
Midterm

CS121

(TRUE)

a) Yes, this is because the regression line fits well

(FALSE)

b) No, this is because the regression line is not near $y = x$, instead it is around $y = 20x$. Thus, Sample B is around 20x of Sample A.

c) FALSE

d) FALSE

e) TRUE

f) TRUE

Problem 2

a) $X_{ij} \sim \text{Poisson}(S_i, B_j \tilde{I}_j)$

Likelihood = $\prod_{i=1}^6 (\text{PMF for poisson distribution})$

$$= \prod_{i=1}^6 \frac{(e^{-S_i B_j \tilde{I}_j} \times (S_i B_j \tilde{I}_j)^{X_{ij}})}{X_{ij}!}$$

MLE: Take log of the value above

$$\log(\mathcal{L}_n) = \log \sum_{i=1}^6 -S_i B_j \tilde{I}_j + X_{ij} \log(S_i B_j \tilde{I}_j) - \log(X_{ij}!)$$

taking derivative w.r.t B_j

$$\frac{\partial (\log \mathcal{L}_n)}{\partial \log B_j} = \sum_{i=1}^6 -S_i \tilde{I}_j + \frac{X_{ij}}{B_j}$$

derivative = 0

$$\sum_{i=1}^6 -S_i \tilde{I}_j = \sum_{i=1}^6 \frac{X_{ij}}{B_j}$$

$$B_j = \frac{\sum_{i=1}^6 X_{ij}}{\tilde{I}_j}$$

$$\tilde{I}_j \sum_{i=1}^6 -S_i$$

double derivative = $-\frac{X_{ij}}{B_j^2}$, which is always

going to be negative as all variables are positive, thus ~~minimizing~~ maximizing likelihood.

b) This accounts for the avg of the raw counts from sample 1-6. s_i and \tilde{s}_i are normalization factors ~~as~~. This would give a count for B_{ij} , divided by 6 to ensure the 6 samples are considered.

c) $X_{ij} = \text{Poisson}(s_i B_j \tilde{T}_{ij})$

Like likelihood = $\prod_{i=1}^6 (\text{prob of poisson distribution})$

$$= \prod_{i=1}^6 \left(e^{-s_i B_j \tilde{T}_{ij}} \times (s_i B_j \tilde{T}_{ij})^{x_{ij}} \right) / x_{ij}!$$

MLE: Take log of the value above

$$\log(\mathcal{L}_n) = \log \sum_{i=1}^6 -s_i B_j \tilde{T}_{ij} + x_{ij} \log(s_i B_j \tilde{T}_{ij}) - \log(x_{ij}!)$$

taking derivative w.r.t B_j

$$\frac{\partial \log \mathcal{L}_n}{\partial \log B_j} = \sum_{i=1}^6 -s_i \tilde{T}_{ij} + \frac{x_{ij}}{B_j}$$

derivative = 0

$$\sum_{i=1}^6 -s_i \tilde{T}_{ij} = \sum_{i=1}^6 \frac{x_{ij}}{B_j}$$

$$B_j = \frac{\sum_{i=1}^6 x_{ij}}{\sum_{i=1}^6 (-s_i \tilde{T}_{ij})} \rightarrow \text{Term need to be in the bracket.}$$

double derivative is also negative similar to a)

d) Now the bottom term does a summation over the lengths. Thus, it now calculates the denominator, where for each sample, it is multiplied by the length. Thus, it now accounts for the ~~this length~~ effective length of each sample.

$$\sum_{i=1}^6 -S_i \tilde{I}_{ij} \rightarrow \left(\sum_{i=1}^6 -S_i \right) \tilde{I}_j$$

Problem 3

$$N = 100$$

a) 100 ready ~~30~~ $N_B = 30$ $N_A = 70$

$$P(AB | O_1, O_2, O_3, \dots, O_{100}) = \frac{P(O_1, O_2, O_3, \dots, O_{100} | AB) P(AB)}{P(O_1, O_2, O_3, \dots, O_{100})}$$

$$O_i = A \quad E_i = 0$$

$$P(O_i = A | E_i = 0, i = A, G = AB) P(E_i = 0) P(i = A | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$1 \quad 1 - r \quad 0.5$$

$$P(O_i = A | E_i = 0, i = B, G = AB) P(E_i = 0) P(i = B | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$0 \quad 1 - r \quad 0.5$$

