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Security

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Foundations of Security Data Science

Machine Learning:

Intro

Jay Jacobs
Charles Givre
Bob Rudis

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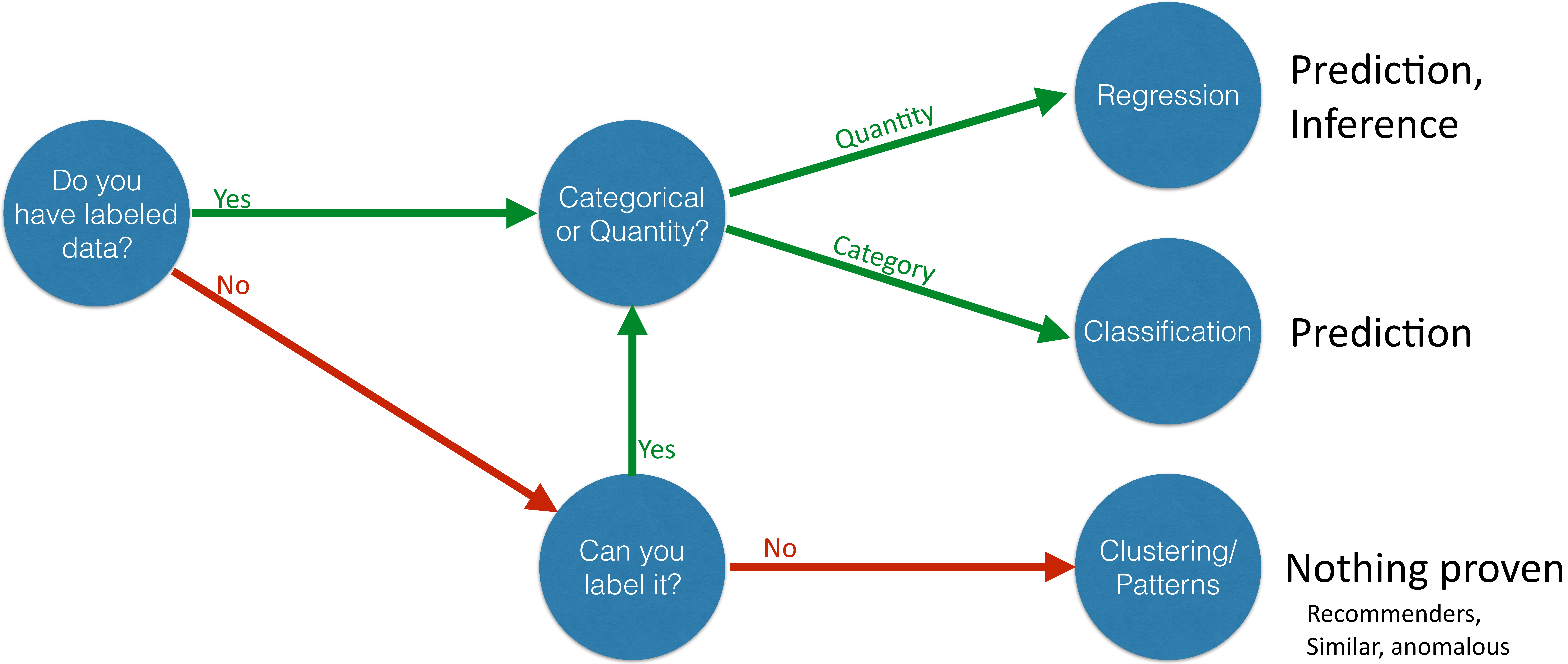
What we learned yesterday

What Data Science kind of is…



Data Science Topics

Core Statistics
Descriptive (range, median, mean)
Confidence Intervals
Correlation
Tests (t.test, ks.test, fitting)

Regression/Classification
Labeled Data
Can falsify claims
Prediction, maybe inference
No free lunch

Clustering/Unsupervised
Unlabeled data
Cannot falsify claims
Clustering
Anomoly Detection

Visualization
Visual cues, coord. system, scale, context
Pre-attentive processing, saccadic
Working and Long-term memory
Accuracy in Decoding, mumbling

Feature Engineering

1. Define the Object of Measurement
   These will become the rows in your data (one per object)

2. Define one or more "features" that describe each object
   These will become the columns in your data

3. Run Algorithm (more on this later)

4. Optimally, measure feature contribution and model performance

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Measuring Distance

(precursor to clustering)

Unsupervised Clustering Algorithm

1. Select Features
2. Calculate a distance measure
3. Apply a clustering algorithm
4. Validate?

Which Departments are Similar?

	Malware events
Dept1	6
Dept2	1
Dept3	8

Which Departments are Similar?

	Malware events	Phishing
Dept1	6	6
Dept2	1	2
Dept3	8	1

Which Departments are Similar?

	Malware events	Phishing	Open Tickets
Dept1	6	6	3
Dept2	1	2	1
Dept3	8	1	9

Computing Distance

	Malware events
Dept1	6
Dept2	1
Dept3	8

Compare:

Dept1 to Dept2: $|6 - 1| = 5$

Dept2 to Dept3: $|1 - 8| = 7$

Dept1 to Dept3: $|6 - 8| = 2$

Two-Dimenionsal Distance

	Malware events	Phishing
Dept1	6	6
Dept2	1	2
Dept3	8	1

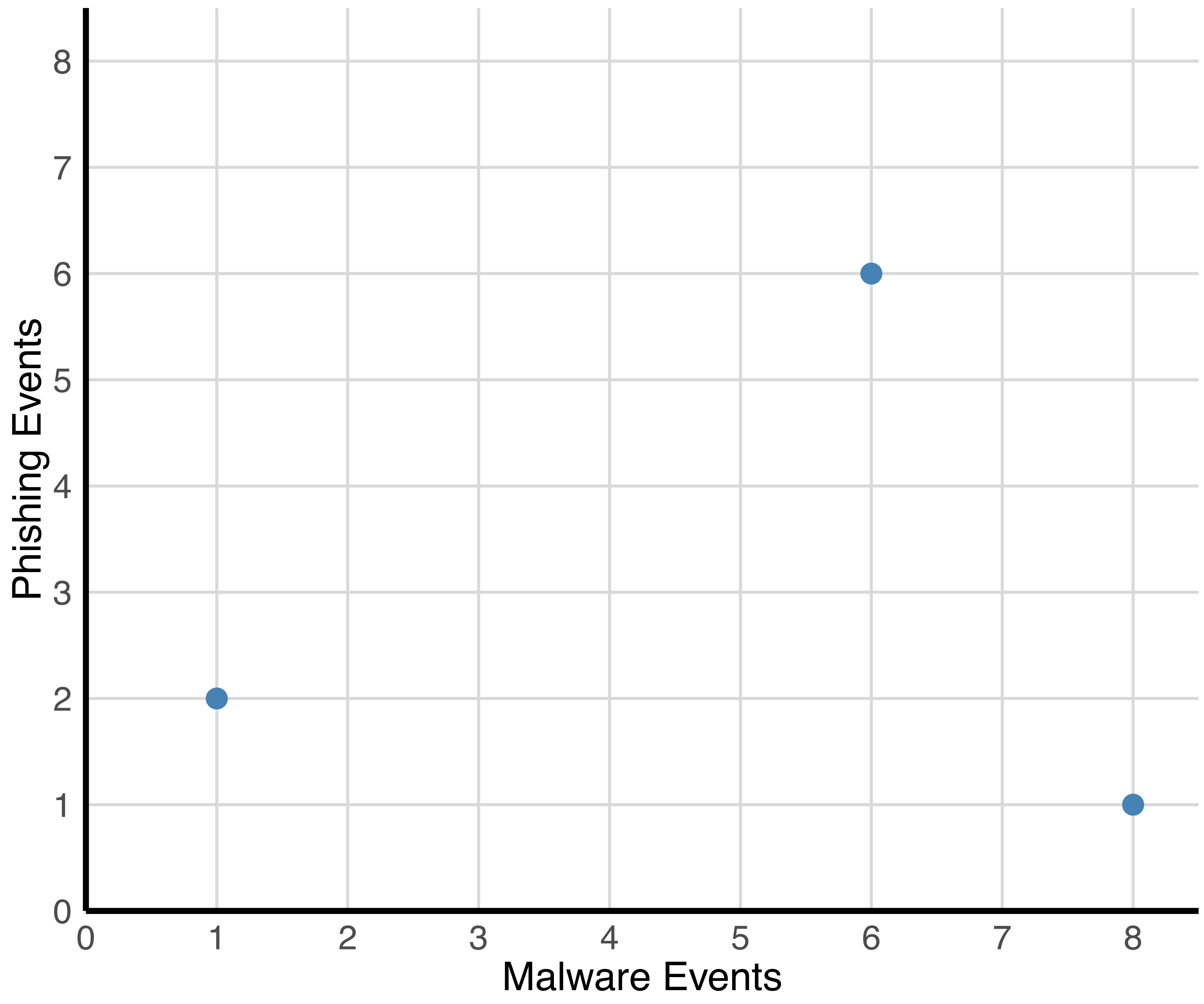
Multiple Distance methods

- Euclidean
- Manhattan
- Maximum
- Canberra
- Binary
- Minkowski

… (to name a few)

Two-Dimenionsal Distance

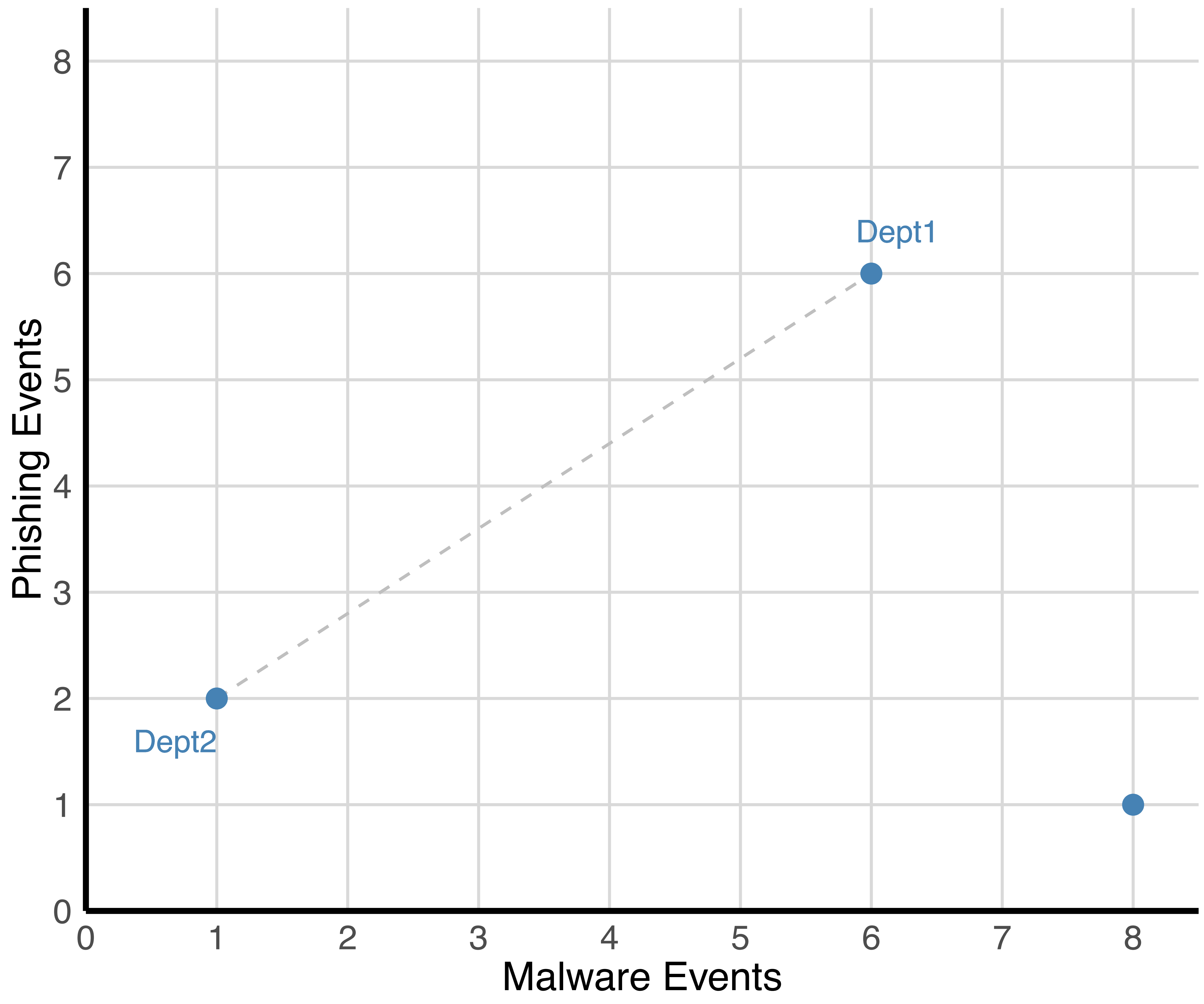
	Malware events	Phishing
Dept1	6	6
Dept2	1	2
Dept3	8	1



Two-Dimenionsal Distance

Euclidean very common and easy to grok

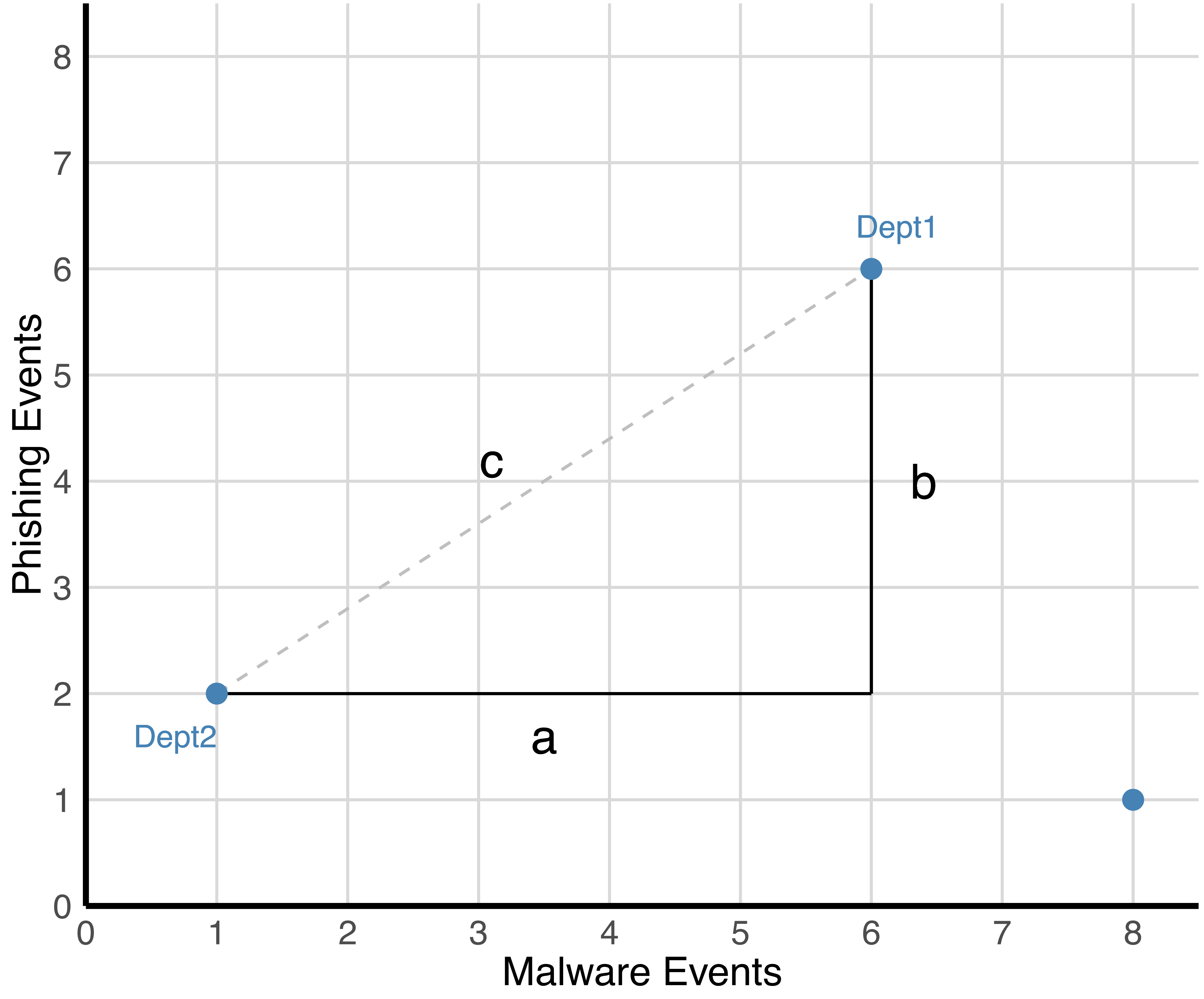
	Malware events	Phishing
Dept1	6	6
Dept2	1	2
Dept3	8	1



