## STAT432 Assignment 2

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## Question 1

a)

These are independent binomial processes (despite happening in sequence), so the three trapping occasions can be denoted:

$$\begin{split} n_1 &\sim Binomial(N,\theta) = \binom{N}{n_1} \theta^{n_1} (1-\theta)^{N-n_1} \\ n_2 &\sim Binomial(N-n_1,\theta) = \binom{N-n_1}{n_2} \theta^{n_2} (1-\theta)^{N-n_1-n_2} \\ n_3 &\sim Binomial(N-n_1-n_2,\theta) = \binom{N-n_1-n_2}{n_3} \theta^{n_3} (1-\theta)^{N-n_1-n_2-n_3} \\ \text{So the probability of catching } n_1 + n_2 + n_3 \text{ rats is given by} \\ Binomial(N,\theta) &\times Binomial(N-n_1,\theta) &\times Binomial(N-n_1-N-2,\theta) \\ \text{b)} \\ \ell(N,\theta) &= \ln[\frac{N!}{n_1(N-n_1)!} \theta^{n_1} (1-\theta)^{N-n_1} \\ &\quad \times \frac{(N-n_1)!}{n_2(N-n_1-n_2)!} \theta^{n_2} (1-\theta)^{N-n_1-n_2} \\ &\quad \times \frac{(N-n_1-n_2)!}{n_3(N-n_1-n_2-n_3)!} \theta^{n_3} (1-\theta)^{N-n_1-n_2-n_3}] \\ \ell(N,\theta) &= \ln N! - [\ln n_1 + \ln(N-n_1)] + n_1 \ln \theta + (N-n_1) \ln(1-\theta) + \\ &\quad \ln(N-n_1)! - [\ln n_2 + \ln(N-n_1-n_2)] + n_2 \ln \theta + (N-n_1-n_2) \ln(1-\theta) + \\ &\quad \ln(N-n_1-n_2)! - [\ln n_3 + \ln(N-n_1-n_2-n_3)] + n_3 \ln \theta + (N-n_1-n_2-n_3) \ln(1-\theta) \end{split}$$
We can reduce the components 
$$n_1 \ln \theta + n_2 \ln \theta + n_3 \ln \theta = (n_1 + n_2 + n_3) \ln \theta \end{split}$$

$$n_1 \ln \theta + n_2 \ln \theta + n_3 \ln \theta = (n_1 + n_2 + n_3) \ln \theta$$

$$(N - n_1) \ln(1 - \theta) + (N - n_1 - n_2) \ln(1 - \theta) + (N - n_1 - n_2 - n_3) \ln(1 - \theta) = (3N - 3n_1 - 2n_2 - n_3) \ln(1 - \theta)$$

$$\ln N! + \ln(N - n_1)!...$$

Gives

$$\ln N! - \ln(N - n_1 - n_2 - n_3)! + (n_1 + n_2 + n_3) \ln \theta + (3N - 3n_1 - 2n_2 - n_3) \ln(1 - \theta)$$

finish that bit of algebra somehow

c)
llfunc <- function(par, n1, n2, n3) {
 N <- par[1]
 theta <- par[2]
 lfactorial(N) - lfactorial(N - n1 - n2 - n3) +
 sum(n1, n2, n3)\*log(theta) +
 (3\*N - 3\*n1 - 2\*n2 - n3)\*log(1 - theta)
}</pre>

```
n1 <- 82L
n2 <- 54L
n3 <- 23L
## since N >= n1 + n2 + n3
N_0 < -n1 + n2 + n3
par_start <- c(N_0, 0.5)
optim_fit <- optim(par = par_start,</pre>
                    fn = llfunc,
                    n1 = n1, n2 = n2, n3 = n3,
                    lower = c(N_0, 1e-4),
                    upper = c(Inf, 1),
                    method = "L-BFGS-B",
                    control = list(fnscale = -1),
                    hessian = TRUE)
MLE <- optim_fit$par</pre>
SE <- sqrt(diag(solve(-optim_fit$hessian)))</pre>
LowerBound <- MLE - qnorm(0.975) * SE
UpperBound <- MLE + qnorm(0.975) * SE</pre>
results <- cbind(MLE, SE, LowerBound, UpperBound) %>% round(2)
rownames(results) <- c("N", "theta")</pre>
##
             MLE
                    SE LowerBound UpperBound
## N
          189.43 13.23
                            163.49
                                        215.36
## theta
           0.45 0.06
                              0.34
                                          0.57
The maximum likelihood point \hat{N} = 189.43 with confidence interval (163.49, 215.36)
The maximum likelihood point \hat{\theta} = 0.45 with confidence interval (0.34, 0.57)
  d)
Contour map of (N, \theta) surface
n_{vals} \leftarrow seq(from = n1+n2+n3, to = 260, length = 100)
theta_vals \leftarrow seq(from = 0.2, to = 0.7, length = 100)
combos <- expand.grid(n_vals, theta_vals)</pre>
surface <- apply(expand.grid(n_vals, theta_vals), 1, llfunc, n1 = n1, n2 = n2, n3 = n3) %% round(2)
outcome <- cbind(combos, surface)</pre>
names(outcome) <- c("N", "theta", "value")</pre>
ggplot(data = outcome, mapping = aes(N, theta)) +
  geom_contour(aes(z = value),
                breaks = seq(from = min(outcome$value), to = max(outcome$value), by = 12)) +
  geom_contour(aes(z = value,
                    colour = factor(..level.. == max(surface) - 1.92,
                                      levels = c(F, T),
                                      labels = c("Single 95% CI "))),
                breaks = max(surface) - 1.92) +
  geom_contour(aes(z = value,
                    colour = factor(..level.. == max(surface) - 3,
                                      levels = c(F, T),
                                      labels = c("Joint 95% CI "))),
```

```
breaks = max(surface) - 3) +
  geom_point(mapping = aes(x = MLE[1], y = MLE[2]), colour = "darkblue") +
  labs(colour = "Of interest:") +
  \#ggtitle("Contour\ map\ of\ (N,\ \ \ u03B8)\ surface")\ +
  #ylab("\u03B8") +
  theme_minimal()
  0.7
  0.6
  0.5
                                                                           Of interest:
theta
                                                                            — Joint 95% CI 2
                                                                              Single 95% CI 2
  0.4
  0.3
  0.2
                    180
                                     210
                                                       240
                                      Ν
```

