Making predictions

INTRODUCTION TO REGRESSION IN R

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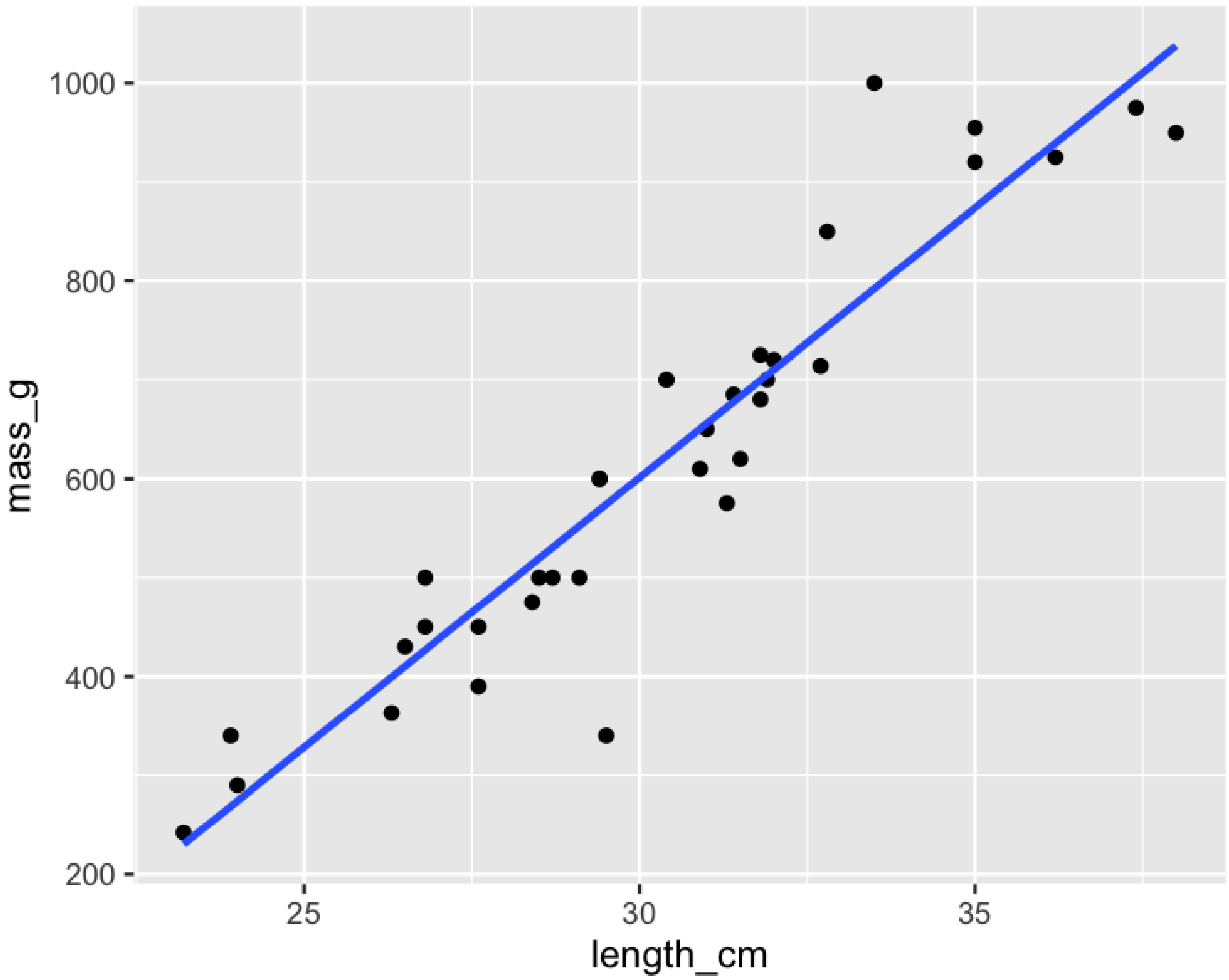
The fish dataset: bream

```r
bream <- fish %>%
  filter(species == "Bream")
```

species	length_cm	mass_g
Bream	23.2	242
Bream	24.0	290
Bream	23.9	340
Bream	26.3	363
Bream	26.5	430
...	...	...

Plotting mass vs. length

```
ggplot(bream, aes(length_cm, mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```



Running the model

```
mdl_mass_vs_length <- lm(mass_g ~ length_cm, data = bream)
```

```
Call:
lm(formula = mass_g ~ length_cm, data = bream)

Coefficients:
(Intercept)    length_cm
   -1035.35        54.55
```

Data on explanatory values to predict

> If I set the explanatory variables to these values,
> what value would the response variable have?

```
library(dplyr)
explanatory_data <- tibble(length_cm = 20:40)
```

Call predict()

