

Wk] - Quiz 1.

$$1. f(x_1, x_2) = \frac{1}{2x_2} e^{-(\frac{x_1}{4} + \frac{2x_1}{x_2})}, x_1, x_2 > 0$$

$$(a) f_{x_2}(x_2) = \int_0^{\infty} \frac{1}{2x_2} e^{-(\frac{x_1}{4} + \frac{2x_1}{x_2})} dx_1$$

$$= \frac{1}{2x_2} \int_0^{\infty} e^{-\frac{x_1}{4}} e^{-\frac{2x_1}{x_2}} dx_1$$

$$= \frac{1}{2x_2} e^{-\frac{x_1}{4}} \int_0^{\infty} e^{-\frac{2x_1}{x_2}} dx_1$$

$$= \frac{1}{2x_2} e^{-\frac{x_1}{4}} \left[-\frac{x_2}{2} e^{-\frac{2x_1}{x_2}} \right]_0^{\infty}$$

$$= \frac{1}{2x_2} e^{-\frac{x_1}{4}} \left[-\frac{x_2}{2}(0) + \frac{x_2}{2}(1) \right]$$

$$= \frac{1}{2x_2} e^{-\frac{x_1}{4}} \left[\frac{x_2}{2} \right]$$

$$f_{x_2}(x_2) = \underline{\underline{\frac{1}{4} \cdot e^{-\frac{x_1}{4}}}}$$

$$(b) f_{x_1|x_2}(x_1|x_2) = \frac{f_{x_1, x_2}(x_1, x_2)}{f_{x_2}(x_2)}$$

$$= \frac{\frac{1}{2x_2} e^{-(\frac{x_1}{4} + \frac{2x_1}{x_2})}}{\frac{1}{4} e^{-\frac{x_1}{4}}}$$

$$= \frac{\frac{2}{4} e^{-\frac{x_1}{4}} \cdot e^{-\frac{2x_1}{x_2}}}{2x_2 \cdot e^{-\frac{x_1}{4}}}$$

$$= \underline{\underline{\frac{2 e^{-\frac{2x_1}{x_2}}}{x_2}}}$$

$$1. (c) g^*(x_2) = E(X_1 | X_2 = x_2)$$

$$\begin{aligned} &= \int_{x_1}^{\infty} f_{X_1|X_2}(x_1 | x_2) dx_1 \\ &= \int_0^{\infty} x_1 \cdot \frac{2}{x_2} e^{-2x_1/x_2} dx_1 \\ &= \frac{2}{x_2} \int_0^{\infty} x_1 e^{-2x_1/x_2} dx_1 \end{aligned}$$

Integration by parts:

$$\begin{array}{l} u = x_1, \quad \left| \begin{array}{l} du = dx_1 \\ dv = e^{-2x_1/x_2} dx_1 \\ v = \int e^{-2x_1/x_2} dx_1 \\ = -\frac{x_2}{2} e^{-2x_1/x_2} \end{array} \right. \\ du = dx_1, \quad \left| \begin{array}{l} dv = e^{-2x_1/x_2} dx_1 \\ v = \int e^{-2x_1/x_2} dx_1 \\ = -\frac{x_2}{2} e^{-2x_1/x_2} \end{array} \right. \end{array} \quad (\text{Neglect constants of integration here.})$$

$$\begin{aligned} \therefore \int u dv &= uv - \int v du \\ &= -\frac{x_1 x_2}{2} e^{-2x_1/x_2} - \int -\frac{x_2}{2} e^{-2x_1/x_2} dx_1 \\ &= -\frac{x_1 x_2}{2} e^{-2x_1/x_2} + \frac{x_2}{2} \int e^{-2x_1/x_2} dx_1 \\ &= -\frac{x_1 x_2}{2} e^{-2x_1/x_2} - \frac{x_2^2}{4} e^{-2x_1/x_2} \\ &= -e^{-2x_1/x_2} \left(\frac{x_1 x_2}{2} + \frac{x_2^2}{4} \right) \end{aligned}$$

$$\therefore g^*(x_2) = \frac{2}{x_2} \left[-e^{-2x_1/x_2} \left(\frac{x_1 x_2}{2} + \frac{x_2^2}{4} \right) \right]_0^{\infty}$$

$$\begin{aligned} &= \left[-e^{-2x_1/x_2} \left(x_1 + \frac{x_2}{2} \right) \right]_0^{\infty} \\ &= 0 + 1 \cdot \frac{x_2}{2} \end{aligned}$$

