

# Multiple Regression: General things

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Tim Frasier

# General Idea

- Multiple regression
  - Influence of multiple variables on a single other variable (how does one change in relation to the others?)
  - Predict values of one parameter based on values of the others
- **Allows us to assess the affect of one variable on the predicted variable while accounting for the effects of other predictor variables**

# Creates Problems!

1. Proper interpretation of coefficients
2. Deciding what predictor variables are important

Neither of these are trivial!!!

# Problem #1: Interpretation of Coefficients

- Differs depending on if interaction term(s) is included
  - Two variables

no interaction

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

with interaction

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$$

What do each of these coefficients represent?

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The intercept (what  $y$  would be if both  $x$  values were zero) represents?

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The independent effect of  $x_1$  on  $y$ , once you've considered the effects of  $x_2$ . How much  $y$  increases when  $x_1$  increases by 1 unit.

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How much  $y$  increases when  $x_1$  increases by 1 and  $x_2 = 0$ .

$$x_2 = 0.$$

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How much  $y$  increases when  $x_2$  increases by 1 and  $x_1 = 0$ ?

$$x_1 = 0.$$

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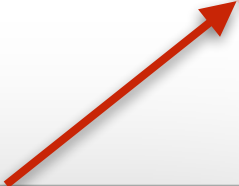
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no interaction

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

with interaction

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$$



How much  $y$  increases when the product of  $x_1$  and  $x_2$  increases by 1. Should only be included if it is thought that  $x_1$  and  $x_2$  have a multiplicative interaction that effects  $y$  above and beyond the additive variation covered in  $\beta_1$  and  $\beta_2$  (i.e., it should not be included "just because").

## **Understanding Interaction Models: Improving Empirical Analyses**

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## **Hypothesis Testing and Multiplicative Interaction Terms**

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**NEWS AND VIEWS**

**OPINION**

**A note on the use of multiple linear regression in molecular ecology**

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# Problem #1: Interpretation of Coefficients

- Differs depending on how many variables are included
  - Three variables

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 + \beta_7 x_1 x_2 x_3$$

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Intercept. Value of  $y$  when  $x_1$ ,  $x_2$ , and  $x_3$  are all 0



# Problem #1: Interpretation of Coefficients

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Individual effects of each predictor variable when all others are 0.

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$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 + \beta_7 x_1 x_2 x_3$$



Multiplicative effects of each possible pair of predictor variables when the third is 0.

# Problem #1: Interpretation of Coefficients

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Multiplicative effects of all three predictor variables.

# Problem #1: Interpretation of Coefficients

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$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 + \beta_7 x_1 x_2 x_3$$

- Again, multiplicative effects should only be included if you have a good hypothesis for why (and how) they are important.
- If you include a higher-level effect, must include all lower-level ones as well.
  - If you want to estimate  $\beta_7$ , you must also estimate  $\beta_1 - \beta_6$

# Your Model Is Like An Oracle

- It will answer the exact question you ask it (**not** the question you **meant** to ask)
- If you don't interpret this correctly, your empire may burn down

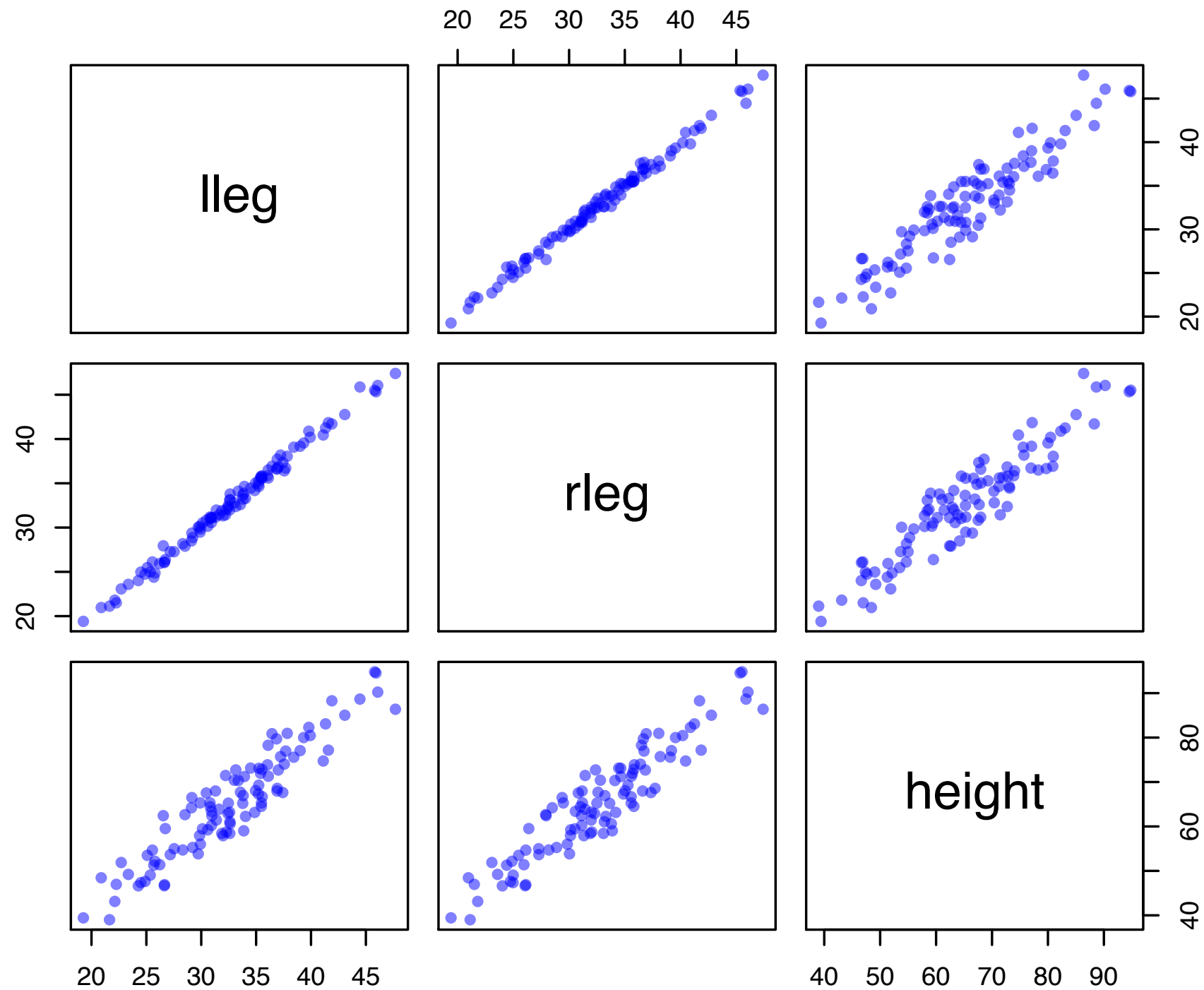


# Example: Effect of leg length on height

- Data: "legs.csv"

lleg	rleg	height
32.29583	32.03853	58.74574
29.90474	29.48348	65.29385
38.43200	39.07677	75.58189
45.92355	45.33978	94.53371
30.11240	30.52035	59.46205
39.01288	39.18316	77.06575
30.93059	30.56523	63.40671
45.80013	45.51175	94.79874
26.63675	26.05267	46.65168
33.78126	33.63838	65.19896

