# Econometrics I TA Session 

Wang Xin

May 19, 2022

## 1 Idempotent and Symmetric Matrix

The matrix $\mathbf{A}$ is idempotent and symmetric if and only if $\mathbf{A}^{2}=\mathbf{A}=\mathbf{A}^{\prime}$.

## 1.1 $\quad \mathrm{X}\left(\mathrm{X}^{\prime} \mathrm{X}\right)^{-1} \mathrm{X}^{\prime}$

From the previous note, we know that

$$
\hat{\boldsymbol{\beta}}=\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime} \mathbf{Y}
$$

Therefore, the predicted value of $\mathbf{Y}$ can be written as

$$
\begin{equation*}
\hat{\mathbf{Y}}=\mathbf{X} \hat{\boldsymbol{\beta}}=\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime} \mathbf{Y} \tag{1}
\end{equation*}
$$

Let $\mathbf{N}=\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime}$, then the below equations can be found:

$$
\begin{gather*}
\mathbf{N}^{\prime}=\left(\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}\right)^{\prime}=\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}=\mathbf{N}  \tag{2}\\
\mathbf{N N}=\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime} \mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}=\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime}=\mathbf{N} \tag{3}
\end{gather*}
$$

## $1.2 \quad \mathrm{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}$

The residuals are defined as $\mathbf{e}=\mathbf{Y}-\mathbf{X} \hat{\boldsymbol{\beta}}$, so using equation (1), we have

$$
\mathbf{e}=\mathbf{Y}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime} \mathbf{Y}=\left(\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}\right) \mathbf{Y}
$$

Let $\mathbf{M}=\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime}$, similar to $N$, we can find

$$
\begin{align*}
& \mathbf{M}^{\prime}=\left(\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime}\right)^{\prime}=\mathbf{I}^{\prime}-\left(\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime}\right)^{\prime}=\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}=\mathbf{M}  \tag{4}\\
& \begin{aligned}
\mathbf{M M} & =\left(\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime}\right)\left(\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}\right) \\
& =\mathbf{I}+\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime} \mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}-\mathbf{2} \mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime} \\
& =\mathbf{I}+\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime}-\mathbf{2} \mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime} \\
& =\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}=\mathbf{M}
\end{aligned}
\end{align*}
$$

### 1.3 Other Relationships

Both $\mathbf{N}$ an $\mathbf{M}$ are projection matrices.
A projection matrix $\mathbf{P}$ describes the influence each response value has on each fitted value, whenever $\mathbf{P}$ is applied twice to any vector, it gives the same result as if it were applied once.

According to the properties of projection matrix, the below relationships can be found:

$$
\begin{equation*}
\mathbf{N X}=\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-\mathbf{1}} \mathbf{X}^{\prime} \mathbf{X}=\mathbf{X} \tag{6}
\end{equation*}
$$

$$
\begin{gather*}
\mathbf{M X}=\left(\mathbf{I}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime}\right) \mathbf{X}=\mathbf{X}-\mathbf{X}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1} \mathbf{X}^{\prime} \mathbf{X}=\mathbf{X}-\mathbf{X}=\mathbf{0}  \tag{7}\\
\mathbf{M N}=\mathbf{N M}=\mathbf{0} \tag{8}
\end{gather*}
$$

## $2 \quad \mathcal{X}^{2}$ Distribution

### 2.1 Definition

At TA Session, gamma distribution was introduced last week.

$$
g(x)=\left\{\begin{array}{l}
\frac{x^{\alpha-1} e^{-x / \beta}}{\beta^{\alpha} \Gamma(\alpha)}, \quad x>0 \\
0, \quad \text { elsewhere }
\end{array}\right.
$$

Let us now consider a special case of the gamma distribution in which $\alpha=r / 2$, where r is a positive integer, and $\beta=2$. A random variable X of the continuous type that has the pdf

$$
f(x)=\left\{\begin{array}{l}
\frac{x^{r / 2-1} e^{-x / 2}}{2^{r / 2} \Gamma(r / 2)}, \quad x>0  \tag{9}\\
0, \quad \text { elsewhere }
\end{array}\right.
$$

and the mgf

$$
M(\theta)=(1-2 \theta)^{-r / 2}, \quad \theta<\frac{1}{2}
$$

is said to have a chi-square distribution ( $\mathcal{X}^{2}$-distribution), and any $f(x)$ of this form is called a chi-square pdf.

