Making predictions

INTRODUCTION TO REGRESSION WITH STATSMODELS IN PYTHON

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The fish dataset: bream

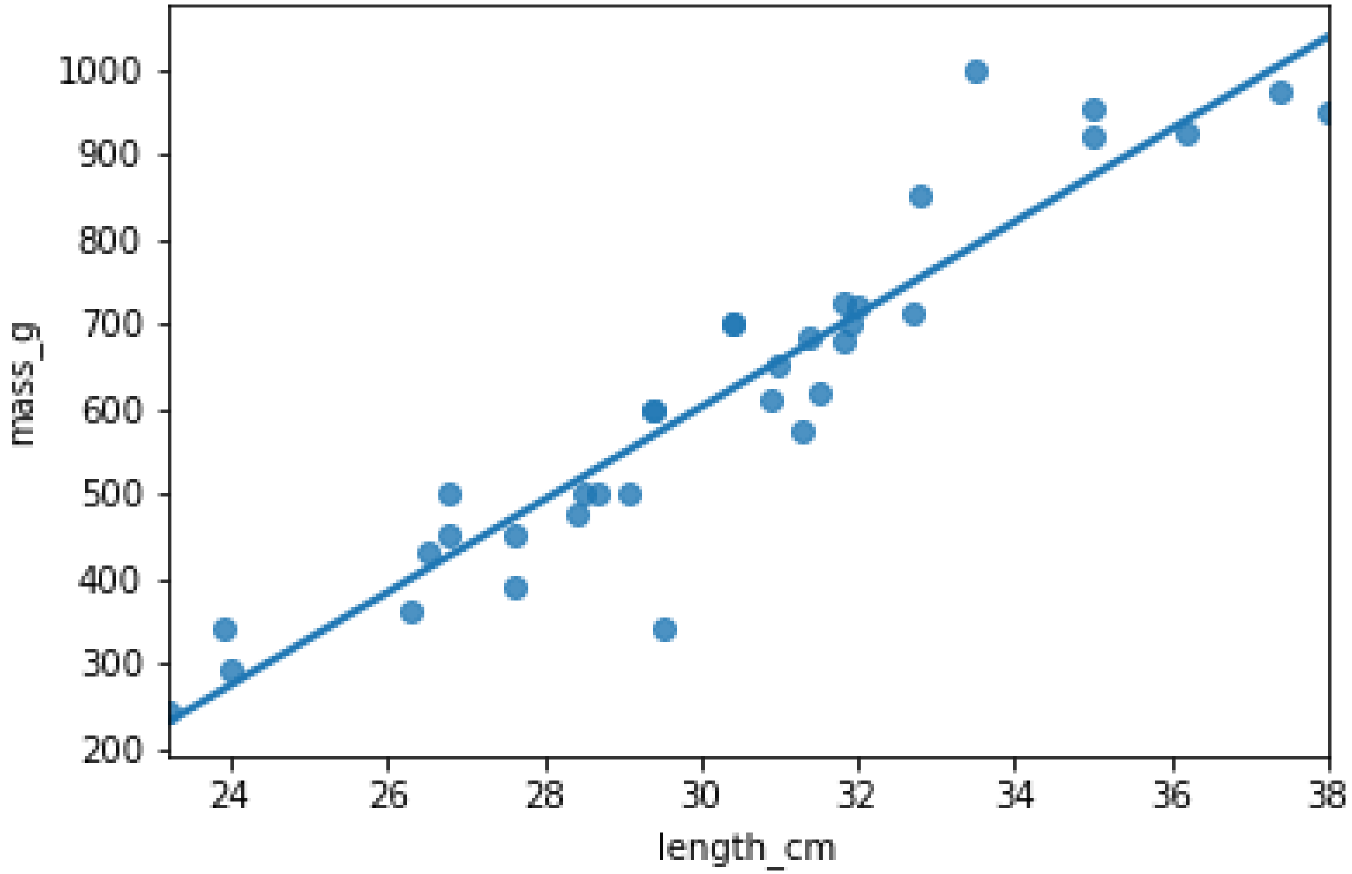
```
bream = fish[fish["species"] == "Bream"]
print(bream.head())
```

```
  species  mass_g  length_cm
0   Bream   242.0       23.2
1   Bream   290.0       24.0
2   Bream   340.0       23.9
3   Bream   363.0       26.3
4   Bream   430.0       26.5
```

Plotting mass vs. length

```
sns.regplot(x="length_cm",
            y="mass_g",
            data=bream,
            ci=None)

plt.show()
```



Running the model

```
mdl_mass_vs_length = ols("mass_g ~ length_cm", data=bream).fit()
print(mdl_mass_vs_length.params)
```

```
Intercept   -1035.347565
length_cm      54.549981
dtype: float64
```

Data on explanatory values to predict

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

```
explanatory_data = pd.DataFrame({"length_cm": np.arange(20, 41)})
```

```
    length_cm
0          20
1          21
2          22
3          23
4          24
5          25
       ...
```

Call predict()

```
print(mdl_mass_vs_length.predict(explanatory_data))
```

```
0       55.652054
1      110.202035
2      164.752015
3      219.301996
4      273.851977
    ...
16     928.451749
17     983.001730
18    1037.551710
19    1092.101691
20    1146.651672
Length: 21, dtype: float64
```

