Model Data

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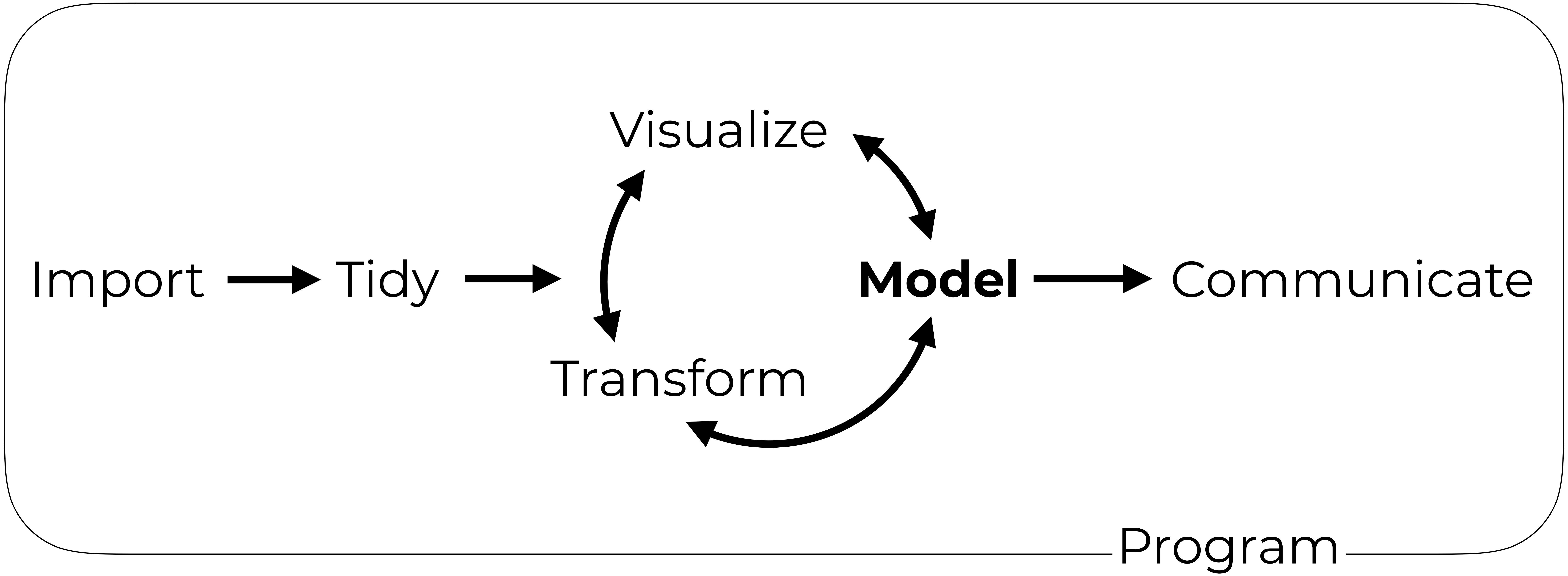
ATLAS
Accessible Teaching, Learning, and Assessment Systems

Your Turn 0

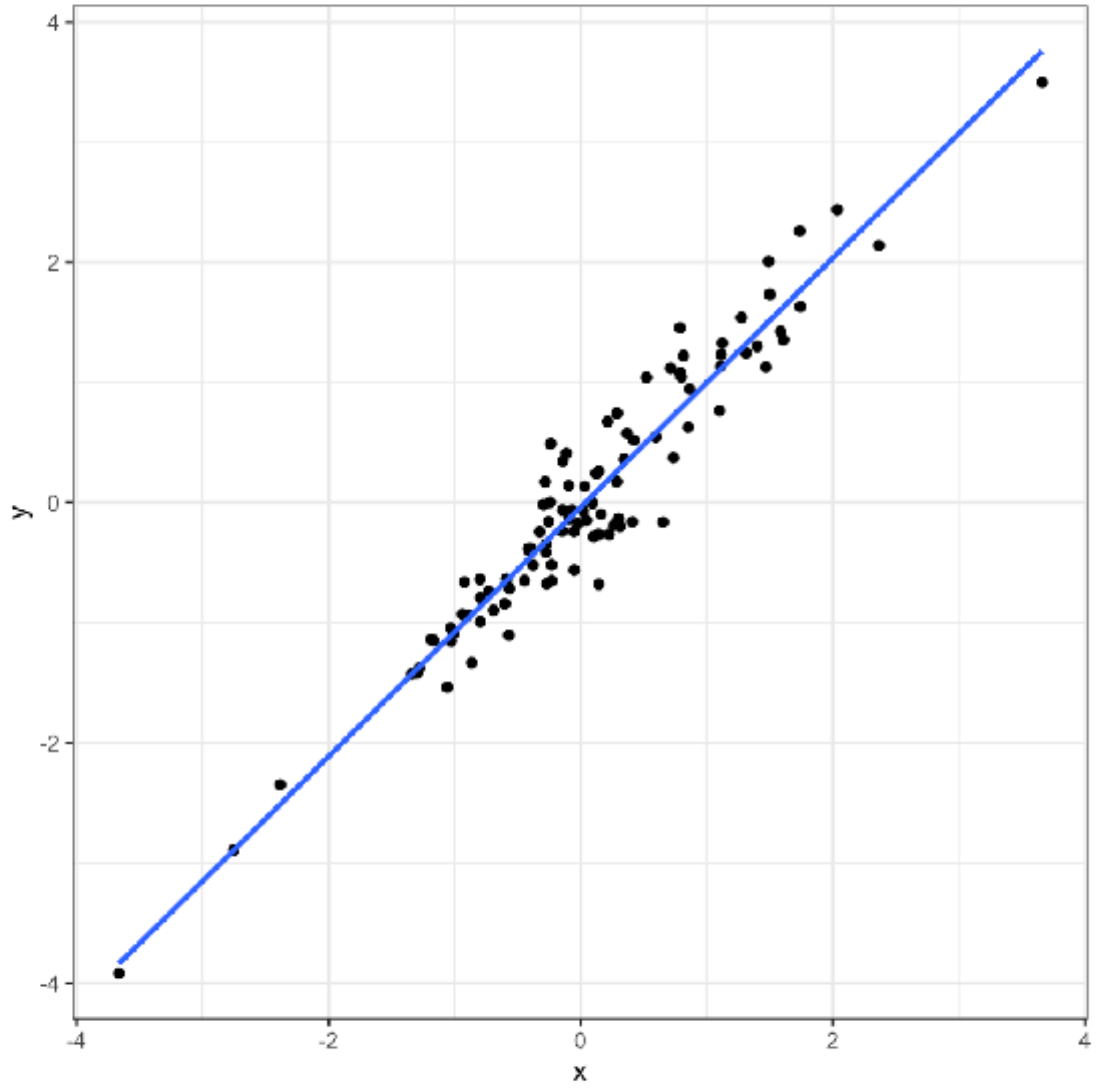
- Open **07-Model.Rmd**
- Run the setup chunk

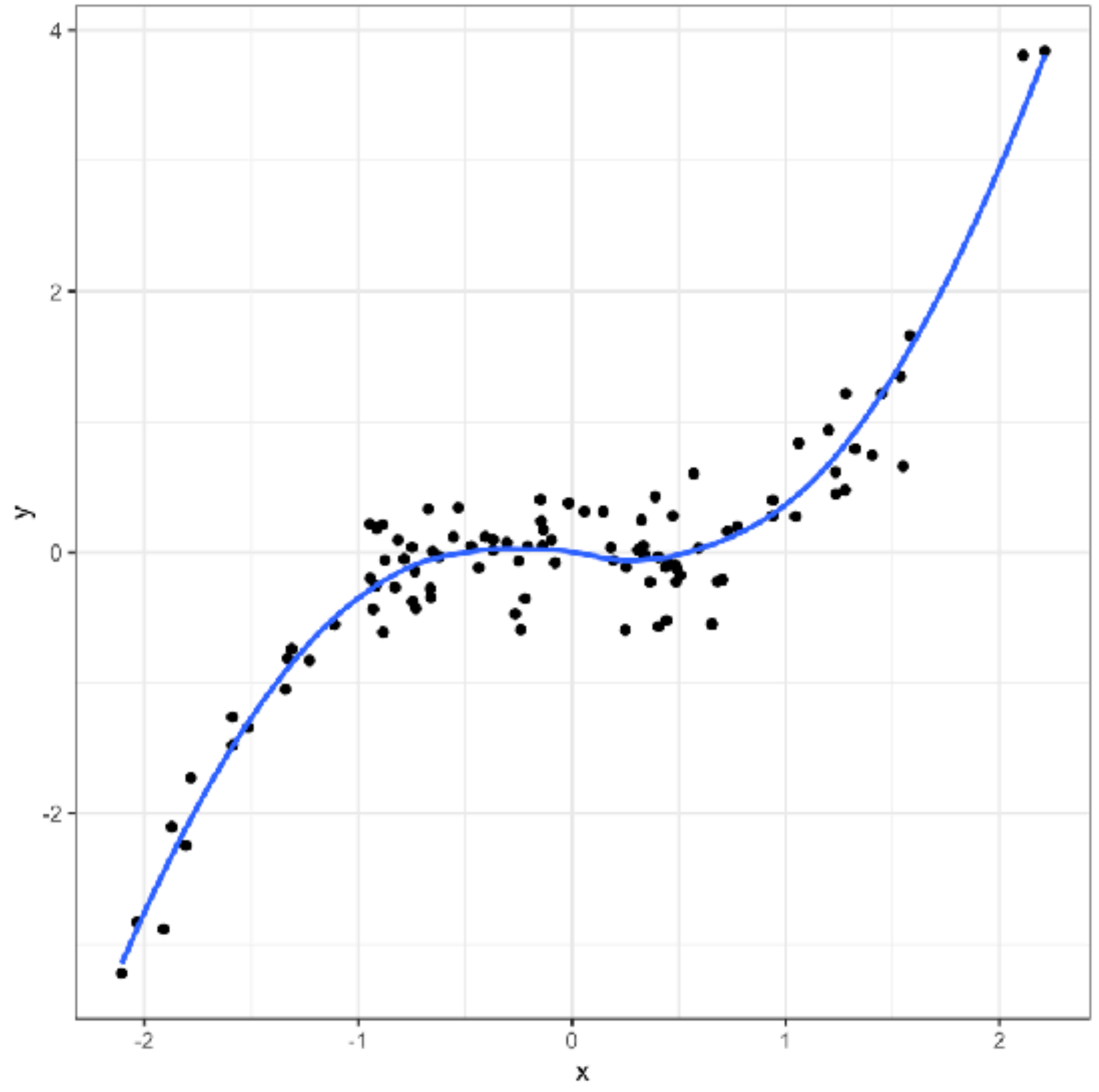

Visualize
Import
Tidy
Model
Communicate
Transform
Program

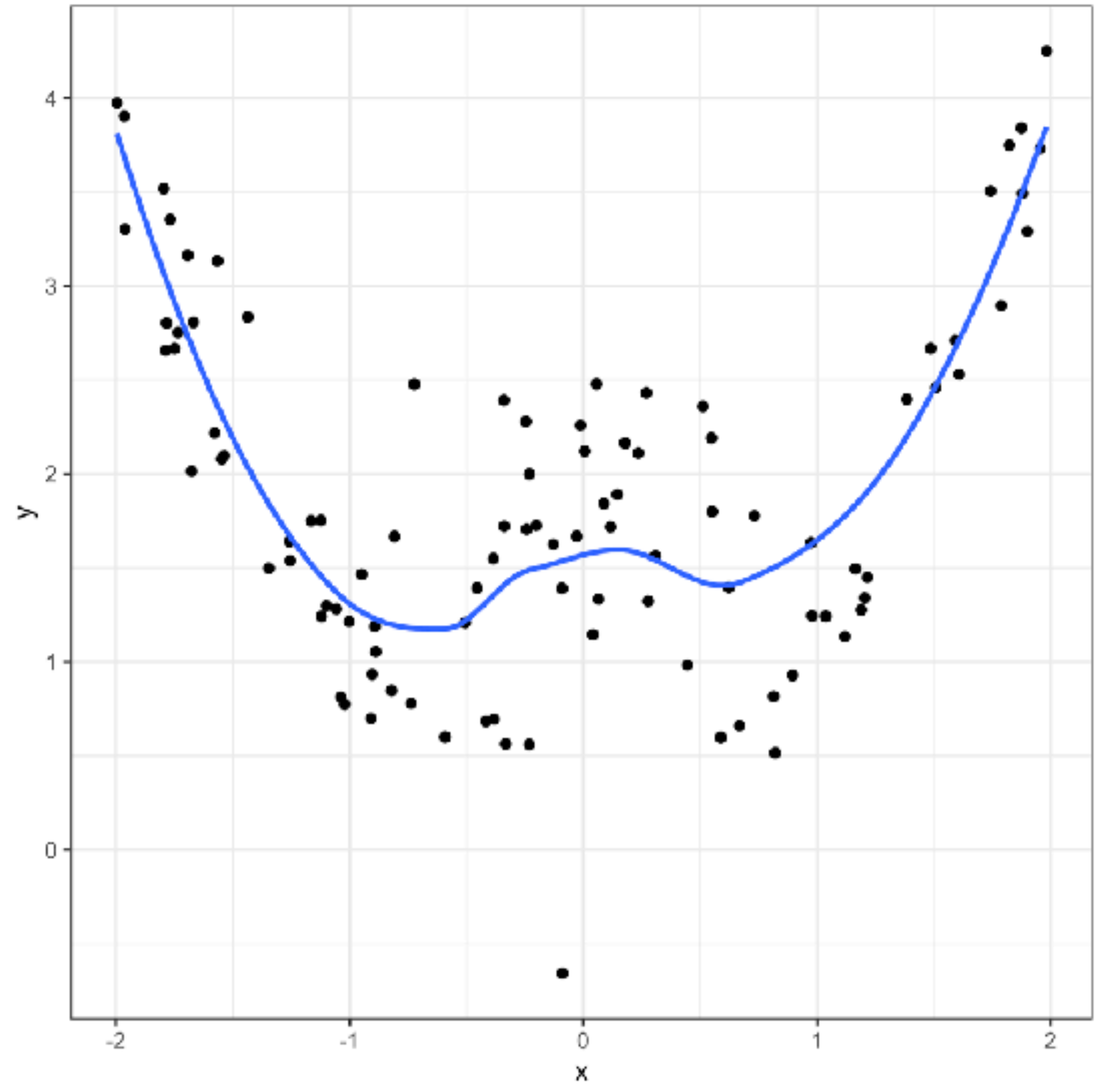
The basics

Models

A low dimensional description of a higher dimensional data set.







