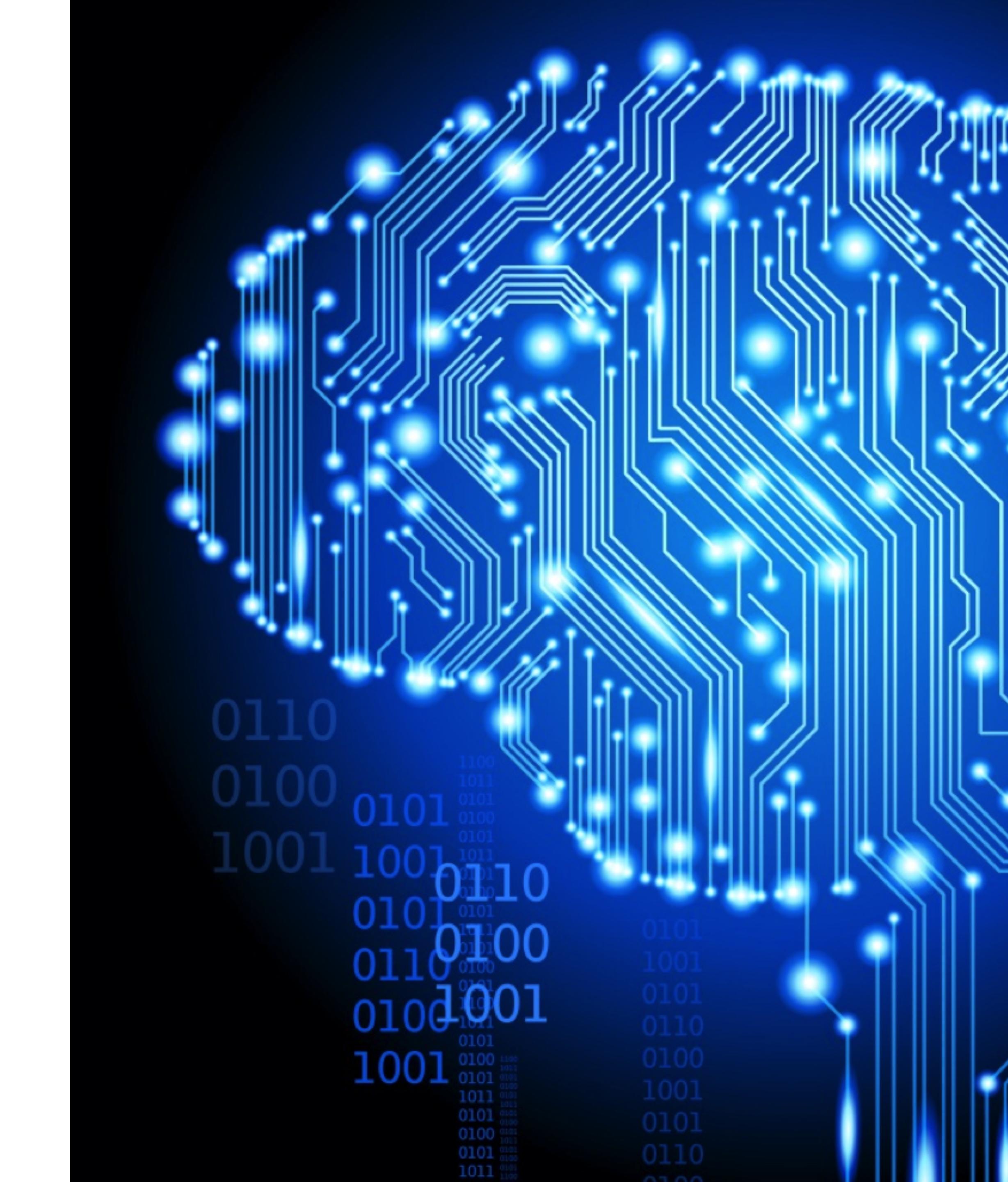


Introduction to Machine Learning

A horizontal row of 20 black dots arranged in two rows of 10. The dots are evenly spaced and aligned horizontally.

Instructor: Warasinee Chaisangmongkon, PhD



Day 3-4

- Day 3 Morning : Nearest-Neighbor Methods, Feature Selection
- Day 3 Afternoon : Recommender System, Unsupervised Learning
- Day 4 Morning : Neural Network
- Day 4 Afternoon : Advanced Concepts in Machine Learning

- ▶ Recommender in Business
- ▶ User-based CF
- ▶ Item-based CF
- ▶ Performance

RECOMMENDER SYSTEM

RECOMMENDATIONS



The image shows a screenshot of the Facebook news feed. At the top, there are input fields for 'Update Status' and 'Add Photos/Videos'. Below is a text input field with placeholder 'What's on your mind?'. The feed displays several posts:

- A post from 'The Kernel' sharing a link to 'Why I hate-read' by Ezra Koltai.
- A post from 'The Kernel' sharing a link to 'Adventure Time'.
- A post from 'Milo Yiannopoulos' sharing a link to 'New York City's Hidden Subway Station'.
- A post from 'Lena Baker via Hector Marcell' sharing a link to 'Hasty - Healthy Food, on demand'.
- A post from 'David Langer' sharing a link to 'Hasty - Healthy Food, on demand'.

At the bottom, there is a large blue 'facebook' logo.

The image shows a screenshot of the LinkedIn 'People You May Know' feature. It includes a blue 'in' logo and a section titled 'PEOPLE YOU MAY KNOW'.

- Jay Kreps**: Principal Staff Engineer at LinkedIn. Connect button.
- Igor Perisic**: VP Engineering at LinkedIn. Connect button.
- Sam Shah**: Principal Engineer at LinkedIn. Connect button.

Below this, there is a 'See more' link and a section for 'Toys & Games' recommendations:

- Vtech Toy Cook ...
- Vtech Robot ...
- Vtech Sing and ...
- Vtech Read & Play ...
- Learning Resources ...
- Vtech Count and Learn ...

At the bottom, there is a section for 'Books' recommendations:

- The Four Boxes in the ...
- Made to Stick ...
- more faster ...
- START WITH WHY ...
- Lean Startup ...
- The Lean ...

The image shows a screenshot of the Amazon.com website displaying product recommendations. The top part shows a grid of toy and game products:

- Vtech Toy Cook ...
- Vtech Robot ...
- Vtech Sing and ...
- Vtech Read & Play ...
- Learning Resources ...
- Vtech Count and Learn ...

The bottom part shows a grid of book recommendations:

- The Four Boxes in the ...
- Made to Stick ...
- more faster ...
- START WITH WHY ...
- Lean Startup ...
- The Lean ...

The image shows a social media interface with follow suggestions and a Netflix logo.

Who to follow (Refresh - View all):

- Joyent** (@joyent) Followed by Park Hoon and ...
Follow Promoted
- APIdays Global** (@APIdaysG...) Follow

Find friends

NETFLIX

RECOMMENDATIONS



CUSTOMER A



12 times



SHOP A

0 times



SHOP B

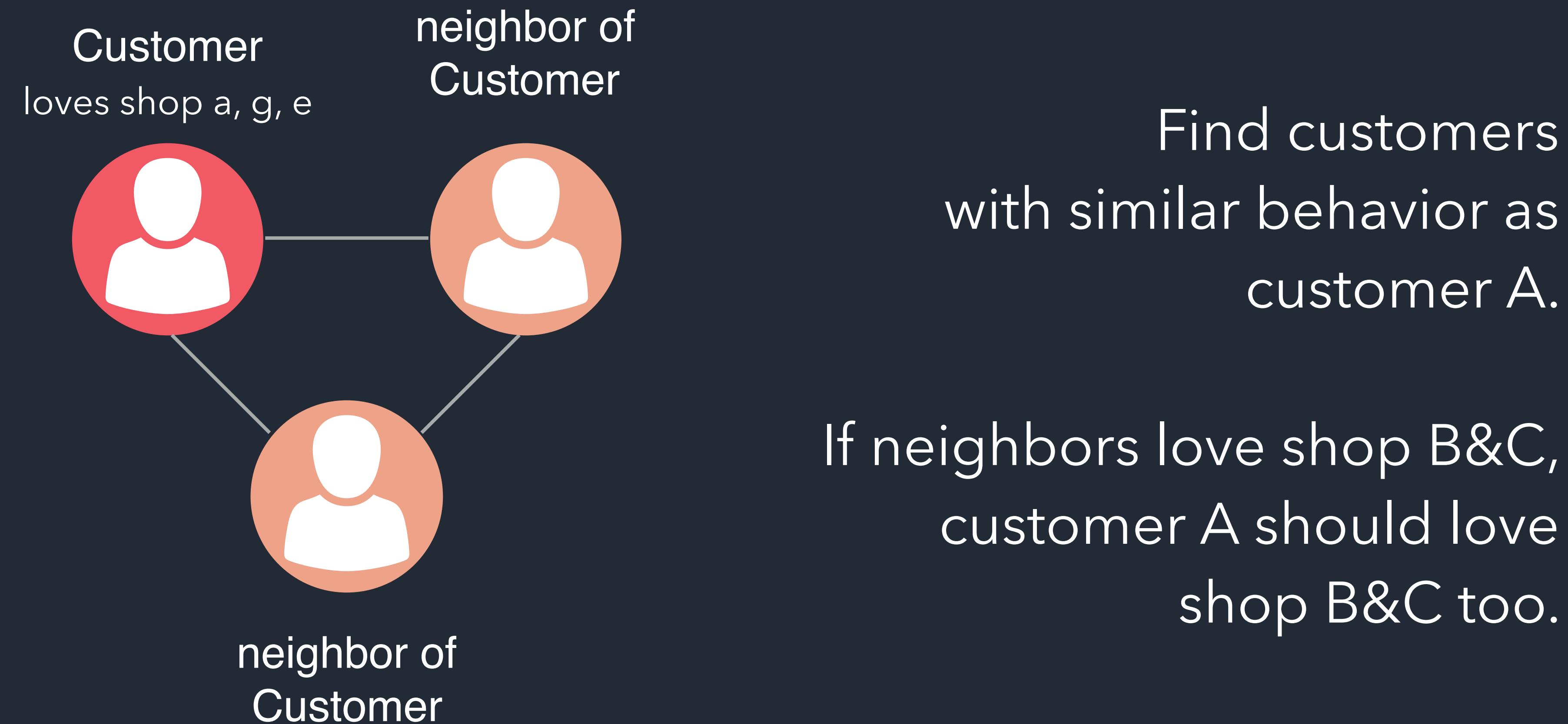
0 times



SHOP C

Will customer A
like shop B and C?

RECOMMENDATIONS



Problem Definition

	u1	u2	u3	u4
m1	5	5	0	0
m2	4	?	?	0
m3	?	4	0	?
m4	0	0	5	4
m5	0	0	5	?

- Given the past ratings predict the ratings of movies that users have not watched.
- Once you predict their preference, recommend the movie you think they like.

Content-Based Recommendation

- Suppose we can define 'features' of each movie based on its genre:
 - x_1 : the amount of romantic content in the movie
 - x_2 : the amount of action in the movie

Content-Based Recommendation

	u1	u2	u3	u4		x1	x2
m1	5	5	0	0	m1	0.9	0
m2	4	?	?	0	m2	0.99	0.01
m3	?	4	0	?	m3	0.8	0.05
m4	0	0	5	4	m4	0.05	0.9
m5	0	0	5	?	m5	0.1	0.9

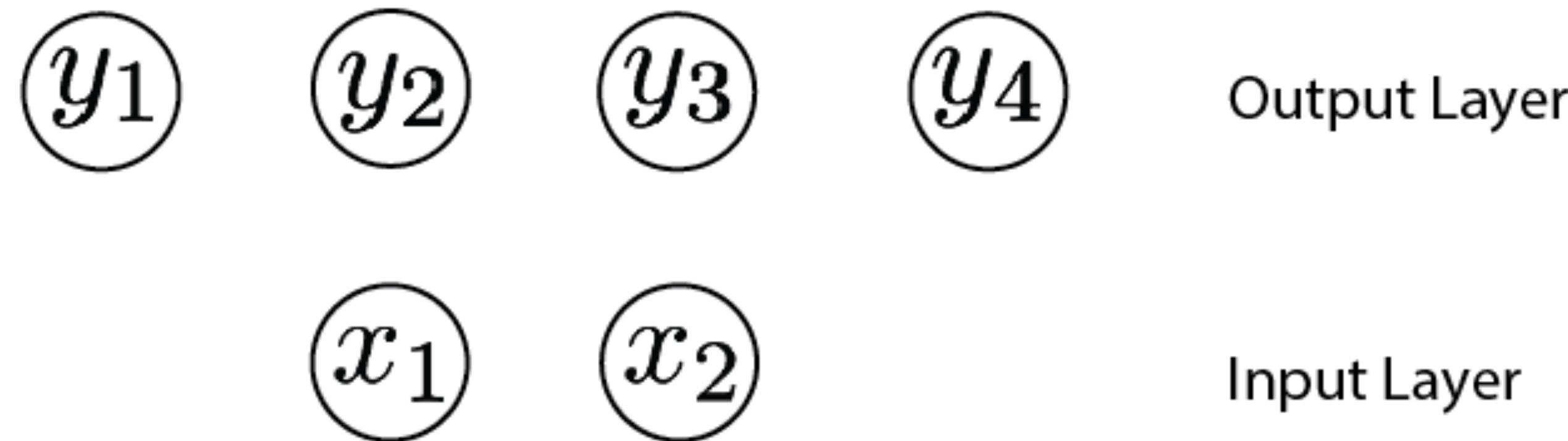
Content-Based Recommendation

- This problem would be like linear regression problem with multiple inputs:

	u_1	u_2	u_3	u_4		x_1	x_2
m_1	5	5	0	0		m_1	0.9
m_2	4	?	?	0		m_2	0.99
m_3	?	4	0	?		m_3	0.8
m_4	0	0	5	4		m_4	0.05
m_5	0	0	5	?		m_5	0.1

Content-Based Recommendation

- Or you might view it as a neural network model

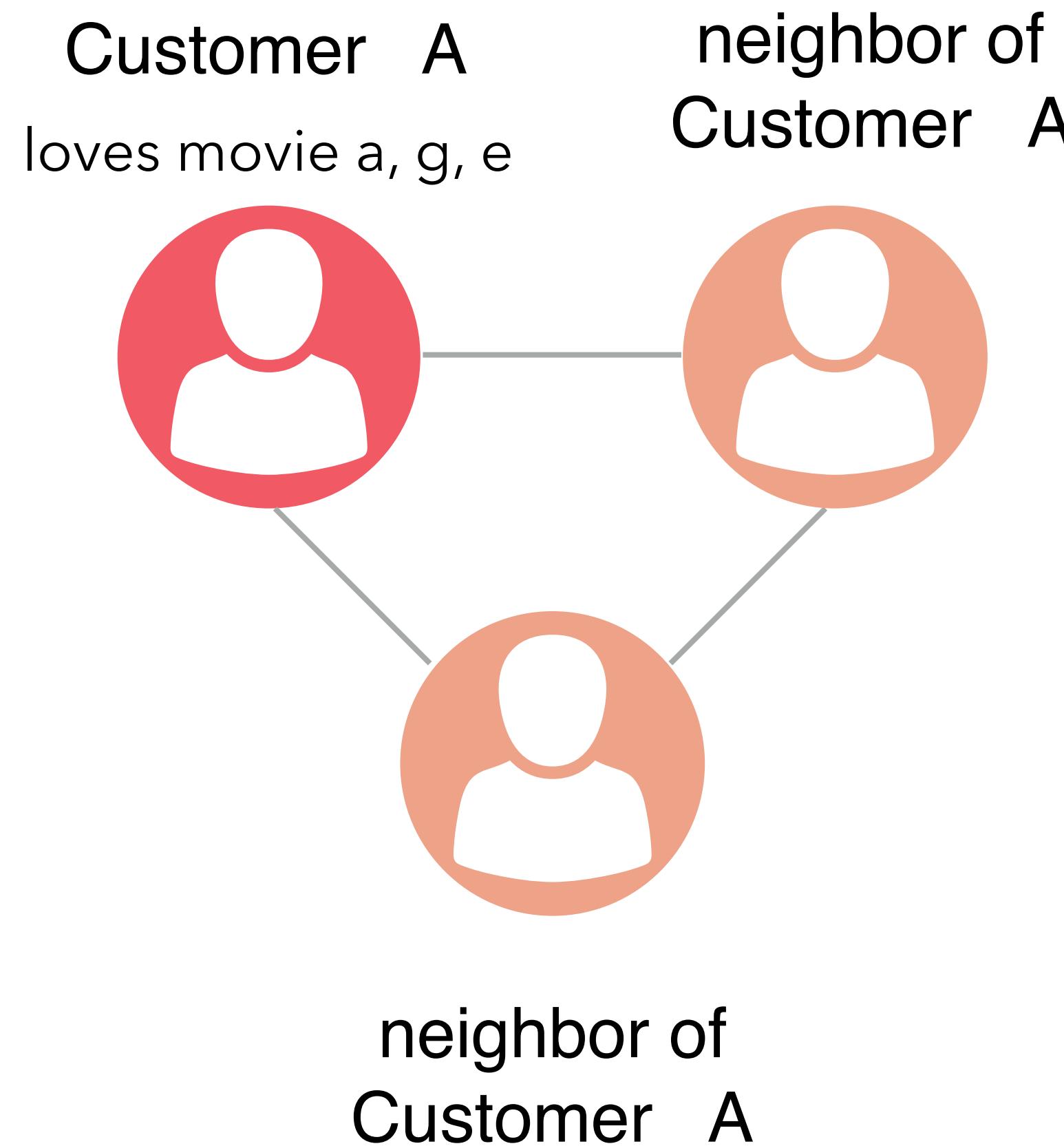


- How many weight parameters are there in this neural network?

