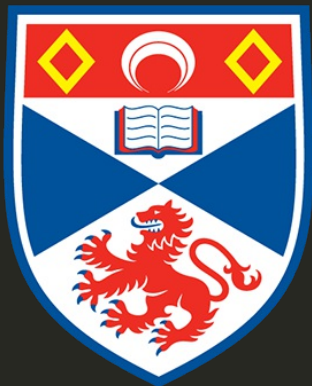


# Generalized Additive Models



University of  
St Andrews

# Overview

- What is a GAM?
- What is smoothing?
- How do GAMs work?
- Fitting GAMs using

What is a GAM?

"gam"

1.

2.

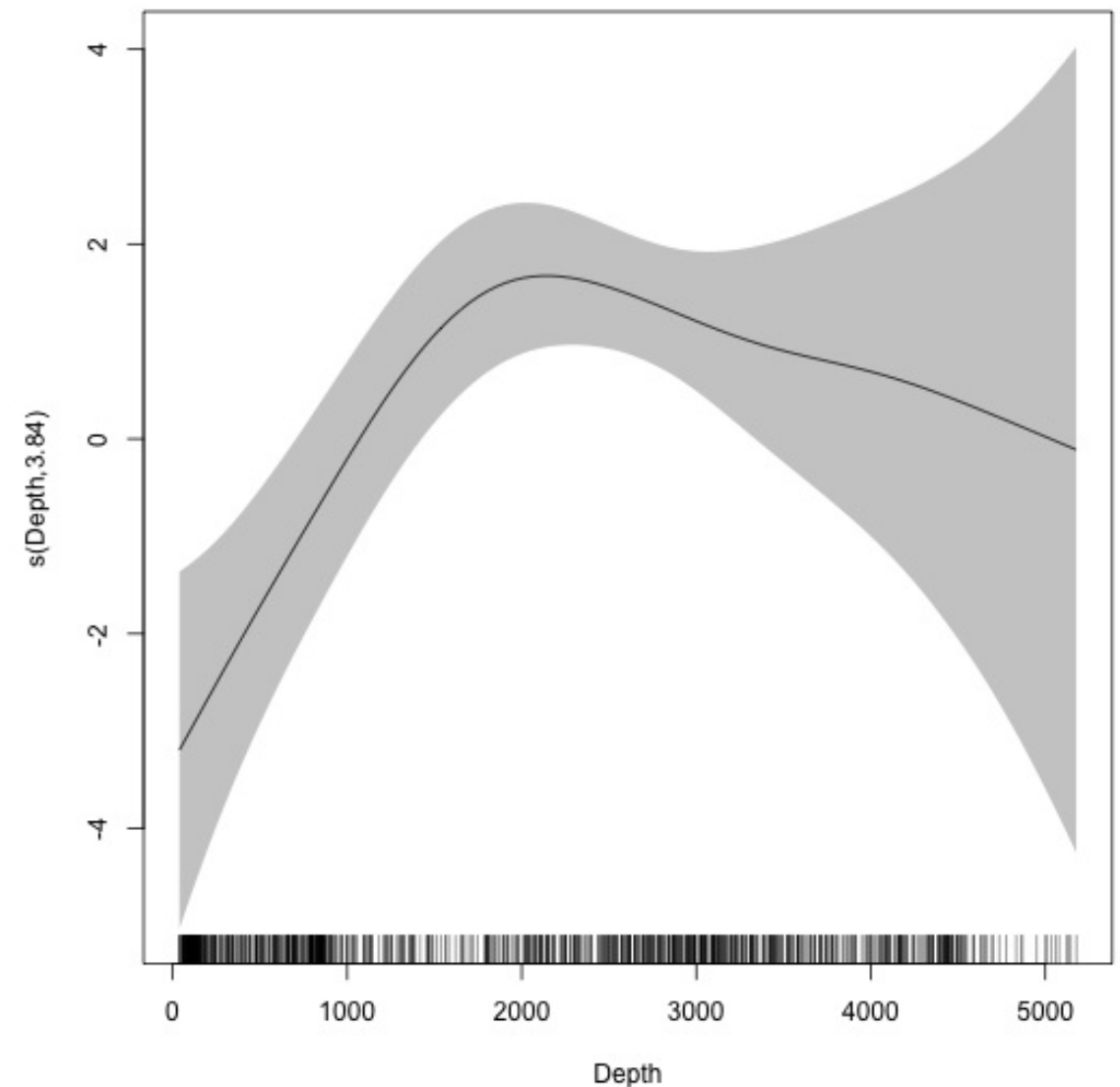
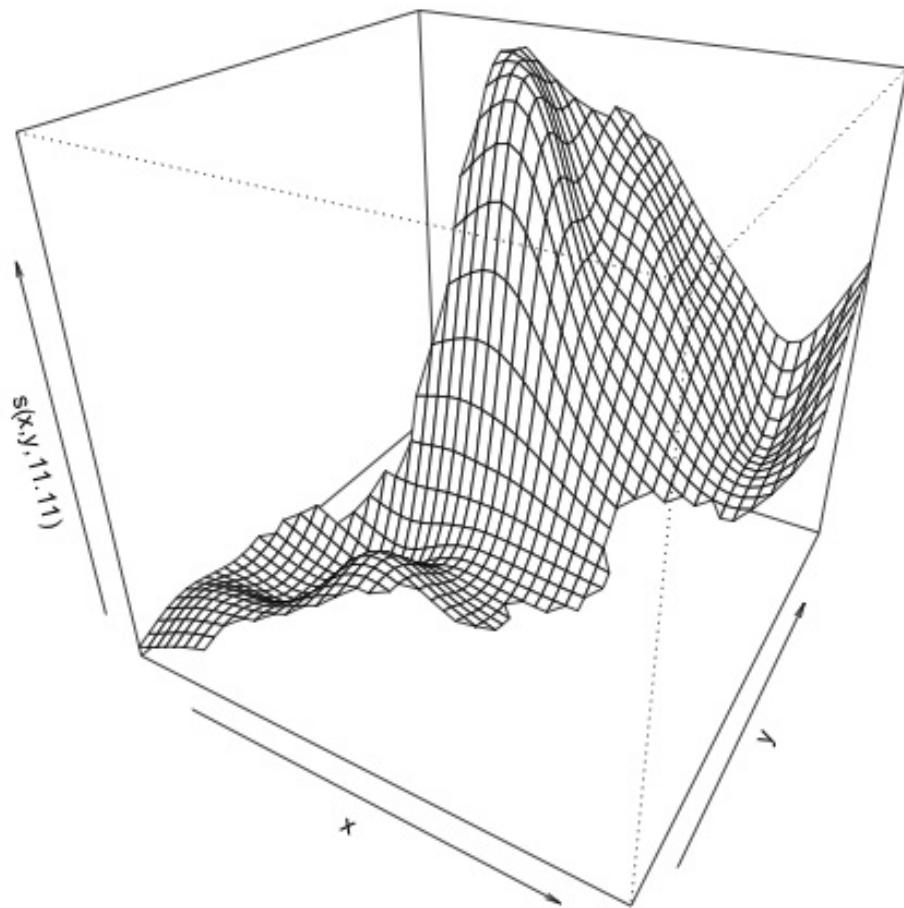
(via Natalie Kelly, AAD. Seen in Moby Dick.)

# Generalized Additive Models

- Generalized: many response distributions
- Additive: terms **add** together
- Models: well, it's a model...

