



概念

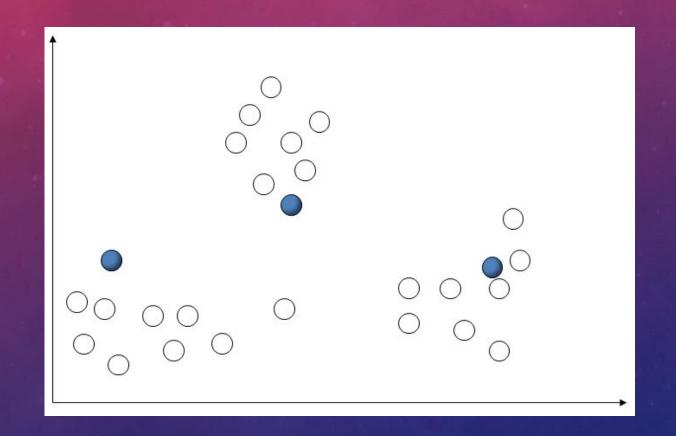
- 把許多事物按照某種標準歸為數個類別,其中較為相近/類似的聚為一類,反之較不相近的則聚為不同類。目的是企圖從一大堆雜亂無章的原始資料中,找出少數幾個較小的群體,使得群體內的分子在某些變項的測量值均很類似,而群體與群體間的分子在該測量值上差異較大。
- 同一組樣本會因不同目的、資料輸入方式、所選擇分群特徵或 資料屬性,形成不同的分群結果



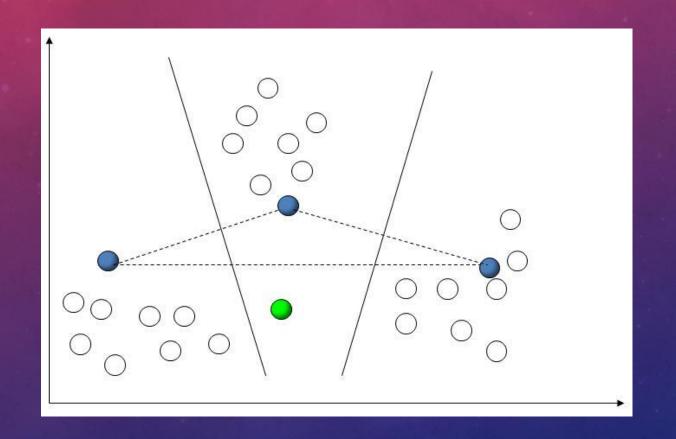
概念

隨機選取 k 個樣本作為起始中心點,將其餘樣本歸入相似度最高中心點所在的群;再計算目前群內樣本座標的平均值為新的中心點,依次循環反覆運算,直到所有樣本所屬的群不再變動。

