



STATISTICS AND BIG DATA '25-'26

# K-means Clustering

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— 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**

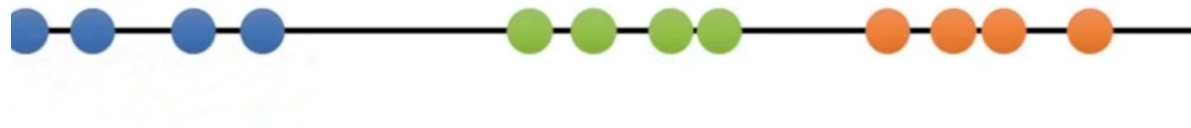


## Cluster on a line

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”.



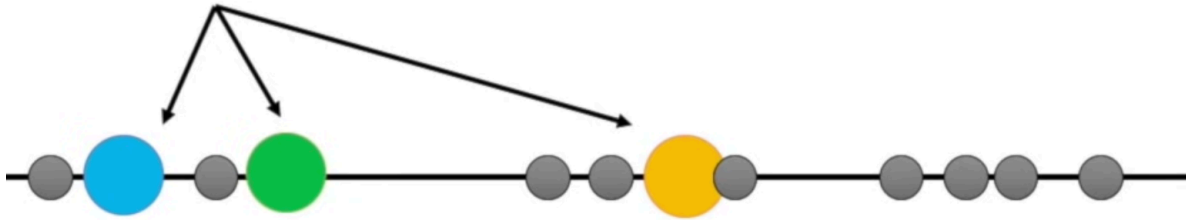
## select # k

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.

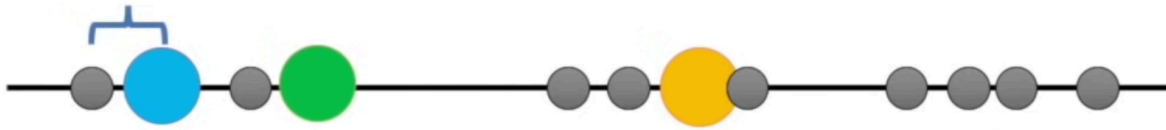


## step 1

init algorithm, randomly assign some grey bubbles to clusters.

# cluster with **heatmaps**

Distance from the 1<sup>st</sup>  
point to the **blue**  
cluster



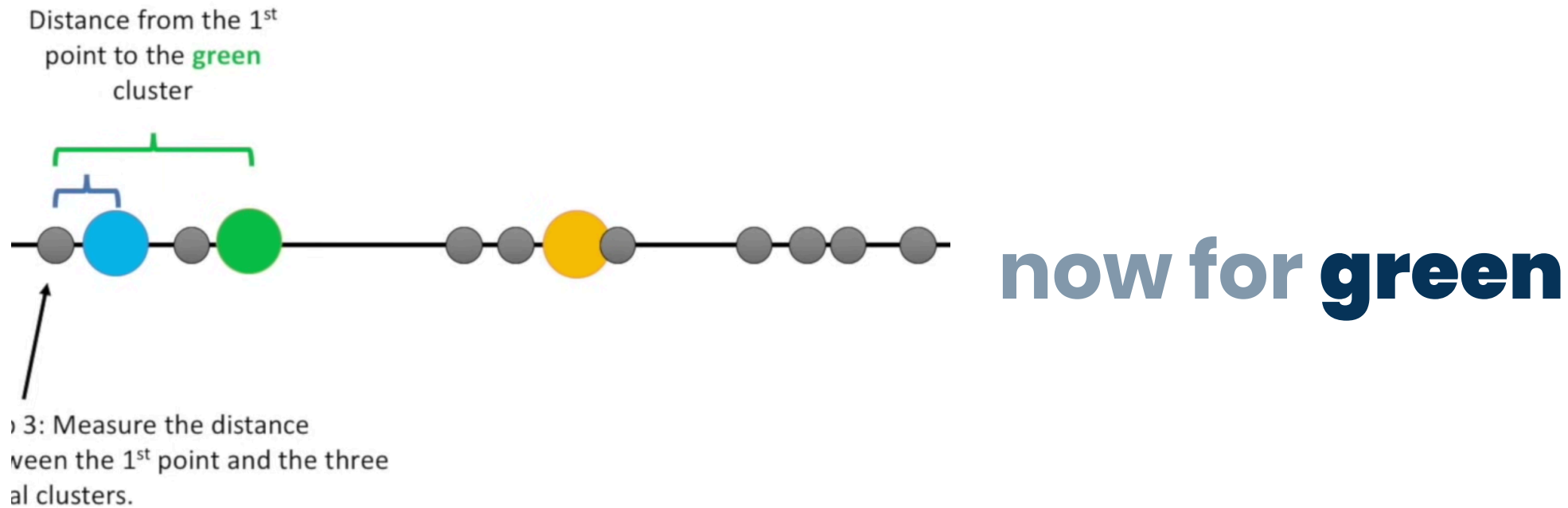
Step 3: Measure the distance  
between the 1<sup>st</sup> point and the three  
initial clusters.