# What does a model look like?

- Count  $n_j$  distributed according to some count distribution
- Model as sum of terms



# Mathematically...

Taking the previous example...

$$n_j = A_j \hat{p}_j \exp [\beta_0 + s(y_j) + s(\text{Depth}_j)] + \epsilon_j$$

where  $\epsilon_j \sim N(0, \sigma^2)$ ,  $n_j \sim \text{count distribution}$

- area of segment - offset
- probability of detection in segment
- link function
- model terms

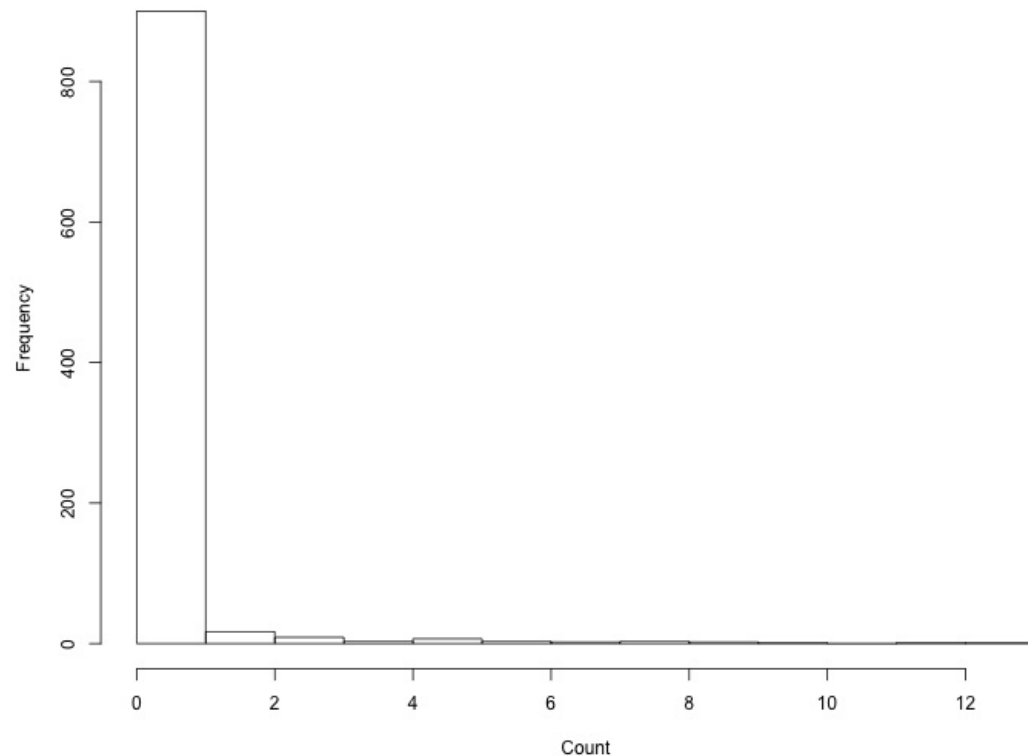
# Response

$$\mathbf{n}_j = A_j \hat{p}_j \exp [\beta_0 + s(y_j) + s(\text{Depth}_j)] + \epsilon_j$$

where  $\epsilon_j \sim N(0, \sigma^2)$ ,  $\mathbf{n}_j \sim \text{count distribution}$

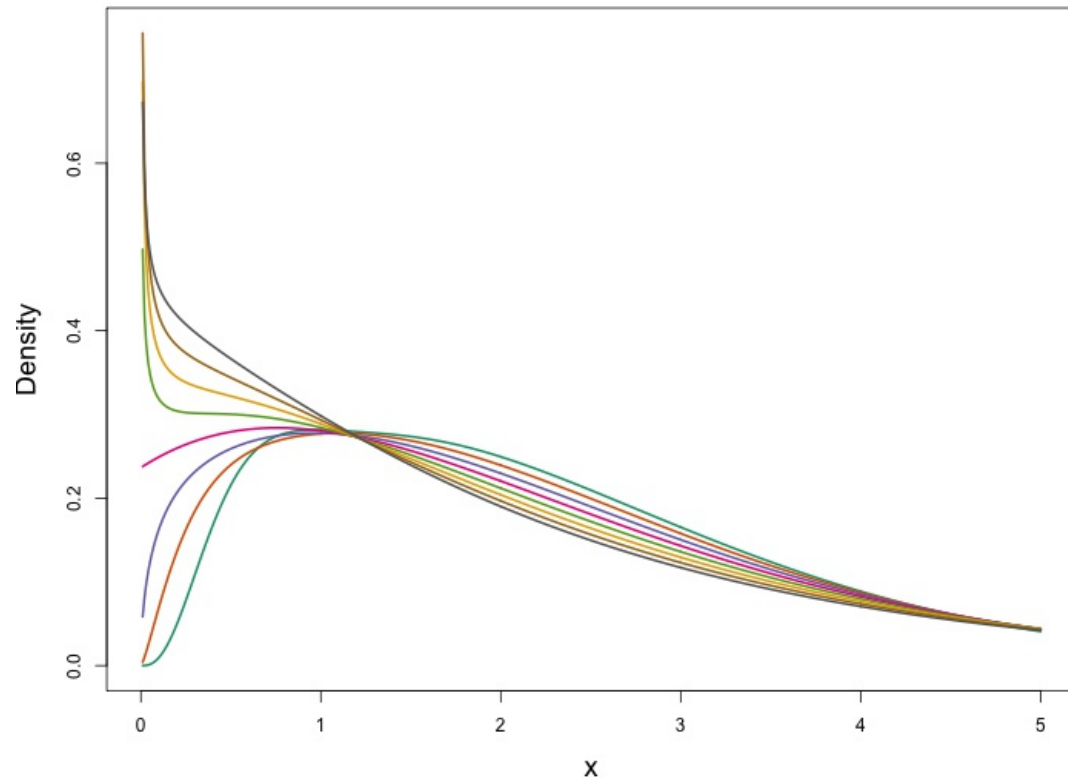


# Count distributions



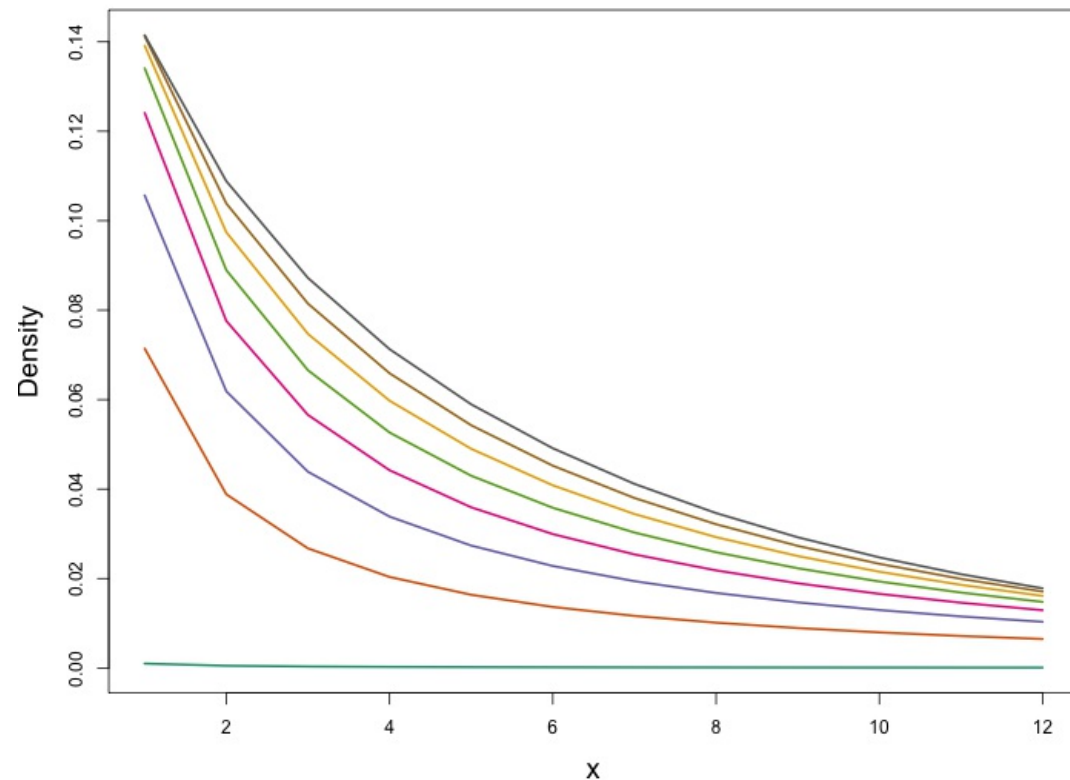
- Response is a count (not not always integer)
- Often, it's mostly zero (that's complicated)
- Want response distribution that deals with that
- Flexible mean-variance relationship

