

Monday, Feb 28

## Modeling Counts

**Example:** Consider the following data.

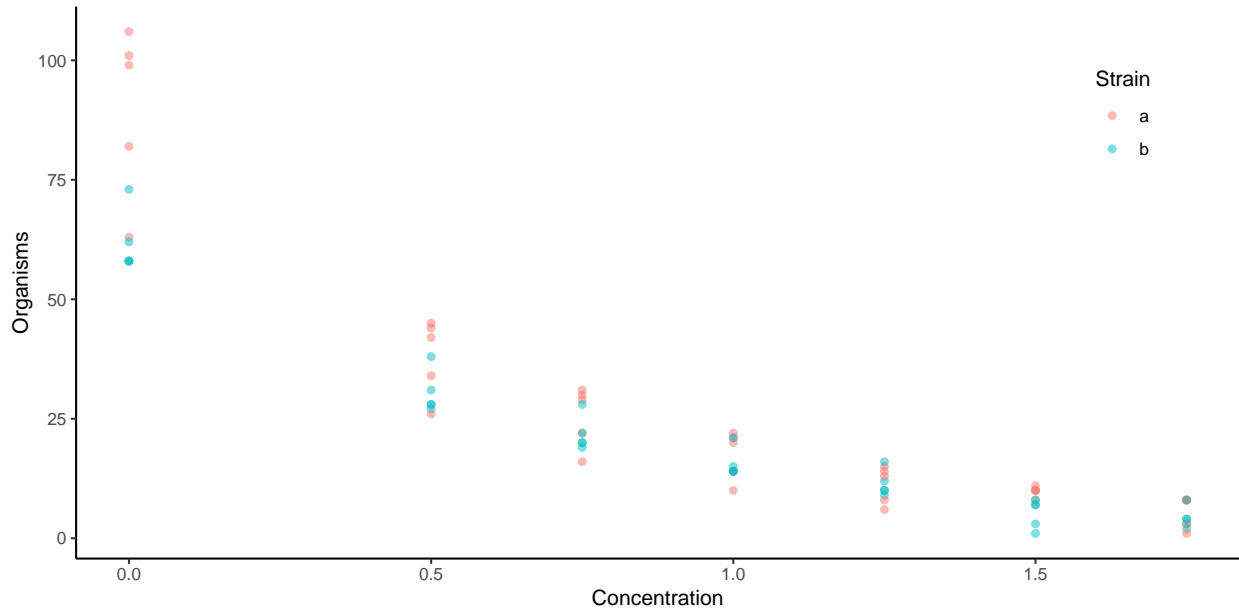
```
library(trtools) # for ceriodaphniastrain data
ceriodaphniastrain$strainf <- factor(ceriodaphniastrain$strain,
  levels = c(1,2), labels = c("a","b"))
head(ceriodaphniastrain)
```

	count	concentration	strain	strainf
1	82	0	1	a
2	58	0	2	b
3	106	0	1	a
4	58	0	2	b
5	63	0	1	a
6	62	0	2	b

```
tail(ceriodaphniastrain)
```

	count	concentration	strain	strainf
65	3	1.75	1	a
66	2	1.75	2	b
67	8	1.75	1	a
68	8	1.75	2	b
69	1	1.75	1	a
70	4	1.75	2	b

```
p <- ggplot(ceriodaphniastrain, aes(x = concentration, y = count, color = strainf)) +
  geom_point(alpha = 0.5) + theme_classic() +
  theme(legend.position = c(0.9, 0.8)) +
  labs(x = "Concentration", y = "Organisms", color = "Strain")
plot(p)
```



What are the complications when the response variable is a count?

1. Nonlinear models may be necessary because  $E(Y_i) > 0$ .
2. Heteroscedasticity because  $\text{Var}(Y_i)$  tends to increase with  $E(Y_i)$ .
3. Non-normal discrete distribution.

One solution would be to use a *nonlinear* regression model combined with some method to account for the heteroscedasticity, and we will revisit this approach, but for now we will consider instead a specialized model that assumes a *Poisson* rather than a normal distribution of  $Y_i$ .

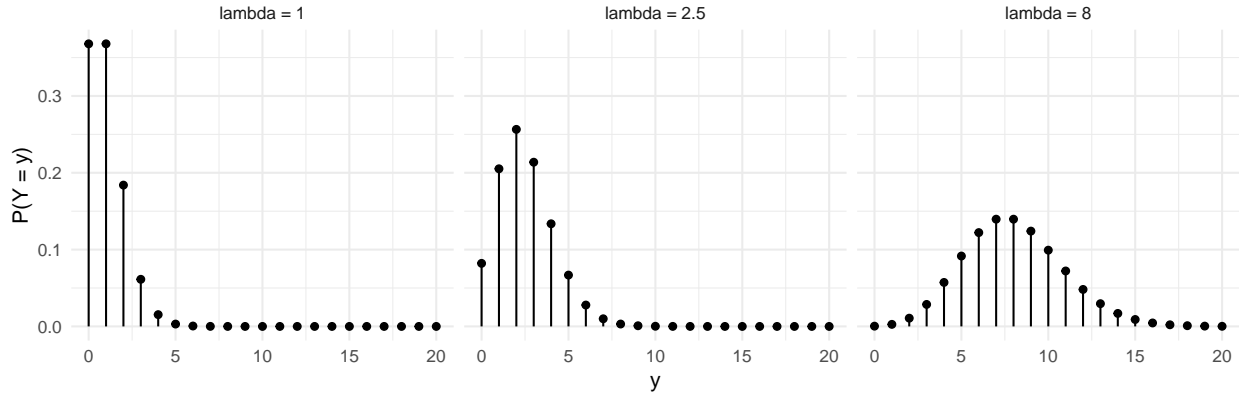
## Poisson Regression

A random variable  $Y$  has a *Poisson distribution* if

$$P(Y = y) = \frac{\lambda^y e^{-\lambda}}{y!},$$

where  $y$  is a non-negative integer (i.e.,  $y = 0, 1, 2, \dots$ ) and  $\lambda > 0$  is the parameter of the distribution. Also note that  $y!$  is the *factorial* of  $y$ , defined as  $y! = y \times (y - 1) \times (y - 2) \times \dots \times 2 \times 1$  and  $0! = 1$ .

It can be shown that if  $Y$  has a Poisson distribution then  $E(Y) = \lambda$  and  $\text{Var}(Y) = \lambda$ . The parameter  $\lambda$  is sometimes called a “rate” parameter.



A regression model can be specified for a response variable with a Poisson distribution by assuming that

$$P(Y_i = y) = \frac{\lambda_i^y e^{-\lambda_i}}{y!}$$

where  $\lambda_i$  is a function of  $x_{i1}, x_{i2}, \dots, x_{ik}$ . Since  $\lambda_i > 0$  we might use

$$\lambda_i = \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik}).$$

This implies the *nonlinear* regression model

$$E(Y_i) = \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik}),$$

which can also be written as

$$\log E(Y_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik}.$$

This kind of model is sometimes called a *log-linear* model. And because  $\text{Var}(Y_i) = E(Y_i)$  the model assumes a certain pattern of heteroscedasticity. This kind of regression model is called a *Poisson regression* model.

## Generalized Linear Models

Poisson regression is a member of a family of models known as *generalized linear models* (GLM). A generalized linear model has the form

$$g[E(Y_i)] = \underbrace{\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik}}_{\eta_i}$$

where  $g$  is the *link function* and  $\eta_i$  is the *linear predictor* or *systematic component*. The link function is invertible so that we can also write

$$E(Y_i) = g^{-1}(\underbrace{\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik}}_{\eta_i}) = g^{-1}(\eta_i).$$

**Example:** A linear regression model can be written as

$$E(Y_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik},$$

which implies that the link function is the “identity” function  $g(u) = u$ , and thus so is the inverse link function  $g^{-1}(v) = v$ .

**Example:** A Poisson regression model can be written as

$$\log E(Y_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik},$$

so the link function is  $g(u) = \log(u)$ , and the inverse link function is the exponential function  $g^{-1}(v) = \exp(v)$ , also written as  $e^v$ .

In a GLM the variance of  $Y_i$  is

$$\text{Var}(Y_i) = \phi V[E(Y_i)]$$

where  $\phi$  is a *dispersion parameter* and  $V$  is the *variance function*. That is, the variance of  $Y_i$  is proportional to some function of  $E(Y_i)$ .

**Example:** Linear models typically assume homoscedasticity meaning that  $\text{Var}(Y_i) = \sigma^2$  is a constant. Here the dispersion parameter is  $\phi = \sigma^2$ , and the variance function is just  $V[E(Y_i)] = 1$ .