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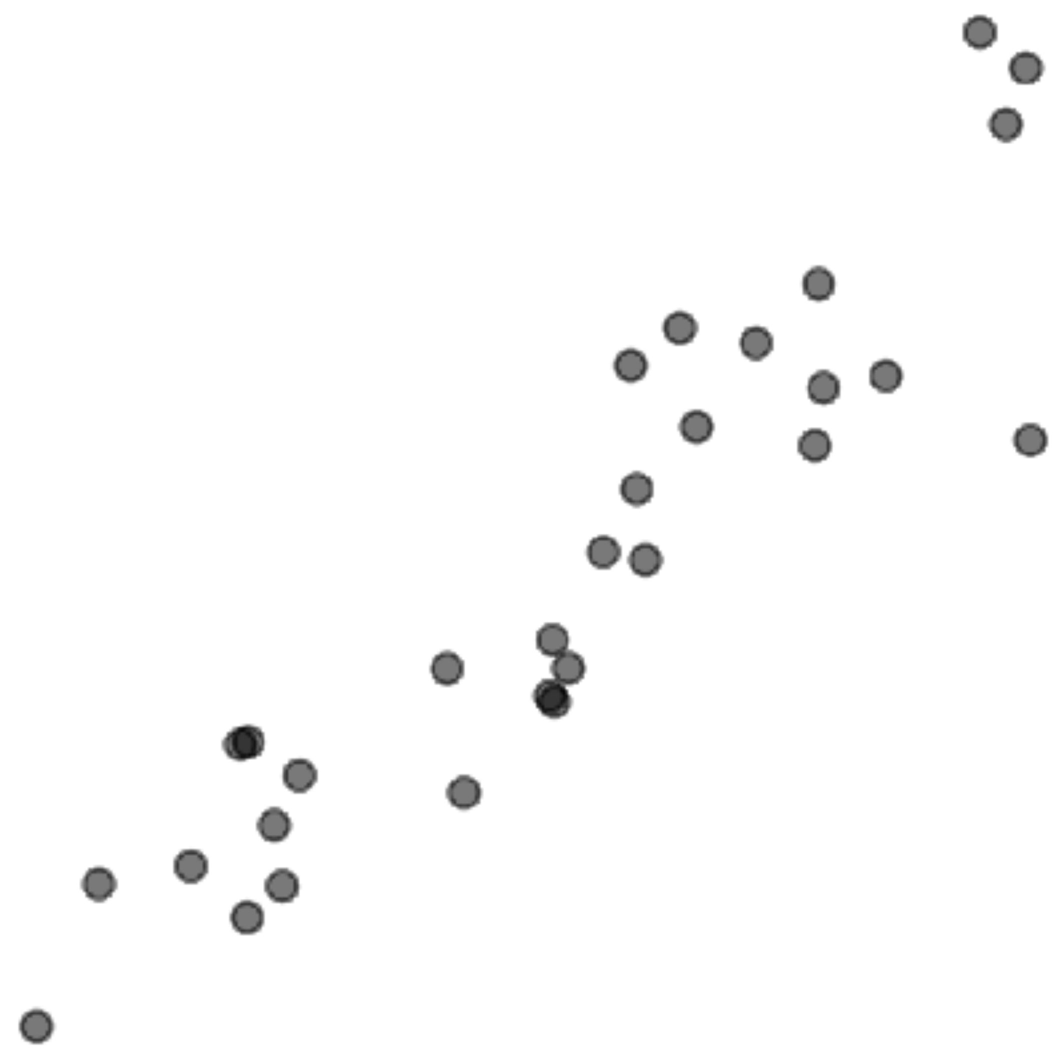
Models



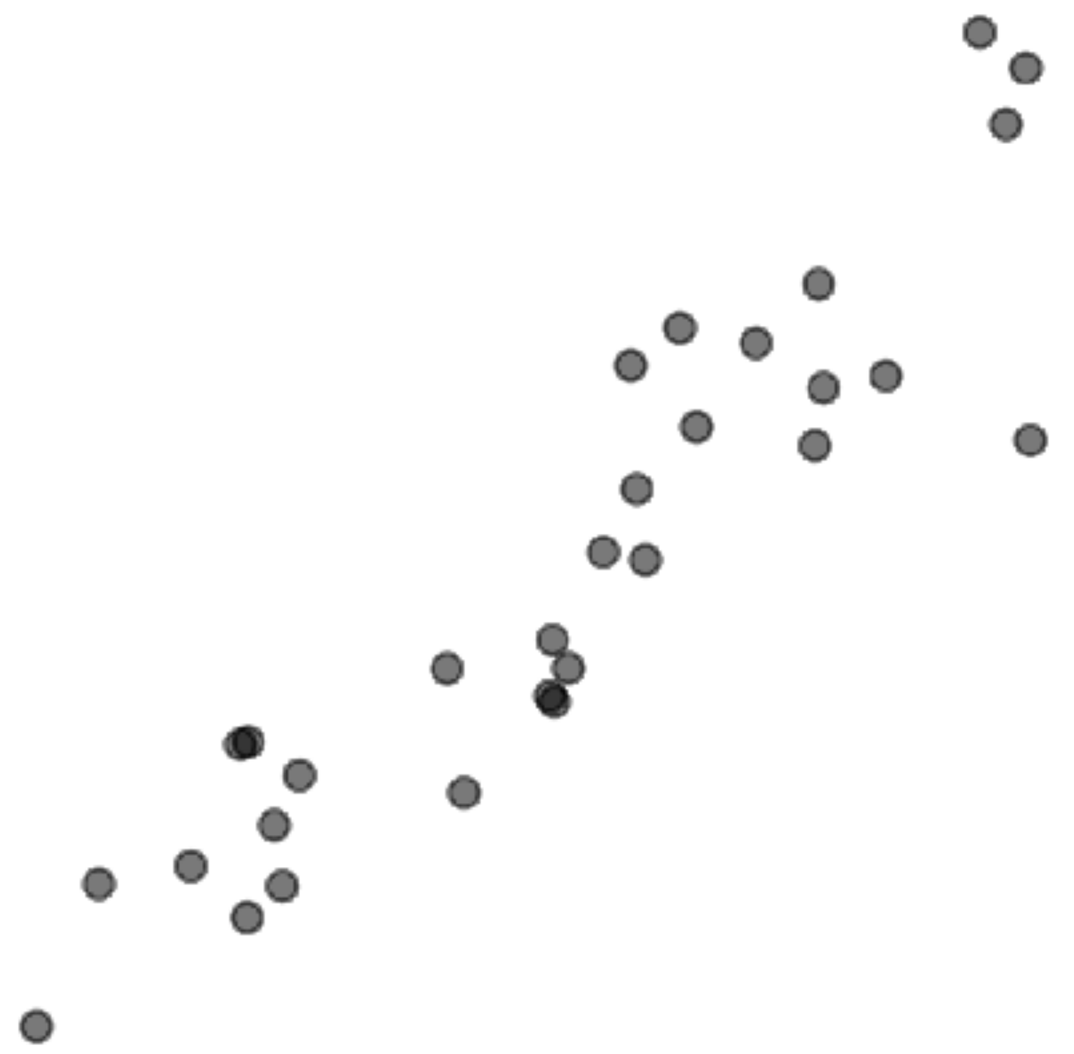
Algorithm

Data

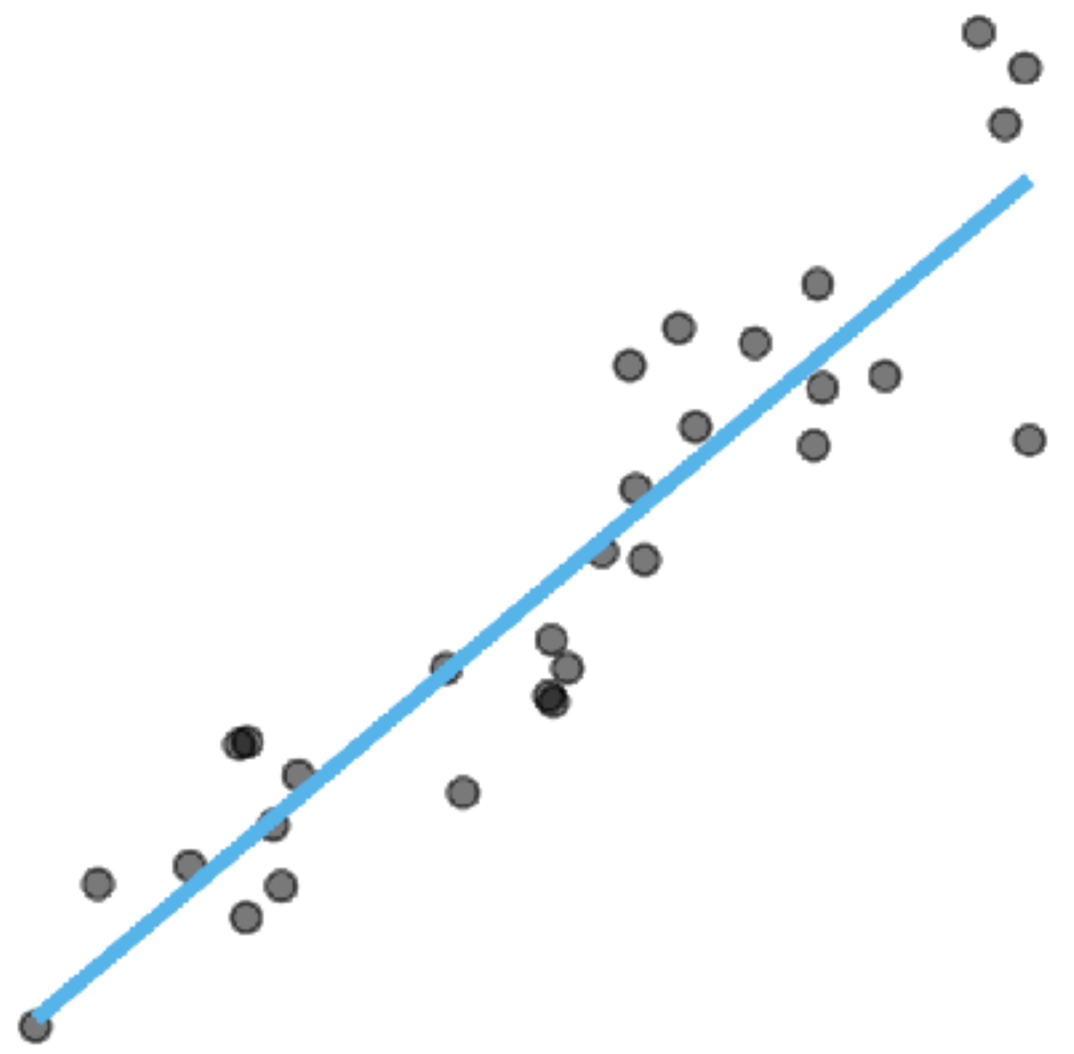
Model Function

Models

What is the **model function**?



Algorithm



Data

Model Function

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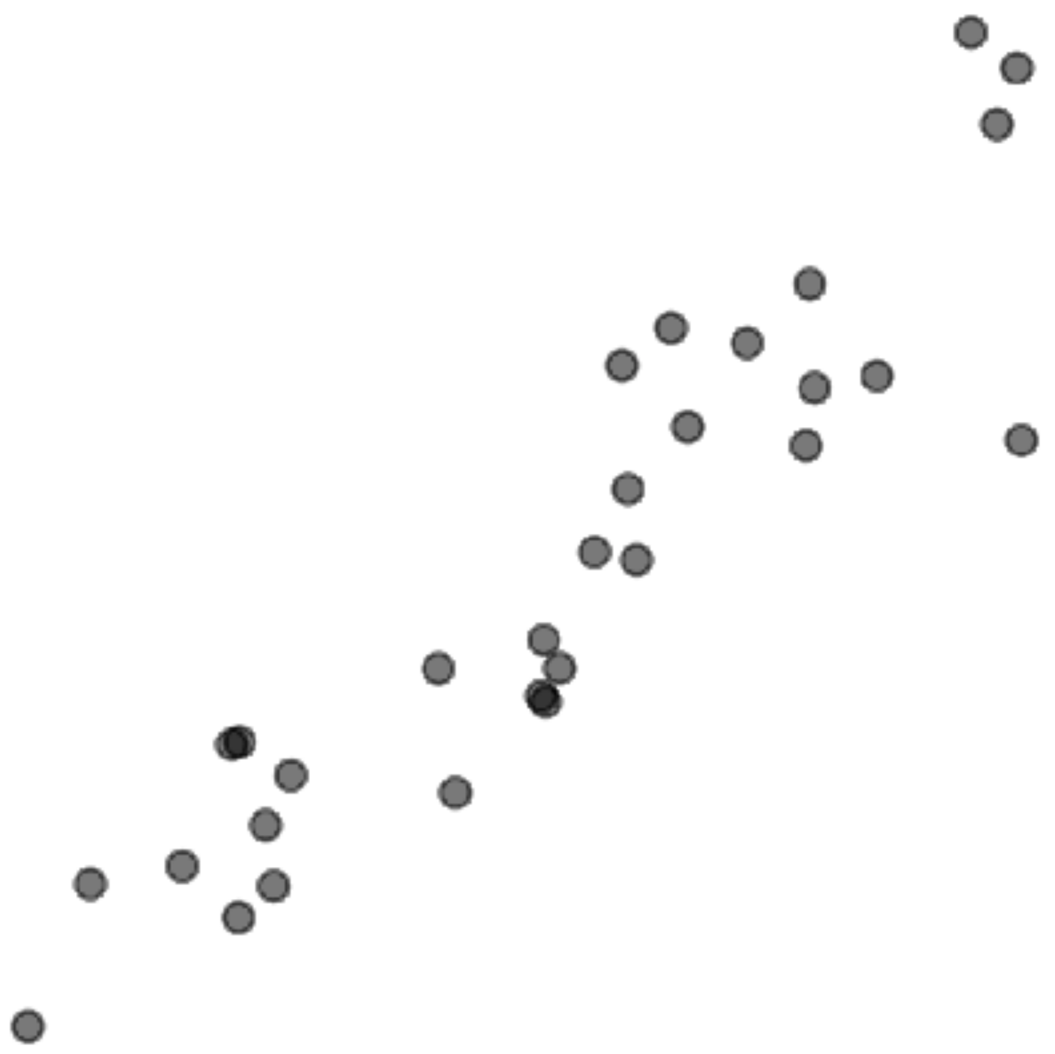
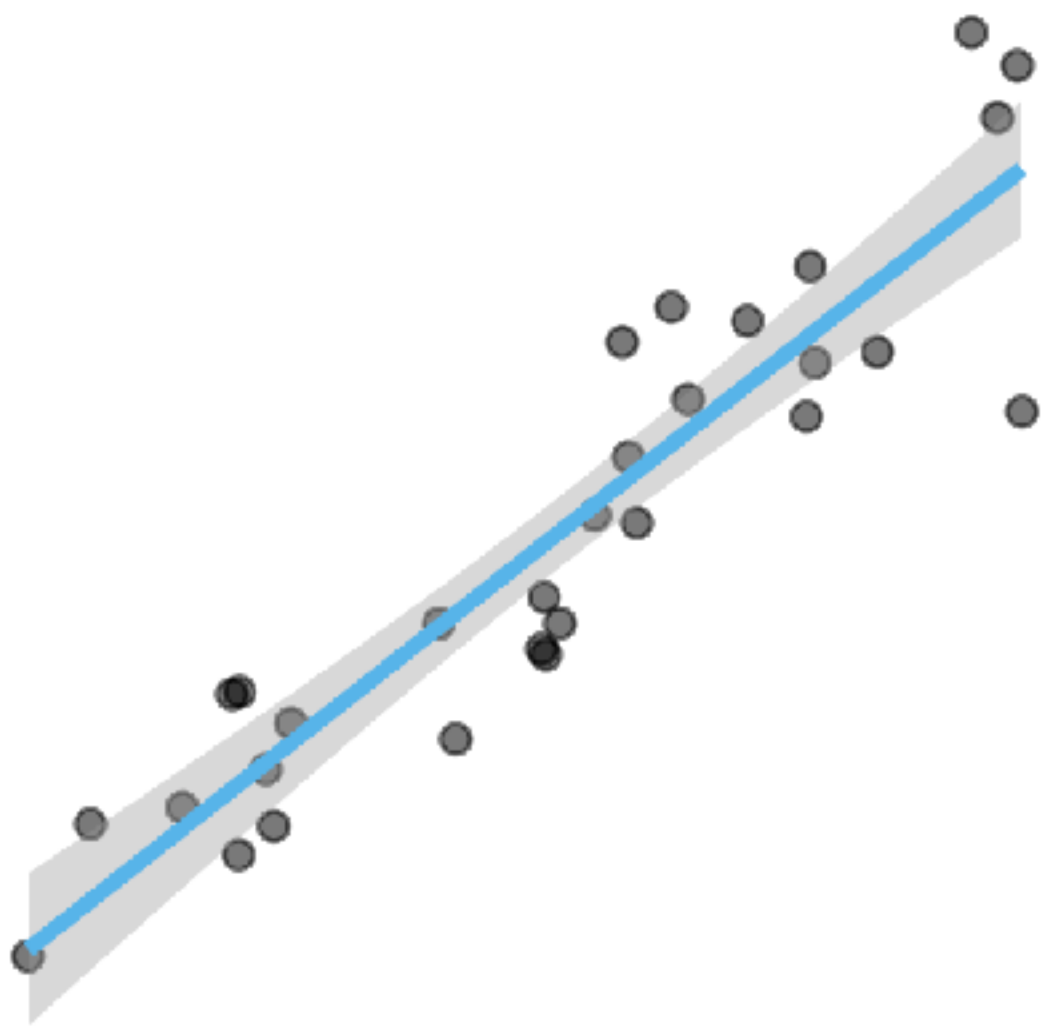
Models

What **uncertainty** is associated with it?



