# Special Preliminary Examination on Linear Models and Multivariate Statistics 

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Name: $\qquad$

1. It is a closed-book and in-class exam.
2. One page (letter size, 8.5 -by-11in) cheat sheet is allowed.
3. Calculator is allowed. No laptop (or equivalent).
4. Show your work to receive full credits. Highlight your final answer.
5. Solve any five problems out of the six problems.
6. Total points are $\mathbf{5 0}$. Each question is worth $\mathbf{1 0}$ points.
7. If you work out more than five problems, your score is the sum of five highest points.
8. Time: 180 minutes. (8:30am - 11:30am, Wednesday, December 07, 2011)

| 1 | 2 | 3 | 4 | 5 | 6 | Total |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |

1. Let $X_{1}, \ldots, X_{n}$ be a random sample from $N_{p}(\mu, \Sigma)$ population. Denote $\bar{x}$ and $S$ as the sample mean and the sample covariance matrix, respectively. Consider the hypothesis $H_{0}: \mu=\mu_{0}$ against $H_{1}: \mu \neq \mu_{0}$, where $\mu_{0}$ is a given vector.
(a) Work out the rejection region based on the test statistic

$$
T^{2}=n\left(\bar{x}-\mu_{0}\right)^{T} S^{-1}\left(\bar{x}-\mu_{0}\right) .
$$

(b) Work out the rejection region based on the likelihood ratio test.
(c) Show that the above two tests are equivalent.
2. Describe factor analysis and principal component analysis. What are the differences and similarities between these two methods?
3. Suppose that the covariance ( $n \times n$ matrix) given below

$$
S=\left(\begin{array}{ccccc}
1 & \rho & \rho & \cdots & \rho \\
\rho & 1 & \rho & \cdots & \rho \\
\rho & \rho & 1 & \cdots & \rho \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\rho & \rho & \rho & \cdots & 1
\end{array}\right)
$$

Show that if $\rho>0$ then the first principal component accounts for a proportion ( $1+$ $\rho(n-1)) / n$ of the total variation in the data. What can be said about the other $n-1$ components?
Hint: You may want to use the following result.

$$
\left|a I_{p}+b J_{p}\right|=a^{p-1}(a+b p)
$$

where $J_{p}=1_{p} 1_{p}^{T}$ and $1_{p}$ is a $p \times 1$ vector of ones.
4. Suppose $y_{1}, y_{2}, y_{3}$ and $y_{4}$ are observations of angles $\theta_{1}, \theta_{2}, \theta_{3}$, and $\theta_{4}$ of a quadrilateral on the ground. If the observations are subject to independent normal errors with zero means and common variance $\sigma^{2}$. (Note: The sum of the angles of a quadrilateral is $2 \pi$.)
(a) Find the least squares estimates for $\theta_{1}, \theta_{2}, \theta_{3}$ and $\theta_{4}$.
(b) Derive a test statistic for the hypothesis that the quadrilateral is a parallelogram with $\theta_{1}=\theta_{3}$ and $\theta_{2}=\theta_{4}$.
5. In a linear regression model $\mathbf{y}=\mathbf{X} \boldsymbol{\beta}+\boldsymbol{\varepsilon}$, where $\boldsymbol{\varepsilon} \sim N\left(\mathbf{0}, \sigma^{2} \mathbf{I}_{n}\right)$, show how to find a confidence interval for the ratio $\mathbf{a}_{1}^{\prime} \boldsymbol{\beta} / \mathbf{a}_{2}^{\prime} \boldsymbol{\beta}$ of two linear parametric functions.
6. Consider a regression model

$$
y_{i}=\beta_{0}+\beta_{1} x_{i 1}+\beta_{2} x_{i 2}+\cdots+\beta_{p-1} x_{i, p-1}+\varepsilon_{i}, \quad i=1,2, \ldots, n .
$$

Suppose that $\beta_{1}=\beta_{2}=\cdots=\beta_{p-1}=0$. Find the distribution of $R^{2}$ (coefficient of determination) and hence prove that $E\left(R^{2}\right)=(p-1) /(n-1)$.

