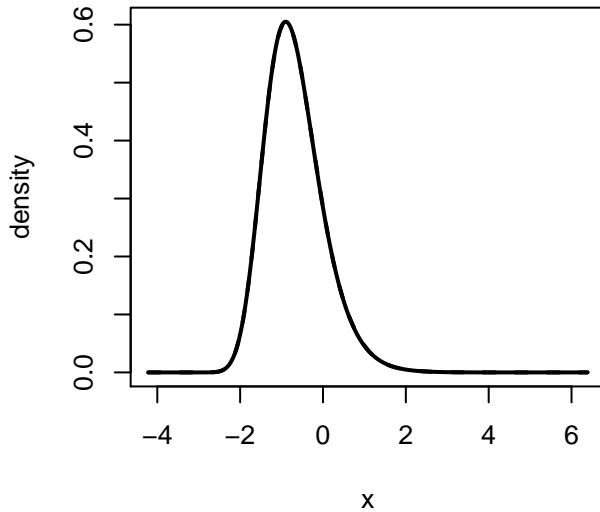
alpha = 2.453125



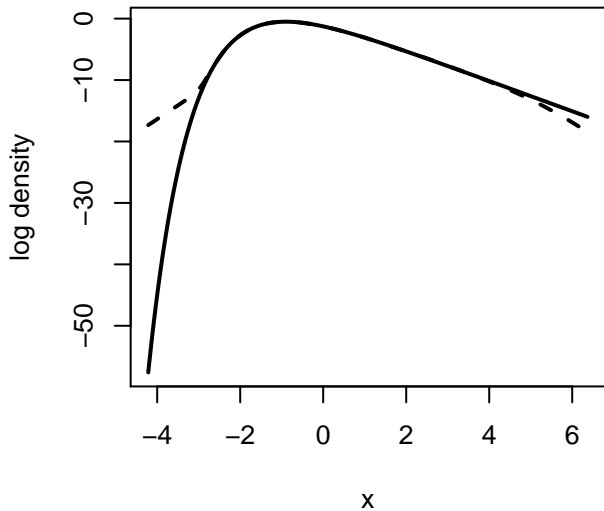
alpha = 2.4609375



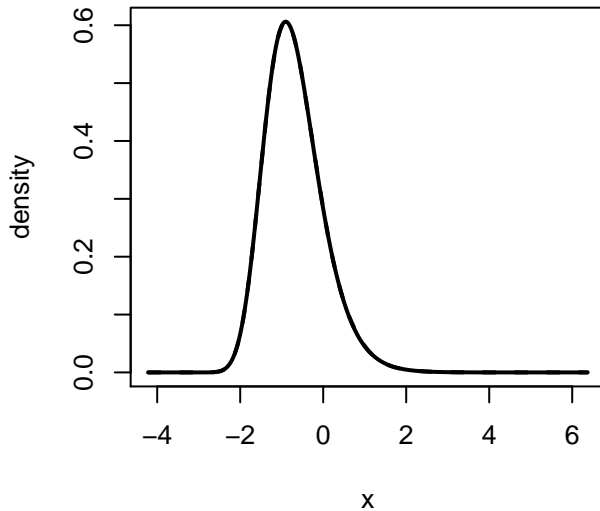
alpha = 2.4609375



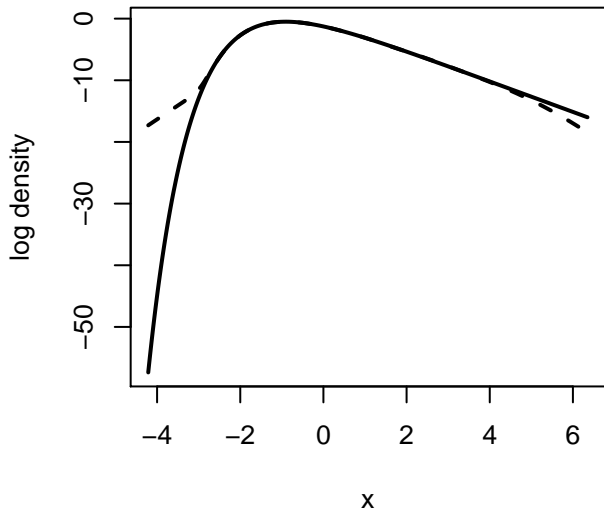
alpha = 2.46875



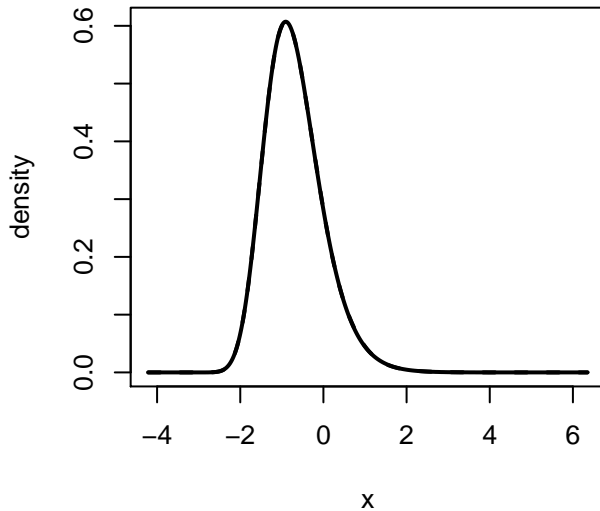
alpha = 2.46875



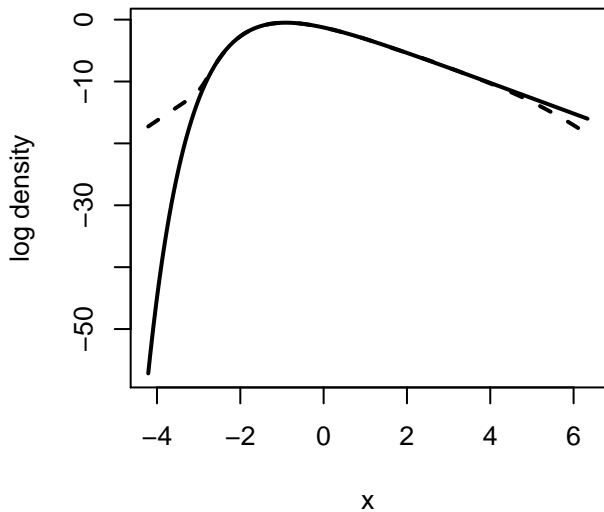
alpha = 2.4765625



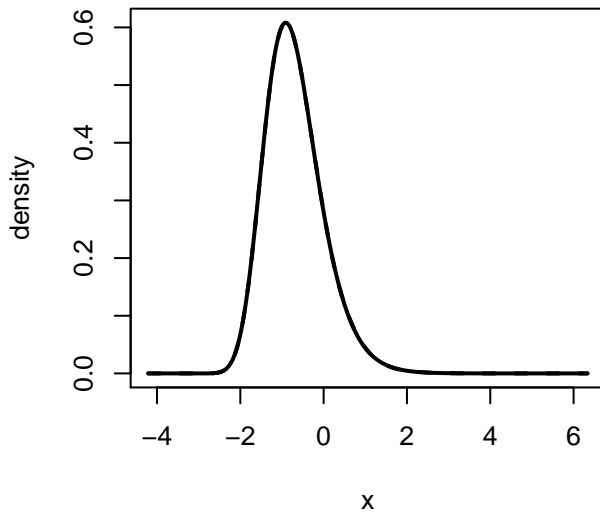
alpha = 2.4765625



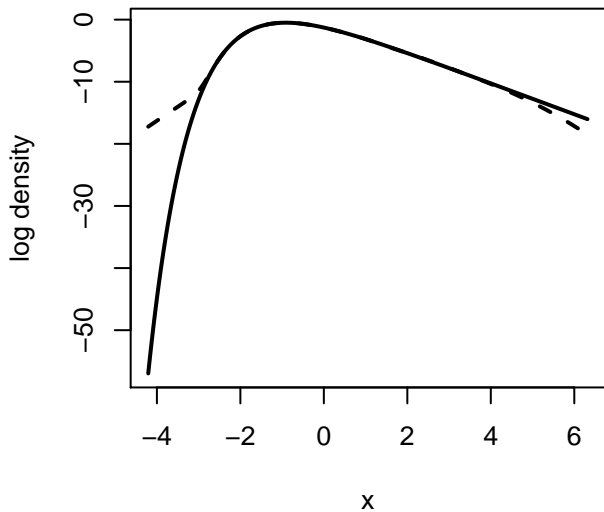
alpha = 2.484375



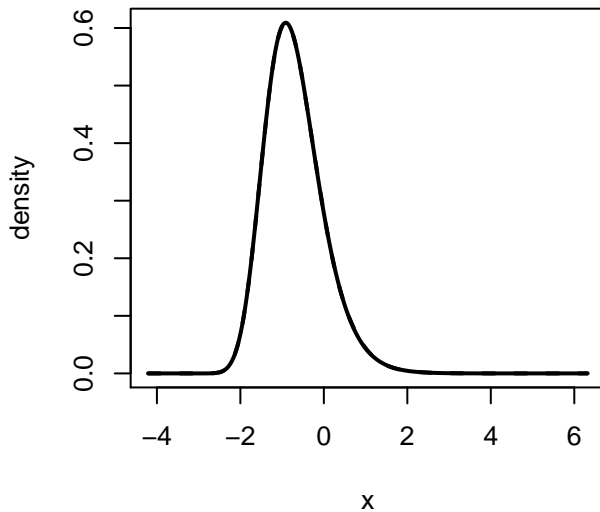
alpha = 2.484375



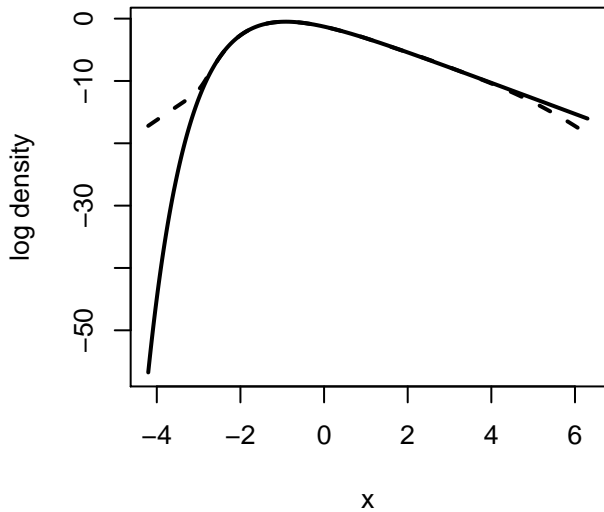
alpha = 2.4921875



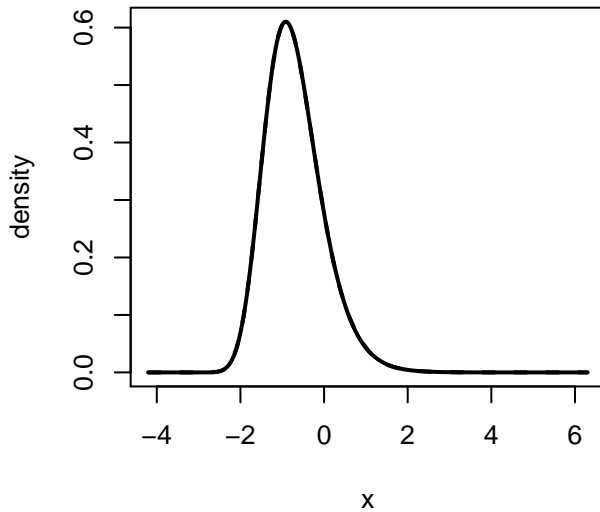
alpha = 2.4921875



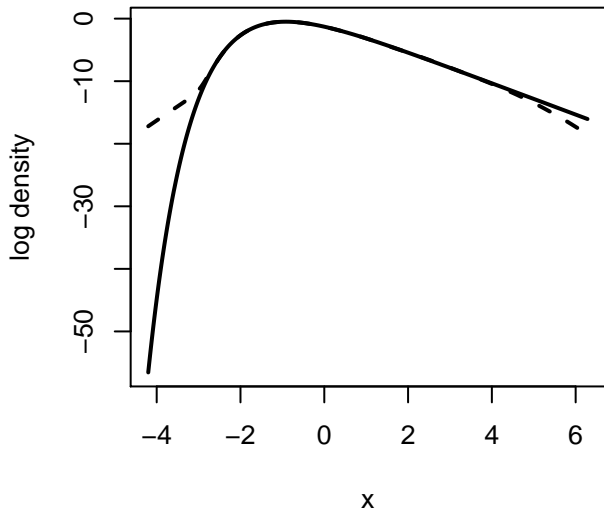
alpha = 2.5



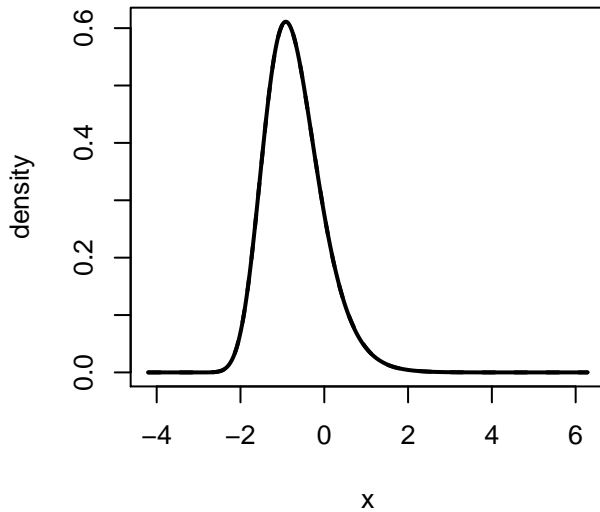
alpha = 2.5



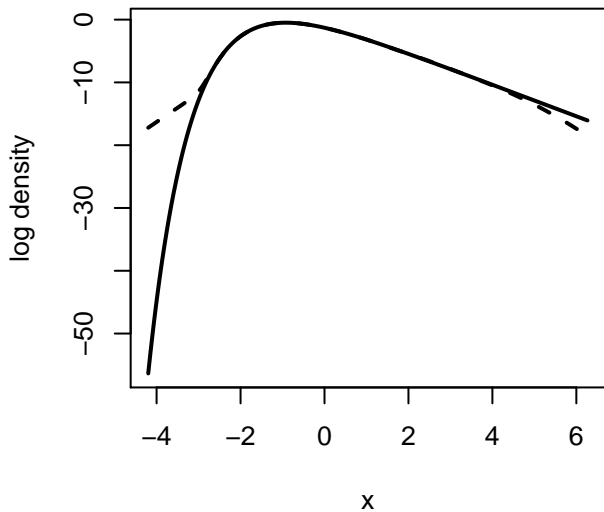
alpha = 2.5078125



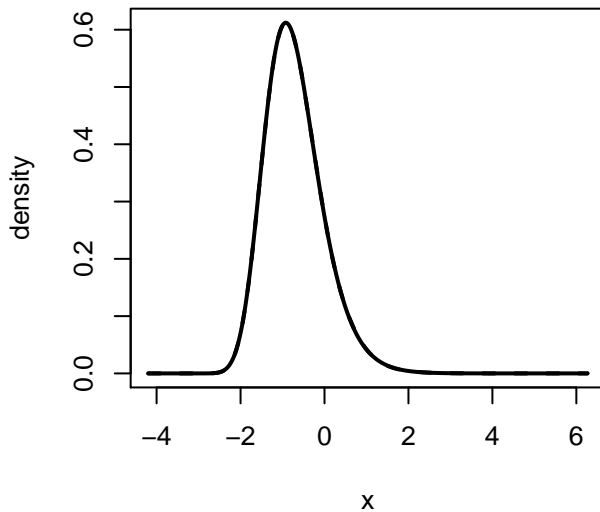
alpha = 2.5078125



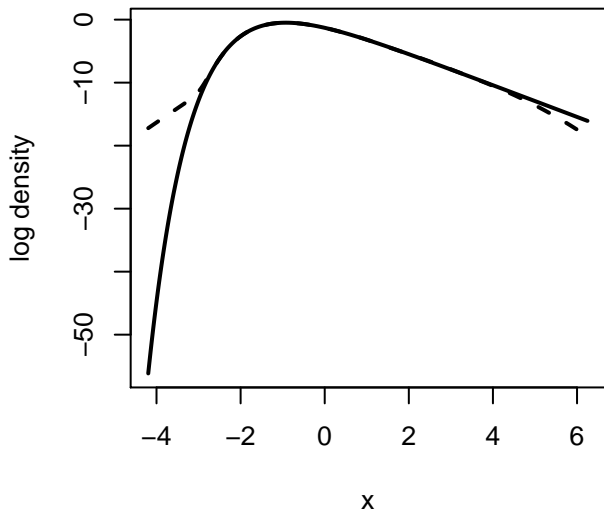
alpha = 2.515625



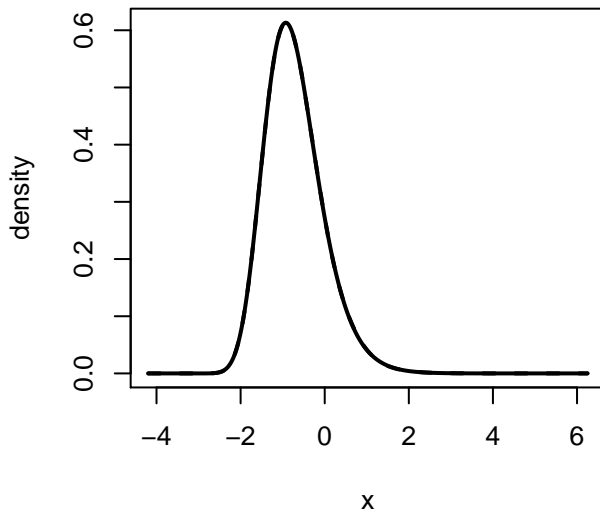
alpha = 2.515625



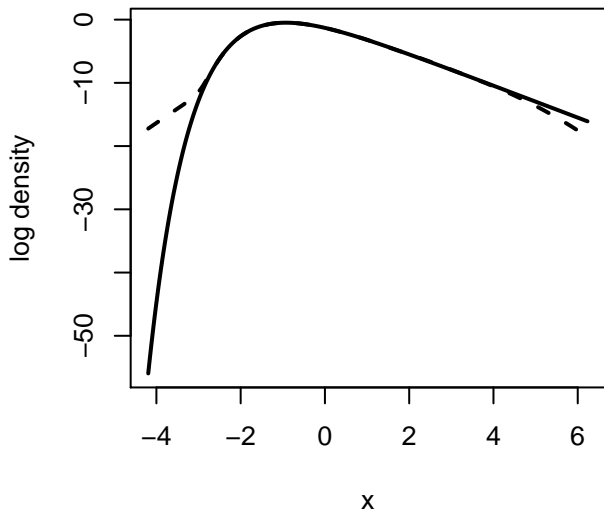
