

Solving the model representation problem with broom

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Who am I?

Statistical models

The model representation problem

The broom package

Use cases

Who am I?

About Me



- Summer intern at RStudio last summer

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- Summer intern at RStudio last summer
- Primary maintainer of the [broom](#) package

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- Active on [#rstats](#) Twitter and Github

Statistical models

What is a model?

Let x be values that live in some space \mathcal{X} , and let y be observations of interest that live in some space \mathcal{Y} . A **statistical model** is a *set* of probability distributions $\mathcal{P}(y|x)$ indexed by parameters $\theta \in \Theta$ ¹.

¹In some cases we treat θ as itself random, which means that our model is a class of probability distributions $\mathcal{P}(y, \theta|x)$.

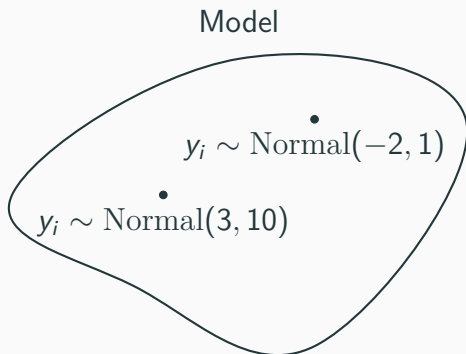
Example: the normal model

$$y_i \stackrel{\text{iid}}{\sim} \text{Normal}(\mu, \sigma^2)$$

Here $\theta = (\mu, \sigma^2)$ and the parameter space is $\mathbb{R} \times \mathbb{R}^+$.

Visualizing the normal model

Again: a model is a *set*.



We call a single element of a model a **fit**. The distribution with $\mu = -2, \sigma^2 = 1$ is a fit, for example.

Another (parametric) example: the linear model

Given response y and predictor variables x_1 and x_2 , the linear model looks like:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i \quad \varepsilon_i \stackrel{\text{iid}}{\sim} \text{Normal}(0, \sigma^2)$$

This model says that y is i.i.d with a mean that depends on x and $\vec{\beta}$, and with fixed variance σ^2 .

Estimation

An **estimator** is a way to calculate the parameters of a model from data². There are many estimators for any given model, and which one we think is best depends on how we define “agrees best with the data.”

²This is equivalent to selecting the best fit!

Some estimators for the normal model

- $\hat{\mu} = 1$ $\hat{\sigma}^2 = 10$

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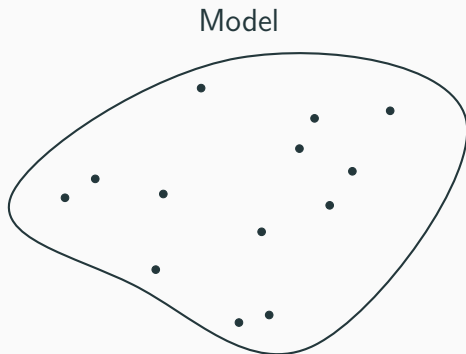
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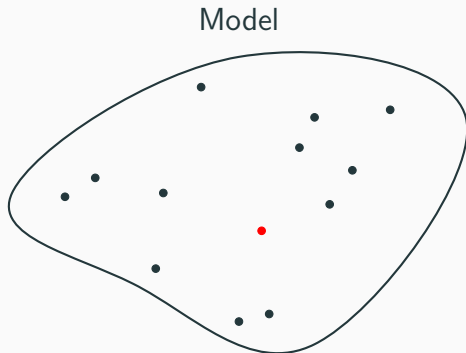
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- $\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i \quad \hat{\sigma}^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$