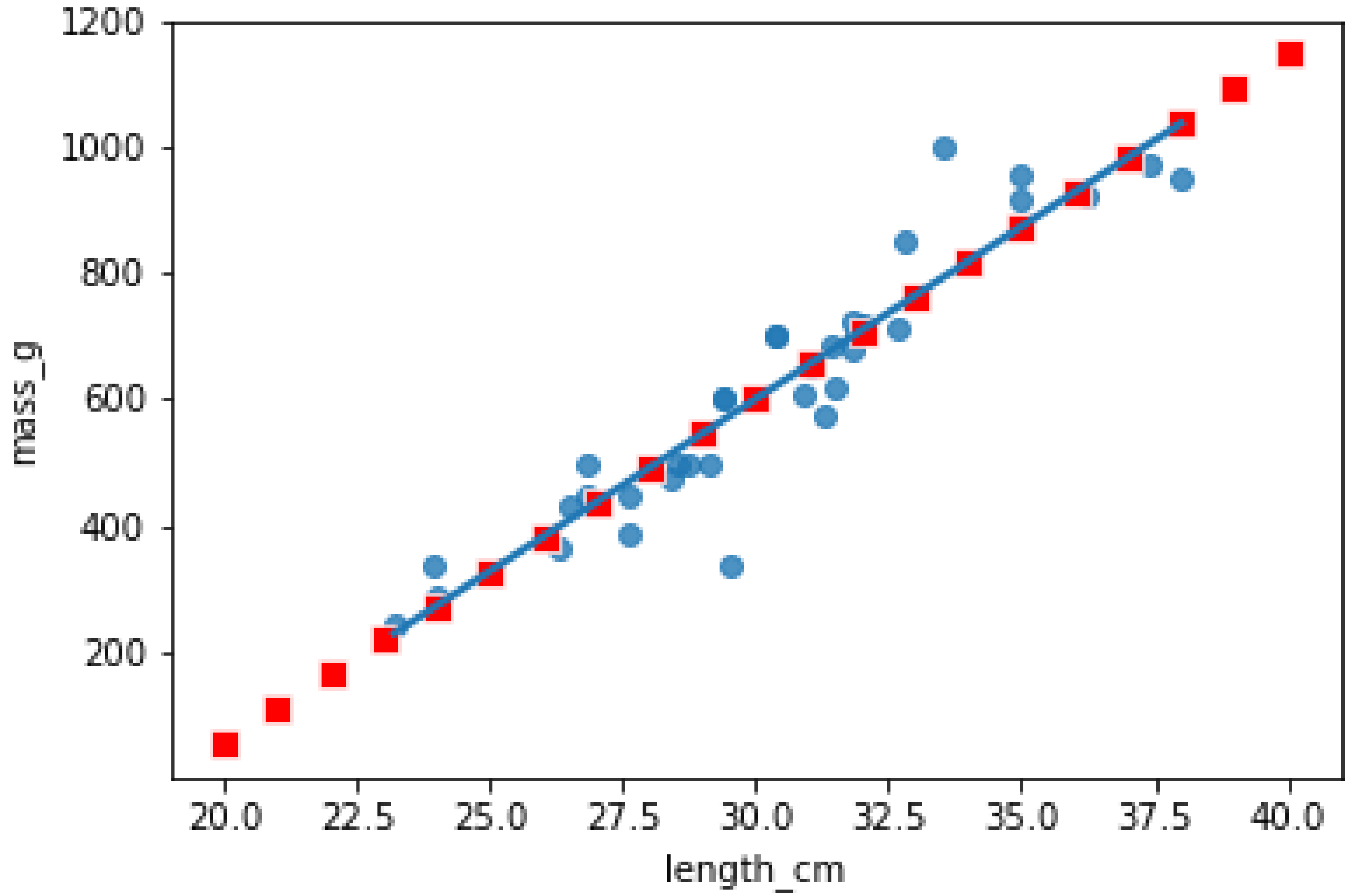
Predicting inside a DataFrame

```
explanatory_data = pd.DataFrame(
  {"length_cm": np.arange(20, 41)}
)
prediction_data = explanatory_data.assign(
    mass_g=mdl_mass_vs_length.predict(explanatory_data)
)
print(prediction_data)
```

```
    length_cm       mass_g
0          20    55.652054
1          21   110.202035
2          22   164.752015
3          23   219.301996
4          24   273.851977
..        ...          ...
16         36   928.451749
17         37   983.001730
18         38  1037.551710
19         39  1092.101691
20         40  1146.651672
```

Showing predictions

```
import matplotlib.pyplot as plt
import seaborn as sns
fig = plt.figure()
sns.regplot(x="length_cm",
            y="mass_g",
            ci=None,
            data=bream,)
sns.scatterplot(x="length_cm",
                y="mass_g",
                data=prediction_data,
                color="red",
                marker="s")
plt.show()
```



Extrapolating

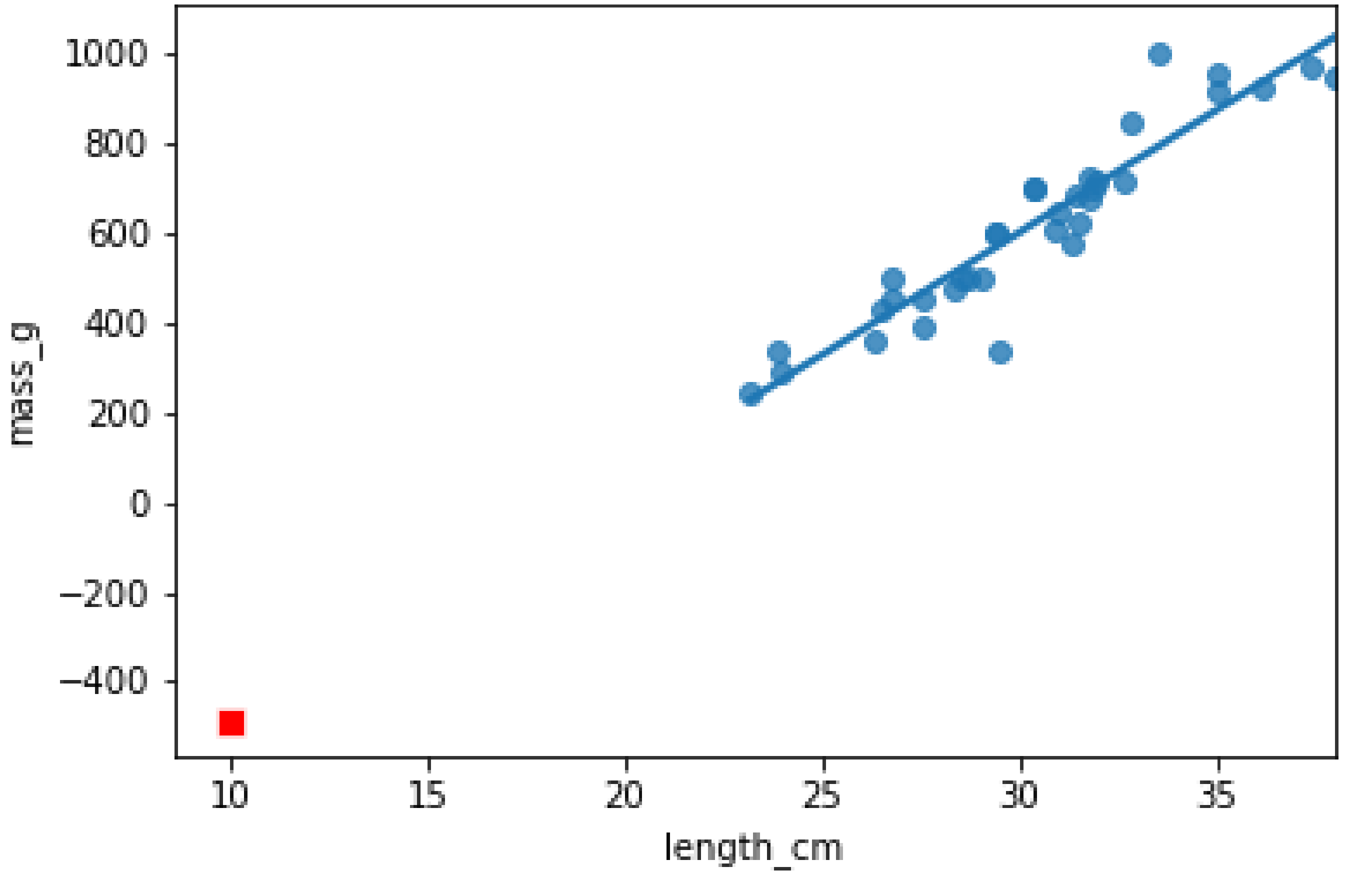
Extrapolating means making predictions outside the range of observed data.

```
little_bream = pd.DataFrame({"length_cm": [10]})

pred_little_bream = little_bream.assign(
    mass_g=mdl_mass_vs_length.predict(little_bream))

print(pred_little_bream)
```

```
   length_cm      mass_g
0         10 -489.847756
```



Let's practice!

