

# Clustering

\* taken from Ron Yurta's slides

Q. Cluster NBA players into offensive Roles OR Archetypes based on How they play.

\* First, need variables that describe How they play.

\* Todd Whitehead: try using Synergy Play Type data!

```
[1] "FGA_freq_Spotup"           "FGA_freq_PRRollMan"       "FGA_freq_Postup"
[4] "FGA_freq_Cut"             "FGA_freq_OffRebound"     "FGA_freq_PRBallHandler"
[7] "FGA_freq_Isolation"       "FGA_freq_OffScreenOrHandoff"
```

\* Then, with this data, how to cluster players??

## What is **unsupervised learning**?

We have  $p$  variables for  $n$  observations  $x_1, \dots, x_n$ , and for observation  $i$ :

$$x_{i1}, x_{i2}, \dots, x_{ip}$$

- *unsupervised*: none of the variables are **response** variables, i.e., there are no labeled data

Think of unsupervised learning as **an extension of EDA...**

- $\Rightarrow$  **there is no unique right answer!**

## What is clustering (aka cluster analysis)?

ISLR 10.3:

**|** *very broad set of techniques for finding subgroups, or clusters, in a dataset*

- observations **within** clusters are **more similar** to each other,
- observations **in different** clusters are **more different** from each other

How do we define **distance / dissimilarity** between observations?

- e.g. **Euclidean distance** between observations  $i$  and  $j$

$$d(x_i, x_j) = \sqrt{(x_{i1} - x_{j1})^2 + \dots + (x_{ip} - x_{jp})^2}$$

### **Units matter!**

- one variable may *dominate* others when computing Euclidean distance because its range is much larger
- can standardize each variable / column of dataset to have mean 0 and standard deviation 1 with `scale()`
- **but we may value the separation in that variable!** (so just be careful...)

# What's the clustering objective?

- $C_1, \dots, C_K$  are sets containing indices of observations in each of the  $K$  clusters
  - if observation  $i$  is in cluster  $k$ , then  $i \in C_k$
- We want to minimize the **within-cluster variation**  $W(C_k)$  for each cluster  $C_k$  and solve:

$$\text{minimize}_{C_1, \dots, C_K} \left\{ \sum_{k=1}^K W(C_k) \right\}$$

- Can define using the **squared Euclidean distance** ( $|C_k| = n_k = \#$  observations in cluster  $k$ )

$$W(C_k) = \frac{1}{|C_k|} \sum_{i, j \in C_k} d(x_i, x_j)^2$$

- Commonly referred to as the within-cluster sum of squares (WSS)

## Lloyd's algorithm

- 1) Choose  $K$  random centers, aka **centroids**
- 2) Assign each observation closest center (using Euclidean distance)
- 3) Repeat until cluster assignment stop changing:
  - Compute new centroids as the averages of the updated groups
  - Reassign each observations to closest center

**Converges to a local optimum**, not the global

**Results will change from run to run** (set the seed!)

**Takes  $K$  as an input!**

## things to check when clustering

- do the units of the variables make sense?
- Should you standardize the variables?
- is "nstart", the number of starting random configurations, large enough?

## So, how do we choose the number of clusters?!



There is no universally accepted way to conclude that a particular choice of  $K$  is optimal!

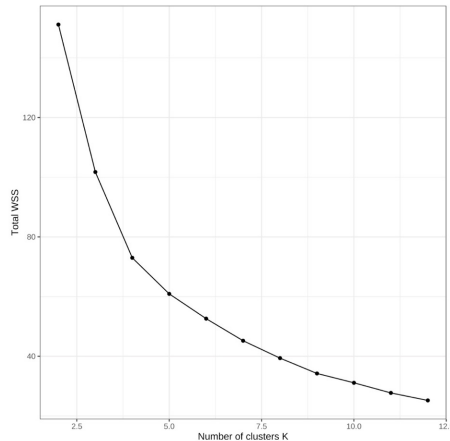
## Popular heuristic: elbow plot (use with caution)

