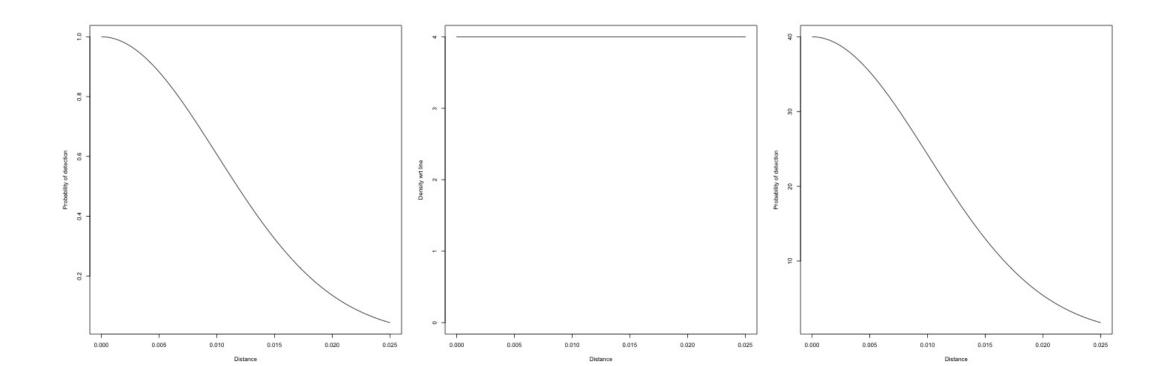
Distance sampling: Advanced topics

David L Miller

Recap

Line transects - general idea

- Calculate average detection probability
 - using detection function (g(x))
- $\hat{p} = \int_0^w \frac{1}{w} g(x; \hat{\theta}) dx$
- $\frac{1}{w}$ tells us about assumed density wrt line
 - uniform from the line



Line transects - distances

- Model drop-off using a detection function
- Use extra information estimate \hat{N}
- How should we adjust n? (inflate by n/p))

Fitting detection functions

- Using the package Distance
- Need to have data setup a certain way
 - At least columns called object, distance

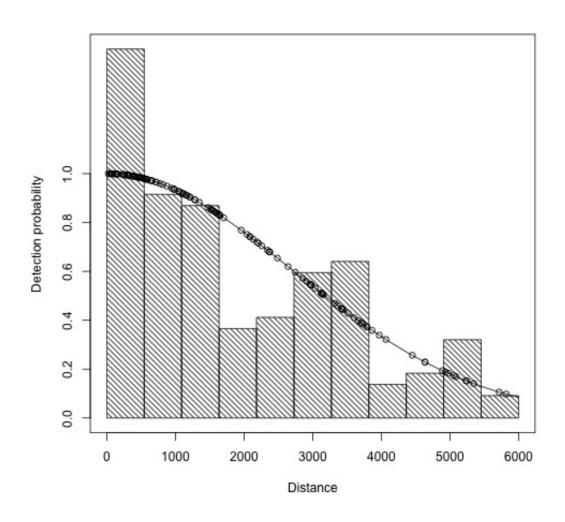
```
library(Distance)
df_hn <- ds(distdata, truncation=6000, adjustment = NULL)</pre>
```

Model summary

summary(df_hn)

```
Summary for distance analysis
Number of observations: 132
Distance range : 0 - 6000
Model: Half-normal key function
AIC : 2252.06
Detection function parameters
Scale Coefficients:
           estimate
                          se
(Intercept) 7.900732 0.07884776
                     Estimate
                                     SE
                    0.5490484 0.03662569 0.06670757
Average p
N in covered region 240.4159539 21.32287580 0.08869160
```

Plotting models



plot(df_hn)

New stuff

Overview

Here we'll look at:

- Model checking and selection
- What else affects detection?
- Estimating abundance and uncertainty
- More R!

Why check models?

