

3a) $I=2 \quad J=2$

②

1pt

$$\bar{X}_{1, \cdot, \cdot} = \frac{1}{J} \sum_j \bar{X}_{1, j, \cdot} = \frac{67+83}{2} = \underline{75}$$

$$\bar{X}_{2, \cdot, \cdot} = \frac{139+211}{2} = \underline{175}$$

$$\bar{X}_{\cdot, 1, \cdot} = \frac{1}{I} \sum_i \bar{X}_{i, 1, \cdot} = \frac{67+139}{2} = \underline{103}$$

$$\bar{X}_{\cdot, 2, \cdot} = \frac{83+211}{2} = \underline{147}$$

$$\bar{X}_T = \bar{X}_{\cdot, \cdot, \cdot} = \frac{67+83+139+211}{4} = 125 \quad \left(\text{or via } \frac{75+175}{2} \right)$$

optional or $\frac{103+147}{2}$

1pt.

$I \backslash J$	Pt	M_0	all
RT	67	139	103
LN	83	211	147
all	75	175	125

optional

Transpose is ok.

$$3b) \text{ opt } SS_{E, i, j} = S_{ij}^2 \cdot (N_j - 1) = S_{ij}^2 \cdot 10$$

②

$$\begin{cases} 0.5 \text{ pt } & SS_{E, 1, 1} = 11^2 \cdot 10 = \underline{1210} \\ & SS_{E, 1, 2} = 8^2 \cdot 10 = \underline{640} \\ & SS_{E, 2, 1} = 14^2 \cdot 10 = \underline{1960} \\ & SS_{E, 2, 2} = 17^2 \cdot 10 = \underline{2890} \end{cases}$$

(1 pt if correct without explicit formula)

$$\begin{aligned} 1 \text{ pt } \quad \underline{SS_{E(TOT)}} &= \sum_i \sum_j SS_{E, i, j} = 1210 + 640 + 1960 + 2890 \\ &= \underline{\underline{6700}} \end{aligned}$$

$$3c) \quad SS_{B, I} = \sum_i j \cdot N_j \cdot (\bar{X}_{i, j} - \bar{X}_T)^2 \quad N_j = 11$$

①

$$= 2 \cdot 11 \cdot [(75 - 125)^2 + (175 - 125)^2] = 2 \cdot 11 \cdot 5000$$

$$= \underline{\underline{110'000}}$$

$$SS_{B, 2} = 2 \cdot 11 [(103 - 125)^2 + (147 - 125)^2] =$$

$$= 2 \cdot 11 \cdot 968$$

$$= \underline{\underline{21'296}}$$

3 d) for this we have to compare the

① MEAN SQUARE ERROR, $\frac{SS_{B,I}}{v_B} = MS_B$

$v_{B,I} = v_{B,J} = 2-1 = 1$ so $SS_B = MS_B$ here.

$$\underline{MS_{B,I} > MS_{B,J}}$$

So factor I ("type of metal") is dominant.

0.5pt if only compared $SS_{B,I}$ to $SS_{B,J}$

$$y_{B, I: j} = (I-1)(j-1) = 1 \cdot 1 = \underline{1} \quad 0.5 \text{ pt}$$

$$3e) \quad y_{B, I} = y_{B, j} = 2 - 1 = \underline{1} \quad 0.5 \text{ pt}$$

$$5) \quad y_E = I - j \cdot (N_s - 1) = 2 - 2 \cdot (11 - 1) = \underline{40} \quad 0.5 \text{ pt}$$

$$\underline{MS_{B, I}} = \frac{SS_{B, I}}{y_{B, I}} = \frac{110'000}{1} = 110'000$$

$$\underline{MS_{B, j}} = \frac{SS_{B, j}}{y_{B, j}} = \frac{21'296}{1} = \underline{21'296}$$

$$\underline{MSE} = \frac{SSE}{y_E} = \frac{6700}{40} = \underline{167.5}$$

0.5 pt

$$\underline{SS_{B, I: j}} = N_s \sum_i \sum_j (\bar{X}_{i, j, i_0} - \bar{X}_{i, i_0} - \bar{X}_{\cdot, j, i_0} + \bar{X}_T)^2$$

$$= 11 \cdot \left[\begin{aligned} &(\cancel{67} - 75 - 103 + 125)^2 \\ &+(\cancel{83} - 75 - 147 + 125)^2 \\ &+(\cancel{139} - 175 - 103 + 125)^2 \\ &+(\cancel{211} - 175 - 147 + 125)^2 \end{aligned} \right]$$

