

# Observed Confidence Levels: Theory and Practice

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## Statistical Framework

- Suppose  $\mathbf{X}_1, \dots, \mathbf{X}_n \stackrel{\text{iid}}{\sim} F \in \mathcal{F}$ , a collection of  $d$ -dimensional random vectors.
- $\mathbf{X} = \{\mathbf{X}_1, \dots, \mathbf{X}_n\}$
- $\theta = T(F)$  where  $T : \mathcal{F} \rightarrow \mathbb{R}^p$ .
- Parameter Space:  $\Theta = \{T(F) : F \in \mathcal{F}\}$
- Let  $\hat{F}$  be an estimator of  $F$  based on  $\mathbf{X}$  such that  $\hat{F} \in \mathcal{F}$  with probability 1.
- Let  $\hat{\theta} = T(\hat{F})$  be a plug-in estimator of  $\theta$ .

## The Problem of Regions

- Suppose there exist subsets  $\{\Theta_i\}_{i=1}^{\infty} \subset \Theta$  such that

$$\Theta = \bigcup_{i=1}^{\infty} \Theta_i.$$

- The **problem of regions** consists of determining if  $\theta \in \Theta_i$  for each  $i$  based on  $\mathbf{X}$ .

## Example Applications

- Selecting the best treatment in a designed experiment.
- Determining the number of modes of an unknown density.
- Determining whether a mean profile in longitudinal data analysis is monotonically increasing, decreasing, or neither.
- Determining the ranking of the means of  $k$  populations.

## Methods

- Multiple comparison techniques
- Best subset selection
- Posterior probabilities
- Confidence measures
  - Attained confidence levels (Efron and Tibshirani, 1998) based on one-sided  $p$ -values (paradoxes).
  - Observed confidence levels (Polansky, 2003) based on confidence regions.

## Observed Confidence Levels

- Let  $C(\alpha, \omega; \mathbf{X}) \subset \Theta$  be a  $100\alpha\%$  confidence region for  $\theta$  based on  $\mathbf{X}$ .
- $\omega \in \Omega_\alpha \subset \mathbb{R}^q$  is a vector parameter that controls the shape of the confidence region for a given  $\alpha$ .
- Suppose there exists sequences  $\{\alpha_i\}_{i=1}^\infty \in [0, 1]$  with associated  $\omega_i \in \Omega_{\alpha_i}$  such that

$$C(\alpha_i, \omega_i; \mathbf{X}) = \Theta_i$$

for  $i = 1, 2, \dots$

- The confidence coefficient  $\alpha_i$  is the **observed confidence level** of  $\Theta_i$  for  $i = 1, 2, \dots$

## Example: Normal Mean

- Suppose  $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\theta, \sigma^2)$ .
- Let  $\Theta_i = [t_i, t_{i+1}]$  where  $-\infty < t_i < t_{i+1} < \infty$ .

- Confidence Region: For  $\alpha = \omega_U - \omega_L$ ,

$$C(\alpha, \omega; X) = [\hat{\theta} - t_{n-1; 1-\omega_L} n^{-1/2} \hat{\sigma}, \hat{\theta} - t_{n-1; 1-\omega_U} n^{-1/2} \hat{\sigma}]$$

- Observed Confidence Level for  $\Theta_i = [t_i, t_{i+1}]$ :

$$\alpha(\Theta_i) = T_{n-1} \left[ \frac{n^{1/2}(\hat{\theta} - t_i)}{\hat{\sigma}} \right] - T_{n-1} \left[ \frac{n^{1/2}(\hat{\theta} - t_{i+1})}{\hat{\sigma}} \right]$$

## Smooth Function Model

- Suppose  $\mu = E\{\mathbf{X}_i\}$  with  $\theta = g(\mu)$  for some smooth function  $g : \mathbb{R}^d \rightarrow \mathbb{R}^p$ .
- $\hat{\theta} = g(\bar{\mathbf{X}})$ .
- $F$  satisfies Cramér's continuity condition, which states that  $\psi$  is the characteristic function of  $F$ , then

$$\limsup_{\|t\| \rightarrow \infty} |\psi(\mathbf{t})| < 1.$$

- The asymptotic covariance matrix of  $\hat{\theta}$  is

$$\Sigma = \lim_{n \rightarrow \infty} V\{n^{1/2}\hat{\theta}\} = h(\mu)$$

for a smooth function  $h : \mathbb{R}^d \rightarrow \mathbb{R}^p \times \mathbb{R}^p$ .

