Making predictions

INTRODUCTION TO REGRESSION IN R

Richie Cotton
Data Evangelist at DataCamp

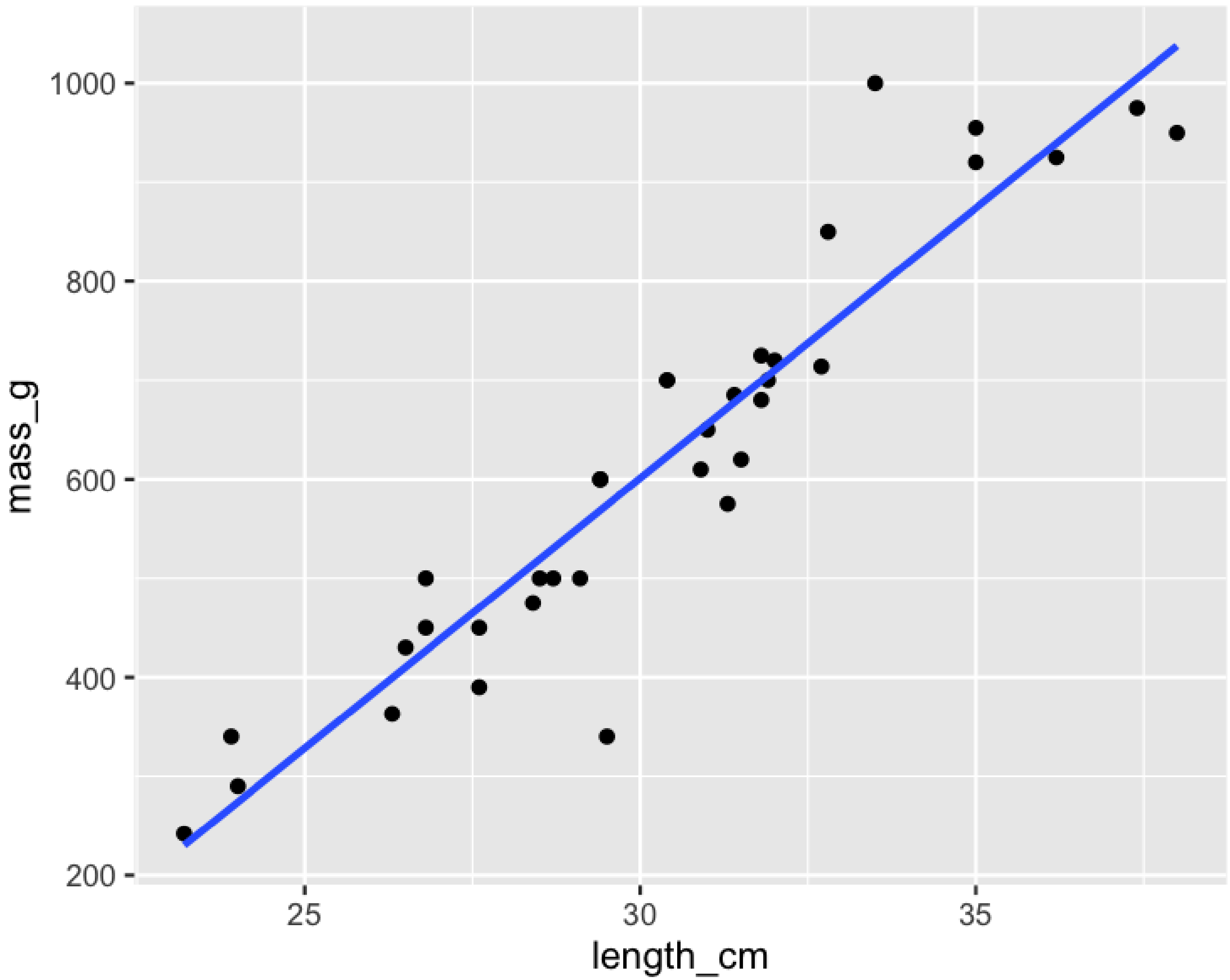
The fish dataset: bream

```
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

```r
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()