$$= \frac{x_2}{2}$$

1.(d). $E[(X_1 - g^*(X_2))^2 | X_2 = x_2]$

$$= E\left[\left(X_1 - \frac{x_2}{2}\right)^2 \mid X_2 = x_2\right]$$

$$= E\left[X_1^2 - x_1 x_2 + \frac{x_2^2}{4} \mid X_2 = x_2\right]$$

$$= E(X_1^2 \mid X_2 = x_2) - E(x_1 X_1 \mid X_2 = x_2) + E\left(\frac{x_2^2}{4} \mid X_2 = x_2\right)$$

$$= \frac{x_2^2}{2} - x_2 \cdot \frac{x_2}{2} + \frac{x_2^2}{4}$$

$$= \frac{x_2^2}{2} - \frac{x_2^2}{2} + \frac{x_2^2}{4}$$

$$= \frac{x_2^2}{4}$$

Used CAS for
 $E(X_1^2 \mid X_2 = x_2)$

$$2. \Sigma = \begin{bmatrix} 8 & 3 \\ 3 & 9 \end{bmatrix}$$

(a) Characteristic polynomial

$$= |\Sigma - \lambda I|$$

$$= \left| \begin{pmatrix} 8 & 3 \\ 3 & 9 \end{pmatrix} - \lambda \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right|$$

$$= \left| \begin{pmatrix} 8 & 3 \\ 3 & 9 \end{pmatrix} - \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} \right|$$

$$= \begin{vmatrix} 8-\lambda & 3-0 \\ 3-0 & 9-\lambda \end{vmatrix}$$

$$= (8-\lambda)(9-\lambda) - (3)^2$$

$$= 72 - 8\lambda - 9\lambda + \lambda^2 - 9$$

$$= \lambda^2 - 17\lambda + 63$$

$$(b) \lambda = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$a = 1$$

$$b = -17$$

$$c = 63$$

$$= \frac{17 \pm \sqrt{37}}{2} = \frac{17 + \sqrt{37}}{2}, \frac{17 - \sqrt{37}}{2}$$

$$\lambda_1$$

$$\lambda_2$$

Now for the eigenvectors: $(A - \lambda I) \vec{x} = 0$

$$\text{For } \lambda_1: (\Sigma - \lambda_1 I) \vec{x} = 0$$

$$\begin{pmatrix} 8 - \frac{17 + \sqrt{37}}{2} & 3 \\ 3 & 9 - \frac{17 + \sqrt{37}}{2} \end{pmatrix} \vec{x} = 0$$

$$\begin{pmatrix} \frac{-1 - \sqrt{37}}{2} & 3 \\ 3 & \frac{1 - \sqrt{37}}{2} \end{pmatrix} \vec{x} = 0$$

$$\frac{-1-\sqrt{57}}{2}x_1 + 3x_2 = 0$$

$$3x_1 + \frac{1-\sqrt{57}}{2}x_2 = 0$$

$$x_1 + \frac{1-\sqrt{57}}{6}x_2 = 0$$

$$x_1 = -\left(\frac{1-\sqrt{57}}{6}\right)x_2 = \frac{-1+\sqrt{57}}{6}x_2$$

$$\text{For } x_2: (\lambda - \lambda_2 I)\vec{x} = 0$$

$$\begin{pmatrix} 8-\lambda_2 & 3 \\ 3 & 9-\lambda_2 \end{pmatrix} \vec{x} = 0$$

$$\begin{pmatrix} 8-\frac{17-\sqrt{57}}{2} & 3 \\ 3 & 9-\frac{17-\sqrt{57}}{2} \end{pmatrix} \vec{x} = 0$$

$$\begin{pmatrix} \frac{-1+\sqrt{57}}{2} & 3 \\ 3 & \frac{1+\sqrt{57}}{2} \end{pmatrix} \vec{x} = 0$$

$$\frac{-1+\sqrt{57}}{2}x_1 + 3x_2 = 0$$

$$3x_1 + \frac{1+\sqrt{57}}{2}x_2 = 0$$

$$x_1 + \frac{1+\sqrt{57}}{6}x_2 = 0$$

$$x_1 = -\left(\frac{1+\sqrt{57}}{6}\right)x_2 = \frac{-1-\sqrt{57}}{6}x_2$$

Used SymPy

$$\therefore \vec{x} = \begin{pmatrix} \frac{-1+\sqrt{57}}{6} \\ 1 \end{pmatrix}$$

$$\therefore \vec{x}_{\text{norm}} \approx \begin{pmatrix} 0.6464 \\ 0.763 \end{pmatrix}$$

$$\therefore \vec{x} = \begin{pmatrix} \frac{-1-\sqrt{57}}{6} \\ 1 \end{pmatrix}$$

$$\therefore \vec{x}_{\text{norm}} \approx \begin{pmatrix} -0.763 \\ 0.6464 \end{pmatrix}$$