## Sampling Distributions

- Standardized Distribution:

$$G_n(\mathbf{t}) = P\{n^{1/2}\Sigma^{-1/2}(\hat{\theta} - \theta) \leq \mathbf{t} | \mathbf{X}_1, \dots, \mathbf{X}_n \stackrel{\text{iid}}{\sim} F\}$$

- Studentized Distribution:

$$H_n(\mathbf{t}) = P\{n^{1/2}\hat{\Sigma}^{-1/2}(\hat{\theta} - \theta) \leq \mathbf{t} | \mathbf{X}_1, \dots, \mathbf{X}_n \stackrel{\text{iid}}{\sim} F\}$$

# Confidence Regions

- Studentized Region

$$C(\alpha, \omega; \mathbf{X}) = \{\hat{\theta} - n^{-1/2}\hat{\Sigma}^{1/2}\mathbf{t} : \mathbf{t} \in \mathcal{H}_\alpha\}$$

where  $\mathcal{H}_\alpha$  is any region such that

$$\int_{\mathcal{H}_\alpha} dH_n(\mathbf{t}) = \alpha.$$

- Hybrid Region: Uses the approximation  $\mathcal{H}_\alpha \simeq \mathcal{G}_\alpha$ ,

$$C(\alpha, \omega; \mathbf{X}) = \{\hat{\theta} - n^{-1/2}\hat{\Sigma}^{1/2}\mathbf{t} : \mathbf{t} \in \mathcal{G}_\alpha\}$$

where  $\mathcal{G}_\alpha$  is any region such that

$$\int_{\mathcal{G}_\alpha} dG_n(\mathbf{t}) = \alpha.$$

## Confidence Regions

- **Normal Approximation** Uses the approximation  $\mathcal{H}_\alpha \simeq \mathcal{N}_\alpha$ ,

$$\mathbf{C}(\alpha, \omega; \mathbf{X}) = \{\hat{\theta} - n^{-1/2}\hat{\Sigma}^{1/2}\mathbf{t} : \mathbf{t} \in \mathcal{N}_\alpha\}$$

where  $\mathcal{N}_\alpha$  is any region such that

$$\int_{\mathcal{N}_\alpha} d\Phi(\mathbf{t}) = \alpha.$$

## Observed Confidence Levels

- Let  $\Psi \subset \Theta$  be an arbitrary region in the parameter space.
- Studentized

$$\alpha_{\text{stud}}(\Psi) = \int_{n^{1/2}\hat{\Sigma}^{-1/2}(\hat{\theta} - \Psi)} dH_n(\mathbf{t})$$

where

$$n^{1/2}\hat{\Sigma}^{-1/2}(\hat{\theta} - \Psi) = \{n^{1/2}\hat{\Sigma}^{-1/2}(\hat{\theta} - \psi) : \psi \in \Psi\}$$

## Observed Confidence Levels

- Hybrid

$$\alpha_{\text{hyb}}(\Psi) = \int_{n^{1/2}\hat{\Sigma}^{-1/2}(\hat{\theta}-\Psi)} dG_n(\mathbf{t})$$

- Normal Approximation

$$\hat{\alpha}_{\text{stud}}(\Psi) = \int_{n^{1/2}\hat{\Sigma}^{-1/2}(\hat{\theta}-\Psi)} d\Phi(\mathbf{t})$$

