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# Branch and Bound for Regular Bayesian Network Structure Learning: Supplementary Material

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Joe Suzuki\* and Jun Kawahara†

\* Osaka University, Japan. j-suzuki@sigmath.es.osaka-u.ac.jp

† Nara Institute of Science and Technology, Japan. jkawahara@is.naist.ac.jp

## Appendix A

Under  $c_n(x, y) = c_n(y)$  for each  $(x, y)$ , we have

$$\begin{aligned}
& Q^n(X|Y) \geq Q^n(X|YZ) \\
\iff & \frac{\Gamma(\frac{\alpha\beta}{2})}{\Gamma(n + \frac{\alpha\beta}{2})} \prod_{x,y} \frac{\Gamma(c_n(x, y) + \frac{1}{2})}{\Gamma(\frac{1}{2})} \cdot \frac{\Gamma(\frac{\beta\gamma}{2})}{\Gamma(n + \frac{\beta\gamma}{2})} \\
& \cdot \prod_{y,z} \frac{\Gamma(c_n(y, z) + \frac{1}{2})}{\Gamma(\frac{1}{2})} \\
& \geq \frac{\Gamma(\frac{\alpha\beta\gamma}{2})}{\Gamma(n + \frac{\alpha\beta\gamma}{2})} \prod_{x,y,z} \frac{\Gamma(c_n(x, y, z) + \frac{1}{2})}{\Gamma(\frac{1}{2})} \\
& \cdot \frac{\Gamma(\frac{\beta}{2})}{\Gamma(n + \frac{\beta}{2})} \prod_y \frac{\Gamma(c_n(y) + \frac{1}{2})}{\Gamma(\frac{1}{2})} \\
\iff & \frac{\Gamma(\frac{\alpha\beta}{2})}{\Gamma(n + \frac{\alpha\beta}{2})} \cdot \frac{\Gamma(\frac{\beta\gamma}{2})}{\Gamma(n + \frac{\beta\gamma}{2})} \\
& \geq \frac{\Gamma(\frac{\alpha\beta\gamma}{2})}{\Gamma(n + \frac{\alpha\beta\gamma}{2})} \cdot \frac{\Gamma(\frac{\beta}{2})}{\Gamma(n + \frac{\beta}{2})}.
\end{aligned}$$

The last inequality can be proved using induction w.r.t.  $n$ , which completes the proof.

## Appendix B

From Stirling's formula  $\log \Gamma(z) = z \log z - z + \frac{1}{2} \log \frac{2\pi}{z} + \epsilon(z)$  with  $\frac{1}{12z} < \epsilon(z) < \frac{1}{12z+1}$ , we have for  $\beta = \sigma(S)$

$$\begin{aligned}
& \log \Gamma(n + \frac{\alpha\beta}{2}) - \log \Gamma(n + \frac{\beta}{2}) \\
= & -(n + \frac{\beta}{2}) \log(n + \frac{\beta}{2}) + (n + \frac{\beta}{2}) - \frac{1}{2} \log \frac{2\pi}{n + \frac{\beta}{2}} \\
& + (n + \frac{\alpha\beta}{2}) \log(n + \frac{\alpha\beta}{2}) - (n + \frac{\alpha\beta}{2}) \\
& + \frac{1}{2} \log \frac{2\pi}{n + \frac{\alpha\beta}{2}} + O(\frac{1}{n})
\end{aligned}$$

$$\begin{aligned}
= & -n \log \frac{n + \frac{\beta}{2}}{n + \frac{\alpha\beta}{2}} - \frac{\beta}{2} \log(n + \frac{\beta}{2}) \\
& + \frac{\alpha\beta}{2} \log(n + \frac{\alpha\beta}{2}) - \frac{1}{2} \log(n + \frac{\alpha\beta}{2}) \\
& + \frac{1}{2} \log(n + \frac{\beta}{2}) - \frac{\alpha\beta - \beta}{2} + O(\frac{1}{n}) \\
= & \frac{(\alpha - 1)\beta}{2} \log n + O(\frac{1}{n}),
\end{aligned}$$

which means

$$\begin{aligned}
& -\log \left\{ \prod_{i=1}^n \frac{i - 1 + 0.5\beta}{i - 1 + 0.5\alpha\beta} \right\} \\
= & \log \frac{\Gamma(n + \frac{\alpha\beta}{2}) \Gamma(\frac{\beta}{2})}{\Gamma(n + \frac{\beta}{2}) \Gamma(\frac{\alpha\beta}{2})} \\
= & \frac{(\alpha - 1)\beta}{2} \log n + \log \frac{\Gamma(\frac{\beta}{2})}{\Gamma(\frac{\alpha\beta}{2})} + O(\frac{1}{n}).
\end{aligned}$$

For the second statement, from

$$\begin{aligned}
& \log \Gamma(c_n(x, s) + \frac{1}{2}) \\
= & c_n(x, s) \log \{c_n(x, s) + \frac{1}{2}\} - \{c_n(x, s) + \frac{1}{2}\} \\
& + \frac{1}{2} \log(2\pi) \\
= & c_n(x, s) \log c_n(x, s) - c_n(x, s) + O(\frac{1}{c_n(x, s)})
\end{aligned}$$

and

$$\log \Gamma(c_n(s) + \frac{1}{2}) = c_n(s) \log c_n(s) - c_n(s) + O(\frac{1}{c_n(s)}),$$

we have

$$\begin{aligned}
& -\log \left\{ \prod_{i=1}^n \frac{c_{i-1}(x_i, s_i) + 0.5}{c_{i-1}(s_i) + 0.5} \right\} \\
= & -\log \prod_s \left\{ \frac{\prod_x \Gamma(c_n(x, s) + \frac{1}{2})}{\Gamma(c_n(s) + \frac{1}{2})} \right\}
\end{aligned}$$

$$\begin{aligned}
&= -\sum_s \sum_x c_n(x, s) \log \frac{c_n(x, s)}{c_n(s)} + O(1) \\
&= -n \sum_s \frac{c_n(s)}{n} \sum_x \frac{c_n(x, s)}{c_n(s)} \log \frac{c_n(x, s)}{c_n(s)} + O(1).
\end{aligned}$$

Since  $H(X|S) = -\sum_s \frac{c_n(s)}{n} \sum_x \frac{c_n(x, s)}{c_n(s)} \log \frac{c_n(x, s)}{c_n(s)}$ , this completes the proof.