Exploratory Data Analysis: Clustering

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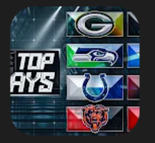

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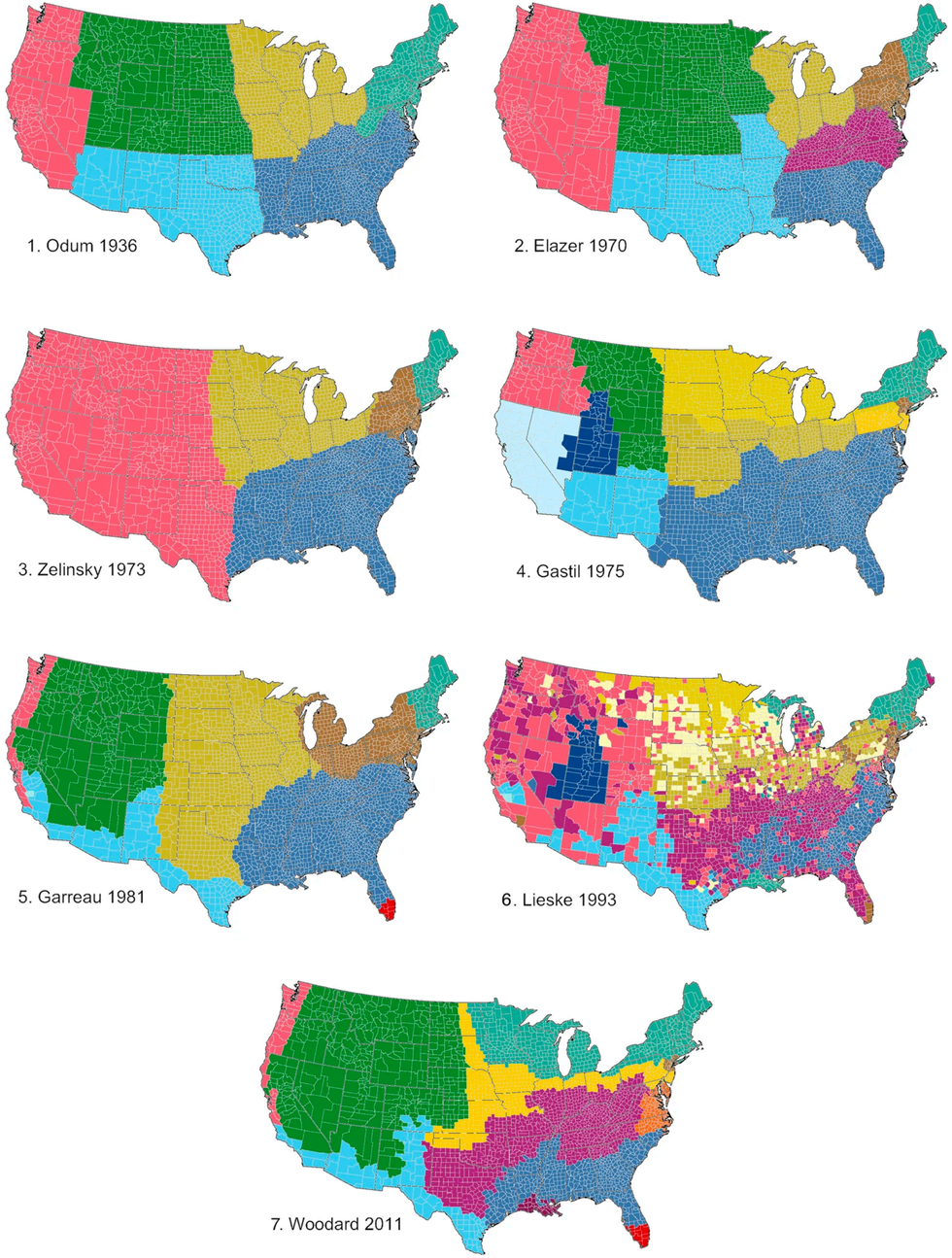
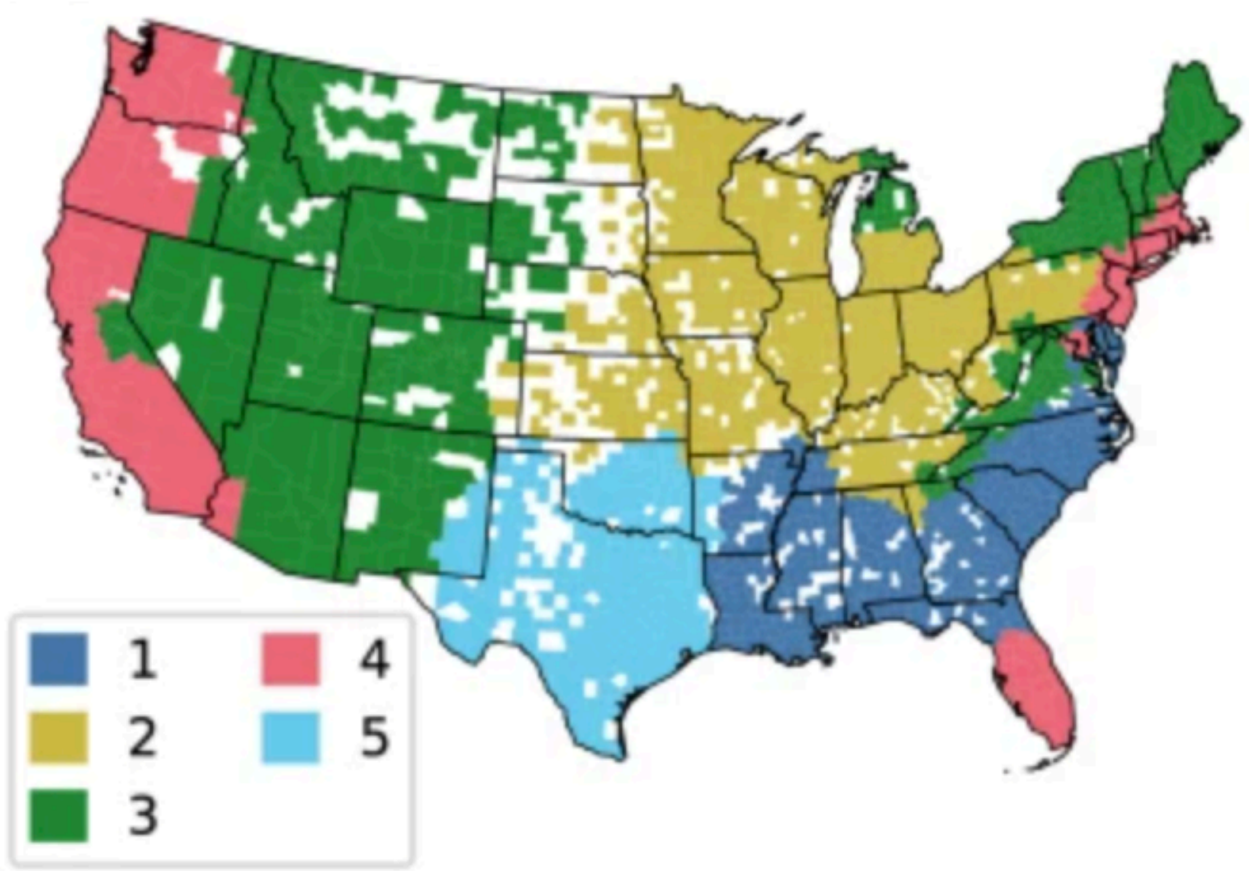