**Example:** In Poisson regression we have that  $\text{Var}(Y_i) = E(Y_i)$ . Here the dispersion parameter is  $\phi = 1$ , and the variance function is the identity function  $V[E(Y_i)] = E(Y_i)$ .

We can write a GLM concisely as

$$E(Y_i) = g^{-1}(\eta_i), \tag{1}$$

$$\text{Var}(Y_i) = \phi V[g^{-1}(\eta_i)], \tag{2}$$

where again

$$\eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik},$$

to define the *mean structure* and a *variance structure* for  $Y_i$ , respectively. In general, specification of a GLM involves specifying three component parts:

1. The *linear predictor*  $\eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik}$ .
2. The *link function*  $g$  to relate  $E(Y_i)$  to  $\eta_i$  as  $g[E(Y_i)] = \eta_i$ .
3. The *distribution* of  $Y_i$ , or the *variance structure*  $\phi V[g^{-1}(\eta_i)]$ .

The choice of distribution implies a certain variance structure when using `glm`. The distribution comes from a family of distributions known as the *exponential family* (not to be confused with what is called an *exponential distribution*).

**Example:** Normal linear regression is a GLM where  $g(u) = u$ ,  $g^{-1}(v) = v$ ,  $\phi = \sigma^2$ , and  $V(u) = 1$  so that

$$E(Y_i) = \eta_i, \tag{3}$$

$$\text{Var}(Y_i) = \sigma^2. \tag{4}$$

**Example:** Poisson regression is a GLM where  $g(u) = \log(u)$ ,  $g^{-1}(v) = e^v$ ,  $\phi = 1$ , and  $V(u) = u$  so that

$$\log[E(Y_i)] = \eta_i, \tag{5}$$

$$\text{Var}(Y_i) = \exp(\eta_i). \tag{6}$$

In R the function `glm` can be used to specify a generalized linear model.

**Example:** Recall the model for the `whiteside` data.

```
library(MASS)
m <- lm(Gas ~ Insul + Temp + Insul:Temp, data = whiteside)
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	6.8538	0.13596	50.409	7.997e-46
InsulAfter	-2.1300	0.18009	-11.827	2.316e-16
Temp	-0.3932	0.02249	-17.487	1.976e-23
InsulAfter:Temp	0.1153	0.03211	3.591	7.307e-04

```
m <- glm(Gas ~ Insul + Temp + Insul:Temp, data = whiteside,
  family = gaussian(link = identity))
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	6.8538	0.13596	50.409	7.997e-46
InsulAfter	-2.1300	0.18009	-11.827	2.316e-16
Temp	-0.3932	0.02249	-17.487	1.976e-23
InsulAfter:Temp	0.1153	0.03211	3.591	7.307e-04

Note that we do not explicitly state the variance structure (although we could — more on that later). Here the variance structure is implied by the choice of distribution.

**Example:** Now consider the following Poisson regression model for the `ceriodaphniastrain` data.

```
m <- glm(count ~ concentration + strainfb, data = ceriodaphniastrain,
  family = poisson(link = log))
summary(m)$coefficients
```

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	4.455	0.03914	113.819	0.000e+00
concentration	-1.543	0.04660	-33.111	2.057e-240
strainfb	-0.275	0.04837	-5.684	1.313e-08

This model can be written as

$$E(Y_i) = \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2}),$$

or

$$\log E(Y_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2}$$

where  $x_{i1}$  is the concentration for the  $i$ -th observation, and  $x_{i2}$  is an indicator variable for strain such that

$$x_{i2} = \begin{cases} 1, & \text{if the strain is b,} \\ 0, & \text{otherwise,} \end{cases}$$

so that the model can be written case-wise as

$$\log E(Y_i) = \begin{cases} \beta_0 + \beta_1 c_i, & \text{if the strain is a,} \\ \beta_0 + \beta_2 + \beta_1 c_i, & \text{if the strain is b,} \end{cases}$$

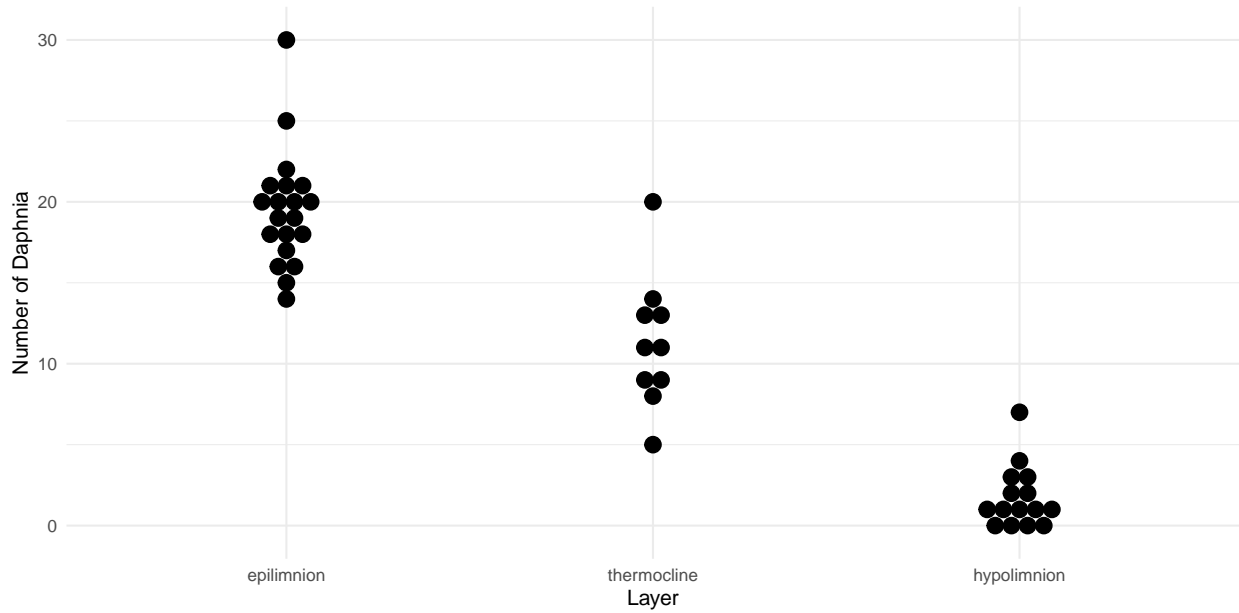
or

$$E(Y_i) = \begin{cases} \exp(\beta_0 + \beta_1 c_i), & \text{if the strain is a,} \\ \exp(\beta_0 + \beta_2 + \beta_1 c_i), & \text{if the strain is b,} \end{cases}$$

if we let  $c_i = x_{i1}$  denote the concentration for the  $i$ -th observation. Also note that because  $Y_i$  is assumed to have a Poisson distribution,  $\text{Var}(Y_i) = E(Y_i)$ .

**Example:** Recall the daphnia survey.

```
library(trtools) # for daphniastrat
library(ggplot2)
p <- ggplot(daphniastrat, aes(x = layer, y = count)) +
  geom_dotplot(binaxis = "y", binwidth = 1, stackdir = "center") +
  labs(x = "Layer", y = "Number of Daphnia") + theme_minimal()
plot(p)
```



A Poisson regression model for these data might be specified as follows.

```
m <- glm(count ~ layer, family = poisson(link = log), data = daphniastrat)
summary(m)$coefficients
```

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	2.9704	0.05064	58.661	0.000e+00
layerthermocline	-0.5456	0.10683	-5.107	3.272e-07
layerhypolimnion	-2.4204	0.20255	-11.950	6.519e-33

So the model is  $\log E(Y_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2}$ , where  $Y_i$  is the  $i$ -th count, and  $x_{i1}$  and  $x_{i2}$  are defined as

$$x_{i1} = \begin{cases} 1, & \text{if the } i\text{-th observation is from the thermocline layer,} \\ 0, & \text{otherwise,} \end{cases}$$

and

$$x_{i2} = \begin{cases} 1, & \text{if the } i\text{-th observation is from the hypolimnion layer,} \\ 0, & \text{otherwise.} \end{cases}$$

So the model can be written case-wise as

$$\log E(Y_i) = \begin{cases} \beta_0, & \text{if the } i\text{-th observation is from the epilimnion layer,} \\ \beta_0 + \beta_1, & \text{if the } i\text{-th observation is from the thermocline layer,} \\ \beta_0 + \beta_2, & \text{if the } i\text{-th observation is from the hypolimnion layer,} \end{cases}$$

or

$$E(Y_i) = \begin{cases} \exp(\beta_0), & \text{if the } i\text{-th observation is from the epilimnion layer,} \\ \exp(\beta_0 + \beta_1), & \text{if the } i\text{-th observation is from the thermocline layer,} \\ \exp(\beta_0 + \beta_2), & \text{if the } i\text{-th observation is from the hypolimnion layer.} \end{cases}$$

And of course we have that  $\text{Var}(Y_i) = E(Y_i)$ .

