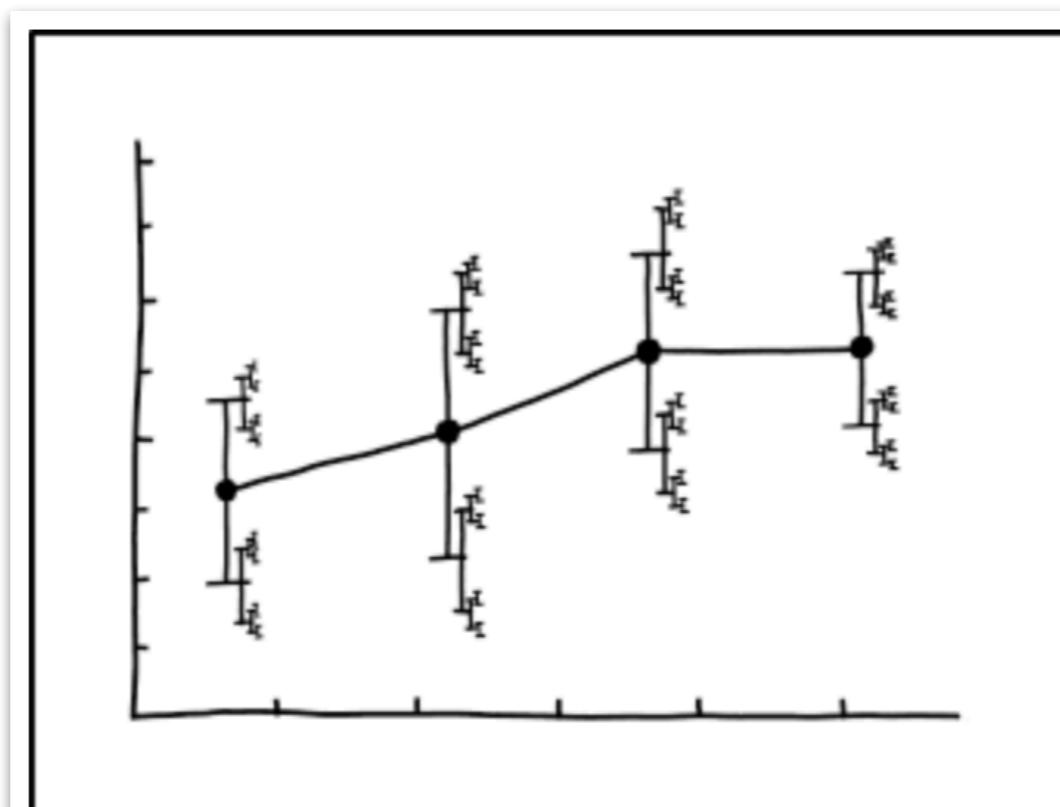
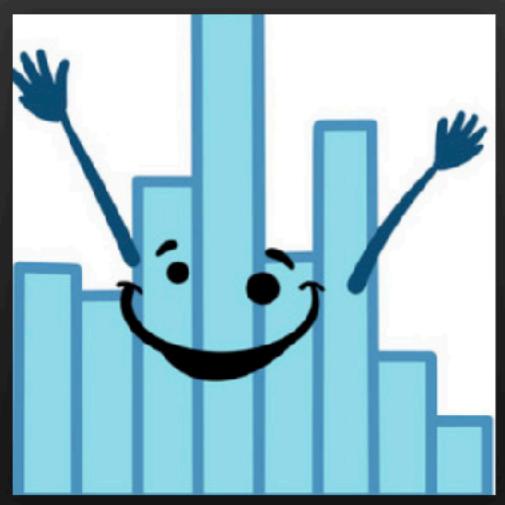


Linear mixed effects models 2



I DON'T KNOW HOW TO PROPAGATE
ERROR CORRECTLY, SO I JUST PUT
ERROR BARS ON ALL MY ERROR BARS.



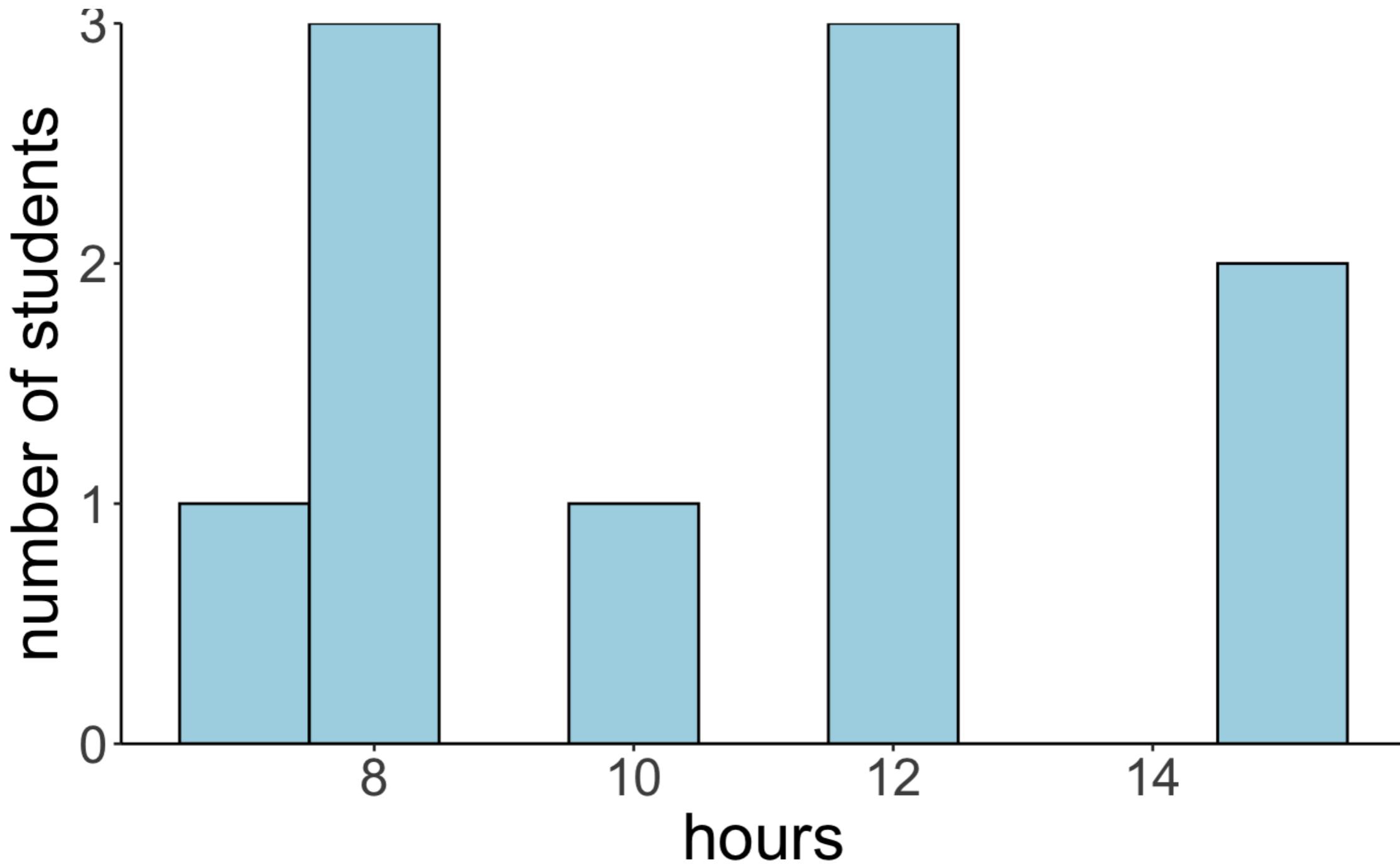
O COLLABORATIVE PLAYLIST
psych252
<https://tinyurl.com/psych252spotify24>

PLAY ...

A Spotify playlist cover for "psych252". It features a dark background with light blue bars resembling a histogram. A cartoon character with a smiling face and arms is superimposed on the bars. The title "psych252" is in large white font, and the URL "https://tinyurl.com/psych252spotify24" is in white text below it. There are "PLAY" and "..." buttons at the bottom.

Feedback

Feedback: Midterm



Plan for today

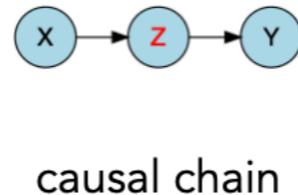
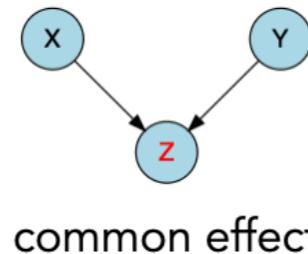
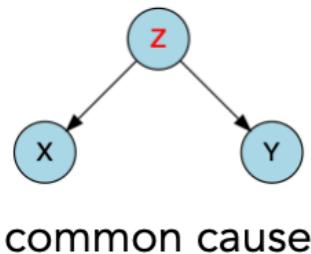
- Quick recap
- Linear mixed effects model
 - Modeling dependence in data
 - Understanding `lmer()` syntax
 - A worked example
 - Reporting results
 - Simpsons Paradox

Quick recap

Quick recap: Controlling

Patterns of inference

We want to estimate the (causal) relationship between X and Y



by controlling for Z we hope to get a better estimate of the relationship between X and Y

When should I control for variables?

How can I tell whether two variables are independent?

Recipe for independence

1. Draw the ancestral graph
 2. "Moralize" the graph by "marrying" the parents
 3. "Disorient" the graph by replacing arrows with edges
 4. Delete the givens and their edges
 5. Read the answer off the graph
- if variables are **disconnected** they are independent
 - if variables are connected (have a path between them) they are not guaranteed to be independent

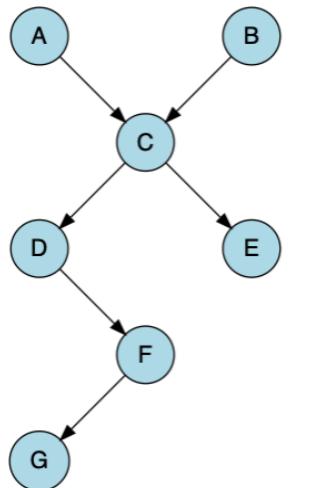
<http://web.mit.edu/jmn/www/6.034/d-separation.pdf>

37

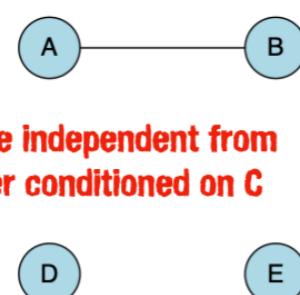
When should I control for variables?

Are D and E independent, given C? 5. Read answer off the graph

$$p(D|E, C) = p(D|C) ?$$



D and E are independent from each other conditioned on C



they aren't connected via a path

- if variables are **disconnected** they are independent
- if variables are connected (have a path between them) they are not guaranteed to be independent

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When should I control for variables?

```

1 set.seed(1)
2
3 n = 1000
4 b_zx = 2
5 b_xy = 2
6 b_zy = 2
7 sd = 1
8
9 df = tibble(z = rnorm(n = n, sd = sd),
10           x = b_zx * z + rnorm(n = n, sd = sd),
11           y = b_zy * z + b_xy * x + rnorm(n = n, sd = sd))

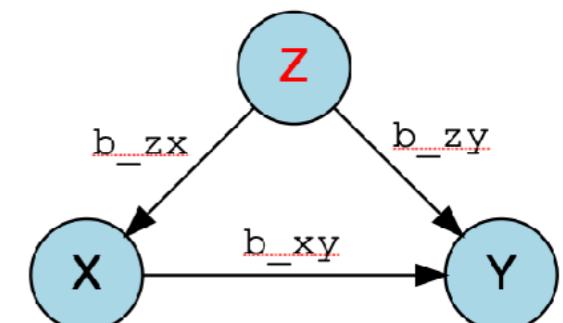
```

$$Y = b_0 + b_1 \cdot X + e$$

```

1 # without control
2 lm(formula = y ~ x,
3   data = df) %>%
4   summary()

```



overestimating
X's effect on Y

```

Call:
lm(formula = y ~ x, data = df)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.6011 -0.9270 -0.0506  0.9711  4.0454 

Coefficients:
Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.02449  0.04389  0.558  0.577    
x            2.82092  0.01890 149.225 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

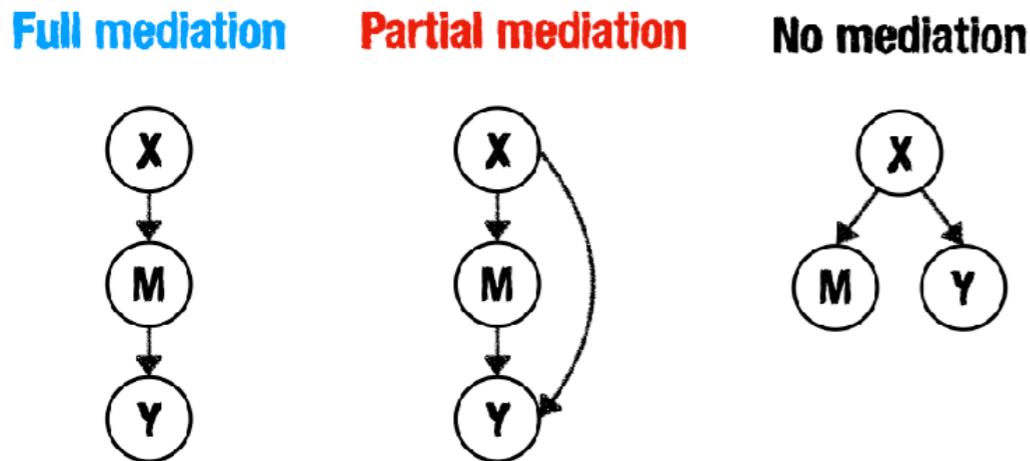
Residual standard error: 1.388 on 998 degrees of freedom
Multiple R-squared:  0.9371, Adjusted R-squared:  0.9371 
F-statistic: 2.227e-04 on 1 and 998 DF,  p-value: < 2.2e-16

```

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Quick recap: Mediation and Moderation

Underlying causal model

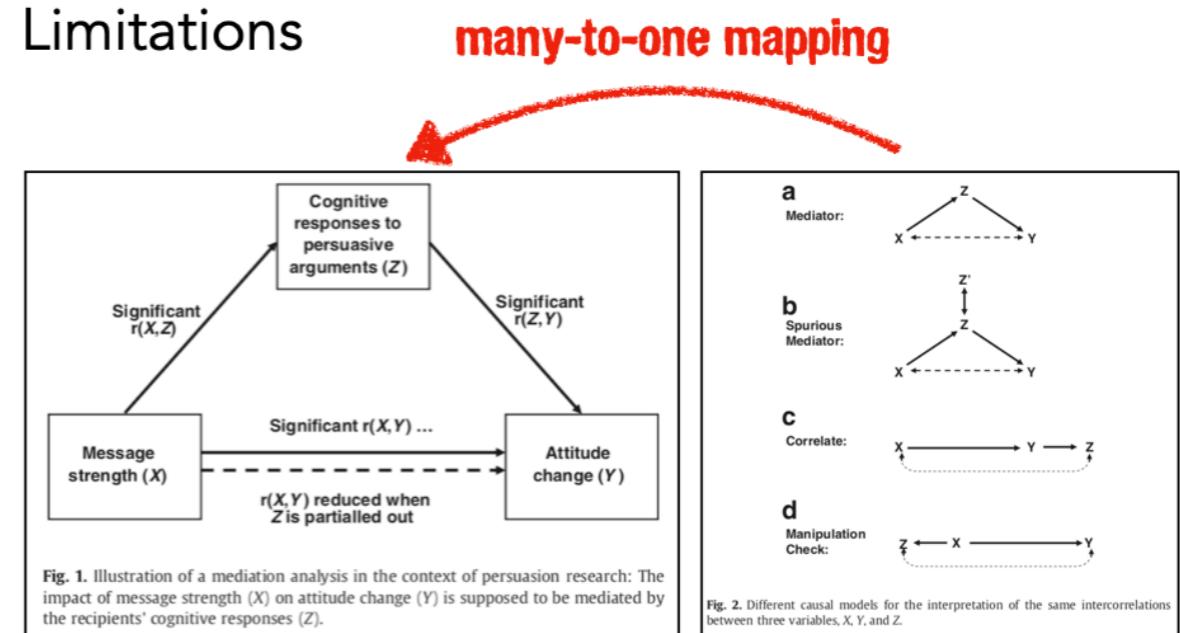


Full mediation: When the effect of **X** on **Y** completely disappears, **M** fully mediates between **X** and **Y**.

Partial mediation: When the effect of **X** on **Y** still exists, but in a smaller magnitude, **M** partially mediates between **X** and **Y**.

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Limitations

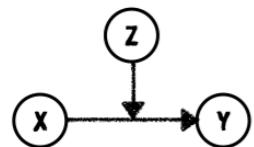


only experiments allow us to tell apart possible causal structures

Fiedler, K., Schott, M., & Meiser, T. (2011). What mediation analysis can (not) do. *Journal of Experimental Social Psychology*, 47(6), 1231-1236.

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Definition

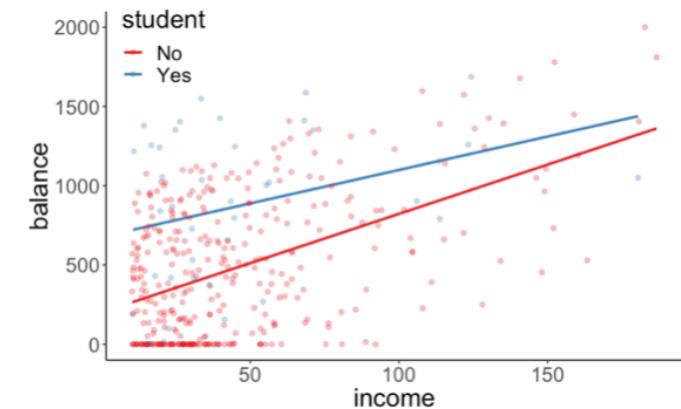


Moderation means that the effect of a predictor depends on the value of another.

Here, the nature of the relationship between **X** and **Y** depends on **Z**.

Have we come across moderation already?

