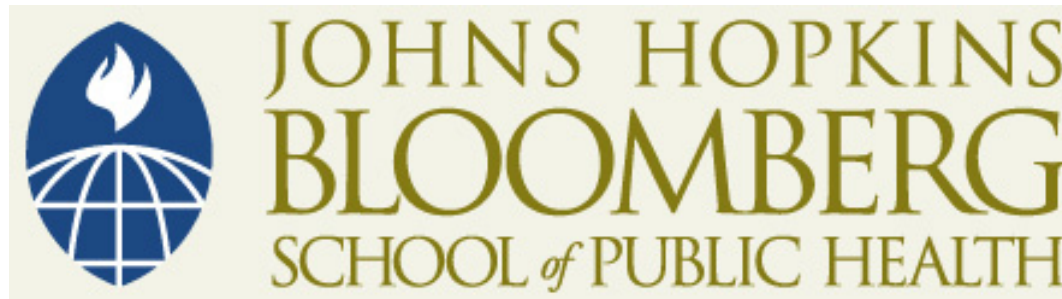


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Spider mites example

Dose of DDT	No. survived	No. dead
0.0	18	7
0.5	19	6
1.0	12	13
1.5	5	20
2.0	6	19
2.5	2	23
3.0	1	24

Binary vs. continuous outcomes

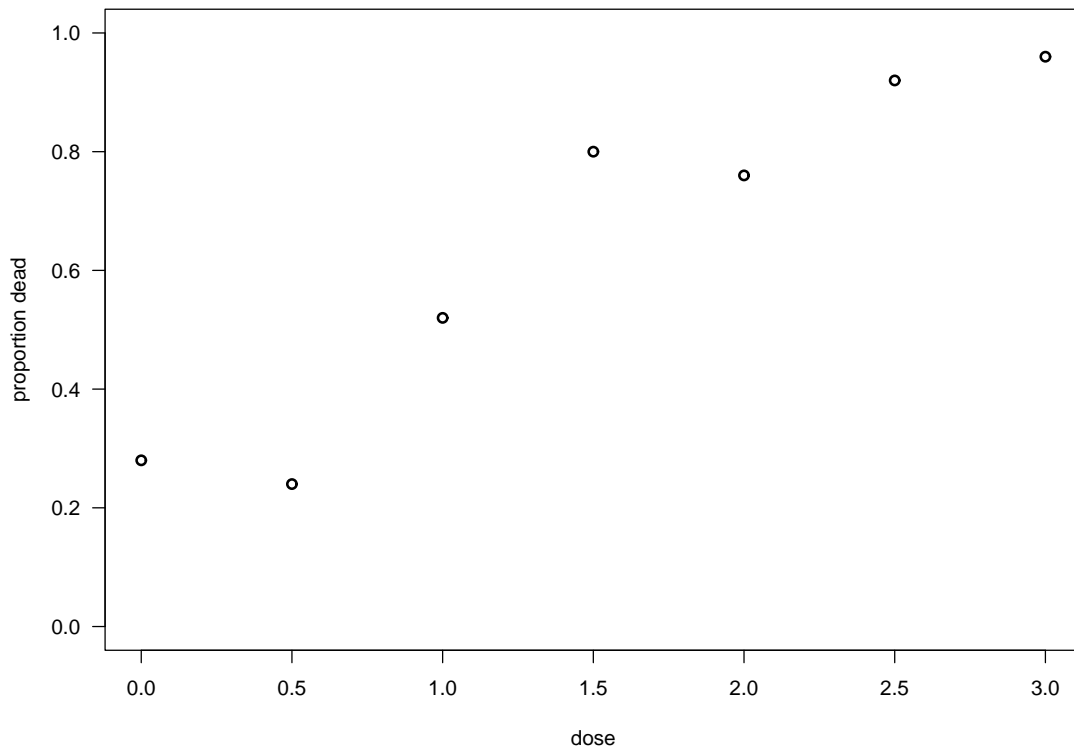
Continuous: ANOVA \longleftrightarrow Regression

Binary: $k \times 2$ table \longleftrightarrow ?

Goals:

- Relationship between dose and $\Pr(\text{dead})$.
- Dose at which $\Pr(\text{dead}) = 1/2$.

A plot of the data



Linear regression

Model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon, \quad \epsilon \sim \text{iid Normal}(0, \sigma^2)$$

This implies:

$$E(y \mid x_1, \dots, x_k) = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$

β_i = increase in mean of Y associated with a unit change in x_i

Binary outcomes

Let $p_d = \Pr(\text{dead} \mid \text{dose } d)$

$$p_d = \beta_0 + \beta_1 d ?$$

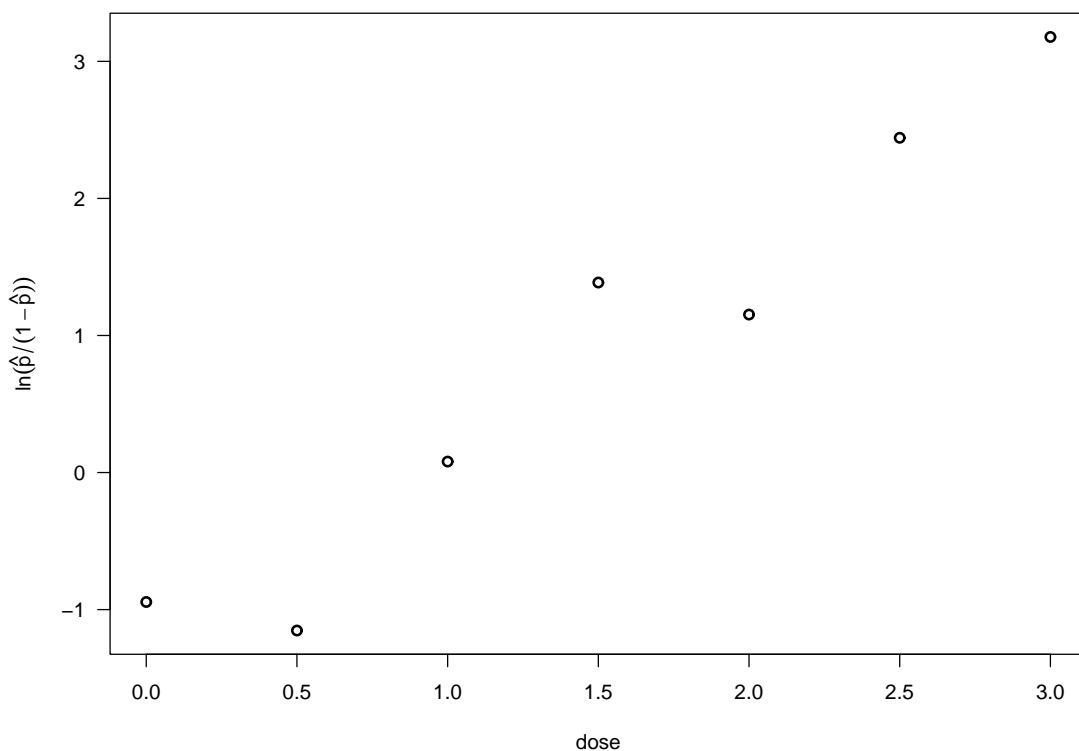
$$0 \leq p_d \leq 1 \quad \text{but} \quad -\infty \leq \beta_0 + \beta_1 d \leq \infty$$

Odds of death: $0 \leq \frac{p_d}{1 - p_d} \leq \infty$

log odds of death: $-\infty \leq \ln\left(\frac{p_d}{1 - p_d}\right) \leq \infty$

$\ln\left(\frac{p}{1 - p}\right)$ is also called $\text{logit}(p)$ or the logistic function.

$\text{logit}(\hat{p}_d)$ vs d



Logistic regression

$$\ln \left(\frac{p_d}{1 - p_d} \right) = \beta_0 + \beta_1 d$$

Try least squares, regressing $\ln \left(\frac{\hat{p}_d}{1 - \hat{p}_d} \right)$ on the dose, d ?

Problems:

- What if $\hat{p}_d = 0$ or 1 ?
- $SD(\hat{p}_d)$ is not constant with d .

Maximum likelihood

Assume $y_d \sim \text{Binomial}(n_d, p_d)$, y_d independent

$$\text{with } \text{logit}(p_d) = \ln \left(\frac{p_d}{1 - p_d} \right) = \beta_0 + \beta_1 d$$

Note:
$$p_d = \frac{e^{\beta_0 + \beta_1 d}}{1 + e^{\beta_0 + \beta_1 d}}$$

Likelihood:

$$L(\beta_0, \beta_1 | \mathbf{y}) = \prod_d p_d^{y_d} (1 - p_d)^{(n_d - y_d)}$$

Logistic regression in R

Logistic regression is a special case of a “generalized linear model”.

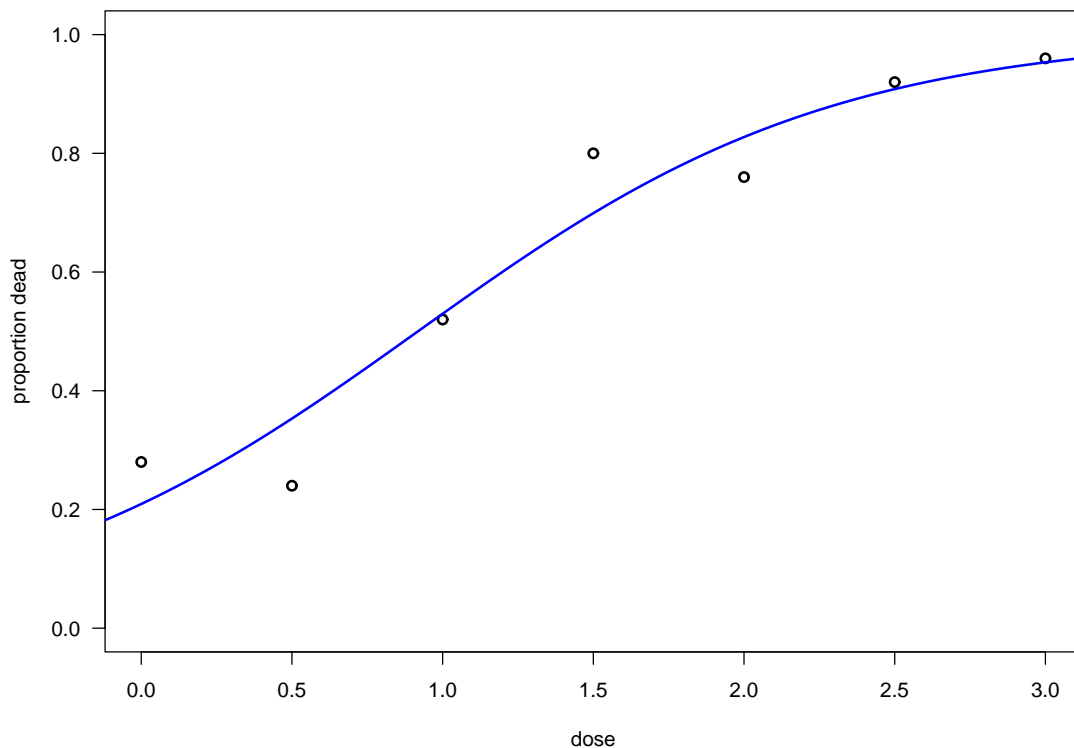
Function in R: `glm()`

```
> glm.out <- glm(n.dead/n ~ dose, weights=n, data=spiders,  
                family=binomial(link=logit))
```

```
> summary(glm.out)$coef
```

	Est	SE	t-val	P-val
(Intercept)	-1.33	0.33	-4.06	<0.001
dose	1.44	0.23	6.29	<0.001

Fitted curve



Interpretation of β 's

$$\ln \left(\frac{p_d}{1 - p_d} \right) = \beta_0 + \beta_1 d$$

β_0 = log odds when dose = 0

Note: $\beta_0 = 0 \longrightarrow p_0 = \frac{1}{2}$

β_1 = change in log odds with unit increase in dose

Note: $\beta_1 = 0 \longrightarrow$ survival unrelated to dose.

LD50

LD50 = dose at which $\Pr(\text{dead} \mid \text{dose}) = \frac{1}{2}$.

$$\ln \left(\frac{1/2}{1 - 1/2} \right) = \beta_0 + \beta_1(\text{LD50})$$

$$\implies 0 = \beta_0 + \beta_1(\text{LD50})$$

$$\implies \text{LD50} = -\beta_0/\beta_1$$

$$\widehat{\text{LD50}} = -\hat{\beta}_0/\hat{\beta}_1$$

$$\widehat{\text{SE}}(\widehat{\text{LD50}}) \approx |\widehat{\text{LD50}}| \sqrt{\left(\frac{\widehat{\text{SE}}(\hat{\beta}_0)}{\hat{\beta}_0} \right)^2 + \left(\frac{\widehat{\text{SE}}(\hat{\beta}_1)}{\hat{\beta}_1} \right)^2 - 2 \frac{\text{cov}(\hat{\beta}_0, \hat{\beta}_1)}{\hat{\beta}_0 \hat{\beta}_1}}$$

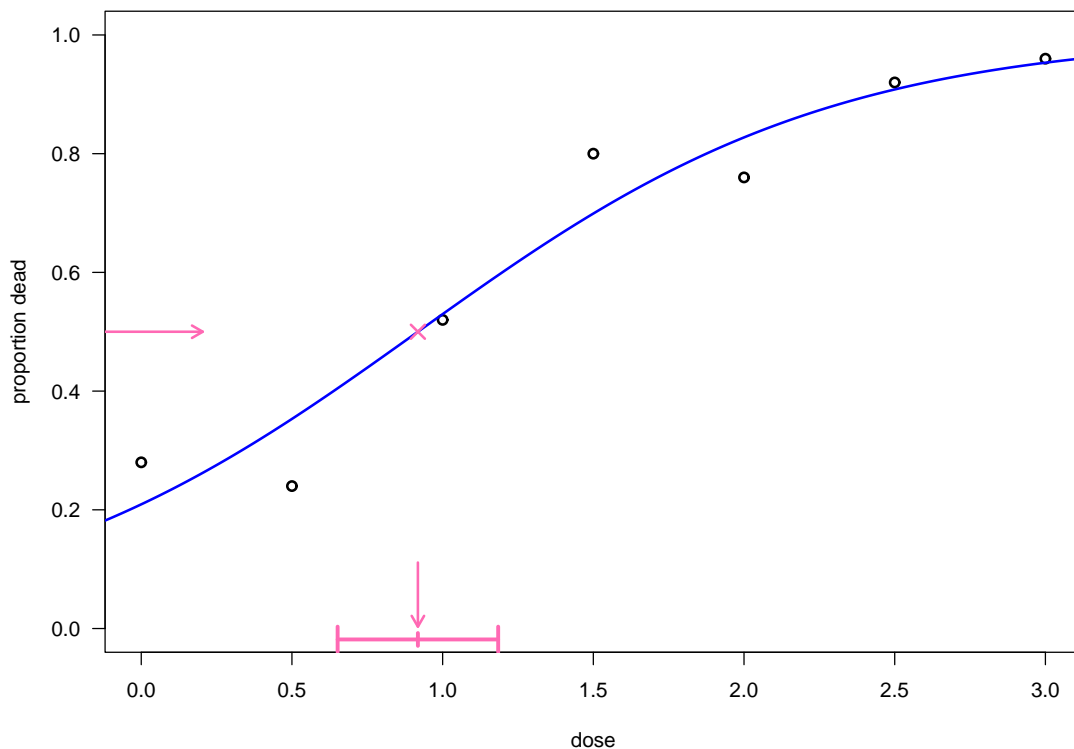
Estimating LD50 in R

```
> glm.out <- glm(n.dead/n ~ dose, weights=n, data=spiders,
                 family=binomial(link=logit))
> glm.sum <- summary(glm.out)

> co <- glm.out$coef
> ld50 <- -co[1]/co[2]
> se.co <- glm.sum$coef[,2]
> cov.co <- glm.sum$cov.scaled[1,2]
> se.ld50 <- abs(ld50) * sqrt( (se.co[1]/co[1])^2 +
                              (se.co[2]/co[2])^2 -
                              2*cov.co/(co[1]*co[2]) )

> ld50
  0.92
> se.ld50
  0.14
> ld50 + c(-1,1) * qnorm(0.975) * se.ld50
  0.65  1.18
```

LD50



Another example

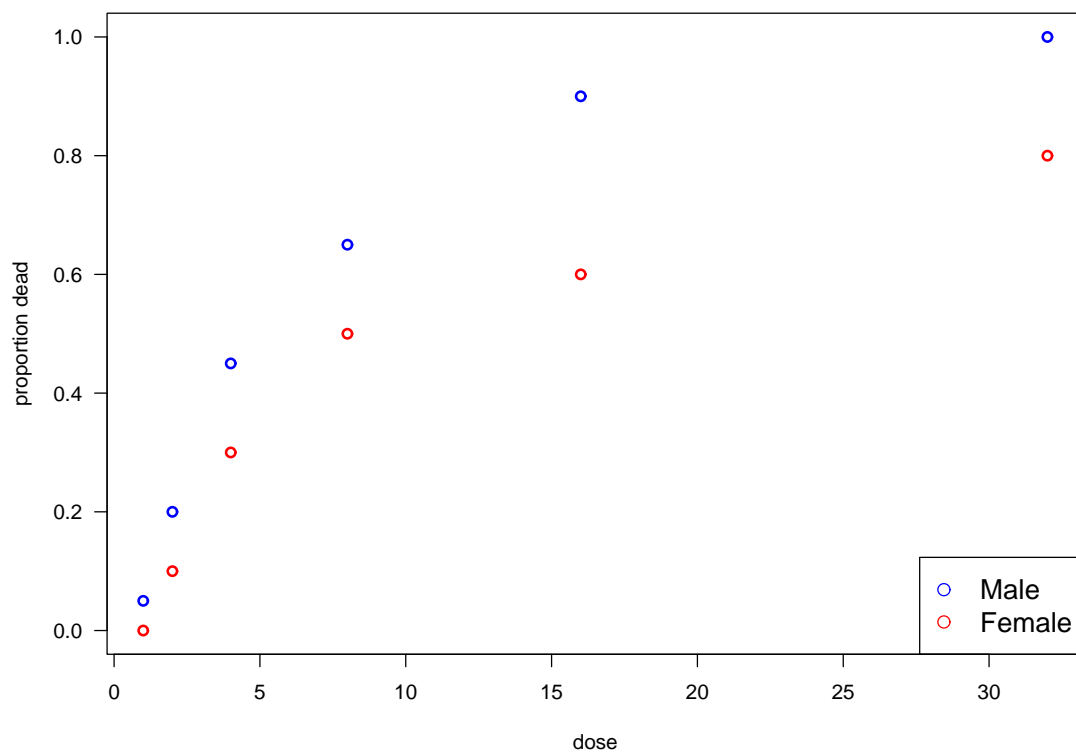
Tobacco budworm, *Heliothis virescens*

Batches of 20 male and 20 female worms were given a 3-day dose of pyrethroid *trans*-cypermethrin

The no. dead or “knocked down” in each batch was noted.

	Dose					
Sex	1	2	4	8	16	32
Male	1	4	9	13	18	20
Female	0	2	6	10	12	16

A plot of the data



Analysis in R

Assume no sex difference

```
> glm.out <- glm(n.dead/n ~ dose, weights=n, data=worms,  
                family=binomial(link=logit))
```

```
> summary(glm.out)$coef  
              Est      SE  t-val  P-val  
(Intercept) -1.57   0.23   -6.8 <0.001  
dose          0.153  0.022    6.8 <0.001
```

Assume sexes completely different

```
> glm.outB <- glm(n.dead/n ~ sex*dose, weights=n, data=worms,  
                 family=binomial(link=logit))
```

```
> summary(glm.outB)$coef  
              Est      SE  t-val  P-val  
(Intercept) -1.72   0.32   -5.3 <0.001  
sexmale      -0.21   0.51   -0.4  0.68  
dose         0.116  0.024    4.9 <0.001  
sexmale:dose 0.182  0.067    2.7  0.007
```

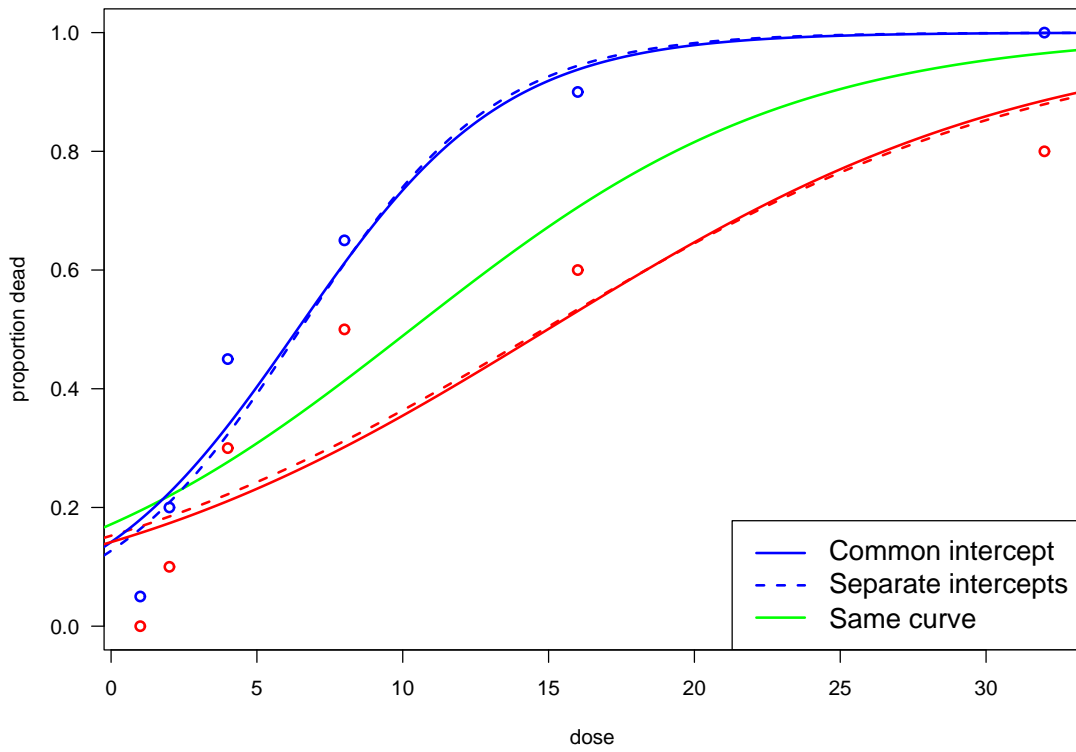
Analysis in R (continued)

Different slopes but common “intercept”

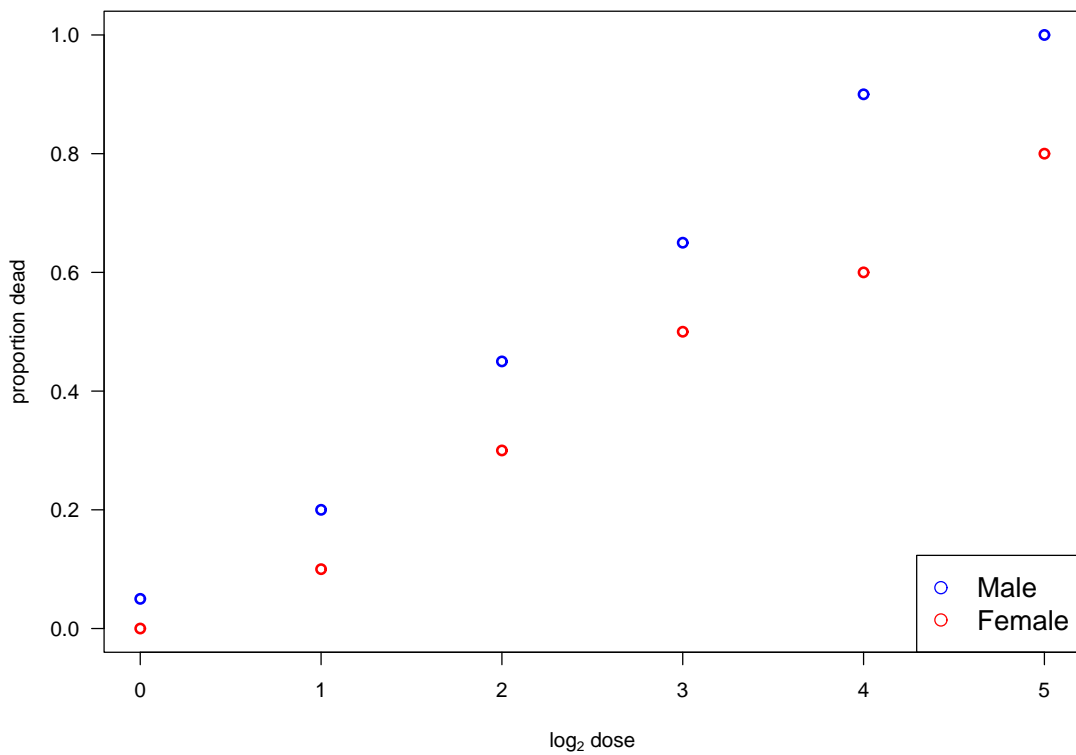
```
> glm.outC <- glm(n.dead/n ~ dose + sex:dose, weights=n,  
                 data=worms, family=binomial(link=logit))
```

```
> summary(glm.out)$coef  
              Est      SE  t-val  P-val  
(Intercept) -1.80   0.25   -7.2 <0.001  
dose         0.120  0.021    5.6 <0.001  
dose:sexmale 0.161  0.044    3.7 <0.001
```

Fitted curves



Plot using \log_2 dose



Use \log_2 of the dose

Assume no sex difference

```
> glm.out <- glm(n.dead/n ~ dose, weights=n, data=worms,  
                family=binomial(link=logit))
```

```
> summary(glm.out)$coef  
              Est      SE  t-val   P-val  
(Intercept) -2.77  0.37   -7.6  <0.001  
dose          1.01  0.12    8.1  <0.001
```

Assume sexes completely different

```
> glm.outB <- glm(n.dead/n ~ sex*dose, weights=n, data=worms,  
                 family=binomial(link=logit))
```

```
> summary(glm.outB)$coef  
              Est      SE  t-val   P-val  
(Intercept) -2.99  0.55   -5.4  <0.001  
sexmale       0.17  0.78   -0.2   0.82  
dose          0.91  0.17    5.4  <0.001  
sexmale:dose  0.35  0.27    1.3   0.19
```

Use \log_2 of the dose (continued)

Different slopes but common “intercept”

```
> glm.outC <- glm(n.dead/n ~ dose + sex:dose, weights=n,  
                 data=worms, family=binomial(link=logit))
```

```
> summary(glm.out)$coef  
              Est      SE  t-val   P-val  
(Intercept) -2.91  0.39   -7.5  <0.001  
dose          0.88  0.13    6.9  <0.001  
dose:sexmale  0.41  0.12    3.3   0.001
```

Fitted curves