Algorithm

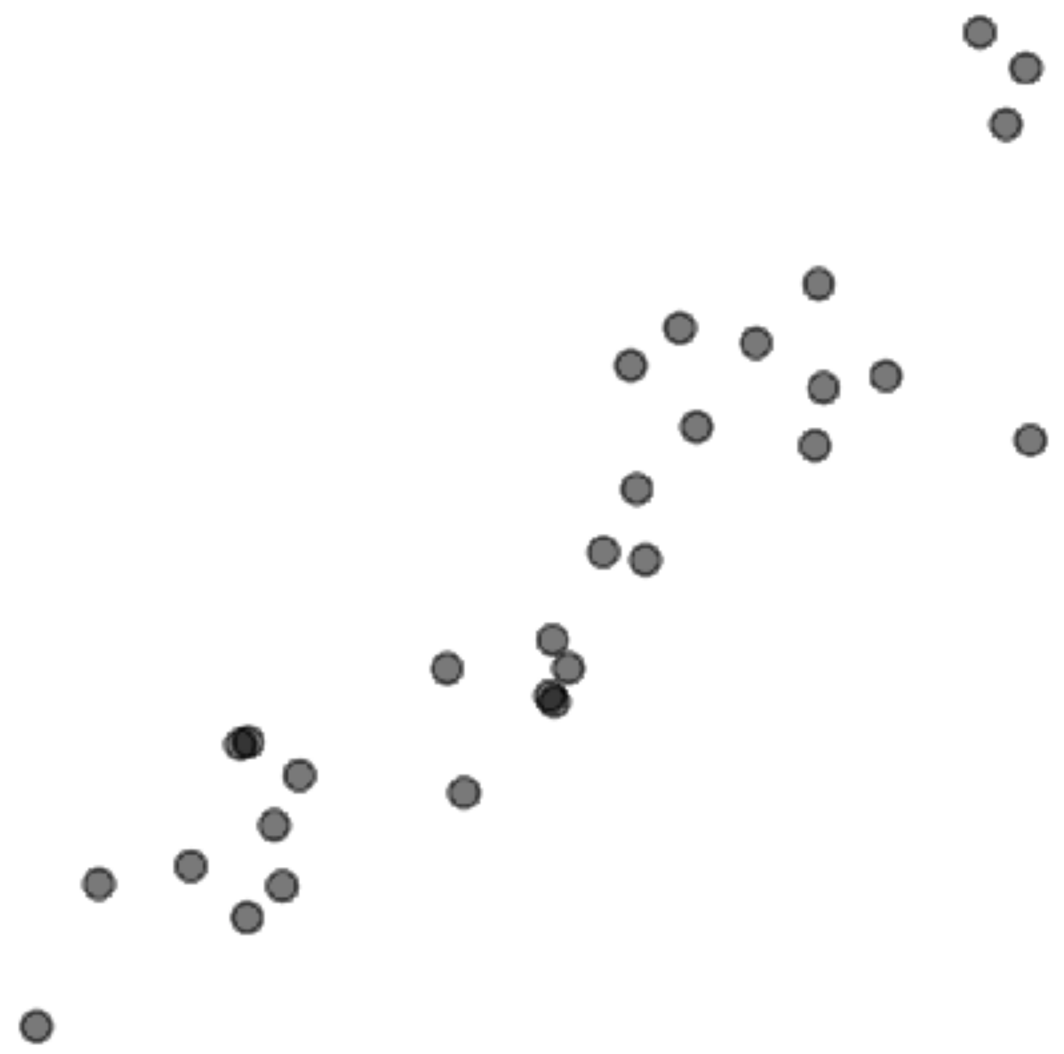


Data

Model Function

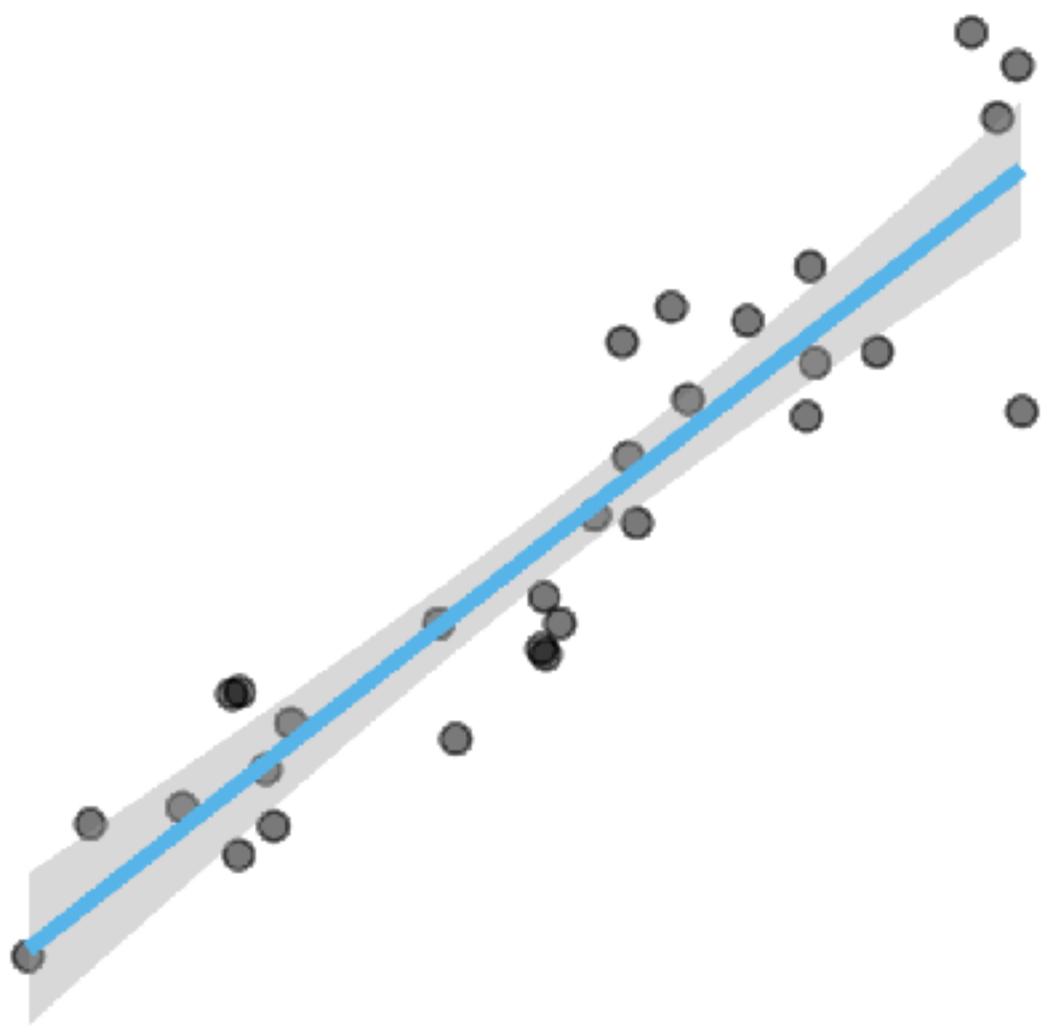
Models

How "good" is the model?



Data

Algorithm



Model Function

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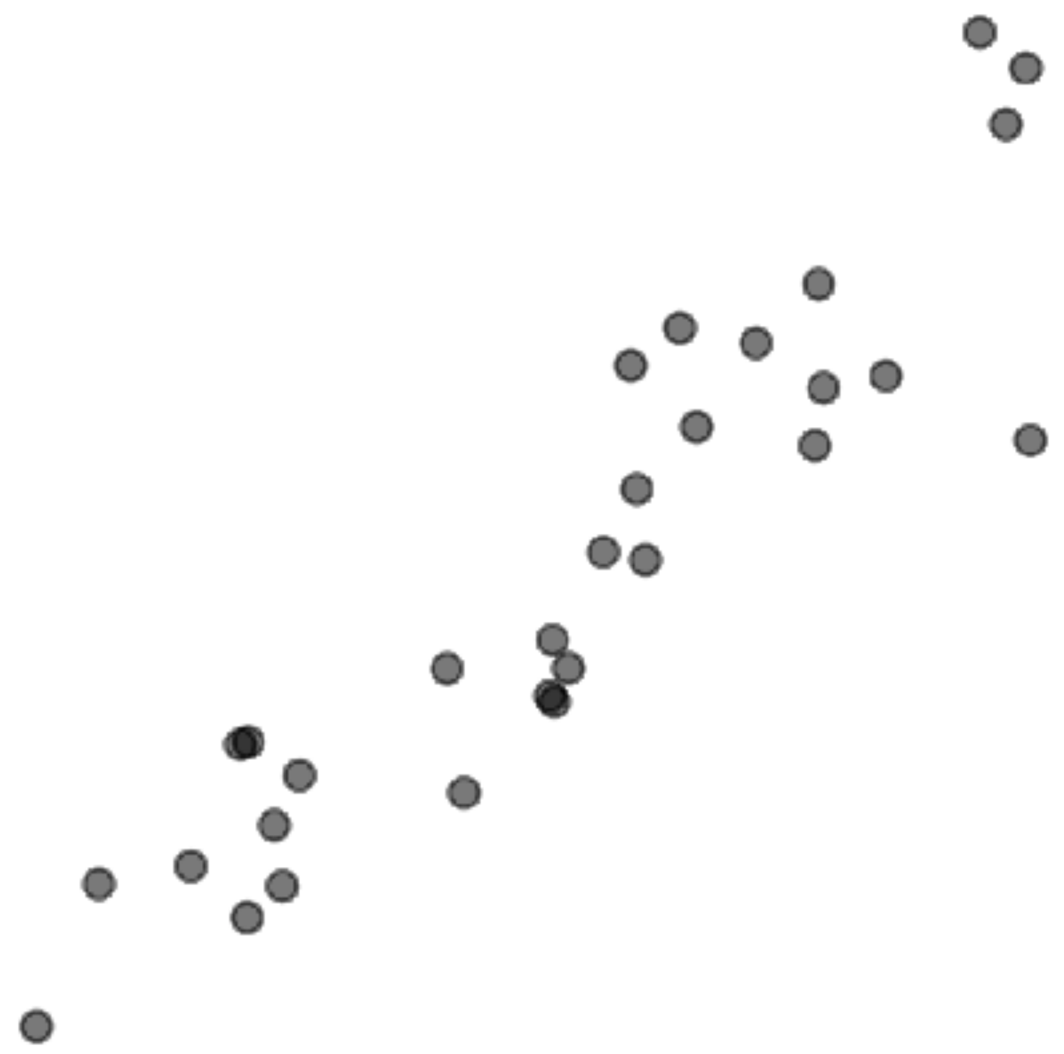
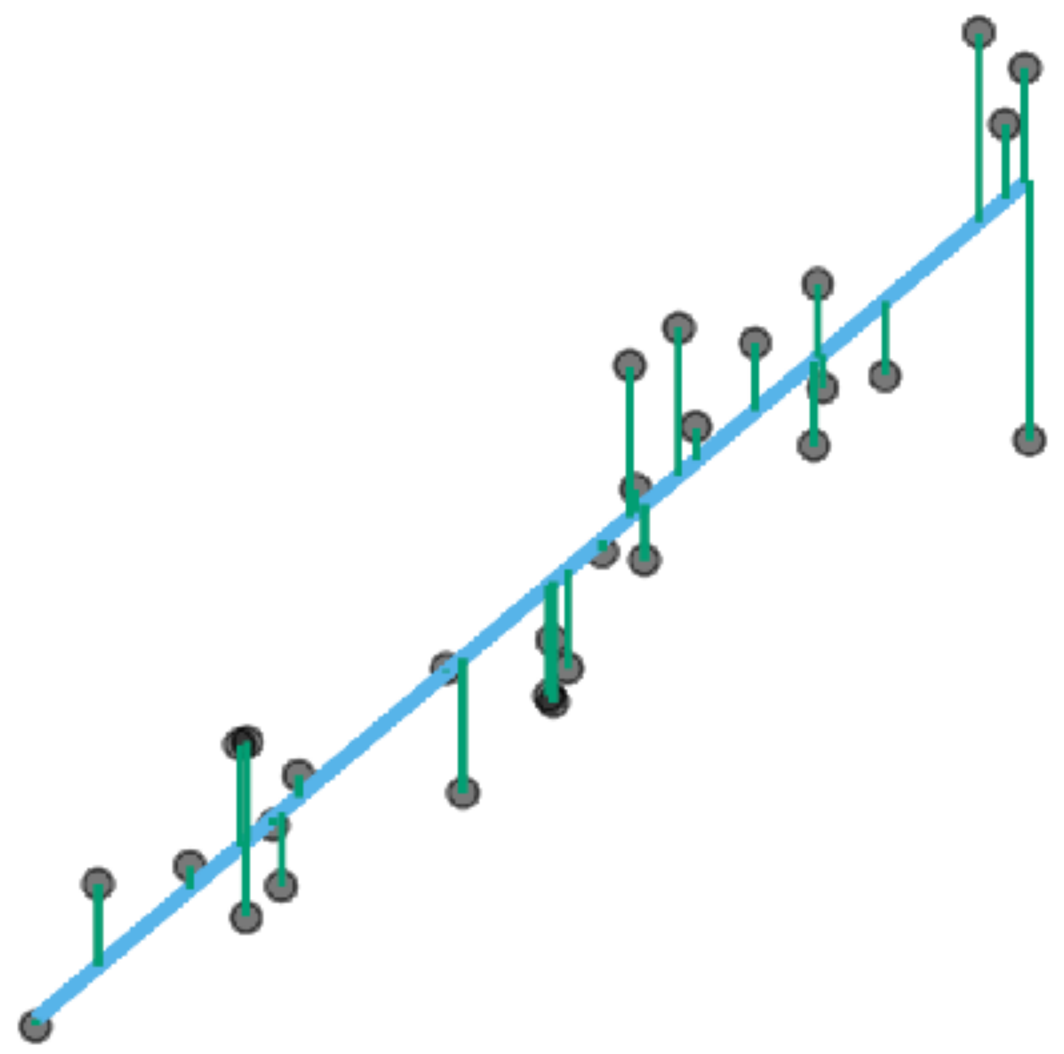
What are the **residuals**?



Algorithm



Data

Model Function

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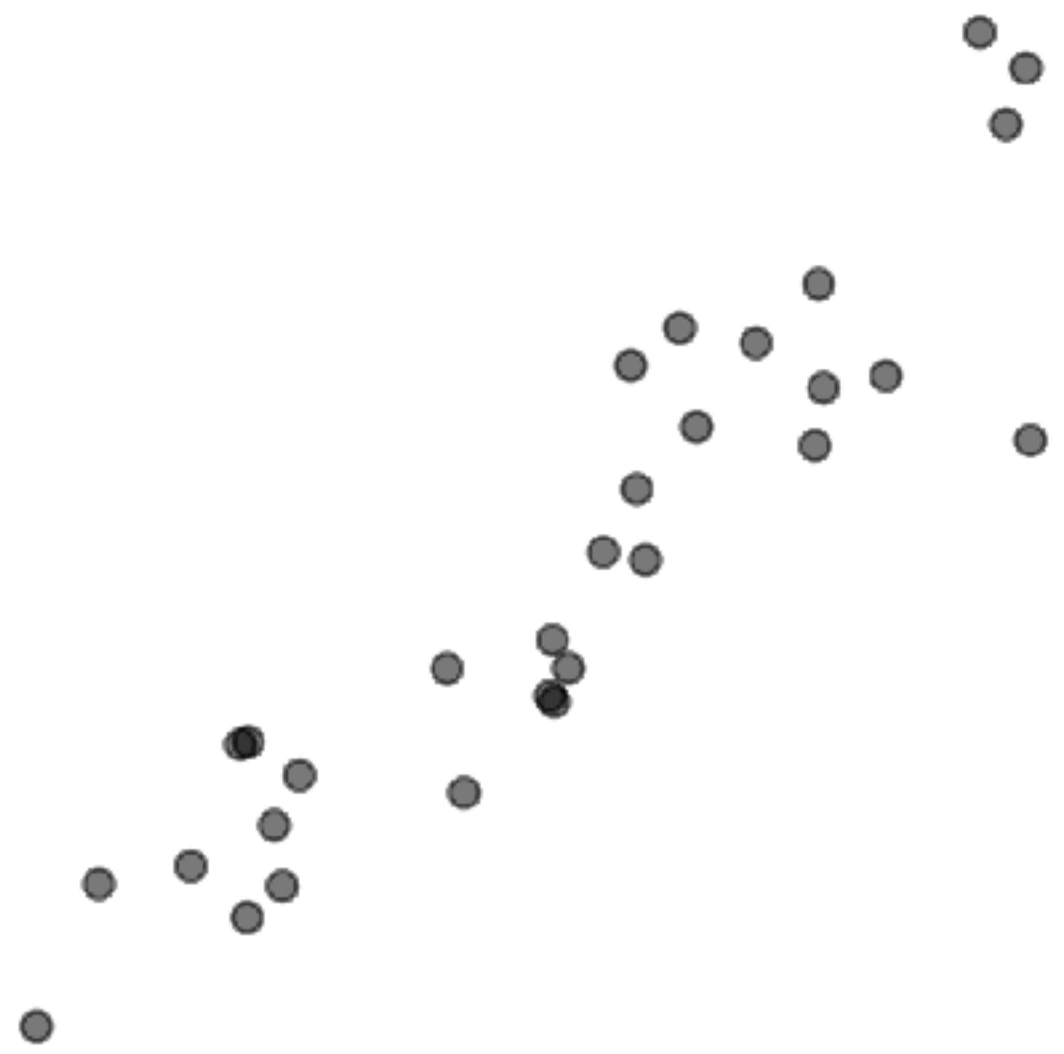
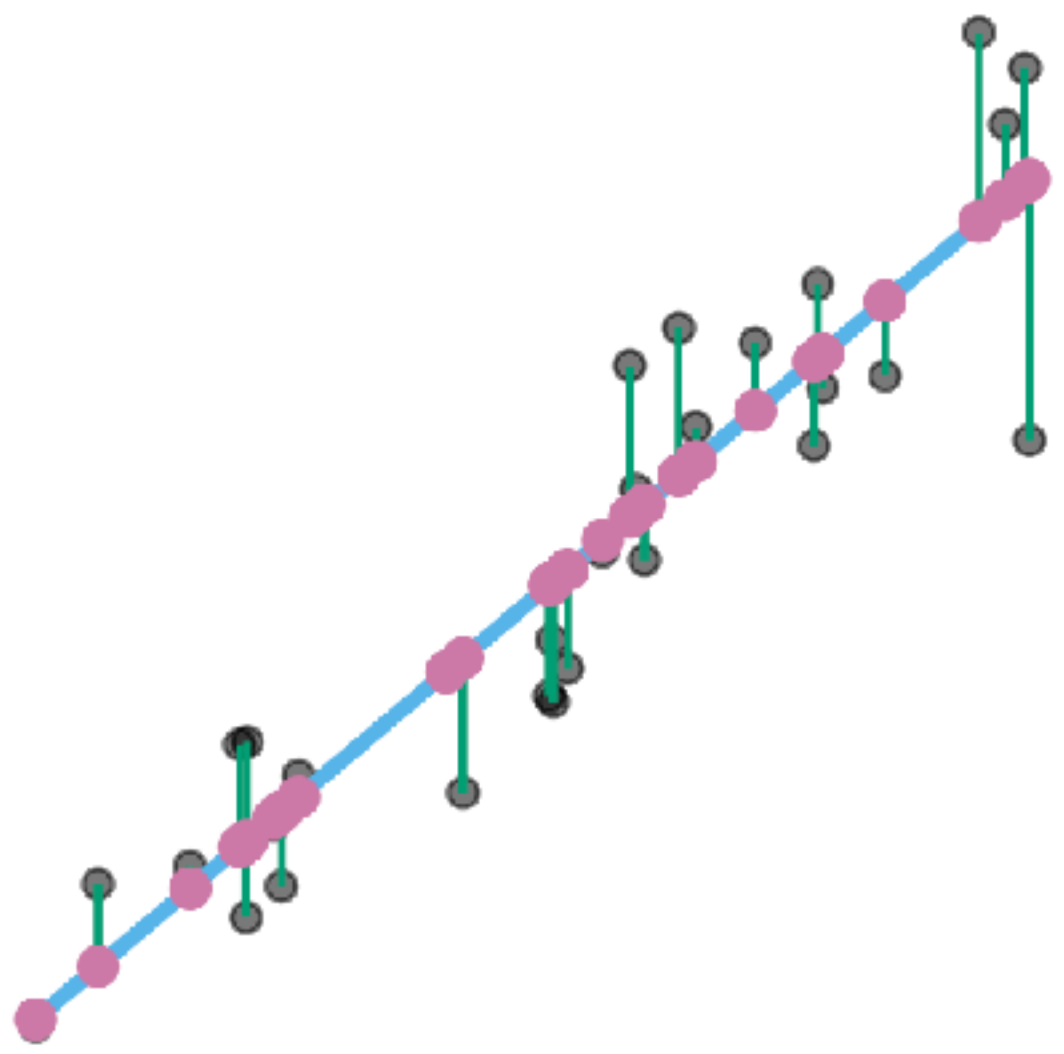
What are the **predictions**?