# Example: Effect of leg length on height



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```
cor(legs)
```

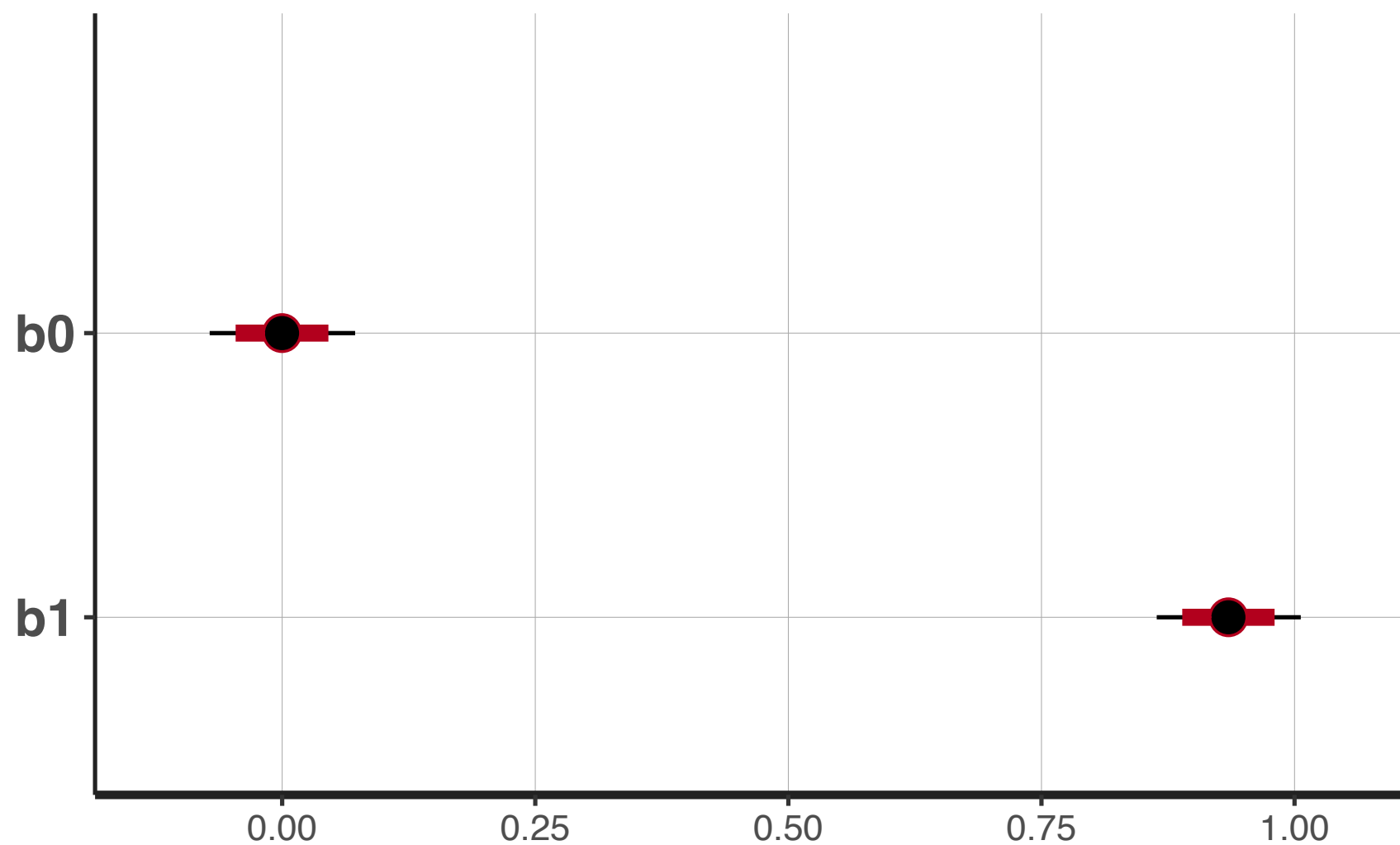
	lleg	rleg	height
lleg	1.00000000	0.9962084	0.9358207
rleg	0.9962084	1.00000000	0.9363314
height	0.9358207	0.9363314	1.00000000



# Model With Just Left Leg

$height \sim \text{normal}(\mu, sd)$

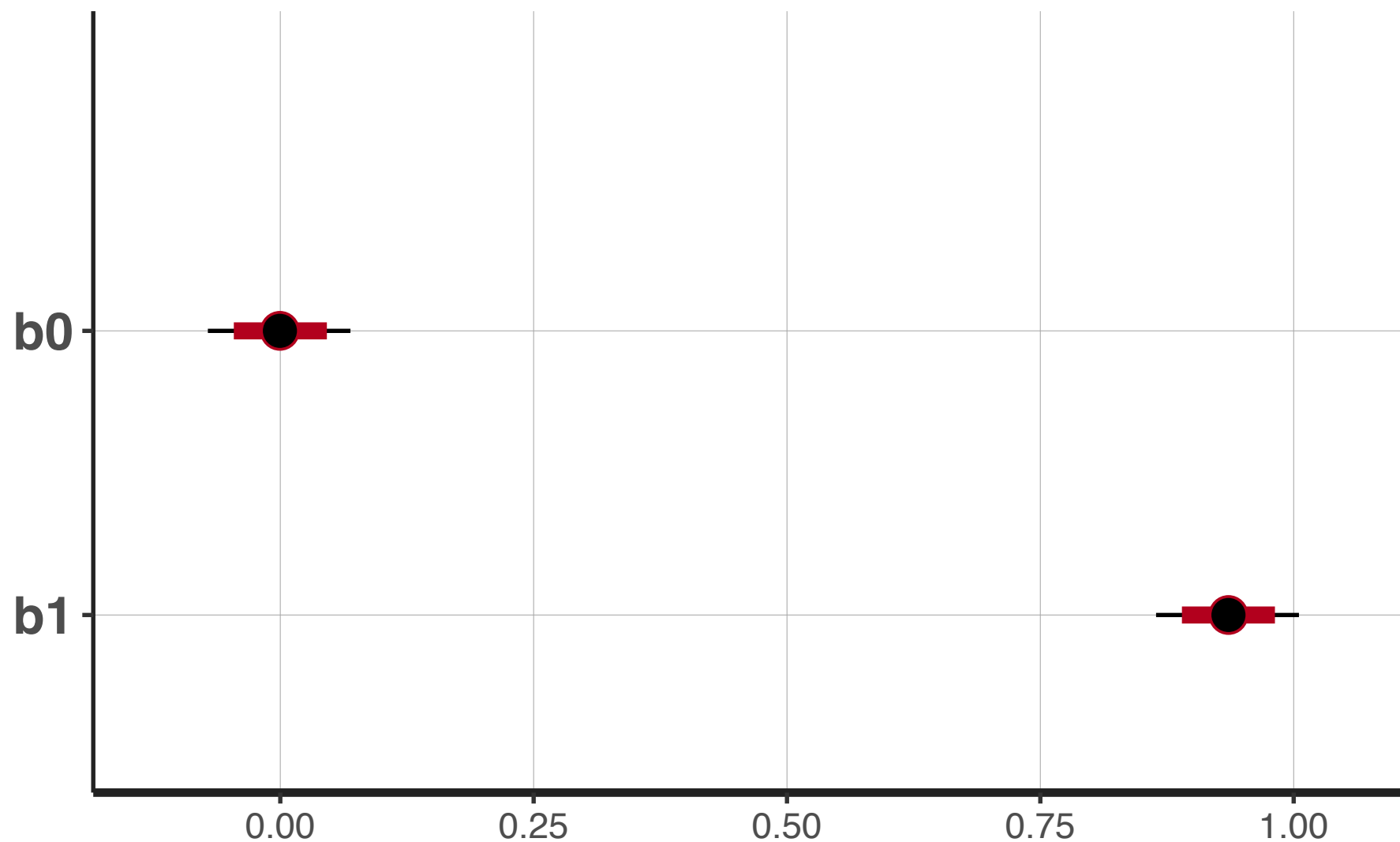
$\mu = \beta_0 + \beta_1 l_{leg}$



# Model With Just Right Leg

$height \sim \text{normal}(\mu, sd)$

$\mu = \beta_0 + \beta_1 rleg$



# Model With Both Legs

$$height \sim \text{normal}(\mu, sd)$$

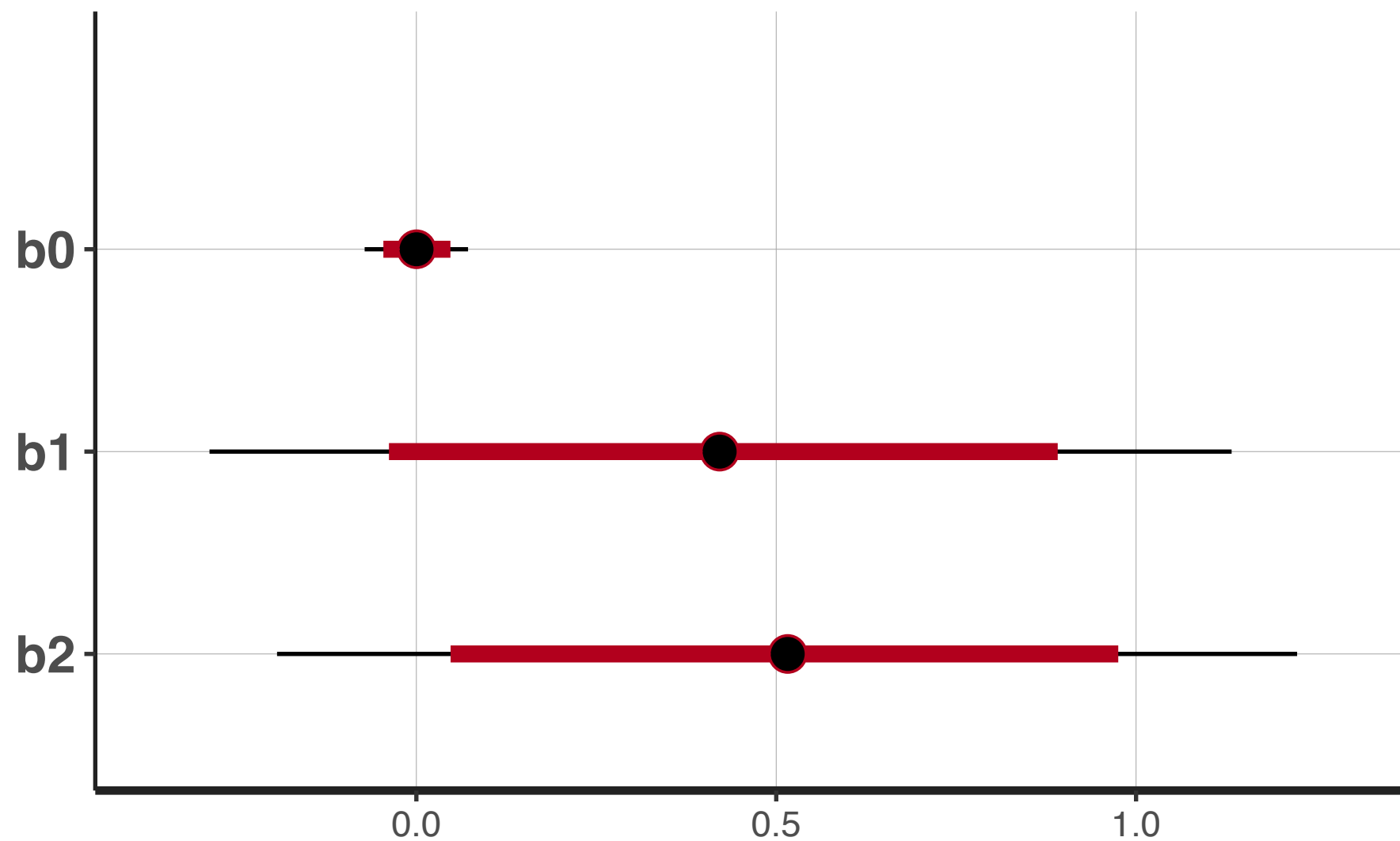
$$\mu = \beta_0 + \beta_1 l_{leg} + \beta_2 l_{leg}$$

- What do you think will happen?

# Model With Both Legs

$height \sim \text{normal}(\mu, sd)$

$\mu = \beta_0 + \beta_1 l_{leg} + \beta_2 l_{leg}$

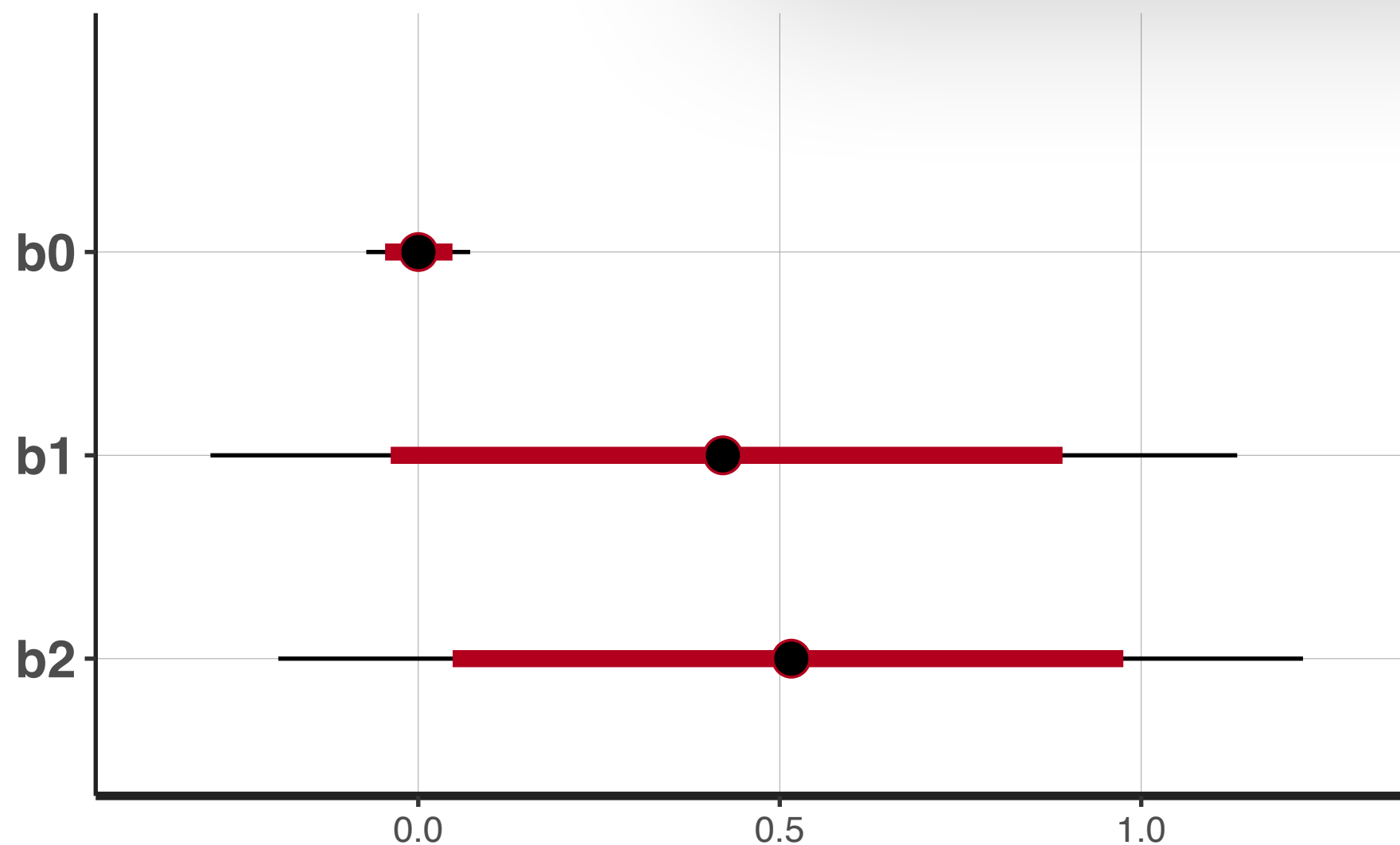


# Model With Both Legs

$height \sim \text{normal}$

$$\mu = \beta_0 + \beta_1$$

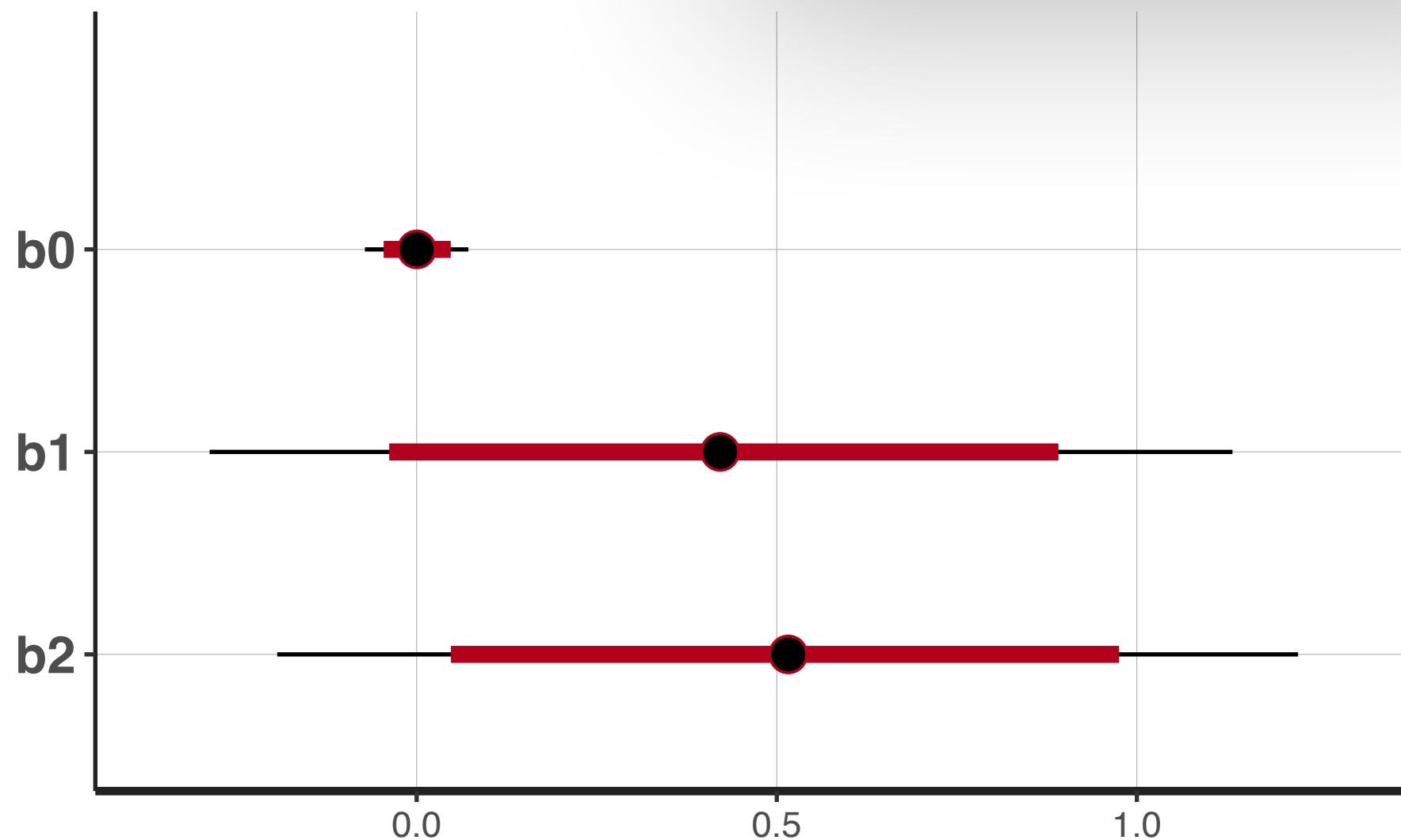
What happened?!!



# Model With Both Legs

$$\text{height} \sim \text{normal}$$
$$\mu = \beta_0 + \beta_1$$

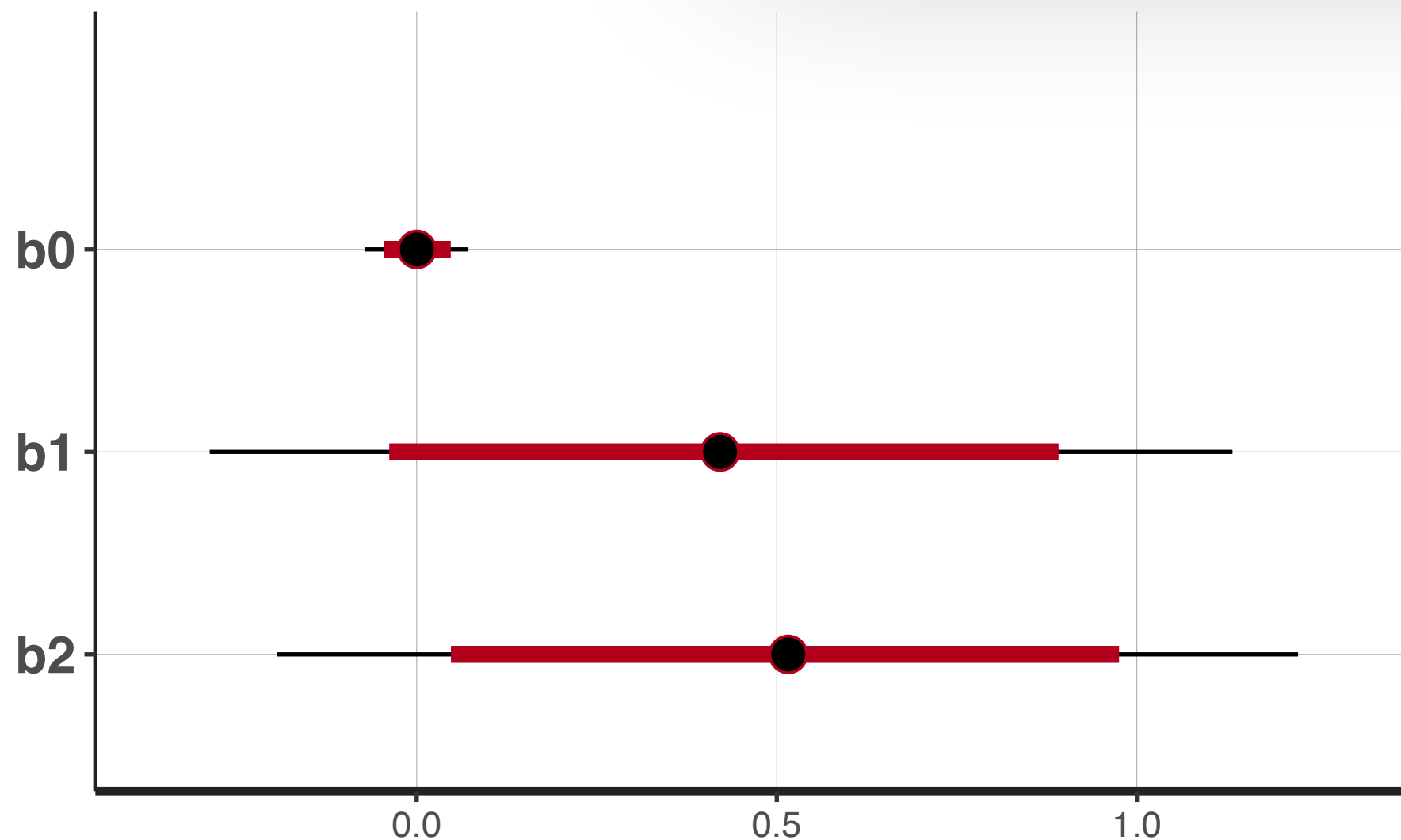
Very large ranges are a sign you have a problem



# Model With Both Legs

$$\text{height} \sim \text{normal}$$
$$\mu = \beta_0 + \beta_1$$

How would these typically be interpreted?!



# Model With Both Legs

$$\begin{aligned} height &\sim \text{normal} \\ \mu &= \beta_0 + \beta_1 \end{aligned}$$

How would these typically be interpreted?!

