

# Digital World (2019)

## Week 10, SI: Linear Regression

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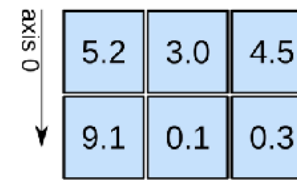


1D array



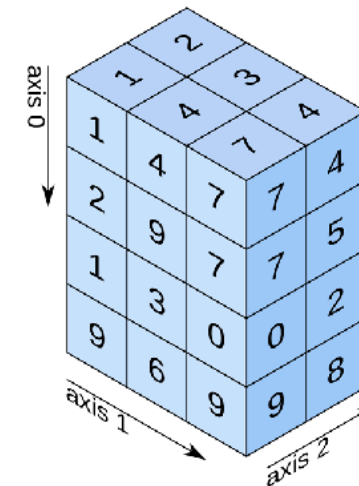
shape: (4,)

2D array



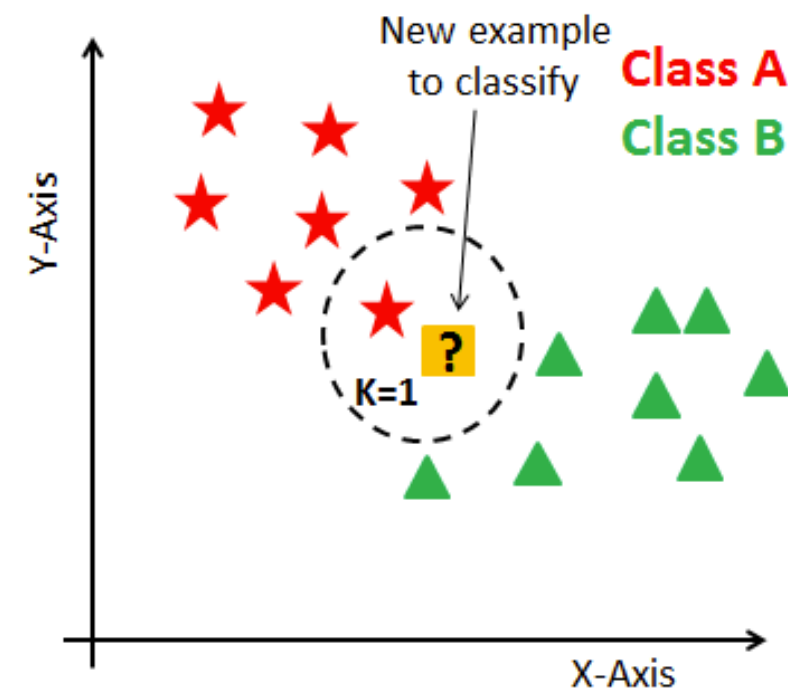
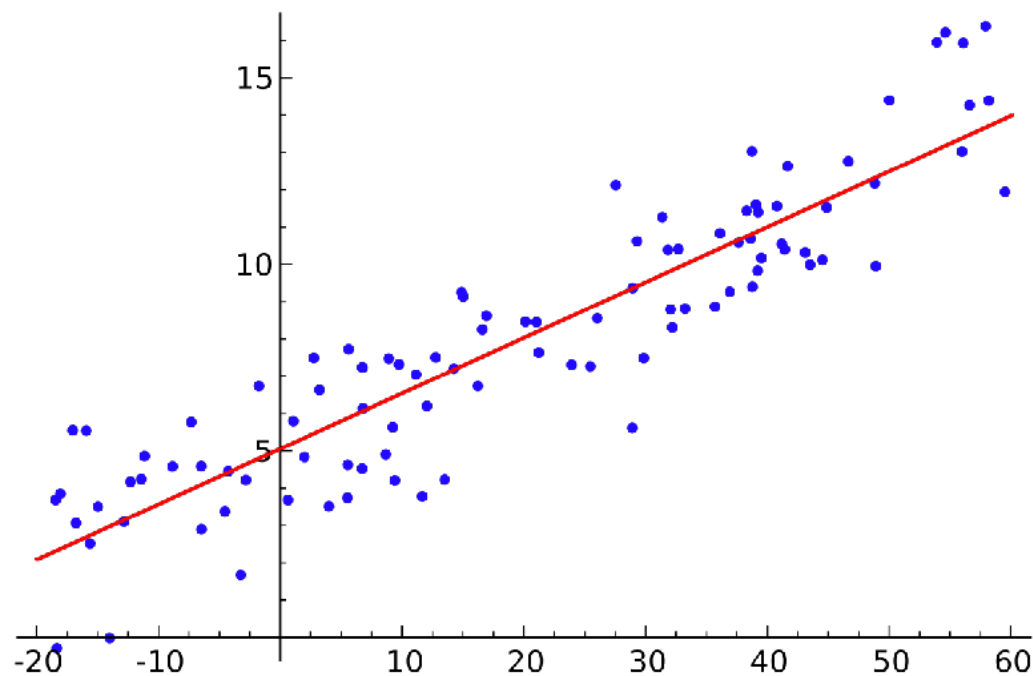
shape: (2, 3)

