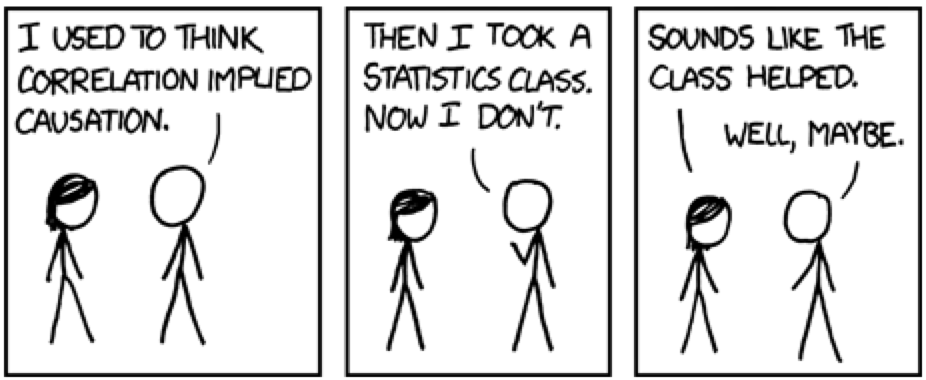
Regressions

Cause and Effect

Correlation: Two variables are correlated when changes in one variable occur in a pattern corresponding to changes in the other.

Cause and Effect

Causation: One variable moves, and the second variable changes because of the movement of the first.



Questioning Causality

When we suspect a causal relationship (that x causes y), it is important to ask ourselves several questions:

1. Is it possible that y causes x instead?
2. Is it possible that z (a new factor that we haven't considered before) is causing both x and y?
3. Could the relationship have been observed by chance?

Establishing Causality

In order to establish causality, we need to meet several conditions:

- We can explain (or at lest hypothesize) **why** x causes y
- We can demonstrate that **nothing else is driving the changes** (within reason)
- We can show that there is a **correlation** between x and y

Ceteris Paribus

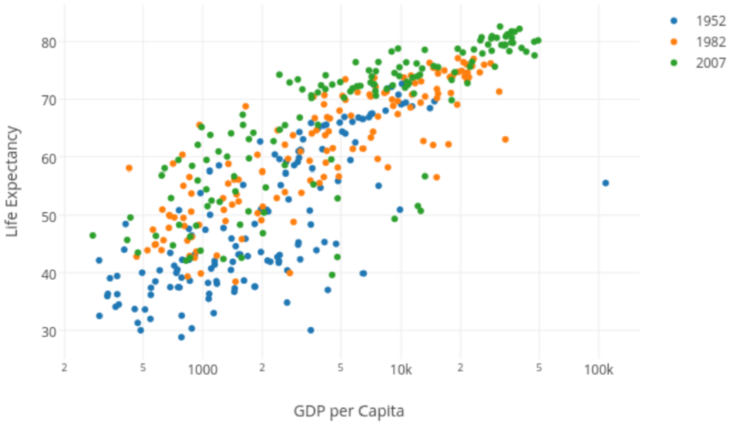
ceteris paribus means "all else equal"

Regression analysis

- Allows us to **act as if nothing else were changing**
- Mathematicaly isolates the effect of each individual **variable** on the outcome of interest
    - Variables are the factors that we want to include in our model

Regression analysis

- Think about it like a trend line!

