



STATISTICS AND BIG DATA '25-'26

K-means Clustering

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MADE WITH

beautiful.ai

— K-means clustering concepts —

1 principal ideas and overview

— K-means in R —

2 minimal R code!

— live coding session! —



Section 1

K-means Principles

cluster with **heatmaps**



Cluster on a line

some data on a line...

You may guess some clusters, how would you do that?



cluster with **heatmaps**



**This is how a human
would do that**



cluster with **heatmaps**

Step 1: Select the number of clusters you want to identify in your data. This is the "K" in "K-means clustering".



select # k

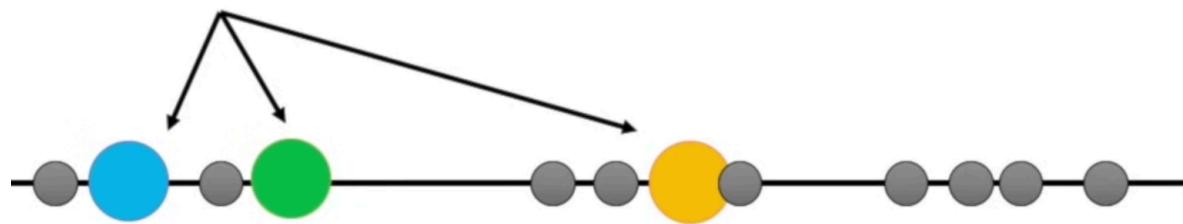
there a way to do that, we are going to see that later on. For now let's trust our guts feelings



cluster with **heatmaps**

Step 2: Randomly select 3 distinct data points.

These are the initial clusters.

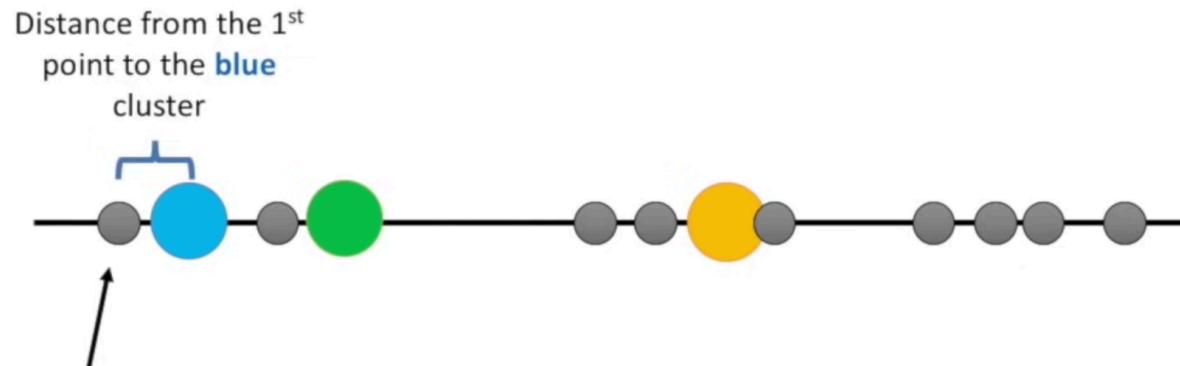


step 1

init algorithm, randomly assign some grey bubbles to clusters.



cluster with heatmaps



Step 3: Measure the distance
between the 1st point and the three
initial clusters.