## Bootstrap Approximation

- If  $G_n$  and  $H_n$  are unknown, and the normal approximation is not accurate enough, then  $G_n$  and  $H_n$  can be estimated using the bootstrap:

$$\hat{G}_n(\mathbf{t}) = P^*\{n^{1/2}\hat{\Sigma}^{-1/2}(\hat{\theta}^* - \hat{\theta}) \leq \mathbf{t} | \mathbf{X}_1^*, \dots, \mathbf{X}_n^* \stackrel{\text{iid}}{\sim} \hat{F}_n\}$$

$$\hat{H}_n(\mathbf{t}) = P^*\{n^{1/2}\hat{\Sigma}^{*-1/2}(\hat{\theta}^* - \hat{\theta}) \leq \mathbf{t} | \mathbf{X}_1^*, \dots, \mathbf{X}_n^* \stackrel{\text{iid}}{\sim} \hat{F}_n\}$$

where

- $P^*\{A\} = P\{A | \mathbf{X}\}$
- $\hat{F}_n$  is the empirical distribution of  $\mathbf{X}_1, \dots, \mathbf{X}_n$ .
- $\hat{\theta}^* = g(\bar{\mathbf{X}}^*)$ ,  $\hat{\Sigma}^* = h(\bar{\mathbf{X}}^*)$ .
- $\bar{\mathbf{X}}^* = n^{-1} \sum_{i=1}^n \mathbf{X}_i^*$

## Bootstrap Estimates

- Studentized

$$\hat{\alpha}_{\text{stud}}^*(\Psi) = \int n^{1/2} \hat{\Sigma}^{-1/2} (\hat{\theta} - \Psi) d\hat{H}_n(t)$$

- Hybrid

$$\hat{\alpha}_{\text{hyb}}^*(\Psi) = \int n^{1/2} \hat{\Sigma}^{-1/2} (\hat{\theta} - \Psi) d\hat{G}_n(t)$$

## Calculating the Bootstrap Estimates

- $\hat{G}_n(\mathbf{t})$  and  $\hat{H}_n(\mathbf{t})$  rarely exist in a closed form.
- Simulation methods are used to approximate the bootstrap estimates:
  - Simulate  $b$  samples of size  $n$  from  $\hat{F}_n$  conditional on  $\mathbf{X}$  (**resampling**).
  - For each sample, calculate  $\mathbf{T}_i^* = n^{1/2} \hat{\Sigma}^{*-1/2} (\hat{\theta}^* - \hat{\theta})$ .
  - The bootstrap estimate  $\hat{H}_n(\mathbf{t})$  can then be approximated by the empirical distribution of  $\mathbf{T}_1^*, \dots, \mathbf{T}_b^*$ :

$$\hat{H}_n(\mathbf{t}) \simeq \tilde{H}_n(\mathbf{t}) = b^{-1} \sum_{i=1}^b \delta(\mathbf{T}_i^* \leq \mathbf{t})$$

## Calculating the Bootstrap Estimates

- The bootstrap estimate of  $\alpha_{\text{stud}}$  can then be approximated by

$$\begin{aligned}\hat{\alpha}_{\text{stud}}^*(\Psi) &\simeq \int n^{1/2} \hat{\Sigma}^{-1/2} (\hat{\theta} - \Psi) d\tilde{H}_n(\mathbf{t}) \\ &= b^{-1} \sum_{i=1}^b \delta(\mathbf{T}_i^* \in n^{1/2} \hat{\Sigma}^{-1/2} (\hat{\theta} - \Psi)) \\ &= b^{-1} \sum_{i=1}^b \delta(\hat{\theta} - \hat{\Sigma}^{1/2} \hat{\Sigma}_i^{*-1/2} (\hat{\theta}_i^* - \hat{\theta}) \in \Psi)\end{aligned}$$

- Similar methods can be used to approximate  $\hat{\alpha}_{\text{hyb}}^*$ .

