

An extension for smoothed empirical likelihood confidence intervals for extreme quantiles and small sample sizes

Master Thesis

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Motivation

- ▶ Application: Calculating process capability without a distribution assumption.
 - ▶ Compute confidence intervals for "extreme" quantiles (e.g. $q = 0.01$).
 - ▶ Using a non-parametric method.
- ▶ Problem: small sample sizes are desired but lead to
 - ▶ Infinite confidence intervals.
 - ▶ Bad coverage rates.
- ▶ Method: Smoothed empirical likelihood.
 - ▶ Capable of returning non symmetrical confidence intervals.
 - ▶ Smoothing reduces coverage error.

Existing Methods



- ▶ Empirical likelihood was first introduced by Owen (1988)
- ▶ When quantiles are considered, the log likelihood is dependent on the empirical distribution function F_n (Adimari, 1998):

$$l(\Theta) = 2n \left[F_n(\Theta) \log\left(\frac{F_n(\Theta)}{q}\right) + (1 - F_n(\Theta)) \log\left(\frac{1 - F_n(\Theta)}{1 - q}\right) \right] \quad (1)$$

- ▶ Owen (1988) shows that the Wilks theorem is applicable to compute asymptotic confidence intervals: $\lim_{n \rightarrow \infty} P(l(\Theta) \leq c) = P(\chi_1^2 \leq c)$
- ▶ As this results in a step function, several methods of smoothing have been proposed:
 - ▶ Smoothing using a kernel function. (Chen, Hall, 1993)
 - ▶ Linear smoothing of F_n (Adimari, 1998)

Linear Smoothing

- ▶ Let $x_{(1)} \leq \dots \leq x_{(n)}$ be the ordered sample.
- ▶ The smoothing proposed by Adimari (1998) is achieved by using a linear smoothing F^* of F_n in equation 1.

$$F_n^*(\Theta) = \begin{cases} 0 & \text{if } \Theta < x_{(1)} \\ H(\Theta) & \text{if } \Theta \in [x_{(1)}, x_{(n)}] \\ 1 & \text{if } \Theta \geq x_{(n)} \end{cases}$$

where

$$H(\Theta) = \begin{cases} \frac{2i-1}{2n} & \text{if } \Theta = x_{(i)}; i \in \{1, \dots, n-1\} \\ (1-\lambda)\frac{2i-1}{2n} + \lambda\frac{2i+1}{2n} & \text{if } \Theta \in (x_{(i)}, x_{(i+1)}); \lambda = \frac{\Theta - x_{(i)}}{x_{(i+1)} - x_{(i)}}; i \in \{1, \dots, n-1\} \end{cases}$$

Problems:

- ▶ Constant likelihood values outside of the observed data can lead to infinite CI's.
- ▶ likelihood function still has two jumps (at $x_{(1)}$ and $x_{(n)}$).

