

# **DATA SCIENCE**

**11 WEEK PART TIME COURSE**

**Week 4 – Clustering**  
**Wednesday 13th January 2016**

1. Motivation / Review
2. What is Clustering?
3. What is K-Means and how does it work?
4. Lab
5. Discussion - Homework, Project, Kaggle

---

**DATA SCIENCE PART TIME COURSE**

---

# **WHAT IS CLUSTERING AND WHY DO IT?**

# scikit-learn algorithm cheat-sheet

START

## classification



## regression



## clustering

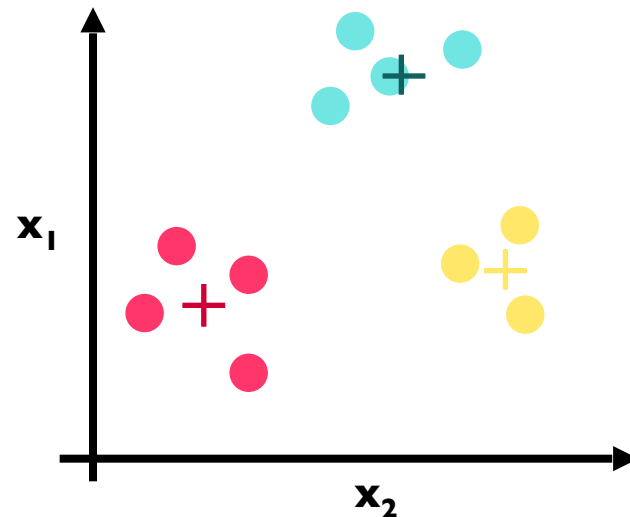


## dimensionality reduction

Back

scikit  
learn

- What is a Cluster?
- Why would we do this?
- What is K-Means?



Recall unsupervised learning is when we are trying to find interesting patterns or groups in our data. We don't have a variable we are trying to predict (a Y value).

Clustering aims to discover subgroups in our data where the points are similar to each other. So we have a collection of groups and all points belonging to the same group are similar. Points in different groups are different to each other.

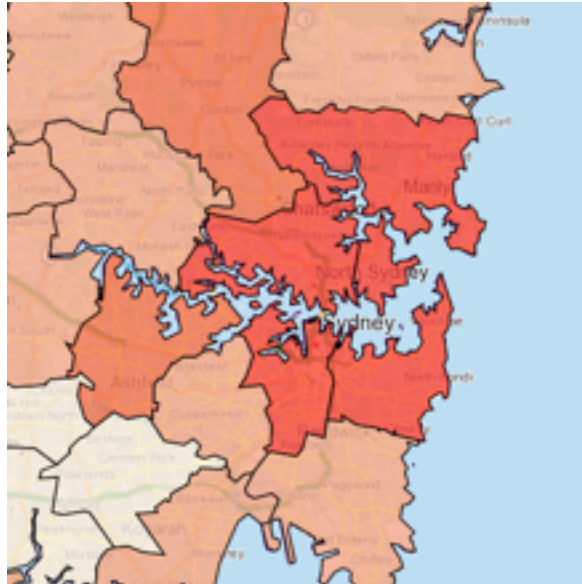
We have to decide what variables we will construct the groups on. What makes them different (or similar)?

To enhance our understanding of a dataset by dividing the data into groups.

Clustering provides a layer of abstraction from individual data points.

The goal is to extract and enhance the natural structure of the data

Marketing teams might want to group customers into like groups as a way of summarising the data