Two-Dimenionsal Distance

Euclidean very common and easy to grok: $a^2 + b^2 = c^2$

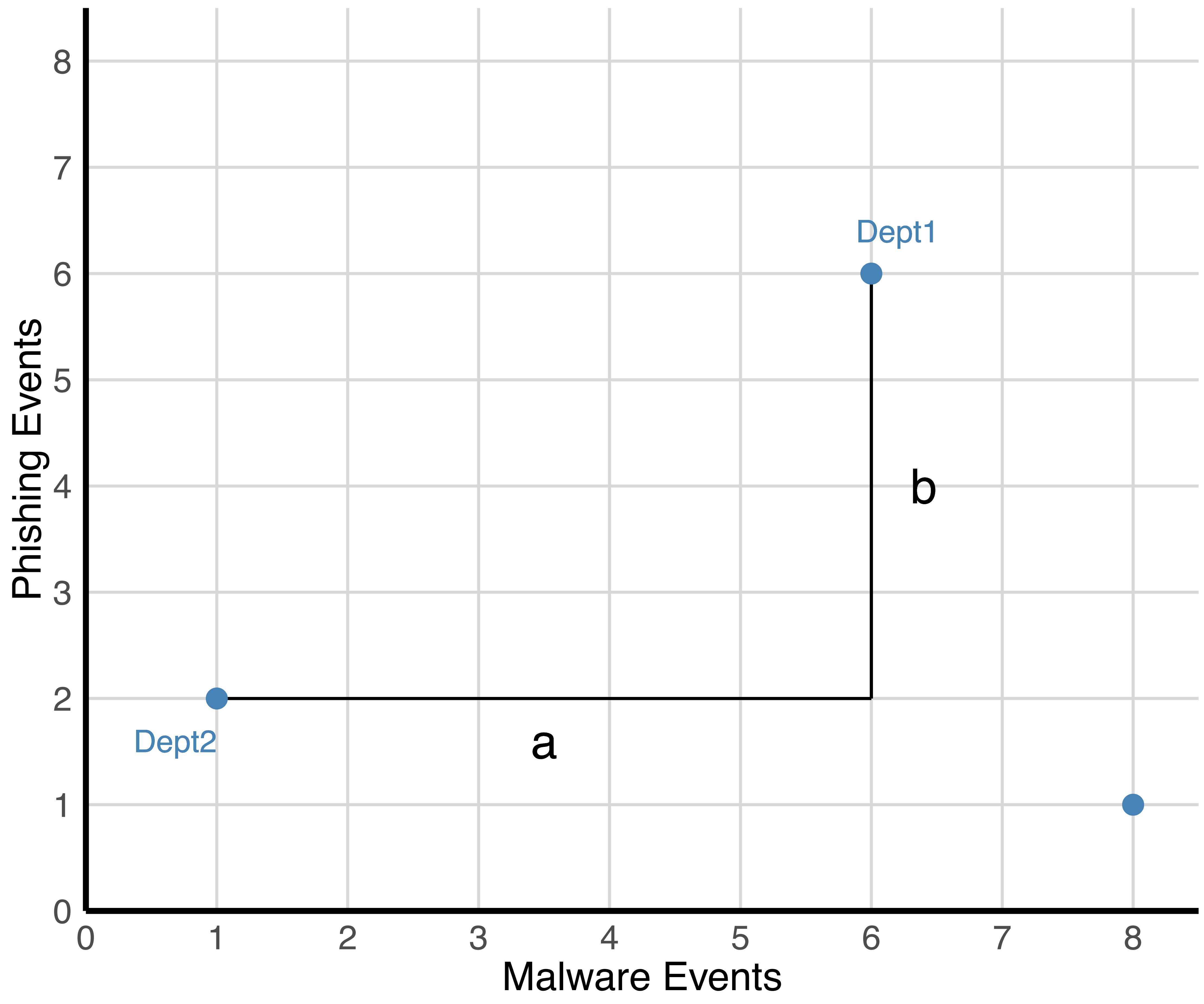
	Malware events	Phishing
Dept1	6	6
Dept2	1	2
Dept3	8	1



Two-Dimenionsal Distance

Manhattan also easy to comprehend: a + b

	Malware events	Phishing
Dept1	6	6
Dept2	1	2
Dept3	8	1



Computing Distance

	Malware events	Phishing
Dept1	6	6
Dept2	1	2
Dept3	8	1

Compare:

Dept1 to Dept2: sqrt((6-1)^2 + (6-2)^2) = **6.4**

Dept2 to Dept3: ... = **7.1**

Dept1 to Dept3: ... = **5.4**

Euclidean Distance calculations

```
def dist(x,y):
    return np.sqrt(np.sum((x-y)**2))

> mat = np.array([[ 6,6,3 ], [1,2,1], [8,1,9]])
> dist(mat[0], mat[1])
6.708203932499369
> dist(mat[1], mat[2])
10.677078252031311
> dist(mat[0], mat[2])
8.06225774829855
```

Python

R

```
> mat <- matrix(c(6,1,8,6,2,1,3,1,9), nrow = 3)
> mat
     [,1] [,2] [,3]
[1,]    6    6    3
[2,]    1    2    1
[3,]    8    1    9
> dist(mat) # default is euclidean
         1         2
2  6.708204
3  8.062258 10.677078
```

Which Departments are Similar?

	Malware events	Phishing	Open Tickets
Dept1	6	6	3
Dept2	1	2	1
Dept3	8	1	9

6.7

8.1

10.7

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Applying Distances
(MDS)

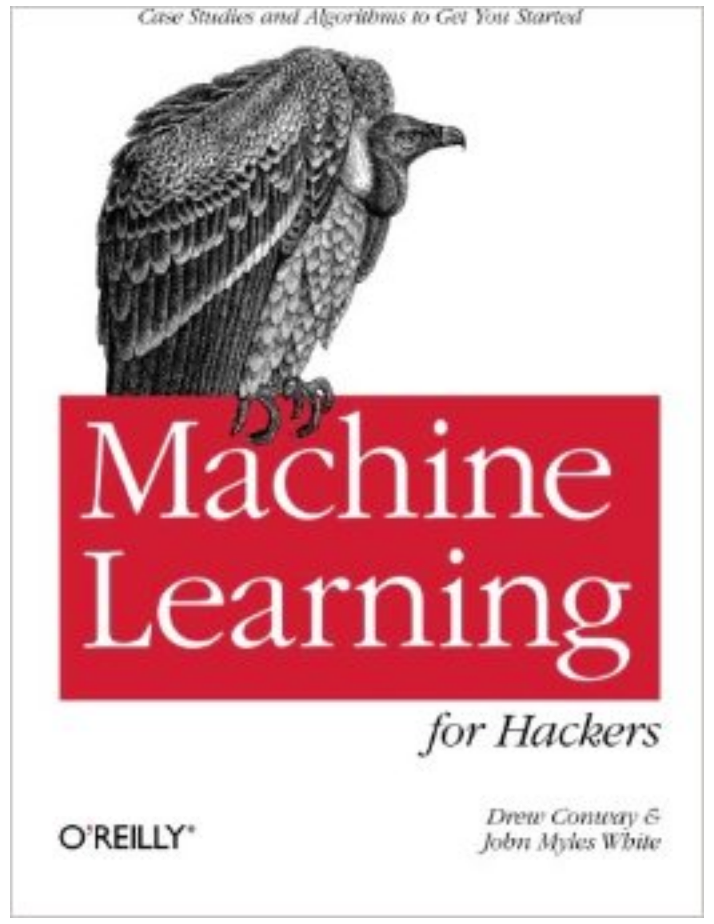
So what now?

US Senator Similarity: 111th US Congress

cong	id	state	dist	lstate	party	eh1	eh2	name	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	…	…	…
111	49300	71	0	CALIFOR	100	0	1	FEINSTEIN	1	1	1	1	6	1	6	1	9	1	1			
111	29906	62	0	COLORAD	100	0	1	UDALL	1	1	1	1	6	1	6	1	1	1	1			
111	40500	62	0	COLORAD	100	1	1	SALAZAR	1	1	1	1	6	0	0	0	0	0	0			
111	40910	62	0	COLORAD	100	2	5	BENNET	0	0	0	0	0	0	0	0	0	0	1			
111	14213	1	0	CONNECT	100	0	1	DODD	1	1	1	1	6	1	6	1	1	1	1			
111	15704	1	0	CONNECT	100	0	1	LIEBERMAN	1	1	1	1	6	1	6	1	1	1	1			
111	14101	11	0	DELAWAR	100	1	1	BIDEN	9	9	9	1	6	0	0	0	0	0	0			
111	40901	11	0	DELAWAR	100	2	5	KAUFMAN	0	0	0	0	0	1	6	1	1	1	1			
111	40916	11	0	DELAWAR	100	3	2	COONS	0	0	0	0	0	0	0	0	0	0	0			
111	15015	11	0	DELAWAR	100	0	1	CARPER	1	1	1	1	6	1	6	1	1	1	1			

sen1	sen2	distance
...	...	...
CHAMBLISS (R)	SCHUMER (D)	45.287967
WICKER (R)	SCHUMER (D)	44.452222
WYDEN (D)	ENZI (R)	45.376205
BROWN (R)	LAUTENBERG (D)	33.120990
LEVIN CARL (D)	WICKER (R)	44.698993
BINGAMAN (D)	COBURN (R)	47.180504
LEVIN CARL (D)	CASEY (D)	12.727922
UDALL (D)	GOODWIN (D)	25.495098
DURBIN (D)	CARDIN (D)	9.433981
BROWN (R)	SPECTER (R)	21.213203
...	...	...

What can we do with these distances?

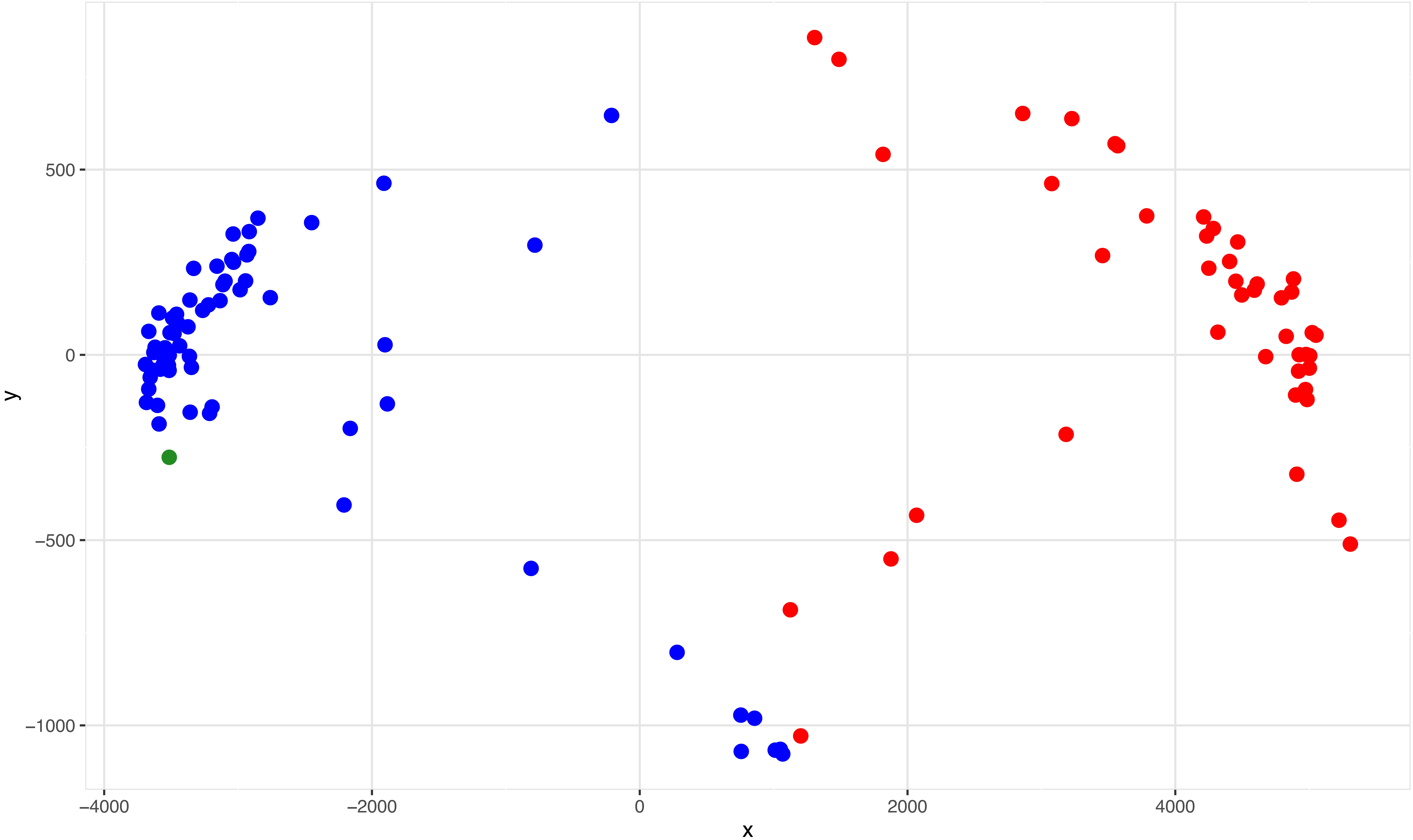


Multi-Dimensional Scaling (MDS)

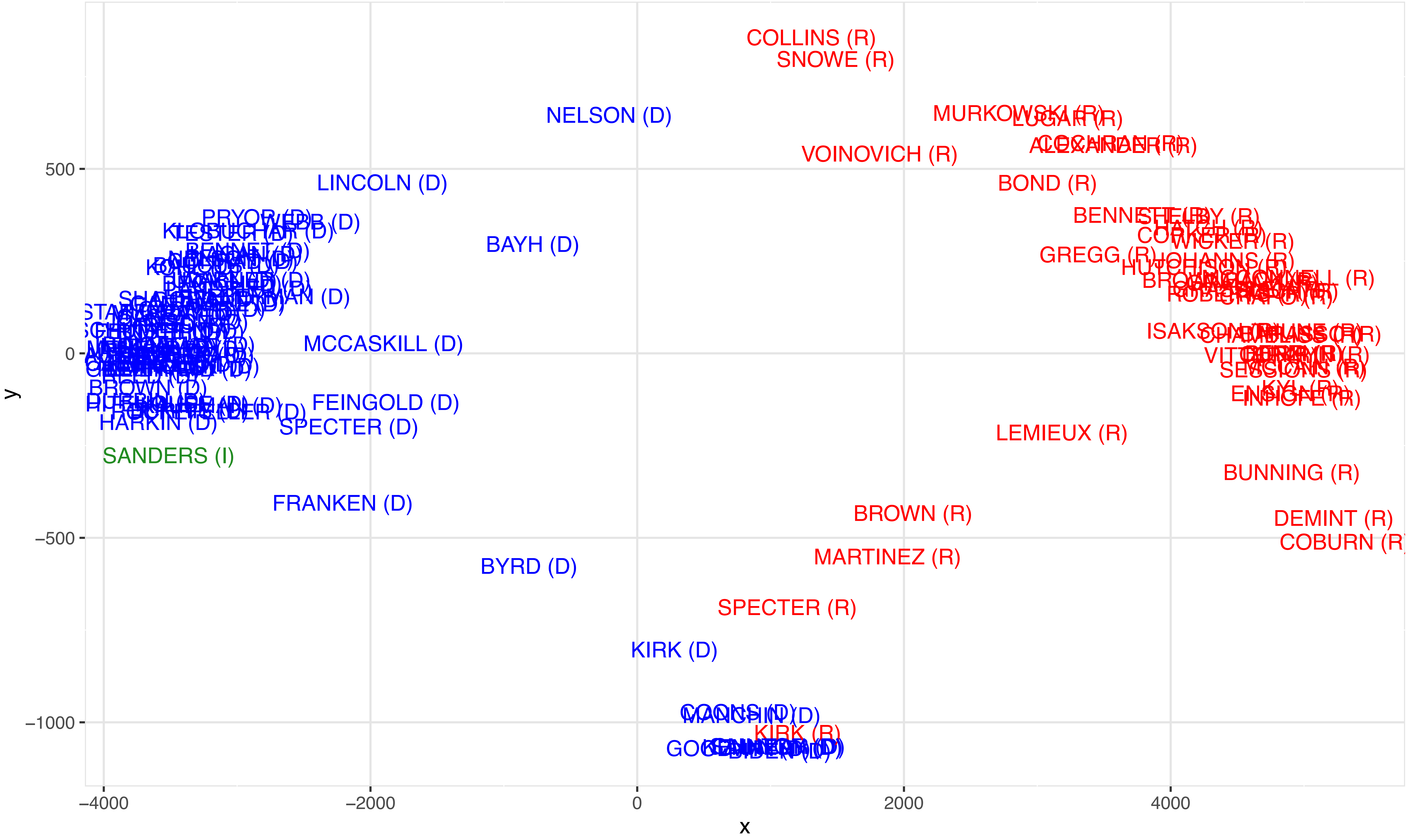
"An MDS algorithm aims to place each object in N-dimensional space such that the between-object distances are preserved as well as possible." (wikipedia)

x	y	name
...	...	...
-2759.2620	154.41524	LIEBERMAN (D)
-3520.0632	-28.39657	MERKLEY (D)
-1910.7153	463.20060	LINCOLN (D)
1202.5691	-1028.44244	KIRK (R)
-3691.4226	-25.88029	CARDIN (D)
-2943.8030	199.57122	WARNER (D)
-3459.6420	109.54234	MURRAY (D)
4972.5638	-93.60466	KYL (R)
-210.5705	646.20845	NELSON (D)
-3113.0023	189.57231	BEGICH (D)
...	...	...