3D array



shape: (4, 3, 2)

# This week — *Data Analysis and Prediction*



# NumPy Arrays

# Refresher: how we *used* to do matrices

$$M = \begin{bmatrix} [0, 0, 0, 1, 0], \\ [0, 0, 0, 0, 0], \\ [0, 2, 0, 0, 0], \\ [0, 0, 0, 0, 0], \\ [0, 0, 0, 3, 0] \end{bmatrix}$$

**M** =

(0, 3)	→	1
(2, 1)	→	2
(4, 3)	→	3

*how would we slice **row** 3?*

*how would we slice **column** 3? (🤮)*

# Matrices in NumPy

- matrices are represented as 2-dimensional array objects

*=>  $M = \text{np.array}([[...], ...])$*

- equipped with several powerful and efficient methods

*=>  $M.\text{sum}()$ ,  $M.T$ ,  $\text{np.sqrt}(M)$ ,  $\text{np.add}(M_1, M_2)$ , ...*

- in general, an ndarray object can be N-dimensional

*=>  $M.\text{shape}$  returns the length of each dimension*

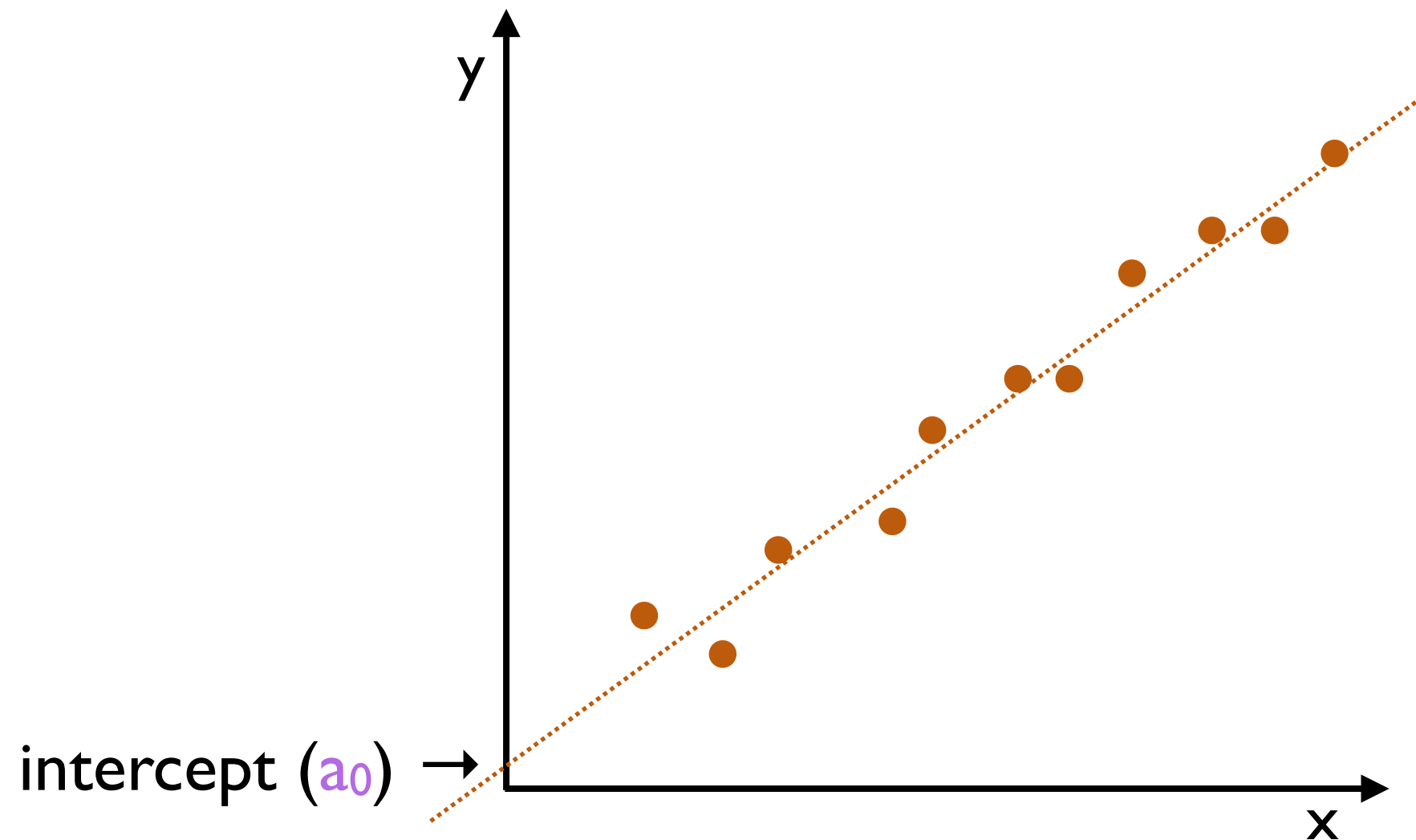
- 1D arrays are like lists: no rows/cols; just ordered elements