Distribution Function

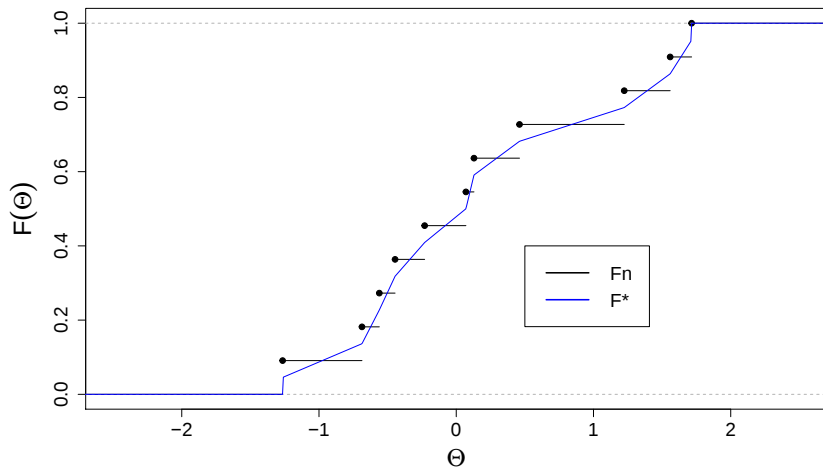


Figure: Smoothing of F_n for 11 observations from a standard normal distribution

Likelihood Function

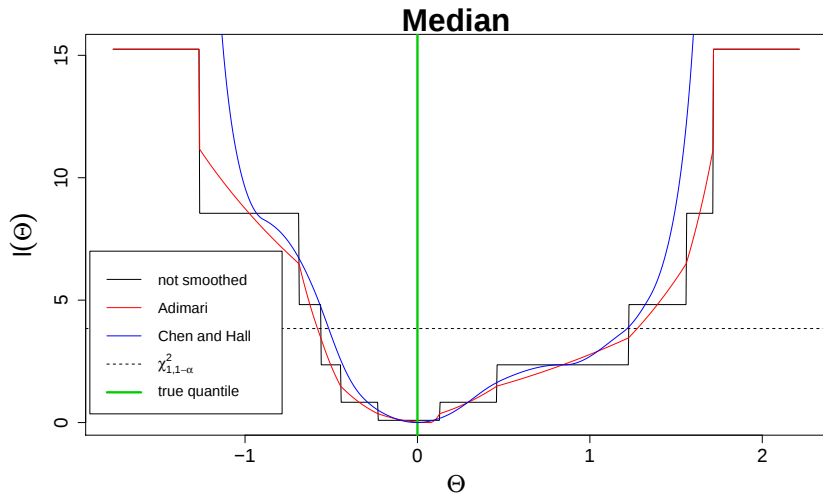


Figure: Smoothed empirical likelihood functions ($n = 11$; $q = 0.5$; $\alpha = 0.05$)

Likelihood Function

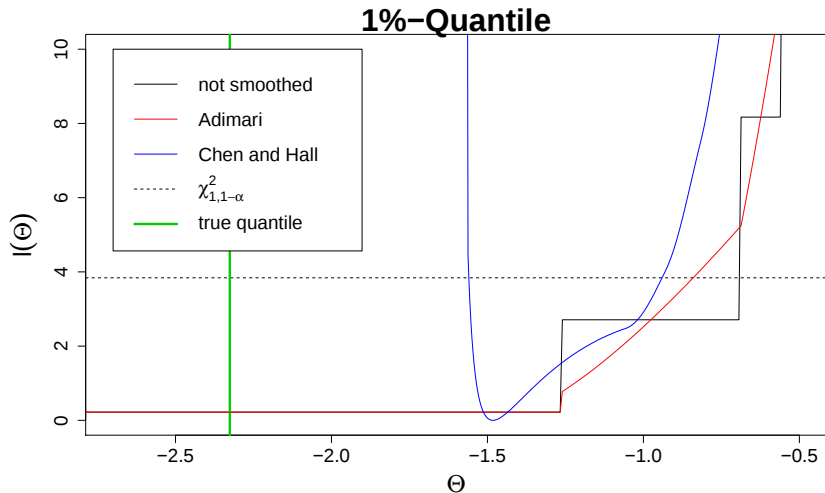


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Coverage Rates

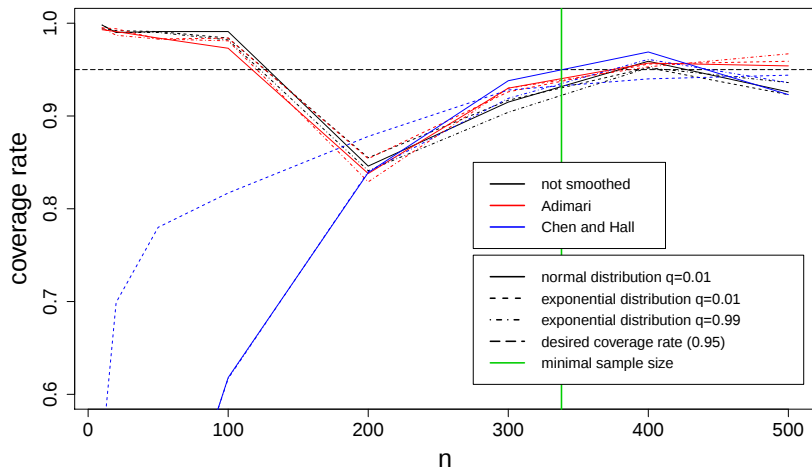


Figure: Estimated coverage rates based on 1000 samples

The Extension

Idea:

- ▶ Find an extension of the likelihood function for values outside of the observed data so that
 - ▶ finite confidence intervals are guaranteed.
 - ▶ the desired coverage rate is achieved.