- We made some assumptions
- Were we right to do so?
- AIC best model can still be a terrible model

What to check?

- Convergence
 - Fitting ended, but our model is not good
- Monotonicity
 - Our model is "lumpy"
- "Goodness of fit"
 - Our model sucks statistically
- (Other sampling assumptions are also important!)

Convergence

Distance will warn you about this:

```
** Warning: Problems with fitting model. Did not
converge**
Error in detfct.fit.opt(ddfobj, optim.options, bounds,
misc.options):
   No convergence.
```

This can be hard, see?"mrds-opt" for info.

Monotonicity

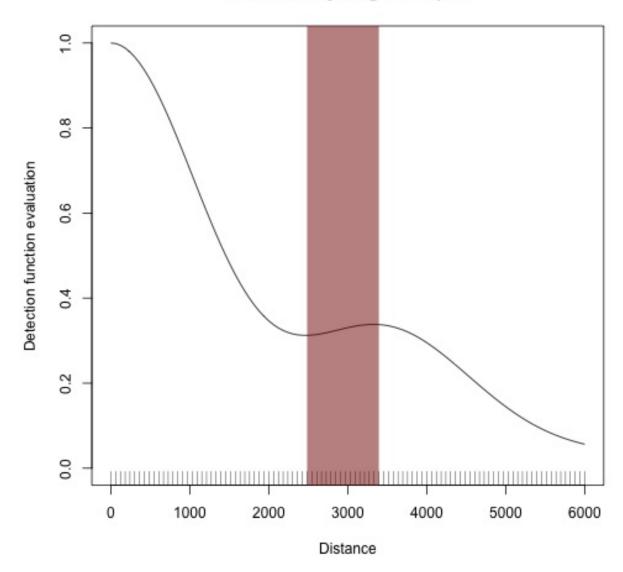
- Only a problem with adjustments
- check.mono can help

```
check.mono(df_hr$ddf)

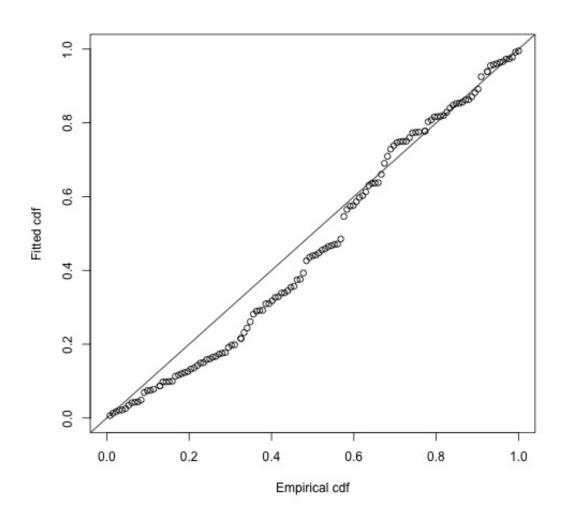
[1] TRUE
```

Monotonicity (when it goes wrong)