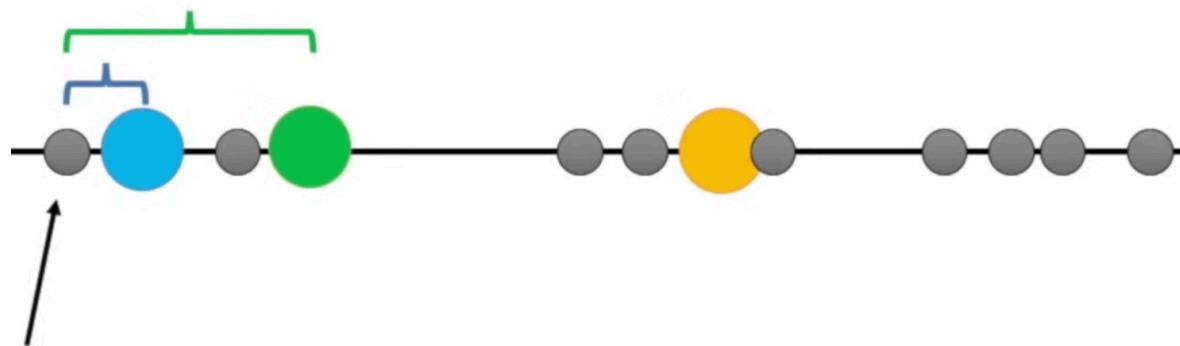
step 2

compute each distance from first point to
each of assigned colored bubble,



cluster with **heatmaps**

Distance from the 1st
point to the **green**
cluster

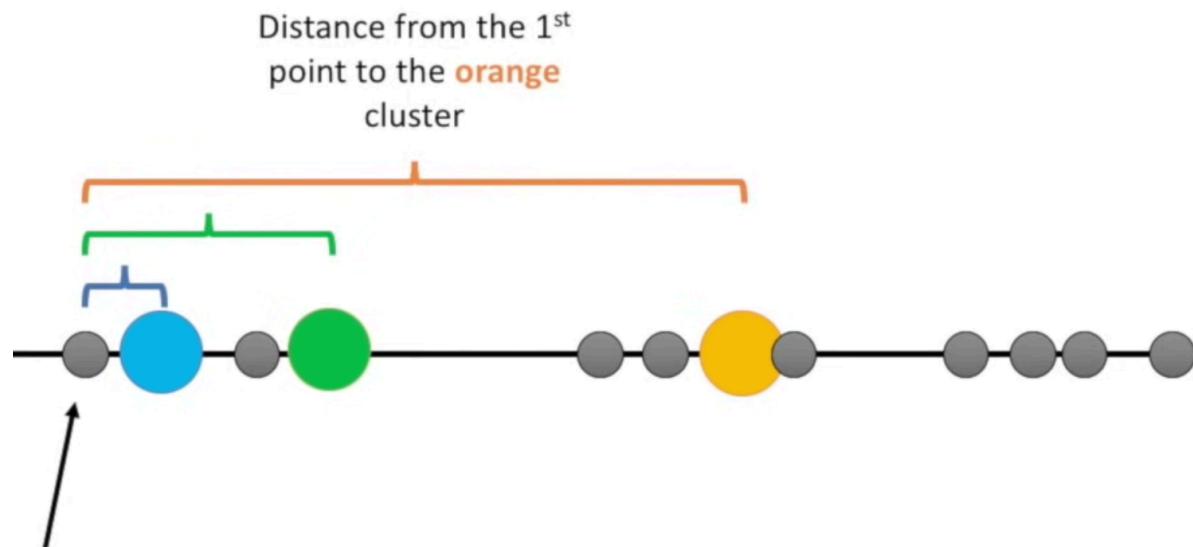


- › 3: Measure the distance between the 1st point and the three final clusters.

now for green



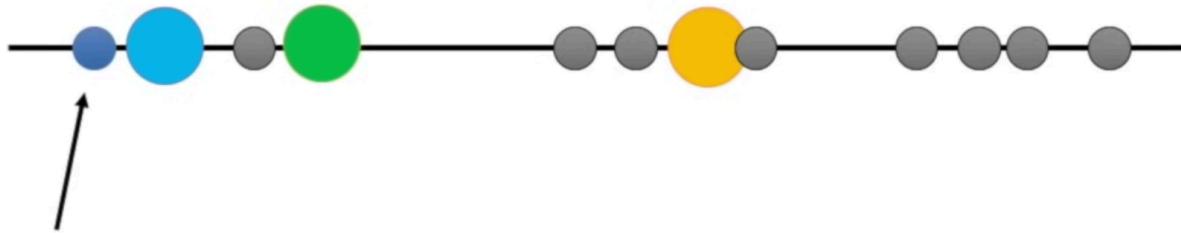
cluster with heatmaps



now for yellow



cluster with **heatmaps**



step 4 assign color based on proximity

the one with shortest distance is the cluster the grey point should be assigned to...

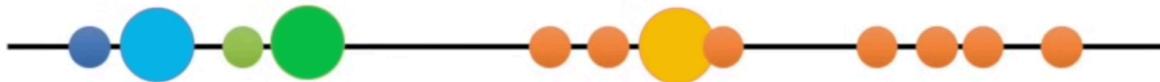


cluster with **heatmaps**

now for second grey
point



cluster with **heatmaps**



The rest of these points are closest to the **orange** cluster, so they'll go in that one, too.

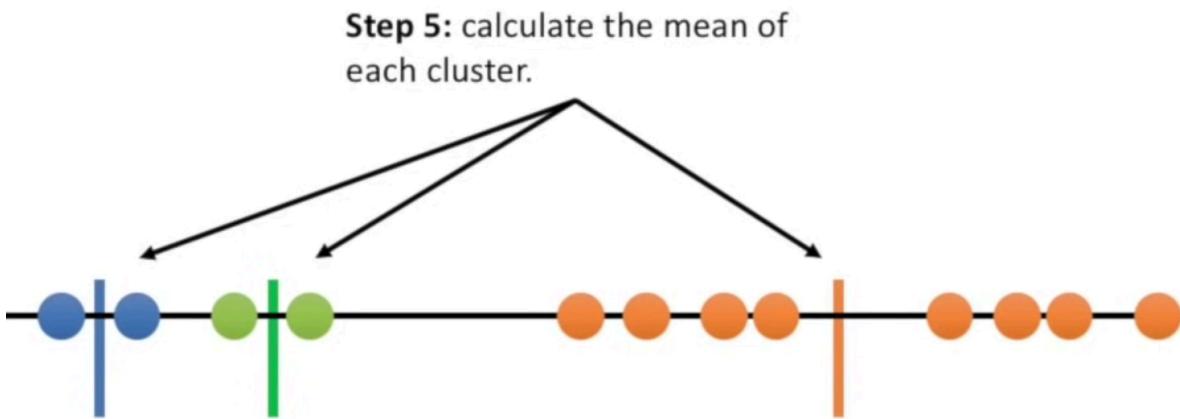
... for all the points in the line

results:

- **blue cluster:** 2 obs
- **green cluster:** 2 obs
- **yellow cluster:** 8 obs



cluster with heatmaps



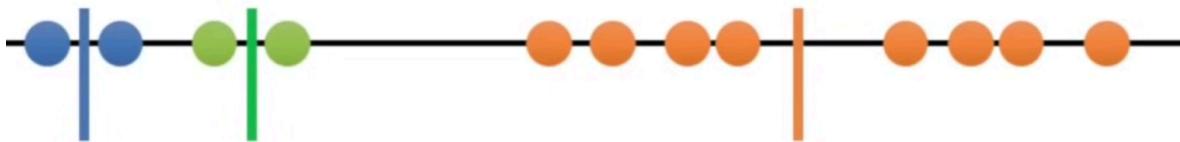
step 5

compute the mean for each cluster. That's why **k-means**



cluster with **heatmaps**

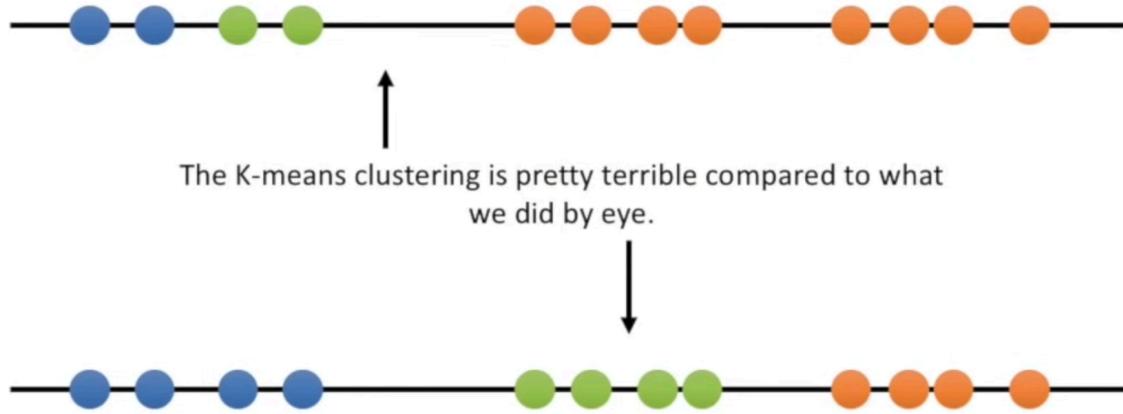
Since the clustering did not change at all during the last iteration, we're done...



