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- ✓ in recent two monographs, Silvapulle and Sen (2004) and Van Eeden (2006).

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- ✓ We discuss the estimation of two ordered means, individually and/or simultaneously, under Pitman closeness criterion.

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- ✓ if

$$P_r\{|T_1 - \theta| < |T_2 - \theta|\} > 1/2.$$

# About Pitman closeness criterion

- ✓ refer the reader to Rao (1981), Keating and Manson (1985), Peddada (1985), Rao, Keating and Mason (1986), Khattree and Peddada (1987) for details.

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- ✓ Many works related to Pitman's criterion were published in the special issue of Communications in Statistics - Theory and Methods A20 (11) in 1992 and
- ✓ were unified in the monograph by Keating, Manson and Sen (1993).

# The purpose

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- ✓ Here we consider the estimation of two ordered normal means when unknown variances are ordered using Pitman closeness criterion.
- ✓ We propose the estimators which is closer to the unknown means than the usual estimators which ignore the order restriction on variances using the modified Pitman closeness criterion suggested by Gupta and Singh (1992).

# The history background

- ✓ First, we state some fundamental results on the estimation of common mean and ordered means when the MSE or stochastic domination is concerned.

# the unbiased estimators of $\mu_i$ and $\sigma_i^2$ ,

- ✓ Let  $X_{ij}, i = 1, 2, j = 1, \dots, n_i$  be independent observations from normal distribution with mean  $\mu_i$  and variance  $\sigma_i^2$ , where both  $\mu_i$  and  $\sigma_i^2$  are unknown.

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- ✓ Also let

$$\bar{X}_i = \sum_{j=1}^{n_i} X_{ij} / n_i \text{ and } s_i^2 = \sum_{j=1}^{n_i} (X_{ij} - \bar{X}_i)^2 / (n_i - 1)$$

be the unbiased estimators of  $\mu_i$  and  $\sigma_i^2$ , respectively.

# Estimation of Common mean

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$$\hat{\mu}^{GD} = \frac{n_1 s_2^2}{n_1 s_2^2 + n_2 s_1^2} \bar{X}_1 + \frac{n_2 s_1^2}{n_1 s_2^2 + n_2 s_1^2} \bar{X}_2$$

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- ✓ and gave a necessary and sufficient condition on  $n_1$  and  $n_2$  for  $\hat{\mu}^{GD}$  to have a smaller variance than both  $\bar{X}_1$  and  $\bar{X}_2$ .



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$$\hat{\mu}^{Nair} = \begin{cases} \hat{\mu}^{GD}, & \text{if } s_1^2 \leq s_2^2 \\ \frac{n_1}{n_1+n_2} \bar{X}_1 + \frac{n_2}{n_1+n_2} \bar{X}_2, & \text{if } s_1^2 > s_2^2, \end{cases}$$

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- ✓ Elfessi and Pal (1992) showed that  $\hat{\mu}^{Nair}$  stochastically dominates  $\hat{\mu}^{GD}$ . (As for the definitions of stochastic dominance and universal dominance, see Hwang (1985).)



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- ✓ Lee (1981) showed that RMLE (restricted MLE) uniformly improves upon sample means under MSE.
- ✓ Kelly (1989) and Hwang and Peddada (1994) proved that RMLE universally dominates sample means.

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- ✓ For the case when  $\sigma_i^2, i = 1, 2$  are unknown and two normal means satisfy the simple order restriction,  $\mu_1 \leq \mu_2$ ,
- ✓ Oono and Shinozaki (2005) proposed a truncated estimators of  $\mu_i, i = 1, 2$ ,

$$\hat{\mu}_1^{OS} = \min\{\bar{X}_1, \hat{\mu}^{GD}\}, \quad \hat{\mu}_2^{OS} = \max\{\bar{X}_2, \hat{\mu}^{GD}\},$$

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- ✓ they showed that  $\hat{\mu}_i^{OS}$  uniformly improves upon  $\bar{X}_i$ , if and only if the risk of  $\hat{\mu}_i^{OS}$  is not larger than that of  $\bar{X}_i$  when  $\mu_1 = \mu_2$ . (See also Garren (2000).)

## When order restrictions are given on both means and variances

- ✓ When order restrictions are given on both means and variances, Chang and Shinozaki (2010) have considered the estimators based on the estimators given by Oono and Shinozaki (2005) as follow:

# When order restrictions are given on both means and variances



$$\hat{\mu}_1^{CS} = \begin{cases} \hat{\mu}_1^{OS}, & \text{if } s_1^2 \leq s_2^2 \\ \min\{\bar{X}_1, \frac{n_1}{n_1+n_2}\bar{X}_1 + \frac{n_2}{n_1+n_2}\bar{X}_2\}, & \text{if } s_1^2 > s_2^2. \end{cases}$$

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$$\hat{\mu}_2^{CS} = \begin{cases} \hat{\mu}_2^{OS}, & \text{if } s_1^2 \leq s_2^2 \\ \max\{\bar{X}_2, \frac{n_1}{n_1+n_2}\bar{X}_1 + \frac{n_2}{n_1+n_2}\bar{X}_2\}, & \text{if } s_1^2 > s_2^2. \end{cases}$$



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- ✓ They also showed that  $(\hat{\mu}_1^{CS}, \hat{\mu}_2^{CS})$  stochastically dominates  $(\hat{\mu}_1^{OS}, \hat{\mu}_2^{OS})$  when estimating  $(\mu_1, \mu_2)$ , simultaneously.