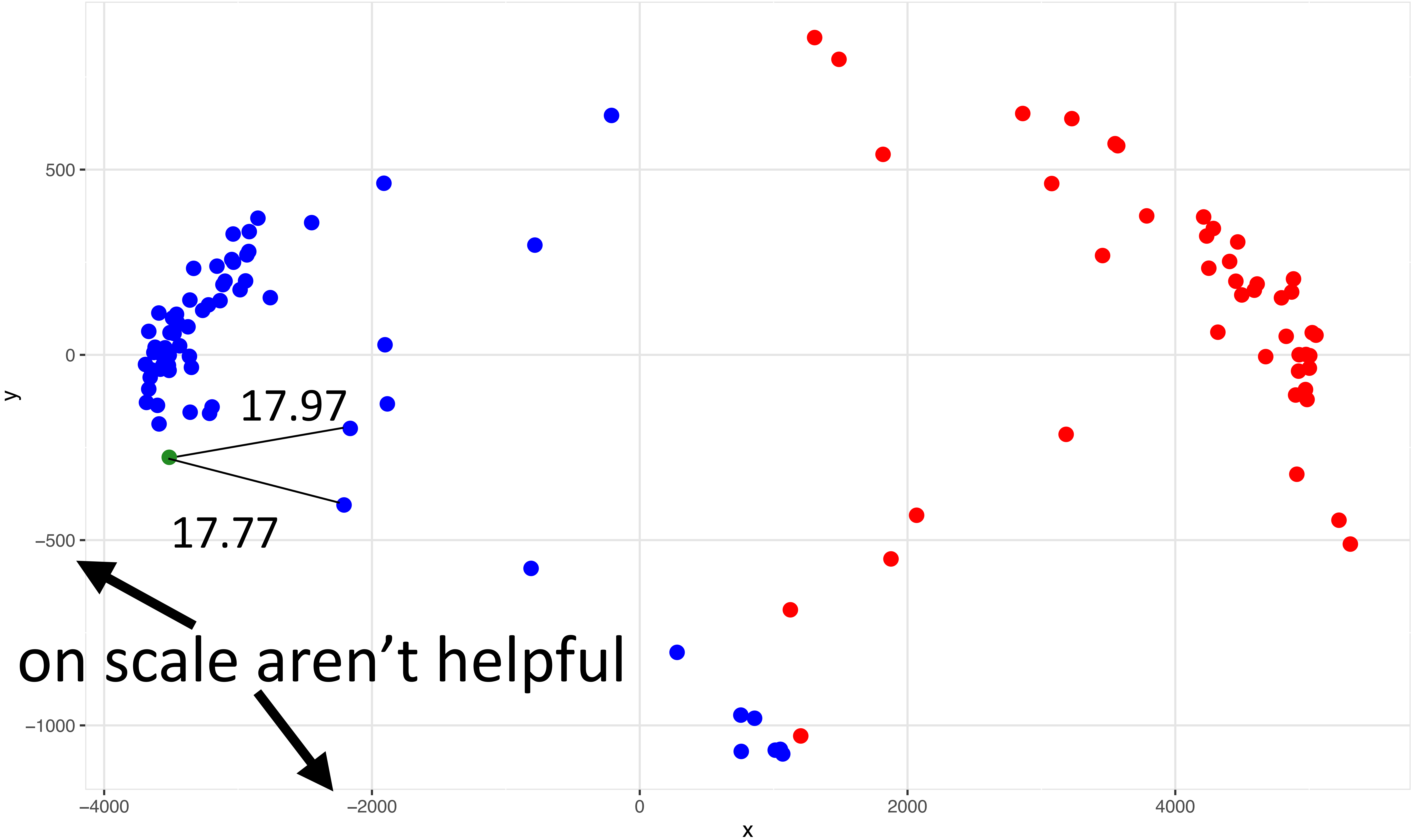
Multi-Dimensional Scaling (MDS)



Multi-Dimensional Scaling (MDS)



Multi-Dimensional Scaling (MDS)



Values on scale aren't helpful

Recognize this?

“Constellations” added with compliments of the graphic design team

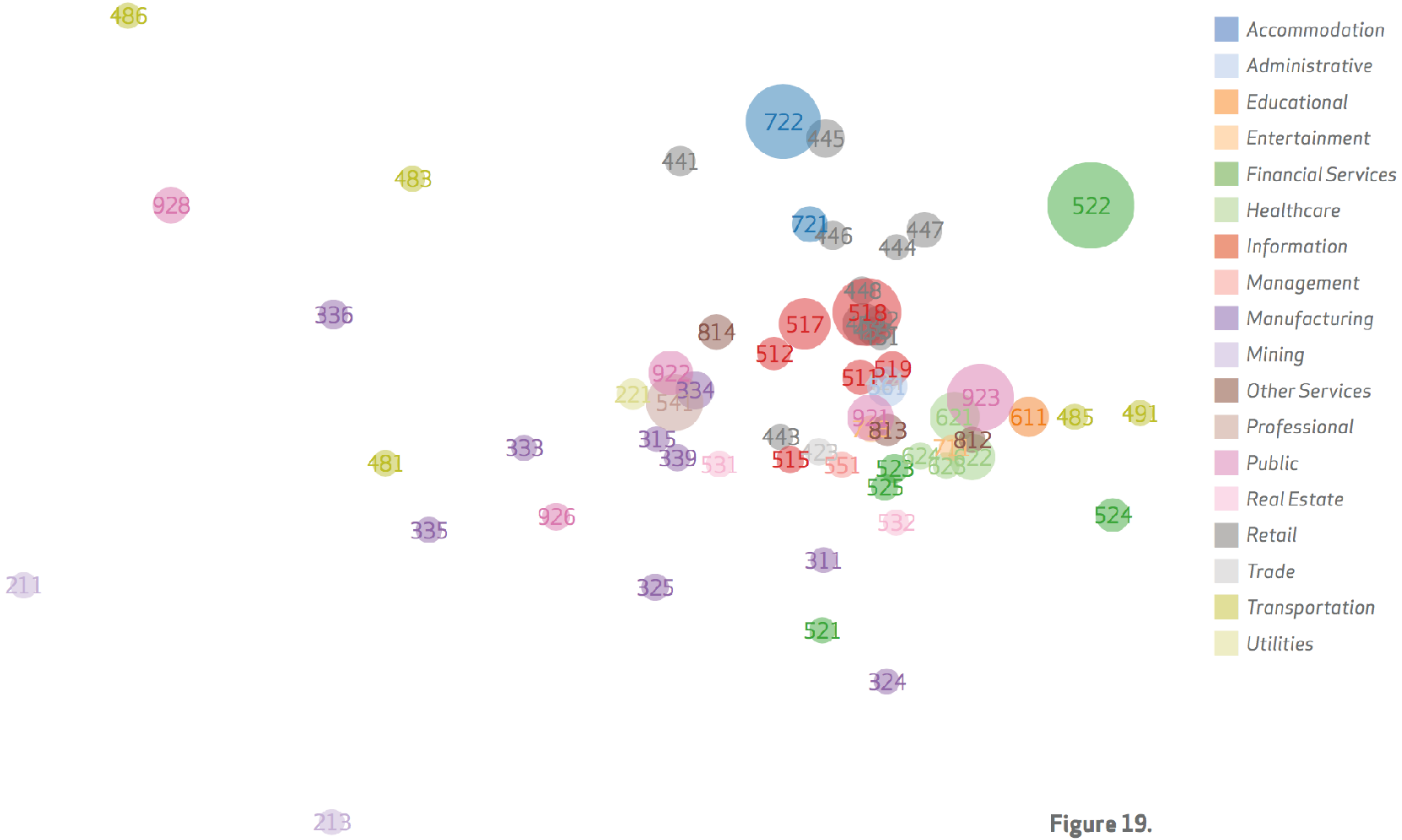


Figure 19.

Clustering on breach data across industries

28 To look up the three-digit NAICS codes, visit: www.census.gov/eos/www/naics/index.html

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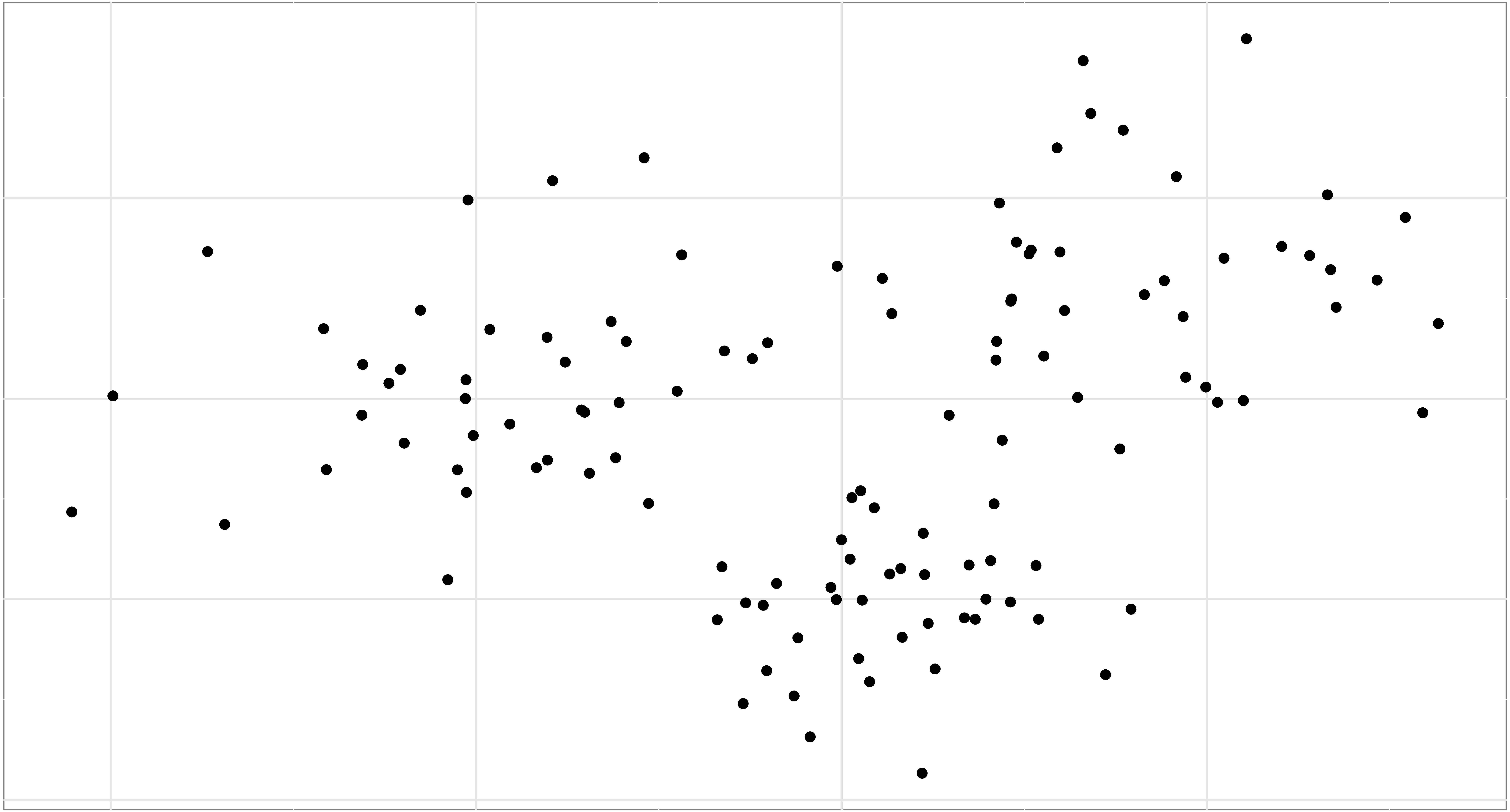
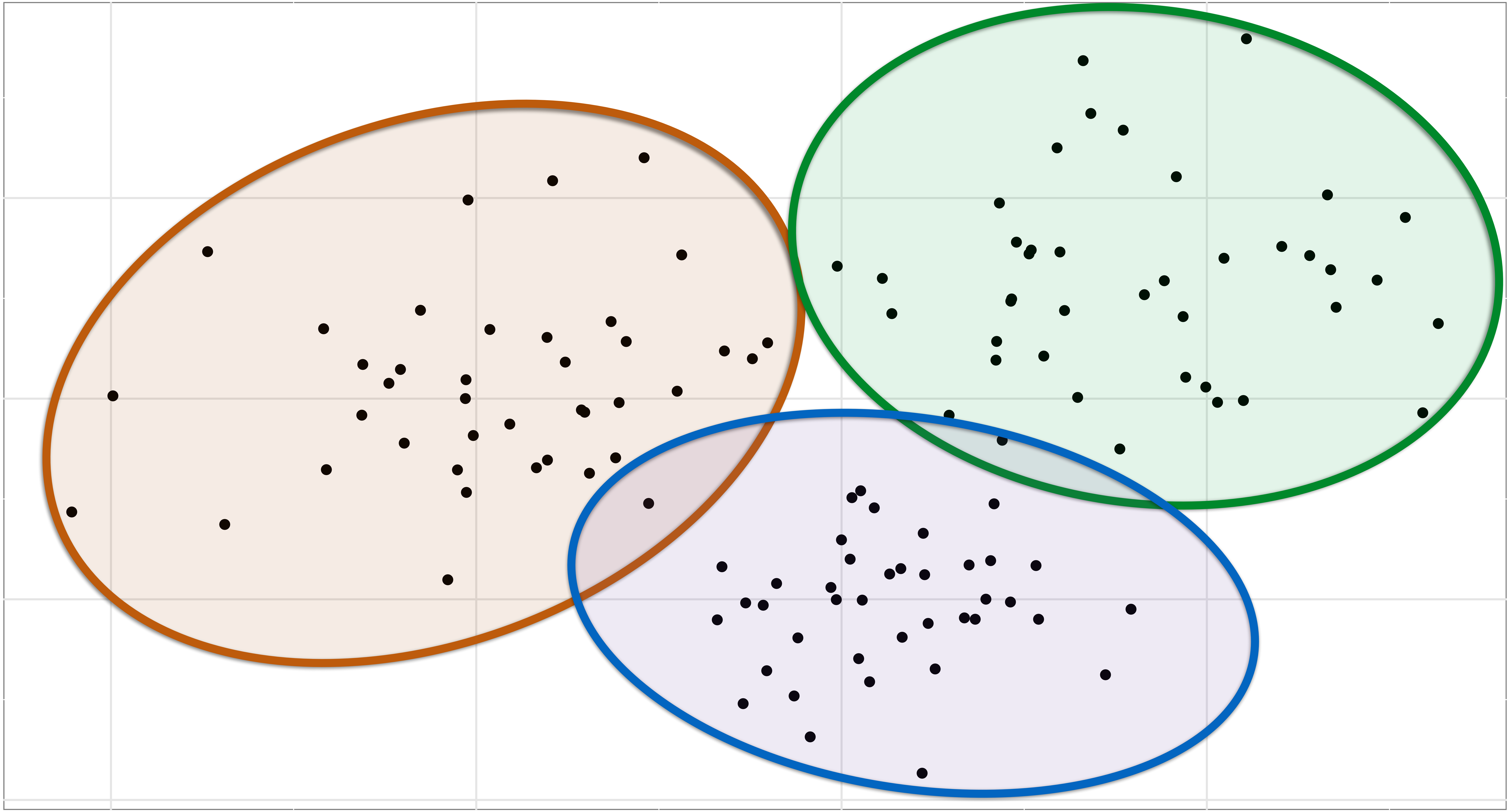
Identifying membership of Clusters