Data

Algorithm



Model Function

Algorithm

(Popular) **model functions in R**

function	package	fits
`lm()`	stats	linear models
`glm()`	stats	generalized linear models
`lmer()`	lme4	multi-level models
`stan_glm()`	rstanarm	Bayesian regression models
`gam()`	mgcv	generalized additive models
`glmnet()`	glmnet	penalized linear models
`rlm()`	MASS	robust linear models
`rpart()`	rpart	trees
`randomForest()`	randomForest	random forrests
`xgboost()`	xgboost	gradient boosting machines

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(Popular) **model functions in R**

function	package	fits
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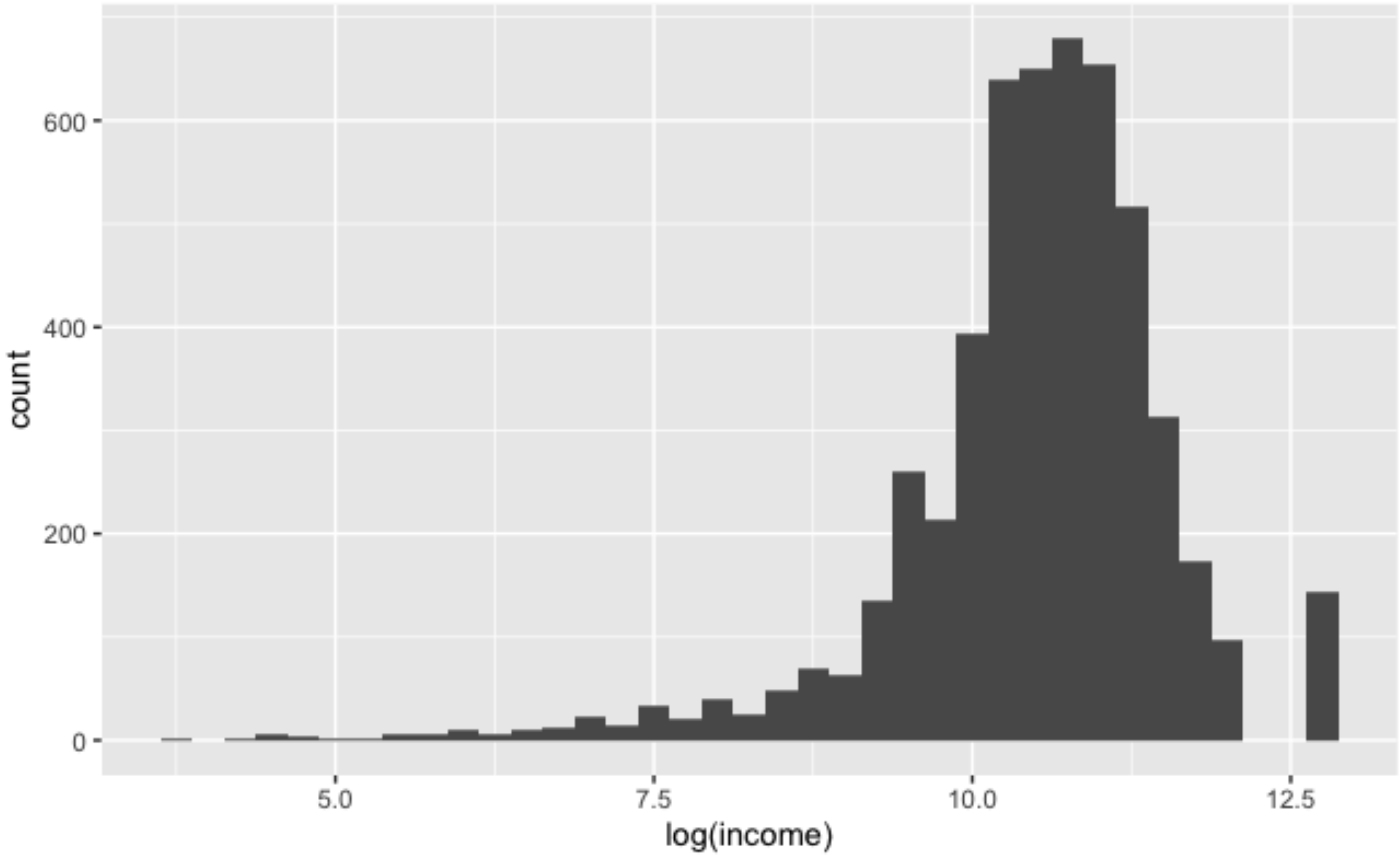
`rlm()`	MASS	robust linear models
`rpart()`	rpart	trees
`randomForest()`	randomForest	random forrests
`xgboost()`	xgboost	gradient boosting machines

```
wages
# A tibble: 5,266 x 8
   income height weight   age marital  sex    education  afqt
    <int>  <dbl>  <int> <int> <fct>    <fct>      <int> <dbl>
 1  19000     60    155    53 married  female        13  6.84
 2  35000     70    156    51 married  female        10 49.4
 3 105000     65    195    52 married  male          16 99.4
 4  40000     63    197    54 married  female        14 44.0
 5  75000     66    190    49 married  male          14 59.7
 6 102000     68    200    49 divorced female        18 98.8
 7  70000     64    160    54 divorced female        12 50.3
 8  60000     69    162    55 divorced male          12 89.7
 9 150000     69    194    54 divorced male          13 96.0
10 115000     64    145    53 married  female        16 67.0
# … with 5,256 more rows
```

```
wages %>%
  ggplot(mapping = aes(x = log(income))) +
    geom_histogram(binwidth = 0.25)
```



lm()

lm()

Fit a linear modle 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

$$y = \beta_0 + \beta_1 x + \epsilon$$

```
y ~ x
```

Your Turn 1

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

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

02:00

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```r
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)
# [1] "lm"
```

1. Not pipe friendly to have data as second argument 😢

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

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```
summary(mod_e)
# Call:
# lm(formula = log(income) ~ education, data = wages)
#
# Residuals:
#     Min      1Q  Median      3Q     Max
# -6.7893 -0.3563  0.1328  0.5798  2.9136
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 8.557691   0.073260  116.81   <2e-16 ***
# education   0.141840   0.005305   26.74   <2e-16 ***
# ---
# Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
#
# Residual standard error: 0.9923 on 5262 degrees of freedom
#   (2 observations deleted due to missingness)
# Multiple R-squared:  0.1196, Adjusted R-squared:  0.1195
# F-statistic:   715 on 1 and 5262 DF,  p-value: < 2.2e-16
```

Still not a data frame, but more information

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

www.tidyverse.org

In R4DS

Many Models

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()
# A tibble: 2 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)    8.56    0.0733      117.  0.
2 education      0.142   0.00530      26.7 8.41e-148
```

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glance()

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

```
mod_e %>% glance()
# A tibble: 1 x 11
  r.squared adj.r.squared sigma statistic   p.value    df logLik    AIC    BIC deviance df.residual
      <dbl>         <dbl> <dbl>     <dbl>     <dbl> <int>  <dbl>  <dbl>  <dbl>    <dbl>       <int>
1     0.120         0.119 0.992      715. 8.41e-148     2 -7428. 14862. 14881.    5182.        5262
```

augment()

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

```
mod_e %>% augment()
# A tibble: 5,264 x 10
   .rownames log.income. education .fitted .se.fit  .resid      .hat .sigma      .cooksd .std.resid
   <chr>           <dbl>     <int>   <dbl>   <dbl>   <dbl>     <dbl>  <dbl>        <dbl>      <dbl>
 1 1                9.85        13   10.4   0.0140 -0.549  0.000199  0.992 0.0000305       -0.554
 2 2               10.5         10    9.98  0.0234  0.487  0.000554  0.992 0.0000668        0.491
 3 3               11.6         16   10.8   0.0188  0.735  0.000359  0.992 0.0000984        0.740
 4 4               10.6         14   10.5   0.0139  0.0532 0.000195  0.992 0.000000281      0.0536
 5 5               11.2         14   10.5   0.0139  0.682  0.000195  0.992 0.0000461        0.687
 6 6               11.5         18   11.1   0.0272  0.422  0.000751  0.992 0.0000680        0.425
 7 7               11.2         12   10.3   0.0160  0.896  0.000260  0.992 0.000106         0.904
 8 8               11.0         12   10.3   0.0160  0.742  0.000260  0.992 0.0000728        0.748
 9 9               11.9         13   10.4   0.0140  1.52   0.000199  0.992 0.000233         1.53
10 10              11.7         16   10.8   0.0188  0.826  0.000359  0.992 0.000124         0.832
# … with 5,254 more rows
```

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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

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Your Turn 2

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

```r
mod_h <- wages %>% lm(log(income) ~ height, data = .)
mod_h %>%
  tidy()
# A tibble: 2 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)   6.98     0.237        29.4 4.13e-176
2 height        0.0520   0.00352      14.8 2.44e- 48

mod_h %>%
  glance() %>%
  select(adj.r.squared, p.value)
# A tibble: 1 x 2
  adj.r.squared  p.value
          <dbl>    <dbl>
1        0.0396 2.44e-48
```

```
mod_h %>%
  tidy() %>% filter(p.value < 0.05)
# A tibble: 2 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)   6.98     0.237        29.4 4.13e-176
2 height        0.0520   0.00352      14.8 2.44e- 48

mod_e %>%
  tidy() %>% filter(p.value < 0.05)
# A tibble: 2 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)    8.56    0.0733      117.  0.
2 education      0.142   0.00530      26.7 8.41e-148
```

So which determines income?

Multiple Regression

To fit multiple predictors, add multiple variables to the formula

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

Your Turn 3

Model **log(income)** against **education** *and* **height**. Do the coefficients change?

03 : 00

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

mod_eh %>%
  tidy()
# A tibble: 3 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)   5.35     0.231        23.1 1.00e-112
2 education     0.139    0.00521      26.6 7.12e-147
3 height        0.0483   0.00331      14.6 2.50e- 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()
# A tibble: 4 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
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
```

What does this mean?

Where is **sexmale**?

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```
# A tibble: 4 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
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
```

For factors, R treats the first level as the baseline level, e.g. the mean log(income) for a male is:

log(income) = 8.25 + 0.15 * education + 0 * height

Each additional level gets a coefficient that acts as an *adjustment* between the baseline level and the additional level, e.g. the mean income for a female is:

log(income) = 8.25 + 0.15 * education + 0 * height - 0.46