## Visualization of a GLM

Visualization of a GLM be done in the usual way provided we use the `type = response` option when using `predict`. The default, which is `type = link`, returns  $\hat{\eta}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \dots + \hat{\beta}_k x_{ik}$  which is the estimate of  $\log E(Y_i)$ .

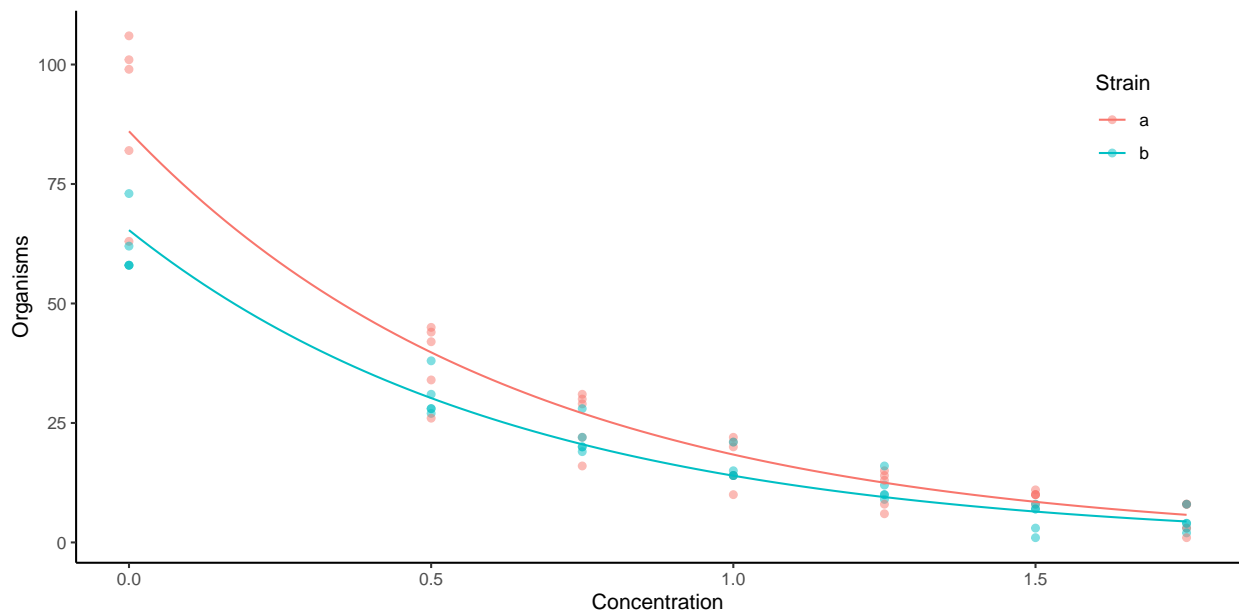
```

m <- glm(count ~ concentration + strainf, data = ceriodaphniastrain,
  family = poisson(link = log))

d <- expand.grid(concentration = seq(0, 1.75, length = 100), strainf = c("a","b"))
d$yhat <- predict(m, newdata = d, type = "response")

p <- ggplot(ceriodaphniastrain, aes(x = concentration, y = count, color = strainf)) +
  geom_point(alpha = 0.5) + theme_classic() + geom_line(aes(y = yhat), data = d) +
  theme(legend.position = c(0.9, 0.8)) +
  labs(x = "Concentration", y = "Organisms", color = "Strain")
plot(p)

```



To compute confidence intervals for the expected response you can use the `glmint` function from the `trtools` package.

```

d <- expand.grid(concentration = seq(0, 1.75, length = 100), strainf = c("a","b"))
d <- cbind(d, glmint(m, newdata = d))
head(d)

```

	concentration	strainf	fit	low	upp
1	0.00000	a	86.03	79.67	92.88
2	0.01768	a	83.71	77.60	90.30
3	0.03535	a	81.46	75.58	87.79
4	0.05303	a	79.27	73.61	85.35
5	0.07071	a	77.13	71.69	82.99
6	0.08838	a	75.06	69.82	80.68