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

```
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

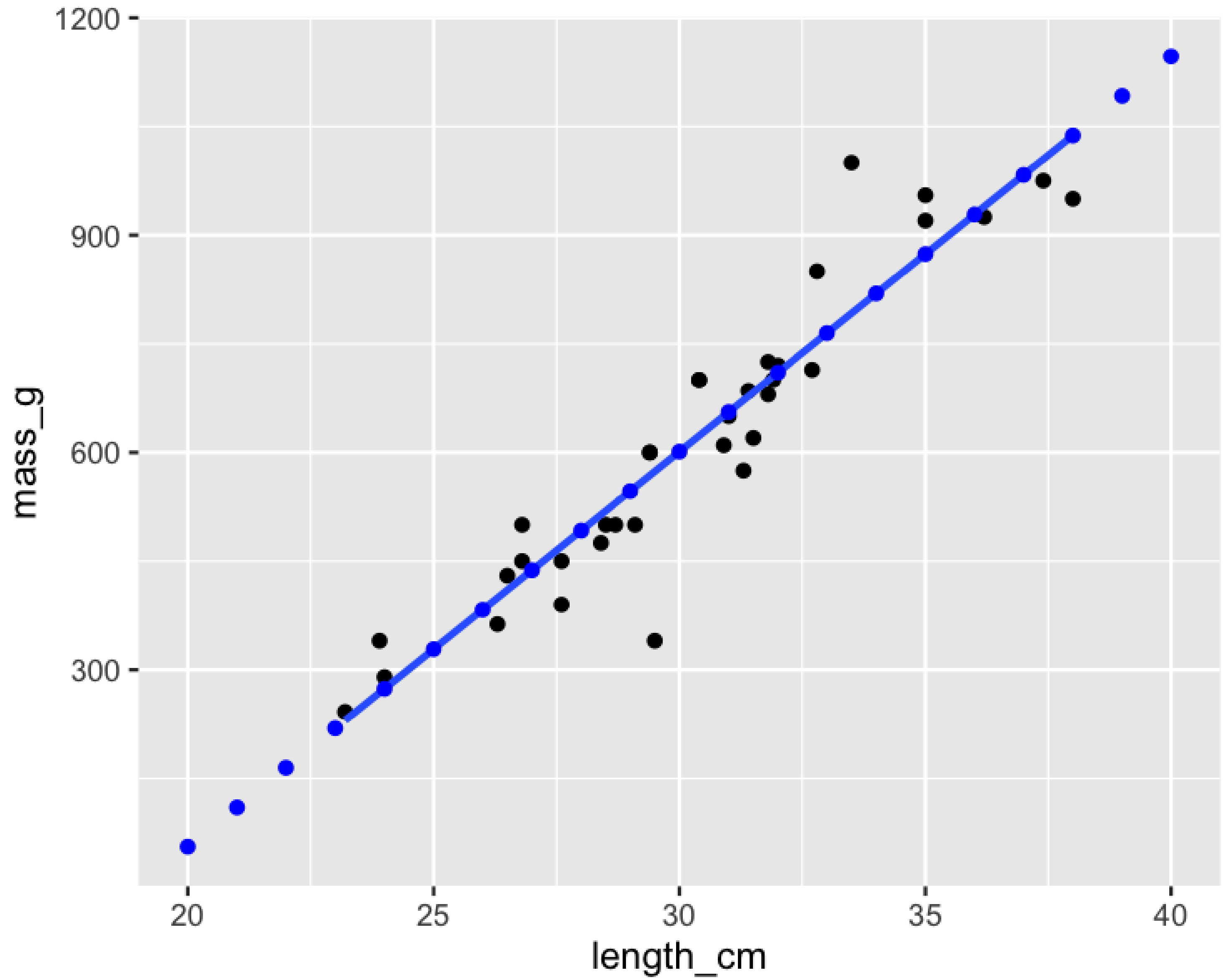
```
library(dplyr)
explanatory_data <- tibble(length_cm = 20:40)
```

