

# Estimating cue rates for animals with silence-burst sound patterns

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## Introduction

Reliable methods for estimating animal abundance are fundamental for effective management and conservation of wildlife. In recent years passive acoustic monitoring density estimation as seen a steep increase in use, since that under some setting it might be more effective than traditional methods. Examples include frogs Measey *et al.* (2016), gibbons Kidney (2016), cetaceans Marques *et al.* (2009) and. There are many ways one can use animal produced sounds to derive animal density, but perhaps one of the most appealing is cue counting. In cue counting we rely on the sounds detected on a field of sensors covering the area we intend to make inferences to estimate density. Of course we need to scale these detected sounds according to (1) sensor performance, which might include both the effective area of detection of the sensors and their probability of generating false positives, and (2) an estimate of cue rate, to estimate animal density. Here we focus on this second component, cue production. Dealing with the first component is not the focus of this paper, but Marques *et al.* (2013) provide an overview of what is involved in the former regarding sensor performance characterization.

When conducting a passive acoustic density estimation survey, reliable cue rates for the time and place a survey might be conducted are required (e.g. Marques *et al.* (2013)). However, perhaps surprising, little is know about sound production in for many species of animals. Therefore, to obtain cue rates for passive acoustic density estimation, dedicated data collection is typically required. At sea, cue rates are often estimated by placing animal borne tags with acoustic sensors on individuals. By counting the number of cues produced over the tag duration for a sample of animals cue rates can be obtained (e.g. Warren *et al.* (2017)). However, on terrestrial animals, like birds, focal follows of animals are typically considered (e.g. Sebastián-González *et al.* (2018)). If the start and end of a focal follow are independent of the mechanism by which animals produce sounds, then we are home free. One just needs a sample of focal animals and using

these we can obtain an average cue rate for the population of interest. However, if the inclusion of an animal in the focal follow also depends on its acoustic state, and in particular, if we start and/or end the focal follow at the time of sound emission, we might introduce positive bias in the sound production rate. This would then lead to a negative bias in abundance or density estimates.

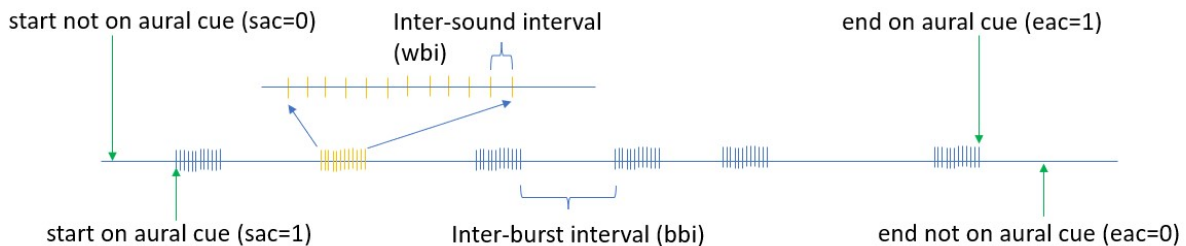
Here we present one such scenario, that might be plausible for a variety of taxa, where sounds are produced in pulses interspersed with silences. Animals will be therefore tendentially included in a focal follow when in a burst of sounds, and then the follow will stop when the animal is no longer detected acoustically. This will, unless corrected for, induce bias in cue rates. We present a method to correct for that bias by proposing a new estimator for cue rates that adjusts the time considered in the focal follow accordingly. We discuss the implications for estimates of cue rates from individual animals with a discussion of the implications for passive acoustic density estimation via cue counting that extends beyond the strict case of animals that produce sounds in bursts.

## Methods

### Silence-burst sound patterns

Consider a situation where animals tend to be silent for some periods, interspersed with periods where sounds are emitted in a relatively regular manner for a short period of time. We refer to such sound process describing the emission times of sounds of interest by a given species as a silence-burst sound pattern. If we consider the time between two successive sounds as inter sound interval ( $isi$ ), we can distinguish two types of  $isi$ , the time between successive sounds within a burst as the within-burst-interval ( $wbi$ ) and the sound in between bursts as the between-burst-interval ( $bbi$ ). The image below represents sounds produced by one such silence-burst hypothetical animal:

We propose a novel way to estimate the  $bbi$  value based on focal follows where the times of sound emission are recorded. Instead of defining strictly what are the observations corresponding to  $wbi$ 's and  $bbi$ ' for the data, we model the  $isi$  as a two-part finite mixture, and assume that the component with the smaller mean corresponds to distribution of the  $wbi$ , while the component with the higher mean will correspond to the  $bbi$ . Therefore, all the data can be used in an integrated procedure estimating the  $bbi$ . The estimate of  $bbi$  will be required for the cue rate estimator, as described below.



When we want to estimate cue production rates for terrestrial animals, required to convert estimates of sound density into estimates of animal density, we often select animals over which focal follows are conducted. During the focal follow a human observer will record the times of each sound emission, and at the end typically the number of sounds emitted divided by the focal follow duration are used as estimates of the individual cue production rate. A population averaged cue rate is obtained as an average of the individual cue rates. Typically, however, two potential sources of bias might be at play:

1. if an animal is first detected by an aural cue, then the animal is most likely to be in a sound producing mode, here in particular, in a burst. Since this is the most likely way an animal will be found, we will tend to start recording during bursts, which means that the cue rate will be biased high;
2. if the animal is last detected exclusively aurally, then we are not sure whether the animal has left the

area or not since it was last heard, and if it did, when it did, and so there is uncertainty about the time one should record to end the focal follow. The only natural choice is the last sound detected, but then this is likely to be the last sound in a burst, and again this will bias the cue rate estimate up.

Since both 1 and 2 are highly likely and both lead to overestimating cue rates, these will both contribute to underestimate animal density.

In this note we propose an approach to alleviate the problem, inspired by a real case study of Chaffinch (*Fringilla coelebs*) in Portugal.

## The proposed estimator

Considering a focal follow, where the start  $T_s$  and end  $T_e$  of the focal follow are independent with respect to the song production mechanism, an unbiased estimate of individual sound production rate given a total observation period  $T = T_e - T_s$  and  $n_c$  detected cues will be, by definition of cue production rate

$$\hat{r} = \frac{n_c}{T}.$$

However, if the inclusion of the animal in a focal follow or the end of the focal follow are dependent on the sound production mechanism, as would be likely for sound producing species, also detected aurally, this cue rate estimator might be biased up.

