Introduction to distance sampling

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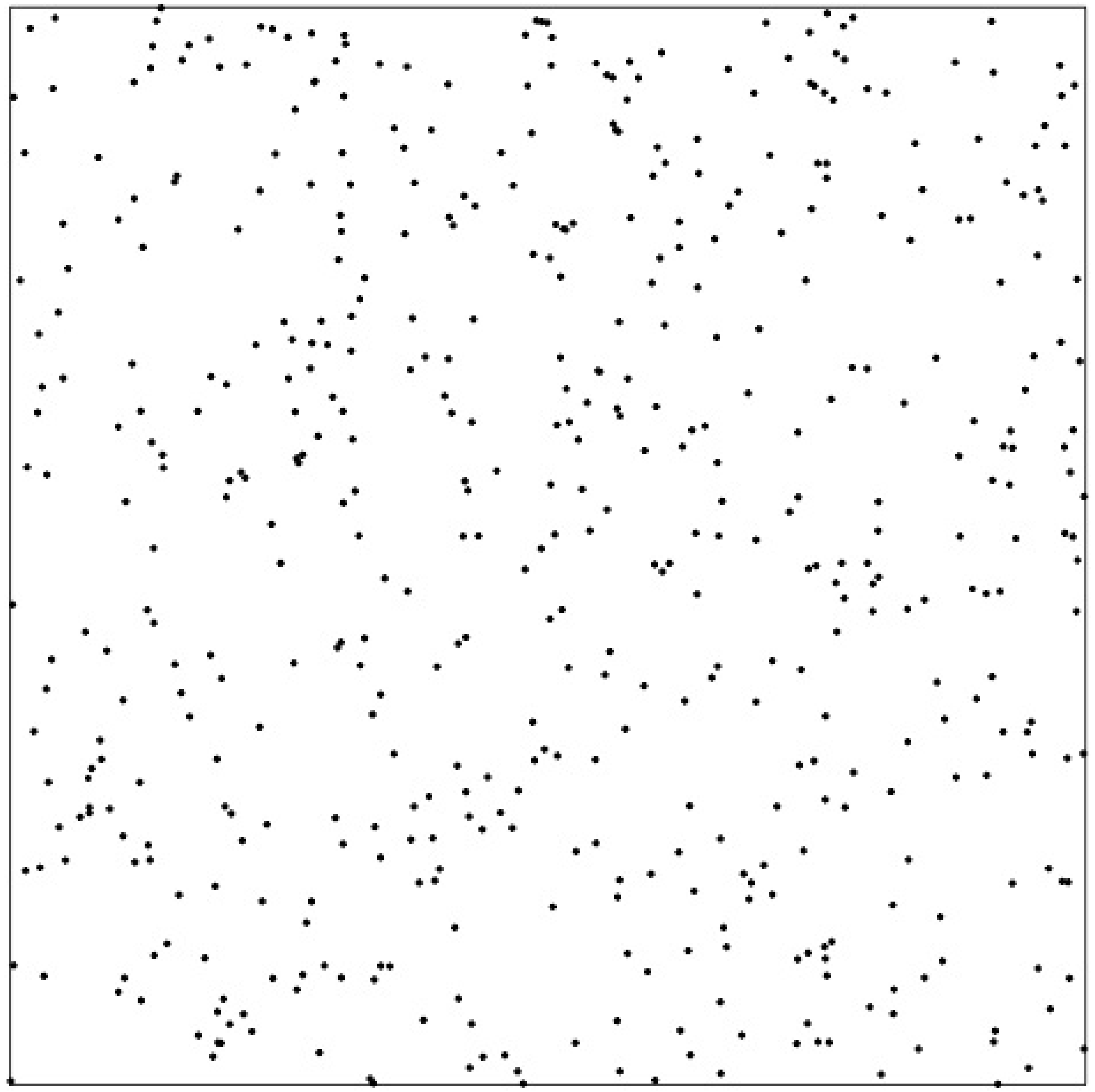
Overview

- Line transects
- Simple estimates of abundance
- Why is detectability important?
- What is a detection function?
- First look at fitting models in R

How many animals are there? (500!)



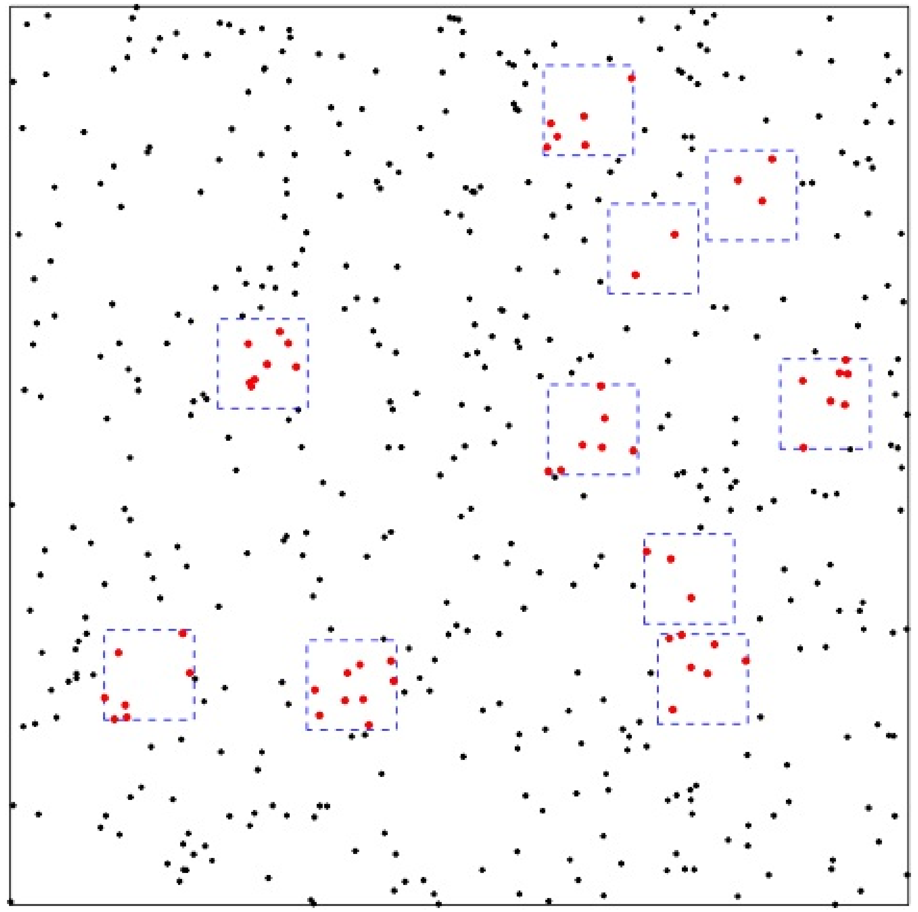
General strategy

- Take a sample in some fixed areas
- Find density/abundance in *covered area*
- Multiply up to get abundance

General strategy (What did we assume?)