e)

$$\frac{\partial \ell}{\partial \theta} = \frac{n_1 + n_2 + n_3}{\theta} - \frac{3N - 3n_1 - 2n_2 - n_3}{1 - \theta}$$
$$= \frac{(n_1 + n_2 + n_3) - (n_1 + n_2 + n_3)\theta - (3N - 3n_1 - 2n_2 - n_3)\theta}{\theta(1 - \theta)}$$

Setting this to 0

$$(n_1 + n_2 + n_3) - [(n_1 + n_2 + n_3) + (3N - 3n_1 - 2n_2 - n_3)]\theta = 0$$

$$[(n_1 + n_2 + n_3) + (3N - 3n_1 - 2n_2 - n_3)]\theta = (n_1 + n_2 + n_3)$$

$$\theta = \frac{(n_1 + n_2 + n_3)}{(n_1 + n_2 + n_3) + (3N - 3n_1 - 2n_2 - n_3)} = \frac{(n_1 + n_2 + n_3)}{3N - 3n_1 + n_1 - 2n_2 + n_2 - n_3 + n_3}$$

$$\hat{\theta} = \frac{n_1 + n_2 + n_3}{3N - 2n_1 - n_2}$$

f)

We have

$$\hat{\theta} = \frac{n_1 + n_2 + n_3}{3N - 2n_1 - n_2}$$

and

$$1 - \hat{\theta} = \frac{3N - 2n_1 - n_2}{3N - 2n_1 - n_2} - \frac{n_1 + n_2 + n_3}{3N - 2n_1 - n_2} = \frac{3N - 3n_1 - 2n_2 - n_3}{3N - 2n_1 - n_2}$$

So we can rewrite the original kernel of the log likelihood in terms of N as:

$$\ell(N) = \ln N! - \ln(N - n_1 - n_2 - n_3)! + (n_1 + n_2 + n_3) \ln\left(\frac{n_1 + n_2 + n_3}{3N - 2n_1 - n_2}\right) + (3N - 3n_1 - 2n_2 - n_3) \ln\left(\frac{3N - 3n_1 - 2n_2 - n_3}{3N - 2n_1 - n_2}\right)$$

$$\ell(N) = \ln N! - \ln N! - \ln(N - n_1 - n_2 - n_3)! + (n_1 + n_2 + n_3) \ln(n_1 + n_2 + n_3) - (n_1 + n_2 + n_3) \ln(3N - 2n_1 - n_2) + (3N - 3n_1 - 2n_2 - n_3) \ln(3N - 3n_1 - 2n_2 - n_3) - (3N - 3n_1 - 2n_2 - n_3) \ln(3N - 2n_1 - n_2)$$

$$\ell(N) = \ln N! - \ln N! - \ln(N - n_1 - n_2 - n_3)! + (3N - 3n_1 - 2n_2 - n_3) \ln(3N - 3n_1 - 2n_2 - n_3) - (n_1 + n_2 + n_3 + 3N - 3n_1 - 2n_2 - n_3) \ln(3N - 2n_1 - n_2)$$