1. extending the smoothed ecdf F^* as follows:

$$F_{\text{ext}}(\Theta) = \begin{cases} 0 & \text{if } \Theta \leq x_{(1)} - d_1 c \\ \frac{1}{2n} - \frac{1}{2n \cdot d_1 \cdot c} (x_{(1)} - \Theta) & \text{if } x_{(1)} - d_1 c < \Theta < x_{(1)} \\ H(\Theta) & \text{if } x_{(1)} \leq \Theta \leq x_{(n)} \\ \frac{2n-1}{2n} + \frac{1}{2n \cdot d_2 \cdot c} (\Theta - x_{(n)}) & \text{if } x_{(n)} < \Theta < x_{(n)} + d_2 c \\ 1 & \text{if } \Theta \geq x_{(n)} + d_2 c \end{cases}$$

Where $c \geq 1$; $d_1 = \frac{1}{10} \sum_{i=1}^5 (x_{(i+1)} - x_{(i)})$ and
 $d_2 = \frac{1}{10} \sum_{i=1}^5 (x_{(n-i+1)} - x_{(n-i)})$

2. linear extension of the likelihood function.

Visualising F_{ext}

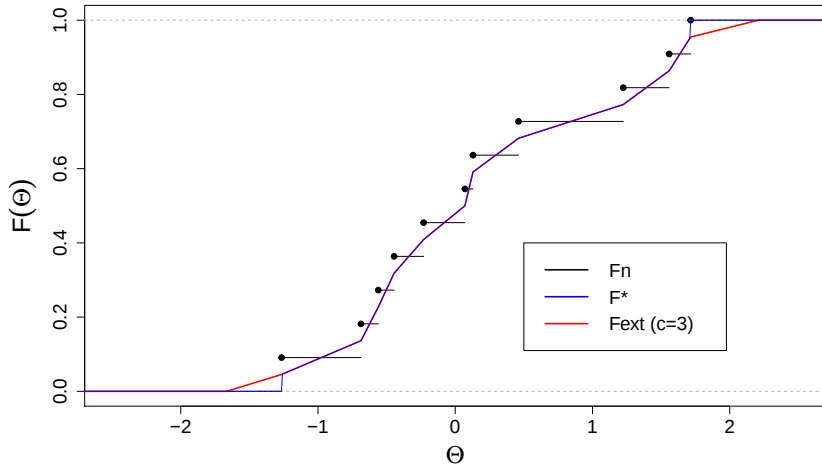


Figure: Smoothing of F_n using F_{ext}

Visualising F_{ext}

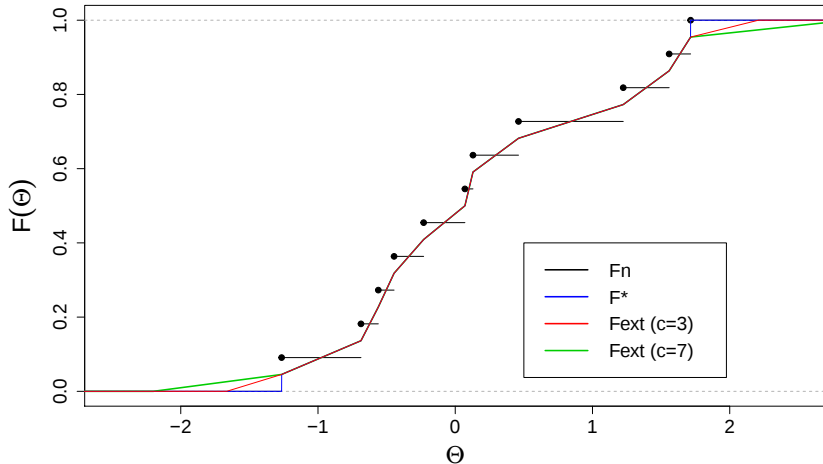


Figure: Visualising the influence of the parameter c on F_{ext}

Visualising F_{ext}

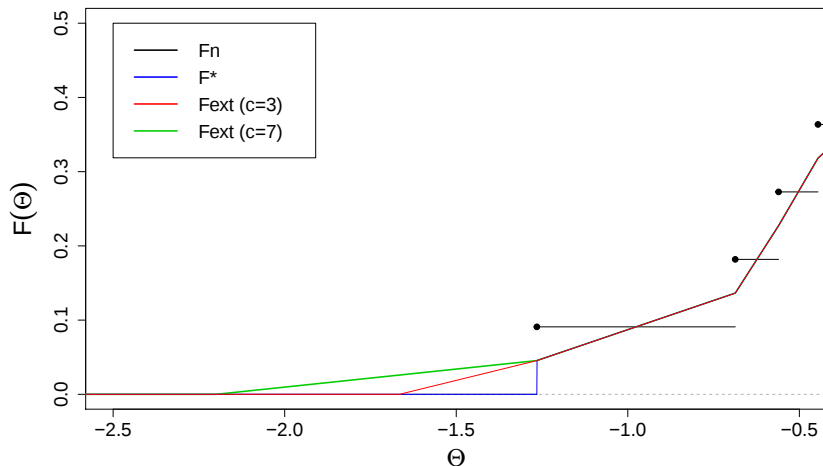


Figure: Visualising the influence of the parameter c on F_{ext}

Visualising $I(\Theta)$

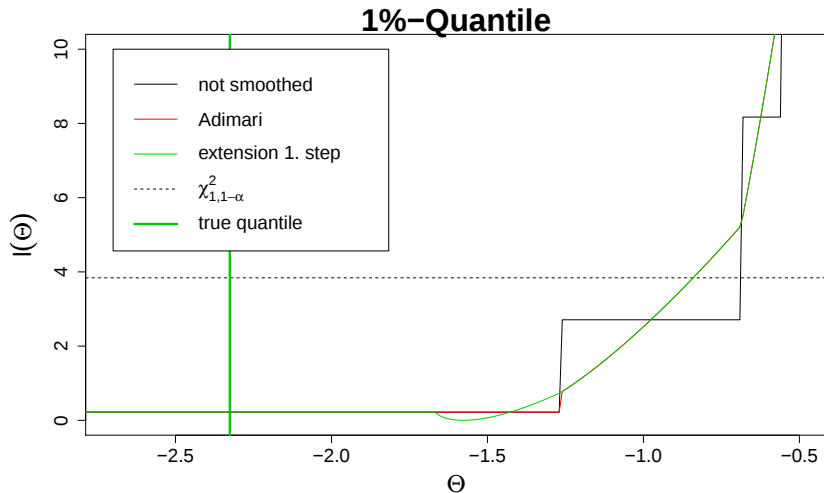


Figure: First step of the extension ($c = 3$)

Visualising $l(\Theta)$

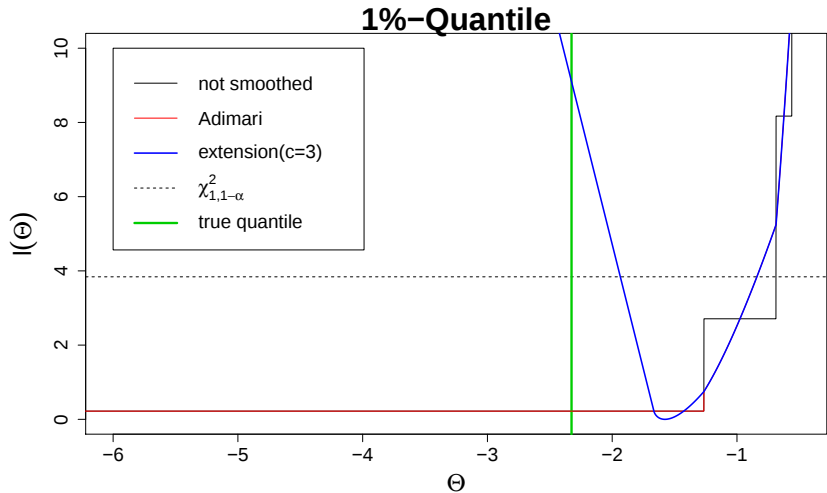


Figure: Second step: further linear extension ($c = 3$)

