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# The Extended Bayesian Information Criterion for Gaussian Graphical Models

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**Rina Foygel**  
University of Chicago  
rina@uchicago.edu

**Mathias Drton**  
University of Chicago  
drton@uchicago.edu

## A Supplementary materials

This document gives the proof for Lemma 1 in the main paper, and fills in the details of the proofs of Theorem 3 and Theorem 4 in the main paper.

**Lemma 1.** *For any  $\lambda \in (0, 1)$ , for any  $n \geq 4\lambda^{-2} + 1$ ,*

$$P\{\chi_n^2 < n(1 - \lambda)\} \leq \frac{1}{\lambda\sqrt{\pi(n-1)}} e^{-\frac{n-1}{2}(\lambda - \log(1+\lambda))} .$$

*Remark 1.* We note that some lower bound on  $n$  is intuitively necessary in order to be able to bound the ‘left tail’, because the mode of the  $\chi_n^2$  distribution is at  $x = n - 2$  (for  $n \geq 2$ ). If  $\lambda$  is very close to zero, then the ‘left tail’ ( $\chi_n^2 \in [0, n(1 - \lambda)]$ ) actually includes the mode  $x = n - 2 \leq n(1 - \lambda)$ ; therefore, we could not hope to get an exponentially small probability for being in the tail. However, this intuitive explanation suggests that we should have  $n \geq \mathbf{O}(\lambda^{-1})$ ; perhaps the bound in this lemma could be tightened.

We first prove a preliminary lemma:

**Lemma A.1.** *For any  $\lambda > 0$ , for any  $n \geq 4\lambda^{-2} + 1$ ,*

$$P\{\chi_{n+1}^2 < (n+1)(1 - \lambda)\} \leq P\{\chi_n^2 \leq n(1 - \lambda)\} .$$

*Proof.* Let  $f_n$  denote the density function for  $\chi_n^2$ , and let  $\tilde{f}_n$  denote the density function for  $\frac{1}{n}\chi_n^2$ . Then, using  $y = x/n$ , we get:

$$f_n(x) = \frac{1}{2^{n/2}\Gamma(n/2)} x^{n/2-1} e^{-x/2} \Rightarrow \tilde{f}_n(y) = \frac{1}{2^{n/2}\Gamma(n/2)} y^{n/2-1} e^{-ny/2} n^{n/2} .$$

So,

$$\tilde{f}_{n+1}(y) = \tilde{f}_n(y) \times \left[ \sqrt{\frac{n+1}{2}} \frac{\Gamma(n/2)}{\Gamma((n+1)/2)} \left(\frac{n+1}{n}\right)^{n/2} \sqrt{ye^{-y}} \right] .$$

First, note that  $ye^{-y}$  is an increasing function for  $y < 1$ , and therefore

$$y \in [0, 1 - \lambda] \Rightarrow ye^{-y} \leq (1 - \lambda)e^{-(1-\lambda)} \leq e^{-1} \left(1 - \frac{\lambda^2}{2}\right) .$$

(Here the last inequality is from the Taylor series). Next, since  $\log \Gamma(x)$  is a convex function (where  $x > 0$ ), and since  $\Gamma((n+1)/2) = \Gamma((n-1)/2) \times \frac{n-1}{2}$ , we see that

$$\frac{\Gamma((n+1)/2)}{\Gamma(n/2)} \geq \sqrt{\frac{n-1}{2}} .$$

Finally, it is a fact that  $(1 + \frac{1}{n})^n \leq e$ . Putting the above bounds together, and assuming that  $y \in [0, 1 - \lambda]$ , we obtain

$$\tilde{f}_{n+1}(y) \leq \tilde{f}_n(y) \times \left[ \sqrt{\frac{n+1}{2}} \sqrt{\frac{2}{n-1}} \sqrt{e} \sqrt{e^{-1} \left(1 - \frac{\lambda^2}{2}\right)} \right]$$

$$= \tilde{f}_n(y) \times \left[ \sqrt{\frac{n+1}{n-1}} \sqrt{1 - \frac{\lambda^2}{2}} \right] .$$

Since we require  $n \geq 4\lambda^{-2} + 1$ , the quantity in the brackets is at most 1, and so

$$\tilde{f}_{n+1}(y) \leq \tilde{f}_n(y) \quad \forall y \in [0, 1 - \lambda] .$$

Therefore,

$$P \left\{ \frac{1}{n+1} \chi_{n+1}^2 < (1 - \lambda) \right\} \leq P \left\{ \frac{1}{n} \chi_n^2 < (1 - \lambda) \right\} .$$

□

Now we prove Lemma 1.