Here we propose a more sensible estimator. It essentially adjusts the time of the focal follow duration based on the data collected. Two possible options are described below.

Consider  $T_{cs}$  and  $T_{ce}$  to be the times of the first sound detected and the time of the last sound detected, respectively. Additionally, define two indicator variables, the Start on an Aural Cue ( $sac$ ) and the End on Aural Cue ( $eac$ ). Consider that  $sac=1$  if the start of a focal follow was on an aural cue,  $sac = 0$  otherwise. Therefore if  $sac = 1$ ,  $T_{cs} = T_s$ . On the other hand,  $eac=1$  if the end of the focal follow was defined at the last aural cue detected, otherwise  $eac = 0$ . Therefore if  $eac = 1$ ,  $T_{ce} = T_e$ . We suggest that if  $sac = 0$  the data are truncated such that the recording time starts at  $T_{cs}$ , and if  $eac = 0$  we truncate the data such that the recording time ends at  $T_{ce}$ , while adjusting for the average  $bbi$  at the start and end of the recording time, leading to the estimator

$$\hat{r} = \frac{n_c}{\frac{bbi}{2} + (T_e - T_s) + \frac{bbi}{2}} = \frac{n_c}{(T_e - T_s) + bbi}.$$

The focal follow duration will then be assumed to correspond to the time difference between the first and the last cue detected to which we add an estimate of the  $bbi$ . This corresponds to half the  $bbi$  at the start and to half the  $bbi$  at the end of the focal follow. This assumes that, if the focal follow start and end coincided with a cue production time, or if we truncate the recording time to make it so, instead of taking these as the observed start and end of the focal follow, we must add the average amount of time that an animal would be silent in between bursts, that is, half of the  $bbi$ .

Note that for any given focal follow, if  $sac = 0$  one might assume that the start was random with respect to the sound process. On the other hand if  $eac = 0$ , one might assume that the end of the focal follow was random with respect to the sound generating process. If the mean value for  $T_{c1} - T_s | sac = 0$  or  $T_e - T_{cn} | eac = 0$  is considerably different from  $bbi/2$  it is likely that the start and end of the follow are actually not independent with respect to the sound generating process. In such cases, the above procedure is recommended. If one is willing to assume that the start and end of a focal follow not coinciding with a sound are independent of the sound producing mechanism, then we could use the following estimator

$$\hat{r} = \frac{n_c}{sac \frac{bbi}{2} + (T_e - T_s) + eac \frac{bbi}{2}}$$

where one-half of the *bbi* is added only if the start for a given animal focal follow was an acoustic cue, and one half of the *bbi* is added only if the end for a given animal follow was an acoustic cue.

Considering a random sample of  $n$  animals for which focal follows are available, we can therefore estimate the cue production rate as usual as

$$\hat{r} = \frac{\sum_{i=1}^n \hat{r}_i}{n}.$$

Given the above expression, the simplest way to obtain a precision measure for the cue rate over a population will be using a non-parametric bootstrap, where the individual animals are taken as the independent sampling units. Therefore, at each iteration of the bootstrap, an estimate of the *bbi*, and given that of the corresponding individual cue rates, will be obtained.

The proposed methods are illustrated below for a dataset of chaffinch, which after a number of focal follows, we identified as having a clear silence-burst sound pattern. We compare the results obtained using a naive approach with our new estimator. We hypothesize that the naive approach will be biased high for estimating cue rate and correspondingly biased low for estimating density.

## The example dataset

### Study area:

The study was carried out in Companhia das Lezírias, a large farm in Santarém, Portugal, with around 11 000 ha. Cork oak woodlands are the most common habitat present, making up to 75% of the total forested area. Oak woodlands (*Quercus suber* and *Quercus rotundifolia*) managed as silvopastoral systems, known as montados in Portugal and dehesas in Spain Pinto-Correia *et al.* (2011), and are recognized as an excellent example of balance between socio-economic development and biodiversity conservation Leal *et al.* (2016) Tellería (2007).

### Chosen Species:

The Common Chaffinch (*Fringilla coelebs*) is one of the most common species in these oak woodland area. Given its distinct and characteristic song compared to other species, it makes it easier to identify individuals of this species in studies where we have to apply acoustic monitoring methods.

### Data collection using recorders:

The fieldwork occurred between March and May of 2022, and data was collected using automatic sound recorders called AudioMoth (AM, Open Acoustics Devices). AudioMoths are small and light weighted, affordable recorders with an inbuilt microphone that can be programmed to record within specific filters and schedules, ranging in frequencies up to 348 kHz and recording throughout 24h with 5s intervals between each recording Hill *et al.* (2018) Hill *et al.* (2019).

For this study, AudioMoths were programmed to record at 48 kHz, which is the recommended frequency for birds, and they were set to start recording the first 4 hours after sunrise, for periods of 1 hour with a 5 seconds interval between each recording. No surveys were conducted under rainy or windy conditions.

Birds produce two main types of vocalizations: songs and calls. Songs are usually loud and often long, more complex vocalizations that are mostly used by males to defend their territory, and they are formed by syllables (basic units), phrases (repeated syllables) and trills (rapid repetitions of 3 or more simple syllables) Gill (2006). Calls, on the other hand, are short and simple vocalizations, that are used by both males and females that can be warning calls, distress calls, flight calls, nest calls and flock calls Gill (2006). In this study, we used songs as our vocalization-type focus, given the fact that it will be a longer and easier to detect vocalization in an area with other vocalizing species. Regarding cue rates estimation, fieldwork was based on focal follows of individual chaffinches. The observer walked in the field and, once an individual was spotted,

we registered every time it sang during a maximum of 12 minutes. During the data collection, if by any chance we would lose track of the individual we were following or we couldn't be certain anymore that it was the same individual, we would stop the timer and stop registering data for that individual. After each bird focal follow we would change location to reduce the likelihood of repeated inclusion in our sample of the same individuals.

## Results for Appendix

Here we read the data from the focal follows

The times of calls are recorded as the fraction of the day since the beginning of the day, at midnight, so we recode these fractions of the day to represent seconds.

```
#recode inter-event-intervals (iei) to be in seconds
cantos$iei<-cantos$iei*((24*60*60))
```

We pre-process the data to get which of the events are inter-sound-intervals. Most of those records for which `Event=call` correspond indeed to *isi*'s, but the notable exception are:

- those which end with a `call`, which will have no `iei`, and
- those for focal follows not initiated at a sound, labelled as `Event=rec.start`. For these, the first `iei` corresponds to a time between the start of the focal follow and the first call produced, and hence must be removed for when modelling *isi*'s.