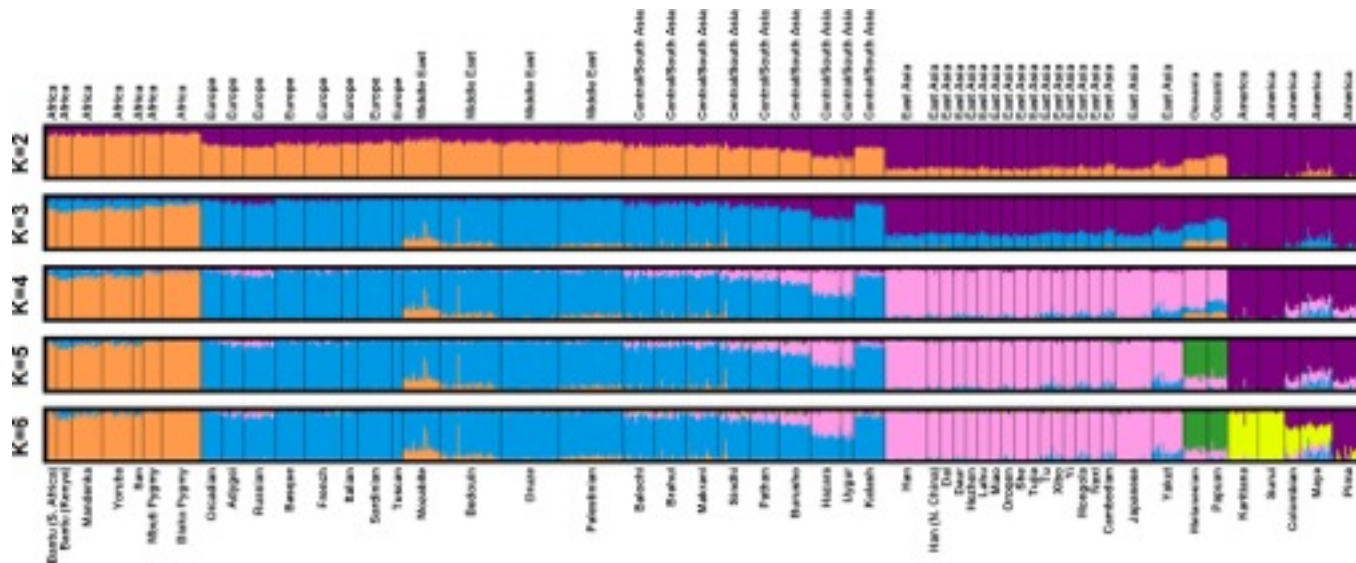
Financial groups may want to group transactions into like groups as a way to find unusual payments



## WHY WOULD WE CLUSTER DATA?

10

## Genetics data can be clustered to identify ancestry



**DATA SCIENCE PART TIME COURSE**

---

# **HOW DO WE CLUSTER DATA?**

- 1) Choose  $k$  initial centroids (note that  $k$  is an input)
- 2) For each point:
  - find distance to each centroid
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met

There are several options:

- randomly (but may yield divergent behavior)
- perform alternative clustering task, use resulting centroids as initial k-means centroids
- start with global centroid, choose point at max distance, repeat (but might select outlier)

The similarity criterion is determined by the measure we choose.

In the case of k-means clustering, the similarity metric is the **Euclidian distance**:

$$d(x_1, x_2) = \sqrt{\sum_{i=1}^N (x_{1i} - x_{2i})^2}$$

**Q:** How do we re-compute the positions of the centres at each iteration of the algorithm?

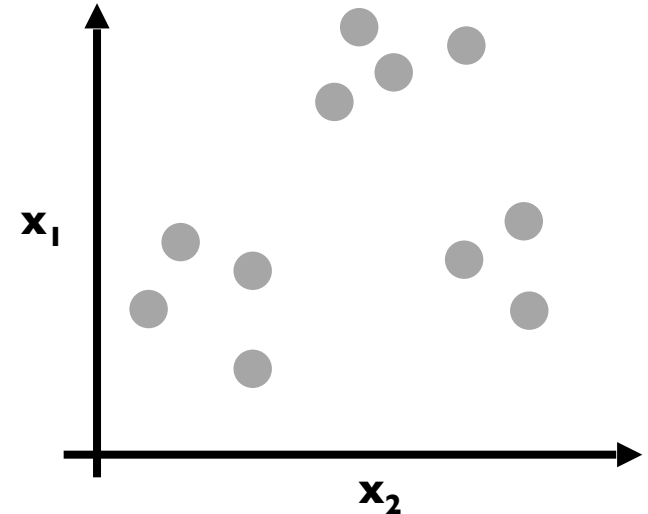
**A:** By calculating the centroid (i.e., the geometric centre)

We iterate until some stopping criteria are met; in general, suitable convergence is achieved in a small number of steps.

Stopping criteria can be based on the centroids (eg, if positions change by no more than  $\epsilon$ ) or on the points (eg, if no more than  $x\%$  change clusters between iterations).