Working with model objects

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.params attribute

```python
from statsmodels.formula.api import ols
mdl_mass_vs_length = ols("mass_g ~ length_cm", data = bream).fit()
print(mdl_mass_vs_length.params)
```

```
Intercept   -1035.347565
length_cm      54.549981
dtype: float64
```

.fittedvalues attribute

Fitted values: predictions on the original dataset

```
print(mdl_mass_vs_length.fittedvalues)
```

or equivalently

```
explanatory_data = bream["length_cm"]

print(mdl_mass_vs_length.predict(explanatory_data))
```

```
0      230.211993
1      273.851977
2      268.396979
3      399.316934
4      410.226930
    ...
30     873.901768
31     873.901768
32     939.361745
33    1004.821722
34    1037.551710
Length: 35, dtype: float64
```

.resid attribute

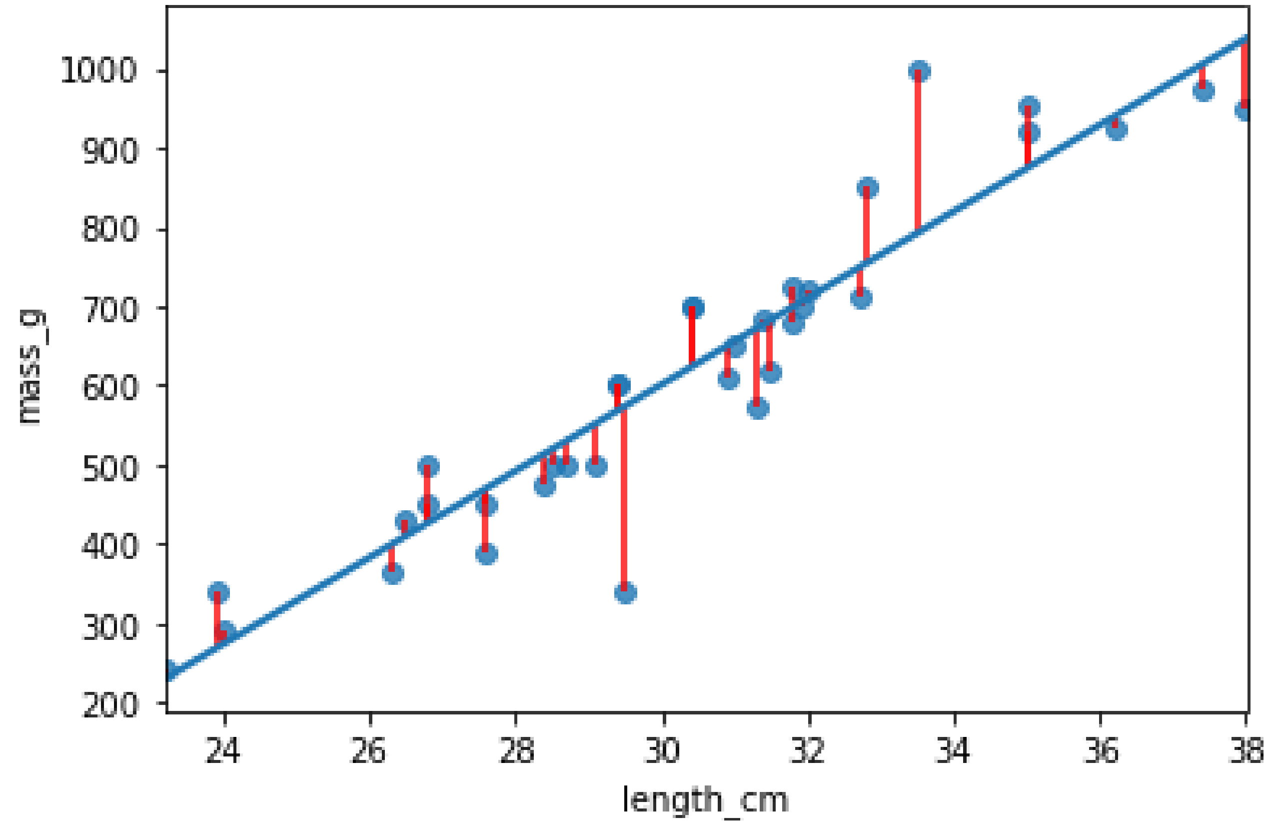
Residuals: actual response values minus predicted response values

```
print(mdl_mass_vs_length.resid)
```

or equivalently

```
print(bream["mass_g"] - mdl_mass_vs_length.fittedvalues)
```

```
0     11.788007
1     16.148023
2     71.603021
3    -36.316934
4     19.773070
    ...
```



.summary()

```
mdl_mass_vs_length.summary()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 mass_g   R-squared:                       0.878
Model:                            OLS   Adj. R-squared:                  0.874
Method:                 Least Squares   F-statistic:                     237.6
Date:                Thu, 29 Oct 2020   Prob (F-statistic):           1.22e-16
Time:                        13:23:21   Log-Likelihood:                -199.35
No. Observations:                  35   AIC:                             402.7
Df Residuals:                      33   BIC:                             405.8
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
<-----------------------------------------------------------------------------
Intercept  -1035.3476    107.973     -9.589      0.000   -1255.020    -815.676
length_cm     54.5500      3.539     15.415      0.000      47.350      61.750
==============================================================================
Omnibus:                        7.314   Durbin-Watson:                   1.478
Prob(Omnibus):                  0.026   Jarque-Bera (JB):               10.857
Skew:                          -0.252   Prob(JB):                      0.00439
Kurtosis:                       5.682   Cond. No.                         263.
```

```
                         OLS Regression Results
==============================================================================
Dep. Variable:                 mass_g   R-squared:                       0.878
Model:                            OLS   Adj. R-squared:                  0.874
Method:                 Least Squares   F-statistic:                     237.6
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```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
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Prob(Omnibus):                  0.026   Jarque-Bera (JB):               10.857
Skew:                          -0.252   Prob(JB):                      0.00439
Kurtosis:                       5.682   Cond. No.                         263.
```

Let's practice!