## Solution.

1. 
2. 
3. 
4. We can write the model as

$$
\begin{aligned}
y_{1} & =\theta_{1}+\varepsilon_{1} \\
y_{2} & =\theta_{2}+\varepsilon_{2} \\
y_{3} & =\theta_{3}+\varepsilon_{3} \\
y_{4}-2 \pi & =-\theta_{1}-\theta_{2}-\theta_{3}+\varepsilon_{4}
\end{aligned}
$$

Therefore,

$$
\mathbf{y}=\left(\begin{array}{c}
y_{1} \\
y_{2} \\
y_{3} \\
2 \pi-y_{4}
\end{array}\right), \quad \mathbf{X}=\left(\begin{array}{ccc}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
-1 & -1 & -1
\end{array}\right), \quad \boldsymbol{\beta}=\left(\begin{array}{c}
\theta_{1} \\
\theta_{2} \\
\theta_{3}
\end{array}\right)
$$

The LSE of $\boldsymbol{\beta}$ is

$$
\hat{\boldsymbol{\beta}}=\frac{1}{4}\left(\begin{array}{ccc}
3 & -1 & -1 \\
-1 & 3 & -1 \\
-1 & -1 & 3
\end{array}\right)\left(\begin{array}{l}
y_{1}-y_{4}+2 \pi \\
y_{2}-y_{4}+2 \pi \\
y_{3}-y_{4}+2 \pi
\end{array}\right)=\left(\begin{array}{c}
\left(3 y_{1}-y_{2}-y_{3}-y_{4}+2 \pi\right) / 4 \\
\left(3 y_{2}-y_{1}-y_{3}-y_{4}+2 \pi\right) / 4 \\
\left(3 y_{3}-y_{1}-y_{2}-y_{4}+2 \pi\right) / 4
\end{array}\right)
$$

Therefore,

$$
\hat{\theta}_{4}=\left(3 y_{4}-y_{1}-y_{2}-y_{3}+2 \pi\right) / 4 .
$$

Now consider the hypothesis. If $\theta_{1}=\theta_{3}$ and $\theta_{2}=\theta_{4}$, then the model can be written as

$$
\begin{aligned}
y_{1} & =\theta_{1}+\varepsilon_{1} \\
y_{2}-\pi & =-\theta_{1}+\varepsilon_{2} \\
y_{3} & =\theta_{1}+\varepsilon_{3} \\
y_{4}-\pi & =-\theta_{1}+\varepsilon_{4}
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
& \hat{\theta}_{1}=\hat{\theta}_{3}=\left(y_{1}-y_{2}+y_{3}-y_{4}+2 \pi\right) / 4 \\
& \hat{\theta}_{2}=\hat{\theta}_{4}=\left(y_{2}-y_{1}+y_{4}-y_{3}+2 \pi\right) / 4
\end{aligned}
$$

Calculate RSS and $\mathrm{RSS}_{H}$,

$$
\begin{aligned}
\mathrm{RSS} & =\left(y_{1}+y_{2}+y_{3}+y_{4}-2 \pi\right)^{2} / 4 \\
\mathrm{RSS}_{H}-\mathrm{RSS} & =\left(y_{1}-y_{3}\right)^{2} / 2+\left(y_{2}-y_{4}\right)^{2} / 2
\end{aligned}
$$

Therefore, an $F$-statistic is

$$
F=\frac{\left(\operatorname{RSS}_{H}-\mathrm{RSS}\right) / 2}{\operatorname{RSS}}=\frac{\left(y_{1}-y_{3}\right)^{2}+\left(y_{2}-y_{4}\right)^{2}}{\left(y_{1}+y_{2}+y_{3}+y_{4}-2 \pi\right)^{2}}
$$