alpha = 2.5234375



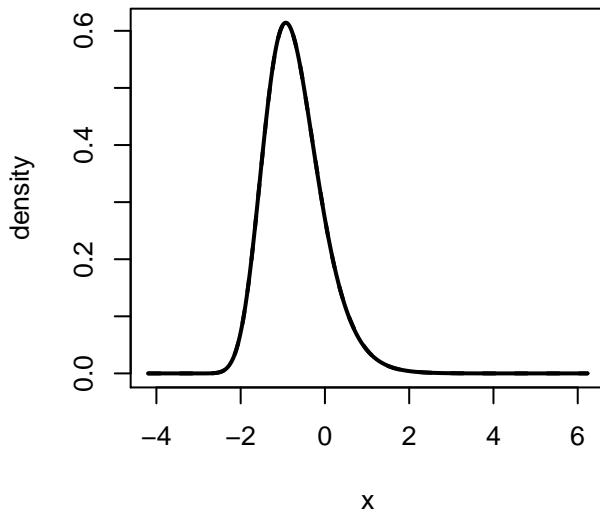
alpha = 2.5234375



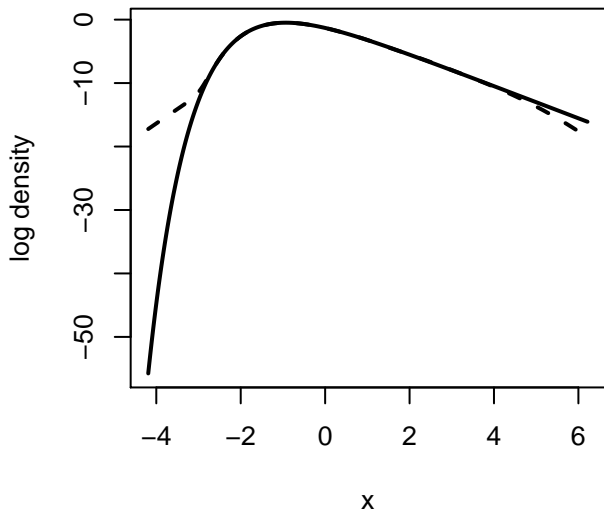
alpha = 2.53125



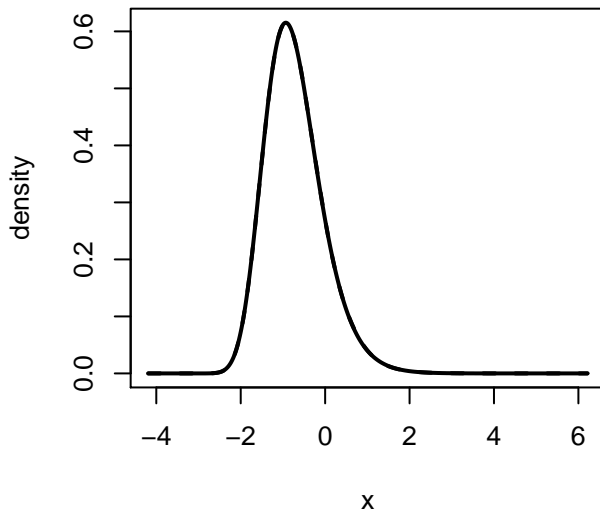
alpha = 2.53125



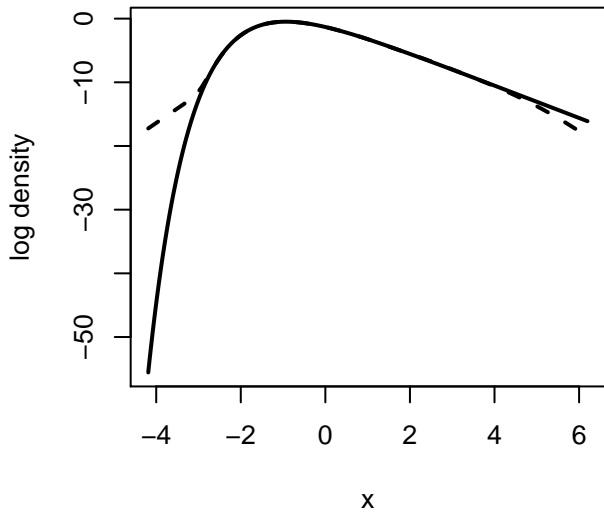
alpha = 2.5390625



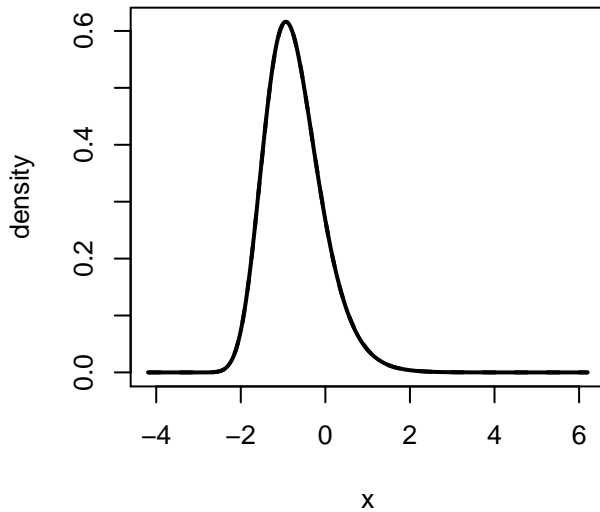
alpha = 2.5390625



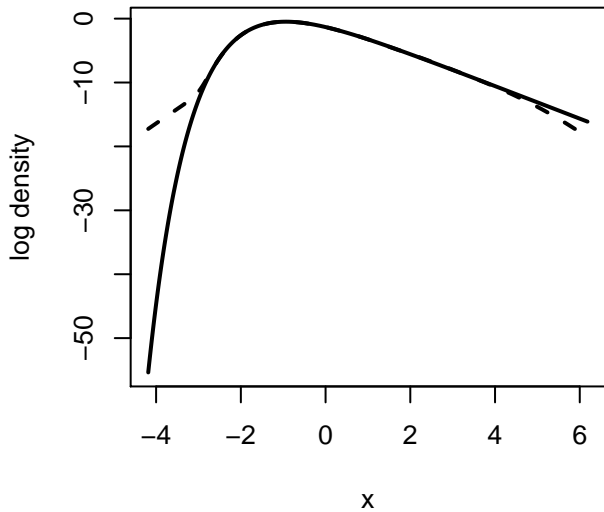
alpha = 2.546875



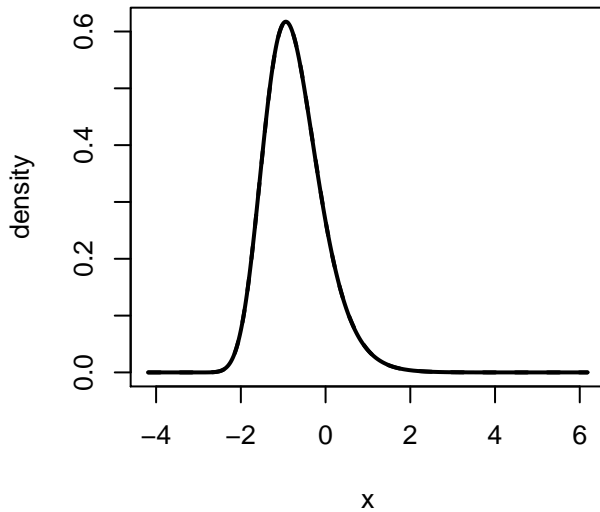
alpha = 2.546875



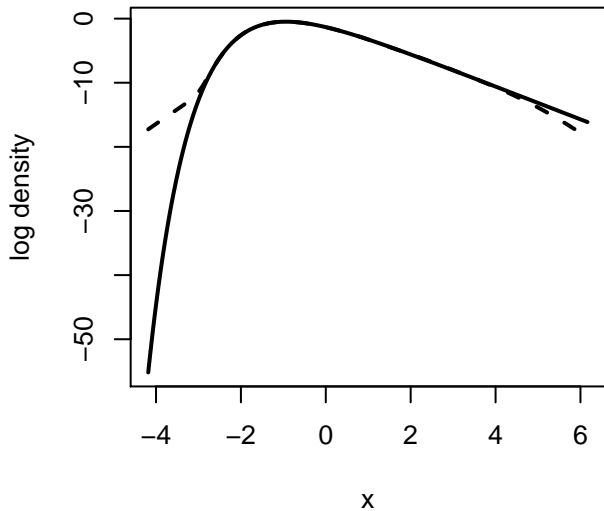
alpha = 2.5546875



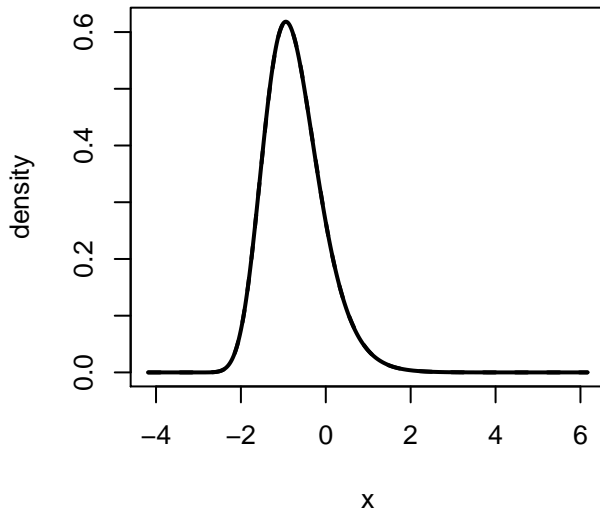
alpha = 2.5546875



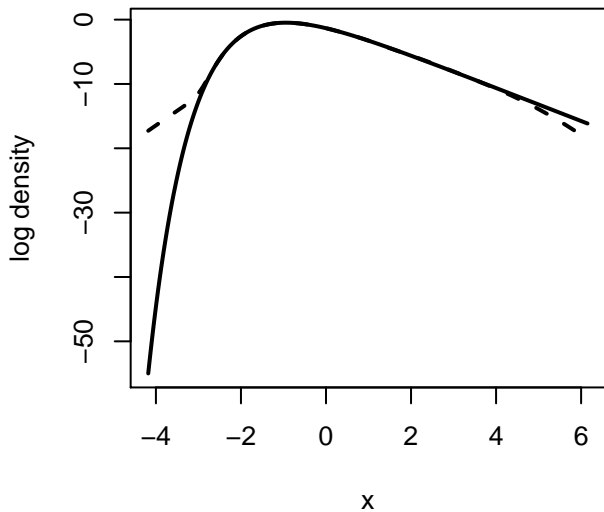
alpha = 2.5625



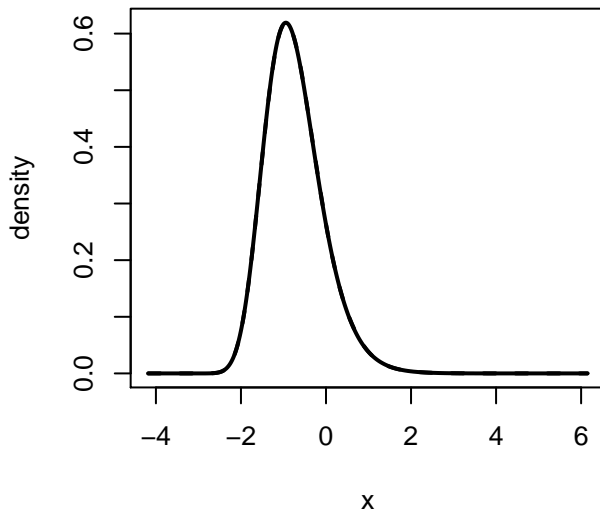
alpha = 2.5625



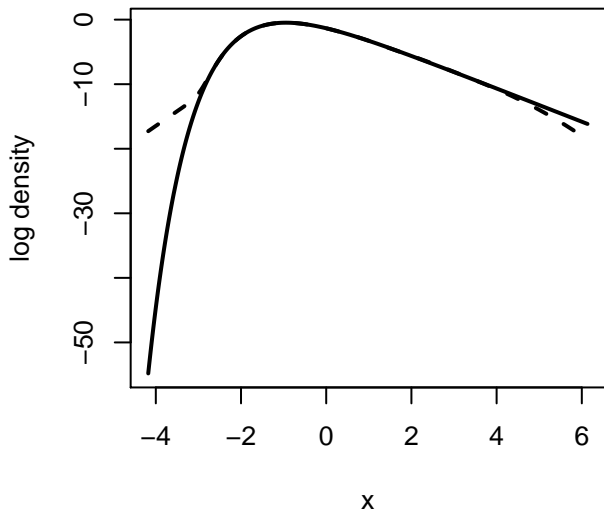
alpha = 2.5703125



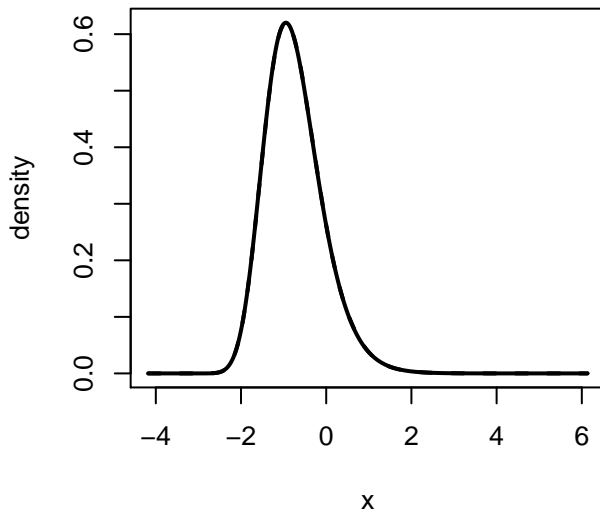
alpha = 2.5703125



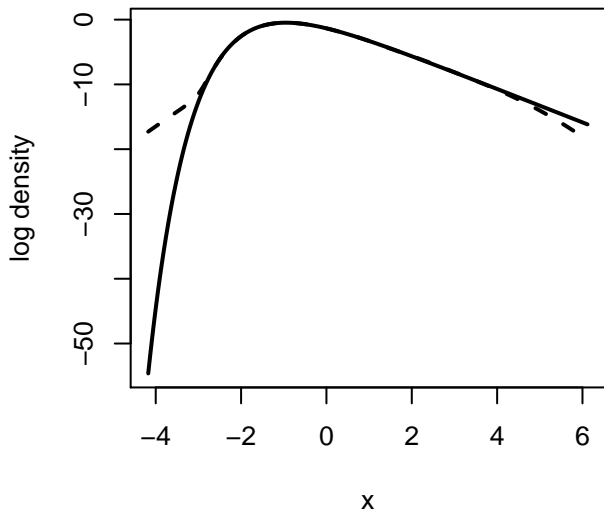
alpha = 2.578125



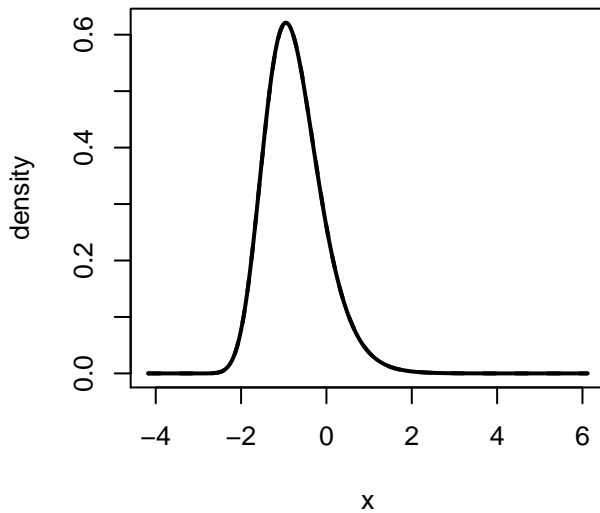
alpha = 2.578125



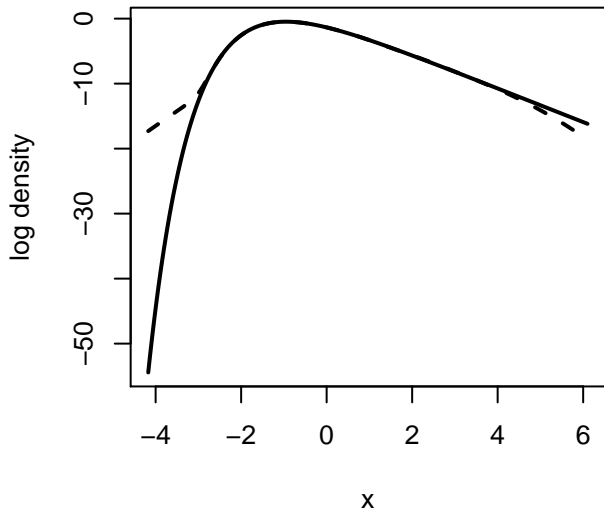
alpha = 2.5859375



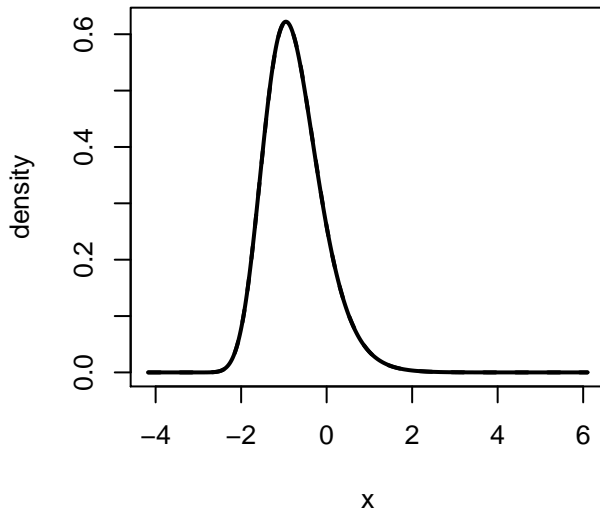