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

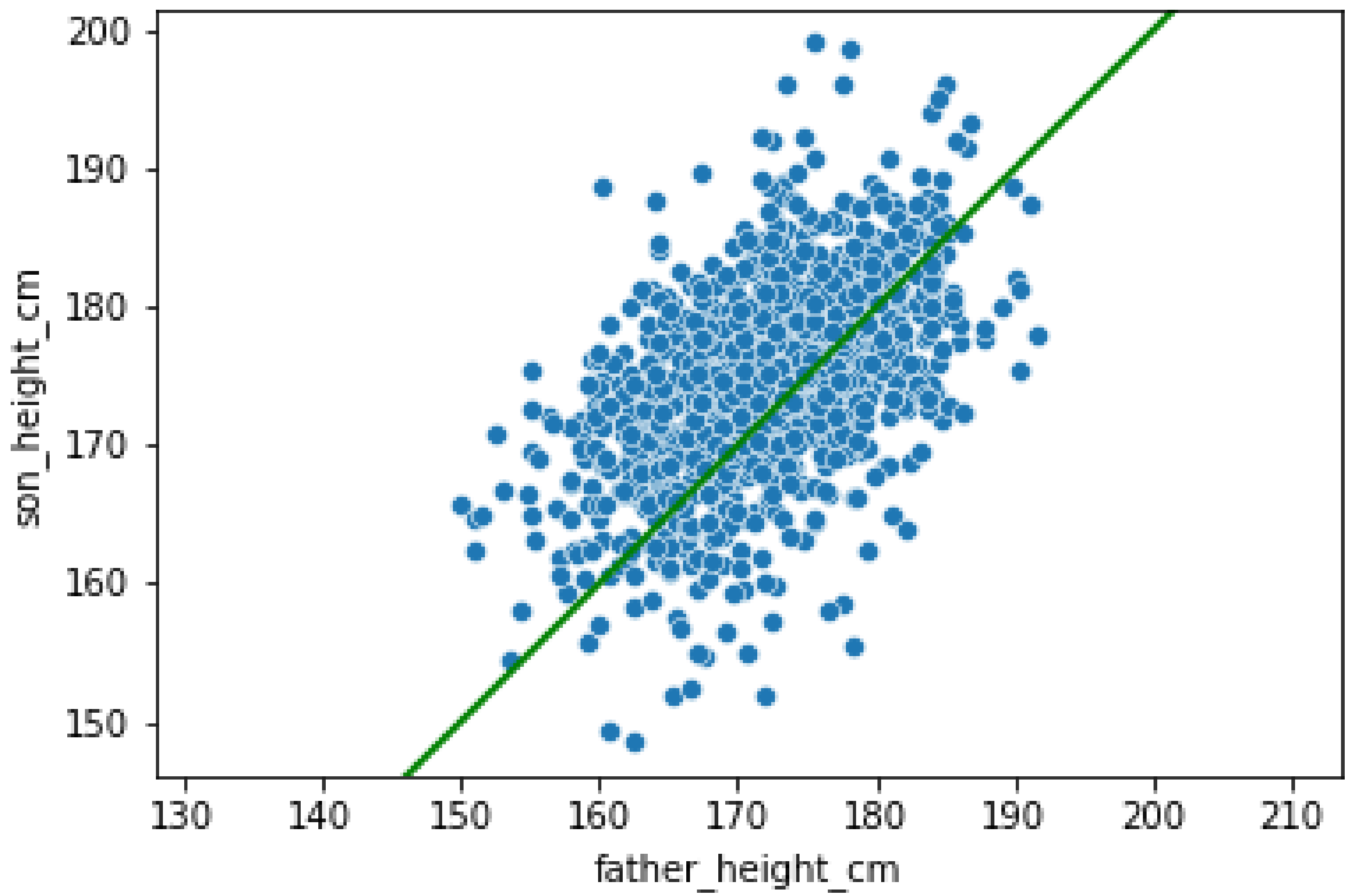
Scatter plot

```
fig = plt.figure()
```

```
sns.scatterplot(x="father_height_cm",
                y="son_height_cm",
                data=father_son)
```

```
plt.axline(xy1=(150, 150),
           slope=1,
           linewidth=2,
           color="green")
```

```
plt.axis("equal")
plt.show()
```



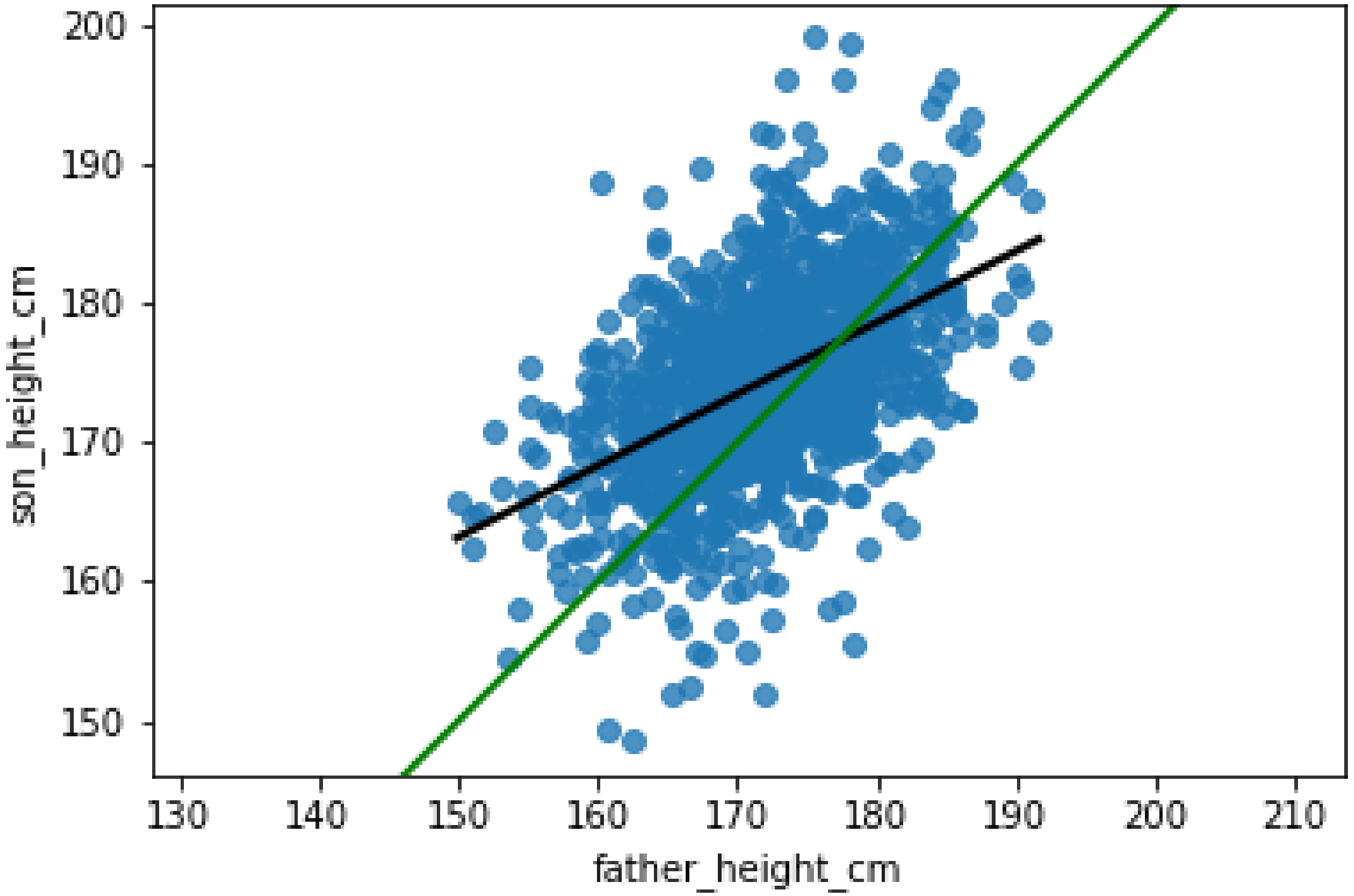
Adding a regression line

```
fig = plt.figure()

sns.regplot(x="father_height_cm",
            y="son_height_cm",
            data=father_son,
            ci = None,
            line_kws={"color": "black"})

plt.axline(xy1 = (150, 150),
           slope=1,
           linewidth=2,
           color="green")

plt.axis("equal")
plt.show()
```