Visualising $l(\Theta)$

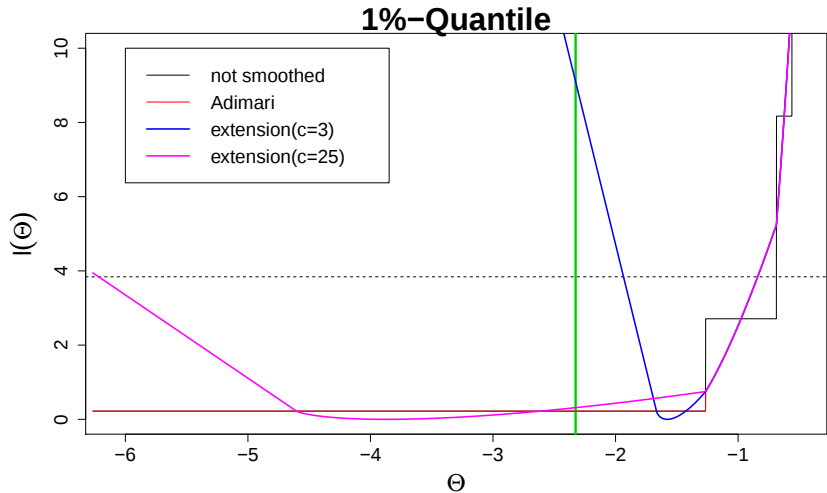


Figure: Fully extended likelihood function for different values of c

Extension parameter

- ▶ The smallest value of c which results in a coverage rate of at least $(1 - \alpha)$ is desired.
- ▶ The extension is necessary, if the confidence region extends beyond the observed data.
- ▶ The necessity of the extension depends on the significance level α and the product R :

$$R := \begin{cases} q * n & \text{if } q \leq 0.5 \\ (1 - q) * n & \text{if } q > 0.5 \end{cases}$$

- ▶ Assumption:
 - ▶ The required value for c depends on q , n , R and α
 - ▶ The required value for c does not depend on the distribution of the data.

Modelling c

Simulation study:

- ▶ For different values of n ; q and α choose the smallest value $c \in \mathbb{N}$ that produces a coverage of at least $(1 - \alpha)$.
- ▶ Evaluate coverage using $m = 5000$ samples of size n from a normal distribution.
- ▶ Try to find a model for c given q , n , R and α

Modelling c

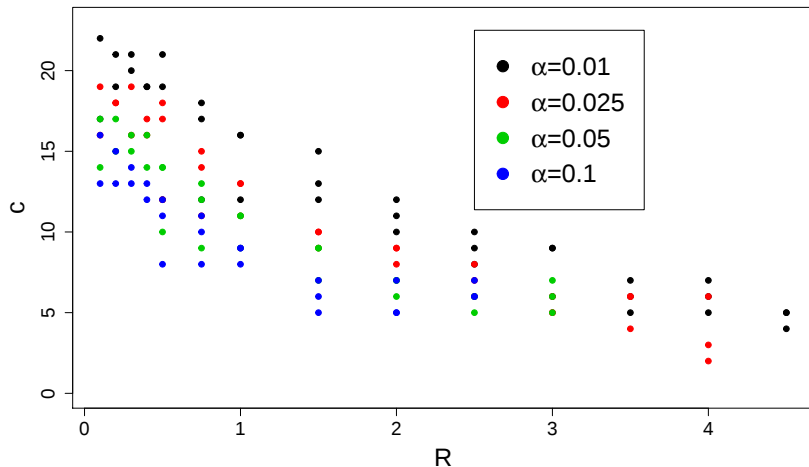


Figure: Chosen value of c for different values of R

Modelling c

Simulation study:

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- ▶ Evaluate coverage using $m = 5000$ samples of size n from a normal distribution.
- ▶ Model chosen:
$$\hat{c} = 12.344 - 7.082 * \sqrt{R} - 2.454 * \log(\alpha) - 75.125 * q - 0.004 * n.$$
 - ▶ $(1 - q)$ is used for $q > 0.5$
- ▶ adjusted $R^2 = 0.933$

