Clustering

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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 the system is a set of unlabeled data
  - the algorithm infers the labels from the data and assigns a label to each input instance

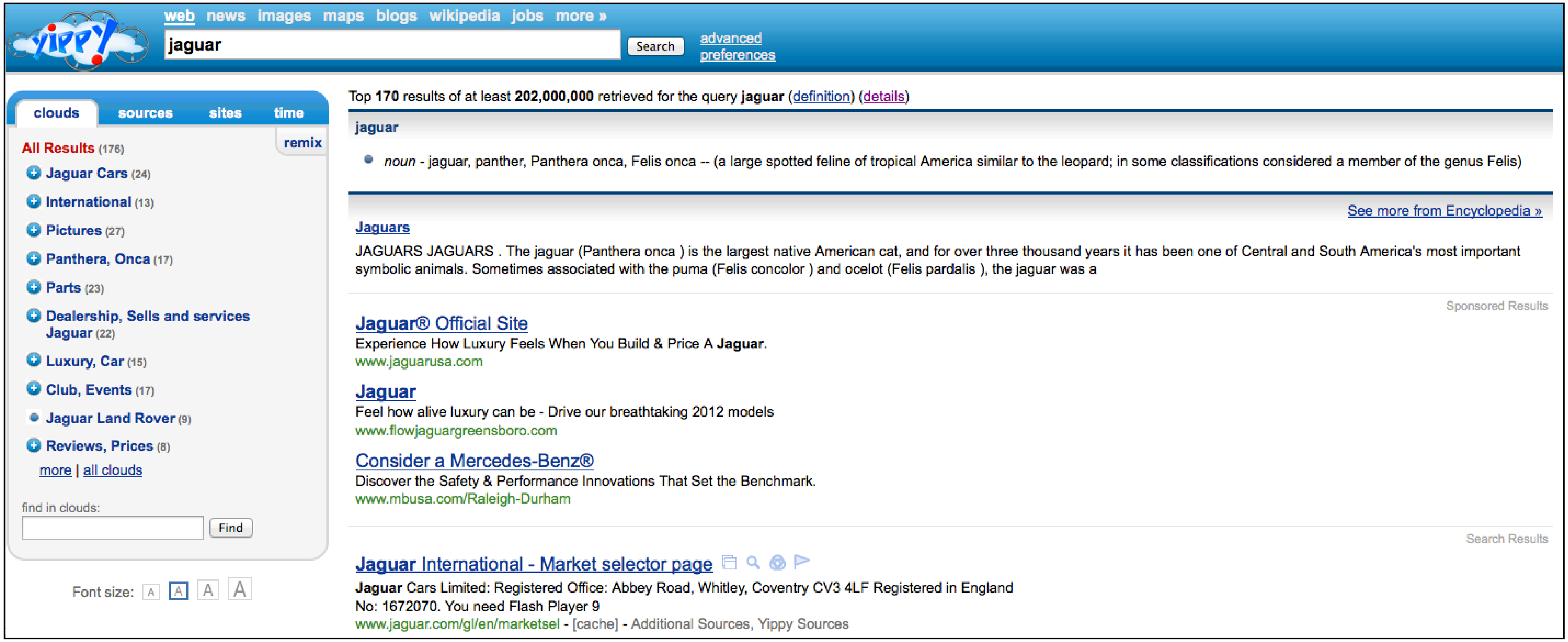
Clustering

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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jaguar

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

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

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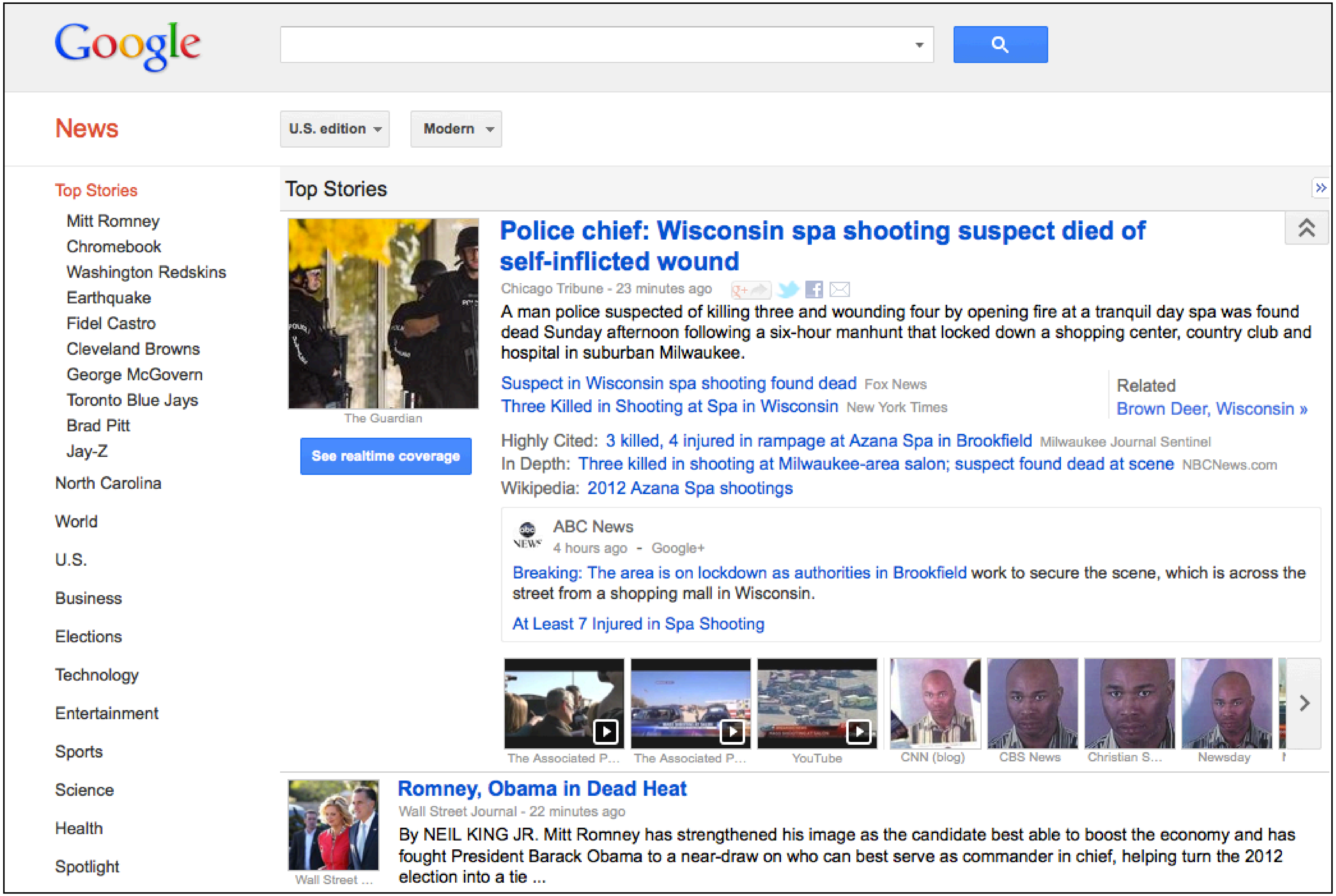
Search Results

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



Top Stories

Police chief: Wisconsin spa shooting suspect died of self-inflicted wound

Chicago Tribune - 23 minutes ago

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.

Suspect in Wisconsin spa shooting found dead Fox News

Three Killed in Shooting at Spa in Wisconsin New York Times

Related

Brown Deer, Wisconsin »

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

Wikipedia: 2012 Azana Spa shootings

ABC News

4 hours ago - Google+

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

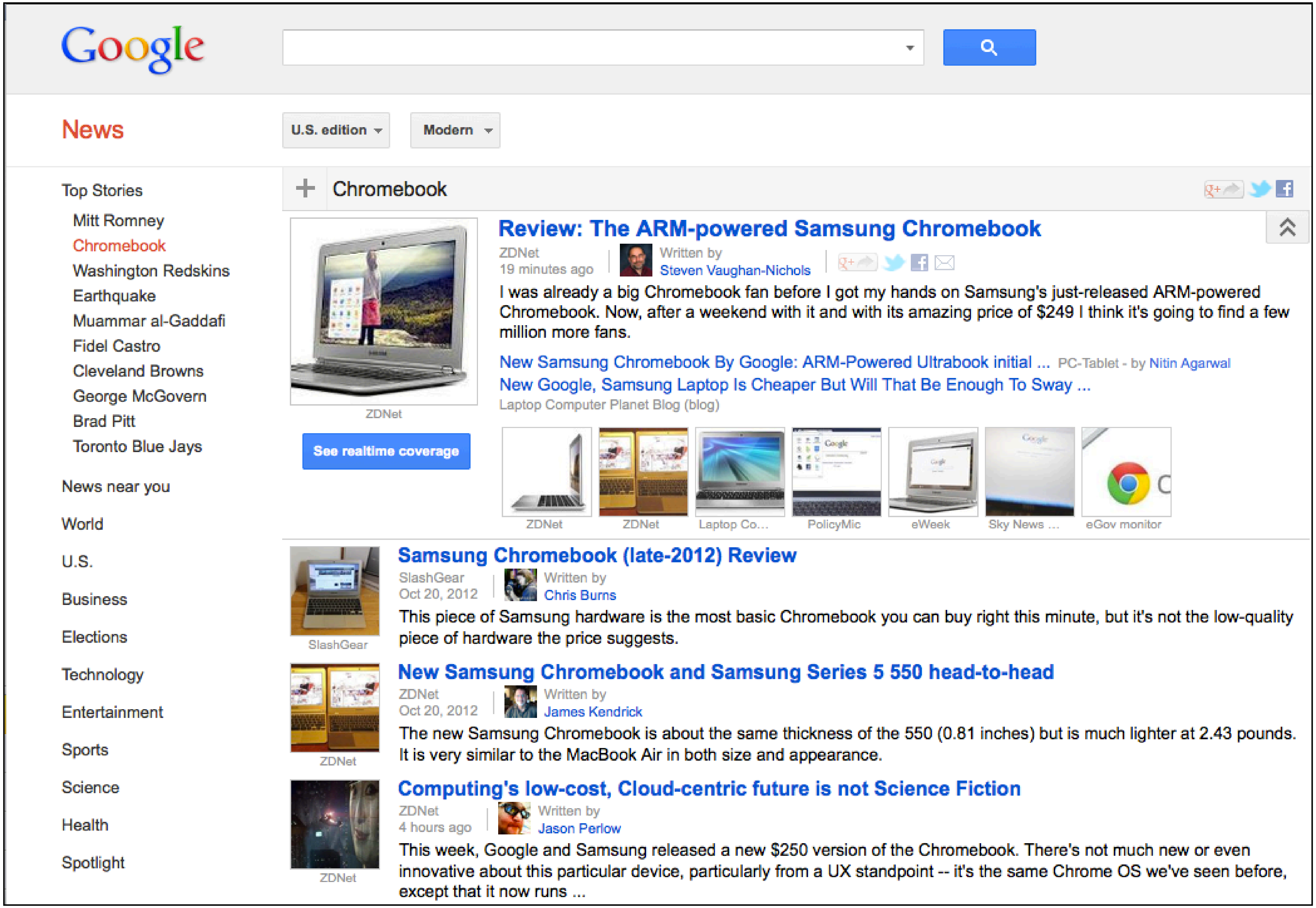
Romney, Obama in Dead Heat

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 ...

Clustering Applications

collection clustering



News

Top Stories
- Mitt Romney
- Chromebook
- Washington Redskins
- Earthquake
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- Toronto Blue Jays

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Chromebook

Review: The ARM-powered Samsung Chromebook
ZDNet
19 minutes ago
Written by
Steven Vaughan-Nichols

I was already a big Chromebook fan before I got my hands on Samsung's just-released ARM-powered Chromebook. Now, after a weekend with it and with its amazing price of $249 I think it's going to find a few million more fans.

New Samsung Chromebook By Google: ARM-Powered Ultrabook initial ... PC-Tablet - by Nitin Agarwal
New Google, Samsung Laptop Is Cheaper But Will That Be Enough To Sway ...
Laptop Computer Planet Blog (blog)

Samsung Chromebook (late-2012) Review
SlashGear
Oct 20, 2012
Written by
Chris Burns

This piece of Samsung hardware is the most basic Chromebook you can buy right this minute, but it's not the low-quality piece of hardware the price suggests.

New Samsung Chromebook and Samsung Series 5 550 head-to-head
ZDNet
Oct 20, 2012
Written by
James Kendrick

The new Samsung Chromebook is about the same thickness of the 550 (0.81 inches) but is much lighter at 2.43 pounds. It is very similar to the MacBook Air in both size and appearance.

Computing's low-cost, Cloud-centric future is not Science Fiction
ZDNet
4 hours ago
Written by
Jason Perlow

This week, Google and Samsung released a new $250 version of the Chromebook. There's not much new or even innovative about this particular device, particularly from a UX standpoint -- it's the same Chrome OS we've seen before, except that it now runs ...

