STAT 3690 Lecture 09

zhiyanggeezhou.github.io

Zhiyang Zhou (zhiyang.zhou@umanitoba.ca)

Feb 11, 2022

Sampling distributions of \bar{X} and S (J&W Sec 4.4)

- Recall the univariate case: $X_1, \ldots, X_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2), n > p$
 - $-S^2 \perp \!\!\! \perp \bar{X}$
 - $\sqrt{n}(\bar{X} \mu)/\sigma \sim N(0, 1)$
 - $-(n-1)S^2/\sigma^2 \sim \chi^2(n-1), \text{ where } S^2 = (n-1)^{-1} \sum_{i=1}^n (X_i \bar{X})^2 \sqrt{n}(\bar{X} \mu)/S \sim t(n-1)$
- The multivariate case

 - $\begin{array}{l} \ \mathbf{S} \perp \!\!\! \perp \bar{\mathbf{X}}, \, \mathrm{i.e.}, \, \widehat{\boldsymbol{\Sigma}}_{\mathrm{ML}} \perp \!\!\! \perp \hat{\boldsymbol{\mu}}_{\mathrm{ML}} \\ \sqrt{n} \boldsymbol{\Sigma}^{-1/2} (\bar{\mathbf{X}} \boldsymbol{\mu}) \sim MVN_p(\mathbf{0}, \mathbf{I}) \end{array}$

 - $-(n-1)\mathbf{S} = n\widehat{\boldsymbol{\Sigma}}_{\mathrm{ML}} \sim W_p(n-1,\boldsymbol{\Sigma})$ $-n(\bar{\mathbf{X}} \boldsymbol{\mu})^{\top} \mathbf{S}^{-1}(\bar{\mathbf{X}} \boldsymbol{\mu}) \sim \text{Hotelling's } T^2(p,n-1)$
- Wishart distribution
 - Def: $W_p(\mathbf{\Sigma}, n)$ is the distribution of $\sum_{i=1}^n \mathbf{Y}_i \mathbf{Y}_i^{\top}$ with $\mathbf{Y}_1, \dots, \mathbf{Y}_n \stackrel{\text{iid}}{\sim} MVN_p(\mathbf{0}, \mathbf{\Sigma})$ * A generalization of χ^2 -distribution: $W_p(\mathbf{\Sigma}, n) = \chi^2(n)$ if $p = \mathbf{\Sigma} = 1$
 - Propoties
 - * $\mathbf{A}\mathbf{A}^{\top} > 0$ and $\mathbf{W} \sim W_p(\mathbf{\Sigma}, n) \Rightarrow \mathbf{A}\mathbf{W}\mathbf{A}^{\top} \sim W_p(\mathbf{A}\mathbf{\Sigma}\mathbf{A}^{\top}, n)$
 - * $\mathbf{W}_i \stackrel{\text{iid}}{\sim} W_p(\mathbf{\Sigma}, n_i) \Rightarrow \mathbf{W}_1 + \mathbf{W}_2 \sim W_p(\mathbf{\Sigma}, n_1 + n_2)$
 - * $\mathbf{W}_1 \perp \mathbf{W}_2$, $\mathbf{W}_1 + \mathbf{W}_2 \sim W_p(\mathbf{\Sigma}, n)$ and $\mathbf{W}_1 \sim W_p(\mathbf{\Sigma}, n_1) \Rightarrow \mathbf{W}_2 \sim W_p(\mathbf{\Sigma}, n n_1)$
 - * $\mathbf{W} \sim W_n(\mathbf{\Sigma}, n)$ and $\mathbf{a} \in \mathbb{R}^p \Rightarrow$

$$\frac{\boldsymbol{a}^{\top} \mathbf{W} \boldsymbol{a}}{\boldsymbol{a}^{\top} \boldsymbol{\Sigma} \boldsymbol{a}} \sim \chi^{2}(n)$$

* $\mathbf{W} \sim W_p(\mathbf{\Sigma}, n), \, \boldsymbol{a} \in \mathbb{R}^p \text{ and } n \geq p \Rightarrow$

$$\frac{\boldsymbol{a}^{\top} \boldsymbol{\Sigma}^{-1} \boldsymbol{a}}{\boldsymbol{a}^{\top} \mathbf{W}^{-1} \boldsymbol{a}} \sim \chi^{2} (n - p + 1)$$

* $\mathbf{W} \sim W_n(\mathbf{\Sigma}, n) \Rightarrow$

$$\operatorname{tr}(\mathbf{\Sigma}^{-1}\mathbf{W}) \sim \chi^2(np)$$

- Hotelling's T^2 distribution
 - A generalization of (Student's) t-distribution
 - If $\mathbf{X} \sim MVN_p(\mathbf{0}, \mathbf{I})$ and $\mathbf{W} \sim W_p(\mathbf{I}, n)$, then

$$\mathbf{X}^{\mathsf{T}}\mathbf{W}^{-1}\mathbf{X} \sim T^2(p,n)$$

$$-Y \sim T^2(p,n) \Leftrightarrow \frac{n-p+1}{np}Y \sim F(p,n-p+1)$$

- Wilk's lambda distribution
 - Wilks's lambda is to Hotelling's T^2 as F distribution is to Student's t in univariate statistics.
 - Given independent $\mathbf{W}_1 \sim W_p(\mathbf{\Sigma}, n_1)$ and $\mathbf{W}_2 \sim W_p(\mathbf{\Sigma}, n_2)$ with $n_1 \geq p$,

$$\Lambda = \frac{\det(\mathbf{W}_1)}{\det(\mathbf{W}_1 + \mathbf{W}_2)} = \frac{1}{\det(\mathbf{I} + \mathbf{W}_1^{-1}\mathbf{W}_2)} \sim \Lambda(p, n_1, n_2)$$