$$= 11 [14^2 + (-14)^2 + (-14)^2 + 14^2]$$

$$= 11 \cdot 4 \cdot 196$$

$$= \underline{8624}$$

all same as in teacher
has only one diff

$$\underline{MS_{B, I: j}} = \frac{SS_{B, I: j}}{y_{B, I: j}} = \frac{8624}{1} = \underline{8624}$$

$$F_I = MS_{B, I} / MSE = \frac{110'000}{167.5} = 656.7 \dots \approx \underline{657} \quad 0.5 \text{ pt}$$

$$F_j = 21'296 / 167.5 \approx \underline{127}$$

$$F_{I: j} = 8624 / 167.5 \approx 51.50 \dots \approx \underline{52}$$

	y	SS	MS	F
FAKT I	1	110'000	110'000	657
FAKT j	1	21'296	21'296	127
INTER I: j	1	8'624	8'624	52
ERROR	40	6700	167.5	-

0.5 pt
(for table)

$$3) F_{\text{OBS}, I:J} = 51$$

$$② \quad qF_{v_1=1, v_2=40} (\alpha=5\%) = 4.085$$

} 1 pt.

$$F_{\text{OBS}, I:J} > 4.085 \Rightarrow$$

We reject the no-interaction hypothesis
at the ~~5% level~~ 5% significance level.

} 1 pt

$$3g) \quad \frac{\partial SSE}{\partial \hat{a}} = \frac{\partial}{\partial \hat{a}} \sum_{i=1}^{N_T} [K_i - (\hat{a} + \hat{b}_1 T_i)]^2$$

(3)

$$= (-1) \cdot 2 \sum_i [K_i - (\hat{a} + \hat{b}_1 T_i)]$$

$$= -2 (N_T \bar{K} - N_T \cdot \hat{a} - N_T \cdot \hat{b}_1 \cdot \bar{T}) \stackrel{!}{=} 0$$

$$\Rightarrow \underline{\underline{\hat{a} = \bar{K} - \hat{b}_1 \bar{T}}}$$

This shows it is an extremum. To show it is a minimum we also need to show $\frac{\partial^2 SSE}{\partial \hat{a}^2} > 0$ at $\hat{a} = \bar{K} - \hat{b}_1 \bar{T}$

$$\frac{\partial^2 SSE}{\partial \hat{a}^2} = \frac{\partial}{\partial \hat{a}} [-2 N_T (\bar{K} - \hat{a} - \hat{b}_1 \bar{T})]$$

$$= \underline{\underline{2 N_T > 0}} \quad \checkmark$$

$$3 \text{ l) } \overset{= N_{\text{Tot}} - 1 - \nu_M}{\nu_{E, m1}} = 7 - 1 - 1 = \underline{5} = \nu_{E, \text{restricted}}$$

↑
slope parameter

①

$$\nu_{E, m2} = 7 - 1 - 2 = \underline{4} = \nu_{E, \text{full}}$$

$$3 \text{ i) } \underline{\underline{F_{m1, m2}}} = \frac{\Delta SSE / \Delta \nu_M}{SSE_{\text{full}} / \nu_{E, \text{full}}}$$

$$= \frac{(1255 - 405) / (2 - 1)}{405 / 4}$$

$$= \frac{850}{101.25} = 8.39506... \approx \underline{\underline{8.4}}$$

$$q F_{\Delta \nu, \nu_{E, \text{full}}} (\alpha=5\%) = q F_{1, 4} (\alpha=5\%) = \underline{\underline{7.709}} \quad 0.5$$

$F_{\text{OBS}} > qF \Rightarrow$ The second model is statistically significantly (at 5% significance) better.

0.5

3 j) Calibrated Data = measured Data * 1.2

① (numpy arrays multiply element-wise)

3 k) [68.4 72.1]

① (for 0:2 yang gab elements 0 and 1).

0.5 pts for [68.4 72.1 1200.2]

3 l) I) ^{print} np.max (calibrated Data)

② II) ^{print} calibrated Data [calibrated Data > 1000]

III) for i in calibrated Data:

if i > 1000:
print("spike")

else:
pass

etc...

3 m)

I) use

`print(np.vectorize(my Filter)(calibrated Data))`

(ok. in words)

II)

run a loop:

for i in ^{range}(calibrated Data):

~~Open~~ calibrated Data[i] = my Filter(calibrated Data[i])

etc...