Laplace Likelihood and LAD Estimation for Non-invertible MA(1)

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MA(1) unit root problem

MA(1):

$$Y_t = Z_t - \theta Z_{t\text{-}1}, \quad \{Z_t\} \sim \mathrm{IID}\,(0, \sigma^2)$$

Properties:

- $|\theta| < 1 \quad \Rightarrow \quad Z_t = \sum_{j=0}^{\infty} \theta^{j} Y_{t-j}$ (invertible)
- $|\theta| > 1 \quad \Rightarrow \quad Z_t = -\sum_{j=1}^{\infty} \theta^{-j} Y_{t+j}$ (non-invertible)
- $|\theta| = 1 \quad \Rightarrow \quad Z_t \in \mathrm{sp}\{Y_t, Y_{t-1}, \ldots,\}$ and $Z_t \in \mathrm{sp}\{Y_{t+1}, Y_{t+2}, \ldots,\}$

  $\Rightarrow \quad \mathrm{P}_{\mathrm{sp}\{Y_s,\, s \neq 0\}} Y_0 = Y_0$ (perfect interpolation)

- $|\theta| < 1 \quad \Rightarrow \quad \hat{\theta}_{mle}$ is $\mathrm{AN}(\theta, (1-\theta^2)/n)$

MLE = maximum (Gaussian) likelihood, n = sample size

What if $\theta = 1$?

Why study non-invertible MA(1)?

a) over-differencing

- linear trend model: $X_t = a + bt + Z_t$.

  $Y_t = X_t - X_{t\text{-}1} = b + Z_t - Z_{t\text{-}1} \sim$ MA(1) with $\theta = 1$.

- seasonal model: $X_t = s_t + Z_t$, s_t seasonal component w/ period 12.

  $Y_t = X_t - X_{t\text{-}12} = Z_t - Z_{t\text{-}12} \sim$ MA(12) with $\theta = 1$.

b) random walk + noise

$X_t = X_{t\text{-}1} + U_t$ (random walk signal)

$Y_t = X_t + V_t$ (random walk signal + noise)

Then

$$Y_t - Y_{t\text{-}1} = U_t + V_t - V_{t\text{-}1} \sim \text{MA}(1)$$

with θ=1 if and only if $\text{Var}(U_t) = 0$.

Identifiability and Gaussian likelihood

Identifiability

- $|\theta| > 1 \quad \Rightarrow \quad Y_t = \varepsilon_t - \theta^{-1}\,\varepsilon_{t\text{-}1}$, where $\{\varepsilon_t\} \sim \mathrm{WN}(0,\theta^2\sigma^2)$.
- $\{\varepsilon_t\}$ is IID *if and only if* $\{Z_t\}$ is Gaussian (Breidt and Davis `91)

Gaussian Likelihood

$$L_G(\theta, \sigma^2) = L_G(1/\theta, \theta^2\sigma^2) \Rightarrow \theta \text{ is only identifiably for } |\theta| \le 1.$$

Notes:

i) this implies $L_G(\theta) = L_G(1/\theta)$ for the profile likelihood and $\theta = 1$ is a critical point, $L'_G(1) = 0$.