Used SymPy

$$2.(c). X^{\frac{1}{2}} = \sum_{i=1}^p \sqrt{\lambda_i} \vec{e}_i \vec{e}_i^T$$

$$= \sqrt{\lambda_1} \vec{e}_1 \vec{e}_1^T + \sqrt{\lambda_2} \vec{e}_2 \vec{e}_2^T$$

$$= \frac{\sqrt{17+\sqrt{57}}}{2} \vec{e}_1 \vec{e}_1^T + \frac{\sqrt{17-\sqrt{57}}}{2} \vec{e}_2 \vec{e}_2^T$$

from (b)

$$\approx \begin{bmatrix} 2.7796 & 0.5232 \\ 0.5232 & 2.9540 \end{bmatrix}$$

$$(d). X^{-\frac{1}{2}} = \sum_{i=1}^p \lambda_i^{-\frac{1}{2}} \vec{e}_i \vec{e}_i^T$$

$$= \lambda_1^{-\frac{1}{2}} \vec{e}_1 \vec{e}_1^T + \lambda_2^{-\frac{1}{2}} \vec{e}_2 \vec{e}_2^T$$

$$\approx \begin{bmatrix} 0.3722 & -0.0659 \\ -0.0659 & 0.3502 \end{bmatrix}$$

3. $S = \begin{bmatrix} 6 & 1 \\ 1 & 6 \end{bmatrix}$, $n = 12$ $\vec{x} = \begin{bmatrix} 1.2 \\ -3.9 \end{bmatrix}$ $\alpha = 0.1$

For eigenvalues:

$$|S - \lambda I| = 0$$

$$\left| \begin{pmatrix} 6 & 1 \\ 1 & 6 \end{pmatrix} - \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} \right| = 0$$

$$|6-\lambda - 1| = 0$$

$$|1 - \lambda| = 0$$

$$(6-\lambda)^2 - 1 = 0$$

$$(6-\lambda-1)(6-\lambda+1) = 0$$

$$-\lambda + 5 = 0, -\lambda + 7 = 0$$

$$\lambda = 5, 7$$

For eigenvectors:

$$\lambda = 5$$

$$(S - 5I)\vec{x} = 0$$

$$\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = 0$$

$$x_1 + x_2 = 0$$

$$x_1 + x_2 = 0$$

$$x_1 = -x_2$$

$$\lambda = 7$$

$$(S - 7I)\vec{x} = 0$$

$$\begin{pmatrix} -1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = 0$$

$$-x_1 + x_2 = 0$$

$$x_1 - x_2 = 0$$

$$x_1 = x_2$$

$$\therefore \vec{x} = \begin{pmatrix} -1 \\ 1 \end{pmatrix} \div \sqrt{r^2 + r^2}$$

$$= \begin{pmatrix} -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix} \text{ normalised}$$

$$\therefore \vec{x} = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \div \sqrt{r^2 + r^2}$$

$$= \begin{pmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix} \text{ normalised}$$

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3(a) To locate the ellipse:

Centre is at \vec{x} i.e. determined by mean vector . ^{sample}

then endpoints stretch out from centre, using a scale.

Major axis determined by $\lambda = 7$, and $\vec{e} = \begin{pmatrix} \sqrt{2} \\ \sqrt{2} \end{pmatrix}$:

$$\begin{array}{l} \text{endpoint D} = \vec{x} - \vec{e} \sqrt{7 \times \text{scale}} \\ \text{endpt C} = \vec{x} + \vec{e} \sqrt{7 \times \text{scale}} \end{array}$$

8

9

Minor axis determined by $\lambda = 5$, and $\vec{e} = \begin{pmatrix} -\sqrt{2} \\ \sqrt{2} \end{pmatrix}$:

$$\begin{array}{l} \text{endpoint B} = \vec{x} - \vec{e} \sqrt{5 \times \text{scale}} \\ \text{endpt A} = \vec{x} + \vec{e} \sqrt{5 \times \text{scale}} \end{array}$$

$$\text{Scale} = \sqrt{\frac{\lambda \cdot p(n-p)}{n(n-p)}} F_{1-\alpha, p, n-p}$$

(b) Same as before, but scale becomes $\chi^2_{1-\alpha, p}$ as this is the distribution when Σ is known.

(c) For simultaneous CIs, for each variable: $\bar{x} \pm \sqrt{2} \times \text{scale}$ from (a)

(d) Bonferroni method:

Use "naive" t-statistic to get CI for each variable, but use $\alpha_{\text{new}} = \alpha/m$ $m = \# \text{ linear combinations} = 4$.

\therefore For each variable, $\bar{x} \pm t_{1-\alpha, p} \cdot \sqrt{\frac{2}{n}}$.

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4. Pairwise plots & MVN tests.

SW's year built: YES (normal)

SW's length: NO (not normal - looks skewed)

Mardia's skewness: NO

Mardia's kurtosis: NO

5. $\alpha = 0.05$

2 independent samples:

- bridges in Monongahela (M)
- bridges in Allegheny. (A).