## step 2

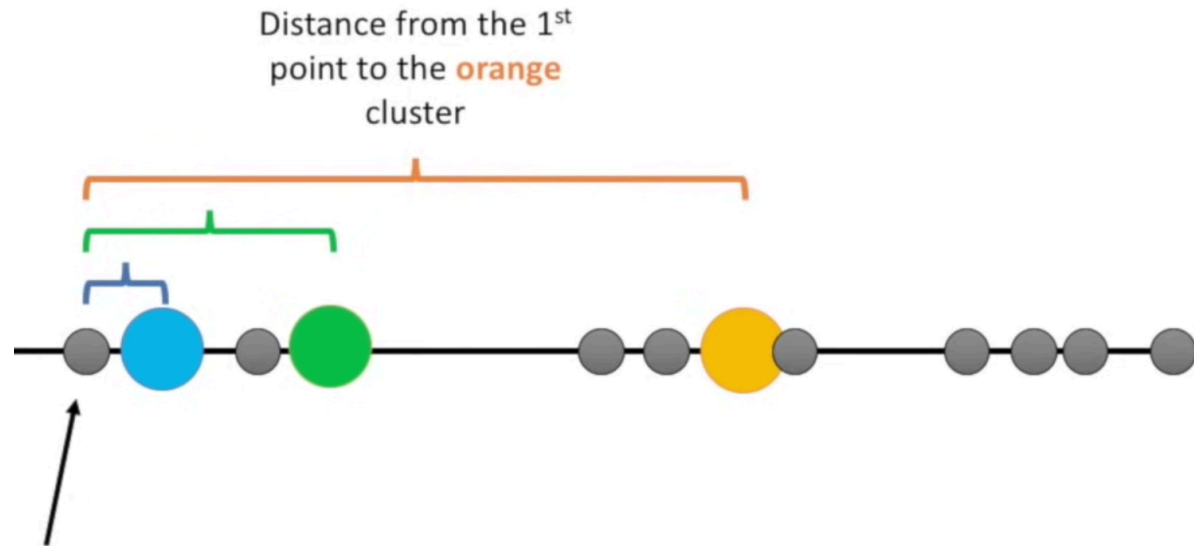
compute each distance from first point to  
each of assigned colored bubble,