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

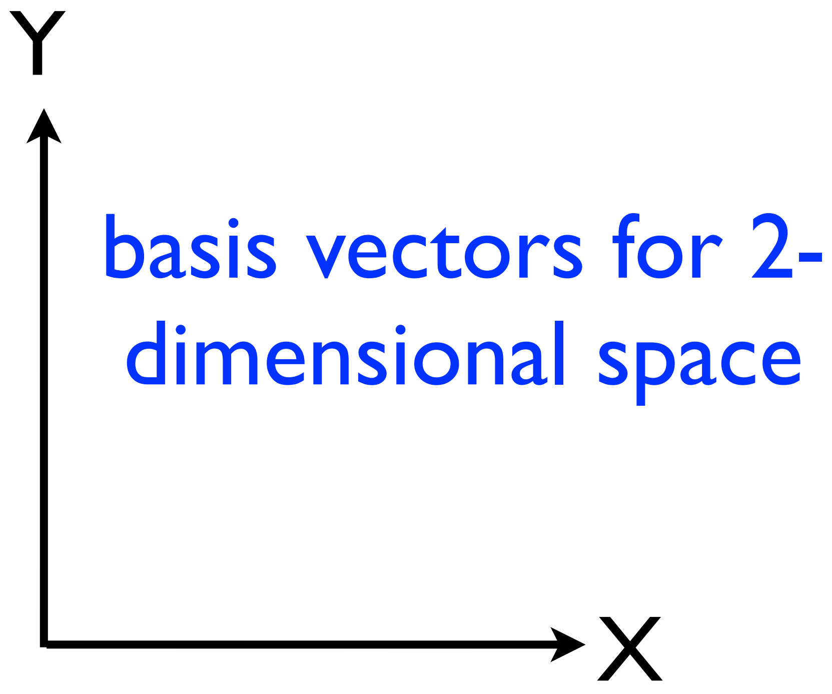
basics

- 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

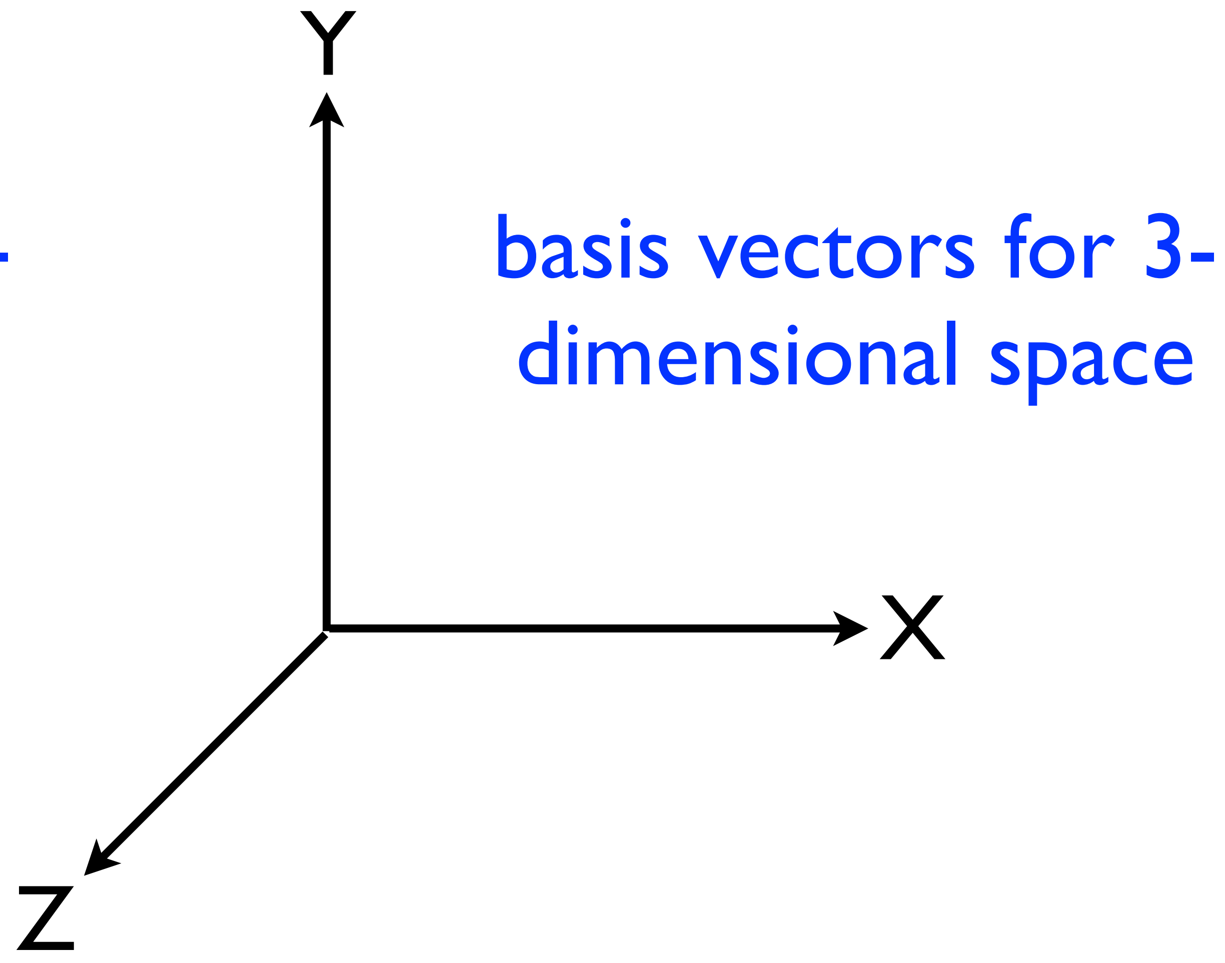
Vector Space Representation

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



basis vectors for 2-dimensional space

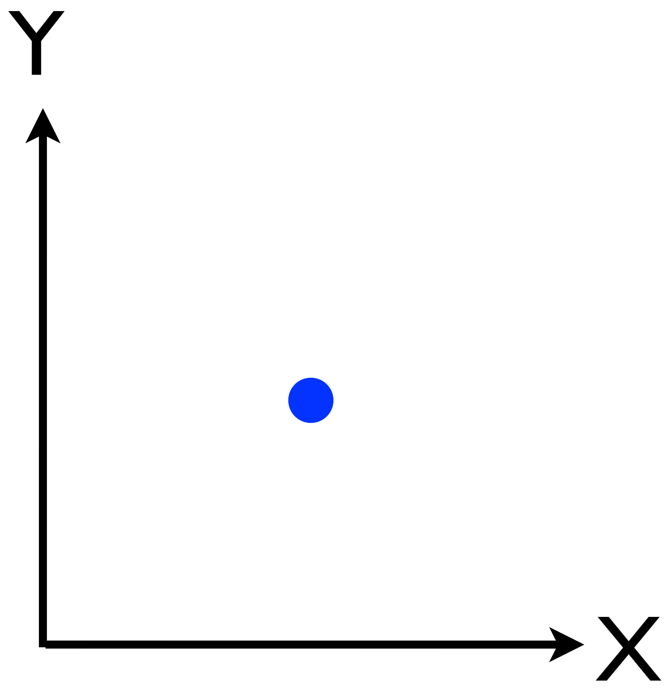


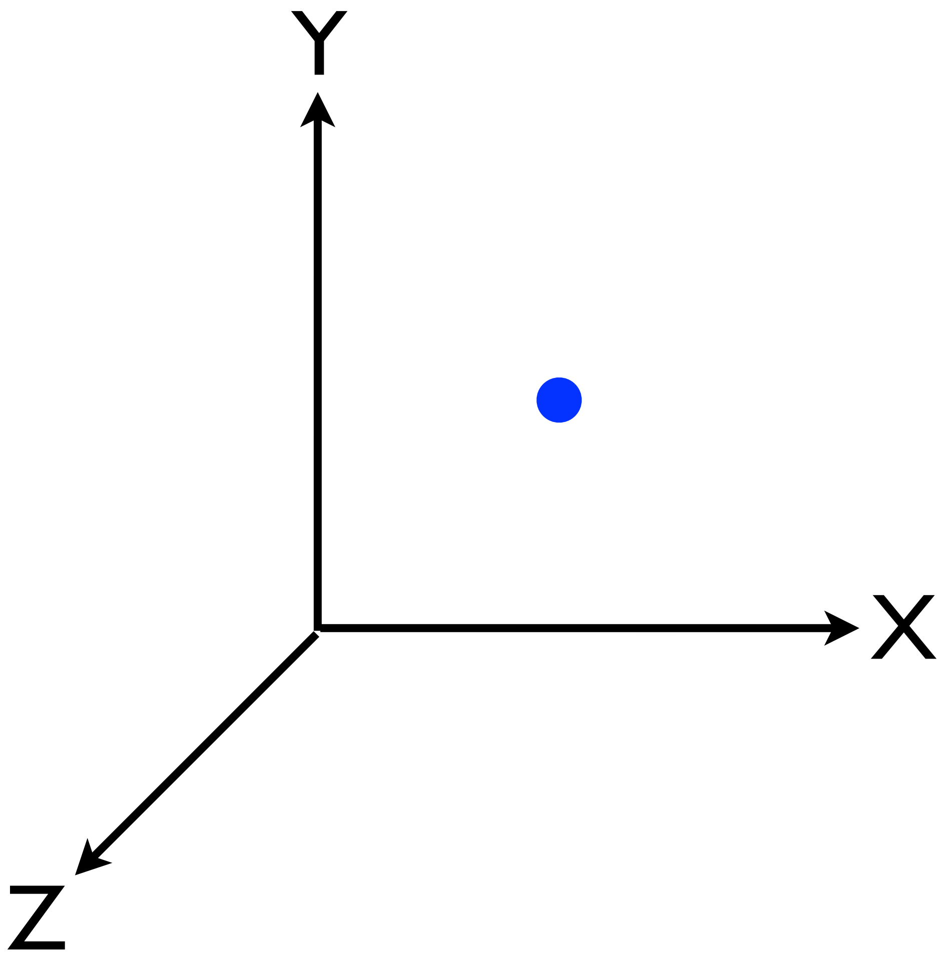
basis vectors for 3-dimensional space

Vector Space Representation

review

- A vector is a point in a vector space

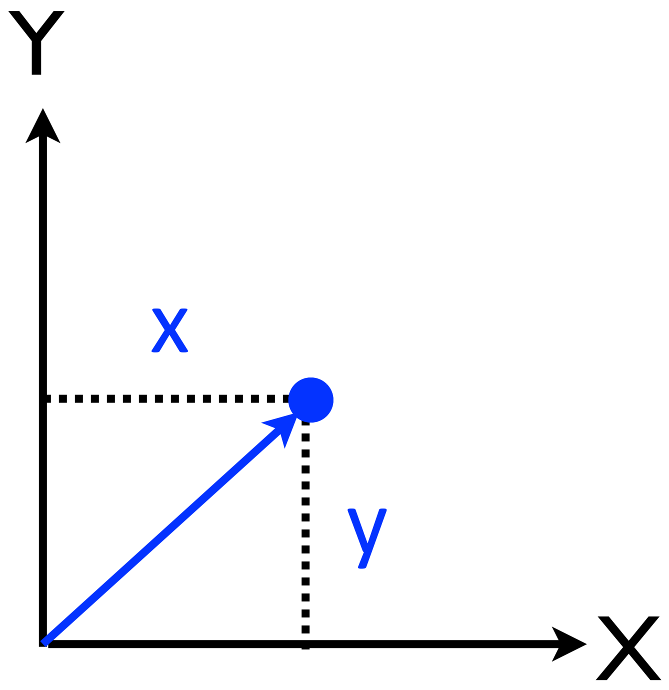


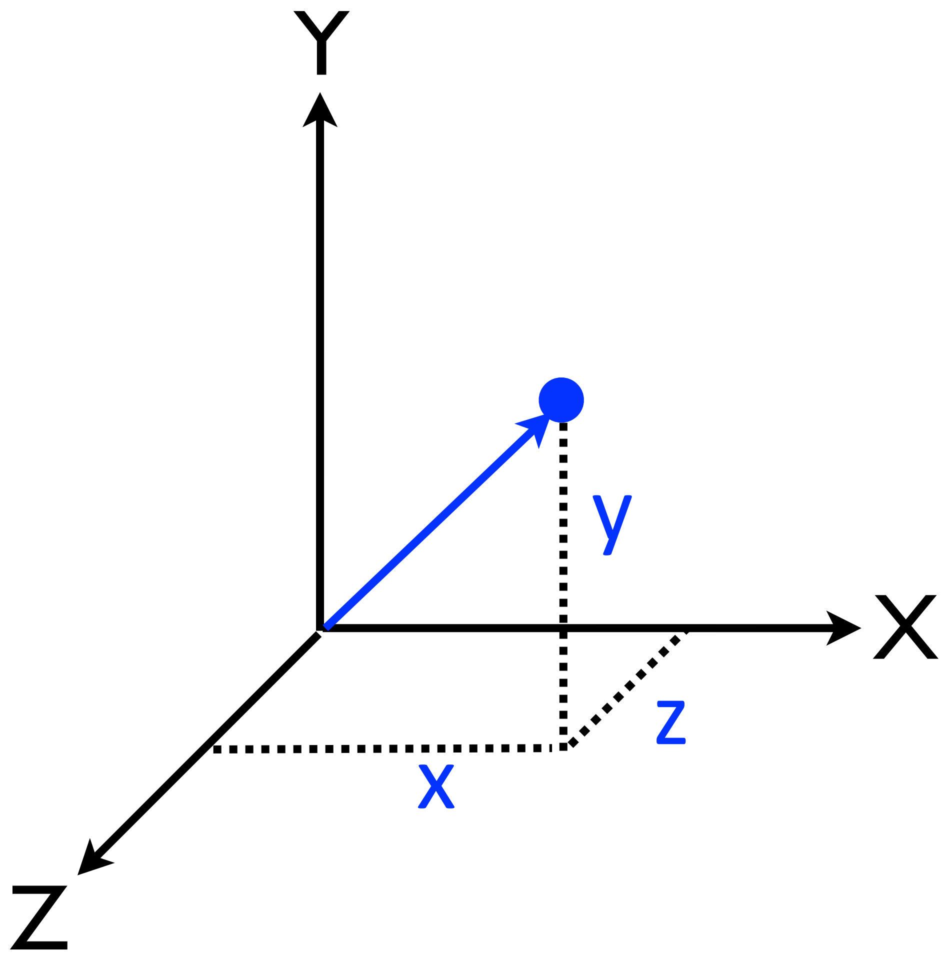


Vector Space Representation

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
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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
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

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

TF, IDF, or TF.IDF?

adrain 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 earns every exhibition extra far fight for gazzo gets girl go has he heavyweight her himself his if 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 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

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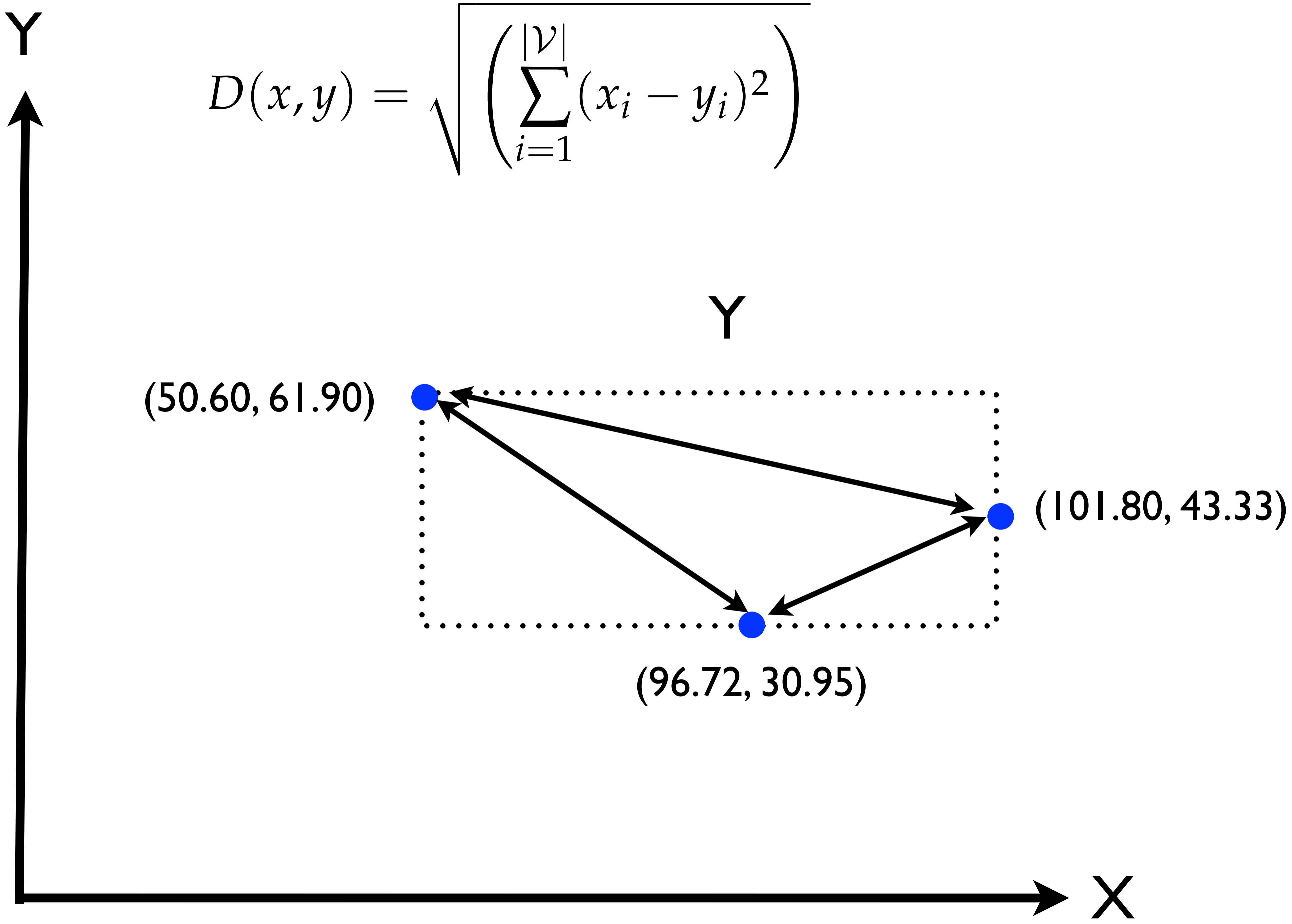
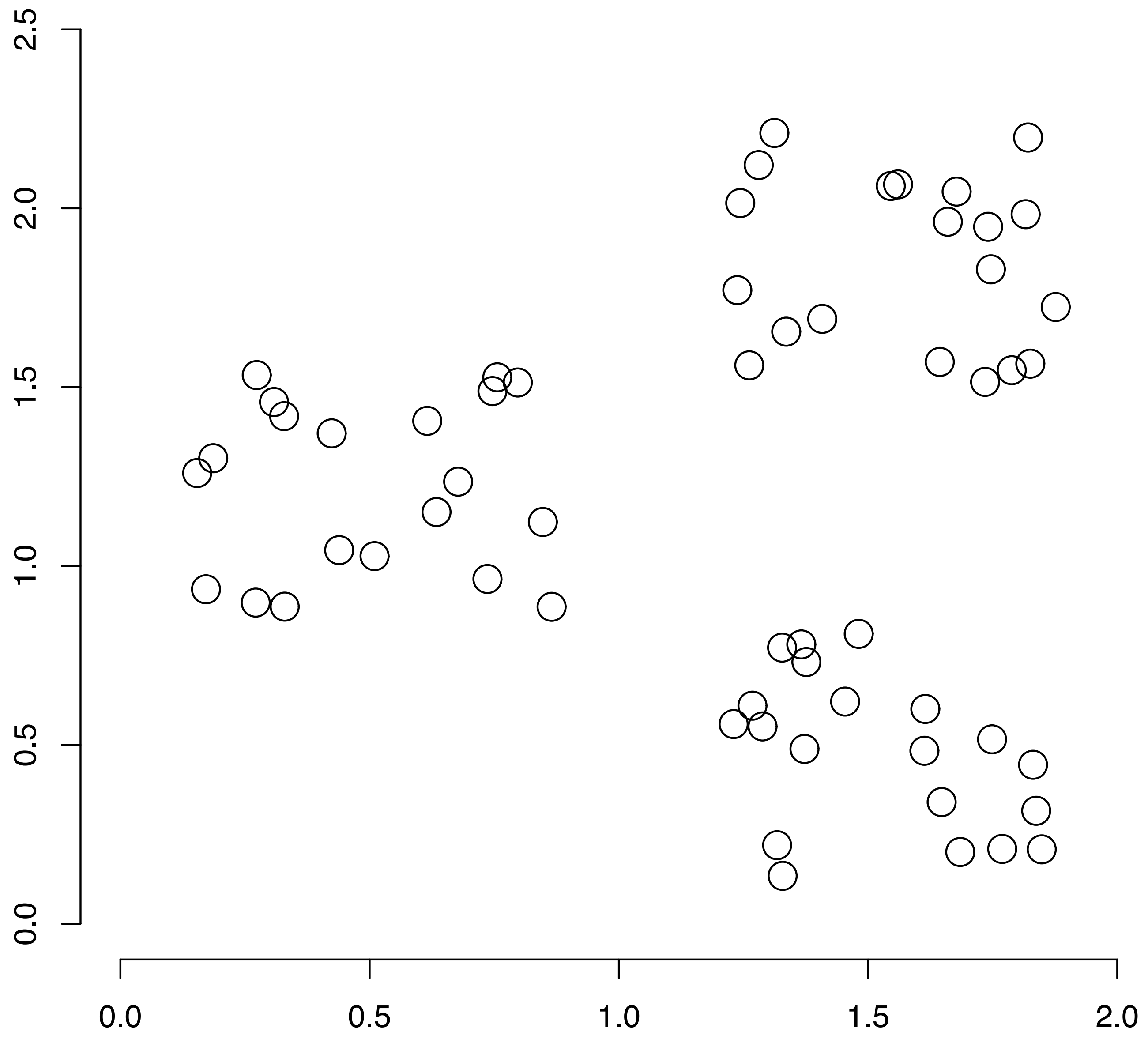


