Note that $X(X'X)^{-1}X'$ is symmetric and idempotent, i.e., $A'A = A$.

$$\frac{u'X(X'X)^{-1}X'u}{\sigma^2} \sim \chi^2\Big(\mathrm{tr}(X(X'X)^{-1}X')\Big)$$

The degree of freedom is given by:

$$\mathrm{tr}(X(X'X)^{-1}X') = \mathrm{tr}((X'X)^{-1}X'X) = \mathrm{tr}(I_k) = k$$

Therefore, we obtain:

$$\frac{u'X(X'X)^{-1}X'u}{\sigma^2} \sim \chi^2(k)$$

3. (*) Formula:

   Suppose that $X \sim N(0, I_k)$.

   If A is symmetric and idempotent, i.e., $A'A = A$, then $X'AX \sim \chi^2(\mathrm{tr}(A))$.

   Here, $X = \dfrac{1}{\sigma}u \sim N(0, I_n)$ from $u \sim N(0, \sigma^2 I_n)$, and $A = X(X'X)^{-1}X'$.

4. **Sum of Residuals:** e is rewritten as:

$$e = (I_n - X(X'X)^{-1}X')u.$$

Therefore, the sum of residuals is given by:

$$e'e = u'(I_n - X(X'X)^{-1}X')u.$$

Note that $I_n - X(X'X)^{-1}X'$ is symmetric and idempotent.

We obtain the following result:

$$\frac{e'e}{\sigma^2} = \frac{u'(I_n - X(X'X)^{-1}X')u}{\sigma^2} \sim \chi^2\Big(\mathrm{tr}(I_n - X(X'X)^{-1}X')\Big),$$

where the trace is:

$$\mathrm{tr}(I_n - X(X'X)^{-1}X') = n - k.$$

Therefore, we have the following result:

$$\frac{e'e}{\sigma^2} = \frac{(n-k)s^2}{\sigma^2} \sim \chi^2(n-k),$$

where

$$s^2 = \frac{1}{n-k} e'e.$$

5. We show that $\hat{\beta}$ is independent of e.

Proof:

Because $u \sim N(0, \sigma^2 I_n)$, we show that $\mathrm{Cov}(e, \hat{\beta}) = 0$.

$$\begin{aligned}
\mathrm{Cov}(e, \hat{\beta}) &= \mathrm{E}(e(\hat{\beta} - \beta)') = \mathrm{E}\Big((I_n - X(X'X)^{-1}X')u((X'X)^{-1}X'u)'\Big) \\
&= \mathrm{E}\Big((I_n - X(X'X)^{-1}X')uu'X(X'X)^{-1}\Big) = (I_n - X(X'X)^{-1}X')\mathrm{E}(uu')X(X'X)^{-1} \\
&= (I_n - X(X'X)^{-1}X')(\sigma^2 I_n)X(X'X)^{-1} = \sigma^2(I_n - X(X'X)^{-1}X')X(X'X)^{-1} \\
&= \sigma^2(X(X'X)^{-1} - X(X'X)^{-1}X'X(X'X)^{-1}) = \sigma^2(X(X'X)^{-1} - X(X'X)^{-1}) = 0.
\end{aligned}$$

$\hat{\beta}$ is independent of e, because of normality assumption on u

[Review]

• Suppose that X is independent of Y. Then, $\mathrm{Cov}(X, Y) = 0$. However, $\mathrm{Cov}(X, Y) = 0$ does not mean in general that X is independent of Y.

• In the case where X and Y are normal, $\mathrm{Cov}(X, Y) = 0$ indicates that X is independent of Y.

[End of Review]

[Review] Formulas — F Distribution:

- $\dfrac{U/n}{V/m} \sim F(n,m)$ when U $sim\chi^2(n)$, $V \sim \chi^2(m)$, and U is independent of V.

- When $X \sim N(0, I_n)$, A and B are $n \times n$ symmetric idempotent matrices, $\text{Rank}(A) = \text{tr}(A) = G$, $\text{Rank}(B) = \text{tr}(B) = K$ and $AB = 0$, then $\dfrac{X'AX/G}{X'BX/K} \sim F(G,K)$.