# A realistic dataset for practice

- `sklearn.datasets` provides some datasets for practice
- we will use the `Wisconsin breast cancer` dataset
- several `features` of different malignant/benign masses  
*=> radius, texture, perimeter, area, smoothness, ...*
- we will load a `dictionary-like “bunch object”`, with attributes such as `data`, `feature_names`, `target`, ...

# Linear Regression

# Linear regression: *line of best fit*



$$y = a_0 + a_1 x$$



# Implementing linear regression

- we can train a linear regression model using sklearn

*=> in particular, the **sklearn.linear\_model** module*

- first, split our data into training and testing sets

*=> typically a 60% : 40% split*

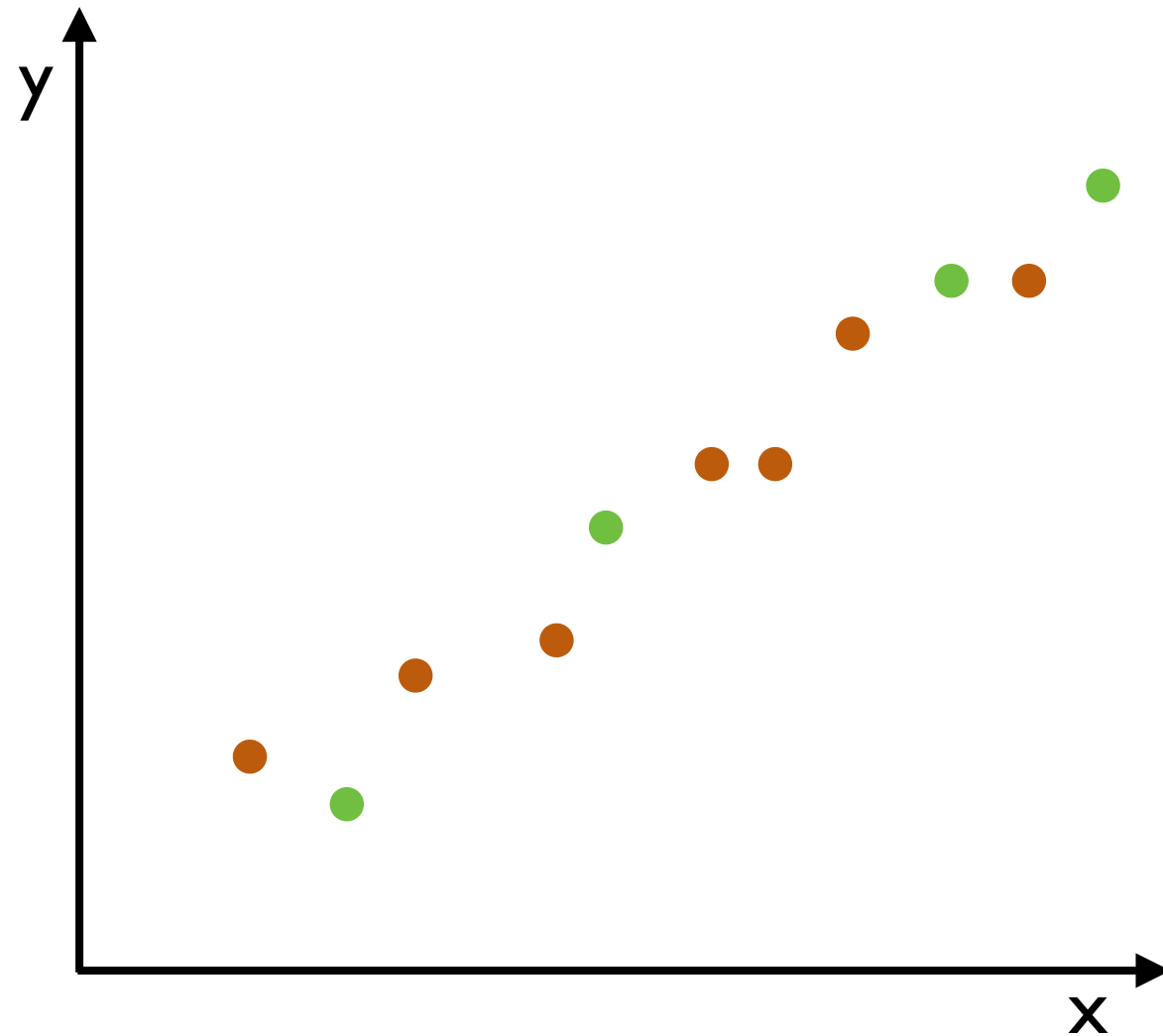
*=> use the **train\_test\_split()** function to do so*