ii) a *pile-up effect* ensues, i.e.,

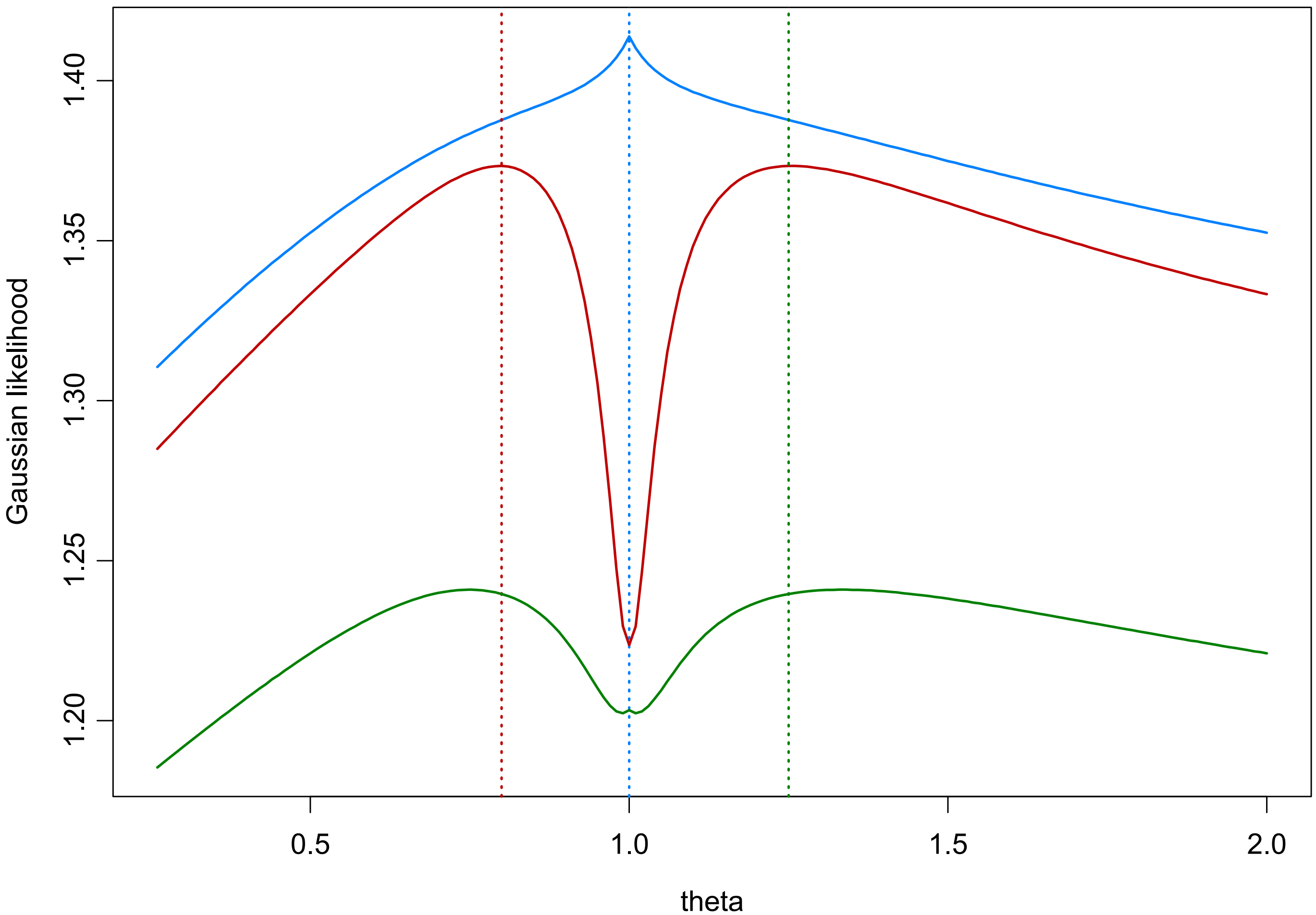
$$P(\hat{\theta} = 1) > 0$$

even if $\theta < 1$.

Gaussian likelihood examples

100 observations from $Y_t = Z_t - \theta_0 Z_{t-1}$, $\{Z_t\} \sim \text{IID}(0, \sigma^2)$, Laplace pdf

$\theta_0 = .8$ $\theta_0 = 1.0$ $\theta_0 = 1.25$



MLE (Gaussian likelihood)

Idea: build parameter normalization into the likelihood function.

Model: $Y_t = Z_t - (1-\beta/n)\, Z_{t-1}$, $t = 1,\ldots,n$.

$\beta = n(1-\theta)$, $\theta = 1-\beta/n$, $\theta_0 = 1-\gamma/n$

Gaussian Likelihood:

$L_n(\beta) = l_n(1-\beta/n) - l_n(1)$, $l_n(\ )$ = profile log-like.

Theorem (Davis and Dunsmuir `96): Under $\theta_0 = 1-\gamma / n$,

$$L_n(\beta) \to_d Z_\gamma(\beta) \quad \text{on } C[0,\infty).$$

Results:

- $n(1-\hat{\theta}_{mle}) \to \hat{\beta}_{mle} = \text{argmax } Z_\gamma(\beta)$
- $n(1-\hat{\theta}_{lm}) \to \hat{\beta}_{lm} = \text{arg}\mathit{local}\text{max } Z_\gamma(\beta)$
- $P(\hat{\theta}_{lm} = 1) \to P(\hat{\beta}_{lm} = 0) = .6518$ if $\gamma = 0$.

Extensions of MLE (Gaussian likelihood)

i) non-zero mean (Chen and Davis `00): same type of limit, except pile-up is more excessive.

$$P(\hat{\theta}_{mle} = 1) \to .955$$

This makes hypothesis testing easy!

Reject H_0: θ = 1 if $\hat{\theta}_{mle} < 1$ (size of test is .045)

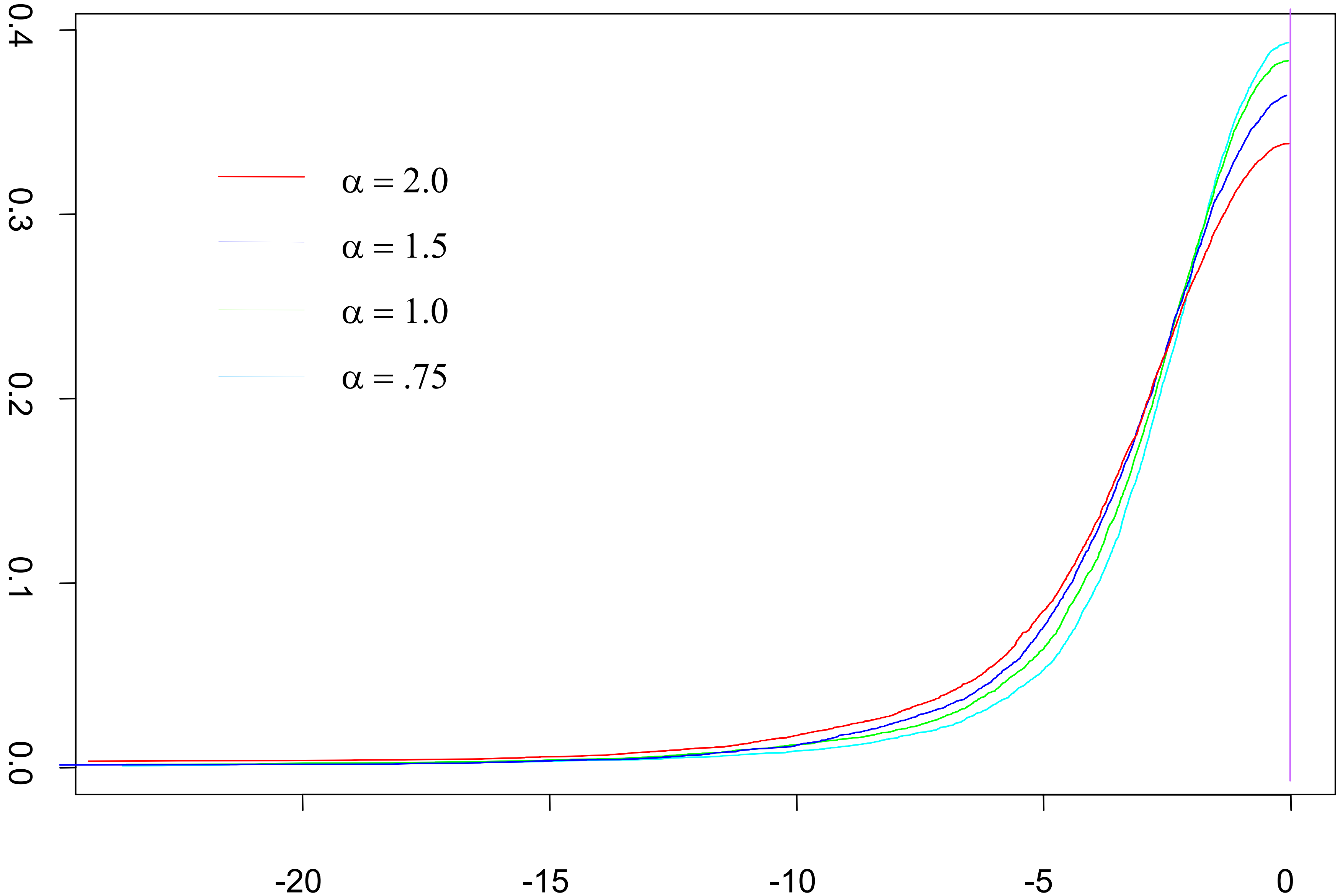
ii) heavy tails (Davis and Mikosch `98): $\{Z_t\}$ symmetric alpha stable ($S\alpha S$). Then the max Gaussian likelihood estimator has the same normalizing rate, i.e.,