```
model = lm(zheight ~ zlleg + zrleg)
summary(model)
```

Call:

```
lm(formula = zheight ~ zlleg + zrleg)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.70416	-0.23767	-0.00562	0.23696	0.66119

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-6.622e-16	3.530e-02	0.000	1.000
zlleg	4.016e-01	4.077e-01	0.985	0.327
zrleg	5.363e-01	4.077e-01	1.315	0.192

Residual standard error: 0.353 on 97 degrees of freedom

Multiple R-squared: 0.8779, Adjusted R-squared: 0.8754

F-statistic: 348.8 on 2 and 97 DF, p-value: < 2.2e-16



# What Can You Do?

- **Always** plot data first, to see if any potential correlations
- **Always** check for correlations among predictor variables before fitting your model
  - Be wary of correlations  $> \sim 0.7$
  - Check model performance with each, then with both

# Creates Problems!

1. Proper interpretation of coefficients
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# Frequentist Approach

- Which model should we use/trust?
- “Stargazing”
  - Fit a bunch of predictor variables (and perhaps interactions) and keep those that are significant

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1057.8982	44.3287	23.865	<2e-16	***
guber\$StuTeaRat	-4.6394	2.1215	-2.187	0.0339	*
guber\$Salary	2.5525	1.0045	2.541	0.0145	*
guber\$PrcntTake	-2.9134	0.2282	-12.764	<2e-16	***

# Frequentist Approach

- Which model should we use/trust?
- “Stargazing”
  - Fit a bunch of predictor variables (and perhaps interactions) and keep those that are significant
- Not all “significant” predictors improve the model
- Some “non-significant” predictors may have important effects
- Plays havoc with interpretation of coefficients (with interactions)

# Seque On Goals of Models

- Common diagnostics ( $P$ -values on parameters and  $R^2$ ) tell us about fit to current data
  - Surprise - this isn't what we're interested in!!!

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- Common diagnostics ( $P$ -values on parameters and  $R^2$ ) tell us about fit to current data
  - Surprise - this isn't what we're interested in!!!
- All data sets contain a combination of information and noise
  - Want to gain as much information as we can from the data without being tricked into thinking that noise is information

# Seque On Goals of Models

- “Underfitting”
  - Learn too little from the data
- “Overfitting”
  - Learning “too much” from the data (interpreting noise as information)

# Sampling



## Small world

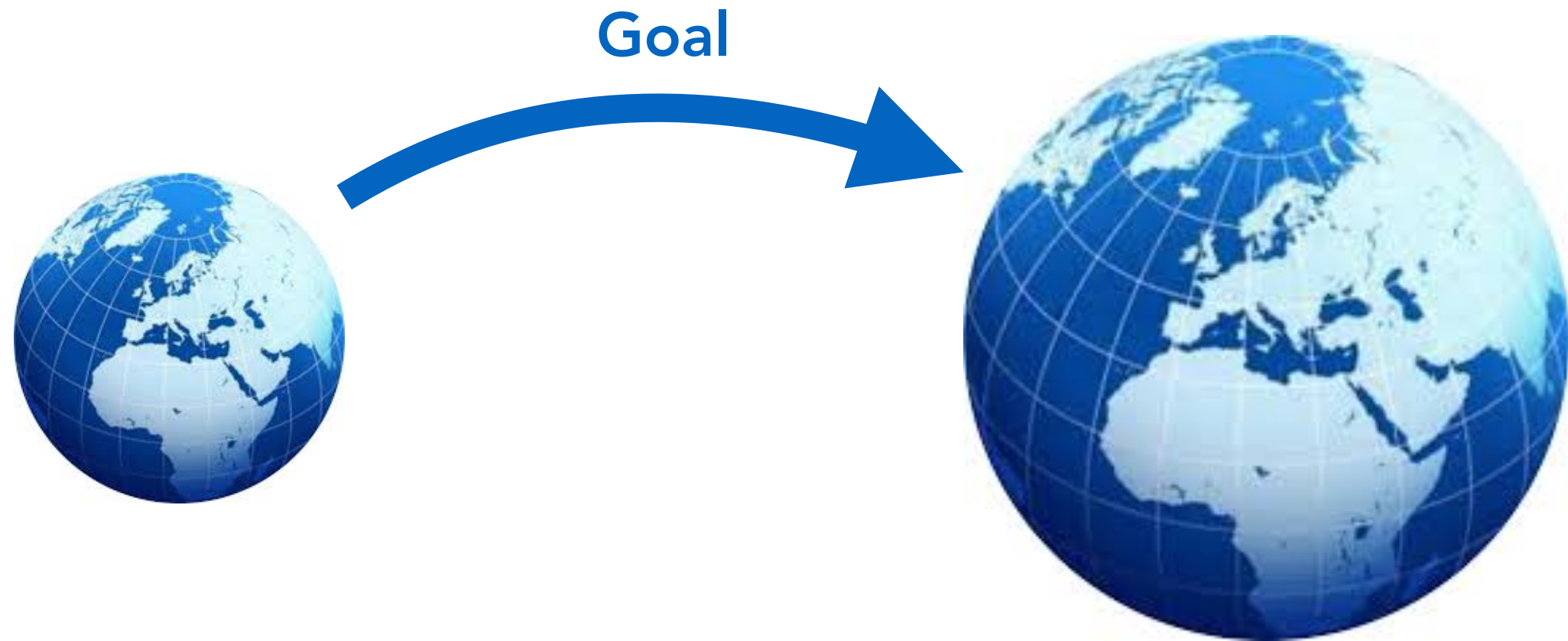
- Our data set
- Our model

## Large world

- The population we are trying to learn about
- The processes we are trying to learn about



# Inference



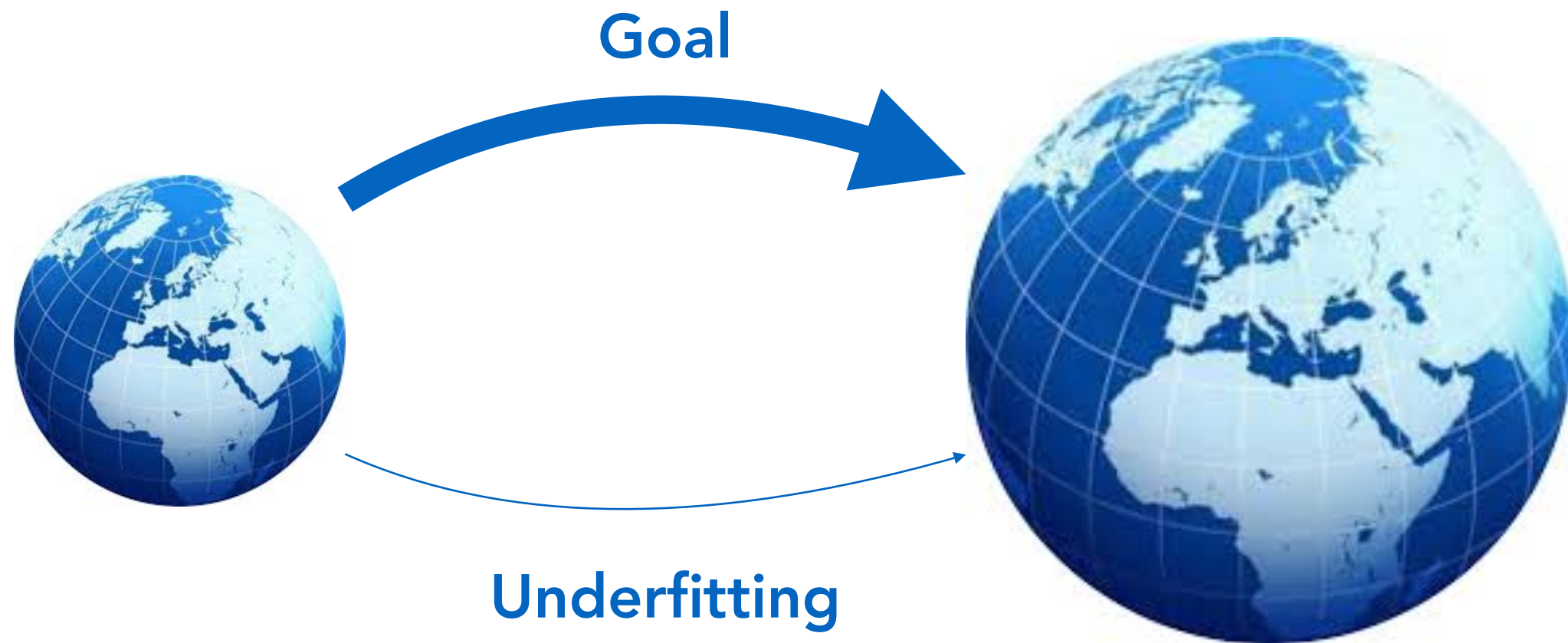
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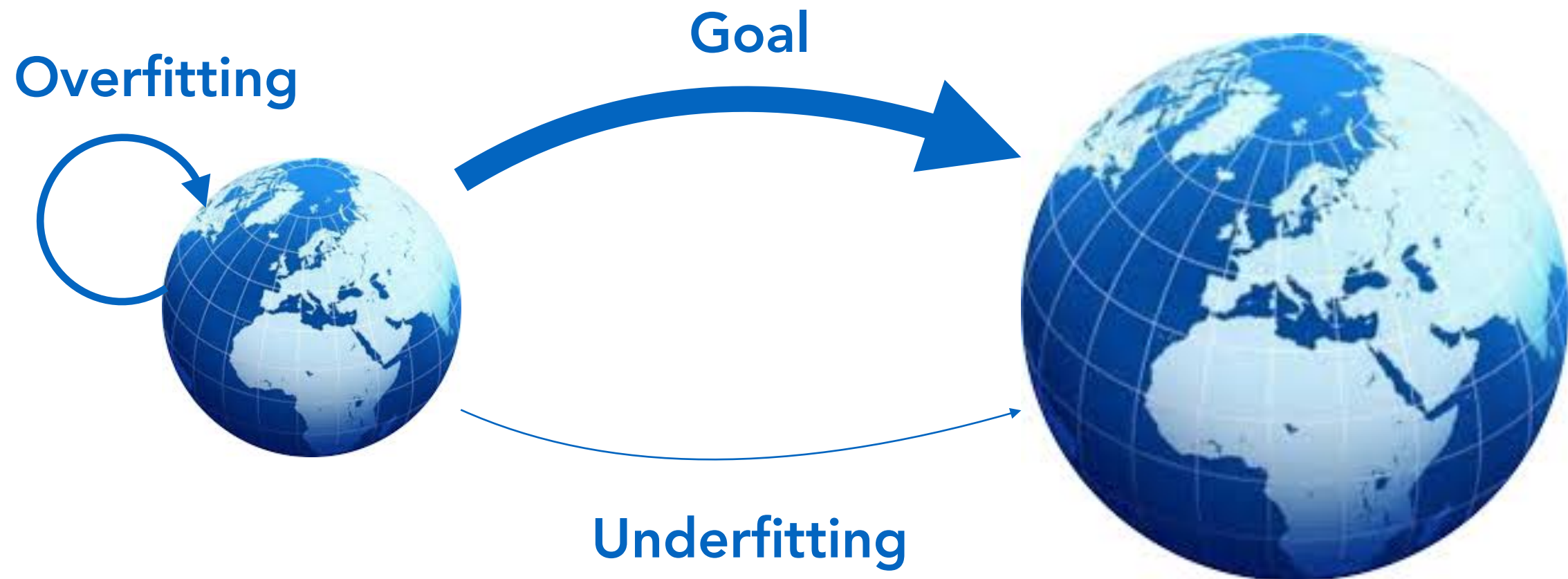
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## Small world