Relationship between credit card balance, income, and whether the person is a student.



$$\widehat{\text{balance}}_i = 200.62 + 6.22 \cdot \text{income}_i + 476.68 \cdot \text{student}_i - 2.00 \cdot (\text{income}_i \times \text{student}_i)$$

if student = "No" $\widehat{\text{balance}}_i = 200.62 + 6.22 \cdot \text{income}_i$

if student = "Yes"

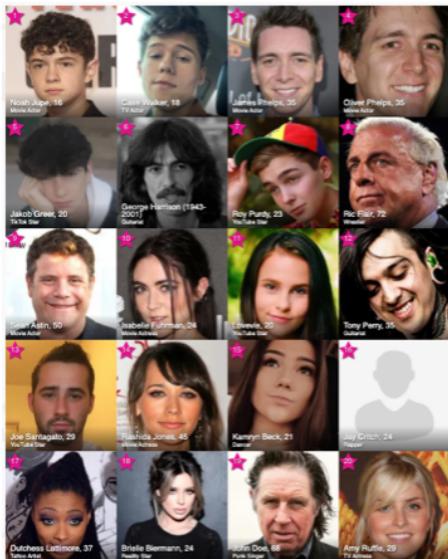
$$\begin{aligned} \widehat{\text{balance}}_i &= 200.62 + 6.22 \cdot \text{income}_i + 476.68 \cdot 1 - 2.00 \cdot (\text{income}_i \times 1) \\ &= 677.3 + 6.22 \cdot \text{income}_i - 2.00 \cdot \text{income}_i \\ &= 677.3 + 4.22 \cdot \text{income}_i \end{aligned}$$

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66

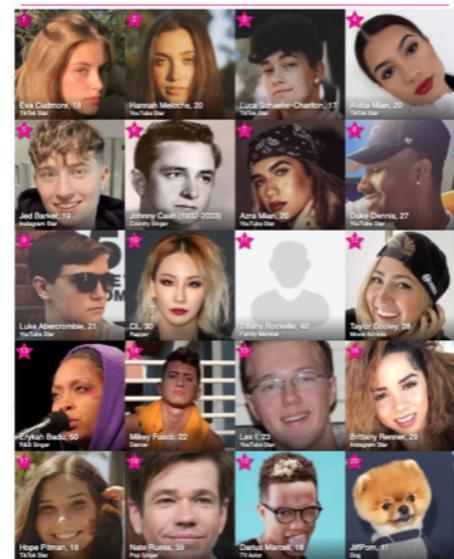
Quick recap: Dependent data points

Are faces of people born on February 25th more trustworthy than faces of people born on February 26th?



born on February 25th

N = 100 participants

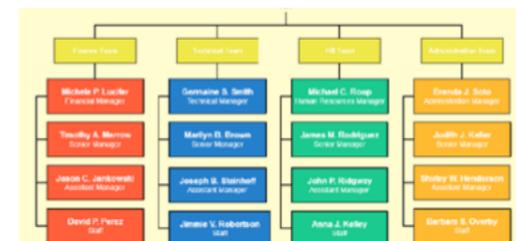


born on February 26th

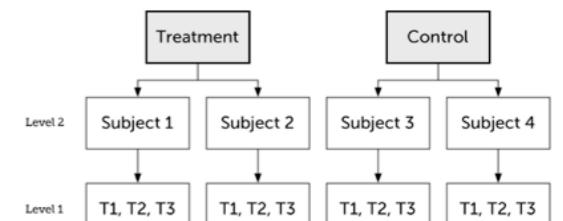
```
1 lmer(formula = trustworthy ~ 1 + birthday +
       (1 | item) + (1 | participant),
2 data = df.birthday)
```

Linear mixed effects models

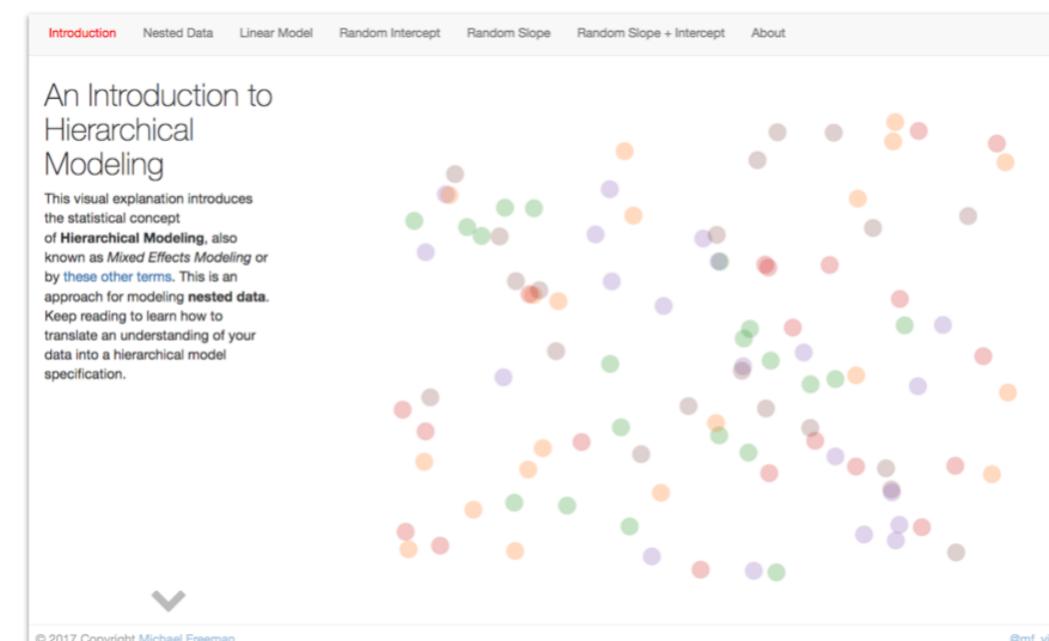
Hierarchical models



Longitudinal models



- allow us to account for dependencies in our data
- hierarchical models:** schools > teachers > students
- longitudinal models:** repeated observations from the same people



<http://mfviz.com/hierarchical-models/>

Linear mixed effects models

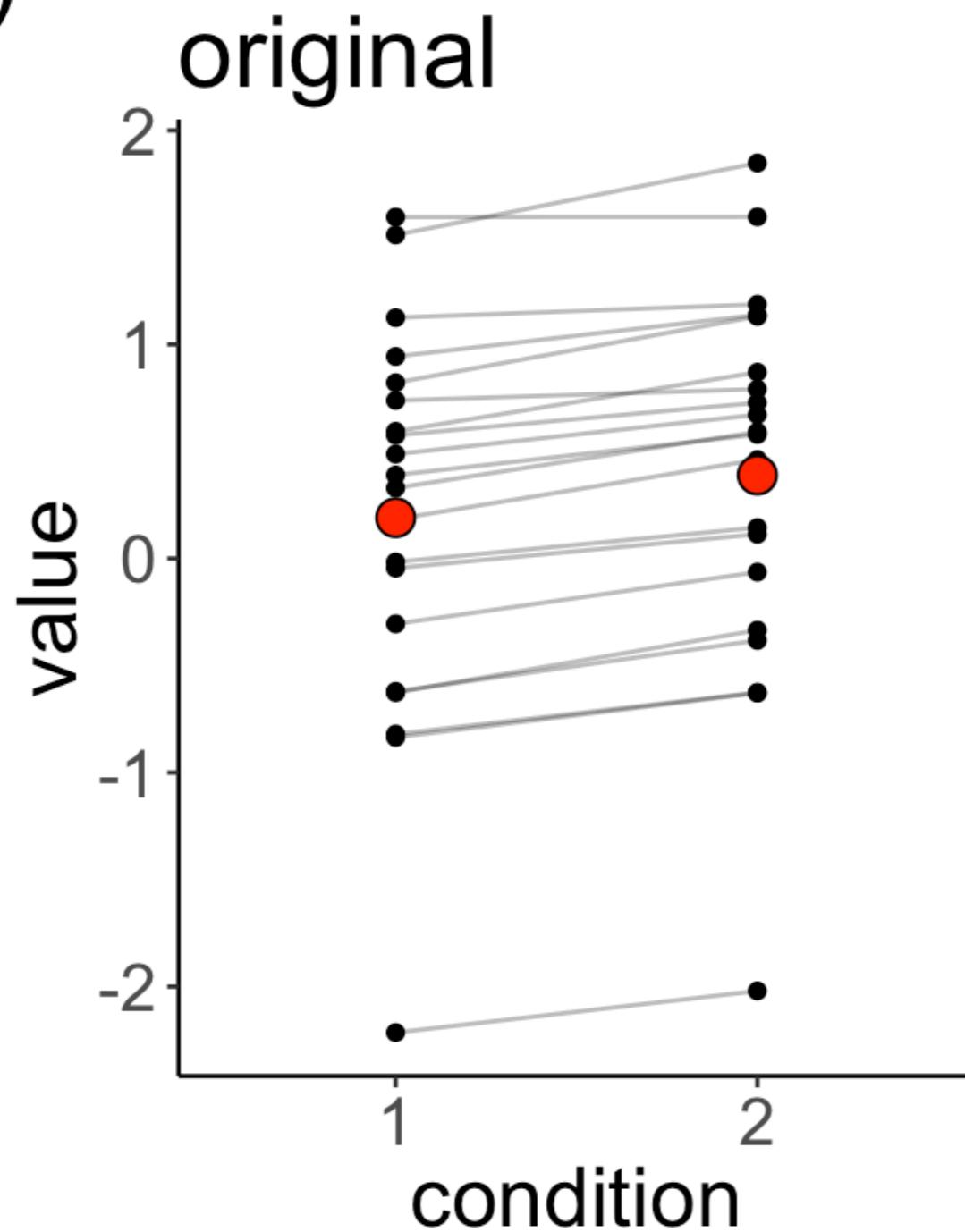
Modeling dependence in data

Dependence

Does it really matter?

Is there a significant difference
between conditions 1 and 2?

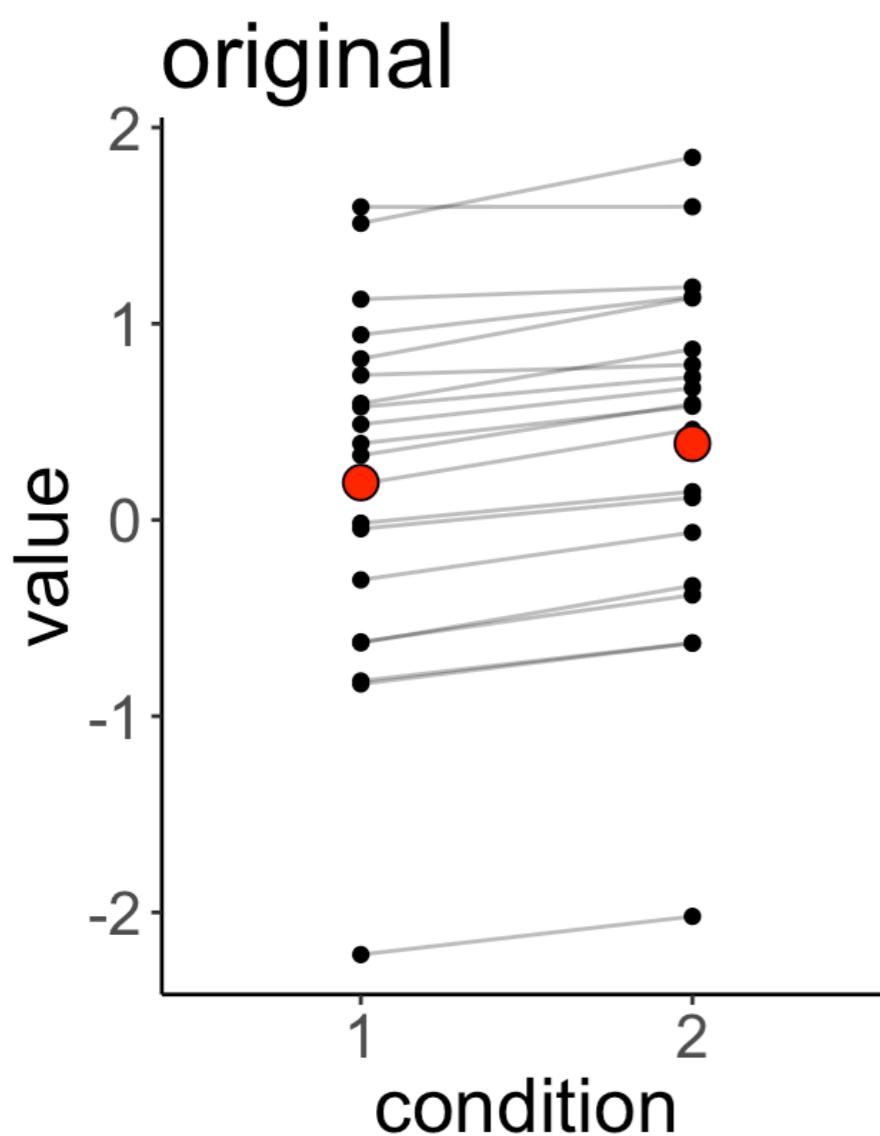
a)



Dependence

assuming independence!

```
1 # linear model  
2 lm(formula = value ~ condition,  
3     data = df.original) %>%  
4 summary()
```



```
Call:  
lm(formula = value ~ condition, data = df.original)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-2.4100 -0.5530  0.1945  0.5685  1.4578  
  
Coefficients:  
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)  0.1905    0.2025   0.941  0.353  
condition2   0.1994    0.2864   0.696  0.491  
  
Residual standard error: 0.9058 on 38 degrees of freedom  
Multiple R-squared:  0.01259,    Adjusted R-squared: -0.0134  
F-statistic: 0.4843 on 1 and 38 DF,  p-value: 0.4907
```

- we ignore the fact that we have repeated observations from the same participants
- in the data it looks like there is a small but consistent effect of condition

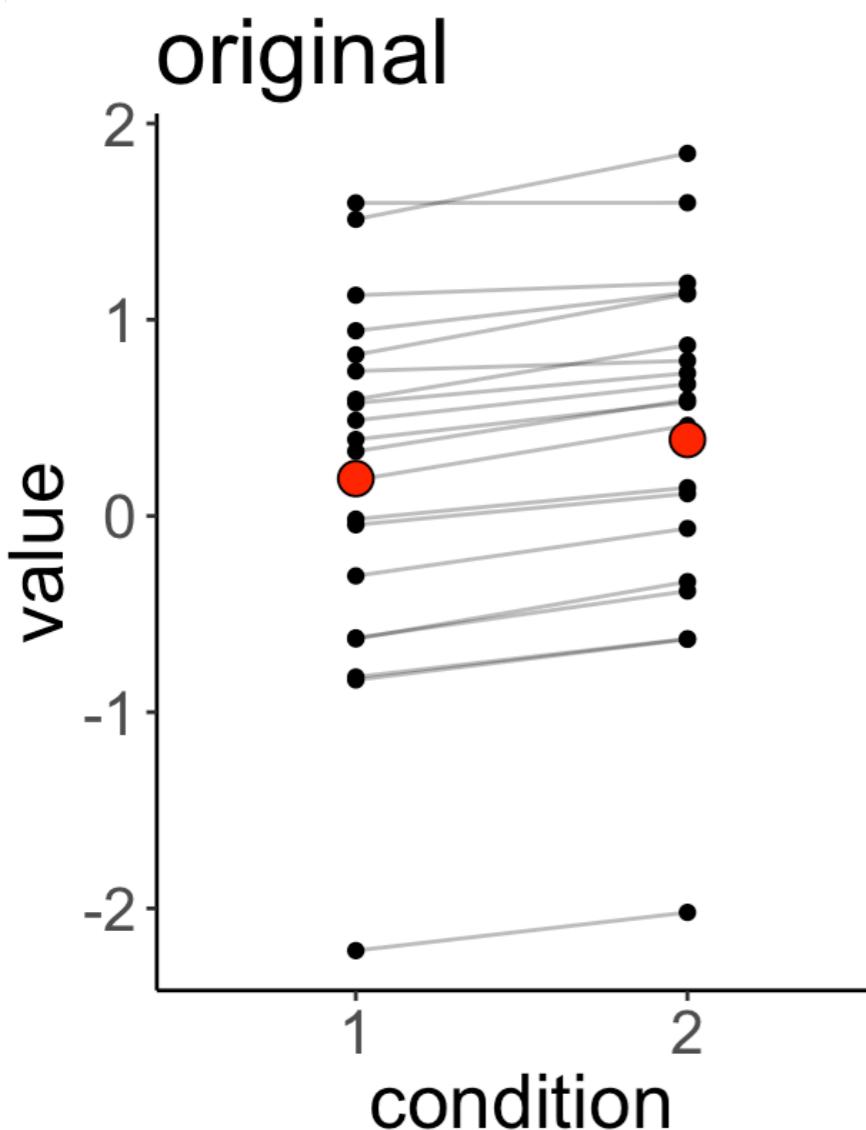
meet **lmer()**



Dependence

new syntax

```
1 # fit a linear mixed effects model
2 lmer(formula = value ~ condition + (1 | participant),
3       data = df.original) %>%
4 summary()
```



```
Linear mixed model fit by REML ['lmerMod']
Formula: value ~ condition + (1 | participant)
Data: df.original

REML criterion at convergence: 17.3

Scaled residuals:
    Min     1Q   Median     3Q    Max 
-1.55996 -0.36399 -0.03341  0.34400 1.65823 

Random effects:
Groups      Name        Variance Std.Dev. 
participant (Intercept) 0.816722 0.90373 
Residual            0.003796 0.06161 
Number of obs: 40, groups: participant, 20

Fixed effects:
Estimate Std. Error t value
(Intercept) 0.19052  0.20255  0.941 
condition2   0.19935  0.01948 10.231 

Correlation of Fixed Effects:
          (Intr) condition2 
condition2 -0.048
```

no p-value!

