# Regression analysis with scikit-learn

HAS Tools - Sept 29

## DISCLAIMER

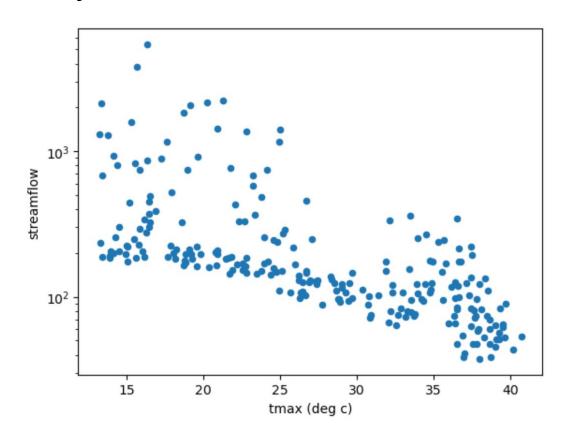
We are playing fast and loose with some stats today, please be sure to follow up on formal methods either by taking some real stats classes or using prior knowledge!!!

### Where we left off on Tuesday

You saw how to load data from the USGS streamflow database for the Verde River

You also learned how to apply the same technique to the DayMet dataset, which lets us get things like temperature and precipitation

We finished up by making this plot



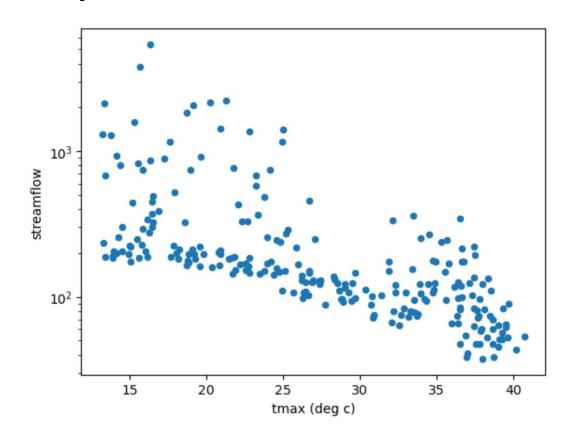
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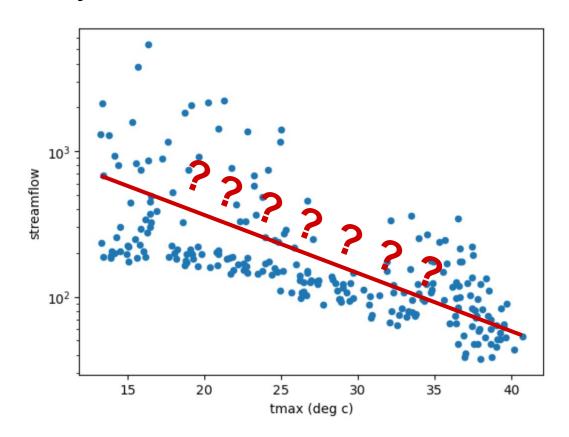
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## Enter linear regression

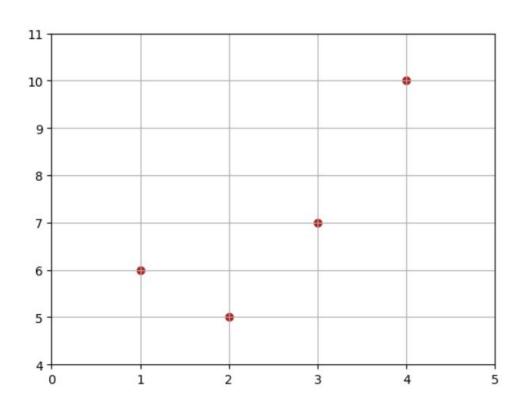
We're going to do just a little bit of theory here before

Suppose we have data with:

- x=[1,2,3,4]
- y=[6,5,7,10]

We will call x the "explanatory variable"

And we call y the "response variable"