Collaborative Filtering

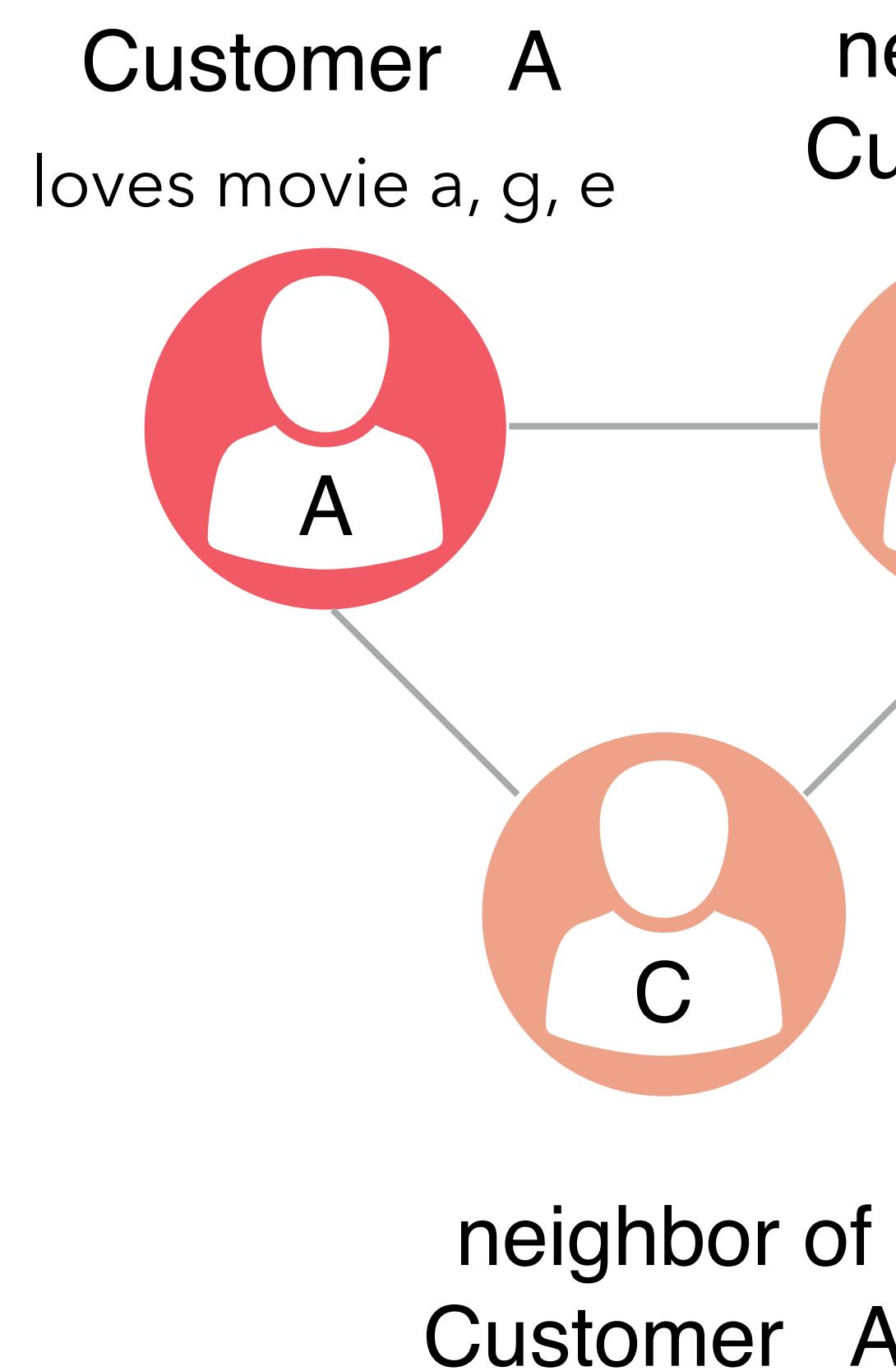
- **Collaborative Filtering:** filtering a bunch of items down to only a few items based on collaborative knowledge (knowledge about other people in the population)
- There are several ways to achieve collaborative filtering objectives. Some of the most popular ways are:
 - User-based Collaborative Filtering
 - Item-based Collaborative Filtering
 - Matrix Factorization

User-Based Collaborative Filtering



- Search for nearest neighbors of A, we could use n=1, 5, 50. (n depends on the number of total populations).
- Use the nearest neighbor formula to predict customer A's preference from neighbors' preference.

User-Based Collaborative Filtering



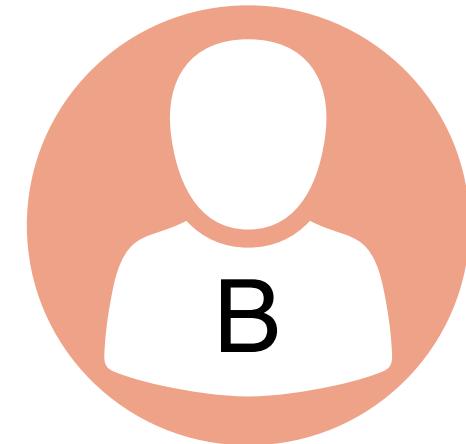
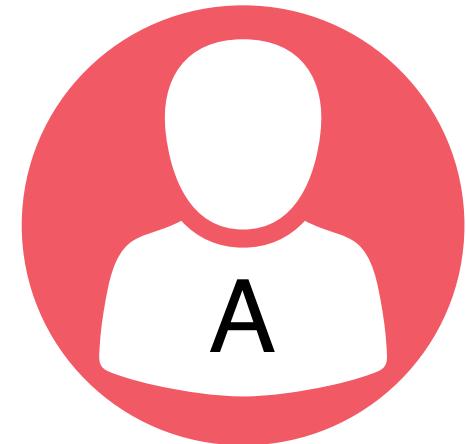
How much user A would rate movie “The Matrix”?

$$r(A, \text{Matrix}) = \frac{w(A, B) * r(B, \text{Matrix}) + w(A, C) * r(C, \text{Matrix})}{w(A, B) + w(A, C)}$$

$w(A, B)$ = how similar A and B are in their taste

This is basically equivalent to K-Nearest Neighbor Regression model

Similarity Between A and B



- Similarity can be thought of as the inverse of distance.

$$w(A, B) = \frac{1}{d(A, B)}$$

- Demographic similarity
- Past preference similarity
- Browsing history similarity
- Facebook likes similarity

- So any distance metrics we have learned about can be used here.
- Or you can look for other similarity metrics.

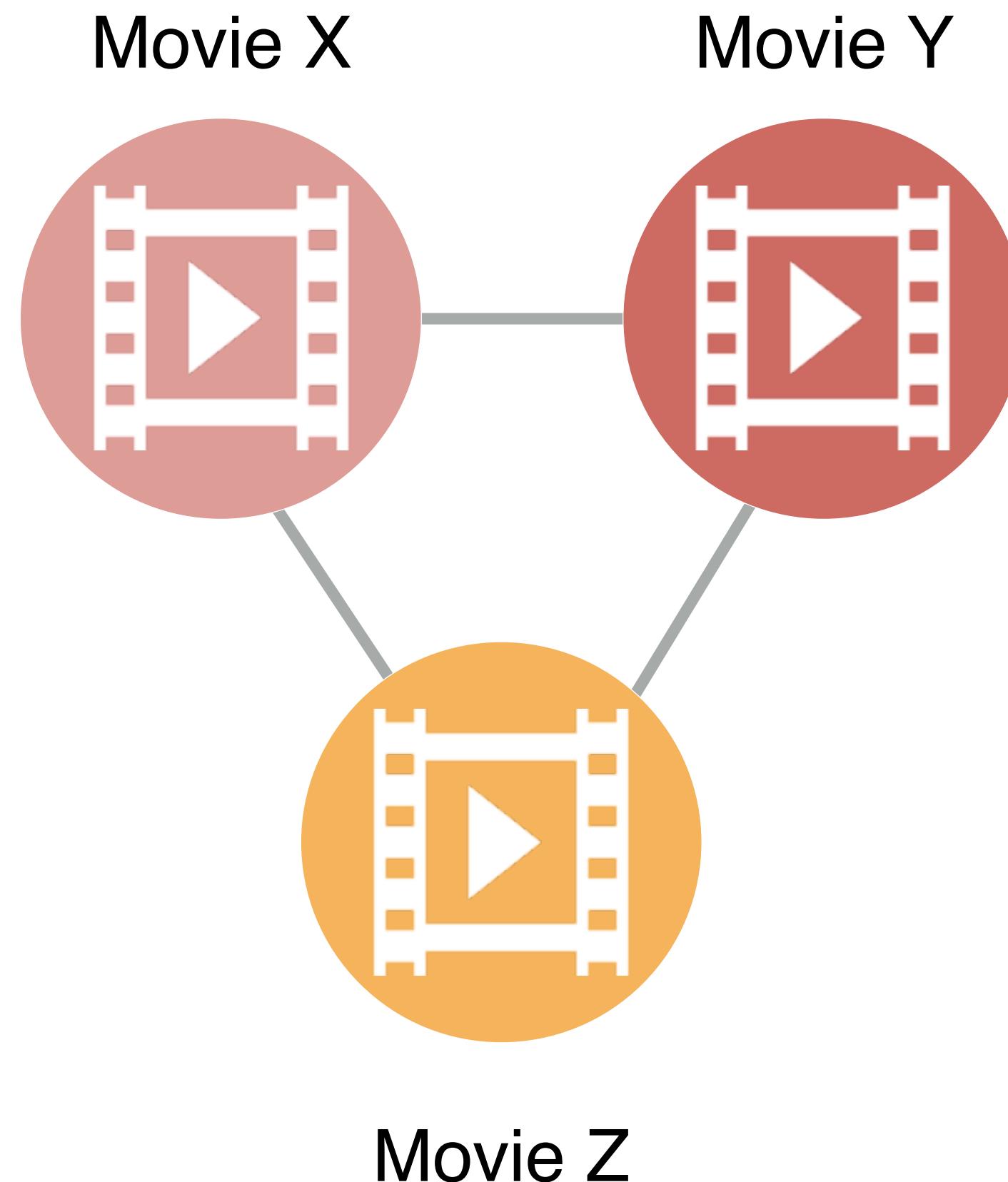
<http://scikit-learn.org/stable/modules/metrics.html#metrics>

User-Based CF Quiz

	u1	u2	u3	u4
m1	5	5	0	0
m2	4	?	?	0
m3	?	4	0	?
m4	0	0	5	4
m5	0	0	5	?

- Which user is most similar to user 1?
- Do you think user 2 would like movie 2?
- Which user is most similar to user 3?
- Do you think user 4 would like movie 3?

Item-Based Collaborative Filtering

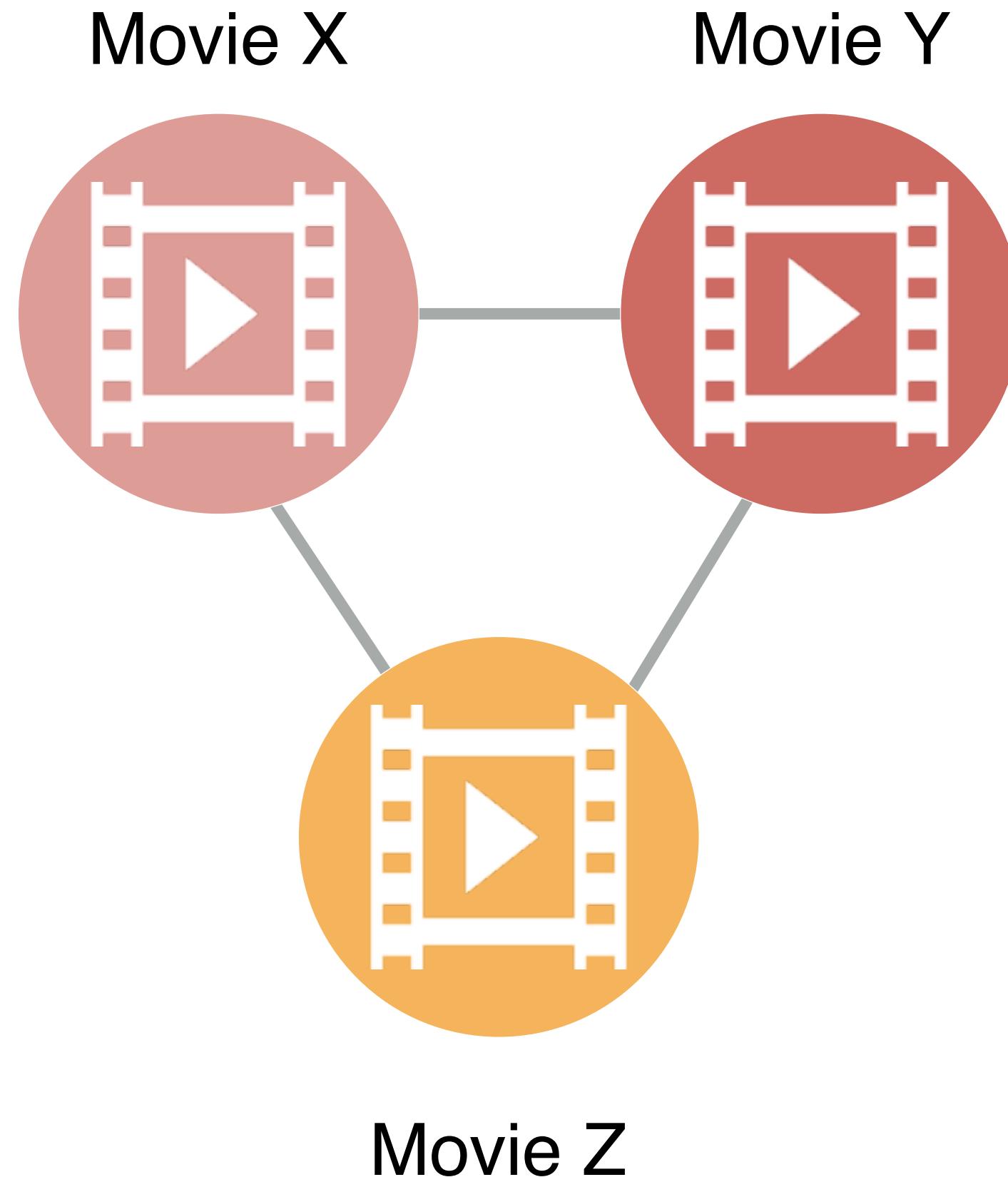


How much user A would rate movie X?

- If user A loves the movie "Beauty and The Beast", will user A like "Frozen"?
- If user A loves the movie "Fight Club", will user A like "Frozen"?

$$r(A, X) = \frac{w(X, Y) * r(A, Y) + w(X, Z) * r(A, Z)}{w(X, Y) + w(X, Z)}$$

Item-Based Collaborative Filtering



- Content / genre similarity
- Fan base similarity
- Common favorite lists
- Products:
 - Buyers
 - Browsers
 - Product spec (brand, qualification)

Item-Based vs. User-Based

- Users change all the time.
- Similarity matrix computation is super expensive
(1M customer would result in $1M*1M$ computation)
- Expensive computation happening too often -> not good!
- Items rarely change, so item-based is much less expensive than user-based.
- Precompute to be used over time.

Collaborative Filtering Performance

- Recommender system solves a regression problem, so we use regression to measure performance.

$$E(W) = \frac{1}{2m} \sum_{c=1}^k \sum_{i=1}^m [y_c^i - h(x^i)_c]^2$$

- In business setting you can also measure 'click-through rate' or rank items from most favorite to least favorite and measure how often people click the top-ranked items versus low-ranked items.

Variations of Collaborative Filtering

- **Normalization:** each person has different 'toughness' in the rating so typically you won't use the raw rating but use normalized rating instead.
- **Hybrid collaborative filtering:** if you cannot decide on which aspect of similarity you should focus on (demographic or preference?), combine them.
- **Alternative Least Square Model (ALS):** solve multi-output regression problem in a smarter way, using matrix factorization technique instead of KNN. Much faster to train with similar performance.

Software Library for Recommender

- There's no simple Python library for recommender. Although *Surprise* is under active development.

<http://surpriselib.com/>

- Corporations use library like Apache Spark ML to build big-data recommender system (beyond scope of this course).