```r
library(tibble)
explanatory_data <- tibble(length_cm = 20:40)
```

```r
predict(mdl_mass_vs_length, explanatory_data)
```

```
         1          2          3          4          5          6 
  55.65205  110.20203  164.75202  219.30200  273.85198  328.40196 
         7          8          9         10         11         12 
 382.95194  437.50192  492.05190  546.60188  601.15186  655.70184 
        13         14         15         16         17         18 
 710.25182  764.80181  819.35179  873.90177  928.45175  983.00173 
        19         20         21 
1037.55171 1092.10169 1146.65167 
```

Predicting inside a data frame

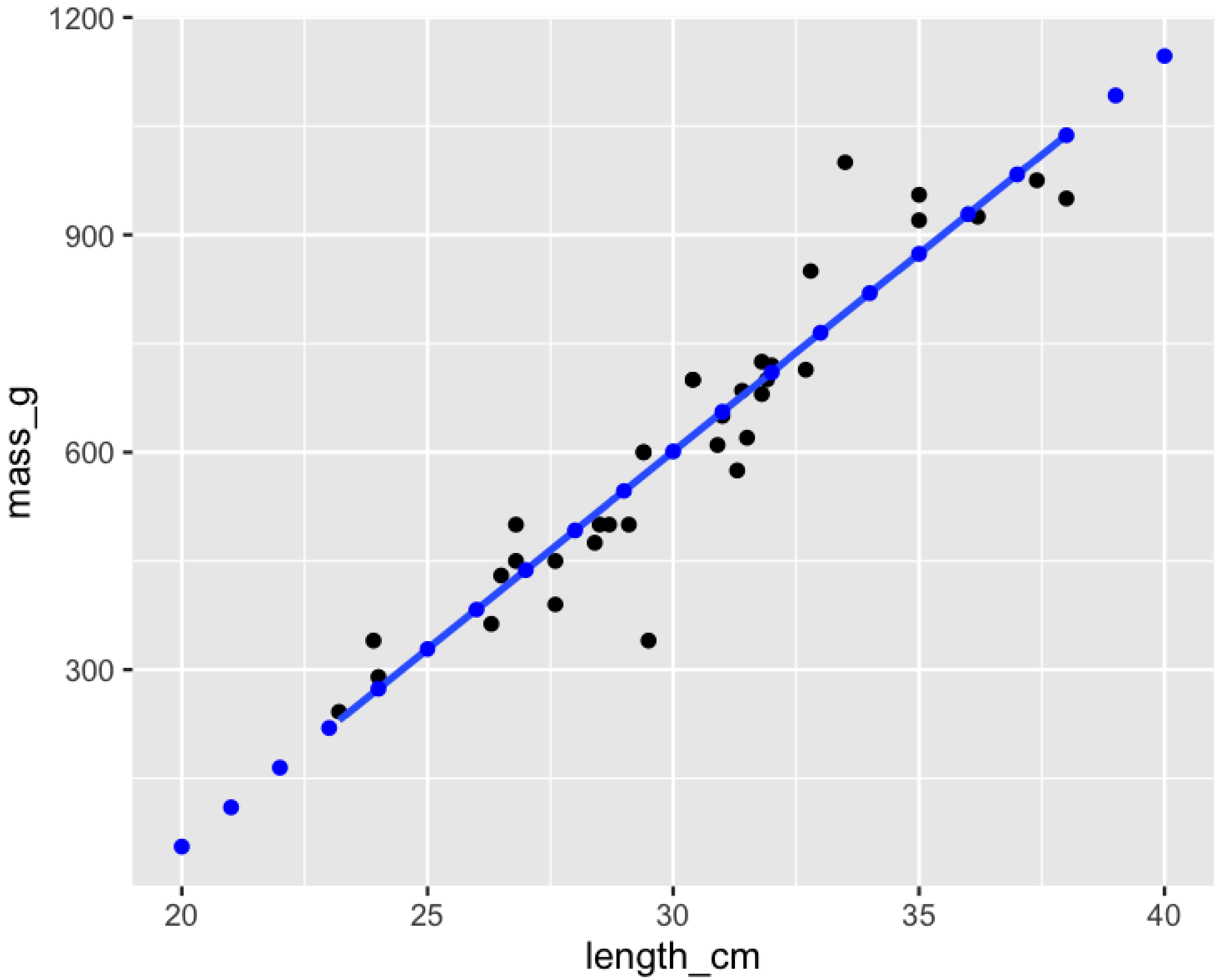
```r
library(dplyr)
explanatory_data <- tibble(length_cm = 20:40)
```

```r
prediction_data <- explanatory_data %>%
  mutate(
    mass_g = predict(
      mdl_mass_vs_length, explanatory_data
    )
  )
```

```
# A tibble: 21 x 2
   length_cm mass_g
       <int>  <dbl>
 1        20   55.7
 2        21  110.
 3        22  165.
 4        23  219.
 5        24  274.
 6        25  328.
 7        26  383.
 8        27  438.
 9        28  492.
10        29  547.
# ... with 11 more rows
```

Showing predictions

```r
ggplot(bream, aes(length_cm, mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  geom_point(
    data = prediction_data,
    color = "blue"
  )
```

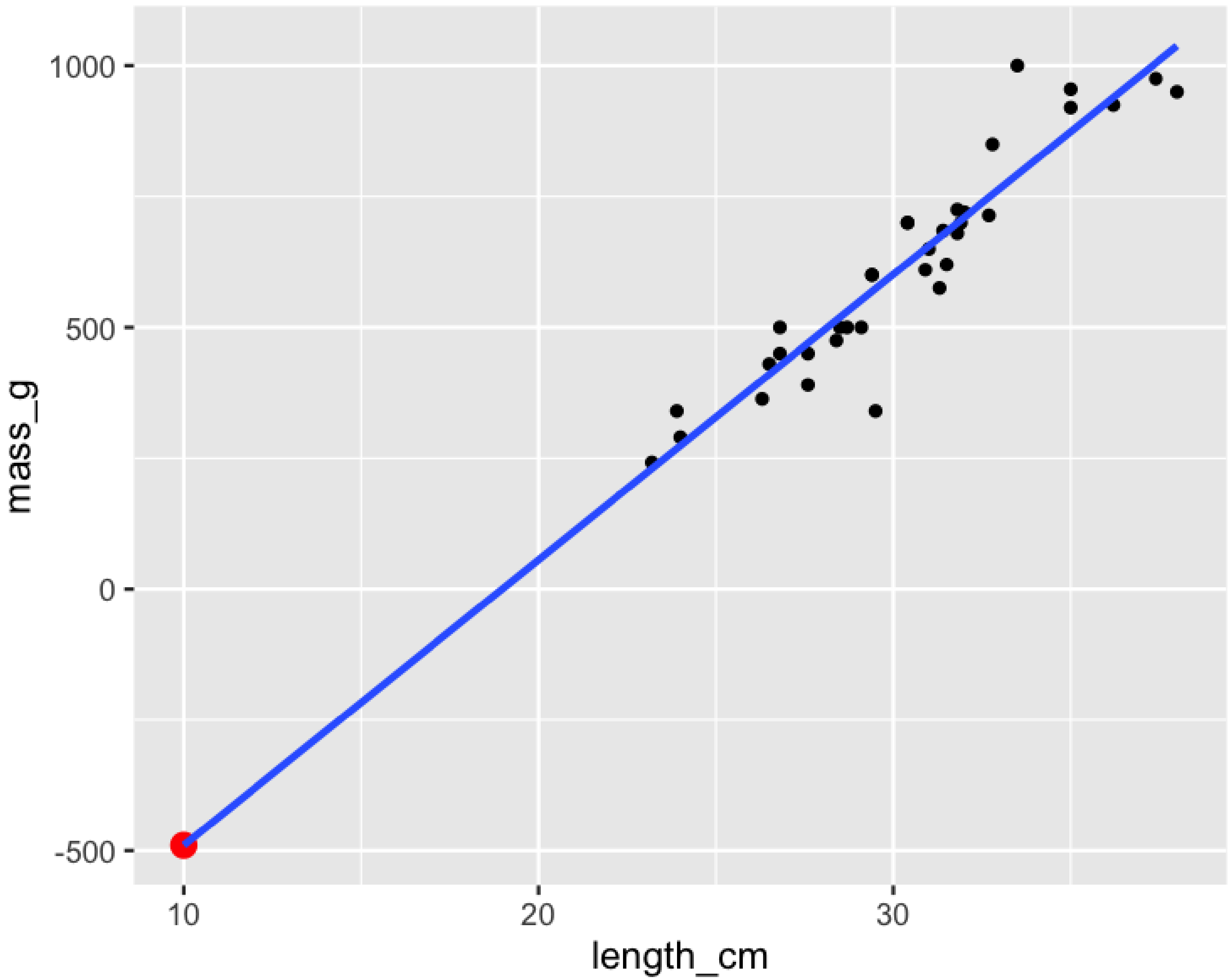


Extrapolating

Extrapolating means making predictions outside the range of observed data.