*Proof.* First suppose that  $n$  is even. Let  $f_n$  denote the density function of the  $\chi_n^2$  distribution. From Cai [10] (as cited in the paper), if  $n > 2$ ,

$$P\{\chi_n^2 < x\} = 1 - 2f_n(x) - P\{\chi_{n-2}^2 > x\} = -2f_n(x) + P\{\chi_{n-2}^2 < x\} .$$

Iterating this identity, we get

$$\begin{aligned} P\{\chi_n^2 < x\} &= P\{\chi_2^2 < x\} - 2f_n(x) - 2f_{n-2}(x) - \cdots - 2f_4(x) \\ &= 1 - e^{-\frac{x}{2}} - 2 \sum_{k=1}^{n/2-1} f_{2k+2}(x) \\ &= 1 - e^{-\frac{x}{2}} - 2 \sum_{k=1}^{n/2-1} \frac{1}{2^{k+1} \Gamma(k+1)} x^k e^{-\frac{x}{2}} \\ &= 1 - e^{-\frac{x}{2}} \left( \sum_{k=0}^{n/2-1} \frac{1}{2^k k!} x^k \right) \\ &= 1 - e^{-\frac{x}{2}} \left( \sum_{k=0}^{\infty} \frac{(x/2)^k}{k!} - \sum_{k=n/2}^{\infty} \frac{(x/2)^k}{k!} \right) \\ &= 1 - e^{-\frac{x}{2}} \left( e^{\frac{x}{2}} - \sum_{k=n/2}^{\infty} \frac{(x/2)^k}{k!} \right) \\ &= e^{-\frac{x}{2}} \sum_{k=n/2}^{\infty} \frac{(x/2)^k}{k!} . \end{aligned}$$

Now set  $x = n(1 - \lambda)$  for  $\lambda \in (0, 1)$ . We obtain

$$\begin{aligned} P\{\chi_n^2 < x\} &= e^{-\frac{n(1-\lambda)}{2}} \sum_{k=n/2}^{\infty} \frac{(n(1-\lambda)/2)^k}{k!} \\ &\leq e^{-\frac{n(1-\lambda)}{2}} \frac{(n/2)^{n/2}}{(n/2)!} \sum_{k=n/2}^{\infty} (1 - \lambda)^k \\ &= e^{-\frac{n(1-\lambda)}{2}} \frac{(n/2)^{n/2}}{(n/2)!} \frac{(1 - \lambda)^{n/2}}{\lambda} . \end{aligned}$$

By Stirling's formula,

$$\frac{(n/2)^{n/2}}{(n/2)!} \leq \frac{e^{\frac{n}{2}}}{\sqrt{\pi n}} ,$$

and so,

$$P\{\chi_n^2 < n(1-\lambda)\} \leq e^{-\frac{n(1-\lambda)}{2}} \frac{e^{\frac{n}{2}}}{\sqrt{\pi n}} \frac{(1-\lambda)^{n/2}}{\lambda} = \frac{1}{\lambda\sqrt{\pi n}} e^{\frac{n}{2}(\lambda+\log(1-\lambda))} .$$

This is clearly sufficient to prove the desired bound in the case that  $n$  is even. Next we turn to the odd case; let  $n$  be odd. First observe that if  $\lambda > 1$ , the statement is trivial, while if  $\lambda \leq 1$ , then  $n \geq 4\lambda^{-2} + 1 \geq 5$ , therefore  $n-1$  is positive. By Lemma A.1 and the expression above,

$$P\{\chi_n^2 < n(1-\lambda)\} \leq P\{\chi_{n-1}^2 \leq (n-1)(1-\lambda)\} \leq \frac{1}{\lambda\sqrt{\pi(n-1)}} e^{\frac{n-1}{2}(\lambda+\log(1-\lambda))} .$$

□

Next we turn to the theorems in the paper. Recall the assumptions made in the paper: we assume the following, where  $\epsilon_0, \epsilon_1 > 0$ ,  $C \geq \sigma_{max}^2 \lambda_{max}$ ,  $\kappa = \log_n p$ , and  $\gamma_0 = \gamma - (1 - \frac{1}{4\kappa})$ :

$$\frac{(p+2q)\log p}{n} \times \frac{\lambda_{max}^2}{\theta_0^2} \leq \frac{1}{3200 \max\{1+\gamma_0, (1+\frac{\epsilon_1}{2})C^2\}} , \quad (1)$$

$$2(\sqrt{1+\gamma_0}-1) - \frac{\log \log p + \log(4\sqrt{1+\gamma_0}) + 1}{2 \log p} \geq \epsilon_0 . \quad (2)$$

Lemmas A.2 and A.3 below are sufficient to fill in the details of Theorem 3 in the paper.