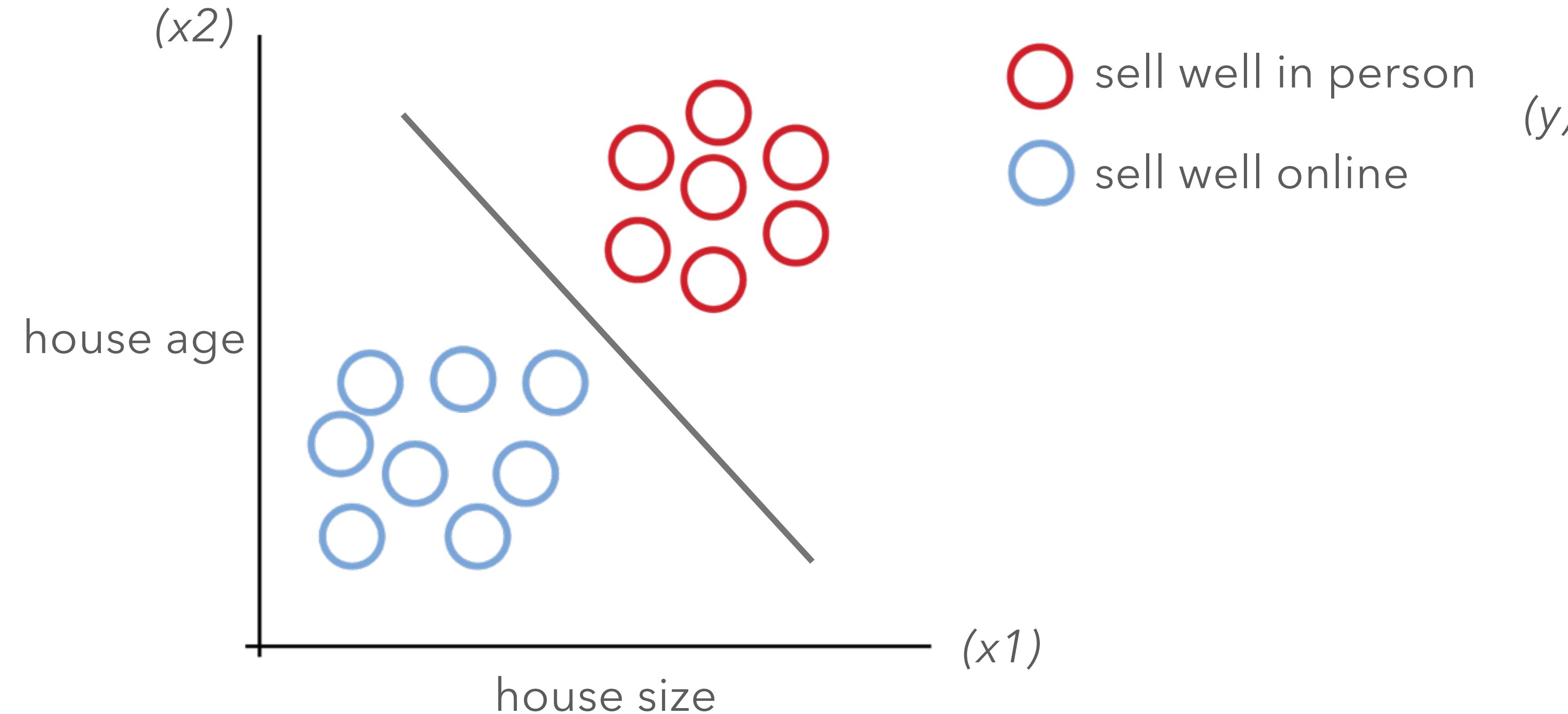
<https://spark.apache.org/docs/latest/mllib-collaborative-filtering.html>

- ▶ Unsupervised Learning
- ▶ K-Means Algorithm
- ▶ Clustering Performance

K-MEANS CLUSTERING

Supervised vs. Unsupervised Learning

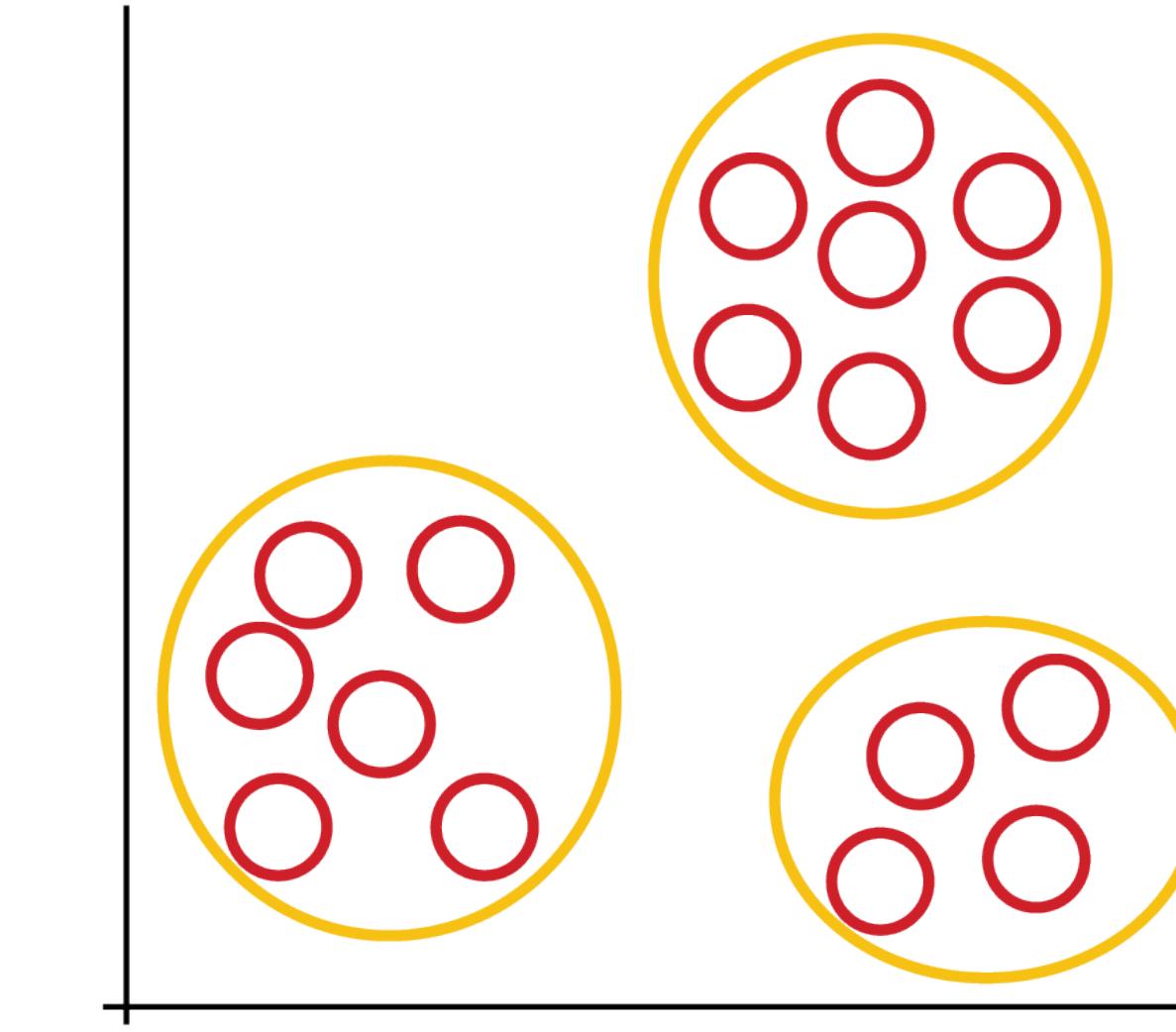
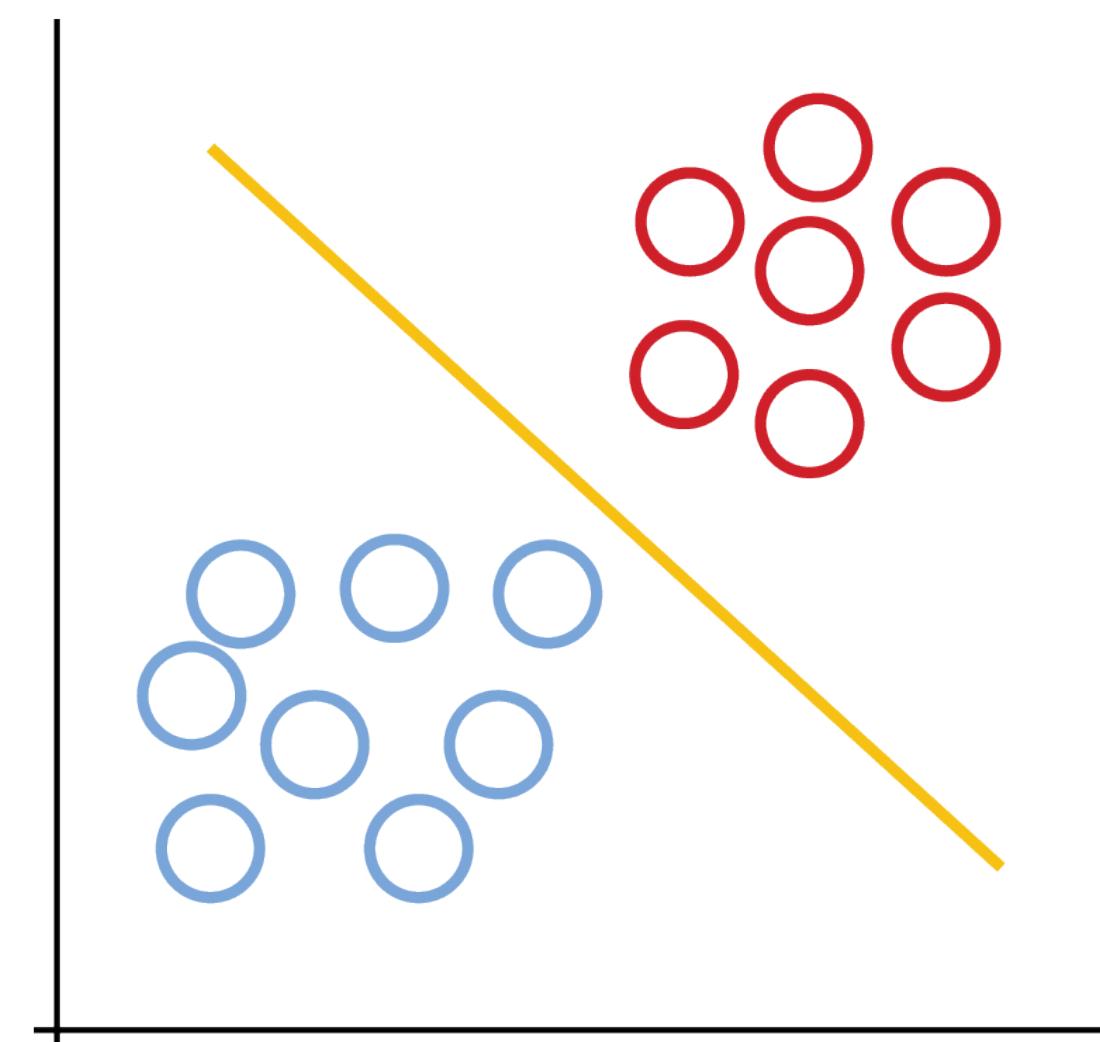
- **Classification:** predicting **discrete** output from input
 - Example: predicting whether a house would sell well in person or online



Unsupervised Learning

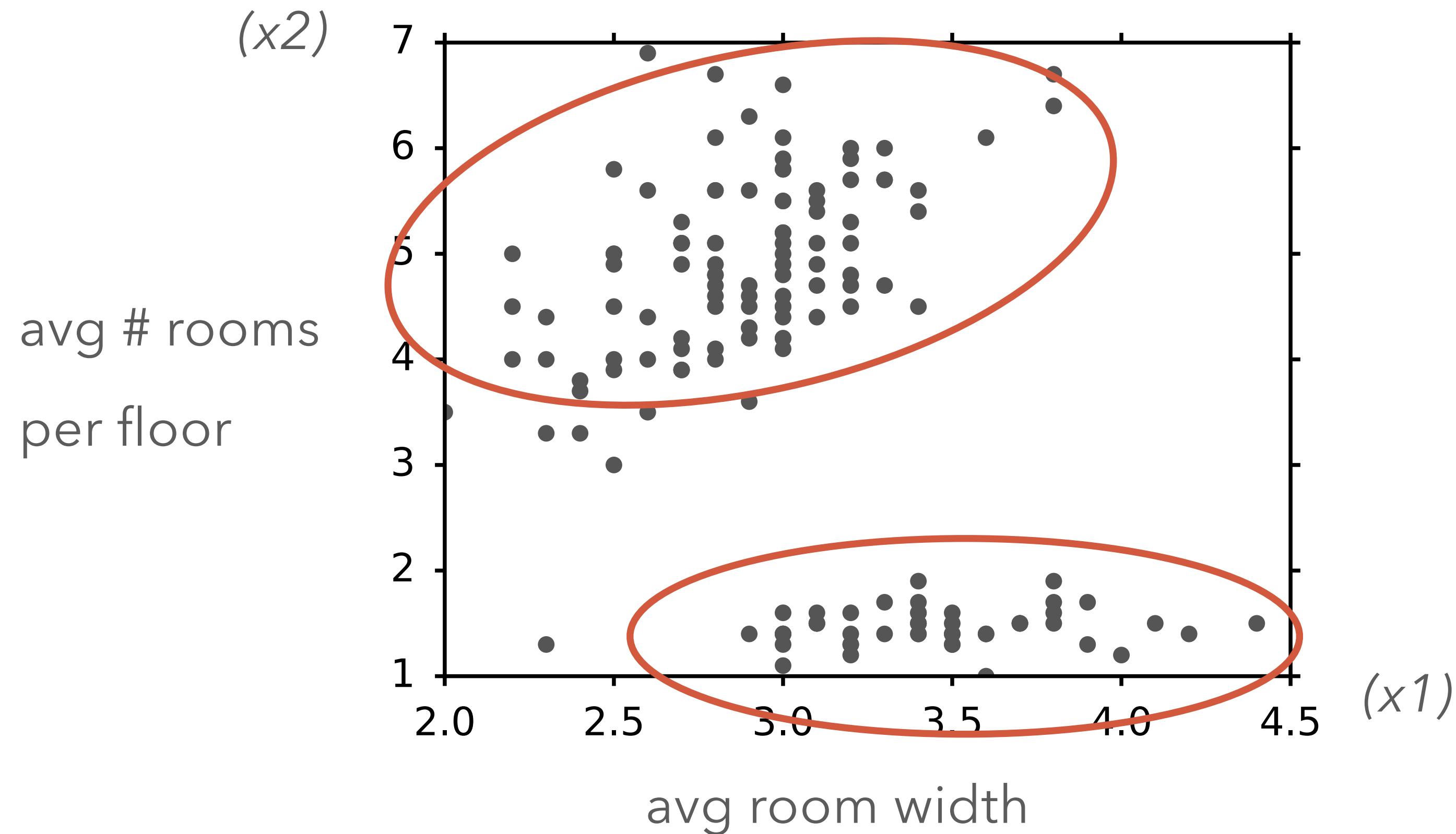
In **supervised learning**, your data come with labels indicating what class corresponds to each sample.

Sometimes, data do not come with categorical labels, but you can tell that there is a grouping structure.



Unsupervised Learning

- **Clustering:** grouping unlabeled input by similarities
 - Example: grouping houses in the database



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If the White House and Democrats would take off their blinders, this is exactly what half of Americans fear about the colossal **health care "reform"** that has ...

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[Defaults](#) [JSON](#)
[Filters](#)

LABEL SCORERS

LABEL CLUSTERING

Organizing labels into non-overlapping clusters.

Similarity weighting

RR

Softening

0.6

Input preference

0

Preference initializer

None

Preference initializer scaling

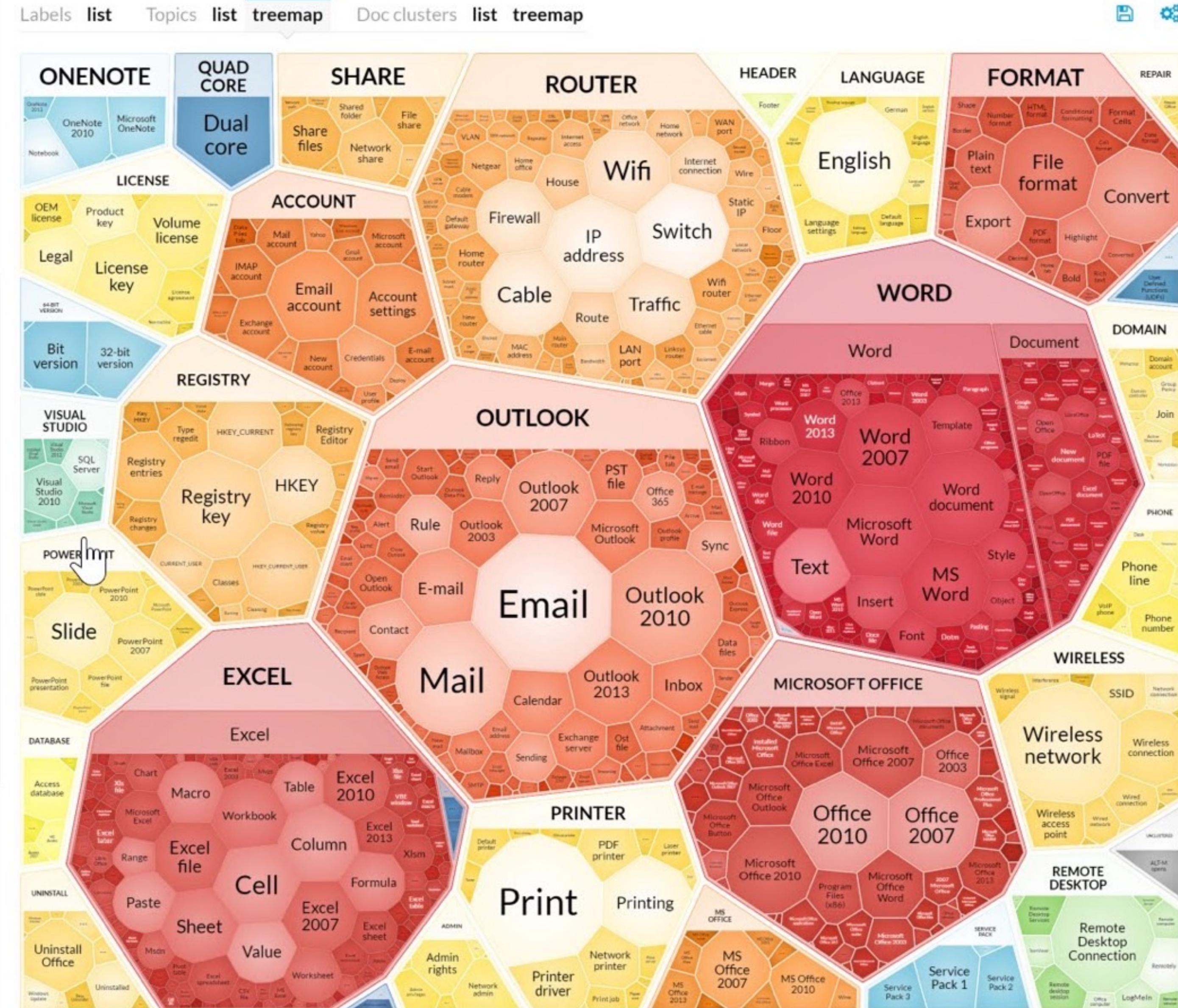
1

Max iterations

2000

Min steady iterations

100



Top 10 of 9107 docs in scope

Connecting 2 External Monitors to a Laptop?

Equaling 3 Displays Total (or 2, if the laptop display cannot be used). I work at home on two large monitors, but at the office on a laptop with a single large monitor. Is it possible to attach two (or more?) external monitors to a laptop without having them clone each-others display?

Matrox DualHead2Go (for two monitors) or Matrox TripleHead2Go (for three monitors) could be a solution. Jeff Atwood also has a blog post about this.

type: question tag: laptop, display
answered: true score: 59

- Two monitors (3)
- Docking station (2)
- Switch (1)
- High speed (1)

Why aren't all applications 'portable'?

