Supplement to the paper "Accurate distributions of Mallows' Cp and its unbiased modifications with applications to shrinkage estimation"

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This article supplements Ogasawara (2017).

Proof of Theorem 1

Since

$$\mathbf{C}_{pq} = (n - p_{\Omega}) \operatorname{tr}(\mathbf{U}_{\Omega}^{-1}\mathbf{U}) - nq + 2pq$$

$$= (n - p_{\Omega}) \operatorname{tr}(\mathbf{I}_{(q)} + \mathbf{U}_{\Omega}^{-1}\mathbf{U}_{p|\Omega}) - nq + 2pq$$
and
$$\mathbf{E}(\mathbf{\Sigma}_{0}^{1/2}\mathbf{U}_{\Omega}^{-1}\mathbf{U}_{p|\Omega}\mathbf{\Sigma}_{0}^{-1/2} \mid \mathbf{\Lambda} = \mathbf{O}) = \frac{p_{\Omega} - p}{n - p_{\Omega} - q - 1}\mathbf{I}_{(q)}$$
(A.1)

(see e.g. Siotani, Hayakawa & Fujikoshi, 1985, Equation (2.4.11)), we have

$$E(C_{pq} | \mathbf{\Lambda} = \mathbf{O}) = (n - p_{\Omega}) \left(1 + \frac{p_{\Omega} - p}{n - p_{\Omega} - q - 1} \right) q - nq + 2pq$$

$$= -p_{\Omega}q + 2pq + \frac{(n - p_{\Omega})(p_{\Omega} - p)q}{n - p_{\Omega} - q - 1} = pq + \frac{q(q + 1)(p_{\Omega} - p)}{n - p_{\Omega} - q - 1}.$$

When $\Lambda = \mathbf{O}$, $E(GD_{pq}) = pq$, which gives from the above result

$$E(\overline{C}_{pq}) - E(GD_{pq}) = E(C_{pq}) - \frac{q(q+1)(p_{\Omega} - p)}{n - p_{\Omega} - q - 1} - pq = 0$$

Proof of Theorem 2

The expectations in (3.4) are given by (2.2), (2.4), (2.5) and (2.6) for $\mathbf{\Lambda} = \mathbf{O}$. For the variances of (3.4), noting that under normality \mathbf{U}_{Ω}^{-1} and $\mathbf{U}_{p|\Omega}$ are independent, the following result will be used when X_i is independent of Y_j (i, j = 1, 2):

$$\begin{aligned} & \operatorname{cov}(X_{1}Y_{1}, X_{2}Y_{2}) = \operatorname{E}(X_{1}Y_{1}X_{2}Y_{2}) - \operatorname{E}(X_{1}Y_{1})\operatorname{E}(X_{2}Y_{2}) \\ & = \operatorname{E}(X_{1}X_{2})\operatorname{E}(Y_{1}Y_{2}) - \operatorname{E}(X_{1})\operatorname{E}(Y_{1})\operatorname{E}(X_{2})\operatorname{E}(Y_{2}) \\ & = \left\{\operatorname{cov}(X_{1}, X_{2}) + \operatorname{E}(X_{1})\operatorname{E}(X_{2})\right\} \left\{\operatorname{cov}(Y_{1}, Y_{2}) + \operatorname{E}(Y_{1})\operatorname{E}(Y_{2})\right\} \\ & - \operatorname{E}(X_{1})\operatorname{E}(X_{2})\operatorname{E}(Y_{1})\operatorname{E}(Y_{2}) \\ & = \operatorname{cov}(X_{1}, X_{2})\operatorname{cov}(Y_{1}, Y_{2}) + \operatorname{E}(X_{1})\operatorname{E}(X_{2})\operatorname{cov}(Y_{1}, Y_{2}) \\ & + \operatorname{cov}(X_{1}, X_{2})\operatorname{E}(Y_{1})\operatorname{E}(Y_{2}). \end{aligned} \tag{A.2}$$