- Resort to approximations for computation: $\{(p-n_2+1)/2-n_1\}\ln\Lambda(p,n_1,n_2)\approx\chi^2(n_2p)$

Hypothesis testing

- Model: $\mathbf{X}_1, \dots, \mathbf{X}_n \sim f_{\boldsymbol{\theta}^*} \in \{f_{\boldsymbol{\theta}} : \boldsymbol{\theta} \in \boldsymbol{\Theta}\}$
 - $\boldsymbol{\theta}^* \in \mathbb{R}^p$: the *p*-vector of parameters of interest, fixed and unknown
 - $-\Theta \subset \mathbb{R}^p$: the parameter space
- Hypotheses $H_0: \boldsymbol{\theta}^* \in \boldsymbol{\Theta}_0$ v.s. $H_1: \boldsymbol{\theta}^* \in \boldsymbol{\Theta}_1$
 - $\mathbf{\Theta}_0 \cap \mathbf{\Theta}_1 = \emptyset$
 - $\ \mathbf{\Theta}_0 \cup \mathbf{\Theta}_1 = \mathbf{\Theta}$
- Rejection/critical region R
 - Reject H_0 if observations $\in R$
- Level α : $\sup_{\theta \in \Theta_0} \Pr_{\theta}(\text{observations} \in R) \leq \alpha$
 - When $\theta^* \in \Theta_0$, $\Pr(\text{type I error}) = \Pr_{\theta^*}(\text{observations} \in R) \leq \sup_{\theta \in \Theta_0} \Pr_{\theta}(\text{observations} \in R) \leq \alpha$
 - Type I error: H_0 is incorrectly rejected
 - Type II error: H_0 is incorrectly accepted
- p-value: a specific rejection region
 - Reject H_0 if p-value $\in [0, \alpha]$
 - Not always well-defined
- Necessary components in reporting a testing result
 - 1. Hypotheses
 - 2. Name of approache
 - 3. Value of test statistic
 - 4. Rejection region/p-value
 - 5. Conclusion: e.g., at the α level, we reject/do not reject H_0 , i.e., we believe XXX

Likehood ratio test (LRT)

- Minimize the type II error rate subject to a capped type I error rate (under certain classical circumstances)
- Test statistic

$$\lambda(\mathbf{X}_1,\ldots,\mathbf{X}_n) = \frac{\sup_{\boldsymbol{\theta}\in\boldsymbol{\Theta}_0} L(\boldsymbol{\theta};\mathbf{X}_1,\ldots,\mathbf{X}_n)}{\sup_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} L(\boldsymbol{\theta};\mathbf{X}_1,\ldots,\mathbf{X}_n)} = \frac{L(\hat{\boldsymbol{\theta}}_0;\mathbf{X}_1,\ldots,\mathbf{X}_n)}{L(\hat{\boldsymbol{\theta}};\mathbf{X}_1,\ldots,\mathbf{X}_n)}$$

- $-\hat{\boldsymbol{\theta}}_0$: ML estimator for $\boldsymbol{\theta} \in \boldsymbol{\Theta}_0$
- $-\hat{\boldsymbol{\theta}}$: ML estimator for $\boldsymbol{\theta} \in \boldsymbol{\Theta}$
- Rejection region $R = \{x_1, \dots, x_n : \lambda(x_1, \dots, x_n) \le c\}$
 - x_i is the realization of X_i
 - -c is chosen such that

$$\sup_{\boldsymbol{\theta} \in \boldsymbol{\Theta}_0} \Pr_{\boldsymbol{\theta}}(\lambda(\mathbf{X}_1, \dots, \mathbf{X}_n) \le c) = \alpha.$$

- * Have to know the null distribution of $\lambda(\mathbf{X}_1, \dots, \mathbf{X}_n)$, i.e., the distribution of $\lambda(\mathbf{X}_1, \dots, \mathbf{X}_n)$ with $\boldsymbol{\theta} \in \boldsymbol{\Theta}_0$
- p-value

$$p(\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n) = \sup_{\boldsymbol{\theta} \in \boldsymbol{\Theta}_0} \Pr_{\boldsymbol{\theta}} \{\lambda(\mathbf{X}_1,\ldots,\mathbf{X}_n) \leq \lambda(\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n)\}$$

• Null distribution of $\lambda(\mathbf{X}_1,\ldots,\mathbf{X}_n)$

- Use the accurate distribution of $\lambda(\mathbf{X}_1,\ldots,\mathbf{X}_n)$ if it is known; otherwise see below for an approximation.
- As $n \to \infty$,

$$-2\ln\lambda(\mathbf{X}_1,\ldots,\mathbf{X}_n)\approx\chi^2(\nu)$$

- * ν : the difference in numbers of free parameters between H_0 and H_1 * Leading to an (asymptotic) rejection region $\{\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n:-2\ln\lambda(\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n)\geq\chi^2_{\nu,1-\alpha}\}$ · $\chi^2_{\nu,1-\alpha}$ is the $(1-\alpha)$ quantile of $\chi^2(\nu)$.