

Clustering

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INLS 613: Text Data Mining

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(some material taken or adapted from slides by Hinrich
Schutze)

Clustering

objective

- Grouping documents or instances into subsets or clusters
- Documents in the same cluster should be similar
- Documents in different clusters should be dissimilar
- A common form of **unsupervised learning**
- Unsupervised = no human-produced labels
- The goal is to discover structure from the data

Clustering vs. Classification

- Classification:
 - ▶ the input to the system is a set of labeled data
 - ▶ the algorithm learns a model for predicting the label on new examples
- Clustering:
 - ▶ the input to the system is a set of unlabeled data
 - ▶ the algorithm infers the labels from the data and assigns a label to each input instance

Clustering applications

- **Search engine results clustering:** grouping search engine results by topic
 - ▶ the user can identify the relevant clusters and ignore the non-relevant ones
- **Collection clustering:** grouping documents by topic to support navigation and exploration
- **Data analytics:** grouping instances to identify popular trends (big clusters) and outliers (small clusters)

Clustering Applications

search engine results clustering

The screenshot shows the Yippy search engine interface. At the top, there's a navigation bar with links for 'web', 'news', 'images', 'maps', 'blogs', 'wikipedia', 'jobs', and 'more'. The search bar contains the word 'jaguar' and has a 'Search' button and a link to 'advanced preferences'. Below the search bar, there are tabs for 'clouds', 'sources', 'sites', and 'time'. The 'clouds' tab is active, showing a list of categories with their respective result counts: 'All Results (176)', 'Jaguar Cars (24)', 'International (13)', 'Pictures (27)', 'Panthera, Onca (17)', 'Parts (23)', 'Dealership, Sells and services Jaguar (22)', 'Luxury, Car (15)', 'Club, Events (17)', 'Jaguar Land Rover (9)', and 'Reviews, Prices (8)'. There are also links for 'more' and 'all clouds', and a 'find in clouds' search box with a 'Find' button. The main search results area shows 'Top 170 results of at least 202,000,000 retrieved for the query jaguar (definition) (details)'. The first result is a definition of 'jaguar' as a noun. Below it, there's a section for 'Jaguars' with a link to 'See more from Encyclopedia'. This is followed by 'Sponsored Results' for 'Jaguar® Official Site' and 'Consider a Mercedes-Benz®'. At the bottom, there's a link for 'Jaguar International - Market selector page' with social media icons, and a footer for 'Jaguar Cars Limited' with contact information and a link to 'www.jaguar.com/gl/en/marketsel'.

web news images maps blogs wikipedia jobs more »

jaguar Search advanced preferences

clouds sources sites time remix

All Results (176)

- Jaguar Cars (24)
- International (13)
- Pictures (27)
- Panthera, Onca (17)
- Parts (23)
- Dealership, Sells and services Jaguar (22)
- Luxury, Car (15)
- Club, Events (17)
- Jaguar Land Rover (9)
- Reviews, Prices (8)

more | all clouds

find in clouds: Find

Font size: A A A A

Top 170 results of at least 202,000,000 retrieved for the query jaguar (definition) (details)

jaguar

- noun - jaguar, panther, Panthera onca, Felis onca -- (a large spotted feline of tropical America similar to the leopard; in some classifications considered a member of the genus Felis)

See more from Encyclopedia »

Jaguars

JAGUARS JAGUARS . The jaguar (Panthera onca) is the largest native American cat, and for over three thousand years it has been one of Central and South America's most important symbolic animals. Sometimes associated with the puma (Felis concolor) and ocelot (Felis pardalis), the jaguar was a

Sponsored Results

Jaguar® Official Site

Experience How Luxury Feels When You Build & Price A Jaguar.
www.jaguarusa.com

Jaguar

Feel how alive luxury can be - Drive our breathtaking 2012 models
www.flowjaguargreensboro.com

Consider a Mercedes-Benz®

Discover the Safety & Performance Innovations That Set the Benchmark.
www.mbusa.com/Raleigh-Durham

Search Results

Jaguar International - Market selector page

Jaguar Cars Limited: Registered Office: Abbey Road, Whitley, Coventry CV3 4LF Registered in England
No: 1672070. You need Flash Player 9
www.jaguar.com/gl/en/marketsel - [cache] - Additional Sources, Yippy Sources

Clustering Applications

collection clustering

The image is a screenshot of the Google News homepage. At the top left is the Google logo. To its right is a search bar with a magnifying glass icon. Below the search bar, there are two dropdown menus: "U.S. edition" and "Modern". The main content area is titled "Top Stories" and features a large article about a shooting in Wisconsin. The article title is "Police chief: Wisconsin spa shooting suspect died of self-inflicted wound". The byline is "Chicago Tribune - 23 minutes ago". The article text states: "A man police suspected of killing three and wounding four by opening fire at a tranquil day spa was found dead Sunday afternoon following a six-hour manhunt that locked down a shopping center, country club and hospital in suburban Milwaukee." Below the article text are several links: "Suspect in Wisconsin spa shooting found dead" (Fox News), "Three Killed in Shooting at Spa in Wisconsin" (New York Times), "Highly Cited: 3 killed, 4 injured in rampage at Azana Spa in Brookfield" (Milwaukee Journal Sentinel), "In Depth: Three killed in shooting at Milwaukee-area salon; suspect found dead at scene" (NBCNews.com), and "Wikipedia: 2012 Azana Spa shootings". There is also a "Related" link for "Brown Deer, Wisconsin". Below the article is a video player from ABC News with the headline "Breaking: The area is on lockdown as authorities in Brookfield work to secure the scene, which is across the street from a shopping mall in Wisconsin." and a sub-headline "At Least 7 Injured in Spa Shooting". At the bottom of the page, there is another article titled "Romney, Obama in Dead Heat" from the Wall Street Journal, dated 22 minutes ago, with the byline "By NEIL KING JR." and the start of the text: "Mitt Romney has strengthened his image as the candidate best able to boost the economy and has fought President Barack Obama to a near-draw on who can best serve as commander in chief, helping turn the 2012 election into a tie ...". On the left side of the page, there is a "News" section with a list of categories: "Top Stories", "Mitt Romney", "Chromebook", "Washington Redskins", "Earthquake", "Fidel Castro", "Cleveland Browns", "George McGovern", "Toronto Blue Jays", "Brad Pitt", "Jay-Z", "North Carolina", "World", "U.S.", "Business", "Elections", "Technology", "Entertainment", "Sports", "Science", "Health", and "Spotlight".

Clustering objective

- Grouping documents or instances into subsets or clusters
- Documents within a the same cluster should be similar
- Documents from different clusters should be dissimilar

Clustering

basics

- What does it mean for documents to be “similar” or “dissimilar”?

Clustering

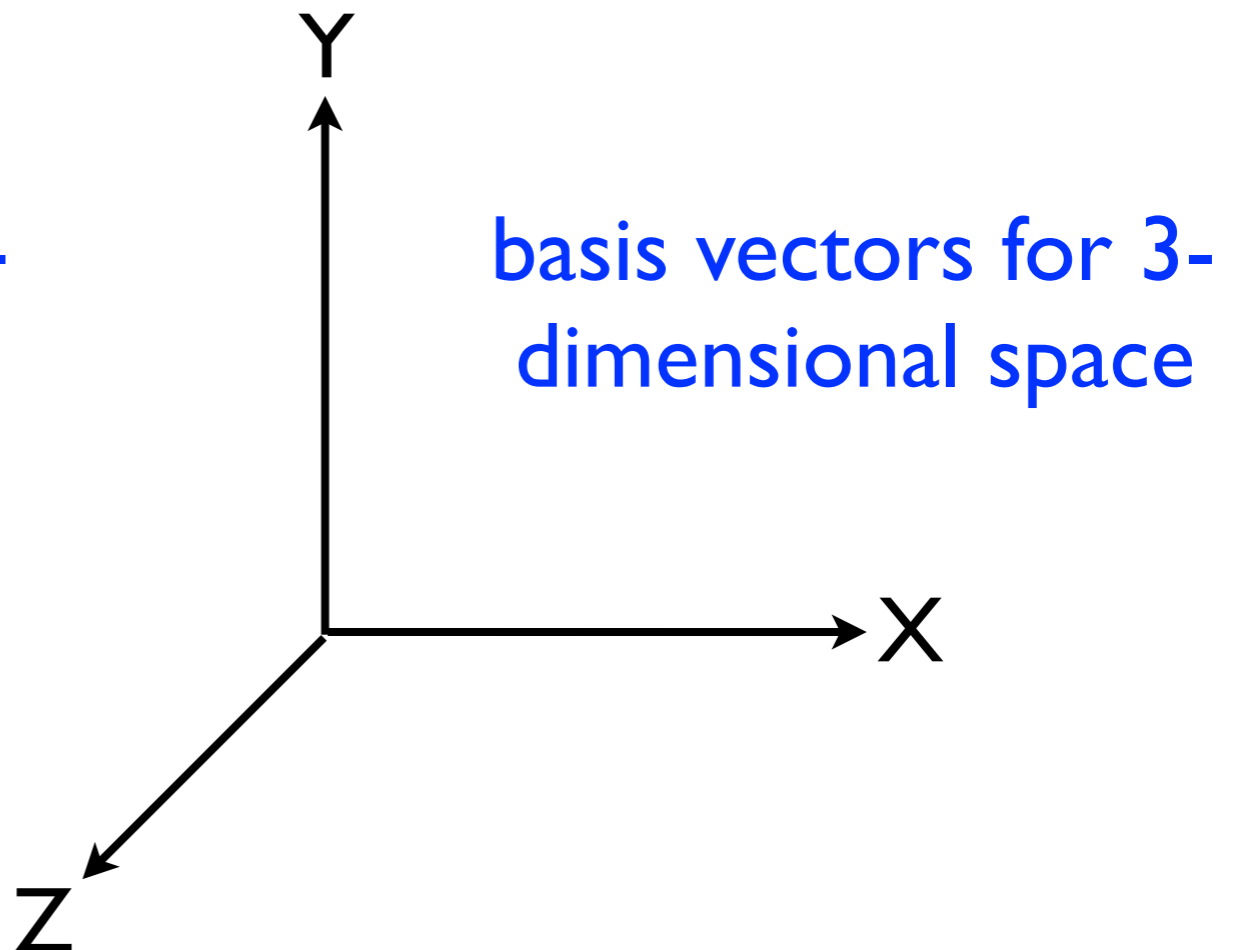
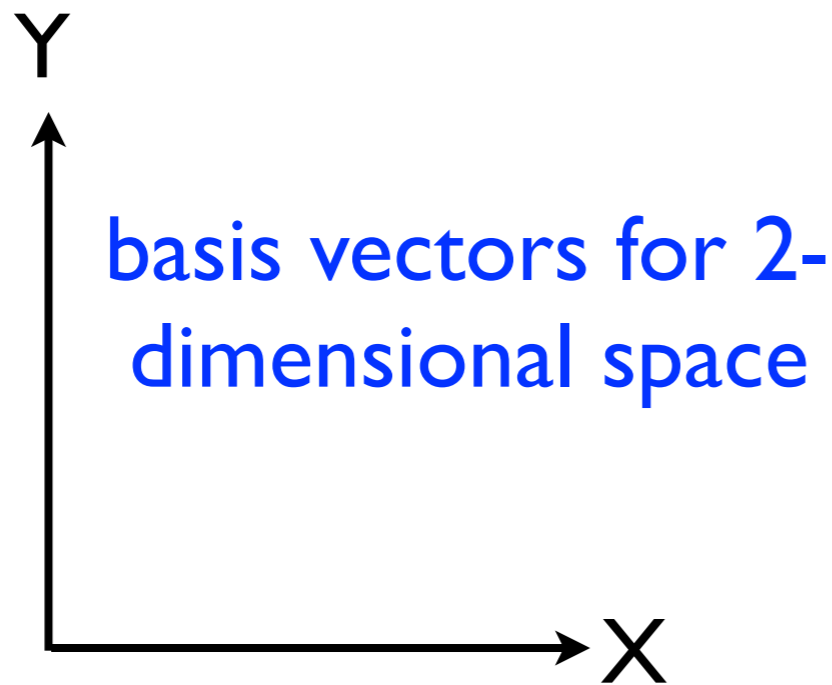
basics

- What does it mean for documents to be similar or dissimilar?
- We need a computational way of modeling similarity
- **One solution:** model similarity using distance in a vector space representation of the collection or dataset
 - small distance = high similarity
 - long distance = low similarity

Vector Space Representation

review

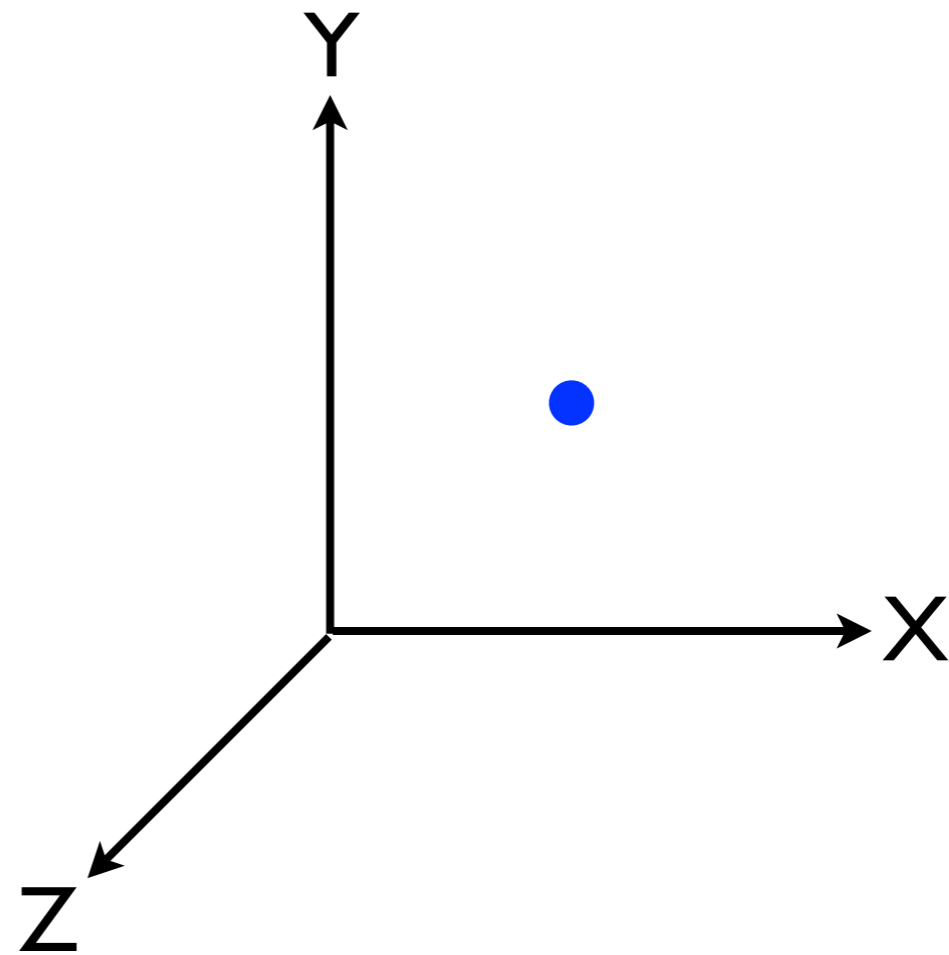
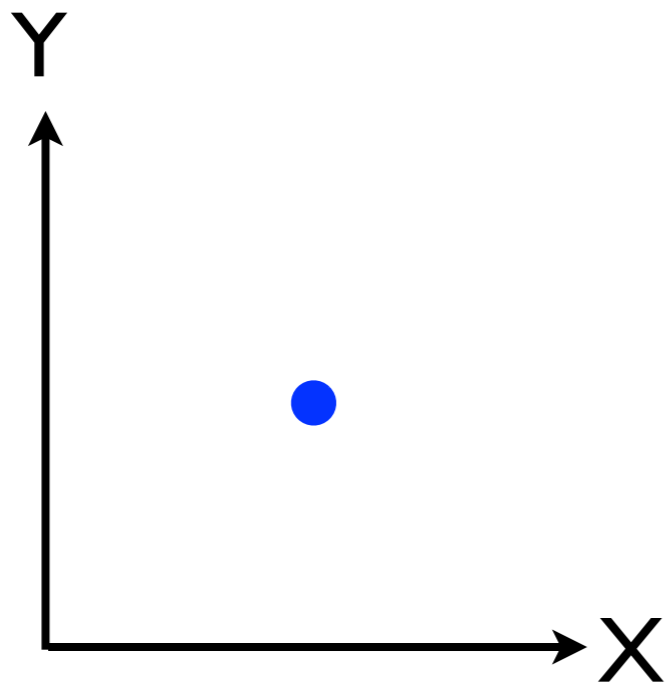
- A **vector space** is defined by a set of linearly independent basis vectors
- The **basis vectors** correspond to the dimensions or directions of the vector space