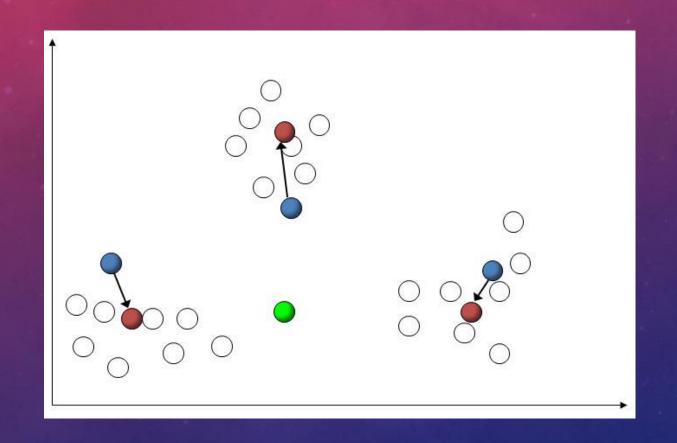
STEP 1. 隨機指派群集中心



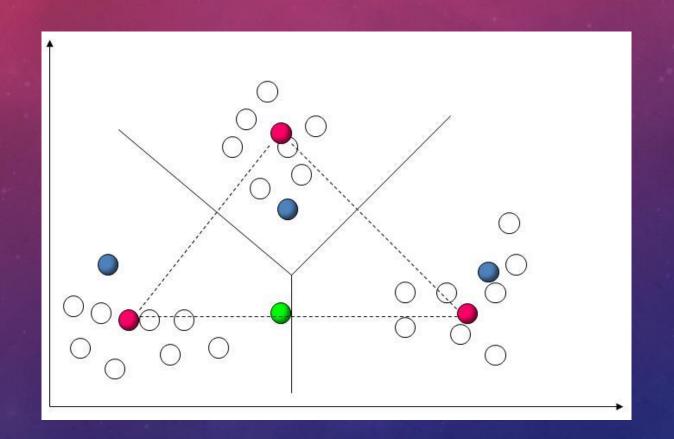
STEP 2. 產生初始群集



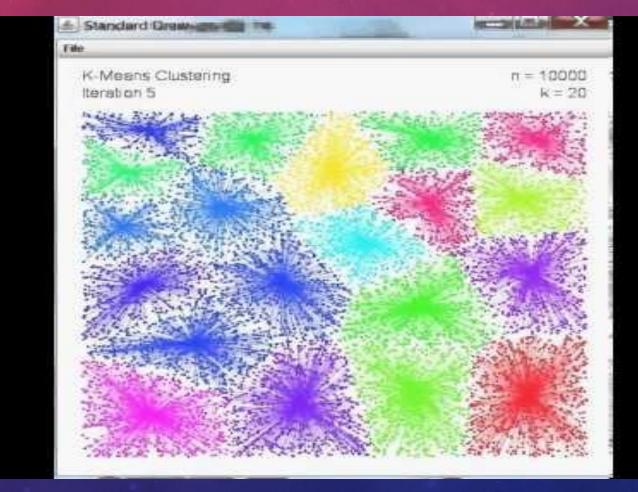
STEP 3. 產生新的質量中心



STEP 4. 變動群集邊界



EXAMPLE



10

https://youtu.be/BVFG7fd1H30

參考來源

- 1. https://rpubs.com/skydome20/R-Note9-Clustering
- 2. https://jgpan.gitbooks.io/the-study-of-r/content/clustering.html
- 3. K-Means Clustering Example
- 4. http://ccckmit.wikidot.com/ai:kmeans



