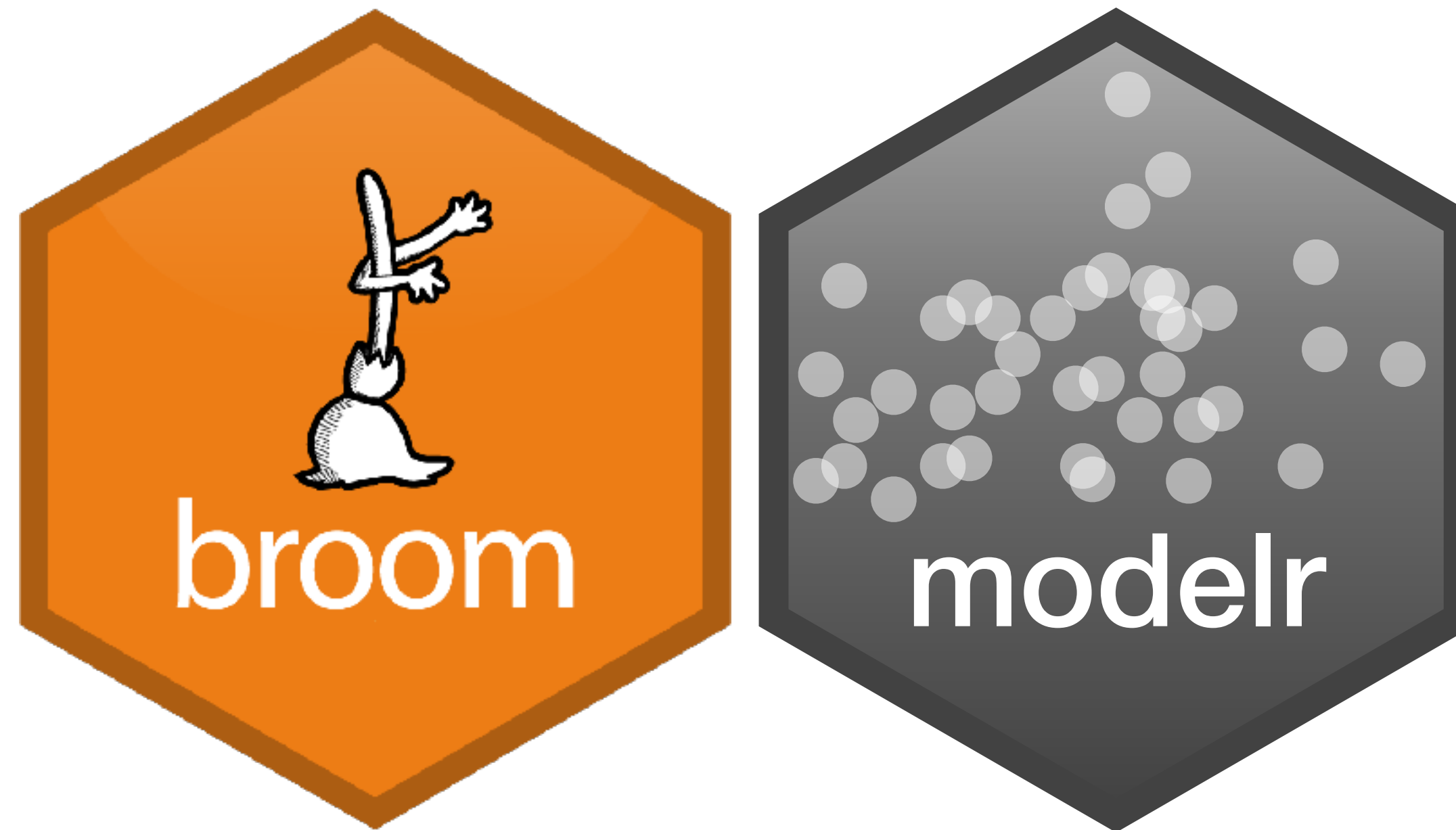


Modeling with



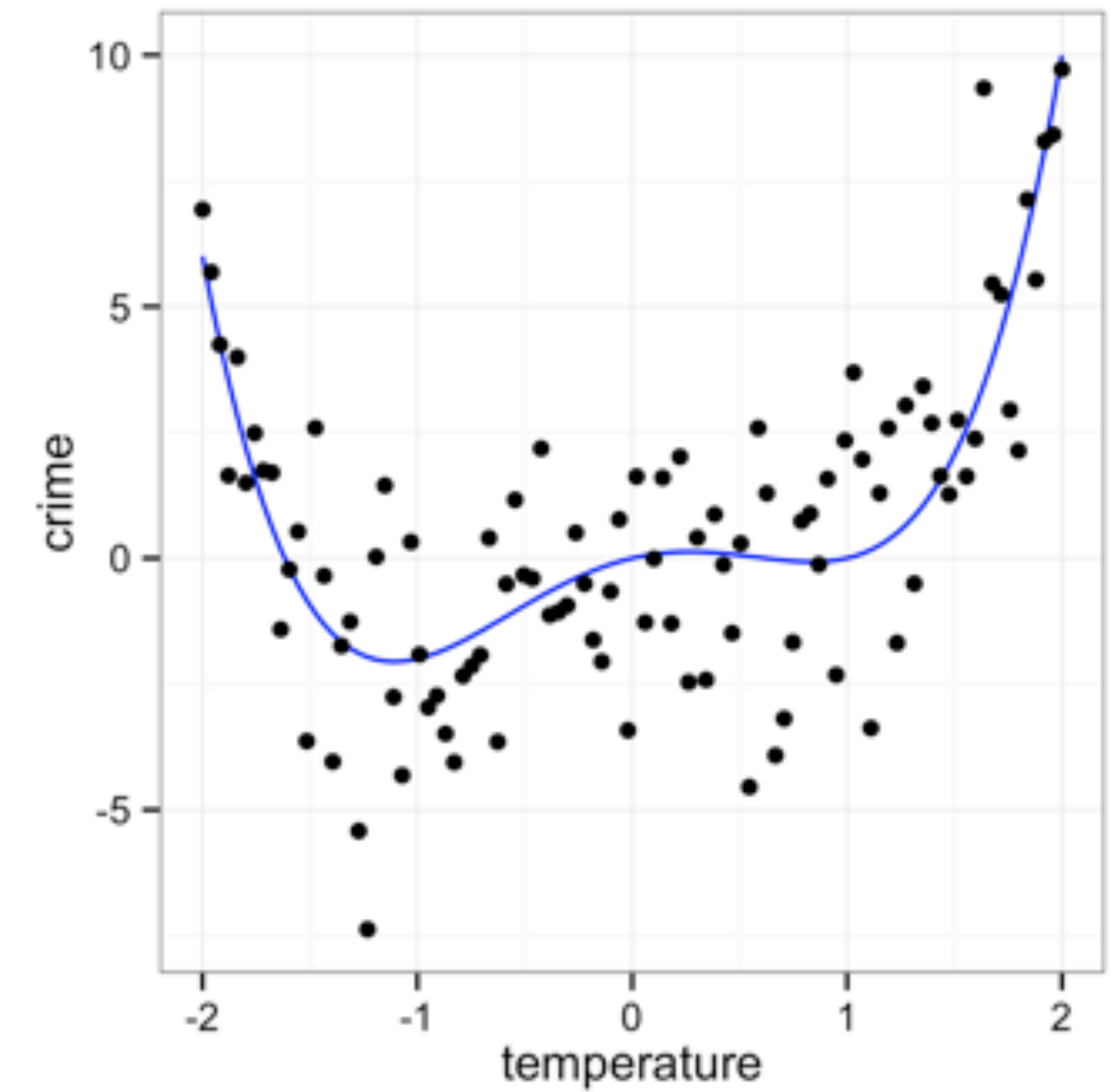
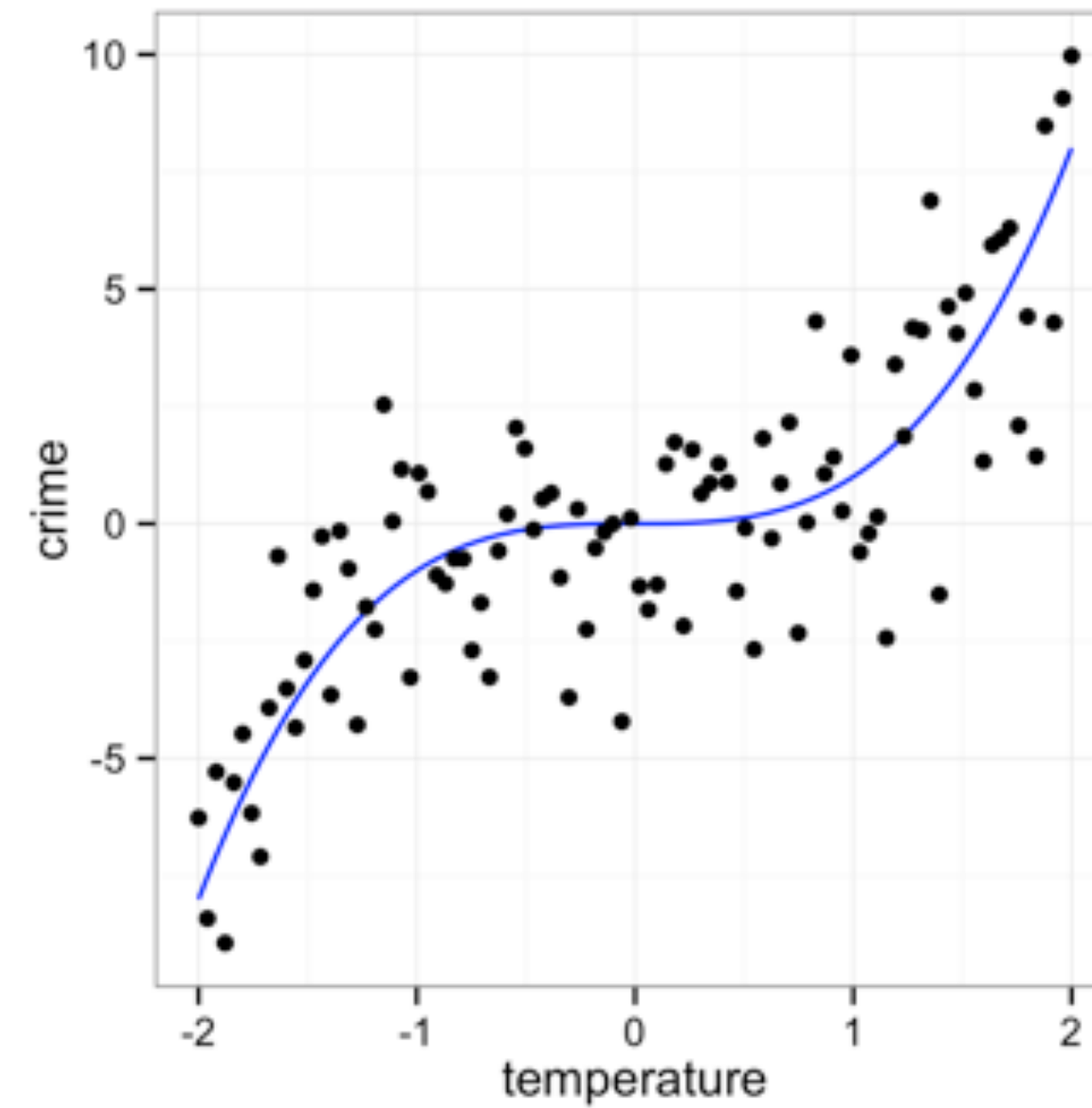
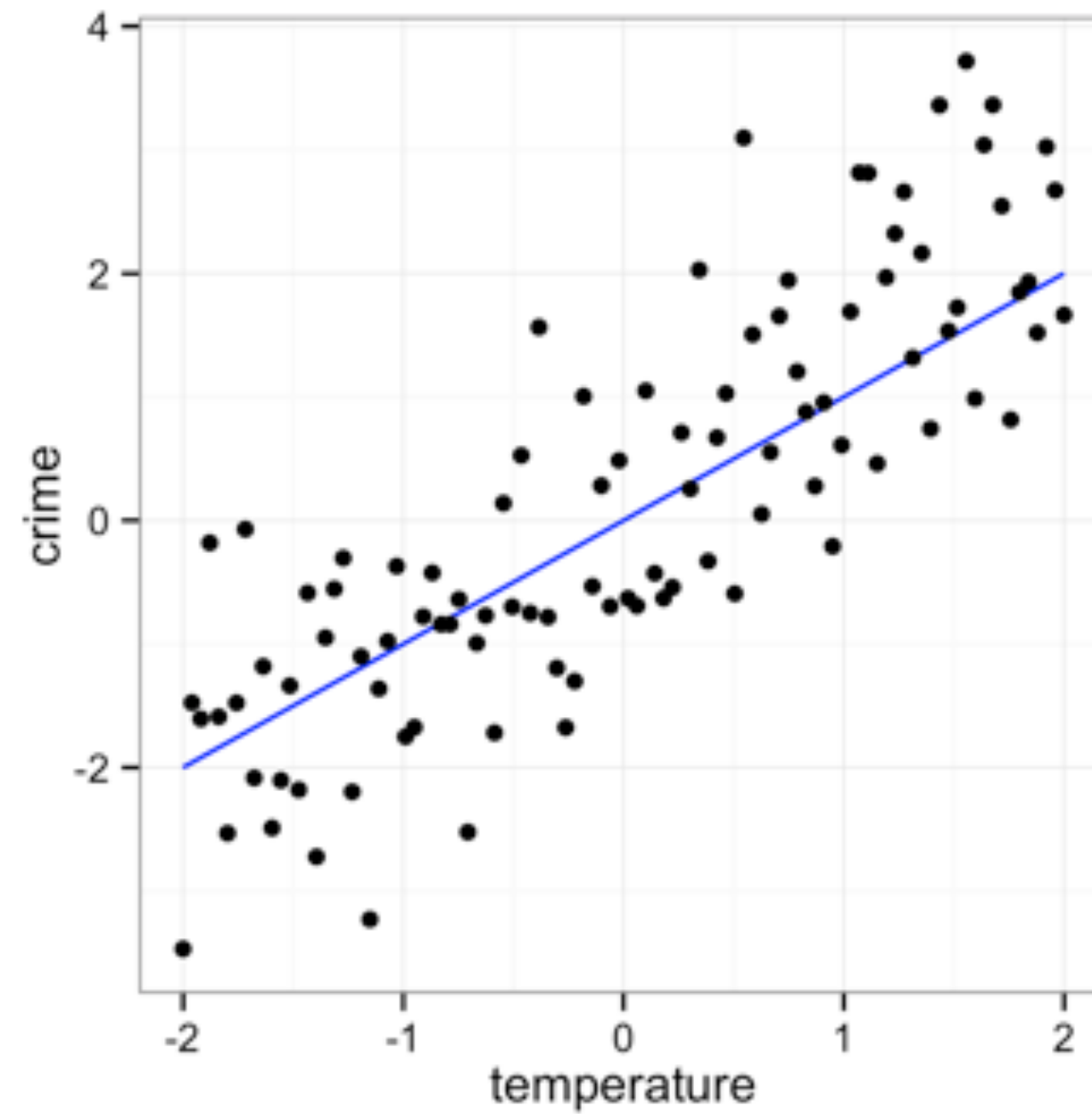
Navigate to the **04-Model** folder.
Open **04-Model-Exercises.Rmd**

