K-means Clustering

//Flatiron School

By the end of the lesson students will be able to:

Assess what scenarios could use k-means

Articulate the methodology used by k-means

Apply `KMeans` to relevant datasets

Select the appropriate number of clusters using k-means and use the Silhouette and the elbow method

Evaluate the weaknesses and remedies to k-means

Compare and contrast K-means with Hierarchical Clustering

Scenario:

You work for the marketing department within large company that manages a customer base.

For each customer you have a record of average purchase cost and time since last purchase.

You **know** that if you want to retain your customers you cannot treat them the same. You can use targeted marketing ads towards groups that demonstrate different behavior, but how will you divide the customers into groups?

Scenario Review:

Goal:
Groups (or Categories)

Problem type:
Unsupervised

You work for the marketing department within large company that manages a customer base.

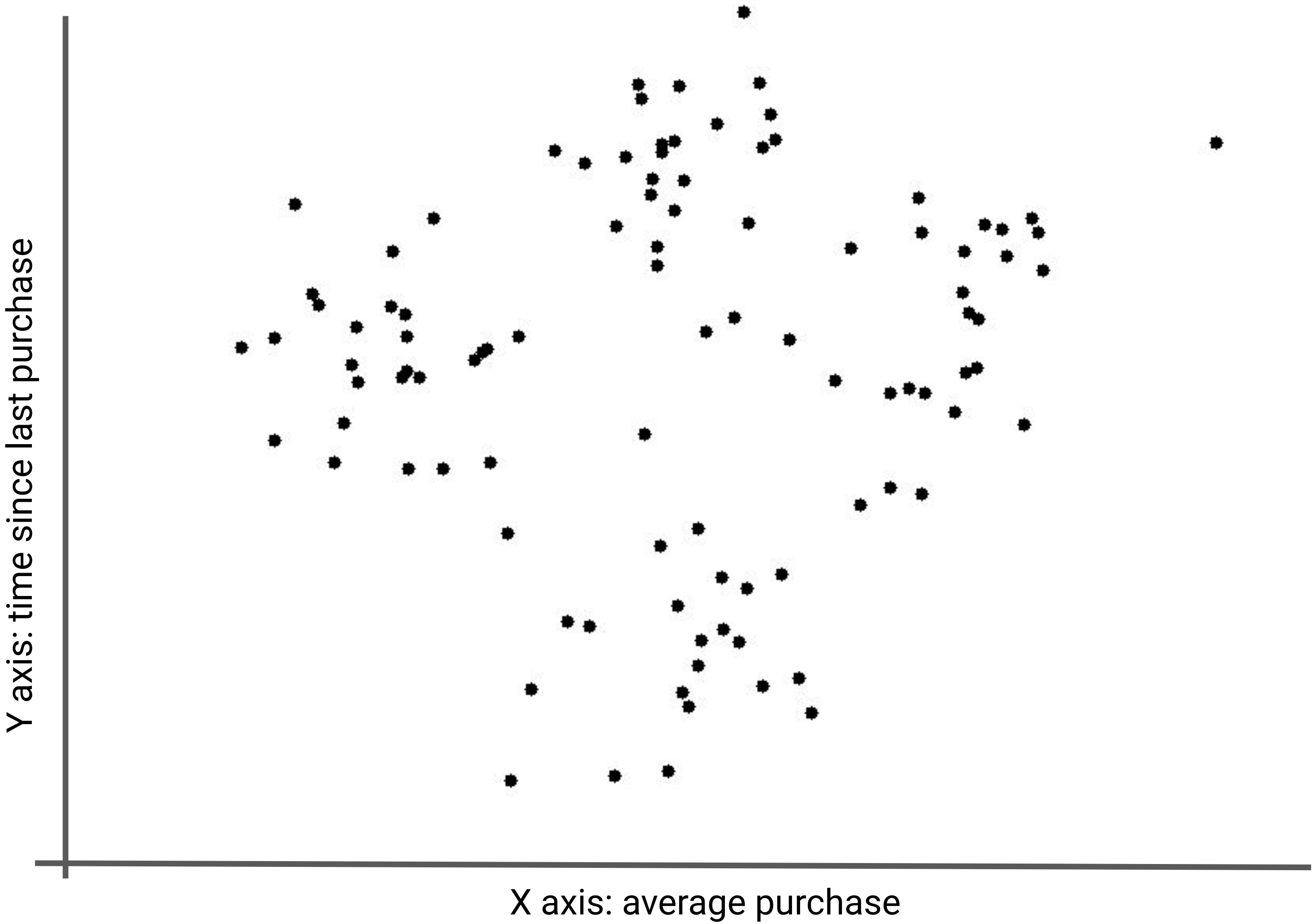
For each customer you have a record of average purchase cost and time since last purchase.