Inference on ^{joint}means of year built & length,

$$\vec{\mu}_1 = \begin{pmatrix} \mu_{1,M} \\ \mu_{2,M} \end{pmatrix}$$

$$\vec{\mu}_2 = \begin{pmatrix} \mu_{1,A} \\ \mu_{2,A} \end{pmatrix}$$

means of year built
K length for M.

means of year built
K length for A.

$$H_0: \vec{\mu}_1 = \vec{\mu}_2 \quad \text{Unknown } \Sigma. \text{ Assume } \Sigma_m = \Sigma_A \text{ i.e. pooled.}$$

$$H_1: \vec{\mu}_1 \neq \vec{\mu}_2$$

$$\text{First find: } S_p = \frac{(n_1-1)S_1 + (n_2-1)S_2}{n_1+n_2-2}$$

$$T^2 = (\bar{X}_1 - \bar{X}_2 - \vec{\delta}_0)^T \cdot (S_p(\frac{1}{n_1} + \frac{1}{n_2}))^{-1} \cdot (\bar{X}_1 - \bar{X}_2 - \vec{\delta}_0)$$

$$= (\bar{X}_1 - \bar{X}_2)^T \cdot (S_p(\frac{1}{n_1} + \frac{1}{n_2}))^{-1} \cdot (\bar{X}_2 - \bar{X}_1) \quad \text{because } \vec{\delta}_0 = \vec{\mu}_1 - \vec{\mu}_2 = 0$$

$$T^2_{\text{critical}} = F_{p, n_1+n_2-p-1, 1-\alpha} \cdot \frac{p(n_1+n_2-2)}{n_1+n_2-p-1} = 6.366864 \quad (\text{under } H_0)$$

$$S_{...} \quad T^2 < F_{\text{critical}}$$

\therefore Do not reject H_0 .

Alternatively, compare F & F_{critical}

$$F = T^2 \times \frac{n_1 + n_2 - p - 1}{p(n_1 + n_2 - 2)} \approx 0.5891$$

$$F_{\text{critical}} = F_{p, n_1 + n_2 - p - 1, 1 - \alpha} \approx 3.1359.$$

$F < F_{\text{critical}}$. \therefore Do not reject H_0 .

Alternatively, compare p-value of F with level 0.05:

$$\text{p-value} = P(F > 0.5891) \approx 0.56$$

p-value > 0.05 \therefore Do not reject H_0 .

6. **False** (as seen in Week 1 & demo.)

7. **Always** - Only the error has to be normal.

8. **Normal**

In general, $\hat{\Sigma} = \left(\frac{1}{n} \right) \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^T$

↳ Unbiased but not necessarily MLE.

For normal, $\hat{\Sigma} = \left(\frac{1}{n} \right) \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^T$

↳ this is MLE

So $\hat{\Sigma}$ can only be MLE if the $\hat{\Sigma}$ is MLE,

which won't happen unless the dist is normal.

9. **Always** $\text{Var}(A\vec{x}) = A \cdot \text{Var}(\vec{x}) \cdot A^T$ for $A \in \mathbb{M}_{q,p}$

10. **Always**. General property of covariances.

Quiz 1 - Questions 1 & 2

Amanjit Gill

```
In [44]: from sympy import *
from sympy.integrals import *
```

Question 1

(a)

```
In [45]: # define symbols
x1 = Symbol('x_1')
x2 = Symbol('x_2')
```

```
In [46]: # define joint density
f = (1/(2*x2)) * exp(-(x2/4 + 2*x1/x2))
f
```

```
Out[46]: 
$$\frac{e^{-\frac{2x_1}{x_2} - \frac{x_2}{4}}}{2x_2}$$

```

```
In [47]: # integrate to get marginal density of x2

wrt = x1
lower = 0
upper = oo

f_x2 = integrate(f, (wrt, lower, upper), conds='none')
f_x2
```

```
Out[47]: 
$$\frac{e^{-\frac{x_2}{4}}}{4}$$

```

(b)

```
In [48]: # divide f by f_x2 to get conditional probability of x1/x2

f_x1_cond = simplify(f/f_x2)
f_x1_cond
```

```
Out[48]: 
$$\frac{2e^{-\frac{2x_1}{x_2}}}{x_2}$$

```

(c)

```
In [49]: # obtain g*(X1) by E(X1 | X2 = x2)

wrt = x1
lower = 0
upper = oo
```

```
g_star = integrate(x1*f_x1_cond, (wrt, lower, upper), conds='none')
g_star
```

Out[49]: $\frac{x_2}{2}$

(d)

