## Lsningar till tentamen i Matematisk statistik och diskret matematik D (MVE055/MSG810) Den 25 oktober 2016.

1. Since  $P(A) = P(A|B) = 0.9$ , therefore A and B are independent and  $P(A \cap B) = P(A)P(B)$ . Then, we have:

$$
P(A|B^c) = \frac{P(B^c|A)P(A)}{P(B^c)}
$$
  
= 
$$
\frac{(1 - P(B|A))P(A)}{1 - P(B)}
$$
  
= 
$$
\frac{(1 - \frac{P(A \cap B)}{P(A)})P(A)}{1 - P(B)}
$$
  
= 
$$
\frac{(1 - P(B))P(A)}{1 - P(B)}
$$
  
= 
$$
P(A) = 0.9
$$

One can conclude that if A and B are independent, then A and  $B<sup>c</sup>$  are independent too.

2. (a)  $m_X(t) = E(e^{tX})$ , which is the generating function of the sequence of the moments of the random variable  $\overline{X}$ .

Let  $X \sim N(\mu, \sigma^2)$ , then

$$
m_X(t) = E(e^{tX}) = \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} e^{tx} dx
$$
  
\n
$$
= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{-\mu^2}{2\sigma^2}} e^{-\frac{1}{2\sigma^2}(x^2-2\mu x-2\sigma^2 tx)} dx
$$
  
\n
$$
= e^{-\frac{-\mu^2}{2\sigma^2} + \frac{1}{2\sigma^2}(\mu+\sigma^2t)^2} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-(\mu+\sigma^2t))^2} dx
$$
  
\n
$$
= e^{\mu t + \frac{t^2}{2}\sigma^2}
$$

where the final equality follows from the fact that the expression under the integral is the  $N(\mu + \sigma^2 t, \sigma^2)$  probability density function which integrates to unity.

(b)Let 
$$
X_i \sim N(\mu_i, \sigma_i^2)
$$
 for  $i = 1, 2, ..., n$  and  $X_i$ 's are independent random

variables. Then,

$$
m_{\bar{X}}(t) = E(e^{t\bar{X}})
$$
  
\n
$$
= E(e^{\frac{t}{n}\sum_{i=1}^{n}X_i})
$$
  
\n
$$
= E(e^{\frac{t}{n}X_1} \cdot e^{\frac{t}{n}X_2} \cdot \dots e^{\frac{t}{n}X_n})
$$
  
\n
$$
= E(e^{\frac{t}{n}X_1}) \cdot E(e^{\frac{t}{n}X_2}) \cdot \dots E(e^{\frac{t}{n}X_n})
$$
  
\n
$$
= m_{X_1}(t/n) \cdot m_{X_2}(t/n) \cdot \dots m_{X_n}(t/n)
$$
  
\n
$$
= e^{\mu_1 t/n + \frac{t^2}{2n^2} \sigma_1^2} \cdot e^{\mu_2 t/n + \frac{t^2}{2n^2} \sigma_2^2} \dots e^{\mu_n t/n + \frac{t^2}{2n^2} \sigma_{n1}^2}
$$
  
\n
$$
= \prod_{i=1}^{n} e^{\mu_i t/n + \frac{t^2}{2n^2} \sigma_i^2}
$$
  
\n
$$
= e^{\sum_{i=1}^{n} (\mu_i t/n + \frac{t^2}{2n^2} \sigma_i^2)}.
$$

3.  $X, Y \sim U[0, 1]$  and they are independent. Define  $U = min(X, Y)$  and  $V = max(X, Y)$ . Then,  $cov(U, V) = E(UV) - E(U)E(V)$ .  $F_X(x) = x, 0 \le x \le 1$  and  $F_Y(y) = y, 0 \le y \le 1$ .

The cdf of  $\cal U$  is:

$$
F_U(u) = P(U \le u) = P(min(X, Y) \le u)
$$
  
= 1 - P(min(X, Y) \ge u)  
= 1 - P(X \ge u)P(Y \ge u)  
= 1 - (1 - F\_X(u))^2  
= 1 - (1 - u)^2.

and the pdf of  $U$  is:

$$
f_U(u) = F'_U(u) = 2(1 - u), 0 \le u \le 1
$$

Then, the expectation of  $U$  is:

$$
E(U) = \int_0^1 u f_U(u) du = \int_0^1 2u(1-u) du = 1/3.
$$

The cdf of  $V$  is:

$$
F_V(v) = P(V \le v) = P(max(X, Y) \le v)
$$
  
= 
$$
P(X \le v)P(Y \le v)
$$
  
= 
$$
F_X(v)^2
$$
  
= 
$$
v^2.
$$

and the pdf of  $\boldsymbol{V}$  is:

$$
f_V(v) = F'_V(v) = 2v, 0 \le v \le 1
$$

Then, the expectation of  $V$  is:

$$
E(V) = \int_0^1 v f_V(v) dv = \int_0^1 2v^2 dv = 2/3.
$$

$$
cov(U, V) = E(UV) - E(U)E(V)
$$
  
=  $E(XY) - E(U)E(V)$   
=  $E(X)E(Y) - E(U)E(V)$   
=  $\frac{1}{2} \times \frac{1}{2} - \frac{1}{3} \times \frac{2}{3} = \frac{1}{36}.$ 