$$n(1 - \hat{\theta}_{lm}) \to_d \hat{\beta}_{lm}$$

$$P(\hat{\theta}_{lm} = 1) \to P(\hat{\beta}_{lm} = 0)$$

The pile-up decreases with increasing tail heaviness.

Comparison of limit cdf's for different α's



Laplace likelihood/LAD estimation

If noise distribution is non-Gaussian, the MA(1) parameter θ is identifiable for all real values.

Q1. For MLE (non-Gaussian) does one have n or $n^{1/2}$ asymptotics?

Q2. Is there a *pile-up* effect?

Laplace likelihood – joint and exact

Model. $Y_t = Z_t - \theta Z_{t-1}$, $\{Z_t\} \sim \text{IID}(0, \sigma^2)$ with median 0 and $EZ^4 < \infty$.

Initial variable.

$$Z_{init} = \begin{cases} Z_0, & \text{if } |\theta| \le 1, \\ Z_n - \sum_{t=1}^{n} Y_t, & \text{otherwise.} \end{cases}$$

Joint density: Let $\mathbf{Y}_n = (Y_1, \ldots, Y_n)$, then

$$f(\mathbf{y}_n, z_{init}) = f(z_0, z_1, \ldots, z_n)\left(1_{\{|\theta|\le 1\}} + |\theta|^{-n}\, 1_{\{|\theta|>1\}}\right),$$

where the z_t are solved

forward by: $z_t = Y_t + \theta z_{t-1}$, $t = 1, \ldots, n$ for $|\theta| \le 1$ with $z_0 = z_{\text{init}}$

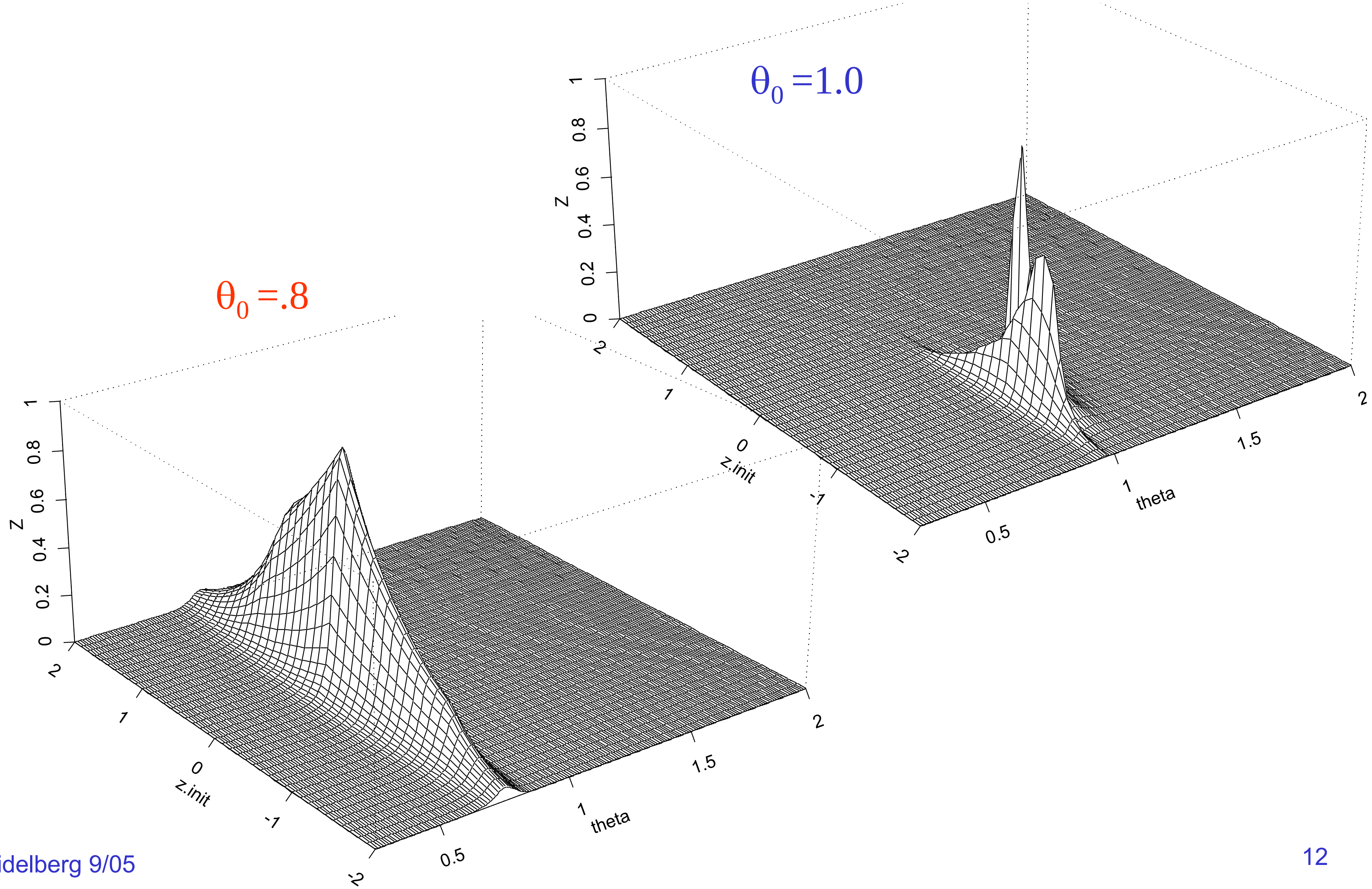
backward by: $z_{t-1} = \theta^{-1}(z_t - Y_t)$, $t = n, \ldots, 1$ for $|\theta| > 1$ with $z_n = z_{\text{init}} + Y_1 + \ldots + Y_n$