重點

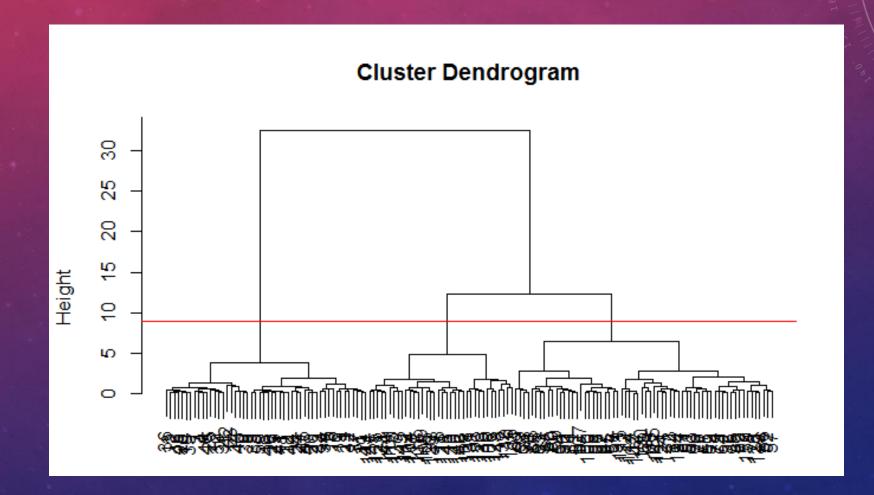
- 1. K 如何決定?
- 2. 相似度的方法



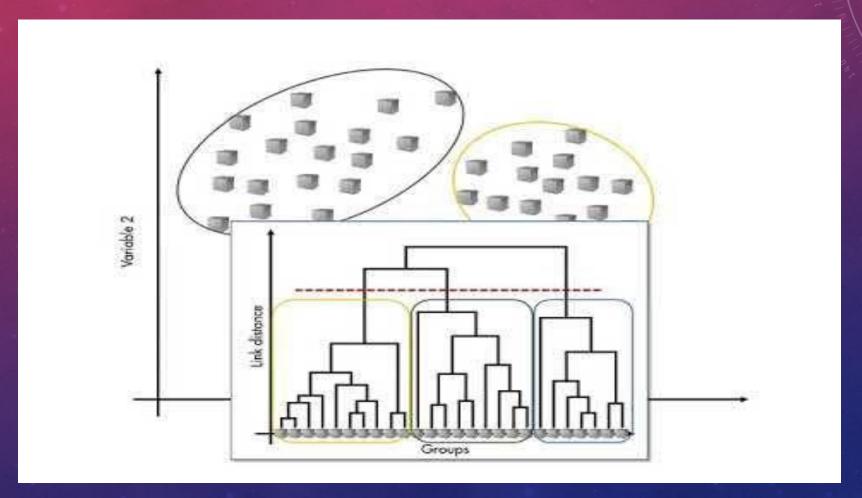
概念

- 不須事先設定群數 k,每次反覆運算過程僅將距離最近的兩個 樣本/群聚為一類,直到符合設定的群集數條件
 - 由下往上聚合: 從樹狀結構底部開始,將資料或各分群逐次合併,一開始將每個資料都視為一個獨立的分群,然後依據分群間相似度計算公式,不斷合併兩個最相似的資料/分群,直到所有資料/分群都合併成一個大的群集或達到所訂定的停止條件(設定的數量)為止。

PROCESSES



EXAMPLE



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https://youtu.be/iy7-Q7Y1Klk

參考來源

- 1. https://rpubs.com/skydome20/R-Note9-Clustering
- 2. https://jgpan.gitbooks.io/the-study-of-r/content/clustering.html
- 3. MATLAB skills, machine learning, sect 5: Hierarchical Clustering



重點

- 1. 由上往下分裂?
- 2. 與 K means 的差異?



鳶尾花資料集

- · 花瓣 (Petal) 的長
- 花瓣 (Petal) 的寬
- 花萼 (Sepal) 的長
- 花萼 (Sepal) 的寬

[5.1 3.5 1.4 0.2]

在設定某K的KMEANS

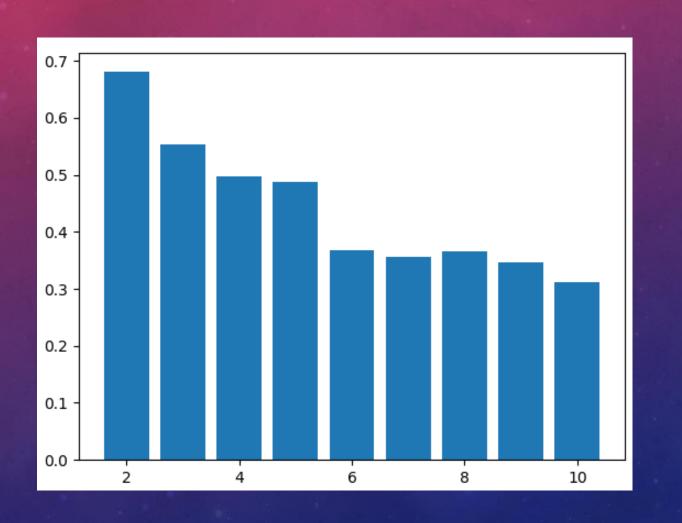
```
from sklearn import cluster, datasets
    iris = datasets.load_iris()
    iris_X = iris.data
    kmeans_fit = cluster.KMeans(n_clusters = 3).fit(iris_X)
    cluster_labels = kmeans_fit.labels_
    print("分群結果:")
    print(cluster_labels)
    print("---")
15
16 # 印出品種看看
    iris_y = iris.target
    print("真實品種:")
    print(iris_y)
```