# cluster with **heatmaps**

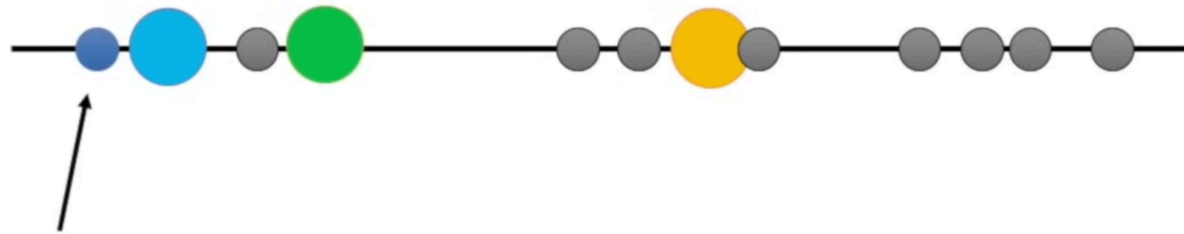


# cluster with **heatmaps**



now for **yellow**

# cluster with **heatmaps**



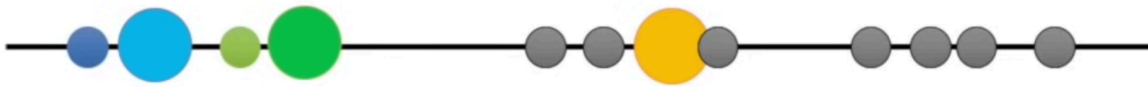
tep 4: Assign the 1<sup>st</sup> point to the earest cluster. In this case, the earest cluster is the **blue** cluster.

## step 4 assign color based on **proximity**

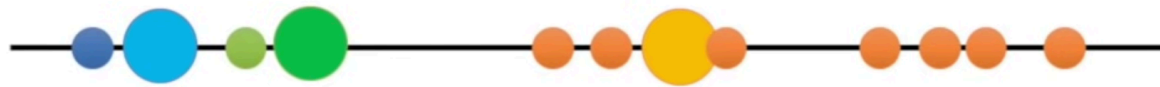
the one with shortest distance is the cluster the grey point should be assigned to...

# cluster with **heatmaps**

## now for second **grey** point



# cluster with **heatmaps**



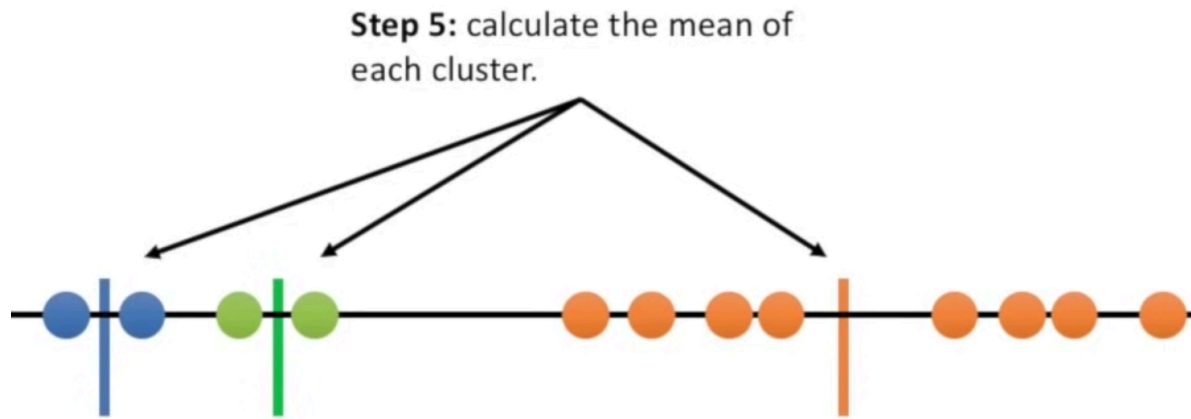
The rest of these points are closest to the **orange** cluster, so they'll go in that one, too.