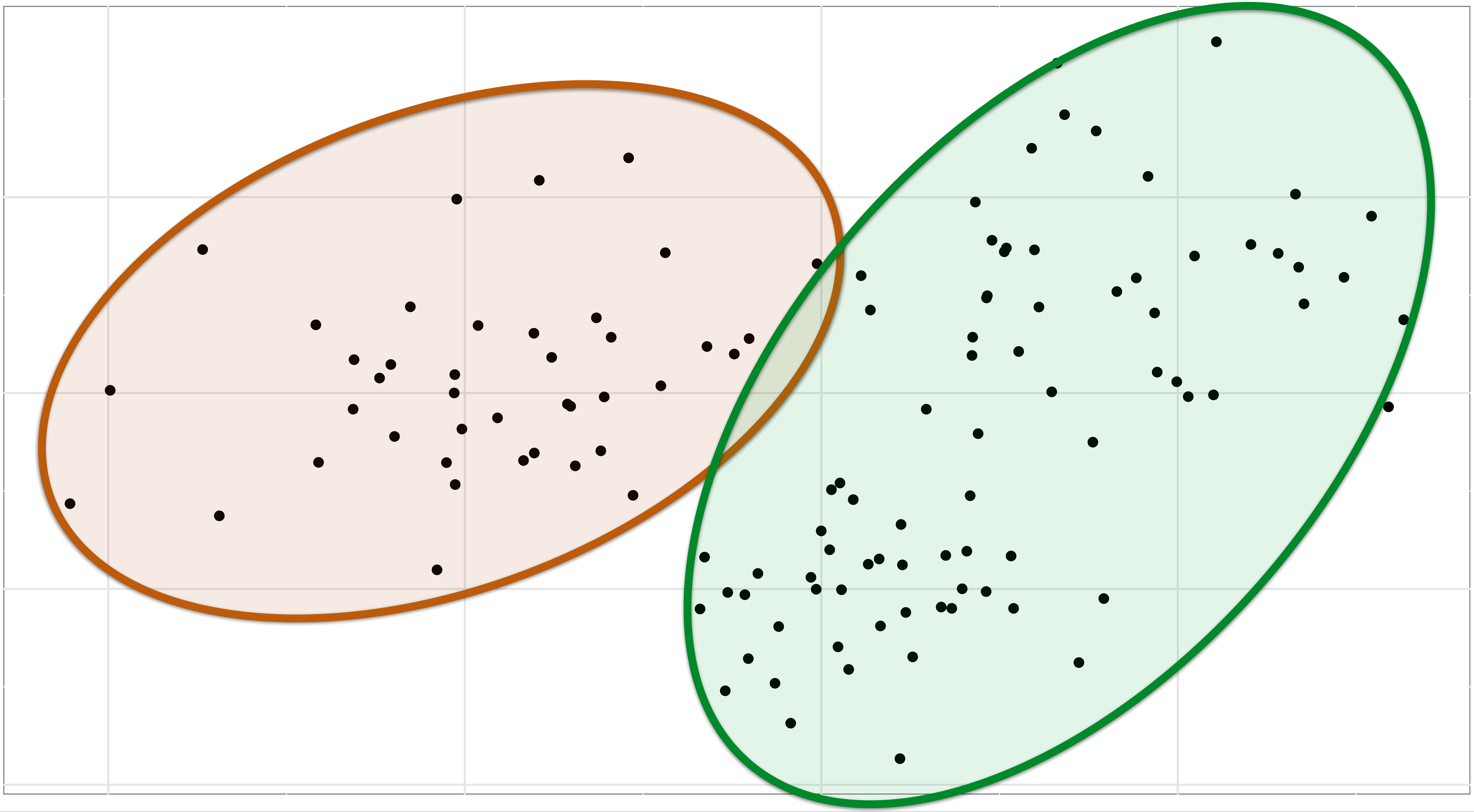
Clustering...



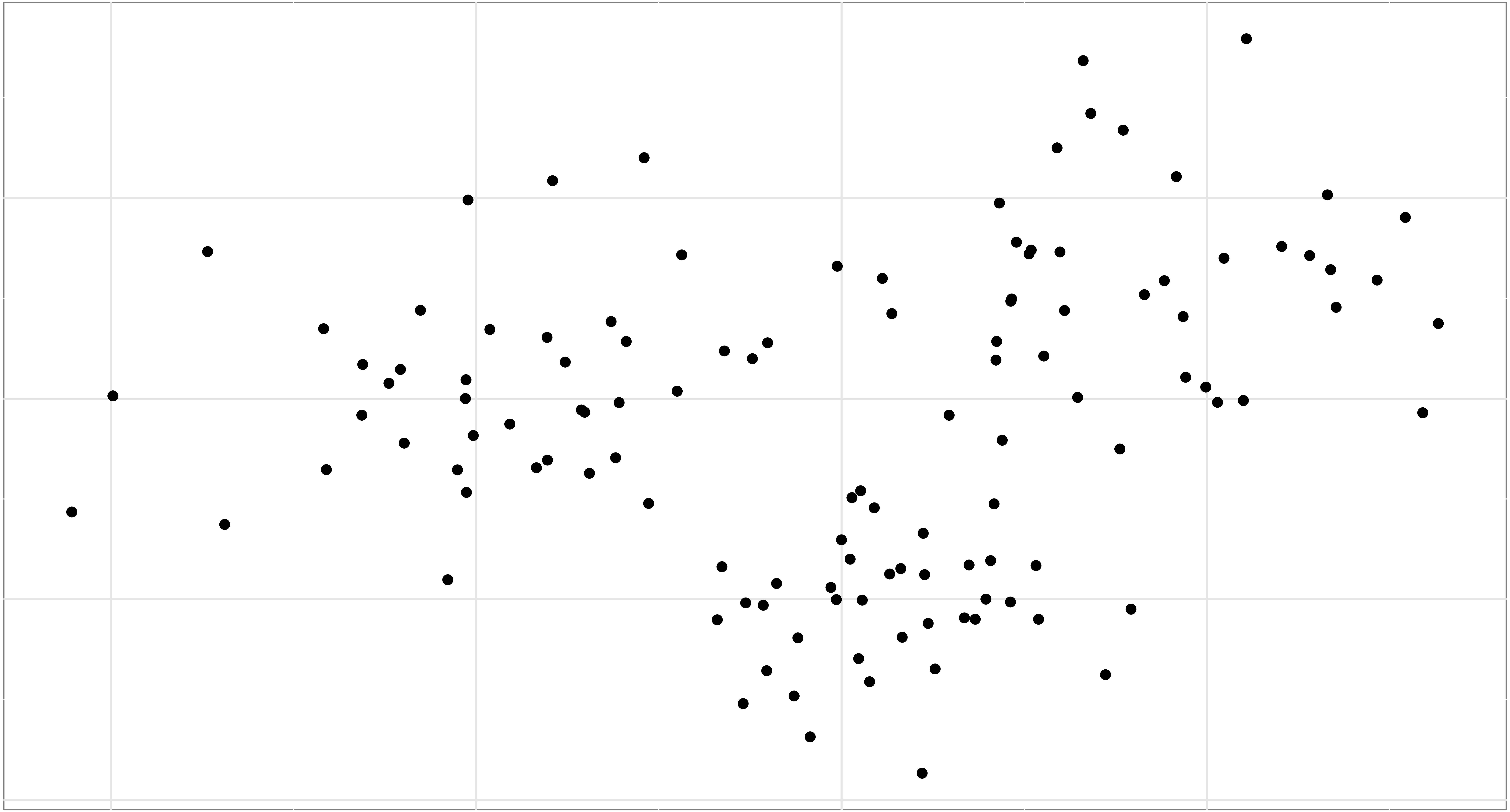
Clustering…



Clustering…



Clustering…

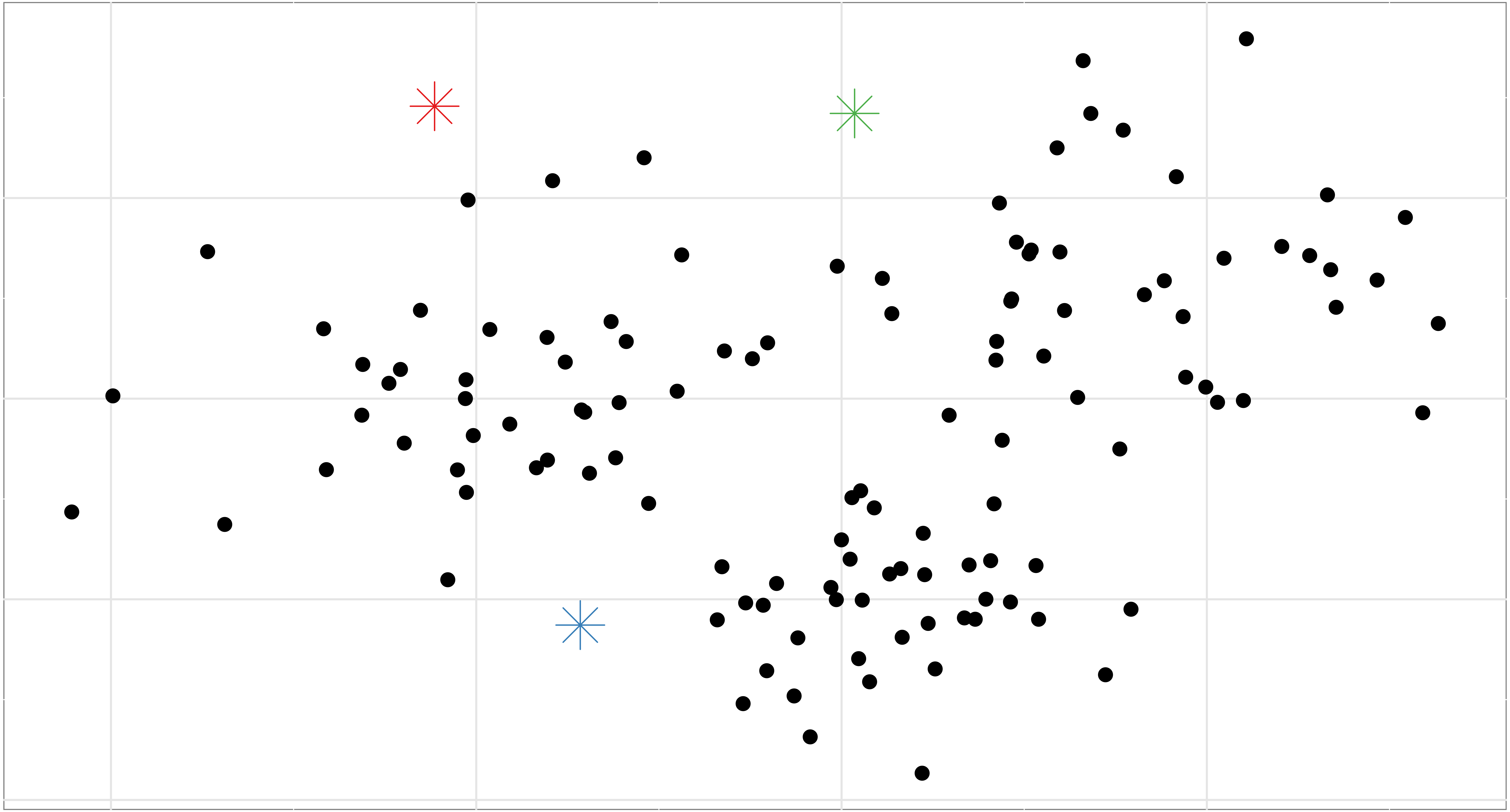


K-Means

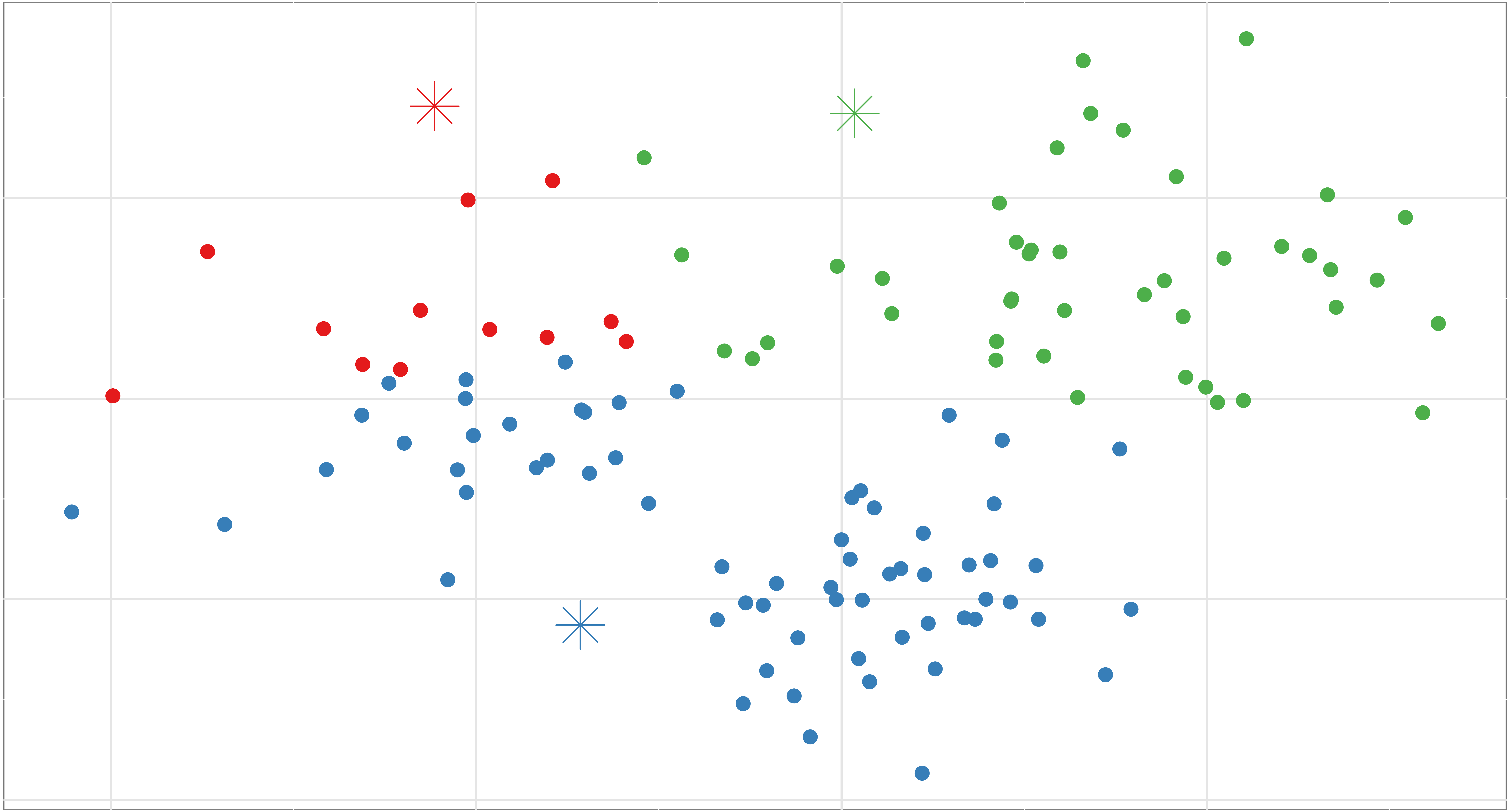
Before starting, pick the number of clusters, K

1. Pick K random centroids within data range
2. Assign each data point to the nearest centroid
3. Move centroid to center of assigned points
4. Repeat steps 2 and 3 until centroid stops shifting

