

# On MLE boundary values for skew-symmetric distributions

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# Skew-normal distribution and friends

- Basic form: skew-normal (SN) random variable  $Z$  with pdf

$$f(z) = 2 \phi(z) \Phi(\alpha z), \quad z \in \mathbb{R}$$

- friends of the form

$$f(z) = 2 f_0(z) G_0\{w(z)\}$$

where

$$f_0(x) = f_0(-x), \quad G_0'(x) = G_0'(-x), \quad w(-x) = -w(x)$$

- add location and scale parameter

$$Y = \xi + \omega Z$$

- multivariate versions exist

# Two sides of the coin

Two sides of the coin:

- formulation allows nice treatment of probability side
- statistical side somewhat peculiar aspects

Challenging side:

- 1 under SN model,  $\text{Info}(\xi, \omega, \alpha)$  is singular at  $\alpha = 0$
- 2 for finite samples  $\mathbb{P}\{\hat{\alpha} = \pm\infty\} > 0$

Deal with problem No. 2

# One parameter case, $d = 1$

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$$\begin{aligned}f(z) &= 2 \phi(z) \Phi(\alpha z) \\ \log L(\alpha) &= \text{const} + \sum_{i=1}^n \log \Phi(\alpha z_i)\end{aligned}$$

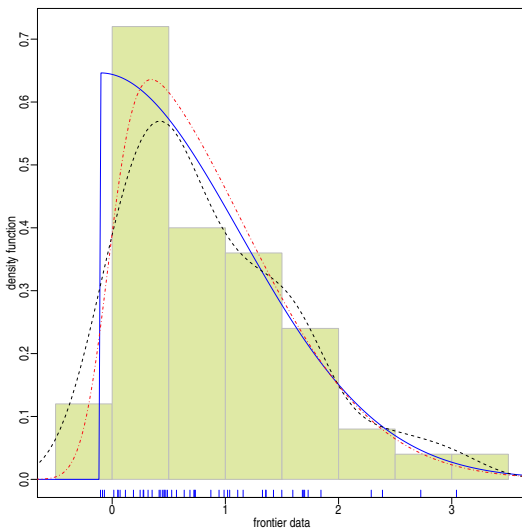
- $\log L$  monotone if all elements are of equal sign
- (monotone but bounded!)

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$$\begin{aligned}p_{n,\alpha} &= \mathbb{P}\{\hat{\alpha} = \pm\infty\} \\ &= \left(\frac{1}{2} - \frac{\arctan \alpha}{\pi}\right)^n + \left(\frac{1}{2} + \frac{\arctan \alpha}{\pi}\right)^n\end{aligned}$$

- e.g.  $p_{25,5} \approx 0.197$  and  $p_{50,5} \approx 0.039$ .

# A three-parameter example: frontier data



$n = 50$  values from  $SN(0, 1, 5)$ , fit  $SN(\xi, \omega^2, \alpha)$

# Options and remarks

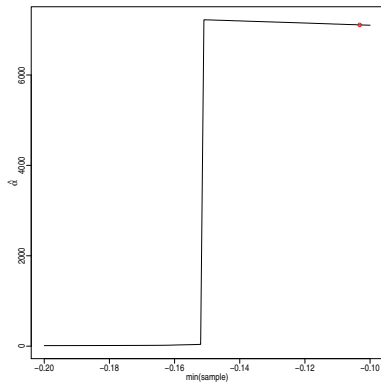
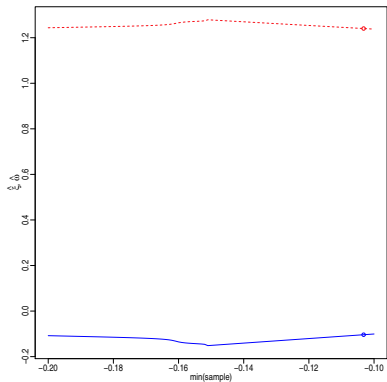
Alternative routes:

- 1 live with MLE as it is (must learn how!)
- 2 look for alternatives/adjustments

Remarks on illustrative 'frontier' data:

- histogram & nonparameteric  $\hat{f}$  not like half-normal
- $\hat{\gamma}_1 = 0.902$  inside admissible region  $(-0.995, 0.995)$
- MLE behaves discontinuously

