

Confidence Envelopes for Model Selection Criteria and Post-Model Selection Inference

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- **GIC:** A *generalized information criterion* (statistic) consists of the normalized log-likelihood plus a penalty term; includes AIC, BIC, etc.
- **Goal:** Estimate a high quantile of distribution of minimum GIC (confidence envelope)
- **3 cases of special relevance:** IID, regression, time series
- **Methods:**
 - analytical by invoking central limit theorems
 - bootstrap (3 versions)
- **Simulations:** accuracy of coverage probabilities of confidence envelopes
- **Illustrations:** practical implementation on real datasets

Consider 14 positive-valued models

Rank	AIC	Model
1	4.9354	Gamma3
2	4.9355	Gamma
3	4.9374	Burr
4	4.9418	Weibull
5	4.9418	Weibull3
6	4.9438	Gumbel
7	4.9631	LogNormal3
8	4.9658	Lognormal
9	4.9695	Logistic3
10	4.9706	Logistic
11	4.9776	Inverse Gaussian
12	5.0532	Kappa
13	5.1380	Gpareto
14	7.1821	F

Regression Models for Strength of Concrete

Consider all subsets with 8 predictors (only top 20 out of 256 shown)

Rank	BIC	Model
1	7.570316919	{0123458}
2	7.571444201	{012348}
3	7.57664502	{01234568}
4	7.576713773	{0123478}
5	7.576790141	{01234578}
6	7.577886861	{0123468}
7	7.579900096	{012345678}
8	7.582701966	{01234678}
9	7.586709991	{01235678}
10	7.614226865	{0123678}
11	7.619886251	{01245678}
12	7.628053092	{0124678}
13	7.628516874	{0124578}
14	7.637781395	{012458}
15	7.643862937	{0123568}
16	7.644318814	{0124568}
17	7.651154208	{0123578}
18	7.662647169	{012358}
19	7.671062354	{01345678}
20	7.672409034	{0134678}

Models for Wolfer Sunspot Numbers: annual time series of 100 values (1770–1869)

Rank	AICc	Model
1	836.6704608	ARMA(8, 0)
2	837.8329215	ARMA(3, 5)
3	838.1403819	ARMA(5, 3)
4	838.2688009	ARMA(5, 5)
5	838.844269	ARMA(4, 4)
6	838.8467446	ARMA(8, 1)
7	838.9254096	ARMA(9, 0)
8	839.0495172	ARMA(9, 1)
9	839.8700548	ARMA(3, 2)
10	840.0848802	ARMA(9, 2)
11	840.5555259	ARMA(11, 1)
12	840.9585325	ARMA(4, 2)
13	841.1186244	ARMA(8, 2)
14	841.1439068	ARMA(4, 5)
15	841.1898953	ARMA(10, 1)
16	841.1954145	ARMA(11, 0)
17	841.3298421	ARMA(9, 13)
18	841.7005855	ARMA(12, 13)
19	841.7189501	ARMA(12, 0)
20	842.4678861	ARMA(3, 3)
21	842.4705473	ARMA(10, 2)
22	842.5017981	ARMA(9, 3)
23	842.8640372	ARMA(11, 2)

- Observations:: $y_1, \dots, y_n \sim Y$, cdf $F(y)$, pdf $f(y)$.
- Candidate model set: $\mathcal{G} = \{g_{\theta} : \theta \in \Theta \subset \mathbb{R}^d\}$.
- Inference on θ for g_{θ} : maximize log-likelihood

$$\ell_n(\theta) = \sum_{i=1}^n \log g(y_i; \theta), \quad \hat{\theta} = \text{MLE}$$

- SLLN: empirical KL-discrepancy converges to distance $f \mapsto g_f$:

$$\Delta_n(\hat{\theta}) := -\frac{1}{n} \ell_n(\hat{\theta}) \xrightarrow{a.s.} -\mathbb{E}_F \log g(Y; \theta) := \Delta(\theta)$$