在設定某K的KMEANS

K從2到10的KMEANS效能

```
from sklearn import cluster, datasets, metrics
    import matplotlib.pyplot as plt
    iris = datasets.load_iris()
    iris X = iris.data
    silhouette_avgs = []
    ks = range(2, 11)
11 \vee \text{for k in ks:}
        kmeans_fit = cluster.KMeans(n_clusters = k).fit(iris X)
        cluster labels = kmeans fit.labels
        silhouette_avg = metrics.silhouette_score(iris_X, cluster_labels)
        silhouette avgs.append(silhouette avg)
17 # 作圖並印出 k = 2 到 10 的績效
    plt.bar(ks, silhouette avgs)
    plt.show()
    print(silhouette_avgs)
```

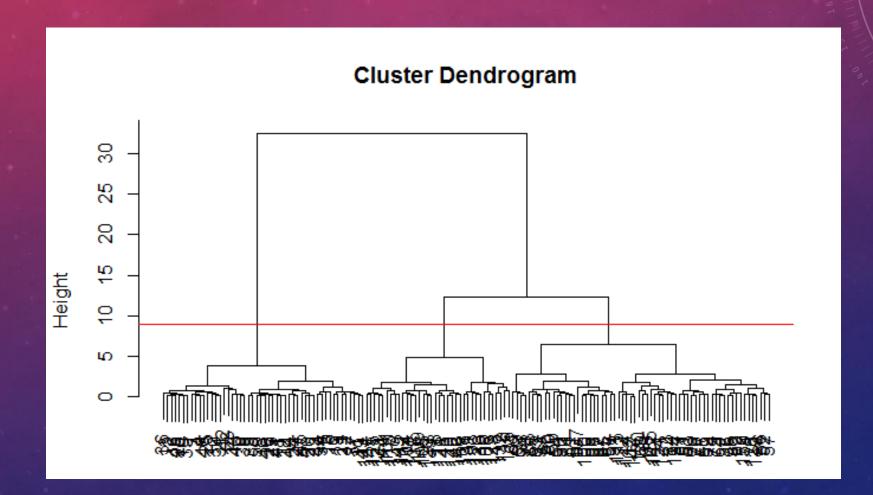
K從2到10的KMEANS效能



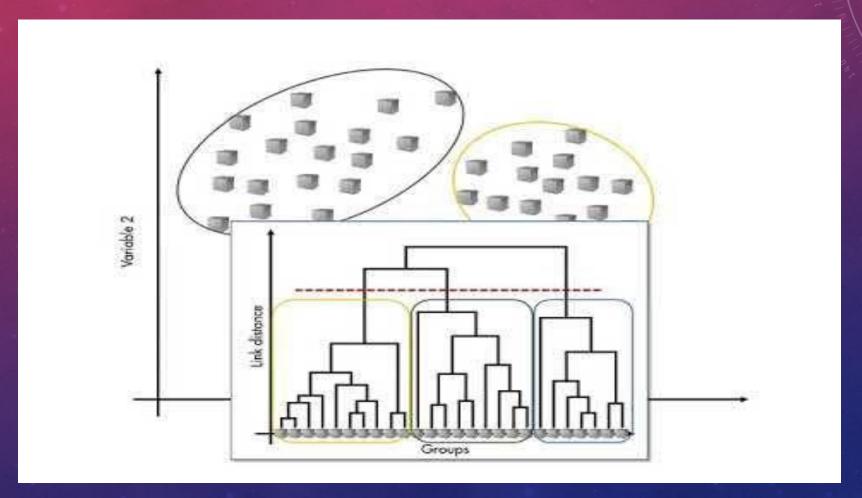
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PROCESSES