To account for both of these we create a new column labelled `isi` with an indicator that takes the value 1 if the `iei` corresponds to an *isi*, and 0 otherwise. Only those `iei` with `isi=TRUE` will be considered for modelling the *isi* components

```
cantos$isi<-1
#removing iei's that are not isi's
#those not calls are not isi's
cantos$isi[cantos$Event!="call"]<-0
#those that are calls but the end of the ofcal follow is with a call are 0 (these always happen with ie
cantos$isi[is.na(cantos$iei)]<-0
#those for focal follows not initiated at a sound, labelled as `Event=rec.start`
cantos$isi[which(cantos$Event=="rec.start")+1]<-0
```

summaries by bird:

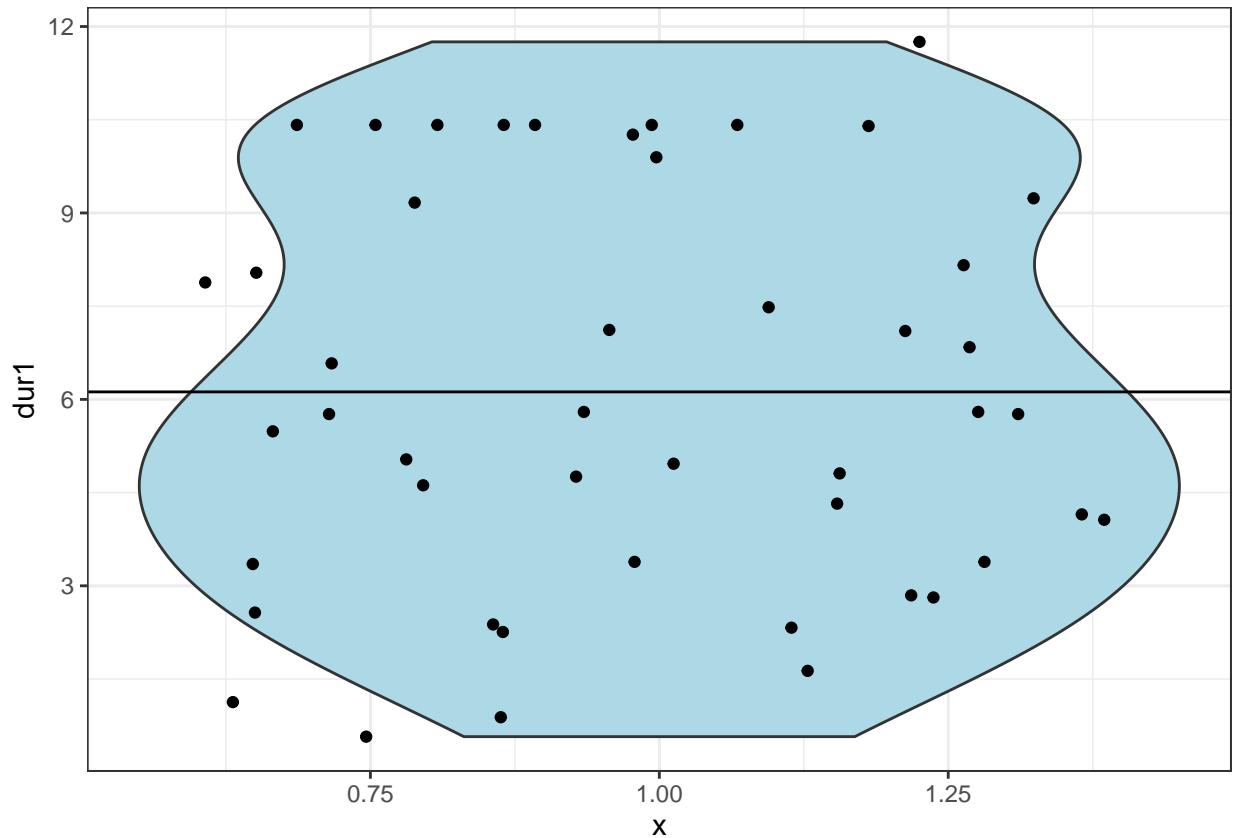
```
#compute cue rates per animal etc
#cr is cue rate per minute
# sounds: number of sounds produced
# n: number of records, at most "sounds"+2 (if sac=0 and eac=0), at least "sounds" (if sac=1 and eac=1)
# start1: recording start and first sound if sac=1
# start2: the first sound if sac=0
# end1: recording end and last sound if eac=1
# end2: the last sound if eac=0
# dur1: the "standard" duration as in end time minus start time (in minutes)
# cr1: the conventional cue rate, number of sounds / duration
# sac: the indicator of whether recording started with a sound
# eac: the indicator of whether recording ended with a sound
crs.by.indiv<-cantos %>% group_by(Indiv) %>% summarise(sounds=sum(Event=="call"),n = n(),start1=min(Tim
#adding dur2: the duration from the first to the last sound produced, in minutes
#this will be required for our suggested estimator
start<-with(crs.by.indiv,ifelse(sac==1,start1,start2))
end<-with(crs.by.indiv,ifelse(eac==1,end1,end2))
crs.by.indiv$dur2<-25*60*(end-start)
```

```
#the isi times
st <- cantos %>% drop_na("isi")
```

We have a total of 0 times of sound production obtained from focal follows of 47 individuals.

Individuals were followed on average for 6.12 minutes, ranging from 0.57 to 11.75 minutes. The distribution of these focal follow times is shown below:

```
ggplot(crs.by.indiv,aes(x=1,y=dur1),fill="lightblue")+
  theme_bw()+geom_violin(fill="lightblue")+geom_jitter()+geom_hline(yintercept=mean(crs.by.indiv$dur1))
```