Vector Space Representation

review

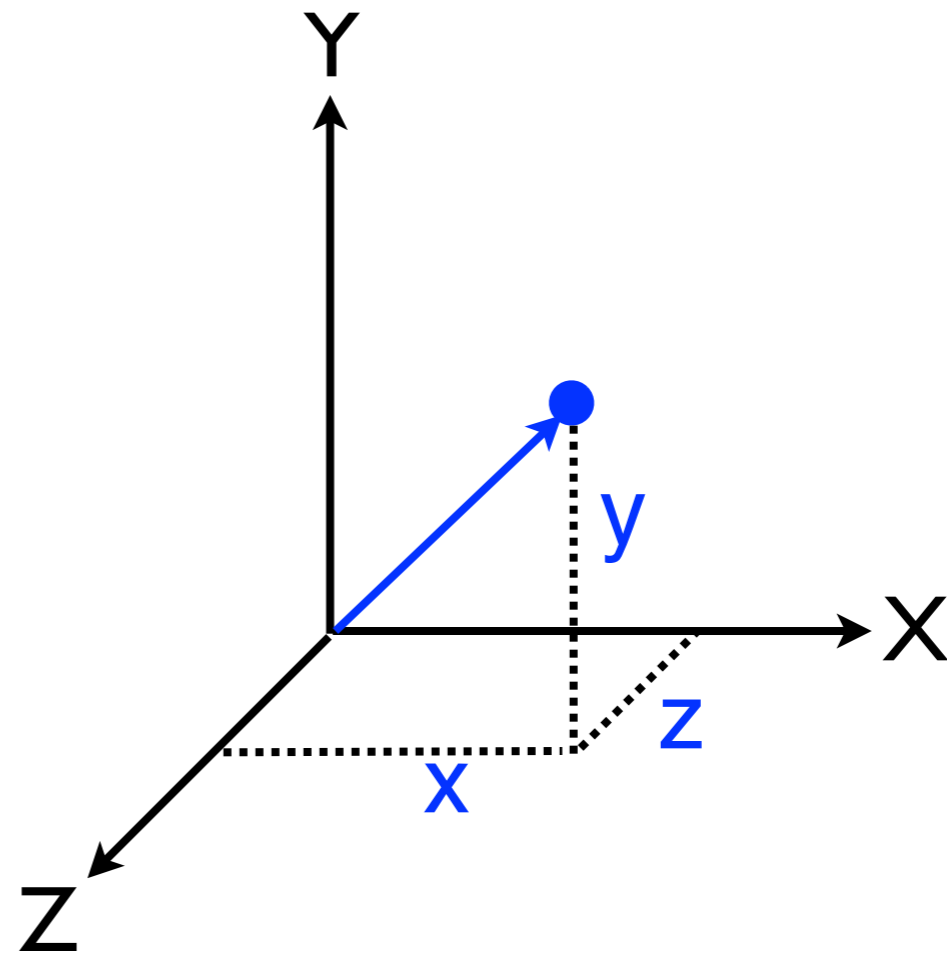
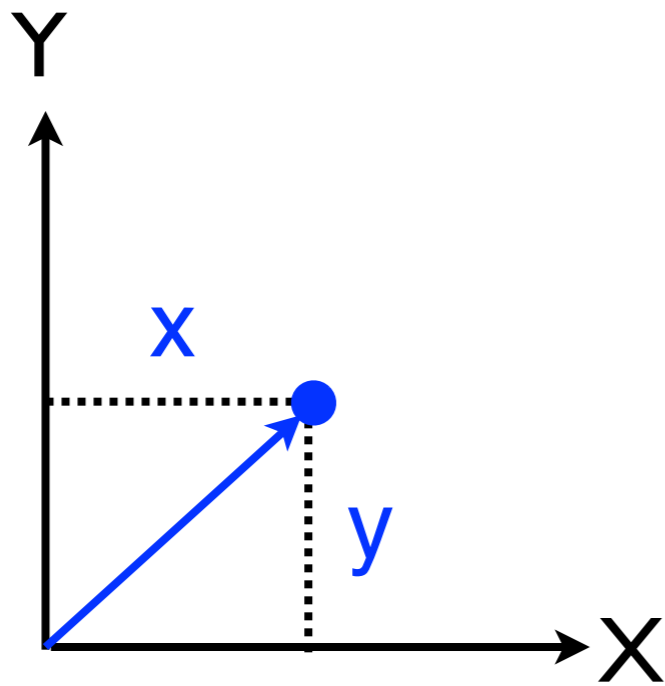
- A **vector** is a point in a vector space



Vector Space Representation

review

- A 2-dimensional vector can be written as $[x,y]$
- A 3-dimensional vector can be written as $[x,y,z]$



Vector Space Representation

review

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10
1	0	1	0	1	0	0	1	1	0
0	1	0	1	1	0	1	1	0	0
0	1	0	1	1	0	1	0	0	0
0	0	1	0	1	1	0	1	1	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1

Vector Space Representation

review

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10
1	0	1	0	1	0	0	1	1	0
0	1	0	1	1	0	1	1	0	0
0	1	0	1	1	0	1	0	0	0
0	0	1	0	1	1	0	1	1	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1

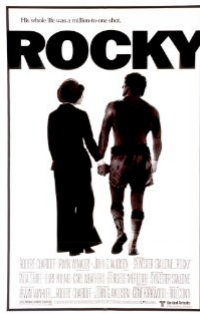
- We can represent this document as a vector in a 10-dimensional vector space

Vector Space Representation

review

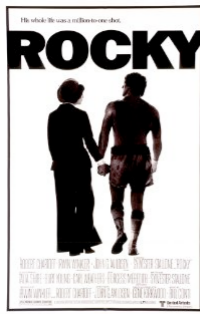
w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10
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0	1	0	1	1	0	1	0	0	0
0	0	1	0	1	1	0	1	1	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1

- This representation assumes binary term-weights.
- Are there other term-weighting schemes?



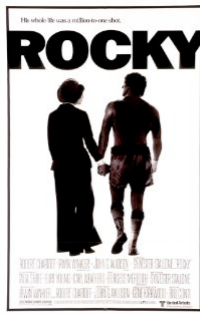
TF, IDF, or TF.IDF?

adrian adrian all already also an and apartment apollo as aspiring at
balboa become better big boxer boxing but by can career champion
chance creed current debt doesn't earns every exhibition extra far fight for gazzo gets girl
go has he heavyweight her himself his in is it keep later life living loan lovers
make man match meat men mickey named nobody of paulie pet philadelphia
rocky set she shot small somebody someone still store struggling supplies surprised
that the they think this through time title to trainer training up want when where
who willing with woman won works



TF, IDF, or TF.IDF?

ability **adrain** adrian already apollo aspiring **balboa**
beat **befriended** befriends better boxer **boxes** boxing
canvas cash champion checks chooses **collecting**
collector **creed** current **deadbeats** debt debts
distance **doesn** downtown earns ease easily
exhibition explains extra extremely factory far **forgot**
gazzo gear giving gotten **heavyweight** idea interested
italian **jergens** keep living loan lot lovers **managers** match meat
mickey nobody odds **packing** paulie pennsylvania pet
philadelphia **pittance** promoter prove **publicity**
ready rocky sells shark sharp shop shy skills **somebody** spends
stallion struggling **stunt** supplies supposed surprised
thanksgiving think **thrilled** title **touting** trainer training
triumph unknown **ve** **viciousness** visits want willing win
won



TF, IDF, or TF.IDF?

ability adrain **adrian** already apartment **apollo** aspiring **balboa** become
befriended befriends big **boxer** boxes **boxing** canvas champion chance checks
chooses collecting collector **creed** current deadbeats debt debts distance doesn't downtown
earns ease easily exhibition extra extremely factory fight forgot **gazzo** gear gotten
heavyweight his is jergens later loan lot lovers managers match meat mickey named
nobody odds packing paulie pennsylvania **pet philadelphia** pittance promoter
publicity ready **rocky** sells set shark sharp shot shy somebody someone stallion store
struggling stunt supplies supposed surprised thanksgiving think thrilled time title **touting** trainer training
triumph up ve **viciousness** visits where who willing won works

Vector Space Representation

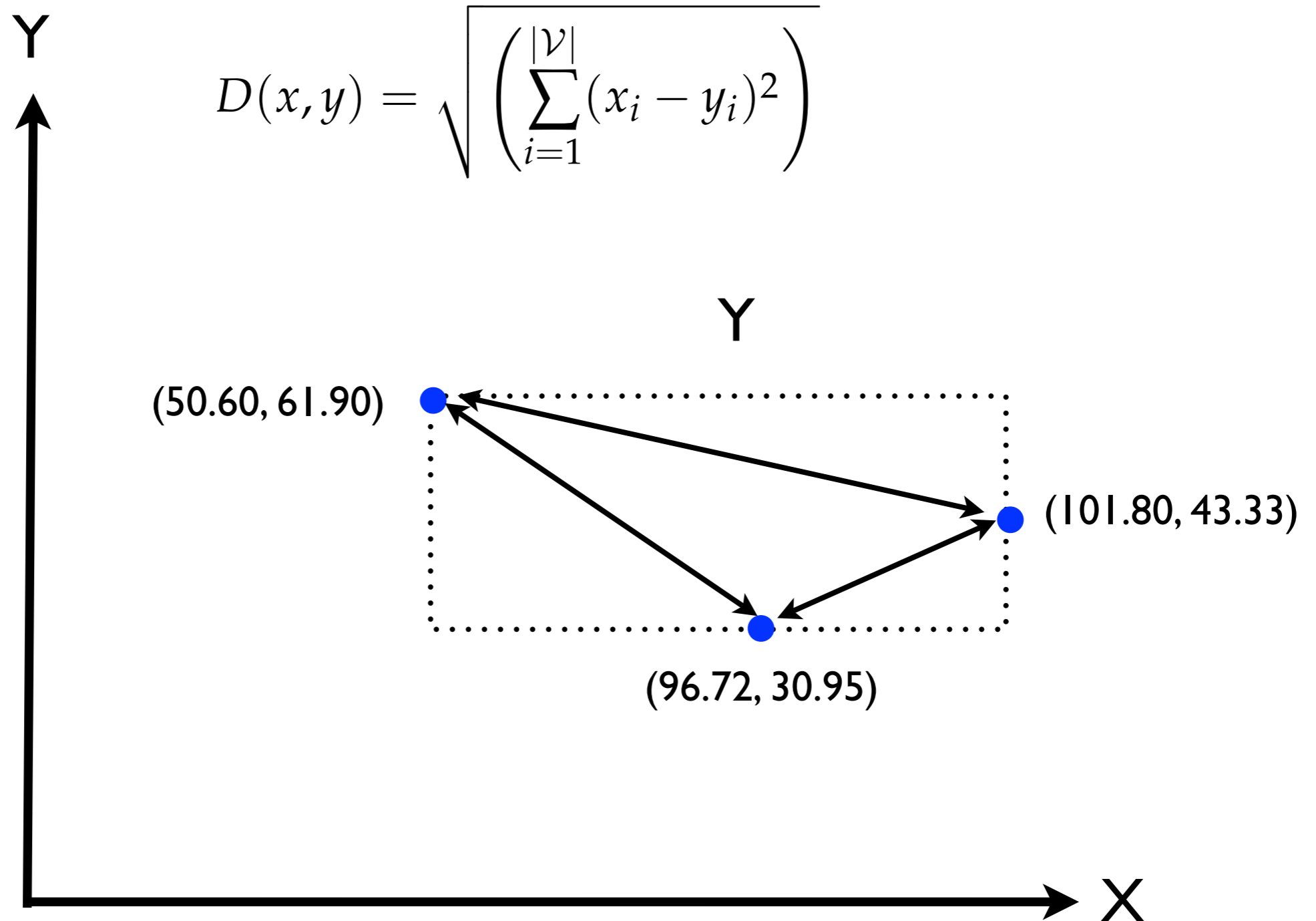
review

- Similarity = Euclidean Distance:

$$D(x, y) = \sqrt{\left(\sum_{i=1}^{|\mathcal{V}|} (x_i - y_i)^2 \right)}$$

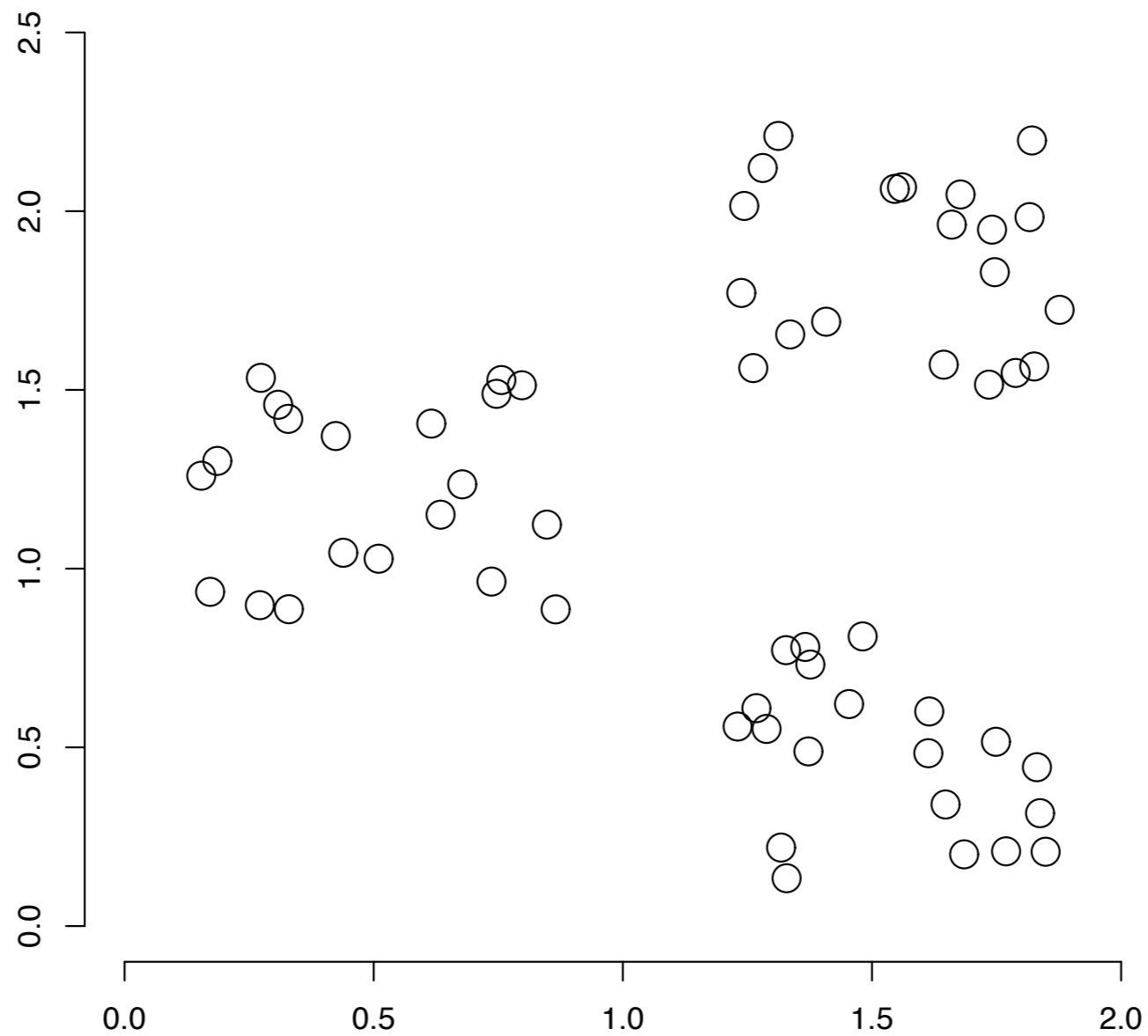
Vector Space Representation

review



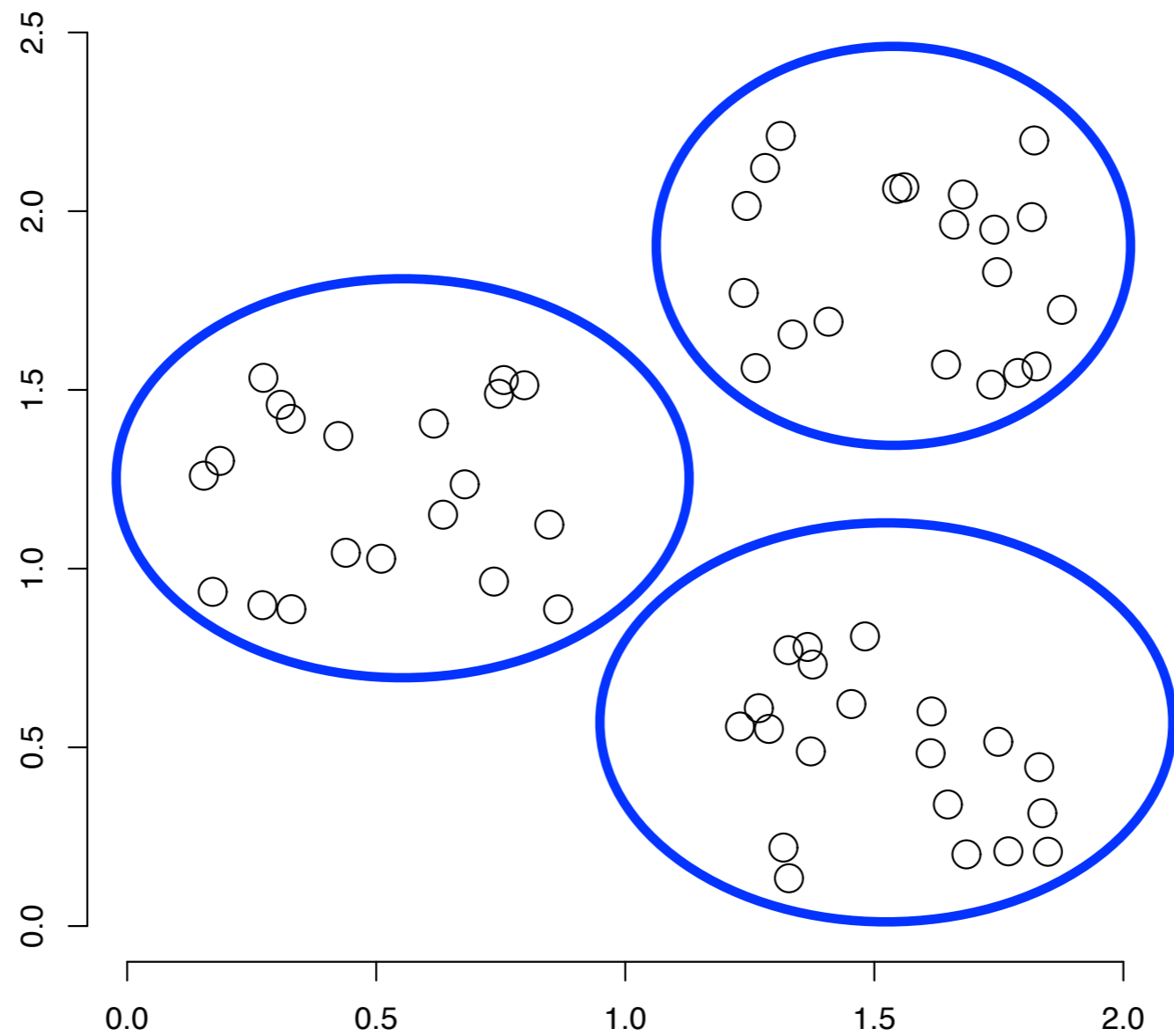
Clustering

- What would we expect a clustering algorithm to do with this dataset?



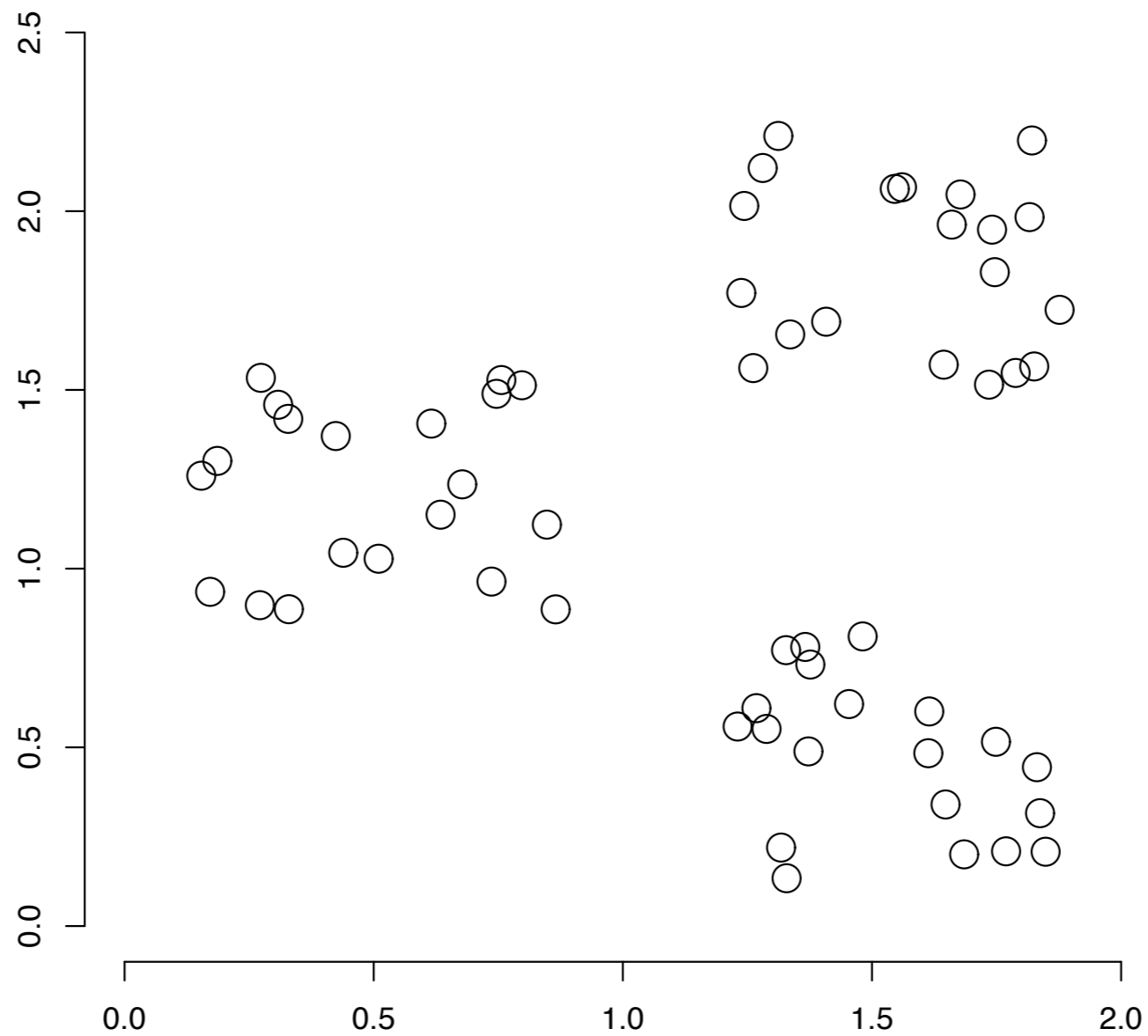
Clustering

- What would we expect a clustering algorithm to do with this dataset?



Clustering

- Propose an algorithm that might be able to do this!

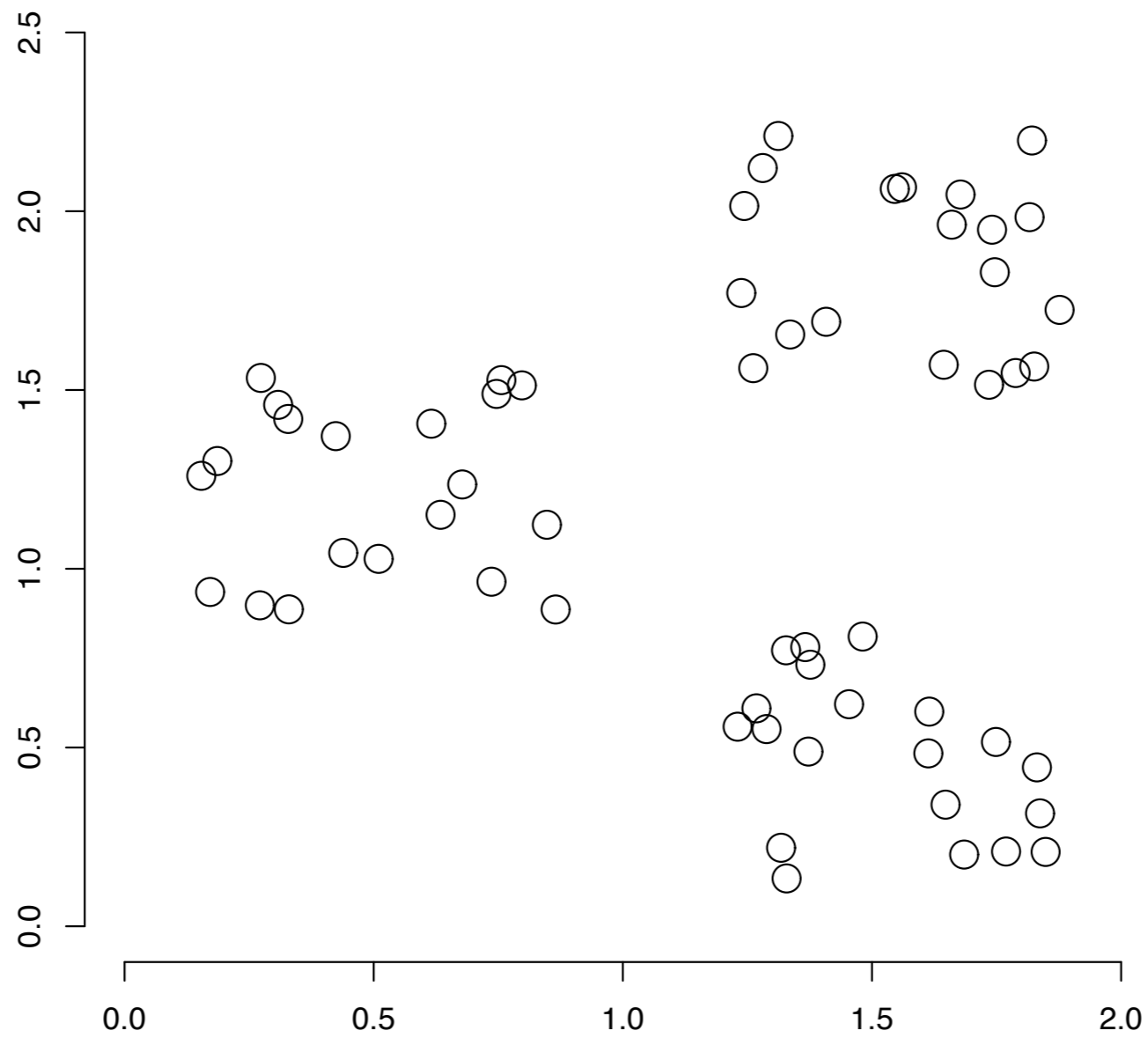


Clustering

- **Input:** number of desired clusters K
- **Output:** assignment of documents to K clusters
- **Algorithm:**
 - ▶ randomly select K documents (seeds)
 - ▶ assign each remaining document to its nearest seed

Clustering

- Could this work?

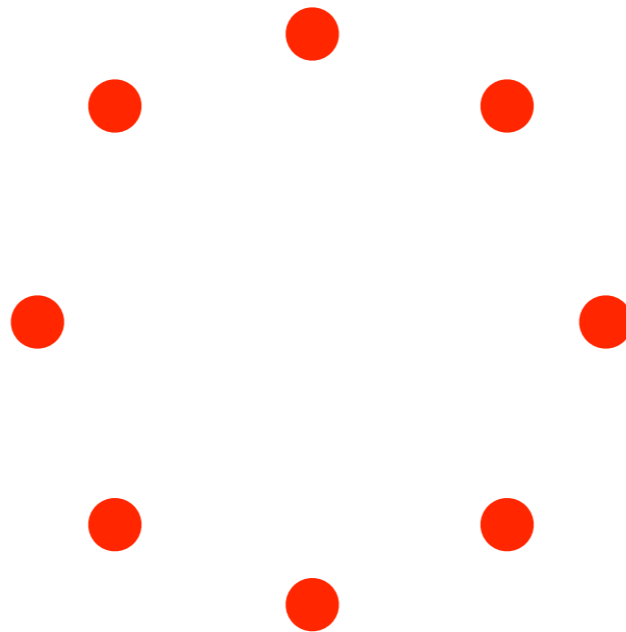


K-Means Clustering

K-means Clustering

cluster centroid

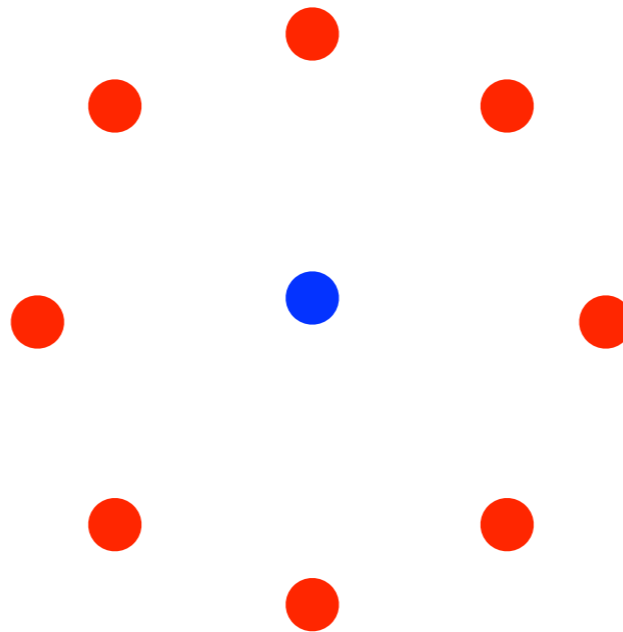
- The key to understanding K-means clustering is to understand the concept of a **cluster centroid**
- Given a cluster, you can think of its centroid as a point (or vector) that corresponds to its “center of mass”



K-means Clustering

cluster centroid

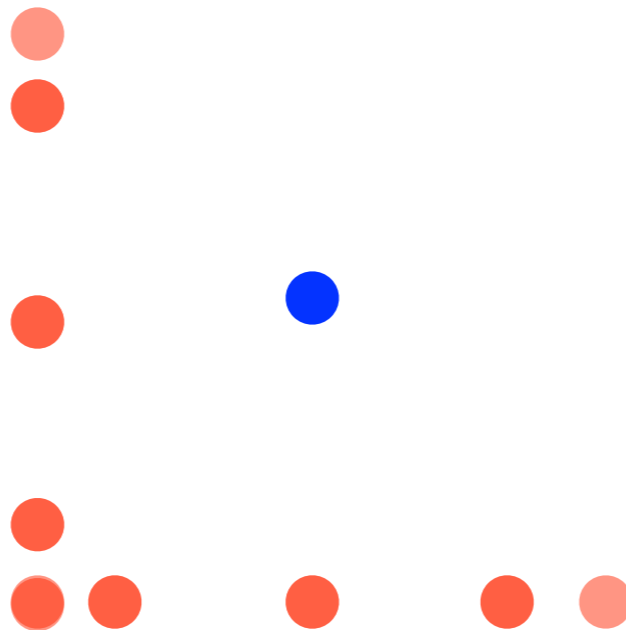
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K-means Clustering

cluster centroid

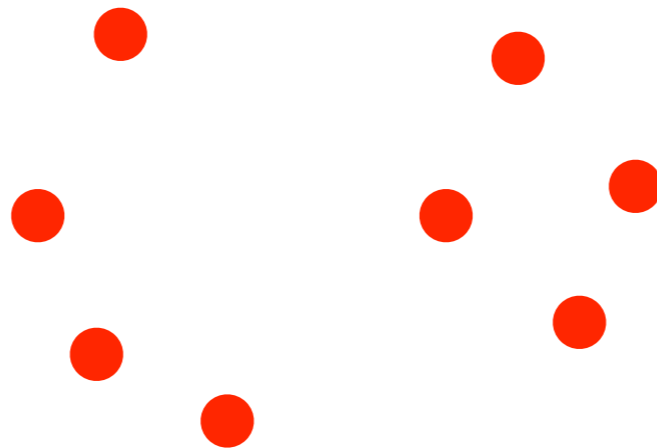
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K-means Clustering

cluster centroid

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K-means Clustering

cluster centroid

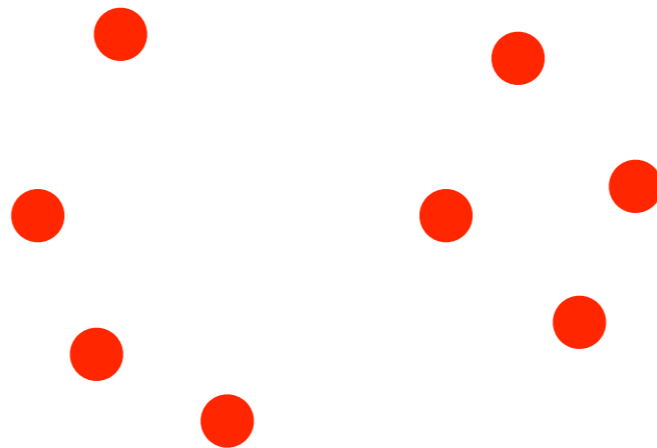
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K-means Clustering

cluster centroid

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K-means Clustering

cluster centroid

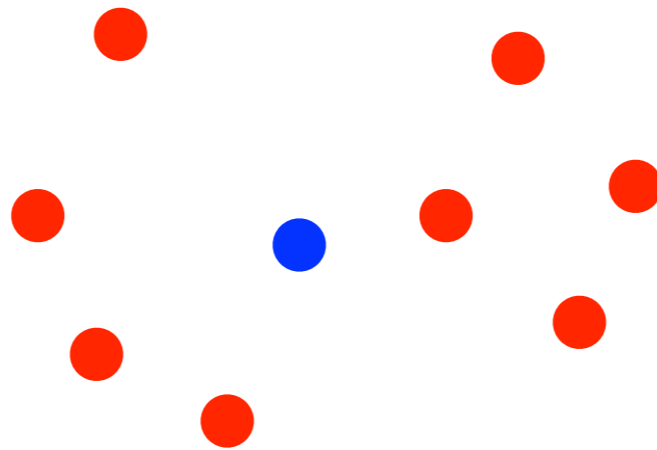
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K-means Clustering

cluster centroid

- The key to understanding K-means clustering is to understand the concept of a **cluster centroid**
- Given a cluster, you can think of its centroid as a point (or vector) that corresponds to its “center of mass”



K-means Clustering

cluster centroid

docs
assigned
to cluster
1

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10
1	0	1	0	1	0	0	1	1	0
0	1	0	1	1	0	1	1	0	0
0	1	0	1	1	0	1	0	0	0
0	0	1	0	1	1	0	1	1	1
0	0	1	0	1	1	0	1	1	1
1	1	0	1	1	0	0	1	0	1

cluster 1
centroid

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10
?	?	?	?	?	?	?	?	?	?