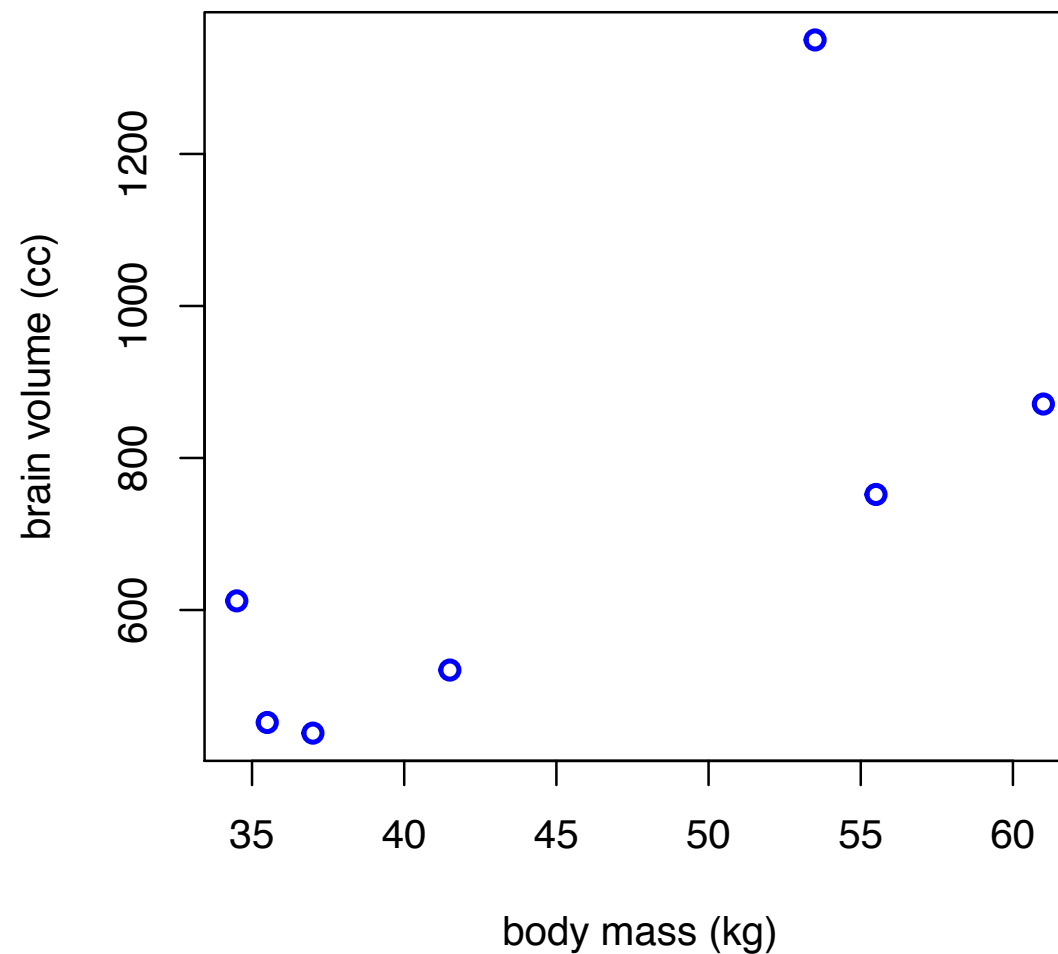
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# Example

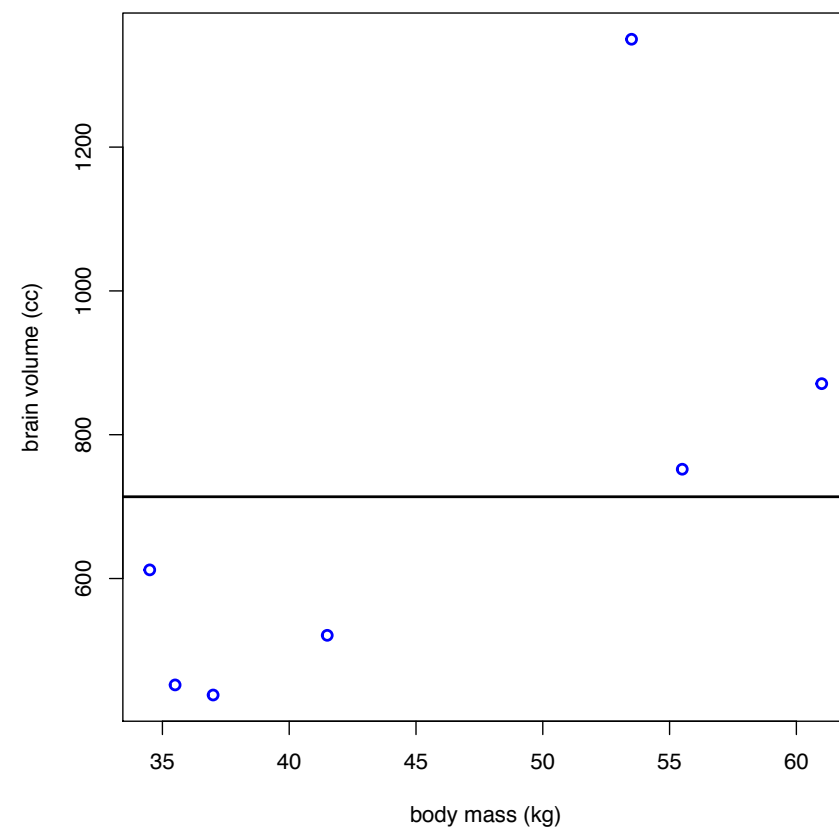
- Brain volume (in cubic centimetres) and body mass (kilograms) information for 6 hominin species



# Example

- Simplest model (severe underfitting)

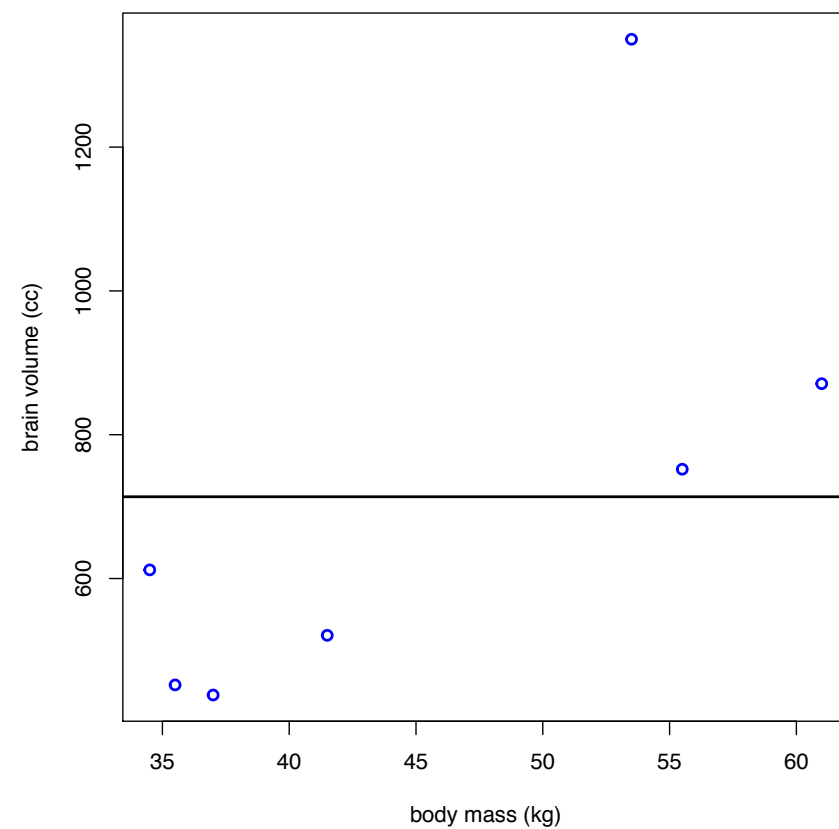
$$y = \alpha$$



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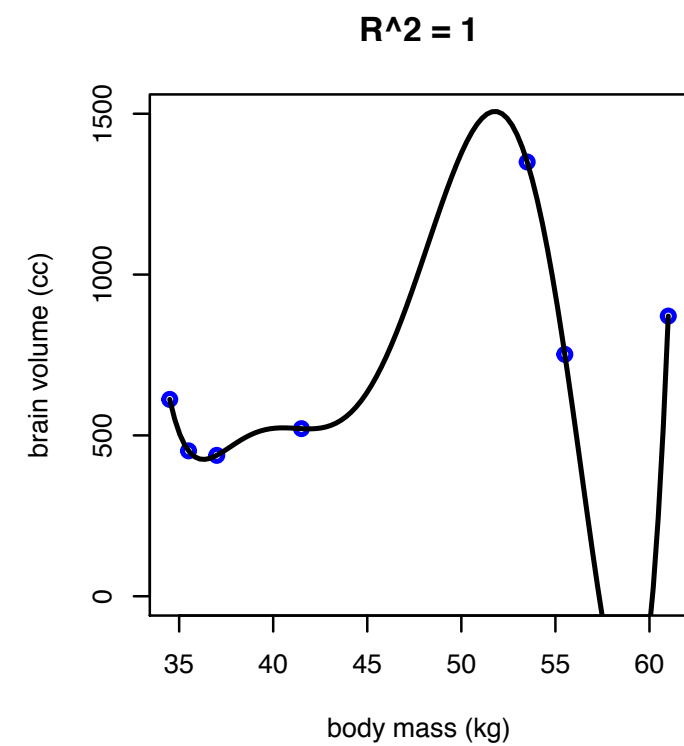
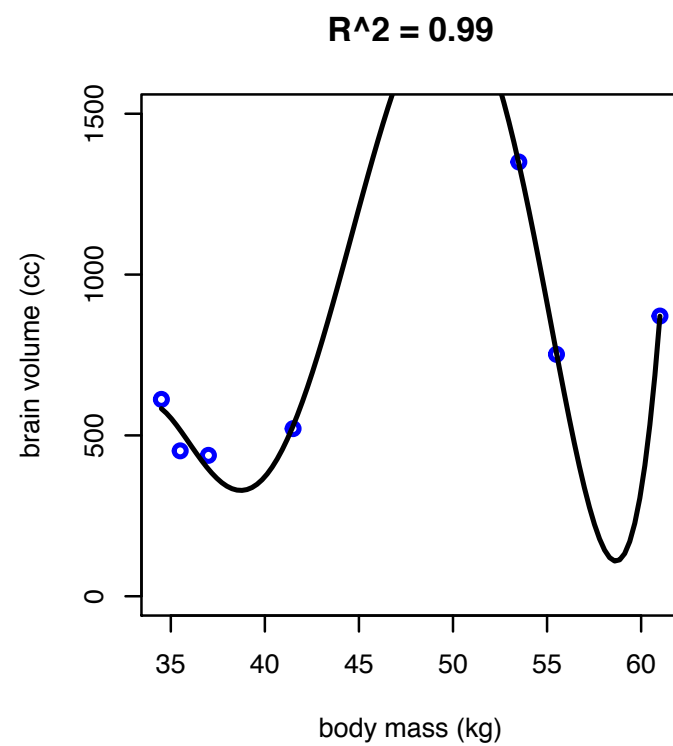
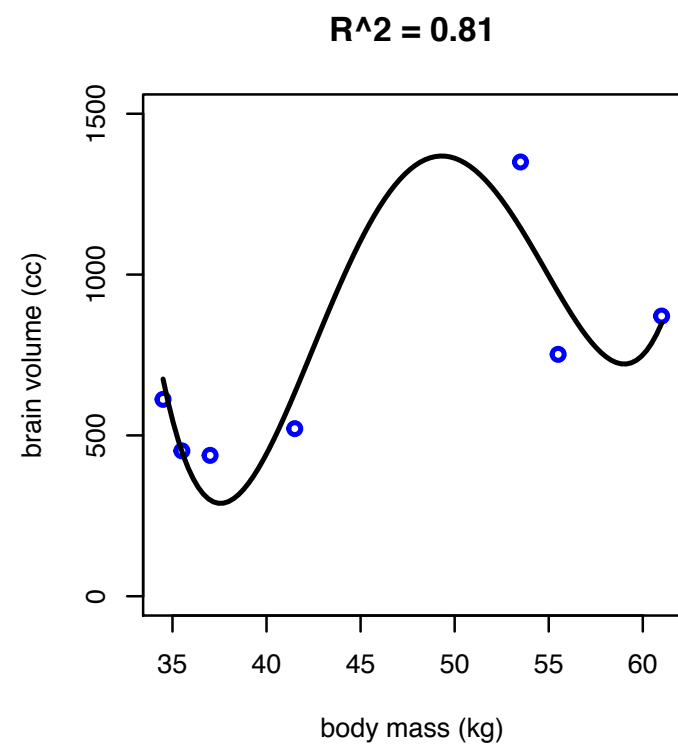
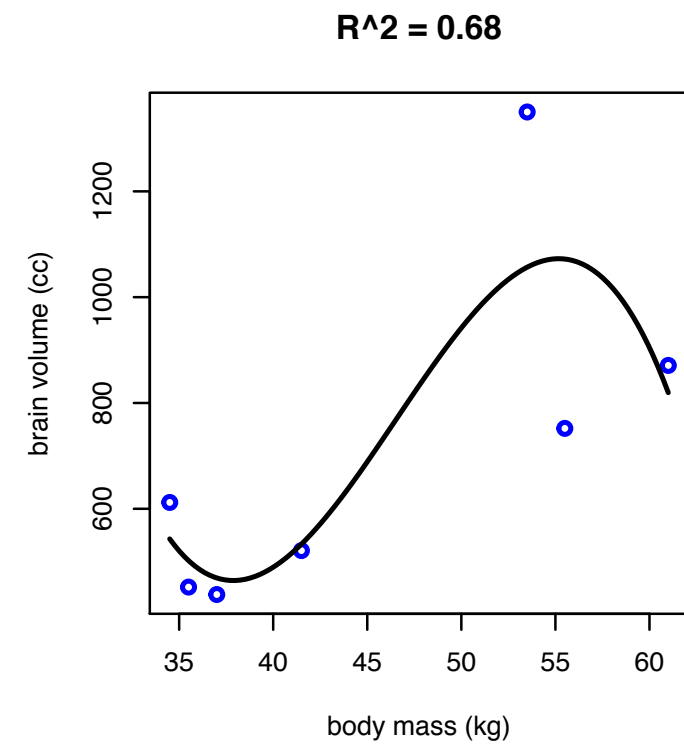
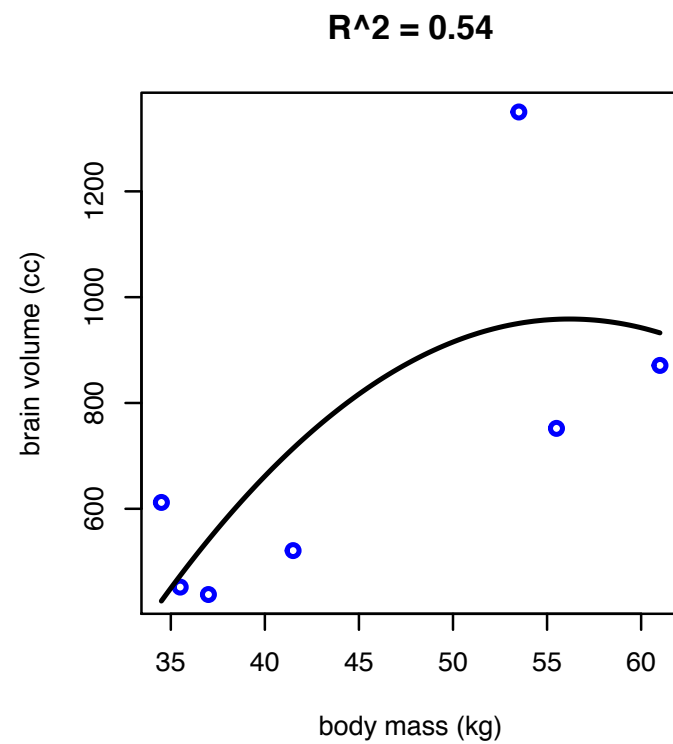
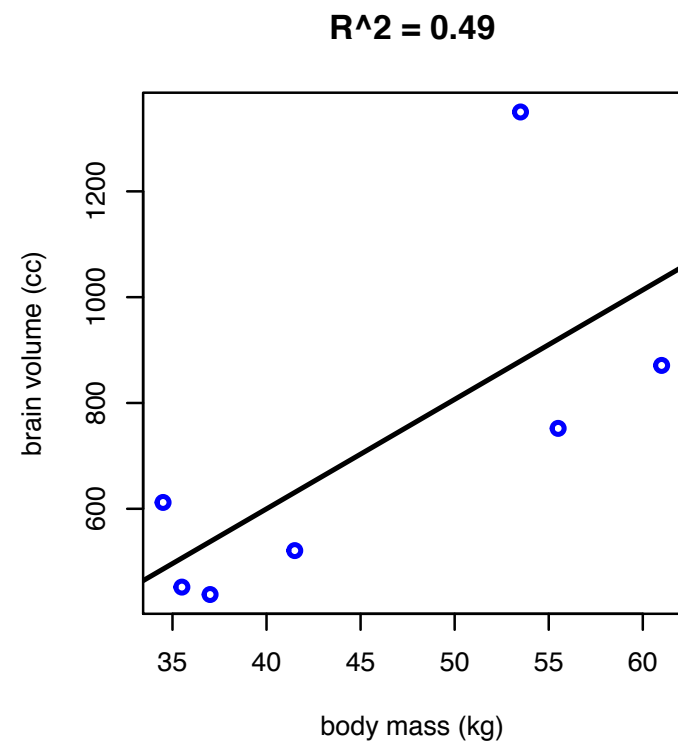
Try