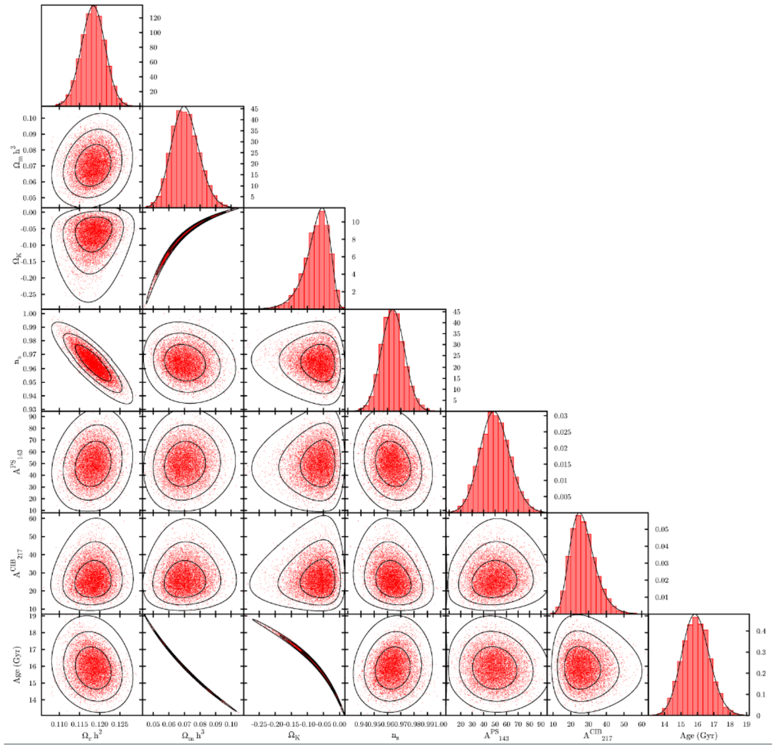


Regression analysis

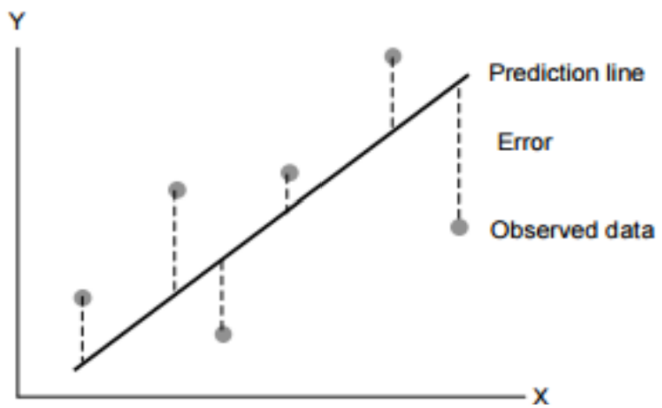
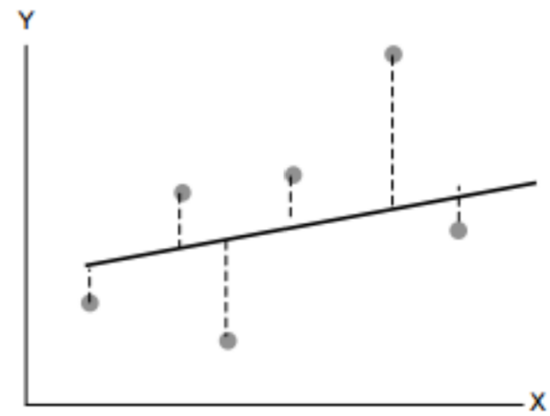
Whoops! What if there is another variable?

Regression analysis

Or lots of variables??