K-means Clustering

cluster centroid

docs
assigned
to cluster
1

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10
1	0	1	0	1	0	0	1	1	0
0	1	0	1	1	0	1	1	0	0
0	1	0	1	1	0	1	0	0	0
0	0	1	0	1	1	0	1	1	1
0	0	1	0	1	1	0	1	1	1
1	1	0	1	1	0	0	1	0	1

cluster 1
centroid
(average!)

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10
0.33	0.5	0.5	0.5	1	0.33	0.33	0.83	0.5	0.5

K-means Clustering

cluster centroid

- For each dimension i , set:

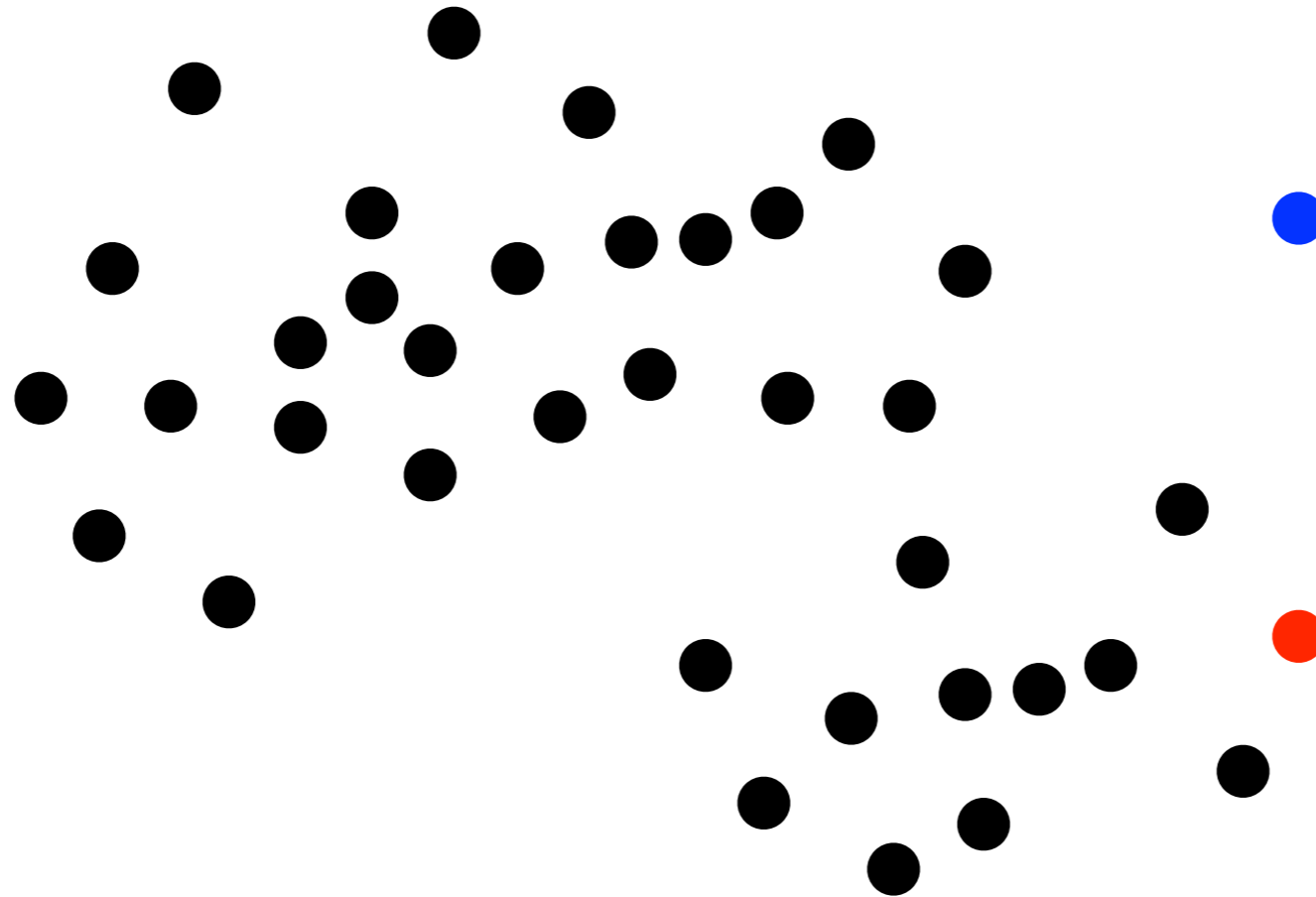
$$c_i = \frac{1}{|C|} \sum_{d \in C} d_i$$

K-means Clustering

- **Input:** number of desired clusters K
- **Output:** assignment of documents to K clusters
- **Algorithm:**
 - ▶ **Step 1:** randomly select K documents (seeds)
 - ▶ **Step 2:** assign each document to its nearest seed
 - ▶ **Step 3:** compute all K cluster centroids
 - ▶ **Step 4:** re-assign each document to its nearest centroid
 - ▶ **Step 5:** re-compute all K cluster centroids
 - ▶ **Step 6:** repeat steps 4 and 5 until terminating condition

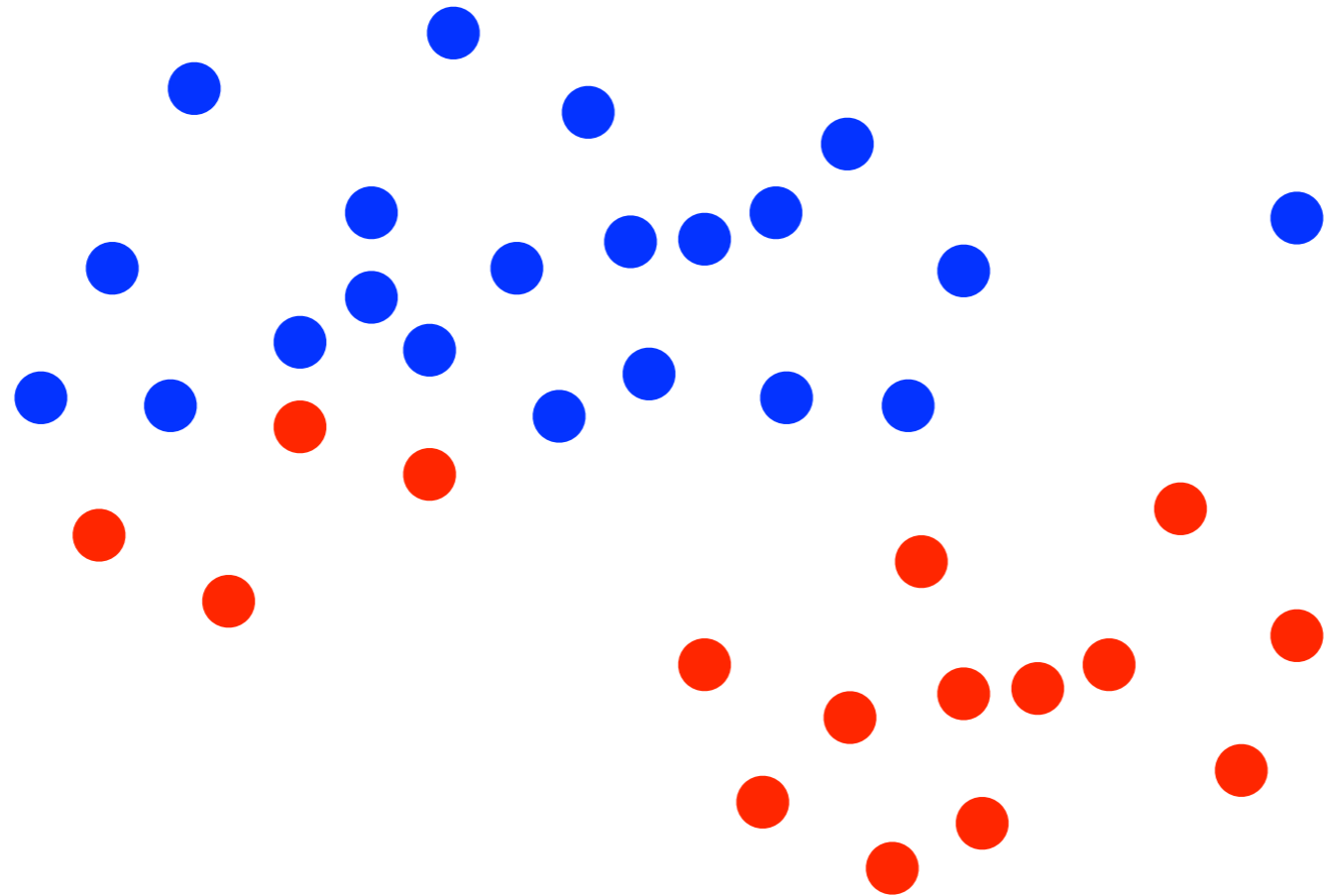
K-means Clustering

- Step 1: randomly select K documents (seeds)