Clustering

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



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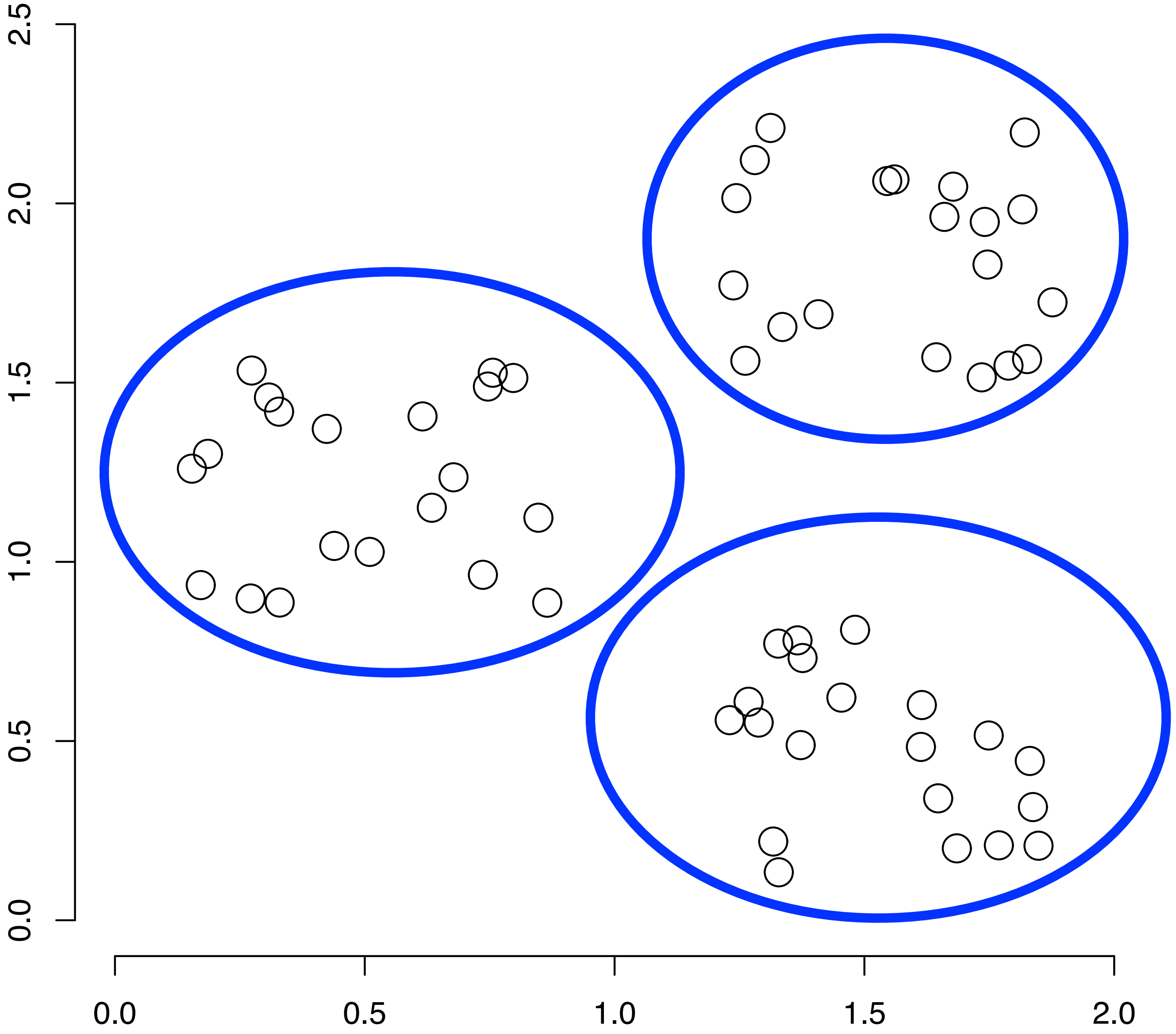
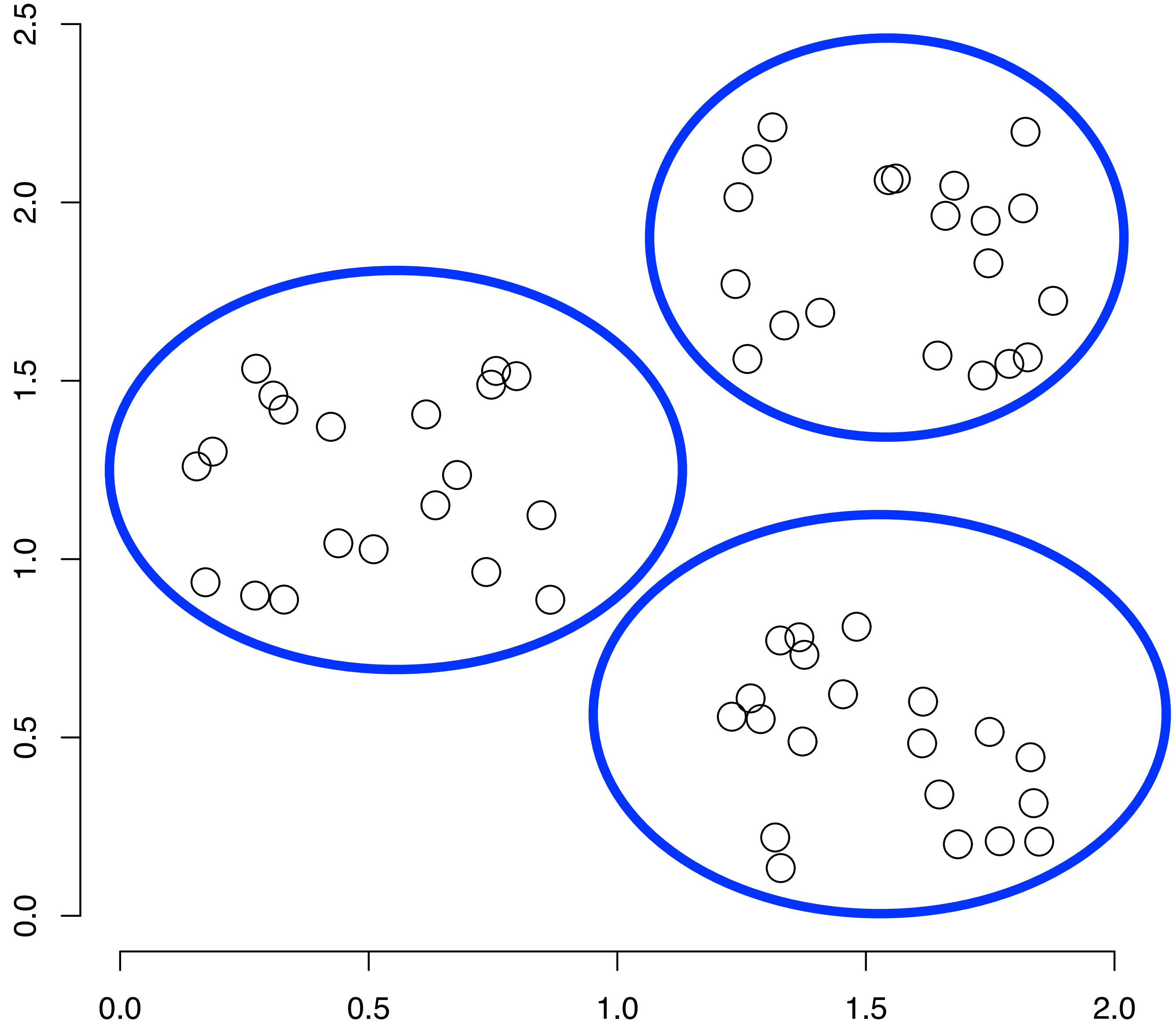


Clustering

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

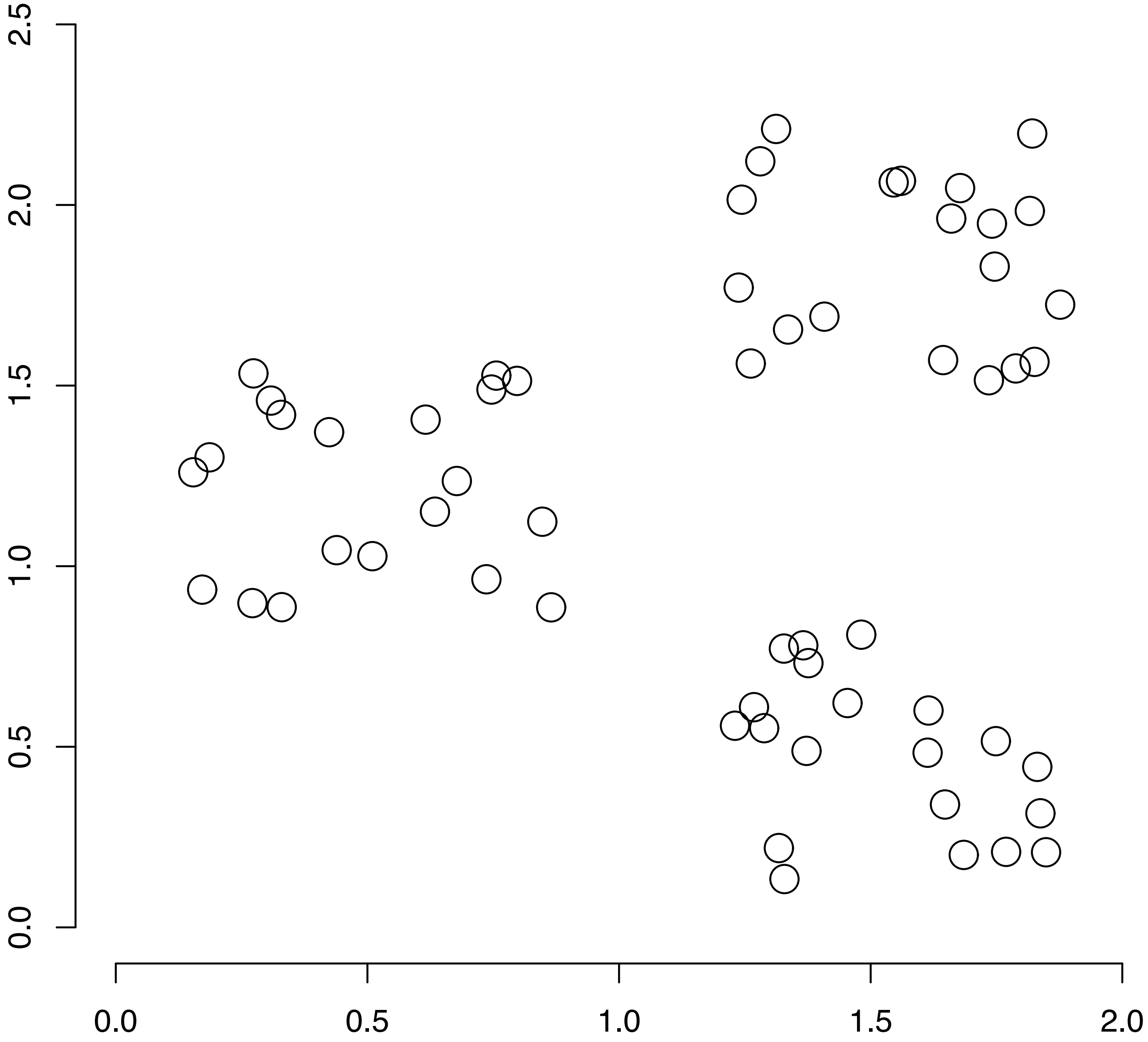


Clustering

- 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

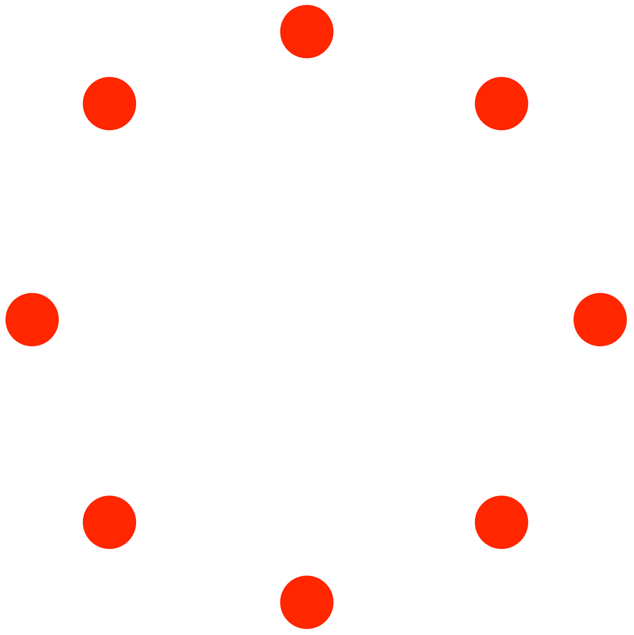
- Could this work?