Example courtesy wikipedia: https://en.wikipedia.org/wiki/Linear\_least\_squares

## So how do we go about fitting a line through the data?

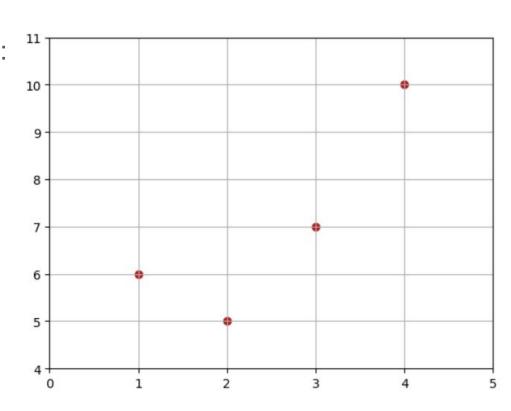
Recall that the equation for a line is:

$$y = \beta_2 x + \beta_1$$

Where:

$$eta_2$$
 Is the slope

 $\beta_1$  Is the intercept



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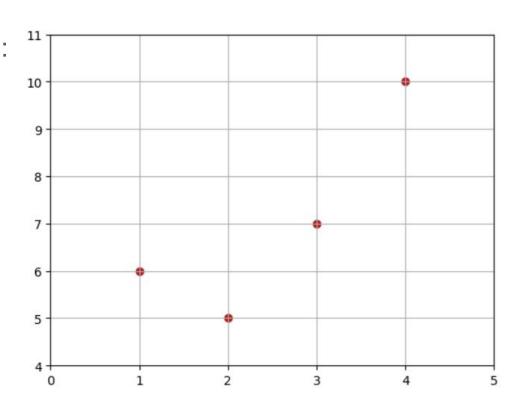
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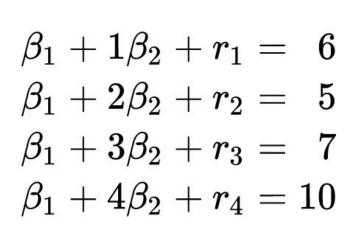
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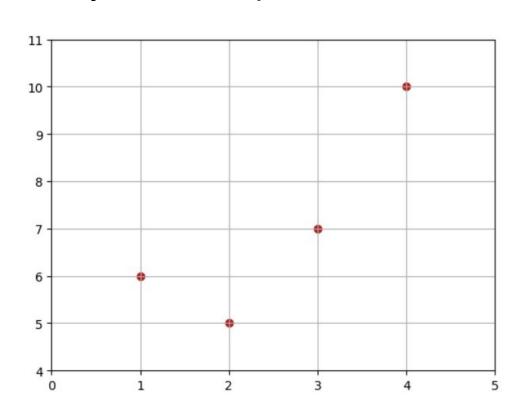
 $\beta_1$  Is the intercept

 $\gamma$  Is a residual term



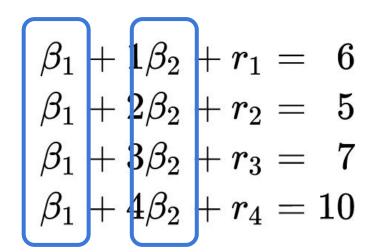
## Now we can frame things into a system of equations

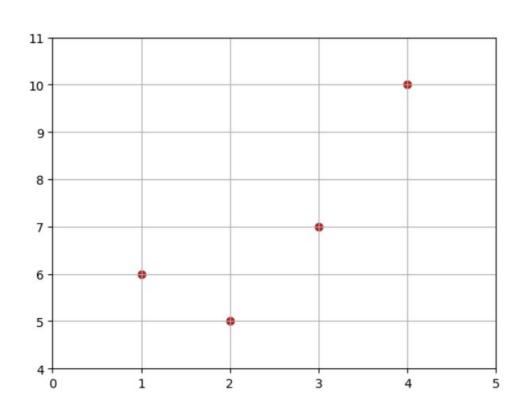




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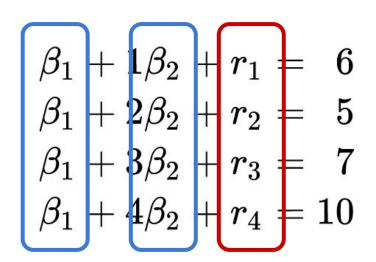
### We want the value of these