```
explanatory_little_bream <- tibble(length_cm = 10)
explanatory_little_bream %>%
  mutate(
    mass_g = predict(
      mdl_mass_vs_length, explanatory_little_bream
    )
  )
```

```
# A tibble: 1 x 2
  length_cm mass_g
      <dbl>  <dbl>
1        10  -490.
```



Let's practice!

INTRODUCTION TO REGRESSION IN R

Working with model objects

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coefficients()

```
mdl_mass_vs_length <- lm(mass_g ~ length_cm, data = bream)
```

```
Call:
lm(formula = mass_g ~ length_cm, data = bream)

Coefficients:
(Intercept)    length_cm
   -1035.35        54.55
```

```
coefficients(mdl_mass_vs_length)
```

```
(Intercept)   length_cm
-1035.34757    54.54998
```

fitted()

fitted values: predictions on the original dataset

```
fitted(mdl_mass_vs_length)
```

or equivalently

```
explanatory_data <- bream %>%
  select(length_cm)

predict(mdl_mass_vs_length, explanatory_data)
```

```
        1         2         3         4         5 
 230.2120  273.8520  268.3970  399.3169  410.2269 
        6         7         8         9        10 
 426.5919  426.5919  470.2319  470.2319  519.3269 
       11        12        13        14        15 
 513.8719  530.2369  552.0569  573.8769  568.4219 
       16        17        18        19        20 
 568.4219  622.9719  622.9719  650.2468  655.7018 
       21        22        23        24        25 
 672.0668  677.5218  682.9768  699.3418  704.7968 
       26        27        28        29        30 
 699.3418  710.2518  748.4368  753.8918  792.0768 
       31        32        33        34        35 
 873.9018  873.9018  939.3617 1004.8217 1037.5517 
```

residuals()

Residuals: actual response values minus predicted response values

```
residuals(mdl_mass_vs_length)
```

or equivalently

```
bream$mass_g - fitted(mdl_mass_vs_length)
```

```
       1        2        3        4        5
  11.788   16.148   71.603  -36.317   19.773
       6        7        8        9       10
  23.408   73.408  -80.232  -20.232  -19.327
      11       12       13       14       15
 -38.872  -30.237  -52.057 -233.877   31.578
      16       17       18       19       20
  31.578   77.028   77.028  -40.247   -5.702
      21       22       23       24       25
 -97.067    7.478  -62.977  -19.342   -4.797
      26       27       28       29       30
  25.658    9.748  -34.437   96.108  207.923
      31       32       33       34       35
  46.098   81.098  -14.362  -29.822  -87.552
```

summary()

```
summary(mdl_mass_vs_length)
```

```
Call:
lm(formula = mass_g ~ length_cm, data = bream)

Residuals:
   Min     1Q Median     3Q    Max
-233.9  -35.4   -4.8   31.6  207.9

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1035.35     107.97   -9.59  4.6e-11 ***
length_cm      54.55       3.54   15.42  < 2e-16 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 74.2 on 33 degrees of freedom
Multiple R-squared:  0.878,    Adjusted R-squared:  0.874
F-statistic:  238 on 1 and 33 DF,  p-value: <2e-16
```

summary(): call

```
Call:
lm(formula = mass_g ~ length_cm, data = bream)
```

summary(): residuals

```
Residuals:
   Min     1Q Median     3Q    Max 
-233.9  -35.4   -4.8   31.6  207.9 
```

summary(): coefficients

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1035.35     107.97   -9.59  4.6e-11 ***
length_cm      54.55       3.54   15.42  < 2e-16 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

summary(): model metrics

```
Residual standard error: 74.2 on 33 degrees of freedom
Multiple R-squared:  0.878,    Adjusted R-squared:  0.874
F-statistic:  238 on 1 and 33 DF,  p-value: <2e-16
```

tidy()

```r
library(broom)

tidy(mdl_mass_vs_length)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)  -1035.     108.       -9.59 4.58e-11
2 length_cm       54.5      3.54     15.4  1.22e-16
```

augment()

```
augment(mdl_mass_vs_length)
```

```
# A tibble: 35 x 9
   mass_g length_cm .fitted .se.fit .resid   .hat .sigma .cooksd .std.resid
    <dbl>     <dbl>   <dbl>   <dbl>  <dbl>  <dbl>  <dbl>   <dbl>      <dbl>
 1    242      23.2    230.    28.1   11.8 0.144    75.3 0.00247      0.172
 2    290      24      274.    25.6   16.1 0.119    75.2 0.00364      0.232
 3    340      23.9    268.    25.9   71.6 0.122    74.1 0.0738       1.03
 4    363      26.3    399.    18.9  -36.3 0.0651   75.0 0.00894     -0.507
 5    430      26.5    410.    18.4   19.8 0.0616   75.2 0.00248      0.275
 6    450      26.8    427.    17.6   23.4 0.0566   75.2 0.00317      0.325
 7    500      26.8    427.    17.6   73.4 0.0566   74.1 0.0311       1.02
 8    390      27.6    470.    15.8  -80.2 0.0452   73.9 0.0291      -1.11
 9    450      27.6    470.    15.8  -20.2 0.0452   75.2 0.00185     -0.279
10    500      28.5    519.    14.1  -19.3 0.0360   75.2 0.00132     -0.265
# ... with 25 more rows
```

glance()