You **know** that if you want to retain your customers you cannot treat them the same. You can use targeted marketing ads towards groups that demonstrate different behavior, but how will you divide the customers into groups?

Scenario:

Without the aid of an algorithm, how would you separate them into groups?

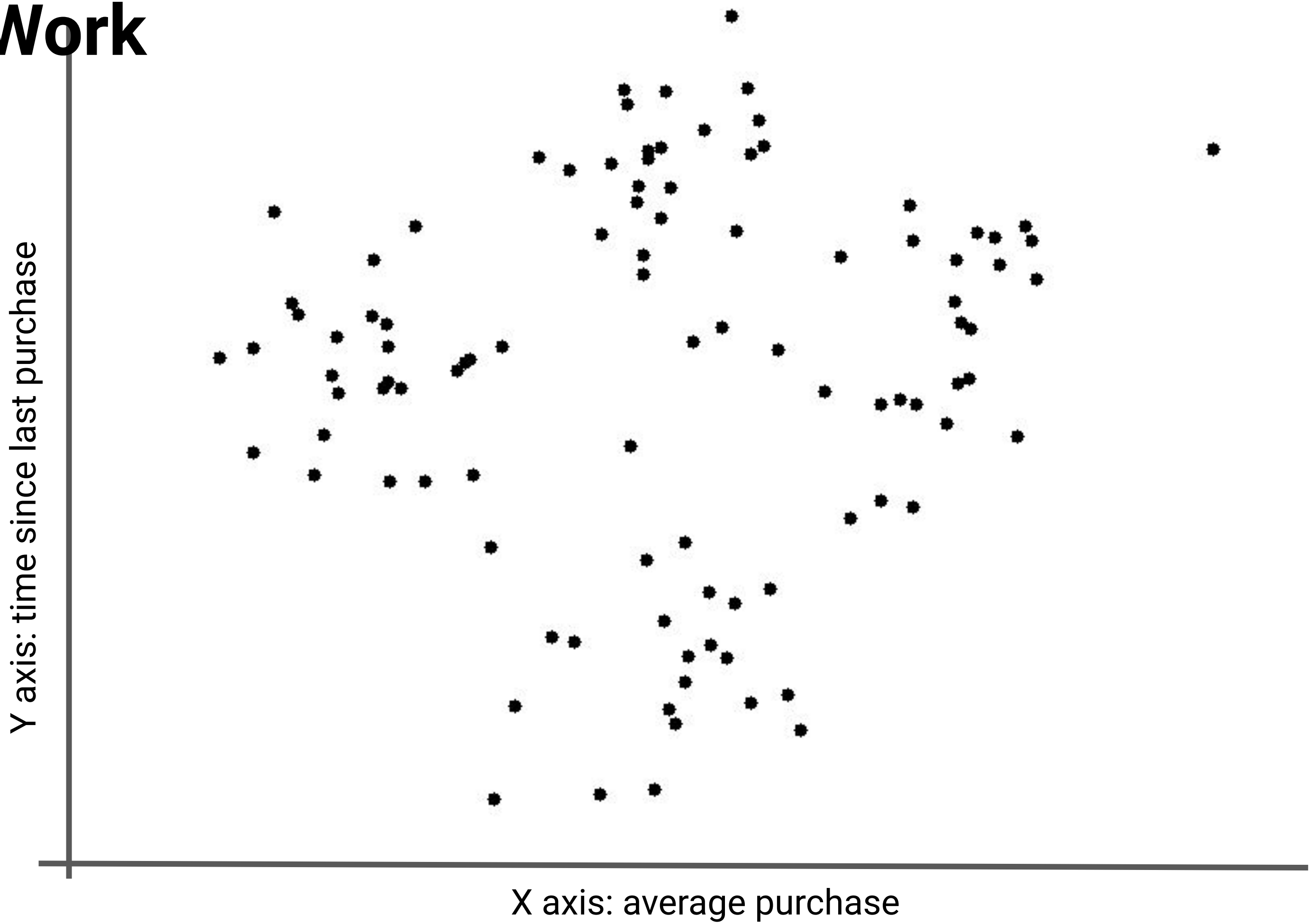
How many groups?