## Efron's Percentile Method

- An additional observed confidence level can be computed based on the **percentile method** confidence region of Efron (1979).
- A  $100\alpha\%$  percentile method confidence region for  $\theta$  is any region  $\mathcal{V}_\alpha$  such that

$$\int_{\mathcal{V}_\alpha} d\hat{V}_n(\mathbf{t}) = \alpha,$$

where  $V_n(\mathbf{t}) = P\{\hat{\theta} \leq \mathbf{t} | \mathbf{X}_1, \dots, \mathbf{X}_n \stackrel{\text{iid}}{\sim} F\}$  and the bootstrap estimate of  $V_n(\mathbf{t})$  is given by

$$\hat{V}_n(\mathbf{t}) = P^*\{\hat{\theta}_i^* \leq \mathbf{t} | \mathbf{X}_1^*, \dots, \mathbf{X}_n^* \stackrel{\text{iid}}{\sim} \hat{F}_n\}$$

## Percentile Observed Confidence Level

- The corresponding observed confidence level based on the percentile method is

$$\hat{\alpha}_{\text{perc}}^*(\Psi) = \int_{\Psi} d\hat{V}_n(\mathbf{t})$$

## Simulation Approximation

- Simulate  $b$  samples of size  $n$  from  $\hat{F}_n$ .
- For each sample compute  $\hat{\theta}^*$ .
- The distribution  $\hat{V}_n$  is approximated with the empirical distribution of  $\hat{\theta}_1^*, \dots, \hat{\theta}_b^*$ ,

$$\hat{V}_n(\mathbf{t}) \simeq \tilde{V}_n(\mathbf{t}) = b^{-1} \sum_{i=1}^b \delta\{\hat{\theta}_i^* \leq \mathbf{t}\}$$

- The corresponding approximation of  $\hat{\alpha}_{\text{perc}}^*$  is

$$\hat{\alpha}_{\text{perc}}^*(\Psi) \simeq \int_{\Psi} d\tilde{V}_n(\mathbf{t}) = b^{-1} \sum_{i=1}^b \delta\{\hat{\theta}_i^* \in \Psi\}$$

## Asymptotic Accuracy

- A method for computing an observed confidence level is **accurate** if  $\alpha(\Psi) = \alpha$  whenever  $\Psi$  is a  $100\alpha\%$  confidence region for  $\theta$ .
- The studentized measure  $\alpha_{\text{stud}}$  is accurate by this definition.
- A method for computing an observed confidence level is  **$k^{\text{th}}$ -order accurate** if

$$\alpha(\Psi) = \alpha + O(n^{-k/2})$$

as  $n \rightarrow \infty$  whenever  $\Psi$  is a  $100\alpha\%$  confidence region for  $\theta$ .

## Asymptotic Accuracy

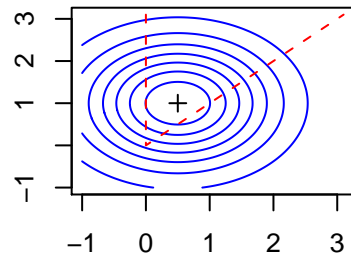
- Accurate:  $\alpha_{\text{stud}}$
- Multivariate Edgeworth expansion theory can be used to prove the following asymptotic accuracy results:
  - First-Order Accurate:  $\hat{\alpha}_{\text{stud}}, \alpha_{\text{hyb}}, \hat{\alpha}_{\text{hyb}}^*, \hat{\alpha}_{\text{perc}}^*$
  - Second-order Accurate:  $\hat{\alpha}_{\text{stud}}^*$