Note: integrate out z_{init} to get exact likelihood.

$$f(\mathbf{y}_n) = \int_{-\infty}^{\infty} f(\mathbf{y}_n, z_{init})\, dz_{init}$$

Laplace likelihood examples

100 observations from $Y_t = Z_t - \theta_0 Z_{t-1}$, $\{Z_t\} \sim \text{IID}(0, \sigma^2)$, Laplace pdf



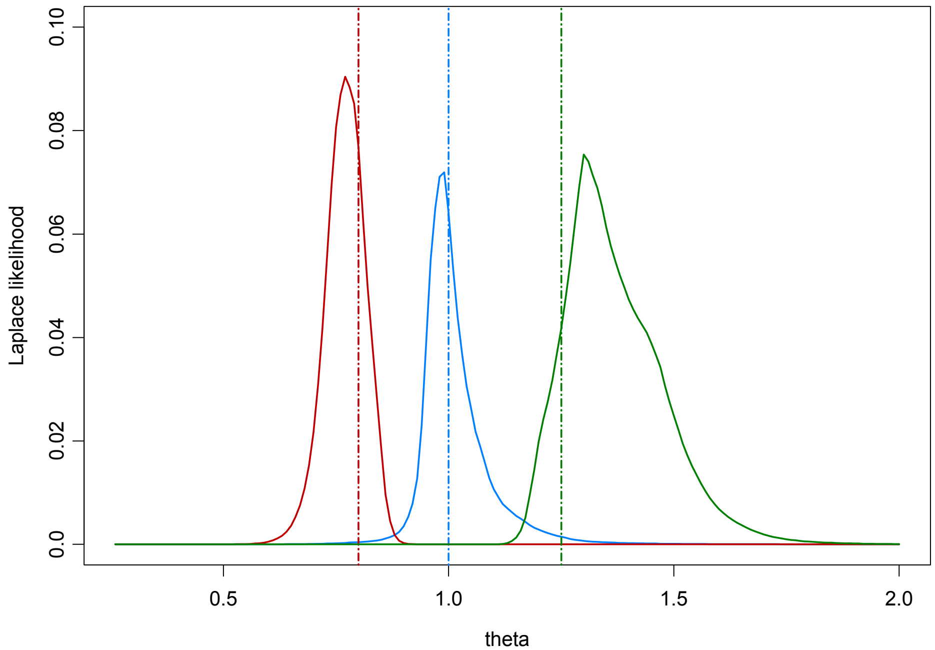
Laplace likelihood examples (cont)

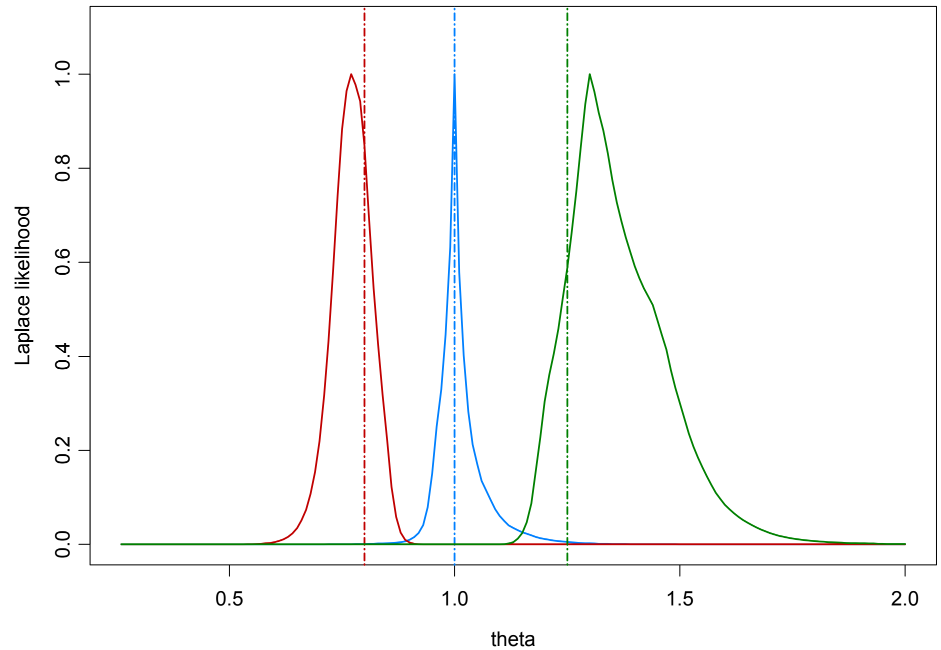
100 observations from $Y_t = Z_t - \theta_0 Z_{t-1}$, $\{Z_t\} \sim \text{IID}(0, \sigma^2)$, Laplace pdf

$\theta_0 = .8$ $\theta_0 = 1.0$ $\theta_0 = 1.25$

Exact likelihood

Joint likelihood at $z_{max}(\theta)$





Laplace likelihood-LAD estimation

(Joint) Laplace log-likelihood.

$$L(\theta, z_{init}, \sigma) = -(n+1)\log 2\sigma - \sigma^{-1}\sum_{t=0}^{n} |z_t| - n(\log|\theta|)1_{\{|\theta|>1\}}$$