```
glance(mdl_mass_vs_length)
```

```
# 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     0.878         0.874  74.2      238. 1.22e-16     2  -199.  405.  409.  181452.          33
```

Let's practice!

INTRODUCTION TO REGRESSION IN R

Regression to the mean

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The concept

- Response value = fitted value + residual
- "The stuff you explained" + "the stuff you couldn't explain"
- Residuals exist due to problems in the model *and* fundamental randomness
- Extreme cases are often due to randomness
- *Regression to the mean* means extreme cases don't persist over time

Pearson's father son dataset

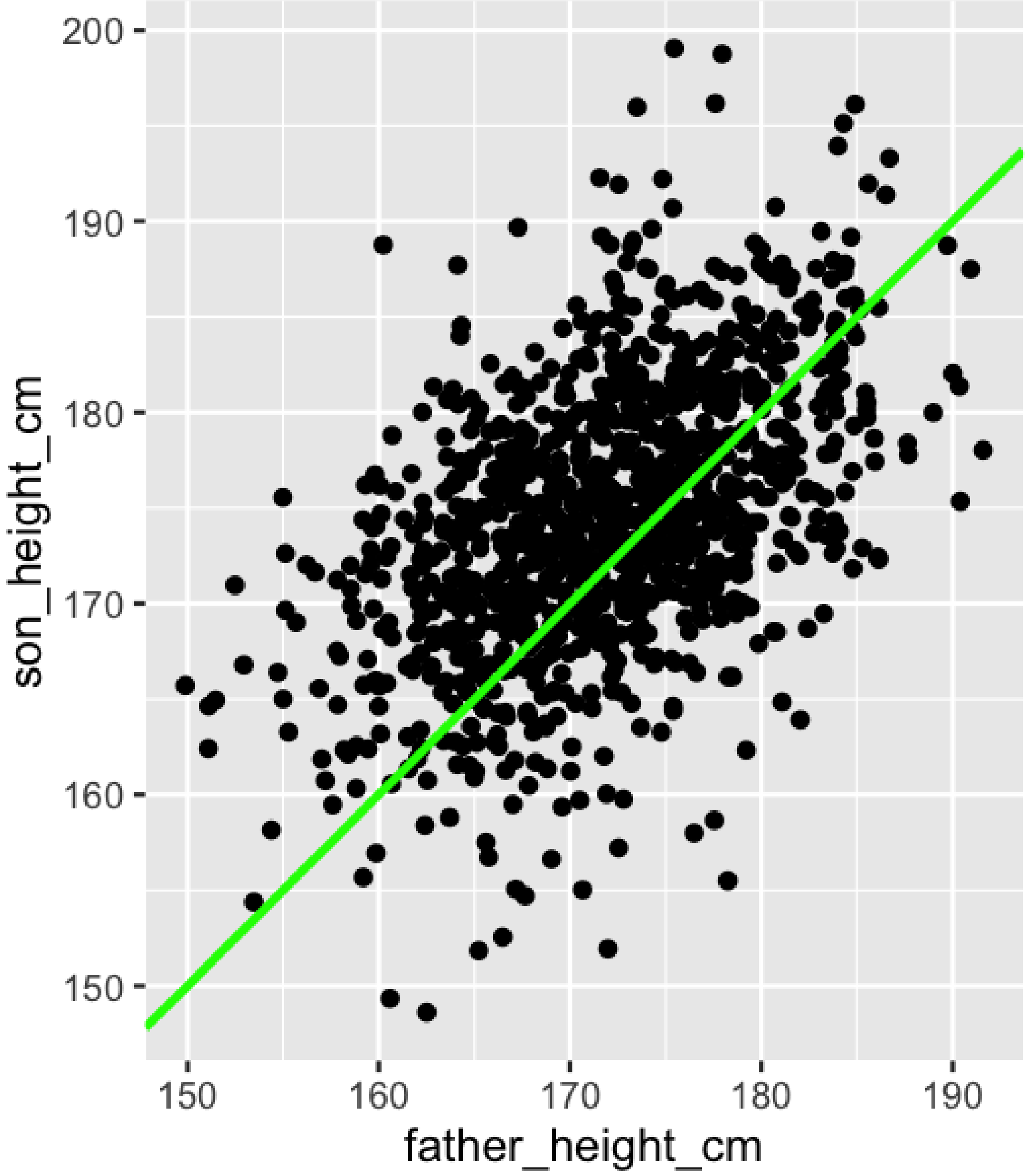
- 1078 father/son pairs
- Do tall fathers have tall sons?

father_height_cm	son_height_cm
165.2	151.8
160.7	160.6
165.0	160.9
167.0	159.5
155.3	163.3
...	...

[1] Adapted from https://www.rdocumentation.org/packages/UsingR/topics/father.son

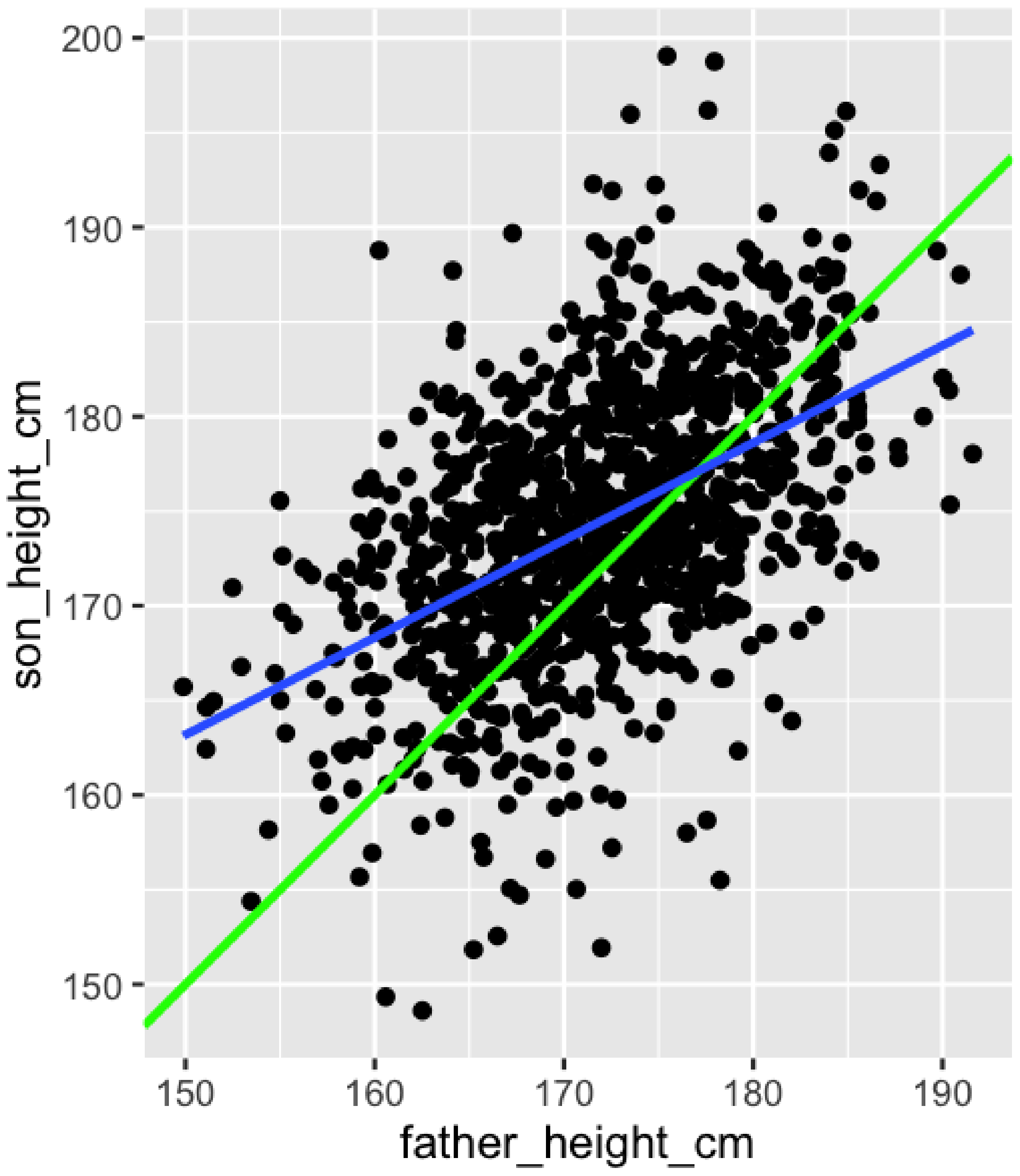
Scatter plot