## Empirical Study

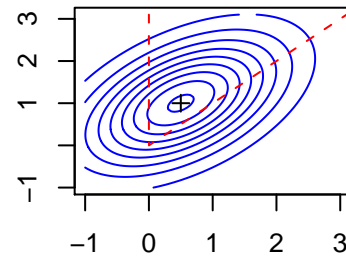
- $\mathbf{X}_1, \dots, \mathbf{X}_n \stackrel{\text{iid}}{\sim} F$ , where  $F$  is a bivariate normal mixture and  $n = 10, 25$  and  $50$ .
- $\theta = E\{\mathbf{X}_i\} = (0.5, 1.0)'$  with  $\Theta = \mathbb{R}^2$
- $\Psi = \{\theta' = (\theta_1 \ \theta_2) : 0 \leq \theta_1 \leq \theta_2 < \infty\}$
- 100 samples for each size and distribution were generated using R.
- The average observed confidence level over the 100 simulated samples for each of the methods  $\alpha_{\text{stud}}$ ,  $\hat{\alpha}_{\text{stud}}^*$ ,  $\hat{\alpha}_{\text{stud}}$ ,  $\alpha_{\text{hyb}}$ ,  $\hat{\alpha}_{\text{hyb}}^*$  and  $\hat{\alpha}_{\text{perc}}^*$  was computed.