$$O_i = B \quad E_i = 0$$

$$P(O_i = B | E_i = 0, i = A, G = AB) P(E_i = 0) P(i = A | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$0 \quad 1 - r \quad 0.5$$

$$P(O_i = B | E_i = 0, i = B, G = AB) P(E_i = 0) P(i = B | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$1 \quad 1 - r \quad 0.5$$

$$O_i = A \quad E_i = 1$$

$$P(O_i = A | E_i = 1, i = A, G = AB) P(E_i = 1) P(i = A | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$0 \quad r \quad 0.5$$

$$P(O_i = A | E_i = 1, i = B, G = AB) P(E_i = 1) P(i = B | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$1 \quad r \quad 0.5$$

$$O_i = B \quad E_i = 1$$

$$P(O_i = B | E_i = 1, i = A, G = AB) P(E_i = 1) P(i = A | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$1 \quad r \quad 0.5$$

$$P(O_i = B | E_i = 1, i = B, G = AB) P(E_i = 1) P(i = B | G = AB)$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$0 \quad r \quad 0.5$$

Total = 1

$$P(O_1, O_2, \dots, O_{100} | AB) = \left(\frac{1}{2}\right)^N$$

$$P(O_1, O_2, \dots, O_{100} | AA) = \underbrace{(1-\gamma)^{N_A} (\gamma)^{N - N_A}}$$

$$\hookrightarrow \prod_{i: O_i = A} P(O_i = A | AA) \prod_{i: O_i = B} P(O_i = B | AA)$$

Similarly

$$P(O_1, O_2, \dots, O_{100} | BB) = \gamma^{N_A} (-\gamma)^{N - N_A}$$

$$\text{Total Probs} = \underbrace{\left(\frac{1}{2}\right)^{100} \cdot \chi_4}_{\frac{1}{2} \cdot \left(\frac{1}{2}\right)^{100} + \frac{(1-\gamma)^{30} \gamma^{70}}{2} + (-\gamma)^{70} \frac{\gamma^{30}}{4}}$$

b) $P(C_i = A | G = AB) = S$

$$P(C_i = B | G = AB) = 1 - S$$

$$P(O_i = B | C_i = A, G = AB) = \gamma$$

$$P(O_i = B | C_i = B, G = AB) = 1 - \gamma$$

$$P(O_i = B | G = AB) = P(O_i = B | G = AB)$$

$$= S \times \gamma + (1-S)(1-\gamma)$$

$$= 1 - S - \gamma + 2S\gamma$$

Expected Count = $100 \times (1 - S - \gamma + 2S\gamma)$

rounded up/down to nearest read.

$$c) P(AB | O_1, \dots, O_N) \geq \alpha$$

$$P(AB | O_1, O_2, \dots, O_N)$$

$$= \underbrace{\left(\frac{1}{2}\right)^N P(AB)}_{\frac{\gamma}{4} \left(\frac{1-\gamma}{2}\right)^{N/2}} + \underbrace{\left(\frac{1}{2}\right)^N \cdot \frac{1}{4}}_{\frac{1}{4} \left(\frac{1-\gamma}{2}\right)^{N/2}} + \underbrace{\frac{\gamma}{2} \left(\frac{1-\gamma}{2}\right)^{N/2}}_{\geq \alpha} \geq \alpha$$

$$N_A = N_B = \frac{N}{2}$$

$$\underbrace{P_X \frac{1}{4} \left(\frac{1}{2}\right)^N}_{\frac{1}{4} \left(\frac{1-\gamma}{2}\right)^{N/2}} + \underbrace{\left(\frac{1}{2}\right)^N \cdot \frac{1}{4}}_{\frac{1}{4} \left(\frac{1-\gamma}{2}\right)^{N/2}} + \underbrace{\frac{\gamma}{2} \left(\frac{1-\gamma}{2}\right)^{N/2}}_{\geq \alpha} \geq \alpha$$

~~$$(0.5)^N \geq 3 \gamma^{N/2} (1-\gamma)^{N/2} \alpha + \left(\frac{1}{2}\right)^N \alpha$$~~

$$(0.5)^N (1-\alpha) \geq 3 \gamma^{N/2} (1-\gamma)^{N/2} \alpha$$

$$2(0.5)^N - 3(\gamma^{N/2})(1-\gamma)^{N/2} - 1 \geq 0$$

Solving for inequality, we get
over