In [76]:

```
# MSE

wrt = x1
lower = 0
upper = oo

integrate((x1 - x2/2)**2 * f_x1_cond, (wrt, lower, upper), conds='none')
```

Out[76]: $\frac{x_2^2}{4}$

Question 2

(a)

In [83]:

```
# characteristic polynomial

lam = Symbol('lambda')

Sigma = Matrix([[8, 3], [3, 9]])

char_poly = det(Sigma - lam*eye(2))
char_poly
```

Out[83]: $\lambda^2 - 17\lambda + 63$

(b)

In [117...]:

```
# eigenvalues

eigs = solve(char_poly, lam)
eigs
```

Out[117]: $[17/2 - \sqrt{37}/2, \sqrt{37}/2 + 17/2]$

In [163...]:

```
# eigenvectors

Sigma.eigenvecs()
```

Out[163]:

```
[(17/2 - sqrt(37)/2,
 1,
 [Matrix([
 [-sqrt(37)/6 - 1/6],
 [1]])]),
(sqrt(37)/2 + 17/2,
 1,
 [Matrix([
 [-1/6 + sqrt(37)/6],
 [1]])])]
```

In [219...]:

```
# normalise eigenvector  $(17 - \sqrt{37})/2$ 
```

```

vect1 = Sigma.eigenvecs()[0][2][0]
length = sqrt(vect1[0]**2 + vect1[1]**2)
vect1_norm = cancel(vect1/length)
vect1_norm

```

Out[219]:

$$\begin{bmatrix} \frac{-\sqrt{37}-1}{\sqrt{2\sqrt{37}+74}} \\ \frac{6}{\sqrt{2\sqrt{37}+74}} \end{bmatrix}$$

In [227... vect1_norm.applyfunc(lambda x : round(x, 4))

Out[227]:

$$\begin{bmatrix} -0.763 \\ 0.6464 \end{bmatrix}$$

In [221... # normalise eigenvector $(17 + \sqrt{37})/2$

```

vect2 = Sigma.eigenvecs()[1][2][0]
length = sqrt(vect2[0]**2 + vect2[1]**2)
vect2_norm = cancel(vect2/length)
vect2_norm

```

Out[221]:

$$\begin{bmatrix} \frac{-1+\sqrt{37}}{\sqrt{74-2\sqrt{37}}} \\ \frac{6}{\sqrt{74-2\sqrt{37}}} \end{bmatrix}$$

In [228... vect2_norm.applyfunc(lambda x : round(x, 4))

Out[228]:

$$\begin{bmatrix} 0.6464 \\ 0.763 \end{bmatrix}$$

(c)

In [251... # use eigenvalues and eigenvectors to compute $X^{(1/2)}$

```

eigval1 = Sigma.eigenvecs()[0][0]
eigval2 = Sigma.eigenvecs()[1][0]

(sqrt(eigval1)*vect1_norm*vect1_norm.T + sqrt(eigval2)*vect2_norm*vect2_norm.T).evalf()

```

Out[251]:

$$\begin{bmatrix} 2.77961 & 0.523229 \\ 0.523229 & 2.95402 \end{bmatrix}$$

(d)

In [254... # use eigenvalues and eigenvectors to compute $X^{(1/2)}$

```

(eigval1**-0.5*vect1_norm*vect1_norm.T + eigval2**-0.5*vect2_norm*vect2_norm.T).evalf()

```

Out[254]:

