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## MVE055 / MSG810 Matematisk statistik och diskret matematik

Exam 24 October 2017, 8:30 - 12:30

Allowed aids: Chalmers-approved calculator and one (two-sided) A4 sheet of paper with your own notes. Total number of points: 30. To pass, at least 12 points are needed. Note: All answers should be motivated.

## **1** Solutions

1. (a) Consider X = "number of men in the group", then X follows an hypergeometric distribution with parameters N = 13, n = 4, r = 5. The answer is then

$$\Pr(X=2) = \frac{\binom{5}{2}\binom{8}{2}}{\binom{13}{4}} = 0.3916$$
(1)

(b) We need to compute

$$\Pr(X=0) = \frac{\binom{5}{0}\binom{8}{4}}{\binom{13}{4}} = 0.0979$$
(2)

(c) Denote by (F, F, M, M) the sequence of female,female,male,male extracted. The first female is picked randomly from a set of 13 people with 8 women. So the probability that the sequence starts with female is  $\frac{8}{13}$ . The second female has to be picked from a set of 12 people, as we have removed the first woman selected in the group, of which 7 are female. Similarly, the probabilities for picking the two men are respectively  $\frac{5}{11}$  and  $\frac{4}{10}$ . Thus, the probability of the sequence (F, F, M, M) is given by

$$\frac{8}{13}\frac{7}{12}\frac{5}{11}\frac{4}{10} = 0.0653$$

2. (a) The distribution of  $\overline{X}$  is Normal  $(\mu_x, \frac{\sigma_x}{\sqrt{n}})$ , thus the probability distribution is given by

$$f_{\overline{X}}(x) = \frac{1}{\sqrt{2\pi\frac{\sigma_x^2}{n}}} \exp\left(-\frac{(x-\mu_x)^2}{2\frac{\sigma_x^2}{n}}\right)$$
(3)

(b) The distribution of  $\overline{X} - \overline{Y}$  is Normal  $\left(\mu_x - \mu_y, \sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}\right)$ , thus the probability distribution is given by

$$f_{\overline{X}-\overline{Y}}(z) = \frac{1}{\sqrt{2\pi \left(\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}\right)}} \exp\left(-\frac{(z-\mu_x+\mu_y)^2}{2\left(\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}\right)}\right)$$
(4)

(c) From the previous point, and given that if  $Z \sim \text{Normal}(\mu, \sigma)$  then  $\frac{Z-\mu}{\sigma} \sim \text{Normal}(0, 1)$ , we conclude that the denominator should be the standard deviation of  $\overline{X} - \overline{Y}$ , so the random variable is

$$\frac{\overline{X} - \overline{Y} - (\mu_x - \mu_y)}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}}$$

(d) We know that

$$\Pr\left(-1.96 \le \frac{\overline{X} - \overline{Y} - (\mu_x - \mu_y)}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} \le 1.96\right) = 0.95$$
(5)

which means

$$\Pr\left(-1.96\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}} \le \overline{X} - \overline{Y} - (\mu_x - \mu_y) \le 1.96\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}\right) = 0.95.$$
(6)

Hence,

$$\Pr\left(\overline{X} - \overline{Y} - 1.96\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}} \le (\mu_x - \mu_y) \le \overline{X} - \overline{Y} + 1.96\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}\right) = 0.95 \quad (7)$$

and finally we find

$$L_1 = \overline{X} - \overline{Y} - 1.96\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}, \qquad L_2 = \overline{X} - \overline{Y} + 1.96\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}$$

- 3. Define the following events:
  - HD=the person has the disease, Pr(HD) = 0.01,  $Pr(HD^c) = 0.99$  ( $HD^c$  means healthy);
  - TP=the test is positive, Pr(TP|HD) = 0.8,  $Pr(TP|HD^c) = 0.05$

$$Pr(TP) = Pr(TP \cap HD) + Pr(TP \cap HD^{c}) =$$

$$Pr(TP|HD) Pr(HD) + Pr(TP|HD^{c}) Pr(HD^{c}) = 0.8 * 0.01 + 0.05 * 0.99 = 0.0575;$$
(8)

(b)

$$\Pr(HD|TP) = \frac{\Pr(TP \cap HD)}{\Pr(TP)} = \frac{\Pr(TP|HD)\Pr(HD)}{\Pr(TP)} = \frac{0.8 * 0.01}{0.0575} = 0.1391$$
(9)

4. (a) The transition matrix is

$$P = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0.75 & 0 & 0.25 & \dots & 0 \\ \vdots & \ddots & & & \\ 0 & \dots & 0.75 & 0 & 0.25 \\ 0 & \dots & 0 & 0.75 & 0.25 \end{bmatrix}$$

(b) For N = 2,

$$P = \begin{bmatrix} 1 & 0 & 0\\ 0.75 & 0 & 0.25\\ 0 & 0.75 & 0.25 \end{bmatrix}$$

thus

$$N = \begin{bmatrix} \frac{4}{3} & \frac{4}{9} \\ \frac{4}{3} & \frac{16}{9} \end{bmatrix}$$

and  $N[1,1]^T = [\frac{16}{9}, \frac{28}{9}]^T$ . Thus, the expected time to extiction if the initial state is  $X_0 = 2$  is  $\frac{28}{9}$ .