K-Means Clustering

K-means Clustering
cluster centroid

- The key to understanding K-means clustering is to understand the idea 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”



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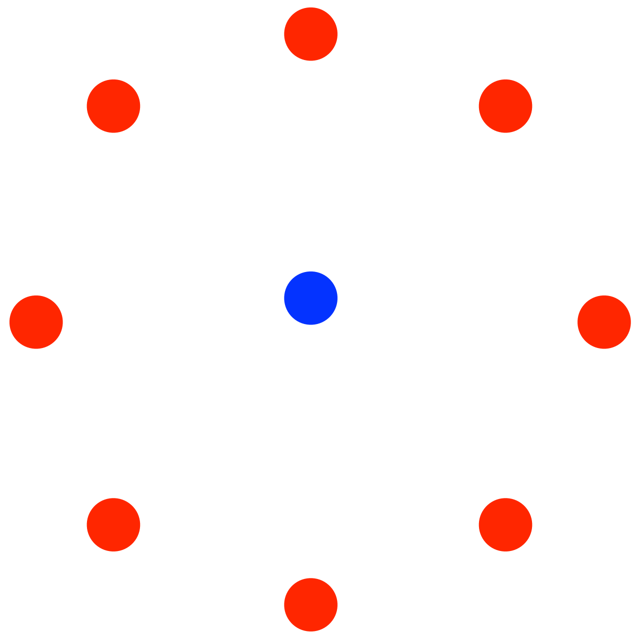

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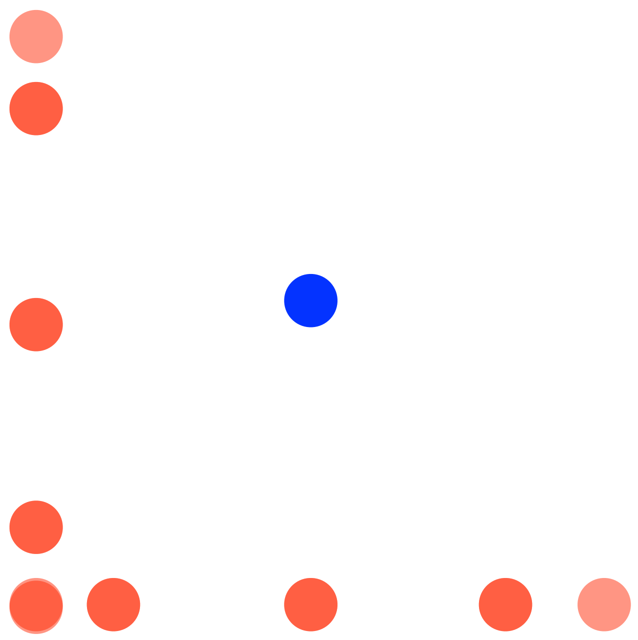

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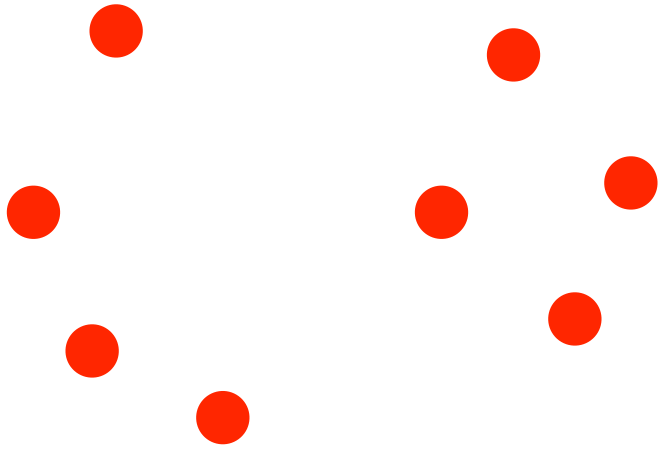

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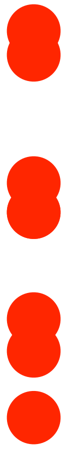

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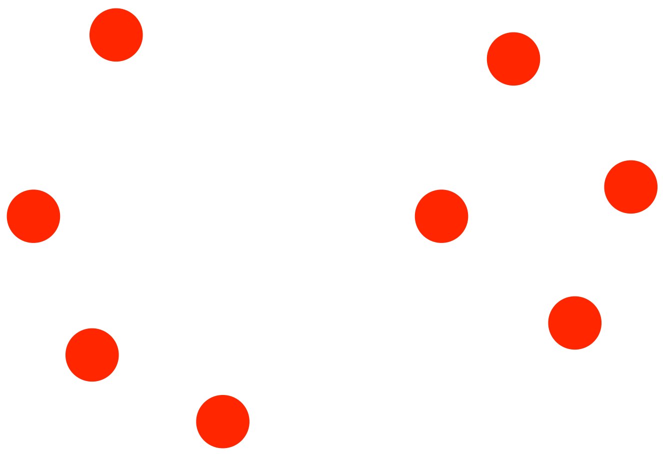

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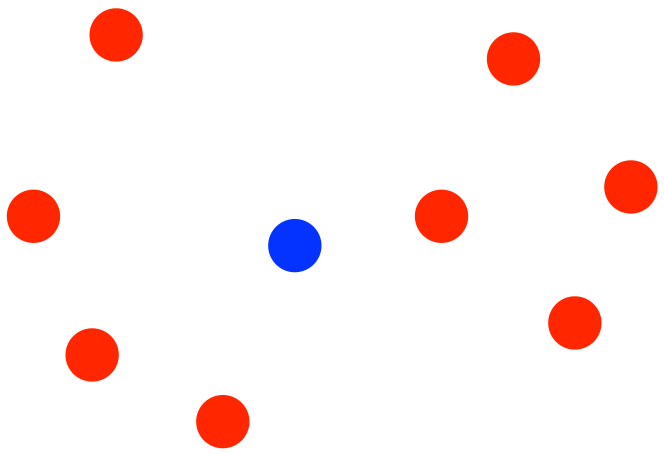


K-means Clustering

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	0.50	0.50	0.50	1.00	0.33	0.33	0.83	0.50	0.50

K-means Clustering

cluster centroid

- For each dimension i , set:

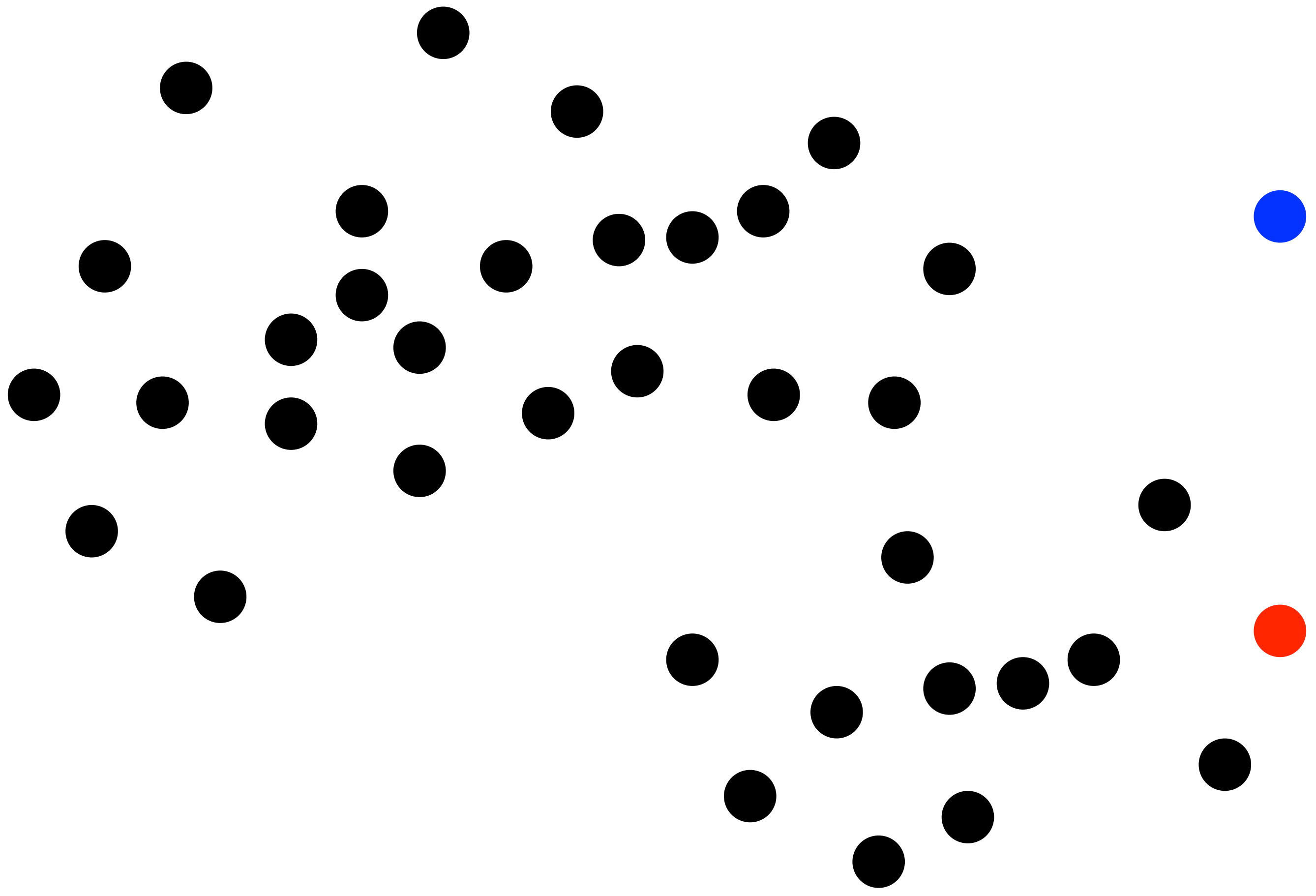
$$c_i = \frac{1}{|C|} \sum_{d \in C} d_i$$

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 <u>terminating condition</u>

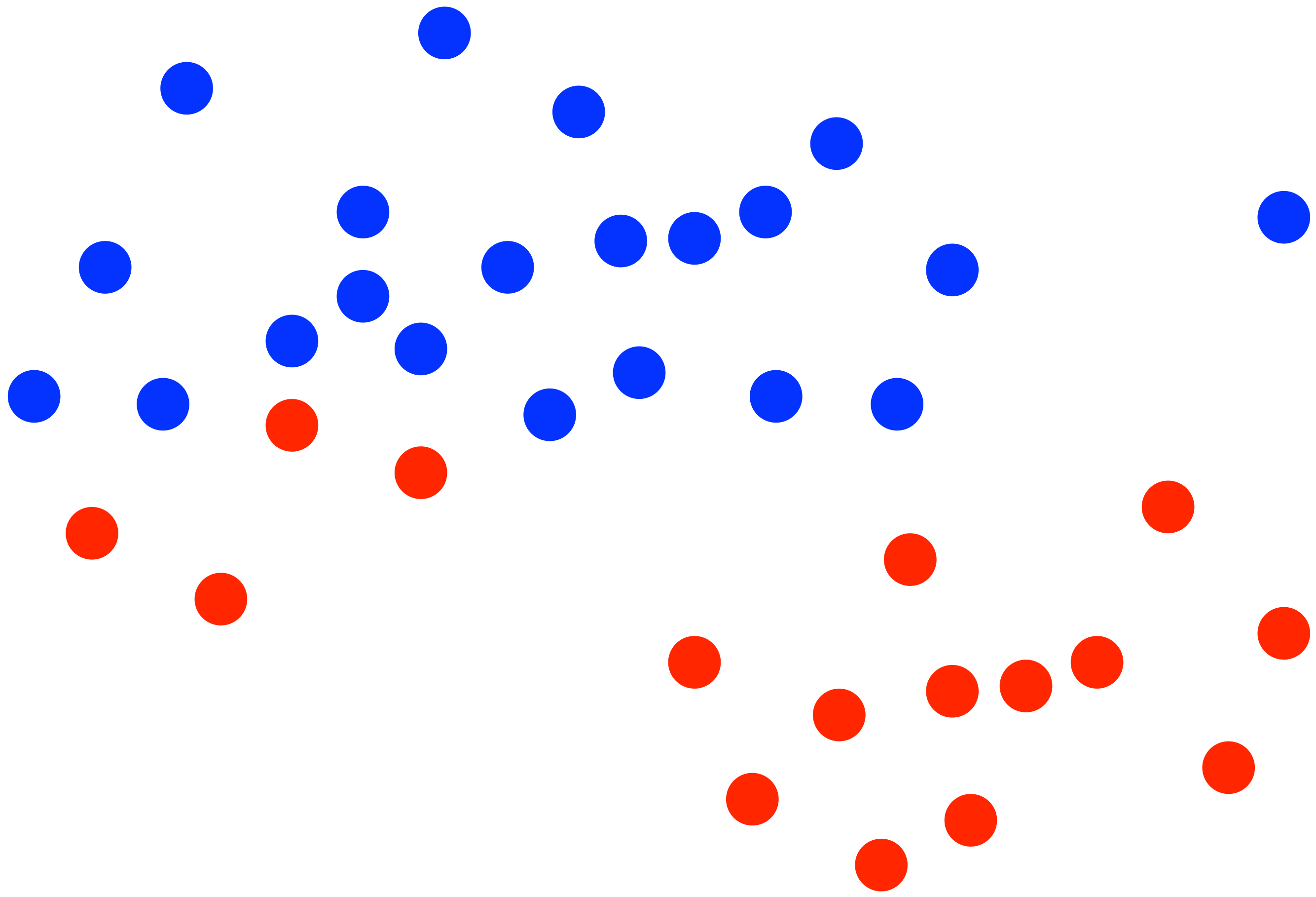
K-means Clustering

- Step 1: randomly select K documents (seeds)