## ... 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***

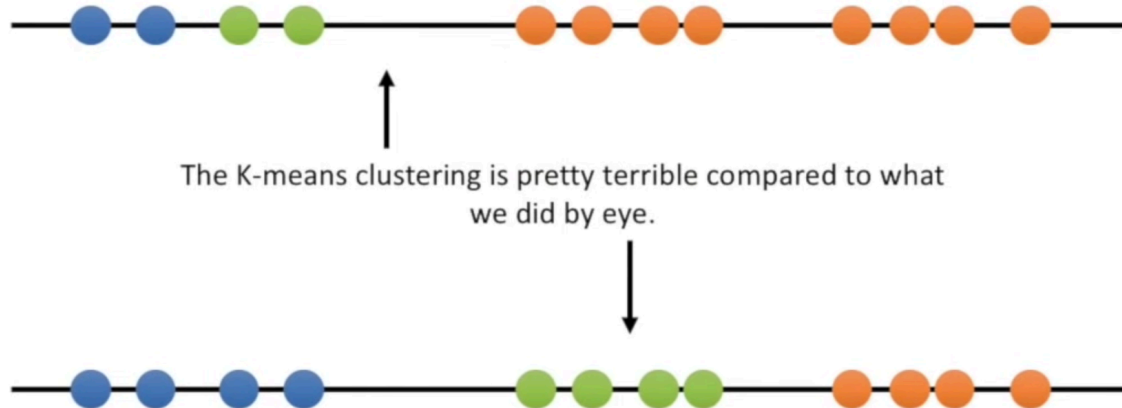
# cluster with **heatmaps**

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



then reassigning  
cluster **based on**  
**mean**

# cluster with **heatmaps**

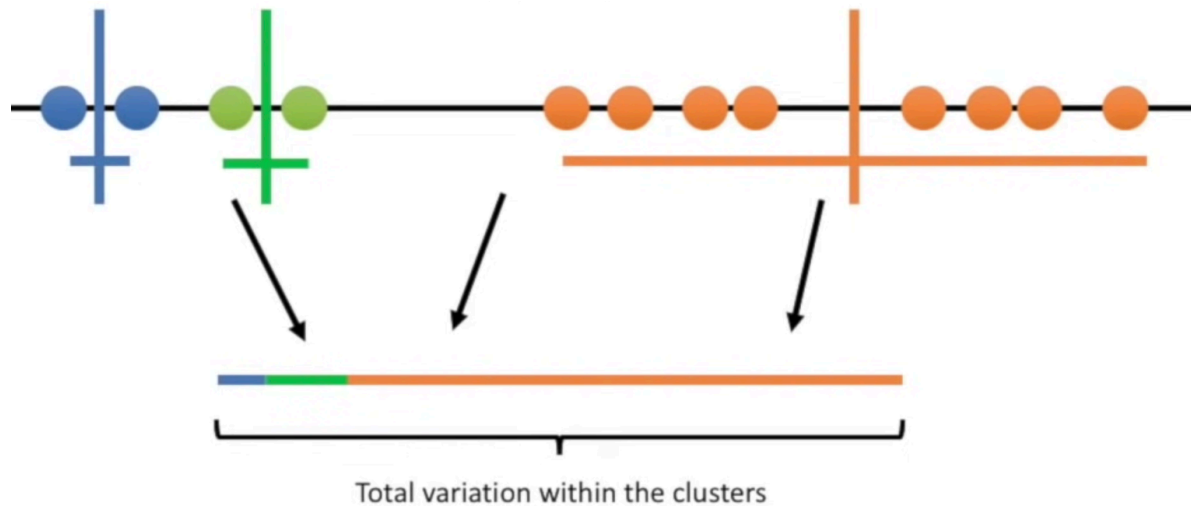


## human vs **computer**

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:

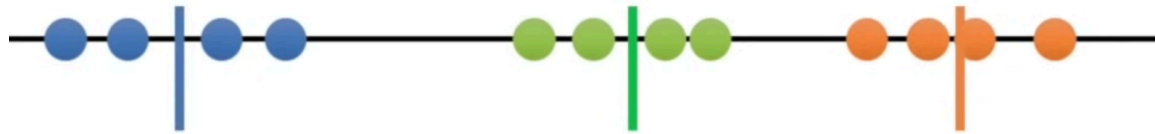
- **blue cluster:** 5 obs
- **green cluster:** 3 obs
- **yellow cluster:** 4 obs

# cluster with **heatmaps**



recompute **means**..