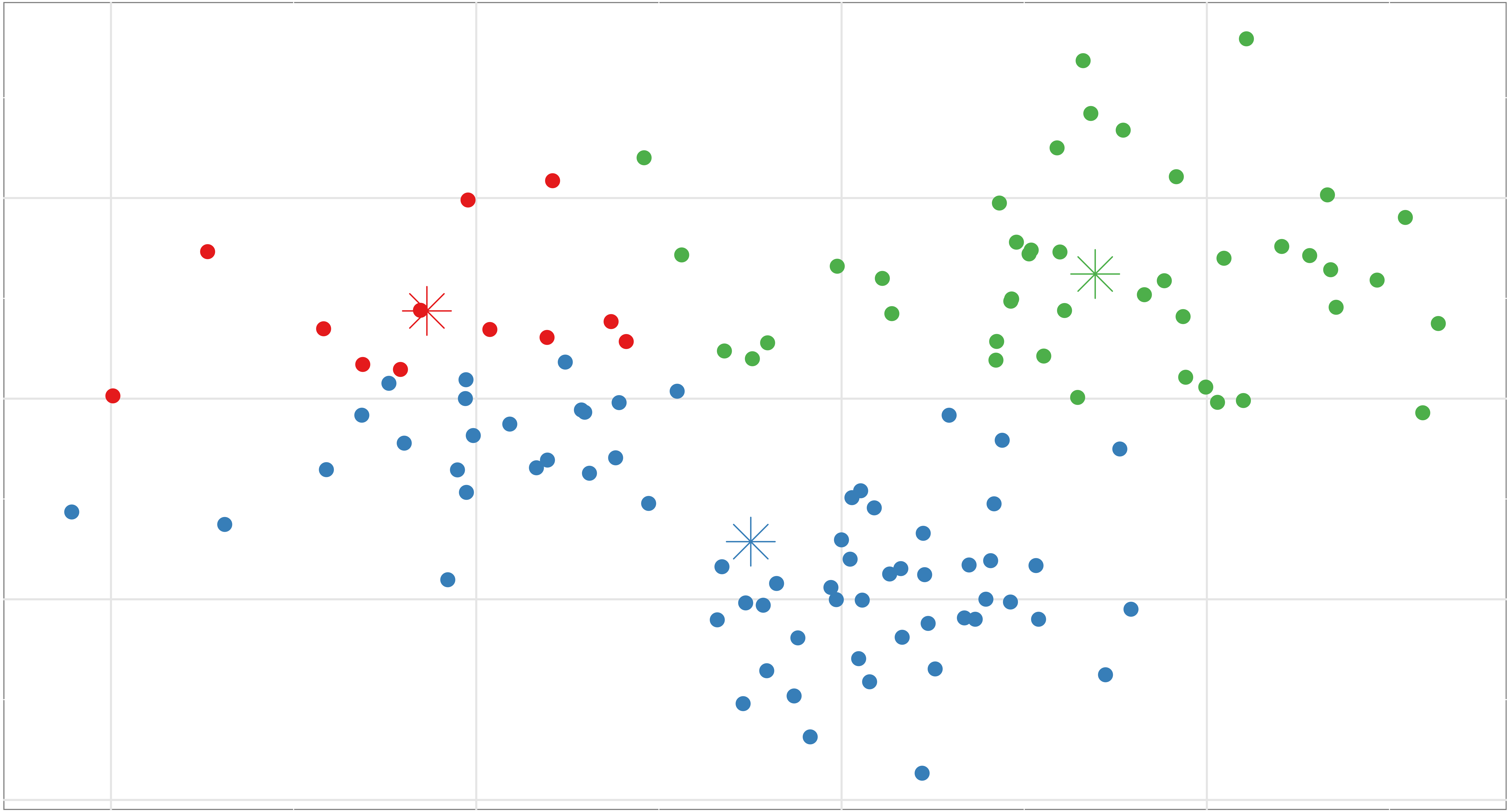
Step 1: Pick 3 random centroids within data range



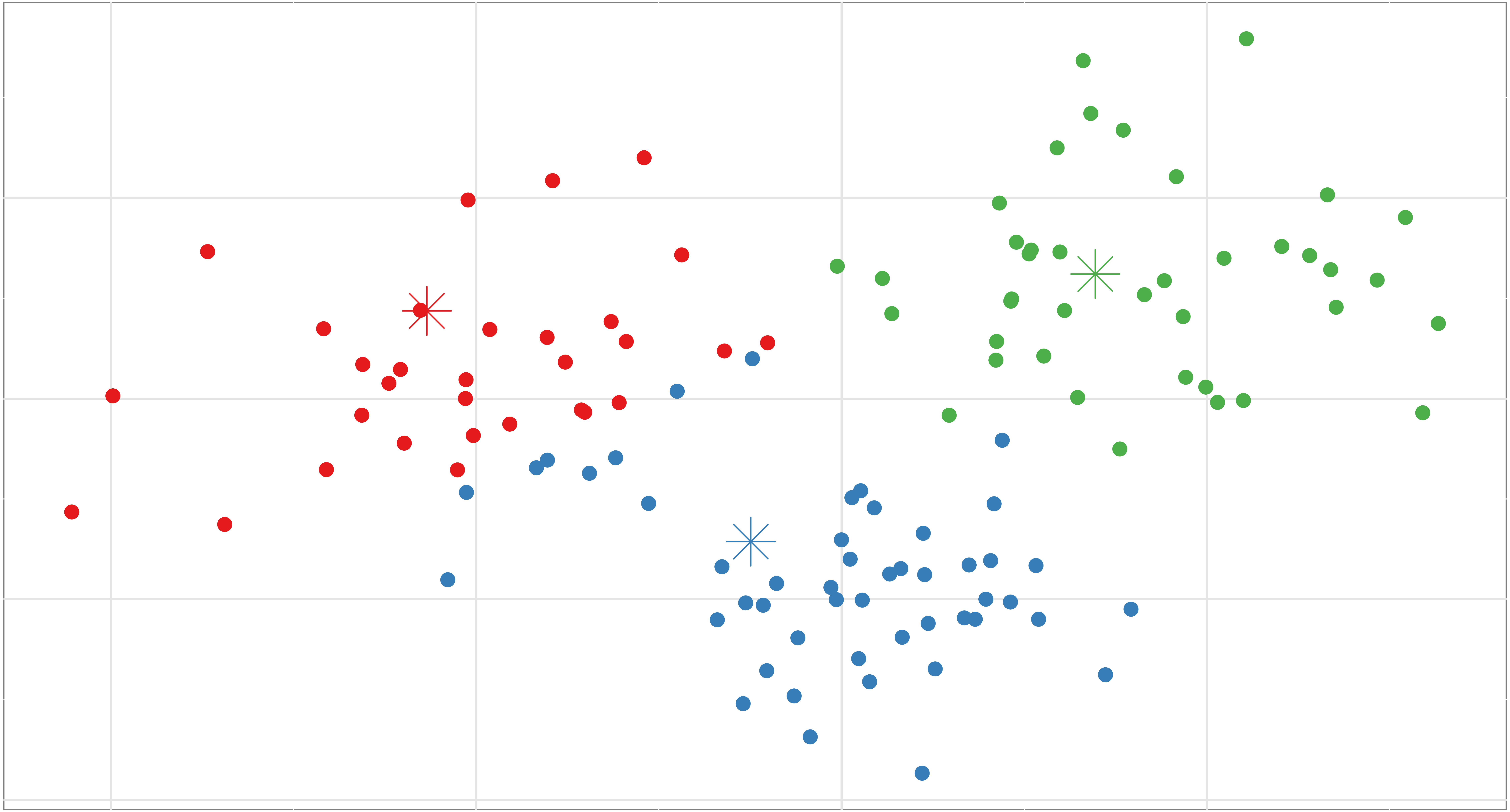
Step 2: Assign each data point to the nearest centroid (1)



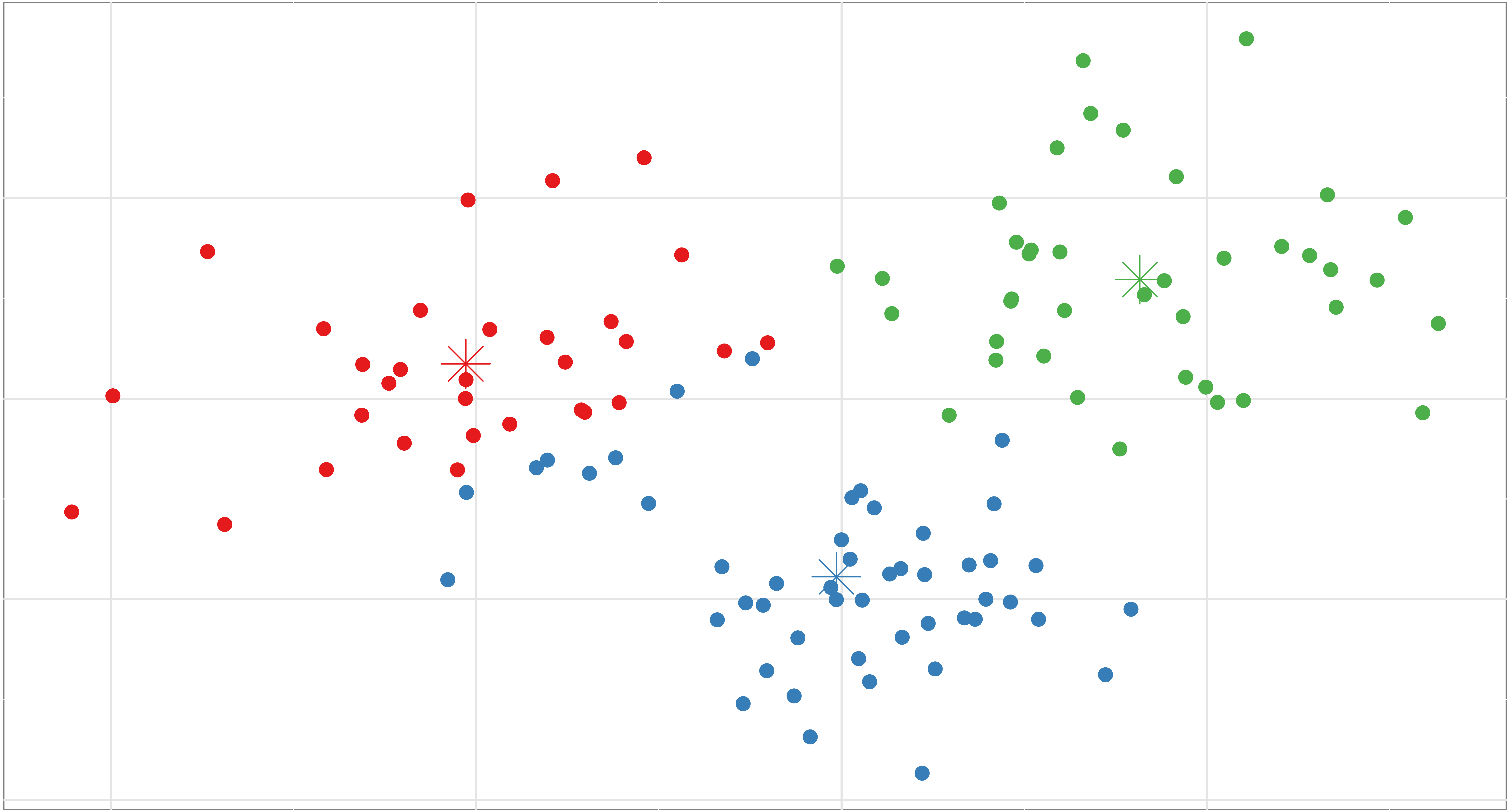
Step 3: Move centroid to center of assigned points (1)



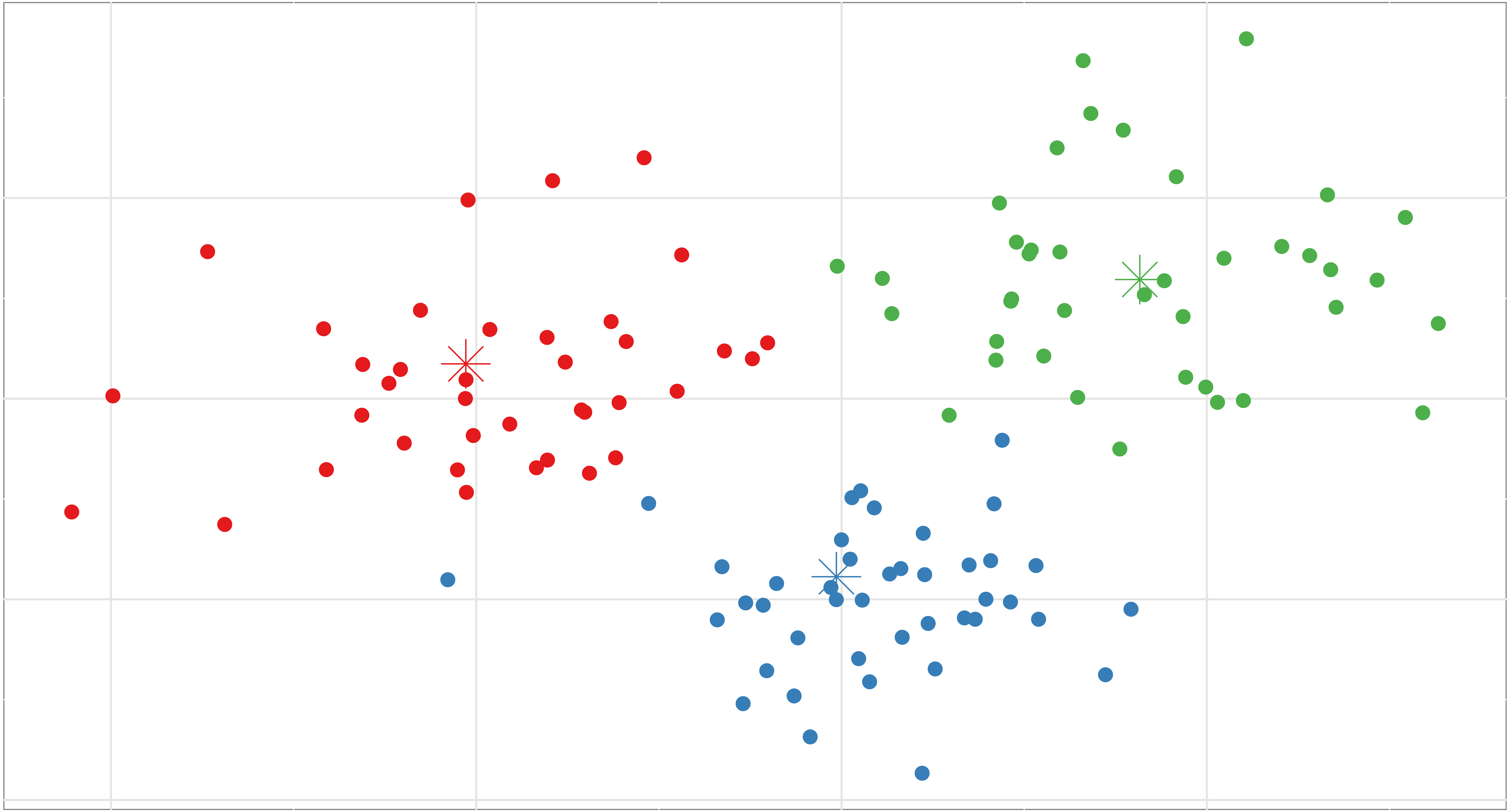
Step 2: Assign each data point to the nearest centroid (2)



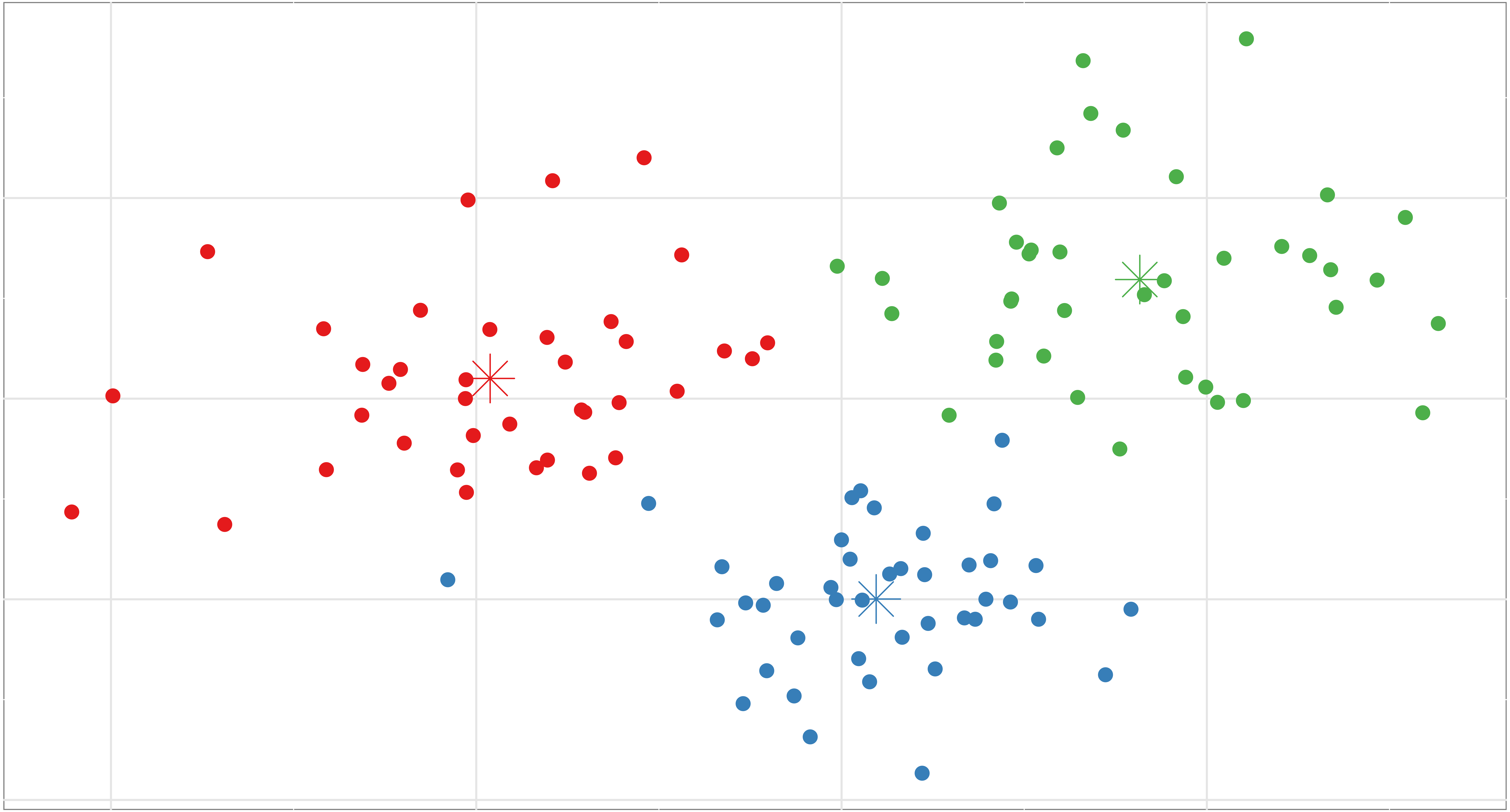
Step 3: Move centroid to center of assigned points (2)