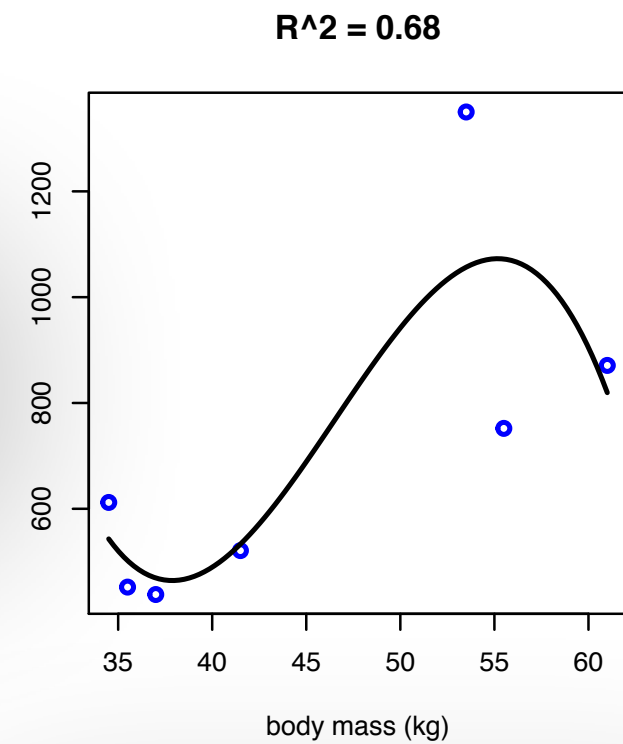
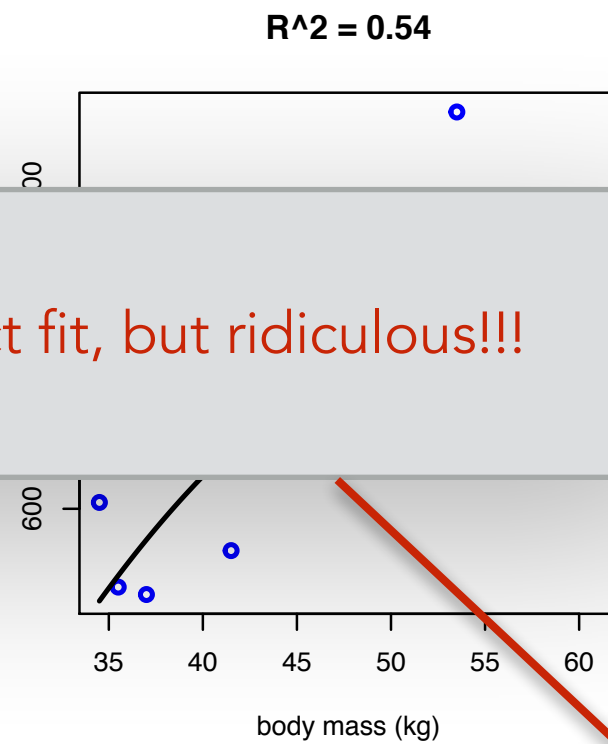
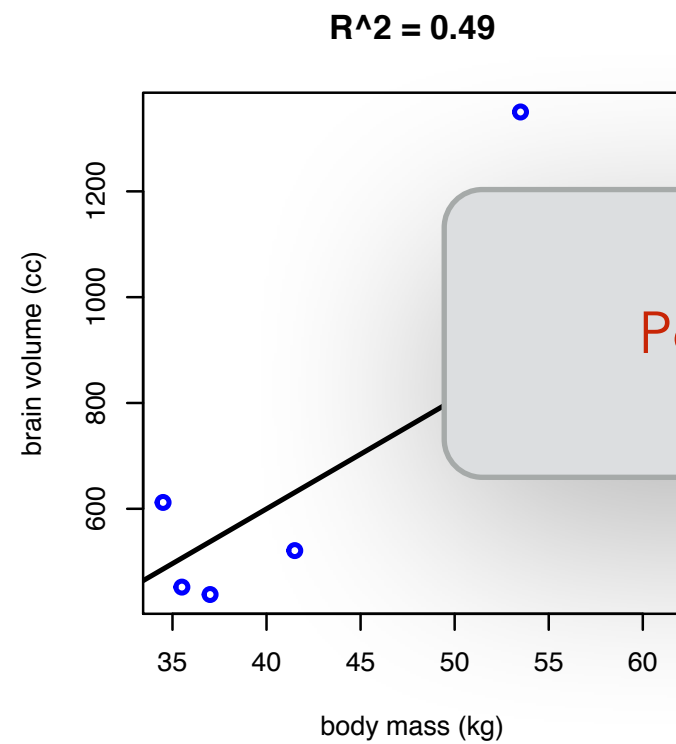
$$y = \alpha + \beta_1 x_1$$

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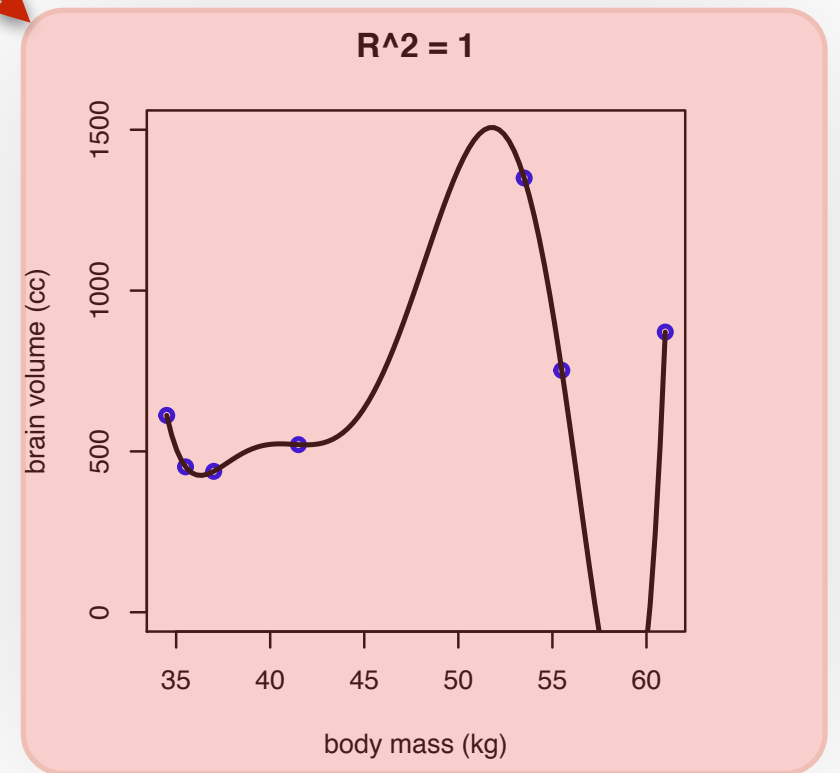
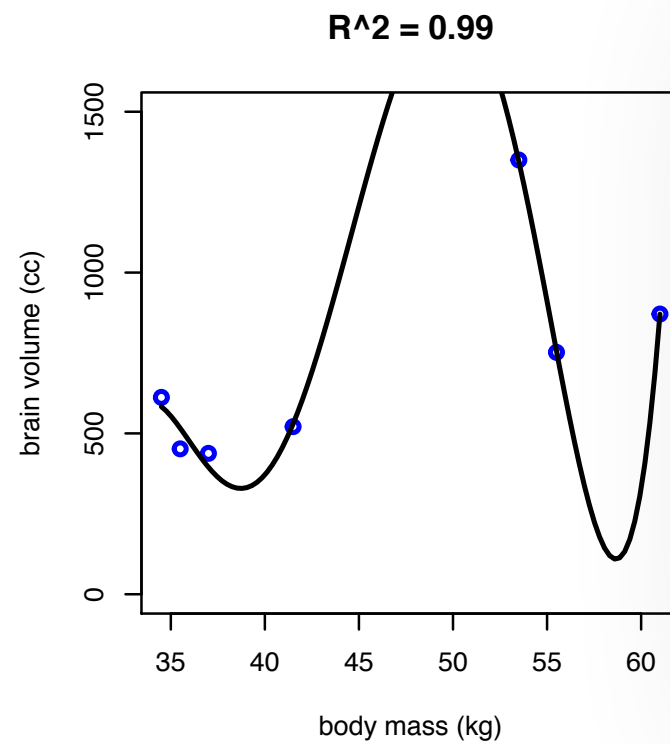
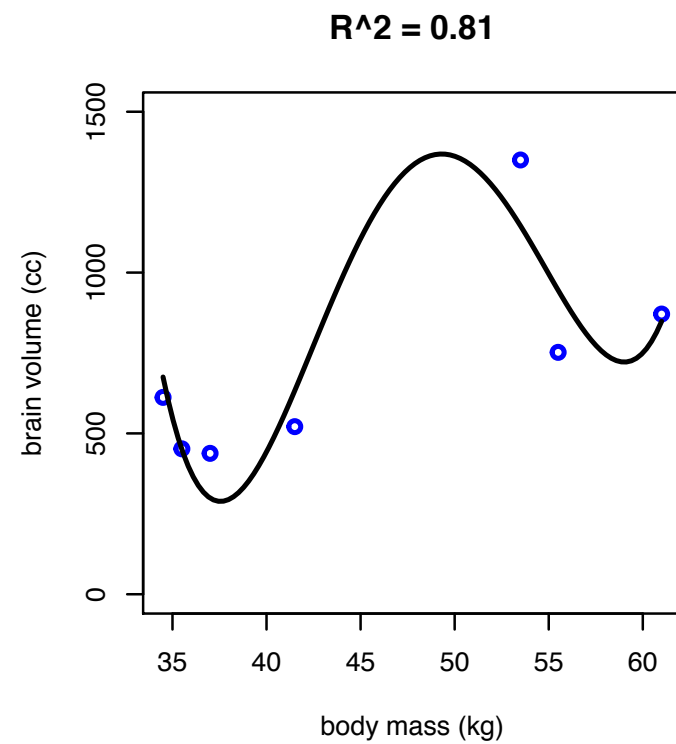
$$y = \alpha + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_1^3$$

...

