Advanced Methods in Biostatistics I Lecture 14

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October 12, 2017

Quadratic Forms - continued

- Last time we discussed the distributional properties of quadratic forms and how they apply to linear models.
- Today we will expand upon these results.

Quadratic Forms

Definition

A quadratic form is a function $f : \mathbb{R}^n \mapsto \mathbb{R}$ of the form:

$$f(\mathbf{y}) = \mathbf{y}' \mathbf{A} \mathbf{y} = \sum_{i,j} A_{ij} y_i y_j.$$

Quadratic Forms

- Note that $\mathbf{y}'\mathbf{A}\mathbf{y} = \mathbf{y}'\mathbf{A}'\mathbf{y}$, so if we let $\mathbf{B} = (\mathbf{A} + \mathbf{A}')/2$, then $\mathbf{B}' = \mathbf{B}$, and $\mathbf{y}'\mathbf{A}\mathbf{y} = \mathbf{y}'\mathbf{B}\mathbf{y}$.
- Thus when studying a quadratic form y'Ay, we will assume that A is symmetric.

Distribution of quadratic form

Theorem

If $\mathbf{y} \sim N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ then

$$\mathbf{y}'\mathbf{A}\mathbf{y}\sim\chi_{r}^{2}(\mu'\mathbf{A}\mu/2))$$

if and only if $\mathbf{A}\Sigma$ is idempotent of rank r

t distribution

Theorem

If $Z \sim N(0,1)$ and $U \sim \chi_r^2$ are independent, then the random variable

$$T = \frac{Z}{\sqrt{U/r}}$$

follows t distribution with r > 0 degrees of freedom.

We write $T \sim t_r$.

Non-central t distribution

Theorem

If $Z \sim N(\mu, 1)$ and $U \sim \chi_r^2$ are independent, then the random variable

$$T = \frac{Z}{\sqrt{U/r}}$$

follows a noncentral t distribution with r > 0 degrees of freedom and noncentrality parameter μ .

We write $T \sim t_r(\mu)$.

F distribution

Theorem

If U_1 and U_2 are independent central χ^2 random variables with degrees of freedom m_1 and m_2 , respectively, then the random variable

$$W=\frac{U_1/m_1}{U_2/m_2}$$

follows a (central) F distribution with $m_1 > 0$ and $m_2 > 0$ degrees of freedom.

We write $W \sim F_{m_1,m_2}$.

Noncentral F distribution

Theorem

If $U_1 \sim \chi^2_{m_1}(\lambda)$ and $U_2 \sim \chi^2_2$ be independent, then the random variable

$$W = \frac{U_1/n_1}{U_2/n_2} \sim F_{n_1,n_2}(\lambda).$$

follows a noncentral F distribution with $m_1>0$ and $m_2>0$ degrees of freedom and noncentrality parameter $\lambda>0$

We write $W \sim F_{m_1,m_2}(\lambda)$.

Independence

- Let's continue by discussing some independence results related to quadratic forms.
- In particular, we seek conditions for when y'Ay and By are independent and when y'Ay and y'By are independent.

Independence

Theorem

Let $\mathbf{y} \sim N_p(\mu, \Sigma)$, \mathbf{A} be symmetric idempotent matrix, and \mathbf{B} a matrix of constants, and suppose $\mathbf{B}\Sigma\mathbf{A}=\mathbf{0}$. Then $\mathbf{y}'\mathbf{A}\mathbf{y}$ and $\mathbf{B}\mathbf{y}$ are independent.

- Assume $\mathbf{y} \sim N_n(\mu \mathbf{J}_n, \sigma^2 \mathbf{I})$.
- Recall, we can write the sample variance as follows:

$$(n-1)s^2 = \mathbf{y}'(\mathbf{I} - \mathbf{J}_n(\mathbf{J}'_n\mathbf{J}_n)^{-1}\mathbf{J}'_n)\mathbf{y}$$

= $\mathbf{y}'\mathbf{A}\mathbf{y}$

where
$$\mathbf{A} = (\mathbf{I} - \mathbf{J}_n(\mathbf{J}'_n\mathbf{J}_n)^{-1}\mathbf{J}'_n)$$
.

Also recall, we can write

$$\bar{y} = (\mathbf{J}'_n \mathbf{J}_n)^{-1} \mathbf{J}'_n \mathbf{y}$$

$$= \mathbf{B} \mathbf{y}$$

where
$$\mathbf{B} = (\mathbf{J}'_n \mathbf{J}_n)^{-1} \mathbf{J}'_n$$
.