- 1) Choose  $k$  initial centroids
- 2) For each point:
  - find distance to each centroid
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met



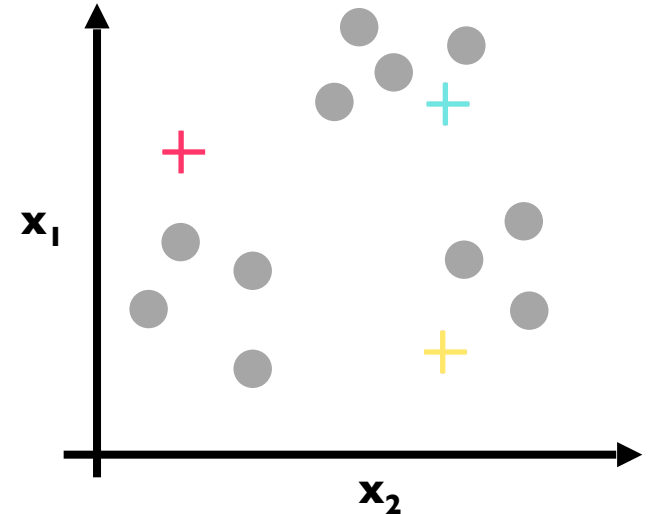
1) Choose  $k$  initial centroids

2) For each point:

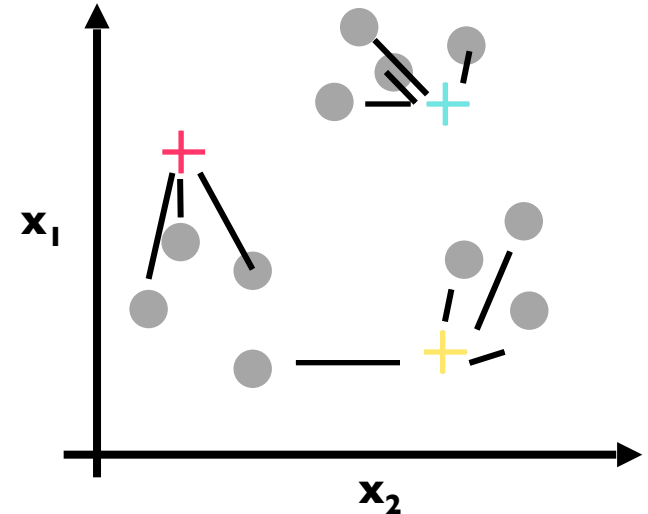
- find distance to each centroid
- assign point to nearest centroid

3) Recalculate centroid positions

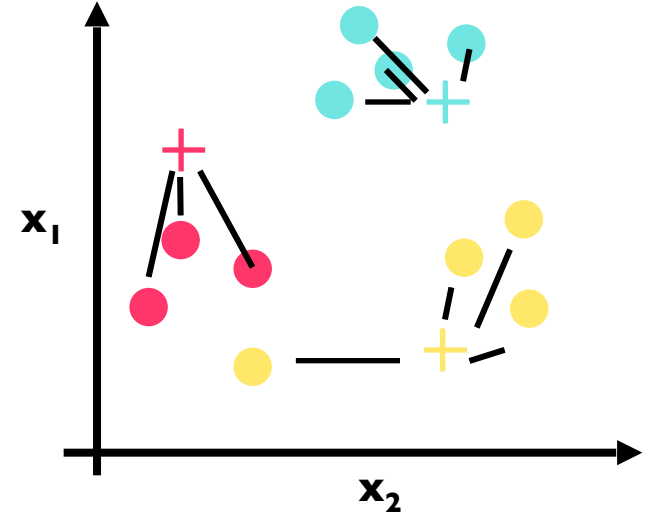
4) Repeat steps 2-3 until stopping criteria met