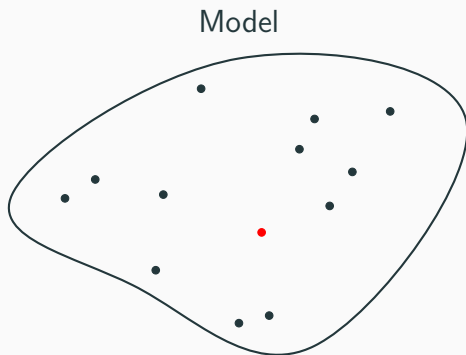
Visualizing estimation



Visualizing estimation

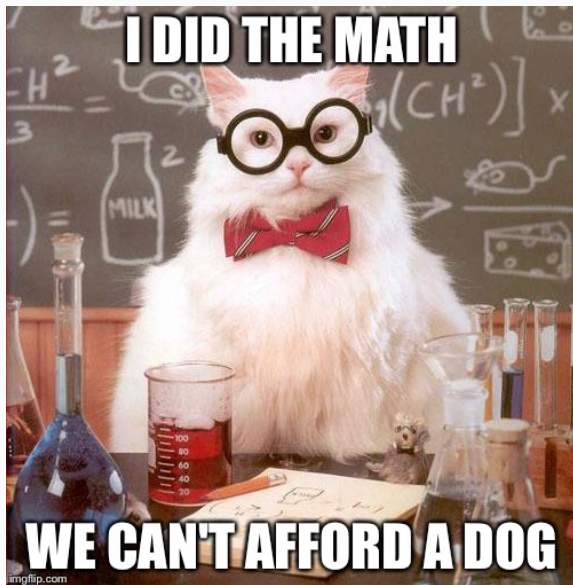


Estimates found!



Best fit: $y_i \sim \text{Normal}(-2, 1)$. Finally we can do inference!

Do all the inference



Some intuition about models, estimators and fits

A **model** corresponds to a set of possible truths about the world. A **fit** is a single truth about the world. An **estimator** is a way to choose the truth most suggested by the data from a set of many possible truths.

Aside: the actual truth is almost certainly *not* in the model!

The model representation problem

Representing a fit in mathematical terms

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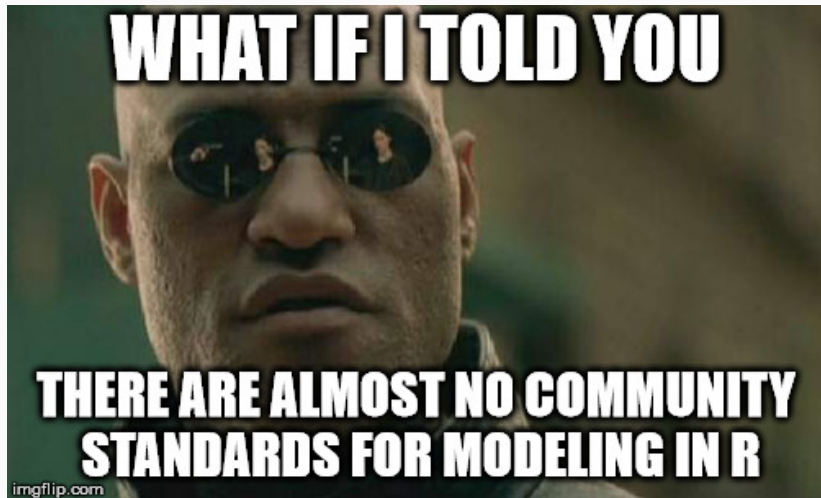
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 - Can also identify fits by parameter vectors: $\theta = (-2, 1)$
- Estimators for normal model:
 - $\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i \quad \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$
- Key: shared notation and community standards

How does R represent models, estimators and fits?

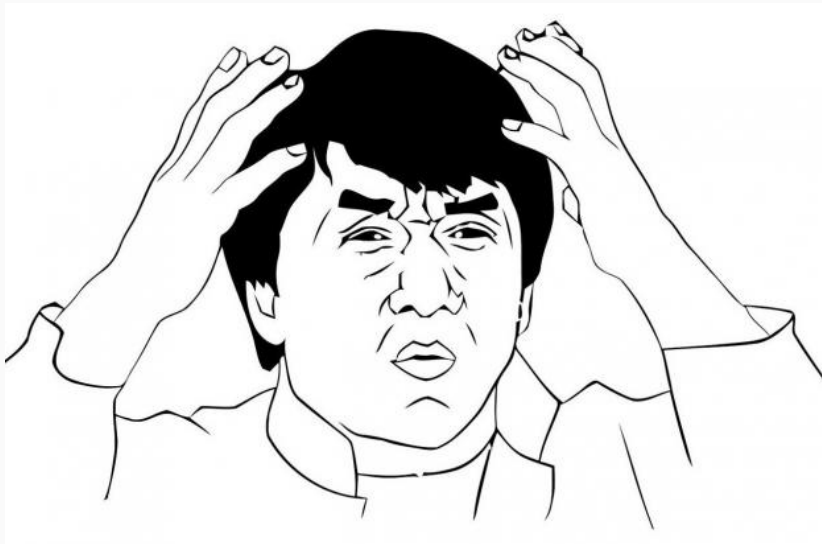


A taste of the pain

Suppose you want class probabilities from a fit called `obj`:

Object	Code
<code>lda</code>	<code>predict(obj)</code>
<code>glm</code>	<code>predict(obj, type = "response")</code>
<code>gbm</code>	<code>predict(obj, type = "response", n.trees)</code>
<code>mda</code>	<code>predict(obj, type = "posterior")</code>
<code>rpart</code>	<code>predict(obj, type = "prob")</code>
<code>Weka</code>	<code>predict(obj, type = "probability")</code>
<code>logitboost</code>	<code>predict(obj, type = "raw", nIter)</code>
<code>pamr.train</code>	<code>pamr.predict(obj, type = "posterior")</code>

How am I supposed to keep track of all this!?



The model representation problem

We have no shared framework or understanding of how to represent statistical models, estimation methods and fits with R objects.

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- This isn't anyone's fault
- Trying to get things done can still be frustrating

The broom package

The scene

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1. pick a model,
 2. pick an estimator for that model, and then
 3. get an R object `fit` using that estimator.
- The `fit` object is different for every model.
 - The `fit` object could be great to work with, or awful.

`broom` provides a standard way to represent fits

`broom` treats fits as having three parts:

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 - Each of table reported as a tidy tibble.

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broom treats fits as having three parts:

1. A table of information about fit parameters
 2. A table of information about each observation used to estimate the fit
 3. A table of overall goodness-of-fit measures
- Each of table reported as a tidy tibble.
 - Together these constitute a *tidy representation* of a fit.

What is a tibble

A **tibble** is a more consistent data.frame. tibbles are used widely throughout the **tidyverse**.

```
library(tibble)
```

```
tibble(x = 1:2, y = 3:4)
```

```
## # A tibble: 2 x 2
```

```
##       x     y
```

```
##   <int> <int>
```

```
## 1     1     3
```

```
## 2     2     4
```

What does it mean to be tidy?

I highly recommend reading Hadley Wickham's [Tidy Data](#) paper! The short version: a **tidy dataset** is one where:

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1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

The broom generics

So how do we turn fits into tidy tibbles?

- `tidy()` summarizes information about fit components

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So how do we turn fits into tidy tibbles?

- `tidy()` summarizes information about fit components
- `glance()` reports information about the entire fit
- `augment()` adds information about observations to a dataset

Continuing with the normal model example

```
# simulate Normal(-2, 1) data
x <- rnorm(5000, -2, 1)

# create a fit object using
# MLE estimator and normal model
normal_fit <- MASS::fitdistr(
  x,
  dnorm, # use the normal model!
  start = list(mean = 0, sd = 1)
)
```

What is normal_fit?

```
str(normal_fit)
## List of 5
## $ estimate: Named num [1:2] -2.03 1.01
## ..- attr(*, "names")= chr [1:2] "mean" "sd"
## $ sd       : Named num [1:2] 0.0143 0.0101
## ..- attr(*, "names")= chr [1:2] "mean" "sd"
## $ vcov      : num [1:2, 1:2] 2.06e-04 -4.62e-13 -4.62e-13 1.03
## ..- attr(*, "dimnames")=List of 2
## .. ..$ : chr [1:2] "mean" "sd"
## .. ..$ : chr [1:2] "mean" "sd"
## $ loglik    : num -7165
## $ n         : int 5000
## - attr(*, "class")= chr "fitdistr"
```

What is the tidy representation of `normal_fit`?

```
library(tidyverse)
library(broom)

tidy(normal_fit)
## # A tibble: 2 x 3
##   term      estimate std.error
##   <chr>      <dbl>      <dbl>
## 1 mean      -2.03      0.0143
## 2 sd         1.01      0.0101
```


What is the tidy representation of `normal_fit`?

```
glance(normal_fit)
## # A tibble: 1 x 4
##       n logLik    AIC    BIC
##   <int> <dbl> <dbl> <dbl>
## 1  5000 -7165. 14334. 14347.
```

There's no `augment()` method defined for univariate distributions at the moment.