```
# A tibble: 4 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
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
```

For factors, R treats the first level as the baseline level, e.g. the mean log(income) for a male is:

log(income) = 8.25 + 0.15 * education + 0 * height

Each additional level gets a coefficient that acts as an *adjustment* between the baseline level and the additional level, e.g. the mean income for a female is:

log(income) = 8.25 + 0.15 * education + 0 * height - 0.46

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```
# A tibble: 4 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
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

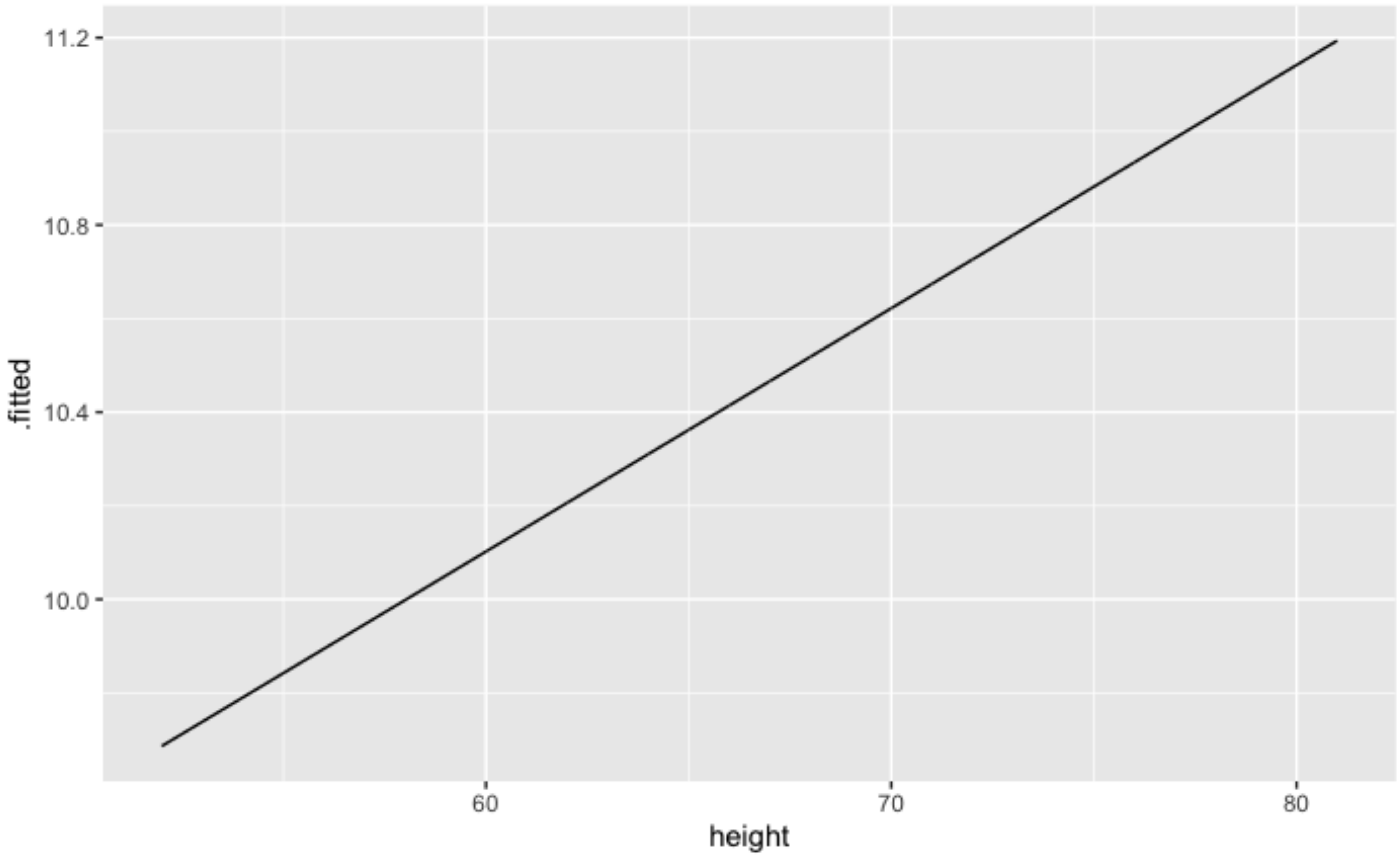
Your Turn 5

Use a broom function and ggplot2 to make a line graph of **height** vs. **.fitted** for our heights models, **mod_h**.

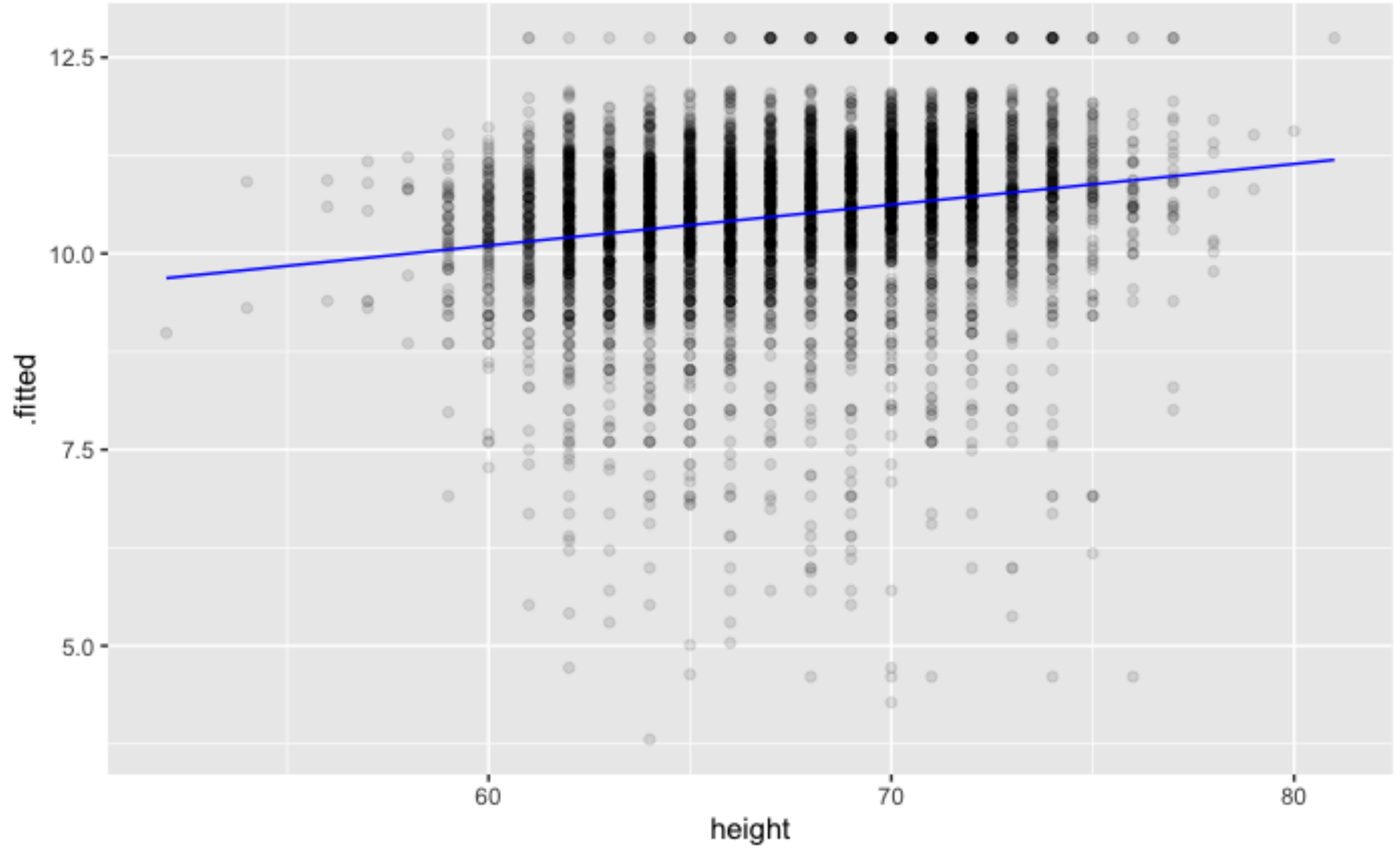
Bonus: Overlay the plat on the original data points.

03:00

```r
mod_h %>%
  augment(data = wages) %>%
  ggplot(mapping = aes(x = height, y = .fitted)) +
    geom_line()
```



```r
mod_h %>%
  augment(data = wages) %>%
  ggplot(mapping = aes(x = height, y = .fitted)) +
    geom_point(mapping = aes(y = log(income)), alpha = 0.1) +
    geom_line(color = "blue")
```



Your Turn 6

Repeat the process to make a line graph of **height** vs. **.fitted** colored by **sex** for model **mod_ehs**. Are the results interpretable?

Add **+ facet_wrap(~education)** to the end of the your code. What happens?

02 : 00

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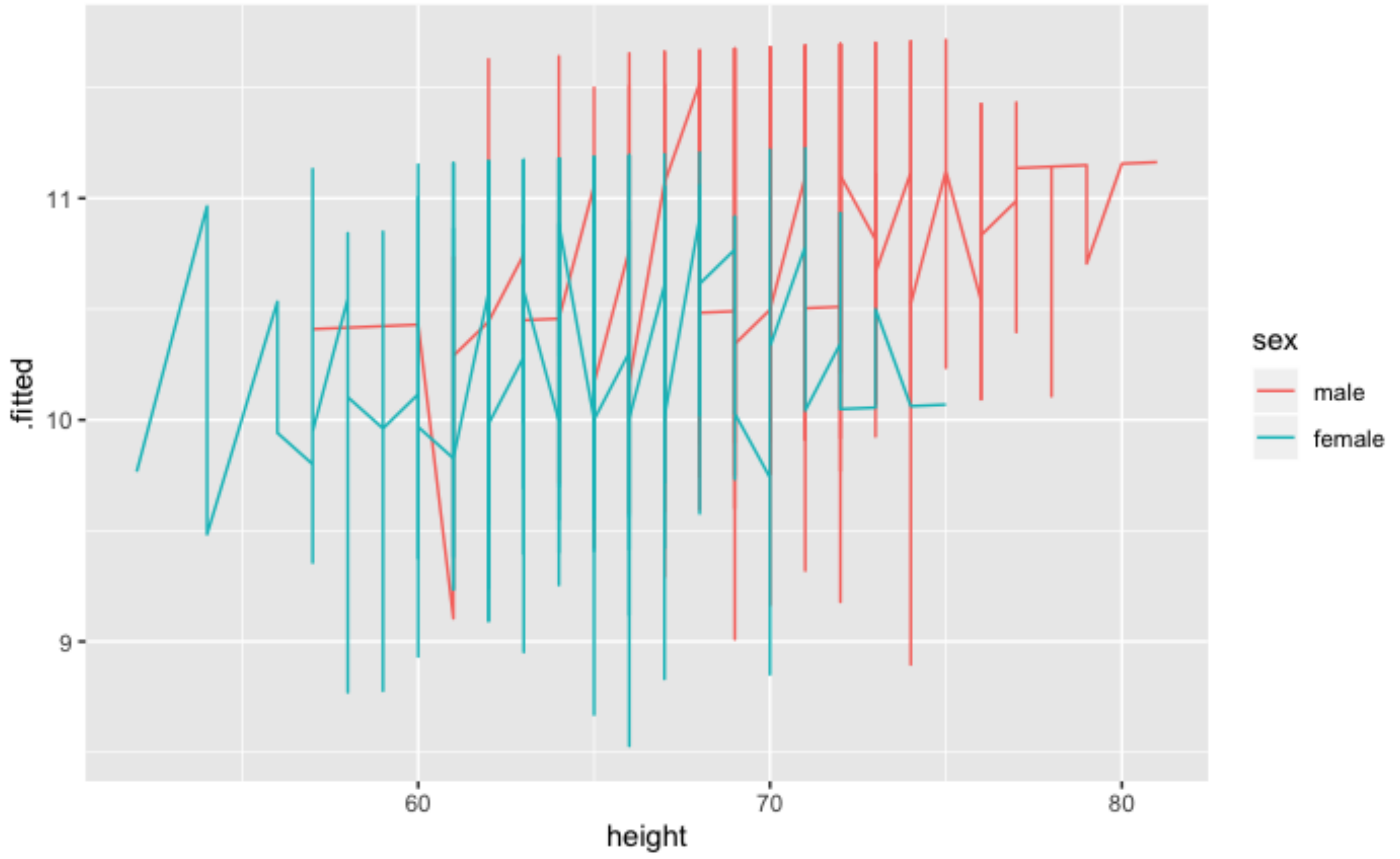
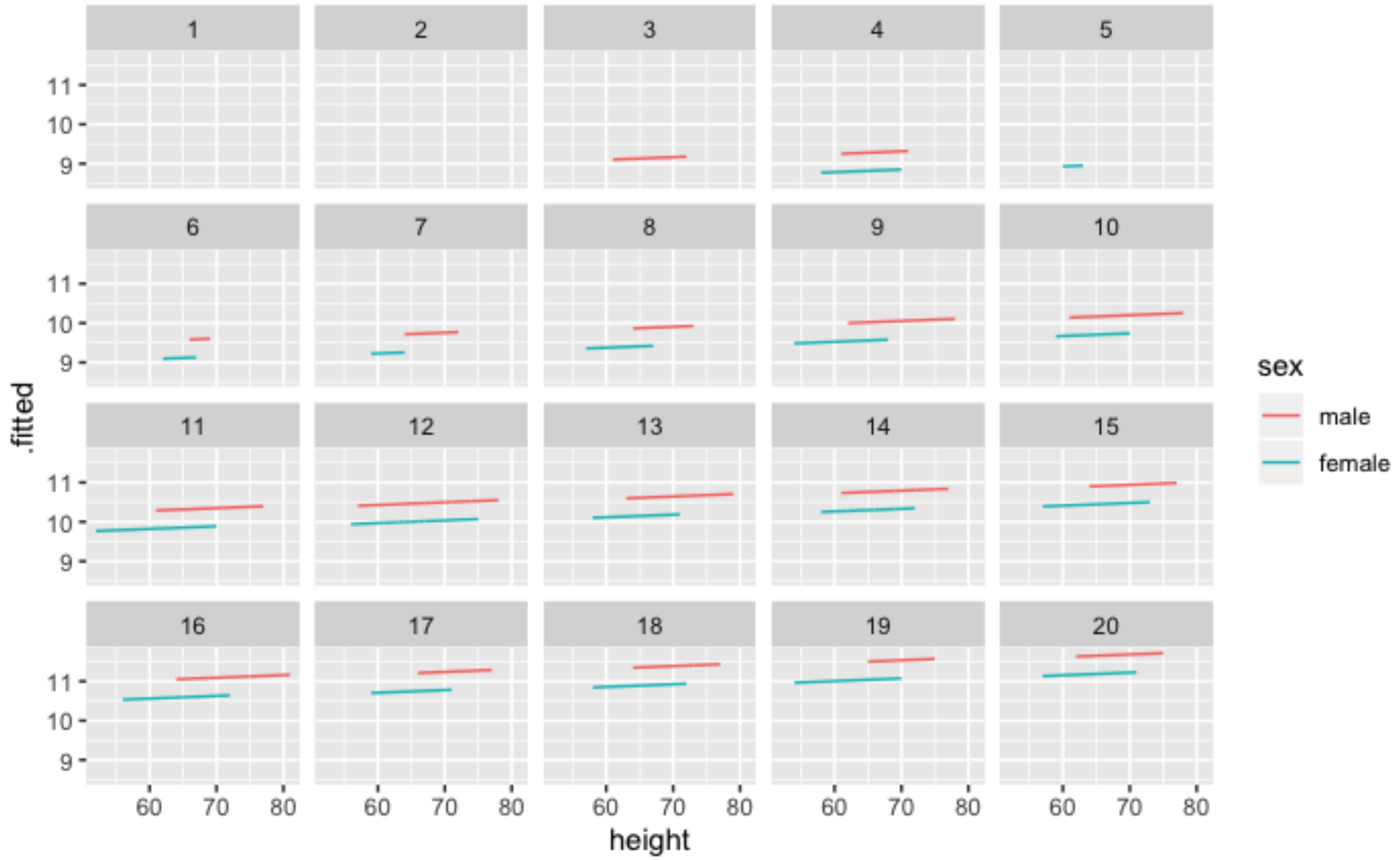
```
mod_ehs %>%
  augment(data = wages) %>%
  ggplot(mapping = aes(x = height, y = .fitted, color = sex)) +
    geom_line()
```