- θ_0 : parameter that gets g_{θ_0} as close as possible to true f (Kullback-Leibler sense):

$$\hat{\theta} \xrightarrow{a.s.} \theta_0 = \arg \min_{\theta \in \Theta} \Delta(\theta),$$

- $g(y; \theta_0)$ is best approximating model (Claeskens & Hjort, 2008)

- Define Generalized Information Criterion (GIC):

$$GIC = \Delta_n(\hat{\theta}) + \frac{\psi(n, d)}{n}$$

- $\psi(n, d)$ is penalty term:

AIC: $\psi(n, d) = d.$

BIC: $\psi(n, d) = (d/2) \log(n).$

AICc: $\psi(n, d) = nd/(n - d - 1).$

- Define GIC for j -th candidate model (a statistic):

$$X_j := \text{GIC}_j := \Delta_n(\hat{\theta}^{(j)}) + \frac{\psi(n, d_j)}{n},$$

- Under mild regularity conditions (Linhart, 1988):

Theorem

$$\sqrt{n} \begin{pmatrix} X_j - \Delta(\boldsymbol{\theta}_0^{(j)}) \\ X_k - \Delta(\boldsymbol{\theta}_0^{(k)}) \end{pmatrix} \xrightarrow{d} \mathcal{N}(\mathbf{0}, \Lambda),$$

provided $\psi(n, d) = o(\sqrt{n})$ for each model, where (j, k) element of Λ is given by:

$$\lambda_{jk} = \text{Cov}_F \left(\log g^{(j)}(Y; \boldsymbol{\theta}_0^{(j)}), \log g^{(k)}(Y; \boldsymbol{\theta}_0^{(k)}) \right) \quad (1)$$

- Entire set of K GIC values: a **dependent and non-identically distributed** sequence of approximately normal random variables.
- Use obvious empirical estimates for Λ .
- Approximate cdf of min GIC:

$$F_{X_{(1)}}(x) = 1 - P(X_1 > x, \dots, X_K > x).$$

- Efficient computation via R package **mvtnorm** for up to $K = 1000$.
- **Confidence envelope for min GIC of level $(1 - \alpha)100\%$:**
 $(1 - \alpha)$ quantile of $X_{(1)}$

$$CE(\alpha) = F_{X_{(1)}}^{-1}(1 - \alpha)$$

(This is the Analytical method)

Three choices (at least):

- **Parametric:**

- resample from model with lowest GIC;
- calculate quantile analytically from selected model;
- biased if incorrect model identified...

- **Nonparametric:**

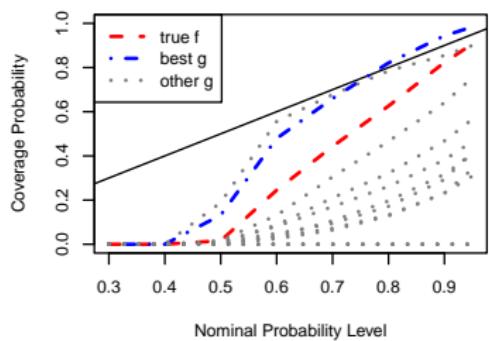
- resample from raw data;
- calculate quantile empirically;
- low accuracy...

- **Semiparametric:**

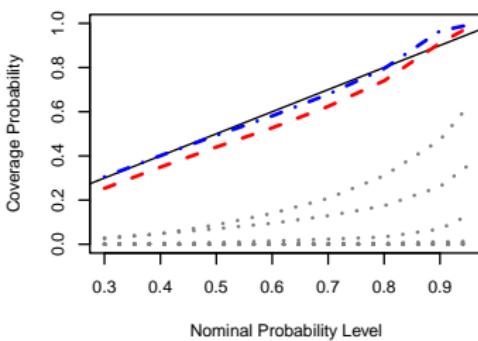
- resample from raw data to calculate Λ ;
- get quantile as in Analytical method;
- **best!**

IID Case Simulations: Coverage Probabilities of $\text{CE}(\alpha)$ (14 models)

