## STAT 3690 Lecture 13

## zhiyanggeezhou.github.io

## Zhiyang Zhou (zhiyang.zhou@umanitoba.ca)

## Testing for equality of population means (one-way multivariate analysis of variance (1-way MANOVA), J&W Sec. 6.4)

- Generalization of two-sample problem
  - Model: m independent samples, where

\* 
$$\mathbf{X}_{11}, \dots, \mathbf{X}_{1n_1} \stackrel{\mathrm{iid}}{\sim} MVN_p(\boldsymbol{\mu}_1, \boldsymbol{\Sigma})$$

$$\mathbf{X}_{m1},\ldots,\mathbf{X}_{mn_m}\stackrel{\mathrm{iid}}{\sim} MVN_p(\boldsymbol{\mu}_m,\boldsymbol{\Sigma})$$

- \*  $\mathbf{X}_{m1}, \dots, \mathbf{X}_{mn_m} \stackrel{\text{iid}}{\sim} MVN_p(\boldsymbol{\mu}_m, \boldsymbol{\Sigma})$  Hypotheses  $H_0: \boldsymbol{\mu}_1 = \dots = \boldsymbol{\mu}_m$  v.s.  $H_1:$  otherwise
- Alternatively
  - Model: m independent samples, where

\* 
$$\mathbf{X}_{11}, \dots, \mathbf{X}_{1n_1} \stackrel{\mathrm{iid}}{\sim} MVN_p(\boldsymbol{\mu} + \boldsymbol{\tau}_1, \boldsymbol{\Sigma})$$

$$* \mathbf{X}_{m1}, \dots, \mathbf{X}_{mn_m} \overset{\mathrm{iid}}{\sim} MVN_p(\boldsymbol{\mu} + \boldsymbol{ au}_m, \boldsymbol{\Sigma})$$

- \*  $\mathbf{X}_{m1}, \dots, \mathbf{X}_{mn_m} \stackrel{\text{iid}}{\sim} MVN_p(\boldsymbol{\mu} + \boldsymbol{\tau}_m, \boldsymbol{\Sigma})$ · Identifiability:  $\sum_i \boldsymbol{\tau}_i = 0$  otherwise there are infinitely many models that lead to the same data-generating mechanism.
- Hypotheses  $H_0: \boldsymbol{\tau}_1 = \cdots = \boldsymbol{\tau}_m = 0$  v.s.  $H_1:$  otherwise
- Alternatively

- Model: 
$$\mathbf{X}_{ij} = \boldsymbol{\mu} + \boldsymbol{\tau}_i + \mathbf{E}_{ij}$$
 with  $\mathbf{E}_{ij} \stackrel{\text{iid}}{\sim} MVN_p(\mathbf{0}, \boldsymbol{\Sigma})$   
\* Identifiability:  $\sum_i \boldsymbol{\tau}_i = 0$ 

- Hypotheses  $H_0: \boldsymbol{\tau}_1 = \cdots = \boldsymbol{\tau}_m = 0$  v.s.  $H_1:$  otherwise

- Sample means and sample covariances
  - Sample mean for the *i*th sample  $\bar{\mathbf{X}}_i = n_i^{-1} \sum_j \mathbf{X}_{ij}$
  - Sample covariance for the *i*th sample  $\mathbf{S}_i = (n_i 1)^{-1} \sum_j (\mathbf{X}_{ij} \bar{\mathbf{X}}_i) (\mathbf{X}_{ij} \bar{\mathbf{X}}_i)^{\top}$
  - Grand mean  $\bar{\mathbf{X}} = \sum_{i} n_{i} \bar{\mathbf{X}}_{i} / \sum_{i} n_{i} = \sum_{ij} \mathbf{X}_{ij} / \sum_{i} n_{i}$  Sum of squares and cross products matrix (SSP)
    - - \* Within-group SSP

$$\mathbf{SSP}_{\mathbf{w}} = \sum_{i} (n_i - 1)\mathbf{S}_i = \sum_{ij} (\mathbf{X}_{ij} - \bar{\mathbf{X}}_i)(\mathbf{X}_{ij} - \bar{\mathbf{X}}_i)^{\top}$$

