

APPENDIX 2

Sequence of commands for spatial distribution of count data (Negative Binomial Distribution).

Aggregated distribution of individuals of *Scolelepis squamata* in a sandy beach on the Caribbean, Costa Rica.

#The data file is called beach.fauna in format .csv, and it is available at :

<http://www.kerwa.ucr.ac.cr/handle/10669/29428>

#Commands based in Krebs (1999) and Crawley (2007)

attach(beach_fauna)

#STEP 1) SAMPLE SIZE.

n<-length(Scolelepis)

n

#STEP 2) POPULATION PARAMETERS.

Mean<-mean(Scolelepis)

Mean

Variance<-var(Scolelepis)

Variance

#STEP 3) OBSERVED VALUES

#Table of observed values = first row: number of individuals, and second row: number of sampling units.

table(Scolelepis)

#Observed values including the full range of number of individuals.

Scolelepis1 <- factor(Scolelepis, levels = c(0:max(Scolelepis+1)))

table(Scolelepis1)

#Frequency of sampling units by counts of individuals.

TableCounts<-data.frame(table(Scolelepis1))

freq<- c(TableCounts\$Freq)

freq

#STEP 4) INDEX OF DISPERSION:

#random pattern (ID=1), uniform pattern (ID < 1), and clumped pattern (ID > 1).

ID<-var(Scolelepis)/mean(Scolelepis)

ID

#Index of dispersion test, based in a chi-squared.

CHI<-ID*(n-1)

CHI

#if chi-squared value is between tabular values the null hypothesis of random pattern (ID = 1) is not rejected.

qchisq(0.975,(n-1), lower.tail = FALSE) #tabular value of chi-squared 0.975

qchisq(0.025,(n-1), lower.tail = FALSE) #tabular value of chi-squared 0.025

#In this case, if the value of the index of dispersion is higher than tabulated values the pattern is clumped (ID > 1).

#STEP 5) NEGATIVE BINOMIAL FIT FOR CLUMPED PATTERN (ID > 1).

#Probability of obtaining X individuals in a sample follows a clumped pattern modeled by the binomial negative distribution.

#To fit the data to the negative binomial, the approximate negative-binomial exponent need be calculated:

k=mean(Scolelepis)^2/ (var(Scolelepis)- mean(Scolelepis))

k

#Negative-binomial exponent for large samples (n > 20)

#The following commands for Crawley (2007) calculate the maximum likelihood estimate of the aggregation parameter, K:

```
x<-0:max(Scolelepis+1)
kfit <-function(x)
{lhs<-numeric()
rhs<-numeric()
y <-0:(length(x) - 1)
j<-0:(length(x)-2)
m <-sum(x * y)/(sum(x))
s2 <-(sum(x * y^2) - sum(x * y)^2/sum(x))/(sum(x)- 1)
k1 <-m^2/(s2 - m)
a<-numeric(length(x)-1)
for(i in 1:(length(x) - 1)) a[i] <-sum(x [- c(1:i)])
i<-0
for (k in seq(k1/1.2,2*k1,0.001)) {
  i<-i+1
  lhs[i] <-sum(x) * log(1 + m/k)
  rhs[i] <-sum(a/(k + j))}
k<-seq(k1/1.2,2*k1,0.001)
plot(k, abs(lhs-rhs),xlab="k",ylab="Difference",type="l")
d<-min(abs(lhs-rhs))
sdd<-which(abs(lhs-rhs)==d)
k[sdd]}
K<-kfit(freq)
```

```
#approximate k
k
#maximum likelihood K
K
```

#STEP 6) AGGREGATION PROBABILITIES BY NEGATIVE BINOMIAL

#density function to obtain the p-value of found x individuals in a sample, with a mean (μ) and Negative-binomial exponent (k)

$$p(x) = \left(1 + \frac{\mu}{k}\right)^{-k} \frac{(k + x - 1)!}{x! (k - 1)!} \left(\frac{\mu}{\mu + k}\right)^x$$

```
binneg<-function(x,Mean,K) (1+ Mean /K)^(-K)*( Mean /( Mean +K))^ x *gamma(K+ x)/(factorial(x)*gamma(K))
binnegprob<-sapply(x, function(i) binneg(i,Mean,K))
```

#STEP 7) EXPECTED FREQUENCIES FOR A THEORETICAL NEGATIVE BINOMIAL

#The negative binomial probabilities can be expressed as frequencies by multiplying each by the sample size (n)
binnegfreq<-n*(1+ Mean /K)^(-K)*(Mean /(Mean +K))^ x *gamma(K+ x)/(factorial(x)*gamma(K))

#STEP 8) SUMMARY TABLE WITH OBSERVED AND EXPECTED VALUES

```
SummaryTable<-data.frame(x=TableCounts,binnegfreq,binnegprob)
SummaryTable
```

#STEP 9) COMPARISON OF THE OBSERVED AND EXPECTED FREQUENCIES WITH A BARPLOT

```
E<-(max(Scolelepis+1)+1)*2
both<-numeric(E)
both[1:E %% 2 != 0]<-freq
both[1:E %% 2 == 0]<-binnegfreq
```

```

labels<-character(E)
labels[1:E %% 2 == 0]<-as.character(0:max(Scolelepis+1))
par(mfrow=c(1,1), pch=22)
Fig<-barplot(both,col=rep(c("black","white"),max(Scolelepis+1)),names=labels, ylab="Frequency of samples",
             xlab="Counts")
legend(x = "topright",c("observed","expected"),fill=c("black","white"))

#STEP 10) GOODNESS OF FIT (G TEST):
#The null hypothesis is that observed values follow a negative binomial distribution
#To follow the assumption of all expected values should be 1 or more, the last observations need be pooled (Krebs, 1999):

cs<-factor(0:max(Scolelepis+1))
a<-min(which(SummaryTable$binnegfreq<1))
#for a first tail with expected values bellow of one use the command: a<-max(which(SummaryTable$binnegfreq>1))

levels(cs)[a:max(Scolelepis+a)]<-"+",levels(cs)

#expected values for G test:
ef<-as.vector(tapply(SummaryTable$binnegfreq,cs,sum))

#observed values for G test:
of<-as.vector(tapply(SummaryTable$x.Freq,cs,sum))

#Table of contingency for G test:
p<-as.vector(tapply(SummaryTable$binnegprob,cs,sum))
ContingenceTable<-data.frame(of,ef,p)
ContingenceTable

#G test:
G<-2*sum((of)*log(of/ef))
G
# Degrees of freedom= frequency classes (counts) - 3 statistics (total, mean and k) used to fit the negative binomial.
df<-sum(of>0)-3
df
#Theoretical values of G test (using chi-squared distribution).
qchisq(0.95, df)
#probability of the null hypothesis.
pchisq(G, df, lower.tail = FALSE)
#In this case p>0.05, the null hypothesis can not be rejected.
#Conclusion: The data follows a negative binomial distribution.

#G test adjusted by Williams' correction for continuity for small samples (n < 200)(Krebs, 1999).
q<-1+((a+1)/(6*sum(of)*df))
q
Gadj<-G/q
Gadj
qchisq(0.95, df)
pchisq(Gadj, df, lower.tail = FALSE)
#in this case p > 0.05, and null hypothesis can not be rejected.
#Conclusion: The data follows a negative binomial distribution.

```