

Theory Section II Exam 2015

1). $Y \sim N(\mu, \Sigma)$

Σ symmetric & full rank.

A = symmetric matrix

(a) Show that the quadratic form $Y^T A Y$ can be represented as

$$Y^T A Y = \sum_{i=1}^K \lambda_i W_i$$

W_i = indep. noncentral Chi-square

w/ df = d_i & δ_i = noncentrality param.

$$\sim \chi^2_{d_i}(\delta_i) \quad i=1, \dots, K$$

Indicate what λ_i , d_i , & δ_i are equal to

X Since A is symmetric, use spectral decomposition to decompose it to $P \Lambda P$

P = eigenvectors } of A

Λ = diag (eigenvalues)

Σ = positive semidefinite

$$Y^T A Y = Y^T \Sigma^{-1/2} \Sigma^{1/2} A \Sigma^{1/2} \Sigma^{-1/2} Y$$

If Σ positive semidefinite

$\Rightarrow \Sigma^{1/2}$ positive semidefinite

$\Rightarrow \Sigma^{1/2} A \Sigma^{1/2}$ positive semidefinite

} At the very least,

Symmetric, which

is all that is necessary for spectral decomp.

$$\text{let } Q = \Sigma^{1/2} A \Sigma^{1/2}$$

By spectral decomposition, can write

$$Q = P \Lambda P$$

P = eigenvectors of $\Sigma^{1/2} A \Sigma^{1/2}$

Λ = diag (eigenvalues of $\Sigma^{1/2} A \Sigma^{1/2}$)

$$Y' \Sigma^{-1/2} Q \Sigma^{-1/2} Y$$

$$\text{Let } B = \Sigma^{-1/2} Y$$

$$B = \Sigma^{-1/2} Y \sim N(\Sigma^{-1/2} \mu, \Sigma^{-1/2} \Sigma \Sigma^{-1/2}) \\ \equiv N(\Sigma^{-1/2} \mu, I)$$

$$B' Q B$$

$$= B' P' \Lambda P B \quad \text{by spectral decomp}$$

$$\text{Let } Z = P B$$

$$Z = P B \sim N(P \Sigma^{-1/2} \mu, P' I P)$$

Note: Since P = matrix of eigenvectors

$\Rightarrow P$ is orthogonal matrix (orthonormal columns)

$$\Rightarrow P' P = I$$

$$\Rightarrow Z \sim N(P \Sigma^{-1/2} \mu, I)$$

Therefore, $Z' \Lambda Z$

$$= \sum_{i=1}^n z_i^2 (\lambda_i) \quad \begin{array}{l} \lambda_i = \text{eigenvalue of } \Sigma^{-1/2} A \Sigma^{-1/2} \\ z_i^2 \sim W_i \end{array}$$

Since each $z_i \sim N([P \Sigma^{-1/2} \mu]_i, 1)$

$$\begin{array}{l} \downarrow W_i \quad \uparrow i^{\text{th}} \text{ value of } P \Sigma^{-1/2} \mu \text{ matrix} \\ \Rightarrow z_i^2 \sim \chi^2(\text{df} = 1, \delta_i) \\ \quad \text{-- noncentral} \end{array}$$

$$\text{where } \delta_i = \frac{[P \Sigma^{-1/2} \mu]_i^2}{2}$$

each z_i indep since Z vector has ^{matrix} cov of I

$$\Rightarrow z_i \text{ have covariance of } 0 \text{ for } \text{cov}(z_i, z_j)$$

$$\Rightarrow z_i \text{ indep (thm: normal r.v's indep if cov} = 0)$$

Since $Y'AY = Z'AZ$

$$\Rightarrow Y'AY = \sum_{i=1}^K \lambda_i z_i^2 \equiv \sum_{i=1}^K \lambda_i W_i$$

Where $W_i \sim \chi^2(d_i=1, \delta_i)$

+ W_i 's indep for $i=1, \dots, n$.

+ λ_i = eigenvalue of $\Sigma^{1/2} A \Sigma^{1/2}$

(b) Use part (a) to derive the MGF of $Y'AY$

Let $M(t) = \text{MGF}$

Show $M(t)$ exists in small neighborhood of $t=0$

Find maximal area of $|t| < \underline{t_0}$.