Monotonicity diagnostic plot



Goodness of fit

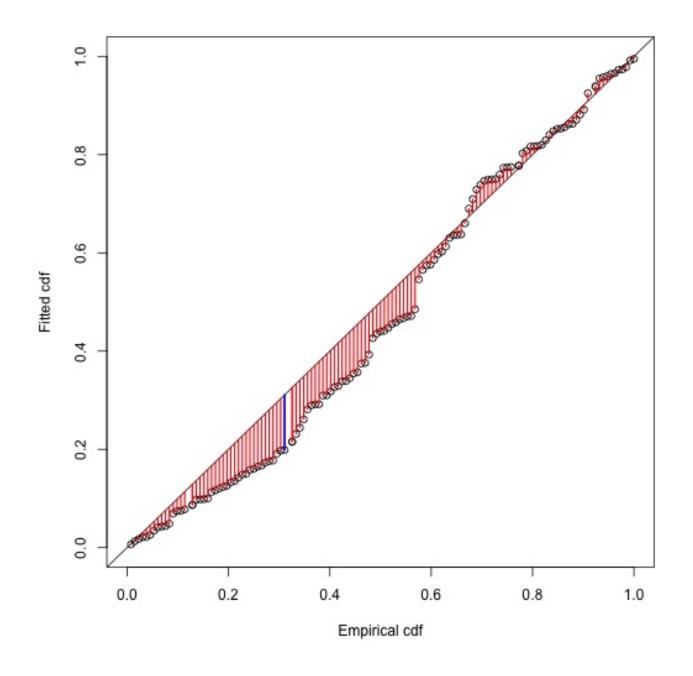


ddf.gof(df_hn\$ddf)

Goodness of fit

- As well as quantile-quantile plot, tests
- Kolmogorov-Smirnov: largest distance on Q-Q plot
- Cramer-von Mises: tests sum of distances

Goodness of fit



- blue: Kolmogorov-Smirnov
- red: Cramer-von Mises

Detection function model selection

- Fit models
- Look at summary and plot (fitting issues?)
- Look at goodness of fit results, ddf.gof
- AIC to select between models
 - Parsimonous: "robust" and "efficient" models

Example: fitting detection functions

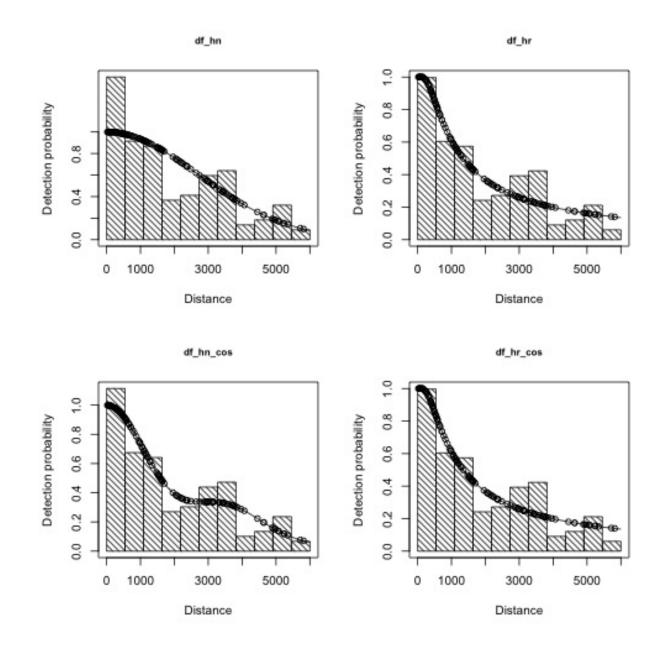
```
df_hn <- ds(distdata, truncation=6000, adjustment = NULL)

df_hn_cos <- ds(distdata, truncation=6000)

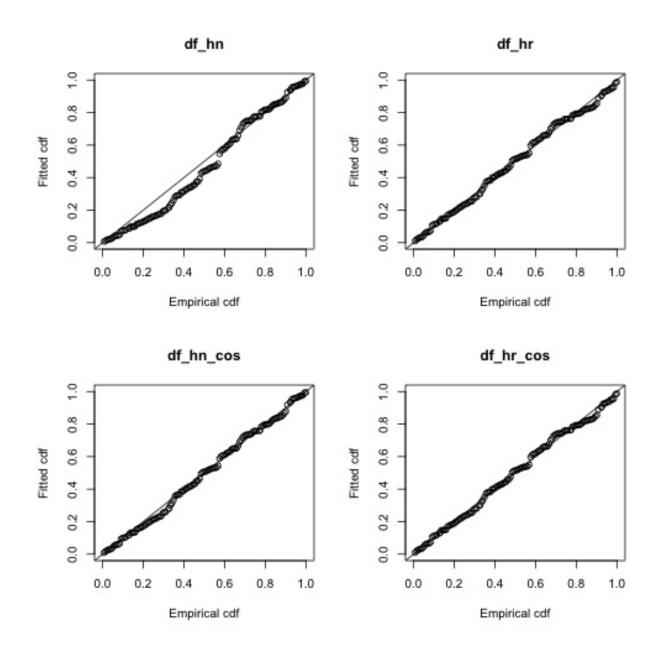
df_hr <- ds(distdata, truncation=6000, key="hr", adjustment = NULL)

df_hr_cos <- ds(distdata, key="hr", truncation=6000)</pre>
```