The basics

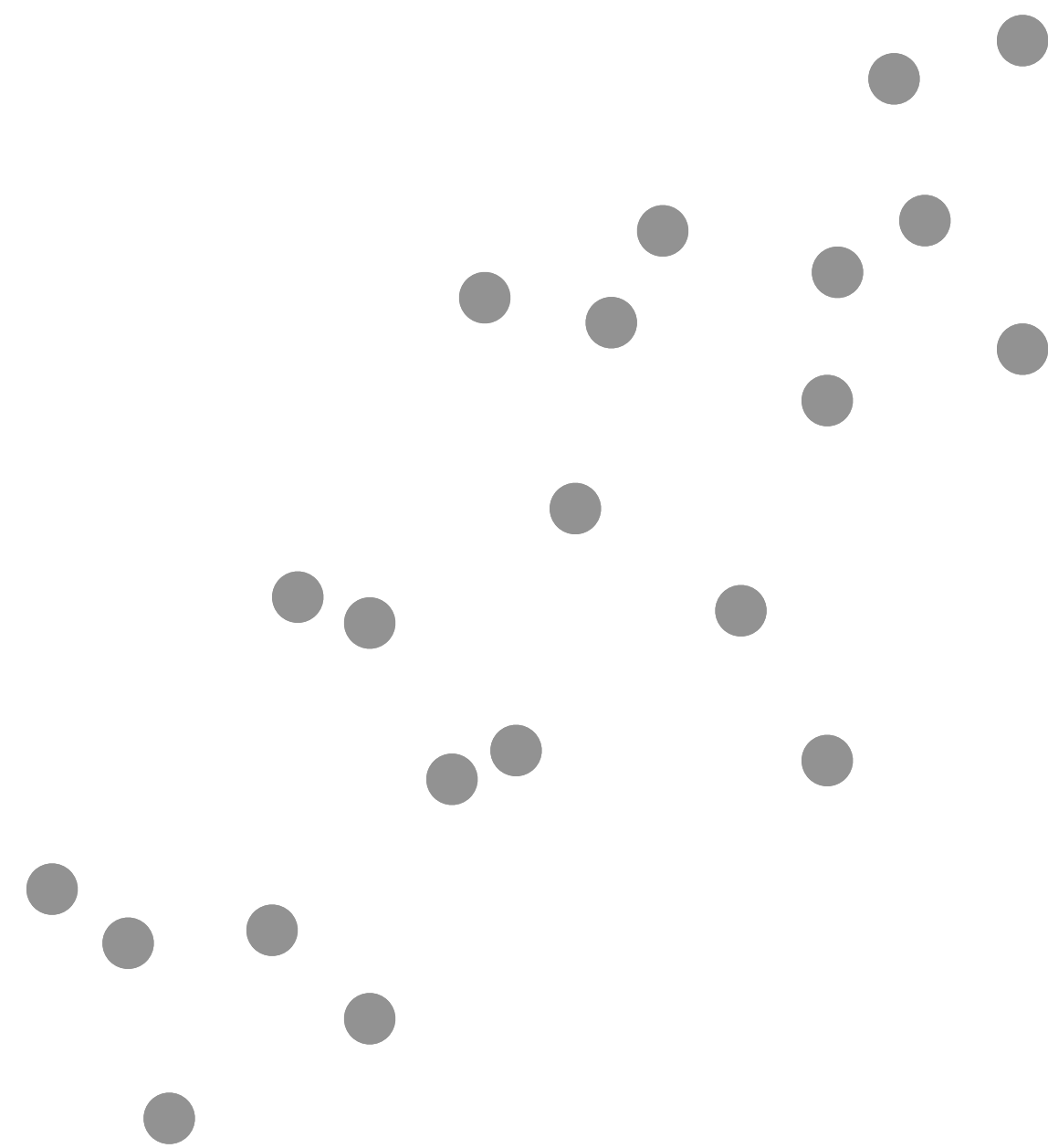


Models

A low dimensional description of a higher dimensional data set.



Models



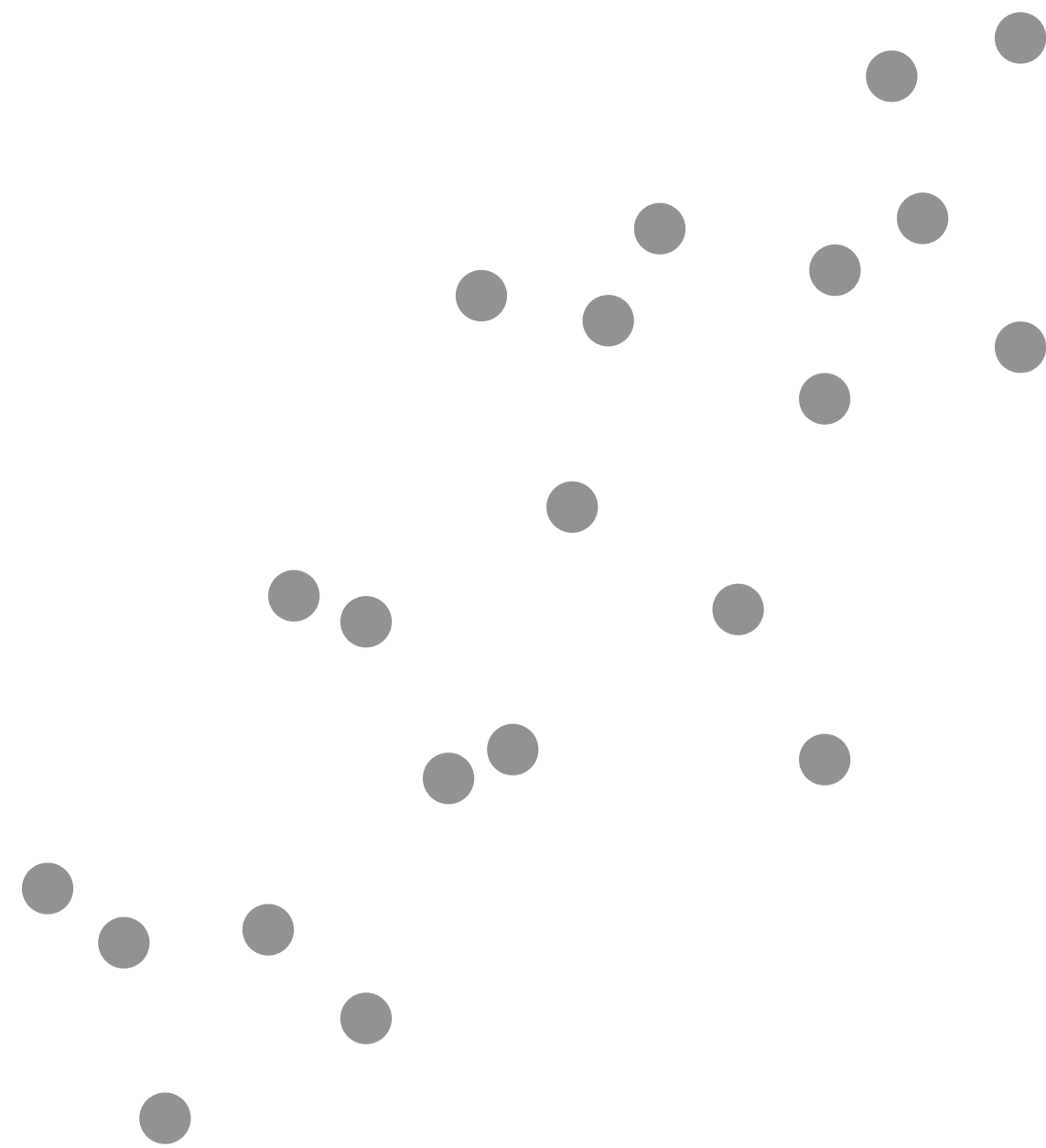
Data

Algorithm

Model Function

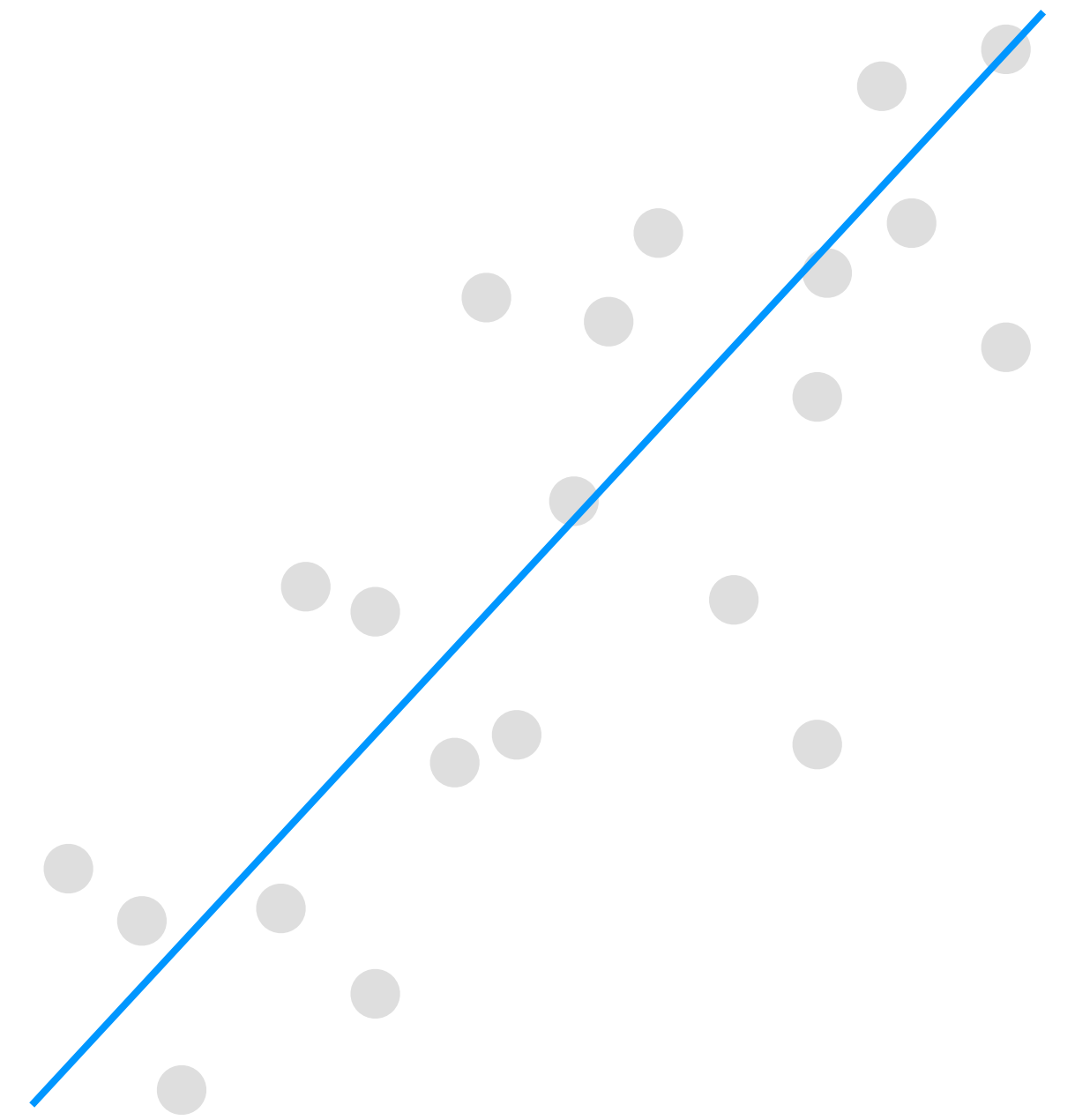
Models

What is the **model function**?