How k-means work

1. The process begins with k centroids initialized at random.
2. These centroids are used to assign points to its nearest cluster.
3. The mean of all points within the cluster is then used to update the position of the centroids.
4. The above steps are repeated until the values of the centroids stabilize.

K-Means at Work



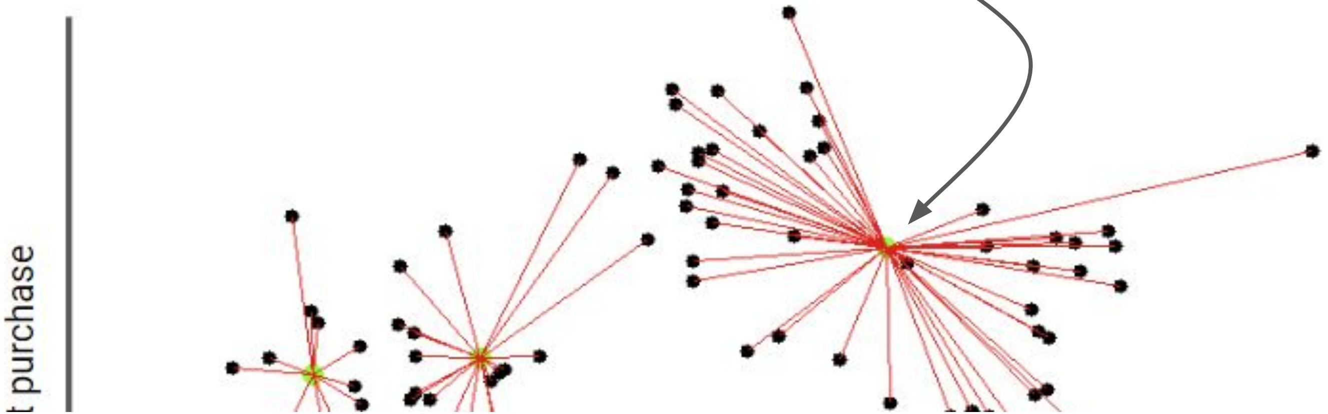
Process:

1. Pick and specify k (n_clusters)
2. Algorithm return an array of “cluster centers” or “centroids”

```
In [20]: model = KMeans(n_clusters=4).fit(test)

In [21]: model.cluster_centers_

Out[21]: array([[ 69.92418447, -10.11964119],
                [ 31.78831061,  59.67227949],
                [  9.43391214,  10.63898036],
                [ 48.13340973,  59.66325939]])
```