I've recently been trying to 'install' stuff a lot less on my Windows machine (I hate installers - I need to know where programs put stuff...), choosing to use portable or standalone versions of applications instead. I put them all in a 'Programs' dir on a drive separate from my Windows partition, so whenever I reinstall, I have all my applications available with minimal effort and on the plus side, I get a nice clean setup. Applications like Office and Creative Suite still require me to go through a h...

Installers are a result of years of evolution and a little bit of (simplified) history helps understand why they do what they do.. The windows 3.1 model suggested config.ini style

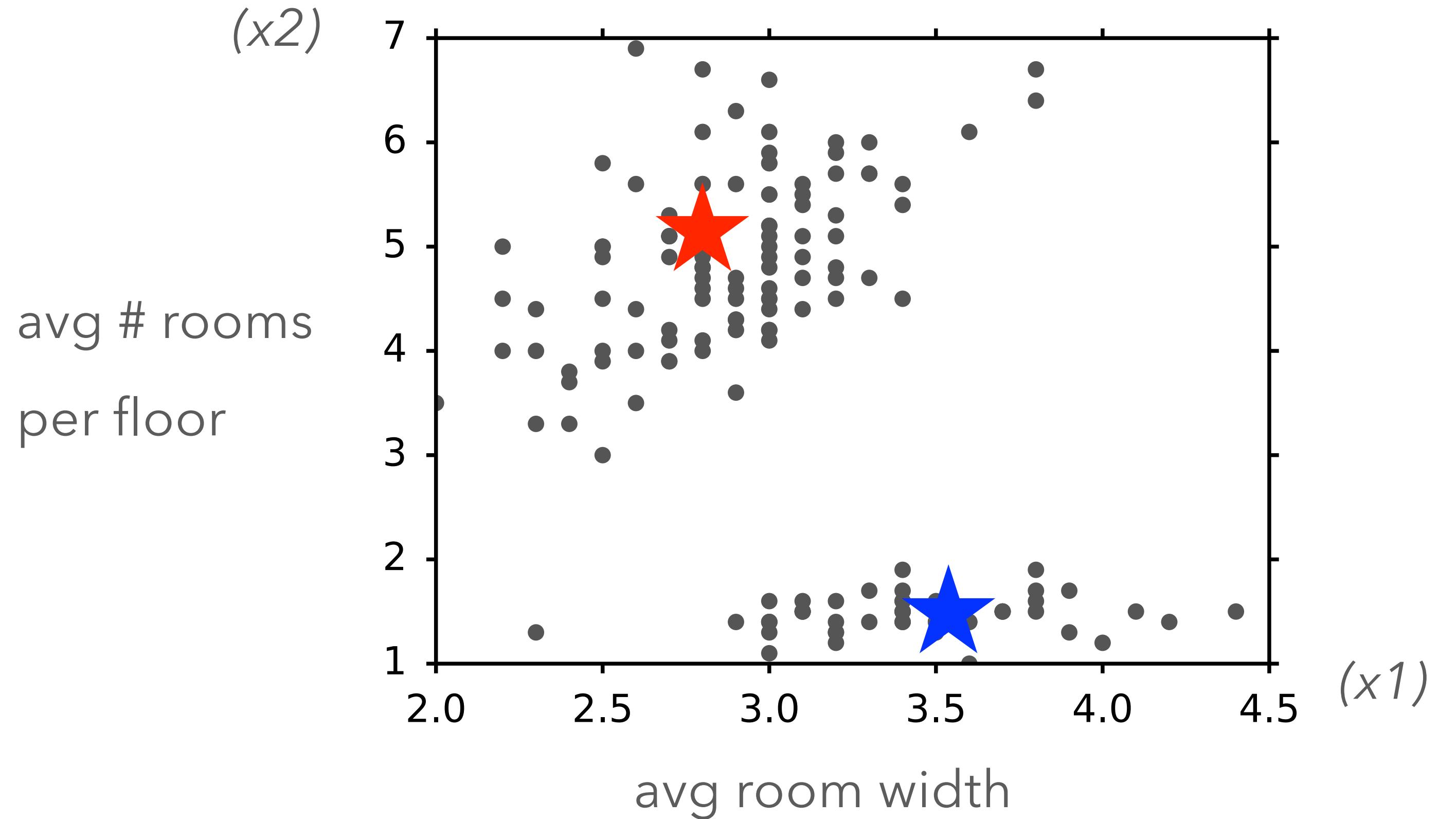
Supervised vs. Unsupervised Learning

- Supervised learning problem: “given all history of feature data points (X) and their labels (Y), find a model that computes label (y') for a given sample data point (x'). The prediction must minimize a cost function (minimize errors).”
- Clustering problem: “given all feature data points (X), find their labels (Y). The label Y must minimize a given objective function.”

	X	Y	x'	y'	Predict	Cost Function
Supervised	Yes	Yes	Yes	No	y'	Error
Unsupervised	Yes	No	Yes	No	Y, y'	Objective F.

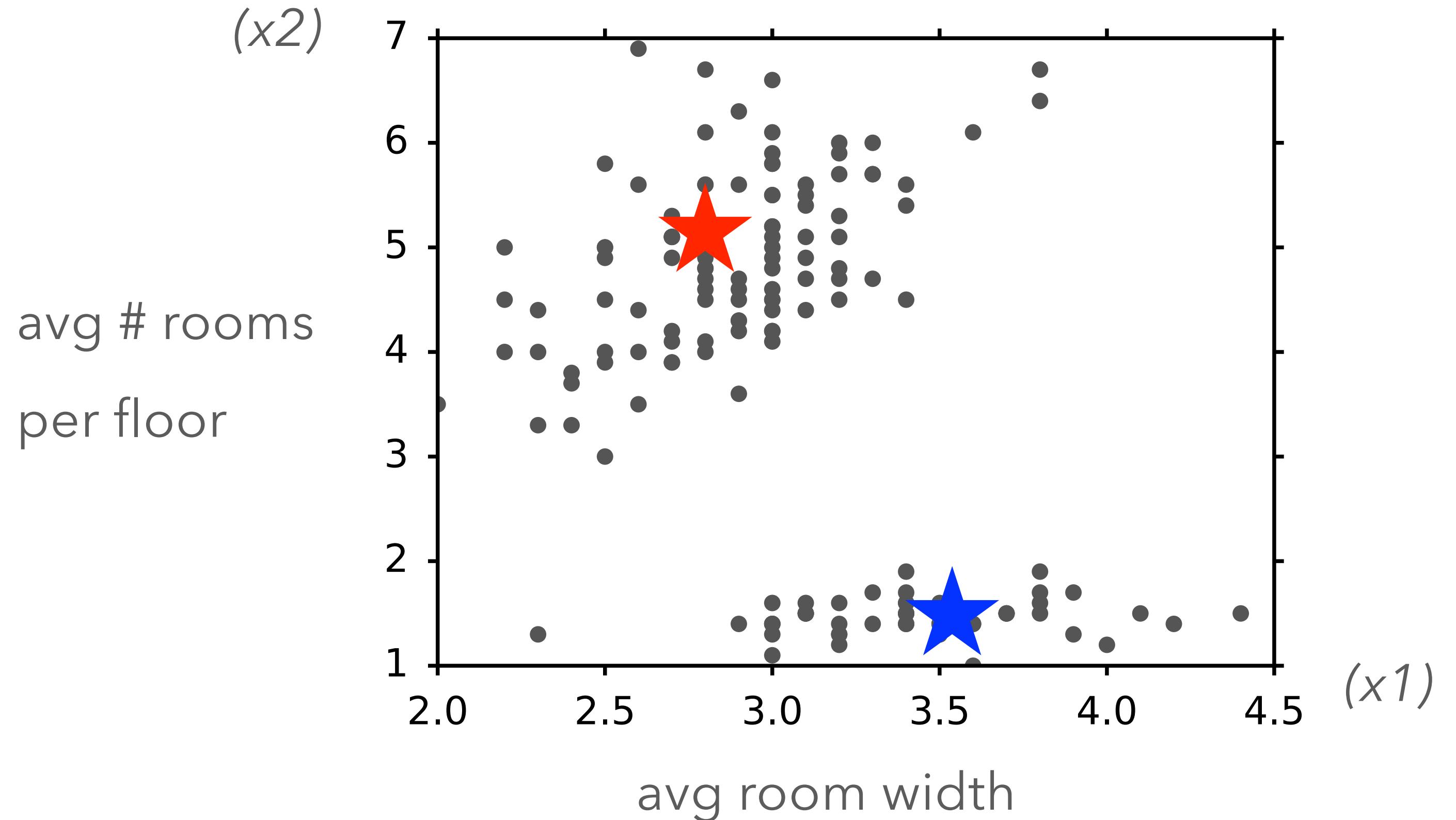
K-Means Clustering

- K-means clustering is the most popular clustering algorithm.
- K-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster.



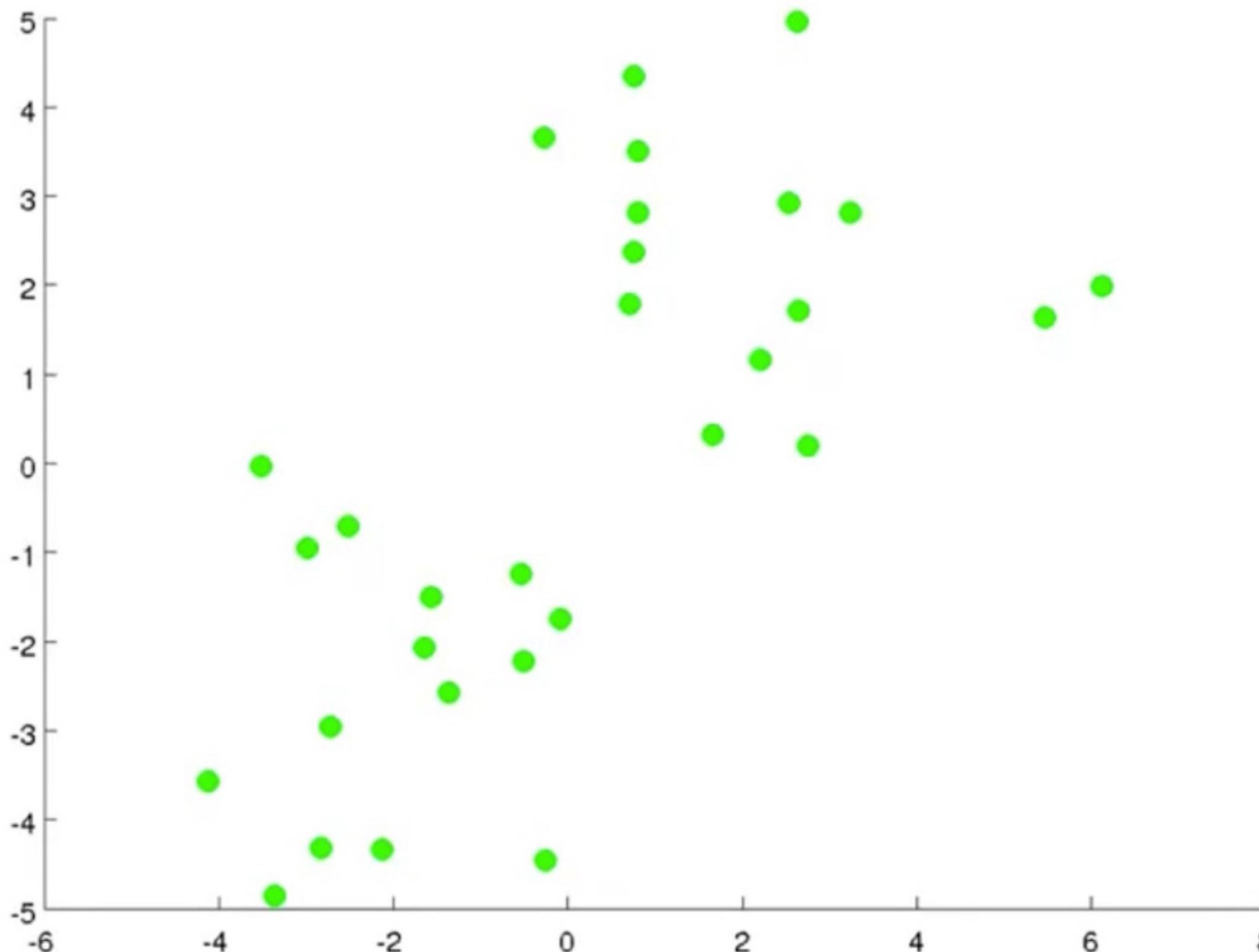
K-Means Clustering

- The red and blue stars are called “centroids”.
- The red star is the centroid of top cluster.
- The blue star is the centroid of the bottom cluster.
- The location of the centroid is at the mean of all points in the cluster.



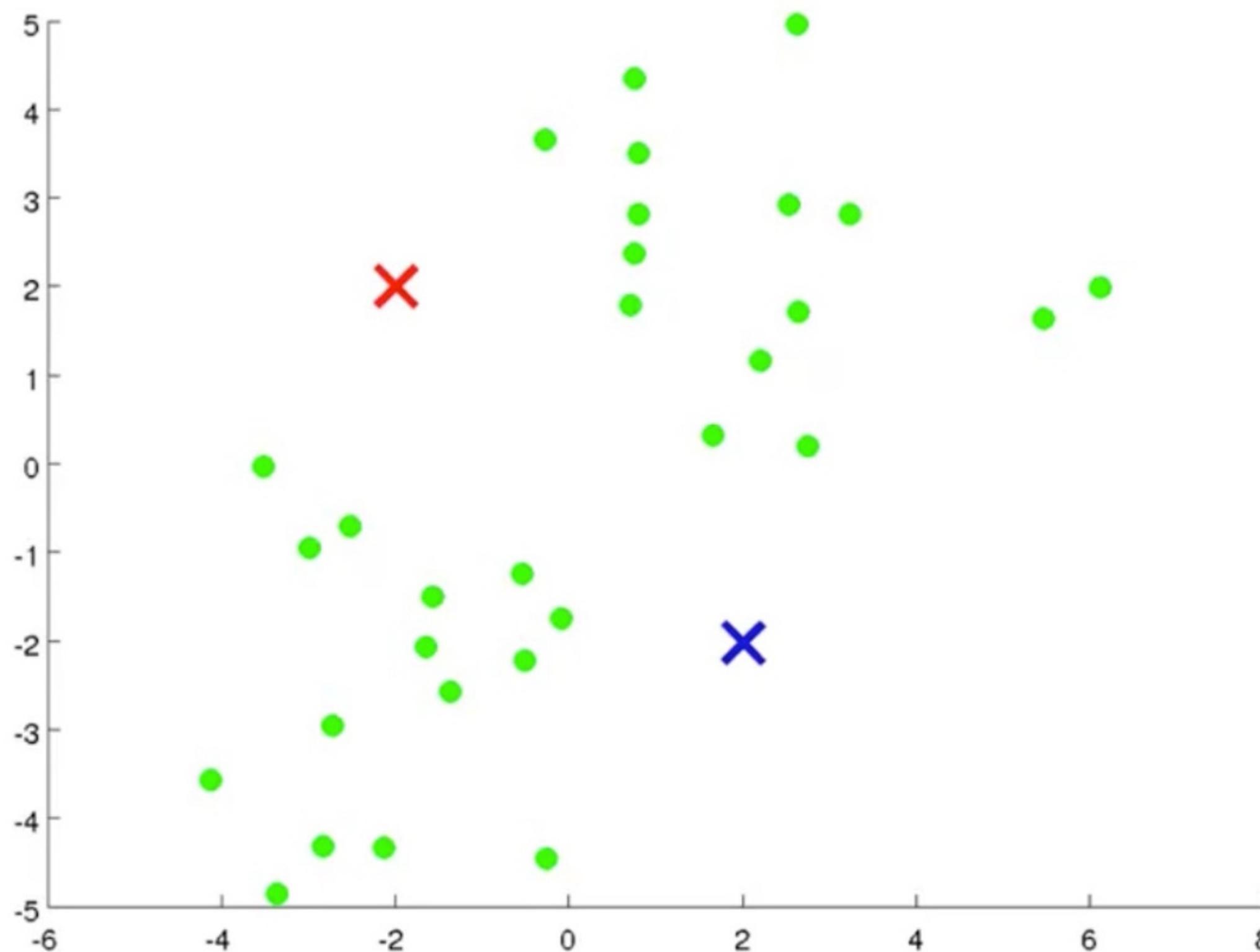
K-Means Algorithm

First, we have a bunch of unlabeled data points. We decide that we are going to find two clusters in this data.