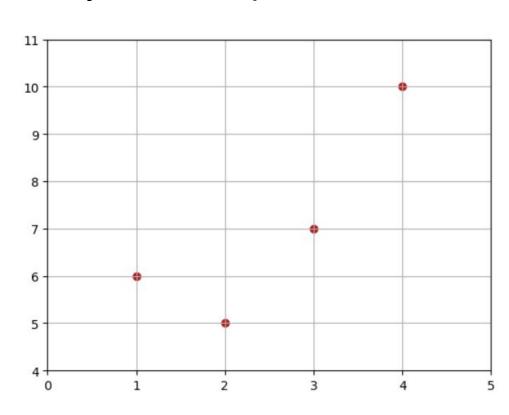


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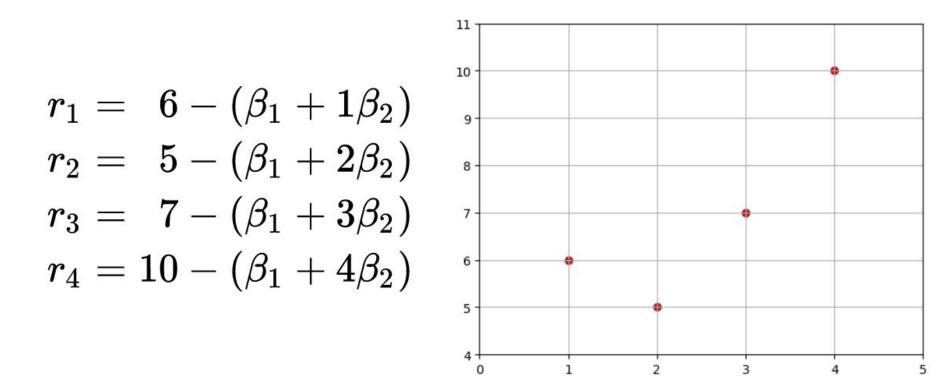
### We want the value of these



And we want to minimize the "total" of these

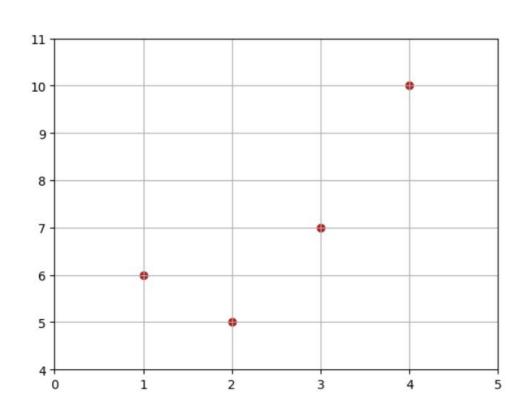


### We rearrange to put the residual terms on the LHS

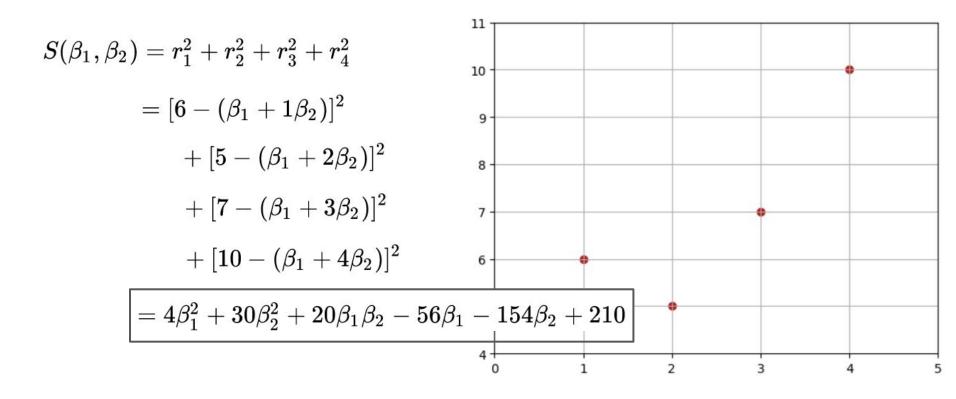


## Then we reframe in terms of a sum of squares equation

$$egin{aligned} S(eta_1,eta_2) &= r_1^2 + r_2^2 + r_3^2 + r_4^2 \ &= [6 - (eta_1 + 1eta_2)]^2 \ &+ [5 - (eta_1 + 2eta_2)]^2 \ &+ [7 - (eta_1 + 3eta_2)]^2 \ &+ [10 - (eta_1 + 4eta_2)]^2 \end{aligned}$$