Data

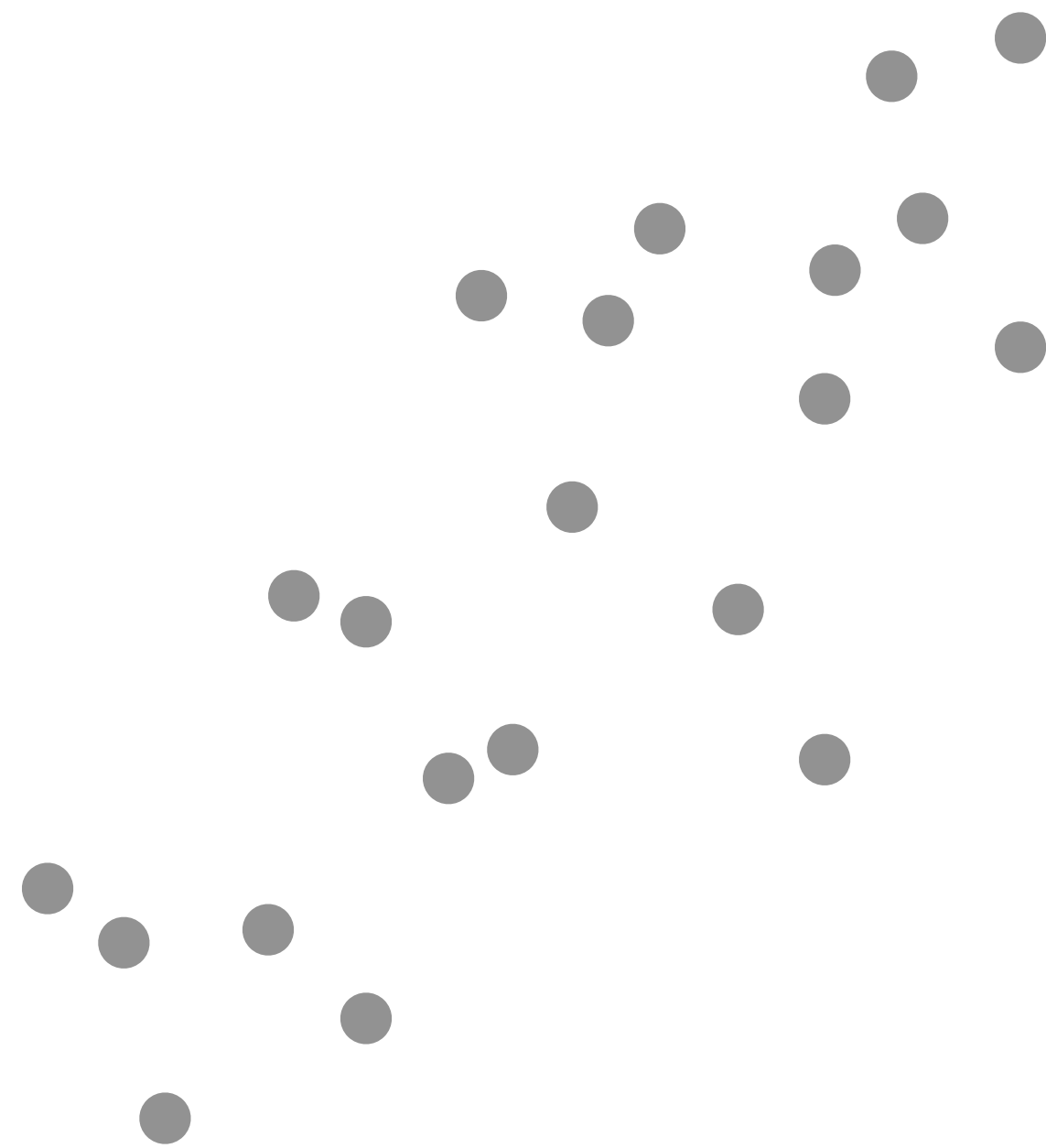
Algorithm



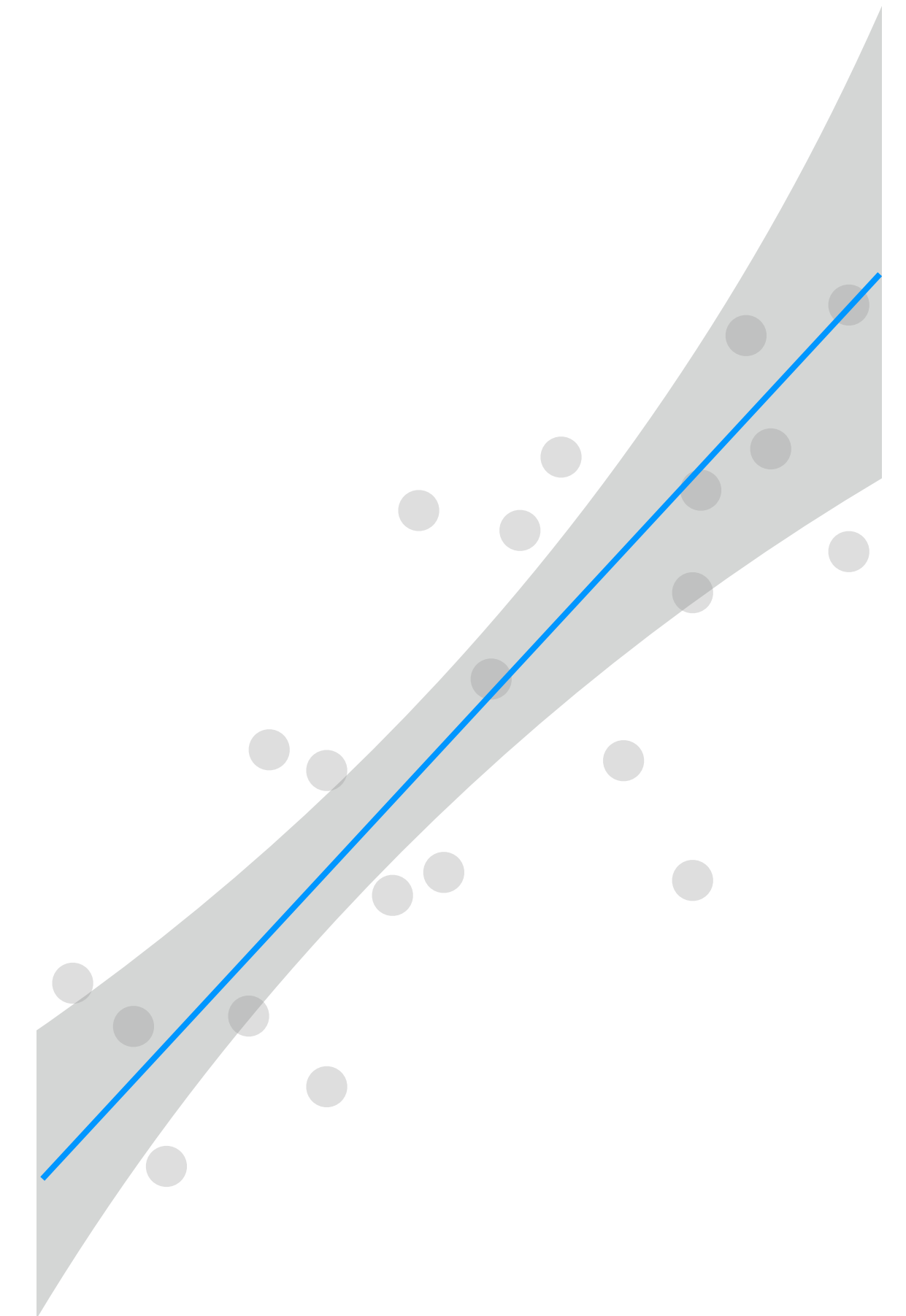
Model Function

Models

What **uncertainty** is associated with it?



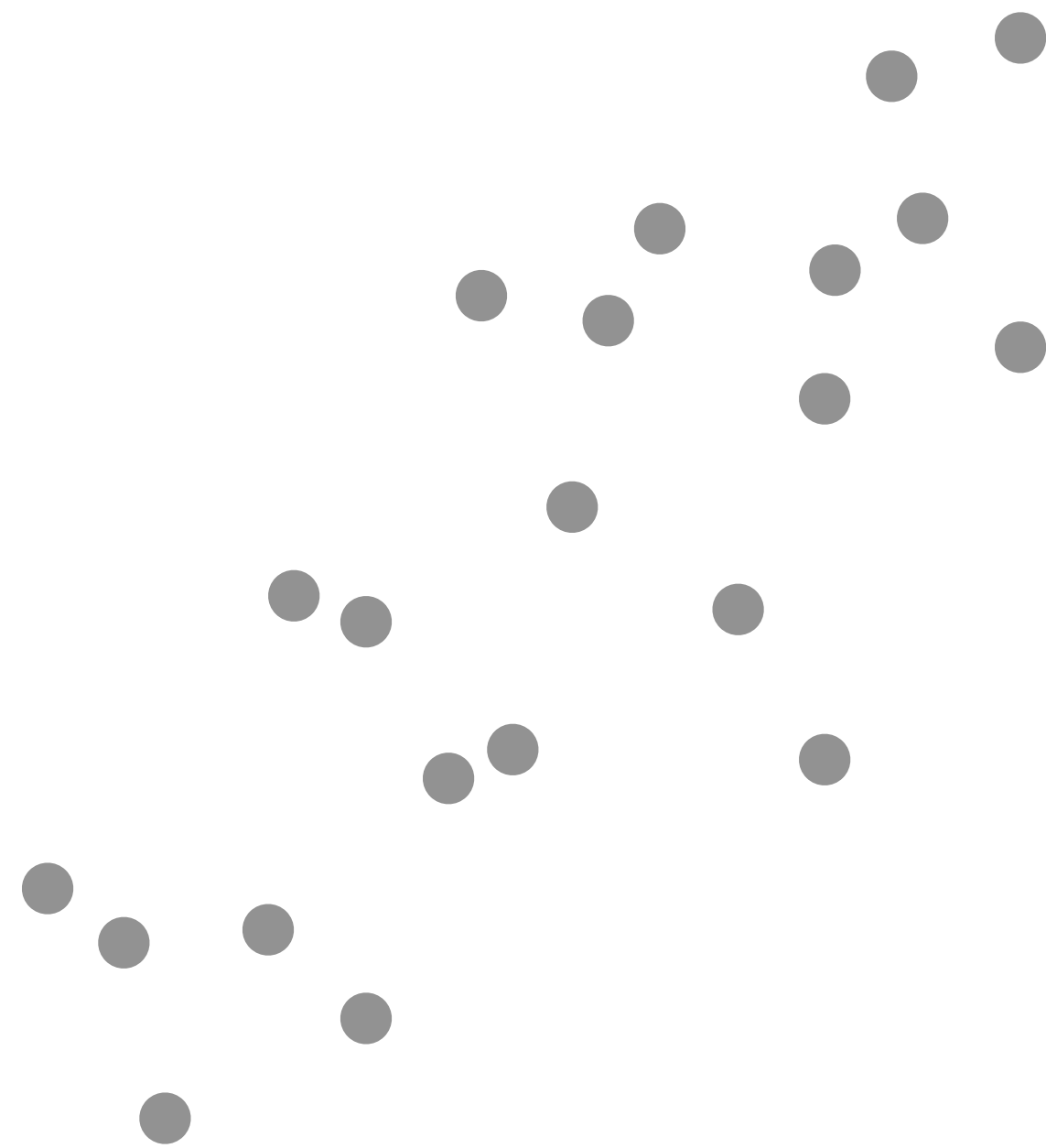
Data



Model Function

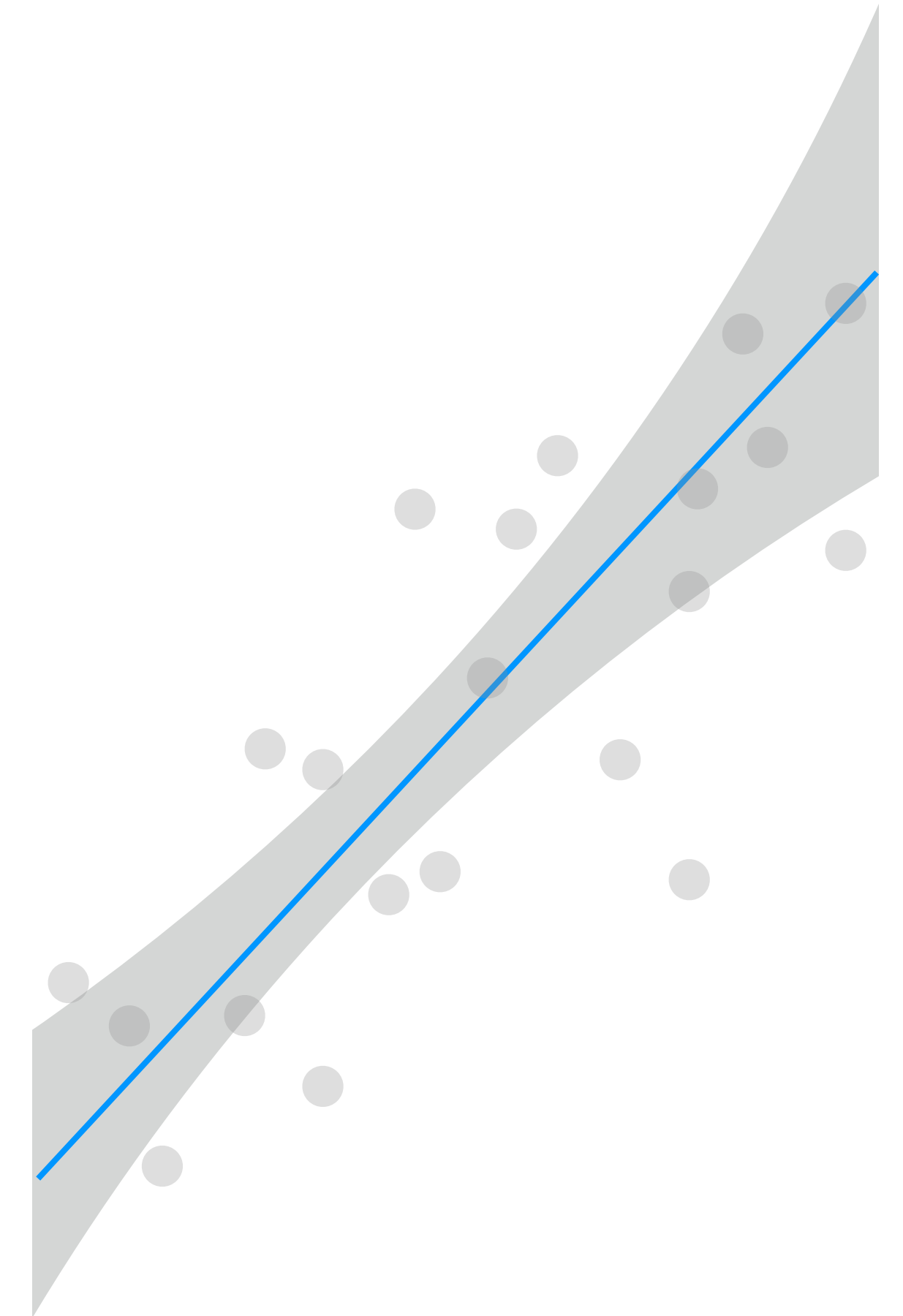
Models

How "good" is the model?



