

An introduction to Generalized Linear Models (GLMs)

FW 891

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Purpose

- Introduce design matrices for linear models
- Introduce Generalized Linear Models
 - In particular, the Poisson and binomial GLMs
- Simulate fake data from these models
- Write Stan code to estimate the parameters of these models
- A fun question

Breaking statistical models down

response = deterministic component + random component

- This section / lecture is based heavily on Kery and Schaub 2012; Kery and Royle 2016

The random (noise) component

- Hallmark of statistical models: they must account for randomness
- Check out `?d $dist$` in R, and replace *dist* by any of the following: `pois`, `binom`, `norm`, `multinom`, `exp`, and `unif`
- Changing first letter `d` to `p`, `q`, or `r` allows one to get the density, the distribution function, the percentiles, and random numbers from these distributions, respectively.
 - Note R calls mass functions density functions (e.g., `dbinom()`)

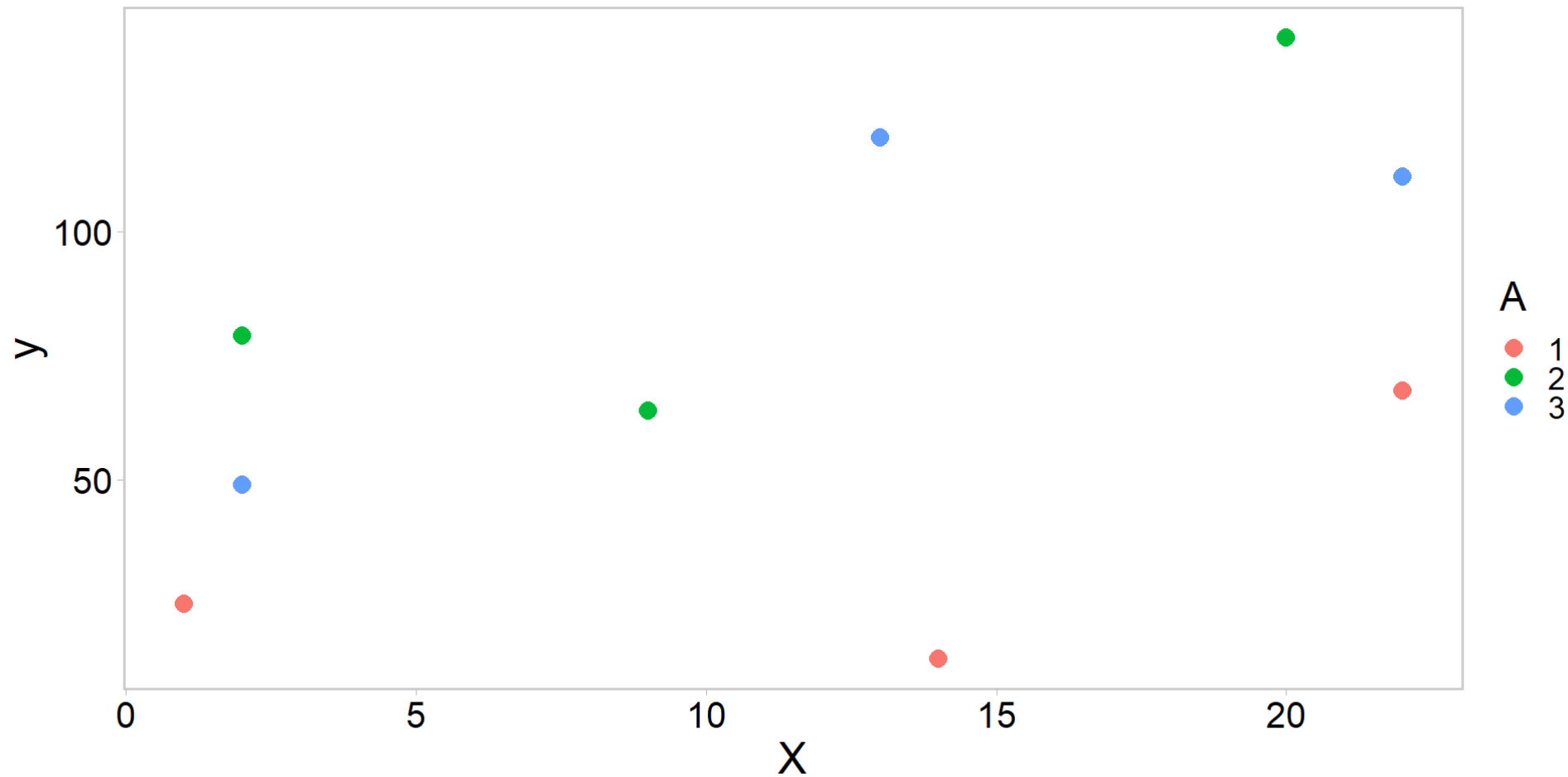
The deterministic (signal) component

- The signal component of the model contains the predictable parts of a response or the mean structure of a model
- Often the mean structure is described by a linear model, although nonlinear models can also be used (Seber and Wild 2003)
- Linear model is just one specific way to describe how we imagine our explanatory variables influencing our response
- This model is linear in the parameters and does not need to represent a straight line when plotted
- t-test, simple and multiple linear regressions, ANOVA, ANCOVA, and many mixed models are all linear models

A brief illustration of an analysis of covariance ANCOVA

```
1 library(tidyverse)
2 library(ggqfc)
3 y <- c(25, 14, 68, 79, 64, 139, 49, 119, 111) # obs
4 A <- factor(c(1, 1, 1, 2, 2, 2, 3, 3, 3)) # group
