# Simple Linear Regression

Partitioning variability

Intro Regression

Dr. Maria Tackett

## **Topics**

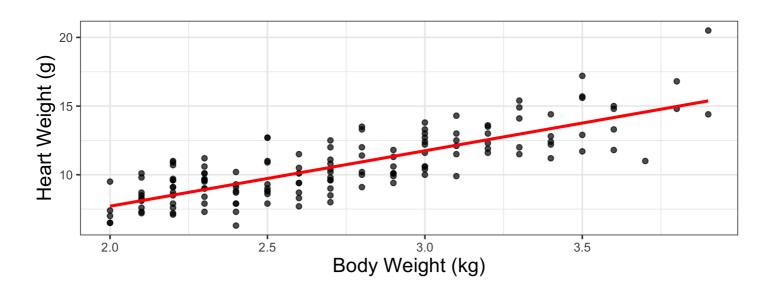
- Use analysis of variance to partition variability in the response variable
- Define and calculate  $R^2$
- Use ANOVA to test the hypothesis  $H_0: \beta_1 = 0$

## **Topics**

- Use analysis of variance to partition variability in the response variable
- Define and calculate  $R^2$
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### Cats data

The data set contains the **heart weight** (**Hwt**) and **body weight** (**Bwt**) for 144 domestic cats.

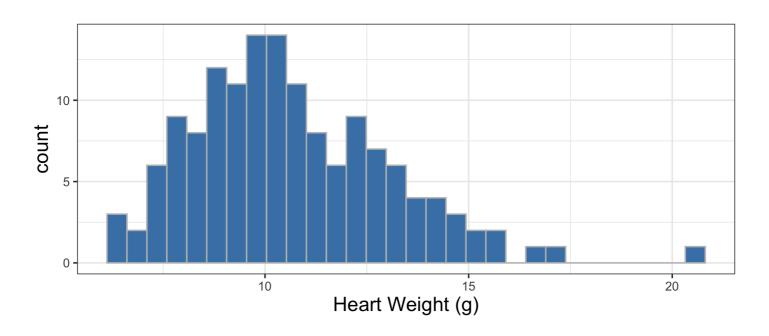


## The model

$$\hat{\text{Hwt}} = -0.357 + 4.034 \times \text{Bwt}$$

term	estimate	std.error	statistic	p.value
(Intercept)	-0.357	0.692	-0.515	0.607
Bwt	4.034	0.250	16.119	0.000

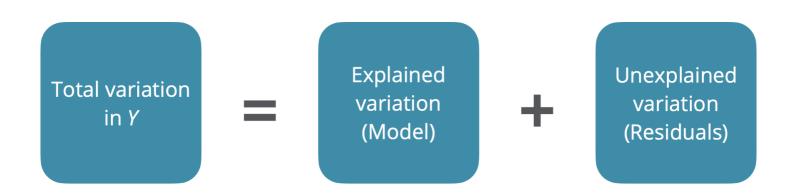
# Distribution of response



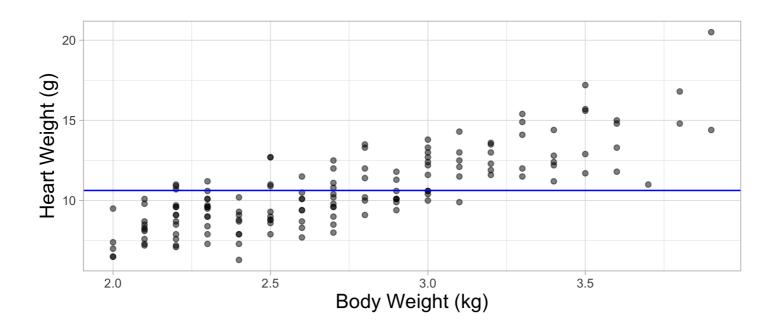
Mean	Std. Dev.	IQR
10.631	2.435	3.175

How much of the variability in cats' heart weights can be explained by knowing their body weights?

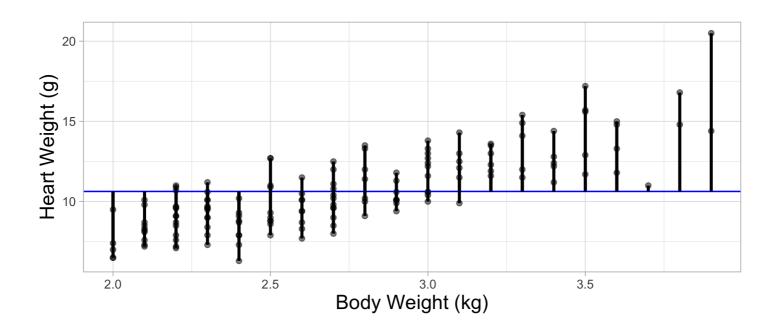
We will use **Analysis of Variance (ANOVA)** to partition the variation in the response variable Y.