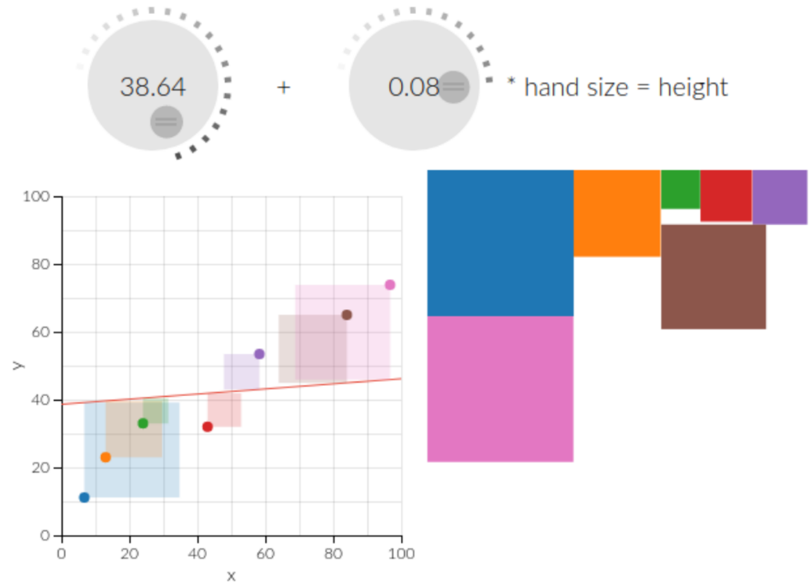


Minimize Errors and Best Fit Lines

Best Fit	Something Else
	

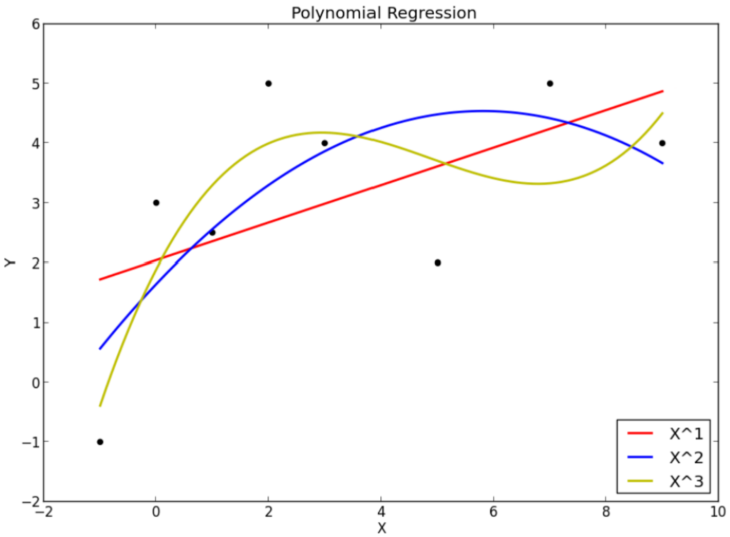
Minimize Errors and Best Fit Lines

Try it by hand!



Why LINEAR regression?

- Faster
- More honest



OLS in Python

```
import pandas as pd
import statsmodels.formula.api as smf

data = pd.read_csv(
    "https://github.com/dustywhite7/pythonMikkeli/raw/master/exampleData/fishWeight.csv")

reg = smf.ols("Weight ~ Length1", data=data)

reg = reg.fit()

print(reg.summary())
```

In [5]:
```
reg.summary()
```

Out[5]:

OLS Regression Results

Dep. Variable:	Weight	**R-squared:**	0.839
Model:	OLS	**Adj. R-squared:**	0.837
Method:	Least Squares	**F-statistic:**	815.3
Date:	Tue, 09 Jun 2020	**Prob (F-statistic):**	4.75e-64
Time:	20:09:35	**Log-Likelihood:**	-1015.1
No. Observations:	159	**AIC:**	2034.
Df Residuals:	157	**BIC:**	2040.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-462.3751	32.243	-14.340	0.000	-526.061	-398.690
Length1	32.7922	1.148	28.554	0.000	30.524	35.061

Omnibus:	9.385	**Durbin-Watson:**	0.369
Prob(Omnibus):	0.009	**Jarque-Bera (JB):**	9.768
Skew:	-0.489	**Prob(JB):**	0.00757
Kurtosis:	3.721	**Cond. No.**	79.2

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression Equations

```
dependent ~ x1 + x2 + x3 + ...
```

We can force variables to be categorical:

```
dependent ~ x1 + x2 + C(x3) + ...
```

Here, we make `x3` categorical

Regression Equations

```
dependent ~ x1 + x2 + x3 + ...
```

We can use arithmetic transformations:

```
dependent ~ x1 + I(x2**2) + x3 + ...
```

Here, we square `x2`

When OLS Fails

OLS is an inappropriate model whenever you have a binary or discrete dependent variable (think "yes" or "no" questions)

In this case, you should use Logistic Regression instead. More details can be found in the class notes on Mimir/Github.

Implementing Logistic Regressions

```
formula = "y ~ all_of_the_xs"

reg = smf.logit(formula, data)

reg = reg.fit()

reg.summary()
```

Lab Time!