alpha = 2.5859375



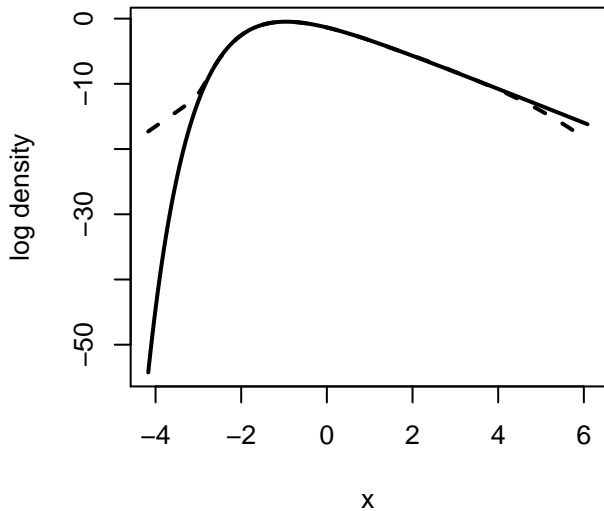
alpha = 2.59375



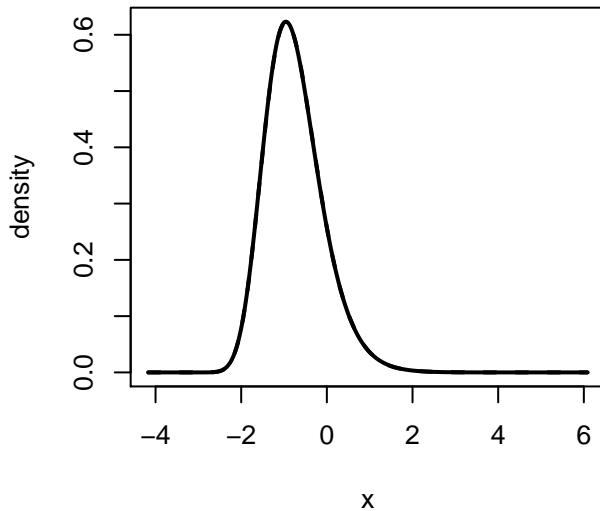
alpha = 2.59375



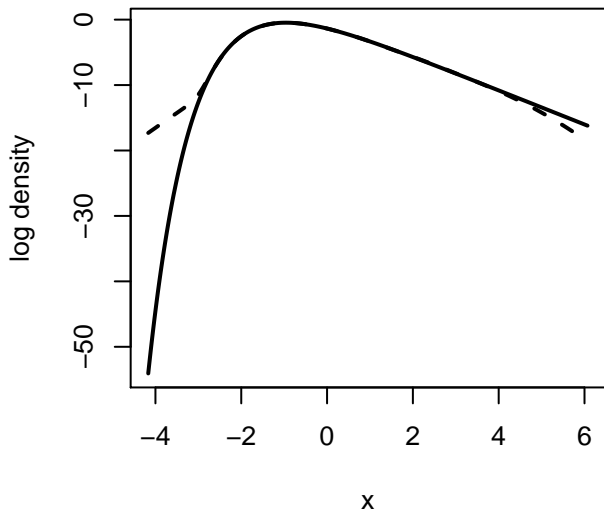
alpha = 2.6015625



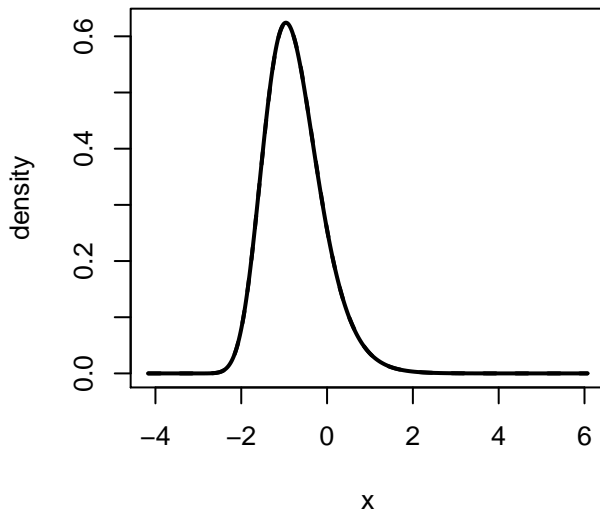
alpha = 2.6015625



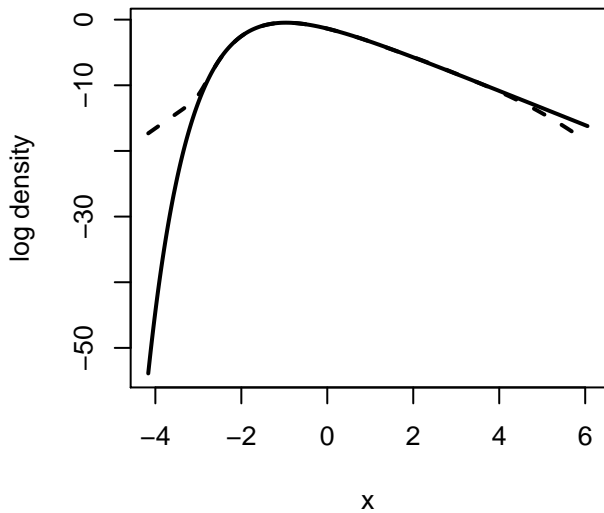
alpha = 2.609375



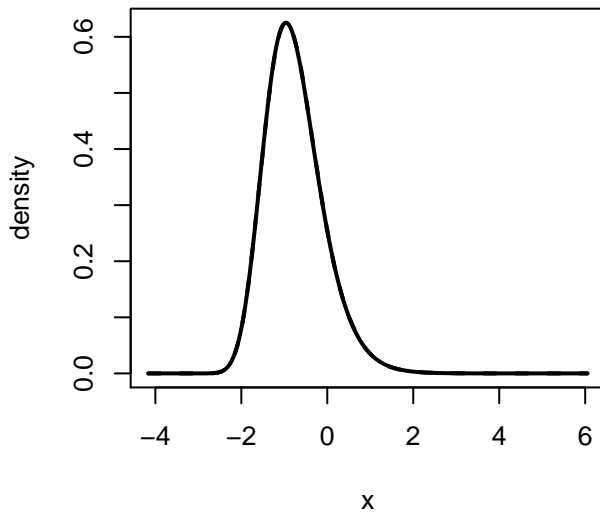
alpha = 2.609375



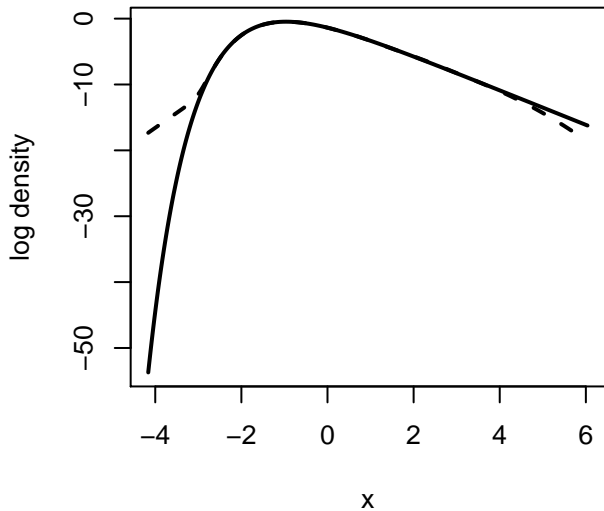
alpha = 2.6171875



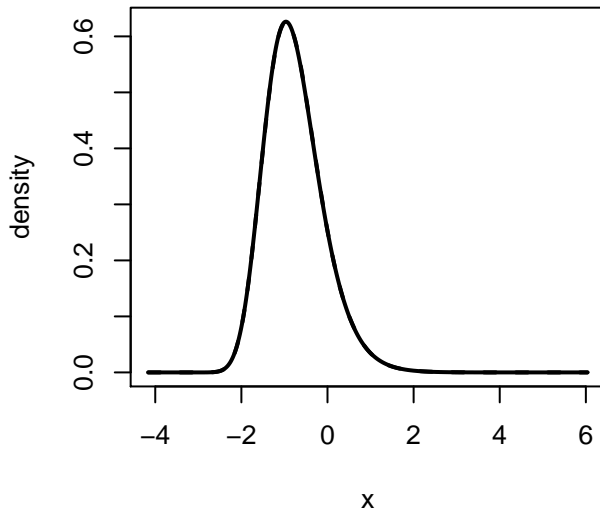
alpha = 2.6171875



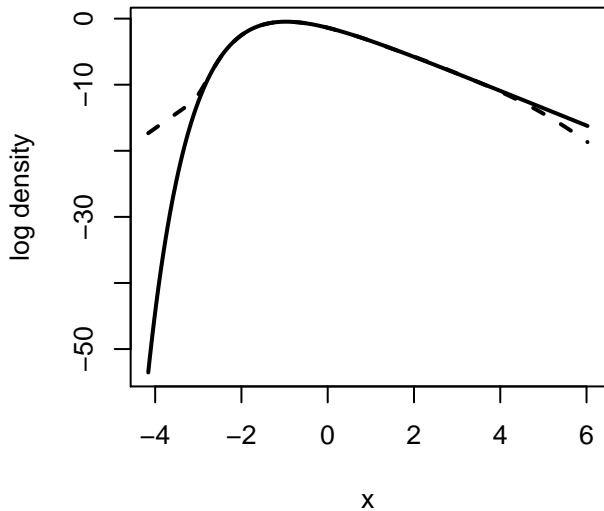
alpha = 2.625



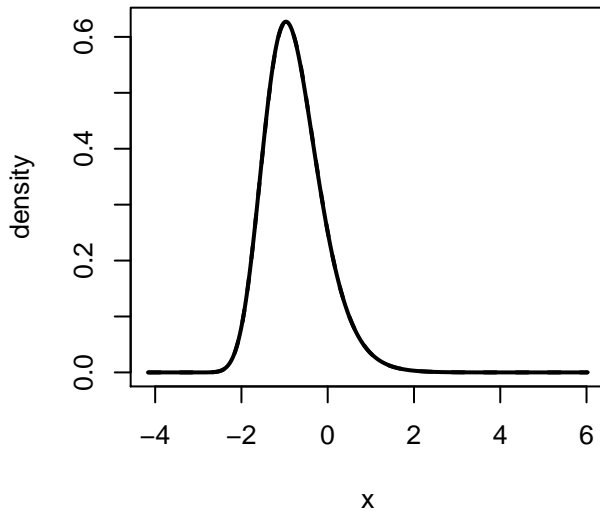
alpha = 2.625



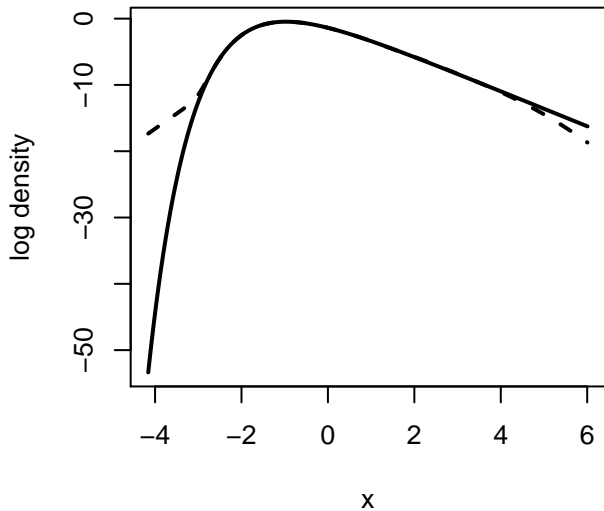
alpha = 2.6328125



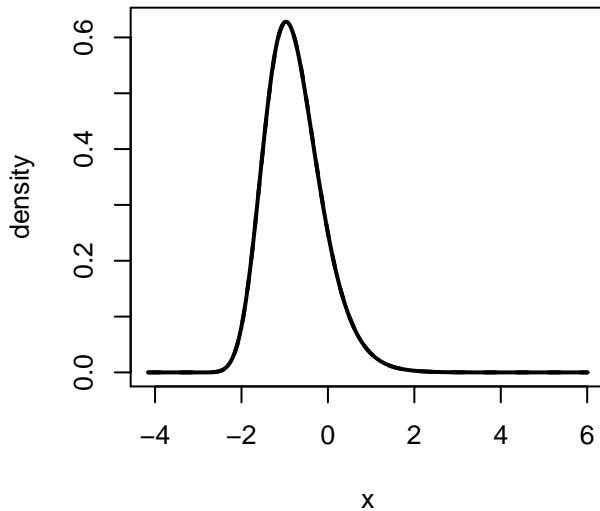
alpha = 2.6328125



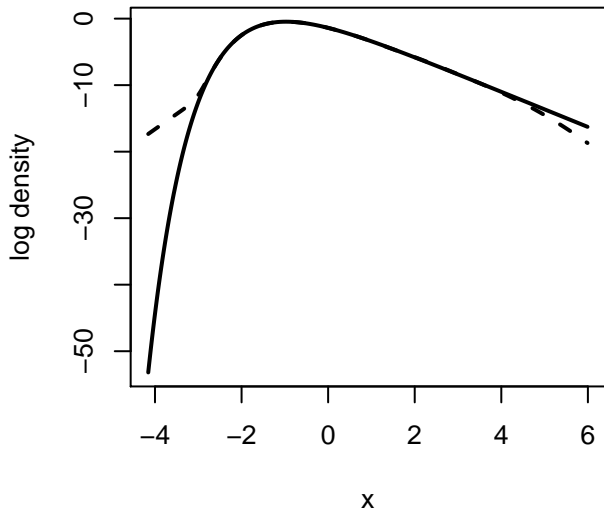
alpha = 2.640625



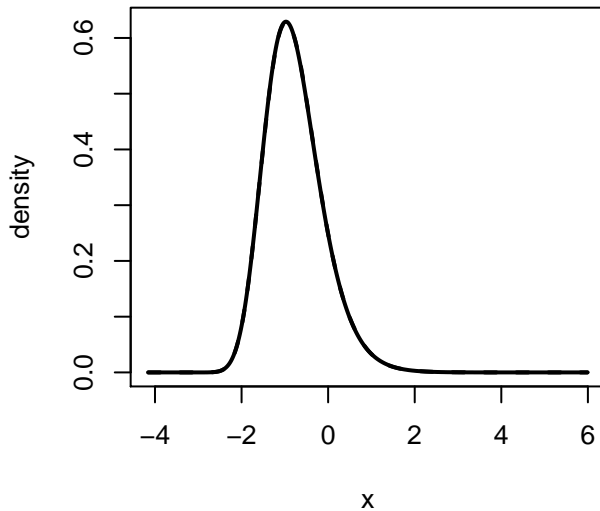
alpha = 2.640625



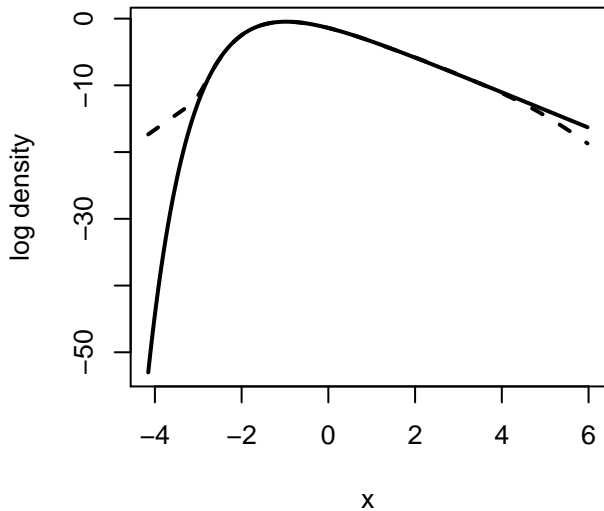
alpha = 2.6484375



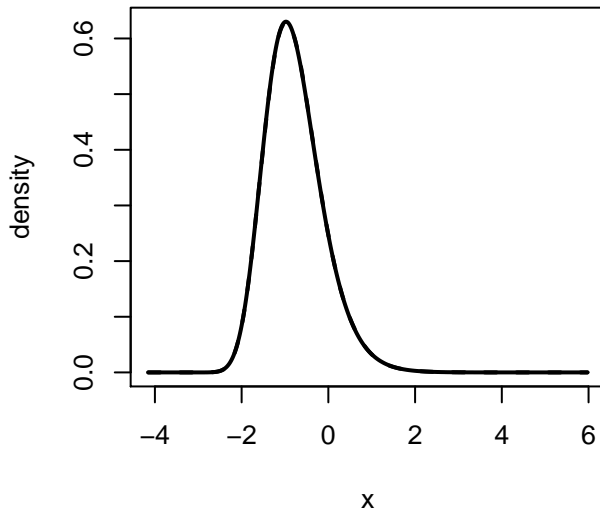
alpha = 2.6484375



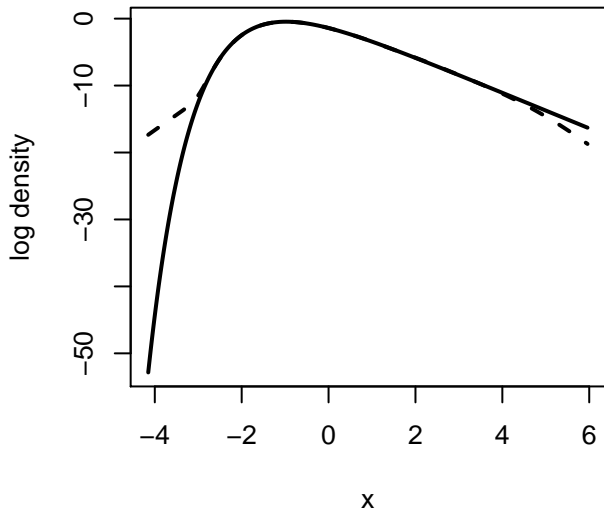
alpha = 2.65625