```r
plt_son_vs_father <- ggplot(
  father_son,
  aes(father_height_cm, son_height_cm)
) +
  geom_point() +
  geom_abline(color = "green", size = 1) +
  coord_fixed()
```



Adding a regression line

```
plt_son_vs_father +
  geom_smooth(method = "lm", se = FALSE)
```



Running a regression

```
mdl_son_vs_father <- lm(
  son_height_cm ~ father_height_cm,
  data = father_son
)
```

```
Call:
lm(formula = son_height_cm ~ father_height_cm, data = father_son)

Coefficients:
     (Intercept)  father_height_cm
          86.072             0.514
```

Making predictions

```r
really_tall_father <- tibble(
  father_height_cm = 190
)
predict(mdl_son_vs_father, really_tall_father)
```

```
183.7
```

```r
really_short_father <- tibble(
  father_height_cm = 150
)
predict(mdl_son_vs_father, really_short_father)
```

```
163.2
```

Let's practice!

INTRODUCTION TO REGRESSION IN R

Transforming variables

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Perch dataset

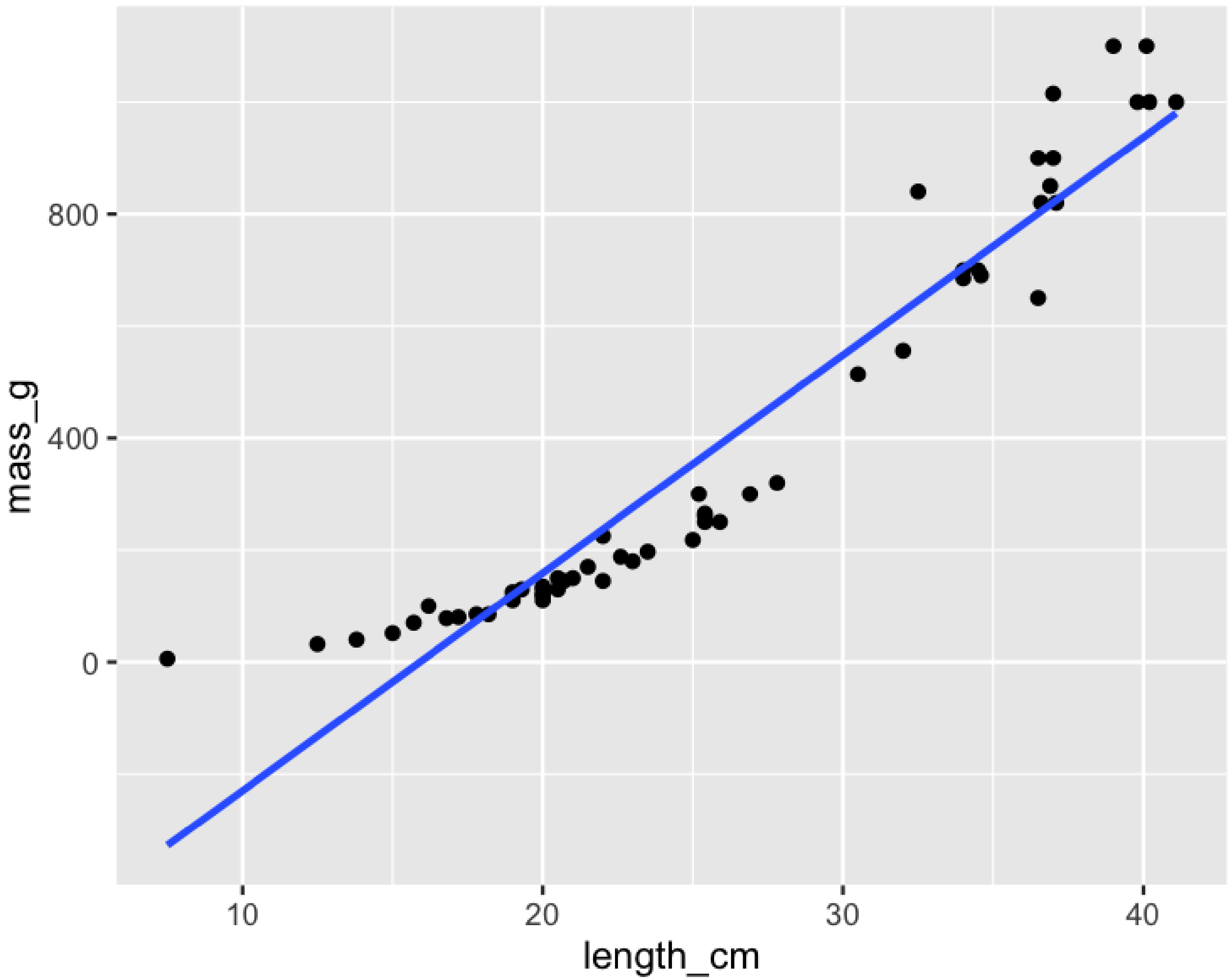
```
library(dplyr)