Running a regression

```
mdl_son_vs_father = ols("son_height_cm ~ father_height_cm",
                        data = father_son).fit()
print(mdl_son_vs_father.params)
```

```
Intercept           86.071975
father_height_cm     0.514093
dtype: float64
```

Making predictions

```
really_tall_father = pd.DataFrame(
  {"father_height_cm": [190]})

mdl_son_vs_father.predict(
  really_tall_father)
```

```
183.7
```

```
really_short_father = pd.DataFrame(
  {"father_height_cm": [150]})

mdl_son_vs_father.predict(
  really_short_father)
```

```
163.2
```

Let's practice!

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Transforming variables

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Perch dataset

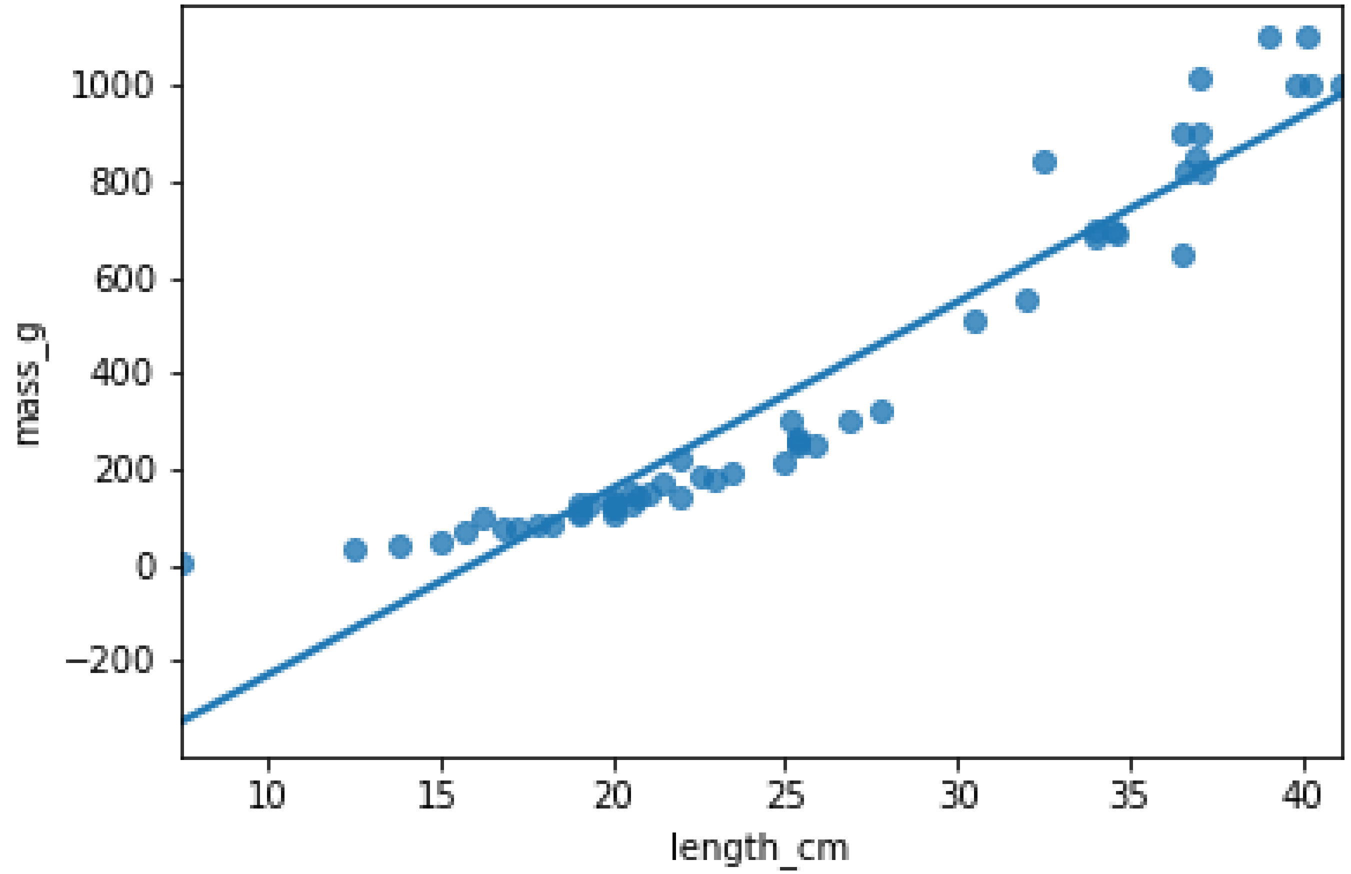
```
perch = fish[fish["species"] == "Perch"]
print(perch.head())
```

```
   species  mass_g  length_cm
55   Perch     5.9        7.5
56   Perch    32.0       12.5
57   Perch    40.0       13.8
58   Perch    51.5       15.0
59   Perch    70.0       15.7
```

It's not a linear relationship

```
sns.regplot(x="length_cm",
            y="mass_g",
            data=perch,
            ci=None)

plt.show()
```