These two statistics are independent because

$$\begin{aligned} \mathbf{BVA} &= (\mathbf{J}_n'\mathbf{J}_n)^{-1}\mathbf{J}_n'\sigma^2\mathbf{I}(\mathbf{I} - \mathbf{J}_n(\mathbf{J}_n'\mathbf{J}_n)^{-1}\mathbf{J}_n') \\ &= \mathbf{0} \\ \end{aligned}$$
 since $\mathbf{J}_n'(\mathbf{I} - \mathbf{J}_n(\mathbf{J}_n'\mathbf{J}_n)^{-1}\mathbf{J}_n') = 0$

 Since functions of independent statistics are also independent, it must hold that \(\bar{y}\) and \(s^2\) are independent.

Last time we showed that

$$(n-1)s^2/\sigma^2 \sim \chi_{n-1}^2$$
.

In addition, it is easy to see that

$$\bar{y} \sim N(\mu, \sigma^2/n).$$

- Note that \bar{y} and s^2 are independent as shown above.
- Thus,

$$T = \frac{(\bar{y} - \mu)/(\sigma/\sqrt{n})}{\sqrt{s^2/\sigma^2}}$$
$$= \frac{\bar{y} - \mu}{s/\sqrt{n}}$$
$$\sim t_{n-1}$$

Independence

Theorem

Let $\mathbf{y} \sim N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, \mathbf{A} be symmetric idempotent of rank m, and \mathbf{B} be symmetric idempotent of rank s, and suppose $\mathbf{B}\boldsymbol{\Sigma}\mathbf{A}=\mathbf{0}$. Then $\mathbf{y}'\mathbf{A}\mathbf{y}$ and $\mathbf{y}'\mathbf{B}\mathbf{y}$ are independent.

- Consider the linear model: $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, where $\boldsymbol{\varepsilon} \sim N_n(\mathbf{0}, \sigma^2 \mathbf{I})$.
- Previously, we showed that

$$\mathbf{y}'(\mathbf{I} - \mathbf{H})\mathbf{y}/\sigma^2 \sim \chi^2_{n-p}$$

and

$$\mathbf{y}'\mathbf{H}\mathbf{y}/\sigma^2 \sim \chi_p^2(eta\mathbf{X}'\mathbf{X}eta/(2\sigma^2)).$$

Let

$$\mathbf{y}'(\mathbf{I}-\mathbf{H})\mathbf{y}/\sigma^2=\mathbf{y}'\mathbf{A}\mathbf{y}$$
 where $\mathbf{A}=\sigma^{-2}(\mathbf{I}-\mathbf{H}).$

Also, let

$$\mathbf{y}'\mathbf{H}\mathbf{y}/\sigma^2 = \mathbf{y}'\mathbf{B}\mathbf{y}$$

where $\mathbf{B} = \sigma^{-2}\mathbf{H}$.

Note,

$$\mathbf{B} \mathbf{\Sigma} \mathbf{A} = \sigma^{-2} \mathbf{H} \sigma^{2} \mathbf{I} \sigma^{-2} (\mathbf{I} - \mathbf{H})$$
$$= \mathbf{0}$$

• Thus, $\mathbf{y}'(\mathbf{I} - \mathbf{H})\mathbf{y}/\sigma^2$ and $\mathbf{y}'\mathbf{H}\mathbf{y}/\sigma^2$ are independent quadratic forms.

Thus,

$$F = \frac{\mathbf{y}' \mathbf{H} \mathbf{y}/p}{\mathbf{y}'(\mathbf{I} - \mathbf{H}) \mathbf{y}/(n - p)}$$
$$= \frac{\sigma^{-2} \mathbf{y}' \mathbf{H} \mathbf{y}/p}{\sigma^{-2} \mathbf{y}'(\mathbf{I} - \mathbf{H}) \mathbf{y}/(n - p)}$$
$$\sim F_{p,n-p}(\beta' \mathbf{X}' \mathbf{X} \beta/2\sigma^2)$$

Cochran's Theorem

Theorem

Let $\mathbf{y} \sim N_p(\mu, \sigma^2 \mathbf{I})$ and suppose that $\mathbf{A}_1, \mathbf{A}_2, \dots \mathbf{A}_k$ are $n \times n$ symmetric idempotent matrices with $rank(\mathbf{A}_i) = s_i$. If

$$\mathbf{A}_1 + \mathbf{A}_2 + \dots + \mathbf{A}_k = \mathbf{I},$$

then

$$\mathbf{y}'\mathbf{A}_1\mathbf{y}/\sigma^2$$
, $\mathbf{y}'\mathbf{A}_2\mathbf{y}/\sigma^2$, ... $\mathbf{y}'\mathbf{A}_k\mathbf{y}/\sigma^2$

follow independent $\chi_{s_i}^2(\lambda_i)$ distributions, where $\lambda_i = \mu' \mathbf{A}_i \mu/2\sigma^2$, for i = 1, 2, ..., k and $\sum_{i=1}^k s_i = n$.