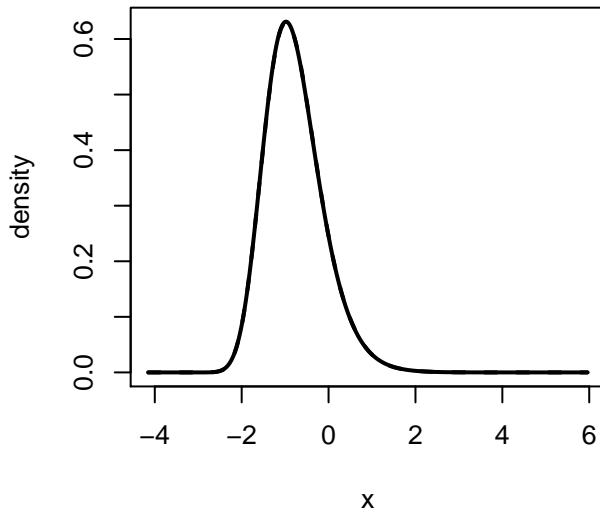
alpha = 2.65625



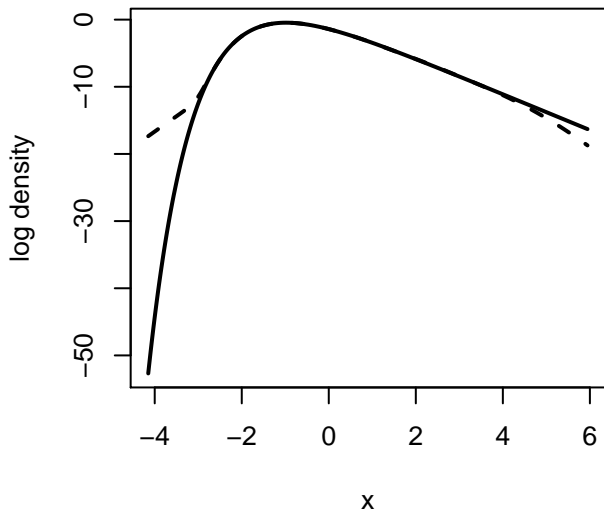
alpha = 2.6640625



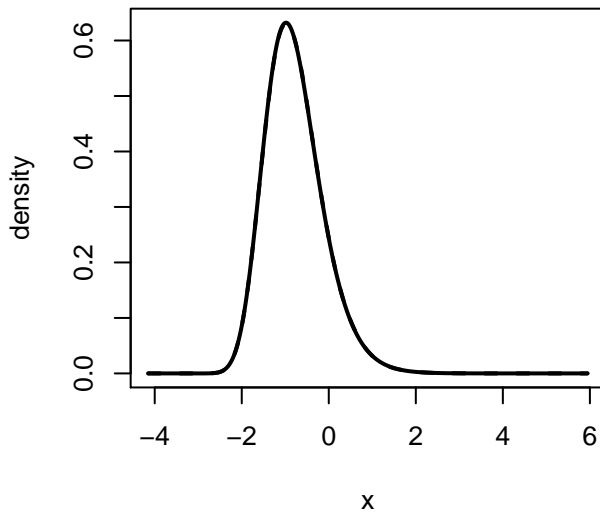
alpha = 2.6640625



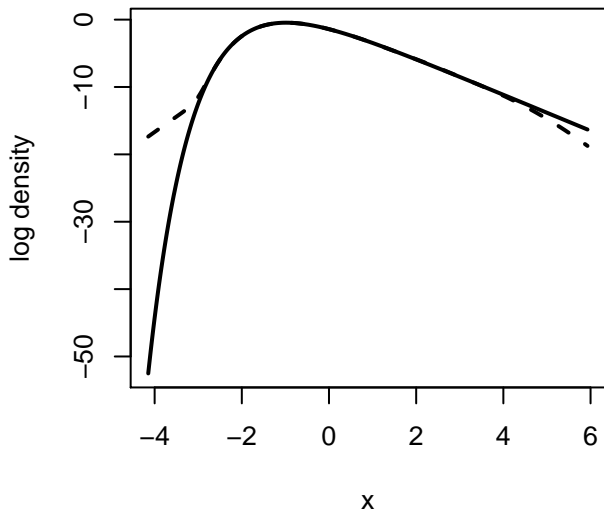
alpha = 2.671875



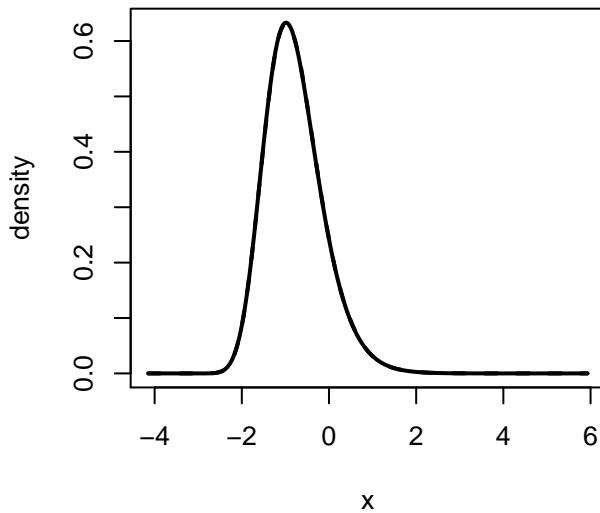
alpha = 2.671875



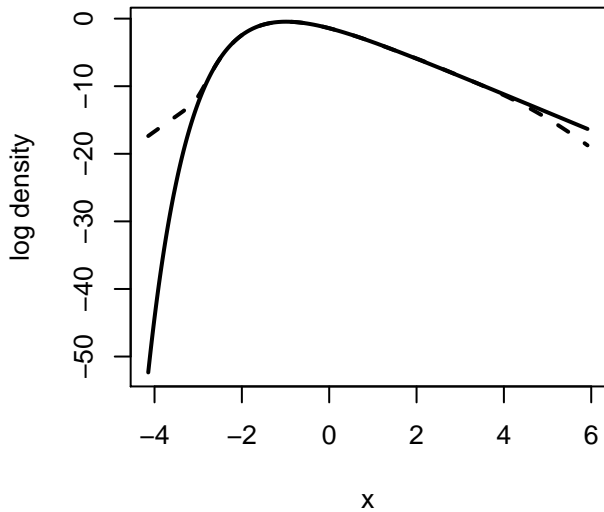
alpha = 2.6796875



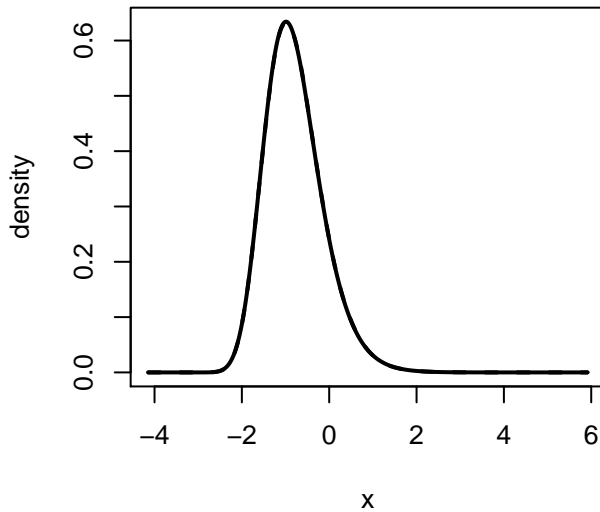
alpha = 2.6796875



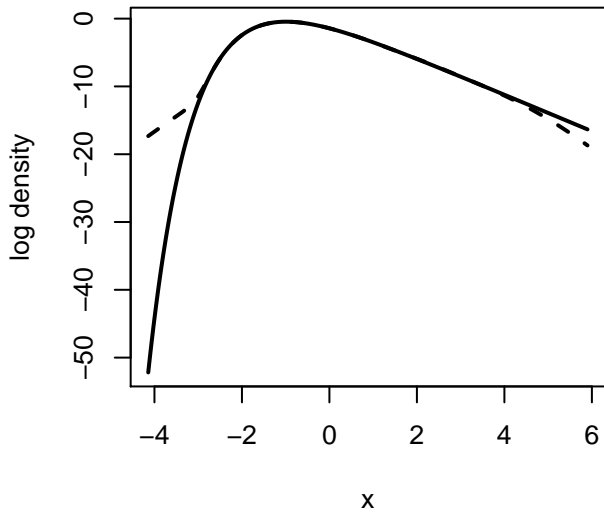
alpha = 2.6875



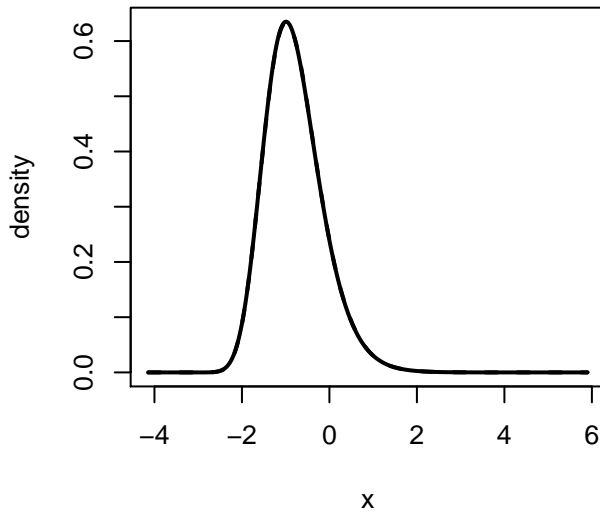
alpha = 2.6875



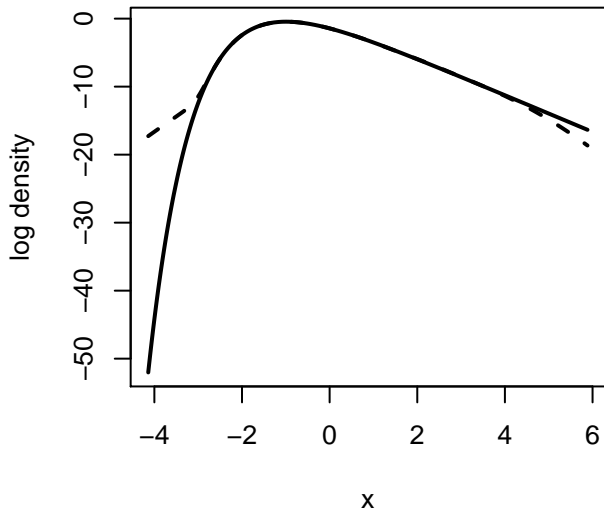
alpha = 2.6953125



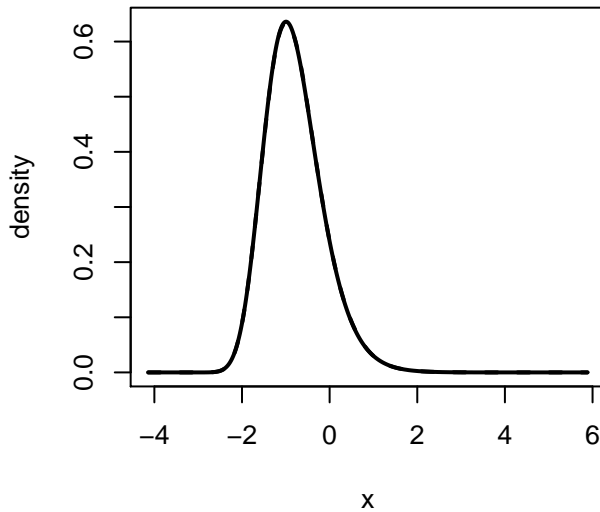
alpha = 2.6953125



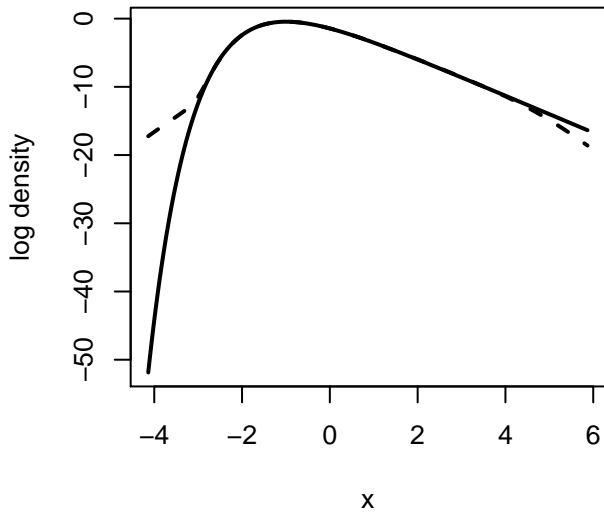
alpha = 2.703125



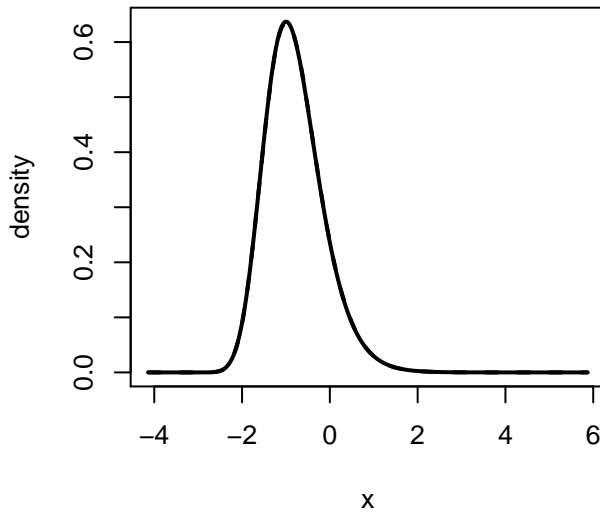
alpha = 2.703125



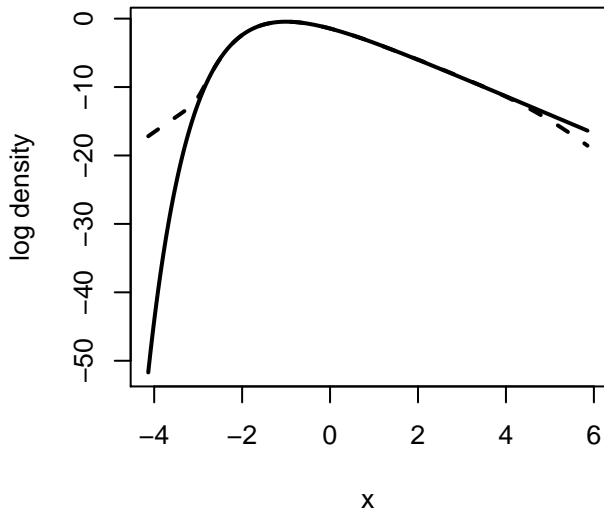
alpha = 2.7109375



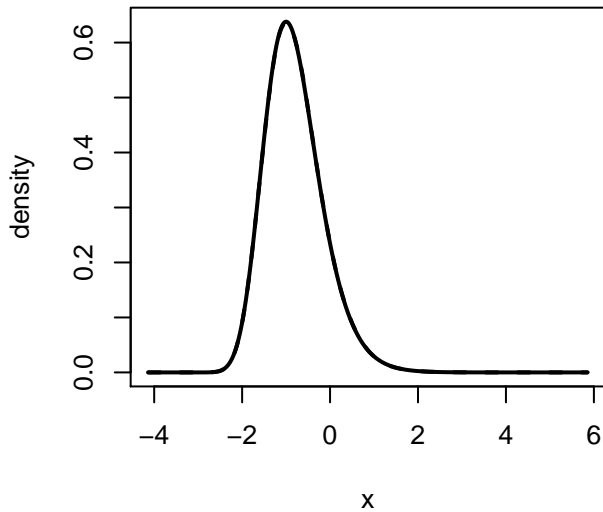
alpha = 2.7109375



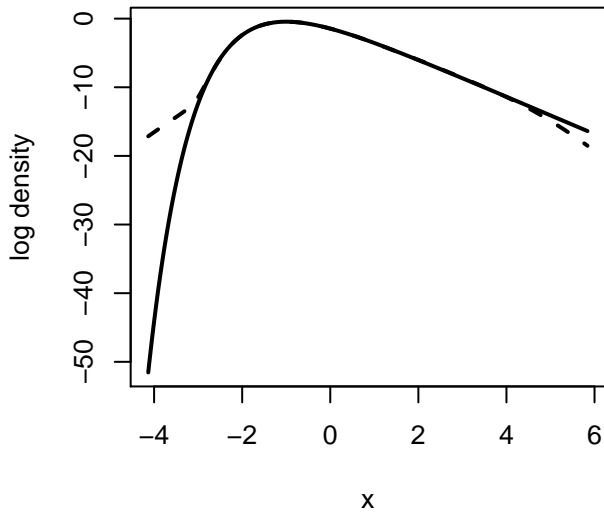
alpha = 2.71875



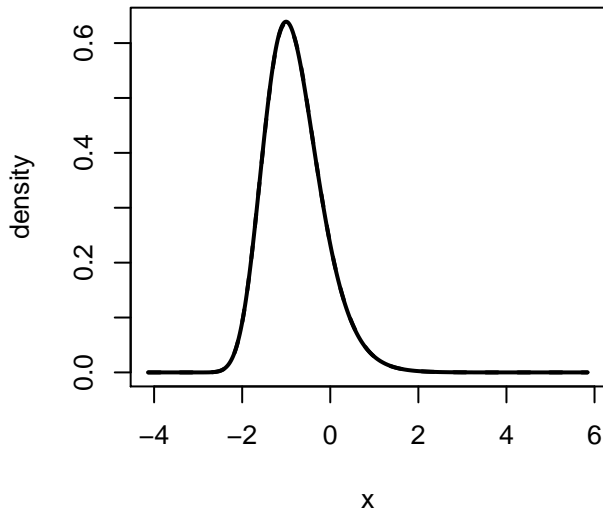
alpha = 2.71875



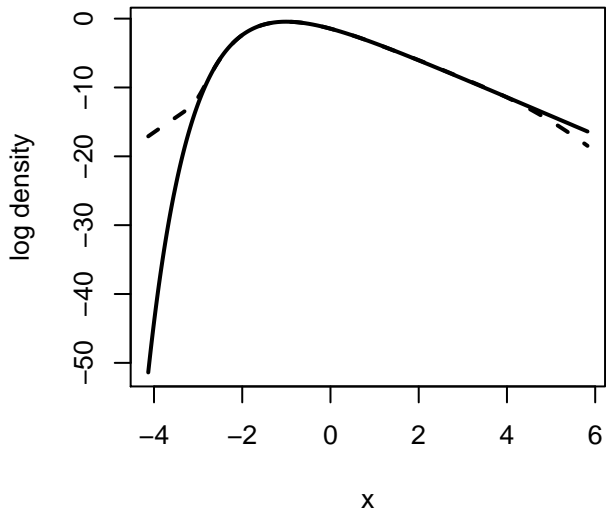