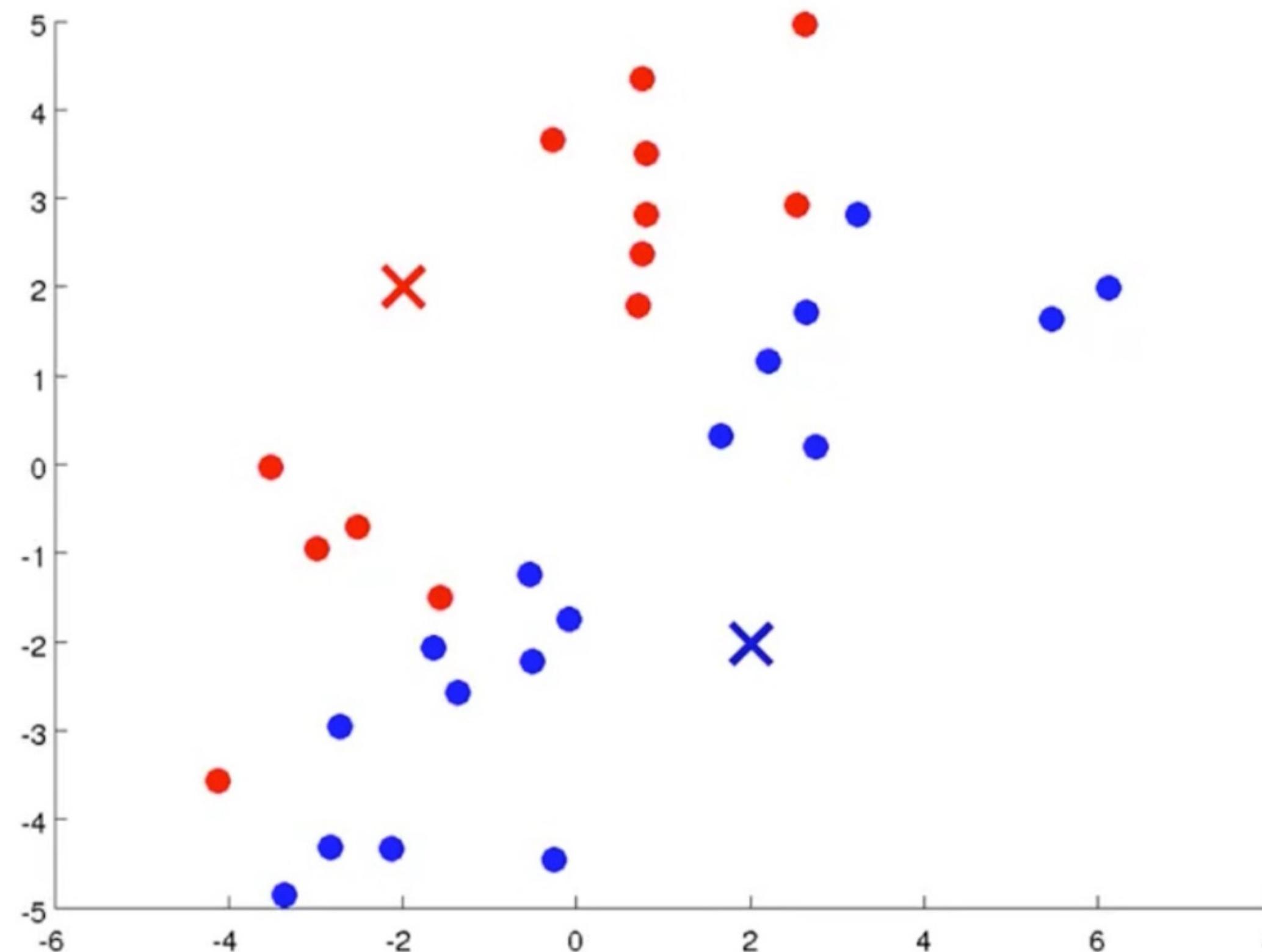
K-Means Algorithm

The first step is to pick two random locations to be our cluster centroids.



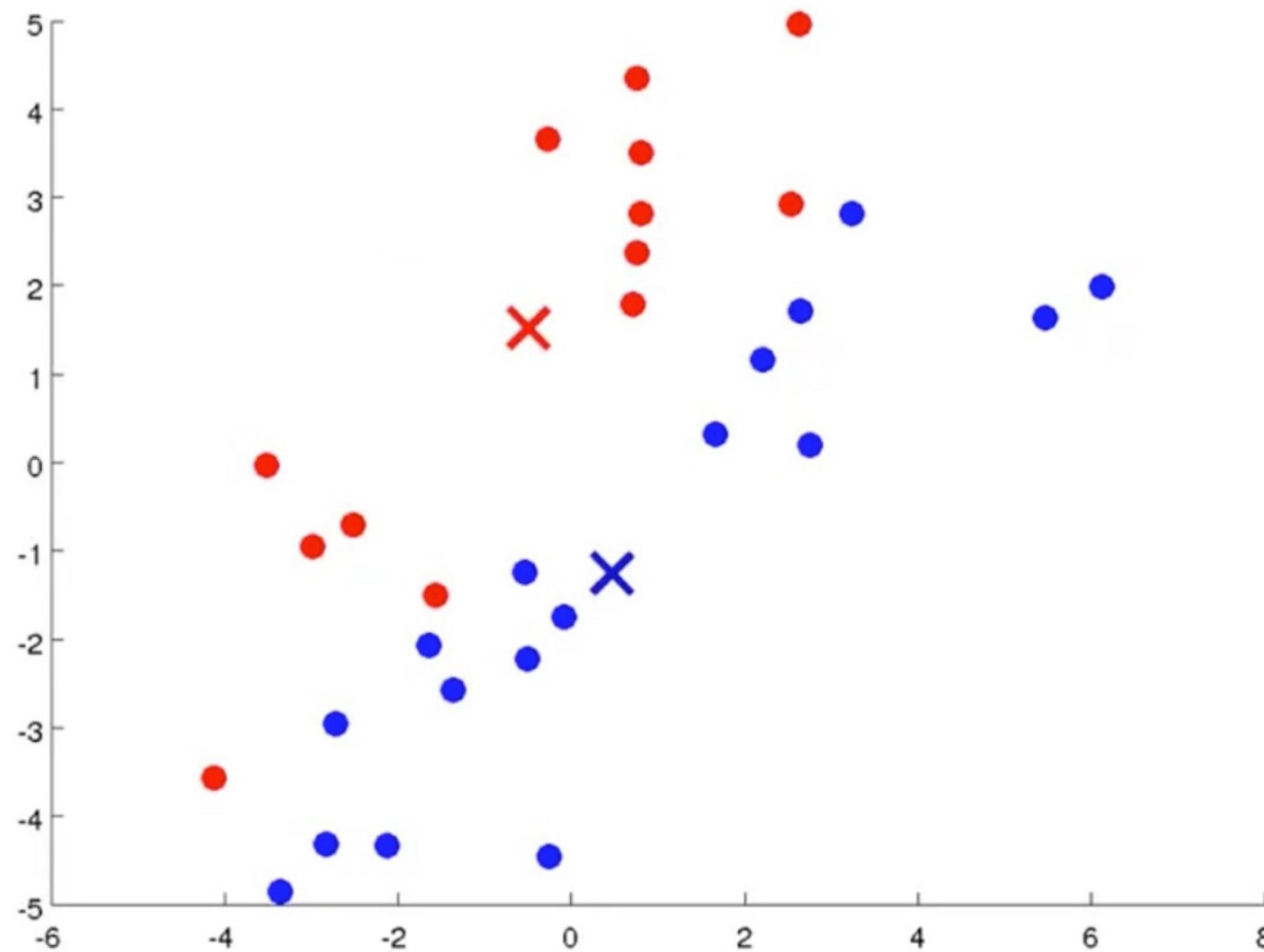
K-Means Algorithm

Then, we do **cluster assignment** step, where we go through every sample and determine whether each dot is closer to red or blue centroid. Label the sample to red/blue accordingly.



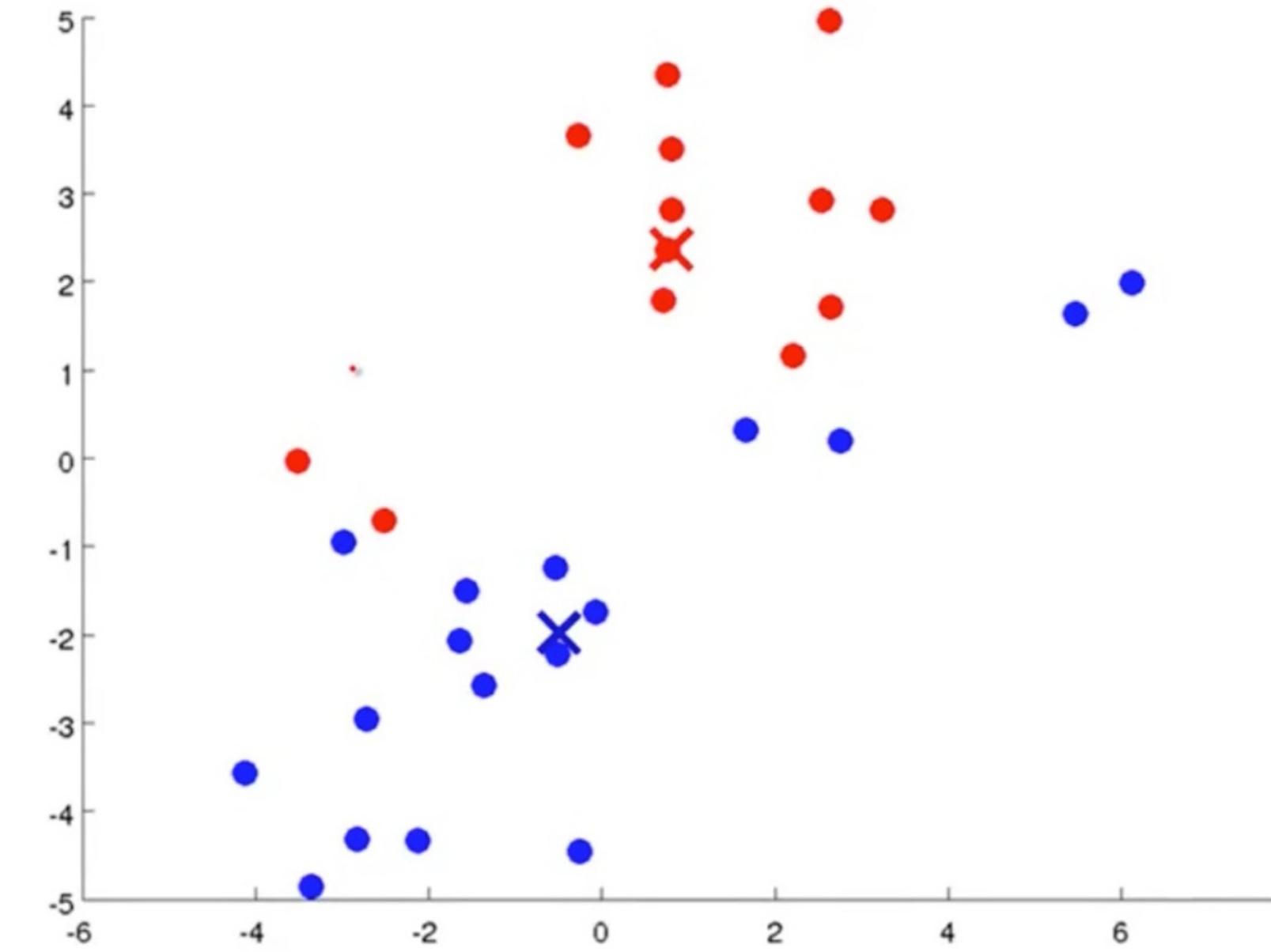
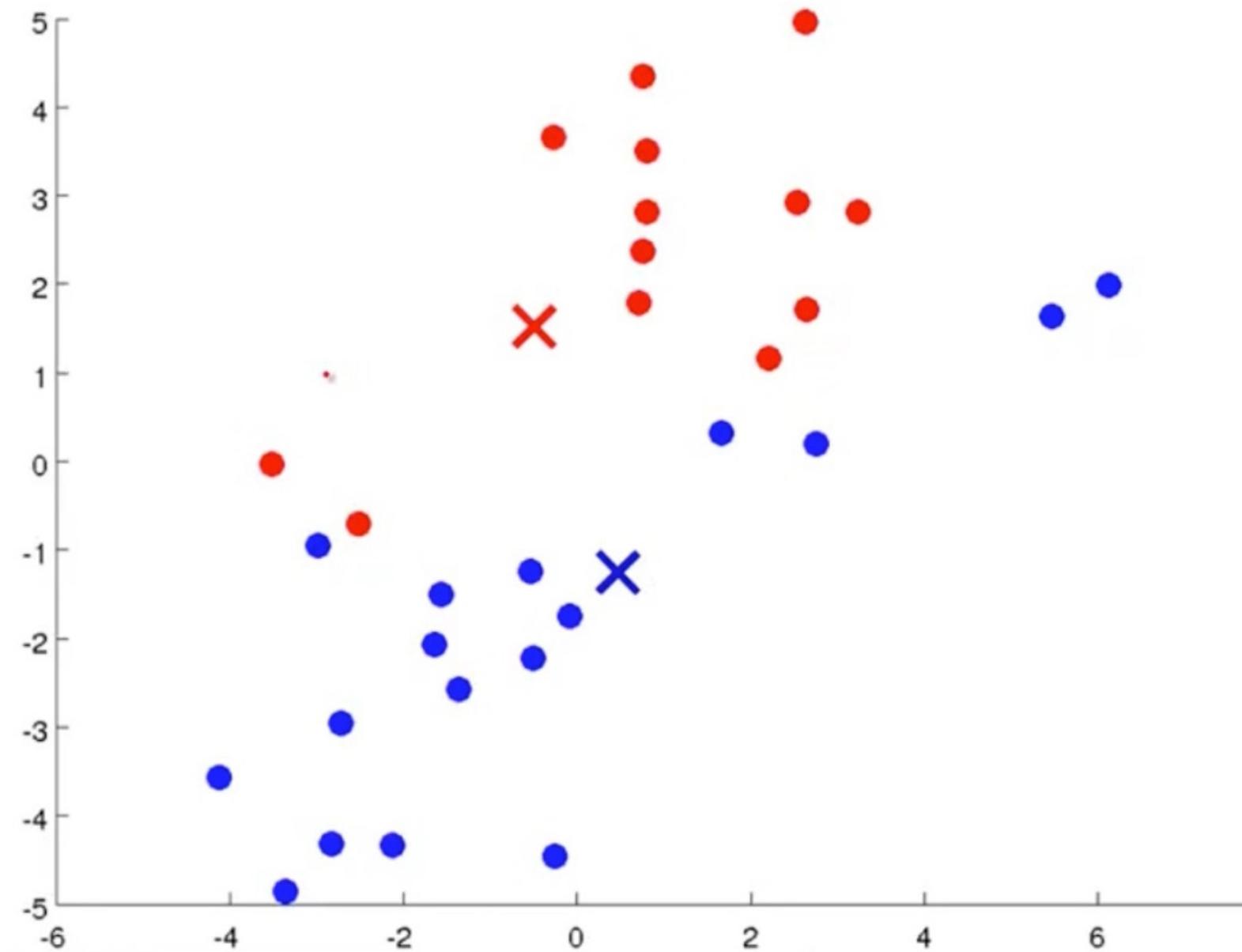
K-Means Algorithm

After the assignment step, we do **centroid movement** step where we move the red and blue centroids to the means of our clusters.



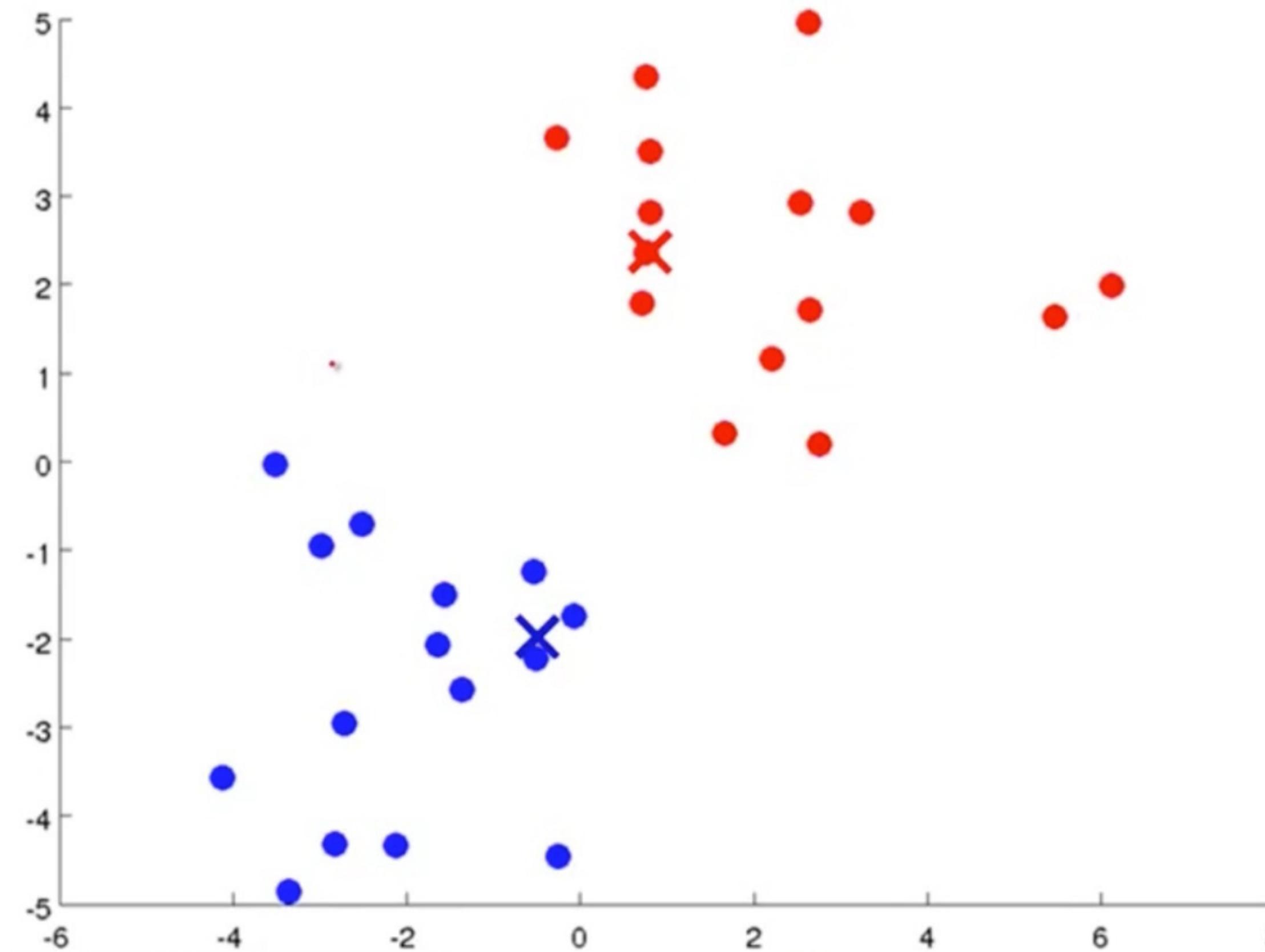
K-Means Algorithm

Repeat the **cluster assignment** step and **centroid movement** step,
alternately.