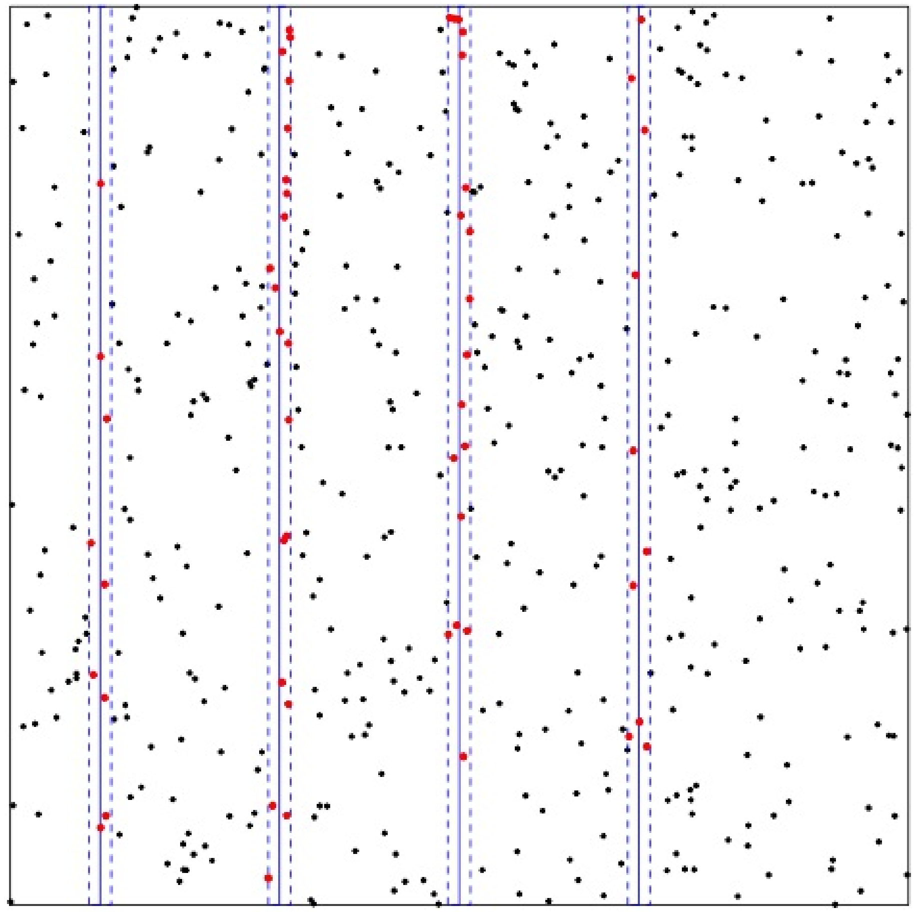
- Take a sample in some fixed areas
  - *Sample is representative*
- Find density/abundance in *covered area*
  - *Estimator is "good"*
- Multiply up to get abundance
  - *Uniform distribution outside covered area*

Plot sampling



- Surveyed 10 quadrats (each 0.1^2 units)
  - Total covered area $a = 10 * 0.1^2 = 0.1$
- Saw $n = 59$ animals
- Estimated density $\hat{D} = n/a = 590$
- Total area $A = 1$
- Estimated abundance $\hat{N} = 590$

Strip transect



- Surveyed 4 lines (each $1 * 0.025$ units)
  - Total covered area $a = 4 * 1 * 0.025 = 0.1$
- Saw $n = 57$ animals
- Estimated density $\hat{D} = n/a = 570$
- Total area $A = 1$
- Estimated abundance $\hat{N} = 570$

Detectability

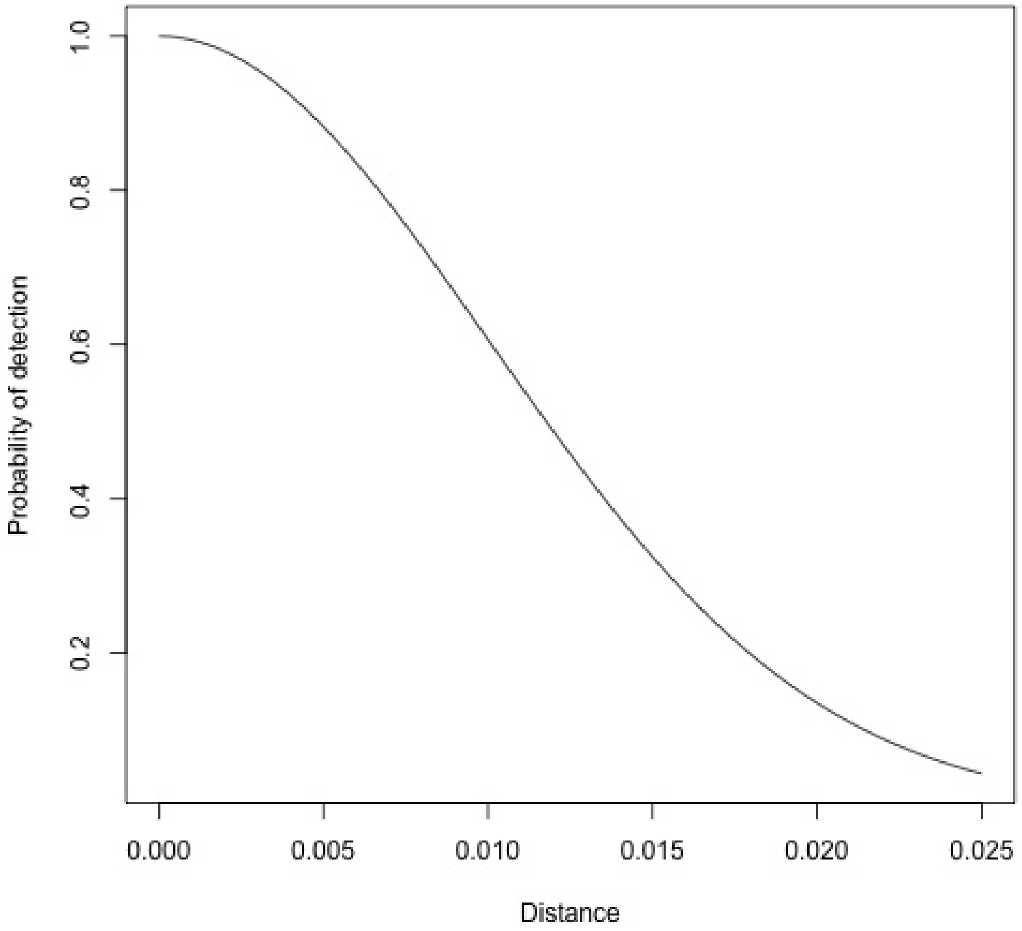
Detectability matters!

- We've assumed certain detection so far
- This rarely happens IRL
- Distance to the line is important
  - (Other things too, more on that later)
  - Detectability should decrease with increasing distance