$$\begin{bmatrix} 0.372171 & -0.0659206 \\ -0.0659206 & 0.350198 \end{bmatrix}$$

QUIZ 1 - QUESTION 3

Amanjit Gill

October 31, 2022

```
library("ellipse")

##
## Attaching package: 'ellipse'
## The following object is masked from 'package:graphics':
##      pairs
par(mar = c(4, 4, 0.5, 0.5))
dev.new(width = 2.5, height = 2.5, unit = "in")

n <- 12
p = 2
xbar <- cbind(c(-1.2, -3.9))
S <- rbind(c(6,1), c(1,6))
Sinv <- solve(S)

# PART A - confidence ellipsoid at level 90%

alpha <- 0.1
S.eig <- eigen(S)
scale <- p*(n-1)*qf(1-alpha, p, n-p)/(n*(n-p))

# major axis endpoints
(major_pt1 <- xbar - S.eig$vectors[,1] * sqrt(S.eig$values[1]*scale))

##          [,1]
## [1,] -2.569866
## [2,] -5.269866
(major_pt2 <- xbar + S.eig$vectors[,1] * sqrt(S.eig$values[1]*scale))

##          [,1]
## [1,]  0.1698658
## [2,] -2.5301342

# minor axis endpoints
(minor_pt1 <- xbar - S.eig$vectors[,2] * sqrt(S.eig$values[2]*scale))

##          [,1]
## [1,] -0.04225209
## [2,] -5.05774791
(minor_pt2 <- xbar + S.eig$vectors[,2] * sqrt(S.eig$values[2]*scale))
```

```

##           [,1]
## [1,] -2.357748
## [2,] -2.742252

# vector of x-coordinates for major axis
major_xvals <- c(major_pt1[1], major_pt2[1])

# vector of y-coordinates for major axis
major_yvals <- c(major_pt1[2], major_pt2[2])

# vector of x-coordinates for minor axis
minor_xvals <- c(minor_pt1[1], minor_pt2[1])

# vector of y-coordinates for minor axis
minor_yvals <- c(minor_pt1[2], minor_pt2[2])

# plot ellipse and major and minor axes
plot(ellipse(cov2cor(S), centre=c(-1.2, -3.9), t=qt(1-alpha/2, n-1), npoints=1000),
      pch=". ", cex.lab=.8, cex.axis=.7, xlim=c(-8,6), ylim=c(-10,2),
      xlab=expression(mu*" $^1$ "), ylab=expression(mu*" $^2$ "))
points(c(major_xvals,minor_xvals), c(major_yvals,minor_yvals),
       pch=4, col="blue", lwd=2)
lines(major_xvals, major_yvals)
lines(minor_xvals, minor_yvals)
points(xbar[1], xbar[2], pch=16, col="blue")

# PART B - confidence ellipsoid for known variance

# everything stays the same except for the scale
scale <- qchisq(1-alpha, p)

# major axis endpoints
(major_pt1 <- xbar - S.eig$vectors[,1] * sqrt(S.eig$values[1]*scale))

##           [,1]
## [1,] -5.214735
## [2,] -7.914735

(major_pt2 <- xbar + S.eig$vectors[,1] * sqrt(S.eig$values[1]*scale))

##           [,1]
## [1,] 2.8147348
## [2,] 0.1147348

# minor axis endpoints
(minor_pt1 <- xbar - S.eig$vectors[,2] * sqrt(S.eig$values[2]*scale))

##           [,1]
## [1,] 2.19307
## [2,] -7.29307

(minor_pt2 <- xbar + S.eig$vectors[,2] * sqrt(S.eig$values[2]*scale))

##           [,1]
## [1,] -4.5930702
## [2,] -0.5069298

```

```

# vector of x-coordinates for major axis
major_xvals <- c(major_pt1[1], major_pt2[1])

# vector of y-coordinates for major axis
major_yvals <- c(major_pt1[2], major_pt2[2])

# vector of x-coordinates for minor axis
minor_xvals <- c(minor_pt1[1], minor_pt2[1])

# vector of y-coordinates for minor axis
minor_yvals <- c(minor_pt1[2], minor_pt2[2])

# plot major and minor axes
lines(ellipse(cov2cor(S), centre=c(-1.2, -3.9),
  scale=c(sqrt(qchisq(1-alpha, p)),sqrt(qchisq(1-alpha, p))), npoints=1000,
  pch=". ", cex=1, lty="dashed"))
points(c(major_xvals,minor_xvals), c(major_yvals,minor_yvals), pch=4, lwd=1.5)
lines(major_xvals, major_yvals, lty="dashed")
lines(minor_xvals, minor_yvals, lty="dashed")
points(xbar[1], xbar[2], pch=16, col="blue")

# PART C - projection to get confidence interval

# change back to Part A scale
scale <- p*(n-1)*qf(1-alpha, p, n-p)/(n*(n-p))

# for variable x1
l_x1 <- c(1,0)
(x1_ci_low <- c(crossprod(l_x1, xbar)) - sqrt(scale * t(l_x1) %*% S %*% l_x1))

## [1]
## [1,] -2.993575
(x1_ci_high <- c(crossprod(l_x1, xbar)) + sqrt(scale * t(l_x1) %*% S %*% l_x1))

## [1]
## [1,] 0.5935754
# for variable x2
l_x2 <- c(0,1)
(x2_ci_low <- c(crossprod(l_x2, xbar)) - sqrt(scale * t(l_x2) %*% S %*% l_x2))

## [1]
## [1,] -5.693575
(x2_ci_high <- c(crossprod(l_x2, xbar)) + sqrt(scale * t(l_x2) %*% S %*% l_x2))

## [1]
## [1,] -2.106425
# plot x1 CI as vertical lines
# plot x2 CI as horizontal lines
abline(v=c(x1_ci_low, x1_ci_high), col="blue", lty="dashed")
abline(h=c(x2_ci_low, x2_ci_high), col="blue", lty="dashed")

# PART D - Bonferroni method to get confidence intervals