American cultural regions from surveys



American cultural regions mapped from social media text

Story so far

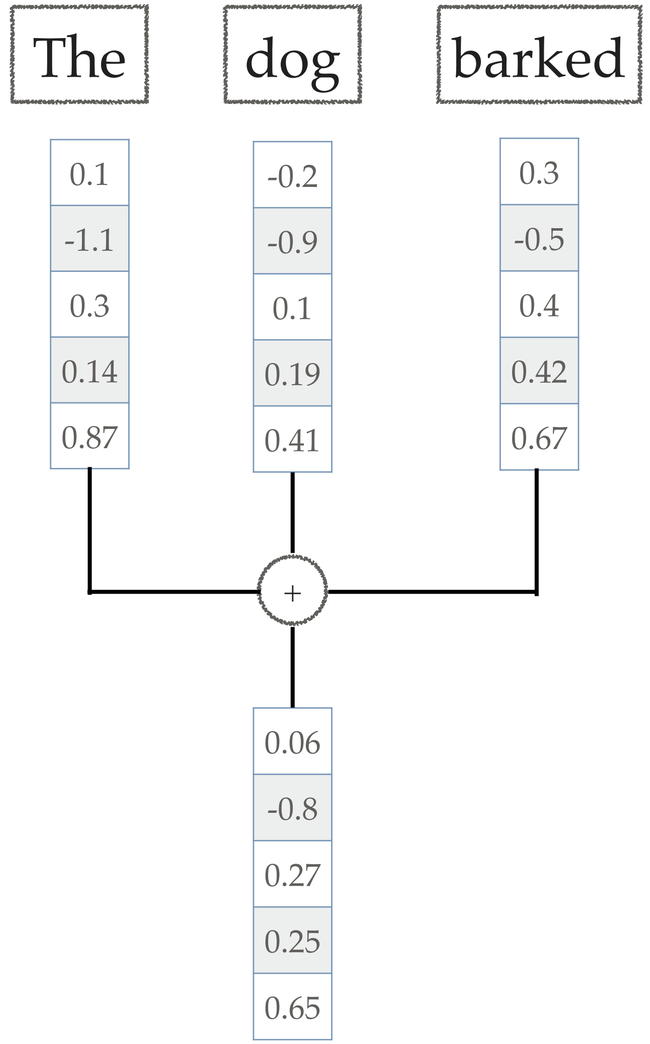
- The term document matrix is a representation to encode the statistics of a corpus
- In this matrix, words and documents can both be treated as vectors.

	d_1	d_2	d_3	…	d_m
w_1	2				1
w_2		3		1	
w_3	1				
…					
w_n			5	3	

Term-Document Matrix

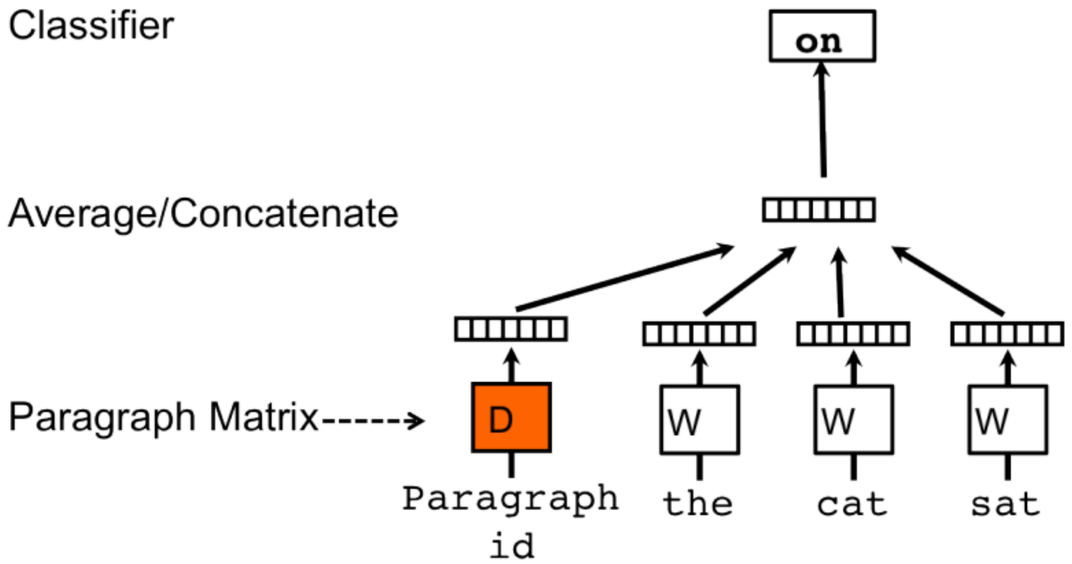
Sparse to dense representations

- We can learn dense representations of words using word2vec and then derive a document vector from the word vectors by simple averaging



Doc2Vec

- We can also directly learn a document vector by modifying the word2vec algorithm



Source: Le and Mikolov (2014) "Distributed Representations of Sentences and Documents"

Matrix Factorization

	d_1	d_2	d_3	…	d_m
w_1	2				1
w_2		3		1	
w_3	1				
…					
w_n			5	3	

Term-Document Matrix

$\approx$

w_1	0.1	-0.13	-1.2	0.15	1.23
w_2	0.2	-0.1	-0.2	0.45	1.4
w_3	…	…	…	…	…
…	…	…	…	…	…
w_n	0.15	-0.5	-0.3	0.23	-1.2

Word vectors

$\times$

	…	…	…	…	…
	…	…	…	…	…
	…	…	…	…	…
	…	…	…	…	…
	…	…	…	…	…

$\times$

	d_1	d_2	d_3	…	d_m
	0.1	-0.1	-0.2	0.11	1.21
	0.4	-0.2	-0.7	0.41	1.1
	…	…	…	…	…
	…	…	…	…	…
	0.35	-0.1	-0.2	0.32	-1.9

