7.10

March 12, 2018

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At http://www.statsci.org/data/oz/physical.html, you will find a dataset of measurements by M. Larner, made in 1996. These measurements include body mass, and various diameters. Build a linear regression of predicting the body mass from these diameters.

- Plot the residual against the fitted values for your regression.
- Now regress the cube root of mass against these diameters. Plot the residual against the fitted values in both these cube root coordinates and in the original coordinates.
- Use your plots to explain which regression is better.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pylab as plt
# import statsmodels.api as sm
from scipy.stats import linregress

%matplotlib inline
```

In [2]:
```
df2 = pd.read_table('physical.txt')
df2.head()
```

Out[2]:

	Mass	Fore	Bicep	Chest	Neck	Shoulder	Waist	Height	Calf	Thigh	Head
0	77.0	28.5	33.5	100.0	38.5	114.0	85.0	178.0	37.5	53.0	58.0
1	85.5	29.5	36.5	107.0	39.0	119.0	90.5	187.0	40.0	52.0	59.0
2	63.0	25.0	31.0	94.0	36.5	102.0	80.5	175.0	33.0	49.0	57.0
3	80.5	28.5	34.0	104.0	39.0	114.0	91.5	183.0	38.0	50.0	60.0
4	79.5	28.5	36.5	107.0	39.0	114.0	92.0	174.0	40.0	53.0	59.0

In [3]:
```
y = df2.Mass
X = df2.drop('Mass', axis=1)
X.head()
```

Out[3]:

	Fore	Bicep	Chest	Neck	Shoulder	Waist	Height	Calf	Thigh	Head
0	28.5	33.5	100.0	38.5	114.0	85.0	178.0	37.5	53.0	58.0
1	29.5	36.5	107.0	39.0	119.0	90.5	187.0	40.0	52.0	59.0
2	25.0	31.0	94.0	36.5	102.0	80.5	175.0	33.0	49.0	57.0
3	28.5	34.0	104.0	39.0	114.0	91.5	183.0	38.0	50.0	60.0
4	28.5	36.5	107.0	39.0	114.0	92.0	174.0	40.0	53.0	59.0

```
In [4]: from sklearn.linear_model import LinearRegression
```

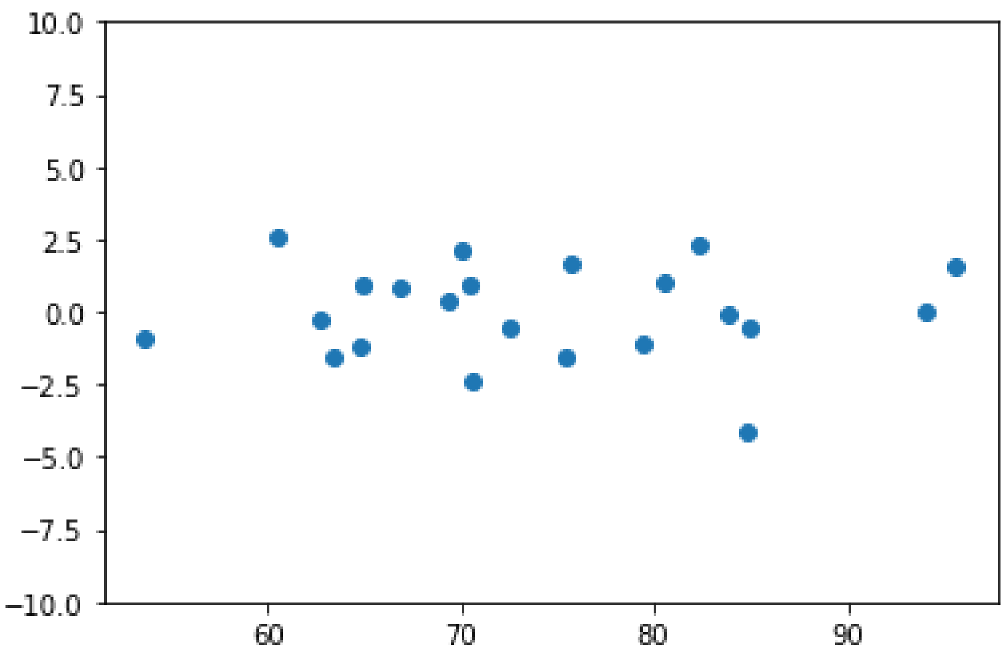
```
In [5]: lm = LinearRegression()
        lm.fit(X, y)
        #predX = lm.predict(X)
        residual = lm.predict(X) - y
        residual.head()
```

```
Out[5]: 0   -1.580892
        1   -0.500839
        2   -0.230191
        3   -1.106940
        4    1.021275
        Name: Mass, dtype: float64
```

1.0.1 a) Plot the residual against the fitted values for your regression.