NO P-VALUE



Dependence

we can still do our good ol' model comparison trick

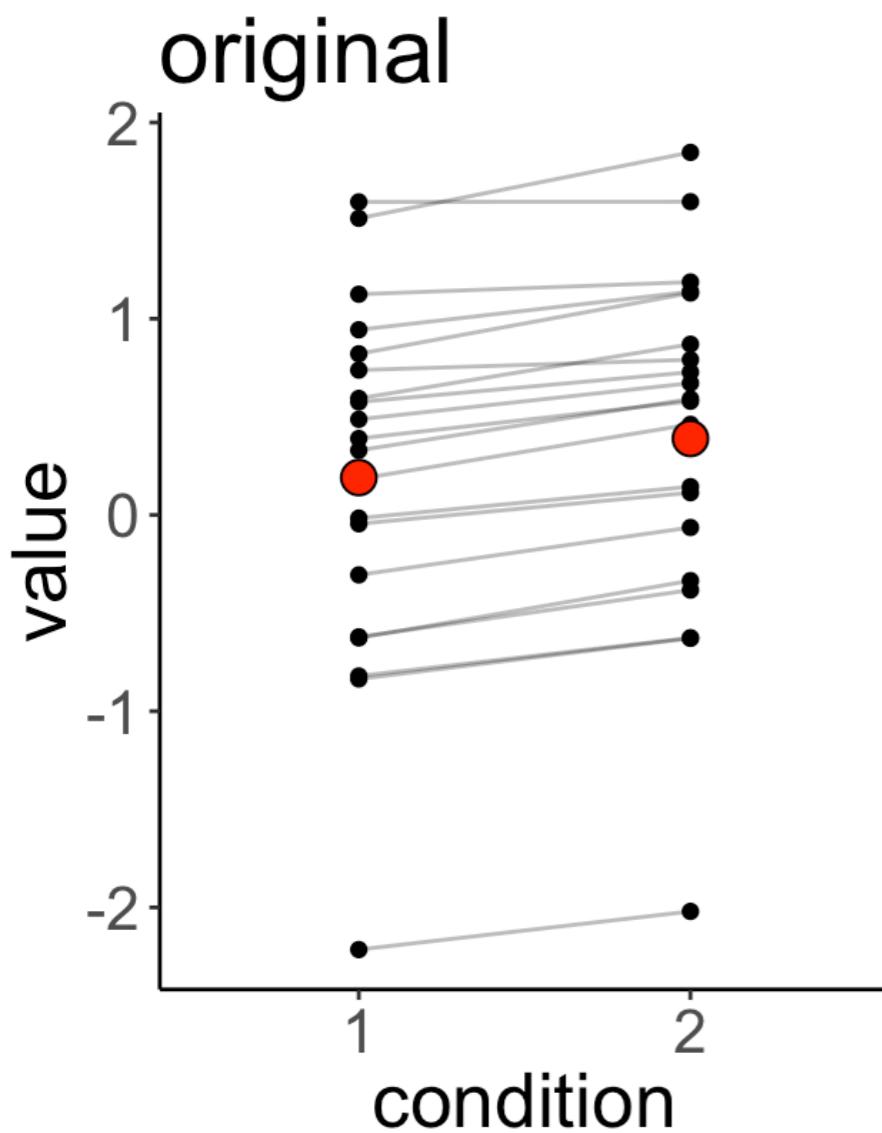
```
1 # fit models
2 fit.compact = lmer(formula = value ~ 1 + (1 | participant),
3                     data = df.original)

4 fit.augmented = lmer(formula = value ~ 1 + condition + (1 | participant),
5                     data = df.original)
6
7 # compare via Chisq-test
8 anova(fit.compact, fit.augmented)
```

```
refitting model(s) with ML (instead of REML)
Data: df.original
Models:
fit.compact: value ~ 1 + (1 | participant)
fit.augmented: value ~ 1 + condition + (1 | participant)
              Df     AIC     BIC   logLik deviance    Chisq Chi Df Pr(>Chisq)
fit.compact     3 53.315 58.382 -23.6575     47.315
fit.augmented   4 17.849 24.605  -4.9247      9.849 37.466          1 9.304e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Dependence

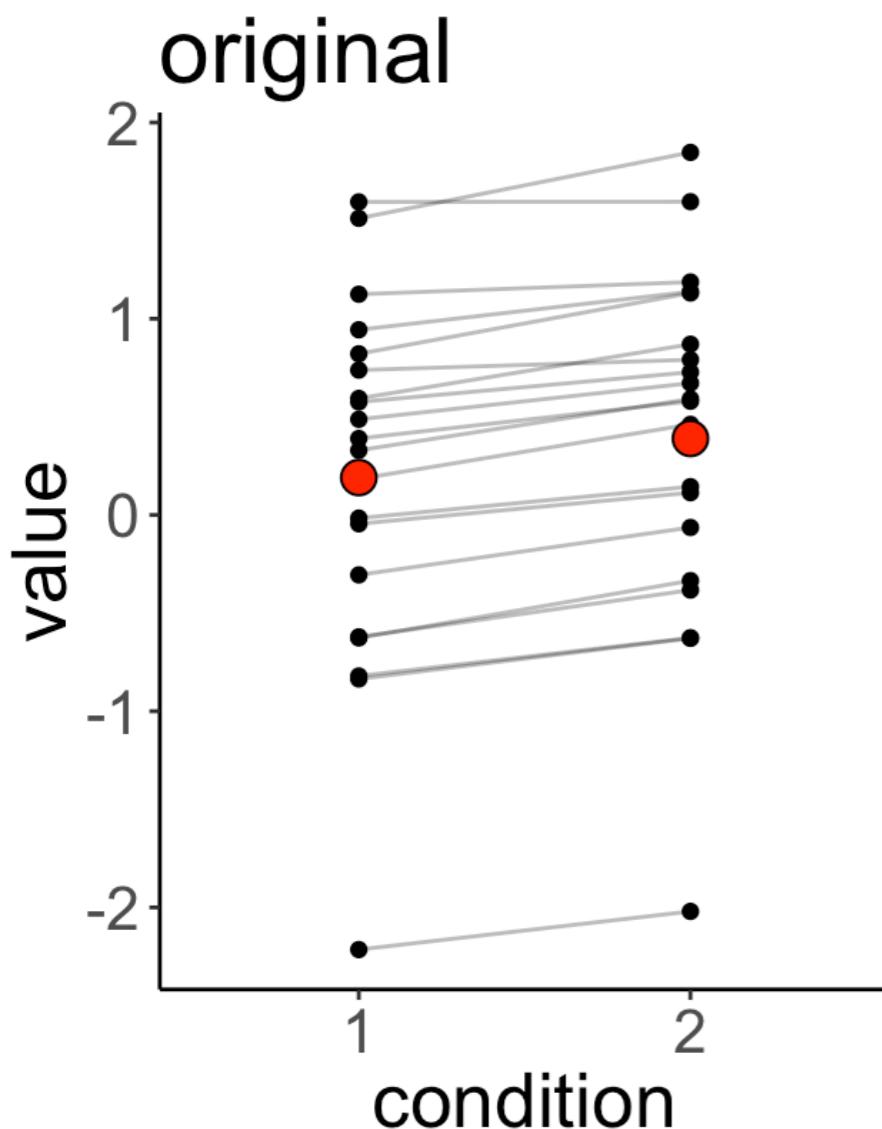
Why is the effect of condition significant when we account for the dependence in the data?



- there are large interindividual differences in the baseline
- the variance explained by the effect of condition is (much) smaller than the interindividual variance
- **but:** the effect of condition is highly consistent

Dependence

Why is the effect of condition significant when we account for the dependence in the data?



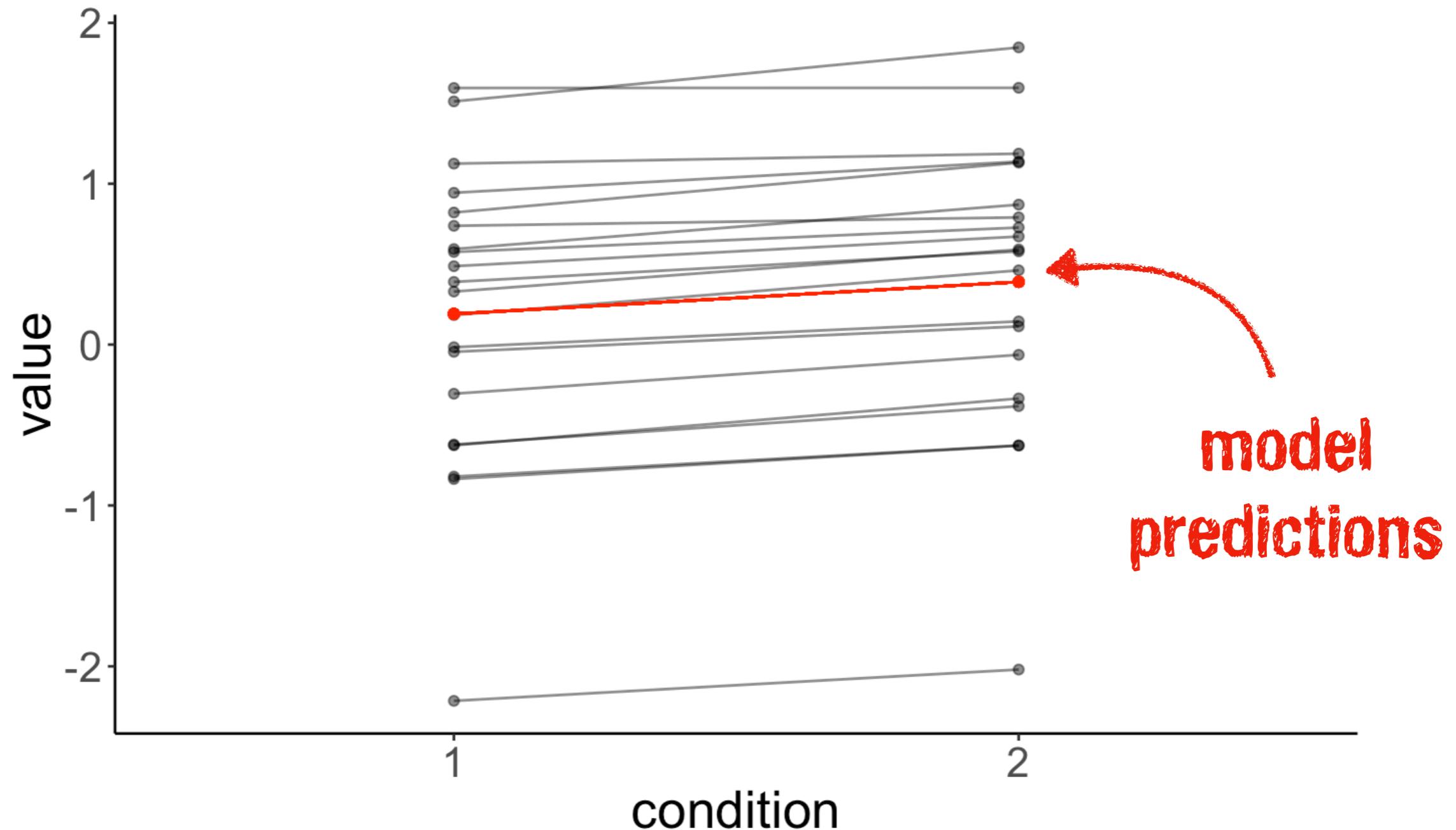
- by explicitly modeling the dependence in the data, we account for the interindividual differences

let's visualize the model predictions!

Linear model (assuming independence)

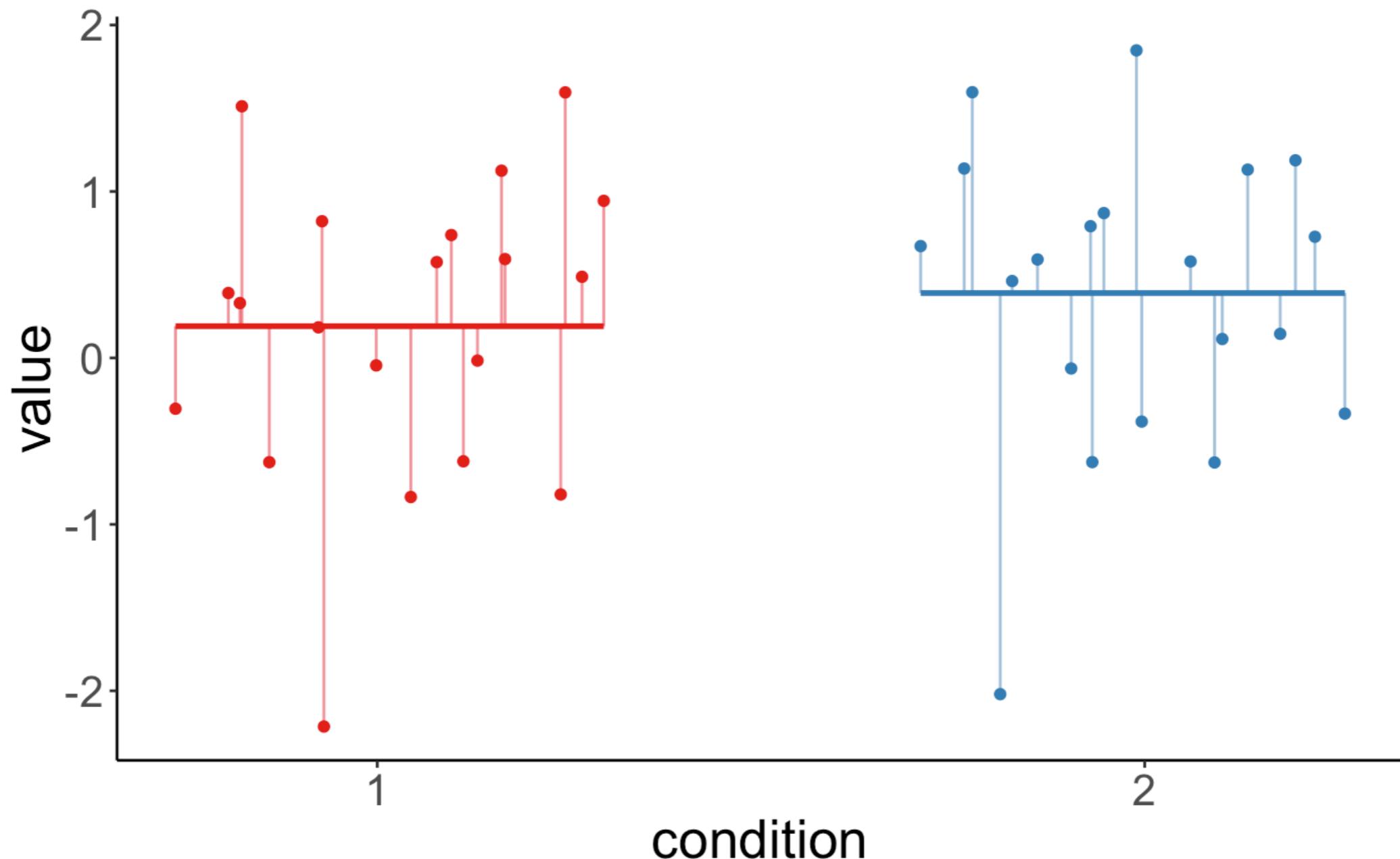
Predictions by the linear model which assumes independence

```
lm (formula = value ~ condition,  
    data = df.original)
```



Linear model (assuming independence)

Residuals of the model

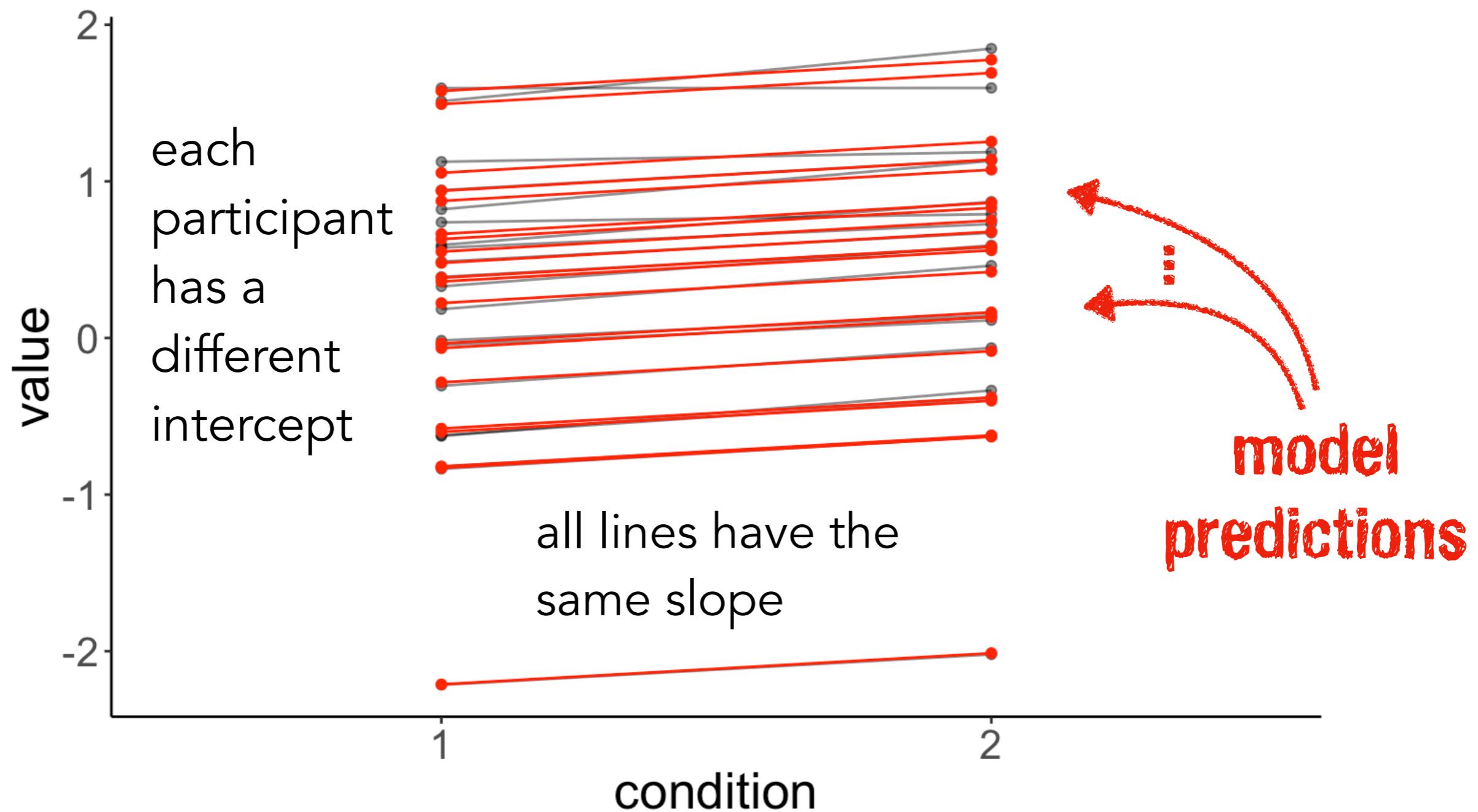


This is not much better than fitting a single line (point).

Linear mixed effects model (accounting for dependence)

Predictions by the linear mixed effects model

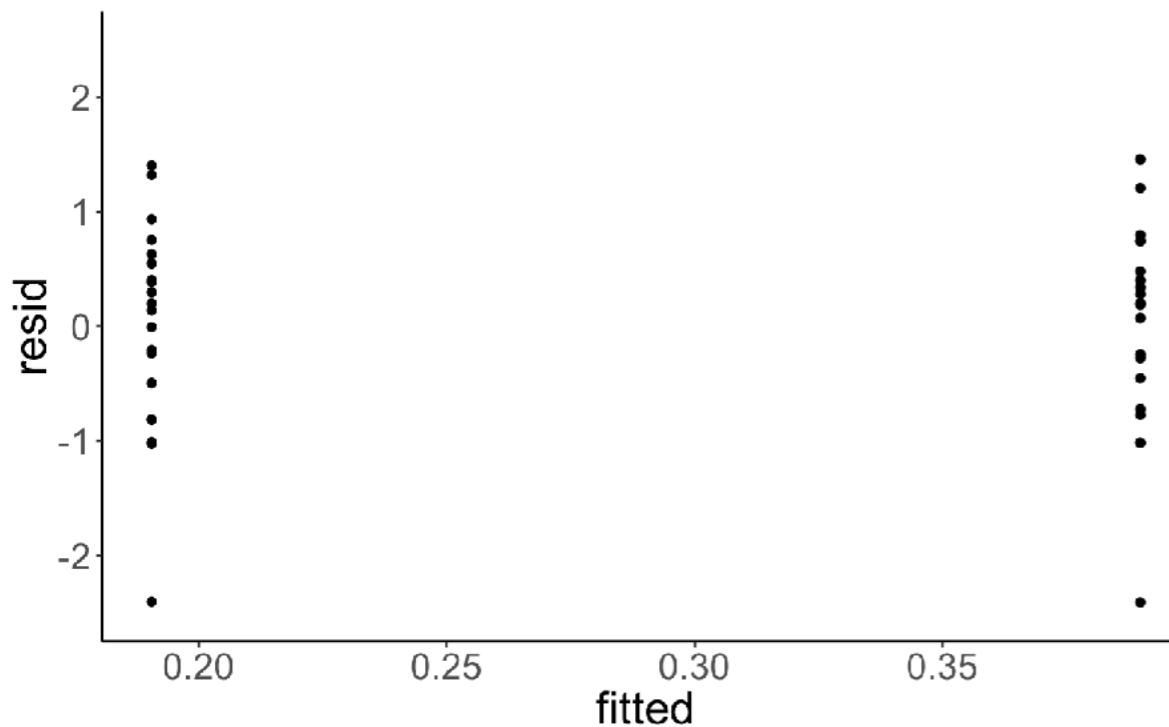
```
lmer (formula = value ~ condition + (1 | participant),  
      data = df.original)
```



Model comparison

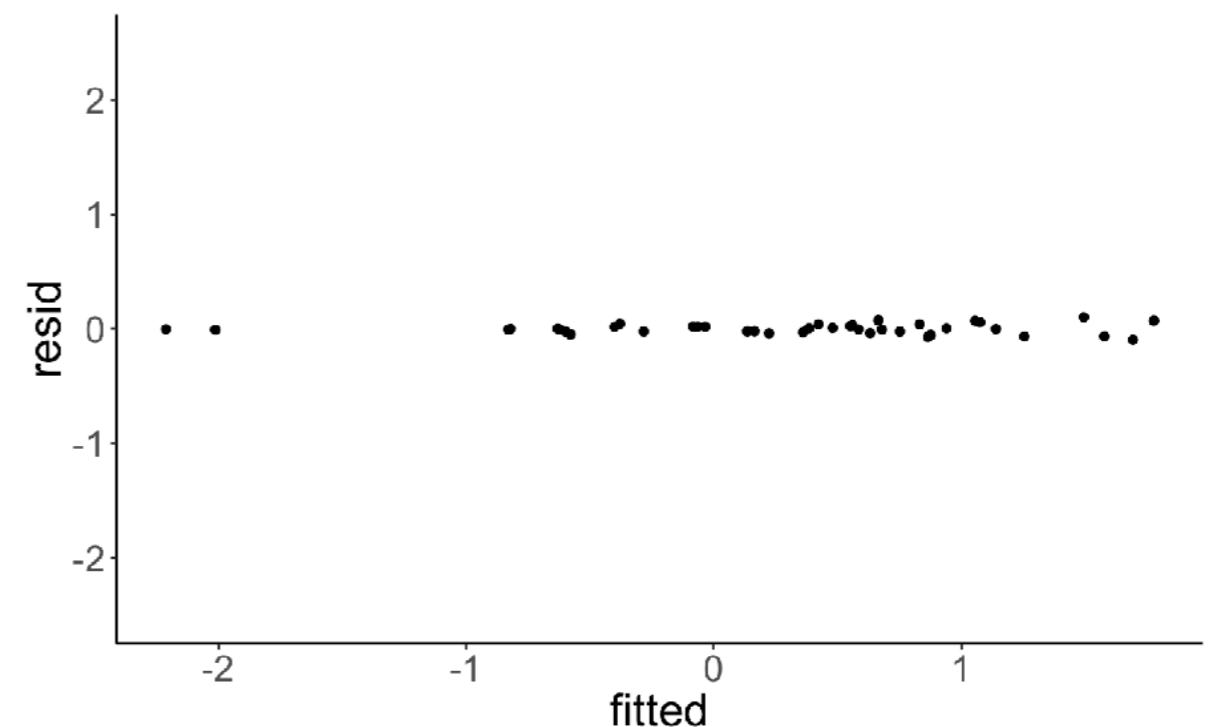
Residual plots

```
lm(formula = value ~ 1 + condition,  
  data = df.original)
```



much variance left
to be explained

```
lmer(formula = value ~ 1 + condition +  
      (1 | participant),  
      data = df.original)
```



almost all variance
explained

Model comparison

Hypothesis test

Is taking into account individual differences worth it?