Document vectors

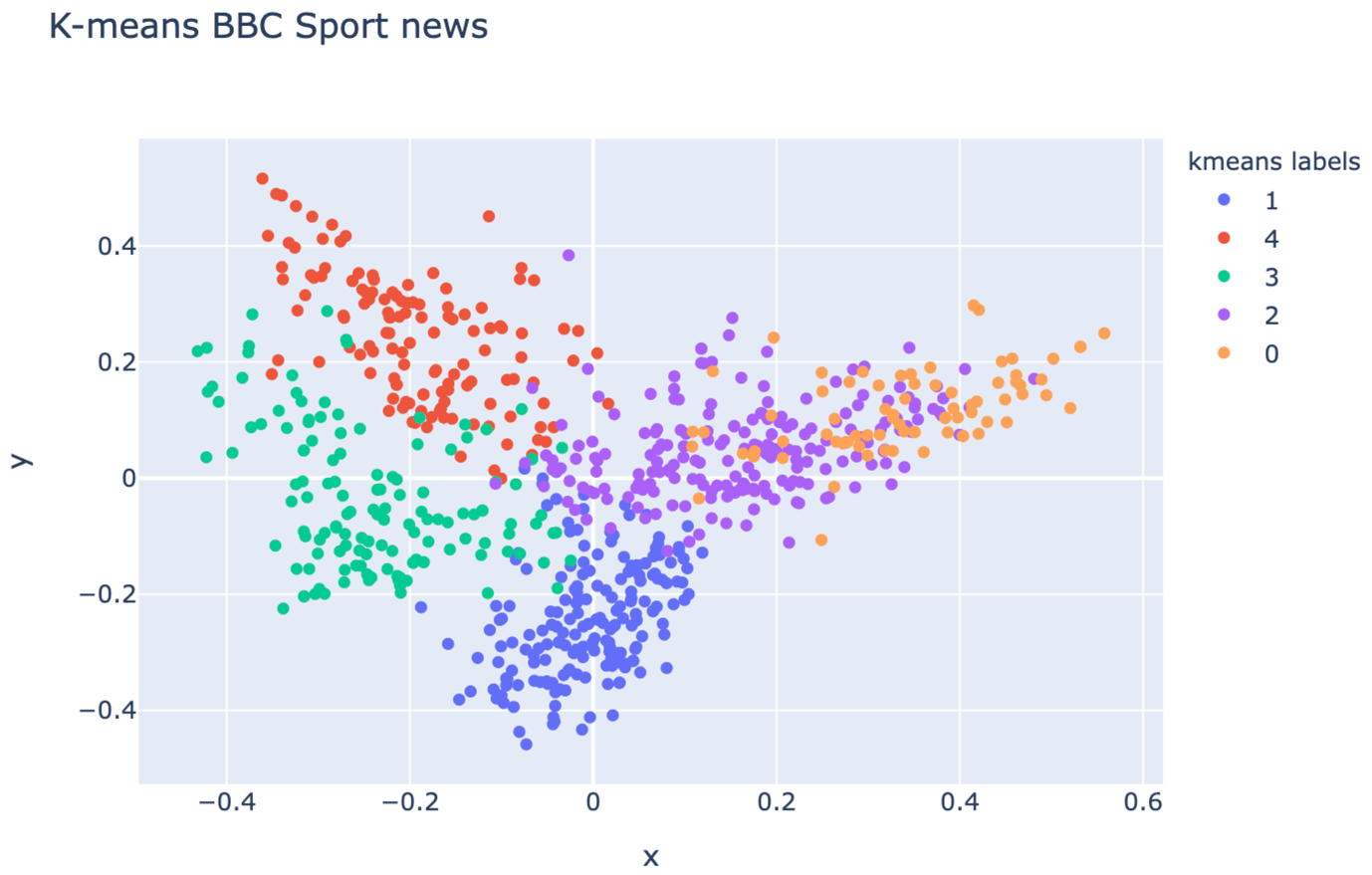
$\mathbb{R}^{n \times m}$ $\mathbb{R}^{n \times k}$ $\mathbb{R}^{k \times k}$ $\mathbb{R}^{k \times m}$

Question for the day

"How to group documents (e.g., speeches, lyrics, papers, tweets, etc) using their text?"