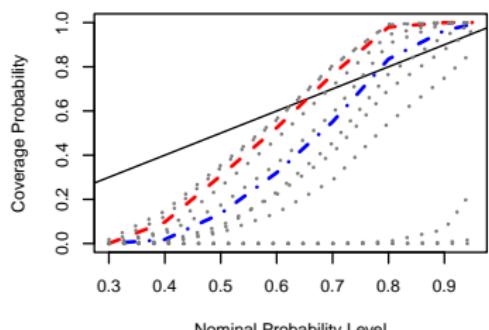
Analytical Method: $n=100$



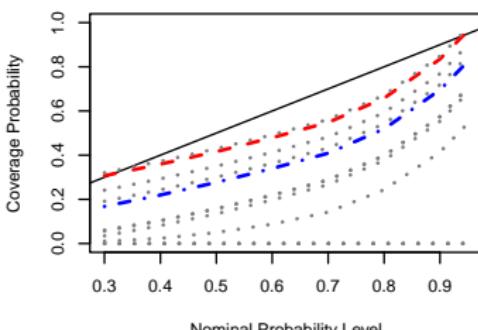
Analytical Method: $n=1000$



Bootstrap (semiparametric): $n=100$



Bootstrap (semiparametric): $n=1000$



- Observations: $(y_1, \mathbf{x}_1), \dots, (y_n, \mathbf{x}_n) \sim Y|\mathbf{x}$, in GLM setup.
- Closely parallels iid case; main modification is that:

$$y \mapsto y|\mathbf{x}$$

- X_j is GIC for j -th candidate model.
- Under Lindeberg-Feller regularity conditions have analogous asymptotics:

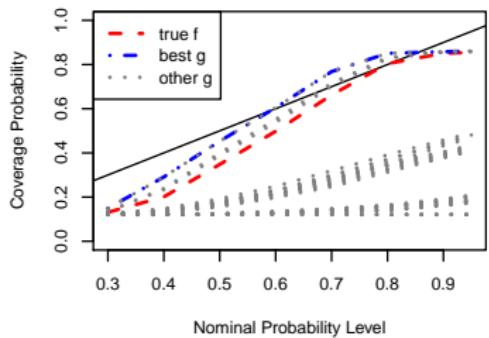
$$\sqrt{n} \begin{pmatrix} X_j - \Delta(\boldsymbol{\theta}_0^{(j)}) \\ X_k - \Delta(\boldsymbol{\theta}_0^{(k)}) \end{pmatrix} \xrightarrow{d} \mathcal{N}(\mathbf{0}, \Lambda),$$

with

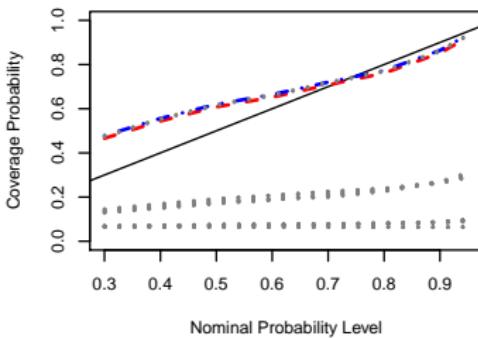
$$\lambda_{j,k} = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \text{Cov}_F \left(\log g^{(j)}(Y|\mathbf{x}_i; \boldsymbol{\theta}_0^{(j)}), \log g^{(k)}(Y|\mathbf{x}_i; \boldsymbol{\theta}_0^{(k)}) \right).$$

Regression Case Simulations: Coverages of $\text{CE}(\alpha)$ (5 predictors, all subset models)