Data

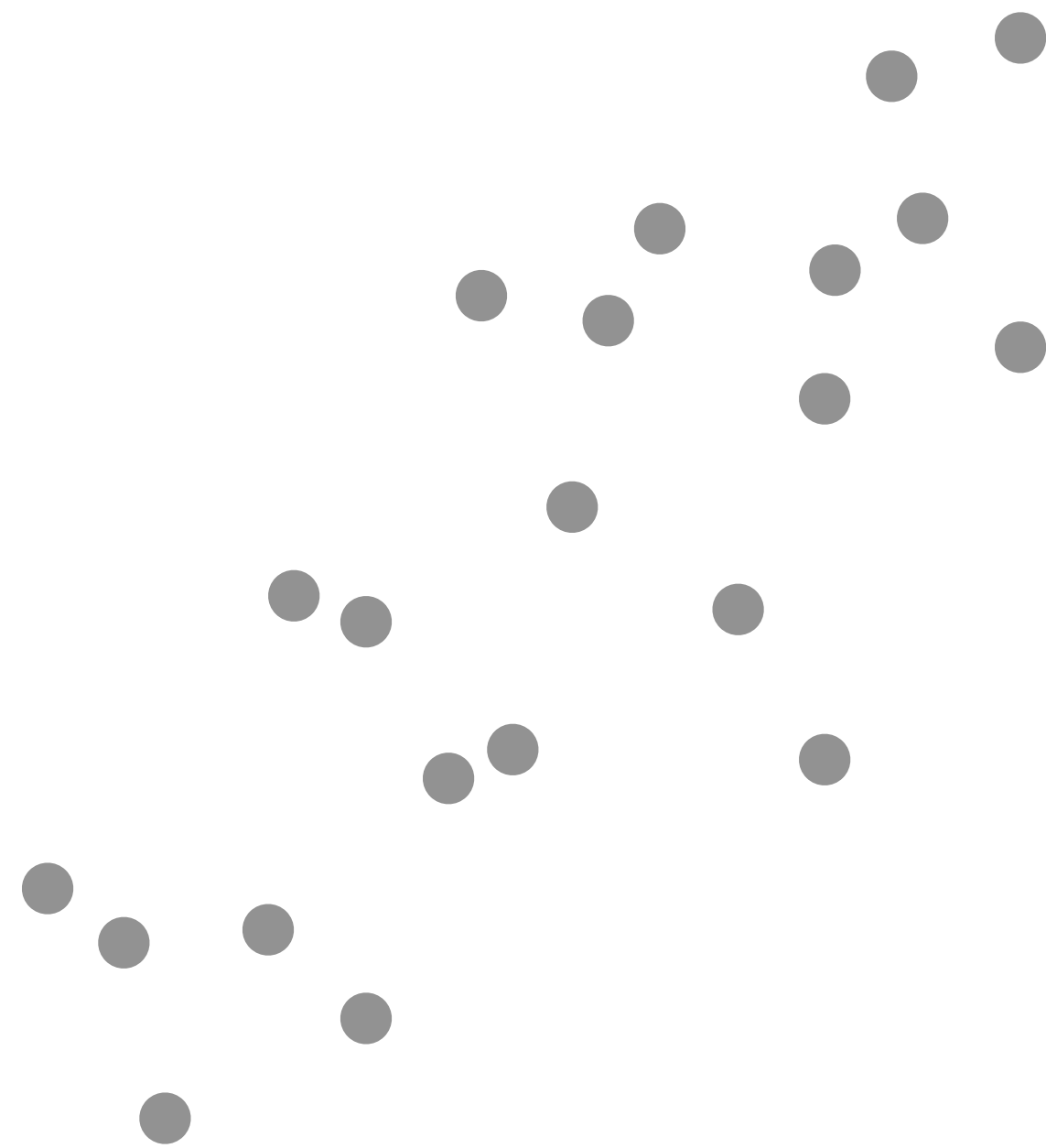
Algorithm



Model Function

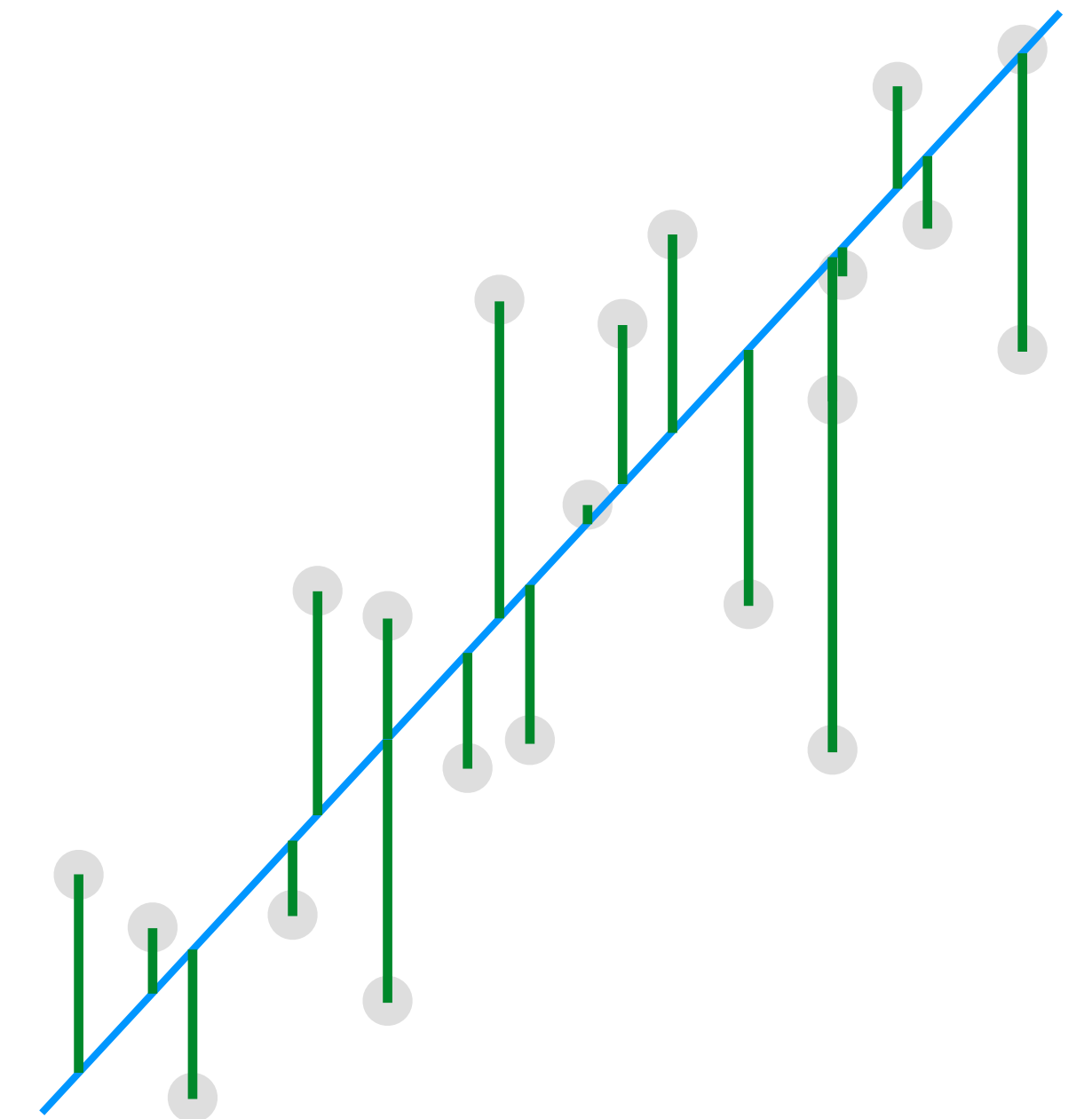
Models

What are the **residuals**?