# Frontier data, MLE's vs min(sample)



# Sartori-Firth method of bias reduction

- Firth (1993) method for bias reduction: solve

$$\ell'(\alpha) + M(\alpha) = 0$$

where

$$M(\alpha) = -i(\alpha) b(\alpha)$$

- in our case bias is infinite!
- Sartori (2006):

$$M(\alpha) = -\frac{\alpha}{2} \frac{a_4(\alpha)}{a_2(\alpha)}$$

$$a_p(\alpha) = \mathbb{E}\{Z^p \zeta_1(\alpha Z)^2\}, \quad \zeta_1(x) = \frac{\phi(x)}{\Phi(x)}$$

- needs two numerical integrations for each function evaluation
- extension to three-parameter case not easy



# Bayesian approach

- prior  $\pi(\alpha)$  avoids MAP at  $\alpha = \pm\infty$
- Jeffreys' prior  $\pi_J(\alpha)$  is a proper distribution
- in three-parameter, expression of reference-integrated likelihood is known, but not usable in practice
- a proposed approximation

$$\pi_J(\alpha) \approx \text{const} \times \left(1 + \frac{2\alpha^2}{\pi^2/4}\right)^{-3/4}$$

a scaled  $t(1/2)$  distribution

- this is numerically close to  $M(\alpha)$
- in practice inference via Gibbs sampling

References: Liseo & Loperfido (2006), Bayes & Branco (2007)

# Penalized log-likelihood and MPLE

- Consider penalized log-likelihood

$$\ell_p(\theta) = \log L_p(\theta) = \log L(\theta) - Q(\theta)$$

where  $\theta$  is the parameter set with 1 or 3 (or more) components

- penalty  $Q$  such that:

$$Q \geq 0, \quad Q|_{\alpha=0} = 0, \quad \lim_{\alpha \rightarrow \pm\infty} Q = \infty$$
$$Q = \mathcal{O}_p(1) \quad \text{as } n \rightarrow \infty$$

- recall that  $\log L$  is bounded

$$\implies \tilde{\theta} = \arg \max_{\theta} \ell_p(\theta) \text{ exists}$$
$$\tilde{\theta} \equiv \text{MPLE}$$

# Basic asymptotics

- $\hat{\theta}$  is MLE,  $\tilde{\theta}$  is MPLE



$$\begin{aligned}\tilde{\theta} - \hat{\theta} &= \ell''_p(\hat{\theta})^{-1} Q'(\hat{\theta}) + \text{remainder} \\ &= \mathcal{O}_p(n^{-1})\end{aligned}$$



$$\text{var}\{\tilde{\theta}\} \approx -\ell''_p(\tilde{\theta})^{-1}$$

# Choosing $Q$

- 'natural' proposal for  $Q$

$$Q = c_1 \log(1 + c_2 \alpha^2), \quad c_1, c_2 > 0$$

- equate

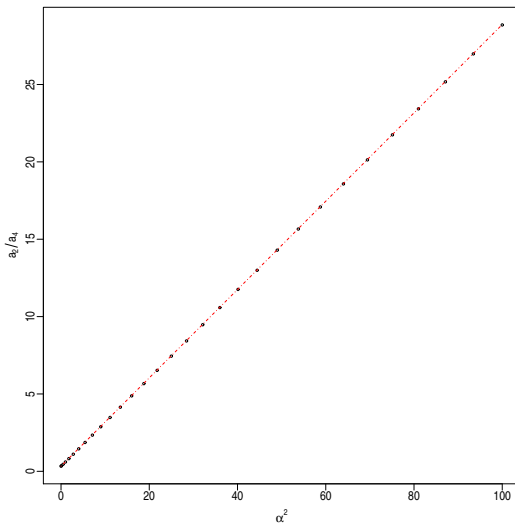
$$\ell'_p(\theta) = \ell'(\theta) - Q'(\alpha) = \ell'(\theta) + M(\alpha)$$

- write

$$-\frac{\alpha}{2 M(\alpha)} = \frac{a_2(\alpha)}{a_4(\alpha)} \approx e_1 + e_2 \alpha^2$$