K-Means Algorithm

The algorithm converges to the solution when cluster centroids are not changed anymore.

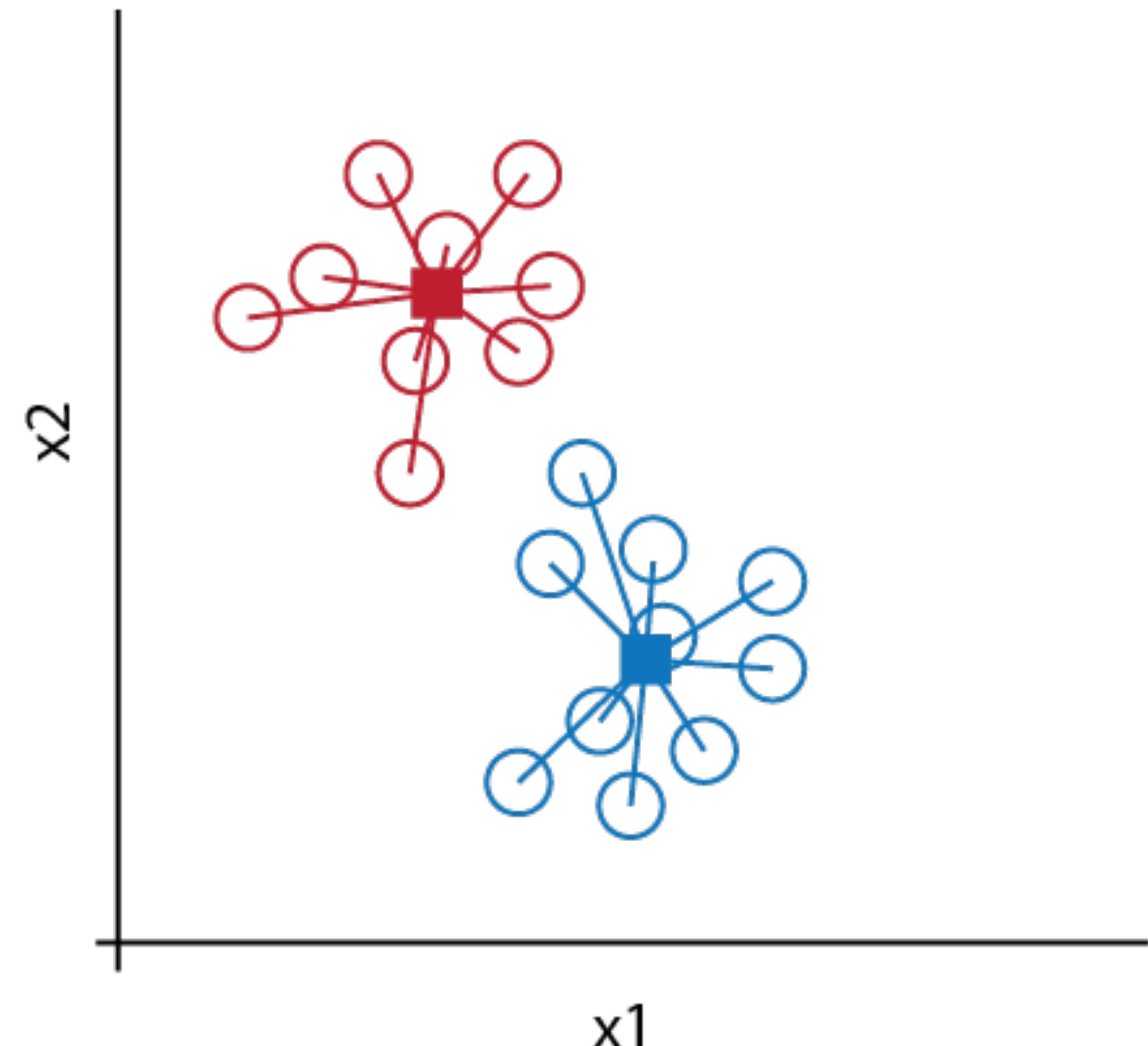


K-Means Algorithm

- To summarize, k-means algorithm has two steps:
 - In **cluster assignment step**, we fixed the centroids and label each data point to belong to the nearest cluster centroid.
 - In **centroid movement step**, we fixed data point labels and move each centroid to the mean of its data points.
- Iterating over these two steps and you will achieve the best clusters.

K-Means Algorithm

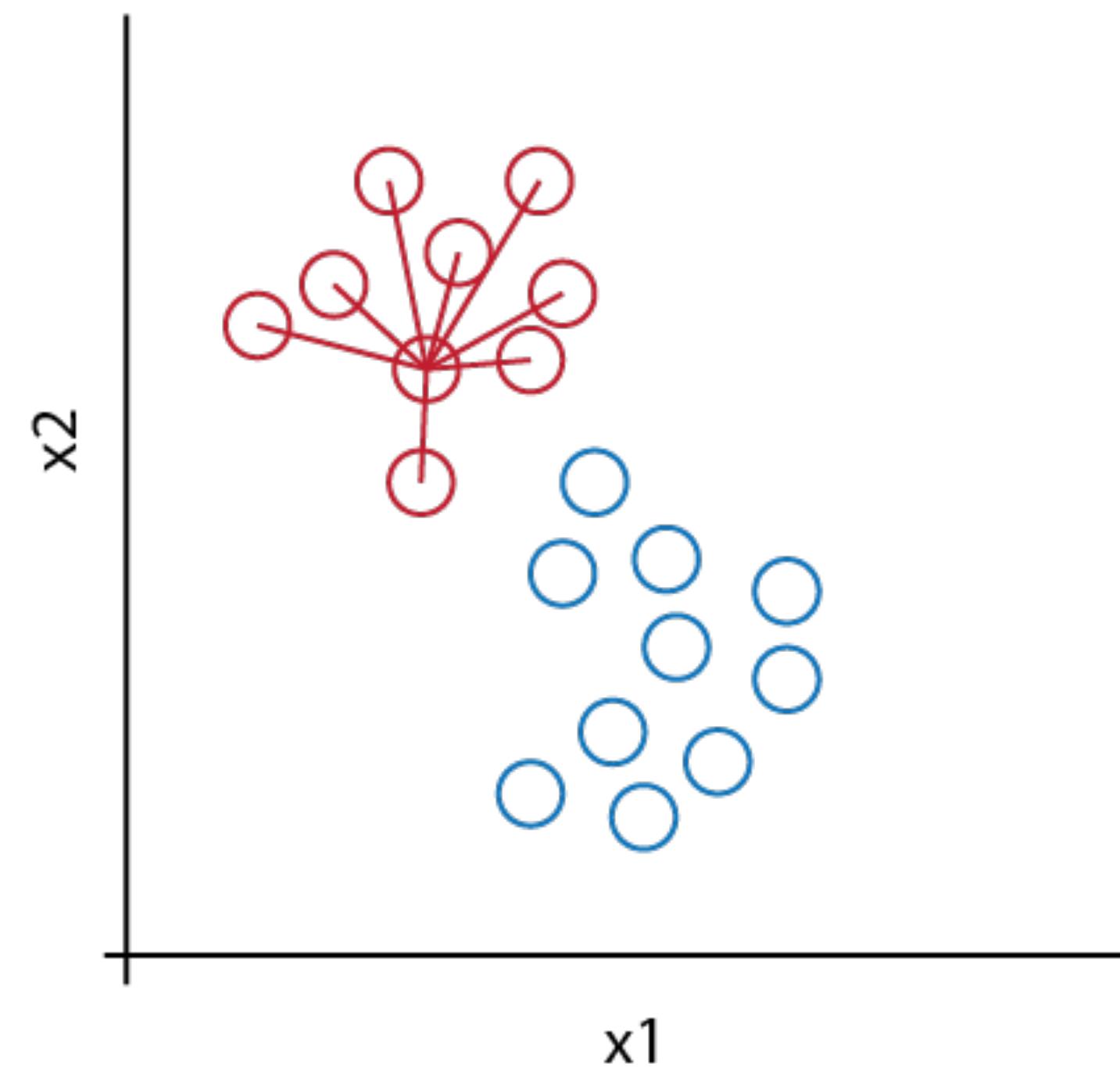
- What K-Means algorithm is doing?
- The algorithm minimize the total distances between all data points and the centroids of the clusters they belong to.



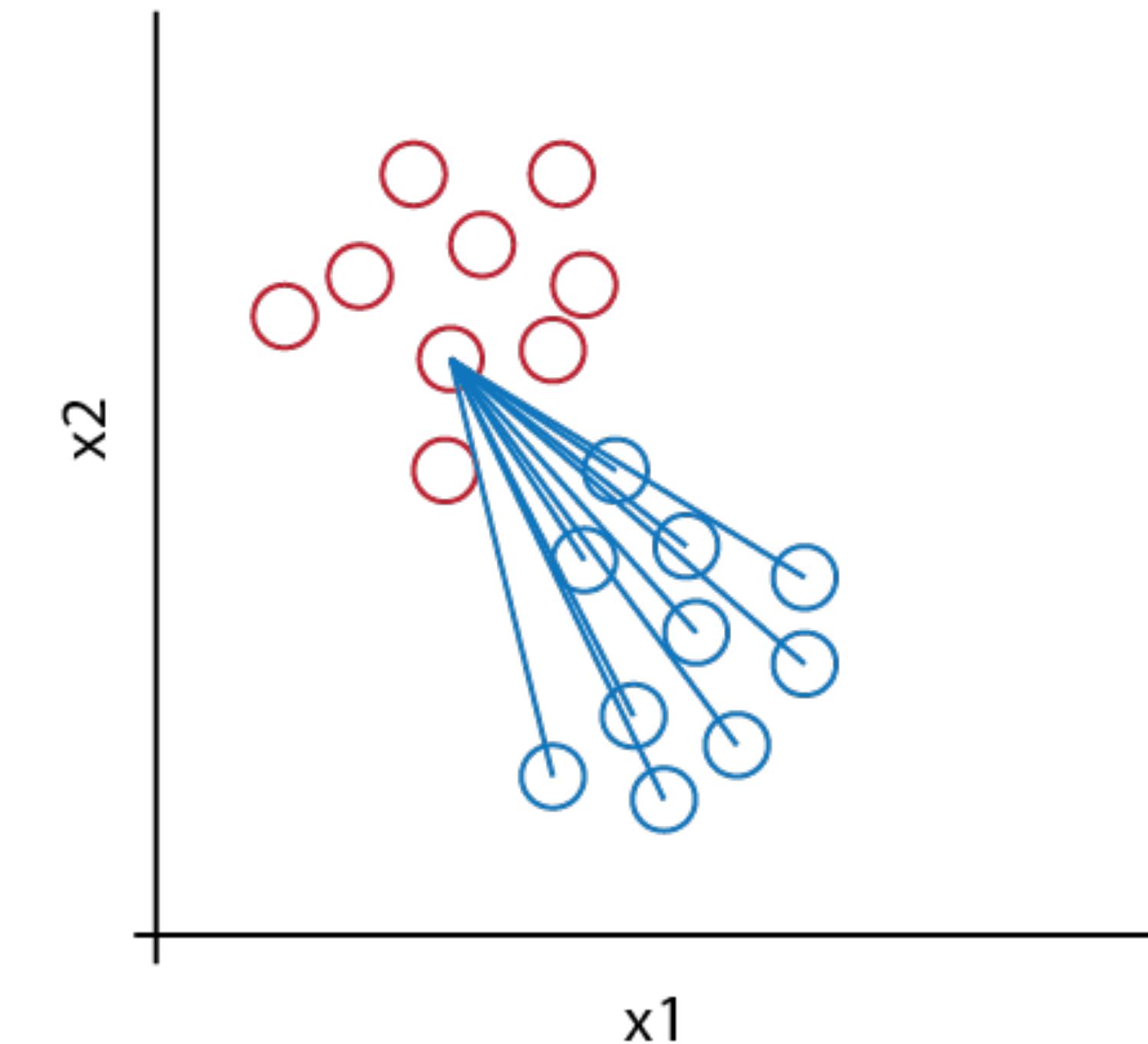
Clustering Performance

- How good is your clustering results? It is not as simple as counting right and wrong predictions. Performance of clustering algorithm is often judged based on how well you algorithm separates out the data into several clusters.

Cohesion



Separation

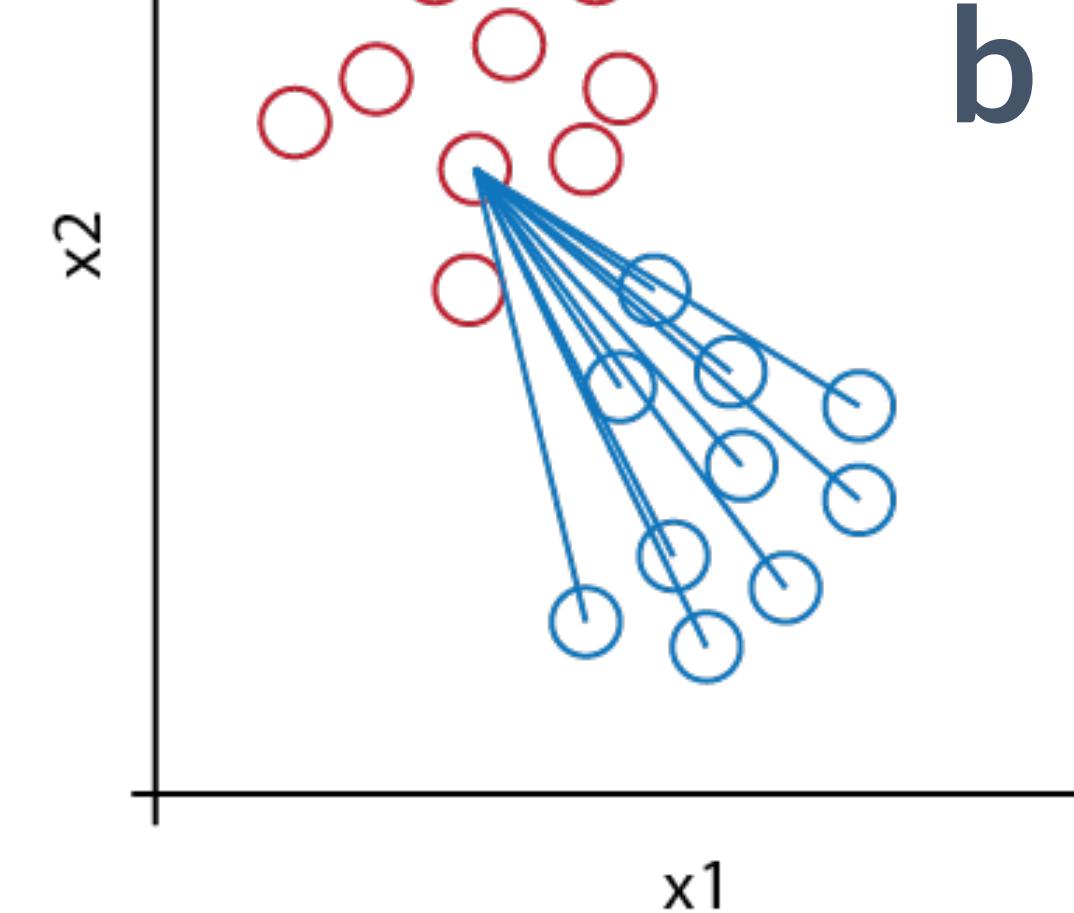
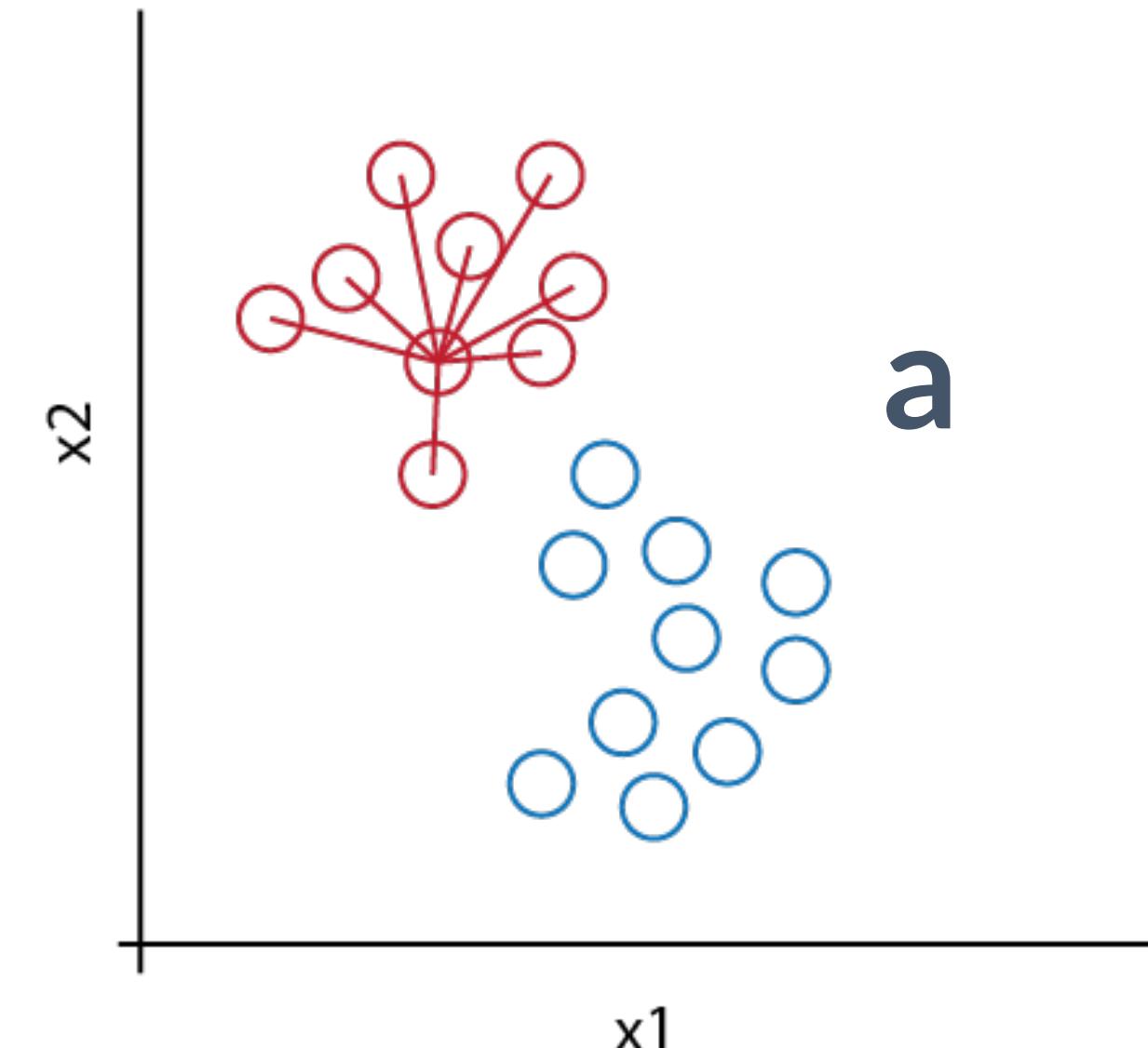