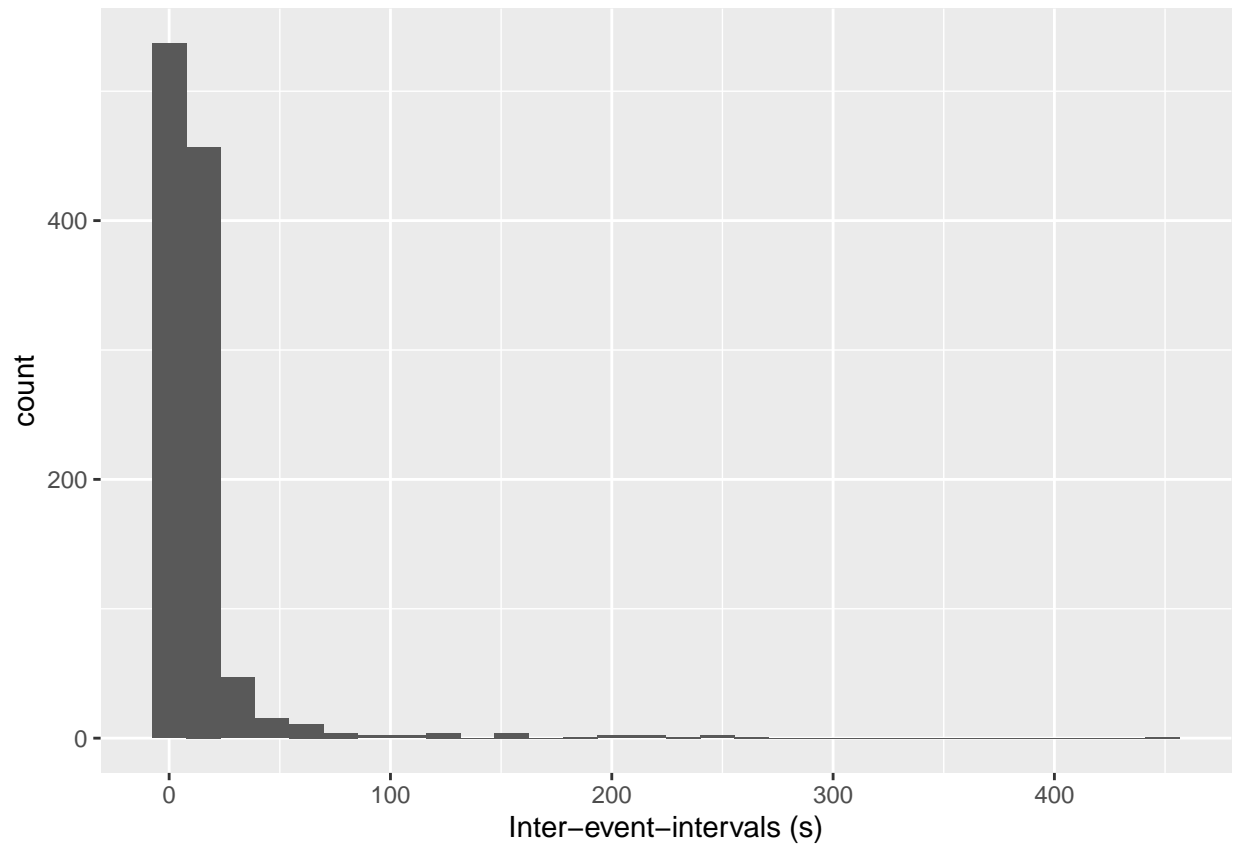


We can take a look at the data.

```
ggplot(cantos, aes(x=iei)) + geom_histogram() + xlab("Inter-event-intervals (s)")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 85 rows containing non-finite values (`stat_bin()`).
```



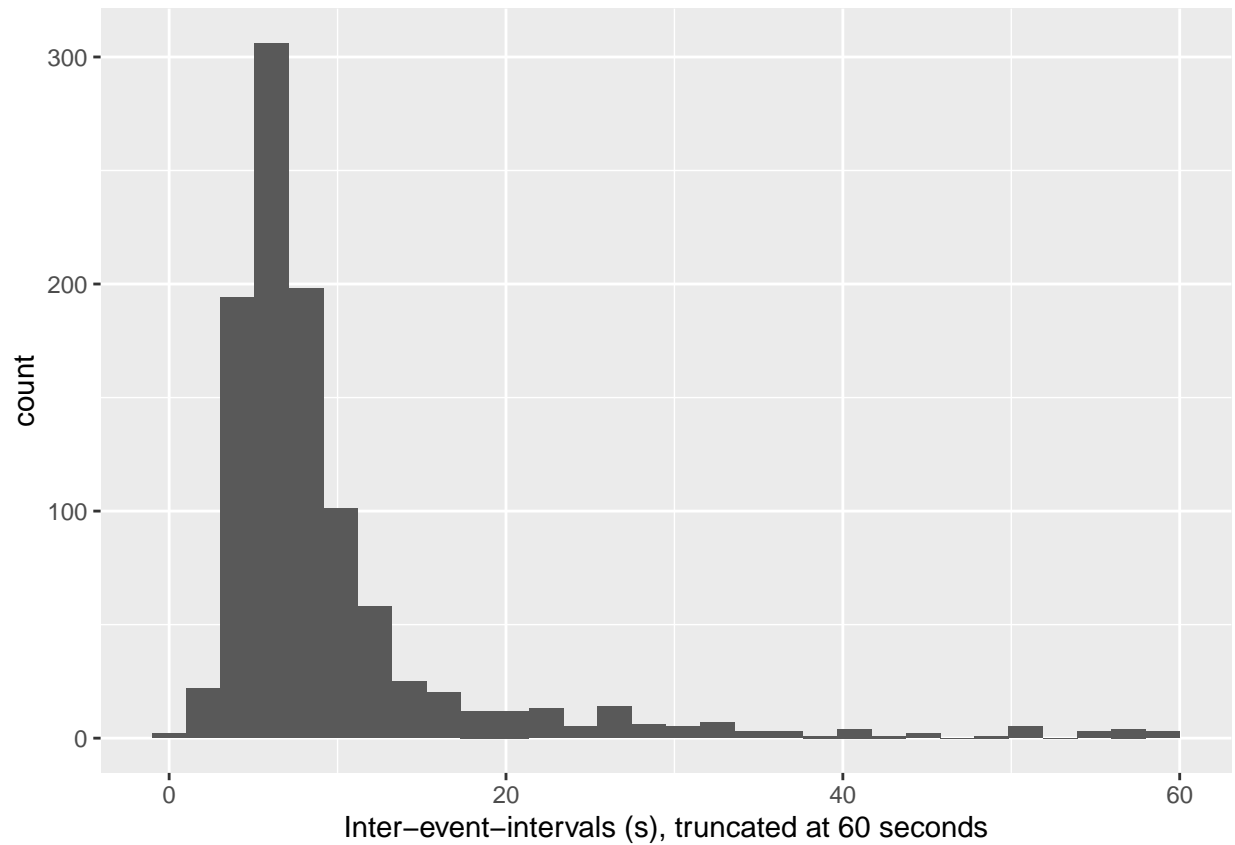
```
#hist(cantos$iei, breaks = 20, main="", xlab="Inter-event-intervals (s)")
```