```
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

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

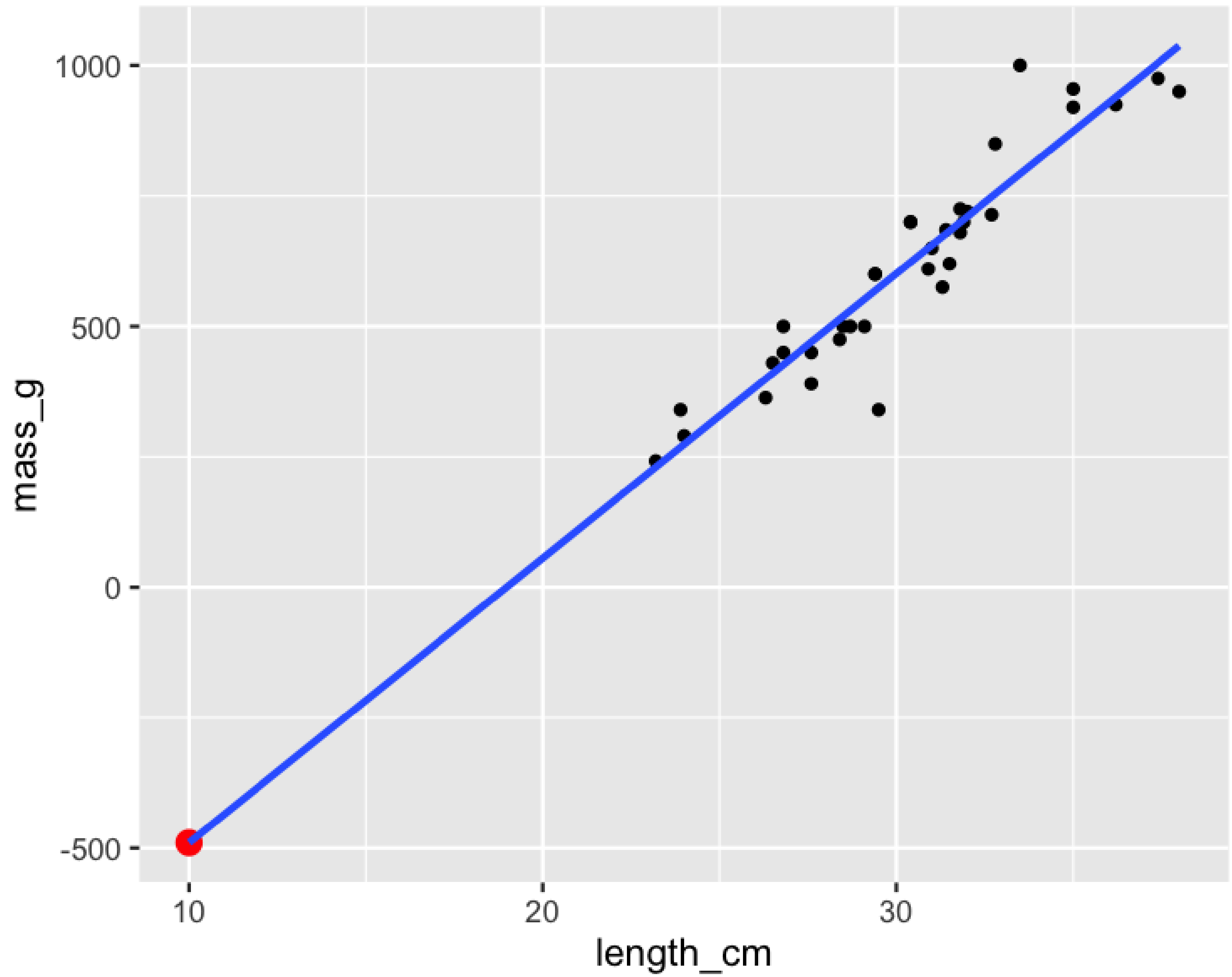


Extrapolating

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!

Working with model objects

INTRODUCTION TO REGRESSION IN R

Richie Cotton
Data Evangelist at DataCamp

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()