Maximizing wrt σ, we obtain

$$\hat{\sigma} = \sum_{t=0}^{n} |z_t| / (n+1)$$

so that maximizing L is equivalent to minimizing

$$l_n(\theta, z_{init}) = \begin{cases} \sum_{t=0}^{n} |z_t|, & \text{if } |\theta| \le 1, \\ \sum_{t=0}^{n} |z_t||\theta|, & \text{otherwise.} \end{cases}$$

Joint Laplace likelihood — limit results

Theorem 1. Under the parameterizations,

$$\theta = 1 + \beta/n \quad \text{and} \quad z_{\text{init}} = Z_0 + \alpha\sigma/n^{1/2},$$

we have

$$U_n(\beta,\alpha) = \sigma^{-1}(l_n(\theta, z_{init}) - l_n(1, Z_0)) \to_d U(\beta,\alpha)$$

on C(R²), where

$$U_n(\beta,\alpha) = \int_0^1 \left(\beta \int_0^{s-} e^{\beta(s-t)} dS(t) + \alpha e^{\beta s} \right) dW(s)$$

$$+ f(0) \int_0^1 \left(\beta \int_0^{s} e^{\beta(s-t)} dS(t) + \alpha e^{\beta s} \right)^2 ds$$

for $\beta \leq 0$, and

$$U_n(\beta,\alpha) = \int_0^1 \left(-\beta \int_{s+}^{1} e^{\beta(s-t)} dS(t) + \alpha e^{-\beta(1-s)} \right) dW(s)$$

$$+ f(0) \int_0^1 \left(\beta \int_s^1 e^{\beta(s-t)} dS(t) + \alpha e^{-\beta(1-s)} \right)^2 dW(s)$$

for $\beta > 0$, in which $S(t)$ and $W(t)$ are the limits of the partial sum processes

Joint Laplace likelihood — limit results

$$S_n(t) = \frac{1}{\sigma\sqrt{n}} \sum_{i=0}^{[nt]} Z_i \to_d S(t), \qquad W_n(t) = \frac{1}{\sigma\sqrt{n}} \sum_{i=0}^{[nt]} sign(Z_i) \to_{\mathrm{d}} W(t).$$

From the limit,

$$U_n(\beta, \alpha) \to_d U(\beta, \alpha)$$

it follows that

$$(n(\hat{\theta}_{lm} - 1), \sqrt{n}\sigma^{-1}(\hat{z}_{init}^L - Z_0)) \to_d (\hat{\beta}_{lm}, \hat{\alpha}_{lm})$$

where

$$(\hat{\beta}_{lm}, \hat{\alpha}_{lm}) = \arg(\text{local}) \min U(\beta, \alpha).$$

Exact Laplace likelihood — limit results

Exact Laplace Likelihood:

$$L_n(\theta,\sigma) = \int_{-\infty}^{\infty} f(\mathbf{y}_n, z_{init})\, dz_{init}$$

Theorem 2. For the MLE $\tilde{\theta}_n, \tilde{\sigma}_n$, we have

$$(n(\tilde{\theta}_{mle} - 1), \sqrt{n}(\tilde{\sigma}_{mle} - E\,|\,Z_0\,|)) \to_d (\tilde{\beta}_{mle}, N),$$

where

$$\tilde{\beta}_{mle} = \arg\min U^*(\beta)\,, \quad \mathrm{N} \sim \mathrm{N}(0, \mathrm{var}(|\,Z_0\,|)),$$

and $U^*(\beta)$ is a stochastic process defined in terms of *S*(*t*) and *W*(*t*).

In addition,

$$n(\tilde{\theta}_{lm} - 1) \to_d \tilde{\beta}_{lm}, \quad \tilde{\beta}_{lm} = \arg\ (\text{local})\ \min U^*(\beta).$$

Simulating from the limit process

Step 1. Simulate two indep sequences $(W_1, \ldots, W_m)$ and $(V_1, \ldots, V_m)$ of iid N(0,1) random variables with m=100000.

Step 2. Form $W(t)$ and $V(t)$ by the partial sum processes,

$$W(t) = \sum_{j=1}^{[100000\,t]} W_j / \sqrt{100000} \quad \text{and} \quad V(t) = \sum_{j=1}^{[100000\,t]} V_j / \sqrt{100000}.$$

Step 3. Set $S(t) = c_1 W(t) + c_2 V(t)$, where

$$c_1 = E\,|Z_t|/\sigma \quad \text{and} \quad c_2 = \sqrt{\mathrm{Var}(Z_t)/\sigma^2 - c_1^2}.$$

Limit process depends only on c_1, c_2, and $f(0)$.

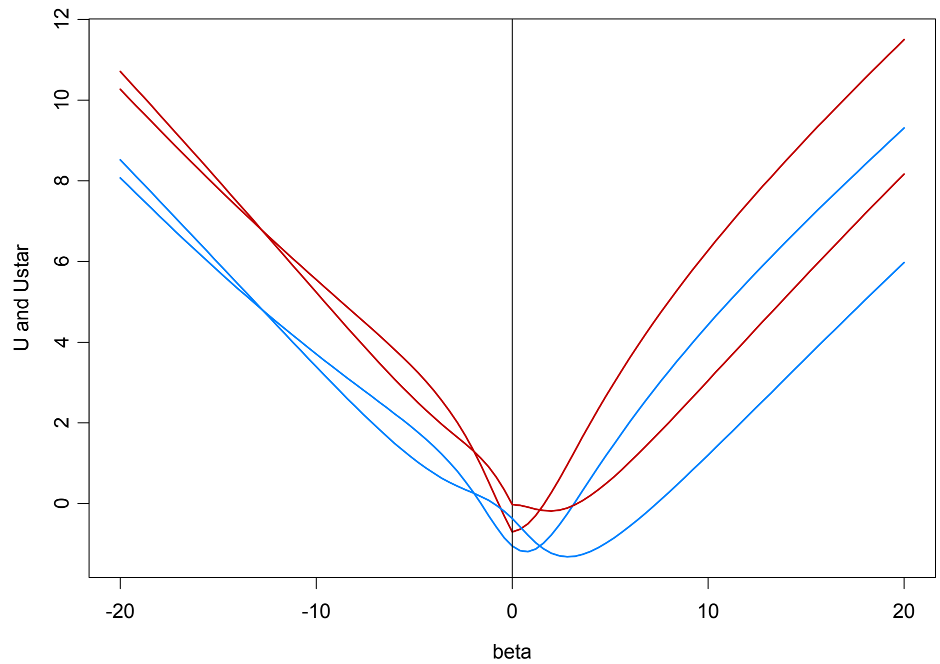
Step 4. Compute $U(\beta,\alpha)$ and $U^*(\beta)$ from the definition.