When $H$ is true, $F \sim F_{2,1}$.
5. Denote $\phi=\mathbf{a}_{1}^{\prime} \boldsymbol{\beta} / \mathbf{a}_{2}^{\prime} \boldsymbol{\beta}$ and consider statistic $\mathbf{a}_{1}^{\prime} \hat{\boldsymbol{\beta}}-\phi \mathbf{a}_{2}^{\prime} \hat{\boldsymbol{\beta}}=\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right)^{\prime} \hat{\boldsymbol{\beta}}$, where $\hat{\boldsymbol{\beta}}$ is the LSE of $\boldsymbol{\beta}$. This statistic follows a normal distribution with mean and variance,

$$
\begin{aligned}
E\left(\mathbf{a}_{1}^{\prime} \hat{\boldsymbol{\beta}}-\phi \mathbf{a}_{2}^{\prime} \hat{\boldsymbol{\beta}}\right) & =\mathbf{a}_{1}^{\prime} \boldsymbol{\beta}-\phi \mathbf{a}_{2}^{\prime} \boldsymbol{\beta}=0 \\
\operatorname{var}\left(\mathbf{a}_{1}^{\prime} \hat{\boldsymbol{\beta}}-\phi \mathbf{a}_{2}^{\prime} \hat{\boldsymbol{\beta}}\right) & =\sigma^{2}\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right)^{\prime}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1}\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right),
\end{aligned}
$$

where $\mathbf{X}$ is the regression matrix. Therefore,

$$
\frac{\mathbf{a}_{1}^{\prime} \hat{\boldsymbol{\beta}}-\phi \mathbf{a}_{2}^{\prime} \hat{\boldsymbol{\beta}}}{S \sqrt{\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right)^{\prime}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1}\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right)}}
$$

follows a $t$-distribution with $n-p$ degrees of freedom, where $S^{2}=\operatorname{RSS} /(n-p)$. From

$$
1-\alpha=P\left(\left|\mathbf{a}_{1}^{\prime} \hat{\boldsymbol{\beta}}-\phi \mathbf{a}_{2}^{\prime} \hat{\boldsymbol{\beta}}\right| \leq t_{\alpha / 2, n-p} \cdot S \sqrt{\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right)^{\prime}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1}\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right)}\right)
$$

we know that a confidence interval should satisfy

$$
\left(\mathbf{a}_{1}^{\prime} \hat{\boldsymbol{\beta}}-\phi \mathbf{a}_{2}^{\prime} \hat{\boldsymbol{\beta}}\right)^{2} \leq F_{\alpha, 1, n-p} \cdot S^{2}\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right)^{\prime}\left(\mathbf{X}^{\prime} \mathbf{X}\right)^{-1}\left(\mathbf{a}_{1}-\phi \mathbf{a}_{2}\right) .
$$

Solve this inequality to obtain an confidence interval.
6. The coefficient of determination is

$$
R^{2}=\frac{\sum\left(\hat{y}_{i}-\bar{y}\right)^{2}}{\sum\left(y_{i}-\bar{y}\right)^{2}}=\frac{\sum\left(\hat{y}_{i}-\bar{y}\right)^{2}}{\sum\left(y_{i}-\hat{y}_{i}\right)^{2}+\sum\left(\hat{y}_{i}-\bar{y}\right)^{2}} .
$$

Notice that $\sum\left(y_{i}-\hat{y}_{i}\right)^{2} \sim \sigma^{2} \chi_{n-p}^{2}$ is independent of $\sum\left(\hat{y}_{i}-\bar{y}\right)^{2} \sim \sigma^{2} \chi_{p-1}^{2}$. Therefore, the distribution of $R^{2}$ is $\chi_{p-1}^{2} /\left(\chi_{n-p}^{2}+\chi_{p-1}^{2}\right)$, which is a $\operatorname{Beta}((p-1) / 2,(n-p) / 2)$ distribution. So $E\left(R^{2}\right)=(p-1) /(n-1)$.
Note: $\chi_{p}^{2}$ is also a $\operatorname{Gamma}(p / 2,2)$ distribution. If $X \sim \operatorname{Gamma}\left(\alpha_{1}, \beta\right)$ is independent of $Y \sim \operatorname{Gamma}\left(\alpha_{2}, \beta\right)$, then $X /(X+Y) \sim \operatorname{Beta}\left(\alpha_{1}, \alpha_{2}\right)$.