# Tweedie distribution



- $\text{Var}(\text{count}) = \varphi(\text{count})^q$
- Common distributions are sub-cases:
  - $q = 1 \Rightarrow \text{Poisson}$
  - $q = 2 \Rightarrow \text{Gamma}$
  - $q = 3 \Rightarrow \text{Normal}$
- We are interested in  $1 < q < 2$
- (here  $q = 1.2, 1.3, \dots, 1.9$ )

# Negative binomial distribution



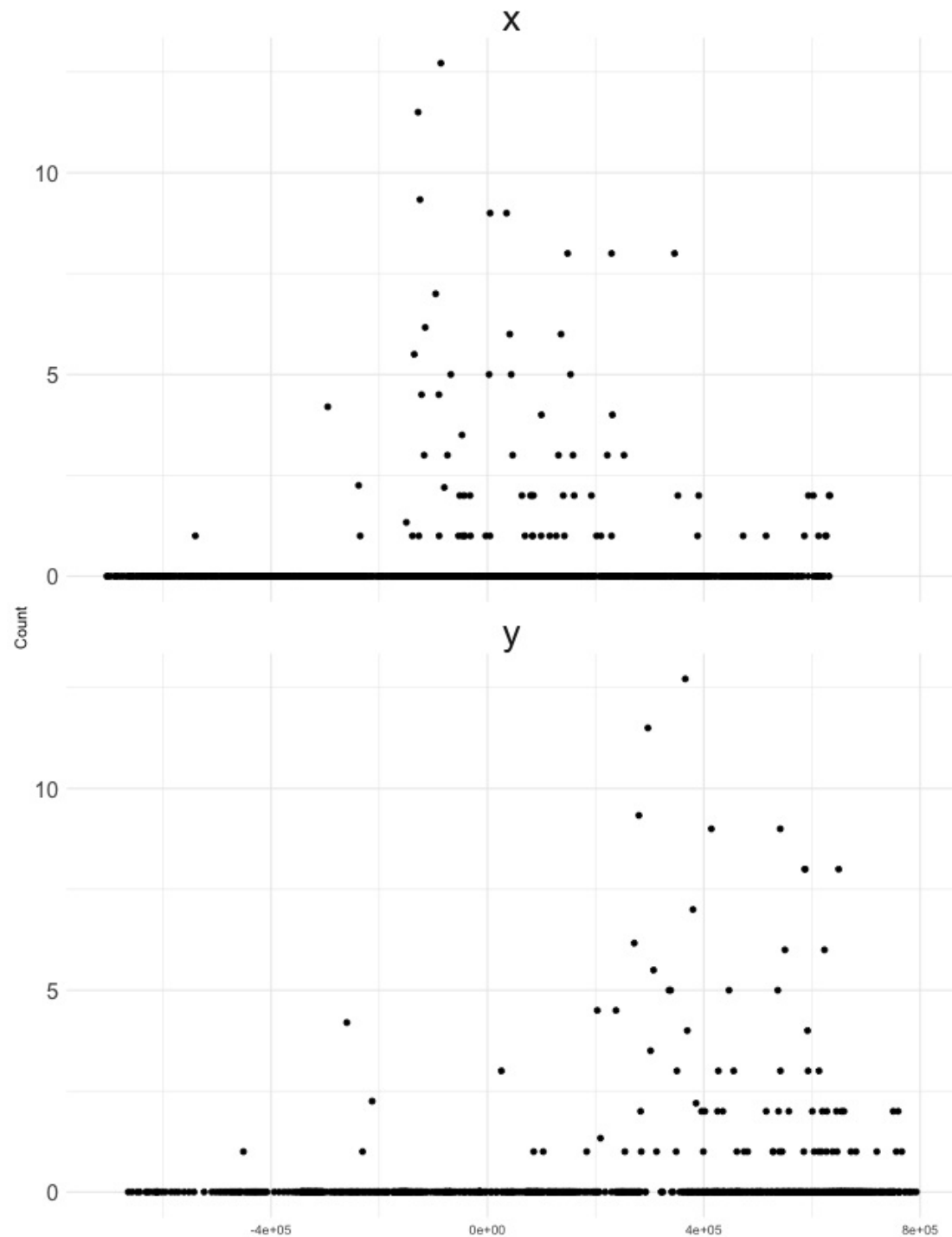
- $\text{Var}(\text{count}) = (\text{count}) + \kappa(\text{count})^2$
- Estimate  $\kappa$
- Is quadratic relationship a "strong" assumption?
- Similar to Poisson:  
 $\text{Var}(\text{count}) = (\text{count})$

# Smooth terms

$$n_j = A_j \hat{p}_j \exp [\beta_0 + s(y_j) + s(\text{Depth}_j)] + \epsilon_j$$

where  $\epsilon_j \sim N(0, \sigma^2)$ ,  $n_j \sim \text{count distribution}$

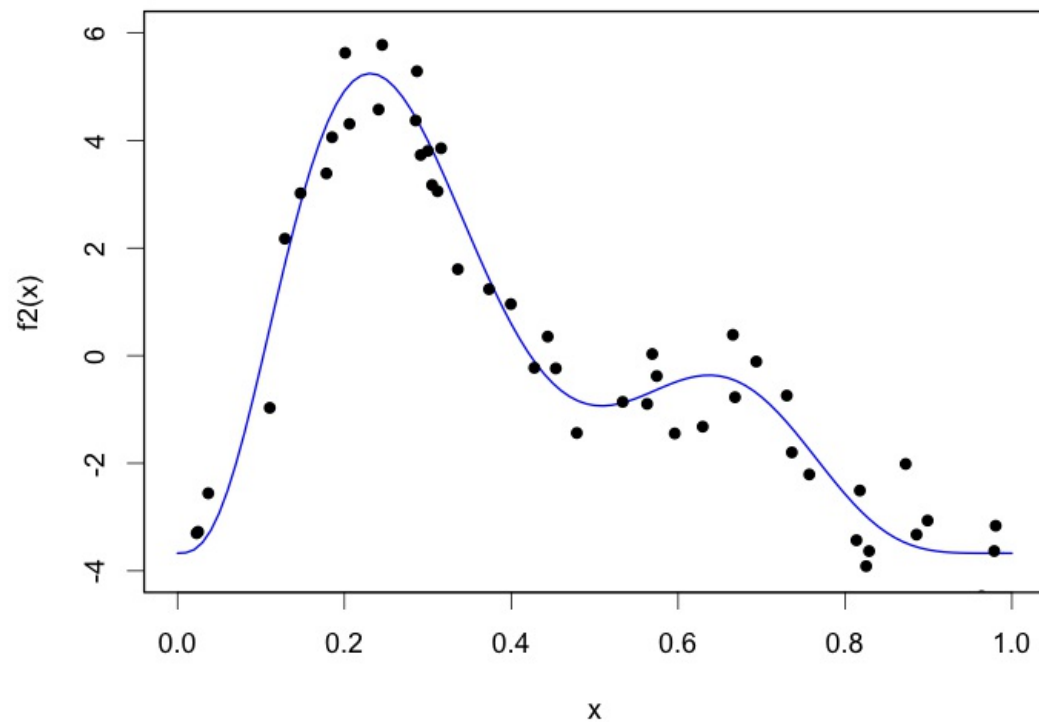
# Okay, but what about these "s" things?