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

glance()

```
glance(mdl_mass_vs_length)
```

```
# A tibble: 1 × 12
  r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
      <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
1     0.878         0.874  74.2      238. 1.22e-16     1  -199.  405.  409.
# ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Let's practice!

Regression to the mean

INTRODUCTION TO REGRESSION IN R

Richie Cotton
Data Evangelist

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

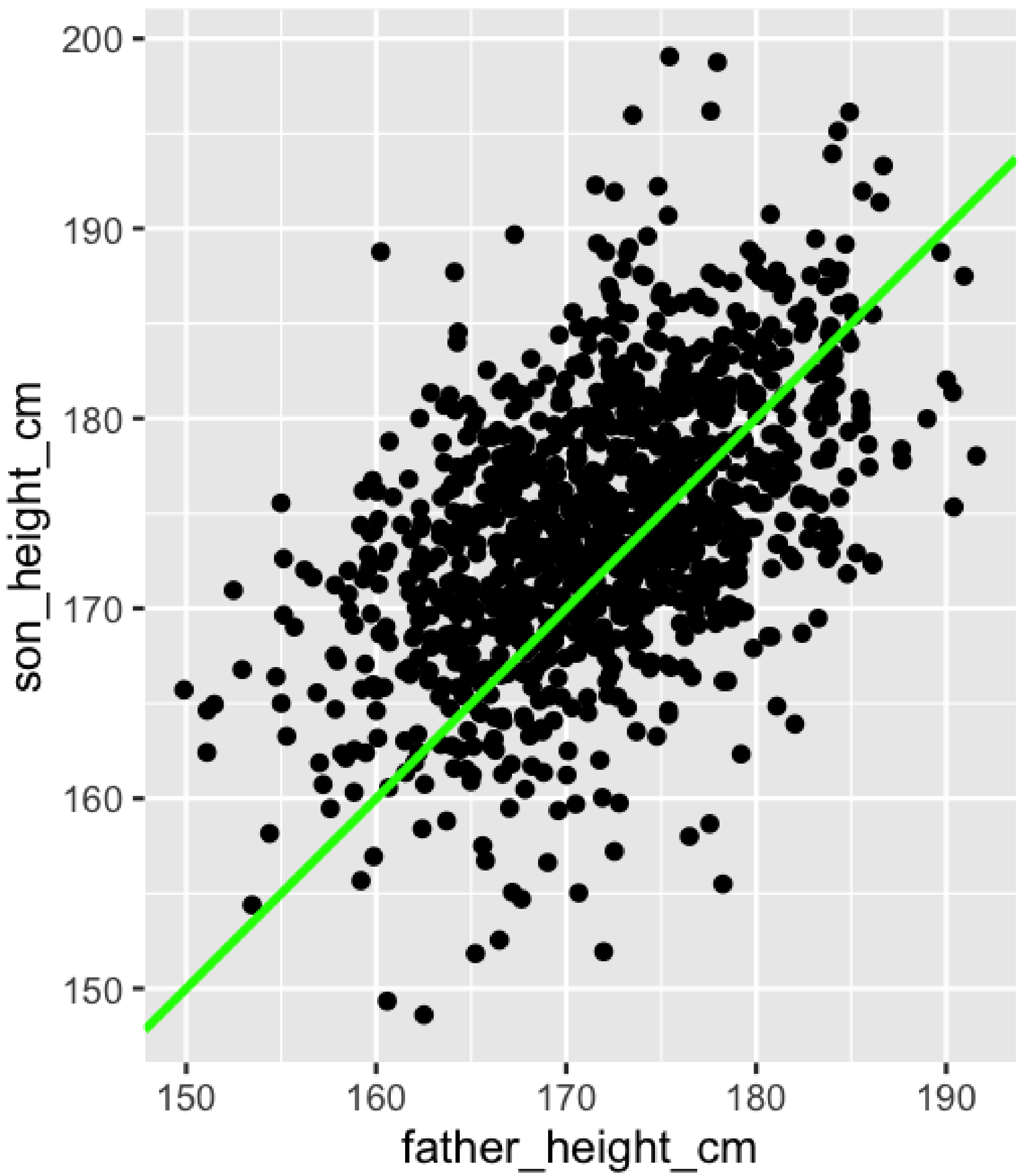
- 1078 father/son pairs
- Do tall fathers have tall sons?

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

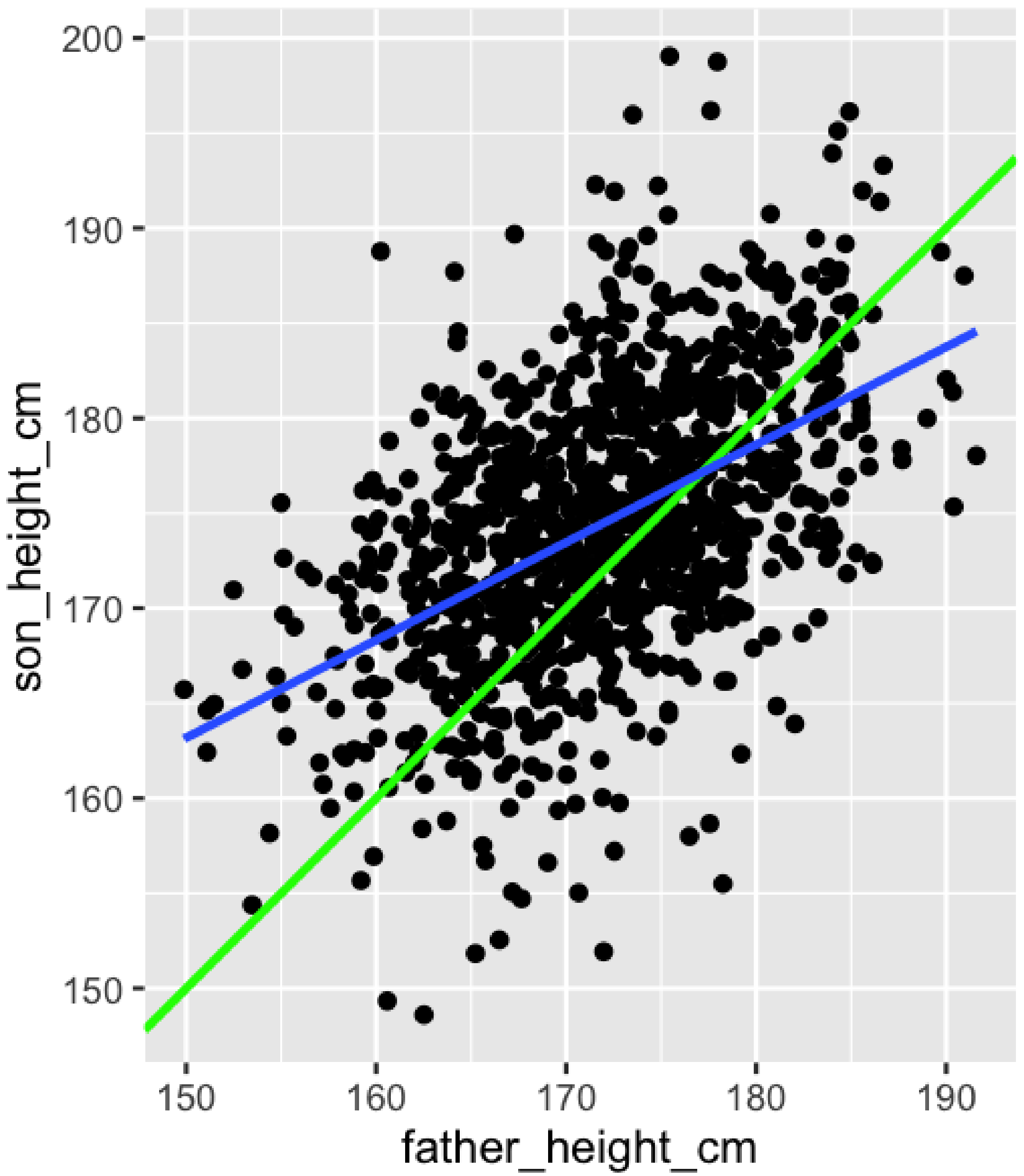
Scatter plot