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- ✓ Shi (1994) and Ma and Shi (2002) discussed the order restricted MLE of  $\mu_i$  and  $\sigma_i^2$  under squared error loss.

## A wider class estimators of two means

- ✓ Let that  $\gamma$ ,  $\tilde{\gamma}$ , and  $\gamma^+$  are functions of  $n_1, n_2, s_1^2, s_2^2$ , and  $\bar{X}_1 - \bar{X}_2$  and that  $0 \leq \gamma, \tilde{\gamma}, \gamma^+ \leq 1$  and,

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$$\gamma^+ = \begin{cases} \gamma, & \text{if } \gamma \geq \frac{n_1}{n_1+n_2}, \\ \tilde{\gamma}, & \text{if } \gamma < \frac{n_1}{n_1+n_2}. \end{cases}$$

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- ✓ Chang, Oono and Shinozaki(2011C) have considered estimators of the forms

$$\hat{\mu}_1(\gamma) = \min\{\bar{X}_1, \gamma\bar{X}_1 + (1 - \gamma)\bar{X}_2\} \quad (1.4)$$

and

$$\hat{\mu}_2(\gamma) = \max\{\bar{X}_2, \gamma\bar{X}_1 + (1 - \gamma)\bar{X}_2\}. \quad (1.5)$$

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- ✓  $\hat{\mu}_1(\gamma)$  has smaller MSE than  $\hat{\mu}_1(\gamma^+)$  for sufficiently large  $\Delta = \mu_2 - \mu_1$ .

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$$P \left\{ \sum_{i=1}^2 \left( \frac{\hat{\mu}_i(\gamma^+) - \mu_i}{\tau_i} \right)^2 \leq d \right\} \geq P \left\{ \sum_{i=1}^2 \left( \frac{\hat{\mu}_i(\gamma) - \mu_i}{\tau_i} \right)^2 \leq d \right\}$$

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- ✓ For the case, when the estimators are equal with positive probability, Nayak (1990) modified Pitman's criterion as follows :
- ✓  $T_1$  is said to be closer to  $\theta$  than  $T_2$  if

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$$\begin{aligned} MPN_{\theta}(T_1, T_2) &= P_r\{|T_1 - \theta| < |T_2 - \theta| | T_1 \neq T_2\} \\ &= \frac{P_r\{|T_1 - \theta| < |T_2 - \theta|, T_1 \neq T_2\}}{P_r\{T_1 \neq T_2\}}, \end{aligned}$$

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✓  $T_1$  is closer to  $\theta$  than  $T_2$  if  $MPN_{\theta}(T_1, T_2) > 1/2$ .

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are closer to respective means than  $\bar{X}_i, i = 1, 2$ ,  
that is,  $MPN_{\mu_i}(\hat{\mu}_i^{GS}, \bar{X}_i) > 1/2, i = 1, 2, .$



## Our results under modified Pitman's criterion

### ✓ Theorem

Suppose that  $P\{\gamma < n_1/(n_1 + n_2)\} > 0$ , then the estimator  $\hat{\mu}_2(\gamma^+)$  is closer to  $\mu_2$  than  $\hat{\mu}_2(\gamma)$ ,

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✓ if we choose  $\tilde{\gamma}$  so that

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### ✓ Theorem

The estimator  $\hat{\mu}_1(\gamma^+)$  is not closer to  $\mu_1$  than  $\hat{\mu}_1(\gamma)$  for sufficiently large  $\Delta$ .

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✓

$$\begin{aligned} & MPN_{\mu}(\hat{\mu}(\gamma^+), \hat{\mu}(\gamma)) \\ &= \frac{Pr\{\sum_{i=1}^2 (\hat{\mu}_i(\gamma^+) - \mu_i)^2 / \tau_i^2 \leq \sum_{i=1}^2 (\hat{\mu}_i(\gamma) - \mu_i)^2 / \tau_i^2, \hat{\mu}(\gamma^+) \neq \hat{\mu}(\gamma)\}}{Pr\{\hat{\mu}(\gamma^+) \neq \hat{\mu}(\gamma)\}} \\ &> 1/2. \end{aligned}$$



# Conclusion

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# Conclusion

- ✓ Rao (1981) compared the minimum MSE and Pitman's closeness criteria and suggested that Pitman's closeness criterion could be used as an alternative criterion to compare estimators.
- ✓ However, Blyth (1972) pointed out the intransitivity drawback of Pitman's closeness criterion and also pointed out that there is some inconsistency among Pitman's closeness, minimum MSE, and minimum mean absolute error criteria.

# Conclusion

- ✓ For the estimation problem of two ordered normal means with ordered variances, we have confirmed that the result obtained by using the Pitman's closeness criterion is consistent with the one obtained by using the MSE criterion.

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- ✓ For the estimation problem of two ordered normal means with ordered variances, we have confirmed that the result obtained by using the Pitman's closeness criterion is consistent with the one obtained by using the MSE criterion.
- ✓ Thank you for your attention.