- then, use the fit method on the training data

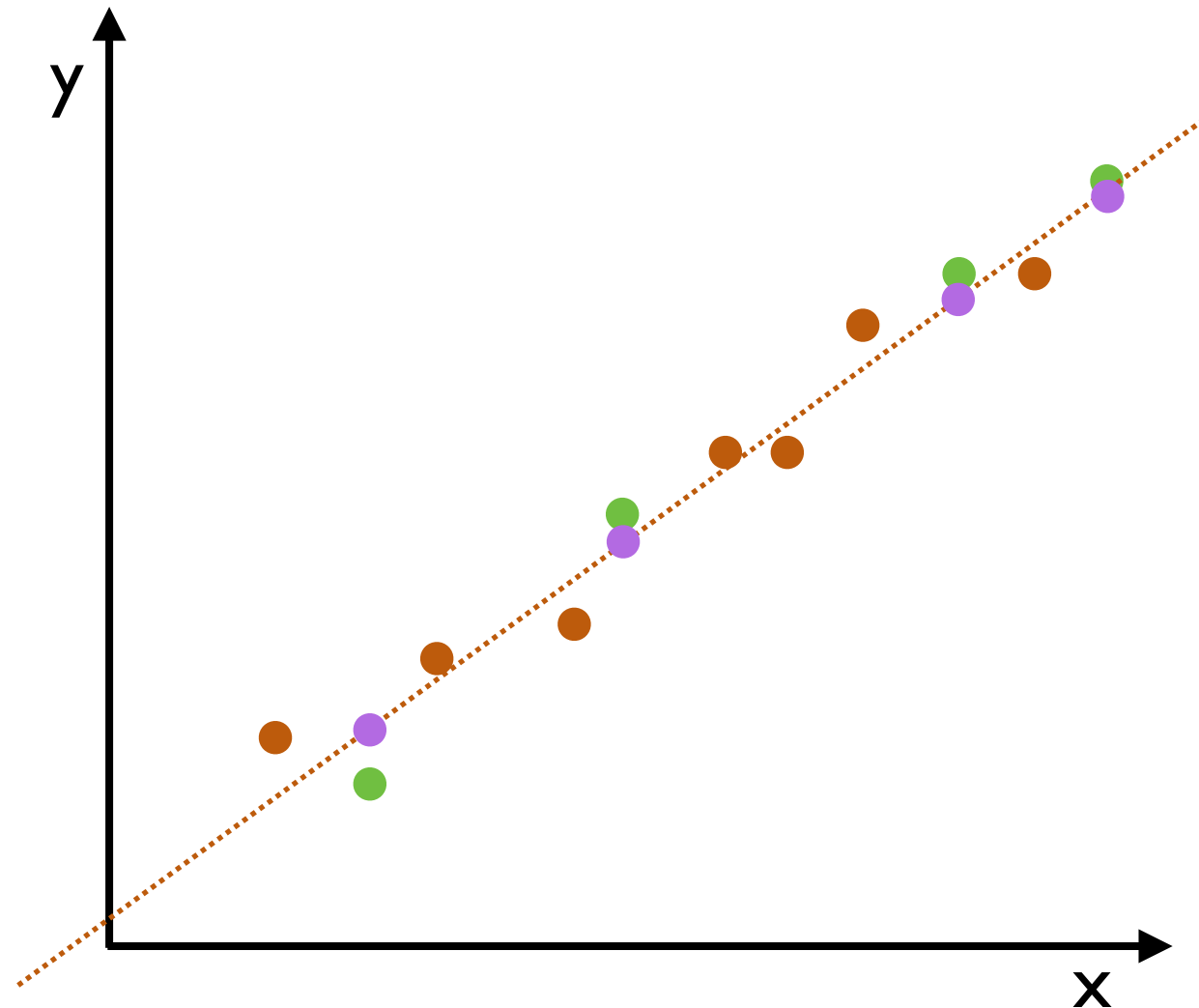
```
model = linear_model.LinearRegression()  
model.fit(x_train, y_train)
```