```

```

# adapt Part C to do this efficiently

m <- 2*p

scale <- qt(1-alpha/m, n-1)

# for variable x1
l_x1 <- c(1,0)
(x1_ci_low <- c(crossprod(l_x1, xbar)) - scale*sqrt(t(l_x1) %*% S %*% l_x1 / n))

## [,1]
## [1,] -2.756332

(x1_ci_high <- c(crossprod(l_x1, xbar)) + scale*sqrt(t(l_x1) %*% S %*% l_x1 / n))

## [,1]
## [1,] 0.3563315

# for variable x2
l_x2 <- c(0,1)
(x2_ci_low <- c(crossprod(l_x2, xbar)) - scale*sqrt(t(l_x2) %*% S %*% l_x2 / n))

## [,1]
## [1,] -5.456332

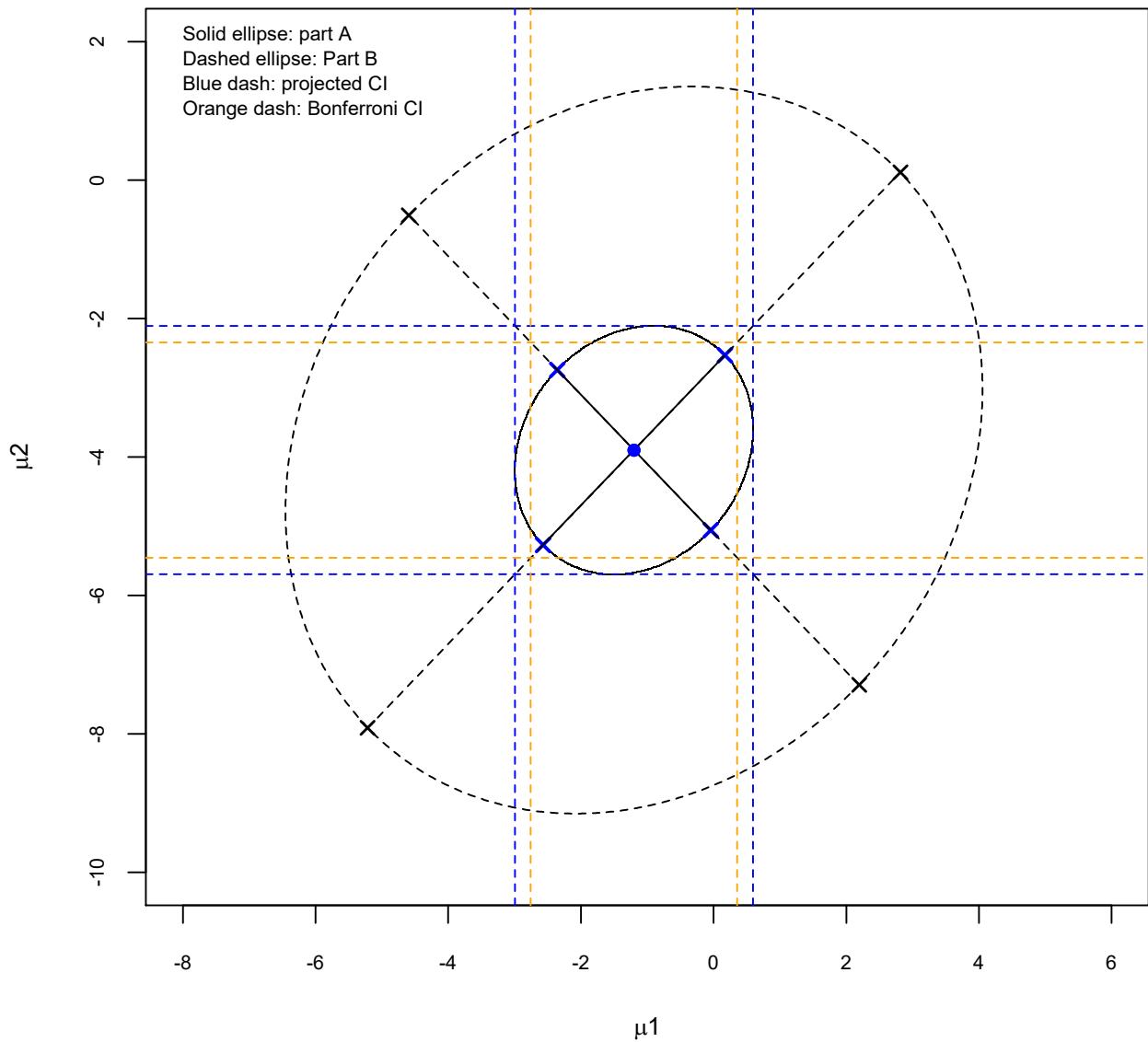
(x2_ci_high <- c(crossprod(l_x2, xbar)) + scale*sqrt(t(l_x2) %*% S %*% l_x2 / n))

## [,1]
## [1,] -2.343668

# plot x1 CI as vertical lines
# plot x2 CI as horizontal lines
abline(v=c(x1_ci_low, x1_ci_high), col="orange", lty="dashed")
abline(h=c(x2_ci_low, x2_ci_high), col="orange", lty="dashed")

# add legend for all 4 parts
legend(
  x="topleft",
  legend=c("Solid ellipse: part A", "Dashed ellipse: Part B",
          "Blue dash: projected CI", "Orange dash: Bonferroni CI"),
  bty='n',
  cex=0.55
)

