## Homework #2

Student name: Alex Towell (atowell@siue.edu)

Course: STAT 579 - Discrete Multivariate Analysis - Professor: Dr. Andrew Neath Due date: 02/4/2021

## Question 1

Suppose  $n_1$  is observed from a BIN $(n;\pi)$  distribution. Derive the maximum likelihood estimate  $\hat{\pi}$ .

**Answer.** Let  $X \sim \text{BIN}(n;\pi)$ . Then,  $f_X(k|n,\pi) = \binom{n}{k} \pi^k (1-\pi)^{n-k}$  and the likelihood is

$$\ell(\pi; n_1) = \pi^{n_1} (1 - \pi)^{n - n_1} .$$

which has a log-likelihood

$$L(\pi; n_1) = n_1 \log \pi + (n - n_1) \log(1 - \pi). \tag{1}$$

Assuming  $\pi \in (0,1)$ , to find the maximum likelihood of  $\pi$  given that we observe  $X = n_1$ , we find

$$\hat{\pi} = \operatorname*{arg\,max}_{\pi} \mathrm{L}(\pi; n_1)$$

by solving for the zeros of the derivative of L,

$$\frac{\frac{\mathrm{d}\,\mathbf{L}}{\mathrm{d}\pi}}{\hat{\pi}} = 0$$

$$\frac{n_1}{\hat{\pi}} - \frac{n - n_1}{1 - \hat{\pi}} = 0$$

$$\frac{n_1(1 - \hat{\pi}) - (n - n_1)\hat{\pi}}{\hat{\pi}(1 - \hat{\pi})} = 0$$

$$n_1(1 - \hat{\pi}) - (n - n_1)\hat{\pi} = 0$$

$$n_1 - n_1\hat{\pi} - n\hat{\pi} + n_1\hat{\pi} = 0$$

$$n_1 - n\hat{\pi} = 0$$

$$n\hat{\pi} = n_1,$$

and thus the MLE of  $\pi$  given an observation  $X = n_1$  is

$$\hat{\pi} = \frac{n_1}{n} \,. \tag{2}$$

## Question 2

Prove that if P(A|B) > P(A|B') then P(B|A) > P(B|A').

*Proof.* Starting at the proposition P(A|B) > P(A|B'), we apply rewrite rules that preserve the relation, eventually reaching the goal state P(B|A) > P(B|A').

If P(A|B) > P(A|B') then odds(A|B) > odds(A|B') where odds(X) := P(X)/P(X'). Making this substitution, we have

$$\frac{\mathrm{P}(A|B)}{\mathrm{P}(A'|B)} > \frac{\mathrm{P}(A|B')}{\mathrm{P}(A'|B')} \,.$$

Multiplying the LHS and RHS by convenient expressions for 1, respectively P(B)/P(B) and P(B')/P(B'), we rewrite the above as

$$\frac{\operatorname{P}(A|B)\operatorname{P}(B)}{\operatorname{P}(A'|B)\operatorname{P}(B)} > \frac{\operatorname{P}(A|B')\operatorname{P}(B')}{\operatorname{P}(A'|B')\operatorname{P}(B')}$$

Both sides are now a ratio of joint distributions. We rewrite them as

$$\frac{\operatorname{P}(B|A)\operatorname{P}(A)}{\operatorname{P}(B|A')\operatorname{P}(A')} > \frac{\operatorname{P}(B'|A)\operatorname{P}(A)}{\operatorname{P}(B'|A')\operatorname{P}(A')} \,.$$

Discarding the common factor P(A)/P(A') from both sides, we rewrite the above as

$$\frac{\mathrm{P}(B|A)}{\mathrm{P}(B|A')} > \frac{\mathrm{P}(B'|A)}{\mathrm{P}(B'|A')}.$$

Multiplying both sides by P(B|A')/P(B'|A), we may rewrite the above as

$$\frac{\mathrm{P}(B|A)}{\mathrm{P}(B'|A)} > \frac{\mathrm{P}(B|A')}{\mathrm{P}(B'|A')}$$

which may be rewritten as odds(B|A) > odds(B|A'). Finally, observe that

$$\operatorname{odds}(B|A) > \operatorname{odds}(B|A') \implies P(B|A) > P(B|A').$$