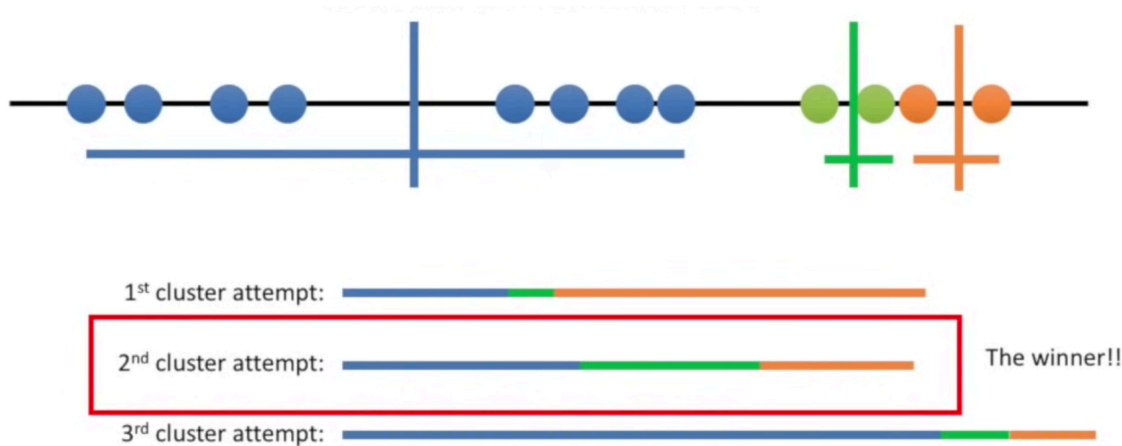
# cluster with **heatmaps**



reassign cluster  
based on **mean**

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

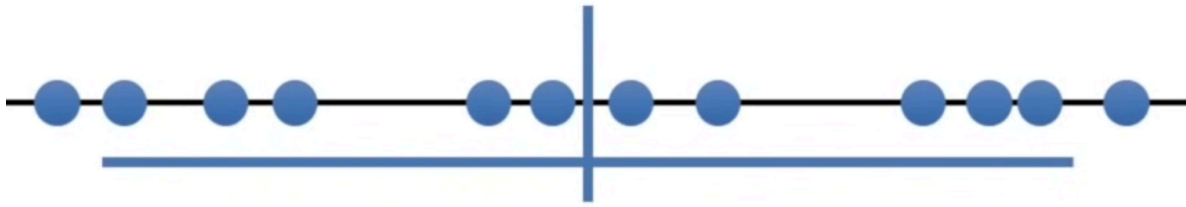
# cluster with **heatmaps**



**stop when assign =  
clust**

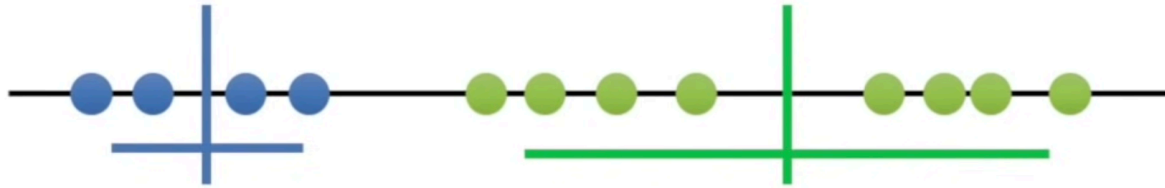
measure differences over attempts (algo iterations)

# 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

K = 1

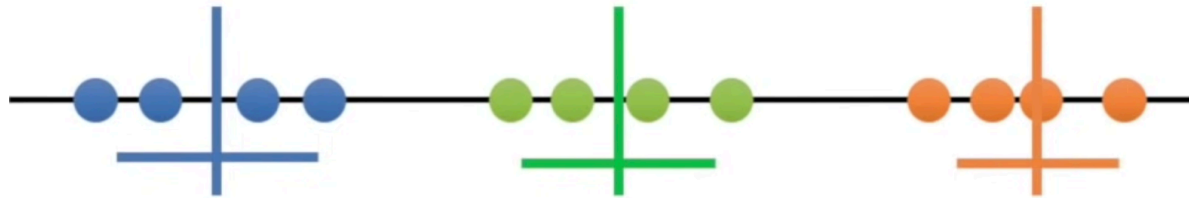
K = 2

if we would have  
chosen **# k = 2**

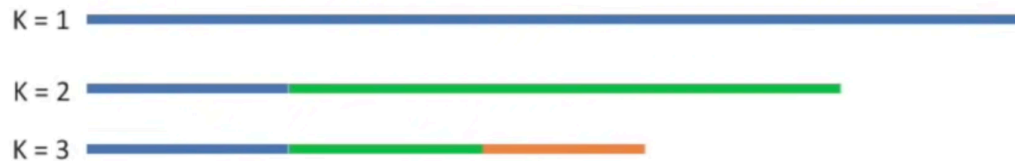
compare below variation within clusters  
based on number of clusters.