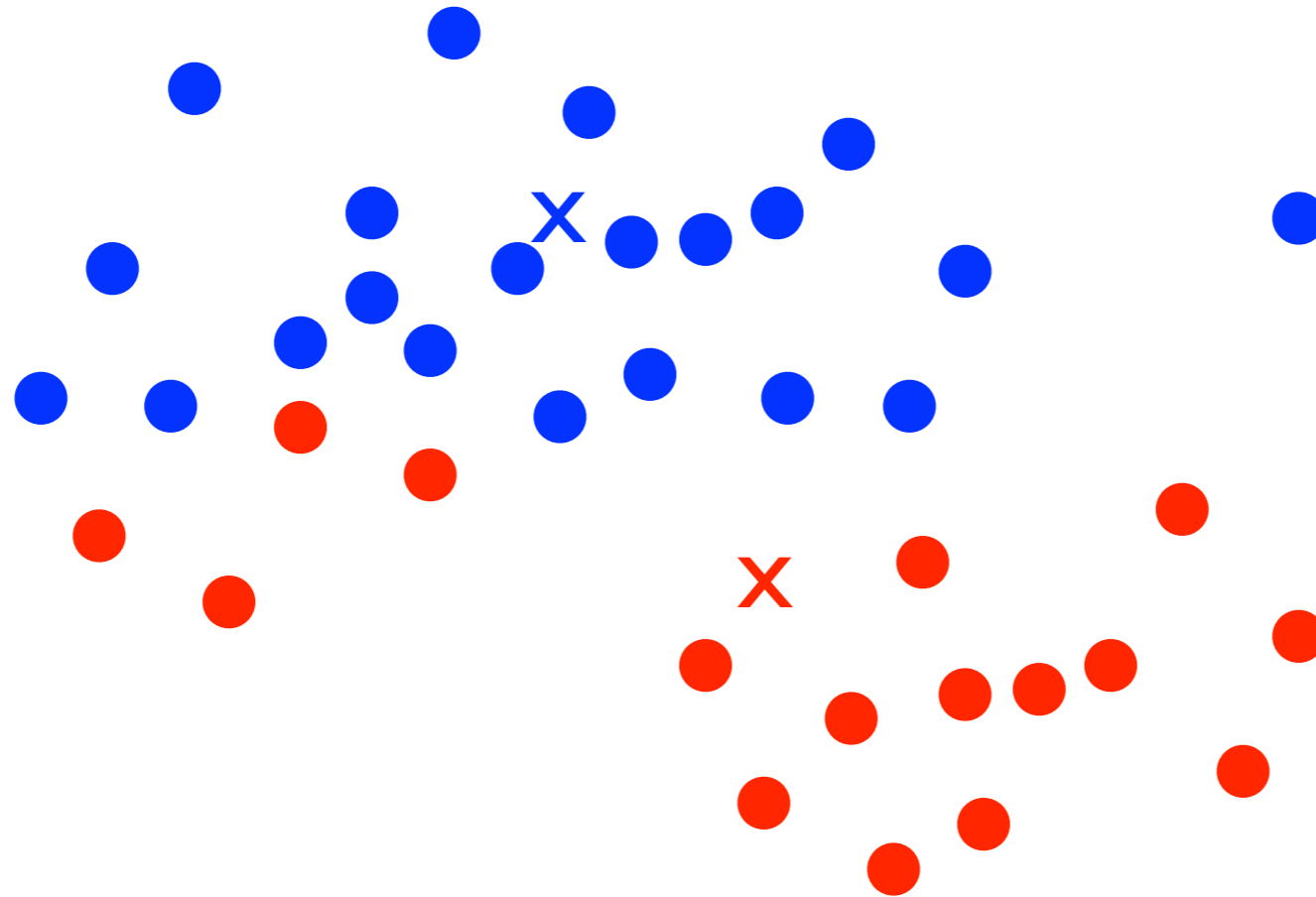
K-means Clustering

- **Step 2:** assign each document to its nearest seed



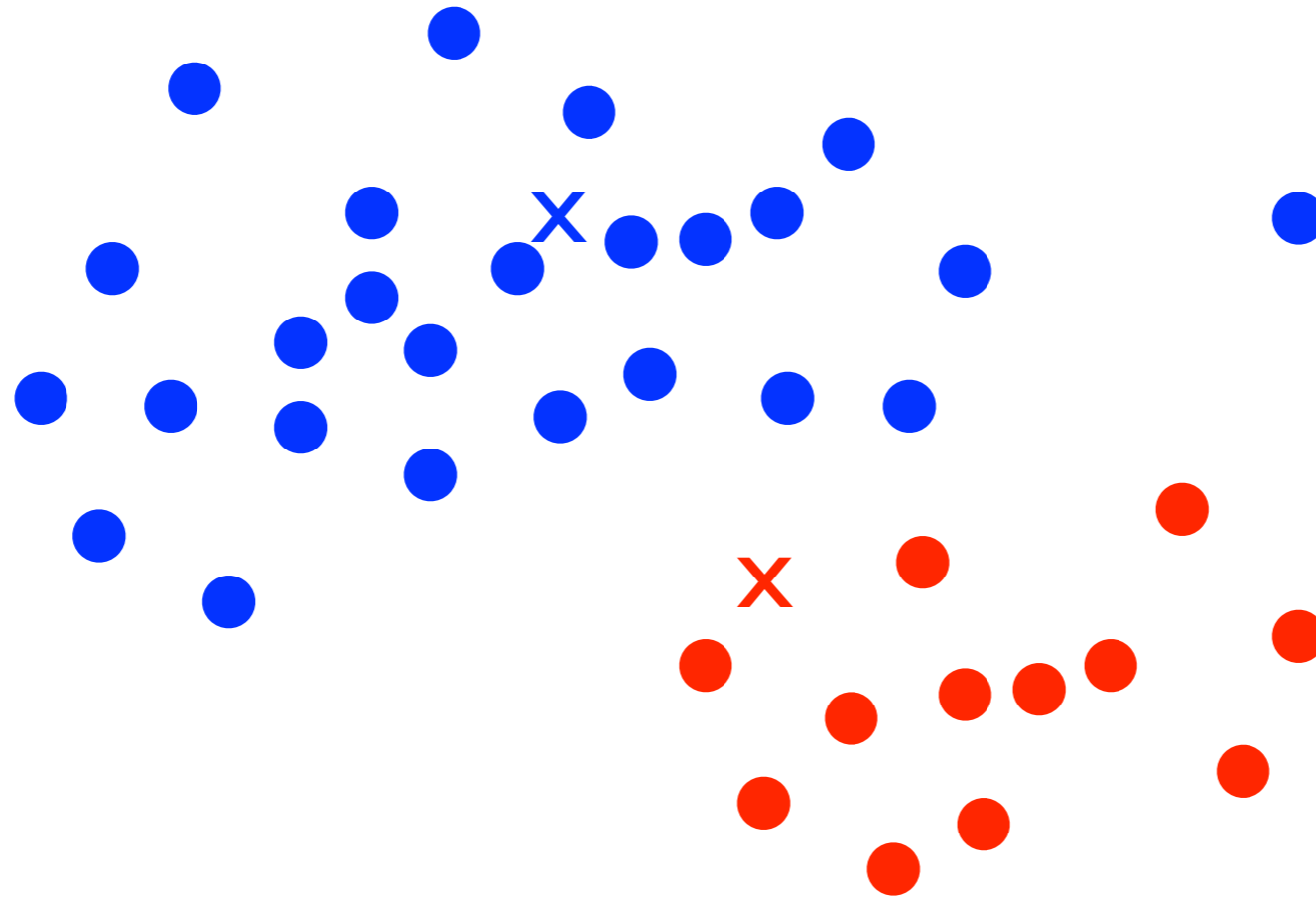
K-means Clustering

- Step 3: compute all K cluster centroids



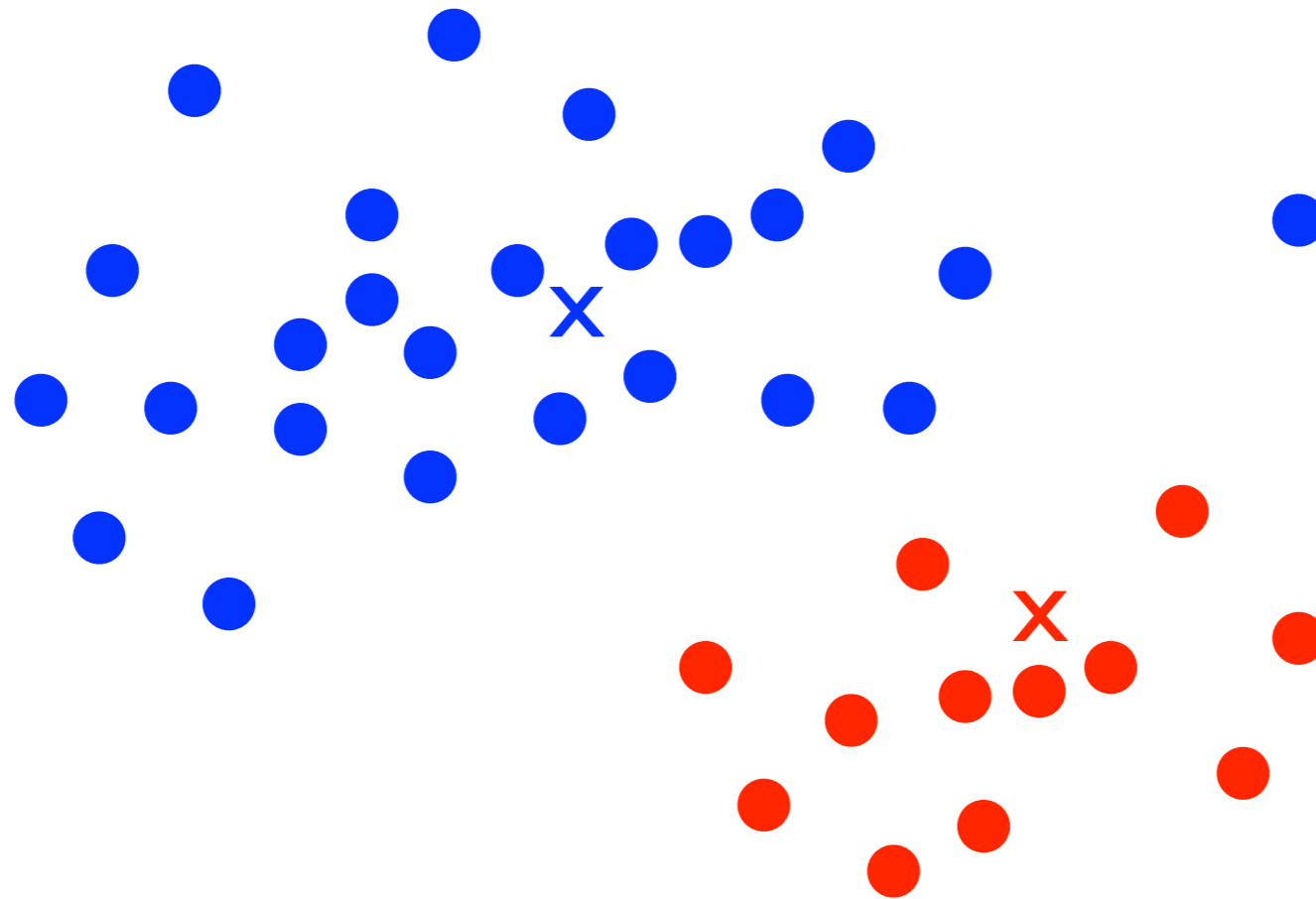
K-means Clustering

- **Step 4:** re-assign each document to its nearest centroid



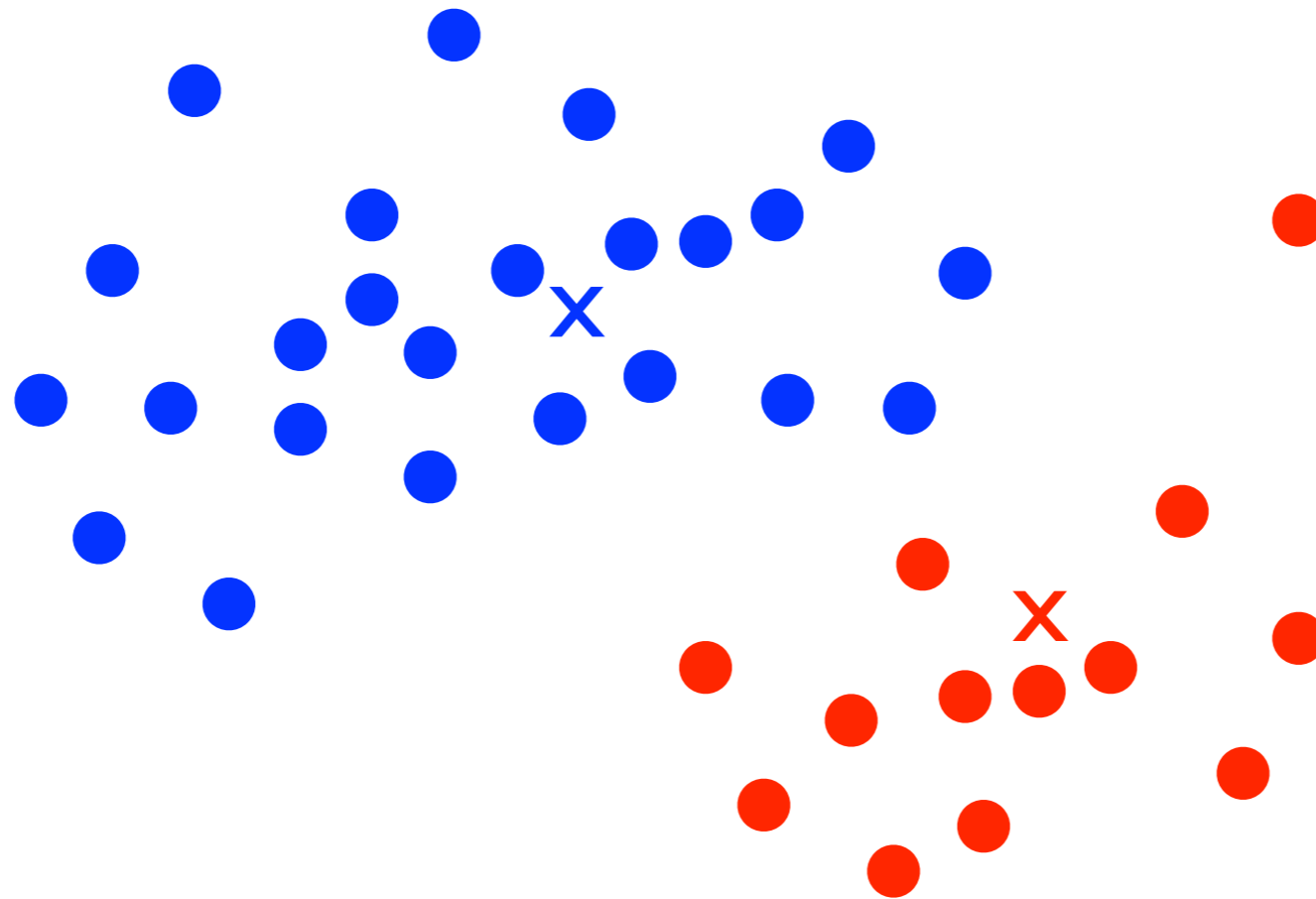
K-means Clustering

- Step 4: re-compute all K cluster centroids



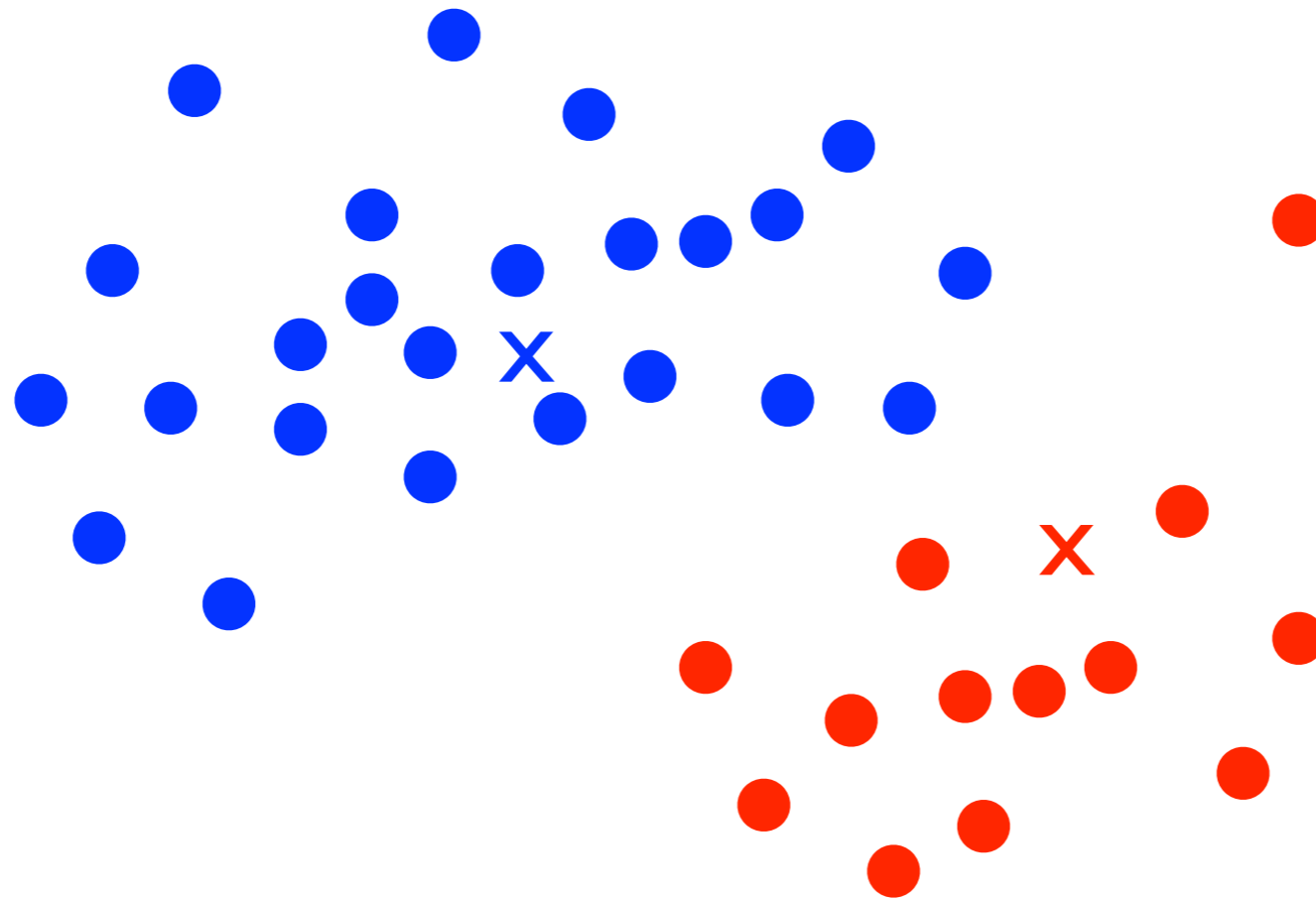
K-means Clustering

- Step 5: re-assign each document to its nearest centroid



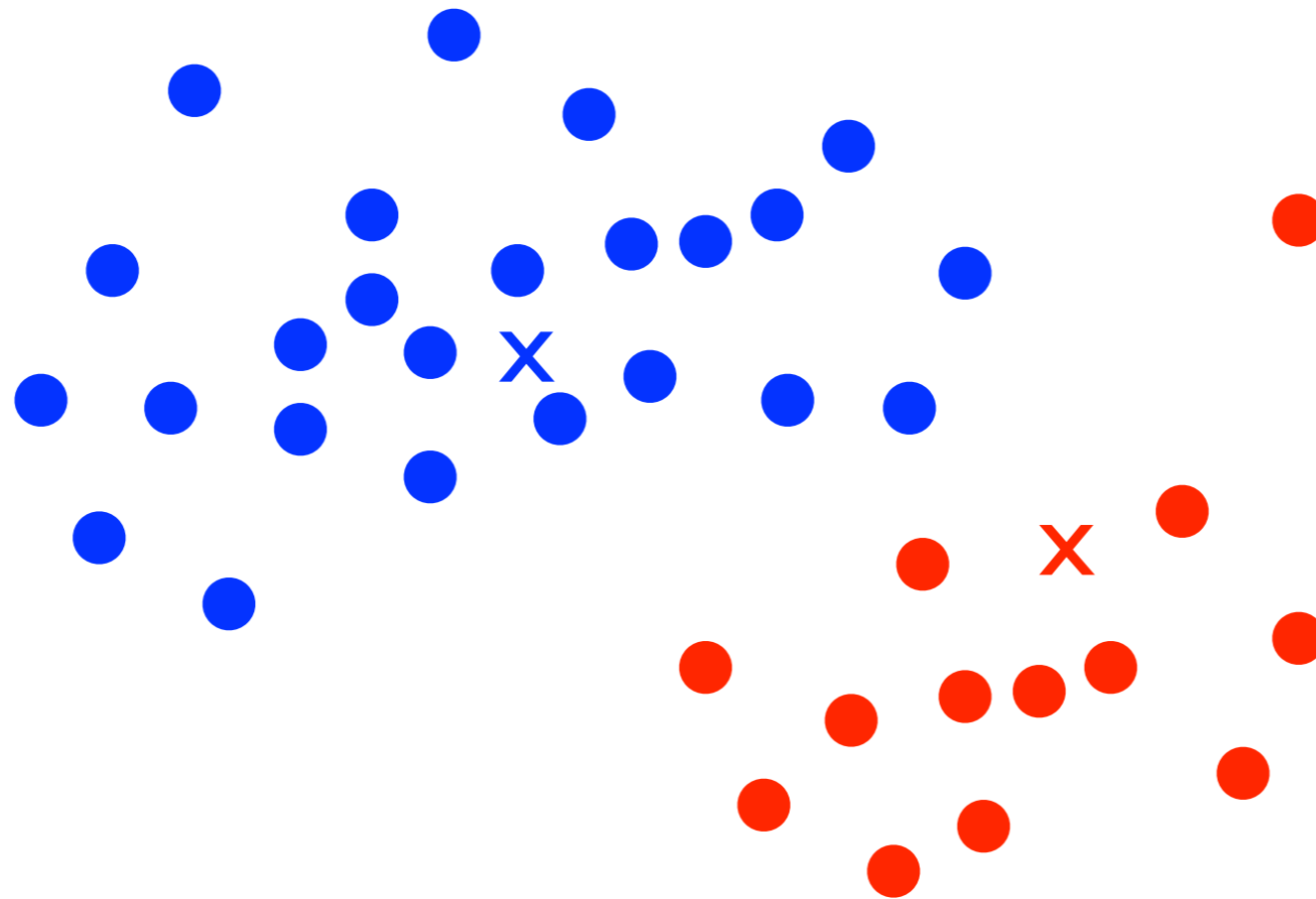
K-means Clustering

- Step 4: re-compute all K cluster centroids



K-means Clustering

- **Step 5:** re-assign each document to its nearest centroid



K-means Clustering

- **Input:** number of desired clusters K
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 - ▶ **Step 6:** repeat steps 4 and 5 until terminating condition