Data

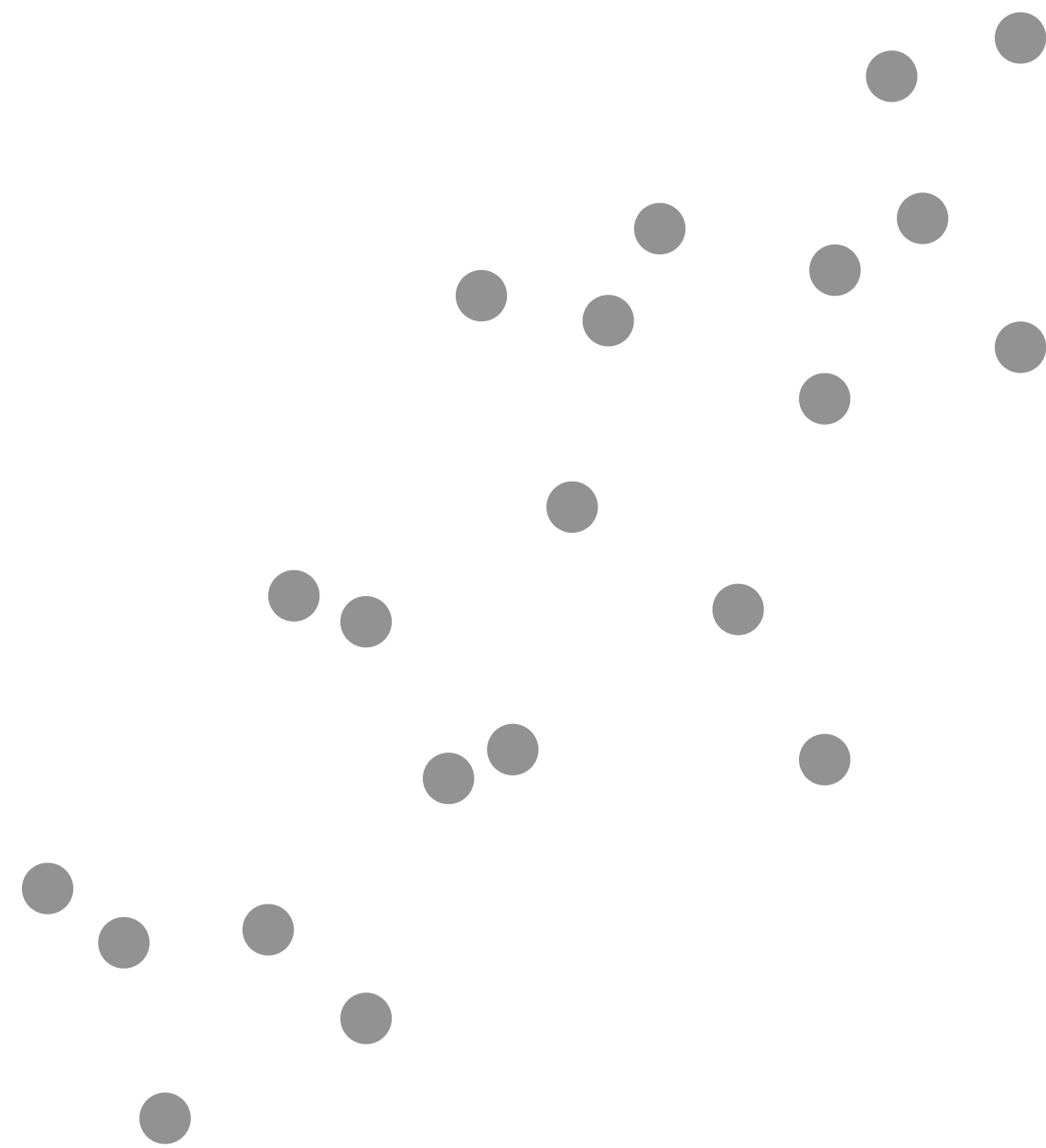
Algorithm



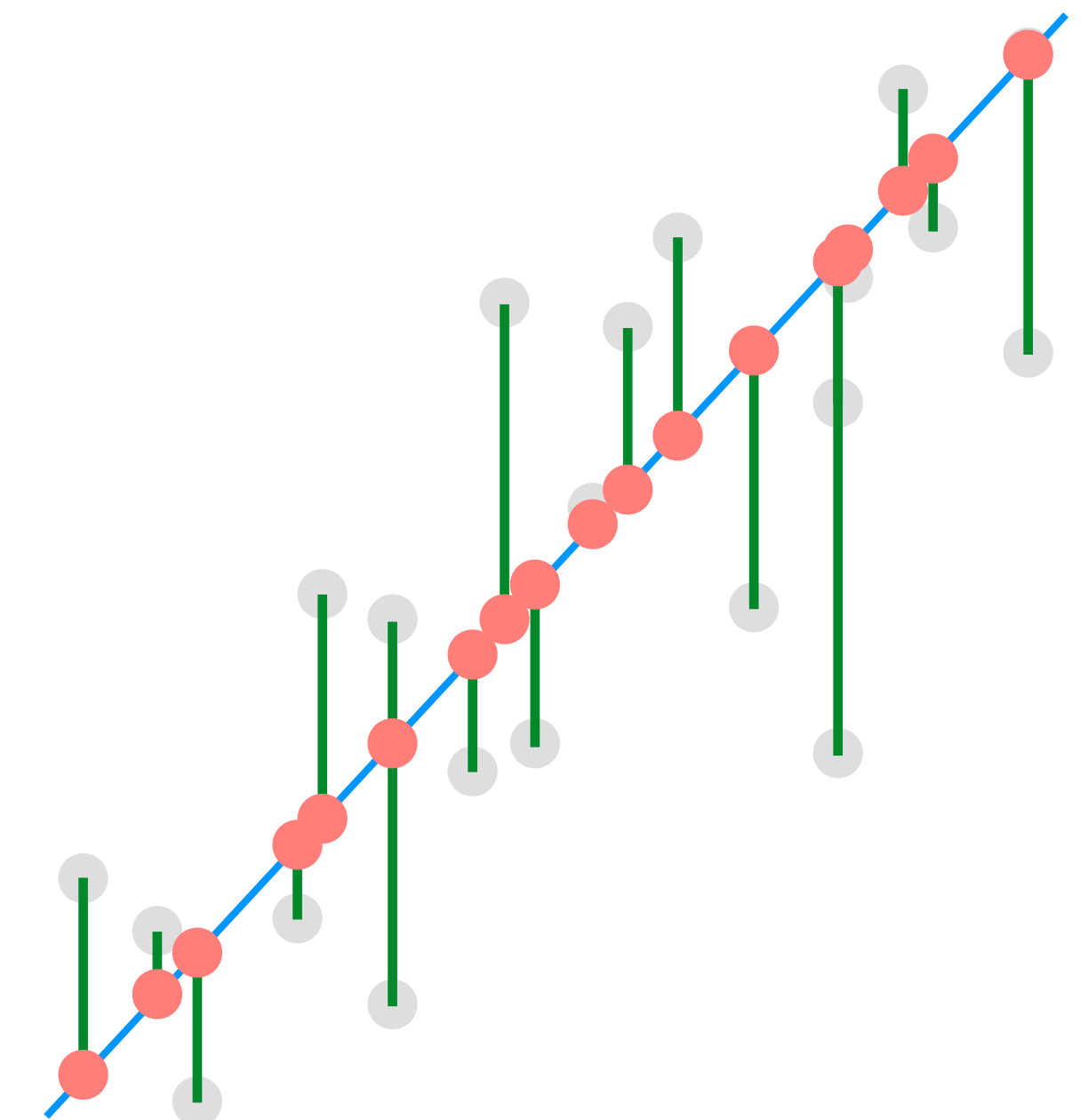
Model Function

Models

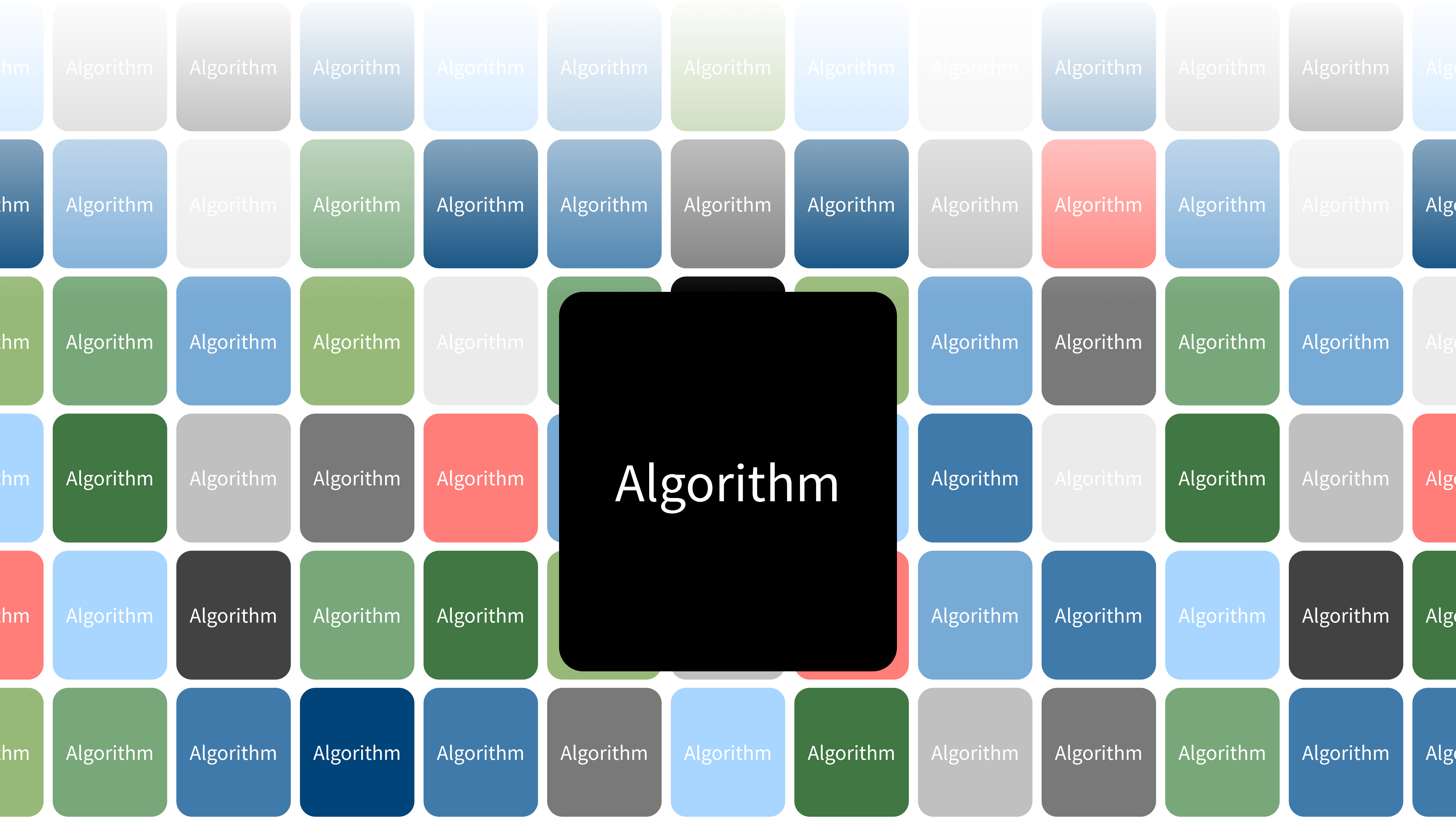
What are the **predictions**?



Data

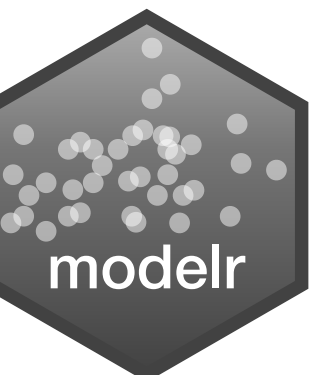


Model Function



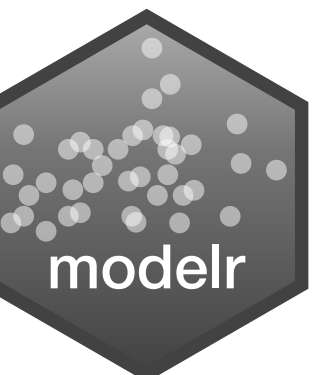
(Popular) modeling functions in R

function	package	fits
lm()	stats	linear models
glm()	stats	generalized linear models
gam()	mgcv	generalized additive models
glmnet()	glmnet	penalized linear models
rlm()	MASS	robust linear models
rpart()	rpart	trees
randomForest()	randomForest	random forests
xgboost()	xgboost	gradient boosting machines



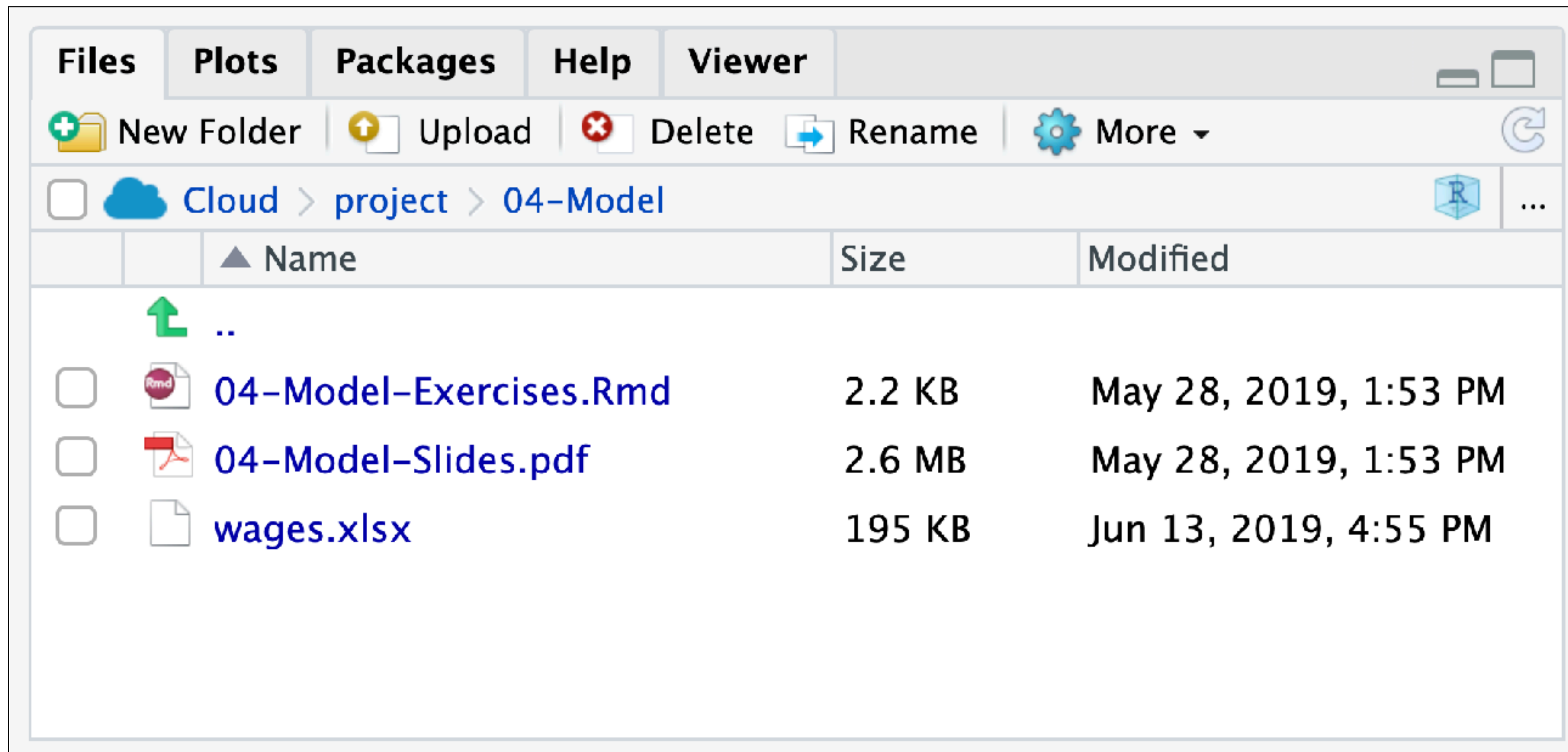
(Popular) modeling functions in R




function	package	fits
lm()	stats	linear models
glm()	stats	generalized linear models
gam()	mgcv	generalized additive models
glmnet()	glmnet	penalized linear models
rlm()	MASS	robust linear models
rpart()	rpart	trees
randomForest()	randomForest	random forests
xgboost()	xgboost	gradient boosting machines



wages.xlsx

Income predictors extracted from the [National Longitudinal Study](#), sponsored by the U.S. Bureau of Labor Statistics.



Files					Plots		Packages		Help		Viewer	
New Folder					Upload		Delete		Rename		More	
Cloud > project > 04-Model												
		Name			Size		Modified					
		..										
<input type="checkbox"/>		04-Model-Exercises.Rmd			2.2 KB		May 28, 2019, 1:53 PM					
<input type="checkbox"/>		04-Model-Slides.pdf			2.6 MB		May 28, 2019, 1:53 PM					
<input type="checkbox"/>		wages.xlsx			195 KB		Jun 13, 2019, 4:55 PM					

Your Turn 1

Change the working directory to **04-Models**.

Then import wages.xlsx as wages and **copy the code to your setup chunk**.

Be sure to set NA: to NA.

02:00

wages

**income**

<int>

height

<dbl>

weight

<int>

age

<int>

marital

<fctr>

sex

<fctr>

education

<int>

afqt

<dbl>

19000

60

155

53

married

female

13

6.841

35000

70

156

51

married

female

10

49.444

105000

65

195

52

married

male

16

99.393

40000

63

197

54

married

female

14

44.022

75000

66

190

49

married

male

14

59.683

102000

68

200

49

divorced

female

18

98.798

0

74

225

48

married

male

16

82.260

70000

64

160

54

divorced

female

12

50.283

60000

69

162

55

divorced

male

12

89.669

150000

69

194

54

divorced

male

13

95.977

1-10 of 7,006 rows

Previous

1

2

3

4

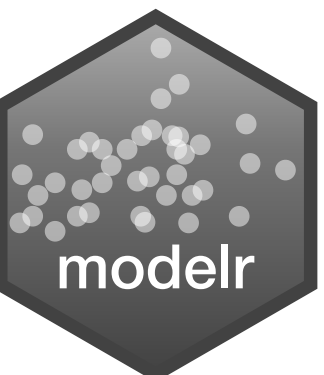
5

6

...

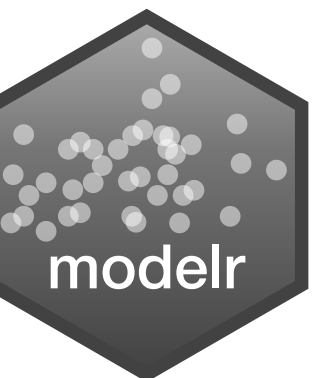
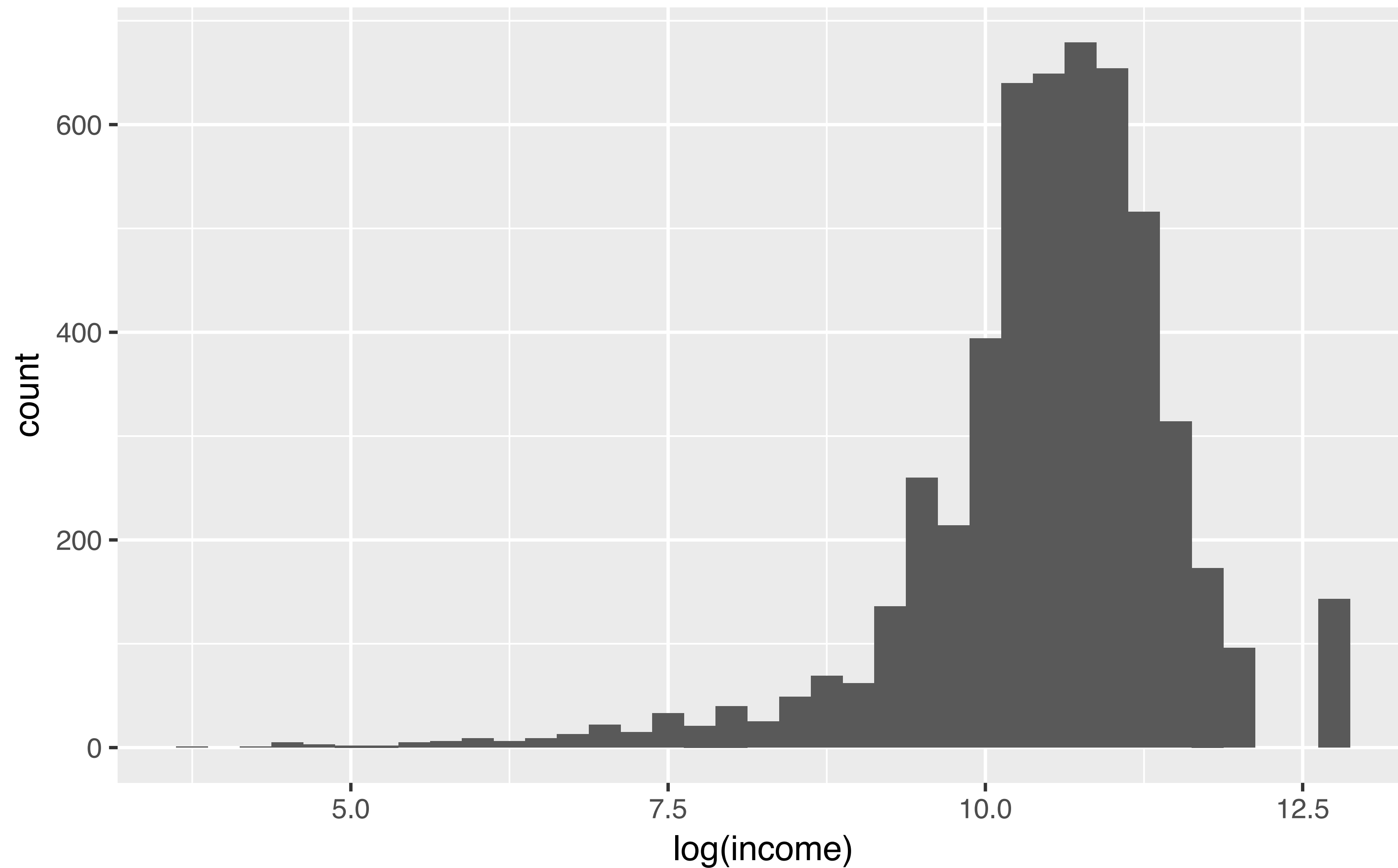
100