- Think  $s = \text{smooth}$
- Want to model the covariates flexibly
- Covariates and response not necessarily linearly related!
- Want some wiggles

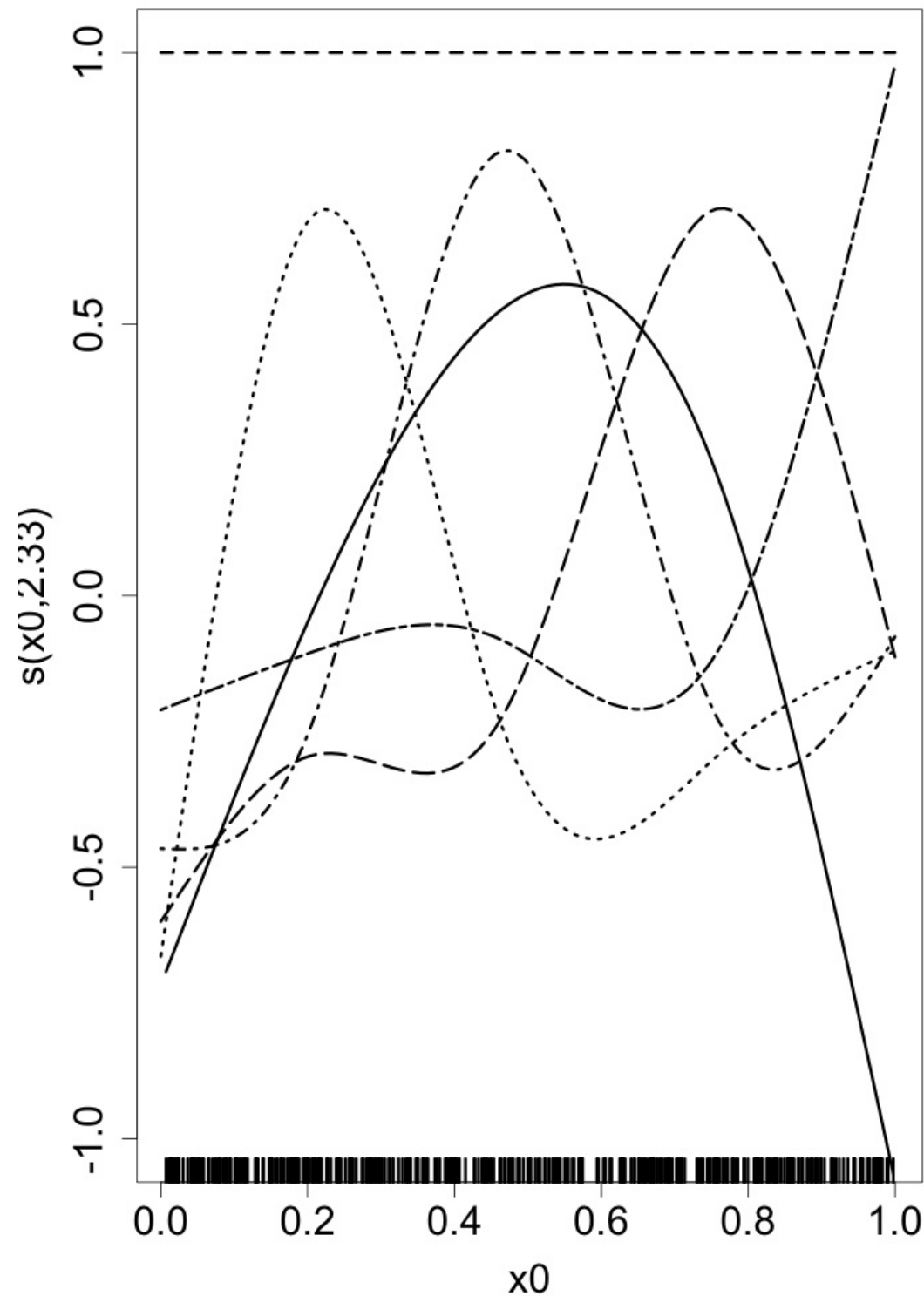
What is smoothing?

# Straight lines vs. interpolation



- Want a line that is "close" to all the data
- Don't want interpolation -- we know there is "error"
- Balance between interpolation and "fit"

# Splines



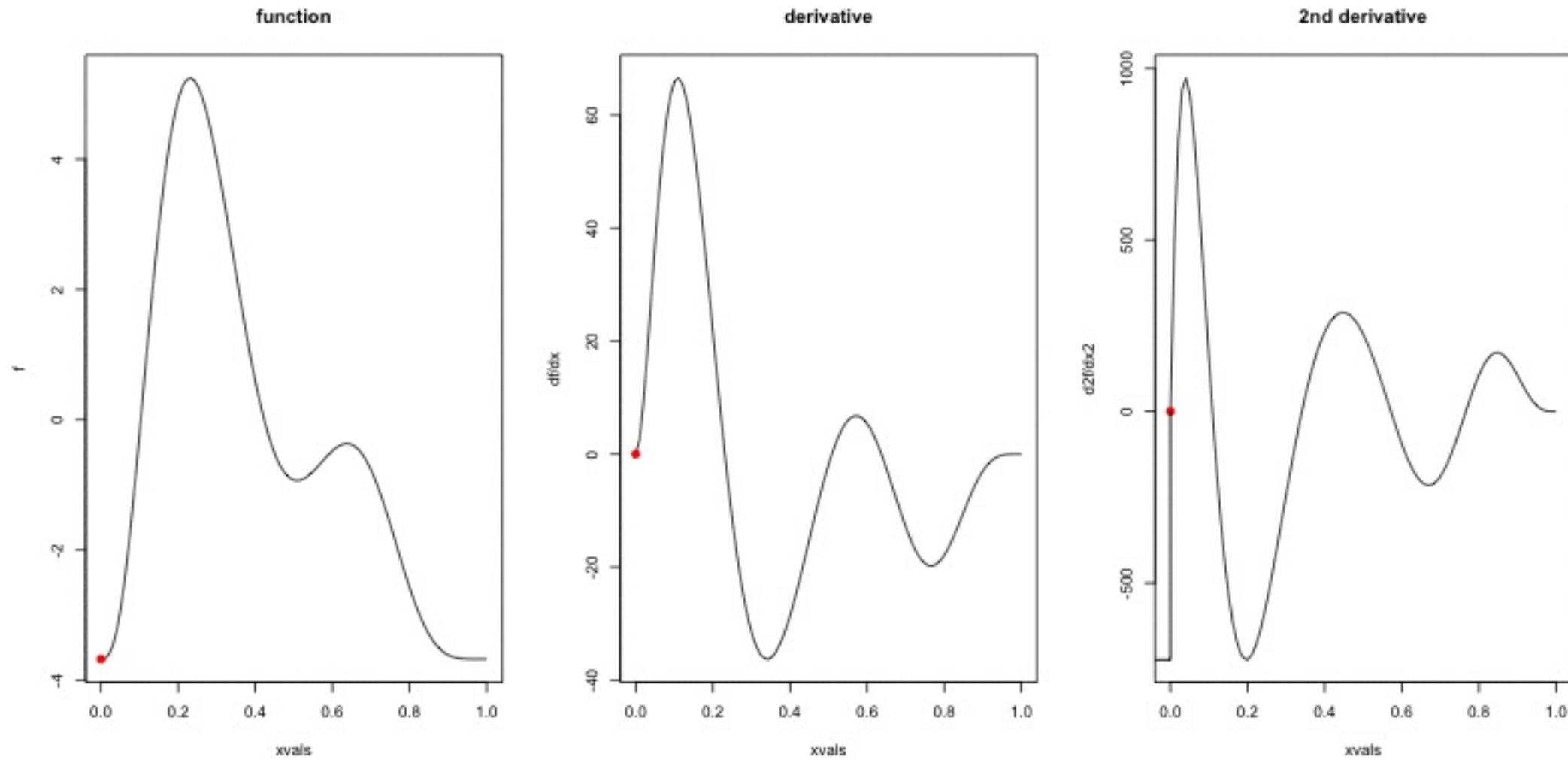
- Functions made of other, simpler functions
- **Basis functions**  $b_k$ , estimate  $\beta_k$
- $s(x) = \sum_{k=1}^K \beta_k b_k(x)$
- Makes the maths much easier



# Measuring wigglyness

- Visually:
  - Lots of wiggles == NOT SMOOTH
  - Straight line == VERY SMOOTH
- How do we do this mathematically?
  - Derivatives!
  - (Calculus        a useful class after all)