Recording distances is more efficient

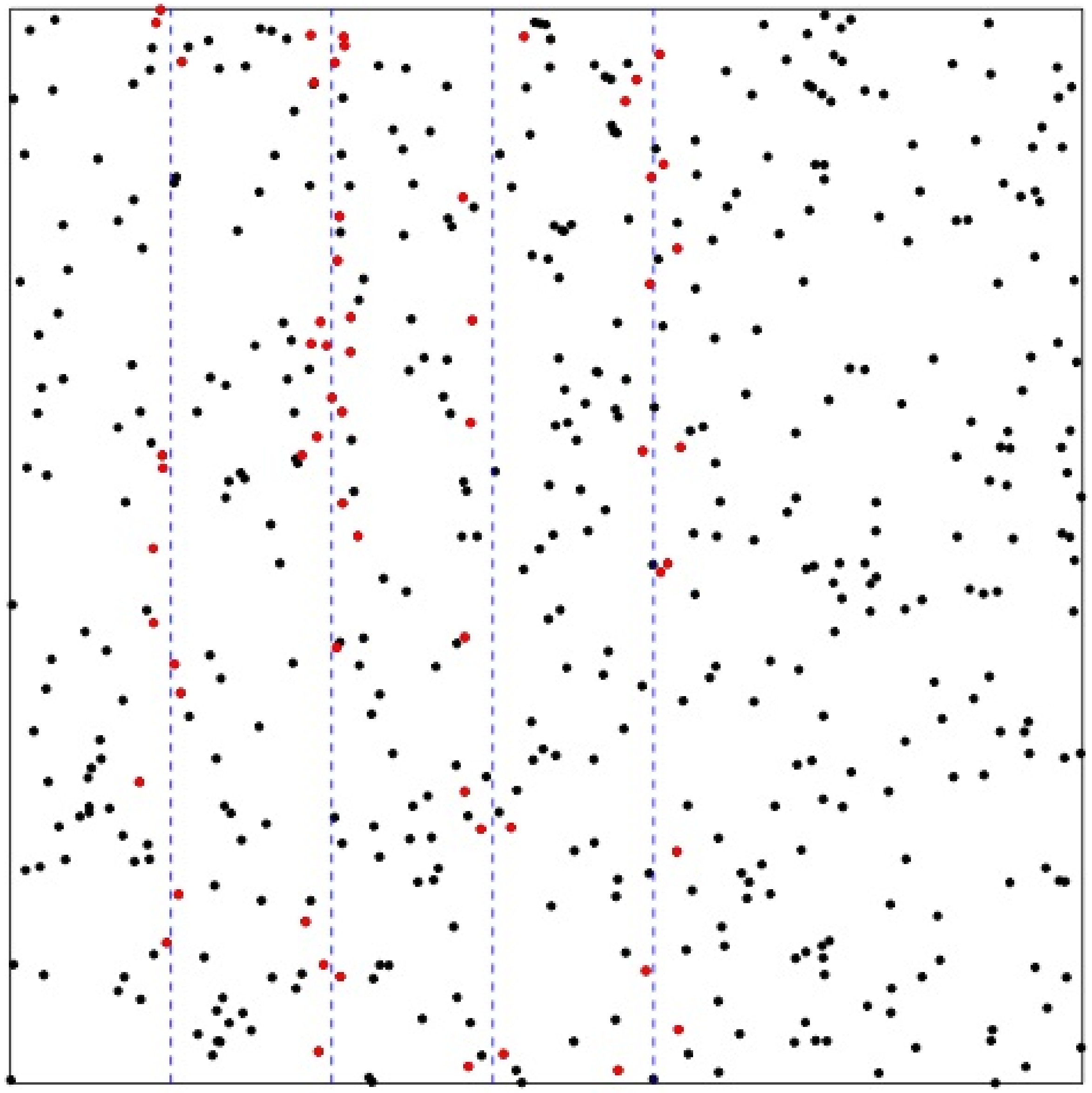
- Plots: what if an animal is *just* outside the box?
- Strips: what if an animal is *just* outside the strip?
- Line transects: record **everything**, then discard later
    - Decide strip width (*truncation distance*) later

Detection as a function of distance

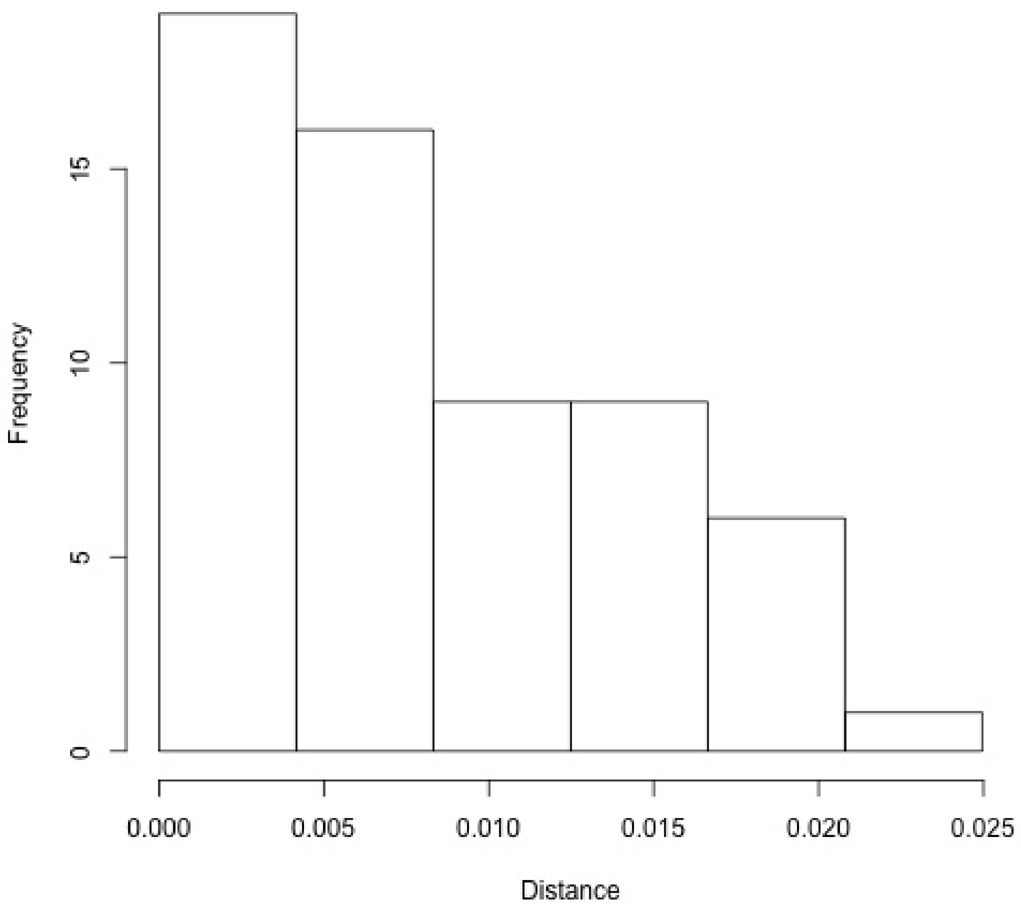


- Model probability of detection, given distance
- Fit models for the curve
- Derive a probability of detection from this model