Another example: the linear model

```
# create a fit object using the  
# OLS estimator for the linear model  
ols_fit <- lm(hp ~ mpg + cyl, mtcars)
```

```
# try the following for yourself:
```

```
str(ols_fit)
```

The tidy representation of `lm` objects

```
tidy(ols_fit)
## # A tibble: 3 x 5
##   term          estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)    54.1       86.1       0.628 0.535
## 2 mpg           -2.77       2.18      -1.27 0.213
## 3 cyl            24.0       7.35       3.26 0.00281
```

The tidy representation of `lm` objects

```
glance(ols_fit)[, 1:5]
## # A tibble: 1 x 5
##   r.squared adj.r.squared sigma statistic      p.value
##   <dbl>      <dbl> <dbl>    <dbl>      <dbl>
## 1    0.709      0.689  38.2    35.4 0.0000000166
```

The tidy representation of lm objects

```
augment(ols_fit)[, 1:7]
## # A tibble: 32 x 7
##   .rownames      hp    mpg    cyl .fitted .se.fit .resid
##   <chr>          <dbl> <dbl> <dbl>   <dbl>   <dbl>   <dbl>
## 1 Mazda RX4      110    21      6    140.     6.84 -29.7
## 2 Mazda RX4 Wag  110    21      6    140.     6.84 -29.7
## 3 Datsun 710      93   22.8     4     86.7    13.3   6.28
## # ... with 29 more rows
```

Notes about the tidy representation

- Always get a tibble back

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- Always get a tibble back
- Column names in returned tibbles are consistent
- Some information in the original R object is lost

Use cases

Report model coefficients with tidy()

```
kable2 <- function(data)
  knitr::kable(mutate_if(data, is.numeric, round, 2))

tidy(ols_fit) %>%
  kable2()
```

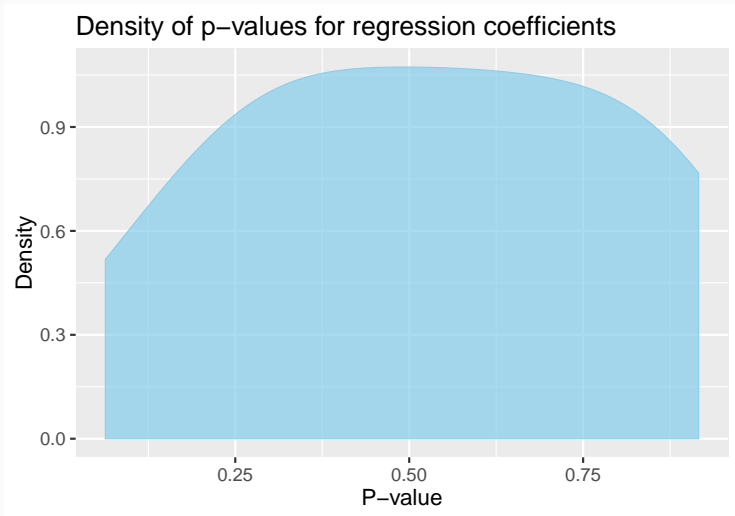
term	estimate	std.error	statistic	p.value
(Intercept)	54.07	86.09	0.63	0.53
mpg	-2.77	2.18	-1.27	0.21
cyl	23.98	7.35	3.26	0.00

Plot histograms/densities of p-values

```
fit <- lm(mpg ~ ., mtcars)
td <- tidy(fit)

p <- ggplot(td, aes(p.value)) +
  geom_density(
    fill = "skyblue", color = "skyblue", alpha = 0.7
  ) +
  labs(
    title = "Density of p-values for regression coefficients",
    x = "P-value",
    y = "Density"
  )
```

Plot histograms/densities of p-values



Comparing models by goodness of fit measures

```
fits <- list(  
  fit1 = lm(hp ~ cyl, mtcars),  
  fit2 = lm(hp ~ cyl + mpg, mtcars),  
  fit3 = lm(hp ~ ., mtcars)  
)  
  
gof <- map_df(fits, glance, .id = "model") %>%  
  arrange(AIC)
```

Comparing models by goodness of fit measures

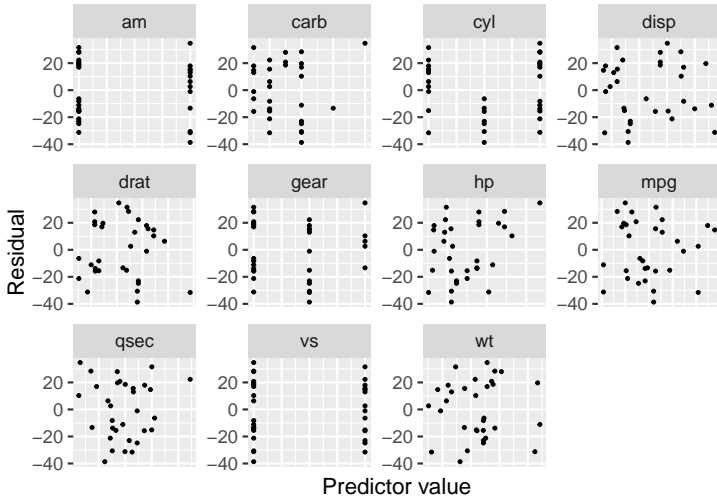
```
select(gof, -c(2:7))
## # A tibble: 3 x 6
##   model logLik   AIC   BIC deviance df.residual
##   <chr>  <dbl> <dbl> <dbl>    <dbl>      <int>
## 1 fit3  -143.   310.   327.   14165.        21
## 2 fit1  -161.   329.   333.   44743.        30
## 3 fit2  -160.   329.   335.   42369.        29
```