# cluster with **heatmaps**



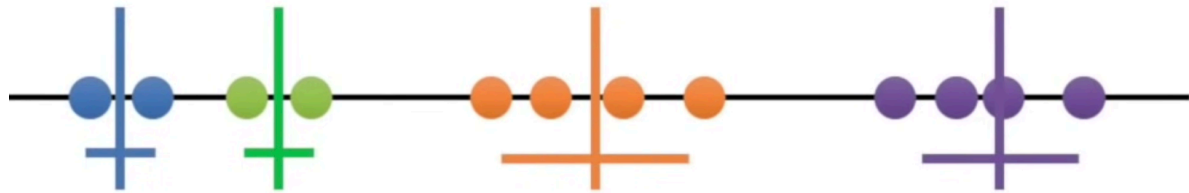
K = 3 is even better! We can quantify how much better by comparing the total variation within the 3 clusters to K = 2



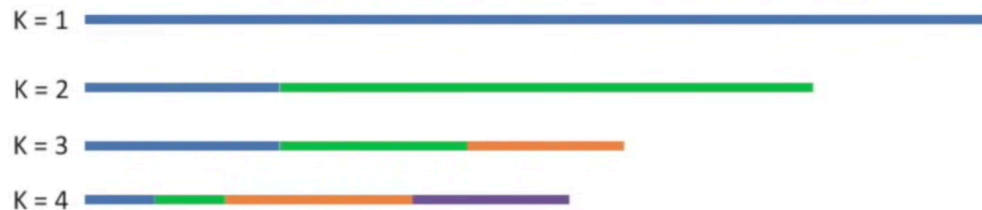
if we would have  
chosen # **k = 3**

variation within when k = 3 is actually  
lower.