Choose  $K$  where marginal improvements is low at the bend (hence the elbow)

**This is just a guideline and should not dictate your choice of  $K$ !**

Gap statistic is a popular choice (see `cLusGap` function in `cluster` package)

**Next Tuesday:** model-based approach to choosing the number of clusters!



## Better alternative to nstart: K-means++

Pick a random observation to be the center  $c_1$  of the first cluster  $C_1$

- This initializes a set  $Centers = \{c_1\}$

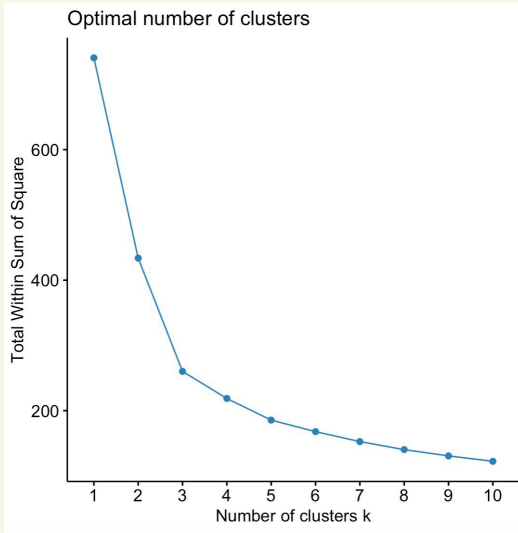
Then for each remaining cluster  $c^* \in 2, \dots, K$ :

- For each observation (that is not a center), compute  $D(x_i) = \min_{c \in Centers} d(x_i, c)$ 
  - Distance between observation and its closest center  $c \in Centers$
- Randomly pick a point  $x_i$  with probability:  $p_i = \frac{D^2(x_i)}{\sum_{j=1}^n D^2(x_j)}$
- As distance to closest center increases  $\Rightarrow$  probability of selection increases
- Call this randomly selected observation  $c^*$ , update  $Centers = Centers \cup c^*$ 
  - Same as `centers = c(centers, c_new)`

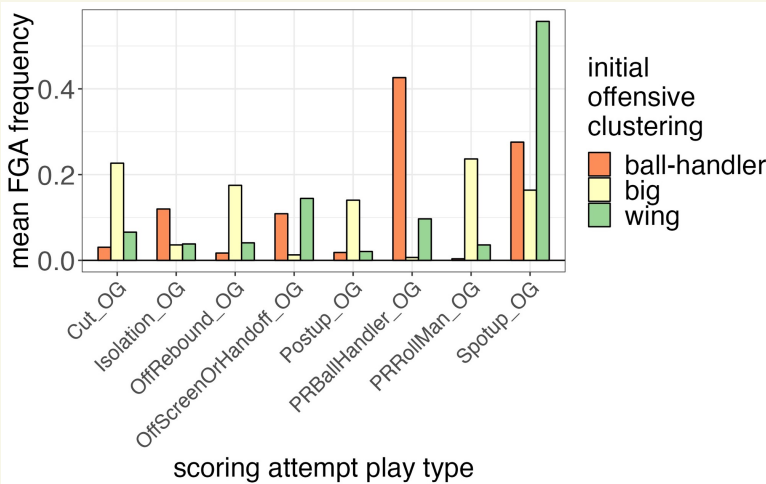
**Then run K-means using these  $Centers$  as the starting points**