Clustering Performance

- Silhouette Coefficient is one such measure. It's defined by two separate scores:
 - a: mean distance between a sample and all other points in the same class.
 - b: mean distance between a sample and all other points in the next nearest cluster.
- Silhouette Coefficient

$$= (b-a)/\max(b,a)$$

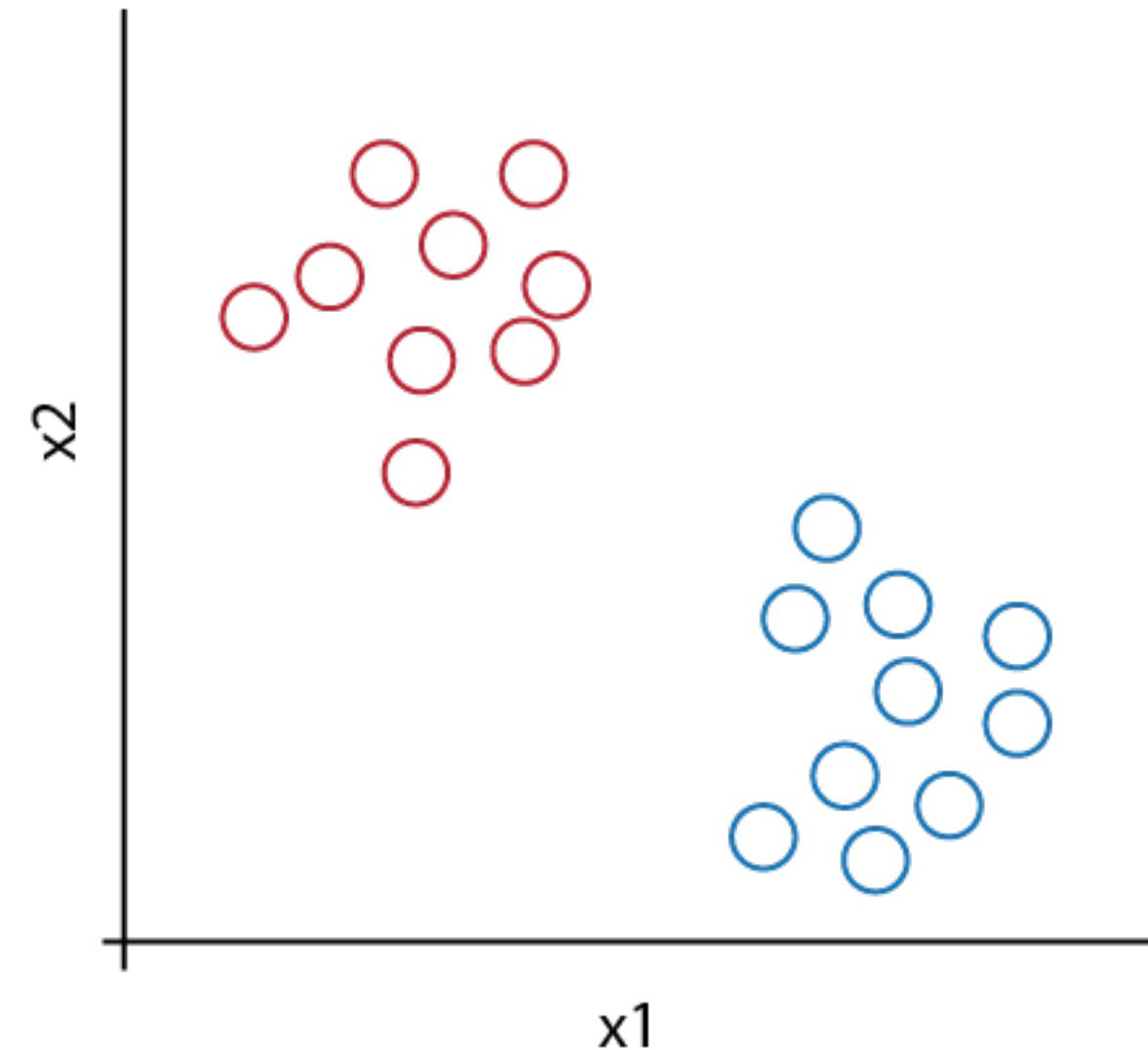
$$= 1 - (a/b) \quad - \text{ if } b > a$$



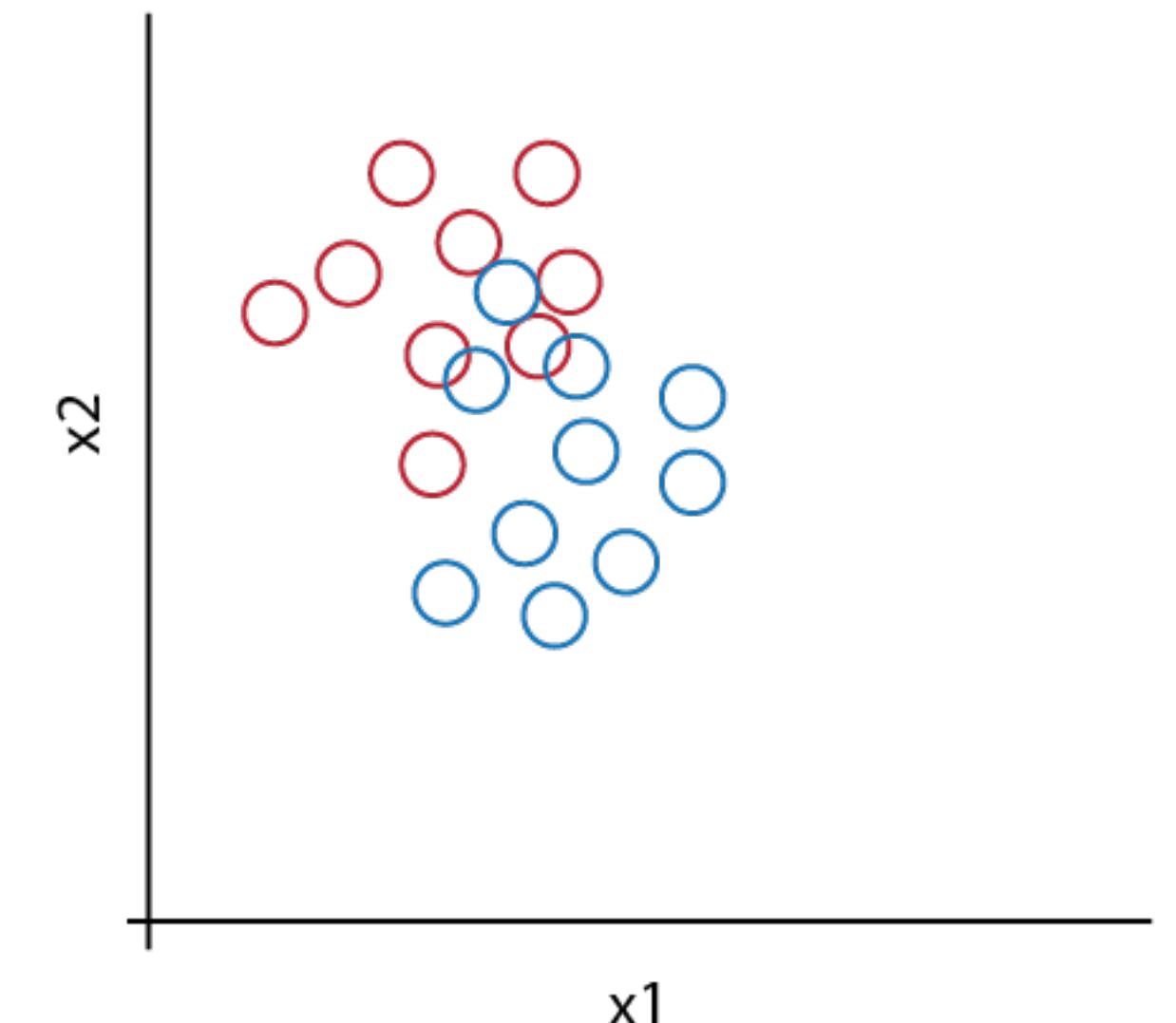
Clustering Performance

- Silhouette Coefficient = $1 - (a/b)$
- If $b \gg a$, SC is close to 1.
- If $a \ll b$, SC is close to -1.

Silhouette close to 1
Good Clusters



Silhouette close to -1
Bad Clusters



Clustering Performance

- Other methods of clustering performance include Calinski-Harabaz Index (dispersion from centroid), percentage of explained variance (between-group variance / total variance), and many others.
- We can calculate these performance metrics using any distance metrics we learned about (Euclidean, Manhattan, Jaccard).
- Typically, it would be best if we could find some ground truth to validate our clusters. For example, if we cluster 1M news articles, we could get people to label 5000 news articles to establish ground truth for validating our clusters.

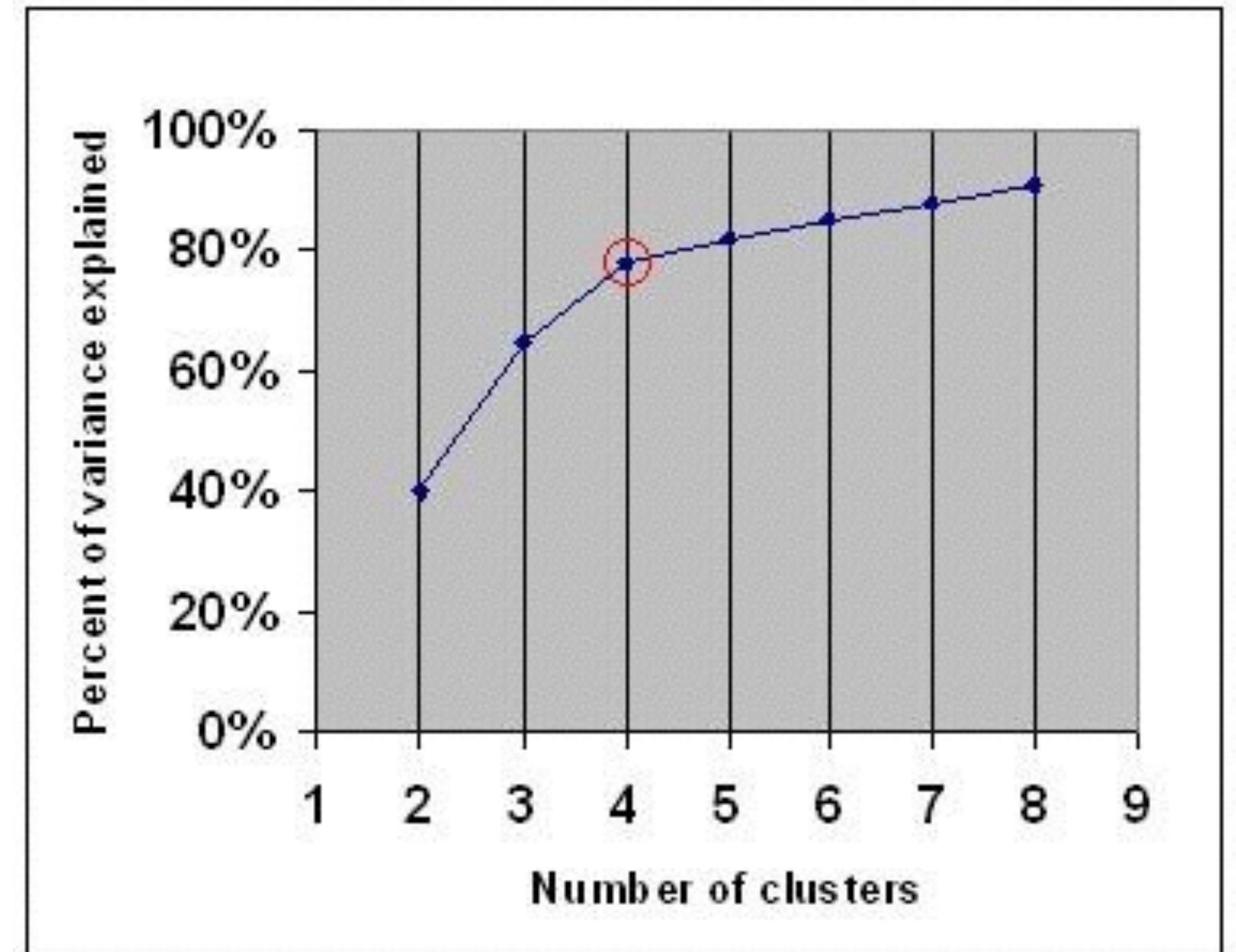
Clustering Performance

- When ground-truth labels are provided, people talk about clustering performance in terms of homogeneity, completeness, and v-measure
 - Homogeneity: each cluster contains only members of a single class.
 - Completeness: all members of a given class are assigned to the same cluster.
 - Both homogeneity and completeness are bounded below by 0.0 and above by 1.0 (higher is better)
- **V-Measure Score:** the harmonic mean between homogeneity and completeness.

$$v = \frac{2 * (\text{homogeneity} * \text{completeness})}{(\text{homogeneity} + \text{completeness})}$$

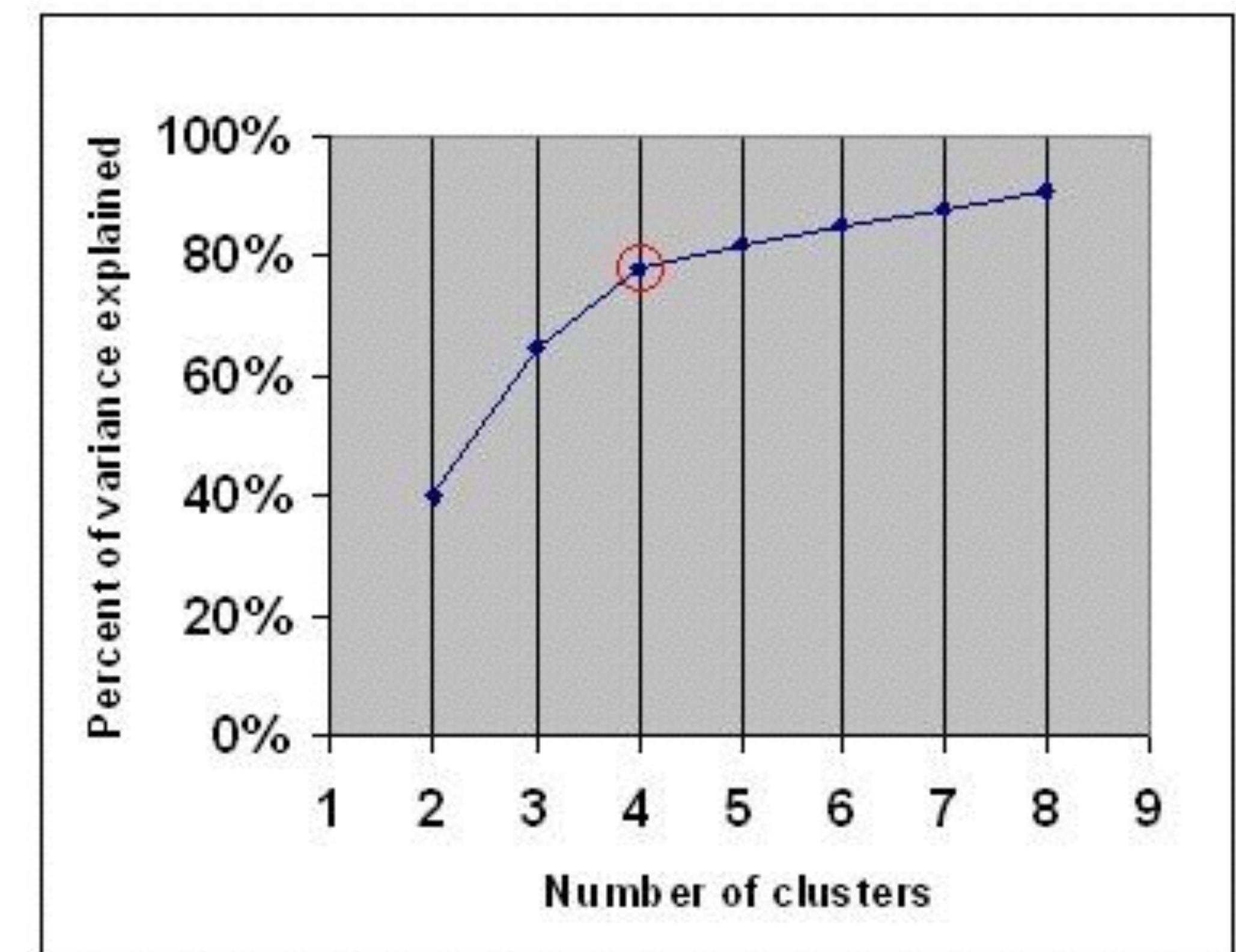
Choosing the Right K

- How to determine the number of clusters in the dataset?
- The most common way is called elbow methods.
- You compute performance metrics such as Silhouette Coefficient or Percentage of Variance (in the figure), while varying k.