**then reassingn
cluster **based on
mean****



cluster with **heatmaps**

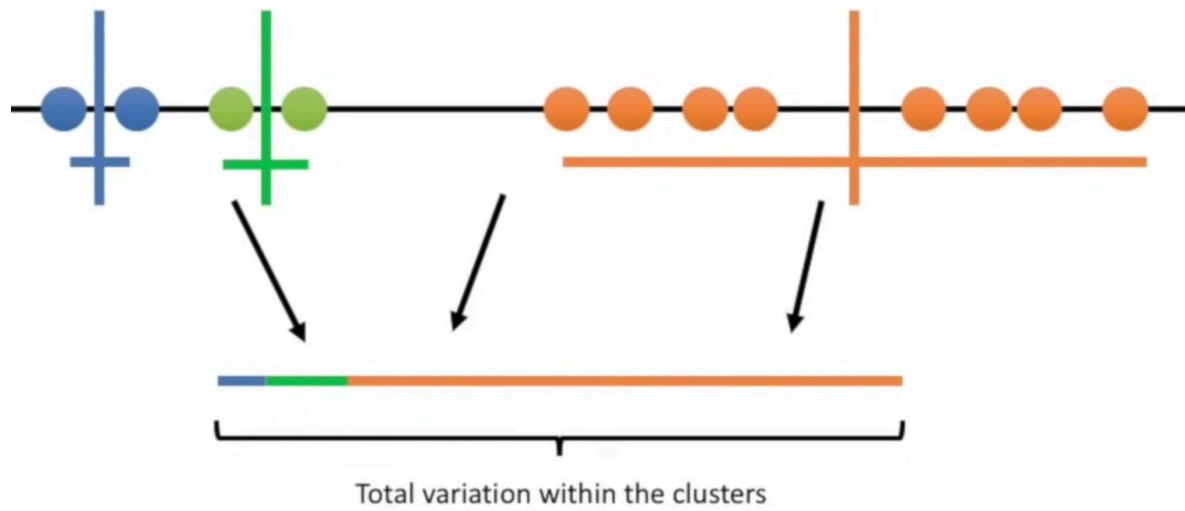


human vs computer

we would have done better....



cluster with **heatmaps**



variation within

let's also compute variation within each cluster



cluster with **heatmaps**



... step 1

The algo restarts...



cluster with **heatmaps**



**reassign cluster
based on new init**

in this case:

- **blue cluster:** 5 obs
- **green cluster:** 3 obs
- **yellow cluster:** 4 obs



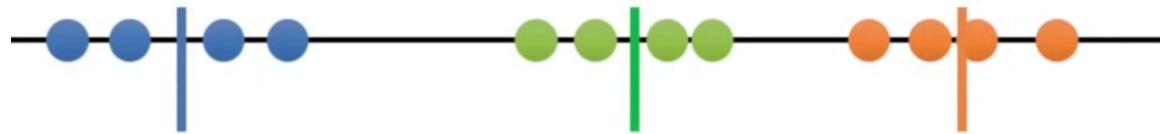
cluster with **heatmaps**



recompute means..