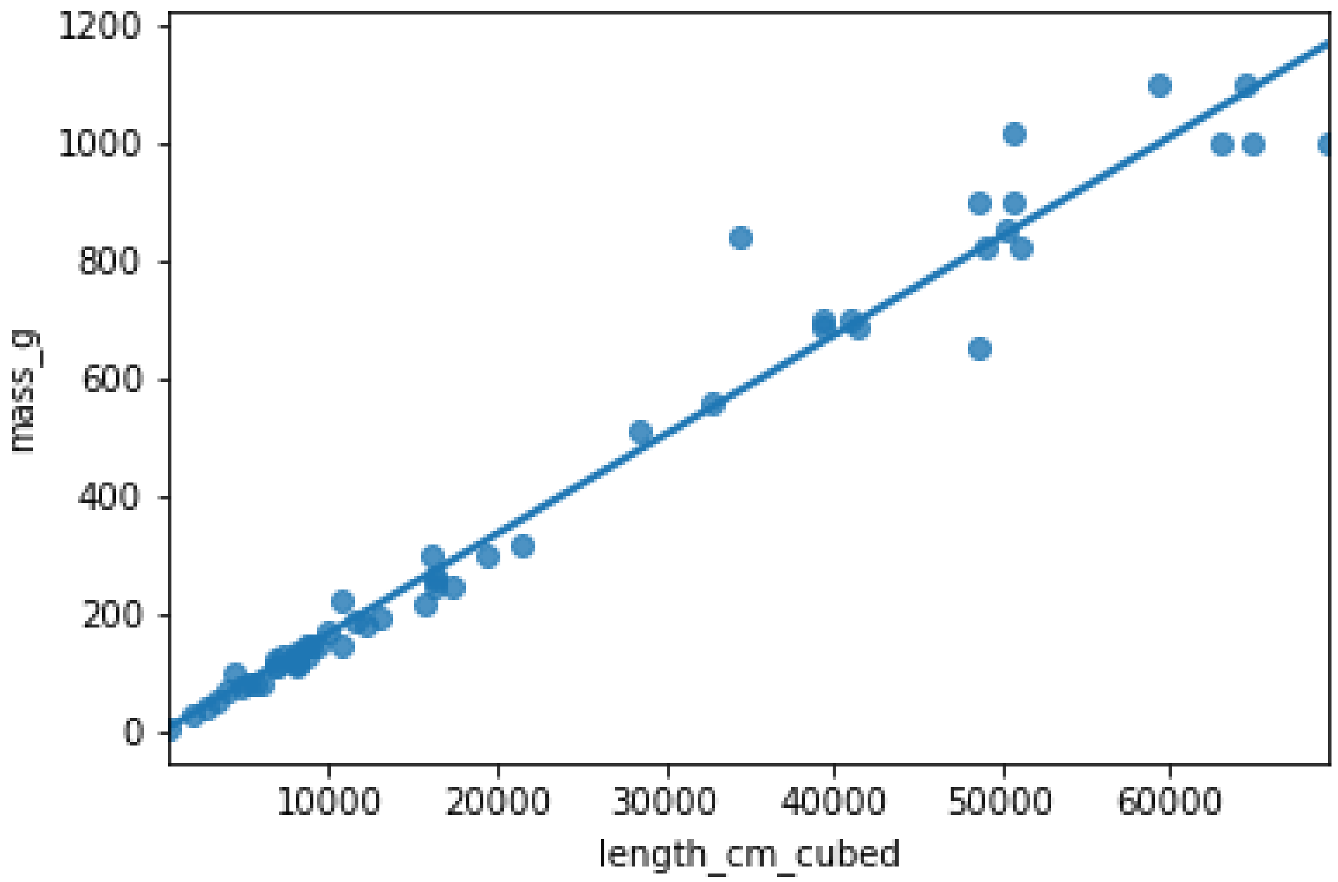


Bream vs. perch

Plotting mass vs. length cubed

```
perch["length_cm_cubed"] = perch["length_cm"] ** 3
```

```
sns.regplot(x="length_cm_cubed",
            y="mass_g",
            data=perch,
            ci=None)
plt.show()
```



Modeling mass vs. length cubed

```
perch["length_cm_cubed"] = perch["length_cm"] ** 3

mdl_perch = ols("mass_g ~ length_cm_cubed", data=perch).fit()
mdl_perch.params
```

```
Intercept          -0.117478
length_cm_cubed     0.016796
dtype: float64
```

Predicting mass vs. length cubed

```
explanatory_data = pd.DataFrame({"length_cm_cubed": np.arange(10, 41, 5) ** 3,
                                 "length_cm": np.arange(10, 41, 5)})
```

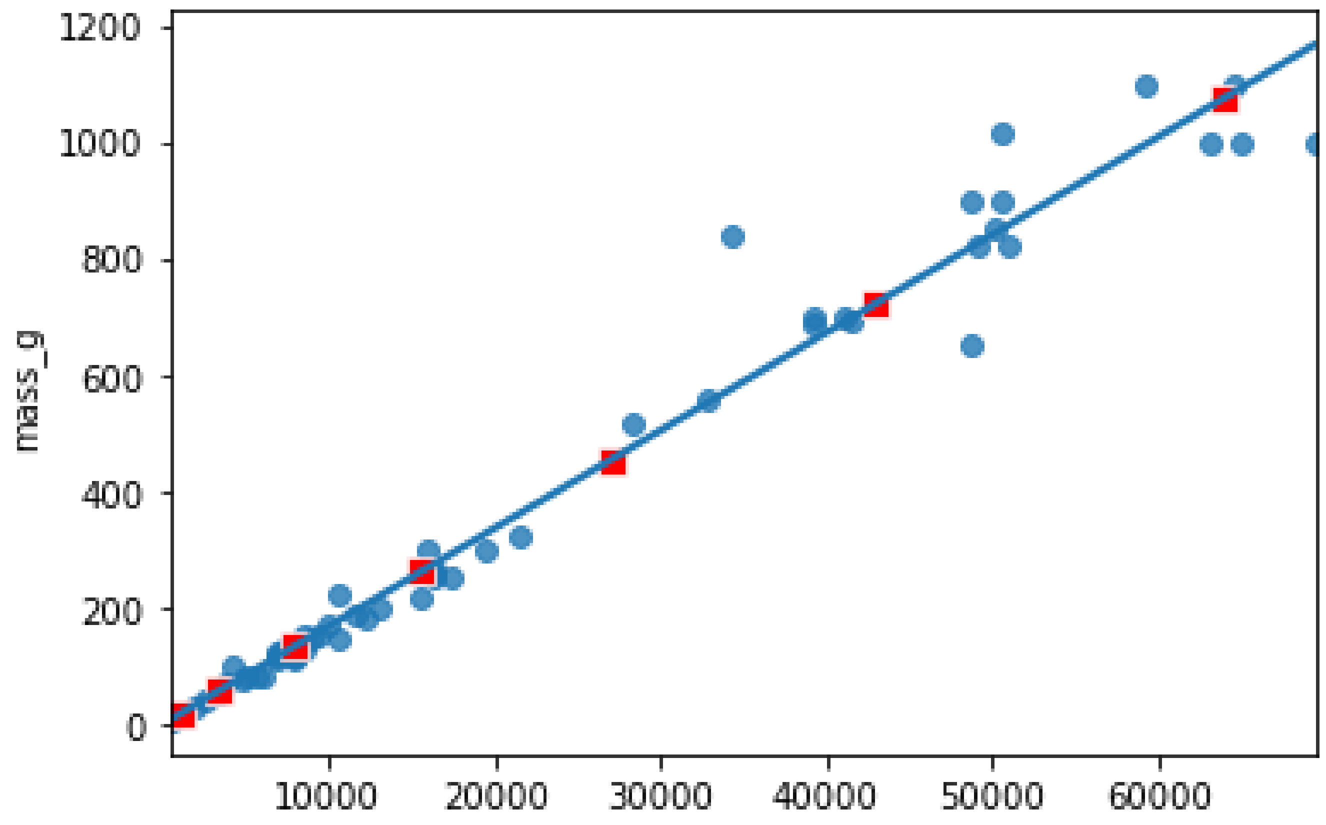
```
prediction_data = explanatory_data.assign(
  mass_g=mdl_perch.predict(explanatory_data))
print(prediction_data)
```