5 X <- c(1, 14, 22, 2, 9, 20, 2, 13, 22) # covariate
6 my_df <- data.frame(y, A, X)
7
8 my_df %>%
9   ggplot(aes(X, y, color = A)) +
10   geom_point(pch = 16, size = 3.5) + theme_qfc()
```

A brief illustration of an analysis of covariance ANCOVA



Running the (Frequentist) ANCOVA in R

```
1 lm(y ~ A - 1 + X)
```

Call:

```
lm(formula = y ~ A - 1 + X)
```

Coefficients:

A1	A2	A3	X
1.315	65.218	58.648	2.785

- This so-called “formula language” is clever because it is quick and error-free *if you know how to specify your model*
- What does $y \sim A - 1 + X$ actually mean?

ANCOVA maths

- When we fitted that model, we were doing the following:

$$y_i = \beta_{g(i)} + \beta_1 \cdot X_i + \varepsilon_i \quad \text{where} \quad \varepsilon_i \sim N(0, \sigma^2)$$

ANCOVA maths: one way

$$y_i = \beta_{g(i)} + \beta_1 \cdot X_i + \varepsilon_i \quad \text{where} \quad \varepsilon_i \sim N(0, \sigma^2)$$

- The random (noise) part of the model consists of the part of the response which we cannot explain using our linear combination of explanatory variables
 - Represented by residuals ε_i
 - Assume they come from a normal distribution with common variance σ^2
- How many parameters in total does this model have?

ANCOVA maths another way

Old way:

$$y_i = \beta_{g(i)} + \beta_1 \cdot X_i + \varepsilon_i \quad \text{where} \quad \varepsilon_i \sim N(0, \sigma^2)$$

Shifting the structure of the model via algebra:

$$y_i \sim N(\beta_{g(i)} + \beta_1 \cdot X_i, \sigma^2).$$

ANCOVA maths even more ways

A further possibility:

$$y_i \sim \text{N}(\mu_i, \sigma^2), \quad \text{where} \quad \mu_i = \beta_{g(i)} + \beta_1 \cdot X_i$$

- Being able to write a linear model in algebra helps code the model in Stan (or any other modeling platform)
- Also helps you understand commonalities between many common statistical tests and what `lm()` in R is doing