Plotting those models



Q-Q plots



AIC

```
df_hn$ddf$criterion
[1] 2252.06
df_hn_cos$ddf$criterion
[1] 2247.69
## same model!
df_hr$ddf$criterion
[1] 2247.594
df_hr_cos$ddf$criterion
[1] 2247.594
```

Selection

- Not much between these models!
- You'll get to investigate these and more in the lab

What else affects detectability?

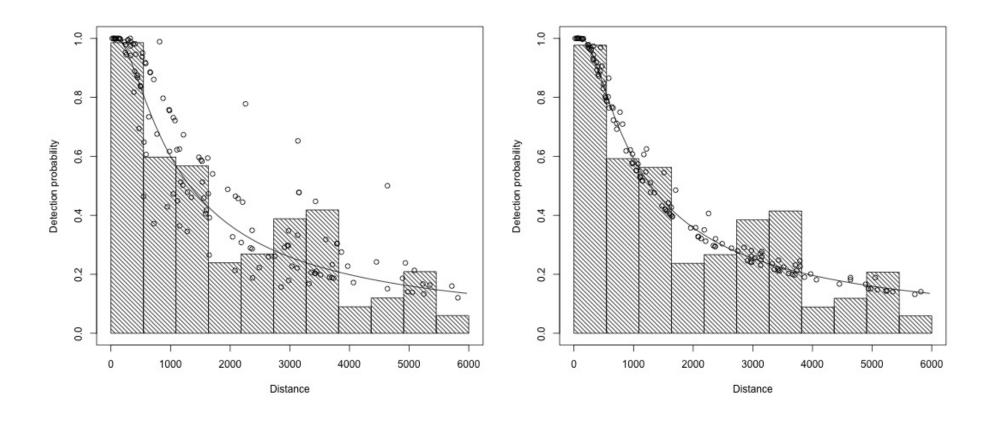
Covariates

- Observer characteristics
 - observer name
 - platform
- Animal characteristics
 - sex
 - size
 - group size

- Weather conditions
 - sea state
 - glare
 - fog

How do we include covariates?

• Affects scale, not shape



Covariates in the scale

$$\exp\left(\frac{-x^2}{2\sigma^2}\right) \text{ or } 1 - \exp\left[\left(\frac{-x}{\sigma}\right)^{-b}\right]$$

Decompose
$$\sigma = \exp(\beta_0 + \beta_1 z_1 + ...)$$

What does detectability mean?

- \hat{p} is now \hat{p}_{i} (or $\hat{p}(\mathbf{z}_{i})$)
- Average probability of detection (average over distances)
- Also calculate an average \hat{p} as a summary

Covariates in R

• Add formula=... to our ds() call:

Summaries of covariate models

summary(df_hr_ss)

```
Summary for distance analysis
Number of observations: 132
Distance range : 0 - 6000
Model: Hazard-rate key function
AIC : 2247.347
Detection function parameters
Scale Coefficients:
            estimate
                         se
(Intercept) 8.1019226 0.7906353
SeaState -0.4473291 0.2797965
Shape parameters:
            estimate
(Intercept) 0.07319982 0.2417426
                   Estimate
                  Average p
N in covered region 368.3357858 79.54571167 0.2159598
```