Find MGF of $Z_i^2 \sim \chi^2(1, \delta_i)$

$$\Rightarrow M(t) = \prod_{i=1}^K M_{Z_i^2}(t)$$

$$\chi^2(1, 0) \equiv \text{Gamma}(1/2, 2)$$

Let $X \sim \chi^2(1)$

$$f_X(x) = \frac{1}{\Gamma(1/2) 2^{1/2}} x^{-1/2} \exp(-x/2)$$

$$E[e^{tx}] = \int_0^\infty e^{tx} \frac{1}{\sqrt{\pi} \cdot 2^{1/2}} x^{-1/2} \exp(-x/2) dx$$

$$= \int_0^\infty \frac{1}{\Gamma(1/2) 2^{1/2}} x^{-1/2} \exp(-x(1/2 - t)) dx$$

$$= \frac{(1/2 - t)^{1/2}}{2^{1/2}} \int_0^\infty \frac{1}{\Gamma(1/2) (1/2 - t)^{1/2}} x^{-1/2} \exp(-x(1/2 - t)) dx$$

$$= (1/2)^{1/2} (1/2 - t)^{1/2}$$

$$= \left(\frac{1}{2} \left(\frac{1}{2} - t \right) \right)^{1/2}$$

$$= \left(\frac{1}{2^2} \left(1 - t/2 \right) \right)^{1/2} = \frac{(1 - t/2)^{1/2}}{2}$$

$$Z = x + r, \quad x \sim N(0, 1)$$

Find dist of $V = Z^2 = (x+r)^2$

$$\Rightarrow V^{1/2} = x + r$$

$$\Rightarrow x = V^{1/2} - r$$

$$f_V(v) = f_X(x = V^{1/2} - r) |J|$$

$$|J| = \left| \frac{dx}{dv} \right| = \frac{1}{2} |V|^{-1/2}$$

$$= \frac{1}{\sqrt{2\pi}} \left(\frac{1}{2} \right) |V|^{-1/2} \exp \left(-\frac{(V^{1/2} - r)^2}{2} \right)$$

$$E[e^{tv}] = \int_0^\infty \frac{(2)}{2} \frac{1}{\sqrt{2\pi}} v^{-1/2} \exp \left(-\frac{(v - 2rv^{1/2} + r^2)}{2} \right) e^{tv} dv$$

$$= \int_0^\infty \frac{1}{\sqrt{2\pi}} v^{-1/2} \exp \left(-\frac{1}{2} (v - 2rv^{1/2} + r^2) \right) dv$$

$$= \int_0^\infty \frac{1}{\Gamma(1/2) 2^{1/2}} v^{-1/2} \exp \left(-\frac{1}{2} (1-2t) \left(v - \frac{2rv^{1/2}}{(1-2t)} + \frac{r^2}{(1-2t)} \right) \right) dv$$

$$(v^{1/2} + c)^2 = v + 2cv^{1/2} + c^2$$

$$c = \frac{r}{(1-2t)}$$

$$= \exp \left(-\frac{1}{2} (1-2t) \frac{r^2}{(1-2t)} - \left(-\frac{1}{2} \right) (1-2t) \frac{r^2}{(1-2t)^2} \right)$$

$$\int_0^\infty \frac{1}{\Gamma(1/2) 2^{1/2}} v^{-1/2} \exp \left(-\frac{1}{2} (1-2t) \left(v - \frac{2rv^{1/2}}{(1-2t)} + \frac{r^2}{(1-2t)^2} \right) \right) dv$$

$$= \exp \left(-\frac{1}{2} r^2 \right) \int_0^\infty \frac{1}{\Gamma(1/2) 2^{1/2}} v^{-1/2} \exp \left(-\frac{1}{2} (1-2t) \left(\frac{v^{1/2} - r}{1-2t} \right)^2 \right) dv$$

$$\text{let } y = \frac{v^{1/2} - r}{1-2t}$$

$$\Rightarrow v^{1/2} = y + \frac{r}{(1-2t)}$$

$$y = \frac{v^{1/2} - v}{1-2t}$$

$$dy = \frac{1}{2} v^{-1/2} dv$$

$$\Rightarrow 2v^{1/2} dy = dv$$

$$= \exp\left(-\frac{1}{2} y^2\right) \int_0^\infty \frac{(2v^{1/2}) v^{1/2} \exp\left(-\frac{1}{2} (1-2t) y^2\right) dy}{\Gamma(1/2) 2^{1/2}}$$

$$= \sqrt{\frac{2}{\pi}} \exp\left(-\frac{\delta + \delta}{1-2t}\right) \int_0^\infty \exp\left(-\frac{(1-2t) y^2}{2}\right) dy$$

$$= \exp\left(-\delta \left(1 - \frac{1}{1-2t}\right)\right) \frac{2^{1/2}}{(1-2t)^{1/2}} \int_0^\infty \frac{1}{\sqrt{2\pi}} \frac{1}{(1-2t)^{1/2}} \exp\left(-\frac{1}{2} (1-2t) y^2\right) dy$$

$$= \frac{1}{2^{1/2} (1-2t)^{1/2}} \exp\left(-\delta \left(\frac{-2t}{1-2t}\right)\right)$$

$$= \frac{1}{2^{1/2} (1-2t)^{1/2}} \exp\left(\frac{2\delta t}{1-2t}\right)$$

not right

$$\Rightarrow M_V(t) = \frac{1}{(1-2t)^{1/2}} \exp\left(\frac{2\delta t}{1-2t}\right)$$

$$M(t) = \prod_{i=1}^K M_{V_i}(t) = \frac{1}{(1-2t)^{K/2}} \exp\left(\frac{2t \sum_{i=1}^K \delta_i}{1-2t}\right)$$