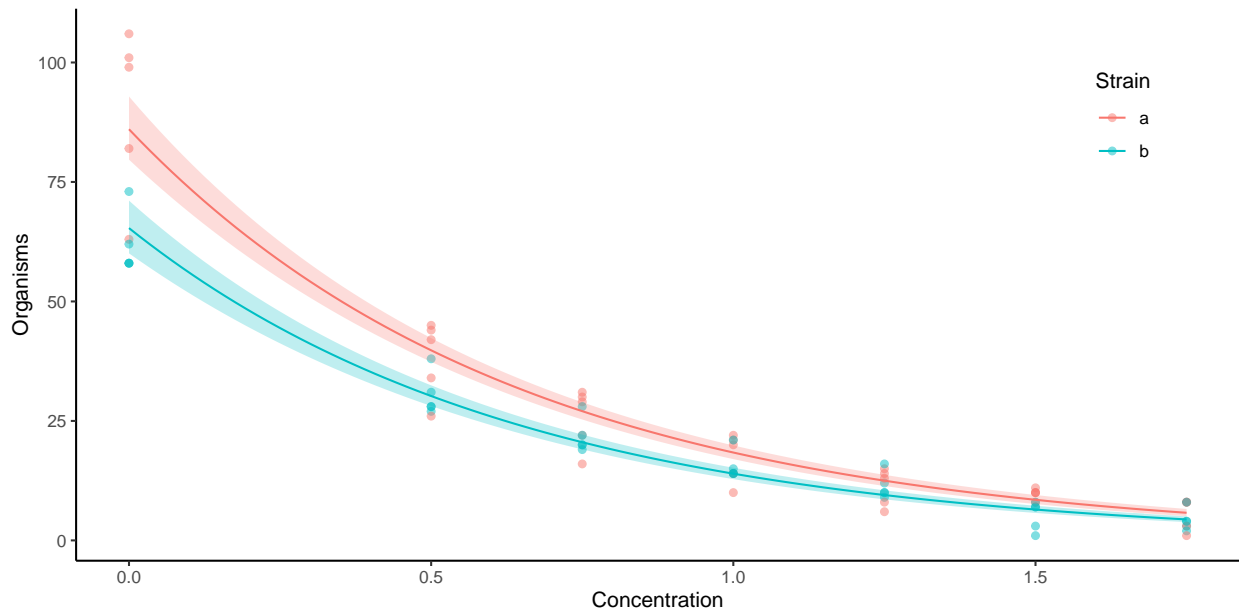
```

p <- ggplot(ceriodaphniastrain, aes(x = concentration, y = count, color = strainf)) +
  geom_point(alpha = 0.5) + theme_classic() +
  geom_line(aes(y = fit), data = d) +
  geom_ribbon(aes(ymin = low, ymax = upp, y = NULL, fill = strainf),
    color = NA, alpha = 0.25, data = d) +
  theme(legend.position = c(0.9, 0.8)) + guides(fill = FALSE) +
  labs(x = "Concentration", y = "Organisms", color = "Strain")

```

Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> = "none")` instead.

```
plot(p)
```