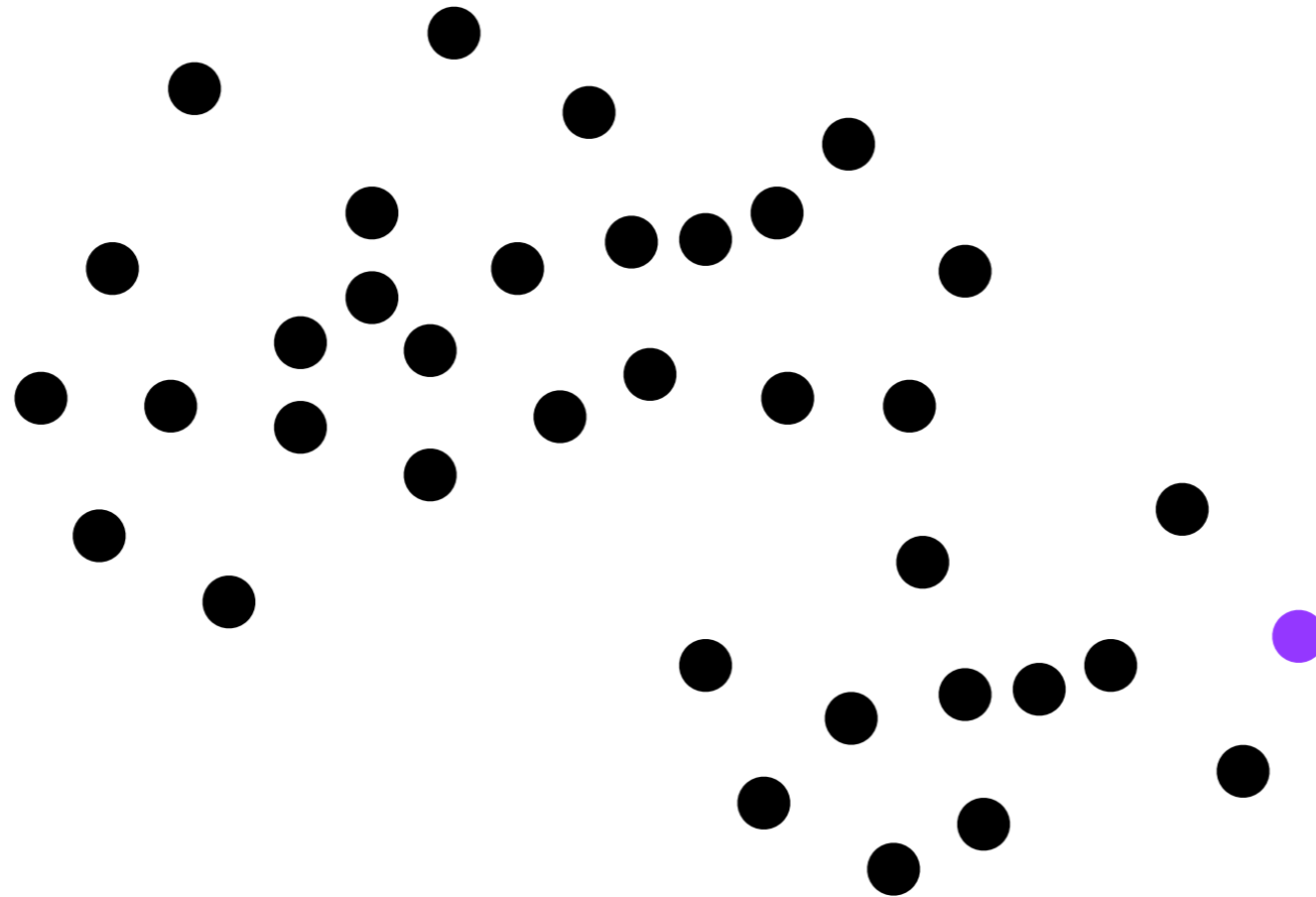
K-means Clustering

potential drawback

- The quality of the output clustering depends on the choice of **K** and on the **initial seeds**
- In many cases, the choice of **K** is pre-determined by the application
 - ▶ **Search engine results clustering:** grouping search engine results by topic
 - ▶ **Collection clustering:** grouping documents by topic to support navigation and exploration
- Later we'll see ways of setting **K** dynamically

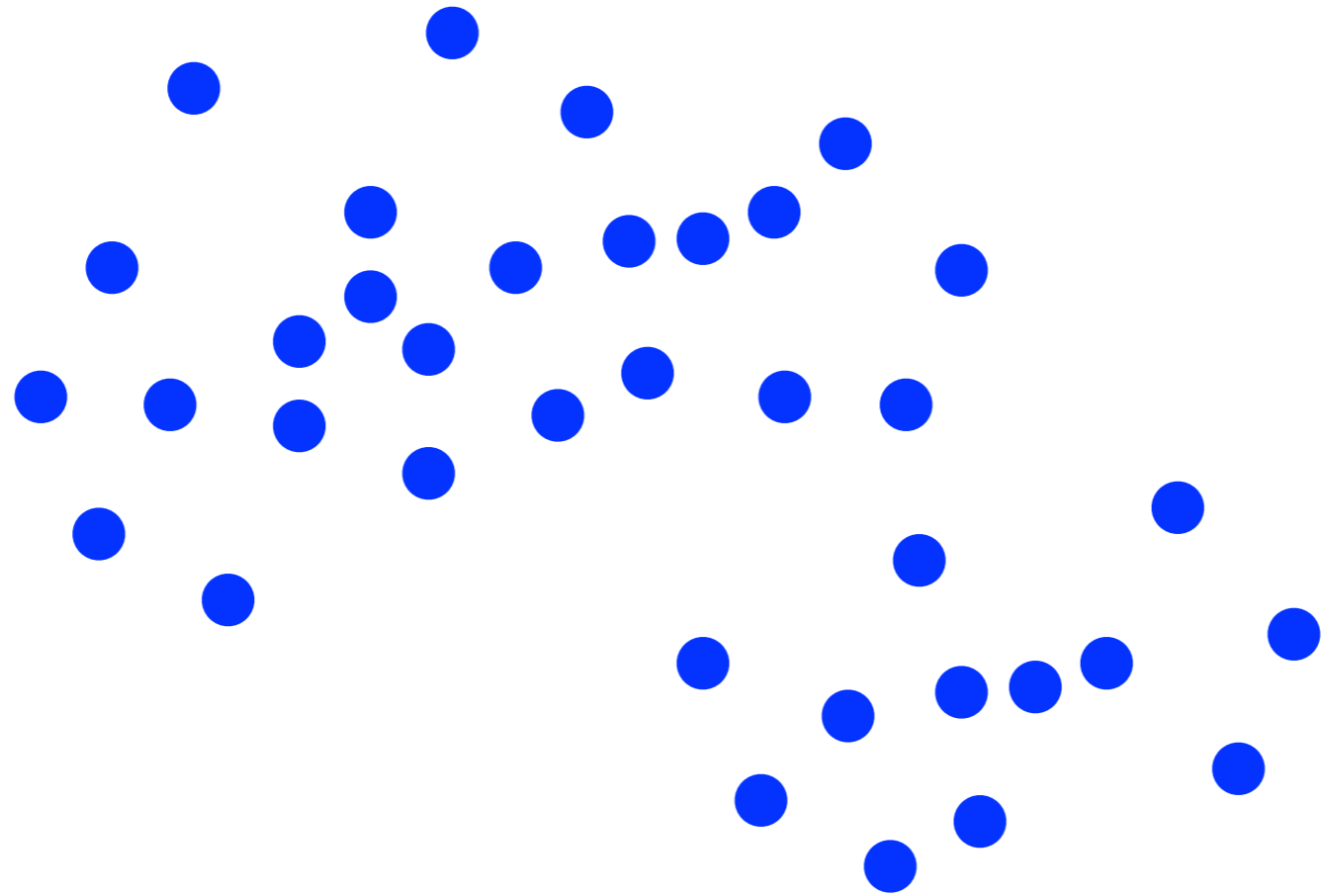
K-means Clustering

bad seeds?



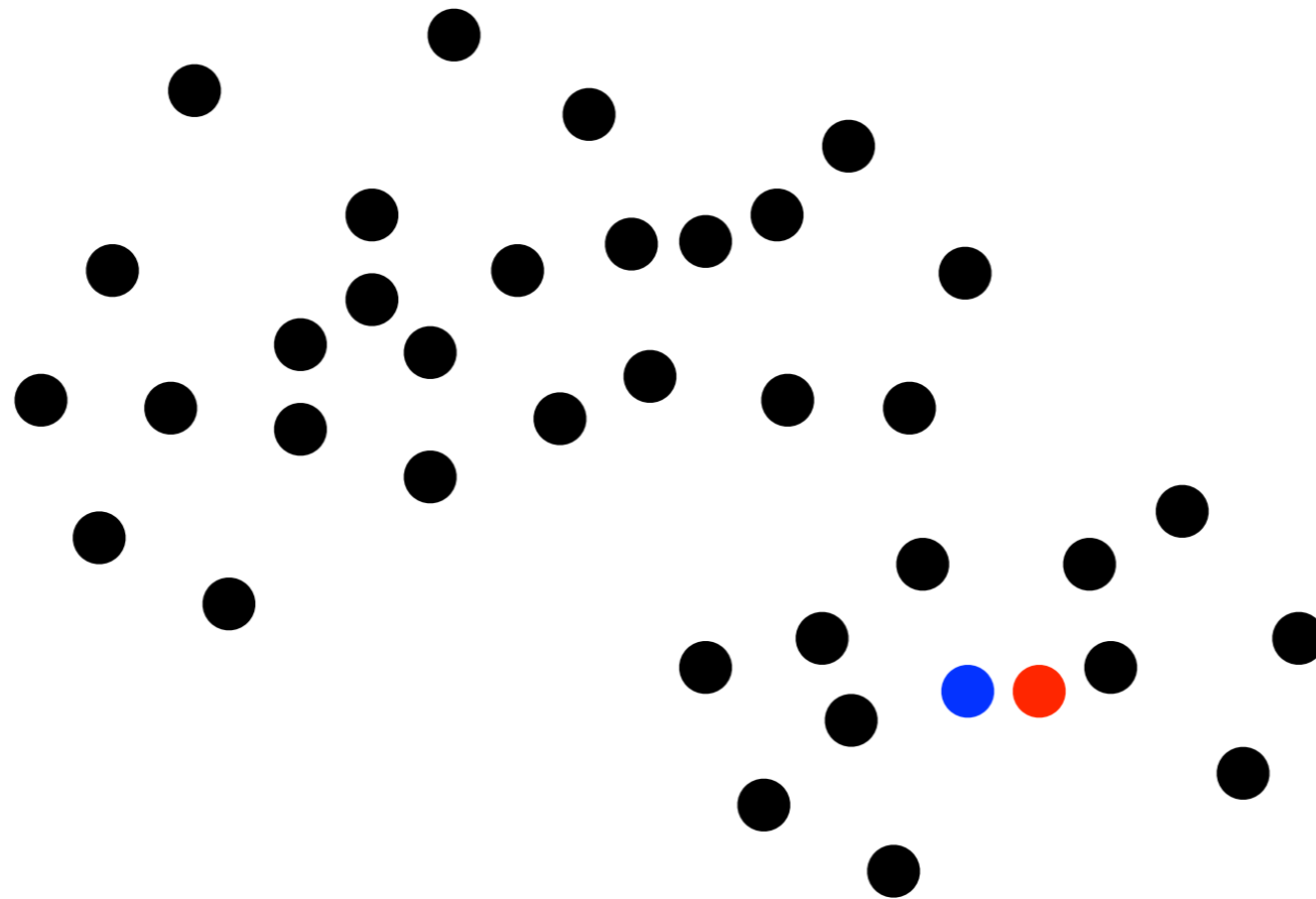
K-means Clustering

bad seeds?



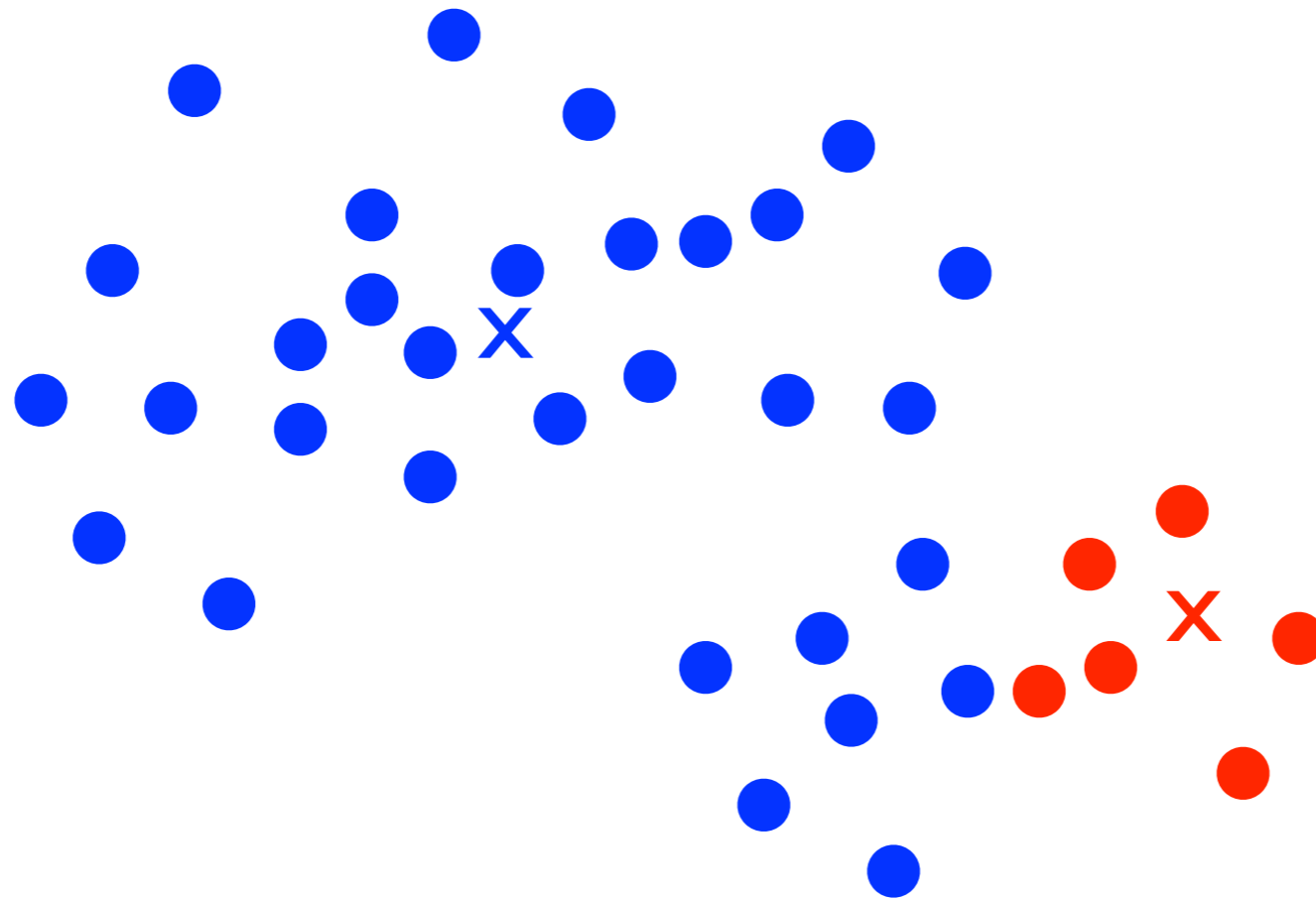
K-means Clustering

bad seeds?