Line transect



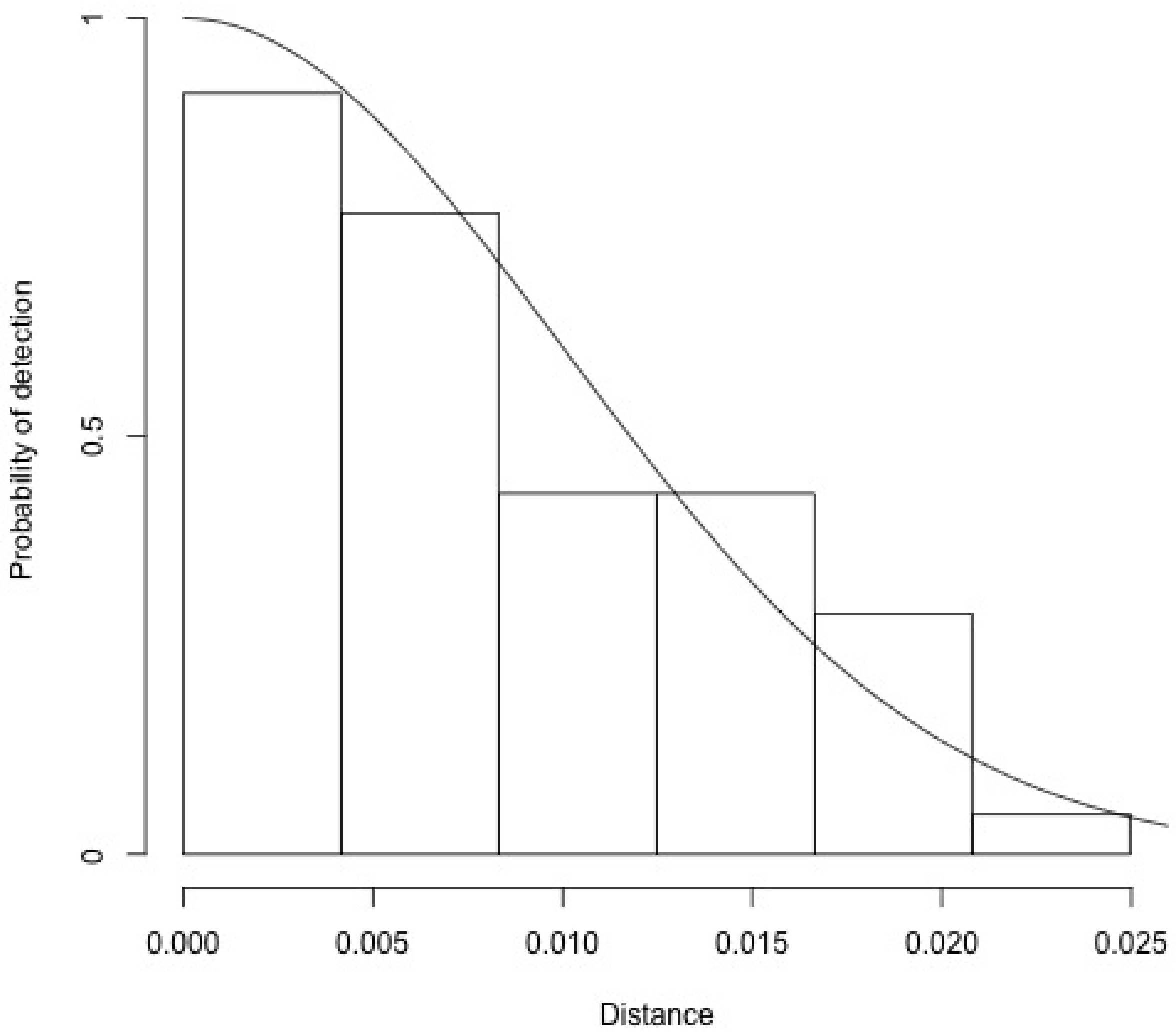
Line transects - distances



- Now we recorded distances, what do they look like?
- Drop-off in # observations w. increasing distance

”You should model that”

Detection function



Using distance information

- Detection function: $\mathbb{P}(\text{ detection } | \text{ at distance x})$
- Integrate out the conditioning $\Rightarrow$ $\mathbb{P}(\text{ detection }) = \hat{\text{p}}$
- "Inflate" n by $\hat{\text{p}}$ to estimate abundance

Distance sampling estimate

- Surveyed 5 lines (each $1 * 0.025$ units)
  - Total covered area $a = 5 * 1 * 0.02$ = 0.2
- Probability of detection $\hat{p} = \int_0^w \frac{g(x)}{w} dx$ = 0.5981
- Saw $n = 60$ animals
- Inflate to $n/\hat{p}$
- Estimated density $\hat{D} = \frac{n/\hat{p}}{a}$ = 502
- Total area $A = 1$
- Estimated abundance $\hat{N}$ = 502

Summary: line transects

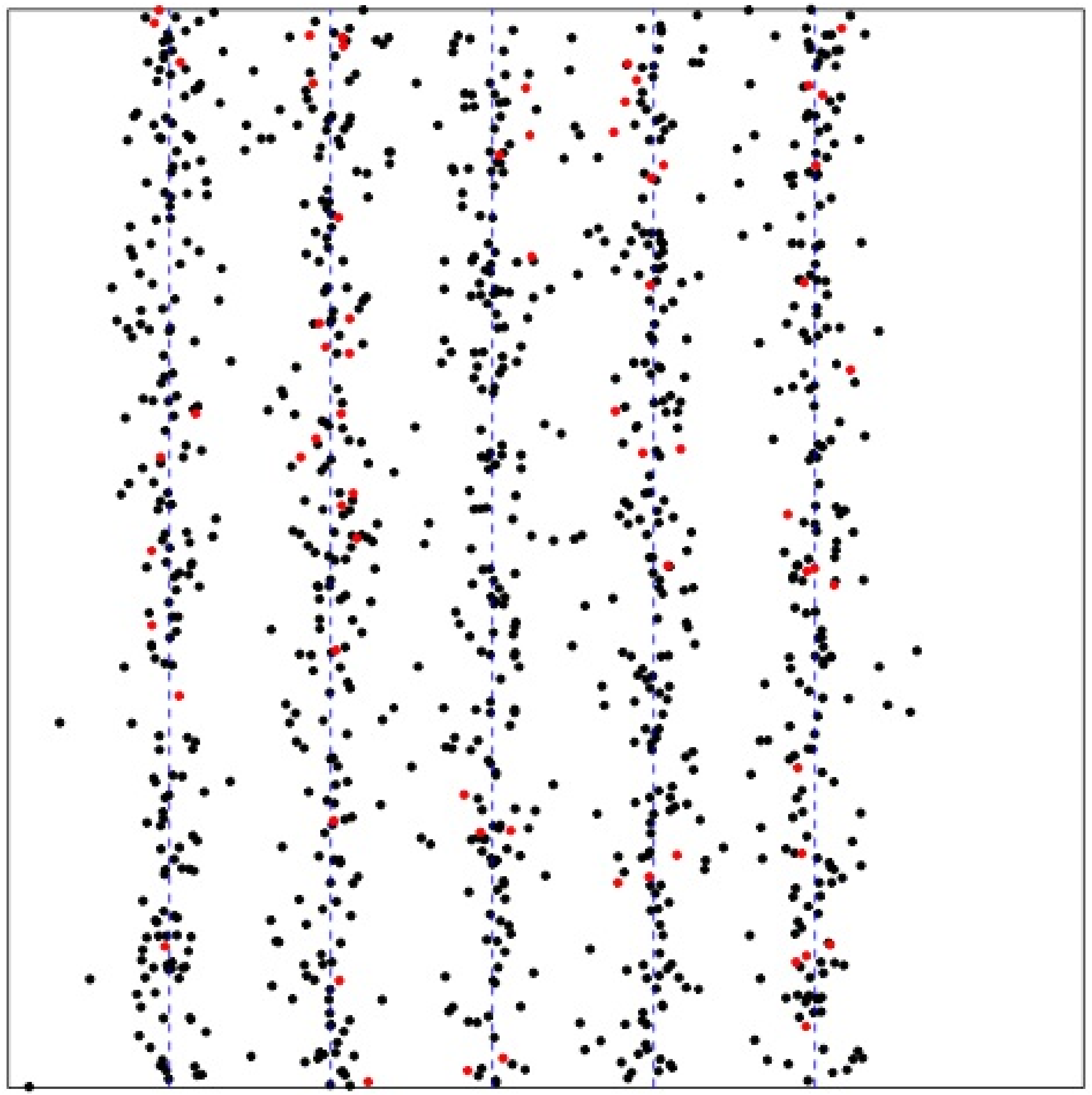
- Efficient survey design
- Relax the assumption of perfect detection
- More information = better inference