Modelling c

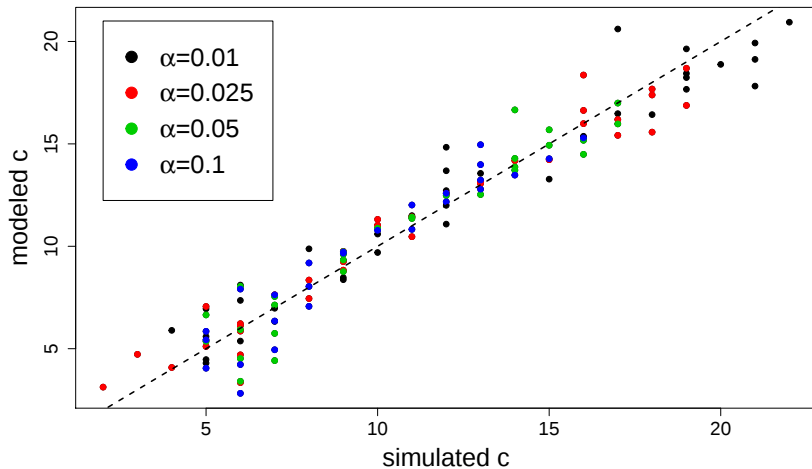


Figure: Visualising the Model

Modelling c

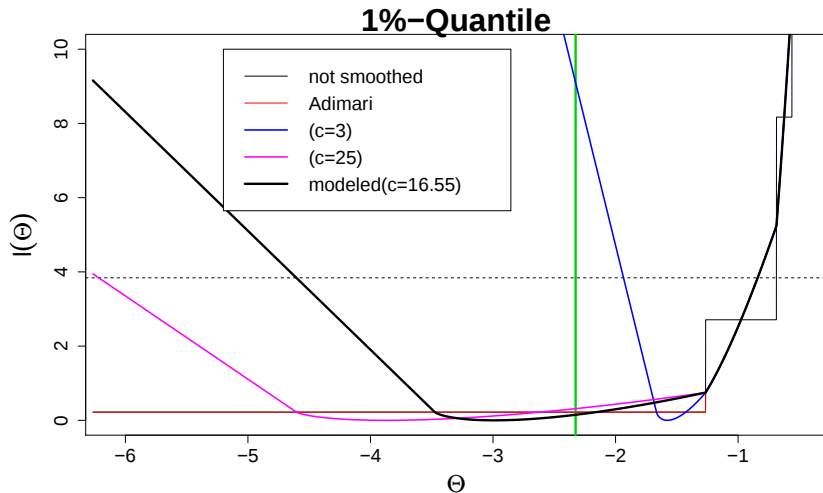


Figure: Example for the modeled value of c ($n = 11$, $q = 0.01$, $\alpha = 0.05$)