Input: documents/words

Output: partitions

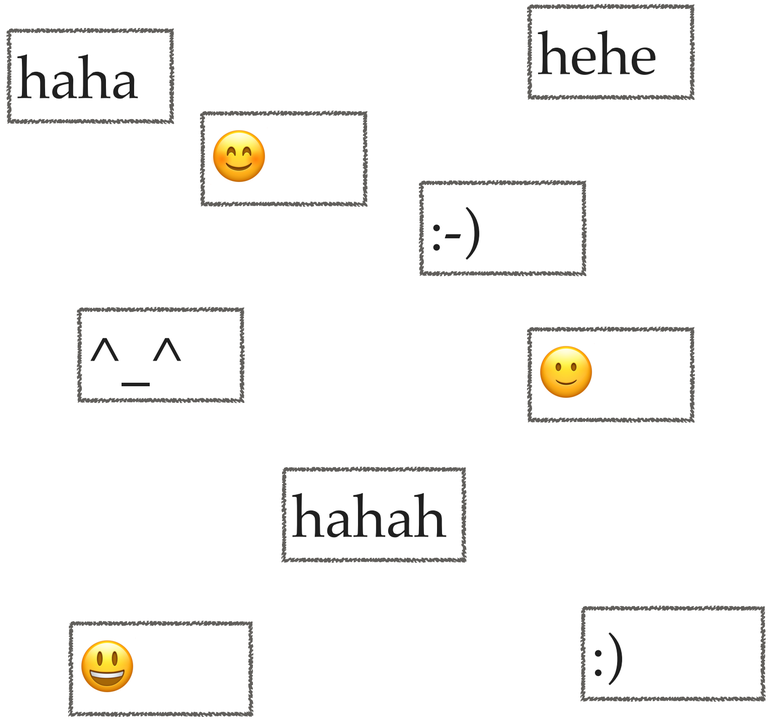


https://github.com/jbesomi/texthero

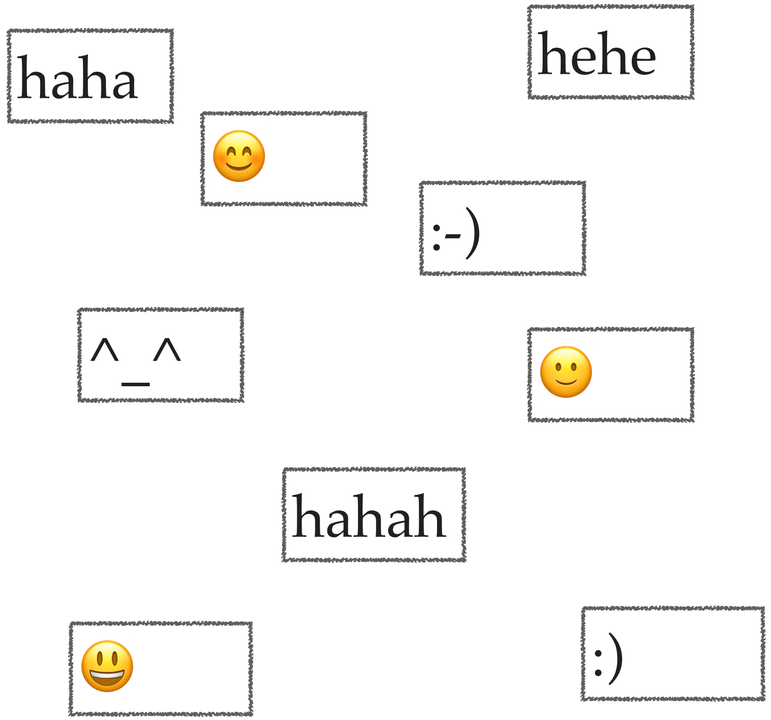
Agenda

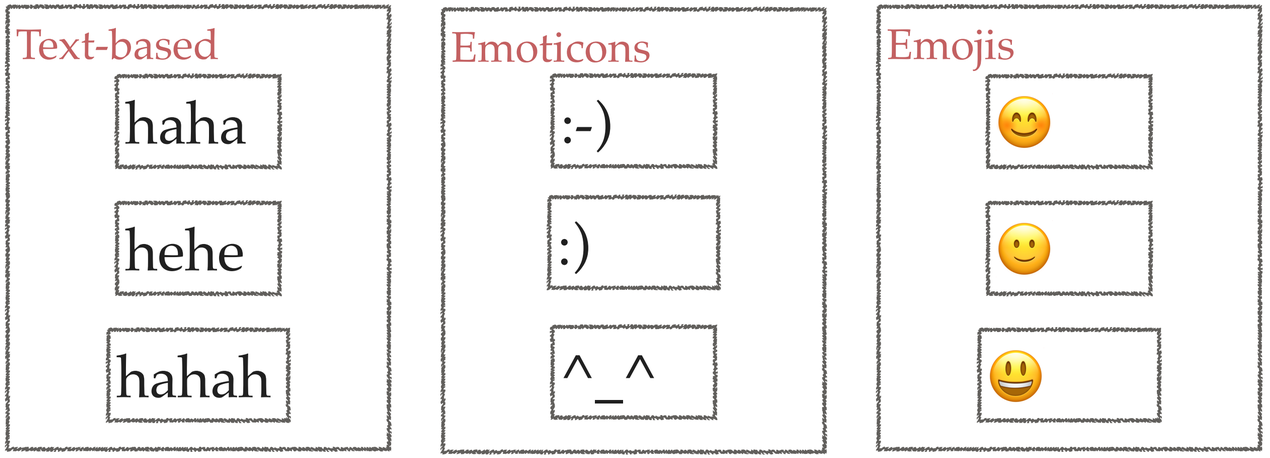
- What are the techniques of grouping documents?
- What are the challenges in grouping documents?
- How to evaluate grouping?

Example I

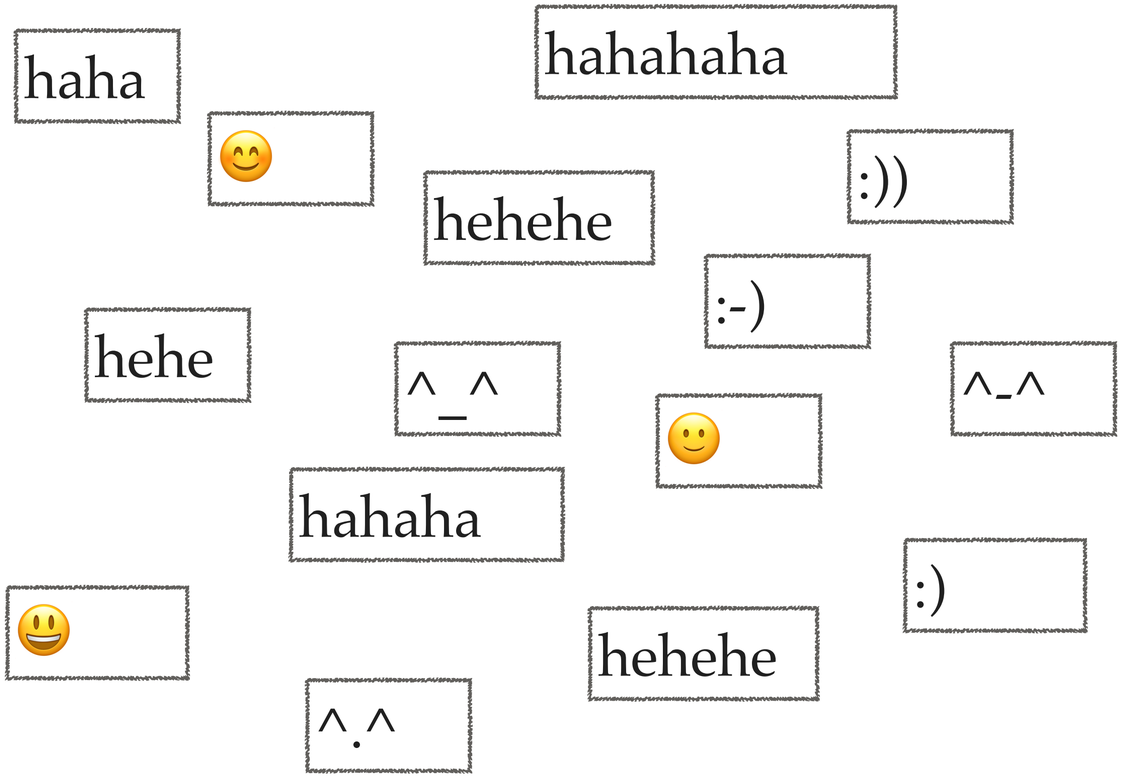


Example I

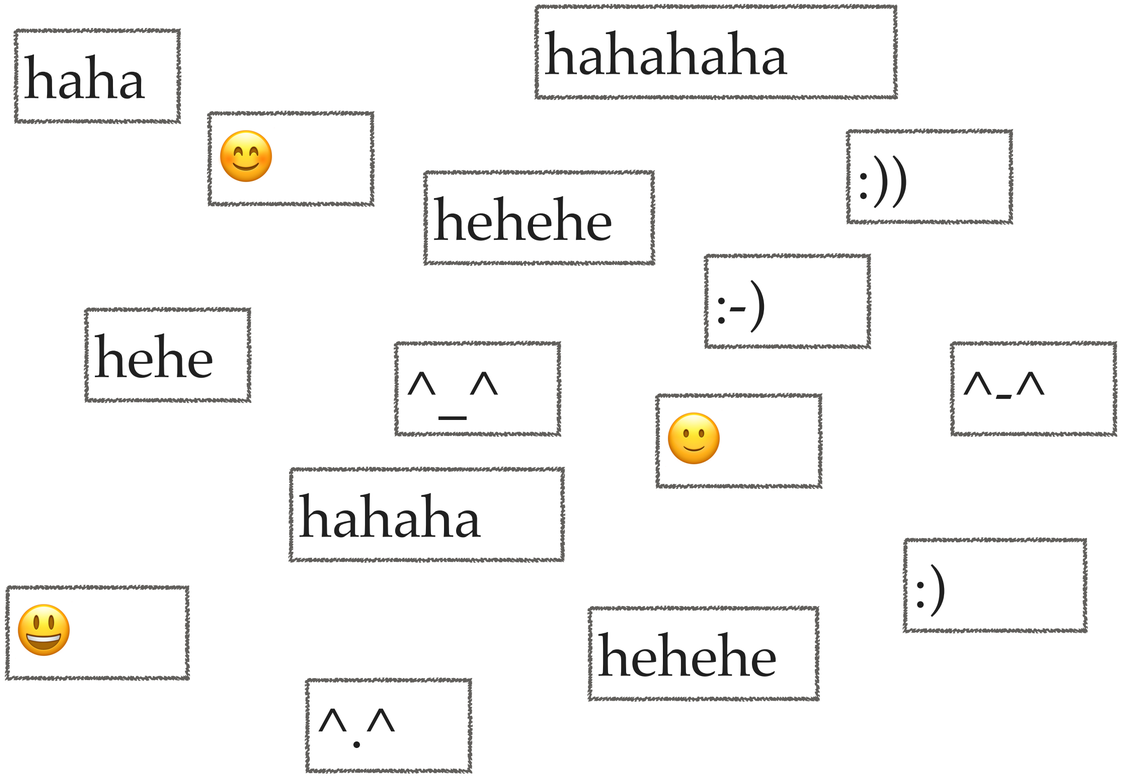

haha
hehe
😊
:-)
^_^
🙂
hahah
😀
:)