cluster with **heatmaps**

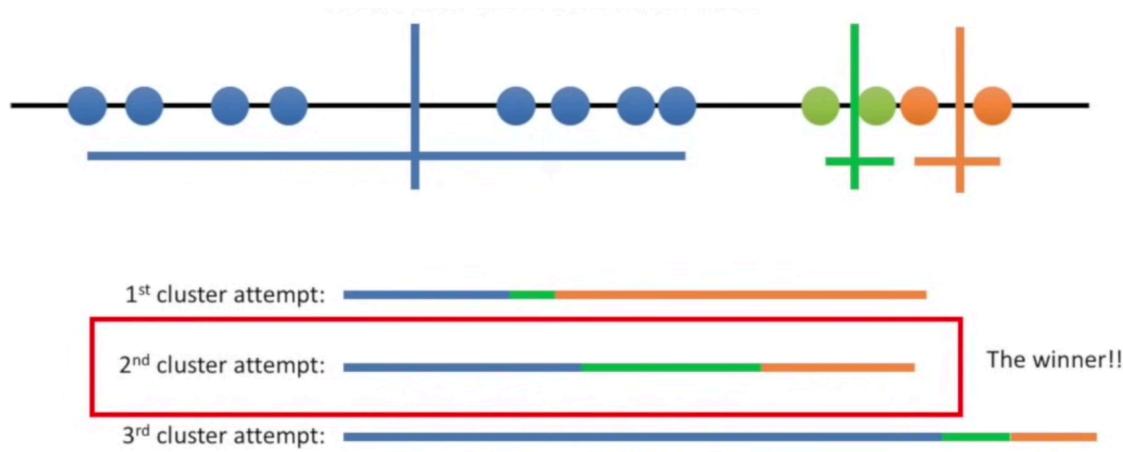


**reassign cluster
based on mean**

*... well this time is better: *human and computer did the same**



cluster with heatmaps

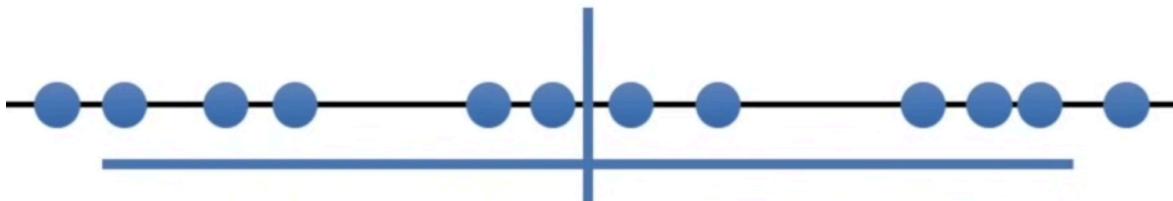


stop when $\text{assign} = \text{clust}$

measure differences over attempts (algo iterations)



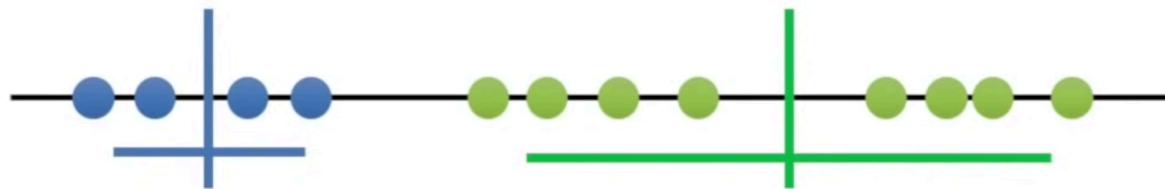
cluster with **heatmaps**



**if we would have
chosen # k = 1**



cluster with heatmaps



K = 2 is better, and we can quantify how much better by comparing the total variation within the 2 clusters to K = 1

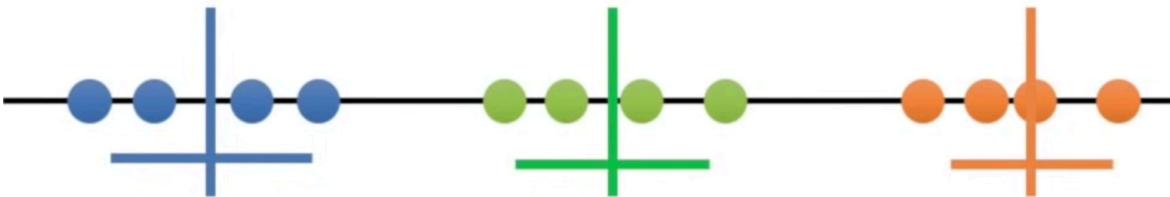


if we would have chosen # k = 2

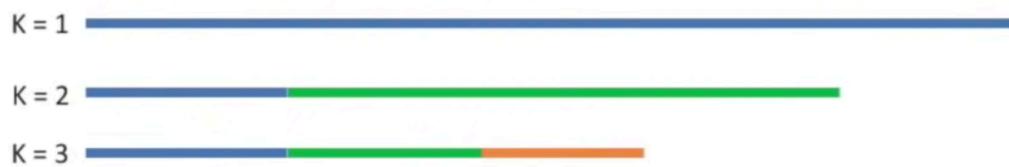
compare below variation within clusters based on number of clusters.



cluster with heatmaps



K = 3 is even better! We can quantify how much better by comparing the total variation within the 3 clusters to K = 2