EXAMPLE



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https://youtu.be/iy7-Q7Y1Klk

鳶尾花資料集

- · 花瓣 (Petal) 的長
- 花瓣 (Petal) 的寬
- 花萼 (Sepal) 的長
- 花萼 (Sepal) 的寬

[5.1 3.5 1.4 0.2]

在設定某K的HIERARCHICAL CLUSTERING

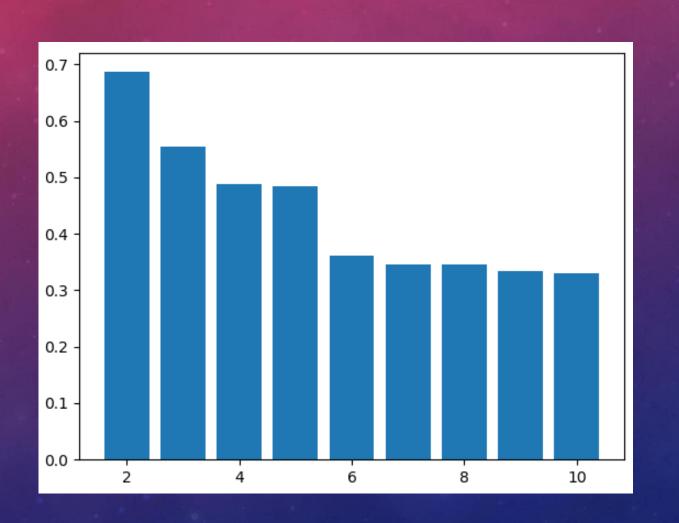
```
from sklearn import cluster, datasets
    iris = datasets.load iris()
    iris X = iris.data
    print(iris_X[0])
10 # Hierarchical Clustering 演算法
    hclust = cluster.AgglomerativeClustering(linkage = 'ward', affinity = 'euclidean', n clusters = 3)
12
    hclust.fit(iris X)
15 cluster labels = hclust.labels
    print(cluster labels)
    print("---")
19 # 印出品種看看
20 iris y = iris.target
    print(iris_y)
```

在設定某K的HIERARCHICAL CLUSTERING

K從2到10的效能

```
from sklearn import cluster, datasets, metrics
     import matplotlib.pyplot as plt
    iris = datasets.load_iris()
    iris X = iris.data
    silhouette avgs = []
    ks = range(2, 11)
    for k in ks:
12
        hclust fit = cluster.AgglomerativeClustering(linkage = 'ward', affinity = 'euclidean', n clusters = k).fit(iris X)
13
14
        cluster labels = hclust fit.labels
        silhouette avg = metrics.silhouette_score(iris X, cluster_labels)
15
         silhouette avgs.append(silhouette avg)
16
17
    plt.bar(ks, silhouette avgs)
    plt.show()
    print(silhouette avgs)
```

K從2到10的效能



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Wine Dataset

[1.207e+01, 2.160e+00, 2.170e+00, 2.100e+01, 8.500e+01, 2.600e+00, 2.650e+00, 3.700e-01, 1.350e+00, 2.760e+00, 8.600e-01, 3.280e+00, 3.780e+02]

- (1) Alcohol \rightarrow 1.207e+01
- (3) Ash \rightarrow 2.170e+00
- (5) Magnesium \rightarrow 8.500e+01
- (7) Flavanoids \rightarrow 2.650e+00
- (9) Proanthocyanins \rightarrow 1.350e+00
- (11)Hue \rightarrow 8.600e-01
- (13)Proline \rightarrow 3.780e+02

- (2) Malicacid \rightarrow 2.160e+00
- (4) Alcalinity of ash \rightarrow 2.100e+01
- (6) Total phenols \rightarrow 2.600e+00
- (8) Nonflavanoid phenols \rightarrow 3.700e-01
- (10)Color intensity \rightarrow 2.760e+00
- (12)OD280/OD315 of diluted wines \rightarrow

3.280e+00