This exists for $1-2t > 0$

$$\Rightarrow 1 > 2t$$

$$\Rightarrow t < 1/2$$

$$\Rightarrow \boxed{t_0 = 1/2}$$

(C) Use part (B) to show that if

$$\text{tr}((A\Sigma)^2) = \text{tr}(A\Sigma) = r$$

$$r = \text{rank}(A)$$

$Y'AY$ = chi square dist (find df + noncentrality param).

$$Y'AY = Y^T A^{1/2} A^{1/2} Y$$

↳ by spectral decomp (?)

$$\Rightarrow A^{1/2} Y \sim N(\mu, A^{1/2} \Sigma A^{1/2})$$

$$\text{tr}((A\Sigma)^2) = \text{tr}(A\Sigma A\Sigma)$$

by cyclic permutation property

$$\Rightarrow \text{tr}(A\Sigma A\Sigma) = \text{tr}(\Sigma A \Sigma A)$$

Consequently

$$\text{tr}((A\Sigma)^2) = \text{tr}((\Sigma A)^2) = \text{tr}(A\Sigma) = \text{tr}(\Sigma A)$$

$Y'AY$ has a non-central χ^2 dist if

$$Y'AY = \sum_i w_i \text{ where } w_i \sim \chi^2(1, s_i)$$

\Rightarrow Show all $\lambda_i = 0$ or 1

(i) Show eigenvalues of $A\Sigma$ = eigenvalues of $\Sigma^{1/2} A \Sigma^{1/2}$

(ii) Show if $\text{tr}((A\Sigma)^2) = \text{tr}(A\Sigma) = r$

$$\Rightarrow \lambda_i = \{0, 1\} \text{ for all } i=1, \dots, K$$

(1) Defn of eigenvalues: $Ax = \lambda x$ for all non-zero x

$$\Leftrightarrow |A - \lambda I| = 0$$

$$|\Sigma^{1/2} A \Sigma^{1/2} - \lambda I| = 0$$

$$\Rightarrow |\Sigma^{1/2} A \Sigma^{1/2} - \lambda \Sigma^{1/2} \Sigma^{1/2}| = 0$$

$$\Rightarrow |\Sigma^{1/2}| |A \Sigma^{1/2} - \lambda \Sigma^{-1/2}| = 0$$

$$\Rightarrow |A \Sigma^{1/2} - \lambda \Sigma^{-1/2}| = 0$$

$$\Rightarrow |A \Sigma^{1/2} - \lambda \Sigma^{-1/2}| |\Sigma^{1/2}| = 0$$

$$\Rightarrow |A \Sigma - \lambda I| = 0$$

\Rightarrow if λ = eigenvalue of $\Sigma^{1/2} A \Sigma^{1/2}$

$\Rightarrow \lambda$ eigenvalue of

$A\Sigma$ as well ✓

(ii) Recall:

$$\text{tr}(B) = \sum_{i=1}^m \text{eigenvalues of } B$$

$$\Rightarrow \text{tr}(A\Sigma) = \sum_{i=1}^m \lambda_i \quad \text{equal}$$

$$\Rightarrow \text{tr}((A\Sigma)^2) = \sum_{i=1}^m \lambda_i^2$$

$$\Rightarrow \sum_{i=1}^m \lambda_i = \sum_{i=1}^m \lambda_i^2$$

$$\Rightarrow \lambda_i = 0, 1 \text{ for all } i \in 1, \dots, m.$$

W/o loss of generality, let

$$\lambda_1 = \dots = \lambda_k = 1, \quad \lambda_{k+1} = \dots = \lambda_m = 0$$

$$\begin{aligned} \Rightarrow \sum_{i=1}^m \lambda_i W_i &= \sum_{i=1}^k \lambda_i W_i + \sum_{i=k+1}^m \lambda_i W_i \quad \xrightarrow{0} \\ &= \sum_{i=1}^k (1) W_i \\ &= \sum_{i=1}^k W_i \end{aligned}$$

If $W_i \sim \chi^2(1, \delta_i)$

$$\Rightarrow \sum_{i=1}^k W_i \sim \chi^2(k, \sum_{i=1}^k \delta_i)$$

Note: if λ_i of $(A\Sigma)$ only 0 or 1 \Rightarrow

λ_i of $\Sigma^{1/2} A \Sigma^{1/2}$ only 0 or 1

① Show that $Y^T A Y$ has a noncentral chi square dist if & only if $A \Sigma$ is idempotent

$$Y^T A Y = Y^T \Sigma^{-1/2} \Sigma^{1/2} A \Sigma^{1/2} \Sigma^{-1/2} Y$$

$A \Sigma$ idempotent

$$\Rightarrow A \Sigma A \Sigma = A \Sigma$$

Again, show λ of $\Sigma^{1/2} A \Sigma^{1/2}$ is $\{0, 1\}$ if this is the case

Have shown previously λ of $\Sigma^{1/2} A \Sigma^{1/2} = A \Sigma$

Since both A & Σ symmetric $\Rightarrow A \Sigma$ also symmetric

If $A \Sigma$ also idempotent $\Rightarrow A \Sigma$ is an orthogonal projection operator