ANCOVA: but wait, there's more



The same model via matrix and vector notation:

$$\begin{pmatrix} 25 \\ 14 \\ 68 \\ 79 \\ 64 \\ 139 \\ 49 \\ 119 \\ 111 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 14 \\ 1 & 0 & 0 & 22 \\ 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 9 \\ 0 & 1 & 0 & 20 \\ 0 & 0 & 1 & 2 \\ 0 & 0 & 1 & 13 \\ 0 & 0 & 1 & 22 \end{pmatrix} \times \begin{pmatrix} \beta_{g=1} \\ \beta_{g=2} \\ \beta_{g=3} \\ \beta_1 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \\ \varepsilon_9 \end{pmatrix}, \text{ with } \varepsilon_i \sim N(0, \sigma^2)$$

ANCOVA: but wait, there's more



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$$\begin{pmatrix} 25 \\ 14 \\ 68 \\ 79 \\ 64 \\ 139 \\ 49 \\ 119 \\ 111 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 14 \\ 1 & 0 & 0 & 22 \\ 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 9 \\ 0 & 1 & 0 & 20 \\ 0 & 0 & 1 & 2 \\ 0 & 0 & 1 & 13 \\ 0 & 0 & 1 & 22 \end{pmatrix} \times \begin{pmatrix} \beta_{g=1} \\ \beta_{g=2} \\ \beta_{g=3} \\ \beta_1 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \\ \varepsilon_9 \end{pmatrix}, \text{ with } \varepsilon_i \sim N(0, \sigma^2)$$

A trick for learning about the design matrix in R: `model.matrix()`

```
1 # Means parameterization
2 X_ij <- model.matrix(~ A - 1 + X)
3 X_ij # rows = i, j = columns
```

```
  A1 A2 A3  X
1  1  0  0  1
2  1  0  0 14
3  1  0  0 22
4  0  1  0  2
5  0  1  0  9
6  0  1  0 20
7  0  0  1  2
8  0  0  1 13
9  0  0  1 22
attr(,"assign")
[1] 1 1 1 2
attr(,"contrasts")
attr(,"contrasts")$A
[1] "contr.treatment"
```

- see also effects or treatment contrast parameterization

`model.matrix(~ A + X)`

for more information on linear model see: Kery 2010

The ANCOVA in Stan

- The code looks very similar to the algebraic specification of this linear model
 - Note I am picking vague-ish priors but the specific priors aren't the point of this lesson

The ANCOVA.stan file

```
1 data {
2   int<lower=0> n_obs;          // number of observations = i
3   int<lower=0> n_col;          // columns of design matrix = j
4   vector[n_obs] y_obs;        // observed data
5   matrix[n_obs, n_col] X_ij;  // design matrix: model.matrix(~A-1+X)
6 }
7 parameters {
8   vector[n_col] b_j; // one parameter for each column of Xij
9   real<lower=0> sig; // sigma must be positive
10 }
11 model {
12   vector[n_obs] y_pred;        // container for mean response
13   b_j ~ normal(0,100);          // priors for b_j
14   sig ~ normal(0,100);          // prior for sig
15   y_pred = X_ij * b_j;          // linear algebra sneakery
16   y_obs ~ normal(y_pred, sig); // likelihood
17 }
```

And the corresponding R code:

```
1 library(cmdstanr)
2 mod <- cmdstan_model("week3/soln_files/ANCOVA.stan") # compile
3
4 # names in tagged list correspond to the data block in the Stan program
5 X_ij <- model.matrix(~ A - 1 + X)
6 stan_data <- list(n_obs = nrow(X_ij), n_col = ncol(X_ij),
7                  y_obs = my_df$y, X_ij = as.matrix(X_ij)
8                  )
9
10 # write a function to get starting values
11 inits <- function() {
12   list(
13     b_j = jitter(rep(0, ncol(X_ij)), amount = 0.5),
14     sig = jitter(10, 1)
15   )
16 }
17
18 fit <- mod$sample(
19   data = stan_data,
20   init = inits,
21   seed = 1, # ensure simulations are reproducible
22   chains = 4, # multiple chains
23   iter_warmup = 1000, # how long to warm up the chains
24   iter_sampling = 1000, # how many samples after warmup
25   parallel_chains = 4 # run them in parallel?
26 )
```