Only 27 of the *isi*'s, corresponding to 0.03 % of the *isi*'s, are longer than 1 minute. Below we focus the attention on those *isi* that are under a minute below:

```
#hist truncated for iei < 60s
```

```
ggplot(cantos[(cantos$isi==1 & cantos$iei<60),], aes(x=iei)) + geom_histogram() + xlab("Inter-event-int")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

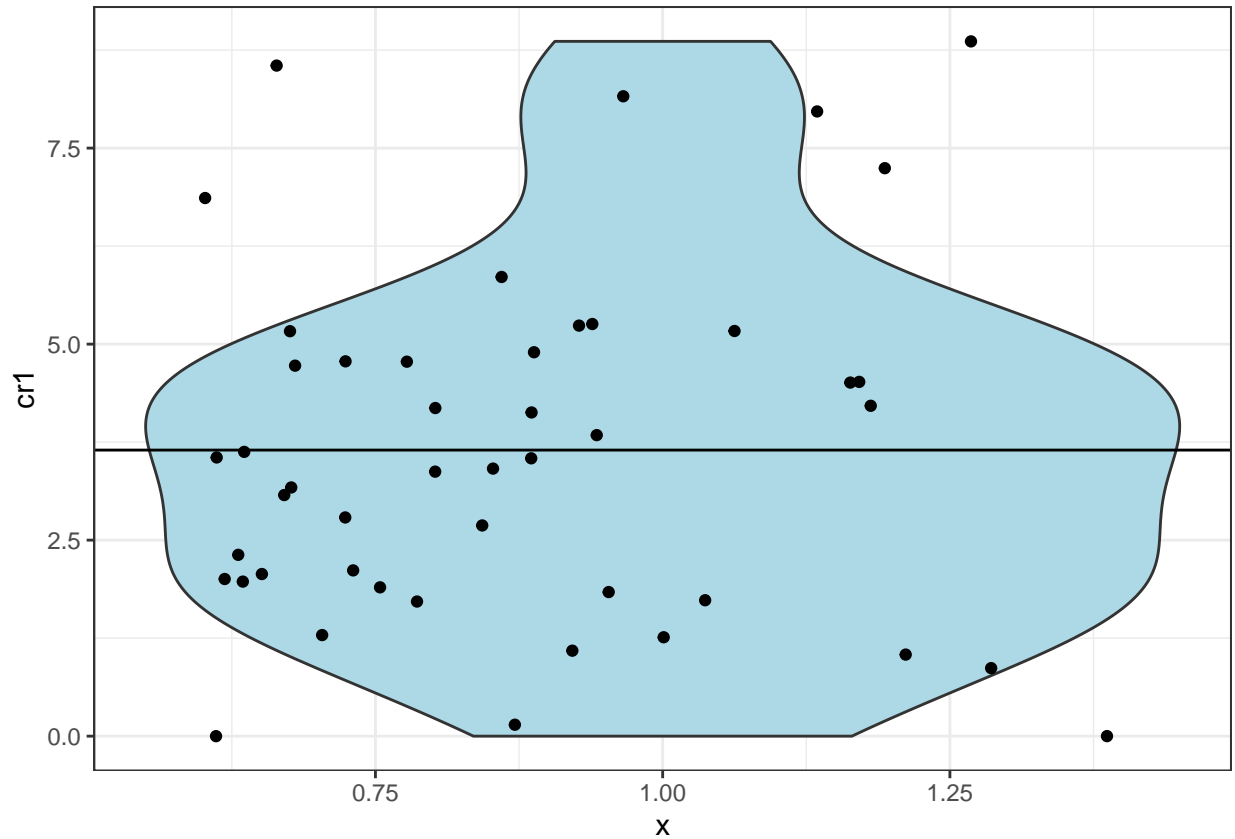


```
#hist(cantos$iei[(cantos$isi==1 & cantos$iei<60),], main="", xlab="Inter-event-intervals (s), truncated
```

The per animal cue rates are shown below:

```
ggplot(crs.by.indiv,aes(x=1,y=cr1),fill="lightblue")+  
  theme_bw()+geom_violin(fill="lightblue")+geom_jitter()+geom_hline(yintercept=mean(crs.by.indiv$cr1))
```





```
ci.cr1<-t.test(crs.by.indiv$cr1)$conf.int
cv.cr1<-100*(sd(crs.by.indiv$cr1)/sqrt(nrow(crs.by.indiv)))/mean(crs.by.indiv$cr1)
```

The corresponding estimate of the average cue rate, estimated using a standard mean, is 3.65, with 95% CI of 2.98-4.31. The coefficient of variation is 9.04 %.

Finally, we model the *isi*'s as a two-part mixture, as suggested above.

```
#the isi's to model and separate into two components, one for bbi's and one for wbi's
isis<-cantos$iei[cantos$isi==1]
mixmdl = normalmixEM(isis,k=2)
```

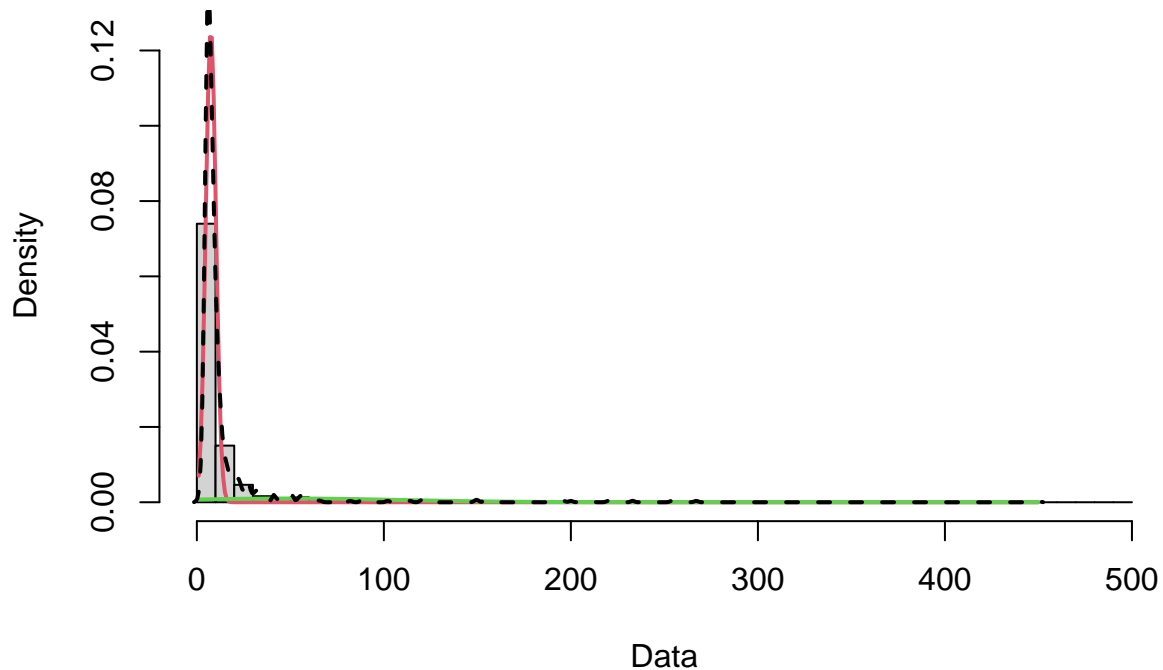
```
## number of iterations= 21
```