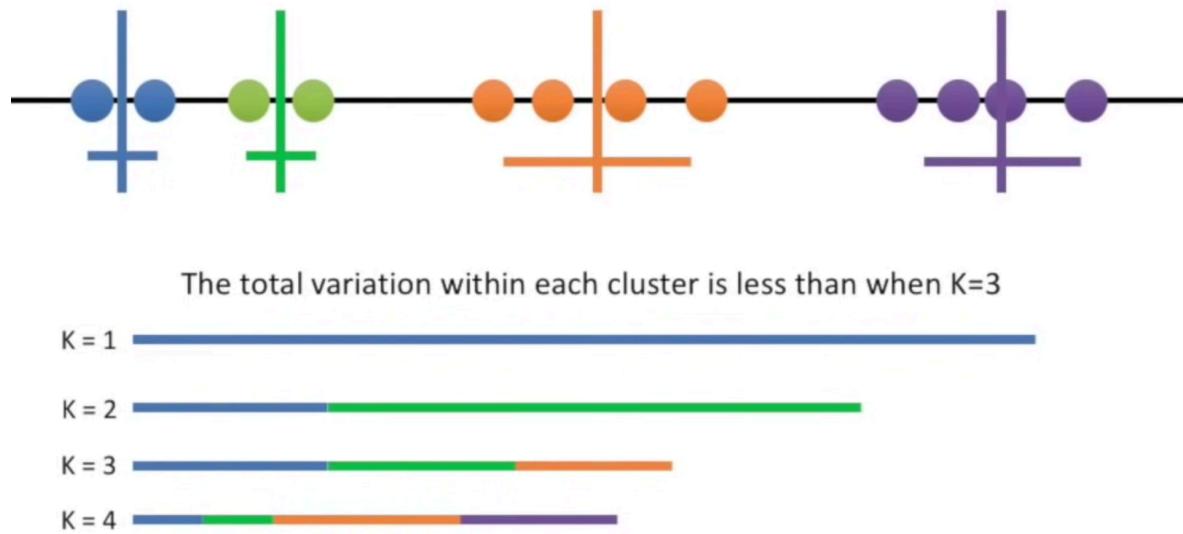


if we would have chosen # k = 3

variation within when k = 3 is actually lower.



cluster with heatmaps



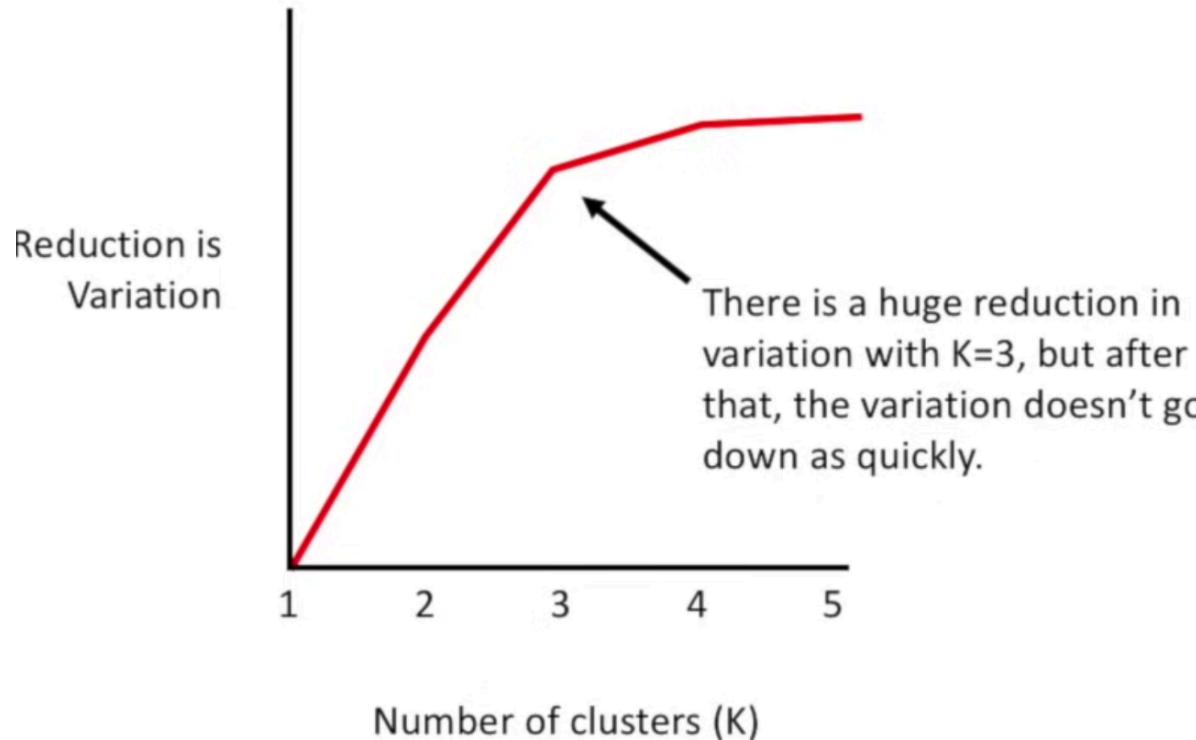
if we would have chosen # k = 4

- keeps decreasing.
- that really resembles R² behaviour, the more params you insert in the model, the better R²
- extreme case 1 clust per obs

we need to find a way to decide which is the best # k.