```
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

```r
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

INTRODUCTION TO REGRESSION IN R

Richie Cotton
Data Evangelist at DataCamp

Perch dataset

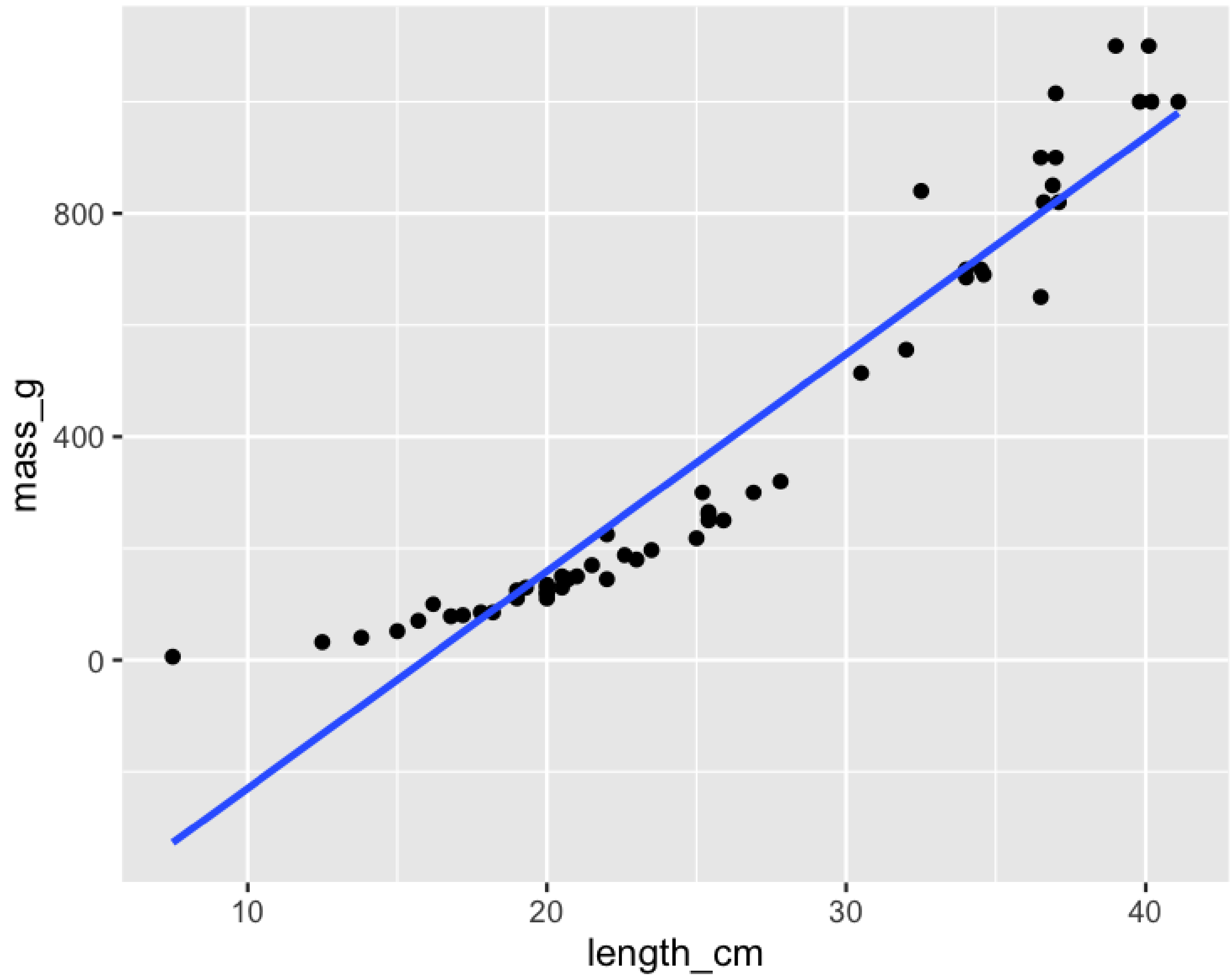
```
library(dplyr)

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

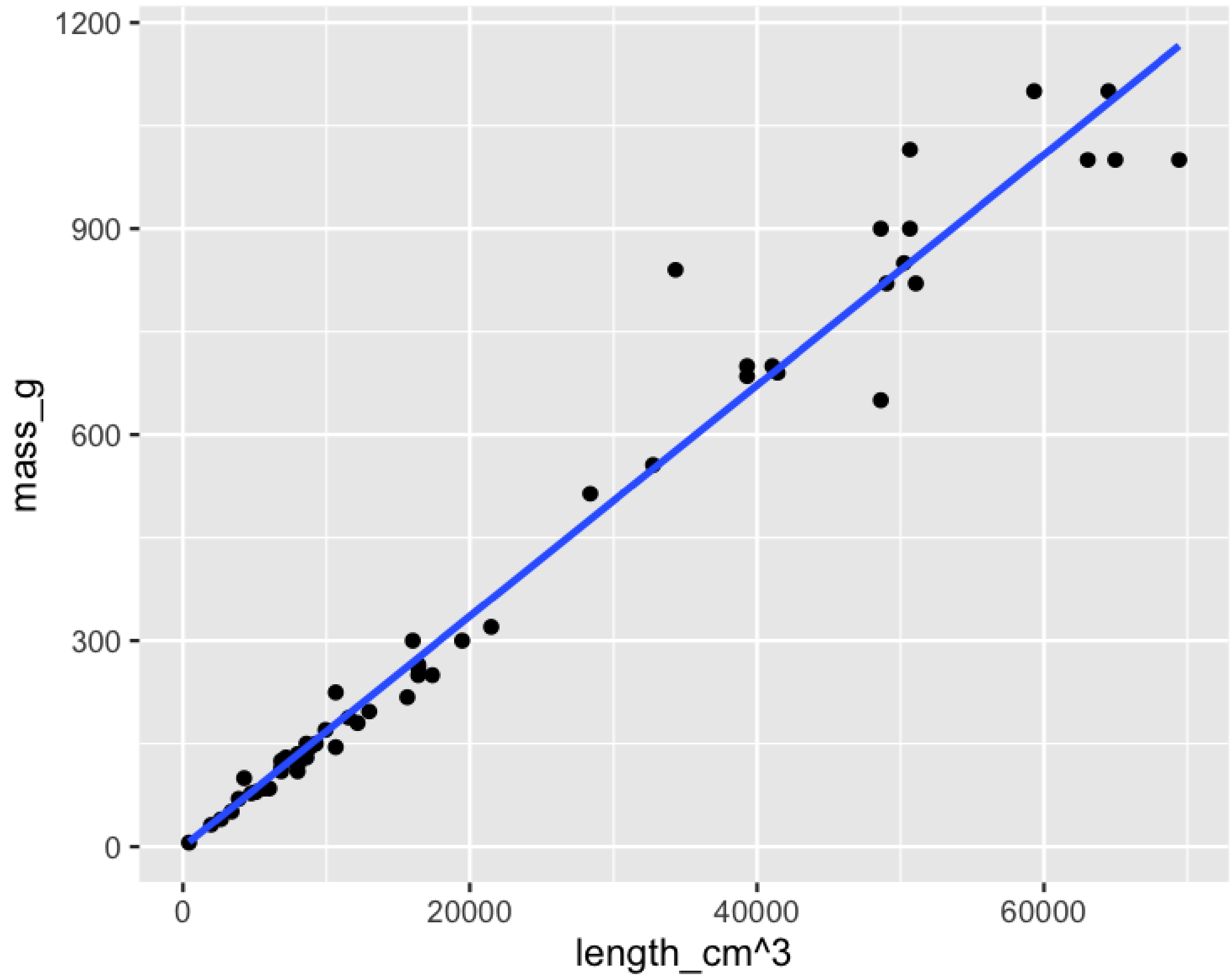
```
ggplot(perch, aes(length_cm, mass_g)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```



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