```
1 # fit models (without and with dependence)
2 fit.compact = lm(formula = value ~ 1 + condition,
3                   data = df.original)
4
5 fit.augmented = lmer(formula = value ~ 1 + condition + (1 | participant),
6                       data = df.original)
7
8 # compare models
9 # note: the lmer model has to be supplied first
10 anova(fit.augmented, fit.compact)
```

```
refitting model(s) with ML (instead of REML)
Data: df.original
Models:
fit.compact: value ~ 1 + condition
fit.augmented: value ~ 1 + condition + (1 | participant)
              Df     AIC     BIC logLik deviance   Chisq Chi Df Pr(>Chisq)
fit.compact    3 109.551 114.617 -51.775   103.551
fit.augmented  4 17.849  24.605  -4.925      9.849  93.701      1 < 2.2e-16 ***
---
Signif. codes:  0 '****' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 '.' 1
```

Linear model

```
lm(formula = value ~ 1 + condition,  
  data = df.original)
```

$$\text{value}_i = b_0 + b_1 \cdot \text{condition}_i + e_i$$

i = observation

$$e_i \sim \mathcal{N}(\text{mean} = 0, \text{sd} = s_{\text{error}})$$

3 parameters: $b_0, b_1, s_{\text{error}}$

Linear mixed effects model

```
lmer(formula = value ~ 1 + condition +  
      (1 | participant),  
      data = df.original)
```

$$\text{value}_{i,j} = b_0 + b_1 \cdot \text{condition}_{i,j} + U_i + e_i$$

i = participant,
j = time point

$$e_i \sim \mathcal{N}(\text{mean} = 0, \text{sd} = s_{\text{error}})$$

$$U_i \sim \mathcal{N}(\text{mean} = 0, \text{sd} = s_U)$$

b_0, b_1 = fixed effects

U_i = random effect

 here: random intercept

4 parameters: $b_0, b_1, s_{\text{error}}, s_U$

Model coefficients

Linear model

```
fit = lm(formula = value ~ 1 + condition,  
         data = df.original)  
coef(fit)
```

	(Intercept)	condition2
	0.1905239	0.1993528

- one intercept
- one slope for condition

Linear mixed effects model

```
fit = lmer(formula = value ~ 1 + condition +  
           (1 | participant),  
           data = df.original)  
coef(fit)
```

	participant	(Intercept)	condition2
1		-0.57839428	0.1993528
2		0.22299824	0.1993528
3		-0.82920677	0.1993528
4		1.49310938	0.1993528
5		0.36042775	0.1993528
6		-0.82060123	0.1993528
7		0.47929171	0.1993528
8		0.66401020	0.1993528
9		0.55135879	0.1993528
10		-0.28306703	0.1993528
11		1.57681676	0.1993528
12		0.38457642	0.1993528
13		-0.59969682	0.1993528
14		-2.21148391	0.1993528
15		1.05439374	0.1993528
16		-0.06476643	0.1993528
17		-0.03505690	0.1993528
18		0.93945348	0.1993528
19		0.87495531	0.1993528
20		0.63135911	0.1993528

```
attr(),"class")  
[1] "coef.mer"
```

- different intercept for each participant
- one slope for condition

Understanding the lmer() summary

Understanding the `lmer()` summary

```
1 # fit a linear mixed effects model
2 lmer(formula = value ~ condition + (1 | participant),
3           data = df.original) %>%
4 summary()
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: value ~ condition + (1 | participant)
Data: df.original

REML criterion at convergence: 17.3

Scaled residuals:
    Min      1Q  Median      3Q     Max 
-1.55996 -0.36399 -0.03341  0.34400  1.65823

Random effects:
Groups   Name        Variance Std.Dev.
participant (Intercept) 0.816722 0.90373
Residual            0.003796 0.06161
Number of obs: 40, groups: participant, 20

Fixed effects:
            Estimate Std. Error t value
(Intercept) 0.19052   0.20255  0.941
condition2   0.19935   0.01948 10.231

Correlation of Fixed Effects:
  (Intr) condition2 
condition2 -0.048
```

REML = restricted maximum likelihood method for fitting models with **random effects**

Understanding the **lmer()** summary

```
1 # fit a linear mixed effects model  
2 lmer(formula = value ~ condition + (1 | participant),  
3 data = df.original) %>%  
4 summary()
```

```
Linear mixed model fit by REML ['lmerMod']  
Formula: value ~ condition + (1 | participant)  
Data: df.original  
  
REML criterion at convergence: 17.3
```

```
Scaled residuals:  
    Min     1Q   Median     3Q     Max  
-1.55996 -0.36399 -0.03341  0.34400  1.65823  
  
Random effects:  
Groups      Name        Variance Std.Dev.  
participant (Intercept) 0.816722 0.90373  
Residual             0.003796 0.06161  
Number of obs: 40, groups: participant, 20  
  
Fixed effects:  
            Estimate Std. Error t value  
(Intercept) 0.19052    0.20255   0.941  
condition2   0.19935    0.01948  10.231
```

```
Correlation of Fixed Effects:  
           (Intr)  
condition2 -0.048
```

fitting **lmer()** doesn't always work ...

lmer() complains when it didn't work

Understanding the `lmer()` summary

```
1 # fit a linear mixed effects model  
2 lmer(formula = value ~ condition + (1 | participant),  
3 data = df.original) %>%  
4 summary()
```

```
Linear mixed model fit by REML ['lmerMod']  
Formula: value ~ condition + (1 | participant)  
Data: df.original  
REML criterion at convergence: 17.3
```

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.55996	-0.36399	-0.03341	0.34400	1.65823

Random effects:

Groups	Name	Variance	Std.Dev.
participant	(Intercept)	0.816722	0.90373
Residual		0.003796	0.06161

Number of obs: 40, groups: participant, 20

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	0.19052	0.20255	0.941
condition2	0.19935	0.01948	10.231

Correlation of Fixed Effects:

	(Intr)
condition2	-0.048

summary information
about residuals

Understanding the `lmer()` summary

```
1 # fit a linear mixed effects model  
2 lmer(formula = value ~ condition + (1 | participant),  
3      data = df.original) %>%  
4 summary()
```

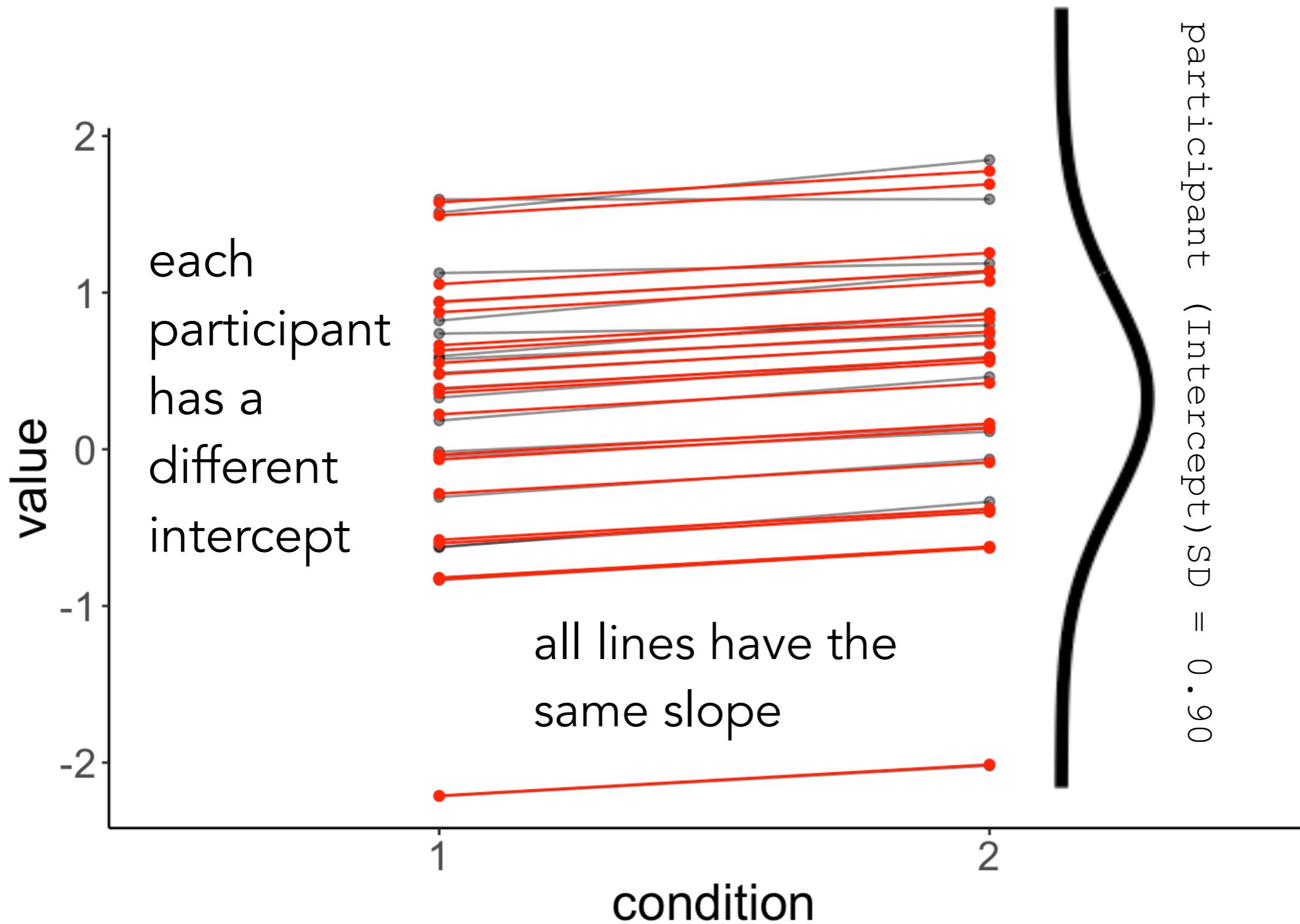
```
Linear mixed model fit by REML ['lmerMod']  
Formula: value ~ condition + (1 | participant)  
Data: df.original  
  
REML criterion at convergence: 17.3  
  
Scaled residuals:  
    Min     1Q Median     3Q     Max  
-1.55996 -0.36309 -0.03341  0.34400  1.65823  
  
Random effects:  
Groups   Name        Variance Std.Dev.  
participant (Intercept) 0.816722 0.90373  
Residual             0.003796 0.06161  
Number of obs: 40, groups: participant, 20  
  
Fixed effects:  
            Estimate Std. Error t value  
(Intercept) 0.19052   0.20255  0.941  
condition2   0.19935   0.01948 10.231  
  
Correlation of Fixed Effects:  
  (Intr) condition2  
condition2 -0.048
```

Random effects

one parameter to capture the variance between participants (gives us a sense for whether there are interindividual differences)

one parameter to capture the residual variance (just like sigma in an `lm()`)

Understanding the `lmer()` summary



Understanding the `lmer()` summary

```
1 # fit a linear mixed effects model
2 lmer(formula = value ~ condition + (1 | participant),
3           data = df.original) %>%
4 summary()
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: value ~ condition + (1 | participant)
Data: df.original

REML criterion at convergence: 17.3

Scaled residuals:
    Min      1Q  Median      3Q     Max 
-1.55996 -0.36399 -0.03341  0.34400  1.65823 

Random effects:
Groups   Name        Variance Std.Dev.
participant (Intercept) 0.816722 0.90373
Residual            0.003796 0.06161
Number of obs: 40, groups: participant, 20

Fixed effects:
Estimate Std. Error t value
(Intercept) 0.19052   0.20255   0.941
condition2  0.19935   0.01948  10.231

Correlation of Fixed Effects:
  (Intr) condition2 
condition2 -0.048
```

Fixed effects

one parameter for the global intercept (value for the baseline condition)

one parameter for the condition effect (difference between the two conditions)

interpretation the same as for `lm()`, also: we can use contrasts!

Understanding the `lmer()` summary

```
1 # fit a linear mixed effects model
2 lmer(formula = value ~ condition + (1 | participant),
3           data = df.original) %>%
4 summary()
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: value ~ condition + (1 | participant)
Data: df.original
```

```
REML criterion at convergence: 17.3
```

```
Scaled residuals:
```

Min	1Q	Median	3Q	Max
-1.55996	-0.36399	-0.03341	0.34400	1.65823

```
Random effects:
```

Groups	Name	Variance	Std.Dev.
participant	(Intercept)	0.816722	0.90373
Residual		0.003796	0.06161

```
Number of obs: 40, groups: participant, 20
```

```
Fixed effects:
```

	Estimate	Std. Error	t value
(Intercept)	0.19052	0.20255	0.941
condition2	0.19935	0.01948	10.231

```
Correlation of Fixed Effects:
  (Intr) condition2
condition2 -0.048
```

correlation between intercept and condition2

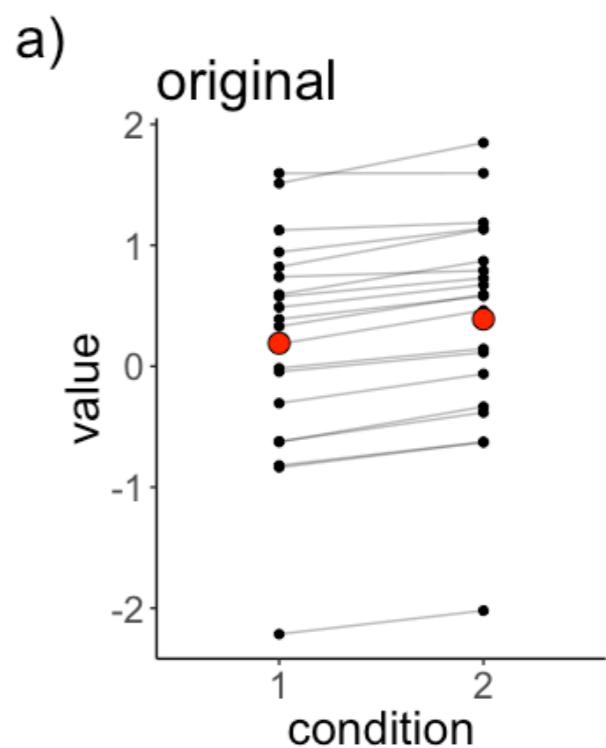
The "correlation of fixed effects" output doesn't have the intuitive meaning that most would ascribe to it. Specifically, is not about the correlation of the variables. It is in fact about the expected correlation of the regression coefficients.

we just performed a paired t-test ...

```
1 t.test(df.original$value[df.original$condition == "1"],  
2         df.original$value[df.original$condition == "2"],  
3         alternative = "two.sided",  
4         paired = T)
```

```
Paired t-test  
  
data: df.original$value[df.original$condition == "1"] and  
df.original$value[df.original$condition == "2"]  
t = -10.231, df = 19, p-value = 3.636e-09  
alternative hypothesis: true difference in means is not equal to 0  
95 percent confidence interval:  
 -0.2401340 -0.1585717  
sample estimates:  
mean of the differences  
 -0.1993528
```

If we take the differences for each participant between condition 1 and condition 2, are these difference scores significantly different from 0?



we just performed a paired t-test ...

```
lmer(formula = value ~ condition + (1 | participant),  
      data = df.original)
```

- explicitly models the interindividual variation
- much more flexible ...

```
1 t.test(df.original$value[df.original$condition == "1"],  
2         df.original$value[df.original$condition == "2"],  
3         alternative = "two.sided",  
4         paired = T)
```

Paired t-test

```
data: df.original$value[df.original$condition == "1"] and  
df.original$value[df.original$condition == "2"]  
t = -10.231, df = 19, p-value = 3.636e-09  
alternative hypothesis: true difference in means is not equal to 0  
95 percent confidence interval:  
-0.2401340 -0.1585717  
sample estimates:  
mean of the differences  
-0.1993528
```

```
Linear mixed model fit by REML ['lmerMod']  
Formula: value ~ condition + (1 | participant)  
Data: df.original  
  
REML criterion at convergence: 17.3  
  
Scaled residuals:  
    Min     1Q Median     3Q    Max  
-1.55996 -0.36399 -0.03341  0.34400  1.65823  
  
Random effects:  
Groups   Name        Variance Std.Dev.  
participant (Intercept) 0.816722 0.90373  
Residual           0.003796 0.06161  
Number of obs: 40, groups: participant, 20  
  
Fixed effects:  
Estimate Std. Error t value  
(Intercept) 0.19052  0.20255  0.941  
condition2  0.19935  0.01948 10.231  
  