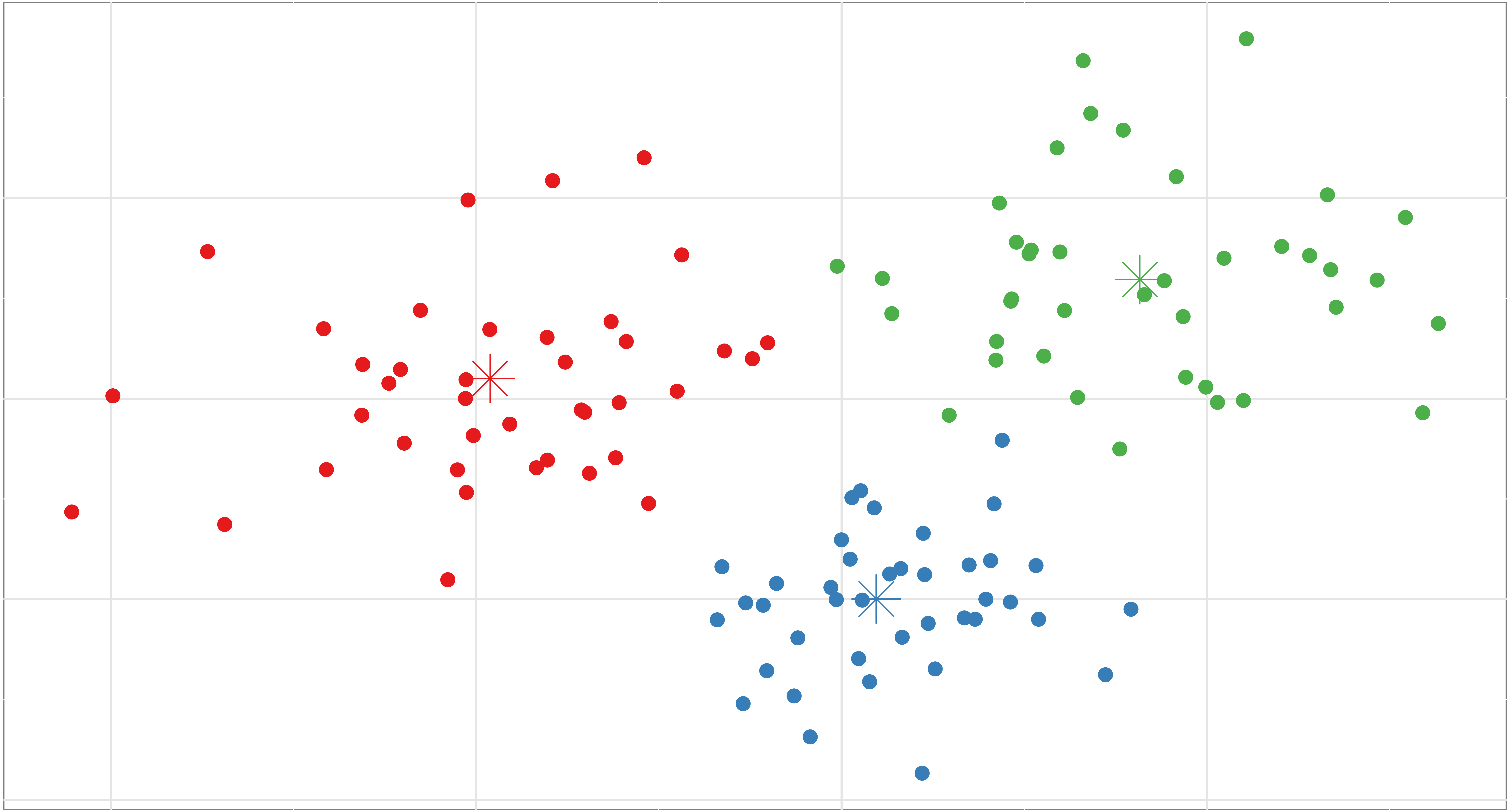
Step 2: Assign each data point to the nearest centroid (3)



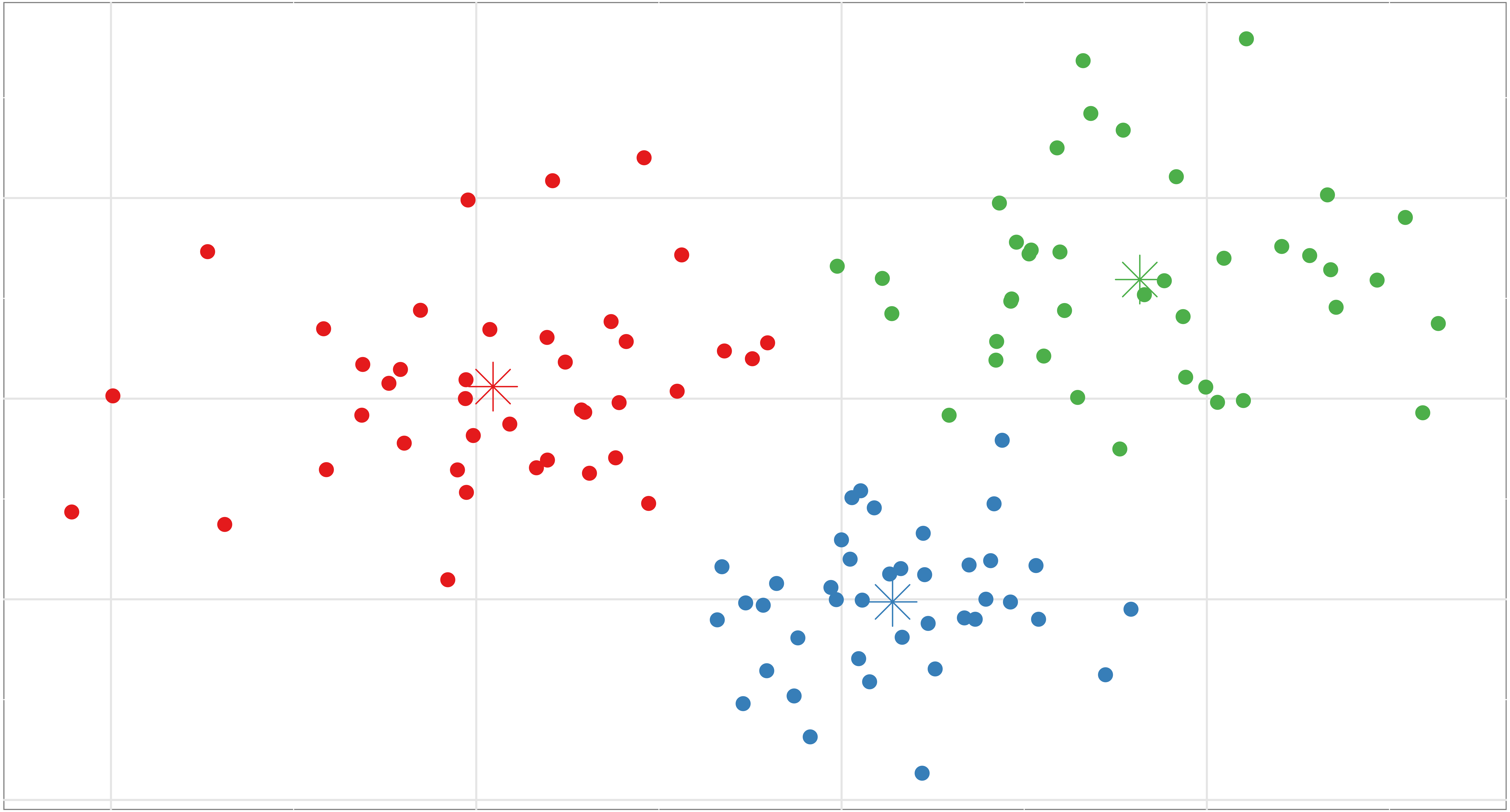
Step 3: Move centroid to center of assigned points (3)



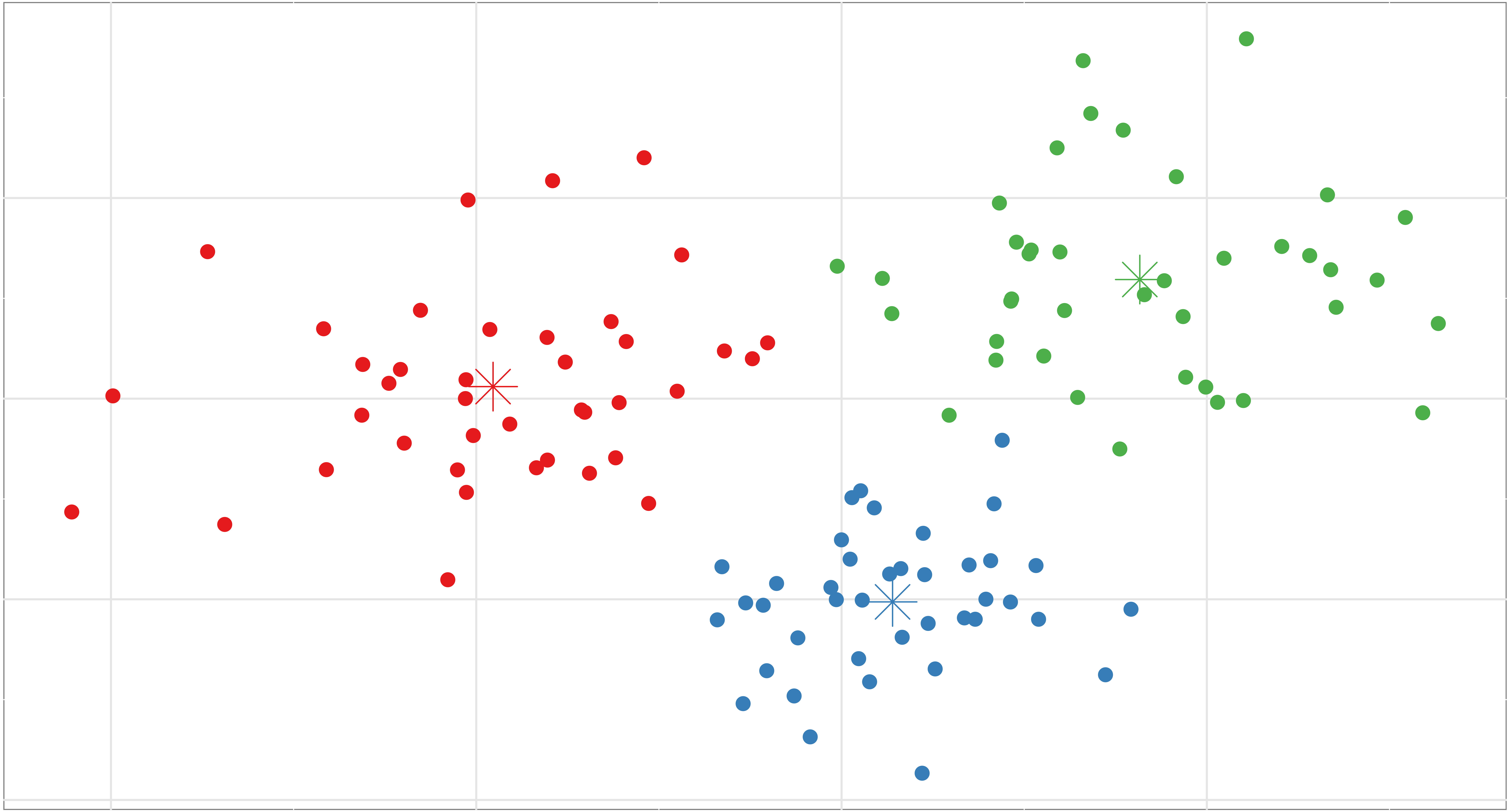
Step 2: Assign each data point to the nearest centroid (4)



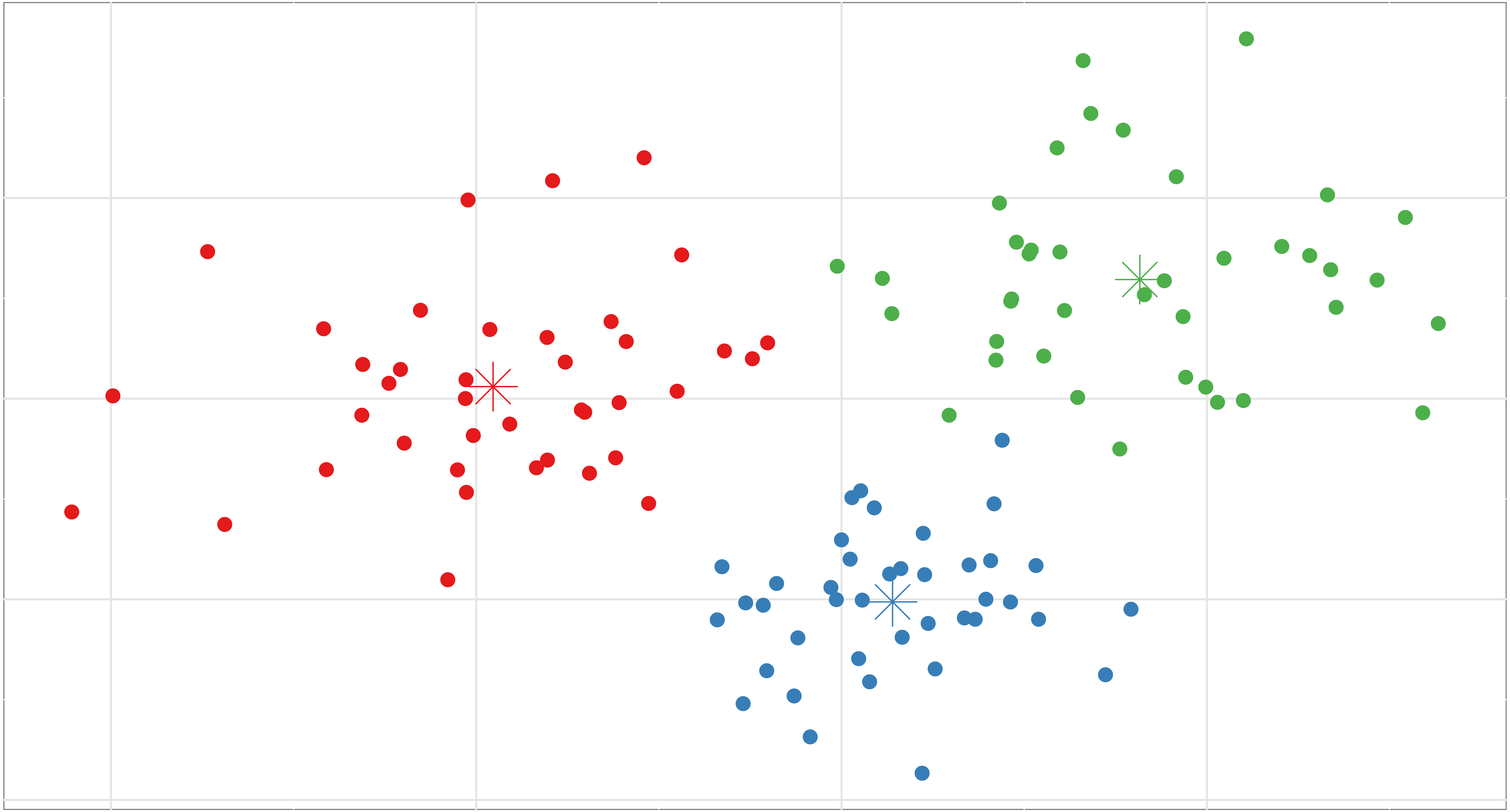
Step 3: Move centroid to center of assigned points (4)