**Lemma A.2.** *With probability at least  $1 - \frac{1}{\sqrt{\pi \log p}} e^{-\epsilon_1 \log p}$ , the following holds for all edges  $\mathbf{e}$  in the complete graph:*

$$(s_n(\Theta_0))_{\mathbf{e}}^2 \leq 6\sigma_{max}^4(2+\epsilon_1)n \log p .$$

*Proof.* Fix some edge  $\mathbf{e} = \{j, k\}$ . Then

$$(s_n(\Theta_0))_{(j,k)} = \frac{n}{2}(\Sigma_0)_{jk} - \frac{1}{2}X_j^T X_k = -\frac{1}{2} \sum_{i=1}^n ((X_j)_i (X_k)_i - (\Sigma_0)_{jk}) .$$

Write  $Y_j = ((\Sigma_0)_{jj})^{-1} X_j$ ,  $Y_k = ((\Sigma_0)_{kk})^{-1} X_k$ ,  $\rho = ((\Sigma_0)_{jj}(\Sigma_0)_{kk})^{-1}(\Sigma_0)_{jk} = \text{corr}(Y_j, Y_k)$ . Then

$$(s_n(\Theta_0))_{(j,k)} = -\frac{1}{2}(\Sigma_0)_{jj}(\Sigma_0)_{kk} \sum_{i=1}^n ((Y_j)_i (Y_k)_i - \rho) .$$

By Lemma 2 in the paper, there are some independent  $A, B \sim \chi_n^2$  such that

$$(s_n(\Theta_0))_{(j,k)} = -\frac{1}{2}(\Sigma_0)_{jj}(\Sigma_0)_{kk} \left[ \left( \frac{1+\rho}{2} \right) (A-n) - \left( \frac{1-\rho}{2} \right) (B-n) \right] .$$

There are  $\binom{p}{2} \leq \frac{1}{2}p^2$  edges in the complete graph. Therefore, by the union bound, it will suffice to show that, with probability at least  $1 - (\frac{1}{2}p^2)^{-1} \frac{1}{\sqrt{\pi \log p}} e^{-\epsilon_1 \log p}$ ,

$$\frac{1}{4}\sigma_{max}^4 \left[ \left( \frac{1+\rho}{2} \right) (A-n) - \left( \frac{1-\rho}{2} \right) (B-n) \right]^2 \leq 6\sigma_{max}^4(2+\epsilon_1)n \log p .$$

Suppose this bound does not hold. Then

$$\left| \left( \frac{1+\rho}{2} \right) (A-n) \right| > \sqrt{6(2+\epsilon_1)n \log p} \text{ or } \left| \left( \frac{1-\rho}{2} \right) (B-n) \right| > \sqrt{6(2+\epsilon_1)n \log p} .$$

Since  $\rho \in [-1, 1]$ , this implies that

$$|A-n| > \sqrt{6(2+\epsilon_1)n \log p} \text{ or } |B-n| > \sqrt{6(2+\epsilon_1)n \log p} .$$

Since  $A \stackrel{\mathcal{D}}{=} B$ , it will suffice to show that with probability at least  $1 - p^{-2} \frac{1}{\sqrt{\pi \log p}} e^{-\epsilon_1 \log p}$ ,

$$|A-n| \leq \sqrt{6(2+\epsilon_1)n \log p} .$$

Write  $\lambda = \sqrt{6(2 + \epsilon_1) \frac{\log p}{n}}$ . Observe that, by assumption (1),  $\lambda \leq \frac{1}{2}$  and  $n \geq 3$ ; therefore (by Taylor series),

$$\begin{aligned} \frac{n}{2}(\lambda - \log(1 + \lambda)) &\geq \frac{n}{2} \left( \frac{\lambda^2}{2} - \frac{\lambda^3}{3} \right) \geq \frac{n}{2} \cdot \frac{\lambda^2}{3} = (2 + \epsilon_1) \log p, \text{ and} \\ -\frac{n-1}{2}(\lambda + \log(1 - \lambda)) &\geq \frac{n-1}{2} \left( \frac{\lambda^2}{2} \right) \geq \frac{n}{2} \cdot \frac{\lambda^2}{3} = (2 + \epsilon_1) \log p. \end{aligned}$$