# Wigglyness by derivatives



# Making wigglyness matter

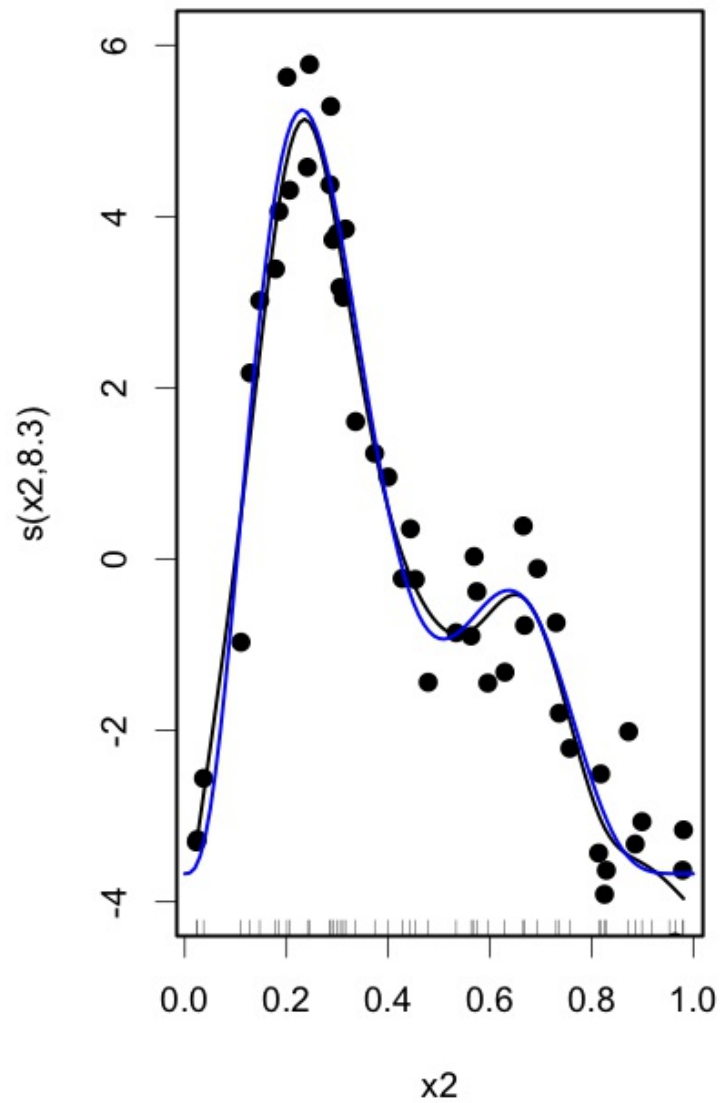
- Integration of derivative (squared) gives wigglyness
- Fit needs to be **penalised**
- **Penalty matrix** gives the wigglyness
- Estimate the  $\beta_k$  terms but penalise objective
  - "closeness to data" + penalty

# Penalty matrix

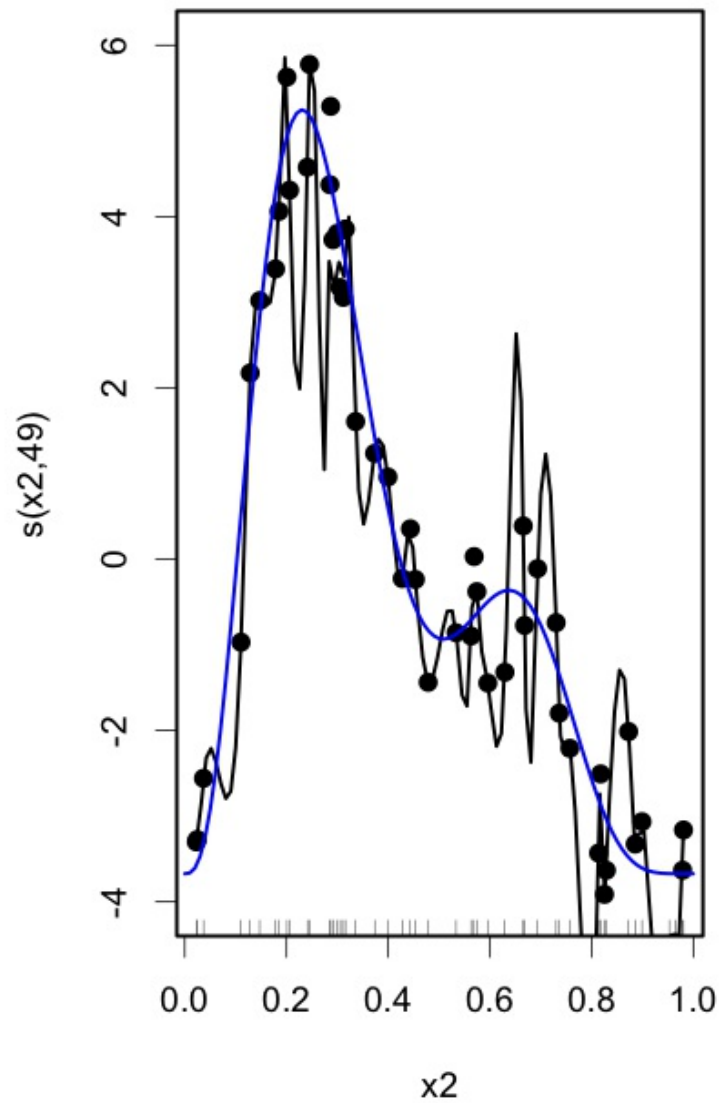
- For each  $b_k$  calculate the penalty
- Penalty is a function of  $\beta$ 
  - $\lambda \beta^T S \beta$
- $S$  ( ) calculated once
- ,  $\lambda$  dictates influence

# Smoothing parameter

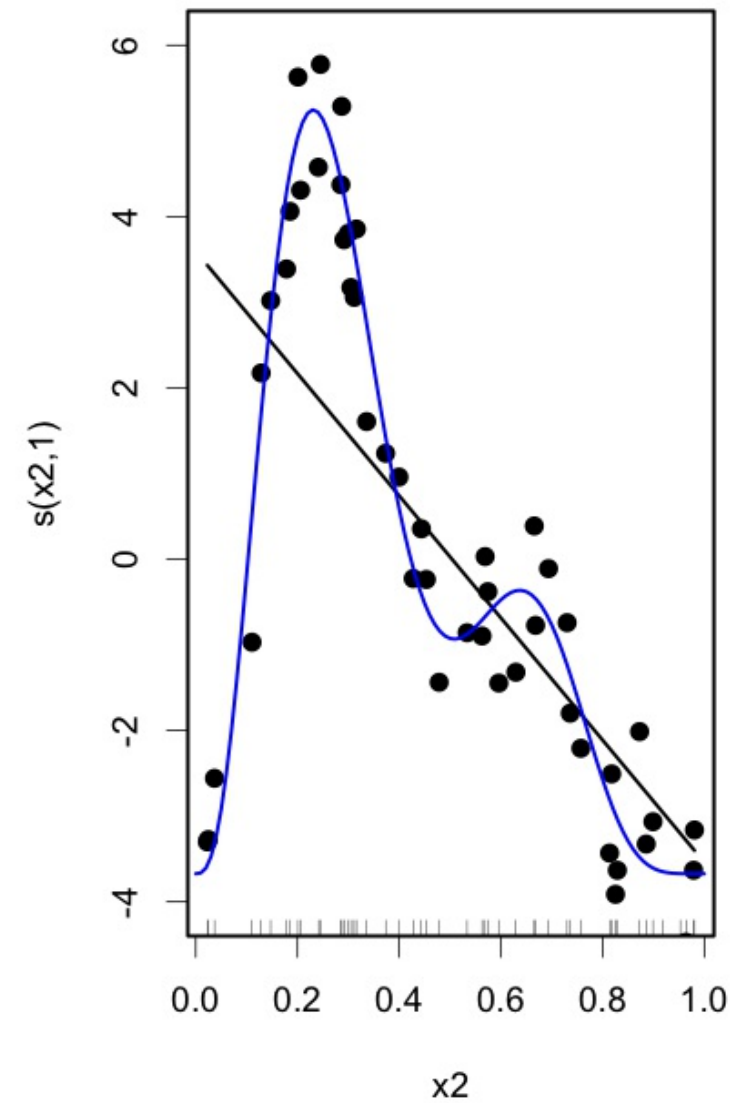
$\lambda = \text{estimated}$



$\lambda = 0$



$\lambda = \infty$



# How wiggly are things?

- We can set **basis complexity** or "size"  $k$ 
  - Maximum wigglyness
- Smoother have **effective degrees of freedom** (EDF)
- $\text{EDF} < k$
- Set  $k$  "large enough"

# Why GAMs are cool...

Okay, that was a lot of theory...