Step 5. Determine the respective local and global minimizers of $U(\beta,\alpha)$ and $U^*(\beta)$ numerically.

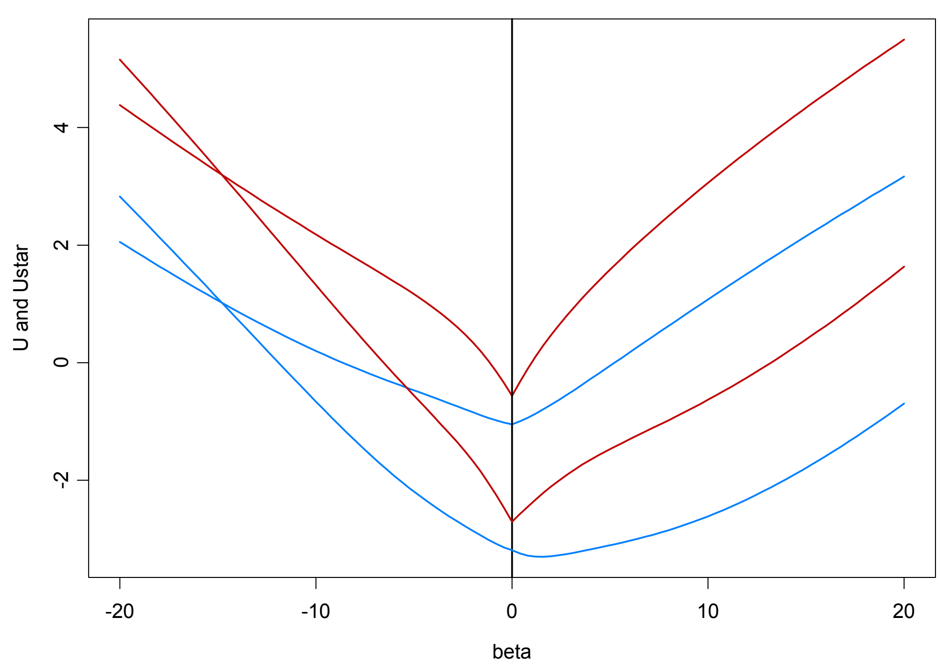
Limit process

2 realizations of the limit processes, $U(\beta,\alpha(\beta))$, $U^*(\beta)$.