### 2.2 Operation on Normal Variable

Theorem 1. If the random variable $X \stackrel{i i d}{\sim} \mathcal{N}\left(\mu, \sigma^{2}\right), \sigma^{2}<0$, then the random variable $V=(X-\mu)^{2} / \sigma^{2}$ is $\mathcal{X}^{2}(1)$.

Proof. Because $V=W^{2}$, where $W=(X-\mu) / \sigma$ is $N(0,1)$, the cdf $G(v)$ for V is, for $v \geq 0$,

$$
\begin{aligned}
G(v) & =P\left(W^{2} \leq v\right)=P(-\sqrt{v} \leq w \leq \sqrt{v}) \\
& =2 \int_{0}^{\sqrt{v}} \frac{1}{\sqrt{2 \pi}} e^{-w^{2} / 2} d w, \quad v \geq 0
\end{aligned}
$$

and

$$
G(v)=0, \quad v<0
$$

If we change the variable of integration by writing $w=\sqrt{y}$, then

$$
G(v)=2 \int_{0}^{v} \frac{1}{\sqrt{2 \pi} \sqrt{y}} e^{-y / 2} d y, \quad v \geq 0
$$

Hence the pdf $g(v)=G^{\prime}(v)$ of the continuous-type random variable $V$ is

$$
g(v)=\left\{\begin{array}{l}
\frac{1}{\sqrt{2 \pi}} v^{1 / 2-1} e^{-v / 2} \quad 0<v<\infty \\
0, \quad \text { elsewhere }
\end{array}\right.
$$

Since $\Gamma\left(\frac{1}{2}\right)=\sqrt{\pi}$, thus V is $\mathcal{X}^{2}(1)$.

### 2.3 F-distribution

Consider two independent chi-square random variables $U$ and $V$ having $r_{1}$ and $r_{2}$ degrees of freedom, respectively. The joint pdf $h(u, v)$ of $U$ and $V$ is then

$$
h(u, v)=\left\{\begin{array}{l}
\frac{u^{r_{1} / 2-1} v^{r_{2} / 2-1} e^{-(u+v) / 2}}{\Gamma\left(r_{1} / 2\right) \Gamma\left(r_{2} / 2\right) 2^{\left(r_{1}+r_{2}\right) / 2}}, \quad 0<u, v<\infty \\
0, \quad \text { elsewhere }
\end{array}\right.
$$

We define the new random variable

$$
W=\frac{U / r_{1}}{V / r_{2}}
$$

and we propose finding the pdf $g_{1}(w)$ of $W$. The equations

$$
w=\frac{u / r_{1}}{v / r_{2}}, \quad z=v
$$

define a one-to-one transformation that maps the set $\mathcal{S}=(u, v): 0<u, v<\infty$ onto the set $T=(w, z): 0<w, z<\infty$. Since $u=\left(r_{1} / r_{2}\right) z w, v=z$, the absolute value of the Jacobian of the transformation is $|J|=\left(r_{1} / r_{2}\right) z$. The joint pdf $g(w, z)$ of the random variables $W$ and $Z=V$ is then

$$
\begin{equation*}
g(w, z)=\frac{1}{\Gamma\left(r_{1} / 2\right) \Gamma\left(r_{2} / 2\right) 2^{\left(r_{1}+r_{2}\right) / 2}}\left(\frac{r_{1} z w}{r_{2}}\right)^{\frac{r_{1}-2}{2}} z^{\frac{r_{2}-2}{2}} \exp \left[-\frac{z}{2}\left(\frac{r_{1} w}{r_{2}}+1\right)\right] \frac{r_{1} z}{r_{2}} \tag{10}
\end{equation*}
$$

provided that $(w, z) \in T$, and zero elsewhere. The marginal $\operatorname{pdf} g_{1}(w)$ of $W$ is the