```
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)
)
```

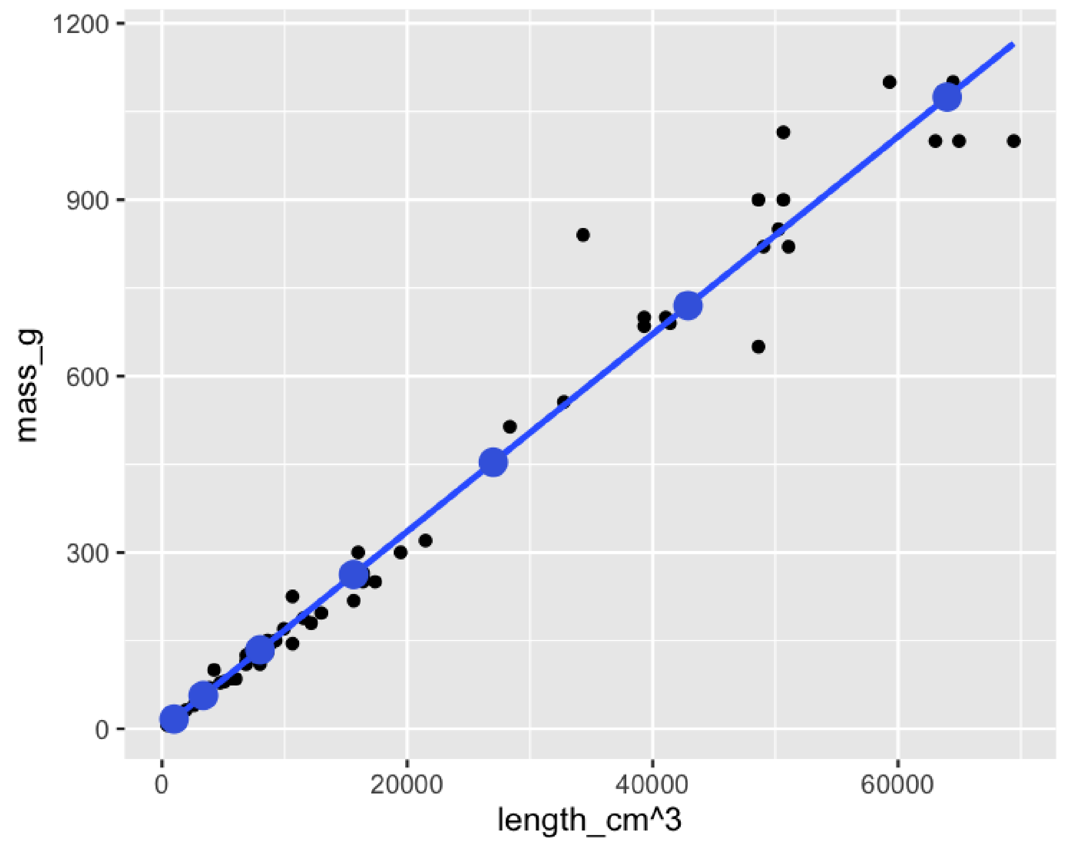
```
prediction_data <- explanatory_data %>%
  mutate(
    mass_g = predict(mdl_perch, explanatory_data)
  )
```

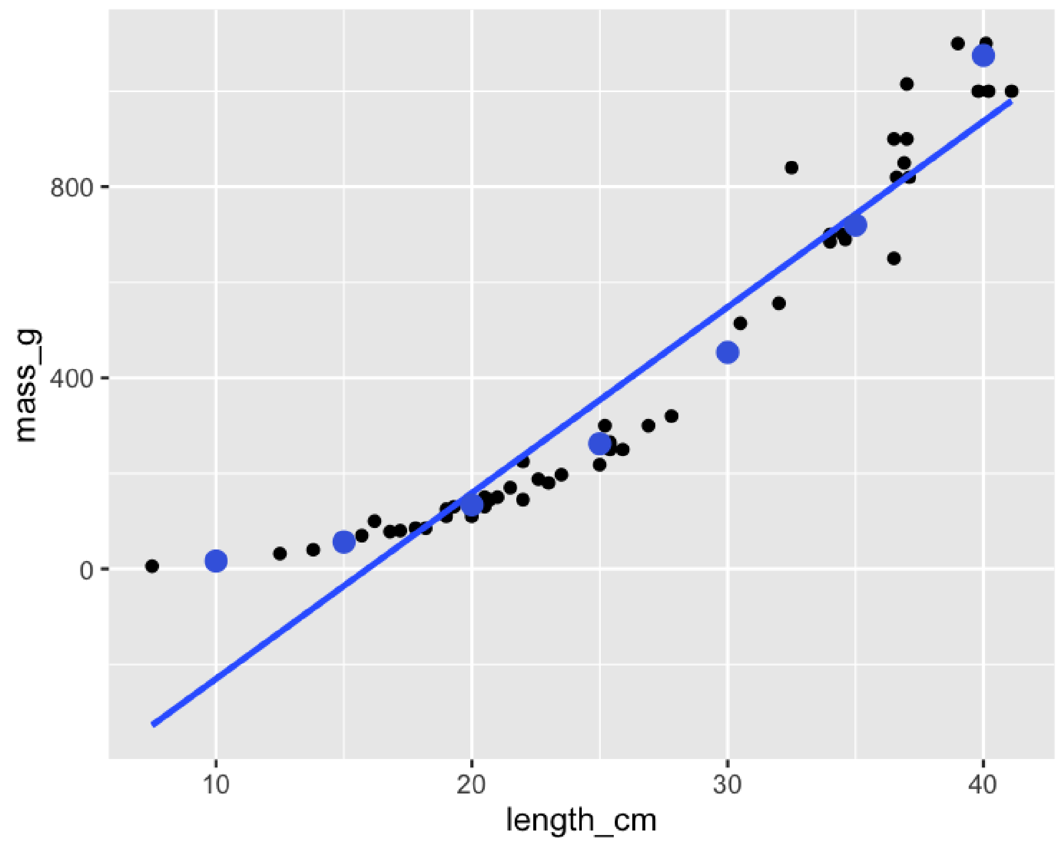
```
# A tibble: 7 x 2
  length_cm mass_g
      <dbl>  <dbl>
1        10   16.7
2        15   56.6
3        20  134.
4        25  262.