# cluster with **heatmaps**



The total variation within each cluster is less than when  $K=3$

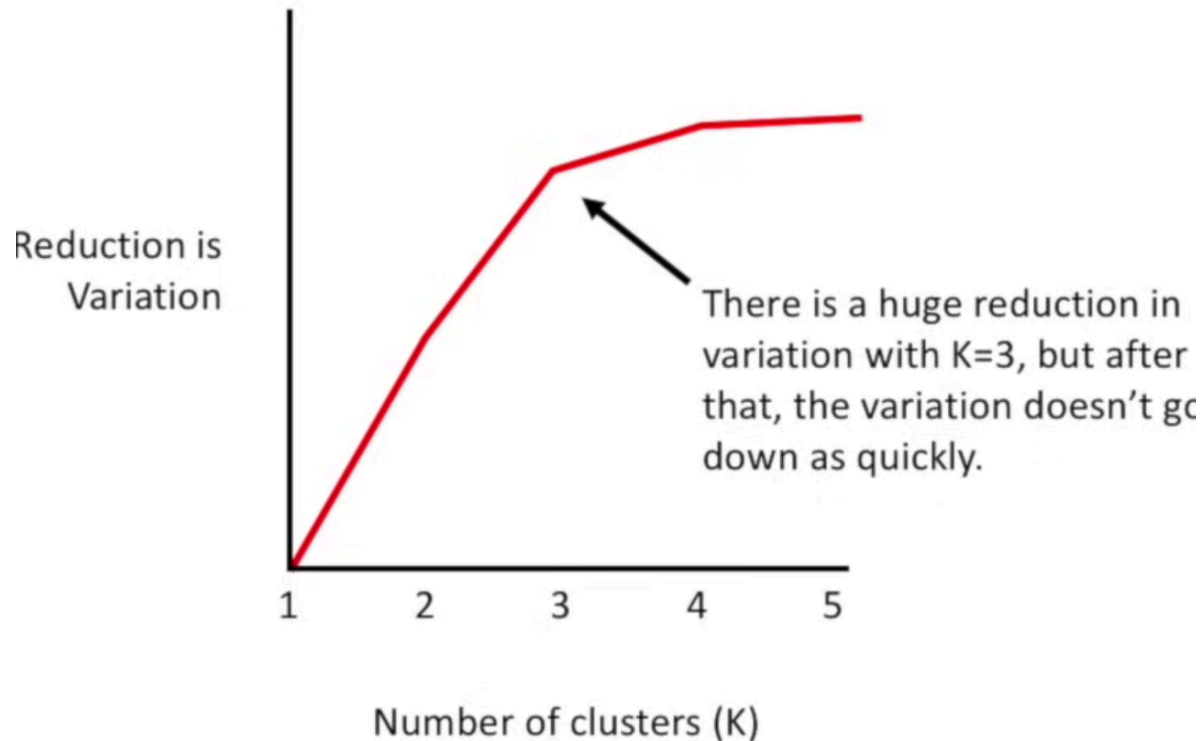


if we would have  
chosen **#  $k=4$**

- keeps decreasing.
- that really resembles  $R^2$  behaviour, the more params you insert in the model, the better  $R^2$
- 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 #  $k$ ).

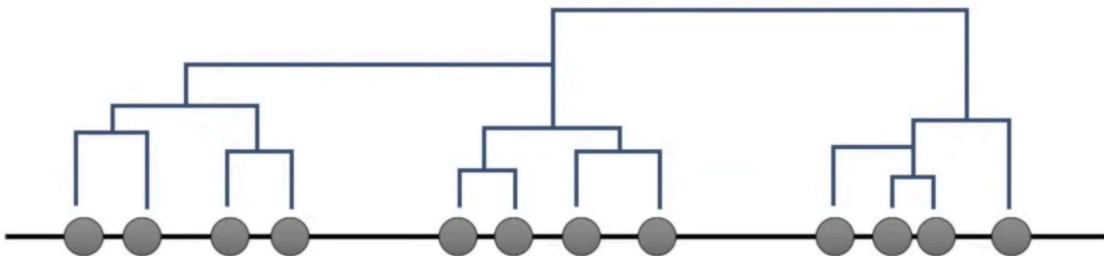
at some point the reduction in variation considerably stop increasing.

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

# cluster with **heatmaps**



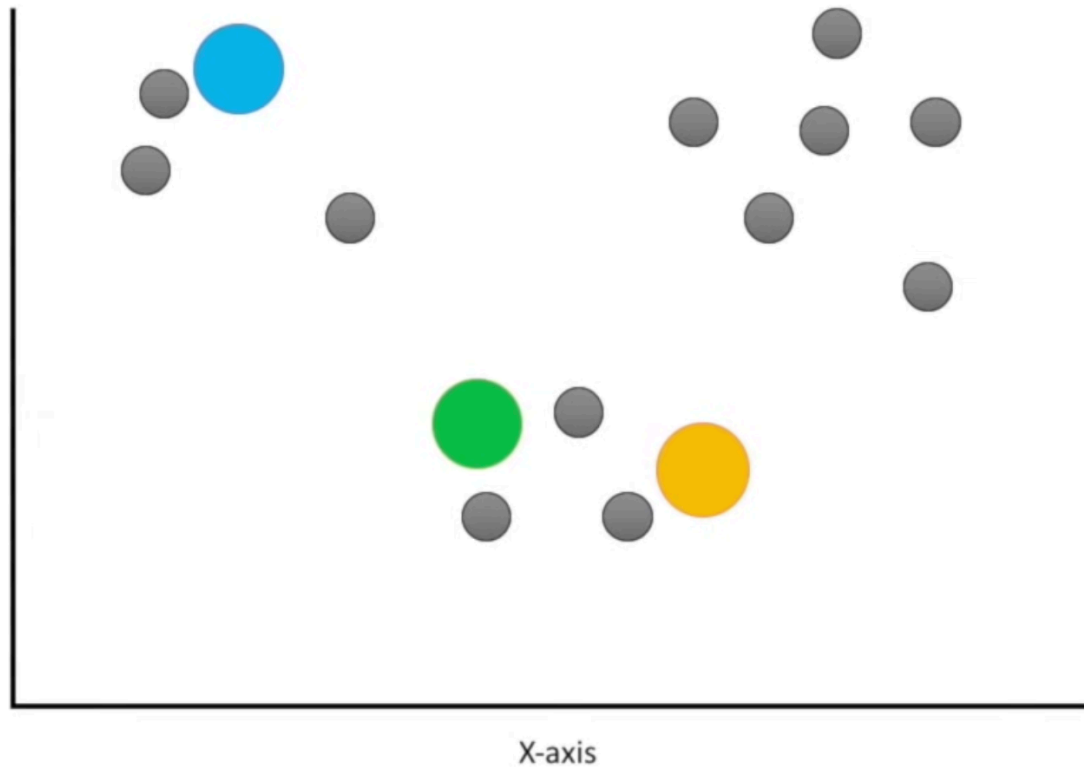
Hierarchical clustering just tells you, pairwise, what two things are most similar.