"Average p"

```
unique(predict(df_hr_ss$ddf)$fitted)
```

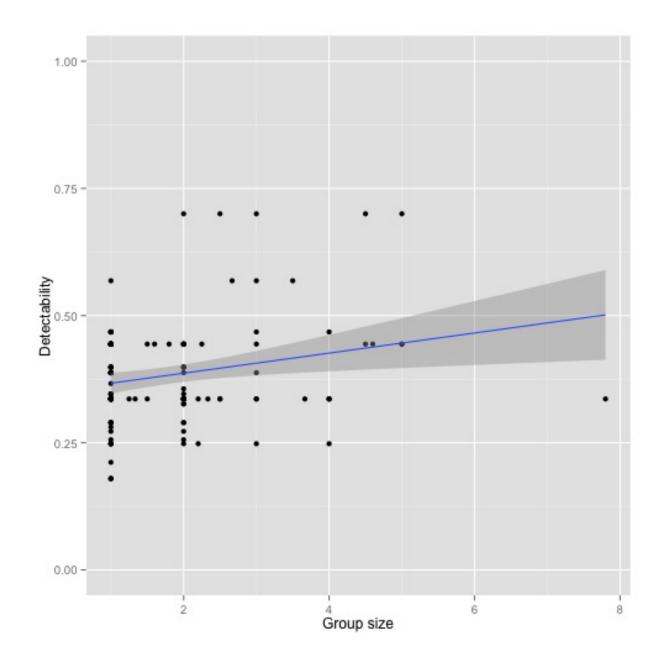
```
[1] 0.3360342 0.3876026 0.2895189 0.2480620 0.3985064 0.4439768 0.2723358 [8] 0.2559550 0.2808264 0.3459473 0.3263237 0.3663789 0.5684780 0.2114896 [15] 0.3560627 0.4677557 0.1795108 0.7000862
```

Group size

What are groups?

- Functional definition (NO ecology!)
 - If animals are near each other, they are in a group
- This probably affects detectability
 - Bigger groups ⇒ easier to detect
- Two inferential targets
 - abundance of groups
 - abundance of individuals

Detection and groups



Estimating abundance

Estimating abundance

- As before, assume density same in sampled/unsampled area
- Horvitz-Thompson estimator

$$\hat{N} = \frac{A}{a} \sum_{i=1}^{n} \frac{S_i}{p_i}$$

where s_i is group size

Estimating uncertainty

Sources of uncertainty

$$\hat{N} = \frac{A}{a} \sum_{i=1}^{n} \frac{S_i}{\hat{p}_i}$$

- Uncertainty in n is from sampling
- Uncertainty in \hat{p} is from the model

Uncertainty from sampling

- Usually calculate encounter rate variance
- Encounter rate is n/L
- (Effectively an average, so there is uncertainty)
- "Objects per unit length of transect surveyed"
- Fewster et al. (2009) is the definitive reference

Uncertainty from the model

- Model uncertainty from estimating parameters
- Maximum likelihood theory gives uncertainty in model pars

Putting those parts together

Obtain overall CV by adding squared CVs:

$$CV^{2}(\mathring{D}) = CV^{2}(\frac{n}{L}) + CV^{2}(\mathring{p})$$

(Running through this quickly, see bibliography for more details)

(One other thing...)