Example data

# Example data

# Example data

# Sperm whales off the US east coast

# Model formulation

- Pure spatial, pure environmental, mixed?
- May have some prior knowledge
  - Biology/ecology
- What are drivers of distribution?
- Inferential aim
  - Abundance
  - Ecology

Fitting GAMs using dsm

# Translating maths into R

$$n_j = A_j \hat{p}_j \exp[\beta_0 + s(y_j)] + \epsilon_j$$

where  $\epsilon_j \sim N(0, \sigma^2)$ ,  $n_j \sim$  count distribution

- inside the link:
- response distribution: or
- detectability:
- offset, data:

# Your first DSM

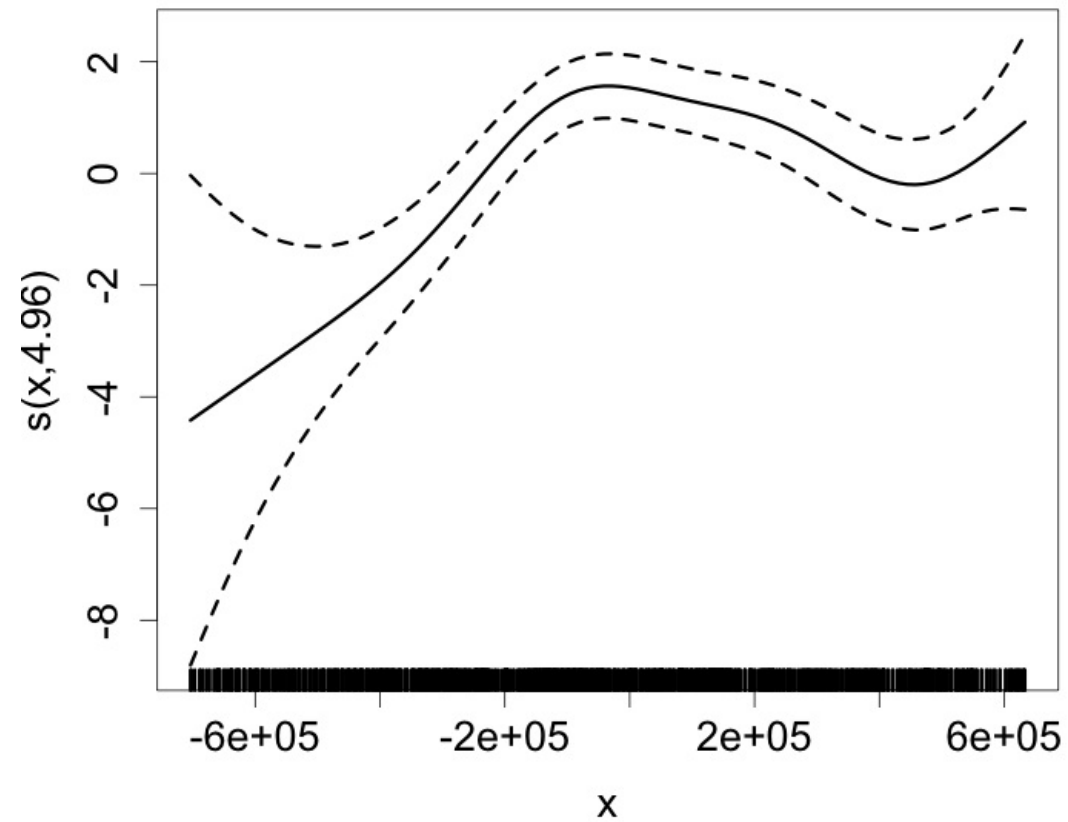
is based on by Simon Wood



# What did that do?

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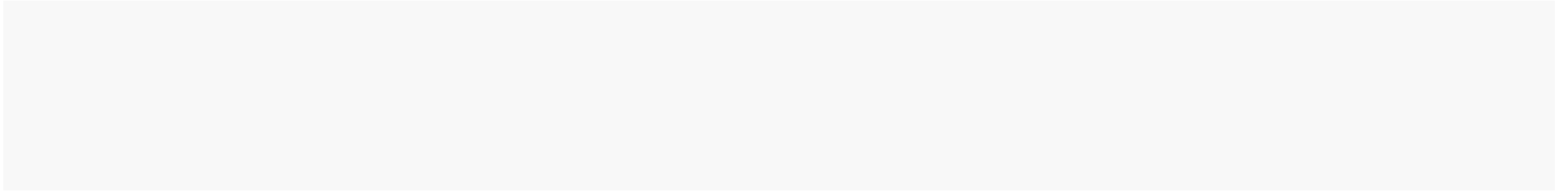
# Plotting



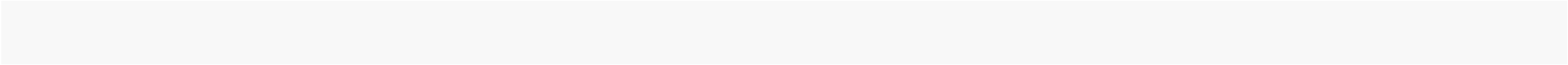
- 
- Dashed lines indicate  $\pm 2$  standard errors
- Rug plot
- On the link scale
- EDF on y axis

# Adding a term

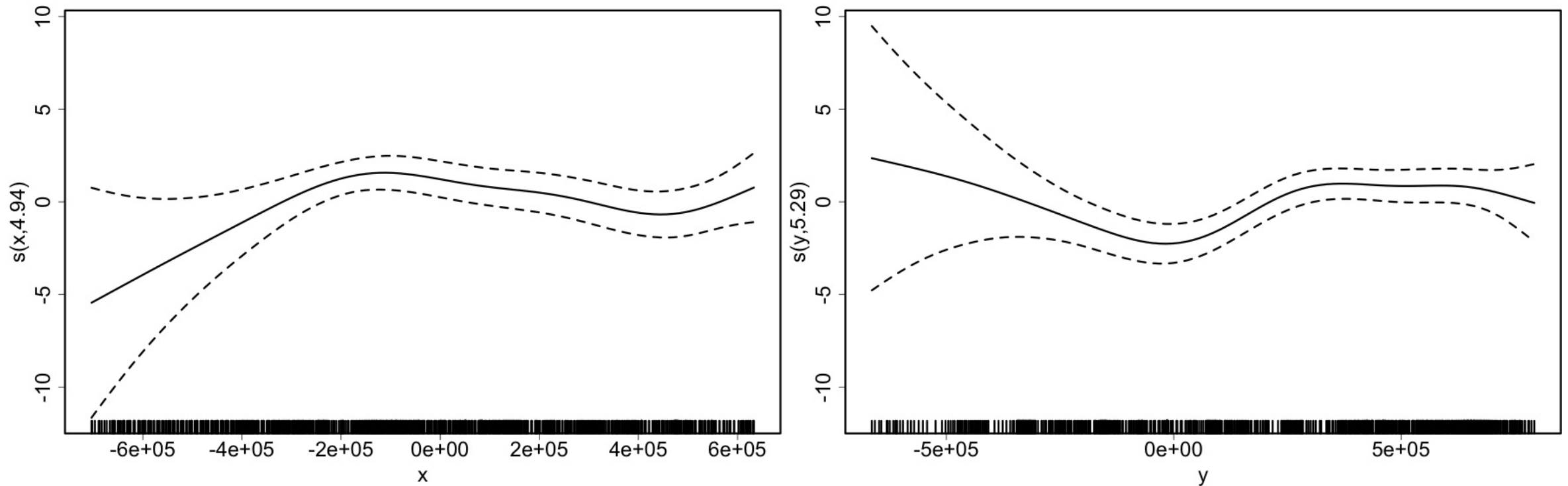
- Just use



# Summary



# Plotting



- : each plot on different scale
- : plot together

# Bivariate terms

- Assumed an additive structure
- No interaction
- We can specify (and )