# Time to Cluster NBA players into offensive Roles by Synergy FGA play type frequencies

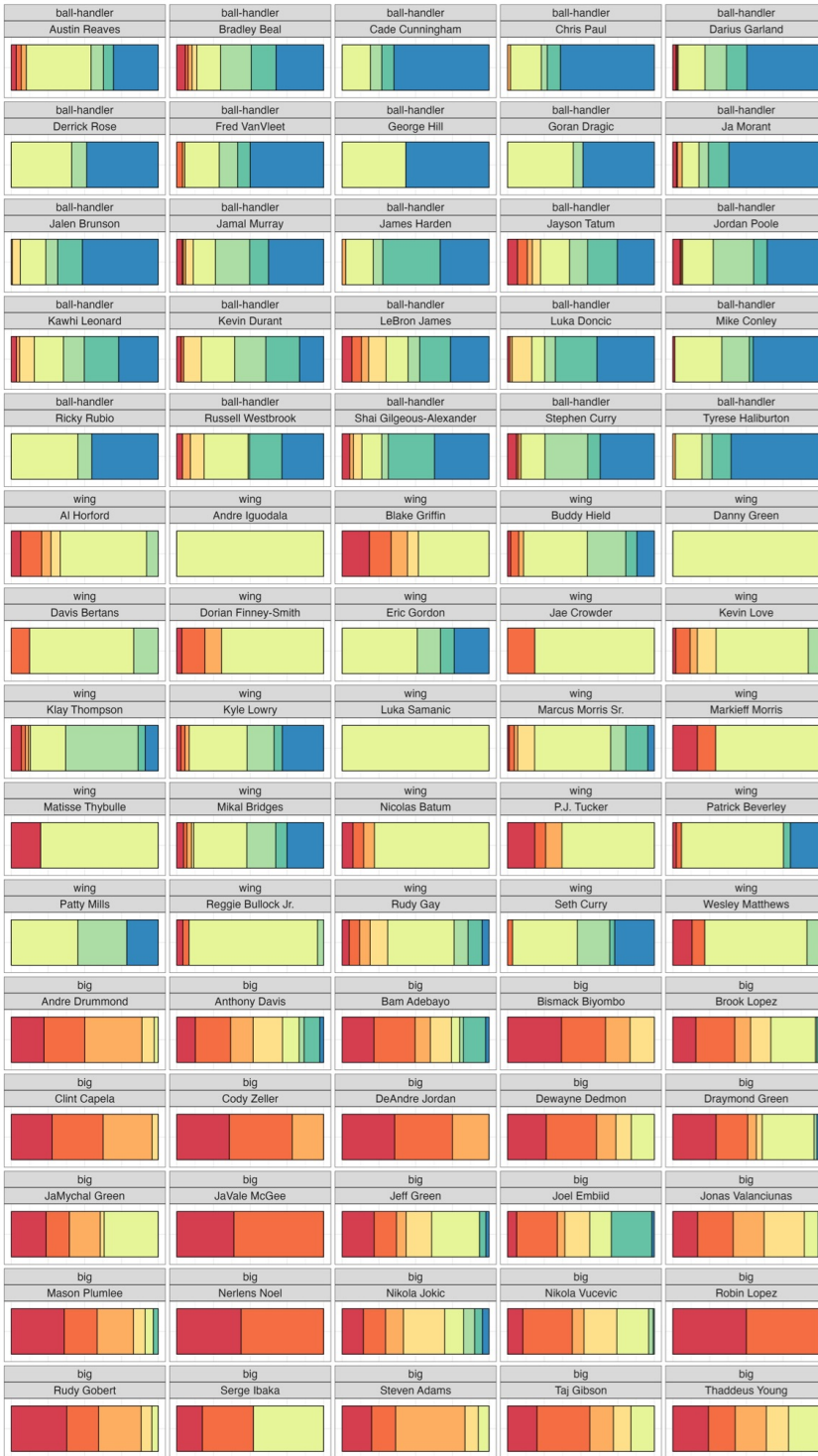
```
### Hard Clustering: K means  
set.seed(387397)  
km1 <- flexclust::kcca(mat_train, K1)  
print(km1)
```