4. (a)  $X \sim Poi(\lambda_1)$  and  $Y \sim Poi(\lambda_2)$  and they are independent. To find the distribution of  $X + Y$ , we use moment generating function:

$$
m_{X+Y}(t) = E(e^{t(X+Y)})
$$
  
=  $E(e^{tX}).E(e^{tY})$   
=  $m_X(t).m_Y(t)$   
=  $e^{\lambda_1(e^t-1)} \cdot e^{\lambda_2(e^t-1)}$   
=  $e^{(\lambda_1+\lambda_2)(e^t-1)}$ 

Therefore,  $X + Y \sim Poi(\lambda_1 + \lambda_2)$ .

(b)

$$
P(X = x|X + Y = n) = \frac{P(X + Y = n|X = x)P(X = x)}{P(X + Y = n)}
$$
  
= 
$$
\frac{P(Y = n - x|X = x)P(X = x)}{P(X + Y = n)}
$$
  
= 
$$
\frac{P(Y = n - x)P(X = x)}{P(X + Y = n)}
$$
  
= 
$$
\frac{e^{-\lambda_2} \lambda_2^{n-x}}{(n-x)!} \cdot \frac{e^{-\lambda_1} \lambda_1^x}{x!}
$$
  
= 
$$
\binom{n}{x} \left(\frac{\lambda_1}{\lambda_1 + \lambda_2}\right)^x \left(\frac{\lambda_2}{\lambda_1 + \lambda_2}\right)^{n-x}
$$

Therefore,  $X|X + Y \sim Bin(n, \frac{\lambda_1}{\lambda_1 + \lambda_2}).$ 

5. If X and Y be independent, then  $E[g(X)h(Y)] = E[g(X)]E[h(Y)]$ . If  $f(x)$  be the pdf of (X), then  $E[g(X)] = \int_x f_X(x)g(x)dx$ .

In this question,  $X, Y \sim U[0, 1]$ , and  $f_X(x) = f_Y(y) = 1$  for  $0 \le x \le$  $1, 0 \leq y \leq 1$ . Therefore:

(a)  $E[XY] = E[X]E[Y],$ 

(b) 
$$
E[X/Y] = E[X]E[1/Y]
$$
 and  $E[1/Y] = \int_0^1 \frac{1}{y} dy$ ,

(c) 
$$
E[\log(XY)] = E[log(X)] + E[log(Y)] = \int_0^1 \log x dx
$$
.  $\int_0^1 \log y dy$ .

6. There are two samples  $X_1, ..., X_{n_A} \sim N(\mu_A, \sigma_A^2)$  and  $Y_1, ..., Y_{n_B} \sim N(\mu_B, \sigma_B^2)$ , where  $n_A = 7$  and  $n_B = 5$ , and  $\sigma_A^2 = \sigma_B^2 = \sigma^2$  (unknown). The 90% confidence intervals for the difference in mean vitamin E content between the two types is:

$$
\mu_A - \mu_B \in (\bar{X}_A - \bar{X}_B \pm t_{1-\alpha/2}(n_A + n_B - 2)S_P\sqrt{\frac{1}{n_A} + \frac{1}{n_B}}),
$$

where  $\bar{X}_A$  and  $\bar{X}_B$  are the sample means,  $S_P^2 = \frac{(n_A-1)S_A^2 + (n_B-1)S_B^2}{n_A+n_B-2}$  is the pooled variance and  $t_{0.05}(10) = 1.812$ .

7. 
$$
\bar{x} = 4.3
$$
,  $\bar{y} = 12.9$ ,  $\sum x_i^2 = 123.25$ ,  $\sum y_i^2 = 839.09$  and  $\sum x_i y_i = 262.75$ .  
\n
$$
\hat{\beta}_1 = \frac{\sum x_i y_i - 5\bar{x}\bar{y}}{\sum x_i^2 - 5\bar{x}^2} = -0.47
$$
\n
$$
\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = 14.94
$$

The fitted regression line is:

$$
\hat{y} = 14.94 - 0.47x.
$$

To do the test  $H_0: \beta_1 = 0$  vs  $H_1: \beta_1 \neq 0$ , we use the following test statistic:

$$
T = \frac{\hat{\beta}_1}{S/\sqrt{S_{xx}}}
$$

where  $S_{xx} = \sum x_i^2 - 5\bar{x}^2$  and  $S = \frac{SSE}{n-2}$ . Therefore, we have:

$$
T = \frac{-0.47}{\sqrt{0.0397/30.8}} = -13.2
$$

and,

$$
P-value = 2.min[P(T > -13.2), P(T < -13.2)] \approx 0.0001
$$

which is much less than  $\alpha = 0.05$  and we reject  $H_0$ .