- the model object stores the coefficient and intercept as attributes — *see the documentation!*

# Training / testing split



# Applying `model.predict(x_test)`



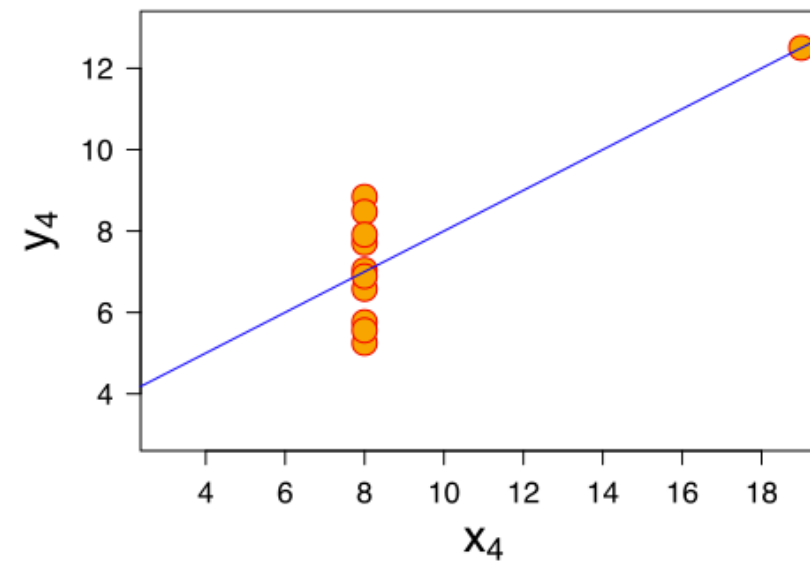
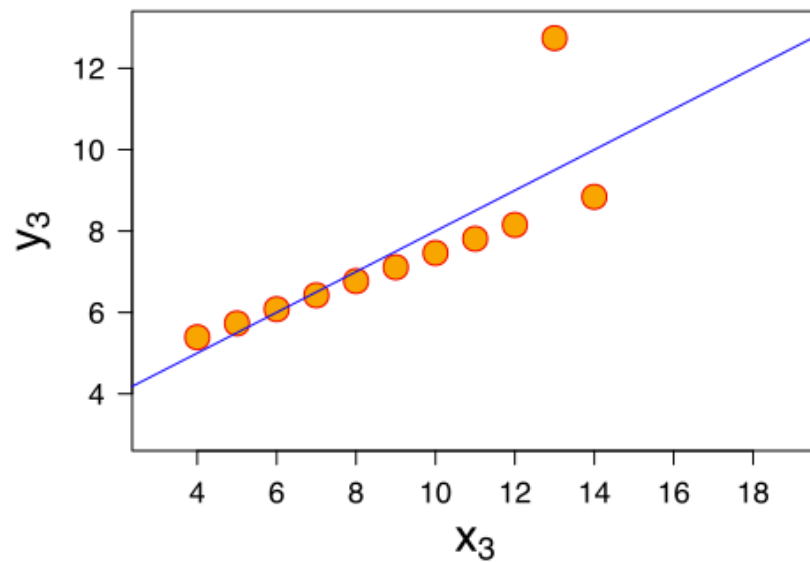
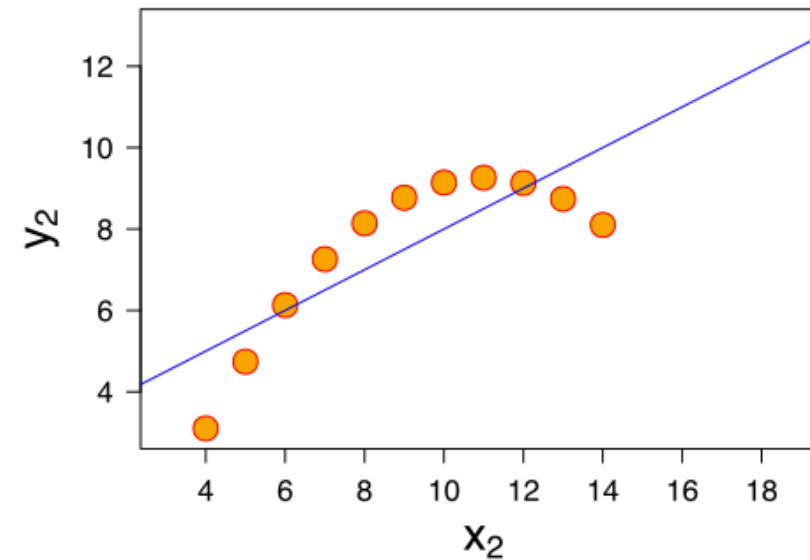
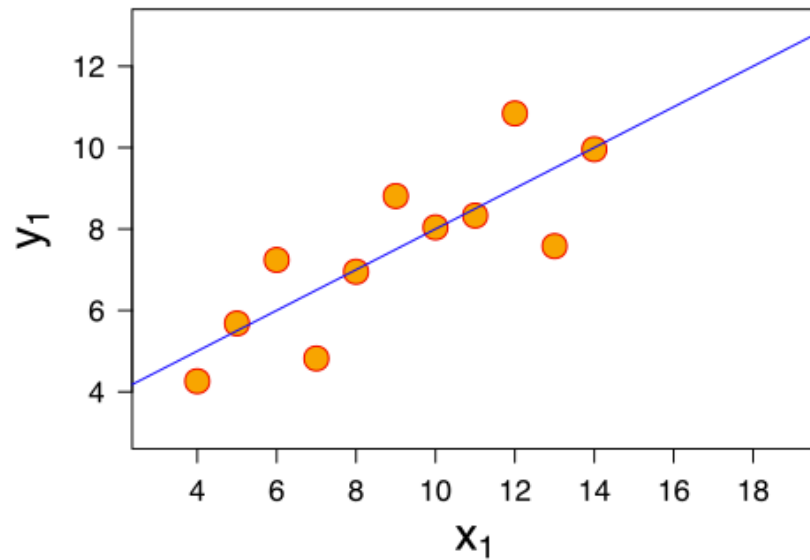
$$y = \text{model.coef\_} + \text{model.intercept\_}x$$