If $A \Sigma$ is an (orthogonal) projection operator, then

all $\lambda_i = 0$ or 1 for $i = 1, \dots, K$

\uparrow result just needs idempotent \Rightarrow projection operator

WLOG, let $\lambda_1 = \dots = \lambda_r = 1, \lambda_{r+1} = \dots = \lambda_K = 0$

② $A \Sigma$ idempotent $\Rightarrow Y^T A Y$ noncentral χ^2

$A \Sigma$ idempotent \Rightarrow (see work above)

$\Rightarrow \lambda_1 = \dots = \lambda_r = 1, \lambda_{r+1} = \dots = \lambda_K = 0$

From ① we know $Y^T A Y = \sum_{i=1}^K \lambda_i W_i$

$$\begin{aligned} \Rightarrow Y^T A Y &= \sum_{i=1}^r (1) W_i + \sum_{i=r+1}^K (0) W_i \\ &= \sum_{i=1}^r (W_i \sim \chi^2(1, \delta_i)) \\ &\sim \chi^2(r, \sum_{i=1}^r \delta_i) \quad \checkmark \end{aligned}$$

(ii) $Y'AY$ noncentral $\chi^2 \Rightarrow A\Sigma$ idempotent

$Y'AY$ noncentral χ^2

\Rightarrow all $\lambda_i = 0, 1$

$\Rightarrow \sum_{i=1}^r W_i = Y'AY$

\uparrow WLOG, $\lambda_1 = \dots = \lambda_r = 1, \lambda_{r+1} = \dots = \lambda_K = 0$

Have shown λ of $\Sigma^{1/2} A \Sigma^{1/2} = \lambda$ of $A\Sigma$

$$(A\Sigma)x = \lambda x \quad \forall x \in \mathbb{R}^K$$

since $\lambda = \{0, 1\}$

$$\Rightarrow (A\Sigma)x = \lambda^2 x$$

We also know $(A\Sigma)^2 x = \lambda^2 x$ if $A\Sigma x = \lambda x$

$$\Rightarrow (A\Sigma)^2 = A\Sigma$$

$\Rightarrow A\Sigma$ idempotent

2). $Y = XB + \epsilon$

$$\epsilon \sim N(0, \sigma^2 I)$$

X full rank $n \times p$

$$B_{p \times 1}$$

(B, σ^2) unknown

$$H = X(X'X)^{-1}X'$$

h_{ii} = i th diag element of H

$$\hat{\sigma}^2 = \frac{Y'(I-H)Y}{n-p} \quad (H = M)$$

$$\hat{\epsilon} = Y - X\hat{B} = Y - HY = (I-H)Y$$

$$\hat{\epsilon}_i = d_i^T(I-H)Y$$

d_i = vector w/ 1 in i th position, 0 elsewhere

$$A_i = \frac{\hat{\epsilon}_i^2}{\sigma^2(1-h_{ii})} \quad ; \quad B_i = \frac{(n-p)\hat{\sigma}^2 - \hat{\epsilon}_i^2}{\sigma^2(1-h_{ii})}$$

(a) Show $B_i \sim \chi^2(n-p-1)$

$$B_i = \frac{1}{\sigma^2} \left(Y'(I-H)Y - \frac{(d_i^T(I-H)Y)^2}{1-h_{ii}} \right) \quad \checkmark \quad v^2 = v'v$$

$$= \frac{1}{\sigma^2} \left(Y'(I-H)Y - \frac{Y'(I-H)d_i d_i^T(I-H)Y}{1-h_{ii}} \right)$$

$$= \frac{1}{\sigma^2} Y'(I-H) \left(I - \frac{d_i d_i^T}{1-h_{ii}} \right) (I-H)Y$$

By thm, if M = orthog proj matrix

$$\Rightarrow \frac{Y'MY}{\sigma^2} \sim \chi^2(\text{rank}(M), \delta)$$

$$\delta = \frac{E(Y)'ME(Y)}{2\sigma^2} \quad E(Y) = XB$$

$$\text{since } ME(Y) = (\dots)(I-H)XB = 0$$

$$\Rightarrow \delta = 0$$

$$\text{Show rank}(M) = n-p-1$$

If we can show

$(I-H) \left(I - \frac{didi^T}{1-hii} \right) (I-H)$ is an orthog. proj. matrix

of rank $n-p-1$, then ✓

Symmetric:

$(I-H)$ symmetric ✓

$$\left(I - \frac{didi^T}{1-hii} \right)^T = I - \frac{didi^T}{1-hii} \quad \checkmark$$

Idempotent

$$\begin{aligned} & \overbrace{(I-H) \left(I - \frac{didi^T}{1-hii} \right) (I-H)}^{I-H} \\ &= (I-H) \left[(I-H) - \frac{didi^T (I-H)}{1-hii} \right] \left(I - \frac{didi^T}{1-hii} \right) (I-H) \\ &= (I-H) \left[(I-H) - \frac{didi^T (I-H)}{1-hii} - (I-H) \frac{didi^T}{1-hii} + \frac{(1-hii)}{(1-hii)^2} didi^T (I-H) \right] (I-H) \\ &= (I-H) \left[(I-H) - \cancel{\frac{didi^T (I-H)}{1-hii}} - \frac{(I-H) didi^T}{1-hii} + \cancel{\frac{didi^T (I-H)}{(1-hii)}} \right] (I-H) \\ &= (I-H) \left[(I-H) - \frac{(I-H) didi^T (I-H)}{1-hii} \right] \\ &= (I-H) \left[I - \frac{didi^T}{1-hii} \right] (I-H) \quad \checkmark \end{aligned}$$

We don't care what it projects onto or along ✓

rank (orthog proj matrix) = $\text{tr}(\text{orthog proj matrix})$

$$= \text{tr} \left((I-H) \left[I - \frac{didi^T}{1-hii} \right] (I-H) \right)$$

→

by cyclic permutation property

$$= \text{tr} \left((I-H) \left(I - \frac{didi^T}{1-h_{ii}} \right) \right)$$

$$= \text{tr}(I-H) - \text{tr} \left((I-H) didi^T / (1-h_{ii}) \right)$$

$$= n-p - \text{tr} \left(di^T (I-H) di / (1-h_{ii}) \right)$$

$$= n-p - \text{tr} \left(\frac{1-h_{ii}}{1-h_{ii}} \right)$$

$$= n-p-1 \quad \checkmark$$

$$\Rightarrow B_i \sim \chi^2_{(n-p-1)} \quad \checkmark$$

(b) Show A_i & B_i indep.

$$A_i = Y'AY$$

$$B_i = Y'BY$$

$Y'AY + Y'BY$ indep iff $AY + BY$ indep
 \Rightarrow if $AB = 0$

$$A_i = \frac{\hat{\epsilon}_i^2}{\sigma^2(1-h_{ii})} = Y'(I-H)didd_i^T(I-H)Y$$

$$B_i = Y' \left[(I-H) \left(\frac{I - didd_i^T}{1-h_{ii}} \right) (I-H) \right] Y$$

$$\begin{aligned} AB &= (I-H) \overbrace{didd_i^T}^{I-H} (I-H) (I-H) \left(\frac{I - didd_i^T}{1-h_{ii}} \right) (I-H) \\ &= (I-H) didd_i^T (I-H) - (I-H) \overbrace{didd_i^T}^{I-H} (I-H) \left(\frac{didd_i^T}{1-h_{ii}} \right) (I-H) \end{aligned}$$

$$= (I-H) didd_i^T (I-H) - (I-H) didd_i^T (I-H)$$

$$= 0 \quad \checkmark$$

$$c) r_i = \frac{\hat{\epsilon}_i}{\hat{\sigma} \sqrt{1-h_{ii}}}$$

Find exact dist of $\frac{r_i^2}{n-p}$ using a) + b)

$$r_i^2 = \frac{\hat{\epsilon}_i^2}{\hat{\sigma}^2 (\sqrt{1-h_{ii}})^2}$$

$$\begin{aligned} \frac{r_i^2}{n-p} &= \left(\frac{\hat{\epsilon}_i^2}{\hat{\sigma}^2 (1-h_{ii})} \right) \left(\frac{\sigma^2}{(n-p) \hat{\sigma}^2} \right) \\ &= \frac{A_i}{B_i + A_i} \end{aligned}$$

$$B_i \sim \chi^2(n-p-1)$$

$$A_i = Y' (I-H) \overbrace{\frac{d_i d_i^T}{1-h_{ii}}}^M (I-H) Y$$

Show M = orthog proj matrix
- symmetric & idempotent

Symmetric ✓

$$\begin{aligned} & (I-H) \left(\frac{d_i d_i^T}{1-h_{ii}} \right) \overbrace{(I-H)(I-H) \frac{d_i d_i^T (I-H)}{1-h_{ii}}}^{1-h_{ii}, I=H} \\ &= (I-H) \frac{d_i d_i^T}{1-h_{ii}} (I-H) \quad \checkmark \end{aligned}$$

$$A_i \sim \chi^2(\text{rank}(M), \delta) \Rightarrow \chi^2(\text{rank}(M))$$

$$\delta = \frac{E(Y)'(M)E(Y)}{2\sigma^2}$$

$$E(Y) = XB$$

$$\text{since } (I-H)XB = 0 \Rightarrow \delta = 0$$

$\text{rank}(M) = \text{tr}(M)$ since orthog. proj. matrix

$$\begin{aligned} & \text{tr}(M) \text{ due to cyclic permutation properties of tr} \\ &= \text{tr}((I-H) d d^T / (1-h_{ii})) \\ &= \text{tr}(d d^T (I-H) d / (1-h_{ii})) \\ &= \text{tr}(1-h_{ii} / (1-h_{ii})) \\ &= 1 \end{aligned}$$

We know that

$$\begin{aligned} X &= \frac{\chi^2(p)}{\chi^2(p) + \chi^2(q)} \sim \text{Beta}(p/2, q/2) \\ p &= 1, q = n-p-1 \end{aligned}$$

$$\Rightarrow \frac{r_i^2}{n-p} \sim \text{Beta}(1/2, n-p-1/2) \quad \checkmark$$

⑤ i th case = outlier

Mean shift outlier model:

$$y = x\beta + d_i\phi + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I)$$

ϕ unknown scalar, d_i $n \times 1$

$d_i = 1$ in i th position, 0 elsewhere

(i) Derive the MLE of ϕ

$$L(\beta, \phi) \propto \exp\left(-\frac{1}{2\sigma^2} (y - x\beta - d_i\phi)' (y - x\beta - d_i\phi)\right)$$

$$\ell(\beta, \phi) = \log L(\beta, \phi)$$

$$= -\frac{1}{2\sigma^2} (y - x\beta - d_i\phi)' (y - x\beta - d_i\phi) + C$$

$C = \text{constant not including } \beta \text{ or } \phi$

$$= -\frac{1}{2\sigma^2} [(y - x\beta)'(y - x\beta) - 2(y - x\beta)'d_i\phi + d_i'd_i\phi^2]$$

$$\frac{\partial}{\partial \phi} (\text{above}) \stackrel{\text{set}}{=} 0$$

$$\Rightarrow -2(y - x\beta)'d_i + d_i'd_i(2\phi) = 0$$

$$\Rightarrow d_i'd_i\phi = (y - x\beta)'d_i$$

$$\Rightarrow \phi = \frac{(y - x\beta)'d_i}{d_i'd_i} \quad (d_i' d_i = 1)$$
$$= (y - x\beta)'d_i$$

MLE of $x\beta = Hy$

$$\Rightarrow \hat{\phi} = (I - H)Y'd_i$$

(ii) Suppose we wish to test $H_0: \phi = 0$

- Derive the test statistic for this hypothesis & derive its exact dist under H_0 .

Wald test & statistic

$$\begin{aligned} I(\phi) &= E[-\partial^2 / \partial \phi^2 \ell(B, \phi)] \\ &= E\left[-\left(\frac{-2}{2\sigma^2} d_i' d_i\right)\right] \\ &= E[1/\sigma^2] \\ &= \frac{1}{\sigma^2} \end{aligned}$$

MLE of σ^2 :

$$\begin{aligned} \frac{\partial}{\partial \sigma^2} \ell(B, \phi) &= \frac{1}{2\sigma^4} (Y - XB - d_i \phi)' (Y - XB - d_i \phi) + \frac{\partial}{\partial \sigma^2} \left[-\frac{1}{2} \log(\sigma^2)^{1/2} \right] \\ &= \frac{1}{2\sigma^4} \|Y - XB - d_i \phi\|^2 - \frac{1}{2\sigma^2} \stackrel{\text{set}}{=} 0 \end{aligned}$$

$$\Rightarrow \|Y - XB - d_i \phi\|^2 - \sigma^2 = 0$$

$$\Rightarrow \sigma^2 = \|Y - XB - d_i \phi\|^2$$

$$\text{MLE of } XB = MY$$

$$\text{MLE of } \phi = \hat{\phi}$$

$$\hat{\sigma}^2 = \|(I-H)Y - d_i \hat{\phi}\|^2$$

Wald statistic

$$= (\hat{\phi} - \phi_0)' I_n(\phi) (\hat{\phi} - \phi_0)$$

$$= d_i' T Y (I-H) \left(\frac{n}{\| (I-H)Y + d_i \hat{\phi} \|^2} \right) (I-H) Y' d_i$$

\uparrow
 $\left(\frac{n}{\hat{\sigma}^2} \right)$

$$\text{Under } H_0 \Rightarrow \sim \chi^2(1)$$

② $I = \{1, \dots, m\}$

- subset of the first m cases in the dataset

D_I = Cook's distance based on simultaneously deleting m cases from the dataset

$$D_I = \frac{(\hat{\beta} - \hat{\beta}_I)' (X'X) (\hat{\beta} - \hat{\beta}_I)}{p \hat{\sigma}^2}$$

Show $D_I = \frac{1}{p} \sum_{i=1}^m h_i^2 \left(\frac{\lambda_i}{1 - \lambda_i} \right)$