Text-based
haha
hehe
hahah
Emoticons
:-)
:)
^_^
Emojis
😊
🙂
😀

Example II



Example II



Text-based

ha-variation
haha
hahaha
hahahaha

he-variation
hehe
hehehe
hehehehe

Emoticons

Sideface emoticons
:)
:))
:-)

Frontface emoticons
^_^
^.^
^_^

Emojis

Clustering techniques

- Many ways but the most popular is kmeans clustering and its variations

KMeans

KMeans

- Let d be a document; $d \in \mathbb{R}^m$
- D is a set of documents; $D = [d^{(1)}; d^{(2)}; \cdots; d^{(|D|)}] \in \mathbb{R}^{|D| \times m}$

KMeans

- Let d be a document; $d \in \mathbb{R}^m$
- D is a set of documents; $D = [d^{(1)}; d^{(2)}; \cdots; d^{(|D|)}] \in \mathbb{R}^{|D| \times m}$
- Objective: Find a partition set $\Pi = \{\pi_1, \pi_2, \ldots, \pi_k\}$ such that:
  - $\pi_i \cap \pi_j = \phi$ and $\pi_i \cup \pi_j = D$
  - dist($d_i^{(q)}$,$d_j^{(r)}$) should be small if $i = j$
  - dist($d_i^{(q)}$,$d_j^{(r)}$) should be big if $i \neq j$

KMeans

KMeans

- Choose k

KMeans

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- Initialize k vectors of m dimensions as cluster centers

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- Repeat until convergence:

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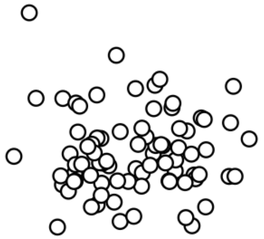
  - For every document, assign closest cluster center

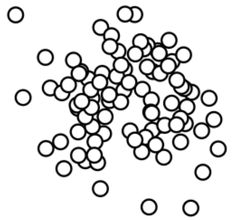
KMeans

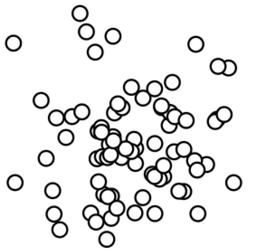
- Choose k
- Initialize k vectors of m dimensions as cluster centers
- Repeat until convergence:
  - For every document, assign closest cluster center
  - Recalculate cluster centers based on recent assignments