- Note this is all in the solution file for this week

Break

- Now we will move into Generalized Linear Models (GLM), where all of the information we just learned still applies
- Primary difference for GLMs is that they will allow us to model non-normal response variables in a manner similar to what we just did with an ANCOVA
 - Do this via a **link** function

Generalized Linear Models (GLMs)

- The GLM is a flexible generalization of linear regression, developed by Nelder and Wedderburn in 1972 while working together at the Rothamsted Experimental Station in the U.K.
- Extend the concept of linear effect of covariates to response variables for statistical distributions where something other than a normal is assumed
 - e.g., Poisson, binomial/Bernoulli, gamma, exponential, etc.
- Linear effect of covariates is expressed not for the expected response directly, but rather for a transformation of the expected response (McCullagh and Nelder 1989)
- Unifies various statistical methods, and thus fundamental to much contemporary statistical modeling

Generalized Linear Models (GLMs)

- The linear effect of covariates is expressed not for the expected response directly, but for a transformation of the expected response (Kery and Royle 2016)
 - This transformation is called a *link* function

We generally describe a GLM for a response y_i in terms of three things:

1. A random component (i.e., the likelihood)
2. A link function (i.e., a mathematical transformation)
3. Systematic component (i.e., the linear predictor)

The three parts of a GLM

1. Random component of the response: a statistical distribution f with parameter(s) θ :

$$y_i \sim f(\theta)$$

2. A link function g , which is applied to the expected response $E(y) = \mu_i$, with η_i known as the linear predictor:

$$g(E(y)) = g(\mu_i) = \eta_i$$

3. Systematic part of the response (mean structure of the model containing a linear model):

$$\eta_i = \beta_0 + \beta_1 \cdot x_i$$

We can combine elements 2 and 3 and define a GLM succinctly as:

$$y_i \sim f(\theta)$$

$$g(\mu_i) = \beta_0 + \beta_1 \cdot x_i$$

- A response y follows a distribution f with parameter(s) θ , and a transformation g of the expected response, which is modeled as a linear function of covariates
- This is how we will code them in Stan, which makes the Bayesian framework powerful for learning GLMs

Thinking about distributions

Common distributions for data

– Discrete

Name	Notation	Domain	Range
Bernoulli	$B \sim \text{Bernoulli}(p)$	$0 \leq p \leq 1$	$B \in \{0,1\}$
Binomial	$N \sim \text{Binomial}(p, n)$	$0 \leq p \leq 1$	$N \in \{0,1, \dots, n\}$
Poisson	$N \sim \text{Poisson}(\lambda)$	$\lambda > 0$	$N \in \{0,1,2, \dots\}$
Negative binomial	$N \sim \text{NegativeBinomial}(\lambda, \theta)$	$\lambda > 0$ $\theta > 0$	$N \in \{0,1,2, \dots\}$
Conway-Maxwell-Poisson	$N \sim \text{CMP}(\mu, \nu)$	$\mu > 0$ $\nu > 0$	$N \in \{0,1,2, \dots\}$

Thinking about distributions

Common distributions for data

– Continuous

Name	Notation	Domain	Range
Normal	$Y \sim \text{Normal}(\mu, \sigma^2)$	$\sigma^2 > 0$	Unrestricted
Lognormal	$Y \sim \text{Lognormal}(\mu, \sigma^2)$...which is similar to... $\log(Y) \sim \text{Normal}(\mu, \sigma^2)$	$\sigma^2 > 0$	$Y > 0$
Gamma	$Y \sim \text{Gamma}(\mu, CV)$	$\mu > 0$ $CV > 0$	$Y > 0$
Beta	$p \sim \text{Beta}(\alpha, \beta)$	$\alpha > 0, \beta > 0$	$0 < p < 1$