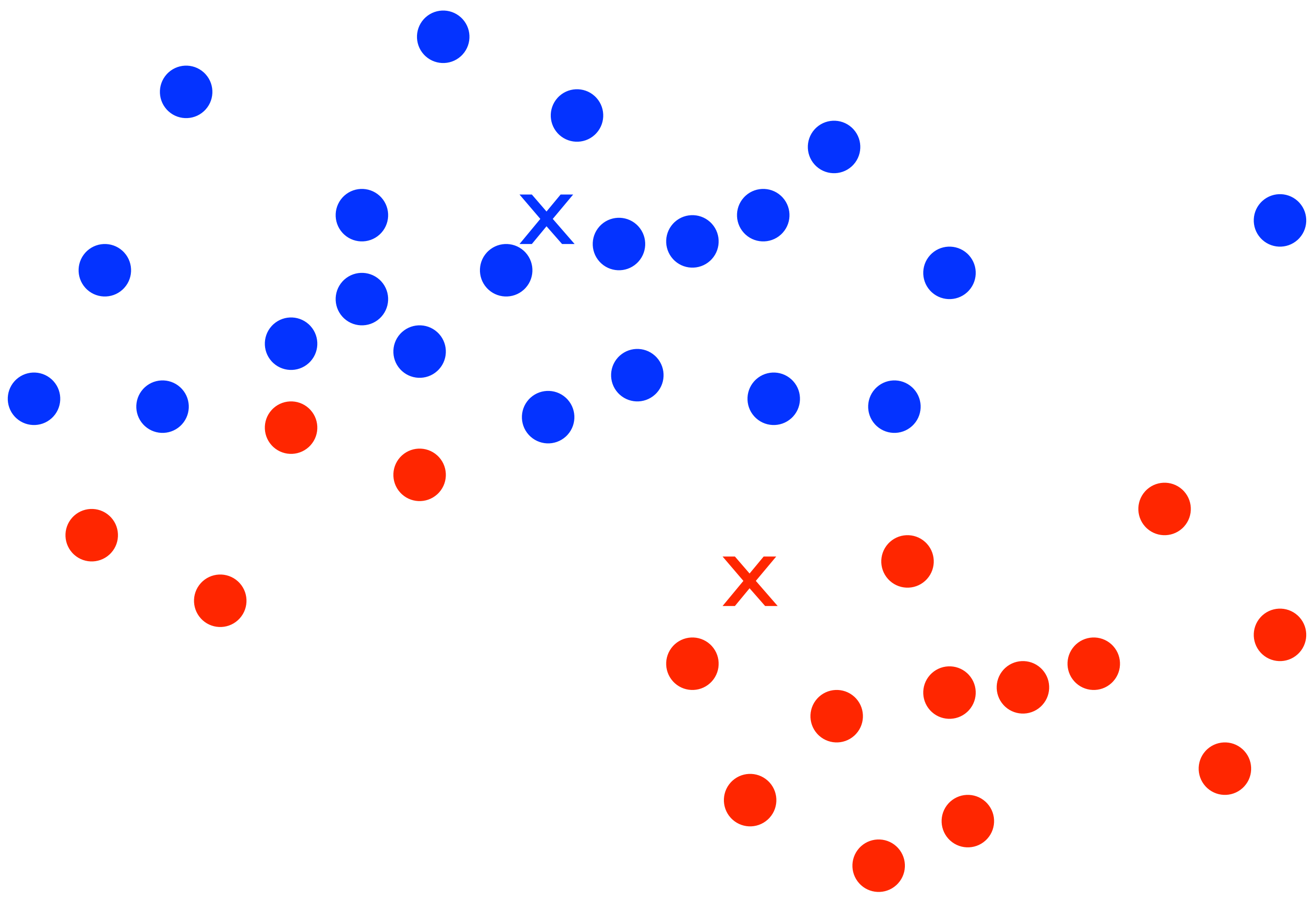
K-means Clustering

- Step 2: assign each document to its nearest seed



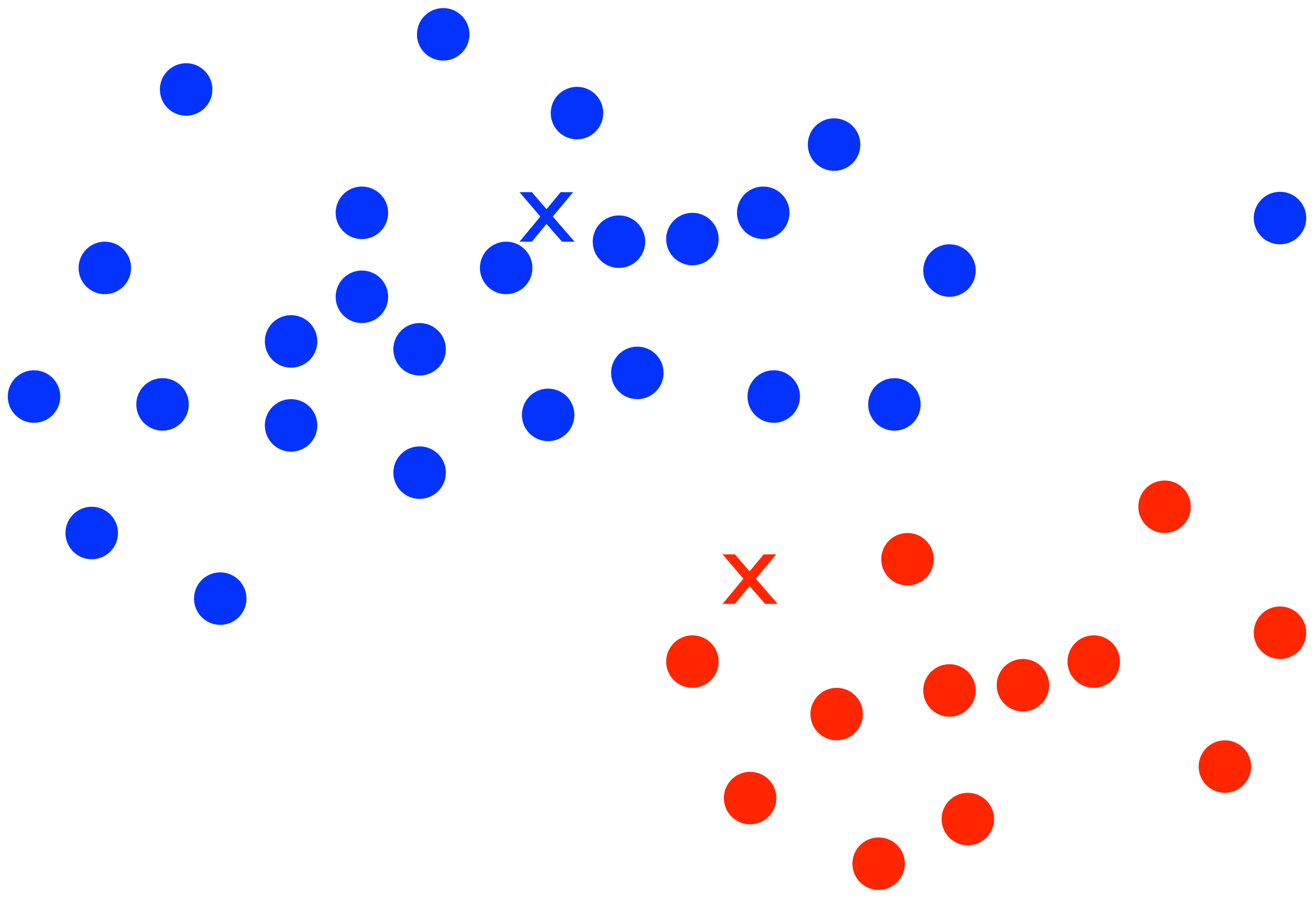
K-means Clustering

- Step 3: compute all K cluster centroids



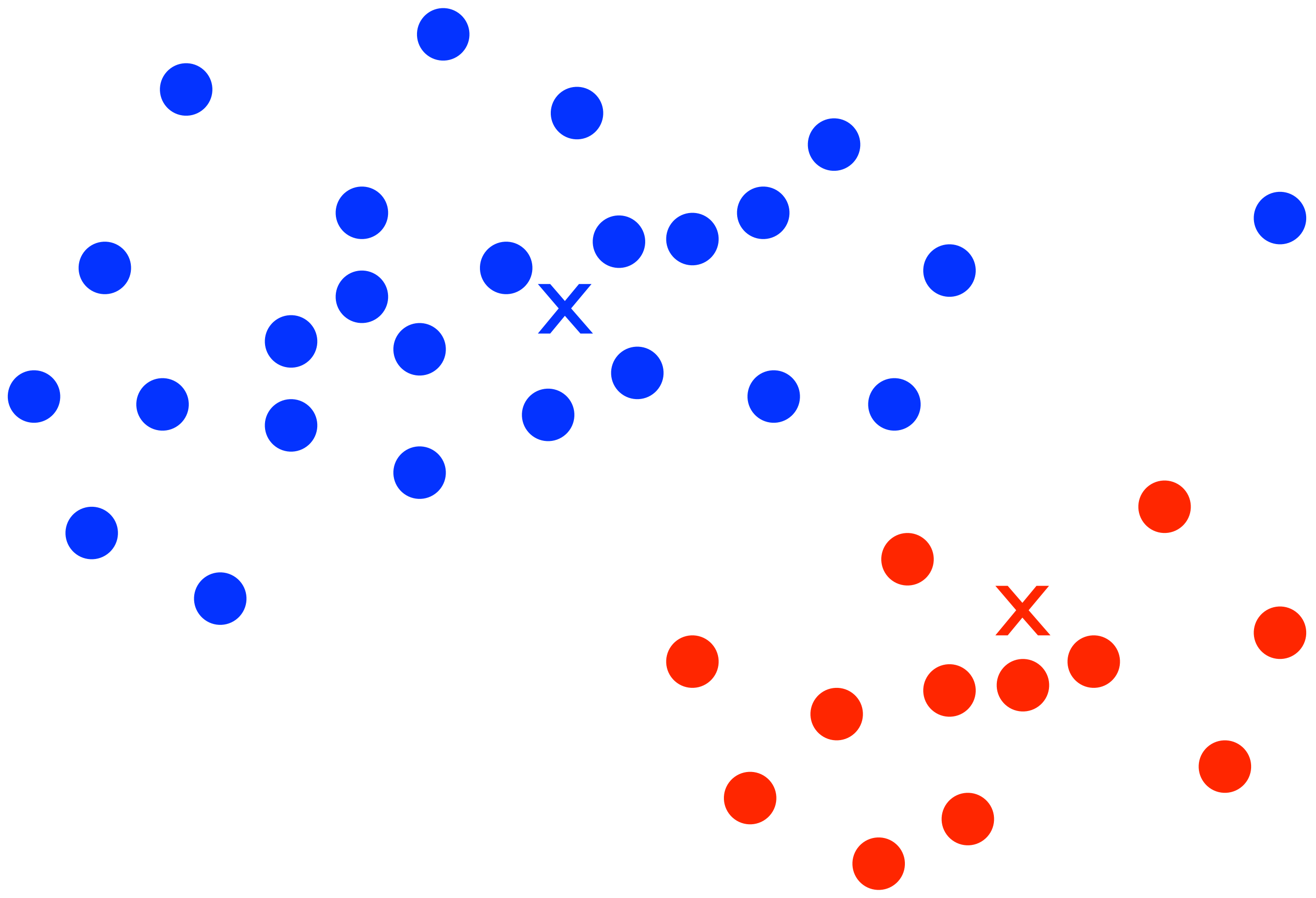
K-means Clustering

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



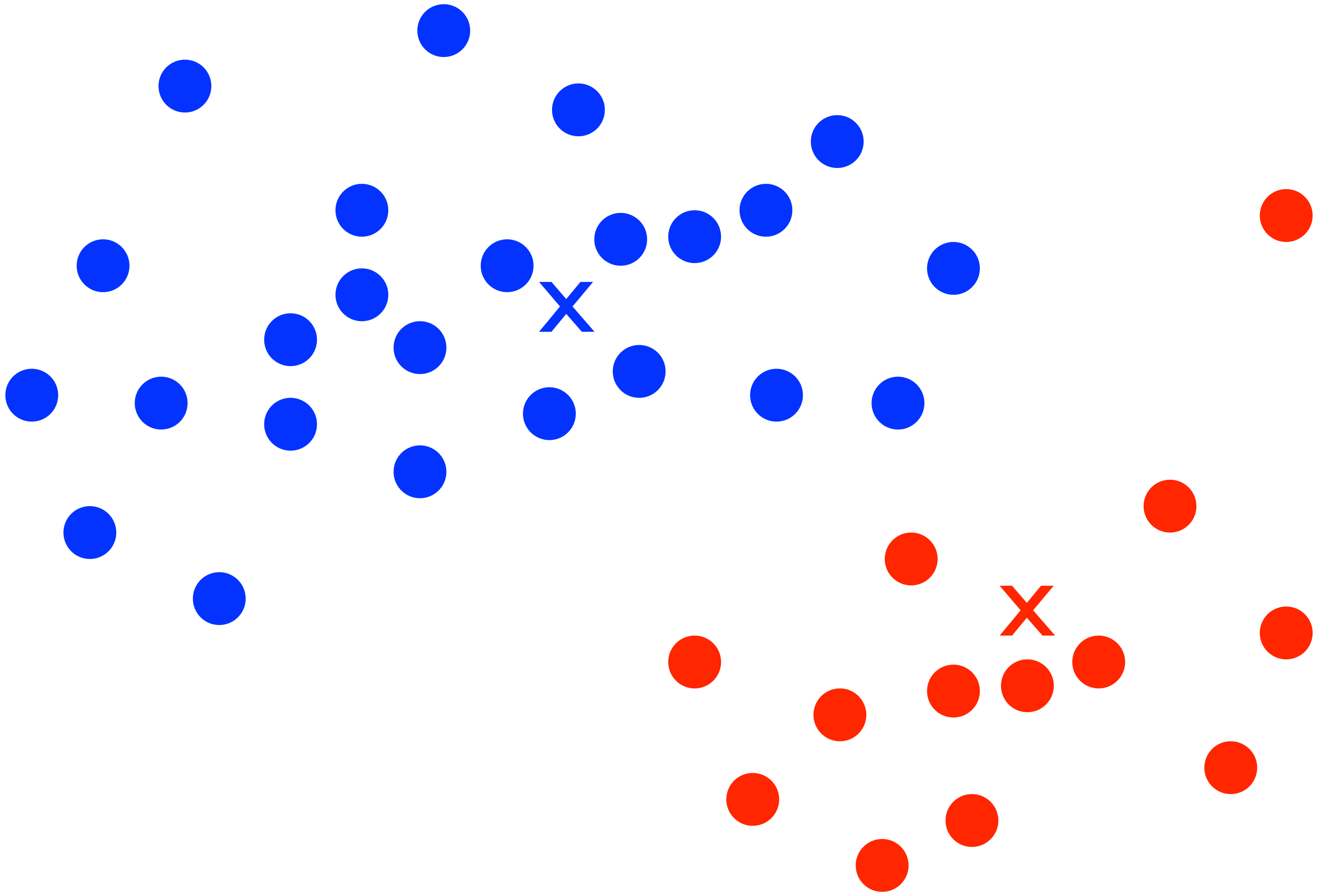
K-means Clustering

- Step 4: re-compute all K cluster centroids



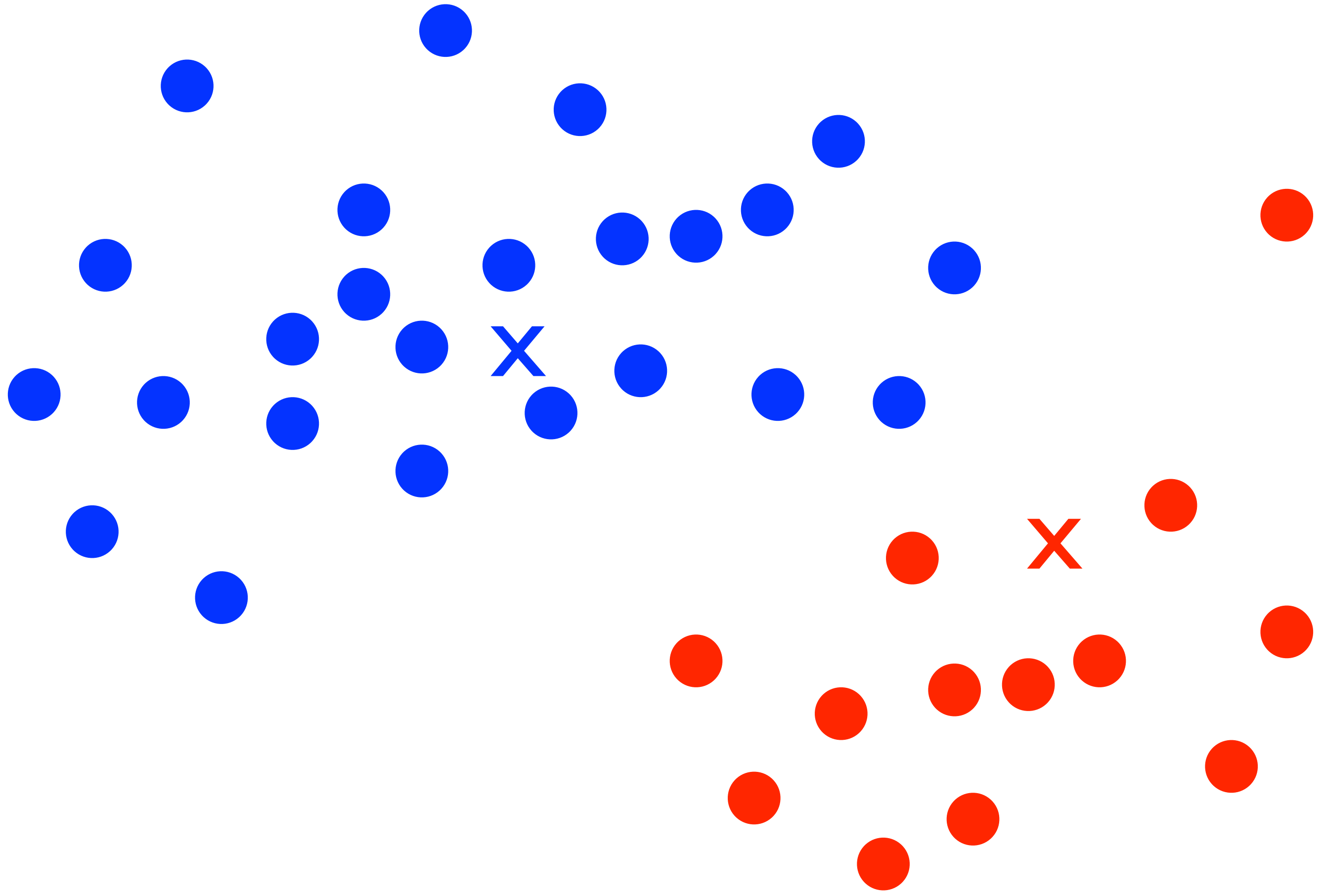
K-means Clustering

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



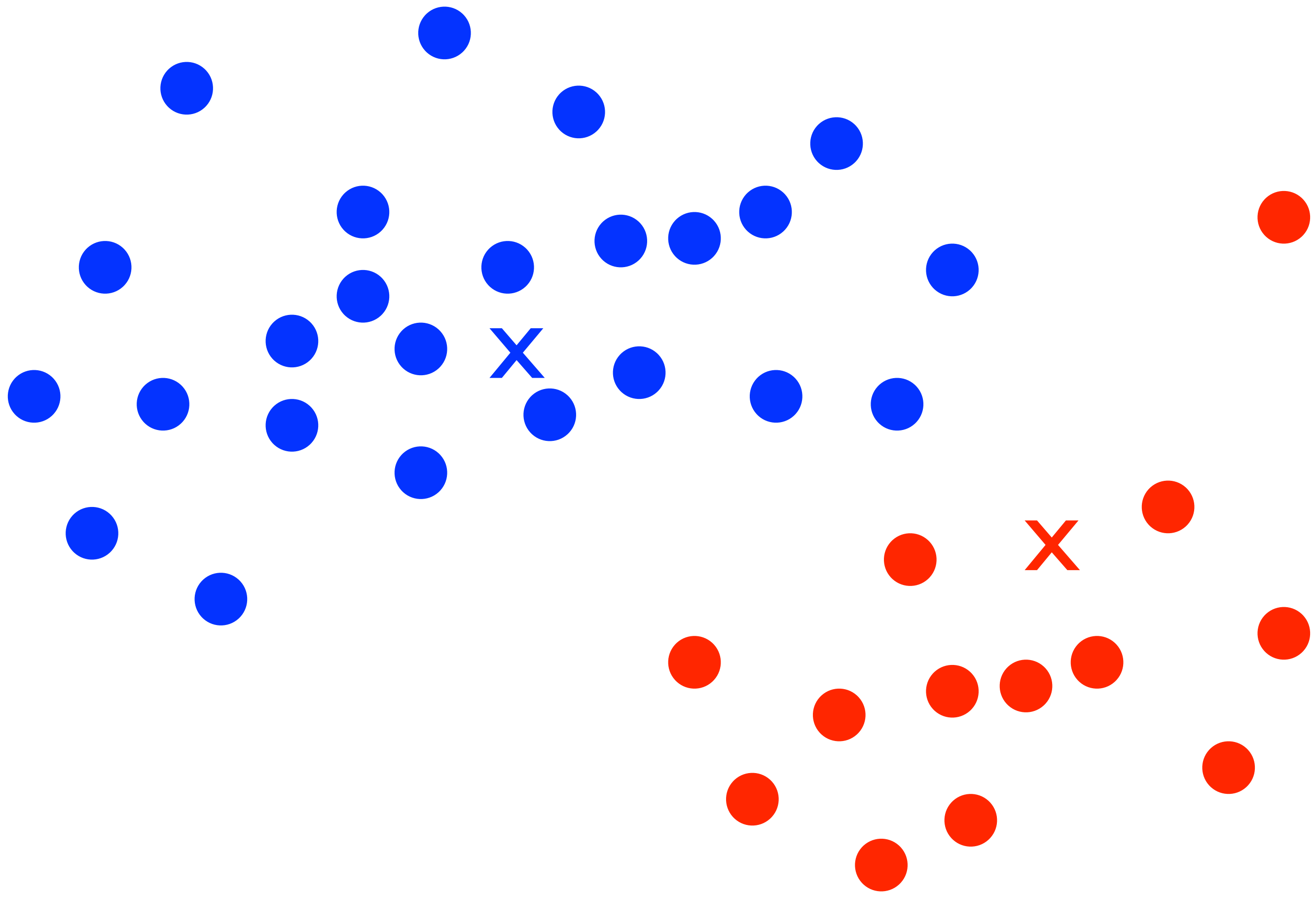
K-means Clustering