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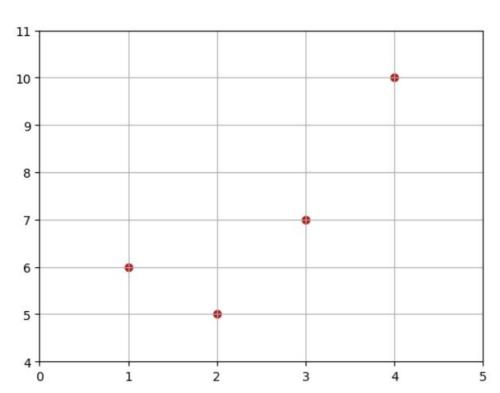


Set the partial derivatives equal to zero to find the

"least squares error"

$$rac{\partial S}{\partial eta_1} = 0 = 8eta_1 + 20eta_2 - 56$$

$$rac{\partial S}{\partial eta_2} = 0 = 20eta_1 + 60eta_2 - 154.$$



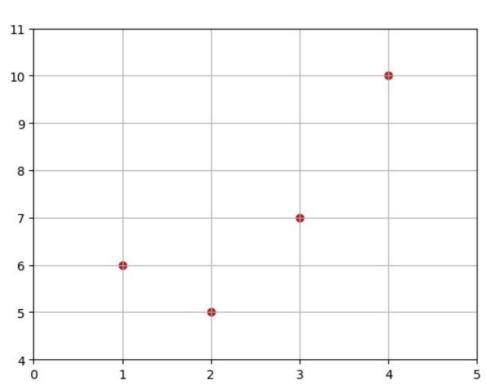
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2 equations, 2 unknowns, easy-peasy



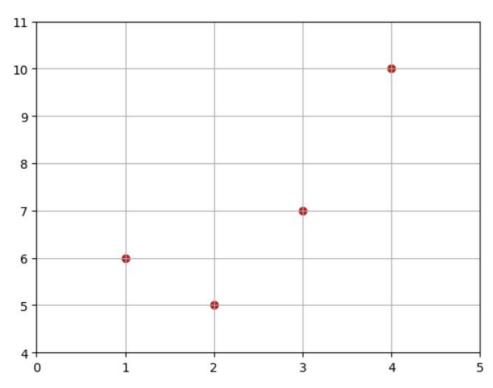
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$$\beta_1=3.5$$

$$\beta_2=1.4$$

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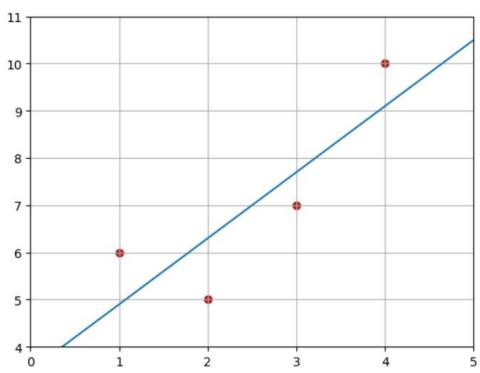


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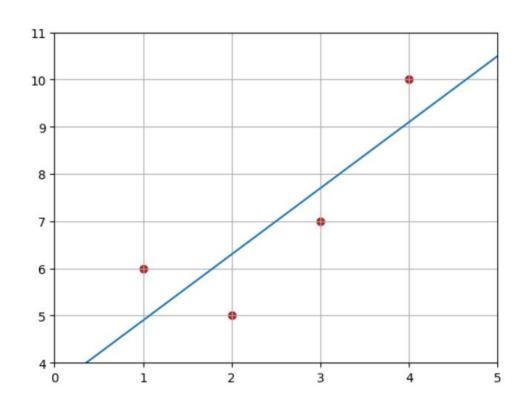


## Looks pretty good! But I'm glossing over A TON

The statistical procedure for fitting Ordinary Least Squares (OLS) models is generally understood

However there are many caveats, conditions, etc

And, particularly, linear least squares is not always the best model (actually almost never)