5        30  453.
6        35  720.
7        40 1075.
```

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

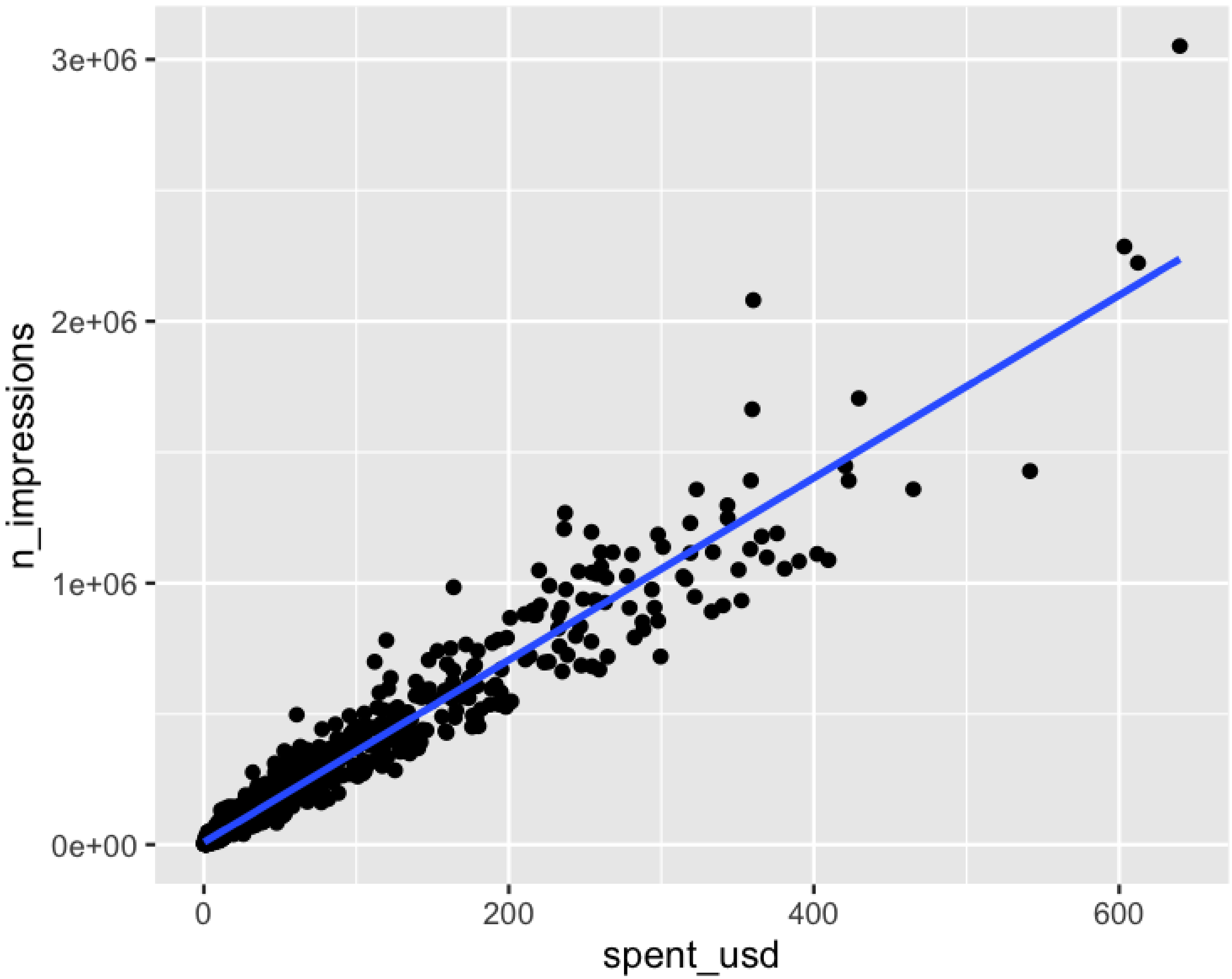
1. Pay Facebook to shows ads.
2. People see the ads ("impressions").
3. Some people who see it, click it.

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
...	...	...

- 936 rows
- Each row represents 1 advert

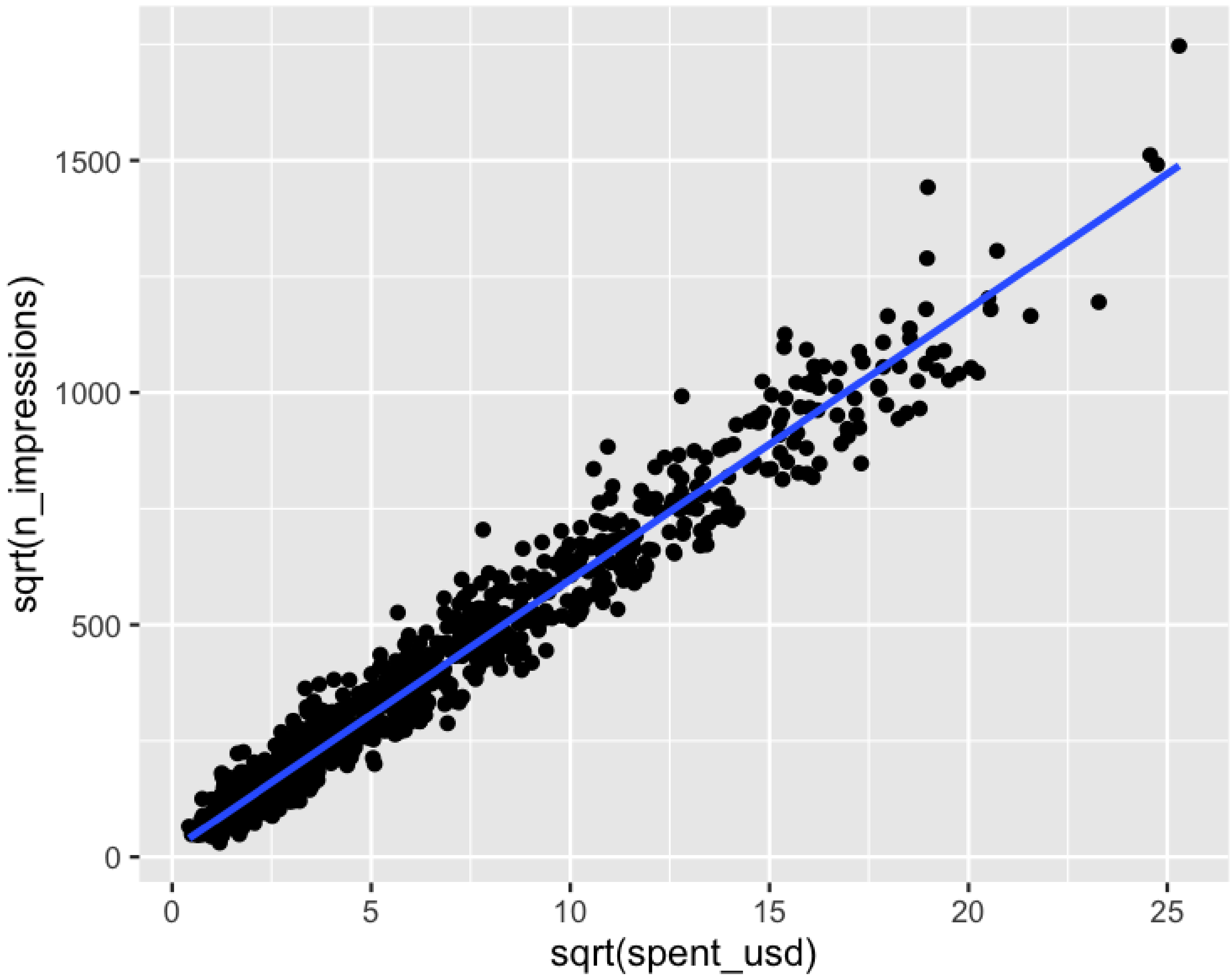
Plot is cramped

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



Square root vs square root

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



Modeling and predicting

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

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

```
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!

INTRODUCTION TO REGRESSION IN R