alpha = 2.7265625



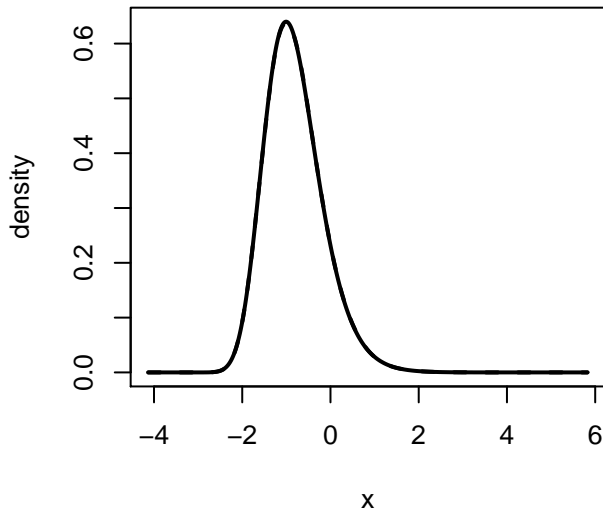
alpha = 2.7265625



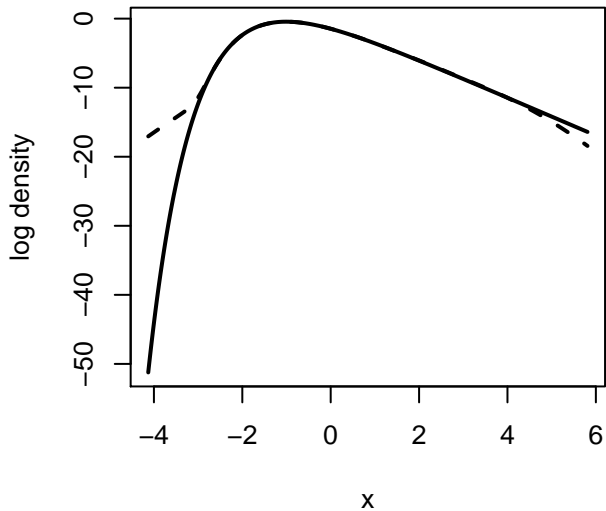
alpha = 2.734375



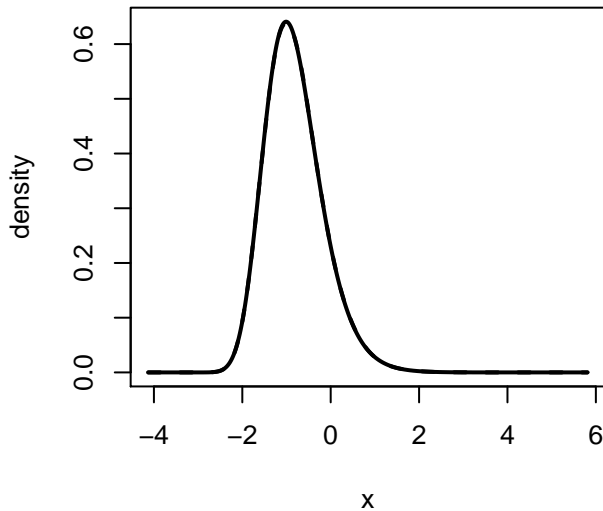
alpha = 2.734375



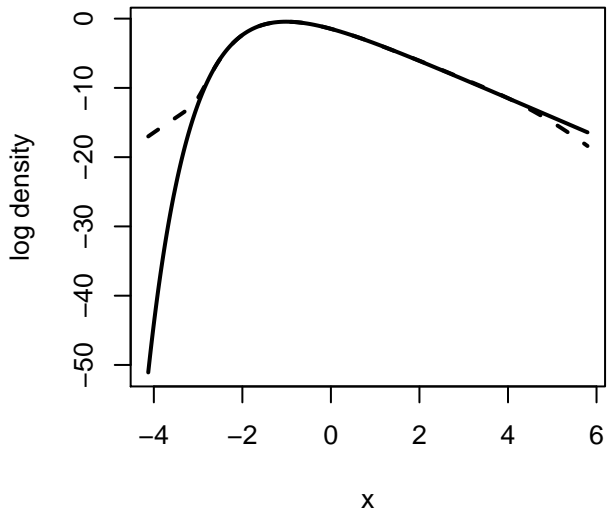
alpha = 2.7421875



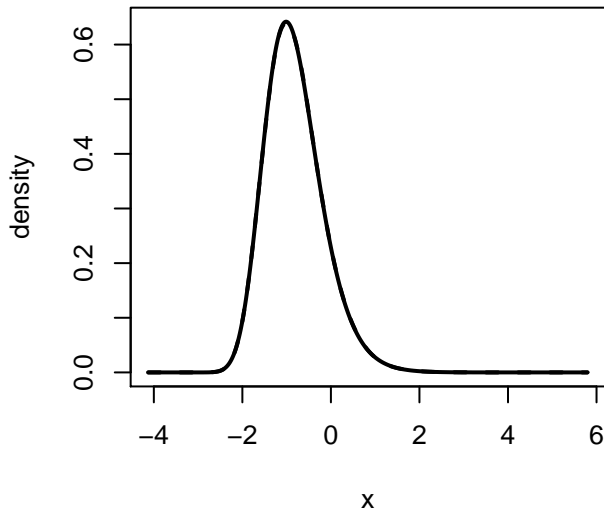
alpha = 2.7421875



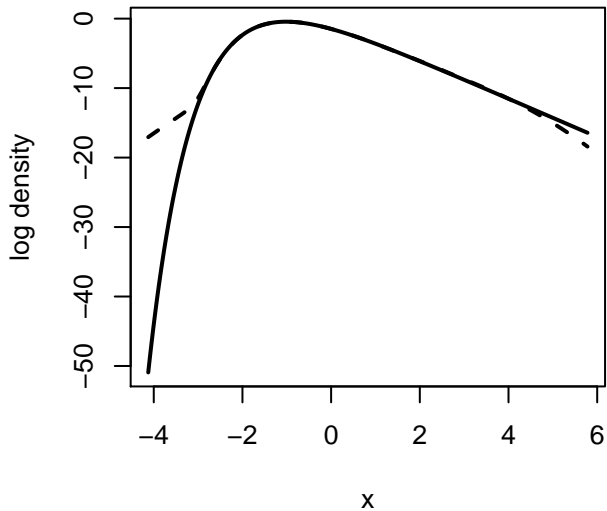
alpha = 2.75



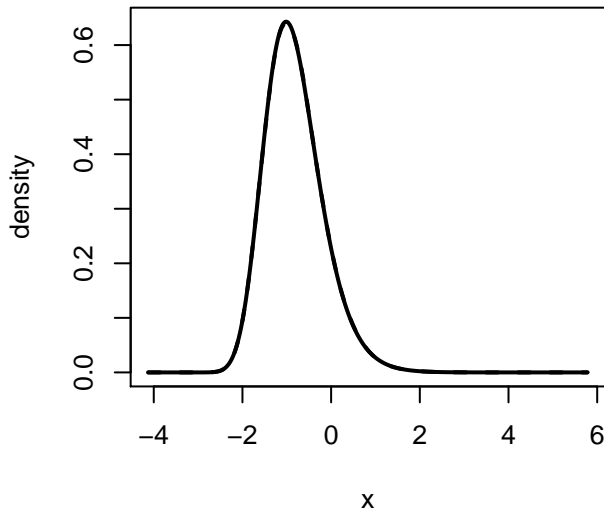
alpha = 2.75



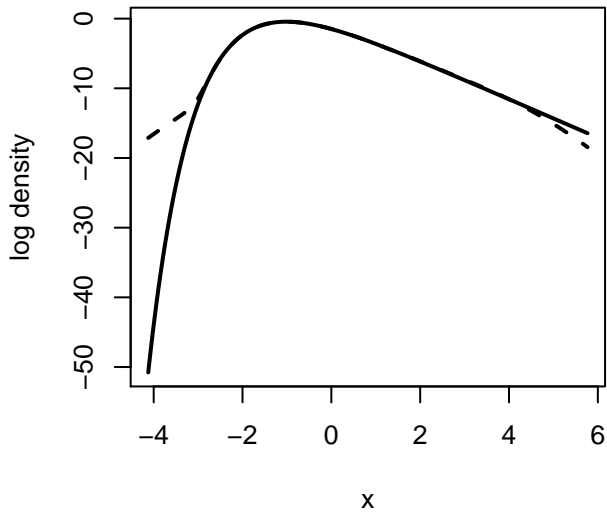
alpha = 2.7578125



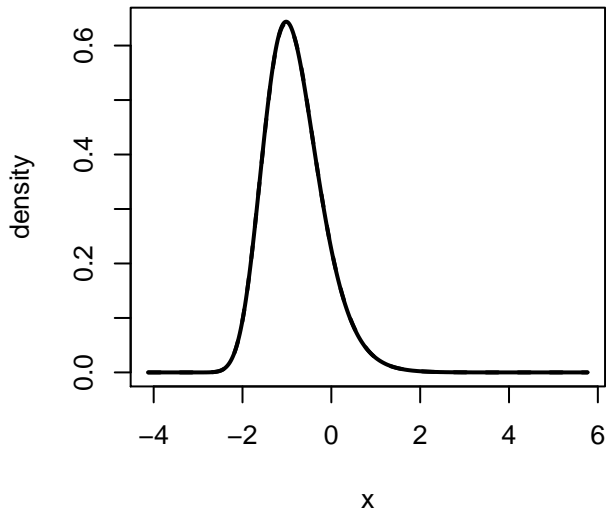
alpha = 2.7578125



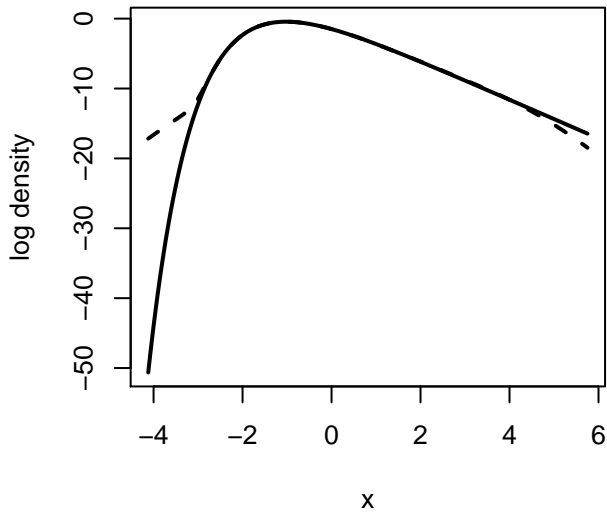
alpha = 2.765625



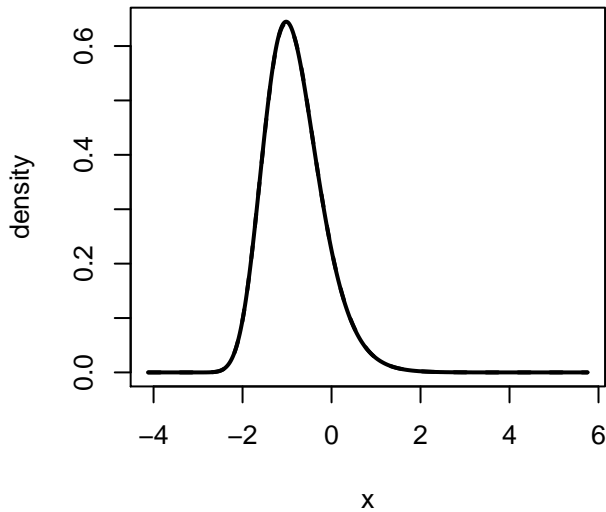
alpha = 2.765625



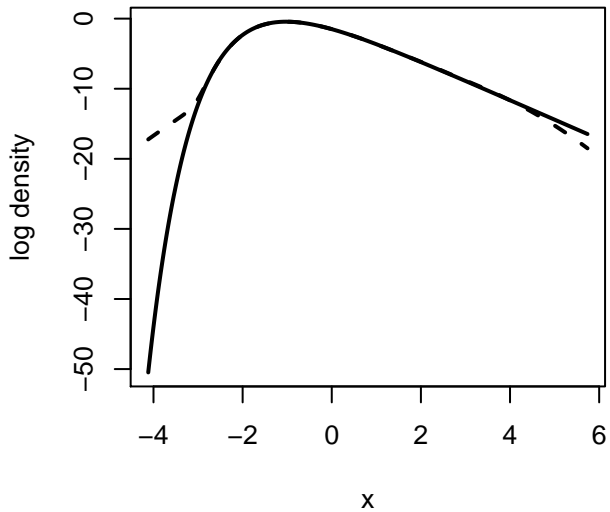
alpha = 2.7734375



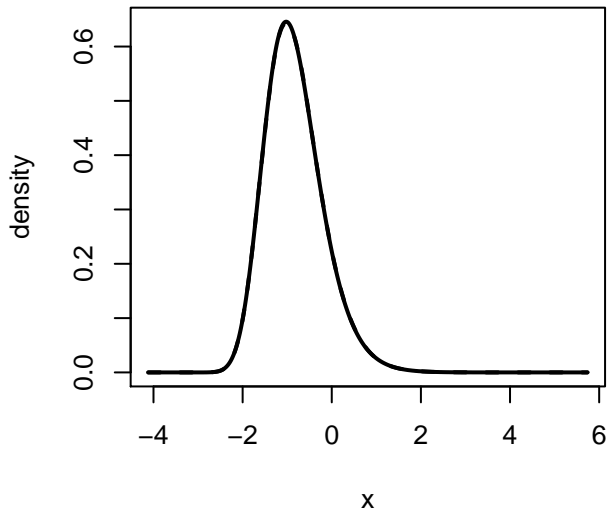
alpha = 2.7734375



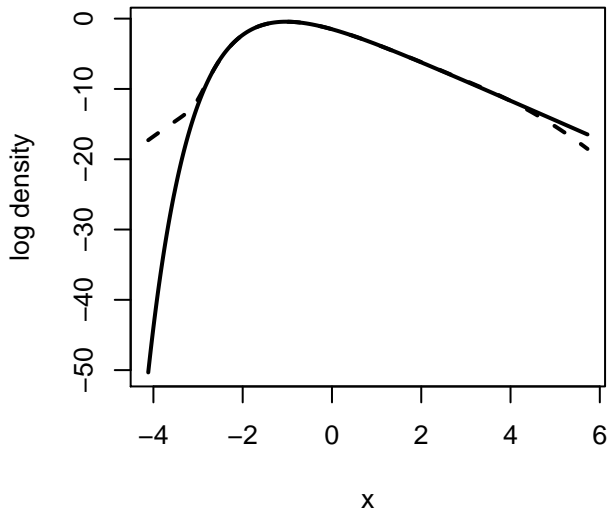
alpha = 2.78125



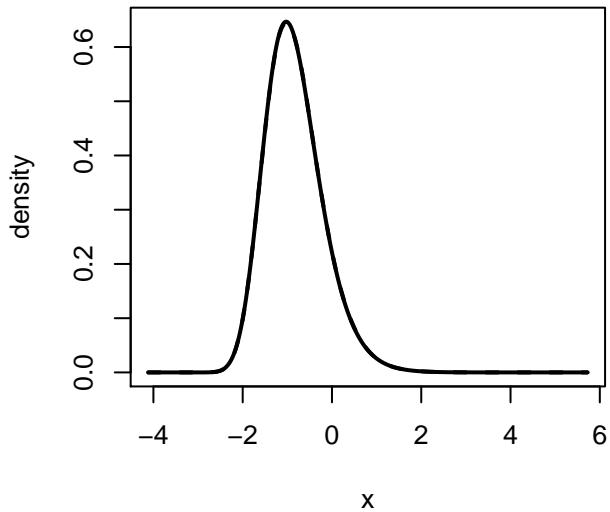
alpha = 2.78125



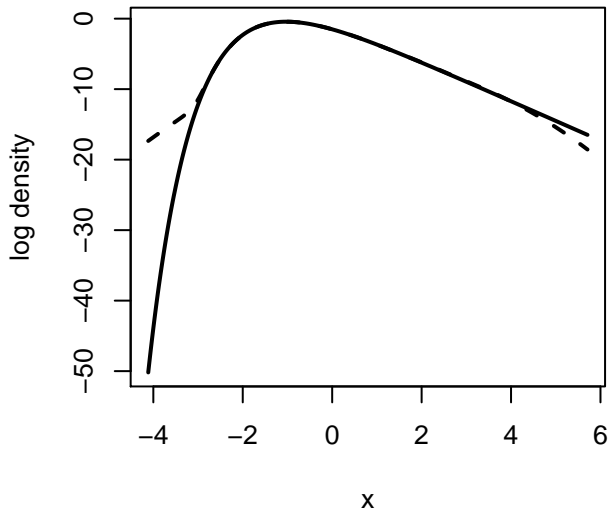
alpha = 2.7890625



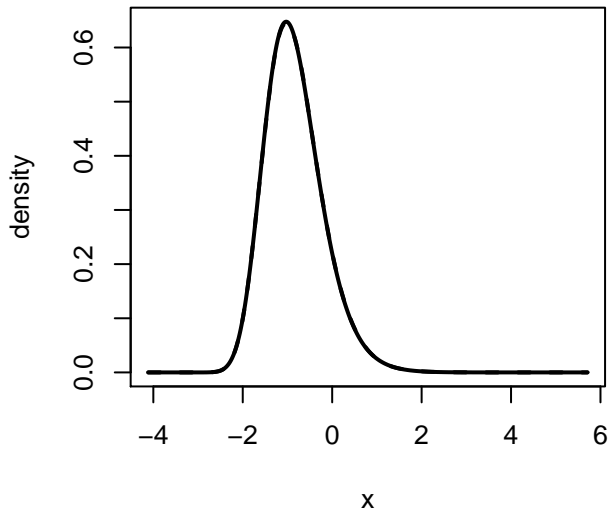