- Step 4: re-compute all K cluster centroids



K-means Clustering

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



K-means Clustering

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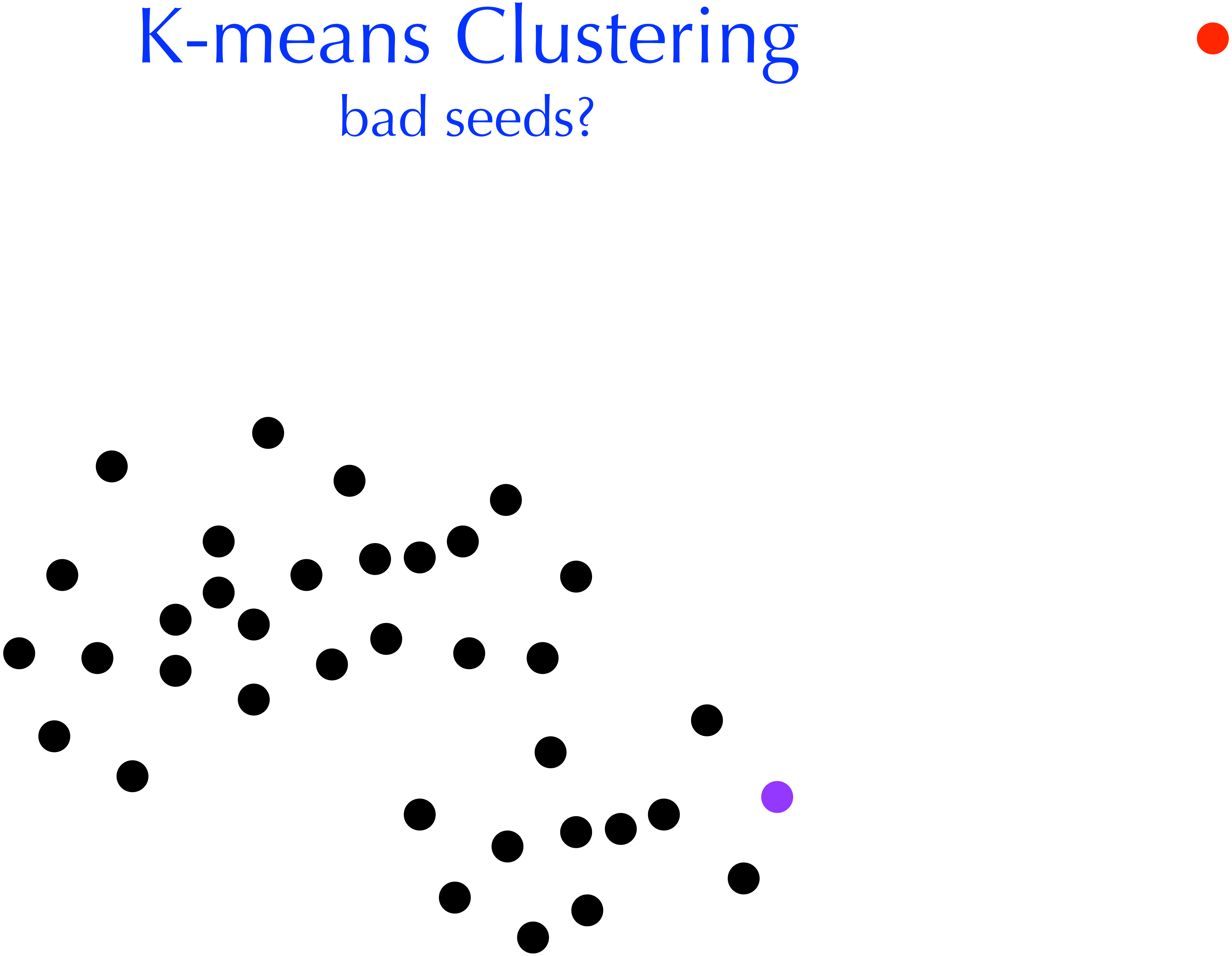
  - Step 6: repeat steps 4 and 5 until terminating condition

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

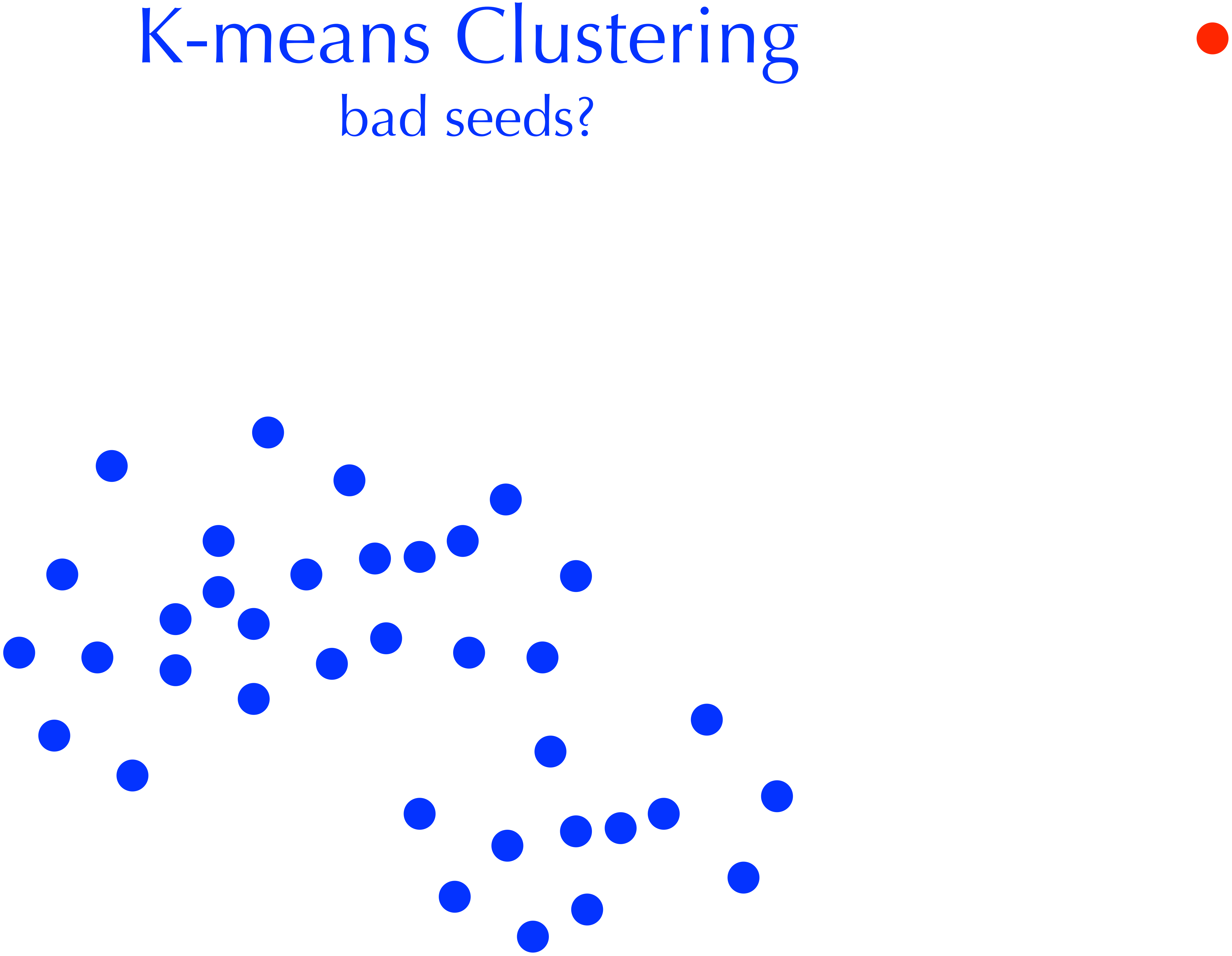
K-means Clustering

bad seeds?



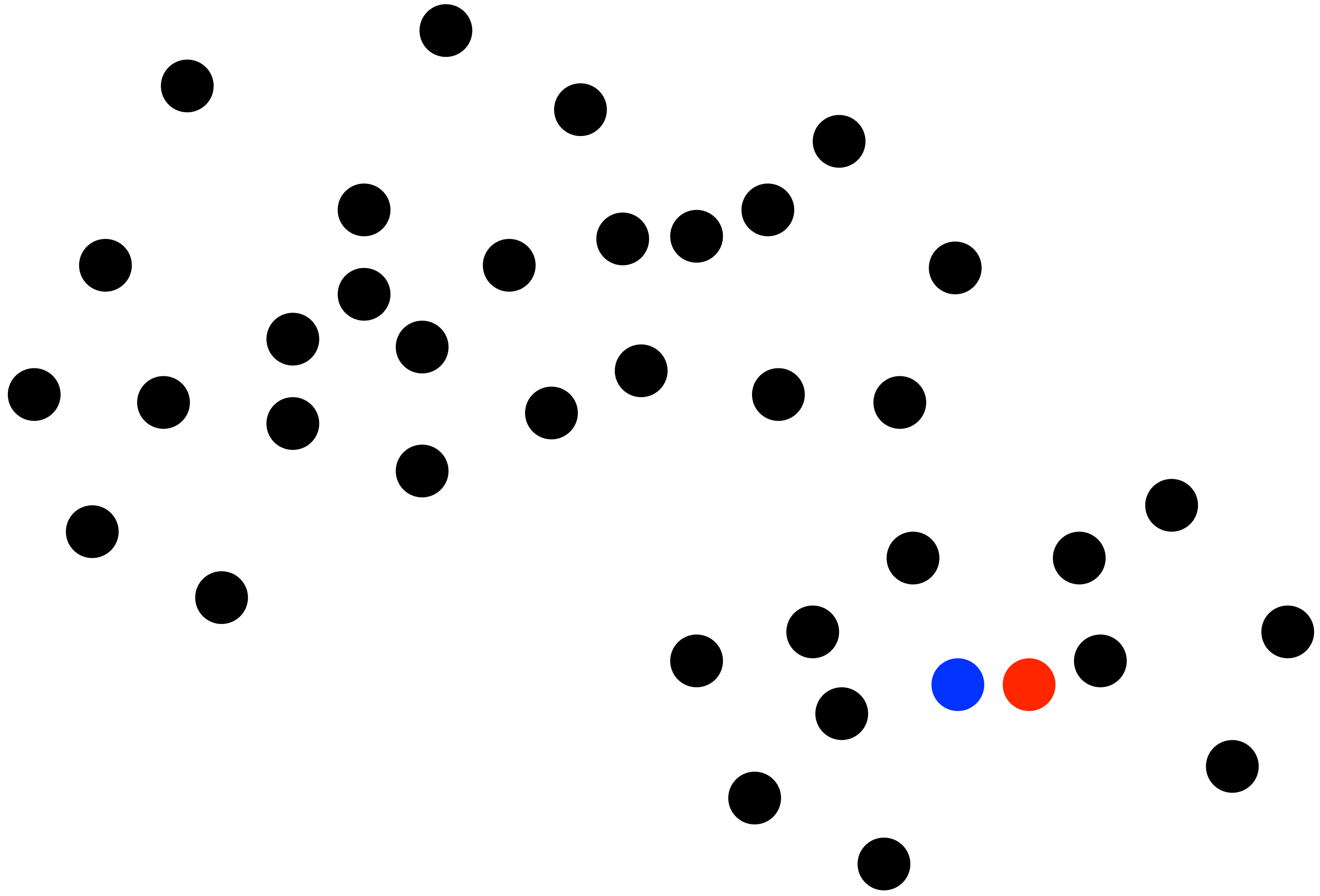
K-means Clustering

bad seeds?



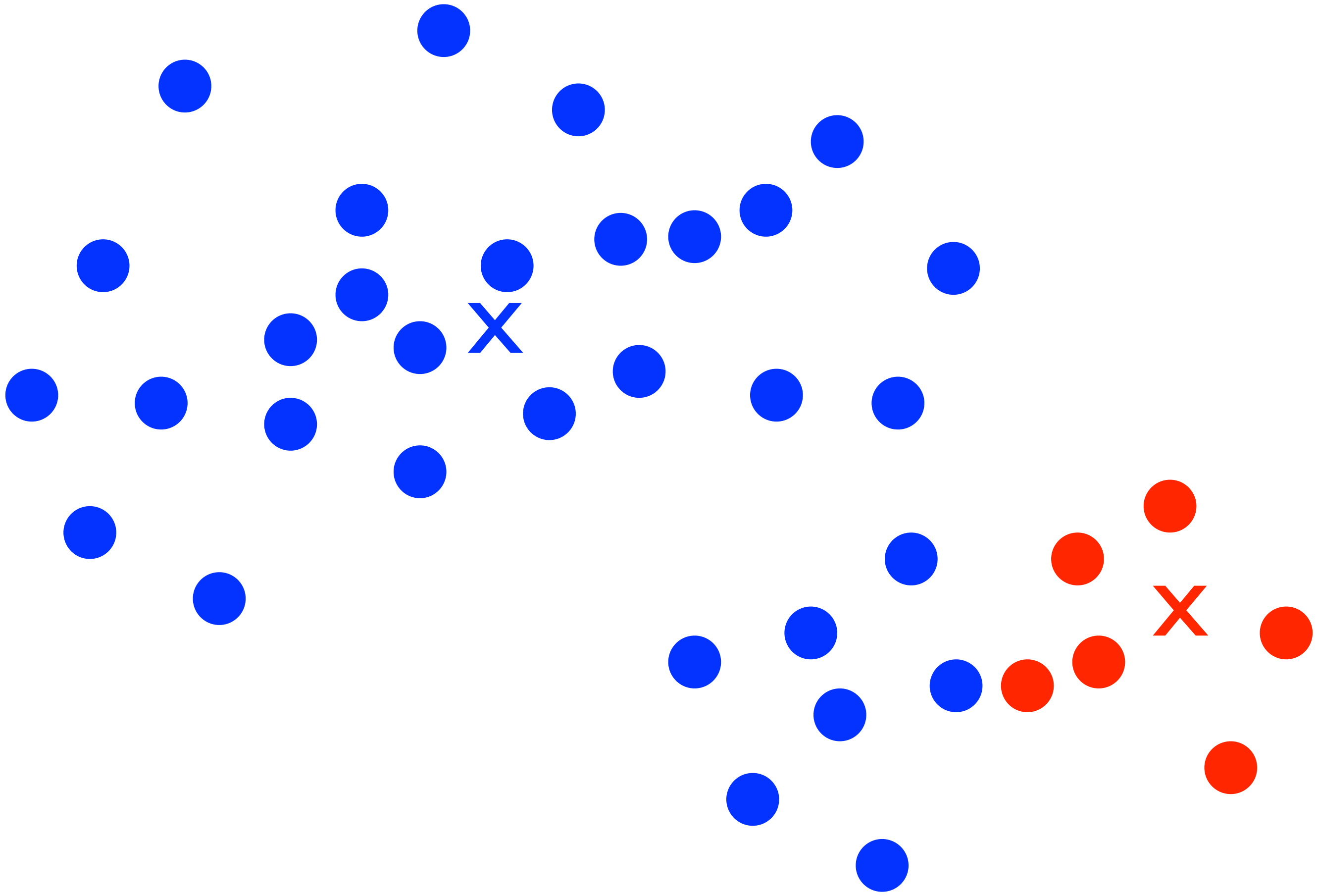
K-means Clustering

bad seeds?



K-means Clustering

bad seeds?