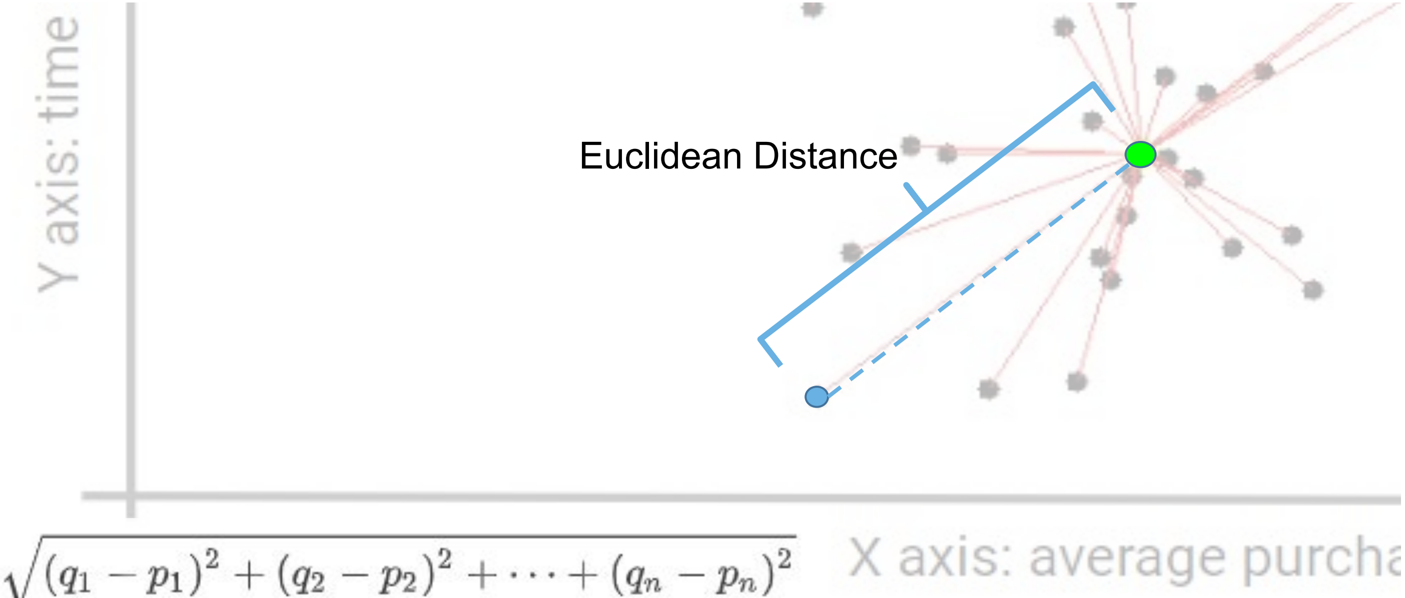
Alert! New vocabulary!

‘K’ is the number of **clusters**, or groups, in the dataset you specify the algorithm define.

The **centroids**, or cluster centers, are the points at the **center** of each **cluster**. The coordinates of the centroid are the **mean value** of each variable within the defined group.

K-means is called such because it returns the **mean** values of **k**-specified **clusters**.