When $\Lambda = \mathbf{O}$, since $\mathbf{U}_{p|\Omega}^* \equiv \Sigma_0^{-1/2} \mathbf{U}_{p|\Omega} \Sigma_0^{-1/2}$ is Wishart-distributed with the covariance matrix $\mathbf{I}_{(n)}$ and $p_{\Omega} - p$ degrees of freedom, which is denoted by $\mathbf{W}(\mathbf{I}_{(n)}, p_{\Omega} - p)$, we have

$$cov\{(\mathbf{U}_{p|\Omega}^{*})_{ij},(\mathbf{U}_{p|\Omega}^{*})_{kl}\} = (p_{\Omega} - p)(\delta_{ik}\delta_{jl} + \delta_{il}\delta_{jk}) (i, j, k, l = 1, ..., q),$$

where $(\cdot)_{ij}$ indicates the (i, j)th element of a matrix and δ_{ik} is the Kronecker delta. On the other hand, $\mathbf{U}_{\Omega}^{*-1} \equiv \mathbf{\Sigma}_{0}^{1/2} \mathbf{U}_{\Omega}^{-1} \mathbf{\Sigma}_{0}^{1/2}$ is inverse-Wishart distributed as $\mathbf{W}^{-1}(\mathbf{I}_{(n)}, n - p_{\Omega})$ and

$$cov\{(\mathbf{U}_{\Omega}^{*-1})_{ij}, (\mathbf{U}_{\Omega}^{*-1})_{kl}\} = \frac{2\delta_{ij}\delta_{kl} + (n - p_{\Omega} - q - 1)(\delta_{ik}\delta_{jl} + \delta_{il}\delta_{jk})}{(n - p_{\Omega} - q)(n - p_{\Omega} - q - 1)^{2}(n - p_{\Omega} - q - 3)}$$

$$(i, j, k, l = 1, ..., q)$$
(A.3)

(see e.g. Siotani et al., 1985, Equation (2.4.12)).

From (A.2),

$$\operatorname{var}\left\{\operatorname{tr}(\mathbf{U}_{\Omega}^{-1}\mathbf{U}_{p|\Omega})\right\} = \operatorname{var}\left\{\operatorname{tr}(\mathbf{U}_{\Omega}^{*-1}\mathbf{U}_{p|\Omega}^{*})\right\}$$

$$= (p_{\Omega} - p)^{2} \operatorname{var}\left\{\sum_{i=1}^{q} (\mathbf{U}_{\Omega}^{*-1})_{ii}\right\} + (n - p_{\Omega} - q - 1)^{-2} \operatorname{var}\left\{\sum_{i=1}^{q} (\mathbf{U}_{p|\Omega}^{*})_{ii}\right\}$$

$$+ \sum_{i,j,k=1}^{q} \operatorname{cov}\left\{(\mathbf{U}_{\Omega}^{*-1})_{ij}, (\mathbf{U}_{\Omega}^{*-1})_{kl}\right\} \operatorname{cov}\left\{(\mathbf{U}_{p|\Omega}^{*})_{ij}, (\mathbf{U}_{p|\Omega}^{*})_{kl}\right\},$$

where

$$\operatorname{cov}\{(\mathbf{U}_{\Omega}^{*-1})_{ii},(\mathbf{U}_{\Omega}^{*-1})_{jj}\} = \frac{2 + 2(n - p_{\Omega} - q - 1)\delta_{ij}}{(n - p_{\Omega} - q)(n - p_{\Omega} - q - 1)^{2}(n - p_{\Omega} - q - 3)},$$

$$\operatorname{cov}\{(\mathbf{U}_{p|\Omega}^{*})_{ii},(\mathbf{U}_{p|\Omega}^{*})_{jj}\} = 2(p_{\Omega} - p)\delta_{ij} \quad (i, j = 1, ..., q).$$

Consequently,

$$\operatorname{var}\left\{\operatorname{tr}(\mathbf{U}_{\Omega}^{-1}\mathbf{U}_{p|\Omega})\right\}$$