K-means Clustering

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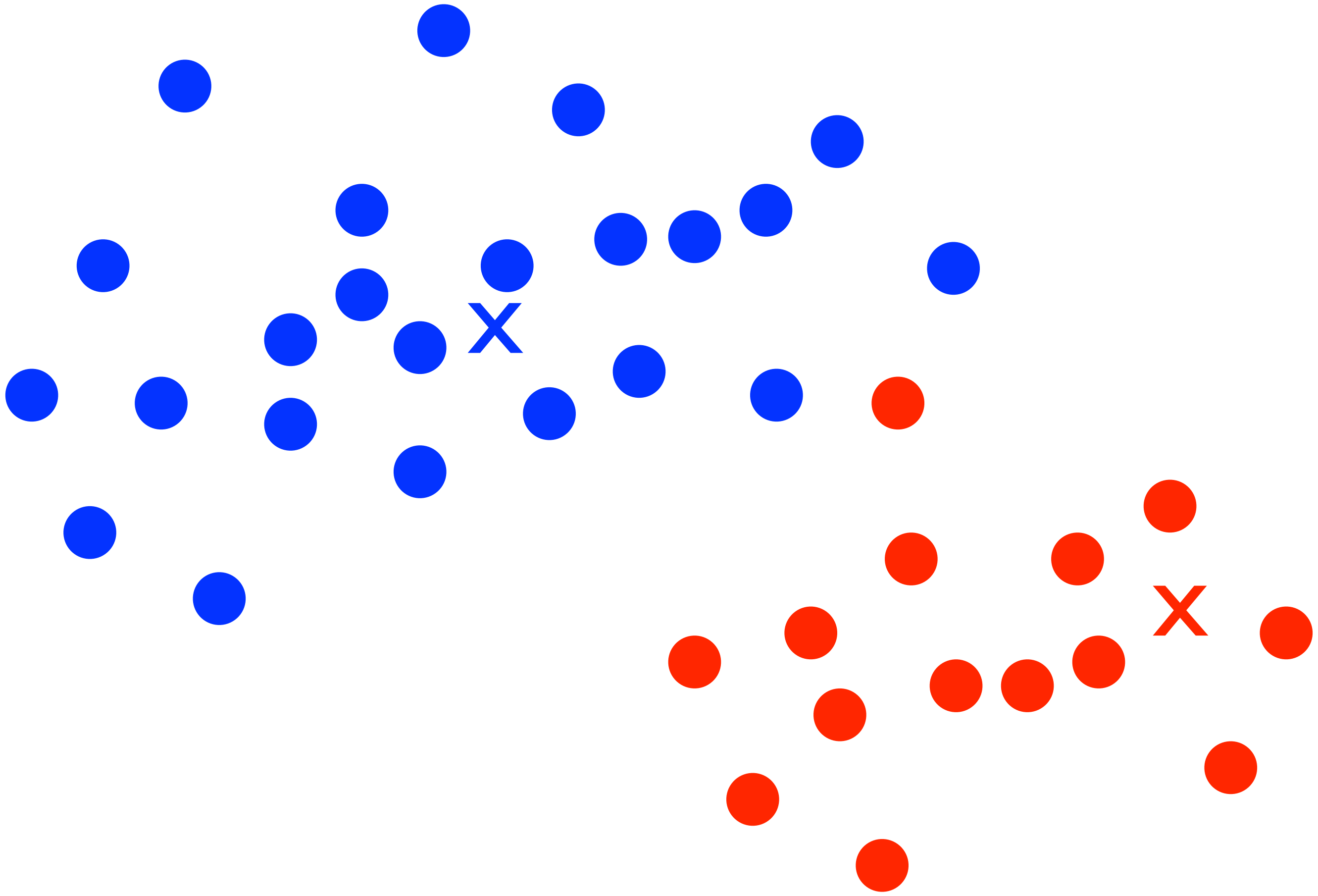
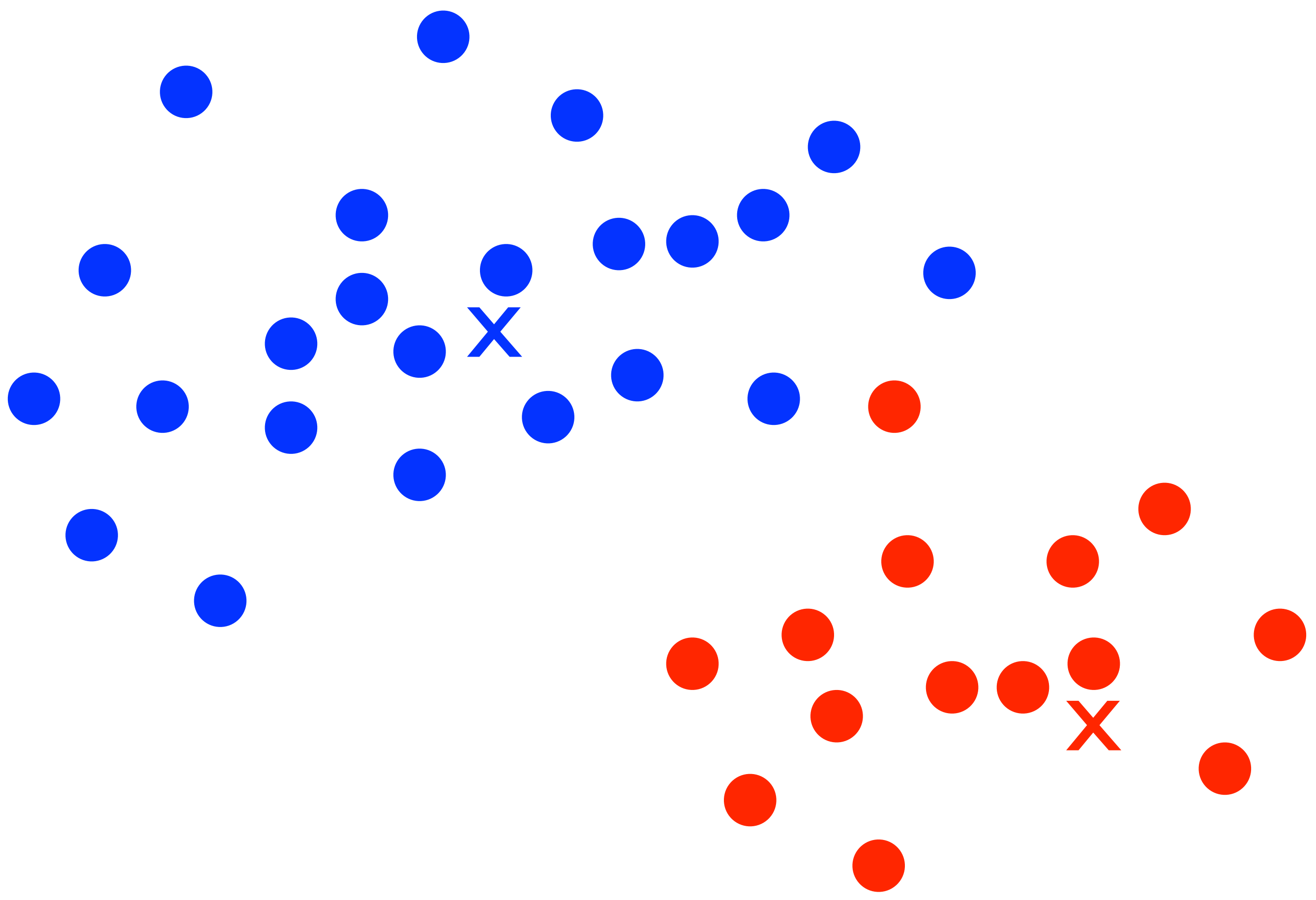


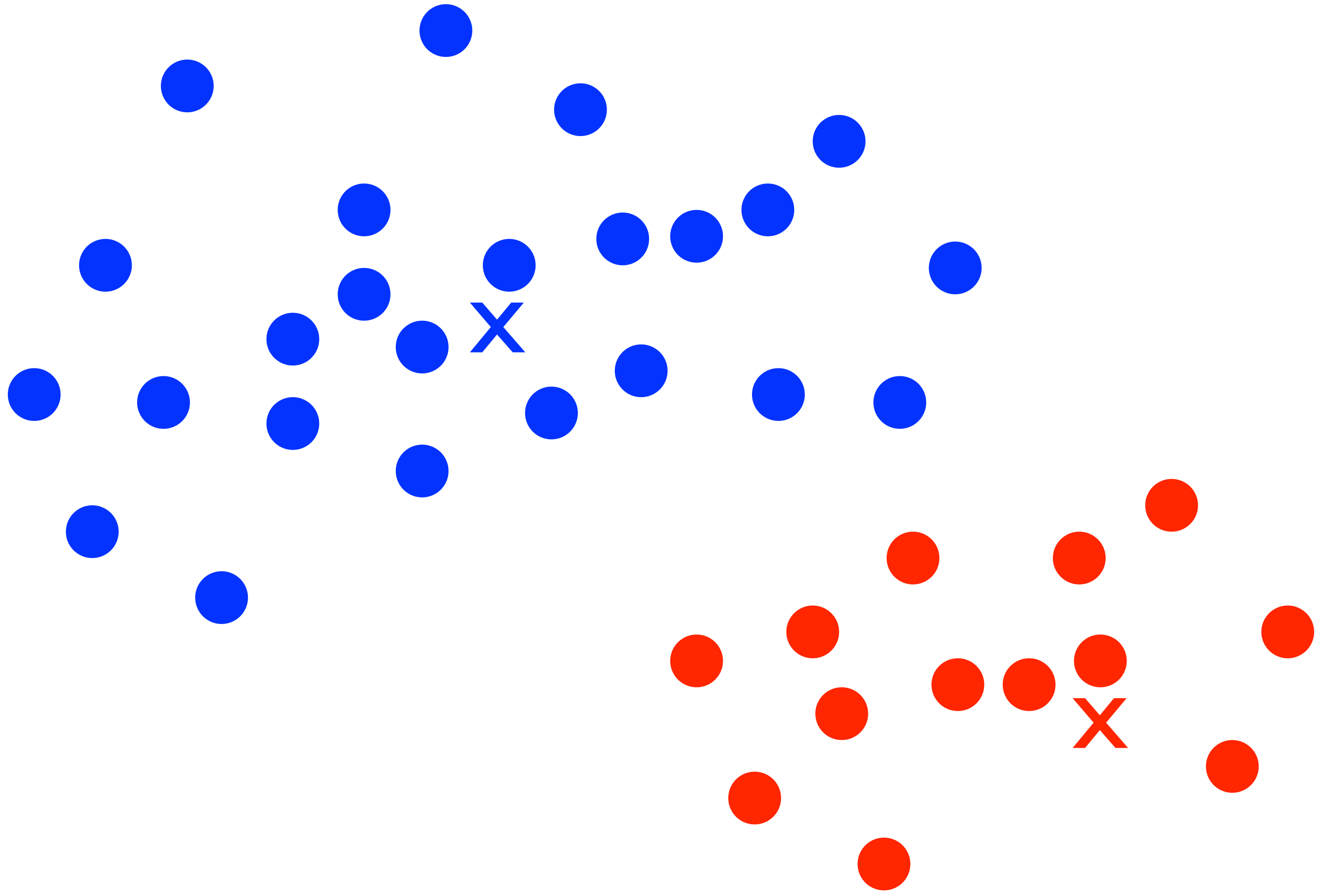
K-means Clustering

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

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

K-means Clustering

improved k-means

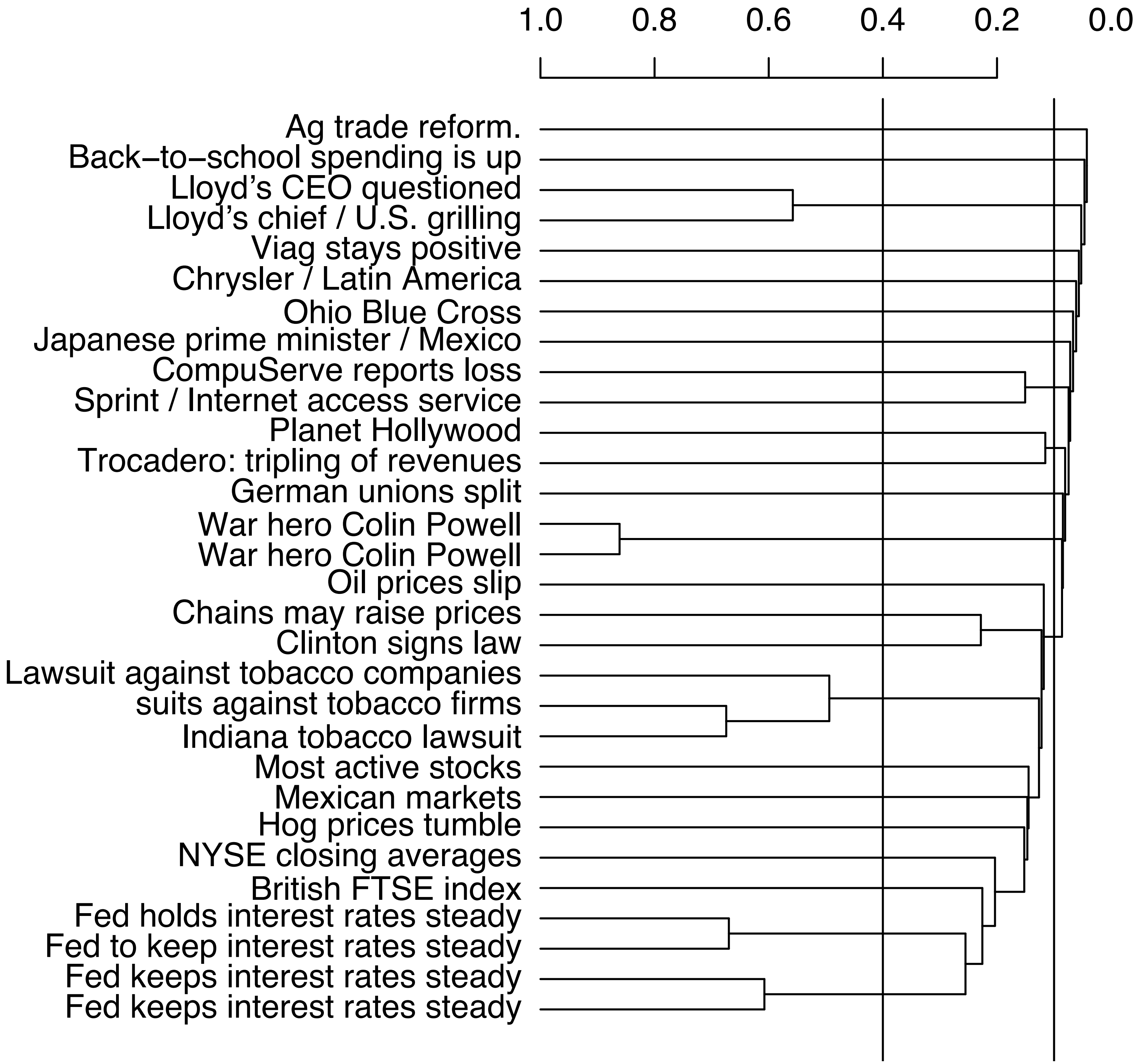
- Given a set of documents and a value K, run K-means clustering N times and keep the clustering that produces the greatest difference between the inter-cluster distance and the intra-cluster distance

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
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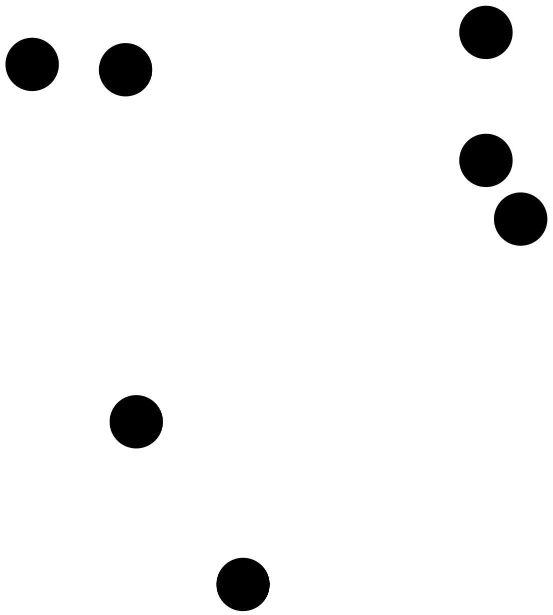
Bottom-up Clustering

- 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

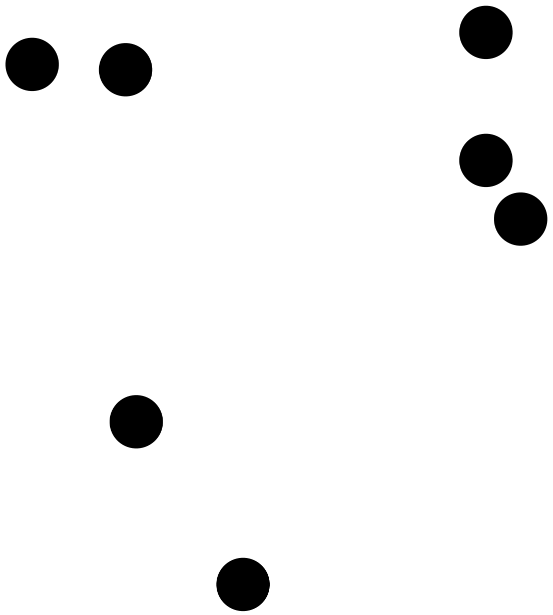
- Step 1: consider each document its own cluster