# Response variable, Y,

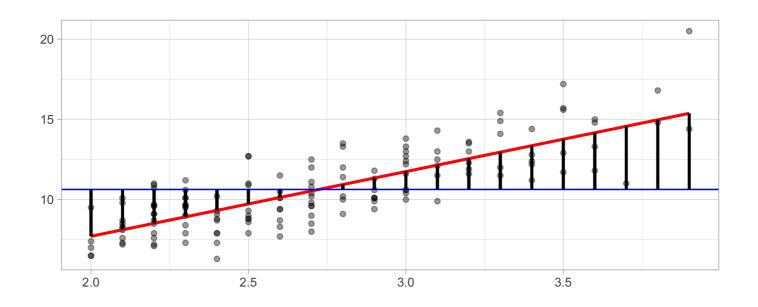


### **Total variation**



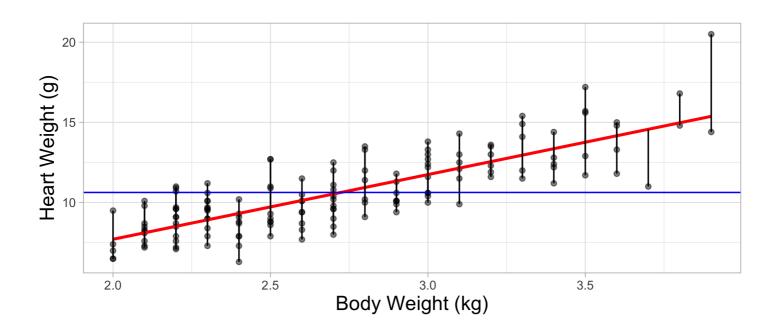
$$SS_{Total} = \sum_{i=1}^{n} (y_i - \bar{y})^2 = (n-1)s_y^2$$

## **Explained variation (Model)**



$$SS_{Model} = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$$

## Unexplained variation (Residuals)



$$SS_{Error} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

$$\sum_{i=1}^{n} (y_i - \bar{y})^2 = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

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$$R^{2} = \frac{SS_{Model}}{SS_{Total}} = 1 - \frac{SS_{Error}}{SS_{Total}}$$

# $R^2$ for our model

$$SS_{Model} = 548.092$$

$$SS_{Error} = 299.533$$

$$SS_{Total} = 847.625$$

# $\mathbb{R}^2$ for our model

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$$R^2 = \frac{548.092}{847.625}$$

$$= 0.647$$

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$$= 0.647$$

About 64.7% of the variation in the heart weight of cats can be explained by variation in body weight.

Source	Df	Sum Sq	Mean Sq	F Stat	Pr(> F)
Model	1	548.092	548.092	259.835	0
Residuals	142	299.533	2.109		
Total	143	847.625			

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#### Sum of squares

$$SS_{Total} = 847.625$$

$$SS_{Model} = 548.092$$

$$SS_{Error} = 847.625 - 548.092 = 299.533$$

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$$H_0: \beta_1 = 0$$

$$H_a: \beta_1 \neq 0$$

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#### Degrees of freedom

$$df_{Total} = 144 - 1 = 143$$

$$df_{Model} = 1$$

$$df_{Error} = 143 - 1 = 142$$

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#### Mean squares

$$MS_{Model} = \frac{548.092}{1} = 548.092$$

$$MS_{Error} = \frac{299.533}{142} = 2.109$$

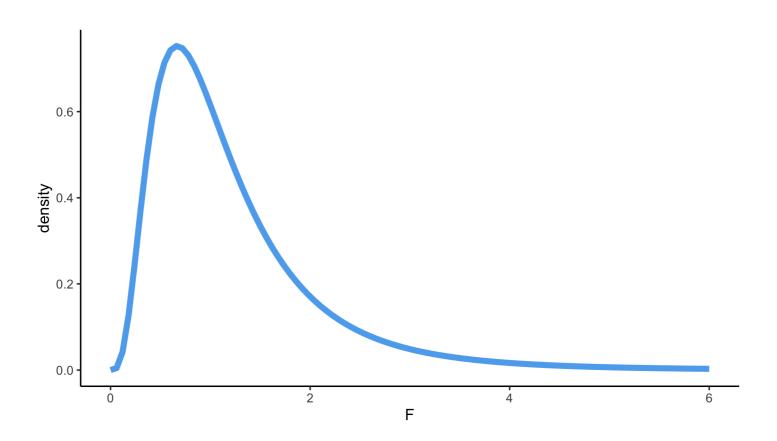
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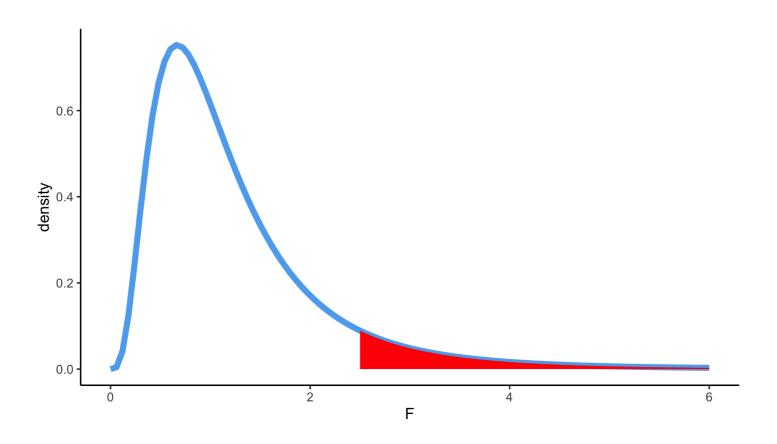
**F test statistic**: ratio of explained to unexplained variability

$$F_{(1,142)} = \frac{MS_{Model}}{MS_{Residuals}} = \frac{548.092}{2.109} = 259.835$$

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**P-value**: Probability of observing a test statistic at least as extreme as F Stat given the true slope parameter is 0, i.e.  $H_0: \beta_1 = 0$ 

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The p-value is very small ( $\approx 0$ ), so we reject  $H_0$ .

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There is evidence of a linear relationship between a cat's heart weight and body weight.

## Recap

- Used analysis of variance to partition variability in the response variable
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