- (c) Consider  $Y_n = \max\{X_0, ..., X_n\}$ .  $Y_n$  is not a Markov chain as the future is not independent of the past. Consider  $X_n$  as above with  $X_0 = 2$  and N = 3, and take  $Y_n = 1$  for some integer *n*, thus the maximum state reached by  $X_m, m \le n$  is 1. Now the probability that at the next step  $Y_{n+1}$  is equal to 2, correspond to the probability that  $X_{n+1} = 2$ . This probability, depends on all the  $X_m, m \le n$ . In fact, consider the case in which we have  $X_0 = 2, X_1 = 1, X_2 = 0$ , i.e. we get extinct as fast as possible. Then the probability that  $Y_3 = 2$  is zero, as the population cannot grow if there is no one left. On the other hand, consider  $X_0 = 2, X_1 = 1, X_2 = 2$  (one death followed by a birth). Then  $Y_3 = 2$  happens if we get a birth, i.e. with probability 0.25. Thus, the past has an effect on the future.
- 5. (a)

$$P(Y = y) = {n \choose y} p^{y} (1 - p)^{n - y}, \quad y = 0, ..., n.$$

(a)

$$\Pr[X = n] = \sum_{k=0}^{n} P(X_A = k, X_B = n - k) = \sum_{k=0}^{n} P(X_A = k) P(X_B = n - k) = \sum_{k=0}^{n} e^{-\lambda_A} \frac{\lambda_A^k}{k!} e^{-\lambda_B} \frac{\lambda_B^{n-k}}{(n-k)!} = e^{-(\lambda_A + \lambda_B)} \sum_{k=0}^{n} \frac{\lambda_A^k}{k!} \frac{\lambda_B^{n-k}}{(n-k)!} = e^{-(\lambda_A + \lambda_B)} \sum_{k=0}^{n} \binom{n}{k!} \frac{1}{n!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_A^k \lambda_B^k \lambda_B^{n-k} = e^{-(\lambda_A + \lambda_B)} \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k!} \sum_{k=0}^{n} \binom{n}{k!} \lambda_B^k \lambda$$

where in the last passage we used the hint:

$$(a+b)^{n} = \sum_{k=0}^{n} \binom{n}{k} a^{k} b^{(n-k)}$$
(11)

(c)

$$P[X_A = k|X = n] = \frac{P(X_A = k, X = n)}{P(X = n)} = \frac{P(X_A = k, X_B = n - k)}{P(X = n)} =$$
$$= \frac{e^{-\lambda_A} \frac{\lambda_A^k}{k!} e^{-\lambda_B} \frac{\lambda_B^{n-k}}{(n-k)!}}{e^{-(\lambda_A + \lambda_B)} \frac{(\lambda_A + \lambda_B)^n}{n!}} = \binom{n}{k} \frac{\lambda_A^k}{(\lambda_A + \lambda_B)^k} \frac{\lambda_B^{n-k}}{(\lambda_A + \lambda_B)^{n-k}} =$$
(12)
$$= \binom{n}{k} \left(\frac{\lambda_A}{(\lambda_A + \lambda_B)}\right)^k \left(1 - \frac{\lambda_A}{(\lambda_A + \lambda_B)}\right)^{n-k}$$

We obtained a binomial distribution with probability of success equal to  $\frac{\lambda_A}{(\lambda_A + \lambda_B)}$ .

6. Assume the continuous random variable has a probability distribution with expectation  $\mu$  and variance  $\sigma^2$ , and assume  $X_1, \ldots, X_n$  is a random sample from this distribution.

(a)

$$s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (X_{i} - \overline{X})^{2}.$$
 (13)

(b)

$$E\left[(X_1 - \overline{X})^2\right] = Var(X_1 - \overline{X}) + \left(E[X_1 - \overline{X}]\right)^2$$
(14)

where the second term on the right hand side above is

$$E[X_1 - \overline{X}] = E[X_1] - \frac{1}{n} \sum_{i=1}^n E[X_i] = \mu - \frac{n\mu}{n} = 0$$
(15)

(b)

and by using independence we handle the first term

$$Var(X_{1} - \overline{X}) = Var\left(\frac{n-1}{n}X_{1} - \frac{1}{n}\sum_{i=2}^{n}X_{i}\right) = Var\left(\frac{n-1}{n}X_{1}\right) + Var\left(\frac{1}{n}\sum_{i=2}^{n}X_{i}\right)$$

$$= \left(\frac{n-1}{n}\right)^{2}\sigma^{2} + \frac{n-1}{n^{2}}\sigma^{2} = \frac{n-1}{n}\sigma^{2}$$
(16)

(c)

$$E[s^{2}] = \frac{1}{n-1} \sum_{i=1}^{n} E\left[ (X_{i} - \overline{X})^{2} \right] = \frac{1}{n-1} n \frac{n-1}{n} \sigma^{2} = \sigma^{2}$$
(17)

and thus is an unbiased estimator.