Next



```
wages %>%
```

```
  ggplot(aes(log(income))) + geom_histogram(binwidth = 0.25)
```



lm()



lm()

Fit a linear model to data

```
lm(log(income) ~ education, data = wages)
```

**A formula that
describes the model
equation**

The data set

formulas

Formula only needs to include the response and predictors

$$y = \alpha + \beta x + \epsilon$$

$$y \sim x$$

Response

A tilde

**The
predictors**

Your Turn 2

Fit the model below and then examine the output. What does it look like?

```
mod_e <- lm(log(income) ~ education, data = wages)
```

02:00

```
mod_e <- lm(log(income) ~ education, data = wages)
```

```
mod_e
```

```
## Call:
```

```
## lm(formula = log(income) ~ education, data = wages)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept)      education
```

```
##      8.5577      0.1418
```

```
class(mod_e)
```

```
## "lm"
```

1. Not pipe friendly to have data as second argument :(

2. Output is not tidy, or even a data frame

•

Use "." to pipe input to somewhere other than the first argument

```
mod_e <- wages %>%  
  lm(log(income) ~ education, data = .)
```

**wages will be
passed to here**

broom



broom



Turns model output into data frames

```
# install.packages("tidyverse")  
library(broom)
```



broom




Broom includes three functions which work for most types of models (and can be extended to more):

1. **tidy()** - returns model coefficients, stats
2. **glance()** - returns model diagnostics
3. **augment()** - returns predictions, residuals, and other raw values

tidy()

Returns useful **model output** as a data frame

```
mod_e %>% tidy()
```

  				
term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
(Intercept)	8.5576906	0.073259622	116.81320	0.0000000e+00
education	0.1418404	0.005304577	26.73924	8.408952e-148

2 rows

glance

Returns common **model diagnostics** as a data frame

```
mod_e %>% glance()
```

r.squared <dbl>	adj.r.squared <dbl>	sigma <dbl>	statistic <dbl>	p.value <dbl>
0.1196233	0.119456	0.9923358	714.987	8.408952e-14

1 row | 1-10 of 11 columns

augment()

Returns data frame of **model output related to original data points**

```
mod_e %>% augment()
```

.rownames <chr>	log.income. <dbl>	education <int>	.fitted <dbl>	.se.fit <dbl>	.resid <dbl>	.hat <dbl>	.sigma <dbl>	.a
1	9.852194	13	10.401615	0.01400504	-0.549421141	0.0001991827	0.9924012	3.05413
2	10.463103	10	9.976094	0.02335067	0.487009048	0.0005537086	0.9924074	6.67558
3	11.561716	16	10.827137	0.01880219	0.734579123	0.0003590043	0.9923784	9.84331
4	10.596635	14	10.543456	0.01386811	0.053178965	0.0001953068	0.9924299	2.80556
5	11.225243	14	10.543456	0.01386811	0.681787624	0.0001953068	0.9923856	4.61145
6	11.532728	18	11.110817	0.02719979	0.421910848	0.0007513008	0.9924131	6.80081
7	11.156251	12	10.259775	0.01600734	0.896475490	0.0002602083	0.9923532	1.06237
8	11.002100	12	10.259775	0.01600734	0.742324811	0.0002602083	0.9923774	7.28429
9	11.918391	13	10.401615	0.01400504	1.516775174	0.0001991827	0.9922098	2.32766
10	11.652687	16	10.827137	0.01880219	0.825550901	0.0003590043	0.9923648	1.24323

augment()

Returns data frame of **model output related to original data points**

```
mod_e %>% augment(data = wages)
```

Adds the original wages
data set to the output

Your Turn 3

Use a pipe to model **log(income)** against **height**. Then use broom and dplyr functions to extract:

1. The coefficient estimates and their related statistics
2. The adj.r.squared and p.value for the overall model

05:00

```

mod_h <- wages %>% lm(log(income) ~ height, data = .)

mod_h %>%
  tidy()
##           term      estimate  std.error statistic      p.value
## 1 (Intercept) 6.98342583 0.237484827  29.40578 4.129821e-176
## 2      height 0.05197888 0.003521666  14.75974 2.436945e-48

mod_h %>%
  glance() %>%
  select(adj.r.squared, p.value)
##      adj.r.squared      p.value
## 1      0.03955779 2.436945e-48

```

```
mod_h %>%
```

```
  tidy() %>% filter(p.value < 0.05)
```

```
##           term      estimate  std.error statistic      p.value
## 1 (Intercept) 6.98342583 0.237484827  29.40578 4.129821e-176
## 2      height 0.05197888 0.003521666  14.75974 2.436945e-48
```

```
mod_e %>%
```

```
  tidy() %>% filter(p.value < 0.05)
```

```
##           term      estimate  std.error statistic      p.value
## 1 (Intercept) 8.5576906 0.073259622 116.81320 0.000000e+00
## 2   education 0.1418404 0.005304577  26.73924 8.408952e-148
```

**so which determines
income?**

multivariate regression



To fit multiple predictors,
add multiple variables to the formula:

```
log(income) ~ education + height
```

```
mod_eh <- wages %>%
```

```
  lm(log(income) ~ education + height, data = .)
```

```
mod_eh %>%
```

```
  tidy()
```

##		term	estimate	std.error	statistic	p.value
##	1	(Intercept)	5.34837618	0.231320415	23.12107	1.002503e-112
##	2	education	0.13871285	0.005205245	26.64867	7.120134e-147
##	3	height	0.04830864	0.003309870	14.59533	2.504935e-47

Your Turn 4

Model **log(income)** against **education** and **height** and **sex**. Can you interpret the coefficients?

03:00

```
mod_ehs <- wages %>%
```

```
  lm(log(income) ~ education + height + sex, data = .)
```

```
mod_ehs %>%
```

```
  tidy()
```

##	term	estimate	std.error	statistic	p.value
## 1	(Intercept)	7.79	0.307	25.3	9.41e-134
## 1 2	education	0.148	0.00520	28.5	5.16e-166
## 1 3	height	0.00673	0.00479	1.40	1.61e- 1
## 1 4	sexmale	0.462	0.0389	11.9	5.02e- 32

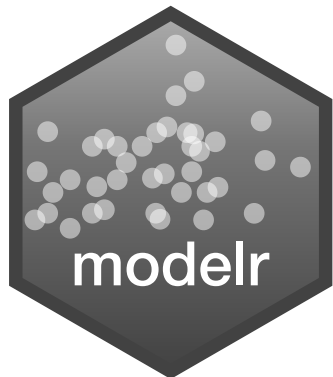
Where is sexmale?

What does this mean?

wages

CHARACTER

income <dbl>	height <dbl>	weight <dbl>	age <dbl>	marital <chr>	sex <chr>	education <dbl>
19000	60	155	53	married	female	13
35000	70	156	51	married	female	10
105000	65	195	52	married	male	16
40000	63	197	54	married	female	14
75000	66	190	49	married	male	14
102000	68	200	49	divorced	female	18
70000	64	160	54	divorced	female	12
60000	69	162	55	divorced	male	12
150000	69	194	54	divorced	male	13
115000	64	145	53	married	female	16

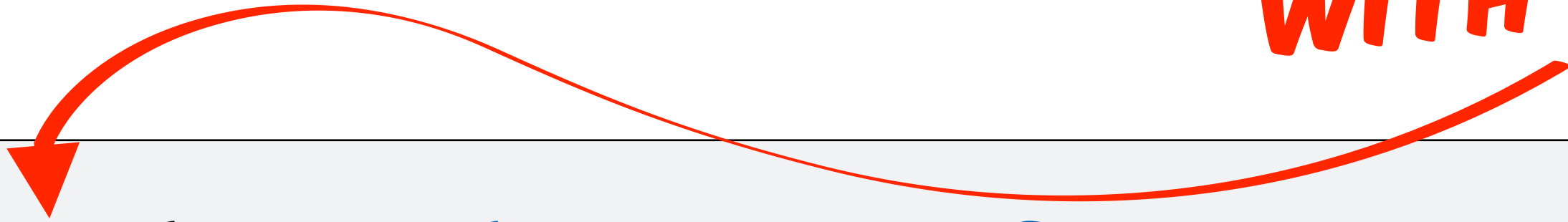


factors

R's representation of categorical data. Consists of:

1. A set of **values**
2. An ordered set of **valid levels**

**YOU CAN MAKE
WITH FACTOR()**



```
sexes <- factor(x = c("male", "female", "male"),  
               levels = c("male", "female", "other"))  
  
sexes  
## male    female male  
## Levels: male female other
```



factors

Stored as an integer vector with a levels attribute

```
unclass(sexes)
## 1 2 1
## attr(,"levels")
## "male" "female" "other"
```

##	term	estimate	std.error	statistic	p.value
## 1	(Intercept)	7.79	0.307	25.3	9.41e-134
## 1 2	education	0.148	0.00520	28.5	5.16e-166
## 1 3	height	0.00673	0.00479	1.40	1.61e- 1
## 1 4	sexmale	0.462	0.0389	11.9	5.02e- 32

Mean log(income) for a female (baseline) is:

$$\log(\text{income}) = 8.25 + 0.15 * \text{education} + 0 * \text{height}$$

Mean log(income) for a male (baseline + adjustment) is:

$$\log(\text{income}) = 8.25 + 0.15 * \text{education} + 0 * \text{height} + 0.46$$



To change the levels, refactor.

```
sexes <- factor(sexes, levels = c("male", "female", "other"))
```

```
sexes
```

```
## male    female male
```

```
Levels: female male other
```

```
unclass(sexes)
```

```
## 2 1 2
```

```
## attr(,"levels")
```

```
## "female" "male"    "other"
```



NEW LEVEL ORDER

To change the levels, refactor.

```
sexes <- factor(sexes, levels = c("male", "female", "other"))

wages <-
  wages %>%
  mutate(sex = factor(sex, levels = c("male", "female")))
```

##	term	estimate	std.error	statistic	p.value
## 1	(Intercept)	8.25	0.335	24.6	4.68e-127
## 2	education	0.148	0.00520	28.5	5.16e-166
## 3	height	0.00673	0.00479	1.40	1.61e- 1
## 4	sexfemale	-0.462	0.0389	-11.9	5.02e- 32

But what does all of this look like?

model visualization



Your Turn 5

Add + **geom_smooth(method = lm)** to the code below.
What happens?

```
wages %>%
```

```
  ggplot(aes(x = height, y = log(income))) +  
  geom_point(alpha = 0.1)
```

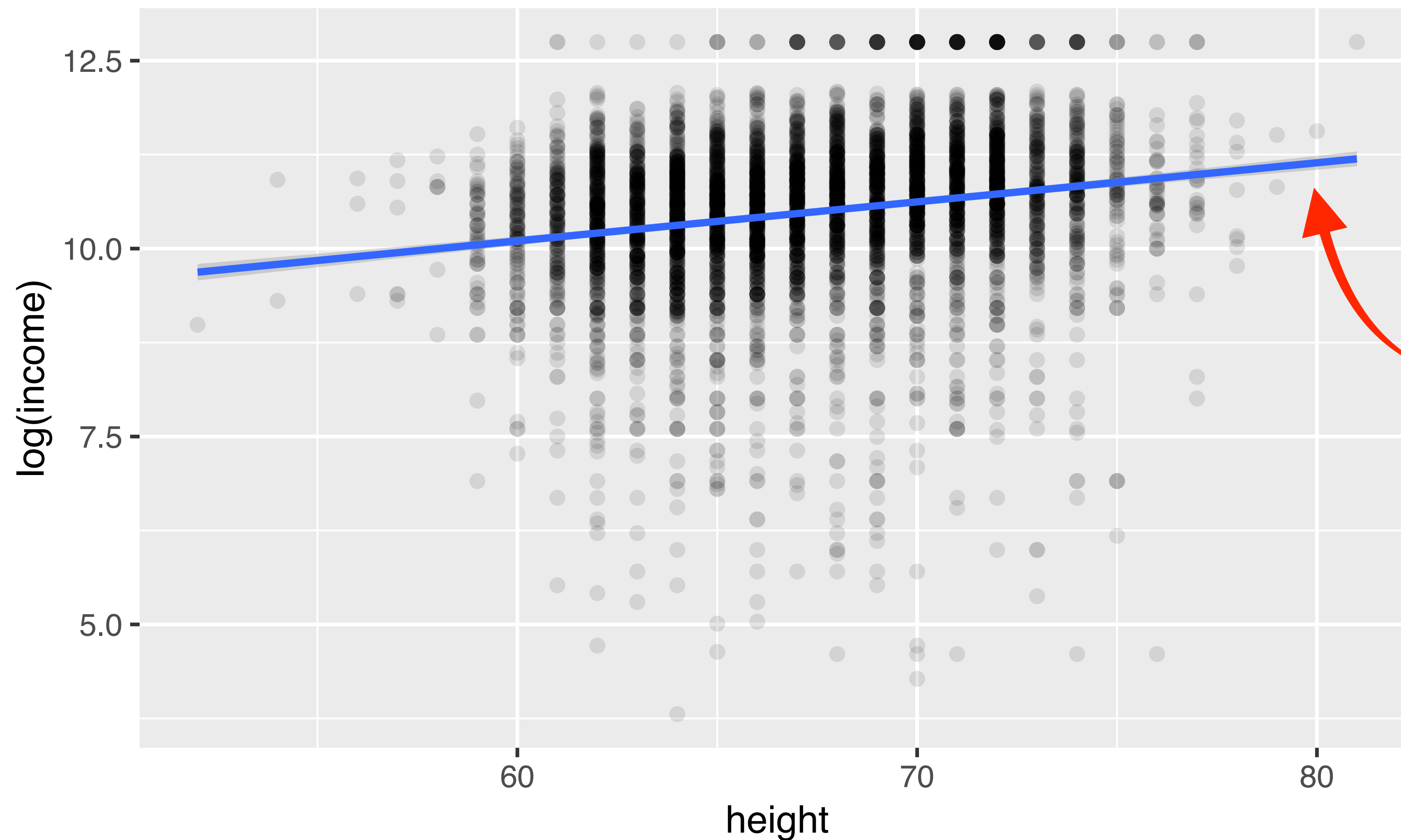
01:00


```
wages %>%
```

```
  ggplot(aes(x = height, y = log(income))) +
```

```
    geom_point(alpha = 0.1) +
```

```
    geom_smooth(method = lm)
```