Note that the covariance of AX and BX is zero, which implies that AX is independent of BX under normality of X.

[End of Review]

6. Therefore, we obtain the following distribution:

$$\frac{(\hat{\beta}-\beta)'X'X(\hat{\beta}-\beta)}{\sigma^2} = \frac{u'X(X'X)^{-1}X'u}{\sigma^2} \sim \chi^2(k),$$

$$\frac{e'e}{\sigma^2} = \frac{u'(I_n - X(X'X)^{-1}X')u}{\sigma^2} \sim \chi^2(n-k)$$

$\hat{\beta}$ is independent of e, because $X(X'X)^{-1}X'(I_n - X(X'X)^{-1}X') = 0$.

Accordingly, we can derive:

$$\frac{\dfrac{(\hat{\beta}-\beta)'X'X(\hat{\beta}-\beta)}{\sigma^2}\Big/k}{\dfrac{e'e}{\sigma^2}\Big/(n-k)} = \frac{(\hat{\beta}-\beta)'X'X(\hat{\beta}-\beta)/k}{s^2} \sim F(k, n-k)$$

Under the null hypothesis $H_0: \beta = 0$, $\dfrac{\hat{\beta}'X'X\hat{\beta}/k}{s^2} \sim F(k, n-k)$.

Given data, $\dfrac{\hat{\beta}'X'X\hat{\beta}/k}{s^2}$ is compared with $F(k, n-k)$.

If $\dfrac{\hat{\beta}'X'X\hat{\beta}/k}{s^2}$ is in the tail of the F distribution, the null hypothesis is rejected.

Coefficient of Determination (決定係数), R^2:

1. Definition of the Coefficient of Determination, R^2: $\quad R^2 = 1 - \dfrac{\sum_{i=1}^n e_i^2}{\sum_{i=1}^n (y_i - \overline{y})^2}$

2. Numerator: $\quad \displaystyle\sum_{i=1}^n e_i^2 = e'e$

3. Denominator: $\quad \displaystyle\sum_{i=1}^n (y_i - \overline{y})^2 = y'(I_n - \frac{1}{n}ii')'(I_n - \frac{1}{n}ii')y = y'(I_n - \frac{1}{n}ii')y$

   (*) Remark

$$\begin{pmatrix} y_1 - \overline{y} \\ y_2 - \overline{y} \\ \vdots \\ y_n - \overline{y} \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} - \begin{pmatrix} \overline{y} \\ \overline{y} \\ \vdots \\ \overline{y} \end{pmatrix} = y - \frac{1}{n}ii'y = (I_n - \frac{1}{n}ii')y,$$

   where $i = (1, 1, \cdots, 1)'$.

4. In a matrix form, we can rewrite as: $R^2 = 1 - \dfrac{e'e}{y'(I_n - \frac{1}{n}ii')y}$

F Distribution and Coefficient of Determination:

$\Longrightarrow$ This will be discussed later.

Testing Linear Restrictions (F Distribution):

1. If $u \sim N(0, \sigma^2 I_n)$, then $\hat{\beta} \sim N(\beta, \sigma^2 (X'X)^{-1})$.

   Consider testing the hypothesis $H_0 : R\beta = r$.

   $R : \; G \times k, \qquad \text{rank}(R) = G \leq k.$

   $R\hat{\beta} \sim N(R\beta, \sigma^2 R(X'X)^{-1}R')$.

   Therefore, $\dfrac{(R\hat{\beta} - r)'(R(X'X)^{-1}R')^{-1}(R\hat{\beta} - r)}{\sigma^2} \sim \chi^2(G)$.

   Note that $R\beta = r$.

   (a) When $\hat{\beta} \sim N(\beta, \sigma^2 (X'X)^{-1})$, the mean of $R\hat{\beta}$ is:

   $$\mathrm{E}(R\hat{\beta}) = R\mathrm{E}(\hat{\beta}) = R\beta.$$

   (b) When $\hat{\beta} \sim N(\beta, \sigma^2 (X'X)^{-1})$, the variance of $R\hat{\beta}$ is: