

1) An overparameterized two way Anova model is $Y_{ijk} = \mu + \alpha_i + \beta_j + \tau_{ij} + \epsilon_{ijk}$ for $i = 1, \dots, a$ and $j = 1, \dots, b$ and $k = 1, \dots, m$. Suppose $a = 2$, $b = 2$, and $m = 2$. Then

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$$\begin{bmatrix} Y_{111} \\ Y_{112} \\ Y_{121} \\ Y_{122} \\ Y_{211} \\ Y_{212} \\ Y_{221} \\ Y_{222} \end{bmatrix} = \mathbf{X} \begin{bmatrix} \mu \\ \alpha_1 \\ \alpha_2 \\ \beta_1 \\ \beta_2 \\ \tau_{11} \\ \tau_{12} \\ \tau_{21} \\ \tau_{22} \end{bmatrix} + \begin{bmatrix} \epsilon_{111} \\ \epsilon_{112} \\ \epsilon_{121} \\ \epsilon_{122} \\ \epsilon_{211} \\ \epsilon_{212} \\ \epsilon_{221} \\ \epsilon_{222} \end{bmatrix}$$

$$\mathbf{X}\beta = \begin{bmatrix} \mu + \alpha_1 + \beta_1 + \tau_{11} \\ \mu + \alpha_1 + \beta_2 + \tau_{12} \\ \mu + \alpha_2 + \beta_1 + \tau_{21} \\ \mu + \alpha_2 + \beta_2 + \tau_{22} \end{bmatrix}$$

a) Give the matrix \mathbf{X} .

	μ	α_1	α_2	β_1	β_2	τ_{11}	τ_{12}	τ_{21}	τ_{22}
1	1	1	0	1	0	1	0	0	0
2	1	1	0	1	0	1	0	0	0
3	1	1	0	0	1	0	1	0	0
4	1	1	0	0	1	0	1	0	0
5	1	0	1	1	0	0	0	1	0
6	1	0	1	1	0	0	0	1	0
7	1	0	1	0	1	0	0	0	1
8	1	0	1	0	1	0	0	0	1

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b) Write the above model as $\mathbf{Y} = \mathbf{X}\beta + \epsilon$. This model is **not full rank**. What is the projection matrix \mathbf{P} (onto the column space of \mathbf{X})? Hint: $\mathbf{X}^T\mathbf{X}$ is singular, so use the generalized inverse.

$$\mathbf{X}(\mathbf{X}'\mathbf{X})^{-}\mathbf{X}'$$

e 2) In numerical linear algebra, the least squares solution to " $\mathbf{Ax} = \mathbf{b}$ " is of interest where the problem is actually the multiple linear regression model $\mathbf{b} = \mathbf{Ax} + \boldsymbol{\epsilon}$ where \mathbf{A} has full rank p , and we will assume that $E(\boldsymbol{\epsilon}) = \mathbf{0}$, and $Cov(\boldsymbol{\epsilon}) = \sigma^2 \mathbf{I}_n$.

a) What is the (formula for the) projection matrix \mathbf{P} onto the column space of \mathbf{A} ?

$$\mathbf{A} (\mathbf{A}'\mathbf{A})^{-1} \mathbf{A}'$$

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b) What is the OLS estimator $\hat{\mathbf{x}}$?

$$(\mathbf{A}'\mathbf{A})^{-1} \mathbf{A}' \underline{\mathbf{b}}$$

c) What is the vector of fitted values $\hat{\mathbf{b}}$?

$$\mathbf{P} \underline{\mathbf{b}}$$

d) What is the residual vector \mathbf{e} ?

$$(\mathbf{I} - \mathbf{P}) \underline{\mathbf{b}}$$

3) Consider the multivariate linear regression model $\mathbf{Z} = \mathbf{X}\mathbf{B} + \mathbf{E}$.

a) What is $E(\mathbf{Z})$?

$$\mathbf{X}\mathbf{B}$$

b) What is $E(\widehat{\mathbf{B}})$?

$$\mathbf{B}$$

c) What is $E(\mathbf{E})$?

$$\mathbf{0}$$

d) Consider testing $H_0 : \mathbf{L}\mathbf{B} = \mathbf{0}$. What is the limiting distribution of $(n-p)U(\mathbf{L})$?

$$(n-p)U(\mathbf{L}) \xrightarrow{D} \chi^2_{rm}$$

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4) The data below are a sorted residuals from a lasso regression where $n = 1000$ and $p = 17$. Find $\text{shorth}(997)$ of the residuals.

number	1	2	3	4	...	997	998	999	1000
residual	-3.28	-3.06	-3.04	-2.96	...	2.66	2.71	2.81	3.62

$$5.94 = 2.66 - (-3.28)$$

$$5.77 = 2.71 - (-3.06)$$

$$5.85 = 2.81 - (-3.04)$$

$$6.58 = 3.62 - (-2.96)$$

$$\boxed{[-3.06, 2.71]} = \text{shorth } 997$$

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$$E(\mathbf{Y}) = \mathbf{X}\boldsymbol{\beta} = \begin{pmatrix} \beta_1 - 2\beta_2 \\ \beta_1 - 2\beta_2 \end{pmatrix} \Rightarrow \mathbf{X} = \begin{bmatrix} 1 & -2 \\ 1 & -2 \end{bmatrix} \Rightarrow \mathbf{X}^T = \begin{bmatrix} 1 & 1 \\ -2 & -2 \end{bmatrix}$$

$$C(\mathbf{X}^T) = \text{span} \left(\begin{bmatrix} 1 \\ -2 \end{bmatrix} \right)$$

5) Suppose that $\mathbf{Y} = (Y_1, Y_2)'$, $\text{Var}(\mathbf{Y}) = \sigma^2 \mathbf{I}$, $E(Y_1) = E(Y_2) = \beta_1 - 2\beta_2$. Show whether or not the following functions are estimable. Hint $E(\mathbf{Y}) = \mathbf{X}\boldsymbol{\beta}$, so find \mathbf{X} .

a) $\beta_1 = \begin{pmatrix} 1 & 0 \end{pmatrix} \boldsymbol{\beta}$, $\begin{pmatrix} 1 & 0 \end{pmatrix} \notin C(\mathbf{X}^T)$

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(NO)

b) $\beta_2 = \begin{pmatrix} 0 & 1 \end{pmatrix} \boldsymbol{\beta}$, $\begin{pmatrix} 0 & 1 \end{pmatrix} \notin C(\mathbf{X}^T)$

(NO)

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c) $-\beta_1 + 2\beta_2 = \begin{pmatrix} -1 & 2 \end{pmatrix} \boldsymbol{\beta}$, $\begin{pmatrix} -1 \\ 2 \end{pmatrix} \in C(\mathbf{X}^T)$

(Yes)

d) $4\beta_1 - 8\beta_2 = \begin{pmatrix} 4 & -8 \end{pmatrix} \boldsymbol{\beta}$, $\begin{pmatrix} 4 \\ -8 \end{pmatrix} \in C(\mathbf{X}^T)$

(Yes)

5 got 16
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6) Suppose $Y^* = X\hat{\beta} + r^W$ where $E(r^W) = 0$ and $Cov(r^W) = Cov(Y^*) = MSE I_n$. Then $\hat{\beta}^* = (X^T X)^{-1} X^T Y^*$. Recall that X is an $n \times p$ constant matrix. Simplify quantities when possible.

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a) What is $E(\hat{\beta}^*)$?

$$= (X^T X)^{-1} X^T E Y^* = (X^T X)^{-1} X^T X \hat{\beta}$$

$$= \hat{\beta}$$

→ b) What is $Cov(\hat{\beta}^*)$?

$$= A Cov(Y^*) A^T = (X^T X)^{-1} X^T MSE I_n X (X^T X)^{-1}$$

$$= MSE (X^T X)^{-1} X^T X (X^T X)^{-1} = MSE (X^T X)^{-1}$$

c) Recall that $X\hat{\beta} = PY$. What is $E(\hat{\beta}_I^*) = E[(X_I^T X_I)^{-1} X_I^T Y^*]$?

$$= (X_I^T X_I)^{-1} X_I^T X \hat{\beta} = (X_I^T X_I)^{-1} X_I^T P Y =$$

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

→ d) What is $Cov(\hat{\beta}_I^*)$?

$$= (X_I^T X_I)^{-1} X_I^T [Cov(Y^*)] X_I (X_I^T X_I)^{-1}$$

$$= (X_I^T X_I)^{-1} X_I^T MSE I_n X_I (X_I^T X_I)^{-1}$$

$$= MSE (X_I^T X_I)^{-1} X_I^T X_I (X_I^T X_I)^{-1}$$

$$= MSE (X_I^T X_I)^{-1}$$

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$$Cov(A Y^*) = A Cov(Y^*) A^T$$

7) Suppose you are estimating the mean μ of losses with $T = \bar{X}$.

actual losses 14, 3, 5, 12, 20, 10, 9: $\bar{X} = 10.4286$,

a) Compute T_1^*, \dots, T_4^* , where T_i^* is the sample mean of the i bootstrap sample.
bootstrap samples:

12, 3, 10, 14, 5, 9, 10: $63/7 = 9$
 10, 14, 5, 10, 10, 10, 9: $68/7 = 9.7143$
 20, 5, 5, 3, 5, 20, 5: $63/7 = 9$
 12, 20, 5, 14, 12, 14, 20: $97/7 = 13.8571$

b) Now compute the bagging estimator which is the sample mean of the T_i^* : the bagging estimator $\bar{T}^* = \frac{1}{B} \sum_{i=1}^B T_i^*$ where $B = 4$ is the number of bootstrap samples.

$$\frac{9 + 9.7143 + 9 + 13.8571}{4} = \frac{41.5714}{4} = 10.3928$$

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8) The output below is for forward selection and I_{min} is the minimum C_p model. Here $Y = \text{height}$, the constant $x_{i,1} \equiv 1$, $x_{i,2} = \text{height when sitting}$, $x_{i,3} = \text{height when kneeling}$, $x_{i,4} = \text{head length}$, $x_{i,5} = \text{nasal breadth}$, and $x_{i,6} = \text{span}$.

	Estimate	Std.Err	95% shorth	CI
Intercept	-42.4846	51.2863	[-192.281,	52.492]
X2	0		[0.000,	0.268]
X3	1.1707	0.0598	[0.992,	1.289]
X4	0		[0.000,	0.840]
X5	0		[0.000,	1.916]
X6	0.1467	0.0368	[0.0747,	0.215]

	(Intercept)	a	b	c	d	e
1	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE
2	TRUE	FALSE	TRUE	FALSE	FALSE	TRUE
3	TRUE	FALSE	TRUE	TRUE	FALSE	TRUE
4	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE
5	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

> tem2\$cp
 [1] 14.389492 0.792566 2.189839 4.024738 6.000000

What is the value of $C_p(I_{min})$ and what is $\hat{\beta}_{I_{min},0}$?

$$C_p(I_{min}) = 0.792566$$

$$\hat{\beta}_{I_{min},0} = (-42.48486, 0, 1.1707, 0, 0, 0.1467)^T$$