Correlation of Fixed Effects:  
          (Intr)  
condition2 -0.048
```

general points about `lmer()`

- **fixed effects:**
 - parameters are estimated
 - often: factors that we manipulate experimentally
- **random effects:**
 - variation we want to take into account
 - often: differences between participants (or items) in our experiment
 - sampling viewpoint: we explicitly model the variation in participants

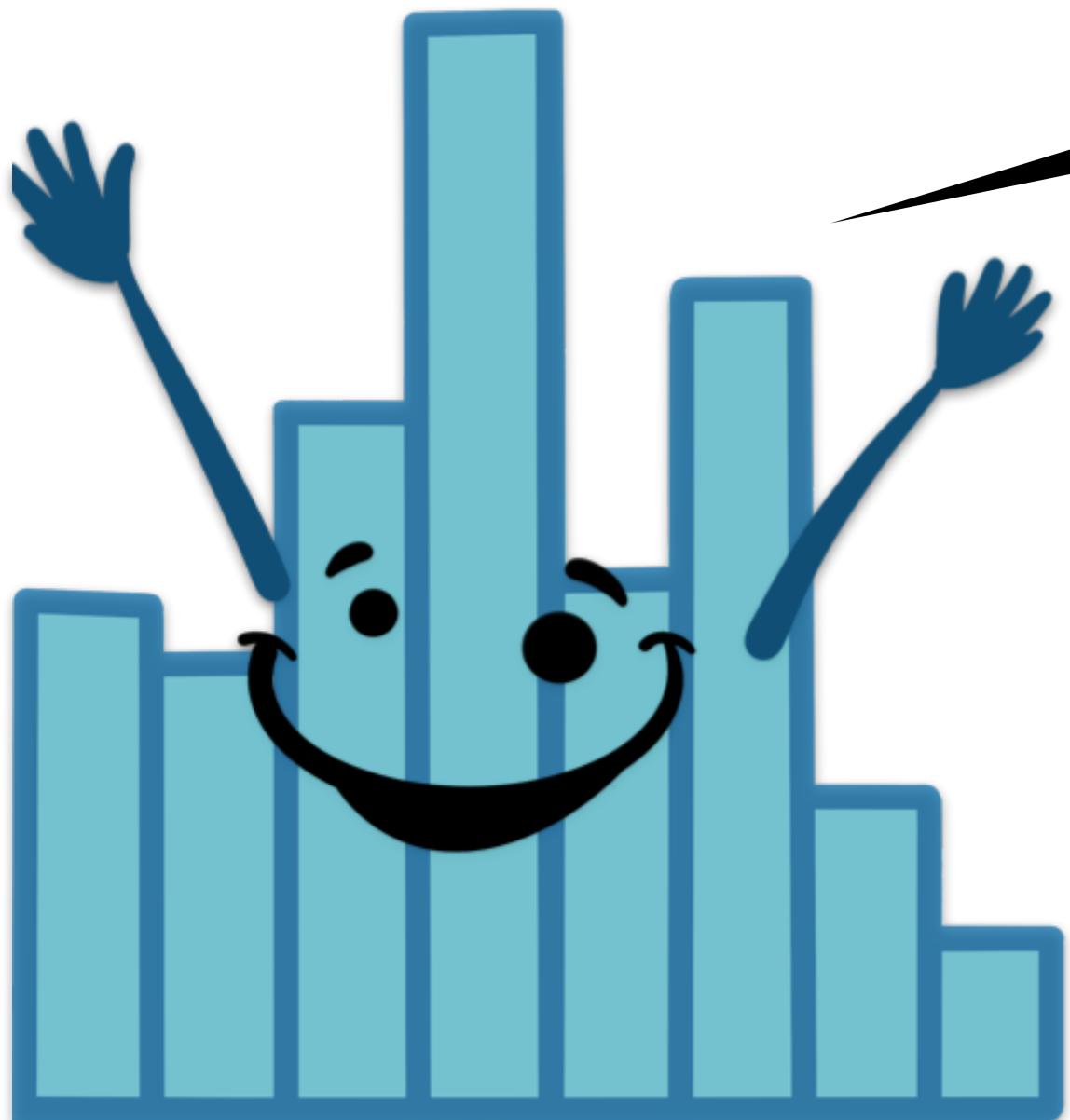
general points about `lmer()`

- Why don't we just run individual regressions?
 - overfitting ...
 - inflating type 1 error
 - larger uncertainty in parameter estimates because only few data points are used for each model
 - unclear how to aggregate the results to make an overall statement
- Why don't we just run a regression on the means?
 - we throw away a lot of information
 - what to do when the design is unbalanced?
- Mixed effects model:
 - makes use of all available information
 - addresses the main problems of the other two approaches

let's take a look
at an example

02:00

stretch break!



SUPER FLEXIBLE

A worked example

**Tristan Mahr**

Language and data scientist

 [Madison, WI](#) [Email](#) [Twitter](#) [GitHub](#) [Stackoverflow](#) [R Bloggers](#)

Plotting partial pooling in mixed-effects models

In this post, I demonstrate a few techniques for plotting information from a relatively simple mixed-effects model fit in R. These plots can help us develop intuitions about what these models are doing and what “partial pooling” means.

The sleepstudy dataset

For these examples, I’m going to use the `sleepstudy` dataset from the `lme4` package. The outcome measure is reaction time, the predictor measure is days of sleep deprivation, and these measurements are nested within participants—we have 10 observations per participant. I am also going to add two fake participants with incomplete data to illustrate partial pooling.

<https://www.tjmahr.com/plotting-partial-pooling-in-mixed-effects-models/>

Data set

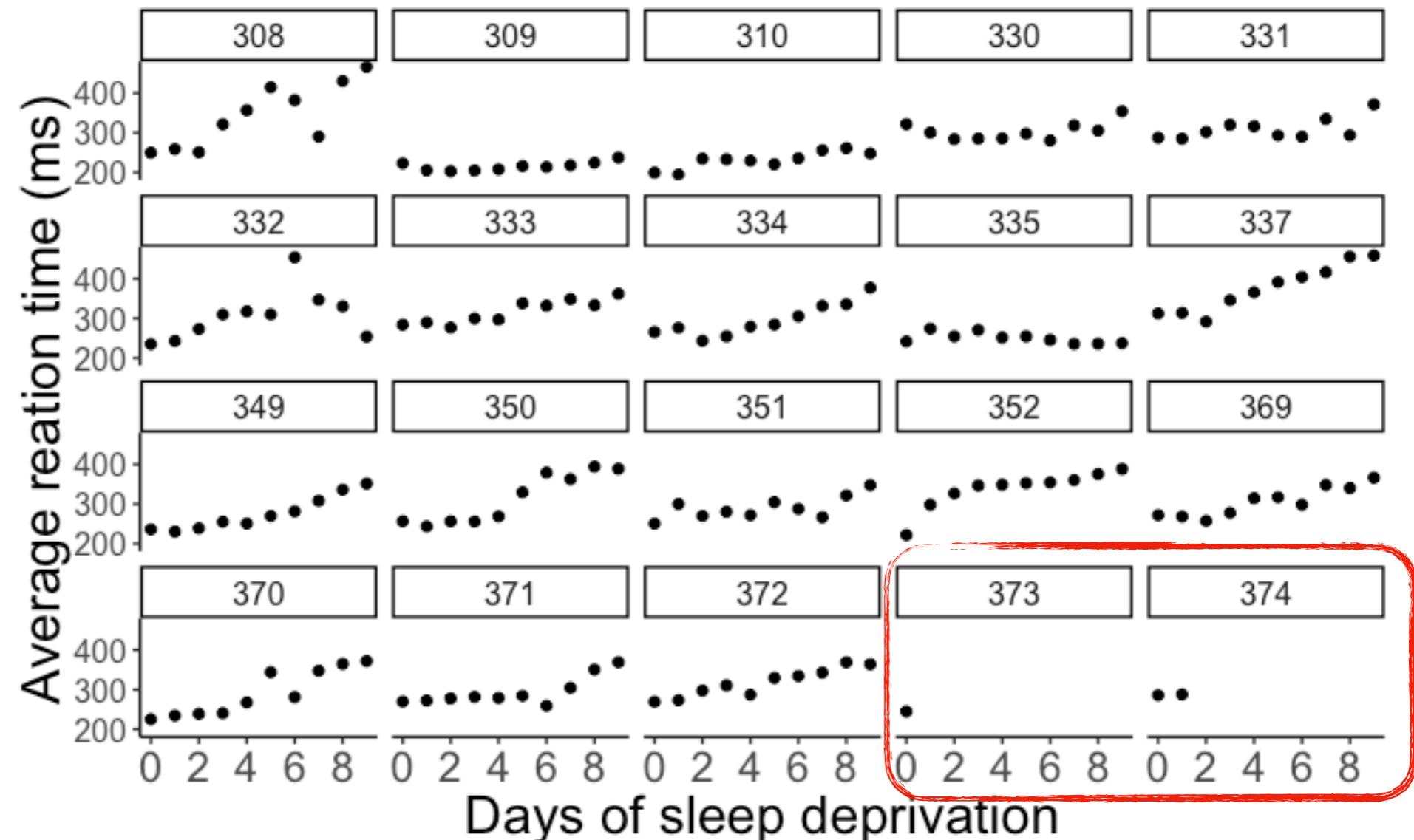
How does sleep deprivation affect reaction time?

subject	days	reaction
308	0	249.56
308	1	258.70
308	2	250.80
308	3	321.44
308	4	356.85
309	0	222.73
309	1	205.27
309	2	202.98
309	3	204.71
309	4	207.72

Data set

How does sleep deprivation affect reaction time?

subject	days	reaction
308	0	249.56
308	1	258.70
308	2	250.80
308	3	321.44
308	4	356.85
309	0	222.73
309	1	205.27
309	2	202.98
309	3	204.71
309	4	207.72



20 participants

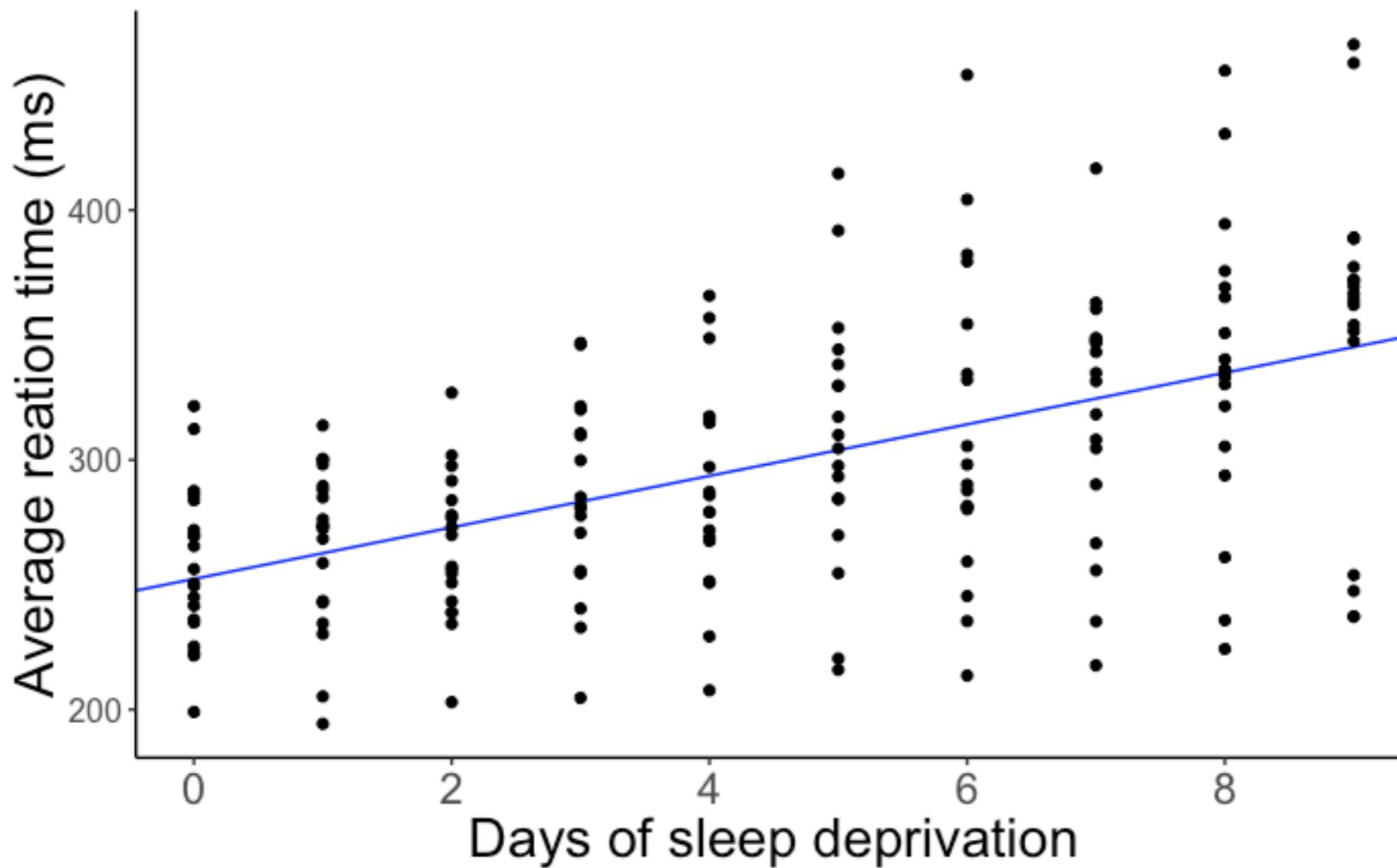
2 with incomplete information

Pooling information

- **complete pooling**
 - combine data from all participants and fit one global regression
- **no pooling**
 - don't combine any of the data and fit a separate regression to each individual participant
- **partial pooling**
 - take into account all information by explicitly modeling the variation between participants

Complete pooling: Fit one global regression

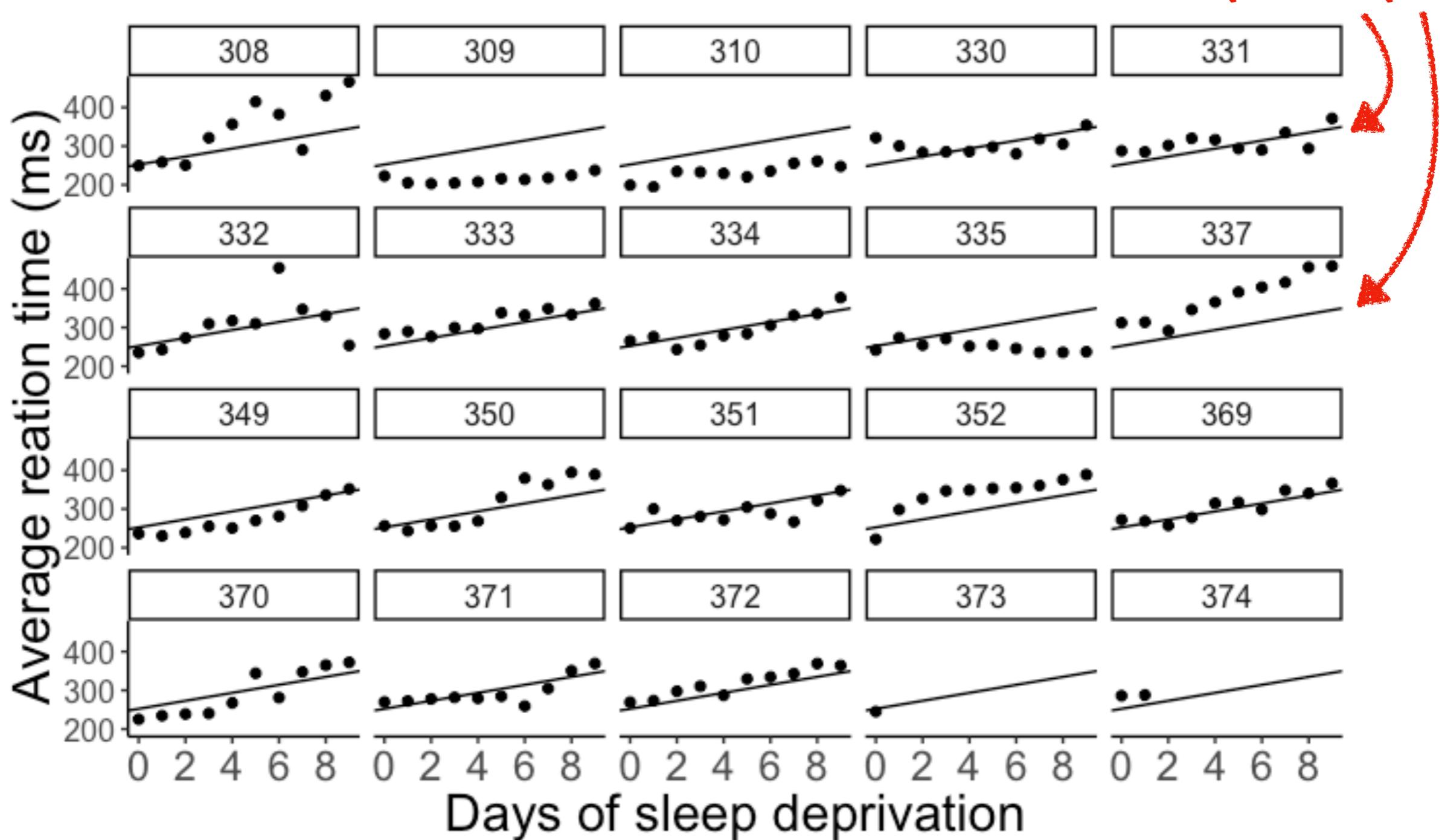
```
lm(formula = reaction ~ days,  
  data = df.sleep)
```



Complete pooling: Fit one global regression

```
lm(formula = reaction ~ days,  
   data = df.sleep)
```

same line for
each participant



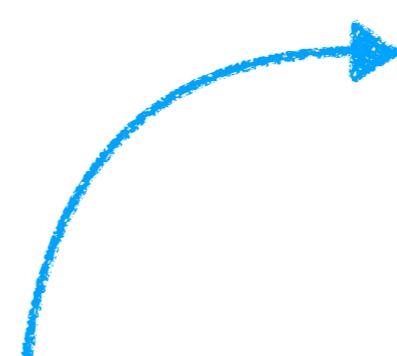
No pooling: Fit separate regressions