Assumptions

Assumptions

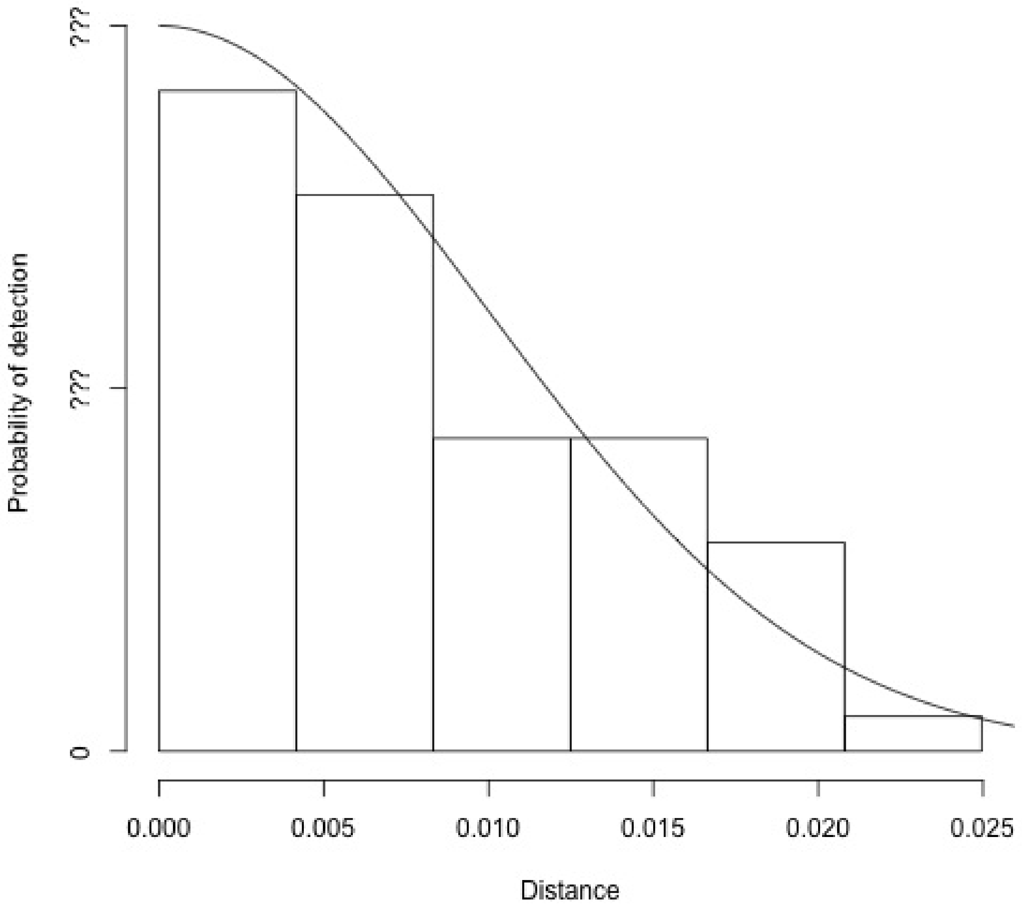
1. Animals are distributed independent of lines
2. On the line, detection is certain
3. Distances are recorded correctly
4. Animals don't move before detection

Animals are distributed independent of lines



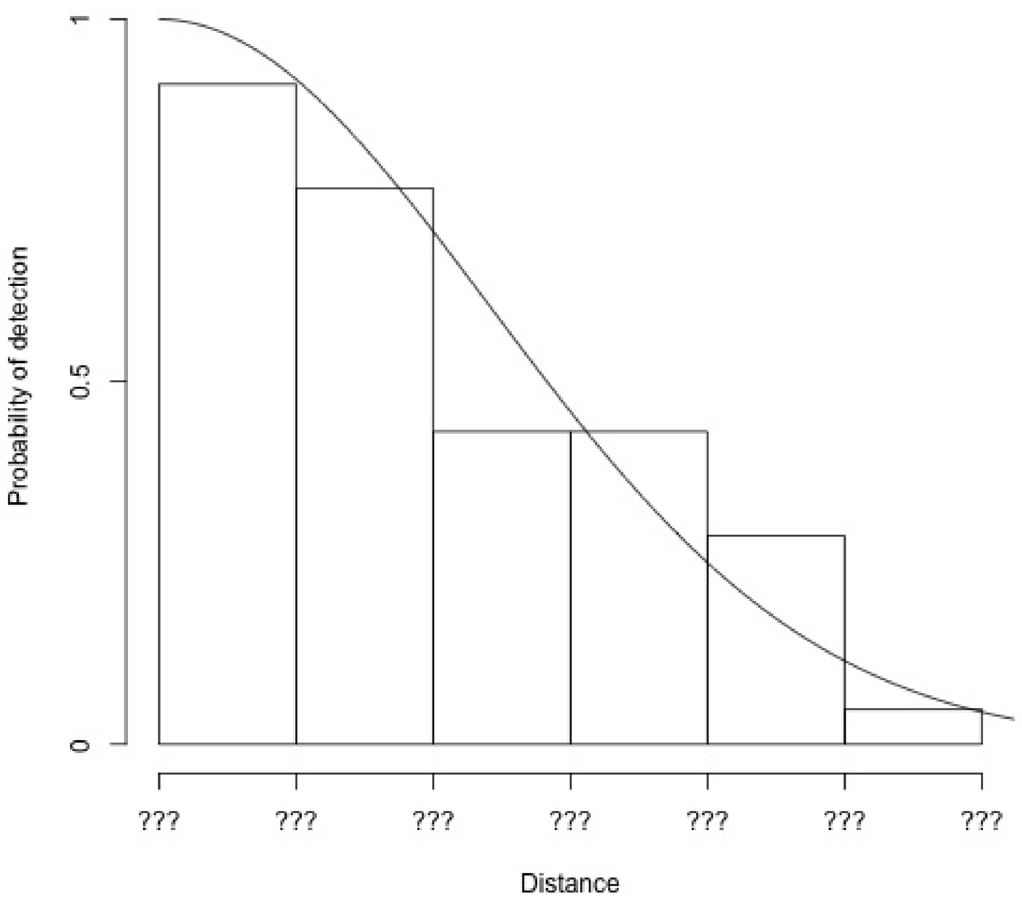
- When transects follow features
- Difficult to work out detectability vs. distribution