```



QUIZ 1 - QUESTION 4

Amanjit Gill

October 31, 2022

```
library(GGally)

## Loading required package: ggplot2
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
library(dplyr)

##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
## 
##   filter, lag
## The following objects are masked from 'package:base':
## 
##   intersect, setdiff, setequal, union
library(MVN)

dev.new(width = 2.5, height = 2.5, unit = "in")

b <- as_tibble(read.csv("bridges.csv"))
head(b)

## # A tibble: 6 x 5
##   river erected purpose  length material
##   <chr>    <int> <chr>     <int> <chr>
## 1 A          1819 HIGHWAY    1037 WOOD
## 2 A          1837 HIGHWAY    1000 WOOD
## 3 A          1840 HIGHWAY     990 WOOD
## 4 A          1844 AQUEDUCT    1000 IRON
## 5 M          1846 HIGHWAY    1500 IRON
## 6 A          1851 HIGHWAY    1000 WOOD

# PART A - pairwise plots and normality test

b.subset <- b %>% select(erected, length)
b.subset

## # A tibble: 81 x 2
##   erected length
##       <int>  <int>
## 1     1819    1037
```

```

##   2    1837    1000
##   3    1840     990
##   4    1844    1000
##   5    1846    1500
##   6    1851    1000
##   7    1856    1200
##   8    1859    1030
##   9    1863    1000
##  10    1864    1200
## # ... with 71 more rows
ggpairs(b.subset)

mvn(b.subset, mvnTest = "mardia", univariateTest = "SW")

## $multivariateNormality
##           Test      Statistic      p value Result
## 1 Mardia Skewness 44.4848070981332 5.08777517344877e-09    NO
## 2 Mardia Kurtosis 3.78231712161238 0.000155375239301536    NO
## 3          MVN          <NA>          <NA>    NO
##
## $univariateNormality
##           Test Variable Statistic      p value Normality
## 1 Shapiro-Wilk erected     0.9832  0.3674      YES
## 2 Shapiro-Wilk length      0.8188 <0.001       NO
##
## $Descriptives
##      n      Mean Std.Dev Median Min Max 25th 75th      Skew      Kurtosis
## erected 81 1910.222  34.76852 1910 1819 1978 1890 1931 -0.3205326 -0.3713876
## length   81 1567.469  747.49152 1300  804 4558 1000 2000  1.6723769  3.1325645
# PART B - Hypothesis Test

alpha <- 0.05

# separate into separate sets by river (M or A)
# river 1 = M, river 2 = A
x1 <- b[b$river == 'M', ] %>% select(ereected, length)
x2 <- b[b$river == 'A', ] %>% select(ereected, length)

p <- ncol(x1)

(n1 <- nrow(x1))

## [1] 32
(n2 <- nrow(x2))

## [1] 37
xbar1 <- colMeans(x1)
S1 <- cov(x1)

xbar2 <- colMeans(x2)
S2 <- cov(x2)

(Sp <- ((n1 - 1)*S1 + (n2 - 1)*S2)/(n1+n2-2))

```

```

##           erected      length
## erected 1240.460   4091.154
## length  4091.154 411748.065
# approach 1: compare  $T^2$  with critical  $T^2$ 

(Tsq <- t(xbar1-xbar2) %*% solve(Sp*(1/n1 + 1/n2)) %*% (xbar1-xbar2))

##           [,1]
## [1,] 1.196022

(Tsq_crit <- qf(1-alpha, p, n1+n2-p-1) * p*(n1+n2-2)/(n1+n2-p-1))

## [1] 6.366864

# approach 2: compare  $F$  with critical  $F$ 

(F <- Tsq * (n1+n2-p-1)/(p*(n1+n2-2)))

##           [,1]
## [1,] 0.5890852

(F_crit <- qf(1-alpha, p, n1+n2-p-1))

## [1] 3.135918

# approach 3: compare  $p$ -value with critical  $p$  (0.05)

(prob_of_F <- pf(F, p, n1+n2-p-1, lower.tail = FALSE))

##           [,1]
## [1,] 0.5577251

```

erected

0.009
0.006
0.003
0.000

length

Corr:
0.182

4000
3000
2000
1000

1850 1900 1950

erected

length

1000 2000 3000 4000