```
1 df.no_pooling = df.sleep %>%
2   group_by(subject) %>%
3   nest(data = c(days, reaction)) %>%
4   mutate(fit = map(data, ~ lm(reaction ~ days, data = .)),
5         params = map(fit, tidy)) %>%
6   unnest(c(params)) %>%
7   select(subject, term, estimate) %>%
8   complete(subject, term, fill = list(estimate = 0)) %>%
9   pivot_wider(names_from = term, values_from = estimate) %>%
10  clean_names()
```

	subject	data	regression fit	extracted parameters
1	308	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 244.1926690909...	list(term = c("(Intercept)", "days"), estimate = c(244.1...
2	309	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 205.0549454545...	list(term = c("(Intercept)", "days"), estimate = c(205.0...
3	310	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(1...	list(coefficients = c(`(Intercept)` = 203.4842254545...	list(term = c("(Intercept)", "days"), estimate = c(203.4...
4	330	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(3...	list(coefficients = c(`(Intercept)` = 289.6850927272...	list(term = c("(Intercept)", "days"), estimate = c(289.6...
5	331	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 285.7389654545...	list(term = c("(Intercept)", "days"), estimate = c(285.7...
6	332	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 264.2516145454...	list(term = c("(Intercept)", "days"), estimate = c(264.2...
7	333	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 275.0191054545...	list(term = c("(Intercept)", "days"), estimate = c(275.0...
8	334	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 240.1629145454...	list(term = c("(Intercept)", "days"), estimate = c(240.1...
9	335	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 263.0346927272...	list(term = c("(Intercept)", "days"), estimate = c(263.0...
10	337	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(3...	list(coefficients = c(`(Intercept)` = 290.1041272727...	list(term = c("(Intercept)", "days"), estimate = c(290.1...
11	349	list(days = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9), reaction = c(2...	list(coefficients = c(`(Intercept)` = 215.1117727272...	list(term = c("(Intercept)", "days"), estimate = c(215.1...
			⋮	
19	374	list(days = c(0, 1), reaction = c(286, 288))	list(coefficients = c(`(Intercept)` = 286, days = 2.000...	list(term = c("(Intercept)", "days"), estimate = c(286, 2...
20	373	list(days = 0, reaction = 245)	list(coefficients = c(`(Intercept)` = 245, days = NA), r...	list(term = "(Intercept)", estimate = 245, std.error = ...

No pooling: Fit separate regressions

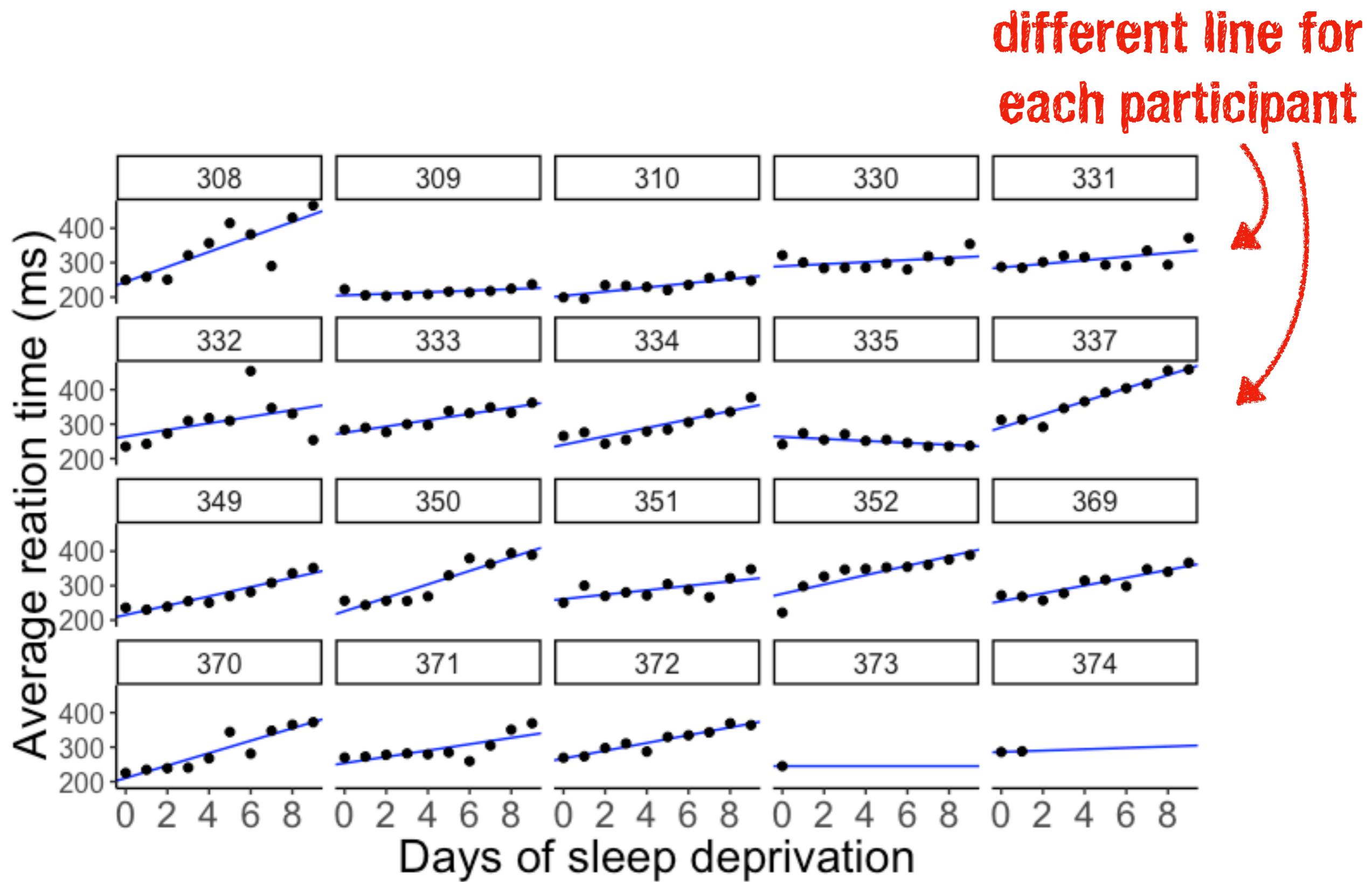
```
1 df.no_pooling = df.sleep %>%
2   group_by(subject) %>%
3   nest(data = c(days, reaction)) %>%
4   mutate(fit = map(data, ~ lm(reaction ~ days, data = .)),
5         params = map(fit, tidy)) %>%
6   unnest(c(params)) %>%
7   select(subject, term, estimate) %>%
8   complete(subject, term, fill = list(estimate = 0)) %>%
9   pivot_wider(names_from = term, values_from = estimate) %>%
10  clean_names()
```



separate intercept and
slope for each participant

	subject	intercept	days
1	308	244.1927	21.764702
2	309	205.0549	2.261785
3	310	203.4842	6.114899
4	330	289.6851	3.008073
5	331	285.7390	5.266019
6	332	264.2516	9.566768
7	333	275.0191	9.142045
8	334	240.1629	12.253141
9	335	263.0347	-2.881034
10	337	290.1041	19.025974
11	349	215.1118	13.493933
12	350	225.8346	19.504017
13	351	261.1470	6.433498
14	352	276.3721	13.566549
15	369	254.9681	11.348109
16	370	210.4491	18.056151
17	371	253.6360	9.188445
18	372	267.0448	11.298073
19	373	245.0000	0.000000
20	374	286.0000	2.000000

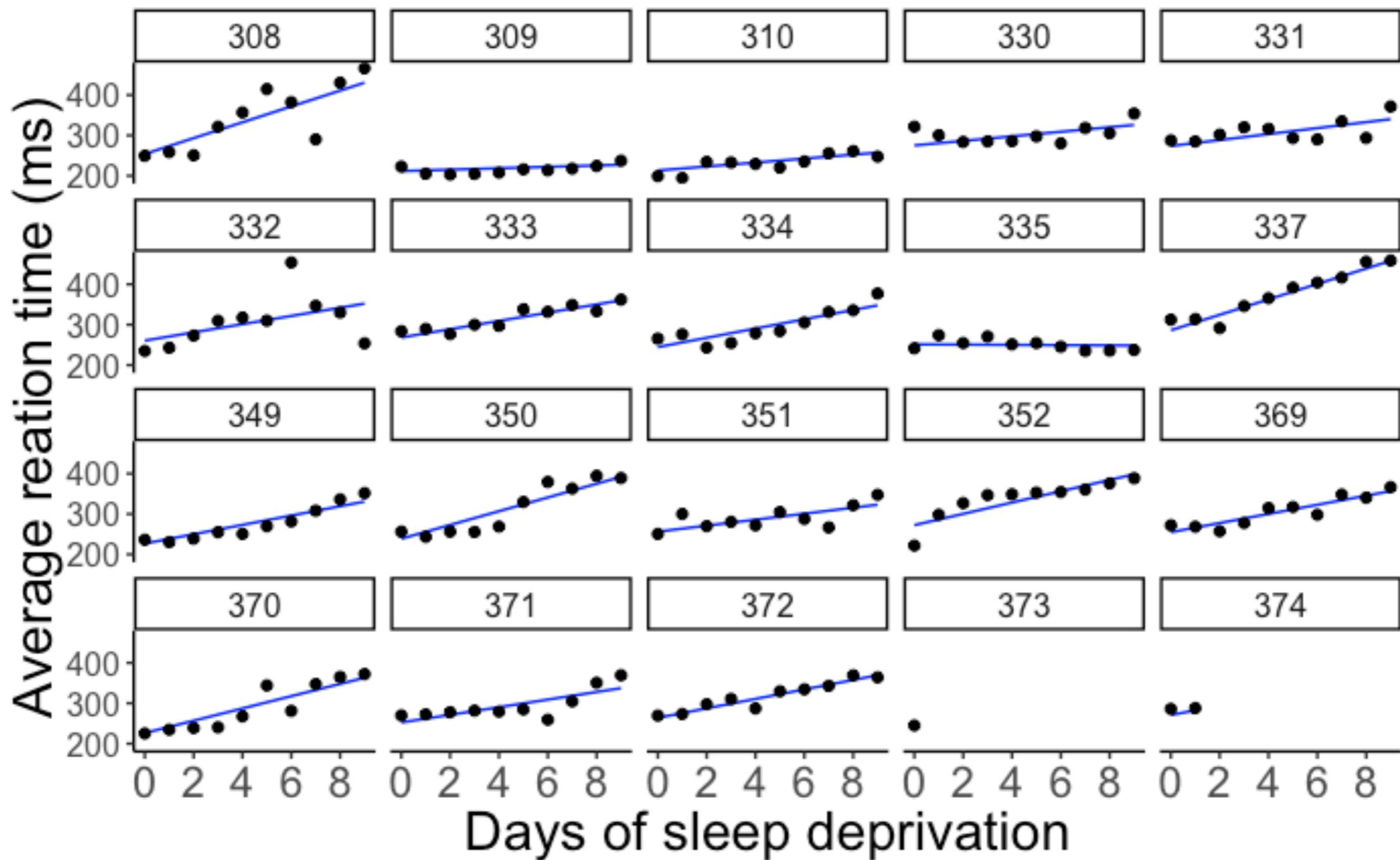
No pooling: Fit separate regressions



Partial pooling: Fit mixed effects model

intercepts and slopes differ
between participants

`lmer` (`formula = reaction ~ 1 + days + (1 + days | subject)`,
data = df.sleep)

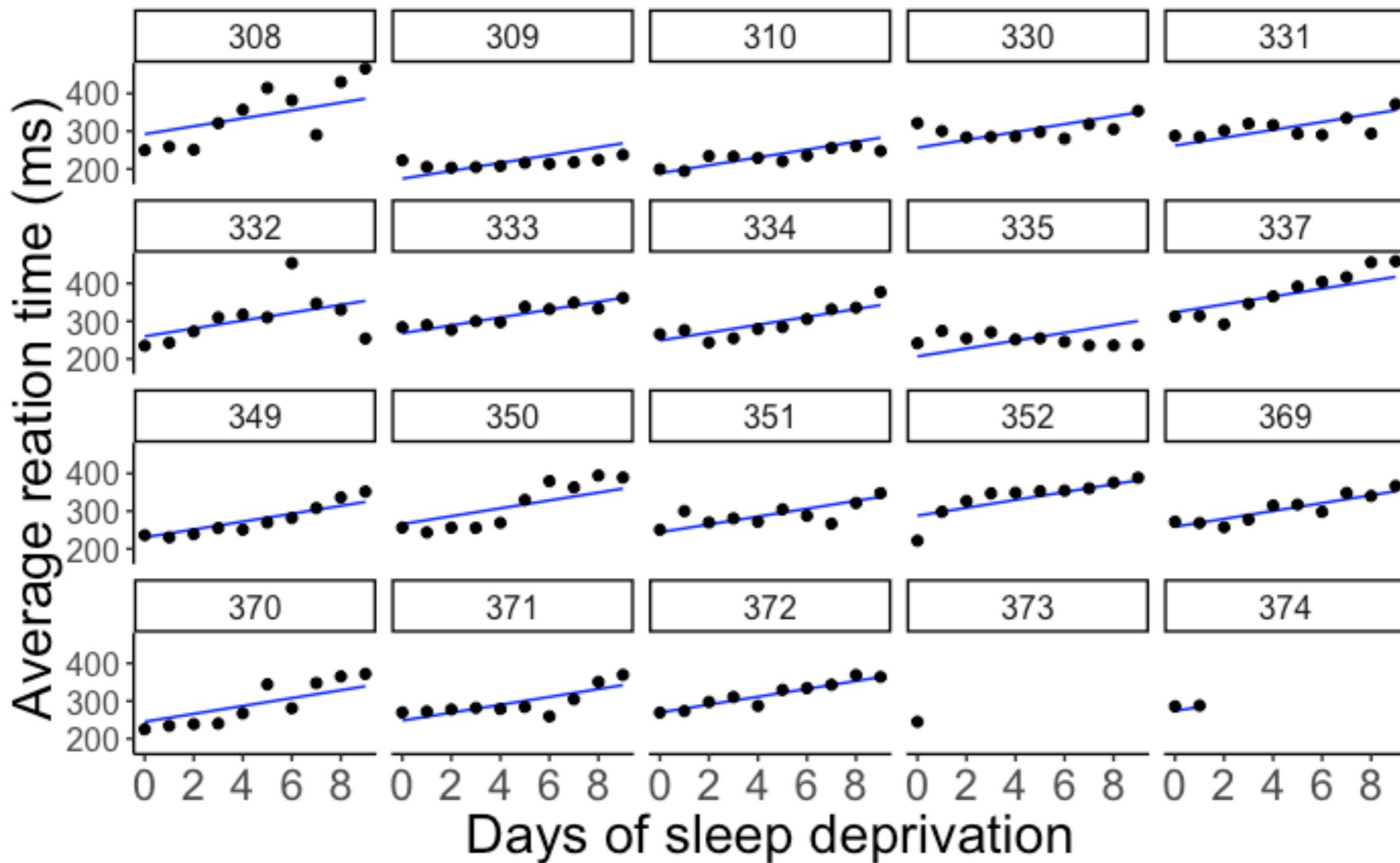


Partial pooling: Fit mixed effects model

only intercepts differ
between participants

random intercept

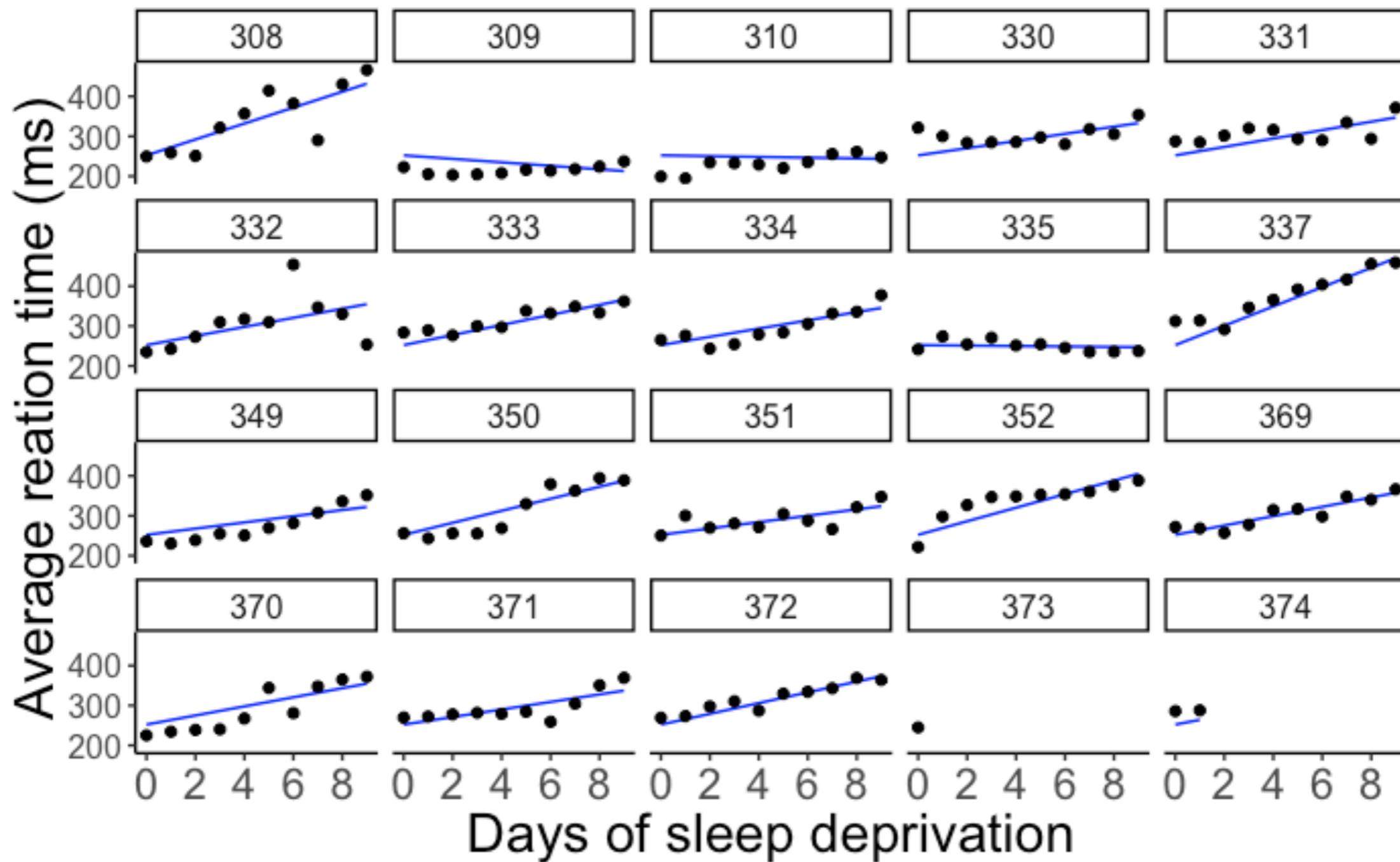
```
lmer (formula = reaction ~ 1 + days + (1 | subject),  
      data = df.sleep)
```



Partial pooling: Fit mixed effects model

only slopes differ between participants

`lmer (formula = reaction ~ 1 + days + (0 + days | subject),
data = df.sleep)`



Coefficients