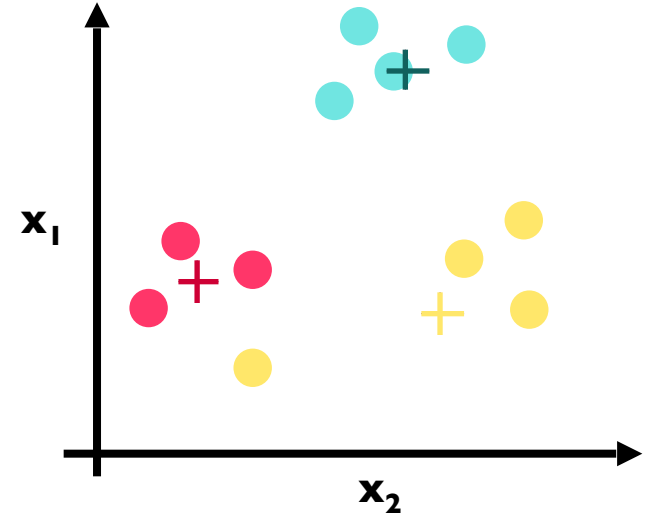
- 1) Choose  $k$  initial centroids
- 2) For each point:
  - **find distance to each centroid**
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met



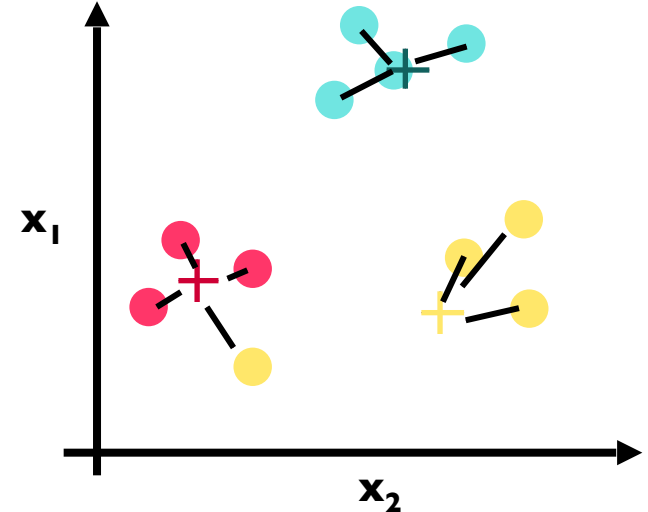
- 1) Choose  $k$  initial centroids
- 2) For each point:
  - find distance to each centroid
  - **assign point to nearest centroid**
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met



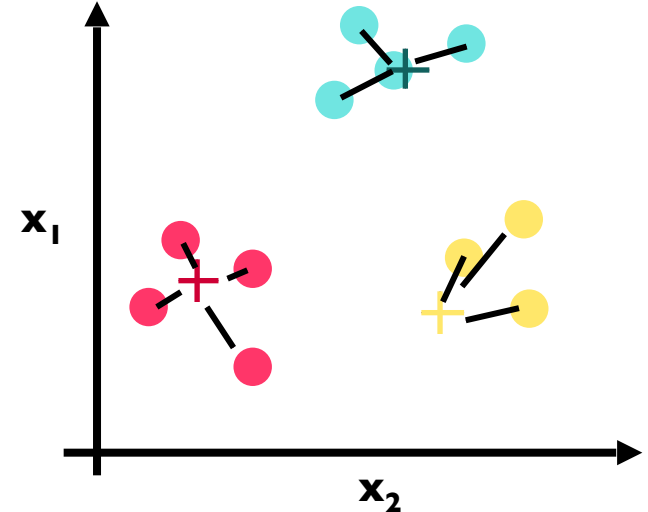
- 1) Choose  $k$  initial centroids
- 2) For each point:
  - find distance to each centroid
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met



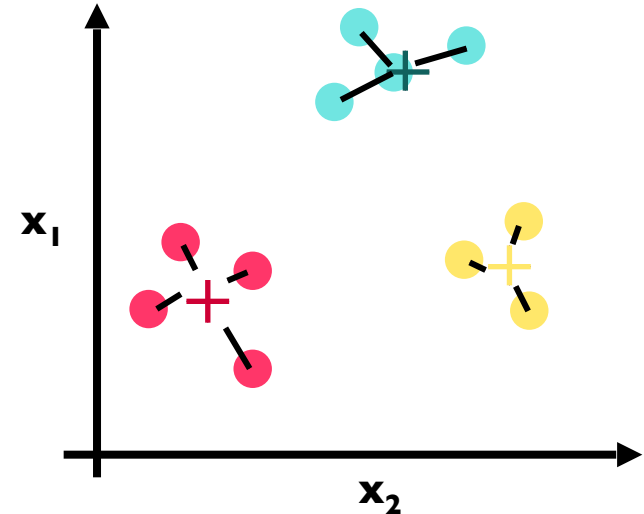
- 1) Choose  $k$  initial centroids
- 2) For each point:
  - find distance to each centroid
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met