perch <- fish %>%
  filter(species == "Perch")
```

species	mass_g	length_cm
Perch	5.9	7.5
Perch	32.0	12.5
Perch	40.0	13.8
Perch	51.5	15.0
Perch	70.0	15.7
...	...	...

It's not a linear relationship

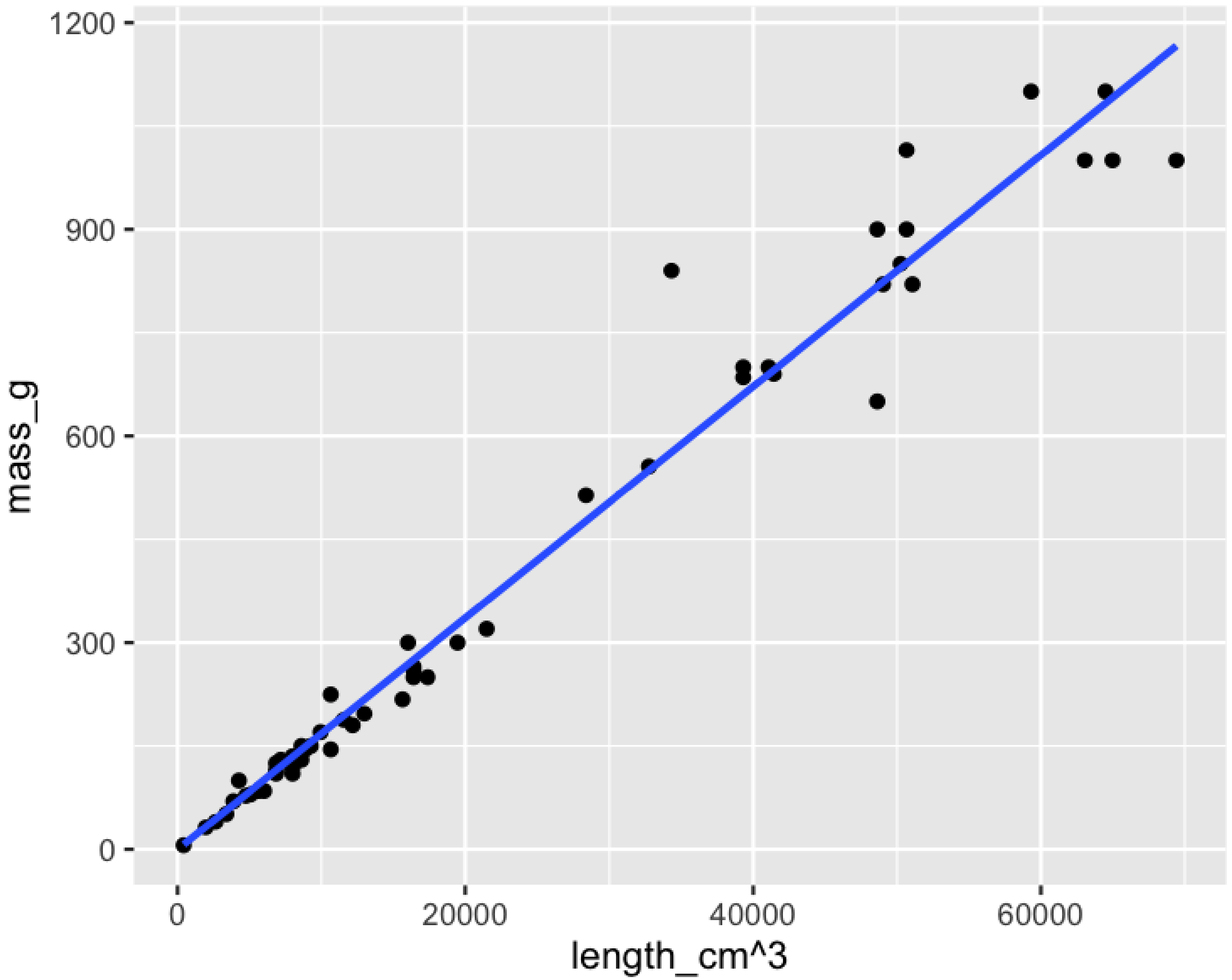
```
ggplot(perch, aes(length_cm, mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```



Bream vs. perch

Plotting mass vs. length cubed

```
ggplot(perch, aes(length_cm ^ 3, mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```



Modeling mass vs. length cubed

```r
mdl_perch <- lm(mass_g ~ I(length_cm ^ 3), data = perch)
```

```
Call:
lm(formula = mass_g ~ I(length_cm^3), data = perch)

Coefficients:
   (Intercept)  I(length_cm^3)
       -0.1175          0.0168
```

Predicting mass vs. length cubed