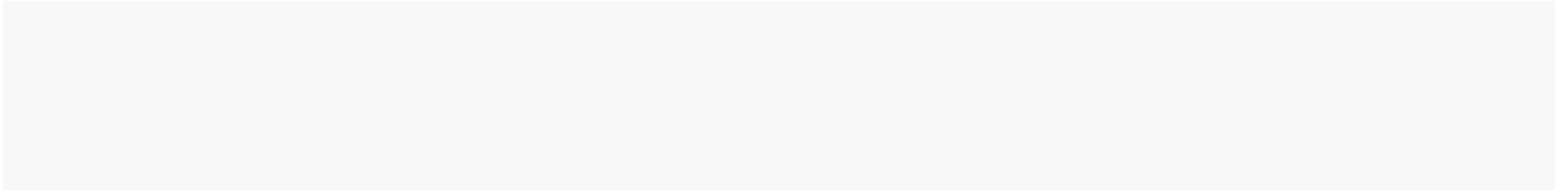
# Thin plate regression splines

- Default basis
- One basis function per data point
- Reduce # basis functions (eigendecomposition)
- Fitting on reduced problem
- Multidimensional

# Thin plate splines (2-D)



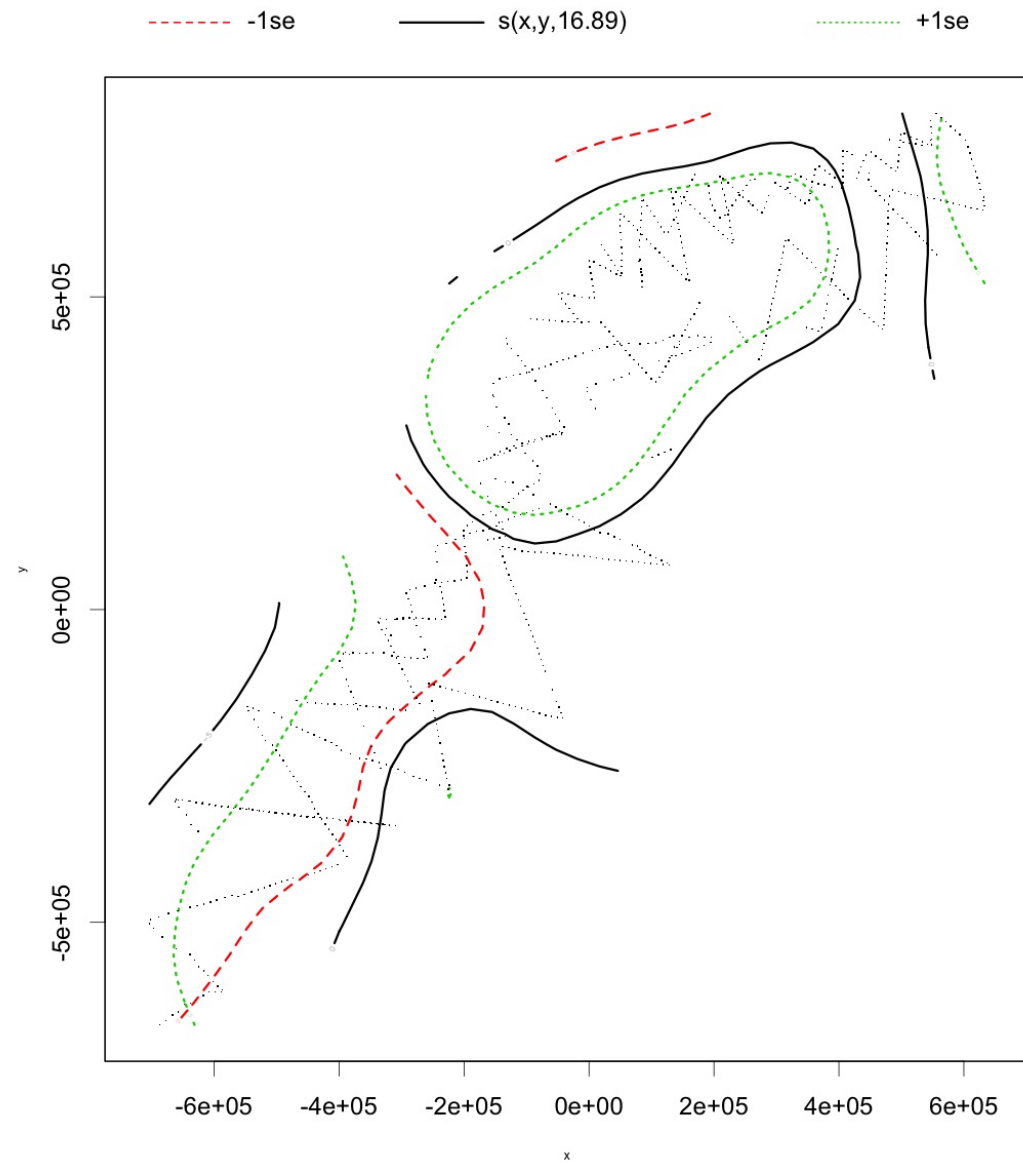
# Bivariate spatial term



# Summary

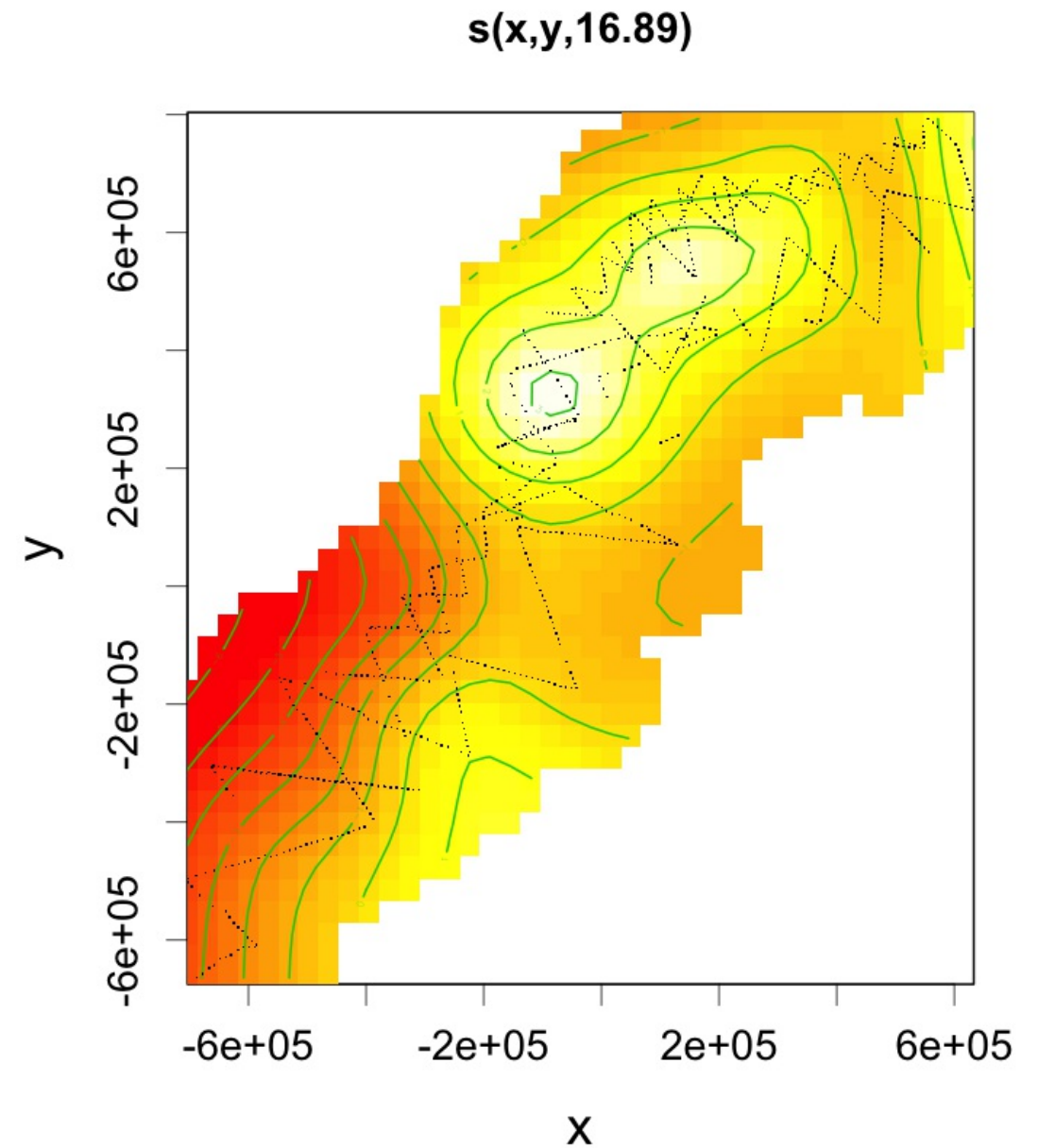