```
In [6]: plt.scatter(lm.predict(X), residual)
        plt.ylim([-10,10])
```

```
Out[6]: (-10, 10)
```



Now regress the cube root of mass against these diameters. Plot the residual against the fitted values in both these cube root coordinates and in the original coordinates.

```
In [7]: newY = (y ** (1./3.))
        newX = X
```

```
In [8]: newY.head()

Out[8]: 0    4.254321
        1    4.405434
        2    3.979057
        3    4.317828
        4    4.299874
        Name: Mass, dtype: float64

In [10]: lm2 = LinearRegression()
         lm2.fit(newX, newY)
         resCubeRoot = lm2.predict(newX) - newY
         resCubeRoot.head()

Out[10]: 0   -0.026243
         1   -0.007233
         2   -0.004892
         3   -0.026709
         4    0.015893
         Name: Mass, dtype: float64
```

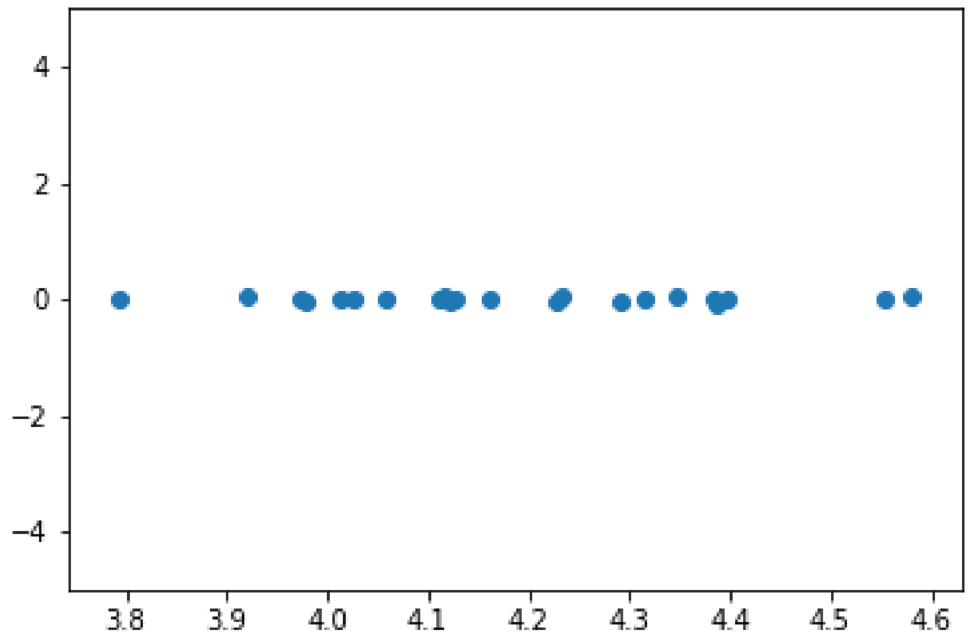
From Piazza: https://piazza.com/class/jchzguhsowz6n9?cid=892

- Transform the original data into the cube root space
- Learn a regression in this transformed space
- Make predictions for all points in your data. These points have the units of kg^(1/3)

1.0.2 b) Plot the residual against the fitted values in these cube root coordinates.

```
In [12]: #plot for after step 3 "make predictions for all points in your data. These points ha
         plt.scatter(lm2.predict(newX), resCubeRoot)
         plt.ylim([-5,5])

Out[12]: (-5, 5)
```




```
In [13]: residualCube = lm2.predict(newX)**3 - (newY)**3
         residualCube.head()