alpha = 2.7890625



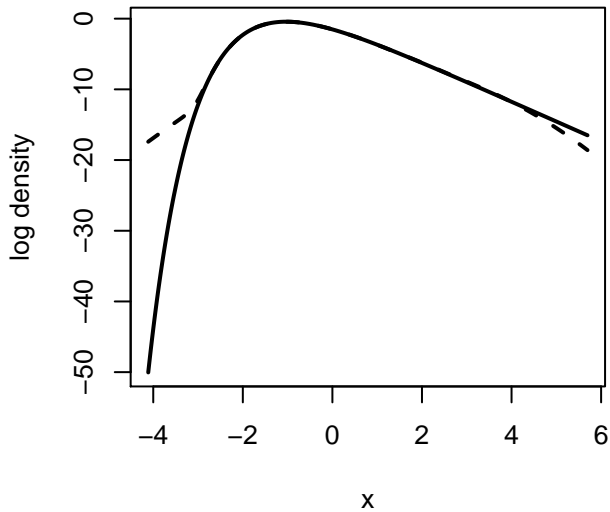
alpha = 2.796875



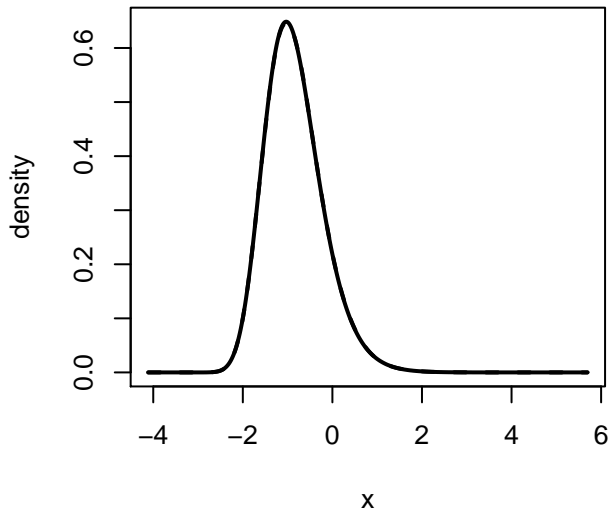
alpha = 2.796875



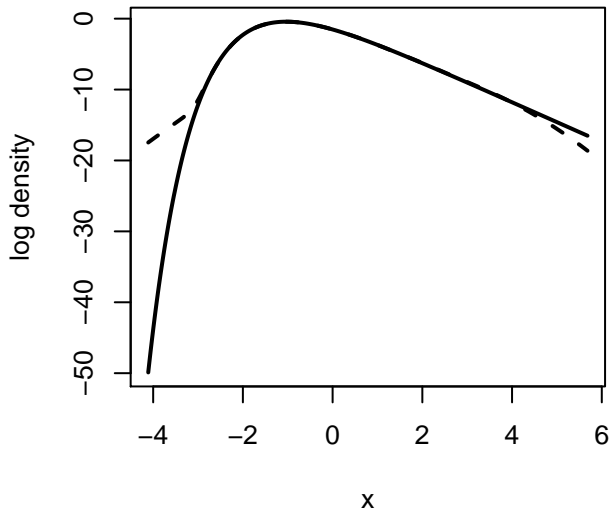
alpha = 2.8046875



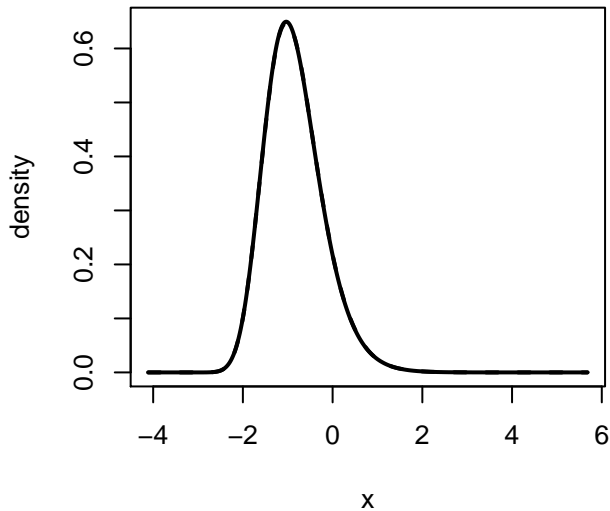
alpha = 2.8046875



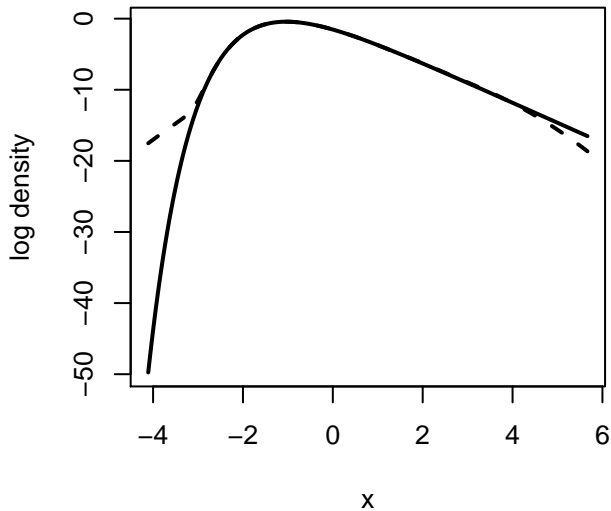
alpha = 2.8125



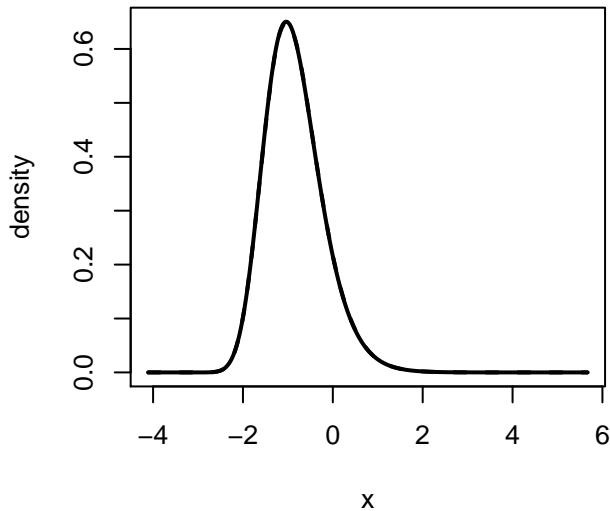
alpha = 2.8125



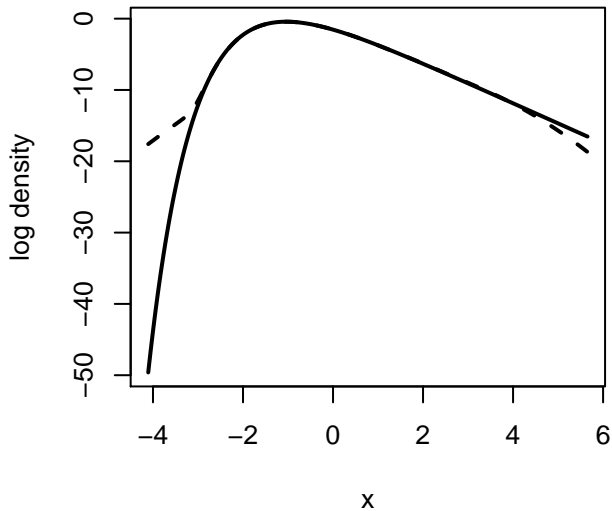
alpha = 2.8203125



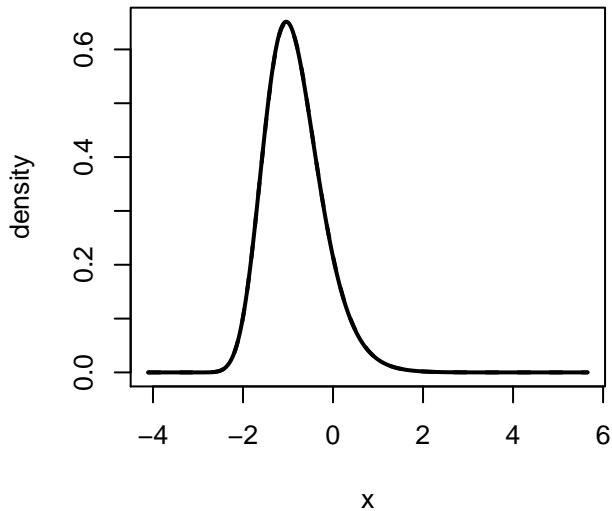
alpha = 2.8203125



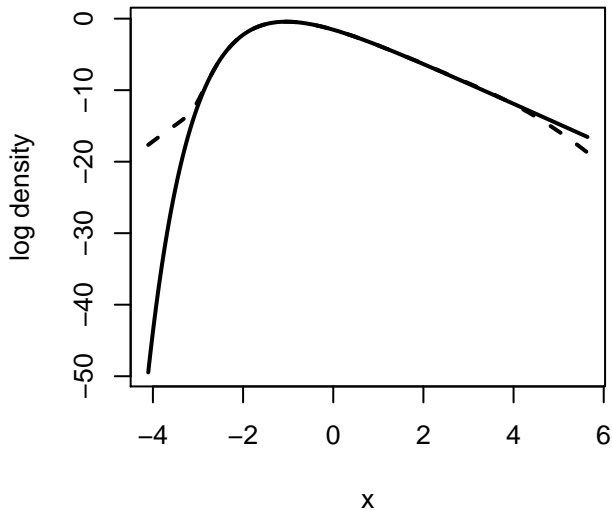
alpha = 2.828125



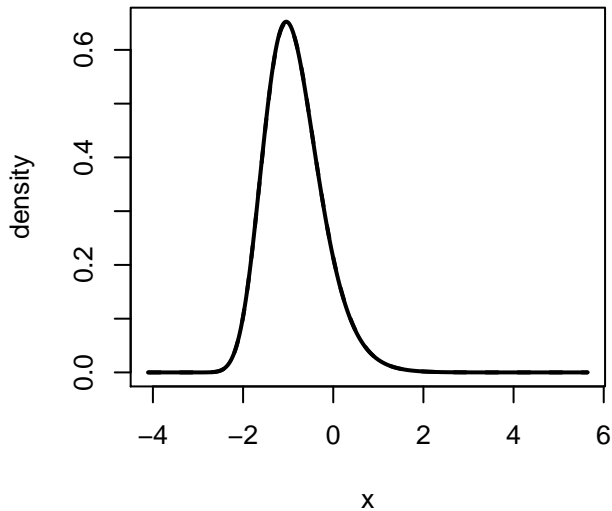
alpha = 2.828125



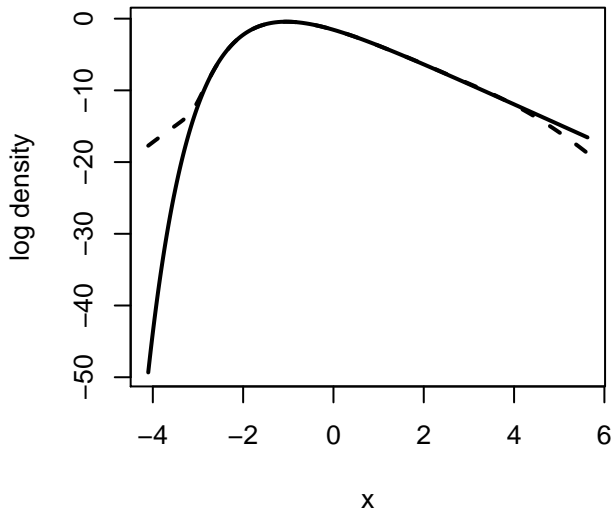
alpha = 2.8359375



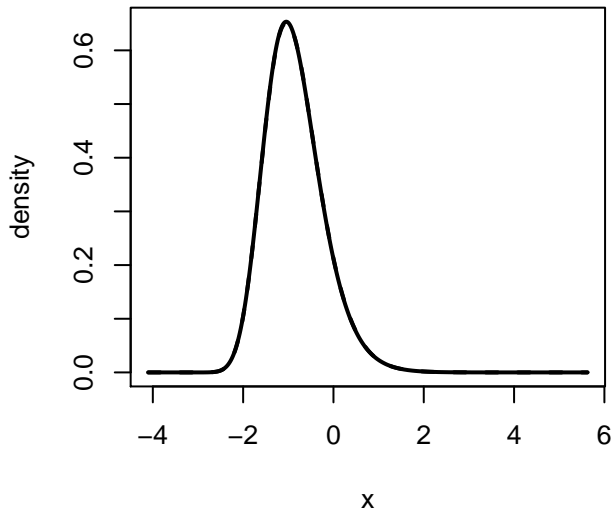
alpha = 2.8359375



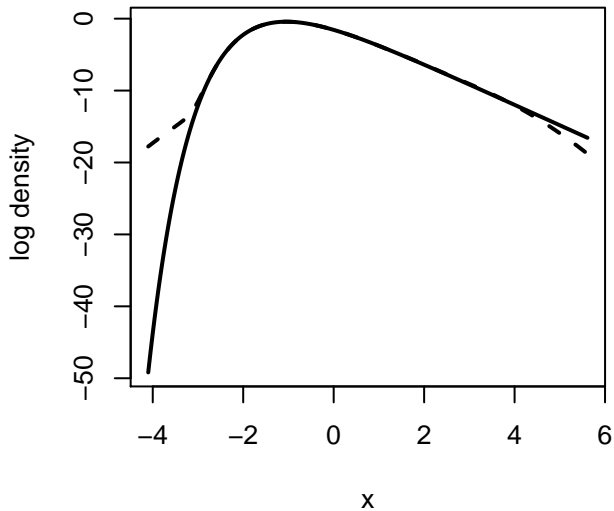
alpha = 2.84375



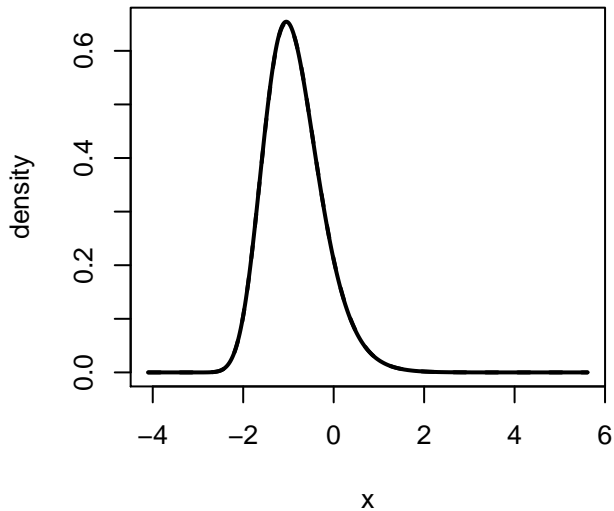
alpha = 2.84375



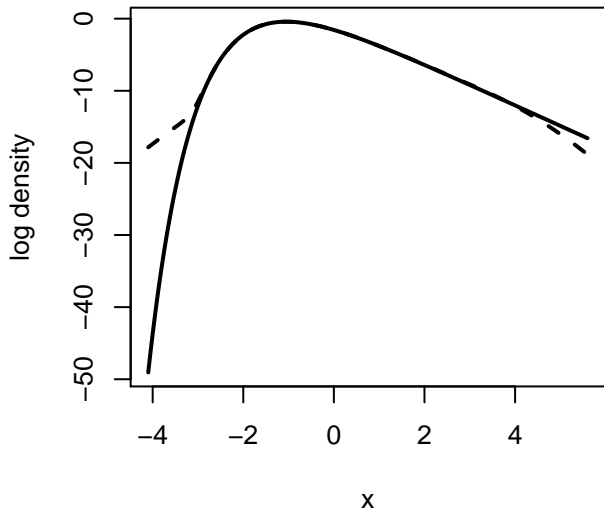
alpha = 2.8515625



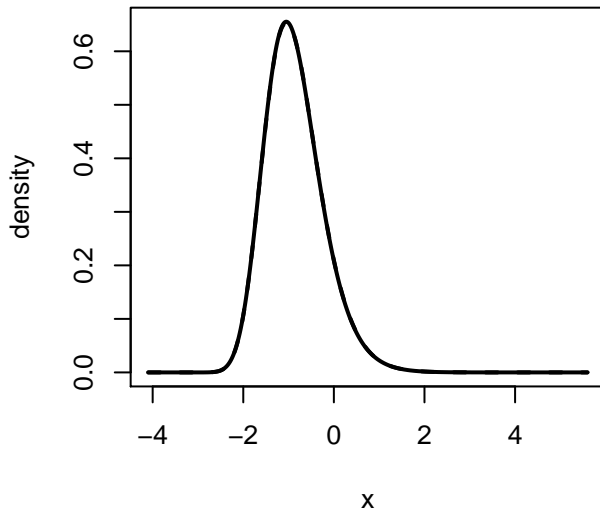
alpha = 2.8515625



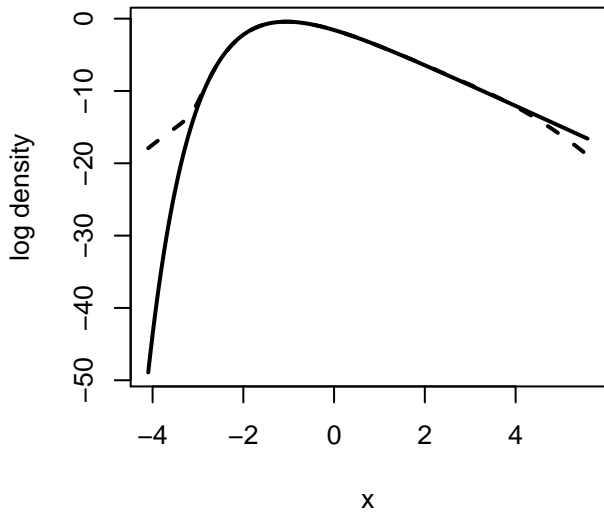
alpha = 2.859375