- 1) Choose  $k$  initial centroids
- 2) For each point:
  - find distance to each centroid
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met

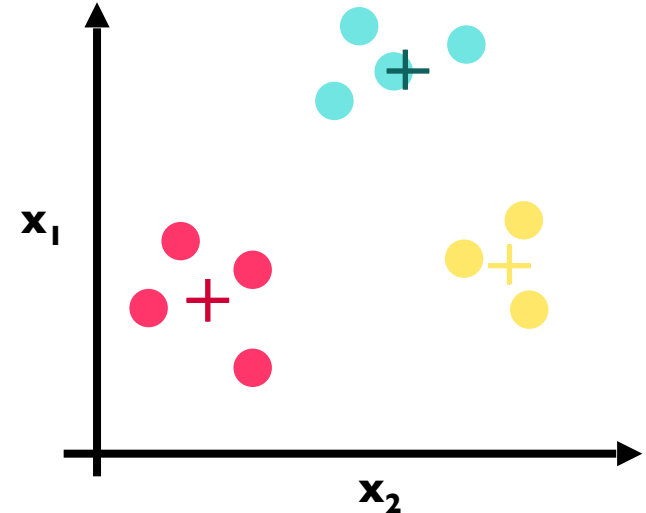


- 1) Choose  $k$  initial centroids
- 2) For each point:
  - find distance to each centroid
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met





- 1) Choose  $k$  initial centroids
- 2) For each point:
  - find distance to each centroid
  - assign point to nearest centroid
- 3) Recalculate centroid positions
- 4) Repeat steps 2-3 until stopping criteria met



**DATA SCIENCE PART TIME COURSE**

---

**HOW DO WE KNOW  
OUR CLUSTERS ARE  
ANY GOOD?**

In general, k-means will converge to a solution and return a partition of  $k$  clusters, even if no natural clusters exist in the data.

We will look at two validation metrics useful for partitional clustering, **cohesion** and **separation**.

Cohesion measures clustering effectiveness within a cluster.

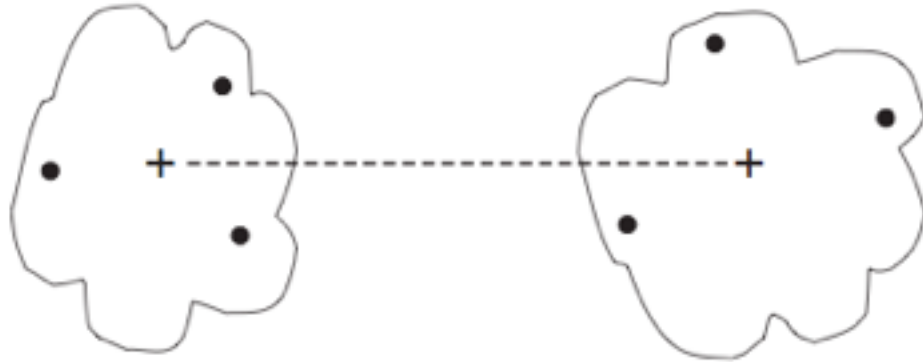
$$\hat{C}(C_i) = \sum_{x \in C_i} d(x, c_i)$$

Separation measures clustering effectiveness between clusters.

$$\hat{S}(C_i, C_j) = d(c_i, c_j)$$



(a) Cohesion.



(b) Separation.

**Figure 8.28.** Prototype-based view of cluster cohesion and separation.

One useful measure than combines the ideas of cohesion and separation is the silhouette coefficient. For point  $x_i$ , this is given by:

$$SC_i = \frac{b_i - a_i}{\max(a_i, b_i)}$$

such that:

$a_i$  = average in-cluster distance to  $x_i$

$b_{ij}$  = average between-cluster distance to  $x_i$

$b_i = \min_j(b_{ij})$

The silhouette coefficient can take values between -1 and 1.

In general, we want separation to be high and cohesion to be low. This corresponds to a value of SC close to +1.