On the line, detection is certain



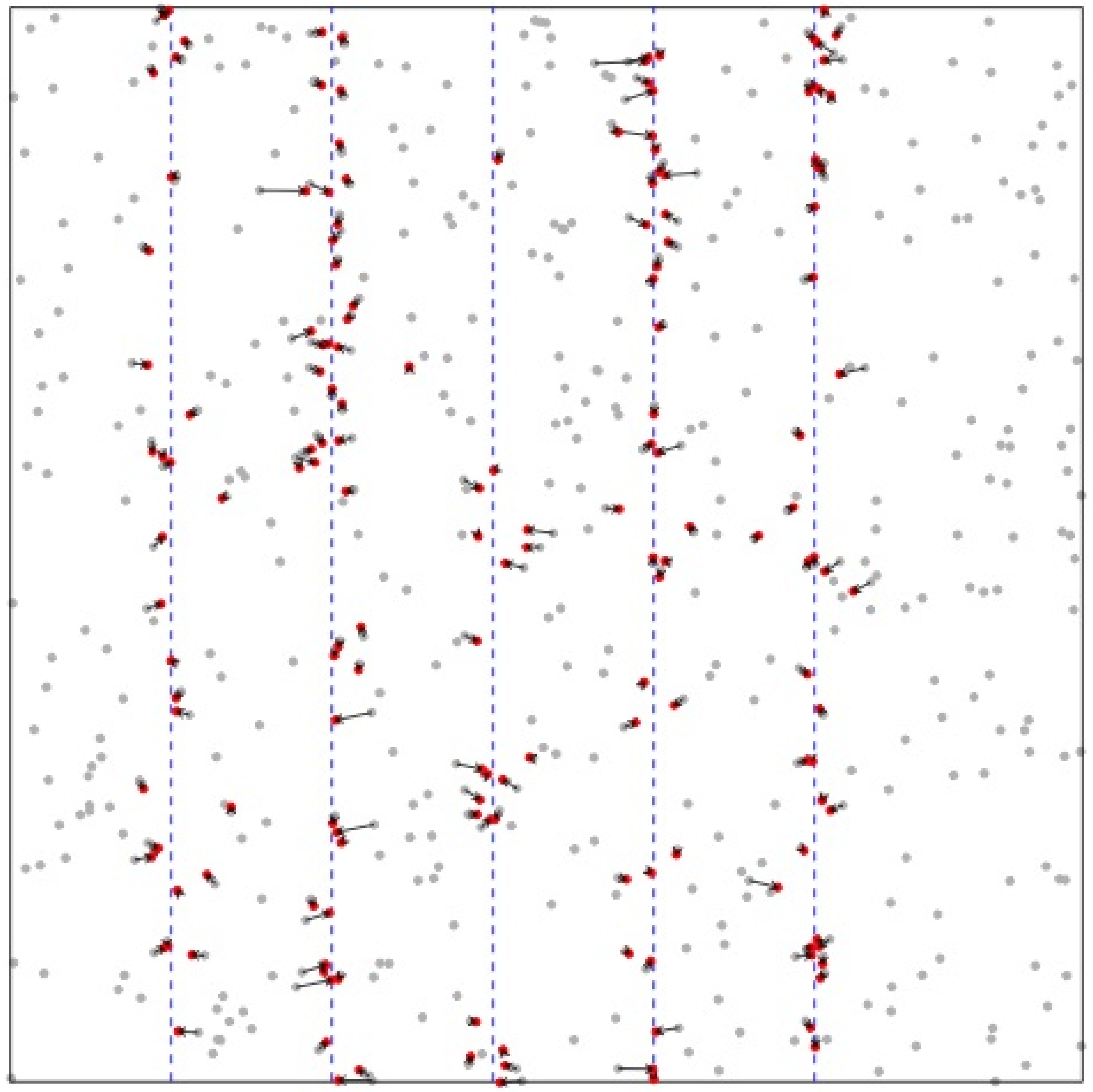
- Perception bias
- Availability bias
- Don't know y axis scale

Distances are recorded correctly



- Measurement error
- Don't know x axis scale
- This can be systematic

Animals don’t move before detection



- Animals can be attracted or repelled
- Problems with distribution wrt line and/or measurement error

Detection functions

What are detection functions?

- Model $\mathbb{P}\left(\text{detection} \mid \text{animal at distance x}\right)$
- (Hence the integration)
- Many different forms, depending on the data
- All share some characteristics

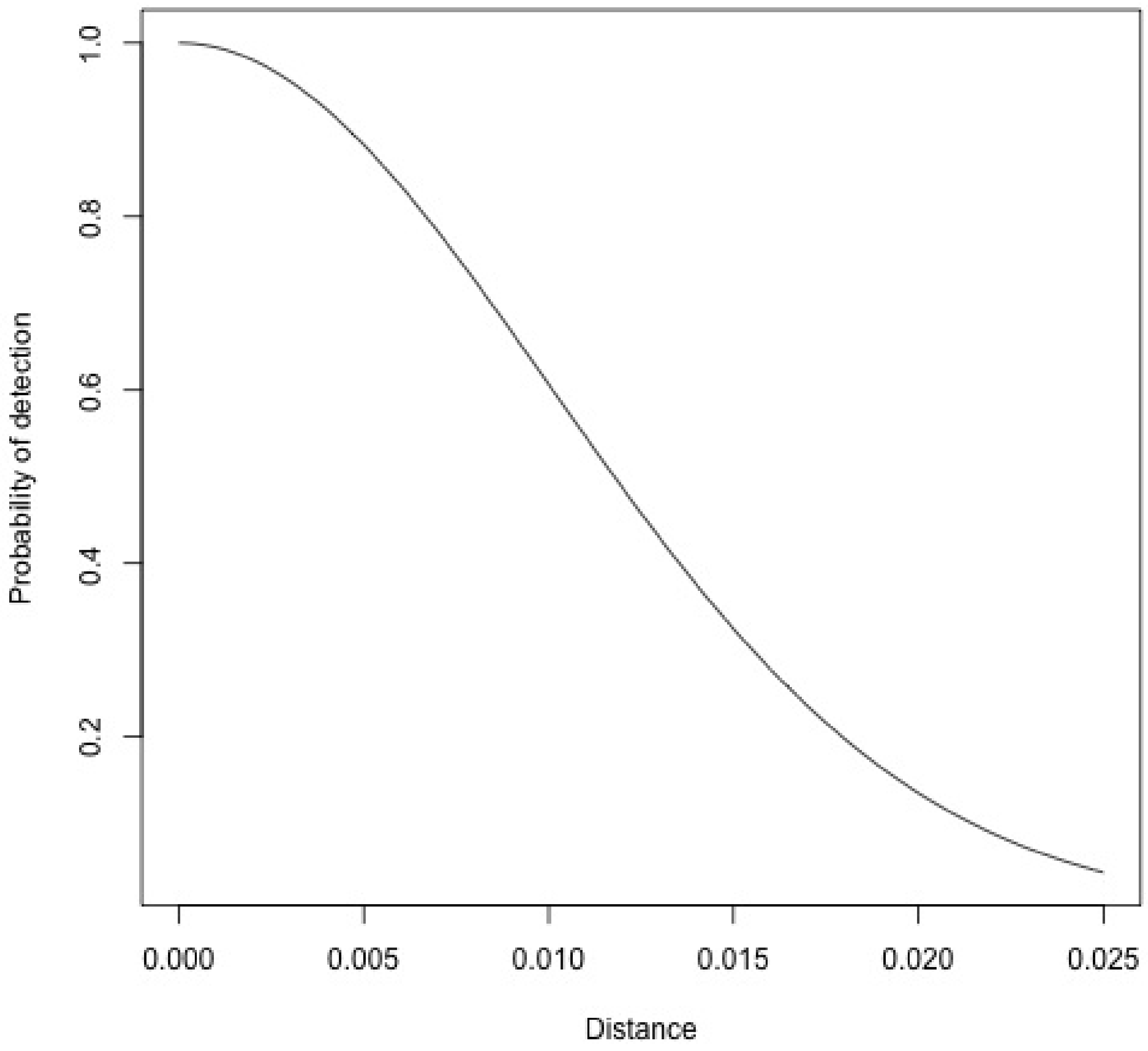
Detection function assumptions

- Have a “shoulder”
  - *we see things nearby easily*
- Monotonic decreasing
  - *never increasing with increasing distance*
- “Model robust”
  - *lots of forms/flexible models*
- “Pooling robust”
  - *individual heterogeneity averages out*
- “Efficient”
  - *models don't need lots of parameters*