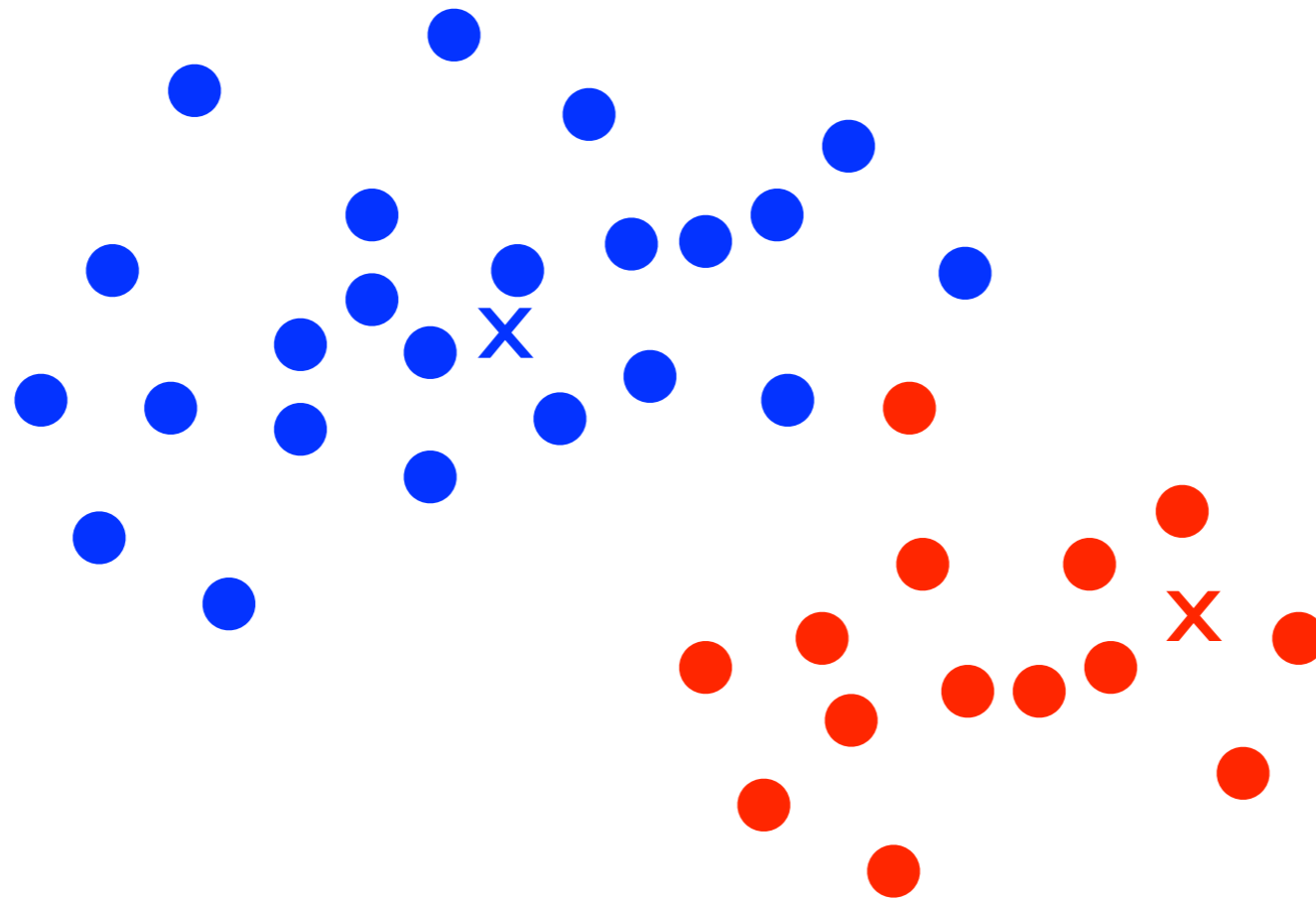
K-means Clustering

bad seeds?



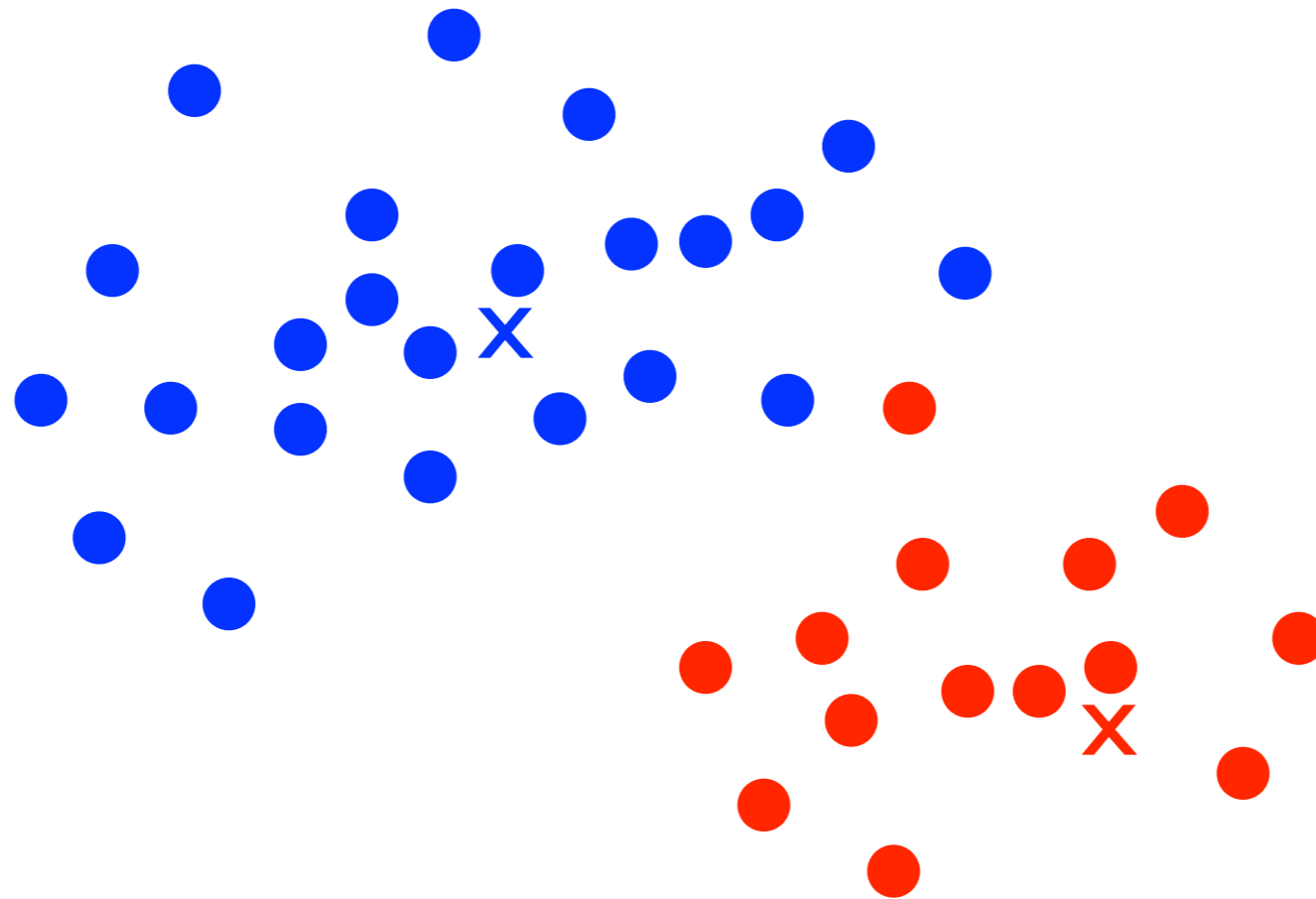
K-means Clustering

bad seeds?



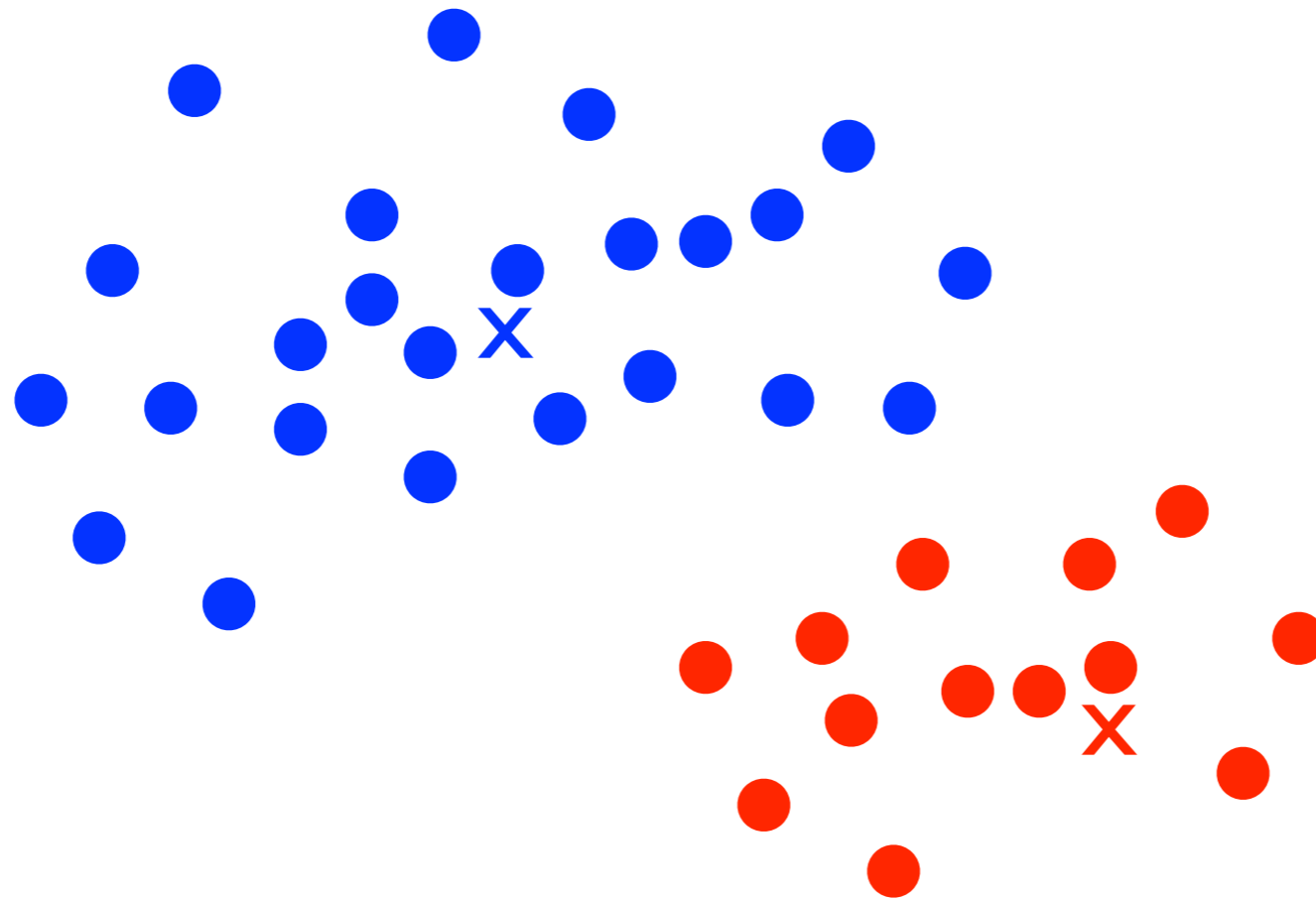
K-means Clustering

bad seeds?



K-means Clustering

bad seeds?



K-means Clustering

bad seeds

- It's difficult to know which seeds will yield a high-quality clustering
- However, it's usually a good idea to avoid seeds that are outliers
- How would you detect outliers?

K-means Clustering

clustering evaluation

- What does it mean for a clustering to be high quality anyway?
- What is the goal of clustering again?

K-means Clustering

internal evaluation

- In theory, a good clustering should have:
 - ▶ Similar documents in the same clusters
 - ▶ Different documents in different clusters

K-means Clustering

internal evaluation

$$\text{Clustering Quality} = \left(\begin{array}{c} \text{Average} \\ \text{distance} \\ \text{between all pairs} \\ \text{of documents in} \\ \text{different clusters} \end{array} \right) - \left(\begin{array}{c} \text{Average distance} \\ \text{between all pairs} \\ \text{of documents in} \\ \text{the} \\ \text{same cluster} \end{array} \right)$$

K-means Clustering

improved k-means

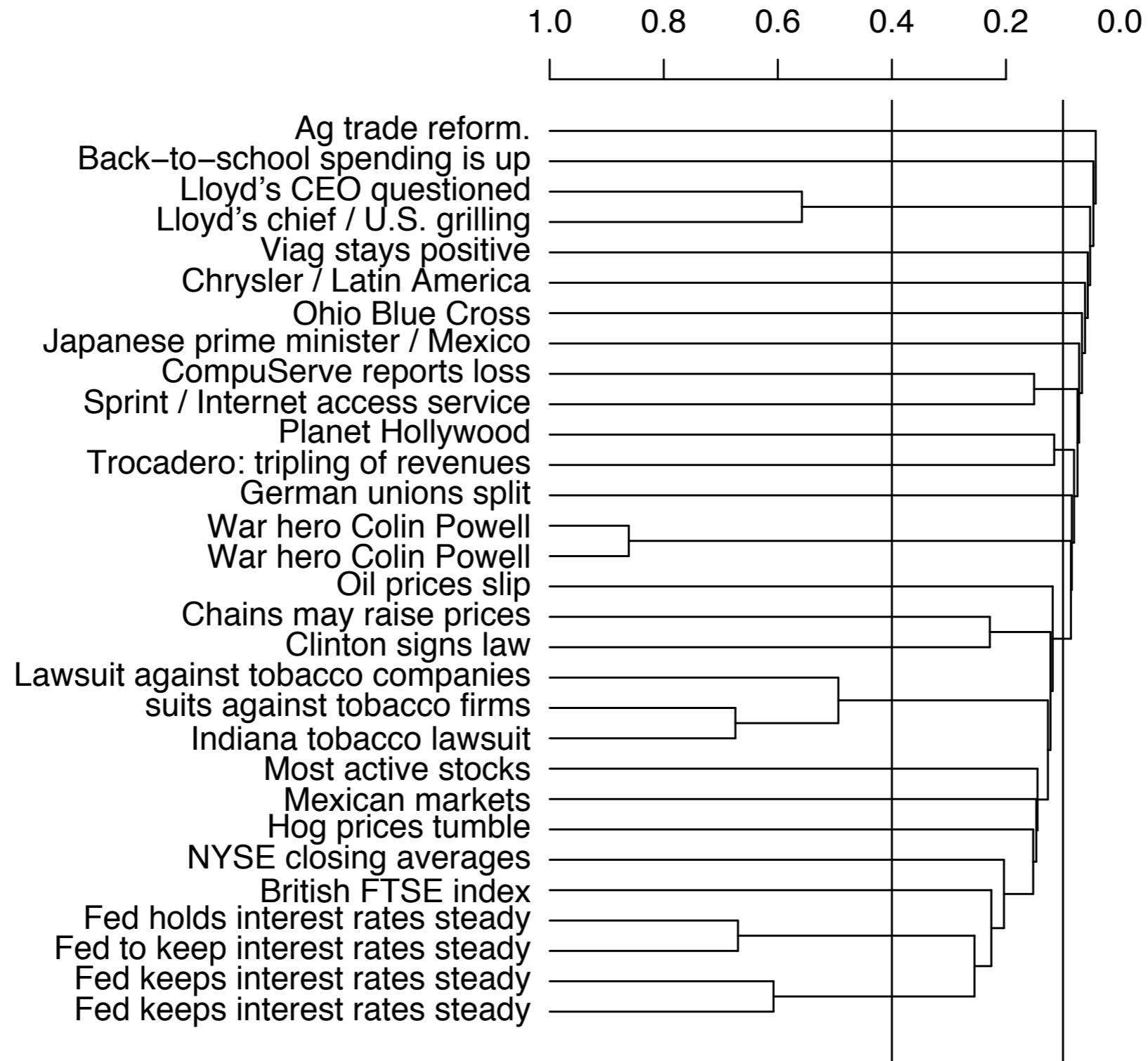
- Given a set of documents and a value K , run K-means clustering N times and keep the clustering that produces the greatest difference between the inter-cluster distance and the intra-cluster distance

Bottom-up Agglomerative Clustering

Bottom-up Clustering

- While K-means requires setting K , bottom-up clustering groups the data in a hierarchical fashion
- We can then set K after the clustering is done or use a distance threshold to set K dynamically (more on this later)

Bottom-up Clustering



Bottom-up Clustering

- Input: data
- Output: cluster hierarchy
- Algorithm:
 - ▶ Step 1: consider every document its own cluster
 - ▶ Step 2: compute the distance between all cluster pairs
 - ▶ Step 3: merge/combine the nearest two clusters into one
 - ▶ Step 4: repeat steps 2 and 3 until every document is in one cluster

Bottom-up Clustering

- Input: data
- Output: cluster hierarchy
- Algorithm:
 - ▶ Step 1: consider every document its own cluster
 - ▶ Step 2: compute the distance between all cluster pairs
 - ▶ Step 3: merge/combine the nearest two clusters into one
 - ▶ Step 4: repeat steps 2 and 3 until every document is in one cluster

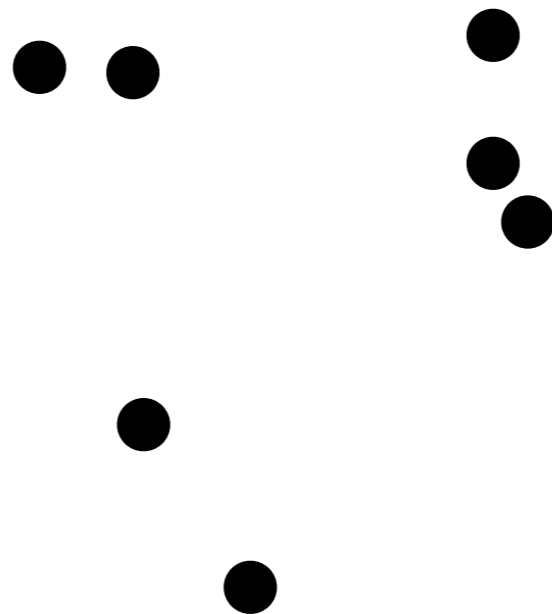
Bottom-up Clustering

- Computing the distance between two clusters
- **Single-Link**: the distance between the two nearest documents
- **Complete-Link**: the distance between the two documents that are farthest apart
- **Average-Link**: the average distance between all document pairs in the two different clusters
 - ▶ this is equivalent to using the distance between the two cluster centroids