# Normal Mixtures

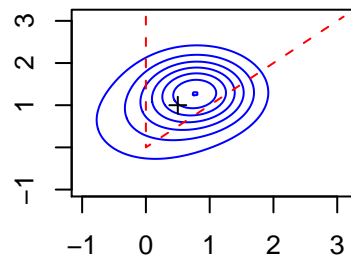
**Independent Normal**



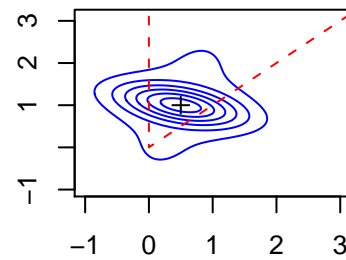
**Dependent Normal**



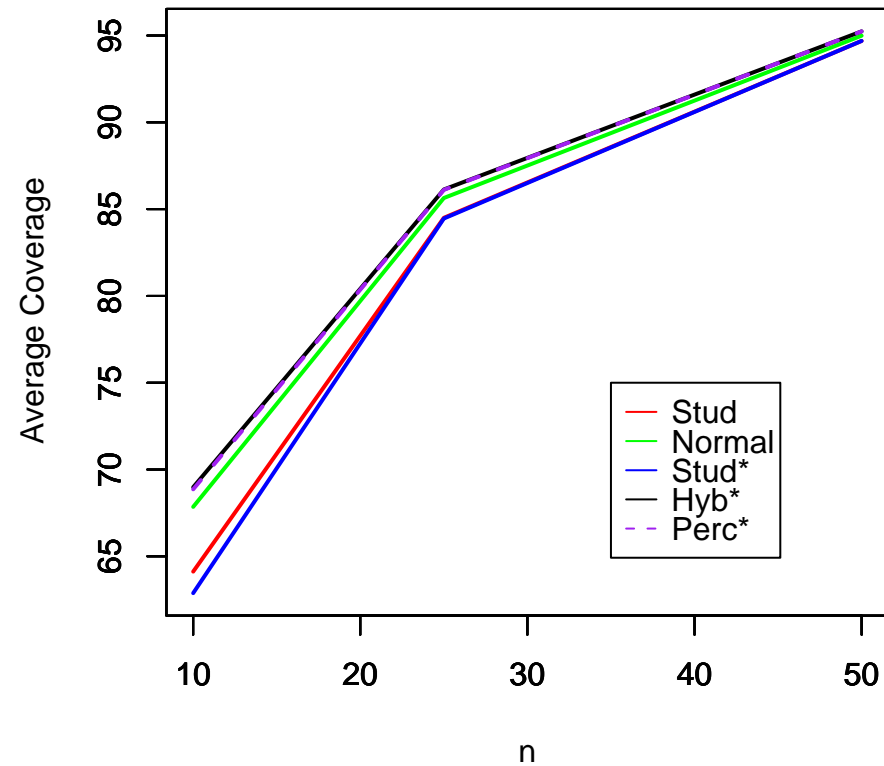