Out[13]: 0   -1.416141
         1   -0.420432
         2   -0.232065
         3   -1.484633
         4    0.884790
         Name: Mass, dtype: float64
```

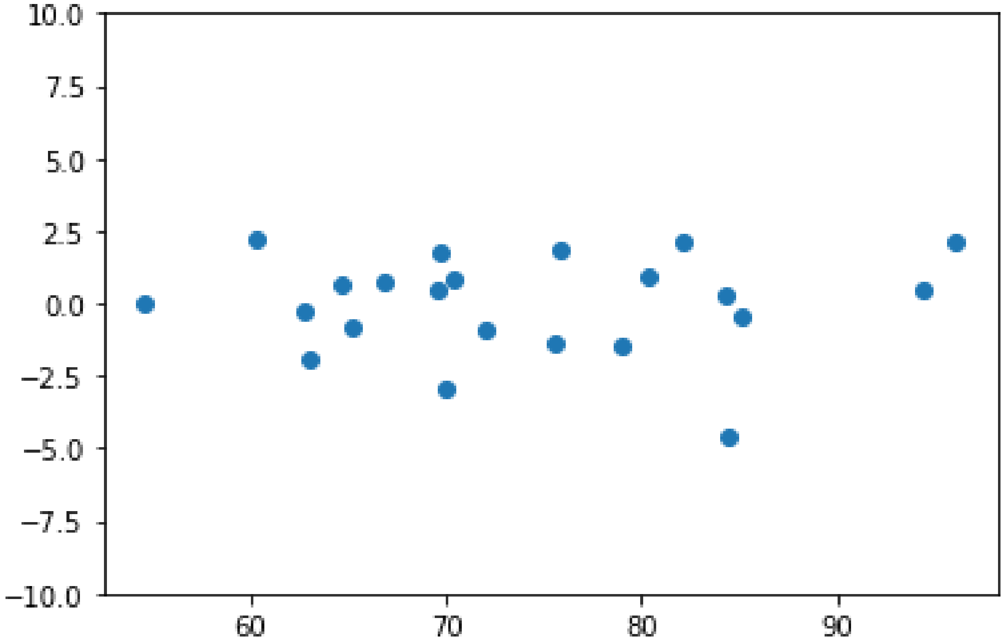
From Piazza: https://piazza.com/class/jchzguhsowz6n9?cid=892

- Transform these predictions back into the original space by cubing them (now they have the units of kg)
- Compute the residuals between the true values and these predicted values, both of which are now in kg.

1.0.3 b) Plot the residual against the fitted values in the original coordinates.

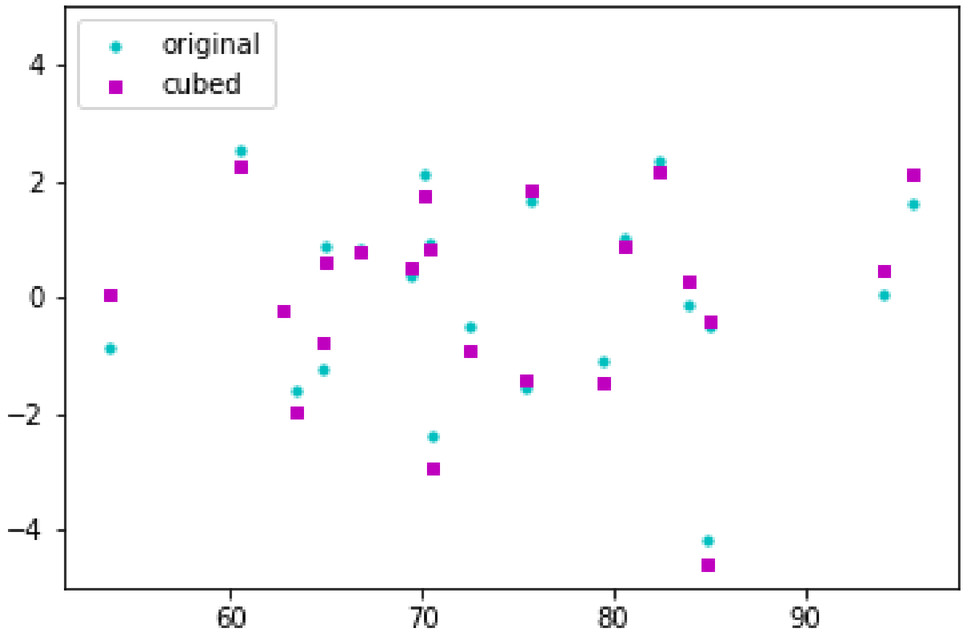
```
In [25]: #plot for after step 5 "Compute the residuals between the true values and these predi
         plt.scatter(lm2.predict(newX)**3, residualCube)
         plt.ylim([-10,10])

Out[25]: (-10, 10)
```



In [26]:
```
#A comparison chart for both residual against original predictions and cubed residual
fig = plt.figure()
ax1 = fig.add_subplot(111)

ax1.scatter(lm.predict(X), residual, s=10, c='c', marker="o", label='original')
ax1.scatter(lm.predict(X), residualCube, s=10, c='m', marker="s", label='cubed')
plt.legend(loc='upper left')
plt.ylim([-5,5])
plt.show()
```



1.0.4 c) Use your plots to explain which regression is better.

Per the graph above, it is easy to see that both regressions appear similar to the other. There is no clear indication that there is any plot better than the other, and therefore we used R-squared to evaluate the performance of each regression model.

```
In [34]: from sklearn import metrics
```

```
In [35]: metrics.r2_score(lm.predict(X), newY**3)
```

```
Out[35]: 0.9766791960516823
```

```
In [36]: metrics.r2_score(lm.predict(X), y)
```

```
Out[36]: 0.97667919605168241
```

The original model (non-cube-root) performs only **slightly** better than the other cube-root model

```
In [37]: #all homework questions were discussed with our study group consisting of Mallory, Yu
```