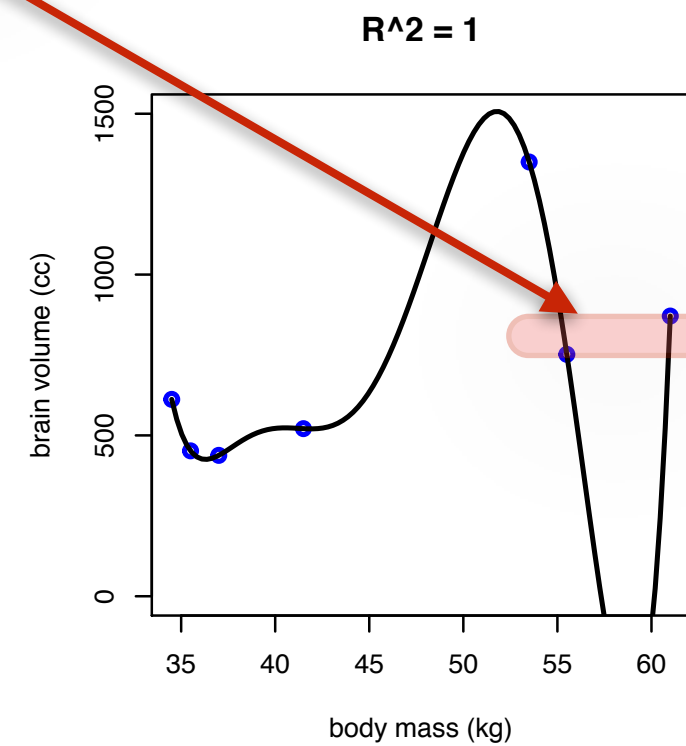
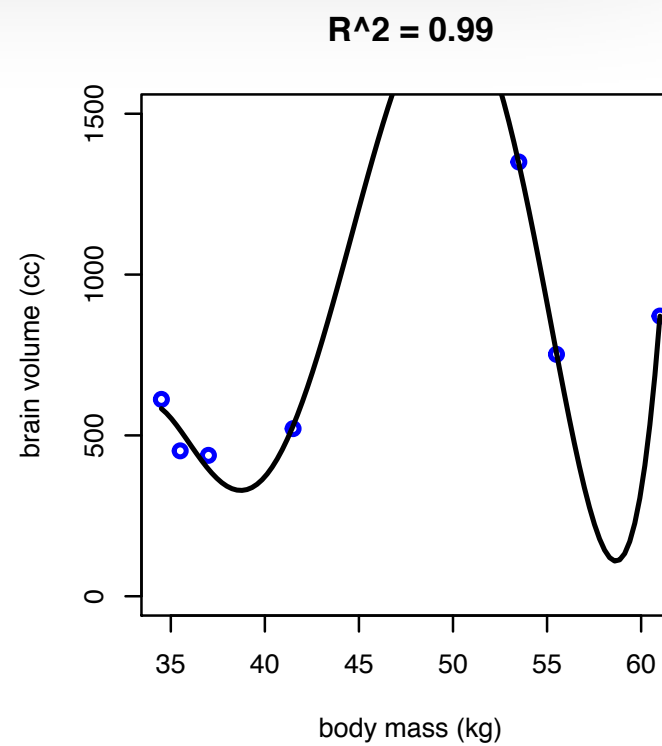
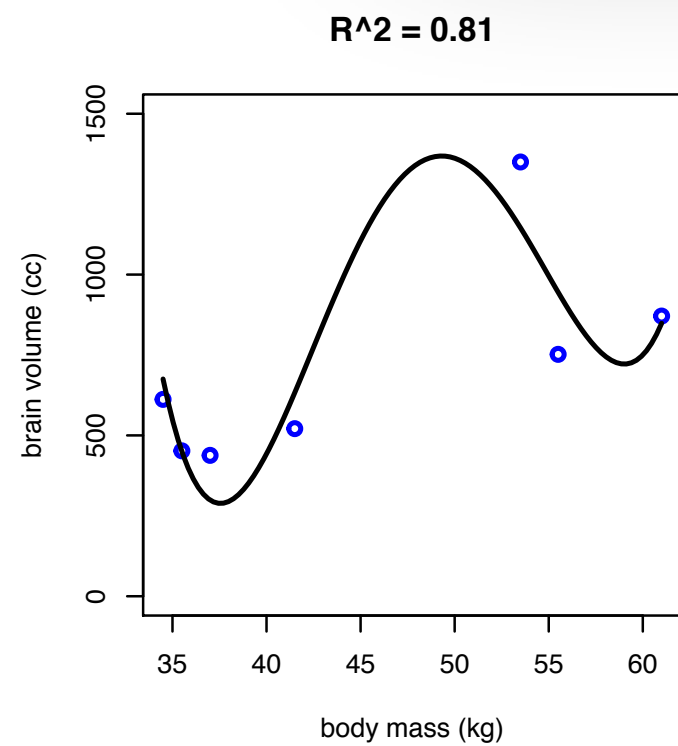
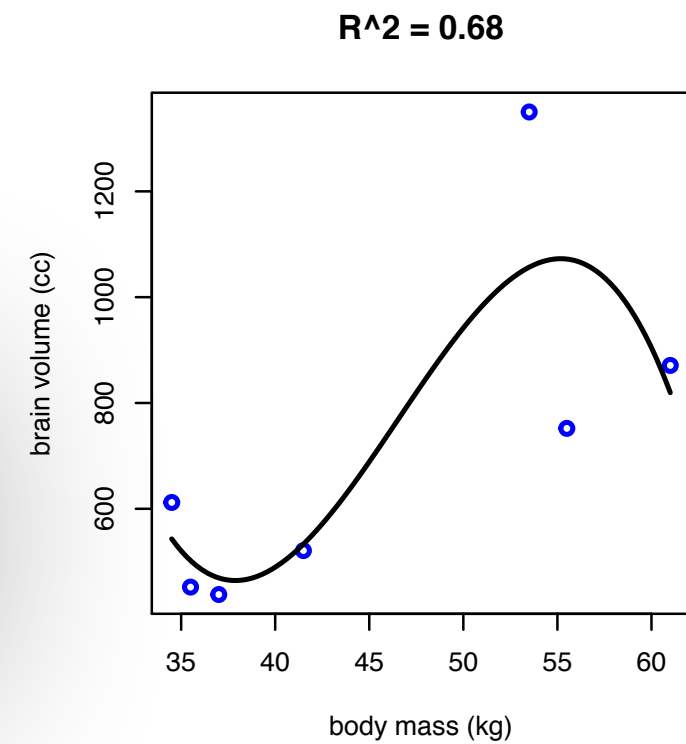
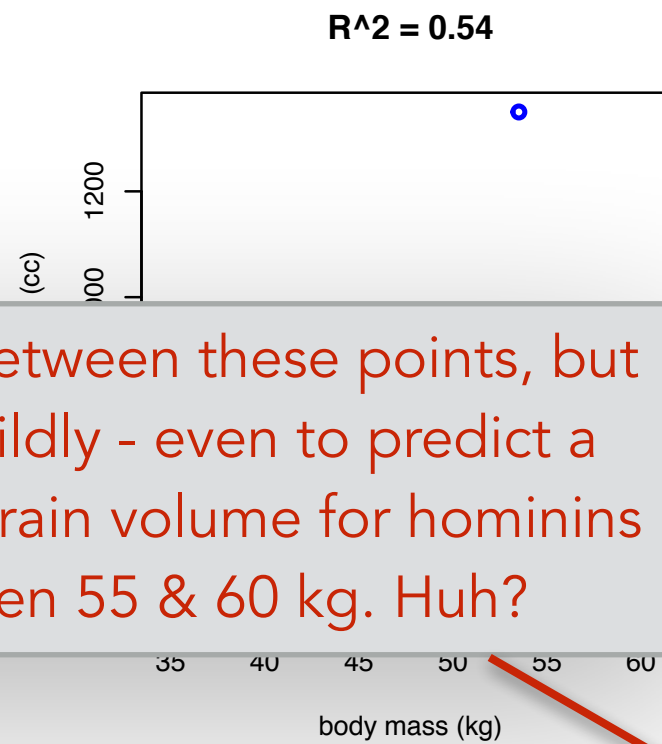
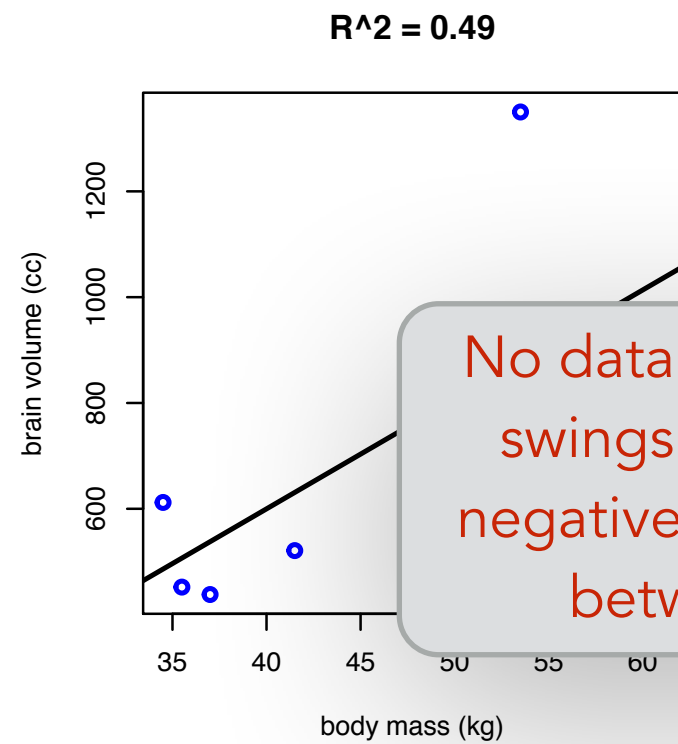




Perfect fit, but ridiculous!!!

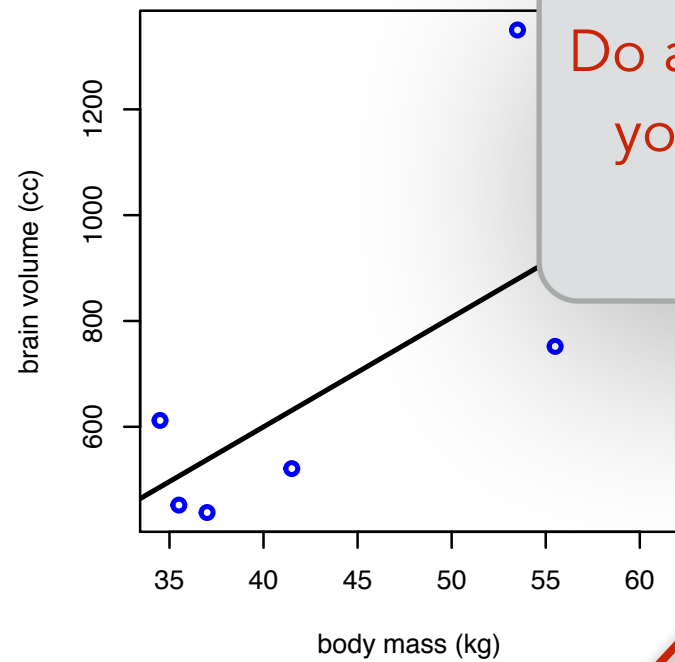




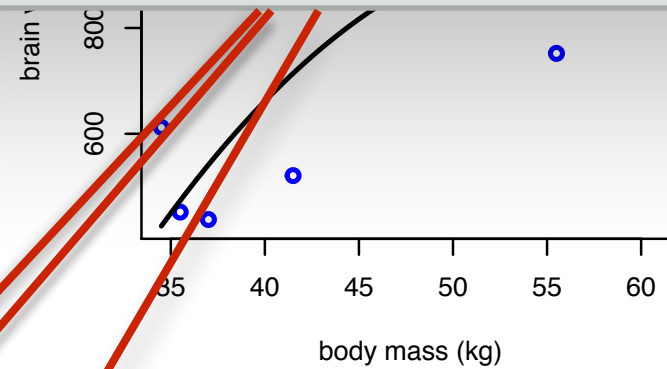


No data between these points, but swings wildly - even to predict a negative brain volume for hominins between 55 & 60 kg. Huh?

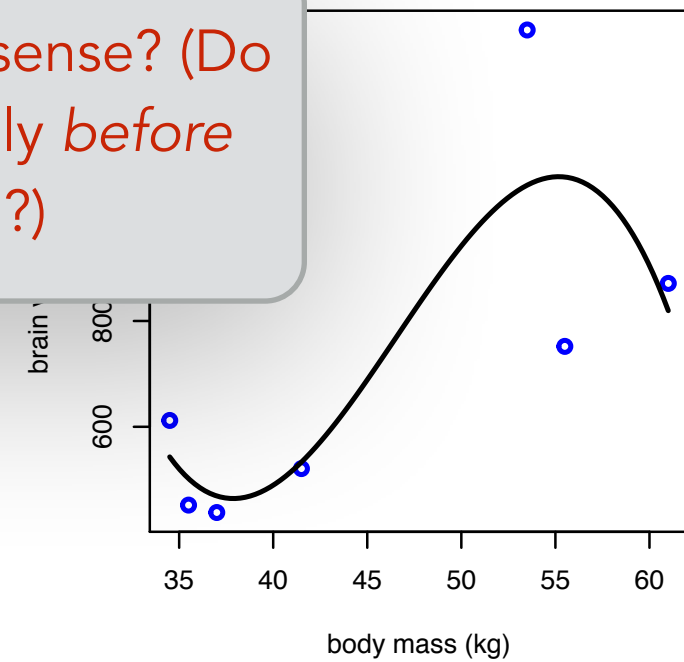
$R^2 = 0.49$



$R^2 = 0.54$

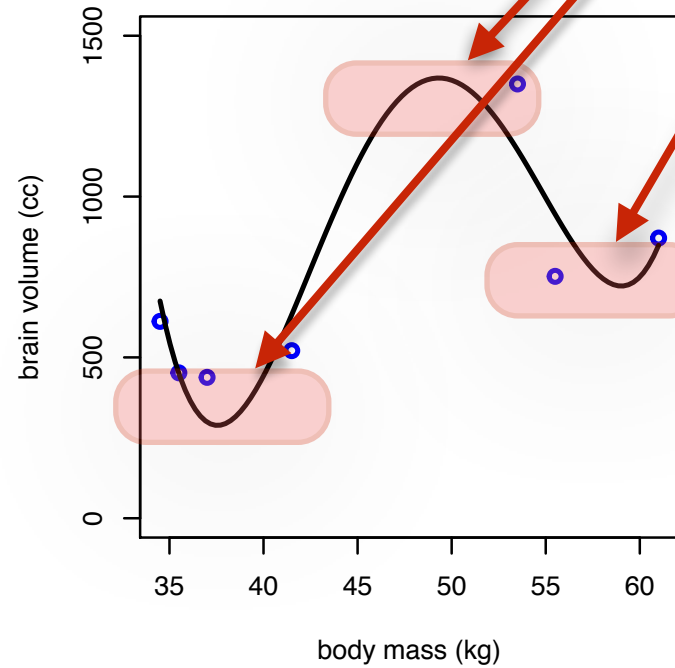


$R^2 = 0.68$

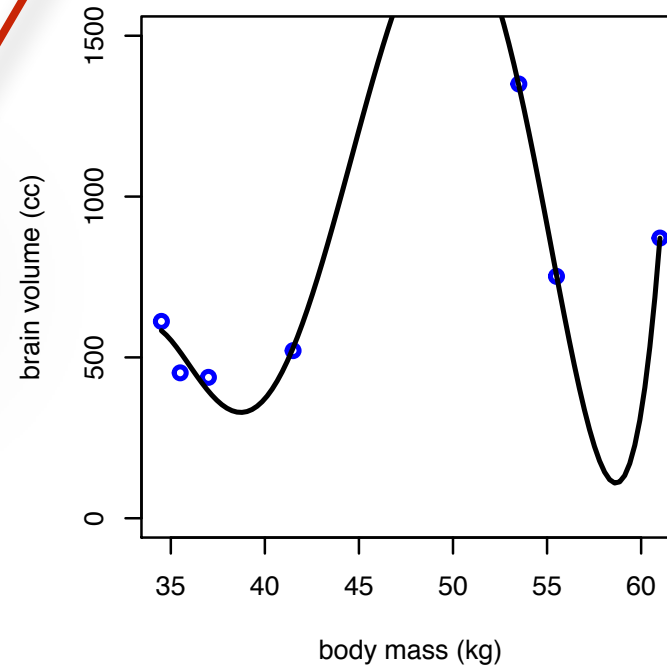


Do all inflections make biological sense? (Do you have a hypothesis...preferably *before* you've looked at the data?)