KMeans

We may have a gaussian data distribution



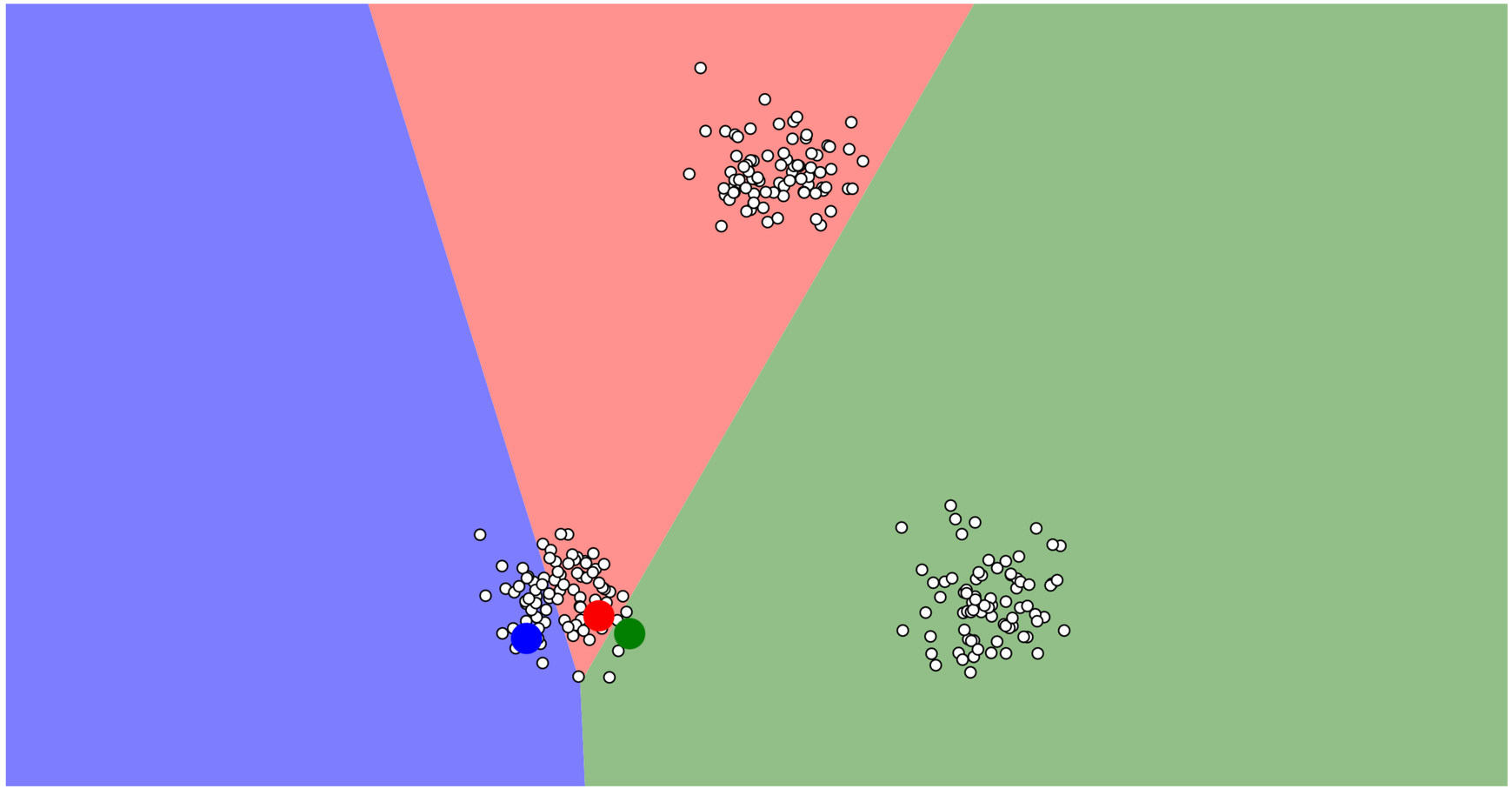




Source: https://www.naftaliharris.com/blog/visualizing-k-means-clustering/

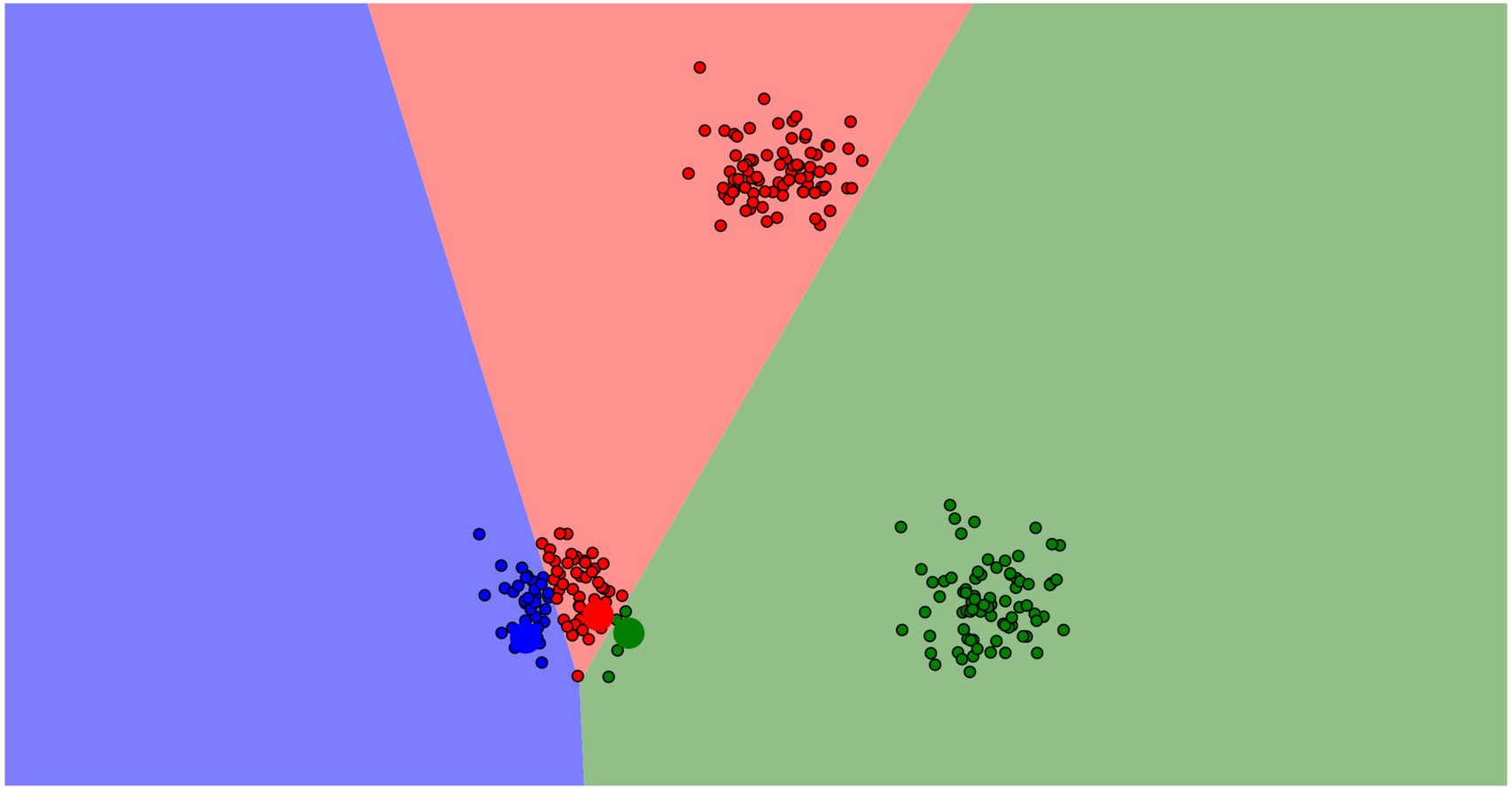
KMeans

Initialize the cluster centers



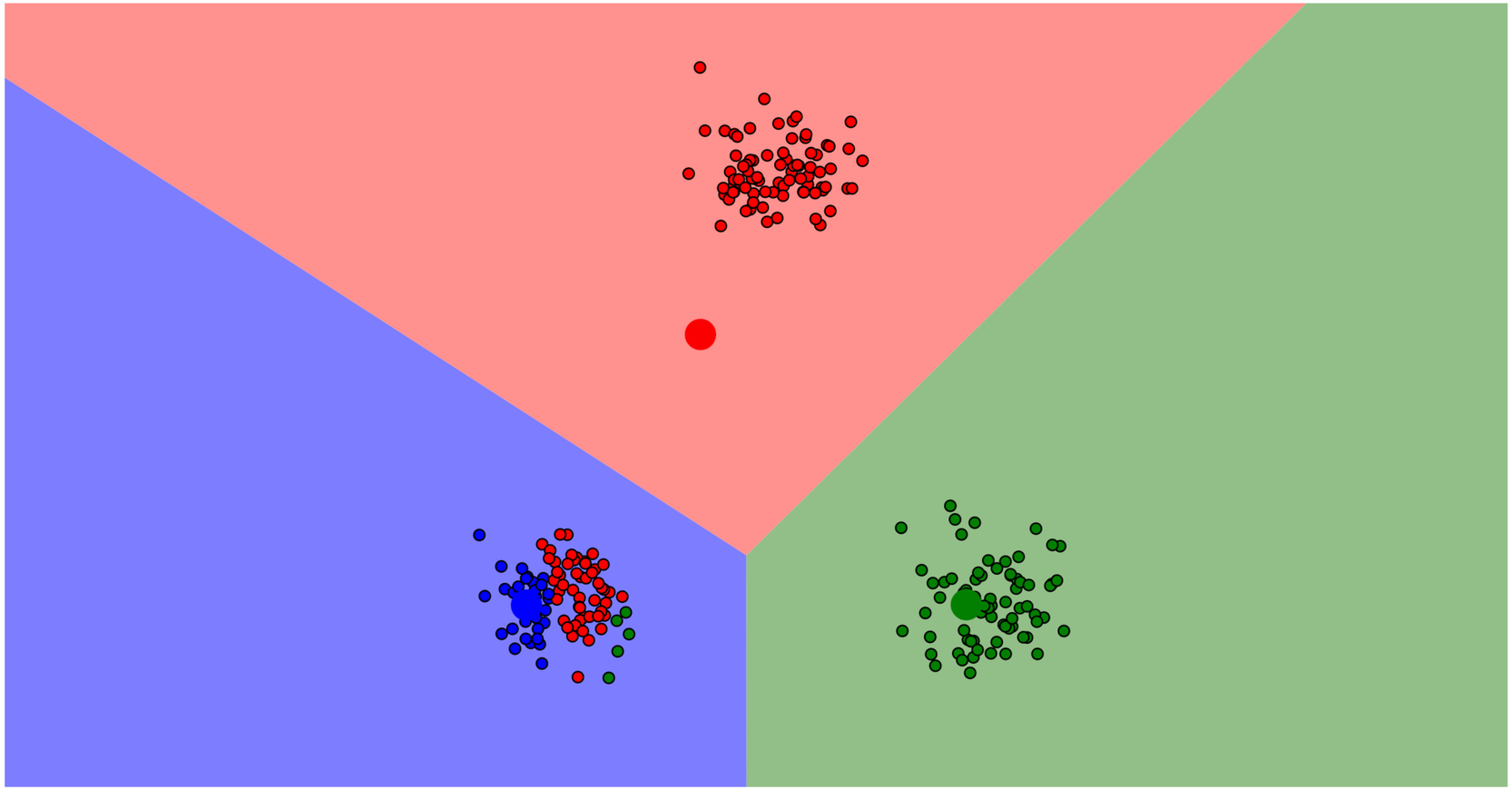
KMeans

Partitions formed based on cluster centers



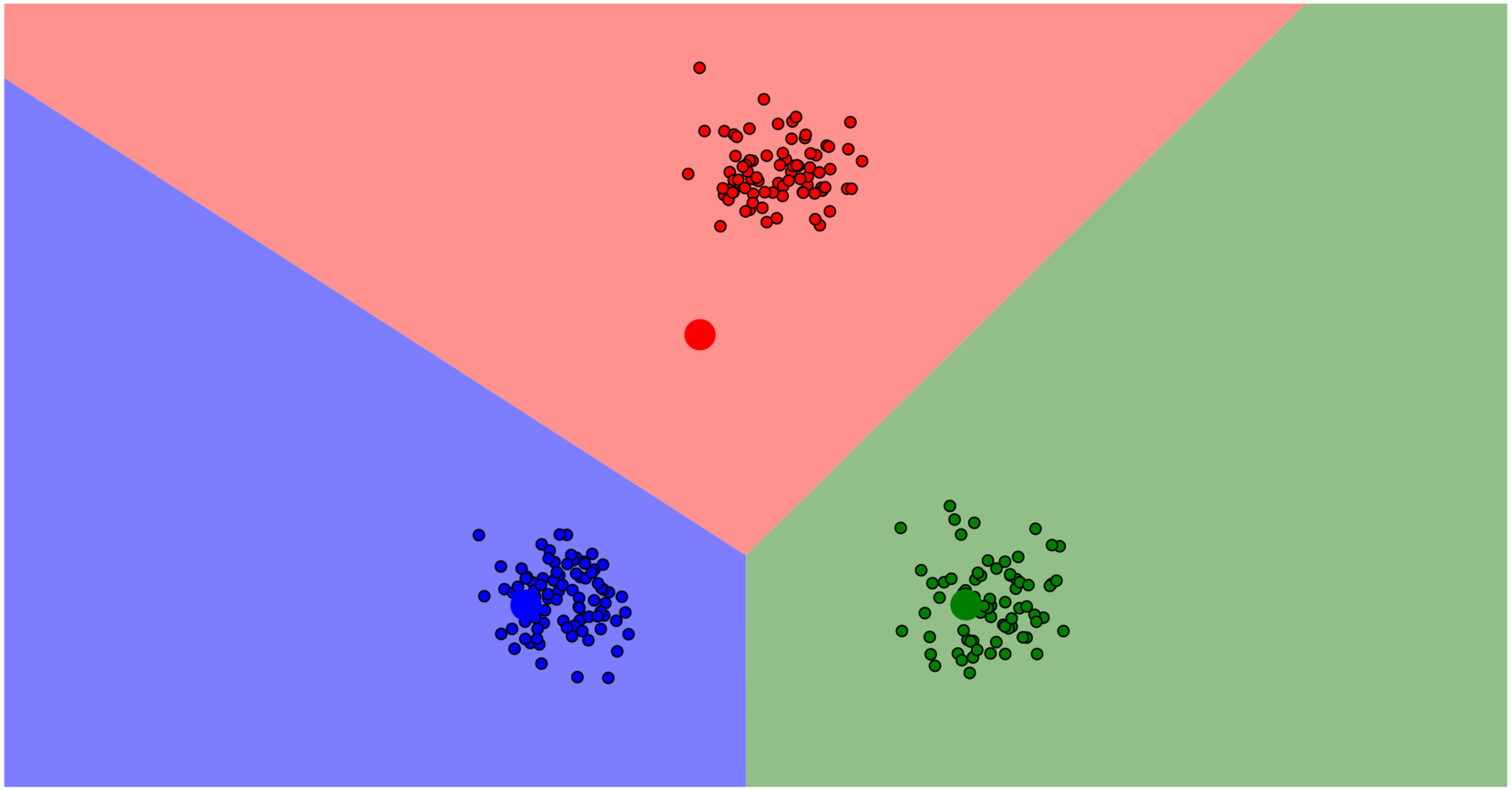
KMeans

Update the cluster centers



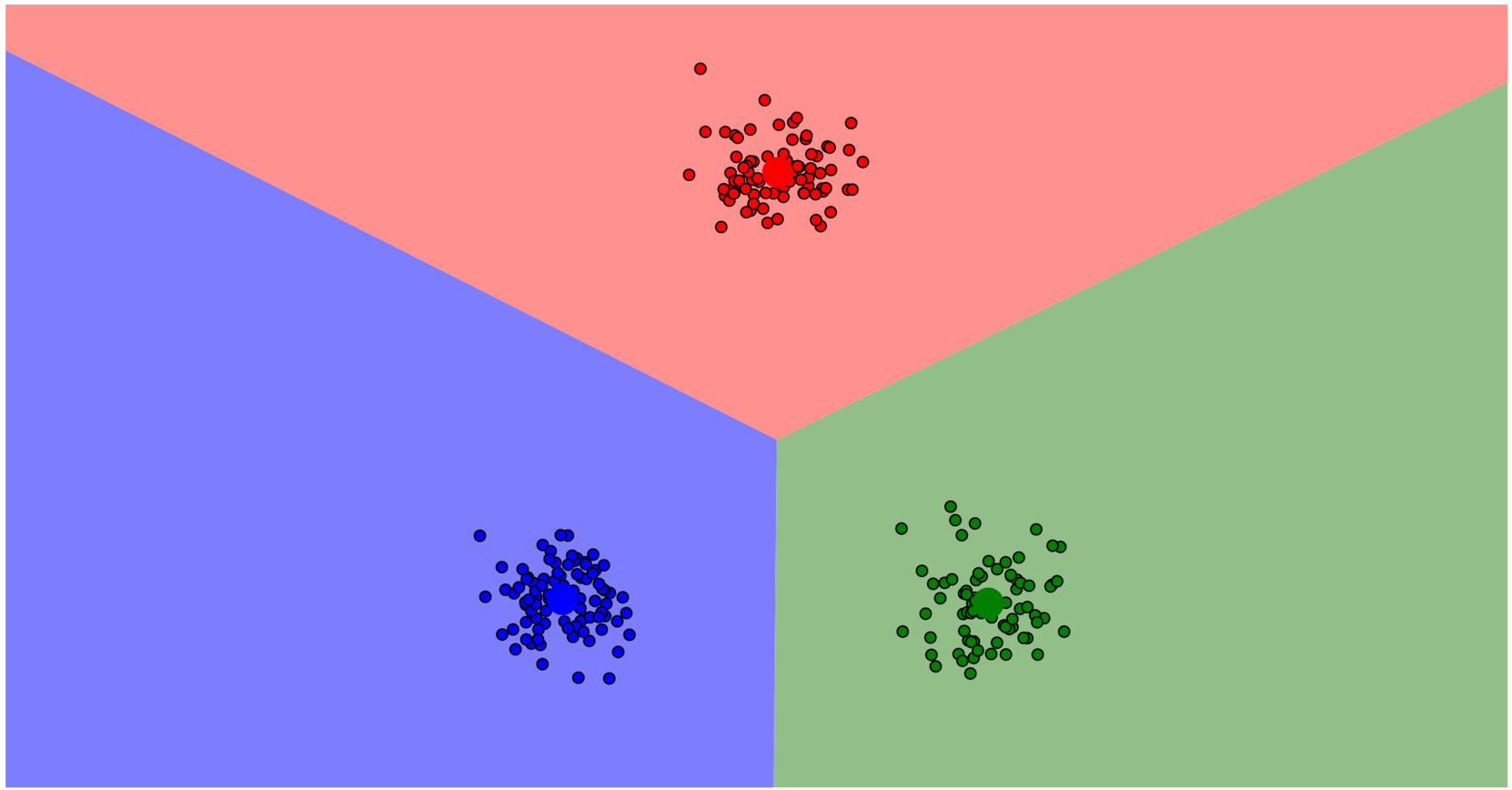
KMeans

Reassign the data points



KMeans

Repeat
until
convergence

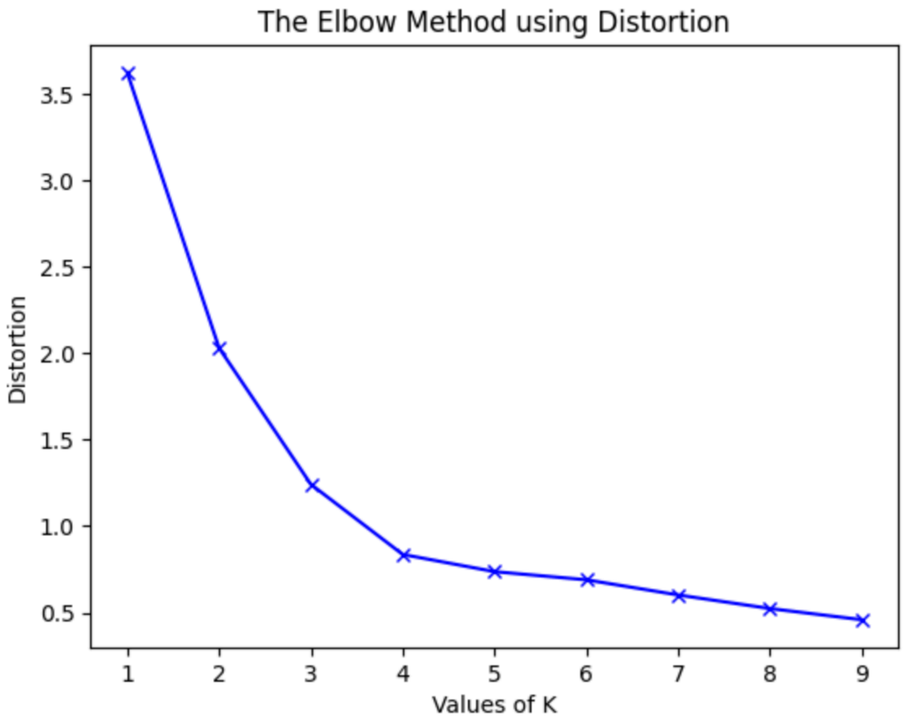


KMeans

- Choose k
- Initialize k vectors of m dimensions as cluster centers
- Repeat until convergence:
  - For every document, assign closest cluster center
  - Recalculate cluster centers based on recent assignments

Choosing K

- Sometimes we know the value k (e.g., political parties)