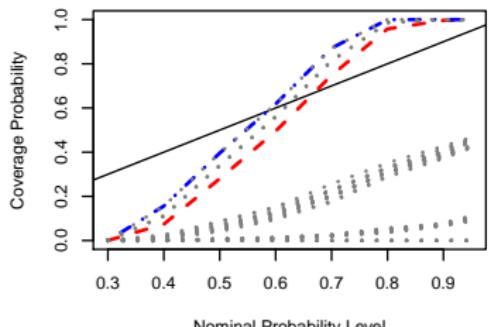
Analytical Method: $n=100$



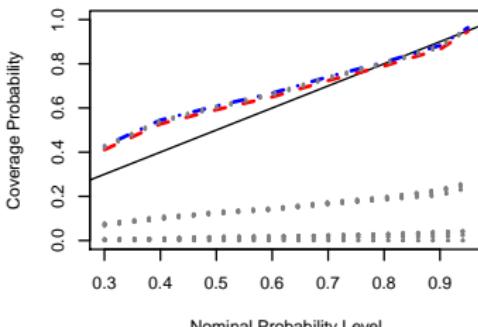
Analytical Method: $n=1000$



Bootstrap (semiparametric): $n=100$



Bootstrap (semiparametric): $n=1000$



- **Observations:** $y_1, \dots, y_n \sim Y \sim f$, an ARMA(p, q) model with:

$$\Sigma(\theta) = \text{ACVF matrix.}$$

- Candidate models: $\{g_\theta\}$, where $\theta = (\phi_1, \dots, \phi_p, \psi_1, \dots, \psi_q, \sigma)^\top$.
- (Gaussian) log-likelihood for g_θ is:

$$\ell_n(\theta) = -\frac{1}{2} \log |\Gamma(\theta)| - \frac{1}{2} \mathbf{y}^\top \Gamma^{-1}(\theta) \mathbf{y}, \quad \Gamma(\theta) = \text{ACVF matrix.}$$

- **KL discrepancy:** between f and g_θ

$$\Delta_n(\hat{\theta}) = \frac{1}{n} \log |\Gamma(\hat{\theta})| + Q_n(\hat{\theta}), \quad Q_n(\hat{\theta}) = \frac{1}{n} \mathbf{y}^\top \Gamma^{-1}(\hat{\theta}) \mathbf{y}$$

- Since $\log |\Gamma(\hat{\theta})|/n \xrightarrow{P} 0$, just need to focus on $QF = Q_n(\hat{\theta}) \dots$

Under mild regularity conditions (Mikosch, 1991) we have:

Theorem

$$\sqrt{n} \begin{pmatrix} Q_n(\hat{\theta}^{(j)}) - \Delta(\theta_0^{(j)}) \\ Q_n(\hat{\theta}^{(k)}) - \Delta(\theta_0^{(k)}) \end{pmatrix} \xrightarrow{d} \mathcal{N}(0, \Lambda)$$

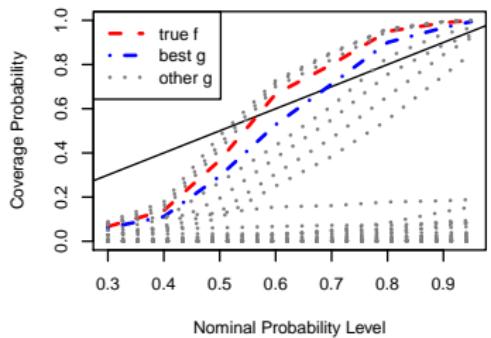
where (j, k) -th element of Λ is given by:

$$\lambda_{j,k} = \frac{2}{n} \text{Tr} \left(\Sigma(\theta_0) \Gamma_j^{-1}(\theta_0^{(j)}) \Sigma(\theta_0) \Gamma_k^{-1}(\theta_0^{(k)}) \right).$$

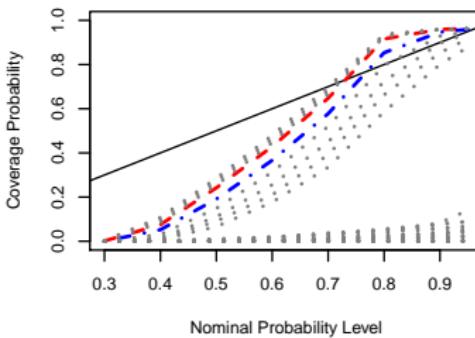
- **Problem:** must identify $f \leftrightarrow \Sigma(\theta)$ to estimate $\Lambda!!!$
- **Solution:** Identify f with lowest GIC model...