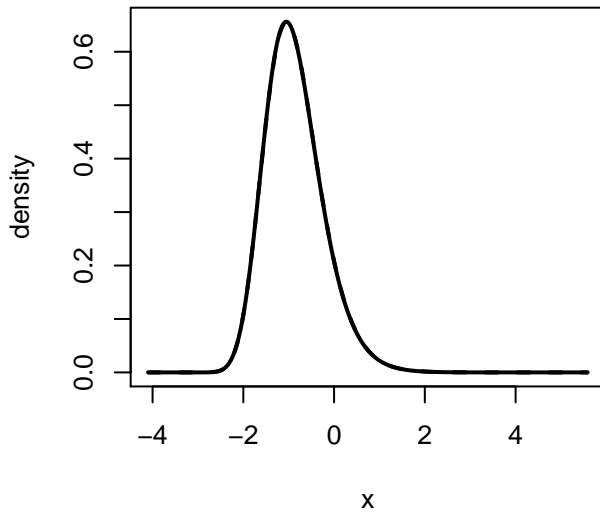
alpha = 2.859375



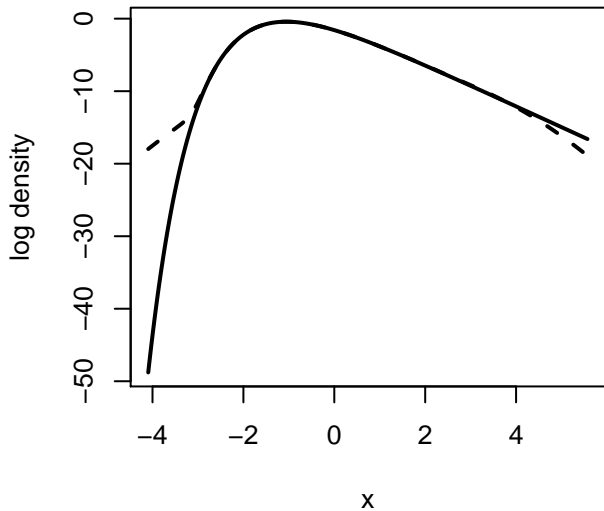
alpha = 2.8671875



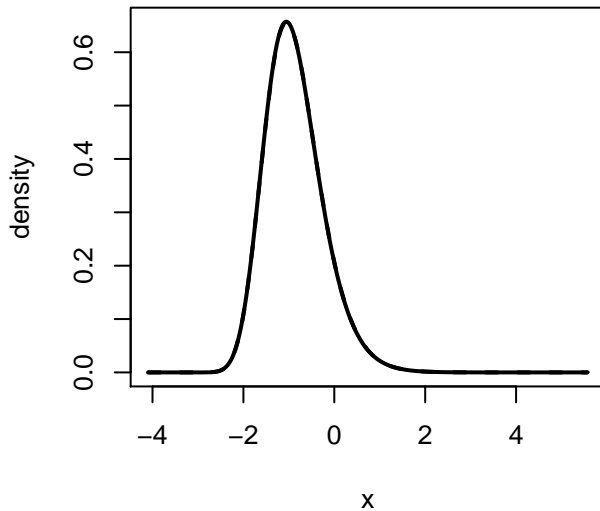
alpha = 2.8671875



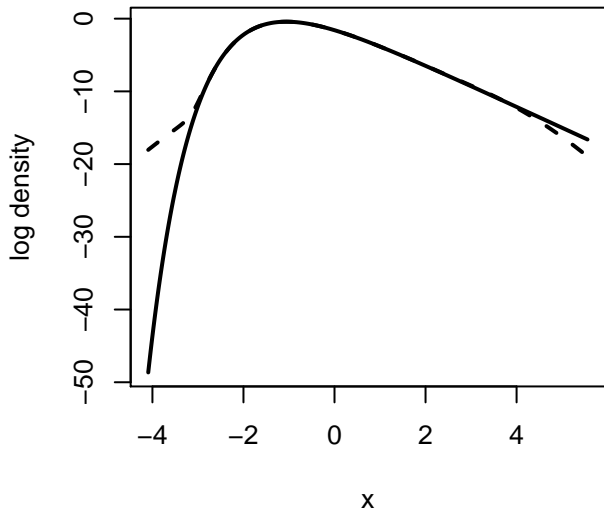
alpha = 2.875



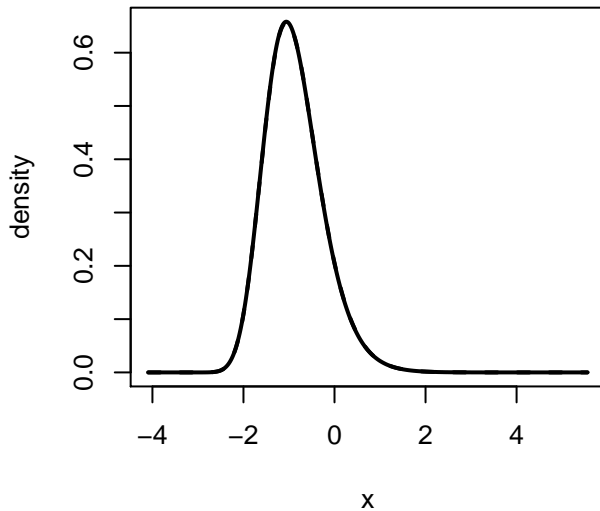
alpha = 2.875



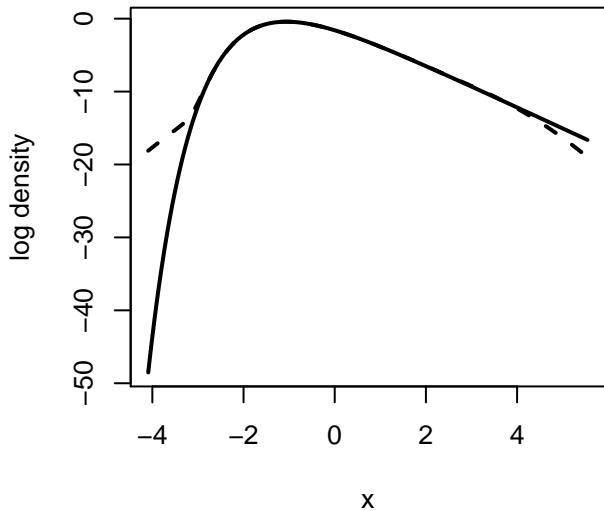
alpha = 2.8828125



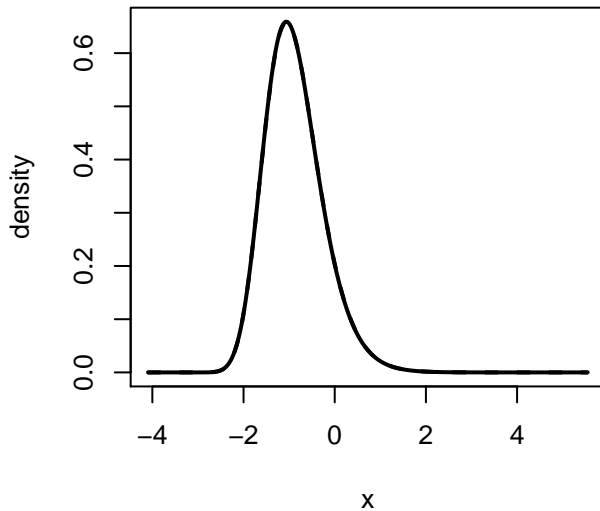
alpha = 2.8828125



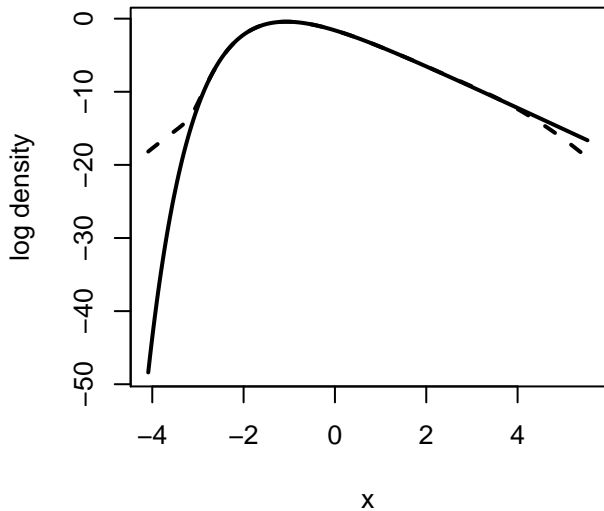
alpha = 2.890625



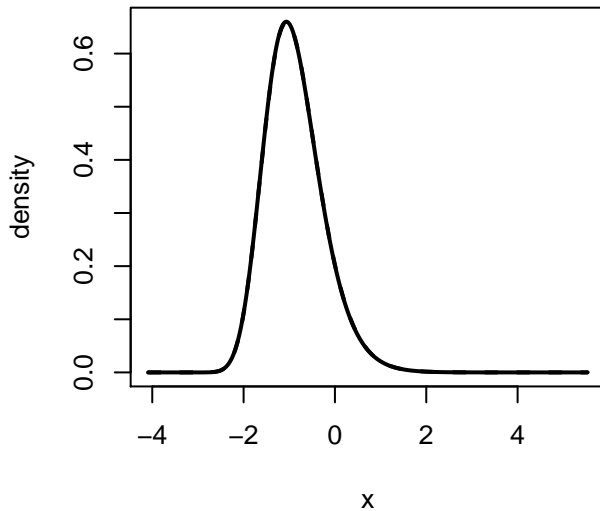
alpha = 2.890625



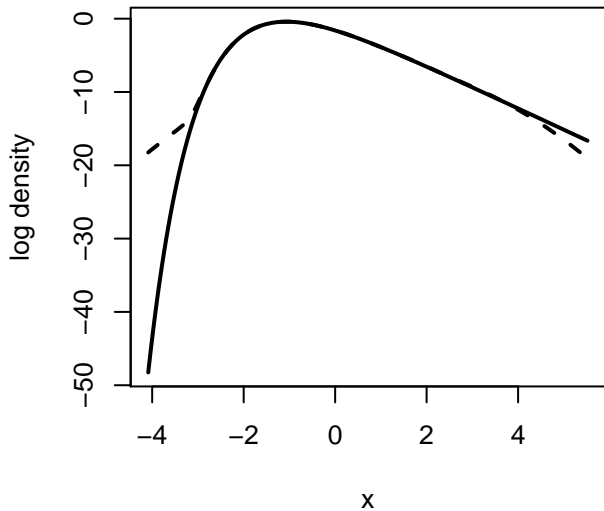
alpha = 2.8984375



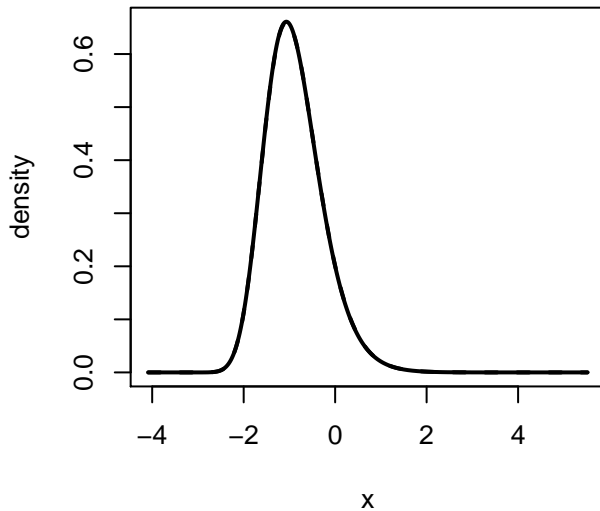
alpha = 2.8984375



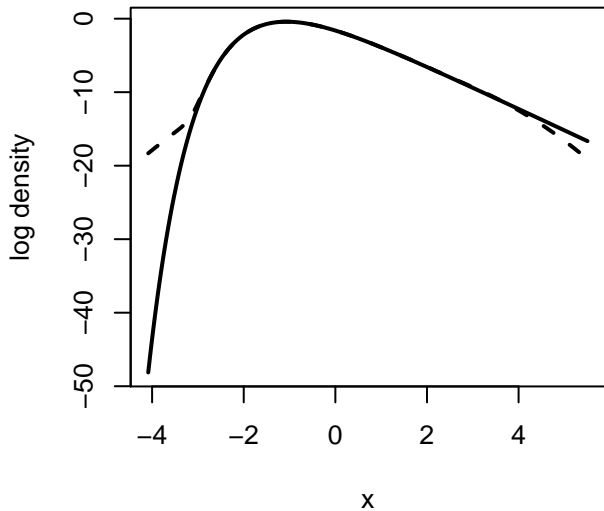
alpha = 2.90625



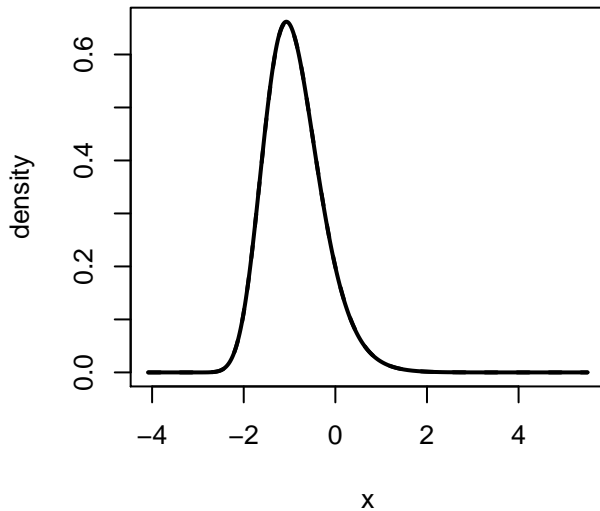
alpha = 2.90625



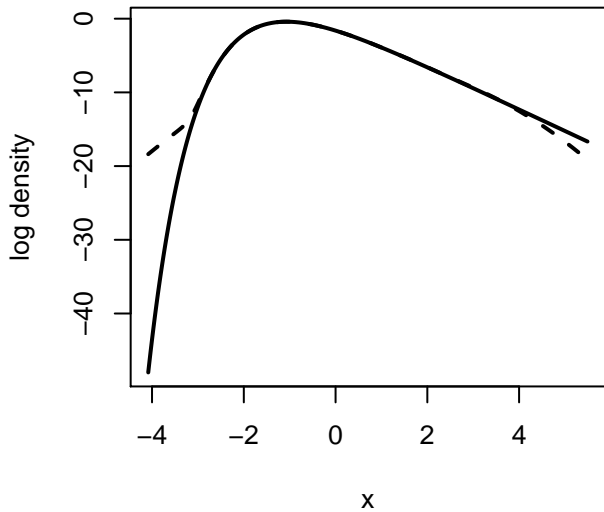
alpha = 2.9140625



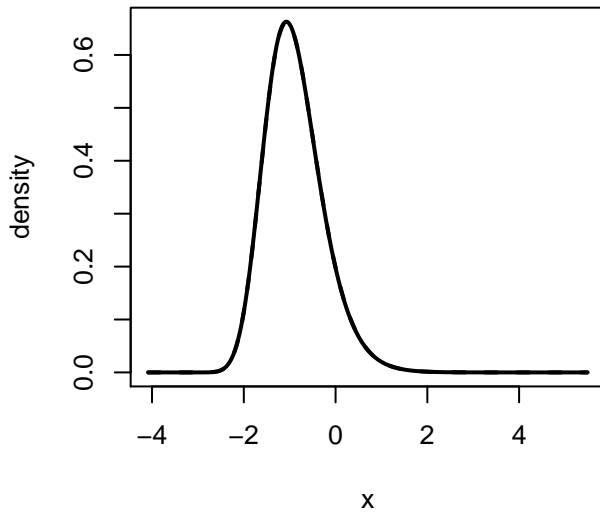
alpha = 2.9140625



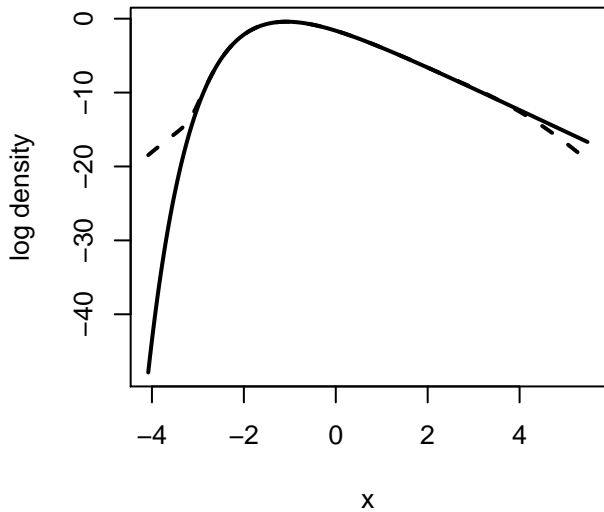
alpha = 2.921875



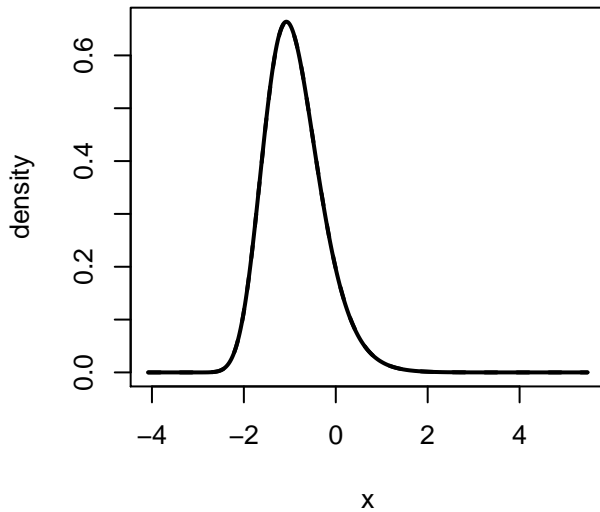
alpha = 2.921875



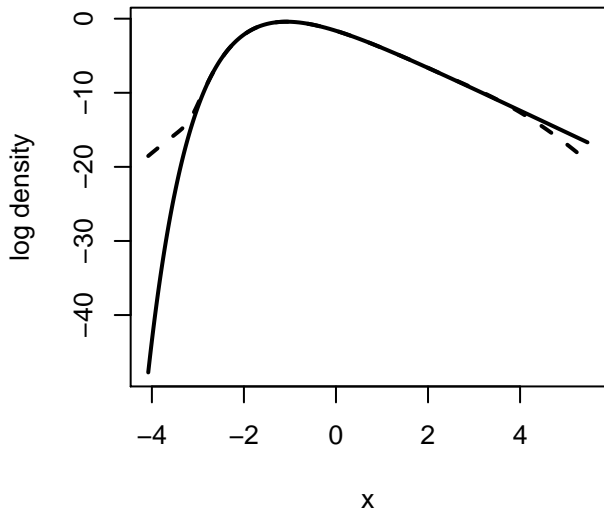