λ_i = eigenvalues of $P_I = X_I (X_I' X_I)^{-1} X_I'$

- based on spectral decomp of P_I

$$h_i^2 = \frac{(\gamma_i' \hat{\epsilon}_I)^2}{\hat{\sigma}^2 (1 - \lambda_i)} \quad \gamma_i = \text{eigenvector corresponding to } \lambda_i$$

$$\hat{\epsilon}_I = y_I - X_I \hat{\beta}$$

$$\sum_{i=1}^m h_i^2 \left(\frac{\lambda_i}{1 - \lambda_i} \right) = \sum_{i=1}^m \frac{(\gamma_i' \hat{\epsilon}_I)^2}{\hat{\sigma}^2 (1 - \lambda_i)} \left(\frac{\lambda_i}{1 - \lambda_i} \right)$$

$$= \sum_{i=1}^m \left(\frac{\lambda_i}{(1 - \lambda_i)^2} \right) \frac{(\gamma_i' (y_I - X_I \hat{\beta}))^2}{\hat{\sigma}^2}$$

(*) Show $\sum_{i=1}^m \left(\frac{\lambda_i}{(1 - \lambda_i)^2} \right) (\gamma_i' (y_I - X_I \hat{\beta}))^2 = (\hat{\beta} - \hat{\beta}_I)' (X'X) (\hat{\beta} - \hat{\beta}_I)$

$$= [X(\hat{\beta} - \hat{\beta}_I)]' [X(\hat{\beta} - \hat{\beta}_I)]$$

Note: X full rank p (in original description)

$$\hat{\beta} = (X'X)^{-1} X'Y$$

$$\hat{\beta}_I = (X_I' X_I)^{-1} X_I' Y$$

We know for a single deletion case,

$$\hat{\beta}_{(-i)} = \hat{\beta} - \frac{(x'x)^{-1}x_i'\hat{\epsilon}_i}{1-h_{ii}}$$

$$\Rightarrow \hat{\beta}_I = \hat{\beta} - (x'x)^{-1}x_I'[(I-H)_I]^{-1}\hat{\epsilon}_I$$

$d_I = n \times m$ Like before, let d_I = matrix of 1's in the I ^{diag} position + 0 elsewhere (partial identity matrix)

$$\begin{aligned} &= \hat{\beta} - (x'x)^{-1}(d_I'x)'[d_I'(I-H)d_I]^{-1}(d_I'\hat{\epsilon}) \\ &= \hat{\beta} - (x'x)^{-1}(d_I'x)'[d_I'd_I - d_I'Hd_I]^{-1}(\underbrace{d_I'\hat{\epsilon}}_{\hat{\epsilon}_I}) \end{aligned}$$

Notes

$$\begin{aligned} d_I'Hd_I &= d_I'x(x'x)^{-1}x'd_I \\ &= x_I(x'x)^{-1}x_I' \\ &= P_I \end{aligned}$$

$$= \hat{\beta} - (x'x)^{-1}(x_I')\underbrace{[d_I'd_I - P_I]^{-1}}_{I_m \text{ (identity matrix } m \times m)}\hat{\epsilon}_I$$

$$(\hat{\beta} - \hat{\beta}_I) = (x'x)^{-1}x_I'(I - P_I)^{-1}\hat{\epsilon}_I$$

$$\begin{aligned} &(\hat{\beta} - \hat{\beta}_I)'(x'x)(\hat{\beta} - \hat{\beta}_I) \\ &= \hat{\epsilon}_I'(I - P_I)^{-1} \underbrace{x_I(x'x)^{-1}(x'x)^{-1}x_I'}_{P_I}(I - P_I)^{-1}\hat{\epsilon}_I \\ &= \hat{\epsilon}_I'(I - P_I)^{-1}P_I(I - P_I)^{-1}\hat{\epsilon}_I \end{aligned}$$

Since we want to transition this into terms of eigenvectors + eigenvalues of P_I , perform spectral decomposition of P_I

$$P_I = B'\Lambda B$$

B = matrix of eigenvectors (matrix of \hat{v}_i as rows)

Λ = diag (eigenvalues = λ_i)

Note: since B = orthogonal matrix (columns orthonormal), then $B'B = BB' = I$

→

$$\Rightarrow I = B'B + P_I = B'\Lambda B$$

$$\Rightarrow I - P_I = B'B - B'\Lambda B = B'(I - \Lambda)B$$

$$\begin{aligned} [I - P_I]^{-1} &= [B'(I - \Lambda)B]^{-1} \\ \text{Since } B'B &= BB' = I \\ \Rightarrow B^{-1} &= B' \text{ and } (B')^{-1} = B \\ &= B^{-1}(I - \Lambda)^{-1}(B')^{-1} \\ &= B'(I - \Lambda)^{-1}B \end{aligned} \quad \left. \begin{array}{l} \text{By rules of spectral decomp,} \\ \text{If } A = P'\Lambda P \Rightarrow A^{-1} = P'\Lambda^{-1}P \\ \text{Consequently, if} \\ I - P_I = B'(I - \Lambda)B \\ \Rightarrow [I - P_I]^{-1} = B'(I - \Lambda)^{-1}B \end{array} \right\}$$