# Is your model any good?

- from the x test values **predict** the y values
- compare them against what the **actual y values** were
- there are different **metrics** we can then apply:
  - => **MSE**: mean of the squared errors (actual vs. predicted)
  - => **R2**: measure of how well actual outcomes are predicted by the model (“% of variance accounted for”)



# Anscombe's quartet



**lesson:** don't rely *only* on your favourite metric!

Today: questions CS5 and CS6 only

*(we'll do CS1-4, 7 on Tuesday and Thursday)*

# Polynomial regression

- often a **simple linear** model is **not enough**; we need:

$$y = a_0 + a_1x + a_2x^2 + a_3x^3 + \dots$$

- train a **polynomial regression** model

*=> special case of multiple linear regression*

- **idea**: take the original  $x$  data, and compute  $x^2, x^3, \dots$

*=> take  $x^2, x^3, \dots$  as **new features** to train on*

- use **PolynomialFeatures** from **sklearn.preprocessing**

```
poly = PolynomialFeatures(order, include_bias=False)
poly_data = poly.fit_transform(x_data)
```

# Summary

- NumPy provides powerful and efficient operations for analysing N-dimensional arrays
- sklearn can be used to train linear models
- metrics and plotting complement each other
  - => *metrics alone can mislead — see Anscombe's quartet!*
- polynomial regression can take into account higher orders
  - => *...but don't overfit!*