```
explanatory_data <- tibble(
  length_cm = seq(10, 40, 5)
)
```

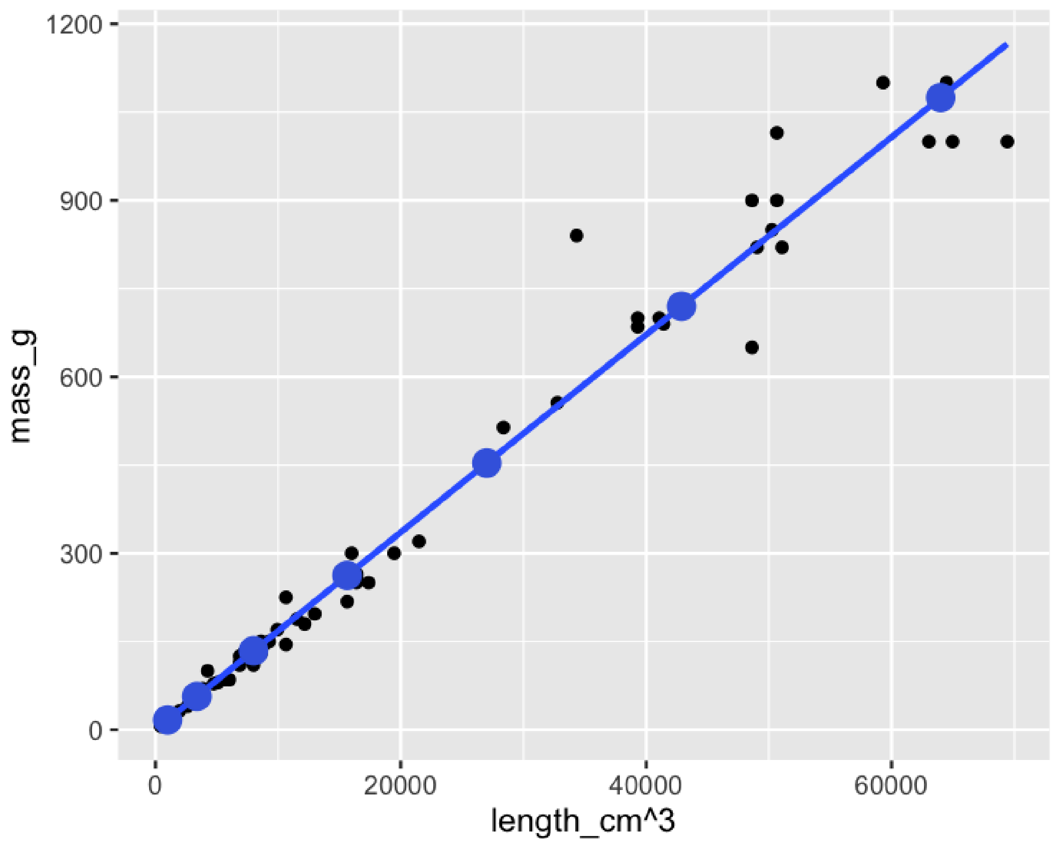
```
prediction_data <- explanatory_data %>%
  mutate(
    mass_g = predict(mdl_perch, explanatory_data)
  )
```

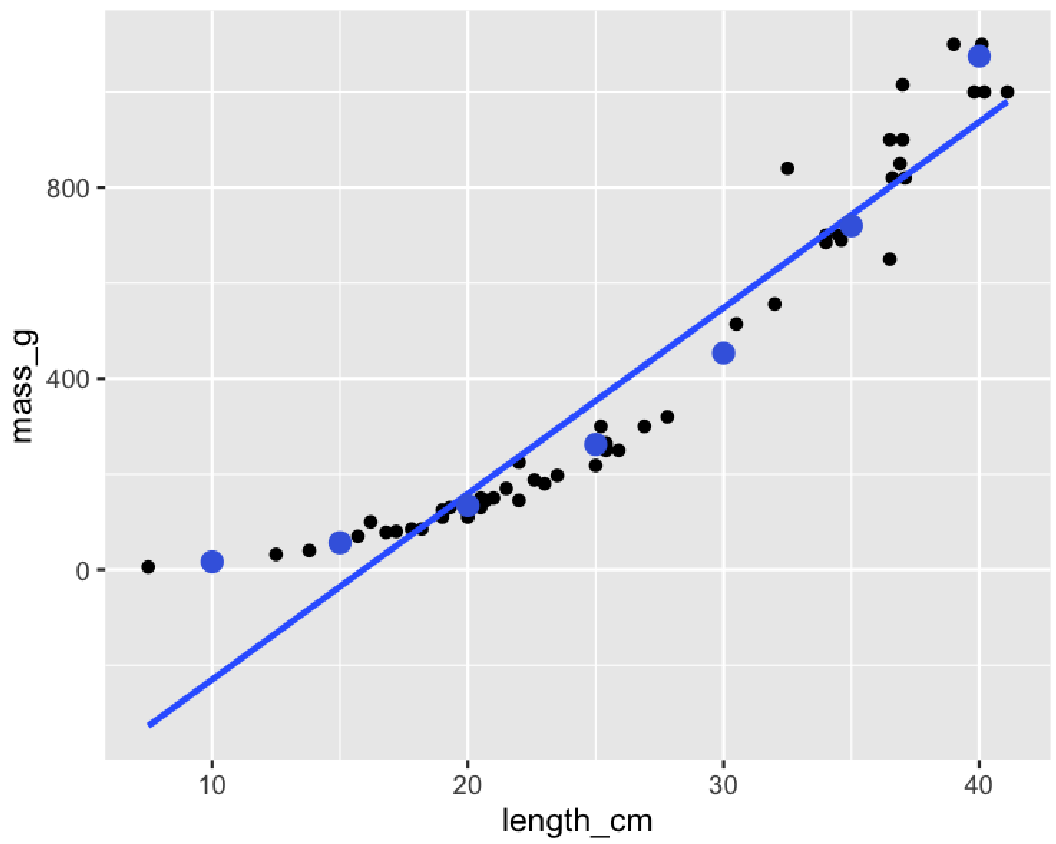
```
# A tibble: 7 x 2
  length_cm mass_g
      <dbl>  <dbl>
1        10   16.7
2        15   56.6
3        20  134.
4        25  262.
5        30  453.
6        35  720.
7        40 1075.
```

Plotting mass vs. length cubed

```
ggplot(perch, aes(length_cm ^ 3, mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  geom_point(data = prediction_data, color = "blue")
```