Cochran's Theorem

- Cochran's Threorem can be used to determine the distributions of partitioned sums of squares of normally distributed random variables.
- It allows us to split the sum of the squares of observations into a number of quadratic forms where each corresponds to some cause of variation.

Consider the model:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

where

$$\varepsilon \sim N_n(\mathbf{0}, \sigma^2 \mathbf{I}).$$

- Suppose we can write: $\mathbf{X} = (\mathbf{X}_1 \ \mathbf{X}_2)$ and $\boldsymbol{\beta} = (\beta_1' \ \beta_2')'$.
- Further suppose X_i is a $n \times p_i$ matrix where $p_1 + p_2 = p$.

Now consider both the full model:

$$\mathbf{y} = \mathbf{X_1}\boldsymbol{\beta_1} + \mathbf{X_2}\boldsymbol{\beta_2} + \boldsymbol{\varepsilon}$$

and the submodel

$$\mathbf{y} = \mathbf{X_1}\boldsymbol{\beta_1} + \boldsymbol{\varepsilon}.$$

Let us define the following projections matrices:

$$\begin{array}{lcl} {\bm A}_1 & = & {\bm P}_{{\bm X}_1} \\ {\bm A}_2 & = & {\bm P}_{{\bm X}} - {\bm P}_{{\bm X}_1} \\ {\bm A}_3 & = & {\bm I} - {\bm P}_{{\bm X}} \end{array}$$

- All **A**_i are symmetric and idempotent.
- Further

$$\mathbf{A}_1 + \mathbf{A}_2 + \mathbf{A}_3 = \mathbf{I}$$

and

$$r(\mathbf{A}_1) + r(\mathbf{A}_2) + r(\mathbf{A}_3) = p_1 + (p - p_1) + (n - p)$$

= n

where $r(\mathbf{A}_i)$ is the rank of \mathbf{A}_i .

Therefore Cochran's theorem applies, and

$$\begin{array}{cccc} \sigma^{-2}\mathbf{y}'\mathbf{P}_{1}\mathbf{y} & \sim & \chi^{2}_{\rho_{1}}(\beta'\mathbf{X}'\mathbf{P}_{\mathbf{X}_{1}}\mathbf{X}\beta) \\ \sigma^{-2}\mathbf{y}'(\mathbf{P}_{\mathbf{X}}-\mathbf{P}_{\mathbf{X}_{1}})\mathbf{y} & \sim & \chi^{2}_{\rho_{2}}(\beta'\mathbf{X}'(\mathbf{P}_{\mathbf{X}}-\mathbf{P}_{\mathbf{X}_{1}})\mathbf{X}\beta) \\ \sigma^{-2}\mathbf{y}'(\mathbf{I}-\mathbf{P}_{\mathbf{X}})\mathbf{y} & \sim & \chi^{2}_{n-\rho} \end{array}$$

• Note, the last term follows a central χ^2 distribution because

$$eta' \mathbf{X}' (\mathbf{I} - \mathbf{P}_{\mathbf{X}}) \mathbf{X} eta = 0.$$

Note, it also holds that

$$\sigma^{-2}\mathbf{y}'(\mathbf{P_X}-\mathbf{P_{X_1}})\mathbf{y}$$

and

$$\sigma^{-2}\mathbf{y}'(\mathbf{I}-\mathbf{P_X})\mathbf{y}$$

are independent

In addition,

$$F = \frac{\mathbf{y}'(\mathbf{P_X} - \mathbf{P_{X_1}})\mathbf{y}/p_2}{\mathbf{y}'(\mathbf{I} - \mathbf{P_X})\mathbf{y}/(n - p)} \sim F_{p_2, n - p}(\beta'\mathbf{X}'(\mathbf{P_X} - \mathbf{P_{X_1}})\mathbf{X}\beta)$$

- This is an example of sequential sums of squares.
- It allows us to study the contribution of adding additional variables to a model.