$$\begin{split} &=(p_{\Omega}-p)^{2}\sum_{i,j=1}^{q}\frac{2+2(n-p_{\Omega}-q-1)\delta_{ij}}{(n-p_{\Omega}-q)(n-p_{\Omega}-q-1)^{2}(n-p_{\Omega}-q-3)}\\ &+(n-p_{\Omega}-q-1)^{-2}\sum_{i,j=1}^{q}2(p_{\Omega}-p)\delta_{ij}\\ &+\sum_{i,j,k,l=1}^{q}(p_{\Omega}-p)(\delta_{ik}\delta_{jl}+\delta_{il}\delta_{jk})\frac{2\delta_{ij}\delta_{kl}+(n-p_{\Omega}-q-1)(\delta_{ik}\delta_{jl}+\delta_{il}\delta_{jk})}{(n-p_{\Omega}-q)(n-p_{\Omega}-q-1)^{2}(n-p_{\Omega}-q-3)}\\ &=\frac{2(p_{\Omega}-p)^{2}\{q^{2}+q(n-p_{\Omega}-q-1)\}}{(n-p_{\Omega}-q)(n-p_{\Omega}-q-1)^{2}(n-p_{\Omega}-q-3)}+\frac{2(p_{\Omega}-p)q}{(n-p_{\Omega}-q-1)^{2}}\\ &+\frac{(p_{\Omega}-p)\{4q+2(n-p_{\Omega}-q-1)(q^{2}+q)\}}{(n-p_{\Omega}-q)(n-p_{\Omega}-q-1)^{2}(n-p_{\Omega}-q-3)}, \end{split}$$

which gives the variances in (3.4). Equation (A.4) is partially justified in that when q = 1, (A.4) with (3.3) gives the well-known variance

$$var(F) = \frac{2(n - p_{\Omega})^{2}(n - p - 2)}{(p_{\Omega} - p)(n - p_{\Omega} - 2)^{2}(n - p_{\Omega} - 4)}$$
(A.5)

of the central F distribution with $p_{\Omega} - p$ and $n - p_{\Omega}$ degrees of freedom.

Proof of Corollary 2

From (3.2) when q = 1,

$$C_{p} = (n - p_{\Omega}) \left(1 + \frac{p_{\Omega} - p}{n - p_{\Omega}} F^{*} \right) - n + 2p = (p_{\Omega} - p)F^{*} + 2p - p_{\Omega},$$

$$\bar{C}_{p} = C_{p} - \frac{2(p_{\Omega} - p)}{n - p_{\Omega} - 2} = (p_{\Omega} - p)F^{*} + 2p - p_{\Omega} - \frac{2(p_{\Omega} - p)}{n - p_{\Omega} - 2},$$

$$MC_{pq} = (p_{\Omega} - p)\frac{n - p_{\Omega} - 2}{n - p_{\Omega}} F^{*} + 2p - p_{\Omega}$$

$$\left(= \bar{C}_{p} + 2(p_{\Omega} - p) \left(\frac{1}{n - p_{\Omega} - 2} - \frac{F^{*}}{n - p_{\Omega}} \right) \right),$$
(A.6)

which yield the results of Corollary 2.

Proof of Corollary 3

The properties of the noncentral F distribution are well documented (e.g., Johnson, Kotz & Balakrishnan, 1994, Chapter 30). The expectation when $n > p_{\Omega} + 2$ and variance when $n > p_{\Omega} + 4$ for the noncentral F distribution denoted by F^* in Corollary 2 are

$$E(F^*) = \frac{(p_{\Omega} - p + \lambda)(n - p_{\Omega})}{(p_{\Omega} - p)(n - p_{\Omega} - 2)},$$

$$var(F^*) = 2\left(\frac{n - p_{\Omega}}{p_{\Omega} - p}\right)^2 \frac{(p_{\Omega} - p + \lambda)^2 + (p_{\Omega} - p + 2\lambda)(n - p_{\Omega} - 2)}{(n - p_{\Omega} - 2)^2(n - p_{\Omega} - 4)},$$
(A.7)

respectively. Then, when $\lambda = O(n)$

$$\begin{split} & \mathrm{E}(\mathrm{C}_{p}) = (p_{\Omega} - p)\mathrm{E}(F^{*}) + 2p - p_{\Omega} \\ & = \frac{(p_{\Omega} - p + \lambda)(n - p_{\Omega})}{n - p_{\Omega} - 2} + 2p - p_{\Omega} = \lambda + O(1), \\ & \mathrm{E}(\overline{\mathrm{C}}_{p}) = (p_{\Omega} - p)\mathrm{E}(F^{*}) + 2p - p_{\Omega} - \frac{2(p_{\Omega} - p)}{n - p_{\Omega} - 2} \\ & = \frac{(p_{\Omega} - p + \lambda)(n - p_{\Omega})}{n - p_{\Omega} - 2} + 2p - p_{\Omega} - \frac{2(p_{\Omega} - p)}{n - p_{\Omega} - 2} = \lambda + O(1), \\ & \mathrm{E}(\mathrm{MC}_{pq}) = (p_{\Omega} - p)\frac{n - p_{\Omega} - 2}{n - p_{\Omega}} \mathrm{E}(F^{*}) + 2p - p_{\Omega} \\ & = (p_{\Omega} - p + \lambda) + (2p - p_{\Omega}) = p + \lambda = \lambda + O(1), \end{split}$$

which give (3.7).

