## STAT 5703 Homework 1

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## Exercise 2

(1)

$$E[\bar{X}^2] = E[\frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n X_i X_j] = E[\frac{1}{n^2} \sum_{i=1}^n X_i^2] + E[\frac{1}{n^2} \sum_{i \neq j}^n X_i X_j]$$

We know:

$$E[X_i^2] = var(X_i) + (E[X_i])^2 = \lambda + \lambda^2$$

Hence,

$$E[\frac{1}{n^2} \sum_{i=1}^{n} X_i^2] = \frac{1}{n} (\lambda + \lambda^2)$$

Since  $X_i$ s are independent, we can get:

$$E[\frac{1}{n^2} \sum_{i \neq j} X_i X_j] = \frac{2}{n^2} \binom{n}{2} E[X_1] E[X_2] = \frac{n-1}{n} \lambda^2$$

Thus,

$$E[\bar{X}^2] = \frac{1}{n}(\lambda + \lambda^2) + \frac{n-1}{n}\lambda^2 = \lambda^2 + \frac{1}{n}\lambda$$

**(2)** 

$$E[s^2] = \frac{1}{n-1} E[\sum_{i=1}^n X_i^2 - n\bar{X}^2] = \frac{1}{n-1} (nE[X_i^2] - nE[\bar{X}^2]) = \frac{n}{n-1} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1}{n}\lambda) = \lambda - \frac{1}{n} (\lambda + \lambda^2 - \lambda^2 - \frac{1$$

Thus,  $s^2$  is an unbiased estimator of  $\lambda$ .

(3) 
$$E[Y_i] = E[(X_i - \lambda)^2 - X_i] = var(X_i - \lambda) + (E[X_i - \lambda])^2 - E[X_i] = \lambda - \lambda = 0$$

$$var(Y_i) = E[Y_i^2] - (E[Y_i])^2 = E[(X_i - \lambda)^4 - 2X_i(X_i - \lambda)^2 + X_i^2] = E[X_i^4 - (4\lambda + 2)X_i^3 + (6\lambda^2 + 4\lambda + 1)X_i^2 - (4\lambda^3 + 2\lambda^2)X_i + \lambda^4]$$

To find the expected value of  $X^n$ , we use moment generating function:

$$M_X(t) = e^{\lambda(e^t - 1)}$$

Hence,

$$E[X^{3}] = \frac{d^{3}}{dt^{3}} M_{X}(t)|_{t=0} = e^{\lambda(e^{t}-1)} (\lambda^{3} e^{3t} + 3\lambda^{2} e^{2t} + \lambda e^{t})|_{t=0} = \lambda^{3} + 3\lambda^{2} + \lambda e^{t}$$
$$E[X^{4}] = \frac{d^{4}}{dt^{4}} M_{X}(t)|_{t=0} = \lambda^{4} + 6\lambda^{3} + 7\lambda^{2} + \lambda$$

Putting things together, we can get:

$$var(Y_i) = \lambda^4 + 6\lambda^3 + 7\lambda^2 + \lambda - (4\lambda + 2)(\lambda^3 + 3\lambda^2 + \lambda) + (6\lambda^2 + 4\lambda + 1)(\lambda^2 + \lambda) - (4\lambda^3 + 2\lambda^2)\lambda + \lambda^4 = 2\lambda^2$$

Thus,  $E[Y_i] = 0$ ,  $var(Y_i) = 2\lambda^2$ 

(4)

$$\begin{split} s^2 - \bar{X} &= \frac{1}{n-1} (\sum_{i=1}^n X_i^2 - n\bar{X}^2) - \bar{X} \\ &= \frac{1}{n-1} (\sum_{i=1}^n Y_i + (2\lambda n + n)\bar{X} - n\lambda^2 - n\bar{X}^2) - \bar{X} \\ &= \frac{1}{n-1} \sum_{i=1}^n Y_i + \frac{2\lambda n + 1}{n-1} \bar{X} - \frac{n}{n-1} (\lambda^2 + \bar{X}^2) \\ &= \frac{1}{n-1} (\sum_{i=1}^n Y_i - n(\bar{X} - \lambda)^2 + \bar{X}) \end{split}$$

(5)

As 
$$var(\bar{X}) \xrightarrow[n \to \infty]{p} 0$$
,  $P(\bar{X} = \lambda) \xrightarrow[n \to \infty]{p} 1$ .

Hence, as n approximates infinity, the distribution of  $s^2 - \bar{X}$  can approximately equal to the distribution of  $\frac{1}{n-1} \sum_{i=1}^{n} Y_i$ .

Since,

$$\frac{1}{n-1} \sum_{i=1}^{n} Y_i \xrightarrow[n \to \infty]{D} N(0, \frac{2\lambda^2}{n})$$

we can get:

$$\sqrt{n}(s^2 - \bar{X}) \xrightarrow[n \to \infty]{D} N(0, 2\lambda^2)$$

As 
$$\bar{X} \xrightarrow[n \to \infty]{P} \lambda$$
,

$$\sqrt{\frac{n}{2}} \frac{(s^2 - \bar{X})}{\bar{X}} \xrightarrow[n \to \infty]{D} N(0, 1)$$

**(6)** 

Calculate the test statistic  $T = \sqrt{\frac{n}{2}} \frac{(s^2 - \bar{X})}{\bar{X}}$ . If the  $T < -z_{1-\frac{\alpha}{2}}$  or  $T > z_{1-\frac{\alpha}{2}}$ , reject the null hypothesis. Otherwise, fail to reject the null hypothesis.

(7)

```
samplea = c()
sa = c()
for (i in 1:500){
 x = rpois(50,5)
 s_a = c(s_a, var(x))
 samplea = c(samplea, mean(x))
mean_a = mean(samplea)
s_a = mean(s_a)
sampleb = c()
s_b = c()
for (i in 1:500){
 theta = rgamma(50, shape = 2.5, rate = 0.5)
 y = c()
 for (j in 1:50){
   y = c(y, rpois(1, theta[j]))
 sampleb = c(sampleb, mean(y))
 s_b = c(s_b, var(y))
mean_b = mean(sampleb)
s_b = mean(s_b)
cat("Test statistic for model a is: ", sqrt(500/2)*(s_a-mean_a)/mean_a, "\n")
## Test statistic for model a is: 0.132675
```

## Test statistic for model b is: 31.85603

For significance level  $\alpha = 0.05$ ,  $z_{0.975} = 1.96$ . Thus, we do not reject null hypothesis for model a, but reject null hypothesis for model b.

cat("Test statistic for model b is: ", sqrt(500/2)\*(s\_b-mean\_b)/mean\_b)

(8)

## Test statistic is: 0.9786746

We do not reject null hypothesis. Thus, there is no overdispersion for this data set.