cluster with **heatmaps**



Elbow method

popular ML method, plot delta var over # algo iterations (in this case # k).

at some point the reduction in variation considerably stop increasing.

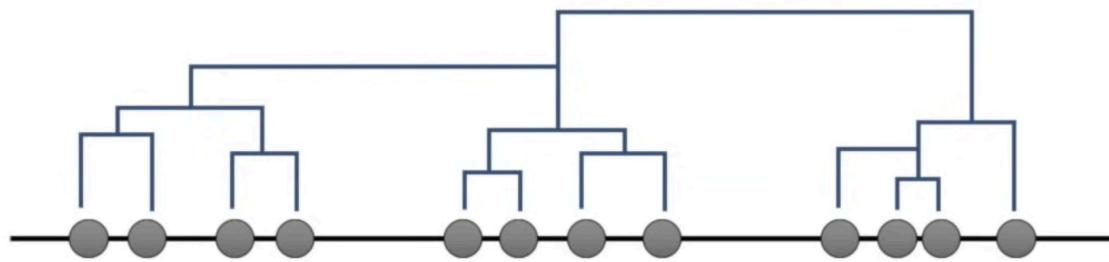
the question you should be asking:
where should I stop?



cluster with heatmaps



Hierarchical clustering just tells you, pairwise, what two things are most similar.

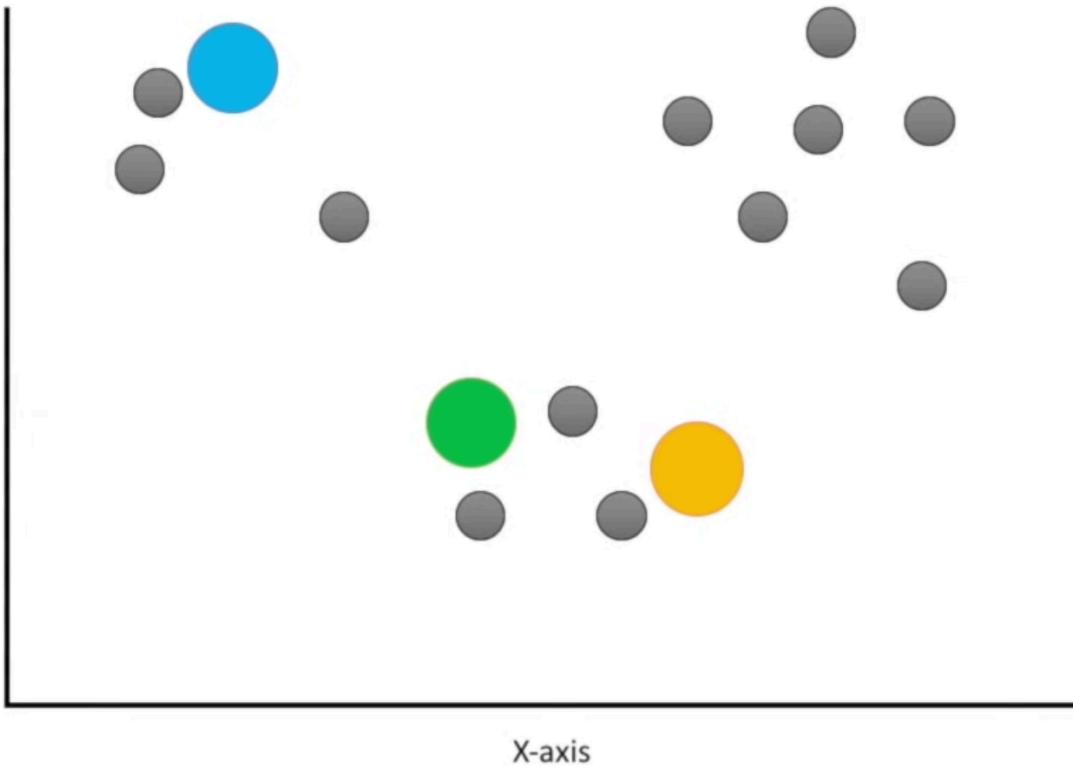


hclust vs k-means



cluster with **heatmaps**

Just like before, you pick three random points...