# Plotting... erm...



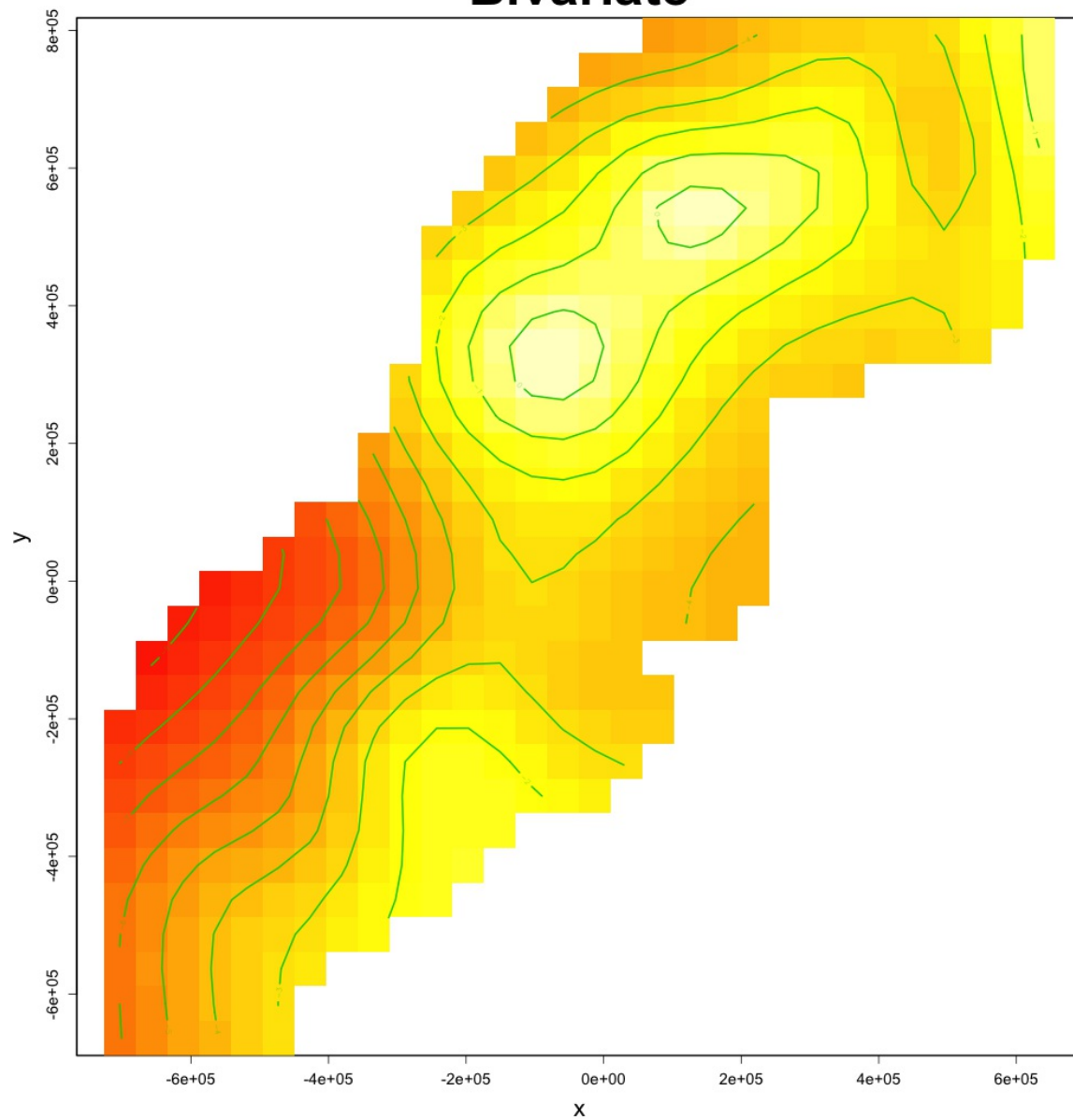
# Let's try something different

- Still on link scale
- $s(x,y,16.89)$  excludes points far from data

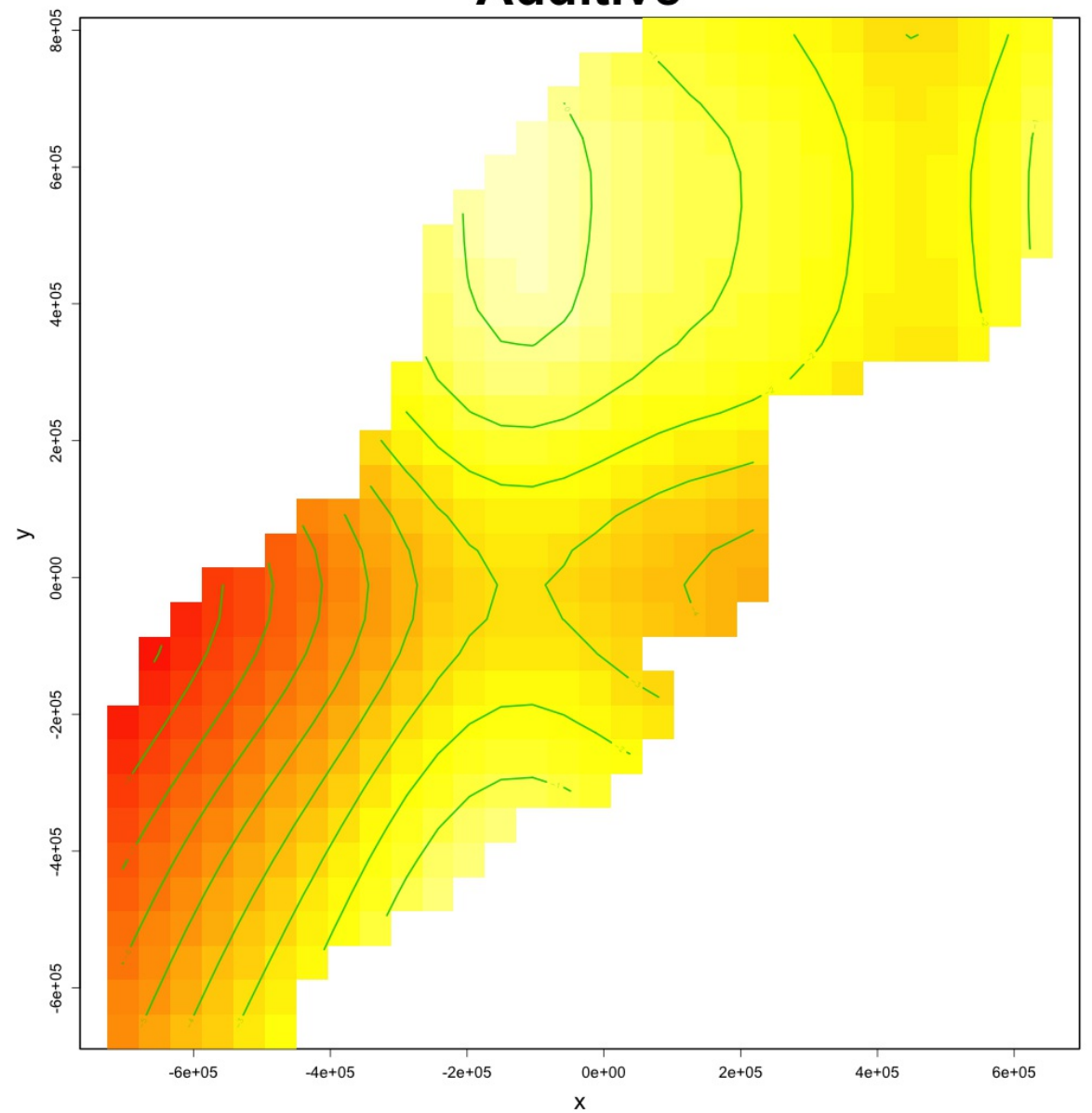


# Comparing bivariate and additive models

**Bivariate**



**Additive**



Let's have a go...