Justin Bois' Distribution explorer

<https://distribution-explorer.github.io/>

Thinking about link functions

Common link functions

Name	Notation	Implies that...	Range
Identify	$\lambda_i = \mathbf{x}_i\boldsymbol{\beta}$	$\lambda_i = \mathbf{x}_i\boldsymbol{\beta}$	$-\infty < \lambda_i < \infty$
Log	$\log(\lambda_i) = \mathbf{x}_i\boldsymbol{\beta}$	$\lambda_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$	$0 < \lambda_i < \infty$
Logit	$\text{logit}(\lambda_i) = \mathbf{x}_i\boldsymbol{\beta}$	$\lambda_i = \text{logistic}(\mathbf{x}_i\boldsymbol{\beta})$	$0 < \lambda_i < 1$

Why you should care part I

- GLM concept gives you considerable creative freedom in combining the three components
 - However, there are typically pairs of response distributions and link functions that go well together
 - These are called *canonical* link functions
 - Identity link for normal responses
 - Log link for Poisson responses
 - Logit link for binomial or Bernoulli responses

Why you should care part II

- Bernoulli/binomial: survival, maturity, presence/absence, data either 0 or 1
- Poisson: abundance, recruitment, unbounded counts $[0, \text{Inf}]$
- Many exciting ecological models can be viewed as coupled GLMs
- GLMs are defined for all members of statistical distributions belonging to the so-called “exponential family” (McCullagh and Nelder 1989; Dobson and Barnett 2008)
 - normal, Poisson, binomial/Bernoulli, multinomial, beta, gamma, lognormal, exponential, and Dirichlet
- Principles of linear modeling can be carried over to models other than normal linear regression 🧐

The Poisson GLM for unbounded counts

$$C_i \sim \text{Poisson}(\lambda_i)$$

$$\log(\lambda_i) = X_{i,j} \cdot \beta_j$$

- C is count of observation i , $X_{i,j}$ is a design matrix, j is number of columns, β_j is a vector of parameters
- simulate Poisson data in R:

```
1 set.seed(1)
2 rpois(n = 100, lambda = 15) # 100 deviates from lambda = 15
```

```
[1] 12 20 19 16  9 16 17 17 13 20 16 12 13 13 15 11 18 17 18 18 15  7 16 19
12
[26] 13 16 20 14 16 14  9 18 13 19 13 21 17 13 11 12  8 17 14 18 16 12 11 20
22
```

The Poisson GLM for unbounded counts

$$C_i \sim \text{Poisson}(\lambda_i)$$

$$\log(\lambda_i) = X_{i,j} \cdot \beta_j$$

- C is count of observation i , $X_{i,j}$ is a design matrix, j is number of columns, β_j is a vector of parameters
- log-probability mass of Poisson count data in R:

```
1 C_i <- c(10, 17, 18) # fake count data
2 dpois(x = C_i, lambda = 15, log = TRUE) # return log-Poisson likelihood
```

```
[1] -3.023911 -2.468220 -2.650542
```

The Poisson GLM for unbounded counts

$$C_i \sim \text{Poisson}(\lambda_i)$$

$$\log(\lambda_i) = X_{i,j} \cdot \beta_j$$

- Assumptions
 - The mean and variance of the Poisson distribution are equal
 - Almost never holds and usually requires a negative binomial or another model structure
 - Causes of over/under dispersion are complex

Testing for over- or under-dispersion: Poisson GLM

- mean = variance = λ
- Another way: Bayesian p-value
- Idea: define a test statistic and compare the posterior distribution of that statistic for the original data to the posterior distribution of that test statistic for “replicate” datasets
- Note we could also use graphical posterior predictive checks

Bayesian p-value

- Pearson residuals:

$$D(y_i, \theta) = \frac{(y_i - E(y_i))}{\sqrt{\text{Var}(y_i)}}.$$

- Begin by calculating the sum of squared residuals (our test statistic) for the observed data:

$$T(\mathbf{y}, \theta) = \sum_i D(y_i, \theta)^2$$

Bayesian p-value

- Next, we calculate the same statistic for replicate (simulated) datasets

$$T(\mathbf{y}^{\text{new}}, \theta) = \sum_i D(y_i^{\text{new}}, \theta)^2$$

- Bayesian p-value is simply the posterior probability

$$\Pr\left(T(\mathbf{y}^{\text{new}}) > T(\mathbf{y})\right)$$

- Should be close to 0.5 for a good model, too near 0 or 1 indicates lack of fit (somewhat subjective)