Bottom-up Clustering

single-link

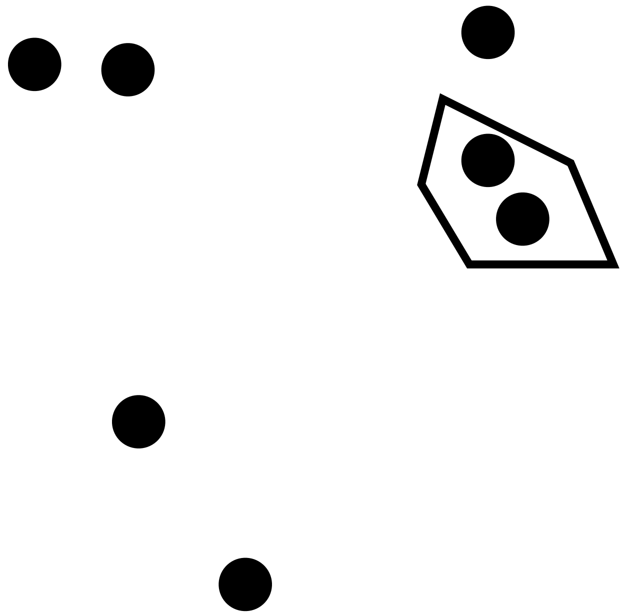
- Step 2: compute the distance between all cluster pairs
- Step 3: merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

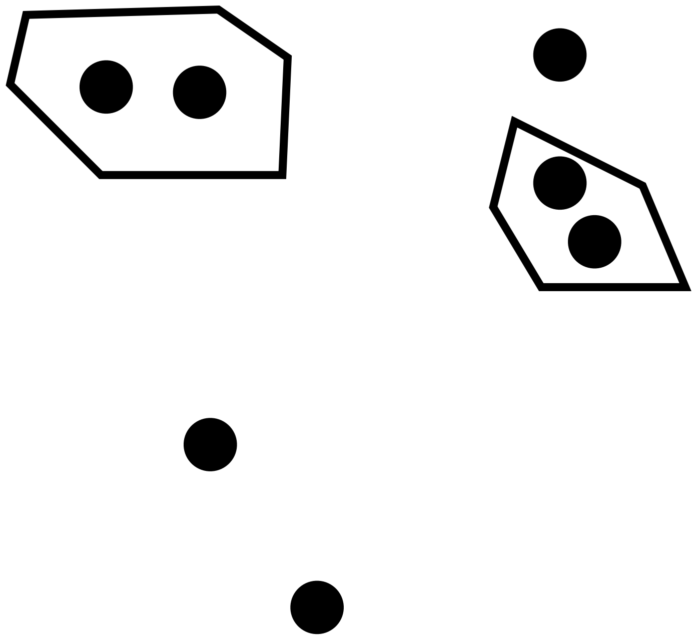
- Step 2: compute the distance between all cluster pairs
- Step 3: merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

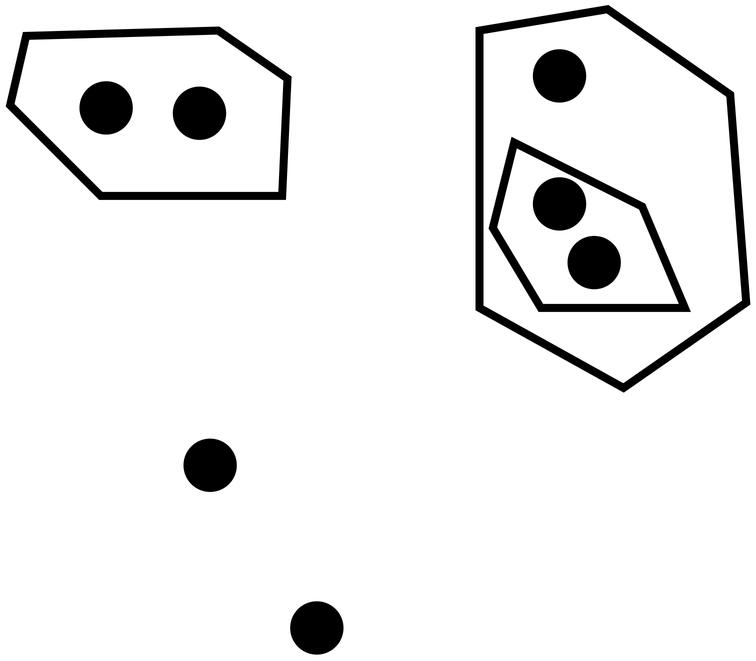
- Step 2: compute the distance between all cluster pairs
- Step 3: merge/combine the nearest two clusters into one



Bottom-up Clustering

single-link

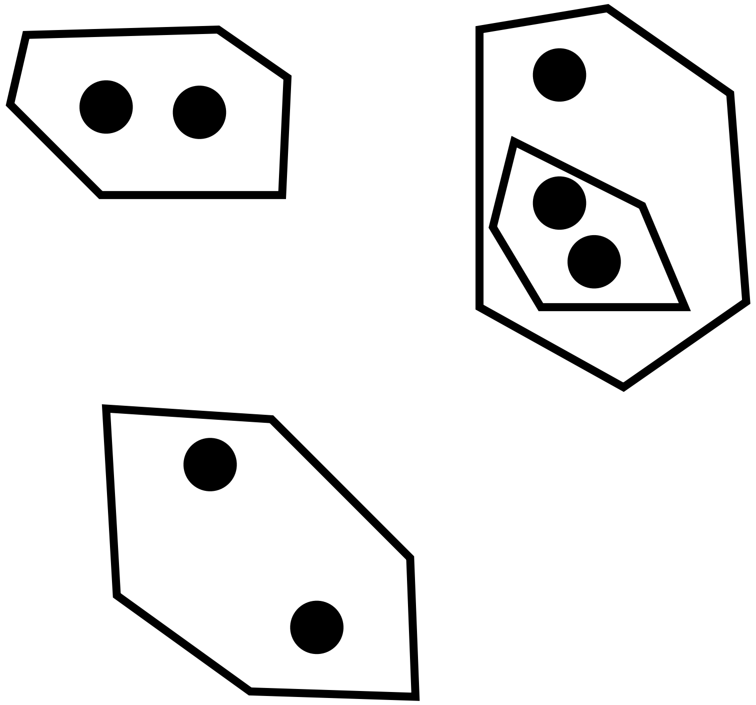
- Step 2: compute the distance between all cluster pairs
- Step 3: merge/combine the nearest two clusters into one



Bottom-up Clustering

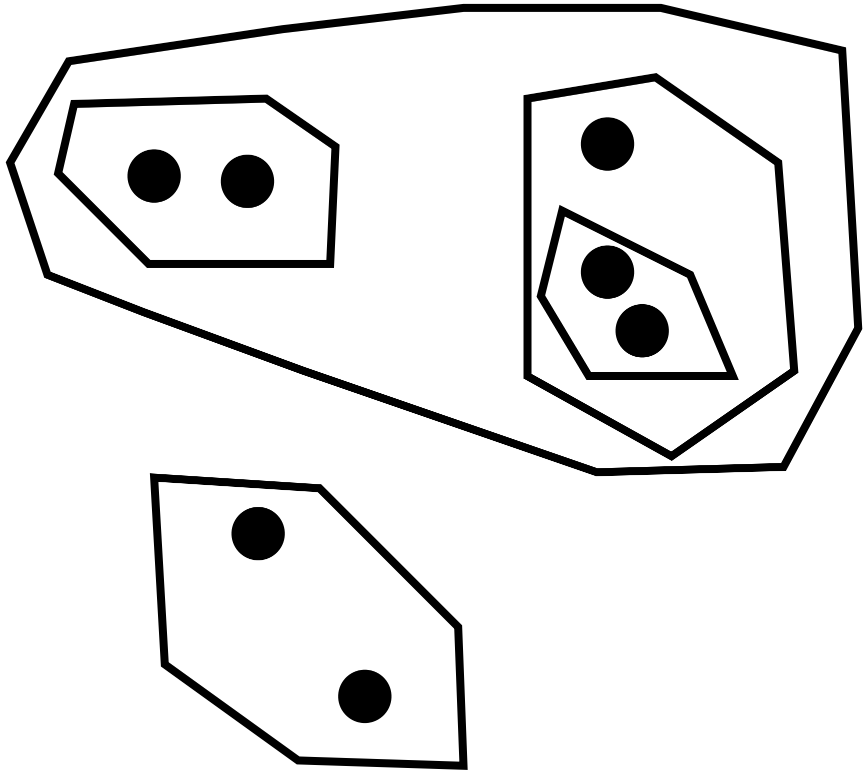
single-link

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



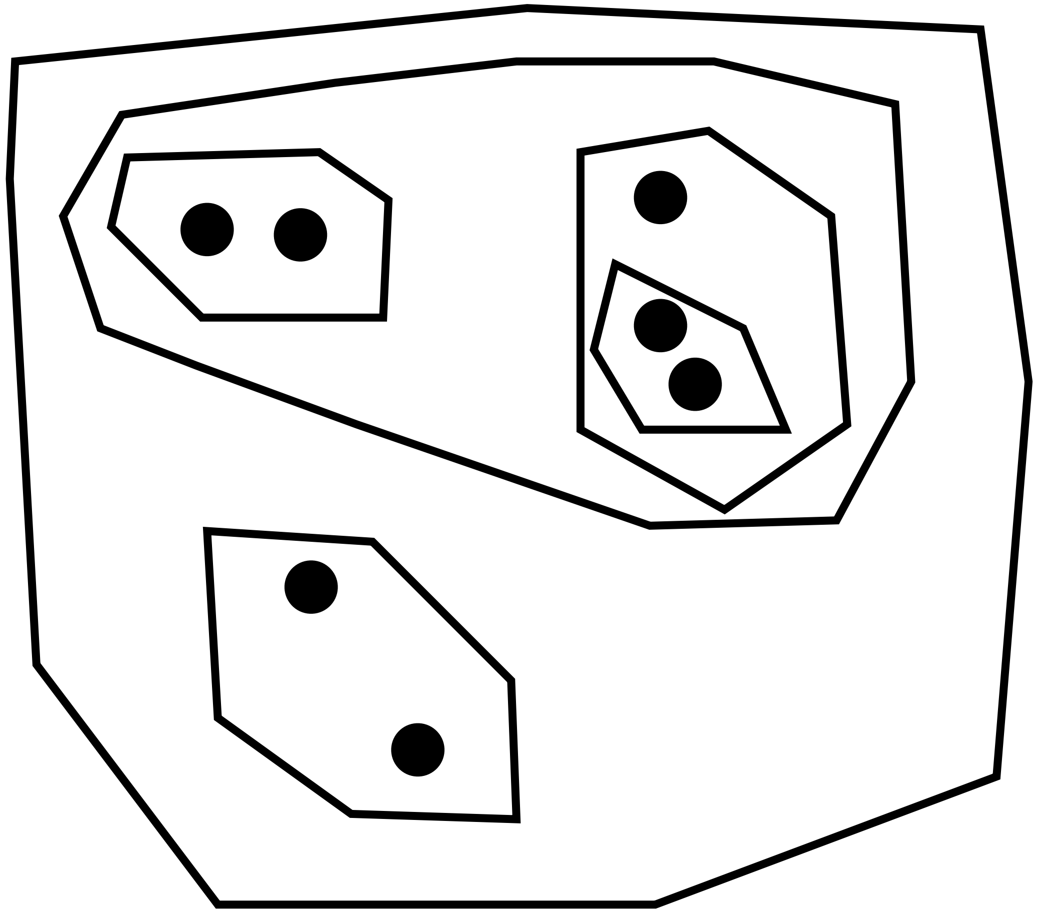
Bottom-up Clustering
single-link

- 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



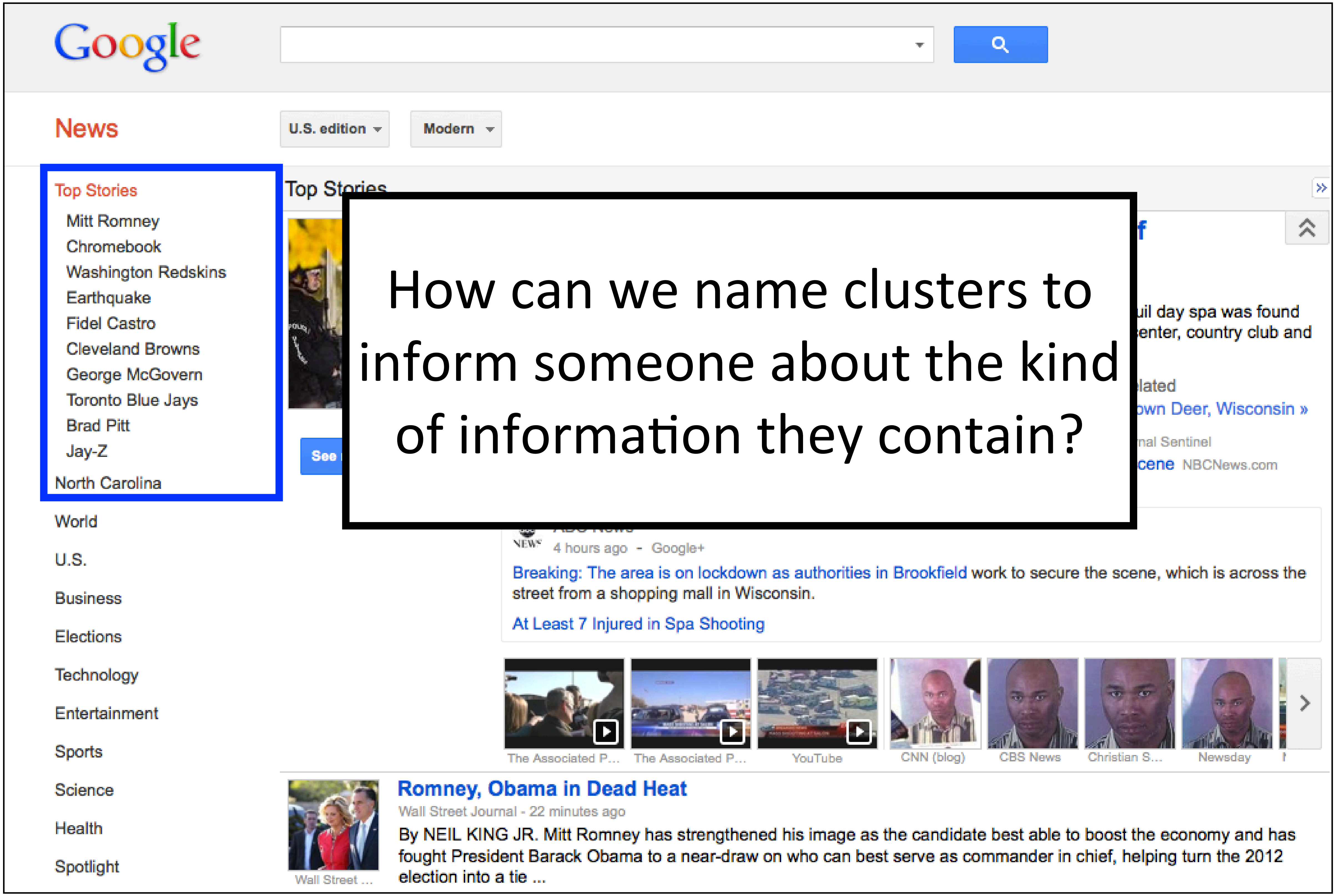
Bottom-up Clustering

- 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



News

Top Stories

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

North Carolina

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U.S.

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Top Stories

uil day spa was found
enter, country club and

lated
own Deer, Wisconsin »
nal Sentinel
cene NBCNews.com

ABC News
4 hours ago - Google+

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

The Associated P... The Associated P... YouTube CNN (blog) CBS News Christian S... Newsday

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 ...

Wall Street ...

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

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

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

- **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

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

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

Mutual Information

- Every document falls under one of these quadrants

	belongs to cluster **c**	does not belong to cluster **c**
contains word **w**	a	b
does not contains word **w**	c	d

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

P(w,c) = ???

P(c) = ???

P(w) = ???

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

Mutual Information

- Every document falls under one of these quadrants

	belongs to cluster c	does not belong to cluster c
contains word w	a	b
does not contains word w	c	d

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

P(w,c) = a / N

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

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

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

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

Predictive Analysis with Noisy Labelers (Assignment 3)

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October 31, 2016

- What are the best strategies for training ML models using noisy labels?