\* Between-group SSP

$$\mathbf{SSP}_{\mathrm{b}} = \sum_{i} n_{i} (\bar{\mathbf{X}}_{i} - \bar{\mathbf{X}}) (\bar{\mathbf{X}}_{i} - \bar{\mathbf{X}})^{\top}$$

\* Total (corrected) SSP

$$\mathbf{SSP}_{\mathrm{cor}} = \sum_{ij} (\mathbf{X}_{ij} - \bar{\mathbf{X}})(\mathbf{X}_{ij} - \bar{\mathbf{X}})^{\top} = \mathbf{SSP}_{\mathrm{w}} + \mathbf{SSP}_{\mathrm{b}}$$

- Exercise: verify the decomposition  $SSP_{cor} = SSP_{w} + SSP_{b}$ .
- MLE of  $(\boldsymbol{\mu}_1,\ldots,\boldsymbol{\mu}_m,\boldsymbol{\Sigma})$ 
  - Under  $H_0$

\* 
$$\hat{\boldsymbol{\mu}}_i = \bar{\mathbf{X}}$$
 for each  $i$   
\*  $\hat{\boldsymbol{\Sigma}} = (\sum_i n_i)^{-1} \mathbf{SSP}_{cor}$ 

- - \*  $\hat{\boldsymbol{\mu}}_i = \bar{\mathbf{X}}_i = n_i^{-1} \sum_j \mathbf{X}_{ij}$
- \*  $\widehat{\mathbf{\Sigma}} = (\sum_i n_i)^{-1} \mathbf{SSP_w}$  Likelihood ratio

$$\lambda = \left\{ rac{\det(\mathbf{SSP_w})}{\det(\mathbf{SSP_{cor}})} 
ight\}^{\sum_i n_i/2}$$

• Wilk's lambda test statistic

$$\Lambda = \lambda^{2/\sum_{i} n_{i}} = \frac{\det(\mathbf{SSP_{w}})}{\det(\mathbf{SSP_{cor}})}$$

- Under  $H_0$ :  $\Lambda \sim \text{Wilk's lambda distribution } \Lambda(\Sigma, \sum_i n_i m, m 1)$ 

  - \* Since  $\mathbf{SSP_w} \sim W_p(\mathbf{\Sigma}, \sum_i n_i m)$  and  $\mathbf{SSP_b} \sim W_p(\mathbf{\Sigma}, m 1)$ \* When  $\sum_i n_i m$  is large (i.e.,  $(p + m)/2 \sum_i n_i + 1 \ll 0$ ), Bartlett's approximation

$$\{(p+m)/2 - \sum_{i} n_i + 1\} \ln \Lambda \approx \chi^2(p(m-1))$$

• Rejection region at level  $\alpha$ 

$$\left\{ x_{11}, \dots, x_{1n_1}, x_{21}, \dots, x_{mn_m} : \left\{ (p+m)/2 - \sum_i n_i + 1 \right\} \ln \Lambda \ge \chi_{1-\alpha, p(m-1)}^2 \right\}$$

$$= \left\{ x_{11}, \dots, x_{1n_1}, x_{21}, \dots, x_{mn_m} : \Lambda \le \exp \left\{ \frac{\chi_{1-\alpha, p(m-1)}^2}{(p+m)/2 - \sum_i n_i + 1} \right\} \right\}$$

• p-value

$$1 - F_{\chi^2(p(m-1))} \left[ \{ (p+m)/2 - \sum_i n_i + 1 \} \ln \Lambda \right]$$

- Exercise: factors in producing plastic film
  - W. J. Krzanowski (1988) Principles of Multivariate Analysis. A User's Perspective. Oxford UP,
  - Three response variables (tear, gloss and opacity) describing measured characteristics of the resultant film
  - A total of 20 runs
  - One factor RATE (rate of extrusion, 2-level, low or high) in the production test