Time Series Case Simulations: Coverages of $\text{CE}(\alpha)$ ($f \sim \text{AR}(1)$, $g \sim \text{ARMA}(p, q)$)

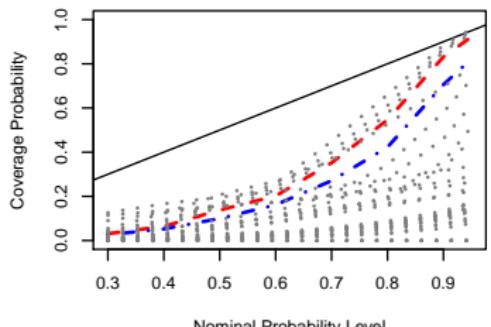
Analytical Method: $n=100$



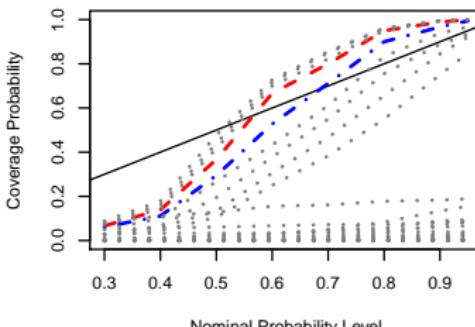
Analytical Method: $n=1000$



Bootstrap (nonparametric): $n=100$



Bootstrap (nonparametric): $n=1000$



Revisit: Models for Groundbeef Serving Sizes

Rank	AIC	Model	Confidence Envelope (Quantile)
1	4.9354	Gamma3	
2	4.9355	Gamma	50% (4.9365)
3	4.9374	Burr	
4	4.9418	Weibull	
5	4.9418	Weibull3	
6	4.9438	Gumbel	60% (4.9463), 70% (4.9561)
7	4.9631	LogNormal3	80% (4.9658)
8	4.9658	Lognormal	
9	4.9695	Logistic3	
10	4.9706	Logistic	
11	4.9776	Inverse Gaussian	90% (4.9854), 95% (5.0037)
12	5.0532	Kappa	
13	5.1380	Gpareto	
14	7.1821	F	

Revisit: Regression Models for Strength of Concrete

Rank	BIC	Model	Confidence Envelope (Quantile)
1	7.5703	{123458}	50% (7.5705)
2	7.5714	{12348}	
3	7.5766	{1234568}	60% (7.5723), 70% (7.5742), 80% (7.5754)
4	7.5767	{123478}	
5	7.5768	{1234578}	90% (7.5772)
6	7.5779	{123468}	95% (7.5790)
7	7.5799	{12345678}	
8	7.5827	{1234678}	
9	7.5867	{1235678}	
10	7.6142	{123678}	

Revisit: Models for Wolfer Sunspot Numbers

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19	841.7189501	$ARMA(12, 0)$	
20	842.4678861	$ARMA(3, 3)$	

- Pivot cdf of minimum GIC to do PMSI...
- Ex: $f \sim \text{Gamma}(1, b)$ and $g \sim \text{Gamma}(2, \beta)$.
- Let: $\hat{x} = \text{observed min GIC}$; $\hat{\beta} = \text{MLE of } \beta$.
- $(1 - \alpha)100\%$ CI for b : solve for b_L & b_U in:

$$F_{X_{(1)}}(\hat{x}; b_L, \hat{\beta}) = 1 - \frac{\alpha}{2}, \quad \text{and} \quad F_{X_{(1)}}(\hat{x}; b_U, \hat{\beta}) = \frac{\alpha}{2}.$$

- Compare with Wald CI: $\hat{b} \pm z_{1-\alpha/2} \hat{b}/\sqrt{n}$
- Simulations show (b_L, b_U) always wider!

Thank You!