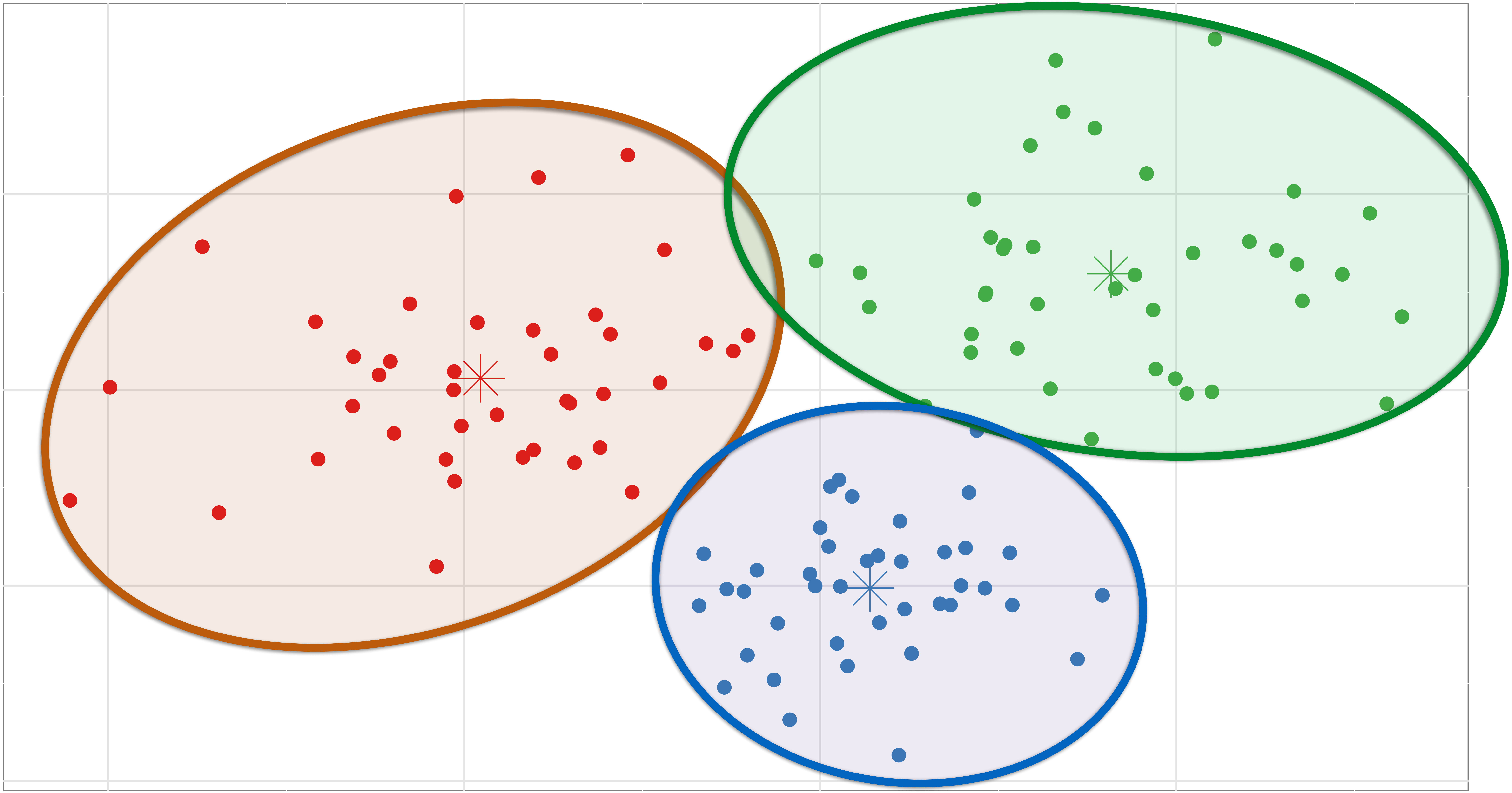
Step 2: Assign each data point to the nearest centroid (5)



Step 3: Move centroid to center of assigned points (5)



Step 3: Move centroid to center of assigned points (5)



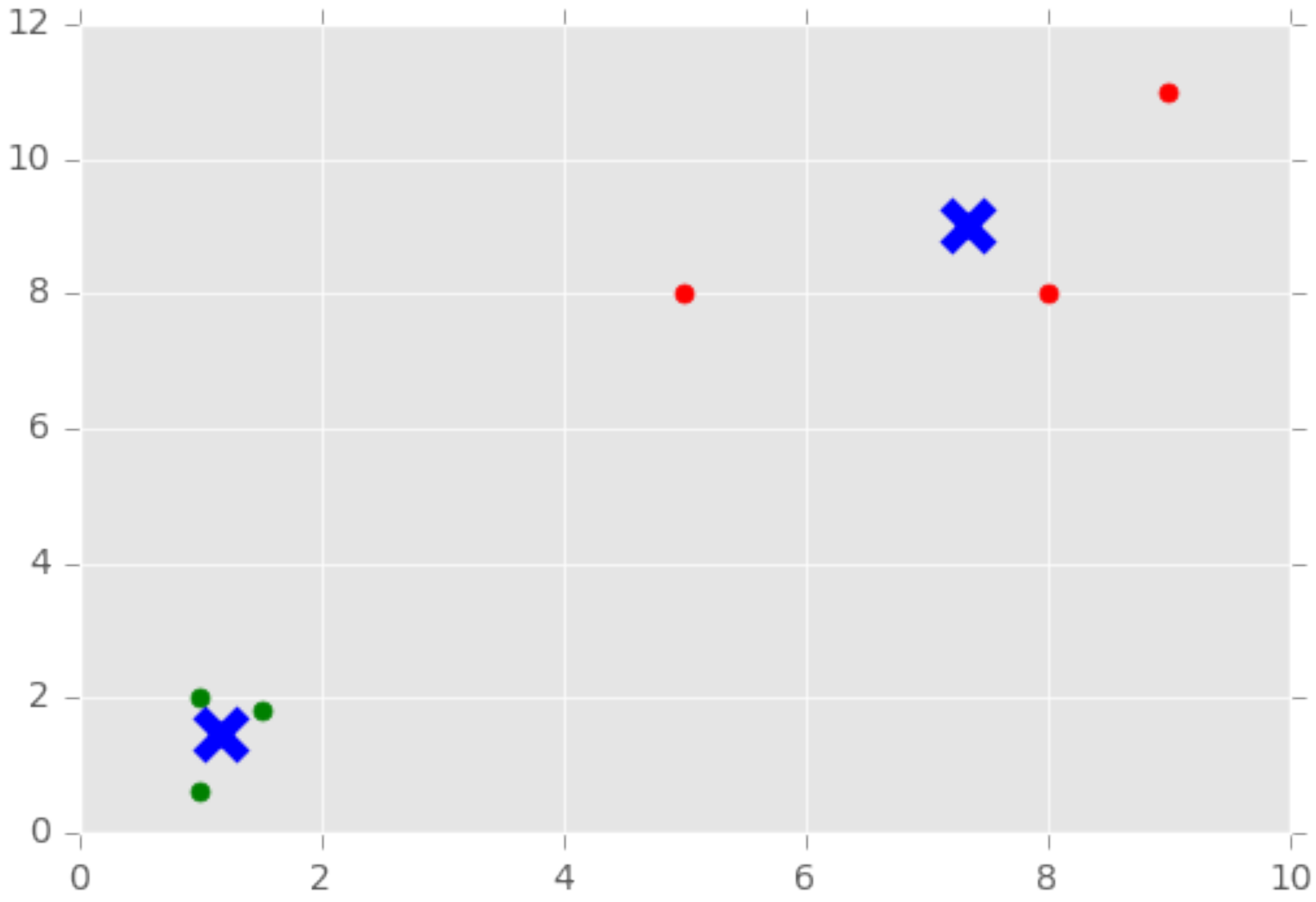
K-Means in practice (Python version)

Python

```
#Import from Scikit-learn
from sklearn.cluster import Means

kmeans = KMeans(n_clusters=2)
kmeans.fit(data)

centroids = kmeans.cluster_centers_
labels = kmeans.labels_f
```



K-Means in practice (R version)

```
> points <- data.frame(x=c(rnorm(50, mean=5), rnorm(50, mean=10)),
+                      y=c(rnorm(50, mean=5), rnorm(50, mean=10)))
> km.out <- kmeans(points, centers = 2)
> print(km.out)
K-means clustering with 2 clusters of sizes 50, 50

Cluster means:
         x         y
1 9.981532 10.073307
2 5.416039  4.917267

Clustering vector:
  [1] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1 1 1 1 1
 [56] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Within cluster sum of squares by cluster:
[1]  73.6352 112.3886
 (between_SS / total_SS =  86.4 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss" "betweenss"    "size"
[8] "iter"         "ifault"
> points$cluster <- km.out$cluster
```

K-Means: Got a problem with it?

Before starting, pick the number of clusters, K

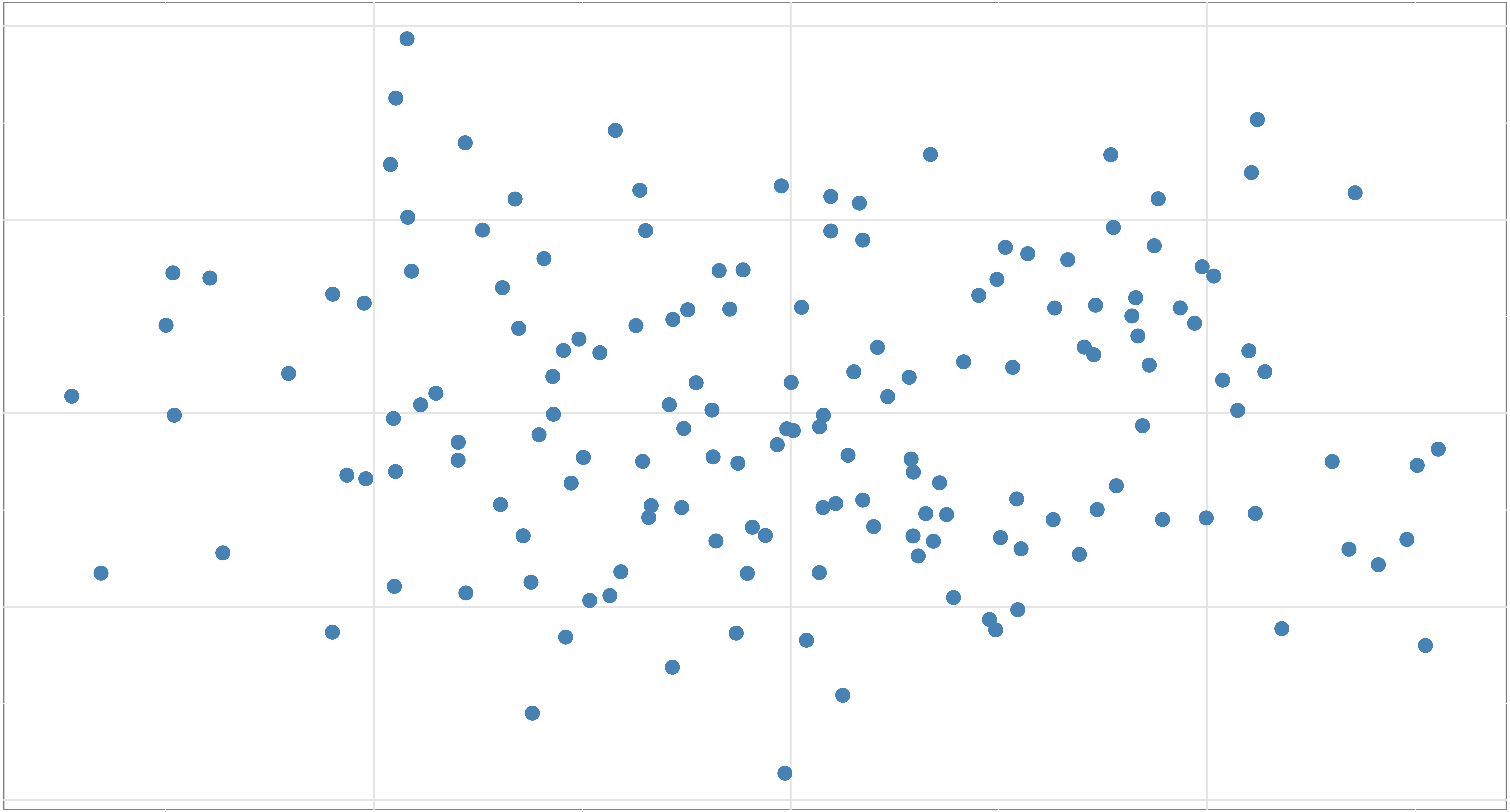
1. Pick K random centroids within data range
2. Assign each data point to the nearest centroid
3. Move centroid to center of assigned points
4. Repeat steps 2 and 3 until centroid stops shifting

K-Means: Got a problem with it?

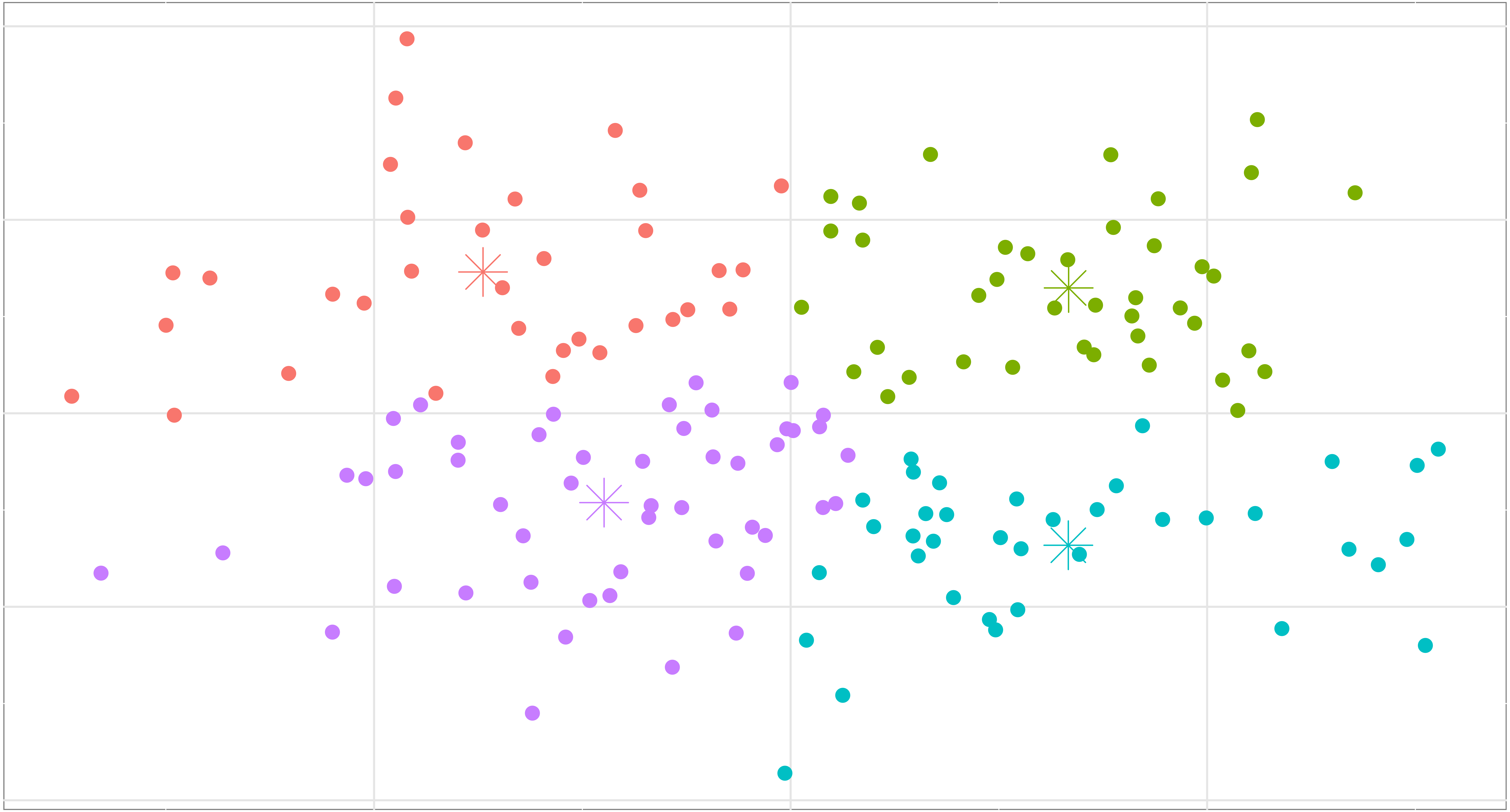
Before starting, pick the number of clusters, K   Subjective