**FITS $Y \sim X$
(MOD_H)**



geom_smooth()

Adds model line for predicting $y \sim x$ (default).

```
p + geom_smooth(method = lm, se = TRUE, ...)
```

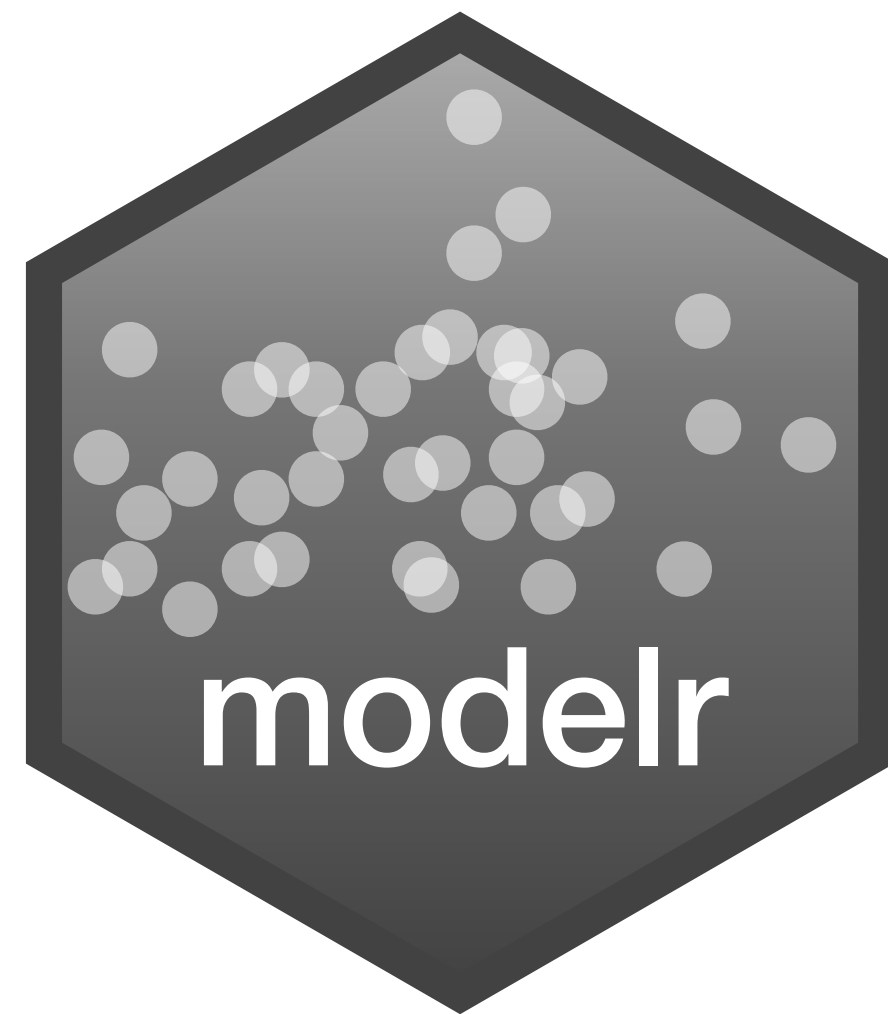
**An R modeling
function to use to
generate the line**

**Include
standard
error bars?**

**Other args to
pass to modeling
function**

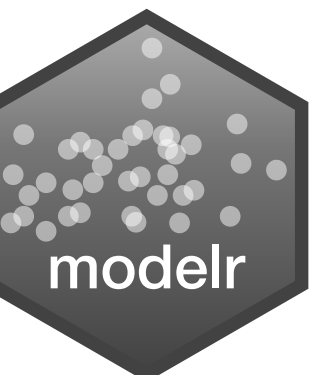
**What about complex
models, or residuals?**

modelr



Tidy functions that make it easier to work with models in R

```
# install.packages("tidyverse")  
library(modelr)
```



add_predictions()

Uses the values in a data frame to generate a prediction for each case. Overlaps with augment()*

```
add_predictions(data, model, var = "pred")
```

Uses this model

To add predictions
to these cases

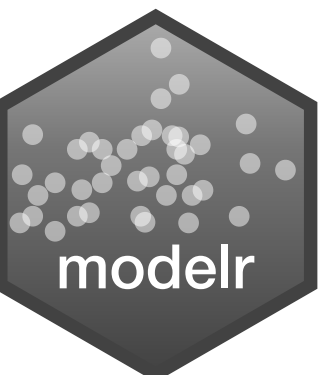
Gives new
column this
name

```
wages %>% add_predictions(mod_h)
```

	height <dbl>	weight <int>	age <int>	marital <fctr>	sex <fctr>	education <int>	afqt <dbl>	pred <dbl>
	60	155	53	married	female	13	6.841	10.102158
	70	156	51	married	female	10	49.444	10.621947
	65	195	52	married	male	16	99.393	10.362053
	63	197	54	married	female	14	44.022	10.258095
	66	190	49	married	male	14	59.683	10.414032
	68	200	49	divorced	female	18	98.798	10.517989
	64	160	54	divorced	female	12	50.283	10.310074
	69	162	55	divorced	male	12	89.669	10.569968
	69	194	54	divorced	male	13	95.977	10.569968
	64	145	53	married	female	16	67.021	10.310074

1–10 of 5,266 rows | 2–9 of 9 columns

Previous **1** 2 3 4 5 6 ... 100 Next



add_residuals()

Uses the values in a data frame to generate a residual for each case. Overlaps with `augment()`*

```
add_residuals(data, model, var = "resid")
```

Uses this model

**To add residuals
to these cases**

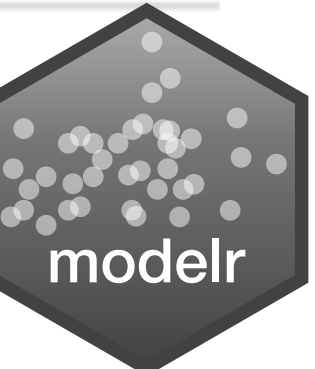
**Gives new
column this
name**


```
wages %>% add_residuals(mod_h)
```

income <int>	height <dbl>	weight <int>	age <int>	marital <fctr>	sex <fctr>	education <int>	afqt <dbl>	resid <dbl>
19000	60	155	53	married	female	13	6.841	-0.2499641042
35000	70	156	51	married	female	10	49.444	-0.1588437767
105000	65	195	52	married	male	16	99.393	1.1996628894
40000	63	197	54	married	female	14	44.022	0.3385397443
75000	66	190	49	married	male	14	59.683	0.8112117773
102000	68	200	49	divorced	female	18	98.798	1.0147387260
70000	64	160	54	divorced	female	12	50.283	0.8461766568
60000	69	162	55	divorced	male	12	89.669	0.4321315995
150000	69	194	54	divorced	male	13	95.977	1.3484223314
115000	64	145	53	married	female	16	67.021	1.3426135431

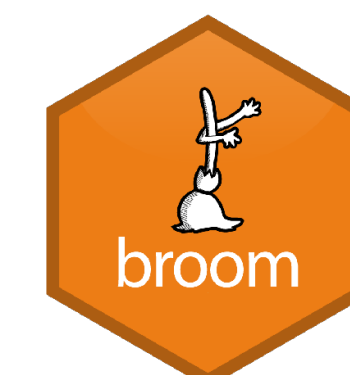
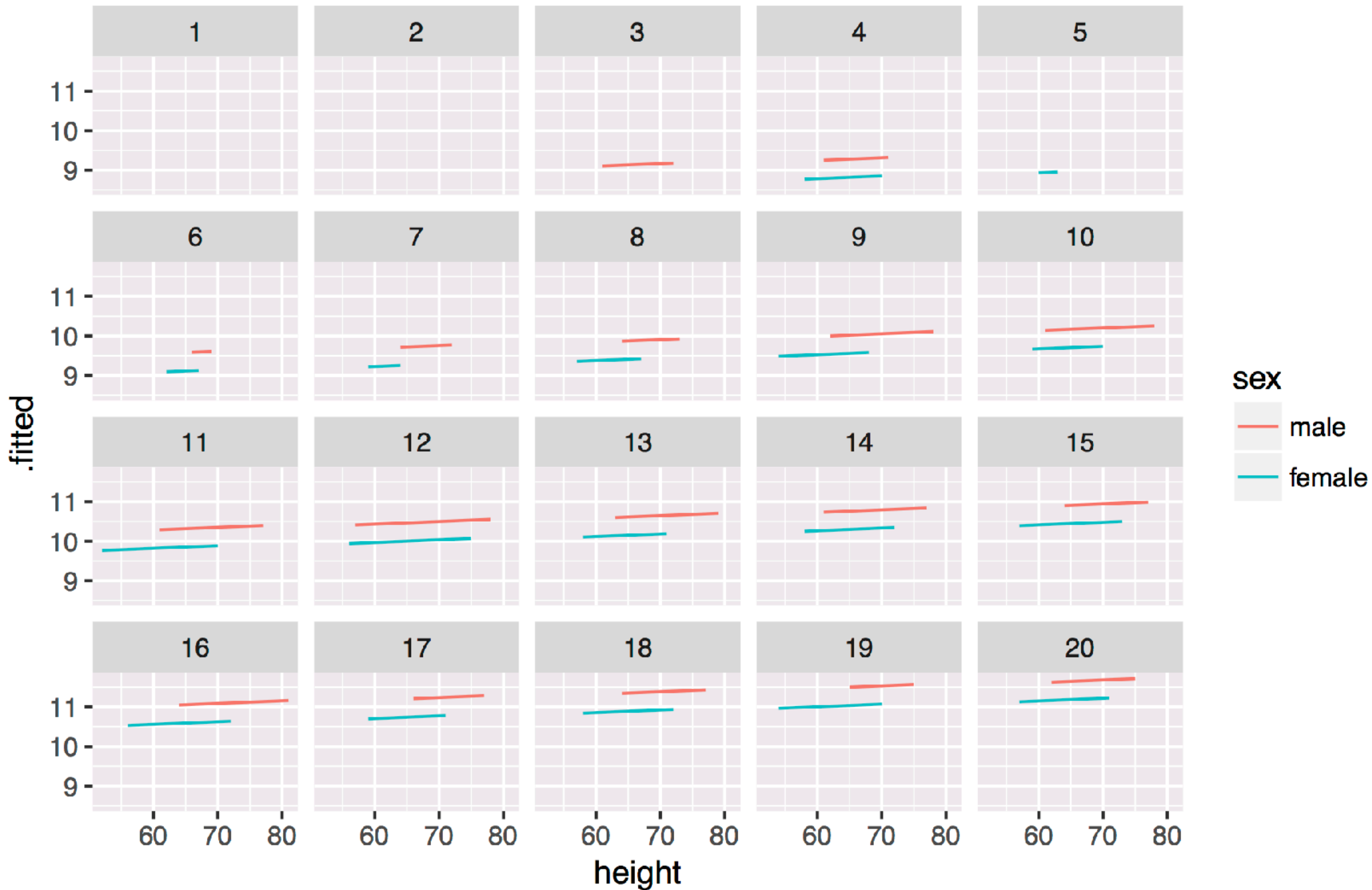
1–10 of 5,266 rows

Previous 1 2 3 4 5 6 ... 100

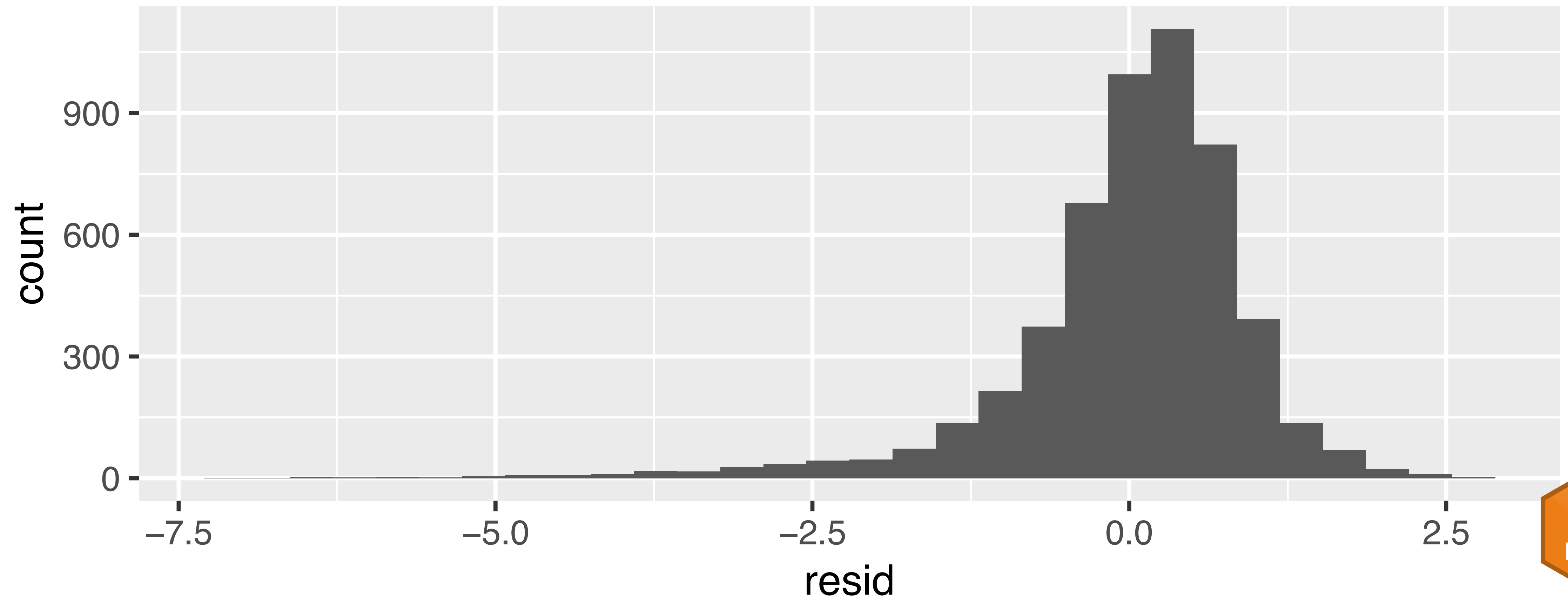


Help Me

Help me add the predictions of **mod_ehs** and then visualize the results



```
wages %>%  
  add_residuals(mod_ehs) %>%  
  ggplot() +  
    geom_histogram(aes(resid))
```



spread_residuals()

Adds residuals for multiple models, each in their own column.

```
spread_residuals(data, ...)
```