$$
\begin{aligned}
g_{1}(w) & =\int_{-\infty}^{+\infty} g(w, z) d z \\
& =\int_{0}^{\infty} \frac{\left(r_{1} / r_{2}\right)^{r_{1} / 2} w^{\frac{r_{1}}{2}-1}\left(r_{2} / r_{1}\right)}{\Gamma\left(r_{1} / 2\right) \Gamma\left(r_{2} / 2\right) 2^{\left(r_{1}+r_{2}\right) / 2}} z^{r_{1}-2} z^{\frac{r_{2}-2}{2}} \frac{r_{1} z}{r_{2}} \exp \left[-\frac{z}{2}\left(\frac{r_{1} w}{r_{2}}+1\right)\right] d z \\
& =\int_{0}^{\infty} \frac{\left(r_{1} / r_{2}\right)^{r_{1} / 2} w^{\frac{r_{1}}{2}-1}}{\Gamma\left(r_{1} / 2\right) \Gamma\left(r_{2} / 2\right) 2^{\left(r_{1}+r_{2}\right) / 2}} z^{\frac{r_{1}+r_{2}}{2}-1} \exp \left[-\frac{z}{2}\left(\frac{r_{1} w}{r_{2}}+1\right)\right] d z
\end{aligned}
$$

If we change the variable of integration by writing $y=\frac{z}{2}\left(\frac{r_{1} w}{r_{2}}+1\right)$, then

$$
\begin{gathered}
\frac{d y}{d z}=\frac{1}{2}\left(\frac{r_{1} w}{r_{2}}+1\right) \\
g_{1}(w)=\frac{\left(r_{1} / r_{2}\right)^{r_{1} / 2} w^{\frac{r_{1}}{2}-1}}{\Gamma\left(r_{1} / 2\right) \Gamma\left(r_{2} / 2\right) 2^{\left(r_{1}+r_{2}\right) / 2}} \int_{0}^{\infty}\left(\frac{2 y}{r_{1} w / r_{2}+1}\right)^{\frac{r_{1}+r_{2}}{2}-1} e^{-y} \frac{2}{r_{1} w / r_{2}+1} d y \\
=\frac{\left(r_{1} / r_{2}\right)^{r_{1} / 2}}{\Gamma\left(r_{1} / 2\right) \Gamma\left(r_{2} / 2\right)} \frac{w^{\frac{r_{1}}{2}-1}}{\left(r_{1} w / r_{2}+1\right)^{\left(r_{1}+r_{2}\right) / 2}} \int_{0}^{\infty} y^{\frac{r_{1}+r_{2}}{2}-1} e^{-y} d y
\end{gathered}
$$

In the above equation, a gamma function is contained

$$
\Gamma\left(\frac{r_{1}+r_{2}}{2}\right)=\int_{0}^{\infty} y^{\frac{r_{1}+r_{2}}{2}-1} e^{-y} d y
$$

Therefore, the pdf $g_{1}(w)$ of $W$ can be simplified as

$$
g_{1}(w)=\left\{\begin{array}{l}
\frac{\Gamma\left[\left(r_{1}+r_{2}\right) / 2\right]\left(r_{1} / r_{2}\right)^{r_{1} / 2}}{\Gamma\left(r_{1} / 2\right) \Gamma\left(r_{2} / 2\right)} \frac{w^{r_{1} / 2-1}}{\left(1+r_{1} w / r_{2}\right)^{\left(r_{1}+r_{2}\right) / 2}}, \quad 0<w<\infty  \tag{11}\\
0, \quad \text { elsewhere }
\end{array}\right.
$$

Accordingly, if U and V are independent chi-square variables with $r_{1}$ and $r_{2}$ degrees of freedom, respectively, then $W=\left(U / r_{1}\right) /\left(V / r_{2}\right)$ has the pdf $g_{1}(w)$. The distribution of this random variable is usually called an F-distribution; and we often call the ratio, which we have denoted by $W, F$. That is

$$
\begin{equation*}
F=\frac{U / r_{1}}{V / r_{2}} \tag{12}
\end{equation*}
$$

It should be observed that an F-distribution is completely determined by the two parameters $r_{1}$ and $r_{2}$.