**Skewed Bivariate**



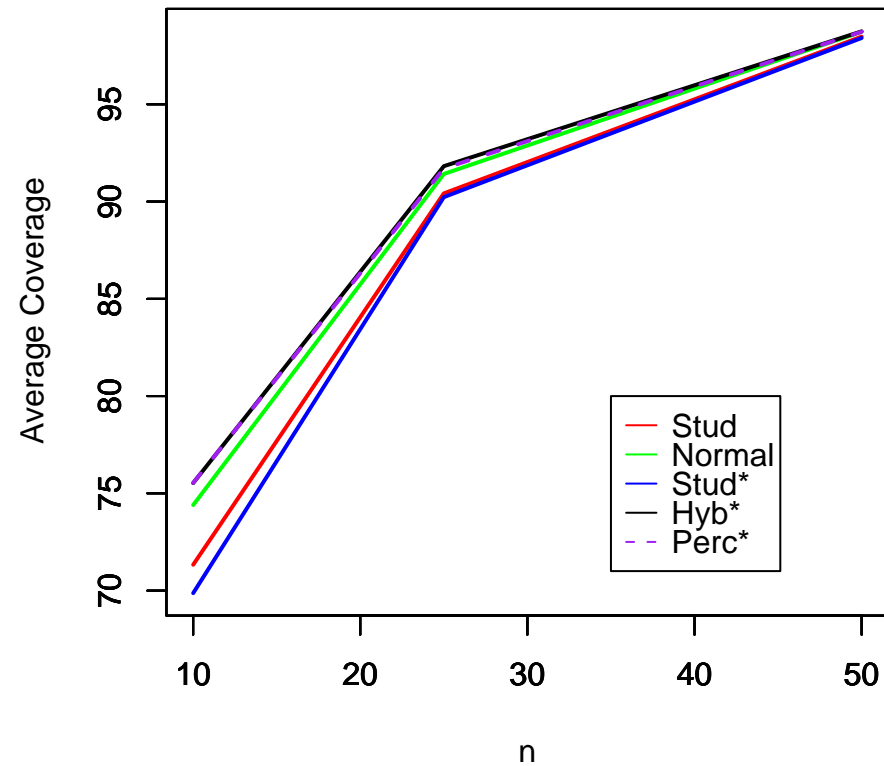
**Kurtotic Bivariate**



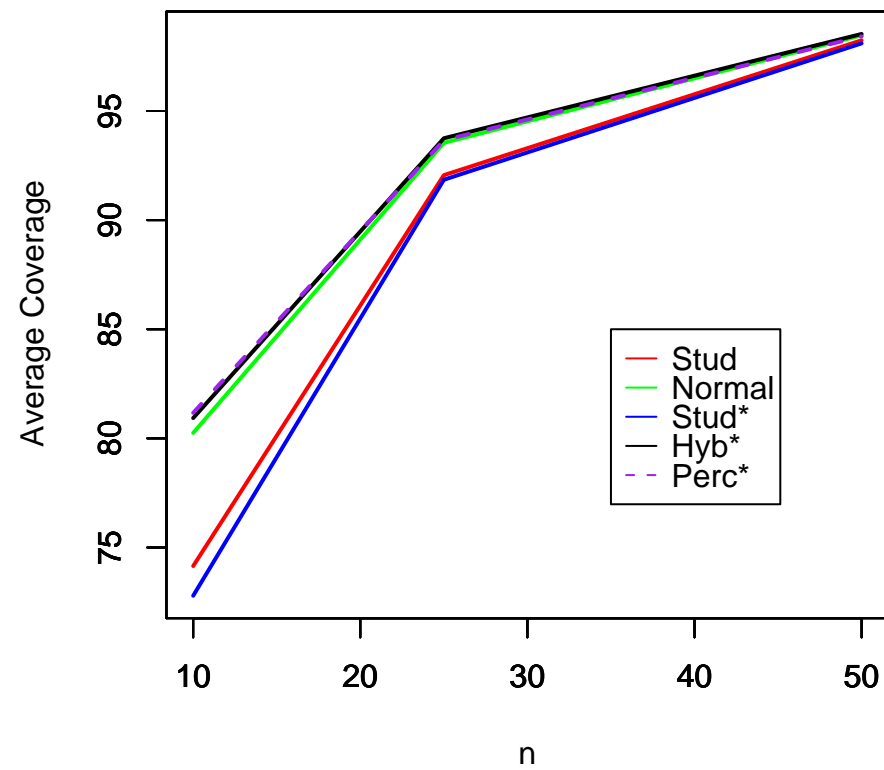
# Simulation Results: Independent Normal



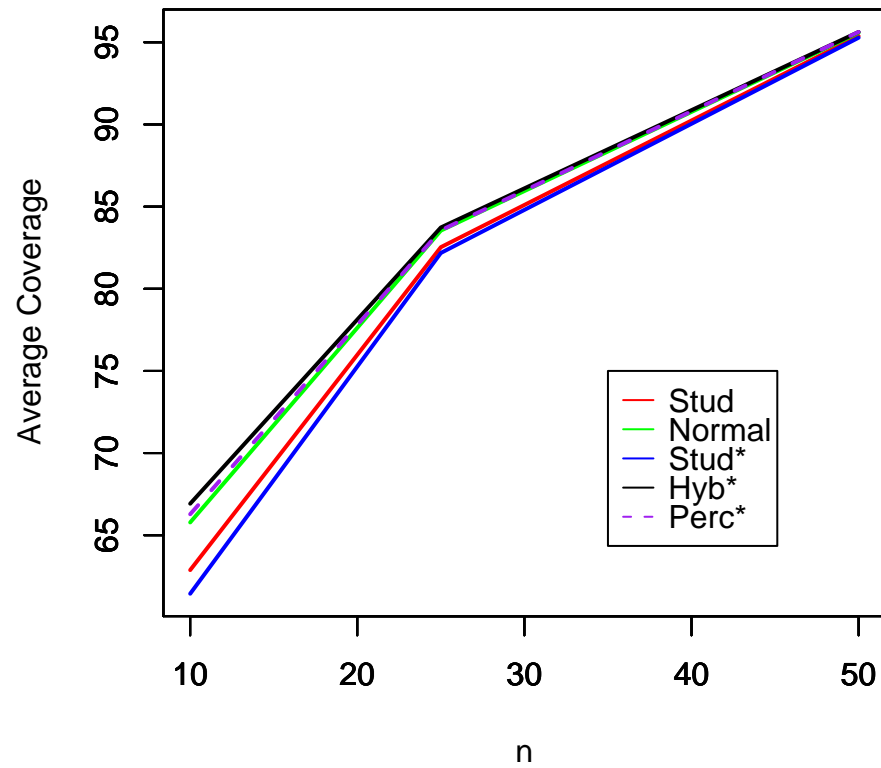
# Simulation Results: Dependent Normal



# Simulation Results: Skewed Bivariate



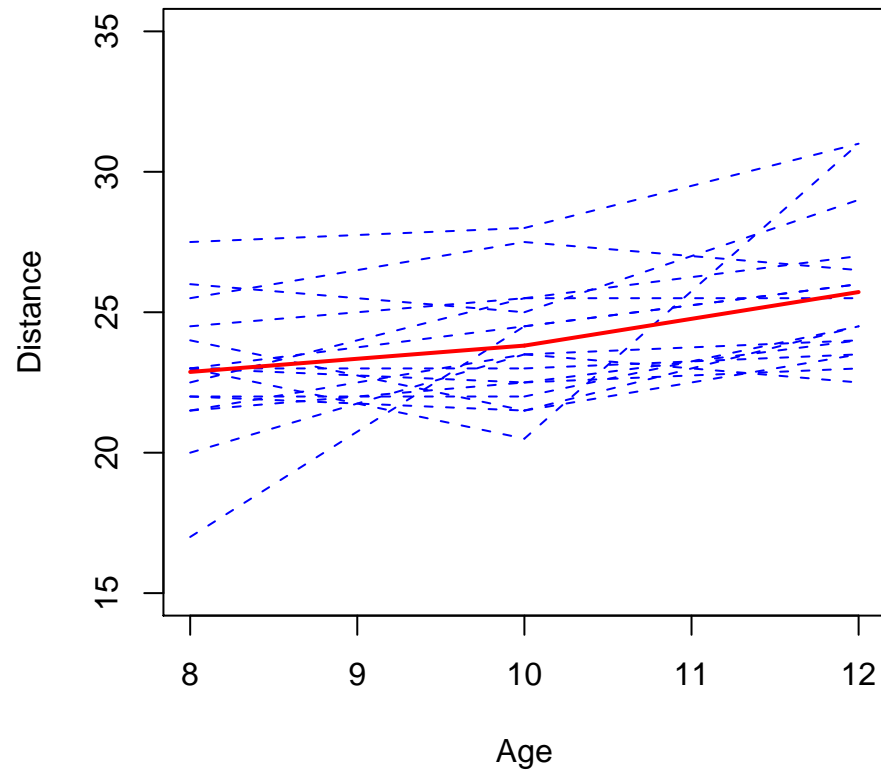
# Simulation Results: Kurtotic Bivariate



## Example: Growth Curves

- Data from Potthoff and Roy (1964).
- Growth curves of the distance (mm) from the center of the pituitary gland to the pterygomaxillary fissure in young children.
- First three observations from the male subjects.

## Example: Growth Curves



## Example: Growth Curves

- Let  $\mathbf{X}_i$  be a random vector containing the three measurements from subject  $i = 1, \dots, 16$ .
- Assume  $\mathbf{X}_1, \dots, \mathbf{X}_{16} \stackrel{\text{iid}}{\sim} F$  where  $F$  is unknown.
- Let  $\theta = E\{\mathbf{X}_i\}$ .
- Regions of interest:  $\Theta_1 = \{\theta : \theta_1 \leq \theta_2 \leq \theta_3\}$ ,  $\Theta_2 = \{\theta : \theta_1 \leq \theta_3 \leq \theta_2\}$ ,  $\Theta_3 = \{\theta : \theta_2 \leq \theta_1 \leq \theta_3\}$ ,  $\Theta_4 = \{\theta : \theta_2 \leq \theta_3 \leq \theta_1\}$ ,  $\Theta_5 = \{\theta : \theta_3 \leq \theta_1 \leq \theta_2\}$ ,  $\Theta_6 = \{\theta : \theta_3 \leq \theta_2 \leq \theta_1\}$ .

## Observed Confidence Levels

Region	Ordering	$\hat{\alpha}_{\text{stud}}^*$	$\hat{\alpha}_{\text{hyb}}^*$	$\hat{\alpha}_{\text{perc}}^*$
$\Theta_1$	$\theta_1 \leq \theta_2 \leq \theta_3$	72.2	92.5	96.1
$\Theta_2$	$\theta_1 \leq \theta_3 \leq \theta_2$	13.6	0.2	0.0
$\Theta_3$	$\theta_2 \leq \theta_1 \leq \theta_3$	6.6	7.2	3.9
$\Theta_4$	$\theta_2 \leq \theta_3 \leq \theta_1$	0.1	0.0	0.0
$\Theta_5$	$\theta_3 \leq \theta_1 \leq \theta_2$	7.5	0.0	0.0
$\Theta_6$	$\theta_3 \leq \theta_2 \leq \theta_1$	0.0	0.1	0.0

## Further Research

- Regression and Linear Models [in progress and Polansky (2003)]
- Nonparametric regression and density estimation [Efron and Tibshirani (1998), Hall and Ooi (2004)].
- Generalized Linear Models
- Goodness-of-Fit