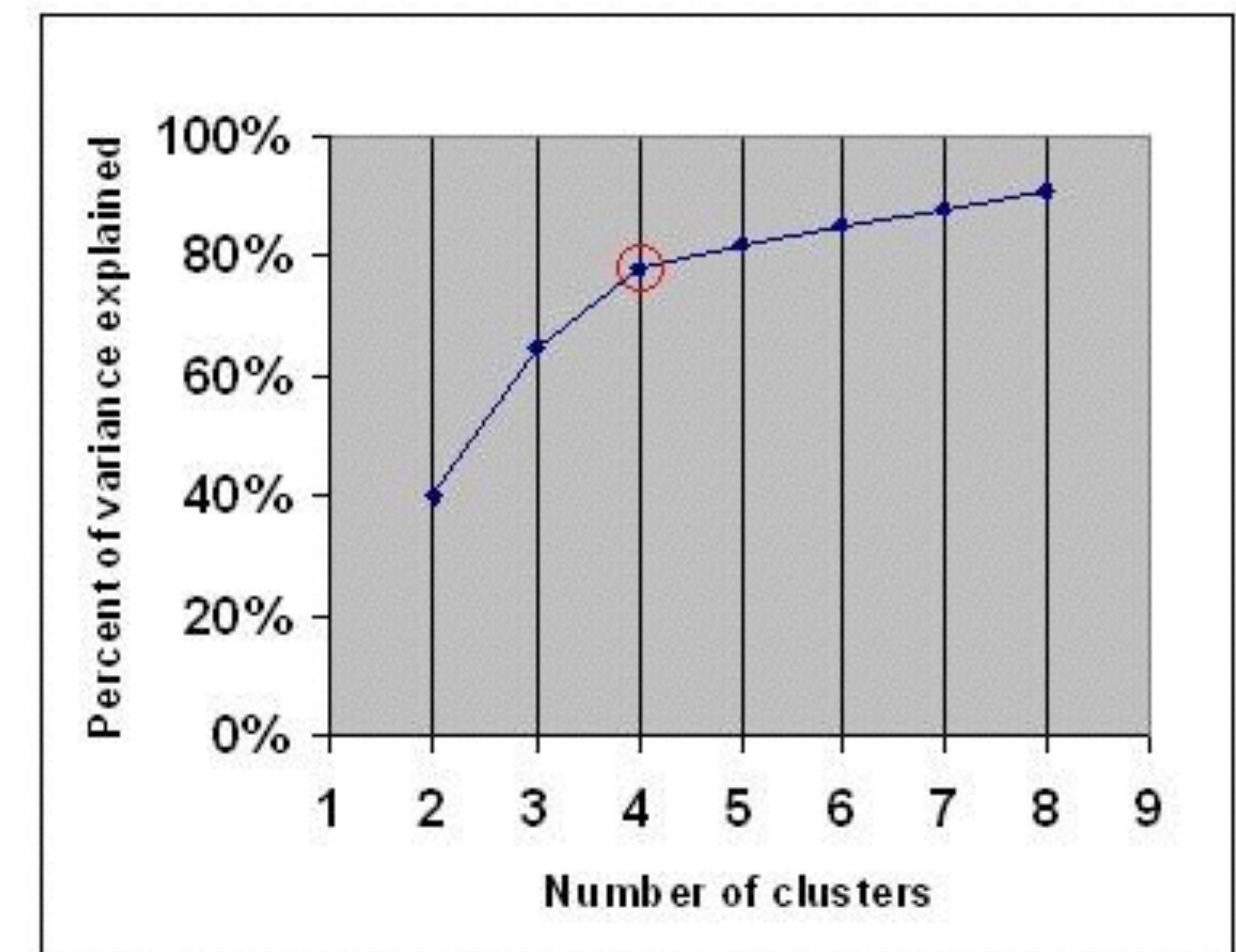
Choosing the Right K

- Pick the k at the elbow point. At this point, more clusters do not necessarily mean higher performance.
- Similarly we use metrics like Information Criterion (the famous one being Bayesian - BIC, and Akaike - AIC). These are measures that find a good balance between the variance explained and the complexity of the model.



Choosing the Right K

- Pick the k at the elbow point. At this point, more clusters do not necessarily mean higher performance.
- Similarly we use metrics like Information Criterion (the famous one being Bayesian - BIC, and Akaike - AIC). These are measures that find a good balance between the variance explained and the complexity of the model.

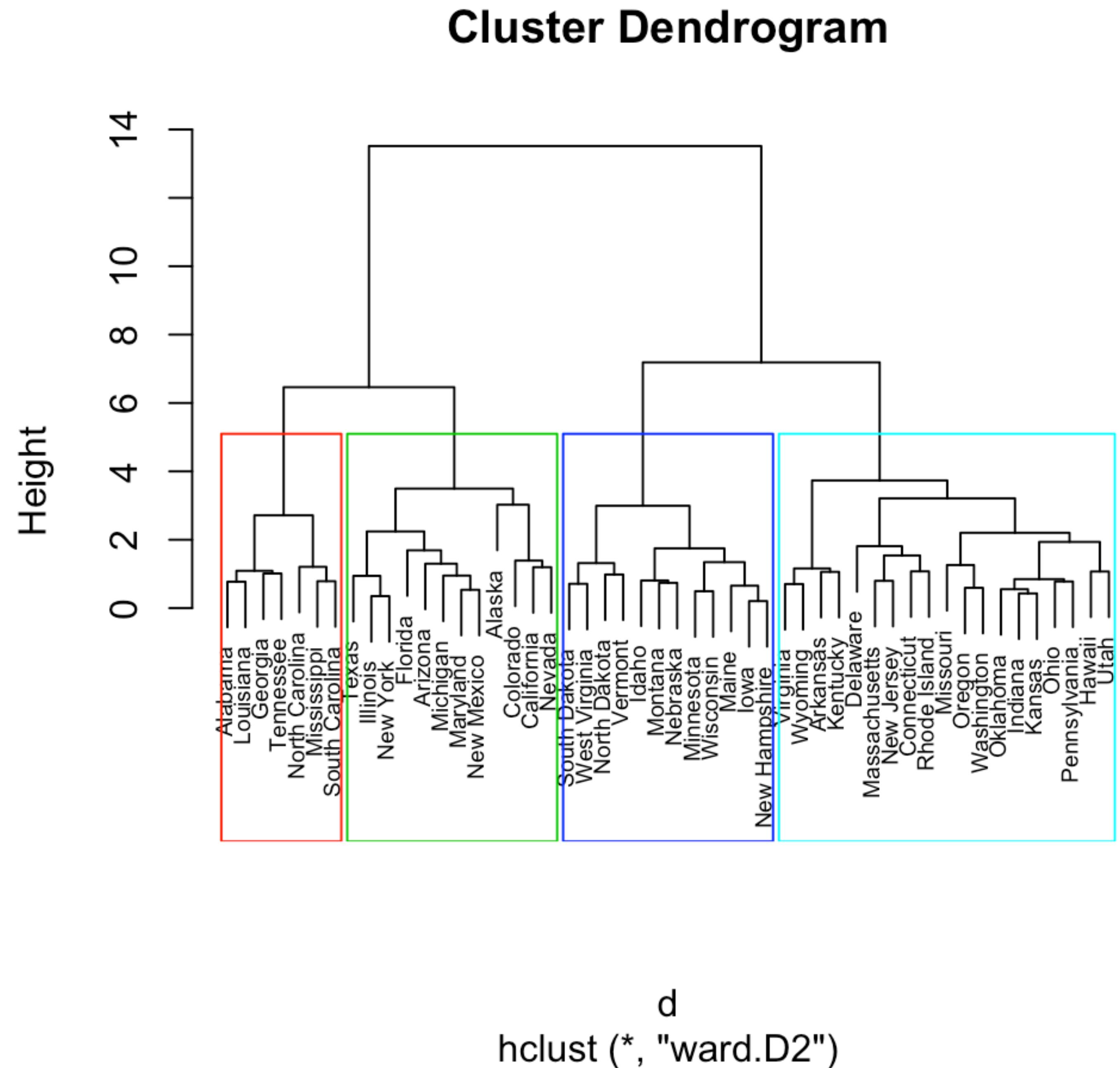




HIERARCHICAL CLUSTERING

Hierarchical Clustering

- Hierarchical clustering does not require to pre-specify the number of clusters to be generated.
- The result is a tree-based representation of the observations which is called a dendrogram.
- It uses pairwise distance matrix between observations as clustering criteria.



Two Approaches

- **Agglomerative:** This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy.
 - Each object is initially considered as a single-element cluster (leaf).
 - At each step of the algorithm, the two clusters that are the most similar are combined into a new bigger cluster (nodes).
 - Iterated until all points are member of just one single big cluster (root)
- **Divisive:** This is a "top down" approach: all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy.
 - It begins with the root, in which all objects are included in a single cluster. At each step of iteration, the most heterogeneous cluster is divided into two.

Measuring Dissimilarity

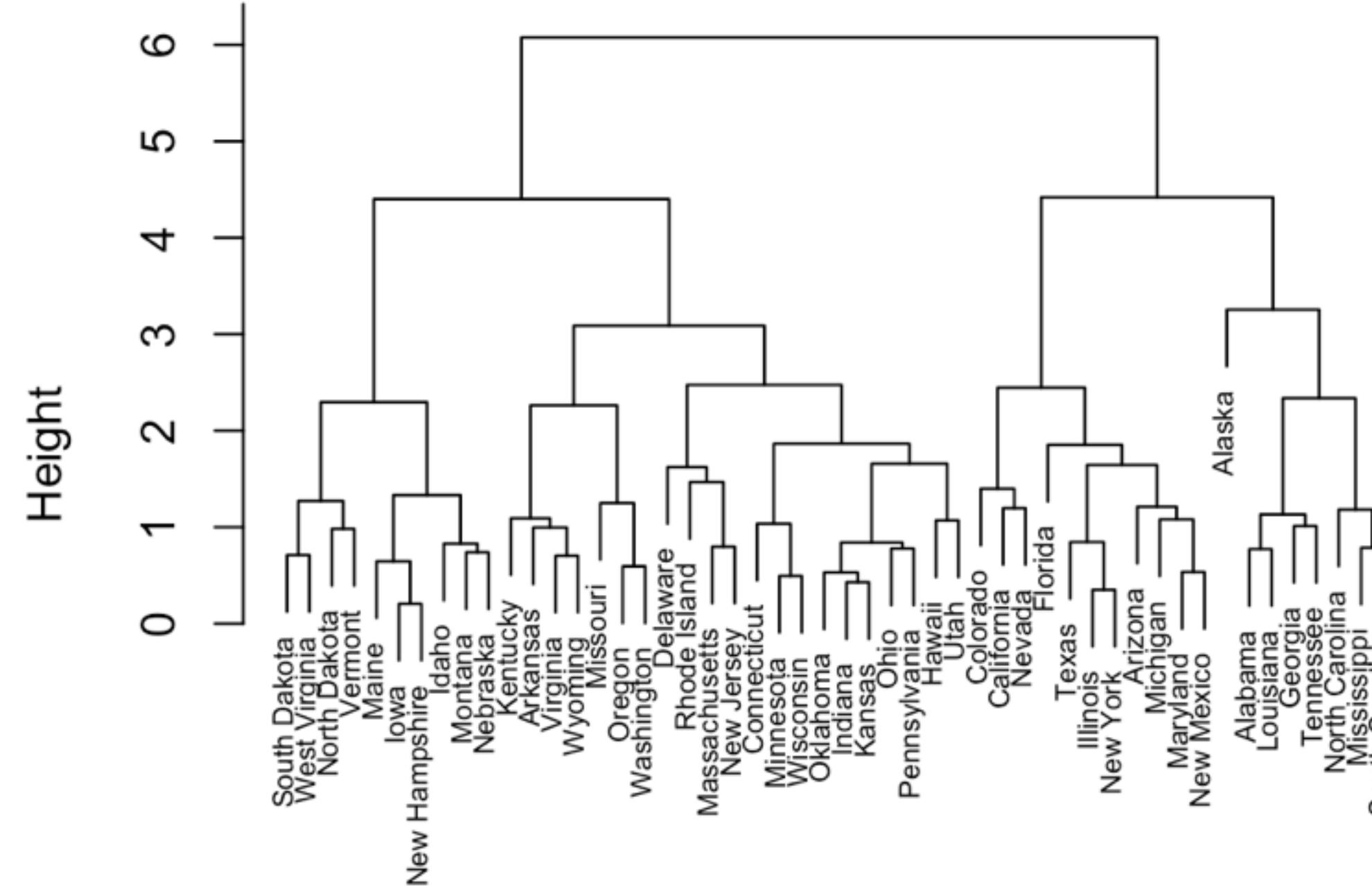
- How to measure the dissimilarity between two clusters of observations?
- A number of different linkage methods has been developed to answer to this question.
- **Maximum or complete linkage clustering:** It computes all pairwise dissimilarities between cluster 1 and cluster 2, and considers the maximum dissimilarity as the distance between the two clusters. It tends to produce more compact clusters.
- **Minimum or single linkage clustering:** Same as above, and considers the smallest of these dissimilarities as a linkage criterion. It tends to produce long, “loose” clusters.

Measuring Dissimilarity

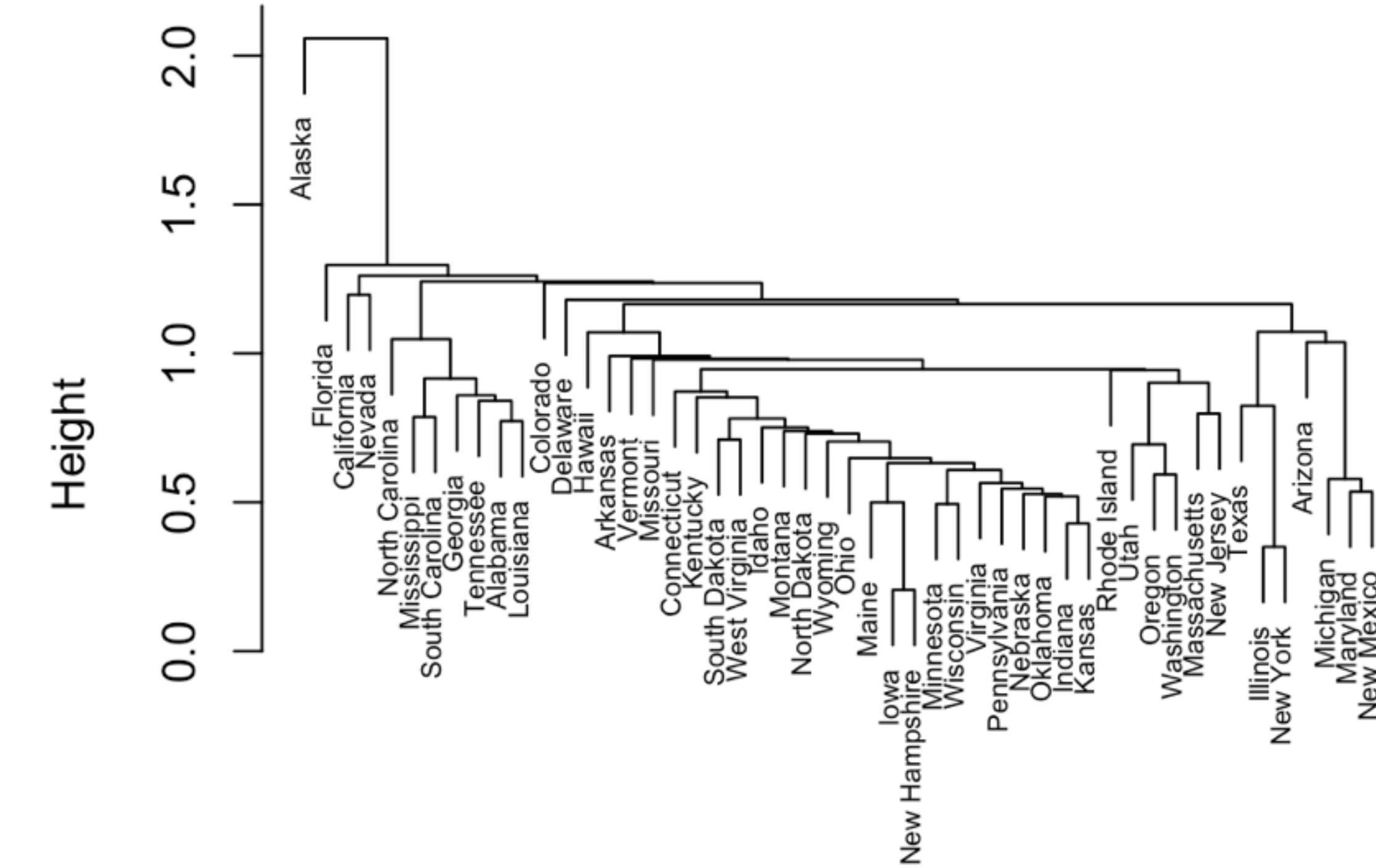
- How to measure the dissimilarity between two clusters of observations?
- A number of different linkage methods has been developed to answer to this question.
- **Mean or average linkage clustering:** Same as above, and considers the average of these dissimilarities as the distance between the two clusters.
- **Centroid linkage clustering:** It computes the dissimilarity between the centroid for cluster 1 and the centroid for cluster 2.

Hierachical Clustering

Complete linkage



Single linkage



Other Unsupervised Learning Flavors

- **Random Optimization:**
 - Ways to find the right solution (x) from a large space of solutions
 - Example: factories need to find the right setting for their old refinement plants. There are 100 variables, which one would yield the best old quality?
 - Hill Climbing, GA, Simulated Annealing, etc.
- **Dimensionality Reduction**
 - Transform a set of huge data (1000 dimension) to a small data (3 dimensions) without information loss
 - Find a set of weights that optimize an objective function
 - Principle component analysis, Independent component analysis

Other Unsupervised Learning Flavors

- **Neural Network Unsupervised Learning**
 - Self-organizing map: a grid of neuron nodes being continuously updated until there are nodes that represent significant subclasses of the inputs.
 - Embedding techniques: creating neural-network-like representation of the inputs that might be abstract such as modeling relationships between words from reading articles.
 - Auto encoder: training neural network to photocopy the images in order to create a feature space of images.



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