1. Pick K random centroids within data range   Not Repeatable
2. Assign each data point to the nearest centroid   Sensitive to Scale
3. Move centroid to center of assigned points
4. Repeat steps 2 and 3 until centroid stops shifting

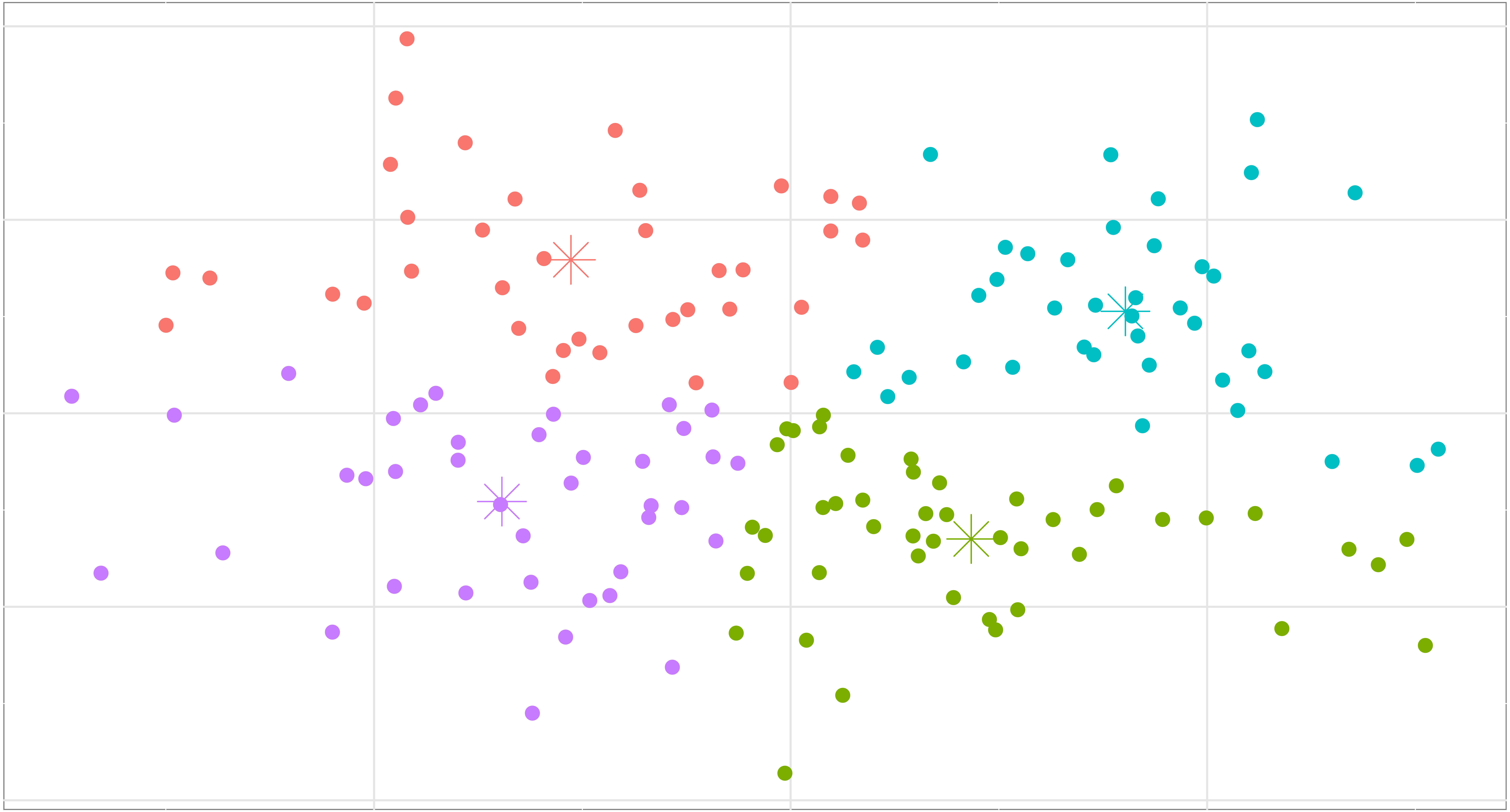
How many clusters?



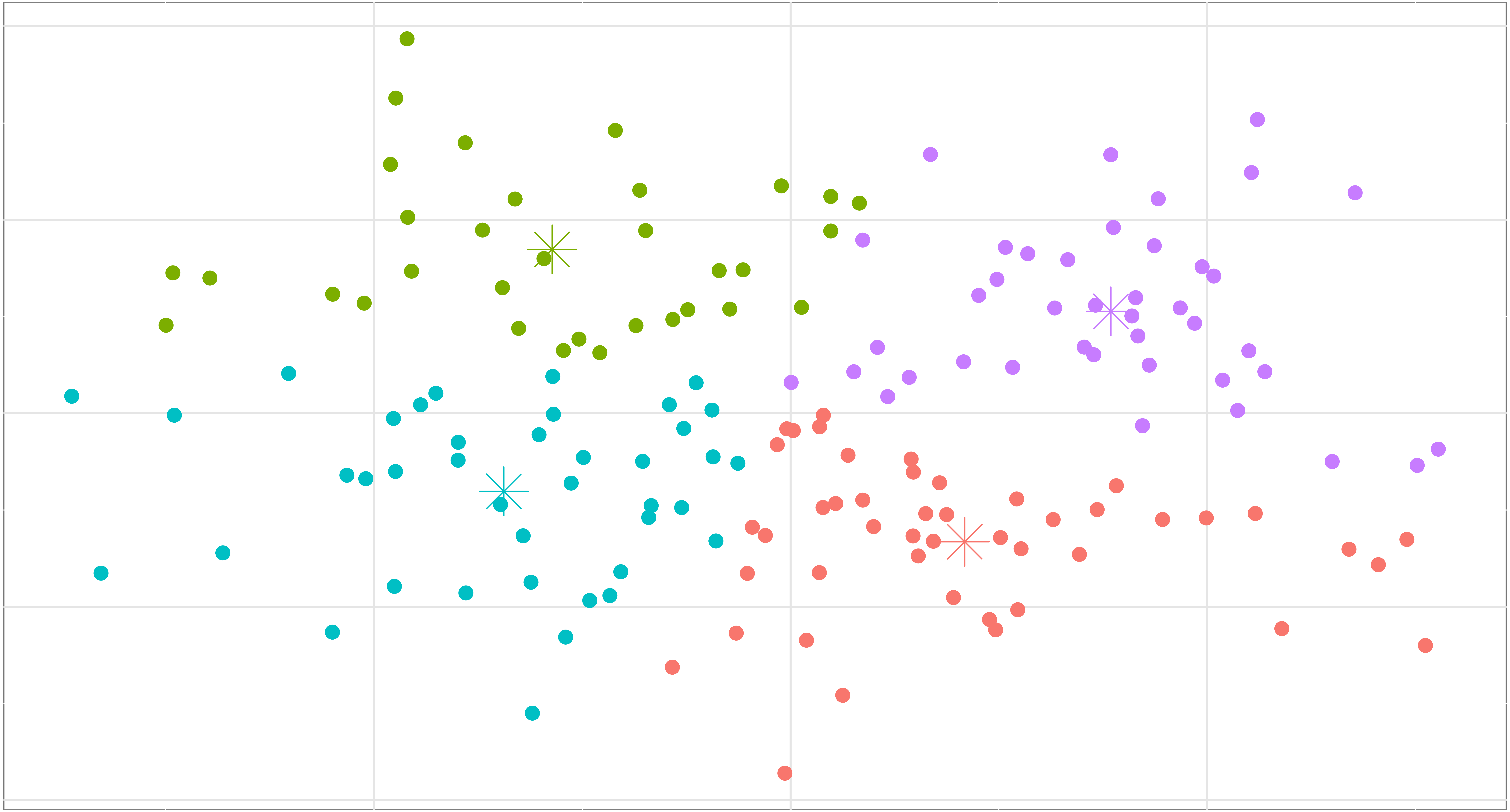
Random Start...



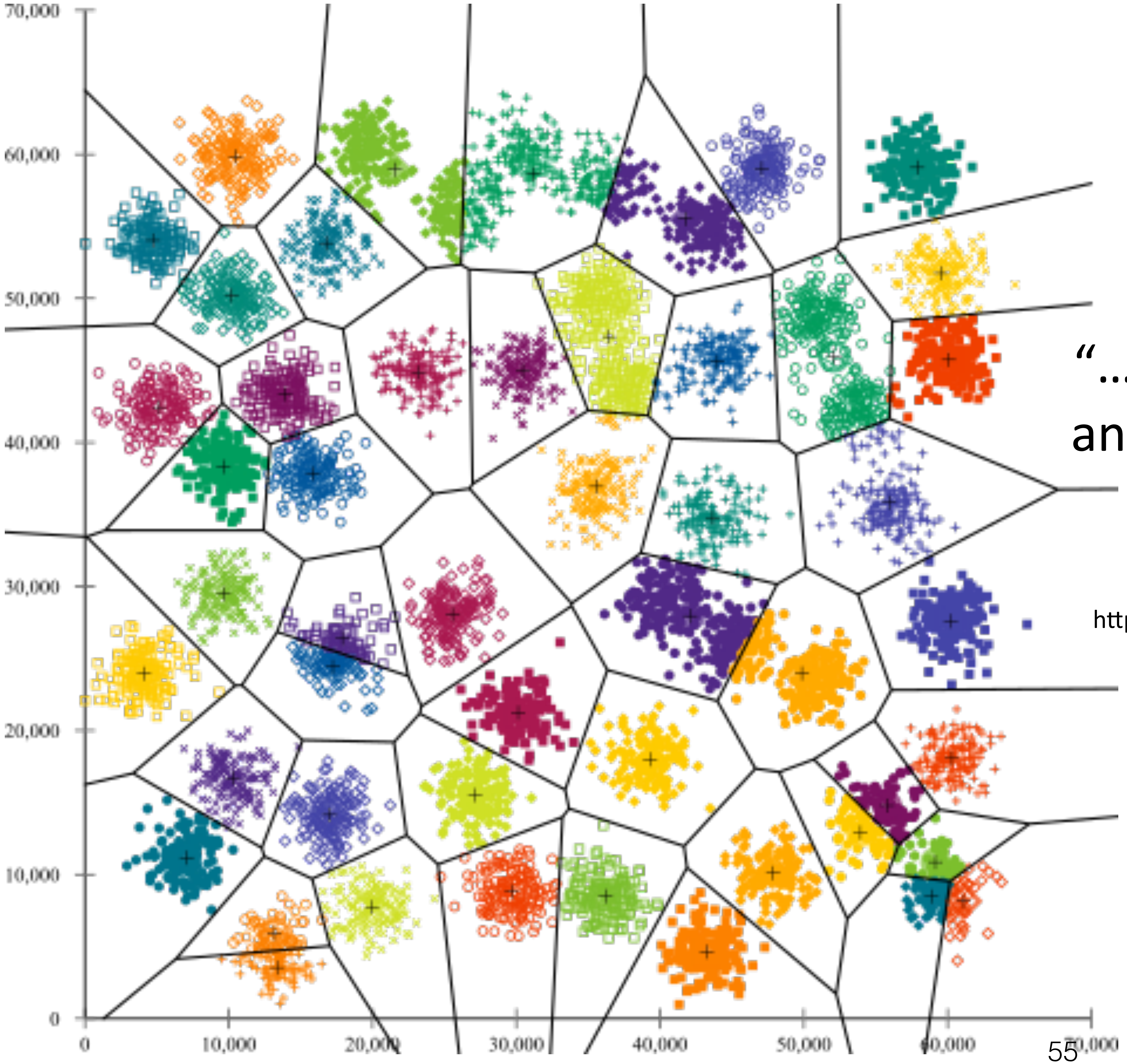
Random Start...



Random Start...



K-Means



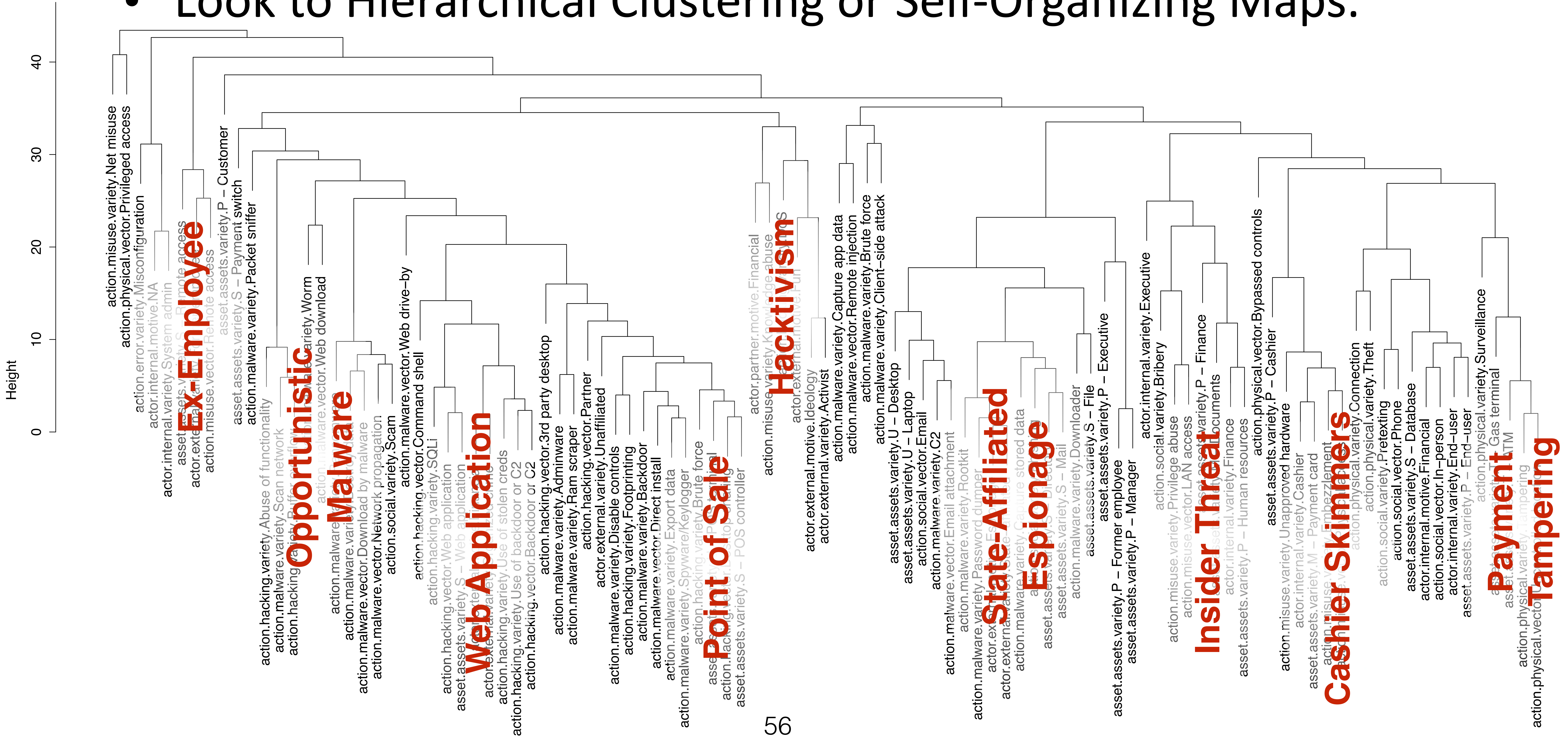
"…it's too easy to throw k-means on your data, and nevertheless get a result out (that is pretty much random, but you won't notice)."

— Anony-Mousse

http://stats.stackexchange.com/questions/133656/how-to-understand-the-drawbacks-of-k-means

After K-Means

- K-Means has many, many alternatives and corrections to the core shortcomings.
- Look to Hierarchical Clustering or Self-Organizing Maps.



{LAB} time

Please Complete “K-Means Worksheet”