## hclust **vs** k-means

# cluster with **heatmaps**

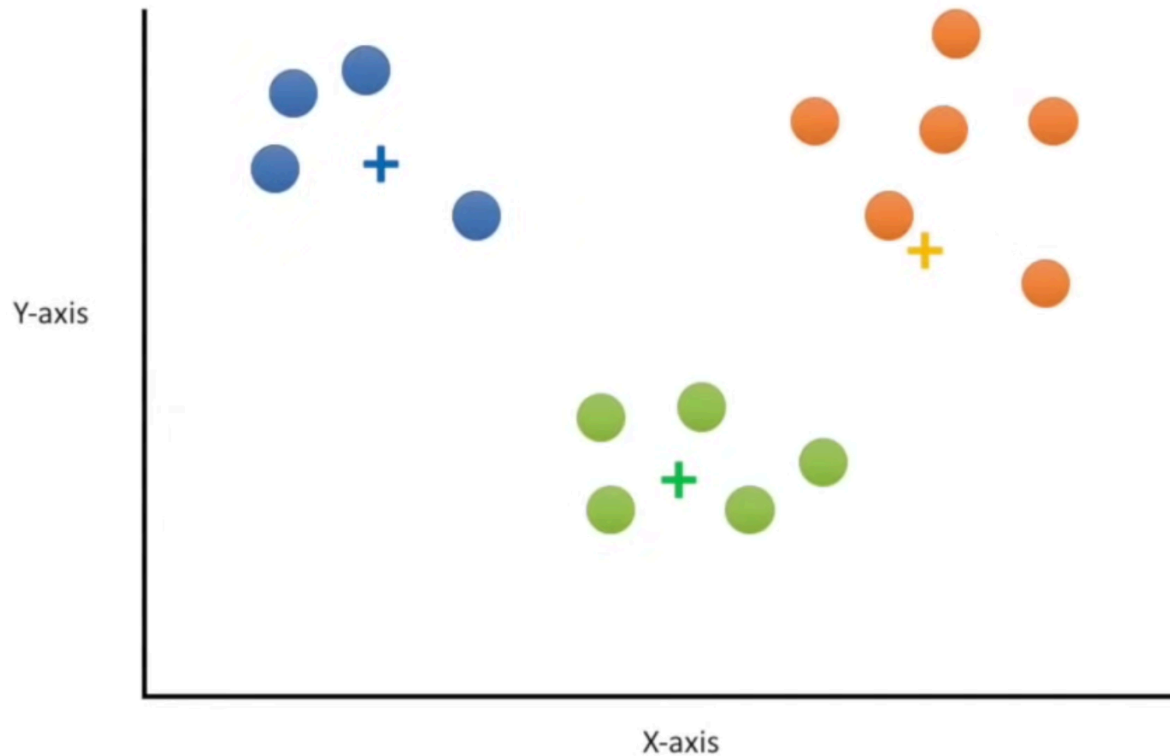
Just like before, you pick three random points...



**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!