```
#was checking the inclusion of a 3rd component - weirdly AIC seems to favour that
#mixmdl3 = normalmixEM(isis,k=3)
```

We can see what this two mixture distribution corresponds to:

```
plot(mixmdl,which=2,breaks=seq(0,500,by=10))
lines(density(isis), lty=2, lwd=2)
```

## Density Curves



And a summary of the fitted two part mixture

```
kable(summary(mixmdl))
```

```
## summary of normalmixEM object:
##      comp 1    comp 2
## lambda 0.851094 0.148906
## mu      7.491447 49.135665
## sigma   2.702793 59.973762
## loglik at estimate: -3408.058
```

```
p.mix<-mixmdl$lambda
means.mix<-mixmdl$mu
sds.mix<-mixmdl$sigma
```

Note this implies that the mean value of the first component, corresponding to the *wbi*, is 7.49 seconds, with a standard error of 2.7, and we estimate that 0.85 of the observations come from the *wbi*'s, while the mean value of the second component, corresponding to the *bbi*, is 49.14 seconds, with a standard error of 59.97, and we estimate that 0.15 of the observations come from the *wbi*'s. Actually, this means that for each *bbi* we have  $0.85/0.15=6$  *wbi*'s, or in other words, each call burst contains on average 6 calls.

```
crs.by.indiv$dur3<-with(crs.by.indiv,dur2+(means.mix[2]/60))
crs.by.indiv$cr2<-with(crs.by.indiv,sounds/dur3)
```