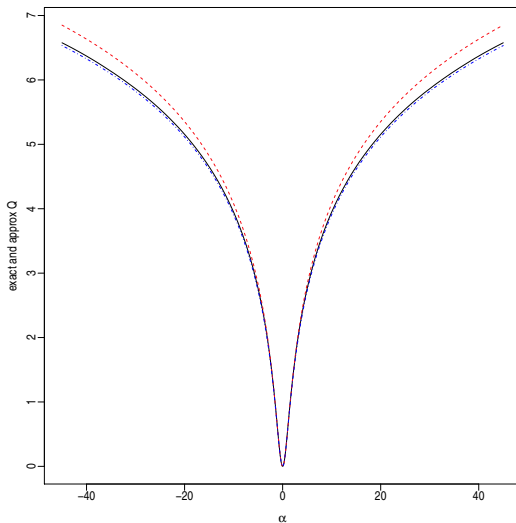
- find  $e_1$  and  $e_2$  by matching limits at  $\alpha^2 = 0$  and  $\alpha^2 \rightarrow \infty$
- $c_1 = 1/(4 e_2)$ ,  $c_2 = e_2/e_1$

# Linearization of $a_2/a_4$



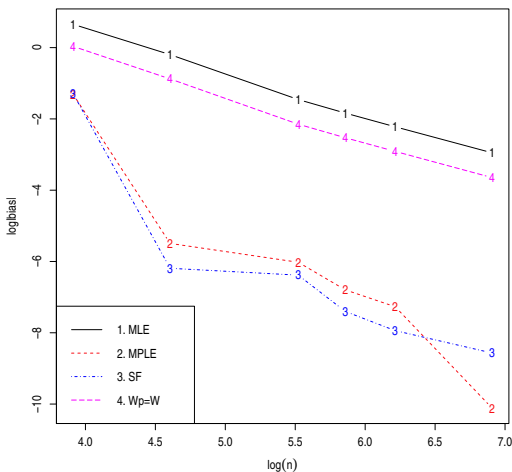
dots: exact points, red line: linearized expression

# Penalty $Q$ and approximations



exact  $Q$ , Bayes-Branco approx., using linearization

## Simulation work



estimate  $\text{SN}(\xi, \omega^2, \alpha)$  when sample is from  $\text{SN}(0, 1, 5)$

# Skew- $t$ distribution

- pdf:

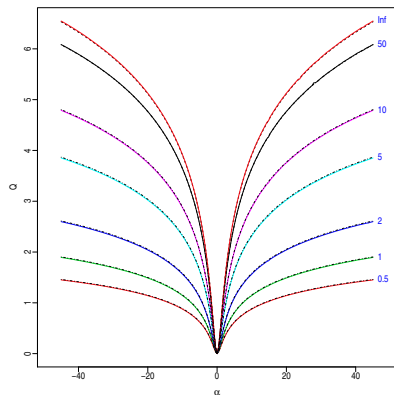
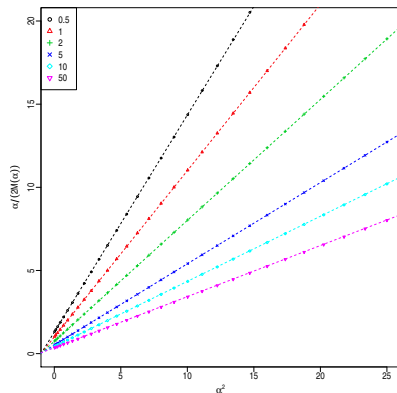
$$f(x) = 2 \omega^{-1} t(z; \nu) T\{w(z); \nu + 1\}, \quad z = \omega^{-1}(x - \xi) \in \mathbb{R}$$

- proceed as for SN case, but  $\nu$  affects coefficients
- 

$$-\frac{\alpha}{2 M(\alpha)} \approx e_{1\nu} + e_{2\nu} \alpha^2$$



# Penalty $Q$ and approximations for ST



# SN distribution in $d$ -dimensions

- pdf:

$$f(x) = 2 \phi_d(x - \xi; \Omega) \Phi(\alpha^\top \omega^{-1}(x - \xi)), \quad x \in \mathbb{R}^d$$

- many aspects encapsulated in summary quantity

$$\alpha_* = \left( \alpha^\top \bar{\Omega} \alpha \right)^{1/2}, \quad \text{where } \bar{\Omega} = \omega^{-1} \Omega \omega^{-1}$$

- use penalty

$$Q = c_1 \log(1 + c_2 \alpha_*^2)$$

- do similarly for the multivariate skew- $t$  distribution

# Final comments

- penalized log  $L$  is linked to earlier work for specific cases
- in basic cases, MPLE essentially coincident with SF
- but MPLE is of more general applicability, within this context (possibly outside)
- MPLE can be combined with parameter transformations

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