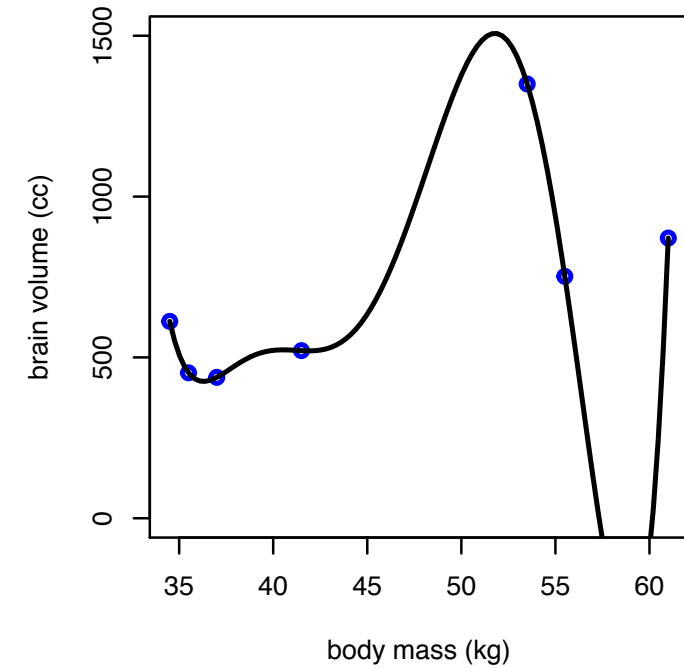
$R^2 = 0.81$



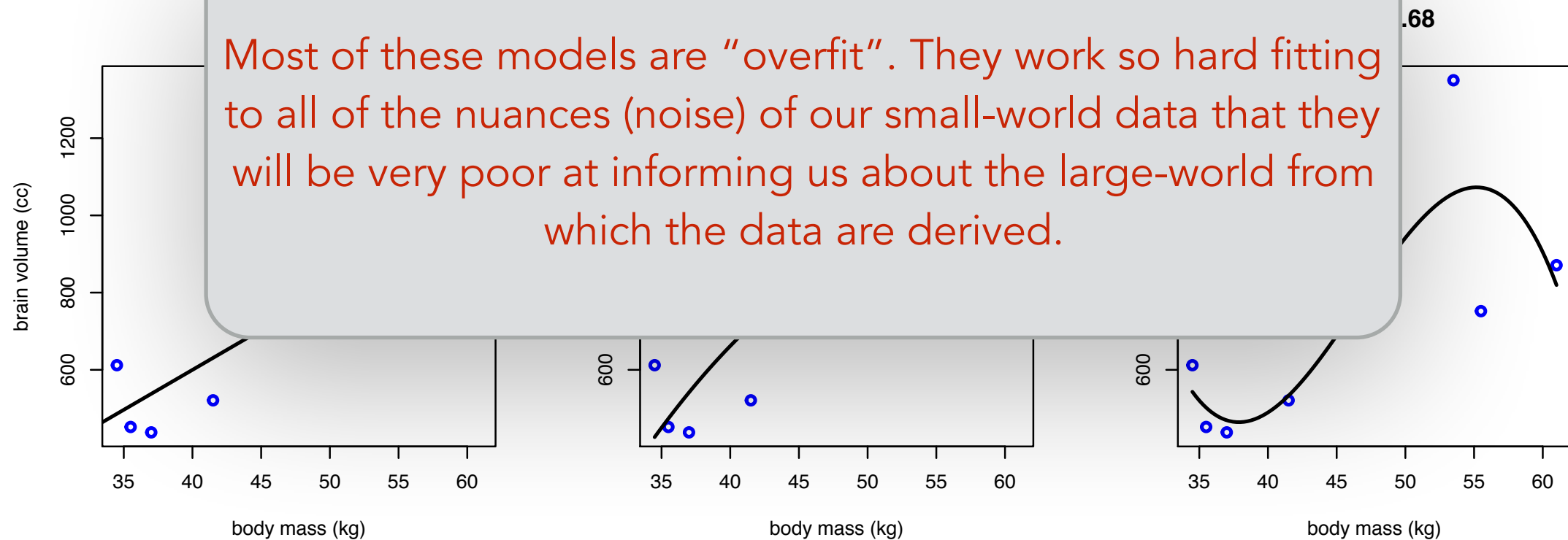
$R^2 = 0.99$



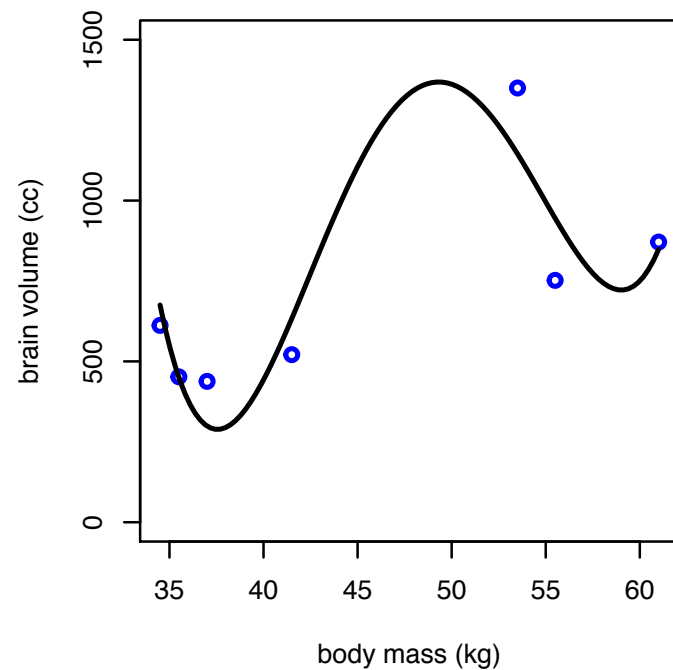
$R^2 = 1$



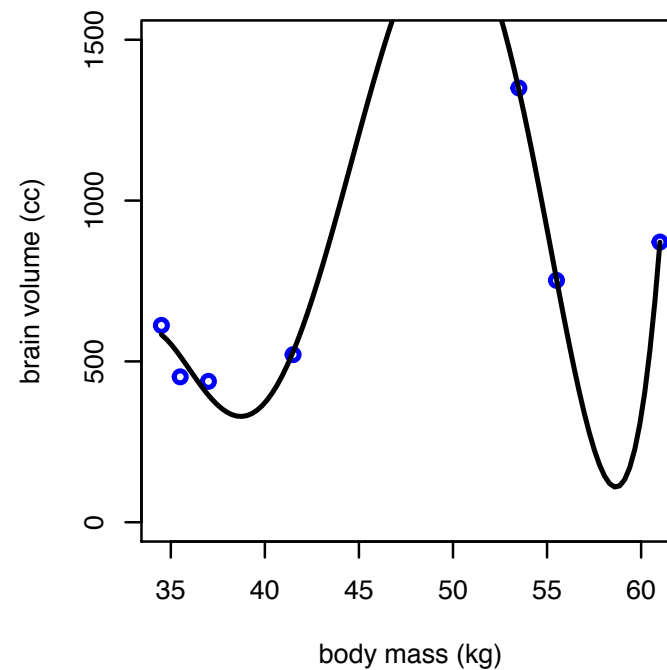
Most of these models are "overfit". They work so hard fitting to all of the nuances (noise) of our small-world data that they will be very poor at informing us about the large-world from which the data are derived.



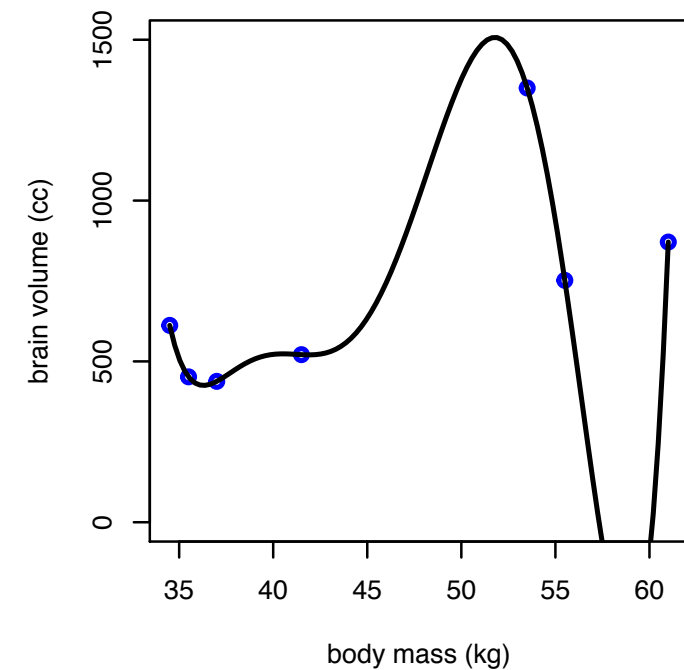
$R^2 = 0.81$



$R^2 = 0.99$

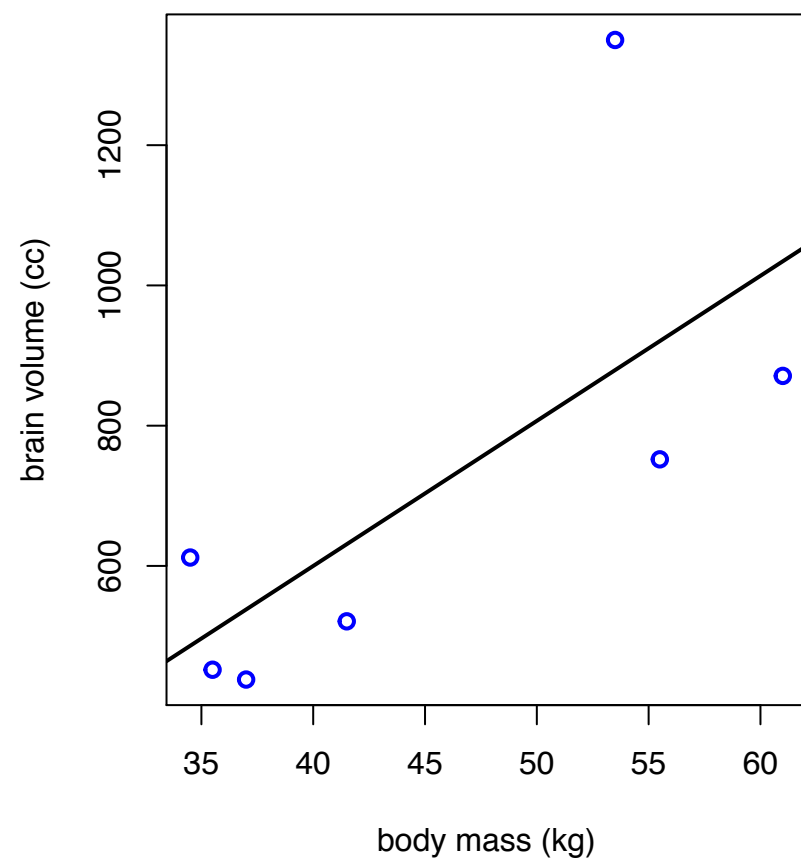


$R^2 = 1$

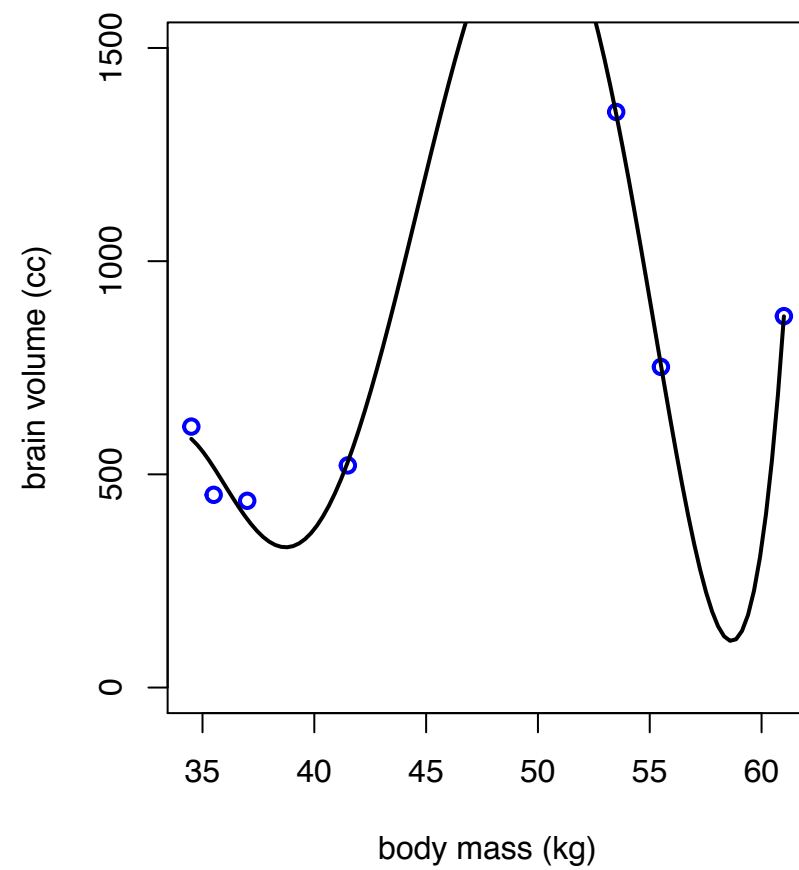


- Can visualize this by removing one point at a time, and seeing how much that changes the pattern (perceived relationships)
- In an underfit model, removing one point will not change the patterns
- In an overfit model, removing one point will change the patterns dramatically