K-means uses Euclidean Distance

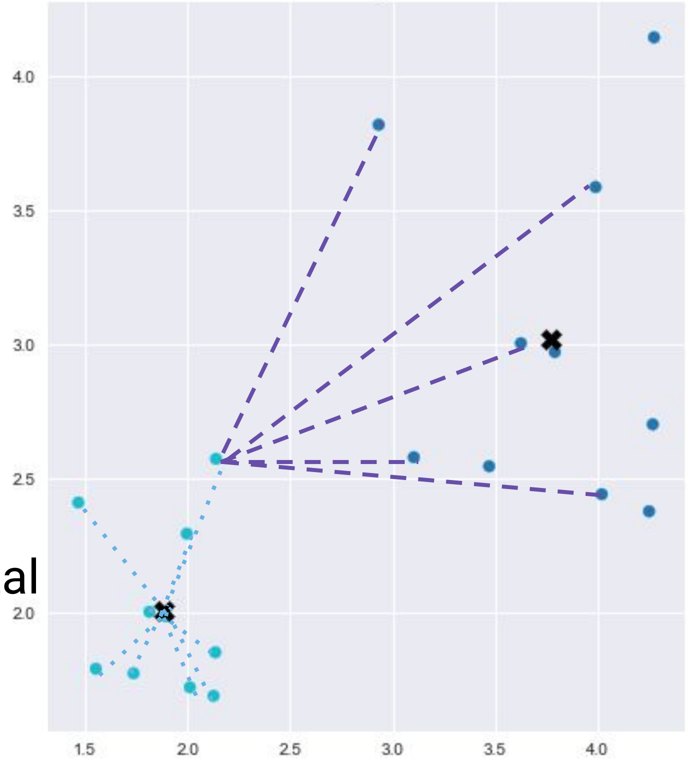


$$d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2 + (q_2-p_2)^2 + \cdots + (q_n-p_n)^2}$$

$$= \sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}.$$

K-means is an optimization algorithm

That recalculates centroids and reassigns group labels in order to:



MAXIMIZE sum total of inter-cluster distance

MINIMIZE sum total of intra-cluster distance

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Silhouette coefficient and elbow method

Silhouette coefficient ranges between 1 and -1. The closer to 1 the more clearly defined are the clusters. The closer to -1, the more incorrect assignment.

It calculates a score for all data points and then averages across all points.

Elbow method uses the sum of squared error (`inertia_` in k-means python) for all points

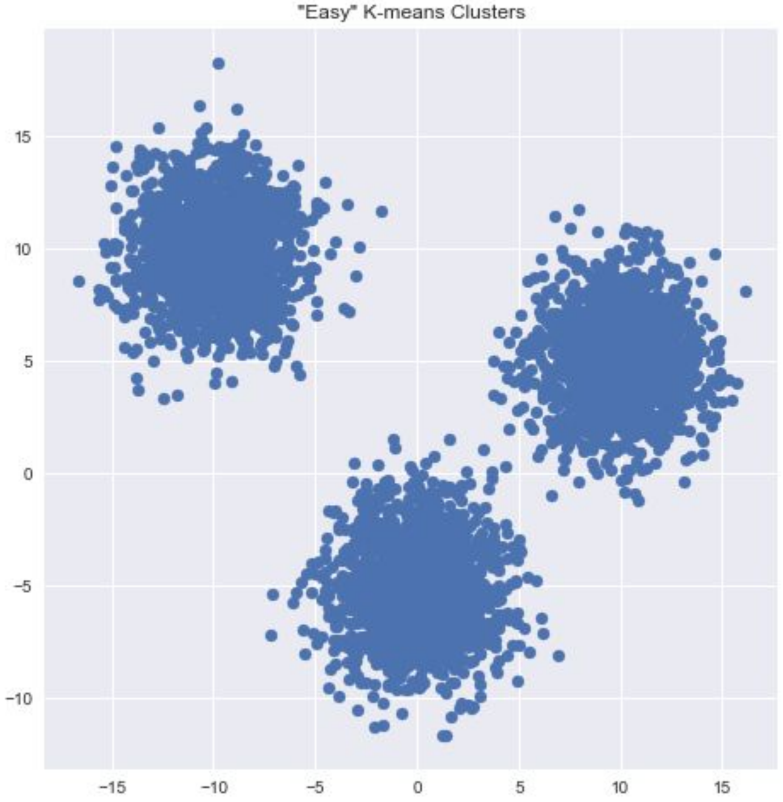
$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

A refers to the average distance between a point and all other points in that cluster.

B refers to the average distance between that same point and all other points in clusters to which it does not belong

Find best k

Ideal K-means scenario



Assumptions of K-means

- Independent variables
- Balanced cluster sizes
- Clusters have similar density
- Spherical clusters/equal variance of variables

When K-means struggles