Furthermore,

$$\lambda \sqrt{n-1} = \sqrt{6(2 + \epsilon_1) \log p \times \frac{n-1}{n}} \geq \sqrt{\log p}.$$

By (CSB) from the paper,

$$\begin{aligned} P\{A - n > \sqrt{6(2 + \epsilon_1)n \log p}\} &= P\{A > n(1 + \lambda)\} \leq \frac{1}{\lambda \sqrt{\pi n}} e^{-\frac{n}{2}(\lambda - \log(1 + \lambda))} \\ &\leq \frac{1}{\lambda \sqrt{\pi(n-1)}} e^{-(2 + \epsilon_1) \log p} \leq \frac{1}{\sqrt{\pi \log p}} e^{-(2 + \epsilon_1) \log p}, \end{aligned}$$

and also,

$$\begin{aligned} P\{A - n < -\sqrt{6(2 + \epsilon_1)n \log p}\} &= P\{A < n(1 - \lambda)\} \leq \frac{1}{\lambda \sqrt{\pi(n-1)}} e^{\frac{n-1}{2}(\lambda + \log(1 - \lambda))} \\ &\leq \frac{1}{\lambda \sqrt{\pi(n-1)}} e^{-(2 + \epsilon_1) \log p} \leq \frac{1}{\sqrt{\pi \log p}} e^{-(2 + \epsilon_1) \log p}. \end{aligned}$$

This gives the desired result.  $\square$

**Lemma A.3.** Recall that, in the proof of Theorem 3 in the paper, we showed that

$$l_n(\Theta) - l_n(\Theta_0) \leq \sqrt{\theta_0^2(p + 2q) \times 6\sigma_{max}^4(2 + \epsilon_1)n \log p} - \frac{1}{2}\theta_0^2 \times \frac{n}{2}(2\lambda_{max})^{-2}.$$

Then this implies that

$$l_n(\Theta) - l_n(\Theta_0) \leq -2q(\log p)(1 + \gamma_0).$$

*Proof.* It is sufficient to show that

$$\sqrt{\theta_0^2(p + 2q) \times 6\sigma_{max}^4(2 + \epsilon_1)n \log p} - \frac{1}{2}\theta_0^2 \times \frac{n}{2}(2\lambda_{max})^{-2} \leq -(p + 2q)(\log p)(1 + \gamma_0).$$

We rewrite this as

$$\sqrt{A \times n^2 \theta_0^4 \lambda_{max}^{-2} 6\sigma_{max}^4(2 + \epsilon_1)} - \frac{1}{2}\theta_0^2 \times \frac{n}{2}(2\lambda_{max})^{-2} \leq -A \times n \times \theta_0^2 \lambda_{max}^{-2} (1 + \gamma_0),$$

where

$$A = \frac{(p + 2q) \log p}{n} \times \frac{\lambda_{max}^2}{\theta_0^2}.$$

Using  $C \geq \sigma_{max}^2 \lambda_{max}$ , it's sufficient to show that

$$\sqrt{A \times n^2 \theta_0^4 \lambda_{max}^{-4} 6C^2(2 + \epsilon_1)} - \frac{1}{2}\theta_0^2 \times \frac{n}{2}(2\lambda_{max})^{-2} \leq -A \times n \times \theta_0^2 \lambda_{max}^{-2} (1 + \gamma_0).$$

Dividing out common factors, the above is equivalent to showing that

$$\sqrt{A \times 6C^2(2 + \epsilon_1)} - \frac{1}{16} \leq -A \times (1 + \gamma_0).$$

By assumption (1), we know:

$$A \times (1 + \gamma_0) \leq \frac{1}{3200},$$

and also,

$$A \times 6C^2(2 + \epsilon_1) \leq 12 \times \frac{1}{3200}.$$

Therefore,

$$A \times (1 + \gamma_0) + \sqrt{A \times 6C^2(2 + \epsilon_1)} \leq \frac{1}{3200} + \sqrt{\frac{12}{3200}} < \frac{1}{16},$$

as desired.  $\square$

Lemma A.4 below is sufficient to fill in the details of Theorem 4 in the paper.

**Lemma A.4.** *Recall that, in the proof of Theorem 4 in the paper, we showed that, stochastically,*

$$l_n(\hat{\Theta}(\mathbf{s})) - l_n(\hat{\Theta}(\mathbf{s}_0)) \leq \frac{n}{2} \times \frac{1}{n - \sqrt{2q} - 1} \chi_m^2 .$$

*Then this implies that*

$$P\{l_n(\hat{\Theta}(\mathbf{s})) - l_n(\hat{\Theta}(\mathbf{s}_0)) \geq 2(1 + \gamma_0)m \log(p)\} \leq \frac{1}{4\sqrt{\pi} \log p} e^{-\frac{m}{2} (4(1 + \frac{\epsilon_0}{2}) \log p)} .$$

*Proof.* First, we show that  $\frac{n - \sqrt{2q} - 1}{n} \geq (1 + \gamma_0)^{-\frac{1}{2}}$ . By assumption (2) we see that:

$$\frac{1}{\log p} \leq 4(\sqrt{1 + \gamma_0} - 1) .$$

Now turn to assumption (1). We see that the right-hand side of (1) is  $\leq \frac{1}{4\sqrt{1 + \gamma_0}}$ . On the left-hand side of (1), by definition,  $\lambda_{max}^2 \geq \theta_0^2$ . Therefore,

$$\frac{(p + 2q) \log p}{n} \leq \frac{1}{4\sqrt{1 + \gamma_0}} .$$

Therefore,

$$\frac{\sqrt{2q} + 1}{n} \leq \frac{p + 2q}{n} \leq \frac{4(\sqrt{1 + \gamma_0} - 1)}{4\sqrt{1 + \gamma_0}} = 1 - \frac{1}{\sqrt{1 + \gamma_0}} ,$$

and so,

$$\frac{n - \sqrt{2q} - 1}{n} \geq (1 + \gamma_0)^{-\frac{1}{2}} .$$

Therefore, using the stochastic inequality in the statement in the lemma,

$$\begin{aligned} P\{l_n(\hat{\Theta}(\mathbf{s})) - l_n(\hat{\Theta}(\mathbf{s}_0)) &\geq 2(1 + \gamma_0)m \log(p)\} \\ &\leq P\{\chi_m^2 \geq 4(1 + \gamma_0)m \log p \times \frac{n - \sqrt{2q} - 1}{n}\} \\ &\leq P\{\chi_m^2 \geq 4\sqrt{1 + \gamma_0}m \log p\} . \end{aligned}$$

Now we apply Cai's [10] (CSB) as cited in the paper, and obtain that

$$P\{\chi_m^2 \geq 4\sqrt{1 + \gamma_0}m \log p\} \leq \frac{1}{(4\sqrt{1 + \gamma_0} \log p - 1)\sqrt{\pi m}} e^{-\frac{m}{2} (4\sqrt{1 + \gamma_0} \log p - 1 - \log(4\sqrt{1 + \gamma_0} \log p))} .$$

Since  $m \geq 1$  and  $\frac{1}{\log p} \leq 4(\sqrt{1 + \gamma_0} - 1)$ , we obtain that the upper bound is at most

$$\begin{aligned} &\frac{1}{4\sqrt{\pi} \log p} e^{-\frac{m}{2} (4\sqrt{1 + \gamma_0} \log p - 1 - \log(4\sqrt{1 + \gamma_0} \log p))} \\ &= \frac{1}{4\sqrt{\pi} \log p} e^{-\frac{m}{2} (4\sqrt{1 + \gamma_0} \log p - (\log \log p + \log(4\sqrt{1 + \gamma_0}) + 1))} \\ &= \frac{1}{4\sqrt{\pi} \log p} e^{-\frac{m}{2} (2 \log p) (2\sqrt{1 + \gamma_0} - (\log \log p + \log(4\sqrt{1 + \gamma_0}) + 1) / (2 \log p))} . \end{aligned}$$

By assumption (2), we may further bound this expression from above as

$$\frac{1}{4\sqrt{\pi} \log p} e^{-\frac{m}{2} (2 \log p) (2 + \epsilon_0)} = \frac{1}{4\sqrt{\pi} \log p} e^{-\frac{m}{2} 4(1 + \frac{\epsilon_0}{2}) \log p} .$$

□