Bottom-up Clustering

single-link

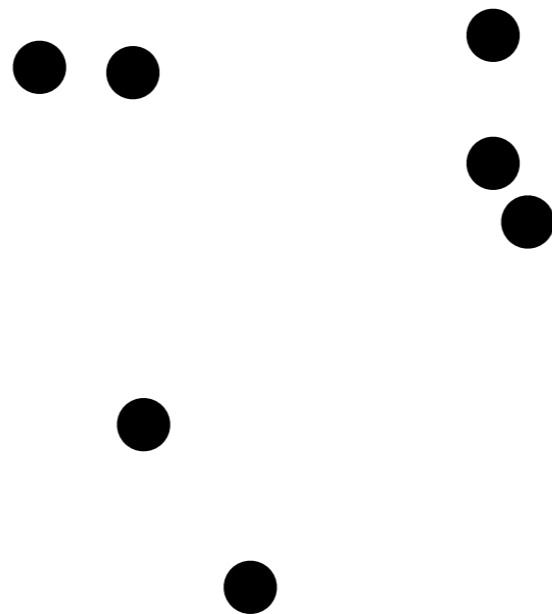
- Step 1: consider each document its own cluster



Bottom-up Clustering

single-link

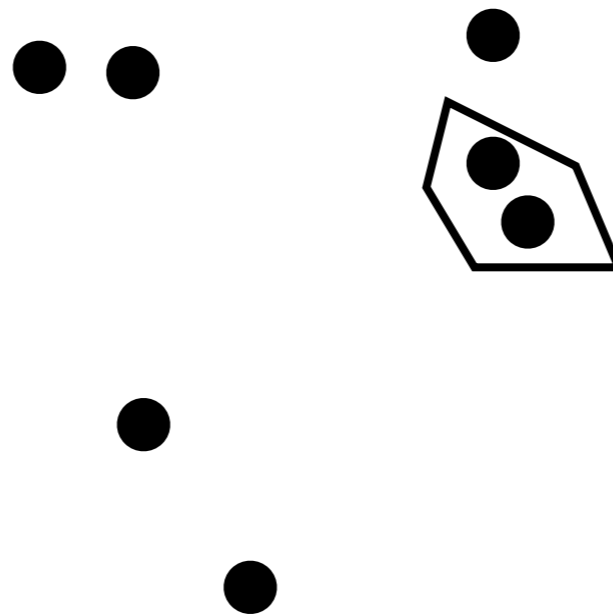
- **Step 2:** compute the distance between all cluster pairs
- **Step 3:** merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

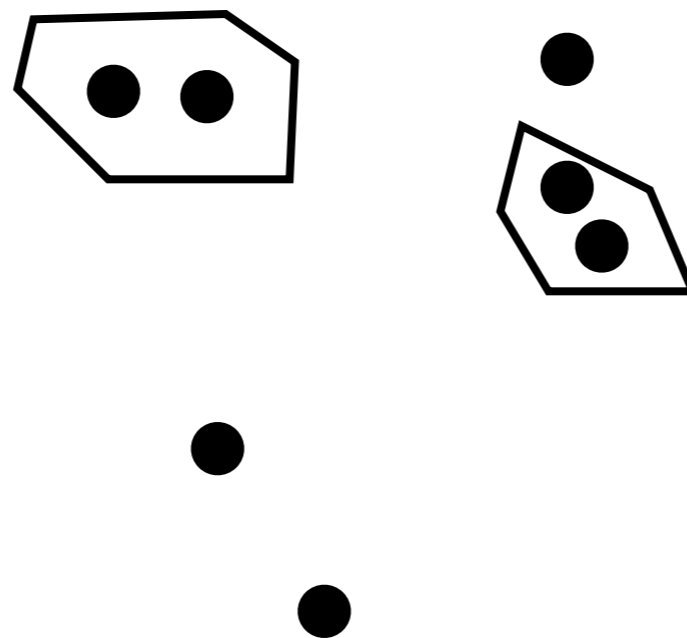
- **Step 2:** compute the distance between all cluster pairs
- **Step 3:** merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

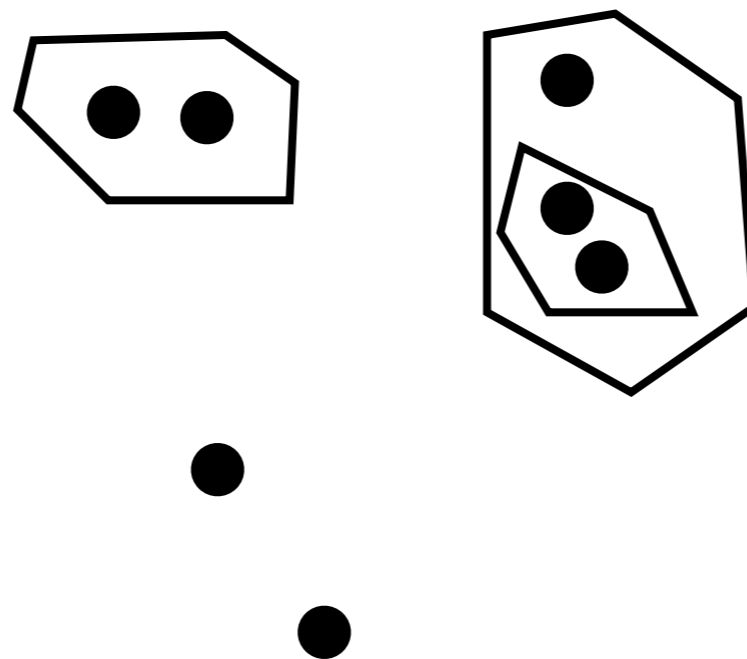
- **Step 2:** compute the distance between all cluster pairs
- **Step 3:** merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

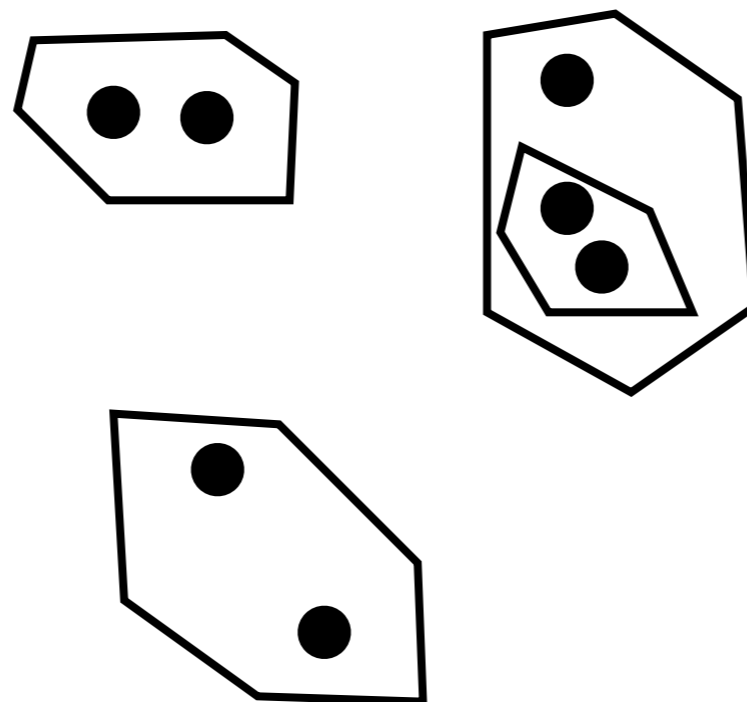
- **Step 2:** compute the distance between all cluster pairs
- **Step 3:** merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

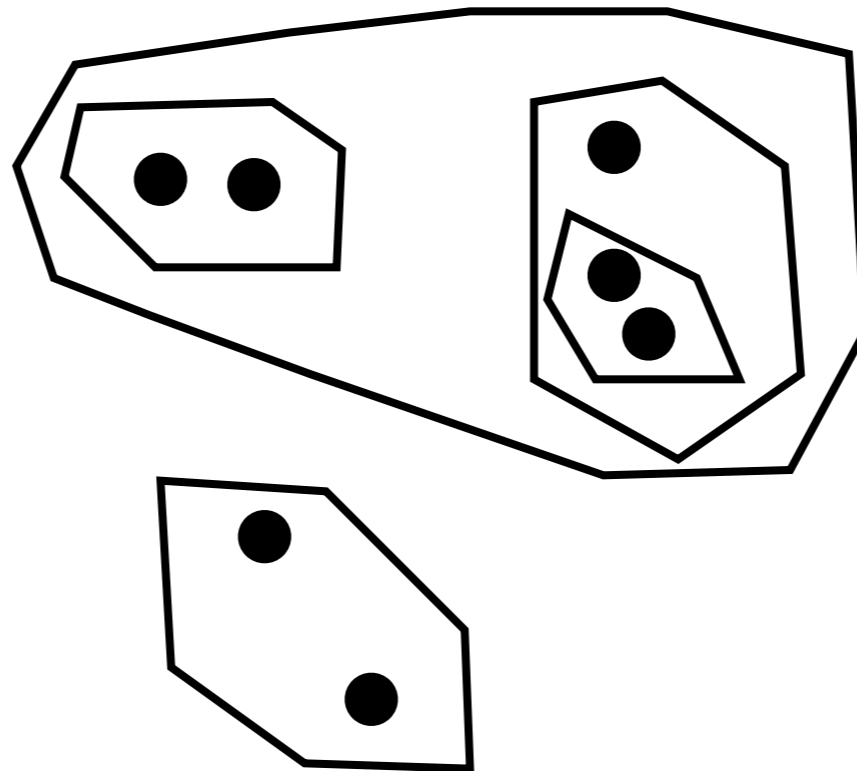
- **Step 2:** compute the distance between all cluster pairs
- **Step 3:** merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

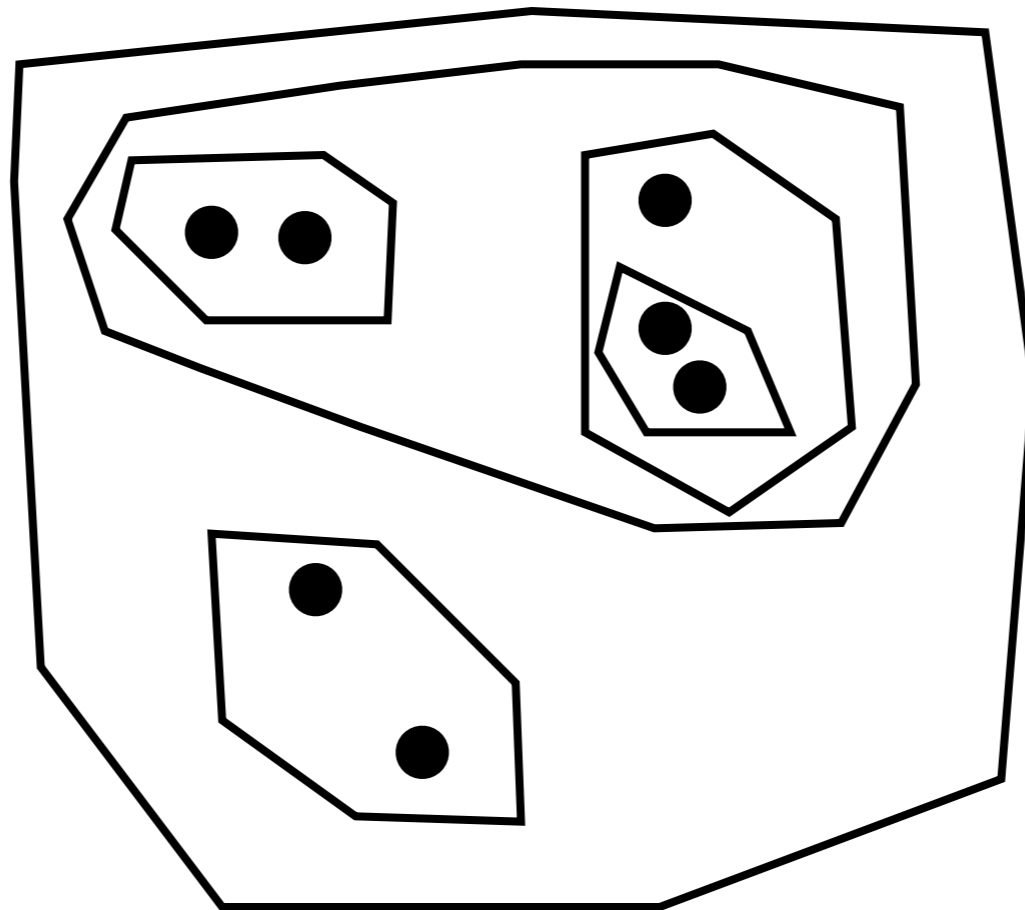
- **Step 2:** compute the distance between all cluster pairs
- **Step 3:** merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

- **Step 2:** compute the distance between all cluster pairs
- **Step 3:** merge/combine the nearest two clusters into one



Bottom-up Clustering

- Setting K dynamically
- Instead of setting K , we could set a distance threshold T
- Stop merging/combining clusters when the distance between the two nearest clusters $> T$
- Using a distance threshold can help prevent “concept drift” (especially with single-link clustering)
 - ▶ text mining --> inls 613 --> unc --> basketball

Labeling Clusters

Clustering Applications

collection clustering

The image shows a screenshot of the Google News homepage. At the top is the Google logo and a search bar. Below that are navigation options for 'U.S. edition' and 'Modern'. The 'News' section is highlighted with a blue border. On the left, a 'Top Stories' sidebar lists various topics: Mitt Romney, Chromebook, Washington Redskins, Earthquake, Fidel Castro, Cleveland Browns, George McGovern, Toronto Blue Jays, Brad Pitt, Jay-Z, and North Carolina. A large black-bordered text box is overlaid on the center of the page, containing the question: 'How can we name clusters to inform someone about the kind of information they contain?'. Below the text box, a news article snippet is visible with the headline 'Breaking: The area is on lockdown as authorities in Brookfield work to secure the scene, which is across the street from a shopping mall in Wisconsin.' and a sub-headline 'At Least 7 Injured in Spa Shooting'. At the bottom, there is a video player showing a news report titled 'Romney, Obama in Dead Heat' from the Wall Street Journal, dated 22 minutes ago. The video player includes a thumbnail and a list of sources: The Associated P..., The Associated P..., YouTube, CNN (blog), CBS News, Christian S..., and Newsday.

Google

News

U.S. edition Modern

Top Stories

Mitt Romney
Chromebook
Washington Redskins
Earthquake
Fidel Castro
Cleveland Browns
George McGovern
Toronto Blue Jays
Brad Pitt
Jay-Z
North Carolina

World
U.S.
Business
Elections
Technology
Entertainment
Sports
Science
Health
Spotlight

How can we name clusters to inform someone about the kind of information they contain?

Breaking: The area is on lockdown as authorities in Brookfield work to secure the scene, which is across the street from a shopping mall in Wisconsin.
At Least 7 Injured in Spa Shooting

Romney, Obama in Dead Heat
Wall Street Journal - 22 minutes ago
By NEIL KING JR. Mitt Romney has strengthened his image as the candidate best able to boost the economy and has fought President Barack Obama to a near-draw on who can best serve as commander in chief, helping turn the 2012 election into a tie ...

Labeling Clusters

A simple solution

- Construct a vocabulary of terms and/or phrases (n-grams) that are frequent in the data
- Assign each cluster the term(s) or phrase(s) with the highest mutual information

Mutual Information

$$\text{MI}(w, c) = \log \left(\frac{P(w, c)}{P(w)P(c)} \right)$$

- **P(w,c)**: the probability that a document contains word **w** and belongs to cluster **c**
- **P(w)**: the probability that word **w** occurs in a document from any cluster
- **P(c)**: the probability that a document belongs to cluster **c**

Mutual Information

$$\text{MI}(w, c) = \log \left(\frac{P(w, c)}{P(w)P(c)} \right)$$

- If $P(w, c) = P(w) P(c)$, it means that the word **w** is independent of cluster **c**
- If $P(w, c) > P(w) P(c)$, it means that the word **w** is not independent of of cluster **c**

Mutual Information

- Every document falls under one of these quadrants

belongs to cluster **c** does not belong to cluster **c**

total # of instances $N = a + b + c + d$

$$P(w, c) = ???$$

$$P(c) = ???$$

$$P(w) = ???$$

contains word **w**

a	b
c	d

does not contain word **w**

$$MI(w, c) = \log \left(\frac{P(w, c)}{P(w)P(c)} \right)$$

Mutual Information

- Every document falls under one of these quadrants

belongs to cluster **c** does not belong to cluster **c**

total # of instances $N = a + b + c + d$

$$P(w, c) = a / N$$

$$P(c) = (a + c) / N$$

$$P(w) = (a + b) / N$$

contains word **w**

a	b
c	d

does not contain word **w**

$$MI(w, c) = \log \left(\frac{P(w, c)}{P(w)P(c)} \right)$$

Summary

- Clustering: grouping similar documents (or instances) into subsets
- Exploratory analysis: the goal is to discover common and uncommon properties of the data
- K-means and Agglomerative Bottom-up Clustering (there are many, many others)
- Labeling clusters