The binomial GLM for bounded counts or proportions

- Often have counts bounded by an upper limit
 - Number of successful breeding pairs cannot be higher than all observed breeding pairs
- Proportion of nestlings surviving
- These types of data require the binomial GLM

The binomial GLM for bounded counts or proportions

1. Random part of the response (statistical distribution)

$$C_i \sim \text{Binomial}(N_i, p_i)$$

2. Link of the random and systematic bit (logit link):

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1 - p_i}\right) = \eta_i$$

3. Systematic part (linear predictor):

The binomial GLM for bounded counts or proportions

$$C_i \sim \text{Binomial}(N_i, p_i)$$

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1 - p_i}\right) = \eta_i$$

$$\eta_i = \beta_0 + \beta_1 * X_i + \beta_2 * X_i^2$$

The binomial GLM for bounded counts or proportions

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1 - p_i}\right) = \eta_i$$

- Logit maps the probability scale (i.e., range 0 to 1) to the entire real line (i.e., $-\infty$ to ∞)
- The rest of the model (linear predictor) is up to you, your data, your questions, and your imagination

Overdispersion and underdispersion in the binomial distribution

- Note that the binomial distribution variance is equal to

$$N \cdot p \cdot (1 - p)$$

- Need to check the binomial for under and over dispersion similar to how we check for the Poisson
- See [this paper](#) for some useful logistic regression checks

In-class exercise

In-class exercise

- Let's simulate a Poisson GLM, where we model peninsular homing clam 🐚 counts as a function of year:

$$C_i \sim \text{Poisson}(\lambda_i)$$

$$\log(\lambda_i) = \beta_0 + \beta_1 \cdot \text{year}_i + \beta_2 \cdot \text{year}_i^2 + \beta_3 \cdot \text{year}_i^3$$

- Clam counts follow a cubic polynomial function of time
 - Note this equation is still linear in the predictors
- Where do we begin?