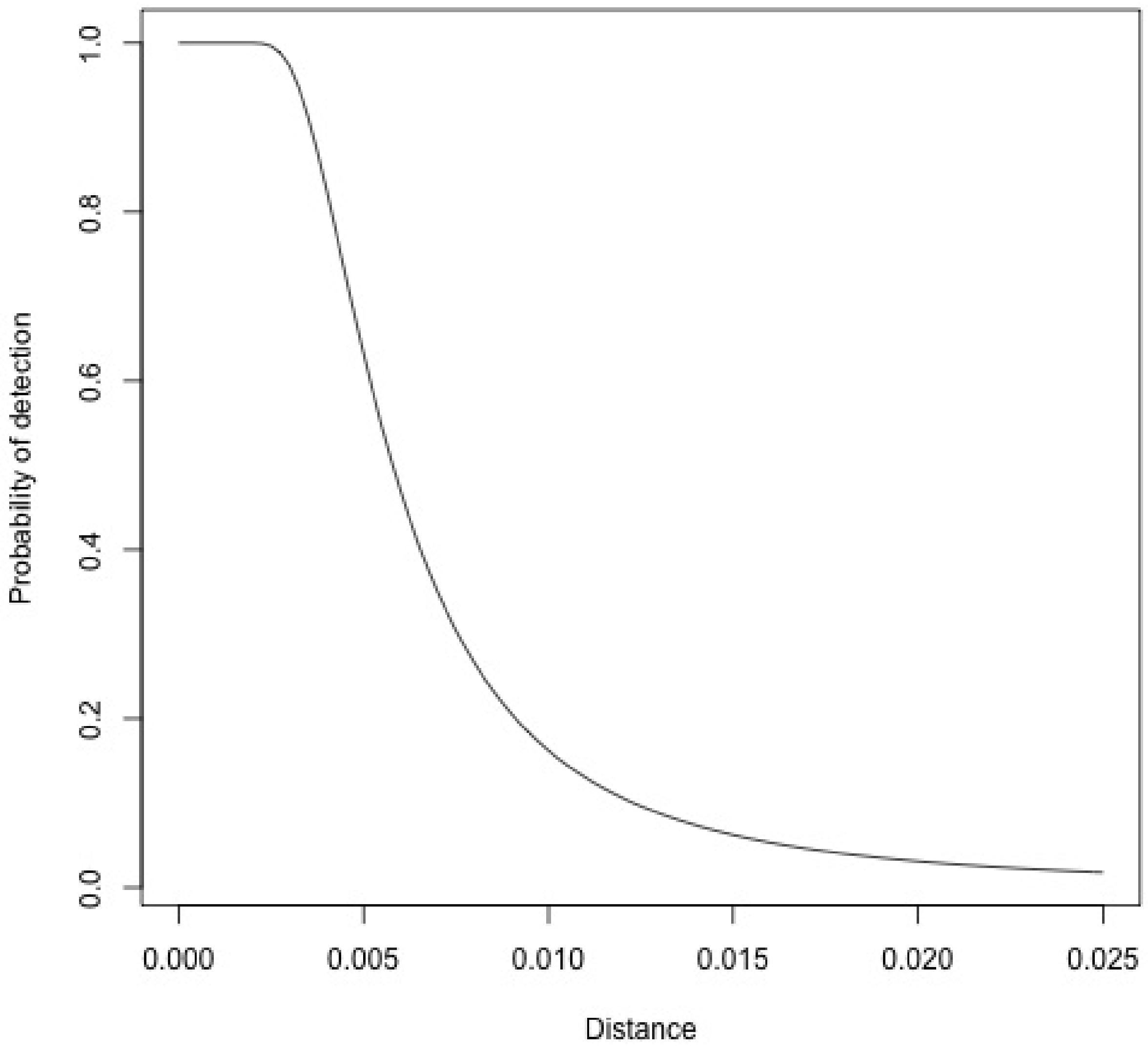
Possible detection functions

- There are many options
- A restricted set we'll cover in this course...
  - Half-normal
  - Hazard-rate
  - adjustments to the above

Half-normal detection functions



Hazard-rate detection functions



Adjustment terms

- These models are flexible
- What about adding more flexibilty by “adjusting” them
- Options:
  - Cosine series
  - Polynomials
  - Hermite polynomials
- Add extra flexibility

Okay, but how can we actually do this?

Modelling strategy

1. Pick some formulations, fit models
2. Check assumptions are violated
3. Goodness of fit
4. Select models
5. Estimate $\hat{N}$ (and uncertainty!)

Distance sampling data

- Need to have data setup a certain way
  - a `data.frame` with one row per observation
  - at least 2 columns, named "`object`" and "`distance`"

```
   distance object size SeaState
1  246.0173      1    2      3.0
2 1632.3934      2    2      2.5
3 2368.9941      3    1      3.0
4  244.6977      4    1      3.5
5 2081.3468      5    1      4.0
6 1149.2632      6    1      2.4
```

Fitting detection functions (in R!)

- Using the package `Distance`
- Function `ds()` does most of the work

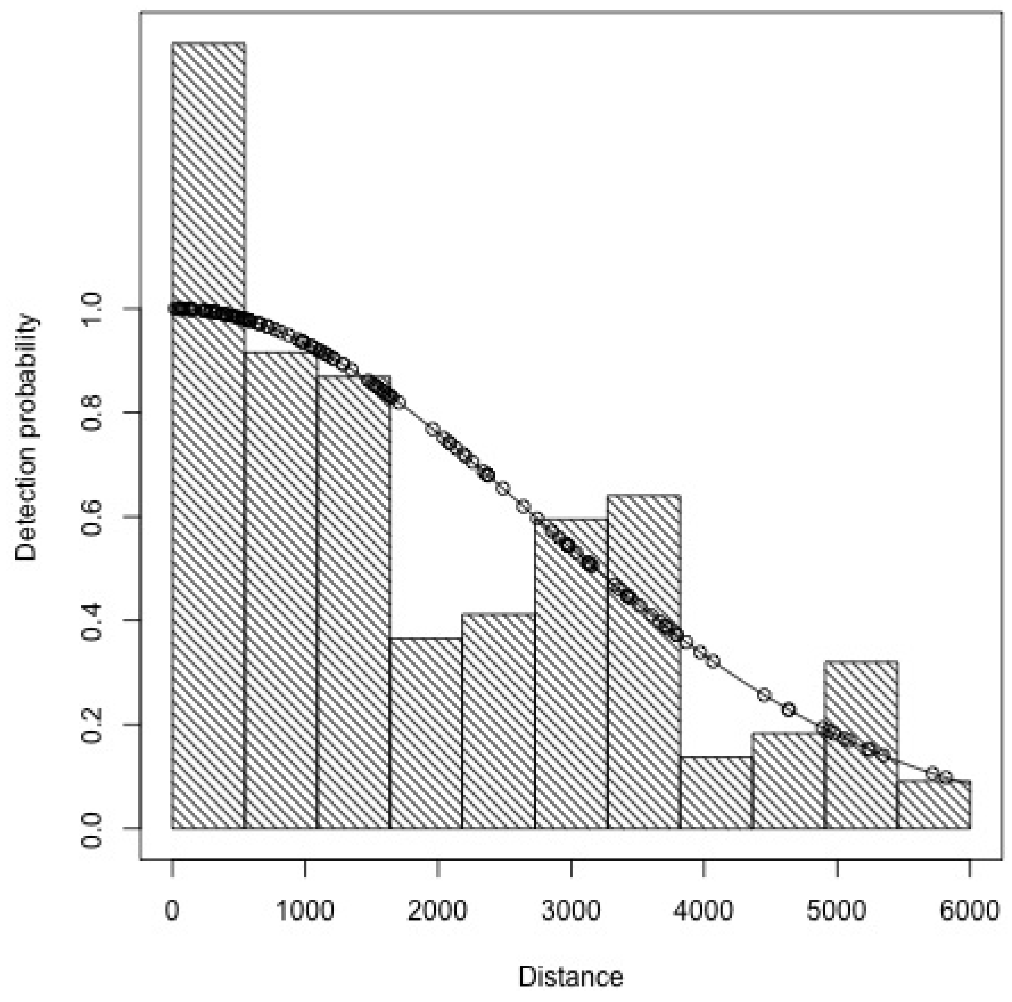
```
library(Distance)
df_hn <- ds(distdata, truncation=6000, adjustment = NULL)
df_hr <- ds(distdata, truncation=6000, key="hr",
adjustment = NULL)
```