A negative silhouette coefficient means the cluster radius is larger than the space between clusters, and thus clusters overlap

The silhouette coefficient for the cluster  $C_i$  is given by the average silhouette coefficient across all points in  $C_i$ :

$$SC(C_i) = \frac{1}{m_i} \sum_{x \in C_i} SC_i$$

The overall silhouette coefficient is given by the average silhouette coefficient across all clusters:

$$SC_{total} = \frac{1}{k} \sum_1^k SC(C_i)$$



One useful application of cluster validation is to determine the best number of clusters for your dataset.

Q: How would you do this?

A: By computing the SSE or SC for different values of  $k$ .

Ultimately, cluster validation and clustering in general are suggestive techniques that rely on human interpretation to be meaningful.

**Strengths:**

K-means is a popular algorithm because of its computational efficiency and simple and intuitive nature.

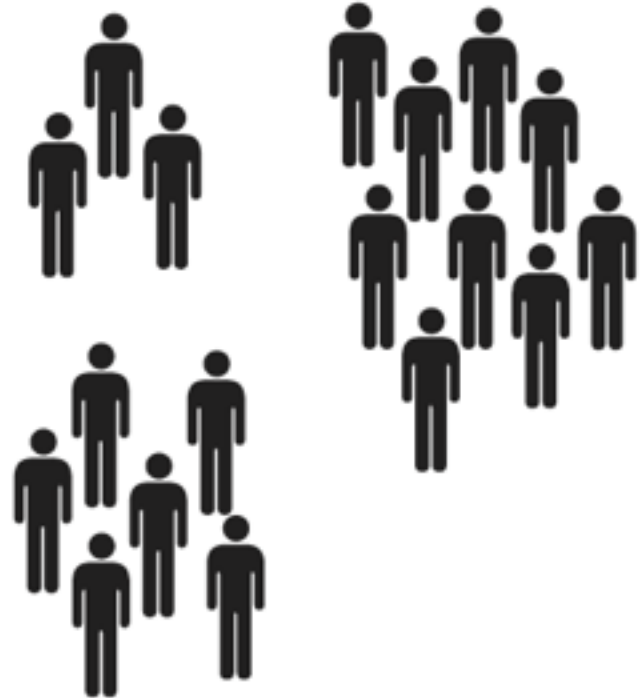
**Weaknesses:**

However, K-means is highly scale dependent, and is not suitable for data with widely varying shapes and densities.

## DATA SCIENCE PART TIME COURSE

---

# LAB



```
git remote -v
```

```
git remote add upstream https://github.com/ihansel/SYD_DAT_3.git
```

```
git remote -v
```

```
git fetch upstream
```

```
git checkout master
```

```
git merge upstream/master
```

```
OR git reset --hard upstream/master
```



## WEEK 4 Monday

Monday 11<sup>th</sup> January - Regularization

- ☒ Select Variables for a Regression Model
- ☒ Learn 3 Methods to automatically select variables
- ☒ Explain difference between Ridge Regressor & Lasso
- ? ☒ Tie together concepts of X-Validation, Sub-Set Selection + Regularization

GA-GUEST  
yellowpencil

# **DISCUSSION TIME**

- **Homework 2**
- **Homework 3**
- **Presentations next Wednesday – 5 slides on a data science topic of your choice**
- **Project**
- **Kaggle**

---

## **DATA SCIENCE – Week 3 Day 1**

---

# **HOMEWORK 2**

### **Highlights**

- **Good communication on the basics of what regression is, some might have been a little too technical but that's ok**
- **Most were able to interpret the outputs of the linear regression and calculate the Y variables by hand**
- **Nice reviews of Small Multiple visualisations**
- **More in depth thinking about the projects**



## **DATA SCIENCE – Week 4 Day 2**

---

# **HOMEWORK 3**

### **Tasks**

- **Prepare a 5 minute presentation for class next Wednesday (details in homework notebook)**
- **Data in github for your project (or transferred to me in some form)**
- **Read your data in Python**
- **Visualise your data in Python**
- **One of the following with your data; Linear or Logistic Regression (with regularization), or Clustering**

# READINGS

**Read the following before class on Monday**

- **<http://www.slideshare.net/MrChrisJohnson/algorithmic-music-recommendations-at-spotify>**
- **<http://techblog.netflix.com/2012/04/netflix-recommendations-beyond-5-stars.html>**