```
cr.new<-mean(crs.by.indiv$cr2)
ci.cr2<-t.test(crs.by.indiv$cr2)$conf.int
cv.cr2<-100*(sd(crs.by.indiv$cr2)/sqrt(nrow(crs.by.indiv)))/mean(crs.by.indiv$cr2)
```

This would then lead to an estimate of cue rate of 3.87, with 95% CI of 3.26-4.47. The coefficient of variation

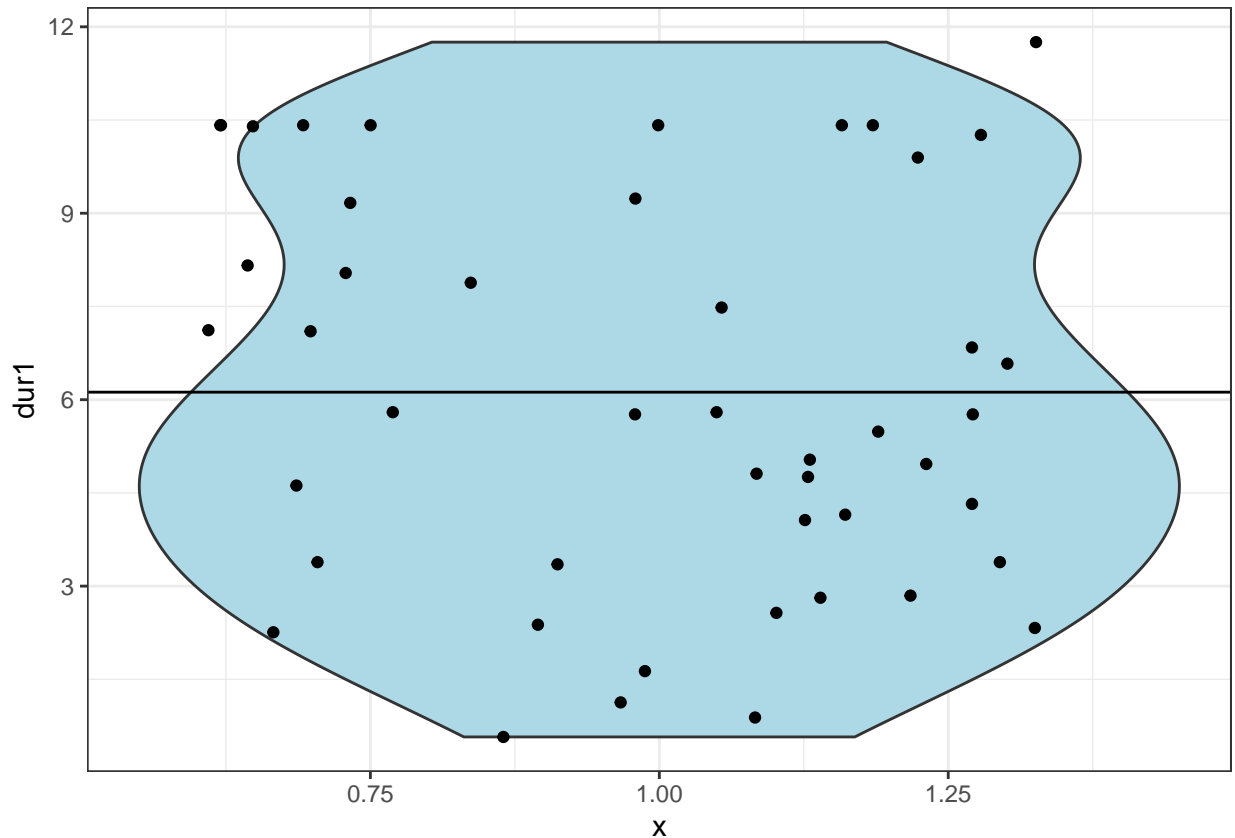
is 7.78 %.

The confidence interval above does not propagate the uncertainty in estimating the mean of the bbi's. To do so we could incorporate a non-parametric bootstrap procedure, resampling the birds subjected to focal follows.

This leads to a point estimate of 3.87 with corresponding 95% CV of 3.24-4.52. This corresponds to a CV of 8.62.

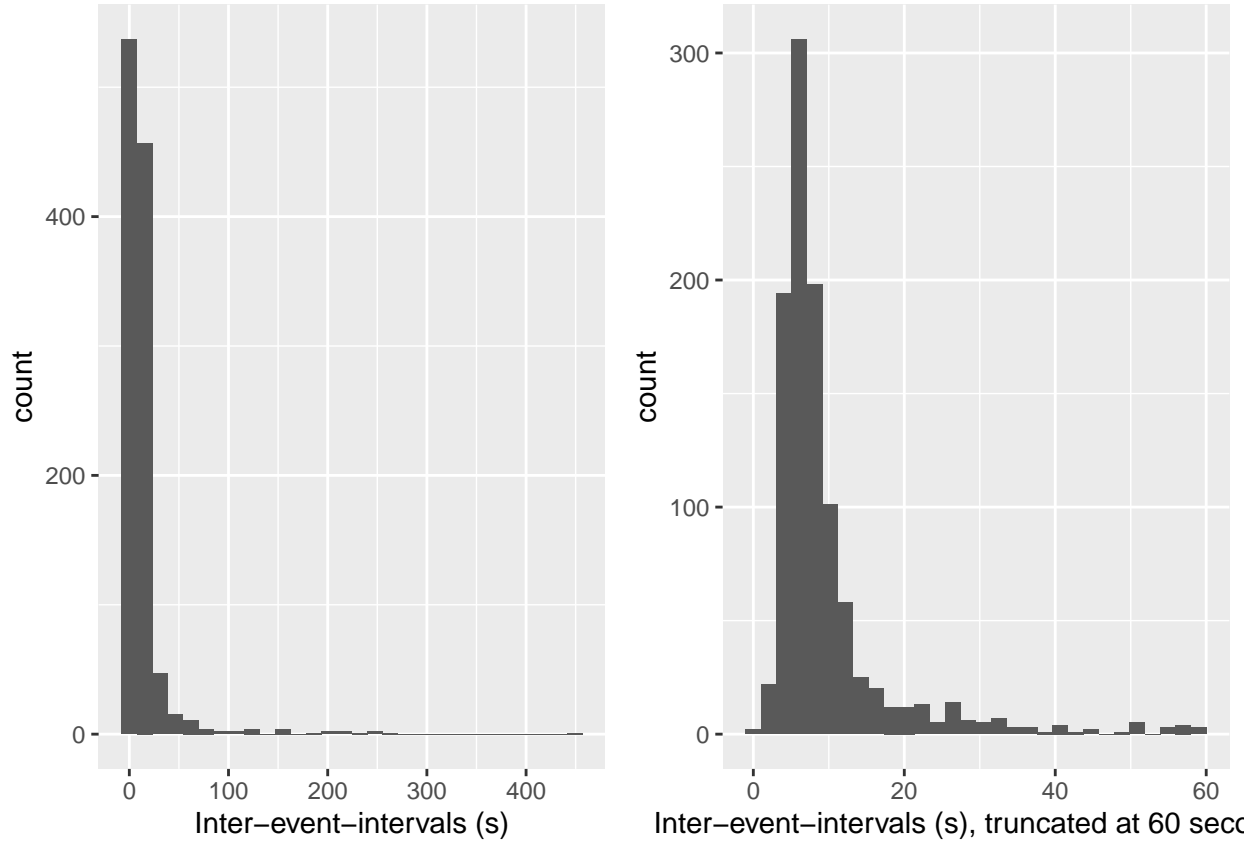
## Results

We have a total of 0 times of sound production obtained from focal follows of 47 individuals. Individuals were followed on average for 6.12 minutes, ranging from 0.57 to 11.75 minutes. The distribution of these focal follow times is shown in Figure 1.

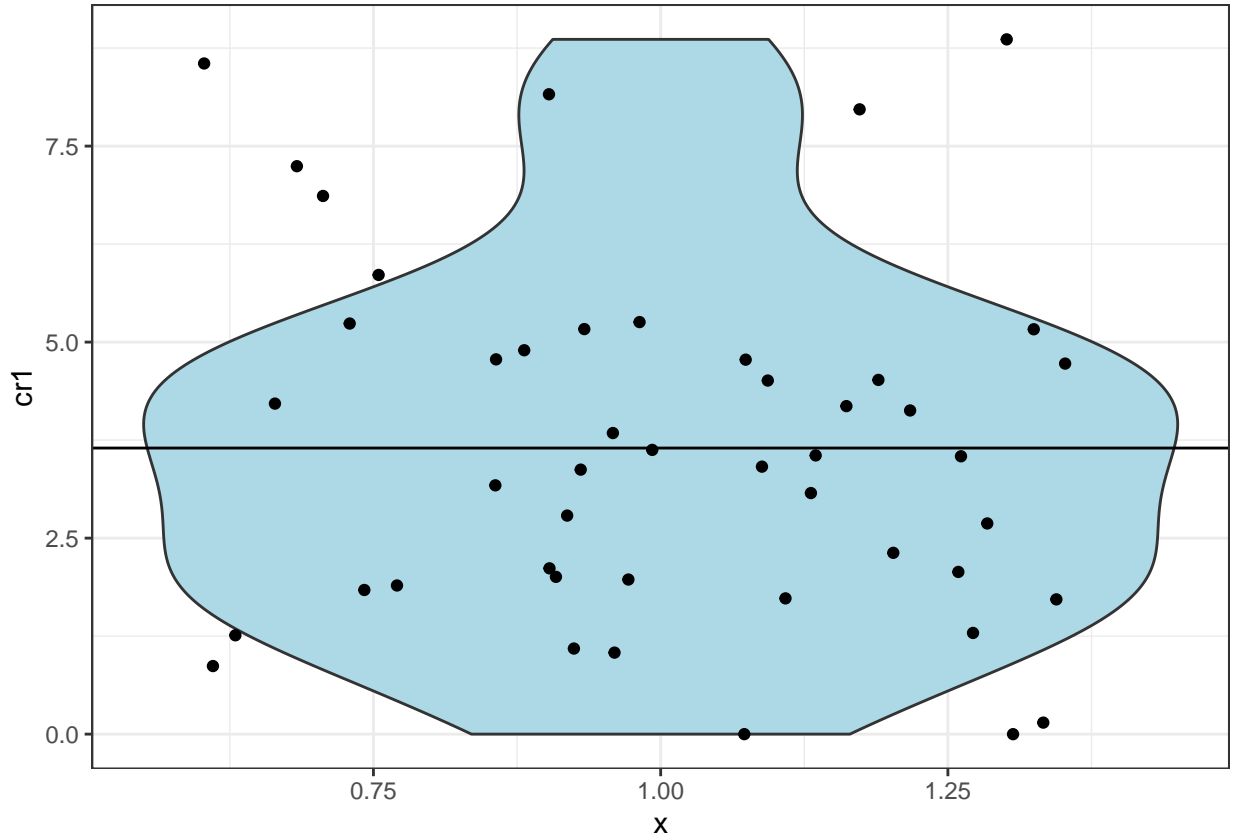


The times in between events are represented in figure 2. Only 27 of the *isi*'s, corresponding to 0.03 % of the *isi*'s, are longer than 1 minute. We focus the attention on those *isi* that are under a minute (Figure 2, right panel).

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.  
## Warning: Removed 85 rows containing non-finite values (`stat_bin()`).  
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



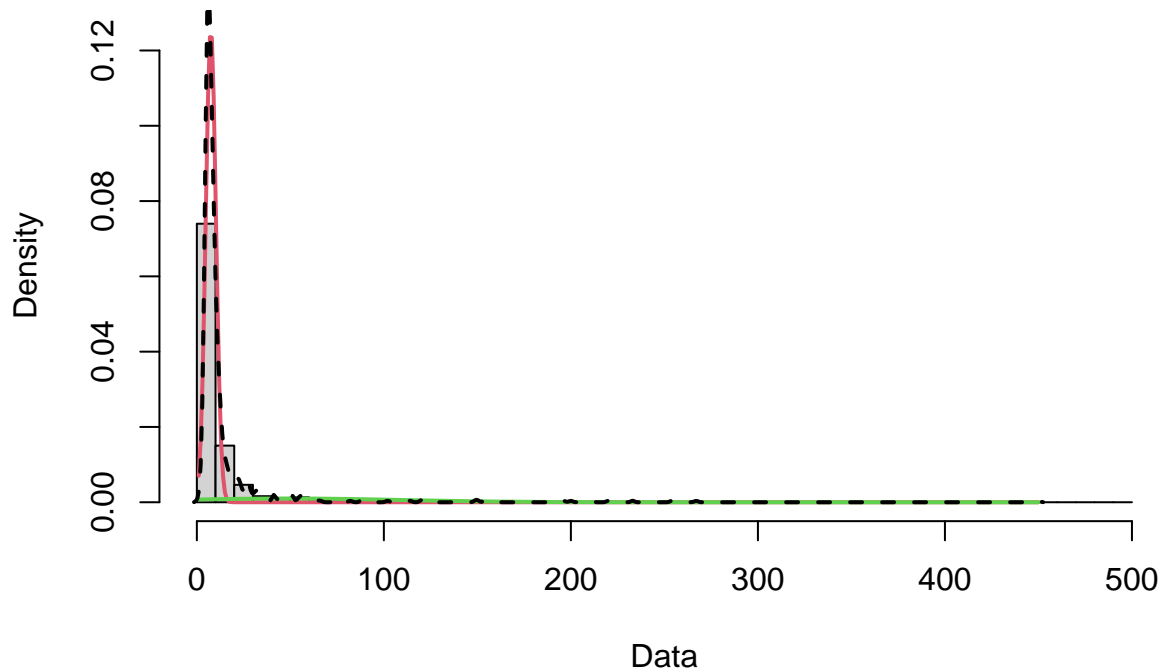
Based on the number of sounds recorded divided by the recording duration, conventional estimates of cue rates per animal are shown in figure 3. The corresponding estimate of the average cue rate, estimated using a standard mean, is 3.65, with 95% CI of 2.98-4.31. The coefficient of variation is 9.04 %. As described in the methods, we suspect this might be a biased estimate of cue rate.



A graphical representation of the modelling of the *iei*'s as a two-part Gaussian mixture is shown in figure 4. A summary of the two mixture component is shown in table 2. Note this implies that the mean value of the first component, corresponding to the *wbi*, is 7.49 seconds, with a standard error of 2.7. We estimate that 0.85 of the observations come from the *wbi*'s. On the other hand, the mean value of the second component, corresponding to the *bbi*, is 49.14 seconds, with a standard error of 59.97. We estimate that 0.15 of the observations come from the *wbi*'s. This means that for each *bbi* we have  $0.85/0.15=6$  *wbi*'s, or in other words, each call burst contains on average 6 calls. This would then lead to an estimate of cue rate of 3.87, with 95% CI of 3.26-4.47. A naive coefficient of variation, taking the estimated value of the mean *ibi* as a constant, is 7.78 %. Incorporating a non-parametric bootstrap procedure, resampling the birds subjected to focal follows leads to corresponding 95% CV of 3.24-4.52 (CV of 8.62).