Using (A.7),

$$\operatorname{var}(F^*) = \frac{2(\lambda^2 + 2\lambda n)}{(p_0 - p)^2 n} + O(1) = O(n)$$
(A.8)

follows. Equation (A.8) gives (3.8). From the unbiased property of MC_{pq} and the definitions of C_p and \overline{C}_p , we have the results of (3.9) except its last inequality $MSE(\overline{C}_p) < MSE(C_p)$, which is given by

$$\begin{aligned} \{ \mathrm{E}(\mathrm{C}_p) - (p+\lambda) \}^2 &= \left\{ \frac{(p_{\Omega} - p + \lambda)(n - p_{\Omega})}{n - p_{\Omega} - 2} + p - \lambda - p_{\Omega} \right\}^2 \\ &= \frac{4(p_{\Omega} - p + \lambda)^2}{(n - p_{\Omega} - 2)^2}, \\ \{ \mathrm{E}(\overline{\mathrm{C}}_p) - (p+\lambda) \}^2 &= \frac{1}{(n - p_{\Omega} - 2)^2} \{ -2(p - \lambda - p_{\Omega}) - 2(p_{\Omega} - p)) \}^2 \\ &= \frac{4\lambda^2}{(n - p_{\Omega} - 2)^2} < \{ \mathrm{E}(\mathrm{C}_p) - (p + \lambda) \}^2 \end{aligned}$$

(recall the assumption $p_{\Omega} > p$ in Section 1) and $var(C_p) = var(\overline{C}_p)$.

Proof of Lemma 1

Since
$$\text{MSE}(d\hat{\theta}) = (d-1)^2 \theta_0^2 + d^2 \sigma_{\theta n}^2$$
, $\text{MSE}(d\hat{\theta})$ is minimized when $d = d_{\min} = \theta_0^2 / (\theta_0^2 + \sigma_{\theta n}^2) = 1/\{1 + c_{\text{V}}^2(\hat{\theta})\}$. The minimized MSE is $\theta_0^2 - \frac{\theta_0^4}{\theta_0^2 + \sigma_{\theta n}^2} = \frac{\sigma_{\theta n}^2}{1 + c_{\text{V}}^2(\hat{\theta})} = \frac{\text{MSE}(\hat{\theta})}{1 + c_{\text{V}}^2(\hat{\theta})}$.

Proof of Corollary 4

First, we obtain

$$\begin{aligned} & \text{MSE}(\text{MC}_{pq}) - \text{MSE}(d_{\min \overline{C}_{pq}} \overline{C}_{pq}) \\ &= \left\{ \left(\frac{n - p_{\Omega} - q - 1}{n - p_{\Omega}} \right)^{2} - \frac{1}{1 + \text{var}(\overline{C}_{pq})(pq)^{-2}} \right\} \text{var}(\overline{C}_{pq}) \\ &= \frac{(n - p_{\Omega} - q - 1)^{2} \{(pq)^{2} + \text{var}(\overline{C}_{pq})\} - (n - p_{\Omega})^{2} (pq)^{2}}{(n - p_{\Omega})^{2} \{(pq)^{2} + \text{var}(\overline{C}_{pq})\}} \text{var}(\overline{C}_{pq}), \end{aligned}$$
(A.9)

which can be positive or negative, as shown in the following examples. When q = 1, the numerator of the first factor on the right-hand side of the last equation of (A.9) is

$$(n - p_{\Omega} - 2)^{2} \{p^{2} + \text{var}(\overline{C}_{p})\} - (n - p_{\Omega})^{2} p^{2}$$

$$= -4(n - p_{\Omega})p^{2} + 4p^{2} + \frac{2(p_{\Omega} - p)(n - p_{\Omega})^{2}(n - p - 2)}{n - p_{\Omega} - 4}$$

$$= -|O(n)| + |O(1)| + |O(n^{2})|,$$
(A.10)

where for $var(\overline{C}_p)$, (3.2) and (A.5) are used.