Therefore

$$\ell(N) = \ln N! - \ln N! - \ln(N - n_1 - n_2 - n_3)! + (3N - 3n_1 - 2n_2 - n_3) \ln(3N - 3n_1 - 2n_2 - n_3) - (3N - 2n_1 - n_2) \ln(3N - 2n_1 - n_2)$$

```
g)
llfunc_N <- function(N, n1, n2, n3) {</pre>
  lfactorial(N) - lfactorial(N - n1 - n2 - n3) +
    (3*N - 3*n1 - 2*n2 - n3)*log(3*N - 3*n1 - 2*n2 - n3) -
    (3*N - 2*n1 - n2)*log(3*N - 2*n1 - n2)
}
n1 <- 82L
n2 <- 54L
n3 <- 23L
## since N >= n1 + n2 + n3
N_0 < -n1 + n2 + n3
N_{start} \leftarrow c(N_{0})
optim_fit <- optim(par = N_start,</pre>
                    fn = llfunc_N,
                    n1 = n1, n2 = n2, n3 = n3,
                    lower = c(N_0, 1e-4),
                    upper = c(Inf, 1),
                    method = "L-BFGS-B",
                    control = list(fnscale = -1),
                    hessian = TRUE)
N_hat <- optim_fit$par</pre>
log_max <- optim_fit$value</pre>
## calculate 95% CI
crit_point \leftarrow \log_{max} - 0.5 * qchisq(0.95, df = 1)
ci_func <- function(critical_value, ...) {</pre>
  llfunc_N(...) - critical_value
lower_ci <- uniroot(ci_func, interval = c(N_0, N_hat),</pre>
                     n1 = n1, n2 = n2, n3 = n3,
                     critical_value = crit_point)$root
upper_ci <- uniroot(ci_func, interval = c(N_hat, 300),
                     n1 = n1, n2 = n2, n3 = n3,
                     critical_value = crit_point)$root
cbind(N_hat, lower_ci, upper_ci)
```

```
## N_hat lower_ci upper_ci
## [1,] 189.4255 170.918 229.9337
```

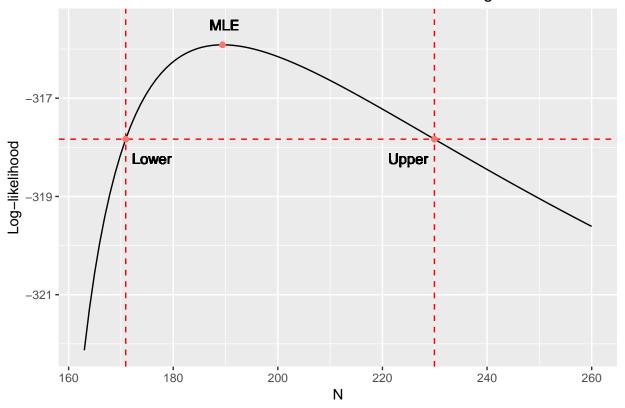
The univariate log-likelihood estimate for  $\hat{N}=189.4254905$ 

with 95% confidence interval (170.92, 229.93).

Compared with the confidence interval in (c), this interval is similar in size, but is no longer symmetric around the MLE.

```
ggplot(data = data, mapping = aes(x = x, y = y)) +
    geom_line() +
    geom_point(aes(x = N_hat, y = log_max, color = "red")) +
    geom_text(aes(x = N_hat + 0.4, y = log_max + 0.4, label = "MLE")) +
    geom_hline(yintercept=crit_point, linetype="dashed", color = "red") +
    geom_vline(xintercept=lower_ci, linetype="dashed", color = "red") +
    geom_vline(xintercept=upper_ci, linetype="dashed", color = "red") +
    geom_point(aes(x = lower_ci, y = crit_point, color = "red")) +
    geom_point(aes(x = upper_ci, y = crit_point, color = "red")) +
    geom_text(aes(x = lower_ci + 5, y = crit_point - 0.4, label = "Lower")) +
    geom_text(aes(x = upper_ci - 5, y = crit_point - 0.4, label = "Upper")) +
    ggtitle("Confidence interval boundaries for MLE of Univariate log-likelihood for N") +
    xlab("N") + ylab("Log-likelihood") +
    theme(legend.position="none")
```

## Confidence interval boundaries for MLE of Univariate log-likelihood for N



h)

Given the 95% profile liklihood-ratio for N calculated above, and that we know a total of 159 rats were caught over the three occasions, we can our confidence interval for R to be (lower-159, upper-159) = (171-159, 230-159) = (12,71) (with rounding to the nearest whole rat).

## Question 2

a)

$$\ell(\lambda, x) = \log(\prod_{i=1}^{n} \left(\frac{e^{-\lambda} \lambda^{x_i}}{x_i!}\right))$$

$$= \sum_{i=1}^{n} (-\lambda + x_i \ln \lambda - \ln(x_i!))$$

$$= -n\lambda + \left(\sum_{i=1}^{n} x_i\right) \ln \lambda - \sum_{i=1}^{n} \ln(x_i!)$$

The last term can be dropped, giving the kernel of the log likelihood

$$-n\lambda + \left(\sum_{i=1}^{n} x_i\right) \ln \lambda$$

Differentiating gives

$$\frac{d\ell}{d\lambda} = -n + \frac{\sum_{i=1}^{n} x_i}{\lambda}$$

Setting this to 0 gives

$$\hat{\lambda} = \frac{\sum_{i=1}^{n} x_i}{n}$$

We can calculte the standard error by taking the second derivative of the log-likelihood at the MLE and calculating the negative inverse

$$\frac{d^2\ell}{d\lambda^2} = -\frac{\sum_{i=1}^n x_i}{\lambda^2}$$

$$\left. \frac{d^2 \ell}{d\lambda^2} \right|_x$$