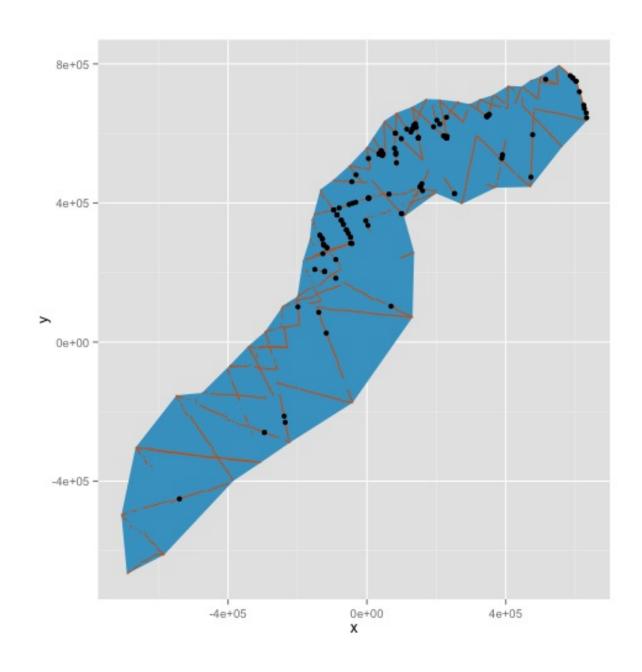
- Assume that group size is recorded correctly
- This is almost never true
- There are ways to deal with this
- See bibliography for more details

Variance and abundance in R...

Data required

- Need three tables
 - region: whole area
 - sample: the samples (transects)
 - observation: relate samples to observations

Schematic



- region
- sample
- observations

Region table

```
head(region.table)
```

```
Region.Label Area
1 StudyArea 5.285e+11
```

Sample table

head(sample.table)

```
Sample.Label Effort Region.Label
1 en0439520040624 144044.67 StudyArea
2 en0439520040625 167646.84 StudyArea
3 en0439520040626 59997.33 StudyArea
4 en0439520040627 33821.89 StudyArea
5 en0439520040628 147414.92 StudyArea
6 en0439520040629 101107.83 StudyArea
```

Observation table

```
head(obs.table)
```

Abundance and variance

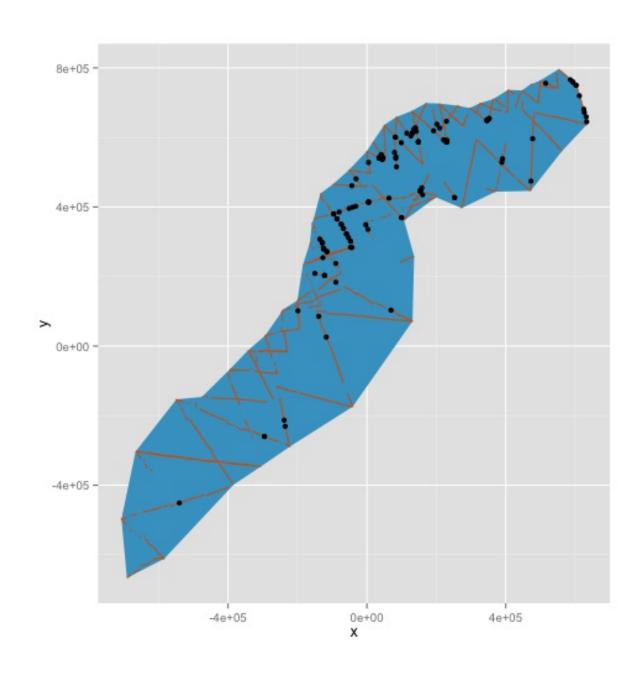
This generates a lot of output (here is a snippit):

```
dht(df_hr$ddf, region.table, sample.table, obs.table)
```

```
Summary for individuals
Summary statistics:
    Region Area CoveredArea Effort
                                        n
         se.ER cv.ER mean.size
ER
1 StudyArea 5.285e+11 113981689066 9498474 238.7
2.513035e-05 5.667492e-06 0.2255238 1.808333
   se, mean
1 0.1020928
Abundance:
 Label Estimate se cv lcl
                                          ucl
1 Total 3053.558 943.7425 0.3090632 1682.187 5542.912
170.9157
```

More investigation in the practical exercises...

What about making the region smaller?



Recap

Summary

- How to check detection function models
- Covariates can affect detectability
- Group size
- Sources of uncertainty
- Estimation of abundance and variance