

Exercise 1: A common approach to estimating the total number of animals, nests, etc. is to (1) fly or walk a transect (2) mark down each sighted object (3) record characteristics such as experience of observer, weather, vegetation type, size of object and especially distance from object to the transect (4) use a model to assign detection probabilities to each object.

1. To estimate total number of animals, we will set $y_i = 1$ for all animals sighted. Why will this be an estimate of N , the number of animals?

Solution:

This method allows us to take advantage of the detection probability. Suppose you knew the proportion of animals that you could actually sample with your sampling scheme, that is the detection probability. Multiplying by the total number of possible animals in a population will give you your expected sample size.

2. The chance that an animal is sighted is π_i , the Detection Probability. Note that the detection probability is the chance of seeing the animal the one time we pass it. Why is this the inclusion probability only if we walk the transect exactly one time.?

Solution:

Like we stated in the problem statement, the detection probability is the chance of seeing the animal the one time we pass it, the inclusion probability is simply the probability that a sample is included in our experiment which is subject to change if we walk a transect more than once.

3. We assume that sighting one animal does not change the chance of seeing another one, so that $\pi_{ij} = \pi_i \pi_j$. Can you think of a situation where that would not be reasonable?

Solution:

If the animal population exhibits herding behavior it's possible that a sighting of one animal could influence the probability of sighting another.

4. Why would the Hansen-Hurvits estimator be wrong, wrong, wrong for this data.

Solution:

Hansen-Hurvits assumes we are taking multiple samples with replacement so there is no benefit to making our sample larger. If we were walking multiple transects where the detection probability stayed the same between transects it might be work. Also

usually the probability used in the Hansen-Hurvets is related to sample/cluster size and in this data it is connected to a detection function.

5. Assume independent detection as in (c), use the Horvits-Thompson estimator (actually Hajek) to get an estimate of the total number of animals and find its standard error.

Solution:

Like the questions suggests when we assume independent detection, the second term in the variance of the Horvits-Thompson estimator goes to zero and we are left with just the Hajek estimator. Computing in r with the sample values set to 1 we get, an estimate of 29 animals with a CI of (52, 8).

Code:

```
> prob <- c( 0.3 , 0.5 , 0.1 , 0.4 , 0.6 ,
             0.2 , 0.4 , 0.5 )
> EstTotal = sum(1/prob)
[1] 29

> se = sqrt(sum((1 - prob)/prob^2))
[1] 11.4188

> CI <- c(EstTotal + 2*se , EstTotal - 2*se)
      51.837591  6.162409

> CI <- c(EstTotal + 2*se , length(prob))
      51.83759  8.00000
```

Exercise 2: We fly a transect and 'sample' a wolf track if it intersects our flight path. The probability of sampling a track is the fraction of possible transects that intersect the path (π_i) while π_{ij} is the fraction of possible transects that cross both paths. The transects are rows of the table below and each transect is equally-likely to be selected as our path. The marked path is the one we actually flew (so only consider paths that cross this). The number of wolves y_i is at the end of the path. Compute an estimator of the number of wolves and its standard error. [NOTE: In reality we would likely fly several independent transects, compute the estimated total wolves (based on Horvitz-Thompson) for each one, then treat the transects as units of a SRS and perform the simple SRS analysis.

Solution:

First we need to compute the table of track sampling probabilities for the tracks in our

transect. Assume that the tracks are sampled left to right we get the following table.

<i>Track</i>	y_i	π_i	π_{ij}
1	7	4/12	2/12, 1/12
2	6	3/12	2/12, 2/12
3	11	4/12	1/12, 2/12

Computing the estimator and standard error in r we get a estimated total of 78 and a confidence interval of (174, 24)

Code:

```
Pij = matrix(ncol=3,byrow=TRUE,c(4/12, 2/12, 1/12,
                                   2/12, 3/12, 2/12,
                                   1/12, 2/12, 4/12))
```

```
Pi <- c(4/12, 3/12, 4/12)
y <- c(7, 6, 11)
estTau = sum(y/Pi)
[1] 78
```

```
##We setup up Pij to use compact variance formula
```

```
estVar = 0
```

```
for(i in 1:3){ for(j in 1:3){
```

```
estVar = estVar + (Pij[i,j] - Pi[i]*Pi[j])*y[i]*y[j]/(Pij[i,j]*Pi[i]*Pi[j])
}}
```

```
estVar
```

```
[1] 2286
```

```
SE = sqrt(estVar)
```

```
[1] 47.81213
```

```
CI = c(estTau + 2*SE, estTau - 2*SE)
```

```
[1] 173.62426 -17.62426
```

```
sum(y)
```

```
[1] 24
```

```
CI = c(estTau + 2*SE, 24)
```

```
[1] 173.6243 24.0000
```

Exercise 3: We have divided a region into $N = 2000$ plots, each with area .1 Ha. We only observed whether a fox has been in the area or not. From a SRS of size , we get the following presence/absence data: absent in 8 of the 20 locations.

- a We assume complete spacial randomness. What does this tell us about foxes?