- In general, use your judgment or some heuristics to find k
- Bayesian non-parametric methods find the optimal k



Initialization

- Initialization may affect convergence time and optimal clustering
- There are some smart initializations but this is a non-trivial problem [see Caleb et. al]

Celebi, M. Emre, Hassan A. Kingravi, and Patricio A. Vela. "A comparative study of efficient initialization methods for the k-means clustering algorithm." Expert systems with applications 40.1 (2013): 200-210.

Repeat

- Each cluster assignment and centroid recalculation step is repeated several times
- Since the algorithm is sensitive to initialization, the entire procedure may be repeated to get stability.

Measuring closeness

- Typically euclidean distances are used to measure closeness
- Non-euclidean metrics or kernel transformations of vectors useful when data is not linearly separable

Text preprocessing

Text preprocessing

- Preprocessing steps such as stop words removal, lemmatization, normalization, etc are crucial

Text preprocessing

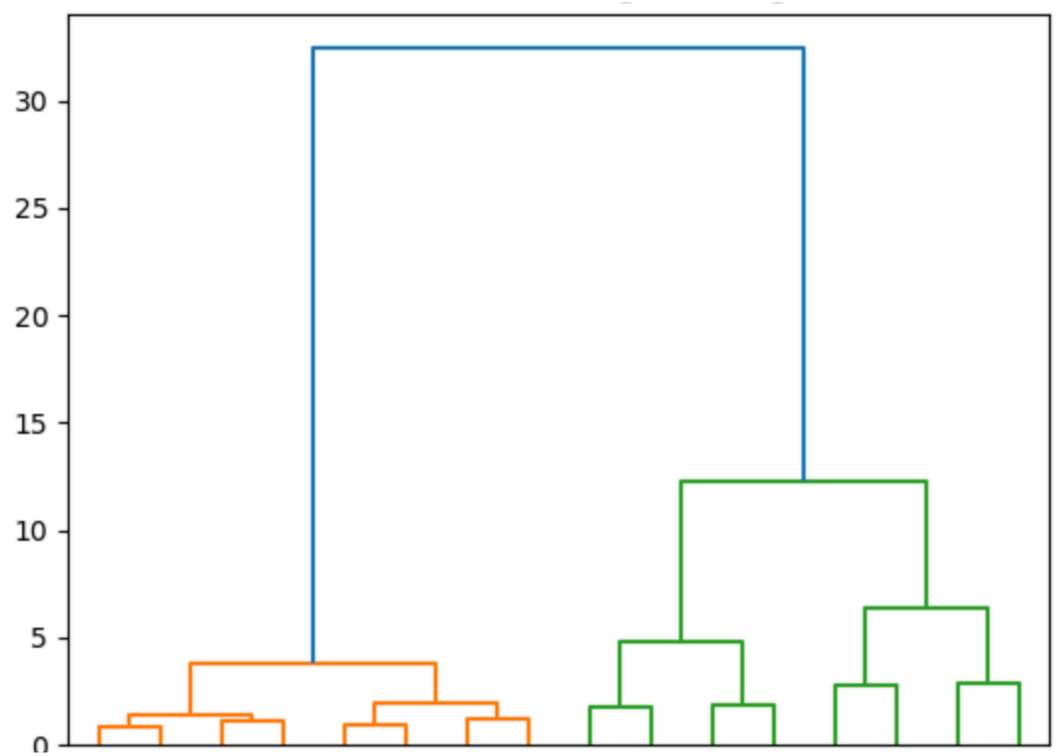
- Preprocessing steps such as stop words removal, lemmatization, normalization, etc are crucial
- In general, clustering works best with dense features than sparse, so some dimensionality reduction technique can also be useful

Shortcomings

- Knowing K is not easy (e.g., how many genres of books?)
- Outliers can have a strong effect on cluster formation
- Kmeans does not extract a hierarchical structure from the data

Other methods

- Agglomerative clustering can extract hierarchical clustering
- Affinity propagation algorithm on a graph



In class

- Clustering demo