```
mod_ehs %>%
  augment(data = wages) %>%
  ggplot(mapping = aes(x = height, y = .fitted, color = sex)) +
    geom_line() +
    facet_wrap(vars(education))
```



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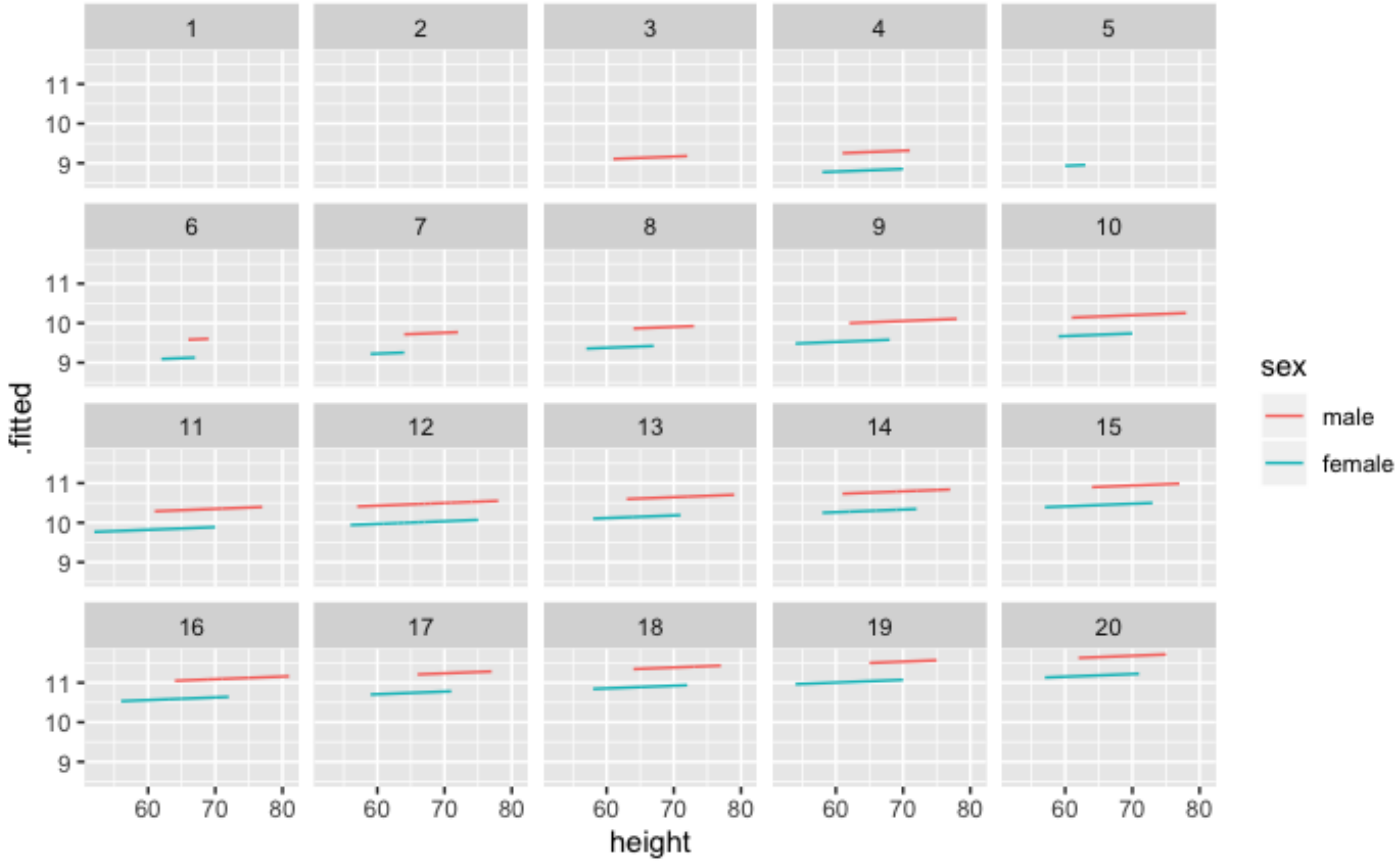


1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
.fitted
height
sex
male
female

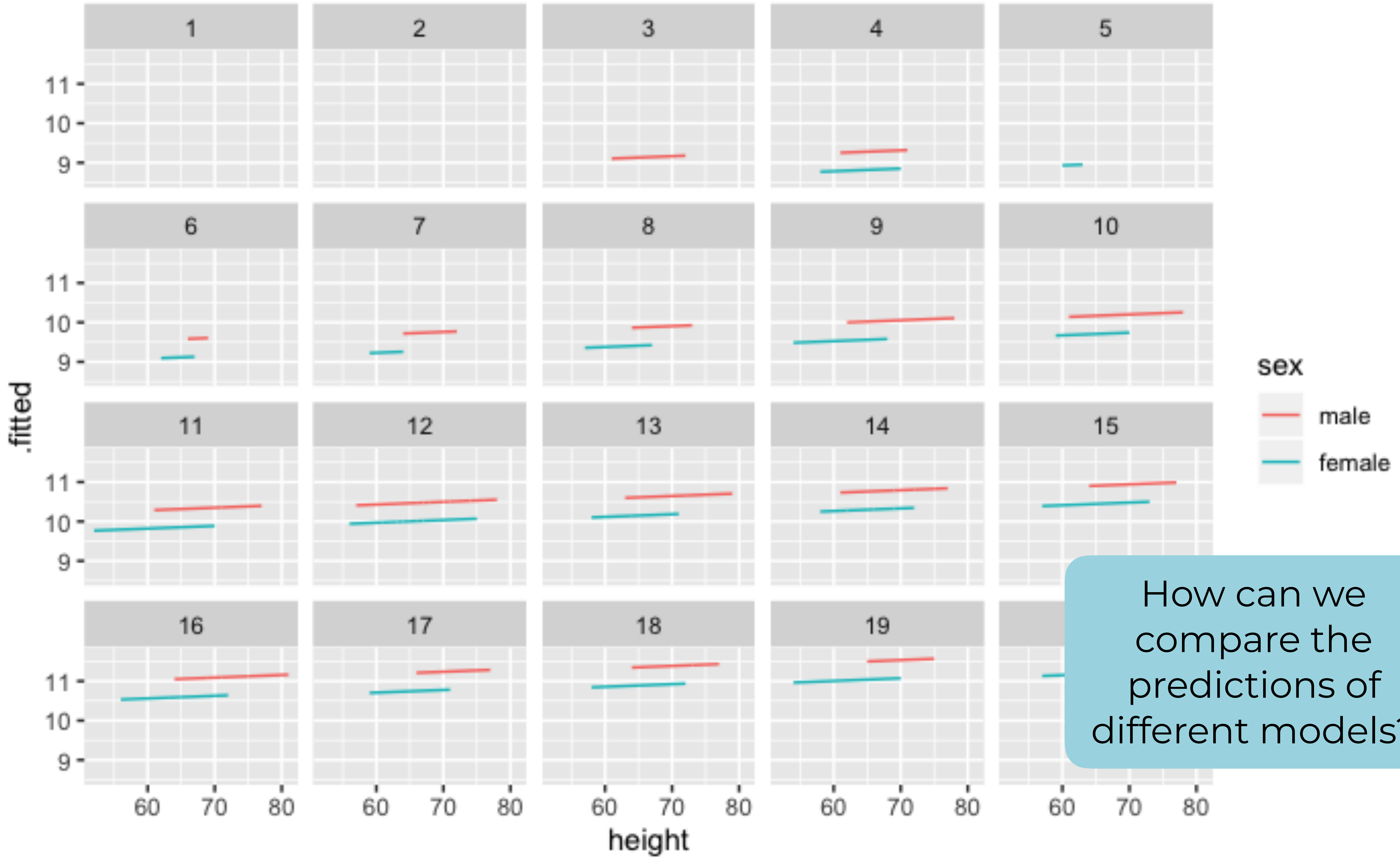
facet_wrap()

Divides plot into subplots based on a grouping variable.
"Wraps" subplots into rectangular collection.

```
+ facet_wrap(vars(var))
```

vars() - find a variable in the data frame

The grouping variable



How can we compare the predictions of different models?

Visualizing Multiple Models

modelr

www.rstudio.com

In R4DS

Model Basics

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modelr

modelr includes three functions for working with model predictions:

1. **add_predictions()** - adds the model prediction for each case in the data set. Overlaps with broom::**augment()**

2. **spread_predictions()** - Adds predictions in separate columns

3. **gather_predictions()** - Adds predictions in a pair of key:value columns (model:pred)

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add_predictions()

Uses the values in a data frame to generate a prediction for each case.

```
add_predictions(data, model)
```

Uses this model

To add predictions to these cases

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```
wages %>% add_predictions(mod_h)
# A tibble: 5,266 x 9
   income height weight   age marital  sex     education  afqt  pred
    <int>  <dbl>  <int> <int> <fct>    <fct>       <int> <dbl> <dbl>
 1  19000     60    155    53 married  female         13  6.84  10.1
 2  35000     70    156    51 married  female         10 49.4   10.6
 3 105000     65    195    52 married  male           16 99.4   10.4
 4  40000     63    197    54 married  female         14 44.0   10.3
 5  75000     66    190    49 married  male           14 59.7   10.4
 6 102000     68    200    49 divorced female         18 98.8   10.5
 7  70000     64    160    54 divorced female         12 50.3   10.3
 8  60000     69    162    55 divorced male           12 89.7   10.6
 9 150000     69    194    54 divorced male           13 96.0   10.6
10 115000     64    145    53 married  female         16 67.0   10.3
# … with 5,256 more rows
```

spread_predictions()

Adds predictions for multiple models, each in their own column

```
spread_predictions(data, ...)
```

Add predictions from each of these models

To the cases in this data frame

```
wages %>% spread_predictions(mod_h, mod_eh, mod_ehs)
# A tibble: 5,266 x 11
   income height weight   age marital  sex     education  afqt mod_h mod_eh mod_ehs
    <int>  <dbl>  <int> <int> <fct>    <fct>       <int> <dbl> <dbl>  <dbl>   <dbl>
 1  19000     60    155    53 married  female         13  6.84  10.1   10.1   10.1
 2  35000     70    156    51 married  female         10 49.4   10.6   10.1    9.74
 3 105000     65    195    52 married  male           16 99.4   10.4   10.7   11.1
 4  40000     63    197    54 married  female         14 44.0   10.3   10.3   10.3
 5  75000     66    190    49 married  male           14 59.7   10.4   10.5   10.8
 6 102000     68    200    49 divorced female         18 98.8   10.5   11.1   10.9
 7  70000     64    160    54 divorced female         12 50.3   10.3   10.1    9.99
 8  60000     69    162    55 divorced male           12 89.7   10.6   10.3   10.5
 9 150000     69    194    54 divorced male           13 96.0   10.6   10.5   10.6
10 115000     64    145    53 married  female         16 67.0   10.3   10.7   10.6
# … with 5,256 more rows
```

gather_predictions()

Adds predictions for multiple models as a pair of model:pred columns

```
gather_predictions(data, ...)
```

Add predictions from each of these models

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

modelr

```
wages %>% gather_predictions(mod_h, mod_eh, mod_ehs)
# A tibble: 15,798 x 10
   model    income height weight   age marital sex     education  afqt  pred
   <chr>     <int>  <dbl>  <int> <int> <fct>   <fct>       <int> <dbl> <dbl>
 1 mod_h     19000     60    155    53 married female         13  6.84 10.1
 2 mod_eh    19000     60    155    53 married female         13  6.84 10.1
 3 mod_ehs   19000     60    155    53 married female         13  6.84 10.1
 4 mod_h     35000     70    156    51 married female         10 49.4  10.6
 5 mod_eh    35000     70    156    51 married female         10 49.4  10.1
 6 mod_ehs   35000     70    156    51 married female         10 49.4   9.74
 7 mod_h    105000     65    195    52 married male           16 99.4  10.4
 8 mod_eh   105000     65    195    52 married male           16 99.4  10.7
 9 mod_ehs 105000     65    195    52 married male           16 99.4  11.1
10 mod_h     40000     63    197    54 married female         14 44.0  10.3
# … with 15,788 more rows
```

Your Turn 7

Use one of **spread_predictions()** or **gather_predictions()** to make a line graph of **height** vs. **pred** colored by **model** for each of **mod_h**, **mod_eh**, and **mod_ehs**. Are the results interpretable?

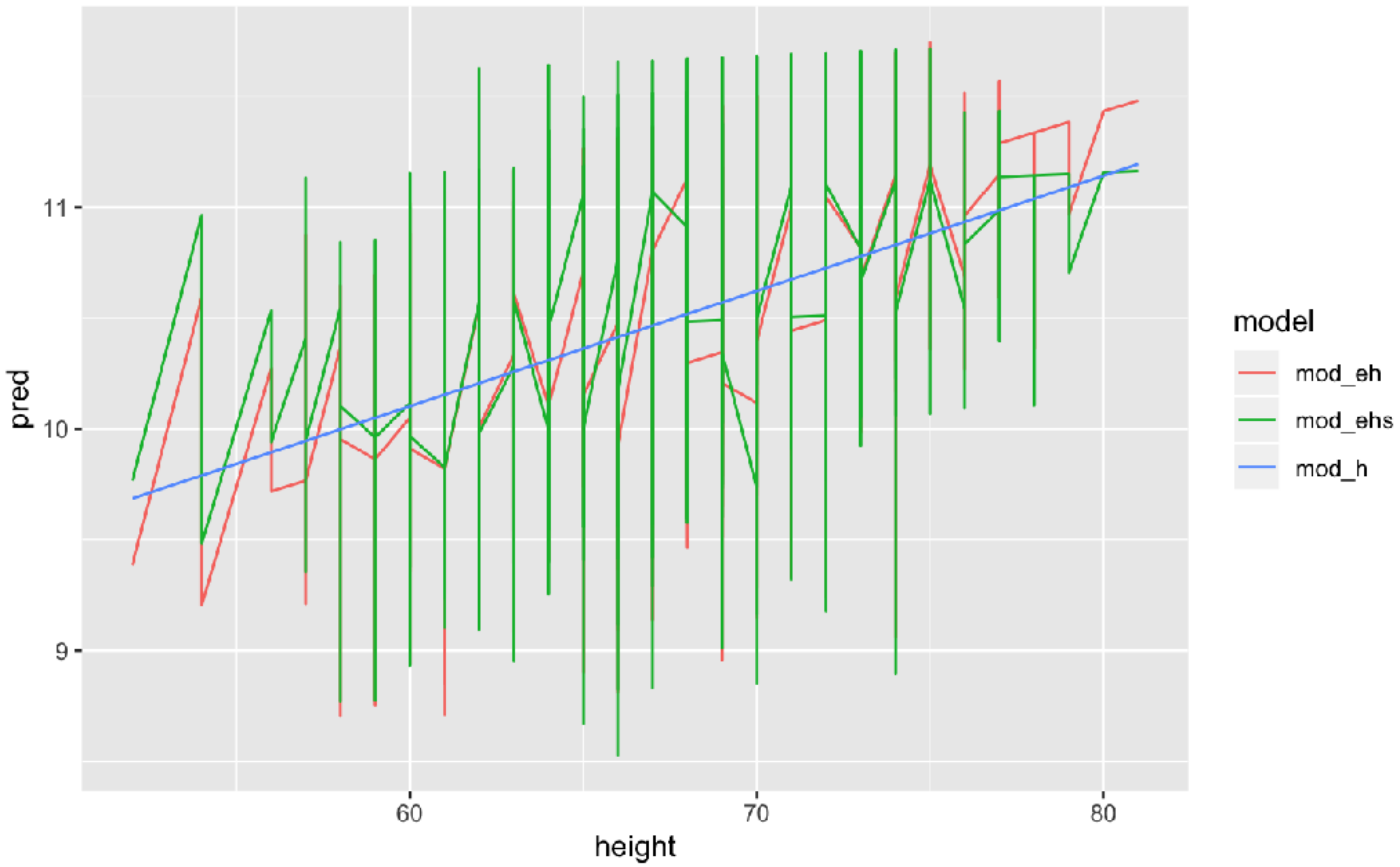
Add **+ facet_grid(sex ~ education)** to the end of your code. What happens?

04 : 00

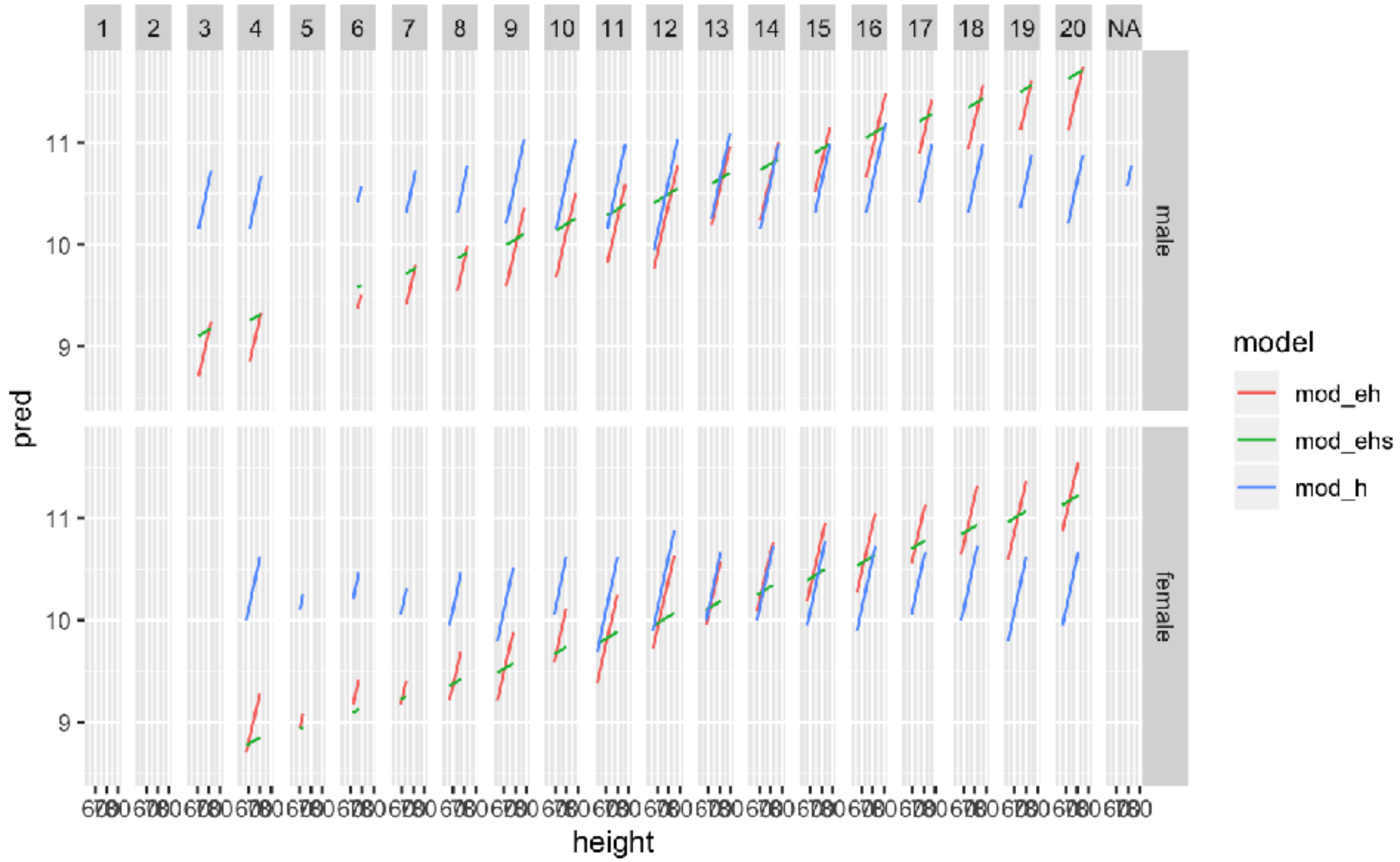
ATLAS

modelr

```
wages %>%
  gather_pedictions(mod_h, mod_eh, mod_ehs) %>%
  ggplot(mapping = aes(x = height, y = pred, color = model)) +
    geom_line()
```



```r
wages %>%
  gather_pedictions(mod_h, mod_eh, mod_ehs) %>%
  ggplot(mapping = aes(x = height, y = pred, color = model)) +
    geom_line() +
    facet_grid(rows = vars(sex), cols = vars(education))
```