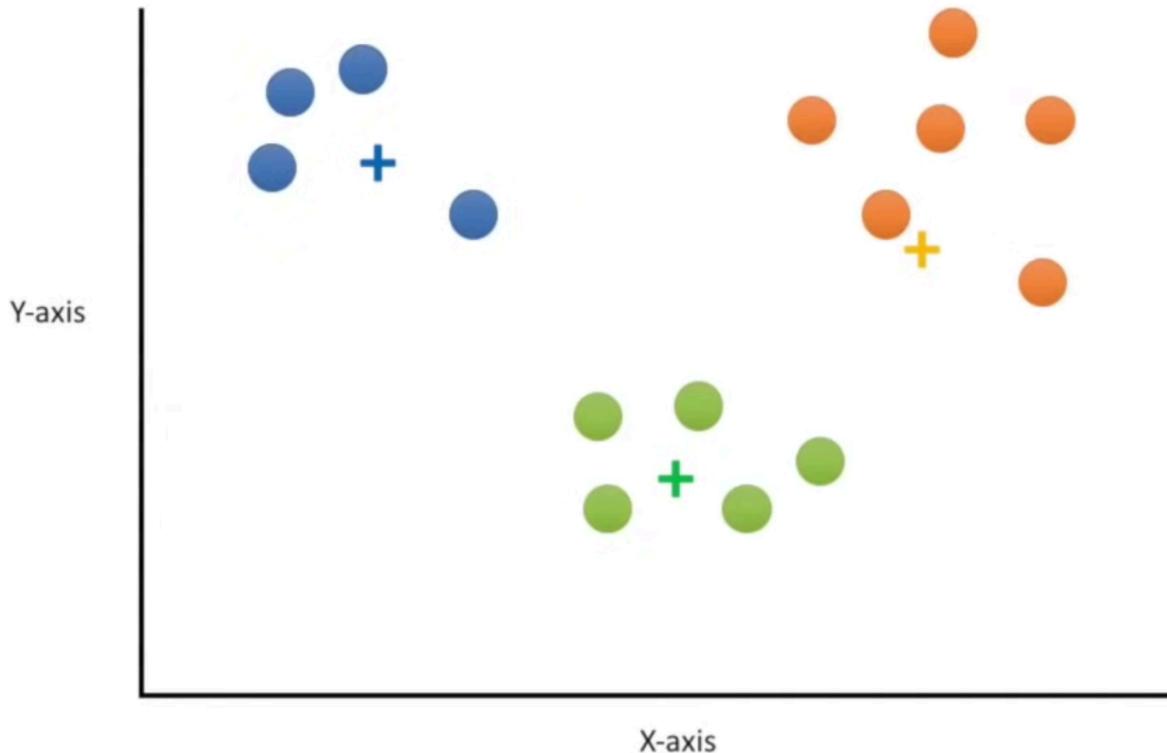


from 2D to 3D



cluster with heatmaps

And, just like before, we then calculate the center of each cluster and recluster...



...exactly the same

step 1: randomly assign and observation to each of the 3 clusters.
step 2: compute diff from first assigned to each other point
step 3: assign point to cluster
step 4: iterate over all the clusters
step 5: compute means
step 6: reassign cluster based on mean.



Section 3

K-means R code

```
# Installing Packages
install.packages("cluster")

library(cluster)# Species from original dataset
iris_1 <- iris[, -5]

# Fitting K-Means clustering Model
# to training dataset
set.seed(240) # Setting seed
kmeans.re <- kmeans(iris_1, centers = 3, nstart = 20)
kmeans.re$cluster

y_kmeans <- kmeans.re$cluster
clusplot(iris_1[, c("Sepal.Length", "Sepal.Width")],
          y_kmeans,
          lines = 0,
          shade = TRUE,
          color = TRUE,
          labels = 2,
          plotchar = FALSE,
          span = TRUE,
          main = paste("Cluster iris"),
          xlab = 'Sepal.Length',
          ylab = 'Sepal.Width')
```

Section 4

Live coding session!

JUMP TO RSTUDIO!