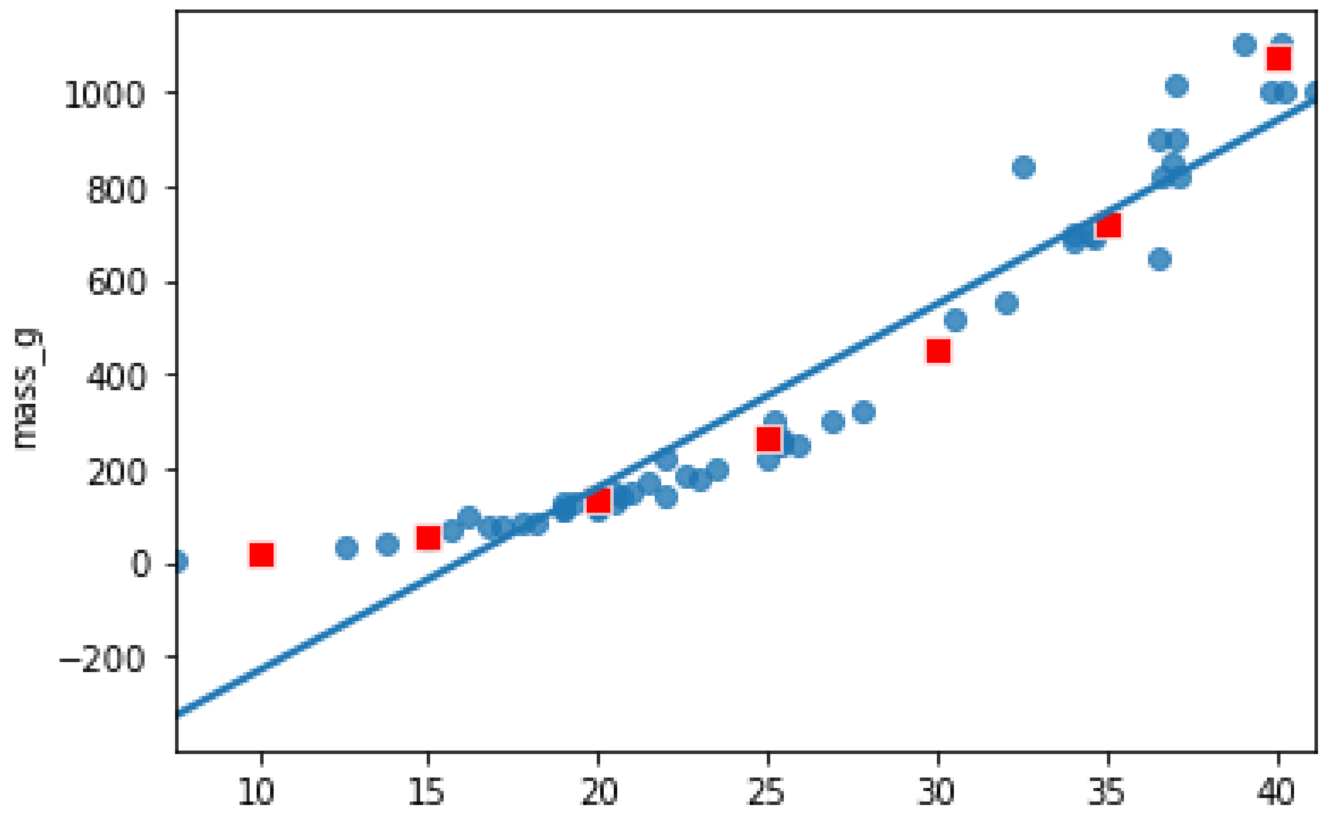
```
   length_cm_cubed  length_cm       mass_g
0             1000         10    16.678135
1             3375         15    56.567717
2             8000         20   134.247429
3            15625         25   262.313982
4            27000         30   453.364084
5            42875         35   719.994447
6            64000         40  1074.801781
```

Plotting mass vs. length cubed

```python
fig = plt.figure()
sns.regplot(x="length_cm_cubed", y="mass_g",
            data=perch, ci=None)
sns.scatterplot(data=prediction_data,
                x="length_cm_cubed", y="mass_g",
                color="red", marker="s")
```

```python
fig = plt.figure()
sns.regplot(x="length_cm", y="mass_g",
            data=perch, ci=None)
sns.scatterplot(data=prediction_data,
                x="length_cm", y="mass_g",
                color="red", marker="s")
```





Facebook advertising dataset

How advertising works

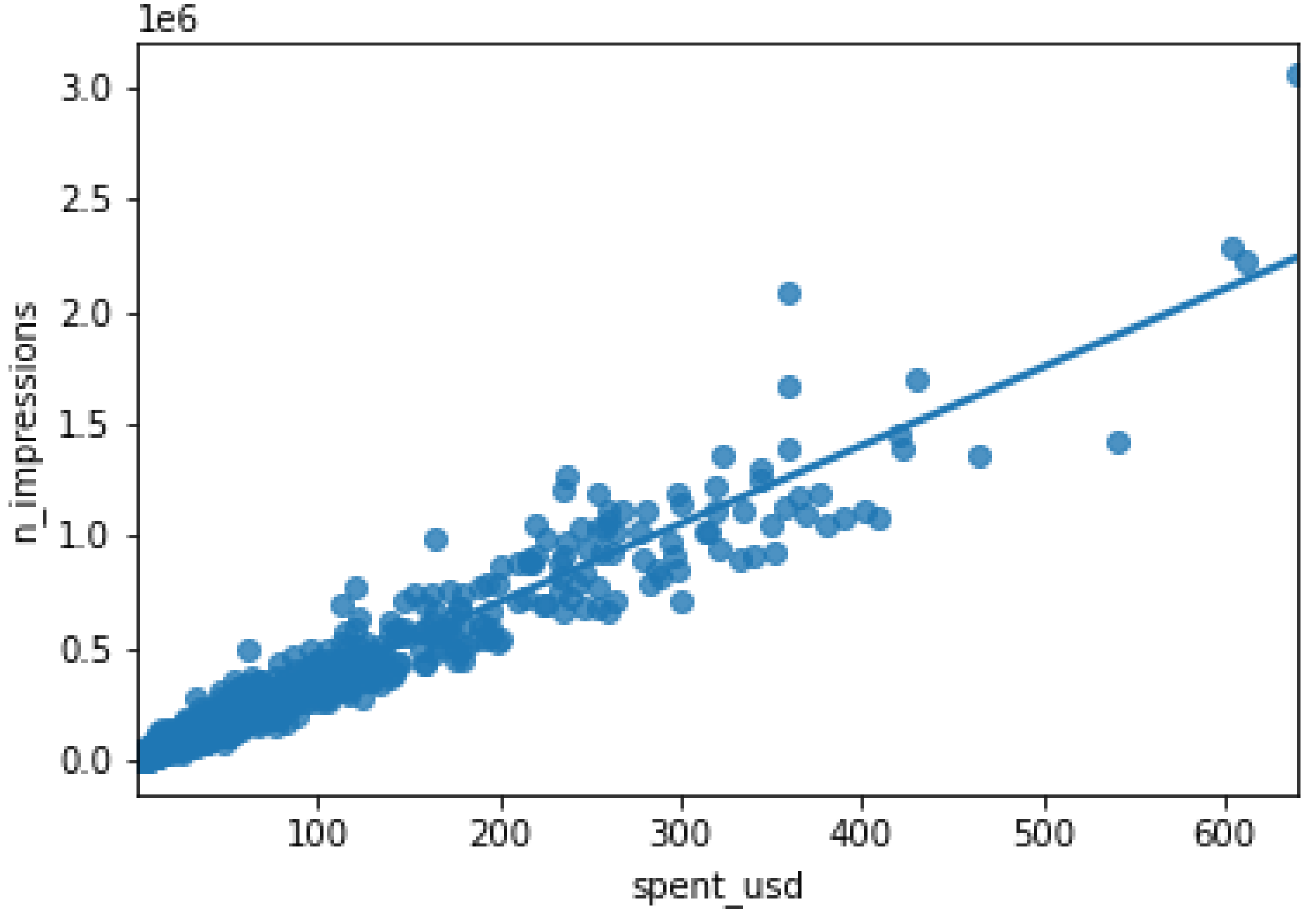
1. Pay Facebook to shows ads.
2. People see the ads ("impressions").
3. Some people who see it, click it.