ATLAS

facet_grid()

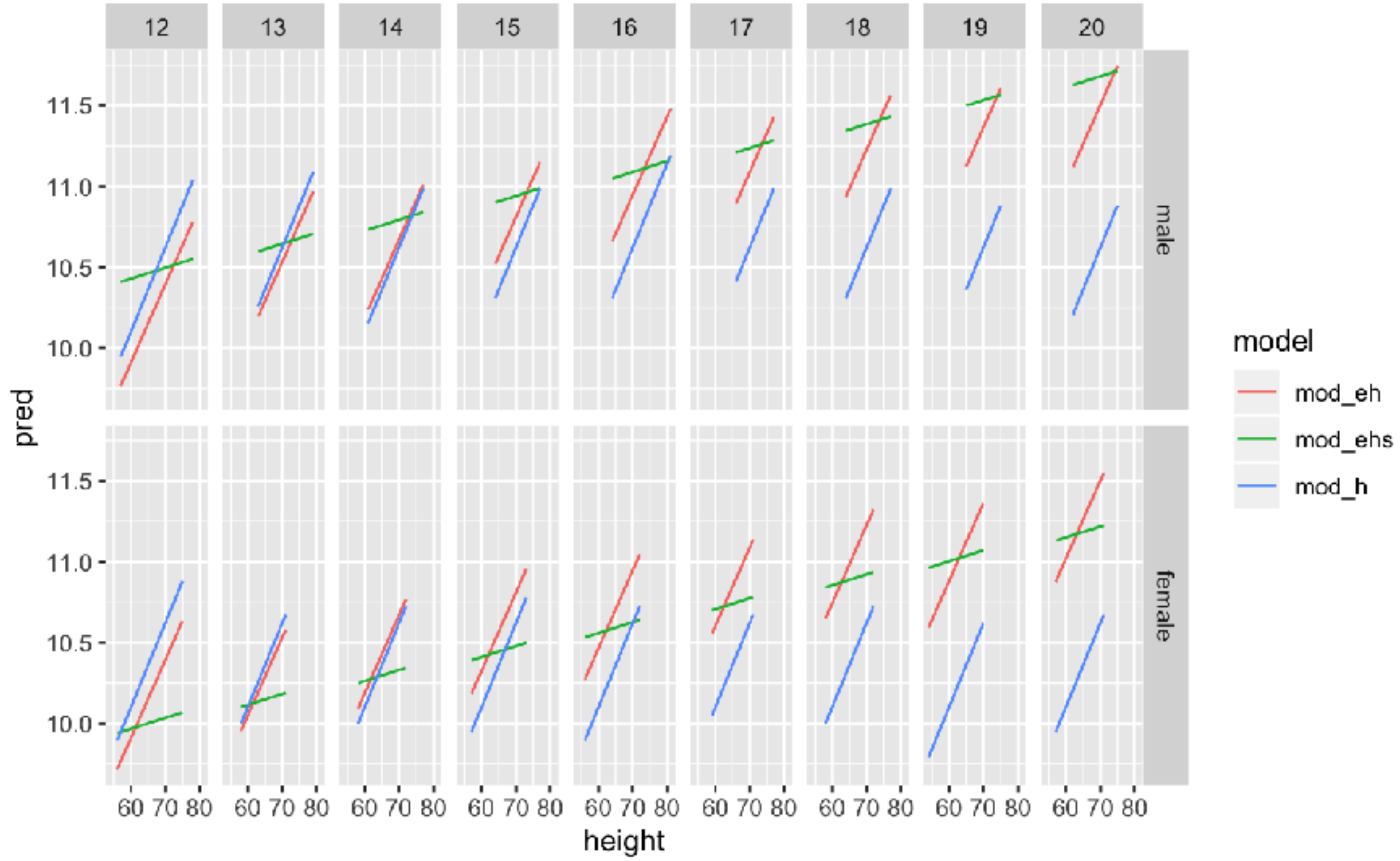
Divides plot into subplots based on a grouping variable.
Forms a matrix of panels based on row and column faceting variables.

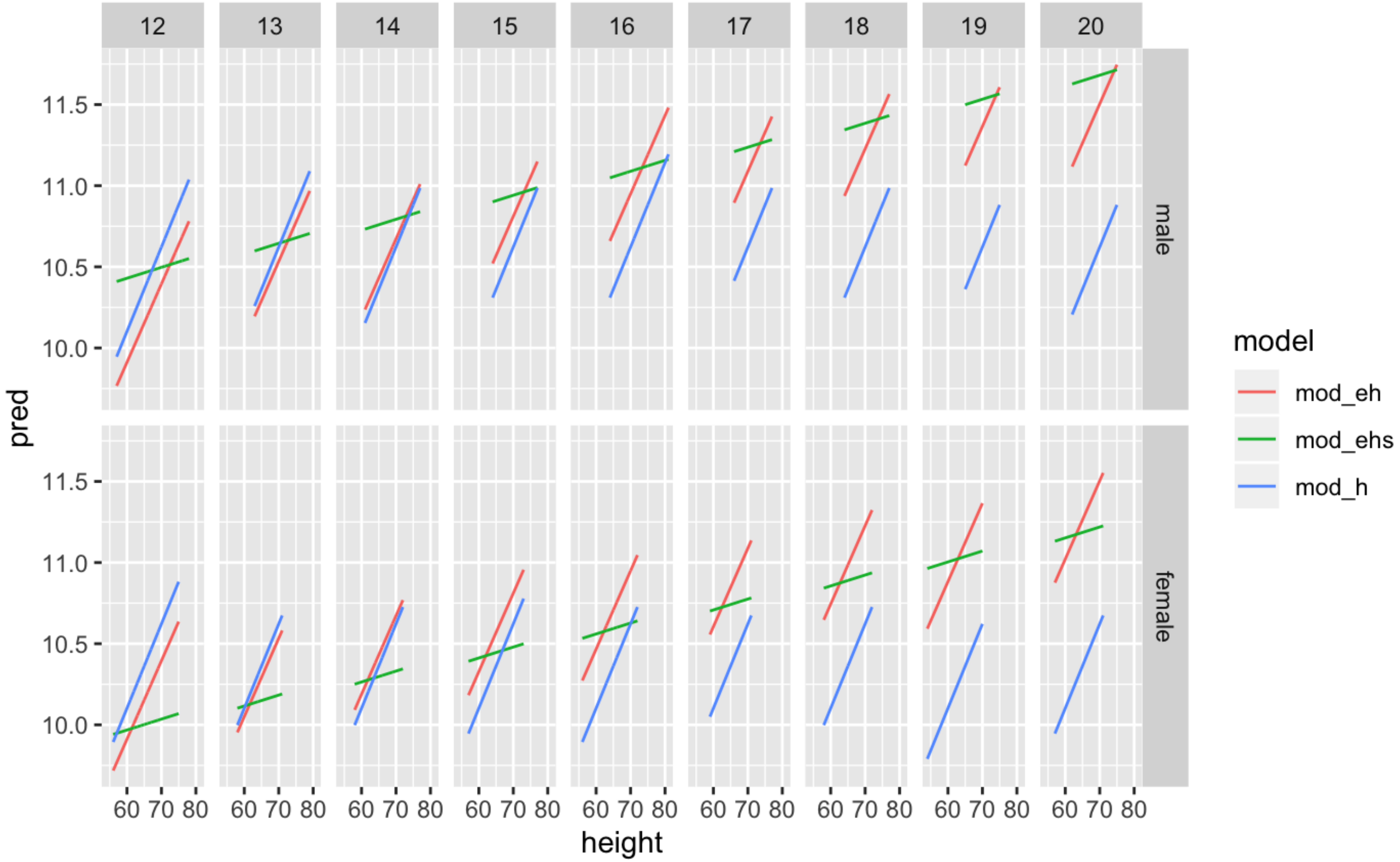
```
+ facet_grid(rows = vars(sex), cols = vars(education))
```

The grouping variable for the rows

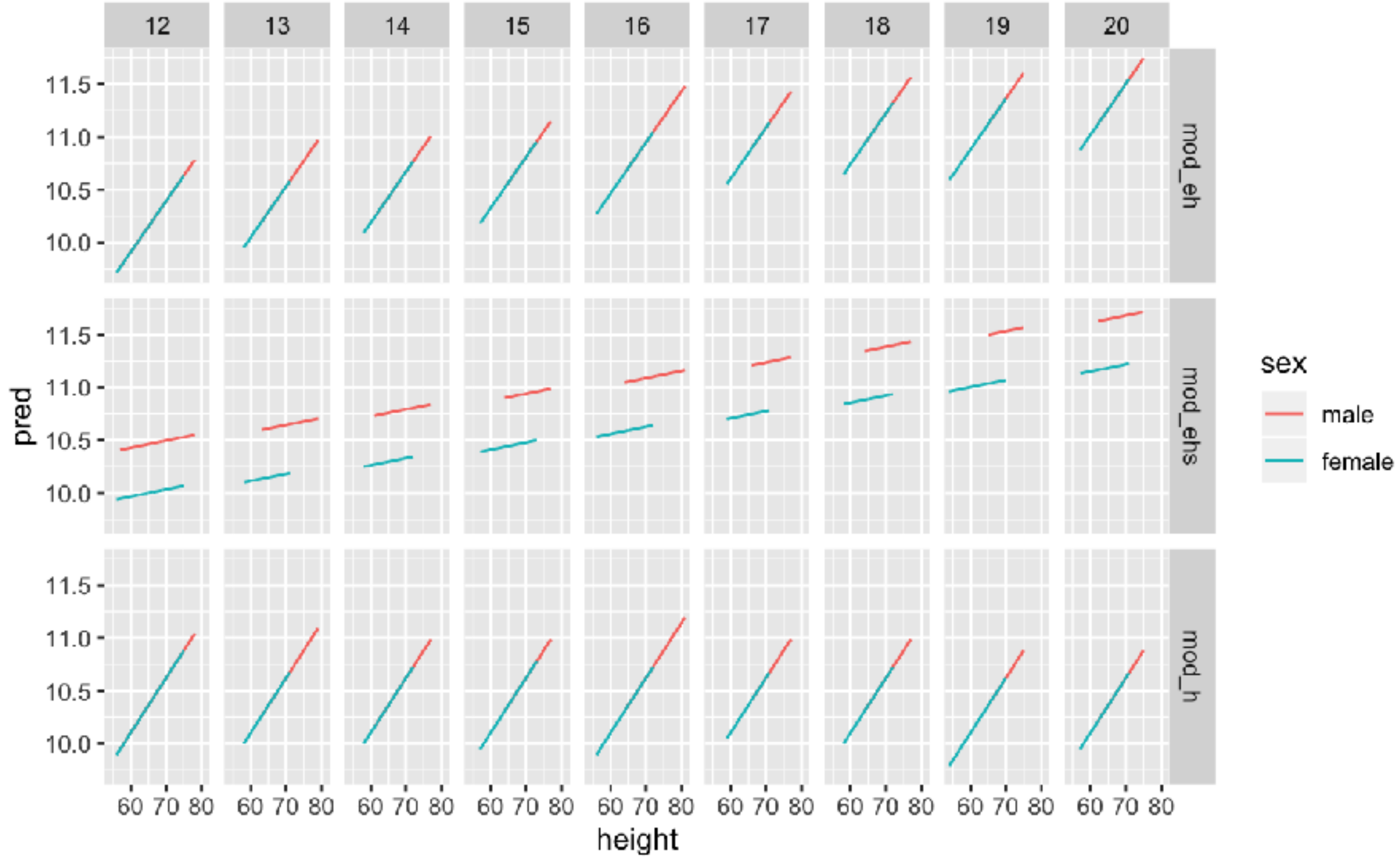
The grouping variable for the columns

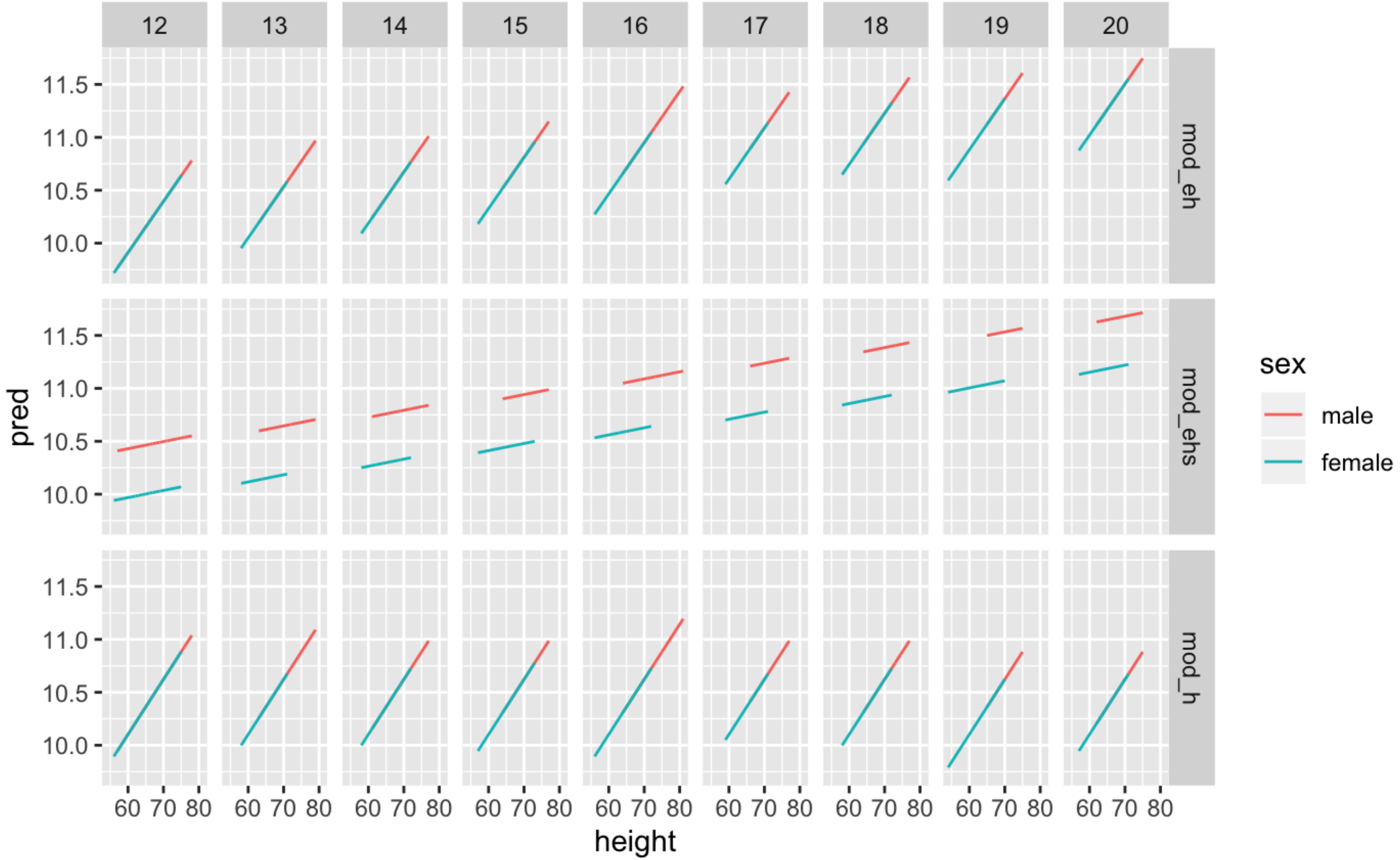
```
wages %>%
  gather_pedictions(mod_h, mod_eh, mod_ehs) %>%
  filter(education > 11) %>%
  ggplot(mapping = aes(x = height, y = pred, color = model)) +
    geom_line() +
    facet_grid(rows = vars(sex), cols = vars(education))
```




12
13
14
15
16
17
18
19
20
pred
11.5
11.0
10.5
10.0
male
female
60 70 80
height
model
mod_eh
mod_ehs
mod_h

```r
wages %>%
  gather_pedictions(mod_h, mod_eh, mod_ehs) %>%
  filter(education > 11) %>%
  ggplot(mapping = aes(x = height, y = pred, color = sex)) +
    geom_line() +
    facet_grid(rows = vars(model), cols = vars(education))
```