```
lmer (formula = reaction ~ 1 + days +  
      data = df.sleep)
```

$(1 \mid \text{subject})$

random intercepts

\$subject	(Intercept)	days
308	292.2749	10.43191
309	174.0559	10.43191
310	188.7454	10.43191
330	256.0247	10.43191
331	261.8141	10.43191
332	259.8262	10.43191
333	268.0765	10.43191
334	248.6471	10.43191
335	206.5096	10.43191
337	323.5643	10.43191
349	230.5114	10.43191
350	265.6957	10.43191
351	243.7988	10.43191
352	287.8850	10.43191
369	258.6454	10.43191
370	245.2931	10.43191
371	248.3508	10.43191
372	269.6861	10.43191
373	248.2086	10.43191
374	273.9400	10.43191

$(0 + \text{days} \mid \text{subject})$

random slopes

\$subject	(Intercept)	days
308	252.2965	19.9526801
309	252.2965	-4.3719650
310	252.2965	-0.9574726
330	252.2965	8.9909957
331	252.2965	10.5394285
332	252.2965	11.3994289
333	252.2965	12.6074020
334	252.2965	10.3413879
335	252.2965	-0.5722073
337	252.2965	24.2246485
349	252.2965	7.7702676
350	252.2965	15.0661415
351	252.2965	7.9675415
352	252.2965	17.0002999
369	252.2965	11.6982767
370	252.2965	11.3939807
371	252.2965	9.4535879
372	252.2965	13.4569059
373	252.2965	10.4142695
374	252.2965	11.9097917

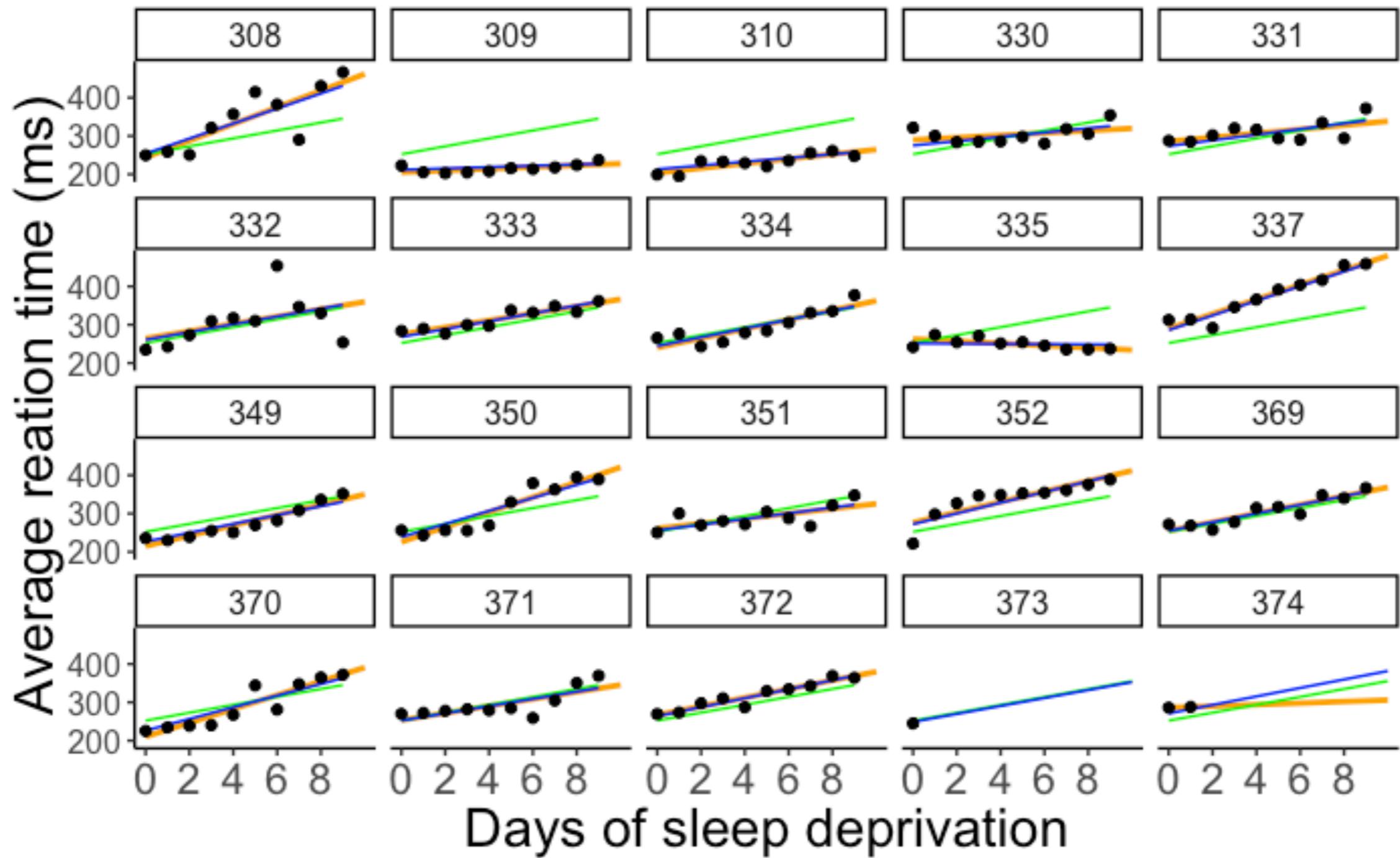
\dots
 $(1 + \text{days} \mid \text{subject})$

random intercepts and
slopes (+ correlation)

\$subject	(Intercept)	days
308	253.9479	19.6264139
309	211.7328	1.7319567
310	213.1579	4.9061843
330	275.1425	5.6435987
331	273.7286	7.3862680
332	260.6504	10.1632535
333	268.3684	10.2245979
334	244.5523	11.4837825
335	251.3700	-0.3355554
337	286.2321	19.1090061
349	226.7662	11.5531963
350	238.7807	17.0156766
351	256.2344	7.4119501
352	272.3512	13.9920698
369	254.9484	11.2985741
370	226.3701	15.2027922
371	252.5051	9.4335432
372	263.8916	11.7253342
373	248.9752	10.3915245
374	271.1451	11.0782697

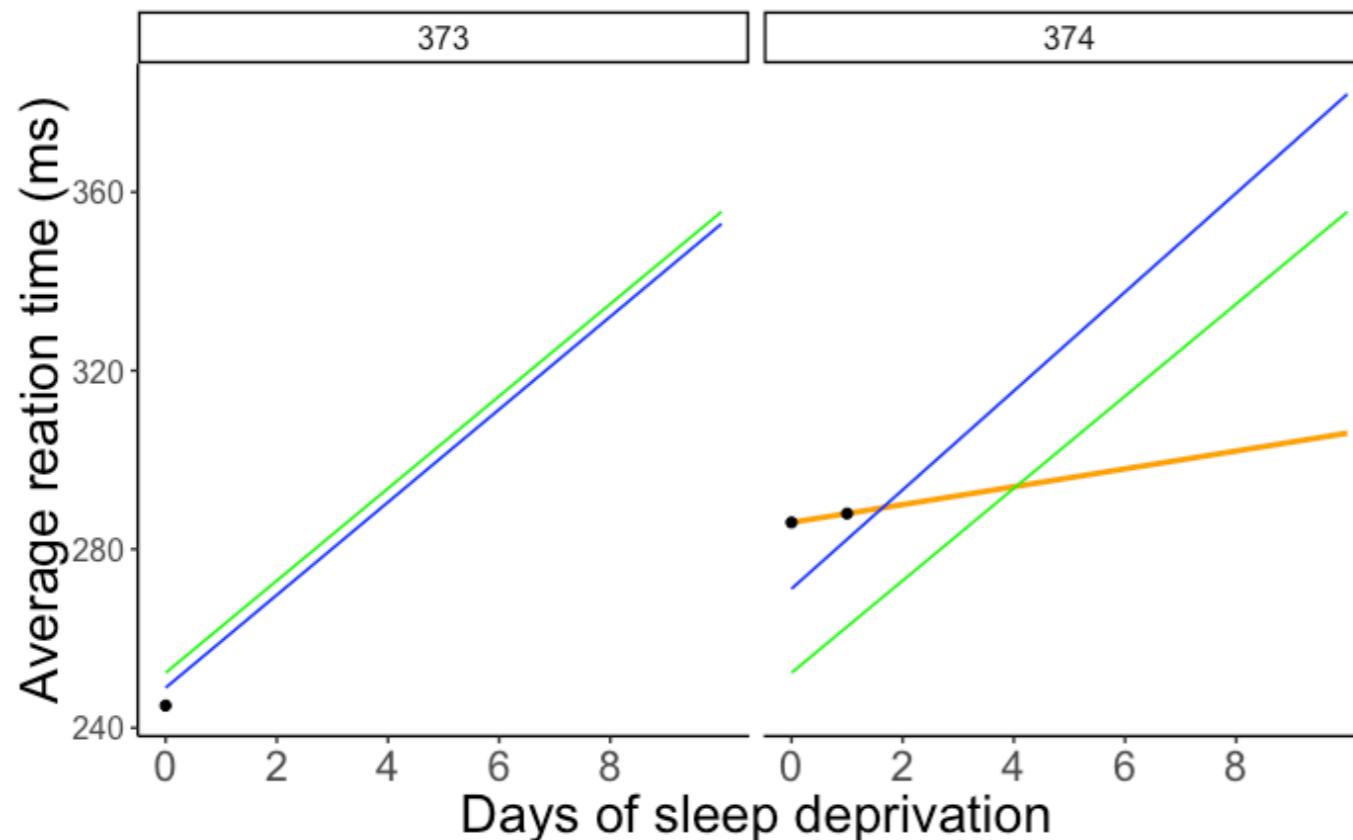
Comparison

complete pooling
no pooling
partial pooling



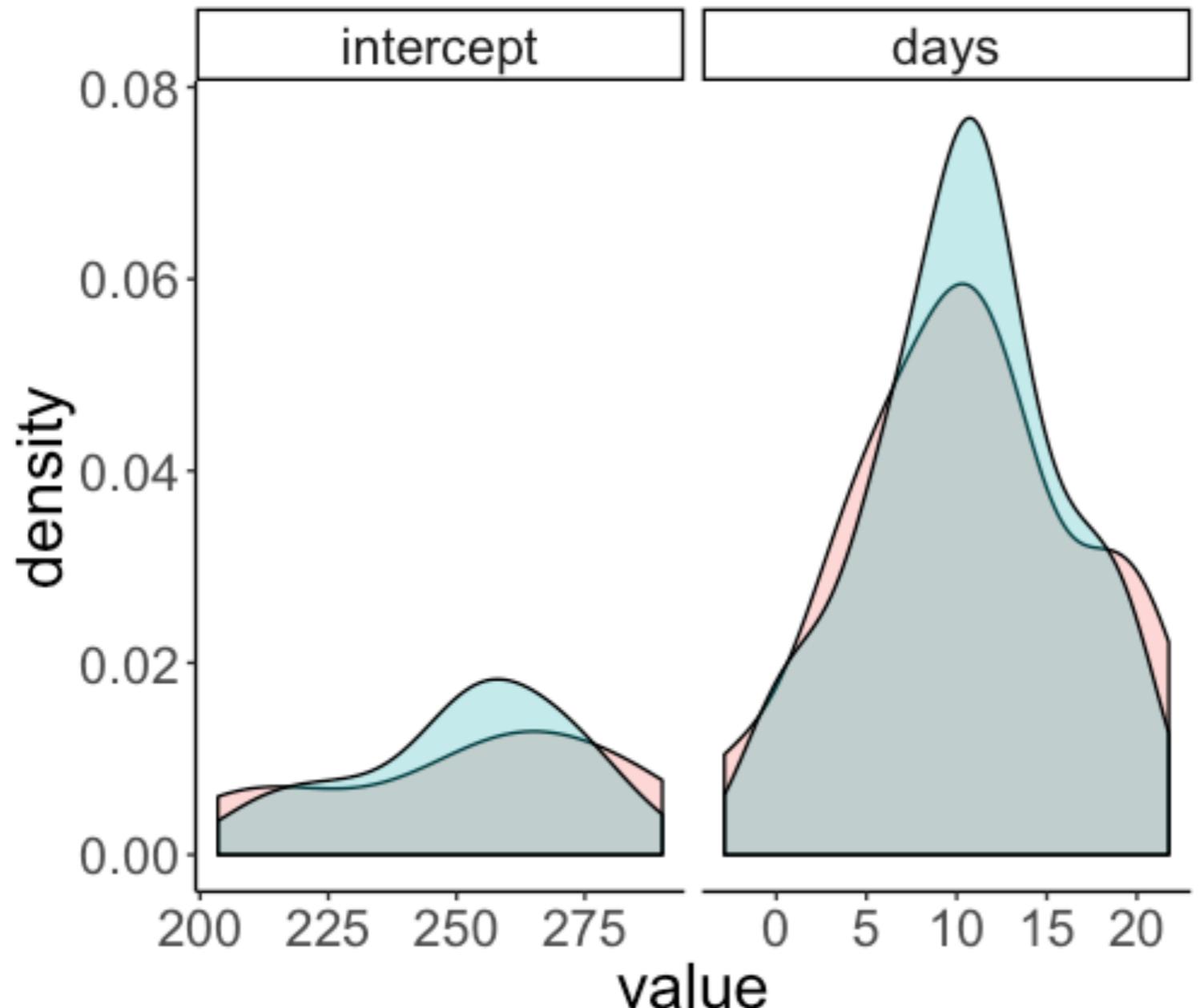
Comparison

complete pooling
no pooling
partial pooling



- **complete pooling:**
 - doesn't account for any individual variation
- **no pooling:**
 - doesn't yield predictions when we only have one observation
 - doesn't consider the general effect of sleep deprivation when making predictions
- **partial pooling:**
 - draws on all the information in the data
 - extrapolates based on information about the individual participants, as well as information based on the whole sample

Shrinkage



method
no pooling
partial pooling

standard deviation

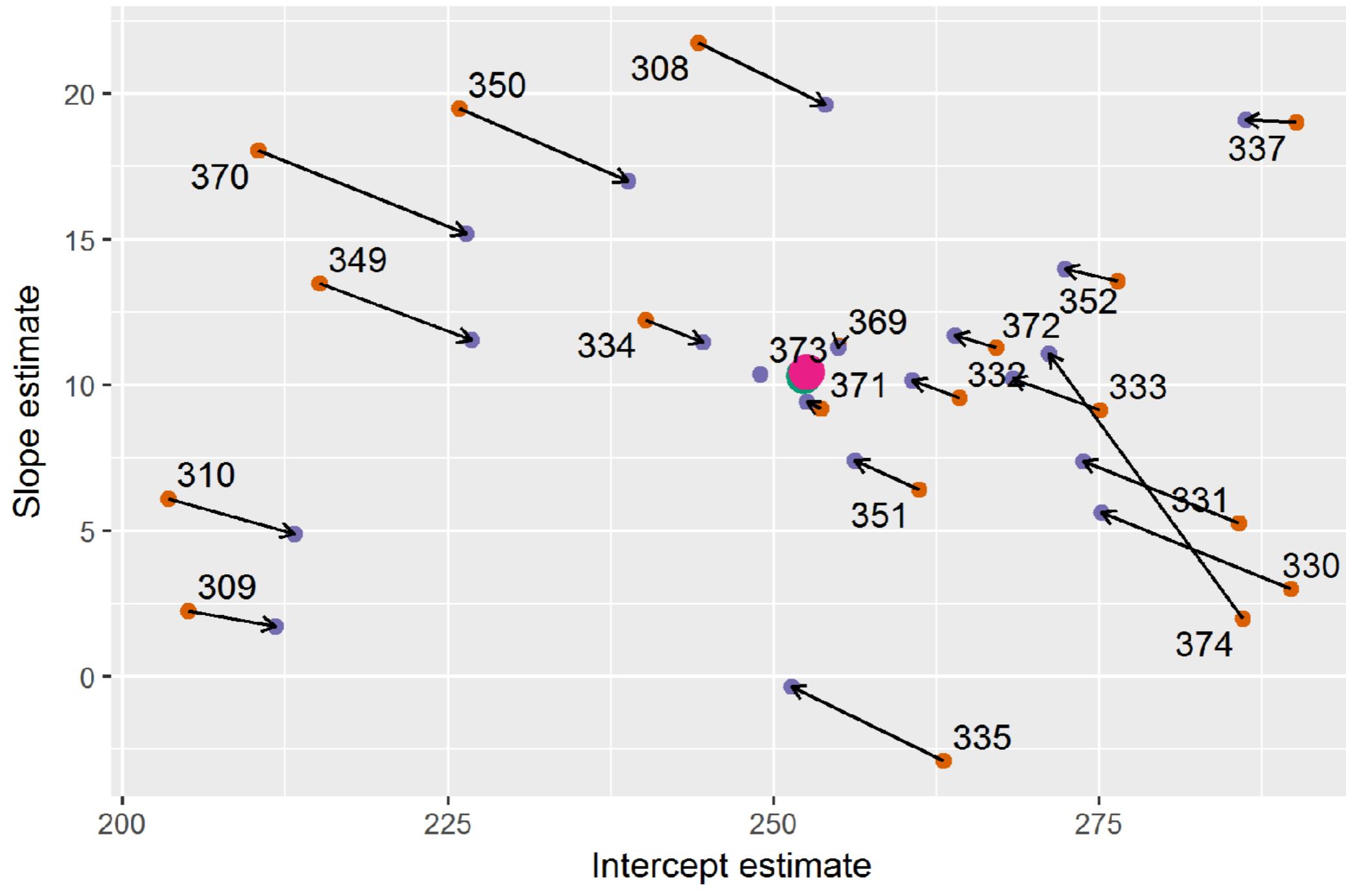
method	intercept	days
no pooling	28.95	6.56
partial pooling	21.59	5.46

variance "shrinks"



Shrinkage

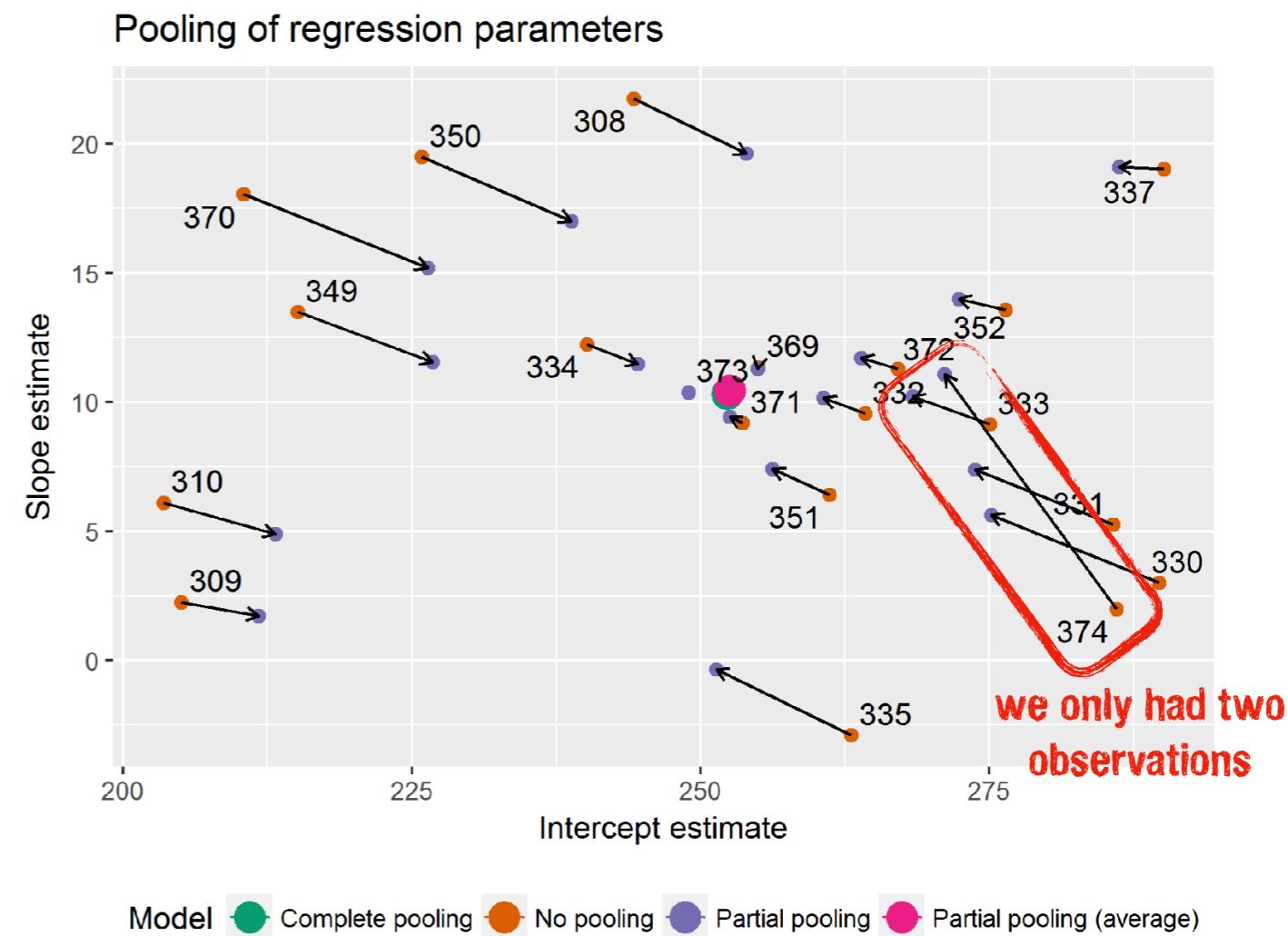
Pooling of regression parameters



Model Complete pooling No pooling Partial pooling Partial pooling (average)

Shrinkage

- more shrinkage when estimate is further from the average
- more shrinkage when estimate is more uncertain (based on fewer observations); more information "borrowed" from other clusters



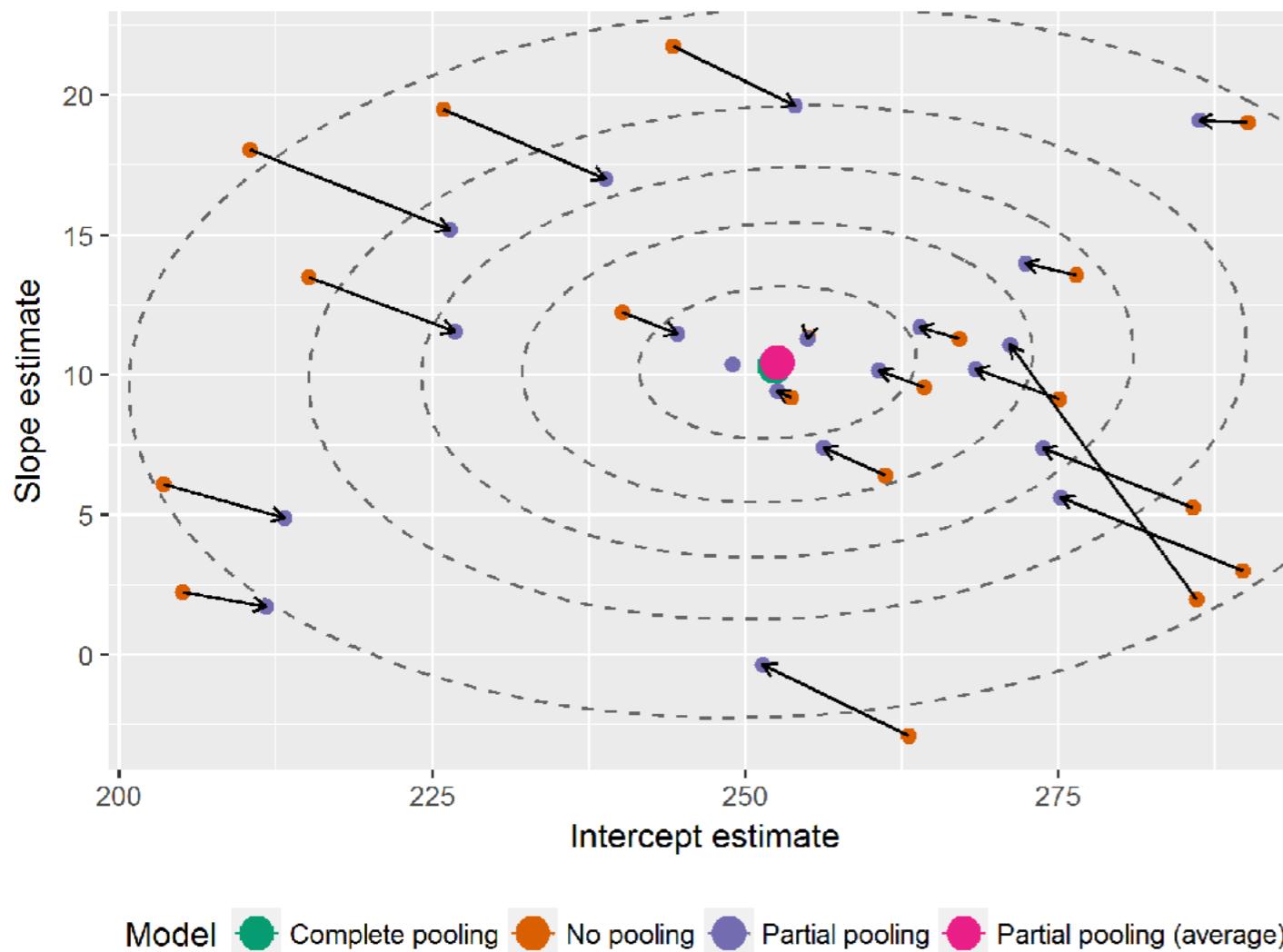
In [the lme4 book](#), Douglas Bates provides an alternative to *shrinkage*:

The term “shrinkage” may have negative connotations. John Tukey preferred to refer to the process as the estimates for individual subjects **“borrowing strength” from each other.**

This is a fundamental difference in the models underlying mixed-effects models versus strictly fixed effects models. In a mixed-effects model we assume that the levels of a grouping factor are a selection from a population and, as a result, can be expected to share characteristics to some degree. Consequently, the predictions from a mixed-effects model are attenuated relative to those from strictly fixed-effects models.

Shrinkage

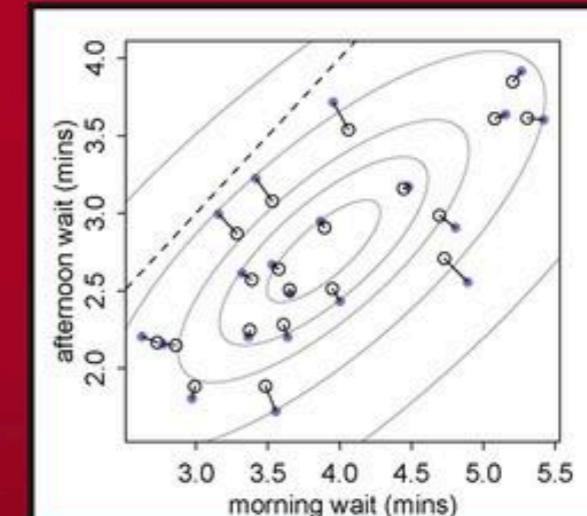
Topographic map of regression parameters



mixed effects model estimates a multi-variate Gaussian to account for (possible) correlations between intercepts and slopes

Texts in Statistical Science

Statistical Rethinking
A Bayesian Course with Examples in R and Stan

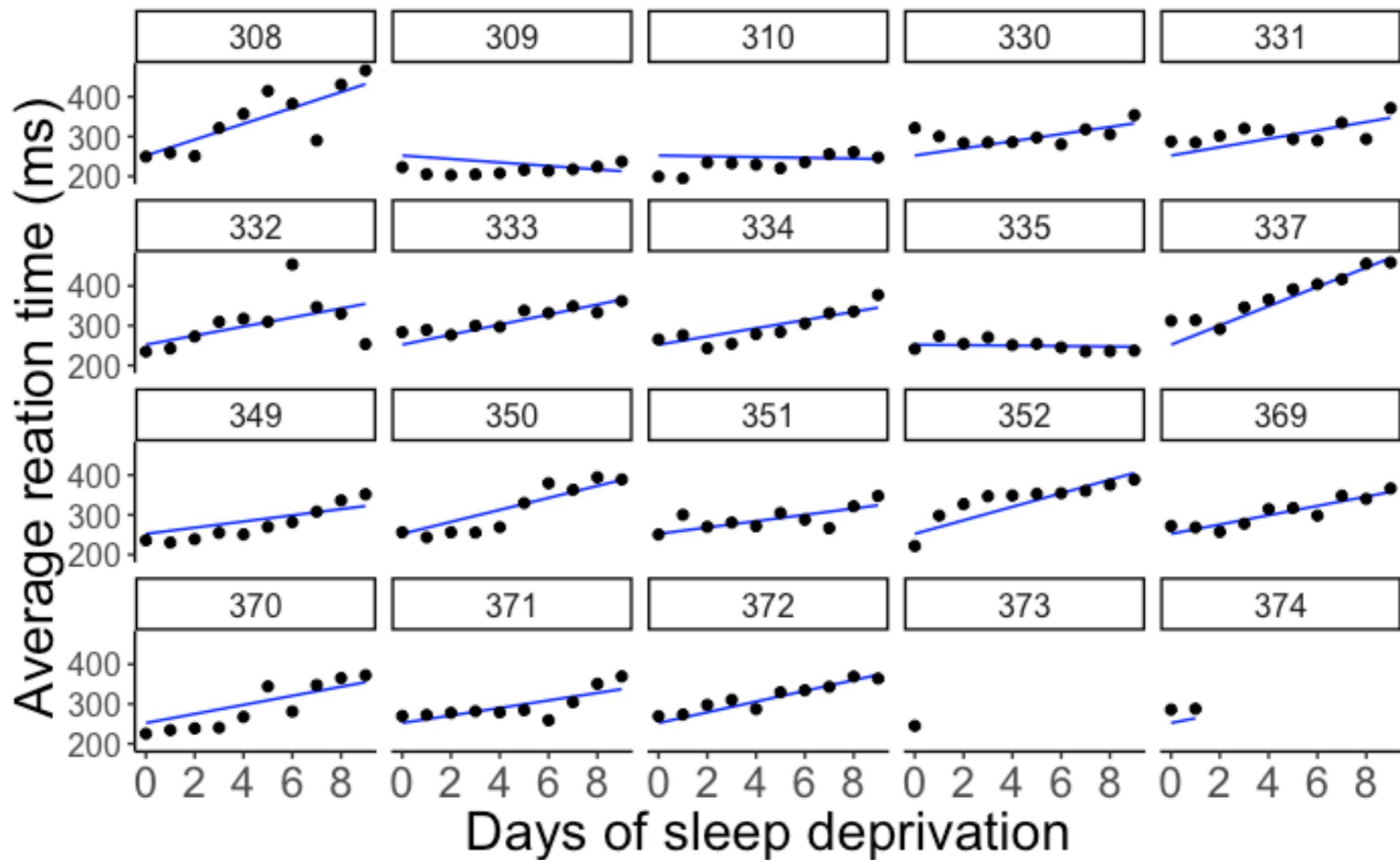


Richard McElreath

CRC Press
Taylor & Francis Group
A CHAPMAN & HALL BOOK

Reporting results

Visualization

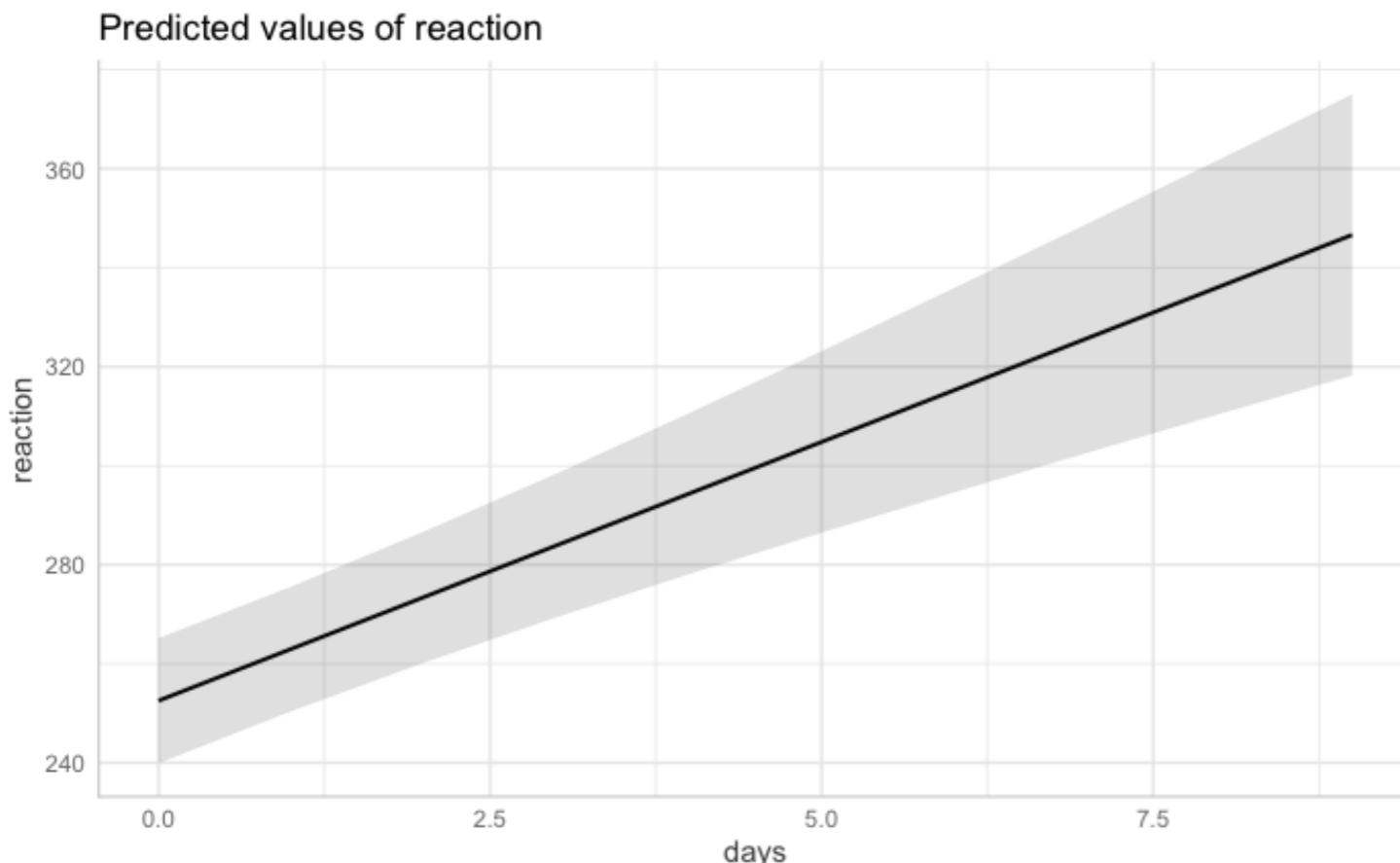


show the data together with the model predictions

Visualization