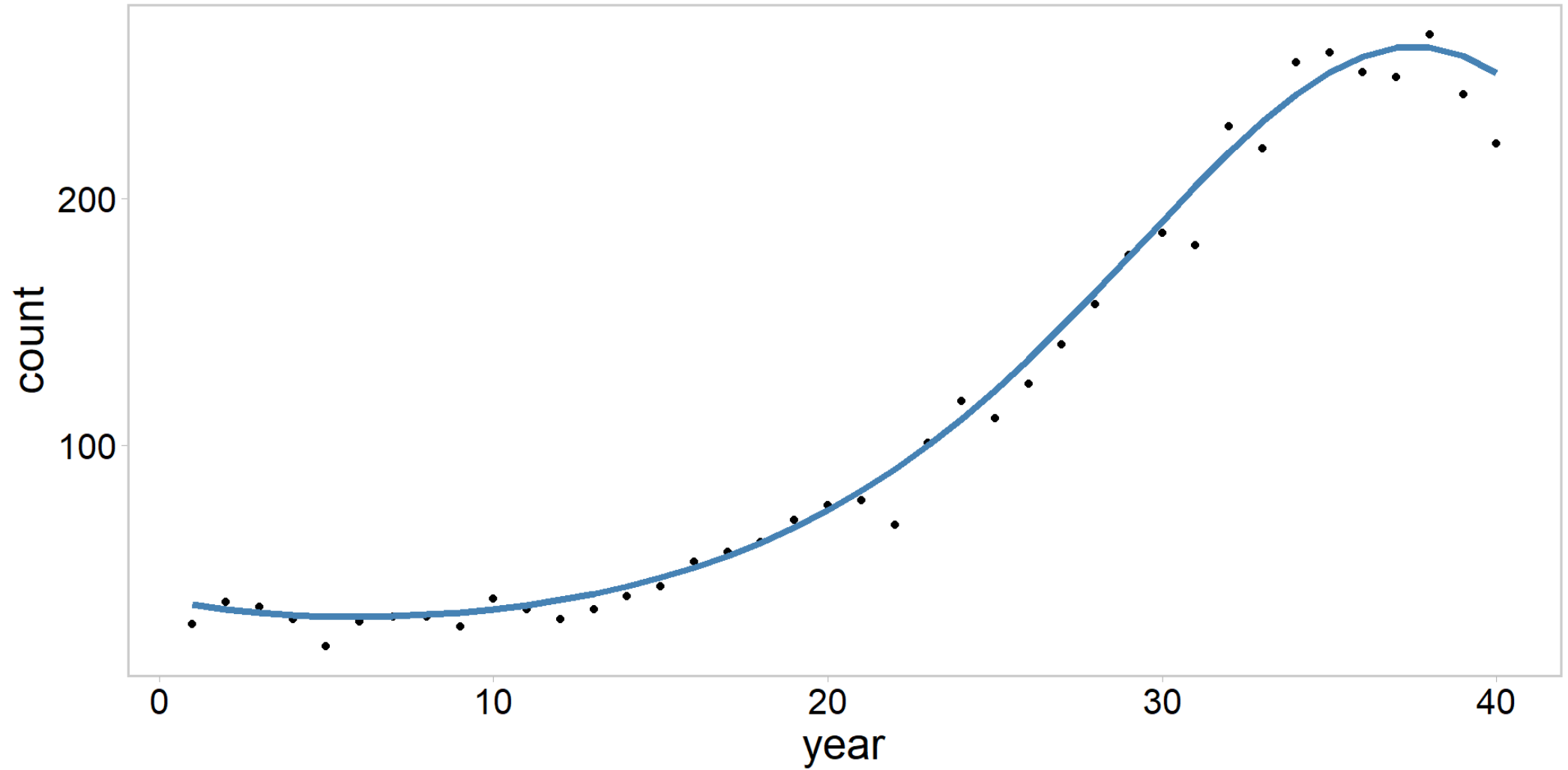
Peninsular homing clams 🦑 : simulating fake data

- Let's get it started (in here)

```
1 n_year <- 40
2 beta0 <- 3.5576
3 beta1 <- -0.0912
4 beta2 <- 0.0091
5 beta3 <- -0.00014
6 set.seed(1)
```

- Exercise: see if you can generate fake data for this model
- Start by calculating the systematic component, then apply the link function, and lastly generate random deviates according to the Poisson distribution

Homing clam simulation solution 🌞



Coding the 🍷 model in Stan

- Assume $\text{Normal}(0, 10)$ priors for everything
- Should look similar to the simulation code
- Hint: you will get a funny error message and we will work through it as a group

Writing the `clams.stan` file

```
1 data {  
2   ...  
3 }  
4 parameters {  
5   ...  
6 }  
7 transformed parameters {  
8   ...  
9 }  
10 model {  
11   ...  
12 }
```

- Work together to get this model estimating

Go to solution files

Summary and Recap

- We have covered much ground
- Statistical models as response = deterministic + random
 - ANCOVA
- Introduced GLMs, which allow us to model data coming from distributions other than the normal
- Examined Poisson and Binomial GLMs
- Talked about dispersion
- This material lays the foundation for more complicated models

References

- Gelman et al. 2015. Stan: A probabilistic programming language for Bayesian inference and optimization
- Gelman et al. 2006. Bayesian Data Analysis.
- Gelman and Hill 2007. Data analysis using regression and multilevel models
- Hilbe et al. 2017. Bayesian models for Astrophysical data
- Kery 2010. Introduction to WinBUGS for ecologists
- Kery and Royle 2016. Applied hierarchical modeling in ecology
- Kery and Schaub. 2012. Bayesian Population Analysis using WinBUGS. Chapter 3
- McCullagh and Nelder 1989. Binary data. In Generalized linear models (pp. 98-148). London: Chapman and Hall. 511 pp
- Zuur et al. 2017. Beginner's Guide to spatial, temporal, and spatial-temporal ecological data analysis with R-INLA. Highland Statistics Ltd.