Elbow Plot  
Began with  $K=3$   
clusters

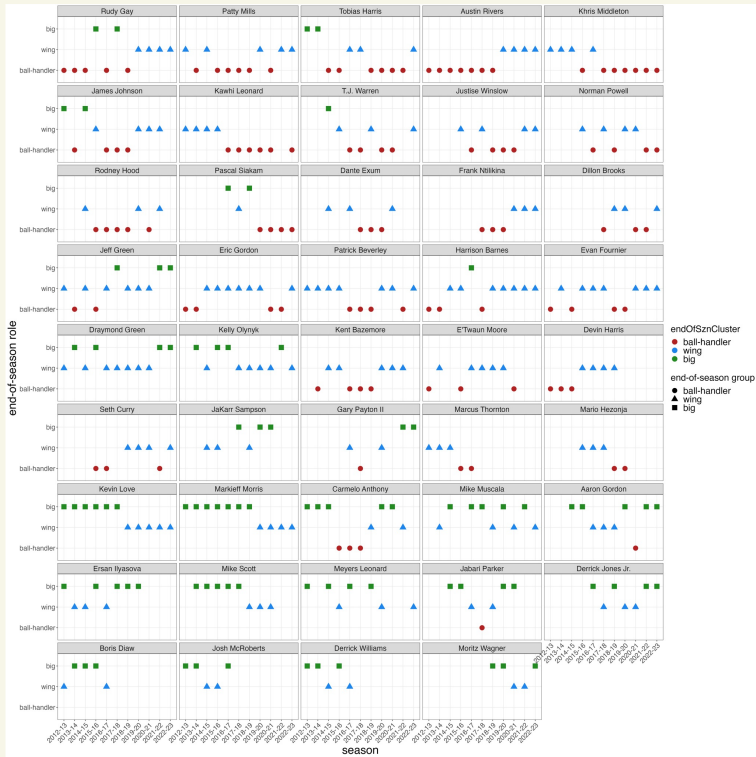
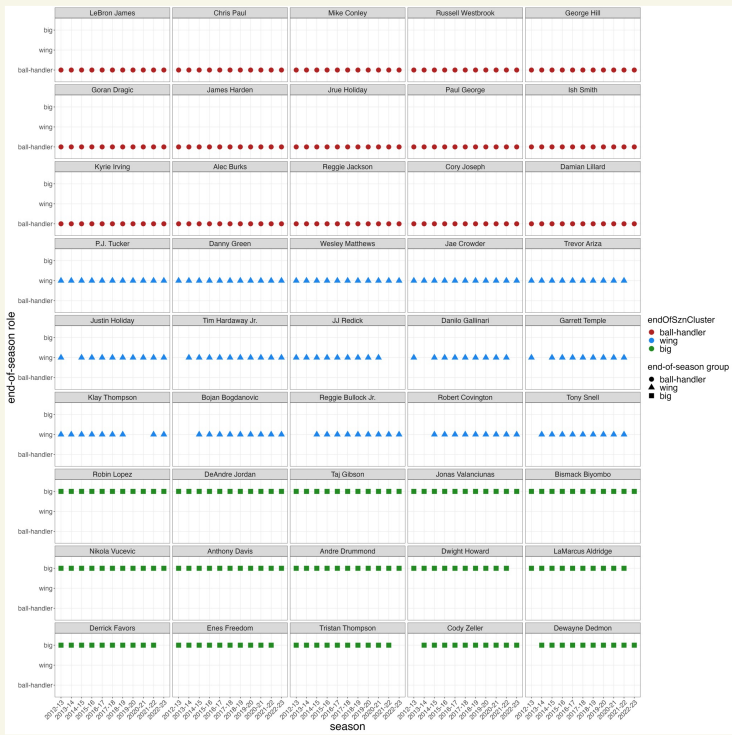


2022-23



scoring  
attempt  
play  
type

- PRBallHandler
- Isolation
- OffScreenOrHandoff
- Postup
- OffRebound
- PRRollMan
- Cut





# I further clustered the 3 groups into more refined Roles:

2022-23



scoring attempt play type

- PRBallHandler
- Isolation
- OffScreenOrHandoff
- Spotup
- Postup
- OffRebound
- PRRollMan
- Cut