When n is sufficiently large, (A.10) is positive, demonstrating that in this case, $\mathrm{MSE}(\mathrm{MC}_{pq}) > \mathrm{MSE}(d_{\min \overline{C}_{pq}} \overline{C}_{pq})$. However, when n is relatively small, we define $n-p_\Omega=a>4$ (see a condition for (A.3)) and $p_\Omega-p=b>0$ (recall the assumption $p_\Omega > p$ in Section 1). Then, (A.10) becomes $-4ap^2+4p^2+2ba^2(a+b-2)/(a-4)$, which is negative when $p^2>ba^2(a+b-2)/\{2(a-1)(a-4)\}$. For instance, when a=5 and b=1, the last inequality holds when $p\geq 4$. From this result, we have the central inequality $\min\{\cdot\} \leq \max\{\cdot\}$ in (4.2). The remaining inequalities are given by the unbiased property of MC_{pq} and the definitions of C_{pq} and $\mathrm{\overline{C}}_{pq}$.

Proof of Theorem 4

From (A.6) and (A.7), we have

$$\operatorname{var}(MC_{pq}) = (p_{\Omega} - p)^{2} \left(\frac{n - p_{\Omega} - 2}{n - p_{\Omega}}\right)^{2} \operatorname{var}(F^{*})$$

$$= 2 \frac{(p_{\Omega} - p + \lambda)^{2} + (p_{\Omega} - p + 2\lambda)(n - p_{\Omega} - 2)}{n - p_{\Omega} - 4}.$$
(A.11)

Substituting (A.11) for the first equation of (4.3) given by Lemma 1, the second equation of (4.3) follows.

Results associated with Theorem 4 when $\lambda = O(1)$ and $\lambda = 0$

When $\lambda = O(1)$, from (A.11) we have

$$\operatorname{var}(\operatorname{MC}_{pq}) = 2(p_{\Omega} - p + 2\lambda) + O(n^{-1}),$$

$$d_{\min \operatorname{MC}_{pq}}^* = \frac{(p + \lambda)^2}{(p + \lambda)^2 + 2(p_{\Omega} - p + 2\lambda)} + O(n^{-1}). \tag{A.12}$$

Note that when
$$\lambda = 0$$
, (3.2) and (A.7) yield

$$\operatorname{var}(C_{p}) = \operatorname{var}(\overline{C}_{p}) = (p_{\Omega} - p)^{2} \operatorname{var}(F_{p_{\Omega} - p, n - p_{\Omega}})$$

$$= \frac{2(p_{\Omega} - p)(n - p_{\Omega})^{2}(n - p - 2)}{(n - p_{\Omega} - 2)^{2}(n - p_{\Omega} - 4)} = \left(\frac{n - p_{\Omega}}{n - p_{\Omega} - 2}\right)^{2} \operatorname{var}(\operatorname{MC}_{pq})$$

$$> \operatorname{var}(\operatorname{MC}_{pq}) = \frac{2(p_{\Omega} - p)(n - p - 2)}{n - p_{\Omega} - 4},$$

$$\operatorname{var}(C_{p}) = \operatorname{var}(\overline{C}_{p}) = 2(p_{\Omega} - p) + O(n^{-1}),$$

$$\operatorname{var}(\operatorname{MC}_{pq}) = 2(p_{\Omega} - p) + O(n^{-1}),$$

$$d_{\min \operatorname{MC}_{pq}} = \frac{p^{2}}{p^{2} + \operatorname{var}(\operatorname{MC}_{pq})} = \frac{p^{2}(n - p_{\Omega} - 4)}{p^{2}(n - p_{\Omega} - 4) + 2(p_{\Omega} - p)(n - p - 2)}$$

$$= \frac{p^{2}}{n^{2} + 2(n - p)} + O(n^{-1})$$

(see (4.1)). From (A.12) and (A.13), when $\lambda = O(1)$, it is seen that (A.12) is given from the last two sets of results of (A.13) by replacing $p_{\Omega} - p$ and p^2 with $p_{\Omega} - p + 2\lambda$ and $(p + \lambda)^2$, respectively. However, as described earlier, generally $\lambda = O(n)$, giving (A.8).

References

- Johnson, N. L., Kotz, S., & Balakrishnan, N. (1994). Continuous univariate distributions Vol.2 (2nd ed.). New York: Wiley.
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