Inspecting residuals from multiple linear regression

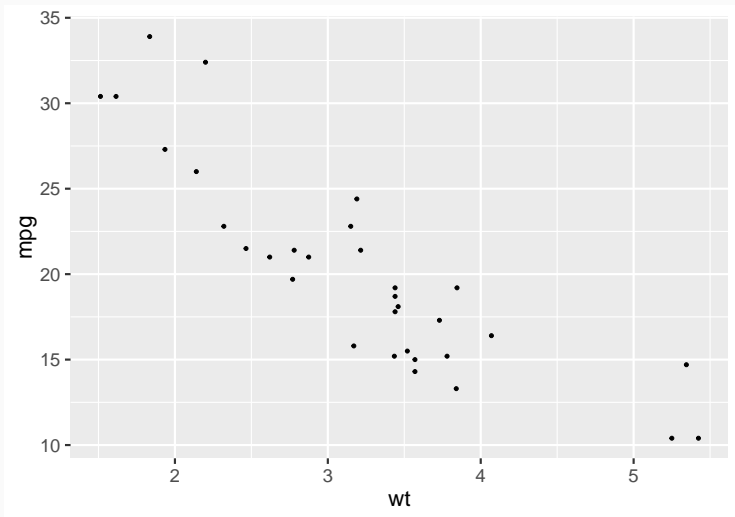
```
fit <- lm(hp ~ ., mtcars)
au <- broom::augment(fit)

p <- au %>%
  gather(x, val, -contains(".")) %>%
  ggplot(aes(val, .resid)) +
  geom_point() +
  facet_wrap(~x, scales = "free") +
  labs(x = "Predictor value", y = "Residual") +
  theme(axis.text.x = element_blank(),
        axis.ticks.x = element_blank())
```

Inspecting residuals from multiple linear regression



Bootstrapping



Bootstrapping

Consider a model:

$$\text{mpg} = \frac{k}{\text{wt}} + b + \varepsilon, \quad \varepsilon \sim \text{Normal}(0, \sigma^2)$$

Suppose we want to know the sampling distributions of k and b via bootstrapping

Bootstrapping

```
library(rsample)

boots <- bootstraps(mtcars, times = 100)
boots
## # Bootstrap sampling
## # A tibble: 100 x 2
##   splits      id
##   <list>      <chr>
## 1 <S3: rsplit> Bootstrap001
## 2 <S3: rsplit> Bootstrap002
## 3 <S3: rsplit> Bootstrap003
## # ... with 97 more rows
```

Bootstrapping

```
fit_nls_on_bootstrap <- function(split) {  
  nls(  
    mpg ~ k / wt + b,  
    analysis(split),  
    start = list(k = 1, b = 0)  
  )  
}
```

Bootstrapping

```
boot_models <- boots %>%  
  mutate(model = map(splits, fit_nls_on_bootstrap),  
         coef_info = map(model, tidy))
```

```
boot_models  
## # Bootstrap sampling  
## # A tibble: 100 x 4  
##   splits      id      model      coef_info  
## * <list>      <chr>    <list>    <list>  
## 1 <S3: rsplit> Bootstrap001 <S3: nls> <tibble [2 x 5]>  
## 2 <S3: rsplit> Bootstrap002 <S3: nls> <tibble [2 x 5]>  
## 3 <S3: rsplit> Bootstrap003 <S3: nls> <tibble [2 x 5]>  
## # ... with 97 more rows
```

Bootstrapping

```
boot_coefs <- boot_models %>%  
  unnest(coef_info)
```

```
boot_coefs
```