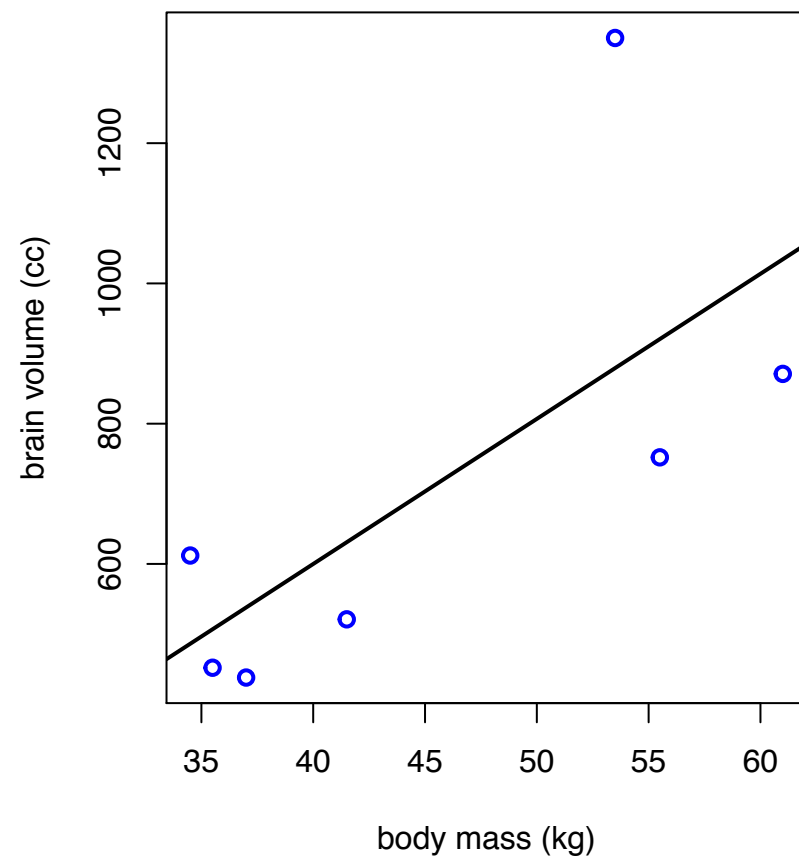
$R^2 = 0.49$



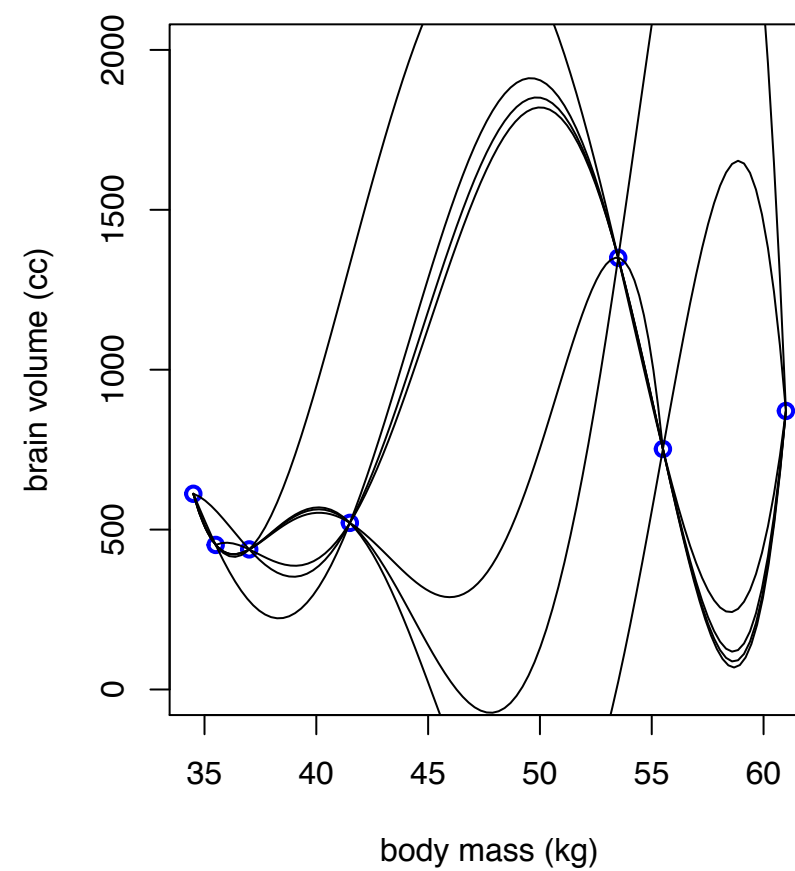
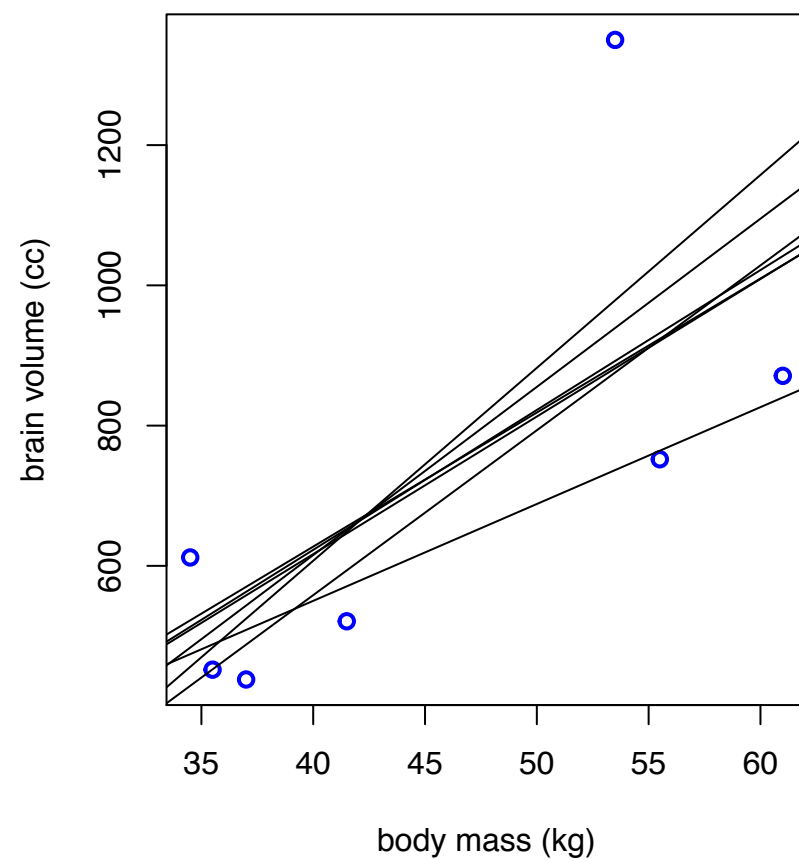
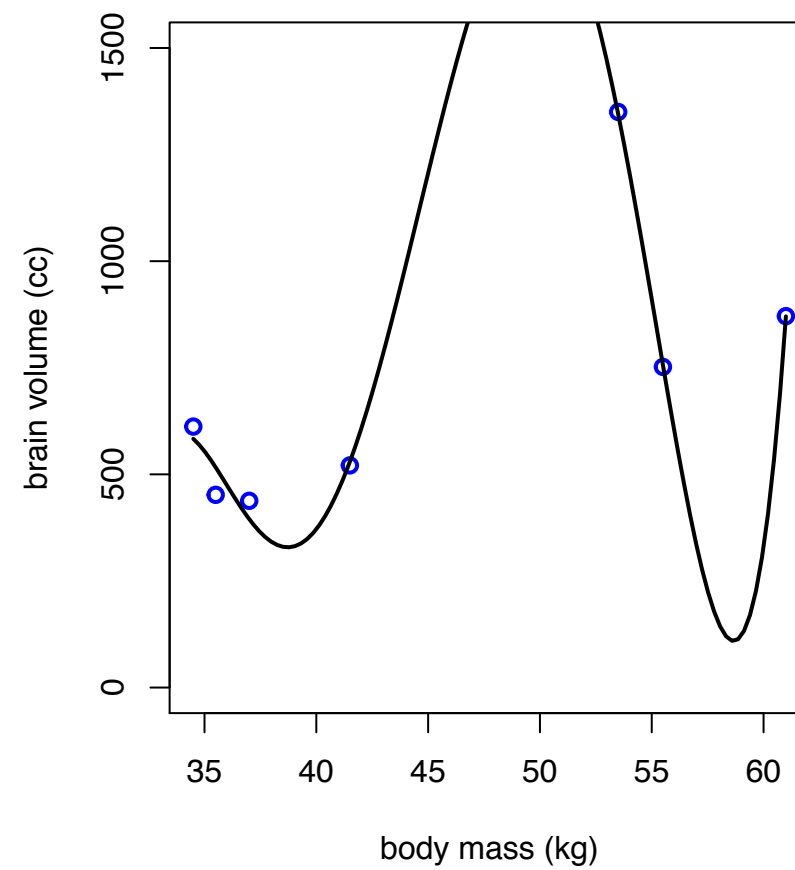
$R^2 = 0.99$



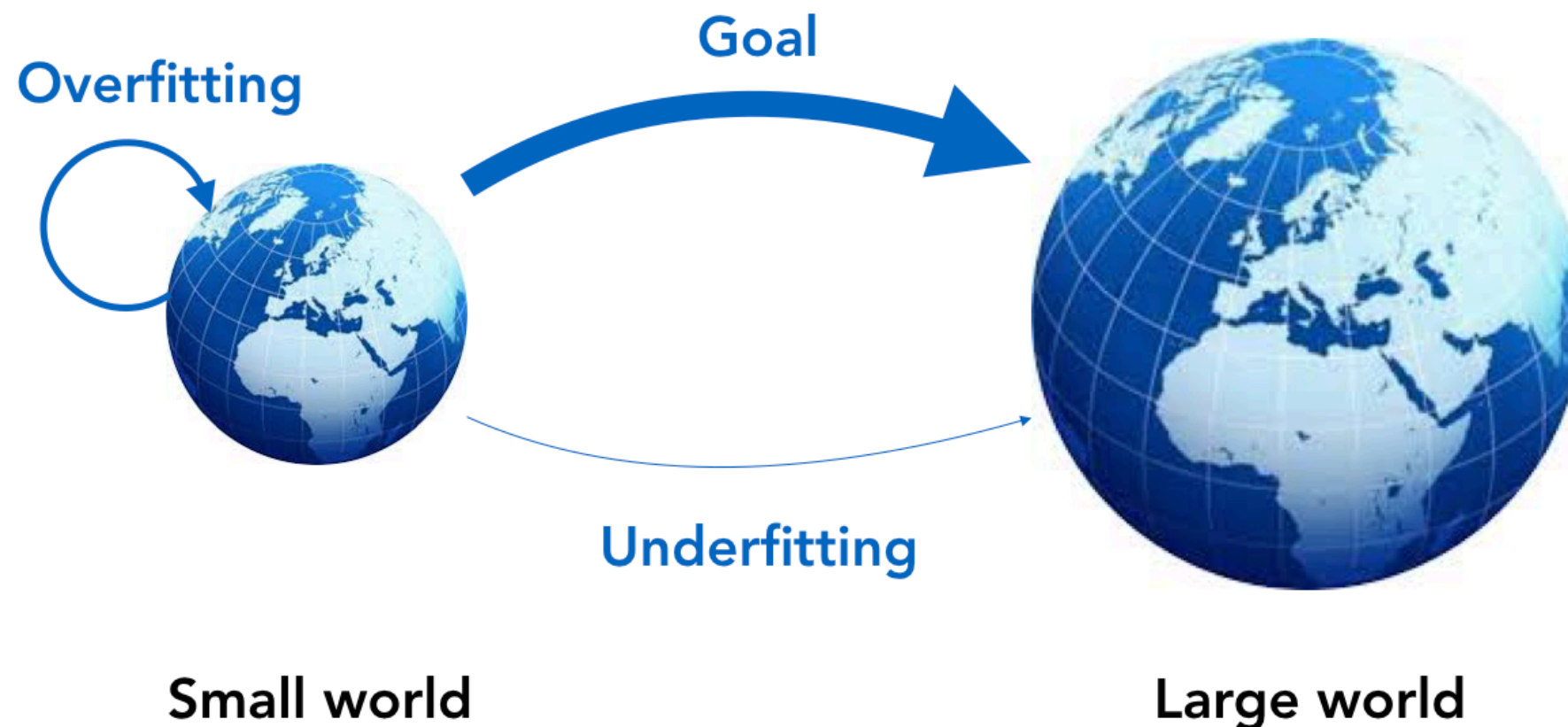
$R^2 = 0.49$



$R^2 = 0.99$

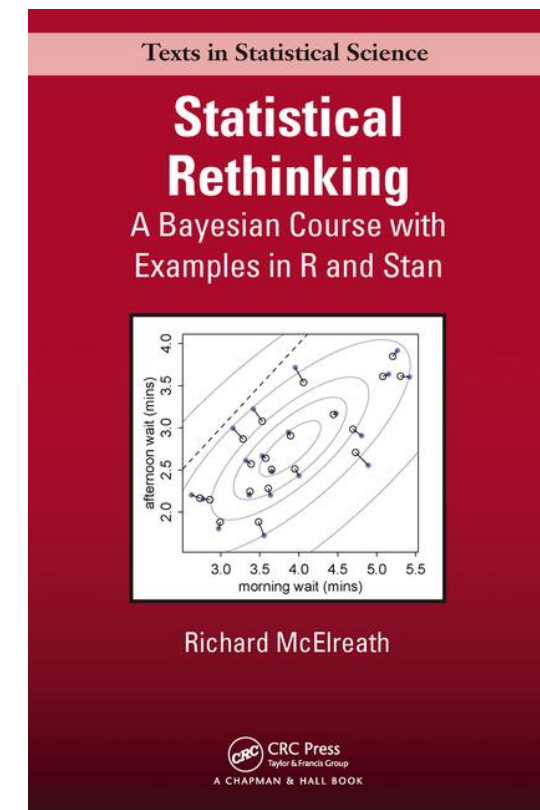


- Ideally, have a method to quantify how well our model will perform “out of sample”
- This is the idea of **information criteria**



# Information Criteria

- Details can be found elsewhere
  - e.g., Chapter 6 in *Statistical Rethinking*
- “Score” **nested** models on their out-of-sample predictive abilities, with some penalty for adding parameters

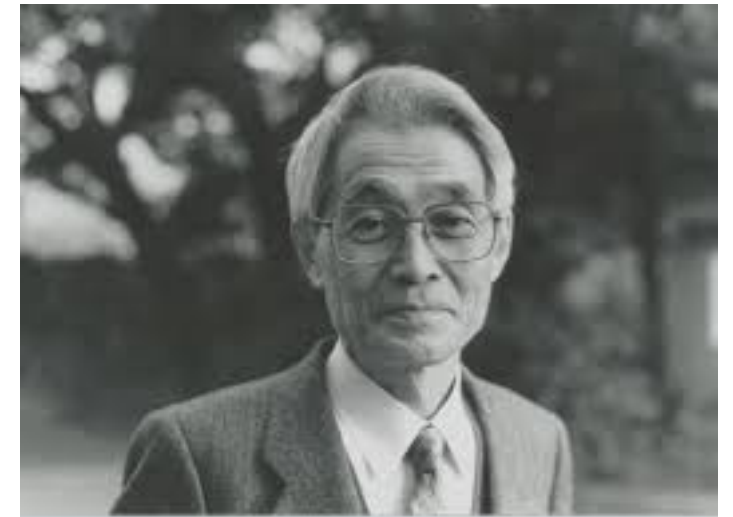


A trade-off between the goodness of fit of the model  
and the complexity of the model.



# Information Criteria

- Akaike Information Criterion (AIC)
- Deviance Information Criterion (DIC)
- Widely Applicable Information Criterion (WAIC)
- Others...



Hirotugu Akaike  
(1927-2009)

# Information Criteria

- Preferred model should be the one with the **lowest** IC
- Provides information on the **relative** informativeness of **compared** models. Tells nothing of the potential truth or usefulness of any
  - All tested models may be poor approximations of the truth
- Think of as less for “model selection” and more as a means to tell you about parameters

# Frequentist Approach

## Potential solution - AIC

```
model_both = lm(legs$height ~ legs$lleg + legs$rleg)
model_lleg = lm(legs$height ~ legs$lleg)
model_rleg = lm(legs$height ~ legs$rleg)
```

```
AIC(model_both, model_lleg, model_rleg)
```

	df	AIC
model_both	4	578.8851
model_lleg	3	578.6527
model_rleg	3	577.8802

# Frequentist Approach

## Potential solution - AIC

```
model_both = lm(legs$height ~ legs$lleg + legs$rleg)
model_lleg = lm(legs$height ~ legs$lleg)
model_rleg = lm(legs$height ~ legs$rleg)

AIC(model_both, model_lleg, model_rleg)
```

	df	AIC
model_both	4	578.8851
model_lleg	3	578.6527
model_rleg	3	577.8802

Including just the right leg has the lowest AIC.

Should not be used to find "the best model", but rather to understand effects of parameters.

Should **not** be interpreted as "left leg had no effect". It **does** still have an effect, but we need to account for it in a different way.

**Questions?**