Adds residuals
from each of
these models

To the cases in this
data frame

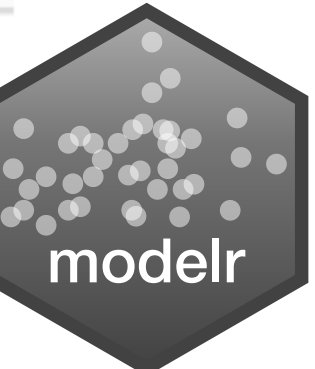

```
wages %>%
```

```
spread_residuals(mod_h, mod_eh, mod_ehs)
```

income <int>	height <dbl>	sex <fctr>	education <int>	mod_h <dbl>	mod_eh <dbl>	mod_ehs <dbl>
19000	60	female	13	-0.2499641042	-0.197967581	-0.2638576582
35000	70	female	10	-0.1588437767	0.345993609	0.7237344726
105000	65	male	16	1.1996628894	0.853872025	0.5063344524
40000	63	female	14	0.3385397443	0.262834114	0.3124199119
75000	66	male	14	0.8112117773	0.746516842	0.4591017275
102000	68	female	18	1.0147387260	0.402532860	0.6229479494
70000	64	female	12	0.8461766568	1.051566955	1.1612752115
60000	69	male	12	0.4321315995	0.655873056	0.5117444599
150000	69	male	13	1.3484223314	1.433450940	1.2800521289
115000	64	female	16	1.3426135431	0.993152447	1.0657798463

1–10 of 5,266 rows

Previous 1 2 3 4 5 6 ... 100 Next



gather_residuals()

Adds residuals for multiple models as a pair of key:value columns (model:resid)

```
gather_residuals(data, ...)
```

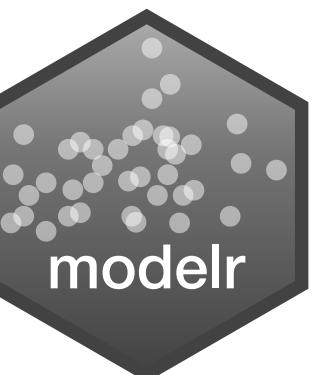
Adds residuals
from each of
these models

To the cases in this
data frame
(duplicating rows as
necessary)


```
wages %>%
```

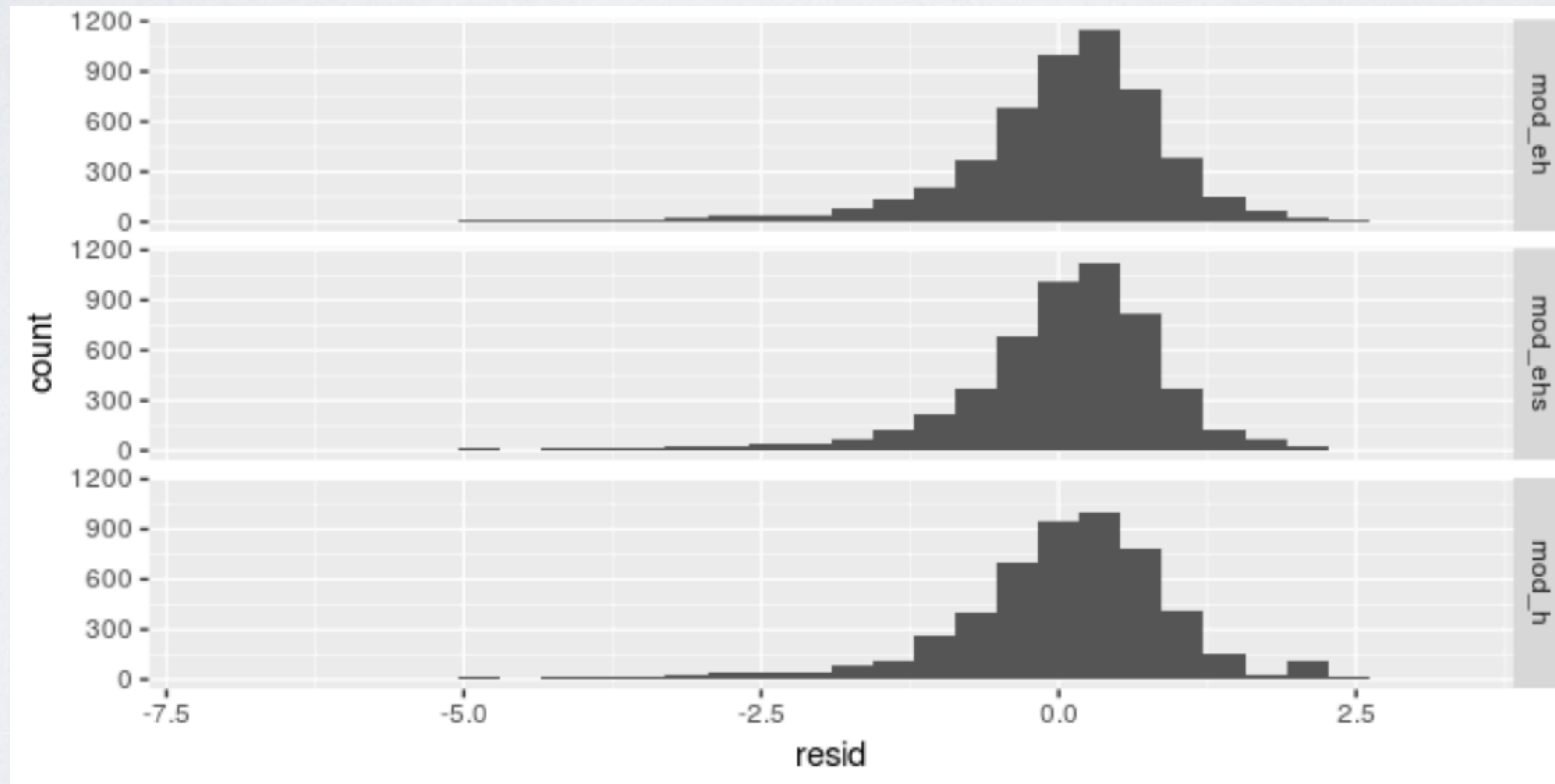
```
gather_residuals(mod_h, mod_eh, mod_ehs)
```

income <int>	height <dbl>	sex <fctr>	education <int>	model <chr>	resid <dbl>
19000	60	female	13	mod_h	-0.2499641042
19000	60	female	13	mod_eh	-0.1979675815
19000	60	female	13	mod_ehs	-0.2638576582
115000	64	female	16	mod_h	1.3426135431
115000	64	female	16	mod_eh	0.9931524472
115000	64	female	16	mod_ehs	1.0657798463
41000	65	female	16	mod_h	0.2592746059
41000	65	female	16	mod_eh	-0.0865162582
41000	65	female	16	mod_ehs	0.0276931707
19000	63	female	12	mod h	-0.4059007306



Your Turn 6

Complete the code skeleton: use `gather_residuals` to make the plot below.



05:00

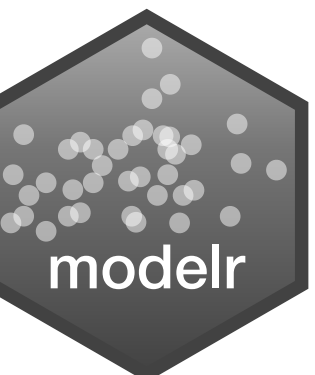
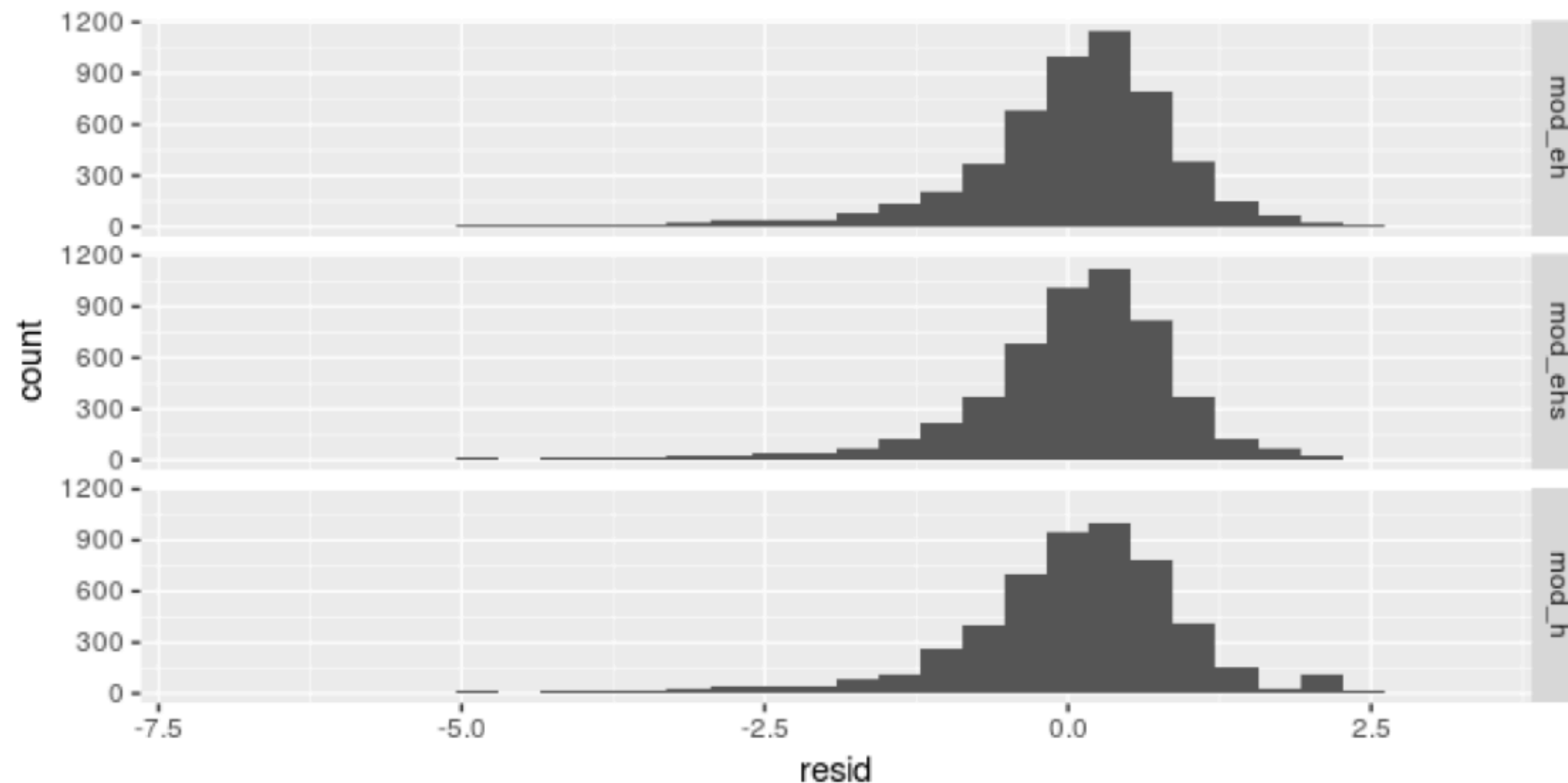
```
wages %>%
```

```
gather_residuals(mod_h, mod_eh, mod_ehs) %>%
```

```
ggplot() +
```

```
geom_histogram(aes(resid)) +
```

```
facet_grid(model ~ .)
```

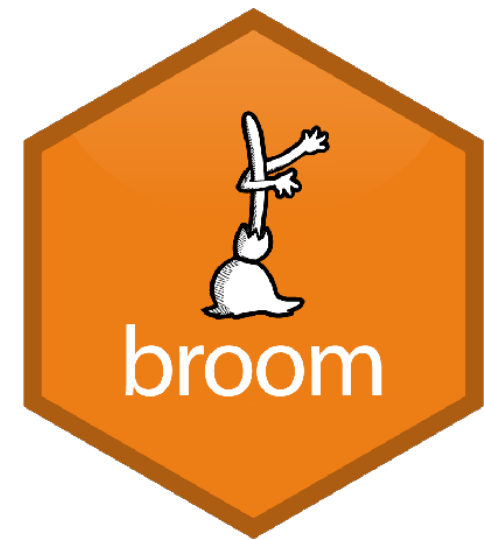


Predications

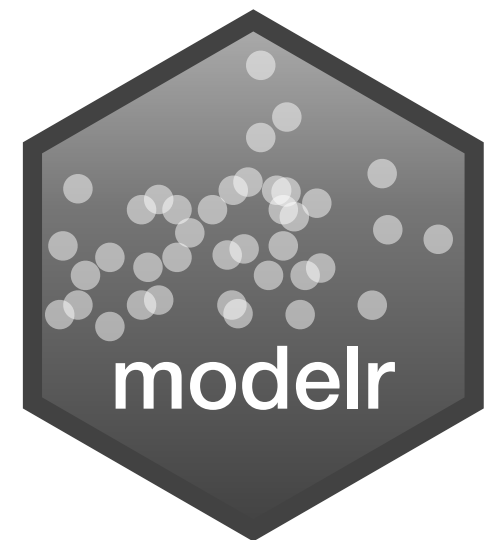
Modelr provides the equivalent functions for predictions

<code>add_predictions()</code>	↔	<code>add_residuals()</code>
<code>spread_predictions()</code>	↔	<code>spread_residuals()</code>
<code>gather_predictions()</code>	↔	<code>gather_residuals()</code>

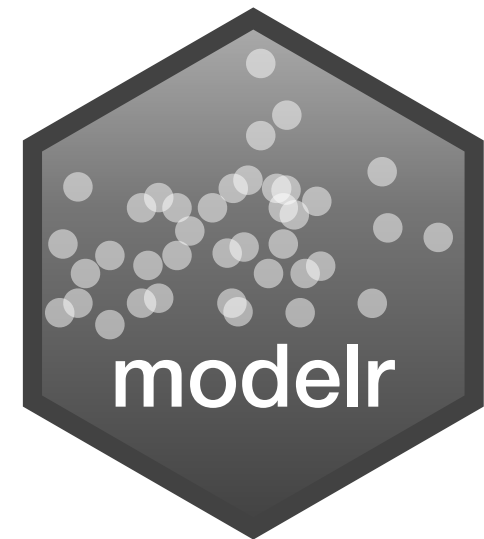
Recap



Use `glance()`, `tidy()`, and `augment()` to return model values in a data frame.



Use `add_predictions()` or `gather_predictions()` or `spread_predictions()` to visualize predictions.



Use `add_residuals()` or `gather_residuals()` or `spread_residuals()` to visualize residuals.

Modeling with