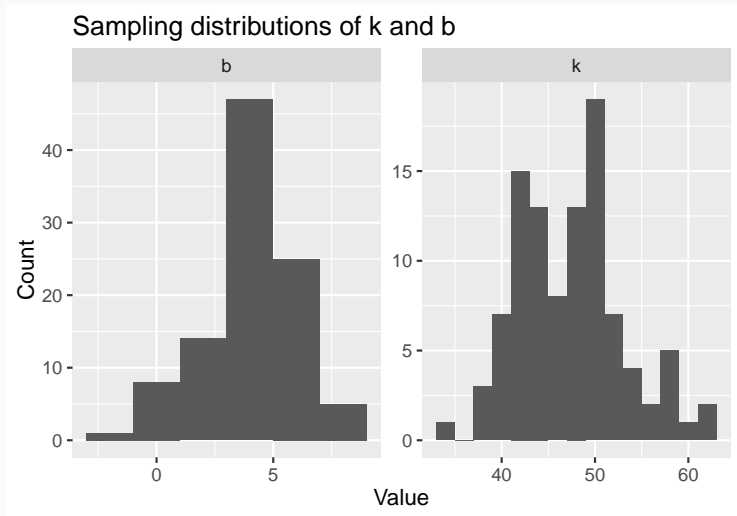
```
## # A tibble: 200 x 6
```

```
##   id          term estimate std.error statistic  p.value  
##   <chr>        <chr>   <dbl>    <dbl>    <dbl>    <dbl>  
## 1 Bootstrap001 k      41.8     4.05     10.3  2.18e-11  
## 2 Bootstrap001 b       5.96     1.64      3.64  1.01e- 3  
## 3 Bootstrap002 k      50.6     3.96     12.8  1.16e-13  
## # ... with 197 more rows
```

Bootstrapping

```
p <- ggplot(boot_coefs, aes(estimate)) +  
  geom_histogram(binwidth = 2) +  
  facet_wrap(~ term, scales = "free") +  
  labs(  
    title = "Sampling distributions of k and b",  
    y = "Count",  
    x = "Value"  
  )
```

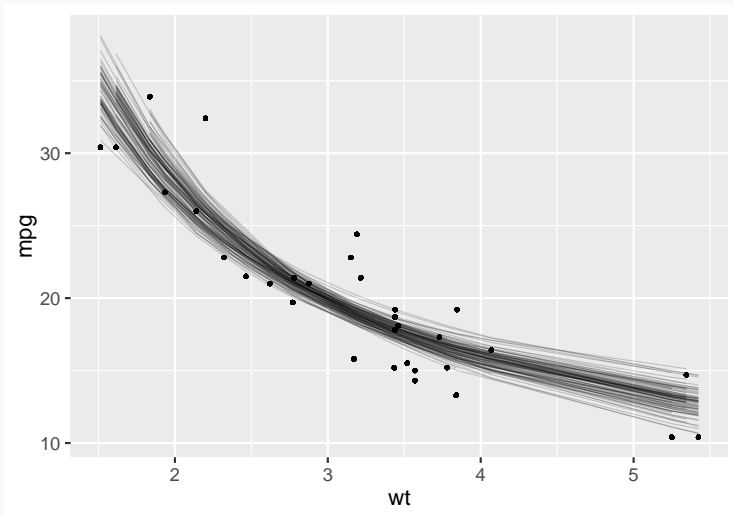
Bootstrapping



Bootstrapping

```
boot_aug <- boot_models %>%  
  mutate(augmented = map(model, augment)) %>%  
  unnest(augmented)  
  
p <- ggplot(boot_aug, aes(wt, mpg)) +  
  geom_point() +  
  geom_line(aes(y = .fitted, group = id), alpha = 0.2)
```

Bootstrapping



General strategy

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1. Put fits in a list, or a list-column of a tibble

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General strategy

`broom` provides tidying methods for 100+ classes!

1. Put fits in a list, or a list-column of a tibble
2. Use `purrr::map()` to apply `tidy()`, `glance()` or `augment()` to each fit
3. Use tidyverse tools to manipulate and visualize resulting data!

Questions?

Read about the recent broom release on the [tidyverse blog](https://broom.tidyverse.org).



<https://broom.tidyverse.org>



<https://github.com/tidymodels/broom/>



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<https://github.com/tidymodels/tidymodels>

A general attempt to make modeling in R more consistent and tidy. Lots of [big projects](#). Highlights:

- [best practices for developing modeling packages](#)
- [parsnip](#): standardized modeling interfaces (in progress)
- [recipes](#): data pre-processing
- [rsample](#): infrastructure for resampling