- 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

```
sns.regplot(x="spent_usd",
            y="n_impressions",
            data=ad_conversion,
            ci=None)
```

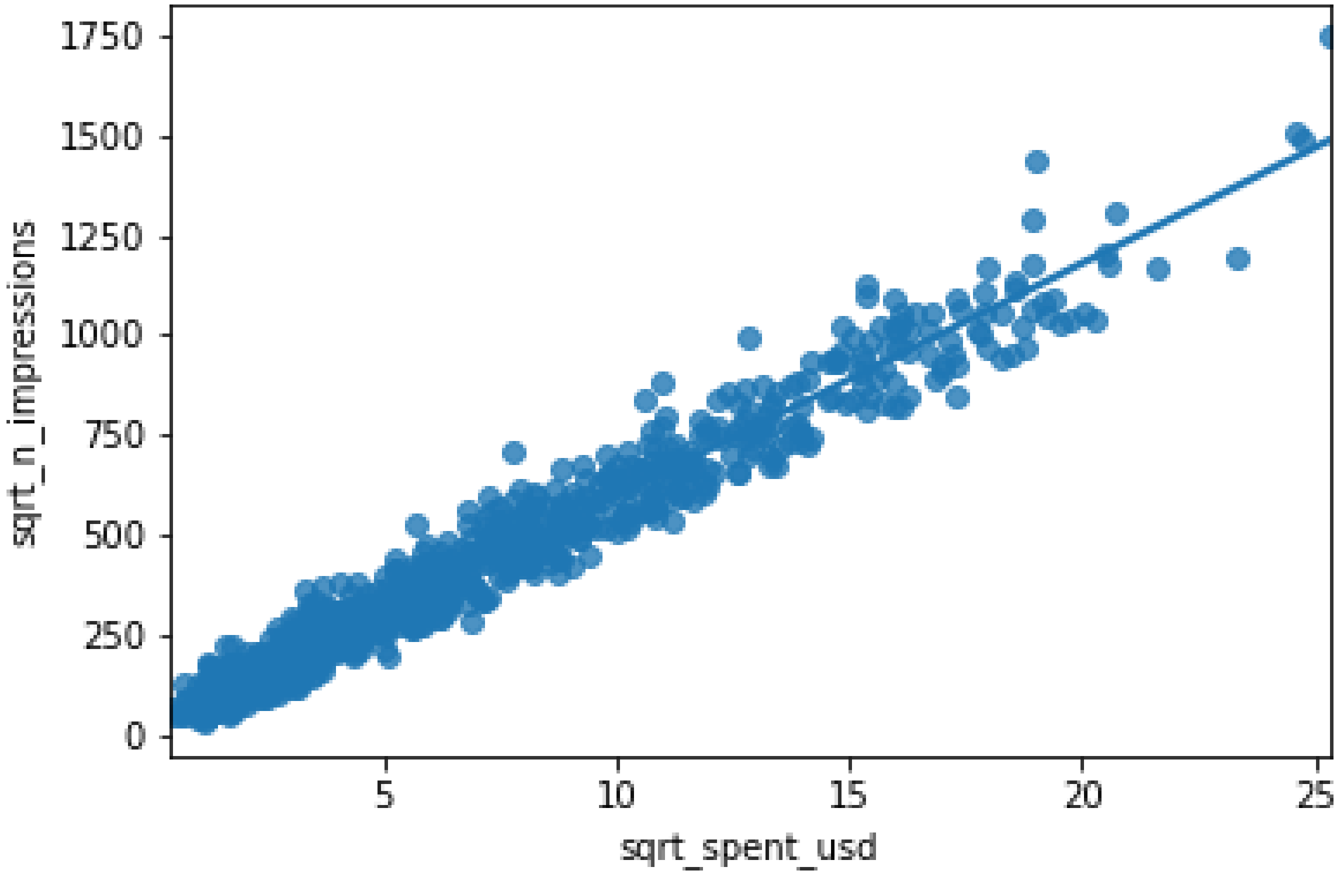


Square root vs square root

```
ad_conversion["sqrt_spent_usd"] = np.sqrt(
  ad_conversion["spent_usd"])

ad_conversion["sqrt_n_impressions"] = np.sqrt(
  ad_conversion["n_impressions"])

sns.regplot(x="sqrt_spent_usd",
            y="sqrt_n_impressions",
            data=ad_conversion,
            ci=None)
```



Modeling and predicting

```
mdl_ad = ols("sqrt_n_impressions ~ sqrt_spent_usd", data=ad_conversion).fit()
```

```
explanatory_data = pd.DataFrame({"sqrt_spent_usd": np.sqrt(np.arange(0, 601, 100)),
                                 "spent_usd": np.arange(0, 601, 100)})
```

```
prediction_data = explanatory_data.assign(sqrt_n_impressions=mdl_ad.predict(explanatory_data),
                          n_impressions=mdl_ad.predict(explanatory_data) ** 2)
print(prediction_data)
```

```
   sqrt_spent_usd  spent_usd  sqrt_n_impressions  n_impressions
0        0.000000          0           15.319713   2.346936e+02
1       10.000000        100          597.736582   3.572890e+05
2       14.142136        200          838.981547   7.038900e+05
3       17.320508        300         1024.095320   1.048771e+06
4       20.000000        400         1180.153450   1.392762e+06
5       22.360680        500         1317.643422   1.736184e+06
6       24.494897        600         1441.943858   2.079202e+06
```

Let's practice!