```
1 library("ggeffects")
2
3 ggpredict(model = fit.random_intercept_slope,
4            terms = "days",
5            type = "fe") %>%
6 plot()
```



- the relationship between the variables of interest (marginalizing over other variables)

show the (marginalized) model prediction

Reporting results

7.1. In Writing

Our reports include a description of the following parts (also see [Meteyard & Davies, 2019](#); [Barr et al., 2013](#)):

- Model specification, including:
 - Dependent variable, and all fixed and random effects (intercepts, slopes, correlations), both in words and possibly also by providing the model equation/R-pseudo code (so-called Wilkinson notation)
 - Transformation of variables, e.g., standardizing or centering variables
 - Contrast coding (typically sum-to-zero coding)
- Inference:
 - Description of how p -values were obtained (in case of a frequentist approach) or what other (Bayesian) decision rule was used for inference.
 - Description of what post-hoc or follow-up tests were performed
 - Any convergence issues that may arise while running the model (in particular if they require adjustments in the model specification) and how they were dealt with should be described, as well as the subsequent adjustments that were made.
- Model output, at minimum the following:
 - Model results: (un)standardized regression coefficients, standard errors and/or confidence / credible intervals, test statistics, degrees of freedom, p -values

Reporting results

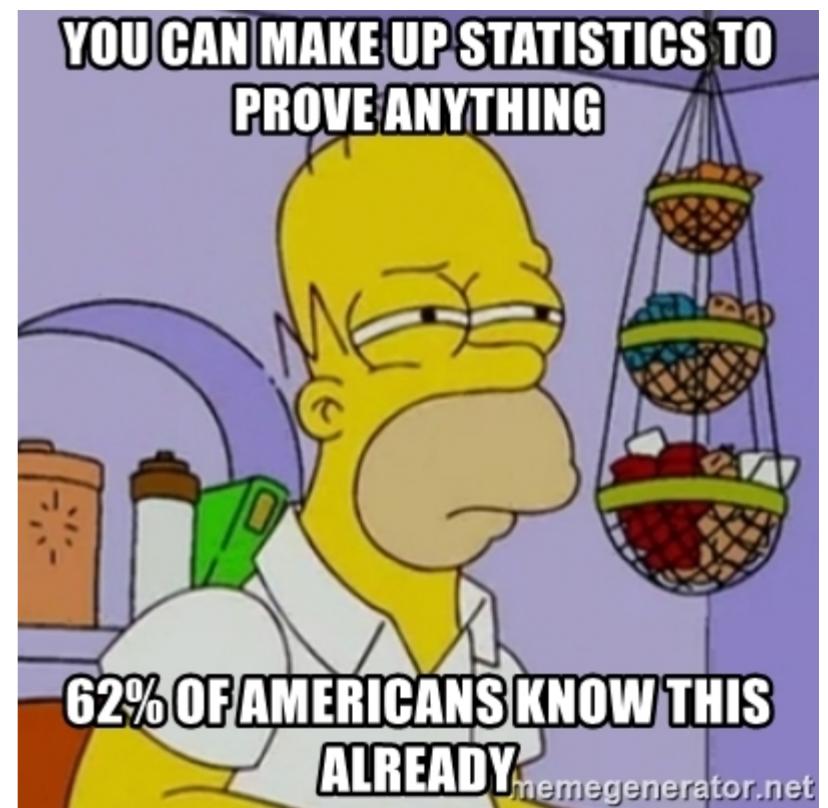
Table 2

Experiment 1 – Normality inference: Estimates of the posterior mean and 95% highest density intervals (HDIs) for the different predictors in the Bayesian regression model. Note: For the dependent variable (normality rating), 100 = abnormal and 0 = normal.

model specification: `normality rating ~ 1 + structure * norm`

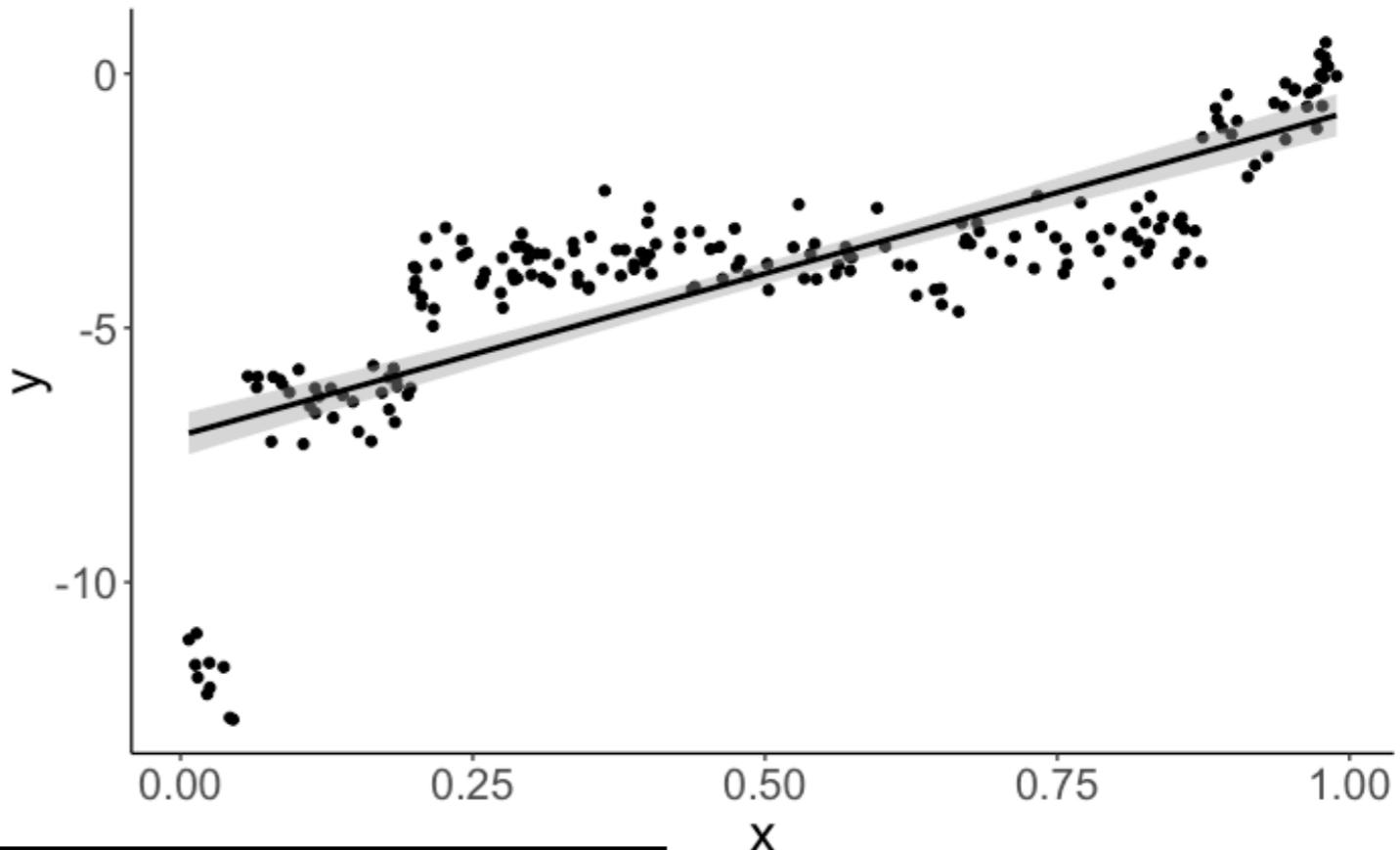
term	estimate	lower 95% CI	upper 95% CI
intercept	62.83	57.57	68.11
structure	21.22	16.27	26.35
norm	-1.47	-6.37	3.83
structure:norm	-1.46	-6.41	3.53

⁷All categorical predictors were coded using sum contrasts. We adopt the convention of calling something an effect if the 95% highest density interval (HDI) of the estimated parameter in the Bayesian model excludes 0.



Simpsons Paradox

Simpson's paradox



```
1 lm(formula = y ~ x,  
2     data = df.simpson) %>%  
3     summary()
```

```
Call:  
lm(formula = y ~ x, data = df.simpson)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-5.8731 -0.6362  0.2272  1.0051  2.6410  
  
Coefficients:  
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -7.1151    0.2107 -33.76 <2e-16 ***  
x             6.3671    0.3631  17.54 <2e-16 ***  
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
  
Residual standard error: 1.55 on 198 degrees of freedom  
Multiple R-squared:  0.6083, Adjusted R-squared:  0.6064  
F-statistic: 307.5 on 1 and 198 DF,  p-value: < 2.2e-16
```

positive relationship
between x and y

Simpson's paradox

```
1 lmer(formula = y ~ 1 + x + (1 | participant),  
2       data = df.simpson) %>%  
3   summary()
```

```
Linear mixed model fit by REML ['lmerMod']  
Formula: y ~ 1 + x + (1 | participant)  
Data: df.simpson
```

```
REML criterion at convergence: 345.1
```

```
Scaled residuals:
```

Min	1Q	Median	3Q	Max
-2.43394	-0.59687	0.04493	0.62694	2.68828

```
Random effects:
```

Groups	Name	Variance	Std.Dev.
participant	(Intercept)	21.4898	4.6357
Residual		0.1661	0.4075

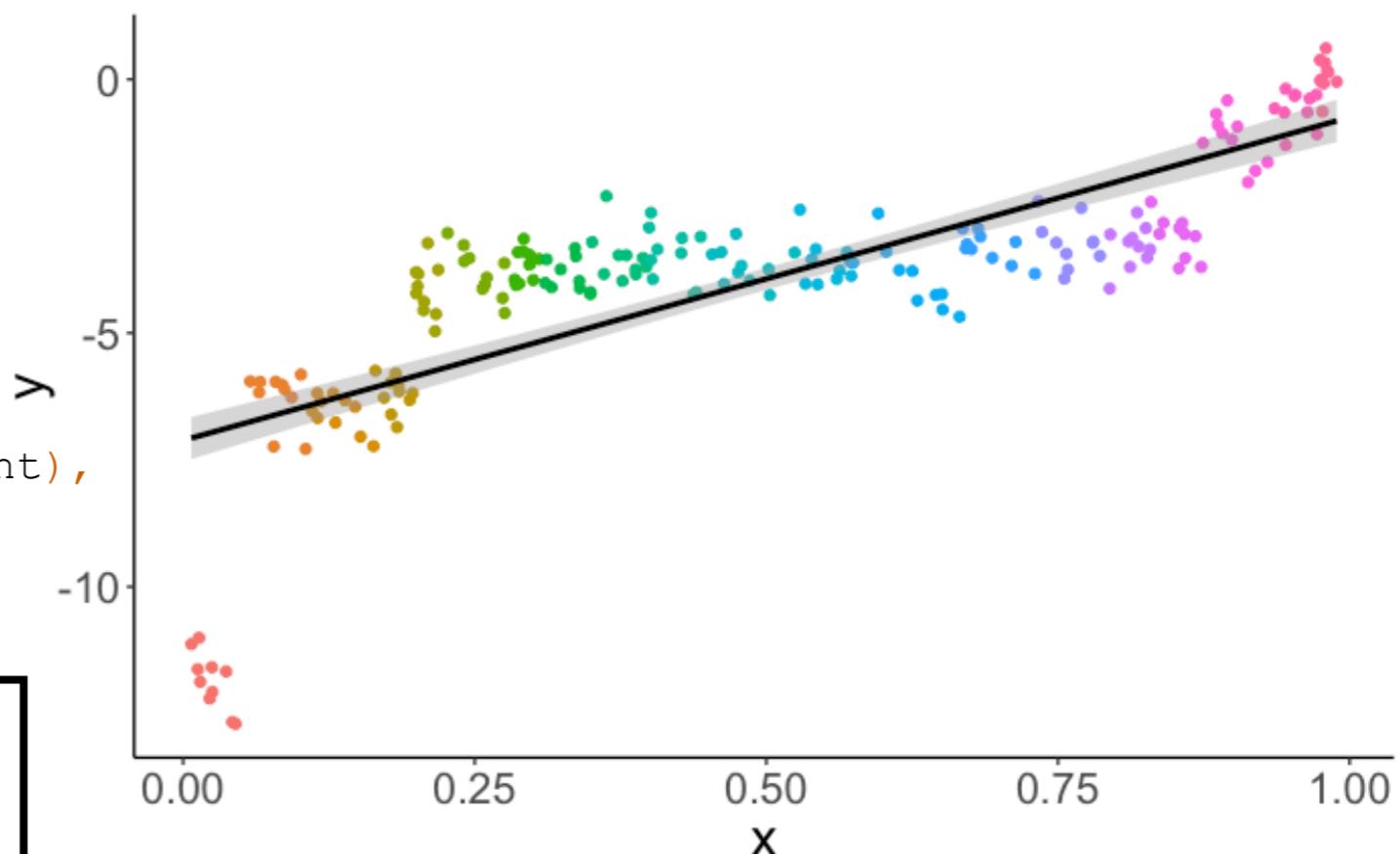
```
Number of obs: 200, groups: participant, 20
```

```
Fixed effects:
```

	Estimate	Std. Error	t value
(Intercept)	-0.1577	1.3230	-0.119
x	-7.6678	1.6572	-4.627

```
Correlation of Fixed Effects:
```

(Intr)	x
-0.621	



**negative (!)
relationship between
x and y**

Simpson's paradox

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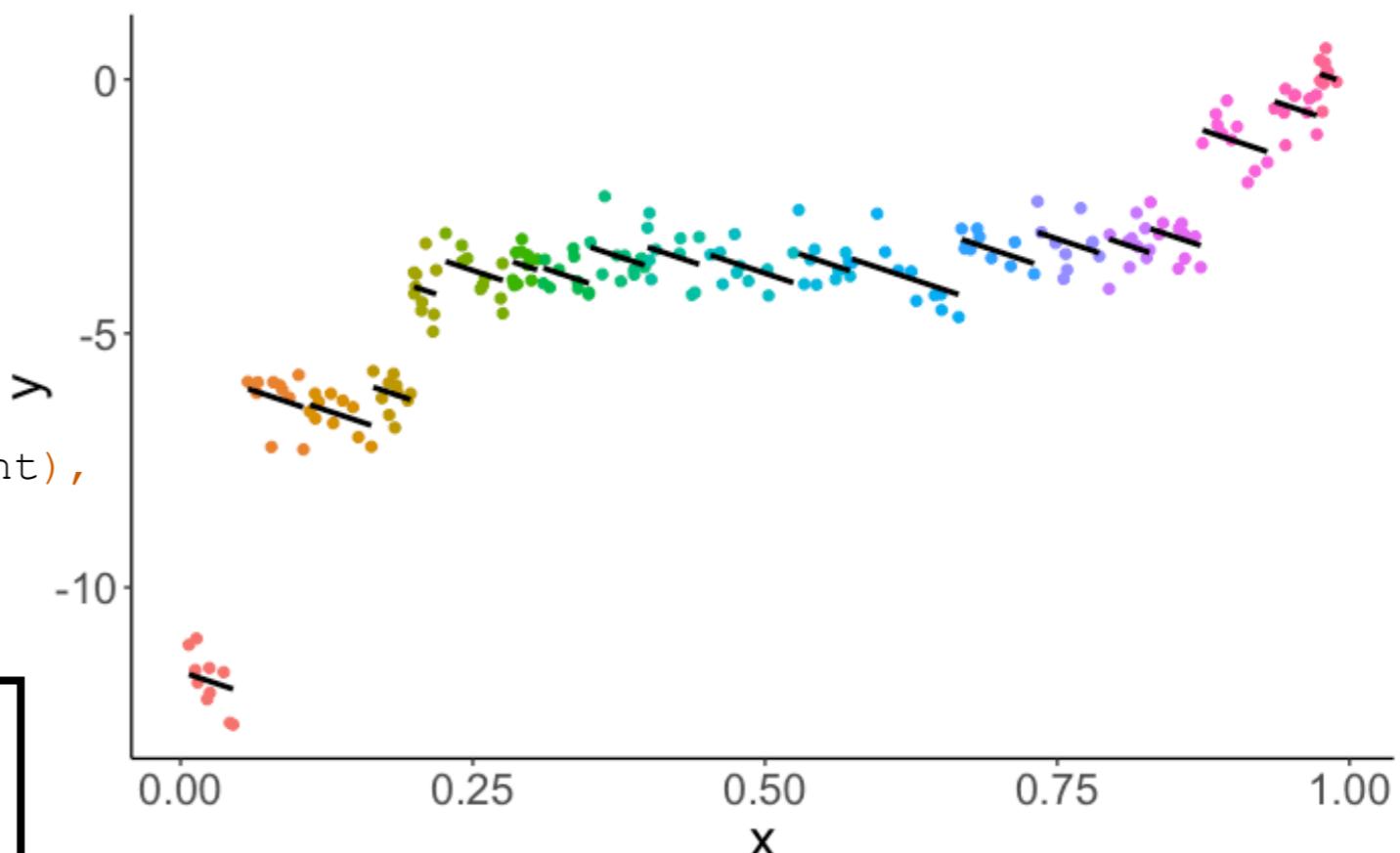
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**negative (!)
relationship between
x and y**

**(once we take into
account individual
differences)**

Simpson's paradox

UC Berkeley gender bias (1973)

	Men		Women	
	Applicants	Admitted	Applicants	Admitted
Total	8442	44%	4321	35%

Department	Men		Women	
	Applicants	Admitted	Applicants	Admitted
A	825	62%	108	82%
B	560	63%	25	68%
C	325	37%	593	34%
D	417	33%	375	35%
E	191	28%	393	24%
F	373	6%	341	7%

overall men are more likely to be admitted

men not more likely to be admitted when broken down by department

In fact, the pooled and corrected data showed a "small but statistically significant bias in favor of women."

women applied to more competitive departments

Summary

- Quick recap
- Linear mixed effects model
 - Modeling dependence in data
 - Understanding `lmer()` syntax
 - A worked example
 - Reporting results
 - Simpsons Paradox

Feedback

How was the pace of today's class?

much a little just a little much
too too right too too
slow slow

How happy were you with today's class overall?



What did you like about today's class? What could be improved next time?

Thank you!