```
ggplot(perch, aes(length_cm, mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  geom_point(data = prediction_data, color = "blue")
```





Facebook advertising dataset

How advertising works

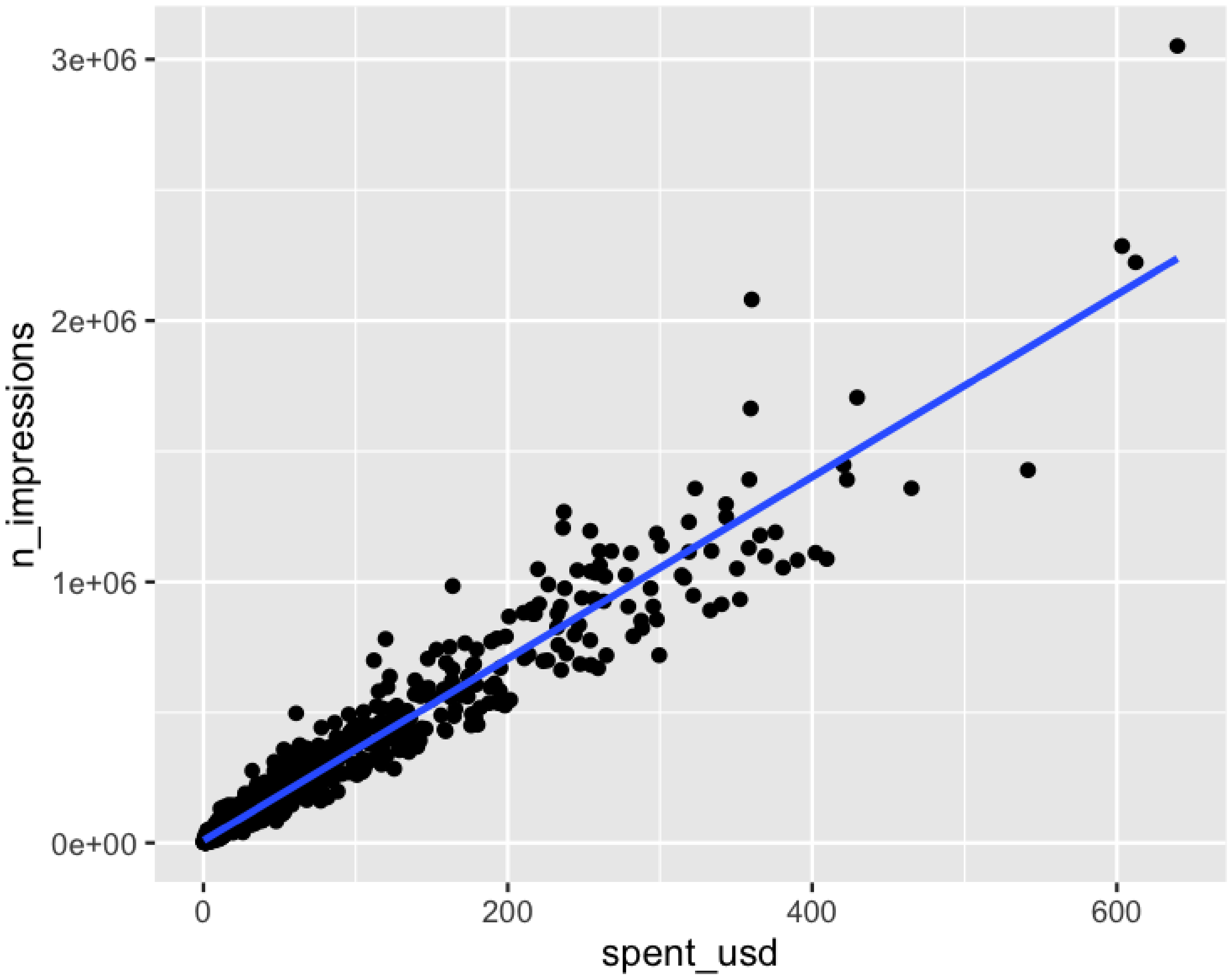
1. Pay Facebook to shows ads.
2. People see the ads ("impressions").
3. Some people who see it, click it.

- 936 rows
- Each row represents 1 advert

spent_usd	n_impressions	n_clicks
1.43	7350	1
1.82	17861	2
1.25	4259	1
1.29	4133	1
4.77	15615	3
...	...	...

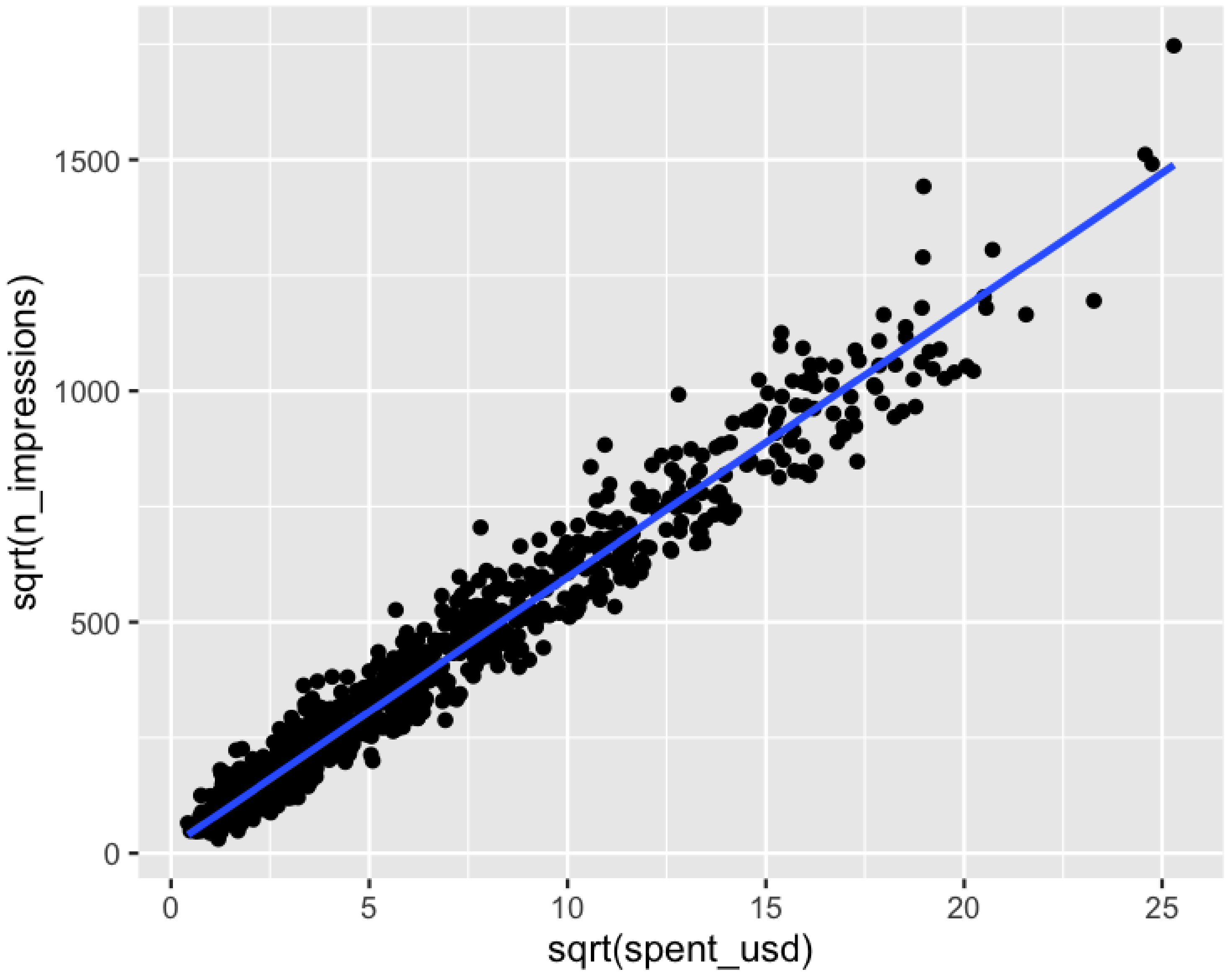
Plot is cramped

```r
ggplot(
  ad_conversion,
  aes(spent_usd, n_impressions)
) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```



Square root vs square root

```
ggplot(
  ad_conversion,
  aes(sqrt(spent_usd), sqrt(n_impressions))
) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```



Modeling and predicting

```r
mdl_ad <- lm(
  sqrt(n_impressions) ~ sqrt(spent_usd),
  data = ad_conversion
)
```

```r
explanatory_data <- tibble(
  spent_usd = seq(0, 600, 100)
)
```

```r
prediction_data <- explanatory_data %>%
  mutate(
    sqrt_n_impressions = predict(
      mdl_ad, explanatory_data
    ),
    n_impressions = sqrt_n_impressions ^ 2
  )
```

```
# A tibble: 7 x 3
  spent_usd sqrt_n_impressions n_impressions
      <dbl>              <dbl>         <dbl>
1         0               15.3          235.
2       100              598.        357289.
3       200              839.        703890.
4       300             1024.       1048771.
5       400             1180.       1392762.
6       500             1318.       1736184.
7       600             1442.       2079202.
```

Let's practice!

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