$$\begin{aligned} &\hat{\epsilon}_I' (I - P_I)^{-1} P_I (I - P_I)^{-1} \hat{\epsilon}_I \\ &= \hat{\epsilon}_I' B'(I - \Lambda)^{-1} \underbrace{B(B'\Lambda B)}_I \underbrace{B'(I - \Lambda)^{-1}B}_{I} \hat{\epsilon}_I \end{aligned}$$

$$= \hat{\epsilon}_I' B'(I - \Lambda)^{-1} \Lambda (I - \Lambda)^{-1} B \hat{\epsilon}_I$$

$$(I - \Lambda)^{-1} = \text{diag}(1 - \lambda_i)$$

$$\Lambda = \text{diag}(\lambda_i)$$

$$\Rightarrow (I - \Lambda)^{-1} \Lambda (I - \Lambda)^{-1} = \text{diag}\left(\frac{\lambda_i}{(1 - \lambda_i)^2}\right)$$

$$\Rightarrow \hat{\epsilon}_I' B' \text{diag}\left(\frac{\lambda_i}{(1 - \lambda_i)^2}\right) B \hat{\epsilon}_I$$

$$= \left(\text{diag}\left(\frac{\lambda_i^{1/2}}{(1 - \lambda_i)}\right) B \hat{\epsilon}_I \right)' \left(\text{diag}\left(\frac{\lambda_i}{1 - \lambda_i}\right) B \hat{\epsilon}_I \right)$$

$$= \sum_{i=1}^n \left(\frac{\lambda_i^{1/2}}{1 - \lambda_i} \right)^2 (\hat{\epsilon}_i' \hat{\epsilon}_I)^2 \quad \text{since rows of } B = \hat{\epsilon}_i$$

$$= \sum_{i=1}^n (\hat{\epsilon}_i' \hat{\epsilon}_I)^2 \left(\frac{\lambda_i}{(1 - \lambda_i)^2} \right) \checkmark$$

Note: Can write $A = P\Lambda P'$ or $A = P'\Lambda P$

in $P\Lambda P'$ form, columns of P = eigenvectors

in $P'\Lambda P$ form, rows of P = eigenvectors

→ First matrix (P first or P' first) has columns as the eigenvectors.

3) (a) $\mu(x) = [1 \ x^T] \beta_0$

$$E[Y|x] = \mu(x)$$

$$E[Y|x, D] = \tilde{\mu}(x, D)$$

Show $\mu(x) = \tilde{\mu}(x, 1) P(D=1|x) + \tilde{\mu}(x, 0) P(D=0|x)$

and

$$\tilde{\mu}(x, D) = E[Y|x, D, S=1] = \mu(x) + [D - P(D=1|x)] \gamma(x)$$

$\gamma(x)$ = association between y & D .

- Derive explicit form of $\gamma(x)$ in terms of $\tilde{\mu}(x, 1)$ &

$$\tilde{\mu}(x, 0)$$

(i) $E[Y|x] = E[E[Y|x, D]|x]$

Since $D \sim \text{Bern}(p)$

$$= E[Y|x, D=1] P(D=1|x) + E[Y|x, D=0] P(D=0|x)$$

$$= \tilde{\mu}(x, 1) P(D=1|x) + \tilde{\mu}(x, 0) P(D=0|x) \checkmark$$

(ii) $\tilde{\mu}(x, D) = E[Y|x, D]$

$$E[E[Y|x, D, S]|x, D]$$

$S=1 \Rightarrow$ subject sampled

$S=0 \Rightarrow$ subject not sampled

$$= E[Y|x, D, S=1] P(S=1|x, D) + E[Y|x, D, S=0] P(S=0|x, D)$$

If D is measured at all ($D=0, 1$) then individual is in study

$$\Rightarrow P(S=1|x, D=\{0, 1\}) = 1$$

$$P(S=0|x, D=\{0, 1\}) = 0$$

$$= E[Y|x, D, S=1] \checkmark$$

$$(ii) \mu(x) = \tilde{\mu}(x, 1) P(D=1|x) + \tilde{\mu}(x, 0) P(D=0|x)$$

Since $D \sim \text{Bernoulli}$,

$$P(D=0|x) = 1 - P(D=1|x)$$

$$= \underset{\uparrow E[Y|x, D=1]}{\tilde{\mu}(x, 1)} P(D=1|x) + \underset{\uparrow E[Y|x, D=0]}{\tilde{\mu}(x, 0)} (1 - P(D=1|x))$$

$$E[Y|x, D=1] P(D=1|x) + E[Y|x, D=0] (1 - P(D=1|x)) + \\ + D\gamma(x) - P(D=1|x)\gamma(x)$$