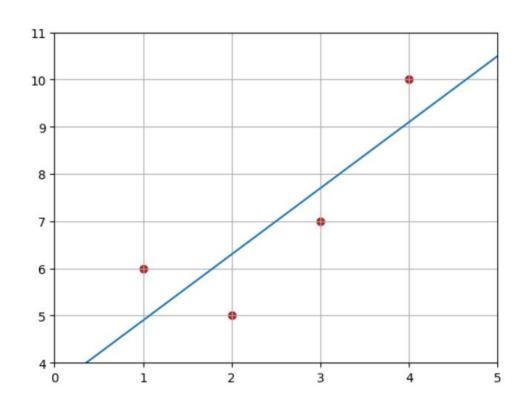


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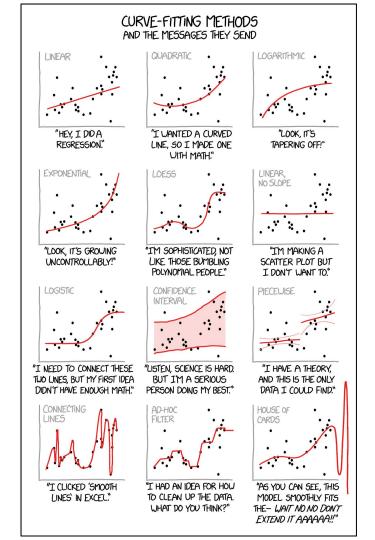
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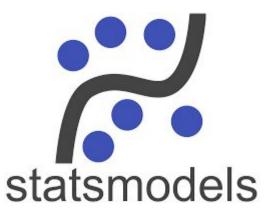
And then there's non-linear regression....





## The big 3

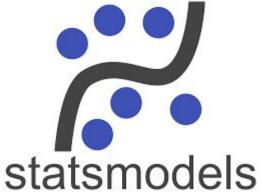






## The big 3







## Why scikit-learn?



It is well established, same for statsmodels & scipy

It has a consistent interface (or API) between model types

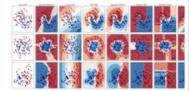
It has a number of other applications I hope you find useful



#### Classification

identifying which category an object belongs to.

Applications: Spam detection, image recognition. Algorithms: SVM, nearest neighbors, random forest, and more....

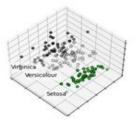


Examples

### Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency Algorithms: PCA, feature selection, non-negative matrix factorization, and more....



Examples

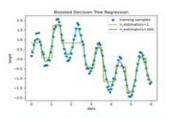
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Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.

Algorithms: SVR, nearest neighbors, random for-

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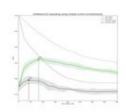
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#### Model selection

Comparing, validating and choosing parameters and models.

Applications: Improved accuracy via parameter tuning

Algorithms: grid search, cross validation, metrics, and more...



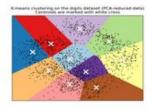
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### Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes

Algorithms: k-Means, spectral clustering, meanshift, and more...



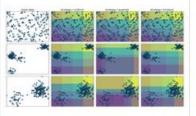
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### Preprocessing

Feature extraction and normalization.

Applications: Transforming input data such as text for use with machine learning algorithms.

Algorithms: preprocessing, feature extraction, and more....



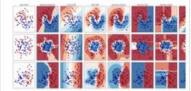
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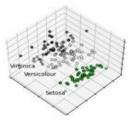


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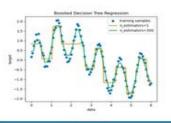
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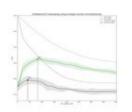
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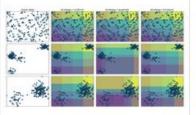
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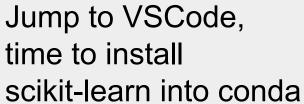
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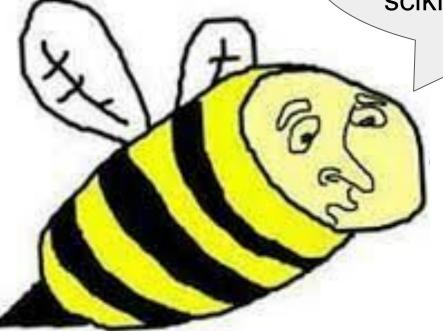
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https://scikit-learn.org/stable/auto\_e xamples/linear\_model/plot\_ols.html