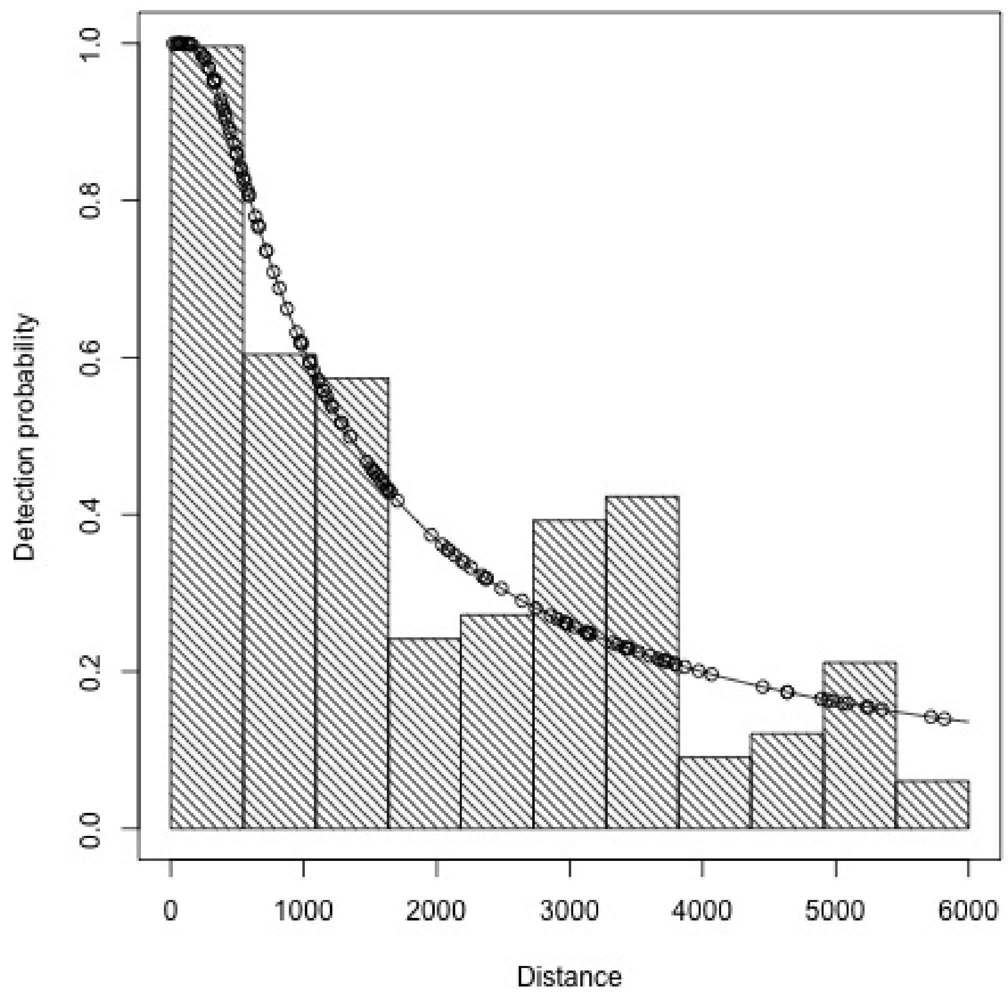
Model summary

```r
summary(df_hn)
```

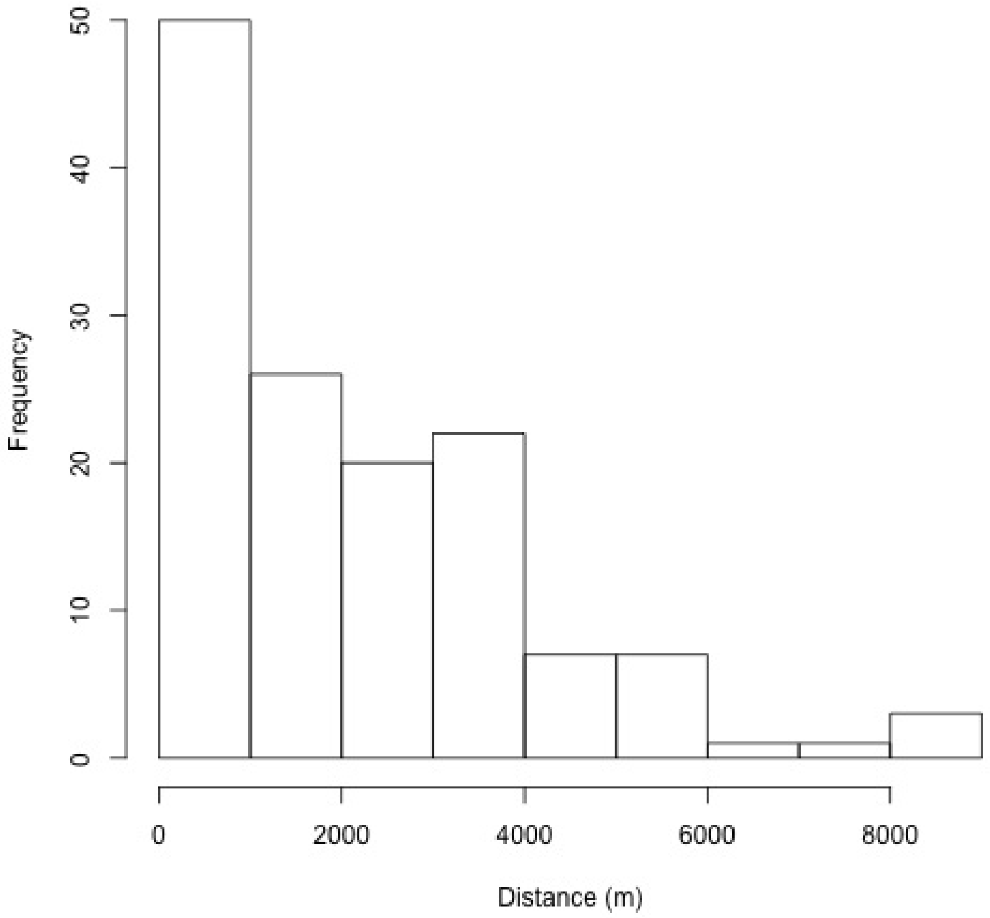
```

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         CV
Average p              0.5490484  0.03662569 0.06670757
N in covered region  240.4159539 21.32287580 0.08869160
```

Plotting models





Truncation



- We set `truncation=6000`, why?
- Remove observations in the tail of the distribution
- Such observations lead to bad model fit
- Care about g near 0!
- Trade-off! (Here we use ~96% of the data)
- Len Thomas suggests $g(w) \approx 0.15$

Recap

Distance sampling

- More efficient sampling
- Collect additional information
- Estimate detection
- Use $\mathbb{P}(\text{detection})$ to correct counts

What's next?

- Model checking and selection
- Estimating abundance in R
- Stratification
- What else affects detectability?