alpha = 2.9296875



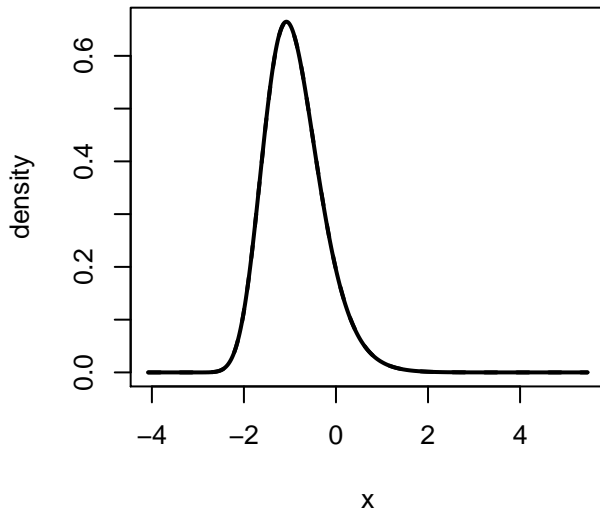
alpha = 2.9296875



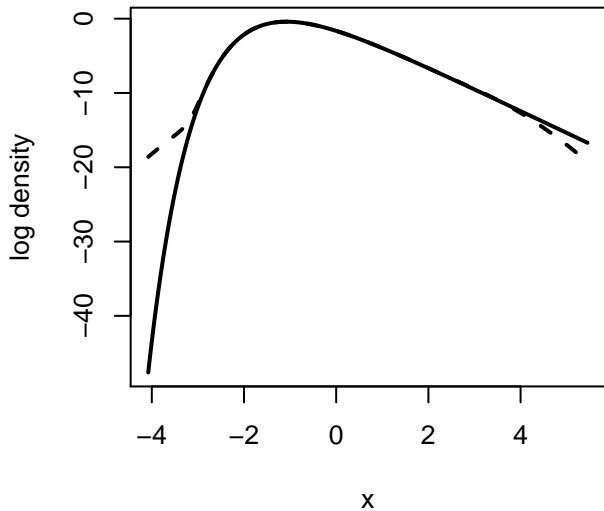
alpha = 2.9375



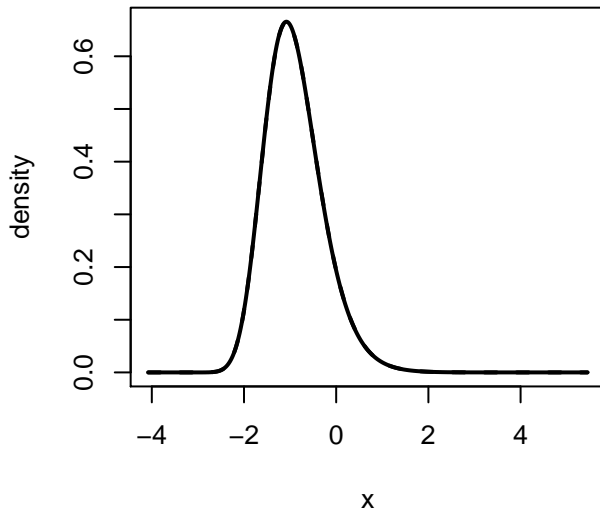
alpha = 2.9375



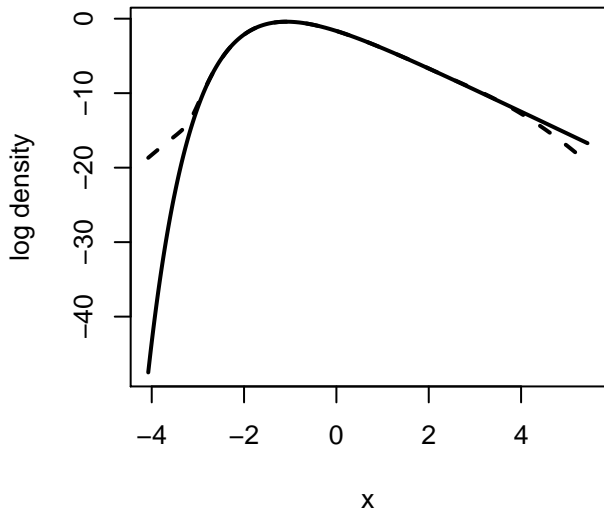
alpha = 2.9453125



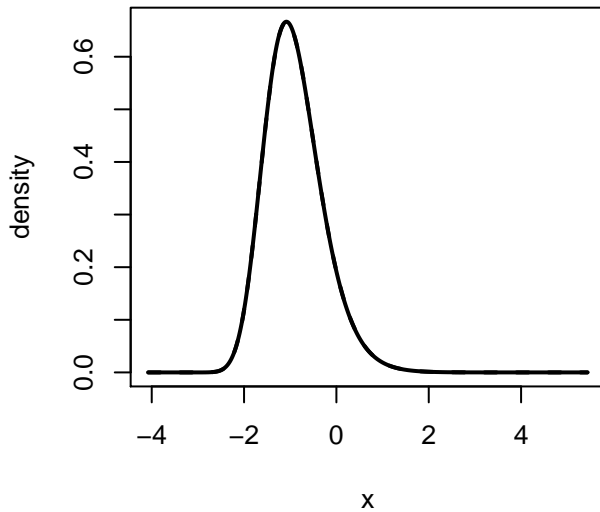
alpha = 2.9453125



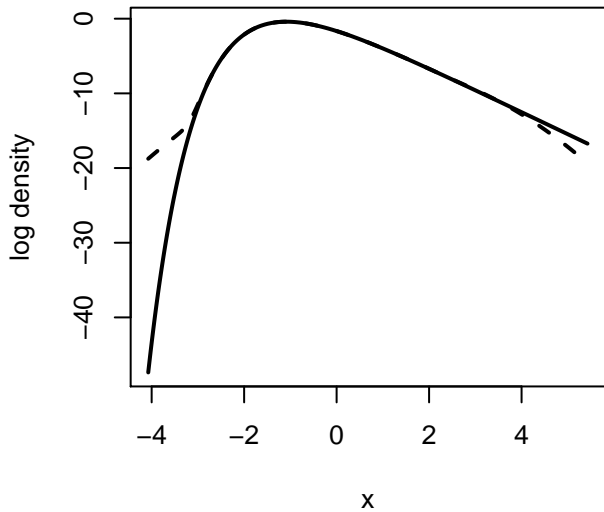
alpha = 2.953125



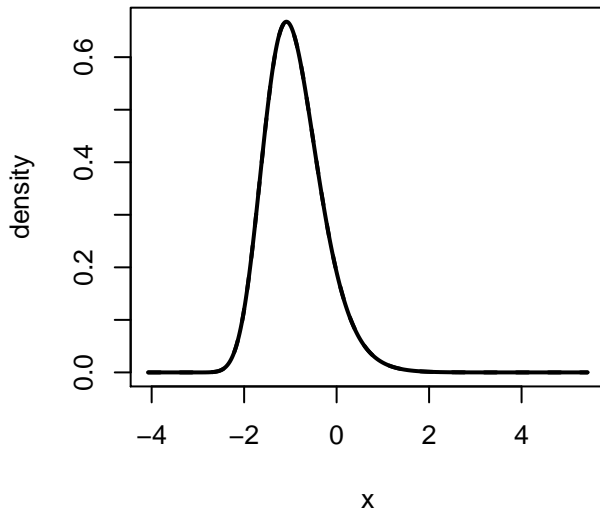
alpha = 2.953125



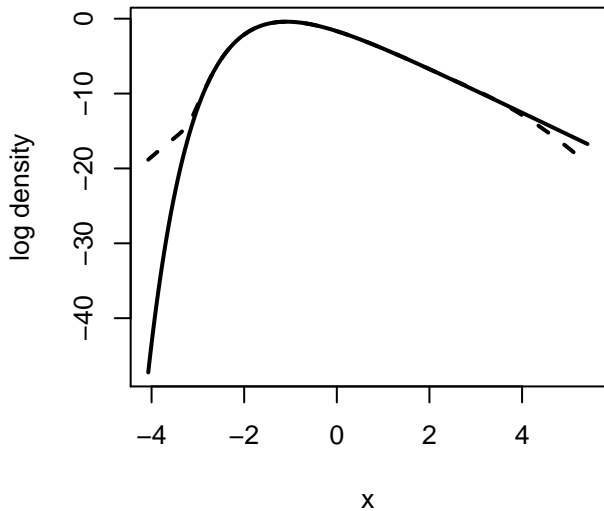
alpha = 2.9609375



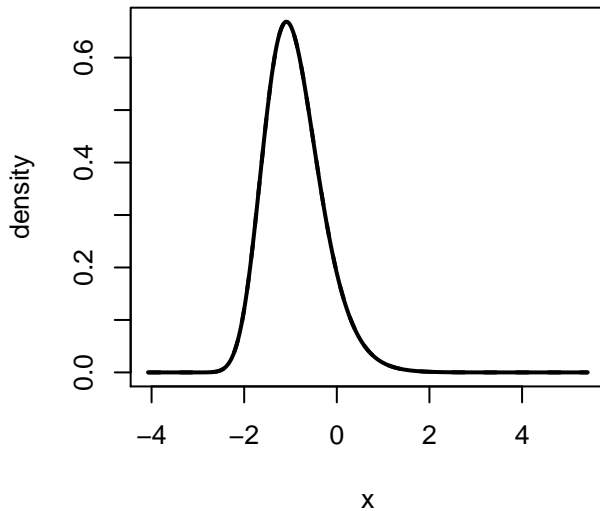
alpha = 2.9609375



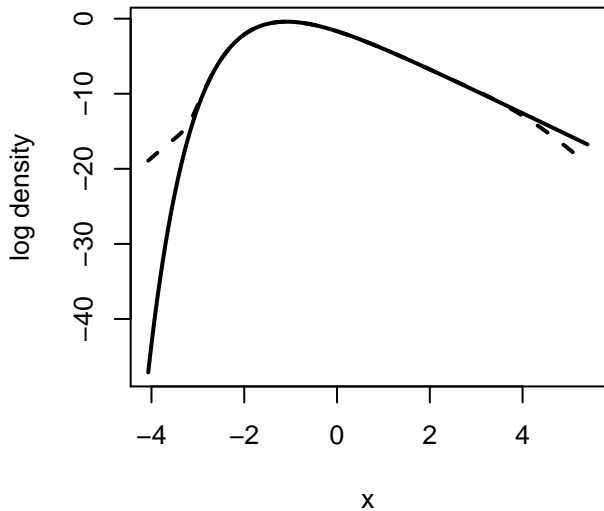
alpha = 2.96875



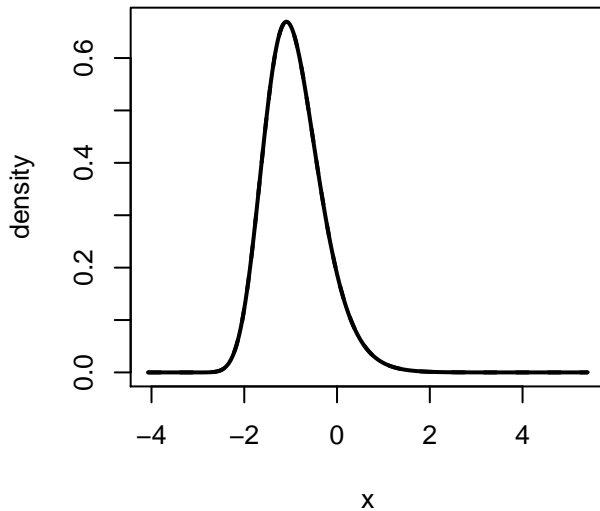
alpha = 2.96875



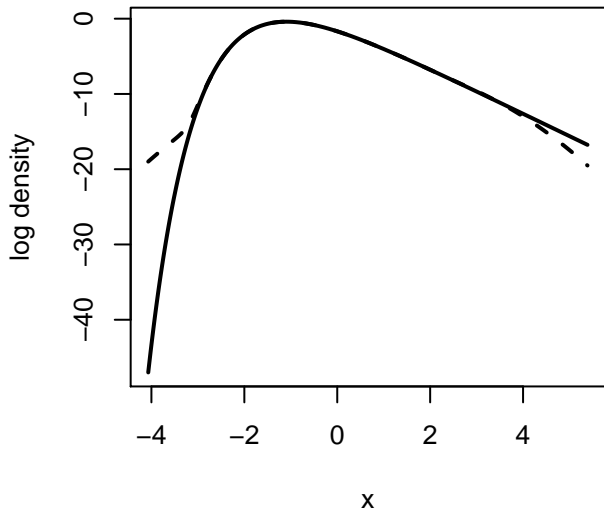
alpha = 2.9765625



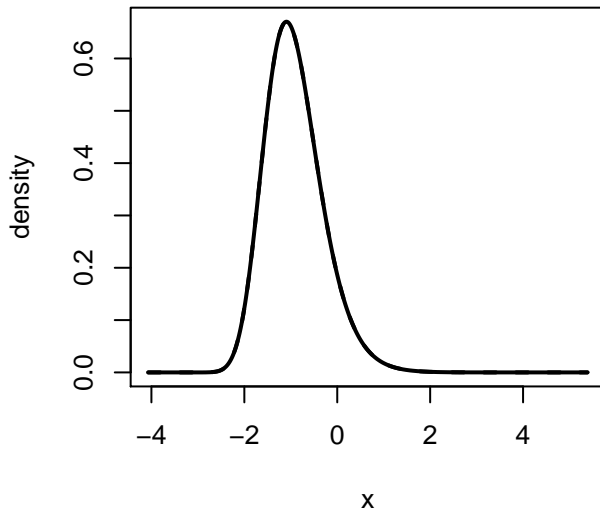
alpha = 2.9765625



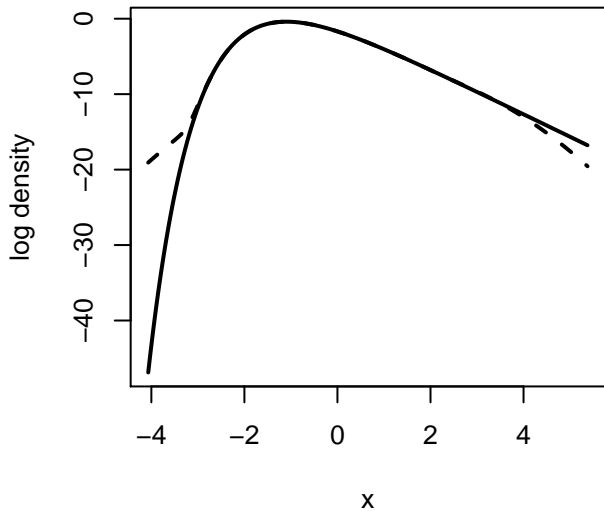
alpha = 2.984375



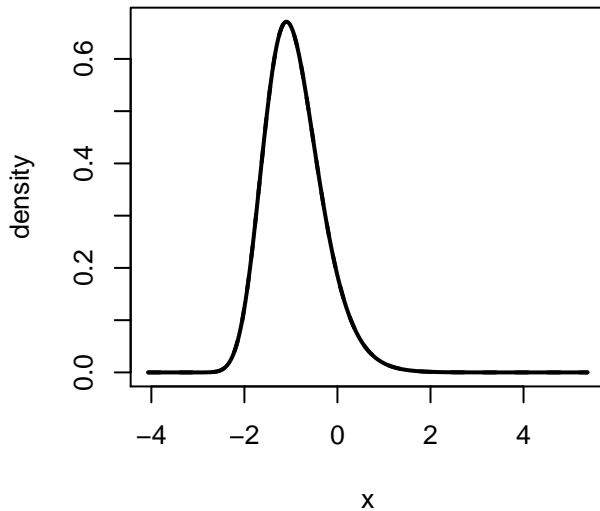
alpha = 2.984375



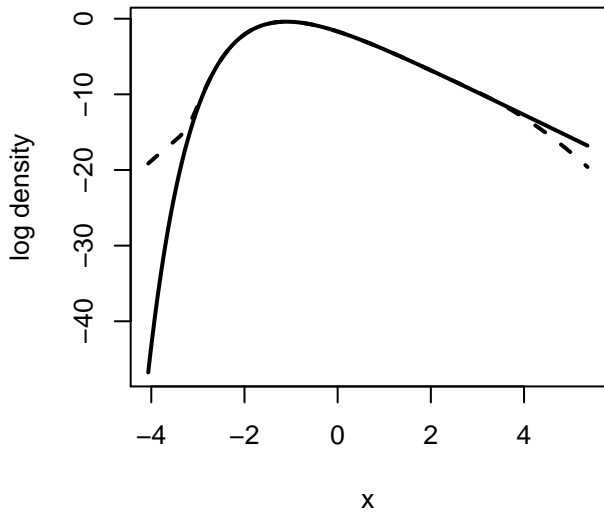
alpha = 2.9921875



alpha = 2.9921875



alpha = 3



alpha = 3