```
## summary of normalmixEM object:
##      comp 1    comp 2
## lambda 0.851094 0.148906
## mu      7.491447 49.135665
## sigma   2.702793 59.973762
## loglik at estimate: -3408.058
```

## Density Curves



## Discussion

Perhaps surprisingly, we get an estimate that overestimated the cue rate obtained initially. This might reflect something we initially overlooked. Instead of having a sample of animals that is somehow biased towards animals producing sounds, these animals are quite active, and easily seen while flying, and therefore, animals tended to be included in the sample as they came into the area of detection of the observer looking for potential individuals for focal follows. Hence, most animals were detected when flying in, and hence oversampled for the silence periods that they tend to make once they arrive at a new location. In fact, of the 47 individuals, only 9 started to be followed by acoustics, reflecting that it is rather hard for an animal to come into the effective search zone of the researcher unnoticed. On the other hand, only 8 animals were last recorded as acoustics, showing that the researcher was quite effective at keep tracking of the animals once they went silent. In total only 2 of the animals recording period started and ended at a sound event. This indicates that the desire to avoid biasing results by including only vocal birds might have had the unexpected outcome of biasing the cue rate low, by mostly picking up birds during silent periods. This reflects, once again, the dangers of trying to do random sampling in a scenario where the ability to truly randomize sampling is not possible. Trying to undo expected biases might lead to overcorrection of such a possible expected bias.

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