Solution:

Under the assumption of complete spatial randomness we know that the number of foxes in the i th plot will follow a poisson distribution with mean $\lambda(.1)$ where λ is hectare density. With that in mind consider the probability that a plot is empty, we get the following,

$$P(X = 0) = e^{-\lambda \cdot 1}$$

Note that from our SRS we have an estimate for the proportion of empty hectares, and therefore we can solve for $\hat{\lambda}$ with,

$$\hat{\lambda} = -\frac{1}{.1} \ln\left(\frac{8}{20}\right) = 9.162907$$

Since there are $N = 1000$ plots we get that $\hat{\tau} = 9162.907$

- b. Use the stocked quadrats method to get a 95 percent confidence interval fo the density of foxes.

Solution:

Recall the stocked quadrats variance for λ ,

$$V(\hat{\lambda}) \approx \left(\frac{1}{na^2}\right)(e^{\lambda a} - 1) = \left(\frac{1}{20 \cdot 1^2}\right)(e^{9.162907 \cdot 1} - 1) = 7.5$$

Therefore our 95 percent confidence interval comes out to,

$$95CI = (14.64013, 3.685681)$$

Exercise 4: We want to estimate the number of ants in a large colony. Each day we will capture 20 ants, count the number that are unmarked, then mark all of them with a small colored dot. We get the following data:

Effort: 20, 20, 20, 20, 20, 20, 20, 20

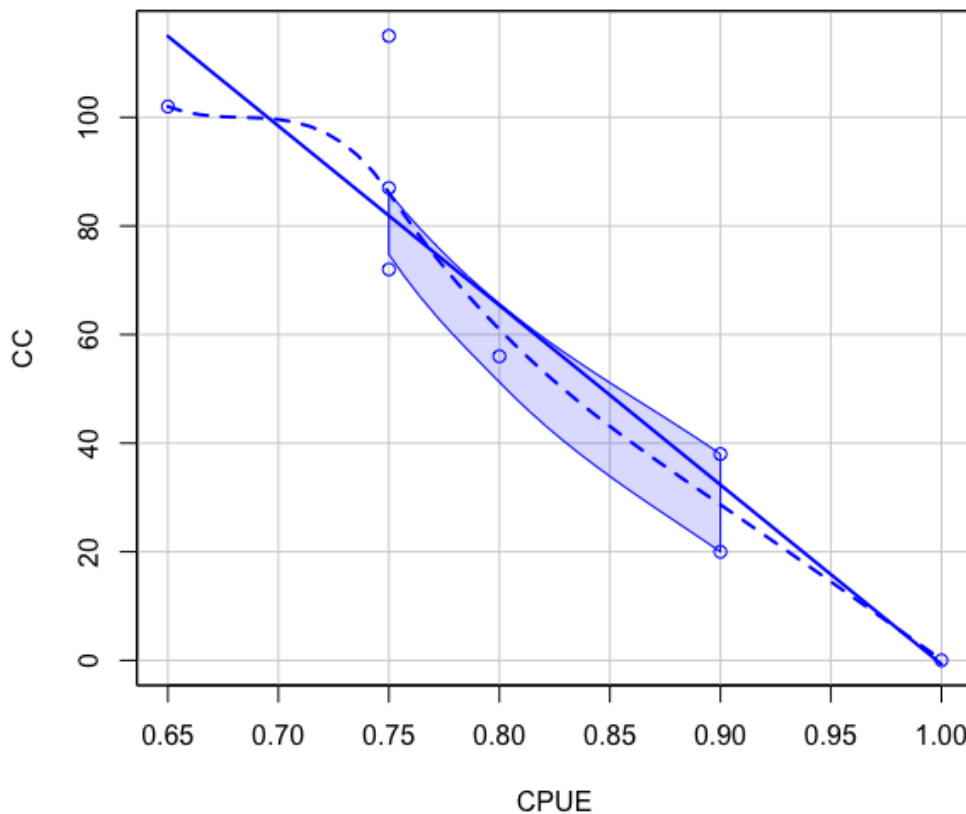
Catch (unmarked ants): 20, 18, 18, 16, 15, 15, 13, 15.

- a. Compute CPUE and CC at each time period. Plot them against each other. Does CPUE seem to decrease over time?

Solution:

From the plot it does seem as though CPUE is dropping as we continue to catch more of the population. It helps that the effort is staying constant and we can attribute this relationship to the change in population size. Plotting in r we get,

Figure 1: (CPUE vs CC)



Code:

```
> Effort <- c(20, 20, 20, 20, 20, 20, 20, 20)
> Catch <- c(20, 18, 18, 16, 15, 15, 13, 15)
> CPUE = Catch / Effort
[1] 1.00 0.90 0.90 0.80 0.75 0.75 0.65 0.75
```

```
> CC = c(0,cumsum(Catch)[1:(length(Catch) - 1)])  
[1] 0 20 38 56 72 87 102 115  
  
> scatterplot(CPUE, CC, boxplots = FALSE)
```

- b. Get a 95 percent confidence interval for the total number of ants.

Solution:

Code:

```
> Effort <- c(20, 20, 20, 20, 20, 20, 20, 20)  
> Catch <- c(20, 18, 18, 16, 15, 15, 13, 15)  
> CPUE = Catch/Effort  
[1] 1.00 0.90 0.90 0.80 0.75 0.75 0.65 0.75  
> CC = c(0,cumsum(Catch)[1:(length(Catch) - 1)])  
[1] 0 20 38 56 72 87 102 115  
  
> scatterplot(CPUE, CC, boxplots = FALSE)
```