Performance: coverage

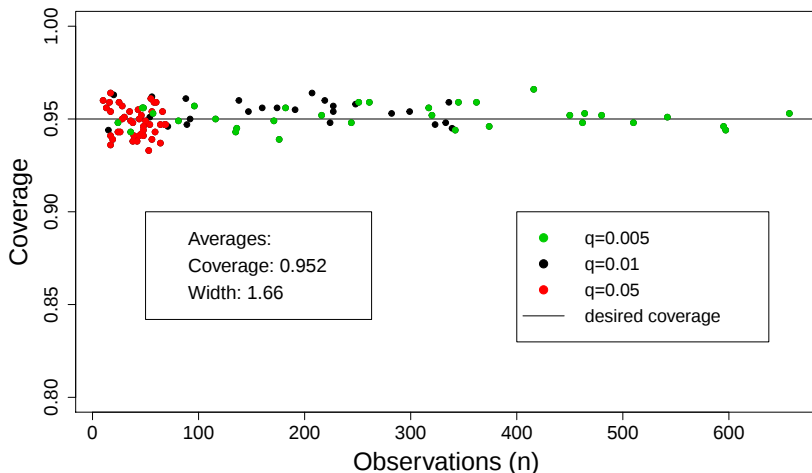


Figure: coverage rates based on 1000 samples for normally distributed data

Performance: coverage

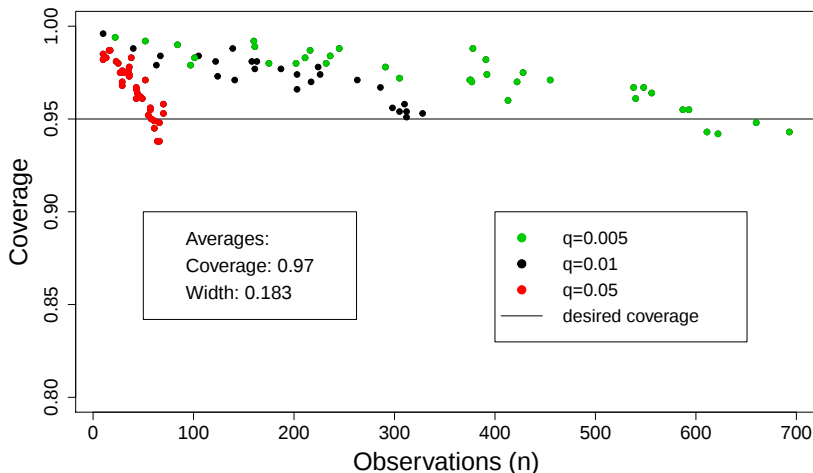


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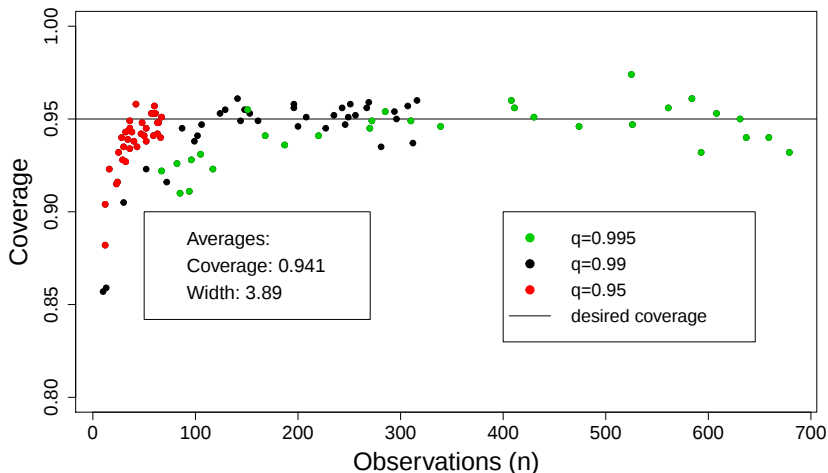


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Performance: discussion

Table: Average width if coverage is acceptable.
 $q = 0.01, 0.99$, $\alpha = 0.05$, based on 1000 samples

	n= 10	n= 20	n= 50	n= 100	n= 200	n= 300	n= 400	n= 500
g-NV	Inf	Inf	Inf	Inf		0.858	0.918	0.664
A-NV	Inf	Inf	Inf	Inf		0.877	0.844	0.729
H-NV						0.856	0.963	0.662
Af-NV	4.554	3.383	2.522	1.953	1.517	1.028	0.849	0.728
g-Exp1	Inf	Inf	Inf	Inf		0.021	0.020	0.016
A-Exp1	Inf	Inf	Inf	Inf		0.022	0.020	0.018
H-Exp1						0.020	0.018	0.016
Af-Exp1	2.043	0.785	0.255	0.109	0.044	0.024	0.020	0.018
g-Exp99	Inf	Inf	Inf	Inf		2.479	2.688	1.886
A-Exp99	Inf	Inf	Inf	Inf		2.573	2.390	2.041
H-Exp99						2.423	2.695	1.806
Af-Exp99			5.463	4.943	4.065	2.882	2.411	2.050

Legend: g-not smoothed; A- Adimari, H-Chen and Hall, Af- Adimari extended,
 NV-(standard) normal distribution, Exp1-exponential distribution $q = 0.01$,
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Outlook

- ▶ Better account for the shape of the data by assigning higher weights to extreme observations:
 - ▶ Using a weighted mean for computing d_1 and d_2 .
- ▶ Test of a semi parametric variation:
 - ▶ Assume a class of distributions (e.g. exponential) and Modell c using samples from that distribution.

References

- Adimari, G. (1998). An empirical likelihood statistic for quantiles. *Journal of Statistical Computation and Simulation*, 60(1) pages 85-95.
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- Zhu, H. (2007) Smoothed Empirical Likelihood for Quantiles and Some Variations/Extension of Empirical Likelihood for Buckley-James Estimator, Ph.D. dissertation, University of Kentucky.