Laplace pdf



t(5) pdf



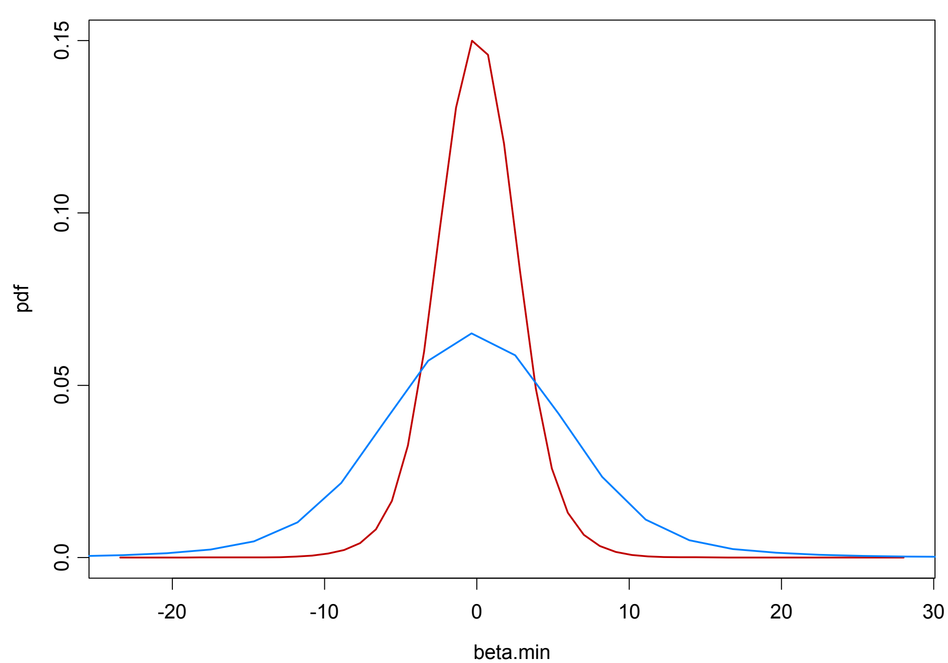
Limit distribution

red graph = Laplace pdf for Z_t

blue graph = Gaussian pdf for Z_t

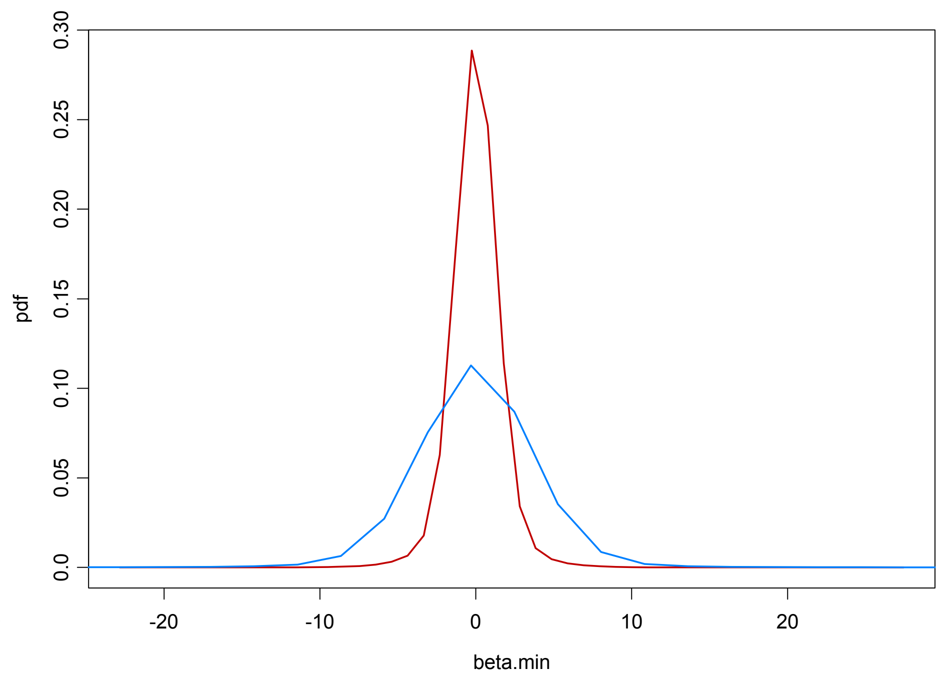
Joint Lap Likelihood

$$n(\hat{\theta}_{lm} - 1) \to_d \hat{\beta}_{lm}$$



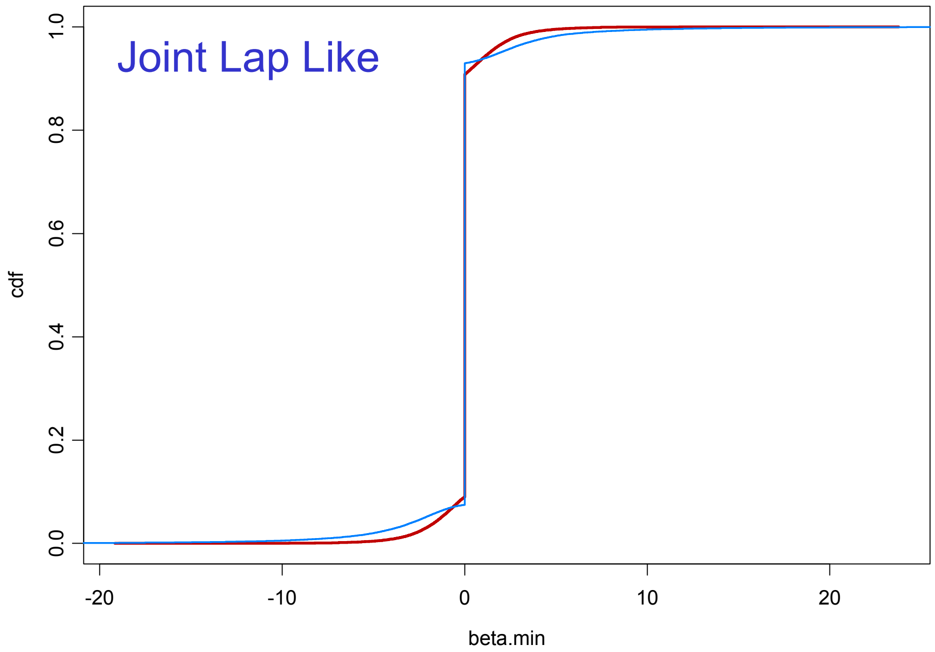
Exact Lap Likelihood

$$n(\tilde{\theta}_{lm} - 1) \to_d \tilde{\beta}_{lm}$$

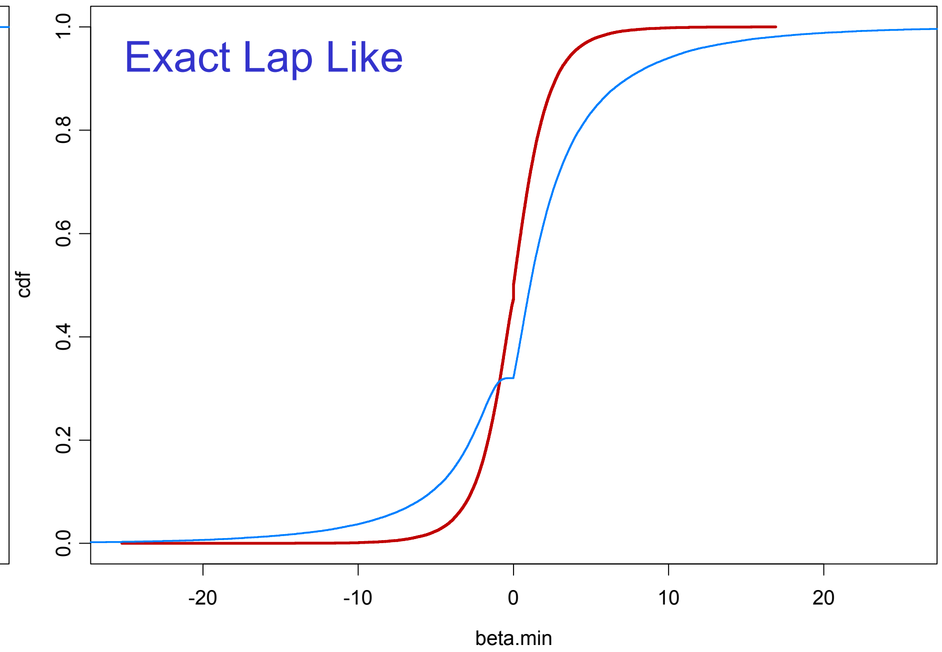


Limit cdf

red graph = Laplace pdf for Z_t



blue graph = Gaussian pdf for Z_t



Laplace noise

$\theta = 1, \ \sigma = 1$

1000 reps

n		Exact $\tilde{\theta}_{lm}$	Joint $\hat{\theta}_{lm}$	$\hat{\sigma}$
$n = 20$	bias	-.0057	-.0033	-.0208
	s.d.	.1438	.0656	.2430
	rmse	**.1439**	**.0657**	**.2438**
	asymp	.1207	.0526	.2236
$n = 50$	bias	.0000	.0004	.0293
	s.d.	.0574	.0208	.1511
	rmse	**.0574**	**.0208**	**.1539**
	asymp	.0483	.0211	.1414
$n = 100$	bias	.0005	-.0003	-.0025
	s.d.	.0303	.0107	.1000
	rmse	**.0303**	**.0107**	**.1000**
	asymp	.0241	.0105	.1000
$n = 200$	bias	.0005	.0000	-.0016
	s.d.	.0140	.0058	.0718
	rmse	**.0141**	**.0058**	**.0718**
	asymp	.0121	.0053	.0707

Simulation results

Exact = MLE

Joint = maximize over θ and z_{init}

Cond = maximize over θ conditional on $z_{init} = 0$

Laplace noise

$\theta = 1, \ \sigma = 1$

1000 reps

Note:

- LM dominates ML
- joint dominates exact (rmse is half the size)

n		Exact $\tilde{\theta}_{ml}$	Joint $\hat{\theta}_{ml}$	Cond $\bar{\theta}_{ml}$
n = 20	bias	-.047	-.050	-.057
	rmse	**.224**	**.213**	**.297**
n = 50	bias	-.013	.002	-.026
	rmse	**.096**	**.078**	**.171**
n = 100	bias	.003	-.003	-.009
	rmse	**.051**	**.034**	**.105**
n = 200	bias	.000	.000	.007
	rmse	**.028**	**.014**	**.070**

Pile-up probabilities

Theorem 3. (joint Laplace likelihood)

$$P(\hat{\theta}_{lm} = 1) \to P(0 < Y < \int_0^1 dS(s)dW(s)),$$

where

$$Y = \int_0^1 S(s)dW(s) - W(1)\int_0^1 S(s)ds + \frac{W(1)}{2f(0)}\left(\int_0^1 W(s)ds - W(1)/2\right)$$

Idea:

$$P(\hat{\theta}_{lm} = 1) = P(\lim_{\beta\uparrow 0} \frac{\partial}{\partial\beta} U_n(\beta, \hat{\alpha}(\beta)) < 0 \text{ and } \lim_{\beta\downarrow 0} \frac{\partial}{\partial\beta} U_n(\beta, \hat{\alpha}(\beta)) > 0)$$