ATLAS

modelr

Residuals

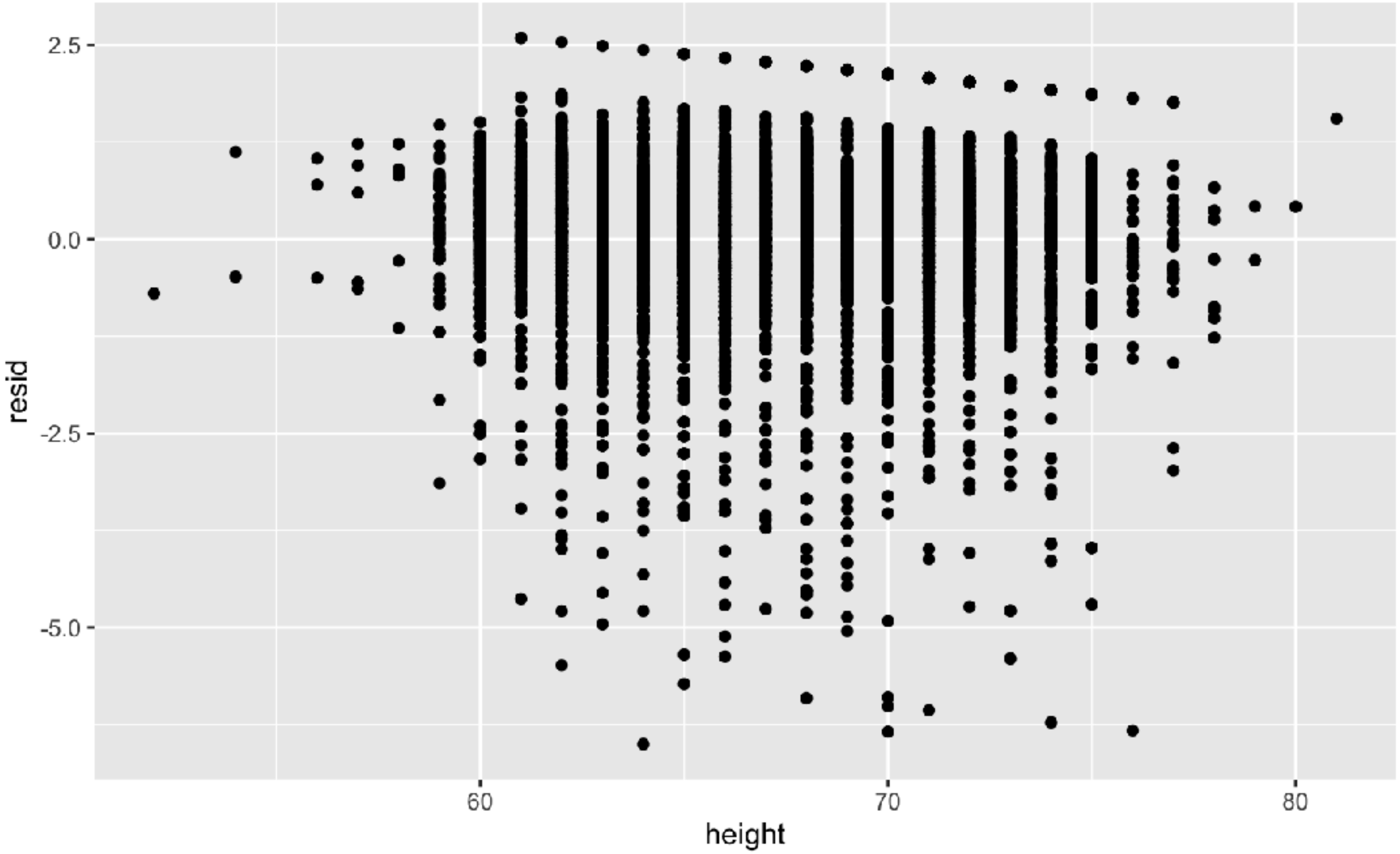
modelr provides the equivalent functions for residuals

`add_predictions()` → `add_residuals()`

`spread_predictions()` → `spread_residuals()`

`gather_predictions()` → `gather_residuals()`

```
wages %>%
  add_residuals(mod_h) %>%
  ggplot(mapping = aes(x = height, y = resid)) +
    geom_point()
```



Your Turn 8

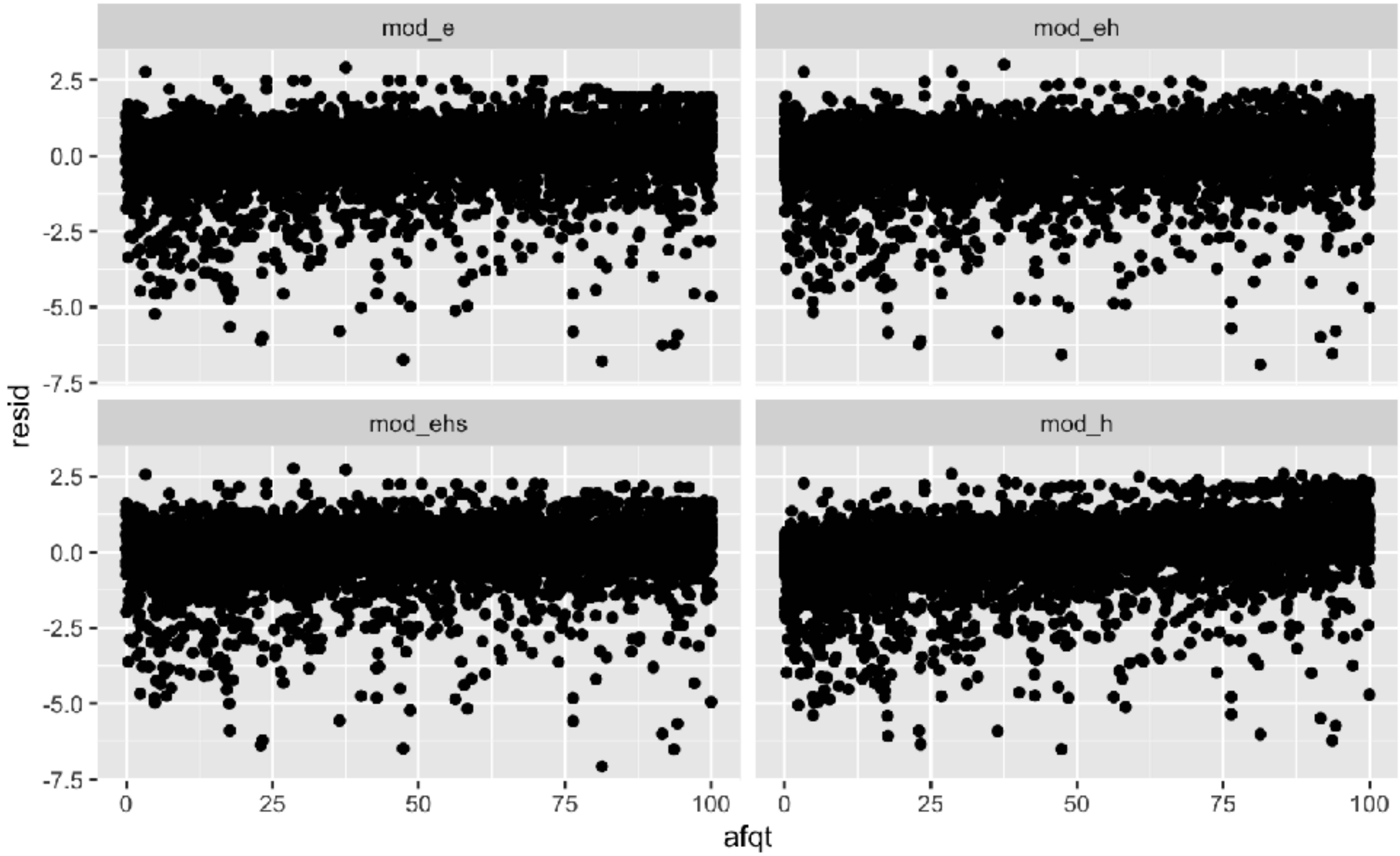
Use one of **spread_residuals()** or **gather_residuals()** to make a scatter plot of **afqt** vs. **resid** for each of **mod_e**, **mod_h**, **mod_eh**, and **mod_ehs**.

Use a faceting function to create a subplot for each model.

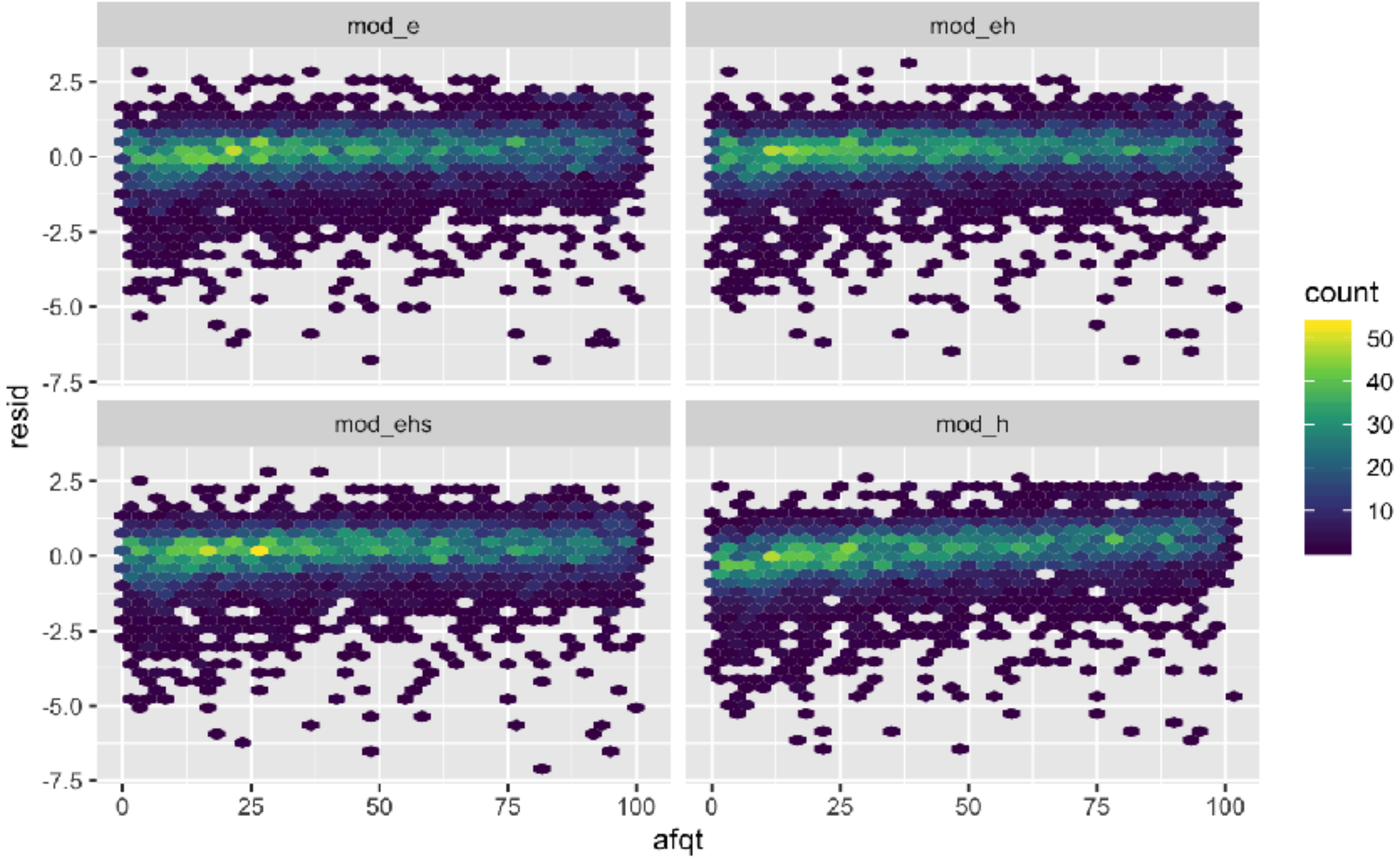
04 : 00

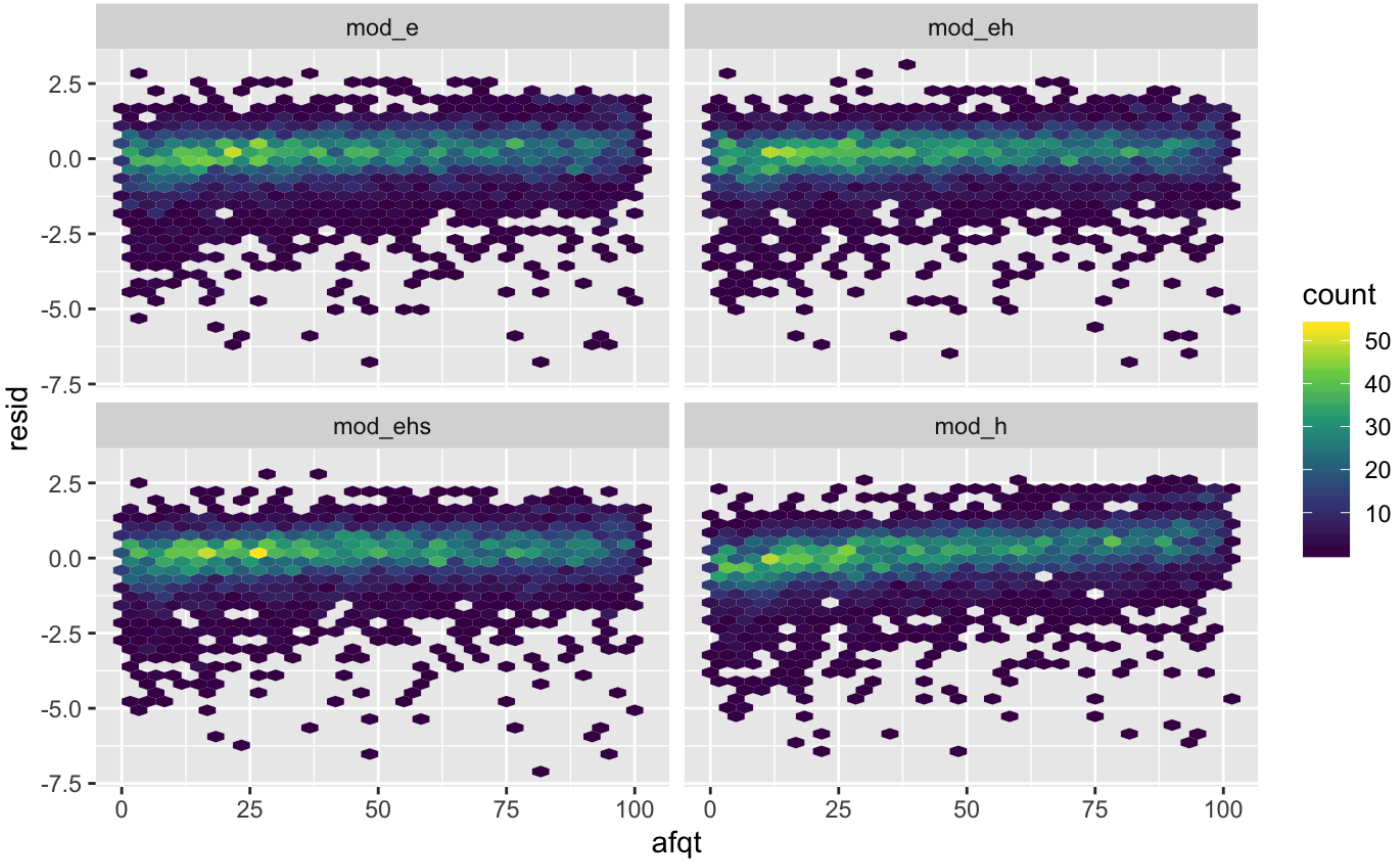
ATLAS

```r
wages %>%
  gather_residuals(mod_e, mod_h, mod_eh, mod_ehs) %>%
  ggplot(mapping = aes(x = afqt, y = resid)) +
    geom_point() +
    facet_wrap(vars(model))
```



```r
wages %>%
  gather_residuals(mod_e, mod_eh, mod_ehs, mod_h) %>%
  ggplot(mapping = aes(x = afqt, y = resid)) +
    geom_hex() +
    scale_fill_viridis_c() +
    facet_wrap(vars(model))
```




mod_e
mod_eh
mod_ehs
mod_h
2.5
0.0
-2.5
-5.0
-7.5
resid
0
25
50
75
100
afqt
count
50
40
30
20
10

Recap

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

Use **add_predictions()**, **spread_predictions()**, or **gather_predictions()** to visualize predictions.

Use **add_residuals()**, **spread_residuals()**, or **gather_residuals()** to visualize residuals.

Model Data

broom

modelr

ATLAS

Accessible Teaching, Learning, and Assessment Systems