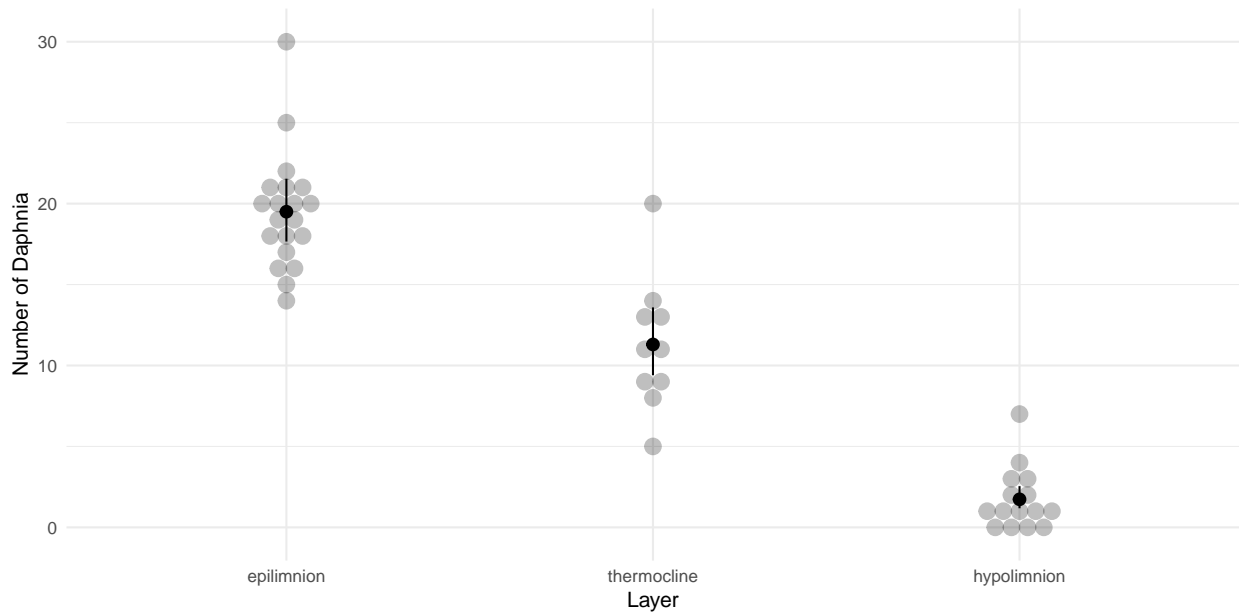
We might visualize the model for the `daphniastrat` data as follows.

```
m <- glm(count ~ layer, family = poisson(link = log), data = daphniastrat)

d <- data.frame(layer = unique(daphniastrat$layer))
d <- cbind(d, glmint(m, newdata = d))

p <- ggplot(daphniastrat, aes(x = layer, y = count)) +
  geom_dotplot(binaxis = "y", binwidth = 1, stackdir = "center", alpha = 0.25) +
  labs(x = "Layer", y = "Number of Daphnia") +
  theme_minimal() + geom_pointrange(aes(y = fit, ymin = low, ymax = upp), data = d)
plot(p)
```





## GLMs Versus Nonlinear Regression

There is a very close relationship between a GLM and a nonlinear regression model. We can try to estimate the model above using `nlm` as follows, using the estimates as starting values for convenience.

```
m <- nls(count ~ exp(b0 + b1 * concentration + b2 * (strainf == "b")),
  data = ceriodaphniastrain, start = list(b0 = 7, b1 = -2, b2 = 0.12))
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t )
b0	4.4821	0.02894	154.86	2.486e-87
b1	-1.5679	0.06232	-25.16	7.441e-36
b2	-0.3267	0.04506	-7.25	5.402e-10

The estimates are not the same. But consider that the GLM assumes that

$$\text{Var}(Y_i) = E(Y_i),$$

so our weights should be  $w_i = 1/E(Y_i)$ . Consider then an iteratively weighted least squares algorithm with  $w_i = 1/\hat{y}_i$ .

```
ceriodaphniastrain$w <- 1
for (i in 1:10) {
  m <- nls(count ~ exp(b0 + b1 * concentration + b2 * (strainf == "b")),
    data = ceriodaphniastrain, start = list(b0 = 7, b1 = -2, b2 = 0.12),
    weights = w)
  ceriodaphniastrain$w <- 1 / predict(m, type = "response")
}
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t )
b0	4.455	0.04272	104.273	7.167e-76
b1	-1.543	0.05087	-30.334	7.309e-41
b2	-0.275	0.05280	-5.208	1.988e-06

Compare that with what we obtained using `glm`.

```
m <- glm(count ~ concentration + strainf, data = ceriodaphniastrain,
  family = poisson(link = log))
summary(m)$coefficients
```

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	4.455	0.03914	113.819	0.000e+00
concentration	-1.543	0.04660	-33.111	2.057e-240
strainfb	-0.275	0.04837	-5.684	1.313e-08

The parameter estimates are the same, but the standard errors are not. Why? The GLM assumes  $\text{Var}(Y_i) = E(Y_i)$  whereas the iteratively weighted least squares approach assumes  $\text{Var}(Y_i) \propto E(Y_i)$ .

## GLMs Versus Response Variable Transformations

It is important to note that, for example, the GLM

$$\log E(Y_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}.$$

is *not* equivalent to a linear model with a transformed response,

$$E[\log(Y_i)] = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik},$$

because  $\log[E(Y_i)] \neq E[\log(Y_i)]$  (although in practice they can produce similar results).