$$\to P(\lim_{\beta\uparrow 0} \frac{\partial}{\partial\beta} U(\beta, \hat{\alpha}(\beta)) < 0 \text{ and } \lim_{\beta\downarrow 0} \frac{\partial}{\partial\beta} U(\beta, \hat{\alpha}(\beta)) > 0)$$

Now,

$$\lim_{\beta\downarrow 0} \frac{\partial}{\partial\beta} U(\beta, \hat{\alpha}(\beta)) = Y$$

$$\lim_{\beta\uparrow 0} \frac{\partial}{\partial\beta} U(\beta, \hat{\alpha}(\beta)) = Y - \int_0^1 dS(s)dW(s)$$

and the result follows.

Pile-up probabilities (cont)

Theorem 4. (exact Laplace likelihood)

$$P(\tilde{\theta}_{lm} = 1) \to P\left[\frac{1}{2} < Y < \int_0^1 dS(s)dW(s) - \frac{1}{2}\right]$$

The *pile-up probability* is always *smaller* for the exact MLE than for the joint MLE (see Theorem 3).

Remark 1.

If Z_t has a Laplace density $f(z) = \frac{1}{2\sigma} e^{-|z|/\sigma}$, then

$$Y = \int_0^1 \left[W(1)s - W(s)\right] dV(s) + \frac{1}{2}.$$

where $W(s)$ and $V(s)$ are independent standard Brownian motions.

Pile-up probabilities (cont)

It follows that

$$P(\hat{\theta}_{lm} = 1) \to P(0 < Y < \int_0^1 dS(s)dW(s))$$

$$= P(0 < \int_0^1 [W(1)s - W(s)]\, dV(s) + .5 < 1)$$

$$= E\left[P(-.5 < \int_0^1 [W(1)s - W(s)]\, dV(s) < .5 \,|\, W(t),\ t \in [0,1]) \right]$$

$$= E\left[2\Phi\left(.5 \left\{ \int_0^1 [W(1)s - W(s)]^2 ds \right\}^{-1/2} \right) \text{-} 1 \right]$$

$$\approx 0.820$$

$$P(\tilde{\theta}_{lm} = 1) \to P(1/2 < Y < \int_0^1 dS(s)dW(s)) - 1/2)$$

$$= P(1/2 < Y < 1 - 1/2)$$

$$= 0. \qquad \Rightarrow \text{no pile-up}$$

Pile-up probabilities (cont)

Remark 2.

$$P(\hat{\theta}_{lm} = 1) \to P(0 < Y < \int_0^1 dS(s)dW(s))$$

$$= P(0 < Y < c_1), \quad \text{where} \quad c_1 = E|Z_t|/\sigma$$

$$> 0.$$

On the other hand

$$P(\tilde{\theta}_{lm} = 1) \to P(1/2 < Y < c_1 - 1/2)$$

$$> 0 \quad \text{if and only if } c_1 > 1.$$

That is, there is a *pile-up* if and only if $c_1 > 1$.

Remark 3. Pile-up probability tends to be larger if the density is more concentrated around 0.

Simulation results – pile-up probabilities

Pile-up probabilities for local maximum: $P(\hat{\theta}_{lm} = 1)$

n	Gau	Lap	Unif	t(5)
20	.827	.796	.831	.796
50	.859	.806	.864	.823
100	.873	.819	.864	.817
200	.844	.819	.843	.831
500	.855	.809	.841	.846
∞	.858	.820	.836	.827